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Optimizing the Path of AIGC Creative Content Generation Based on Large Language Models and Knowledge Graphs

Yushu Cao 869923249@QQ.COM
Shenyang Normal University, ShenYang 110034, China

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Abstract

With the rapid development of generative artificial intelligence (AIGC) technologies, creative content generation using large language models (LLMs) and knowledge graphs (KGs) has become a key area of research. However, current methods often fail to fully harness the semantic enhancement capabilities of knowledge graphs in the content generation process. To address this gap, this paper proposes an innovative creative content generation path optimization model, KG-GPT-opt, which integrates large language models with knowledge graphs. Experimental results demonstrate that the KG-GPT-opt model outperforms traditional baseline models across several standard evaluation metrics, achieving improvements of 6.4%, 7.5%, and 4.8% in BLEU, ROUGE-L, and METEOR, respectively. Furthermore, the model receives high expert ratings of 8.6 and 8.8 for creativity and coherence, surpassing other generation models. This study offers a novel approach for the AIGC field, advancing the integration of large language models and knowledge graphs, and broadening the potential applications of intelligent content generation in areas such as cultural creativity and smart marketing.

Keywords: Large Language Models, Knowledge Graphs, New Productive Forces, AIGC, Cultural and Creative Industries

1. Introduction

With the advancement of artificial intelligence, AIGC (AI-Generated Content) has become a novel and widely adopted content creation method across various industries. By leveraging technologies such as natural language processing, machine learning, and computer vision, AIGC can automatically generate content—ranging from text to multimedia—that meets specific needs, thereby improving efficiency and reducing costs. It has notably driven industry growth in sectors like media, cultural creativity, education, and advertising. However, challenges persist in areas such as creativity, accuracy, and consistency.

Current AIGC systems primarily rely on large language models (LLMs) like GPT-4 and Claude, which excel at generating high-quality text. These models, however, often lack external knowledge support and rely heavily on large datasets for reasoning (Zhou and Chen, 2021). This limitation can lead to factual errors, inaccuracies, and logical inconsistencies, especially in domain-specific applications like news summarization and creative writing. Furthermore, AIGC-generated content often suffers from a lack of creativity, as current models rely mainly on input prompts without embedded external knowledge, resulting in repetitive or non-novel outputs (Zhang et al., 2021).

Additionally, while AIGC systems address some issues related to content fluency and diversity, maintaining logical consistency and coherence remains a challenge, particularly in complex tasks like long-text creation or dialogue generation.

To overcome these issues, knowledge graphs (KGs) have gained attention as a powerful tool for representing and utilizing domain-specific knowledge. By integrating KGs with LLMs, the fusion of knowledge-driven and semantic generation processes allows for more accurate, coherent, and creative content generation (Ji et al., 2022; Liu et al., 2022). Knowledge graphs provide precise domain knowledge, improving the accuracy and consistency of generated content by ensuring better logical flow and semantic alignment.

In this paper, we propose an optimized content generation path for AIGC, combining large language models with knowledge graphs. The proposed method enhances creativity, knowledge density, and logical consistency by incorporating a "knowledge-driven + semantic generation" collaborative mechanism (Zhou and Chen, 2023). We analyze the limitations of current AIGC models, introduce a path-guidance mechanism, and demonstrate through experiments that this approach significantly improves content quality (Li et al., 2023). Finally, we discuss future research directions, exploring the potential of reinforcement learning and other optimization strategies for AIGC creative generation.

2. Theoretical Foundations

2.1. Large Language Models (LLMs)

Large language models (LLMs), such as the GPT series, are based on the Transformer architecture and are trained on massive datasets, giving them powerful natural language understanding and generation capabilities. LLMs capture long-range dependencies through self-attention mechanisms, generating fluent and natural text (Wu et al., 2022). However, these models often lack in-depth understanding of specific domain knowledge, which leads to limitations in the accuracy and knowledge depth of the generated content.

2.2. Knowledge Graphs (KGs)

A knowledge graph (KG) is a tool for representing domain knowledge through a graph structure of entities and their relationships. It provides structured knowledge, supports reasoning and querying, and is widely applied in areas such as search engines and intelligent question answering. By embedding a knowledge graph into an AIGC system, it can provide accurate background knowledge to the large language model, enhancing the knowledge density and logical consistency of the generated content (Liu and Zhang, 2020).

