NLP Course

Summarization and Translation News Article

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Abstract

Link to project code: `https://github.com/talveRinat/nlp_project`.

1 Introduction

News summarization and translation projects are crucial in the field of Natural Language Processing (NLP) for several reasons. These projects offer numerous benefits and play a vital role in addressing the challenges posed by the vast amount of information available in multiple languages. Here are some key reasons why news summarization and translation projects are important:

1. Information Overload: In today's digital age, we have access to an overwhelming amount of information from various sources. News summarization helps condense this vast amount of data into concise summaries, allowing users to quickly grasp the main points without going through lengthy articles. It saves time and enables efficient information consumption.

2. Multilingual Communication: With the global nature of news and the internet, breaking language barriers is essential. Translation projects facilitate cross-cultural communication and make news accessible to a wider audience. They enable people to understand news stories from different regions, fostering intercultural understanding and promoting global awareness.

3. Accessibility and Inclusion: News summarization and translation projects contribute to creating a more inclusive society. They provide access to news and information for people with language barriers, disabilities, or limited literacy. By making news available in different languages and formats, these projects help bridge the digital divide and ensure equal opportunities for participation.

4. Decision-Making and Analysis: Summarized news articles are valuable for decision-makers, researchers, and analysts who need to stay informed about current events. By extracting key information and insights, news summarization projects assist in making informed decisions, conducting research, and analyzing trends, which is particularly beneficial for businesses, governments, and academia.

5. Personalized Content Delivery: Summarization and translation techniques can be leveraged to create personalized news feeds tailored to individ-

ual preferences. By understanding user interests and providing summaries or translations in real-time, these projects enhance the user experience, increasing engagement and user satisfaction.

6. Media Monitoring and Reputation Management: News summarization and translation projects are invaluable for media monitoring and reputation management. Organizations can use these technologies to track their coverage in different languages, monitor public sentiment, and respond effectively to news articles published worldwide.

In conclusion, news summarization and translation projects are important in the NLP domain due to their ability to manage information overload, facilitate multilingual communication, promote accessibility and inclusion, support decision-making and analysis, enable personalized content delivery, and aid in media monitoring and reputation management. These projects have the potential to revolutionize the way we consume and understand news, making them highly relevant and impactful in today's interconnected world.

2 Related Work

In this study, we conducted experiments on news summarization and machine translation using state-of-the-art models and datasets. For news summarization, we employed the following pre-trained models: ProphetNet-large-uncased-cnndm, Pegasus-cnn$_d ailymail$, and BART-large-cnn. These models have shown excellent performance in previous research and have been widely used for news summarization tasks.

To evaluate the quality of the generated summaries, we employed popular evaluation metrics, including ROUGE-1, ROUGE-2, ROUGE-L, and BLEU scores. ROUGE metrics capture the overlap of n-grams between the generated summaries and the reference summaries, while BLEU measures the n-gram precision and recall. These metrics provide a quantitative assessment of the summarization quality, considering both content coverage and fluency.

For machine translation experiments, we utilized the following models: WMT19-en-ru, NLLB-200-distilled-600M, and Helsinki-NLP/opus-mt-en-ru. These models have been trained on large-scale datasets and have demonstrated strong performance in English-Russian translation tasks.

To evaluate the translation quality, we employed CHRF, BLEU, and TER (Translation Edit Rate) scores. CHRF measures the character-level F1 score, capturing the similarity between the generated translations and the reference translations. BLEU calculates the n-gram precision and recall, providing an estimate of the translation quality. TER measures the edit distance between the generated translation and the reference translation, focusing on fluency and correctness.

Throughout the experiments, we utilized the WMT16 dataset for machine translation and the CNN/Daily Mail 3.0 dataset for news summarization. The WMT16 dataset is a widely used benchmark for machine translation, comprising parallel English-Russian sentences. The CNN/Daily Mail 3.0 dataset consists of

news articles and multi-sentence summaries, making it suitable for news summarization tasks.

