Neural Nets and Knowledge Bases

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Why not Deep Learning

- For a model to be called a 'deep model' it must have more than 2-3 layers
- All the models discussed are shallow networks with a single hidden layer.
- The first layer projects the entities(and in some cases relations) in latent/embedding space.
- The second layer then optimizes the objective function to endow certain desirable properties to embedding and learn scoring functions. More on this later

What can it be used for?

- Link Prediction(Internal Expansion)
- Semantic Parsing
- Question Answering?
- Knowledge Base Expansion(External)
- Ontology Alginment?

Problem Formulation

- All the models use a similar general approach with changes in relation representation, entity representation and initialization and loss function definition definition.
- General approach is as follows:
  - Initialize entity (in some cases relation too) embedding in latent space
  - Define a scoring function over triplet.
  - Define a training objective that minimizes the score for valid triplets and maximizes the score for invalid triplets
- Scoring function S should be such that, given a set of triplets X

$$S(e_i^l, r_i, e_i^r) < S(e_j^l, r_i, e_i^r), \forall j : (e_j^l, r_i, e_i^r) \notin X \quad (1)$$

$$S(e_i^l, r_i, e_i^r) < S(e_i^l, r_i, e_j^r), \forall j : (e_i^l, r_i, e_j^r) \notin X \quad (2)$$

Training Objective

- As with the problem formulation, almost all papers follow the similar max-margin training objective defined by [4].
- Let S be the scoring function, T be a valid triplet. We first define a invalid triplet T'

$$T' = (e_j^l, r_i, e_i^r) \vee (e_i^l, r_i, e_j^r)$$

where

$$(e_j^l, r_i, e_i^r) \notin D \wedge (e_i^l, r_i, e_j^r) \notin X$$

- Loss function L can be defined as

$$L = max(0, 1 + S(T) - S(T'))$$

Training

- Let D be the set of all entities, E be $\mathbb{R}^{n \times d}$ matrix of entity embedding .
- Select a positive training triplet at random $x_i \in X$.
- Select at random either constraint type (1) or (2).
  - We select an entity $e^{neg} \in D$ at random and construct a negative training triplet based on chosen constraint.

$$x^{neg} = (e^{neg}, r_i, e_i^r) or x^{neg} = (e_i^l, r_i, e^{neg})$$

- If $S(x_i) > S(x^{neg}) - 1$ then make a gradient step to minimize objective.
- Enforce the constraints that each column $||E_i|| = 1 \forall i$

Semantic Embedding[1]

- Published by Bordes et.al. In 2011.
- First work to use neural energy based methods for embedding
- The objective was to embed KB's in continous space for use by ML models.
- Datasets
  - Freebase (entities with Freebase type deceased people)
  - Wordnet (a subset of relation types)
- Evaluation
  - Mean-Rank for inference
  - Nearest Neighbor for Embedding and Extraction

Semantic Embedding

- Scoring Function
  - Maps left and right entities in a common latent space.
  - Uses L1 distance as a score.

$$S_k(E_i, E_j) = ||R_k^{lhs} E_i - R_k^{rhs} E_j||_p$$

  - E_i, E_j are embedding of i^{th}, j^{th} entity and $E_* \in \mathbb{R}^d$ where d is the dimension of embedding space.
  - Every relation is represented as a tuple $R_k = (R_k^{lhs}, R_k^{rhs})$ and $R_k^{lhs}, R_k^{rhs} \in \mathbb{R}^{dxd}$

Semantic Embedding

- Intuition behind such scoring function is to capture the essence that relations maybe non-symmetric.
- Single embedding used per entity for both subject and object role.
- The biggest drawback of this model is that entities never interact directly which was rectified in other models.
- Applications
  - Inference
  - Entity Embedding to be used in ML related task that use KB's.
  - Knowledge Extraction from Raw Text

