Debugging Frame Semantic Role Labeling

Towards robust error analysis of statistical models for automatic frame semantic structure extraction

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Abstract

We propose a quantitative and qualitative analysis of the performances of statistical models for frame semantic structure extraction. We report on a replication study on FrameNet 1.7 data and show that preprocessing toolkits play a major role in argument identification performances, observing gains similar in their order of magnitude to those reported by recent models for frame semantic parsing. We report on the robustness of a recent statistical classifier for frame semantic parsing to lexical configurations of predicate-argument structures, relying on an artificially augmented dataset generated using a rule-based algorithm combining valence pattern matching and lexical substitution. We prove that syntactic preprocessing plays a major role in the performances of statistical classifiers to argument identification, and discuss the core reasons of syntactic mismatch between dependency parsers output and FrameNet syntactic formalism. Finally, we suggest new leads for improving statistical models for frame semantic parsing, including joint syntax-semantic parsing relying on FrameNet syntactic formalism, latent classes inference via split-and-merge algorithms and neural network architectures relying on rich input representations of words.
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Frame semantics (Fillmore, 1982) is an approach to the study of lexical meaning where schematic representations of events, relations or entities called frames provide semantic background for interpreting the meaning of words and illustrating their syntactic valence. Its implementation for English through the FrameNet lexicon has proven greatly beneficial for the field of natural language processing over the past twenty years. Indeed, FrameNet (Baker et al., 1998) provides a fine-grained classification of predicate-argument structures in English, relying on an exhaustive taxonomy of inter-connected semantic classes and roles, which is particularly suited for drawing useful semantic inferences from text while abstracting away from surface syntactic structures. FrameNet has been used in tasks as diverse as paraphrase recognition (Padó and Erk, 2005), question answering (Shen and Lapata, 2007), stock price movements prediction (Xie et al., 2013), student essay clarity modeling (Persing and Ng, 2013), knowledge extraction from Twitter (Søgaard et al., 2015) and event detection (Liu et al., 2016; Spiliopoulou et al., 2017).

In order to make use of FrameNet annotation for the tasks at hand, the aforementioned systems have typically relied on statistical models to perform automatic extraction of frame semantic structures – a task also referred to as frame semantic parsing – so as to project frame semantic annotation on custom data for which no FrameNet annotation was available. However, the low performances of frame semantic parsers, especially in out-of-domain settings (Croce et al., 2010; Hartmann et al., 2017), have persistently limited the exploitation of FrameNet’s full potential.

Past research (Das et al., 2014; FitzGerald et al., 2015; Hartmann et al., 2016) have argued that frame semantic parsing suffers from the sparsity of FrameNet annotated data. Yet, previous attempts at augmenting training data, either manually (Kshirsagar et al., 2015), or through automatic generation via annotation projection (Fürstenau and Lapata, 2012) and transfer from linked lexical resources (Hartmann et al., 2016) have resulted in limited improvements. The limited improvements of Kshirsagar et al. (2015) are particularly worrisome, as they relied on previously unused gold FrameNet annotated data, which
augmented training data by an order of magnitude. It is all the more concerning that they
did try to compensate for out-of-domainness effects – the fact that data used to evaluate a
statistical model may contain patterns absent from the training data used to generate the
model – following remarks of Das et al. (2014), but to no avail. Two questions arise from
those observations:

1. Are prediction failures due to a lack of annotation, which translates to the absence
in the training data of linguistic patterns necessary for any machine learning model
to properly predict the frame semantic structures included in the evaluation data?

2. Does failure to capture structural generalization principles necessary to correctly
predict frame semantic structures lie with the probabilistic models used so far?

Past results already offer preliminary leads which can guide reflection: several research
have successfully attempted to incorporate features relating to information hard-coded in
FrameNet – such as frame relations (Kshirsagar et al., 2015), or frame element semantic
types (Roth and Lapata, 2015) – to statistical models for frame semantic parsing, suggest-
ing that improvements can still be made on the modeling side, as current statistical models
fail to capture structural information available in FrameNet. It is therefore more than ever
crucial to understand exactly what statistical models learn, and what they fail to learn.
In addition, it is important to understand whether statistical models’ failures to capture
structural generalizations correlate with properties of language and linguistic phenomena
at large, or whether they lie in engineering approximations and optimization constraints.
The question of what statistical models do learn in the end is all the more relevant today
as recent approaches to frame semantic parsing have relied on neural networks (FitzGerald
et al., 2015; Roth, 2016; Swayamdipta et al., 2017; Yang and Mitchell, 2017), which are
notoriously hard to debug. Careful error analysis are still lacking to understand qualita-
tively rather than quantitatively what those models have contributed to and why they do
seem to learn better than previous models.

Although it is likely true that statistical models for frame semantic parsing can still
be improved, it is evenly likely that the performances of those models remain bounded
by domain-specific limitations and annotation redundancies (Croce et al., 2010; Hartmann
et al., 2017). Redundancies are particularly problematic given the cost of FrameNet an-
notation which requires extensive linguistic expertise and time. If such redundancies do
exist, they should be clearly identified to prevent annotators from wasting time and energy.
Given those considerations, the purpose of this memoir is threefold:

1. Demonstrate our understanding of frame semantics theory, FrameNet and the liter-
ature on frame semantic parsing;

2. Formalize the challenges posed by frame semantic parsing, replicate past results and
rationalize experimental setups;
3. Report on the preliminary results of a model used to artificially augment FrameNet annotated data in order to ultimately perform qualitative analysis of statistical models for frame semantic parsing.

More specifically, we propose a model to artificially augment FrameNet annotated data with paraphrastic examples generated via a rule-based algorithm combining lexical substitution and valence pattern\(^1\) matching. For example, given the sentence *John gave an apple to Mary*, our system could generate the sentence *John handed out an apple to Mary* given that both *give* and *hand out* predicates bear semantic and argumental similarities. The core idea of the model is to generate data reflecting at the surface level\(^2\) structural information encoded in FrameNet through valence patterns. In theory, such artificial data, highly consistent with the underlying logic of FrameNet annotation, should not contribute significantly (if not at all) to improving performances of (good) statistical models for frame semantic parsing. Indeed, our model would only provide new information in terms of lexical configurations of predicate-argument structures – the association of a given predicate with a given set of arguments in a given syntactic configuration, as previously exemplified in the sentence *John handed out an apple to Mary*. It would not introduce predicates, arguments or predicate-argument configurations previously absent from the data. Therefore, if the performances of the aforementioned statistical models were to improve when trained on an artificially augmented dataset, it would only demonstrate that such models fail to properly generalize predicate-argument structures in FrameNet when exposed to a limited set of gold data. Our paraphrastic data augmentation approach could offer an easy alternative to compensate for the shortcomings of such models, and a simple way to understand under which conditions those models fail to generalize and what kind of additional data, in terms of lexical predicate-argument configurations, those models require to better learn.

The structure of the memoir is as follows: in Chapter 2 we introduce in more details frame semantics theory, FrameNet and the frame semantic parsing task. In Chapter 3, we go over the literature on frame semantic parsing and critically analyze challenges posed by current approaches to frame semantic parsing as well as the limitations of past error analysis. In Chapter 4, we introduce our paraphrastic data augmentation model and the experimental setup used to generate artificial data. In Chapter 5 we replicate the results of several past studies on frame semantic parsing and detail the baseline used for quantifying the contribution of our data augmentation model. We report our results in Chapter 6, and analyze them using different metrics in Chapter 7. Finally, we discuss possible improvements in Chapter 8 and conclude in Chapter 9.

\(^1\) defined as a specific combination of syntactic realizations of the arguments of a predicate, see Section 2.2

\(^2\) i.e. at the sentence level, versus, encoded as a high-level feature
Frame semantic parsing (Fillmore, 1982; Fillmore et al., 2003; Fillmore and Baker, 2009; Andor, 2010) is an approach to the study of lexical meaning where schematic representations of events, relations or entities called frames provide semantic background for interpreting the meaning of words and illustrating their syntactic valence. Frame semantic parsing is the task of automatically predicting predicate-argument structures following the classification framework of frame semantics. Pioneered by Gildea and Jurafsky (2002), it was more formally defined during the SemEval 2007 shared task 19 (Baker et al., 2007) on Frame Semantic Structure Extraction.

In this Chapter we present an introduction to the theory of frame semantics, its implementation into the FrameNet lexicon, and the frame semantic parsing task. In Section 2.1 we introduce the theory of frame semantics, its historical development, and its relation to other linguistic theories such as case grammar. In Section 2.2 we introduce the FrameNet lexicon, an implementation of frame semantics theory for English. We present its core concepts, statistics on annotated data, and several implementation specifications crucial to the task of frame semantic parsing. In Section 2.3 we briefly compare FrameNet to other lexical resources for English such as WordNet, PropBank or VerbNet. Finally, in Section 2.4, we introduce the frame semantic parsing task as defined during the SemEval 2007 shared task, its datasets and evaluation protocols.

2.1 A brief history of frame semantics theory

2.1.1 Historical motivations

The motivations underpinning the frame semantics enterprise can be traced back to Fillmore’s early work on the classification of English verbs (Fillmore, 1961, 1963) and to the fundamental idea that discoveries in the behavior of particular classes of words could lead to discoveries in the structure of the grammar of English. Fillmore’s approach at the time
was resolutely transformationalist – influenced by work such as (Chomsky, 1957), (Lees, 1960) or (Chomsky, 1965) – in that it attempted to classify verbs according to \textit{surface-syntactic frames} and \textit{grammatical behavior} defined as sensitivity of certain classificatory structures to particular grammatical transformations.

### 2.1.2 The case for case

Later on, in his seminal work on \textit{case grammar} (Fillmore, 1968, 1977a), Fillmore proposed a more semantically-grounded theory where verbs could be classified according to the semantic roles of their associated arguments. Fillmore’s work was then largely influenced by \textit{dependency grammar} and \textit{valence theory} (Tesnière, 1959), notably in its treating all arguments of the predicate equally, without special consideration for the subject, contrary to previous transformationalist approaches. Still motivated by considerations over the universality of the deep syntactic structure of clauses, he introduced a set of six (potentially) universal semantic role categories called \textit{deep cases}.\(^1\) \textit{Shared semantic valence} – defined as a set of co-occurrence restrictions over the arguments of predicates according to their semantic roles – allowed for grouping verbs into what Fillmore called \textit{case frames}, which provided the necessary background for understanding the formation of valid minimal clauses across languages. Abstracting over surface syntactic configurations, case grammar made it possible to account for cases where semantic roles occupy different syntactic positions, as in:\(^2\)

\begin{equation}
(2.1) \text{[John]}_{\text{Agent}} \text{ broke the window}
\end{equation}

\begin{equation}
(2.2) \text{[A hammer]}_{\text{Instrument}} \text{ broke the window}
\end{equation}

\begin{equation}
(2.3) \text{[John]}_{\text{Agent}} \text{ broke the window [with a hammer]}_{\text{Instrument}}
\end{equation}

In sentence 2.1 the item marked with the \textit{AGENT} case is the subject whereas in sentence 2.2, the \textit{INSTRUMENT} is the subject. Both \textit{AGENT} and \textit{INSTRUMENT} cases may appear in the same sentence as in 2.3 but only the \textit{AGENT} is subject.

The theory allowed for interesting predictions: the fact that the subject in (2.1) and (2.2) have different deep cases explain why the combined meaning of the two sentences could not be produced by co-joining the subjects, as in:

\begin{equation}
(2.4) *\text{John and a hammer broke the window.}
\end{equation}

According to Fillmore, additional restrictions which may hold between cases and lexical features (e.g. between \textit{AGENT} and animateness) could also explain why certain sentences are unacceptable, such as:

\begin{equation}
(2.5) *\text{A hammer broke the glass with a chisel.}
\end{equation}

\(^1\) Agentive, instrumental, dative, factitive, locative and objective

\(^2\) In all our examples containing semantic roles annotation, we follow FrameNet annotation style: we rely on a phrase structure grammar rather than a dependency grammar, i.e., we tag the whole constituents rather than just the head words of the constituents
Both co-occurrence restrictions over deep cases and constraints between cases and lexical features are fundamental properties of language that every parser aiming at automatically predicting predicate-argument structure must capture in order to properly identify and classify semantic roles. As we will see in the following chapters, this poses major challenges to the task of frame semantic parsing in general.

2.1.3 From case grammar to frame semantics

The theory of frame semantics was formalized in 1982 to overcome the shortcomings of case grammar which, according to Fillmore, failed to provide the details needed for semantic description, especially for verbs in particular limited domains. The concept of a (cognitive) semantic frame which would provide background for semantic analysis was already salient in case grammar, where Fillmore considered case frames to characterize small abstract scenes or situations, so that to understand the semantic structure of a verb it was necessary to understand the properties of such schematized scenes.

Some of the core concepts of frame semantics theory were introduced in (Fillmore, 1977b) focusing on the characterization of the cognitive scene related to the notion of a commercial event. In his work, Fillmore argued that an important set of English verbs could be seen as semantically related to each other given that they evoked the same general scene. The commercial event schematic scene, or frame, were to include concepts such as Buyer, Seller, Goods and Money. Verbs such as buy.v would be said to focus on the actions of the Buyer with respect to the Goods, backgrounding the Seller and the Money, allowing sentences such as:

(2.6) [John]_Buyer bought [a car]_Goods
(2.7) [John]_Buyer bought [a car]_Goods [from Mary]_Seller
(2.8) [John]_Buyer bought [a car]_Goods [from Mary]_Seller [for $5,000]_Money

while disallowing sentences such as:

(2.9) *[John]_Buyer bought [from Mary]_Seller
(2.10) *[John]_Buyer bought [for $5,000]_Money

Similarly, the verb sell.v would be said to focus on the actions of the Seller with respect to the Goods, backgrounding the Buyer and the Money, while the verb pay.v would be said to focus on the actions of the Buyer with respect to both the Money and the Seller, backgrounding the Goods. The point of the description was to argue that nobody could be said to know the meanings of these verbs who did not know the details of the kind of scenes that these words could represent.

In the following section we introduce the FrameNet implementation of frame semantics theory for English.
2.2 Introduction to FrameNet

2.2.1 Core concepts

FrameNet (Baker et al., 1998; Fillmore et al., 2003; Fillmore and Baker, 2009; Ruppenhofer et al., 2016) is a computational lexicography project whose purpose is to provide reliable descriptions of the syntactic and semantic combinatorial properties of each word in the lexicon, and to assemble information about alternative ways of expressing concepts in the same conceptual domain. Its output takes the form of a database of corpus-extracted sentences annotated in terms of frame semantics. FrameNet is articulated around the following core concepts:

- **frames**: schematic representations of events, relations or entities. They provide semantic background for understanding the meaning of words;

- **lexical units**: words paired with meaning. A lexical unit corresponds to a specific word sense and is formalized as a link between a *lemma* and a *frame*. The lexical unit is said to *evoke* the frame it belongs to. A polysemous word will be formalized as a single lemma with references to multiple lexical units in distinct frames;

- **frame elements**: frame-specific semantic roles. Frame elements are said to be *core* if they are obligatorily expressed, and *non-core* if they are not (see examples 2.11 and 2.12 as well as Section 2.2.4.1 for additional details on frame elements categorization in FrameNet). Frame element names generalize over frames, i.e. different frames with similar frame elements are considered to share semantic information. Frame elements can also be connected via frame element-to-frame element relations, to indicate semantic relations between them (see Section 2.2.3);

- **valence units**: syntactic realizations of frame elements. A valence unit is represented as a triplet FE.PT.GF of frame element (FE), phrase type (PT) and grammatical function (GF);

- **valence patterns**: the range of combinatorial possibilities of valence units for each lexical unit. A single valence pattern is usually represented as a string of multiple valence units FE.PT.GF separated by whitespaces.

Let us now turn to a concrete example illustrating the aforementioned concepts. In FrameNet, the *Commerce_buy* frame is defined as follows:

These are words describing a basic commercial transaction involving a Buyer and a Seller exchanging Money and Goods, taking the perspective of the Buyer. The words vary individually in the patterns of frame element realization they allow. For example, the typical pattern for the verb BUY: Buyer buys Goods from Seller for Money.
2.2. Introduction to FrameNet

It contains six lexical units: \textit{buy.v, buyer.n, client.n, purchase [act].n, purchase.v} and \textit{purchaser.n}. It also contains two core frame elements, \textit{Buyer} and \textit{Goods}, which are necessary to form grammatical clauses with lexical units belonging to the frame, as in:

\[(2.11) \text{[John]}_{\text{Buyer}} \text{ bought } \text{[a car]}_{\text{Goods}}\]

It also contains thirteen non-core frame elements, such as, e.g., \textit{Money, Place, Seller, Recipient} or \textit{Time} which may or may not be expressed in a given clause without altering its grammaticality, as in:

\[(2.12) \text{[John]}_{\text{Buyer}} \text{ bought } \text{[Susan]}_{\text{Recipient}} \text{[a car]}_{\text{Goods}} \text{[yesterday]}_{\text{Time}} \text{[for $5,000]}_{\text{Money}}\]

The two core frame elements \textit{Buyer} and \textit{Goods}, occur in valence patterns such as:³

- \text{Buyer.NP.Ext Goods.NP.Obj}, as in the simple direct object construction:
  \[(2.13) \text{[John]}_{\text{Buyer.NP.Ext}} \text{ bought } \text{[a car]}_{\text{Goods.NP.Obj}}\]
- \text{Buyer.PP.Dep Goods.NP.Ext}, for the passive construction:
  \[(2.14) \text{[A car]}_{\text{Goods.NP.Ext}} \text{ was bought by } \text{[John]}_{\text{Buyer.PP.Dep}}\]
- \text{Buyer.NP.Ext Goods.AJP.Dep} for the adjectival construction:
  \[(2.15) \text{[John]}_{\text{Buyer.NP.Ext}} \text{ bought } \text{[American]}_{\text{Goods.AJP.Dep}}\]

2.2.2 Data and statistics

FrameNet mostly annotates the British National Corpus (BNC) and the American National Corpus (ANC). FrameNet annotation is divided into two sets:

1. \textbf{exemplar}: also referred to as \textit{lexicographic annotation}. Exemplars are the core of the FrameNet lexicographic project. Each exemplar sentence exemplifies the use of a valence pattern for a single lexical unit;

2. \textbf{fulltext}: developed with NLP applications in mind, fulltext annotations cover FrameNet annotation for entire corpus-extracted texts where all possible lexical units and subsequent valence patterns of each sentence are annotated.

Table 2.1 and Table 2.2 below provide interesting statistics regarding three major releases of the English FrameNet data: 1.3, 1.5 and 1.7.⁴ Release 1.3 formed the basis of the SemEval 2007 shared task (see Section 2.4), release 1.5 was used in most recent state-of-the-art work on frame semantic parsing (see Section 3.1), while release 1.7, the latest, is used throughout our work (see Chapter 5).

