CCF ADL 65

知识图谱前沿

Representation Learning for Large-Scale Knowledge Graphs

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ML = Representation + Objective + Optimization

Yoshua Bengio. Deep Learning of Representations. AAAI 2013 Tutorial.

What is Representation Learning

- 1-hot Representation
  - Foundation of Bag-of-Words Model

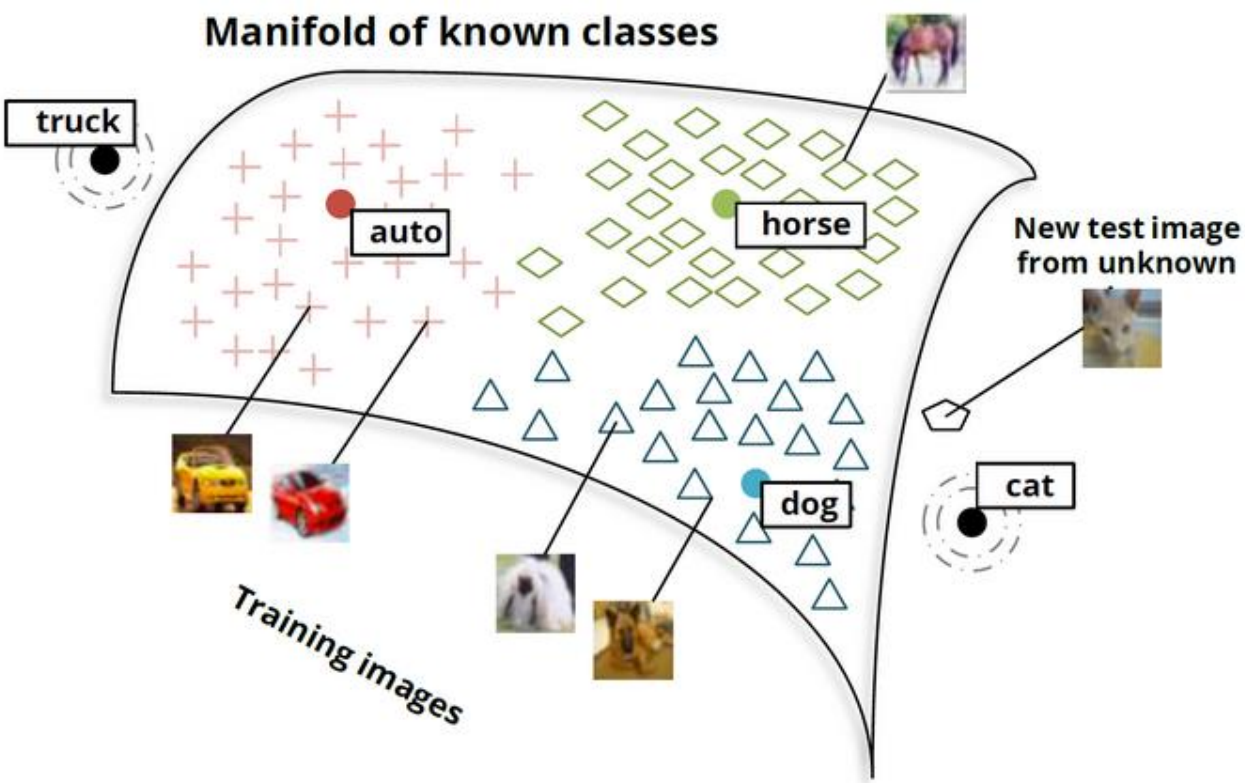
star $[0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, \cdots]$

sun $[0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, \cdots]$

sim(star, sun) = 0 ☹

What is Representation Learning

- Distributed Representation / Embeddings
- Objects are represented as dense, real-valued, and low-dimensional vectors



Foundation of RL

- Learn from human brains / Brain-inspired Learning

- Power of human brains
  - Low signal speed vs High computation speed
  - High processing capacity vs Low energy consumption

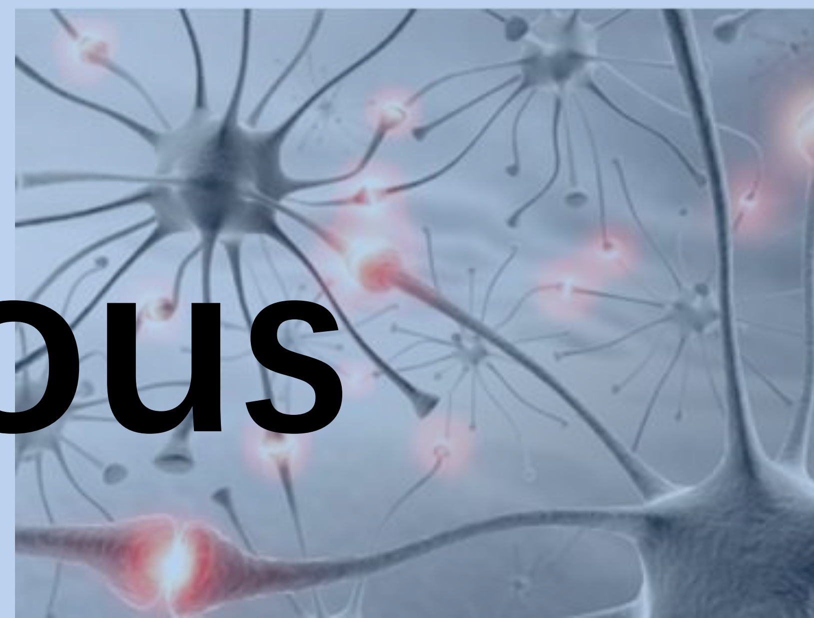
Foundation of RL

Real World

Discrete

Cognitive World

Continuous



Foundation of RL

Real World

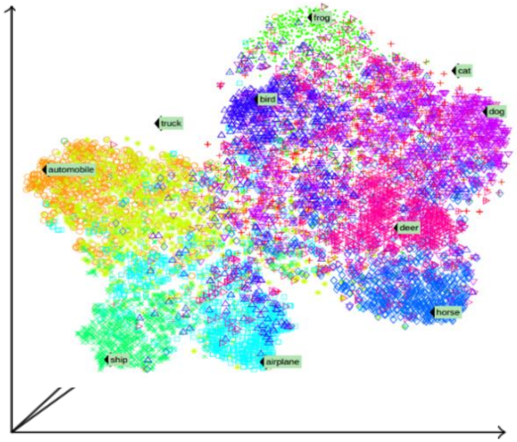
Hierarchy

Cognitive World

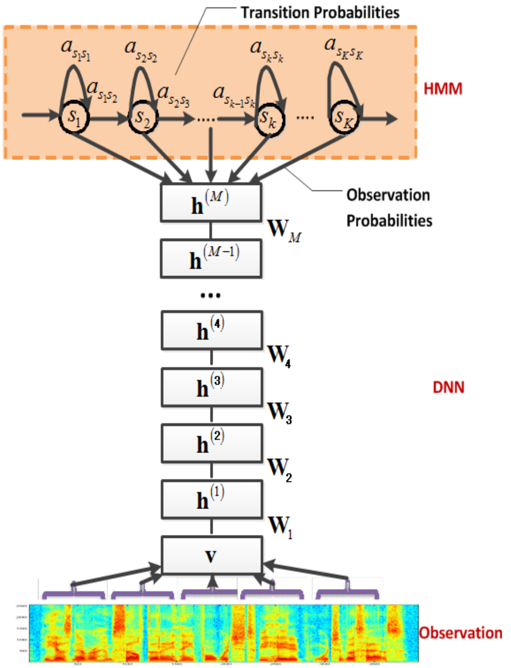
Hierarchy

Main Ideas of RL

- Distributed Representation
  - Embeddings
  - Dense, real-valued, and low-dimensional vectors

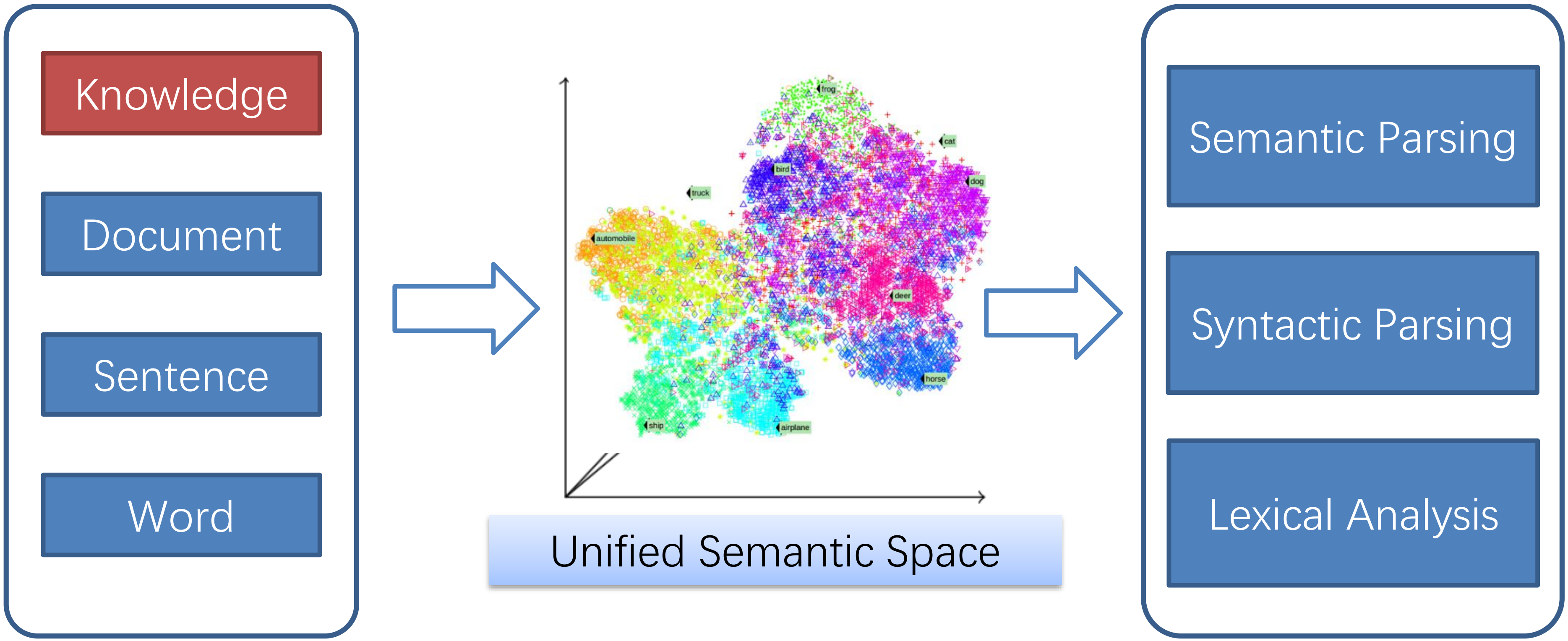


- Hierarchical Network Structure
  - Corresponding to hierarchical real world
  - Abstraction and generalization



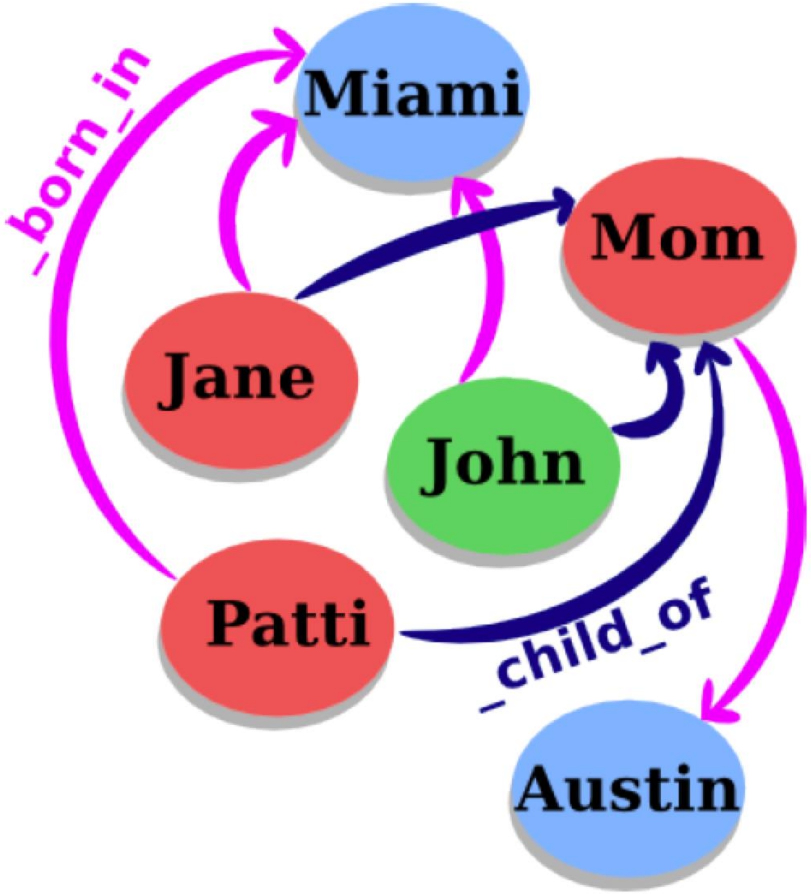
RL for NLP

- Alleviate sparsity issue in large-scale NLP
- Enable knowledge transfer across domains and objects



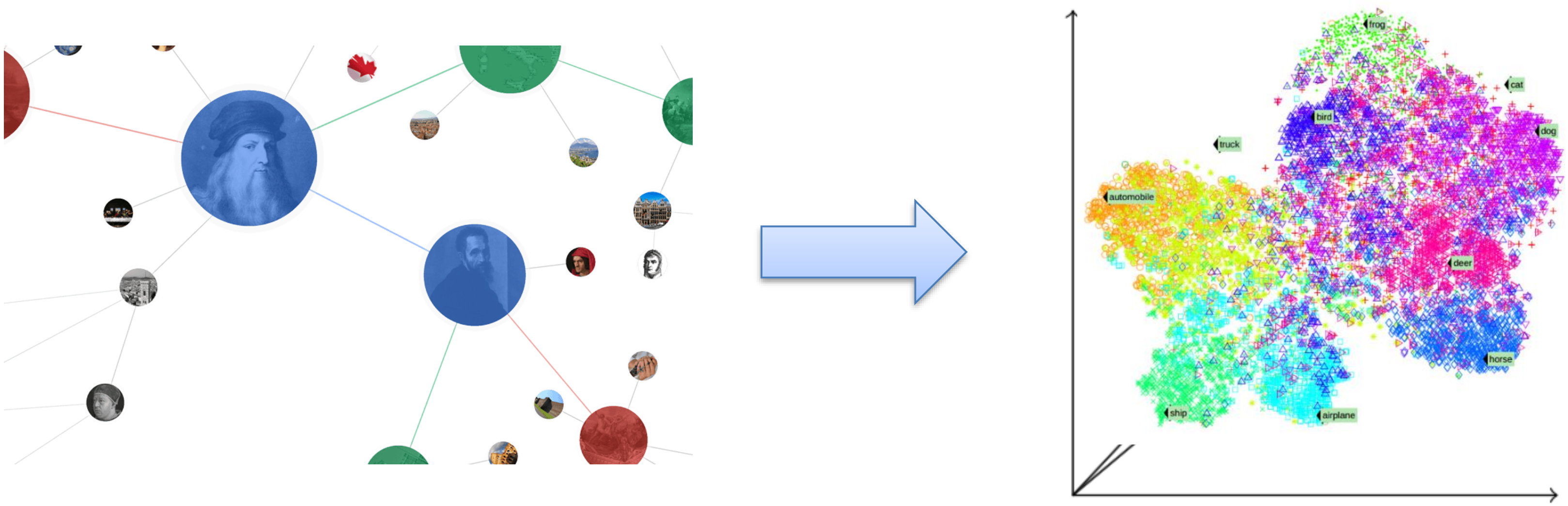
Entities and Relations in Knowledge Graph

- Knowledge structured as graph
  - Each node = an entity
  - Each edge = a relation
- Fact: (head, relation, tail)
  - head = subject entity
  - relation = relation type
  - tail = object entity
- Typical KGs
  - WordNet: Linguistic KG
  - Freebase: World KG