		WordNet		Freebase
		rank e^l	rank e^r	rank e^r
COUNTS	*Train*	5.0%	5.0%	0.4%
	Test	0.3%	1.3%	1.7%
EMB	*Train*	76.4%	75.7%	–
	Test	4.0%	4.1%	–
EMB_{MT}	*Train*	83.9%	82.0%	95.8%
	Test	**71.7%**	**76.7%**	14.0%
EMB_{MT}+KDE	*Train*	**88.1%**	**85.8%**	**99.2%**
	Test	64.2%	68.3%	**17.0%**

Precision @ Top 10

Semantic Energy Matching Approach

- First introduced by Bordes et.al in [2] in 2012 and further expanded in [3] .
- Embeds relation too as a vector in latent space, hence useful in open-domain semantic parsing.
- In the formulation of [2] the objective is to map WordNet and text corpus in the same embedding domain and learn an energy function that is small for likely triplets.
- This setting is done to achieve two goals
  - Knowledge Base expansion using raw text
  - Word Sense Disambiguation for the text corpus

Algorithm

- Two Step Process

  Step 1: Structure Inference

  - Uses SENNA toolkit[4] for triplet extraction by applying POS, Chunking, Lemmatization and SRL.
  - Only sentences with structure of (subject, verb, direct object) were considered.
  - These parsed sentence are called lemma.

  Step 2: Entity Detection

  - In this step all-words word-sense disambiguation is done by assigning each word to a synset.

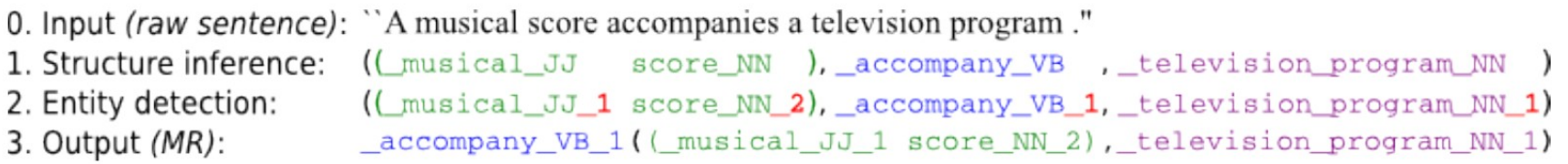


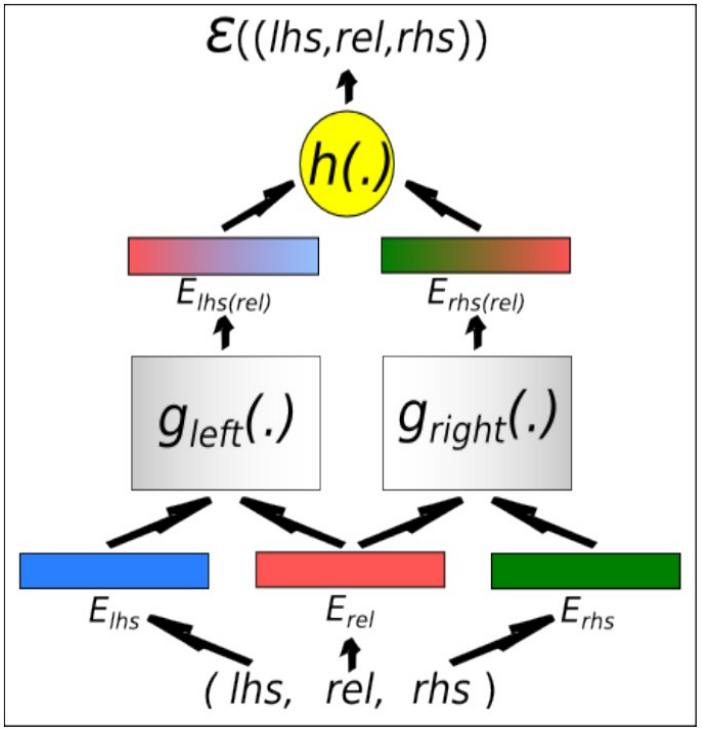
Figure 1: **Open-text semantic parsing.** To parse an input sentence (step 0), a preprocessing (lemmatization, POS, chunking, SRL) is first performed (step 1) to clean data and uncover the MR structure. Then, to each lemma is assigned a corresponding WordNet synset (step 2), hence defining a complete meaning representation (step 3).