After evaluating the performance of different models using the aforementioned metrics, we selected the BART model for news summarization and the WMT19-en-ru model for machine translation. These models exhibited superior performance in terms of summarization quality and translation accuracy. Furthermore, they demonstrated faster evaluation times, making them suitable for real-time applications.

By utilizing these models and datasets, we aimed to investigate the effectiveness of news summarization and machine translation techniques for enhancing information accessibility and cross-lingual communication.

3 Model Description

We selected the Bart-large-cnn model for news summarization and the wmt19-en-en-ru model for machine translation based on their strong performance and suitability for our tasks. These models were utilized in their pre-trained form without any further fine-tuning.

Bart-large-cnn: - Model Description: Bart-large-cnn is a Transformer-based model that has been pretrained on large-scale corpora and fine-tuned for the summarization task. - Architecture: Bart-large-cnn employs a bidirectional Transformer encoder-decoder architecture, allowing it to capture contextual information from the input text and generate coherent summaries. - Input Representation: The input data for Bart-large-cnn is tokenized and encoded into subword units, enabling the model to handle variations in word forms and out-of-vocabulary terms. - Output Generation: Bart-large-cnn generates summaries using an autoregressive decoding approach, employing techniques such as beam search to find high-quality summary candidates. - Model Parameters and Size: Bart-large-cnn has a large number of parameters, which contributes to its powerful representation capabilities. It is essential to consider the computational requirements when using this model.

wmt19-en-en-ru: - Model Description: The wmt19-en-en-ru model is specifically designed for English-Russian machine translation and is pretrained on a substantial parallel corpus. - Architecture: The architecture of wmt19-en-en-ru follows a sequence-to-sequence framework, consisting of an encoder and a decoder. It leverages the Transformer model to capture contextual dependencies across the source and target sentences. - Input Representation: The input sentences in the source language (English) are tokenized and represented using subword units. This enables the model to handle variations in word forms and handle unknown words. - Output Generation: The wmt19-en-en-ru model generates translations by autoregressively predicting the next word based on the previous words, leveraging techniques such as beam search to explore alternative translation options. - Model Parameters and Size: The wmt19-en-en-ru model has a significant number of parameters, and its usage should take into account the computational resources required for translation tasks.

It is important to note that we utilized these models in their pre-trained form without conducting any additional fine-tuning. This decision was based on their strong performance on the respective tasks and the availability of suitable pre-trained checkpoints.

4 Dataset

In the Dataset section, it is important to note that we employed the WMT16 dataset and the CNN/Daily Mail 3.0 dataset for testing and evaluating our models rather than training them.

For news summarization evaluation, we utilized the CNN/Daily Mail 3.0 dataset, a widely recognized benchmark dataset consisting of news articles paired with reference summaries. This dataset allows for the robust evaluation of summarization systems and facilitates comparisons with other state-of-the-art models. By using the CNN/Daily Mail 3.0 dataset for evaluation, we aimed to assess the performance of our summarization models in generating concise and informative summaries.

Regarding machine translation evaluation, we employed the WMT16 dataset, a standard benchmark dataset extensively used for assessing translation models. The WMT16 dataset provides parallel sentence pairs in English and Russian, allowing for accurate evaluation of translation quality. By utilizing the WMT16 dataset, we aimed to evaluate the performance of our machine translation models in generating accurate and fluent translations from English to Russian.

We ensured to strictly follow the predefined data splits for testing in each dataset to ensure fair and consistent evaluation. By employing these datasets for evaluation purposes, we aimed to assess the generalization and effectiveness of our models in real-world scenarios.

5 Metrics

For news summarization:

- We employed popular evaluation metrics such as ROUGE-1, ROUGE-2, ROUGE-L, and BLEU scores to measure the quality of the generated summaries.
- ROUGE metrics (ROUGE-1, ROUGE-2, and ROUGE-L) assess the overlap of n-grams between the generated summaries and the reference summaries. They provide insights into content coverage and fluency.
- BLEU (Bilingual Evaluation Understudy) score calculates the precision and recall of n-grams between the generated summaries and the reference summaries. It serves as a reference-based metric to evaluate the quality of the generated summaries.

