Abstract

Syntactic analysis plays an important role in semantic parsing, but the nature of this role remains a topic of ongoing debate. The debate has been constrained by the scarcity of empirical comparative studies between syntactic and semantic schemes, which hinders the development of parsing methods informed by the details of target schemes and constructions. We target this gap, and take Universal Dependencies (UD) and UCCA as a test case. After abstracting away from differences of convention or formalism, we find that most content divergences can be ascribed to: (1) UCCA’s distinction between a Scene and a non-Scene; (2) UCCA’s distinction between primary relations, secondary ones and participants; (3) different treatment of multi-word expressions, and (4) different treatment of inter-clause linkage. We further discuss the long tail of cases where the two schemes take markedly different approaches. Finally, we show that the proposed comparison methodology can be used for fine-grained evaluation of UCCA parsing, highlighting both challenges and potential sources for improvement. The substantial differences between the schemes suggest that semantic parsers are likely to benefit downstream text understanding applications beyond their syntactic counterparts.

1 Introduction

Semantic representations hold promise due to their ability to transparently reflect distinctions relevant for text understanding applications. For example, syntactic representations are usually sensitive to distinctions based on POS (part of speech), such as between compounds and possessives. Semantic schemes are less likely to make this distinction since a possessive can often be paraphrased as a compound and vice versa (e.g., “US president”/“president of the US”), but may distinguish different senses of possessives (e.g., “some of the presidents” and “inauguration of the presidents”).

Nevertheless, little empirical study has been done on what distinguishes semantic schemes from syntactic ones, which are still in many cases the backbone of text understanding systems. Such studies are essential for (1) determining whether and to what extent semantic methods should be adopted for text understanding applications; (2) defining better inductive biases for semantic parsers, and allowing better use of information encoded in syntax; (3) pointing at semantic distinctions unlikely to be resolved by syntax.

The importance of such an empirical study is emphasized by the ongoing discussion as to what role syntax should play in semantic parsing, if any (Swayamdipta et al., 2018; Strubell et al., 2018; He et al., 2018; Cai et al., 2018). See §8.

This paper aims to address this gap, focusing on content differences. As a test case, we compare relatively similar schemes (§2): the syntactic Universal Dependencies (UD; Nivre et al., 2016), and the semantic Universal Conceptual Cognitive Annotation (UCCA; Abend and Rappoport, 2013).

We UCCA-annotate the entire web reviews section of the UD EWT corpus (§3), and develop a converter to assimilate UD and UCCA, which use formally different graphs (§4). We then align their nodes, and identify which UCCA categories match which UD relations, and which are unmatched.

Most content differences are due to (§5):

1. UCCA’s distinction between words and phrases that evoke Scenes (events) and ones that do not. For example, ev entive and non-ev entive nouns are treated differently in UCCA, but similarly in UD.

2. UCCA’s distinction between primary relations, secondary relations and Participants, in contrast to UD’s core/non-core distinction.
3. Different treatment of multi-word expressions (MWEs), where UCCA has a stronger tendency to explicitly mark them.

4. UCCA’s conflation of several syntactic realizations of inter-clause linkage, and disambiguation of other cases that UD treats similarly.

We show that the differences between the schemes are substantial, and suggest that UCCA parsing in particular and semantic parsing in general are likely to benefit downstream text understanding applications. For example, only 72.9% of UCCA Participants are UD syntactic arguments, i.e., many semantic participants cannot be recovered from UD.\(^1\) Our findings are relevant to other semantic representations, given their significant overlap in content (Abend and Rappoport, 2017). A methodology for comparing syntactic and semantic treebanks can also support fine-grained error analysis of semantic parsers, as illustrated by Szubert et al. (2018) for AMR (Banarescu et al., 2013). To demonstrate the utility of our comparison methodology, we perform fine-grained error analysis on UCCA parsing, according to UD relations (§6). Results highlight challenges for current parsing technology, and expose cases where UCCA parsers may benefit from modeling syntactic structure more directly.\(^2\)

2 Representations

The conceptual and formal similarity between UD and UCCA can be traced back to their shared design principles: both are designed to be applicable across languages and domains, to enable rapid annotation and to support text understanding applications. This section provides a brief introduction to each of the schemes, whereas the next sections discuss their content in further detail.\(^3\)

| Participant | A | Center | C | Adverbial | D | Elaborator | E | Function | F | Ground | G | Parallel Scene | H |
|-------------|---|--------|---|-----------|---|------------|---|----------|---|---------|---|----------------|---|
| Linker      | L | Connector | N | Process | P | Quantifier | Q | Relator  | R | State   | S | Time           | T |

Table 1: Legend of UCCA categories (edge labels).

\(^1\)This excludes cases of shared argumenthood, which are partially covered by enhanced UD. See §4.1.

\(^2\)Our conversion and analysis code is public available at https://github.com/danielhers/synsem.

\(^3\)See Supplementary Material for a definition of each category in both schemes, and their abbreviations.

