



FYP-1 Final Evaluation Report

FINE PRINT

Privacy Policies and Cyber Laws

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Introduction

Problem Domain

In recent times in the field of Natural Language Processing, work has been done on privacy policies but none that caters to the problem of verifying if a given privacy policy adheres to the data protection laws of a given country or state. A possible solution is to create a system powered by machine learning to review the privacy policy and see if it is in accordance to the laws of the country (or countries) and identify any areas where a violation between them is detected.

Privacy policies and cyber laws regulating these policies are both highly extensive and full of legal jargon. In fact, it is estimated that about 201 hours on average are needed by any average user just to read all the privacy policies encountered in a year [1]. As a result, consumers don't fully understand what they are signing up for [2] and often do not know whether the policies that they are agreeing to are infringing on their legal rights.

Moreover, a company's legal department spends hours to review its privacy policies to see if it is compatible with a given country's laws. This is a rigorous process because each country has its own data protection laws and also because with the upsurge of Internet of things there has been an escalation in the number and complexity of privacy policies themselves [3].

Research Problem Statement

The automation of checking compliance of privacy policies with laws can be of great value. It will arm users to understand policies with respect to laws without getting into the apprehension of legal jargon and details.

The analysis of privacy policies on their own is not enough. There needs to be a mechanism to relate those policies with laws. The policies dictate what they are doing with the user's data and how they are doing it but that information alone is not adequate to judge a policy's transparency and its usefulness. [4]

Using such an automation tool, a user can have a deeper understanding of what's happening with their data in legal light.

Literature Review

Research Item 1

Unsupervised Topic Extraction from Privacy Policies[6]

Summary

The paper focuses on labelling privacy policies using topic modeling, which is an unsupervised approach. The research provides insight into the topics that are being addressed in privacy policies these days.

The privacy policies of mobile apps were collected from the Google play store. 4982 privacy policies were left after data pre-processing. The policies were segmented based on paragraphs which resulted in 45,622 paragraphs in total. The Latent Dirichlet Allocation (LDA) method for topic modeling was used. LDA doesn't require the data to be pre-labelled. It works by randomly grouping words together into topics and then iteratively improving the grouping till convergence. The method is based on the assumption that both words belonging to a specific topic and topics in a document are few. After 600 iterations of LDA with number of topics set to 100, words were grouped into topics along with their probabilities. Those probabilities were then used to assign paragraphs to topics by summing the probabilities of each word of a paragraph appearing in a topic. The topic with the maximum score was assigned the paragraph. The topics were then manually checked and merged by an expert. The merging process involved selecting 30 paragraphs from each topic, the expert then gave a one sentence summary of each topic. The topics were merged together according to their redundancy and relevance with one another. The merging left 36 topics.

The merged topics reveal the underlying structure of privacy policies. Some topics have thousands of paragraphs associated with them, in part because those topics were created after merging several sub-topics together. On the other hand, some topics were created after merging only one or two sub-topics but still have thousands of paragraphs mapped to them. Those topics represent the areas that privacy policies address the most. Amongst them are privacy policy change notifications, contact information and the option to opt-out of privacy policies. The topics were also validated against the OPP-115[5], which is a data set of 115 privacy policy annotated into 22 topics by legal experts. The mapping showed that the current method of extracting topics revealed more fine-grained details from privacy policies.

Critical Analysis

- Strengths:
 - This method can be used to analyze privacy policies and their evolution over time. As it is not dependent on any labelled data set like the OPP-115 which was created in 2016. This is of crucial importance because many firms are updating their policies to comply with the ever stricter laws coming into place like the Europe's GDPR.

- It also provides more finer details about privacy policies. The number of paragraphs being mapped to a certain topic and the number of sub-topics under one topic. Insights like these can be helpful to determine what the makers of privacy policies are considering crucial and addressing the most.
 - It is one of the first unsupervised method of annotating privacy policies.
 - The results obtained are compared with the standard OPP-115 dataset as a means of validation.
- Weaknesses:
 - The segmentation of privacy policies was done on the basis of paragraphs. This was done on the assumption that different paragraphs describe different legal aspects. Where as this may not be true in all cases.
 - The method is not completely independent of human annotator as it requires a domain expert to merge the topics.
 - The topics were summarised by the expert based on a sampling of 30 paragraphs only from each topic. There is no proof that those samples were a good representation of the topics.