FrameNet is also being developed in other languages such as Spanish (Subirats and Petruck, 2003), Swedish (Borin et al., 2010) or Japanese (Ohara et al., 2004), for which we provide comparative annotation statistics in Table 2.3.

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³In the following examples, ‘NP’ is a noun phrase, ‘Ext’ an external argument (the subject), ‘Obj’ an object, ‘PP’ a prepositional phrase, ‘AJP’ and adjective phrase and ‘Dep’ a dependent

⁴See the release notes on https://framenet.icsi.berkeley.edu
2.2.3 Frame and frame element relations

Frames in FrameNet form a network of interconnected entities, connected to each other via eight types of frame-to-frame relations. Frame elements are similarly connected to each other via frame element-to-frame element relations. Frame relations include:

1. **Inheritance**: a child frame inherits from a parent frame if its equally or more specific than its parent. For example, the Commerce_buy frame inherits from the Getting frame, which can be understood intuitively by the fact that buying something is getting it, with the additional assumption that the thing received was exchanged for
money. Hence, the BUYER frame element of the Commerce_buy frame is related
to the RECIPIENT frame element of the Getting frame but is semantically more
specific.

(2.16) [John]Recipient acquired [a house]Theme
(2.17) [John]Buyer bought [a house]Goods

2. **Perspective_on**: a given frame is in a Perspective_on relationship to a neutral
frame if it provides a specific perspective on the neutral frame. For example, both the
Commerce_buy frame and the Commerce_sell frame are in a Perspective_on re-
lationship to the Commerce_goods-transfer frame: the Commerce_buy frame
provides the point-of-view of the buyer while the Commerce_sell frame provides
the point-of-view of the seller, although both frames relate to the same scene, as
shown by the following sentences with the lexical units Commerce_buy.buy.v and
Commerce_sell.sell.v:

(2.18) [John]Buyer bought [a car]Goods [from Mary]Seller [for $5,000]Money
(2.19) [John]Seller sold [a car]Goods [to Mary]Buyer [for $5,000]Money

3. **Using**: a target frame is in a Using relationship to a source frame if a part of
the scene evoked by the target frame refers to the source frame. Note that a
frame can be in a Using relationship with multiple other frames. For example, the
Judgment_communication frame is in a Using relationship to both the Judgment
frame and the Statement frame. It does not Inherit from the Judgment frame as
it is not a simple sub-type of a purely cognitive state. Similarly, it does not Inherit
from the Statement frame as its frame element corresponding to the Statement
frame’s MESSAGE frame element is actually split in two separate frame elements:
Evaluee and Reason;

4. **SubFrame**: a target frame is in a SubFrame relationship to a source frame if
the source frame refers to a sequence of states and transitions, of which the tar-
get frame is a particular instance. For example, the Arrest, Arraignment,
Trial, Sentencing and Appeal frames are all in a SubFrame relationship with
the Criminal_process frame;

5. **Precedes**: a target frame is in a Precedes relationship to a source frame if both
target and source frames refer to specific states in a sequence of states and if the
target frame has temporal or ordinal precedence to the source frame. For example,
the aforementioned Arrest frame is in a Precedes relationship to the Arraignment
frame;

6. **Causative_of and Inchoative_of**: a target frame is in a Causative_of, Inchoa-
tive_of relationship to a stative source frame if it describes the causative / inchoative
view on a given stative scene. Causative frames will typically also inherit from the
Transitive_action frame and contain an AGENT frame element as in “John
broke the window”, and inchoative frames will typically inherit from the Event, State or Gradable_attribute frame;

7. **Metaphor**: a *target* frame is in a Metaphor relationship to a *source* frame if many of the lexical units in the target frame are to be understood at least partially in terms of the source frame. Consider the Metaphor relation between the Cause_motion frame and the Susasion frame, as in:

   (2.20) The judge was not moved by the lawyer’s argument

In 2.20, “moved” would be annotated in the Cause_motion frame, with the annotation set marked with the Metaphor label;

8. **See also**: a *target* frame is in a See also relationship to a *source* frame if it is similar to the source frame but should be carefully differentiated, compared and contrasted. This is intended to help human users better make sense of the FrameNet frame differentiation.

We will detail in Section 3.1 and Section 3.2 how frame and frame element relations have been successfully used to improve automatic predictions of frame element labels, in work such as (Kshirsagar et al., 2015) or (Matsubayashi et al., 2014).

### 2.2.4 Frame element attributes

#### 2.2.4.1 Core types

FrameNet distinguishes between core and non-core frame elements, following the traditional distinction between core arguments and peripheral adjuncts (such as *time, place* and *manner*). Those frame element categories are referred to in FrameNet as **core** and **peripheral**. FrameNet also contains two additional frame element categories:

1. **Extra-thematic** frame elements, which are frame elements that introduce information which is not a necessary part of the description of the central frame they belong to. For example, the Recipient frame element in the Commerce_buy frame is extra-thematic: it introduces a concept incorporated from the Giving (and subsequent) frame which is not core in the Commerce_buy frame, as shown in the following sentences:

   (2.21) [Mary]Buyer *bought* [a car]Goods

   (2.22) [Mary]Buyer *bought* [a car]Goods [for John]Recipient

The difference between extra-thematic and peripheral frame elements is that peripheral frame elements do not uniquely characterize a frame, and can be instantiated in any semantically appropriate frame;
2. **Core-unexpressed** frame elements, which are frame elements that behave like core frame elements in the frame they belong to but are not necessarily listed among the frame elements in the descendant frames. This can be explained by cases where information bear by the frame element is *included* in the lexical units in the descendant frame, and cannot be separately expressed. This is exemplified in the Choosing frame which inherits from the Intentionally_act frame containing a core-unexpressed ACT frame element, which cannot be passed on to the Choosing frame without forming ungrammatical sentences as in 2.24:

(2.23) [I]Agent will do [the cooking]Act
(2.24) *[I]Cognizer will choose [decision]Act [to cook]Chosen

2.2.4.2 Null instantiations

There are many occurrences in corpora where core frame elements do not appear in given sentences. Those cases are referred to in FrameNet as *null instantiations*. FrameNet categorizes three cases of null instantiation:

1. **Indefinite Null Instantiation** (INI): refers to cases where an argument is omitted for intransitive lexical units. FrameNet marks transitive and intransitive lexical units as both transitive and, in intransitive cases, marks the core argument as INI, as in:

   (2.25) [I]Ingestor ate [a cake]Ingestibles
   (2.26) [I]Ingestor ate Ingestibles.INI

2. **Definite Null Instantiation** (DNI): refers to cases where an argument is omitted under lexically licensed zero anaphora, where all parties in a conversation are assumed to know what the argument is, as in:

   (2.27) [We]Competitor won! Competition.DNI
   (2.28) When did [they]Theme arrive? Goal.DNI

3. **Construction Null Instantiation** (CNI): refers to cases where the grammar considerations require or permit the omission of some arguments in particular structures. This is typically the case for imperative sentences which omit the subject, and passive sentences which omit the agent, as in:

   (2.29) Get out! Theme.CNI
   (2.30) We have been robbed Perpetrator.CNI

Null instantiations exhibit different linguistic phenomena which have been shown to be particularly hard to learn by machine learning algorithms used for frame semantic parsing. Indeed, frame semantic parsers have a tendency to wrongly predict core frame elements when confronted to null instantiations, negatively affecting recall metrics (see (Chen et al., 2010) detailed in Section 3.2).
2.2.4.3 Semantic types

Frame element semantic types in FrameNet are designed primarily to aid frame parsing and automatic frame element recognition. They provide a general and limited set of categories which characterize the basic typing of fillers of frame elements. For example, the Cognizer frame element is marked as ‘Sentient’, the Place frame element as ‘Locative_relation’, and the Purpose or Means frame elements as ‘State_of_affairs’. We will detail in Section 3.2 how Matsubayashi et al. (2014) successfully used frame elements semantic types to improve automatic predictions of frame element labels.

2.3 FrameNet and alternative lexical resources

2.3.1 WordNet

WordNet (Miller, 1995) is a large electronic lexical database of English, which was inspired by psycholinguistics research investigating how and what type of information is stored in the human mental lexicon. WordNet groups words into sets of synonyms called synsets and records a number of relations among lexical entries, such as synonymy/antonymy, hyponymy/hypernymy, meronymy/holonymy, troponymy or entailment. It has a large coverage, with more than 200,000 word-sense pairs documented in four morphosyntactic categories: nouns, verbs, adjectives and adverbs. Contrary to FrameNet, WordNet contains little syntagmatic information. Its purpose is not to document predicate-argument structures in general. It does, however, offer more fine-grained distinctions across lexical entries, especially for nouns, and is therefore complementary to FrameNet.

2.3.2 PropBank

PropBank (Palmer et al., 2005) is a resource which annotates predicate-argument structures on top of the phrase structure annotation of the Penn TreeBank (Marcus et al., 1993). Predicates senses are classified according to frames, as in FrameNet, but, unlike FrameNet, PropBank postulates predicate-specific roles which are then generalized to a set of 5 core roles classes (ARG0 to ARG4) and 18 adjunct/modifier classes (ARGM-*). PropBank annotates verbs exclusively and does not offer the same granularity of semantic roles and frames as in FrameNet. It also does not provide semantic relations across frames and roles. Its generalized roles set does however make the task of automatic semantic role labeling simpler and it has been made it a popular resource in parsing and computational linguistics consequently.

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5 ARG0: agent, ARG1: patient, ARG2: instrument, benefactive, attribute, ARG3: starting point, benefactive, attribute, ARG4: ending point

6 Such as ARGM-LOC for location and ARGM-TMP for time
2.3.3 VerbNet

VerbNet (Kipper-Schuler, 2005) is a digital database that provides predicate-argument structures documentation for English verbs, relying on a hierarchical classification of verbs inspired by Levin’s verb classes (Levin, 1993). Arguments in VerbNet consist of a list of 23 generic thematic roles. Each (syntactic) frame groups together verbs that have similar semantic and syntactic characterizations, and VerbNet provides documentation for frame-specific thematic role syntactic realizations and co-occurrence constraints. VerbNet has a much lower coverage than FrameNet, with only 4526 senses of 3769 verbs annotated, and, unlike FrameNet, does not encompass (semantic) relations across its entities.

2.3.4 Others

Several other resources also aim at documenting predicate-argument structures for English: the Valency Dictionary of English (Herbst et al., 2004), which, unlike previously mentioned resources, is not free and not entirely machine-readable; VALEX (Korhonen et al., 2006), a large valency subcategorization lexicon for English verbs, which is, unlike previously mentioned resources, partially automatically annotated and therefore somehow noisy; and Abstract Meaning Representation (AMR) (Banarescu et al., 2013), the newest resources of all. AMR offers a graph-based representation of lexical concepts and typed relations between those concepts, denoted by an English sentence. It covers PropBank predicate-argument semantics, entity linking, coreference, modality, negation, questions, relations between nominals and canonicalization of content words. Its graph-based representation allows for abstracting away grammatical specificities, and its single-structure representation is designed to support rapid corpus annotation and data-driven natural language processing.

2.4 The frame semantic parsing task

2.4.1 Definition

Frame semantic parsing is the task of automatically predicting frame-evoking words, frames, and corresponding frame element spans and labels in a given sentence. The task, formally defined in the SemEval 2007 shared task 19 on Frame Semantic Structure Extraction (Baker et al., 2007), was divided into three subtasks:

1. **target identification**: identify all frame evoking words in a given sentence;

2. **frame identification**: label all frames of pre-identified targets in a given sentence;

3. **argument identification**: identify all frame-specific frame element spans and labels for pre-identified lexical units in a given sentence.
2.4.2 Datasets

Data were based on an extended version of the FrameNet 1.3 data release. Training data comprised about 2,000 annotated sentences with about 11,000 annotation sets in fulltext documents. Testing data comprised about 3 annotated fulltexts composed of 120 sentences and about 1,000 annotation sets (See details in (Das et al., 2014)). Texts were extracted from the American National Corpus (ANC) and the NTI website.\(^7\)

In this work, we first attempt to replicate past studies and therefore rely on the original FrameNet 1.5-based training and testing sets of Das et al. (2014) (see Chapter 5 and Section 4.2.1). However, we also report results on FrameNet 1.7-based datasets, where the testing set contains the same list of fulltext documents as the original list of Das et al. (2014), but contains more annotated data as those documents were further annotated in the 1.7 release (see Table 2.2) and therefore produce a more robust testing set.

2.4.3 Evaluation

2.4.3.1 Scoring

The original task was evaluated globally, each subtask taking as input the predicted output of the previous subtask and global precision recall and \(F_1\) scores were computed for frames and arguments microaveraged across a concatenation of the test set sentences.

In this work, we focus mostly on the subtask of argument identification and therefore evaluate predictions of arguments spans and labels given gold targets and gold frames. We use the modified evaluation script of the SemEval shared task introduced by Kshirsagar et al. (2015). The modified evaluation script does not give extra credit for gold frames, unlike the standard SemEval script. This allows for better evaluation of parsers’ improvements in argument identification, as it does not dilute argument identification scores by blending them with (gold) frame scores, necessarily 100% accurate. For example, Figure 2.1 which shows the original SemEval evaluation script output for the sentence *The college’s students were forced to take shelter in the gymnasium*, contains full M/S/G scores on the fourth line of the output script, corresponding to the frame (FR) *Education_teaching* evoked by the target ranging from character 20 to character 27. A contrario, Figure 2.2, which shows the modified evaluation script output for the same sentence, does not contain any M/S/G scores for the same line.

The evaluation script scores each frame and argument independently. In our configuration, argument spans and labels are scored jointly. Core frame elements are given one point and non-core frame elements are given half a point. The ‘Match’ column M is assigned a value each time a correct argument is identified (true positive); the ‘Score’ column ‘S’ is assigned a value each time an argument is wrongly predicted (false positive); and the ‘Gold’ column G is assigned a value each time the corresponding span and label is gold annotation.

\(^7\)http://www.nti.org/
2.4. The frame semantic parsing task

Precision is then computed by summing over all true positives and false positives for all predicted labels in a given sentence:

$$P = \frac{\sum tp}{\sum tp + \sum fp} = \frac{M}{S} \quad (2.31)$$

Recall is computed in a similar fashion with true positives and false negatives:

$$R = \frac{\sum tp}{\sum tp + \sum fn} = \frac{M}{G} \quad (2.32)$$

$$F_1 \text{ score is then given by:}$$

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R} \quad (2.33)$$

2.4.3.2 Statistical significance

Finally, we measure the statistical significance of all our results relying on the bootstrapping approach of Berg-Kirkpatrick et al. (2012): let us consider a system $A$ which we compare to
a baseline system B. Let us consider additionally a test set $x = x_1, \ldots, x_n$ on which $A$ beats $B$ by $\delta(x)$. $b$ bootstrap samples $x^{(i)}$ of size $n$ are drawn by sampling with replacement from $x$. For each $x^{(i)}$, a variable $s$, initialized at 0, is incremented if and only if $\delta(x^{(i)}) > 2\delta(x)$. The $p$ value is then given by:

$$p(x) = \frac{s}{b}$$

(2.34)
3.1 A historical overview of frame semantic parsing

Early work on frame semantic parsing has relied almost exclusively on statistical classifiers based on an exhaustive list of carefully handcrafted features (Gildea and Jurafsky, 2002; Johansson and Nugues, 2007; Das et al., 2014; Hermann et al., 2014; Kshirsagar et al., 2015; Roth and Lapata, 2015; Täckström et al., 2015). Such approaches usually require extensive feature engineering which can prove particularly time-consuming, in addition to risking biasing systems for the task at hand (Roth and Lapata, 2016). Moreover, those approaches have typically made use of heavy preprocessing, be it through part-of-speech tagging, dependency-parsing, or coreference resolution (e.g. Das et al., 2014; Roth and Lapata, 2015). However, preprocessing has been shown to significantly impact the overall performances of statistical models for frame semantic parsing (see Chapter 5 for details), and even to strictly bound the performances of those models below an unsatisfactory threshold (Das et al., 2014; Täckström et al., 2015). On top of this, previous research have relied on different preprocessing toolkits, and those inconsistent experimental setups have prevented fair comparison between models, as they do not allow discounting the contribution of the preprocessing toolkit from the contribution of the statistical model itself.

Given those considerations, recent neural-network-based approaches to frame semantic parsing appear very promising (FitzGerald et al., 2015; Roth, 2016; Swayamdipta et al., 2017; Yang and Mitchell, 2017), given the limited number of core features they require as input. In this regard, the most exciting approach is probably that of Swayamdipta et al. (2017), which proposed two very interesting models: one requiring no syntactic preprocessing and one acquiring syntactic representations alongside other distributional representations in a multi-task setting. Both models yielded competitive if not above state-of-the-art results.

Recent approaches have also called into question how the frame semantic parsing task
itself has been formalized, confirming what intuition long suggested: frame and argument identification performed jointly yield better results than performed sequentially (Yang and Mitchell, 2017).

State-of-the-art results on frame identification are reported in (Hermann et al., 2014) at 88.41% $F_1$ score; on argument identification with gold frames, in (Swayamdipta et al., 2017) at 68.9% $F_1$ and on argument identification with predicted frames in (Yang and Mitchell, 2017) at 76.6% $F_1$. Readers can refer to Appendix A for a more exhaustive historical overview of supervised and semi-supervised methods for frame semantic parsing.

### 3.2 Challenges of frame semantic parsing

Some important challenges posed by frame semantic parsing are deeply rooted in its underlying theoretical formalization. Indeed, frame semantics theory operates many fine-grained distinctions within predicate-argument structures classification, many of which are semantically motivated and do not translate into linguistic phenomena that can easily be captured at the surface syntactic level (Croce et al., 2010). Concretely, those considerations have turned FrameNet into an exhaustive taxonomy which has rendered the task of frame semantic structure prediction very complex (see Section 3.2.1).

The richness of FrameNet’s classification, which is also its main asset compared to other lexical resources, has lead researchers to operate multiple approximations in order to be able to solve the task at hand. Those approximations dealt with the definition of the frame semantic parsing task itself, and with its resolution, both in terms of modeling and optimization (see Section 3.2.2).

In addition, the fined-grained nature of FrameNet annotation has rendered its production extremely costly, resulting in limited annotated data compared to what is usually required for machine learning algorithms to learn the kind of generalizations necessary to properly predict frame semantic structures, within and across domains (see Section 3.2.3).

In this section we skim through the existing literature on each of those challenges and detail some of the solutions that have been proposed to tackle them.

