Outline

Entities are polysemic

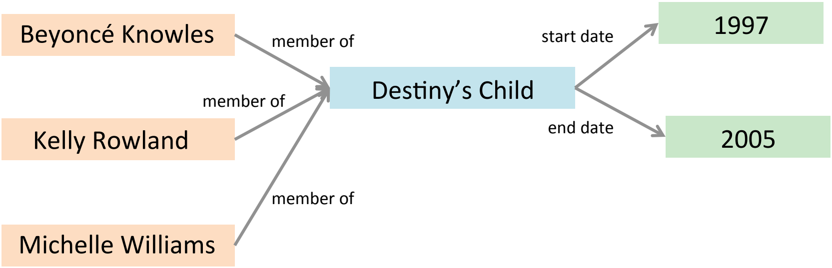
"Finding entities" has multiple meanings.

Entities can be

- nodes in knowledge graphs,
- mentions in unstructured texts or queries,
- retrievable items characterized by texts.

Outline

Knowledge graphs



Triples

```
(beyoncé_knowles, member_of, destinys_child)
(kelly_rowland, member_of, destinys_child)
(michelle_williams, member_of, destinys_child)
(destinys_child, start_date, 1997)
(destinys_child, end_date, 2005)

...
```

Nice overview on using knowledge bases in IR: [Dietz et al., 2017]

Knowlegde graphs

Tasks

- Link prediction
  Predict the missing `h` or `t` for a triple `(h, r, t)`
  Rank entities by score. Metrics:
  - Mean rank of correct entity
  - Hits@10
- Triple classification
  Predict if `(h, r, t)` is correct.
  Metric: accuracy.
- Relation fact extraction from free text
  Use knowledge base as weak supervision for extracting new triples.
  Suppose some IE system gives us `(steve_jobs, ‘‘was the initiator of’’, apple)`, then we want to predict the `founder_of` relation.

Datatsets

WordNet
`(car, hyponym, vehicle)`
Freebase/DBPedia
`(steve_jobs, founder_of, apple)`

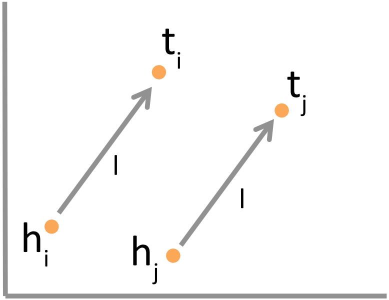
Knowlegde graphs

Knowledge graph embeddings

- TransE [Bordes et al., 2013]
- TransH [Wang et al., 2014]
- TransR [Lin et al., 2015]

TransE

"Translation intuition"
For a triple (`h`, `l`, `t`) : $\vec{\mathtt{h}} + \vec{\mathtt{l}} \approx \vec{\mathtt{t}}$.



TransE

“Translation intuition”

For a triple `(h, l, t)` : $\vec{\mathtt{h}} + \vec{\mathtt{l}} \approx \vec{\mathtt{t}}$.

$$\mathcal{L} = \sum_{(h,\ell,t)\in S} \sum_{(h',\ell,t')\in S'_{(h,\ell,t)}} \left[\gamma + d(\boldsymbol{h}+\boldsymbol{\ell},\boldsymbol{t}) - d(\boldsymbol{h'}+\boldsymbol{\ell},\boldsymbol{t'})\right]_+$$

positive examples

negative examples

distance function

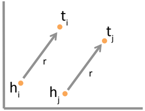
[Bordes et al., 2013]

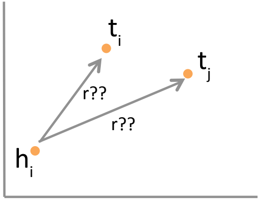
TransE

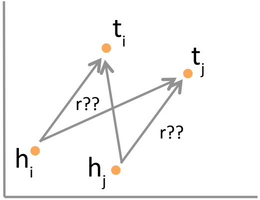
"Translation intuition"
For a triple (h, l, t) : $\vec{h} + \vec{l} \approx \vec{t}$.

