Summarization, Simplification, and Generation:  
The Case of Patents

Silvia Casola\textsuperscript{a, b}, Alberto Lavelli\textsuperscript{b}

\textsuperscript{a}Università di Padova, Human Inspired Technology Research Centre, Via Luzzatti, 4, 35121 Padova, Italy
\textsuperscript{b}Fondazione Bruno Kessler, Via Sommarive, 18, Trento, 38123, Italy

Abstract

We survey Natural Language Processing (NLP) approaches to summarizing, simplifying, and generating patents’ text. While solving these tasks has important practical applications – given patents’ centrality in the R&D process – patents’ idiosyncrasies open peculiar challenges to the current NLP state of the art. This survey aims at a) describing patents’ characteristics and the questions they raise to the current NLP systems, b) critically presenting previous work and its evolution, and c) drawing attention to directions of research in which further work is needed. To the best of our knowledge, this is the first survey of generative approaches in the patent domain.

Keywords: Natural Language Processing, Patent Mining, Summarization, Simplification, Natural Language Generation, Survey

1. Introduction

Patents disclose what their creators consider valuable inventions – so valuable, in fact, that they spend a nontrivial amount of time and money on protecting them legally. Not only do patents define the extent of the legal protection, but they also describe in detail the invention and its embodiments, its relation to prior art, and contain metadata. It is common wisdom among patent professionals that up to 80\% of the information in patents cannot be found elsewhere [Asche 2017].

As a result, patents have been widely studied, with various aims. Recently, Natural Language Processing (NLP) approaches – which aim at automatically analyzing text – are emerging. This survey explores the application of NLP techniques to patent summarization, simplification, and generation. There are several reasons why we focus on these tasks: first of all, they have been explored less when compared, for example, to Patent Retrieval [Lupu & Hanbury].

*Corresponding author.

Email addresses: scasola@fbk.eu (Silvia Casola), lavelli@fbk.eu (Alberto Lavelli)

Accepted in Expert Systems with Applications [https://doi.org/10.1016/j.eswa.2022.117627]
and automatic patent classification (Gomez & Moens, 2014). However, their practical importance is hard to overstate: the volume of patent applications is enormous (according to the World Intellectual Property Organization, WIPO, 3.2 million patents were filed in 2019), and keeping pace with the technology is becoming difficult. One of the patents’ aims is to make knowledge circulate and accelerate the transfer of technology: however, this is hardly achievable given the information overload. Patent agents, R&D groups, and professionals would thus highly benefit from tools that digest information from patents or make them easier to process, given their length and complexity. The other reason is more technical and rises from patents’ peculiar linguistic characteristics. Patents are primarily textual documents, and they have proved an interesting testbed for NLP researchers. Interesting yet challenging: being a mixture of legal and technical terms, patents’ language differs severely from the general discourse.

Our contributions are the following: we present an analysis of patents’ linguistic characteristics and focus on the idiosyncrasies that negatively affect the use of off-the-shelf NLP tools (Section 2); after defining the patent summarization, simplification and generation tasks (Section 3) we describe the few available datasets and the evaluation approaches (Sections 4 and 5). Next, we review previous work in Sections 6, 7, and 8. Our review is rather comprehensive and covers works from the early 2000s to date. We pay special attention to the algorithms and models used from an NLP perspective. To the best of our knowledge, this is the first work that surveys summarization, simplification and generation techniques specifically in the patent domain. Note that, however, since patent processing has historically been application-oriented, previous work often used project-specific datasets, making it difficult to compare approaches directly in terms of performance. Finally, we present interesting lines of investigation for future research.

2. A primer on patents

Patents are primarily legal documents. Their owner controls the use of an invention for a limited time in a given geographic area and thus excludes others from making, using, or selling it without previous authorization. In exchange, the inventor discloses the invention to facilitate the transfer of technology.

This section defines some domain-specific concepts that we will reference in the following; we use patent US4575330A\(^1\) (the antecedent of a 3D printer, designed by Hull in 1989) as a running example.

2.1. Patent documents

Patent documents are highly structured and must follow strict rules\(^2\). Typically, they contain the following sections:
Title  E.g., Apparatus for production of three-dimensional objects by stereolithography

Claim  Specifies the extent of legal protection. This section can include multiple claims with a hierarchical structure.

1. A system for producing a three-dimensional object from a fluid medium capable of solidification when subjected to prescribed synergistic stimulation, said system comprising: means for drawing upon and forming successive cross-sectional laminae of said object at a two-dimensional interface; and means for moving said cross-sections as they are formed and building up said object in stepwise fashion, whereby a three-dimensional object is extracted from a substantially two-dimensional surface.

2. An improved system for producing a three-dimensional object from a fluid medium capable of solidification when subjected to prescribed synergistic stimulation, said system comprising: [...]

3. A system as set forth in claim 2, and further including: programmed control means for varying the graphic pattern of said reaction means operating upon said designated surface of said fluid medium.

Claims 1 and 2 are independent, while claim 3 is dependent on claim 2, which it further specifies. The document comprises 47 claims, which this paper is too small to contain. Following patent rules, each claim consists of a single sentence, therefore long, complex, and highly punctuated. The language is abstract to obfuscate the invention's limitations and full in legal jargon.

Description  A description detailed enough for a person skilled in the art to make and understand the invention.

Briefly, and in general terms, the present invention provides a new and improved system for generating a three-dimensional object by forming successive, adjacent, cross-sectional laminae of that object at the surface of a fluid medium capable of altering its physical state in response to appropriate synergistic stimulation, the successive laminae being automatically integrated as they are formed to define the desired three-dimensional object.

---

3We will refer to the whole document section using the cased form Claim, while the individual claims contained in such section will be lowercase.

4A “person skilled in the art” has ordinary skills in the invention technical field. For a formal definition, refer to the PCT International Search and Preliminary Examination Guidelines.
In a presently preferred embodiment, by way of example and not necessarily by way of limitation, the present invention harnesses the principles of computer generated graphics in combination with stereolithography, i.e., the application of lithographic techniques to the production of three dimensional objects, to simultaneously execute computer aided design (CAD) and computer aided manufacturing (CAM) in producing three-dimensional objects directly from computer instructions. [...] 

While the Claim section aims at legally protecting the invention (the construct in the mind of the inventor, with no physical substance), the Description discloses one or more embodiments (physical items). Drawings are standard in this section. The Description illustrates the invention to the public on the one hand and supports the Claim on the other. Notice how, while the language is still convoluted, it is less abstract.

**Abstract** Summarizes the invention description.

A system for generating three-dimensional objects by creating a cross-sectional pattern of the object to be formed at a selected surface of a fluid medium capable of altering its physical state in response to appropriate synergistic stimulation by impinging radiation, particle bombardment or chemical reaction, successive adjacent laminae [...].

**Other metadata** Includes standard classification codes, prior art citations, relevant dates, and inventors’, assignees’, and examiners’ information.

**Patent classifications** Patents are classified using standard codes. The Patent Classification (IPC) and the Cooperative Patent Classification (CPC) are the most widespread. Patent examiners assign codes manually depending on the invention’s technical characteristics. Patent US4575330A has 14 IPC classification codes. For example, code G09B25/02 indicates that the patent is in the Physics (G) section and follows to specify the class (G09), sub-class (G09B), group (G09B25/00), and sub-group (G09B25/02).

2.2. **Patent language**

In this section, we describe what makes patent documents unique from a linguistic perspective. Few documents are, in fact, as hard to process (for both humans and automatic systems) as patents, with their obscure language and complex discourse structure.

**Long sentences** According to patents’ rules, each claim must be written in a single sentence, which is therefore particularly long. [Verberne et al. (2010)] examined over 67 thousand Claim sections and found a median length of

[1] wipo.int/classifications/ipc/en/ [Last accessed: March 2021]
[2] cooperativepatentclassification.org [Last accessed: March 2021]
22 and a mean of 55; note that this figure is highly underestimated, as
the authors segment sentences using semicolons in addition to full stops.
In contrast, they found that the British National Corpus median length
(when segmented using the same methodology) is less than 10. For com-
parison, the first claim in patent US4575330A (a “rather short” one) is
69 words long, while claim 2 contains 152 words. Shinmori et al. (2003)
found similar characteristics in Japanese. While most quantitative work
focuses on the Claim, sentences in other sections are also remarkably long.

