A Survey of Knowledge Enhanced Pre-trained Models

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Abstract—Pre-trained models learn informative representations on large-scale training data through a self-supervised or supervised learning method, which has achieved promising performance in natural language processing (NLP), computer vision (CV), and cross-modal fields after fine-tuning. These models, however, suffer from poor robustness and lack of interpretability. Pre-trained models with knowledge injection, which we call knowledge enhanced pre-trained models (KEPTMs), possess deep understanding and logical reasoning and introduce interpretability. In this survey, we provide a comprehensive overview of KEPTMs in NLP and CV. We first introduce the progress of pre-trained models and knowledge representation learning. Then we systematically categorize existing KEPTMs from three different perspectives. Finally, we outline some potential directions of KEPTMs for future research.

Index Terms—Pre-trained models, symbolic knowledge, natural language processing, computer vision, knowledge representation learning, knowledge enhanced pre-trained models.

1 INTRODUCTION

CURRENT advances in deep learning [1], [2], [3], pre-trained models (PTMs) [4], [5], [6], [7], [8], [9], in particular have reached unprecedented impact not only within the academic and industrial research communities. Deep learning can fully leverage large-scale data by virtue of distributed representation and hierarchical structure generalization of neural networks. Based on deep learning, pre-trained models have undergone a qualitative leap forward, facilitating a wide range of downstream NLP and CV applications.

Despite their achievement, there is still a long way to reach new level of robust artificial intelligence. In Marcus’s word: intelligence can be counted on to apply what it knows to a wide range of problems systematically and reliably, synthesizing knowledge from a variety of sources such that it can reason flexibly and dynamically about the world, transferring what it learns in one context to another, in the way that we would expect of an ordinary adult [10]. Existing PTMs do have the following downsides. First, taking pre-trained language models as an example, they learn the semantics of the frequent words well but under-perform on rare words limited by long-tailed data distribution. Similarly, such data distribution also limits the practicality of PTMs of CV in real-world applications with long-tailed class imbalance. Second, PTMs are not adept at reasoning. For instance, pre-trained language models are statistical models and learn implicit relations according to the co-recurrence signals, resulting in the lack of logical reasoning. Although pre-trained language models can capture a wealth of linguistic [11], semantic [12], syntactic [13] and even world knowledge [14], Cao et al. [15] shows that the descent factual knowledge extraction performance of pre-trained language models mainly owes to the biased prompts. The experiments in [16] also indicate that the poor performance of pre-trained language models in tasks required reasoning. Likewise, PTMs of CV cannot extract semantic relationships between detected objects. Finally, ethical and societal concerns have been raised with the outperforming of PTMs over humans in certain tasks. As we observe, pre-trained language models lack commonsense knowledge and generate illogical sentences [17]. Thereby, interpretability and accountability of PTMs have become paramount for applying them generally.

The combination of neural networks and symbolic knowledge shed light on possible solutions to these problems. On the one hand, symbolic knowledge like knowledge graphs has high coverage of rare words, which addresses the lack of textual supervision [18], [19]. Beyond that, they also provide comprehensive relational information [20], [21] and/or explicit rules [22] for models to enhance the reasoning of pre-trained language models. On the other hand, symbolic knowledge improves interpretability in knowledge usage in downstream tasks [23]. In addition, it is practical to ingest knowledge [1] into a pre-trained checkpoint without training from scratch for a specific downstream application [24], [25]. Therefore, it is promising to integrate knowledge with pre-trained language models to achieve more general artificial intelligence.

This paper provides a comprehensive overview of KEPTMs in NLP and CV and discuss the pros and cons of

1. we use knowledge and symbolic knowledge interchangeably in this paper
each models in detail. The contributions of this survey can be summarized as follows:

- **Comprehensive review.** We provide a comprehensive review for pre-trained models in NLP and CV, and knowledge representation learning.
- **New taxonomy.** We propose a taxonomy of KEPTMs, which categorizes existing KEPTMs from the granularity of knowledge, the method of knowledge injection, and degree of symbolic knowledge parameterization.
- **Performance analysis.** We analyze the advantages and limitations for different categories of PTMs from the perspective of the scope of application scenarios, effectiveness of knowledge injection, management of knowledge, and interpretability.
- **Future directions.** We discuss the challenges of existing KEPTMs and suggest some possible future research directions.

The rest of the survey is organized as follows. Section 2 outlines the progress of pre-trained models and knowledge representation learning. Sections 3 introduces a classification principle and a corresponding comprehensive taxonomy. Following Section 3 categorization, Section 4 introduces the working principle of each kind of KEPTMs and analyzes its pros and cons, and compares existing KEPTMs from different dimensions. Section 5 discusses the current challenges and suggests future directions.

## 2 BACKGROUND

### 2.1 Pre-trained Models

We call the model that can extract high-level features from a large amount of raw sensory data to obtain effective representations and apply them to downstream tasks after fine-tuning a pre-trained model. The effectiveness of the pre-trained model largely depends on the representation learning of the model’s encoder. Representation learning refers to learning representations of the data that make it easier to extract useful information when building classifiers or other predictors [26]. There are two mainstream paradigms within the community of representation learning: probabilistic graphical models and neural networks. Probabilistic graph models learn feature representation by modeling the posterior distribution of potential variables in sample data, including directed graph model and undirected graph model. Neural network models mostly use an autoencoder composed of an encoder and a decoder. The encoder is responsible for feature extraction, while the decoder reconstructs the input by applying a regularized reconstruction objective.

Neural networks based models are preferable with the following advantages than probabilistic graphical models. Firstly, neural networks can express more possible features with distributed vectors instead of sparse vectors. Secondly, considering the existing data is mainly the result of the interaction between multiple latent factors, distributed vectors can represent different impact factors by designing a specific network structure. Finally, the underlying neural layers of deep neural networks transform concrete features learned from data into abstract features in upper layers and keep stable as the local change of the input data, enhancing the robustness of representation to generalize in many downstream tasks.

Following autoencoder-based neural models, pre-trained models design specific neural networks to encode input data while using pre-trained tasks to decode learned representations. After fine-tuning, pre-trained models can easily be adapted to all kinds of NLP and CV, even cross-modal tasks. We mainly divide models into pre-trained CV and pre-trained language models.

#### 2.1.1 Pre-trained CV Models

Pre-trained CV Models have emerged as a powerful strategy for image classification, object detection, and semantic segmentation. As the first to explore convolutional neural network (CNN) for generic object detection, Girshick et al. [27] achieves high object detection quality by integrating AlexNet [28] with a region proposal selective search [29]. Motivated by its inefficiency during testing, He et al. [30] introduced traditional spatial pyramid pooling into CNN architectures. Fast RCNN [31] simultaneously learns a softmax classifier and class-specific bounding box regression to further improve detection speed and quality, while Faster RCNN [7] relieves the dependency on external region proposals. Based on the Faster RCNN, Mask RCNN [32] achieves promising results for object detection and instance segmentation with just a small overhead to Faster RCNN. Beyond region-based approaches, researchers also have developed unified detection strategies. As the winner of the ILSVRC2013 [33] localization and detection competition, OverFeat [34] performs object detection via a single forward pass through the fully convolutional layers in the network and thus possesses a significant speed advantage. The YOLO series transform the object detection into a regression problem and reach state of the art results on standard detection tasks. Compared to YOLO, SSD [35] achieves a faster detection speed while still preserving high detection quality. VGG [8] is applicable to both classification and image recognition tasks as a popular architecture. Based on the object detection results, SDS [35] performs the semantic segmentation with category-independent bottom-up object proposals. Long et al. [36] propose the convolutional networks trained end-to-end without relying on region proposal. For more details of pre-trained CV models, we refer readers to [27], [38].

