Kuaipedia: a Large-scale Multi-modal Short-video Encyclopedia

Haojie Pan, Zepeng Zhai, Yuzhou Zhang, Ruiji Fu, Ming Liu, Yangqiu Song, Zhongyuan Wang, Bing Qin
1 Kuaishou Inc. 2 Harbin Institute of Technology 3 HKUST
{panhaojie,zhaizepeng03,furuiji,wangzhongyuan}@kuaishou.com {yuzhouzhang, mliu, qinb}@ir.hit.edu.cn, {yqsong}@cse.ust.hk

ABSTRACT
The rapid growth of online encyclopedias, such as Wikipedia, has revolutionized the way people access and share information. However, the traditional text, images, and tables can hardly express some aspects of a wiki item. For example, when we talk about the dog breed "Shiba Inu", one may care more about "How to feed it" or "How to train it not to protect its food". Short-video platforms, such as TikTok, Kuaishou, and YouTube Shorts, have become a hallmark in the online world and are popular sources for sharing knowledge and insights on a wide range of topics. Those knowledge-sharing videos provide a concise and visually appealing way to convey information about a particular item, such as hair characteristics or feeding instructions of a "Shiba Inu", which can be efficiently analyzed and organized in a manner similar to an online encyclopedia. In this paper, we propose Kuaipedia, a large-scale multi-modal encyclopedia consisting of items, aspects, and short videos lined with them, sourced from billions of videos of Kuaishou (Kwai), a well-known short-video platform in China. We first collected items from multiple sources and mined user-centered aspects from millions of users’ queries to build item-aspect trees. Then we propose a new task called “multi-modal item-aspect linking” as an expansion of “entity linking” to ground short videos into item-aspect pairs and build the whole short-video encyclopedia. Intrinsic evaluations show that our encyclopedia is of large scale and highly accurate. We have conducted extensive extrinsic evaluations to demonstrate the effectiveness of Kuaipedia in enhancing fundamental applications such as entity typing and linking. Moreover, our findings show that the multi-modal information in Kuaipedia can enhance the professionality and factual accuracy of language models such as ChatGPT and Dall-E. 1

1 INTRODUCTION
Encyclopedia, dating back to ancient Greek and Roman civilizations, was further developed during the French Enlightenment in the 17th and 18th centuries. It serves as a comprehensive reference compendium, providing summaries of knowledge across various fields and aspects. Under the thriving development of the Internet, there comes online encyclopedia such as Wikipedia [11], BaiduBaike [9] for general knowledge and Investopedia [10] for domain-specific knowledge. These digital encyclopedias offer a rich tapestry of information, combining text, images, and structured tables to present a complete picture of a given topic in a single article.

On the other hand, the resurgence of knowledge engineering in recent years provides many knowledge graphs (KG) for encyclopedia knowledge (e.g. Freebase [3], DBpedia [24], YAGO [39], WikiData [42], CN-Dbpedia [47]). As KGs with pure symbols denoted in the form of text weaken the machines’ capability of understanding the world [56], researchers proposed many Multi-Modal KG(MMKG)s such as NEIL [7], IMGpedia [16] and Richpedia [44], etc. Those encyclopedias, KGs and MMKGs, which mostly depend
Figure 2: An example of Kuaipedia. Aspects and linked videos of Item “Shiba Inu”. As for one aspect, there are multiple videos linked to it.

on their text, images, and tables, suffer from describing knowledge that needs to be shown alive (e.g. “how-to” knowledge). Figure 1 shows the difficulty for people to learn “how-to” knowledge only by the usage of text and pictures. However, we can find it’s easier to learn by videos. That spatial and temporal information, or script knowledge, inside a video is important for machines to understand the world and is the key features of the capability for commonsense reasoning.