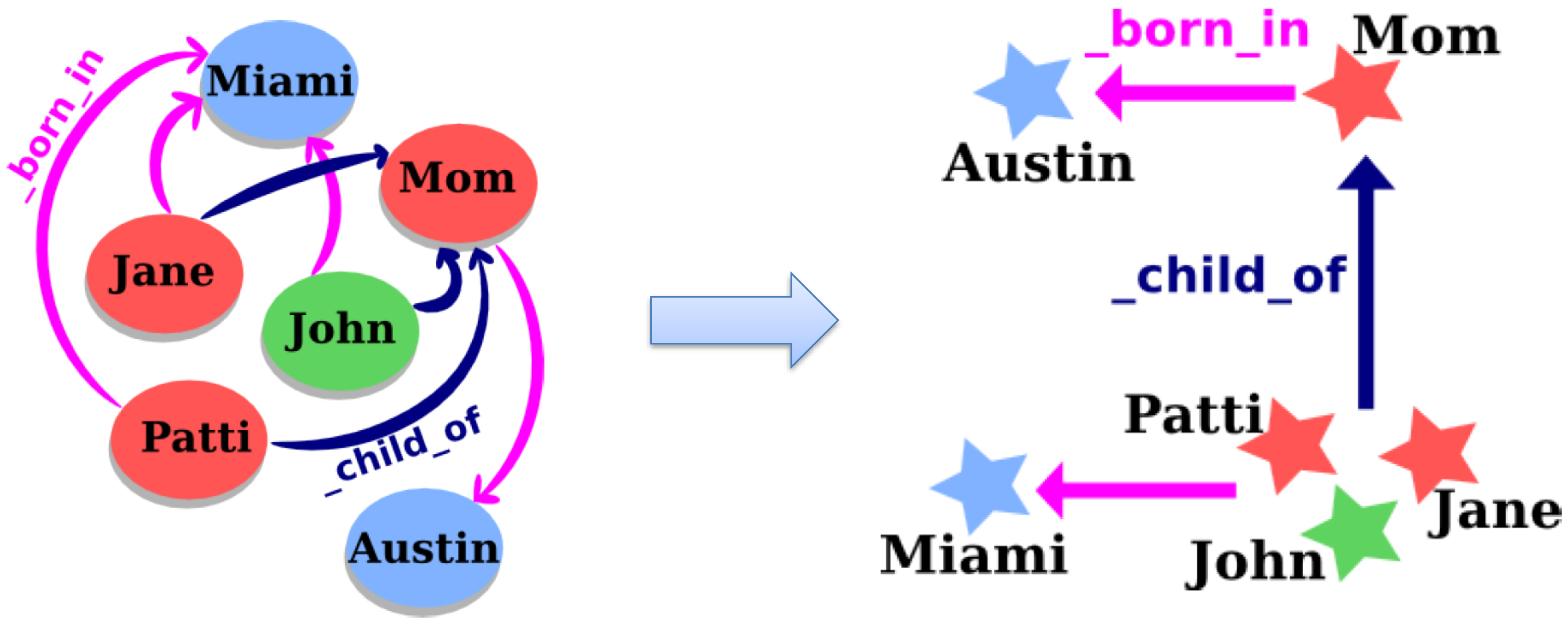
RL4KG

- Typical representations for KG
  - Symbolic triples (RDF)
  - Cannot efficiently measure semantic relatedness of entities
- How: Encode KGs into low-dimensional vector spaces



TransE

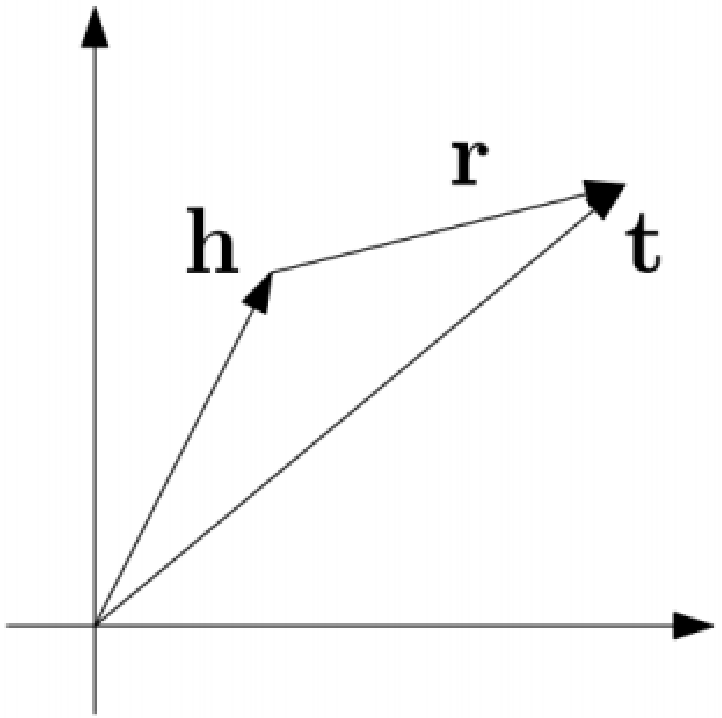
For each triple (head, relation, tail), relation as a translation from head to tail



Learning objective: **h + r = t**

TransE

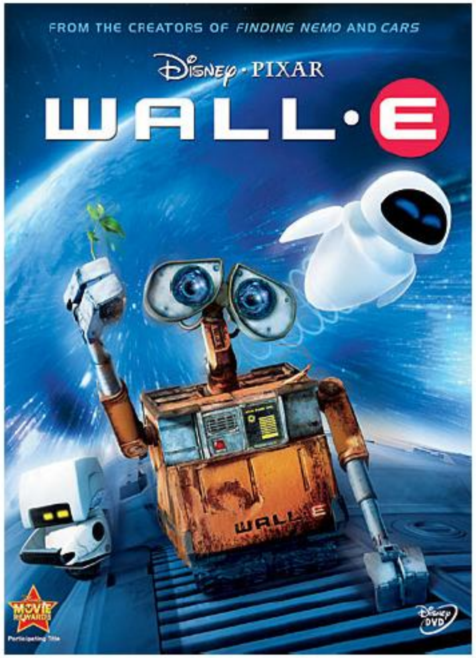
For each triple (head, relation, tail), relation as a translation from head to tail



Learning objective: **h + r = t**

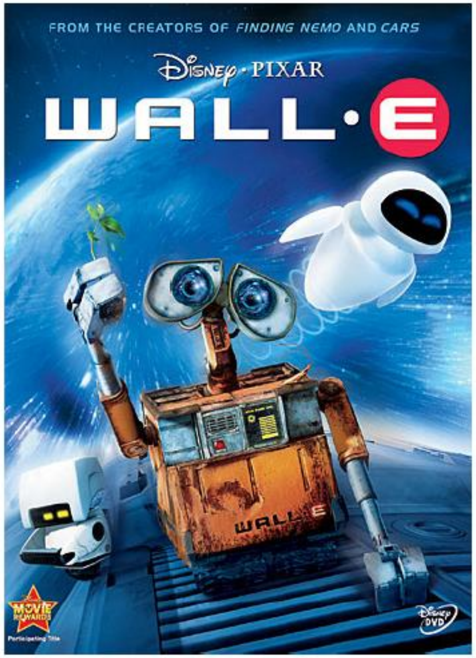
Evaluation: Entity Prediction

WALL-E _has_genre ?



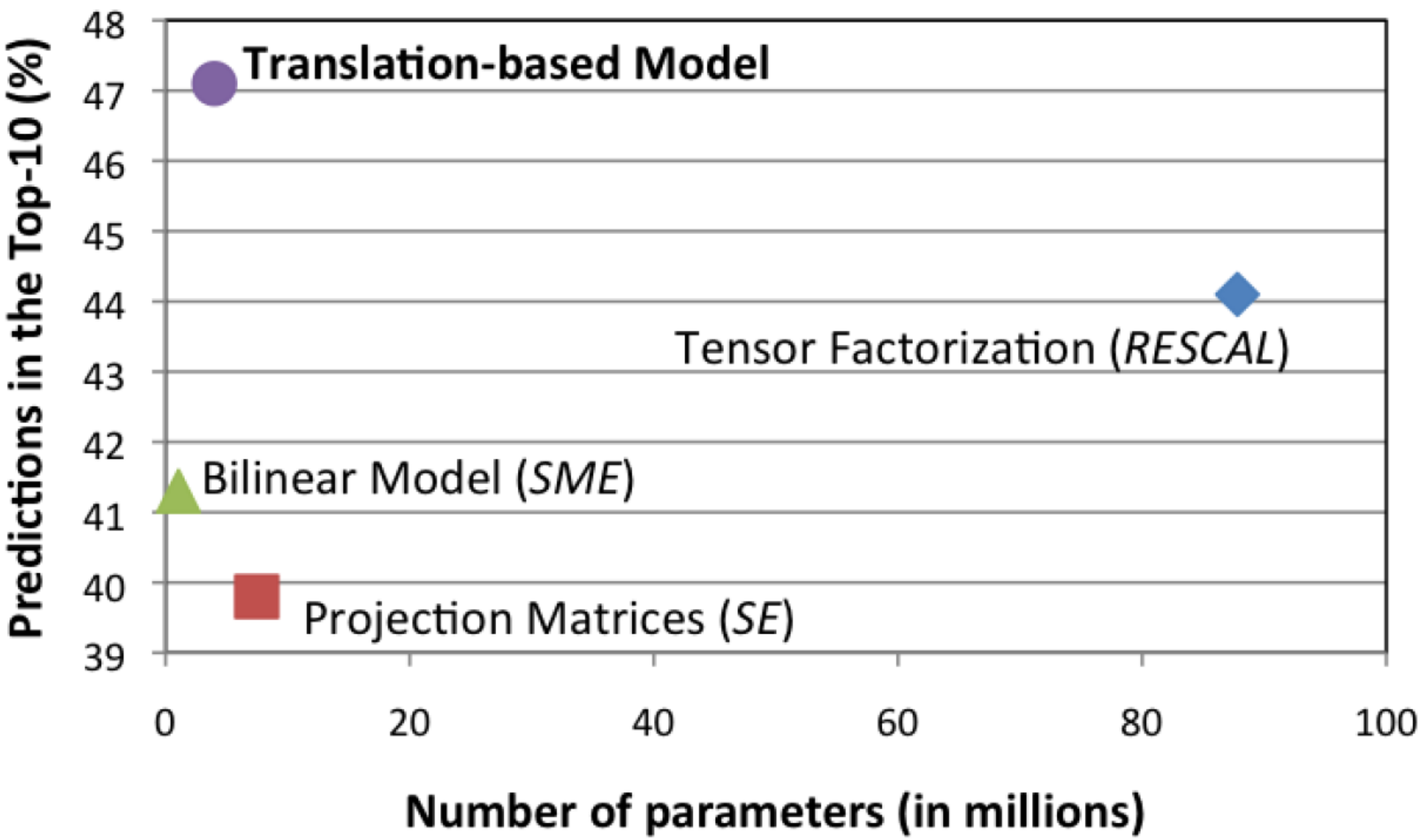
Evaluation: Entity Prediction

WALL-E _has_genre



- Animation
- Computer animation
- Comedy film
- Adventure film
- Science Fiction
- Fantasy
- Stop motion
- Satire
- Drama
- Connecting

Simple and Effective



TransE Examples

Entity	**Tsinghua_University**	**A.C._Milan**
1	University_of_Victoria	Inter_Milan
2	St._Stephen's_College,_Delhi	Celtic_F.C.
3	University_of_Ottawa	FC_Barcelona
4	University_of_British_Columbia	Genoa_C.F.C.
5	Peking_University	Udinese_Calcio
6	Utrecht_University	Real_Madrid_C.F.
7	Dalhousie_University	FC_Bayern_Munich
8	Brasenose_College,_Oxford	Bolton_Wanderers_F.C.
9	Cardiff_University	Borussia_Dortmund
10	Memorial_University_of_Newfoundland	Hertha_BSC_Berlin

TransE Examples

Entity	China	Barack_Obama	Apple
1	Japan	George_W._Bush	Onion
2	Taiwan	Nancy_Pelosi	Strawberries
3	South_Korea	John_Kerry	Avocado
4	Argentina	Hillary_Rodham_Clinton	Pear
5	North_Korea	Al_Gore	Cabbage
6	Hungary	George_H._W._Bush	Broccoli
7	Israel	John_McCain	Egg
8	Australia	Colin_Powell	Cheese
9	Iceland	Bill_Clinton	Bread
10	Hong_Kong	Charles_B._Rangel	Tomato

TransE Examples

Relation	/people/person/nationality	/location/location/contains
1	/people/person/places_lived	/base/aareas/schema/administrative_area/administrative_children
2	/people/person/place_of_birth	/location/country/administrative_divisions
3	/people/person/spouse_s	/location/country/first_level_divisions
4	/base/popstra/celebrity/vacations_in	/location/country/capital
5	/government/politician/government_positions_held	/award/award_nominee/award_nominations
6	/people/deceased_person/place_of_death	/location/administrative_division/capital
7	/olympics/olympic_athlete/country	/location/us_county/county_seat
8	/olympics/olympic_athlete/medals_won	/base/aareas/schema/administrative_area/capital
9	/music/artist/origin	/location/us_county/hud_county_place
10	/people/person/employment_history	/award/award_winner/awards_won

TransE Examples

Head	China	Barack_Obama
Relation	**/location/location/adjoin**	**/education/education/institution**
1	Japan	Harvard_College
2	Taiwan	Massachusetts_Institute_of_Technology
3	Israel	American_University
4	South_Korea	University_of_Michigan
5	Argentina	Columbia_University
6	France	Princeton_University
7	Philippines	Emory_University
8	Hungary	Vanderbilt_University
9	North_Korea	University_of_Notre_Dame
10	Hong_Kong	Texas_A&M_University

TransE Examples

Head	Stanford_University	Apple	Titanic
Relation	**/education/educational_institution/students_graduates**	**/food/food/nutrients**	**/film/film/genre**
1	Steven_Spielberg	Lipid	War_film
2	Ron_Howard	Protein	Period_piece
3	Stan_Lee	Valine	Drama
4	Barack_Obama	Tyrosine	History
5	Milton_Friedman	Serine	Biography
6	Walter_F._Parkes	Iron	Film_adaptation
7	Michael_Cimino	Cystine	Adventure_Film
8	Gale_Anne_Hurd	Pantothenic_acid	Action_Film
9	Bryan_Singer	Vitamin_A	Political_drama
10	Aaron_Sorkin	Sugar	Costume_drama

TransE Examples

Head	Barack_Obama
Tail	**Columbia_University**
1	/education/education/institution
2	/business/employment_tenure/company
3	/organization/leadership/organization
4	/base/popstra/paid_support/company
5	/location/location/contains
6	/education/education/institution
7	/american_football/player_game_statistics/team
8	/organization/organization_board_membership/organization
9	/music/artist/album
10	/baseball/batting_statistics/team

TransE Examples

Head	Barack_Obama
Tail	United_States_of_America
1	/people/person/nationality
2	/government/politician/government_positions_held./government/government_position_held/jurisdiction_of_office
3	/people/person/spouse_s./people/marriage/location_of_ceremony
4	/government/politician/government_positions_held./government/government_position_held/district_represented
5	/people/person/places_lived
6	/base/popstra/celebrity/vacations_in
7	/people/person/place_of_birth
8	/government/political_appointer/appointees./government/government_position_held/jurisdiction_of_office
9	/royalty/monarch/kingdom
10	/people/person/languages

TransE Examples

Head	Titanic
Tail	Drama
1	/film/film/genre
2	/media_common/netflix_title/netflix_genres
3	/film/film/subjects
4	/film/film_cut/type_of_film_cut
5	/film/film_regional_release_date/film_release_distribution_medium
6	/law/inventor/inventions
7	/government/government_position_held/jurisdiction_of_office
8	/tv/tv_program/genre
9	/film/dubbing_performance/language
10	/film/film_film_distributor_relationship/film_distribution_medium

