An AI-based Approach for Tracing Content Requirements in Financial Documents

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Abstract

The completeness (in terms of content) of financial documents is a fundamental requirement for investment funds. To ensure completeness, financial regulators have to spend a huge amount of time for carefully checking every financial document based on the relevant content requirements, which prescribe the information types to be included in financial documents (e.g., the fund name, the description of shares’ issue conditions and procedures). Although several techniques have been proposed to automatically detect certain types of information in documents in various application domains, they provide limited support to help regulators automatically identify the text chunks related to financial information types, due to the complexity of financial documents and the diversity of the sentences characterizing an information type.

In this paper, we propose FITI, an artificial intelligence (AI)-based method for tracing content requirements in financial documents. Given a new financial document, FITI first selects a set of candidate sentences for efficient information type identification. Then, FITI uses a combination of rule-based and data-centric approaches, by leveraging information retrieval (IR) and machine learning (ML) techniques that analyze the words, sentences, and contexts related to an information type, to rank candidate sentences. Finally, using a list of domain-specific indicator phrases related to each information type, a heuristic-based selector, which considers both the sentence ranking and the domain-specific phrases, determines a list of sentences corresponding to each information type.

We evaluated FITI by assessing its effectiveness in tracing financial content requirements in 100 real-world financial documents. Experimental results show that FITI is able to provide accurate identification with average precision and recall values of 0.824 and 0.646, respectively. Furthermore, FITI can help regulators detect about 80% of missing information types in financial documents.

Keywords — Content requirements, Information type identification, Financial document, Machine Learning

1 Introduction

In the financial market, each type of investment fund, such as UCITS\textsuperscript{1}, is presented to clients through one or more financial documents (such as KIIDs — Key Investor Information Document — and prospectuses). Before these documents are made publicly available, they are submitted to national financial regulators, which check their compliance with the content requirements prescribed by relevant national and international laws. Content requirements specify the different information types that must be included in documents; in this work we will consider the content requirements of financial documents, also called financial content requirements. For example, the following article of the Luxembourgish law \textsuperscript{10} “the frequency of the calculation of issue prices (should be presented)” prescribes the inclusion of the information related to “issue price” in the prospectuses of UCITS funds.

\textsuperscript{1}UCITS (Undertakings for the Collective Investment in Transferable Securities) funds) refers to a regulatory framework that allows for the sale of cross-Europe mutual funds.
After the submission of a financial document, agents of a financial regulator peruse the document and manually identify the passages of text (e.g., sentences or paragraphs) related to each mandated information type to ensure the document completeness, since missing information may lead to substantial fines and cause legal problems and severe investment losses when conducting activities on financial markets. However, the manual identification of information types is a non-trivial task. First, financial documents are lengthy with typically hundreds of pages and more than 3000 sentences, and contains several tables and lists. Considerable time could be spent even by simply going through the entire document. Second, the language used in financial documents is highly nuanced with sophisticated jargon; the meaning of a sentence could drastically change when only a specific word or the context is different. Agents have to carefully read and analyze every sentence to avoid any misunderstanding of the content. Since the amount of manual work involved often leads to higher fund setup costs and longer time-to-market of investment funds, it is important to develop approaches for automatically identifying the passages of text related to the content requirements, which can then further enable automated compliance checking techniques.

Mining financial data play a critical role in improving the quality of financial services. Existing studies focus on mining financial data from both Web media (e.g., financial news and discussion boards [27]) and traditional financial documents (e.g., annual financial reports and 10-K [28]). In contrast to these studies, we focus on the task of tracing content requirements in financial documents, which is important to ensure the completeness of financial documents. Although tracing requirements in documents have been widely studied in the areas of information extraction and software engineering [8, 17], existing approaches may not suit our task due to the complexity, peculiarities, and the domain-specific vocabulary of financial documents. In the field of information extraction, the work typically focuses on extracting entities and relations (e.g., named entities such as persons and locations) from natural language (NL) documents [22, 26] instead of identifying sentences related to financial content requirements. Although recent advances in deep learning make the accurate identification of sentences possible [14, 29], the large training set required to train the underlying models [32] is usually unavailable in the financial area, due to the cost of annotating thousands of financial documents by domain experts and the differences among documents determined by national regulations. In software engineering, several studies [7, 38] infer trace links between high-level NL requirements (e.g., regulatory code) and low-level NL requirements (e.g., privacy policies). However, a typical NL requirement is often explained with one or two sentences in the regulatory text [20]; in contrast, the meaning of the same sentence in financial documents can be different when it is used in different contexts, which is seldom the case for SE requirements (where ambiguities are typically avoided). Hence, we need to design algorithms to trace financial content requirements while fully accounting for the characteristics of financial documents.

In this paper, we present FITI (Financial Information Type Identification), an AI-based method for tracing financial content requirements. The basic idea of FITI is to learn the characteristics of sentences related to an information type combining both IR and ML techniques from a small set of labeled documents. Given a new financial document, FITI selects sentences for an information type based on the analysis results of IR and ML models. Specifically, FITI first preprocesses financial documents with typical natural language processing (NLP) techniques. To conduct efficient analysis on thousands of sentences in a new financial document, a set of candidate sentences is retrieved by comparing the similarity between the related sentences in the labeled documents and every sentence in the new document. For the candidate sentences, FITI conducts a fine-grained analysis with IR and ML techniques. Since the meaning of a sentence could drastically change when only a specific word or the context is different, FITI uses an IR-based analysis to compare the words, sentences, and contexts between candidate sentences and the sentences related to an information type in the labeled documents. In addition, we also mine and learn a set of features relevant to an information type with an ML-based statistical model. According to the IR- and ML-based analysis, FITI ranks each new sentence. At last, FITI uses a heuristic-based selector to select the final sentences. We built a list of domain-specific phrases that are commonly used to explain an information type (e.g., financial jargon), as well as some excluded synonyms which are seldom used to express that information type according to domain experts’ suggestions and the labeled documents. By considering both sentence ranking and phrase lists, FITI identifies sentences for an information type from the candidate sentences.

