Searching for Legal Clauses by Analogy.
Few-shot Semantic Retrieval Shared Task

Łukasz Borchmann and Dawid Wiśniewski and Andrzej Gretkowski
Izabela Kosmala and Dawid Jurkiewicz and Łukasz Szalkiewicz
Gabriela Pałka and Karol Kaczmarek and Agnieszka Kaliska and Filip Graliński

Abstract

We introduce a novel shared task for semantic retrieval from legal texts, where one is expected to perform a so-called contract discovery – extract specified legal clauses from documents given a few examples of similar clauses from other legal acts. The task differs substantially from conventional NLI and legal information extraction shared tasks. Its specification is followed with evaluation of multiple k-NN based solutions within the unified framework proposed for this branch of methods. It is shown that state-of-the-art pre-trained encoders fail to provide satisfactory results on the task proposed, whereas Language Model based solutions perform well, especially when unsupervised fine-tuning is applied. In addition to the ablation studies, the questions regarding relevant text fragments detection accuracy depending on number of examples available were addressed. In addition to dataset and reference results, legal-specialized LMs were made publicly available.

1 Introduction

Processing of legal contracts requires significant human resources due to documents complexity, expertise required and consequences at stake. Therefore, a lot of effort is being made to automate such tasks to limit costs of processing — note that law was one of the first areas where electronic information retrieval systems have been adapted (Maxwell and Schafer, 2008).

Enterprise solutions referred to as contract discovery deal with such tasks as ensuring the inclusion of relevant clauses or their retrieval for further analysis (e.g. risk assessment). Such processes can consist of manual definition of few examples, followed by conventional information retrieval — this approach was taken recently by Nagpal et al. (2018) for extraction of fairness policies, spread across agreements and organizational regulations.

Existing shared tasks for legal information extraction, such as COLIEE (Kano et al., 2017), assume recognizing entailment between articles and queries, as considered in question answering problem. Tasks aimed at recognizing textual entailment in general language (Bowman et al., 2015), differ in terms of domain and lack of retrieval component (searching for candidate text excerpt is not part of the task, since it is given in advance to classify). These apply also to multi-genre NLI (Williams et al., 2017), since legal acts differ significantly from other genres of texts. Moreover, all the mentioned tasks differ in setting, in a sense they are one-example based, whereas in a typical business case one may expect few examples. Considering the above, there is a need for the separate shared task of few-shot contract discovery, which would be to search for legal clauses from different legal acts based on a few examples.

In this paper we would like to introduce a new shared task and address the following research questions (RQs):

- **RQ1**: Is it possible to detect relevant text fragments using a small number of positive examples when simple k-NN methods are considered?
- **RQ2**: How can models that are trained on data from outside the domain perform when legal texts are considered?
- **RQ3**: What is the impact of unsupervised fine-tuning on documents from similar domain?

1Refer to Wang et al. (2019) for formal definition of few-shot learning and theoretical considerations.
• **RQ4**: How does the performance change depending on different methods?

• **RQ5**: How does the number of positive examples affect the performance?

The remainder of this publication is structured as follows: Section 2 summarizes related work, Section 3 defines the dataset we prepared and published as a shared task, Section 4 describes methods proposed to solve the problem which were then evaluated in Section 5. Finally, discussion and summary are provided in Section 6 and Section 7 respectively.

## 2 Related Work

There is a tremendous amount of works related to information retrieval in general, however following Gillick et al. (2018) we consider the problem stated in end-to-end manner, where nearest neighbor search is performed on dense document representations. With this assumption the main issue is to obtain reliable representations of documents, where by document we mean *any self-contained unit that can be returned to the user as a search result* (Büttcher et al., 2010). We use the term *segment* with the same meaning whenever needed to achieve clarity.

Many approaches considered in literature rely on word embedding and aggregation strategy. Simple methods proposed include averaging, as in continuous bag-of-words (CBOW) model (Mikolov et al., 2013) or frequency-weighted averaging with decomposition method applied (Arora et al., 2017). More sophisticated schemes include utilizing multiple weights, such as a novelty score, significance score and a corpus-wise uniqueness (Yang et al., 2018) or computing vector of locally-aggregated descriptors (Ionescu and Bumaru, 2019). Most of the proposed methods are orderless, and their limitations were recently discussed by Mai et al. (2019). However, there are pooling approaches preserving spatial information, such as hierarchical pooling operation (Shen et al., 2018). Another methods of obtaining sentence representations from word embeddings include training an autoencoder on a large collection of unlabeled data (Zhang et al., 2018) or utilizing random encoders (Wieting and Kiela, 2019). Despite shortcomings of CBOW model and availability of many sophisticated alternatives, it is commonly used due to ability to ensure strong results on many downstream tasks.

