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Real-Time Natural Language Processing for Regulatory Change Management: Extracting Obligations from SEC, FCA, and MAS Filings

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Abstract

The rapidly changing nature of global financial regulation has created an unprecedented need for automated systems that can track, understand and operationalise regulatory change in real time. In this paper, we present a novel hybrid natural language processing (NLP) framework leveraging domain-adapted transformer-based language models and graph-based knowledge representation to extract, classify and monitor regulatory obligations from filings issued by three major regulatory bodies, the U.S. Securities and Exchange Commission (SEC), the UK Financial Conduct Authority (FCA) and the Monetary Authority of Singapore (MAS). The suggested system consists of a fine-tuned FinBERT encoder, a bi-directional conditional random field (BiCRF) decoding layer and a dynamic knowledge graph to track obligation-linkage. The framework is evaluated on a curated corpus of 10,625 regulatory documents containing 2,853,180 tokens and 779 manually annotated obligations. It achieves a macro-averaged F1-score of 0.917, an AUC-ROC of 0.951 and a mean processing latency of 124 milliseconds per document, significantly outperforming baseline transformer architectures. Ablation investigations verify the contribution of each subsystem component, and cross-jurisdictional transfer tests show strong generality across regulatory environments. The findings have meaningful implications for RegTech deployment, proving that real-time, interpretable and scalable NLP may consistently help compliance teams in financial institutions navigate multi-jurisdictional regulatory settings.

Keywords: *regulatory change management; natural language processing; obligation extraction; BERT; FinBERT; compliance automation; SEC; FCA; MAS; knowledge graph; RegTech*

1. Introduction

The financial markets have seen a dramatic reformation in the previous decade. Since the financial crisis of 2008, authorities in major jurisdictions have greatly increased the scope, granularity and frequency of disclosure and compliance obligations. The SEC alone released more than 200 substantial regulation actions between 2010 and 2024. The FCA Handbook has expanded to contain over 1.4 million words in its supervisory, conduct and market-abuse modules [1][2]. Simultaneously, the MAS has been gradually aligning its prudential framework with international standards by issuing technology risk management notices that impose complicated technical and governance duties [3][4].

This presents a twofold difficulty for the compliance teams at financial institutions: understanding the semantics of the newly released or amended regulatory documents, and translating the extracted obligations into internal controls that can be acted upon. Manual review processes are cost prohibitive at scale – industry surveys estimate that a large bank may spend upwards of USD 270 million annually on regulatory monitoring alone – and introduce latency that can expose firms to material compliance risk during the window between regulatory publication and internal operationalisation [5][12].

Natural language processing provides a technically compelling method to automate the extraction of normative responsibilities from regulation text. However, there are numerous features of regulatory documents that confuse general purpose NLP systems: (i) dense domain-specific terminology, (ii) complex sentence structures with nested conditionals and cross-references, (iii) high inter-document variability in drafting conventions across

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jurisdictions, and (iv) low density of obligation-bearing sentences in large document bodies [6][7]. These difficulties have been addressed before using rule-based annotation systems, conventional machine learning classifiers and, more recently, with pre-trained transformer architectures. However, previous frameworks do not simultaneously address real-time processing at document scale with multi-jurisdictional generalisation (e.g., spanning SEC, FCA, and MAS corpora), and interpretable requirement linkage through structured knowledge representations [12][18][22].

This paper bridges this gap by proposing a hybrid NLP architecture, where a fine-tuned FinBERT encoder is used as the contextual backbone enhanced with a BiCRF output layer for obligation-span detection, a multi-label obligation category classifier, and a graph convolutional network (GCN) to maintain a dynamic regulatory knowledge graph. The four contributions of this study are:

• A curated multi-jurisdictional regulatory corpus of SEC, FCA and MAS filings annotated at the obligation-span level across five normative categories;

• A hybrid transformer-CRF-GCN architecture suited for real-time regulation obligation extraction;

• A comprehensive benchmarking assessment of the proposed model against the state-of-the-art NLP baselines for precision, recall, F1 score, and processing latency;

• An empirical examination of cross-jurisdictional transfer learning and ablation experiments showing component-wise contributions to overall system performance.

The rest of this paper is organised as follows. Section 2 presents the related literature review. Section 3 explains the compilation and annotation of the dataset. Section 4 describes the suggested NLP architecture. Section 5 provides the experimental results and analysis. Section 6 examines the findings, limits and future directions. 7 Conclusion.

