Abstract—Machine learning has become pervasive in multiple domains, impacting a wide variety of applications, such as knowledge discovery and data mining, natural language processing, information retrieval, computer vision, social and health informatics, ubiquitous computing, etc. Two essential problems of machine learning are how to generate features and how to acquire labels for machines to learn. Particularly, labeling large amount of data for each domain-specific problem can be very time consuming and costly. It has become a key obstacle in making learning protocols realistic in applications. In this paper, we will discuss how to use the existing general-purpose world knowledge to enhance machine learning processes, by enriching the features or reducing the labeling work. We start from the comparison of world knowledge with domain-specific knowledge, and then introduce three key problems in using world knowledge in learning processes, i.e., explicit and implicit feature representation, inference for knowledge linking and disambiguation, and learning with direct or indirect supervision. Finally we discuss the future directions of this research topic.

Index Terms—Machine learning, knowledge discovery, feature engineering, knowledge representation, world knowledge, natural language processing.

1 INTRODUCTION

Machine learning has become pervasive in multiple domains, impacting a wide variety of applications, such as knowledge discovery and data mining, natural language processing, information retrieval, computer vision, social and health informatics, ubiquitous computing, etc. Two major problems of machine learning in practice are how to generate or extract features from data and how to acquire labels for machines to learn. There have been many studies about feature engineering and labeling work reduction in the past decades.

- **Feature extraction and representation.** Feature engineering, such as handcrafting features for domain dependent problems, has been recognized as a key problem in applications (such as Kaggle or KDD Cup). Given the features, with or without labels, one can perform feature selection (131) or feature extraction (191, 192, 40) to find a better representation than the handcrafted features for learning algorithms. More recently, deep learning has been proposed to deal with big data through end-to-end learning which enables the representation learning within...
the deep architecture of neural networks [81], [114]. However, there are still problems related to high-level intelligence that current machine learning systems cannot handle. For example, human knowledge about the world is highly structured. When human imagines something, the higher-order relationships among “knowledge dots” (facts, entities, events or activities, etc.) can be the key clue. However, current machine learning systems may not be able to capture the inference process of such remote relationship among the dots. Even with the rapid development of deep learning, which has much better representation ability of data, discovering relationships is still a problem. For example, although current neural network language model can capture long-short term memory of words [145], [83], [209] in language process, it is still difficult to capture the global dependencies across documents, e.g., cross-document co-reference [196].

- **Labeling work reduction.** Labeling large amount of data for each domain-specific problem can be very time consuming and costly. It has become a key obstacle in making learning protocols realistic in applications. Machine learning community has also elaborated to reduce the labeling work done by human for supervised machine learning algorithms or to improve unsupervised learning with only minimum supervision. For example, semi-supervised learning [85] is proposed to use only partially labeled data and a lot of unlabeled data to perform learning with the hope that it can perform as good as fully supervised learning. Transfer learning [163] uses the labeled data from other relevant domains to help the learning task in the target domain or learns multiple domains simultaneously. Both semi-supervised learning and transfer learning needs domain knowledge, and there are multiple ways to achieve these learning settings. However, there is no general solution or a principle when applying both learning settings to most tasks. In other words, for each of the target domain, specific domain knowledge is still needed to be engineered into the learning process. Crowdsourcing [113], [76] has been considered to acquire cheap labels from general-level human intelligence. However, current crowdsourcing mechanisms can still be applied to relatively simple and well-defined tasks, and it is still a challenge for applying machine learning to the labels for more diverse and more specific data [115].

We use some specific open problems from natural language processing and computer vision to further illustrate the above problems.

**Example 1: text semantics and topics.**

Text semantic similarity/relatedness is one of the fundamental problem in natural language processing. Regarding to different levels of text span, e.g., word, phrase, sentence, or document, there are different ways to compute the similarity/relatedness [98]. For example, we consider short texts such as following [224].

Text 1.1: On Feb. 10, 2007, Obama announced his candidacy for President of the United States in front of the Old State Capitol located in Springfield, Illinois.

Text 1.2: Bush portrayed himself as a compassionate conservative, implying he was more suitable than other Republicans to go to lead the United States.

An intuitive way is to compute the bag-of-words similarity between two texts. However, given the above text fragments, the overlapped words are few. Nonetheless, the similarity/relatedness between these two fragments should be high, since they are talking to the same topic. Therefore, one can consider to use the context of each word to enrich the similarity between two fragments, where the context could be obtained from a lot of texts from all over the world [44], [222], [145], [146]. Another way is to relate the words or entities in the texts by the external knowledge [193], [225]. For example, we know that “Obama” is related to “Bush” since they were both the President of the “United States.” Thus, if we can find a path between “Obama” and “Bush” in the external knowledge base, we can directly relate the two text fragments without seeing other words related to them. Both approaches are not dependent to the target two pieces of short texts but leverage the knowledge from general purpose texts or knowledge bases.

**Example 2: events: language and vision.** Event extraction is another key component in natural language understanding. Given its complex definition of event trigger, agents, instruments, targets, location, and time [160], [150], a joint inference must be applied to identify the corresponding events. Traditional event extraction approaches train the machine learning models based on the annotation on specific domains, e.g., 33 event types in ACE 2005 [160] or 38 event types in TAC KBP 2015 [150]. Consequently, the supervised learning systems easily overfit these domains. However, there are many more types of events. When generalizing the trained models to other domains, more annotation should be used. Especially, the relationships among agents, instruments, and targets are very difficult to discover using the small number of annotated data. Thus, a more global approach is expected to avoid training models overfitting small domains. For example, the determination of event nugget can be decided by simply computing a structured similarity between seed examples and the new events [166], where the similarity is coming from general purpose knowledge base, and the structure can be obtained by general purpose semantic role labeling [173]. Furthermore, if we can extract knowledge about entities and relations from existing knowledge bases, such information can help us perform joint inference about the entities involved in the event extraction problem across documents.

Similarly in computer vision, event [227], [172] and scene [96], [103] recognition problems are also the most key and complicated problems of image understanding. When parsing an image, not only the pixels or features, but all of the functionality, attribute, intentionality, and causality factors should be considered. The above constrains again make event/scene recognition problem a joint inference problem. When performing inference, commonsense knowledge is one of the key problem to perform joint inference. For example, when we see a fish, most likely it is in water. When it is not in water, the scene may be interpreted as some specific event, e.g., fish hunting or cooking.

**Example 3: co-reference.** Co-reference resolution is a problem of finding different entities or mentions in texts referring to the same person or thing. It is also one of the key problems in natural language understanding. Typical co-reference resolution systems use rule-based method [115] or learning-based method [31]. For the learning based methods, it is common to extract the features for the entities or mentions, and define some deterministic function to compare pairs of entities or mentions to identify whether they are co-referent. Even if declarative constraints have been considered

3. http://www.stat.ucla.edu/~sczhu/research_blog.html
based on some background knowledge of co-reference in natural language [31], some of the hard problems are still very difficult for these systems to solve. For example, here are some examples of hard co-reference problem [177], [118], [165].

Example 3.1: [Martha Stewart]$_e$ is hoping people don’t run out on her. [The celebrity]$_{NP}$ indicted on charges stemming from...

Example 3.2: [Martha Stewart]$_e$ is hoping people don’t run out on [Tom]$_e$. [The celebrity]$_{NP}$ indicted on charges stemming from...

Example 3.3: [A bird]$_{e,1}$ perched on the [limb]$_{e,2}$ and [it]$_{pro}$ bent.

Example 3.1 was initially shown in [177]. It illustrates that if a noun phrase (NP) refers to a named entity (e), some external knowledge about the entity as a celebrity can improve the determination of co-reference. Otherwise, only based on the lexical or syntactical features, the developed rules may not be perfect to generalize to other cases [177]. Example 3.2 shows an even harder case. If the first sentence has two named entities, we should know which one is the celebrity to perform the inference. Example 3.3 shows another example from the Winograd schema challenge [118], [178] indicating that we should have the commonsense knowledge that a bird cannot be bent whereas a branch of a tree can. So here we have shown that certain knowledge about the entities, categories, or attributes can help identify the co-reference.

All the above examples show that traditionally when we perform machine learning, we mostly focused on how to train a model that can avoids overfitting and have best generalization ability. However, even we have the best model and the parameter tuning skills, the machine learning algorithms may still lack of knowledge and the higher-order relationships about the entities they have seen, or they are still easily overfitting to a specific domain they are trained based on. Therefore, more general approaches should be considered.

In this paper, we present the idea of “machine learning with world knowledge.” Instead of only considering the data in a specific domain, we also consider the general purpose knowledge about the world. The general knowledge includes common and commonsense knowledge, and partially the domain dependent knowledge. We position the idea of using world knowledge as an intersection of many fields, including machine learning, data mining, natural language processing, knowledge representation, etc. We start with comparing the traditionally used domain/background knowledge for machine learning algorithms and the world knowledge. Then we discuss why world knowledge is useful and what are the important problems when using world knowledge for machine learning algorithms. Specifically, we need to adapt world knowledge, which is domain independent, to domain problems. Then we introduce how the two important factors in machine learning algorithms, features and labels, are affected by world knowledge. There are multiple ways to represent world knowledge as features for machine learning algorithms. We survey the existing approaches and summarize them into three categories, homogeneous and heterogeneous explicit features and implicit features. To use world knowledge as supervision, we introduce the linking and inference techniques that can relate a domain problem to a general-purpose knowledge base. Then we introduce some new learning paradigms that can be enabled by world knowledge. Finally we discuss the future directions of the ideas of machine learning with world knowledge and conclude our paper. Note that, we will not focus on machine learning for world knowledge acquisition or organization. Instead, we assume that the world knowledge is already existing for machines to use.

2 DOMAIN VS. WORLD KNOWLEDGE

In this section, we present the concepts of domain knowledge and world knowledge, and extend to the related problems when using both of them.

2.1 Domain Knowledge and Domain Adaptation

As we mentioned in the introduction, most of the feature engineering needs domain knowledge. For example, to identify a disease, certain related symptoms should be observed. Moreover, supervised learning and semi-supervised learning [35] both require labels or side information, e.g., must-link and cannot-link constraints [9], for the domain to perform machine learning. The domain knowledge is reflected by the labels or the constraints. In this section, we focus on three aspects of machine learning with domain knowledge. First, we introduce the most intuitive semi-supervised learning based on partially labeled data, which is formulated as a generative process setting. This is the simplest case of applying domain knowledge to machine learning algorithms, and strongly related to posterior regularization in Section 2.1.2. For more examples and learning settings of semi-supervised learning, we refer to the corresponding references for further reading [35], [9]. Then, we survey the declarative knowledge constrained learning since the declarative knowledge is very related to the form of world knowledge. Finally, we focus on the domain knowledge that can be transferred to other domains. On one hand, this learning setting is a very good comparison with semi-supervised learning to have more insight about domain knowledge. On the other hand, we can compare it with setting of domain adaptation with world knowledge.

