PET: A new Dataset for Process Extraction from Natural Language Text

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Abstract

Although there is a long tradition of work in NLP on extracting entities and relations from text, to date there exists little work on the acquisition of business processes from unstructured data such as textual corpora of process descriptions. With this work we aim at filling this gap and establishing the first steps towards bridging data-driven information extraction methodologies from Natural Language Processing and the model-based formalization that is aimed from Business Process Management. For this, we develop the first corpus of business process descriptions annotated with activities, gateways, actors and flow information. We present our new resource, including a detailed overview of the annotation schema and guidelines, as well as a variety of baselines to benchmark the difficulty and challenges of business process extraction from text.

1 Introduction

Information Extraction (IE), a key area of research focused on extracting structured representations from unstructured text, has a long-standing tradition in Natural Language Processing (NLP), from seminal contributions in the context of the Message Understanding Conference using finite-state techniques [HSAM93] to current neural approaches to document-level relation extraction [YYL+19]. Despite this large volume of work, historically, most of it has concentrated on standard newswire text. Moreover, most successful approaches are rather schema-weak, an approach epitomized by a very successful line of research such as Open Information Extraction [BCS+07, CWZ18]. In this light, we propose first steps towards shifting part of this focus in IE to a new domain and task. Specifically, we focus on the problem of extracting business process models from textual content – which can, in turn, be viewed as the problem of extracting activities and workflow elements from process descriptions that can be represented adopting the Business Process Management and Notation (BPMN) or compiled into Petri Nets [Aal15].

While there has been growing interest in recent years from the Business Process Management (BPM) community on the extraction of processes from text [PMP11, vdACLR19, QWK+20], current work has major limitations. Arguably this is in part due to the limited availability of domain-specific, human annotated gold-standard data that could be used to train from scratch or fine-tune...
data-driven methods, and which are essential to enable task-specific comparisons across competing approaches \cite{BDG20, Bel20}. Creating benchmarks from text, however, is at the heart of much work the NLP community – cf. the long-standing tradition of SENSEVAL and SemEval evaluation campaigns in computational semantics: despite the major limitations shown by current ‘leaderboardism’ \cite{EJ20}, the availability of reference gold-standard datasets has the potential of fostering the application of NLP techniques to other fields, such as for instance BPM, and crucially makes clear what the applicability and limitations of state-of-the-art approaches for the domain of interest are.

With this work we aim at at filling this gap and foster bridging of work in IE and data-driven BPM by providing a novel dataset of human-annotated processes in a corpus of process descriptions. The key contributions of this work are:

1. We provide a new reference corpus, annotation schema, and guidelines for the task of annotating business process models in running text. Our corpus includes annotations for different kinds of extraction levels, such as actors, activities and relations between them (i.e., workflow patterns).

2. We quantify for the first time the difficulty of fundamental information extraction tasks for process model extraction by deploying a variety of baselines on our annotated data, thus providing an initial assessment of the feasibility of process extraction from natural language text.

Our vision builds upon bringing together heterogeneous communities such as NLP and BPM practitioners by defining shared tasks and resources (cf. previous work from \cite{NGP+18} at the intersection of NLP and political science). All resources described in this paper are freely available for the research community at w3id.org/pet.

2 Problem Background

The extraction of process models from documents is a complex task, since the analysis of the natural language description of a process has to take care of the multiple linguistics levels (syntactical, semantics, and pragmatics) and to mitigate linguistic phenomena such as syntactic leeway, simultaneously. Moreover, it has to handle the multiple possible interpretations (in terms of process behavior) that can be inferred from the same text, because the same semantic can be conveyed in multiple ways, maybe not always equivalent. For example, there are different ways to represent, in a process model, a repeated event or activity, but it may be the case that only one of these possible interpretations is the correct one to represent in the formal model.