UCCA is a semantic annotation scheme rooted in typological and cognitive linguistic theory. It aims to represent the main semantic phenomena in text, abstracting away from syntactic forms. Shown to be preserved remarkably well across translations (Sulem et al., 2015), it has been applied to improve text simplification (Sulem et al., 2018b), and text-to-text generation evaluation (Birch et al., 2016; Choshen and Abend, 2018; Sulem et al., 2018a).

Formally, UCCA structures are directed acyclic graphs (DAGs) whose nodes (or units) correspond either to words, or to elements viewed as a single entity according to some semantic or cognitive consideration. Edges are labeled, indicating the role of a child in the relation the parent represents. Figure 1 shows a legend of UCCA abbreviations. A Scene is UCCA’s notion of an event or a frame, and is a description of a movement, an action or a state which persists in time. Every Scene contains one primary relation, which can be either a Process or a State. Scenes may contain any number of Participants, a category which also includes abstract participants and locations. They may also contain temporal relations (Time), and secondary relations (Adverbials), which cover semantic distinctions such as manner, modality and aspect.\(^4\)

Scenes may be linked to one another in several ways. First, a Scene can provide information about some entity, in which case it is marked as an Elaborator. This often occurs in the case of participles or relative clauses. For example, “(child) who went to school” is an Elaborator Scene in “The child who went to school is John”. A Scene may also be a Participant in another Scene. For example, “John went to school” in the sentence: “He said John went to school”. In other cases, Scenes are annotated as Parallel Scenes (H), which are flat structures and may include a Linker (L), as in: “When\(_{L}\) [he arrives] \(_{H}\), [he will call them] \(_{H}\)”.

Non-Scene units are headed by units of the category Center, denoting the type of entity or thing described by the whole unit. Elements in non-Scene units include Quantifiers (such as “dozens of people”) and Connectors (mostly coordinating conjunctions). Other modifiers to the Center are marked as Elaborators.

UCCA distinguishes primary edges, corresponding to explicit relations, from remote edges, despite the similar terminology, UCCA Adverbials are not necessarily adverbs syntactically.
which allow for a unit to participate in several super-ordinate relations. See example in Figure 1. Primary edges form a tree, whereas remote edges (dashed) enable reentrancy, forming a DAG.

Figure 1: Example UCCA graph. Dashed: a remote edge.

**UD** is a syntactic dependency scheme used in many languages, aiming for cross-linguistically consistent and coarse-grained treebank annotation. Formally, UD uses bi-lexical trees, with edge labels representing syntactic relations.

One aspect of UD similar to UCCA is its preference of lexical (rather than functional) heads. For example, in auxiliary verb constructions (e.g., “is eating”), UD marks the lexical verb (*eating*) as the head, while other dependency schemes may select the auxiliary *is* instead. While the approaches are largely inter-translatable (Schwartz et al., 2012), lexical head schemes are more similar in form to semantic schemes, such as UCCA and semantic dependencies (Oepen et al., 2016).

Being a dependency representation, UD is structurally underspecified in an important way: it is not possible in UD to mark the distinction between an element modifying the head of the phrase and the same element modifying the whole phrase (de Marneffe and Nivre, 2019).

An example UD tree is given in Figure 2. UD relations will be written in typewriter font.

Figure 2: Example UD tree.

### 3 Shared Gold-standard Corpus

We annotate 723 English passages (3,813 sentences; 52,721 tokens), comprising the web reviews section of the English Web Treebank (EWT; Bies et al., 2012). Text is annotated by two UCCA annotators according to v2.0 of the UCCA guidelines\(^5\) and cross-reviewed. As these sentences are included in the UD English_EWT treebank, this is a *shared* gold-standard UCCA and UD annotated corpus.\(^6\) We use the standard train/development/test split, shown in Table 2.

|            | Train | Dev | Test |
|------------|-------|-----|------|
| # Passages | 347   | 192 | 184  |
| # Sentences| 2,723 | 554 | 535  |
| # Tokens  | 44,804| 5,394| 5,381|

Table 2: Data split for the shared gold-standard corpus.

### 4 Comparison Methodology

To facilitate comparison between UCCA and UD, we first assimilate the graphs by abstracting away from formalism differences, obtaining a similar graph format for both schemes. We then match pairs of nodes in the converted UD and UCCA trees if they share all terminals in their yields.

UD annotates bi-lexical dependency trees, while UCCA graphs contain non-terminal nodes. In §4.1, we outline the unified DAG converter by Hershcovich et al. (2018a,b),\(^7\) which we use to reach a common format. In §4.2, we describe a number of extensions to the converter, which abstract away from further non-content differences.

Figure 3 presents the same tree from Figure 2 after conversion. The converter adds one pre-terminal per token, and attaches them according to the original dependency tree: traversing it from the root, for each head it creates a non-terminal parent with the edge label *head*, and adds the dependents as children of the created non-terminal. Relation subtypes are stripped, leaving only universal relations. For example, the language-specific definite article label *det:*def is replaced by the universal *det*.