2.1.1 Generative Semi-supervised Learning

A typical generative semi-supervised learning setting (e.g., [152]) is to learn a set of parameters $\Theta$, given a set of unlabeled data $\{X, Y\}$ and a small portion of labeled data $\{X_L, Y_L\}$. Then the maximum likelihood estimation of $\Theta$ is:

$$\max_{\Theta} \log \sum_{Y} P(X, Y|\Theta) + \log P(X_L, Y_L|\Theta).$$

This cannot be solved directly since there is a sum operation inside logarithm. When the posterior of $Y$ is analytically tractable, an expectation-maximization algorithm can be employed. We can re-write the first term in the likelihood as:

$$\max_{\Theta} \sum_{Y} Q(Y) \log \frac{P(X, Y|\Theta)}{Q(Y)} - \sum_{Y} Q(Y) \log \frac{P(Y|X, \Theta)}{Q(Y)} + KL[Q(Y)||P(Y|X, \Theta)].$$

By substituting Eq. [2] into Eq. [1], we can derive the EM algorithm. In the E-step, we have $Q(Y) = P(Y|X, \Theta)$, when there is analytical solution, to minimize the KL-divergence $KL[Q(Y)||P(Y|X, \Theta)]$. In the M-step, we substitute
introduced. First, CCM can be used to decouple the learning and inference parts of the algorithm. The learning part corresponds to the parameter estimation of the learning model, while the inference part corresponds to the label assignment for the structured output of learning algorithm. We will introduce in more detail in Section 3. Then this decoupling will further introduce the second advantage. If we can focus only on the inference part, we can use a much simpler representation and algorithm to handle the constraints. For example, we can in general represent satisfiability of boolean formulas (SAT) as a linear algebra form and solve the SAT problem using some well developed optimization tools to solve it \cite{129}. For example, in CCM, it uses integer linear programming (ILP) and A-star algorithms to solve the problems \cite{33}.

It has been shown that this general form of constraints is useful to represent many constrained learning problems \cite{33}.

### 2.1.3 Transfer Learning

Transfer learning \cite{219, 163} is a learning paradigm that uses data in relevant tasks to help the target machine learning tasks. Formally, if we have a source domain data \( S = \{x_S, y_S\} = \{x_{S_i}, y_{S_i}\}_{i=1}^{N_S} \), where \( x_{S_i} \) is the feature vector of sample \( i \) in source domain, \( y_{S_i} \) is the label vector (without loss of generality we use vector to represent label(s) of a data sample), and \( N_S \) is the number of available data in source domain. We also have some target domain data \( T = \{x_T, y_T\} = \{x_{T_i}, y_{T_i}\}_{i=1}^{N_T} \), where \( x_{T_i} \) is the feature vector of sample \( i \) in target domain, \( y_{T_i} \) is the label vector, and \( N_T \) is the number of available data in source domain. In most cases, we have \( N_T \ll N_S \). Sometimes, we have no labeled data but some unlabeled data in the target domain. The goal of transfer learning is to use the source domain data \( S \) to help improve the learning/prediction performance of the target domain data \( T \). In the problem of transfer learning, the two domains can be different in terms of \( x_T \neq x_S, y_T \neq y_S \) or \( P(S) \neq P(T) \). For example, we can train a newsgroup classifier based on “Christian vs. Hockey” and transfer the knowledge of classification to “Atheism vs. Autos” \cite{180}, where \( y_T \neq y_S \) and \( P(x_T) \neq P(x_S) \). We can use a “motorbike” object detector to detect “bicycle” from images \cite{6}, where \( P(x_T) \neq P(x_S) \). We can also even transfer the knowledge from text to images \cite{236}, where \( x_T \neq x_S \).

The domain here in transfer learning corresponds to the specific tasks that are relevant to the target task. The domain knowledge usually means the implicit knowledge incorporated in the learned models, the distributions of source data, or the latent factors that are related to the factors in the target domain \cite{163}. Thus, when applying the knowledge from source domain to the target domain, we first need to know what are the relevant tasks that can provide such knowledge. Second, we need to develop specific algorithm that can incorporate or use the existing knowledge from the source domain. These can be regarded as the major characteristics of domain knowledge in transfer learning.

### 2.2 World Knowledge and Domain Adaptation

If we analyze the above learning paradigms, we can find something in common: they all use domain knowledge to help learning algorithms better find a solution for a domain specific problem. For example, semi-supervised learning needs seed labels or must-link and cannot-link constraints for the domain, which should be i.i.d. with the unlabeled data and the new prediction data. Declarative constraint driven learning needs the background knowledge about...
the task, and incorporates the knowledge into the constraints. Transfer learning requires the source task relevant to the target task, and the knowledge can be transferred or adapted. This means that when dealing with a new task, all of them need human to evaluate the new task and incorporate the “correct” knowledge in to the learning process. Compared to the above learning paradigms, the paradigm “machine learning with world knowledge” does not require human to justify the domain knowledge. Whereas, it uses the general-purpose knowledge, which can be obtained from large scale general knowledge base, or in general the data from the Web, to help learning algorithms to improve the learning performance.

In the past decades, especially in recent years, there are a lot of general-purpose knowledge bases (or knowledge graphs) developed, e.g., WordNet[61], Cyc project[117], Wikipedia, Freebase[18], KnowItAll[53], TextRunner[7], WikiTaxonomy[169], Probase[232], DBpedia[5], YAGO[208], NELL[25], Illinois-Profiler[60], and Knowledge Vault[49]. We call these knowledge bases world knowledge[65], because they are universal knowledge that are either collaboratively annotated by human labelers or automatically extracted from big data. For example, collaboratively constructed knowledge bases include WordNet, Cyc, Wikipedia, and Freebase. Knowledge bases extracted based on information extraction includes Probase, DBpedia, YAGO, NELL, Illinois-Profiler, and Knowledge Vault. A more comprehensive of comparison of scales and methodologies of knowledge bases can be found in[157]. When world knowledge is annotated or extracted, it is not collected for any specific domain. The first paper explicitly mentioning machine learning with world knowledge is[65].

In general, slightly different from traditional definition[65], we summarize world knowledge as commonsense knowledge, common knowledge, and domain knowledge following[24], since we find this way will better distinguish different kinds of knowledge that can be used.

- Commonsense knowledge[4] Commonsense knowledge is an important sub-topic in artificial intelligence[190]. Here we refer commonsense knowledge as the knowledge that an ordinary person is expected to know, but they normally leave unstated when they write or talk. For example, “cats can hunt mice;” “birds can fly;” etc. Thus, commonsense is the most difficult part of knowledge to collect from the Web since there is too few resources mentioning such knowledge in purpose.

- Common knowledge[5] Common knowledge refers to the knowledge that humans generally know about the world. For example, “the United States is a country;” “the current President of the United States;” etc. Different from commonsense knowledge, there is a lot of resources mentioning such knowledge on the Web. Note that people with different educational or cultural background should have different common knowledge. Nonetheless, collectively speaking, common knowledge can be extracted mostly from the Web now (in a noisy way).

- Domain knowledge. Domain knowledge is the knowledge in a specific domain. For example, the meaning of a term in molecular biology may only be understood by a biologist. Currently, some world knowledge bases such as Wikipedia also contain some of the domain knowledge. However, for a complete ontology or dictionary of concepts, a more domain specific knowledge base is expected.

From the above categorization, we can see that most of the mentioned world knowledge bases only tried to cover the common knowledge part, and partially cover the commonsense and domain knowledge, especially the knowledge bases constructed based on information extraction. Therefore, it is still far away from solving every problem using current world knowledge bases. However, the common knowledge is already very useful for us to enrich our data representation and introduce weak supervision. In general, we will have machine learning algorithms to learn from following data:

$$\max_{\Theta} \log P(\mathcal{Y}, \mathcal{X}_W, \Theta)$$

or

$$\max_{\Theta} \log P(\mathcal{Y}, \mathcal{X}, \Theta),$$

where $\mathcal{X}_W$ are the features that can be obtained from the world to extend the representation of data and $\mathcal{Y}_W$ can be weak labels automatically obtained from the world knowledge base. Then the learned model parameter $\Theta$ should be able to apply to new coming data:

$$y^* = \arg \max_{y \in \mathcal{Y}} P(y|x, \Theta).$$

Thus, from Eq. (7) we can see that, we will have a domain adaptation problem to either adapt the world knowledge about the labels to the target domain, or adapt the data in feature space to the target domain.

In the following of the paper, we will introduce how to leverage the existing world knowledge for machines to learn.

### 3 Machine Learning with World Knowledge: An Overview

In both collaborative data collection (or crowdsourcing)[40], [19], [143], [213] and information extraction from the Web[53], [7], [25], machine learning is widely used. Moreover, learning algorithms are also used to do inference over knowledge bases[158], [157]. Instead of using machine learning to construct knowledge bases or do inference over knowledge bases, “machine learning with world knowledge” considers how to use the existing world knowledge bases to help improving existing learning algorithms or applications.

In this section, we consider the general machine learning framework that can incorporate world knowledge into machine learning algorithms. There are multiple ways to use world knowledge for machine learning. As we mentioned in the introduction, two key machine learning problems are feature extraction/representation and label reduction. Thus, the intuitive ways to incorporate world knowledge into machine learning algorithms can be classified into these two categories. However, world knowledge is not designed for any specific domain. For example, if the world knowledge is about all kinds of named entities in the world, then when we want to process the documents about entertainment or sports, the world knowledge about names of celebrities and athletes may help while the terms used in science and technology may not be very useful. Thus, another key issue is how we should specify the world knowledge to the domain specific tasks, or adapt the world knowledge to domains. Thus, here we summarize the issues about machine learning with world knowledge into three categories: representation, inference, and learning, which is analogous to other machine.

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4. [https://en.wikipedia.org/wiki/Common_sense](https://en.wikipedia.org/wiki/Common_sense)
5. [https://en.wikipedia.org/wiki/Common_knowledge](https://en.wikipedia.org/wiki/Common_knowledge)
learning problems such as sequence labeling [33] and Bayesian networks [100]. We summarize the three categories of problems in Table 3.

**Representation.** As many other machine learning algorithms, learning with world knowledge needs the representation of data samples. For example, in sequence labeling for text, such as named entity recognition, to predict each word’s label, a set of features should be extracted. The features can be one-hot distributional lexical features [20], [101], or neural network word embeddings [12], [145], [146]. In Bayesian networks, we need to determine which distribution should be used to describe the data, and the (conditional) independency among random variables [223], [100]. Since world knowledge is usually about the entities all over the world and their relations, the representation of knowledge can be categorical and structured. Moreover, the knowledge can be either used as features or used as (indirect) labels. Thus, the representation of world knowledge used for machine learning can be multiple ways.

**Inference.** Inference means to infer more knowledge from the data, or discover the relationships from data. For example, in sequence labeling, label assignment is determined by considering all possible assignment of labels in a sequence. However, there are more efficient ways to do this, e.g., beam search [218] or Viterbi algorithm [175]. Other possible ways such as A-star algorithm [33] or policy based search [46] can also be applied. In Bayesian networks, inference involves to infer the posteriors or marginal of random variables such as using variational inference, belief propagation, and random sampling [223], [100]. Here in learning with world knowledge, we consider the inference problem as specifying world knowledge to domain problems (For the problem of inferring more knowledge given a knowledge base, such as link prediction, please refer to the corresponding survey paper [157]).

