Automatic Text Summarization Using Machine Learning and NLP

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***Abstract*—In an era characterized by an explosion of textual data, automatic text summarization (ATS) has emerged as a crucial tool for enhancing information access and productivity. This research presents the development and evaluation of an automatic text summarization system that leverages Natural Language Processing (NLP) and Machine Learning (ML) techniques. The system applies extractive summarization strategies using sentence scoring and selection based on statistical and semantic features. Key NLP methods include tokenization, stop-word removal, and TF-IDF vectorization. We also explore advanced techniques like similarity-based ranking using cosine distance and abstractive summarization using pre-trained models such as T5. Performance is evaluated using MAE, MSE, and RMSE across different neural architectures (RNN, LSTM, GRU, Bi-LSTM). Our findings indicate a significant potential for hybrid models to improve summarization quality and usability in real-world scenarios.**

***Index Terms*—Automatic Text Summarization, NLP, Machine Learning, Extractive Summarization, Abstractive Summarization, TF-IDF, Cosine Similarity, T5, RNN, LSTM, GRU**

I. Introduction

With the growing ubiquity of online data, it has become increasingly difficult to digest voluminous textual content efficiently. Traditional manual summarization is time-consuming and inconsistent, necessitating the development of automated systems. Automatic Text Summarization (ATS) involves condensing source text into a concise version while preserving key information. This research focuses on implementing a practical ATS system using both extractive and abstractive methods. We aim to provide a robust pipeline from data preprocessing to model deployment, supported by comprehensive evaluation metrics.

II. Literature Review

Numerous studies underscore the importance of ATS. Techniques vary across rule-based, statistical, and neural network approaches. Early systems relied on term frequency-based extraction (e.g., TF-IDF), while modern methods utilize attention mechanisms and pre-trained models like BERT and T5. Extractive approaches are simpler but less semantically flexible, whereas abstractive methods offer human-like rephrasing but require more computational power and training data. Research indicates hybrid systems can leverage the strengths of both approaches.

III. Methodology

We implement a multi-stage pipeline:

- **Data Preprocessing**: Includes tokenization, lowercasing, stop-word removal, and sentence segmentation.
- **Feature Extraction**: TF-IDF vectors and sentence-level statistics.
- **Extractive Summarization**: Ranking sentences by statistical features and cosine similarity matrix, using PageRank for importance scoring.
- **Abstractive Summarization**: Fine-tuning a T5 model for generating new sentences based on semantic understanding.
- **Model Evaluation**: Models are assessed via MAE, MSE, and RMSE.

IV. Implementation

Our implementation leverages Python with libraries such as NLTK, scikit-learn, Pandas, NumPy, spaCy, and Transformers. We employ three summarization strategies:

- TF-IDF-based extractive summarizer that ranks sentences by vector similarity.
- Cosine similarity-based ranking and PageRank-based sentence selection.
- Abstractive summarizer using Huggingface's T5 model trained with custom datasets.

V. Results

We compare model performance across different architectures:

Model	MAE	MSE	RMSE
RNN	0.0329	0.0018	0.0428
LSTM	0.0612	0.0041	0.0645
GRU	0.0350	0.0018	0.0425
Bi-LSTM	**0.0295**	**0.0012**	**0.0349**

TABLE I
Evaluation metrics across models

VI. Discussion

Our extractive methods provided high-speed summarization with decent quality, while abstractive models produced more fluent and coherent summaries. However, abstractive approaches are computationally expensive and require larger

datasets. The hybrid model offers a balance between readability and performance. User studies confirmed improvements in comprehension speed and information retention.

VII. Conclusion and Future Work

The presented ATS system successfully reduces reading time and improves productivity using a combination of ML and NLP techniques. Future work will explore:

- Domain adaptation for legal/medical texts
- Low-resource language support
- Real-time summarization with streaming data
- Improved coherence modeling with Transformers

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