

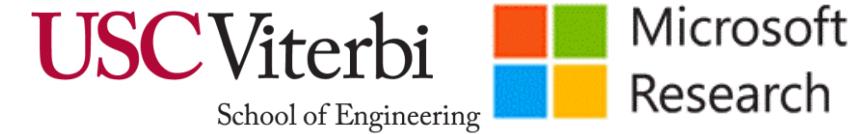
Knowledge Acquisition with Transferable Representation Learning

Muhao Chen
University of Southern California
<http://muhaochen.github.io>

A Bit About Myself



2020.8-present Research Faculty Member at USC CS & ISI



2019-2020 Postdoctoral Fellow, UPenn (CogCompGroup)

- Hosted by Dan Roth, worked on DARPA KAIROS Project (event-centric NLU)
- **Best Paper Award Nomination** at CoNLL

2019 Ph.D. in Computer Science, UCLA

- Advisor: Carlo Zaniolo
- Close collaboration with Kai-Wei Chang, Wei Wang, Yizhou Sun and Mario Gerla (in memoriam)
- Dissertation: Multi-relational Representation Learning and Knowledge Acquisition (awarded **UCLA Dissertation Fellowship**)
- **Best Student Paper Award** at ACM BCB

2014 B.S. in Computer Science, Fudan University

- Advisor: X. Sean Wang
- Topic: Temporal/Spatial reasoning (awarded **Chun-Tsung** and **Wang-Dao** Research Scholarships)

Understanding Relations Is Prominent In Practice

QA and Semantic Search

Google Microphone Search

All Images News Shopping Videos More Settings Tools

About 34,600,000 results (1.04 seconds)

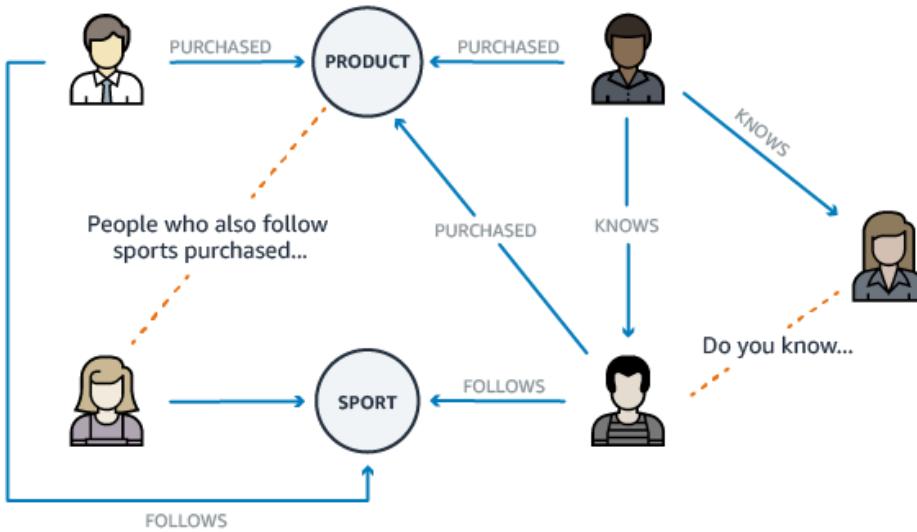
787B

(?car, *produced by*, Mazda)
(?car, *won*, 24 Hours of Le Mans)

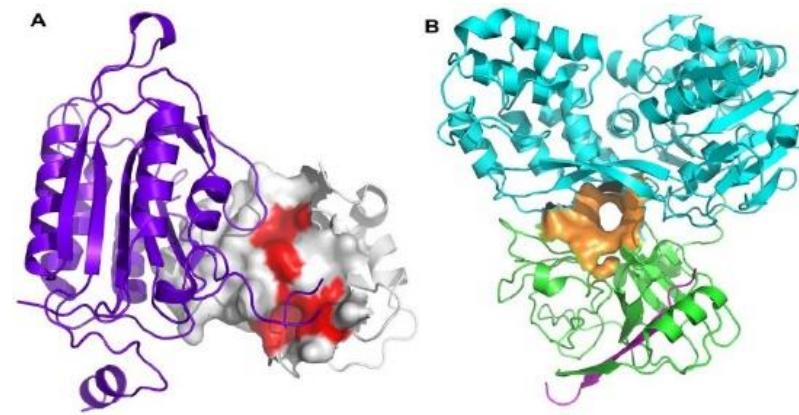


Understanding Relations Is Prominent In Practice

Recommender Systems



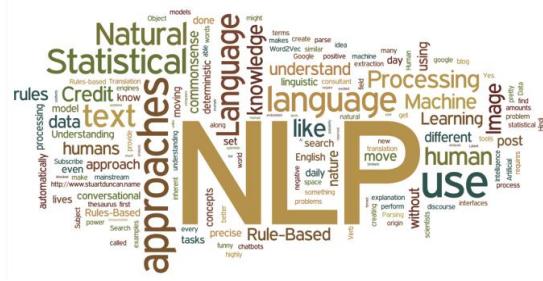
Computational Biology Research



- Co-purchase relations of products
- Social relations of users

- Interactions of molecules and biomolecules.

Understanding Relations Is Prominent In Practice



- QA
- Discourse relation detection
- Dialogue state tracking
- Event prediction
- Narrative cloze
- Entity/event typing and linking
- Semantic search
- Relational rule mining
- Ontology population
- Ontology matching and knowledge integration
- Interaction prediction of biomolecules
- Mutation effect estimation
- Non-coding RNA alignment
- Drug discovery
- Polypharmacy side effect detection

Multi-relational Data

Knowledge Graphs



ConceptNet
An open, multilingual knowledge graph



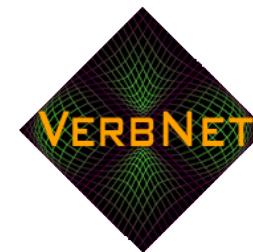
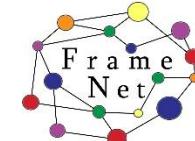
Product & E-Commerce Graphs



Bio-med Ontologies /Data Banks



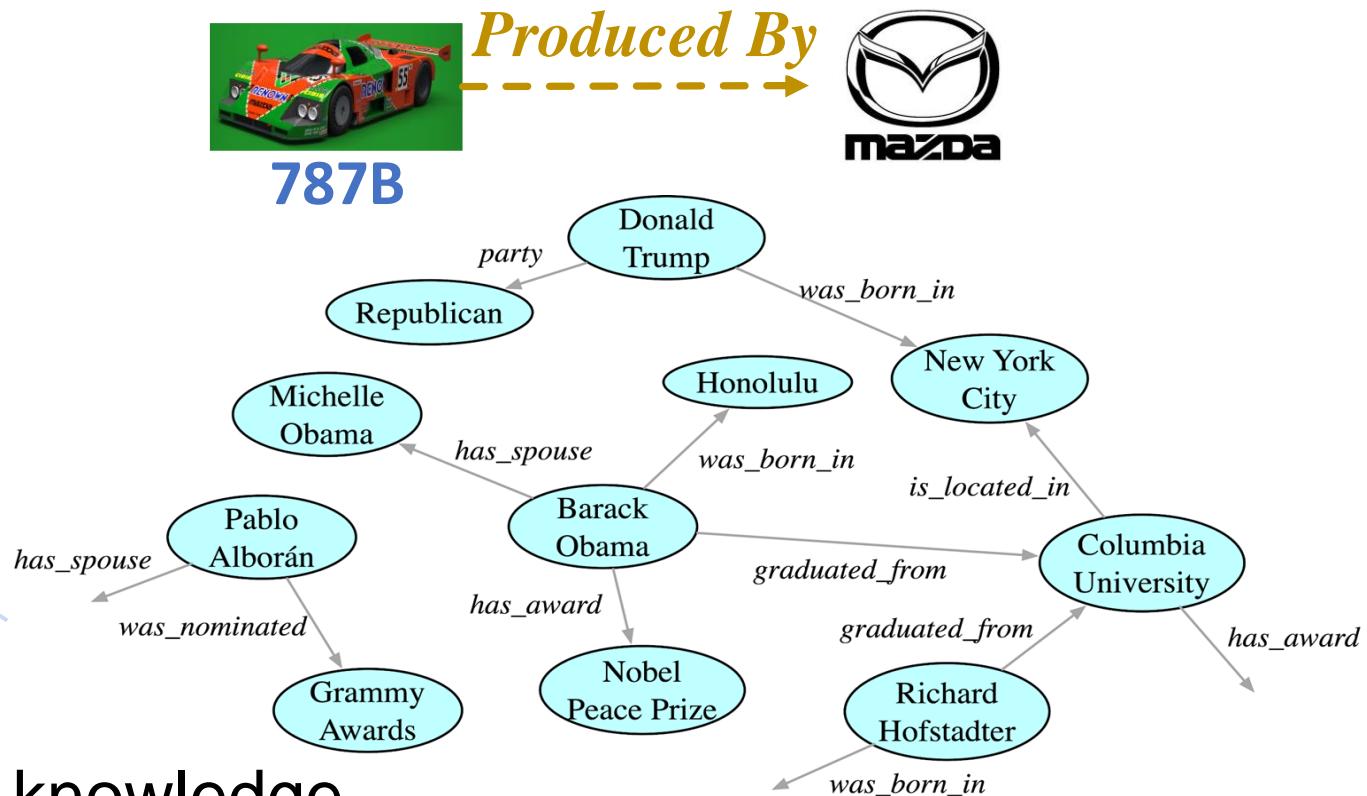
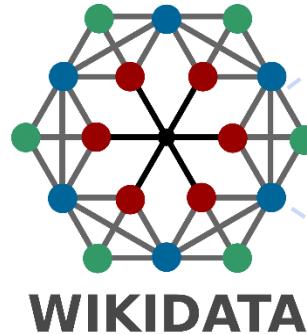
Lexical and Semantic Graphs