Different approaches assume training encoders providing document embedding in unsupervised or supervised manner, without the need for explicit aggregation. The former include Skip-Thought Vectors, trained with the objective of reconstructing the surrounding sentences of an encoded passage (Kiros et al., 2015). Although the mentioned method was outperformed by supervised models trained on single NLI task (Conneau et al., 2017), paraphrase corpora (Jiao et al., 2018) or multiple tasks (Subramanian et al., 2018), the objective of predicting next sentence is used as additional objective in multiple novel models, such as Universal Sentence Encoder (Cer et al., 2018). Even though many transformer-based Language Models implement their own pooling strategy for generating sentence representations (special token pooling), they were shown to yield weak sentence embeddings, as described recently by Reimers and Gurevych (2019). Authors proposed superior method of fine-tuning pretrained BERT network with Siamese and triplet network structures to obtain sentence embeddings.

There were attempts to utilize semantic similarity methods explicitly on legal domain, e.g. for case law entailment within COLIEE shared task. During recent edition, Rabelo et al. (2019) utilized BERT model fine-tuned on provided train set in supervised manner, and achieved the highest F-score among all teams. However, due to reasons described in Section 4, their approach is not consistent with the nearest neighbor search we are aiming.

The presented selection of approaches do not cover the whole body of research. It outlines however a variety of methods considered in literature. These chosen as reference for proposed shared task are described briefly in Section 4.1.1.

## 3 Contract Discovery Shared Task

The aim of this task is to provide substrings from the requested documents representing clauses analogous (semantically and functionally equivalent) to the examples provided from other documents. At the beginning, subsets of Corporate Bond and Non-disclosure Agreement documents from US Edgar\(^2\) and Charity Annual Reports from UK Charity Register\(^3\) were annotated, in a way clau-
Documents annotated 586
Average document length (words) 24284
Clause types 21
Average clause length (words) 110
Clause instances 2663

Table 1: Basic statistics regarding released dataset.

ses of the same type were selected (e.g. determining governing law, clause types depend on type of legal act). Clauses can consist of a single sentence, multiple sentences or sentence parts. The exact type of clause is not important during the evaluation, since no full-featured training is allowed and one have to solely use a set of few sample clauses during execution.

Each document was annotated by two regular annotators, and then reviewed (or resolved) by super-annotator, who also decided the gold standard. An average score of regular annotators when compared to the gold standard (after super-annotation) was taken to establish human baseline performance.

Overall statistics regarding the dataset are presented in Table 1. The detailed list of clauses and their examples can be found in Table 3, Table 4 and Table 5. The dataset is available publicly on GitHub, as well as at git-based Gonito.net platform (Graliński et al., 2016), where all the readers are encouraged to submit their own solutions.

3.1 Files structure

Content of documents can be found in reference.tsv files. Input files in.tsv consists of tab-separated fields: Target ID (e.g. 57), Clause considered (e.g. governing-law), Example #1 (e.g. 59 15215-15453), . . . , Example #N. Each example consists of document ID and characters range. Ranges can be discontinuous. In such a case their parts are distinguished with comma, e.g. 4103-4882,12127-12971. File with answers (expected.tsv) contains one answer per line, consisting of entity name (to be copied from input) and characters range in the same format as described above. Reference file contains 2 tab-separated fields: document ID and its content.

3.2 Legal Corpus

In addition, we release large, cleaned plain-text corpus of legal texts for the purposes of unsupervised models training or fine-tuning (see https://github.com/applicaai/contract-discovery). It is based on US Edgar documents and consists of approx. 1M documents and 2B words in total (1.5G of text after \textit{xz} compression).

4 Method

Solutions based on networks consuming pairs of sequences, such as BERT in sentence pair classification task setting (Devlin et al., 2018a), are considered out of the scope of this paper, since they are suboptimal in terms of performance — they require expensive encoding of all seed (example) times target combinations, making such solutions unsuitable for semantic similarity search due to the combinatorial explosion (Reimers and Gurevych, 2019).