Words’ distribution and vocabulary Claims do not use much lexicon not
covered in general English, but their word frequency is different, and novel
technical multi-word terms are created ad hoc (Verberne et al., 2010).
Moreover, many words are used unusually: said, for example, typically
refers back to a previously mentioned entity, repeated to minimize am-
biguity (e.g., A system for [...], said system comprising [...], in claim 1):
transitions (e.g., comprising, including, wherein, consisting) have specific
legal meanings. The Claim’s language is abstract (system, object, medium
in claim 1), not to limit the invention’s scope, while the Description is
more concrete (Codina-Filbà et al., 2017).

Complex syntactic structure Patent claims are built out of noun phrases
instead of clauses, making it nontrivial to use general NLP resources. As
a result, previous work has tried to adapt existing parsers with domain-
specific rules (Burga et al., 2013) or simplify the claim before parsing (Mille
& Wanner, 2008b).

3. Task description

In this section, we will discuss the tasks of text summarization, simplifica-
tion, and generation. We will define them from an NLP perspective and discuss
their practical importance in the patent domain.

3.1. Summarization

Loosely speaking, a summary is a piece of text that, based on one or more
source documents, 1) contains the main information in such document(s) and 2)
is shorter, denser, and less redundant. For a recent survey on text summariza-
tion, see (El-Kassas et al., 2021). Automatic summarization is an open problem
in modern Natural Language Processing, and approaches vary widely. We will
categorize previous work according to the following dimensions:

Extractive vs. abstractive Extractive summaries consist of sentences or chunks
from the original document. To this end, most approaches divide the in-
put into sentences and score their relevance. In contrast, abstractive
approaches build an intermediate representation of the document first, from
which they generate text that does not quote the input verbatim. Fi-
nally, hybrid systems take from both approaches; for example, they might
select sentences extractively and then generate a paraphrased summary. Patent summaries have traditionally been extractive, but an interest in abstractive summarization is emerging.

Generic vs. query-based Query-based models (Girthana & Swamynathan, 2019b,a, 2020) receive a query and summarize information of relevance to such query. For example, during a prior art search, the user might only be interested in aspects of the retrieved documents that might invalidate their patent.

Human- vs. machine-focused While summaries are typically intended for humans, producing a shorter dense representation is equally relevant when the input is too long to be processed directly, e.g., by a machine learning algorithm. In this case, summarization constitutes a building block of a more complex pipeline. Tseng et al. (2007a,b), for example, perform summarization in view of patent-map creation and classification.

Language-specific vs. multilingual While published research has primarily been anglocentric, some works in other languages and multilingual techniques have been proposed.

As expected, patents’ summarization comes with its challenges. For example, while in some domains (e.g., news) the essential facts are typically in the first paragraphs, this assumption does not hold for patents, whose important content is spread in the whole input. Summaries also contain a high percentage of n-grams not in the source and shorter extractive fragments. Finally, summaries’ discourse structure is complex, and entities recur in multiple sentences. All these characteristics make patents an interesting testbed for summarization, for which a real semantic understanding of the input is crucial (Sharma et al., 2019).

In addition to the research interest, patents summaries are practically relevant for R&D teams, companies, and stakeholders. A brief search of online services showed that some companies sell patent summaries and related data as a paid service. For example, Derwent[7] produces patent abstracts distilling the novelty, use and advantages of the invention in plain English; to the best of our knowledge, the abstract is manually compiled by experts.

3.2. Simplification

Automatic simplification reduces the linguistic complexity of a document to make it easier to understand. In contrast with summarization, all information is usually kept in the simplified text. Generally, approaches vary depending on the system’s target user (e.g., second-language learners, people with reading disorders, children). Sikka & Mago (2020) is a recent survey addressing text simplification in the general domain. Given patents’ complexity – lexically and syntactically – the challenge lies in making their content accessible to the lay

https://clarivate.com/derwent [Last accessed: March 2021]
reader (which justifiably gets scared away from patents) and simplifying the experts’ work.

We will consider the following aspects:

**Expert vs. lay target reader** Patents’ audience ranges from specialists (e.g., attorneys and legal professionals), to laypeople (including academics) that might be interested, for example, in the invention’s technical features. Depending on the target user (and, in turn, on the target task), the degree of simplification might vary. When considering the legal nature of patents, for example, special attention should be given to keeping their scope unchanged. The first claim of patent US4575330A, for example, states: “A system for producing […] comprising: means for drawing […]; and means for moving […]”. A system “comprising” a feature might include additional ones; thus, replacing the term with “consisting of” – which, in patent jargon, excludes any additional component – would be problematic, even if thesauruses treat the terms as synonyms. Obviously, the attention to the jargon can be loosened if the target user is more interested in the technical characteristics than in the legal scope.

**Textual vs. graphical output** The simplification system’s output can be either a text or a more complex data structure. A textual output can be formatted appropriately (e.g., coloring essential words (Okamoto et al., 2017)), annotated with explanations (e.g., with links from a claim to a Description passage (Shinmori & Okumura, 2004)), or paraphrased (Bouayad-Agha et al., 2009a). Alternatively, a graphical representation, in the form of trees or graphs – which e.g. highlights the relation among the invention components – can be used.

**Application** The simplification system can be designed with a specific application in mind: in (Okamoto et al., 2017), for example, authors designed an interface to help patent experts in comparing documents from the same patent family.

As in the case of summaries, designing appropriate simplification systems has interesting use cases. Suominen et al. (2018) performed a user study with both experts and laypeople: most of their participants considered patents difficult to read. When presented with various reading aids, most considered them useful. Even law scholars have called for the use of a simpler language in patents (Feldman, 2008). Commercially, companies that provide patent reports do so in plain language. Somewhat ironically, Derwent goes as far as replacing the document title with a less obscure one, of more practical use.

### 3.3. Generation

We will use Patent Generation to refer to methods that aim at generating a patent or part of it. To the best of our knowledge, this line of research is

---

8see, for example, [Collins Online Thesaurus](http://www.collinsdictionary.com/dictionary/)
relatively new and is likely inspired by the recent success of modern generative models (e.g. GPT and its evolutions \cite{radford2018improving,radford2019language,brown2020language}) in various domains, including law \cite{huang2020intellectual}, health \cite{aminnejad2020language} and journalism \cite{shu2020language}, to name a few.  
Some approaches only produce “patent-like” text (i.e., employing technical terminology and respecting patents’ writing rules): their generation is unconstrained or constrained to a short user prompt – the first words of a text that the system needs to extend coherently. Their practical use is likely limited, but their success shows that even patents’ obscure language can be mastered by machines, at least at a superficial level. Another class of approaches conditions the generation to a fragment of the patent to produce a coherent output. For example, one might want to produce a plausible patent Abstract given its Title or a set of coherent claims with a given Description. In this case, the generation is constrained to the whole input section (e.g., the Title text) and the type of output section (e.g., Abstract).

While patent generation is still in its early days, researchers dream of “augmented inventing” \cite{lee2020augmented}, assisting inventors in redefining their ideas and helping with patent drafting. To this end, some hybrid commercial solutions are already in the market.

4. Datasets

Patent documents are issued periodically by the responsible patent offices. The United States Patent and Trademark Office (USPTO), for example, publishes patent applications and grants weekly, along with other bibliographic and legal data\cite{developer.uspto.gov/data}. To access the documents programatically, Application Programming Interfaces (APIs) are available. PatentsView\cite{www.patentsview.org} for example, is a visualization and mining platform to search and download USPTO patents, updated every three months. It provides several endpoints (patent, inventor, assignees, location, CPC, etc.) and a custom query language. Google also provides public datasets\cite{console.cloud.google.com/marketplace/browse?q=google%20patents%20datasets&filter=solution-type:dataset} accessible through BigQuery.

While it is relatively easy to obtain raw patent text, few curated datasets exist. These data are of the greatest importance: having a set of shared benchmarks allows to directly compare approaches, which is much more difficult otherwise. The only large-scale dataset for patent summarization is BigPatent\cite{evasharma.github.io/bigpatent} (Sharma et al., 2019). The dataset was recently built for abstractive summarization and contains 1.3 million patents’ Descriptions and their Abstracts (a.k.a. Summary).

\footnotesize{see, for example https://bohemian.ai/case-studies/automated-patent-drafting/ https://www.patentclaimmaster.com/automation.html https://harrityllp.com/services/patent-automation/ [Last accessed: March 2021]
\footnotesize{developer.uspto.gov/data [Last accessed: March 2021]
\footnotesize{www.patentsview.org/ [Last accessed: March 2021]
\footnotesize{console.cloud.google.com/marketplace/browse?q=google%20patents%20public%20datasets&filter=solution-type:dataset [Last accessed: March 2021]
\footnotesize{evasharma.github.io/bigpatent [Last accessed: March 2021]
5. Evaluation

The evaluation of a generated text, be it a summary, a simplification, or a completely new document, is currently an open problem in Natural Language Generation (Celikyilmaz et al., 2020; Lloret et al., 2018). Qualitative approaches resort to humans to evaluate the generated text (either overall or in some specific dimensions, e.g., relevance, coherence, readability, redundancy) and are to date considered the gold-standard for evaluation. In contrast, automatic approaches usually measure the output similarity with human written gold-standards (e.g. ROUGE (Lin, 2004), BLUE (Papineni et al., 2002), and PYRAMID (Nenkova & Passonneau, 2004)); while not perfect, automatic metrics have a certain degree of correlation with human judgment and are used when performing human evaluation is too expensive or labour-intensive.