シ 𩫂 韓
λ W ش
ヰ 维 უ

Wiktionary
The free dictionary

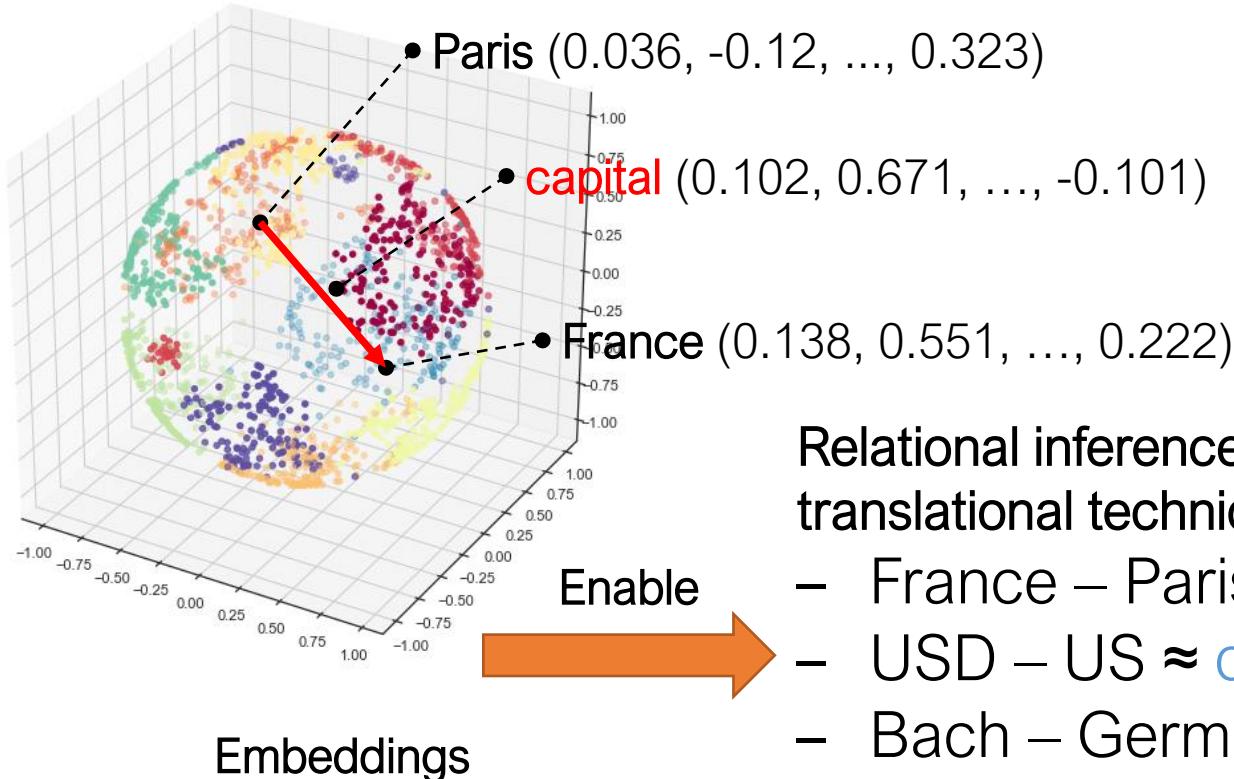
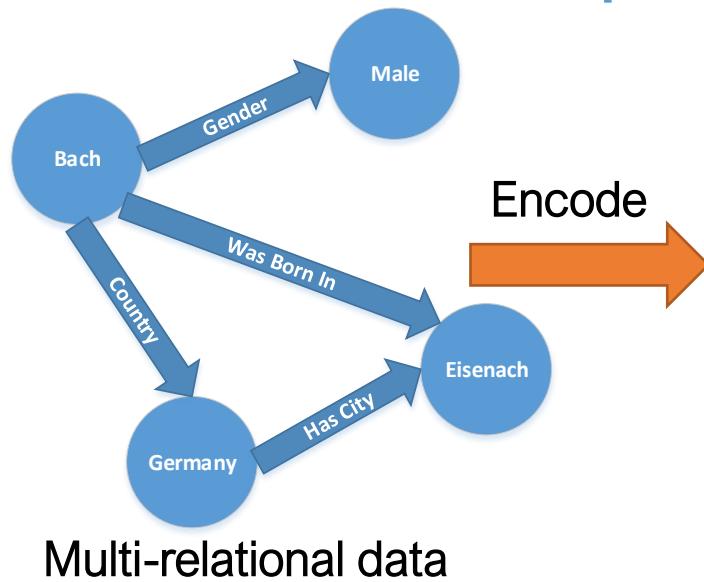
Multi-relational Data: Precise But **Expensive** Knowledge Representation



Obtaining the structural knowledge

- Is expensive (Avg \$5.71 per triple [Paulheim+, ISWC-18] in open domain; higher cost in scientific domains).
- Has relied on massive human efforts.
- Has never been close to complete.

Representation Learning: Cheap Knowledge Acquisition from The Embedding Space

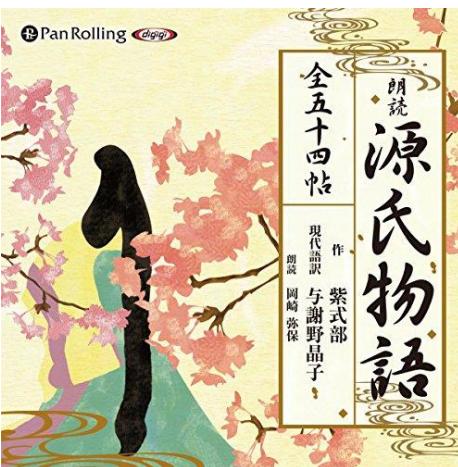
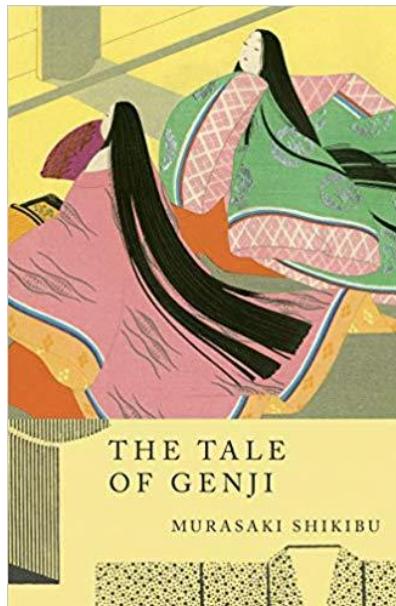


Automatically predicting knowledge: $787B + \text{ProducedBy} \approx \text{Mazda}$

- A much less expensive way for knowledge acquisition
- Yet can still suffer from sparsity and noise of known knowledge

Knowledge Is Not Isolated

Different sources of data can possess **complementary knowledge**



(The Tale of Genji, Genre, ?e)



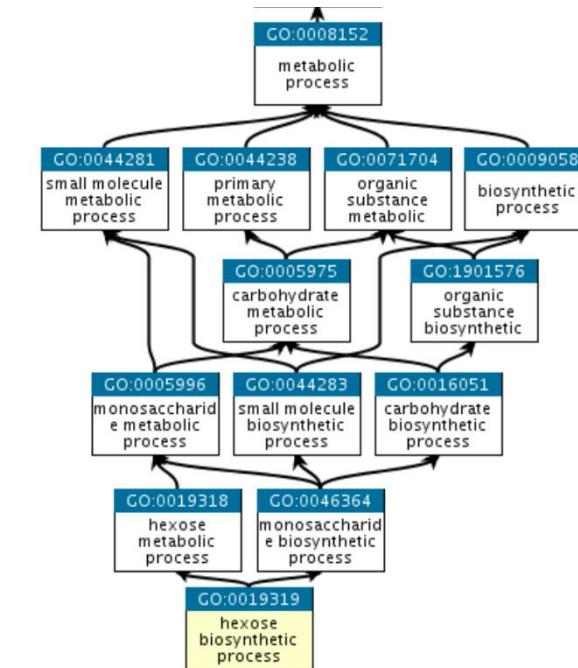
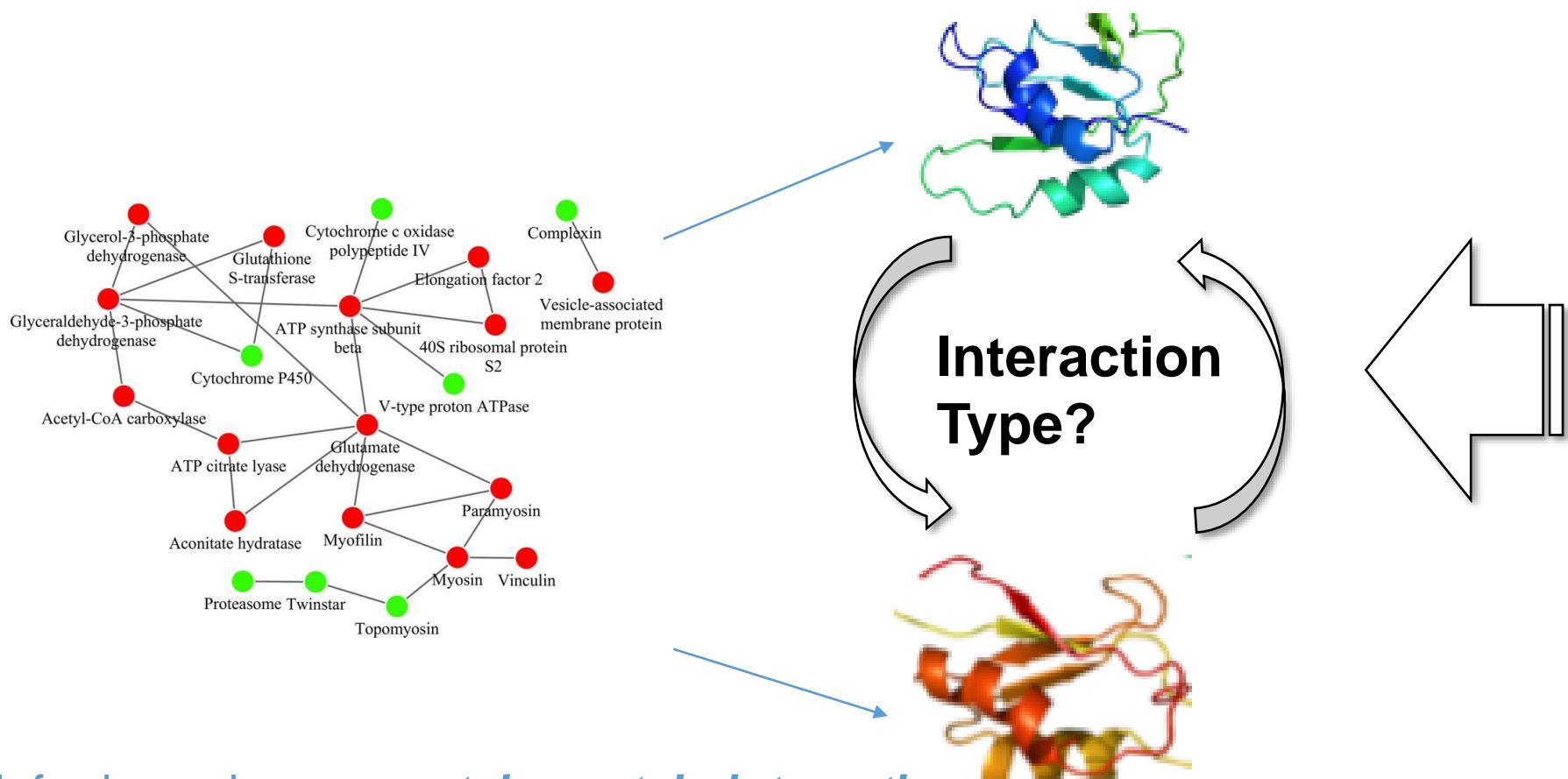
Novel