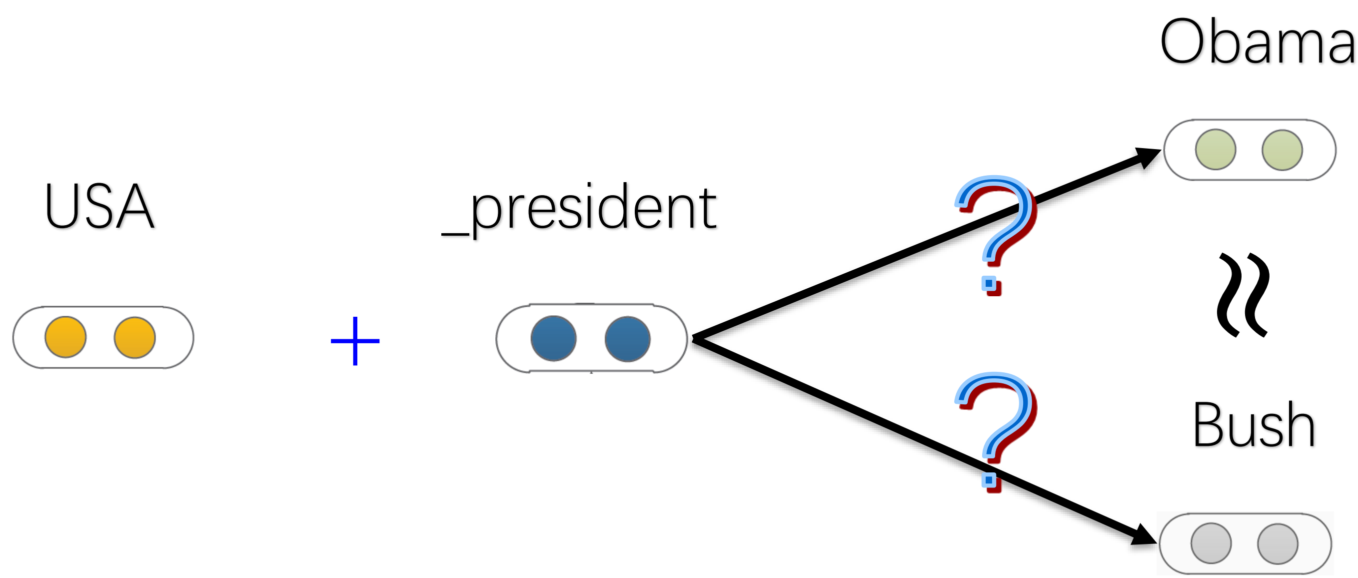
Key Challenges in RL4KG

- Modeling Complex Relations
- Fusion of Text and KG
- Modeling Relation Paths

MODELING COMPLEX RELATIONS

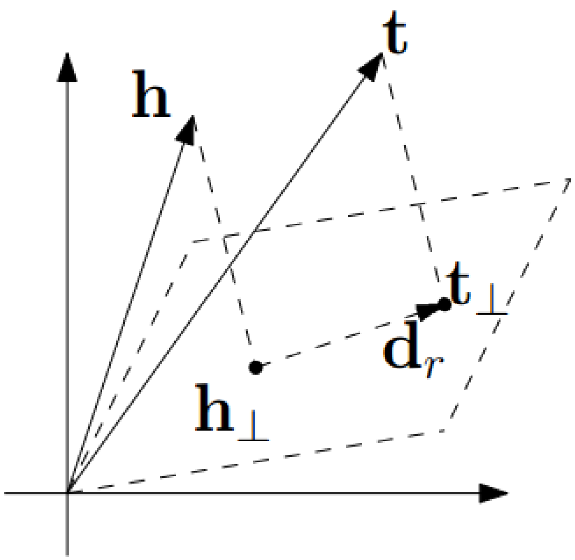
Complex Relations

- 1-to-N, N-to-1, N-to-N relations
  - (USA, _president, Obama)
  - (USA, _president, Bush)

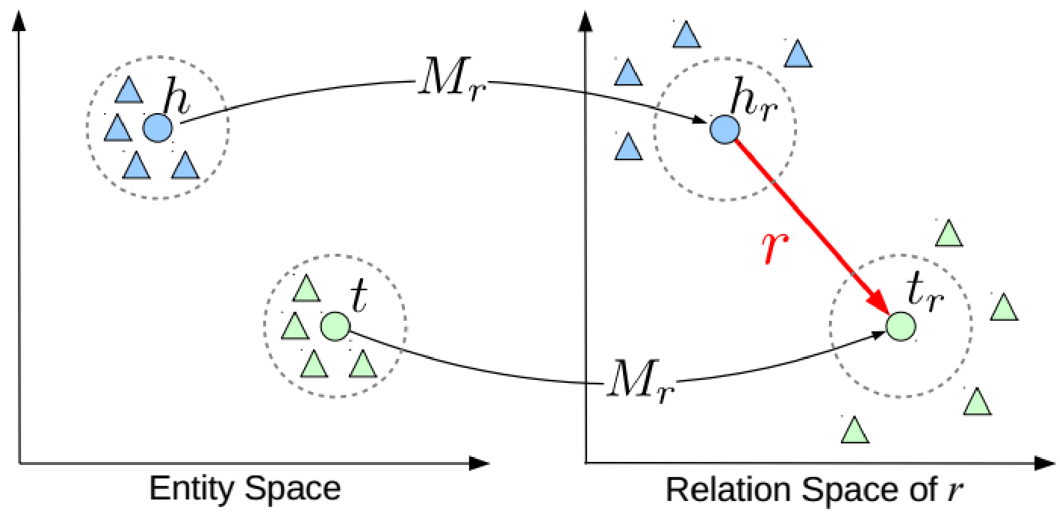


Complex Relations

- Build relation-specific entity embeddings



TransH



TransR

Wang, et al. (2014). Knowledge graph embedding by translating on hyperplanes. AAAI.
Lin, et al. (2015). Learning entity and relation embeddings for knowledge graph completion. AAAI.

Link Prediction Results

Data Sets	WN18				FB15K			
Metric	Mean Rank		Hits@10 (%)		Mean Rank		Hits@10 (%)	
	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter
Unstructured (Bordes et al. 2012)	315	304	35.3	38.2	1,074	979	4.5	6.3
RESCAL (Nickel, Tresp, and Kriegel 2011)	1,180	1,163	37.2	52.8	828	683	28.4	44.1
SE (Bordes et al. 2011)	1,011	985	68.5	80.5	273	162	28.8	39.8
SME (linear) (Bordes et al. 2012)	545	533	65.1	74.1	274	154	30.7	40.8
SME (bilinear) (Bordes et al. 2012)	526	509	54.7	61.3	284	158	31.3	41.3
LFM (Jenatton et al. 2012)	469	456	71.4	81.6	283	164	26.0	33.1
TransE (Bordes et al. 2013)	263	251	75.4	89.2	243	125	34.9	47.1
TransH (unif) (Wang et al. 2014)	318	303	75.4	86.7	211	84	42.5	58.5
TransH (bern) (Wang et al. 2014)	401	388	73.0	82.3	212	87	45.7	64.4
TransR (unif)	232	219	78.3	91.7	226	78	43.8	65.5
TransR (bern)	238	225	**79.8**	92.0	**198**	77	48.2	68.7
CTransR (unif)	243	230	78.9	**92.3**	233	82	44	66.3
CTransR (bern)	**231**	**218**	79.4	**92.3**	199	**75**	**48.4**	**70.2**

Examples

Head Entity	**Titanic**		
Relation	**/film/film/genre**		
Model	TransE	TransH	TransR
1	War_film	Drama	Costume_drama
2	Period_piece	Romance_Film	Drama
3	Drama	Costume_drama	Romance_Film
4	History	Film_adaptation	Period_piece
5	Biography	Period_piece	Epic_film
6	Film_adaptation	Adventure_Film	Adventure_Film
7	Adventure_Film	LGBT	LGBT
8	Action_Film	Existentialism	Film_adaptation
9	Political_drama	Epic_film	Existentialism
10	Costume_drama	War_film	War_film

Examples

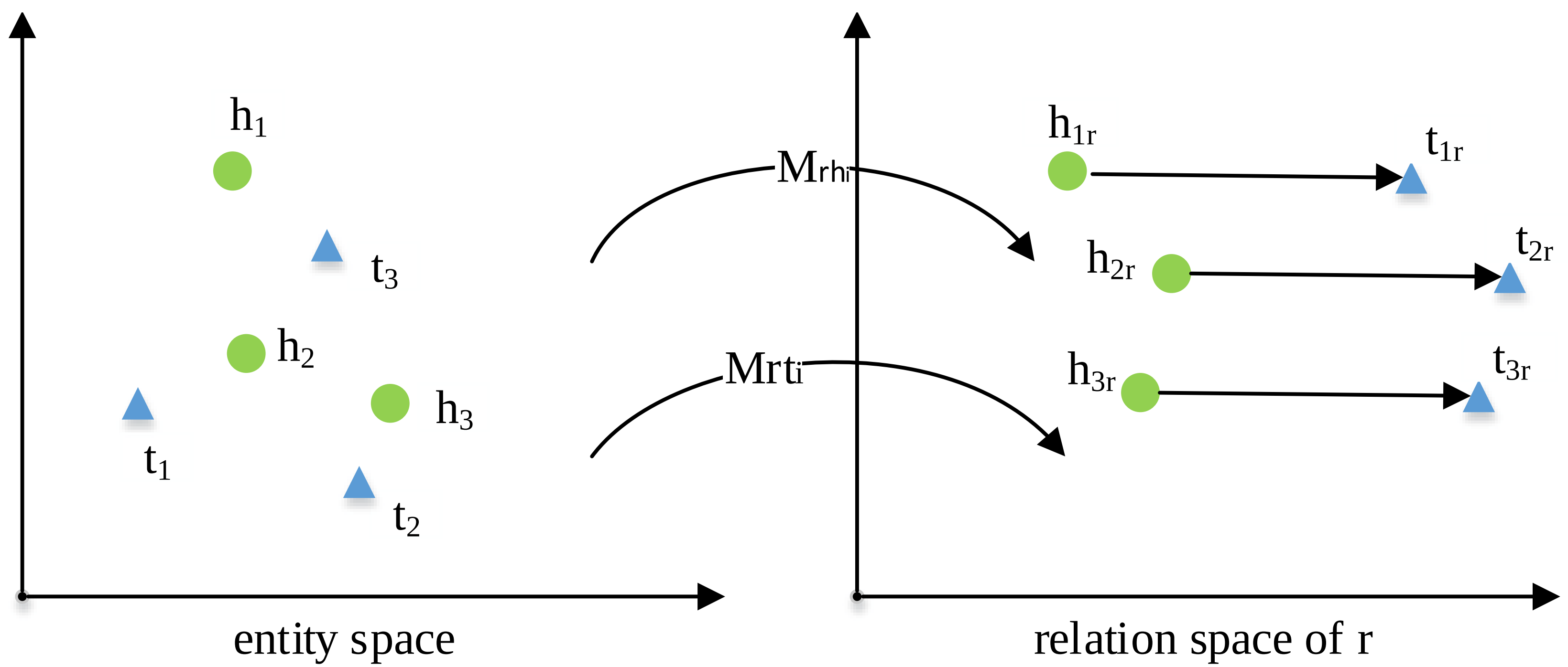
Head	Barack_Obama		
Relation	/people/person/education		
Model	TransE	TransH	TransR
1	Harvard_College	University_of_Virginia	University_of_Virginia
2	Massachusetts_Institute_of_Technology	George_Washington_University	George_Washington_University
3	American_University	University_of_Michigan	Stanford_University
4	University_of_Michigan	Harvard_College	Harvard_College
5	Columbia_University	Princeton_University	Purdue_University
6	Princeton_University	University_of_Washington	Princeton_University
7	Emory_University	Yale_University	University_of_Michigan
8	Vanderbilt_University	Stanford_University	Occidental_College
9	University_of_Notre_Dame	Purdue_University	University_of_Maryland,_College_Park
10	Texas_A&M_University	Columbia_University	Columbia_University

Examples

Head	University_of_Cambridge		
Relation	**/education/education/student**		
Model	TransE	TransH	TransR
1	John_Cleese	Stephen_Fry	David_Attenborough
2	Samuel_Beckett	David_Attenborough	Stephen_Fry
3	Harold_Pinter	Ralph_Vaughan_Williams	Stephen_Hawking
4	Virginia_Woolf	Alan_Bennett	Ralph_Vaughan_Williams
5	Graham_Chapman	Francis_Bacon	Alan_Bennett
6	Philip_Pullman	Julian_Fellowes	Julian_Fellowes
7	Ian_McEwan	Hugh_Bonneville	Ernest_Rutherford
8	Douglas_Adams	Graham_Chapman	Jonathan_Lynn
9	Terry_Gilliam	Miriam_Margolyes	Tom_Hollander
10	Richard_Dawkins	Stephen_Hawking	Chris_Weitz

TransD

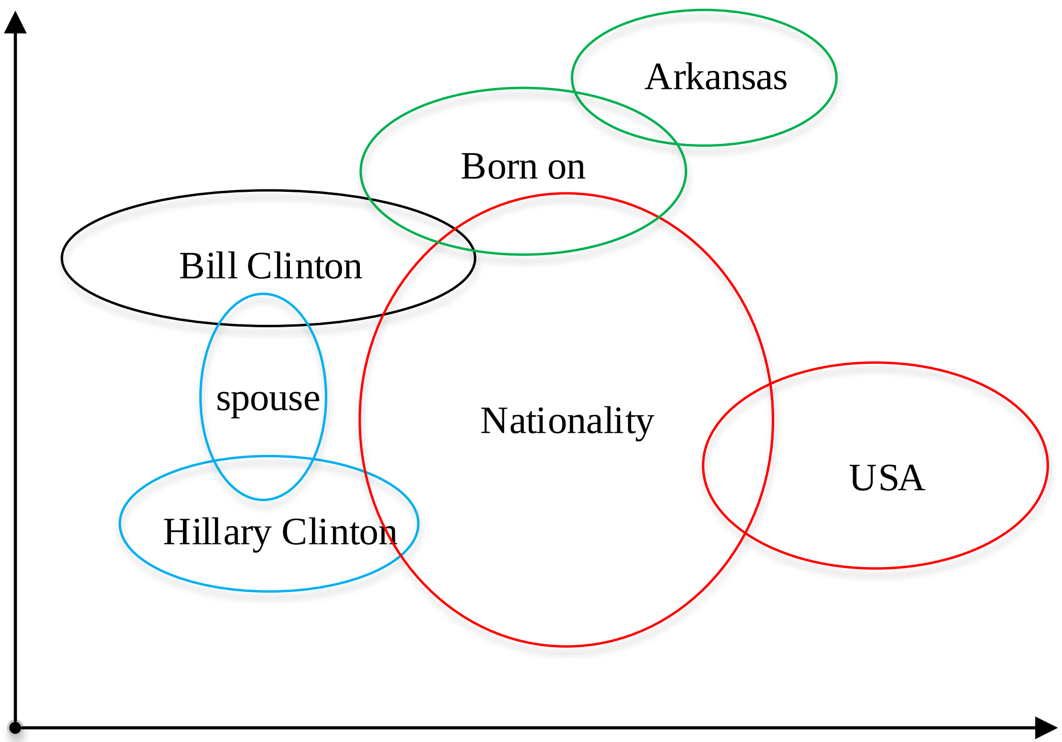
- Projection matrices not only related to relation but also head/tail entities



Ji, et al. (2015) Knowledge Graph Embedding via Dynamic Mapping Matrix. ACL-IJCNLP.

KG2E

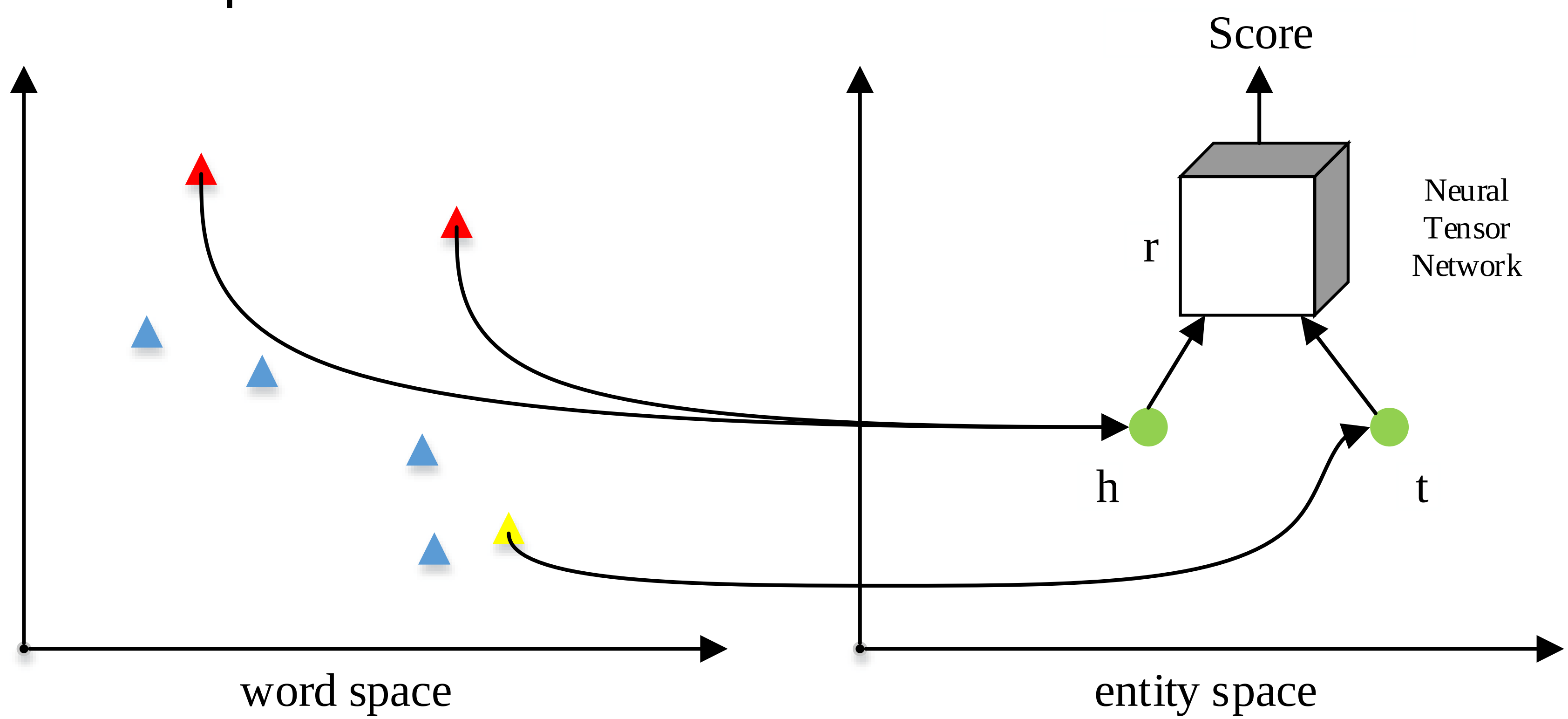
- Represent relations / entities with Gaussian distribution
- Consider (un)certainties of entities and relations



He, et al. (2015) Learning to Represent Knowledge Graphs with Gaussian Embedding. CIKM.

