Automatic Hilghter of Lengthy Legal Documents

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1. Introduction

Legal documents are known for being lengthy. To our knowledge, some categories of legal documents contain duplicated information that do not require our attention. However, manually extracting non-duplicate information from documents requires considerable amount of effort. Thus, we want to use machine learning algorithms to pick up unordinary sentences for us. In this paper, we propose a set of algorithms that filters out duplicate information and returns useful information to the user. We are able to train a learner that can mark unordinary parts of a legal document for manual scrutinization.

Our learning process contains two phases. At the first phase, we pick some legal documents that contain common patterns, e.g. software user agreements, to form a knowledge base for the trainer. We then run *LDA* [1] model on these documents. The *LDA* model will return us with a set of common topics across the knowledge base.

At the second phase, we take a new piece of legal document as the test sample. We first remove common topic words from the test document to increase differences between sentences. We then use *Word2Vec* [2], [3] to convert sentences into vectors. After generating the feature space, we run *Agglomerative Clustering* and *Local Outlier Factor(LOF)* [4] algorithms on the feature vectors to detect special sentences in the given document. Last, we use *PCA* and *t-SNE* to visualize our result.

2. Related Work

Though text-mining related works are often seen, few of them address the issue of sentence-level anormaly detection. However, we are able to draw inspirations from previous works on unsupervised auto-generation of document summary.

Qazvinian and Radev (2008) [7] presented two sentences selection models based on clusters generated by hierarchical clustering algorithms. *C-RR* finds the largest cluster and rank the importance of sentences by their order of appearance in the cluster. *C-lexrank* selects the most centered sentences within the cluster to be the salient ones. While their clustering strategy performs well on segmenting an article, their strategy on finding the salient sentences does not apply to our case. Based on their design, a sentence with the most common pattern would be chosen as a salient one. However, it is also the case that such sentence would contain the most duplicate information; therefore it should not require much attention from the reader.

Similarly, Nanba and Okumura (1999) [9] discussed ways of citation categorization, which essentially cluster sentences and extract ones closer to the center.

Based on the work of Qazvinian and Radev, Cai (2010) [8] presented a salient sentence extraction strategy by adding a ranking policy for sentences within each cluster. However, Cai did not discuss on how to select the initial condition of centroids. In fact, it seems to be the case that the centroids are randomly selected in Cai's proposed algorithm. Since the final clustering would vary a lot as the intial condition changes, we choose to not adopt Cai's path.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan (2003) presented the *LDA* model to extract common topic words from a set of documents. We find this model very robust, and in fact *LDA* is used widely accross contextual anormaly detection. For example, Mahapatra and Amogh [10] presented a text clustering strategy based on *LDA*. Their model works well; however their feature extraction part can be improved by using algorithms that translate the relation between words into vectors. Having this in mind, we use *Word2Vec* as our major text feature extraction framework.

3. Dataset and Features

We generate our samples by parsing html pages of legal documents. Here is a sample text from iTunes user agreement:

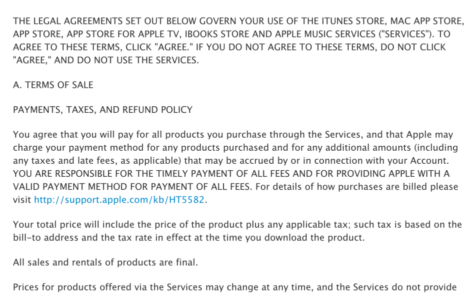

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Figure 1. A sample text

Our training dataset contains 35 legal documents, which include 124,546 words. We use two documents for testing. One is the iTunes user agreement, which contains 1,329 words. We manually label some special sentences in this document. We then run our pipeline on this document, and use the number of labeled sentences highlighted by our pipeline as a measure of how successful the pipeline is.

The other document is the Atlassian's user agreement, which contains 7,934 words. Due to the size of this document, we cannot label all the sentences. Instead, we use this document for generalization test. We run our pipeline on Atalassian's user agreement, read the highlighted sentences, and subjectively check if these sentences are unordinary. Since the problem we defined is unsupervised, we can only evaluate the final results by subjective means. To increase the credibility of our evaluation, we also use quantitative methods for evaluating the robustness of our pipeline. We will discuss more about these methods in section 5.