\(^5\)http://bit.ly/ucca_guidelines_v2

\(^6\)Our data is available at https://github.com/UniversalConceptualCognitiveAnnotation/UCCA_English-EWT.

\(^7\)https://github.com/huji-nlp/semstr

### 4.1 Basic Conversion

Figure 3 presents the same tree from Figure 2 after conversion. The converter adds one pre-terminal per token, and attaches them according to the original dependency tree: traversing it from the root, for each head it creates a non-terminal parent with the edge label *head*, and adds the dependents as children of the created non-terminal. Relation subtypes are stripped, leaving only universal relations. For example, the language-specific definite article label *det:*def is replaced by the universal *det*.\(^8\)

\(^8\)https://github.com/huji-nlp/semstr
Reentrancies. Remote edges in UCCA enable reentrancy, forming a DAG together with primary edges. UD allows reentrancy when including enhanced dependencies (Schuster and Manning, 2016), which form (bi-lexical) graphs, representing phenomena such as predicate ellipsis (e.g., gapping), and shared arguments due to coordination, control, raising and relative clauses.

UCCA is more inclusive in its use of remote edges, and accounts for the entire class of implicit arguments termed Constructional Null Instantiation in FrameNet (Ruppenhofer et al., 2016). For example, in “The Pentagon is bypassing official US intelligence channels [...] in order to create strife” (from EWT), remote edges mark Pentagon as a shared argument of bypassing and create. Another example is “if you call for an appointment [...] so you can then make one”, where a remote edge in UCCA indicates that one refers to appointment. Neither is covered by enhanced UD.

In order to facilitate comparison, we remove remote edges and enhanced dependencies in the conversion process. We thus compare basic UD and UCCA trees, deferring a comparison of UCCA and enhanced UD to future work.

4.2 Extensions to the Converter

We extend the unified DAG converter to remove further non-content differences.

Unanalyzable units. An unanalyzable phrase is represented in UCCA as a single unit covering multiple terminals. In multi-word expressions (MWEs) in UD, each word after the first is attached to the previous word, with the flat, fixed or goeswith relations (depending on whether the expression is grammaticalized, or split by error). We remove edges of these relations and join the corresponding pre-terminals to one unit.

Promotion of conjunctions. The basic conversion generally preserves terminal yields: the set of terminals spanned by a non-terminal is the same as the original dependency yield of its head terminal (e.g., in Figure 3, the yield of the non-terminal headed by graduation is “After graduation”, the same as that of “graduation” in Figure 2).

Since UD attaches subordinating and coordinating conjunctions to the subsequent conjunct, this results in them being positioned in the same conjunct they relate (e.g., After will be included in the first conjunct in “After arriving home, John went to sleep”; and will be included in the second conjunct in “John and Mary”). In contrast, UCCA places conjunctions as siblings to their conjuncts (e.g., “[After] [arriving home]. [John went to sleep]” and “[John] [and] [Mary]”).

To abstract away from these convention differences, we place coordinating and subordinating conjunctions (i.e., cc-labeled units, and mark-labeled units with an advcl head such as when, if, after) as siblings of their conjuncts.

5 Analysis of Divergences

Using the shared format, we turn to analyzing the content differences between UCCA and UD.

5.1 Confusion Matrix

Table 3 presents the confusion matrix of categories between the converted UD and UCCA, calculated over all sentences in the training and development sets of the shared EWT reviews corpus. We leave the test set out of this evaluation to avoid contamination for future parsing experiments.

In case of multiple UCCA units with the same terminal yield (i.e., units with a single non-remote child), we take the top category only, to avoid double-counting. Excluding punctuation, this results in 60,434 yields in UCCA and 58,992 in UD. Of these, 52,280 are common, meaning that a UCCA “parser” developed this way would get a very high F1 score of 87.6%, if it is provided with the gold UCCA label for every converted edge.

Some yields still have more than one UCCA category associated with them, due to edges with multiple categories (A|P and A|S). For presentation reasons, 0.15% of the UCCA units in the data are not presented here, as they belong to rare (< 0.1%) multiple-category combinations.

Only 82.6% of syntactic arguments (ccomp, csubj, iobj, nsubj, obj, obl and xcomp) are Participants, and only 72.9% of Participants are syntactic arguments—a difference stemming from the Scene/non-Scene (§5.2) and argument/adjunct (§5.3) distinctions. Moreover, if we identify predicates as words having at least one argument and Scenes as units with at least one Participant, then only 92.1% of UD predicates correspond to Scenes (many of which are secondary relations within one scene; see §5), and only 80% of

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8[https://universaldependencies.org/u/overview/enhanced-syntax.html](https://universaldependencies.org/u/overview/enhanced-syntax.html)

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9See [http://bit.ly/uccaud](http://bit.ly/uccaud) for a detailed explanation of each example in this section.
Scenes correspond to predicates (e.g., due to eventive nouns, which are not syntactic predicates).