NTN

- NTN models KG with a Neural Tensor Network and represents entities via word vectors



Socher, et al. (2013) Reasoning with neural tensor networks for knowledge base completion. NIPS.

Other Models

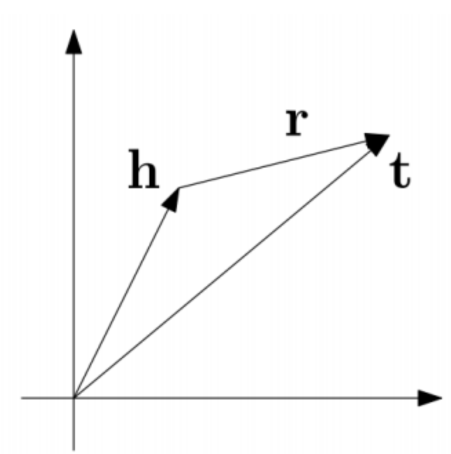
- **TranSparse** uses sparse projection matrices to deal with the issue of entities and relations are heterogeneous and unbalanced

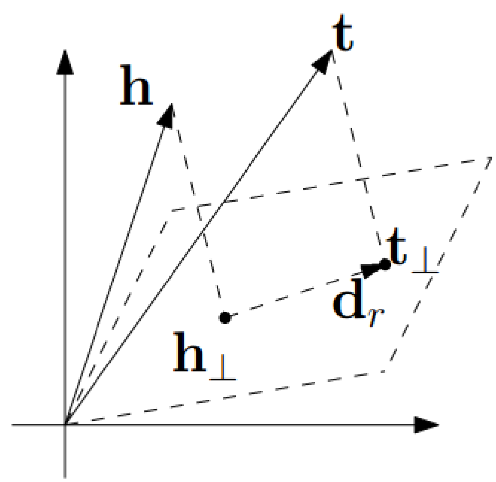
- **Holographic Embeddings (Hole)** uses the circular correlation to combine the expressive power of the tensor product with the efficiency and simplicity of TransE

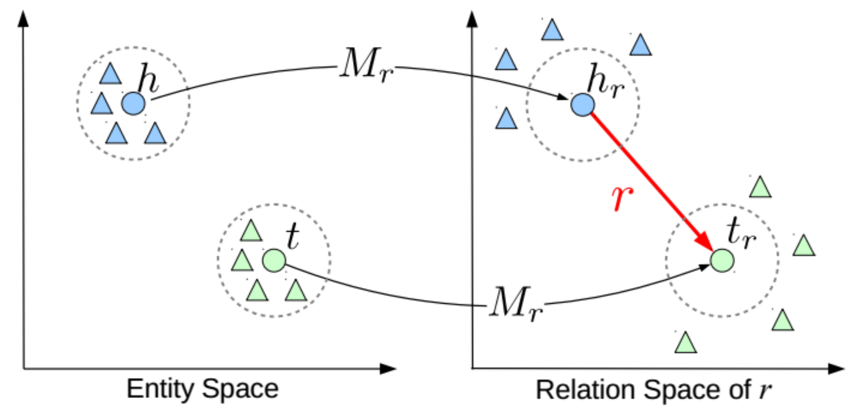
Ji, et al. (2016) Knowledge Graph Completion with Adaptive Sparse Transfer Matrix. AAAI.
Nichkel, et al. (2015) Holographic Embeddings of Knowledge Graphs. Arxiv.

Summary

- TransE is too simple to handle complex relations well
  - 1-N, N-1, N-N
  - TransA，TransD，TransE，TransG，TransH，TransR, KG2E, TranSparse, Hole







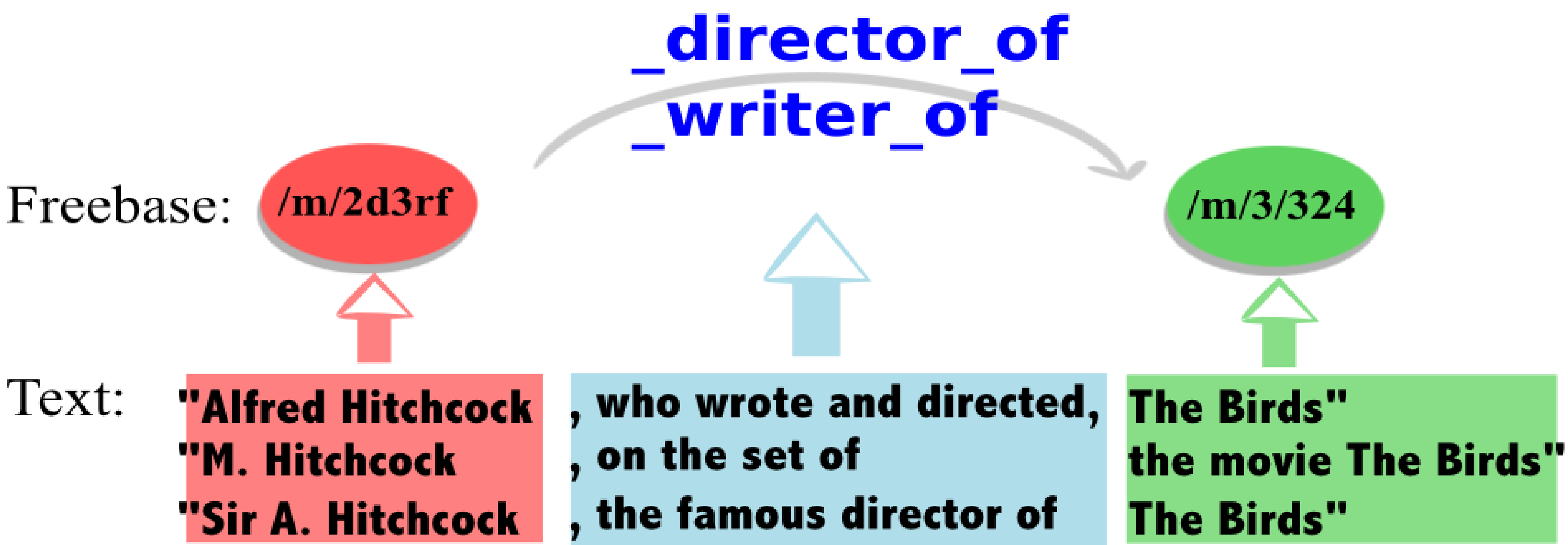
Summary

- More complex relations
  - Relations of different types
  - Facts with more than two entities
  - Facts with temporal and spatial information

FUSION OF TEXT AND KG

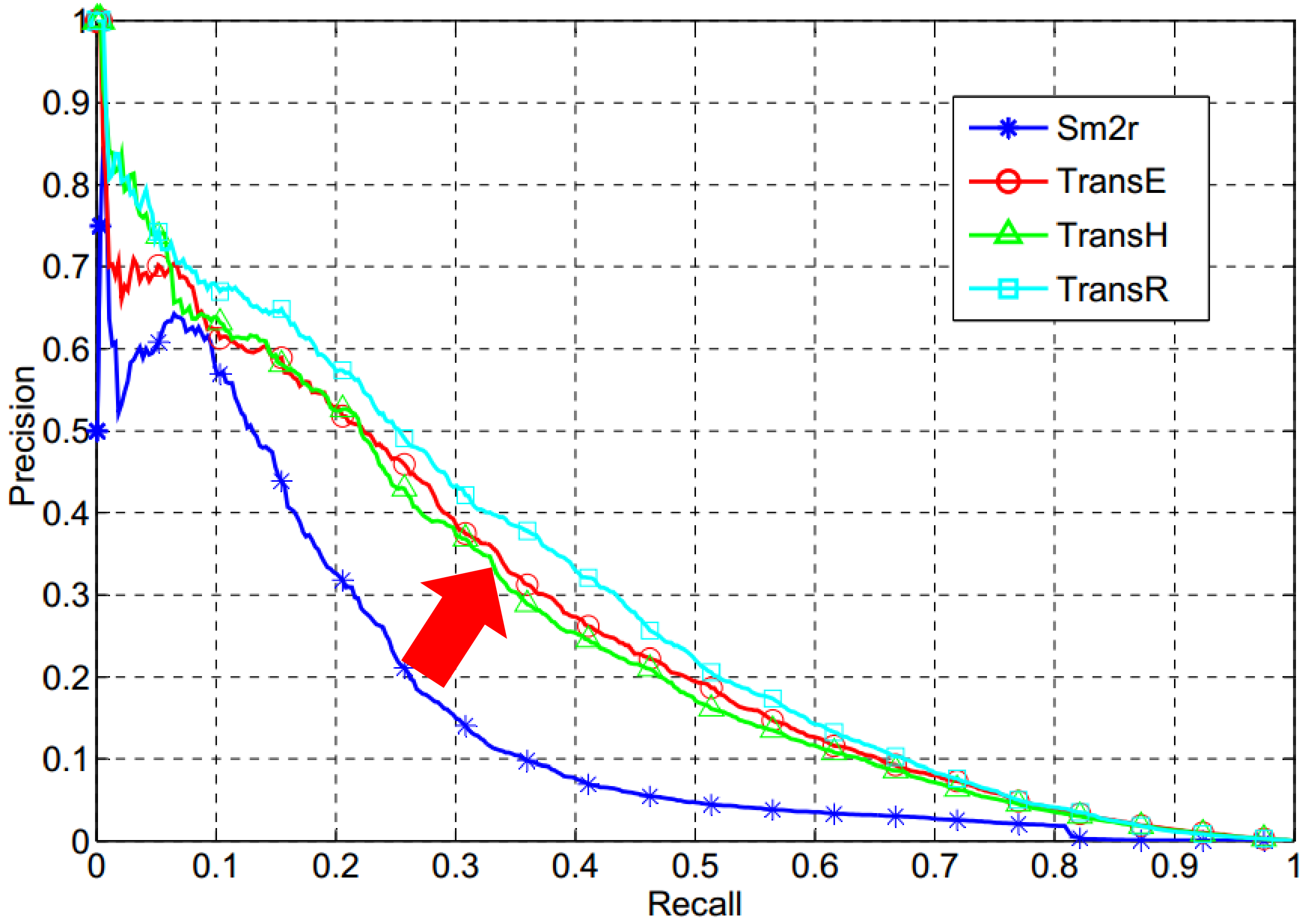
Fusion of Text and KG

- Relation prediction for KG
  - **r ~ t-h**
- Relation extraction from text



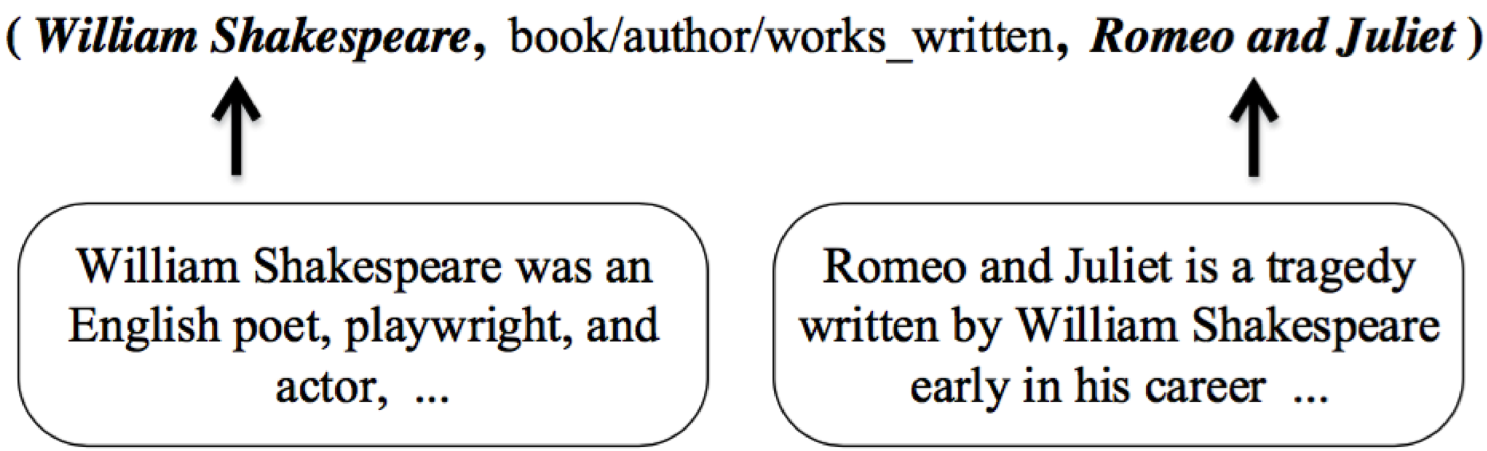
Relation Extraction with Text and KG

- NYT+FB (Weston et al.2013)



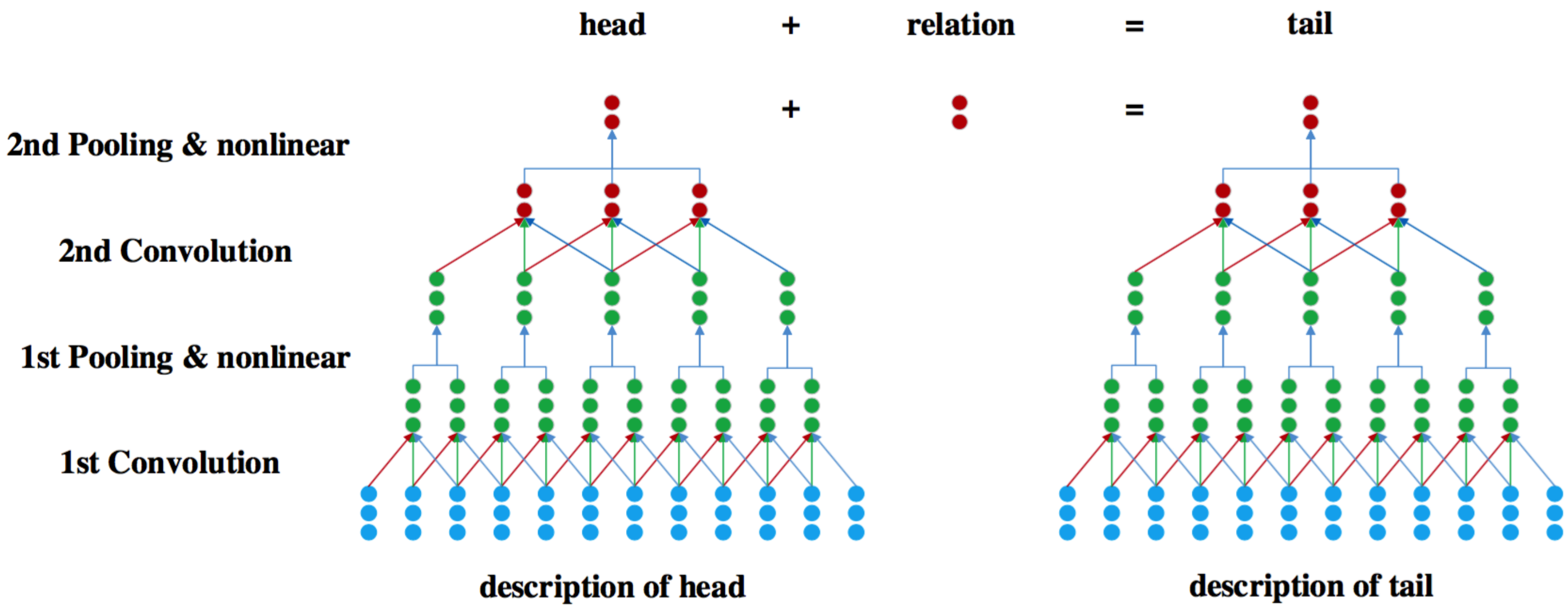
RL4KG with Entity Descriptions

- KG contains rich information besides network structure



Description-Embodied RL4KG

- Enhance entity representation with descriptions
- Model descriptions with CNN



Xie, et al. (2016). Representation Learning of Knowledge Graphs with Entity Descriptions. AAAI.