For example, given the knowledge base and the document, we want to infer the most probable categories of the entities in the document, and their relationships. The process of grounding the entities in a document to the knowledge base is usually called entity linking [189], [194]. If the relations are also considered, it is usually called semantic parsing [152], [4]. In general, we want to solve the ambiguity problem of the knowledge for a specific problem, by considering either the structural label relationship as sequence labeling problem or posterior inference as Bayesian network inference problems.

**Learning.** Learning refers to the process that estimate the parameters of models. For example, in sequence labeling, the parameters are the weights for the features. In Bayesian networks, learning can refer to learning the parameters of the distributions, or learning the structure of latent variables. Similar to other machine learning problems, learning with world knowledge also has a learning process. Depending on different representations of world knowledge, the learning processes are also different. Moreover, one particular issue is that world knowledge is not built for a specific domain. Thus, the learning process will also have the problem of domain adaptation similar to what we introduced in transfer learning. However, in transfer learning, the domain adaptation usually refers to adapt the knowledge from one domain to another, where in learning with world knowledge, domain adaptation refers to adapt general knowledge to domains.

In the following sections, we will survey existing work and summarize them in the above three categories.

### 4 Representation: World Knowledge as Features

In this section, we survey the existing studies on using machine learning with world knowledge as features. Particularly, we categorize the feature representations as explicit features, implicit features, and graph based features.

#### 4.1 Explicit Homogeneous Features

Most of the traditional distributional representation can be regarded as explicit features, if the representation is generated based on a corpus in a specific domain. For example, we can use the co-occurrence of syntactic or semantic patterns in the context [80], [73], [75], [58], [59], [41]. If the corpus is a world knowledge base, such as Wikipedia, then more specific distributional representations can be developed. Here, we review the most significant development of knowledge base based representations for textual documents, i.e., the explicit semantic analysis (ESA) [68], probabilistic conceptualization (PC) [204], and their extension and combinations, since these models reveal important insight of generating features with world knowledge. To summarize from the modeling perspective, analogous to the image conceptualization frameworks discussed in [248], we introduce and analyze three ways to generate the representations: descriptive, generative and discriminative models.

For world knowledge representation, we consider generating world knowledge based features \( x_{bf} = c \) from the original features \( x = \{ e_1, ..., e_M \} \), where \( e_i \)'s are the features related to a term (a word or an entity) in a document [6]. In the descriptive and generative models, we consider to model the probability \( P(e_1, ..., e_M | c) \). In the discriminative model, we consider directly modeling the probability \( P(c | e_1, ..., e_M) \). The major discussion of this section follows the previous paper [205].

6. For other types of data, such image, the features for an entity could be different.
4.1.1 Explicit Semantic Analysis: Generative Models

The first paper using the term “world knowledge” [65] extends the bag-of-words features with the categories in Open Directory Project (ODP), and shows that it can help improve text classification with additional knowledge. Following this, by mapping the text to the semantic space provided by Wikipedia pages or other ontologies, it has been proven to be useful for short text classification [66], [67], clustering [87], [88], [89], [64], and information retrieval [51]. In this line of research, the approaches are generally called Explicit Semantic Analysis (ESA).

ESA [68] simply combines the weighted concepts of each term in a short text. We use $e_m = (e_{m,1}, ..., e_{m,T}) \in \mathbb{R}^T$ to represent the concept vector of the term $e_m$. For example, we can set $e_{m,t} = f(n(e_m, c_t))$ as a function of the co-occurrence of the term $e_m$ and $c_t$, where $e_m$ is an entity and $c_t$ is a higher-level concept. In the original ESA, it uses TF-IDF (term frequency-inverse document frequency) score of $e_m$ shown in the $t$-th Wikipedia page, which is denoted as a concept $c_t$. We use a vector $c = (c_1, ..., c_T) \in \mathbb{R}^T_+$ to denote the concept proportion that can describe the whole text containing $E = \{e_1, ..., e_M\}$. Then ESA recalls the concepts with scores as this:

$$c = \sum_{m=1}^{M} w_m e_m,$$

where $w_m$ is the weight associated to $e_m$, e.g., the TF-IDF score of $e_m$ in the short text. The benefit of using this representation is that the values in the concept vectors $e_m$ are not restricted to the co-occurrence frequencies, but can be arbitrarily tuned.

ESA can be regarded as a generative model since it uses the concept-term relationship as the evidence of generated features of terms, and estimates the latent concept distribution which generates the features. If we formulate the probability $P(e_1, ..., e_M | c)$ as:

$$P(e_1, ..., e_M | c) = \prod_{m=1}^{M} P(e_m | c) \propto \prod_{m=1}^{M} \exp\{-||e_m - c||^2\},$$

where $P(e_m | c)$ is assumed to be a Gaussian distribution centered by the underlying concept distribution $c$. Then $c = \sum_{m=1}^{M} e_m$ is the maximum likelihood estimate with the probability $P(e_1, ..., e_M | c)$. Here $P(e_m | c)$ is more flexible and not necessarily to be factorized as $\prod_{m=1}^{M} P(e_m | c_t)$. For example, $e_{m,t}$ $(t = 1, ..., T)$ in the concept vector $e_m$ can be the co-occurrence frequency of concept $c_t$ and term $e_m$ in the same sentence or same document. We can also define $e_{m,t} = P(c_t | e_m)$ which is the typicality of a concept $c_t$ to describe the term $e_m$, or $P(e_m | c_t)$, which is the typicality of how much a term $e_m$ can instantiate the concept $c_t$.

4.1.2 Probabilistic Conceptualization: Descriptive Models

Probabilistic conceptualization tries to find the concepts associated with scores that can best describe the terms. Suppose we have a general and open domain concept set $C = \{c_1, ..., c_T\}$. In probabilistic conceptualization, it makes the naive Bayes assumption of the conditional probabilities and uses

$$P(c_t | E) = P[E | c_t] P(c_t) / P[E] \propto P(c_t) \prod_{m=1}^{M} P(e_m | c_t)$$

as the score associated with $c_t$. Here, $P(e_m | c_t)$ is the co-occurrence frequency of concept $c_t$ and term $e_m$ in the sentences used by information extraction, and $P(c_t)$ is the overall number of concept $c_t$. Moreover, $P(c_t) = \frac{n(e_m, c_t)}{n(c_t)}$ is normalized by the number of all the concepts in $C$. The basic assumption behind this model is that given each concept $c_t$, all the observed terms $e_m \in E$ are conditionally independent. Then it uses the probability $P(c_t | E)$ to rank the concepts and selects the concepts with the largest probabilities to represent the text containing the terms in $E$.

The probabilistic conceptualization can be regarded as a simple causal Markov model, since it imposes the partial order of the probabilities of concept-term relationship. We first assume the conditional independency of $e_m$ given $c$: $P(e_1, ..., e_M | c) = \prod_{m=1}^{M} P(e_m | c)$. Then we define $P(e_m | c) \propto \prod_{t=1}^{T} P(e_{m,t} | P(e_m | c_t)) = \prod_{t=1}^{T} P(e_{m,t} | c_{m,t})$ as a multinomial distribution where $P(e_{m,t} | c_{m,t})$ is calculated based on the evidence of co-occurrence in knowledge base (explained under Eq. [10]). We define $e_{m,t} = 1$ if for this trial $c_t$ is selected as the description of the short text and $e_{m,t'} = 0$ for $t' \neq t$. Now we can factorize $P(e_1, ..., e_M | c)$ as:

$$P(c_1 | E) = \prod_{t=1}^{T} P(c_t | e_{c_t}^{t-1} \cdots e_{c_T}^{t-M} \cdots e_{c_M}^{t-M,T})$$

By incorporating the prior $P(c) = \prod_{t=1}^{T} P(c_t)$, we can re-write the posterior of $c$:

$$P(c | e_1, ..., e_M) \propto P(e_1, ..., e_M | c) P(c) = \prod_{t=1}^{T} P(c_t) \prod_{m=1}^{M} P(e_m | c_t)$$

Then selecting the top $k$ concepts using Eq. [10] among all the $T$ concepts can be considered as the maximum a posterior (MAP) estimation of this posterior in Eq. [12]. This illustrates what probabilistic conceptualization really optimizes. Thus, if one of the probability $P(e_m | c_t)$ equals to zero, then the whole probability $P(c | e_1, ..., e_M)$ equals to zero. Even if a smoothing technique can be applied [204], the probability mass $P(c | e_1, ..., e_M)$ could be too small to be reasonable in this case.

We can see that both the simple descriptive and generative approaches factorize the probability as $\prod_{m=1}^{M} P(e_m | c)$, which do not consider the relationships between $e_m$’s. Thus, a generative + descriptive model that tries to jointly model $P(e_1, ..., e_M | c)$ to incorporate the relationships between terms with more descriptive power is also introduced [205].

4.1.3 Hierarchical Classification: Discriminative Model

Another way for conceptualization is to classify the short text onto a predefined taxonomy or ontology [132], [72], [42], [200], [201]. Classification can be regarded as the discriminative model which wants to estimate $c$ by directly modeling the probability $P(c | e_1, ..., e_M)$. For example, we can learn (or simply find) a set of projection vectors $w_t, t = 1, ..., T$, to project the observed text to maximize $P(c_t | w_t, e_1, ..., e_M) = \frac{1}{2} f(w_t, g(e_1, ..., e_M))$. 

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7. Parsing short text to be words or multi-word expressions can be non-trivial [203]. We ignore this since it is not the focus of this paper.
Explicit Flat Features

A more comprehensive survey on HIN has been given by [195]. It is not a purely graph based feature. However, developing such features should consider the structure between entities. Thus, here we call this approach the “explicit heterogeneous features.” It is not a purely graph based feature. However, developing such features should consider the structure between entities. Thus, here we call this approach the “explicit heterogeneous features.”

Table 2: Summarization of Learning with World Knowledge Features.

| Representation | Explicit Flat Features | Explicit Heterogeneous Features | Implicit Features |
|---------------|------------------------|---------------------------------|------------------|
| **Traditional Approaches** | Corpus driven distributional representations [65], [71], [75], [58], [59], [41] | Features [64] based on word sense disambiguation [21] | Topic models [48], [65], [127], word embeddings and language models [12], [155], [151], [223], [44], [144], [145], [119], [120] |
| **Typical World Knowledge based Approaches** | ESA [68], Probabilistic Conceptualization [204] | Heterogeneous information networks based meta-path features [222] | OHLDA [77], KB-LDA model [154], joint text and knowledge embedding [228], [247], [234], [220] |
| **Applications** | Text classification [65], [64], [68], [64], [229], text clustering [61], bag-of-words labeling [210], search relevance measurement [203], search log mining [61], [230], advertising keywords semantic matching [133], [99], semantic frame identification [164] | Text classification [222], text clustering [225], [224], [227] | Text classification [221], [124], relation classification [228], relation extraction [220], entity disambiguation [50], word analogy [228], recommendation system [244] |

where the concept vector is considered as a feature vector to generate the representation of the short text. A typical $g(e_1, \ldots, e_M)$ can be $\sum_{m=1}^{M} e_m$. Since hierarchical classification to an extremely large set of labels will be very costly, this may not be a best choice when we are trying to use world knowledge base simply as features for other machine learning tasks.

The summary of the above discussion is shown in Table 2.