For patent summarization, qualitative evaluation involves experts and non-experts; Mille & Wanner (2008b), for example, assess summaries intelligibility, simplicity, and accuracy on a Likert scale (Robinson, 2014). Quantitatively, the most widespread automatic summarization metrics is ROUGE (Recall-Oriented Understudy for Gisting Evaluation) (Lin, 2004). It measures the overlap between the generated sentence and the gold-standard. ROUGE-N is n-gram based and is measured as:

\[
\text{ROUGE-N} = \frac{\sum_{S \in \text{Reference}} \sum_{\text{gram}_n \in S} \text{Count}_{\text{match}}(\text{gram}_n)}{\sum_{S \in \text{Reference}} \sum_{\text{gram}_n \in S} \text{Count}(\text{gram}_n)}.
\]

ROUGE-L measures the similarity in terms of the Longest Common Subsequence (LCS). Words of the LCS must appear in the same relative order but not necessarily be contiguous. ROUGE-1, ROUGE-2 (for relevance), and ROUGE-L (for fluency) are generally used in practice, as they best correlate with human judgment. Similarly, some studies measure the similarity between the generated text and the reference summary in uni-gram Precision, Recall, and \(F_1\). The Compression Ratio and the Retention Ratio (the percentage of original information kept in the summary) are also frequently reported. Finally, when summarization is part of a more complex pipeline, the relative improvement of the downstream task is considered.

When evaluating simplification approaches, two different points of view exist. The first only considers the method’s correctness: if the algorithm needs to segment the text, one can manually annotate a segmented gold-standard and measure accuracy. However, assessing the readability improvement requires qualitative studies. Suominen et al. (2018), for example, use a questionnaire...
for quantifying patents’ complexity and test simplification solutions. Following their work’s findings, experts’ and laypeople’s opinions should be analyzed separately, as they are concerned with different issues. For instance, experts worry that the simplified patent might be misrepresented and its legal scope changed while laypeople demand strategies to understand the invention and find information.

Finally, measuring the quality of generated patent text is generally tricky. When no gold-standard exists, some authors have introduced ad hoc measures (see, for example (Lee & Hsiang, 2020b)); when a human-written reference exists, metrics as ROUGE can be used. Finally, note that some studies criticize the use of ROUGE; Lee (2020), for example, also reports the results using the Universal Sentence Encoder (Cer et al., 2018) representation, which they speculate handles semantics better.

6. Approaches for patent summarization

In this section, we describe extractive and abstractive approaches to patent summarization. As we discussed already, their direct comparison is difficult, as publications tend to use slightly different tasks on unshared data. The approaches discussed in the paper are summarized in Table 1.

6.1. Extractive summarization

Extractive approaches select the most informative sentences in the original document. A typical pipeline comprises the following steps:

1. Document segmentation: documents are split into segments, sentences, or paragraphs, using punctuation or heuristics. While many approaches work at the sentence level, Codina-Filbà et al. (2017) argue that patents sentences are too long to be used directly, and further segment them. In many cases, only some Sections (e.g. Description, Claims) are considered.

2. Sentence preprocessing: includes standard text preprocessing, e.g., removing stopwords or stemming. Given the peculiar patent style, patent-specific stopwords (cured by experts) also need to be removed. Some approaches (Trappey et al., 2006, 2008) only keep specific Parts of Speech.

3. Feature extraction: for each sentence, general-domain features include keywords, title words, cue words (from expert-designed lists), and the sentence position. In particular, patents contain several multi-word entities that need to be identified. To this end, Tseng et al. (2007a) propose an algorithm that merges nearby uni-grams words and extracts maximally repeated strings as multi-word terms. Given that text is often full in technical terms, Trappey et al. (2008, 2009) use a domain ontology for identifying domain-specific key-phrases. The approaches above try to customize general-discourse features to the patent domain; in contrast, Codina-Filbà et al. (2017) propose a domain-specific approach. They consider the lexical chain length as a measure of an entity importance: i.e., invention
| Study                        | Approach                        | Main contribution                                                                 | Limitations                                                                 | Dataset                      |
|-----------------------------|---------------------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------------------|------------------------------|
| Tseng et al. (2007a,b)      | Extractive                      | Domain-specific considerations; key-phrase extraction algorithm                    | Extrinsic eval. only (classification surrogates)                             | National Science Council Patent Set (612 patents) |
| Trappey et al. (2006, 2008)  | Extract information-dense paragraphs | Application of general-domain techniques                                        | Evaluation                                                                 | 111 patents                  |
| Milie & Wanner (2008)       | Abstractive (Deep-Syntactic Structs) | Multilinguality                                                                    | Complexity                                                                  | 50 patents                   |
| Mille & Wanner (2008)       | Extract information-dense paragraphs | Ontology for key-phrase extraction                                                |                                                                              | 200 patents                  |
| Brigmann et al. (2015)      | Hybrid                           | Patent-specific approach (lexical chain, Claim-Description alignment, sentence fragmentation) | Complexity                                                                  | 26 patents (test)            |
| Codina et al. (2017)        |                                  |                                                                                   |                                                                              |                              |
| Girithana & Swamynathan (2020) | Extractive (query-oriented)     | Query-oriented approach                                                            | Query expansion strategies                                                   | Smartphone-related patents   |
| Sharma et al. (2019)        |                                  | Dataset                                                                             | Complex Abstract style                                                      | 1.3M patents                 |
| de Souza et al. (2019)      | Extractive, semantic similarity  | Summarization to name patent groups                                               |                                                                              | 733 patents (test)           |
| Trappey et al. (2020)       | Hybrid (abstractive to extractive) | Attention-based method for extracting keywords                                     | Complexity                                                                  | 1708 (train) 30 (test) patents |
| Zhang et al. (2020)         | Abstractive (transformer-based)  | Analysis of SOTA general-domain NLP systems in the patent domain                  | Data requirements                                                           | BigPatent                    |
| de Souza et al. (2021)      | Abstractive (LSTM), semantic similarity | Summarization to name patents group                                                | Abstractive approaches inferior to extractive ones                          | 41,527 (train), 733 patents (test) |

Table 1: Surveyed studies for Patent Summarization.
components that appear many times in the Claim and Description are particularly relevant. Given the abnormal patents’ sentences length, they further segment sentences and use fragments as extractive candidates.

In most approaches, the segment position is also considered (favoring sentences at the beginning of paragraphs or paragraphs at the beginning or end of a Section). Query-oriented approaches also measure the sentence similarity to the query (e.g., with overlapping words (Girthana & Swamynathan, 2020)), which can be further expanded using a domain ontology (Girthana & Swamynathan, 2019a) or general-domain resources (Girthana & Swamynathan, 2019b) like WordNet. Query expansion can be particularly important as different patent documents can purposefully use a completely different wording for similar components. Table 2 includes some frequent features in extractive patent summarization.

4. Sentence weighting: the extracted features are used to score the sentence relevance in the summary. For example, Tseng et al. (2007a) score sentences as:

\[
\text{score}(S) = \left( \sum_{w \in \text{key}, \text{title}} TF_w + \sum_{w \in \text{clue}} \text{mean}(TF) \right) \times FS \times P
\]

where TF is the term frequency of word w in sentence S, mean(TF) is the average term frequency over keywords and title words in S, and FS and P are the sentence position weights, assigned heuristically. In particular, FS is set to 1.5 if the sentence is the first in the paragraph and to 1 otherwise; P is the position weight of the sentence with respect to the Section, and is set to 2 or 4 if the sentence is in the first or last two paragraphs of the Section respectively, and to 1 otherwise.

Another option is to learn weights from data directly: for example, Codina-Filbà et al. (2017) score each segment as \( \text{score}(S) = \sum_i w_i f_i \); they use linear regression to learn features weights based on textual segments and their cosine similarity to the gold-standard. Lastly, sentences can be classified as relevant or not relevant: to this end, Girthana & Swamynathan (2019a, 2020) train a Restricted Boltzmann Machine (Larochelle & Bengio, 2008) without supervision. To minimize repetitions, Trappey et al. (2006, 2008); Trappey & Trappey (2008) cluster semantically similar sentences and only select one sentence per cluster.