Evaluation in Zero-Shot Scenario

- Effective for generating representations for new entities

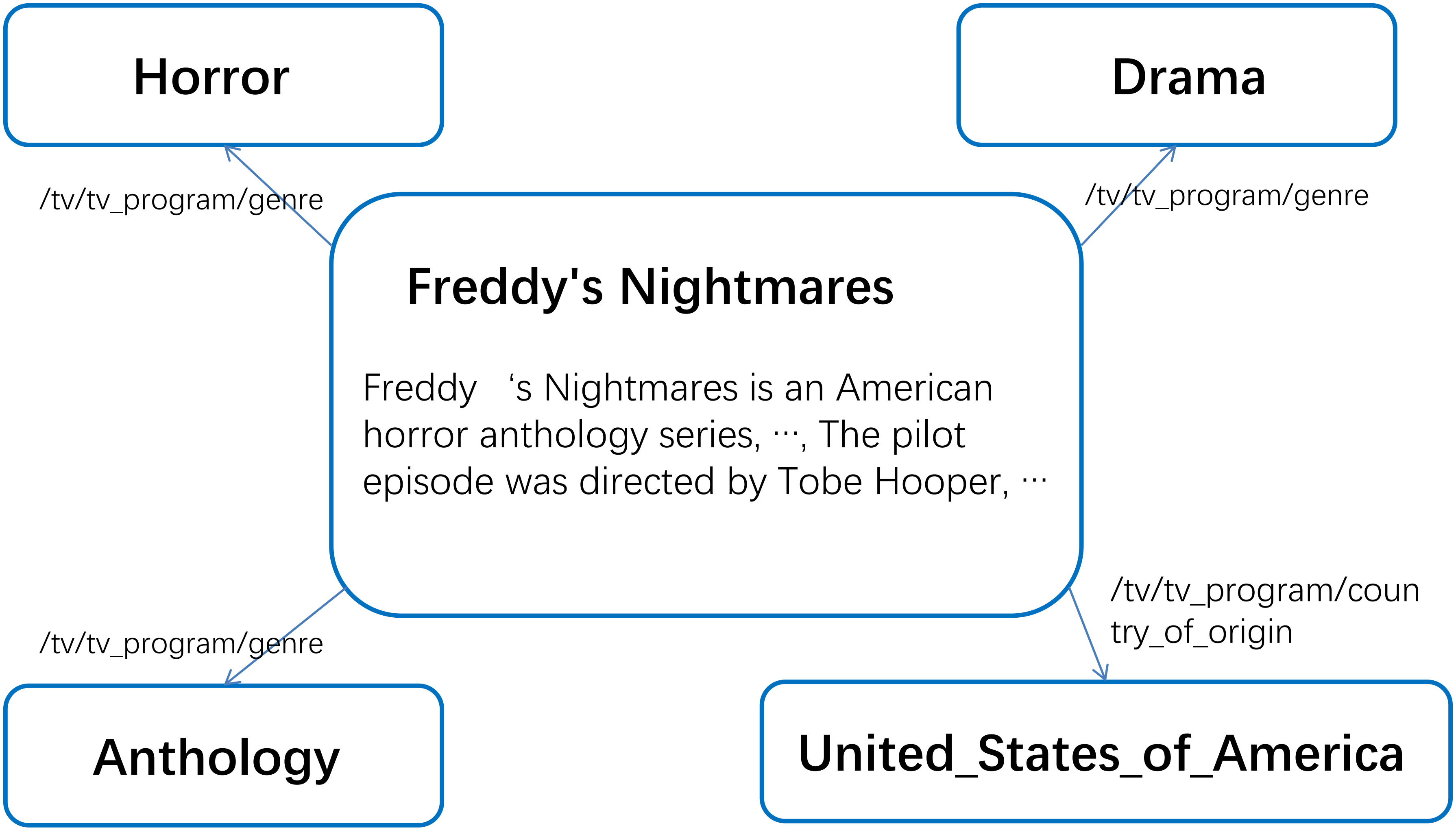
Table 5: Evaluation results on entity prediction in zero-shot scenario

Metric	$d-e$	$e-d$	$d-d$	Total
Partial-CBOW	26.5	20.9	67.2	24.6
CBOW	27.1	21.7	66.6	25.3
Partial-CNN	26.8	20.8	69.5	24.8
CNN	**31.2**	**26.1**	**72.5**	**29.5**

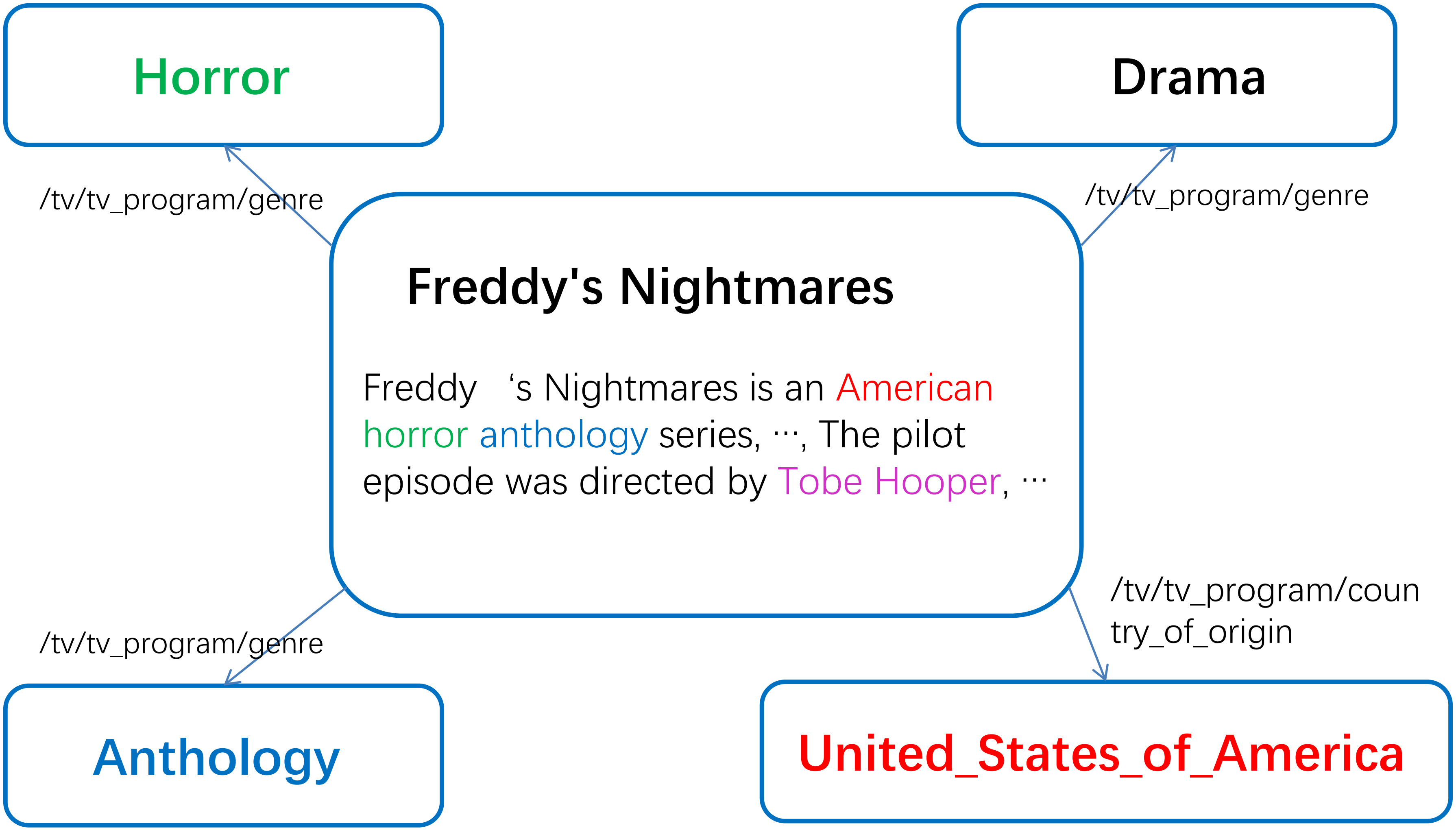
Table 6: Evaluation results on relation prediction in zero-shot scenario

Metric	$d-e$	$e-d$	$d-d$	Total
Partial-CBOW	49.0	42.2	0.0	46.2
CBOW	52.2	47.9	0.0	50.3
Partial-CNN	56.6	52.4	4.0	54.8
CNN	**60.4**	**55.5**	**7.3**	**58.2**

Examples


Horror
Drama
/tv/tv_program/genre
/tv/tv_program/genre
Freddy's Nightmares
Freddy 's Nightmares is an American horror anthology series, …, The pilot episode was directed by Tobe Hooper, …
/tv/tv_program/country_of_origin
/tv/tv_program/genre
Anthology
United_States_of_America

Examples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/tv/tv_program/genre
/tv/tv_program/country_of_origin
Anthology
United_States_of_America

TransE+Word2Vec

- KG=>TransE, Text=>Word2Vec
- Make embeddings of the same entities in KGs and text related to each other

$$\mathcal{L}_K = \sum_{(h,r,t)\in\Delta} \mathcal{L}_f(h,r,t)$$

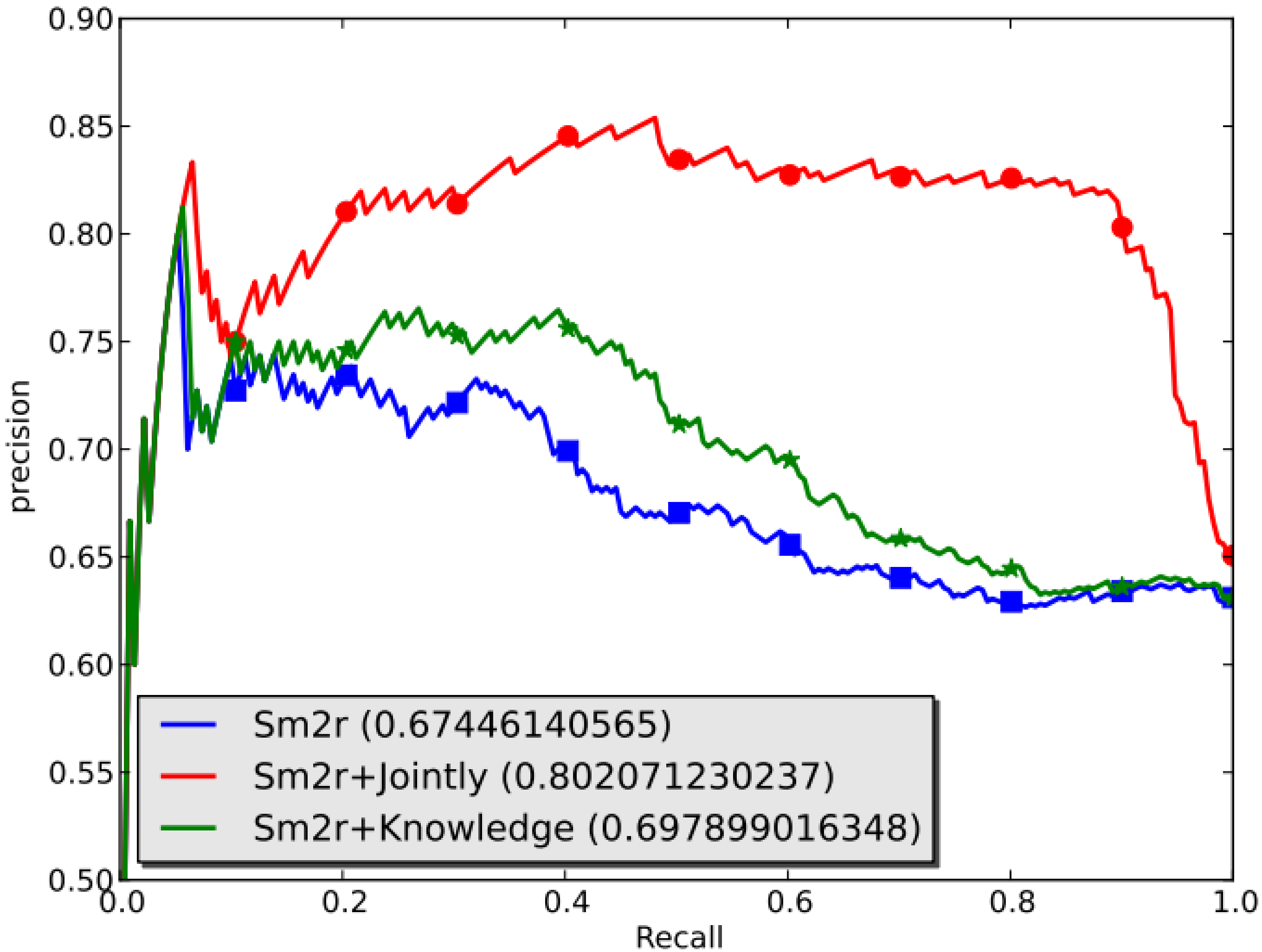
$$\mathcal{L}_{AN} = \sum_{(h,r,t)\in\Delta} \mathbf{I}_{[w_h\in\mathcal{V}\wedge w_t\in\mathcal{V}]} \cdot \mathcal{L}_f(w_h,r,w_t) +$$

$$\mathbf{I}_{[w_h\in\mathcal{V}]} \cdot \mathcal{L}_f(w_h,r,t) + \mathbf{I}_{[w_t\in\mathcal{V}]} \cdot \mathcal{L}_f(h,r,w_t)$$

Wang, et al. (2014). Knowledge graph and text jointly embedding. EMNLP.

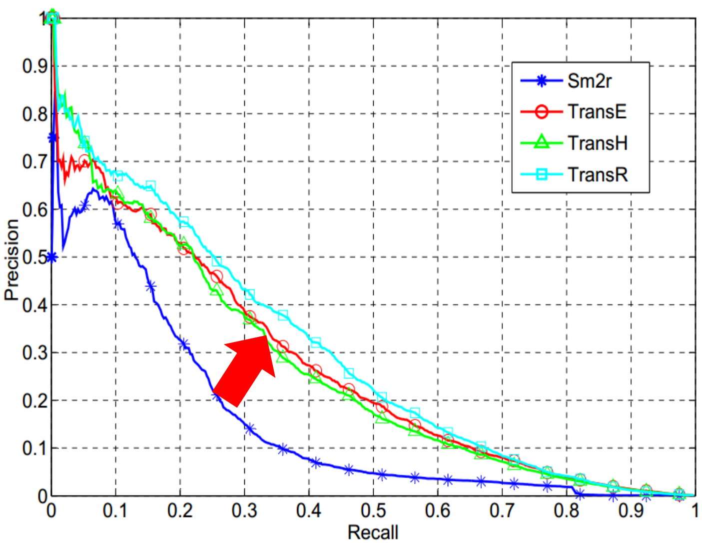
TransE+Word2Vec的效果

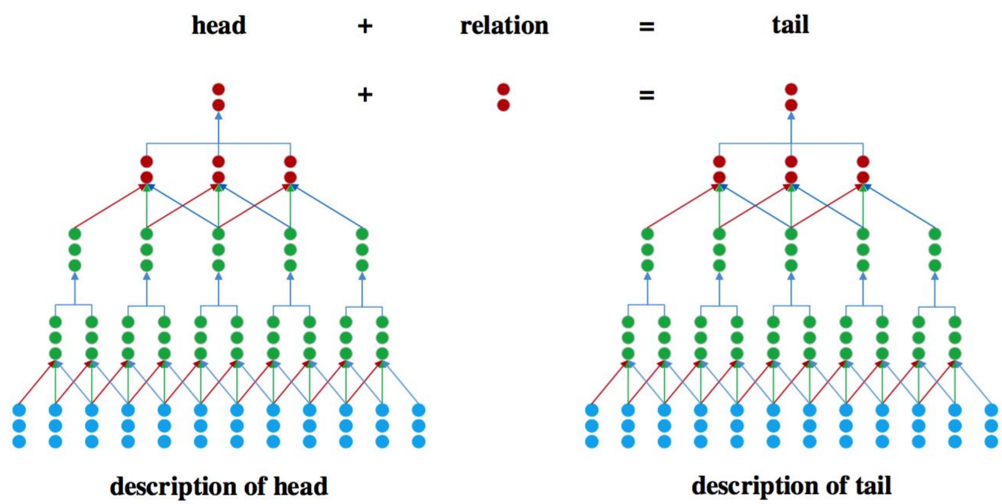
- 数据 NYT+FB



Summary

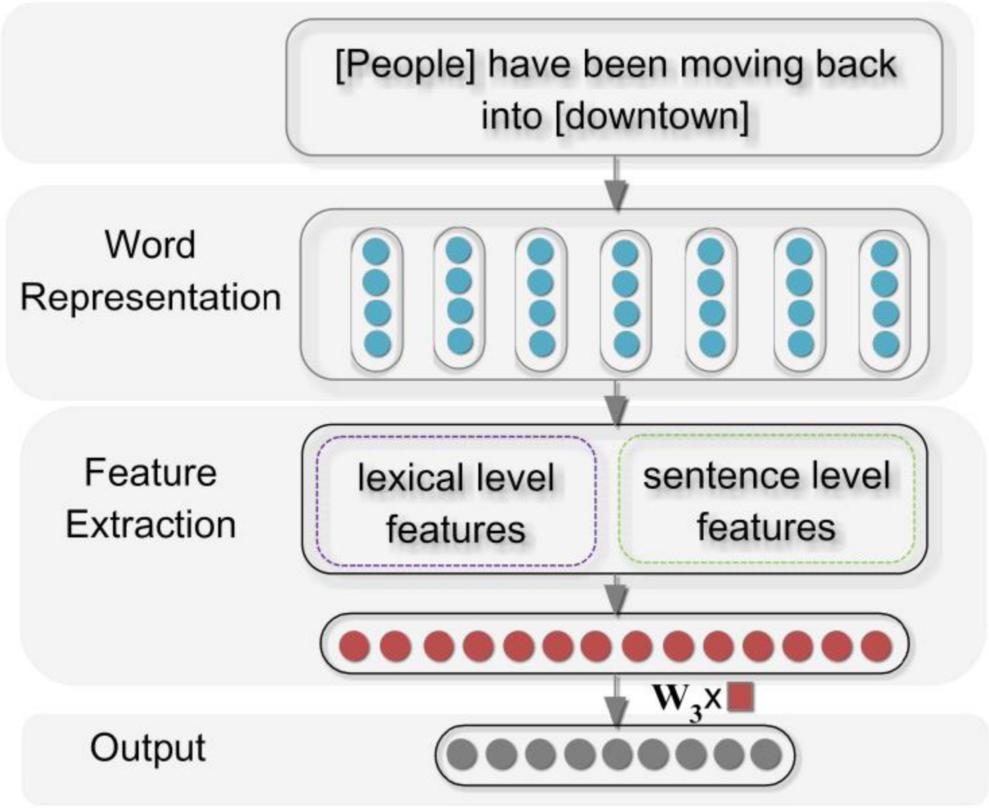
- Information in KGs and text are complementary
- Joint RL for text and KG is important for relation extraction and knowledge representation