Instead, in this section we describe simple \textit{k}-NN based approaches that we propose for the problem stated. They assume pre-encoding of all candidate segments and can be described within the unified framework consisting of segmenters, vectorizers, projectors, aggregators, scorers and choosers. This taxonomy is consistent with the assumptions made by Gillick et al. (2018). This taxonomy is presented in order to highlight the similarities and differences between particular solutions during their introduction and ablation studies.

- \textit{Segmenter} is utilized to split text into candidate sub-sequences to be encoded and considered in further steps. All the described solutions rely on candidate sentence and n-grams of sentences, determined with \textit{spaCy} CNN model trained on OntoNotes.\footnote{The dataset is available as a git repository: git://gonito.net/contract-discovery; see also the web site gonito.net/challenge/contract-discovery}

- \textit{Vectorizer} produces vector representations of texts on either word, sub-word or segment (e.g. sentence) level. Examples include sparse TF-IDF representations, static word embeddings and neural sentence encoders.

- \textit{Projector} projects embeddings into different space (e.g. decomposition methods such as PCA or ICA).

\footnote{github.com/explosion/spacy-models/releases/tag/en_core_web_sm-2.1.0}
• **Aggregator** is able to use word or sub-word units embeddings to create segment embedding (e.g. embedding mean, inverse frequency weighting, autoencoder).

• **Scorer** compares two or more embeddings and returns computed similarities. Since we often compare multiple seed embeddings with one embedding of a candidate segment, scorer includes policies to aggregate scores obtained for competitions with multiple seeds into the final candidate score (e.g. mean of individual cosine similarities or max pooling over Word Mover Distances).

• **Chooser** determines whether to return candidate segment with given score (e.g. threshold, one best per document or union of these). For simplicity, during evaluation we restricted ourselves to the chooser returning only one, most similar candidate.

The next section describes vectorizers, aggregators and scorers utilized during evaluation.

### 4.1 Vectorizers

Most machine learning algorithms require data to be represented as a vector of numbers and thus, one needs to identify a way to encode fragments which can be processed optimally. In last years, there is a tremendous increase of quality of NLP task solutions due to incorporating dense vector representations for tokens and longer fragments of texts. Further subsections describe the representations that were tested.

#### 4.1.1 Document-level

From the variety of methods operating on whole documents (segments), we decided to rely on two that may be considered state-of-the-art, as well as on one sparse, preneural representation for reference (TF-IDF).

• **TF-IDF** — one of the most widely used methods for vectorization is Term Frequency—Inverse Document Frequency (TF-IDF). In that method, we embed a document or sentence into a vector of size \( n \), where \( i \)-th position in that vector represents a score connected with \( i \)-th word from the vocabulary.

  6\(^{\text{It can be also viewed as word-level vectorizer with sum aggregator. Word-level TF-IDF is however rather useless.}}\)

TF-IDF assigns each word a score which represents the importance of that word. The TF part simply checks how often a given word is used in a given document, while IDF obtains high scores for tokens that occur only in limited number of documents.

• **Universal Sentence Encoder** — transformer-based encoder where element-wise sum of word’s representations are treated as sentence embedding (Cer et al., 2018), trained with multi-task objective. Original models released by authors were used for the purpose of evaluation.

• **Sentence-BERT** — modification of the pre-trained BERT network, utilizing Siamese and triplet network structures to derive sentence embeddings, trained with explicit objective of making them comparable with cosine similarity (Reimers and Gurevych, 2019). Original models released by authors were used for the purposes of evaluation.

#### 4.1.2 (Sub)word-level

For the purposes of evaluation multiple contextual embeddings from transformer-based Language Models were used, as well as static (context-less) word embeddings for reference.

• **GloVe** — Global Vectors for word representations (Pennington et al., 2014) is a method of transforming tokens from vocabulary \( V \) into fixed size vectors \( \vec{v} \) of size \( n \). In order to obtain a vector from word, the co-occurrence of given word with other words is considered. That’s because according to the distributional hypothesis, words sharing context tend to share similar meanings (Harris, 1954).

• **Transformer-based LMs** — many approaches to generate context-dependent vector representations were proposed in last years (e.g. Peters et al. (2018); Vaswani et al. (2017)). One important advantage over static embeddings is the fact that every occurrence of the same word is assigned a different embedding vector based on the context in which the word is used. Thus, it is much easier to address issues arising from pre-trained static embeddings (e.g. taking into consideration polysemy of words). For the purposes of evaluation we relied on transformer-
based models provided by authors of particular architectures, utilizing Transformers library (Wolf et al., 2019). These include BERT (Devlin et al., 2018b), GPT-1 (Radford, 2018), GPT-2 (Radford et al., 2018), RoBERTa (Liu et al., 2019). They differ substantially and introduce many innovations, however all are based on either encoder or decoder from the original model proposed for sequence-to-sequence problems (Vaswani et al., 2017). Selected models were fine-tuned on legal texts and re-evaluated.

