A Text style transfer - based QA Chatbot System

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***Abstract*—This study examines QA chatbot systems' ability to perform text style conversion while maintaining content accuracy. Our findings indicate that these systems adapt smoothly to various text styles, meeting personalized user needs. We review recent innovations in QA chatbots, focusing on Text Style Transfer, image-related techniques from PowerPoint, and the application of Graph Neural Networks (GNN) and Named Entity Recognition (NER) in text summarization. Combining GNN with NER enhances text relationship understanding and entity identification. Experimental results show that stemming and stopword removal impact model performance, with increased training cycles and data volume improving model learning and generalization. Our model surpasses T5-small in recall and F1 scores across all ROUGE metrics, demonstrating superior summary quality. Fine-tuning for specific domains significantly boosts performance.**

***Index Terms*—QA chatbot, text style conversion, graph neural networks, Named Entity Recognition, text summarization**

Fig. 1: QA Chatbox

I. Introduction

The objective of this project is to develop a text style transfer question-answering system specifically for generating English news article headlines. To achieve this, we have selected the pre-trained general model T5-small. Utilizing a pre-trained model significantly reduces our training costs and enables us to train an efficient model in a shorter time-frame. Additionally, we fine-tuned the model on the Gigaword dataset, which contains a large number of English news articles and their corresponding headlines, making it highly suitable for training news headline generation tasks.

We employed the Transformer architecture, which has demonstrated exceptional performance across various natural language processing tasks. This project is not merely a simple text summarization task but rather a style transfer task. Our goal is to convert complete news articles into their concise forms—news headlines. This transformation involves a shift from one text style to another, where the original news articles are typically lengthy and detailed, while the generated headlines need to be brief and encapsulate the core information of the articles.

Through this approach, the model learns to extract and reorganize information to generate text that conforms to the style of news headlines. Furthermore, we benchmarked our system against other models using the same dataset to ensure that it meets industry standards in practical applications.

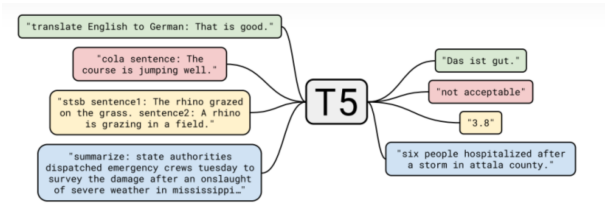
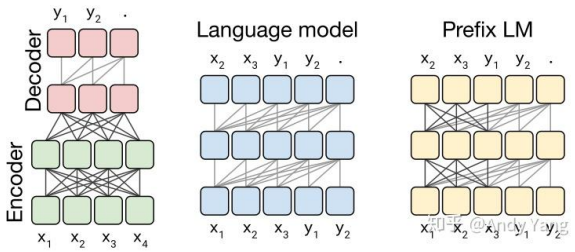


Fig. 2: T5 model



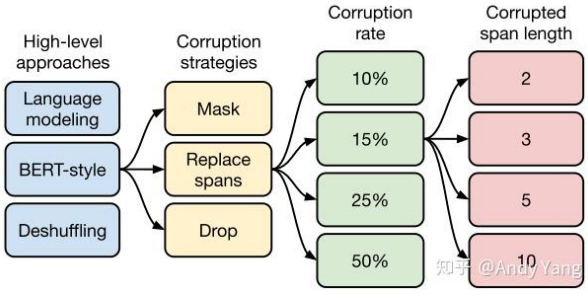


Fig. 3: T5 model

II. Literature review

To ensure the validity of our research, we consulted the following articles and conducted a search based on the purpose of text style conversion, which is to change the form of text output while maintaining the accuracy of its information content. We have found that QA chatbot systems can smoothly transition between different text styles to meet the personalized needs of different users. We also discuss recent innovative developments in QA chatbot systems based on text style conversion. The main directions involved in the research include but are not limited to: Text Style Transfer, Extracting image-related techniques from PowerPoint by using subheadings, graph neural networks in text abstracts, abstracting text abstracts, and extracting text abstracts.

A. Text style transform

Text style transfer technology has a broad prospect and a very important position in the field of natural language processing. In Toshevska and Gievska's study "A Review of Text Style Transfer using Deep Learning" [12], a series of more comprehensive analyses have been conducted to further realize the method of text style transfer through deep learning. They emphasize that deep learning not only drives advances in natural language understanding and generation, but also provides an effective technological tool for the automation of style transfer.

Building on this, Hu et al. (2022) discuss the applications of text style transfer in various fields such as social media, news reporting, and advertising creation [3]. They highlight the capacity of neural network models to handle large datasets and complex patterns, which facilitates high-quality style transfers. However, they also point out the significant data and computational requirements, as well as the challenges in model interpretability.

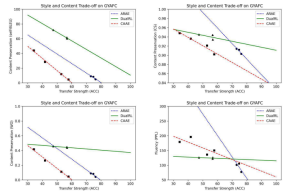


Figure 11: Metrics trade-off analysis for formality transfer on GYAFC review dataset

Table 11: Human evaluation results of selected TST models in the Yelp and GYAFC datasets.