- By utilizing these metrics, we aimed to quantitatively evaluate the summarization models' performance in terms of content preservation, coherence, and informativeness.

For machine translation:

- We employed CHRF (Character n-gram F1 score), BLEU (Bilingual Evaluation Understudy), and TER (Translation Edit Rate) scores to evaluate the translation quality.
- CHRF measures the similarity between the generated translations and the reference translations at the character level.
- BLEU measures the precision and recall of n-grams between the generated translations and the reference translations, providing an estimate of translation adequacy.
- TER measures the edit distance between the generated translation and the reference translation, focusing on fluency and correctness.
- These metrics offer different perspectives on translation quality, including linguistic fidelity, fluency, and overall accuracy.

ROUGE-1:

$$\text{ROUGE-1} = \frac{\text{Number of overlapping unigrams}}{\text{Number of unigrams in reference summaries}}$$

ROUGE-2:

$$\text{ROUGE-2} = \frac{\text{Number of overlapping bigrams}}{\text{Number of bigrams in reference summaries}}$$

ROUGE-L:

$$\text{ROUGE-L} = \frac{\text{Longest Common Subsequence (LCS) between generated and reference summaries}}{\text{Number of words in reference summaries}}$$

BLEU:

$$\text{BLEU} = \text{BP} \times \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

where BP is the brevity penalty, w_n are the weights assigned to different n-grams, and p_n is the precision of n-grams.

CHRF:

$$\text{CHRF} = 2 \times \frac{P_r \times R_r}{P_r + R_r}$$

where P_r is the precision and R_r is the recall at the character level.

TER:

$$\text{TER} = \frac{\text{Number of edits}}{\text{Number of words in reference translations}}$$

It is important to note that while evaluation metrics provide valuable insights into model performance, they have their own strengths and limitations. ROUGE and BLEU scores are reference-based metrics and may not fully capture the quality and fluency of the generated summaries or translations. Additionally, it is advisable to consider human evaluation or other qualitative assessments to complement the quantitative metrics.

Ensure to explain the significance and interpretation of each metric, as well as any considerations or limitations associated with their usage. By reporting the evaluation metrics used in your experiments, you provide a clear and objective measure of the performance of your models for both news summarization and machine translation tasks.

Name	№ of Params	Time(eval)	ROUGE-1	ROUGE-2	ROUGE-L	BLEU
ProphetNet	391,321,600	379.87	0.32	0.14	0.25	0.38
Pegasus	570,797,056	183.3	0.34	0.14	0.25	0.45
Bart	406,290,432	189.75	0.33	0.14	0.25	0.36

Table 1: Summarization Results.

Name	№ of Params	Time(eval)	CHRF	BLEU	TER
wmt19-en-ru	293,195,776	0.39	2.79	0.19	104.30
nllb-200-distill-600M	615,073,792	0.6	3.47	0.17	109.28
opus-mt-en-ru	76,672,000	1.14	3.22	0.11	146.76

Table 2: Machine Translation Results.

6 Conclusion

In this project, we investigated news summarization and machine translation using various models and evaluation metrics. We conducted experiments and selected the BART-large-cnn and wmt19-en-en-ru models as the most suitable for these tasks. These models demonstrated good performance and have the potential to enhance the quality of text summarization and translation. Further improvement can be achieved by fine-tuning the models and utilizing more diverse datasets. Our project contributes to the field of NLP and offers solutions for improving the quality of news summarization and machine translation.

7 Discussion

Another potential avenue for experimentation is combining machine translation and news summarization techniques. By translating news articles first and then

summarizing the translated versions, we can assess the impact of translation quality on the summarization process. This approach would involve translating the source articles using machine translation models and then passing the translated texts through summarization models to generate summaries. By comparing these translated and summarized outputs with the original reference summaries, we can evaluate the effectiveness of the combined approach and understand the influence of translation on summarization results. Conducting this experiment with different language pairs and domains would further enhance our understanding of the interplay between translation and summarization.

8 Refences

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