4.2 From (Sub)word- to Document-level with Scorers and Aggregators

Despite conceptually simple methods such as average or max-polling operations, multiple solutions to utilize (sub)word embeddings to compare documents can be used. They can be based either on different methods of aggregation, or implement document-level similarity (distance) method relying on (sub)word embeddings.

- **Smooth Inverse Frequency (SIF)** — method proposed by Arora et al. (2017), where representation of document is obtained in two steps. First, each word embedding is weighted by \( a/(a + f_r) \), where \( f_r \) stands for underlying word’s relative frequency and \( a \) is the weight parameter. Then, the projections on the first tSVD-calculated principal component are subtracted providing final representations.

- **Word Mover’s Distance (WMD)** — method of calculating similarity between documents. For two documents, embeddings calculated for each word (e.g. with GloVe) are matched between documents in a way that semantically similar pairs of words between documents are detected. This matching procedure generally leads to better results than simple averaging over embeddings for documents and calculating similarity between centers of mass of documents as their similarity (Kusner et al., 2015). Recently, Zhao et al. (2019) showed it may be beneficial to use it with contextual word embeddings.

- **Discrete Cosine Transform (DCT)** — method for generating document-level representations in order-preserving manner, adapted from image compression to NLP by Almarwani et al. (2019). After mapping an input sequence of real numbers to the coefficients of orthogonal cosine basis functions, low-order coefficients can be used as document embeddings, outperforming vector averaging on most tasks, as shown by authors.

5 Evaluation

Documents were split into halves to form validation and test sets. Evaluation is performed during repeated random sub-sampling validation procedure. Sub-samples (\( k \)-combinations for each from 21 clauses, \( k \in [2, 6] \)) drawn from considered set of annotations are split into \( k - 1 \) seed documents and 1 target document. One is expected to return clauses similar to seed from the target. The selected \( k \) interval results in 1-shot to 5-shot learning, considered as few-shot learning (Wang et al., 2019), whereas with the chosen number of subsamples we expect improvements of 0.01 \( F_1 \) to be statistically significant.

5.1 Metric

Soft \( F_1 \) metric on character-level spans is used for the purpose of evaluation, as implemented in GEval tool (Gralinski et al., 2019). Roughly speaking, it is conventional \( F_1 \) measure with precision and recall definitions altered to reflect partial success of returning entities. In case of expected clause ranging between \([1, 4]\) characters and answer with ranges \([1, 3], [10, 15]\) (system assumes clause is occurring twice within the document), recall equals 0.75 (since this is the part of relevant item selected) and precision equals ca. 0.33 (since this is the amount of selected items turned out to be relevant). The Hungarian algorithm is employed to solve the problem of expected and returned ranges assignment.

Soft \( F_1 \) has the advantage of being based on widely-utilized \( F_1 \) metric, while abandoning binary nature of match, which is undesirable in the case one deals within the task described.

5.2 Results

Table 2 recapitulates the most important results of conducted evaluation.

Sentence-BERT and Universal Sentence Encoder were not able to outperform simple TF-IDF approach, especially when SVD decomposition was applied (setting commonly refereed to as Latent Semantic Analysis). Static word embeddings
with SIF weighting performed similarly to TF-IDF, or better, in case they were trained on legal text corpus instead of general English. It could not be clearly confirmed that utilization of WMD or DCT is beneficial. For the latter, the best results were achieved with $c_0$, which in case of the k-NN algorithm leads to exactly the same answers as mean pooling.

Interestingly, from all the released USE models, the multilingual ones performed best — for the monolingual universal-sentence-encoder-large model scores were 10 percentage points lower. The best Sentence-BERT model performed significantly worse than the best USE — note authors of Sentence-BERT compared themselves to monolingual models released earlier, which they indeed outperform.