Relationship to the proposed research work

The initial part of our problem is to label laws and privacy policies. While there is a corpus of labelled privacy policies, there is none for data protection laws. We can use the unsupervised methodology proposed in this paper to label laws. As the terminology used in laws and policies overlap and the method has performed well on privacy policies.

Research Item 2

Leveraging Linguistic Structure For Open Domain Information Extraction[7]

Summary

The paper describes a method which can be used in open domain information extraction for extracting relation tuples from sentences. These tuples can be used in natural language processing for question-answering, information retrieval and relation extraction. The tuples are extracted in two stages. In the first stage, the sentence is broken down into self-contained clauses to reduce false triples. A classifier is used to create clauses which are logically in accordance with the original sentence. A greedy search approach is used in which a sentence is traversed using a dependency tree. The traversal is recursive and at each edge it is decided if an independent clause should be yielded. This decision is taken by using a multinomial logistic regression classifier which predicts whether an edge should be recursed with or without yielding a clause or if the recursion should stop.

In the second stage natural logic is used to obtain the most specific triple form the clauses by removing superfluous information. These triples are of the form subject-verb-object and

retain the essential semantics which the original sentence had. Natural language formalism is used to find operators such as all, no and many and to determine from these if a proposed triple can be turned into something more general or specific.

Critical Analysis

- Strengths:
 - Incomplete utterances are avoided by allowing a sub-clause whose subject is controlled by the governing clause's subject to inherit from the governing clause. By doing so, the long-range dependencies of a sentence can be captured.
 - Removing non-subjective adjectives is prohibited as doing so would not to loss of information.
 - A better generalization is done by splitting sentences into clauses which is useful for working with out-of-domain texts.
- Weaknesses:
 - The errors made in splitting the clauses manifest themselves across an array of sentences.
 - Complex assertions are not interpreted correctly. There is no mechanism to determine if the assertion in a sentence is only conditionally true or hypothetical in nature.

Relationship to the proposed research work

The relation triples produced as the result of this paper can be used to extract information from the laws. These triples can then be used to compare them with the privacy policy more efficiently to find if the policies comply with them.

Research Item 3

Polisis: Automated Analysis and Presentation of Privacy Policies Using Deep Learning[12]

Summary

The paper presents a framework for automated analysis of privacy policies. It uses the OPP-115[5] dataset for labelling of data followed by a hierarchy of neural network classifiers. The framework is manifested in the form of two applications, automating assignment of icons to privacy policies and a question answer system.

The framework is based on three layers: Application layer, Data layer and Machine Learning layer. A privacy policy is first split into smaller segments. The application layer consists of a query and a class comparison module. It allows users both structured and free-form querying. The responses are segments of the privacy policy that satisfy the query. The policy from the application layer is passed on to the Data Layer and the query to the Machine

Learning. The Data Layer crawls a privacy policy from the website URL. It then segments the policy first on the basis of its representation in <div> and <p> tags in HTML format. Then a more detailed segmentation is done using custom word embeddings generated by using a corpus of 130K privacy policies. The high level along with the fine-grained segments are then passed to the Machine Learning layer. This layer also has two components: query analyzer and segment classifier. The ML layer first generates a custom word embeddings as mentioned above. These word embeddings are then used to train an array of neural network classifiers based on the OPP-115[5] dataset. The segments are assigned from 10 high level categories and several low level attributes. The classifiers assign class labels to the segments in two stages. In the first stage, the classifier predicts one or more than one high level categories for the paragraph segments. In the second stage, the classifier predicts values for the attributes under each high level category. Thus, the ML layer analysis and assigns labels to the policy segments at a much detailed level using CNN. In total 22 multi-class classifiers are trained at the ML layer. The output from this layer in the form of class-value pairs for both query and the segments of policy which are then passed back to the Application layer's class comparison module. This module finally matches the labels of the query with those of segmented policy and gives results to the user.