#### 3.2.1 A rich underlying taxonomy

The FrameNet taxonomy, albeit rich and complex, is also well structured. From this observation, Matsubayashi et al. (2014) proposed to exploit the structural information available in FrameNet – such as frame and frame element relations and semantic types – combined with other lexical resources such as PropBank and VerbNet, to infer generalizations on frame elements which would reduce the number of classes for the argument identification task, and thereby its complexity. Although they did show significant improvements, with a 19.16% error reduction in terms of total accuracy, their approach can be viewed as a simplification of the task of frame semantic parsing in general, a simplification which discards many interesting distinctions made by the FrameNet framework. It does however support in an indirect fashion the underlying annotation of FrameNet, as it shows that
generalizations motivated by theoretical considerations from frame semantics theory generate systematic linguistic phenomena in as they can be captured by a machine learning system.

Other forms of linguistic knowledge annotated in FrameNet have proven harder to capture through automatic means, whether directly or indirectly. Das et al. (2014) for instance, showed that a traditional log-linear model relying on a latent variable over frame and argument representations failed to capture the kind of structural constraints on frame elements which are hard-coded in FrameNet. Such constraints included a vast majority of non-overlapping frame element labels, – which the system violated 441 times\(^1\) – and other forms of constraints, such as argument pairwise requirement/exclusion, a constraint exemplified in the following sentences:

(3.1) \([\text{A blackberry}]_{\text{Entity}_1} \text{resembles} [\text{a loganberry}]_{\text{Entity}_2}\)

(3.2) \([\text{Most berries}]_{\text{Entities}} \text{resemble each other}\)

The frame elements \(\text{ENTITY}_1\) and \(\text{ENTITY}_2\) require one another and exclude the \(\text{ENTITIES}\) frame element and vice versa.

In a similar vein Chen et al. (2010) showed that the frame semantic parser of Das et al. (2014) often failed to correctly identify null instantiations of core frame elements. As for Kshirsagar et al. (2015), they showed that the same parser also failed to capture linguistic knowledge encoded in frame relations, and that such information could only be adequately captured through active supervision.

### 3.2.2 Necessary approximations

In order to simplify automatic frame semantic structure extraction, past research have proceeded to multiple approximations.

The first approximation deals with the definition of the task itself, which has been artificially split into the three subtasks of target identification, frame identification and argument identification. Nothing in the theory of frame semantics requires this subdivision of labor, which is more commanded by requirements in terms of evaluation for natural language processing. On the contrary, it is often useful in order to perform frame identification for a given predicate, to process the arguments of the predicates in context. The recent work of Yang and Mitchell (2017) has confirmed this intuition, achieving a significant improvement in both frame and argument identification tasks by performing those two tasks jointly rather than sequentially.

The second approximation deals with input processing, which has systematically been performed at the sentence level, despite theoretical considerations in frame semantics stressing the importance of processing language at a higher level than the mere sentence (Fillmore, 1982). Again, this constraint is due to computational considerations, and the recent work of Roth and Lapata (2015) who improved argument identification performance by

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\(^1\)About 10% of the time, given the size of the test set
incorporating discourse features through, e.g., coreference resolution, confirms the limitations posed by this approximation.

Other approximations have been performed to ease the modeling and better fit it into a machine learning pipeline. Such approximations include that of Das et al. (2014) on the nature and the systematicity of structural constraints which operate on frame elements. Those approximations, which often have no theoretical grounds, allow formulating the problem of argument identification as a constrained optimization problem, turning a complex structured prediction problem into a more standard optimization problem, easier to process with, e.g., linear programming solvers.

Finally, work such as (Das et al., 2014; Täckström et al., 2015; FitzGerald et al., 2015) have demonstrated how the performances of traditional approaches to frame semantic parsing, relying on heavy syntactic preprocessing, could be bounded by the performances of syntactic parsers. This is particularly striking in the case of argument span identification methods, which, in the aforementioned work, have relied on heuristics-based algorithms exploiting syntactic features derived from syntactic parsers, and which have bounded arguments span identification recall to a low 80%.

The impact of preprocessing on frame semantic parsing will be further detailed in Chapter 5, where we will discuss how inconsistent preprocessing pipelines across research and experimental setups may pose problems for replicating past results and quantifying systems contributions.

3.2.3 Annotation data scarcity and domain specificity

It has frequently been argued that FrameNet lacked the necessary amount of annotated data for machine learning systems to properly predict frame semantic structure (Palmer and Sporleder, 2010; Das et al., 2014; Das, 2014; FitzGerald et al., 2015), or generalize across domains (Croce et al., 2010; Das et al., 2014; Hartmann et al., 2017).

The negative impact of coverage gaps has been extensively documented by Palmer and Sporleder (2010), albeit limited to the task of frame identification, which had a knock-on effect on argument identification for frame semantic parsing pipelines processing tasks sequentially.

While Johansson and Nugues (2007) noted a 20 $F_1$ loss on argument identification when tested on a different domain than that of the training set, Das et al. (2014) argued further that exemplar sentences could not successfully be used for training frame semantic parsers on the SemEval data. According to them, possible explanations included the fact that exemplars were not representative as a sample, did not have complete annotations, and were not from a domain similar to the fulltext test data.

Yet, recent work of Kshirsagar et al. (2015) and Yang and Mitchell (2017) have shown a few $F_1$ points gain when training on both fulltexts and exemplars of the FrameNet 1.5 dataset, with and without domain adaptation techniques. Those improvements, however, remain limited considering that the exemplar sentences represent more than three times the amount of annotated data available in fulltext data.
3.3 Shortcomings of past error analysis

Many approaches have been tried to overcome the problems of data sparsity, coverage gaps and domain specificities. Croce et al. (2010) and Hartmann et al. (2017) proposed to rely on distributional representations of lexical features to better generalize in out-of-domain settings. Fürstenau and Lapata (2012) augmented the FrameNet annotation set by projecting FrameNet role annotation to syntactically similar sentences, while Hartmann et al. (2016) augmented the set of annotation for both FrameNet senses and roles using distant supervision to transfer annotation for linked lexical resources. Rastogi and Van Durme (2014) and Pavlick et al. (2015) proposed to augment FrameNet annotation automatically via paraphrasing, while Hong and Baker (2011), Fossati et al. (2013), Chang et al. (2015) and Chang et al. (2016) proposed to do so via crowdsourcing.

However, the aforementioned methods have either yielded limited improvements, either not been tested in traditional frame semantic parsing setups for proper comparison, either not been tested at all. It is therefore difficult to measure the true impact of FrameNet data augmentation on frame semantic parsing. Even if such improvements were to be attested, its impact would remain limited without a proper error analysis which would help us understand exactly what kind of linguistic knowledge additional data helped capture.

3.3 Shortcomings of past error analysis

Although much work has been done over the past ten years in the field of frame semantic parsing, very little has been done in terms of error analysis to understand exactly the contribution of each new models to the tasks at hand, as well as what systems still fail to capture in terms of linguistic phenomena.

The seminal work of Gildea and Jurafsky (2002) provided extensive error analysis, including performance of the system broken down by feature and roles, measuring the contribution of each feature to the identification and labeling of each semantic role. Their work also provided accuracy, recall and $F_1$ scores for most frequent frame elements, as well as performance measures of each learning algorithm used. This provided a detailed overview of what their system was good at (e.g., identifying and labeling Agent frame elements), and what it was bad at (e.g., identifying Manner and Location frame elements). Their analysis of each feature's coverage and contribution to frame element identification and labeling helped craft a carefully selected set of features (highly motivated and backed by experimental data and analysis) which has been used almost as-is (though extended) in subsequent studies of semantic role labeling.

Since then, however, very little has been done in terms of error analysis. If work such as (Palmer and Sporleder, 2010) or (Kshirsagar et al., 2015) do provide coverage and frequency metrics of lexical units and/or frame elements, potentially exhibiting correlations between coverage gaps, low frequency frame elements and low performance of system, we still lack the kind of analysis done on PropBank work (e.g. Woodsend and Lapata, 2014), in order to identify linguistic knowledge which proves systematically hard to predict by frame semantic parsers. This is especially true for recent approaches relying on neural networks. If work such as FitzGerald et al. (2015) or Roth and Lapata (2016) have provided very
useful 2D-graphics of the representations learned by their model, projections of learned representations exemplifying how models could operate classification of semantic roles and group together similar semantico-syntactic configurations, such as nested agents, relative clauses, complements of nominal predicates, etc., error analysis are often absent, or limited to the mere comparison of performance based on sentence length (Yang and Mitchell, 2017).

A notable exception to this absence of error analysis is work by Roth and Lapata (2015). They were indeed among the only ones to provide an exhaustive qualitative analysis of the improvements of their system, based on discourse and context features. They showed for instance that adding contextual features helped the model capture semantic properties of unseen tokens, such as being able to properly label ‘Dec. 1’ with the Time frame element. Similarly, their system proved able to capture certain semantic categorizations, such as the fact that aunt, uncle and grandmother were all of the human semantic type and therefore could more likely fill roles such as Recipient than that of Goal. They additionally showed that their system, and more specifically the contextual features on semantic types and the discourse feature on salience, better captured the agency property of certain frame elements, which translated into an increase in recall from 56% to 78%. They also showed that contextual word representations lead to better identification of Time frame elements, especially when the label was filled by an infrequent adverb.

3.4 Using FrameNet for automatic paraphrase generation

A major question that arises from previous sections is whether data in FrameNet contain many redundancies and whether they are well-balanced for parsers to properly learn useful generalizations, or whether the fault lies in machine learning systems used so far which prove unable to capture useful generalizations from the available training data.

In order to test the robustness and ability of statistical models for frame semantic parsing to extract information from FrameNet annotated data, we propose, in the next chapters, a model to artificially augment FrameNet annotation with paraphrastic examples generated via a rule-based algorithm combining lexical substitution and valence pattern matching. The core idea of the model is to generate data reflecting at the surface level – via lexical configurations of predicate-argument structures – structural information encoded in FrameNet through valence patterns. By recombining information already latently present in FrameNet, our paraphrastic data augmentation approach should provide a simple way to understand under which conditions statistical models for frame semantic parsing fail to generalize and what kind of additional data, in terms of lexical predicate-argument configurations, those models require to better learn.

Our paraphrastic data augmentation model uses FrameNet-internal knowledge to generate near-paraphrases which are in turn used to try and improve frame semantic parsing. It is worth mentioning that both ideas have antecedents in the literature: the potential of FrameNet for paraphrasing has already been thoroughly documented (Ellsworth and Janin, 2007; Coyne and Rambow, 2009; Hasegawa et al., 2011), and several work have argued that paraphrasing could prove to be beneficial to frame semantic parsing (Rastogi...
3.4. Using FrameNet for automatic paraphrase generation

and Van Durme, 2014; Pavlick et al., 2015). However, no open-source system exists today to generate paraphrases with FrameNet, and no previous work have actually *proved* paraphrases to quantifiably improve frame semantic parsing performances.

Several other work have attempted to augment training data, sometimes relying on paraphrase generation, be it for Propbank (Woodsend and Lapata, 2014), or FrameNet (Fürstenau and Lapata, 2012), but none of those approaches used resource-internal knowledge to generate paraphrases and/or augment the training set. Moreover, they have both exhibited limited improvements, while significantly increasing the size of the training set. With our approach, we hope that a system relying on FrameNet-internal logic to augment the training set will prove more consistent with the gold annotation and lead to better performances ultimately.
In this chapter we introduce two models: (1) a rule-based model for **paraphrastic data augmentation** used for augmenting our training set of FrameNet annotated data with artificial examples generated from the FrameNet database via a valence patterns matching algorithm; and (2) a statistical model for **argument identification** as originally defined by Das et al. (2014) and refined by Kshirsagar et al. (2015).

In Section 4.1.1 we introduce the paraphrastic data augmentation model, detail its core motivations and implementation specifications, and discuss its robustness. In Section 4.1.2 we introduce the argument identification model, its features, and its learning and decoding strategies. Additionally, in Section 4.2, we detail the experimental setup used throughout this work, in terms of training, development and testing datasets, toolkits and hyperparameters used for all the models.

### 4.1 Model

#### 4.1.1 Paraphrastic data augmentation

##### 4.1.1.1 Philosophy

Our data augmentation model is grounded in frame semantics theory which argues that lexical units sharing similar valence patterns should be considered as semantically equivalent (Fillmore, 1982; Ruppenhofer et al., 2016). This fundamental idea is at the core of past research which have relied on FrameNet to generate sentential paraphrases (Ellsworth and Janin, 2007; Hasegawa et al., 2011). For example, both *buy.v* and *purchase.v* lexical units in the *Commerce_buy* frame are compatible with the *Buyer.NP.Ext Goods.NP.Obj* valence pattern. Therefore, the following sentences should be considered as *grammatically correct and semantically equivalent*:\(^1\)

\(^1\)In all the following examples boldface indicates targets, i.e. frame-evoking words in context.
Chapter 4. Models and Experimental Setup

(4.1) [John]Buyer.NP.Ext bought [a car]Goods.NP.Obj

(4.2) [John]Buyer.NP.Ext purchased [a car]Goods.NP.Obj

Note that the semantic equivalence is not strict, as FrameNet may classify in the same frame lexical units with different semantics – sometimes even antonyms – provided that those lexical units share some commonalities in the semantico-syntactic realizations of their arguments. For example, both make.v and lose.v lexical units belong to the same Earnings_and_losses frame and are compatible with the Earner.NP.Ext Earnings.NP.Obj valence pattern, as in:

(4.3) [I]Earner.NP.Ext like working and making [money]Earnings.NP.Obj

(4.4) [I]Earner.NP.Ext like working and losing [money]Earnings.NP.Obj

As lexical units with diverging (or even opposite) meanings may share common valence patterns in FrameNet, the lexical units generated by our valence pattern matching algorithm will not necessarily form true or valid paraphrases of the original target. Hence, we call them paraphrastic candidates and describe our data augmentation method as paraphrastic data augmentation.

4.1.1.2 Implementation

Our paraphrastic data augmentation is implemented in a system called pFN, which workflow is as follows:

1. Extract all annotation sets from FrameNet XML files and unmarshall to a list of standardized annotation sets for easy manipulation;

2. Filter the list of standardized annotation sets according to the filtering options (detailed in Section 4.1.1.4);

3. For each filtered annotation set, extract the corresponding valence pattern and fetch all the lexical units in training data compatible with the source valence pattern. The list of lexical units output by the system, enriched with the set of annotation labels extracted from the original annotation set, will constitute the list of paraphrastic candidates;

4. Filter the list of paraphrastic candidates according to the filtering options (detailed in Section 4.1.1.4);

5. Generate all possible sentences from the list of filtered candidates, project FrameNet annotation label to the new sentences, and export all newly generated sentences to FrameNet XML format.
4.1. Model

Figure 4.1: pFN paraphrastic data generation pipeline

Figure 4.1 presents the overall pipeline of the pFN system. The generation step is where the list of paraphrastic candidates is generated for a given source annotation set. To provide a concrete example, consider the following sentence:

(4.5) Your contribution to Goodwill will mean more than you may know

This sentence has exactly six annotation sets in FrameNet (one per target):²

(4.6) [Your]Donor contribution [to Goodwill]Recipient will mean more than you may know
(4.7) [Your contribution]Trajector to [Goodwill]Landmark will mean more than you may know
(4.8) [Your contribution to Goodwill]Means will mean [more than you may know]Value
(4.9) Your contribution to Goodwill will mean [more]than you may know]Class|Added_set
(4.10) Your contribution to Goodwill will mean more than [you]Hypothetical_event may
|know]Hypothetical_event
(4.11) Your contribution to Goodwill will mean more than [you]Cognizer may know

The pFN system will return paraphrastic candidates for only four of those targets: contribution, to, may and know. Targets for which no paraphrastic candidates are returned usually indicate that they are the sole lexical units found in the input valence patterns. The list of paraphrastic candidates can be represented as a word lattice, as shown in Figure 4.2, following traditional studies on sentential paraphrase (e.g. Madnani and Dorr, 2010).

pFN will perform loose valence pattern matching, i.e., two valence patterns will be considered matching as long as all their core valence units³ do match. For example, the valence patterns Earner.NP.Ext Earnings.NP.Obj and Earner.NP.Ext Earnings.NP.Obj Time.AVP.Dep will be considered matching as the TIME frame element is peripheral in the

²for clarity we only show the frame element labels, omitting phrase types and grammatical functions
³the syntactic realizations of the core frame elements
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Figure 4.2: A word lattice showing all paraphrasing candidates output by the pFN system for the sentence: *You contribution to Goodwill will mean more than you may know*. Original targets are represented in the upper edges and paraphrastic candidates are represented in the lower edges.

Earner.NP.Ext Earnings.NP.Obj Time.AVP.Dep valence pattern. This approach has the advantage of augmenting the pool of candidates generated by the system when only a limited number of valence patterns has been annotated for a given lexical unit and when those valence patterns contain peripheral frame elements.

The number of possible paraphrastic sentences \( N_p \) output by the pFN system for a given sentence \( s \) containing \( N_a \) annotation sets is given by:

\[
N_p = \prod_{j=1}^{N_a} (N_{c_j} + 1) - 1
\]  

(4.12)

where \( N_{c_j} \) is the number of paraphrastic candidates generated by pFN for the \( j \)-th annotation set. \( N_p \) simplifies to:

\[
N_p = \prod_{j=1}^{N_a} (N_{c_j} + 1) - 1
\]  

(4.13)

For sentence 4.5, and without any filtering, pFN will therefore generate 47 paraphrastic sentences:

\[
N_p = 2 \cdot 2 \cdot 1 \cdot 1 \cdot 3 \cdot 4 - 1 = 47
\]  

(4.14)

4.1.1.3 Robustness

Our approach for augmenting FrameNet annotation via paraphrastic sentences is more robust than what previous approaches to automatic FrameNet data augmentation have attempted, as it guarantees strong consistency with the underlying FrameNet annotation framework. Indeed, past research have often combined word-based semantic similarity with dependency-tree-based syntactic similarity to project annotation to new data, be it on FrameNet (Fürstenau and Lapata, 2012), or PropBank (Woodsend and Lapata, 2014).
4.1. Model

However, the challenge of such approaches is to be able to reproduce the structure of FrameNet annotation. Consider first the following example:

(4.15) [John]_Buyer.NP.Ext bought [a car]_Goods.NP.Obj this morning

(4.16) Mary acquired a house yesterday

Although both Commerce_buy.buy.v and Getting.acquire.v lexical units share some apparent syntactic and semantic similarities, FrameNet clearly distinguishes them and assigns them to different frames with distinct frame elements in order to account explicitly for the semantic specificity of the lexical unit buy.v which implies an exchange of money for the thing acquired. Consider then the following example:

(4.17) [I]_Ingestor.NP.Ext ate [cheese]_Ingestibles.NP.Obj

(4.18) [I]_Ingestor.NP.Ext drank [wine]_Ingestibles.NP.Obj

Although both eat.v and drink.v lexical units share syntactic similarities, they appear somehow slightly more distant semantically than buy.v and acquire.v. They are nonetheless annotated within the same Ingestion frame in FrameNet, and are both compatible with the Ingestor.NP.Ext Ingestibles.NP.Obj valence pattern.