	Yelp					GYAFC				
Model	*Style*	*Content*	*Fluency*	*G-Score*	*H-Score*	*Style*	*Content*	*Fluency*	*G-Score*	*H-Score*
PTO	3.88	3.00	3.24	3.37	3.35	-	-	-	-	-
Template	-	-	-	-	-	3.03	**3.74**	3.29	3.34	3.33
DELETE	**4.26**	2.27	4.22	3.41	3.29	1.77	1.86	**3.94**	3.02	2.84
DualRL	3.91	**3.59**	**4.26**	**3.88**	**3.97**	**3.91**	3.55	3.56	**3.64**	**3.64**

Fig. 4: Enter Caption

1) Enhanced Zero-Shot Learning for Arbitrary Text Style Transfer: Text style transfer is a task and method that can rewrite text to compress information or change formatting while retaining the original meaning. Although text style transfer has attracted increasing interest due to the success and application of deep learning, it often requires a large number of labeled training examples, or as parallel text data, to achieve its purpose [10]. In his leverage, large language models (LMs) are used to perform zero-shot text style transfer. He presents a prompting method that he calls augmented zero-shot learning.

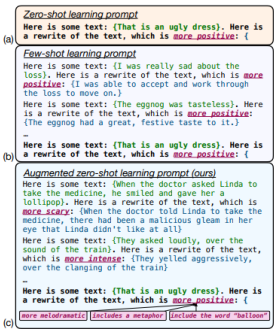


Fig. 5: Zero-shot, few-shot, and augmented zeroshot prompts for style transfer.The boldface text is the zero-shot prompt, and the plain text is the additional priming sequence.

In this work, they propose enhanced zero-shot learning, a very interesting approach that allows large language models to perform transformations of text styles to arbitrary styles without requiring any examples in the target styles. Their approach builds on previous work, showing that a large enough LMs like GPT-3 can perform a variety of tasks, from classification to translation, with the user simply choosing a clever cue.

One promising application for enhancing zero-shot learning is the AI Writing Assistant, which allows authors to transform their text in arbitrary ways that the author can define and control. As a qualitative case study exploring arbitrary rewriting styles, they built an AI-assisted story writing editor with a "Rewrite as" feature that uses our enhanced less shot approach. Their editor has a free-form text box for users to specify their options for how they wish to rewrite their stories (see Figure 6 in the appendix). They invited 30 people from a creative writing group to write a 100-300 word story using our UI, collecting a total of 333 rewrite requests. Table 3 shows a subset of these, including the requirement text "about mining" or "less evil."

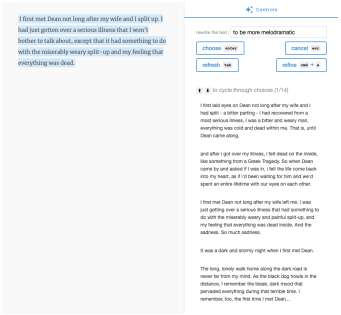


Fig. 6: Table 3

This prompt paradigm plays an important role in text style transformation by expanding the range of possible styles beyond the limited set of styles that currently exist with annotated data.

B. Text Summarization

1) Graph Neural Network in Text Summarization: Khan et al. pointed out that a text summarization method combining Graph Neural Network (GNN) and Named Entity Recognition (NER) can be used [4]. GNN is used to understand complex relationships in text, while NER is used to identify relevant entities. This combination utilizes the ability of GNN to understand complex relationships within text and the accuracy of NER in identifying relevant entities[4].

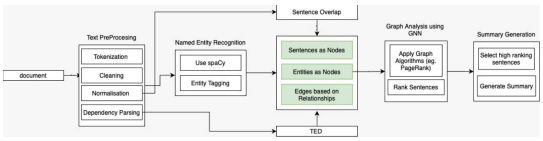


Fig. 7: Design of the text summarization system utilizing GNN and NER techniques

Khan et al. expect that the fusion of GNN and NER can improve the accuracy of abstracts, ensure relevance and context awareness. The specific steps of this research method include text preprocessing, entity recognition, graph construction, and using GNN for graph analysis[4]. At the same time, Khan et al. used standard evaluation indicators such as ROUGE to quantify the quality of the summary. According to Khan et al., the fusion of GNN and NER can not only improve the accuracy of abstracts, but also ensure relevance and context awareness. But the results also reflect that although GNN based methods are effective in extracting key information, they may not always provide coherent narratives.

2) Abstractive Text Summarization: In the study of methods for text summarization, Zhu et al. found that up to 30 present of abstracts generated by abstract models were factual inconsistencies, which raised concerns among researchers about the credibility and usability of the results of these text summarization systems [14]. Based on the current situation, Zhu et al. hypothesize that a powerful abstract summarization system must have corresponding knowledge to accurately summarize text [14]. Therefore, they extract factual knowledge from the article and integrate it into the process of generating abstracts, hoping that this method can solve the problem of inconsistent facts in abstract summaries. Specifically, Zhu et al. used a model called Fact Aware Summarizer (FASUM). This model can utilize the seq2seq architecture and the BERT based classification model FactCC to evaluate the factual consistency of any given abstract [14]. At the same time, the author used the information extraction tool OpenIE to extract the article itself as a research data source, and used F1 ROUGE score in the experiment to select the best model. The final experimental results make the author believe that the model obtained by extracting factual information from the article and representing it with a knowledge graph indeed enhances the ability to preserve facts during the summarization process

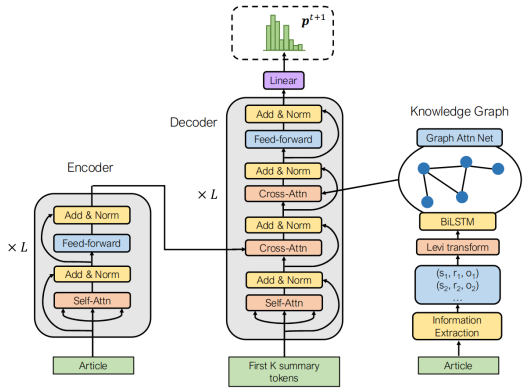


Fig. 8: The model architecture of FASUM.