How about:

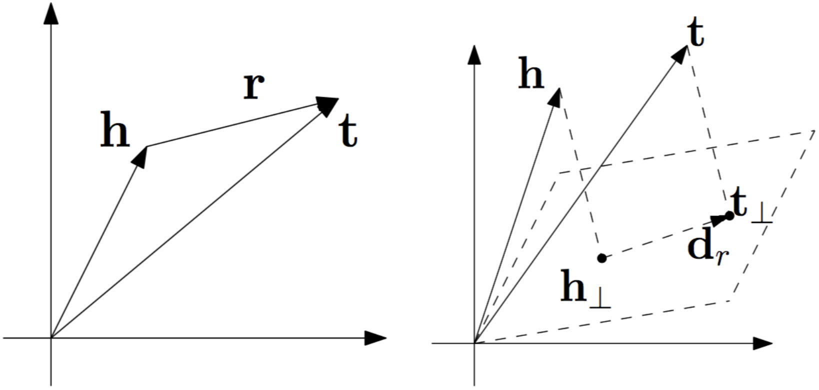
- one-to-many relations?
- many-to-many relations?
- many-to-one relations?







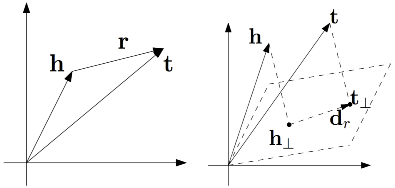
TransH



(a) TransE (b) TransH

[Wang et al., 2014]

TransH



(a) TransE (b) TransH

$$f_r(\mathbf{h},\mathbf{t}) = \|\overbrace{(\mathbf{h} - \mathbf{w}_r^\top \mathbf{h}\mathbf{w}_r)}^{\mathbf{h}_\perp} + \mathbf{d}_r - \overbrace{(\mathbf{t} - \mathbf{w}_r^\top \mathbf{t}\mathbf{w}_r)}^{\mathbf{t}_\perp}\|_2^2$$

$$\mathcal{L} = \sum_{(h,r,t)\in\Delta} \sum_{(h',r',t')\in\Delta'_{(h,r,t)}} [f_r(\mathbf{h},\mathbf{t}) + \gamma - f_{r'}(\mathbf{h}',\mathbf{t}')]_+$$

distance function

[Wang et al., 2014]

TransH

i.e., translation vector d_r is in the hyperplane

Constraints

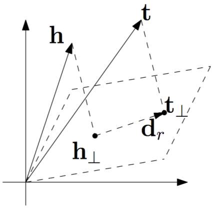
$\forall e \in E, \|\mathbf{e}\|_2 \leq 1,$ //scale

$\forall r \in R, |\mathbf{w}_r^\top \mathbf{d}_r| / \|\mathbf{d}_r\|_2 \leq \epsilon,$ //orthogonal

$\forall r \in R, \|\mathbf{w}_r\|_2 = 1,$ //unit normal vector

soft constraints

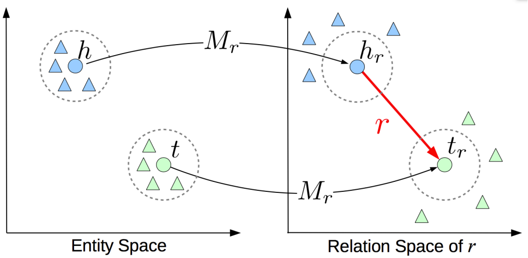
$$\mathcal{L} = \sum_{(h,r,t)\in\Delta} \sum_{(h',r',t')\in\Delta'_{(h,r,t)}} \left[f_r(\mathbf{h},\mathbf{t}) + \gamma - f_{r'}(\mathbf{h}',\mathbf{t}')\right]_+ + C\left\{\sum_{e\in E}\left[\|\mathbf{e}\|_2^2 - 1\right]_+ + \sum_{r\in R}\left[\frac{(\mathbf{w}_r^\top \mathbf{d}_r)^2}{\|\mathbf{d}_r\|_2^2} - \epsilon^2\right]_+\right\}, \quad (4)$$



(b) TransH

[Wang et al., 2014]

