**Concept learning as modeled via modern knowledge-base models**

Categories are an important tool that allow us to make broad inferences about the world based on limited evidence. For example, they lead us to make generalizations from an individual (e.g., this individual dog barks) to the broader category (e.g., dogs bark)—and, in turn, we use them to make inferences about a novel individual exemplar based on its category membership (e.g., this poodle barks because it’s a kind of dog). One question of interdisciplinary interest: how should we characterize the process of conceptual learning, both in humans and in machines? The present paper explores two computational approaches—the classic parallel distributed processing model and modern embedding models—as viable models of knowledge acquisition.

*How do children learn about the world? A brief summary of the importance of concepts.*

Children—and even infants (Graham, Kilbreath, & Welder, 2004)—use category membership as a basis for generalization, extending information from one individual to another of the same category, even when the they differ perceptually (Gelman & Markman, 1986). This process of category-based induction requires understanding that categories have fundamental similarities between members (e.g., all snakes don’t have legs)—that is, one most hold an assumption of category homogeneity—while also acknowledging that they have important variation (e.g., only some snakes are poisonous; Gelman, 2003; Murphy, 2002). While categories tend to have a coherent and, at times, homogeneous structure, neither the similarity of its members nor the frequency of shared features are sufficient for learning concepts. Rather, concepts are tightly linked with our intuitive theories of the world, and we more readily learn concepts consistent with those theories (Keil, 1989; Murphy & Medin, 1985). Specifically, our theories play an important role in learning by imposing order on observed evidence and guiding our interpretations of it (see Carey, 1985; 2009).

A significant body of work demonstrates that children and infants are sensitive to patterns in their environment (e.g., Saffran, Aslin, & Newport, 1996, see Aslin & Newport, 2012 for review)—and can use these patterns to generate rules and update theories (Gopnik et al., 2001, Kushnir, Wellman, & Gelman, 2009,). Importantly, knowledge is *domain-specific*. People hold distinct theories for various domains (e.g., an intuitive theory of biology, Keil, 1994; of artifacts, Keil, Greig, & Kermer, 2007; of psychology, Wellman, 1990) that ascribe different causal mechanisms (e.g., natural selection applies to biological kinds but not artificial kinds) and appeal to different unobservable entities (e.g., DNA, beliefs). We use these theories to guide the inferences we make about novel kinds. Young children have a bias to view categories as largely homogeneous (e.g., Cimpian & Park, 2013; Moty & Brandone, submitted), resulting in the *overgeneralization* of properties (e.g., assuming all birds). But young kids also show some sensitivity to factors limiting generalizability, including category domain and property type (Brandone & Gelman, 2009; 2013)—and their appreciation for variability within categories increases with age (Gelman, 1988).

*Parallel distributed process model account of knowledge acquisition.*

In contrast to the theory-driven approach to conceptual development and knowledge acquisition described above, Rogers and McClelland (2004) argue for a computational account that does not posit domain-specific theories nor assumes any prior or innate knowledge on the part of the learner. Their parallel distributed processing (PDP) model (along with other models within the same framework, e.g., Mareschal, French, & Quinn, 2000; Mayor & Plunkett, 2010) demonstrated that many of the characteristic behaviors of knowledge acquisition (e.g., overgeneralization, domain-specific category-based induction) can unfold naturally as a consequence of domain-general learning mechanisms.

*Aim of the present project.*

The Rogers and McClelland's (2004) PDP model accounts for a number of behaviors we see in during knowledge acquisition and early conceptual learning, including phenomenon like overgeneralization (e.g., children’s initial assumption that penguins can fly). Yet this model is trained on a small amount of data (~20 entities) compared to modern knowledge bases with significantly larger datasets. It is unclear whether the Roger & McClelland model would scale to larger datasets. On the other hand, modern knowledge-base researchers (e.g., Bordes et al 2013; Yang et al 2014) have developed a variety of parallel processing models that can be successfully trained on large knowledge bases (eg. WordNet with over 40K entities; Freebase 15K with 15K entities). Yet, they usually focus on the final performance of triplet completion without examining the learning process that led to the final result.