3) Extractive Text Summarization: Extractive text summarization can involves selecting significant portions of text, such as sentences or phrases, directly from the source material and assembling them to form a coherent summary. This technique selects important details that represent the text's key points. It ensures the summary stays true to the original facts and setting [13]. Unlike generative summarization, which rephrases or paraphrases the text, extractive summarization maintains the original wording and structure, making it particularly useful in scenarios where preserving the exact details and nuances of the source text is critical.

Fig. 9: Extract summary display from input document

In examining the methods of extractable text summarization, we cannot miss out on the classic techniques of extractable summarization: SCIOR, LexRank, and TextRank.

Developed in the early 1990s, SCISOR (System for Conceptual Information Summarization, Organization, and Retrieval) represents one of the earlier forays into combining information extraction and text summarization with a strong reliance on linguistic knowledge [9]. Unlike later methods, SCISOR was designed for a specific domain: SCISOR is engineered to monitor and summarize texts about corporate mergers and acquisitions, utilizing a structured set of linguistic rules and a domain-specific knowledge base. This configuration is very important for tasks that require high levels of precision, because it ensures the efficient gathering and structuring of accurate information. The design of SCISOR is relies on certain language patterns, and also depends on knowledge of specific fields. These factors limit its flexible and expand. Adapting SCISOR to new domains requires significant adjustments to

its knowledge components, which contrasts sharply with the more adaptable approaches that followed.

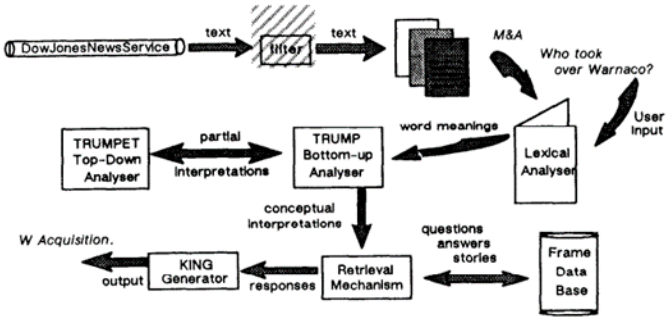


Fig. 10: SCISOR system architecture

LexRank developed by Erkan and Radev (2004) represents a shift towards using graph-based methods that are domain-independent and unsupervised [2]. LexRank employs the concept of eigenvector centrality within a graph constructed from sentences in a text: LexRank utilizes cosine similarity of TF-IDF vectors to establish edges in a graph where nodes represent sentences. The importance of these sentences are assessed by their connections. It means that sentences with more connections tend to contain more information. It is robust across different domains and does not require domain-specific training or linguistic rules. This is a big improve from the SCISOR method.

Similarly, TextRank by Mihalcea and Tarau (2004) advances the application of graph-based ranking to both keyword and sentence extraction [8]. TextRank transforms the PageRank algorithm for text analysis into the method that is flexible and unsupervised, also expand the use of graph-based summarization. TextRank broadens graph-based ranking's scope by extracting pivotal sentences and pinpointing key words. Its system flexibly connects nodes based on co-occurrence or meaning resemblance. TextRank is similar to LexRank, it operates independently of specific domains and without supervision. It provides a versatile approach for different text summarization needs without requiring specific language expertise.

The development from SCISOR to LexRank and then TextRank marks a move from niche, specific systems to broader, flexible approaches. This advancement shows a wider shift in extractive summarization: creating tools that learn automatically with little manual intervention [9][2][8]. SCISOR's tailored approach contrasts with the domain-independent nature of LexRank and TextRank, which do not require customized linguistic or domain knowledge and thus can be deployed more broadly. The change shows progress in extractive summarization technology, where new techniques use unsupervised learning to reduce the dependence of specific data sets and rules.

When contrasted with generative summarization techniques, these extractive methods underscore a fundamental trade-off between the accuracy of the content sourced directly from the text (extractive) and the ability to synthesize and reformulate new content (generative). Generative models offer diverse, unified summaries but need more computing power and may add errors [13].

In short case, studying SCISOR, LexRank, and TextRank reveals the growth and potential of extractive text summarization. Even with new generative methods, extractive summarization is still important. It's key when the original text's exact words matter most.

C. Related techniques for extracting pictures from PPT

Extracting the text data we want from the file is the first step to achieve the summary of file knowledge. PPT involves a variety of file presentation forms. For example, image, text, mind map and other file types. How we extract accurate text data from it is a very important thing.