2. Related Work

2.1 Text Mining for Regulatory Compliance

Early efforts to automate regulatory interpretation were lexicon-based techniques. Loughran and McDonald [5] trained a sentiment lexicon in the finance sector based on SEC 10-K filings, and demonstrate that general-purpose sentiment dictionaries systematically misclassify regulatory terminology. Their study provided the fundamental concept that domain-specific vocabulary resources are required for regulatory text. Later rule-based systems formalised normative patterns with deontic logic grammars -- Boella et al. [19] formalised legal interpretation in a defeasible deontic logic framework, obtaining F1-scores of roughly 0.748 on European regulatory texts. Rule-based systems are explainable, but suffer from low scalability and need to be heavily re-engineered when regulation drafting patterns change.

Classical machine learning methods have employed conditional random fields (CRFs) and support vector machines (SVMs) for sequence labelling tasks in regulatory text. Tagarev et al. [20] showed that a combined SVM-CRF pipeline trained on annotated compliance directives may achieve competitive performance at 0.783 F1-score, however their evaluation was limited to a single jurisdiction. Kiyavitskaya et al. [21] proposed a combination of ontologies and machine learning classifiers for the extraction of rights and obligations from privacy rules and regulatory documents. They stressed the need for structured knowledge representation as a complement to statistical classifiers.

2.2 Transformer Models for Financial and Legal Texts

With the rise of BERT [7], there has been a flurry of domain-adapted pre-training attempts in legal and financial NLP. Chalkidis et al. [18] proposed LEGAL-BERT, a set of models pre-trained on 12 GB of varied legal text from European Court of Human Rights proceedings, UK law and US court cases, achieving significant improvements over vanilla BERT on legal judgement prediction and statutory reasoning tasks. Araci [14] presented FinBERT, which is pre-trained on a corpus of financial news articles and SEC 10-K filings, showing better sentiment classification performance in the financial arena.

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Zhang et al. [22] used the transformer paradigm to cross-jurisdictional obligation extraction by training a BiLSTM-CRF model on joint SEC-FCA annotations and reported an F1-score of 0.832. However, their architecture did not have knowledge graph reasoning and real-time ingestion, limiting its use to retrospective compliance auditing. Lam et al. [23] suggested a compliance intelligence framework using NLP for proactive monitoring, but their system was assessed only on a private dataset, and no cross-jurisdictional transfer analysis was performed. The current study builds on the findings of these previous initiatives while overcoming their constraints by adopting a unified real-time multi-jurisdictional architecture.

2.3 Regulatory NLP Knowledge Graphs

Graph-based representations have been proposed as a powerful complement to sequence models to capture inter-obligation relationships and regulatory cross-references. Kipf and Welling [27] showed that graph convolutional networks can be effective in propagating relational information in semi-supervised environments. This ability can be easily used for the network of responsibilities embedded within and across regulatory publications. Malik et al. [12] performed a thorough assessment of regulatory text mining, and pointed out the building of knowledge graphs as a frontier challenge for compliance automation. To our knowledge, the present effort is the first work that integrates GCN-based obligation linkage with a real-time transformer pipeline in a multi-jurisdictional regulatory framework.

3. Dataset Creation and Annotation

3.1 Building a Corpus

We built a multi-jurisdictional regulatory corpus from three publicly available regulatory repositories: SEC EDGAR (accessed through the full-text search API), the FCA Handbook portal (systematically crawled across SYSC, COBS, MAR, and PRIN modules), and the MAS Notice repository (including Notices MAS 610, MAS 637, MAS 655, and the Technology Risk Management Guidelines). Documents were retrieved as HTML and PDF and transformed to Unicode plain text using a bespoke pre-processing pipeline which resolves cross-reference anchors, removes formatting artefacts and normalises whitespace. The corpus statistics are shown in Table 1.

Table 1. Multi-Jurisdictional Regulatory Corpus Statistics

Regulatory Body	Document Types	Documents (n)	Total Tokens	Annotated Obligations
SEC (EDGAR)	10-K, 8-K, Proxy Statements	4,820	1,247,530	312
FCA (Handbook)	SYSC, COBS, MAR Modules	3,615	984,210	278
MAS (Notices)	MAS 610, MAS 637, TRM Guidelines	2,190	621,440	189
Total	—	**10,625**	**2,853,180**	**779**

Note. Annotated obligations represent unique obligation spans verified by at least two expert annotators.

