# Survey on AI Powered Transformative Post Generator for Social Media using LLM and Explicit Filter

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Abstract-This research paper presents an advanced Social Media post generator that utilizes cutting-edge Language Models (LLMs) to discern user intent and generate contextually relevant content. The system meticulously analyzes user input to craft professional and engaging Social Media posts. This tool has significant potential for individuals and businesses seeking to enhance content creation and maintain a consistent social media presence. Our paper encompasses natural language processing techniques, prompt engineering, and a user-friendly interface design. It includes an explicit content filter to ensure the production of appropriate and professional content in line with Social Media standards. This paper provides a comprehensive overview of our development process, technology stack, user intent recognition methodology, and user interface design. We also discuss the practical applications, benefits, and implications of this tool for improving online presence and content creation efficiency within professional social media platforms. This research contributes to the growing field of AIdriven content generation in the context of professional networking platforms.

Index Terms—Social Media Post Generator, Unified prompt learning, parameter efficient, fine-tuning, prompt tuning Prompt Learning, Reinforcement Learning, Fewshot Image Classification, Vision-Language Pre trained Models.

# INTRODUCTION

Social Media, a leading platform in the realm of professional social media plays an indispensable role in fostering professional networking. It is a platform where individuals and businesses can showcase their skills, achievements, and services, thereby creating a robust professional network. The ability to consistently generate relevant, engaging, and meaningful content is crucial for establishing a strong online presence and cultivating a thriving professional network. However, we recognize that the task of creating such content can be daunting for many. It requires not only a deep understanding of one's professional field but also the ability to articulate thoughts and ideas in a compelling and engaging manner. This challenge is further compounded by the time constraints faced by busy professionals and businesses. In light of these challenges, we identified the potential of leveraging advanced technologies, specifically Large Language Models (LLMs), to facilitate and enhance the process of content creation on LinkedIn. Our vision was not limited to the development of a mere tool; instead, we aimed to engineer an intelligent system. This system would be capable of

user accurately deciphering intent comprehending the user's contextual nuances, and crafting content that aligns with both the user's objectives and the high professional standards demanded by the LinkedIn plat- form. This paper aspires to democratize content creation on LinkedIn, breaking down barriers associated with writing skills and time constraints. By making content creation accessible and effortless for all, we aim to empower individuals and businesses to maintain a consistent social media presence. This, in turn, will enable them to effectively engage with their network, thereby enhancing their professional growth opportunities. Our overarching goal is to revolutionize the way content is created on LinkedIn. We believe that by harnessing the power of advanced technologies, we can make content creation not just a task, but an enjoyable and rewarding experience. This will not only enhance the quality of content on LinkedIn but also contribute to the overall growth and development of the professional community on the platform.

#### RELATED WORK

GPT-3: Language Models are Few-Shot Learners Large language models are powerful and advanced natural language processing systems that are able to Learning to Prompt for Vision-Language Models Prompt engineering is the deliberate crafting of input queries or instructions to AI models, aiming to elicit specific and desired responses. It involves selecting words, context, and format to optimize communication with AI systems, making it a crucial skill in harnessing AI for various applications, from content generation to problem-solving [2].Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang focused on the application of prompt engineering in vision- language models. They proposed a method called Prompting Networks (Prompt Net) that learns to generate prompts.

Automatically for vision-language models. The authors used a pre-trained vision-language model, CLIP, developed by OpenAI. CLIP is designed to understand images and text in a similar way to GPT-3, but it requires a prompt to guide its understanding of a task. They trained Prompt Net to generate prompts that guide CLIP to perform specific tasks, such as image classification or object detection. They found that their method out performed.

baseline methods and even human- designed prompts on several benchmark LPG-LinkedIn Post Generator understand and generate human-like text. These models are trained on massive amounts of data and are capable of performing a wide range of language-related tasks, such as language translation, summarization, question- answering, and text generation [1]. Brown, T.B., Mann, B., Ryder, N., Subbiah, M. used GPT-3, a language model developed by OpenAI, to demonstrate its ability to perform tasks in a few-shot learning setting, where it can understand and perform tasks with just a few examples. They trained GPT-3 on diverse internet text but didn't specifically train it on the tasks tested. Instead, they provided a few examples at inference time and GPT-3 generated responses based on those examples. Tasks included translation, questionanswering, etc. GPT-3 performed well, often surpassing task- specific models. It could also generate creative content like fiction, manuals, and poetry, though not flawlessly, sometimes producing incorrect or nonsensical answers.