### 4.2 Explicit Heterogeneous Features

Instead of treating knowledge base as a source of generating flat features, it is also possible to consider the structural information provided by the knowledge base. Traditionally, the graph based algorithms only consider the knowledge base as homogeneous graph, and use homogeneous graph based features, e.g., least common ancestor, shortest paths, etc., to disambiguate the words [21] and further refine the features in the text documents [64]. Even though different kinds of relations can be considered and incorporated, there was no clear framework to formulate them explicitly as graph based features [64]. However, when working on the world knowledge graphs, the sparsity of entity relations and computational complexity of finding shortest paths over all possible entities makes shortest path less useful. In this sense, simpler approaches such as count based features are preferred. Moreover, traditional approaches focus more on the polysemous and synonymous properties of words, which means focusing more on certain types such as synonym and hyponymy-hypernymy relations. However, much more types of relations can be considered. For example, in Freebase, there are thousands of entity types and relations. A more effective way of using such types and relations should be considered. In this section, we review the recent development of using heterogeneous information networks to represent the knowledge graph, and using the meta-path to characterize the count-based features through certain relations between entities. Thus, here we call this approach the “explicit heterogeneous features.” It is not a purely graph based feature. However, developing such features should consider the structure of the graph, as well as a more abstractive level knowledge of the graph.

We first briefly introduce the key concepts related to heterogeneous information network (HIN) [211]. A more comprehensive survey on HIN has been given by [195].

**Definition 1.** A heterogeneous information network (HIN) is a graph $G = (V, E)$ with an entity type mapping $\phi: V \rightarrow A$ and a relation type mapping $\psi: E \rightarrow R$, where $V$ denotes the entity set and $E$ denotes the link set, $A$ denotes the entity type set and $R$ denotes the relation type set, and the number of entity types $|A| > 1$ or the number of relation types $|R| > 1$. The network schema for network $G$, denoted as $T_G = (A, R)$, is a graph with nodes as entity types from $A$ and edges as relation types from $R$.

The network schema provides a high-level description of a given heterogeneous information network. Another important concept, meta-path [212], is proposed to systematically define relations between entities at the schema level.

**Definition 2.** A meta-path $\mathcal{P}$ is a path defined on the graph of network schema $T_G = (A, R)$, and is denoted in the form of $A_1 \rightarrow_{R_1} A_2 \rightarrow_{R_2} \ldots \rightarrow_{R_L} A_{L+1}$, which defines a composite relation $R = R_1 \cdot R_2 \cdot \ldots \cdot R_L$ between types $A_1$ and $A_{L+1}$, where $\cdot$ denotes relation composition operator, and $L$ is the length of $\mathcal{P}$. For simplicity, we use type names connected by “$-$” to denote the meta-path when there exist no multiple relations between a pair of types: $\mathcal{P} = (A_1 - A_2 - \ldots - A_{L+1})$. We say a path $p = (e_1 - v_2 - \ldots - v_{L+1})$ between $v_1$ and $v_{L+1}$ in network $G$ follows the meta-path $\mathcal{P}$, if $\forall i, \phi(v_i) = A_i$ and each edge $e_i = (v_{i-1}, v_i)$ belongs to each relation type $R_i$ in $\mathcal{P}$. We call these paths as *path instances* of $\mathcal{P}$, denoted as $p \in \mathcal{P}$.

To construct the features based on meta-paths over HIN, the concept of commuting matrix is defined by Y. Sun et al. [212].

**Definition 3.** Commuting matrix. Given a network $G = (V, E)$ and its network schema $T_G$, a commuting matrix $M_{\mathcal{P}}$ for a meta-path $\mathcal{P} = (A_1 - A_2 - \ldots - A_{L+1})$ is defined as $M_{\mathcal{P}} = W_{A_1 A_2} W_{A_2 A_3} \ldots W_{A_L A_{L+1}}$, where $W_{A_i A_j}$ is the adjacency matrix between types $A_i$ and $A_j$. $M_{\mathcal{P}}(i,j)$ represents the number of path instances between objects $x_i$ and $y_j$, where $\phi(x_i) = A_i$ and $\phi(y_j) = A_{L+1}$, under meta-path $\mathcal{P}$.

For text data, such as a document, we can use semantic parsing and semantic filtering [224] to ground the text to world knowledge base. Then the document can be represented as an HIN. In addition to the named entities provided by the knowledge base, document and word are also regarded as types. Following [224], we use

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Definition 4. A meta-graph \( T_s = (A_s, R_s) \) is a sub-graph of network schema \( T_G = (A, R) \), where \( A_s \subseteq A \) and \( R_s \subseteq R \). We also denote the subgraph of original HIN as \( G_s = (V_s, E_s) \), where \( V_s \subseteq V \) and \( E_s \subseteq E \). The entities on the subgraph of HIN also follow the mapping \( \phi: \ V_s \rightarrow A_s \) and a relation type mapping \( \psi: \ E_s \rightarrow R_s \).

Different from meta-path, where a chain in the network schema is used, meta-graph uses a sub-graph to define the similarities between nodes. However, computing the similarities based on meta-graph is more difficult than meta-path based similarities.

4.3 Implicit Features

Analogous to explicit distributional representations, there have been many latent/implicit feature representation for natural language representation. For example, latent semantic indexing (LSI) [48] has been proposed to work on the explicit features derived by the context. Later on, probabilistic latent semantic analysis (PLSA) [86] interpret the LSI in a probabilistic way, and further latent Dirichlet allocation (LDA) [12], [24] uses a Bayesian model to formulate the generative process of textual documents as bag-of-words. The key point here is that we can use topic model train the representation of document-topic distributions and topic-word distributions over very large scale, domain independent corpus. There are many variants of topic models, such as distributed topic models [156], [215], [171], [121], [242], [243], etc. Then the topic model can be used to classify the domain dependent documents in the future.

Both PLSA and LDA regard the whole document as word’s context, which is more “global” consideration compared to other distributional representations [89], [23], [25], [59], [38]. However, for some natural language processing tasks, such as information extraction and tagging, local contexts are more useful. To remedy this constrain, neural network language models (NNLMs) [12], [153], [151], [222], [44], [144], [143], [119], [120], or the so called “distributed word embedding,” have attracted a lot of attention recently given their compact representation form and generalization property compared to the traditional lexical representations. Language models [138] have been widely used in information retrieval and natural language processing for many years. However, NNLMs share the advantage of continuous representation of words, and showed the capability of generalization to unseen contexts.

One can argue that in general topic models and NNLMs can incorporate world knowledge if the models are train on the world’s available resources. However, these resources are unstructured, compared to the highly structured knowledge bases/graphs. In general, when we consider the knowledge base/graph, we want to use the entities and relations, and their types, since they are very semantically useful. For example, in a knowledge graph, we can find a node “Microsoft,” and when we look at its first-hot neighbors, we can retrieve a lot of properties (attributes such as headquarter), related entities (such as its CEO), and similar entities (such as its acquired companies).

Thus, here, we focus on the implicit feature representation that is related to knowledge bases or knowledge graphs. Compared to explicit features, which are easy to interpret, implicit features are encoded in a way that can not be read by human. However, implicit features are usually more compact, and has good generalization.
performance. In \cite{157}, the authors summarized the representation of knowledge graph in the sense of statistical relation learning. The implicit/latent features of the entities and their relations are mainly used to predict the links of the entities or do inference over the knowledge bases or knowledge graphs themselves. Note that if we consider link prediction problem being handled by machine learning algorithms, all the approaches surveyed in \cite{157} are related, in a generalized way.

Instead of reviewing the knowledge base embedding methodologies, here we emphasize the representation learning algorithms that can generate features based on natural language texts and can be used for other applications. Such representation can be regarded as incorporating world knowledge since it is not domain dependent, and it can naturally characterize the sparsity and structural information of our knowledge based on the compositional semantics of words. Moreover, these generated features are more general to be used for machine learning algorithms to work on different tasks.

Knowledge based topic models. The most related work is to train a topic model over the knowledge base. Ontology Guided Hierarchical Latent Dirichlet Allocation (OHLDA) \cite{77} uses class labels in a hierarchy to retrieve documents from Wikipedia, and then trains the topic models on the domain defined by the class labels. In this case, the ontology information are used as queries to submit to search Wikipedia. On the other hand, Wikipedia, as a world knowledge base, severs as an additional source to provide cleaned and relevant documents for the queries. The topic models, in turn, can incorporate the ontology information to guide the topical hierarchy construction, and the topics trained on Wikipedia articles represent the general knowledge about the word distribution of the queries for the topics. The trained topic models can be used for a lot of applications such as text classification \cite{77} as traditional topic models do. More recently, a KB-LDA model \cite{154} was proposed to not only model the hierarchical relations between concepts as OHLDA did, but also model the relations like “Subject-Verb-Object (SVO)” to incorporate linked information. It is showed that KB-LDA can better capture richer semantic information in its topics, and show advantage in open IE tasks \cite{154}.

Knowledge enhanced word embeddings. Word embedding can also be enhanced by knowledge graphs. For example, joint embedding of words and knowledge graph entities can be performed \cite{228, 247, 234, 220} by first aligning text with knowledge graph (which may be imperfect), combining the objective functions of word embedding and knowledge graph embedding, and jointly optimize both together. Moreover, the similar approaches can be used to improve knowledge graph embedding \cite{228, 56}. These approaches are interesting since they are related to the new learning paradigms we will introduce later in Section 4. When using the knowledge graph to improve the word embedding, it is highly related to distant supervision and indirect supervision. For distant supervision, it means the supervision of entity embedding from knowledge graph is incorporated in an inexact way. The alignment of entities and unstructured texts is not perfect. Thus, different entity senses can bring noise in the word embedding results. For indirect supervision, it means the supervision of entity embedding is not directly used to supervise words. Instead, the relation embeddings are shared with word embedding and knowledge graph embedding objective functions, while the entities shown in the text are freely optimized based on composition of word embeddings.

Combined representations. One can also combine the explicit and implicit representations of knowledge graph to improve the results. For example, the ESA can be simply augmented by considering a bag-of-concept-embeddings representation \cite{201}. This approach is later refined by directly incorporate the knowledge graph embedding into ESA \cite{123}. It has been shown that this approach can be more robust than original ESA, especially when the number of concepts used in ESA is chosen to be small.

A summary of traditional text representation and knowledge enhanced models and applications are shown in Table 2.

5 Inference with World Knowledge

In this section, we review the inference techniques related to world knowledge. To incorporate a world knowledge base in either representation or learning, it is important as a first step to link the free texts to the knowledge base entities and relations (which are also called grounding). We call these tasks inference because when assigning labels to the entities or phrases we need to look at global information in a document or even in a corpus. This cannot be simply learned but to be inferred based on statistics and constraints. When doing inference, there are two most important issues need to be considered.

Ambiguity. Similar to the polysemy of words, the entities or relation expressions in free texts can express multiple meanings. For example, “Alex Smith” can refer to “Quarterback of the Kansas City Chiefs” or “Tight End of the Cincinnati Bengals.” It will be the context to determine the real reference when the entities are mentioned.

Variability. The other problem is that a given concept can be expressed in many ways, which is similar to the synonyms of words. For example, “cat” can be expressed by “feline,” “kitty,” and “moggy.”