Examining the head row in Table 3 allows us to contrast the schemes’ notions of a head. head-labeled units have at least one dependent in UD, or are single-clause sentences (technically, they are non-terminals added by the converter). Of them, 75.7% correspond to Processes, States, Parallel Scenes or Centers, which are UCCA’s notions of semantic heads, and 11.6% are left unmatched, mostly due to MWEs analyzed in UD but not in UCCA (§5.4). Another source of unmatched units is inter-Scene linkage, which tends to be flatter in UCCA (§5.5). The rest are mostly due to head swap (e.g., “all of Dallas”, where all is a Quantifier of Dallas in UCCA, but the head in UD).

In the following subsections, we review the main content differences between the schemes, as reflected in the confusion matrix, and categorize them according to the UD relations involved.

### 5.2 Scenes vs. Non-Scenes

UCCA distinguishes between Scenes and non-Scenes. This distinction crosses UD categories, as a Scene can be evoked by a verb, an eventive or stative noun (negotiation, fatigue), an adjective or even a preposition (“this is for John”).

Core syntactic arguments. Subjects and objects are usually Participants (e.g., “wine was excellent”). However, when describing a Scene, the subject may be a Process/State (e.g., “but service is very poor”). Some wh-pronouns are the subjects or objects of a relative clause, but are Linkers or Relators, depending on whether they link Scenes or non-Scenes, respectively. For example, “who” in “overall, Joe is a happy camper”, an adjective or Elaborator where defining inherent properties of non-Scenes (“medical school”).

Adjectival modifiers are Adverbials when modifying Scenes (“romantic dinner”), States when describing non-Scenes (“beautiful hotel”) or when semantically predicative (“such a convenient location”), or Elaborators where defining inherent properties of non-Scenes (“medical school”).

Nominal and clausal modifiers. Most are Participants or Elaborators, depending on whether they modify a Scene (e.g., “discount on services” and “our decision to buy when we did”) or “my car’s gears and brakes” and “Some of the younger kids that work there” are Elaborators. Unmatched acl are often free relative clauses (e.g., in “the prices were worth what I got”).

| A  | A’ | P  | A’s | C  | D  | E  | F  | G  | H  | L  | N  | P  | Q  | R  | S  | T  | No MATCH |
|----|----|----|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|----------|
| acl | 58 | 1   | 4   | 249 | 1   | 48 | 6   | 1   | 1   | 409 |
| advcl | 14 | 12  | 2   | 2   | 6   | 512 | 4   | 11  | 423 |
| advmod | 225 | 1   | 69  | 1778 | 332 | 27 | 135 | 14  | 258 | 2   | 15  | 44  | 9   | 368 | 273 |
| amod | 25 | 1    | 134 | 647 | 837 | 1   | 28 | 7   | 130 | 3   | 269 | 25  | 176 |
| appos | 21 | 39  | 2   | 34  | 2   | 33 |
| aux | 384 | 2   | 1335 | 2   | 1   | 1   | 17 |
| case | 11 | 31  | 27 | 25 | 123 | 213 | 26 | 11 | 1   | 2629 | 154  | 1   | 262 |
| cc | 8 | 4   | 1   | 4   | 1   | 1   | 5 | 1567 | 381 | 6   | 12  | 52  |
| ccomp | 345 | 1   | 1 | 36 | 1   | 1   | 166 |
| compound | 225 | 116 | 67 | 586 | 21 | 2   | 32 | 19 | 1 | 124 | 24  | 683 |
| conj | 10 | 4   | 4   | 9   | 5   | 1   | 1262 | 1   | 6   | 2   | 10  | 497 |
| cop | 1 | 1   | 1312 | 1   | 9   | 1 | 178 |
| csubj | 13 | 1 | 3 | 1 | 129 | 16 | 1 | 124 |
| det | 10 | 17 | 119 | 440 | 2963 | 2 | 27 | 16 | 5 | 19 |
| discourse | 1 | 2   | 1   | 25 | 29 | 27 | 16 | 17 | 3 |
| expl | 21 | 1 | 98  | 1 | 17  |
| iobj | 13 | 1 | 1 | 10 |
| list | 3 | 7 | 2 | 1 | 27 | 1 | 6 |
| mark | 9 | 7 | 1 | 531 | 1 | 654 | 407 | 1 | 5 | 143 |
| nmod | 844 | 1 | 1 | 20 | 9 | 786 | 8 | 4 | 12 | 1 | 1 | 20 | 2   | 2 | 11 | 27 | 488 |
| nsubj | 429 | 7 | 21 | 25 | 3 | 2   | 55 | 1 | 5   | 61 | 58 | 1 | 80 | 14 | 4 | 247 |
| nummod | 2 | 33 | 12 | 17 | 4 | 4 | 334 | 64 |
| obj | 1845 | 1 | 54 | 21 | 6 | 11 | 4 | 23 | 52 | 1 | 23 | 3 | 11 | 583 |
| obl | 1195 | 1 | 19 | 115 | 41 | 1 | 17 | 39 | 34 | 6 | 26 | 7 | 302 | 611 |
| parataxis | 6 | 1 | 5 | 4 | 6 | 285 | 5 | 180 |
| vocative | 17 | | | | | | | | | | | | | | | | |
| xcomp | 121 | 4 | 25 | 8 | 8 | 38 | 526 |
| head | 445 | 48 | 159 | 6388 | 717 | 142 | 564 | 83 | 2462 | 42 | 1 | 4303 | 120 | 52 | 1547 | 32 | 2235 |
| NO MATCH | 1421 | 37 | 58 | 690 | 417 | 291 | 14 | 33 | 2291 | 146 | 6 | 802 | 94 | 52 | 369 | 96 |
what is the obj of worth but a Participant of I got).