#### 2.1.2 Pre-trained Language Models

We divide the pre-trained language models [4], [5], [6], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50] into token-based and context-based models according to whether the models capture sequence-level semantics.

**Token-based Pre-trained Models** Originating from the NNLM [51] proposed by Bengio in 2003, distributed representations of words are generated as a by-product during the training. According to the hypothesis that words with similar context have similar semantics, Mikolov et al. [39], [40] propose two shallow architectures: Continuous Bag-of-Words (CBOW) and Skip-Gram (SG) to capture latent syntactic and semantic similarities between words. Besides, GloVe [41] computes word-word cooccurrence statistics from a large corpus as a supervised signal, and FastText
trains the model with text classification data. With the emergence of all the above token-based pre-trained models, word embeddings have been commonly used as text representation in NLP tasks. Although these models are simple and effective, they are only suited to attain fixed representations rather than capturing polysemy. That is also why we call this type of model static pre-trained models.

**Context-based Pre-trained Models** To address the problem of polysemy, pre-trained models need to distinguish the semantics of words and dynamically generate word embeddings in different contexts. Given a text \( x_1, x_2, \cdots, x_T \) where each token \( x_i \) is a word or sub-word, the contextual representation of \( x_i \) depends on the whole text.

\[
[h_1, h_2, \cdots, h_T] = f_{\text{enc}}(x_1, x_2, \cdots, x_T),
\]

where \( f_{\text{enc}}(\cdot) \) is neural encoder and \( h_i \) is contextual embedding.

Taking LSTM [52] as neural encoder, the ELMo [43] model extracts context-dependent representations from a bidirectional language model, which has shown to bring large improvement on a range of NLP tasks. However, ELMo is usually used as a feature extractor to produce initial embeddings for the main model of downstream tasks, which means the rest parameters of the main model have to be trained from scratch.

At the same period, the proposal of ULMFiT [53] provides valuable multi-stage transfer and fine-tuned skills for models. Besides, Transformer [54] has achieved surprising success on machine translation and proven to be more effective than LSTM in dealing with long-range text dependencies. In this background, OpenAI proposes GPT [4] that adopts the modified Transformer’s decoder as a language model to learn universal representations transferable to a wide range of downstream tasks, which outperforms task-specific architectures in 9 of 12 NLP tasks. GPT-2 and GPT-3 [5] mainly follow the architecture and train on larger and more diverse datasets to learn from varied domains. However, limited by a unidirectional encoder, the GPT series can only attend its left context resulting in sub-optimal for learning sentence-level semantics. To overcome this deficiency, BERT [6] adopts a masked language modelling (MLM) objective where some of the tokens of a sequence are masked randomly, and the goal is to predict these tokens considering the corrupted sentence. Inspired by Skip-Thoughts [56], BERT also employs the next sentence prediction (NSP) task to learn the semantic connection between sentences, which obtains new state-of-art results on eleven NLP tasks and even becomes the basis of subsequent models. Based on BERT, RoBERTa [45] design a few improved training recipes, including training longer with bigger batches over more data, modifying objectives, training over long sequences, and dynamically changing the masking pattern, which enhances significantly performance of BERT. To overcome the discrepancy between pre-training and fine-tuning of BERT, XLNet [44] proposes a new autoregressive method based on permutation language modelling to capture contextual information without introducing any new symbols.

Unlike all these above pre-trained models that aim at natural understanding or generation tasks, T5 [46] adopts an encoder-decoder framework to unify natural understanding and generation by converting the data into the text-to-text format. For more details of pre-trained language models, we refer readers to [57], [58].

### 2.2 Knowledge Representation Learning

In this section, we first introduce the definition of knowledge and then the conventional methods of knowledge representation, and comprehensive knowledge representation learning based on them.

#### 2.2.1 Knowledge

Knowledge is a familiarity, awareness, or understanding of someone or something, such as facts (descriptive knowledge), skills (procedural knowledge), or objects. David et al. [59] divided knowledge into four categories, namely factual knowledge, conceptual knowledge, procedural knowledge, and metacognitive knowledge. Factual knowledge refers to the knowledge of terminology and specific details and elements to describe objective things. Conceptual knowledge is the interrelationships among the fundamental elements within a larger structure that enables them to function together, such as principles, generalizations, and theories. Procedural knowledge is about the knowledge that guides action, including methods of inquiry and criteria for using skills, algorithms, techniques, and methods. Metacognitive knowledge emphasizes self-initiative and is the knowledge of cognition in general as well as awareness.

#### 2.2.2 Methods of Knowledge Representation

Davis et al. [60] puts forward the definition of knowledge representation in 1993, arguing that the notion can best be understood in terms of five distinct roles. First, a knowledge representation is most fundamentally a surrogate, a substitute for the thing itself, and we can reason about the world through thinking without practice. Second, it is a set of ontological commitments about how to think about the world. Third, it is a fragmentary theory of intelligent reasoning. Fourth, it is a medium for pragmatically efficient computation, which supports recommended inferences through the effective knowledge organization. Fifth, it is the medium of human expression used to express cognition of the world.

Conventional knowledge representation methods include first-order predicate logic, frame representation [61], script representation [62], semantic network representation [63], and ontology representation. The basic grammatical elements of first-order predicate logic are symbols representing objects, relations, and functions, among which the objects refer to the individual or category of things, the relationships refer to the mapping between things, and the functions require the object in each domain to have a mapping value as a special form of a predicate. Although this method can guarantee the consistency of knowledge representation and the correctness of inference results, it is difficult to represent procedural knowledge.

A semantic network is a conceptual network represented by a directed graph where nodes represent concepts and edges represent semantic relations between concepts, which can also be transformed into triplets. It can describe knowledge in a unified and straightforward way that is beneficial for computer storage and retrieval. However, it can only
and alleviates sparsity issues. More importantly, symbolic measures semantic correlations of entities and relations in the knowledge base, which effectively deep learning focuses on representation learning of entities as nodes and relations as edges. Specifically, the KG (KG) is the knowledge base represented as a network with entities and relations. Scripted representation represents the basic behaviour of things through a series of atomic actions, which describes the occurrence of things in a definite temporal or causal order and is used for dynamic knowledge. Although it can represent procedural knowledge to a certain extent, it is not appropriate for conceptual or factual knowledge.

Originally, the term ontology comes from philosophy where it is employed to describe the existence of beings in the world. For the sake of obtaining models with reasoning capabilities, researchers adopt the term ontology to describe what can be computationally represented of the world in a program. CYC [64] is a knowledge base constructed following ontology specifications, aiming to organize human commonsense knowledge. Since ontologies can represent unambiguously recognized static domain knowledge, it is also used in information retrieval and NLP. WordNet [65] is created based on word ontologies. In addition to static knowledge modelling, task-specific ontologies are also designed to add reasoning capabilities based on static knowledge.

In order to promote semantic understanding, Tim et al. propose the Semantic Web concept in 2001 to build a massive distributed database that links data through semantics instead of strings. To make data understandable for computers, W3C proposes the Resource Description Framework (RDF) [2] that uses the semantic network representation to express semantics in the form of triples. This form can be easily implemented by a graph to apply graph algorithms of probability graph and graph theory to solve problems. Besides, Web Ontology Language (OWL) is designed to enable computers reasoning ability, which describes categories, attributes and instances of things complying with ontology representation.

In engineering implementation, the knowledge graph (KG) is the knowledge base represented as a network with entities as nodes and relations as edges. Specifically, the KG obtains knowledge and corresponding descriptions from the network by semantic web technology and is organized in the form of triplets. Since the procedural knowledge is hard to manage and its certainty is weak, most of the existing KGs only contain conceptual and factual knowledge without procedural knowledge.