When we consider grounding the free text to the world knowledge bases, we need to carefully consider the above two problems. In this section, we review two important problems related to inference with world knowledge, i.e., entity linking and semantic parsing.

5.1 Entity Linking

A comprehensive survey of different approaches of entity linking has been given by \cite{194}. Here we focus on the inference problem in entity linking to discuss the entity linking in two perspectives: local and global inference.

We first introduce the notations and definition of entity linking. We first define a mention (a concept or an entity) detected or needed to be highlighted in free text as $c$. The mentions in free text can be multi-word expression, referring to named entities (person, location, organization), objects, events, philosophy, mental states, rules, etc. Then we determine what is the target encyclopedic knowledge (or knowledge base), e.g., Wikipedia or Freebase. Then the task of entity linking is to define what mentions to point to the entities/concepts in the knowledge base. More specifically, we define the title of an entity or a concept in the knowledge base as $c_i \in C = \{c_1, \ldots, c_T\}$. Here we use $c_i$ to be consistent with Section 4 where the title can refer to either a concept or an entity. For example, in Example 3, we can detect “Martha Stewart” linked to Wikipedia, which is categorized as “person,” “founder,” “winner,” etc. When the mentions are linked to Wikipedia, the task is also called Wikification. There is also a subtle difference
between entity linking and Wikification. When mentions cannot be linked to Wikipedia, Wikification only returns “Null” as the link, while entity linking task also requires the program to cluster the relevant mentions to represent a unique concept and map the cluster to certain “Null” category. Compared with ESA introduced in Section 4 which links to many related concepts as a text representation, Wikification only links to the best candidate of concept. In this section, we do not discuss the difference between the tasks but only focus the inference problem involved.

### 5.1.1 Mention Identification

Before linking to the knowledge bases, the first step is mention detection or identification. This is a non-trivial task since the our natural language is arbitrary, and the boundary of mentions is also arbitrary. Thus, a lot of approaches have been proposed in different ways, e.g., using shallow parsing to find NP (noun phrase) chunks, leveraging the named taggers [182], developing specific mention extractors [63], [123], considering only n-grams [183], and a lot of other methods [189]. Existing systems include Illinois Wikifier [182], [39], which uses NP chunks and sub-strings as candidates, and uses prior anchor texts to determine other potential string; TAGME [62], which uses prior anchor texts to identify mentions; DBPedia Spotlight [142], which uses dictionary based chunking with string matching to DBPedia lexicon; AIDA [241], which uses name tagging system for mention detection; and RPI Wikifier [37], [28], [27], [92], which uses mention extraction sub-routine to detect mentions [123]. A comparison of different approaches is presented in [141].

### 5.1.2 Local Inference

Given a set of mentions being detected, the entity linking task mainly considers to link the mentions to the entities or concepts in the knowledge base (for Wikipedia, the titles). Thus, in general, if we have a mention $e_m$, and a set of entities or concepts $c_t \in C$, then local inference uses the mention itself and a set of local context features to determine which entity or concept it refers to. For example, we can use the joint probability $P(e_m, c_t)$, and conditional probabilities $P(c_t | e_m)$ and $P(e_m | c_t)$ to rank the candidates. The probability $P(c_t | e_m)$ characterizes the “commonness” of a mention referring to a title [139]. If we see a mention “Chicago” in the text, the probability of $P(\text{“title”}(Chicago)$ is used to rank the titles such as “Chicago” as a city, “Chicago (band),” "Chicago (2002 film)", etc. This is very related to the method mentioned in probabilistic conceptualization in Section 4. While PC uses $P(c_t | e_m)$ to generate a lot of concepts to describe the entity, here this probability is used to rank the best one for the mention. This method is usually used as an initial ranking since it is not robust across different domains. For example, in [183], [140], the results have shown that for different topics/genres and different domains (e.g., news and tweets), the performance diverse a lot. Some extension of initial count based ranking using graph based features were also proposed [78], [79].

To further improve the local inference results, more complicated contextual features have been proposed. In general, the features can be used to compute the similarity between the mention and the title $\phi(e_m, c_t)$, then the overall inference is to solve the following maximization problem:

$$f^*_{m \rightarrow t} = \arg \max_{f_{m \rightarrow t}} \sum_{e_m \in d} \phi(e_m, c_t). \quad (13)$$

### 5.2 Semantic Parsing

Entity linking only works on linking the entity mentions in free texts to the knowledge base. However, the relations between the entities are not considered. If we also want to map their relations in the text to the knowledge base, semantic parsing should be developed. Traditionally, semantic parsing refers to the task of mapping a piece of natural language text to a formal meaning representation [152]. In different context, semantic parsing can mean different tasks. For example, when there is no knowledge base to be grounded, semantic parsing can be in the form of CCG (Combinatory Categorial Grammar) parsing [4] or shallow semantic role labeling [102]. Formally, we convert a given sentence to the most appropriate logic forms. For example, for the two questions shown below, we can convert them to different logic forms:

**Example 4** [106]: natural language texts and their logic forms.
Example 4.1: What is the population of Seattle?
Example 4.2: How many people live in Seattle?
Example 4.3: $x$·population($Seattle$, $x$)
Example 4.4: count($\lambda x$. person$(x)$ ⊓ live$(x, Seattle)$)

Both Examples 4.1 and 4.2 refer to the same meaning. However, their logic forms could be different (Examples 4.3 and 4.4), depending on which semantic parsing algorithm we rely on, as well as the lexicon we can build to determine the paraphrasing similarities between predicates [106].

However, such semantic parsing does not provide the fine-grained entity types as knowledge bases do. When grounding to knowledge bases, semantic parsing is well known for question answering. Most previous semantic parsing algorithms or tools developed are for small scale problems but with complicated logical forms [108]. More recently, large scale semantic parsing grounding to world knowledge bases has been investigated, e.g., using Freebase [104], [23], [106], [14], [15], [237], [184] or ReVerb [54]. More formally, let $E$ be a set of entities and $R$ be a set of relations in the knowledge base. Then a knowledge graph $K$ consists of triplets in the form of $(e_1, r, e_2)$, where $e_1, e_2 \in E$ and $r \in R$. Here we take Lambda Dependency-Based Compositional Semantics [14] as an example to demonstrate the specific forms of grounding natural language texts to logic forms with types.

Example 5: Lambda Dependency-Based Compositional Semantics [14] (λ-DCS) [126].

The simplified LA-DCS [126] defines the logic language to query the knowledge base. The logical form in simple λ-DCS is either in the form of unary (a subset of $E$) or binary (a subset of $E \times E$). We briefly introduce the definition of basic λ-DCS logical forms and the corresponding denotations $x_K$ as below:

1. (U)ary base: an entity $e \in E$ is a unary logic form (e.g., Seattle, University) with $x_K = \{e\}$; (2) Binary base: a relation $r \in R$ is a binary logic form (e.g., Type, Education, PlaceOfBirth) with $x_K = \{(e_1, e_2) : (e_1, r, e_2) \in K\}$; (3) Join: $b.u$ is a unary logic form, denoting a join and projection, where $b$ is a binary and $e$ is a unary. $b.u_k = \{e \in E : \exists e_1, e_2 \in b.K \wedge e \in u.K\}$ (e.g., Type.University, Education.BarackObama, PlaceOfBirth.BarackObama); (4) Intersection: $u_1 \cap u_2$ are both unaries) denotes set intersection: $u_1 \cap u_2.K = u_1.K \cap u_2.K$ (e.g., Type.University \ Education.BarackObama). Then overall, for the text below, we can parse the logic forms Most grounding based semantic parsing approaches are applied to answer questions with the world knowledge bases [14], [15], [237], [184]. For example:

Example 5.1: Who is the president of United States.
Example 5.2: Type, People ⊓ PresidentOfCountry.USA

Here the two relations PresidentOfCountry and Country.USA join together to have PresidentOfCountry.USA. Moreover, the word “Who” is lexically mapped to Type, People where Type is the predicate of the “is a” relationship of entity and its concept. Thus, both the relationship between entities and the type information (or higher level concepts) of entities are naturally incorporated into the logic form by grounding to the knowledge graph.

Similar to entity linking, semantic parsing also has different approaches, i.e., local inference based and global inference based approaches.

5.2.1 Local Inference

Most of the existing semantic parsing approaches are local inference based, since most of them are applied to question answering, which only targets to parse very simple sentences. There are multiple ways of finding a proper semantic parsing results for natural language texts. First, local inference involves mapping the entity mentions and relation expressions in natural language texts to the entities and relations (or predicates) in the knowledge base. The entity identification is similar to the mention identification and linking problems in entity linking. However, for knowledge bases like Freebase, Yago, there are less texts to describe the entities as Wikipedia has. Therefore, the entity identification and linking problems are more difficult. For the relation expressions, paraphrasing are usually used to identify the relations [54].

To identify the correct logic forms from text, the typical way is to determine a logic form based on some cost function:

$$z^* = \arg\min_{z \in K} \psi(z, s, w^*)$$

(15)

where $z$ is a possible logic form that can be mapped to a sub-graph of the knowledge graph, $s$ is the give natural language sentence (or utterance), and $w$ is the parameter in the parameter space $\Theta$ to minimize the cost function:

$$w^* = \arg\min_{z \in K} \sum_{z \in K} \psi(y, z, s, w^*)$$

(16)

where $y$ is possible supervision for the logic forms. Different from entity linking, there is no naive unsupervised similarity to evaluate the candidate logic form and the sentence. Therefore, to find a proper logic form for the give text, different strategies has been investigated.

The most intuitive way is to use supervised learning to learn the parameters for the cost function, when the correct logic forms are annotated for the sentence [231], [107], [240]. However, such supervision heavily requires laboring cost since the grounded logic forms in the knowledge graph can be exponentially many for a human to judge. Thus, a lot of studies have been done to reduce or replace the annotation requirement for such problems.

Instead of direct supervision of logic forms, indirect supervision from the answer can be used to train the parameters [43], [128], where the logic forms are treated as hidden variables in the cost function. Then to optimize the cost function, latent variables should be integrated out when working with parameters. There could be exponentially increasing logic forms candidates extracted from the sentence. Thus, heuristic pruning or beam search should be performed [14], [15]. Recently, staged parsing has been investigated [239], which reports more efficient and effective results. Other learning strategies such as combining imitation learning and agenda based parsing can also be used to improve the efficiency and effectiveness of semantic parsing, which also significantly reduce the search space [16].