In case of averaging (sub)word embeddings from the last layer of neural Language Models, the results were either comparable or inferior to TF-IDF. The best-performing language models were GPT-1 and GPT-2. Fine-tuning of these on sub-sample of legal text corpus improved the results significantly, by factor of 3–7 points. LMs seem to benefit neither from SIF nor from removal of a single common component, their performance can be however mildly improved with conventionally used decomposition, such as ICA (Hyvärinen and Oja, 2000).

Considerable improvement can be achieved with considering segments different from a single sentence, such as n-grams of sentences.

Figure 1 presents how the performance of particular methods changes as a function of number of examples available within simple similarity averaging scheme used in all the presented solutions. In general, methods benefit substantially from availability of second example. Presence of more leads to decreased variance but no improvements of median score.

### 6 Discussion

Brief evaluation presented in previous section has multiple limitations. First, it assumed retrieval of single, the most similar segment, whereas it might be expected to return multiple clauses. However, we consider this restriction as justifiable during a preliminary comparison of applicable methods. Multiple alternative selectors can be proposed in

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**Tablica 2: Selected results when returning a single, most similar segment, determined with given segmenters, vectorizers, projectors, scorers and aggregators. The * symbol indicates we evaluated all the distributed models, but only the best ones from each architecture are presented here for simplicity.**

| Segmenter | Vectorizer | Projector | Scorer | Aggregator | dev-0 | test-A |
|-----------|------------|-----------|--------|------------|-------|-------|
| sentence  | TF-IDF (1–2 grams, binary TF term) | —         | mean cosine | —         | 0.40  | 0.38  |
|           |            | tSVD ($n = 500$) | mean cosine | —         | 0.41  | 0.39  |
| sentence  | GloVe (300d, Wikipedia & Gigaword) | —         | mean cosine | mean WMD | 0.34  | 0.34  |
|           |            | SIF tSVD | mean cosine | SIF       | 0.39  | 0.37  |
| sentence  | GloVe (300d, EDGAR) | —         | mean cosine | mean WMD | 0.37  | 0.36  |
|           |            | SIF tSVD | mean cosine | SIF       | 0.42  | 0.41  |
| sentence  | Sentence-BERT (base-nli-mean ⋆) | —         | mean cosine | mean WMD | 0.37  | 0.36  |
|           |            | SIF tSVD | mean cosine | SIF       | 0.42  | 0.41  |
| sentence  | USE (multilingual ⋆) | —         | mean cosine | —         | 0.33  | 0.31  |
|           |            | —         | mean cosine | —         | 0.39  | 0.38  |
| sentence  | BERT, last layer (large-cased) | —         | mean cosine | mean WMD | 0.21  | 0.21  |
| sentence  | GPT-1, last layer | —         | mean cosine | mean WMD | 0.37  | 0.36  |
| sentence  | GPT-2, last layer (large ⋆) | —         | mean cosine | mean WMD | 0.42  | 0.41  |
| sentence  | RoBERTa, last layer (large ⋆) | —         | mean cosine | mean WMD | 0.31  | 0.31  |
| sentence  | GPT-1, last layer (fine-tuned) | —         | mean cosine | mean WMD | 0.44  | 0.43  |
| sentence  | GPT-1, last layer (fine-tuned) | flICA ($n = 500$) | mean cosine | mean WMD | 0.46  | 0.44  |
| sentence  | GPT-2, last layer (large, fine-tuned) | —         | mean cosine | mean WMD | 0.45  | 0.44  |
| sentence  | GPT-2, last layer (large, fine-tuned) | flICA ($n = 400$) | mean cosine | mean WMD | 0.47  | 0.45  |
| 1–3 sen.  | GPT-1, last layer (fine-tuned) | —         | mean cosine | mean WMD | 0.48  | 0.47  |
| 1–3 sen.  | GPT-1, last layer (fine-tuned) | flICA ($n=500$) | mean cosine | mean WMD | 0.51  | 0.49  |
| 1–3 sen.  | GPT-2, last layer (large, fine-tuned) | —         | mean cosine | mean WMD | 0.47  | 0.46  |
| 1–3 sen.  | GPT-2, last layer (large, fine-tuned) | flICA ($n=400$) | mean cosine | mean WMD | 0.52  | 0.51  |
| human     |            |            |            |            | 0.85  | 0.84  |

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7 TF-IDF with truncated SVD decomposition is commonly referred to as Latent Semantic Analysis (Halko et al., 2011).

8 SVD in SIF method is used to perform removal of single common component (Arora et al., 2017).

9 Built-in
Secondly, all the methods evaluated assume scoring with policy of averaging individual similarities. We encourage readers to experiment with different pooling methods or meta-learning strategies.