2.2.3 Knowledge Representation Learning

Knowledge representation learning (KRL) delegated by deep learning focuses on representation learning of entities and relations in the knowledge base, which effectively measures semantic correlations of entities and relations and alleviates sparsity issues. More importantly, symbolic knowledge can be much easier to integrate with the neural network based models after knowledge representation learning.

Translational Distance Models With distance-based scoring functions, this type of models measure the plausibility of a fact as the distance between the two entities after a translation carried out by the relation. Inspired by linguistic regularities in [68], TransE [69] represents entities and relations in d-dimension vector space so that the embedded entities h and t can be connected by translation vector r, i.e., \( h + r \approx t \) when \( (h, r, t) \) holds. To tackle this problem of insufficiency of a single space for both entities and relations, TransH [70] and TransR [71] allows an entity to have distinct representations when involved in different relations. TransH introduces relational hyperplanes assuming that entities and relations share the same semantic space, while TransR exploits separated space for relations to consider different attributes of entities. TransD [72] argues that entities serve as different types even with the same relations and construct dynamic mapping matrices by considering the interactions between entities and relations. Owning to heterogeneity and imbalance of entities and relations, TransSparse [73] simplifies TransR by enforcing sparseness on the projection matrix.

Semantic Matching Models Semantic matching models measure plausibility of facts by matching latent semantics of entities and relations with similarity-based scoring functions. RESCAL [74] associates each entity and relation with a vector and matrix respectively. The score of a fact \( (h, r, t) \) is defined by a bilinear function. To decrease the computing complexity, DistMult [75] simplifies RESCAL by restricting relation to diagonal matrices. Combining the expressive power of RESCAL with the efficiency and simplicity of DistMult, HolE [28] composes the entity representations with the circular correlation operation, and the compositional vector is then matched with the relation representation to score the triplet. Unlike models above, SME [76] conducts semantic matching between entities and relation using neural network architectures. NTN [77] combines projected entities with a relational tensor and predicts scores after a relational linear output layer.

Graph Neural Network Models The above models embed entities and relations by only facts stored as a collection of triplets, while graph neural network based models take account of the whole structure of the graph. Graph convolutional network (GCN) is first proposed in [78] and has been an effective tool to create node embeddings after continuous efforts [79, 80, 81, 82], which aggregates local information in the graph neighborhood for each node. As the extension of graph convolutional networks, R-GCN [83] is developed to deal with the highly multi-relational data characteristic of realistic knowledge bases. SACN [84] employs an end-to-end network learning framework where the encoder leverages graph node structure and attributes, and the decoder simplifies ConvE [85] and keeps the translational property of TransE. Following the same framework of SACN, Nathani et al. propose an attention-based feature embedding that captures both entity and relation features in the encoder. Vashishth et al. [87] believe that the combination of relations and nodes should be considered comprehensively during the message transmission. There-
fore they propose CompGCN that leverages various entity-relation composition operations from knowledge graph embedding techniques and scales with the number of relations to embed both nodes and relations jointly.

3 Classification of Knowledge Enhanced Pre-trained Models

To gain insight about how to attain effective KEPTMs, we performed a systematic classification of existing KEPTMs based on board literature study. The objectives are to offer guidelines for users and researchers by comparing their pros and cons.

3.1 The Principle of Classification

Symbolic knowledge provides rich information in the form of entity descriptions, KGs, and rules for the pre-trained model, which delivers extra entity features, inter-entity associations, and guides the inference process for the PTMs, respectively. Different granularities of knowledge are required by PTMs for solving different downstream tasks. However, it is not enough for PTMs to possess knowledge alone but an effective method of knowledge injection. The methods have a significant influence on the efficiency of knowledge injection, how knowledge is stored, and the ease of knowledge management. Besides that, interpretability and accountability have become vital to extend the PTMs to a broader range of application scenarios. Much effort has been devoted to look at the knowledge encoded in PTMs by different probing ways [88]. Researchers find that token representations of PLMs can capture syntactic and semantic knowledge by probing classifiers [89], [90]. The quantitative analysis in question answering tasks demonstrates that PLMs can encode structured commonsense knowledge [91]. Clark et al. [92] explore the functions of self-attention heads and report that they attend to words significantly in certain syntactic positions. Despite these achievements, there is no study into interpretability of how knowledge is utilized in downstream tasks, especially for tasks requiring intensive knowledge. PTMs lack a determined and rigorous computing formalism that is especially significant for reasoning tasks requiring an explicit process. Thus, we categorize existing KEPTMs from the following three dimensions: the granularity of knowledge, the method of knowledge injection, and the degree of symbolic knowledge parameterization to analyze their impact on the scope of applications, the efficiency of knowledge injection and the ease of knowledge management, and interpretability, respectively.

3.2 A Taxonomy of Knowledge Enhanced Pre-trained Models

This section gives a concrete taxonomy according to dimensions discussed above.

3.2.1 The Granularity of Knowledge

KEPTMs integrate different granularity of knowledge for applying to scenarios requiring information at different detail levels. In general, sentimental analysis mainly relies on word features and thus requires more information about individual entities. In contrast, the text generation task relies on commonsense knowledge, and the question answering task relies on rules and KG to infer. According to the granularity of knowledge integrated, we divide KEPTMs into unstructured and structured knowledge. The former consists of entity fused and text fused KEPTMs, while the latter is further divided into syntax-tree fused, KG fused, rule fused KEPTMs.

Entity fused KEPTMs As basic semantic unit, entity exists in the form of words, phrases, and literals. Existing KEPTMs usually treated entities as supervised data to learn its semantic or attain extra key features from it. The information of rare or ambiguous entity enables PTMs to learn its semantics well and achieve promising performance in named entity recognition [93], sentiment analysis [94], word sense disambiguation and even question answering tasks [95].

Text fused Pre-trained Models Since the pre-trained take sequence as input, text can be easily encoded without extra processing. Despite its flexibility in expression, it can not provide explicit relation and is mainly beneficial for question answering.

Syntax-tree fused KEPTMs Syntactic knowledge present the key constituents of sentence which are beneficial not only for natural language inference and understanding task [96], but also syntactic parsing [97], semantic role labelling task and coreference resolution. More importantly, it can be utilized by various methods. For instance, it can be used for supervision data by choosing different constituents of syntax tree. Besides, the structure of syntax tree can also be encoded by the graph neural network (GNN) [98].

KG fused KEPTMs With the advance of technique of information extraction, a plenty of general and domain-specific KGs have emerged. KGs provide a structured way to represent rich information in the form of entities and relations between them. They have become central to a variety of tasks after adopting by PTMs, including general natural language understanding and generation task, and image classification and visual question answering. Similar to syntax-tree, they serve as the semantic embeddings by appropriate KRL [18], [19] or guide inference process by the query [21], [99].

Rule fused KEPTMs Rules exist as informal constraints or strict logical expressions. The main benefit of it is its interpretability and accountability brought by rigorous mathematical formalism and explicit inference process. The rules can not only be adopted as supervised signal to assign weight [100], but as an independent reasoning system to make decisions [23].

3.2.2 The Method of Knowledge Injection

The method of knowledge injection plays an important role in effectiveness and efficiency of integration between PTMs and knowledge, as well as the management and storage of knowledge. In fact, it determines which knowledge can be integrated and the form of knowledge. To gain insight into how knowledge is injected, we classify models into feature fused, embedding combined, knowledge supervised, data structure unified, retrieval-based and rule guided KEPTMs.