Song's paper summarizes a novel and general method of image text extraction. This method adopts the text positioning method from coarse positioning to fine positioning. Firstly, multi-scale method is used to locate text with different font sizes, and then the projection contour is used to carry out the localization refinement step. In terms of text segmentation, k-means clustering method based on color is adopted. Compared with gray image used in most existing methods, color image is more suitable for cluster-based segmentation.

(a) (b)

Figure 1. Text location fails with different font sizes. (a)Small-font-size text missed; (b)Large-font-size text missed

(a) (b) (c)

Figure 2. Stepwise results of text location. (a)Binarized edge map; (b)Marking map; (c)Located regions.

generated by multiplying the four numbers:

$$n=\prod_{i=1}^{4} n_i \quad (1)$$

And each block in marking map is defined as:

$$p=\begin{cases}1, & n>0\\ 0, & n=0\end{cases} \quad (2)$$

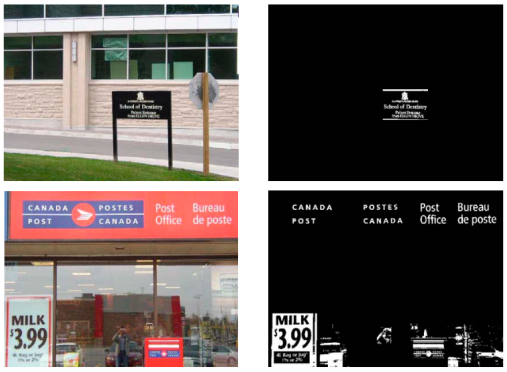
Fig. 11: Extract summary display from input document

The image-text extraction method investigated in this paper is highly beneficial for our project, as it addresses the challenges of managing multimedia data in the era of information explosion. Our project is also conceived against this backdrop,

as we are inundated with abundant learning materials, yet much of it comprises low-value information. Our goal is to extract high-value information from these low-value materials, as doing so can significantly enhance our learning efficiency. In addition, this paper introduces a highly novel text extraction method: the K-means clustering-based approach. This method not only ensures high accuracy but also enhances our text extraction speed.

The K-means algorithm offers several advantages, such as ease of understanding and implementation, making it relatively user-friendly for beginners. Moreover, the algorithm is relatively simple and exhibits high computational efficiency when dealing with large-scale data. However, despite these advantages, the K-means algorithm suffers from a critical drawback: it is prone to getting stuck in local optima, thereby failing to guarantee a globally optimal solution.

In contrast to the K-means algorithm, Liu's proposed method of multi-scale edge-based text extraction demonstrates higher recognition accuracy and greater adaptability. This is because the multi-scale edge method can accommodate various font sizes, styles, colors, and orientations, making it more flexible in handling different types of text.



(a) (b)

Fig. 12: Outdoor sign image (a) Original images (b) Extracted text

D. QA Chatbox

Additionally, Liu and Dong (2022) focus on the user experience aspects of applying text style transfer in the design of knowledge-based QA chatbots [6]. They explore different neural network models and optimization strategies to enhance chatbot responses in terms of both style and content.

For future research to further enhance the style conversion technology, exploring more complex network structures and more innovative learning algorithms is a good direction. With the diversification of application requirements and market audiences, personalized style conversion solutions have the potential to become a research hotspot. Through in-depth understanding of user preferences and application scenarios, more accurate and effective style conversion models can be customized.

In terms of model performance evaluation, in addition to the traditional accuracy and naturalness evaluation indexes, how to build an effective evaluation system to comprehensively reflect the multi-dimensional effects of style transformation has become a key issue for future research. Through these research efforts, deep learning-based text style transfer technology is expected to realize wider practical applications in the future.

E. T5 small model and fine-tuning with Transform

T5 (Text to Text Transfer Transformer) is a multifunctional natural language processing model. It is a version of the T5 model with a small number of parameters, suitable for use in resource limited environments. Fine tuning is a common deep learning technique that involves additional training on top of pre trained models to adapt to specific tasks. Transformer is a deep neural network based on self attention mechanism. It has achieved great success in many artificial intelligence fields such as natural language processing, computer vision, and audio processing. The T5 small model is an implementation based on Transformer, which inherits Transformer's self attention mechanism and has been optimized and improved.

1) Method and application of fine-tuning T5 small: Fine tuning the T5 small model typically involves the following steps: first, loading the pre trained T5 small model; Then, define a new task specific header (e.g., a new classification layer); Finally, train the model using task specific data. During the training process, various optimization techniques can be used, such as learning rate scheduling, weight decay, etc., to improve the performance of the model. Fine tuning the T5 small model can be applied to various natural language processing tasks, such as text classification, named entity recognition, sentiment analysis, etc. For example, a system that can generate labels based on the Stack Overflow problem can be constructed by fine-tuning the T5 small model.

