Applying Information Extraction for Patent Structure Analysis

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ABSTRACT

Patent engineers are spending significant time analyzing patent claim structures to grasp the range of technology covered or to compare similar patents in the same patent family. Though patent claims are the most important section in a patent, it is hard for a human to examine them. In this paper, we propose an information-extraction-based technique to grasp the patent claim structure. We confirmed that our approach is promising through empirical evaluation of entity mention extraction and the relation extraction method. We also built a preliminary interface to visualize patent structures, compare patents, and search similar patents.

CCS CONCEPTS

• **Information systems → Information extraction**;

KEYWORDS

Information extraction, patent analysis, visualization

1 INTRODUCTION

Patent engineers are spending significant time analyzing claim sections of patent documents to grasp the scope of legal protection of the inventions or the differences between similar claims. A typical case is that of evaluating a patent family. A patent family is a set of either patent applications or publications in multiple countries to protect a single invention by a common inventor(s) that is then patented in more than one country[1]. When patent engineers analyze the scope of legal protection of a claim, they often analyze claims of other patents in the same family because the scope of a patent may be wider than that of the original claim or may contain a different combination of elements.

Though patent claims are the most important section in a patent, it is hard for a human to examine them. The claim sections of patent documents are typical low-readability technical texts. Considerable research has been done to improve claim readability by modification-based approaches, e.g., simplification, paraphrasing, and summarization, and clarifying-presentation-based approaches
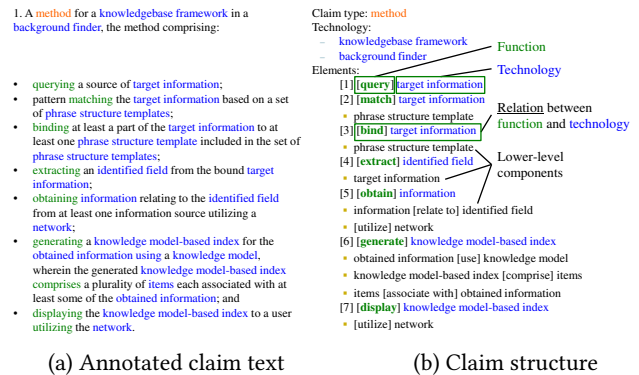
[1]http://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families.html

(a) Annotated claim text　　　　　(b) Claim structure

Figure 1: Desired output.

[3]. In this paper, we propose an information-extraction-based technique to grasp the patent claim structure for a special user group of patent engineers. Our idea is claim structure extraction with a relation extraction technique. Figure 1 shows an example of the extraction of the structure from a claim text. Applying machine learning-based information extraction techniques instead of using only syntactic parsing is useful for reducing the cost of extracting important terms from patent claims and organizing them. We use DeepDive [12, 15], which has been successfully applied to document analysis tasks [4, 7, 9, 19], as an information extraction platform in the present work.

2 BACKGROUND

2.1 Patent Claim Structure

In general, patent documents consist of several sections, e.g., summary of the invention, title, abstract, background, brief description of the drawings, and claims. A patent contains one or more independent claims that describe the essential features of the invention[2]. Additionally, a patent may contain dependent claims that impose further limitations and restrictions on other dependent or independent claims. Each claim has to be defined in a single sentence [8]. The claim section defines the boundaries of the legal protection of the invention by describing complex technical issues and using specific legal terminology [10]. Each claim consists of preamble, transition, and body. The preamble is an introductory part defining and clarifying the subject matter of the scope of a claim. The transition is the part showing the condition of listed features with regard to the subject matter in the preamble. The body is the part listing the features of the invention[3]. Each invention element in the body

[2]https://www.epo.org/law-practice/legal-texts/guidelines.html
[3]http://www.wipo.int/edocs/mdocs/africa/en/wipo_pat_hre_15/wipo_pat_hre_15_t_11.pdf

text is separated by a semicolon [11]. From the viewpoint of evaluating the value of a patent, it is important to understand the claim structure quickly. Thus, technologies improving the readability of the claim structure are required.

