Novel Embedding Model for Knowledge Base Completion Based on Convolutional Neural Network

Vikram Bhatt
Kapil Pathak

Department of Computational and Data Sciences
Department of Computer Science and Automation

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Outline

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Motivation

- Previous works[TWR+16] [YYH+14] [BGWB14] [BUGD+13] on link prediction focused on shallow,fast models which can scale to large knowledge graphs.
- These models learn less expressive features than deep multilayers models which potentially limits it's performance.

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- These models learn less expressive features than deep multilayers models which potentially limits it's performance.
- A novel embedding model ConvKB[NNNP17] employs Convolutional Neural networks for knowledge base completion task.
- Captures global relationships and transitional characteristics between entities and relations.

ConvKB Model

- Embedding of each triple (h, r, t) defined by (v_h, v_r, v_t) stacked in matrix $A = [v_h, v_r, v_t] \in \mathbb{R}^k$
- We use a filter $\omega \in \mathbb{R}^{1\times 3}$ operated on convolutional layer.
- Filter aims to capture global relationships + generalize transistional charectersitics as in other models.

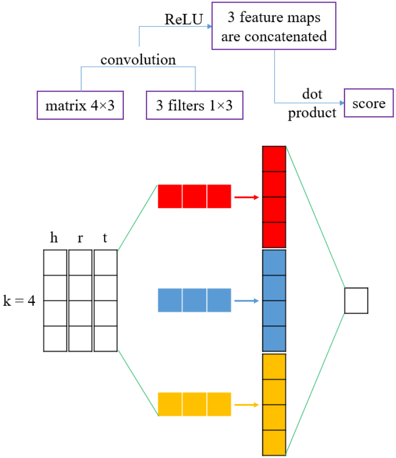

Figure 1: Process involved in ConvKB with embedding size $k = 4$ and number of filters $\tau = 3$

ConvKB Model

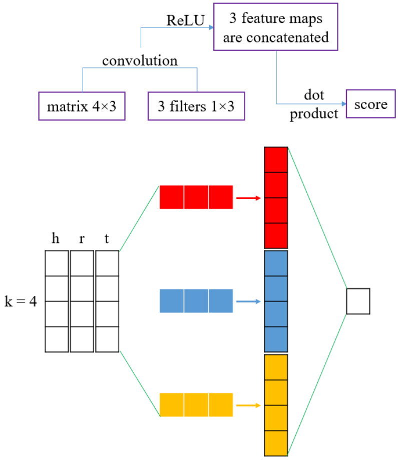

Figure 2: Process involved in ConvKB with embedding size $k = 4$ and number of filters $\tau = 3$

- Apply ω repeatedly over all rows and concatenate feature maps $\boldsymbol{v} = [v_1, v_2, \ldots, v_k] \in \mathbb{R}^k$
- $v_i = g(\omega.A_{i,:} + b)$ where b is bias and g is non-linear activation function.
- We use τ different filters and these τ feature maps concated into single vector $\chi \in \mathbb{R}^{\tau k \times 1}$

ConvKB Model

- Score function $f(h,r,t) = concat(g([v_h, v_r, v_t] * \omega)).w$
- Ω(set of all filters) and w are shared parameters and $*$ denotes convolution operation.

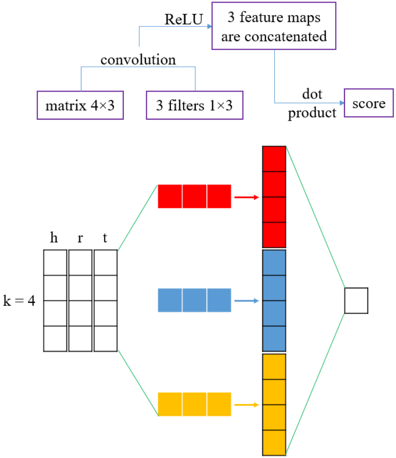

Figure 3: Process involved in ConvKB with embedding size $k = 4$ and number of filters $\tau = 3$

Loss function

$$L = \sum_{(h,r,t) \in \mathbb{G} \bigcup \mathbb{G}'} \log_e(1 + exp(l_{(h,r,t)}.f(h,r,t)))) + \frac{\lambda}{2}||w||^2$$

$$l_{(h,r,t)} = \begin{cases} 1 \text{ for } (h,r,t) \in \mathbb{G} \\ -1 \text{ for } (h,r,t) \in \mathbb{G}' \end{cases}$$

$\mathbb{G}$ is collection of valid triples in knowledge base.