Algorithm: Entity Detection

- Both relation and entities are embedded in latent space.
- In first step, a relation dependent embedding $E_{lhs(rel)}, E_{rhs(rel)}$ is calculated for both left and right entities.
- In final step relation dependent right and left embeddings are combined to compute energy
- The paper [] proposes to use dot product for h
- For g_{left}, g_{right} paper uses bilinear form given by

$$E_{lhs(rel)} = (W_{ent,l} E_{lhs}) \otimes (W_{rel,l} E_{rel}) + b_l$$
$$E_{rhs(rel)} = (W_{ent,r} E_{rhs}) \otimes (W_{rel,r} E_{rel}) + b_r$$
$$h(E_{lhs(rel)}, E_{rhs(rel)}) = -E_{lhs(rel)} \cdot E_{rhs(rel)}$$

- The scoring function gives high score to valid triplet hence, we maximize it by changing sign in loss function.



Algorithm: Entity Detection

- The entity detection is done in following way
  - For each lemma $(e_{lhs}^{lemma}, r^{lemma}, e_{rhs}^{lemma})$ of the form extracted from corpus
  - Replace one entity or relation, for example e_{lhs}^{lemma} with a suitable synset.
  - Suitable synset is the one that minimizes the energy of the triplet with substitution. Formally,

$$e_{lhs}^{syn} = argmin_{k \in C(syn|lem)} S((k, r^{lemma}, e_{rhs}^{lemma}))$$

where $C(syn|lem)$ is set of all synsets that can be mapped to e_{lhs}^{lemma}

- As relations too are embedded, it uses an additional constraint, namely

$$S(e_i^l, r_i, e_i^r) < S(e_i^l, r_j, e_i^r), \forall j : (e_i^l, r_j, e_i^r) \notin X(1)$$

Datasets and Results

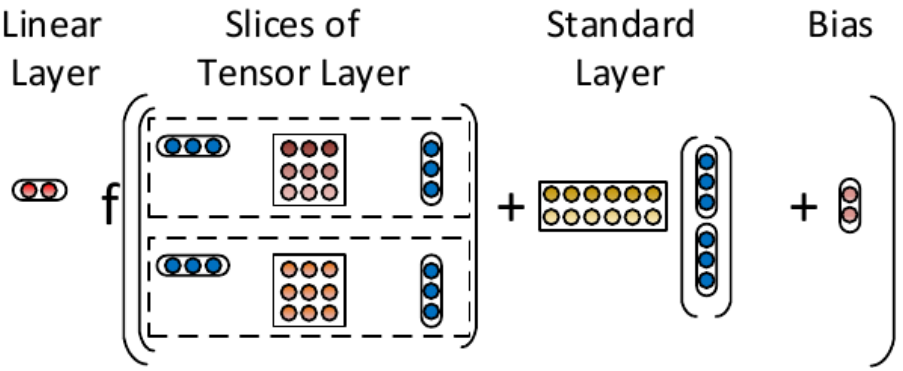
- Uses multi-task training, by training on multiple datasets at the same time.
- Dataset used are
  - WordNet, ConceptNet, Wikipedia (for raw text), Extended WordNet

Table 1: **WordNet Knowledge Acquisition (cols. 2-3) and Word Sense Disambiguation (cols. 4-5).** MFS uses the Most Frequent Sense. **All+MFS** is our best system, combining all sources of information.

