Automated Compliance Blueprint Optimization with Artificial Intelligence

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ABSTRACT
For highly regulated industries such as banking and healthcare, one of the major hindrances to the adoption of cloud computing is compliance with regulatory standards. This is a complex problem due to many regulatory and technical specification (techspec) documents that the companies need to comply with. The critical problem is to establish the mapping between technical specifications and regulation controls so that from day one, companies can comply with regulations with minimal effort. We demonstrate the practicality of an approach to automatically analyze regulatory standards using Artificial Intelligence (AI) techniques. We present early results to identify the mapping between technical specifications and regulation controls, and discuss challenges that must be overcome for this solution to be fully practical.

CCS CONCEPTS
• Security and privacy → Software security engineering.

KEYWORDS
compliance, regulation, AI

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1 INTRODUCTION
For years now, cloud computing has been proven to be the go-to-market strategy for enterprises. The staggering growth of the cloud market is expected to reach $832.1 billion by 2025 [11]. However, only 20% of the mission-critical enterprise workloads and sensitive data have been deployed so far in cloud, and the rest are still running on-premises [9]. One of the significant challenges to adopting cloud for this remaining 80% of the applications is the need to constantly comply with changing regulations. Particularly, businesses that operate in highly regulated industries such as finance, healthcare and defense must meet stringent compliance requirements.

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For example, financial institutions need to be compliant with the Payment Card Industry Data Security Standard (PCI/DSS) [22]. In healthcare, companies need to be compliant with Health Insurance Portability and Accountability Act (HIPAA) [12]. Since healthcare companies usually need to process payments, they also need to comply with PCI/DSS. On the other hand, regulations can be location-specific, for example, organizations handling personally identifiable information of European citizens must comply with General Data Protection Regulation (GDPR) [10], and the equivalence of that for California residents is California Consumer Privacy Act (CCPA) [4]. It is not uncommon for enterprises to comply with several regulations at once to conduct business for a given country.

In response to the increase in compliance requirements, several cloud providers have setup specific clouds to serve their highly regulated industry customers. For example, Microsoft’s Trusted Cloud supports financial, healthcare and government customers. Likewise, AWS’s GovCloud addresses stringent compliance requirements of United States Government customers, offering protective measures to sensitive data, ranging from Personally Identifiable Information, financial data, to patient medical records. With the hybrid cloud market set to reach 145 billion U.S. dollars in 2026, the burden is on an enterprise to have an understanding of their compliance posture across platforms and services. This visualization start with the mapping of techspecs to regulation controls.

Regulation controls can be implemented and governed by technical specifications (techspecs). Center for Information Security (CIS) benchmarks [7] and Security Technical Implementation Guides (STIGs) from US Department of Defense [23] are major techspecs that enterprises follow to enforce regulation controls. Usually, mappings between regulation controls and techspec checks are manually constructed by Subject Matter Experts (SME) to prove compliance with regulations. This exercise requires familiarity with the regulation landscape along with the technical knowledge of security implementations. This rare combination of skills make compliance process a time-consuming and expensive task. With the constantly evolving regulation and techspecs landscape, a solution is needed to help SMEs perform mapping tasks more efficiently.

In this paper, we outline a vision for an AI-assisted compliance blueprint optimizer (CBO) – see Figure 1, that will ease the compliance process for cloud-based systems by automatically:

• mapping any given techspec text to a set of related regulation controls,
• incorporating SME feedback into the process to improve and provide more accurate mapping over time,
• providing an analysis of how what regulation controls have been covered based on the mappings (coverage analysis),
and what outstanding controls need to be implemented with the techspecs (gap analysis).

![Diagram](image)

**Figure 1: Overview of how our proposed approach improves enterprise compliance process.**

## 2 MOTIVATION AND RELATED WORK

It is pretty common for organizations to adopt multiple compliance frameworks (i.e., satisfy multiple regulatory standards) due to business requirements, geographical locations, or the domain of business functions. Security professionals then decode the controls specified in these regulations and implement systems, policies, and procedures to enforce security. However, there is often an overlap between the techspec checks and regulation controls. Similar relationships can also be found between controls of different regulations.

Regulatory documents and techspecs are often text-based. We consider mapping techspec checks to regulation controls as a supervised multilabel machine learning classification problem, where a single techspec check can be mapped to multiple regulation controls. In general, the multilabel problem has been addressed in the literature with many different approaches. [13] presented a simple neural network for multilabel text classification with the cross entropy error function. Long Short Term Memory (LSTM) [27, 28] and Convolutional Neural Networks (CNN) models [6, 13, 26] have also been used for sentence and character level multilabel text classification.