Monogatari (story)
Love story
Royal family story
Realistic novel
Ancient literature

Knowledge Is Not Isolated

Different sources of data can possess **complementary knowledge**



GENEONTOLOGY
Unifying Biology

Inferring unknown **protein-protein interaction**
information in a proteomic knowledge base

Key Research Questions

Interrelated knowledge in different domains/sources

- Multiple language-specific KGs
- Multiple knowledge bases
- Instance KGs and concept ontologies (different specificity)
- Protein-protein interaction (PPI) data, gene ontologies and cell clusters
- Drug-drug interaction data, disease ontologies and PPI data
- Social networks and product graphs
- ...

Can we capture the association of knowledge with representation learning?
And use knowledge transfer to populate missing knowledge?

Key Research Questions

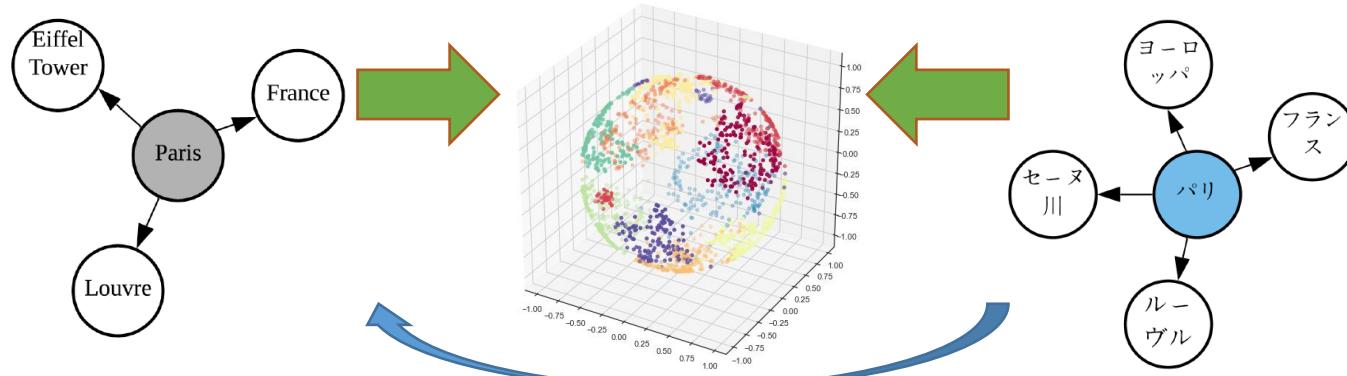
How to acquire structured knowledge from unstructured data?

- Provide globally consistent inference
 - Learning to acquire knowledge with limited and indirect supervision
 - Acquisition from modalities beyond human languages (molecular and biomolecular sequences, EHR, etc.)



Roadmap of Research Contributions

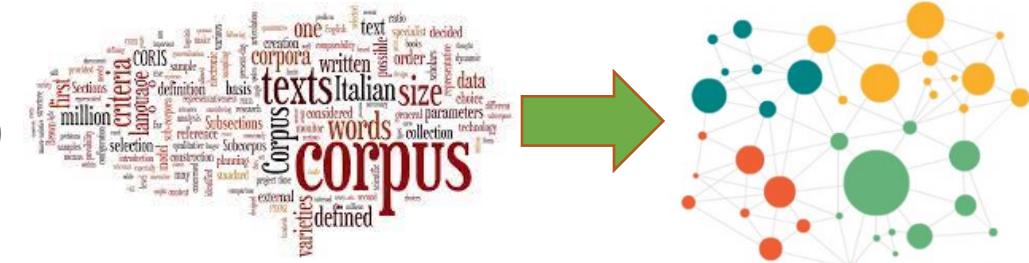
Transferable Rep. Learning for Relational Data



How do we capture the **association of knowledge** with **minimal supervision**?

How do we identify and transfer **complementary knowledge**?

Knowledge Acquisition from Unstructured Data



How to provide reliable inference (e.g. ensuring the **logical or probabilistic constraints**)?

Generalizable learning, but with **limited supervision**?

Roadmap of Research Contributions

Transferable Rep. Learning for Relational Data

Minimally supervised knowledge alignment

- Semi-supervised knowledge alignment (first prototype) [IJCAI-17, AKBC-17] ◀
- Co-training [IJCAI-18] ◀
- Distant supervision [KDD-19] ◀
- Visual pivoting [AAAI-21a] ◀
- Incidental supervision [EACL-21] ◀

Robust embedding learning and knowledge transfer

- Property-aware embedding [SDM-18]
- Hyperbolic embedding [SIGIR-19, EMNLP-20a] ◀
- Multi-view learning [IJCAI-19]
- Noise-aware GNN [AAAI-20a]
- Meta-learnable knowledge transfer [EMNLP-20b] ◀

Knowledge Acquisition from Unstructured Data

Learning with constraints and indirect supervision

- Logical constraints [EMNLP-20c] ◀
- Probabilistic soft constraints [AAAI-19]
- Few-shot learning with indirect supervision [CoNLL-20, Best Paper Nomination] ◀

Robust and generalizable learning and inference

- Paraphrase-aware retrofitting [EMNLP-19]
- Analogy-aware inference [EMNLP-20d]
- Language modeling for proteins [ISMB-19, *Bioinformatics* [J] 2019, NAR GaB [J] 2020]

KB Construction

- KB Completion [AAAI-19, EMNLP-20b]
- Entity alignment [many above]
- Type inference [KDD-19, EMNLP-20a] ◀

Natural Language Understanding

- Relation extraction [EMNLP-20c]
- Event prediction [EMNLP-20d]
- Event process typing [CoNLL-20, Best Paper Nomination] ◀
- DocRel extraction [ECML-18, Plenary]

Bio/medical Informatics

- Proteomics [ISMB-19, *Bioinformatics* [J] 2019, NAR GaB [J] 2020] ◀
- Diagnostic prediction [AIME-20]
- Disease target prediction [ACM BCB-20, Best Student Paper] ◀

Method

Tasks

Outreach

Outline

Transferable Representation Learning of Multi-relational Data

Knowledge Acquisition from Unstructured Data

Future research agenda

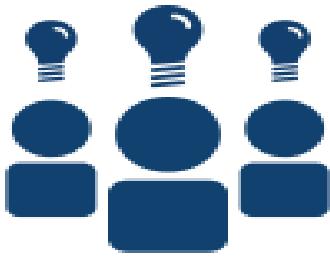
Transferable Representation Learning for Multi-relational Data

Capture the knowledge association with **minimal supervision** in a **universal embedding scheme** for

- Multiple language-specific KGs
- Multiple KBs
- Abstract concepts and specific entities
- Proteomic interactions and gene ontologies
- Cells and genomic interaction data
- Molecular data, medical ontologies and drug interaction data
- Social relations and product graphs
- ...