Distant supervision (which will be introduced in Section 6) can also be used to supervise semantic parsing. Here distant supervision refers to the approach using the knowledge base to find entity relation triples $(e_1, r, e_2)$ in Web scale documents, and then use high frequent triples as “gold” to supervise the lexical mapping from knowledge graph entities and predicates and the texts where triples exist [104], [23], [184]. For example, Google released a data set using Freebase to automatically annotate the large Web document collection ClueWeb [69]. In this way, we can obtain a lot of cheap annotation, but the annotation is very noisy and incomplete when training the model. Some neural network based learning models has been proposed to replace some components or the final learning algorithm of grounded semantic parsing [239].
Some systems or approaches also consider an “unsupervised” way to train the parameters [71], [54], [170]. To our best knowledge, [71] was the first grounded unsupervised semantic parsing, which adopted a “self-training” strategy. It uses some initial seeds which is evaluated by a translation based score (which also relies on a lexicon related to the knowledge base predicates), and further bootstraps the learning procedure to update the system parameters. Fader et al. [54] use a paraphrasing to evaluate similarities between questions and the possible grounded results, where the grounding should be restricted to simple forms, such as unary and binary relations. Poon [170] uses dependency tree as the backbones of candidate logic forms, and tries to annotate the tree with knowledge base entities and relations (predicates). All the above approaches assume that given a set of questions, the logic forms can be induced by maximizing the likelihood of certain constrained logic forms. Thus, they are still limited to either small scale knowledge graphs or simple logic forms.

5.2.2 Global Inference

When semantic parsing are applied to a document, global inference can also be performed. This is very similar to the unsupervised approaches introduced in local inference. However, local inference leverages a set of question to determine the parameters, but not uses the relationships among entities and relations extracted from the questions to disambiguate each other. As entity linking, the logic forms can be filtered when we know a lot of logic forms from other sentences in a document or a corpus.

Here we show a semantic filtering strategy proposed in [224], [227]. For example, motivated by the approaches of “generative-discriminative” conceptualization [204], we can represent each entity with a feature vector $c_i = (e_1, \ldots, e_T)^T$ of entity types and use standard K-means to cluster the entities in a document. Suppose in one cluster we have a set of entities $E = \{e_1, \ldots, e_{N_E}\}$. Then we can use the probabilistic conceptualization proposed in [204] to find the most likely entity types for the entities in the cluster. We make the naive Bayes assumption and use $P(c_k|E) \propto P(c_k) \prod_{i=1}^{N_E} P(e_i|c_k)$ as the score of entity type $c_k$. Here, $P(e_i|c_k) = \frac{n(e_i, c_k)}{n(c_k)}$, where $n(e_i, c_k)$ is the co-occurrence count of entity type $c_k$ and entity $e_i$ in the knowledge base, and $n(c_k)$ is the overall number of entities with type $c_k$ in the knowledge base. Besides, $P(c_k) = \frac{n(c_k)}{\sum_t n(c_t)}$. The probability $P(c_k|E)$ is used to rank the entity types and the largest ones are selected. In this case, for each cluster of entities, only the common types are retained, and concepts with conflicts are filtered out. It is also possible to apply the global inference approaches used in entity linking shown in Section 5.1.3.

6 LEARNING: RELATED LEARNING PARADIGMS

In this section, we introduce the new learning paradigms that are enabled by world knowledge. We categorize the paradigms into ways related to world knowledge features and ways related to world knowledge supervision. For the paradigms related to world knowledge features, the representations introduced in Section 4 are incorporated into the learning algorithms. For the paradigms related to world knowledge supervision, the inferences are mainly used to find the categorized entities and relations that are inferred by the approaches introduced in Section 5.

6.1 Paradigms Enabled by World Knowledge Features

We first review the new learning paradigms that are enabled by the features generated by world knowledge.

6.1.1 Self-taught Learning

The first learning setting enabled by universal world knowledge is called “self-taught learning” [79], [116]. Self-taught learning uses a large amount of unlabeled data crawled from the Web to train an unsupervised representation learning. The a supervised classifier can be applied to the features trained based on the unlabeled data. It can be regarded as using a lot of data to find a better universal data distribution $P(\mathcal{X})$, which may not be strongly related to $P(\mathcal{Y}|\mathcal{X})$. Then the discriminative classifier is fine-tuned for $P(\mathcal{Y}|\mathcal{X}')$. Essentially this is a semi-supervised learning setting, where large amount of unlabeled data is used to help supervised learning tasks with less labels. Particularly, self-taught learning decouples the representation learning part using unlabeled data and classifier training using labeled data, and it does not require that the labeled data and unlabeled data are sampled from the same distribution. ESA applied to text classification also shares this idees [63], [66], [67], [68], where the features for a piece of short text can be generated from Wikipedia, and then the classification is performed over the knowledge based features.

The deep learning community also found unsupervised learning using restricted Boltzmann machines (RBM) [82], auto-encoders [13], [183], [111], and their variants (see [11] for more comprehensive survey) are helpful for training very deep neural network architectures. They use unsupervised learning as pre-training trained on a lot of unlabeled data, and then introduce a fine-tuning process to refine the model with very deep architectures. In natural language processing, it has also been shown that using the Brown clusters of words [125] or word embeddings [222], [44] learned from large scale of unlabeled data, and training another classifier (either traditional [125] or deep learning [222], [44]) for specific tasks can help improve the task specific performance. Thus, the representations introduced in Section 4.3 can be regarded as a pre-training or a self-taught learning step for many NLP applications.

6.1.2 Source-free Transfer Learning

Originally, as shown in Section 2.1.3, transfer learning refers to the setting of training with a source domain containing a lot of labeled data. However, there are two major challenges. One is the availability of source domain data, and the other is how to automatically select a source domain for transfer learning. Source-free transfer learning tries to solve this problem with world knowledge instead of domain knowledge [233], [136].

One way to use world knowledge in source-free transfer learning is to use the Wikipedia categories [233]. Wikipedia categories provide large amount of categorized text data. Then a large set of classifiers can be built based on the categorized data. For a new coming target domain (in text, other format of data needs do consider heterogeneous transfer learning [163]), the label similarities can be evaluated between source domains and target domain to automatically find a source domain to transfer. The other way of using world knowledge is that when an initial classifier can be built for a target domain, then a meta-learning algorithm can be designed to automatically use the key features (keywords) in the classifier to query more unlabeled data from cleaned Wikipedia corpus [136]. Then traditional semi-supervised
learning algorithms, such as graph regularization [10], can be applied to iteratively train a new classifier based on the labeled and incrementally increasing unlabeled data. OHILDA [77] can also be regarded as in the source-free transfer learning framework. It uses the topical label keywords as search query to search Wikipedia or Google, and then uses the retrieved documents to train a hierarchical topic model. The topic model can be used as the classifier to classify the documents to the given ontology of labels.

### 6.1.3 Dataless Classification with Semantic Supervision

Dataless classification performs a nearest neighbor search of labels for a document in an appropriately selected semantic space [32], [200]. Let \( \phi(d) \) be the representation of document \( d \) in a semantic space (to be defined later) and let \( \{ \phi(l^{(1)}), \ldots, \phi(l^{(N)})) \) be the representations of the \( N \) labels in the same space. Then we can evaluate similarity using an appropriate metric \( f(\phi(d), \phi(l^{(i)})) \), (e.g., cosine similarity between two sparse vectors) and select label(s) that maximizes the similarity:

\[
 l^* = \arg \max_l f(\phi(d), \phi(l^{(i)})).
\]

Essentially this learning paradigm should be called “supervisionless” or semantic supervision with label names.

The core problem in dataless classification is to find a semantic space that enables good representations of documents and labels. Traditional text classification makes use of a bag-of-words (BOW) representation of documents. However, when comparing labels and documents in dataless classification, the brevity of labels makes this simple minded representation and the resulting similarity measure unreliable. For example, a document talking about “sports” does not necessarily contain the word “sports.” Consequently, other more expressive distributional representations have been applied, e.g., Brown cluster [20], [125], neural network embedding [44], [222], [146], [145], topic modeling [17], ESA [68], and their combinations [201]. It has been shown that ESA gives the best and most robust results for dataless classification for English documents [200]. This idea can be generalized to hundreds of languages with Wikipedia with language links to English [202] where both English labels and documents in other languages can be mapped to the same semantic space using cross-lingual ESA [172], [206]. Then it can be further extended to classify any languages in the world with a dictionary mapping from the target language and a pivot language that can be linked to English [198].

Zero-shot learning [161], [197], [52], [188] were also introduced in the computer vision community and are now recognized by the natural language processing community [238], [112], [97]. Zero-shot learning means that there is no labeled data in the new coming target domain. However, it requires some source data to train the model. The target classifier is bridged based on the label similarities between target labels and the source labels. In this sense, zero-shot learning is very similar to the first mechanism of source-free transfer learning. Another learning mechanism with similar name is one-shot learning [122], [109]. However, one-shot learning requires one example for training, while in zero-shot learning, the test data is different from the training data (e.g., a new label space).

A comparison of different related learning paradigms is shown in Table 1.

### 6.2 Paradigms Enabled by World Knowledge Supervision

World knowledge can not only be used as features, but also used as supervision. In this section, we review two learning paradigms that are enabled by world knowledge supervision, i.e., distant supervision and indirect supervision.

#### 6.2.1 Distant Supervision

The idea of using minimal supervision not aligned to the entity mentions in texts (or weak supervision from domain knowledge bases) [22] has been explored previously. Distant supervision extends this idea to use the knowledge of entities and their relationships from world knowledge bases, e.g., Freebase, as supervision for the task of entity and relation extraction [149]. Since the entities and their relations in the world knowledge bases are not aligned with the mentions in the texts, the first step of distant supervision is to find the entities in the texts. Entity linking can be considered, but cheaper ways such as simple string matching or named entity tagger [149] can be employed since for the training step, only the most confident examples are needed. Then the sentences with matched entities and their relations can be used as labeled examples to train a relation classifier. Since there is no direct annotation about the entities and relations in the sentence but only the automatically mapped annotation from knowledge base is used, this approach is called distant supervision.

During the whole process, one can argue that no human annotation...
(directly related to the task) is needed for the (open-domain) relation extraction problem.

The automatically aligned entities are not accurate enough for relation extraction. If we assume that for multiple sentences with the same pair of entities extracted, only part of them support the decision of relation between the two entities, then the problem can be formulated as a multi-instance learning problem \[ \text{representation learning with knowledge graph studies} \]. This approach claims they can unify the open information extraction (openIE) and relation classification. Moreover, it has been shown that the joint representation of words and knowledge graph can also help improve the distant supervision for relation classification \[ \text{representation learning with knowledge graph studies} \]. More recently, neural network learning based algorithm has been tested on distant supervision setting \[ \text{representation learning with knowledge graph studies} \].

Another extension of different learning settings have also been proposed. For example, the combination of semi-supervised learning \[ \text{representation learning with knowledge graph studies} \] and background knowledge \[ \text{representation learning with knowledge graph studies} \] can also help distant supervision’s performance \[ \text{representation learning with knowledge graph studies} \]. Other extensions of different learning settings have also been proposed. For example, the combination of semi-supervised learning \[ \text{representation learning with knowledge graph studies} \] and background knowledge \[ \text{representation learning with knowledge graph studies} \] can also help distant supervision’s performance \[ \text{representation learning with knowledge graph studies} \].