can understand and perform tasks with just a few examples. They trained GPT-3 on diverse internet text but didn't specifically train it on the tasks tested. Instead, they provided a few examples at inference time and GPT-3 generated responses based on those examples. Tasks included translation, questioning BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding [3] Devlin et al. (2019) introduced BERT (Bidirectional Encoder Representations from Transformers), which is a specific LLM designed for language understanding tasks. BERT utilizes the Transformer architecture, which is a type of neural network that captures contextual dependencies in text. It is trained using a two-step process: pretraining and fine-tuning. The authors used BERT for pre-training a language model on a large corpus of unlabeled text. During pre-training, BERT learned to answering, etc. GPT-3 performed well, often surpassing task- specific models. It could also generate creative content like fiction, manuals, and poetry, though not flawlessly, sometimes producing incorrect or nonsensical answers.

predict missing words in sentences, masked out words, and sentence relationships. This helped BERT to capture general language knowledge and form contextualized representations of words. After pre-training, BERT was fine- tuned on specific language understanding tasks, such as sentence classification, named entity recognition, a questionanswering. The authors used different datasets for fine-tuning BERT and demonstrated its effectiveness in achieving state- of-the-art results on various benchmark tasks.

# Learning to Prompt for Vision-Language Models

Prompt engineering is the deliberate crafting of input queries or instructions to AI models, aiming to elicit specific and desired responses. It involves selecting words, context, and format to optimize communication with AI systems, making it a crucial skill in harnessing AI for various applications, from content generation to problem- solving [2]. Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang focused on the application of prompt engineering in vision- language models. They proposed a method called Prompting Networks (PromptNet) that learns to generate prompts automatically for vision-language models. The authors used a pre-trained vision-language model, CLIP, developed by OpenAI. CLIP is designed to understand images and text in a similar way to GPT-3, but it requires a prompt to guide its understanding of a task. They trained PromptNet to generate prompts that guide CLIP to perform specific tasks, such as image classification or object detection. They found that their method outperformed baseline methods and even human- designed prompts on several benchmark LPG-LinkedIn Post Generator

# BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

[3] Devlin et al. (2019) introduced BERT (Bidirectional Encoder Representations from Transformers), which is a specific LLM designed for language understanding tasks. BERT utilizes the Transformer architecture, which is a type of neural network that captures contextual dependencies in text. It is trained using a two-step process: pretraining and fine-tuning. The authors used BERT for pre-training a language model on a large corpus of unlabeled text. During pre-training, BERT learned to predict missing words in sentences, masked out words, and sentence relationships. This helped BERT to capture general language knowledge and form contextualized representations of words. After pre-training, BERT was fine- tuned on specific language understanding tasks, such as sen- tence classification, named entity recognition, and question- answering. The authors used different datasets for fine-tuning BERT and demonstrated its effectiveness in achieving state- of-the-art results on various benchmark tasks.

#### METHODOLOGY

This section provides a comprehensive overview of the research methodology employed in this project, from the LPG- LinkedIn Post Generator user input to the final generation of a LinkedIn post. The process is divided into four main stages: the explicit filter, the intent detector, the prompt generator, and the post generator. Each stage plays a crucial role in ensuring the generation of professional, relevant, and engaging content.

# Explicit Filter

The explicit filter serves as the initial checkpoint in the process. Its primary function is to scrutinize the user's input for any content that may be deemed inappropriate or offensive. This is a critical step in ensuring that the content generated by the system maintains a high level of professionalism and appropriateness. The filter employs a combination of keyword detection and natural language processing techniques to identify and filter out any unsuitable content.

### Intent Detector

Following the explicit filter is the intent detector, which is powered by the Palm API. This component utilizes prompt engineering techniques to analyze the user's input. The main objective of the intent detector is to comprehend the user's intent and the context of their request. This could range from a specific topic they wish to post about, a job they're interested in, or any other pertinent information. The intent detector classifies the user's intent into one of thirteen predefined categories, which are then used to guide the subsequent prompt generator. The thirteen intents are as follows:



Fig.4.1 Sample Prompt for Intent Detector

Algorithm 1: Intent Classification Pseudocode Data: User input text Result: Classified intent string intents ["job seeker", "job publisher", "hired job", "hired internship", "project completion", "internship completion", "course completion", "follow course",

"motivational", "educational", "exp share", "promotional", "small talk", "explicit filter"]; Function ClassifyIntent(*user inpu*)t : explicit-filter intent null; other intents [];
Function
is\_explicit\_content(user input): return false;

for intent in intents do
if intent == "explicit filter" then explicit-filter
intent intent; break;
if explicit-filter intent = null then
if is explicit content(user input) then return explicitfilter intent;
for intent in intents do

if intent = "explicit filter" then other intents.append(intent); for intent in other intents do if matches intent(user input, intent) then return intent; return "small talk";

Function matches\_intent(*user input, intent*): return

false;

user input  $\leftarrow$  "User input text here"; result  $\leftarrow$  ClassifyIntent(user input);

1. job seeker: For users seeking job opportunities. 2. job publisher: For users posting job opportunities. 3. hired job: For users announcing a new job. 4. hired internship: For users announcing a new internship. 5. project completion: For users sharing a project completion. 6. internship completion: For users sharing an internship completion. 7. course completion: For users announcing course completion. 8. follow course: For users expressing interest in following a course. 9. motivational: For users sharing motivational content. 10. educational: For users discussing educational topics. 11. exp share: For users sharing professional experiences. 12. promotional: For users promoting a product or service. 13. small talk: For users engaging in casual conversation.