We remove prepositions, numbers, punctuations because they add noise to our samples. For example, "I have iphone" and "I have an iphone" are treated as the same sentence in our pipeline.

We also realize that some words with different suffixes may have the same meaning. For example, "mature" and "maturity" should be understood as the same word. In preprocessing step, we run an algorithm called *Porter Stemming* [11] to convert words with the same stem and similar suffixes into one word.

We have two different sets of feature extraction and selection strategies. First, we use *LDA* to construct common topic words across the training dataset. The feature extraction within *LDA* is done by taking all documents as a single corpus and then by applying the variational inference method discussed in the original paper.

After running *LDA* on all the documents, we get a list of topic words. A topic is a list of words, e.g. *trademark, services, may, use, application, agreement, content*. We observe that these topic words do not contribute to the "specialty " of a sentence. Therefore, we remove the topic words from the test document.

Second, for the test document, we use *Word2Vec* to translate a word into a vector. *Word2Vec* is a two-layer neural network. It takes text corpus as input and its output is a set of feature vectors for words in that corpus. For each word, we generate 100 features. These word vectors allow for numeric operations on words. For example, the vector of "king" added by the vector of "woman" would return the vector of "queen". After running *Word2Vec*, we establish a mapping from words to vectors.

```
>>> model['apple']
array([  3.39468718e-01,  -9.81548280e-02,   2.06640467e-01,
        -2.21591026e-01,  -4.72269282e-02,   1.05696611e-01,
```

Figure 2. Part of word vector of "apple"

We assume that the feature vector of a sentence is the sum of feature vectors of all the words in this sentence. We then run clustering algorithms on the vector representations of all the sentences.

4. Methods

We use *EM* algorithm to learn the hidden parameters of the *LDA* model. We then use *Agglomerative Clustering* and *LOF* to learn the distributions of unordinary sentences in the document. We will discuss these methods in the following subsections.

4.1. *EM* for estimating *LDA* parameters

The *LDA* model uses a word *w* as a basic unit. A document is a sequence of N words denoted by $\mathbf{w} = (w_1, \cdots, w_N)$. A corpus contains M documents is denoted by $\mathbf{D} = \{\mathbf{w}_1, \cdots, \mathbf{w}_M\}$.

LDA takes the following generative steps for each document $\mathbf{w}$ in a corpus $\mathbf{D}$:

1) Choose $N \sim$ Poisson(ξ).
2) Choose $\theta \sim$ Dir(α).
3) For each of the N words $\mathbf{w}_n$:
   i Choose a topic $z_n \sim$ Multinomial(θ).
   ii Choose a word w_n from $p(w_n|z_n, \beta)$, where p is a multinomial probability conditioned on z_n and β.

The probability of seeing an N word document, $P(\mathbf{w}|\alpha, \beta)$, is given as:

$P(\mathbf{w}|\alpha, \beta) = \int (\Pi_{n=1}^{N} \sum_z P(w_n|z, \beta) P(z|\theta)) P(\theta|\alpha) d\theta.$

To estimate the two hidden parameters, (α, β), from a corpus $\mathbf{D}$, one needs to maximize the log likelihood:

$\log P(\mathbf{D}|\alpha, \beta) = \sum_{d=1}^{M} \log P(\mathbf{w}^{(d)}|\alpha, \beta),$

which is not tractable. To resolve this issue, the LDA paper recommends to use variational inference method. The key of this method is to apply *Jensen's Inequality* to obtain a lower bound of $\log P(\mathbf{w}|\alpha, \beta)$. Let $q(z, \theta)$ be the joint pdf of z, θ. Then:

$\log P(\mathbf{w}|\alpha, \beta) \geq \int \sum_z q(z, \theta) \log \frac{P(\mathbf{w}, z, \theta|\alpha, \beta)}{q(z, \theta)} d\theta$
$= L(\alpha, \beta).$

