

Translating Embeddings for Modeling Multi-relational Data

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Outline

- Introduction
- Method
- Experiment
- Conclusion

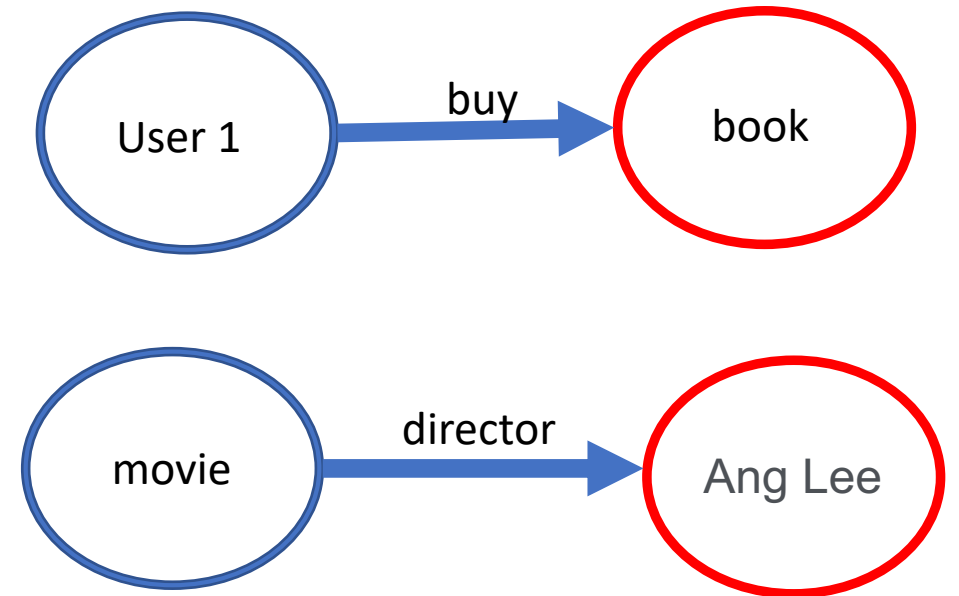
Multi-relational Data

(head, label, tail) (h, l, t)

ex:

(User 1, buy, book)

(movie, director, Ang Lee)



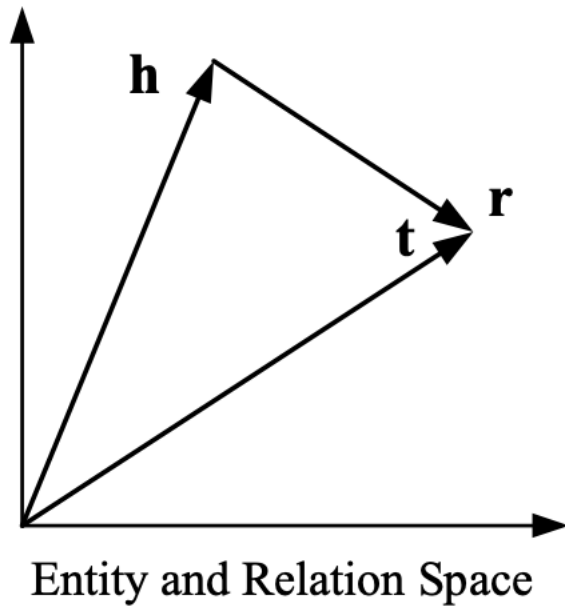
Node : entity

Edge : relationship

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Translation-based model



$$d(\mathbf{h} + \mathbf{l}, \mathbf{t}) = \|\mathbf{h}\|_2^2 + \|\mathbf{l}\|_2^2 + \|\mathbf{t}\|_2^2 - 2(\mathbf{h}^T \mathbf{t} + \mathbf{l}^T (\mathbf{t} - \mathbf{h})).$$

$$\mathbf{h}^T \mathbf{t} + \mathbf{l}^T (\mathbf{t} - \mathbf{h})$$

Algorithm 1 Learning TransE

input Training set $S = \{(h, \ell, t)\}$, entities and rel. sets E and L , margin γ , embeddings dim. k .

