Detecting Compliance of Privacy Policies with Data Protection Laws

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\textbf{ABSTRACT}

Privacy Policies are the legal documents that describe the practices that an organization or company has adopted in the handling of personal data of its users. But as policies are a legal document, they are often written in extensive legal jargon that is difficult to understand. Though 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. We aim to bridge that gap by providing a framework that will analyse privacy policies in light of various data protection laws, such as the General Data Protection Regulation (GDPR). To achieve that, firstly we labelled both the privacy policies and laws. Then a correlation scheme is developed to map the contents of a privacy policy to the appropriate segments of law that a policy must conform to. Then we check the compliance of privacy policies’ text with the corresponding text of the law using NLP techniques. By using such a tool, users would be better equipped to understand how their personal data is managed. For now, we have provided a mapping for the GDPR and PDPA, but other laws can easily be incorporated in the already built pipeline.

Moreover, a company’s legal department spends hours to review its privacy policy 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\cite{3}.

Hallinan et al\cite{15} concluded through surveys that the European population at large remains skeptical now how their data is processed, any knowledge that the public has about data protection is superficial. In this technological era, users’ understanding of how their data is processed is crucial for them to make informed decisions but users either don’t have the basic understanding of their legal rights or not enough time to stay informed with the latest changes. This calls for a way to let users understand what they are signing up for without having to..

\textbf{1. Introduction}

In recent times, in the field of Natural Language Processing (or computer laws and policies?), a lot of work is being carried out to analyze\cite{16}\cite{5}\cite{12}\cite{14}, understand\cite{50} and better represent\cite{12} privacy policies, none of the work targets to relate privacy policies with data protection laws. 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 an application or software is doing with the user’s data but that information alone is not adequate to judge a policies’ transparency and its usefulness \cite{4}.

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

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.

Privacy policies and data protection 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\cite{1}. As a result, consumers don’t fully understand what they are signing up for\cite{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 policy 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\cite{3}.

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\textbf{2. Related work}

In 2016, Wilson et al\cite{5} introduced a taxonomy for privacy policies, OPP-115, and made this corpus of 115 annotated policies publicly available. Since then, much work has been done to understand various aspects of privacy policies\cite{12} \cite{50}. Sarne et al\cite{13} presented how using an unsupervised technique, Latent Dirichlet Allocation(LDA)\cite{55}, can also provide a taxonomy for privacy policies that is much more fine-grained. 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. They also showed that the taxonomy obtained had a substantial overlap with that of OOP-115. The research also provides insight into the topics that are being addressed in privacy policies these days.

Apart from that, Hidden markov models\cite{14} have been used previously to categorize privacy policies in an unsupervised way. The policies are segmented based on their section headings by crowdworkers. A Hidden Markov Model like approach is then used to align the segments such that an is-
sue (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.

Tesfay et al.[54] presented an approach to summarize long privacy policies using Machine Learning and then check against GDPR aspects as a criteria. Work has also been done to visually represent policies, for that Harkous et al.[12] developed a framework using Deep Learning techniques and the power of Convolutional Neural Networks to analyse policies on a finer level and developed a hierarchy to organise the information in privacy policies. They then presented the information in policies in a visual format and also provided a question answering interface where users’ queries about a privacy policy are answered.

Recently, Zimmeck et al.[50] compared the actual practice of a million apps with those stated in their privacy policies and flagged any discrepancies as compliance issues.

Renaud K. [23] analysis General Data Protection Regulation to find six requirements that a privacy policy compliant of GDPR must have. He provided a GDPR compliant privacy policy template for policy makers to use.

While work has been done to categorize, summarize and visualize privacy policies, none of the work has yet provided a universal method to check the privacy policies’ compliance with the very laws that regulate them.

### 3. Methodology

We propose a system which, given a privacy policy checks its compliance with a data protection law. For this, we first labelled privacy policies. Data protection laws were also segmented and labelled. Finally, we checked for the compliance of the resulting chunks of policies with those of the law. The details are mentioned in the following sections.