Note that:

$L(\alpha, \beta) = \int \sum_z q(z, \theta) \log \frac{P(\mathbf{w}, z, \theta|\alpha, \beta)}{q(z, \theta)} d\theta$
$= \int \sum_z q(z, \theta)(\log \frac{P(z, \theta|\mathbf{w}, \alpha, \beta)}{q(z, \theta)} + \log P(\mathbf{w}|\alpha, \beta)) d\theta$
$= -\int \sum_z q(z, \theta) \log \frac{q(z, \theta)}{P(z, \theta; \mathbf{w}, \alpha, \beta)} d\theta$
$+ \int \sum_z q(z, \theta) \log P(\mathbf{w}|\alpha, \beta) d\theta$
$= -KL(q(z, \theta)||P(z, \theta|\mathbf{w}, \alpha, \beta)) + \log P(\mathbf{w}|\alpha, \beta)$
$\leftrightarrow \log P(\mathbf{w}|\alpha, \beta) = L(\alpha, \beta) + KL(q(z, \theta)||P(z, \theta|\mathbf{w}, \alpha, \beta)).$

Since we want to find a $L(\alpha, \beta)$ that is as much close to $\log P(\mathbf{w}|\alpha, \beta)$ as possible, we want to find a parameterized $q(z, \theta)$ that has as small KL-distance to $q(z, \theta)$ as possible.

Let z, θ be parameterized by ϕ, γ respectively,
i.e.: $q(z, \theta) = q(\theta|\gamma) \Pi_{n=1}^{N} q(z_n|\phi^{(n)})$.

Let $L(\phi, \gamma; \alpha, \beta)$ denotes the lower-bound of $\log P(\mathbf{w}|\alpha, \beta)$. Then:

$\log P(\mathbf{D}|\alpha, \beta) \geq \sum_{d=1}^{M} L(\mathbf{w}^{(d)}; \phi^{(1,d), \cdots, \phi^{N_d, d}}, \gamma^{(d)}; \alpha, \beta)$
$= \mathbf{L}\ (\Phi, \Gamma; \alpha, \beta),$

where $\Phi = [\phi^{(n,d)}], \Gamma = [\gamma^{(d)}]$.

The idea of EM is to start from initial α, β, and iteratively improve the estimate:

E-step: Given α, β,
$(\Phi, \Gamma) := \arg\max_{(\Phi, \Gamma)} \mathbf{L}(\Phi, \Gamma; \alpha, \beta);$

M-step: Given Φ, Γ,
$(\alpha, \beta) := \arg\max_{(\alpha, \beta)} \mathbf{L}(\Phi, \Gamma; \alpha, \beta).$

These two steps are repeated until $\mathbf{L}$ converges. We won't show the complete derivation here, but we use the following updating equations for getting (α, β).

In *E-step*, the update equations for Φ and Γ are:

$\phi_i^{(n,d)} :\propto \beta_{i, w_n^{(d)}} \exp(\digamma(\gamma_i^{(d)}) - \digamma(\sum_j \gamma_j^{(d)}))$

where $\digamma$ is the digamma function;

$\gamma_i^{(d)} := \alpha_i + \sum_{n=1}^{N_d} \phi_i^{(n,d)}.$

In *M-step*, the update equation for β is:

$\beta_{ij} :\propto \sum_{d=1}^{M} \sum_{n=1}^{N_d} \phi_i^{(n,d)} \mathbf{1}(w_n^d = j).$

There is no analytical solution to α, but it can be obtained by maximizing

$L_\alpha = \sum_d (\log \bar{\Gamma}(\sum_{i=1}^{K} \alpha_i) - \sum_{i=1}^{K} \log \bar{\Gamma}(\alpha_i)$
$+ \sum_{i=1}^{K} (\alpha_i - 1)(\digamma(\gamma_i^{(d)}) - \digamma(\sum_{j=1}^{K} \gamma_j^{(d)})))$

using Newton's method, where $\bar{\Gamma}$ is the gamma function.