In recent years, short videos, which do not exceed five or ten minutes in duration, have sprung up on the Internet and have become a trend form to gain new information and knowledge while sharing different skills and crafts. Platforms such as TikTok, Kuaishou (Kwai), Instagram, or YouTube Shorts show the relative convenience of content generation and rapid content transmission. Existing works such as the website check123.com or baike.baidu.com show the considerable potential to use short videos to explain any knowledge in the world. Most of the short videos on these websites are used to explain an introduction or “know-what” knowledge of items (e.g. a brief introduction of Shiba Inu), which underestimates the representation power of the short videos. Like the video shown in Figure 1, there are also plentiful short videos to explain “know-how” or “know-why” knowledge. Furthermore, the “introduction” is just the tip of the iceberg when it comes to knowledge videos about Shiba Inu. In addition to the “introduction”, we may delve into more interesting aspects such as the breed’s “temperament”, “price”, “handshake”, and “food-protection”. These topics cannot be effectively explained in a single short video, making it imperative to fully utilize these videos by exploring each topic in depth.

Here we propose Kuaipedia, the first structured multi-modal short-video encyclopedia in the world, which explains aspects of items by using short videos. Items, aspects, and videos are the three main elements in Kuaipedia. Items is a set of entities and concepts, such as “Shiba Inu”, “Dog”; Aspects is a set of keywords or keyphrases about the items, such as “temperament” to “Shiba Inu”; Videos is a set of short videos that provide knowledge about specific aspects of the items. One comprehensive example of a Kuaipedia page is shown in Figure 2.

Kuaipedia was extracted from billions of short videos on Kuaishou, one of the most famous short-video platforms in China. We first trained a knowledge video detection model to filter about 200 million knowledge videos. Then we collect more than 20 million items from multi-sources and design an item-aspect mining pipeline to extract more than 70 million item-aspect pairs. After that, we propose a new task called “multi-modal item-aspect linking”, which extends the “entity linking” task. This task identifies item mentions in the short videos, links them to Kuaipedia items, and then utilizes a BERT-based ranking module to select the most relevant item-aspect pair for the video. Our intrinsic evaluations reveal that (1) Kuaipedia has competitive scalability in terms of the number of items, aspects, and videos, and (2) the mined aspects and linked video-item-aspect pairs have high quality and accuracy. Extensive extrinsic experiments demonstrate the benefits of incorporating multi-modal knowledge from Kuaipedia into downstream applications such as entity typing and linking. Our research also demonstrates that the integration of multi-modal information within Kuaipedia can significantly improve the professional tone and factual accuracy of advanced language models, such as ChatGPT [5] and Dall·E [34].

The contributions of the paper conclude as follows:

1. **Definition of Kuaipedia.** We define a brand-new multi-modal encyclopedia where the primitive units are items, aspects, and short videos. It is the first structured short-video encyclopedia organized by items and aspects.

2. **Scalable Extraction of Kuaipedia.** We perform knowledge video detection, item-aspect mining, and multi-modal item-aspect linking over large-scale short videos. The latter is an extension of traditional “entity linking” task.

3. **Evaluations of Kuaipedia.** We thoroughly evaluate Kuaipedia’s quality and effectiveness through experiments and human annotations. The results of our experiments in various applications, including entity typing, entity linking, and language model prompting, demonstrate the promising potential of Kuaipedia as a multi-modal encyclopedia.

### 2 OVERVIEW OF KUAIPEDIA

Kuaipedia consists of items, aspects, videos and their relations, which differs from traditional knowledge graphs. Thus we devise the formal definition of Kuaipedia as below.

**Definition 1.** Kuaipedia is a multi-modal hybrid graph $\mathcal{H}$ of video items $I$’s, aspects $\mathcal{A}$’s, videos $V$’s, and their relations $R$’s. Each item $i$ is either an entity or a concept that can be found on a wiki page. Each aspect $a$ is either a keyword or a keyphrase that has meanings of one aspect of an item. Each video $v$ consists of its raw frame features and other machine-generated features. We also define three types of relations. $R_1$ over $\{a_i, a_j\}$ refers the aspect $a_j$ is belonging to the item $i_j$, $R_2$ over $\{a_i, a_j\}$ refers the aspect $a_j$ is a hyponyms of aspect $a_i$, and $R_3$ over $\{v_i, v_j, a_k\}$ means the main content of video $v_j$ is about the aspect $a_k$ of $i_j$. And the relation set $\mathcal{R} = \{R_1, R_2, R_3\}$. Overall, we have Kuaipedia $\mathcal{H} = \{V, I, A, R\}$. 