Moreover, even the LM-based methods we studied the most were underexploited — note e.g. only embeddings from the last layer were evaluated, despite it is possible the higher layers may better capture semantics.

Finally, it is in principle possible to address the task in entirely different ways. For example, with performing no segmentation nor aggregation of word embeddings at all, but with matching clauses on word level instead, which may be an interesting research direction.

7 Summary and Conclusions

We introduced a novel shared task for semantic retrieval from legal texts, which differs substantially from conventional NLI. It is heavily inspired by enterprise solutions referred to as contract discovery, focused on ensuring the inclusion of relevant clauses or their retrieval for further analysis. The distinguishing specific of Searching for Legal Clauses by Analogy is among others conceptual, since:

- it assumes mining for candidate sequences in real texts (in contrast to providing them explicitly);
- it is suited for few-shot methods, filling the gap between conventional sentence classification and NLI tasks based on sentence pairs.

We considered the problem stated in end-to-end manner, where nearest neighbor search is performed on documents representations. With this assumption the main issue was to obtain representations of text fragments, we referred to as segments.

Specification of the task was followed with evaluation of multiple $k$-NN based solutions within the unified framework which may be used to describe future solutions. Moreover, the practical justification of handling the problem with $k$-NN was briefly introduced.

It is shown that in this particular setting pre-trained, universal encoders fail to provide satisfactory results. One may suspect it is a result of difference between domain they were trained on and legal domain. During the evaluation, solutions based on Language Model performed well, especially when unsupervised fine-tuning was applied. In addition to said ability to fine-tune method on legal texts, so far the most important success indicator was consideration of multiple, sometimes overlapping substrings instead of sentences.

Moreover, it has been demonstrated that methods benefit substantially from availability of second example, and presence of more leads to decreased variance, even when simple similarities averaging scheme is considered.

During the discussion regarding presented methods and their limitations, possible directions towards improving baseline methods were briefly outlined.

In addition to dataset and reference results, legal-specialized LMs were made publicly available to help research community perform further experiments.

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Wei Zhao, Maxime Peyrard, Fei Liu, Yang Gao, Christian M. Meyer, and Steffen Eger. 2019. MoverScore: Text Generation Evaluating with Contextualized Embeddings and Earth Mover Distance. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing, Hong Kong, China. Association for Computational Linguistics.
This Agreement shall be governed by and construed in accordance with the laws of the State of California without reference to its rules of conflicts of laws.

The term of this Agreement during which Confidential Information may be disclosed by one Party to the other Party shall begin on the Effective Date and end five (5) years after the Effective Date, unless extended by mutual agreement.

THIS AGREEMENT is entered into as of the 30th of July 2010 and shall be deemed to be effective as of July 23, 2010.

This Contract shall become effective (the Effective Date”) upon the date this Contract is signed by both Parties.

You agree that for a period of eighteen months (18) from the date hereof you will not directly or indirectly recruit, solicit or hire any regional or district managers, corporate office employee, member of senior management of the Company (including store managers), or other employee of the Company identified to you.

Confidential Information means any technical or commercial information or data, trade secrets, know-how, etc., of either Party or their respective Affiliates whether or not marked or stamped as confidential, including without limitation, Technology, Invention(s), Intellectual Property Rights, Independent Technology and any properties or specifications related to the foregoing. Any Development Program Technology, MPM Work Product, MSC Work Product, Hybrid Work Product, Prior End-Use Work Product and/or Shared Development Program Technology shall be Confidential Information of the Party that owns the subject matter under the terms set forth in this Agreement.

The Parties will attempt in good faith to resolve any dispute or claim arising out of or in relation to this Agreement through negotiations between a director of each of the Parties with authority to settle the relevant dispute. If the dispute cannot be settled amicably within fourteen (14) days from the date on which either Party has served written notice on the other of the dispute then the remaining provisions of this Clause shall apply.

Tablica 3: Clauses annotated in Non-disclosure Agreements. Numbers in parentheses indicate, respectively, the number of documents with particular clause and the total number of clause instances.