Critical Analysis

- Strengths:
 - The word embeddings are trained using fastText. It allows it to be trained on subwords. This is particularly useful in the case of spelling mistakes when querying the question answering system.
 - The framework's accuracy is tested in the form of two applications. Both are rigorously validated against previous work and through human annotation.
 - Leverages the OPP-115 dataset's labels of does and doesn't indicating the presence or absence of a category.
- Weaknesses:
 - Is dependent on the OPP-115 dataset for labelling of policies and queries. The dataset was revealed in 2016 and since then there has been a radical change in the way privacy policies are being made. [6 , 7].
 - The custom word embedding doesn't take advantage of the already present ones.

Relationship to the proposed research work

The above paper not only segments and labels policies but also correlates query segments with policy segments. It also provides insight into using CNNs to segment and annotate privacy policies. All the steps are an integral part of our research problem.

Research Item 4

Unsupervised Alignment of Privacy Policies using Hidden Markov Models[14]

Summary

This paper presents an approach to align privacy policies. Many privacy policies are similar to each other as they address the same issues and therefore can be aligned using an unsupervised approach. A corpus of 1000 privacy policies was collected for this task manually. This is because despite attaining the URLs of the policies it was difficult to extract the policy with its structure intact as each website is different and presents challenges of its own. The policies were then segmented based on their section headings by crowdworkers. A Hidden Markov Model like approach is then used to align the segments such that an issue (addressed in the policy) corresponds to a hidden state. This correspondence is based on the bigrams in the segment of the policy and its distribution of words. For each state ' t ', a bag of terms is drawn from the section ' t ' of the policy unlike classic Hidden Markov Models where only a single term is drawn each time.

To evaluate the results, the paper presents two evaluation techniques which are reusable. These techniques approached the problem as one of grouping rather than alignment. The first technique was to evaluate the results by creating an answer set. Nine questions were created by domain experts. Then the domain experts not involved in the process of creating the questions selected the segments of policies they thought best answered each of the nine questions. They did this for thirty policies. The model is then evaluated by calculating precision and recall using the answer sets as a gold standard. The second evaluation technique is by direct judgement in which 994 policy segment pairs are selected from the 1000 policies across four ranges of cosine similarity. For each section pairs, crowdworkers are asked if the pairs are talking about the same thing, broadly related to each other or not identical at all. The results of this were then used to calculate precision and recall as before.

Critical Analysis

- Strengths:
 - Created and used a new dataset of 1000 manually segmented privacy policies.
 - Evaluation benchmarks created are better than previous naïve methods. They also do not require a pre-labelled dataset.
- Weaknesses:
 - There is a lot of human effort involved in data gathering.
 - In the first evaluation technique a very small number of policies are selected which may likely be biased

Relationship to the proposed research work

The laws or data protection acts that we will use are not labelled. Therefore we need an unsupervised technique to align them into classes. As the approach mentioned in the paper is using privacy policies and since the laws and policies have similar legal jargon, we can use it to align the laws.

Research Item 5

Multi-Perspective Sentence Similarity Modeling with Convolutional Neural Networks[15]

Summary

The paper proposed a convolutional neural network technique to find similarity in sentences using multiple perspectives. Recent work in sentence similarity is moving towards using distributed representations along with neural networks rather than hand crafted features. This paper also takes a step forward in this direction. Given sentences A and B, the proposed approach finds a measure of similarity $\text{sim}(A, B)$ between the two sentences. This would be done in two steps. Firstly, the sentences are input into identical sentence models where a convolutional neural network is used to extract information from different perspectives and multiple pooling types. Then the outputs from these models act as input for the similarity measurement layer. This layer computes similarity based on multiple distance functions. At the end, two fully connected layers with an activation function in between and a final log-SoftMax layer is used to get the overall similarity score.

The sentence model layer uses two different filters; holistic and per-dimension. The holistic filter is used to extract temporal information. They convolve the entire word vector for the number of words specified by the sliding window width at a time. The per-dimension filter is used to extract information at a finer spatial level. These filters convolve for each dimension of the word vector for the number of words specified by the sliding window width at a time. The holistic filters block then uses min, mean and max pooling whereas the per-dimension filter only uses max and min pooling. The window widths can be of multiple sizes to learn different features as is done in n-gram models. A window width of infinity is added in holistic filter block to ensure that the original word embeddings are also included. The Similarity measurement layer is then used to compare local regions using cosine, euclidean and element-wise distance functions. The local regions for comparison are selected on the basis that they are either from convolution layers with the same type of filter, window size or pooling.