4.2. Agglomerative Clustering

For a new test document, we first get the feature vector of each sentence. We then use *Agglomerative Clustering* to segment the document. We first specify that we want to have N clusters. We then put each sentence into its own cluster, and iteratively merge the closest clusters until only N clusters remain. We then look at these clusters. If there exists a cluster that contains only one sentence, then we know that this sentence is a special one, as it is never merged into other clusters.

We define the cosine similarity between two sentences as the dot product of their normalized vector representations. We then calculate cosine distance from cosine similarity and use this distance as our clustering metric.

The distance between any two clusters A and B is taken to be the mean distance between elements of each cluster [12].

In section 5, we will discuss on how to choose the right number of clusters to achieve the best clustering structure.

It is worth mentioning that we find *K-means* and *K-means++* performing much more unstable than *Agglomerative Clustering* in our case. The final outcome of *K-means* and *K-means++* depends heavily on the initial assignments of the centroids. However, since both methods choose initial centroids in a semi-random fashion, it is not guaranteed that the final clustering would remain the same from run to run. In contrast, *Agglomerative Clustering* does not depend on initial assignments. As a result, it creates more stable outcomes.

Before running *LOF*, we recommend to run *Agglomerative Clustering* first, and then remove the discovered anormaly sentences from the test document. The reason is that we want to decrease the local density around unordinary sentences so that these sentences can be more easily picked up by *LOF*.

4.3. Local Outlier Factor (LOF)

In our feature space, each sentence is represented as a point. Therefore, if we find a point with low local density, then this point is an outlier, and its corresponding sentence is unordinary.

To help explain how *LOF* works, we introduce two terms:

$\mathrm{N}_k(A)$: Set of k nearest neighbors to A.

k-D(A): distance from A to its k^{th} nearest neighbor.

$\mathrm{RD}_k(A, B) = \max\{\text{k-D}(A, B), \text{distance}(A, B)\}$, where RD denotes reachability distance. We use the maximum of two distances to get a stable result.

The local reachability density of A is computed as:

$\mathrm{lrd}(A) = 1/(\frac{\sum_{B \in \mathrm{N}_k(A)} \mathrm{RD}_k(A,B)}{|\mathrm{N}_k(A)|})$.

It is then compared with its neighbors using:

$LOF_k(A) = \frac{\sum_{B \in \mathrm{N}_k(A)} \mathrm{lrd}(B)}{|\mathrm{N}_k(A)|} / \mathrm{lrd}(A)$,

which is the average local density of neighbors divided by the object's own local density. If this value is greater than 1, it tells that the local density around this object is lower than its neighbors, and thus is an outlier.

This method studies the local distribution of points, and helps us improve the performance on top of *Agglomerative Clustering*. Basically, it is hard to have insight of how points are distributed within an agglomerative cluster. Using *LOF* helps us understand the distribution of points within a cluster.

5. Experiments and Results

In this section, we first discuss how we choose the hyperparameters for *LDA* and for *Agglomerative Clustering*. We will then talk about the performance achieved by our pipeline on the test cases.

5.1. Tuning Hyperparameters

In this subsection, we will use the iTunes user agreement as an example to show how our hyperparameter choosing strategy works. There are 42 sentences and 1329 words in this document.

5.1.1. Choosing parameter for *LDA* model. For *LDA* model, number of topics is a critical parameter. We enumerate over possible number of topics and study how the perplexity changes. We then use the number of topics that yields the best perplexity.

Documents in our training dataset are unlabeled. Therefore, we wish to achieve high likelihood on a held-out testset. In fact, we use the perplexity of a held-out test set to evaluate the model.

Intuitively, a lower perplexity score indicates better generalization performance. The perplexity is equivalent to the inverse of the geometric mean per-word likelihood:

$perplexity(D_{\text{test}}) = \exp(-\frac{\sum_{d=1}^{M} \log p(w_d)}{\sum_{d=1}^{M} N_d})$,

using the same notation as in section 4.1.

In our experiment, we use the corpus generated by parsing html pages of legal documents from Atlassian, Github, and Apple. We held out 25% of the data and trained on the remaining 75%.