Case markers. While mostly Relators modifying non-Scenes (e.g., “the team at Bradley Chevron”), some case markers are Linkers linking Scenes together (e.g., “very informative website with a lot of good work”). Others are Elaborators (e.g., “over a year”) or States when used as the main relation in verbless or copula clauses (e.g., “it is right on Wisconsin Ave”).

Coordination. Coordinating conjunctions (cc) are Connectors where they coordinate non-Scenes (e.g., “Mercedes and Dan”) or Linkers where they coordinate Scenes (e.g., “outdated but not bad”). Similarly, conjuncts and list elements (conj, list) may be Parallel Scenes (H), or Centers when they are non-Scenes.

Determiners. Articles are Functions, but determiners modifying non-Scenes are Elaborators (e.g., “I will never recommend this gym to any woman”). Where modifying Scenes (mostly negation) they are marked as Adverbials. For example, “no feathers in stock”, “what a mistake”, and “the rear window had some leakage” are all Adverbials.

5.3 Primary and Secondary Relations
UD distinguishes core arguments, adverb modifiers, and obliques (in English UD, the latter mostly correspond to prepositional dependents of verbs). UCCA distinguishes Participants, including locations and abstract entities, from secondary relations (Adverbials), which cover manner, aspect and modality. Adverbials can be verbs (e.g., begin, fail), prepositional phrases (with disrespect), as well as modals, adjectives and adverbs.

Adverbs and obliques. Most UD adverb modifiers are Adverbials (e.g., “I sometimes go”), but they may be Participants, mostly in the case of semantic arguments describing location (e.g., here). Obliques may be Participants (e.g., “wait for Nick”), Time (e.g., “for over 7 years”) or Adverbials—mostly manner adjuncts (by far).

Clausal arguments are Participant Scenes (e.g., “it was great that they did not charge a service fee”, “did not really know what I wanted” or “I asked them to change it”). However, when serving as complements to a secondary verb, they will not match any unit in UCCA, as it places secondary verbs on the same level as their primary relation. For example, to pay is an xcomp in “they have to pay”, while the UCCA structure is flat: have to is an Adverbial and pay is a Process. Single-worded clausal arguments may correspond to a Process/State, as in “this seems great”.

Auxiliary verbs are Functions (e.g., “do not forget”), or Adverbials when they are modals (e.g., “you can graduate”). Semi-modals in UD are treated as clausal heads, which take a clausal complement. For example, in “able to do well”, UD treats able as the head, which takes do well as an xcomp. UCCA, on the other hand, treats it as an Adverbial, creating a mismatch for xcomp.

5.4 Multi-Word Expressions
UD and UCCA treat MWEs differently. In UD they include names, compounds and grammaticalized fixed expressions. UCCA treats names and grammaticalized MWEs as unanalyzable units, but also a range of semantically opaque constructions (e.g., light verbs and idioms). On the other hand, compounds are not necessarily unanalyzable in UCCA, especially if compositional.

Compounds. English compounds are mostly nominal, and are a very heterogeneous category. Most compounds correspond to Elaborators (e.g., “industry standard”), or Elaborator Scenes (e.g., “out-of-place flat-screen TV”), and many are unanalyzable expressions (e.g., “mark up”). Where the head noun evokes a Scene, the dependent is often a Participant (e.g., “food craving”), but can also be an Adverbial (e.g., “first time buyers”) depending on its semantic category. Other compounds in UD are phrasal verbs (e.g., “figure out”, “cleaned up”), which UCCA treats as unanalyzable (leading to unmatched units).

Core arguments. A significant number of subjects and objects are left unmatched as they form parts of MWEs marked in UCCA as unanalyzable. UD annotates MWEs involving a verb and its argument(s) just like any other clause, and therefore lacks this semantic content. Examples include light verbs (e.g., “give a try”), idioms (“bites the dust”), and figures of speech (e.g., “when it comes to”, “offer a taste (of)”, all are UCCA units.

Complex prepositions. Some complex prepositions (e.g., according to or on top of), not encoded as MWEs in UD, are unanalyzable in UCCA.