Figure 1 presents an example of the process extraction task. The gray shadow boxes link each process description sentence on the left of the figure that describes a process element to its corresponding process element in the process diagram, represented in BPMN, on the right part of the figure. Here, the ninth sentence can also be represented in different ways than the one reported in the diagram. It is possible to represent the same semantic, for example, adopting a sub-process element (in case we need to re-use this part of the diagram somewhere else), or as a multi-instance activity (either parallel or sequential).

In general, the first task to perform when analyzing a process description regards filtering uninformative sentences of the process description out, because not all the sentences represent a process elements. Then, Actions, Actors, Events, Gateways, Artifacts, and various types of process flows can be extracted. However, not only each sentence can describe multiple process elements, but also each word can have multiple meanings. To determine the correct intended meaning and
Figure 1: Example of a text-to-model mapping [vdALR17] in which the meaningful activities described in the process description (on the left) are mapped to the process model diagram (on the right). Two interesting aspects are worthy to note. First, not all the sentences correspond to a process model element. Second, the logical succession described in the text differs from the written sentences’ order (as for example happens with sentences 4 and 5).

to map it into the corresponding process element implies considering these two aspects at once. Finally, process elements discovered have to be logically organized following the semantic conveyed in the process description. So, defining the **logical succession of process model elements** is another challenge to tackle.

Figure 2 shows an abstract level of the process extraction from natural language text task that is conceptualized as an algorithmic function $f$ that aims to “map” a natural language process description into its process model. In the figure the process description is represented with the blue document icon on the left, and the process model generated from the function $f$, represented on the right as a BPMN diagram.

Figure 2: The figure shows an abstraction of the algorithmic function $f$ that maps a natural language process description (represented with the blue document icon) to its formal representation, the process model diagram (displayed on the right part of the figure).
3 Annotation Guidelines

In this Section, we introduce\(^1\) the annotation guidelines we defined to create the dataset. The annotation of a document describing a process is a difficult task. Being able to identify **process elements** requires having at least a rough understanding of the typical elements contained in process modeling languages.

![Business Process Diagram in the BPMN language.](image)

To provide an overview of the graphical language and of the type of elements it typically contains, please refer to the diagram in Figure 3 taken from [ABD+17], which provides a model of a customer buying a flight ticket from a travel agency. Besides illustrating the scenario, the diagram is “annotated” with speech balloons indicating the type of entity denoted by the graphical constructs.

Following the classification made in [ABD+17], we can group these constructs in three macro categories:

1. **Behavioral.** These elements are the ones that refer to the so-called **control flow** of the process, that is the flow determined by the set of activities that are performed in coordination. This category is the most articulated in a business process and contains at least 3 types of objects:

   - **activities** and **events**, that is the things that happen in time\(^2\). In our example the activity **check the flight offer** or the event **payment received**.
   - **flow objects**, that is constructs that enable the routing of the flow between the activities such as the sequence relation between activities, or the gateways that enable the routing of the flow. In our example the (precedence) relation between **make flight offer** and **check flight offer** or the (mutually) exclusive gateway between **reject offer** and **book and pay flight**, and finally

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\(^1\)The reader may find the complete annotation guidelines at https://w3id.org/pet.

\(^2\)While these elements often have a different meaning on some modeling languages we do not distinguish between them here.
• states, that is conditions of the world that affect the flow in the process such as the pre-post conditions for the occurrence of an activity or a guard on a gateway. In our example the (un)satisfied status of the customer w.r.t. a flight offer.

2. Data. These elements usually describe, at a high level of abstraction, the objects upon which an activity acts. Examples in the scenario above are the flight request and the flight ticket. Note that sometimes these data objects complement the activity itself (as in the case of the data object flight request, which is produced by the activity check travel agency web site while in other cases they are implicitly described in the activity itself, as in the case of flight ticket with the activity prepare ticket. In this latter case the data object is often left implicit.

3. Organizational. These elements are usually related to the who question, and often describe, at a high level of abstraction, the roles / organizational structures involved in the activities of the process.