Summary

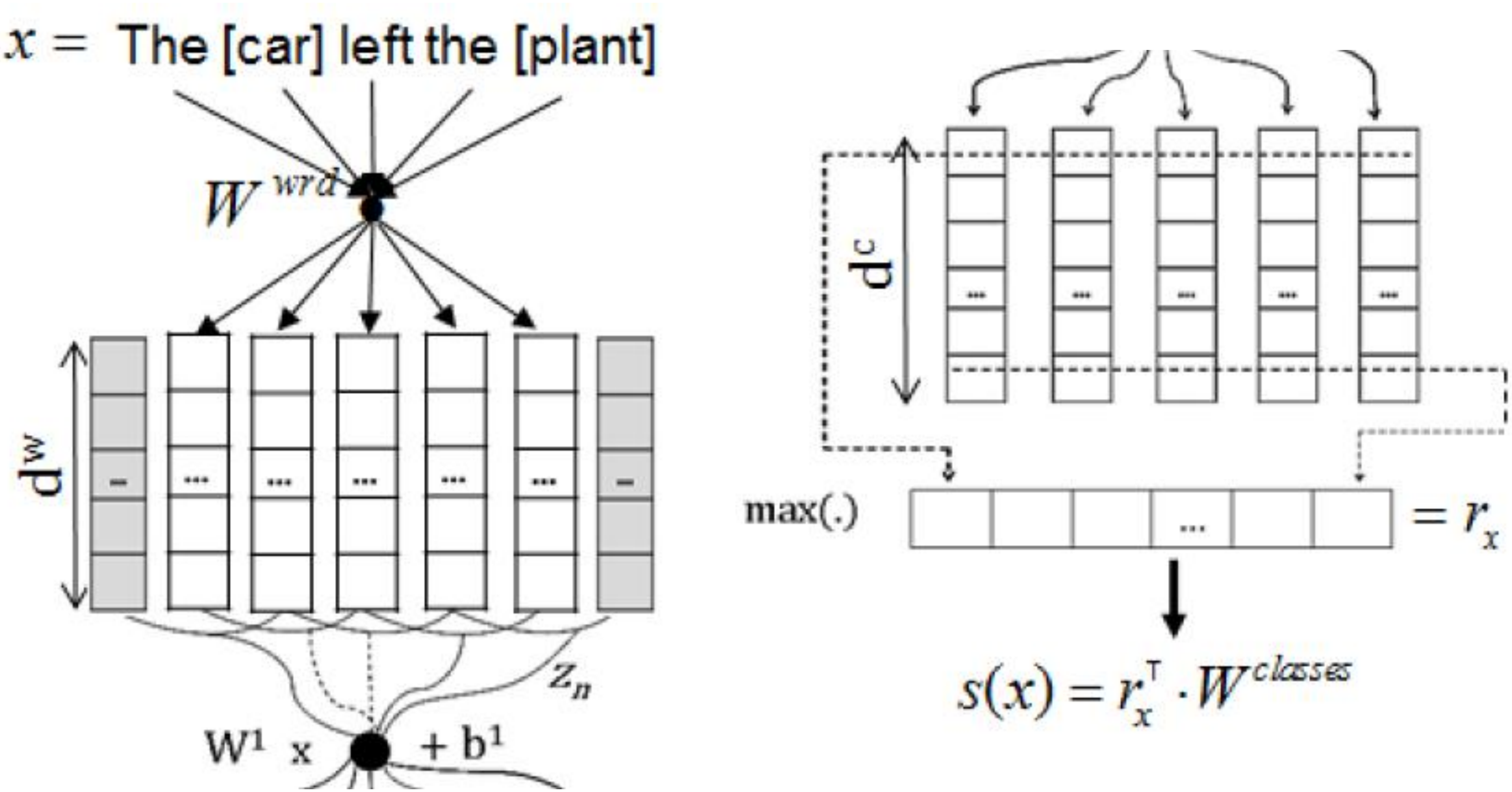
- Relation Classification via CNN



Zeng, et al. (2014). Relation Classification via Convolutional Deep Neural Network. COLING.

Summary

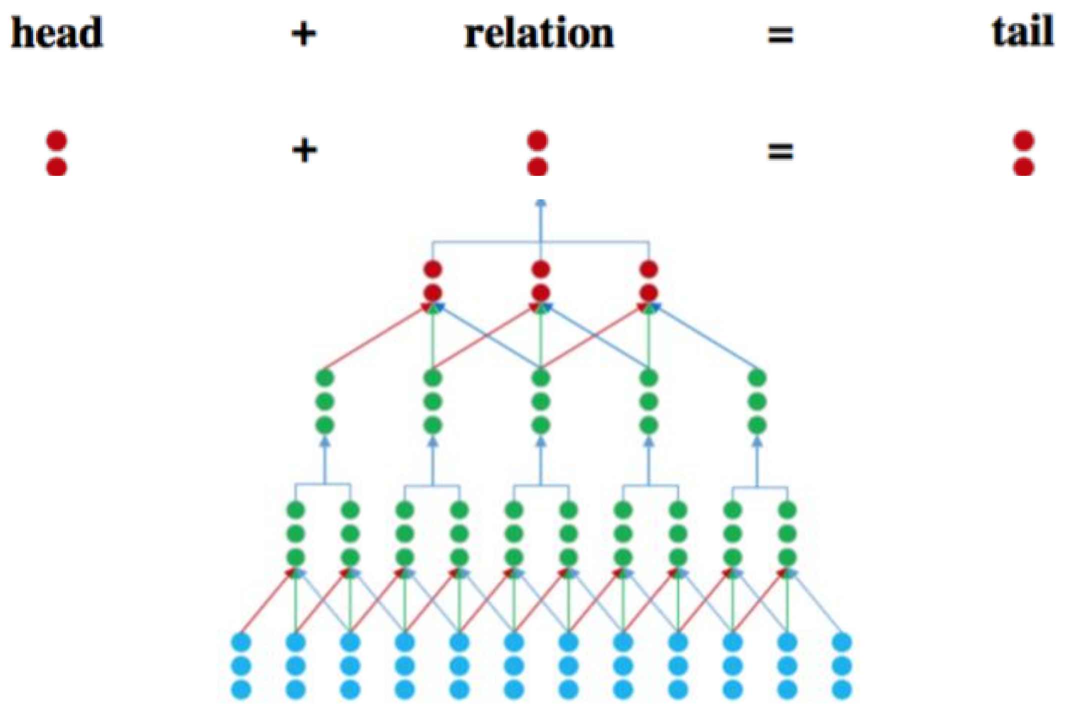
- Relation classification via ranking (CR-CNN)



Santos, et al. (2015). Classifying Relations by Ranking with Convolutional Neural Networks. ACL

Summary

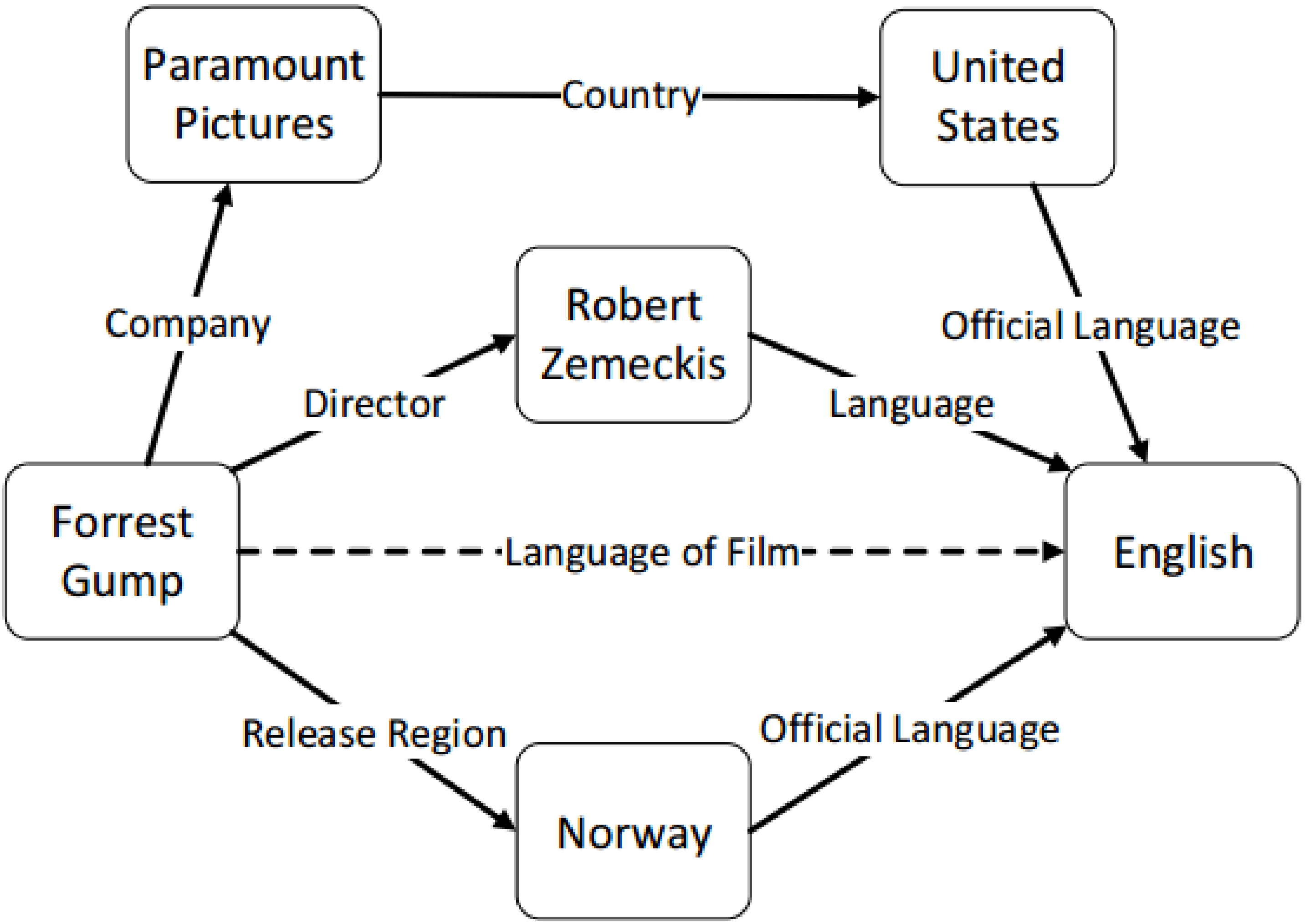
- Joint learning of TransE and CNN



MODELING RELATION PATHS

Relation Paths

- Complex inference patterns between relations



Relation Paths for Relation Extraction

- Path Ranking Algorithm

ID	PRA Path (Comment)
	athletePlaysForTeam
1	$c \xrightarrow{\text{athletePlaysInLeague}} c \xrightarrow{\text{leaguePlayers}} c \xrightarrow{\text{athletePlaysForTeam}} c$ (teams with many players in the athlete's league)
2	$c \xrightarrow{\text{athletePlaysInLeague}} c \xrightarrow{\text{leagueTeams}} c \xrightarrow{\text{teamAgainstTeam}} c$ (teams that play against many teams in the athlete's league)
	athletePlaysInLeague
3	$c \xrightarrow{\text{athletePlaysSport}} c \xrightarrow{\text{players}} c \xrightarrow{\text{athletePlaysInLeague}} c$ (the league that players of a certain sport belong to)
4	$c \xrightarrow{\text{isa}} c \xrightarrow{\text{isa}^{-1}} c \xrightarrow{\text{athletePlaysInLeague}} c$ (popular leagues with many players)
	athletePlaysSport
5	$c \xrightarrow{\text{isa}} c \xrightarrow{\text{isa}^{-1}} c \xrightarrow{\text{athletePlaysSport}} c$ (popular sports of all the athletes)
6	$c \xrightarrow{\text{athletePlaysInLeague}} c \xrightarrow{\text{superpartOfOrganization}} c \xrightarrow{\text{teamPlaysSport}} c$ (popular sports of a certain league)
	stadiumLocatedInCity
7	$c \xrightarrow{\text{stadiumHomeTeam}} c \xrightarrow{\text{teamHomeStadium}} c \xrightarrow{\text{stadiumLocatedInCity}} c$ (city of the stadium with the same team)
8	$c \xrightarrow{\text{latitudeLongitude}} c \xrightarrow{\text{latitudeLongitudeOf}} c \xrightarrow{\text{stadiumLocatedInCity}} c$ (city of the stadium with the same location)
	teamHomeStadium
9	$c \xrightarrow{\text{teamPlaysInCity}} c \xrightarrow{\text{cityStadiums}} c$ (stadiums located in the same city with the query team)
10	$c \xrightarrow{\text{teamMember}} c \xrightarrow{\text{athletePlaysForTeam}} c \xrightarrow{\text{teamHomeStadium}} c$ (home stadium of teams which share players with the query)
	teamPlaysInCity
11	$c \xrightarrow{\text{teamHomeStadium}} c \xrightarrow{\text{stadiumLocatedInCity}} c$ (city of the team's home stadium)
12	$c \xrightarrow{\text{teamHomeStadium}} c \xrightarrow{\text{stadiumHomeTeam}} c \xrightarrow{\text{teamPlaysInCity}} c$ (city of teams with the same home stadium as the query)
	teamPlaysInLeague
13	$c \xrightarrow{\text{teamPlaysSport}} c \xrightarrow{\text{players}} c \xrightarrow{\text{athletePlaysInLeague}} c$ (the league that the query team's members belong to)
14	$c \xrightarrow{\text{teamPlaysAgainstTeam}} c \xrightarrow{\text{teamPlaysInLeague}} c$ (the league that the query team's competing team belongs to)
	teamPlaysSport
15	$c \xrightarrow{\text{isa}} c \xrightarrow{\text{isa}^{-1}} c \xrightarrow{\text{teamPlaysSport}} c$ (sports played by many teams)
16	$c \xrightarrow{\text{teamPlaysInLeague}} c \xrightarrow{\text{leagueTeams}} c \xrightarrow{\text{teamPlaysSport}} c$ (the sport played by other teams in the league)

Lao, et al. (2011). Random walk inference and learning in a large scale knowledge base. EMNLP.