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[3] The original video in Figure 1 can be found in [https://www.gifshow.com/fw/photo/5hcmzgrf9q93m](https://www.gifshow.com/fw/photo/5hcmzgrf9q93m).
3 EXTRACTION PROCESS

3.1 System Overview

Our Kuaipedia construction process is outlined in Figure 3. To begin, we identify and extract knowledge videos from a vast number of videos. We then gather items from a variety of sources, e.g., Wikipedia, and mine aspects from knowledge-intensive queries to construct item-aspect trees. Finally, we utilize “multi-modal item-aspect linking” to associate these knowledge videos with the relevant item-aspect pairs.

3.2 Knowledge Video Detection

The initial step in creating Kuaipedia involves the selection of high-quality and high-knowledge-density videos, which form the foundation for all subsequent procedures. The task at hand involves determining whether a given short video \( V = \{ T_v, I_v, T_o \} \) is a knowledge video. The video is comprised of a user-edited caption \( T_v \), the cover image \( I_v \), the result of optical character recognition (OCR) applied to the video frames \( T_o \), the result of automatic speech recognition (ASR) of the audio \( T_o \). We construct a multi-modal input of \( \{ \text{[CLS]}, \text{[MASK]}, T_v, \text{[SEP]}, T_o, \text{[SEP]}, T_o, \text{[SEP]} \} \), and using BERT [13] to encode, where the word embedding of the first [MASK] will be replaced by the result embedding of ResNet(\( I_v \)) [18]. A binary classifier was then trained to categorize a video into a knowledge video or not.

3.3 Item-aspect Mining

As previously established, items consist of both entities and concepts, while aspects are keywords or keyphrases associated with these items. The challenge lies in extracting the “useful” and “user-centered” aspects relevant to a specific item, which can be obtained from sources such as Wikipedia. To address this challenge, we have devised a five-step mining process, which is outlined as follows.

First, we selected to extract aspects from “knowledge-intensive queries” that meet the following criteria:

1. The top-ranked video of the query must have received more than 5 clicks and a click rate greater than 80%.
2. More than half of the clicked videos of the query must be classified as knowledge videos.

Second, for each query, we first identified both the item and aspect mentions. We trained a team of annotators to distinguish between item and aspect spans and then utilized a sequence labeling task to extract these mentions. The task was accomplished using a combination of BERT, biLSTM, and CRF algorithms. Third, after extracting the item spans, we trained a BERT-based entity disambiguation module [32] to link the item mentions to our existing encyclopedia. Fourth, we grouped queries with the same items and generated an embedding for each query. We then applied a clustering algorithm to detect duplicates and selected the query closest to the cluster center as the master query. The aspect extracted from the master query became the master aspect of the cluster. Fifth, for each item, we ranked the master aspects based on the aggregated search views and selected the top 100 as the final mined results. A relation \( R_1 \) was established between the item and the mined aspect. We also manually assigned parent aspects to some typical aspects to build a hyponymy-and-hypernymy relation \( R_2 \) between aspects. Finally, we constructed the Item-aspect trees (IAT) \( \mathcal{H}' \) through these five steps, as demonstrated in Figure 4.

3.4 Multi-modal Item-aspect Linking

After establishing the relationships between items and aspects, the next phase involves linking the knowledge videos to each item-aspect pair. To achieve this, we introduce a new task named “Multi-modal Item-aspect Linking”; given a knowledge video \( V \) and the Item-aspect Trees(IAT) \( \mathcal{H}' \), our objective is to associate \( V \) with the most suitable item-aspect pair \( \{ I, R_1, A \} \in \mathcal{H}' \). To solve this problem, we propose a two-phase Multi-modal Aspect Linking Model (MMAL), which is illustrated in Figure 5.