It is important to highlight that Data and Organizational objects do not exist per-se in a business process diagram but they usually refer to the activities. More formally, they are participants of the activity as they participate to the activity itself.

We aim at proposing a general annotation schema able to deal in unknown scenarios. In particular, we decided to break down activity to differentiate among the activity elements it is composed of. For instance, we capture the activity “action” expression and the object the activity acts on in two different annotation layers. This choice allows to easier the annotation workload and it also reduces the possibility of making errors (for example, connecting with a Sequence Flow relation the activity data to the actor responsible for the execution of the activity). For instance, we differentiate the expression describing an Activity to the object the activity uses. The overall goal is to annotate process model elements and their relations in documents.

We implemented the annotation schema described in this document in Inception Annotation tool. The schema can be downloaded from w3id.org/pet.

3.1 Layers Overview

Here, we explore the process elements we considered in the proposed dataset and their relations. Figure 4 provides an overview of the different layers and shows their relations.

Behavioral Layer The Behavioral layer captures information about the behavioral elements described and their relations. Figure 4 shows the relations between the Behavioral layer and the other ones. The Behavioral layer is the core layer since it captures activities, gateways, branch condition, and flow relations. An activity element represents a single task performed within a process model. A gateway element represents a decision point, the condition specification represents the condition that a process execution instance must satisfies be be allowed to enter a specific branch of a gateway. A Flow is a relation that defines the process logic by connecting all the elements that belong to this layer together.

The Behavioral layer is composed of six features: Element Type, Uses, Flow, Roles, Further Specification, Same Gateway. Since this layer captures both Activity and Gateways, not all features

3https://inception-project.github.io/
are always required, but they depend on the Element Type and the situation described in the text. For example, if a text does not describe any Actor Performer, the feature Roles is left empty.

The feature **Element Type** defines the type of the process model element marked. The layer behavioral is connected to the layer Activity Data by the *Uses* relation. This feature links an activity to the Activity Data annotated in the layer Activity Data. Hence, this relation allows to connect an activity expression (either verbal or nominal) with the object the activity acts on. Process participants (actors involved in an activity) that are captured in the Organizational layer, are bound to activity through the feature Roles. The **Further Specification** feature allows to connect an activity to its important details (captured in the Further Specification layer). The Further Specification layer captures the important information of an activity that are not captured by the other layers, such as the mean, the manner of execution, or how an activity is executed. The **Same Gateway** feature allows to “connect together” all the parts describing the same gateway, since its description may span over multiple sentences. This means that only gateway elements can be connected by this relation. The Behavioral layer makes a connection to it-self through the relation Flow. This feature allows to define the process logic by connecting behavioral elements together in a sequential order.

**Activity Data Layer** The Activity Data layer captures the object of an activity expression acts on. This layer has no features.

**Further Specification** The Further Specification layer captures important details of an Activity, such as the mean or the manner of its execution. This layer has no features.

**Organizational Layer** The Organizational layer is meant to annotate at a high level of abstraction the process participants that are responsible of activities. They typically represent the Actors involved in a process. This layer has no features.
The PET Dataset

The guidelines described in Section 3 were used for the creation of the PET dataset described in this section and available at https://w3id.org/pet. The creation of the first version of the PET dataset started from the Friedrich dataset: a set of 47 textual documents preliminary exploited within the BPMN community to start the investigation of the process extraction from natural language text research topic. The reader may find the introduction to the raw version of the textual documents used for building PET in [Fri10].

The reasons for which we started from this set of documents are two-fold. First, these documents are well-known within the community. This aspect allows to give continuity to the investigation in this research area as well as to start from a base set of documents that are in-line with the type of process narratives considered relevant by the community. Second, the documents contained in the dataset are not explicitly annotated with the elements described in Section 3. Indeed, the dataset described in [Fri10] contains only the raw text and a possible corresponding BPMN diagram. However, many of these diagrams were translated by the same authors from other process modeling languages into BPMN without any validation performed by experts. Therefore, the diagrams should not be taken as gold standard reference. As a consequence, they can not be used to mark process elements in the process descriptions. Hence, the whole work of text processing and elements annotation has to be provided.