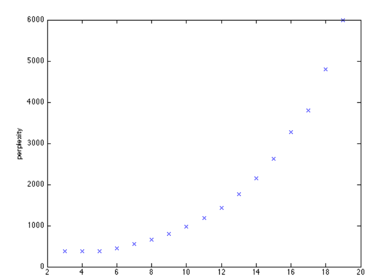

Figure 3. perplexity given number of topics

We found that the perplexity is the lowest when there are around $3 \sim 5$ topics. We found that for the iTunes user agreement, using 5 topics works the best for improving the differences between sentences.

5.1.2. Choosing number of clusters. We use *Silhouettes* [13] score to evaluate the robustness of clusters. We enumerate over possible numbers of clusters, and pick the one that yields the best *Silhouettes* score.

Intuitively, larger *Silhouettes* score indicates that the distance between each cluster is large, and the maximum distance from the farthest point in a cluster to its centroid is small. The formal definition is given as follows:

For each point i, let $a(i)$ be the average dissimilarity of i with all other points in the same cluster. Let $b(i)$ be the lowest average dissimilarity of i to any other cluster, of which i does not belong to. The cluster with the lowest average dissimilarity

is defined to be the neighboring cluster of i. This cluster is also the next best fit for i. *Silhouettes* score is defined as:
$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}}$, where $-1 \leq s(i) \leq 1$.

If $s(i)$ is close to 1, it means that the average dissimilarity between i and its neighboring cluster is much greater than the dissimialrity between i and its own cluster. In this case, we say that i is properly clustered. In contrast, if $s(i)$ is close to -1, it means that i would be more properly labeled by its neighboring cluster. We use the average of $s(i)$ over all sentence vectors of the test document as a measure of how tight each cluster is and how far away each cluster is from its neighbors. The curve is shown in figure 4.

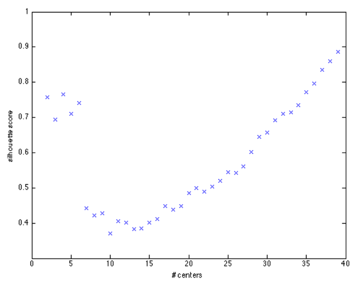

Figure 4. Silhouette score given number of centroids

From figure 4, the average *Silhouettes* score is high when more than 27 clusters are used. The reason is that when having more than 27 clusters, most of these clusters contain only one sentence from the iTunes user agreement. As a result, the average dissimilarity within each of these clusters is 0, and the corresponding *Silhouettes* score goes up to 1.

In practice, we do not use more than 27 clusters. The major concern is that if most of the clusters contain only one sentence, then we cannot tell if this sentence is an anormaly or not. Therefore, we only look at the *Silhouettes* scores when we have few clusters, and we find that having 3 clusters works the best.

5.2. Visualization

In this subsection, we look at how the unordinary sentences picked up by our pipeline distribute in 3D space. We use *t-SNE* [5] and *PCA* to extract three dimensions from features of our results. In both figures, points in dim yellow or blue are farther from the view point. The blue triangles mark positions of unordinary sentences.

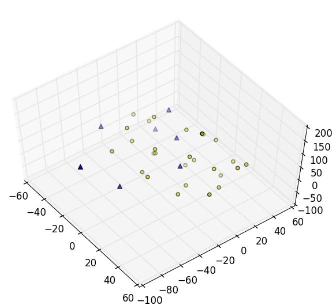

Figure 5. first 3 dimensions of *t-SNE* result

In figure 5, as we can see, the unordinary sentences locate at places with lower local density.

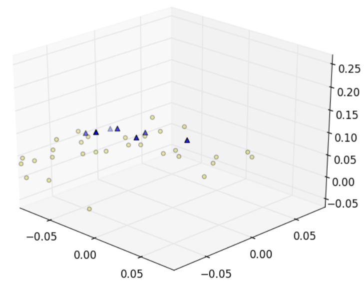

Figure 6. first 3 dimensions of *PCA* result

In figure 6, result of PCA also shows that unordinary sentences are picked up at locations with lower local densities. However, in figure 6, points are denser than in figure 5. This indicates that *t-SNE* does a better job on signifying the differences between points than *PCA* does.