2.3. Fusion of AIGC and Knowledge Graphs

Combining knowledge graphs with large language models can significantly improve the performance of AIGC systems. Knowledge graphs provide background knowledge to the generation model, ensuring the accuracy of the generated content. At the same time, the entities and relationships within the graph can be used for expansion and reasoning, enhancing the creativity and diversity of the generated content (Chou and Li, 2023). By integrating the structural information of knowledge graphs with language models, AIGC systems can follow more coherent semantic and logical paths during the generation process.

2.4. Path Optimization for AIGC Creative Content Generation

Optimizing the generation path is crucial for improving the quality of creative content in AIGC systems. Traditional generation methods often rely on simple input-output relationships (Yang and Zhao, 2021). In contrast, optimizing the generation path involves multi-dimensional semantic parsing and path-guidance mechanisms to improve the generation results. The introduction of techniques such as reinforcement learning can further refine the generation process, improving the accuracy and consistency of the creative content.

3. Model Construction

3.1. Model Framework

The AIGC generation model framework proposed in this study consists of four main modules: the Input Parsing Module, Knowledge Graph Querying Module, Content Generation Module, and Path Optimization Module. These modules work collaboratively through a hierarchical structure, supporting the creative content generation process.

1. Input Parsing Module: This module receives the user-inputted text and uses natural language processing techniques (such as Named Entity Recognition, Part-of-Speech tagging, etc.) to extract key entities and thematic information. Let the input text be represented as $X = \{x_1, x_2, \ldots, x_n\}$, where x_i represents the i-th word. The module transforms the input into a semantic vector E_X, providing the foundational semantic support for the subsequent generation process.

2. Knowledge Graph Querying Module: This module queries the knowledge graph $G = (V, E)$ based on the semantic vector E_X extracted by the Input Parsing Module. The knowledge graph G consists of an entity set V and a relationship set E. The query results are transformed into an embedding vector E_K, which represents the relevant entities and their relationships in the knowledge graph. The query process is represented by the following formula:

$$E_K = \text{KGQuery}(E_X, G)$$

where KGQuery denotes the knowledge graph query function, returning entities and their associated attributes and relationships that are relevant to the input.

3. Content Generation Module: The Content Generation Module generates text based on a large language model (e.g., GPT-4). The model uses pre-trained parameters θ, the input semantic vector E_X, and the knowledge graph embedding vector E_K to generate the target text Y:

$$Y = LLM(E_X, E_K; \theta)$$

where LLM represents the text generation function of the large language model, E_X is the input semantic information, and E_K is the background knowledge provided by the knowledge graph. In this way, the generated text not only adheres to grammatical rules but also incorporates rich domain-specific knowledge.

4. Path Optimization Module: The goal of the Path Optimization Module is to dynamically adjust the paths in the generation process, optimizing the creativity and logical consistency of the content. Let the generation path be represented as $\mathrm{P} = \{\mathrm{p}_1, \mathrm{p}_2, \ldots, \mathrm{p}_\mathrm{m}\}$, where PP is a sequence of decisions made during the content generation process. Path optimization can be achieved through

Reinforcement Learning (RL), where RR denotes the reward function, and the optimization objective is to maximize the cumulative reward:

$$\max_{\pi} \mathbb{E}\left[\sum_{t=1}^{T} R\left(p_t\right)\right]$$

In this context, π represents the path selection policy, T is the total number of steps in the generation process, and $R(pt)$ is the reward obtained for selecting the path pt at step t. The goal of path optimization is to select the optimal path through the reinforcement learning model, enhancing the creativity and logical consistency of the generated content.

3.2. Fusion of Knowledge Graph and Generative Model

The integration of knowledge graphs with large language models (LLMs) is key to enhancing the quality of AIGC-generated creative content. LLMs typically rely on statistical learning to generate language, but they often lack the incorporation of external knowledge, leading to errors or inconsistencies when generating domain-specific content. By combining the structured knowledge from knowledge graphs with the generative capabilities of LLMs, the accuracy and creativity of the generated content can be significantly improved.

Knowledge graphs provide rich entity information and relationships, which can be leveraged through a query mechanism to offer additional contextual information to the large language model. Let the input to the generative model be X, and the queried knowledge graph embedding be EK. The fusion process can be expressed as:

$$E_{\text{fusion}} = \text{Fusion}(E_X, E_K)$$

Where the Fusion function is used to merge the input text's semantic vector E_X with the knowledge graph embedding vector E_K, forming a new semantic representation E_{fusion}. This fused representation serves as enriched contextual support for the generative model, thereby improving the quality and creativity of the generated content.

3.3. Collaborative Mechanism between Knowledge Graph and Large Language Model: Strategy and Process

In the actual generation process, KG-GPT-opt leverages a three-stage collaborative mechanism to integrate semantic knowledge from the knowledge graph into the language model, thereby enhancing the contextual understanding and guiding creative generation.