Critical Analysis

- Strengths:
 - The approach does not rely on resources such as parsers or wordnet as high-quality parsers are not readily available for specialized domains
 - The use of multiple filters leads to better information extraction and makes richer sentence models.

- The need of hand-crafted features of traditional NLP approaches is removed through this approach
- The information loss from flattening the output from a convolved layer is rectified by using structured comparisons over certain areas of the sentence representations in the similarity measurement layer.
- Weaknesses:
 - The architecture engineering of the model is complex as it compensates for hand-picked features.
 - The model may not be able to compete with a simple but deeper neural network which is trained using a large set of data.

Relationship to the proposed research work

The privacy policy and law segments belonging to the same category are compared to find if the policies are semantically similar that is if the policies comply with the laws. The papers approach for finding sentence similarity can be used for this step of our research work.

Research Item 6

BERT:Pre-trainingofDeepBidirectionalTransformersfor LanguageUnderstanding[17]

Summary:

In this paper, the authors have presented a novel language representation model, Bidirectional Encoder Representations from Transformers(BERT). Their proposed model learns representations by concurrently accounting for both left and right context. This enables the representations to be used with some task specific fine-tuning without altering the model architecture.

The framework is divided into two parts; pre-training and fine-tuning. The model architecture comprises of multi-layer bidirectional Transformer encoder. They have experimented with two model sizes: base and large. The former consisting of 110M parameters and the later 340M. The first token of sentences is a special token, [CLS]. As the input can consist of pairs of sentences, so to distinguish between them a special token [SEP] is used.

To pre-train BERT, two supervised tasks are used. First, a Masked Language Model is used. To do this, 15% of the input tokens are masked at random and then the task is to predict those. The vectors of those masked tokens obtained from the final hidden layer are then passed to a softmax layer. Second, Next Sentence Prediction task is used to pre-train the model. The input consists of two sentences, where 50% of the time the 2nd sentence proceeds the 1st and 50% of the time two random sentences are passed.

For fine-tuning, a classification layer is added on top of the pre-trained model and all the learnt parameters are fine-tuned at the same time. Fine-tuning is computationally inexpensive as only the output layer weights are added. No layers are frozen during

fine-tuning. Only $K \times H$ new parameters are added at output layer, where K is the number of labels and H is the size of the hidden state. And then a standard softmax loss is calculated.