5.3. Tests

Since we are trying to solve an unsupervised learning problem, it is hard to quantify test accuracy. To mitigate that, we create test cases by using three groups of sentences:

1) We insert irrelevant sentences into the test document. For example, we added “we are such stuff as dreams are made on our little life is rounded with sleep”, which is a quote from Shakespeare.
2) We modify original text. For example, we change “apple reserves the right ...” to “Apple reserves ... to be scrutinized by great fire wall of China”.
3) We subjectively choose some special sentences. For example, we highlight “you further agree to not... harassing, threatening, defamatory ...” as a special sentence.

For iTunes EULA (small test case), we inserted 3 totally irrelevant sentences, modified 7 original sentences, and subjectively chose 10 special sentences.

For Atlassian’s EULA (large test case), we inserted 3 totally irrelevant sentences, modified 10 orignal sentences, and subjectively chose 10 special sentences.

We choose to not insert or modify a lot of sentences within the test documents. The reason is that as the number of modified or inserted sentences increases, the chance of randomly picking one sentence and observing that the sentence is in Group 1 or 2 also increases. Thus, inserting and modifying few sentences in the large test document help to show that our pipeline does not succeed by choosing sentences randomly.

We run our pipeline on these test cases , and we check how many of sentences in each group are picked up by our pipeline. The result is shown in the following table:

	iTunes’ EULA	Atlassian’s EULA
# of words	1329	7934
# of sentences	42	282
% of Group 1	100 %	100 %
% of Group 2	28.5 %	10 %
% of Group 3	60 %	40 %

From the table, it is shown that our pipeline is very accurate on picking up irrelevant sentences. However, it does poorly on picking up partially modified sentences. We find out that our assumption on generating the sentence vector causes this problem, and we will discuss possible improvements in section 6. It seems that our pipeline does not perform well on picking up Group 3 sentences. The reason is that when manually creating test cases, it is very hard for us to pick up all the unordinary sentences. Moreover, we sometimes pick up sentences that are actually quite common in legal documents due to our limited knowledge of how user agreements are written.

Therefore, to better evaluate the performance on Group 3 sentences, we read the output from our pipeline, and manually construct a confusion matrix for it. For the large test case:

true positives: 10	false positives: 2
false negatives: N/A	true negatives: N/A

We cannot give an account on false negatives and true negatives, because for a lot of sentences we cannot confidently tell if it is too ordinary.

6. Future Work

In this report, we propose a pipeline that finds unordinary sentences in a given legal document. We construct the pipeline by first building a training dataset of many legal documents sharing similar topics. We then use *LDA* model with *EM* algorithm to find the common topic words across the dataset. When coming to a new test document, we first remove common topic words from it to increase differences between sentences. We then use *Word2Vec* to extract sentence features, cluster the sentences and use *LOF* to find the outliers. Finally, we run *t-SNE* and *PCA* to visualize the first 3 dimensions of the result.

We evaluate the performance of our pipeline using two types of method. First, we check perplexity of the *LDA* model and *Silhouettes* score of the clusters to measure the robustness of our model. Second, we manually create test cases by adding three groups of sentences, and we measure the performance of our pipeline on these test cases.

Regarding finding unordinary sentences, the majority of the job is done by *LOF*. This is because most of the sentences use similar words and are clustered closely. As a result, clustering cannot filter out a lot of unordinary sentences. However, *LOF* only considers the local density of an area regardless of which cluster it belongs to. As a result, *LOF* is able to pick up more differences between sentences.

Future work includes improving our sentence model. Meanwhile, we make a naive assumption that the vector of a sentence is the sum of vectors of words. However, this assumption ignores the semantics of phrases in a sentence. Therefore, the next step of improvement would be to consider more of relation between words within a sentence. For example, we can use a bigram or trigram model to address the correlation between words in a sentence.

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