The dilemma for systems combining word-based semantic similarity and dependency tree-based syntactic similarity is therefore to be able to handle both eat/drink and buy/acquire cases, by including one while excluding the other. However, a quick test with a cosine similarity calculated on distributional representations computed with word2vec\footnote{See Section 4.1.1.4 for details} gives us a 0.57 similarity score between buy and acquire.\footnote{See Section 4.1.1.4 for details} and a 0.5 similarity score between eat and drink. We see directly how such a measure would lead to filtering out both cases or including them both in the augmented data, given that the output hierarchy of similarity is the inverse of that of FrameNet.

Although our approach does overcome those limitations, as it generates artificial data fully compliant with FrameNet annotation by construction, it still faces two major shortcomings:

1. as previous approaches, and without filtering, it generates a huge number of paraphrastic sentences, which tend to explode the training set beyond what is computationally reasonable;

2. due to FrameNet’s annotating dissimilar lexical units with similar valence patterns, the pFN system may generate sentences which are unlikely to be seen in a corpus, as:

(4.19) ? I ate wine

The key question is therefore whether or not the statistical classifier used for performing argument identification is sensitive to lexical diversity at the argument level – that is, to lexical co-occurrence (as suggested by the lexical features detailed in Figure 4.3) – which is what our paraphrastic data augmentation brings. We hypothesized two different scenarios:
1. the statistical classifier relies primarily on a latent representation of the arguments, and is less sensitive to predicate-argument lexical configurations, in which case we should be able to observe an improvement in global argument identification scores when training on our augmented training set, even without filtering;

2. the statistical classifier is sensitive to predicate-argument lexical configurations, to the point that bias introduced by unlikely lexical configurations does not compensate for the lexical diversity brought at the argument level. In this case we should observe a decrease in global argument identification scores when training on our augmented training set without filtering.

Following our first results which confirmed scenario 2 (see Chapter 6), we decided to implement an extra layer of filtering in order to filter out unlikely lexical configurations.

4.1.1.4 Filtering

The pFN pipeline includes two different kinds of filtering:

1. **annotation sets filtering**: source annotation sets are filtered based on the part of speech or number of tokens of their lexical units. Filtering out items according to part of speech allows for evaluating the contribution of paraphrastic data augmentation for each morphosyntactic category separately. Filtering out multi-lexeme lemmas allows removing configurations not supported by the Semafor parser which we use for argument identification;\(^5\)

2. **paraphrastic candidates filtering**: paraphrastic candidates are filtered based on the cosine similarity measure between their distributional representation and the distributional representation of the source lexical unit.

The aforementioned distributional representations refer to vectorial representations of the meaning of words where the dimensions of the vectors record contextual information about the co-occurrence of target words with their neighboring words as observed in large text corpora. The distributional representations used for paraphrastic candidates filtering are computed from predictive models and count-based models. Predictive models estimate word vectors via a supervised task where the weights of the word vector are set to maximize the probability of the contexts in which the word is observed in the corpus. Count-based models compute word vectors by extracting co-occurrence counts of target words and their contexts. The cosine similarity measure used is defined as the dot product of two vectors normalized by the product of vectors length. Given two distributional representations \(\mathbf{u} = (u_1, \ldots, u_n)\) and \(\mathbf{v} = (v_1, \ldots, v_n)\), the cosine similarity between \(\mathbf{u}\) and \(\mathbf{v}\) is formally defined as:

\[
\cos(\mathbf{u}, \mathbf{v}) = \frac{\sum_i u_i \cdot v_i}{||\mathbf{u}|| \cdot ||\mathbf{v}||} \tag{4.20}
\]

\(^5\) Semafor does not support distant multi-lexeme lemmas such as phrasal verbs separated by nouns or adjectives, e.g. “give the answer away”
4.1. Model

The semantic filter component of the paraphrastic candidates filter has three possible configurations:

1. **random** which selects \( n \) random paraphrastic candidates in the list;

2. **word2vec** which filters out paraphrastic candidates based on a *word2vec* predictive model (Mikolov et al., 2013) trained on the GoogleNews corpus;\(^6\)

3. **dissect** which filters out paraphrastic candidates using the *dissect* toolkit (Dinu et al., 2013) with two different models: a *word2vec* predictive model trained on a concatenation of the ukWaC, English Wikipedia, and BNC corpora, and a (reduced) count-based model generated from the same concatenated corpus (see Baroni et al., 2014, for details).

Both *word2vec* and *dissect* configurations have two additional setups:

1. **top**: which selects the top \( n \) elements from a list of paraphrastic candidates ranked in a decreasing order according to the cosine similarity between their distributional representations and the distributional representation of the original target;

2. **threshold** which selects all paraphrastic candidates for which the cosine similarity between their distributional representations and the distributional representation of the original target is above a specified value.

4.1.2 Argument identification

For argument identification we rely on the log-linear model of Das et al. (2014), modified by Kshirsagar et al. (2015) to reduce training time and enable training on exemplar sentences.

4.1.2.1 Model

The model performs argument span identification and argument role labeling jointly: all possible spans are pre-identified with a rule-based algorithm and the system then assigns a role to each span from the set of frame elements belonging to the target predicate’s frame, to which has been added the null role \( \varnothing \) in case no role is to be assigned to the span.

**Argument span identification** is performed by identifying all continuous spans in a sentence that contain a single word or comprise a valid subtree of a word and all its descendants in the dependency parse produced by the dependency parser. This bounds recall on argument identification as it covers only 80% of arguments in the FrameNet dataset.

**Argument role labeling** is performed with a log-linear model as follows: Let \( x \) be a dependency-parsed sentence, \( p \) the target predicate and \( f \) the frame evoked by \( p \). Let \( \text{spans}(x, p, f) \) be the set of candidate spans previously identified. For each candidate argument \( a \in \text{spans}(x, p, f) \) and each role (frame element) \( r \), a binary feature vector \( \phi(a, x, p, f, r) \)

---

\(^6\)See details at [https://code.google.com/archive/p/word2vec/](https://code.google.com/archive/p/word2vec/)
is extracted. Let \( w \) be the weight matrix. Each argument \( a \) is given a real-valued score by a linear model:

\[
\text{score}_w(a|x,p,f,r) = w^\top \phi(a,x,p,f,r)
\]  

(4.21)

### 4.1.2.2 Features

Figure 4.3 shows the list of feature templates used by the model. Every feature template has a \( \bigodot \) version that does not take into account the role being filled (so as to incorporate overall biases). The \( \bigcirc \) symbol indicates that the feature template also has a variant that is conjoined with the frame element name being filled, and \( \bullet \) indicates that the feature template additionally has a variant that is conjoined with both the frame element name and the frame name.

### 4.1.2.3 Learning

The model is trained using a local objective where each span-role pair is treated as an independent training instance. Consider the following squared structured hinge loss function \( L_w \) given for a training example \( i \):

\[
L_w(i) = \left( \max_{a'} (w^\top \cdot \phi(a',x,p,f,r) + 1\{a' \neq a\}) - w^\top \cdot \phi(a,x,p,f,r) \right)^2
\]  

(4.22)

The model parameters are learned by minimizing the \( l_2 \)-regularized average loss using the online optimization method AdaDelta (Zeiler, 2012):

\[
w^* = \arg\min_w \frac{1}{N} \sum_{i=1}^N L_w(i) + \frac{1}{2\lambda} \|w\|_2^2
\]  

(4.23)

### 4.1.2.4 Decoding

Decoding is done using beam search which produces a set of \( k \)-best hypotheses of sets of span-role pairs. The approach enforces multiple constraints including the fact that a frame element label may be assigned to at most one span and that spans of overt arguments must not overlap.

### 4.2 Experimental setup

#### 4.2.1 Datasets

In this work we diverge from previous approaches in that we rely on the latest FrameNet 1.7 data release instead of FrameNet 1.5. We split data in three sets: train, dev, test for training, development and testing. For testing, we use the same list of fulltext documents as Das et al. (2014) used for testing on FrameNet 1.5. Using FrameNet 1.7 has the benefit of almost doubling the size of the testing set, providing thereby a more robust set to test model performances. Table 4.1 shows the number of sentences and annotation sets in the
### 4.2. Experimental setup

| Features with both null and non-null variants: | These features come in two flavors: |
|----------------------------------------------|----------------------------------|
| • some word in \( t \) has lemma \( \lambda \) | if the argument is null, then one version fires; if it is overt (non-null), then another version fires. |
| • some word in \( t \) has lemma \( \lambda \), and the sentence uses \emph{PASSIVE} voice | • some word in \( t \) has lemma \( \lambda \), and the sentence uses \emph{ACTIVE} voice |
| • the head of \( t \) has subcategorization sequence \( \tau = (\tau_1, \tau_2, \ldots) \) | • some syntactic dependent of the head of \( t \) has dependency type \( \tau \)
| • the head of \( t \) has many syntactic dependents | • bias feature (always fires) |

### Span content features: apply to overt argument candidates.

- POS tag \( \pi \) occurs for some word in \( s \)
- the first word of \( s \) has POS \( \pi \)
- the last word of \( s \) has POS \( \pi \)
- the head word of \( s \) has POS \( \pi \)
- \( w_s \) and its closed-class POS tag \( \pi_{s2} \)
  - provided that \( |s| \geq 2 \)
- the head word of \( s \) has lemma \( \lambda \)
- the last word of \( s \): \( w_{|s|} \) has lemma \( \lambda \)
- \( w_{|s|} \) and its closed-class POS tag \( \pi_{|s|1} \)
  - provided that \( |s| \geq 3 \)
- \( \lambda \) is realized in some word in \( s \)
- \( \lambda \) is realized in some word in \( s \)
- the voice denoted in the span (\emph{ACTIVE} or \emph{PASSIVE})

### Syntactic features: apply to overt argument candidates.

- dependency path: sequence of labeled, directed edges from the head word of \( s \) to the head word of \( t \)
- length of the dependency path

### Span context POS features: for overt candidates, up to 6 of these features will be active.

- a word with POS \( \pi \) occurs up to 3 words before the first word of \( s \)
- a word with POS \( \pi \) occurs up to 3 words after the last word of \( s \)

### Ordering features: apply to overt argument candidates.

- the position of \( s \) with respect to the span of \( t \): \emph{BEFORE}, \emph{AFTER}, or \emph{OVERLAPPING} (i.e. there is at least one word shared by \( s \) and \( t \))
- linear word distance between the nearest word of \( s \) and the nearest word of \( t \)
  - provided \( s \) and \( t \) do not overlap
- linear word distance between the middle word of \( s \) and the middle word of \( t \)
  - provided \( s \) and \( t \) do not overlap

Figure 4.3: Argument identification feature templates as of Das et al. (2014)
train/dev/test setting on FrameNet 1.7. Table 4.2 shows the same metrics on FrameNet 1.5 and 1.7 in a train/test setting where the content of the development set is included in the training set. Additional data such as counts and coverage metrics for lexical units, frame elements, valence units and valence patterns are provided in Chapter 7.

| FRAMENET 1.7 DATASET METRICS |
|-----------------------------|
|                           | #sentences | #annotationsets |
| TRAIN (FULLTEXT + EXEMPLAR) | 168237     | 184050          |
| TRAIN (FULLTEXT)           | 2804       | 16215           |
| DEV                        | 887        | 5715            |
| TEST                       | 1247       | 6517            |

Table 4.1: FrameNet 1.7 datasets metrics with development and testing sets. The training set does not include the development set

| FRAMENET 1.5 AND 1.7 DATASETS METRICS |
|--------------------------------------|
|                                       | #sentences | #annotationsets |
| TRAIN FT 1.5                          | 2983       | 18228           |
| TRAIN FT 1.7                          | 3691       | 20886           |
| TRAIN FT+EX 1.5                       | 150735     | 168357          |
| TRAIN FT+EX 1.7                       | 169124     | 189553          |
| TEST 1.5                              | 875        | 3702            |
| TEST 1.7                              | 1246       | 6040            |

Table 4.2: Metrics comparison between FrameNet 1.5 and FrameNet 1.7 datasets with no development set

4.2.2 Toolkits

Over the course of our research, we had to develop and entire toolkit so as to replicate past results, implement our models and compare ourselves to previous approaches. The following sections provide a short description of this toolkit.

4.2.2.1 Querying valence patterns

As valence patterns were not accessible out-of-the-box in FrameNet, due to their being deeply embedded in the structure of FrameNet XML and split into lists of valence units, we had to implement a set of tools in order to be able to efficiently search for valence patterns in the FrameNet dataset. For performance reasons, we decided to rely on a NoSQL MongoDB database which provided an optimal architecture with indexed valence units and valence patterns against which FrameNet data could be queried directly. We named our application to import FrameNet XML data to MongoDB NoFrameNet.\textsuperscript{7} We

\textsuperscript{7}available at: https://github.com/akb89/noframenet
then implemented a search engine API to query FrameNet valence patterns in MongoDB. The API would receive HTTP GET requests and return JSON-formatted FrameNet data. We named this API Valencer\(^8\) and published it as a system demonstration during the COLING 2016 conference (see Kabbach and Ribeyre, 2016). To be able to easily visualize the output of our API, we also implemented a web client on top of the Valencer API. We named it myValencer\(^9\) and published it at the eLex 2017 conference as a system demonstration (see Kabbach and Ribeyre, 2017).

### 4.2.2.2 From Semafor to Rofames

We forked the acl2015 branch of the Semafor parser of Das et al. (2014), corresponding to the version of the parser used in Kshirsagar et al. (2015). We re-implemented the whole preprocessing pipeline to generate the train, dev and test splits from FrameNet XML data as it was no longer available in that version of Semafor. This enabled us to train and test on FrameNet 1.7 data in addition to 1.5. We added a branch for the system where we removed the hierarchy feature introduced by Kshirsagar et al. (2015) in order to have a version of Semafor corresponding to previous baselines but we kept the changes in training as it reduced training time by about one order of magnitude and made it possible to train on exemplar sentences as well as fulltext. We named our forked version Rofames, the semordnilap of Semafor.

### 4.2.2.3 Generating paraphrastic examples and debugging Rofames

We implemented a Python wrapper, named pyFN, to handle FrameNet XML data in a more systematic fashion. This proved particularly helpful as we discovered that FrameNet XML data contained many corrupted entries (such as annotation with partially missing label indexes), which bugged our paraphrastic data augmentation system pFN (see Chapter 5 for details). In addition to pyFN and pFN, we also implemented a debugging application named dFN to compute several metrics such as coverage and precision/recall/F\(_1\) scores per frame element given FrameNet data and the model output by Rofames.

### 4.2.3 Hyperparameters

In all our experiments, Rofames is used with \(\lambda = 1e^{-6}\) and a beam of 100. Data are tokenized and part-of-speech tagged with NLP4J (Choi, 2016) and dependency-parsed with BMST (Kiperwasser and Goldberg, 2016). The Valencer API throws requests at a MongoDB database containing the exact same data as in the training set. We experiment pFN configurations with semantic filtering with word2vec predict and dissect reduced count models, all in random mode with random values 2,3,4, in top mode 2,3,4 and in threshold mode 0.5 and 0.7. We filter part of speech to experiment data augmentation on nouns only, verbs only, adjectives only and nouns plus verbs.

\(^8\)available at: https://github.com/akb89/valencer
\(^9\)available at: https://github.com/akb89/myvalencer
In this chapter we report on our attempts to replicate several past results of argument identification with our FrameNet 1.7 datasets. We also discuss several crucial experimental considerations regarding the production of a robust baseline for argument identification on FrameNet. In Section 5.1 we report on results validating our preprocessing implementation in Rofames. In Section 5.2 and Section 5.3, we discuss the impact of part-of-speech taggers and dependency parsers on argument identification. Next, in Section 5.4 and Section 5.5 we report on our attempts at replicating results from (Kshirsagar et al., 2015) with exemplar data and the hierarchy feature. Finally, in Section 5.6 we summarize our results and compile them into a list of recommendations providing a robust baseline against which we will be able to compare our paraphrastic data augmentation approach in Chapter 6.

### 5.1 Validating the preprocessing pipeline

As we re-implemented the preprocessing pipeline of Rofames, we first tested the robustness of our implementation by replicating previous baseline results based on the FrameNet 1.5 splits of Das et al. (2014). We trained Rofames on our train split but tested on the test split of Das et al. (2014). Our train split differed from that of Das et al. (2014) in that we applied strict filtering of potentially erroneous annotation in order not to bias the parser: we removed all annotation sets which contained missing or invalid start/end indexes (except for null instantiations). Splits were tokenized using Robert MacIntyre’s sed script, part-of-speech tagged with MXPOST (Ratnaparkhi, 1996) and dependency-parsed with the MSTParser (McDonald et al., 2006), following the original pipeline of Das et al. (2014). For scoring, we used the two evaluation scripts mentioned in Section 2.4.3:

1. **SEM**: the SemEval 2007 evaluation script as-is (Baker et al., 2007)

2. **ACL**: the modified SemEval 2007 evaluation script used by Kshirsagar et al. (2015), which does not give extra credits for (gold) frames and therefore better accounts for
argument identification performances (refer to Section 2.4.3 for details)

Scores, detailed in Table 5.1, validate our implementation. Results output by the \textit{SEM} scoring script are consistent with the baseline reported in (Roth and Lapata, 2015). Regarding results output by the \textit{ACL} script, we found a 1 point $F_1$ gain over the baseline reported in (Kshirsagar et al., 2015). Both approaches used the train and test splits of Das et al. (2014). Note that we found the decrease in precision to be consecutive to the increase in recall.

| Validating Rofames preprocessing pipeline on FrameNet 1.5 |
|-----------------------------------------------------------|
| \textbf{SEM}                                             |
| #1 ROFAMES + MXPOST + MST                                | P   | R   | $F_1$ |
| Roth and Lapata (2015)                                   | 76.9| 74.4| 75.6  |
| \textbf{ACL}                                             |
| #1 ROFAMES + MXPOST + MST                                | P   | R   | $F_1$ |
| Kshirsagar et al. (2015)                                 | 64.3| 56.4| 60.1  |

Table 5.1: Argument identification results with gold frames output by the \textit{SEM} and \textit{ACL} scoring scripts. Train and test splits are generated from FrameNet 1.5 fulltext XML data. Train split is produced by ROFAMES, test split is that of Das et al. (2014) as-is. All data are part-of-speech tagged with MXPOST and dependency parsed with the MSTParser.