We evaluated FITI using the content requirements for UCITS prospectuses. Three domain experts manually annotated sentences related to five representative information types for 100 UCITS prospectuses to form a dataset. Experimental results show FITI can accurately identify the sentences for the five information types with average precision and recall values of 0.824 and 0.646, respectively; it significantly outperforms a keyword-search baseline by 27.7 pp (with pp = percentage points) in terms of F1-score, which simulates the process of locating information types by searching the list of domain-specific phrases.
in sentences. Further, FITI can help regulator’s agents detect about 80% of missing information types. Last, FITI is effective even when the number of labeled documents is limited. With more than 40 labeled documents, the precision value of FITI is still higher than 70% for identifying most information types.

To summarize, the main contributions of this paper are:

• the first work, to the best of our knowledge, on tracing content requirements in financial documents, which is important for financial enterprises and regulators to further enable automated compliance techniques;

• the FITI approach, which addresses the problem of automated information type identification: it combines IR and ML to conduct fine-grained analysis on the sentences related to each information type;

• an extensive evaluation on the effectiveness of FITI.

The rest of the paper is organized as follows. Section 2 explains the characteristics of financial documents and their content requirements. Section 3 describes the core algorithms of FITI. Section 4 reports on the evaluation of FITI. Section 5 discusses related work. Section 6 concludes the paper and provides directions for future work.

2 Background

2.1 Financial Documents

In the financial domain, every investment fund is required to provide informative financial documents. These documents help the financial regulator and fund clients understand all relevant and critical information of an investment. For example, KIIDs describe the nature and key risks of the fund, while a prospectus provides details about an investment offering to the public. Such financial documents mainly use natural language together with auxiliary tables and mathematical formulae. These documents are the key instruments to guarantee the compliance and controllability of an investment.

Financial documents for investment funds have several key characteristics. First, they are lengthy with typically hundreds of pages. To minimize investment risks, financial documents must completely provide certain elements of information required by the regulator body for an investment fund (and its sub-funds). Based on 100 randomly selected UCITS prospectuses, our statistics show that a prospectus has on average 127 pages with more than 3000 sentences; each information type can be related to diverse numbers of sentences (e.g., from 3 to 50 sentences) depending on the way to explain an information type by the investment company. These characteristics make the document difficult to read and thoroughly analyze. Second, financial documents may use similar sentences to explain different types of required information. The meaning of a sentence could drastically change when only a specific word is different. Even worse, the same sentence structure may also refer to different information types when the context of the sentence (e.g., the surrounding sentences) is different. For example, the following sentences “The swing factor may normally not exceed 3% of the net asset value of a sub-fund . . . In such case, affected shareholders shall be informed as soon as reasonably practicable thereafter . . .” refer to the calculation method for issue price. In contrast, the sentences “The dilution adjustment may normally not exceed 3% of the net asset value. . . . In such case, affected shareholders shall be informed as soon as reasonably practicable thereafter . . .” refer to the charges on issue price. Hence, the regulator and clients have to carefully analyze the document to identify the sentences related to different types of information.

2.2 Content Requirements

Before presenting them to the public, financial documents should be inspected by the regulator. One of the main inspection tasks is to check the completeness of the documents. In practice, the regulator defines content requirements for each type of financial document, specifying types of information that should be present within a document. For example, for a UCITS prospectus submitted to the financial regulator in Luxembourg, regulatory requirements stipulate about 124 information types, including for example the description of the calculation method for issue price and issue conditions and procedures (as presented in Fig. 1). The regulator must analyze the prospectus to identify the sentences discussing each information type specified by content requirements. Since missing information may cause legal problems and severe investment losses, ensuring content completeness is usually the first and most fundamental procedure before looking into the details of the financial documents. However, due to the length and peculiarities of the text in financial documents, this is usually a challenging task.
3 Information Type Identification

In this section, we present our algorithm (FITI: Financial Information Type Identification) to automatically identify the sentences related to an information type in financial documents. Its pseudocode is shown in Algorithm 1. FITI takes as input a document $d$ for analysis, the information type $t$ to identify (from the content requirements), labeled documents $D^L$ (in which sentences related to $t$ have been annotated by domain experts), and some auxiliary parameters; it returns a set of sentences $S$ from $d$ related to $t$.

FITI has four main steps: pre-processing (§3.1), candidate sentence identification (§3.2), fine-grained sentence analysis (§3.3), and sentence selection (§3.4).

It first pre-processes (line 1) the document with a standard NLP pipeline (including sentence splitting, tokenization, stop words removal, stemming, named entity recognition). Then, for an information type $t$, FITI identifies a set of candidate sentences in $d$ for fine-grained analysis (lines 2–4). Next, FITI analyzes the candidate sentences with information retrieval (IR) and machine learning (ML); it assigns scores to each candidate sentence (lines 5–12). Last, a heuristic-based selector is applied to select the final sentences that are most likely related to $t$ (line 14).

3.1 Pre-processing

Financial documents are typically available in PDF format. To ease their manipulation, we convert them to a plain-text format using an off-the-shelf converter PDFBox [1]. We then apply a standard NLP pipeline to preprocess the text. The text is first split into sentences with Stanford CoreNLP [37]. Then, tokenization is applied to identify the words in a sentence. We remove the stopwords [12] and convert each word into its root form with the Porter stemming algorithm [32]. In addition, the content of financial documents often includes named entities such as numbers, person names, dates, and web addresses. To leverage the knowledge of these named entities, we perform named entity recognition [37] on the input document to generalize these named entities with their category names.

Once the above steps are completed, we obtain a list of preprocessed, simplified words and sentences from the financial documents. For example, a sentence “Annex I takes effect from 1 January 2016” is processed to “Annex NUMBER take effect DATE”.