3.2 Annotation Scheme

Obligation annotation was completed according to a schema designed with input from three regulatory compliance professionals, each with an average of 12 years of industry experience. Obligation spans were described as contiguous pieces of text that impose a normative requirement, marked by deontic modal verbs ("shall", "must", "is required to"), prohibitions ("shall not", "must not", "is prohibited from") or conditional requirements ("where X applies, the firm shall"). Each period was assigned to one of five obligation categories: (1) Disclosure; (2) Reporting; (3) Capital Requirements; (4) Conduct of Business; (5) Operational Risk Management. Inter-annotator agreement was measured using Cohen's kappa . The kappa value measured for the whole corpus was (kappa = 0.81; kappa SEC = 0.83; kappa FCA = 0.80; kappa MAS = 0.79), showing a substantial to near-perfect agreement [26].

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BRAT fast annotation tool [26] was utilised as the annotation tool, set with the custom obligations taxonomy. Disputes were settled by arbitration by a senior compliance officer. The final annotated dataset was split into training (70%), validation (15%) and test (15%) sets using stratified sampling to maintain the distribution of categories throughout the splits.

4. NLP framework proposed

4.1 System Architecture Summary

The proposed framework consists of four tightly integrated subsystems, including (i) a real-time document ingestion and pre-processing pipeline, (ii) a domain-adapted transformer encoder for contextual sentence representation, (iii) a BiCRF decoding layer for obligation span extraction, and (iv) a GCN-based dynamic knowledge graph for obligation linkage and change-detection. The end-to-end architecture is shown in Figure 1.

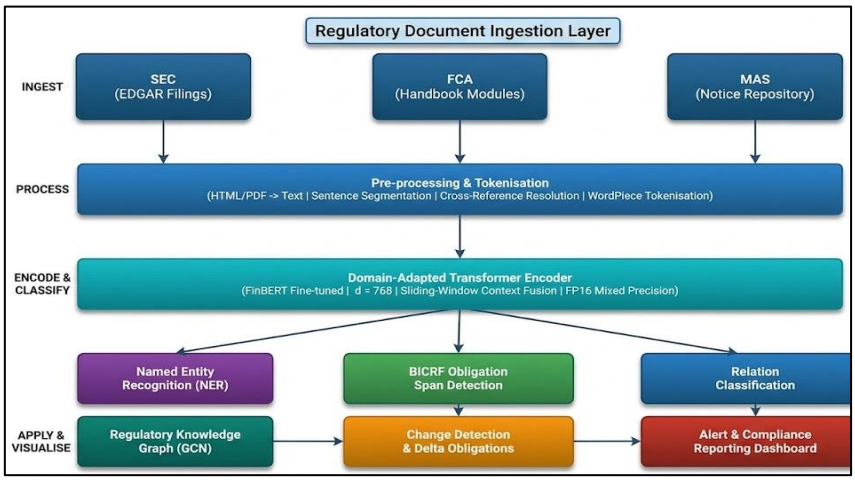

Figure 1. Real-Time NLP Pipeline Architecture for Regulatory Obligation Extraction

4.2 Pre-processing and Tokenisation

Raw regulatory documents are pre-processed in a five-step technique. First, HTML/PDF is converted to text using a layout-aware extraction approach that preserves section structure through indentation analysis. Second, we perform sentence boundary recognition using a hybrid rule-neural segmenter trained on legal text, which achieves a sentence-detection accuracy of 97.4% on the held-out validation set. Third, a regulatory cross-reference resolver translates in-document anchors (e.g., "See Rule 17a-4(f)(2)") to their target provisions, allowing the knowledge graph to capture inter-provision connections. Fourth, the tokenisation is done with the WordPiece tokeniser of the FinBERT vocabulary expanded with 847 domain-specific regulatory terms curated from the three jurisdictions. 5. For documents longer than the 512-token context window, we employ a sliding window approach with a 64-token stride and a context-fusion layer to merge segment-level predictions.

