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Abstract

The rapid proliferation of insurance products and the increasing complexity of policy documents have made it challenging for customers and insurers alike to efficiently navigate and understand contractual details. Traditional manual summarization methods are time-consuming, error-prone, and lack consistency. In recent years, large language models (LLMs) such as GPT-4 and its derivatives have emerged as transformative tools in the field of natural language processing, offering significant promise for automating text summarization tasks across diverse domains. This research investigates the application of LLMs in automating the summarization of insurance policy documents, focusing on the models' ability to preserve semantic integrity, legal accuracy, and readability for lay audiences. We provide an in-depth analysis of current methodologies, benchmark model performances against human-generated summaries, and evaluate their efficacy using both quantitative and qualitative metrics. The results suggest that LLMs exhibit strong potential in transforming insurance policy delivery and comprehension, though several challenges related to domain specificity, factual consistency, and interpretability remain. This study concludes with a discussion of the implications for the insurance industry and proposes future research directions for the integration of domain-adaptive LLMs into automated policy summarization systems.

Keywords: Large Language Models, Insurance Policy Summarization, Natural Language Processing, Legal Document Summarization, GPT-4, Automated Insurance Systems

Introduction

The insurance industry generates vast amounts of textual data in the form of policies, claims, endorsements, and regulations. Among these, policy documents are critical in delineating the rights, obligations, and coverages for policyholders. However, these documents are often lengthy, complex, and densely populated with legal and technical jargon, making them inaccessible to the average consumer. The necessity to enhance policyholder understanding has prompted insurers to explore automated solutions for policy summarization. Traditional rule-based and statistical summarization techniques have had limited success in this domain, largely due to their inability to grasp the contextual and semantic nuances embedded in legal language.

Recent advancements in artificial intelligence, particularly the development of large language models, have unlocked new possibilities for document summarization. These models, trained on massive corpora, have demonstrated unprecedented capabilities in understanding and generating human-like text. In the context of insurance, LLMs promise not only to automate summarization processes but also to improve the clarity, coherence, and accessibility of policy documents. Despite these advantages, concerns persist regarding the factual consistency, ethical implications, and domain-specific adaptation of LLMs. This paper

presents a comprehensive investigation into the deployment of LLMs for insurance policy summarization, with a focus on performance evaluation, methodological rigor, and industrial applicability.

Literature Review

The problem of document summarization has been a long-standing challenge in natural language processing. Early methods relied on extractive approaches, selecting key sentences based on statistical measures such as term frequency and inverse document frequency. While effective in highlighting salient points, these methods often resulted in disjointed and incoherent summaries. Abstractive summarization, which involves generating novel sentences that capture the essence of the source text, emerged as a more promising but computationally intensive alternative.

With the introduction of transformer architectures and the subsequent development of models like BERT, T5, and GPT, the field witnessed a paradigm shift. These models leverage attention mechanisms to capture contextual dependencies across long sequences, enabling them to generate coherent and contextually relevant summaries. In the legal and insurance domains, summarization tasks present unique challenges due to the precision, domain-specific vocabulary, and hierarchical structure of the documents involved.

Several studies have explored the use of LLMs in legal text summarization. Models like LegalBERT and CaseLaw-BERT have shown promising results when fine-tuned on legal datasets. In the insurance sector, limited but growing literature has addressed automated summarization. Research by Yang et al. (2022) demonstrated the potential of fine-tuned BART models for summarizing home insurance policies, noting improvements in readability and information retention. Another study by Singh and Mehta (2023) explored domain adaptation techniques for GPT-based summarizers, highlighting the trade-offs between model generalization and domain fidelity.

Despite these advances, concerns remain regarding hallucinations—where models generate plausible but incorrect information—especially when summarizing documents with legal implications. Addressing these concerns requires robust evaluation frameworks and integration of external validation mechanisms, such as knowledge graphs or retrieval-augmented generation. This study builds upon prior work by evaluating general-purpose and fine-tuned LLMs for insurance policy summarization, assessing their performance using domain-specific benchmarks and human evaluation.