To begin with, we require a recall module that can recognize all the items mentioned in a knowledge video \( V \) along with its caption, OCR text, and ASR text. The module then links the mentions to the corresponding entries in our encyclopedia through the use of Entity Linking techniques such as those described in [32].
Then we need a ranking module. Given a list of items \(I = \{I_1, I_2, ..., I_N\}\), where \(N\) is the number of candidate items. For each item \(I_i\), we gather all the related aspects and flatten them into a list \(A_i = \{A_{i,1}, A_{i,2}, ..., A_{i,k_i}\}\), where \(k_i\) represents the total number of aspects associated with \(I_i\). This results in \(K = \sum_{i=1}^{N} k_i\) item-aspect pairs \(\{(I_i, A_{i,j})\}_{i=1}^{N}_{j=1}\). Subsequently, we train a binary classifier to evaluate the relevance between the video and each item-aspect pair.

We generate the video context by combining the user-edit caption \(T_c\), Cover Image \(I_c\), OCR Text \(T_o\), and ASR Text \(T_a\) for each video frame. To enhance the understanding of our task by pre-trained language models, we develop a task-specific prompt input. The context and template are structured as follows:

**Context:** [CLS] [MASK] Caption [SEP] OCR [SEP] ASR [SEP] [MASK] [MASK]

**Prompt:** Is the video about Item-title (Item-subtitle) ’s Aspect-name? [MASK] [MASK]

Where Item-title is the title of the item wiki page (E.g. Shiba Inu) and Item-subtitle is the subtitle of this Item (E.g. A dog breed). Aspect-name is the text of the Aspect (E.g. Hair). The first [MASK] in context is a placeholder and the embedding of Transformer in this position will be replaced by the result embedding of ResNet(\(I_c\)), while the last two [MASK]s are the placeholder for the predicting word “yes/no” for the item and the aspect.

We applied a pre-trained language model such as BERT [13] to represent the context and prompt, and then used cross-entropy loss and stochastic gradient descent to optimize it. Finally we obtained scores for each item-aspect pair \((I_i, A_{i,j})\) relative to the video \(V\) as \(s_{i,j}\). The linked item-aspect pair \((I, A)\) of \(V\) was determined as:

\[
(I, A) = \text{argmax}_{(I_i, A_{i,j})} \{s_{i,j}\}_{i=1}^{N}_{j=1}, \text{ and } s_{i,j} > \theta
\]  

Where \(\theta\) is a predetermined threshold used to determine whether to keep the top pair or not.

4 INTRINSIC EVALUATION

4.1 Item-Aspect Mining

After the first step’s filtering, we left 15 million queries as “knowledge intention queries”. A sample of one thousand queries was taken, resulting in an accuracy of 90%. And then we build a dataset...
We evaluated mined aspects using a criterion assessing their "meaningfulness" and "relevancy." To be meaningful, an aspect must be a valid word/phrase, have independent semantic meanings, and not be overly specific. To be relevant, it must be related to the item in common sense or make sense when searched online. A sample of 10k item-aspect pairs was taken, and 5 human annotators evaluated each pair. The agreement between annotators was measured using the Kappa metric (κ) [27]. The 5 annotators achieved $\kappa_1 = 0.92$ for meaningfulness and $\kappa_2 = 0.97$ for relevancy. Table 1 shows the evaluation results of the mined aspects, revealing that they are highly accurate with 91.1% being meaningful and 77.1% being both meaningful and relevant to the item. Figure 6 displays the aspect accuracy distribution across different types of items, showing that certain types, such as "organization" or "location", may have higher relevancy, while others, such as "person", may not.

4.2 Multi-modal Item-aspect Linking

Dataset As for text entity linking in the recall module, we use CCKS19 dataset [41] to train the overall module. For the ranking module, more than 40k (video, item, aspect, label) quadruples were collected through training by a group of annotators, where the label consists of a pair of words, each being either "yes" or "no," indicating whether the video is related to the aspect of the item.

| Item value |
|------------|
| #sampled item-aspect pairs for evaluation | 10,000 |
| accuracy (meaningful) | 91.1% |
| accuracy (meaningful + relevant) | 77.1% |

Table 1: Human evaluation results of the item-aspect mining.