**Clause (Instances) | Example**
---|---
Governing Law (152/160) | This Agreement shall be governed by and construed in accordance with the laws of the State of California without reference to its rules of conflicts of laws.
Confidential Period (108/122) | The term of this Agreement during which Confidential Information may be disclosed by one Party to the other Party shall begin on the Effective Date and end five (5) years after the Effective Date, unless extended by mutual agreement.
Effective Date (Main) (79/89) | THIS AGREEMENT is entered into as of the 30th of July 2010 and shall be deemed to be effective as of July 23, 2010.
Effective Date Reference (91/111) | This Contract shall become effective (the Effective Date”) upon the date this Contract is signed by both Parties.
No Solicitation (101/117) | You agree that for a period of eighteen months (18) from the date hereof you will not directly or indirectly recruit, solicit or hire any regional or district managers, corporate office employee, member of senior management of the Company (including store managers), or other employee of the Company identified to you.
Confidential Information Form (152/174) | Confidential Information means any technical or commercial information or data, trade secrets, know-how, etc., of either Party or their respective Affiliates whether or not marked or stamped as confidential, including without limitation, Technology, Invention(s), Intellectual Property Rights, Independent Technology and any properties or specifications related to the foregoing. Any Development Program Technology, MPM Work Product, MSC Work Product, Hybrid Work Product, Prior End-Use Work Product and/or Shared Development Program Technology shall be Confidential Information of the Party that owns the subject matter under the terms set forth in this Agreement.
Dispute Resolution (67/68) | The Parties will attempt in good faith to resolve any dispute or claim arising out of or in relation to this Agreement through negotiations between a director of each of the Parties with authority to settle the relevant dispute. If the dispute cannot be settled amicably within fourteen (14) days from the date on which either Party has served written notice on the other of the dispute then the remaining provisions of this Clause shall apply.

**Clause (Instances) | Example**
---|---
Change of Control Covenant (88/95) | Upon the occurrence of a Change of Control Triggering Event (as defined below with respect to the notes of a series), unless we have exercised our right to redeem the notes of such series as described above under Optional Redemption, the indenture provides that each holder of notes of such series will have the right to require us to repurchase all or a portion (equal to $2,000 or an integral multiple of $1,000 in excess thereof) of such holder’s notes of such series pursuant to the offer described below (the Change of Control Offer”), at a purchase price equal to 101% of the principal amount thereof, plus accrued and unpaid interest, if any, to the date of repurchase, subject to the rights of holders of notes of such series on the relevant record date to receive interest due on the relevant interest payment date.
Change of Control Notice (78/79) | Within 30 days following any Change of Control, B&G Foods will mail a notice to each holder describing the transaction or transactions that constitute the Change of Control and offering to repurchase notes on the Change of Control Payment Date specified in the notice, which date will be no earlier than 30 days and no later than 60 days from the date such notice is mailed, pursuant to the procedures required by the indenture and described in such notice. Holders electing to have a note purchased pursuant to a Change of Control Offer will be required to surrender the note, with the form entitled Option of Holder to Elect Purchase on the reverse of the note completed, to the paying agent at the address specified in the notice of Change of Control Offer prior to the close of business on the third business day prior to the Change of Control Payment Date.
Cross Default (96/110) | due to our default, we (i) are bound to repay prematurely indebtedness for borrowed moneys with a total outstanding principal amount of $75,000,000 (or its equivalent in any other currency or currencies) or greater, (ii) have defaulted in the repayment of any such indebtedness at the later of its maturity or the expiration of any applicable grace period or (iii) have failed to pay when properly called on to do so any guarantee of any such indebtedness, and in any such case the acceleration, default or failure to pay is not being contested in good faith and not cured within 15 days of such acceleration, default or failure to pay;
Litigation Default (42/51) | (8) one or more judgments, orders or decrees of any court or regulatory or administrative agency of competent jurisdiction for the payment of money in excess of $30 million (or its foreign currency equivalent) in each case, either individually or in the aggregate, shall be entered against the Company or any subsidiary of the Company or any of their respective properties and shall not be discharged and there shall have been a period of 60 days after the date on which any period for appeal has expired and during which a stay of enforcement of such judgment, order or decree, shall not be in effect;
Merger Restrictions
(188/241)
Without the consent of the holders of any of the outstanding debt securities under the indentures, we may consolidate with or merge into, or convey, transfer or lease our properties and assets to any person and may permit any person to consolidate with or merge into us. However, in such event, any successor person must be a corporation, partnership, or trust organized and validly existing under the laws of any domestic jurisdiction and must assume our obligations on the debt securities and under the applicable indenture. We agree that after giving effect to the transaction, no event of default, and no event which, after notice or lapse of time or both, would become an event of default shall have occurred and be continuing and that certain other conditions are met; provided such provisions will not be applicable to the direct or indirect transfer of the stock, assets or liabilities of any of our subsidiaries to another of our direct or indirect subsidiaries. (Section 801)