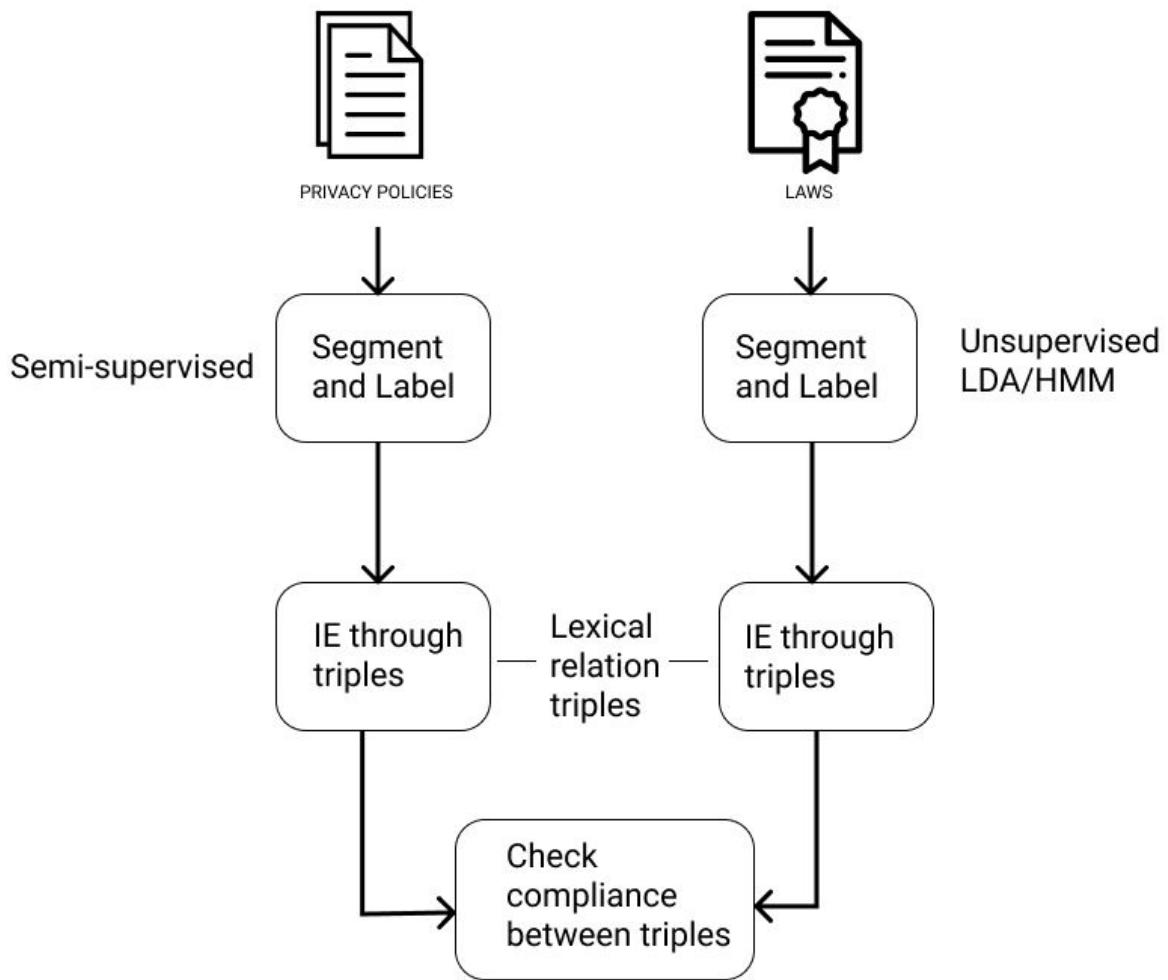
Critical Analysis:

- Strengths:
 - The pre-trained representations are built using both left and right context of words.
 - Bert produces state of the art results in 11 NLP tasks.
 - Also, the architecture remains the same for both pre-training and fine-tuning, the only difference being the output layer. The model works effectively for both single text and text pairs.
 - Although the model mostly focuses on fine-tuning, feature-based techniques can also be used to adapt the model for another task.
- Weaknesses:
 - As with all big models, it is computationally expensive to pre-train BERT.
 - Also, the transformer architecture puts equal weight on each word surrounding the target word but that might not be beneficial in all cases, as words closer to target word do in some cases convey greater meaning.
 - There is a difference in the training and testing data due to the masked language model as in training data there will be no [MASK] tokens.

Relationship to the proposed research work

BERT word embeddings can be used for various downstream tasks. Therefore we can use them with fine-tuning and an additional classification layer for labelling policies. In addition, the embeddings can also be used to find similarity between segments of laws and policies using cosine similarity.

Proposed Approach



Our approach is to first segment policies, annotating them labels according to the OPP-115 dataset[5]. Laws will also get segmented and labelled using an unsupervised technique—either Latent Dirichlet Allocation or Hidden Markov Model. Afterwards, relation triples will be used to extract information from the policies and laws' segments. And lastly those triples of policy and law's chunks will be checked for conformance.

Implementations

1. Crawling Privacy Policies

We have crawled around *60,000* privacy policies from different android applications from GooglePlay store. To do so, we wrote two different scrapers. The first one extracts the privacy policy links itself and then extracts text from them. The crawler visited around *15000* web pages of android applications. Some of the apps did not have privacy policy's link mentioned in their details. Apart from that, most apps coming from the same developer or company shared a single policy. So, in the end we were able to get around *4000* unique links. The second one makes use of the MAPS dataset [16] of around 4 million links to privacy policies. We found that most of the links provided were redundant, after eliminating those we were left with around *150000* unique links. Again, many links from this set turned out to be broken links or policies not in English. We gathered around *60000* policies using these links.