Feature fused KEPTMs This type of models obtain features such as the sentiment polarity, the supersense, and the span of entities from a specific knowledge base. Feature
fused KEPTMs usually take it into account by projecting into embedding with a trainable matrix and learn its meaning by pre-training task [94], [101], [102].

Embedding combined KEPTMs To fill the gap between symbolic knowledge and neural networks, embedding combined KEPTMs transform symbolic knowledge into embedding with a representation learning algorithm at advance that sharply influences the performance of models. Then the tokens in text and entities will be align to combine corresponding embedding of them by attention mechanism or other weighting operations [18], [19]. However, there will be heterogeneous semantic space because of different representation learning algorithm for different forms of knowledge. To solve this problem, some KEPTMs generate the initial embedding of node with its contexts [20], [103].

Data structure unified KEPTMs Due to the structural incompatibility, some works adopt different representation learning algorithms for knowledge injected and original training data of PTMs. However, it causes the heterogeneous semantic space and increases the difficulty of fusion of them. To integrate both of them smoothly, data structure unified KEPTMs covert the relational triplets of the KG to sequences, thus the same encoder is used for learning embeddings [24], [104], [105]. However, the construction of a unified data structure relies on heuristic realization and the structural information of the KG is discarded.

Knowledge supervised KEPTMs To avoid extra training cost and engineering design, Knowledge supervised KEPTMs choose the entities that meet a specific relation and/or relational triplets as training data [94], [103]. As we discuss above, pre-trained language models is a statistical model and learn relations between entities by co-recurrence signals. KEPTMs overcomes the drawback by concatenating relational triplets and/or entity with the input sequence without sacrificing efficiency [106], [107].

Retrieval based KEPTMs Instead of injecting knowledge, retrieval based KEPTMs can update perception by consulting external knowledge. They usually retrieve desired information from knowledge source by computing the relevance between input text and knowledge [105], [109], [110]. One of the strength lies in the initiative of choosing relevant information, which avoids the effect of redundant and ambiguous knowledge that cannot match the input text. Since they do not preserve knowledge within models, they are limited in their application and mainly apply for question answering.

Rule guided KEPTMs Most of the KEPTMs store knowledge and language information within parameters of the pre-trained model. However, it is not intuitive to observe how the knowledge is leveraged in downstream tasks. A straightforward approach to solve it is to maintain the original form of symbolic knowledge, as rule guided KEPTMs do. This type of models consist of perception system and reasoning systems where the former is made up with PTMs and the latter is achieved with rules [22], [23]. A major advantage of such models is that they guarantee the reliability of results using rigorous mathematical formulations and provide interpretability through an explicit reasoning process.

3.2.3 The Degree of Knowledge Parameterization
Knowledge can be harnessed by PTMs in the form of symbol or semantic embeddings. To bridge the symbolic knowledge and neural networks, the former is projected into a dense, low-dimensional semantic space and presented by distributed vectors thorough knowledge representation learning [111]. Current algorithms mainly focus on representation learning toward KGs. Variants of GNN are employed to capture the structure of KGs. However, this approach also poses a challenge in terms of knowledge storage and management. On the one hand, knowledge requires a certain number of parameters for storage. On the other hand, it is not practical for models to repeatedly inject knowledge when the knowledge is constantly updated, especially for those integrate knowledge by pre-training. In contrast, some researchers keep the form of symbolic knowledge and employ them in the learning pipeline. According to the degree of knowledge parameterization, we divide models into fully parameterized, partial parameterized and knowledge form unchanged KEPTMs.

Fully parameterized KEPTMs With the rapid development of GNN, various symbolic knowledge, especially for KGs, can be encoded effectively. Not only for the semantic of entities, this type of models also capture structure information by virtue of the superior method of KRL to support reasoning. By storing knowledge as parameters, models can be knowledge-aware and adaptable to a broad range of scenarios.

Partial parameterized KEPTMs Owning to the limitation of GNN for modelling multi-step relations of KGs, partial parameterized fused KEPTMs just encode for a part of knowledge while keep the rest of them unchanged. For instance, some works [21], [112] encode the entities of KGs but maintain the structural information in the original form. The representation learning of entities is responsible for integration with PTMs, while the structure information of KGs is responsible for retrieving the associated entities. This is particularly efficient for obtaining as many related entities as possible to support decision considering the massive amount of relational triplets in KGs.

Knowledge form unchanged KEPTMs In addition to outstanding performance, researchers have recognised the need for offering a better understanding of the underlying principles of KEPTMs. Rule-based representation provides a mapping mechanism between symbol and PTMs. By integrating symbol reasoning system into the learning pipeline, knowledge form unchanged KEPTMs reconcile the advantages of effective perception of PTMs and reasoning and interpretability of symbolic representation [22], [23].

The taxonomy and the corresponding KEPTMs introduced in the paper are shown in Fig.1.

4 Overview of Knowledge Enhanced Pre-trained Models
In this section, we give a detailed account of the KEPTMs we found in our literature survey. We will focus on methods of knowledge injection and therefore organize our presentation according to this dimension. This is motivated by the assumption that the method of knowledge injection, as the core influencing factor, determines what types of
Fig. 1. Taxonomy of KEPTMs with Representative Examples.
knowledge can be integrated by PTMs and the form that knowledge presents. Following this idea, we introduce existing KEPTMs from the perspective of application scenarios, knowledge injection efficiency, knowledge management and interpretability in knowledge usage.

To visualize the association between the methods of knowledge injection and the type of knowledge and degree of knowledge parameterization, we draw a schematic diagram for each type of KEPTMs. The line thickness of the graph indicates the quantity.

4.1 Feature Fused KEPTMs

Feature fused KEPTMs focus on entity-level knowledge and inject knowledge by infusing entity feature and language representations. They extract task-required features of entities from a KG and project them into embeddings along with sequences for pre-training, which apply for tasks accentuating semantics of entities such as sentiment analysis and word sense disambiguation.

SenseBERT [113] infuses word-sense information into BERT’s pre-training signal, which enhances the ability of lexical understanding and thus solves the problem that BERT cannot well learn representations of rare words affected by heavy-tailed distribution. Following BERT architecture, jointly with the standard MLM, SenseBERT trains a semantic-level language model that predicts the missing words meaning. SenseBERT takes a sequence with masked words as input and feeds it into Transformer block after projecting word information and its supersenses to the embeddings. After that, the model are pre-trained in word-form and word sense tasks. Without compromising performance in General Language Understanding Evaluation (GLUE) [114], SenseBERT boosted word-level semantic awareness considerably outperforms a vanilla BERT on a Supersense Disambiguation task and achieves state of the art results on the Word in Context task [115].

Although BERT has been proved successful in simple sentiment classification, directly applying it to fine-grained sentiment analysis shows less significant improvement [116]. Therefore, to better solve the above issue, SemtiLARE [94] is proposed to inject sentiment polarity and its part-of-speech for BERT by label-aware MLM objective. Takes RoBERTa as the backbone model, SemtiLARE first acquires the part-of-speech tag and computes words sentiment polarity from SentiWordNet by context-aware attention mechanism. Then two pre-training tasks are utilized to capture the relationship between sentence-level language representation and word-level linguistic knowledge. SemtiLARE refreshes the state of the art performance of language representation models on both sentence- and aspect-level sentiment analysis tasks and thus facilitates sentiment understanding.

Limited by the word segmentation methods, the token in vocabulary of pre-trained language model usually is not a semantic unit but the broken pieces of it. Therefore, the span feature of it have a critical impact on the semantic learning. ERNIE 1.0 [101] employs entity and phrase masking strategies to tell the span of semantic units and learns the embeddings of them by the context. Its improved version, ERNIE 2.0 [102] introduces different prediction or classification pre-training tasks to capture lexical, syntactic and semantic information simultaneously. Notably, ERNIE 2.0 employs a continual pre-training framework to achieve incremental learning, which indicates multitask learning technique might be a solution to integrate multiply knowledge into PTMs.

