



Three critical design points: Joint learning, weak supervision, and new representations.

BY ALEX RATNER AND CHRIS RÉ

Research for Practice:

Knowledge Base Construction in the Machine-Learning Era

THIS INSTALLMENT OF Research for Practice features a curated selection from Alex Ratner and Chris Ré, who provide an overview of recent developments in Knowledge Base Construction (KBC). While knowledge bases have a long history dating to the expert systems of the 1970s, recent advances in machine learning

have led to a knowledge base renaissance, with knowledge bases now powering major product functionality including Google Assistant, Amazon Alexa, Apple Siri, and Wolfram Alpha. Ratner and Ré's selections highlight key considerations in the modern KBC process, from interfaces that extract knowledge from domain experts to algorithms and representations that transfer knowledge across tasks. Please enjoy!

—Peter Bailis

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More information is accessible today than at any other time in human history.

From a software perspective, however, the vast majority of this data is unusable, as it is locked away in *unstructured* formats such as text, PDFs, Web pages, images, and other hard-to-parse formats. The goal of KBC (knowledge base construction) is to extract structured information automatically from this “dark data,” so that it can be used in downstream applications for search, question-answering, link prediction, visualization, modeling and much more. Today, knowledge

bases (KBs) are the central components of systems that help fight human trafficking,¹⁹ accelerate biomedical discovery,⁹ and, increasingly, power web-search and question-answering technologies.⁴

KBC is extremely challenging, however, as it involves dealing with highly complex input data and multiple connected subtasks such as parsing, extracting, cleaning, linking, and integration. Traditionally, even with machine learning, each of these subtasks would require arduous *feature engineering* (that is, manually crafting attributes of the input data to feed into the system). For this reason, KBC has traditionally been a months- or years-long process that was approached only by academic groups (for example, YAGO,⁸ DBPedia,⁷ KnowItNow,² DeepDive,¹⁸ among others) or large, well-funded teams in industry and government (for example, Google's Knowledge Vault, IBM Watson, and Amazon's Product Graphs).

Today, however, there is a renewed sense of democratized progress in the area of KBC, thanks to powerful but easy-to-use deep-learning models that largely obviate the burdensome task of feature engineering. Instead, modern deep-learning models operate directly over raw input data such as text or images and get state-of-the-art performance on KBC sub-tasks such as parsing, tagging, classifying, and linking. Moreover, standard commodity architectures are often suitable for a wide range of domains and tasks such as the “hegemony”¹¹ of the bi-LSTM (bidirectional long short-term memory) for text, or the CNN (convolutional neural network) for images. Open source implementations can often be downloaded and run in several lines of code.

For these emerging deep-learning-based approaches to make KBC faster and easier, though, certain critical design decisions need to be addressed—such as how to piece them together, how to collect training data for them efficiently, and how to represent their input and output data. This article highlights three papers that focus on these critical design points: *joint-learning* approaches for pooling information and coordinating among sub-components; more efficient methods of *weakly supervising* the machine-

learning components of the system; and, new ways of representing both inputs and outputs of the KB.

Joint Learning: Sharing Information and Avoiding Cascaded Errors

T.M. Mitchell et al.

Never-ending learning. In *Proceedings of the Conference on Artificial Intelligence*, 2015, 2302–2310.

KBC is particularly challenging because of the large number of related subtasks involved, each of which may use one or more ML (machine-learning) models. Performing these tasks in disconnected pipelines is suboptimal in at least two ways: it can lead to cascading errors (for example, an initial parsing error may throw off a downstream tagging or linking task); and it misses the opportunity to pool information and training signals among related tasks (for example, subcomponents that extract similar types of relations can probably use similar representations of the input data). The high-level idea of what are often termed *joint inference* and *multitask learning*—which we collectively refer to as *joint learning*—is to learn multiple related models jointly, connecting them by logical relations of their output values and/or shared representations of their input values.

Never-Ending Language Learner (NELL) is a classic example of the impact of joint learning on KBC at an impressive scale. NELL is a system that has been extracting various facts about the world (for example, `ServedWith(Tea, Biscuits)`) from the Internet since 2010, amounting to a KB containing (in 2015) more than 80 million entries. The problem setting approached by NELL consists of more than 2,500 distinct learning tasks, including categorizing noun phrases into specific categories, linking similar entities, and extracting relations between entities. Rather than learning all these tasks separately, NELL's formulation includes known (or learned) *coupling constraints* between the different tasks, which Mitchell et al. cite as critical to training NELL. These include logical relations such as subset/superset (for example, `IsSandwich(Hamburger) ⇒ IsFood(Hamburger)`) and mutual-exclusion constraints, which connect the many disparate tasks during inference and learning.