The dataset construction process has been split in five main phases:

1. **Text pre-processing.** As the first operation, we check the content of each document and we tokenized it. This initial check was necessary since some of the original texts were automatically translated into English by the authors of the dataset. The translations were never validated, indeed, several errors have been found and fixed.

2. **Text Annotation.** Each text has been annotated by using the guidelines introduced in Section 3. The team was composed by five annotators with high expertise in BPMN. Each document has been assigned to three experts that were in charge of identifying all the elements and flows with each document. In this phase, we used the the Inception tool\(^4\) to support annotators.

3. **Automatic annotation fixing.** After the second phase, we ran an automatic procedure relying on a rule-based script to automatically fix annotations that were not compliant with the guidelines. For example, if a modal verb was erroneously included in the annotation of an Activity, the procedure removed it from the annotation. Another example is the missing of the article within an annotation related to an Actor. In this case, the script included it in the annotation. This phase allowed to remove possible annotation errors and to obtain annotations compliant with the guidelines.

4. **Agreement Computation.** Here, we computed, on the annotation provided by the experts, the agreement scores for each process element and for each relation between process elements pair adopting the methodology proposed in [HR05].\(^5\) By following such a methodology, an

\(^4\)https://inception-project.github.io/

\(^5\)We measured the agreement in terms of the F1 measure because, besides being straightforward to calculate, it is directly interpretable. Note that chance-corrected measures like $\kappa$ approach the F1-measure as the number of cases that raters agree are negative grows [HR05].
Table 1: Annotation Agreement on Process Elements

|                          | Annotation Agreement on Process Elements |
|--------------------------|------------------------------------------|
|                          | Annotators                                |
|                          | Precision | Recall | F1     |
| Activity                 | 0.960     | 0.869  | 0.912  |
| Activity Data            | 0.934     | 0.734  | 0.822  |
| Actor                    | 0.958     | 0.837  | 0.893  |
| Further Specification    | 0.430     | 0.329  | 0.373  |
| XOR Gateway              | 0.881     | 0.860  | 0.870  |
| AND Gateway              | 0.889     | 0.727  | 0.800  |
| Condition Specification  | 0.856     | 0.761  | 0.806  |
| Overall                  | 0.915     | 0.787  | 0.846  |

annotation was considered in agreement among the experts if and only if they capture the same span of words and they assign the same process element tag to the annotation. In the same way, a relation was considered in agreement if and only if the experts strictly annotated the same span of words representing (i) the process element related to the source element; (ii) the process element related to the target element; and, (iii) the relation tag between source and target. The only exception regards the same gateway relation in which source and target are interchangeable since in this type of relation the relation arrow does not matter. The final agreement scores were obtained by averaging the individual scores obtained by the comparison of annotators pairs. Tables 1 and 2 shows the annotation agreement computed for each process element and each process relation, respectively. We can observe how, in general, experts agreed concerning the main elements and flows contained within a process description. On the contrary, the annotation of information classified as Further Specification led to several disagreement situations. Such situations were analyzed and mitigate within the next phase.

5. Reconciliation. The last phase consisted of the mitigation of disagreements within the annotations provided by the experts. The aim of this phase is to obtain a shared and agreed set of gold standard annotations on each text for both entities and relations. Such entities also enable the generation of the related full-connected process model flow that can be rendered by using, but not limited to, a BPMN diagram. During this last phase, among the 47 documents originally included into the dataset, 2 of them were discarded. These texts were not fully annotated by the annotators since they were not be able to completely understand which process elements were actually included in some specific parts of the text. For this reason, the final size of the dataset is 45 textual descriptions of the corresponding process models together with their annotations.