#### 3.1. 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 0.75 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[5] 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. The details are mentioned in the following sections.

#### 3.2. Labelling Laws

We have worked with two laws i.e., the General Data Protection Regulation-GDPR and the Personal Data Protection Act-PDPA. The first step to labelling the laws is to segment them.

##### 3.2.1. General Data Protection Regulation

For the GDPR, we followed the natural hierarchy in which it is written and segmented it according to the Articles, with one segment consisting of all the subpoints of an Article. By following this segmentation scheme we were left with 371 segments with an average word count of 75.11 words per segment. After that, we removed stopwords, punctuations and lemmatized the words.

### Figure 1: The 8 high level categories in the OPP-115 dataset. The other two categories not shown are other and Do Not Track. The latter category is not useful as it is no longer mentioned in policies.

Then for the classification, we used Towards Automatic Classification of Policy Text[53] as a starting point and trained a Logistic Regression model and a Support Vector Machine model for classification. In addition, we also used a fine tuned version of the BERT[51] model. We took the pre-trained BERT model for classification and fine tuned it using a low learning rate for each policy category. We trained classifiers for all the ten datasets and calculated their F1 scores.

We tested the three models for each category on a held out test set and calculated their F1 scores. The BERT Classifier gave better results than others, so we saved the trained model to use for privacy policy categorization at run time in the final product.

### Figure 2: The structure of the GDPR. The hierarchy consists of Chapters, Sections, Articles and then points in those Articles.

We decided to use topic modelling for grouping together similar segments and thus creating a taxonomy of the law. We used Latent Dirichlet Allocation (LDA)[55] to achieve that. The decision to use LDA was based on the promising results achieved by[13] to label privacy policies. 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, \( k \), the document has. Since it’s a hyperparameter, we experimented with several values of \( k \) and found that setting it to 10 gave the most optimal results in our case.

Perplexity scores (the lower, the better) did not give any insightful information to decide the value of \( k \). Therefore, we used the coherence score (a measure to evaluate topic models) as the deciding factor instead. The best coherence value was achieved when \( k \) was set to 5. But such a coarse labelling would not have served our purpose, since we know that the GDPR contains at least 10 different topics as those are the number of different chapters, so we went with the next favourable value of 15.

But setting the number of topics to 15 gave rise to a few topics containing only one or two segments only and merging them seemed to be a sensible option. So in the end we decided to keep the number of topics to 10.

Figure 6 shows the most occurring words in four of the topics. Most of the words are non-overlapping i.e., do not occur in multiple topics and hence show that the labelling is efficient.

3.2.2. Personal Data Protection Act

The PDPA has two main provisions:

- **Data Protection (DP) provisions.** These provisions are directly concerned with the handling and collection of users’ personal data.

- **Do Not Call (DNC) provisions.** Do Not Call Registry is not applicable to privacy policies as that part is only concerned with how to handle the telephone numbers of Singaporean users but does not in particular detail how the phone number should be collected. Including video or voice calls or text messages. But since these requirements aren’t directly linked with privacy policies, we skipped those divisions.
For the PDPA, we did manual annotation. As the PDPA is a relatively shorter law, we did not feel the need to label it through any unsupervised method to obtain the segment categorizations. Upon manual reading only PART II to PART V of the law were relevant to personal data and we extracted appropriate text from these parts.

Titles of the parts, from where law text was extracted, are mentioned below:

- **PART II**: PERSONAL DATA PROTECTION COMMISSION AND ADMINISTRATION
- **PART III**: GENERAL RULES WITH RESPECT TO PROTECTION OF PERSONAL DATA
- **PART IV**: COLLECTION, USE AND DISCLOSURE OF PERSONAL DATA
- **PART IV**: PART V: ACCESS TO AND CORRECTION OF PERSONAL DATA

3.3. Extracting Relevant Law Segments

3.3.1. General Data Protection Regulation

Leveraging the work done by Karen et al. [57], where they provide a template and lay out the requirements that policies must follow in order to be GDPR compliant. The GDPR requirements that customers must be informed about are:

- **GDPR1**: What Data will be Collected and Why
- **GDPR2**: How Data Will Be Processed
- **GDPR3**: How Long Data Will Be Retained
- **GDPR4**: Who Can Be Contacted to Have Data Removed or Produced

Next we were left with the task of manually extracting all the text from the GDPR that pertained to the specific category of our interest. Because the law was already categorized using LDA, this step became easier. Only some portion of the law was useful for our purpose i.e., the articles related to personal data processing and not the chapters about how the law itself should be implemented or where it is applicable such as the Chapter X: DELEGATED ACTS AND IMPELENTING ACTS.

For example, the Article 14 of GDPR on Information to be provided where personal data have not been obtained from the data subject [21]??, this was categorized as a GDPR segment belonging to “What Data will be Collected and Why” and so will be mapped to the First Party and Third Party category of privacy policy. In total, ten such law segments were made and given one of the four above mentioned requirements.

3.3.2. Personal Data Protection Act

According to the Personal Data Protection Commission (PDPC), there are three broader categories and then further subcategories of the obligations set by PDPA regarding protection of personal data [23]. We extracted only those subcategories that applied to privacy policies. The categories with a brief description are stated below:

- **Collection, use and disclosure of personal data**
  - **Consent** An organization should first ask customers to give consent to collect, use or disclose their personal data. Users should also have the ability to withdraw consent.
  - **Purpose and Notification** Consent should only be taken for data that is essential to provide a given service to users. Users’ data can only be obtained or disclosed for the purposes for which the user was informed about. Users should also be made aware of the reasons for data collection.

- **Accountability to individuals**
  - **Access and Correction** If customers request, they should be provided with their collected personal data along with the ways in which the data was collected and used in the time frame of a year. Users can also request to get their data updated to fix any errors.

- **Care of personal data**
  - **Retention** Data should be deleted once the purpose it was collected for has been fulfilled. Keeping data longer than needed for business reasons is prohibited.

3.4. Correlating Policy and Law Segments

When a new policy is entered to check for compliance, first it is segmented and then each segment gets labelled one or more of the 10 labels. At this stage, we have categorized policy segments (entered at runtime) and have the already labelled law segments. Next, we need to relate each of the policy segments with one or more of the law segments

**General Data Protection Regulation**

For GDPR, we take the labelled segments of policy and map the five privacy policy categories to the four GDPR requirement categories.

**Personal Data Protection Act**

The policy categories are mapped to PDPA based on the guideline provided by the PDPC

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2PERSONAL DATA PROTECTION ACT 2012. Retrieved June 10, 2020 from https://sso.ags.gov.sg/Ace/PDPA2012

3We merged two categories from the paper into one.

4GDPR Article 14(1)(d,e): “Where personal data have not been obtained from the data subject, the controller shall provide the data subject with the following information: the categories of personal data concerned the recipients or categories of recipients of the personal data where applicable”

5Data Protection Starter Kit. Retrieved June 4, 2020 from https://www.pdpc.gov.sg/-/media/files/pdpc/pdf-files/dp-starter-kit—171017.pdf
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3.5. 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 [51][17] word embeddings and Universal Sentence encoding [18] 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 mean across layers of words. These embeddings are then used to find similarity between pairs of policy and law segment using cosine similarity and euclidean distance.

By using Universal Sentence Encoding[52], we obtained sentence embeddings and then used cosine similarity. There are two model architectures present, one uses transformer architecture and gets higher quality embeddings while requiring greater resources and computing power and the second one uses less resources but at the cost of slightly lesser accuracy. We went with the latter one to utilize resources optimally. The architecture we used is the Deep Averaging Network (DAN), first word embeddings along with bi-grams are averaged and then used as input to feedforward deep neural network (DNN) to get sentence embeddings of 512 dimensions.