3.2 Candidate Sentence Identification

Although financial documents include thousands of sentences, a specific information type is usually addressed by less than 50 sentences. Conducting fine-grained analysis on the entire document may therefore be impractical on commodity hardware. To solve this problem, FITI tries to efficiently filter the majority
of unrelated sentences in the pre-processed document \(d\) and identify a small number of candidate sentences for further analysis. The basic hypothesis for candidate sentence identification is that sentences in \(d\) that are similar to existing sentences related to \(t\) in the labeled documents \(D^L\) may also be related to \(t\). Therefore, we calculate similarity between sentences in \(d\) and sentences annotated as related to \(t\) in \(D^L\). We take the top-\(n_c\) most similar sentences as candidates for fine-grained analysis.

Specifically, we collect the sentences annotated as related to \(t\) in \(D^L\). We transform this group of sentences into a single vector (denoted as “group vector”) using a standard IR model, i.e., the bag-of-words model \[29\]. Given a corpus (e.g., documents in \(D^L\)), the bag-of-words model gets its vocabulary (i.e., the unique words) and represents a piece of text into a vector, where the length of the vector is equal to the size of the vocabulary. In our context, each dimension of the group vector means a word in the vocabulary. If the group of related sentences does not contain a word, the value of the corresponding dimension is 0; otherwise, the value is computed by the TF-IDF (Term Frequency-Inverse Document Frequency) \[29\] of the word. TF-IDF is defined as:

\[
\text{TF-IDF}_{w,\text{text}} = f_{w,\text{text}} \times \log \frac{N}{n_w},
\]

where \(f_{w,\text{text}}\) denotes the number of times that \(w\) occurs in \(\text{text}\) (e.g., the group of related sentences), \(N\) is the number of sentences in the corpus, and \(n_w\) is the number of sentences in the corpus that contain \(w\). TF-IDF based vectors assume that sentences can be represented with the frequently used and informative words, where TF (i.e., \(f_{w,\text{text}}\)) calculates the frequency of words and IDF (i.e., \(\log \frac{N}{n_w}\)) identifies informative words that are not used in almost all the sentences (e.g., “swing” and “dilution”).

In this step, we do not use more complex vectorization models (e.g., deep learning based sentence embedding), as the bag-of-words model is easy to deploy and understand; it does not require a large domain-specific corpus (UCITS prospectuses in our case) to learn the embedding of domain-specific words and phrases, which is not always available.

Further, we vectorize each sentence in document \(d\). For each sentence, we collect its surrounding \(n_{\text{ext}}\) sentences, which represent the context of the current sentence. For example, if \(n_{\text{ext}} = 1\), the context of a sentence includes its previous sentence and the next sentence. We transform a sentence and its context into a single vector (hereafter called “context vector”). We consider the context of a sentence because a
single sentence may not contain enough information for our analysis. The context of a sentence provides valuable information for understanding it.

Last, we compute the similarity between the group vector and the context vector of each sentence in \( d \) using cosine similarity \([29]\), defined as:

\[
\text{sim}(\vec{v}_1, \vec{v}_2) = \frac{\vec{v}_1 \cdot \vec{v}_2}{|\vec{v}_1||\vec{v}_2|},
\]

where \( \vec{v}_1 \cdot \vec{v}_2 \) is the inner product of the two vectors and \( |\vec{v}_1||\vec{v}_2| \) is the product of the 2-norm for these vectors. We then rank and select \( n_c \) sentences in \( d \) as candidates for further analysis.

In this study, the number of surrounding sentences \( n_{ext} \) is set to 1 and the number of candidate sentences \( n_c \) is set to 200. Our preliminary experiment shows that on average the candidate sentences contain 90% of sentences related to an information type, which can effectively filter 94.2% unrelated sentences and preserve the vast majority of related sentences.

3.3 Fine-grained Sentence Analysis

FITI analyzes the relevance of candidate sentences in \( d \) for an information type \( t \) (denoted as \( S^d_{ct} \)) with different techniques, including both information retrieval (IR) and machine learning (ML). IR-based analysis calculates the text similarity between a sentence in \( S^d_{ct} \) and the sentences annotated as related to \( t \) in \( D^L \) (denoted as \( S^L_{rt} \)). It assumes that if a sentence is similar to the existing related sentences in \( S^L_{rt} \), this sentence is more likely to be related to \( t \). IR-based analysis outputs similarity values for a sentence in \( S^d_{ct} \), which indicate the degree of text similarity of the candidate sentence with the sentences in \( S^L_{rt} \).

ML-based analysis mines a set of measurable properties of sentences (i.e., features) that can distinguish related sentences from unrelated ones. It represents each sentence with a feature vector, where each dimension is a feature. ML-based analysis uses the feature vectors of related and unrelated sentences in \( D^L \) to train a statistical model. For a sentence in \( S^d_{ct} \), the trained model outputs a probability value, which indicates the probability that the sentence is related to \( t \).

IR- and ML-based techniques analyze sentences from different perspectives: the former calculates the text similarity and the latter trains statistical models with features. They may complement each other.

3.3.1 IR-based analysis

To perform a comprehensive comparison between sentences in \( S^d_{ct} \) and sentences in \( S^L_{rt} \), FITI calculates similarity at different granularity levels, including group similarity, sentence similarity, and word importance similarity. Since financial documents may use similar sentences to explain different information types (as explained in section \([2]\), we use different granularity levels to better identify the candidate sentences that are similar with the overall context of \( S^L_{rt} \), individual sentences in \( S^L_{rt} \), and the words specified to \( t \) at the same time.

**Group similarity** compares the overall similarity between \( S^L_{rt} \) and every sentence in \( S^d_{ct} \). It is calculated the same way as discussed in Section \([2]\): the group similarity is the cosine similarity between the group vector of \( S^L_{rt} \) and the context vector of a candidate sentence \( s \) (denoted as \( s_{group} \)).

**Sentence similarity** calculates the cosine similarity between a candidate sentence \( s \) and each sentence in \( S^L_{rt} \) based on their context vectors. Given \( n \) sentences in \( S^L_{rt} \), we can get \( n \) sentence-level similarity values for \( s \). Based on these values, FITI calculates two sentence-level scores for \( s \): the average and the maximum of the \( n \) similarity values, denoted as \( s_{avg,s} \) and \( s_{max,s} \), respectively.