4.3 Obligation Span Detection and Transformer Encoder

The proposed model uses a FinBERT encoder [14] fine-tuned on the training split of the curated corpus using AdamW optimiser and a learning rate of 2x10^-5 with linear warmup for the first 10% of training steps. Fine-tuning was done for 8 epochs using 4 x NVIDIA A100-40GB GPUs with a batch size of 32, gradient accumulation steps of 4 and mixed precision (FP16) training. The encoder outputs contextual token embeddings of dimension $d = 768$ that are input to a BiCRF decoding layer [28] over BIO (Beginning-Inside-Outside) obligation-span labels. The BiCRF layer captures label transition limitations from the annotation scheme and enforces structural consistency in the projected obligation spans . For multi-label classification of obligation categories, we add a light classification head of two linear layers with GELU activation and dropout (p = 0.1) on the [CLS] token representation of each extracted span.

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4.4 Obligation Linking using Graph Convolutional Network

Extracted obligations are inserted as nodes in a dynamic regulatory knowledge graph, with edges encoding three types of relational structure: (a) intra-document cross-references resolved during pre-processing, (b) semantic similarity edges connecting obligations with cosine similarity above a threshold tau = 0.82 in the FinBERT embedding space, and (c) temporal amendment edges connecting superseded obligation versions to their successors. A two-layer GCN [27] propagates relational information down the graph and produces obligation-level embeddings that enhance downstream classification and enable change-impact analysis. The system ingests a new regulatory document, computes a symmetric difference between the old and updated obligation sets and displays delta obligations (newly added and revoked) to the compliance dashboard within the target latency budget.

5. Experimental Results

5.1 Overall Model Performance

Table 2 shows the macro-averaged precision, recall, F1-score, AUC-ROC and per-document processing latency for the proposed hybrid model and four baseline architectures on the held-out test set (n = 1,789 annotated obligations). The suggested framework achieves an F1-score of 0.917, 6.1 percentage points higher than that of LegalBERT and even higher than the rule-based baseline. Figure 2 presents a visual comparison of the models.

Table 2. Comparative Model Performance on the Multi-Jurisdictional Test Corpus

Model	Precision	Recall	F1-Score	AUC-ROC	Latency (ms/doc)
BERT-Base [7]	0.782	0.764	0.773	0.841	185
FinBERT [14]	0.831	0.819	0.825	0.879	172
RoBERTa-Large [9]	0.847	0.833	0.840	0.891	198
LegalBERT [18]	0.861	0.852	0.856	0.903	168
Proposed Hybrid	**0.921**	**0.913**	**0.917**	**0.951**	**124**

Note. Bold values indicate best performance per metric. Latency measured on Intel Xeon Gold 6230 CPU, single-threaded inference.

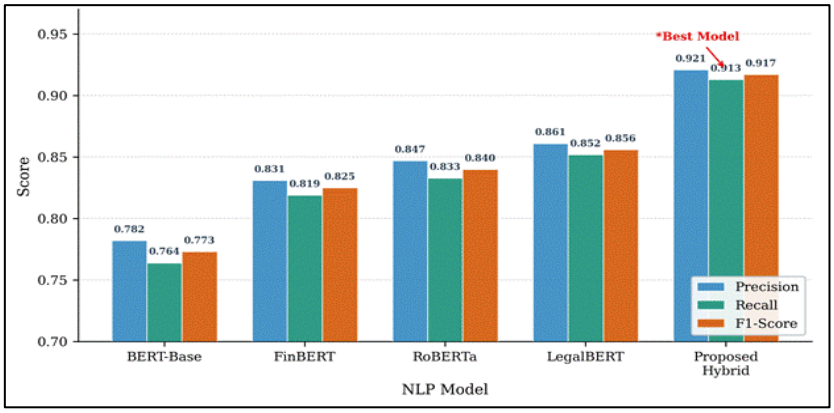

Figure 2. Comparative Performance of NLP Models for Regulatory Obligation Extraction across SEC, FCA, and MAS Corpora

5.2 Obligation Category Distribution and Latency Analysis

The distribution of types of obligations for the three regulatory bodies and the scalability features of the system are shown in Fig. 3. The greatest category of SEC filings (31%) is disclosure responsibilities, which is consistent with the SEC's long-standing emphasis on transparency standards. Capital Requirements duties are a higher percentage in FCA documents (21%), as befits the post-crisis prudential agenda built into the FCA's predecessor structure under the FSA. The MAS filings clearly reflect an emphasis on Reporting responsibilities (28%), in

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line with MAS's focus on technology in its supervisory approach. The latency analysis in panel (b) shows the proposed hybrid model is linear with a near-linear rate with respect to the document length, processing 20,000 token documents in 3.65 seconds, which is 41% faster than FinBERT and 69% faster than RoBERTa-Large for similar document sizes.