Table 3 contains the statistics related to the current version of the document, while, Tables 4 and 5 contains the detailed statistic about process elements and relations respectively. The dataset archive contains three files per document:

- A file (doc_name.txt) containing the textual description of the process formatted in CONLL format (1 word per line with sentences separated by a blank line).
- A file (doc_name.process-elements.IOB2.txt) containing the process elements gold standard annotation of the process described annotated with IOB2 Schema, formatted in CONLL format (1 word annotation per line with sentences separated by a blank line).

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| Statistic                        | Value |
|---------------------------------|-------|
| Total Documents                 | 45    |
| Total Sentences                 | 417   |
| Average sentences per document  | 9.27  |
| Average words per document      | 168.2 |
| Average words per sentence      | 18.15 |

Table 3: Documents Statistics

• A file (`doc_name.relations.tsv`) containing the process relations gold standard between process elements. Each line represents a relation in form of triplet (source, relation tag, target). For example:
  
  `n_sent_1 0 1 2 3 Uses n_sent_2 5 6`

  represents a `uses` relation between the process element composed of the span of words from 0 to 3 in sentence 1 with the process element composed of the span of words from 5 to 6 in sentence 2.

5 Baseline Results

In this section, we present three baselines we developed to provide preliminary results obtained on the dataset and also to show how the dataset can be used to test different extraction approaches. As described in Section 4, there are different type of elements that can be extracted (e.g., activities, actors, relations) and different assumptions that can be made (e.g., the exploitation of gold information or the process of the raw text).

| Statistic                        | Activity | Activity Data | Actor | Further Specification | XOR Gateway | AND Gateway | Condition Specification |
|----------------------------------|----------|---------------|-------|------------------------|-------------|-------------|------------------------|
| Absolute count                   | 501      | 452           | 439   | 64                     | 117         | 8           | 80                     |
| Relative count                   | 30.16%   | 27.21%        | 26.43%| 3.86%                  | 7.04%       | 0.48%       | 4.82%                  |
| Per document                     | 11.13    | 10.04         | 9.76  | 1.42                   | 2.6         | 0.18        | 1.78                   |
| Per sentence                     | 1.2      | 1.08          | 1.05  | 0.15                   | 0.28        | 0.02        | 0.19                   |
| Average length                   | 1.1      | 3.49          | 2.32  | 5.19                   | 1.26        | 2.12        | 6.04                   |
| Standard deviation               | 0.48     | 2.47          | 1.11  | 3.4                    | 0.77        | 1.54        | 3.04                   |

Table 4: Entities Statistics
Table 5: Relations Statistics

|                  | Flows | Uses | Actor Performer | Actor Recipient | Further Specification | Same Gateway |
|------------------|-------|------|-----------------|-----------------|------------------------|--------------|
| Absolute count   | 689   | 477  | 313             | 164             | 64                     | 43           |
| Relative count   | 39.37%| 27.26%| 17.89%          | 9.37%           | 3.66%                  | 2.46%        |
| Count per document | 15.31 | 10.6 | 6.96            | 3.64            | 1.42                   | 0.96         |
| Count per sentence | 1.65  | 1.14 | 0.75            | 0.39            | 0.15                   | 0.1          |

From this perspective, we tested our baselines under three different settings and by using two different families of approaches: Conditional Random Fields (CRF) and Rule-Based (RB):

- **Baseline 1 (B1):** by starting from the raw text (i.e., no information related to process elements or relations has been used), a CRF-based approach has been used for building a model to support the extraction of single entities (e.g., activities, actors).

- **Baseline 2 (B2):** by starting from the existing gold information concerning the annotation of process elements, a RB strategy has been used for detecting relations between entities.

- **Baseline 3 (B3):** this baseline relies on the output of B1 concerning the annotations of process elements. Then, a RB strategy has been used for detecting relations between entities.