**Word importance similarity** analyzes the importance of a word for the information type \( t \) based on the labeled documents \( D^L \). The score of a sentence in \( S^d_{ct} \) is calculated according to word importance. This is automatically determined from three aspects; precisely, we say that the importance of a word \( w \) for \( t \) is determined by the extent to which it satisfies the three following conditions: (a) \( w \) frequently appears in the related sentence set \( S^L_{rt} \); (b) \( w \) is only present in \( S^L_{rt} \); (c) \( w \) can be found in the related sentences of every labeled document. The importance of a word \( w \) is defined as:

\[
\text{imp}(w) = \frac{\text{freq}_{avg}(w) \times \text{spec}(w) \times \text{univ}(w)}{n} = \frac{1}{n} \sum_{r_i \in S^L_{rt}} \frac{\text{freq}(r_i, w)}{|r_i|} \times \frac{|S^L_{rt}(w)|}{|S^L(w)|} \times \frac{|D^L(r_i)(w)|}{|D^L(r_i)|}
\]

(3)

The first factor in the formula calculates the average frequency of \( w \) in \( S^L_{rt} \), where \( n \) is the number of sentences in \( S^L_{rt} \), \( \text{freq}(r_i, w) \) counts the times that \( w \) appears in the \( i \)th related sentence \( r_i \), and \( |r_i| \) is
Table 1: Sentence Features for ML-based Analysis

| ID  | Name (N), Type (T), Description (D), and Intuition (I) |
|-----|-----------------------------------------------------|
| F1–10 | Word importance (T) Float (D) We rank words by their word importance (see Section 3.3.1). We select the top-10 words as 10 features. The value of a feature is 0 if the sentence does not contain the corresponding word; otherwise, the feature value is the word importance. (I) These words are more important for an information type t. |
| F11–20 | Phrase importance (T) Float (D) We pair every two adjacent words in a sentence as a phrase. Similar to F1–10, we select the top-10 most important phrases as features. (I) These phrases are more important for t. |
| F21 | Length of a sentence (T) Integer (D) We count the number of words in a sentence. (I) Some information types are usually expressed with short sentences, e.g., ‘Net Asset Value is calculated daily’ (that explains the calculation frequency for issue price) |
| F22 | Ratio of ‘numbers’ (T) Float (D) We count how many ‘numbers’ in a sentence; the value is divided by the length of the sentence. (I) If most of the words in a sentence are numbers, the sentence is less likely to be related. |
| F23 | Number of ‘person name’ (T) Integer (D) We count the number of ‘person names’ in a sentence. (I) Some information types are associated with specific names, e.g., ‘corporate name’. |
| F24 | Number of ‘date’ (T) Integer (D) We count the number of ‘date’ in a sentence. (I) Some information types are associated with dates, e.g., ‘indication of date of establishment’. |
| F25 | Number of ‘web address’ (T) Integer (D) We count the number of ‘web address’ in a sentence. (I) Some information types may mention certain web addresses, e.g., ‘disclaimer on periodical reports’ may mention the website to retrieve the reports. |

The number of words in $r_t$. The second factor considers the specificity of $w$ to $t$, where $|S_{rt}^L(w)|$ is the number of sentences in $S_{rt}^L$ that contain $w$, and $|S_{r}^L(w)|$ is the number of sentences in $D^L$ containing $w$. Third, we analyze the universality of $w$ in the related sentences of $D^L$, where $|D_{r_t}^L(w)|$ is the number of documents that have related sentences containing $w$, and $|D_{r}^L| is the number of documents having related sentences. Intuitively, the importance of a word $w$ is positive correlated with the three conditions: if $w$ never appears in $S_{rt}^L$, the values of these conditions are zero; in contrast, these values are 1 if $w$ is the only word in $S_{rt}^L$ and it never appears in other sentences. Hence, we multiply the values of three conditions to reflect the importance of $w$.

Based on $imp(w)$ for each word in $D^L$, the word importance similarity for a sentence $s$ (denoted as $s.w$) is calculated as $\sum_{w \in s} \frac{imp(w)}{\sum_{w \in s} imp(w)}$. In this definition, $s.w$ is 0 if there is no overlapped word between $s$ and $S_{rt}^L$, since the $imp(w)$ values of all words in $s$ are zero; otherwise $s$ is more similar with sentences in $S_{rt}^L$ when it contains many words with high $imp(w)$ values.

3.3.2 ML-based analysis

ML-based analysis trains a statistical model with the sentences in $D^L$ and uses this model to predict the probability that a sentence is related to $t$. It includes four main steps: training set preparation, feature engineering, model training, and prediction.

In this work, the training set is comprised of the sentences in labeled documents $D^L$. The positive instances for training are the related sentences $S_{rt}^L$ for an information type $t$. Since the majority of sentences in $D^L$ are unrelated, to avoid biases we perform under-sampling over the unrelated sentences $S_{rt}^L$ to form the negative instances. We sample a subset of $S_{rt}^L$ which are similar to $S_{rt}^L$ because these sentences are expected to be more difficult to distinguish from $S_{rt}^L$: we use ML to learn the potential distinguishing criteria. More specifically, we calculate the similarity between the group vector of $S_{rt}^L$ and the context vector of each sentence in $S_{rt}^L$; we select the top-ranked unrelated sentences according to the size of $S_{rt}^L$. These sentences are textually similar with $S_{rt}^L$. Besides, a sentence in $S_{rt}^L$ is also considered as a negative instance if it is the previous or the next sentence of a related sentence. Since sentences close to each other usually discuss similar topics, ML may learn the reason that some sentences are annotated as unrelated.