In [5], the authors applied text classification approaches to EU legislation documents. Likewise, deep learning models [14, 17, 25] have also been applied to the problem of text classification across multiple domains. Specifically, pre-trained language models are an important part of AI solutions today, with Transformer models like BERT [8], RoBERTa [18], and ALBERT [16]. Pre-trained CNN-based models have also been found to be competitive and sometime outperform the Transformer models with convolutions faster and scale better to long sequences [24].

In [1], the authors set out to match regulatory requirements with actual executable code that enforce the requirements. In [2], authors presented an hierarchical classification approach for mapping customer’s security controls to cloud provider’s control set. Given a security control, [2] presented an hierarchical classification approach to mapping customer’s security controls to cloud provider’s control set. This approach maps the security control to the family within the NIST framework, then attempts to map to the controls within the identified family. The mapping algorithm used is also optimized for high level customer controls rather than technical specifications, and will miss out on mappings to the leaf node in the hierarchy whose top-level family does not show enough correlation.

Different from previous work, CBO attempts to map a given description of a technical specification checks to a given regulation controls with active learning in place to continuously learn from mistakes and improve the accuracy.

## 3 MAPPING PROBLEM

Today, as state-of-the-art, techspec check to regulation controls mapping problem is treated as a text search problem, where a given text is compared against target regulation controls. For example, a user with a techspec check: Rule - "Password expiration is set to 90 Days for existing passwords" intends to map to NIST 800-53 controls. The user identifies the keywords as password, expiration, and days. The NIST 800-53 publication is opened on a preferred file reader, and a manual search of the keywords is performed with the hope of finding the controls relevant to the techspec check. Our goal with CBO is to reduce the latency of this workflow.

CBO takes three inputs: 1) techspec text as a query, 2) the target regulatory standard (whose control set has been previously ingested to CBO), and 3) threshold for the minimum similarity percentage between the query text and the predicted controls. The threshold allow the searcher to smoothly tradeoff prediction accuracy for granularity. Next, we present details of the processes for preparing the training data for CBO, the mapping algorithms used, how the result of the mapping process is presented, and how the SME feedback is continuously captured.

### 3.1 Preprocessing

Regulatory standards are often expressed as text. These documents are often available as spreadsheets, making them relatively easy to parse and process. First, the metadata relevant to the description of each control specification is identified. These metadata are title, rationale and remediate (fix). Stop words and punctuation are removed, resulting in reduced data space and cleaner content. Additionally, the text is tokenized, normalized (all text converted to lower case), and de-noised (e.g., removing extra white spaces and unidentified characters). Each control specification is tagged with the associated regulation control identifier as the mapping.

### 3.2 Text Search with Elasticsearch

Elasticsearch (ES) provides a Lucene based search engine, exposed via APIs [20]. The pre-processed text is batch-loaded into ES with each control specification and its associated meta-data represented as a document. Text is sent via the ES APIs to query a collection, and...
3.3 Text Classification with CNN

Orthogonal to text search with ES, CBO uses a second, machine learning based approach for mapping. Text classification uses a classifier to label unknown text given a pre-trained model. Text representation is an essential step in the training model development. The representation of the training data is vectorized before training the CNN model. Our implementation of the CNN algorithm is an adaptation of [3, 15, 19]. In a nutshell, the CNN model is a 3-layer Neural Network: the first layer is a convolutional layer, the middle layer is a max-over-time pooling, and the last layer is a fully connected output layer with a sigmoid activation function. With the CNN model, a category/label is given as output for any new unclassified text based on the experience derived from the training data.

3.4 Mapping result

The mapping results derived from ES and CNN are represented as a dictionary of regulation controls with a corresponding confidence score. The confidence score measures the similarity between the techspec check input and the predicted regulation control(s). In reality, techspec check mappings are often non-deterministic due to the inherent subjectivity in the mapping point of view. This subjectivity makes it imperative to find all regulation controls relevant to a given techspec check. To do this, the results of both CNN and ES are combined in a hybrid approach to capture more mapping possibilities while maintaining the relevance of the results. Example of mapping results are shown in Table 1.

3.5 Active Learning with SME Feedback

It is difficult to achieve perfect mapping accuracy with any AI technique. CBO addresses this by capturing continuous feedback from SMEs with a simple active learning mechanism where each additional sample is added to ES. CNN is also re-trained after every $y$ new sample where $y$ is a hyper-parameter, e.g., 50.

