Low-resource Learning with Knowledge Graphs: A Comprehensive Survey

JIAOYAN CHEN, Department of Computer Science, University of Oxford, UK
YUXIA GENG, College of Computer Science and Technology, Zhejiang University, China
ZHOU CHEN, College of Computer Science and Technology, Zhejiang University, China
JEFF Z. PAN, School of Informatics, The University of Edinburgh, UK
YUAN HE, Department of Computer Science, University of Oxford, UK
WEN ZHANG, School of Software Technology, Zhejiang University, China
IAN HORROCKS, Department of Computer Science, University of Oxford, UK
HUAJUN CHEN, College of Computer Science and Technology, Zhejiang University, China

Machine learning methods especially deep neural networks have achieved great success but many of them often rely on a number of labeled samples for training. In real-world applications, we often need to address sample shortage due to e.g., dynamic contexts with emerging prediction targets and costly sample annotation. Therefore, low-resource learning, which aims to learn robust prediction models with no enough resources (especially training samples), is now being widely investigated. Among all the low-resource learning studies, many prefer to utilize some auxiliary information in the form of Knowledge Graph (KG), which is becoming more and more popular for knowledge representation, to reduce the reliance on labeled samples. In this survey, we very comprehensively reviewed over 90 papers about KG-aware research for two major low-resource learning settings — zero-shot learning (ZSL) where new classes for prediction have never appeared in training, and few-shot learning (FSL) where new classes for prediction have only a small number of labeled samples that are available. We first introduced the KGs used in ZSL and FSL studies as well as the existing and potential KG construction solutions, and then systematically categorized and summarized KG-aware ZSL and FSL methods, dividing them into different paradigms such as the mapping-based, the data augmentation, the propagation-based and the optimization-based. We next presented different applications, including not only KG augmented prediction tasks in Computer Vision and Natural Language Processing (e.g., image classification, visual question answering, text classification and knowledge extraction), but also tasks for KG curation (e.g., inductive KG completion), and some typical evaluation resources for each task. We eventually discussed some challenges and future directions on aspects such as new learning and reasoning paradigms, and the construction of high quality KGs.

Additional Key Words and Phrases: Knowledge Graph, Low-resource Learning, Zero-shot Learning, Few-shot Learning, Knowledge Graph Construction, Neural-Symbolic Integration

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Authors’ addresses: Jiaoyan Chen, Department of Computer Science, University of Oxford, UK, jiaoyan.chen@cs.ox.ac.uk; Yuxia Geng, College of Computer Science and Technology, Zhejiang University, China, gengyx@zju.edu.cn; Zhuo Chen, College of Computer Science and Technology, Zhejiang University, China, chenzhuo98@zju.edu.cn; Jeff Z. Pan, School of Informatics, The University of Edinburgh, UK, jeff.z.pan@ed.ac.uk; Yuan He, Department of Computer Science, University of Oxford, UK, yuan.he2@st-hughs.ox.ac.uk; Wen Zhang, School of Software Technology, Zhejiang University, China, wenzhang2015@zju.edu.cn; Ian Horrocks, Department of Computer Science, University of Oxford, UK, Ian.horrocks@cs.ox.ac.uk; Huajun Chen, College of Computer Science and Technology, Zhejiang University, China, huajunsir@zju.edu.cn.

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1 INTRODUCTION

Machine learning (ML) especially deep learning is playing an increasingly important role in artificial intelligence (AI), and has achieved great success in many domains and applications in the past decades. For example, Convolutional Neural Networks (CNNs) can often achieve even higher accuracy than human beings in image classification and visual object recognition, leading to the fast development of applications such as self-driving, face recognition, handwriting recognition, image retrieval and remote sensing image processing [104]; Recurrent Neural Networks (RNNs) and Transformer-based models are quite successful in sequence learning and natural language understanding, which boost applications such as time-series prediction, machine translation, speech recognition and chatbot [130]; Graph Neural Networks (GNNs) have been widely applied to prediction tasks involving graph structured data in domains such as social network, chemistry and biology [227].

However, the high performance of most ML models relies on a number of labeled samples for (semi-)supervised learning, while such labeled samples are often very costly or not efficient enough to collect in real-world applications. Even though labeled samples can be collected, re-training a complex model from scratch when new prediction targets (e.g., classification labels) emerge is unacceptable in many contexts where real-time is requested or no enough computation resources are accessible. In the paper, we call such ML contexts where no labeled samples or only a very small number of labeled samples are available for a prediction task as low-resource learning, following some definitions on low-resource scenarios in the natural language processing (NLP) community [74, 231]. According to the number of the available labeled samples, we further divide low-resource learning into zero-shot learning (ZSL) and few-shot learning (FSL). ZSL is formally defined as predicting new classes (labels) that have never appeared in training, where the new classes are named as unseen classes while the classes that have samples in training are named as seen classes [53, 96, 131]. FSL is to predict new classes for which only a small number of labeled samples are given [54, 55]. For convenience, we also call such new classes with no enough labeled samples as unseen classes, and the other classes that have a large number of samples used in training as seen classes. Specially, when each unseen class has only one labeled sample given, FSL becomes one-shot learning [54].

ZSL has attracted wide attention in the past decade with quite a few solutions proposed [28, 59, 184]. One common solution is transferring knowledge which could be samples, features (or data representations), models and model parameters from seen classes to unseen classes so as to address the sample shortage and avoid training new models from the scratch [135]. For example, in zero-shot image classification, image features that have been already learned by CNNs such as ResNet [72] from images of seen classes are often directly re-used to build classifiers for unseen classes. The key challenge is selecting the right knowledge to transfer and adaptively combining these transferred knowledge for a new prediction task. To this end, ZSL methods usually utilize auxiliary information that contains inter-class relationships. When ZSL was originally investigated for visual object recognition and image classification, the methods mainly use attributes that describe objects’ visual characteristics (a.k.a. class attributes) [53, 96]. Next, class textual information such as class name and sentence description is widely studied using text mining and word embedding techniques [58, 139]. In recent five years, Knowledge Graphs (KGs), which are able to represent richer semantics including not only class attributes, class textual information but also class hierarchy (e.g., taxonomies), relational facts and so on, have attracted wide attention and the KG-augmented ZSL methods have achieved the state-of-the-art performance on many benchmarks and tasks [62, 88, 186].

FSL, which started to attract wide attention around when one-shot learning was proposed for image classification [54], has a longer history and even more studies than ZSL [187]. Since the unseen classes have some labeled samples although
their sizes are quite small, techniques of meta learning (a.k.a. learn to learn) [78, 99] have been widely applied [208]. Meta learning is usually applied by either reducing the parameter searching space in training using meta parameters such as more optimized initial parameter settings, or transforming a classification problem to a metric learning problem where a testing sample is matched with the unseen classes based on their few-shot samples and meta learned mappings. KGs have been utilized to optimise such meta learning-based methods; for example, Sui et al. [164] retrieved relevant knowledge from a KG named NELL [123] to construct task-relevant relation networks as mapping functions for addressing few-shot text classification. Meanwhile, the aforementioned idea of knowledge transfer can also adopted for addressing FSL, where KG auxiliary information is becoming increasingly popular in recent years [35, 138, 172, 217]. For example, Chen et al. [35] transferred the feature learned by a CNN from flight delay forecasting tasks with a lot of historical records to a new forecasting task with no enough historical records, by exploiting a KG with different kinds of flight related knowledge about e.g., airports and airlines; Peng et al. [138] extracted a KG from WordNet for representing class hierarchies and then used this KG to augment knowledge transfer for few-shot image classification.

Motivation and Contribution. Since KG has become a very popular form for representing knowledge and graph structured data, acting as the foundation of many successful AI and information systems [75], it is quite reasonable to use KGs to augment both ZSL and FSL as discussed above, quite a few papers have been published on KG-aware low-resource learning especially in recent five years, and this research topic is becoming more and more popular. Note KG-aware low-resource learning includes investigations on not only using KGs to augment ZSL and/or FSL but also addressing tasks of the KG itself (such as KG completion) where the KG context is often considered when ZSL or FSL methods are applied or extended. By the middle of December in 2021, we have collected 50 papers on KG-aware ZSL and 46 papers on KG-aware FSL. To systematically categorize and compare all the proposed methods, and to present an overall picture of this promising field, a comprehensive survey is now in urgent need. In this paper, we (i) introduced KGs and their construction methods for low-resource learning, (ii) categorized, analyzed and compared different kinds of KG-aware ZSL and FSL methods, (iii) presented the low-resource learning tasks as well as their evaluation resources across multiple domains including computer vision (CV), NLP and KG completion, and (iv) discussed the existing challenges and potential directions of KG-aware low-resource learning. This survey is suitable for all AI researchers, especially those who are to enter the domain of low-resource learning, those who have already been working on low-resource learning but are interested in solutions that integrate knowledge representation and reasoning, and those who are working on KG applications and semantic techniques.

Related Literature Reviews. There have been several papers that have literature reviews relevant to low-resource learning, but they are all quite different from this survey.

- The two survey papers [184] and [187] systematically review the ZSL methods by 2019 and the FSL methods by 2020, respectively, mainly from the perspective of problem setting (e.g., whether the unlabeled testing samples are used or not in training), ML theory (e.g., which prediction error to reduce), and methodology (e.g., data focused, model focused and learning algorithm focused). However, they do not consider the categorization and deep analysis from the perspective of auxiliary information, and failed to collect most KG-aware methods.
- The very recently released paper [79] reviews both ZSL and FSL methods that use or aim at structured data. Structured data, however, is more general than KG with a much larger scope, and thus [79] collects only a small part of the papers on KG-aware ZSL and FSL research. It includes 19 papers about KG-aware ZSL and 21 papers about KG-aware FSL, while this survey has 50 papers and 46 papers, accordingly. This survey also has a more fine-grained method categorization, and additional technical analysis on KGs and their construction for
low-resource learning. Meanwhile, [79] focuses more on addressing problems in structured data by ZSL and FSL methods, but less on augmenting ZSL and FSL methods.

- The paper [28] is our previous survey and perspective paper published in IJCAI 2021 Survey Track. It briefly categorizes different external knowledge used in ZSL with incomplete reviews on KG-aware ZSL papers, and it does not cover FSL.
- The benchmarking paper [197] was published in 2018. It reviews around 10 ZSL methods that mainly utilize class attribute and text information as the auxiliary information, focusing on their evaluation and result comparison on image classification task. This paper covers neither state-of-the-art ZSL methods proposed in recent 3 years nor KG-aware ZSL methods. Similarly, the survey paper [59] reviews ZSL papers published before 2018, mainly focusing on ZSL studies on CV tasks.

**Paper Organization.** The remainder of this survey is organized as follows. Section 2 introduces the preliminary, including the definitions of ZSL and FSL, their notations, an overall view of the auxiliary information and general solutions. Section 3 introduces the definition and scope of KG, as well as KG construction methods in low-resource learning. Section 4 reviews KG-aware ZSL methods which are categorized into four paradigms: mapping-based, data augmentation, knowledge propagation and feature fusions. For each paradigm, we further introduce different categories and their corresponding methods. Section 5 is similar to Section 4 but reviews KG-ware FSL methods. Section 6 introduces the development and resources of KG-aware ZSL and FSL in different tasks across CV, NLP and KG completion. Section 7 discusses the existing challenges and the future directions of KG-aware low-resource learning. Section 8 concludes this paper.

## 2 PRELIMINARY ON LOW-RESOURCE LEARNING

### 2.1 Zero-shot Learning

ZSL has been applied in many different tasks, varying from image classification and visual question answering in CV to text classification and knowledge extraction in NLP, from link prediction in KG completion to protein function prediction in bioinformatics. Although the exact ZSL problem definition may vary from task to task and from paper to paper, it can be summarized and expressed in a common way. In this part, we first give the definition and settings of ZSL, and then presents an overall picture of its auxiliary information and the existing method categorization.

#### 2.1.1 Problem Definition

In ML classification, a classifier is trained to approximate a target function $f : x \rightarrow y$, where $x$ represents the input data and $y$ represents the output class which is often known as label. In image or text classification, $x$ is the input image or text while $y$ is the label to output. Sometimes, one input can be annotated by multiple labels, which is known as multi-label classification. Regarding question answering, we refer to giving an answer or multiple answers to a natural language question w.r.t. a given textual context, where $y$ is the answer. Visual question answering is similar but the context is an image or a video. Knowledge extraction refers to extracting entities, relations or events from natural language text, where $x$ includes a textual context like a sentence, a paragraph or a document, while $y$ is the entity, relation or event. Meanwhile, we also regard related tasks such as entity and relation linking, which matches an entity or relation mention in text with an entity or relation in a KG, and entity typing, which assigns defined classes to an entity mention, as knowledge extraction. For KG link prediction, the input $x$ is the two elements of a triple as well as their contexts (e.g., associated triples) while $y$ is the triple’s third element. Although the output of all these tasks are different, in this survey...
we sometimes call them as class or label for simplicity. In usual settings of these tasks, the class \( y \) is often limited to a given candidate set during prediction.

In normal supervised learning, every class to be predicted in testing has associated labeled samples used for training, while standard ZSL aims to predict testing samples with some candidate classes that have never appeared in the training samples. Formally, in the standard ZSL, we denote (i) the training samples as \( D_{tr} = \{(x, y) | x \in X, y \in Y_t \} \) where \( X_t \) and \( Y_t \) represent the training sample inputs and the seen classes, respectively; (ii) the testing samples as \( D_{te} = \{(x, y) | x \in X_u, y \in Y_u \} \) where \( X_u \) and \( Y_u \) represent the testing samples to predict and the unseen classes, respectively, with \( Y_u \cap Y_t = \emptyset \). The target of ZSL methods is to predict the classes of \( X_u \) as correctly as possible. When the candidate classes are set to \( Y_u \cup Y_s \) (i.e., both seen classes and unseen classes are considered in prediction), the problem is known as generalized ZSL.

In addressing some tasks such as link prediction for KG completion, relation and entity extraction from text, and natural language question answering, the original function \( f \) is often transformed into a scoring function by moving \( y \) to the input, denoted as \( f': (x, y) \rightarrow s \), where \( s \) is a score indicating the truth of the combination of \( x \) and \( y \). With \( f' \), the class of a testing sample \( x \) in \( X_u \) is often predicted by finding out the class in \( Y_u \) (or \( Y_u \cup Y_s \)) that maximizes the score \( s \). Namely, the original label prediction problem is modeled as a ranking problem. For example, in modeling link prediction with a head entity and a tail entity given as the input \( x \), the target relation between the two entities is then the class \( y \) to predict, and the score \( s \) quantifies the relation’s correctness for indicating the relationship between the head entity and the tail entity.

### 2.1.2 Auxiliary Information

The auxiliary information is often represented as symbolic forms such as class attribute, class name, class textual description and KG. To be involved for supporting ZSL, they are often encoded into sub-symbolic representations (i.e., vectors) independently or jointly with some other learning modules. We denote the initial encoding function of class auxiliary information as \( h: y \rightarrow y \) where the bolded \( y \) represents the vector of the class \( y, y \in Y_u \cup Y_s \). The raw input \( x \) could also be encoded by e.g., some pre-trained models or hand-craft rules for feature extraction before they are input to the prediction model (\( f \) or \( f' \)). This step is optional but is often adopted. We denote this initial encoding function as \( g: x \rightarrow x \) where the bolded \( x \) represents the pre-processed vector of the original input \( x, x \in X_u \cup X_t \).

Since there are no labeled samples for the unseen classes, ZSL solutions heavily rely on auxiliary information. In early years when ZSL was proposed in around 2009 for image classification, the majority of the solutions utilize class attributes which are often a set of key-value pairs for describing object visual characteristics. The simplest class attributes are those binary annotations; for example, “furry” and “striped” indicate whether an animal looks furry and striped, respectively [96, 97]; while the annotation “has wheel” is used in recognizing vehicles [53]. Relative attributes which enable comparing the degree of each attribute across classes (e.g., “bears are furrier than giraffes”) [136] are more expressive. Another kinds of more expressive visual attributes are those associated with real values for quantifying the degree. One typical example is the animal image classification benchmark named Animals with Attributes (AwA), where each attribute annotated to an animal class is associated with a real value ranging from 0 to 1 [97, 197]. The attribute leads to some very classic methods for zero-shot image classification such as DAP which first predicts the attributes of a testing image and then determines its class based on the predicted attributes [96]. The utilization of attributes in other ZSL tasks is not as popular as in CV tasks, but it is still feasible; for example, [70] utilizes the node attributes with categorical values to address KG link prediction involving unseen entities which have never appeared in the training triples. The advantages and disadvantages of the attribute auxiliary information are quite obvious: it is easy to use and quite accurate with little
noise, but it cannot express complex semantics for some tasks and is not easily accessible, usually requiring annotation by human beings or even domain experts.