In this project, we re-implement the Rogers and McClelland model with some modification. We train it with both the original dataset used in Rogers and McClelland (2004) as well as a larger knowledge base dataset. Additionally, we implement a modern embedding model (Yang et al 2014) and use similar methods employed in Rogers and McClelland (2004) to analyze the learning process of this model and draw parallel with human behaviors. We also develop new tasks like discovering new triplets and surprising facts for the modern embedding model to explore its “cognitive” capability. Finally, we explore whether incorporating additional human cognitive component — logical deduction — would improve the learning of knowledge base.

**Method**

Data

The data used in this paper are derived from 3 sources:

1. *Simple species dataset.* We first extracted a data table of 8 species, with 36 relations each. This table is extracted from Appendix B, table B-1 in [citation, R&M book].
2. *Canadian mammals dataset.* The following dataset was scraped from the website for the FactGuru knowledge base about Canadian mammals (found here: http://www.site.uottawa.ca/~tcl/factguru1/animals/index.html). The dataset contains a hierarchy of 364 unique animal kinds. At the top, the category *mammal* contains all subordinate categories—and at the bottom, the hierarchy consists of categories as narrow as *adult*/*baby* (or *male/female*) groups within a species or subordinate categories of a species (e.g., *short-tailed shrew* or *pigmy shrew* as subordinates of *shrew*). When possible, continuous relations were translated to dichotomous categorical variables (e.g., “has gestation period of 8 months” converted to “has gestation period”); other continuous relations (e.g., “has weight of 8 kg”) were dropped from the dataset. Relations that were true of only a single animal kind were removed from the dataset. After the cleaning process, the final dataset had 2040 relations.

For training embedding model, one additional step is to generate negative sample generation. For each head-relation pair (h-r), we generate negative samples by appending false tails ( ) that: (1) < h-r- > is not in the dataset and (2) <h'-r- > is in the dataset (in other words, r- is a valid relation-tail pair). The ratio between negative and positive pairs is reportedly influential on training performance (Trouillon et al 2016). Here we tentatively set it to at most 3 negative samples per correct triplet (some triplets have less because not enough legitimate .

Model

Reimplementing the classic PDP model

Network and parameters: We implemented the Rumelhart semantic

memory model as shown in Figure 2.2 [citation R &M; could insert figure].

Specifically, head, relation and tails are represented in a one-hot manner;

head is connected to a representation layer of same number of units as the

head layer; then both the representation layer and relation connect to a

hidden layer with 15 units, which feedforward to the output tail layer. Each

layer's output is rectified with ReLU function (instead of softmax as in the

original model), but we didn't test whether this is a significant modification.

Also the output layer had a softmax to constrain the output between 0 and 1.

Training: We used pytorch package to construct this model. RMSprop was

used for optimizing the network. 300 episodes are included in the training

data.

Modern embedding model

Network and parameters: One recent popular trend of knowledge base

model is the embedding model started by transE [citation Bordes et al 2013],

where the head, relation and tail are transformed into an embedding vector

space, and the knowledge triplets correspond to some linear algebra

operations. [cite….] summarized some possible vector and operation choices.

Here we only explored a specific form, "DistMulti model" [cite…], where the

entities (both head and tails) are represented as vector while the relations is

a diagonal matrix. A triplet is represented as a bilinear transformation"

For a correct triplet the score should be 1 while false knowledge would have

a score of -1.

Specifically, we used a somewhat arbitrary embedding of 15 dimensions for

both datasets.

Training: We used pytorch package to construct this model. Adam was used

for optimizing the network. 1500 episodes are included in the training data.

Results

Small biology dataset

Here we first replicate the results shown in [R&M], then observe whether the

embedding model show similar behaviors. Moreover, we introduced an

inference task that has rarely been studied in the current knowledge base

literature and developed algorithms to solve these tasks for the embedding

model.

1. Learning process

First, we see both model could learn to distinguish the correct and wrong

triplets. For example, we test the model output for triplets related with

canary, adding a false triplet ("canary-is-red") as comparison:

[to add: averaged across 10 runs. ]

R&M mentioned an over-generation phenomenon in this dataset: "pine-hasleaves"

might be memorized as correct because the other tree, oak, does have

leaves. This overgeneralization has been observed in the embedding model

as well:

The model at first thought that pine doesn't have leaves.