Regarding feature engineering, we constructed 25 features for model training. Table 1 shows the name, type, and description of these features, and also their rationale. F1–10 and F11–20 are 20 features
Algorithm 2: Selector

| Input: | Candidate sentences $S_{dt}'$ with $s\.group$, $s\.avg_s$, $s\.max_s$, $s\.word$, and $s\.prob$ of each sentence |
|--------|---------------------------------------------------------------------------------------------------------------------------------|
|         | Average number of related sentences per document $n_r$. Related phrase list $rlist$ and unrelated phrase list $ulist$. Threshold $\theta$ for highly similar sentences |
| Output: | Sentences $S$ in $d$ related to $t$ |
| 1      | $S_{dt} \leftarrow \text{mergeSimilar}(S_{dt}', \theta)$; |
| 2      | $S \leftarrow \text{selectBySimilarity}(S_{dt}', \theta)$; |
| 3      | $S_{dt}' \leftarrow S_{dt}' \setminus S$; |
| 4      | foreach $s \in S_{dt}'$ do |
| 5      | $s\.score \leftarrow (s\.group + s\.avg_s + s\.max_s + s\.word + s\.ml)/5$; |
| 6      | end |
| 7      | $S_{t}^{rank} \leftarrow \text{rankByScore}(S_{dt}')$; |
| 8      | $i = 0$; |
| 9      | while $|S| < n_r$ and $i < |S_{t}^{rank}|$ do |
| 10     | $S = S \cup S_{t}^{rank}[i]$; |
| 11     | end |
| 12     | $S_g \leftarrow \text{groupByDistance}(S)$; |
| 13     | $S \leftarrow \emptyset$; |
| 14     | foreach $s_g \in S_g$ do |
| 15     | Boolean $rCheck \leftarrow \text{hasWordsInList}(s_g, rlist)$; |
| 16     | Boolean $uCheck \leftarrow \text{hasWordsInList}(s_g, ulist)$; |
| 17     | if $rCheck \text{ and } !uCheck$ then |
| 18     | $S = \{s_g\} \cup S$; |
| 19     | end |
| 20     | end |
| 21     | return $S$; |

related to the important words and phrases for an information type $t$. F21–F25 calculate the length of a sentence and different types of named entities that could indicate the existence of an information type. With these features, each sentence in the training set can be transformed into a feature vector, in which each dimension corresponds to a feature. The label of the feature vector is 1 or 0, representing whether a sentence is related to $t$ or not.

We trained a random forest model for each information type with the corresponding feature vectors. Random forest constructs a multitude of decision trees. Each decision tree is trained on a randomly selected subset of the training set. We use random forest because it is known to better address overfitting on small datasets [13]; decision trees are also able to automatically identify the most discriminative features for an information type (i.e., feature selection).

During prediction, we transform candidate sentences into feature vectors and feed each of them into the trained model for the information type $t$, thus obtaining the probability of each sentence to be related to $t$ (denoted as $s\.prob$).

### 3.4 Sentence Selection

For an information type $t$, FITI selects sentences from a document $d$ according to Algorithm 2. The basic idea is to select sentences that are either highly similar with $S_{dt}'$ from at least one aspect (i.e., the overall level, the individual sentence level, or the important word level) or ranked higher by the comprehensive score decided by both IR- and ML-based analysis. Combining with the knowledge from key-phrase lists, we can refine the selected sentences and accurately decide the final related sentence set. The inputs include the candidate sentences $S_{dt}'$ and their similarity and probability scores, the average number of related sentences per labeled document $n_r$, a list of domain-specific related phrases $rlist$ and unrelated phrases $ulist$, and the auxiliary parameter $\theta$. Notice that $rlist$ summarizes the phrases frequently used to express $t$; $ulist$ contains the phrases that are synonyms with related phrases but are seldomly used to express $t$. Since domain experts usually use keyword search to help them find the possible location of related sentences, these lists can be manually constructed when deciding the criteria to annotate the training documents $D^t$.

Before sentence selection, FITI detects duplicate sentences in $S_{dt}'$ (line 4). Two sentences are considered as duplicates if the similarity between their context vectors is larger than a threshold $\theta$. Duplicate
sentences are similar and usually express the same semantic meaning. FITI will either select or exclude them together.

FITI first selects sentences by their similarity scores. A sentence (and its duplicates) is selected if one of its similarity score (\(s_{\text{group}}, s_{\text{avg}}, s_{\text{max}}, s_{\text{word}}\)) is greater than \(\theta\), because this sentence may express the same meaning as some related sentences in \(D^L\). For the unselected sentences, we calculate a sentence score for each sentence according to its similarity (from IR) and probability (from ML) scores (lines 3-6). We rank sentences by their sentence scores and select the top-ranked sentences (and their duplicates) until the number of selected sentences reaches \(n_r\) (lines 7-11).

Last, we group the selected sentences based on their position in the document, because information types are usually addressed by several continuous sentences. We put any two sentences into a group if the distance between them is less than three sentences, since these sentences usually share the same context. For example, we put sentences \(s_i\) and \(s_{i+2}\) into a group as they have the same context sentence \(s_{i+1}\). For each group of sentences, we check whether they contain domain-specific phrases in the related list \(rlist\) or unrelated list \(ulist\). We annotate a group of sentences as related if they feature phrases in \(rlist\) but no phrase in \(ulist\) (lines 14-20).

4 Evaluation

In this section, we evaluate our approach (FITI) for financial information type identification. First, we assess the accuracy of FITI in identifying the sentences related to an information type. Then, we evaluate the factors that impact the accuracy of FITI, including different AI techniques and the size of the training set. Last, we analyze how FITI helps inspect financial documents. More specifically, we answer the following research questions:

RQ1 Can FITI accurately identify the information types in financial documents?
RQ2 How do different AI techniques (i.e., IR and ML) affect the accuracy of FITI?
RQ3 What is the impact of the size of labeled documents on the accuracy of FITI?
RQ4 How can FITI support the compliance analysis of financial documents?

4.1 Dataset and Settings

We evaluate FITI with the content requirements for UCITS prospectuses, because UCITS is one of the most popular and representative investment regulatory frameworks, which has over \(€10\) trillion of assets under management across the world [15].