5. Summary generation: most commonly, the final summary consists of the union of the extracted sentences. Trappey et al. (2008, 2009) also draw a summary tree linked to the domain ontology.

While popular, the above pipeline is not the only route to extractive summarization. Alternatively, Bouayad-Agha et al. (2009a) exploit patent’s complex discourse structure, which they prune following predefined domain-specific rules. Finally, de Souza et al. (2019) discuss applying general-domain algorithms to
| Features                              | Description                                                                 |
|--------------------------------------|-----------------------------------------------------------------------------|
| **Entity features**                  |                                                                             |
| Term frequency - Inverse Document Frequency | Measures a keyword importance                                               |
| Ontology-based                       | Concepts from a domain-specific ontology; specific concepts are more relevant|
| Coreference-chain based              | Entities coreferenced repeatedly are more central                           |
| **Segment features**                 |                                                                             |
| Title similarity                     | Computed by considering either word overlap or semantic similarities         |
| Abstract similarity                  | Relevance to the query                                                      |
| Claim similarity                     | Patent section (Claim, Description, etc) and sentence position within the section |
| Query similarity                     | Overly long segments might be discouraged                                   |
| Position                              |                                                                             |
| Length                                |                                                                             |
| Number of keywords                   |                                                                             |
| Number of cue-words                  |                                                                             |

Table 2: Extractive features. We use the term *entity* to generically refer to keywords, phrases or other mentions in the document. Similarly, *segment* indicated both complete sentences and fragments.

patent sub-groups naming\(^{14}\) in that context, LSA (Dokun & Celebi \(^{2015}\)) performs best compared to LexRank (Erkan & Radev \(^{2004}\)) and to a TF-IDF approach.

6.2. **Abstractive models**

Abstractive models exploit a semantic representation of the input. In the patent domain, the first approaches used deep syntactic structures. Given patents’ linguistic structure, Mille & Wanner \(^{2008b}\) need to first simplify the claims (see Bouayad-Agha et al. \(^{2009b}\)) to achieve adequate parsing performance; then, they map the shallow syntactic structures to deep ones, using rules. Deep syntactic structures are closer to a semantic representation and thus used for summarization: to this end, the least relevant chunks are removed using handcrafted rules. Finally, they transfer the summarized deep structures to the target language (English, French, Spanish, or German) and use a generator to convert them to text.

More recently, neural models have revolutionized Natural Language Processing. These models act on the text directly and use neural networks to extract a representation optimized for the task to be solved. For abstractive summarization, a sequence-to-sequence model typically extracts a hidden representation from the input text (encoding) and then uses it to generate the output (decoding). While neural performance is indisputable, models require many input-output samples to learn from: that is probably why they have only spread

\(^{14}\)Patent sub-groups are the most specific level of the patents’ classification hierarchy and are named with a representative name, e.g. “Extracting optical codes from image or text carrying said optical code”.

13
very recently in the patent domain. No large-scale summarization dataset, in fact, existed before 2019, when BigPatent (Sharma et al., 2019) was published. Sharma et al. proposed several baselines: an LSTM (Sutskever et al., 2014) with attention (Bahdanau et al., 2015), a Pointer-Generator (See et al., 2017) with and without coverage, and SentRewriting (Chen & Bansal, 2018) (a hybrid approach).

Given its differences with the previously available datasets (mostly in the news domain) – in terms of style, content distribution and discourse structure – BigPatent became an interesting testbed for general domain NLP summarization models: this is the case of Pegasus (Zhang et al., 2020a), a pre-trained transformer (Vaswani et al., 2017) for summarization. During pre-training, whole sentences from the input are masked, and the model needs to generate them from the rest of the input (Gap Sentence Generation).

One of the significant challenges of the dataset is the input length, which is very large (with a 90% percentile of 7,693 tokens), and is problematic for standard transformers (whose attention mechanism scales quadratically in the input size): to this end, BIGBIRD (Zaheer et al., 2020) proposes a sparse attention mechanism which, to the best of our knowledge, is to date the state of the art on the dataset.

Summarization models’ performance on the BigPatent dataset is shown in Table 3. Note how the pre-trained transformer models obtain the best results, in line with the general trend in Natural Language Processing.

Finally, summarization methods could also be used for solving specific patent tasks. CTRLsum (He et al., 2020), for example, is a system that allows controlling the generated text by interacting through keywords or short prompts. The authors experiment with inputting [the purpose of the present invention is] to retrieve the patent aim. Finally, de Souza et al. (2021) have compared extractive and abstractive models in naming patents’ subgroups. When used to “summarize” the Abstract to produce a patent Title – which should contain, similarly to its subgroup name, the essence of the invention – extractive methods were found superior. This result highlights the challenges met by abstractive models, which are likely to be magnified in the legal domain.

6.3. Hybrid models

Hybrid models integrate elements of extractive and abstractive summarization. For example, the TOPAS workbench (Brügmann et al., 2015) includes a module that first selects segments extractively and then paraphrases them. A similar approach was adopted in (Codina-Filbà et al., 2017). In this approaches, a sentence fragment is the unit of extraction (sentences are too long to be used directly); extracted fragments are then paraphrased. More recently, Pilault et al. (2020) have shown that adding previously extracted sentences to the input when training a language model helps with long dependencies and improves the model’s abstractiveness. While the models described so far train the extractive and the abstractive components separately, SentRewriting (Chen & Bansal, 2018) uses reinforcement learning for selecting salient sentences and train the
| Model                                                                 | R-1    | R-2    | R-L    |
|----------------------------------------------------------------------|--------|--------|--------|
| TextRank (Mihalcea & Tarau, 2004)                                    | 35.99  | 11.14  | 29.60  |
| LexRank (Erkan & Radev, 2004)                                        | 35.57  | 10.47  | 29.03  |
| SumBasic (Nenkova & Vanderwende, 2005)                               | 27.44  | 7.08   | 23.66  |
| RNN-ext RL (Chen & Bansal, 2018)                                     | 34.63  | 10.62  | 29.43  |
| LSTM seq2seq (Sutskever et al., 2014) + attention                    | 28.74  | 7.87   | 24.66  |
| Pointer-Generator (See et al., 2017)                                  | 30.59  | 10.01  | 25.65  |
| Pointer-Generator + coverage (See et al., 2017)                      | 33.14  | 11.63  | 28.55  |
| SentRewriting (Chen & Bansal, 2018)                                  | 37.12  | 11.87  | 32.45  |
| TLM (Pilault et al., 2020)                                           | 36.41  | 11.38  | 30.88  |
| TLM + Extracted sentences                                            | 38.65  | 12.31  | 34.09  |
| CTR-summ (He et al., 2020)                                           | 45.80  | 18.68  | 39.06  |
| Pegasus\textsubscript{base} (Zhang et al., 2020) (no pretraining)    | 42.98  | 20.51  | 31.87  |
| Pegasus\textsubscript{base}                                          | 43.55  | 20.43  | 31.80  |
| Pegasus\textsubscript{large} (C4)                                     | 53.63  | 33.16  | 42.25  |
| Pegasus\textsubscript{large} (HugeNews)                              | 53.41  | 32.89  | 42.07  |
| BIGBIRD-RoBERTa (base, MLM) (Zaheer et al., 2020)                    | 55.69  | 37.27  | 45.56  |
| BIGBIRD-Pegasus (large, Pegasus pretrain)                            | **60.64** | **42.46** | **50.01** |

Table 3: Results on the BigPatent dataset. TextRank, LexRank, SumBasic, and RNN-ext RL are extractive baselines. TLM uses a GPT-like transformer (TLM) and concatenates extracted sentences to the Description (TLM + Extracted sentences). Results reported for CTR refer to unconditioned summarization. For Pegasus, we report results for base model (223M parameters) with and without pre-training and a larger model (568M parameters) independently pre-trained on a dataset of web pages (C4) and a dataset of news articles (HugeNews). For BIGBIRD, results using RoBERTa’s (MLM) and a Pegasus’ (Gap Sentence Generation) pre-training are considered.
model end to end. The last two mentioned models are general-domain, and also test their results on patents.

In contrast with the previous works, Trappey et al. (2020) explore an abstractive to extractive approach. They use an LSTM with attention to guide the extraction of relevant sentences: it receives a set of English and Chinese documents (Title, Abstract, and Claim) and is trained to produce a human-written summary (abstractive component). After the training, the words with the highest attention weights are retrieved and treated as automatically-extracted keywords; sentences are then scored and extracted accordingly (extractive component). This approach is domain-specific, and is used as a way to simplify the keyword extraction, which is complex in the patent domain.