Transfer knowledge from some domains to enrich others

A General Methodology to Benefit A Wide Range of Tasks

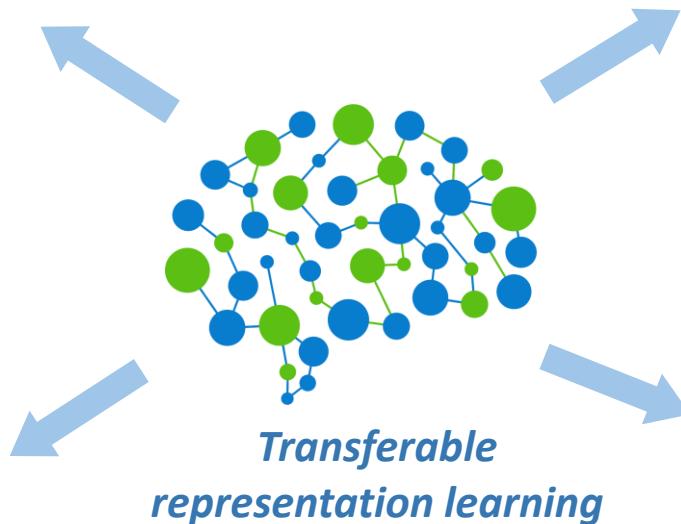


Knowledge Base

Knowledge alignment
KG completion
Ontology population



Semantic search
Entity typing
Dialogue state tracking
Paraphrase identification

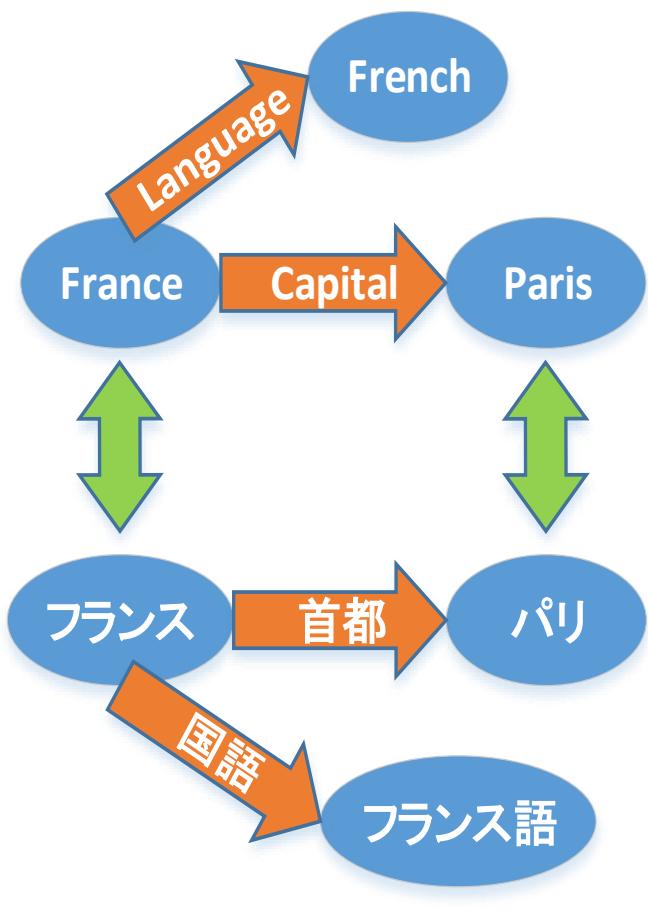


Protein-protein interaction prediction
Protein binding affinity estimation
Single cell RNA-sequence imputation
Gene Ontology term assignment



Polypharmacy side effect detection
Disease and phenotype matching
Clinical event prediction

Scenario 1: KGs in Different Languages



Separately created language-specific KGs

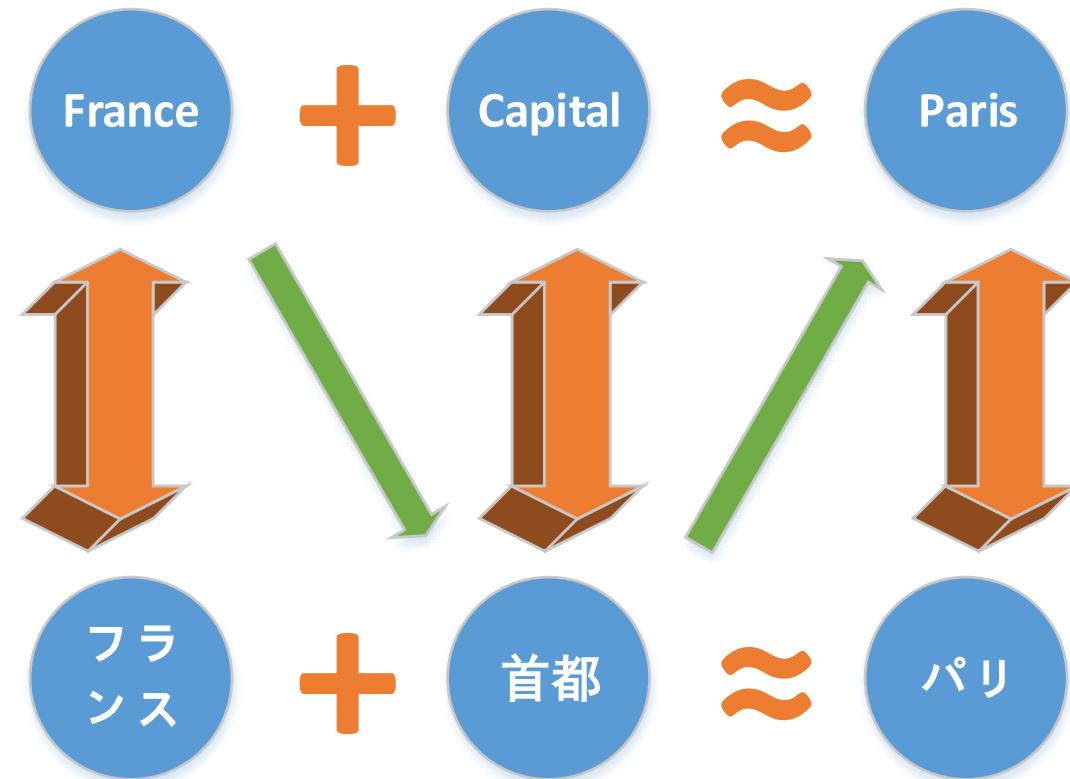
- DBpedia has 125 language-specific versions;
Wikidata has 410 of those.



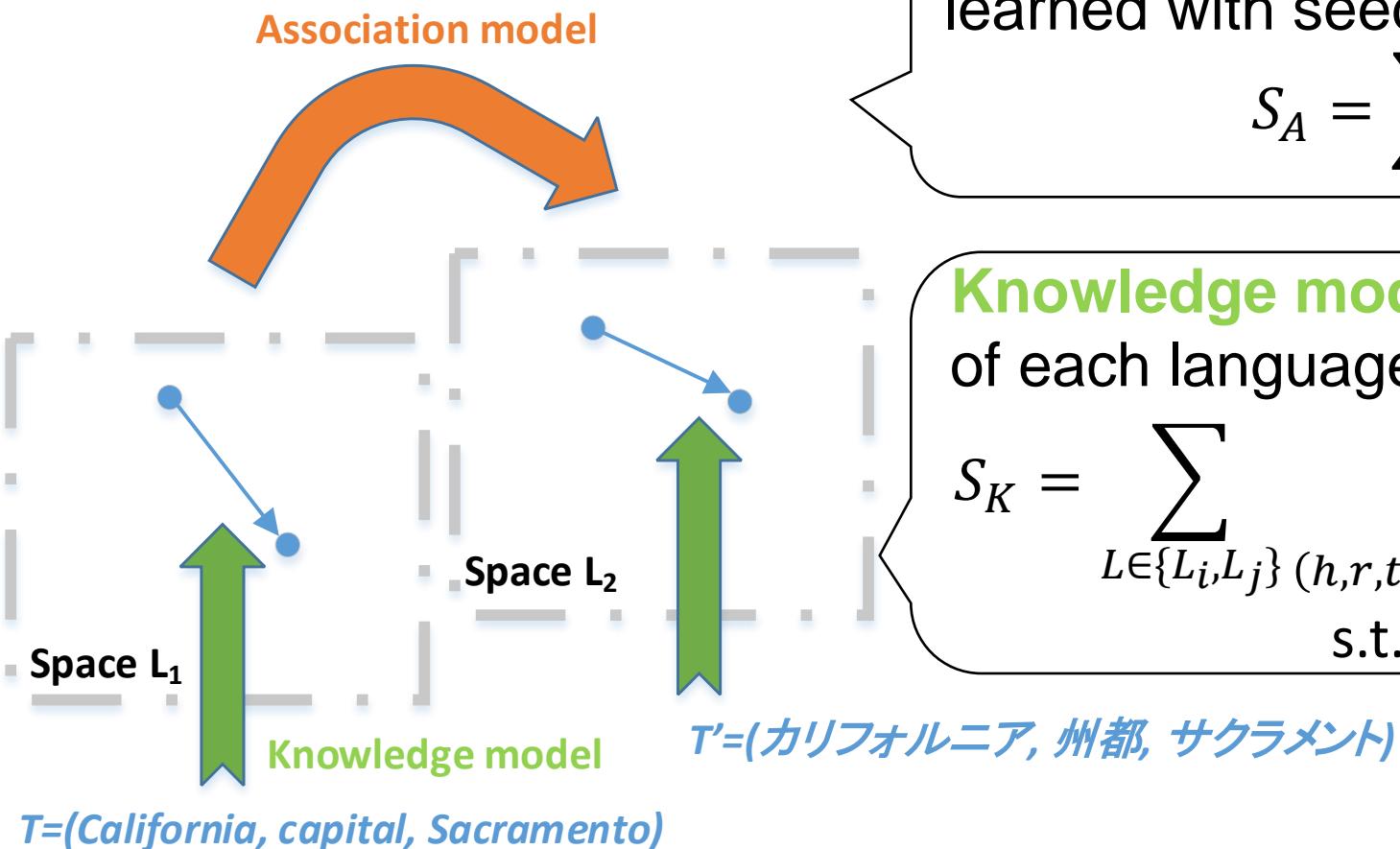
The First Prototype: Simple Translational Model + Supervised Association Learning (MTransE*)

*[IJCAI-17]

- **Training data:** a pair of weakly aligned language-specific KGs
- **Enabling:** cross-lingual semantic transfer + relational inference



Joint Learning of MTransE



Association model: an embedding transformation learned with seed alignment

$$S_A = \sum_{(e, e') \in \delta(L_i, L_j)} \|\mathbf{M}_{ij} \mathbf{e} - \mathbf{e}'\|$$

Knowledge model: encoding entities and relations of each language as a **translational embedding**

$$S_K = \sum_{L \in \{L_i, L_j\}} \sum_{(h, r, t) \in G_L \wedge (\hat{h}, \hat{r}, \hat{t}) \notin G_L} [f_r(h, t) - f_r(\hat{h}, \hat{t}) + \gamma]_+$$

s.t. $f_r(h, t) = \|\mathbf{h} + \mathbf{r} - \mathbf{t}\|_2$

- Joint training loss

$$S_J = S_K + \alpha S_A$$

Application: Knowledge Alignment

Table 8: Examples of cross-lingual entity matching.