In other systems, the importance of connecting or coupling multiple tasks is echoed in slightly different contexts or formulations: for example, as a way to avoid cascading errors between different pipeline steps such as extraction and integration (for example, DeepDive¹⁸), or implemented by sharing weights or learned representations of the input data between tasks as in multitask learning.^{3,17} Either way, the decision of how to couple different subtasks is a critical one in any KBC system design.

Weak Supervision: Programming ML with Training Data

A.J. Ratner, S.H. Bach, H. Ehrenberg,

J. Fries, J., S. Wu, and C. Ré

Snorkel: Rapid training data creation with weak supervision. In *Proceedings of the Very Large Database (VLDB) Endowment* 11, 3 (2017), 269–282.

In almost all KBC systems today, many or all of the critical tasks are performed by increasingly complex machine-learning models, such as deep-learning ones. While these models indeed obviate much of the feature-engineering burden that was a traditional bottleneck in the KBC development process, they also require large volumes of labeled *training data* from which to learn. Having humans label this training data by hand is an expensive task that can take months or years, and the resulting labeled data set is frustratingly static: if the schema of a KB changes, as it frequently does in real production settings, the training set must be thrown out and relabeled. For these reasons, many KBC systems today use some form of *weak supervision*:¹⁵ noisier, higher-level supervision provided more efficiently by a domain expert.^{6,10} For example, a popular heuristic technique is distant supervision, where the entries of an existing knowledge base are heuristically aligned with new input data to label it as training data.^{1,13,16}

Snorkel provides an end-to-end framework for weakly supervising machine-learning models by having domain experts write LFs (labeling functions), which are simply black-box functions that programmatically label training data, rather than labeling any training data by hand. These LFs sub-

sume a wide range of weak supervision techniques and effectively give non-machine-learning experts a simple way to “program” ML models. Moreover, Snorkel automatically learns the accuracies of the LFs and reweights their outputs using statistical modeling techniques, effectively denoising the training data, which can then be used to supervise the KBC system. In this paper, the authors demonstrate that Snorkel improves over prior weak supervision approaches by enabling the easy use of many noisy sources, and comes within several percentage points of performance using massive hand-labeled training sets, showing the efficacy of weak supervision for making high-performance KBC systems faster and easier to develop.

Embeddings: Representation and Incorporation of Distributed Knowledge

S., Riedel, L. Yao, A. McCallum and B.M. Marlin Relation extraction with matrix factorization and universal schemas. In *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics—Human Language Technologies*: 2013, 74–84.

Finally, a critical decision in KBC is how to represent data: both the input unstructured data and the resulting output constituting the knowledge base. In both KBC and more general ML settings, the use of dense vector embeddings to represent input data, especially text, has become an omnipresent tool.¹² For example, word embeddings, learned by applying PCA (principal component analysis) or some approximate variant to large unlabeled corpora, can inherently represent meaningful semantics of text data, such as synonymy, and serve as a powerful but simple way to incorporate statistical knowledge from large corpora. Increasingly sophisticated types of embeddings, such as hyperbolic,¹⁴ multimodal, and graph⁵ embeddings, can provide powerful boosts to end-system performance in an expanded range of settings.

In their paper, Riedel et al. provide an interesting perspective by showing how embeddings can also be used to represent the knowledge base itself. In traditional KBC, an output schema (that is, which types of relations are to be extracted) is selected first and fixed, which is necessarily a manual process.

Instead, Riedel et al. propose using dense embeddings to represent the KB itself and learning these from the union of all available or potential target schemas.

Moreover, they argue that such an approach unifies the traditionally separate tasks of extraction and integration. Generally, *extraction* is the process of going from input data to an entry in the KB—for example, mapping a text string *X* likes *Y* to a KB relation *Likes*(*X*,*Y*)—while *integration* is the task of merging or linking related entities and relations. In their approach, however, both input text and KB entries are represented in the same vector space, so these operations become essentially equivalent. These embeddings can then be learned jointly and queried for a variety of prediction tasks.

KBC Becoming More Accessible

This article has reviewed approaches to three critical design points of building a modern KBC system and how they have the potential to accelerate the KBC process: coupling multiple component models to learn them jointly; using weak supervision to supervise these models more efficiently and flexibly; and choosing a dense vector representation for the data. While ML-based KBC systems are still large and complex, one practical benefit of today's interest and investment in ML is the plethora of state-of-the-art models for various KBC subtasks available in the open source, and well-engineered frameworks such as PyTorch and TensorFlow with which to run them. Together with techniques and systems for putting the pieces all together like those reviewed, high-performance KBC is becoming more accessible than ever. **C**

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