We randomly collected 100 approved UCITS prospectuses from the official website of the regulator body in Luxembourg as our dataset. All the documents were annotated by three domain experts. Due to the time required for annotating documents, the domain experts selected five representative information types for evaluation, including disclaimer on periodic reports (T1), calculation frequency for issue price (T2), calculation method for issue price (T3), liquidation conditions and procedure (T4), and issue conditions and procedure (T5). They selected these information types by considering their complexity and diversity. First, manually identifying these information types is time-consuming, as one has to identify relevant sentences among, on average, 3000 sentences (i.e., the average length of a prospectus document). Second, these information types are diverse in terms of the average number of related sentences (i.e., 3.7 for T1, 8.0 for T2, 18.1 for T3, 16.1 for T4, and 47.3 for T5). Overall, choosing this selection allowed us to assess how FITI identifies information types specified at different levels of details (i.e., from a single sentence to several paragraphs).

The annotation was conducted in two phases. First, the domain experts selected 50 documents from the dataset. They perused these documents to define the detailed criteria for annotation (i.e., what types of sentences/phrases should be related/unrelated to an information type). During the second phase, domain experts annotated all 100 documents with the selected information types based on the established annotation criteria. Each person annotated a disjoint subset of documents individually. They then examined others’ annotations and discussed the possible inconsistency to achieve the final annotations. The two phases took about three months, including one month for defining annotation criteria and two months for the actual annotation.

The phrase lists \(rlist\) and \(ulist\) (see §3.4) used for sentence selection were manually built based on the phrases listed in the criteria. We extended the phrases with synonyms occurring in the first 50 documents.

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2CSSF approved prospectuses. [https://www.bourse.lu/home](https://www.bourse.lu/home)
We set the parameter $\theta$ to 0.9; it was decided empirically by evaluating the accuracy of FITI using a range of values between 0 and 1 with a step of 0.1 on the first group of 50 documents.

We performed the experiments with a computer running macOS 11.1 with a 2.30 GHz Intel Core i9 processor and 32GB memory.

4.2 Accuracy of FITI (RQ1)

To answer RQ1, we assessed the accuracy of FITI in identifying sentences related to different information types.

Methodology

We evaluated FITI using the annotated documents with $k$-fold cross-validation ($k = 5$). Since 50 annotated documents were used for phrase list construction and parameter tuning, we kept them in the training set and only test FITI on the remaining 50 documents. In each fold, we selected 10 documents from the remaining 50 documents as the test set; the training set included the other 90 documents. Given an information type $t$ and a test set, we compared the sentences selected by FITI with the ground truth annotated by the domain experts. We measured the accuracy of FITI with precision, recall, and $F_1$-score ($F_1$). They are defined as $\text{Precision} = \frac{|TP|}{|TP| + |FP|}$ and $\text{Recall} = \frac{|TP|}{|TP| + |FN|}$, where true positives (TP) and false positives (FP) refer to sentences selected by FITI which are related or not to $t$, respectively. False negatives (FN) refer to cases where FITI misses a sentence related to $t$.

$F_1$-score is defined as $F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$.

We compared FITI with a keyword-search strategy (denoted as KW), which is a common way for regulator agents to locate sentences. Since we have constructed two phrase lists containing related phrases (i.e., $rlist$) and unrelated phrases (i.e., $ulist$), KW directly searched the candidate sentences with the phrase lists and selected the sentences that feature phrases in $rlist$ but no phrase in $ulist$ as related to an information type.

Results

Table 2 shows the accuracy of the two algorithms for identifying information types. FITI identified a set of sentences related to each information type with a precision value ranging from 0.784 to 0.882. The recall value of FITI ranges from 0.418 to 0.893, with an average recall value of 0.646. The result means that FITI could find, on average, more than 60% of sentences for an information type.

KW performed poorly compared to FITI, identifying an average of 0.476 related sentences with an average precision value of 0.539. FITI outperformed KW by 0.277 (0.716 vs 0.439) in terms of $F_1$-score. Although keyword search is a common activity for regulator agents, many false positives can be returned due to the similarity of sentences in the same financial document. Moreover, since the writing styles and the number of related sentences can be different for financial documents from different investment companies, regulator agents may not enumerate all keywords for every related sentence, leading to a low recall value. On the contrary, FITI could leverage these (possibly incomplete) keyword lists to improve its accuracy in identifying information types.

When answering this RQ, it is important to remark that in the context of (financial) document compliance checking, it is desirable to use identification algorithms that yield a high precision value. As discussed at the end of section 3.2 after performing candidate sentence identification, the top 200 candidate sentences cover about 90% of the related sentences. Despite this high recall value, the remaining 200 sentences are more difficult to distinguish; users have to carefully read these sentences (or the
associated paragraphs) to find related sentences. With an average precision above 80%, FITI can help users efficiently locate the correct position of related sentences.

The answer to RQ1 is that FITI identifies an average of 64.6% of relevant sentences for an information type, with an average precision value of 0.824, significantly outperforming the baseline based on keywords.

4.3 Impact of Different Components (RQ2)

FITI selects related sentences according to the results from both the IR- and the ML-based analyses (section 3.4). To answer RQ2, we assessed the impact of these two types of analysis on the accuracy of FITI.

Methodology

We implemented two variants of FITI (called FITI_{IR} and FITI_{ML}) to assess the possible impact of each technique. During sentence selection, FITI_{IR} only selects sentences based on the similarity values calculated in the IR-based analysis, while FITI_{ML} performs sentence selection only relying on the probability calculated in the ML-based analysis. To implement FITI_{IR}, we calculated the score of a sentence by averaging the four similarity values (i.e., $s_{group}$, $s_{avg_s}$, $s_{max_s}$, $s_{word}$) at line 5 in Algorithm 2. To implement FITI_{ML}, we disabled the function `selectBySimilarity` at line 2 and assigned the score of a sentence as the probability value calculated from the ML-based analysis ($s_{ml}$). We ran the vanilla version of FITI (i.e., the one presented in section 3) and the additional variants using the same settings as in RQ1.