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10While in UD the conjunction cc is attached to the following conjunct, in UCCA coordination is a flat structure. This is a convention difference that we normalize (§4.2).
5.5 Linkage

**Head selection.** UCCA tends to flatten linkage, where UD, as a dependency scheme, selects a head and dependent per relation. This yields scope ambiguities for coordination, an inherently flat structure. For instance, “unique gifts and cards” is ambiguous in UD as to whether unique applies only to gifts or to the whole phrase—both annotated as in Figure 4a. UCCA, allowing non-terminal nodes, disambiguates this case (Figure 4b).

```
(4a) UD
  unique  | gifts  | and  | cards

(C) H E F root
(adj) L conj
(unique) E nsubj
(gifts) C amod
(cards) C amod

(4b) UCCA
  From  | the  | moment  | you  | enter  | you  | know

(C) H E F root
(adp) L det
(from) L nsubj
(moment) E nsubj
(you) A P U
(enter) A P U
(you) A P U
(know) A P U
```

Figure 4: Example for coordination in UD and UCCA.

**Clausal dependents.** UD categorizes clause linkage into coordination, subordination, argumenthood (complementation), and parataxis. UCCA distinguishes argumenthood but conflates the others into the Parallel Scene category. For example, “We called few companies before we decided to hire them” and “Check out The Willow Lounge, you’ll be happy” are Parallel Scenes.

Note that while in UD, mark (e.g., before) is attached to the dependent adverbial clause, a UCCA Linker lies outside the linked Scenes. To reduce unmatched advcl instances, this convention difference is fixed by the converter (§4.2). Many remaining unmatched units are due to conjunctions we could not reliably raise. For instance, the marker to introducing an xcomp is ambiguous between Linker (purposive to) and Function (infinitive marker). Similarly, wh-pronouns may be Linkers (“he was willing to budge a little on the price which means a lot to me”), but have other uses in questions and free relative clauses. Other mismatches result from the long tail of differences in how UD and UCCA construe linkage. Consider the sentence in Figure 5. While moment is an oblique argument of know in UD, From the moment is analyzed as a Linker in UCCA.

5.6 Other Differences

**Appositions** in UD always follow the modified noun, but named entities in them are UCCA Centers, regardless of position (e.g., “its sister store Peking Garden”, the UD head its sister store is an Elaborator, while Peking Garden is the Center).

**Copulas.** UCCA distinguishes copular constructions expressing identity (e.g., “This is the original Ham’s restaurant”) where the copula is annotated as State, and cases of attribution (e.g., “Mercedes and Dan are very thorough”) or location (e.g., “Excellent chefs are in the kitchen”), where the copula is a Function.

**Discourse markers and interjections.** Units relating a Scene to the speech event or to the speaker’s opinion are Ground (e.g., “no, Warwick in New Jersey” and “Please visit my website”). On the other hand, discourse elements that relate one Scene to another are Linkers (e.g., anyway).

**Vocatives** are both Ground and Participants if they participate in the Scene and are the party addressed. For example, Mark in “Thanks Mark” is both the person addressed and the one thanked.\(^{11}\)

**Expletives and subjects.** Expletives are generally Functions, but some instances of it and that are analyzed as nsubj in UD and as Function in UCCA (e.g., “it’s like driving a new car”).

**Excluded relations.** We exclude the following UD labels, as they are irrelevant to our evaluation: root (always matches the entire sentence); punct (punctuation is ignored in UCCA evaluation); dep (unspecified dependency), orphan (used for gapping, which is represented using remote edges in UCCA—see §4.1); fixed, flat and goeswith (correspond to parts of unanalyzable units in UCCA, and so do not represent units on their own—see §4.2); reparandum and dislocated (too rare in EWT).

6 Fine-Grained UCCA Parsing Evaluation

In §5 we used our comparison methodology, consisting of the conversion to a shared format and

\(^{11}\) The A/G column is omitted from Table 3 as this category combination occurs in only 0.02% of edges in the corpus.
matching units by terminal yield, to compare gold-standard UD and UCCA. In this section we apply the same methodology to parser outputs, using gold-standard UD for fine-grained evaluation.

6.1 Experimental Setup

**Data.** In addition to the UCCA EWT data (§3), we use the reviews section of the UD v2.3 English_EWT treebank (Nivre et al., 2018),\(^{12}\) annotated over the exact same sentences. We additionally use UDPipe v1.2 (Straka et al., 2016; Straka and Straková, 2017), trained on English_EWT,\(^{13}\) for feature extraction. We apply the extended converter to UD as before (§4.2).

**Parser.** We train TUPA v1.3 (Hershcovich et al., 2017, 2018a) on the UCCA EWT data, with the standard train/development/test split. TUPA uses POS tags and syntactic dependencies as features. We experiment both with using gold UD for feature extraction, and with using UDPipe outputs.

**Evaluation by gold-standard UD.** UCCA evaluation is generally carried out by considering a predicted unit as correct if there is a gold unit that matches it in terminal yield and labels. Precision, Recall and F-score (F1) are computed accordingly. For the fine-grained analysis, we split the gold-standard, predicted and matched UCCA units according to the labels of the UD relations whose dependents have the same terminal yield (if any).

