MediumBlink: The Rapid Insight & Web Weaver

Why Longformer?

The Longformer, a breakthrough in natural language processing, emerges as a superior tool for text summarization, specifically designed to overcome the limitations faced by earlier transformer models like BERT and GPT in handling extended documents. This proficiency can be attributed to several key aspects of its design and functionality, which are intrinsically linked to the challenges of processing long text sequences.

Longformer was primarily developed to handle longer sequences, a critical requirement for summarizing complex documents like academic papers, legal documents, or extensive articles. Traditional transformer models are limited to processing about 512 tokens, a constraint stemming from the memory-intensive nature of their self-attention mechanisms. Longformer extends this limit substantially, allowing the processing of documents with thousands of tokens. This extended processing capacity is crucial for summarization, as it enables the model to comprehend the full breadth of a lengthy document, ensuring that key themes and details spread across the text are accurately captured in the summary.

Another significant advancement in Longformer is its efficiency in the attention mechanism. Standard transformers exhibit a quadratic increase in computational complexity with longer sequences, making them inefficient for lengthy texts. In contrast, Longformer introduces an attention mechanism that scales linearly with the length of the sequence. This efficiency is paramount for summarization tasks, as it allows for quick and resource-effective processing of large volumes of text.

Longformer's enhanced performance on specific tasks like document summarization is also noteworthy. Its ability to process and understand extended context makes it particularly well-suited for summarizing long documents, where understanding the entire narrative and its nuances is essential for generating coherent and comprehensive summaries.

Moreover, the model's resource optimization feature is a critical factor in its practical application. By efficiently processing longer texts, Longformer optimizes the use of computational power and memory, making it a viable option for large-scale deployments and real-world applications.

In summary, Longformer's design, characterized by its capability to handle extended text sequences, its efficient attention mechanism, and its optimized resource usage, makes it exceptionally well-suited for summarization tasks. Its ability to process long documents in their entirety, balancing detail and overview, ensures that summaries are not only accurate and comprehensive but also coherent, encapsulating the essential elements of the original text.

Transfer Learning with Longformer:

In this project report, my focus was to apply transfer learning in natural language processing (NLP) by using a fine-tuned Longformer model from Hugging Face. The concept of transfer learning revolves around utilizing a model trained on one type of data or task and adapting it to another. This approach is particularly advantageous in NLP, where large-scale language models require extensive computational resources and time for training.

My project capitalized on a Longformer model already fine-tuned for machine learning article summarization. The original Longformer model, developed by the Allen Institute for AI, excels in handling long text sequences, a common limitation in traditional models like BERT and GPT-2. Its architecture, featuring a sliding window attention mechanism, allows for efficient processing of long documents. However, while the base Longformer is proficient in general language tasks, its application to domain-specific tasks like summarizing machine learning articles necessitates further specialization.

I leveraged the pre-fine-tuned model, which had undergone an initial round of training specific to machine learning content. This model had been adjusted to align with the unique structure, terminology, and style typical of machine learning literature, making it a more suitable starting point for my project. The fine-tuning process involved re-training the model on a curated subset of the arXiv dataset, focusing on papers closely related to machine learning. This dataset was selected using advanced techniques like sentence embeddings and K-means clustering, ensuring that the training material was highly relevant to the task at hand.

The advantage of using this pre-fine-tuned model lies in its prior exposure to relevant content, allowing for a more efficient adaptation to the specific nuances of machine learning articles. This is a key aspect of transfer learning – leveraging existing knowledge and adapting it to similar, yet distinct tasks. By doing so, I avoided the extensive computational resources and time typically required for training large models from scratch.

Link to HuggingFace Model: https://huggingface.co/bakhitovd/led-base-7168-ml

Link to HuggingFace Dataset: https://huggingface.co/datasets/bakhitovd/ML_arxiv

Link Extraction:

```
def get_all_links(content):
    soup = BeautifulSoup(content, 'html.parser')
    links = set()
    for a in soup.find_all('a', href=True):
        href = a['href']
        # Filter to include only clean-looking links
        if href.startswith('http') and '?' not in href and not href.endswith('/'):
            links.add(href)
    return links
```

The `get_all_links` function in Python is designed to extract all unique, clean-looking hyperlinks from a given HTML content. Here's a step-by-step explanation:

1. **Parse HTML Content**: It uses BeautifulSoup, a popular Python library for web scraping, to parse the provided HTML content. `soup = BeautifulSoup(content, 'html.parser')` initializes a BeautifulSoup object with the given content.
2. **Initialize an Empty Set**: `links = set()` initializes an empty set to store the unique links.
3. **Find All Hyperlinks**: The function iterates over all anchor (`<a>`) tags with an `href` attribute, which are hyperlinks in HTML. `for a in soup.find_all('a', href=True)` loops through each hyperlink found in the HTML content.
4. **Extract and Filter Links**: Within the loop, `href = a['href']` extracts the hyperlink reference. The function then applies a filter to include only 'clean-looking' links: those that start with 'http' (to ensure they are complete URLs), do not contain a '?' (often indicating a dynamic URL with parameters), and do not end with a '/' (often a sign of a directory, not a specific page).
5. **Add Unique Links to the Set**: If a hyperlink meets the criteria, it's added to the set using `links.add(href)`. Using a set ensures that each link is unique (duplicates are automatically removed).
6. **Return the Set of Links**: Finally, the function returns the set of unique, filtered links.

DEMO:

EXAMPLE: TYPE 1: MEDIUM ARTICLES ON MACHINE LEARNING AND RELATED TOPICS

LINK :

https://medium.com/@bakhitovd/fine-tuning-a-longformer-model-for-summarization-of-machine-learning-articles-fa6a9b31182a

SUMMARY:

In this report, a machine learning strategy was built on a decision tree algorithm and a reinforcement learning algorithm. The models were limited to holding a maximum of 1000 shares either short or long. The strategies are stock symbol agnostic, and data has been provided in my github repository to be able to play around with additional symbols and parameters. The purpose of this report and further analysis is to decide upon which indicators to use to inform the decision of whether to enter a long or short position. Bollinger bands percentage, relative strength index, and an exponential moving average cross were chosen as the three technical indicators that all three strategies used. Secondly, the models have been limited to hold a maximum number of 1000 stocks either short (or long). Thirdly, the algorithms are stock symbols agnostic and data is provided on my github to allow the models to be played around with more symbols and parameter values. For the purpose, this report shows the results of four different strategies when used on the training data (data the models are seen and trained on). The first strategy was to build a model that increases portfolio value over time. Again, the model was constrained to holding only 1000 shares or until the model converges (whichever comes first). Second, the strategy was limited to only historical stock price data and any indicators secondarily created are based off historical stock prices (**adjusted close price). Third, the strategies were limited only to holding 1000 shares. Fourth, they were limited not only to short (buying 1000 shares) but also long (entering a long position). Fifth, the first machine learning algorithm was reinforcement learning (reinforcement learning).

LINKS PROVIDED:

https://github.com/Bakhitovd/led-base-7168-ml

https://huggingface.co/datasets/bakhitovd/ML_arxiv

https://huggingface.co/bakhitovd/led-base-7168-ml

LINK:

https://medium.com/@wesleywarbington_22315/ai-stock-trading-d71955621834

SUMMARY:

In this report, a machine learning strategy was built on a decision tree algorithm and a reinforcement learning algorithm. The models were limited to holding a maximum of 1000 shares either short or long. The strategies are stock symbol agnostic, and data has been provided in my GitHub repository to be able to play around with additional symbols and parameters. The purpose of this report and further analysis is to decide upon which indicators to use to inform the decision of whether to enter a long or short position. Bollinger bands percentage, relative strength index, and an exponential moving average cross were chosen as the three technical indicators that all three strategies used. Secondly, the models have been limited to hold a maximum number of 1000 stock either short (or long). Thirdly, the algorithms are stock symbols agnostic and data is provided on my GitHub to allow the models to be played around with more symbols and parameter values. For the purpose, this report shows the results of four different strategies when used on the training data (data the models are seen and trained on). The first strategy was to build a model that increases portfolio value over time. Again, the model was constrained to holding only 1000 shares or until the model converges (whichever comes first). Second, the strategy was limited to only historical stock price data and any indicators secondarily created are based off historical stock prices (**adjusted close price). Third, the strategies were limited only to holding 1000 shares. Fourth, they were limited not only to short (buying 1000 shares) but also long (entering a long position). Fifth, the first machine learning algorithm was reinforcement learning (reinforcement learning).