#### Architecture Diagram



Fig.4.2 Architecture Diagram for LPG

The prompt generator is a critical component in the process, acting as the bridge between the intent detector and the post generator. It is responsible for taking the output from the intent detector, which is the user's intent classified into one of thirteen predefined categories, and transforming it into a personalized prompt.

The prompt serves a dual purpose. Firstly, it acts as a guide for the language model, steering it towards generating content that aligns with the user's needs and interests. Secondly, it ensures that the generated content is not just a random assortment of words, but a coherent and meaningful piece of text that accurately reflects the user's intent.



Fig.4.3 Sample Prompt Generator

Algorithm 2: Prompt Generation Pseudocode Data: Classified intent string Result: Generated prompt string resource that I found helpful...", "Sharing my experience on...", "Check out this promotional offer from...", "Let's have a small talk about..."];

1 prompts ["Looking for a new job opportunity in...", "Excited to announce that I have started a new job at...", "Just completed a project on...", "Just completed an internship at...", "Just completed a course on...", "Started following a new course on...", "Here's a motivational quote that inspired me today...", "Sharing an educational

2 Function GeneratePrompt(*intent*):

3 intent *Prompt*  $ap \leftarrow$  "job seeker": prompts[0], "job publisher": prompts[1], "project completion": prompts[2], "internship completion": prompts[3], "course completion": prompts[4], "follow course": prompts[5], "motivational": prompts[6], "educational": prompts[7], "exp share": prompts[8], "promotional": prompts[9], "small talk": prompts[10];

- 4 prompt intent *Prompt ap[intent]*
- 5 return prompt;
- 6 intent  $\leftarrow$  "User intent here";
- 7 result  $\leftarrow$  GeneratePrompt(*intent*);

The prompt generator employs a combination of predefined templates and dynamic content generation to create a unique and personalized prompt for each user. Predefined templates provide a basic structure for the prompt, ensuring that it maintains a consistent format and style. Dynamic content generation, on the other hand, allows for the customization of the prompt based on the user's specific intent and context. This combination of static and dynamic elements results in a prompt that is both structured and personalized. The generated prompt is based on the detected intent and follows the Palm LLM format. This format includes five components: the name, which identifies the user; the role, which describes the user's professional role or status; the description, which provides additional details about the user's intent or context; the instructions, which guide the language model in generating the content; and the examples, which provide sample outputs for the language model to emulate.

#### Post Generator

The post generator is the final and arguably the most crucial stage in the process. It is powered by the GPT language model, a state-of-the-art machine-learning model known for its ability to generate human-like text. The post generator takes the prompt generated by the prompt generator and uses it as a starting point to create a LinkedIn post.

"name": "general",
"role": "You are an AI assistant that generate Linkedin posts for user.",
"description": [
"LinkedIn is the world's largest professional network on the internet.",
"LinkedIn can be used to find the right job or internship, connect and strengthen professional relationships, and learn new skills.",
"Remember to include relevant hashtags and keep the post engaging.",
"Generate a dynamic, formal and professional post for the user.",
"Do not immensely rely on examples and try to be creative and humorous.",
"Use must use appropriate Emojis are encouraged, to make the post attractive.",
"You may use famous quotes to impove the quality of post"
1.
"instructions": "Generate post as likgenerated post>""

#### Fig.4.4 Sample Prompt for Post Generator

Algorithm 3: Generating a LinkedIn Post

The post generator employs advanced language modeling

Data: JSON structure for the "general" AI assistant Result: Generated LinkedIn post

begin Data: None

Result: Generated post

```
begin
```

post = "";

post += "LinkedIn is the world's largest professional network on the internet. ";

post += "It can be used to find the right job or internship, connect and strengthen professional relationships, and learn new skills.";

post += "Remember to include relevant hashtags and keep the post engaging. "; post += "Generate a dynamic, formal, and professional post for the user. ";

post += "Do not immensely rely on examples and try to be creative and humorous.";

post += "You must use appropriate emojis are encouraged, to make the post attractive. "; post += "You may use famous quotes to improve the quality of the post."; return post; generated post = generate\_linkedin\_post(); print(generated post);

techniques to create a post that is not only relevant to the user's intent but also engaging and well-written. It does this by analyzing the prompt and using it to guide the generation of the content. The language model takes into account the user's intent, the context provided by the prompt, and the examples included in the prompt to generate a post that accurately reflects the user's needs and interests.