Results

As presented in Figure 2, IR- and ML-based analysis show different abilities in analyzing information types. ML-based analysis tends to assign a high probability value to a small fraction of related sentences. Hence, FITI_{ML} achieves higher precision values for the majority of information types (i.e., T2 to T5) than FITI_{IR}. The precision values of T2, T3, and T4 are also higher than those of FITI (in Figure 2a). However, the recall of FITI_{ML} is lower than both FITI_{IR} and FITI (in Figure 2b). As to FITI_{IR}, it tends to retrieve more related sentences than FITI_{ML}, leading to a high recall, though some false positives are included.

By integrating the two components, the accuracy in identifying information types is further improved: FITI achieves a higher F1-score than both FITI_{IR} and FITI_{ML} (in Figure 2c).

The answer to RQ2 is that both IR-based and the ML-based analyses contribute to improving the accuracy of FITI, complementing each other.

4.4 Impact of the Size of the Training Set (RQ3)

FITI conducts information type identification relying on the documents in the training set annotated by domain experts. This RQ assesses the impact of the size of the training set on the accuracy of FITI.
Methodology

We evaluated the accuracy of FITI by varying the size of the training set from 10 to 90 documents with a step of 10. Specifically, we randomly select a subset of the training set as a sampled training set. We trained FITI on each sampled training set and used the trained model to identify sentences in the test set for different information types. We measured the accuracy of FITI for different training set sizes, as when addressing RQ1.

Results

As shown in Figure 3, precision significant increases (i.e., in the case of T1) or becomes relatively stable within a certain range (i.e., in the case of T2, T3, T4, and T5) as the size of the training set increases. With more than 40 annotated documents, precision is stable, varying within a 10% range for all information types. Further, we observe that the precision value is still higher than 70% for most information types (i.e., in the case of T2, T3, T4, and T5) when there are only 10 annotated documents. This is because FITI is able to identify a small fraction of sentences that are highly similar to the annotated related sentences in the training set. However, as shown in Figure 3b, the recall value of FITI is low; for information types T2, T3, and T5, recall is around 40%. As more documents are annotated, recall significantly increases, because FITI may learn more about different expressions or wordings to explain an information type. F1-score also confirms the positive impact of increasing the size of the training set on FITI.

The answer to RQ3 is that the accuracy of FITI improves as the size of the training set increases. FITI requires a minimum size of 40 annotated documents to achieve high and stable precision.

4.5 FITI for Financial Document Compliance Checking (RQ4)

To answer RQ4, we simulate the scenario of compliance checking for financial content requirements and analyze the accuracy of FITI in this scenario.

Methodology

In our experiments, we assessed the accuracy of FITI in identifying information types with a set of approved prospectuses, which satisfy all content requirements. However, in actual compliance checking cases, regulator agents may also inspect (unapproved) prospectuses that do not fulfill some content requirement (i.e., they lack some specific information). We simulated this scenario to understand how FITI can help regulator agents check financial documents for compliance.

Since unapproved prospectuses are usually unavailable due to confidentiality reasons, we simulated such prospectuses by removing sentences related to an information type. Specifically, we first sampled 10 documents from the 50 testing documents as unapproved prospectuses, to simulate the case where a small subset of documents is incomplete. Second, we removed the pages containing sentences related to the five information types. We removed the whole page, because when explaining the core content of an information type, submitters may also write additional sentences near the related sentences (which are usually on the same page) to introduce the context or background. We assume that for missing information types, submitters would also omit these sentences. Additionally, we manually checked the documents to remove sentences that may indicate the existence of an information type. For example,
Table 3: Accuracy of FITI in Detecting Missing Information Types

| ID | Precision | Recall | F₁-score |
|----|-----------|--------|----------|
| T1 | 0.73      | 0.80   | 0.76     |
| T2 | 0.75      | 0.90   | 0.82     |
| T3 | 0.90      | 0.90   | 0.90     |
| T4 | 1.00      | 0.90   | 0.95     |
| T5 | 0.83      | 0.50   | 0.63     |
| Avg.| 0.84      | 0.80   | 0.81     |

for issue condition and procedure (T5), a prospectus contains the sentence “shareholders should consult the Chapter How to Subscribe For Shares” which determines the position of T5 in the text. Lastly, we built a new test set containing 50 testing documents, ten of which are incomplete in terms of information types.

We ran FITI on the new test set using the same cross-validation setting as in RQ1. When FITI reports that it could not find any sentence related to some information types, regulators are warned of missing information types. We defined \( \text{Precision} = \frac{|TP|}{|TP| + |FP|} \) and \( \text{Recall} = \frac{|TP|}{|TP| + |FN|} \), where TP means FITI correctly identifies a missing information type (e.g., no related sentence is recommended); FP represents the case in which FITI reports a missing information type but the document contains some related sentences; FN corresponds to the case in which FITI recommends sentences for a missing information type. We also calculate \( F₁\text{-score} \) according to precision and recall.

Results

As shown in Table 3, FITI achieves a precision ranging from 0.75 to 1.00 and a recall from 0.50 to 0.90 when detecting missing information types on the new test set. For T1 to T4, FITI identifies between 80% and 90% of the missing information types. The recall value of T5 is low. We speculate that this is caused by the high number of sentences (on average, 47.3) in the training set that are related to T5: many of the annotated sentences may discuss the general background of T5 instead of its core investment information. When using such general sentences to analyze a new prospectus, FITI could wrongly consider similar sentences in other locations as related; hence no warning of missing information types is reported. Regarding precision, on average 84% of the reported missing information types are correct.

The answer to RQ4 is that FITI detects 80% of the missing information types with an average precision value of 0.84, which is a first significant step towards semi-automated financial documents compliance checking.