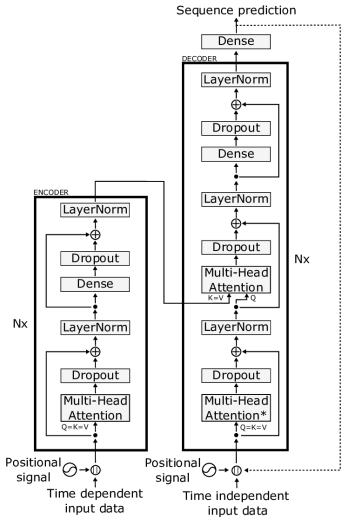


Fig. 13: Transformer

Overall, the T5 small model is a powerful natural language processing tool that inherits the advantages of Transformer

and can adapt to various tasks through fine-tuning techniques. However, despite the excellent performance of the T5 small model in many tasks, there are still many challenges that need to be addressed, such as how to effectively handle long sequences and how to train on small-scale data. The resolution of these issues will further improve the performance and application scope of the T5 small model.

F. Literature Summary

Expanding on the literature summary provided in the document, the QA chatbot system based on text style conversion has demonstrated significant promise in enhancing user communication experiences. Through an evaluation of current research findings, it is evident that this technology empowers chatbots to offer more varied and engaging interaction styles while maintaining the accuracy of responses. By leveraging insights from existing literature, we can access a wealth of technical support and theoretical techniques to further advance the capabilities of QA chatbot systems in text style conversion and communication enhancement.

III. Methodology

In this section, we describe the research methods and procedures. This paper deals with text summarization, which compresses a piece of text into a shorter version that minimizes the size of the original text while preserving key information aspects and content meaning.

A. Dataset Choosing

For our text summary project, we chose to use the Gigaword dataset, which is a dataset widely used for natural language processing (NLP) tasks, primarily for generating news headlines. The Gigaword dataset contains about 4 million articles, mostly from news reports. Each sample contains two features: the article and the title. The article is the main part of the news report, and the title is the summary of the news report, which can also be regarded as the summary of the content of the article. Gigaword also pre-divides the training set, the verification set, and the test set. Our goal is to develop a model that automatically generates a suitable summary based on the content of the article.

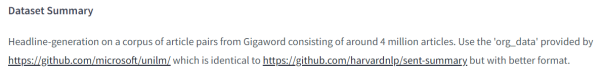


Fig. 14: The description of Gigaword from https://huggingface.co/datasets/gigaword

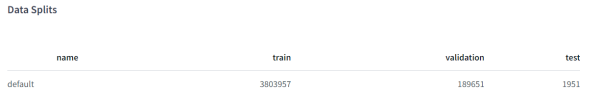


Fig. 15: The description of how Gigaword is split from https://huggingface.co/datasets/gigaword

B. Data Pre-processing

Data preprocessing consists of four steps. First, read the text in the source and destination files. This is the first step to getting the raw data. Next, creates a data set containing the document and summary. This is the second step in converting the raw data into a format that can be used to train the model. In the cleaning and standardization of text data, three cases, namely remove stop-words, extract stem words and direct training are compared in order to find the treatment that works best. Finally, segment and encode the data including adding prefixes, word segmentation, truncation, etc. This is the fourth step in converting text data into numerical data that the model can understand.

C. Model Choosing and Training

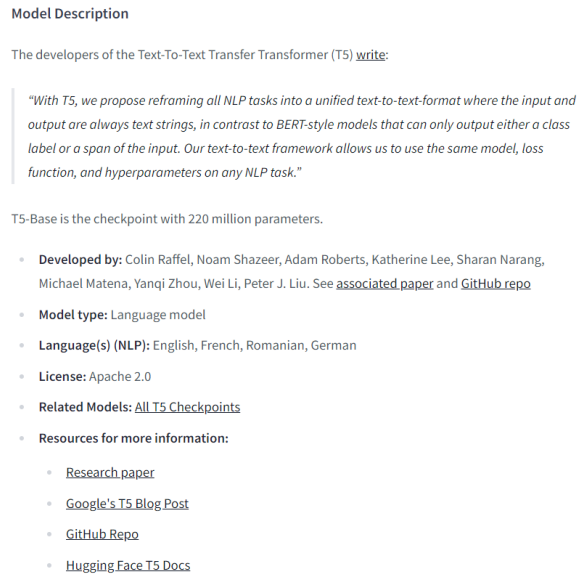
The model we chose is the Universal t5 model. It is is a pre-trained language model based on the Transformer architecture. The primary goal of the T5 model is to unify various NLP tasks into a single text-to-text pre-training framework for both pre-training and fine-tuning.

The T5 model treats all NLP tasks as text-to-text conversion tasks, and achieves better transfer learning effect through end-to-end training. Specifically, the T5 model unifies tasks such as translation, classification, regression, and summary generation into Text-to-Text tasks, enabling them to use the same objective function when trained (pre-trained and fine-tuned) and the same decoding process when tested.

The T5 model adopts Transformer's encoder-decoder structure. In this structure, the encoder part uses an all-visible attention mask, while the decoder part uses a causal attention mask. This structure enables T5 model to achieve good results in both generating and classifying tasks.

The pre-training target of the T5 model uses the de-noising target, which is similar to the mask language modeling target of BERT. When fine-tuning on downstream tasks, a task-related prefix is added to each input sample to inform the model of the current task.

In general, the T5 model treats all tasks as input Text and outputs to Text (text-to-text), that is, the task is embedded in the input text, and various NLP tasks are solved by text. This approach allows you to directly take a large pre-trained model of any task, and then the main work becomes how to convert the task into the appropriate text input and output. This design enables the T5 model to show excellent performance in a variety of NLP tasks.