4. Compliance Score

Using the similarity score between the policy segments and the law segments which are related to each other, as the starting point we calculate the compliance score using the formula shown below:

\[
\text{Compliance} = \frac{\text{Max} - \text{Score}}{\text{Max} - \text{Min}}
\]

As we don’t have a labelled dataset for compliance score between law and policy segment, we created a small set to find the required compliance thresholds(max and min) .To decide on where to set the threshold for compliance and non-compliance from the cosine similarity score obtained from Universal Sentence Encodings of policy and law segments, we created a dummy dataset. The dataset consists of a law segment, for both PDPA and GDPR, and policy segment along with a score from 0 to 5. 1 being the least compliant, 5 being completely compliant and 0 showing absolute irrelevance between texts. Then the problem simply reduced to identifying the correct value of thresholds to turn the similarity score into compliance score.

For the GDPR, the threshold was found to be max 0.6 and minimum 0.25, that is, when a policy segment was in complete compliance of a law segment the similarity score was 0.6 and when it had zero compliance the score was 0.25. Using these thresholds, we find the compliance score for the four GDPR requirements: what data will be collected and why, how data will be processed, how long it will be retained and who can be contacted to have data removed or produced.

For the PDPA, the thresholds that gave the optimal results were max .09 for total compliance and min .21 for \(\frac{1}{2}\) compliance, with the compliance decrementing as the score increased towards .50.

5. Experimental Evaluation

- Labelling Policies: To evaluate the labelling of privacy policies we used a held out dataset and checked the accuracy of our models (SVM, LR, BERT) on that data. The complete results can be seen in figure 9. BERT gave a better F1 score for most categories.
- Labelling Laws: For laws, we are going to have an expert verify the labelling and annotation since there is no labelled dataset of data protection laws available.
- Finding Similarity: Due to the unavailability of policy and law compliance dataset, we evaluate our similarity model by using it on the semantic textual similarity development dataset. 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 Pearson Correlation obtained by using BERT embedding and taking mean of all word vectors and sum of all vectors as well as the correlation obtained by using Universal Sentence encoding is shown in figure 8.

• Test Case: We tested our system by using the nestle privacy policy. This policy contains a clause about data retention which states “Nestlé will only retain your personal data for as long as it is necessary for the stated purpose, taking into account also our need to answer queries or resolve problems, provide improved and new services, and comply with legal requirements under applicable laws. This means that we may retain your personal data for a reasonable period after your last interaction with us. When the personal data that we collect is no longer required in this way, we destroy or delete it in a secure manner.”

We first run the privacy policy against GDPR as it is and the system gives a 99.7 percent data retention compliance score as it should. Then we replace this section with “Nestle will store the data for as long as we want”. When this altered policy is run against GDPR, the compliance report gives a score of around zero percent.

6. Conclusion and Further Work

Our work proves that automated compliance check with regard to legal documents gives plausible results. This opens the possibility of using such techniques to find legal compliance in contracts etc. Further work can be done in this area by adding further data protection laws such as Canada’s PIPEDA and US’ Privacy Shield. Another improvement that can be done is to try more complex architectures and models to correlate laws and policies.

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Table 1

| Model                        | Pearson Correlation |
|------------------------------|---------------------|
| BERT with Cosine Similarity  | 0.55                |
| BERT with euclidean distance | 0.57                |
| Universal Sentence Encoder   | 0.76                |

Table 2

The F1 score of the Logistic Regression, Support Vector Machine and BERT across all the categories.

| Categories                          | LR  | SVM | BERT     |
|-------------------------------------|-----|-----|----------|
| First Party Collection/Use          | 0.79| 0.81| 0.85     |
| Third Party Sharing/Collection     | 0.77| 0.78| 0.87     |
| User Choice/Control                 | 0.68| 0.70| 0.73     |
| User Access, Edit and Deletion      | 0.81| 0.82| 0.66     |
| Data Retention                      | 0.43| 0.40| 0.62     |
| Data Security                       | 0.73| 0.77| 0.77     |
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