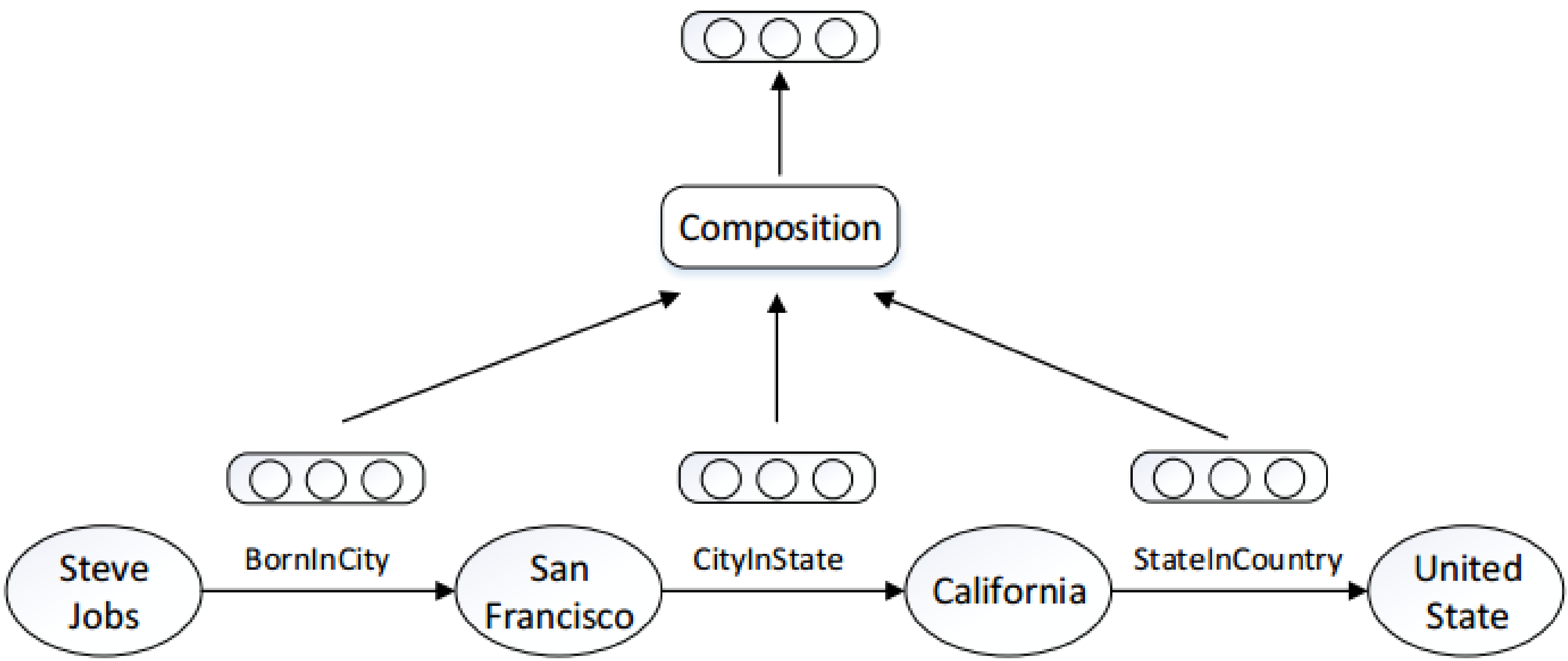
Path-based TransE

	TransE	PTransE
KB	$h \xrightarrow{r} t$	$h \xrightarrow{r_1} e_1 \xrightarrow{r_2} t$
Triples	(h, r, t)	(h, r_1, e_1) (e_1, r_2, t) $(h, r_1 \circ r_2, t)$
Objectives	$\mathbf{h} + \mathbf{r} = \mathbf{t}$	$\mathbf{h} + \mathbf{r}_1 = \mathbf{e}_1$ $\mathbf{e}_1 + \mathbf{r}_2 = \mathbf{t}$ $\mathbf{h} + (\mathbf{r}_1 \circ \mathbf{r}_2) = \mathbf{t}$

Lin, et al. (2015). Modeling Relation Paths for Representation Learning of Knowledge Bases. EMNLP.

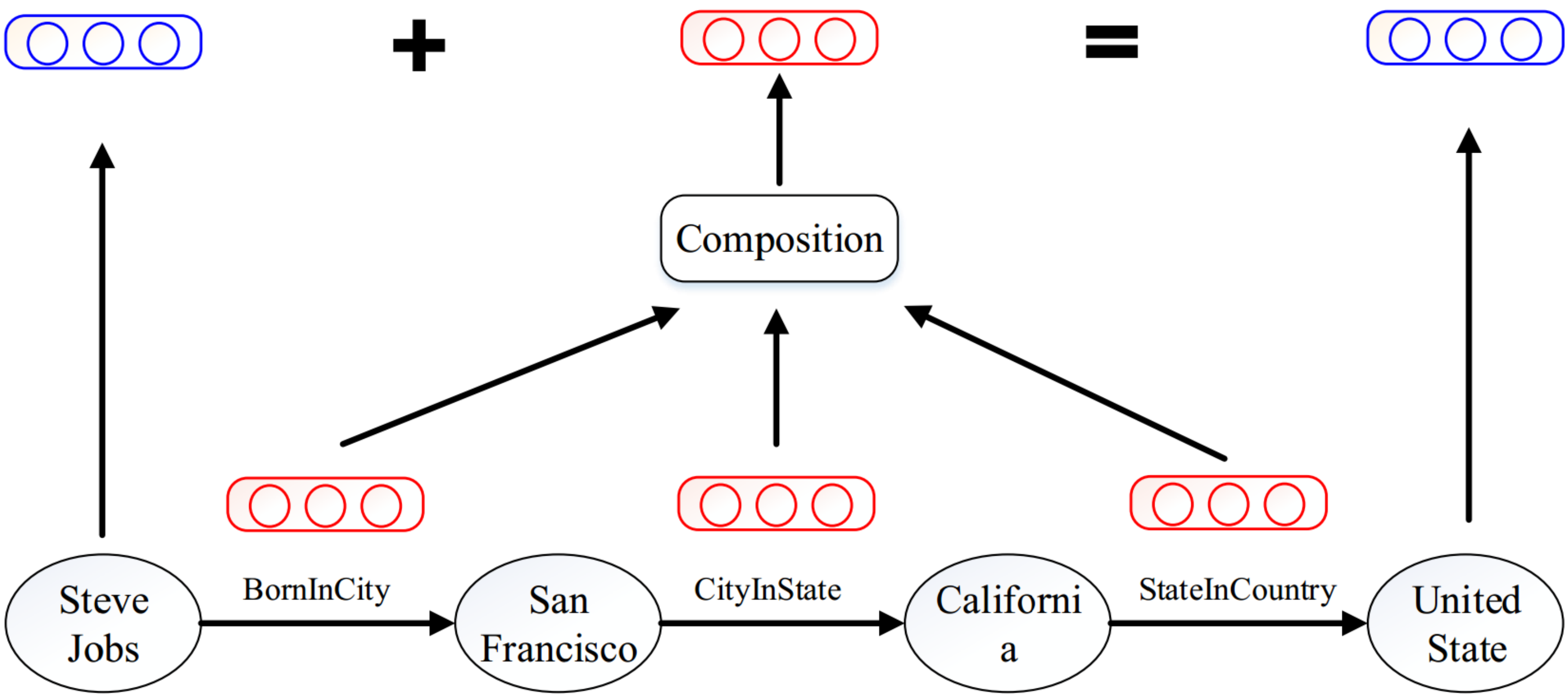
Representation of Relation Paths

- Semantic Composition: Add, Multiply, RNN



Gardner, et al. (2013). Improving learning and inference in a large knowledge-base using latent syntactic cues. EMNLP.

Path-based TransE



Entity Prediction Results

Metric	Mean Rank		Hits@10 (%)	
	Raw	Filter	Raw	Filter
RESCAL	828	683	28.4	44.1
SE	273	162	28.8	39.8
SME (linear)	274	154	30.7	40.8
SME (bilinear)	284	158	31.3	41.3
LFM	283	164	26.0	33.1
TransE	243	125	34.9	$\boxed{47.1}$
TransH	212	87	45.7	64.4
TransR	**198**	77	48.2	68.7
TransE (Our)	205	63	47.9	70.2
PTransE (ADD, 2-step)	200	**54**	**51.8**	83.4
PTransE (MUL, 2-step)	216	67	47.4	77.7
PTransE (RNN, 2-step)	242	92	50.6	82.2
PTransE (ADD, 3-step)	207	58	51.4	$\boxed{\mathbf{84.6}}$

+35%

Lin, et al. (2015). Modeling Relation Paths for Representation Learning of Knowledge Bases. EMNLP.

Entity Prediction Results on FB15K

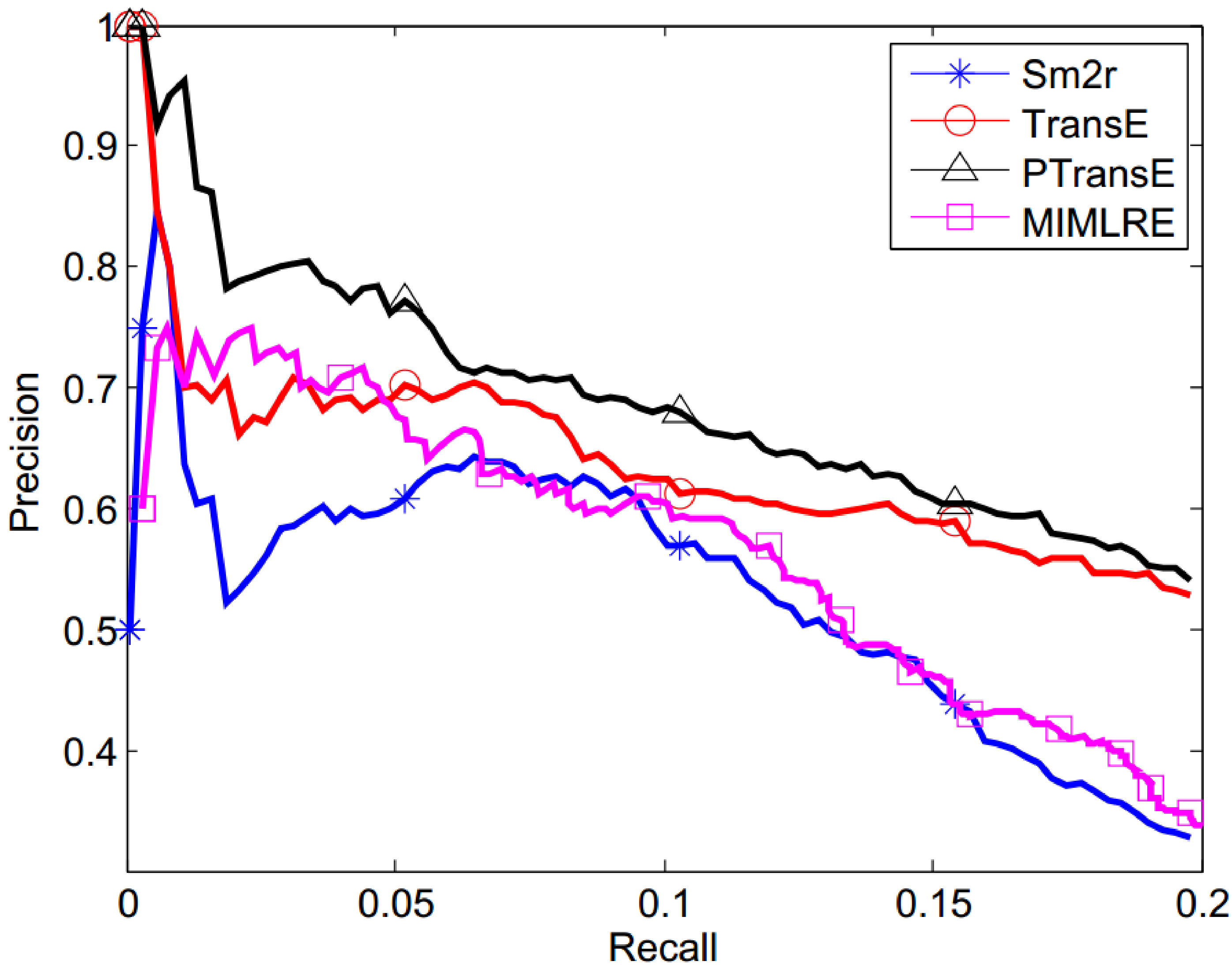
Tasks	Predicting Head Entities (Hits@10)				Predicting Tail Entities (Hits@10)			
Relation Category	1-to-1	1-to-N	N-to-1	N-to-N	1-to-1	1-to-N	N-to-1	N-to-N
SE	35.6	62.6	17.2	37.5	34.9	14.6	68.3	41.3
SME (linear)	35.1	53.7	19.0	40.3	32.7	14.9	61.6	43.3
SME (bilinear)	30.9	69.6	19.9	38.6	28.2	13.1	76.0	41.8
TransE	43.7	65.7	18.2	47.2	43.7	19.7	66.7	50.0
TransH	66.8	87.6	28.7	64.5	65.5	39.8	83.3	67.2
TransR	78.8	89.2	34.1	69.2	79.2	37.4	**90.4**	72.1
TransE (Our)	74.6	86.6	43.7	70.6	71.5	49.0	85.0	72.9
PTransE (ADD, 2-step)	**91.0**	**92.8**	**60.9**	83.8	**91.2**	**74.0**	88.9	86.4
PTransE (MUL, 2-step)	89.0	86.8	57.6	79.8	87.8	71.4	72.2	80.4
PTransE (RNN, 2-step)	88.9	84.0	56.3	84.5	88.8	68.4	81.5	86.7
PTrasnE (ADD, 3-step)	90.1	92.0	58.7	**86.1**	90.7	70.7	87.5	**88.7**

Relation Prediction Results

Metric	Mean Rank		Hits@1 (%)	
	Raw	Filter	Raw	Filter
TransE	2.8	2.5	65.1	$\boxed{84.3}$
+Rev	2.6	2.3	67.1	86.7
+Rev+Path	2.4	1.9	65.2	89.0
PTransE (ADD, 2-step)	**1.7**	**1.2**	69.5	93.6
-TransE	135.8	135.3	51.4	78.0
-Path	2.0	1.6	**69.7**	89.0
PTransE (MUL, 2-step)	2.5	2.0	66.3	89.0
PTransE (RNN, 2-step)	1.9	1.4	68.3	93.2
PTransE (ADD, 3-step)	1.8	1.4	68.5	$\boxed{\mathbf{94.0}}$

+10%

Relation Extraction Results



Examples

Head	Barack_Obama	
Relation	**/education/education/institution**	
Model	TransE	PTransE
1	Harvard_College	Columbia_University
2	Massachusetts_Institute_of_Technology	Occidental_College
3	American_University	Punahou_School
4	University_of_Michigan	University_of_Chicago
5	Columbia_University	Stanford_University
6	Princeton_University	Princeton_University
7	Emory_University	University_of_Pennsylvania
8	Vanderbilt_University	University_of_Virginia
9	University_of_Notre_Dame	University_of_Michigan
10	Texas_A&M_University	Yale_University

Examples

Head	Stanford_University	
Relation	**/education/educational_institution/students_graduates**	
Model	TransE	PTransE
1	Steven_Spielberg	Raymond_Burr
2	Ron_Howard	Ted_Danson
3	Stan_Lee	Delmer_Daves
4	Barack_Obama	D.W._Moffett
5	Milton_Friedman	Gale_Anne_Hurd
6	Walter_F._Parkes	Jack_Palance
7	Michael_Cimino	Kal_Penn
8	Gale_Anne_Hurd	Kurtwood_Smith
9	Bryan_Singer	Alexander_Payne
10	Aaron_Sorkin	Richard_D._Zanuck

Relation Path Examples

Relation1	**/people/person/place_of_birth**
Relation2	**/location/administrative_division/country**
1	/people/person/nationality
2	/people/person/places_lived./people/place_lived/location
3	/people/person/place_of_birth
4	/music/artist/origin
5	/olympics/olympic_athlete_affiliation/country
6	/government/politician/government_positions_held
7	/base/popstra/vacation_choice/location
8	/people/deceased_person/place_of_death
9	/government/political_appointer/appointees
10	/location/administrative_division/country

Relation Path Examples

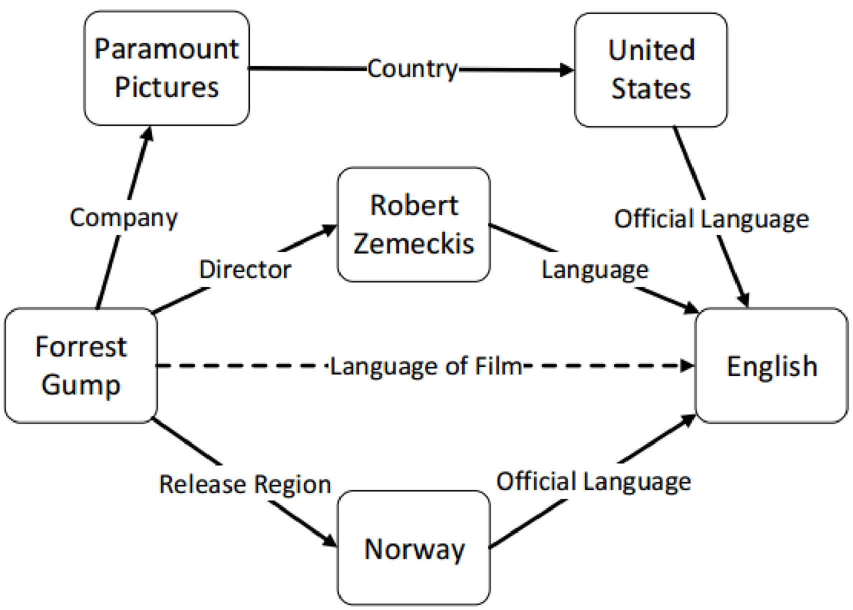
Relation1	**/location/location/contains**
Relation2	**/location/location/contains**
1	/location/location/contains
2	/location/country/second_level_divisions
3	/location/country/administrative_divisions
4	/location/administrative_division/capital
5	/base/locations/continents/countries_within
6	/base/aareas/schema/administrative_area/administrative_children
7	/location/us_county/hud_county_place
8	/location/country/capital
9	/location/country/first_level_divisions
10	/travel/travel_destination/tourist_attractions

Relation Path Examples

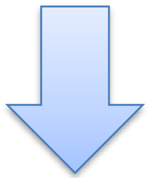
Relation1	**/award/award_category/category_of**
Relation2	**/award/award/presented_by**
1	/award/award/presented_by
2	/award/award_category/presenting_organization
3	/award/award_category/category_of
4	/award/award_nomination/award_nominee
5	/award/award_honor/ceremony
6	/symbols/namesake/named_after
7	/award/award_honor/award_winner
8	/award/award_nomination/nominated_for
9	/award/award_honor/honored_for
10	/food/dish/cuisine

Summary

- Relation paths contain rich inference patterns about knowledge
- More complex inference patterns should be taken into consideration



(Obama, _president, USA)



(Obama, _is, American)

Summary

- Inference confidence measurements
  - Path Ranking Algorithm, …
- Representation of complex relation paths
  - Compositional semantic models: RNN, NTN, …
- Applications
  - QA (Guu, et al. 2015)

Guu, et al (2015). Traversing Knowledge Graphs in Vector Space. EMNLP.