\section{Impact of part-of-speech taggers}

Past studies on frame semantic parsing have used various preprocessing toolkits. In this section, we focus on the impact of part-of-speech tagger performances on argument identification, comparing MXPOST (Ratnaparkhi, 1996) originally used in (Das et al., 2014) with NLP4J (Choi, 2016) used in (Roth, 2016). Results, reported in Table 5.2, show a systematic $F_1$ gain in argument identification when relying on the NLP4J part-of-speech tagger. Improvements gains vary from 0.3 $F_1$ in test to 0.7 $F_1$ in dev, with a systematic improvement in recall. In subsequent experiments, we rely systematically on NLP4J for part-of-speech tagging.

\section{Impact of dependency parsers}

Similarly, past studies on frame semantic parsing have used various dependency parsers. Here, we compare the MSTParser originally used Das et al. (2014) to the BIST parser (Kiperwasser and Goldberg, 2016) in two of its variants: the transition-based BARCH parser and the graph-based BMST parser. The BIST parser was originally used by Roth (2016) for frame semantic parsing. Results, presented in Table 5.3, show a systematic improvement on argument identification when preprocessing data with the BIST parser rather than the MSTParser. $F_1$ gains vary from 1.3 to 2.6 depending on the scoring set and the BIST parser.
5.4. Impact of exemplar annotation

In the next two sections, we report on our attempts to replicate results from Kshirsagar et al. (2015). We first include exemplar data in the training set. Results, displayed in Table 5.4, show a systematic 1.2 $F_1$ gain over training on fulltext data only. This is, however, significantly lower that the 2.8 $F_1$ gain on FrameNet 1.5 data reported by Kshirsagar et al. (2015). In all the following sections, we found $F_1$ gains on our FrameNet 1.7 splits to be systematically lower that those reported in (Kshirsagar et al., 2015). We hypothesize that those may be due to the increased size of the development and testing sets, the reduced size
of the training set when testing with the development set, and the increased robustness of our train, dev and test splits which do not contain duplicate annotation sets likely to bias scores, and no annotation sets with missing or invalid indexes.

### Adding exemplar data on FrameNet 1.7

|       | P   | R   | F₁  |
|-------|-----|-----|-----|
| dev   |     |     |     |
| #9 FT | 59.4| 52.6| 55.8|
| #12 FT + EX | 58.4 | 55.7 | 57.0 |
| test  |     |     |     |
| #9 FT | 60.5| 55.6| 58.0|
| #12 FT + EX | 59.5 | 58.9 | 59.2 |

Table 5.4: Argument identification results with gold frames. ROFAMES is trained on fulltext (FT) and exemplar (EX) data

### 5.5 Impact of the hierarchy feature

Additionally, still following Kshirsagar et al. (2015), we trained ROFAMES on FrameNet 1.7 data with the hierarchy feature comprising Inheritance and SubFrame relations. Results, displayed in Table 5.5, show a F₁ gain of 0.5 to 0.7 when using the hierarchy feature, again lower than the 1.3 gain reported by Kshirsagar et al. (2015) on FrameNet 1.5. When incorporating both the hierarchy feature and exemplar data to the setup, we show a 2.1 to 2.4 F₁ gain, again significantly lower than the 4 points gain reported by Kshirsagar et al. (2015).

### Adding the hierarchy feature on FrameNet 1.7

|       | P   | R   | F₁  |
|-------|-----|-----|-----|
| dev   |     |     |     |
| #9 FT | 59.4| 52.6| 55.8|
| #13 FT + H | 60.0 | 53.5 | 56.5†|
| #14 FT + H + EX | 59.2 | 57.2 | 58.2‡|
| test  |     |     |     |
| #9 FT | 60.5| 55.6| 58.0|
| #13 FT + H | 61.0 | 56.3 | 58.5*|
| #14 FT + H + EX | 60.3 | 60.0 | 60.1‡|

Table 5.5: Argument identification results with gold frames. ROFAMES is trained on fulltext (FT) and exemplar (EX) data, with and without the hierarchy feature (H) of Kshirsagar et al. (2015). Statistical significance is indicated by ‡ for \( p < 0.01 \), † for \( p < 0.05 \) and * for \( p < 0.10 \).
5.6 Baseline

All subsequent experiments in Chapter 6 rely on the baseline scores shown in Table 5.6, computed from FrameNet 1.7 splits. We built on results of previous sections in order to produce the most robust baseline:

- for each train/dev/test split, all annotation sets with missing or invalid start/end indexes are removed (except for null instantiations);
- all duplicate annotation sets and sentences are removed from the test split;
- incomplete annotation – targets with annotated frames but no annotated frame elements – are removed from the training set;
- data are part-of-speech tagged with the NLP4J tagger (Choi, 2016);
- data are dependency-parsed with the BIST BMST parser (Kiperwasser and Goldberg, 2016).

| Argument identification baseline on FrameNet 1.7 |
|-----------------------------------------------|
|                                                |
|                                                |
| P  | R  | F₁   |
|-----------------------------------------------|
| #9  | dev | 59.4 | 52.6 | 55.8 |
| #9  | test| 60.5 | 55.6 | 58.0 |

Table 5.6: Baseline scores for argument identification with gold frames on dev and test splits, scored with the ACL script. Train, dev and test splits are part-of-speech tagged with NLP4J and dependency parsed with the BIST BMST parser.
In this chapter, we report on the contribution of our paraphrastic data augmentation model described in Chapter 4 to argument identification, evaluated against the baseline described in Chapter 5. Our preliminary results, obtained by augmenting nouns and verbs without filtering paraphrastic candidates (see Section 6.1), confirm the need for additional (semantic) filtering: both approaches lead to a systematic decrease in $F_1$ score compared to the baseline, despite the significant increase in size of the datasets produced, almost one order of magnitude higher than the baseline in the case of augmented verbs.

Our semantic filtering approach, detailed in Section 6.3, shows mixed results: on augmented nouns and adjectives, it yields no significant improvements, but it does not lead to significant decreases in performance either. On augmented verbs, it does yield limited improvements, in the order of .5 $F_1$ gain in the best scenario (XP#41). However, none of the reported improvements prove statistically significant in the end, with $p$ values systematically above 0.1, except for XP#29 ($p = 0.08$).

If, overall, our results tend to demonstrate the smartness of the ROFAMES parser, the marginal improvements shown upon training on augmented verbs, albeit not statistically significant, suggest that there could be specific patterns that ROFAMES fails to extract from gold data alone.

Similarly, our results tend to support the robustness of our paraphrastic data augmentation approach: almost none of the approaches relying on filtering of paraphrastic candidates lead to a decrease in performances, suggesting that the core pFN logic, combined with the right candidates filtering, rarely introduces noise in the data.

However, those results should again lead us to tread carefully, as no-filtering approaches do show significant decreases in performance, suggesting that paraphrastic approaches relying on FrameNet annotation logic alone have a natural tendency to generate (noisy) unlikely predicate-argument lexical configurations, to which the ROFAMES parser is not robust.

It would be tempting at first to conclude from our results that semantic filtering of
Chapter 6. Results

paraphrastic candidates, motivated by semantic proximity measures computed from distributional representations of words, is capable of compensating for the natural tendency of pFN to generate unlikely lexical configurations. However, semantic filtering approaches do not actually prove any better than random filtering approaches, as shown in Section 6.3.5.

What is to be made of the observations hereof? We postulate two interpretations, motivated by two distinct phenomena: (1) there exists a latent variable, not necessarily semantically motivated, or at least not in ways distributional models can capture, that determines, among the set of unfiltered pFN candidates, what is noise from what is not; or (2) data generated by pFN are actually always somehow noisy, but the ROFAMES parser is robust enough that it can compensate for the bias introduced by noisy artificial data, provided that those noisy data remain limited in size.

All in all, the results and preliminary explanations presented in this chapter do not suffice to arbitrate, in light of the intricacies that arise. Further systematic analysis of datasets and errors are required in order to properly guide reflection. Those analysis will be presented in Chapter 7, and further discussed in Chapter 8.

6.1 No filtering setup

In the first two experiments we augmented the FrameNet fulltext training set with pFN-generated data produced with minimal filtering: we kept only noun and verb annotation sets and did not apply any semantic filtering on candidates. Our preliminary results for augmented nouns and verbs are shown in Table 6.1. In all subsequent tables, FT refers to FrameNet fulltext data and EX to FrameNet exemplar data.

| No filtering setup | XP | FN | pFN | POS | #sent | #anno | P  | R  | F1 |
|--------------------|----|----|-----|-----|-------|-------|----|----|----|
| baseline           | FT | –  | –   | –   | 2804  | 15389 | 59.4| 52.6| 55.8|
| #16                | FT | FT | N   | –   | 10386 | 34734 | 60.3| 51.5| 55.6|
| #18                | FT | FT | V   | –   | 36234 | 126436| 60.4| 50.9| 55.3|

Table 6.1: Argument identification results with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from FT filtered by part-of-speech (POS). Results are given for nouns (N) and verbs (V) without additional filtering on pFN candidates.

Results confirm the second scenario formulated in Section 4.1.1.3: the statistical classifier used for argument identification seems to be sensitive to predicate-argument lexical configurations, to the point that bias introduced by unlikely lexical configurations does not compensate for the lexical diversity brought at the argument level. Note, in addition, that the size of the training set increases significantly with the paraphrastic data augmentation approach, due to the number of paraphrastic candidates extracted by the valence pattern matching algorithm.
6.2 Introducing multi-tokens filtering

The Rofames system fails to process cases where annotated lexical units contain non-continuous tokens, such as phrasal verbs separated by a noun (e.g. *He gave the answer away*). We therefore tried and filtered out all multi-token targets and candidates to see whether or not it could positively impact the performances of the classifier. Results, displayed in Table 6.2, show a marginal difference compared to the no-filtering approach. We nonetheless applied multi-tokens (or *multiword expressions*) filtering in all subsequent experiments in order to limit the pool of candidates and generate higher quality artificial data.

| train | filters | XP | FN | pFN | POS | MWE | #sent | #anno | P | R | F1 |
|-------|---------|----|----|-----|-----|-----|-------|-------|----|----|----|
| baseline FT – – – 2804 15389 59.4 52.6 55.8 |
| #18 FT FT V false 36234 126436 60.4 50.9 55.3 |
| #19 FT FT V true 34119 119418 60.9 50.5 55.2 |

Table 6.2: Impact of multi-tokens filtering (MWE = true) on argument identification with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from verbs

6.3 Introducing semantic filtering

6.3.1 Semantic filtering on nouns

Following the observations of Section 6.1, we first experimented on filtering noun candidates with a word2vec semantic filter. Overall results, displayed in Table 6.3, show a marginal, though not statistically significant ($p = 0.3$), improvement in one scenario (XP #21), and a systematic decrease in recall otherwise, suggesting that the pFN system mostly introduced noise in the training set.

6.3.2 Semantic filtering on adjectives

Similar observations apply for adjectives, which exhibit not significant improvements overall, regardless of the filtering configuration used (see Table 6.4).

6.3.3 Semantic filtering on verbs

Experiments with semantic filtering on verbs, reported in Table 6.5, show a relative increase in recall over the baseline, especially compared to no-filtering approaches. Overall, results tend to show that filtering candidates by keeping those *closest semantically* to the original target is beneficial, especially when keeping two to three candidates per target only. No significant different is observed between *top* and *threshold* filtering. The most interesting
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Semantic filtering on nouns

| XP  | FN | pFN | POS | MWE | SEM | #sent | #anno | P   | R   | F1  |
|-----|----|-----|-----|-----|-----|-------|-------|-----|-----|-----|
| baseline | FT | –   | –   | –   | –   | 2804  | 15389 | 59.4| 52.6| 55.8|
| #16  | FT | FT  | N   | –   | –   | 10386 | 34734 | 60.3| 51.5| 55.6|
| #20  | FT | FT  | N   | –   | random-3 | 6615  | 24209 | 59.7| 52.0| 55.6|
| #21  | FT | FT  | N   | –   | top-3 | 6537  | 24050 | 60.4| 52.0| 55.9|
| #22  | FT | FT  | N   | –   | threshold-0.5 | 3021  | 15666 | 59.2| 52.5| 55.7|
| #23  | FT | FT  | N   | –   | threshold-0.7 | 2844  | 15434 | 60.0| 52.2| 55.8|

Table 6.3: Impact of various word2vec semantic filtering of pFN candidates on argument identification with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from nouns (N)

Semantic filtering on adjectives

| XP  | FN | pFN | POS | MWE | SEM | #sent | #anno | P   | R   | F1  |
|-----|----|-----|-----|-----|-----|-------|-------|-----|-----|-----|
| baseline | FT | –   | –   | –   | –   | 2804  | 15389 | 59.4| 52.6| 55.8|
| #33  | FT | FT  | A   | –   | random-3 | 6000  | 21811 | 59.7| 52.3| 55.8|
| #34  | FT | FT  | A   | –   | top-3 | 5984  | 21799 | 59.5| 52.6| 55.8|
| #35  | FT | FT  | A   | –   | threshold-0.5 | 3490  | 16221 | 59.4| 52.3| 55.6|

Table 6.4: Impact of various word2vec semantic filtering of pFN candidates on argument identification with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from adjectives (A)

experiment is probably XP#30 which shows a $\Delta F_1$ gain over the baseline with a less that doubled dataset. Note, however, that none of the experiments proved statistically significant ($p > 0.1$) and that the best improvements in precision seen in XP#31 are incidental to the decrease in recall.

6.3.4 Semantic filtering on nouns and verbs

We also attempted to augment data in two dimensions at once, namely nouns and verbs, in order to increase lexical diversity and potentially bring new information to the statistical classifier. Experiments were all performed with a semantic filter on top, to reduce the pool of candidates, for both quality and feasibility reasons. Results, displayed in Table 6.6 show a significant drop in recall (XP#32) in a top-n setting, with an explosion of the size of the augmented dataset generated, suggesting very noisy and low quality data. Results in a threshold setting (XP#36) did not bring statistically significant improvements, and generated a limited number of paraphrastic sentences.
6.3. Introducing semantic filtering

### Semantic filtering on verbs

| train | filters | XP | FN | pFN | POS | MWE | SEM | #sent | #anno | P   | R   | F1  |
|-------|---------|----|----|-----|-----|-----|-----|-------|-------|-----|-----|-----|
| bas.  | FT      | –  | –  | –   | –   | –   | –   | 2804  | 15389 | 59.4| 52.6| 55.8|
| #19   | FT      | FT | V  | true| –   | –   | –   | 34119 | 119418| 60.9| 50.5| 55.2|
| #30   | FT      | FT | V  | true| top-2| 8213| 28772| 60.2 | 52.8 | 55.2|
| #25   | FT      | FT | V  | true| top-3| 11099| 37491| 60.1 | 52.7 | 56.1|
| #31   | FT      | FT | V  | true| top-4| 13548| 45227| 61.1 | 52.0 | 56.2|
| #26   | FT      | FT | V  | true| threshold-0.5| 4720| 18826| 59.2 | 52.7 | 55.8|
| #27   | FT      | FT | V  | true| threshold-0.7| 2969| 15568| 59.7 | 52.5 | 55.9|

Table 6.5: Impact of various word2vec semantic filtering of pFN candidates on argument identification with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from verbs (V). None of the improvements reported proved statistically significant ($p > 0.1$).

### Semantic filtering on nouns and verbs

| train | filters | XP | FN | pFN | POS | MWE | SEM | #sent | #anno | P   | R   | F1  |
|-------|---------|----|----|-----|-----|-----|-----|-------|-------|-----|-----|-----|
| bas.  | FT      | –  | –  | –   | –   | –   | –   | 2804  | 15389 | 59.4| 52.6| 55.8|
| #32   | FT      | FT | N+V| true| top-3| 34367| 153293| 60.4| 49.4 | 54.3|
| #36   | FT      | FT | N+V| true| threshold-0.5| 5118| 19807| 60.0| 52.5 | 56.0|

Table 6.6: Impact of various word2vec semantic filtering of pFN candidates on argument identification with a model trained on FrameNet fulltext (FT) augmented with pFN data generated from nouns and verbs (N+V). In both settings (top and threshold), $p > 0.1$.

6.3.5 Comparing random vs. top filtering

We then tried to quantify the real benefits brought by a semantic filter based on proximity measures between two distributional representations, compared to a control filter selecting candidates randomly. The top-n filter, choosing the n paraphrastic candidates closest to the original target from a given list output by pFN, did not actually perform better than the random-n filter choosing n candidates randomly (see Table 6.7).

6.3.6 Comparing predictive and count-based distributional models

The previous experiment comparing top and random semantic filters raised the question of the quality of the underlying word2vec distributional model and toolkit used to measure semantic proximity between paraphrastic candidates and targets. Past research (Baroni et al., 2014) have shown that the choice of distributional model can significantly impact
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Random vs. top semantic filtering

| XP | FN | POS | MWE | SEM | #sent | #anno | P   | R   | F1  |
|----|----|-----|-----|-----|-------|-------|-----|-----|-----|
| #28 | FT | FT  | V   | true | random-2 | 8278 | 28885 | 60.3 | 52.6 | 56.1 |
| #30 | FT | FT  | V   | true | top-2   | 8213 | 28772 | 60.2 | 52.8 | 56.2 |
| #24 | FT | FT  | V   | true | random-3 | 11188| 37632 | 60.4 | 52.5 | 56.2 |
| #25 | FT | FT  | V   | true | top-3   | 11099| 37491 | 60.1 | 52.7 | 56.1 |
| #29 | FT | FT  | V   | true | random-4 | 13563| 45143 | 60.9 | 52.2 | 56.2 |
| #31 | FT | FT  | V   | true | top-4   | 13548| 45227 | 61.1 | 52.0 | 56.2 |

Table 6.7: Impact of top-n word2vec semantic filters versus n-random filters for pFN data generated from verbs. Improvements reported are not statistically significant ($p > 0.1$ except for XP#29 with $p = 0.08$)

performances on tasks such as semantic relatedness and synonym detection. We therefore experimented with two additional distributional models and toolkits, namely dissect-pred and dissect-rcount, on top of word2vec.\(^1\) However, our experimental results, displayed in Table 6.8, showed only marginal differences across models and toolkits.

| XP | POS | MWE | SEM             | #sent | #anno | P   | R   | F1  |
|----|-----|-----|-----------------|-------|-------|-----|-----|-----|
| #25 | V   | true| word2vec       | top-3 | 11099| 37491| 60.1| 52.7| 56.1|
| #37 | V   | true| dissect-pred   | top-3 | 11006| 37259| 59.8| 52.9| 56.1|
| #38 | V   | true| dissect-rcount | top-3 | 11026| 37281| 60.4| 52.3| 56.0|
| #26 | V   | true| word2vec       | threshold-0.5 | 4720 | 18826| 59.2| 52.7| 55.8|
| #39 | V   | true| dissect-pred   | threshold-0.5 | 3758 | 16855| 59.5| 52.7| 55.9|
| #40 | V   | true| dissect-rcount | threshold-0.5 | 6350 | 23656| 60.1| 52.4| 56.0|

Table 6.8: Comparing predictive and count-based distributional models for paraphrastic candidates filtering. Impact is measured on argument identification. word2vec is the traditional predictive model trained on Google News and used with the word2vec toolkit. dissect-pred is a word2vec predictive model extracted from a different dataset than Google News, and used with the dissect toolkit. dissect-rcount is a count-based model extracted from the same dataset than dissect-pred and used with the dissect toolkit.