Since around 2013, class textual information, varying from words and phrases such as class names to long text such as sentences and documents for describing classes, started to attract wide attention for addressing ZSL problems. In zero-shot image classification, the studies [58, 129, 160] utilize the class names; the studies [51, 139] prefer to use class sentence descriptions from encyclopedia articles; the study [144] collects more fine-grained and compact visual description sentences via crowdsourcing on the Amazon Mechanical Turk (AMT) platform. In zero-shot KG link prediction, the study [140] utilizes relation sentence descriptions from the KG itself for addressing unseen relations. In zero-shot entity extraction from text, the study [108] predicts unseen entities in text of a new domain by using the entities’ encyclopedia articles. To encode the semantics of a class name, one approach is directly using its words’ vectors by a word embedding model (such as Word2Vec [120]) that has been pre-trained by a general purpose or domain specific corpus. However, this makes class semantic encoding and prediction model training detached with no interaction between them. A coupled approach is jointly learning the prediction model and the class semantic encoding; for example, DeViSE jointly fine-tunes a skip-gram word embedding model and an image classifier [58]. Long text such as sentences and documents contains more yet noisy information, and thus some additional methods for feature learning and selection over the text (or text embedding) have been considered. Among the aforementioned studies, [51] and [140] extract features from the text by the TF-IDF algorithm through which the vectors of some critical words get more weights; the study [139] initially encodes the class descriptions into simple bag-of-words vectors, and then jointly learns text features and the image classifier; [144] also jointly learns text features and the image classifier, but considers both word-level and character-level text features. In summary, the text information is easy to access for common ZSL tasks. It can be extracted from not only the data of the ZSL tasks themselves but also encyclopedias, Web pages and other online resources. However, it is often noisy with irrelevant words and the words are always ambiguous, failing to accurately express fine-grained, logical or quantified inter-class relationships.

In recent years, graph structured knowledge that belong to the scope of KG, such as the class hierarchies and the relational facts, are becoming more and more popular in ZSL research with very promising performance achieved. Such knowledge can often express richer semantics than attributes and text, even including logical relationships, and at the same time, they are become more available with the development of KG construction techniques and the availability of many public KGs such as WordNet [121], ConceptNet [162] and Wikidata [176]. In this survey, we mainly review KG-aware ZSL studies, and thus we use Section 3 to independently introduce KGs and their construction for low-resource learning, and Section 4 to review KG-aware ZSL methods.

2.1.3 Existing Method Categorization. The survey paper [184] divides general ZSL methods into the following two categories:

- **Classifier-based.** The classifier-based methods are to directly learn a classifier for each unseen class. They could be further divided into (i) **Corresponding Methods** which exploit the correspondence between the binary one-vs-rest classifier for each class and its corresponding encoding of the auxiliary information, (ii) **Relationship Methods** which calculate and utilize the relationships among classes, and (iii) **Combination Methods** which combine classifiers for basic elements that are used to constitute the classes.

- **Instance-based.** The instance-based methods are to obtain labeled samples belonging to the unseen classes and use them for learning and prediction. They are further divided into several subcategories: (i) **Projection Methods** which learns a function to project the input and the class encoding into the same space (i.e., the class encodings after
projection are regarded as labeled samples), (ii) Instance-borrowing Methods which transfer samples from seen classes to unseen classes, and (iii) Synthesizing Methods which obtain labeled samples for the unseen classes by synthesizing some pseudo samples.

This categorization is mainly from the perspective of ML theory and method. It aims at general ZSL methods, no matter what kind of auxiliary information is utilized. In contrast, our categorization which is to be introduced in Section 4 is from the perspective of auxiliary information, and focuses on more fine-grained comparison and analysis towards those KG-aware ZSL methods. Meanwhile, since the survey [184] was published in 2019 while many KG-aware ZSL methods were proposed in recent two years, the collected KG-aware methods are quite incomplete and they are not fully considered in making the above categorization.

2.2 Few-shot Learning

As ZSL, FSL has been very widely investigated for many different tasks across domains such as CV, NLP, KG completion and urban computing. Although the exact problem definition of FSL varies from task to task and from paper to paper, it can be summarized and uniformly expressed. In this part, we first introduce the definition of FSL and its notations, and then give a brief introduction to its auxiliary information and the existing method categorization.

2.2.1 Problem Definition. Briefly, FSL aims to classify data with the candidate classes that have only a small number of labeled samples. Its definition is very close to ZSL except that the unseen class is associated with some labeled samples which can be utilized in both training and testing. For convenience, we re-use the notations of ZSL, and keep calling the normal classes with a large number of training samples as seen classes \( (Y_s) \) and those classes with only a small number of labeled samples as unseen classes \( (Y_u) \). As in ZSL, the normal training samples of the seen classes are denoted as \( D_{tr} = \{(x, y) | x \in X_s, y \in Y_s\} \), the testing samples are denoted as \( D_{te} = \{(x, y) | x \in X_u, y \in Y_u\} \), and the target function to learn is denoted as \( f : x \rightarrow y \). Specially, the few-shot labeled samples of the unseen classes are denoted as \( D_{few} = \{(x, y) | x \in X_{few}, y \in Y_u\} \). Note \( X_{few} \cap X_{te} = \emptyset \). The original target of learning \( f \) can also be transformed into learning a scoring function for ranking the candidate classes, i.e., \( f' : (x, y) \rightarrow s \), where the original input and a candidate class act as the new input and the new output \( s \) is a score indicating the truth of the class \( y \) w.r.t. \( x \).

The size of the labeled samples of the unseen class is relative. It can have just one labeled sample (i.e., one-shot learning). It can also have multiple labeled samples which, however, are not enough to train a robust model for the unseen class. To be more specific, we introduce the concept of expected risk as in [187]. For an optimal hypothesis \( \hat{h} \) (i.e., the target function \( f \)), its expected risk is composed of two parts: (i) approximation error \( E_{app} \) which measures how close the best hypothesis \( h^* \) in a given hypothesis set \( H \) can approximate \( \hat{h} \), and (ii) estimation error \( E_{est} \) which measures the effect of minimizing the empirical risk of the learned hypothesis \( \hat{h} \) w.r.t. the best hypothesis \( h^* \) [23]. As shown in Figure 1, model training for FSL unseen classes, which have no enough labeled samples, means there is a much higher estimation error than model training for normal classes that have enough samples. However, it is important to note that the few-shot samples may not always be used for model training (or fine-tuning), but can sometimes be directly utilized in prediction (e.g., methods of the transfer-based paradigm to be introduced in Section 5.6).

2.2.2 Auxiliary Information. All the auxiliary information used in ZSL such as class textual information, class attribute and class hierarchy can also be used for augmenting FSL. For example, Tsai and Salakhutdinov [172] utilized the word embeddings of the classes and their ancestors in a hierarchy to generate quasi-samples from \( D_{tr} \) (i.e., samples of seen classes) for unseen classes for addressing one-shot learning; while Zhu et al. [230] utilized visual attributes to address
few-shot image classification by proposing an attribute-constrained image representation learning neural network. Besides, domain specific background knowledge can also be applied in the form of e.g., heuristic rules. Wu et al. [195] proposed a simple heuristic idea to augment the samples, i.e., using the nearest label as a pseudo label to annotate each unlabeled sample. Different from ZSL, a small number of labeled samples are available for the unseen classes in FSL. These few-shot samples can also be regarded as an additional kind of auxiliary information. Most FSL methods now focus on fully utilizing these few-shot samples. To address the sample shortage, they prefer some ML algorithms such as multitask learning which allows parameter sharing between tasks, meta learning which directly predicts some parameters and hyper-parameters that are to learn or to adjust, and metric learning which compares a testing sample with the few-shot samples of each unseen class in some space after projection.

KG has also been investigated in FSL as a form for representing different kinds of auxiliary information. Since this survey focuses on KG-aware low-resource learning, the KGs and their construction for FSL are introduced in Section 3, while methods of KG-aware FSL are reviewed in Section 5.

**2.2.3 Existing Method Categorization.** According to the aspects that are augmented for addressing the sample shortage, the existing FSL methods are divided into the following three general categories in [187]:

- **Methods that augment the data.** They increase the size of the few-shot samples ($D_{few}$) via data augmentation by e.g., transforming samples from the training set $D_{tr}$, transforming samples from similar labeled data, and generating samples from weakly labeled or unlabeled data.

- **Methods that augment the model.** They reduce the original hypothesis set $\mathcal{H}$ to a small one for reducing the searching space in training. They can be further divided into (i) methods of multitask learning which is to share parameters from one task to another task or regularize the parameters of the target task, (ii) methods of embedding learning which is to project samples to an embedding space where similar and dissimilar samples can be easily discriminated, (iii) methods of generative modeling which is to restrict the model distribution, and so on.

- **Methods that augment the algorithm.** They guide and accelerate the searching of the parameters of the best hypothesis $h^*$ by e.g., learning the optimizer and aggregating existing parameters.
This is a systematic categorization towards general FSL. It has a very limited coverage on KG-aware FSL methods, and ignores the role of the auxiliary information especially KGs. In this survey, we categorize and compare KG-aware FSL methods from the perspective of how KG is exploited. See more details in Section 5.

3 KNOWLEDGE GRAPH

3.1 Definition and Scope

Knowledge Graph (KG) is widely used for representing graph structured knowledge, and has achieved great success in many domains, such as search engine, recommendation system, clinic AI, personal assistant and natural language understanding [75, 132, 192]. In this part, we first describe what is a KG from the Semantic Web perspective, and then introduce other KG definitions that are widely used in different domains such as CV and NLP.

In the Semantic Web, a KG is often largely composed of statements in the form of RDF\(^1\) triple [49, 133]. Each RDF triple is denoted as \((s, p, o)\), where \(s\) represents the subject which should be an entity, \(p\) represents the predicate, and \(o\) represents the object, which can be either an entity or a datatype value. Some statements are relational facts. In this case, \(o\) is also an entity, and \(p\) is a relation between two entities (a.k.a., object property). \(s\) and \(o\) are also known as the head entity and tail entity, respectively. A set of relational facts composes a multi-relational graph whose nodes correspond to entities and edges are labeled by relations. Some RDF triples represent literals as e.g., entity attributes. In this case, the predicate \(p\) uses a data property and \(o\) is a literal with some data type such as string, date, integer and decimal. The literals also include KG meta information such as entity’s label, textual definition and comment, which are also represented via built-in or bespoke annotation properties.

In addition to the relational facts and literals, KGs are often accompanied by an ontology as the schema, using languages from the Semantic Web community such as RDFS\(^2\) and OWL\(^3\) for richer semantics and higher quality [49, 76]. They often define hierarchical classes (a.k.a. concepts), properties (i.e., stating the terms used as relations), concept and relation hierarchies, constraints (e.g., relation domain and range, and class disjointness), and logical expressions such as relation composition. The languages such as RDF, RDFS and OWL have defined a number of built-in vocabularies for representing these knowledge, such as \texttt{rdf:type}, \texttt{rdfs:subClassOf}, \texttt{owl:disjointWith} and \texttt{owl:someValuesFrom}. Note RDFS also includes some built-in annotation properties such as \texttt{rdfs:label} and \texttt{rdfs:comment} for defining the above mentioned meta information. With these vocabularies, an ontology can be represented as RDF triples; for example, the subsumption between two classes can be represented by the predicate \texttt{rdfs:subClassOf}, while the membership between an instance and a class can be represented by the predicate \texttt{rdf:type}. The ontology alone, which is widely used to define domain knowledge, conceptualization and vocabularies such as terms and taxonomies, is also widely recognized as a KG, and the classes are sometimes also called entities. One typical example is SNOMED CT which systematically organizes medical terms as classes (entities) with names, definitions, existential restrictions, tree-like categorizations and so on [156]. It is worth mentioning that KGs, especially those OWL ontologies and those relational facts equipped with ontologies, can support symbolic reasoning, such as consistency checking for the change [57] which can find logical violations, and entailment reasoning which infers hidden knowledge, according to Description Logics [7].

Besides the relational facts, literals and ontologies defined following standards in the Semantic Web community, we also regard graph structured knowledge in some other forms as KGs, according to the terminologies and definitions used in other communities including ML, database, CV and NLP. One popular KG form is Semantic Network which can

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1 Resource Description Framework, https://www.w3.org/TR/rdf11-concepts/.

2 RDF Schema, https://www.w3.org/TR/rdf-schema/.

3 Web Ontology Language, https://www.w3.org/TR/ow2-overview/.
be understood as a graph that connects different concepts (entities) often with labeled edges for representing different relationships. Two such KGs that are widely used in many domains are WordNet which is a lexical database with different relationships between words [121] and ConceptNet which stores commonsense knowledge and relationships between different terms [162]. We further relax the scope of KGs to single relation graphs such as simple taxonomy (i.e., a set of hierarchical classes) and graphs with weighted edges which may represent some quantitative relationships such as similarity and distance between entities.

In this survey, we also regard logical rules of different forms, such as Horn clause, Datalog rules and SWRL\(^4\) rules, as well as their soft or fuzzy extensions (i.e., weighted rules) [134], within the scope of KG. This is because many of these rules can be transformed into equivalent relational facts and ontological knowledge, and vice versa [77, 94]. They can often be understood as logic models over KGs, through which hidden knowledge can be inferred.

3.2 Construction

Nowadays, there are many existing KGs which are constructed in different ways. Those high quality domain-specific ontologies such as the medical ontology SNOMED [156] and the food ontology FoodOn [50] are often directly constructed by domain experts via collaboration, while many general purpose KGs such as Yago [143], DBpedia [6] and Wikidata [176] are constructed via crowdsourcing — they are either extracted from existing crowdsourced resources such as Wikipedia or directly contributed by volunteers. To be more comprehensive, many KGs integrate different knowledge resources and databases; for example, ConceptNet [162], which was originally developed by crowdsourcing, further fused knowledge from DBpedia, Wiktionary, OpenCyc and so on. In fact, solutions and technologies of Linked Open Data [17], Ontology Network and Ontology Alignment [52] can all be used for constructing KGs via integration. Last but not the least, with the development of data mining, ML and other data analysis techniques, knowledge extraction from unstructured and semi-structured data such as the Web pages, tables and text have recently been widely investigated and used for KG construction; for example, NELL is continuously extracted from the Web [123], while Google’s KG is extended with knowledge extracted from tables in Web pages [25].

For some specific low-resource learning tasks, there are exactly suitable KGs that can be directly applied. For example, Huang et al. [83] directly used the event ontology named FrameNet [9] for supporting their zero-shot event extraction method. However, for the majority of the low-resource learning tasks, existing KGs usually cannot be directly applied due to their large sizes and irrelevant knowledge, and an (ad-hoc) KG should be extracted or constructed. In this part, we mainly review techniques of constructing KGs for augmenting low-resource learning for specific tasks. We divide these techniques into three categories: sub-KG extraction from existing KGs, KG construction with task-specific data, and knowledge integration.

3.2.1 Sub-KG Extraction. Given a low-resource learning task, a straightforward solution is re-using an existing KG by extracting relevant knowledge (i.e., a sub-KG). Next we will present those large-scale general purpose KGs that have been exploited, briefly review the corresponding studies and summarize the methods used for extracting sub-KGs. Note in this part we mainly focus on KGs for augmenting low-resource learning, and do not cover KGs that are just used for evaluating the KG completion tasks (i.e., we ignore KGs acting only as the target for completion).

- **WordNet** is the most widely used KG for augmenting both ZSL [2, 5, 36, 62, 63, 88, 98, 103, 105, 181, 186, 190] and FSL [2, 39, 85, 124, 138, 172]. As a large lexical database with several different relationships between words, such as synonym, hyponym, hypernym and meronym [121], it is often used to build task-specific class hierarchies,
especially for image classification. A typical solution to extract a sub-KG is first matching the classes of the ML task with nodes (entities) in WordNet and then extracting the matched nodes and their neighbouring nodes within k-hops via e.g., breadth-first search. For some benchmarks, especially those image sets extracted from ImageNet, there are already existing matchings between classes and WordNet nodes. For example, in the study by Wang et al. [186], a WordNet sub-graph with 30K nodes are extracted as a KG for an ImageNet subset that has 1K training classes. For some other benchmarks, the matchings are often built by simple name comparison with the help of human intervention for high accuracy. For example, Kampffmeyer et al. [88] and Geng et al. [62] manually matched all the 50 classes in an animal image classification benchmark named AwA2 with WordNet nodes. In extracting neighbours of the matched entities, when more hops considered, the extracted sub-KG has a higher knowledge coverage but more irrelevant knowledge. Besides the k-hops neighbourhood, some studies such as [2] and [124] just extract the ancestors or parents of the matched nodes for simple class hierarchies as a sub-KG.