LINKS PROVIDED:

https://github.com/wesleywarbington/tradingStrategies

EXAMPLE: TYPE 2: MEDIUM ARTICLES ON GENERAL TOPICS

LINK:

https://medium.com/from-the-red-line/was-the-circle-line-built-on-the-cheap-937e7a6df1a2

SUMMARY:

The circle line was built in the late 1990s to provide the circle line with 73 trains. Since then, the line has been underutilised, and significant investments have been made to keep costs down. But some of them may not have been optimal, especially considering their more polished equivalents along the dtl. This isn’t the first time that the downtown line has been written about, but it is a continuous series of errors and structural failures that got us to this point, so the finger can firmly be pointed at a single politician, civil servant, or group of engineers.

LINKS PROVIDED:

https://t.me/ftrlsg

https://en.wikipedia.org/wiki/No_U-turn_syndrome

https://en.wikipedia.org/wiki/Outer_Ring_Road_System

https://www.todayonline.com/singapore/faulty-circle-line-cables-be-replaced-january

https://eresources.nlb.gov.sg/history/events/5c6485bb-c357-48be-9d12-bf7c1d422d0e

https://eresources.nlb.gov.sg/newspapers/digitised/article/straitstimes20070915-2.2.7.4

https://eresources.nlb.gov.sg/newspapers/digitised/article/straitstimes20090818-1.2.10.1

https://eresources.nlb.gov.sg/newspapers/digitised/article/today20010407-1.2.16.2

https://en.wikipedia.org/wiki/Sim_Wong_Hoo

https://eresources.nlb.gov.sg/newspapers/digitised/article/today20120405-1.2.66.4

EXAMPLE: OTHER SITES ARTICLES ON MACHINE LEARNING AND RELATED TOPICS

LINK:

https://bair.berkeley.edu/blog/2023/11/14/ghostbuster/

SUMMARY:

ai-generated text detection systems often do poorly on data that differs from what they were trained on. In addition, if these models falsely classify real human writing as ai- generated, they can jeopardise students whose genuine work is called into question. We introduce ghostbuster, a state-of-the-art method for detecting ai-based text. Ghostbuster works by finding the probability of generating each token in a document under several weaker language models, then combining functions based on these probabilities as input to a final classifier. We evaluated across a range of ways that text could be generated, including different domains (using newly collected datasets of essays, news, and stories), language models (e.g., different varieties of english), or prompts (e,g., human-edited model generations). We found that a Roberta baseline had catastrophic worst-case generalisation performance, sometimes even worse than a perplexity-only baseline. We hope that ghostbuster can help with a variety of lower-risk applications, including filtering ai-_generated text out of language model training data and flagging online sources of information..

LINKS PROVIDED:

https://arxiv.org/abs/2304.02819

https://medium.com/nlplanet/two-minutes-nlp-perplexity-explained-with-simple-probabilities-6cdc46884584

https://github.com/vivek3141/ghostbuster

https://arxiv.org/abs/2305.15047

https://ghostbuster.app/experiment

http://bair.berkeley.edu

https://arxiv.org/abs/1906.03351

https://arxiv.org/abs/2210.09421

https://arxiv.org/abs/2301.11305

https://www.nytimes.com/interactive/2023/02/17/business/ai-text-detection.html

http://claude.ai

EXAMPLE: OTHER SITES ARTICLES ON GENERAL TOPICS

LINK:

https://www.spendlifetraveling.com/reasons-to-travel/

SUMMARY:

Why travel? Well, that’s what I want to share with you here because there are so many reasons to travel. For as long as my memory, my life has been an ordinary, passive, linear trajectory through life. Since childhood, I have yearned for crazy escapades, dreamed about fantastic experiences, and bemoaned the so- called 'ordinary’ route. Travel is stimulating, exciting, and engaging. You can’t help but feel liberated and inspired to make more of life. You see that you are fallible and life is cruel and that material wealth means very little in the grand scheme of things. You feel blessed and blown away by the generosity of strangers in a foreign land. You might experience true poverty in india. You might have all your worldly possessions stolen in colombia. And you might see the most mind-blowing natural beauty in nepal. But ultimately, though, you come through the other side and are all the better for it. Travel (and the adventures you have along the way) makes everything better..

LINKS PROVIDED:

https://www.whatsdannydoing.com/blog/best-backpacking-flashlight

https://www.spendlifetraveling.com/reasons-to-travel/#comment-140168 https://pinterest.com/sltraveling

https://www.spendlifetraveling.com

https://www.twitter.com/sltraveling

https://www.instagram.com/spendlifetraveling

https://www.facebook.com/spendlifetraveling

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