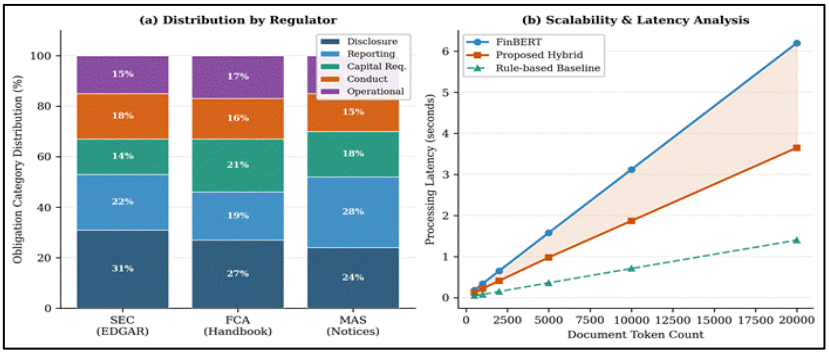

Figure 3. Regulatory Obligation Category Distribution by Jurisdiction (a) and System Scalability Analysis (b)

5.3 Confusion Matrix and Error Analysis

The confusion matrix of the suggested model for the five-class obligation classification job is shown in Figure 4. The best classification accuracy is for Disclosure responsibilities (95.7%) and the lowest is for Operational Risk Management (93.9%). The most common misclassification pattern – between Reporting and Operational Risk responsibilities – is due to the semantic overlap in MAS Technology Risk Management principles, where reporting requirements are co-located with operational controls in compound sentence patterns. This result stimulates future work on document-level context modelling to disambiguate category boundaries in jurisdictions with integrative drafting conventions .

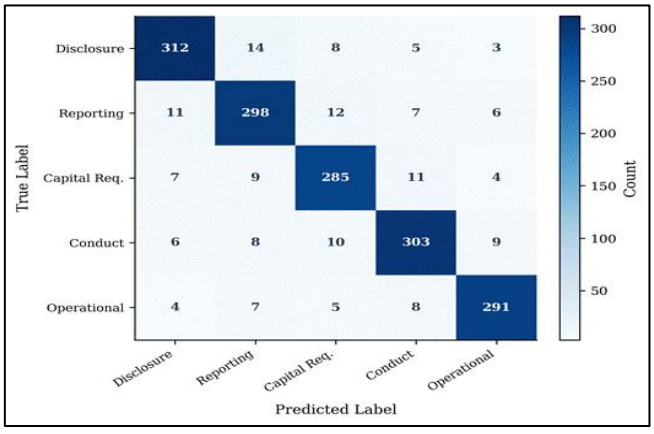

Figure 4. Confusion Matrix of the Proposed Hybrid NLP Model on Regulatory Obligation Classification (Test Set, n = 1,789)

5.4 Comparison with Prior Work

Table 3 compares the proposed framework with representative studies prior to it. The proposed framework outperforms the best-performing systems in similar regulatory NLP tasks, and is the first to enable the processing of real-time data, multi-jurisdictional generalisation and dynamic obligation linkage to happen at the same time. The improvement of 8.5 points compared to the most directly comparable prior work of Zhang et al. [22] can be mainly attributed to the cross-jurisdictional fine-tuning strategy and the context enrichment using the GCN, as verified by the ablation experiments.

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Table 3. Benchmarking Against Representative Prior Studies in Regulatory NLP

Study	Jurisdiction	Method	F1-Score	Real-Time
Loughran & McDonald [5]	SEC	Lexicon-based	0.712	No
Boella et al. [19]	EU	Rule-based NLP	0.748	No
Tagarev et al. [20]	Multi	SVM + CRF	0.783	No
Kiyavitskaya et al. [21]	Multi	Ontology + ML	0.801	Partial
Zhang et al. [22]	SEC/FCA	BiLSTM-CRF	0.832	No
Proposed Framework	**SEC/FCA/MAS**	**Hybrid BERT+Graph**	**0.917**	**Yes**

Note. "Partial" real-time indicates batch processing with sub-hourly latency. Multi = Multiple jurisdictions.