- **ConceptNet** is a freely-available Semantic Network with commonsense knowledge [162]. It stores a large number of entities which are either words or phrases, and facts of quite a few relations including Synonym, Isa, RelatedTo, HasContext, HasA and so on. The Isa relation is used to represent hyponyms and hypernyms. ConceptNet is often used in a similar way as WordNet: a sub-graph which acts as class hierarchies for augmenting ZSL [38, 41, 126, 127, 151, 212, 215] and FSL [205, 212, 215] is extracted via matching classes to entities and selecting neighbouring entities. It is also mostly applied in CV tasks but has also been explored in open information extraction. For example, Nguyen et al. [127], who worked on zero-shot entity extraction from text, first extracted nouns and pronouns with a part-of-speech algorithm from all sentences in the dataset, and then searched for their corresponding entities in ConceptNet and extracted the matched entities and their adjacent ones. Note in many works that utilize ConceptNet, WordNet and some other KGs, the matching between classes and KG entities is rarely introduced in detail and assumed to be fully correct.

- **Freebase** is a large-scale general purpose KG with relational facts, contributed by multiple sources [19]. Its official API has been shut down, but it can still be accessed as a dump or via Google’s Knowledge Graph API, and has been widely used for investigating KG techniques including KG augmented ZSL [5, 84, 113] and FSL [113, 216]. Different from WordNet and ConceptNet, Freebase is mainly applied in open information extraction. Entity mentions and relation mentions are matched with Freebase entities and relations, respectively, and the types of the matched entities, the super- and sub-relations of the matched relations, or the neighbourhood of the matched entities and relations are extracted as a sub-KG for augmentation.

- **Wikidata** is being increasingly used for different kinds of applications, but its application for augmenting ZSL and FSL had not attracted any attention until recently when two studies were proposed for augmenting few-shot relation extraction [141, 216] and another two studies were proposed for augmenting ZSL [62, 102]. Different from the above mentioned methods that extract neighbourhoods of the matched entities or relations, Qu et al. [141] extracted 10 nearest relations to each matched relation in the embedding space by TransE, for constructing a relation graph. Zhang et al. [216] extracted concept-level knowledge of the relations from Wikidata, such as the concepts (classes) that the relation is associated with, and the concepts’ hierarchy. Geng et al. [62] also extracted concept-level knowledge of all the relations involved in a zero-shot KG link prediction task and constructed an RDFS schema. Li et al. [102] considered two solutions to utilize Wikidata for augmenting zero-shot relation extraction: they either directly utilized the relation embeddings by TransE or mined logic rules from Wikidata to further integrate the relation embeddings.
• **DBpedia** is also a large-scale general purpose KG whose knowledge are mainly from Wikipedia [6]. It has also been used to augment ZSL, often acting as a complement of relational facts and literals such as entity descriptions [41, 62, 63]. DBpedia entities are often retrieved via its lookup service which is based on a lexical index built on entity labels and descriptions\(^5\), while the entity associated facts and literals can be accessed from a DBpedia dump or its online SPARQL endpoint\(^6\). DBpedia also includes an ontological schema, and its hierarchical classes have been extracted by Amador et al. [5] for augmenting zero-shot KG completion with unseen entities.

• **NELL** is a popular KG continuously extracted from the Web [123]. We find two ZSL studies and one FSL study that utilize NELL. Wang et al. [186] extracted a sub-KG from NELL for zero-shot classification for images from NEIL — an image repository whose classes are aligned with NELL entities [40]. Geng et al. [62] extracted an RDFS schema (ontology) from NELL for augmenting zero-shot KG link prediction with unseen relations. Sui et al. [164] extracted entity concepts (entity classes) from NELL for augmenting few-shot text classification, where entities are retrieved via exactly string matching using entity mentions in the text.

Sub-KGs of some other KGs have also been extracted and exploited for augmenting low-resource learning, but they are not as popular as the above six. Zhang et al. [216] extracted concept-level relation knowledge from UMLS — an ontology of medical concepts [116], for few-shot relation extraction in the medical domain. Rios et al. [148] extracted class hierarchies and class descriptions from ICD-9 diagnosis and procedure labels for zero-shot and few-shot medical text classification. Luo et al. [110] extracted a sub-KG for object relationships from Visual Genome — a knowledge base that stores connections between image visual concepts and language concepts [93], for augmenting zero-shot object recognition. The KG for augmenting zero-shot VQA in [41] also includes facts from WebChild which is a large collection of commonsense knowledge from the Web [167], besides knowledge from ConceptNet and DBpedia. Zhou et al. [228] trained their zero-shot question answering model with facts extracted from WorldTree (V2.0) [200] — a knowledge base that contains explanations for multiple-choice science questions in the form of graph, covering both commonsense and scientific knowledge.

3.2.2 **Task-oriented KG Construction.** Instead of utilizing existing KGs, some ZSL and FSL studies build task-specific KGs from some non-KG auxiliary information. The classes’ textual information such as labels is the most frequently utilized information for mining inter-class relationships and further for constructing KG edges. Palatucci et al. [131] connected a word (which corresponds to a class in that task) to another according to their co-occurrence in a text corpus. Lee et al. [98] calculated WUP similarity of class labels, and used this similarity to build KG edges for representing positive and negative inter-class relationships. Wei et al. [190], Ghosh et al. [65] and Wang et al. [181] all considered calculating and adding edges to entities that are close to each other according to their labels’ word embeddings. Class attributes have also been exploited for mining inter-class relationships. Zhang et al. [212] built a KG for the CUB benchmark which includes images of birds of fine-grained classes, by computing Hadamard product over the part-level class attributes. Hu et al. [80] and Chen et al. [36] both directly utilized the co-occurrence of class attributes to build edges between KG entities. Specially, Changpinyo et al. [27] considered both class attributes and word embeddings to calculate weighted edges between entities. Different from the above methods that use some auxiliary information for building KG edges, Zhao et al. [222] and Geng et al. [62, 63] modeled the class attributes as additional KG entities and connected them to the entities of the classes; while Li et al. [100, 101] generated new superclasses of the seen and unseen classes by clustering of the class names, so as to constructing class hierarchies for augmenting ZSL and FSL.

\(^5\)https://lookup.dbpedia.org/
\(^6\)https://dbpedia.org/sparql/
Domain knowledge, which is often in the form of heuristics and logic rules, has also been used to construct task-specific KGs. Banerjee et al. [10] used heuristics to create a synthetic KG with science facts from the QASC text corpus and commonsense facts from the Open Mind Commonsense knowledge (text) corpus, for addressing both zero-shot and few-shot question answering. Chen et al. [34] added existential restrictions (a kind of description logic that quantifies a class by associated properties) to some classes of an animal taxonomy extracted from WordNet, so as to build an OWL ontology for the animal image classification benchmark AwA2.

There are also some ZSL and FSL studies that extract structured knowledge from the task data (samples) for constructing KGs which are further fed back to learning for augmentation. When Ghosh et al. [65] constructed a KG for evaluating methods for few-shot action classification where some videos (samples) are given for each unseen class, they first extracted sample features for each class, then took the mean of these features as a KG entity, and finally calculated the cosine similarity between feature means for edges between entities. Bosselut et al. [21] generated a temporary KG on demand for each prediction request of zeroshot question answering, using its text context and a Transformer-based neural knowledge model named COMET [22]. Chen et al. [36] added a co-occurrence relation between two classes (food ingredients) by calculating their co-occurrence frequency in the training samples, besides the common class attributes and class hierarchies.

### 3.2.3 Knowledge Integration

Although some general purpose KGs contain a large quantity of knowledge and are being continuously extended, it is still common that the knowledge extracted from such a KG is incomplete or not fine-grained enough for a specific low-resource learning task. Therefore, some studies proposed to integrate knowledge extracted from different KGs or/and other resources for building a high quality task-specific KG. For example, Chen et al. [41] extracted RDF facts from three KGs — ConceptNet, WebChild and DBpedia to generate a unified commonsense KG for augmenting zero-shot VQA; Geng et al. [62, 63] integrated class hierarchies from WordNet, relational facts and literals from DBpedia, and knowledge transformed from class attributes for constructing KGs for zero-shot image classification; Chen et al. [36] considered and integrated class hierarchies from WordNet, and class co-occurrence relations extracted from class attributes and samples for a KG for zero-shot ingredient recognition from food images. Very recently, Geng et al. [64] proposed a benchmarking study, where six KG equipped ZSL benchmarks were created for three different tasks and used for evaluating different methods under different auxiliary information settings. The KG of each benchmark is based on the integration of multiple knowledge resources: those for zero-shot image classification contain knowledge from WordNet, ConceptNet, class attributes, class names and so on, while those for zero-shot KG completion and relation extract contain relation textual information, schema information from Wikidata or NELL, logic rules by human beings and so on.

As matching classes to KG entities for sub-KG extraction, the alignment of entities and relations in integrating different knowledge parts now is still mostly based on simple name matching or manual matching. There is little attention to investigating automatic knowledge integration methods for low-resource learning, and the impact of the knowledge quality, such as the matching accuracy and the ratio of relevant or redundant knowledge, is often ignored.

### 4 KG-AWARE ZERO-SHOT LEARNING

According to the solutions for exploiting KGs, we divide the KG-aware ZSL methods into Mapping-based Paradigm, Data Augmentation Paradigm, Propagation-based Paradigm and Class Feature Paradigm. Table 1 presents a brief summary of each paradigm, as well as more fine-grained method categorizations and their corresponding papers. We will next introduce the details of each paradigm.
4.1 Mapping-based Paradigm

The mapping-based paradigm aims to build mapping functions towards the input ($X_s$ and $X_u$, or their initial encodings) and/or the classes ($Y_s$ and $Y_u$, or their initial encodings), so that their vector representations after mapping are in the same space and whether a class is the label of a sample can be determined by matching their vectors using metrics such as Cosine similarity and Euclidean distance. We denote the mapping function for the input side as $M$ and the mapping function for the class side as $M'$. This paradigm has a large overlap with the category of Projection Methods defined in [184], but we prefer to understand such solutions from the perspective of distance metric learning [163] instead of sample generation. Meanwhile, the majority of the methods of Project Methods are those that map both the input and the class, while our mapping-based paradigm includes many ZSL methods that only map one side (either the input or the class).

The mapping functions $M$ and $M'$ refer to mapping models such as neural networks that are learned by optimizing the sample-class matching degree among the labeled training data $D_{tr} = \{(x, y) | x \in X_s, y \in X_t\}$, such as by minimizing the sum of the input’s Euclidean distances to their corresponding classes. They are different from the initial encoding functions $g$ and $h$. The mapping function could either directly use the raw input and the symbolic class auxiliary information as the input, or be fed with their initial encodings. In the former case, the mapping includes the initial encoding. According to the side that the mapping is applied, we divide the ZSL methods of the mapping-based paradigm into three categories: Input Mapping, Class Mapping and Joint Mapping. Figure 2 shows these three categories and their insights.

4.1.1 Input Mapping. As shown in Figure 2 (a), the input mapping methods learn a mapping model $M$ to project the input $x$ (or the input’s initial encoding $x$) into the space of the classes’ initial encodings. Input mapping is one of the earliest idea used in ZSL, especially for zero-shot image classification. Palatucci et al. [131], who are among the first for ZSL research, proposed a two-stage mapping function denoted as $L(S(\cdot))$, where $S$ represents the first stage which projects the input to individual dimensions of a semantic space, and $L$ represents the second stage which further projects the output of $S$ to the class. In a case study on neural activity classification, they used class attributes, which are either from classes’ word similarity or manually created via crowdsourcing\(^7\), as the intermediate individual dimensions, and set

\(^7\)The auxiliary information of [131] actually belongs to class attribute instead of KG. Since it claims to use Knowledge Base which is often regarded as KG by many researchers, we prefer to present this paper.
Input mapping has also be explored in ZSL tasks that extract entities and relations from text. Ma et al. [113] pre-trained the class (entity type) embeddings using different KG embedding methods such as prototype-driven label embedding and hierarchical label embedding, and then proposed two mapping settings. One setting is to directly project the input (entity mention features) to the class embeddings, while the other belongs to Joint Mapping which will be introduced later. The input mapping is implemented by a linear transformation which is implemented by multiplying the input by a matrix of weights, and is learned by minimizing a weighted approximate-rank pairwise loss. Imrattanatrai et al. [84] learned initial text representations of relation mentions by word embedding and a Bidirectional LSTM network, and then used a linear transformation function to project these text representations into relation (property) vectors which are calculated with KG TransE [20] embeddings and some ad-hoc relation feature extraction methods. Li et al. [102] projected the input text representation into the class embedding by a simple linear transformation for zero-shot relation extraction (which is
modeled as relation classification), where different class embeddings methods combing word embedding, KG embedding and rule-guided KG embedding were explored and evaluated.

### 4.1.2 Class Mapping

In contrast to input mapping, the class mapping methods learn a mapping model $M$ to project the class $y$ (or the class’s initial encoding $y$) into the space of the input’s initial encodings, as shown in Figure 2 (b). This idea is not as widely investigated as input mapping, and we gather four methods into this category. The first three are for zero-shot image classification, while the last is for zero-shot KG completion with unseen entities. Akata et al. [1, 2] proposed to learn a label embedding model as the mapping function which projects the class initial encoding into the feature of the input image. They studied using class hierarchies as the auxiliary information, where each class was initially represented as a multi-hop vector — the slots of the class and its ancestors are set to 1. Changpinyo et al. [27] first generated a weighted graph where the relatedness between classes are represented, then introduced phantom classes through which seen and unseen classes can be synthesized by convex combination, and finally projected the vectors of phantom classes into the input. Nayak et al. [126] proposed a novel transformer Graph Convolutional Network (GCN) architecture as the class mapping function which non-linearly aggregates a class’s neighbours in the KG to calculate this class’s embedding. This method uses a compatibility score as the metric for the distance between the image CNN feature (input) and the class embedding. Shah et al. [157] predicted KG triples with unseen entities using their text descriptions. Their method first individually embeds the entities from the graph perspective by common link prediction models such as TransE [20] and DistMult [203], and from the text perspective by a word embedding model and an LSTM network, and then transforms the entities’ text embeddings to the space of the entities’ graph embeddings, where both linear and non-linear transformation functions such as Multi-Layer Perceptron (MLP) were explored.

### 4.1.3 Joint Mapping

As shown in Figure 2 (c), the joint mapping methods learn one mapping $M$ from the input $x$ (or the input’s initial encoding $x$) and another mapping $M'$ from the class $y$ (or the class’s initial encoding $y$) at the same time such that the mapped vectors are in the same space where a sample is close to its label w.r.t. some distance metric. When a testing sample is to be predicted, it can be matched with classes in the space after mapping. This idea is often adopted for zero-shot entity/relation extraction where features of both the input (text) and the class (entity/relation in a KG) are jointly learned. The zero-shot entity extraction method in [113] can support both input mapping and joint mapping. For the later, the entity mention features and the class embeddings are jointly mapped to one common space via multiplying them by matrices (parameters) which are learned by minimizing a weighted approximate-rank pairwise loss. Huang et al. [83] mapped the input — features of event mentions and their structural contexts parsed from the text, and the event types whose auxiliary information is an event ontology, jointly into one vector space using a shared CNN with a structure composition layer, by minimizing an ad-hoc loss. Rios et al. [148] worked on zero-shot text classification. They matched the input mapping which is text features learned by a CNN, with the class mapping which is by initial word embedding and GCN-based class hierarchy embedding. Chen et al. [38] also worked on zero-shot text classification by linear joint mapping of the initial input encoding, which is text embedding by BERT, and the initial class encoding, which is word embedding tailored by the ConceptNet KG. Hao et al. [70] investigated joint mapping in zero-shot KG link prediction. They proposed to jointly map the graph structure (input) and the new entity into a vector space for addressing unseen entities, using a ranking motivated loss. The graph structure is mapped via a linear encoder over the one-hot encoding of the KG entities, while the entity is mapped by encoding its attributes using MLP. Roy et al. [151] proposed a joint mapping method for zero-shot image classification. It maps the initial class semantic embedding learned by a GCN on commonsense knowledge, and the initial image feature learned by ResNet101 (a CNN), using a non-linear transformation named Relation Network. This network first attaches a fully connected layer to the class semantic embedding, then
concatenates its output with the initial input feature, and finally attaches two different fully connected layers. It is learned by minimizing a MSE loss. Note we can also understand this method as a composition of two initial encodings without any mappings and one trainable complex function (i.e., the Relation Network) as the distance metric. Chen et al. [41] applied a joint mapping method to zero-shot visual question answering (VQA). They mapped the input (i.e., a pair of image and question) and the KG entity (i.e., the candidate answer) to a common space, where the matched KG entity of the input was taken as the right answer.