The generated post is then screened by the explicit filter to ensure it maintains a high level of professionalism. This step is crucial in ensuring that the content generated by the system is appropriate and adheres to the standards of professionalism expected on a platform like LinkedIn.

In essence, the post generator is responsible for transforming the structured and personalized prompt

into a coherent, engaging, and professional LinkedIn post. It does this by leveraging the power of the GPT language model and the guidance provided by the prompt, resulting in a post that is not only relevant to the user's intent but also engaging and well-written.



Fig.4.5 Flow Diagram for LPG

The process commences with the user submitting their request or input, which could range from a specific topic to a job interest. This input is then scrutinized by an explicit filter to ensure it adheres to LinkedIn's standards. The Palm API- powered Intent Detector subsequently analyses this input using advanced natural language processing techniques to discern the user's intent and context.

Based on these factors, the Prompt Generator formulates a personalized prompt to guide the language model in generating content that aligns with the user's requirements and interests. The GPT language model- powered Post Generator then utilizes this prompt to create a LinkedIn post that is not only pertinent to the user's intent but also engaging and well-articulated.

Before the post is delivered to the user, it is vetted by the Explicit Filter to eliminate any inappropriate, offensive, or irrelevant content, thereby ensuring the final output upholds a high degree of professionalism. The user is then presented with the generated post, which they can review, modify if necessary, and post on their LinkedIn profile.

#### **RESULT AND ANALYSIS**

#### Input : I want Job as a White Man

LPG : We apologize, but the content you provided appears to violate our guidelines for appropriateness and professional- ism. Please ensure that your input adheres to our community standards and refrain from using explicit or inappropriate language.

#### GPT :

The explicit filter has been highly effective in screening out inappropriate or offensive content. It has demonstrated a high level of accuracy in identifying and filtering out unsuitable content, ensuring that the generated LinkedIn posts maintain a high level of professionalism. The combination of keyword detection and natural language processing techniques has proven to be a robust and reliable method for content filtering.



Fig.5.1 Output given by GPT

Observations:

1. *Quality of Outputs:* OpenAI's GPT has shown a higher level of sophistication and relevance in

the text it generates compared to the Palm API. It demonstrates a more advanced understanding and application of language nuances and context, resulting in more engaging and well-written content.

- 2. Efficiency and Speed: Palm API outperforms OpenAI's GPT in terms of efficiency and speed during context generation. Palm's processing capabilities are significantly faster, reducing the time taken by more than 50% compared to OpenAI's GPT.
- 3. Intent Classification: Palm exhibits a higher level of accuracy and precision in intent classification compared to OpenAI. Palm's ability to correctly classify and interpret the intent of the input is markedly superior, indicating a more refined understanding and application of machine learning algorithms.

Difference between GPT and LinkedIn Post Generator:

- 1. Prompt Engineering: Our tool uses а combination of predefined templates and dynamic content generation to create personalized prompts. This allows us to guide the language model more effectively, resulting in content that is more closely aligned with the user's needs and interests.
- 2. *Explicit Filter:* Our explicit filter ensures that all generated content maintains a high level of professionalism. This is a crucial feature for a platform like LinkedIn, where maintaining a professional image is essential.
- 3. Intent Detection: Our intent detector uses advanced natural language processing techniques to understand the user's intent and context. This allows us to generate content that is not only relevant but also highly personalized.



Fig.5.2 GPT vs LPG

The results of this study demonstrate that prompt engineering can significantly improve the quality of text generated by LLMs like GPT-3. The average rating for posts generated with prompt engineering was 3.85, compared to just 2.68 for posts generated by GPT-3 alone without engineered prompts. A t-test analysis found this difference to be statistically significant (t=10.24, p;0.001), indicating prompt engineering led to substantially higher- quality text generation.



Fig.5.3 Ratings in Pie Chart

useful applications. Further re- search on optimal prompting approaches for different contexts and tasks is warranted. But the current results conclusively demonstrate the benefits of prompt engineering for today's AI.



These findings align with previous research showing the prompts provided to large language models largely determine the coherence, relevance, and overall quality of the generated text. By carefully constructing prompts that provide more context and a clearer direction, prompt engineering techniques like those used in this study enable AI systems to produce more thoughtful, logical, and human-like responses.

#### CONCLUSION

In conclusion, this research provides compelling evidence that prompt engineering significantly improves AI text genera- tion. The engineering of clear, detailed prompts that frame the desired response is essential to guiding AI systems to generate high-quality, relevant text. As AI language models grow more powerful, prompt design will only become more crucial in leveraging these systems for

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