7. Approaches for Patent simplification

Patents’ claims are the hardest section of an overall hard-to-read document. As such, a lot of effort has been spent in improving the accessibility and readability of the Claim. Table 4 summarized previous work.

Given the Claim’s legal nature, however, the extent of the modification is crucial, and previous approaches’ views to the task have varied widely. Ferraro et al. (2014), for example, aim at improving the Claim’s presentation without modifying its text. They segment each claim into preamble, transition, and body (rule-based) and then further divide the body into clauses using a Conditional Random Field. Knowing the elements’ boundaries, the claim can then be formatted more clearly, e.g., adding line breaks.

A somewhat opposite approach was taken in the PATExpert project (Wanner et al., 2008), which developed a rewriting and paraphrasing module (Bouayad-Agha et al., 2009a). The researchers considered two levels of simplification: one uses surface criteria to segments the input and reconstructs chunks into shorter, easier-to-read sentences (Bouayad-Agha et al., 2009b). The other (Mille & Wanner, 2008a) is conceptually similar to (Mille & Wanner, 2008b) for multilingual summarization: after shallow simplification and segmentation, patents are parsed and projected to Deep Syntactic Structures. This representation is in turn used to rewrite a text that is simpler to process for the reader (possibly in another language). Both approaches modify the patent text. Note how, in this framework, rewriting and summarization are essentially unified, with the key difference that no content is removed for simplification.

Instead of relying on linguistic techniques, Okamoto et al. (2017) use an Information Extraction engine that detects entities types and their relations using distant supervision. They provide a visualization interface which a) formats each patent claims to improve readability: color is used to highlight the claim type (e.g., apparatus, method), the transaction, and technical components in the patent body; b) shows the Claim structure: for each claim they include its type, dependencies, and references to other technologies and components. They target patent experts, which might use the system to compare claims (e.g., in the same patent family) and search for similar documents.
| Study                        | Approach                              | Main contribution                                                                 | Limitations                        | Dataset                |
|-----------------------------|---------------------------------------|----------------------------------------------------------------------------------|------------------------------------|------------------------|
| Shinmori et al. (2002, 2003)| Rhetorical Structure Theory           | Claim explanation through Description segments                                  | NTCHIR3 data                       | 59,956 patents         |
| Bouayad-Agha et al. (2009a)| Discourse-based and Deep Syntactic    | Shallow and deep strategies                                                       |                                    | 30 patents (test)      |
|                            | Structure-based simplification        |                                                                                  |                                    |                        |
| Mille & Wanner (2008a)      | Deep Syntactic Structure-based        | Legal scope can be modified                                                       |                                    | 500 sentences (test)   |
|                            | simplification                       |                                                                                  |                                    |                        |
| Bouayad-Agha et al. (2009b)| Discourse-structure simplification   |                                                                                  |                                    | 29 patents (test)      |
|                            |                                       |                                                                                  |                                    |                        |
| Andersson et al. (2013)     | Claim Dependencies                   |                                                                                  |                                    |                        |
|                            | Graph                                 | Adaptation of general NLP tools to the patent domain                             | Errors in PoS tagging can lead to graph collapse | EN CLEF-IP 2012 Passage Retrieval topic set (40 train, 600 test claims) |
| Ferraro et al. (2014)       | Text segmentation                     | Increase readability without modifying the text                                    | Body segmentation can be improved  | 821 train, 80 test patents |
|                            |                                       |                                                                                  |                                    |                        |
| Sheremetyeva (2014)         | Rules, linguistic knowledge, statistics | Text highlighting, claims diagram                                                | Complexity                         | 25 patents             |
|                            |                                       |                                                                                  | Linguistic knowledge is domain-specific |                        |
| Okamoto et al. (2017)       | Claim structure analysis through      | Relation extraction techniques for highlighting Claim aspects                     | 12,972 patents on AI               |
|                            | Extraction                            |                                                                                  |                                    |                        |
| Kang et al. (2018)          | Rule-based                             | Machine-oriented simplification for information extraction and graph visualization | Simplification does not improve extraction performance | 30 patents (test)      |
|                            | Improve the readability of an extracted graph |                                                                                  |                                    |                        |
| Suominen et al. (2018)      | User Study                            | Evaluation of users attitude toward patents and simplification solutions           |                                    |                        |

Table 4: Surveyed studies for Patent Simplification.
Toolholder,

**COMPRISING**

a holder body with
an insert site at its forward end
**comprising** a bottom surface and at least one side wall
**where** there projects a pin from said bottom surface
**upon** which there is located an insert
**having** a central hole,
**a** clamping wedge
**for** wedging engagement between a support surface of the holder and an
adjacent edge surface of said insert
**and** an actuating screw
**received** in said clamping wedge
**whilst** threadably engaged in a bore of said holder,
said support surface and said edge surface are at least partially converging
downwards,
said clamping wedge having distantly provided protrusions for abutment against
the top face and the edge surface of said insert,
**wherein** the clamping wedge is provided with a first protrusion for abutment
against a top face of the insert,
**and** a second protrusion for abutment against an adjacent edge surface.

Figure 1: A segmented patent. Adapted from [Ferraro et al., 2014].

![Figure 2: Interface for comparing two patents, from (Okamoto et al., 2017).](image-url)
Lee & Hsiang (2020a) GPT-2 fine-tuning Adaptation of a general-domain LM to patent text Evaluation 555,890 patent

Lee & Hsiang (2020b) Span-pair classification (BERT) Automatic evaluation of generation relevancy Negative examples can have unrelated vocabulary 14M span pairs

Lee (2020) GPT-2-based Conditional generation of patent Sections Google Patents Datasets (1976-2017-08 Utility patents)

Lee & Hsiang (2020c) Similarity and reranking Ranking of most similar training samples to the generated text Mixed results Huge

Table 5: Surveyed studies for Patent Simplification.

The approaches described so far output a simplified and easier-to-read textual version of the original Claim. Another option is to visualize them in a structured way. Andersson et al. (2013), for example, obtain a connected graph of the claim content; each node contains a noun phrase (NP) and is linked through a verb, a preposition, or a discourse relation. Similarly, Kang et al. (2018) constructs a graph for visualizing the patent content in the contest of an Information Retrieval pipeline. Sheremetyeva (2014) uses visualization on two levels: they first construct a hierarchical tree of the whole Claim section (highlighting dependency relations) and simplifies each claim. In this phase, a tailored linguistic analysis is used (Sheremetyeva, 2003); the simplified claim is segmented in shorter phrases (whose NPs are highlighted and linked to the Description) and visualized as a forest of trees.

Note that most approaches do not measure the improvement in readability so that it is not clear how effective they are in enhancing intelligibility.

Finally, the Claim simplification problem was also studied for the Japanese language. In particular, Shinmori et al. propose a method to expose patent structure using manually-defined cue phrases (Shinmori et al., 2002) and explain invention-specific terms using the Description (Shinmori et al., 2003). In Shinmori & Okumura (2004), Description chunks are used to paraphrase corresponding sentences in the Claim and improve readability.

8. Approaches for Patent generation

The task of Patent generation has recently been investigated by Lee and Hsiang, which try to leverage state-of-the-art NLP models to generate patent text. Table 5 reports their main results.

Their early work (Lee & Hsiang, 2020a) fine-tunes GPT-2 – a language model which demonstrated impressive results in generating text from a wide range of domains – using patents’ first claims. Interestingly, only a small number of
A water-based delivery system for topical delivery of cosmetically and/or therapeutically active substance to or through human skin comprises water and lipophilic components. The delivery system comprises a foam phase, a vesicle phase, and a hydrophilic phase. The lipid comprises fatty acids, cholesterol, ceramide, and/or phospholipid.

Figure 3: Top: connected graph for visualizing a patent claim, adapted from [Andersson et al., 2013]; bottom: diagram of a claim, adapted from [Sheremetyeva, 2014].
fine-tuning steps are sufficient to adapt the general domain model and produce patent-like text. However, the quality of the generation is not measured. This gap is partially filled in (Lee & Hsiang 2020b), where a BERT classifier is used to measure if two consecutive spans, generated automatically, are consistent. They train the classifier on consecutive spans from the same patent (positive examples) and from non-overlapping classes and subclasses (negative examples), which might make the classification not particularly difficult (e.g., the model could rely on shallow lexical features). The generation process is further investigated in (Lee & Hsiang 2020c), which, given a generated text, tries to find the most similar example in the generator’s fine-tuning data.