- 1: **initialize** $\ell \leftarrow \text{uniform}(-\frac{6}{\sqrt{k}}, \frac{6}{\sqrt{k}})$ for each $\ell \in L$
 - 2: $\ell \leftarrow \ell / \|\ell\|$ for each $\ell \in L$
 - 3: $\mathbf{e} \leftarrow \text{uniform}(-\frac{6}{\sqrt{k}}, \frac{6}{\sqrt{k}})$ for each entity $e \in E$
 - 4: **loop**
 - 5: $\mathbf{e} \leftarrow \mathbf{e} / \|\mathbf{e}\|$ for each entity $e \in E$
 - 6: $S_{batch} \leftarrow \text{sample}(S, b)$ // sample a minibatch of size b
 - 7: $T_{batch} \leftarrow \emptyset$ // initialize the set of pairs of triplets
 - 8: **for** $(h, \ell, t) \in S_{batch}$ **do**
 - 9: $(h', \ell, t') \leftarrow \text{sample}(S'_{(h, \ell, t)})$ // sample a corrupted triplet
 - 10: $T_{batch} \leftarrow T_{batch} \cup \{((h, \ell, t), (h', \ell, t'))\}$
 - 11: **end for**
 - 12: Update embeddings w.r.t.
$$\sum_{((h, \ell, t), (h', \ell, t')) \in T_{batch}} \nabla [\gamma + d(\mathbf{h} + \ell, \mathbf{t}) - d(\mathbf{h}' + \ell, \mathbf{t}')]_+$$
 - 13: **end loop**
-

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Dataset

Table 2: Statistics of the data sets used in this paper and extracted from the two knowledge bases, Wordnet and Freebase.

DATA SET	WN	FB15K	FB1M
ENTITIES	40,943	14,951	1×10^6
RELATIONSHIPS	18	1,345	23,382
TRAIN. EX.	141,442	483,142	17.5×10^6
VALID EX.	5,000	50,000	50,000
TEST EX.	5,000	59,071	177,404

Dataset-Wordnet

Semantic Relation	Syntactic Category	Examples
Synonymy (similar)	N, V, Aj, Av	pipe, tube rise, ascend sad, unhappy rapidly, speedily
Antonymy (opposite)	Aj, Av, (N, V)	wet, dry powerful, powerless friendly, unfriendly rapidly, slowly
Hyponymy (subordinate)	N	sugar maple, maple maple, tree tree, plant
Meronymy (part)	N	brim, hat gin, martini ship, fleet
Troponymy (manner)	V	march, walk whisper, speak
Entailment	V	drive, ride divorce, marry

Note: N = Nouns Aj = Adjectives V = Verbs Av = Adverbs

Dataset -Freebase

freebase[™]
alpha

Keyword search Freebase Search

Home Data Apps Discuss Help | Welcome back, kurt. Not you? Sign out.

Domains & Types ▶ kurt's types ▶ Medicinal Plant ▶ Medicinal Plant schema

Medicinal Plant

Compound Value Type
 Display as enumerated list

Type Key: medicinal_plant [edit](#)

⋮ **Included types:** [Topic \(Common\)](#)

⋮ **Also known as:** *add a synonym to this type to help others find it*

User Created Properties

[Add a New Property](#)

⌵ **Derived Drugs** [edit](#)
Property Key: derived_medicines [edit](#)

Expected Type	Property Description
<input type="text" value="Drug"/>	<i>no description</i>
Drug <i>Medicine</i>	Drug <i>Medicine</i> A drug is a chemical substance that has a physiological effect on an organism. Medicinal, herbal, and illegal drugs can be included in this type. ...
Drug class <i>Medicine</i>	
Drug brand <i>Medicine</i>	
Drug administration route <i>Medicine</i>	
Drug pregnancy category <i>Medicine</i>	
Drug legal status <i>Medicine</i>	
Narcotic Drug <i>subtext's types</i>	<i>condition</i>
Drug problem <i>Celebrities</i>	
New	
name <i>Text</i>	

⋮ **Included Properties**

⌵ **Topics**

- [Opium poppy](#)
- [Eucalyptus](#)
- [Dandelion](#)
- [Basil](#)
- [Aloe vera](#)
- [Garlic](#)
- [Ginger](#)
- [Ginseng](#)
- [Absinth Wormwood](#)

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none

Table 1: Numbers of parameters and their values for FB15k (in millions). n_e and n_r are the nb. of entities and relationships; k the embeddings dimension.