To ensure the final quality of privacy policies extracted was upto a certain mark, we wrote two different scrapers to extract text from policy links. One of them was more resilient to the way webpages were structured but the text extracted from it contained a lot of gibberish symbols. The other one, though failed to recognise some special symbols, and whenever that happened would not scrape the whole policy, but extracted much neater policy texts. In the end, we went with the latter for the sake of higher quality of policies over their quantity.

It was also important to check if the extracted policy was indeed in English or if it was privacy policy or just the main web page of the website. To do so, we passed the extracted text through a pipeline that checked the following conformities:

- The privacy policy was in English. To do so, we used the 'langdetect' Python library.
- The text was of privacy policy. We employed regular expressions to achieve this. We checked on keywords like "*404 Error*", "*Webpage not found*".. Etc
- The policy was of substantial length. To ensure that the policy was legitimate we also removed any policy that had a length less than 80 characters.

An interesting insight we got from using our own scraper to gather privacy policy links and the MAPS dataset was that, unlike a lot of redundancy of links we saw because of top apps appearing in multiple categories, our extracted links and those from the MAPS dataset had no overlap. This further highlights that our pool of privacy policies is heterogenous, and contains policies written for top apps of several regions and it also has less popular apps.

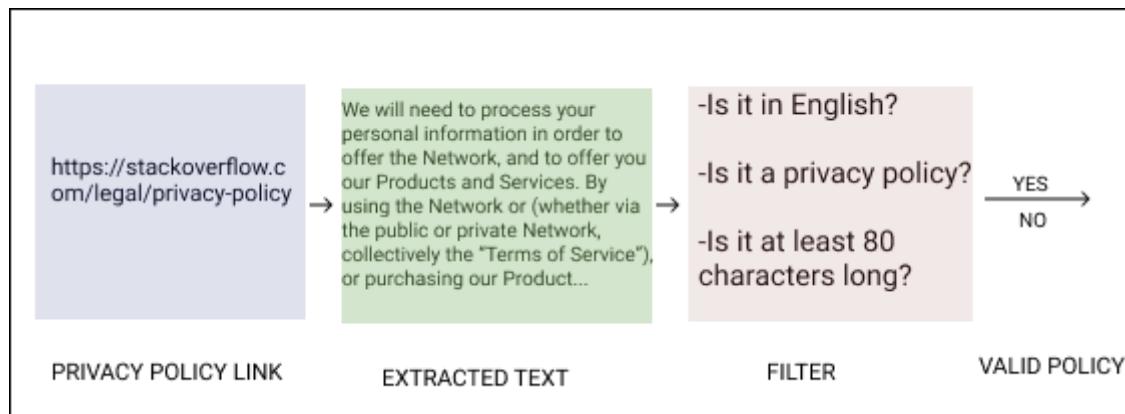
2. Labelling Policies

We have labelled policies based on the taxonomy provided by Wilson et al[5]. The taxonomy is based on a hierarchy of labelling and consists of 10 broad categories and 112 fine grained categories. The policies are segmented at paragraph level and each segment gets assigned multiple labels. The annotations were done by 3 graduate law students; there are three versions of the annotations. We have used the annotations in which there is a .75 overlap between the annotations, i.e., at least 2 of the 3 students have given the same label.

To begin with, we extracted the 115 annotated policies from the OPP-115[13] dataset, and only relevant information like the text segment of policies themselves and the assigned labels were kept. Then to cater for these multi class labels, we made binary models for classification for the 10 broad categories. Thus, for training the classifiers the dataset was divided into ten subsets where each set corresponded to one category and had binary labels (0 if the text segment did not belong to the category and 1 otherwise).

Then for the classification, we used Towards Automatic Classification of Policy Tex[19] as a starting point and trained a logistic regression model and a SVM model for classification. In addition, we also used a fine tuned version of the BERT model. We trained classifiers for all the ten datasets and calculated their F1 scores.