The models described above try to generate consistent text resembling a patent without specific constrains. Lee (2020) takes a different route and trains the model to generate a patent’s Section (Title, Abstract, or claims) given other parts of the same patents. The model uses GPT-2, which receives as input the text on which to condition and learns to produce a section of the same patent accordingly. For example, one can input the Title of a patent and train the model to generate the corresponding Abstract. Two things should be noted: first, the authors frame the problem as self-supervised and use patents’ sections as gold-standard, which simplifies evaluation; second, the problem generalizes abstractive patent summarization, so that it might be interesting to study the performance obtained, e.g., generating the Abstract from the Description.

9. Current and future directions

This survey aimed at showing that patents are an interesting domain both for their practical importance and their linguistic challenges. While generative approaches for patents are still relatively niche topics, with few active groups, the domain is drawing attention from general NLP practitioners for its unique characteristics. In the following, we present some open issues which might be worthy of future research.

**Data, data, data** Labeled and annotated data are few in the patent domain. For summarization, the only available large-scale dataset is BigPatent (Sharma et al. 2019), while no simplified corpus (let alone parallel corpora) exists, to the best of our knowledge. Moreover, while BigPatent represented a milestone for patent summarization, the target Abstract is written in the typical arcane patent language; thus the practical usefulness of systems trained on these data is probably scarce for laypeople – which would rather read a “plain English” abstract, like those provided by commercial companies. A dataset that targets a clearer summary (unifying summarization and simplification) would also help in understanding models’ capabilities in going beyond shallow features and have a global understanding of the source. Finally, while no public corpora of simplified patent text exist to date, other domains have exploited creative ploys for minimizing human effort: in the medical domain, for example, Pattisapu et al. (2020) uses social media contents to create a simplified corpus.
Table 6: The tasks described in this survey and their challenges in the patent domain. In addition, all tasks are challenged by the patents’ peculiar linguistic characteristics described in Section 2.

**Benchmarks** There are many approaches to summarization and simplification. However, it is difficult to compare them given the absence of shared benchmarks. For extractive summarization, for example, many studies have only compared their results with a baseline or a general-domain commercial system. However, directly comparing the performance of different approaches is difficult, as they solve slightly different tasks on different datasets and often fail to report implementation details.

**Evaluation metrics** Generative approaches for patent often resort to general-domain metrics for evaluation (e.g. ROUGE). However, it is not clear how suitable these measures are for the patent domain, given its peculiarities. In the context of abstractive summarization and patent generation, some works (de Souza et al., 2021; Lee, 2020) highlight that ROUGE is unable to find semantically similar sentences expressed in different wording. In the context of Natural Language Generation, some new measures have recently been proposed to solve these issues. BERTScore (Zhang et al., 2020b), for example, evaluates the similarity among the summary and gold-standard tokens instead of their exact match, while QAGS (Wang et al., 2020) uses a set of questions to evaluate factual consistency between a summary and its source (a reference is not needed). It is yet to be explored if these metrics could be applied to the patent domain successfully. Finally, note that even human studies are difficult in the patent domain, as they require a high expertise, which most people lack.

**Factuality** While neural abstractive models have shown impressive performance in summarization, they tend to fabricate information. Cao et al. (2018) studied the phenomenon in the news domain and found that around 30% of documents included fake facts. This behavior is particularly problematic in a legal context; ROUGE, however, is a surface metric and is
unable to detect factual inconsistencies.

**Domain adaptation** Patents’ language hardly resembles general-discourse English (used in pre-training), but the domain adaptation problem has not been studied in detail. Among the previous works, Aghajanyan et al. (2021) propose a second multitask pre-training step, Chen et al. (2020) studies models cross domain performance and Fabbri et al. (2020) evaluates zero and few shot settings; all these works described applications to the patent domain, among the others.

**Input length** Patent documents are extremely long. For summarization, the only datasets which have comparable or longer inputs are the arXiv and the PubMed dataset (Cohan et al., 2018), which summarize entire research papers. While solutions to allow the processing of long inputs have been proposed, the in-depth study of methods and performance for such long documents is still in its early days. For neural models, a very long input translates into prohibitive computational requirements (e.g. several GPUs), which researchers have recently tried to mitigate by modifying the underlying architectures.

**References**

Aghajanyan, A., Gupta, A., Shrivastava, A., Chen, X., Zettlemoyer, L., & Gupta, S. (2021). Muppet: Massive Multi-task Representations with Pre-Finetuning. *CoRR, abs/2101.11038*. URL: https://arxiv.org/abs/2101.11038.

Amin-Nejad, A., Ive, J., & Velupillai, S. (2020). Exploring Transformer Text Generation for Medical Dataset Augmentation. In *Proceedings of the 12th Language Resources and Evaluation Conference* (pp. 4699–4708). Marseille, France: European Language Resources Association. URL: https://www.aclweb.org/anthology/2020.lrec-1.578.

Andersson, L., Lupu, M., & Hanbury, A. (2013). Domain Adaptation of General Natural Language Processing Tools for a Patent Claim Visualization System. In M. Lupu, E. Kanoulas, & F. Loizides (Eds.), *Multidisciplinary Information Retrieval* (pp. 70–82). Berlin, Heidelberg: Springer Berlin Heidelberg.

Asche, G. (2017). “80% of technical information found only in patents”– Is there proof of this? *World Patent Information, 48*, 16–28.

Bahdanau, D., Cho, K., & Bengio, Y. (2015). Neural Machine Translation by Jointly Learning to Align and Translate. In Y. Bengio, & Y. LeCun (Eds.), *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*. URL: http://arxiv.org/abs/1409.0473.
Bouayad-Agha, N., Casamayor, G., Ferraro, G., Mille, S., Vidal, V., & Wanner, L. (2009a). Improving the comprehension of legal documentation: The case of patent claims. In Proceedings of the International Conference on Artificial Intelligence and Law (pp. 78–87). doi:10.1145/1568234.1568244

Bouayad-Agha, N., Casamayor, G., Ferraro, G., Wanner, L., Guesgen, H., & Lane, H. (2009b). Simplification of Patent Claim Sentences for their Paraphrasing and Summarization. In FLAIRS - PROCEEDINGS, International Florida Artificial Intelligence Research Society Conference, 22nd, International Florida Artificial Intelligence Research Society Conference (pp. 302–303). Aai Press.; URL: https://www.tib.eu/de/suchen/id/BLCP%3ACN073481348

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., & Amodei, D. (2020). Language Models are Few-Shot Learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, & H. Lin (Eds.), Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual. URL: https://proceedings.neurips.cc/paper/2020/hash/1457c0d6bfc4967418bf8ac142f64a-Abstract.html

Brügmann, S., Bouayad-Agha, N., Burga, A., Carrascosa, S., Ciaramella, A., Ciaramella, M., Codina-Filba, J., Escorsa, E., Judea, A., Mille, S., Müller, A., Saggion, H., Ziering, P., Schütze, H., & Wanner, L. (2015). Towards content-oriented patent document processing: Intelligent patent analysis and summarization. World Patent Information, 40, 30 – 42. URL: http://www.sciencedirect.com/science/article/pii/S0172219014001410 doi https://doi.org/10.1016/j.wpi.2014.10.003

Burga, A., Codina, J., Ferraro, G., Saggion, H., & Wanner, L. (2013). The challenge of syntactic dependency parsing adaptation for the patent domain. In ESSLI-13 workshop on extrinsic parse improvement.

Cao, Z., Wei, F., Li, W., & Li, S. (2018). Faithful to the original: Fact-aware neural abstractive summarization. In 32nd AAAI Conference on Artificial Intelligence, AAAI 2018 (pp. 4784–4791). AAAI press.