$\mathbb{G}'$ is collection of invalid triples generated by corrupting triples in $\mathbb{G}$

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Given two entities (h,t) log-odd probability that (h,r,t) is true $\sigma(f(h,r,t))$, where σ is sigmoid unit link function[TWR+16].

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Datasets

DATASET	WN	FB15K-237
ENTITIES	40,943	14,951
RELATIONS	18	1,345
TRAIN EX.	141,442	483,142
TEST EX.	5,000	50,000
VALID EX.	5,000	59,071

Table 1: [YYH+14]Some statsitics of datasets we initally used for training our model.

- Freebase(N-Triples RDF,22Gzip,1.9 billion triples)
- Contains too many redudancies, inverse realtions and noisy also.
- Requires lot of pre-processing.
- Eventually we want to scale up our model to the dataset.

Outline

Training Protocol

- Initial embeddings obtained from STransE[NNNP17] which are fed to CNN layer, available at https://github.com/datquocnguyen/STransE.
- Corrupted triples are sampled using Bernoulli trick ([WZFC14][dai13])
- We train our model parameters including entity and relation embeddings, filters and weight vector W

Asynchronous SGD

Figure 4: Learning curve for asynchronous SGD with 5 workers and 1 parameter server

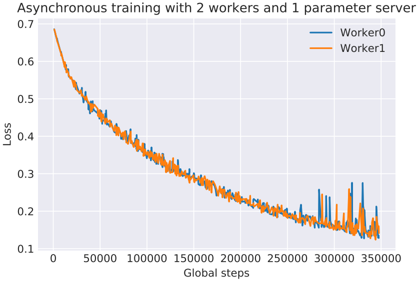


Figure 5: Learning curve for asynchronous SGD with 2 workers and 1 parameter server

Racing Conditions in Asynchronous Training

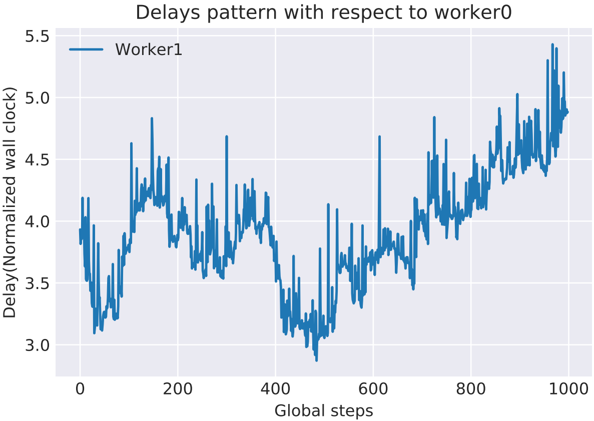


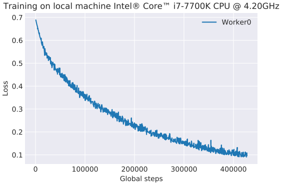
Figure 6: Intially both workers start at same point but eventually worker0 is straggling behind causing stale updates pushed at later steps during local gradient aggregation.Here I hand picked two workers to emphasize stark difference and increasing trend of lag after a certain point.

Bulk Synchronous Parallel Training

Figure 7: Learning curve for synchronous SGD with 5 workers and 1 parameter server

Figure 8: Learning curve for synchronous SGD with 2 workers and 1 parameter server

Just for comparison.....



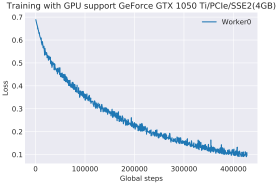


Figure 9: Learning curves in local machine(above Intel® Core™ i7-7700K CPU @ 4.20GHz) and below GPU GeForce GTX 1050 Ti/PCIe/SSE2

Train Setting	WallClock Time
GPU	37m
CPU	1hr 30min
1PS & 2W(Async)	4hr 23min
1PS & 5W(Async)	1hr 45min
1PS & 2W(Sync)	7hr 12min
1PS & 5W(Sync)	3hr

Table 2: Wallclock timings of our experiments took so far.

Outline

Plans Ahead

- We need to implement and scale up the inference part(Not done yet).
- Need to understand and pre-process the entire Freebase dataset(quite messy!).
- A possible direction to explore is stale synchronous parallel training for more stable and faster convergence.
- Identify bottlenecks in training and inference phase.
- A trade off between a possible improved link prediction scores by implementing deeper model and scalability issues due to increasing computational complexity

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