2.2 Related Work

There have been several activities to improve patent claim readability. There are two approaches: the modification approach and the presentation clarification approach. The idea of the modification approach is to change the claim sentence into a more readable form using parsing methodology [13, 14], rule-based methods [17], and paraphrasing and summarization methods [1]. The advantage of this approach is that the claim text is simplified so that patent engineers can understand it in less time. However, there is a risk of changing the meaning of the text [3]. The second approach is presentation clarification. This approach does not change the claim text itself but changes the presentation of the claim to improve the readability. There are several strategies, e.g., aligning claim phrases with relevant text from the description section [16], and segmentation [3]. Segmentation consists of two levels. First, an entire claim is segmented to the components of preamble, transitional phrase and body, using a rule-based approach. Second, a conditional random field is trained to segment the components into clauses.

Our approach combines the advantages of the two approaches described above. In advance, key terms and phrases in claims are annotated by information extraction techniques. When the original claim is being read, highlighted text is shown to improve the readability of the text. If the aim is to grasp the claim structure, a simplified view showing only extracted terms and phrases is shown.

3 CLAIM STRUCTURE EXTRACTION

In this section, we propose an information extraction-based patent claim structure extraction method. Our approach is threefold: extract entity and relation mentions, build claim structure, and implement a patent analysis interface.

3.1 Extraction Target Schema

To analyze patent claim structure, we extract the following information:

Claim type There are many types of claim such as system, method, and apparatus. Usually the claim type is indicated by the first noun(s) of the preamble.

Technology Keywords (important noun phrases) in a claim.

Function How the technologies are used. Basically verbs connected to the noun phrases.

Relation Relation between technology and function. There are two kinds of relations: subject (technology-function) and object (function-technology).

An example of relation is as follows:

- *Using* said first <u>performance data</u> to *compute* a <u>mathematical function</u> ('performance data' is the subject for '*compute*')
- A method of a computer system *predicting* a <u>performance shortage</u> ('performance shortage' is the object for '*predict*')

Subclaim A claim can refer to another claim to extend it.
Example: 2. The system of <u>claim 1</u> further comprises means ...

Examples except subclaim are shown in Figure 1(b).

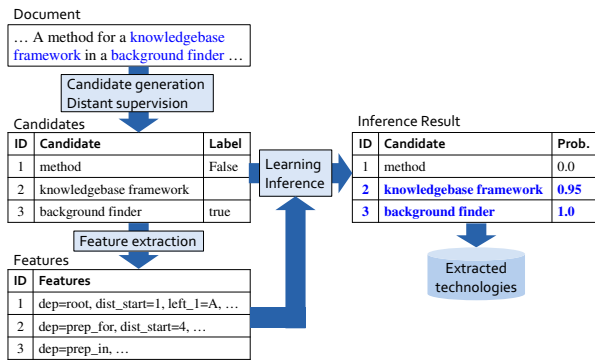## 3.2 Information Extraction Platform

We are using a machine learning-based information extraction approach rather than only a traditional natural language processing (NLP) approach for the following reasons: NLP parsers and taggers are noisy; simply extracting noun phrases is inaccurate; and it is hard to generalize matching dictionaries to unseen terms.