Celikyilmaz, A., Clark, E., & Gao, J. (2020). Evaluation of Text Generation: A Survey. arXiv:2006.14799

Cer, D., Yang, Y., Kong, S.-y., Hua, N., Lintiaco, N., St. John, R., Constant, N., Guajardo-Cespedes, M., Yuan, S., Tar, C., Strope, B., & Kurzweil, R. (2018). Universal Sentence Encoder for English. In Proceedings of the
Chen, Y., Liu, P., Zhong, M., Dou, Z.-Y., Wang, D., Qiu, X., & Huang, X. (2020). CDEvalSumm: An Empirical Study of Cross-Dataset evaluation for Neural Summarization Systems. In Findings of the Association for Computational Linguistics: EMNLP 2020 (pp. 3679–3691). Online: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/2020.findings-emnlp.329 doi:10.18653/v1/2020.findings-emnlp.329

Chen, Y.-C., & Bansal, M. (2018). Fast Abstractive Summarization with Reinforce-Selected Sentence Rewriting. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 675–686). Melbourne, Australia: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/P18-1063 doi:10.18653/v1/P18-1063

Codina-Filbà, J., Bouayad-Agha, N., Burga, A., Casamayor, G., Mille, S., Müller, A., Saggion, H., & Wanner, L. (2017). Using genre-specific features for patent summaries. Information Processing & Management, 53, 151 – 174. URL: http://www.sciencedirect.com/science/article/pii/S0306457316302825 doi:https://doi.org/10.1016/j.ipm.2016.07.002

Cohan, A., Dernoncourt, F., Kim, D. S., Bui, T., Kim, S., Chang, W., & Goharian, N. (2018). A Discourse-Aware Attention Model for Abstractive Summarization of Long Documents. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers) (pp. 615–621). New Orleans, Louisiana: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/N18-2097 doi:10.18653/v1/N18-2097

Dokun, O., & Celebi, E. (2015). Single-document summarization using latent semantic analysis. International Journal of Scientific Research in Information Systems and Engineering (IJSRIZE), 1, 57–64.

El-Kassas, W. S., Salama, C. R., Rafea, A. A., & Mohamed, H. K. (2021). Automatic text summarization: A comprehensive survey. Expert Systems with Applications, 165, 113679. URL: http://www.sciencedirect.com/science/article/pii/S0957417420305030 doi:https://doi.org/10.1016/j.eswa.2020.113679

Erkan, G., & Radev, D. R. (2004). LexRank: Graph-Based Lexical Centrality as Salience in Text Summarization. J. Artif. Int. Res., 22, 457–479.

25
Fabbri, A. R., Han, S., Li, H., Li, H., Ghazvininejad, M., Joty, S. R., Radev, D., & Mehdad, Y. (2020). Improving Zero and Few-Shot Abstractive Summarization with Intermediate Fine-tuning and Data Augmentation. arXiv preprint arXiv:2010.12836.

Feldman, R. (2008). Plain Language Patents. (p. 289). volume 17.

Ferraro, G., Suominen, H., & Nualart, J. (2014). Segmentation of patent claims for improving their readability. In Proceedings of the 3rd Workshop on Predicting and Improving Text Readability for Target Reader Populations (PITR) (pp. 66–73). Gothenburg, Sweden: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/W14-1208 doi:10.3115/v1/W14-1208

Girthana, K., & Swamynathan, S. (2019a). Query Oriented Extractive-Abstractive Summarization System (QEASS). In Proceedings of the ACM India Joint International Conference on Data Science and Management of Data CoDS-COMAD ’19 (p. 301–305). New York, NY, USA: Association for Computing Machinery. URL: https://doi.org/10.1145/3297001.3297046 doi:10.1145/3297001.3297046

Girthana, K., & Swamynathan, S. (2019b). Semantic Query-Based Patent Summarization System (SQPSS). In L. Akoglu, E. Ferrara, M. Deivamani, R. Baeza-Yates, & P. Yogesh (Eds.), Advances in Data Science (pp. 169–179). Singapore: Springer Singapore.

Girthana, K., & Swamynathan, S. (2020). Query-Oriented Patent Document Summarization System (QPSS). In M. Pant, T. K. Sharma, O. P. Verma, R. Singla, & A. Sikander (Eds.), Soft Computing: Theories and Applications (pp. 237–246). Singapore: Springer Singapore.

Gomez, J. C., & Moens, M.-F. (2014). A survey of automated hierarchical classification of patents. In Professional search in the modern world (pp. 215–249). Springer.

He, J., Kryściński, W., McCann, B., Rajani, N., & Xiong, C. (2020). CTRL-sum: Towards Generic Controllable Text Summarization. arXiv preprint arXiv:2012.04281.

Huang, W., Liao, X., Xie, Z., Qian, J., Zhuang, B., Wang, S., & Xiao, J. (2020). Generating Reasonable Legal Text through the Combination of Language Modeling and Question Answering. In C. Bessiere (Ed.), Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20 (pp. 3687–3693). International Joint Conferences on Artificial Intelligence Organization. URL: https://doi.org/10.24963/ijcai.2020/510 doi:10.24963/ijcai.2020/510 main track.

Kang, J., Souili, A., & Cavallucci, D. (2018). Text Simplification of Patent Documents. In D. Cavallucci, R. De Guio, & S. Koziolek (Eds.), Automated
Larochelle, H., & Bengio, Y. (2008). Classification Using Discriminative Restricted Boltzmann Machines. In Proceedings of the 25th International Conference on Machine Learning ICML ’08 (p. 536–543). New York, NY, USA: Association for Computing Machinery. URL: https://doi.org/10.1145/1390156.1390224.

Lee, J.-S. (2020). Controlling Patent Text Generation by Structural Metadata. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management (p. 3241–3244). New York, NY, USA: Association for Computing Machinery. URL: https://doi.org/10.1145/3340531.3418503.

Lee, J.-S., & Hsiang, J. (2020a). Patent claim generation by fine-tuning OpenAI GPT-2. World Patent Information, 62, 101983. URL: http://www.sciencedirect.com/science/article/pii/S0172219019300766 doi:https://doi.org/10.1016/j.wpi.2020.101983.

Lee, J.-S., & Hsiang, J. (2020b). PatentTransformer-1.5: Measuring Patent Claim Generation by Span Relevancy. In M. Sakamoto, N. Okazaki, K. Mineshima, & K. Satoh (Eds.), New Frontiers in Artificial Intelligence (pp. 20–33). Cham: Springer International Publishing.

Lee, J.-S., & Hsiang, J. (2020c). Prior Art Search and Reranking for Generated Patent Text. arXiv:2009.09132.

Lin, C.-Y. (2004). ROUGE: a Package for Automatic Evaluation of Summaries. In Workshop on Text Summarization Branches Out, Post-Conference Workshop of ACL 2004, Barcelona, Spain (pp. 74–81).

Lloret, E., Plaza, L., & Aker, A. (2018). The Challenging Task of Summary Evaluation: An Overview. Lang. Resour. Eval., 52, 101–148. URL: https://doi.org/10.1007/s10579-017-9399-2 doi:10.1007/s10579-017-9399-2.

Lupu, M., & Hanbury, A. (2013). Patent Retrieval. Found. Trends Inf. Retr., 7, 1–97. URL: https://doi.org/10.1561/1500000027 doi:10.1561/1500000027.

Mihalcea, R., & Tarau, P. (2004). TextRank: Bringing Order into Text. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing (pp. 404–411). Barcelona, Spain: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/W04-3252.

Mille, S., & Wanner, L. (2008a). Making Text Resources Accessible to the Reader: the Case of Patent Claims. In Proceedings of the Sixth International Conference on Language Resources and Evaluation.
Mille, S., & Wanner, L. (2008b). Multilingual summarization in practice: the case of patent claims. In Proceedings of the 12th Annual conference of the European Association for Machine Translation (pp. 120–129). Hamburg, Germany: European Association for Machine Translation. URL: https://www.aclweb.org/anthology/2008.eamt-1.18

Nenkova, A., & Vanderwende, L. (2005). The impact of frequency on summarization. Microsoft Research, Redmond, Washington, Tech. Rep. MSR-TR-2005, 101.

Okamoto, M., Shan, Z., & Orihara, R. (2017). Applying Information Extraction for Patent Structure Analysis. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval SIGIR '17 (p. 989–992). Association for Computing Machinery. URL: https://doi.org/10.1145/3077136.3080698 doi:10.1145/3077136.3080698

Papineni, K., Roukos, S., Ward, T., & Zhu, W.-J. (2002). BLEU: A Method for Automatic Evaluation of Machine Translation. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics ACL '02 (p. 311–318). USA: Association for Computational Linguistics. URL: https://doi.org/10.3115/1073083.1073135 doi:10.3115/1073083.1073135

Pattisapu, N., Prabhu, N., Bhati, S., & Varma, V. (2020). Leveraging Social Media for Medical Text Simplification. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval SIGIR '20 (p. 851–860). New York, NY, USA: Association for Computing Machinery. URL: https://doi.org/10.1145/3397271.3401105 doi:10.1145/3397271.3401105

Pilault, J., Li, R., Subramanian, S., & Pal, C. (2020). On Extractive and Abstractive Neural Document Summarization with Transformer Language Models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 9308–9319). Online: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/2020.emnlp-main.748 doi:10.18653/v1/2020.emnlp-main.748
Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners.