4.6 Practical Implications

We discuss how FITI can help regulator agents manually inspect financial documents. Given a new financial document, FITI can analyze it and may warn regulator agents of possibly missing information types. Regulator agents could then browse the document to confirm the warnings. When FITI suggests some sentences, regulators can quickly read this small set of sentences (the set usually contains less than 50 sentences, depending on the average number of related sentences in labeled documents). Thanks to its high precision in identifying information types, in most cases FITI can help regulator agents locate the right position of the sentences related to a certain information type. As part of future work, we plan to conduct a user study to analyze the effect of FITI on reducing the inspection time of financial documents.

4.7 Threats to Validity

There are two primary threats to validity in this work. The first relates to the generality of the study. To address this threat, we chose the content requirements for UCITS prospectuses as it is a representative investment regulatory framework that has managed over €10 trillion of assets across the world for the past 30 years. We evaluated FITI with 100 prospectuses from different investment companies. The difference in writing styles and document structures demonstrates the accuracy of FITI even when analyzing very different financial documents. Regarding generality, we selected only five representative information types due to the time required to annotate documents and build the training set. To increase generality, we selected the information types by considering their complexity and diversity. We remark that FITI is easy to deploy for tracing other information types. It requires domain experts to annotate the related
sentences for the information types in a set of financial documents that will constitute the training set of the ML model and collect the key-phrase lists during the annotation.

The second threat relates to the process of creating the dataset. The annotation of information types is a subjective process. Hence, the annotation was conducted by three domain experts. They annotated the ground truth independently and discussed possible inconsistencies to mitigate the subjectivity from a single domain expert. Meanwhile, to answer RQ4, we simulated unapproved prospectuses by removing related sentences and any sentence indicating the existence of the information type; these documents may be different from real, unapproved prospectuses. However, the experiments show the accuracy of FITI when identifying missing information types. In the future, we plan to use real unapproved prospectuses to evaluate FITI.

5 Related Work

Our approach is related to work done in the areas of mining financial data and requirement traceability.

5.1 Mining financial data

Financial data (e.g., financial news, annual financial reports) play a critical role in improving the quality of financial services and minimizing the risks of financial activities (e.g., portfolio selection [43], stock trading strategy analysis [31], stock price movements prediction [14, 36]). Existing studies report that financial data from Web media (e.g., financial news and discussion boards) has become increasingly salient for analyzing stock markets [27]. Arslan et al. [2] and Fan et al. [13] cluster and classify financial news to help analysts capture the core events in news.

Data mining has been applied not only to financial data from Web media, but also to financial documents (e.g., annual financial reports, 10-K). Li et al. [28] extract financial tables from annual financial reports, and automatically classify them into income statements, balance sheets, and cash flow. Mining financial tables has also enabled activities like financial data cross-checking [25], key performance indicators tracing [5], and financial fraud detection [9, 35].

As to the analysis of NL sentences in financial documents, Kumar et al. [24] present a baseline system AEFDT to identify financial named entities (e.g., amortization expense, swing factor). Azzopardi et al. [3] propose a controlled NL to write financial statements for financial service compliance checking. In contrast to these works, in this paper we focus on the task of tracing content requirements in financial documents, which is important for financial enterprises and regulators to ensure the completeness of financial documents and further enable automated compliance techniques.

5.2 Requirements traceability

Requirements traceability can be considered as a kind of information extraction [17], which extracts entities (e.g., named entities [26], relations (the relationship between two entities [22]), and events (e.g., knowledge about incidents [21]) from the text. The extracted information can be used for tasks like question answering [34] and knowledge aggregation [11]. However, these tasks usually focus on analyzing small pieces of text (e.g., conversations, newsgroups, and weblogs) [34, 10, 14]. Driven by the recent deep learning advances (such as BERT [11] and SpanBERT [23]), the effectiveness of information extraction for analyzing complex documents has also significantly improved. However, applying these techniques to a different area (such as the financial domain) always requires some sort of fine-tuning with domain-specific datasets. Since fine-tuning is sometimes unstable on small datasets (with less than 10k training samples) [42], these techniques cannot be applied in our context. We indeed need to account for the limited size of domain-specific datasets, bounded by the high cost of annotations, which must be performed by domain experts and cannot be, for example, crowd-sourced.

Requirements traceability has also been studied in the area of software engineering [8], where many requirement artifacts are written in NL [4, 30, 39]. Regarding NL requirements, existing work infer trace links between high-level requirements (e.g., regulatory code) and low-level requirements (e.g., requirement specifications and privacy policies). They usually recast the traceability task into an IR problem: taking high- or low-level requirements as queries to retrieve related or similar sentences from low-level requirements [19]. IR techniques including latent semantic indexing, thesaurus, and relevance feedback have been investigated for this task [20]. To address the term mismatch between high- and low-level requirements, the domain ontology [18], word embedding [38], and indicator term mining [7, 39] methods have been explored for better sentence matching. In addition, for a certain type of artifact (e.g., privacy
policies), the NL text can be visualized [33] or standardized with domain-specific languages [6] to improve its traceability.

In the aforementioned works, a typical NL requirement (either high or low-level) is usually one or two sentences in length [20]; in contrast, in this work we have focused on complex NL artifacts (i.e., financial documents), which have thousands of sentences. Further, the same sentence may have different meanings when the context is different; this is not the case for many artifacts (e.g., privacy policies). To address these unique challenges, we proposed FITI to fully consider the context, the content, and indicator words of each sentence for better tracing financial content requirements.

6 Conclusion

In this paper, we proposed FITI, an approach to automatically identify content requirements in financial documents. Our approach utilizes IR and ML to conduct analysis, at multiple levels of granularity, on financial documents to understand the context, semantics, and indicator terms of every sentence. Furthermore, FITI uses a heuristic-based sentence selector, which considers the knowledge of IR, ML, and domain-specific phrases to trace text spans related to the information types specified in the content requirements. We evaluated FITI by assessing its effectiveness in identifying information types based on 100 financial documents from different investment companies. Evaluation results show that FITI can accurately retrieve a large percentage of sentences related to information types, with an average precision value of 0.824. FITI can thus effectively inform regulators about potentially missing information types and assist them in inspecting financial documents. As part of future work, we plan to investigate the applicability of FITI on other types of financial documents with different information types.

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