Model	WordNet rank	WordNet p@10	F1 XWN	F1 Senseval3
All+MFS	–	–	**72.35%**	**70.19%**
All	139.30	3.47%	67.52%	51.44%
WN+CN+Wk	95.9	4.60%	34.80%	34.13%
WN	72.1	5.88%	29.55%	28.36%
MFS	–	–	67.17	67.79%
Gamble (Decadt *et al.*, 2004)	–	–	–	66.41%
SE (Bordes *et al.*, 2011)	53.2	7.45%	–	–
SE (no KDE) (Bordes *et al.*, 2011)	87.6	4.91%	–	–
Random	20512	0.01%	26.71%	29.55%

Neural Tensor Network(NTN) Approach

- Proposed by Richard Socher et.al. [5], [6] using this approach
- They use this approach for Knowledge Base completion i.e. inferring new facts from existing KB.
- In this formulation, the evaluation is done by predicting the accurate triplet in test test



Neural Tensor Model

Neural Tensor Model

- The scoring function used in case of NTN is more generic one
- Contrary to other models that use projection matrices to model relations, NTN uses a tensor of depth k, which is a parameter to the model.
- A way to look at this is the each splice of tensor model is responsible for a type of entity pair
- For instance, the model could learn that both animals and mechanical entities such as cars can have parts from different parts of the semantic word vector space.
- The scoring function is as follows:

$$\mathrm{S}(\mathrm{e}_{lhs}, r, e_{rhs}) = u_R^T f\left(e_{lhs}^T W_R^{[1:k]} e_{rhs} + V_R \begin{bmatrix} e_{lhs} \\ e_{rhs} \end{bmatrix} + b_R\right)$$

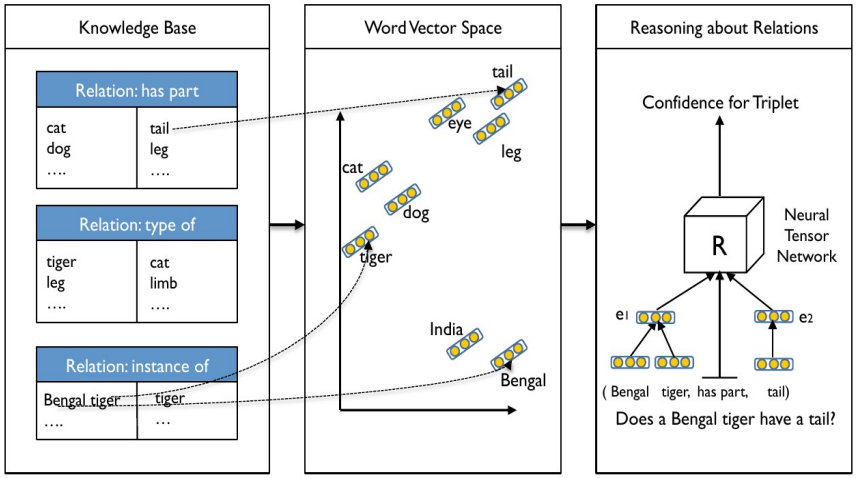
Where W_R, V_R, b_R, U are of the dimension $\mathbb{R}^{d\times d\times k}, \mathbb{R}^{2d\times k}, \mathbb{R}^k, \mathbb{R}^k$ and f is $tanh$.

Entity Representation Approach

- This paper proposes an interesting entity representation approach.
- Entities are represented as mean of vectors of words associated with the entity.
- For example