Catastrophic forgetting is a common phenomenon when diverse knowledge is learned by PTMs. To this end, the multi-task learning technique is prioritized to integrate multiply knowledge into pre-trained models. PLMs can benefit from a regularization effect to alleviate overfitting to a specific task, thus making the learned representations universal across tasks.

4.2 Embedding Combined KEPTMs

Although feature fused KEPTMs can learn the rich semantics of entities, it is challenging to perform reasoning with entities alone. To capture various knowledge, embedding combined KEPTMs encode them by KRL at advance and infuse corresponding embeddings by variant of attention mechanism. They leverage a broader range of knowledge such as entities, syntax-trees, and KGs, and save knowledge in the form of parameter. After equipping knowledge, embedding combined KEPTMs are applied to general natural language understanding, question answering, and image classification tasks.

The span masking strategy is popular to inject boundary features of entities. However, it can only infuse a single entity for each aligned token embedding and results in a mismatch between pre-training and fine-tuning. To avoid these issues and further utilize the semantics within the spans, Li et al. [93] propose a multi-source word aligned attention (MWA) to integrate explicit word information with pre-trained character embeddings. Concretely, they partition the input sequence into non-overlapping spans with word segmentation tools. Then the aligned attention matrix of spans is computed according to mixed pooling strategy [117]. Finally, the enhanced character representation is produced by word-aligned attention. Unlike the previous model, ZEN learns entity representations with an external encoder instead of reassigning attention scores for entities to emphasize the entity information. For learning larger granular text, ZEN considers different combinations of characters during pre-training by attending n-gram representations. Given a
sequence of Chinese characters, the model extracts n-grams and records their positions with an n-gram matching matrix. Then all n-grams are represented by Transformer and combined with associated characters. Compared to the models that adopt masking strategies to infuse entity information, ZEN and MWA can incorporate nested entities and thus significantly improve entity integration’s generality while affording little training cost. Different from the above models, LUKE [106] employs a special vocabulary to store embeddings of entities. It treats words and entities as independent tokens and computes representations for all tokens using the Transformer. Concretely, it uses a large amount of entity-annotated corpus obtained from Wikipedia. Considering the vast cost and computational efficiency, the authors compute entity embeddings decomposing them into two matrices. Besides, the authors introduce an entity-aware self-attention mechanism, which considers the type of the tokens when computing attention scores. Since entities are treated as tokens, LUKE directly models the relationships between entities and achieves strong empirical performance in knowledge-driven NLP tasks.

Beyond entities, syntax-tree can also be utilized to enhance pre-trained language models. Syntactic biases are helpful for various natural language understanding tasks that involve structured output spaces—including tasks like semantic role labelling and coreference resolution. Syntax-BERT [96] models the syntactic knowledge by sparse mask matrices reflecting different syntactic relationships of the input and thus incorporates the syntax knowledge efficiently into pre-trained Transformers via a syntax-aware self-attention mechanism. Unlike the heuristic realization, Sachan et al. [98] encode dependency structure of the input sentence by a graph neural network. As BERT takes sub-words as input units instead of linguistic tokens, the model introduces additional edges in the original dependency tree by defining new edges from the first subword of a token to the remaining subwords of the same token.

As the most common knowledge, KGs provide a comprehensive and rich information of entities and relations and different representation learning algorithms are proposed to attain its embeddings. ERNIE [18] encodes the entities and relations with knowledge representation learning algorithm (e.g., TransE) and integrates entity representations and token embeddings based on the alignments by self-attention mechanism. Similarly, KnowBERT [19] also learns the representation of a KG at advance. Instead of using existing alignment data, it introduces an auxiliary entity linker to obtain more entities of KG. After integrating relational triplets of the KG into BERT, both of the model demonstrate improved ability to recall facts in knowledge-driven tasks like relationship extraction, entity typing. However, they treat triplets as an independent training unit during KRL procedure, ignoring the informative neighbors of entities. BERT-MK [105] captures richer semantic of triplets from KG by utilizing contextualized information of the nodes. The subgraphs of entities are extracted from the KG and transformed into a sequence, which is shown in Fig. 2. Considering mutual influence of entities and relations, the relations are regarded as graph nodes as well. Then the sequence of nodes is fed into Transformer to further encode contextual information of entity. After that, the same knowledge integration framework with ERNIE is utilized. However, not all knowledge plays a positive role in the KEPTMs. Redundant and ambiguous knowledge in KGs will be injected when KEPTMs encode sub-graphs independently of textual context. To solve this, CoKeBERT [118] dynamically select contextual knowledge and embed knowledge context according to textual context.

Beyond NLP, KGs likewise provide characteristics of objects and relationships between them for image classification. Given how large, complex, and dynamic the space of visual concepts is, building large datasets for every concept is unscalable. Integrating knowledge to reason based on what has been learned becomes a possible answer to it. Marino et al. [25] introduce the Graph Search Neural Network to incorporate large knowledge graphs into a vision classification pipeline in which the feature vectors are determined by VGG-16 [8] and Faster R-CNN [7]. Considering the considerable nodes of a KG, it starts with some initial nodes based on our input and only chooses nodes useful for the final output as training data. This graph successfully classify categories that fall into a long-tail distribution by propagating attributes and relations of known nodes. Wang et al. [119] further advanced the study of few sample learning on image classification tasks. They propose the approach that achieves zero-shot object recognition by encoding the KG that describes object category with GCN, which transfers knowledge obtained from familiar classes to describe the unfamiliar one. Specifically, the GCN takes input as the semantic embedding of the category encoded with GLoVE [41] and predicts the visual classifier on the features provided by VGGM [120]. Then the learned visual classifier recognizes the categories it has never seen before. With the help of external knowledge, it generalizes recognition algorithms to the realistic open world.

In all, most entity combined KEPTMs have to experience two stages for integrating knowledge: knowledge representation learning and alignment. However, there are some errors in alignments for tokens and entities. Therefore, it is critical to endow the KEPTMs to realize and correct errors during the alignment. For instance, ERNIE is asked to predict correct entities based on wrong alignments.
introduced deliberately. Notably, conventional methods of knowledge representation learning treats triples independently and thus fails to cover the complex information inherently implicit in the local neighborhood surrounding a triple. Compared to it, GNN is preferred to encode the structure knowledge. The method of knowledge injection we introduce in this section is suitable for most of the granularity of knowledge. Besides, embedding combined KEPTMs are knowledge-aware models by storing knowledge within the model as parameters and suitable for different application scenarios. Its disadvantage is that additional computing overhead is required to learn the representation of knowledge and integrate heterogeneous knowledge. Moreover, this method of knowledge injection makes it difficult to ensure that the model obtains specific knowledge and prevents us from explicitly updating or removing knowledge from the model. Once the key information is refreshed, embedding combined KEPTMs need to be retrained to maintain the correctness of the knowledge, which results in inefficient management of knowledge. Adapter modules might be a promising solution to mitigate the burden of knowledge updating. It can save various knowledge in each adapter with the cost of a few trainable parameters, and new knowledge can be added without revisiting previous ones. The parameters of the original PTMs remain fixed, yielding a high degree of parameter sharing.