Entity	Target	Candidates (in ascending order of rank by Euclidean distance)
Barack Obama	French	Barack Obama , <i>George Bush</i> , <i>Jimmy Carter</i> , George Kalkoa
	German	Barack Obama , <i>Bill Clinton</i> , <i>George h. w. Bush</i> , Hamid Karzai
Paris	French	Paris , <i>Amsterdam</i> , <i>à Paris</i> , <i>Manchester</i> , De Smet
	German	Paris , <i>Languedoc</i> , <i>Constantine</i> , <i>Saint-maurice</i> , <i>Nancy</i>
California	French	<i>San Francisco</i> , <i>Los Angeles</i> , <i>Santa Monica</i> , Californie
	German	Kalifornien , <i>Los Angeles</i> , <i>Palm Springs</i> , <i>Santa Monica</i>

Table 9: Examples of cross-lingual relation matching.

Relation	Target	Candidates (in ascending order of rank by Euclidean distance)
capital	French	capitale , <i>territoire</i> , <i>pays accréditant</i> , <i>lieu de vénération</i>
	German	hauptstadt , <i>hauptort</i> , <i>gründungsstadt</i> , <i>city</i>
nationality	French	nationalité , pays de naissance , <i>domicile</i> , <i>résidence</i>
	German	nationalität , nation , <i>letzter start</i> , <i>sterbeort</i>
language	French	langue , <i>réalisations</i> , <i>lieu deces</i> , <i>nationalité</i>
	German	sprache , originalsprache , <i>lang</i> , <i>land</i>

Bold-faced ones are correct answers, *italic* ones are close answers.
Answers do not include those that have pre-existed in training.

This pilot study got ~30% Hits@1 on DBP15k. But we will introduce lots of improvement to it shortly.

Cross-lingual Fact Prediction, e.g.

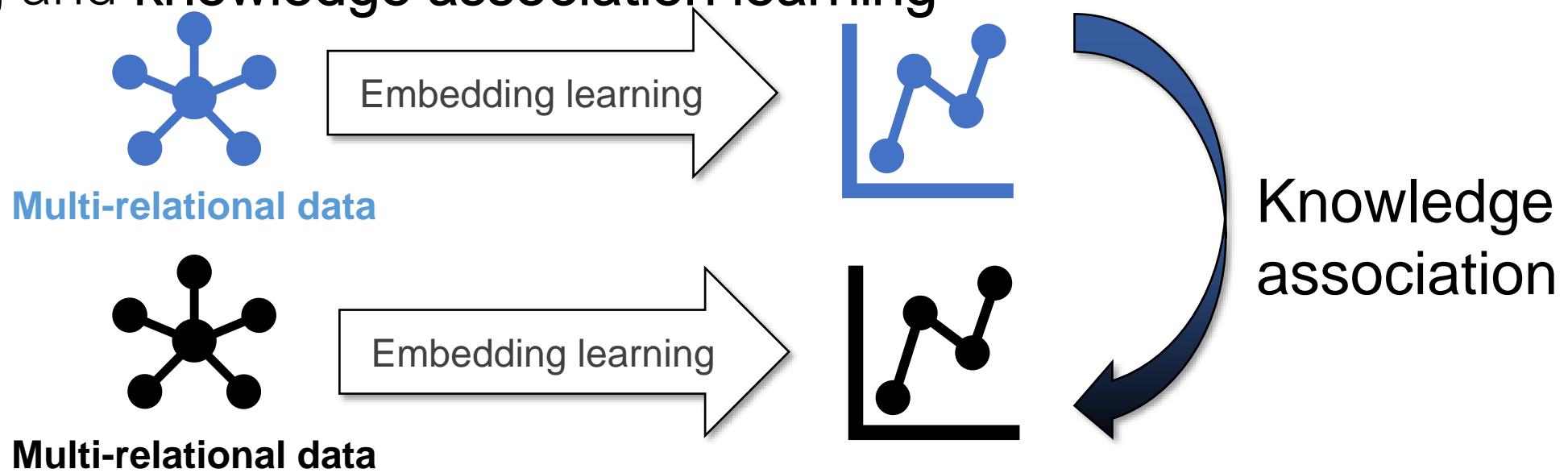
Table 10: Examples of cross-lingual triple completion.

Query	Target	Candidates (in ascending order of rank)
(Adam Lambert, genre, ?t)	French	<i>musique indépendante</i> , musique alternative , ode , glam rock
	German	popmusik , dance-pop , no wave, <i>soul</i>
(Ronaldinho, position, ?t)	French	milieu offensif , attaquant , <i>quarterback</i> , <i>latéral gauche</i>
	German	stürmer , <i>linker flügel</i> , angriffsspieler , <i>rechter flgel</i>
(Italy, ?r, Rome)	French	capitale , plus grande ville , chef-lieu , garnison
	German	hauptstadt , hauptort , verwaltungssitz, stadion
(Barack Obama, ?r, George Bush)	French	<i>ministre-président</i> , prédécesseur , <i>premier ministre</i> , <i>président du conseil</i>
	German	vorgänger , vorgängerin , besetzung, lied

Bold-faced ones are correct answers, *italic* ones are close answers.
Answers do not include those that have pre-existed in training.

General Framework and Further Improvement

Jointly or iteratively conduct two learning processes: **embedding learning** and **knowledge association learning**



Three directions to improvement

1. More precise embedding alignment requiring **less supervision**
2. **Auxiliary supervision** from entity profile information
3. Better **embedding learning** techniques for inconsistent structures

(1) Semi-supervised Co-training With Entity Descriptions*

*[IJCAI-18]

The alignment information is often limitedly provided to connect KG structures

Iterative co-training of embeddings for KG structures and entity descriptions

Inter-lingual Link (ILL): (astronomer@EN, astronome@FR)

EN triple: (*Ulugh Beg*, occupation, astronomer) FR triple: (*Ulugh Beg*, activité, astronome)

An astronomer is a scientist in the field of astronomy who concentrates their studies on a specific question or field outside of the scope of Earth...

Un astronome est un scientifique spécialisé dans l'étude de l'astronomie...

DBpedia covers less than 20% entity alignment for En-Fr, and less for other cases.

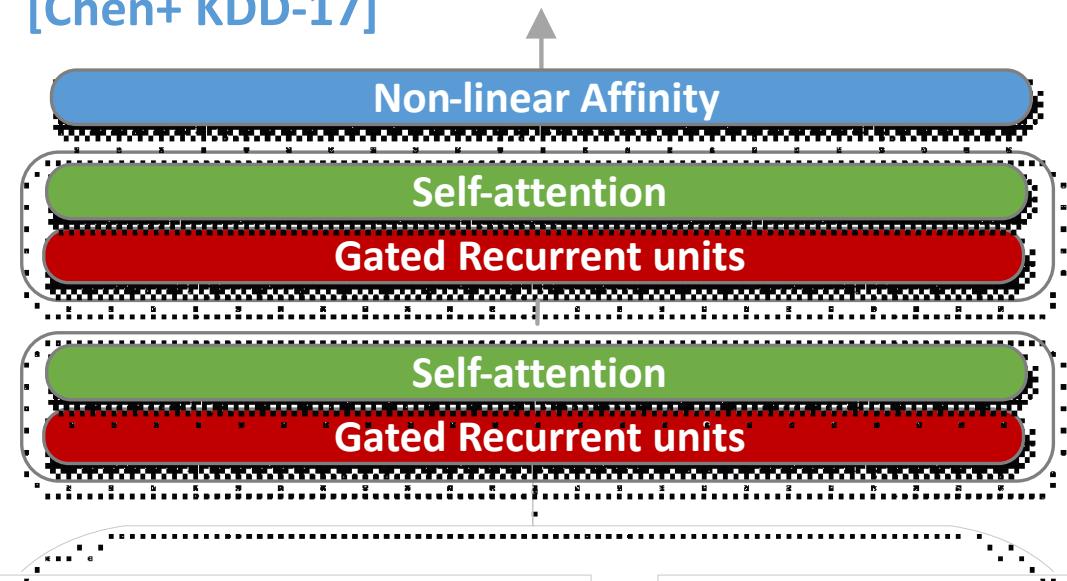
An Entity Description Embedding Model

Siamese document encoder with Self-attention + Pre-trained bilingual word embeddings

To collocate the embeddings of entity description counterparts

Learning-to-rank w/ negative batch sharing
[Chen+ KDD-17]

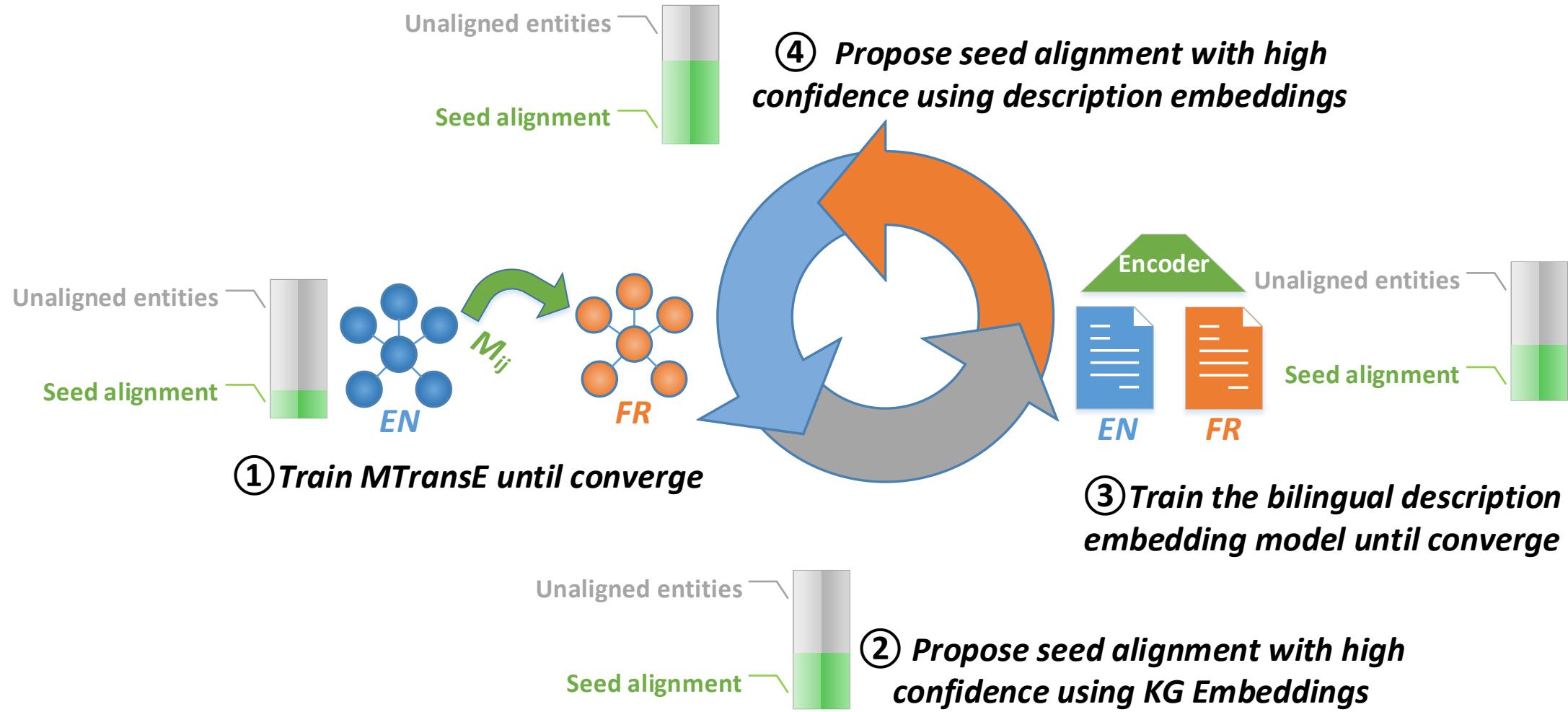
*[IJCAI-18]