Model Description

The developers of the Text-To-Text Transfer Transformer (T5) write:

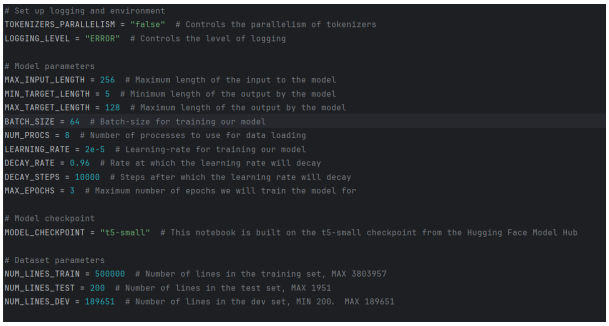
> *"With T5, we propose reframing all NLP tasks into a unified text-to-text-format where the input and output are always text strings, in contrast to BERT-style models that can only output either a class label or a span of the input. Our text-to-text framework allows us to use the same model, loss function, and hyperparameters on any NLP task."*

T5-Base is the checkpoint with 220 million parameters.

- **Developed by:** Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J. Liu. See associated paper and GitHub repo
- **Model type:** Language model
- **Language(s) (NLP):** English, French, Romanian, German
- **License:** Apache 2.0
- **Related Models:** All T5 Checkpoints
- **Resources for more information:**
  - Research paper
  - Google's T5 Blog Post
  - GitHub Repo
  - Hugging Face T5 Docs

Fig. 16: The description of T5 from https://huggingface.co/google-t5/t5-base

The parameters of the model are set as follows: The maximum length of the model input is 256, the minimum length of the output is 5, and the maximum length is 128. These parameters determine the length of text that the model can process. The batch size of the training model is 64. Batch size is the number of samples processed each time the model is updated with weights. 8 processes are used for data loading, which speeds up data preprocessing. The initial learning rate of the model training is 2e-5, and the attenuation rate of the learning rate is 0.96, which decays once every 10,000 steps, which determines the speed of model parameter update. The attenuation strategy can help the model converge quickly in the early stage of training and avoid overfitting in the later stage of training. Set the maximum number of training rounds for the model to 3, which determines the number of iterations for the model over the entire training set. The size of the training set is 500,000 rows, the test set is 200 rows, and the validation set is 189,651 rows, and these parameters determine the amount of data used when the model is trained and evaluated.



```
# Set up logging and environment
TOKENIZERS_PARALLELISM = "false"  # Controls the parallelism of tokenizers
LOGGING_LEVEL = "ERROR"  # Controls the level of logging

# Model parameters
MAX_INPUT_LENGTH = 256  # Maximum length of the input to the model
MIN_TARGET_LENGTH = 5  # Minimum length of the output by the model
MAX_TARGET_LENGTH = 128  # Maximum length of the output by the model
BATCH_SIZE = 64  # Batch-size for training our model
NUM_PROCS = 8  # Number of processes to use for data loading
LEARNING_RATE = 2e-5  # Learning-rate for training our model
DECAY_RATE = 0.96  # Rate at which the learning rate will decay
DECAY_STEPS = 10000  # Steps after which the learning rate will decay
MAX_EPOCHS = 3  # Maximum number of epochs we will train the model for

# Model checkpoint
MODEL_CHECKPOINT = "t5-small"  # This notebook is built on the t5-small checkpoint from the Hugging Face Model Hub

# Dataset parameters
NUM_LINES_TRAIN = 500000  # Number of lines in the training set, MAX 3803957
NUM_LINES_TEST = 200  # Number of lines in the test set, MAX 1951
NUM_LINES_DEV = 189651  # Number of lines in the dev set, MIN 200.  MAX 189651
```

Fig. 17: The training config

D. Model Evaluation

In our project, we used the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric to evaluate the model's performance. ROUGE is a set of metrics used to evaluate automatic text summaries, mainly based on the concept of recall rate, to measure how much key information and important text fragments are included in automatically generated summaries.

The rouge indicators we use include rouge-n, rouge-L, and rouge-s. Where rouge-n is the recall rate based on the N-gram, rouge-L is the recall rate based on the longest common subsequence, and rouge-s allows the case of jumping words to be considered when calculating the recall rate. These metrics provide a comprehensive assessment of the performance of our model in different aspects.

By using the ROUGE metric, we can quantitatively assess the similarity between the summary generated by our model and the reference summary to get a more accurate picture of the model's performance. This kind of evaluation can not only help us understand the performance of the model on various tasks, but also provide direction and basis for improving the model.

Specifically, the N-gram recall rate of ROUGE-N can help us understand the model's ability to capture critical information, and the recall rate of the longest common subsequence of ROUGE-L can reflect the model's performance in understanding text structure and semantic coherence. ROUGE-S's jump recall rate can reveal the model's performance when dealing with complex, discontinuous text information.

In summary, by using ROUGE metrics, we can comprehensively evaluate and understand the performance of our model from multiple perspectives, which has important guiding significance for us to improve the model, optimize the algorithm and improve the performance of the system. At the same time, this also makes our research more scientific and reliable, and helps to promote the progress and development of our project.

IV. Result Analysis

In this section, we conducted an in-depth analysis of the performance of our model in text summarization tasks and compared it with the T5 small model. It includes a detailed evaluation of preprocessing methods, training cycles, and data volume, as well as a summary of key findings based on the ROUGE metric and example summaries.