4.2 Data Augmentation Paradigm

A straightforward solution for addressing sample shortage in ML is generating data with the guidance of task-relevant knowledge. In ZSL, some methods generate samples or sample features for unseen classes and transform the problem into a standard supervised learning problem. We regard these methods as Data Augmentation Paradigm. According to the method of generating new data, we further divide the existing KG-aware ZSL methods of this paradigm into two categories: Rule-based and Generation Model-based.

4.2.1 Rule-based.

Background knowledge of a task could be explicitly represented by different kinds of rules (or other equivalent logic forms such as schema constraints and templates) which are regarded as a part of the KG. They enable deductive reasoning for hidden knowledge as new samples. This solution has been considered and empirically analyzed to generate new samples for training normal KG embedding and link prediction models [30, 219], but has not been widely investigated to address zero-shot settings, as far as we know. Rocktaschel et al. [150] worked on a zero-shot KG completion task which predicts an unseen relation for a pair of entity mentions extracted from the text. They proposed three methods to inject first-order rules which act as commonsense knowledge into a matrix factorization model. One method is logically inferring additional relational facts in advance before training the matrix factorization model. In image classification and some other tasks where the sample input and their features are uninterpretable real value vectors, generating data by rules becomes unfeasible and thus there are few ZSL methods of this category.

4.2.2 Generation Model-based.

With the fast development of conditional generation models such as Generative Adversarial Networks (GANs) [67] and Variational Auto-encoder (VAE) [91], they have become popular tools for generating data for addressing ZSL especially for image classification [28, 62, 82, 184, 198, 212, 229]. We categorize these methods as Generation Model-based. However, since conditional generation models were not widely applied until around 2018, we only find three ZSL studies that combine them with KG. Qin et al. [140] generated multiple features of an unseen relation conditioned on the sentence embedding of its text description for addressing a zero-shot KG completion problem which predicts the tail entity of a triple given a head entity and an unseen relation. The generator is jointly trained together with a discriminator which distinguishes the generated features from the real features of seen relations. Both the generator and the discriminator are neural networks composed of fully connected layers. Note each generated feature of an unseen relation is directly used to calculate a testing triple’s score, and the scores by multiple generated features are averaged. Geng et al. [62] applied a similar generation and discrimination-based model to not only zero-shot KG completion but also zero-shot image classification. In both tasks, an ontology and its embeddings are used as the condition for generating sample features. In image classification, a one-vs-rest classifier is trained for each unseen class through normal supervised learning after multiple sample features are generated. Zhang et al. [212] worked on zero-shot image classification by transforming it into a FSL setting. Their method uses a generation module to generates an instance-level graph, where dummy features (instances) are synthesized for those unseen classes by GANs. They finally addressed the FSL problem over the instance-level graph by a propagation module and a meta learning strategy.
4.3 Propagation-based Paradigm

Since the backbone of a KG is a (multi-relation) graph, information propagation by e.g., GNNs is a straightforward and reasonable solution to utilize the inter-class relationship and has been widely investigated for implementing KG-aware ZSL. We classify those KG-aware ZSL methods whose core techniques are based on graph information propagation as Propagation-based Paradigm. These methods align seen and unseen classes with KG entities. Some of them propagate model parameters from seen classes to unseen classes via the graph for building models for unseen classes. The others directly propagate the beliefs (probabilities) of seen classes of a testing sample to infer the beliefs of unseen classes. The former are classified into Model Parameter Propagation while the later are classified into Class Belief Propagation. The idea of both kinds of methods is shown in Figure 3 (a).

4.3.1 Model Parameter Propagation. These KG-aware ZSL methods usually utilize the KG’s graph structure and some graph propagation models such as GNNs to approximate the parameters of models (classifiers) of unseen classes by aggregating parameters of models of seen classes that are trained by $D_{tr}$. In image classification, the parameters that are approximated are often those weights that linearly combine image features. Wang et al. [186] aligned image classes with WordNet [121] entities, trained a one-vs-rest classifier for each seen class with image features by a pre-trained CNN named ResNet-50, and then directly used a GCN to predict the image feature combination weights of each unseen class. Wei et al. [190] aimed to address the same ZSL problem as [186], but proposed to use a Residual Graph Convolutional Network (ResGCN) which utilized residual connections between hidden layers so as to alleviate the problem of over-smoothing and over-fitting. Ghosh et al. [65] applied a similar idea as the above two papers, using a 6-layer GCN to address zero-shot action recognition which was modeled as video classification. The evaluation, which is based on three different KGs, shows that the accuracy by using GCN is higher than linearly combing the classifiers of the top-4 closest seen classes of an unseen class. Wang et al. [181] constructed two single-relation KGs — one for the class hierarchy from WordNet and the other for the class correlation mined from word embeddings for zero-shot image classification. They used two weight-shared GCNs to utilize the two KGs to approximate classifier parameters for the unseen classes. In training, a
contrastive loss, which encourages the consistency of the approximated classifiers from different KGs and enhances the discriminability of the different classifiers within the same KG, is used, together with the parameter approximate loss.

Geng et al. [63] and Chen et al. [36] both proposed to added some attention mechanism to a GCN for approximating parameters of image classifiers of unseen classes. The method by [63] not only improves the accuracy but also provides explanations for the feature transfer from seen classes to unseen classes. To this end, the authors attached an attention layer after GCN to calculate the weights of contributions of different seen classes to an unseen class so as to find out the most impressive seen classes that are important in transferring features to the unseen class. It is worth mentioning that they also built a KG composed of different kinds of knowledge for generating human understandable explanations. The method by [36] uses a GCN to estimate the parameters of multi-label classifiers for zero-shot ingredient recognition from food images. Since the KG, which is composed of knowledge of ingredient hierarchy, ingredient attributes and ingredient co-occurrence, has multiple different relations, an attentive multi-relational GCN is adopted, where different relations have different contributions in parameter propagation.

Kampffmeyer et al. [88] investigated a similar idea as the above methods, but proposed that GCN, which is originally developed for classification, is not ideal for parameter regression in ZSL. Instead, they used a Graph Propagation Module (GPM) that consists of only two layers, and its two extensions — Dense GPM which enables direct information propagation between entities that are indirectly connected by some intermediate entities, and Attentive Dense GPM which further weights the contributions of different neighbouring entities according to their distances to the target entity whose corresponding classifier is to be predicted. According to the evaluation on a large ImageNet benchmark and the KG of WordNet, GPM and its extensions often achieve better performance than the GCN method proposed in [186].

4.3.2 Class Belief Propagation. This kind of propagation-based ZSL methods usually first initialize a testing sample’s beliefs (probabilities) of all the classes, and then utilize the class connections in the KG and the propagation model learned from \( D_{tr} \) to infer the beliefs of the unseen classes or the beliefs of both the seen and unseen classes. They are often applied to the case where a sample is associated with multiple classes and these classes’ relationships such as co-occurrence can be utilized for decision making. One typical work of this kind is the zero-shot multi-label image classification study by Lee et al. [98], where multiple classes are predicted for each testing image and some classes are unseen in training. The method includes two functions: the first function uses a gated recurrent update mechanism to model the belief propagation between two KG entities, where the propagation between a seen class entity and an unseen class entity is directional (from seen to unseen), while the second function is a standard fully-connected neural network which outputs a final belief for each entity according to its latest belief status after several iterations of propagation. Note that the initial belief status of an entity is determined by the sample’s feature and its corresponding class’s word embedding. Luo et al. [110] worked on a task of recognizing multiple interactive objects in an image where some objects are unseen in training. They proposed a method that uses Conditional Random Field to infer the unseen objects using the recognized seen objects in the image and a KG with prior knowledge about the relationships between objects. Bosselut et al. [21] focused on zero-shot question answering. They proposed to construct a context-relevant commonsense KG from deep pre-trained language models, where the question acts as a root entity and the answer choices act as leaf entities, and then they infer over the graph by aggregating paths to find the right answer. Different from [98] and [110], this work finally predicts only one answer (class) for each question (sample), but associates one question with multiple candidate answers in inference.
4.4 Class Feature Paradigm

Many recent ZSL methods often encode the class \( y \) as features (a vector) and then directly use them together with the original input \( x \) as the new input of a prediction model. Namely they learn the transformed function \( f' : (x, y) \rightarrow s \) where \( s \) is a score that indicates whether \( y \) is a class of \( x \), using samples of seen classes, i.e., \( D_{tr} \). The class features can be either separately learned (i.e., using the initial encoding) or jointly learned with the prediction model. In prediction, the unseen classes are also transformed into features in the same way and their combinations with a testing sample are scored by \( f' \). We regard this kind of ZSL methods as Class Feature Paradigm. Its general idea is shown in Figure 4. This actually transforms the ZSL problem into a classic domain adaptation problem where the input distribution of the training data is different from that of the testing data [12]. In this paradigm, the utilization of KGs for augmenting ZSL is often implemented by injecting their semantics into the class features by e.g., semantic embedding. According to the types of the features of \( x \) and \( y \), we further classify KG-aware ZSL methods of this paradigm into two categories: Text Feature Fusion and Multi-modal Feature Fusion.

4.4.1 Text Feature Fusion. In some KG-aware ZSL studies, text is utilized as critical auxiliary information. One typical example is KG completion with unseen entities, where entities are described by name phrases and/or textual descriptions, while another typical example is zero-shot question answering, where the input and the class are actually both text. With the development of word embedding models, especially those pre-trained language models such as BERT [48], semantics of the text can be well embedded into vectors together with the KG [30, 69, 107, 221]. Therefore, there are quite a few KG-aware ZSL methods whose model architectures or frameworks have the following data flow: both the input and the class are represented in the form of text (e.g., sequences of words and sub-words), encoded as vectors by text embedding models often with the KG contexts considered, and finally fused and fed into a prediction model. We regard these methods as the category of text feature fusion.

The majority of these methods are applied to address zero-shot KG completion. They use text embeddings to represent unseen entities or relations that are associated with text descriptions or other text-relevant auxiliary information. Zhao et al. [224] adopted the TF-IDF algorithm to combine the embeddings of words to represent each entity with its text description. For each candidate triple, they used the text-based representations of the two entities to calculate its score, where the triple’s score function is defined as the sum of the interactions of any two elements of the triple, and the
relation’s interactions with the head entity and the tail entity are represented by two trainable vectors, respectively. Shi et al. [158] proposed a zero-shot KG completion method named ConMask for dealing with unseen entities using their names and text descriptions. Briefly, it feeds the text embeddings of the entities and the relation of a triple into a model that is mainly composed of an attention-based relation-dependent text masking module and a CNN-based target fusion module. Niu et al. [128] followed the general direction of [224] and [158], but worked out a new multiple attention-based method with a Bidirectional LSTM network and an attention layer for modeling and utilizing the interaction between the head entity description, head entity name, the relation name, and the tail entity description. Amador et al. [5] focused on triple classification with unseen entities. The ontological information such as the entity’s hierarchical classes are utilized by their word embeddings which are combined with the entity’s word embeddings by concatenation, averaging or weighted averaging, and fed into a classification model. Wang et al. [179] proposed a commonsense KG link prediction method named InductiveE which can deal with unseen entities by utilizing entity textual descriptions. It first represents an entity using the concatenation of its text embeddings by the fastText word embedding model [87] and the last layer [CLS] token of the pre-trained BERT [48], and then feed the entity representations of the graph into a model composed of an encoder — a gated-relational GCN and a decoder — a simplified version of ConvE [47] to predict each triple’s score. In training, the initial entity representations are fixed and the encoder-decoder model is learned.

Recently, due to the wide investigation of pre-trained language models such as BERT [48], some methods that fine-tune these models for utilizing textual information for addressing zero-shot KG completion have been proposed. Since they represent a triple’s entities and relation as features and feed these features into a model for prediction, we also regard them as the category of text feature fusion. Different from [179] where BERT is used for initial but fixed entity representations, the entity and relation representations in these methods are trained as BERT is fine-tuned. Gong et al. [66] fine-tuned a BERT model for zero-shot relation extraction, where prompts were constructed as the input using the relation’s corresponding knowledge in ConceptNet. Yao et al. [206] proposed a KG triple prediction method called KG-BERT. It transforms a triple’s head entity, relation and tail entity into a text sequence and then makes triple prediction as a downstream text classification task, where BERT is fine-tuned with given training triples. For unseen entities and relations that have name information, the candidate triples associated with them can be directly predicted by transforming them into text sequences. As KG-BERT, Zha et al. [211] also proposed to predict triples as a downstream text classification task of BERT, utilizing the text information of entities and relations. But they fine-tune BERT using not only single triples but also possible paths that connect two entities where reasoning is conducted explicitly. Wang et al. [178] extended KG-BERT with attempts to addressing two cons of KG-BERT: combinatorial explosion in triple inference and failure to utilize structured knowledge. They proposed a structure-aware encoder to represent a triple’s text with different combinations and interactions between its entities and relations. They also combined this BERT-based model with traditional KG embedding models such as RotatE [165] for higher Hits@K when K is small, but note that this ensemble scheme cannot work for testing triples with unseen entities and relations. Wang et al. [185] proposed a joint text and entity embedding method named KEPLER which is also able to predict KG triples with unseen entities and relations. It utilizes the text information of the entities and relations to fine-tune the BERT model via a masked language modeling loss, and at the same time train the KG entity and relation embeddings following the same score function and loss as TransE [20].

Besides KG completion, we also find one KG-aware zero-shot question answering study that fuses text features of the input and the class. Banerjee et al. [10] performed question answering via triple learning where the context, question and answer are modeled as a triple, and one element is predicted given the other two elements in a triple. In implementation, a transformer-based model that generates the answer given the text features of the context and question is learned by span masked language modeling, using triples extracted from text. Similarly, Zhou et al. [228] also modeled the question
answering problem as triple prediction with all the text features fused, and learned the prediction model by alternatively
masking the subjects and the objects of the training triples which are from a corpus named WorldTree.

4.4.2 Multi-modal Feature Fusion. Different from text feature fusion where the input and the class are both represented
as some kind of text and encoded by some text embedding model, the category of multi-modal feature fusion includes
those methods whose input features and the class features are of different kinds. In the zero-shot triple classification study
[5] mentioned above, the authors also considered representing an entity’s hierarchical classes by one-hot vectors instead
of using word embeddings. In that case, the two inputs — the class embeddings and the entity text embedding belong to
different kinds. Nguyen et al. [127] focuses on cross-domain entity recognition from the text, where the testing entities
are not only unseen but from a different domain as the entities involved in training, using an ontology as the auxiliary
information. The input sequence is encoded as token features by a pre-trained BERT, while the entity is encoded as graph
features learned by a Recurrent GNN over the ontology. These two different kinds of features are fed into an integration
network. Similarly, Ristoski et al. [149] fused the features of the entity mention context and the entity description with the
entity graph vector which includes entity mention features extracted from KGs, such as entity types, for zero-shot entity
extraction. Zhang et al. [215] worked on zero-shot text classification. They first fused the input text features, and the
class features extracted from ConceptNet, which encode the associated entity of the class, its superclass entities and its
description entities by a variant of multi-hop encoding, and then fed them into a CNN classifier. Due to the heterogeneity
of the input features, more complicated fusion and prediction models would be requested, and thus methods of this
kind are not as common as text feature fusion. It is worth mentioning that methods of multi-model feature fusion can
sometimes be understood as a special kind of joint mapping, where the mapping functions and the distance metric are
jointly implemented by one model.

5 KG-AWARE FEW-SHOT LEARNING

As KG-aware ZSL, many KG-aware FSL methods also follow the four paradigms of Mapping-based, Data Augmentation,
Propagation-based and Class Feature. However, some other KG-aware FSL methods, belong to none of the above
paradigms. Instead, we regard those that focus on utilizing the few-shot samples by accelerating the adaption in training
with meta learning algorithms, as a new paradigm named Optimization-based, and regard those that directly transfer
models (such as rules) built according to data of seen classes as another new paradigm named Transfer-based. Table 2
presents a brief summary of these paradigms as well as their method categorizations and corresponding papers. We will
next introduce the details of each paradigm.