An **astronomer** is a scientist in the field of astronomy who concentrates their studies on a specific question or field outside of the scope of Earth...

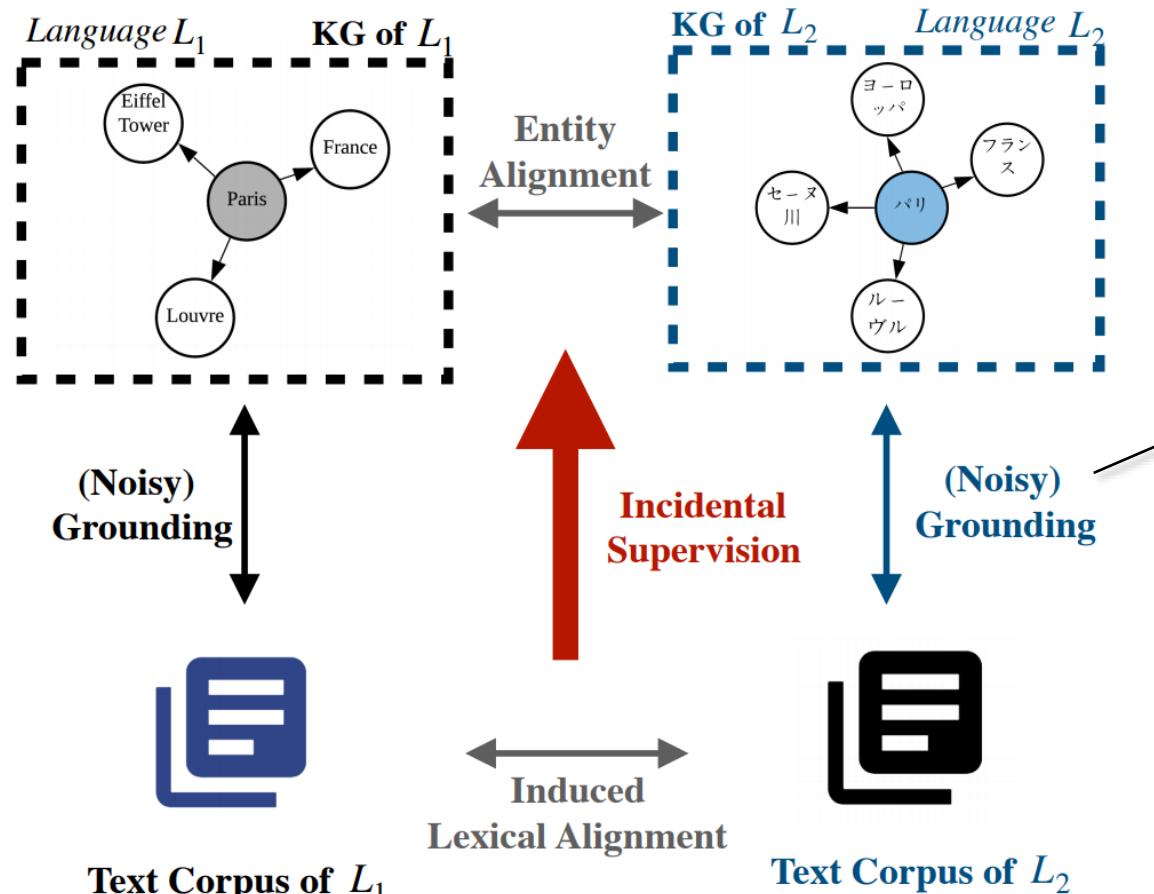
Un **astronome** est un scientifique spécialisé dans l'étude de l'astronomie...

Iterative Co-training Process



(2) Knowledge Alignment Using Incidental Supervision From Free Text*

*[EACL'21 in review]



Three steps

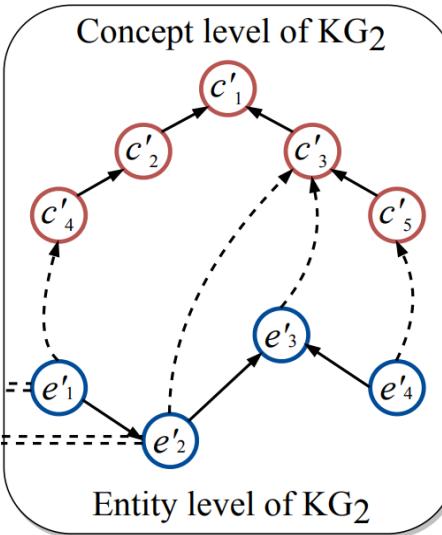
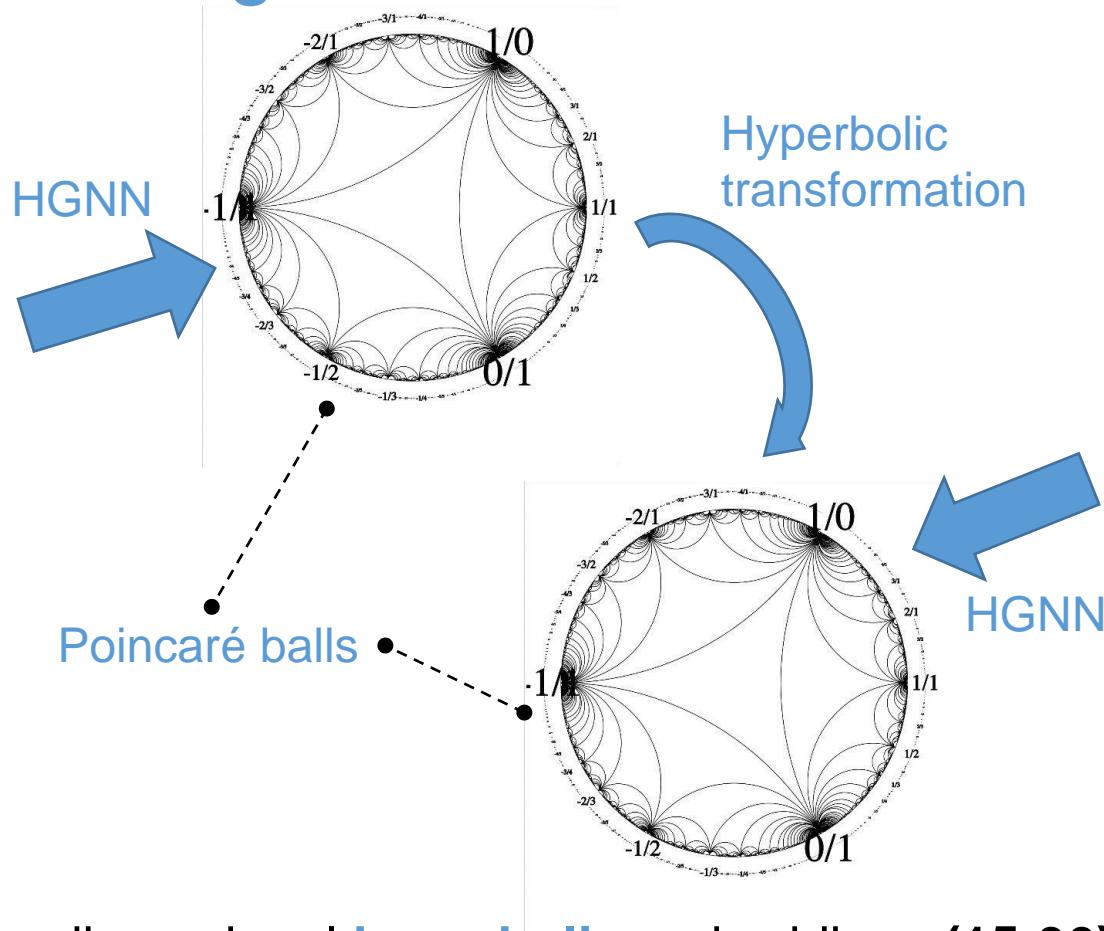
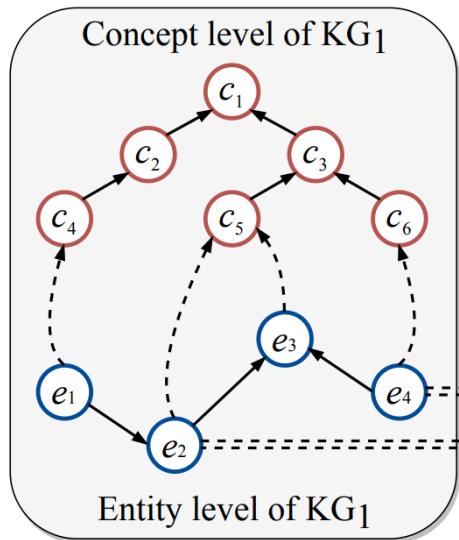
- 1. (Noisy) grounding:** connecting KGs and text corpora
- 2. Embedding learning:** GNN + a neural language model
- 3. Alignment learning:** self-learning for both entity and lexical alignment