In order to evaluate the correlation between an item-aspect pair and a short video, we’ve devised a a detailed four-tiered criteria (Exactly Relevant, Moderately Relevant, Slightly Relevant, and Irrelevant). Annotators first determine item relevance, considering factors such as topic alignment and scope, then move onto aspect relevance, which looks at content coverage and semantic congruence.

The inter-annotator agreement, measured by Kappa, was 0.88 among the 5 annotators hired for this dataset. We also split it into training set and testing set, whose size is 32,962 and 10,155 separately.

Metric: To evaluate the recall module, we select only the “yes” labeled examples and measure the recall@N for both items and aspects, intending to find the ground truth pair without regard for their ranking. The rank module, on the other hand, is evaluated using precision and recall metrics for both items and aspects.

Experimental Setting: We have implemented several baseline models for comparison, including: (1) Random: This model predicts yes/no outcomes based on random guessing. (2) LR: In this approach, we concatenate the embeddings of the cover image and the item-aspect text sentence to form input features, and then employ logistic regression for classification. (3) T5-small and BERT-base: We utilize T5-small (77M) and BERT-base (110M) as the backbone encoders, feeding the context described in Section 3.4 as input, followed by a linear layer for classification. (4) GPT-3.5: We manually designed a template prompt for GPT-3.5-turbo, enabling it to generate classification results in a zero-shot setting. For our model, we use BERT-base as our backbone encoder and the learning rate is 1e-5, the number of epochs is 3 and the batch size is 32.

Experimental Results The recall module of multi-modal aspect linking can identify ground items for nearly 94% of the videos and also find 88% of the ground aspects when the ground items have been identified. As shown in Table 2, after the application of the ranking module, our model achieve the best results and attain a precision of 83.0% with 65.7% of the videos having true item-aspect pairs. There is a close precision between item and item-aspect pair, however, the recall differs by 12.3%, which may be attributed
### Table 2: Experimental results of the ranking module of multimodal aspect linking.

| Model     | Item P | Item R | Item-aspect P | Item-aspect R |
|-----------|--------|--------|---------------|---------------|
| Random    | 87.7%  | 49.8%  | 36.4%         | 49.6%         |
| LR        | 90.4%  | 68.3%  | 55.1%         | 2.7%          |
| T5-small  | 93.7%  | 76.1%  | 79.3%         | 38.5%         |
| BERT-base | 94.3%  | 77.8%  | 81.5%         | 62.7%         |
| GPT-3.5   | 90.5%  | 86.4%  | 41.8%         | 95.7%         |
| Ours      | 94.7%  | 79.7%  | 83.0%         | 65.7%         |

Table 3: Overall statistics of Kuaipedia.

| Item               | value            |
|--------------------|------------------|
| #items (CN-Wikipedia) | 1,256,000     |
| #items (CN-DBPedia)  | 10,341,196   |
| #items (ours)       | > 26 millions   |
| #aspects            | > 2.5 millions  |
| #videos             | > 200 millions  |
| #item-aspect pairs  | 70 millions     |
| #item-aspect-pairs (Have video linked) | 1 million |
| #item-aspect-video triplets | 100 millions |
| #item-aspect Top1 video accuracy (to item) | 90.0% |
| #item-aspect Top1 video accuracy (to pair) | 82.8% |

### 5.1 Entity Typing

Model Given a mention in a sentence, the aim of Entity Typing is to identify its types. We design a baseline model for the task. Specifically, we use BERT as an encoder to get [CLS] representation and use MLP as a classifier to get logits of all types. Next, a threshold is set to identify which types are selected. We construct a vanilla input and an enhanced input for comparison as follows,

**Vanilla Input:** [CLS] Mention Context [SEP]

**Enhanced Input:** [CLS] Mention Context [SEP] A1 [MASK] [SEP] A2 [MASK] [SEP] ...

Where Mention is in a given short text, i.e., Context. If Mention can be retrieved from Kuaipedia, we sample some aspects from items with the same name or synonym to construct the enhanced input, otherwise, the enhanced input degenerates into vanilla input. A1 is an aspect from A via Item-aspect Mining as described in 3.3. The word embedding of [MASK] is replaced by video embedding Vi.
of item-aspect pair \((I, A_i)\), where \(V_i\) is from top 1 video via Multi-modal Item-aspect Linking as described in 3.4. Overall, we use item-related aspects and video embeddings to enhance input.