Methodology

The methodological framework for this study encompasses data acquisition, model selection, fine-tuning, summarization task formulation, and evaluation. We sourced a diverse corpus of insurance policy documents from publicly available databases and anonymized customer policy samples provided by industry partners. The dataset includes a range of policy types, including life, health, automobile, and property insurance, each containing standard sections such as declarations, coverages, exclusions, and endorsements.

Three LLMs were selected for comparative analysis: GPT-3.5, GPT-4, and a fine-tuned version of BART trained on insurance-specific documents. The choice of these models was guided by their prominence in prior research and accessibility through commercial APIs or

open-source frameworks. Each model was tasked with generating abstractive summaries of policy documents constrained to a maximum of 200 words, optimized for clarity, completeness, and layperson comprehension.

Fine-tuning of the BART model involved supervised learning using a subset of the insurance corpus manually annotated with human-generated summaries. Data augmentation techniques such as paraphrasing and section shuffling were employed to enhance model generalization. Summarization tasks were defined using prompt engineering for GPT models and sequence-to-sequence mapping for BART. Evaluation metrics included ROUGE-1, ROUGE-2, and ROUGE-L for n-gram overlap, BERTScore for semantic similarity, and a domain-specific factual consistency score computed through a rule-based policy clause validator.

In addition to quantitative metrics, we conducted a qualitative evaluation involving domain experts and lay users. Experts assessed summaries for legal and factual accuracy, while users rated summaries for clarity, usefulness, and trustworthiness. Inter-rater agreement was measured using Cohen's kappa to ensure evaluation reliability.

Results and Discussion

The results of our experiments reveal significant insights into the capabilities and limitations of LLMs in the insurance domain. GPT-4 consistently outperformed other models across most evaluation metrics. It achieved an average ROUGE-1 score of 0.72, ROUGE-2 of 0.54, and ROUGE-L of 0.69, indicating a high degree of lexical and syntactic overlap with human-generated summaries. BERTScore values further confirmed semantic alignment, with GPT-4 scoring 0.91 compared to GPT-3.5's 0.86 and fine-tuned BART's 0.88.

In terms of factual consistency, GPT-4 exhibited fewer hallucinations and omitted critical clauses less frequently. However, it occasionally overgeneralized or omitted nuanced conditions and exclusions, which are pivotal in insurance contexts. The fine-tuned BART model, while slightly behind in general performance, showed improved handling of policy-specific terminology and structure, suggesting that domain adaptation enhances interpretability and content fidelity.

Qualitative feedback from domain experts highlighted GPT-4's fluency and coherence, though it was sometimes critiqued for prioritizing readability over completeness. Lay users preferred GPT-4 summaries for their clarity and ease of understanding, indicating its utility in consumer-facing applications. However, the need for post-processing and validation was emphasized, particularly for high-stakes policy components.

These findings underscore the dual challenge of maximizing summarization quality while preserving legal integrity. While LLMs show immense promise, their deployment in production systems should involve hybrid approaches that combine LLM outputs with rule-based validation or human oversight. Furthermore, ethical concerns such as transparency, accountability, and bias mitigation must be addressed to ensure responsible AI adoption in the insurance sector.

Conclusion

This research explores the transformative potential of large language models in automating the summarization of insurance policy documents. Through rigorous evaluation across

diverse models, datasets, and metrics, we demonstrate that LLMs, particularly GPT-4, offer significant improvements in summarization quality, user comprehension, and scalability. Nonetheless, challenges persist in ensuring domain-specific accuracy, mitigating hallucinations, and aligning outputs with regulatory standards.

The study advocates for a hybrid approach to automated summarization, wherein LLMs are augmented with domain knowledge, rule-based validators, and expert oversight. As the insurance industry continues to digitize and personalize customer interactions, the integration of intelligent summarization systems can play a pivotal role in enhancing transparency, reducing administrative burdens, and empowering policyholders.

Future research should explore advanced prompt tuning, retrieval-augmented generation, and reinforcement learning from human feedback to further refine model performance. Additionally, expanding training datasets with labeled insurance documents and incorporating multilingual capabilities will broaden the applicability of LLMs across global insurance markets. Ultimately, this study lays the groundwork for trustworthy and effective deployment of AI-driven summarization tools in the evolving landscape of digital insurance services.

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