TransR

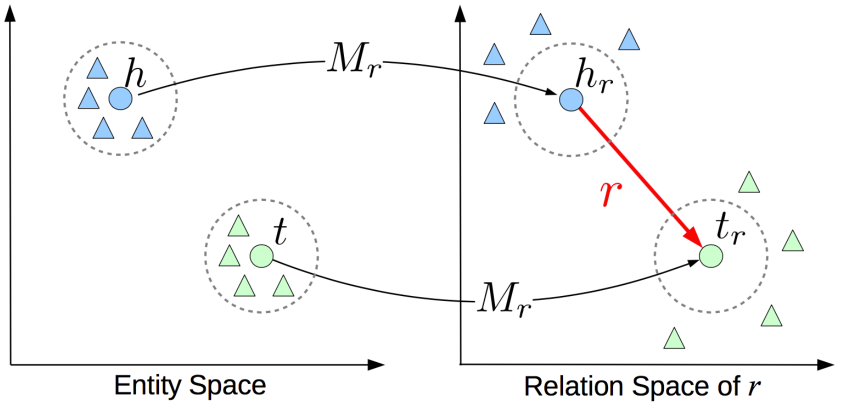


Use different embedding spaces for entities and relations

- 1 entity space
- multiple relation spaces
- perform translation in appropriate relation space

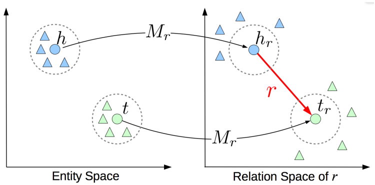
[Lin et al., 2015]

TransR



[Lin et al., 2015]

TransR



Relations: R^d

Entities: R^k

M_r = projection matrix: k * d

$$\mathbf{h}_r = \mathbf{h}\mathbf{M}_r, \quad \mathbf{t}_r = \mathbf{t}\mathbf{M}_r$$

$$f_r(h,t) = \|\mathbf{h}_r + \mathbf{r} - \mathbf{t}_r\|_2^2$$

Constraints:

$$\|\mathbf{h}\|_2 \leq 1$$
$$\|\mathbf{r}\|_2 \leq 1$$
$$\|\mathbf{t}\|_2 \leq 1$$
$$\|\mathbf{t}\mathbf{M_r}\|_2 \leq 1$$
$$\|\mathbf{h}\mathbf{M_r}\|_2 \leq 1$$

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} \max\left(0, f_r(h,t) + \gamma - f_r(h',t')\right)$$

[Lin et al., 2015]

Challenges

- How about time?
  E.g., some relations hold from a certain date, until a certain date.
- New entities/relationships
- Finding synonymous relationships/duplicate entities `(2005, end_date, destinys_child)` `(destinys_child, disband, 2005)` `(destinys_child, last_performance, 2005)`
- Evaluation
  Link prediction? Relation classification? Is this fair? As in, is this even possible in all cases (for a human without any world knowledge)?

Resources: toolkits + knowledge bases

Source Code

KB2E : `https://github.com/thunlp/KB2E` [Lin et al., 2015]

TransE : `https://everest.hds.utc.fr/`

Knowledge Graphs

- Google Knowledge Graph
  `google.com/insidesearch/features/search/knowledge.html`
- Freebase
  `freebase.com`
- GeneOntology
  `geneontology.org`
- WikiLinks
  `code.google.com/p/wiki-links`

Outline

Entity mentions

Recognition Detect mentions within unstructured text (e.g., query).

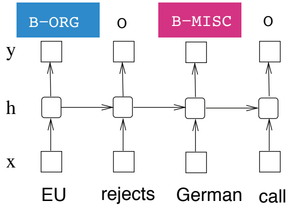
Linking Link mentions to knowledge graph entities.

Utilization Use mentions to improve search.

Named entity recognition

B-ORG	O	B-MISC	O	O	O	B-MISC	O	O
EU	rejects	German	call	to	boycott	British	lamb	.