5.1 Mapping-based Paradigm

The general idea of the mapping-based paradigm of FSL is very close to that of ZSL, as shown in Figure 2. Briefly, it
learns a model to project the sample inputs and the classes (or their initial encodings) into one common vector space
where a sample is close to the class that it belongs to and far away from other classes w.r.t. some distance metric. In
prediction, a testing sample’s class can be determined by calculating its distance to all the candidate classes. In contrast to
ZSL, FSL has a small number of labeled samples associated with each unseen class. They usually can play an important
role and are fully utilized by the FSL methods. For example, they can be used to represent the class prototypes in the
sample space as the auxiliary information of classes which represent the prototypes of classes in the label space, we thus
also view these few-shot samples as a special kind of auxiliary information of the unseen classes in some conditions.
Low-resource Learning with Knowledge Graphs: A Comprehensive Survey

| Paradigm       | Summary                                                                 | Categories                  | Papers                                                                 |
|----------------|-------------------------------------------------------------------------|----------------------------|----------------------------------------------------------------------|
| Mapping-based  | These methods project the input and/or the class into a common vector space where a sample is close to its class w.r.t. some distance metric, and prediction can be implemented by searching the nearest class. ZSL methods can often be extended for FSL. | Input Mapping               | [85, 113, 124]                                                        |
|                |                                                                         | Class Mapping               | [100]                                                                  |
|                |                                                                         | Joint Mapping               | [1, 2, 101, 113, 148, 164, 202, 213, 216, 222]                          |
| Data Augmentation | These methods generate additional samples or sample features for the unseen classes, utilizing KG auxiliary information. | Generation Model-based     | [172, 188, 217]                                                        |
| Propagation-based | These methods propagate model parameters, or class embeddings (or a sample’s class beliefs) from the seen classes to the unseen classes via a KG. | Model Parameter Propagation | [39, 138]                                                              |
|                |                                                                         | Embedding Propagation       | [3, 4, 15, 43, 68, 182, 223]                                          |
| Class Feature  | These methods encode the input and the class into features often with their KG contexts considered, fuse these features and feed them directly into a prediction model. | Text Feature Fusion         | [10]                                                                   |
|                |                                                                         | Multi-modal Feature Fusion  | [114, 205, 218]                                                        |
| Optimization-based | These methods adopt meta learning algorithms to optimize the training that relies on the few-shot samples. | KG-specific Optimization   | [8, 37, 180]                                                           |
|                |                                                                         | KG-agnostic Optimization    | [111, 141, 212-214, 216]                                              |
| Transfer-based | These methods directly apply models of seen classes to unseen classes, often with the few-shot samples utilized in prediction. | Neural Network Transfer     | [29, 106, 170]                                                         |
|                |                                                                         | Rule Transfer               | [44, 117, 118, 152, 174]                                               |

Table 2. A summary of KG-aware FSL paradigms.

Similar to ZSL, we further categorize the KG-aware FSL methods of the mapping-based paradigm into Input Mapping, Class Mapping and Joint Mapping.

5.1.1 **Input Mapping.** The existing ZSL methods of input mapping can often be directly extended to FSL by augmenting the learning of the mapping model with the few-shot samples. Ma et al. [113] pre-trained the initial class (entity type) embeddings via the KG and then proposed two mapping settings, one of which is directly projecting the text input (entity mention features) to the class embedding for both zero-shot and few-shot entity mention typing. In ZSL setting, the mapping, which is a linear transformation function, is learned by samples of the seen classes alone, while in the FSL setting, it is learned by samples of both seen and unseen classes. Jayathilaka et al. [85] also learned a mapping function from the input features to the class embedding for few-shot image classification using labeled samples of both seen and unseen classes, where logical relationships such as class disjointness and class subsumption are represented by an ontology and considered in learning the class embeddings by an algorithm named EL Embedding [95]. Monka et al. [124] investigated KG-augmented image classification under a transfer setting where a model trained by a large number of source domain samples is transferred to a target domain which has only a small number of labeled samples. The proposed method uses a KG curated by experts for modeling the relationship between classes, embeds the KG by a variant of GCN, and adopts a contrastive loss to train an MLP which maps the image features to the space of the class embeddings.

5.1.2 **Class Mapping.** Similar to input mapping, the existing KG-aware ZSL methods of class mapping can be directly extended to the FSL setting by learning the mapping with samples of both seen classes and unseen classes. However, such extension has been rarely investigated. The only relevant one is by Li et al. [100], which projects the embeddings of hierarchical classes into the space of image features learned by CNN to support the zero-shot image classification, and extends to the few-shot setting with almost no modification. The mapping function learning does not use the samples of
seen classes, but in prediction, the average of the CNN features of the few-shot samples as well as the class vector after mapping are used in searching the class label of a testing sample of unseen classes.

5.1.3 Joint Mapping. Some KG-aware FSL methods of joint mapping are simple extensions of KG-aware ZSL methods which were originally developed for utilizing the class auxiliary information. Akata et al. [1, 2] applied their zero-shot image classification method, which jointly projects the WordNet-based class embeddings and the image features into one common space, to FSL by adding an additional loss on the few-shot samples in learning the mappings. Ma et al. [113] utilized the few-shot samples to augment the training of the mapping function which is originally trained by seen class samples alone in ZSL. Their method considers not only input mapping, but also joint mapping which projects both the text input (entity mentions) and the class (entity type) embeddings, for zero-shot and few-shot entity extraction. Similarly, Rios et al. [148] also used the same joint mapping model, which matches the CNN-based input text mapping with the GCN-based class mapping, for both zero-shot and few-shot text classification.

In contrast, some other KG-aware FSL methods of joint mapping are specifically developed for utilizing the few-shot samples. They map the few-shot samples, which can be regarded as a special kind of auxiliary information, and the testing samples into one common vector space. Li et al. [101] jointly learned a mapping of the image CNN features and a mapping of the class embeddings, using labeled samples of seen classes (i.e., \( D_{tr} \)). In prediction, it calculates the center of the mapped vectors of few-shot images of each class, and compares a testing image to this center. Although the mapping of the class embeddings is not directly used in prediction, it is used to guide the mapping learning for the image features. Xiong et al. [202] worked on one-shot KG completion with unseen relations. They developed a matching network to compare a testing entity pair with the one-shot entity pair of each unseen relation, where the features of an entity pair were learned by a neighbourhood encoder, and a matching score was predicted by an LSTM network. Note entity pairs here mean the samples of KG relations. Zhang et al. [213] worked on few-shot KG completion with unseen relations, but the general idea of their solution, which is also based on entity pair matching by neighbourhood encoding and matching score calculation, is quite close to that of [202]. Zhao et al. [222] jointly learned projections of the image features and the knowledge features (the fusion of KG embeddings and text embeddings) into one common space by MLPs, where a cross-entropy loss and two constraint losses over the image features and the knowledge features respectively are used for training. In prediction, a testing sample is compared with the few-shot samples of each unseen class via calculating the Cosine similarity after mapping. As the method in [101], the class embeddings are not directly used in prediction, but used to constrain the learning of the sample mapping. Sui et al. [164] proposed a KG-aware few-shot text classification method. It compares the testing sample with the few-shot samples of each unseen class using not only a task-agnostic relation network but also a task-relevant relation network which is able to apply diverse metrics for diverse tasks armed with external knowledge extracted from NELL. Zhang et al. [216] worked on few-shot relation extraction from text, utilizing concept-level KGs extracted from Wikidata [176] or UMLS [116]. They matched testing samples (i.e., entity mention pairs in text) to both few-shot samples and relation meta (i.e., the relation representations extracted from the embeddings of their associated entities in KGs), and combined the two matching scores. The sample mappings is implemented by a network which considers the sentence features, the entity description features and the KG concept features.

5.2 Data Augmentation Paradigm

There have been some FSL studies that attempt to generate additional samples or sample features for the unseen classes by using KGs. As in KG-aware ZSL, we divide these KG-aware FSL methods into two categories: Rule-based and
Generation-based. The rule-based methods could be directly applied to FSL by e.g., annotating labels to samples via pre-defined heuristic rules as shown in many distant supervision studies [31, 122], but we have not found any KG-aware FSL studies of this kind yet. Instead, we find some KG-aware FSL studies of generation-based, which usually utilize statistical generation models such as GANs [67] and VAEs [91]. We next introduce some works in this category.

5.2.1 Generation-based. The generation-based methods refer to those FSL methods that use some statistical methods to generate labeled samples (or features) conditioned on the auxiliary information. Tsai and Salakhutdinov [172] took an attention mechanism over the KG auxiliary information extracted from WordNet to generate quasi-samples for the unseen classes as additional training samples for one-shot image classification. In generation, probability distribution on the unseen classes is approximated using a regression model for each sample of the seen classes. Wang et al. [188] worked on few-shot KG completion involving both unseen entities and unseen relations. They proposed a triple generator, which generates triple embeddings based on textual descriptions of the entities, using Conditional VAE [161]. Zhang et al. [217] worked out a general feature generation-based framework for addressing unseen relations in two tasks — few-shot KG completion with unseen relations and few-shot relation extraction from text. The framework uses a standard adversarial transfer learning mechanism to generate relation-invariant features and transfer such features to unseen relations with weighted combination. Regarding the adversarial network adopted in the framework, it uses a CNN to iteratively extract features from the entity pair (or from the text sentence for relation extraction) until the discriminator cannot distinguish features of the seen relations and the unseen relations.

5.3 Propagation-based Paradigm

As KG-aware ZSL, KG-aware FSL also can be addressed by methods of model parameter propagation and class belief propagation via a KG some of whose entities are aligned with seen and unseen classes. However, we find only two KG-aware FSL studies that belong to the category of model parameter propagation, and do not find any methods of the category of class belief propagation. This may be because the current methods usually focus on utilizing the few-shot samples of unseen classes. On the other hand, for few-shot KG completion tasks, the propagation over the KG is widely utilized for addressing unseen entities and relations that have few-shot associated triples. They often aggregate the embeddings of the neighbouring entities and relations, which are usually seen, to get the embedding of an unseen relation or entity. Figure 3 (b) shows this idea with an example of aggregating 1-hop neighbours for embedding an unseen entity $e_0$. We regard these methods as a new category named Embedding Propagation.

5.3.1 Model Parameter Propagation. Peng et al. [138] worked on augmenting few-shot image classification by using KGs extracted from e.g., WordNet. They first followed a model parameter propagation idea used in many KG-aware ZSL methods, which uses a GCN and the KG to predict classifier parameters of the unseen classes with classifier parameters of the seen classes, and then they integrated the predicted classifiers with the classifiers learned from the few-shot labeled images. This method can be understood as an ensemble-based extension of those model parameter propagation methods from ZSL to FSL. Chen et al. [39] proposed a model parameter propagation method for few-shot image classification with a KG whose edges are assigned by correlation weights between classes. It first initializes a set of random parameters, which are image classifier weights, for each class, then utilizes a Gated Graph Neural Network (GNN) to propagate classifier parameters between classes with multiple iterations, and finally outputs updated classifier parameters for each class. Different from those KG-aware ZSL methods whose parameter propagation models are trained by minimizing the parameter approximation loss on seen classes (such as [186], [63] and [88]), the propagation model (i.e., GNN) of [39]...
is trained with a cross-entropy loss on all the labeled samples and a regularisation term on the classifier weights of all the classes.

5.3.2 Embedding Propagation. The majority of embedding propagation methods for few-shot KG completion tasks such as link prediction and multi-hop reasoning aim at addressing unseen entities or relations which are associated with only a small number of triples. These unseen entities/relations are also named as out-of-KG entities/relations in some papers since they are usually not observed in the training KGs. Some embedding propagation methods aim to embed such unseen entities or relations with no need of costly re-training the KG embeddings. As far as we know, Hamaguchi et al. [68] proposed the earliest embedding propagation solution for addressing unseen entities. They used a GNN but revised its propagation mechanism for the KG, and adopted a translation-based objective function for scoring the triple and for a loss for training. Wang et al. [182] proposed a Logic Attention Network (LAN) to embed such unseen entities via propagation from their neighbouring entities and relations. In LAN, logic rules are exploited to measure neighbouring relations’ usefulness, and neighbours connected by different relations have different weights in embedding an unseen entity. Bhowmik and Melo [15] used a variant of Graph Transformer encoder [210] to embed an unseen entity by aggregating its neighbours based on their relevance to a given relation. It predicts the object of a triple, and can explain the prediction by finding out paths from the subject to the object. Ali et al. [4] aimed at predicting relations between seen entities and unseen entities (semi-inductive setting), and between unseen entities (fully-inductive setting), utilizing not only the triples but also their Wikidata qualifiers, each of which is composed of a relation and an entity for describing the triple. For fully-inductive setting, they initialized the entity embeddings by entities’ textual information using Sentence BERT [145], and then propagated to update the entities’ embeddings by a graph encoder named StarE [61].

Besides complex neural networks, some simpler propagation operations have also been considered for embedding unseen entities. Ali et al. [4] used a linear projection from the entity embedding to the relation embedding for the semi-inductive setting. Dai et al. [43] used two modules: an estimator which calculates a candidate set of embeddings for an unseen entity according to its all associated triples using the translation operation of TransE [20] or RotatE [165], and a reducer which calculates an unseen entity’s embedding according to all its candidate embeddings using relation correlation and entity degree. Albooyeh et al. [3] used some simple aggregation operations such as averaging to get the embedding of an unseen entity from its neighbours. This solution can support any existing KG embedding models such as DistMult [203], but it requires that the original training procedure of the KG embeddings are adjusted such that the embeddings resemble what is expected at the testing time and are aware of the aggregation operations being used.

Some other embedding propagation methods aim at addressing unseen relations (out-of-KG relations) which have a limited number of connections to existing entities. It is required to predict with these unseen relations, without re-training the KG embeddings, but there are now few studies that investigate addressing such unseen relations under the propagation paradigm. The method proposed by Zhao et al. [223] is a relevant one which can support both unseen entities and unseen relations. It mainly uses specific transition functions, aggregation functions and graph attention mechanisms to transform information from the associated triples to an unseen entity or relation, where a translation-based triple score and a margin loss are used for training. It is worth mentioning that the current embedding propagation methods cannot address both unseen entities and unseen relations at the same time.

5.4 Class Feature Paradigm

The class feature paradigm of FSL is close to that of ZSL. Please see Figure 4 for the general idea. Namely, a new function \( f' : (x, y) \rightarrow s \) is learned, where the class (usually its initial encoding) is used as the input together with the original
input, and a score $s$ is predicted indicating whether $y$ is the class of $x$. An auxiliary KG is injected for augmenting FSL via the new input $y$. As in KG-aware ZSL, according to the types of the features of $x$ and $y$, we classify the KG-aware FSL methods of this paradigm into two categories: **Text Feature Fusion** where $x$ and $y$ are both some kinds of text or text features, and **Multi-modal Feature Fusion** where $x$ and $y$ are of different kinds of features (such as image features and text features). It is worth noting that many KG-aware ZSL methods of the class feature paradigm can be extended to support FSL by training $f'$ with both samples of seen classes (i.e., $D_{tr}$) and few-shot samples of unseen classes (i.e., $D_{few}$). In this part, we will not discuss extending these ZSL methods (please see Section 4.4 for more details), but only review those studies where FSL are originally supported and evaluated. Since class feature fusion under such an FSL setting does not significantly differ from class feature fusion under normal supervised learning settings, we do not find many papers within the scope of this survey.

### 5.4.1 Text Feature Fusion.

There are quite a few text feature fusion methods for KG-aware ZSL, but we only find one such method developed for FSL. It is a KG-aware few-shot question answering method proposed by Banerjee et al. [10]. It fuses the text context, the question and the answer as the input of a transformer-based model which can predict any of the three elements given the other two elements. This transformer-based model is learned by span masked language modeling from a KG whose triples simulate the combination of the context, question and answer, and are extracted from text. Note that the method can also support ZSL and the authors have evaluated it for both ZSL and FSL.

### 5.4.2 Multi-modal Feature Fusion.

Fusing features of different kinds is harder and often requires a more complicated model and more samples for training. We find two KG-aware FSL studies of this category. Zhang et al. [218] investigated text relation extraction for long-tailed relations which have few-shot samples (sentences). The proposed method uses a GCN to learn the embedding of each relation, where a KG derived from Freebase is used to model the hierarchical relationship between relations, and then feeds the relation embedding and the sample features (sentence encoding) into an attention-based model. Yang et al. [205] investigated few-shot visual question answering, where only a small number of samples are given for new unseen contexts. The proposed method PICa does not use KGs but relies on GPT-3 [24] as an implicit and unstructured KG. However a baseline they adopted, named KRISP [114], is not originally developed for ZSL or FSL but uses KGs such as ConceptNet for augmentation and is applied to the few-shot visual question answering task. In KRISP, the features of the image and the question are first fused by a Transformer-based model and then further fused with the knowledge retrieved from the KG to predict the answer.

### 5.5 Optimization-based Paradigm

Since the few-shot samples are often not large enough to train robust models for unseen classes, some meta learning algorithms have bee applied to optimize the training for fast adaption and for voiding over-fitting by obtaining e.g., better initial parameter settings, more optimized searching steps and more suitable optimizers. Such FSL methods are regarded as **Optimization-based Paradigm**. In this literature review, we totally collected quite a few KG-aware FSL methods of this paradigm: some of them are for KG completion tasks such as link prediction and multi-hop reasoning with unseen entities or relations that are associated with a small number of triples [8, 37, 111, 180, 213, 214], while the others are for KG augmented image classification and text relation extraction [141, 212, 216]. We find some studies develop new meta learning algorithms or revise the existing ones w.r.t. the KG, while some other studies just apply meta learning independently without specifically considering the KG context. We thus classify the FSL methods of this paradigm into **KG-specific Optimization** and **KG-agnostic Optimization**.