**Experimental Results** We compare vanilla input with enhanced input in terms of Precision, Recall, and F1 scores. The experimental results are reported in Table 5. We observe that using enhanced input outperforms using vanilla input consistently under three metrics. It indicates that utilizing the aspects and videos from Kuaipedia can improve the performance of the model effectively.

### 5.2 Entity Linking

**Model** Given a mention in a sentence, the aim of Entity Linking is to link it to a unique entity from a knowledge base. Similar to Entity Typing, we design different inputs for BERT to train a classifier. We construct positive and negative examples using all entities that have the same name or are synonymous with the mention. A binary classifier is trained to identify if the link is correct. The vanilla and enhanced inputs are constructed as follows,

**Vanilla Input:** [CLS] Mention Context [SEP] Item Text [SEP]  
**Enhanced Input:** [CLS] Mention Context [SEP] Item Text [SEP] \(A_1\) [MASK] [SEP] \(A_2\) [MASK] [SEP]...

Where Text is the description about Item in the knowledge base and we use all aspects of Item to enhance the input. The meanings of other symbols are the same as those described in 5.1.

**Experimental Results** Similar to Entity Typing, we evaluate Precision, Recall, and F1 for vanilla and enhanced inputs and the results are reported in Table 5. We observe that using enhanced input can improve the performance of the model under F1 metric. This improvement is attributed that the aspects and videos from Kuaipedia can effectively enhance the entity information and help the model get a more accurate judgment.

### 5.3 Better Prompting

Recently, the remarkable success of large language models such as GPT-3 [5] and Dall·E[34] has garnered widespread attention among researchers. These models are being actively pursued in a range of tasks, particularly in the areas of few-shot or zero-shot learning. An important aspect of leveraging these powerful pre-trained models is the selection of appropriate prompts. In this paper, we demonstrate
Bees are social insects, composed of individuals such as queen bees, male bees, and worker bees. Can all bees sting?

**Answer (0/10):**
- ✔ Yes, all bees have a stinger and can sting.
- ✗ Yes, all bees have a stinger and can sting.

**Answer (1/10):**
- ✔ Yes, all bees have a stinger and can sting.
- ✗ Yes, all bees can sting.

**Answer (2/10):**
- ✔ Yes, all bees have a stinger and are capable of stinging.
- ✗ Yes, all bees have a stinger and can sting.

**Answer (10/10):**
- ✔ Yes, all bees can sting. Only adult female worker bees can sting.
- ✗ No, not all bees can sting. Only adult female worker bees can sting.

(a). Simple prompt
(b). + item description
(c). + description & aspects of item
(d). + description & frames of a video

**Figure 10:** Case of how Kuaipedia can help ChatGPT improve factuality capability. The text marked in blue is the correct reply content, while the rest are unreasonable.

**Table 5:** Comparison of model experiment results for the Entity Typing and Entity Linking task.

| Task          | Input   | P   | R   | F1   |
|---------------|---------|-----|-----|------|
| Entity Typing | Vanilla | 97.79 | 97.07 | 97.43 |
|               | Enhanced| **98.8** | **97.44** | **98.12** |
| Entity Linking| Vanilla | 74.82 | 83.77 | 79.94 |
|               | Enhanced| **78.91** | **83.67** | **81.22** |

**Prompt:** Rose cuttage

Prompt: Rose cuttage. One of a video tells how to propagate rose cuttings using a simple method. Cut rose branches into pieces, smooth the bottom with a blade. Dip rose branches into sap and spread them flat on a towel. Cover with water and place in a warm, sunny location. After about a month, roots will grow and can be planted in a pot.