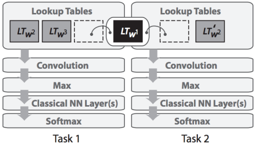
Task



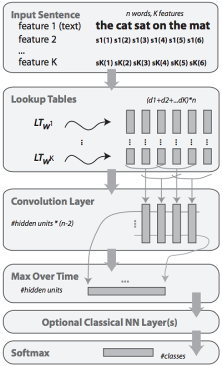
vanilla RNN

Named entity recognition

- A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning [Collobert and Weston, 2008]
- Natural Language Processing (Almost) from Scratch [Collobert et al., 2011]

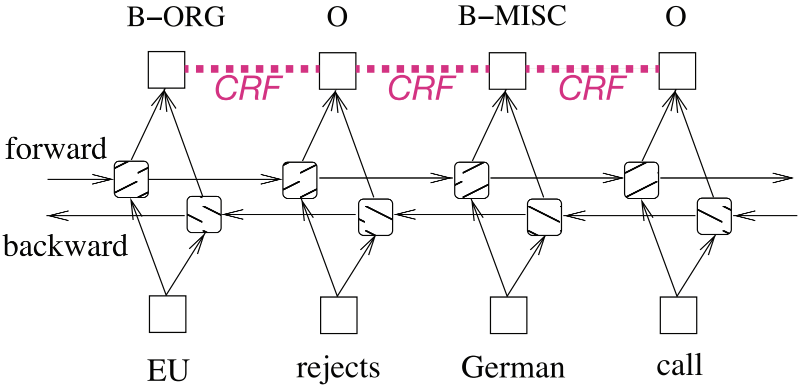


Learning a single model to solve multiple NLP tasks. Taken from [Collobert and Weston, 2008].



Feed-forward language model architecture for different NLP tasks. Taken from [Collobert and Weston, 2008].

Named entity recognition

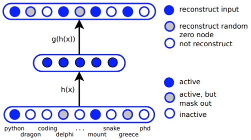


BI-LSTM-CRF model

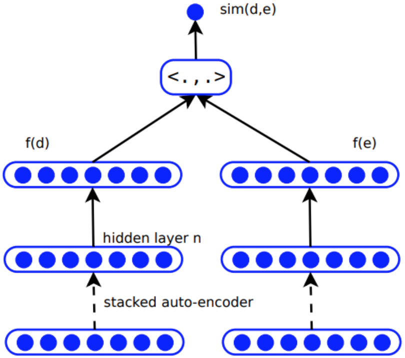
[Huang et al., 2015]

Entity disambiguation

- Learn representations for documents and entities.
- Optimize a distribution of candidate entities given a document using (a) cross entropy or (b) pairwise loss.

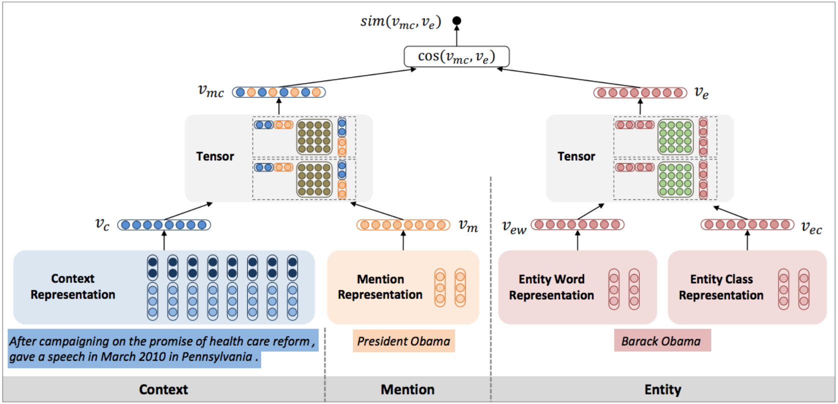


Learn initial document representation in unsupervised pre-training stage. Taken from [He et al., 2013].