(Noisy) grounding process for text corpora

- Entity discovery and linking (EDL)
- Surface form matching

(3) Hyperbolic Knowledge Association*

*[EMNLP-20a]



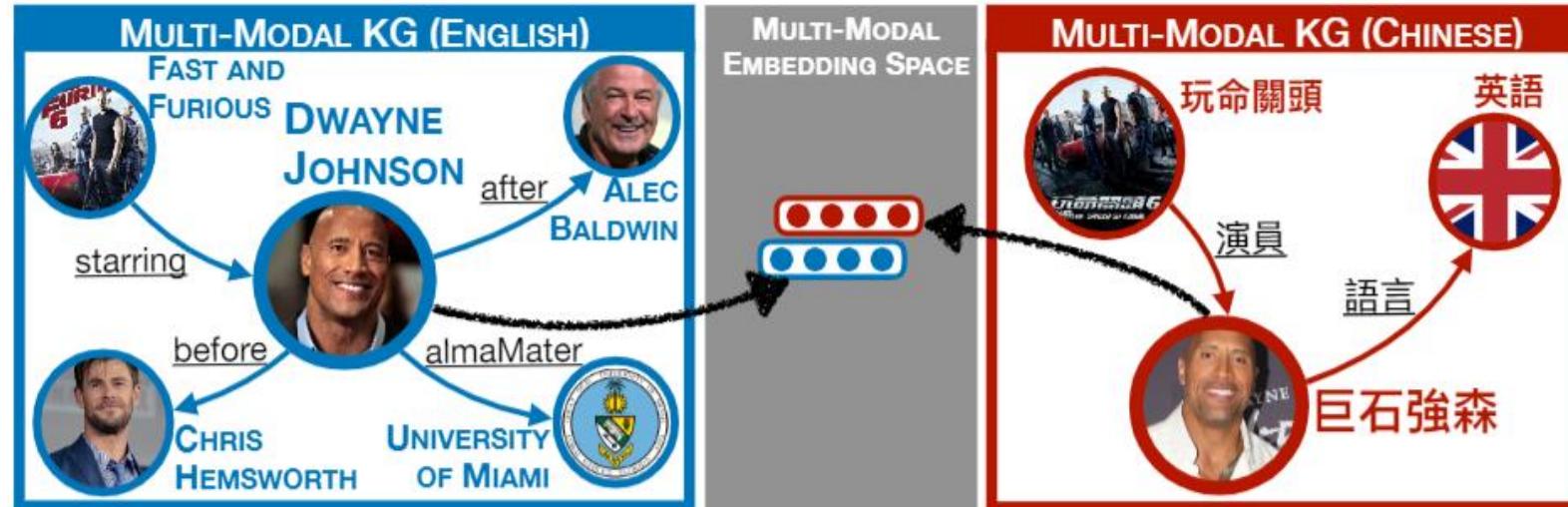
Transferable, ultra low-dimensional **hyperbolic** embeddings (15-30).

- Non-linear distance metric $d_{\mathbb{D}}(\mathbf{u}, \mathbf{v}) = \text{arccosh}\left(1+2\frac{\|\mathbf{u} - \mathbf{v}\|^2}{(1 - \|\mathbf{u}\|^2)(1 - \|\mathbf{v}\|^2)}\right)$
- Suitable for capturing knowledge association between **hierarchical** KGs.
- and KGs with **significantly different scales** (e.g. an instance-graph vs a concept graph).

Also applied to entity type inference.

(4) Multi-modal Entity Alignment*

*[AAAI-21]

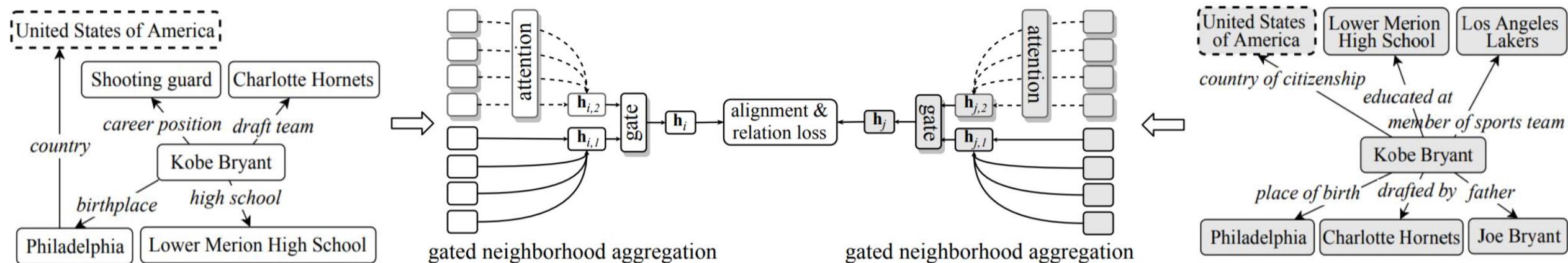


(Unsupervised) visual pivoting by identifying visually similar entities

- ResNet + GCN with bootstrapping
- Particularly benefits long-tail entities

(5) Noise-aware Multi-hop Graph Attention⁺

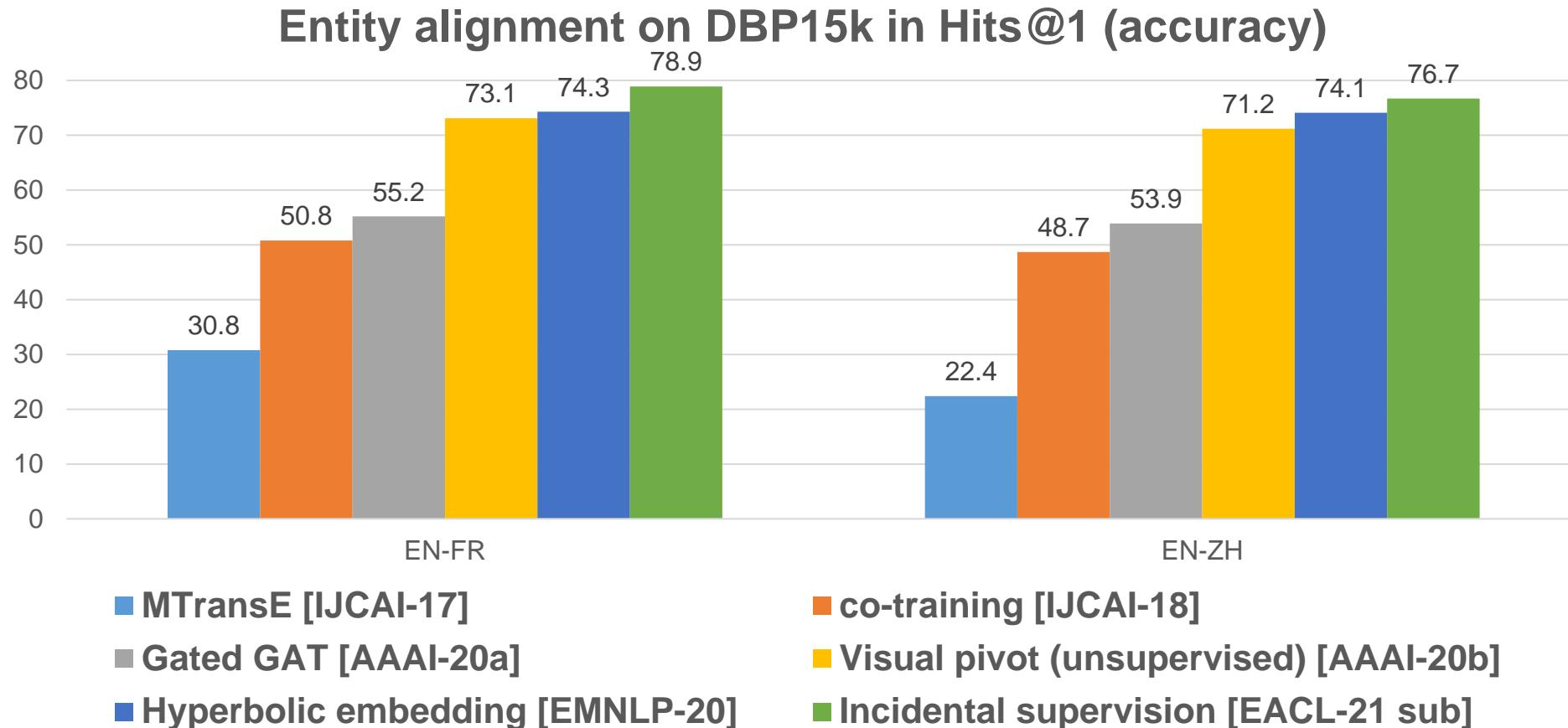
⁺[AAAI-20]



A robust GNN encoder against the inconsistency of entity neighborhoods in different KGs.