6.2.2 Indirect Supervision

Besides the distant supervision, it is also possible to use world knowledge as indirect supervision. The idea of indirect supervision is a general learning setting \[ \text{representation learning with knowledge graph studies} \]. For example, \[ \text{representation learning with knowledge graph studies} \] uses the cheaper annotation as indirect supervision for more complicated learning problems. The document-level topic annotation is cheaper than the information extraction (named entities, events, etc.) annotation. Then the document-level binary or multi-class classification can help refine the parameter estimation problem of structural output learning. \[ \text{representation learning with knowledge graph studies} \] uses answers to supervise the semantic parsing problem in question answering. The target of semantic parsing is to output the formal logic forms. However, it is too costly to label a lot of logic forms for machines to learn. Thus, using indirect supervision is a natural way to reduce the labeling work. \[ \text{representation learning with knowledge graph studies} \] further introduced a new learning setting for privacy preserved machine learning based on indirect supervision. In the context of natural language processing, as an example, they use labeling the number of particular POS tags (such as noun) instead of labeling individual tags as indirect supervision. In summary, different from transfer learning, indirect supervision can be more different when comparing the available annotation and the target of machine learning. It is not a general learning setting but should be introduced case by case.

In the research related world knowledge, Song et al. \[ \text{representation learning with knowledge graph studies} \] considered using fully unsupervised method to generate constraints of words using an external general-purpose knowledge base, WordNet, for document clustering. This can be regarded as an initial attempt to use general knowledge as indirect supervision to help clustering. However, the knowledge from WordNet is mostly linguistically related. It lacks of the information about named entities and their types. Moreover, their approach is still a simple application of constrained co-clustering, where it misses the rich structural information in the knowledge base. To extend this idea, indirect supervision using world knowledge bases such as Freebase and Yago has been proposed and applied to document clustering problem \[ \text{representation learning with knowledge graph studies} \]. It uses semantic parsing to ground the entities and their relations to the world knowledge base, and builds a heterogeneous information network to formulate the structured data for the documents. Then the information about the entity categories, e.g., celebrities, IT companies, politicians, can be propagated to group the documents with topics.

7 Conclusion and Future Directions

In this paper, we have formulated the problems of machine learning with world knowledge, and reviewed the related methodologies and algorithms involved in the respective problems. We first compare learning with world knowledge to learning with domain knowledge, and then we categorize the problems into three folds, i.e., representation, inference, and learning. For representation, we introduced different kinds of representation with world knowledge, which are explicit homogeneous features, explicit heterogeneous features, and implicit features. For inference, we introduced entity linking and semantic parsing to align free text to knowledge bases. For learning, we introduced several new learning paradigms that are enabled by world knowledge. There are still a lot of open problems that have no answer at the current stage, which we think are very important, including:

- **Commonsense acquisition and learning with commonsense knowledge.** Commonsense knowledge has been a key problem since the artificial intelligence has been introduced. World knowledge can cover partial commonsense knowledge but there is still a lot of such knowledge missing. Commonsense knowledge is very important when performing inference about natural language as well as many other applications \[ \text{representation learning with knowledge graph studies} \]. Thus, how to acquire and use commonsense knowledge are still open problems.

- **Representation or representation learning.** Currently there has been a lot of comparison between traditional distributional representation and advanced representation learning. For some of the tasks, such as dataless classification, traditional distributional representation, i.e., ESA, still out performs learning based representations. It would be very important to find out ways to further improve the corresponding representation using the more advances learning techniques.

- **Joint inference and learning.** The problems inference and learning introduced in this paper are mostly separated. Joint inference and learning may help each other to boost the performance \[ \text{representation learning with knowledge graph studies} \]. We regard this as a natural idea of a general machine learning with world knowledge framework. The challenge is that the joint inference and learning will be very costly both in terms of computational efficiency and effectiveness.

- **Cross-lingual and cross-culture world knowledge.** Different communities of people with different background may have different kind of common knowledge \[ \text{representation learning with knowledge graph studies} \]. The information collected from the Web about the world knowledge can be biased and different for different languages and cultures. It will be interesting to compare different languages and cultures, and find ways to correct the bias for them.
• Connecting world knowledge to cognitive science.

There are evidence about human performing transfer learning \textsuperscript{[19]}, semi-supervised learning \textsuperscript{[29]}, and active learning \textsuperscript{[29]}. There is also analysis that connecting one-shot learning \textsuperscript{[109]} and Bayesian learning \textsuperscript{[217]} to human learning. It would be interesting to see how humans leverage their world knowledge when learning new problems or tasks.

The above open problems are still not discovered, and we regard them as equally important. Moreover, as a new problem of machine learning, it would be interesting and important to have a general framework to set up machine learning algorithms when world knowledge is available.

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REFERENCES

[1] S. Ahn, H. Choi, T. Parnamaa, and Y. Bengio, “A neural knowledge language model,” CoRR, vol. abs/1608.00318, 2016.
[2] I. Anastácio, B. Martins, and P. Calado, “Supervised learning for linking named entities to knowledge base entries,” in TAC, 2011.
[3] G. Angeli, J. Tishbiriari, J. Wu, and C. D. Manning, “Combining distant and partial supervision for relation extraction,” in EEMNL, 2014, pp. 1556–1567.
[4] Y. Artzi, N. FritzGerald, and L. S. Zettlemoyer, “Semantic parsing with combinatory categorial grammars,” in ACL Tutorial Abstracts, 2013, p. 2.
[5] S. Auer, C. Bizer, G. Kobilarov, J. Lehmann, R. Cyganiak, and Z. Ives, DBpedia: A nucleus for a web of open data. Springer, 2007.
[6] Y. Aytar and A. Zisserman, “Tabula rasa: Model transfer for object category detection,” in ICCV, 2011, pp. 2252–2259.
[7] M. Banko, M. J. Cafarella, S. Soderland, M. Broadhead, and O. Etzioni, “Open information extraction from the web,” in IJCAI, 2007, pp. 2670–2676.
[8] S. Basu, M. Bilenko, and R. J. Mooney, “A probabilistic framework for semi-supervised clustering,” in KDD, 2004, pp. 59–68.
[9] S. Basu, I. Davidson, and K. Wagstaff, Constrained Clustering: Advances in Algorithms, Theory, and Applications. Chapman & Hall/CRC, 2008.
[10] M. Belkin, P. Niyogi, and V. Sindhwani, “Manifold regularization: A geometric framework for learning from labeled and unlabeled examples,” Journal of Machine Learning Research, vol. 7, pp. 2399–2434, 2006.
[11] Y. Bengio, “Learning deep architectures for AI,” Foundations and Trends in Machine Learning, vol. 2, no. 1, pp. 1–127, 2009.
[12] Y. Bengio, R. Ducharme, P. Vincent, and C. Janvin, “A neural probabilistic language model,” Journal of Machine Learning Research, vol. 3, pp. 1137–1155, 2003.
[13] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, “Greedy layer-wise training of deep networks,” in NIPS, 2006, pp. 153–160.
[14] J. Berant, A. Chou, R. Frostig, and P. Liang, “Semantic parsing on freebase from question-answer pairs,” in EMNLP, 2013, pp. 1533–1544.
[15] J. Berant and P. Liang, “Semantic parsing via paraphrasing,” in ACL, 2014, pp. 1415–1425.
[16] “Imitation learning of agenda-based semantic parsers,” TACL, vol. 3, pp. 545–558, 2015.
[17] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent Dirichlet allocation,” Journal of Machine Learning Research, vol. 3, pp. 993–1022, 2003.
[18] K. D. Bollacker, C. Evans, P. Paritosh, T. Sturge, and J. Taylor, “Freebase: a collaboratively created graph database for structuring human knowledge,” in SIGMOD, 2008, pp. 1247–1250.
[19] J. Bragg, W. Ma, and D. S. Weld, “Crowdsourcing multi-label classification for taxonomy creation,” in AAAI Conference on Human Computation and Crowdsourcing (HCOMP), 2013.
[20] P. F. Brown, V. J. D. Pietra, P. V. de Souza, J. C. Lai, and R. L. Mercer, “Class-based n-gram models of natural language,” Computational Linguistics, vol. 18, no. 4, pp. 467–479, 1992.
[21] A. Budanitsky and G. Hirst, “Evaluating wordnet-based measures of lexical semantic relatedness,” Computational Linguistics, vol. 32, no. 1, pp. 13–47, 2006.
[22] R. C. Bunescu and R. J. Mooney, “Learning to extract relations from the web using minimal supervision,” in ACL, 2007.
[23] Q. Cai and A. Yates, “Large-scale semantic parsing via schema matching and lexicon extension,” in ACL, 2013, pp. 423–433.
[24] E. Cambria, Y. Song, H. Wang, and A. Hinnun, “Isanette: A common and common sense knowledge base for opinion mining,” in Data Mining Workshops (ICDMW), 2011, pp. 315–322.
[25] A. Carlson, J. Betteridge, B. K isi el, B. Settles, E. R. H. Jr., and T. M. Mitchell, “Toward an architecture for never-ending language learning,” in AAAI, 2010, pp. 1306–1313.
[26] T. Cassidy, Z. Chen, J. Artiles, H. J. Hi, H. Deng, L. Ratinov, J. Han, D. Roth, and J. Zheng, “CUNY-UYUC-SRI-TAC-KBP2011 entity linking system description,” in TAC, 2011.
[27] T. Cassidy, H. J., H. Deng, J. Zheng, and J. Han, “Analysis and refinement of cross-lingual entity linking,” in Information Access Evaluation. Multilinguality, Multimodality, and Visual Analytics - Third International Conference of the CLEF Initiative, 2012, pp. 1–12.
[28] T. Cassidy, H. J., L. Ratinov, A. Zubiaga, and H. Huang, “Analysis and enhancement of wikification for microblogs with context expansion,” in COLING, 2012, pp. 441–456.
[29] R. M. Castro, C. Kalish, R. D. Nowak, R. Qian, T. T. Rogers, and X. Zhu, “Human active learning,” in NIPS, 2008, pp. 241–248.
[30] D. Cucarelli, C. Lucchese, S. Orlando, R. Perezgo, and S. Trani, “Learning relatedness measures for entity linking,” in CIKM, 2013, pp. 139–148.
[31] K. Chang, R. Sandani, and D. Roth, “A constrained latent variable model for coreference resolution,” in EMNLP, 2013, pp. 601–612.
[32] M.-W. Chang, L. Ratinov, D. Roth, and V. Srikumar, “Importance of semantic representation: Dataless classification,” in AAAI, 2008, pp. 830–835.
[33] M.-W. Chang, L.-A. Ratinov, and D. Roth, “Structured learning with constrained conditional models,” Machine Learning, vol. 88, no. 3, pp. 399–431, 2012.
[34] M. Chang, V. Srikumar, D. Goldwasser, and D. Roth, “Structured output learning with indirect supervision,” in ICMIL, 2010, pp. 199–206.
[35] O. Chapelle, B. Schölkopf, and A. Zien, Eds., Semi-Supervised Learning. MIT Press, 2006.
[36] J. Chen, K. Li, J. Zhu, and W. Chen, “Warplda: a cache efficient O(1) algorithm for latent dirichlet allocation,” PVLDB, vol. 9, no. 10, pp. 744–755, 2016.
[37] Z. Chen and H. Ji, “Collaborative ranking: A case study on entity linking,” in EMNLP, 2011, pp. 771–781.
[38] Z. Chen, S. Tamang, A. Lee, X. Li, W. Lin, M. G. Snover, J. Artiles, M. Passantino, and H. Ji, “CUNY-BLENDER TAC-KBP2010 entity linking and slot filling system description,” in TAC, 2010.
[39] X. Cheng and D. Roth, “Relational inference for wikification,” in EMNLP, 2013, pp. 1787–1796.
[40] L. B. Chilton, G. Little, D. Edge, D. S. Weld, and J. A. Landay, “Cascade: Crowdsourcing taxonomy creation,” in SIGCHI Conference on Human Factors in Computing Systems. ACM, 2013, pp. 1999–2008.
[41] P. Cimiano, S. Staab, and J. Tane, “Automatic acquisition of taxonomies and common sense knowledge base for opinion mining,” in Data Mining Workshops (ICDMW), 2011, pp. 315–322.
[42] M. Cisse, “Efficient extreme classification,” Theses, Université Pierre et Marie Curie - Paris VI, Jul. 2014. [Online]. Available: https://tel.archives-ouvertes.fr/tel-01142046
M. Niepert and P. M. Domingos, “Learning and inference in tractable probabilistic knowledge bases,” in *UAI*, 2015, pp. 632–641.