To extract the relations from papers, we use an information extraction platform, DeepDive [12, 15]. DeepDive uses Markov logic network-based inference [2] and distant supervision-based labeling [6] to extract relations from unstructured text. To use DeepDive, the user designs a pipeline of the relation extraction including extractors and inference modules. The output is a set of extracted relations in which estimated probability is assigned for the corresponding relation. We use DeepDive as the information extraction platform because it handles noisy input with the probabilistic inference, it integrates NLP with domain-specific knowledge, and it allows systematic error analysis. Also DeepDive worked in several domains such as extracting knowledge about biodiversity from papers [9]. The system has better precision and recall than human efforts. A DeepDive-based system also won the Knowledge Base Population competition [18].
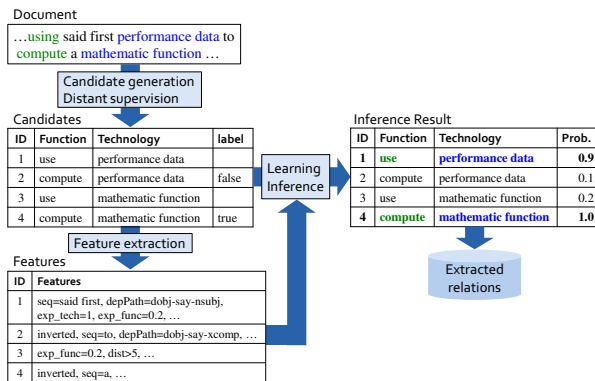
3.3 Pipeline

This section describes the pipeline to extract information shown in Section 3.1. Our patent analysis pipeline consists of entity mention extraction and relation mention extraction. Entity mention extraction consists of candidate generation, feature extraction, distant supervision, learning, and inference. Relation mention extraction consists of steps similar to those of entity mention extraction, built on extracted technology / function mentions. As the preprocess to get part-of-speech (POS) tags, named entity recognition (NER) tags, and dependency paths, we ran Stanford CoreNLP [5]. Figure 2 shows the summary of our application pipeline.

3.3.1 Entity mention extraction. In this section, 'technology' term generation is exemplified as shown in Figure 2(a). Firstly, the candidate generation step extracts the longest phrases that satisfy the following conditions: each word has POS tag of NN* / JJ / VBN / VBG; last word has POS tag of NN*; not all words are stopwords; first word is not an ordinal number (e.g., 'first' and 'second'); length of each word is greater than 1. Secondly, the feature extraction step generates the following features: features generated by DeepDive generic feature library (e.g., bag-of-words and POS tags of mentions or relations), distance to the start of claim / sentence, dependency label (e.g., 'nn' and 'amod'). Thirdly, the distant supervision step labels each candidate phrase with the rules shown in Table 1. Finally, the learning and inference step uses the inference rules (constraints) between two technology phrase candidates t1 and t2: (1) t1 equals t2 if t1 and t2 have the same words, (2) t1 equals t2 if t1's words start with t2's, and (3) t1 equals t2 if t1's words end with t2's. For other types of entities, a similar step is used.

(a) Entity extraction

(b) Relation extraction

Figure 2: Summary of information extraction pipeline.

Table 1: Distant supervision rules for technology mention extraction (P: positive, N: negative).

No.	Label	Condition
1	P	In a domain-specific positive KB (e.g., freebase "software-genre")
2	P	Matches the pattern 'said · · · performed/./,/;/and/to/comprising/VBZ'
3	P	Matches patterns (the · · · in, one · · · of, one · · · and, for · · · of, · · ·)
4	P	Matches patterns ('set of [*] ,|;|.', 'a [*] .*ing', 'a/an/the [*] ,|;|.', 'by the [*] of', '* [*] consist')
5	P	In the second level hierarchy (in a claim element) and the words before are in a/the/empty
6	N	Has intersection with a claim type
7	N	In a domain-independent non-technology dictionary (139 terms)
8	N	Matches patterns ('^first', '^second', '^\w+ of', '^sub .', '=', '\bEQU\b', '#')
9	N	Mention is three letters or less
10	N	Matches the pattern 'in [order] to'
11	N	Some special handling for mentions starting with VBG
12	N	If any word has a person/location/organization NER tag

Table 2: Preliminary evaluation result.

Schema	Precision	Recall
Claim type	99%	99%
Technology	82%	77%
Function	77%	65%
Subject relation	68%	69%
Object relation	91%	39%
Subclaim reference	100%	100%

3.3.2 Relation mention extraction. In this section, technology-function (subject) relation is exemplified as shown in Figure 2(b). The whole step is similar to the entity mention extraction. For the candidate generation, we use technology-function pairs in the same sentence (claim). For the feature extraction step, we use DeepDive's generic feature library and expectation of technology / function calculated in the entity mention extraction step. For the distant supervision, we use linguistic patterns with dependency path, word sequence, and so on. For the function-technology (object) relation, the same step is used.