### 4.3 Data Structure Unified KEPTMs

For accommodating different structure of text and KGs, data structure unified KEPTMs transform sequences and knowledge into a unified structure and encode embeddings with the same encoder to avoid heterogeneous vector space. This type of models enhance PTMs mainly via KGs and capture knowledge by learning corresponding parameters.

| Knowledge graph | Data structure unified KEPTMs | Fully Parameterized |
|-----------------|-----------------------------|---------------------|

K-BERT [24] connects sequences with relevant triples by constructing the knowledge-rich sentence tree to achieve knowledge injection. Specifically, all the entity mentions involved in the sentence are selected out to query corresponding triples in KGs, and then K-BERT stitches the triples to corresponding positions to generate a sentence tree shown in Fig. 3.

![The Structure of the Sentence Tree](image)

Without considering the inconsistency of structure, K-BERT infuses the associated information of entities by fine-tuning on downstream tasks and achieves 1-2% F1 gains in specific domain tasks. It is worth mentioning that K-BERT fine-tuned with CN-DBPedia [121] performs better than that with HowNet [122] in question answering and named entity recognition while the latter gains further improvement in semantic similarity tasks, which demonstrates the importance of an appropriate KG for different scenarios. Although K-BERT infuses triplets and sequences by unifying data structure, it treats relational triplets as independent units and ignores the association between them. To this end, CoLAKE [104] constructs a word-knowledge graph and integrates contextual triplets by pre-training task. The word-knowledge graph is built by replacing mentions in fully connected graph converted by the sequence with the aligned entity.

However, the unified data structure above relies on heuristic realization, and some researchers propose a more general method. Guan et al. [123] and COMET [124] convert the relational triplets of KGs into meaningful sequences by the specific template and feed them into the encoder of PTMs. To generate reasonable stories with commonsense knowledge, Guan et al. [123] transforms the commonsense triples in ConceptNet and ATOMIC into readable natural language sentences using a template-based method [125] and carries out post-training with these sentences by LM objective.

Notably, Daniel et al. [126] finds those entity representations generated by pre-trained language models exhibit strong generalization across inductive link prediction, entity classification, and information retrieval tasks. For instance, by transferring implicit knowledge from deep pre-trained language models, COMET learns to produce new objects coherent to its subject and relation and achieves automatic construction of commonsense knowledge bases. The reason lies in the learned representations capture both contextual information and knowledge. Even though data structure unified KEPTMs inject knowledge without extra engineering, they mainly focus on KGs and discard the structural information of the KG for the sake of concession on the unified data structure.

### 4.4 Knowledge Supervised KEPTMs

The characteristic of Knowledge supervised KEPTMs is that they choose the keywords as training data under the supervision of KGs and learn its semantics by the power of the original PTMs, which enjoy extensive applications.

| Entity | Syntax-tree | Knowledge Supervised KEPTMs | Fully Parameterized |
|--------|-------------|----------------------------|---------------------|

The objective of supervision covers entities and relational triplets. For instance, T5+SSM [95] is pre-trained to reconstruct named entities and dates mined from Wikipedia by BERT and attain competitive results on open-domain question answering benchmarks. Instead of utilizing independent entities, some models, like WKLM [127], LIBERT [128] and GLM [129], choose entities that exist specific
relations from KGs as input data to guide models capture it. To directly derive real-world knowledge from unstructured text, WKLM designs the weakly supervised entity replacement detection training objective to force the model to learn the relation between entities. Compared to the MLM objective, the entity replacement task introduces stronger entity level negative signals and preserves the linguistic correctness of the original sentence. Instead of using a single entity, LIEBRT \cite{128} takes entity pairs meeting semantic similarity constraints as training instances to enable BERT to understand the lexical-semantic relations. Not limited to the specific relation, GLM \cite{129} drives pre-trained models to capture implicit relations underlying raw text between related entities through the guidance of a KG. As we discussed above, entity representations generated by pre-trained language models exhibit strong generalization across linking prediction. To this end, KEPLER \cite{113} jointly optimizes parameters with the knowledge and MLM objectives to obtain representations that applicable to KG related and natural language understanding tasks. The core step is that KEPLER initializes knowledge embeddings with textual descriptions by RoBERTa instead of the KRL. Similar to KEPLER, K-ADAPTER \cite{130} also updates parameters by jointly learning knowledge and language information. The difference is that K-ADAPTER designs an adapter for storing each kind of infused knowledge to keep original parameters of the pre-trained model fixed and isolate the interaction of different knowledge, which addresses the issue of catastrophic forgetting.

So far, the above models focus on exploiting the power of the encoder to capture implicit relations given the entities. However, complex reasoning needs to model the relation between entities directly. Entity can be annotated easily by adopting Wikipedia hyperlinks and aligned with entities in the KG and used as the carrier of knowledge injection. However, this does not hold for the relationship due to the variety of forms in which it is expressed. To directly model the relations between entities, ERICA \cite{107} concatenates input sequences with the relation of the knowledge graph and models the relations between entities by discrimination pre-training tasks. Specifically, the entity discrimination task and the relation discrimination task are adopted. Given head entity and relation, the former aims to infer the tail entity. And the latter aims to distinguish whether two relations are close or not semantically. To endow the ability of syntactic parsing, LIMIT-BERT \cite{27} learns language representations via linguistic supervised mask strategies. Given the sentence, syntactic or semantic constituents of it are predicted by the pre-trainedlinguistics model, and thus masking spans are determined. To solve the mismatch problem caused by [mask] tokens, LIMIT-BERT adopts the generator and discriminator as encoders like ELECTRA \cite{131}, and masked token prediction and replaced token detection tasks are employed to train the model. SKEP \cite{132} provides a unified sentiment representation for multiple sentiment analysis tasks. With the help of automatically-mined sentiment knowledge, it embeds sentiment information at the word, polarity, and aspect level into representation by sentiment knowledge prediction objectives.

Beyond pre-trained language models, knowledge graphs can also be treated as a supervision signal in CV and cross-modal field. \cite{100} defines a classification model based on Conditional Random Field (CRF) \cite{133} in which all labels are assigned according to prior knowledge. Specifically, it first defines a specific graph that encodes hierarchy and exclusion relations. Then the classification scores are computed by the CRF based on the graph and features derived by CNN. In all, it generalizes the image multiclass classification framework by exploiting semantic relations between any two labels. Despite the achievement in classic tasks of CV, pre-trained CV models can not understand the semantics between objects by pictures alone. ERNIE-ViL \cite{134} achieves the detailed semantic alignments between vision and language based on the scene graph parsed from the text. As the essential factor, the scene graph provides fine-grained semantic information for cross-modal models, such as objects, attributes, and relationships between objects as masking targets. With these supervised data, ERNIE-ViL learns the joint representations by predicting nodes of different types in the scene graph during pre-training.

The main benefit of knowledge supervised KEPTMs is that they can be implemented with ease without additional network architecture. Besides, knowledge can be injected flexibly by deciding predicted target during pre-training or fine-tuning. For instance, SKEP achieves promising various sentiment tasks by taking sentiment words as masking targets. It is because sentiment analysis depends mainly on sentiment words and word polarity other than whole texts. Another advantage of the method of knowledge injection is that it can leverage the technique of contrastive learning to improve the effectiveness of integration. Contrastive learning has recently achieved state of the art performance in the field of NLP and CV, which improves the robustness of models by discriminating the variance. KGs can provide specific relationships such as antonym and synonym, appropriate as training data for comparative learning. For example, ERICA achieves better capture in-text relational facts by utilizing entity and relation discrimination.

### 4.5 Retrieval-based KEPTMs

Retrieval-based KEPTMs does not fuse knowledge itself but learn the ability to retrieve, select and encode knowledge. It focuses on extracting desired knowledge from external sources to meet the needs of a single scenario, for which only a small training overhead is required. Crucially, since there is no need to store large amounts of knowledge, such models allow for more efficient and convenient updating facing the frequent change of knowledge.