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5.5.1 **KG-specific Optimization.** In some FSL studies, the existing meta learning algorithms, such as Model-Agnostic Meta-Learning (MAML) which is to meta-learn a good parameter initialization for a new task [56], are revised and augmented for the KG context, or some new meta learning algorithms are proposed for the KG context. Chen et al. [37] proposed a meta learning framework named MetaR for a few-shot KG completion task, which predicts the tail entity of a new triple with an unseen relation. The insight is to utilize two kinds of relation-specific meta information: relation meta which is a relation’s higher-order representation extracted from the embeddings of the associated head entities and tail entities, and gradient meta which guides how the relation meta should be efficiently changed when transferred from few-shot triples to testing triples. The implementation of MetaR includes two learnable components: relation-meta learner which is a fully connected neural network that maps the embeddings of the head entities and tail entities to relation meta, and embedding learner which gets a relation’s embedding by the relation meta and the gradient meta, and scores entity pairs for testing. Wang et al. [180] worked on a few-shot KG reasoning task which is to predict the tail entity given a head entity and an unseen relation and infer paths from the head entity to the tail entity. They augmented the meta learning method MAML with additional task (relation) specific information encoded by a neighbour encoder based on embedding concatenation and linear transformation operations, and a path encoder based on LSTM. Baek et al. [8] worked on a realistic few-shot KG completion task, where links between seen entities and unseen entities, and between unseen entities are both predicted using GNNs. They proposed a meta learning framework named Graph Extrapolation Network for getting embeddings of unseen entities, where a set of tasks are formulated with unseen entities simulated via sampling, and the model learns to generalize by meta-training over these formulated tasks.

5.5.2 **KG-agnostic Optimization.** In some other FSL studies involving KGs, meta learning algorithms are applied in optimization for fast adaption for addressing sample shortage, but the application is independent of the KG context. Lv et al. [111] worked on the same task as [180], i.e., few-show multi-hop KG reasoning with unseen relations. They adopted reinforcement learning to search tail entities and reasoning paths, and directly applied MAML with one relation modeled as one task. Zhang et al. [214] proposed another method for few-shot multi-hop KG reasoning with unseen relations, where MAML is directly applied for well initializing an on-policy reinforcement learning model for fast adaption. Qu et al. [141] worked on few-shot relation extraction by modeling the posterior distribution of prototype vectors for different relations. To this end, they first initialized the relation prototype vectors by a BERT model over the samples (i.e., sentences) and a GNN over a global relation graph extracted from different ways, and then effectively learn their posterior distribution by a Bayesian meta-learning method which is related to MAML but can handle the uncertainty of the prototype vectors.

It is worth mentioning that meta learning can act as a complement for faster adaption in model training in methods of other paradigms. Zhang et al. [213] predicted KG triples with unseen relations. Their few-shot relational learning method FSRL, which is regarded as the mapping-based paradigm since it predicts by comparing a testing entity pair with few-shot samples of each unseen relation after mapping (see Section 5.1.3), uses MAML for fast adaption in training. Zhang et al. [212] attempted to address both zero-shot and few-shot image classification, with an approach named Transfer Graph Generation (TGG) which has a graph generation module for generating instance-level graph, and a propagation module for utilizing this graph for prediction. They trained the whole model with an episodic training strategy of meta learning. Zhang et al. [216] used a joint mapping method to predict relations for entity mentions in a sentence. In this method, a knowledge-enhanced prototypical network and a relation meta learning model, which implement the matching between instances and between instance and relation meta, respectively, are trained with gradient meta.
5.6 Transfer-based Paradigm

Some KG-aware FSL methods directly apply models that are built via data of seen classes ($D_{tr}$) to predicting data of unseen classes ($D_{te}$) with the help of the few-shot samples ($D_{fe}$). These methods are regarded as the transfer-based paradigm. It is worth noting that methods of some categories of the other paradigms, such as model parameter propagation, also have an idea of implicitly transferring data or parameters from seen classes to unseen classes. Method of this paradigm, however, directly applies models learned from $D_{tr}$ to the prediction in $D_{te}$. According to the KG-aware FSL papers we have collected, methods of this paradigm are often applied to a special few-shot KG completion context, where one KG composed of triples of seen entities and relations is given for model training, while another KG composed of triples of unseen entities is for completion (prediction). For convenience, we name the first KG as the seen KG and the second KG as the unseen KG. Such a task in common in real-world: the unseen KG can often be an emerging sub-KG that is to be added to the seen KG, or an individual KG of another domain that sometimes has the same relations as the seen KG. Models are learned from the seen KG and applied in the unseen KG whose few-shot triples are used as additional input of the model for predicting new triples. According to the type of the model, we further classify these FSL methods into two categories: Neural Network Transfer and Rule Transfer.

5.6.1 Neural Network Transfer. Neural networks especially GNNs can encode statistical regularities and structural patterns in a graph. For the few-shot KG completion task mentioned above, a few studies investigate transferring a GNN learned from the seen KG to the unseen KG such that the learned patterns are applied for knowledge inference. Teru et al. [170] proposed a method named GraIL. It learns a GNN by extracting subgraphs from the seen KG and labeling their entities with their structural roles (e.g., the shortest distance between two entities), and apply this GNN to predict the relation between two unseen entities in the unseen KG with their neighbouring unseen entities’ structural roles. Chen et al. [29] extended GraIL by using R-GCN [155] for supporting multiple relations in the KG. More importantly they proposed a relation correlation module which constructs a relation correlation graph whose nodes represent the relations and whose edges indicate the correlation patterns between any two relations in the original KG. They learned a Relational Correlation Network over this relation correlation graph of the seen KG, and applied it to the unseen KG by combing its output with the output of GraIL for scoring triples. Liu et al. [106] proposed to first construct a new graph for encoding the original KG: a pair of entities — two connected KG entities or an entity and its own, are represented as one graph node, and each node is initialized with features indicating the triples in which the two entities are involved. They then learned a GCN from the graph of the seen KG, which is shown to be able to capture common inference patterns represented in Datalog — a well known logic rule language, and applied this GCN to predict the node features of the graph of the unseen KG, through which new triples can be determined.

5.6.2 Rule Transfer. Rules in different forms, such as Horn rules and first-order rules, or their weighted versions can be learned from a KG for represent graph patterns and regularities [60, 90, 146, 204, 219]. They may not be as good as neural networks for representing very complicated statistical regularities, but are more interpretable and can better support inductive reasoning. Sadeghian et al. [152] proposed a method named DRUM for the aforementioned few-shot KG completion task, where first-order logical rules (such as brother($X, Z$) $\land$ fatherOf($Z, Y$) $\rightarrow$ uncleOf($X, Y$)) associated with weights are learned from the seen KG by a differentiable way using the rule mining method named Neural LP [204], and these rules are applied in the unseen KG for deductive reasoning for new triples. This work uses the KG relations as the rule predicates and assumes that the relations of the seen and the unseen KGs are the same, such that the rules can be directly transferred. For the situation where the predicates change (e.g., relations of the unseen KG are different
from those of the seen KG), we find the following two solutions that have been investigated for rule transfer: (i) matching predicates between rules, proposed by Mihalkova et al. [117, 118] who transferred rules mined from relational data by Markov Logic Networks (MLNs) [146], and (ii) extracting and transferring higher order rules from first-order rules, proposed by Davis et al. [44] and Van et al. [174] for transferring rules mined by MLNs.

6 APPLICATIONS AND RESOURCES
In this section, we first very briefly revisit the low-resource learning studies for each application, including the adopted auxiliary information and methods, and then introduce some public resources that can be used for developing and evaluating KG-aware methods.

6.1 Computer Vision
6.1.1 Image Classification. Regarding zero-shot image classification, the early methods mainly utilize class attributes (e.g., [53, 96, 97, 136]) and class text information (e.g., [51, 58, 129, 139, 144, 160]), where the mapping-based paradigm and the data augmentation paradigm are the mainstream solutions. However, the state-of-the-art performance on many tasks now are achieved by those methods utilizing KGs constructed by various sources including existing KGs and task-relevant data and domain knowledge (e.g., [62, 88, 126, 151, 186, 212]). To utilize the KGs, the propagation-based paradigm starts to be widely adopted in some recent studies such as [63, 88, 186]. To support method development and evaluation, some open benchmarks on KG-aware zero-shot image classification have been proposed:

- **ImageNet**, which is a large-scale image database containing a total of 14 million images from 21K classes [46], is widely used in KG-aware ZSL. Each image is labeled with one class, each class is matched to a WordNet [121] entity, and the class hierarchies from WordNet can be used as the auxiliary information. In studies that experiment with ImageNet [88, 186], usually 1K classes with balanced images are used as seen classes for training, while classes that are 2-hops or 3-hops away, or all the other classes are used as unseen classes for testing. The weakness of ImageNet mainly lies in that the auxiliary KG has only class hierarchies (and class names) without any other knowledge such as class attributes and commonsense knowledge.

- **ImNet-A** and **ImNet-O**, are two image sets extracted from ImageNet by Geng et al. [62, 64]. ImNet-A includes 80 classes from 11 animal species, while ImNet-O including 35 classes of general objects. In the experiment in [62], ImNet-A is partitioned into 28 seen classes (37,800 images) and 52 unseen classes (39,523 images), while ImNet-O is partitioned into 10 seen classes (13,407 images) and 25 unseen classes (25,954 images). In their latest version released in [64], each benchmark is equipped with a KG which is semi-automatically constructed with several kinds of auxiliary knowledge, including class attribute, class textual information, commonsense knowledge from ConceptNet, class hierarchy (taxonomy) from WordNet and logical relationships such as disjointness.

- **AwA2**, originally proposed in [197], is a popular zero-shot image classification benchmark with 50 animal classes (37,322 images) and 85 real-valued attributes for describing animal visual characteristics. It can also be used to evaluate KG-aware ZSL methods, since the classes are aligned with WordNet entities and the animal taxonomy from WordNet can be used as a simple KG. In the extended version by Geng et al. [64], a KG is constructed with the same types of knowledge as ImNet-A and ImNet-O. Note the term AwA in [64] actually refers to AwA2, while the original AwA1 is released in [97] does not have public copyright license for its images, and only some image features are publicly available. To enable vision research on the objects of AwA classes, Xian et al. [197] contributed a new dataset AwA2 with raw images collected from public Web sources such as Flickr and Wikipedia.
• NUS-WIDE [42], a multi-label image classification dataset including nearly 270K images and each image has multiple objects for recognition, is widely used for the evaluation of multi-label ZSL due to the nature of its annotated labels [81, 98, 125]. To be more specific, the images in the dataset have two versions of label sets. One comprises 1000 noisy labels collected from Flickr user tags (i.e., NUS-1000) and the other is a dedicated one with 81 human-annotated concepts (i.e., NUS-81). To perform multi-label ZSL, the labels in NUS-81 is taken as the unseen label set, while the seen label set is derived from NUS-1000 with 75 duplicated ones removed and thus results in 925 seen label classes. In KG-aware multi-label ZSL studies such as [98], NUS-WIDE is accompanied by a KG with 3 types of label relations, including a super-subordinate correlation extracted from WordNet as well as positive and negative correlations computed by label similarities such as WUP similarity [196].

For few-shot image classification, the majority of the existing methods aim at utilizing the few-shot samples by e.g., meta learning, while the KG-aware studies often try to combine benefits from the KG external knowledge and the few-shot samples, which actually looks quite reasonable. Some of them simply extend their mapping-based models which are originally developed for zero-shot image classification by training with additional samples of the unseen classes (e.g., [2, 85, 101]), while some others further generate more data for unseen classes conditioned on KGs (e.g., [172]) or utilize KGs to transfer images features from seen classes to unseen classes (e.g., [39, 138]). There are also some open benchmarks that can be used for evaluating KG-aware few-shot image classification. The following are some widely used examples:

• ImageNet-FS [71] and mini-ImageNet [175] are two derivatives of the ImageNet dataset. ImageNet-FS covers 1,000 ImageNet classes with balanced images and these classes are divided into 389 seen classes and 611 unseen classes. During evaluation, images of 193 seen classes and 300 unseen classes are used for cross validation, while images of the remaining 196 seen classes and 311 unseen classes are used for testing. In contrast, mini-ImageNet is relatively small. It has 100 classes, each of which has 600 images. These classes are partitioned into 80 seen classes and 20 unseen classes. Since ImageNet classes are aligned with WordNet entities, WordNet, which includes class hierarchies and class name information, can be directly used as the external knowledge.

• AwA1 [97], AwA2 [197] and CUB [177] are three typical zero-shot image classification benchmarks that can be easily extended for a few-shot setting. AwA1 and AwA2 both have 50 coarse-grained animal classes, with 40 of them being seen classes and the remaining being unseen classes. CUB has 200 fine-grained bird classes, with 150 of them being seen classes and the remaining be unseen classes. A small number of labeled images (usually 10) are added for each unseen class so to support a few-shot setting. Meanwhile, several KGs have been added to these benchmarks for evaluating KG-aware methods. For example, Tsai and Salakhutdinov [172] and Akata et al. [1, 2] both contributed WordNet classes hierarchies to AwA1 and CUB; Zhao et al. [222] constructed a domain-specific KG for CUB based on the attribute annotations of samples; Zhang et al. [212] exploited ConceptNet to construct a KG for AwA2, and utilized part-level attributes to construct a KG for CUB.

6.1.2 Visual Question Answering.

Visual Question Answering (VQA) is to answer a natural language question according given an image as the context. Teney et al. [168] first proposed zero-shot VQA. They introduced novel concepts on the text side. Namely, a testing sample was regarded as unseen if there was at least one novel word in its question or answer. Ramakrishnan et al. [142] considered novel objects in the image. Namely, an image object that had never appeared in the training images was regarded as unseen. They addressed the problem by pre-training the model with external text corpus and labeled images. KGs have been exploited as auxiliary information for addressing zero-shot VQA, but not widely. Chen et al. [41] recently...
proposed a method of the mapping-based paradigm, where answers that have never appeared in training are predicted via comparing the question and answer embeddings which are achieved with the help of KGs; while Chen et al. [34] built and embedded an OWL ontology for establishing connections between seen answers and unseen answers, and addressed the problem also by a method of the mapping-based paradigm. Quite a few VQA datasets have been published, but only a small number of them have been used to evaluate KG-aware methods for zero-shot VQA:

- **ZS-F-VQA** [41], constructed by re-splitting a fact-based VQA benchmark named F-VQA [183], has no overlap between answers of the training samples and answers of the testing samples. It has 5 different splits of the training set and the testing set. In average, the training set has 2,384 questions, 1,297 images, and 250 answers, while the testing set has 2,380 questions, 1,312 images, 250 answers. Chen et al. [41] extracted facts from three KGs (DBpedia [6], ConceptNet [162] and WebChild [167]), and constructed a KG as its auxiliary information for evaluating KG-aware methods.

- **OK-VQA** [115] is a recent benchmark where the visual content of an image is not sufficient to answer the question. It has 14,031 images and 14,055 questions, and the correct answers are annotated by volunteers. Chen et al. [34] used it for evaluating KG-aware zero-shot VQA, by extracting 768 seen answers and 339 unseen answers, using knowledge from ConceptNet as the auxiliary information.

Regarding few-shot VQA, the existing methods often rely on pre-trained language models such as GPT-3 which have already learned a large quantity of knowledge from text corpora (e.g., [173, 205]). To incorporate images, visual language models can be pre-trained with images and text, or images can also be transformed into text by e.g., image captions so as to be utilized in language models (e.g., [11]). Meanwhile, meta learning algorithms have also been utilized for fast model training with only a small number of samples for each unseen answer (e.g., [169]). KGs could be quite useful by providing complementary knowledge besides the pre-trained (visual) language models and the few-shot samples, but we only find few-shot VQA studies that involve KGs. Yang et al. [205] proposed a supervised learning method which uses knowledge retrieved from KGs for augmenting the question-answer samples, and this method was used as a baseline in comparison with the GTP-3-based method. Marino et al. [114] first fused features of the question and the image by a Transformer-based model, and then fused these features with knowledge from ConceptNet. The aforementioned mentioned zero-shot VQA benchmarks ZS-F-VQA and OK-VQA, which rely on external knowledge and reasoning to give the answer, are quite suitable for evaluating KG-aware methods, and they can be easily adjusted by adding few-shot samples for supping the few-shot VQA setting.