4 EVALUATION

The performance of the proposed mapping algorithm is evaluated by running experiments with the dataset that is described next.

4.1 Dataset

We used a set of 429 STIGs documents containing 18757 techspec checks for various technologies as training data for CBO. Each security recommendation in these documents is mapped to one or more regulation controls in the NIST 800-53 v4 family. We combine the title, description, rationale, and fix columns to form the specification text through the text pre-processing step and the corresponding NIST 800-53 v4 regulation control as the label. We divide the dataset into $k = 3$ random folds with one fold used for testing and $k - 1$ folds for training to initialize the algorithms. The testing fold accounts for 15% of the dataset. Results presented are averaged over multiple iterations of the experiment.

4.2 Experimental Result and Analysis

The first set of experiments were designed to prove the advantages of the hybrid proposed approach over the individual CNN and ES...
methodologies. We evaluated the results using the precision and recall metrics with varying confidence thresholds for the mapping result as shown in Figure 2. Varying the confidence threshold provides an opportunity to evaluate the performance of the models based on the likelihood that the mapping result may be associated with the input techspec based on the training data. This provides an alternate approach to choosing the top \( k \) results from the resultset.

![Figure 2: Performance analysis of different approaches on different confidence thresholds.](image)

Across confidence thresholds, the Hybrid approach achieves a better recall than CNN and ES but is outperformed by CNN in terms of Precision. Based on the volume of training data and the structure, the CNN model reaches a tighter fit to the data hence the high precision. With the high recall, CBO gives a better chance at retrieving all possible mappings for a given techspec check but also with a higher chance of having irrelevant mapping outcomes due to the lower precision relative to CNN. The hybrid approach however makes it easier for the SME to verify these mappings since it is often faster to identify incorrect mapping than it is to find correct ones. These verified mappings are subsequently used to improve the performance of CBO in future iterations. We also observe that at high confidence thresholds, the hybrid approach records precision closer to CNN, and achieves better recall than both CNN and ES. This allows the searcher to select higher confidence thresholds in CBO without compromising precision and recall, unlike when using CNN or ES individually.

To evaluate the impact of the active learning mechanism on CBO, SME feedback is simulated by using a dataset of security rules from the RedHat Openshift Compliance Operator [21]. 360 security rules with existing mappings to NIST 800-53 \( v4 \) are selected to enrich the dataset in 5 iterations of equal sizes such that \( y = 72 \). 72 security rules are added to X at each iteration, while CNN is also retrained with the additional rules. Iteration 0 represents the performance of CBO without SME feedback.

As shown in Figure 3, CBO achieves better F-score with SME feedback \(( \geq 0.908 \) \). With no SME feedback captured, the F-score is \(( 0.874 \) \). A significant improvement in the F-score is achieved after the first iteration, indicative of SME feedback’s positive impact. We chose F-score as the evaluation metric as it provides us with an average view of the effect of the active learning process in reducing the number of incorrect mapping results, as well as in providing a good percentage of the actual correct mapping in the mapping result. The cost of active learning by CBO is also measured. Training the CNN model took an average of 0.08 seconds/entry compared to the 2.2 seconds/entry for data entry into ES.

![Figure 3: Effect of SME feedback on the accuracy of CBO](image)

### 5 CHALLENGES AND DISCUSSION

**Level of details in text:** One of the major challenges of a mapping problem is the level of details in text. Regulations are usually written in legal language with high level descriptions, whereas techspecs are written in technical language with low level details. This makes it challenging for AI techniques to match different granularity of information with each other. To alleviate the problem, as a future work, we plan to enrich the texts of regulations and techspecs with self-supervised transformer models to bring additional context in addition to the original content.

**Weak labels for learning:** Keeping human in the loop is critical to the success of CBO. Experts represent years of experience that compliments the AI approach of CBO. However, the combination of skill sets (compliance and technical) required for experts in mapping is both unique and rare. Often this leads to inconsistencies in mappings, which in turn affects the accuracy of the AI model. CBO’s methodology as an ensemble approach \((\text{Search + AI})\), to some extent, is a response to this problem. As a future work, we will extend this approach to rank experts and weight their contribution for better AI models.

### 6 CONCLUSION

In this paper, we propose CBO - an AI-assisted approach for mapping techspec checks to regulation controls with human in the loop. In future work, we will extend CBO to achieve mapping to other regulatory standards, incorporate additional context by using transformer models and account for expertise difference of SMEs to
achieve better accuracy. We will also expand the dataset to further validate the active learning accuracy.

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