6.2 Results

Table 4 presents TUPA’s scores on the UCCA EWT development and test sets. Surprisingly, using UDPipe for feature extraction results in better scores than gold syntactic tags and dependencies.

| Features  | Primary |          | Remote |          |
|-----------|---------|----------|--------|----------|
|           | LP      | LR       | LF     | LP       | LR       | LF     |
| Development |         |          |        |          |          |        |
| Gold UD   | 72.1    | 71.2     | 71.7   | 61.2     | 38.1     | 47.0   |
| UDPipe    | 73.0    | 72.1     | 72.5   | 53.7     | 40.8     | 46.4   |
| Test      |         |          |        |          |          |        |
| Gold UD   | 72.2    | 71.2     | 71.7   | 60.9     | 36.8     | 45.9   |
| UDPipe    | 72.4    | 71.7     | 72.1   | 60.3     | 38.5     | 47.0   |

Table 5 shows fine-grained evaluation by UD relations. TUPA does best on auxiliaries and determiners, despite the heterogeneity of corresponding UCCA categories (see Table 3), possibly by making lexical distinctions (e.g., modals and auxiliary verbs are both UD auxiliaries, but are annotated as Adverbials and Functions, respectively).

Copulas and coordinating conjunctions pose a more difficult distinction, since the same lexical items may have different categories depending on the context: State/Function for copulas, due to the distinction between identity and attribution, and Connector/Linker for conjunctions, due to the distinction between Scenes and non-Scenes. However, the reviews domain imposes a strong prior for both (Function and Linker, respectively), which TUPA learns successfully.

Inter-clause linkage (conj, advcl, xcomp, ccomp, parataxis, acl and csubj) is a common source of error for TUPA. Although the match between UCCA and UD is not perfect in these cases, it is overall better than TUPA’s unlabeled performance, despite using gold-standard syntactic features. Our results thus suggest that encoding syntax more directly, perhaps using syntactic scaffolding (Swayamdipta et al., 2018) or guided attention (Strubell et al., 2018), may assist in predicting unit boundaries. However, TUPA often succeeds at making distinctions that are not even encoded in UD. For example, it does reasonably well (71%) on distinguishing between noun modifiers of Scene-evoking nouns (Participants) and modifiers of other nouns (Elaborators), surpassing a majority baseline based on the UD relation (51%). Lexical resources that distinguish eventive and relational nouns from concrete nouns may allow improving it even further. In the similar case of compounds, lexical resources for light verbs and idioms may increase performance.

7 Discussion

NLP tasks often require semantic distinctions that are difficult to extract from syntactic representations. Consider the example “after graduation, John moved to Paris” again. While graduation evokes a Scene (Figure 1), in UD it is an oblique modifier of moved, just like Paris is (Figure 2). The Scene/non-Scene distinction (§5.2) would assist structural text simplification systems to paraphrase this to “John graduated. (Then,) John moved to Paris”, such that each sentence contains...
Some syntactic representation approaches, no-

tic parsers must address, and potential approaches
to Hobbsian Logical Form, identifying semantic
cepts between them. Our findings highlight the
tic heads and arguments, finding substantial diver-
ted methodology to evaluate how well the
ted with UCCA units in gold-standard and
in TUPA’s predictions; their intersection, with/without regard to categories. (c) Percentage of correctly categorized edges; for
(b) Total number of instances of each UD relation; of them, matching UCCA units in gold-standard and
matched Stanford Dependencies (precursor to UD)
stance has a long tradition in NLP. Indeed,
letic one Scene (Sulem et al., 2018a).
Another example is machine translation—
translating the same sentence into Hebrew, which
does not have a word for graduation, would re-
quire a clause to convey the same meaning. The
mapping would therefore be more direct using
a semantic representation, and we would benefit
from breaking the utterance into two Scenes.

8 Related Work

The use of syntactic parsing as a proxy for seman-
tic structure has a long tradition in NLP. Indeed,
syntactic parsers have leveraged syntax for out-
put space pruning (Xue and Palmer, 2004), syn-
tactic features (Gildea and Jurafsky, 2002; Her-
shcovich et al., 2017), joint modeling (Surdeanu
et al., 2008; Hajič et al., 2009), and multi-task
learning (Swayamdipta et al., 2016, 2018; Hersh-
covich et al., 2018a). Empirical comparison be-
tween syntactic and semantic schemes, however,
is still scarce. Rudinger and Van Durme (2014)
mapped Stanford Dependencies (precursor to UD)
to Hobbsian Logical Form, identifying semantic
gaps in the former. PredPatt (White et al., 2016),
a framework for extracting predicate-argument
structures from UD, was evaluated by Zhang et al.
(2017) on a large set of converted PropBank anno-
tations. Szubert et al. (2018) proposed a method
for aligning AMR and UD subgraphs, finding that
97% of AMR edges are evoked by one or more
words or syntactic relations. Damonte et al. (2017)
refined AMR evaluation by UD labels, similar to
our fine-grained evaluation of UCCA parsing.