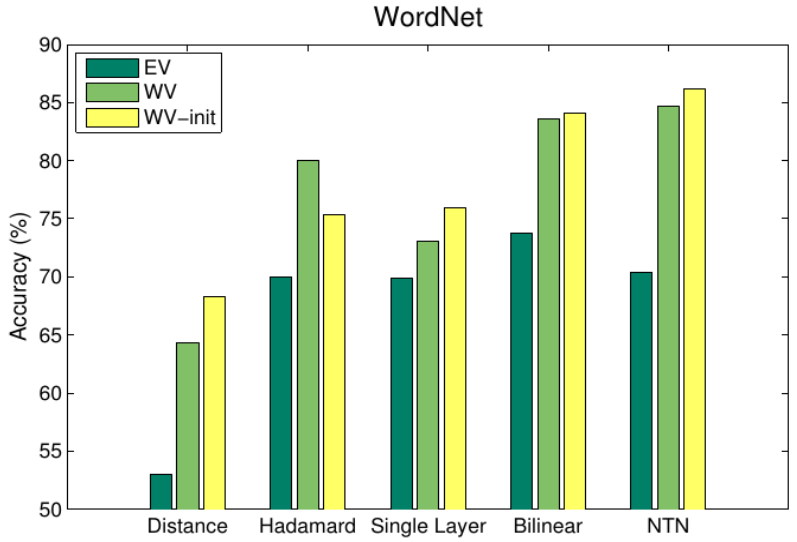
$$\mathrm{E}_{HomoSapiens} = 0.5(V_{Homo} + V_{Sapiens})$$
$$\mathrm{E}_{BengalTiger} = 0.5(V_{Bengal} + V_{Tiger})$$

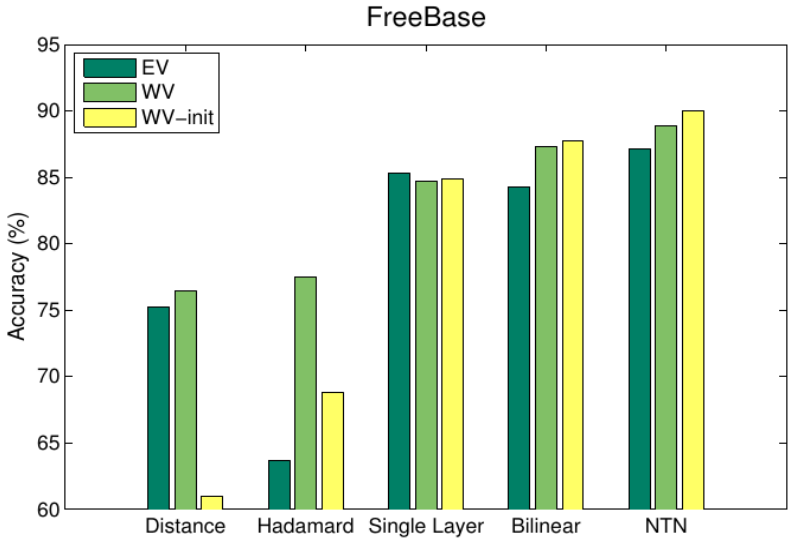
- Pre-trained unsupervised word vectors from [] are used to initialize word vectors.
- This improves generalization as statistical strength of composing words can help in improving confidence for unseen entities
- Ex Bengal Tiger and Sumatran Tiger



Dataset and Results

- Datasets used are
  - Freebase
  - WordNet
- The threshold T_d such that triplet is valid if $S(e_1, r, e_2) > T_d$ is calculated using development set.





EV: Entity Vectors, WV: Word Vectors with random initialization,
WV-Init: Word Vectos initialized with pretrained word vectors

Inferred Examples

Entity e_1	Relationship R	Sorted list of entities likely to be in this relationship
tube	type of	structure; anatomical structure; device; body; body part; organ
creator	type of	individual; adult; worker; man; communicator; instrumentalist
dubrovnik	subordinate instance of	city; town; city district; port; river; region; island
armed forces	domain region	military operation; naval forces; military officier; military court
boldness	has instance	audaciousness; aggro; abductor; interloper; confession;
peole	type of	group; agency; social group; organisation; alphabet; race

Example of right hand side entities inferred from WordNet. Entities are ranked by the assigned score.

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Thank You!