2. Emergence of clusters

To check whether similar entities will gradually gain more similar

embeddings and evolve some hierarchical structure, we compare the

correlation matrix of embeddings from the first episode to 1100 episode.

We can see the clustering structure emerging among the eight living things.

Moreover, higher-order concepts like plants and animals show strong

dissimilarity from each other as the common knowledge would reason. Note

that the training data don't include triplets describing the abstract concept

"animal" — it's only included in statements as "fish-isA-animal". Yet the

model could learn to infer about the properties of animals. In the next

section we more explicitly explore the inference from the embedding model.

3. Inference task

To examine what the model can learn about the abstract concepts that only

appeared in the tails of "isA" relations, we picked some testing triplets using

them as heads (thus not included in the training set) and checked the

learning progress.

The embedding model turns out to be able to learn to assign correct

judgements to these relations, e.g. knowing that "bird-isa-animal" is correct

but "plant-isa-animal" is wrong.

4. Automated discovery

The novel triplets are given by human and approved by the model. Can our

model discover novel knowledge by itself? Turns out we can simply search

all the grammatical relations given an entity, and set a threshold hold to

filter strong positive / negative judgements. With a threshold of score 4.5,

our model learns true triplets such as "animal-has-skin", "flower-is-pretty",

and negative samples as "animal-has-roots". Though this method generates

many promising good triplets, the model also thinks "livingthing-can-grow"

must be false, possibly because of the speciality in the "livingthing" entity

itself.

Bigger Dataset

1. Learning process

Our larger dataset includes 766 entities, many are very specific such as "baby

long-tailed weasel", "female little brown bat", etc. Thus it's hard to pick

representative triplets to demonstrate the training process, and we simply

checked the correctness of triplets:

As is seen the model can indeed reach 100% correctness after around 1.2k

episodes. Note we didn't even adjust the network or learning parameters

from the small dataset. It's unclear to us why is there a dip in correctness at

around episode 300.

2. Emergence of clusters

Since it's hard to look into the clustering of all 766 entities, we here show a

subset of 47 animals which are subset of 6 higher order concepts ('toothed

whale','rodent','deer','cat','dog','bear').

After training, certain degrees of clusters emerge. Some mammal types show

more homogeneity (toothed whales, deers) than the others (rodents, dogs).

TODO: 1) subsub-concepts to show better clustering [use the linkage

function; then think about how to reorder that];

3. Automated discovery

Again we replicate the method for small dataset to find new probable facts.

Specifically we are interested in general concepts about higher-order

categories like the ones we mentioned in last session. We set threshold to 5

and found in total 8 new relations:

'cloven-hoofed mammal-is eaten by-wolf', 'rodent-has habitat-farmlands',

'cat-chases away-opposite sex after mating', 'cat-eats-frog', 'dog-has partshort

tail', 'dog-is a kind of-beaked whale', 'bear-eats-carrion', 'bear-lives inhollow

log'

Apparently most of these make sense ("dog-has part-short tail") while some

are not ("dog-is a kind of-beaked whale").

4. Surprising knowledge

Another kind of discovery is to focus on surprising facts, where people can

ask whether they've made some mistakes in the dataset, or there's some

deeper theoretical insights. For example, people find it surprising that bat

can fly yet it is a mammal, thus further questions of how bats evolve their

flying skill should be asked. This is presumably a source of curiosity as well.

Here we do show an example from our dataset. We first choose a category

like "dog" that includes 6 concepts, then pick the concept with least

correlation with other concepts, which is "coyoto" (as can be seen from the

correlation matrix in section 2). Next, we pair each relations involving

coyote with the same relation but replace "coyote" to its sup-ordinate

concept ("dog"), and compute the difference of prediction score from the

embedding model. This brings to us the attention to some potentially

surprising facts like: "coyote-makes sound-howl", "coyote-makes soundyelp",

and "coyote-is eaten by-wolf".