For instance, it is more efficient to refer to critical information to judge rather than store all potentially related knowledge for question answering and generation tasks.
KT-NET \cite{135} employs an attention mechanism to select desired knowledge from KGs adaptively and then fuses the selected knowledge to enable knowledge-aware predictions for machine reading comprehension. It encodes the KG by the KRL \cite{75} and learn to retrieve potentially relevant entity from WordNet and NELL \cite{136} by fine-tuning. To supply factual knowledge, KGLM \cite{137} is constructed to render information from a local KG that is dynamically built by selecting and copying facts based on context from an external KG.

The models we introduced above encode the KG with traditional methods of KRL that discard structure information. To solve it, various variants of GNN are employed to better model topology structure of KGs. Lv et al. \cite{20} designed a graph-based model that extracts relational triplets from retrieved sentences and constructs self-defined graphs for it. With customized graphs, the model adopts a graph convolutional network (GCN) to encode neighbor information into the representations of nodes and aggregates evidence with the graph attention mechanism for predicting the final answer.

In addition to question answering, KGs also shine in the generation tasks. To endow GPT-2 with reasoning, GRF \cite{138} introduces ConceptNet as an external reference and generates an ending based on the previous context and the knowledge graph. The model’s core lies in the dynamic reasoning module that computes the relevance between triplets and token embeddings to obtain generated words. Without context, Liu et al. \cite{139} proposed KG-BART that generates plausible sentences by only a set of concepts. It first enriches the token representation by considering a concept-reasoning graph structure. After that, the model captures the inherent correlations of intra-concept and inter-concept provided by a concept-expanding graph. The model can generate high-quality sentences even in unseen concept sets by hybridizing the KG and text information. As the supplementation of structured knowledge, plain texts can provide abundant and high coverage evidence. RAG \cite{110} generates answers by retrieving relevant spans across external texts based on pre-trained seq2seq models. Given a query, RAG uses the input sequence to retrieve the top K relevant texts and generate embeddings to obtain generated words. Without context, Liu et al. \cite{139} proposed KG-BART that generates plausible sentences by only a set of concepts. It first enriches the token representation by considering a concept-reasoning graph structure. After that, the model captures the inherent correlations of intra-concept and inter-concept provided by a concept-expanding graph. The model can generate high-quality sentences even in unseen concept sets by hybridizing the KG and text information. As the supplementation of structured knowledge, plain texts can provide abundant and high coverage evidence. RAG \cite{110} generates answers by retrieving relevant spans across external texts based on pre-trained seq2seq models. Given a query, RAG uses the input sequence to retrieve the top K relevant texts and generate embeddings to obtain generated words.

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Besides being efficient in knowledge utilization, another advantage of the retrieval-based models lies in interpretability in the usage of knowledge. FaE \cite{112} designs an explicit interface based on a neural language model to connect symbolically interpretable factual information and language representations, which achieves inspection and interpretation of knowledge. Owning to the decoupling of knowledge representations and language representations, FaE can change the output of the language model by modifying only the non-parametric triplets without any additional training.

Despite the limited application scenarios, this approach allows the flexibility to encode knowledge as needed. More importantly, it enables the inspection of knowledge usage when the symbolic knowledge is preserved, thus increasing interpretability. For instance, FaE employs an external memory to save factual knowledge and observe corresponding predictions by integrating different knowledge. However, retrieval-based KEPTMs rely on labeled data to obtain the ability of retrieval by fine-tuning. Prompt-based models retrieve desired knowledge from PTMs to deal with downstream tasks by few samples. Despite rapid development, it is difficult to retrieve all knowledge the model needs considering the absence of critical knowledge. Utilizing symbolic knowledge during prompt learning can reduce the burden of parameter learning. For instance, PTR \cite{140} designs a prompt made up of embeddings and entities to achieve efficient learning. The combination of prompt learning and knowledge reconciles the few samples learning and retrieval ability.

### 4.6 Rule Guided KEPTMs

As discussed above, presentation learning toward symbolic knowledge, like KGs, is a solution to bridge symbolic knowledge and pre-trained models. By contrast, a prominent research direction is transforming the representation learned by PTMs into concepts and then reasoning with symbolic knowledge, holding effective learning of PTMs and symbolic knowledge’s interpretability and accountability, as rule guided KEPTMs do. Rule guided KEPTMs focuses primarily on reasoning phase based on rules. Knowledge in these models is represented in symbolic form and integrated in modular way, whereas perception is implemented by a PTM. The underlying characteristics of them allow the principled combination of robust learning and efficient reasoning, along with interpretability offered by symbolic systems.

Gangopadhyay et al. \cite{22} propose a structured composition of deep learning and symbolic reasoning for resolving ambiguous image classifications. A semi-lexical language, including rules and alphabet, is defined in advance. Then the string of semi-lexical tokens is recognized as an element of the alphabet by SimpleNet \cite{141}. Finally, the rules are conducted to decide those ambiguous tokens, which provides a reasoning framework based on domain knowledge to interpret complex scenarios. However, the above model
relies on the heuristic realization of the task-dependent domain-specific language. In contrast, Amizadeh et al. propose a more general mathematical formalism for visual question answering that is probabilistically derived from the first-order logic. Compared to traditional tasks on computer vision, visual question answering requires reasoning and specific knowledge about the image subject and thus is a significantly more complex problem. Prompt tuning has been widely adopted on classification tasks. However, manually designing language prompts is fallible, and those auto-generated are time-consuming to verify their effectiveness. To this end, PTR applies logic rules to construct prompts with several sub-prompts to make a trade-off. It determines the subject and object entity types with the PTM and aggregate sub-prompts with logic rules to handle many-class classification tasks. The model casts the question into a first-order logical formula and infers with a functional program to guarantee the correct reasoning process, whereas the detection of images is implemented with Faster-RCNN.

Beyond first-order logic, some models also adopt KGs to achieve reasoning. They relate concepts of a query image to the appropriate information in the KG to construct the local graph and reason subsequent correct answers over it. Ontology organizes knowledge as a logical semantic expression, which enables the sharing between different scenarios and semantic interpretability. introduces a domain ontology and classifies objects and relationships provided by it with Mask R-CNN for identifying potential hazards on construction sites. After the perception of the PTM, extracted information is stored in Neo4j for reasoning and querying. These approaches preserve the structure of the symbolic knowledge, thus achieving semantic inference and retrieval from a concept level.

The main benefit of these models is its composability that entangles the representation and reasoning process, which introduces interpretability of working principle of KEPTMs. Although there are some method to explore interpretability of PTMs, they focus on what knowledge has learned and rely on trivial probing skills. In contrast, this type of models achieves inspection and interpretation of usage of knowledge by indicating how a model might derive an answer.

We illustrate all introduced KEPTMs more details in Table 1 and Table 2.

5 Conclusion and Future Directions

We analyze and compare the existing KEPTMs from three perspectives: the granularity of knowledge, the method of knowledge injection, and the degree of knowledge parameterization and discuss them in detail from the second dimension.

Most KEPTMs blend knowledge during pre-training, while a few do this during fine-tuning. However, compared to fine-tuning, the cost of integration during pre-training is much higher. Besides, choosing a consistent pre-training paradigm with PTMs can alleviate integration difficulties. For example, by masking out the words containing certain types of knowledge in generative pre-training, the model can be more adept at memorizing and completing such knowledge.