### 6.2 Natural Language Processing

#### 6.2.1 Knowledge Extraction.

By knowledge extraction, we refer to those NLP tasks that are to extract structured data including entities, relations, events and so on from natural language text. Note that relational facts, which are sometimes simply called triples in this domain, can also be extracted, after entities and relations are recognized. Since the entities, relations or events can often be directly aligned with elements in a KG (such as a general purpose KG and an event ontology), their relationships represented in the KG can be directly exploited to address both zero-shot and few-shot settings. KG-aware zero-shot methods often follow the mapping-based paradigm utilizing the entities’, relations’ or events’ embeddings in the KG [83, 84, 102, 113], while KG-aware few-shot methods often follow the optimization-based paradigm for utilize meta algorithms for fast training with the few-shot samples [141, 216]. Note the mapping-based zero-shot methods could be easily extended to support the few-shot setting by training the mapping functions with samples.
of both seen classes and unseen classes, as by Ma et al. [113]. There are also some KG-aware methods that fuse features from a KG with the input features for addressing the zero-shot or the few-shot setting [127, 218].

There have been quite a few benchmarks that can be used for evaluating KG-aware zero-shot and few-shot knowledge extraction methods. Here we introduce several representative benchmarks:

- **BBN, OntoNotes and Wikipedia** are three benchmarks for fine-grained named entity typing, where the entity types are (partially) matched with types in Freebase. They are all adopted by Ma et al. [113] for evaluating zero-shot entity typing, where the training set has only coarse-grained types, while the testing set has the second-level (fine-grained) types. They also used a set of manually annotated documents (sentences) for validation and testing with a partitioning ratio of 1:9. Specifically, BBN has 2,311 manually annotated Wall Street Journal articles, with around 48K sentences and 93 two-level hierarchical types [193]. 47 out of 93 types are mapped to Freebase types using the DBpedia Spotlight entity linking tool. 459 documents (6.4K sentences) are used for validation and testing. OntoNotes is an incrementally updated corpus that covers three languages (English, Chinese, and Arabic) and four genres (NewsWire, Broadcast News, Broadcast Conversation, and Web text) [194]. It has 13,109 news documents that are manually annotated using 89 three-level hierarchical types. 76 manually annotated documents (1,300 sentences) are used for validation and testing. Wikipedia has around 780.5K Wikipedia articles (1.15M sentences), and 112 fine-grained Freebase type annotations. 434 manually annotated sentences are used for validation and testing.

- **NYT10** and **WEB19** are two benchmarks used in [84] for zero-shot property (relation) extraction. NYT10 is composed of Freebase triples and New York Times (NYT) corpus [147]. In the evaluation of [84], all of the 54 properties are used as unseen properties. WEB19 is formed by first selecting predicate paths in the FB15k benchmark [20] as properties, then generating samples (a text corpus) associated with these properties using Microsoft Bing search engine API with the aid of human evaluation [84]. Under the ZSL setting, 217 and 54 properties are set to seen and unseen, respectively.

- **ACE05** is a corpus for event extraction, annotated by 33 fine-grained types which are sub-types of 8 coarse-grained main types such as Life and Justice) from the ACE (Automatic Content Extraction) ontology. Huang et al. [83] made two zero-shot event extraction settings: (i) predicting 23 unseen fine-grained sub-types by training on 1, 3, 5, or 10 seen sub-types; (ii) predicting unseen sub-types that belong to different main types by training on seen sub-types of Justice.

It is worth mentioning that all these benchmarks can also be easily extended to support few-shot settings by adding a small number of labeled samples to the unseen classes. For example, for BBN, OntoNotes and Wikipedia, this can be simply implemented by setting some annotated sentences in the validation and testing sets as given.

### 6.2.2 Text Classification

In modern text classification, contextual and non-contextual word embedding models such as Word2Vec [120] and BERT [48] are often used for text representation, through which external knowledge from corpora can be easily incorporated. Zero-shot text classification can also be addressed by simply representing unseen classes by word embeddings and feeding them into a prediction model together with the original text input (e.g., [207]). Therefore, utilizing KGs for augmenting zero-shot text classification has not been widely investigated. Recently, Rios et al. [148] and Zhang et al. [215] utilized the class hierarchies extracted from ICD-9 and ConceptNet, respectively, for augmenting CNN-based zero-shot text classifiers, while Chen et al. [38] used ConceptNet for augmenting a BERT-based zero-shot text classifier where word vectors are tailored by the KG structure for embedding the classes. There are many typical benchmarks for both normal
and zero-shot text classification [209]. They can be used for evaluating KG-aware text classification with a class splitting setting and a strategy to match classes to KG entities. Here are two typical examples of using existing benchmarks for evaluating KG-aware zero-shot text classification:

- **DBpedia-Wikipedia** is a text classification dataset originally proposed in [220]. It has 40,000 training samples and 5,000 testing samples, which are collected from Wikipedia and are annotated by 14 non-overlapping classes defined in the DBpedia ontology [6]. Zhang et al. [215] proposed two ZSL settings for this dataset: using 11 or 7 classes as the seen, and the remaining classes as the unseen.

- **20 Newsgroups** is a popular text classification dataset which consists of around 20,000 newsgroup articles that are almost evenly divided into 20 newsgroups\(^8\). Zhang et al. [215] proposed to use 15 or 10 newsgroups as the seen classes, and the remaining newsgroups as the unseen classes.

Few-shot text classification is similar to zero-shot text classification: the majority of the solutions directly utilize different kinds of word embeddings while the research on KG-aware method is rare. Besides the ICD-9 augmented CNN classifier which was applied to both few-shot and zero-shot text classification [148], the joint mapping method recently proposed by Sui et al. [164] utilizes knowledge retrieved from NELL for augmenting a network which calculates the matching of the input and the class. The existing text classification benchmarks can be adopted for evaluating KG-aware zero-shot text classification. Here is one typical example:

- **ARSC** is a widely used benchmark for binary text classification of sentiment [18]. It was generated from Amazon reviews for 23 products (classes). Product reviews with ratings > 3 and < 3 are labeled as positive and negative, respectively; while the rest are discarded. In the evaluation in [164], 12 products including books, DVDs, electronics and kitchen appliances are selected as the unseen classes, for each of which 5 labeled reviews are given.

### 6.2.3 Question Answering.

Low-resource question answering (QA)\(^9\) started to attract wide attention in recent years, mainly due to the fast development of pre-trained language models such as BERT and GPT-3 which are inherently capable of addressing ZSL and FSL problems in NLP since a large quantity of knowledge are learned from large scale corpora and represented as parameters [112, 189, 205]. Similar to text classification, the output answer (class) is often regarded as an additional input and fed to a prediction model together with the original question input. It is worth mentioning that the specific setting of zero-shot QA may vary a bit from study to study. These settings mostly still satisfy our general ZSL definition which mainly requests that the classes (answer labels) for prediction have no training data, but are often harder. Ma et al. [112] regarded testing the model on a task (dataset) that is different from the tasks (datasets) used for training as zero-shot QA. Under this setting, they evaluated several different methods, including the KG-aware method by [10] and some pretrained language model-based methods, by splitting five different tasks. Zhong et al. [225] proposed to test the QA model in datasets (tasks) that are different enough from the datasets for model training, where all the datasets are described by properties such as domain, emotion and so on. Very recently, Wei et al. [189] proposed an even harder setting. They also fine-tuned language models on a collection of datasets, and tested the models on a different dataset. However, the datasets, which are described via instructions, have not only different tasks but also different task types including commonsense QA, summarization, sentiment classification and so on.

\(^8\)http://qwone.com/~jason/20Newsgroups/

\(^9\)The scope of QA is actually quite wide, often including quite a few problems in VQA, Knowledge Base QA, Table QA, Machine Reading Comprehension (MRC) and so on. In this part, we just refer to the problem of giving an answer or answers to a natural language question w.r.t. a context described by text.

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Although pre-trained language models have contained much knowledge via large scale parameters, symbolic knowledge (including commonsense and domain knowledge with logics) from KGs are often complementary and beneficial for addressing zero-shot QA. Therefore, there have been some KG-aware zero-shot QA studies [10, 21]. For example, Banerjee et al. [10] modeled the QA problem via knowledge triple learning where the context, question and answer are modeled as a triple, and the answer is predicted given the context and question. Their knowledge triple learning model is learned from KG triples. Similar to [10], Zhou et al. [228] also framed the multiple-choice QA task as a knowledge completion (triple prediction) problem, where the model is trained by alternatively masking the subjects and the objects in triples. Bosselut et al. [21] used COMET — a Transformer-based model trained on commonsense KGs such as ConceptNet [22] to generate a context-relevant commonsense triples for each QA sample, through which the answer can be directly inferred via symbolic reasoning. KGs are also beneficial to few-shot QA, although pre-trained language models have already contained much knowledge and have achieved good performance. For example, Banerjee et al. [10] directly extended their knowledge triple learning model from zero-shot QA to a few-shot QA setting where 8% of the training data are given as the few-shot samples. Similarly, Bosselut et al. [21] also extended their zero-shot QA method, which infers the answer of a question according to their context-relevant commonsense triples, to few-shot QA by using 4, 10 or 20 development samples in evaluation. However, due to challenges such as retrieving exactly relevant knowledge from a large KG and injecting KG knowledge into pre-trained language models, the investigation of KG-aware zero-shot and few-shot QA is still quite preliminary.

There are quite a few widely used QA benchmarks such as PhysicalIQA which is for commonsense physical reasoning [16] and MC-TACO which is about multiple choice temporal commonsense (i.e., temporal aspects of events) [226]. They can be used for benchmarking zero-shot and few-shot QA after some suitable dataset partitioning strategies. For evaluating KG-aware low-resource methods, we suggest benchmarks that are constructed with KGs or have been partially aligned with KG entities. The tasks of these benchmarks often rely on external knowledge, and their corresponding external KGs can be directly used for evaluating KG-aware methods. Here are some such benchmarks:

- **SocialIQa** [154] is a large-scale QA resource to evaluates a model’s capability to understand the social dynamics underlying situations described in short text snippets. It has 38K QA pairs. Each sample consists of a context, a question about that context, and three multiple choice answers from crowdsourcing. Commonsense knowledge (i.e., seeds for creating the contexts and answers) are extracted from an event KG ATOMIC [153]. This dataset was used by Bosselut et al. [21] and Banerjee et al. [10] for evaluating their KG-aware zero-shot and few-shot methods.
- **CommonsenseQA** [166] is a challenging dataset for evaluating commonsense QA methods. It has 12,247 questions in total, while each question has 5 answer candidates. The ground truth answers are annotated by crowdsourcing based on question relevant subgraphs of ConceptNet [162]. As SocialIQa, CommonsenseQA was adopted by Banerjee et al. [10] for evaluation.
- **STORYCS** [109] consists of short 5-sentence stories with annotated motivations and emotional responses. It is originally for emotion classification, where the labels are drawn from classical theories of psychology. Bosselut et al. [21] transformed the classification task into a QA task by posing an individual question for each emotion label, and used it for evaluating their KG-aware method for both zero-shot and few-shot settings.
- **aNLI** [13], **QASC** [89], **OpenBookQA** [119] and **ARC** [14] were adopted by Banerjee et al. [10] for evaluating their KG-augmented triple learning model for zero-shot and few-shot QA, besides SocialIQa and CommonsenseQA. Specifically, aNLI which has around 171K QA pairs is a dataset with commonsense knowledge, while QASC,
OpenBookQA and ARC, whose sample sizes range from 6K to 10K, are three QA datasets with scientific knowledge. OpenBookQA and ARC were also adopted by Zhou et al. [228] for zero-shot QA.

6.3 Knowledge Graph Completion

KG completion is to infer new knowledge in a KG, while most existing studies aim at predicting missing relational facts (triples), which is sometimes called link prediction. In this part we mainly consider KG completion for relational facts. Under a low-resource scenario, we are often required to handle the entities or/and relations that newly emerge after the KG embeddings have been learned. Since the majority of current works aim at either unseen entities or unseen relations, and the solutions to addressing unseen entities and unseen relations are often different, we introduce low-resource learning studies for unseen entities and unseen relations separately.

6.3.1 KG Completion with Unseen Entities. To address unseen entities in zero-shot KG completion, the existing studies often utilize their auxiliary information such as names, textual descriptions and attributes, often using methods of the mapping-based paradigm [70, 157] and the class feature paradigm [5, 128, 158, 178, 185, 206, 211, 224]. With the explosive growth of zero-shot KG completion methods for unseen entities, various benchmarks have been proposed for evaluation. They are usually constructed based on existing commonly used normal KG completion datasets, including FB15k [20], FB15k-237 [171], WordNet11 [159], WN18RR [47], NELL-995 [201], and some other sub-KGs extracted from popular KGs such as DBpedia [6] and Wikidata [176]. Their entity auxiliary information is often collected from the benchmarks’ original KGs or some associated public resources. The textual descriptions of entities in DBpedia50k, FB20k and Wikidata5M can be collected from DBpedia, Freebase and Wikipedia, respectively. In [45], the textual descriptions of FB15k-237 entities are extracted from the introduction section of their corresponding Wikipedia pages. Although these benchmarks vary in the ratio of unseen entities, their construction often follows a common way as follows. Given an original KG completion benchmark, a set of entities are selected as unseen entities. Namely, their associated triples in the training set are removed, and their associated triples in the testing set are kept. Then the relations that appear in both the training set and the testing set are selected. For a testing triple to predict, there could be two cases: (i) both its head and tail are unseen entities, and (ii) either its head or its tail is an unseen entity while the other is a seen entity. Accordingly, we regard the benchmark whose testing triples are all of the first case as semi-ZS, the benchmark whose testing triples are all of the second case as fully-ZS, and the benchmark that has both the first case and the second case testing triples as mixture-ZS. Here are some typical benchmarks for zero-shot KG completion with unseen entities:

- **FB15k-237-OWE** [157] is a typical semi-ZS benchmark built on FB15k-237 by a sampling strategy. First, testing triples whose tail entities are to be predicted are constructed. Specifically, a set of tail entities are selected, and some associated head entities are randomly picked from the FB15k-237 triples (by uniform sampling over all the associated head entities). Each picked head entity \(x\) is removed from the training graph by moving all triples of the form \((x, ?, t)\) to the test set and dropping all triples of the form \((?, ?, x)\) if \(x\) still remains in the training set. Similarly, testing triples whose head entities are to be predicted are constructed. Then a testing set is generated by merging the above two kinds of testing triples and removing the testing triples whose relations are not in the training set. This testing set is further splitted into a validation set and the final testing set. The dataset contains 2,081 unseen entities, 12,324 seen entities and 235 relations. The numbers of triples for training, validation and testing are 242,489, 10,963 and 36,250, respectively.

- **DBpedia50k** and **DBpedia500k** [158] are also typical semi-ZS benchmarks, constructed in a similar way as FB15k-237-OWE. DBpedia50k has 49,900 entities and 654 relations, with 32,388, 399 and 10,969 training, validation and testing
Low-resource Learning with Knowledge Graphs: A Comprehensive Survey

and testing triples, respectively. DBpedia500k has 517,475 entities and 654 relations, with 3,102,677,10,000 and 1,155,937 training, validation and testing triples.

- **Wikidata5M** [185], originally developed for evaluating text-aware KG embedding methods, is an important fully-ZS benchmark. It is constructed based on the Wikidata dump and the English Wikipedia dump. Each entity in Wikidata is aligned to a Wikipedia page and this page’s first section is extracted as the entity’s textual description. Entities with no Wikipedia pages or with descriptions being shorter than 5 words are discarded. Next, all the relational facts (triples) are extracted from the Wikidata dump. One triple is kept if both of its entities are not discarded, and its relation has a corresponding nonempty page in Wikipedia. Otherwise, this triple is discarded. The benchmark contains 4,594,485 entities, 822 relations and 20,624,575 triplets. To support the zero-shot setting, Wang et al. [185] randomly extracted two sub-KGs as the validation set and the testing set, respectively, and used the remaining as the training set. They ensured that the entities and triples are mutually disjoint across the training set, the validation set and the testing. As a result, the three sets have 4,579,609, 7,374 and 7,475 entities, respectively, 822, 199 and 201 relations, respectively, and 20,496,514, 6,699 and 6,894 triplets respectively.

- **FB20k** [199] is a complex KG completion benchmark with testing triples of several different kinds. It has the same training set and validation set as the normal KG completion dataset FB15k, but extends FB15k’s testing set by adding testing triples involving unseen entities. Specifically, a candidate set of unseen entities are first selected from Freebase. They should be associated with some entities in FB15k entities within one hop. Then, some new triples are extracted from Freebase and added to the testing set. For each such new triple, its relation should already be in FB15k, either its head or tail should be an unseen entity, and its other entity should already be in FB15k. Consequently, the new testing set has 4 kinds of triples: those whose head and tail are both seen entities, those whose heads are unseen and whose tails are seen, those whose heads are unseen and whose heads are seen, and those whose heads and tails are both unseen. The first kind of testing triples are for normal KG completion, while the other three kinds are for zero-shot KG completion. So the task of FB20k can be understood as generalized zero-shot KG completion. The numbers of the test triples of the above four types are 57,803, 18,753, 11,586, and 151, respectively, and all these triples 19,923 entities. The subsets of FB15k-237 and WN18RR proposed in [45] are also typical benchmarks of this type, but they are constructed by selecting 10% of the entities of the original KGs and using their associated triples for testing.

