CoverGenie: Cover Letter generation using Fine-tuned T5

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Abstract

This project aims to build a mini-ChatGPT model called ***CoverGenie*** for generating cover letters specifically based on the job descriptions and resumes. The study was backed up by the previous study on the The architecture we used is a fine-tuned T5 model. It takes a job description and a resume as input and generates a structured cover letter. The study explored parameter finetuning and prompt engineering to improve the performance of the model. We believe this is important and relevant to us in the way that it can save time and effort for job seekers and hiring managers by automating the process of creating resumes and cover letters. The contribution of the project is the development of an efficient and effective language generation model that can generate cover letters based on job descriptions.

Introduction

The goal of our project is to build a fine-grained mini-ChatGPT (named “CoverGenie”) , which is designed to generate resumes and cover letters based on job descriptions from the tech field. By nature, it is a text generation task, and it takes the job description as input to a sequence of text and turns it into a structured, certain style of resumes and cover letters. This study will involve parameter efficient finetuning, reinforcement learning and prompting engineering to some extent.

Related work

In this paper *Scaling Instruction-Finetuned Language Models,* we learnt that fine-tuning language models on a collection of instructions can greatly improve model performance and generalization to unseen tasks. In this study, the authors worked on scaling the number of tasks, model size, and fine-tuning on chain-of-thought data. The paper concludes that instruction fine-tuning is a general method for improving the performance. The study focuses on the use of FlanT5, but it gave us the inspiration using the base T5 as the starting point of our project.

There’s another paper named *Large Language Models Are Human-Level Prompt Engineers* talking about the importance of prompt engineering. It proposed a method called Automatic Prompt Engineer (APE) for generating and selecting natural language instructions to improve the task performance of large language models (LLMs). This method optimizes the instruction by searching over a pool of candidate instructions proposed by an LLM, maximizing a chosen score function. The experiments show that the APE-generated instructions outperform the prior LLM baseline. We are aware that

We also have reviewed a similar project which was carried out using T5. The model is a fine-tuned version of t5-base on cover letter samples scraped from Indeed and JobHero. The author has explored the following hyperparameters such as learning rate, train batch, eval batch size, seed and optimizer etc., which is a great example of taking multiple hyperparameters into consideration into our project.

Datasets

Our dataset includes sample cover letters scrapped from Indeed. We have created a scrapper to help us collect the data from the website for the next step. The data is about 1000 cover letters, with each containing about 500 words. We used 340 cover letters as a mini batch for the pilot study.

Scope of Corpus

- Genre: job description/cover letters/resumes
- Source: Indeed
- Size: a typical job description consists of around 1000 tokens, we are aiming to collect at least 10000 examples
- Language: English
- Data format: The corpus is stored as a .csv file

Methods

The sample cover letters are the initial input, we generate the job descriptions and resumes using OpenAI API, this way we are making sure we have matched job descriptions and raw resumes. We then stored the cover letters, resumes and job descriptions into a dataframe in .csv format, and found the data. We then used this final data to train and finetune the base T5 model. There are mainly three parameters that were tweaked, *per_device_train_batch_size, gradient_accumulation_steps* and *max_steps.*

Train test split: 80/20

Training Parameter:

1. per_device_train_batch_size=8
2. gradient_accumulation_steps=8
3. max_steps=100 (Flan T5 small) 50 steps (Flan T5 large)
4. optimizer= ‘adam’

Generation Parameters:

1. *Temperature =2.0*
2. *num_beams=3*

Results

We have used the Rogue score as our main metric, which allows us to measure the quality of text summarization by computing the frequency of overlapping n-grams. The following results shown below for reference:

- **Evaluation: Rouge score Flan T5 base model**

```
1. Step Training Loss   Validation Loss     Rouge1        Rouge2         Rougel        Rougelsum     Gen Len
2. 50     2.065400            1.617432            4.993300     4.175800      4.932800       4.975000       19.000000
3. 100  1.910300            1.591844            4.906300   4.072000       4.888400       4.897300       19.000000
```

Generated Output:

```
Amy Chan
(212) 667-5656
amy.chan@email.com
February 1, 2018

Dear Hiring Manager,
I want to apply for the job of Medical Records Clerk at a hospital in Charlotte.
```

- Evaluation: Rouge score Flan T5 Large model with 50 steps

Step	Training Loss	Validation Loss	Rouge1	Rouge2	Rougel	Rougelsum	Gen Len
25	1.845800	1.472070	4.991800	4.126700	4.928300	4.937300	19.000000
50	1.693600	1.450809	5.040200	4.180700	4.971200	4.985700	19.000000

Generated sample cover letter

Output generated:

Amy Chan

(212) 370-7910 <- phone number from the previous data of Amy chan

adamchan@email.com <- made up email id from the name

28-Aug-19 <- made up date but able to have a proper format

Dear Hiring Manager, <- understands the greeting part in the cover letter

As an individual with a desire to work at a hospital where the health of the patients is top priority, I am eager to begin working at the hospital that will best serve your patients. I am excited to be employed at Saint Mary's Health System, and I look forward to fulfilling this need for a medical records clerk. I work in medical records departments in hospitals and have worked in other departments. I am capable of working with both doctors and other staff members to ensure that the medical records are up to date and that they are completely complete. I have an interest in helping to keep our patients as safe and secure as I can. I have a desire to continue my career at the hospital. I have spent five years in medical records departments in several hospitals, so I will bring some of my knowledge and skill that I gained from that time. I enjoy working with the nursing staff to ensure that the records of patients are accurate and up to date and will always do my best to help the other staff members that I work with. This experience allows me to help doctors and other medical staff when necessary. The hospital is looking to hire someone who will take a team approach as a means of ensuring the success of the hospital, as a whole and a particular department within the hospital. I am a student at *St. Helena University, and have a nursing degree*. As such, although my education is not directly related to the medical records office, I have gained some knowledge that may benefit the hospital and the staff. I believe I can bring a great deal of experience and knowledge to the job. I am confident that the hospital is a great place to live and a great place for me to find employment. Thank you so much for your consideration of my application and would love to learn more about Saint Mary's Health System. I look forward to meeting with you and discussing more about the position and what it will be like for my future at the hospital. As a new and dedicated member of the hospital team, I hope to see you in person soon to begin the journey of becoming a great part of the team.

Thanks again for your time.

I look forward to hearing from you soon,

Take care!

Amy Chan,

212-370-7910.

Conclusion

The results indicate that fine-tuning and different prompts lead to diverse outcomes. We can see that the fine-tuned model is able to come up with a coherent and consistent cover letter format given a resume and a job description. Fine-tuning models with more parameters indeed increased the quality of the cover letters. The model stopped hallucinating after tuning hyper parameters.

In terms of limitations, we didn't have the chance to try with many diverse prompts, but even with a little tweak, we could achieve different scores. If given more time, we would have collected additional data and focused more on crafted prompt engineering, as well as experimented with different parameter fine-tuning techniques. Additionally, we are also interested in exploring reinforcement learning in the future. Comparing T5 large and FlanT5 with the base T5 model could be a viable approach, starting from this point. In terms of evaluation, we would like to adopt multiple metrics such as BLEU score and perplexity to evaluate our final results.