Key Challenges in RL4KG

- Modeling Complex Relations
- Fusion of Text and KG
- Modeling Relation Paths

Other Key Challenges in RL4KG

- Online and fast learning for large-scale KGs
- Large-scale KGs are sparse, existing models cannot learn good representations for infrequent entities and relations
- Learning orders of triples is important for fast RL4KG
  - Curriculum Learning

Other Key Challenges in RL4KG

- RL4KG with rich information besides triples

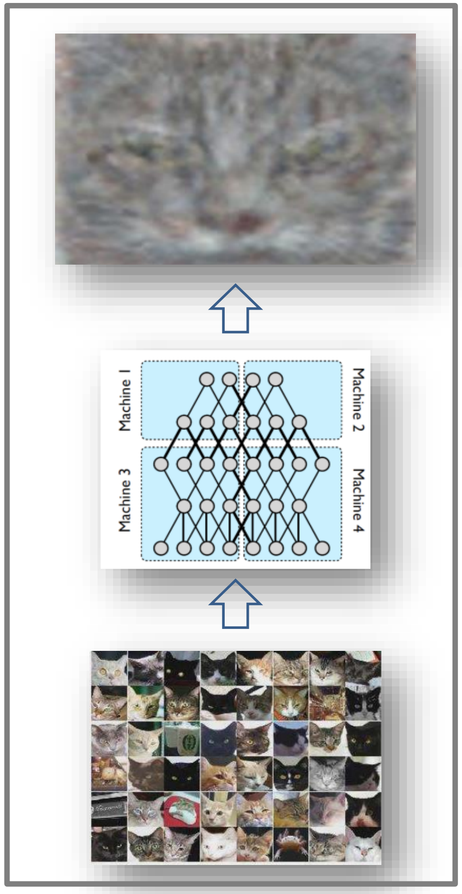
- Entities and relations have external information in KGs and text
  - Descriptions, hierarchical categories
  - Text, tables and lists with entities
  - …

Other Key Challenges in RL4KG

- RL4KG for knowledge acquisition, fusion and inference
  - Relation extraction from both KGs and text
  - Knowledge fusion across domains and languages
  - Knowledge inference in low-dimensional space

Take Home Message

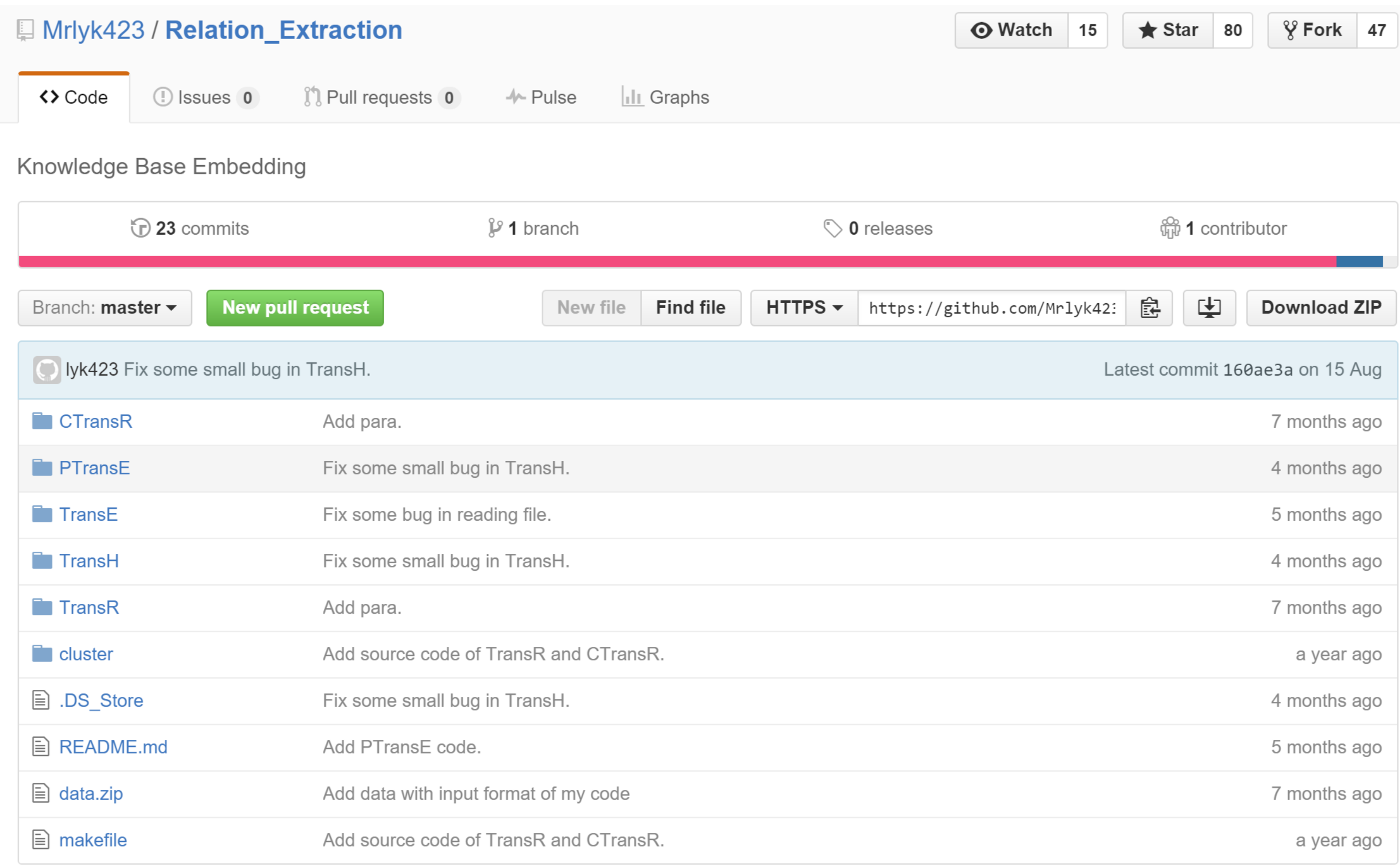
- RL4KG is a promising approach to construction and application of KGs
- RL4KG is still a rising research area, there are many open problems
- Learn from the generalization & abstraction abilities of human
  - Zero / One shot learning



Joshua B. Tenenbaum, et al. (2011) How to grow a mind: statistics, structure, and abstraction. Science.
Lake, et al. (2015) Human-level concept learning through probabilistic program induction. Science.

Open Source Codes

- TransE、TransH、TransR、PTransE
  - https://github.com/mrlyk423/relation_extraction

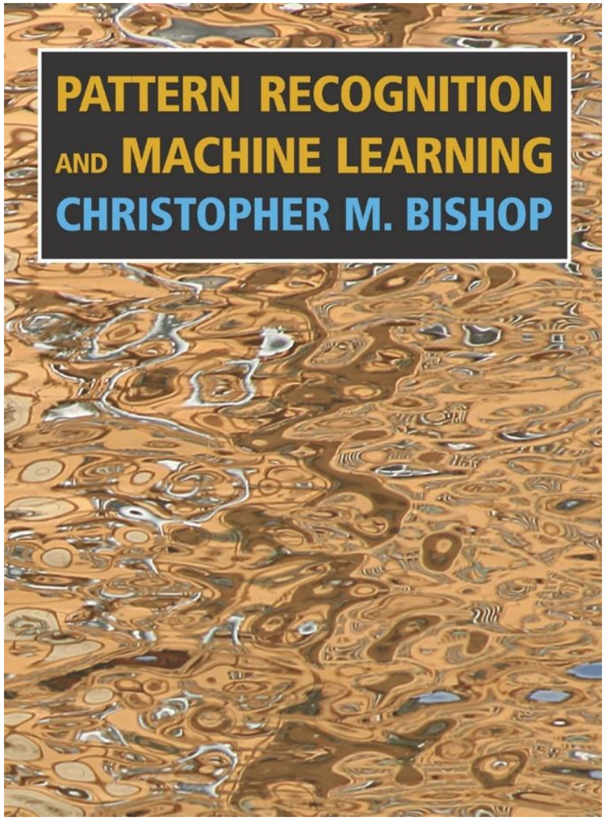


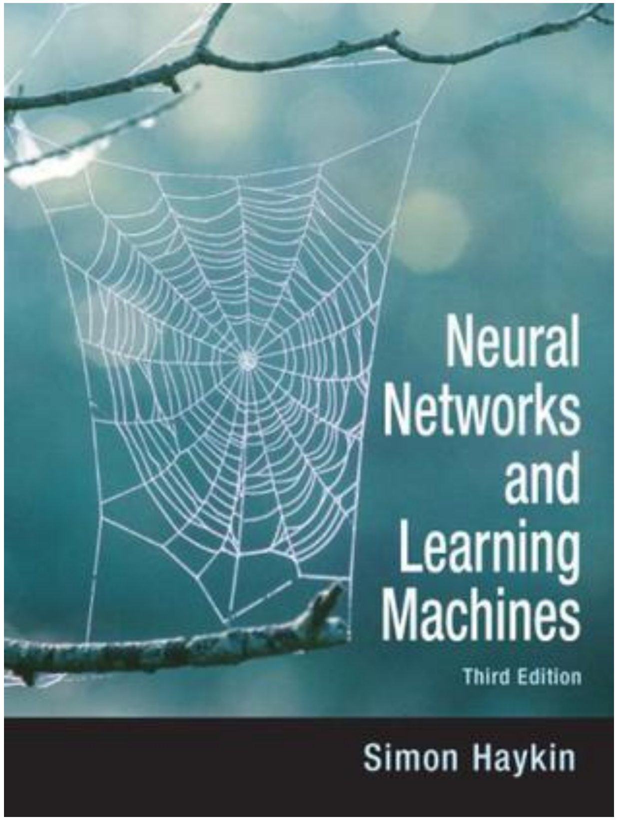
Reference

- Xie, et al. Representation learning of knowledge graphs with entity descriptions. AAAI 2016.
- Lin, et al. Modeling relation paths for representation learning of knowledge bases. EMNLP 2015.
- Lin, et al. Learning entity and relation embeddings for knowledge graph completion. AAAI 2015.
- Zhang, et al. Joint semantic relevance learning with text data and graph knowledge. ACL-IJCNLP 2015.
- dos Santos, et al. Classifying relations by ranking with convolutional neural networks. ACL 2015.
- Wang, et al. Knowledge graph and text jointly embedding. EMNLP 2014.
- Zeng, et al. Relation classification via convolutional deep neural network. COLING 2014.
- Wang, et al. Knowledge graph embedding by translating on hyperplanes. AAAI 2014.
- Socher, et al. Reasoning with neural tensor networks for knowledge base completion. NIPS 2013.
- Bordes, et al. Translating embeddings for modeling multi-relational data. NIPS 2013.

Recommended Books

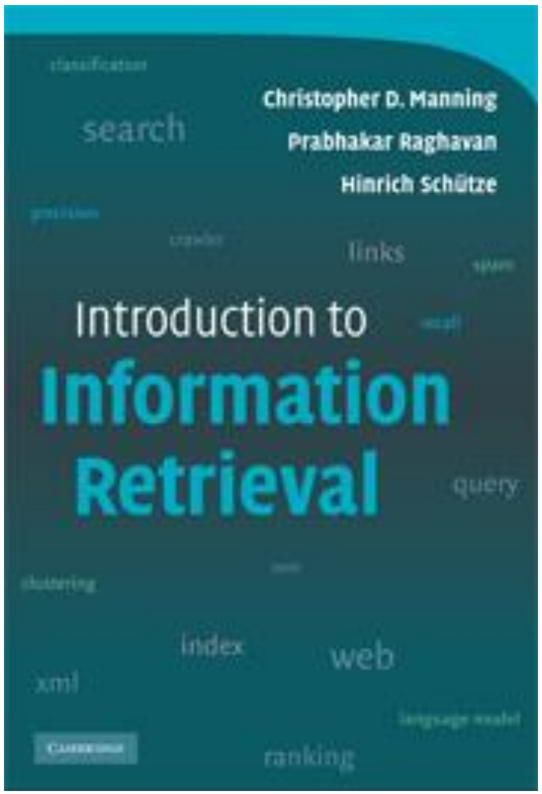
- Machine Learning

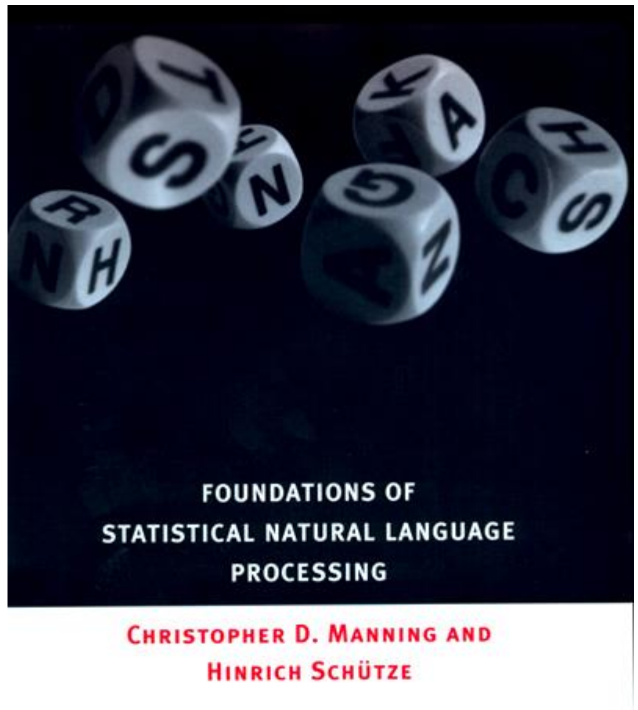


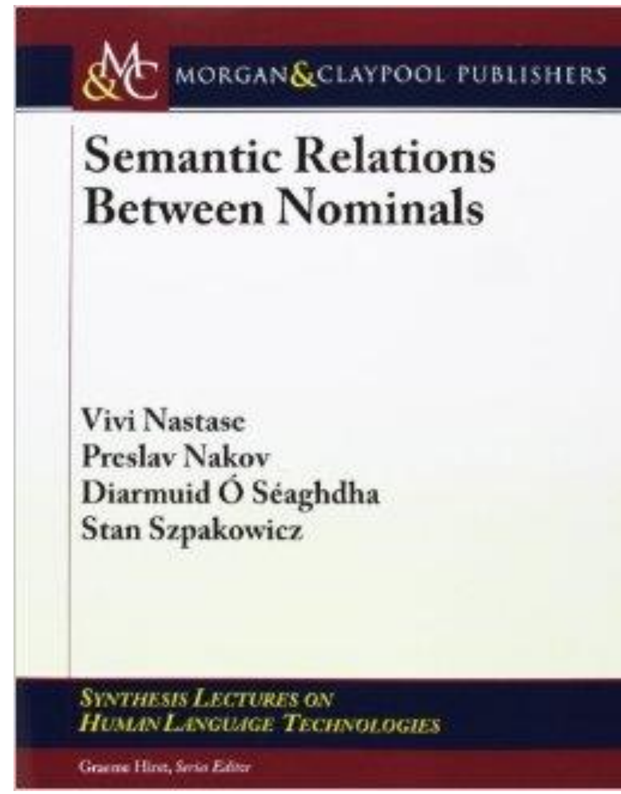


Recommended Books

- NLP and Knowledge Bases







Thanks!

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