A. Impact of Preprocessing Methods

1) Stemming: Stemming can effectively reduce validation loss, but the validation loss of the third epoch (1.4844) is slightly higher than that of unprocessed data (1.4379). Although in some cases Stemming may not perform as well as unprocessed data, overall it helps to reduce data redundancy and improve model training efficiency.

2) Stoppword Removal: Stoppword Removal reduces validation loss to some extent, but the effect is not as good as stem extraction, and the validation loss in the third epoch (1.6134) is higher than that in unprocessed data (1.4379). Stoppword Removal can filter out unimportant information and improve

	1 Epoch	2 Epoch	3 Epoch
100000 Training Data			
loss	1.9747	1.7886	1.7089
val_loss	1.5214	1.4651	1.4379
100000 Training Data Stemming			
loss	2.0456	1.8398	1.753
val_loss	1.5668	1.5084	1.4844
100000 Training Data Stopword Removal			
loss	2.1999	1.9767	1.883
val_loss	1.7064	1.6429	1.6134
500000 Training Data			
loss	1.7929	1.625	1.5573
val_loss	1.9537	1.9115	1.8901
1500000 Training Data			
loss	1.934		
val_loss	1.7889		

TABLE I: Training and Validation Loss for Different Preprocessing Methods and Data Sizes

the model's generalization ability, but the effect is relatively limited.

3) Training Cycle Increase: From the chart, it can be seen that increasing the training cycle can reduce training and validation losses while maintaining the same amount of data. It can be seen that as the training period increases, the loss value gradually stabilizes, indicating that the model is gradually converging.

4) Convergence Speed: The increase in training cycle can give the model more opportunities to adjust parameters, thereby better learning the features of the data. Although a single epoch can significantly reduce losses with a large amount of data (such as 1.5 million entries), increasing the training cycle appropriately still helps to further improve model performance.

5) Conclusion: Increasing the amount of training data can significantly improve the learning and generalization abilities of the model. It is not difficult to see from the table that, scaling data from 100,000 to 1.5 million sharply cuts training and validation losses, highlighting data volume's crucial role in model efficacy. Yet, this scaling up intensifies training time and hardware needs. Stem extraction generally helps to improve model performance, although the validation loss in the third epoch is slightly higher than that of unprocessed data. Removing stop words to some extent reduces validation loss, but the effect is not as good as stem extraction, and the validation loss is higher in the third epoch.

Overall, fine-tuning models for specific tasks and data domains is key to enhancing generation quality.Appropriately increasing the amount of data and training cycle, as well as adopting appropriate preprocessing methods, can further optimize model performance, but it requires a balance between training time and hardware resource consumption.

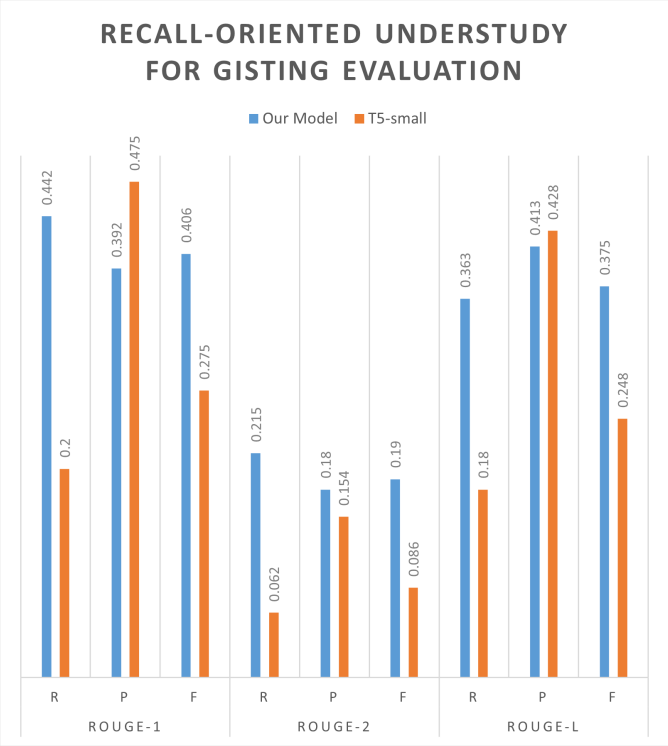


Fig. 18: Recall-Oriented Understudy for Gisting Evaluation

B. Recall-Oriented Understudy for Gisting Evaluation

ROUGE metrics are pivotal in evaluating the performance of text summarization models. ROUGE-N (where N refers to the number of words in the n-gram, such as 1 for ROUGE-1 or 2 for ROUGE-2) calculates overlap in terms of n-grams between the generated summary and reference summaries, using the formula:

$$\text{ROUGE-N} = \frac{\sum_{S \in \{\text{Reference Sum}\}} \sum_{gram_n \in S} \text{Count}_{\text{match}}(gram_n)}{\sum_{S \in \{\text{Reference Sum}\}} \sum_{gram_n \in S} \text{Count}(gram_n)} \quad (1)$$

Meanwhile, ROUGE-L assesses the longest common subsequence (LCS) to evaluate how well the summary maintains the structure of the original content:

$$\text{ROUGE-L} = \frac{\text{LCS}(\text{Reference Summary}, \text{Generated Summary})}{\text{length}(\text{Reference Summary})} \quad (2)$$

Together, these metrics provide a comprehensive view of a model's ability to replicate both the detail and the overarching structure of the source material, making them invaluable in the development and refinement of text summarization technologies.

