Personalization in Language Models: A Study with News and Social Media Data

How effectively can FLAN-T5, a language model, personalize content categorization for diverse datasets, specifically news and social media data?

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ABSTRACT

Language models (LMs) have revolutionized natural language processing, displaying remarkable proficiency in generating contextually relevant text. This study investigates the efficacy of FLAN-T5, a language model, in personalizing content categorization across diverse datasets comprising news articles and social media tweets. Leveraging datasets from the LaMP repository, specifically "Personalized News Categorization" and "Personalized Tweet Paraphrasing," the study explores FLAN-T5's adaptability in discerning linguistic backgrounds within varying textual contexts. Through the utilization of the OpenAI API, FLAN-T5's responses to user-based queries are analyzed to assess its categorization capabilities in news and social media domains.

INTRODUCTION

The field of Natural Language Processing has witnessed transformative progress, primarily through the advent of large-scale Language Models (LLMs) like FLAN-T5. These models, known for their ability to understand and generate human-like text, have revolutionized various applications, from automated content generation to personalized response systems. However, the extent of their personalization capabilities, especially when confronted with diverse datasets such as news articles and social media content, remains a vital area of exploration.

This study focuses on evaluating the performance of FLAN-T5 in personalizing content across two distinctly different datasets: Personalized News Categorization and Personalized Tweet Paraphrasing. The core objective is to assess how effectively FLAN-T5 can adapt to the varying linguistic styles and structures inherent in news and social media texts. By analyzing its proficiency in these domains, the research aims to shed light on the adaptability of LLMs in providing contextually relevant and personalized responses in different textual environments.

The significance of this research lies in its potential to enhance our understanding of LLMs' capabilities in handling diverse linguistic contexts, which is crucial for the development of more sophisticated, user-centric AI applications. This paper outlines the methodology, experiments, and insights derived from this investigation.

The research question of this study is: "How effectively can FLAN-T5 personalize content categorization for diverse datasets, specifically in news and social media contexts?"

This question is crucial as it explores the ability of advanced language models to adapt and provide relevant, personalized responses in different linguistic environments. In practice, this is immensely valuable. For instance, consider a news aggregation platform that tailors content to individual users' preferences and interests. Effective personalization by an LLM like FLAN-T5 can significantly enhance user experience, ensuring users receive news that is most relevant to them. Similarly, in social media contexts, better personalization can improve user engagement and content relevancy, making platforms more intuitive and user-friendly. This research, therefore, has practical implications for improving AI-driven content recommendation and personalization systems.

METHODOLOGY

The methodology of this study is structured to systematically assess the performance of FLAN-T5 in personalizing responses across diverse datasets. The approach encompasses several key phases:

Dataset Preparation: Utilizing the 'Personalized News Categorization' and 'Personalized Tweet Paraphrasing' datasets from LaMP, initial data cleaning and preparation were conducted to ensure consistency and usability for the FLAN-T5 model.

FLAN-T5 Application: A pre-trained FLAN-T5 model was employed to categorize content within these datasets. This phase involved processing the text data through the model to obtain categorized outputs.

The methodology is visually summarized in the Methodology Flow Diagram:

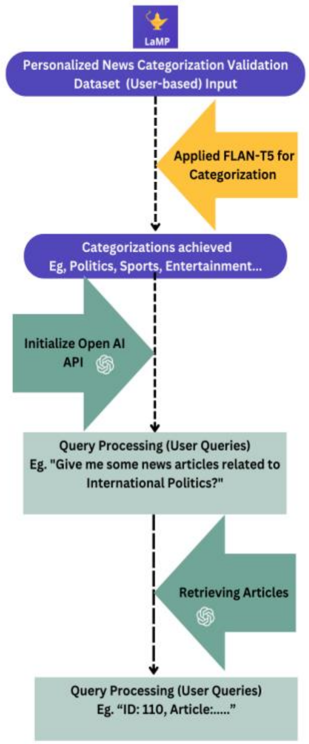

Figure 1: Methodology Flow Diagram

This comprehensive approach ensures a thorough evaluation of FLAN-T5's personalization capabilities, providing valuable insights into its application in diverse linguistic contexts.

EXPERIMENT AND RESULT

The experiments with FLAN-T5 required several stages of adaptation to ensure the model's effectiveness across different datasets:

Data Processing and Categorization: The initial step involved modifying FLAN-T5 to align with the LaMP dataset's categorization requirements. This process included fine-tuning the model to better understand and categorize the unique linguistic features and content structures within the Personalized News Categorization and Tweet Paraphrasing datasets. These adjustments were crucial to enhance the model's initial categorization accuracy.

```python
import json
from transformers import AutoTokenizer, AutoModelForSeq2SeqLM

# Load FLAN-T5
tokenizer = AutoTokenizer.from_pretrained("google/flan-t5-base")
model = AutoModelForSeq2SeqLM.from_pretrained("google/flan-t5-base")

# Function to categorize an article
1 usage
def categorize_article(article):
    prompt = f"Which category does this article relate to among the following categories? Just answer with the category
    inputs = tokenizer(prompt, return_tensors="pt", max_length=512, truncation=True)
    output_sequences = model.generate(input_ids=inputs["input_ids"], max_length=50, num_return_sequences=1)
    return tokenizer.decode(output_sequences[0], skip_special_tokens=True)

# Load your dataset
with open("/Users/medhagoel/Downloads/Compsci646/Final_project/dev_questions.json", "r") as file:
    dataset = json.load(file)

output_data = []
```