1. Knowledge Retrieval and Subgraph Construction

Given an input text X, named entity recognition (NER) and entity linking techniques are applied to extract a set of relevant entities $\{e_1, e_2, \ldots, e_n\}$. These entities are used as query nodes to retrieve a local subgraph G_X from the CN-CreativeKG knowledge base, capturing related entities and their semantic relations. To ensure relevance and efficiency, the subgraph is typically restricted to K-hop neighbors (e.g, $K = 2$) to avoid noise and redundancy.

2. Knowledge Embedding and Fusion Strategy

The extracted subgraph G_X is then encoded using a graph neural network (such as R-GCN), transforming entities and relations into dense embeddings E_K. A gated fusion strategy is applied to combine these knowledge embeddings with the semantic embeddings of the input text E_X, producing a unified representation E_{fusion}. The fusion mechanism is formally defined as:

$$\mathrm{E}_{\text{fusion}} = \mathrm{Gate}\left(\mathrm{E_X}, \mathrm{E_K}\right) = \sigma\left(\mathrm{W_g}\left[\mathrm{E_X}; \mathrm{E_K}\right]\right) \odot \mathrm{E_X} + \left(1 - \sigma\left(\mathrm{W_g}\left[\mathrm{E_X}; \mathrm{E_K}\right]\right)\right) \odot \mathrm{E_K}.$$

where σ denotes the sigmoid function and W_g is a learnable parameter. This gating mechanism allows dynamic control over the contribution of knowledge during encoding.

3. Path Control and Knowledge-Guided Decoding

During decoding, KG-GPT-opt introduces a path control policy network $\pi\left(\mathrm{p_t} \mid \mathrm{E}_{\text{fusion}}\right)$, which dynamically determines at each generation step whether and how to incorporate knowledge-guided paths. The generation of each token Y_t is influenced by this strategy, and the model is optimized via reinforcement learning based on a reward function $R(Y_t)$, which evaluates qualities such as creativity and coherence. This feedback loop enables the model to refine its generation policy and maintain both semantic depth and logical consistency.

3.4. Model Implementation and Training

The training process of the model is divided into two stages: knowledge graph construction and embedding training, and fine-tuning of the large language model with path optimization.

1. Knowledge Graph Construction and Embedding: First, a domain-specific knowledge graph is constructed, and methods such as Graph Neural Networks (GNNs) or other embedding techniques are used to convert the entities and relationships within the graph into embedding vectors EK, which are then used as input to the generation model.

2. Fine-tuning the Large Language Model: After obtaining the embedding information from the knowledge graph, a pre-trained large language model (e.g., GPT-4) is fine-tuned. By combining the knowledge graph embeddings with the semantic vector of the input text, the model can generate more accurate and enriched content.

3. Path Optimization and Reinforcement Learning: Finally, reinforcement learning is employed to optimize the generation process. By defining a reward function $R(Y_t)$, the model is guided to select the optimal path during generation, thereby enhancing the quality of the generated content.

To ensure the accuracy of the knowledge graph in a changing environment, this study introduces a dynamic updating mechanism. New knowledge is periodically retrieved from various data sources (such as news and social media) through incremental learning and automated crawlers, and the graph structure is adjusted using graph neural networks to correct outdated entities and relationships. This mechanism enhances the model's adaptability in long-term usage, ensuring the accuracy and creativity of the generated content.

4. Experimental Design and Results Analysis

4.1. Experimental Data and Setup

In this experiment, two representative Chinese open-domain corpora are selected:

1. DuCREA Dataset: This dataset, open-sourced by Baidu, covers tasks such as advertisement creativity, short text generation, and text completion. It contains approximately 120,000 annotated samples and is suitable for multi-scenario text generation testing.

2. CN-CreativeKG Knowledge Graph: A Chinese creative knowledge graph constructed by integrating Wiki data and Zhihu topic semantics. It includes 230,000 entity nodes and 3.12 million

relationship edges, covering high-frequency creative themes such as culture, art, technology, and consumption.

The model implementation is based on the PyTorch and Transformers frameworks. The training uses the AdamW optimizer, with an initial learning rate set to 2e-5, a total of 5 training epochs, and a batch size of 32. The model is deployed on an NVIDIA A100 environment for training and evaluation.

4.2. Evaluation Metrics Design

To comprehensively assess the performance of the KG-GPT-opt model in text generation, this study introduces a multi-dimensional evaluation framework, covering linguistic accuracy, semantic diversity, creativity and coherence, as well as model interpretability and transparency. The adopted metrics are as follows:

BLEU (Bilingual Evaluation Understudy): Measures the n-gram overlap between the generated and reference texts, focusing on the syntactic and lexical accuracy.