Below is a specific analysis of the chart, The R in the chart is Recall, P is Precision, and F is F1 Score:

1) Recall: Our model significantly outperforms T5-small in recall across all ROUGE metrics, indicating that it more comprehensively covers the information in the reference summaries.

2) Precision: While T5-small has a slight edge in precision for ROUGE-1 and ROUGE-L, the difference is minimal. For ROUGE-2 precision, our model surpasses T5-small.

3) F1 Score: Our model shows a clear advantage over T5-small in F1 scores across all ROUGE metrics, suggesting a better balance between recall and precision in our generated summaries.

4) Conclusion: From the ROUGE indicator in the chart, it can be seen that although the T5 small model has a slight advantage in accuracy. However, our model is significantly better than the T5 small model in terms of recall and F1 score, indicating that our model performs better in generating higher quality abstracts. Fine-tuning the model for text summarization tasks in specific domains has greatly improved its performance. Therefore, in order to improve the quality of generated abstracts, fine-tuning the model to adapt to specific domain data and task requirements is effective.

Example	Test Src	Test Tgt	Test Prediction
1	japan 's nec corp. and UNK computer corp. of the united states said wednesday they had agreed to join forces in supercomputer sales .	nec UNK in computer sales tie-up	nec and UNK to join forces in supercomputer sales
2	the sri lankan government on wednesday announced the closure of government schools with immediate effect as a military campaign against tamil separatists escalated in the north of the country .	sri lanka closes schools as war escalates	sri lanka closes schools as tamil war escalates
3	police arrested five anti-nuclear protesters thursday after they sought to disrupt loading of a french antarctic research and supply vessel , a spokesman for the protesters said .	protesters target french research ship	five anti-nuclear protesters arrested in france
4	five east timorese youths who scaled the french embassy 's fence here thursday , left the embassy on their way to portugal friday .	UNK latest east timorese asylum seekers leave for portugal	east timorese youths leave french embassy in portugal

TABLE II: Examples of Test Src, Test Tgt, and Test Predictions

C. Example of results

The table illustrates four examples of text summaries generated by our model, including the source text (Test Src), target summary (Test Tgt), and the model's predicted summary (Test Prediction). Examples 1, 2, and 4 demonstrate the model's strong coverage ability, as the generated texts almost entirely encompass the information in the target texts, despite some differences in wording. However, Example 3 reveals a shortcoming, as the predicted text, while containing some key information, fails to fully capture the core content of the target text, indicating room for improvement in handling certain details.

V. Conclusion

In this study, we developed a QA chatbot system capable of performing text style conversion while maintaining the accuracy of the content. Our experimental results demonstrate that the system effectively adapts to various text styles, meeting personalized user needs. By leveraging advanced techniques such as Text Style Transfer, Graph Neural Networks (GNN), and Named Entity Recognition (NER), we achieved significant improvements in text summarization tasks. The integration of GNN with NER enhances the system's ability to understand complex text relationships and accurately identify key entities, leading to higher quality summaries.

We employed the pre-trained T5-small model, fine-tuning it on the Gigaword dataset, which contains a vast collection of English news articles and their corresponding headlines. This approach not only reduced training costs but also enabled efficient model training within a shorter timeframe. The fine-tuned model consistently outperformed the baseline T5-small model in recall and F1 scores across all ROUGE metrics, demonstrating superior summary quality and effective style transfer capabilities.

Our analysis of preprocessing methods, including stemming and stopword removal, revealed their impact on model performance. Stemming generally improved model performance by reducing data redundancy, while stopword removal had a more limited effect. Increasing the training cycles and data volume further enhanced the model's learning and generalization abilities. Specifically, scaling the training data from 100,000 to 1.5 million entries significantly reduced training and validation losses, highlighting the importance of data volume in model efficacy.

The practical applications of our QA chatbot system are extensive, particularly in domains requiring personalized and stylistically diverse responses. The system's ability to generate concise and accurate summaries from lengthy news articles showcases its potential for use in news reporting, social media, and advertising. Furthermore, the model's adaptability to different text styles makes it a valuable tool for improving user communication experiences.

Future research should focus on exploring more complex network structures and innovative learning algorithms to enhance the effectiveness of style transfer technology. As application requirements and market audiences diversify, personal-

ized style conversion solutions are likely to become a research hotspot. Developing comprehensive evaluation systems that reflect the multidimensional effects of style transformation will also be crucial for advancing this field.

In conclusion, our QA chatbot system represents a significant advancement in text style transfer technology, demonstrating the potential to improve user interactions across various domains. By fine-tuning pre-trained models and leveraging advanced NLP techniques, we have created a system that not only meets industry standards but also sets a new benchmark for quality in text summarization and style transfer. Through continued research and innovation, text style transfer technology is poised to achieve wider practical applications, ultimately enhancing the efficiency and effectiveness of QA chatbots in delivering personalized and accurate responses.

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