6.3.7 Measuring the impact of exemplar data

Finally, we experimented with a pFN model performing valence pattern matching on the FrameNet fulltext plus exemplar dataset. Our purpose was to analyze whether such a model could actually beneficially incorporate information available in the exemplar dataset,

\(^1\)see Section 4.1.1.4 for details
or, failing that, be able to create an augmented artificial dataset of higher quality given that paraphrastic candidates would be chosen from a larger pool. Results, displayed in Table 6.9, showed no significant improvements over the pFN model based on fulltext alone. Note that improvements reported in XP#30 and XP#41 did not prove statistically significant ($p > 0.1$), while improvements on XP#12 did ($p < 0.01$). This shows that training on gold fulltext and exemplar data leads to much more robust improvements than training on our artificial dataset.

| XP    | train | filters | #sent | #anno | P   | R   | F1  |
|-------|-------|---------|-------|-------|-----|-----|-----|
| base. | FT    | –       | 2804  | 15389 | 59.4| 52.6| 55.8|
| #12   | FT+EX | –       | 168237| 184050| 58.4| 55.7| 57.0|
| #30   | FT    | FT V true | 8213  | 28772 | 60.2| 52.8| 56.2|
| #41   | FT    | FT+EX V true | 14588 | 53536 | 60.3| 52.9| 56.3|

Table 6.9: Impact of using exemplar data for training ROFAMES (XP#12), or for generating artificial data via pFN (XP#41). A top-2 word2vec semantic filter is applied to limit the size of the paraphrastic dataset generated by pFN. Improvements in XP#30 and XP#41 are not statistically significant ($p > 0.1$), while improvements in XP#12 are ($p < 0.01$).
In this chapter we discuss both quantitative and qualitative performances of the statistical classifier used for argument identification. We focus on trying to identify (linguistic) phenomena and/or specific (linguistic) patterns which may account for the performances reported in Chapter 6. Our analysis is articulated around two axis: in Section 7.1, we present an exhaustive error analysis of the baseline system, proposing several angles to tackle the key question of what constitutes easy and hard frame elements, from the perspective of statistical learning. In Section 7.2 we discuss the respective contributions of incorporating exemplar and paraphrastic data into the training set, both in terms of coverage and how it affects data distribution. In the following sections we use exemplar approach to refer to the approach consisting in training on fulltext and exemplar data, and paraphrastic approach to refer to the approach corresponding to experiment 30, augmented on verbs with a word2vec top-2 filter.

7.1 Baseline error analysis

The purpose of this section is to discuss both qualitative and quantitative performances of the statistical classifier at a more fined-grained level than the micro-averaged results presented in Chapter 6. We report on the robustness of the parser to frequency effects (Section 7.1.1), analyze the impact of frame elements bearing targets on argument identification (Section 7.1.2), and discuss both lexical (Section 7.1.3) and syntactic challenges (Section 7.1.4) posed to statistical learning.

7.1.1 Frequency effects on Frame Elements

The first observation that can be made when looking at precision, recall and $F_1$ measure per frame element, is that the ROFAMES parser seems relatively robust to frequency effects. Indeed, Table 7.1 shows that, among the ten most frequent frame elements in the develop-
ment set, $F_1$ measures do not seem to correlate well with frequency and/or distribution in either training or development sets. The lack of pattern is confirmed when classifying frame elements by $F_1$ measure, such as in Table 7.2 or Table 7.3: we find certain frequent frame elements to have relatively low $F_1$ scores, such as Descriptor, Place or Figure, and conversely, certain less frequent frame elements to have higher $F_1$ scores, such a Count, Part, or Material.

| Top 10 Most frequent FEs |
|--------------------------|
|                          | train | dev | P   | R   | $F_1$ |
| Agent                   | 1391  | 347 | 68.5| 64.6| 66.5  |
| Entity                  | 1204  | 318 | 59.4| 55.7| 57.5  |
| Locale                  | 957   | 317 | 87.3| 89.0| 88.1  |
| Weapon                  | 608   | 308 | 67.8| 66.2| 67.0  |
| Time                    | 791   | 275 | 54.3| 34.5| 42.2  |
| Theme                   | 796   | 232 | 56.2| 56.5| 56.3  |
| Message                 | 541   | 215 | 60.3| 53.0| 56.4  |
| Event                   | 670   | 211 | 44.9| 31.3| 36.9  |
| Speaker                 | 598   | 201 | 72.0| 71.6| 71.8  |
| Descriptor              | 527   | 172 | 35.3| 14.0| 20.0  |

Table 7.1: Top 10 most frequent frame elements, with occurrence counts in training and development sets

| Top 10 Best FEs |
|-----------------|
|                 | train | dev | P   | R   | $F_1$ |
| Number          | 207   | 59  | 96.6| 96.6| 96.6  |
| Substance       | 239   | 125 | 91.7| 88.8| 90.2  |
| Locale          | 957   | 317 | 87.3| 89.0| 88.1  |
| Person          | 304   | 70  | 84.9| 88.6| 86.7  |
| Count           | 164   | 82  | 73.5| 74.4| 73.9  |
| Part            | 116   | 72  | 73.2| 72.2| 72.7  |
| Unit            | 382   | 146 | 64.2| 82.2| 72.1  |
| Speaker         | 598   | 201 | 72.0| 71.6| 71.8  |
| Material        | 106   | 61  | 84.4| 62.3| 71.7  |
| Cognizer        | 537   | 129 | 72.5| 67.4| 69.9  |

Table 7.2: Top 10 best frame elements among the top 50 most frequent frame elements in dev set, ranked by $F_1$ score

| Top 10 Worst FEs  |
|-------------------|
|                   | train | dev | P   | R   | $F_1$ |
| Name              | 246   | 54  | 27.3| 11.1| 15.8  |
| Manner            | 251   | 89  | 29.4| 11.2| 16.3  |
| Means             | 144   | 54  | 42.9| 11.1| 17.6  |
| Descriptor        | 527   | 172 | 35.3| 14.0| 20.0  |
| Place             | 354   | 99  | 47.6| 20.2| 28.4  |
| Figure            | 464   | 83  | 31.0| 32.5| 31.8  |
| Cause             | 231   | 53  | 43.8| 26.4| 32.9  |
| State_of_affairs  | 145   | 153 | 42.4| 27.5| 33.3  |
| Use               | 310   | 112 | 40.7| 29.5| 34.2  |
| Hypothetical_event| 215   | 57  | 50.0| 28.1| 36.0  |

Table 7.3: Top 10 worst frame elements among the top 50 most frequent frame elements in dev set, ranked by $F_1$ score

### 7.1.2 Frame elements bearing targets

Looking closer at Table 7.2, we see that a limited number of frame elements, such as Number, Substance, Locale and Person, have significantly higher $F_1$ scores, systematically above 86% when the overall $F_1$ on the top 50 most frequent frame elements is at 56.2% and the average $F_1$ measure at 52.1%. Those frame elements have in common to be realized by
their respective targets, in what is called frame elements bearing targets configurations, as in:

(7.1) These are surrounded by areas of limestone formations, scrub and grassland, coral cliffs, and fine \text{sand} \text{Substance} beaches

In example 7.1, \textit{sand} is both the target evoking the \textit{Shapes} frame and the frame element \textit{Substance}. Such configurations appear particularly easy for the parser to acquire as it requires learning a correlation between a frame element, a frame and a frame-evoking target without special considerations for the frame element spans or syntactic realization. To better account for such cases we introduce the \texttt{febar} ratio, which, for a given frame element, is defined as:

\[
\text{febar}(f_e) = \frac{N_{febc}}{N_c}
\]

where \(N_{febc}\) is the number of frame element bearing configurations for the frame element \(f_e\) and \(N_c\) is the total number of configurations for the frame element \(f_e\).

As shown in Table 7.4 and Table 7.5, we find the \texttt{febar} ratio to correlate nicely with the \(F_1\) score of a given frame element: the higher the \texttt{febar} ratio, the more a given frame element will be realized in a frame element bearing configuration, and the easier it will be for the parser to predict it. There are three notable exceptions which constitute interesting cases: the \textit{Count} and \textit{Speaker} frame elements which have high \(F_1\) scores but low \texttt{febar} ratios, meaning that they are easy to predict despite being realized \textit{outside} of their respective targets; and the \textit{Weapon} frame element which has a high \texttt{febar} ratio but a \(F_1\) significantly lower than frame elements with comparable \texttt{febar} ratios, by almost 20 points of \(F_1\) score. Those examples actually illustrate interesting lexico-syntactic patterns that we will discuss in the following sections.

7.1.3 Lexical challenges

7.1.3.1 Lexical diversity

As mentioned in Chapter 3, lexical coverage and out-of-vocabulary effects play a determining role in frame semantic parsing in general. On argument identification, the impact of lexical coverage is probably best exemplified by the \textit{Name} frame element, which covers mostly proper nouns, as in Sentence 7.3, and as such is typically affected by out-of-vocabulary effects.

(7.3) Your Georgia O’Keeffe membership, please note, includes free admission to all art-related activities of the IMA’s \textit{[Young Friends of Art]Name group}

As shown in Table 7.3, the \textit{Name} frame element has the lowest performances among all frame elements predicted in the development set, with a \(F_1\) score of 15.8%, significantly below both micro-averaged (56.2%) and averaged (52.1%) \(F_1\) scores on all frame elements. The task of identifying \textit{Name} labels is actually a harder task than mere Named Entity
### Chapter 7. Error analysis

#### Top 10 FEs by $F_1$

| Febar  | P    | R    | $F_1$ |
|--------|------|------|-------|
| Number | 100  | 96.6 | 96.6  |
| Substance | 95.2 | 91.7 | 88.8  |
| Locale | 96.5 | 87.3 | 89.0  |
| Person | 92.9 | 84.9 | 86.7  |
| Count | 1.2  | 73.5 | 74.4  |
| Part | 34.7 | 73.2 | 72.7  |
| Unit | 81.5 | 64.2 | 82.2  |
| Speaker | 1.5  | 72.0 | 71.6  |
| Material | 54.1 | 84.4 | 62.3  |
| Cognizer | 9.3  | 72.5 | 67.4  |

Table 7.4: Top 10 best frame elements among the top 50 most frequent frame elements in dev set, with febar ratio and ranked by $F_1$ score

#### Top 10 FEs by febar

| Febar  | P    | R    | $F_1$ |
|--------|------|------|-------|
| Number | 100  | 96.6 | 96.6  |
| Locale | 96.5 | 87.3 | 89.0  |
| Substance | 95.2 | 91.7 | 88.8  |
| Weapon | 94.5 | 67.8 | 66.2  |
| Person | 92.9 | 84.9 | 86.7  |
| Unit | 81.5 | 64.2 | 82.2  |
| Origin | 67.6 | 56.4 | 62.0  |
| Leader | 63.0 | 64.3 | 66.7  |
| Material | 54.1 | 84.4 | 62.3  |
| Text | 45.1 | 71.1 | 52.9  |

Table 7.5: Top 10 frame elements among the top 50 most frequent frame elements in dev set, ranked by febar ratio

Recognition, considering that NAME frame elements can be realized in various syntactic patterns, beyond noun phrases, as in:

(7.4) The island [of Jamaica]_{Name} will be near the top of the list for anyone planning an idyllic holiday getaway.

The difficulty posed by the NAME frame element is encompassed in the larger phenomenon of lexical diversity: if a frame element is realized in a wide range of lexical patterns, the frame element may prove harder to predict, especially if it is realized in a lexical pattern that has not been previously seen in the training set. This is exactly what is happening for the NAME frame element: as there is a multitude of possible lexical patterns that can be labeled with NAME, they will prove almost impossible to predict by the parser if previously unseen in training, as there will be no way for the parser to compensate for its lack of lexical knowledge.

#### 7.1.3.2 Compensating lexical diversity

However, lexical diversity itself is not enough to characterize the difficulty to predict a given frame element. Indeed, high lexical diversity effects can be compensated by systematic syntactic patterns. In other words, a frame element which is realized lexically in a wide range of patterns may prove easy to predict as long as it is realized in clear and systematic syntactic patterns. This is typically the case of frame elements such as Agent or Speaker, which are overwhelmingly realized as subjects in noun phrases (NP.Ext) – 75% of the time for Agent and 85% of the time for Speaker respectively. Moreover, the NP.Ext syntactic
pattern has the benefit of translating well into a single arc \((subj)\) between the predicate and the argument, in the dependency tree produced by the syntactic parser. Therefore, the statistical classifier used for argument identification can adequately learn a correlation between certain predicates and the arguments connected to them by a \(subj\) arc in order to properly predict frame element labels such as \textit{Agent} or \textit{Speaker}. Such phenomena explain why \(F_1\) scores in frame elements such as \textit{Speaker} (71.8\%) can be significantly higher than the micro-averaged and averaged \(F_1\) measures on all frame elements, despite their low respective \textit{febar} ratio.

Such compensating effects become all the more obvious when syntactic representations between output dependencies and FrameNet valence units do not align. In such cases, the statistical classifier clearly fails to properly classify corresponding spans with the adequate frame element label, as in:

\[(7.5)\] The Defense Department has awarded \{BioPort Corporation\}_{Agent} a contract to manufacture, test, bottle and \textbf{store} \{anthrax vaccine\}_{Theme}, the company has announced.

In this particular case \textit{BioPort Corporation} is labeled by the syntactic parser as being in an \textit{obj} – and not \textit{subj} – dependency to the \textit{awarded} – and not \textit{store} – predicate, while it is marked as \textit{NP.Ext} in FrameNet for the \textit{store} target. Consequently, the ROFAMES parser fails to properly label it as the \textit{Agent}, a phenomenon that is found to be systematic and can be grouped into the more general category of \textit{syntactic misalignments}. The question of syntactic challenges will be covered in greater length in Section 7.1.4.

### 7.1.3.3 Semantic considerations

When analyzing more carefully the case of the \textit{Weapon} frame element, we found interesting cases where the appropriate annotation of the frame element label required specific semantic considerations involving deep lexical representations. Indeed, in FrameNet, terms such as \textit{nuclear} will be solely labeled as \textit{Weapon} in constructions such as \textit{nuclear war}, while it is usually labeled as \textit{Weapon} together with the noun it qualifies in constructions such as \textit{nuclear weapon} or \textit{nuclear missile}. While the level of inter-annotator agreement on such cases is questionable, we found the systematicity of the annotation rather consistent and motivated by deep semantic considerations: a \textit{nuclear missile} is indeed a weapon, but the \textit{nuclear} adjective here denotes a missile using nuclear energy. While a \textit{nuclear war} implies a war involving \textit{nuclear weapons}, hence \textit{nuclear} here can be understood in its metonymic sense. Given current statistical models for frame semantic parsing, it seems hardly possible that those models would prove capable of capturing such complex semantic phenomena, given the depth of both lexical and semantic representations that such phenomena would require to be extracted, all the more as they involve information not readily available at the surface syntactic level.
7.1.4 Syntactic challenges

In Section 7.1.3.2 were briefly mentioned problems related to misalignments of syntactic representations between FrameNet annotation and the output of the dependency parser. In addition to those misalignement problems, we found the vast majority of syntactic challenges to come from the argument span identification algorithm, detailed in Section 4.1.2. Table 7.6 provides a detailed account of performances per syntactic realization of the frame elements (PT.GF), which shows flagrant disparities of performances across phrase types and grammatical functions. The lowest scores reported, for PT.GF such as NP.Appositive,

| PT.GF            | dev | P   | R   | F1  |
|------------------|-----|-----|-----|-----|
| Poss.Gen         | 41  | 100.0 | 85.4 | 92.1 |
| Num.Quant        | 58  | 78.6 | 75.9 | 77.2 |
| NP.Ext           | 1031| 78.1 | 60.0 | 67.9 |
| NP.Obj           | 542 | 69.6 | 60.0 | 64.4 |
| Sfin.Dep         | 173 | 77.0 | 54.3 | 63.7 |
| A.Dep            | 64  | 93.5 | 45.3 | 61.1 |
| VPto.Dep         | 179 | 70.5 | 52.0 | 59.8 |
| N.Head           | 252 | 63.1 | 54.4 | 58.4 |
| PP.Dep           | 516 | 80.4 | 42.1 | 55.2 |
| AVP.Dep          | 140 | 97.6 | 29.3 | 45.1 |
| NP.Dep           | 19  | 66.7 | 31.6 | 42.9 |
| N.Dep            | 243 | 50.4 | 24.3 | 32.8 |
| AJP.Dep          | 170 | 91.2 | 18.2 | 30.4 |
| VPbrst.Dep       | 81  | 35.1 | 16.0 | 22.0 |
| Sfin.Head        | 65  | 21.2 | 10.8 | 14.3 |
| NP.Appositive    | 16  | 6.2  | 6.2  | 6.2  |

Table 7.6: Argument identification scores by syntactic realizations of the frame elements

Sfin.Head or VPbrst.Dep are almost exclusively accounted for by approximations of the span identification algorithm and the output representation of the dependency parser. Indeed, the algorithm only considers as possible argument spans all continuous spans in a sentence that contain a single word or comprise a valid subtree of a word and all its descendants in the dependency parse produced by the dependency parser. Therefore, the parser will systematically fail to recover spans in the following configurations:

- **appositive noun phrases** (NP.Appositive) as in:

  (7.6) In a statement, President [Jacob Zuma]Leader.NP.Appositive said Mandela’s condition was unchanged

  where the possible spans output by the algorithm are either [President] [Jacob] [Zuma] taken individually or [President Jacob Zuma] as a whole, given that the dependency
7.1. Baseline error analysis

The parser considers both President and Jacob to be children nodes of Zuma, which can therefore never produce [President] and [Jacob Zuma] as potential spans;

- **Head declarative finite complement clauses** ($S_{fin}$.Head) as in:

  (7.7) After a lifetime of trials, [Donna not only earned her GED]$_{Figure}$.Sfin.Head at Goodwill, she earned a job here

  where the dependency parser considers at to be a child node of the earned predicate, which prevents separating at from the rest of the clause in [Donna not only earned her GED at], necessary to output the correct span;

- **Dependent bare stem verb phrases** ($VP_{brst}.Dep$) as in:

  (7.8) Here’s another story of success from [what]$_{Hypothetical\_event}.NP$.Ext might [seem like an unlikely source]$_{Hypothetical\_event}.VP_{brst}.Dep$ ... where again, due to the output of the dependency parser, the span identification algorithm will output [what might seem like] and [an unlikely source] as possible spans but never [seem like an unlikely source]

7.1.5 Characterizing easy frame elements

In Section 7.1.3 we described several properties of frame elements that conditioned their accurate identification by statistical classifiers. Those properties included a low lexical diversity, or a potentially high lexical diversity combined with consistent syntactic patterns. Such properties illustrate why statistical classifiers are actually less sensitive to frequency effects than to the strict and clear correlation that may exist between a lexico-syntactic configuration and a given frame element. This is best exemplified by cases which combine both low lexical diversity and consistent syntactic patterns, as does the Speaker frame element when realized in an object noun phrase ($Speaker.NP$.Obj). Such a configuration exclusively corresponds to constructions involving according to followed by an object noun phrase, as in:

(7.9) **According to** [John]$_{Speaker.NP}.Obj$, Mary has already left

As expected, it is easily learnable as demonstrated by the 100% $F_1$ score measured on its five occurrences in the development set.