4 EMPIRICAL EVALUATION OF INFORMATION EXTRACTION

We evaluated hundreds of mentions. As a dataset, we used 12,972 granted U.S. patents in the domain of "Data processing: artificial intelligence". One of the authors annotated the test data: 708 technology mentions, 311 function mentions, 126 claim type mentions, 102 subclaim references, 62 technology (subject)-function relations, and 113 function-technology (object) relations. The summary of mention extraction and relation extraction for this dataset is shown as Table 2. Although our experiment is limited in scale and the inter-annotator agreement is the next step, this work clarified the possibility of making applications to extract claim structure.
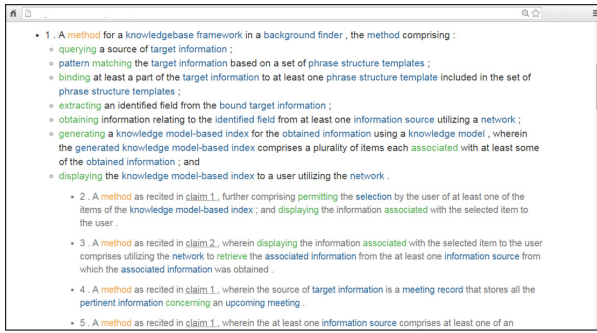
5 APPLICATION

We built a preliminary web-based interface to visualize patent structures, compare patents, and search patents. Functions are as follows: view annotated claim text, view claim structure, compare two patents, and search similar patents for a given (query) patent based on extracted components. The following subsections show the corresponding use cases.

5.1 Viewing annotated claim

Extracted entities and relations can be used to build claim structures. These claim structures are useful for analyzing patents. Figure 3 shows the visualized patent claim. Figure 3(a) shows an annotated patent claim and Figure 3(b) shows the patent structure. Using these views, patent engineers can grasp both the key feature of a patent claim and the structure of the claim.

5.2 Comparing two patent claims

When patent engineers want to compare patent claims precisely, they can use the patent comparison view. Figure 4 shows an example of comparing two patents. Each claim is analyzed in the way described in the previous subsection. Grey terms highlight

(a) Annotated patent text

(b) Patent structure

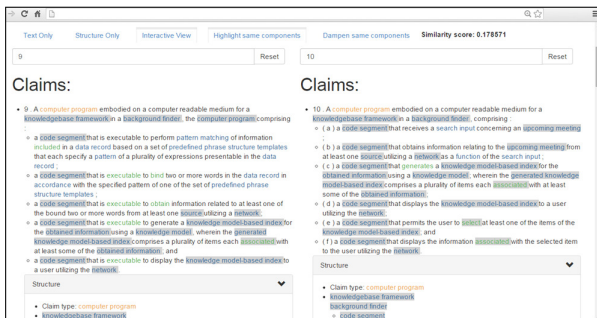**Figure 3: Annotated patent claims.**

Figure 4: Comparing two patents. Grey terms highlight the same extracted components in two patents.

the same extracted components in the two patents. We can grasp how a patent claim covers another patent claim. Additionally the similarity score is shown at the top of the page. This score is also used for the claim search function.

5.3 Searching similar patent claims

We also implemented the preliminary version of a similar claim search function. It calculates the similarity score using simple cosine similarity of extracted entities and relations.

6 CONCLUSIONS

We proposed a claim structure analysis method that uses an information extraction technique. Applying machine learning-based information extraction techniques instead of using only syntactic parsing is useful for reducing the cost of extracting important terms from patent claims and organizing them. We also built a preliminary interface to visualize patent structures, compare patents, and search similar patents.

Our future work includes: compare our method against other baseline methods, improve extraction quality, improve patent search quality, improve comparison interface with alignment functionality, and generalize to other domains.

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