METHOD	NB. OF PARAMETERS	ON FB15K
Unstructured [2]	$O(n_e k)$	0.75
RESCAL [11]	$O(n_e k + n_r k^2)$	87.80
SE [3]	$O(n_e k + 2n_r k^2)$	7.47
SME(LINEAR) [2]	$O(n_e k + n_r k + 4k^2)$	0.82
SME(BILINEAR) [2]	$O(n_e k + n_r k + 2k^3)$	1.06
LFM [6]	$O(n_e k + n_r k + 10k^2)$	0.84
TransE	$O(n_e k + n_r k)$	0.81

Table 3: Link prediction results. Test performance of the different methods.

DATASET	WN				FB15K				FB1M	
METRIC	MEAN RANK		HITS@10 (%)		MEAN RANK		HITS@10 (%)		MEAN RANK	HITS@10 (%)
<i>Eval. setting</i>	<i>Raw</i>	<i>Filt.</i>	<i>Raw</i>	<i>Filt.</i>	<i>Raw</i>	<i>Filt.</i>	<i>Raw</i>	<i>Filt.</i>	<i>Raw</i>	<i>Raw</i>
Unstructured [2]	315	304	35.3	38.2	1,074	979	4.5	6.3	15,139	2.9
RESCAL [11]	1,180	1,163	37.2	52.8	828	683	28.4	44.1	-	-
SE [3]	1,011	985	68.5	80.5	273	162	28.8	39.8	22,044	17.5
SME(LINEAR) [2]	545	533	65.1	74.1	274	154	30.7	40.8	-	-
SME(BILINEAR) [2]	526	509	54.7	61.3	284	158	31.3	41.3	-	-
LFM [6]	469	456	71.4	81.6	283	164	26.0	33.1	-	-
TransE	263	251	75.4	89.2	243	125	34.9	47.1	14,615	34.0

Table 4: Detailed results by category of relationship. We compare Hits@10 (in %) on FB15k in the filtered evaluation setting for our model, TransE and baselines. (M. stands for MANY).

TASK	PREDICTING <i>head</i>				PREDICTING <i>tail</i>			
REL. CATEGORY	1-TO-1	1-TO-M.	M.-TO-1	M.-TO-M.	1-TO-1	1-TO-M.	M.-TO-1	M.-TO-M.
Unstructured [2]	34.5	2.5	6.1	6.6	34.3	4.2	1.9	6.6
SE [3]	35.6	62.6	17.2	37.5	34.9	14.6	68.3	41.3
SME(LINEAR) [2]	35.1	53.7	19.0	40.3	32.7	14.9	61.6	43.3
SME(BILINEAR) [2]	30.9	69.6	19.9	38.6	28.2	13.1	76.0	41.8
TransE	43.7	65.7	18.2	47.2	43.7	19.7	66.7	50.0