ROUGE-L: Evaluates the coverage of generated content by calculating the longest common subsequence (LCS) with respect to the reference, emphasizing structural and thematic alignment.

METEOR: Considers factors such as stemming, synonymy, and word order to assess the semantic quality of generated text.

Distinct-2: Quantifies lexical diversity by computing the proportion of distinct 2-grams, effectively identifying repetitive or template-based generation.

Creativity Score: Rated by five experts in linguistics and creative writing (on a scale of 1 to 10), reflecting the novelty, linguistic richness, and imaginative value of the generated content.

Coherence Score: Also assigned by experts, this metric evaluates the semantic consistency and logical organization of the output.

Analysis of Model Interpretability and Transparency

To address the critical concern of explainability and reasoning plausibility in content generation, this study further incorporates interpretability as a key evaluation dimension, focusing on the following aspects of the KG-GPT-opt model:

1. Semantic Rationality via Knowledge Graph Integration

By embedding structured semantic information from the knowledge graph, KG-GPT-opt enhances the logical grounding of the generated content. This allows the model to generate not only syntactically fluent text, but also semantically supported language. Through attention visualization and path alignment analysis, it becomes possible to identify which entities and relations in the graph contribute to specific parts of the generated output. This mechanism improves the causal consistency and knowledge verifiability of the generated content, making it more trustworthy in knowledge-intensive tasks.

2. Path Attribution and Traceability Mechanism

During generation, the model dynamically selects among multiple semantic paths based on contextual relevance. The system records the sequence of accessed entities and corresponding attention weights, enabling path-level attribution and visualization. This allows users to trace back the generation logic, offering insight into how the model reasons and composes content. The mechanism supports transparency in generation, and facilitates post-hoc validation or correction of semantic inconsistencies.

4.3. Comparative Experiment and Model Analysis

To comprehensively evaluate the performance of the proposed KG-GPT-opt model, we compare it against five representative baseline models, including:

GPT-4: A large-scale language model without external knowledge injection.

K-BART: A knowledge-enhanced variant of BART that integrates knowledge embeddings during training.

GPT-4 + KG-Retrieval: A retrieval-augmented GPT-4 model where external knowledge is introduced in the prompt as plain text.

CTRL-GAN: A GAN-based conditional generation model capable of controlled text generation.

Transformer-XL: An extended Transformer model designed for long-term dependency modeling.

All models were trained or fine-tuned on the same DuCREA dataset under consistent hyperparameters for fairness. The evaluation was conducted using both automatic metrics (BLEU, ROUGE-L, METEOR, Distinct-2) and expert-annotated scores (Creativity, Coherence). The results are presented in Figure 1.