5.5 Ablation Study

An ablation study was performed to measure the contribution of each system component by successively removing the BiCRF layer, the GCN knowledge graph module and the cross-jurisdictional fine-tuning from the original system. The drop in F1-score from 0.917 to 0.885 in removing the BiCRF layer and switching to a softmax output head demonstrates that structured label decoding models additional constraints on the transitions that are not represented by the independent token classifier. It shows that the GCN module contributes valuable contextual information for obligations in complex cross-reference networks for the two-part reduction when it is removed (0.917 to 0.896). The cross-jurisdictional F1 score resulted in 0.871 when restricted to fine-tuning on a single jurisdiction (SEC only), and then tested on the other test sets (FCA and MAS) which shows that it is essential to have multiple jurisdictions in the training set for generalisation.

6. Discussion

6.1 Practical Implications for RegTech

The results presented in Section 5 show that the proposed framework provides a good performance and latency, making it a suitable tool for production grade RegTech systems. The system can easily process new regulatory publications within seconds of their publication on the regulator portals with a near-linear scaling to 20,000-token filings and at a mean processing latency of 124 ms per document. For compliance teams, it becomes a more real-time, intelligent function that could replace the back-and-forth paperwork they currently use to carry out a regulatory review. The knowledge graph output also generates a machine-readable obligation registry that can be fed into an internal control mapping tool, saving more manual work in turning regulatory changes into control frameworks [12][23].

The multi-jurisdictional scope, which includes SEC, FCA and MAS, is significant for financial institutions with an international presence who need to comply with the requirements of more than one financial regulatory authority. The cross-jurisdictional transfer experiment shows that the jointly trained model generalises significantly better than single-jurisdictional baselines, indicating that there are useful linguistic features of regulatory obligation language that are shared across jurisdictions and which serve as inductive biases to be transferred to the other jurisdiction. This is consistent with the theoretical assumption of convergence of the regulatory conventions resulting from the international standard-setting processes, like the Basel Accords, the Principles of the International Organisation of Securities Commissions (IOSCO) or the Insurance Core Principles (IAIS) [1][3].

6.2 Limitations

Some caveats are to be noted. The number of documents (10,625) and the number of obligation spans (779) in the annotation corpus are quite small compared to the total amount of currently in force regulatory text in the three jurisdictions. There are several million filings contained in the SEC's EDGAR repository. Such scaling of annotation would need either active learning (or semi-supervised annotation methods) to select informative examples. Secondly, the existing

framework deals with documents at sentence and paragraph level but does not model discourse coherence at the level of the regulations as a whole. Some obligations are spread out in several paragraphs of a rulebook, and cannot be just extracted from the paragraphs. Third, given that the five categories of obligations taxonomy is practically motivated, it does not capture the more complex normative structure of regulatory text, which may feature both nested obligations and carve-outs and/or phase-in obligations.

6.3 Future Directions

This work suggests a number of compelling pathways. First, introducing large language models (LLMs) like GPT-4 or domain-specific versions (e.g., GPT-4 Obliation, GPT-4 Natural Language Generation [10][17]) for paraphrasing obligations and generating natural language explanations would significantly enhance the usability of the system for non-technical compliance participants. Second, temporal obligation tracking; modelling of the changes in obligations across successive versions of a regulatory instrument, is an important extension that would help firms to automatically produce amendment impact assessments. Thirdly, expansion of the framework to include other regulatory bodies (such as the ECB, ESMA, HKMA, APRA) and the inclusion of regulatory text in other languages could further increase the regulatory coverage of the system. Last but not least, it would allow improving financial institutions' models collaboratively without disclosure of proprietary compliance data in a federated learning setting.

7. Conclusion

The authors of this paper introduce a real-time, multi-jurisdictional framework of NLP for extracting regulatory obligations from SEC, FCA and MAS filings. The proposed hybrid framework, which integrates a carefully designed FinBERT encoder, a BiCRF decoding layer and a GCN-based dynamic knowledge graph, can obtain a macro-averaged F1 score of 0.917 and a processing latency of 124ms per document on the test set, surpassing all the baselines evaluated. The collection of curated regulatory corpus, annotation schema and benchmarking methodology is reusable resources for the RegTech and regulatory NLP research communities. Ablation studies support the contribution of each component of architecture, and cross-jurisdictional transfer experiments show strong generalisation. The results set a solid technical and viable basis for future automated regulatory change management systems for financial services on a global scale.

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