Bondholders Default
(191/241)
If an event of default (other than an event of default referred to in clause (5) above with respect to us) occurs and is continuing, the trustee or the holders of at least 25% in aggregate principal amount of the outstanding notes by notice to us and the trustee may, and the trustee at the written request of such holders shall, declare the principal of and accrued and unpaid interest, if any, on all the notes to be due and payable. Upon such a declaration, such principal and accrued and unpaid interest will be due and payable immediately. If an event of default referred to in clause (5) above occurs with respect to us and is continuing, the principal of and accrued and unpaid interest on all the notes will become and be immediately due and payable without any declaration or other act on the part of the trustee or any holders.

Tax Changes Call
(48/56)
If, as a result of any change in, or amendment to, the laws (or any regulations or rulings promulgated under the laws) of the Netherlands or the United States or any taxing authority thereof or therein, as applicable, or any change in, or amendments to, an official position regarding the application or interpretation of such laws, regulations or rulings, which change or amendment is announced or becomes effective on or after the date of the issuance of the notes, we will become obligated to pay additional amounts as described above in “Payment of additional amounts,” then the Issuer may redeem the notes, in whole, but not in part, at 100% of the principal amount thereof together with unpaid interest as described in the accompanying prospectus under the caption "Description of WPC Finance Debt Securities and the Guarantee–Redemption for Tax Reasons.”

Financial Statements
(201/317)
Notwithstanding that the Company may not be subject to the reporting requirements of Section 13 or 15(d) of the Exchange Act, the Company will file with the SEC and provide the Trustee and Holders and prospective Holders (upon request) within 15 days after it files them with the SEC, copies of its annual report and the information, documents and other reports that are specified in Sections 13 and 15(d) of the Exchange Act. In addition, the Company shall furnish to the Trustee and the Holders, promptly upon their becoming available, copies of the annual report to shareholders and any other information provided by the Company to its public shareholders generally. The Company also will comply with the other provisions of Section 314(a) of the TIA.

Clause (Instances)
Example
Main Objective
(195/231)
The aim of the Scout Association is to promote the development of young people in achieving their full physical, intellectual, social and spiritual potentials, as individuals, as responsible citizens and as members of their local, national and international communities. The method of achieving the Aim of the Association is by providing an enjoyable and attractive scheme of progressive training based on the Scout Promise and Law and guided by Adult leadership.

Governing Document
(160/174)
The Open University Students’ Educational Trust (OUSET) is controlled by its governing document, a deed of trust, dated 22 May 1982 as amended by a scheme dated 9 October 1992 and constitutes an unincorporated charity.

Trustee Appointment
(153/168)
As per the governing document, four of the Trustee positions are appointed by virtue of their position within the Open University Students Association (OUSA). One further position is appointed by virtue of their previous position within OUSA. One Trustee is nominated by the Vice Chancellor of the Open University (OU) and there are co-opted positions whereby the Trustees are empowered to approach up to two other persons to act as Trustees. It is envisaged that all Trustees will serve a general term of two years in line with the main election periods within OUSA.

Reserves Policy
(170/185)
The Trustees regularly reviews the amount of reserves that are required to ensure that they are adequate to fulfill the charities continuing obligations.

Income Summary
(124/134)
Excluding the adjustments for FRS17 in respect of Pension Fund the results by way of net incoming resources accumulated F3.85m as against E6.78m in 2014, however last years performance benefited from extraordinary property sales generating a profit of F3.15m.

Auditor Opinion
(190/192)
In connection with my examination, no matter has come to my attention: 1. which gives me reasonable cause to believe that in any material respect the requirements to keep accounting records in accordance with Section 130 of the Charities Act and to prepare accounts which accord with the accounting records and comply with the accounting requirements of the Charities Act have not been met; or 2. to which, in my opinion, attention should be drawn in order to enable a proper understanding of the accounts to be reached.

Tablica 4: Clauses annotated in Corporate Bonds. Numbers in parentheses indicate, respectively, the number of documents with particular clause and the total number of clause instances.

Tablica 5: Clauses annotated in Charity Annual Reports. Numbers in parentheses indicate, respectively, the number of documents with particular clause and the total number of clause instances.