7.1.6 Characterizing hard frame elements

**A contrario**, we can characterize hard frame elements as frame elements realized in very diverse lexical configurations not compensated by systematic syntactic patterns which can be easily mapped to syntactic representations produced by the dependency parser. Such cases are actually best exemplified by non-core frame elements. Indeed, both peripheral and extra-thematic frame elements often carry the particularity of being realized in potentially
many different frames. In a sense, one could say that they are realized across various *domains*, which could explain why it turns out to be so challenging to extract systematicity – especially lexical – from their surface realizations. Concretely, a MANNER frame element in the *Facial_expression* frame, as in Sentence 7.10, will exhibit very different lexico-syntactic patterns than a MANNER frame element in the *Intentionally_act* frame, as in Sentence 7.11.

(7.10) They are equally direct in their dealings with visitors, too, so don’t expect a shy *Manner* Jamaican smile as you walk by

(7.11) This kind of protection should be *done* [without drawing attention] *Manner* so that people inside the location would feel at ease

Note that the difficulty posed by non-core frame elements explain the poor results observed for adjectival and adverbial phrases in Table 7.6, as AVP.Dep and AJP.Dep patterns are exclusively realized in peripheral frame elements such as Time, Manner or Means. It could be possible to try and provide a systematic *measure* of the difficulty of a given frame element, constructed by quantifying the diversity of its lexico-syntactic realization patterns, but we leave this to future work.

### 7.2 Comparative analysis

The qualitative error analysis on both exemplar and paraphrastic approaches yielded no conclusive results as to which patterns both approaches helped better acquire, in light of what has been described in Section 7.1. The error analysis of the paraphrastic approach confirmed that the improvements observed were not statistically significant and more likely incidental to the data distribution in the development set. In the following sections we discuss two alternative hypothesis as to what each approach contributed to: in Section 7.2.1 we show that the contribution of the exemplar approach is probably best explained and characterized in terms of the positive impact it had on various coverage metrics between the training and the development set. In Section 7.2.2 we confirm the robustness of the statistical classifier to frequency effects and show that none of the aforementioned approaches’ contribution can be explained or characterized in terms of their respective impact on data distribution in the training set.

#### 7.2.1 Coverage

The baseline, paraphrastic and exemplar approaches can be first and foremost distinguished in terms of *coverage* between their respective training sets and the development set against which argument identification is evaluated. Indeed, the specificity of the paraphrastic approach is that it does not bring any *new* data to the training set, with respect to LU – FE – VU – VP items, as shown in Table 7.7 and Table 7.9. The exemplar approach, on the contrary, does introduce information absent from the baseline’s fulltext training set, which significantly improves coverage metrics: for argument identification, the percentage
of unseen frame element labels goes from 9.6% down to 2.9%, and the percentage of unseen valence unit labels goes from 27.2% down to 13.2%. Such improvements in coverage provide a strong hypothesis to account for the robustness of the exemplar approach over the paraphrastic approach: reducing the amount of unseen data reduces out-of-vocabulary effects for both lexical units, frame elements and their syntactic realizations. This concretely means that the parser will be less likely to be confronted to configurations that it has not seen before, and therefore more likely to correctly predict frame element labels, as shown in Section 6.3.7. A concrete example of the benefits of the extended coverage of the exemplar approach is provided by the Name frame element, which is affected almost exclusively by lexical coverage between training and development sets, as detailed in Section 7.1.3.1. In this particular case, we found the exemplar approach to improve $F_1$ score by almost 6 points, when the paraphrastic approach marginally improved it by about 0.6 point of $F_1$ score.

| Coverage metrics on FT | Coverage metrics on FT+EX |
|------------------------|---------------------------|
| Lexical Units          | Lexical Units             |
| 3504                   | 9953                      |
| 1778                   | 1778                      |
| 74.2%                  | 88.2%                     |
| Frame Elements         | Frame Elements            |
| 690                    | 1031                      |
| 511                    | 511                       |
| 90.4%                  | 97.1%                     |
| Valence Units          | Valence Units             |
| 2964                   | 6468                      |
| 1668                   | 1668                      |
| 72.8%                  | 86.8%                     |
| Valence Patterns       | Valence Patterns          |
| 5245                   | 35131                     |
| 2165                   | 2165                      |
| 33.6%                  | 48.8%                     |

Table 7.7: Overlap between training and development sets, with a training set composed of FrameNet fulltext data

| Coverage metrics on FT + PFN |
|-------------------------------|
| Lexical Units                 |
| 3504                          |
| 1778                          |
| 74.2%                         |
| Frame Elements                |
| 690                           |
| 511                           |
| 90.4%                         |
| Valence Units                 |
| 2964                          |
| 1668                          |
| 72.8%                         |
| Valence Patterns              |
| 5245                          |
| 2165                          |
| 33.6%                         |

Table 7.9: Overlap between training and development sets, with a training set composed of FrameNet fulltext data and pFN XP#30 data

7.2.2 Distribution

In light of the coverage results presented in Section 7.2.1, we also questioned whether the differences of performances observed in Section 6.3.7 could be explained in terms of the respective impact of both exemplar and paraphrastic approaches on data distribution in the training set.
Results, presented in Table 7.1 to Table 7.4 confirmed, in a more systematic fashion than previously described in Section 7.1.1, that the statistical classifier could be considered robust to frequency effects in the data. Indeed, those tables show that both exemplar and paraphrastic approaches have a tendency to *zipfianize* data distribution in the training set, by making frequent elements exponentially more frequent. This makes for data distributions in the training set diverging significantly from that of the development set. Nonetheless, those diverging data distributions did not prevent the statistical classifier from extracting systematic lexico-syntactic patterns, independent of LU - FE - VU - VP global frequencies, as shown in Section 6.3.7.

Figure 7.1: Distribution of lexical units in development (dev) set, training set with fulltext (FT), with fulltext and exemplar (FT+EX) and with pFN XP#30 (XP30)

Figure 7.2: Distribution of frame elements in development (dev) set, training set with fulltext (FT), with fulltext and exemplar (FT+EX) and with pFN XP#30 (XP30)

Figure 7.3: Distribution of valence units in development (dev) set, training set with fulltext (FT), with fulltext and exemplar (FT+EX) and with pFN XP#30 (XP30)

Figure 7.4: Distribution of valence patterns in development (dev) set, training set with fulltext (FT), with fulltext and exemplar (FT+EX) and with pFN XP#30 (XP30)
8.1 Impact of syntactic preprocessing

A major outcome of this work is the qualitative confirmation of the predominant impact of syntactic preprocessing on the performances of argument identification. Although the 80% cap on recall has been a well-known limitation of the argument span identification algorithm (Das et al., 2014; Täckström et al., 2015), question remained as to whether syntactic challenges faced by frame semantic parsing were circumscribed to the approximations of the algorithm. Indeed, the underlying assumption of the argument span identification algorithm – to restrict multi-token spans to all terminal nodes of a same parent node in a dependency tree – could only be characterized as an approximation once confronted to the syntactic representation produced by the dependency parser. After all, if possible argument spans were not retrieved by the heuristic algorithm, it was as much due to the algorithm’s presuppositions than to the dependency representations output by the syntactic parser, failing to match all the (syntactic) structures of the arguments in FrameNet. Therefore, beyond the assumptions of the argument span identification algorithm, the question of the core source of those syntactic representation mismatches turned out to be crucial: were syntactic representation misalignments due to discrepancies between the underlying syntactic formalisms of FrameNet and dependency parsers, or were they due to erroneous predictions from those dependency parsers, generating syntactic representations deviating from the expectations of their theoretical frameworks? Our results tend to show that it is probably a bit of both.

In our replication study presented in Section 5.3, we showed that using the state-of-the-art BIST dependency parser (Kiperwasser and Goldberg, 2016) improved argument identification performances by at least 1 point of $F_1$ score over previous approaches relying on the ten-years-older MSTParser (McDonald et al., 2006), although both syntactic parsers relied on the same syntactic formalism and the exact same training data. Those results provide experimental support for hypothesizing strong correlations between the quality of
syntactic parsers’ predictions and the ability of frame semantic classifiers to extract useful patterns to better predict argument roles and spans, independently of the consistency of the syntactic formalisms used by FrameNet and dependency parsers.

Additionally, in Section 7.1.4 of our error analysis, we showed that deep theoretical discrepancies persist between what FrameNet and dependency parsers consider to be syntactic constituents, and that, in several specific syntactic configurations, those discrepancies clearly prevent frame semantic classifiers from properly identifying argument spans and extracting relevant patterns, regardless of the accuracy of syntactic predictions. We notably showed that misalignments between syntactic representations prove particularly detrimental to compensate for high lexical diversity when classifiers cannot make use of syntactic cues consistent with FrameNet annotation.

On both accounts, recent syntax-free and joint syntax-semantic approaches to frame semantic parsing look promising (Swayamdipta et al., 2017). However, even most recent approaches using multitask learning with syntactic scaffolding still rely on different syntactic formalisms than that of FrameNet. As those models consistently yield better results than syntax-free models, it may be worth exploring in future work joint learning of both FrameNet semantic and syntactic representations.

8.2 Consistency of FrameNet annotation

Another major outcome of this work deals with judging the consistency of FrameNet annotation for the frame semantic parsing task. In Chapter 6 we introduced the results of our paraphrastic data augmentation system and showed that, contrary to expectations, a frame semantic parser trained on an artificially augmented dataset, containing data generated by a valence pattern matching algorithm, significantly degraded performances when not relying on any kind of paraphrastic candidates filtering. This result strongly calls into question the consistency of FrameNet annotation, given that frame semantics theory predicts that a valence pattern matching algorithm should generate syntactically compatible and semantically related clauses. Additionally, we showed that the negative impact on performances could be compensated by filtering paraphrastic candidates, even randomly, to the point where we even observed marginal improvements on argument identification, though not statistically significant. At the time we proposed two hypothesis to account for the impact of (random) paraphrastic candidates filtering on argument identification: (1) that there existed a latent variable, not necessarily semantically motivated, or at least not in ways distributional models could capture, that determined, among the set of unfiltered \( pFN \) candidates, what was noise from what was not; or (2) that data generated by \( pFN \) were actually always somehow noisy, but that the ROFAMES parser was robust enough that it could compensate for the bias introduced by noisy artificial data, provided that those noisy data remained limited in size. The results of our error analysis, detailed in Section 7.1.6 and Section 7.1.3.2, show once again that both hypothesis may hold some truth.

First of all, we demonstrated in Section 7.1.6 that frame elements in FrameNet encompassed different degrees of semantic and syntactic specificity. Phrased differently, we could
8.3. The more the merrier?

say that FrameNet includes a great variety of classes of different scope. We showed, in
the same section, how, at the end of the spectrum, non-core frame elements constituted
some of the hardest classes to predict, due to the great variety of domains – defined as
specific syntactic and semantic configurations – that those classes could cover. Those con-
siderations translate directly into differences of scope at the scale of the valence pattern.
As such, our valence pattern matching algorithm generates paraphrastic candidates which
can turn out to be quite far from the original target. In short, the scope of a given valence
pattern could constitute the latent variable that determines whether or not a given lexical
combination output by our algorithm is likely or not, and whether or not it should be
considered as noise. Future work, experimenting on keeping narrow-scope paraphrastic
candidates only, could potentially shed light on this hypothesis.

Second, we showed in Section 7.1.3.2 that the ROFAMES parser was robust to noisy data
in that it used syntactic cues to compensate for high lexical diversity. This experimental
results tend to demonstrate that the noise generated by our paraphrastic data augmenta-
tion approach does not evenly affect argument identification, and does so negatively only
when the parser is unable to rely on syntactic patterns to compensate for the noisy data.

It may be worth noting that the paraphrastic data augmentation approach introduced
in this work remained very preliminary, in that it was limited to introducing lexical diver-
sity at the level of predicate-argument combinations. Work from Hasegawa et al. (2011)
suggest several ways for incorporating syntactic diversity to our approach via FrameNet-
internal knowledge, through, e.g., voice and perspective alternation, or NP–PP–VPing
clauses transformation. As such, it provides interesting developments for testing further
the robustness of FrameNet annotation.

8.3 The more the merrier?

In this work we confirmed two well-known facts of the semantic role labeling literature: (1)
that adjuncts are usually significantly harder to predict that core arguments; and (2) that
core arguments predicted with high precision and recall exhibit strong bias toward specific
syntactic patterns\(^1\) (for both, see Table 13 in Palmer et al., 2005). Our work suggests that
the high number of classes in FrameNet may actually be an asset, as it could provide just
the right number of classes for a statistical classifier to make interesting generalizations
without overfitting or being unable to extract discriminant systematic patterns from too
generic classes.

The poor performances of the ROFAMES parser on non-core frame elements suggest that
it may even be needed to increase the number of those frame elements by splitting them
into subclasses better able to characterize semantic and syntactic phenomena in specific
domains. This intuition goes against past work in frame semantic parsing, notably that
of Matsubayashi et al. (2014), which attempted to reduce the complexity of the frame
semantic parsing task by reducing the number of frame elements to be predicted.

\(^1\)such as agents frequently realized as subjects of noun phrases
Rather than manually increasing the number of classes in FrameNet, it may prove beneficial to make use of the literature on latent variable grammars (e.g. Petrov et al., 2006; Petrov, 2010) for learning latent sub-classes of the gold meta-classes in an unsupervised fashion via split-and-merge algorithms.

However, increasing the number of classes, even latently, raises the question of whether FrameNet data would contain enough representative samples for a statistical model to appropriately extract generic representations for each class. The question is all the more relevant that recent neural network models for frame semantic parsing are designed to learn multiple complex representations at once, while relying on a limited set of features. Would those models prove capable of learning infrequent phenomena and compensating for the lack of syntactic cues provided by dependency parsers? Beyond the question of the sensitivity of deep learning models to frequency effects lies the question of their ability to learn from tiny data. The fact that the syntax-free model proposed by Swayamdipta et al. (2017) achieves comparable results than the previous model of Das et al. (2014), while not being bounded by the approximations of the argument span identification algorithm, suggests that the model may fail to properly extract certain patterns when dispensing with syntactic preprocessing. To further argue on the matter, more research is needed to qualitatively understand the performances of recent neural network models for frame semantic parsing.

8.4 Learning conceptual representations from limited data

Recent neural network approaches to frame semantic parsing (FitzGerald et al., 2015; Roth, 2016; Swayamdipta et al., 2017; Yang and Mitchell, 2017) rely on a similar framing of the statistical learning process: from a limited set of distributional input features, a neural network creates and enriches, via each layer, distributional representations of frame semantic structures. Given the hard constraint posed by the size of the training data and the information bear by input features, the challenge for the model is to converge to distributional representations rich enough to produce accurate predictions of frame semantic structures. Considering the learning problem at hand, we propose two conceptual approaches to improving the model: one is to reduce the distance between input and output representations by relying on more informative input features, acquired independently of FrameNet annotation and potentially closer to the desired output representations; two is to improve the learning rate by guiding the model and constraining its representations at each layer of the network.

The first approach follows from observations made throughout this work: in order to appropriately learn frame semantic structure representations, statistical models need to be able to capture a whole range of linguistic phenomena and handle a great variety of specific problems. Those include, but are not restricted to, being able to: handle out-of-vocabulary and out-of-domain lexical items (see Section 7.1.3.1), model semantic properties which condition the realization of arguments (such as animateness, see Section 2.1.2), operate subtle semantic distinctions (see Section 7.1.3.3) or appropriately resolve coreference when
8.4. Learning conceptual representations from limited data

needed (see Section 3.2.2), not to mention being able to model the constraints which condition the syntactic realization of the arguments of predicates (see Section 7.1.4). If the distributional representations of words based on contextual information on which rely most neural network models for frame semantic parsing have proven quite successful at handling out-of-vocabulary items (Roth and Lapata, 2015), they still fall short of encompassing the depth of information covered by the aforementioned cases. The literature suggests many possible leads to enrich those contextual representations, be it via the modeling of proper names (e.g. Herbelot, 2015) useful for identifying named entities and their (semantic) properties, or via the incorporation of syntactic information (e.g. Levy and Goldberg, 2014), the integration of those representations to models of formal semantics (e.g. Erk, 2016) or the modeling of semantic relations between those representations (e.g. Henderson and Popa, 2016; Roller and Erk, 2016), all of which could contribute to reducing the amount of information statistical models of frame semantic parsing have to extract from limited gold data alone.

The second approach follows from the observation than motivated this work in the very first place: as previously detailed in Section 3.2.1, The FrameNet taxonomy is a well-structured resource which contains rich annotation not necessarily readily available at the surface (sentence) level, but which is nonetheless required for statistical models to learn appropriate generalization principles. Consider the following example from (Hasegawa et al., 2011):

(8.1) [They] Authorities are going to incarcerate [him] Prisoner

(8.2) [They] Agent are going to confine [him] Theme [to prison] Holding_location

Those two sentences, which are considered as paraphrase of each other, exemplify many semantic distinctions: the incarcerate.v lexical unit of the Imprisonment frame is more specific than the confine.v lexical unit of the Inhibit_movement frame, in that it implies that the HOLDING_LOCATION is a PRISON. The PRISON frame element not being required to form a minimal clause in the Imprisonment frame, is hence characterized as non-core. However, acquiring the kind of combinatorial constraints such as Imprisonment = Inhibit_movement + HOLDING_LOCATION as PRISON characterized in FrameNet by frame and frame element relations has proven particularly hard to acquire from textual data alone, and more specifically from distributional (contextual) representations of words (Botschen et al., 2017). However, such informative constraints could be incorporated higher-up in the neural network layered architecture, by retrofitting intermediate representations of frame semantic structures following Faruqui et al. (2015), or designing hybrid models constraining intermediate representations via hard-coded rules.
In this work, we have reported several important results which we hope will contribute to more systematic error analysis of statistical models for automatic frame semantic structure extraction.