Robinson, J. (2014). Likert Scale. In A. C. Michalos (Ed.), Encyclopedia of Quality of Life and Well-Being Research (pp. 3620–3621). Dordrecht: Springer Netherlands. URL: https://doi.org/10.1007/978-94-007-0753-5_1654 doi:10.1007/978-94-007-0753-5_1654.

See, A., Liu, P. J., & Manning, C. D. (2017). Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 1073–1083). Vancouver, Canada: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/P17-1099 doi:10.18653/v1/P17-1099.

Shalaby, W., & Zadrozny, W. (2019). Patent retrieval: a literature review. Knowledge and Information Systems, (pp. 1–30).

Sharma, E., Li, C., & Wang, L. (2019). BIGPATENT: A Large-Scale Dataset for Abstractive and Coherent Summarization. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (pp. 2204–2213). Florence, Italy: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/P19-1212 doi:10.18653/v1/P19-1212.

Sheremetyeva, S. (2003). Natural Language Analysis of Patent Claims. In Proceedings of the ACL-2003 Workshop on Patent Corpus Processing - Volume 20 PATENT '03 (p. 66–73). USA: Association for Computational Linguistics. URL: https://doi.org/10.3115/1119303.1119311 doi:10.3115/1119303.1119311.

Sheremetyeva, S. (2014). Automatic Text Simplification For Handling Intellectual Property (The Case of Multiple Patent Claims). In Proceedings of the Workshop on Automatic Text Simplification - Methods and Applications in the Multilingual Society (ATS-MA 2014) (pp. 41–52). Dublin, Ireland: Association for Computational Linguistics and Dublin City University. URL: https://www.aclweb.org/anthology/W14-5605 doi:10.3115/v1/W14-5605.

Shinmori, A., & Okumura, M. (2004). Aligning Patent Claims with Detailed Descriptions for Readability. In NII Testbeds and Community for Information Access Research.

Shinmori, A., Okumura, M., Marukawa, Y., & IwaYama, M. (2002). Rhetorical Structure Analysis of Japanese Patent Claims using Cue Phrases. In NII Testbeds and Community for Information Access Research.
Shinnori, A., Okumura, M., Marukawa, Y., & Iwayama, M. (2003). Patent Claim Processing for Readability: Structure Analysis and Term Explanation. In Proceedings of the ACL-2003 Workshop on Patent Corpus Processing - Volume 20 PATENT '03 (p. 56–65). USA: Association for Computational Linguistics. URL: https://doi.org/10.3115/1119303.1119310.

doi:10.3115/1119303.1119310.

Shu, K., Li, Y., Ding, K., & Liu, H. (2020). Fact-Enhanced Synthetic News Generation. Conference on Artificial Intelligence, AAAI. AAAI press.

Sikka, P., & Mago, V. (2020). A Survey on Text Simplification. arXiv:2008.08612.

de Souza, C. M., Meireles, M. R. G., & Almeida, P. (2021). A comparative study of abstractive and extractive summarization techniques to label subgroups on patent dataset. Scientometrics, 126, 135–156.

de Souza, C. M., Santos, M. E., Meireles, M. R. G., & Almeida, P. E. M. (2019). Using Summarization Techniques on Patent Database Through Computational Intelligence. In P. Moura Oliveira, P. Novais, & L. P. Reis (Eds.), Progress in Artificial Intelligence (pp. 508–519). Cham: Springer International Publishing.

Suominen, H., Ferraro, G., Nualart Vilaplana, J., & Hanlen, L. (2018). User Study for Measuring Linguistic Complexity and Its Reduction by Technology on a Patent Website. In Conference: 34 International Conference on Machine Learning ICML’17.

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. In Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2 NIPS’14 (p. 3104–3112). Cambridge, MA, USA: MIT Press.

Trappey, A., & Trappey, C. (2008). An R&D knowledge management method for patent document. Industrial Management and Data Systems, 108, 245–257. doi:10.1108/02635570810847608.

Trappey, A., Trappey, C., & Kao, B. H. (2006). Automated Patent Document Summarization for R&D Intellectual Property Management. 2006 10th International Conference on Computer Supported Cooperative Work in Design, (pp. 1–6).

Trappey, A., Trappey, C., & Wu, C.-Y. (2009). Automatic patent document summarization for collaborative knowledge systems and services. Journal of Systems Science and Systems Engineering, 18, 71–94. doi:10.1007/s11518-009-5100-7.
Trappey, A. J., Trappey, C. V., Wu, J.-L., & Wang, J. W. (2020). Intelligent compilation of patent summaries using Machine Learning and Natural Language Processing techniques. *Advanced Engineering Informatics, 43*, 101027. URL: [http://www.sciencedirect.com/science/article/pii/S1474034619306007](http://www.sciencedirect.com/science/article/pii/S1474034619306007) doi: [https://doi.org/10.1016/j.aei.2019.101027](https://doi.org/10.1016/j.aei.2019.101027).

Trappey, A. J. C., Trappey, C. V., & Wu, C.-Y. (2008). A Semantic Based Approach for Automatic Patent Document Summarization. In R. Curran, S.-Y. Chou, & A. Trappey (Eds.), *Collaborative Product and Service Life Cycle Management for a Sustainable World* (pp. 485–494). London: Springer London.

Tseng, Y.-H., Lin, C.-J., & Lin, Y.-I. (2007a). Text mining techniques for patent analysis. *Information Processing & Management, 43*, 1216 – 1247. URL: [http://www.sciencedirect.com/science/article/pii/S0306457306002020](http://www.sciencedirect.com/science/article/pii/S0306457306002020) doi: [https://doi.org/10.1016/j.ipm.2006.11.011](https://doi.org/10.1016/j.ipm.2006.11.011).

Tseng, Y.-H., Wang, Y.-M., Lin, Y.-I., Lin, C.-J., & Juang, D.-W. (2007b). Patent surrogate extraction and evaluation in the context of patent mapping. *Journal of Information Science, 33*, 718–736. URL: [https://doi.org/10.1177/0165551507077406](https://doi.org/10.1177/0165551507077406) doi: [10.1177/0165551507077406](10.1177/0165551507077406).

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L. u., & Polosukhin, I. (2017). Attention is All you Need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems*. Curran Associates, Inc. volume 30. URL: [https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf](https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf).

Verberne, S., D’hondt, E., Oostdijk, N., & Koster, C. (2010). Quantifying the Challenges in Parsing Patent Claims. In *Proceedings of the 1st International Workshop on Advances in Patent Information Retrieval at ECIR 2010* (pp. 14–21). [Sl: sn].

Wang, A., Cho, K., & Lewis, M. (2020). Asking and Answering Questions to Evaluate the Factual Consistency of Summaries. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (pp. 5008–5020). Online: Association for Computational Linguistics. URL: [https://www.aclweb.org/anthology/2020.acl-main.450](https://www.aclweb.org/anthology/2020.acl-main.450) doi: [10.18653/v1/2020.acl-main.450](10.18653/v1/2020.acl-main.450).

Wanner, L., Baeza-Yates, R., Brügmann, S., Codina, J., Diallo, B., Escorsa, E., Giereth, M., Kompatsiaris, I., Papadopoulos, S., Pianta, E., Piella, G., Puhlmann, I., Rao, G., Rotard, M., Schoester, P., Serafini, L., & Zervaki, 31
V. (2008). Towards content-oriented patent document processing. *World Patent Information, 30*, 21–33. doi:10.1016/j.wpi.2007.03.008.

Zaheer, M., Guruganesh, G., Dubey, K. A., Ainslie, J., Alberti, C., Ontanou, S., Pham, P., Ravula, A., Wang, Q., Yang, L., & Ahmed, A. (2020). Big Bird: Transformers for Longer Sequences. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, & H. Lin (Eds.), *Advances in Neural Information Processing Systems* (pp. 17283–17297). Curran Associates, Inc. volume 33. URL: https://proceedings.neurips.cc/paper/2020/file/c8512d142a2d84725f31a9a7a3b1ab9-Paper.pdf.

Zhang, J., Zhao, Y., Saleh, M., & Liu, P. (2020a). PEGASUS: Pre-training with Extracted Gap-sentences for Abstractive Summarization. In H. D. III, & A. Singh (Eds.), *Proceedings of the 37th International Conference on Machine Learning* (pp. 11328–11339). PMLR volume 119 of *Proceedings of Machine Learning Research*. URL: http://proceedings.mlr.press/v119/zhang20ae.html.

Zhang, T., Kishore, V., Wu, F., Weinberger, K. Q., & Artzi, Y. (2020b). BERTScore: Evaluating Text Generation with BERT. In *International Conference on Learning Representations*. URL: https://openreview.net/forum?id=SkeHuCVFDr.