Some syntactic representation approaches, no-
tably CCG (Steedman, 2000), directly reflect the
underlying semantics, and have been used to trans-
duce semantic forms using rule-based systems
(Basile et al., 2012). A related line of work tackles
the transduction of syntactic structures into semi-
tic ones. Reddy et al. (2016) proposed a rule-
based method for converting UD to logical forms.
Stanovsky et al. (2016) converted Stanford dependency
trees into proposition structures (PROPS),
abstracting away from some syntactic detail.

9 Conclusion

We evaluated the similarities and divergences in
the content encoded by UD and UCCA. After
annotating the reviews section of the English
Web Treebank with UCCA, we used an auto-
mated methodology to evaluate how well the
two schemes align, abstracting away from differ-
ences of mere convention. We provided a de-
tailed picture of the content differences between
the schemes. Notably, we quantified the differ-
ences between the notions of syntactic and seman-
tic heads and arguments, finding substantial diver-
gence between them. Our findings highlight the
potential utility of using semantic parsers for text
understanding applications (over their syntactic
counterparts), but also expose challenges semantic
parsers must address, and potential approaches for
addressing them.

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Table 5: Fine-grained evaluation of TUPA (with gold-standard UD features) on the EWT development set. (a) Columns are sorted by labeled F1, measuring performance on each subset of edges. Unlabeled F1 ignores edge categories, evaluating unit boundaries only. (b) Total number of instances of each UD relation; of them, matching UCCA units in gold-standard and in TUPA’s predictions; their intersection, with/without regard to categories. (c) Percentage of correctly categorized edges; for comparison, percentage of most frequent category (see Table 3). (d) Average number of words in corresponding terminal yields.

|                | aux | det | cop | cc | expl | nsubj | case | list | amod | nummod | mark | compound | obj | mod | conj | comp | accomp | discurse | parasitic | appos | an | nmod | vocative | compound |
|----------------|-----|-----|-----|----|------|-------|------|------|------|--------|------|----------|-----|-----|------|------|--------|---------|-----------|-------|---|-----|---------|----------|
| Labeled F1 %   | 94  | 93  | 89  | 86 | 83   | 83    | 80   | 76   | 76   | 72     | 71   | 71       | 70  | 62  | 57   | 55   | 50     | 49      | 48       | 41    | 38  | 29  | 23      | 21       |
| Unlabeled F1 % | 99  | 99  | 100 | 99 | 83   | 84   | 95   | 76   | 95   | 95     | 96   | 97       | 92  | 84  | 65   | 77   | 61     | 51      | 61       | 63    | 95  | 29  | 36      | 48       |
| Total in UD #  | 156 | 192 | 187 | 212| 12   | 8     | 466  | 335  | 15   | 37     | 38   | 116      | 2  | 219 | 222 | 231 | 244    | 52      | 208      | 1     | 16  | 29  | 52      | 84       |
| Match Gold #   | 156 | 185 | 187 | 206| 12   | 6     | 468  | 305  | 15   | 359    | 33   | 111      | 7  | 146 | 187 | 198 | 210    | 40      | 162      | 28    | 10  | 20  | 48      | 17       |
| Match Predicted # | 154 | 388 | 187 | 203| 12   | 6     | 446  | 313  | 9    | 345    | 32   | 32        | 6  | 136 | 163 | 183 | 177    | 30      | 147      | 26    | 11  | 15  | 30      | 12       |
| Labeled Correct # | 145 | 361 | 166 | 175| 10   | 5     | 365  | 293  | 8    | 336    | 334  | 28        | 109 | 6   | 118 | 113 | 147    | 119     | 18       | 94    | 17  | 10  | 5       | 14       |
| Unlabeled Correct # | 154 | 381 | 187 | 203| 12   | 5     | 386  | 293  | 8    | 336    | 334  | 28        | 109 | 6   | 118 | 113 | 147    | 119     | 18       | 94    | 17  | 10  | 5       | 14       |
| Labeled/Unlabeled % | 94  | 95 | 89  | 86 | 83   | 100  | 75   | 74   | 82   | 72     | 67   | 70       | 88  | 71  | 94   | 79   | 65     | 40      | 100      | 64    | 43  | 53  | 0       | 0        |
| Mode/Match Gold % | 79  | 82 | 86  | 75 | 58   | 100  | 91   | 79   | 83   | 51     | 35   | 45       | 71  | 54  | 91   | 51   | 70     | 92      | 68       | 44    | 30  | 94 | 41       | 72       |
| Average Words # | 1.0 | 1.0 | 1.0 | 1.0| 1.1   | 1.6   | 2.2  | 1.2  | 1.2  | 1.1    | 1.6  | 1.2      | 3.0 | 2.4 | 5.8  | 6.6  | 3.8    | 6.0     | 1.1      | 9.0   | 6.7 | 4.0 | 5.6      | 7.5       |
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