K. Nigam, A. McCallum, S. Thrun, and T. M. Mitchell, “Text classification from labeled and unlabeled documents using EM,” *Machine Learning*, vol. 39, no. 2/3, pp. 103–134, 2000.

NIST, “The ACE evaluation plan,” 2005.

M. Palatucci, D. Pomerleau, G. E. Hinton, and T. M. Mitchell, “Zero-shot learning with semantic output codes,” in *NIPS*, 2009, pp. 1410–1418.

M. Palmer, D. Gildea, and N. Xue, *Semantic Role Labeling*, ser. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, 2010.

S. J. Pan and Q. Yang, “A survey on transfer learning,” *IEEE TKDE*, vol. 22, no. 10, pp. 1345–1359, 2010.

J. Park, S. Hwang, and H. Wang, “Fine-grained semantic conceptualization of frameNet,” in *AAAI*, 2016, pp. 2638–2644.

H. Peng, D. Khashabi, and D. Roth, “Solving hard coreference problems,” in *NAACL-HLT*, 2015, pp. 809–819.

H. Peng, Y. Song, and D. Roth, “Event detection and coreference with minimal supervision,” in *EMNLP*, 2016, pp. 392–402.

M. Pershina, B. Min, W. Xu, and R. Grishman, “Infusion of labeled data into distant supervision for relation extraction,” in *ACL*, 2014, pp. 732–738.

G. Pink, A. Naoum, W. Radford, W. Cannings, J. Nothman, D. Tse, and J. R. Curran, “SYDNEY CMCRc at TAC 2013,” in *TAC*, 2013.

S. P. Ponzetto and M. Strube, “Deriving a large-scale taxonomy from wikipedia,” in *AAAI*, 2007, pp. 1440–1445.

H. Poornima and D. Roth, “Grounded unsupervised semantic parsing,” in *ACL*, 2013, pp. 933–943.

I. Porteous, D. Newman, A. T. Ihler, A. Asuncion, P. Smyth, and M. Welling, “Fast collapsed gibbs sampling for latent dirichlet allocation,” in *KDD*, 2008, pp. 569–577.

M. Potthast, B. Stein, and M. Anderka, “A wikipedia-based multilingual retrieval model,” in *ECIR*, 2008, pp. 522–530.

V. Punyakanok, D. Roth, and W. Yih, “The importance of syntactic parsing and inference in semantic role labeling,” *Computational Linguistics*, vol. 34, no. 2, pp. 257–287, 2008.

H. Qi, T. Wu, M. W. Lee, and S.-C. Zhu, “A restricted visual turing test for deep scene and event understanding,” 2015.

L. Rabiner, “A tutorial on hidden markov models and selected applications in speech recognition,” *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

A. Rahagnathan, R. Frostig, J. Duch, and P. Liang, “Estimation from indirect supervision with linear moments,” in *ICML*, 2016, pp. 2568–2577.

A. Rahagnathan and V. Ng, “Coreference resolution with world knowledge,” in *ACL-HLT*, 2011, pp. 814–824.

A. Rahagnathan, A. Nag, and V. Ng, “Coreference resolution with named entities,” in *EMNLP-CoNLL*, 2012, pp. 777–789.

R. Raina, A. Battle, H. Lee, B. Packer, and A. Y. Ng, “Self-taught learning: transfer learning from unlabeled data,” in *ICML*, 2007, pp. 799–806.

R. Raina, A. Y. Ng, and D. Koller, “Constructive informative priors using transfer learning,” in *ICML*, 2006, pp. 713–720.

M. Ranzato, C. S. Poultney, S. Chopra, and Y. LeCun, “Efficient learning of sparse representations with an energy-based model,” in *NIPS*, 2006, pp. 1137–1144.

L. Ratnasingham and D. Roth, “Design challenges and misconceptions in named entity recognition,” in *CoNLL*, 2009, pp. 147–155.

L. Ratnasingham, D. Roth, D. Downey, and M. Anderson, “Local and global algorithms for disambiguation to wikipedia,” in *ACL*, 2011, pp. 1375–1384.

S. Reddy, M. Lapata, and M. Steedman, “Large-scale semantic parsing without question-answer pairs,” *TACL*, vol. 2, pp. 377–392, 2014.

S. Riedel, L. Yao, and A. McCallum, “Modeling relations and their mentions without labeled text,” in *ECML PKDD*, 2010, pp. 148–163.

S. Riedel, L. Yao, A. McCallum, and B. M. Marlin, “Relation extraction with matrix factorization and universal schemas,” in *HLT-NAACL*, 2013, pp. 74–84.

T. Rocktaschel, S. Singh, and S. Riedel, “Inverting logical background knowledge into embeddings for relation extraction,” in *NAACL-HLT*, 2015, pp. 1119–1129.

J. Romero-Paredes and P. H. S. Torr, “An embarrassingly simple approach to zero-shot learning,” in *ICML*, 2015, pp. 2152–2161.

D. Roth, H. Ji, M. Chang, and T. Cassidy, “Wikification and beyond: The challenges of entity and concept grounding,” in *ACL, Tutorial Abstracts*, 2014, p. 7.
[219] L. Torrey and J. Shavlik, “Transfer learning,” in Handbook of Research on Machine Learning Applications, E. Soria, J. Martin, R. Magdalena, M. Martinez, and A. Serrano, Eds. IGI Global, 2009.

[220] K. Toutanova, D. Chen, P. Pantel, H. Poon, P. Choudhury, and M. Ga- mon, “Representing text for joint embedding of text and knowledge bases,” in EMNLP, 2015, pp. 1499–1509.

[221] K. Tu, M. Meng, M. W. Lee, T. E. Choe, and S. C. Zhu, “Joint video and text parsing for understanding events and answering queries,” IEEE MultiMedia, vol. 21, no. 2, pp. 42–70, 2014.

[222] J. Turian, L.-A. Ratinov, and Y. Bengio, “Word representations: A simple and general method for semi-supervised learning,” in ACL, 2010, pp. 384–394.

[223] M. J. Wainwright and M. I. Jordan, “Graphical models, exponential families, and variational inference,” Foundations and Trends in Machine Learning, vol. 1, no. 1-2, pp. 1–305, 2008.

[224] C. Wang, Y. Song, A. El-Kishky, D. Roth, M. Zhang, and J. Han, “Incorporating world knowledge to document clustering via heterogeneous information networks,” in KDD, 2015, pp. 1215–1224.

[225] C. Wang, Y. Song, H. Li, M. Zhang, and J. Han, “Knowsim: A document similarity measure on structured heterogeneous information networks,” in ICDM, 2015, pp. 1015–1020.

[226] ——, “Text classification with heterogeneous information network kernels,” in AAAI, 2016, pp. 2130–2136.

[227] C. Wang, Y. Song, D. Roth, M. Zhang, and J. Han, “World knowledge as indirect supervision for document clustering,” TKDD, 2016. [Online]. Available: [http://arxiv.org/abs/1608.00104](http://arxiv.org/abs/1608.00104)

[228] Z. Wang, J. Zhang, J. Feng, and Z. Chen, “Knowledge graph and text jointly embedding,” in EMNLP, 2014, pp. 1591–1601.

[229] Z. Wang, F. Wang, J.-R. Wen, and Z. Li, “Concept-based short text classification and ranking,” in CIKM, 2014, pp. 1069–1078.

[230] Z. Wang, K. Zhao, H. Wang, X. Meng, and J. Wen, “Query understanding through knowledge-based conceptualization,” in IJCAI, 2015, pp. 3264–3270.

[231] Y. W. Wong and R. J. Mooney, “Learning synchronous grammars for semantic parsing with lambda calculus,” in ACL, 2007.

[232] W. Wu, H. Li, H. Wang, and K. Q. Zhu, “Probase: A probabilistic taxonomy for text understanding,” in SIGMOD, 2012, pp. 481–492.

[233] E. W. Xiang, S. J. Pan, W. Pan, J. Su, and Q. Yang, “Source-selection-free transfer learning,” in IJCAI, 2011, pp. 2355–2360.

[234] C. Xu, Y. Bai, J. Bian, B. Gao, G. Wang, X. Liu, and T.-Y. Liu, “Rc-net: A general framework for incorporating knowledge into word representations,” in CIKM, 2014, pp. 1219–1228.

[235] W. Xu, R. Hoffmann, L. Zhao, and R. Grishman, “Filling knowledge base gaps for distant supervision of relation extraction,” in ACL, 2013, pp. 665–670.

[236] Q. Yang, Y. Chen, G. Xue, W. Dai, and Y. Yu, “Heterogeneous transfer learning for image clustering via the socialweb,” in ACL, 2009, pp. 1–9.

[237] X. Yao and B. V. Durme, “Information extraction over structured data: Question answering with freebase,” in ACL, 2014, pp. 956–966.

[238] Z. Yuan, F. Gao, Q. Ho, W. Dai, J. Wei, X. Zheng, E. P. Xing, T. Liu, and W. Ma, “Lightlda: Big topic models on modest computer clusters,” in WWW, 2015, pp. 1351–1361.

[239] D. Zeng, K. Liu, Y. Chen, and J. Zhao, “Distant supervision for relation extraction via piecewise convolutional neural networks,” in EMNLP, 2015, pp. 1753–1762.

[240] F. Zhang, N. J. Yuan, D. Lian, X. Xie, and W. Ma, “Collaborative knowledge base embedding for recommender systems,” in SIGKDD, 2016, pp. 353–362.

[241] W. Zhang, Y. C. Sim, J. Su, and C. L. Tan, “Entity linking with effective acronym expansion, instance selection, and topic modeling,” in IJCAI, 2011, pp. 1909–1914.

[242] Z. Zheng, F. Li, M. Huang, and X. Zhu, “Learning to link entities with knowledge base,” in HLT-NAACL, 2010, pp. 483–491.

[243] H. Zhong, J. Zhang, Z. Wang, H. Wan, and Z. Chen, “Aligning knowledge and text embeddings by entity descriptions,” in EMNLP, 2015, pp. 267–272.

[244] S. C. Zhu, “Statistical modeling and conceptualization of visual patterns,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 6, pp. 691–712, 2003.

[245] X. Zhu, T. T. Rogers, R. Qian, and C. Kalish, “Humans perform semi-supervised classification too,” in AAAI, 2007, pp. 864–870.