The whole process can be visualised as follows:



3. Labelling Laws

Since there is no available taxonomy of labelled laws along with the fact that we are not dealing with a specific country's law but rather creating a system that would be universal and would work on several countries' law. To account for this adaptability, we decided to use an unsupervised technique to label laws. Leveraging the insights from the work of Sarne et al [13], we chose to use Topic modelling and specifically

Latent Dirichlet Allocation, LDA, to annotate laws. This not only frees us from the need of having an expert in the field to label them, we can easily extend this technique to label multiple laws.

LDA works by assuming that topics in a document and words in a topic follow some specific distribution. Since it's an unsupervised technique, we only need to provide the number of topics the document has. Since it's a hyperparameter, we decided to set it to 50, so that it's broad enough to capture all the finer details of different topics and narrow enough that merging them is not a daunting task.

For our initial work, we are only focusing on GDPR and then we plan to incorporate other laws too. The GDPR is hierarchically structured in chapters, subjects and finally articles. The articles are themselves organised in numbered bullets. We have leveraged this and have split the law on the basis of this organisation. To do this, we have used regular expressions, as the GDPR does not have newlines between different paragraphs and has a unique structure; so, we could not use a built in function or library to achieve the segmentation as we desired. Next, we used GraphLab to perform the topic modelling.

4. Finding Similarity

After allocating categories to segments of laws and policies, we find similarity between segments of the laws and policies which fall under the same category. This similarity is used as a measure to decide if the policy is in compliance with the law.

We used BERT[17] word embeddings to find the similarity. Word embeddings such as word2vec and Glove have been useful in improving accuracy across NLP tasks. BERT word embeddings improve upon these methods because it is the first unsupervised, deeply bidirectional system for pre-training NLP. Context-free models such as word2vec or GloVe generate a single "word embedding" representation for each word in the vocabulary, so bank would have the same representation in bank deposit and river bank.

We use pre trained BERT uncased model to get sentence embeddings by combining word embeddings through sum and mean across layers of words. These embeddings are then used to calculate cosine similarity of the pair of sentences.

In addition, we used Universal Sentence Encoding[18]. Here also we obtained sentence embeddings and then used cosine similarity. Universal Sentence Encoder uses transformers and attention based mechanisms to capture the context of the words in a sentence in a 512 dimensional vector.

Results and Discussions

1. Labelling Policies

Categories	F1 Score of Classifiers		
	LR	SVM	BERT
First Party Collection/Use	0.79	0.81	0.86
Third Party Sharing/Collection	0.77	0.78	0.84
User Choice/Control	0.68	0.70	0.71
User Access, Edit, and Deletion	0.81	0.82	0.41
Data Retention	0.43	0.40	0.0
Data Security	0.73	0.77	0.77
Policy Change	0.83	0.78	0.66
Do Not Track	1.0	1.0	1.0
International and Specific Audiences	0.79	0.85	0.90
Others	-	-	0.73

2. Labelling Laws

Since we set the number of topics to 50, there was a need to manually check the segments assigned to each topic and merge the topics wherever an overlap was found.

3. Finding Similarity

We evaluate our similarity model by using it on the semantic textual similarity dataset as we cannot use it on our own datasets since it is not labelled. The STS dataset comprises of sentence pairs from news, captions, and forums genre. These sentence pairs are labelled for similarity on a scale of 0 to 5 where 5 means complete similarity and 0 means no similarity at all.

The table below shows the accuracy obtained on the STS development set:

Combination of word vectors	Pearson Correlation
BERT with mean of all layers	0.7854
BERT with sum of all layers	0.7854
Universal Sentence Encoder	0.76

For now, we have used feature based approach to find similarity between segments. Going forward, we will use fine-tuning techniques and hope to obtain even better results.

Conclusion and Future Work

We have made a baseline model of the whole technique. Next, we are going to explore more complex models to associate and find correlation between privacy policy segments and corresponding chunks of laws. We plan to employ Autoencoders or multi-perspective CNNs or a combination of both, whichever will give us better results. We are also going to look into the ways we can extract useful information about sentence/segment similarity from their embeddings in n-dimensional space. Also, we are going to expand the laws to incorporate multiple countries' data protection laws, like Canada's PIPEDA, US' Privacy Shield etc..

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