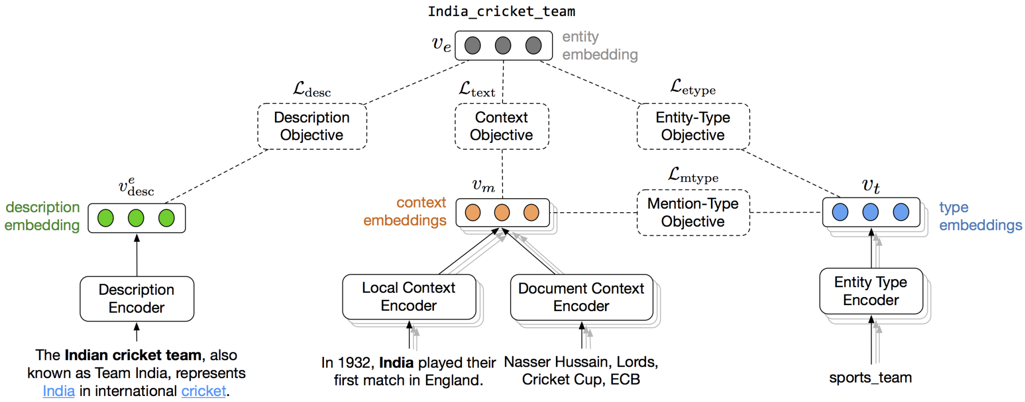
Learn similarity between document and entity representations using supervision. Taken from [He et al., 2013].

Entity linking



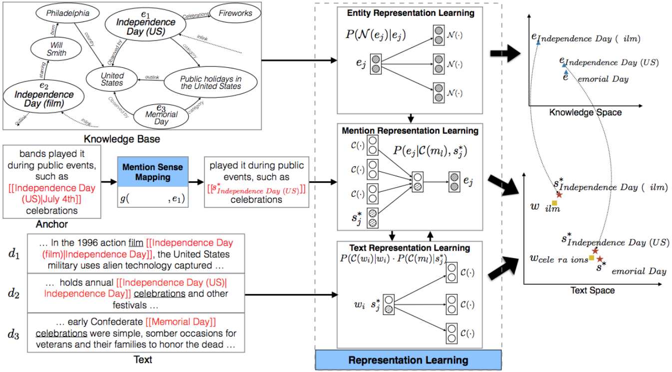
Learn representations for the context, the mention, the entity (using surface words) and the entity class. Uses pre-trained word2vec embeddings. Taken from [Sun et al., 2015].

Entity linking



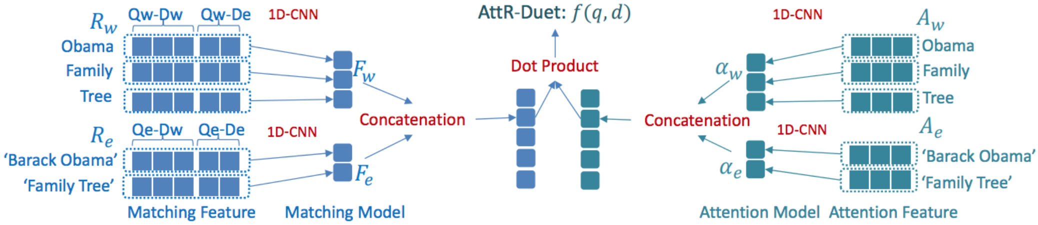
Encode Wikipedia descriptions, linked mentions in Wikipedia and fine-grained entity types. All representations are optimized jointly. Taken from [Gupta et al., 2017].

Entity linking



A single mention phrase refers to various entities. Multi-Prototype Mention Embedding model that learns multiple sense embeddings for each mention by jointly modeling words from textual contexts and entities derived from a KB. Taken from [Cao et al., 2017].

Improving search using linked entities



Attention-based ranking model for word-entity duet. Learn a similarity between query and document entities. Resulting model can be used to obtain ranking signal. Taken from [Xiong et al., 2017a].

Outline

Entity finding

Task definition

Rank entities satisfying a topic described by a few query terms.

Not just document search — (a) topics do not typically correspond to entity names, (b) average textual description much longer than typical document.

Different instantiations of the task within varying domains:

- Wikipedia: INEX Entity Ranking Track [de Vries et al., 2007, Demartini et al., 2008, 2009, 2010] (lots of text, knowledge graph, revisions)
- Enterprise search: expert finding [Balog et al., 2006, 2012] (few entities, abundance of text per entity)
- E-commerce: product ranking [Rowley, 2000] (noisy text, customer preferences)

Semantic Expertise Retrieval [Van Gysel et al., 2016]

- Expert finding is a particular entity retrieval task where there is a lot of text.
- Learn representations of words and entities such that n-grams extracted from a document predict the correct expert.