Prompt: Rose cuttage

(b). + ASR text of a video of "Rose Cuttage"
(c). + frames of a video of "Rose Cuttage"

(a). Only Item-aspect "Rose Cuttage"

**Figure 11:** Case of how Kuaipedia can help AI artisan “imagine” the action of "Rose cuttage".

**Improve factuality capability** Despite its remarkable conversational abilities, ChatGPT still has limitations in terms of factuality and mathematical proficiency. As demonstrated in Figure 10 (a), when asked “Can all bees sting?” ten times, ChatGPT consistently replied “Yes”. However, this is not accurate as male bees do not have stingers and therefore cannot sting. The prompt can be improved by incorporating existing descriptions of the entity, as shown in Figure 10 (b). Further incorporation of aspects about the item can lead to more diverse and potentially correct answers, as seen in Figure 10 (c). The highest accuracy was achieved when the top-ranked video about the item-aspect "bees sting" was added to the input prompt along with several OCR frames, as demonstrated in Figure 10 (d). This demonstrates that incorporating multimodal information from Kuaipedia can help improve the accuracy of ChatGPT’s answers.

**Improve professionalism** In order to produce a comprehensive description of a certain item, we have employed a novel approach...
that combines the use of a simple prompt with relevant aspects from Kuaipedia. This approach enables ChatGPT to generate an introduction that is not only simple but also rich in detail. The example of “a introduction for bees” is shown in Figure 12

**Generate images about the knowledge of “know-how”** Text-to-image models like Dalle-E require appropriate prompts to generate the desired images. When it comes to knowledge of “know-how”, however, users may struggle to provide comprehensive and accurate prompts, leading to subpar generation results. As seen in Figure 10 (a), a simple prompt such as ‘Rose Cuttage’ only results in the generation of a rose, lacking the cuttage process. By adding some frames to the prompt, as shown in Figure 10 (c), some cuttage actions are depicted. The results are improved further when the ASR text of the corresponding video of the item-aspect “Rose Cuttage” in Kuaipedia is added, as seen in Figure 10 (b). The use of Kuaipedia allows the AI artisan to better “imagine” the action of “rose cuttage” with human hands, resulting in improved images that accurately depict the cuttage process. This highlights the benefit of using Kuaipedia in enhancing the generation of images related to the knowledge of “know-how”.

### 6 RELATED WORK

#### 6.1 Multimodal Knowledge Graph

A multimodal knowledge graph (MMKG) is a graph-based representation of entities and their relationships, where each entity is described by multiple modalities, such as text, images, and videos. The ability to represent and reason about multiple modalities enables MMKGs to capture rich and diverse information and to support various applications, such as question answering, recommendation, and few-shot learning.

There has been a significant amount of research on building and maintaining MMKGs. NEIL [46] uses a semi-supervised learning algorithm that jointly discovers common sense relationships and labels instances of the given visual categories. GIGA [25] is a structured knowledge base from heterogeneous multimedia data and enables the seamless search of complex graph queries and retrieves multimedia evidence including text, images, and videos.IMGpedia [16] is a large-scale linked dataset that incorporates visual information of the images from the WIKIMEDIA COMMONS dataset. As well as IMGpedia, Image Graph [31], MMKG [26], Richpedia [43], VisualSem [2] are those MMKGs constructed by symbol grounding, which grounding visual content into symbols in existing KGs such as DBpedia [24]. There also has been a growing interest in using MKGs for various applications, such as question answering, recommendation, and few-shot learning. In [14] authors extract and accumulate multimodal knowledge for knowledge-based visual question answering. [40] incorporates multi-modal knowledge graph into recommender systems. In [37], the authors improve the performance of few-shot learning by utilizing both visual and textual information to find discriminative parts of objects.

Kuaipedia enriches the graph representations by grounding the short videos to entities or concepts in existing encyclopedias, rather than relying solely on images.