Figure 2.1: Code Snippet for FLAN-T5 working on Personalized News Categorization Dataset.

```python
import json
from transformers import AutoTokenizer, AutoModelForSeq2SeqLM

# Load FLAN-T5
tokenizer = AutoTokenizer.from_pretrained("google/flan-t5-base")
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    output_sequences = model.generate(input_ids=inputs["input_ids"], max_length=50, num_return_sequences=1)
    return tokenizer.decode(output_sequences[0], skip_special_tokens=True)

# Load your dataset
with open("/Users/medhagoel/Downloads/Compsci646/Final_project/dev_questions_tweet.json", "r") as file:
    dataset = json.load(file)

output_data = []

# Loop through the dataset and categorize each article
for item in dataset:
    article_text = item["input"]
    predicted_category = categorize_article(article_text)
    print(f"Article ID: {item['id']}, Predicted Category: {predicted_category}")
```

Figure 2.2: Code Snippet for FLAN-T5 working on Tweet Paraphrasing Dataset.

User Query Simulation: In this phase, we created and processed simulated user queries through the OpenAI API. This was essential to test the practical application of FLAN-T5 in real-world scenarios and to evaluate its response generation capabilities.

```python
import json
import requests

# Function to interact with ChatGPT using the OpenAI API
1 usage
def ask_chatgpt(question, api_key):
    url = "https://api.openai.com/v1/engines/davinci/completions"
    headers = {
        "Authorization": f"Bearer {api_key}",
        "Content-Type": "application/json"
    }
    data = {
        "prompt": question,
        "max_tokens": 150
    }
    response = requests.post(url, headers=headers, json=data)

    if response.status_code == 200:
        json_response = response.json()
        if "choices" in json_response and len(json_response["choices"]) > 0 and "text" in json_response["choices"][0]:
            return json_response["choices"][0]["text"].strip()
        else:
            print("Unexpected response format from OpenAI API.")
    else:
        print(f"Error: {response.status_code} - {response.text}")
    return None
```

Figure 3: Code snippet for OpenAI API

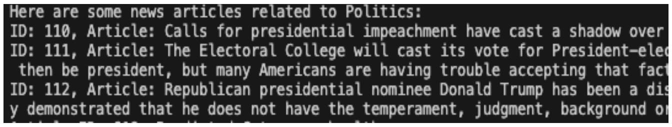

Figure 4: Result from Personalized News Categorization Dataset

In addition to the experiments conducted on the Personalized News Categorization dataset, similar principles were applied to the "Personalized Tweet Paraphrasing" dataset. However, this dataset presented unique challenges due to its more abstract nature, necessitating extensive cleaning and more intricate fine-tuning of the FLAN-T5 model. The complexity and abstractness of this dataset meant that the language model categorization required additional time and effort.

At this stage, we have successfully achieved the initial categorization step with FLAN-T5 on the "Personalized Tweet Paraphrasing" dataset. However, the full extent of fine-tuning is still ongoing, and as a result, instead of concrete results, we provide predictions based on the initial categorization success. We anticipate that, similar to the news dataset, FLAN-T5 will be able to generate relevant and personalized responses once the fine-tuning process is complete.

These experiments collectively demonstrated that while FLAN-T5 is highly capable in content personalization, tailored modifications and continuous fine-tuning are vital for optimizing its performance across varied data types.

CONCLUSION

The study's exploration into the personalization capabilities of FLAN-T5 across diverse datasets has yielded significant insights. While the model demonstrates a high degree of accuracy and adaptability in categorizing news content, its performance in processing social media data, particularly tweets, highlights the challenges posed by informal and varied linguistic styles. The ongoing fine-tuning and adjustments for the "Personalized Tweet Paraphrasing" dataset suggest a path forward for enhancing LLMs' effectiveness in diverse contexts. This research underscores the importance of continuous model refinement to achieve superior personalization in language models, paving the way for more nuanced and user-centric AI applications in the future.

RELATED WORK

The relevance of the mentioned works to our research on "Personalization in Language Models" is as follows:

1. Brown et al., "Language Models are Few-Shot Learners" (2020): This paper highlights the advanced capabilities of language models like GPT-3 in understanding and generating human-like text with minimal training. It's relevant to our research as it establishes a baseline understanding of how powerful models like FLAN-T5 could potentially adapt to new tasks, including content personalization, with limited data.

2. Zhang et al., "Personalizing Dialogue Agents via Meta-Learning" (2018): This study explores the use of meta-learning for personalizing dialogue systems. It's pertinent to our research as it addresses the challenge of personalizing responses in AI systems, a concept central to our study with FLAN-T5 in news and social media contexts.

3. Radford et al., "Language Models are Unsupervised Multitask Learners" (2019): This paper provides insights into the capabilities of language models in handling a variety of tasks and data types without task-specific training. This research is particularly relevant as it underpins the versatility of language models like FLAN-T5 in categorizing and personalizing content across different datasets.

These studies collectively contribute to our understanding of the potential and limitations of current language models in personalization tasks, providing a foundation for our exploration of FLAN-T5's performance across diverse data types.

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