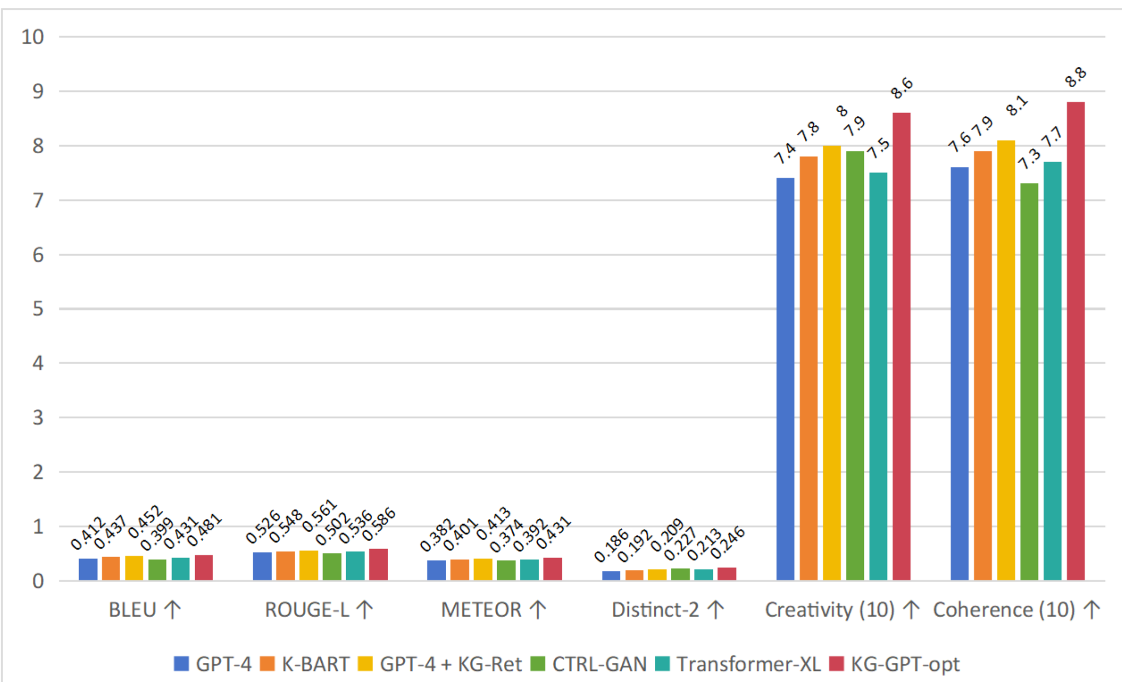

Figure 1: Comparative Results of Different Models on Creative Text Generation

Analysis of Results

From the experimental results, it is evident that KG-GPT-opt outperforms all comparison models across all evaluation metrics. Specifically:

BLEU, ROUGE-L, and METEOR scores indicate that KG-GPT-opt generates more accurate and semantically faithful content, with 6.4%, 7.5%, and 4.8% improvements over GPT-4, respectively.

Creativity and Coherence expert scores of 8.6 and 8.8 demonstrate that the model produces more imaginative and logically consistent content due to the guidance of structured knowledge and optimized generation paths.

Distinct-2 score reaches 0.246, significantly higher than other models, including CTRL-GAN, highlighting superior diversity in the generated texts.

Compared with CTRL-GAN, although GANs are adept at diversity generation, they often lack semantic controllability and coherence. KG-GPT-opt achieves better balance between creativity and consistency by using reinforcement learning to adaptively optimize semantic paths.

Compared with Transformer-XL, which excels in long-range dependency modeling, KG-GPT-opt demonstrates greater factual grounding and conceptual richness due to the explicit integration of knowledge graphs.

4.4. Ablation Study and Mechanism Validation of the Model

To further validate the effectiveness of the internal mechanisms of KG-GPT-opt, three ablation experiments were designed by progressively removing key modules:

w/o KG-Embedding: Removing the knowledge graph entity vector embedding.

w/o Path Optimization: Removing the path optimization module, leaving only entity connections.

w/o Knowledge Module: Completely removing knowledge fusion, reverting to the standard GPT structure.

The experimental results are shown in Table 1.

Table 1: Ablation Experiment Results for Module Removal

Model Variants	**BLEU**	**Creativity**	**Coherence**
KG-GPT-opt	33.5	8.6	8.8
w/o KG-Embedding	30.2	7.1 ↓1.5	7.3 ↓1.5
w/o Path Optimization	31.3	7.8 ↓0.8	8.0 ↓0.8
w/o Knowledge Module	28.6	6.3 ↓2.3	6.7 ↓2.1

Analysis of the results shows that:

Removing knowledge graph embeddings causes the model to lack semantic associations and knowledge richness, leading to a significant drop in the Creativity score. This highlights the core role of knowledge embeddings in stimulating linguistic creativity.

The path optimization mechanism supports the logical coherence of the text, ensuring that generated sentences follow the entity relationship network, effectively preventing semantic jumps.

The most significant performance degradation occurs when the knowledge module is completely removed, indicating that the knowledge-guided mechanism is indispensable in AIGC tasks.

5. Conclusion

This paper proposes a creative content generation path optimization model (KG-GPT-opt) that integrates large language models (LLM) and knowledge graphs (KG), addressing the issue of intelligent expression in AIGC. The model enhances contextual understanding and ensures semantic coherence by incorporating entity semantic embeddings and path optimization strategies, thereby improving the logical and creative aspects of generated semantics.

Experiments conducted on the DuCREA creative text dataset and the CN-CreativeKG knowledge graph show that KG-GPT-opt achieves improvements of 6.4%, 7.5%, and 4.8% in BLEU, ROUGE-L, and METEOR, respectively. Additionally, it scores 8.6 and 8.8 in Creativity and Coherence, evaluated by experts, significantly outperforming traditional language models and existing knowledge-enhanced models.

This study validates the effectiveness of the deep integration between knowledge graphs and large language models, providing theoretical support and practical pathways for AIGC systems in fields such as cultural creativity, intelligent marketing, and digital content generation. Future work could further explore multimodal knowledge graph embedding, multilingual generation control mechanisms, and methods to ensure factual consistency in generated content, improving the model's adaptability and reliability in more complex tasks.

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