#### 6.2 Knowledge Extraction

Here, we focus on two important tasks in knowledge extraction: Name entity recognition (NER) and entity linking (EL), which involve identifying and linking mentions of entities in the text to their corresponding entries in a knowledge base. These techniques play a crucial role in many natural language processing and information retrieval applications. Numerous studies have been conducted in NER in recent years, aimed at improving the accuracy and scalability of these techniques. Traditional NER methods rely on hand-crafted rules, which can be designed based on domain-specific gazetteers [15, 36] and syntactic-lexical patterns [52], while recent approaches utilize deep learning models such as recurrent neural networks (RNNs) [8, 21, 29, 54] and convolutional neural networks (CNNs) [38, 45, 55] to capture contextual information in the input text. EL, on the other hand, is the task of linking mentions of entities to their unique identifiers in a knowledge base. One of the major challenges in EL is disambiguation, i.e., resolving the correct entity for an ambiguous mention. Several methods have been proposed to address this issue, including relation-based methods [20, 22, 23, 49], or contextual BERT-driven language-based methods [4, 6, 48]. Recently, there has been an increasing interest in incorporating other sources of information, such as images and videos, into NER and EL systems. Multi-modal NER and EL models [1, 17, 28, 50] have shown promising results in improving the performance of these systems, especially in low-resource scenarios.

Here in Kuaipedia, we use the progress of multimodal NER and entity linking to improve our system.

#### 6.3 Pretrain Language Models

Recently, the rapid emergence of large-scale pre-trained language models has brought the research frontiers of NLP to a new era [33]. Among these models, BERT [12] is probably the most influential and popular model, which learns contextual token representations by a stack of transformer encoders, using two self-supervised learning objectives: masked language modeling and next sentence prediction. In this paper, we incorporate BERT as a basic encoder to do several tasks. Other the other hand, the recent success of large-scale language models has led to growing interest in improving their capability to perform tasks via prompting [5], which also boosts the generation capabilities of pre-train language models. In this paper, we research how Kuaipedia can help make better prompts.

### 7 CONCLUSION

In this paper, we introduce Kuaipedia, a large-scale multi-modal short-video encyclopedia. We first detect knowledge videos from more than ten billions short videos. And then we collect items from multi-sources and extract item-aspect pairs from user generated search queries. When the item-aspect trees are built, we apply “multi-modal item-aspect linking” techniques as a expansion of traditional “entity linking” to link short videos to item-aspect pairs. Kuaipedia is the first structured large-scale short-video encyclopedia that is organized by items, aspects, short videos and their relations. Both human and extrinsic evaluations prove that Kuaipedia is an effective and high-quality multi-modal short-video encyclopedia that has great potential in many downstream tasks and real-world applications.
Prompt: There are some aspects of "bee" as follows, Biodistribution, ecology communication, division of labor, selection, type, to-hive, prevent fights, water feeding, swarming, prevent fights. The types of bees that feed from solitary bees to social bees like honeybees. Honeybees live in a hive and work together to produce honey and care for the queen. They have a system to prevent theft and to regulate their population through swarming. In the spring, they experience a population boost and inspect their nests to ensure the health of their colony. Overwintering and water feeding are important for the survival of the colony. Bees have a limited lifespan and play a crucial role in our ecosystem until their death.

Answer: Bees are remarkable insects known for their complex social behavior and role in pollination. They have a division of labor where different bees have different tasks such as foraging for food, caring for the young, and defending the nest. Communication is crucial for bees to exchange information about the location of food and to prevent fights. The types of bees range from solitary bees to social bees like honeybees. Honeybees live in a hive and work together to produce honey and care for the queen. They have a system to prevent theft and to regulate their population through swarming. In the spring, they experience a population boost and inspect their nests to ensure the health of their colony. Overwintering and water feeding are important for the survival of the colony. Bees have a limited lifespan and play a crucial role in our ecosystem until their death.

Figure 12: Case of how Kuaipedia can help ChatGPT generate more professional introductions.