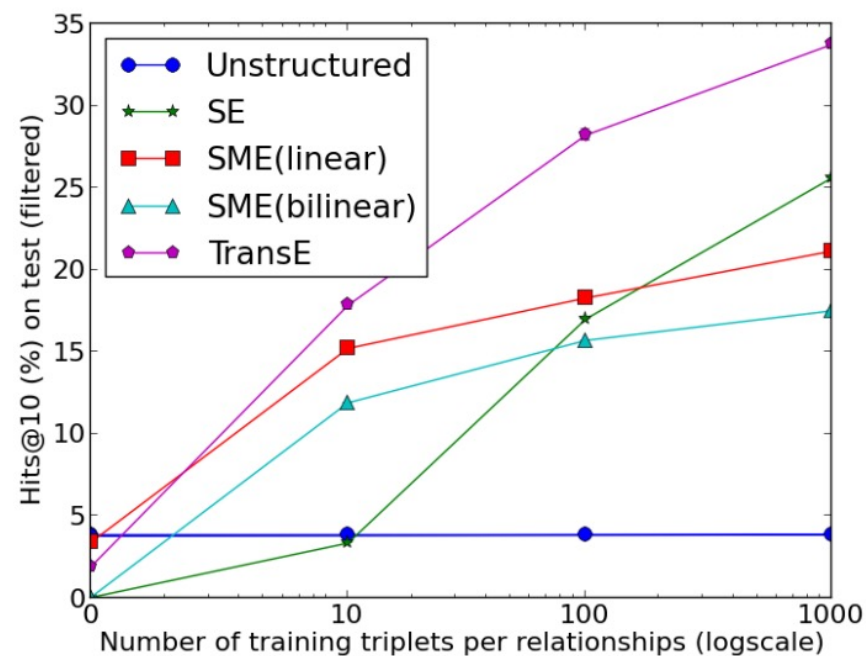
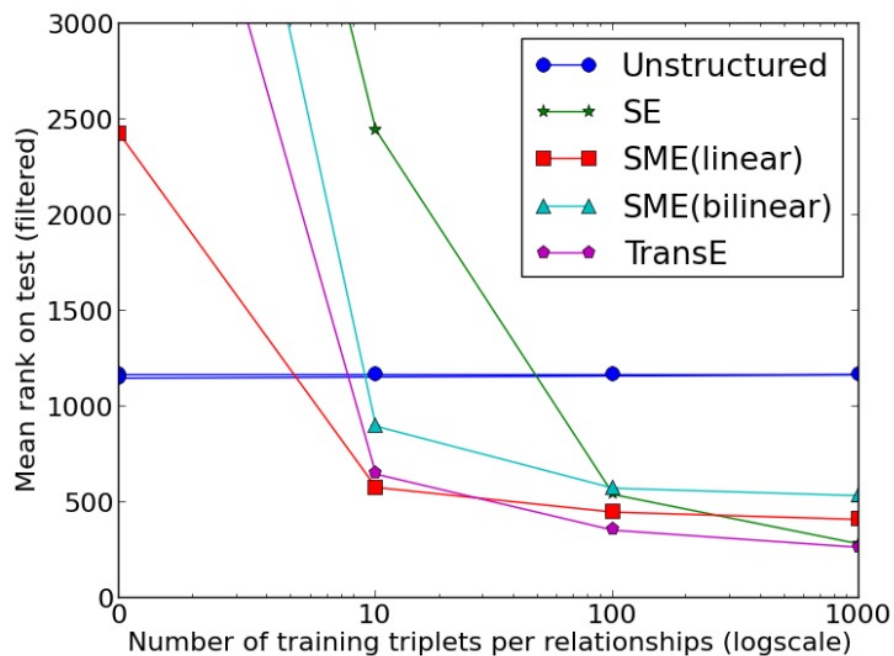


Figure 1: **Learning new relationships with few examples.** Comparative experiments on FB15k data evaluated in mean rank (left) and hits@10 (right). More details in the text.

Table 5: **Example predictions** on the FB15k test set using TransE. **Bold** indicates the test triplet’s true tail and *italics* other true tails present in the training set.

INPUT (HEAD AND LABEL)	PREDICTED TAILS
J. K. Rowling influenced by	<i>G. K. Chesterton</i> , J. R. R. Tolkien, <i>C. S. Lewis</i> , Lloyd Alexander , Terry Pratchett, Roald Dahl, Jorge Luis Borges, <i>Stephen King</i> , Ian Fleming
Anthony LaPaglia performed in	<i>Lantana</i> , <i>Summer of Sam</i> , <i>Happy Feet</i> , <i>The House of Mirth</i> , Unfaithful, Legend of the Guardians , Naked Lunch, X-Men, The Namesake
Camden County adjoins	Burlington County , <i>Atlantic County</i> , <i>Gloucester County</i> , Union County, Essex County, New Jersey, Passaic County, Ocean County, Bucks County
The 40-Year-Old Virgin nominated for	<i>MTV Movie Award for Best Comedic Performance</i> , <i>BFCA Critics’ Choice Award for Best Comedy</i> , <i>MTV Movie Award for Best On-Screen Duo</i> , MTV Movie Award for Best Breakthrough Performance, MTV Movie Award for Best Movie , MTV Movie Award for Best Kiss, D. F. Zanuck Producer of the Year Award in Theatrical Motion Pictures, Screen Actors Guild Award for Best Actor - Motion Picture
Costa Rica football team has position	<i>Forward</i> , <i>Defender</i> , <i>Midfielder</i> , Goalkeepers , Pitchers, Infielder, Outfielder, Center, Defenseman
Lil Wayne born in	New Orleans , Atlanta, Austin, St. Louis, Toronto, New York City, Wellington, Dallas, Puerto Rico
WALL-E has the genre	Animations, Computer Animation, <i>Comedy film</i> , <i>Adventure film</i> , <i>Science Fiction</i> , Fantasy , Stop motion, <i>Satire</i> , Drama

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Conclusion

- proposed a new approach to learn embeddings of KBs, focusing on the **minimal parametrization**
- highly scalable model