Our first contribution is the replication of several past studies on frame semantic parsing, relying this time on the most recent FrameNet 1.7 data release. We proposed more robust and larger development and testing sets containing no duplicate annotation sets, and showed that, when tested on those new data sets, the benefits of past features, such as exemplar or hierarchy, are not as significant as originally reported in (Kshirsagar et al., 2015) as they contribute to a 2 $F_1$ gain rather than 4 $F_1$ gain on argument identification with gold frames. Additionally, we showed that preprocessing toolkits play a crucial role in the performance of statistical models for argument identification, and that differences in preprocessing setups can lead to nearly 3 $F_1$ points differences on argument identification scores. Such variations, being of the same order of magnitude than the gains reported by recent statistical models for frame semantic parsing (Roth, 2016), strongly call into question the real benefits of those models which rely on different preprocessing toolkits than their baselines.

Our second contribution deals with the smartness and robustness of the ROFAMES statistical classifier, originally proposed by (Das et al., 2014). In order to properly test the smartness of the classifier, defined as its ability to extract all useful information for frame semantic structure extraction when exposed to a given set of data, we proposed to train it on an artificially augmented dataset, generated using a rule-based model combining valence pattern matching and lexical substitution on the original FrameNet gold training set. We showed that the ROFAMES parser proves relatively smart, as we saw no statistically significant increase in performances in our best data augmentation setup, but not necessarily robust to noisy data, as performances significantly decreased when the parser was exposed to unlikely lexical configurations of predicate-argument structures. We showed, moreover, that the quality of syntactic preprocessing plays a major role in the performances of the
classifier on argument identification, especially for argument span identification. We discussed how the syntactic representation mismatches between FrameNet and dependency parsers are as much due to erroneous predictions from the dependency parsers than to divergence in FrameNet and dependency parsers’ underlying syntactic formalisms. Additionally, we hypothesized that the varying syntactic and semantic scopes of the different classes of frame elements could act as a latent variable for determining noisy paraphrastic data, and demonstrated that classes which prove hardest to predict usually exhibit a great variety of semantic and syntactic realizations.

We had originally asked the following questions in introduction:

1. Are prediction failures due to a lack of annotation, which translates to the absence in the training data of linguistic patterns necessary for any machine learning model to properly predict the frame semantic structures included in the evaluation data?

2. Does failure to capture structural generalization principles necessary to correctly predict frame semantic structures lie with the probabilistic models used so far?

We can now conclude with the following answers:

1. If the lack of annotation in FrameNet does account for certain failures in frame semantic structure predictions, especially for out-of-domain named entities and lexical items, strong limitations are also posed to machine learning models by FrameNet’s formalism and its definition of large-scope classes, especially for non-core frame elements, which prevent classifiers from extracting systematicity for those specific classes.

2. Strong conceptual limitations do indeed prevent statistical models for frame semantic parsing to properly extract useful generalization principles, especially for identifying argument spans or processing fine-grained semantic distinctions at the argument level.

Our work suggests possible new concrete leads for improving statistical models of frame semantic parsing: it seems clearer and clearer that frames and arguments should be predicted jointly, and that so should (frame) semantic and syntactic representations. Recent approaches relying on neural network architectures also suggest that statistical classifiers should rely on richer input representations of words, better able to characterize deep semantic properties, coreferences, semantic relations and syntactic constraints, and on latent representations of subclasses, better able at characterizing the variety of syntactic and semantic configurations of non-core frame elements.
In the following sections we provide a detailed historical overview of supervised and semi-supervised methods for frame semantic parsing. For practical reasons, we focus on work which relied on the FrameNet 1.5 dataset and postdated the seminal work of Das et al. (2014). We make two important exceptions: we mention the work of Gildea and Jurafsky (2002), given that they were the very first to propose a statistical approach to frame semantic parsing, although they focused exclusively on argument identification given gold targets and gold frames and relied on a very small FrameNet dataset which predated the 1.3 release. We also mention the work of Johansson and Nugues (2007), as their system achieved the best results on the SemEval 2007 shared task 19 and was the first to provide a full frame semantic parsing pipeline comprising target, frame and argument identification.

A.1 Gildea and Jurafsky (2002)

Gildea and Jurafsky (2002) pioneered the task of argument identification\(^1\) with FrameNet, given gold targets and gold frames. They used a pre-1.3 FrameNet dataset which comprised about 50,000 annotated sentences. Their system relied on discriminative models which made use of both lexical and syntactic features such as tokens, part-of-speech tags, dependency paths, tokens positions, and voice. Most subsequent work on semantic role labeling in general made use of their original features set, often enriched with additional features. Gildea and Jurafsky (2002) achieved 82% accuracy on labeling pre-identified constituents and a 63% $F_1$ score on the full argument identification task measured on individual frame elements. Per sentence, the system achieved 38% (0.38) accuracy, significantly lower than the $0.66 – 0.82$ inter-annotator agreement (which usually varies depending on the predicate).\(^2\) This difference between parsers accuracy scores and inter-annotator agree-

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\(^1\)which they referred to as \textit{semantic role labeling} and included both arguments span identification and arguments role labeling

\(^2\)Gildea and Jurafsky (2002) also reported the kappa statistic, but it has been shown to be inadequate for judging inter-annotator agreement on frame semantic annotation, as, contrary to the usual setting
Appendix A. Frame Semantic Parsing History: Detailed Overview

...ement metrics makes semantic role labeling in general, and frame semantic parsing more specially, a hard task in computational linguistics and natural language processing.

A.2 Johansson and Nugues (2007)

Johansson and Nugues (2007) provided the first full system for frame semantic parsing to include target identification, frame identification and argument identification. They achieved the best performance at the SemEval 2007 shared task 19.

For target identification, their system consisted of a set a heuristic rules.

For frame identification, they used a SVM classifier to disambiguate polysemous lemmas and assign the correct frame when multiple options where possible. They also extended the vocabulary of frame-evoking words with WordNet to handle unknown lexical units. They then used a collection of separate SVM classifiers – one for each frame – to predict a single evoked frame for each occurrence of a word in the extended vocabulary.

For argument identification, they divided the task into two subtasks and solved the two tasks sequentially. They first identified candidate spans by classifying them using SVMs. They then assigned frame element labels to the identified arguments using SVMs as well.

On the SemEval 2007 test set, they achieve 76.10% $F_1$ score at target identification, 57.34% $F_1$ score at exact frame identification with predicted targets, and 42.01% $F_1$ score at exact argument identification with predicted targets and frames.

A.3 Das et al. (2014)

Das et al. (2014) improved the results of Johansson and Nugues (2007) on all tasks of the SemEval shared task, and provided a long-standing state-of-the-art system on FrameNet 1.5 data, which was used as a baseline by most subsequent work on frame semantic parsing.

On target identification, they modified the set of heuristic rules of Johansson and Nugues (2007) and improved the $F_1$ score by about 3 points.

On frame identification, they used a discriminative probabilistic conditional log-linear model based on latent variables incorporating lexical-semantic features. They expanded this model with a similarity graph computed with WordNet to handle frame identification for unseen lexical units. They improved the joint score on target and frame identification of Johansson and Nugues (2007) by about 4 points of $F_1$ score.

On argument identification, they treated jointly the two tasks or argument span identification and frame element labeling. They derived the set of spans with a high-recall rule-based algorithm that looks at the dependency syntactic context of the predicate word. They then used a conditional log-linear model over spans for each role of each evoked...

\footnote{where the kappa statistic is used, FrameNet annotators do not have to choose among a fixed pool of label for each annotated instance. See (Burchardt et al., 2006, note n.2) for details}

\footnote{Note that, as Johansson and Nugues (2007) did not provide scores for frame identification with gold targets, it is difficult to evaluate the contribution of the frame identification system of Das et al. (2014) in itself}
frame, which was trained using maximum conditional log-likelihood. Their model used a significant number of features ranging from lexical items combinations to syntactic dependency paths (See Figure 4.3 for a full account of their features). They used beam search for decoding to prevent arguments overlap. They also proposed a system which modeled argument identification as constrained optimization solved dynamically with dual decomposition (Martins et al., 2011), but which did not yield significant improvements.\textsuperscript{4} They improved the full score of argument identification with predicted frames and predicted targets by about 4.5 points of $F_1$ score compared to Johansson and Nugues (2007).

\section*{A.4 Hermann et al. (2014)}

Hermann et al. (2014) proposed a model for frame identification based on distributed representations of predicates and their syntactic contexts. They used the WSABIE algorithm (Weston et al., 2011) to map input and frame representations to a common latent space during training, where the distance between the latent representations of the target predicate and the correct frame is minimized while the distance between the latent representations of the predicate target and all other frames is maximized. Decoding is performed using the maximal cosine similarity between candidate frame representations and the latent representation of the target predicate. They improved frame identification scores with gold targets by about 5 points of $F_1$ score compared to the baseline of Das et al. (2014).

For argument identification they relied on Das et al. (2014)’s log-linear model but formalized the problem as constrained optimization with three ILP constraints:

1. each span could only have one role;
2. each core role could be present only once;
3. all overt arguments had to be non-overlapping.

They solved the problem with an off-the-shelf ILP solver, which is not specified, and which performances could explain why they achieve better results than Das et al. (2014)’s original ILP-based system and Kshirsagar et al. (2015)’s replication results when using Hermann et al. (2014)’s frame identification system. They similarly improved argument identification scores with predicted frames by about 5 points of $F_1$ score over the baseline of Das et al. (2014).

\section*{A.5 Täckström et al. (2015)}

Täckström et al. (2015) used the same ILP formulation of argument identification as Hermann et al. (2014), but proposed to solve it with a custom dynamic programming algorithm\textsuperscript{4} Their approach did form however the basis of subsequent successful work, see (Hermann et al., 2014; Täckström et al., 2015)
instead of an off-the-shelf ILP solver. They achieved better performance compared to the previous approaches, with an improvement of about 0.4 $F_1$ score with predicted frames compared to Hermann et al. (2014).

### A.6 Kshirsagar et al. (2015)

Kshirsagar et al. (2015) were the first to try and train a parser based on that of Das et al. (2014) on both fulltext and exemplar data since Das et al. (2014) reported that training on both fulltext and exemplar sentences hurt performances on the SemEval dataset. They used the model of Das et al. (2014), extracting candidate spans with heuristics, enforcing non-overlapping constraints on arguments and decoding with beam search.

They actually showed that, on the FrameNet 1.5 dataset, training on both fulltext and exemplars improved $F_1$ score on argument identification with gold frames by nearly 3 points. Following the remark of Das et al. (2014) which argued that the damage in performance could be due to the difference of domains between fulltext and exemplar data, they also experimented training on both fulltext and exemplars with domain adaptation (Daume III, 2007). This allowed features to be conditioned on the domain (here, fulltext or exemplar), as, in domain adaptation, each feature has a domain-specific weight and a global weight, which allows systems to better adjust to specific domains while not losing generalization power. They found however a marginal 0.3 points $F_1$ score improvement over training on both fulltext and exemplar annotations without domain adaptation.

They also proposed to incorporate hierarchy features, in this case Inheritance and Sub-Frame relations, in order to capture statistical generalizations about the kinds of arguments seen in frame elements. Finally, they suggested using guide features, in this case PropBank annotated data, to overcome the limitations posed by the sparcity of FrameNet annotated data. Using PropBank as a guide feature consisted in using predictions done on the FrameNet dataset by a model trained on PropBank data as additional features when training the model on FrameNet data. Guide features, however, did not yield significant results.

Their best system, incorporating the hierarchy feature and trained on both fulltext and exemplar data, achieved a 4 $F_1$ gain over the baseline of Das et al. (2014).

### A.7 Roth and Lapata (2015)

Roth and Lapata (2015) were the first to incorporate sentence and discourse context features motivated by linguistic considerations inspired by Fillmore (1982). They proposed to incorporate the following key features:

1. a set of features modeling document-specific aspects of word meaning using distributional semantics. They relied on distributional word representations adapted to documents content;
2. a feature modeling previous role assignment mentioned in discourse, acquired by
resolving coreferences on frame element semantic types with the Stanford Coreference
Resolution system (Lee et al., 2013);

3. a feature derived from automatically computed coreference chains, which helped
determine which frame element labels were likely to be assigned to new entities. For
example, the Result of a Causation is more likely to be discourse-new than the
Effect that caused it;

4. a set of constraints on roles, as defined in previous studies, but exploited using a
re-ranking algorithm.

Their system achieved nearly 1 point $F_1$ gain in argument identification with gold frames
and 0.7 $F_1$ point gain in argument identification with predicted frame.

A.8 FitzGerald et al. (2015)

FitzGerald et al. (2015) proposed the first neural model for frame semantic parsing. Their
model embedded candidate arguments and frame elements for a given frame into a shared
vector space. They used a feed-forward neural network to learn correlations between em-
bedding dimensions in order to create argument and role representations. They then
used the dot product between role representations to score possible roles for candidate
arguments. The decoding process relied on a constrained graphical model which jointly
modeled the assignment of semantic roles to all arguments of a predicate. They achieved
their best results by training their model in a multitask setting on both FrameNet and
PropBank data, made possible by the decoupling of span and frame-role representations
of their model. Note that they used the same preprocessing as Täckström et al. (2015) for
fair replication. They achieved 70.9% $F_1$ on argument identification with predicted frames,
a 0.6 $F_1$ gain over their baseline of Täckström et al. (2015).

A.9 Roth (2016)

Roth (2016) proposed a neural frame semantic parser based on (Roth and Lapata, 2016).
They modeled the semantic relationships between a predicate and its arguments by analyz-
ing the dependency path between the predicate word and each argument head word. They
considered lexicalized paths, which they decomposed into sequences of individual items,
namely the words and dependency relations on a path. They defined the embedding of a
dependency path to be the final memory output state of a LSTM layer that took a path
as input, with each input step representing a binary indicator for a part-of-speech tag,
a word form, or a dependency relation. They used a state-of-the-art dependency parser
(Kiperwasser and Goldberg, 2016) for preprocessing, and achieved 70.0% $F_1$ on argument
identification with predicted frames, 0.9 $F_1$ points short from FitzGerald et al. (2015).
A.10 Swayamdipta et al. (2017)

Swayamdipta et al. (2017) proposed four different neural models for frame semantic parsing.

They first proposed a syntax-free model called the softmax-margin SegRNN, based on the SegRNN of Kong et al. (2015), and which uses a combination of bidirectional RNNs with a semi-Markov CRF with a slight modification to favor recall over precision. Their softmax-margin SegRNN model learns representations of targets, lexical units, frames and frame elements. It achieves 66.4% $F_1$ on argument identification with gold frames, and 69.9% $F_1$ on argument identification with predicted frames using the system of Hermann et al. (2014).

They then proposed three alternative models which make use of syntactic information. Their first syntactic model adds dependency features derived from a dependency parsers (Andor et al., 2016). It achieves 67.8% $F_1$ on argument identification with gold frames and 70.6% on argument identification with predicted frames. Their second syntactic model adds phrase-structure features derived from a state-of-the-art phrase-structure parser (Dyer et al., 2016). It achieves 68.9% $F_1$ on argument identification with gold frames and 70.9% $F_1$ on argument identification with predicted frames.

Finally, authors proposed a model that incorporated their previous syntax-free model into a multitask setting where the second task was to identify unlabeled constituents, a task which they call syntactic scaffolding. Their model achieves 68.3% $F_1$ on argument identification with gold frames and 70.7% $F_1$ on argument identification with predicted frames.

A.11 Yang and Mitchell (2017)

Yang and Mitchell (2017) proposed multiple neural network models for performing both frame identification and argument identification sequentially and jointly.

For frame identification, they proposed a multi-layer neural model which learns to predict a relation between a predicate and a frame given the predicate-frame pair and the sentence containing the predicate. Their system achieves 88.2% $F_1$ on frame identification with gold targets, comparable to the 88.4% $F_1$ score of (Hermann et al., 2014). However, it achieves 75.7% $F_1$ on ambiguous predicates, a 2.5 $F_1$ gain over the baseline.

For argument identification, they proposed an integrated model which combined a sequential neural model and a relational neural model. The sequential neural model formalizes argument identification as a word-by-word labeling task where frame elements are encoded using the IOB tagging scheme and where learning is performed by a CRF layer on top of a DB-LSTM. The benefit of using a neural network architecture is again that the LSTM requires limited input features. Those includes only, for each word in the sentence, the current word, the predicate, and a position mark that denoted whether the current word was in the neighborhood of the predicate. The relational neural model formalizes argument identification as multi-class classification over pre-identified argument spans. The network learns to predict a relation between a predicate and an argument given the predicate-
argument pair and the sentence that contains it. The inputs of the network are discrete features such as words within the argument span, the dependents of the argument’s head, and their dependency label, predicate word(s), its dependents and their dependency labels. These features are mapped to a low dimensional space where each input feature is computed into an embedding that concatenates average of each feature’s embeddings. The feature embeddings are then passed on to a non-linear hidden layer and training operates by minimizing the negative conditional log-likelihood of the training examples, with the conditional probability given by a specific potential function. The integrated model is a relational neural model that is learning using the knowledge of the sequential model, which learns probabilities for argument labels over words instead of spans.

Joint inference involves jointly performing frame and argument identification. To do so, authors relied on standard structural constraints for semantic role labeling, which involves avoiding non-overlapping argument spans and repeated core roles for each frame. They also introduced two new constraints:

1. one which encodes the compatibility between frame types and semantic roles, based on which frame elements belong to each frame;
2. one which encodes type consistencies of frame element fillers of different frames, e.g. the same named entity cannot play both a Person and a Vehicle role.

They identify 6 mutually exclusive entity types: Person, Location, Weapon, Vehicle, Value and Time.

They then solved the constrained optimization problem with AD3 (Martins et al., 2015). Preprocessing, which included part-of-speech tagging and dependency parsing, was done with the Stanford CoreNLP toolkit (Manning et al., 2014).

On argument identification with gold frames, their integrated model achieves 65.5% $F_1$, a 2 points gain over the baseline of Kshirsagar et al. (2015) at 63.1% $F_1$, but still lower than the score of Swayamdipta et al. (2017) at 68.9% $F_1$. On argument identification with predicted frame, they achieve state-of-the-art results with joint inference at 76.6% $F_1$, way above the previous baseline of FitzGerald et al. (2015) at 70.9% $F_1$. 

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