Taken from slides of Van Gysel et al. [2016].

Semantic Expertise Retrieval [Van Gysel et al., 2016] (cont'd)

- Expert finding is a particular entity retrieval task where there is a lot of text.
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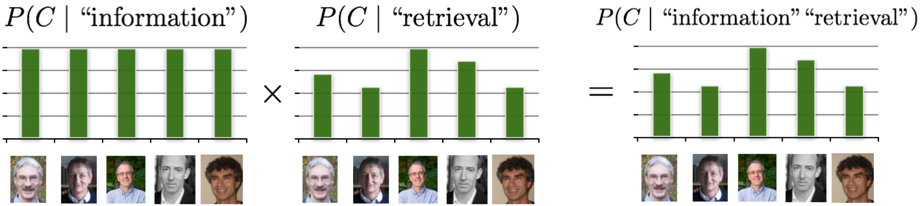


Taken from slides of Van Gysel et al. [2016].

Regularities in Text-based Entity Vector Spaces [Van Gysel et al., 2017b]

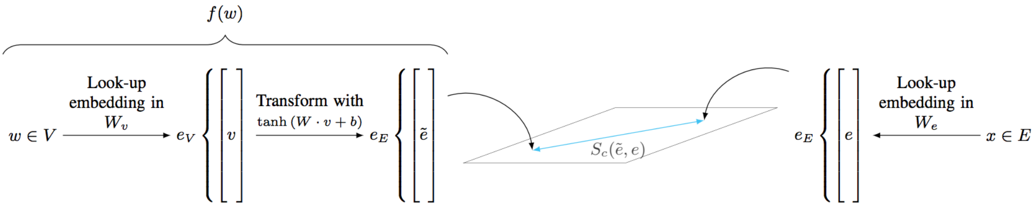
To what extent do entity representation models, trained only on text, encode structural regularities of the entity's domain?

Goal: give insight into learned entity representations.

- Clusterings of experts correlate somewhat with groups that exist in the real world.
- Some representation methods encode co-authorship information into their vector space.
- Rank within organizations is learned (e.g., Professors $>$ PhD students) as senior people typically have more published works.

Latent Semantic Entities [Van Gysel et al., 2016]

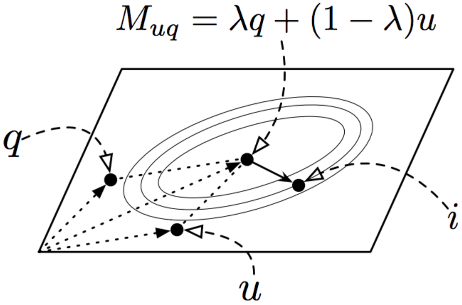
- Learn representations of e-commerce products and query terms for product search.
- Tackles learning objective scalability limitations from previous work.
- Useful as a semantic feature within a Learning To Rank model in addition to a lexical matching signal.



Taken from slides of Van Gysel et al. [2016].

Personalized Product Search [Ai et al., 2017]

- Learn representations of e-commerce products, query terms, and users for personalized e-commerce search.
- Mixes supervised (relevance triples of query, user and product) and unsupervised (language modeling) objectives.
- The query is represented as an interpolation of query term and user representations.



Personalized product search in a latent space with query $\vec{q}$, user $\vec{u}$ and product item $\vec{i}$. Taken from Ai et al. [2017].

Resources: toolkits

SERT : `http://www.github.com/cvangysel/SERT` [Van Gysel et al., 2017a]

HEM : `https://ciir.cs.umass.edu/downloads/HEM` [Ai et al., 2017]

Resources: further reading on entities/KGs

For more information, see the tutorial on "Utilizing Knowledge Graphs in Text-centric Information Retrieval" [Dietz et al., 2017] presented at last year's WSDM.

`https://github.com/laura-dietz/tutorial-utilizing-kg`