Concerning the CRF approach, we adopted the CRF model described in [Oka07] by encoding data following the IOB2 schema. Results have been obtained by performing a 5-folds cross-validation and by averaging observed performance.

While, concerning the RB approach, we defined a set of rules taking into account text position of process elements. Rules defined are the following:

1. Rule 1 (R1): (*sequence flows*) are annotated by connecting two consecutive behavioral process elements.

2. Rule 2 (R2): (*same gateway*) relations are annotated by connecting two gateway of the same type if they are detected in the same sentence or if they are detected in two consecutive sentences.

3. Rule 3 (R3): (*sequence flows*) relations are annotated between each gateway that is not part of any *same gateway* relation and the next activity detected.

4. Rule 4 (R4): for each activity defined in a sentence, (*actor performer/recipient*) relations are annotated by linking the left-side closest actor as actor performer and the right-side closest actor as actor recipient.

5. Rule 5 (R5): (*further specification*) annotations are defined by connecting each further specification element to the closest activity in the text.

6. Rule 6 (R6): (*uses*) annotations are defined by connecting activity data elements to the closest left-side activity of the same sentence. If no activities are defined on the left-side, the right-side is considered.
Table 6: Results obtained by Baseline 1 concerning the extraction of Process Elements.

|                  | Baseline 1 |     |     |
|------------------|------------|-----|-----|
|                  | Precision  | Recall | F1  |
| Activity         | 0.913      | 0.733 | 0.813 |
| Activity Data    | 0.870      | 0.580 | 0.696 |
| Actor            | 0.896      | 0.665 | 0.763 |
| Further Specification | 0.381   | 0.125 | 0.188 |
| XOR Gateway      | 0.872      | 0.701 | 0.777 |
| AND Gateway      | 0.000      | 0.000 | 0.000 |
| Condition Specification | 0.800 | 0.500 | 0.615 |
| Overall          | 0.880      | 0.633 | 0.736 |

Table 7: Results obtained by Baseline 2 and Baseline 3 concerning the extraction of Process Relations.

|                  | Baseline 2 |     |     | Baseline 3 |     |     |
|------------------|------------|-----|-----|------------|-----|-----|
|                  | Precision  | Recall | F1  | Precision  | Recall | F1  |
| Sequence Flow    | 1.000      | 0.787 | 0.881 | 1.000      | 0.370 | 0.540 |
| Uses             | 1.000      | 0.891 | 0.942 | 1.000      | 0.488 | 0.656 |
| Actor Performer  | 0.992      | 0.808 | 0.891 | 0.994      | 0.534 | 0.694 |
| Actor Recipient  | 0.993      | 0.817 | 0.896 | 1.000      | 0.476 | 0.645 |
| Further Specification | 1.000 | 0.828 | 0.906 | 0.875      | 0.109 | 0.194 |
| Same Gateway     | 0.973      | 0.837 | 0.900 | 0.897      | 0.605 | 0.722 |
| Overall          | 0.997      | 0.825 | 0.903 | 0.994      | 0.438 | 0.608 |

Table 6 and 7 provide the results obtained by the three baseline approaches described above.

An observation of baselines’ performance highlights a general capabilities of the adopted approaches in detecting both process elements and relations with a high precision. Exceptions are the further specification and AND Gateway elements where the baseline obtained very poor performance. While on the one hand the observed precision is high, on the other hand the recall is the metric for which lower performance were obtained. In turn, this affected the value of the F1 as well. Hence, an interesting challenge worth of being investigated in this domain seems to be the detection of all elements rather then to detect them correctly.

6 Conclusion

In this paper, we presented the PET dataset. The dataset contains 45 documents containing narrative description of business process and their annotations. Together with the dataset, we provided the set of guidelines we defined and adopted for annotating all documents. The dataset building procedure has been described and, for completeness, we provided three baselines implementing straightforward approaches to give a starting point for designing the next generation of process extraction from natural language text approaches.
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