In few-shot KG completion, unseen entities usually have a small number of associated triples that can be utilized. The current methods often aim to fully utilize these triples, mainly by methods of the propagation-based paradigm [3, 4, 15, 43, 68, 182, 223], the transfer-based paradigm [29, 106, 152, 170] and the optimization-based paradigm [8]. As zero-shot KG completion, several few-shot KG completion benchmarks with unseen entities have been constructed using existing KG completion benchmarks. According to the type of the entity that an unseen entity is linked to, we categorize these benchmarks into three categories. For the first category, the entity linked to is seen in training, which means the few-shot triples connect the unseen entities with seen entities. These few-shot triples can be utilized to propagate embeddings from seen entities to unseen entities by e.g., GNNs [15, 68, 182]. Typical benchmarks of this category include subsets extracted from WordNet1 by [68], subsets extracted from FB15k by [182], and subsets extracted from WN18RR, FB15k-237 and NELL-995 by [15]. For the second category, the entity linked to is also an unseen entity. These benchmarks are to evaluate the generalization ability of a model trained on one KG to another KG with different entities or to an emerging sub-KG with new entities. Methods of the transfer-based paradigm, which transfer learned graph patterns in the form of GNN or rules, can often be adopted. Typical benchmarks of this category include subsets of
WN18RR, FB15k-237 and NELL-995 extracted by [170]. In the third category, the entity linked to can be either unseen or seen. Typical benchmarks include subsets of WN18RR, FB15k-237 and NELL-995 contributed in [8] where a meta learning method is applied to learn the embeddings of unseen entities from their few-shot triples. Next, we will introduce more details of some representative benchmarks of each category:

- **Subsets of WordNet11 by Hamaguchi et al. [68]** are typical benchmarks of the first category. They are constructed in the following way. First, entities involved in the original testing set are extracted as unseen entities, while all the other entities in the original benchmark are regarded as seen entities. Among these unseen entities, those that are associated to only seen entities in the original training triples are kept and the other are discarded. Second, the original training triples that do not contain any unseen entities are selected for the new training set, those that contain exactly one unseen entity are selected as the few-shot samples, and those that contain two unseen entities are discarded. Next, the new testing set is constructed by reusing the original testing triples and removing those containing no unseen entities. Nine subsets of different scales are extracted for the few-shot setting, by setting the size of testing triples for extracting unseen entities to 1,000, 3,000 and 5,000, and by setting the position for extracting unseen entities to head, tail and both.

- **Subsets of WN18RR, FB15k-237 and NELL-995 by Teru et al. [170]** are typical benchmarks of the second category. They are constructed in the following way. Given one original benchmark, two disjoint graphs are sampled: the train-graph for training the model and the ind-test-graph for testing. It is ensured that the two graphs’ entities sets are disjoint, while the relations of the ind-test-graph are all involved in the train-graph. In particular, 10% of the triples of the ind-test-graph are randomly selected for testing. These benchmarks are also adopted for evaluation in [29].

- **Subsets of WN18RR, FB15k-237 and NELL-995 by Baek et al. [8]** are typical benchmarks of the third category. These subsets are extracted from each original benchmark in the following way. First, a set of entities, which have a relatively small amount of associated triples, are randomly sampled as the unseen entities, and they are further partitioned and used for constructing three meta sets of triples: a meta-training set, a meta-validation set and a meta-testing sets. The other entities in the original benchmark are regarded as seen entities. Second, triples composed of seen entities alone are extracted to construct a graph named In-Graph. Finally, the meta sets are cleaned, such that each of their triples has at least one unseen entity and all the triples are out of In-Graph.

### 6.3.2 KG Completion with Unseen Relations

Zero-shot KG completion with unseen relations usually utilize the relations auxiliary information such as their names and descriptions, mainly using methods of the data augmentation paradigm [62, 64, 140] and the class feature paradigm [178, 206, 211], while few-shot KG completion with unseen relations usually relies on the few-shot triples using methods of the optimization-based paradigm [37, 111, 180, 214], the mapping-based paradigm [202, 213] and the propagation-based paradigm [223]. Different from KG completion with unseen entities, there are less benchmarks for KG completion with unseen relations. We find NELL-ZS and Wiki-ZS for the zero-shot setting, and NELL-One and Wiki-One for the few-shot setting. NELL-ZS and NELL-One are sub-KGs extracted from NELL, while Wiki-ZS and Wiki-One are sub-KGs extracted from Wikidata. Their details are introduced as follows:

- **NELL-ZS** and **Wiki-ZS** [140] are two zero-shot KG completion benchmark with unseen relations. Each benchmark has three disjoint relation sets: a training set with seen relations, a validation set and a testing set with unseen relations. They compose triples for training, validation and testing, respectively. The entities in the testing triples and the validation triples have all been involved in some training triples. NELL-ZS has 139, 10 and 32 training,
validation and testing relations, and 65,567 entities, while Wiki-ZS has 469, 20, 48 training, validation and testing relations, respectively, and a total of 605,812 entities. Qin et al. [140] used relation textual descriptions as the auxiliary information and implemented as a text feature learning and generation based method, while Geng et al. [62, 64] constructed ontological schemas, which contain not only textual information but also relation hierarchies, relation domains and ranges, relation characteristics and so on, for both benchmarks, and proposed a text-aware ontology embedding and generation based method.

- **NELL-One** and **Wiki-One** were originally developed by Xiong et al. [202] for evaluating few-shot KG completion with unseen relations that have only one triple given. In construction, relations that are associated with less than 500 triples but more than 50 are extracted from the original KGs as task relations (i.e., one relation corresponds to one task). In NELL-One, 67 such relations are extracted and they are partitioned into 51, 5 and 11 for constructing triples of the training set, validation set and the testing set, respectively; while in Wiki-One, 183 such relations are extracted and they are partitioned into 133, 16 and 34 for constructing triples of the training set, validation set and the testing set, respectively. Meanwhile, 68,545 entities are extracted for NELL-One, and 4,838,244 entities are extracted for Wiki-One. In addition, another 291 and 639 relations are extracted, respectively, as background relations constructing more triples for the entities. Note that that these two benchmarks can also be simply revised and used to support (i) zero-shot KG completion as in [178], since the relations in the training set, validation set and testing set are mutually disjoint, and (ii) $k$-shot ($k > 1$) KG completion by adding more given triples.

To sum up, we find there are quite a few resources for evaluating KG completion with unseen entities, but there is a shortage of widely recognized and adopted resources. In contrast, the benchmarks for KG completion with unseen relations are widely recognized and used in different studies. Thus the methods could be more fairly compared. Besides, there is a shortage of widely recognized benchmarks for evaluating KG completion with both unseen entities and relations, which is more challenging.

### 7 CHALLENGES AND FUTURE DIRECTIONS

#### 7.1 KG Construction for Augmenting Low-resource Learning

One critical challenge of using KGs for augmenting low-resource learning is constructing a high quality KG with exactly necessary knowledge for a task. As introduced in Section 3, there are two mainstream solutions to get the KG: (i) directly using the existing general-purpose or domain specific KGs by extracting relevant parts where the alignment between the task data and KG and between different KGs are often given or manually conducted, and (ii) extracting knowledge from task specific data such as class annotations and samples (e.g., sense graphs extracted from images and class correlation mined from samples).

The challenges and the potential future directions may lie in the follow three aspects. First, the alignment between data and knowledge is rarely investigated, and the impact of wrong mappings as well as other erroneous knowledge in the KG has been never evaluated and analyzed in the current zero-shot and few-shot studies. Applying the existing KG construction tools, especially those for KG alignment, error detection and correction (e.g., [32, 73, 86]), to low-resource learning could lead to higher performance as well as more practical and automatic systems especially for new tasks. Second, the coverage of necessary knowledge and the ratio of irrelevant knowledge are often ignored in investigating a KG’s usefulness towards a ZSL or FSL task, and there is a shortage of methods that are able to retrieve the relevant knowledge from a large scale KG for a given task. Thus analysing the impact of KG quality, such as the error rate and the knowledge coverage, could also be a promising direction, while some new solutions, such as iterative knowledge
retrieval with some feedback from the task in each iteration, are highly needed to make KGs play a more important role in low-resource learning. Third, there is a shortage of resources for evaluating the role of KG in KG-aware ZSL and FSL methods. Some existing ZSL and FSL benchmarks are associated with KGs but the KGs are usually fixed, which makes it harder to investigate different KG settings. Meanwhile, the existing benchmarks are limited to some typical tasks introduced in Section 6. In the future, more ML tasks in not only CV and NLP, but also other domains such as bioinformatics, health data analysis, urban computation and e-commerce, can be considered for benchmarking, with both general-purpose KGs and domain specific ontologies, taxonomies and logical rules.

7.2 KG-aware Low-resource Learning Paradigms

7.2.1 Zero-shot Learning. The existing KG-aware ZSL methods lie in four paradigms: mapping-based, data augmentation, propagation-based and class feature (see Table 1). The mapping-based paradigm is the most widely investigated, while the data augmentation paradigm has only four methods, one of which belongs to the rule-based category while three of which belong to the generation model-based category. Directly using rules to generate numeric samples or features is often quite hard, but in some cases such as zero-shot KG completion, we believe it is feasible to use ontological schemas and logical rules to infer symbolic knowledge (e.g., triples) for the unseen entities and/or relations. In contrast, the generation model-based methods (e.g., OntoZSL [62]) can well generate numeric samples and features by statistical models. They can flexibly choose the downstream model after data are generated, and thus are not biased to unseen classes in prediction in comparison with the widely investigated mapping-based methods. Therefore, we think that generation-based ZSL methods conditioned on the embeddings of KGs could be a promising solution and is worth of more investigation in the future. Meanwhile, we also think that the idea of belief propagation which belongs to the propagation-based paradigm is quite reasonable, especially for CV tasks such as scene understanding and VQA. Extracting semantic relationships of objects in a scene image (a.k.a. scene graph extraction) has been a popular topic (more can be found in the workshop on Scene Graph Representation and Learning and a recent survey paper by Chang et al. [26]). When the scene graph extracted from an image is aligned with an external KG and more semantics is added, unseen objects could then be recognized by knowledge inference.

It is worth mentioning that there are no KG-aware ZSL methods of the optimization-based paradigm and the transfer-based paradigm, which are proposed in categorizing KG-aware FSL methods. This is because the meta learning algorithms applied in the optimization-based paradigm and the models (neural networks or rules) directly transferred both rely on some related samples of the testing sample to predict as additional input. For example, considering a triple to predict with unseen entities or relation, its neighbouring triples, which form a graph with some patterns, are utilized by the transferred rules or GNNs as critical evidences. It could be a feasible solution by first generating some few-shot samples with rules or generation models, and then applying the optimization-based and the transfer-based methods.

7.2.2 Few-shot Learning. As shown in Table 2, there are 6 paradigms for KG-aware FSL methods, which are more diverse than KG-aware ZSL methods, mainly due to the availability of additional few-shot samples. Some of the KG-aware FSL methods extend the models for ZSL by training them with additional few-shot samples or integrating them with the models or the results that are based on the few-shot samples. Most mapping-based ZSL methods (e.g., [2, 113, 148]) could be extended to FSL by training the mapping function(s) with additional few-shot samples, while most data augmentation ZSL methods could also be extended to FSL by merging the generated data with the few-shot samples (e.g., [172]). As in ZSL, we find KG-aware data augmentation could be a promising solution but has not been widely investigated for FSL.
Some other KG-aware FSL methods are originally developed to utilize the few-shot samples, but the utilization methods are augmented by KGs or extended for KG contexts. Two typical kinds of such methods are the optimization-based and the transfer-based, both of which cannot be applied to ZSL due to their dependence on the few-shot samples. We find they are mostly extensions (or straightforward applications) of meta learning and transfer learning methods to few-shot tasks in KG completion, while KG-augmented meta learning and model transfer for none KG completion tasks have not been widely investigated. In the future, representing knowledge on learning (e.g., background on the task and previous learning experience) as KGs, and integrating them with meta learning or transfer learning algorithms could lead to more general neural-symbolic paradigms that are applicable to different FSL tasks. Regarding the propagation-based paradigm, the category of embedding propagation is new to KG-aware FSL. Methods of this kinds often aim at few-shot KG completion by utilizing the few-shot samples i.e., triples that link unseen entities or relations to seen ones. It would be a promising solution by utilizing both these few-shot links and the unseen entities’ or relations’ auxiliary information such as textual descriptions, attributes and schemas.

7.3 Low-resource Learning during KG Construction

Nowadays KG construction uses not only heuristics (hand-craft rules and templates), symbolic knowledge engineering and manual curation, but also ML prediction for (semi-)automation. ML tasks in KG construction range from knowledge extraction (e.g., from unstructured natural language text and semi-structured tables, Web pages and encyclopedia information boxes) to knowledge curation including KG completion, KG alignment, entity resolution, entity typing, schema learning, error detection and correction, and so on [137, 192]. Besides the tasks of KG completion and knowledge extraction from text that we have discussed in this paper, almost all the other prediction-based KG construction tasks would suffer from sample shortage and lead to low-resource learning problems. One typical example is the task of matching table column types to KG classes, which is the foundation of KG population with tabular data. It is common that some ontology classes have no enough table columns for training or some new classes are defined and added to the KG. In that case, some solutions, such as generating synthetic columns according to the hierarchical classes and their entities [33], are needed. Other tasks in building KGs by tables, such as matching inter-column relationship to KG relation and matching table cells to KG entities, all suffer from similar sample shortage issues. Another typical example lies in the context when new knowledge are extracted from data and added to an existing KG. The prediction model built on the existing KG should be efficiently adapted to address new entities, new relations, or even new classes, without re-training from the scratch.

Currently, the sample shortage issue has been widely investigated in extracting knowledge (e.g., entities, relations, triples and events) from text. However, most of the existing low-resource learning studies mainly focus on utilizing existing ML solutions such as distant supervision with heuristics, meta learning algorithms and additional features, and only a small number of them consider integrating KGs. The direction of using KGs for augmenting zero-shot and few-shot text knowledge extraction still has a lot of space for exploration. Using KGs for augmentation in these tasks is actually quite reasonable since the targets for prediction (e.g., entities, relations and events) are often already in an existing KG. Meanwhile, the zero-shot and few-shot settings for knowledge extraction from other kinds of data besides natural language text, such as tabular data and Web pages, should also be investigated so as to making these methods and tools more automatic and adaptable to new or evolving contexts. In KG curation, zero-shot and few-shot link prediction, which are sometimes known as semi-inductive or inductive link prediction, have been widely investigated, while the zero-shot.

11Different forms of tables such as databases, CSV and excel files are still among the most popular for data storage, and it is easier to extract high quality knowledge from tables than from totally unstructured text. Thus tabular data often have the highest priority to be utilized for constructing KGs in applications.
and few-shot settings of the other tasks including entity typing, schema learning, entity resolution and error detection and correction have been rarely considered. In the future, we think it necessary and promising to consider more KG curation contexts such as an evolving ontological schema, a continuously updated KG and a heterogeneous KG constructed by integrating multiple KGs, together with different tasks besides link prediction, for building more zero-shot and few-shot problem settings (e.g., incremental ZSL [191]), tasks and evaluation resources.

8 CONCLUSION

KGs have been a popular approach to augment ZSL and FSL methods, while KG construction and curation also encounter many ML prediction tasks with sample shortage. Thus KG-aware low-resource learning has attracted wide attention in domains including CV, NLP, ML and the Semantic Web, and is becoming increasingly popular. In this survey, we systematically reviewed over 90 KG-aware studies for addressing low-resource ML problems from multiple perspectives including the KG, the methodology and the application. These studies cover KG-augmented ZSL and FSL methods, as well as prediction tasks during KG construction and curation with sample shortage settings. We first introduced KGs that have been applied for low-resource learning as well as methods for constructing task-specific KGs, then separately reviewed the methods for KG-aware ZSL and FSL, by dividing them into different paradigms, each of which was further introduced and summarized with categories, and finally presented the development of ZSL and FSL in different tasks in CV, NLP and KG completion, with resources that can be used for evaluating KG-aware methods listed and summarized. Besides, we also analyzed and discussed the challenges of KG-aware low-resource learning and KG construction as well as future directions on new ZSL and FSL paradigms and methods, and new tasks and resources.

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