Feature fused KEPTMs utilize entity information without introducing additional network and computational overhead, which are simple to implement and suitable for tasks requiring fine-grained entity features. Despite of more efforts, embedding combined KEPTMs can store both entity and relation information and generalize knowledge-driven tasks like entity classification, relationship extraction and knowledge completion. Knowledge supervised KEPTMs achieve knowledge infusion with minimum work, which is implemented by designing an appropriate pre-training task. Retrieval-based and rule guided KEPTMs help us understand how pre-trained models harness knowledge for downstream tasks and provide a guide for better usage and further improvement.

Although KEPTMs have proven their power for various NLP and CV tasks, challenges still exist due to the complexity of knowledge and language, as well as the interaction of different modals. We suggest following future directions for KEPTMs.

(1) Most of the KEPTMs we introduce focus on injecting factual or conceptual knowledge. There are other types of knowledge worthy of being considered. For instance, procedural and metacognitive knowledge also play an significant role in reasoning and judgment for the open world. Thus, a more attractive direction is to explore the utilization of two types of knowledge above.

(2) Based on semantic network representation, relational triplets have become the most popular form to organize knowledge. However, as we have discussed, more works have to be done for heterogeneous infusion caused by different representation methods of original training data and external knowledge. Besides semantic network representation, there are a multitude of knowledge representation methods presenting properties of knowledge in different forms. Therefore, searching an more general knowledge representation for different knowledge is promising.

(3) Although retrieval-based and rule guided KEPTMs makes the procedure of decision-making transparent, they are designed for specific application. Designing a KEPTM with general purpose without destructing inspection of symbolic knowledge will significantly improve interpretability.

(4) The storage and updating of knowledge is barely considered by existing KEPTMs. In an environment where knowledge is changing rapidly, it is practical to store knowledge in less space and update it efficiently. Adapter-based approach set a valuable examples for us. Designing a method that utilizes knowledge in a plug-and-play manner is essential.

(5) Text- and image-based multi-modal models capture rich semantics in the image and associated text by learning image-text representations and have been applied in captioning, visual question answering and visual reasoning tasks. However, the image features learned cannot capture detailed semantics depicted in an image. Moreover, the pre-training of multi-modal models usually rely on a assumption that there is a strong correlation between text data and image data. The utilization of well-organized knowledge for multi-modal models need to be explored to break the
| KEPTMs       | Pre-trained Model | Granularity of Knowledge | KRL          | Method of Injection | Degree of Parameterization |
|-------------|------------------|--------------------------|--------------|---------------------|----------------------------|
| SenseBERT   | BERT             | Entity                   | \            | Feature Fused       | Fully                      |
| SentiLARE   | RoBERTa          | Entity                   | \            | Feature Fused       | Fully                      |
| SKEP        | RoBERTa          | Entity                   | \            | Knowledge Supervised| No                        |
| MWA         | BERT             | Entity                   | \            | Knowledge Supervised| No                        |
| ZEN         | BERT             | Entity                   | Transformer  | Embedding Combined | Fully                      |
| T5+SSM      | T5               | Entity                   | \            | Knowledge Supervised| Fully                      |
| ERNIE 1.0   | BERT             | Entity                   | \            | Feature Fused       | Fully                      |
| ERNIE 2.0   | BERT             | Entity & Text            | \            | Feature Fused       | Fully                      |
| LUKE        | BERT             | Entity                   | \            | Knowledge Supervised| No                        |
| TEK         | RoBERTa          | Text                     | Transformer  | Retrieval Based     | Fully                      |
| REALM       | BERT             | Text                     | \            | Retrieval Based     | Fully                      |
| RAG         | BART             | Text                     | \            | Retrieval Based     | Fully                      |
| Lv et al.   | XLNET            | Text & KG                | GNN          | Retrieval Based     | Fully                      |
| Syntax-BERT | BERT             | Syntax-tree              | Transformer  | Embedding Combined  | Fully                      |
| LIMIT-BERT  | BERT             | Syntax-tree              | \            | Knowledge Supervised| Fully                      |
| Sachan et al.| BERT             | Syntax-tree              | GNN          | Embedding Combined  | Fully                      |
| Wang et al. | VGGM             | KG                       | GNN          | Embedding Combined  | Fully                      |
| WKLM        | BERT             | KG                       | \            | Knowledge Supervised| No                        |
| LIBERT      | BERT             | KG                       | \            | Knowledge Supervised| No                        |
| GLM         | BERT or RoBERTa  | KG                       | \            | Knowledge Supervised| No                        |
| COMET       | GPT2             | KG                       | Transformer  | Unified Data Structure| Fully                      |
| GRF         | LSTM             | KG                       | GNN          | Retrieval Based     | Fully                      |
| KG-BART     | BART             | KG                       | GAT          | Retrieval Based     | Fully                      |
| KT-NET      | BERT             | KG                       | BILINEAR     | Retrieval Based     | Fully                      |
| KGLM        | LSTM             | KG                       | TransE       | Retrieval Based     | Fully                      |
TABLE 2
List of Representative KEPTMs

| KEPTMs         | Pre-trained Model | Granularity of Knowledge | KRL       | Method of Injection | Degree of Parameterization |
|----------------|-------------------|--------------------------|-----------|--------------------|----------------------------|
| ERNIE          | BERT              | KG                       | TransE    | Embedding Combined | Fully                      |
| KnowBERT       | BERT              | KG                       | TuckER    | Embedding Combined | Fully                      |
| Marino         | VGG               | KG                       | GSNN      | Embedding Combined | Fully                      |
| BERT-MK        | ERNIE             | KG                       | Transformer | Embedding Combined | Fully                      |
| K-BERT         | BERT              | KG                       | Transformer | Unified Data Structure | Fully                      |
| CoLAKE         | RoBERTa           | KG                       | Transformer | Unified Data Structure | Fully                      |
| Guan et al.    | GPT-2             | KG                       | Transformer | Unified Data Structure | Fully                      |
| KEPLER         | RoBERTa           | KG                       | \         | Knowledge Supervised | No                         |
| K-ADAPTER      | RoBERTa           | KG                       | \         | Knowledge Supervised | No                         |
| ERICA          | BERT or RoBERTa   | KG                       | \         | Knowledge Supervised | No                         |
| ERNIE-ViL      | Transformer       | KG                       | \         | Knowledge Supervised | No                         |
| Wang* et al.   | VGG & Fast R-CNN  | KG                       | \         | Retrieval Based    | Partial                    |
| Ahab           | Fast R-CNN        | KG                       | \         | Retrieval Based    | No                         |
| FaE            | BERT              | KG                       | \         | Retrieval Based    | Partial                    |
| Lafferty et al.| CNN               | Rule                     | \         | Rule Guided        | No                         |
| Gangopadhyay et al.| SimpleNet  | Rule                     | \         | Rule Guided        | No                         |
| Amizadeh et al.| Fast R-CNN        | Rule                     | \         | Rule Guided        | No                         |
| Fang et al.    | Mask R-CNN        | Rule                     | \         | Rule Guided        | No                         |
| PTR            | RoBERTa           | Rule                     | \         | Rule Guided        | No                         |

* The author of [21].

(6) Knowledge is usually extracted with mutlit-step processing. However, the error will be propagated during this process and thus cause the decreased performance of models. Therefore, integrating knowledge excavated from the raw data to avoid information loss caused is a valuable direction.

(7) Despite the strong performance on the entailment tasks, pre-trained language models fail to perform abductive reasoning [144]. The previous work mainly focuses on formal logic that is too rigid to generalize for complex natural language. Integrating formal logic with pre-trained language models offers a promising avenue for future research.

(8) It is difficult for pre-trained language models to control attributes or topic of the generated contents, especially well-structured contents. It is worth exploring to express the structure of certain genres in the form of knowledge and guide the generation of text with it.

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