Performance by Our Methods on Semi-supervised Entity Alignment

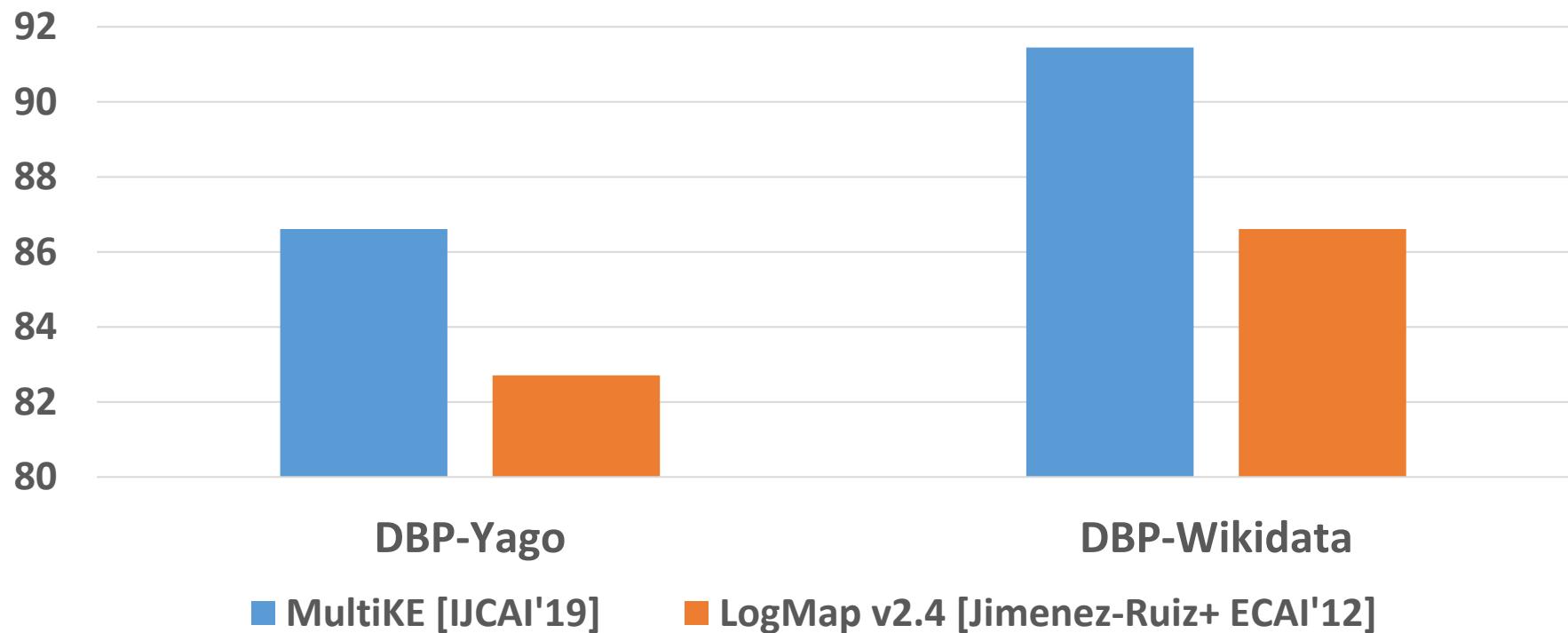
DBP15k: the benchmark dataset for entity alignment.



*The Candidate space of each test case is 63k~98k entities for each language

Our Method Outperforms The Well-known Ontology Matching System (LogMap v2.4)

Multi-KE vs. LogMap2.4 on Aligning 100K-scale Subsets
of DBPedia to Yago and Wikidata



***MultiKE [IJCAI'19]** is a monolingual ontology matching framework with multi-view embeddings of triples, literals, descriptions and attributes.

Recent Advances on Embedding-based Knowledge Alignment

Follow-ups on the same topic

- 2017: IJCAI×2, ISWC×1
- 2018: AAAI×2, COLING×1, ACL×1, EMNLP×1, IJCAI×3
- 2019: AAAI×2, ACL×3, EMNLP×4, ICLR ×1, ICDM×1, ICML×1, IJCAI×6, ISWC×2, KDD×1, WWW×1, WSDM ×1
- 2020: AAAI×3, ACL×1, COLING ×1, CIKM ×1, EMNLP×4, ICDE ×1, ICLR×2, IJCAI×2, ISWC×1, NeurIPS×1, KDD ×2, VLDB×1, WWW×1, WSDM×2

More approaches for embedding learning

- Long-term dependency models, R-GCN, hyperbolic embeddings, holographic embeddings, Gaussian embeddings, etc.

More knowledge association methods

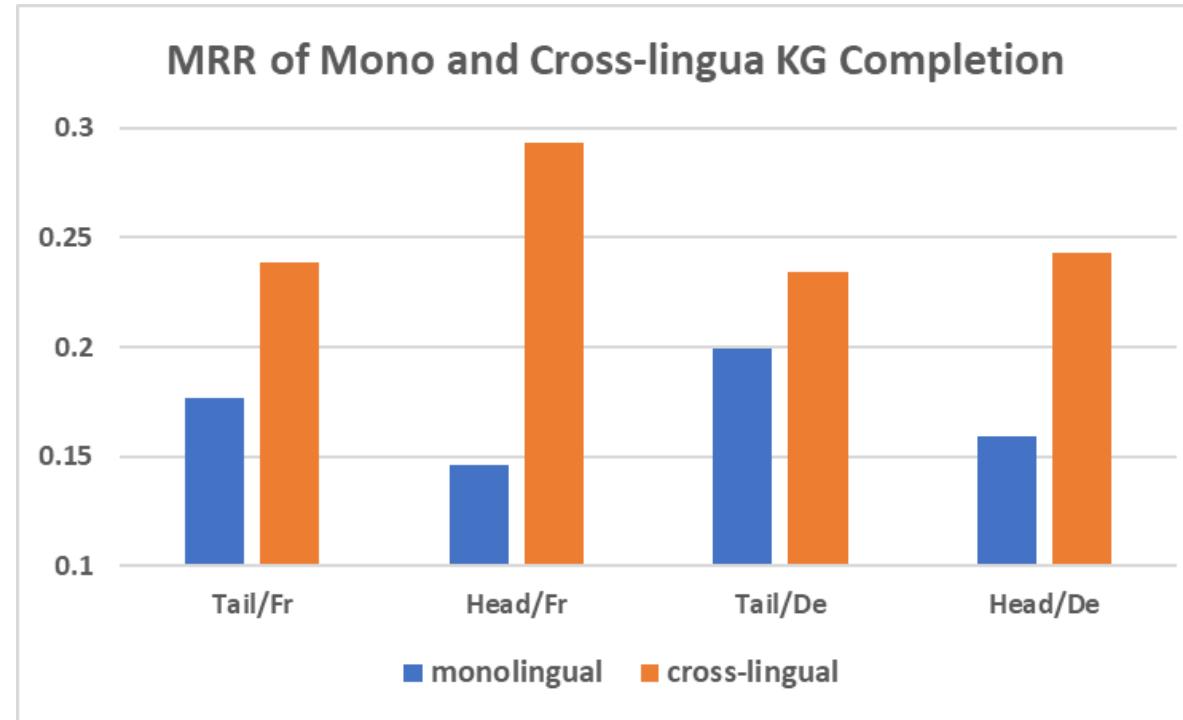
- Adversarial alignment learning, optimal transport, meta learning, noisy supervision, etc.

A systematic summary was given as our [AAAI-2020 tutorial](#), + a benchmarking study and survey in [PVLDB vol. 13 \(2020\)](#).

Relation Inference with Knowledge Transfer

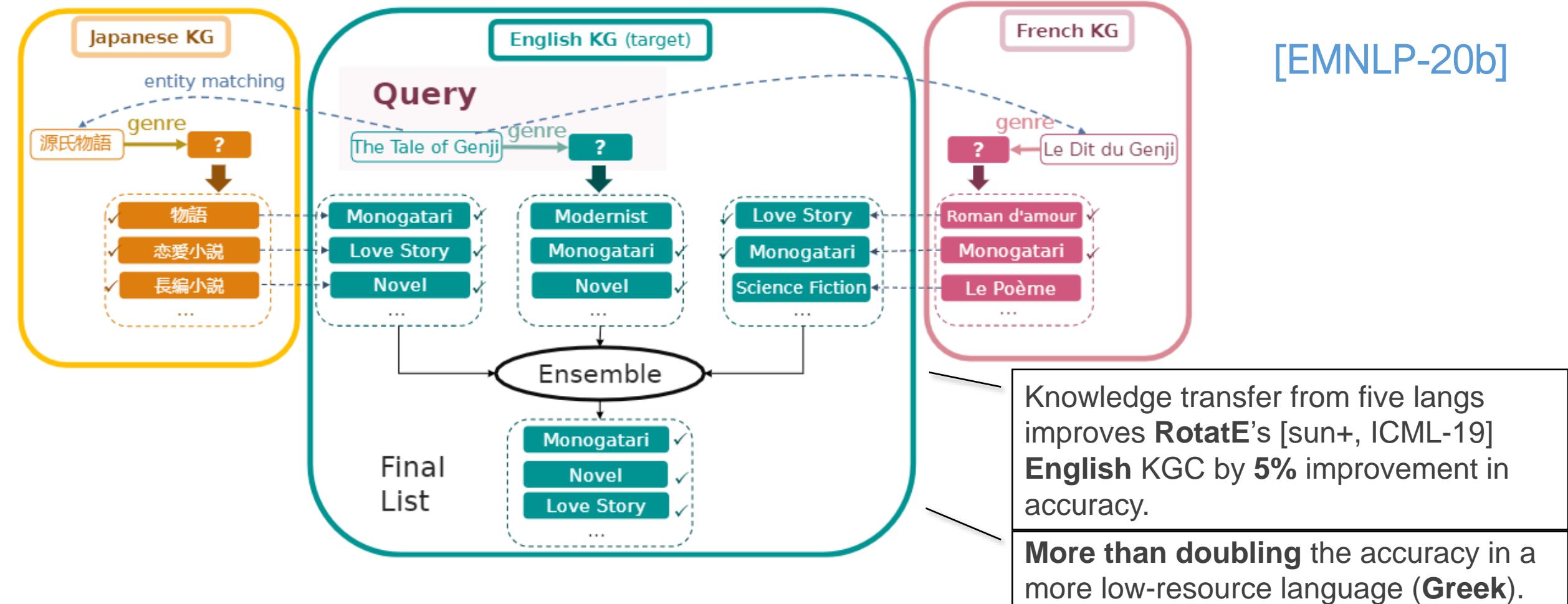
Knowledge transfer to populate a sparser KG (e.g. French)

- Obtain the answer of queries $(h, r, ?t)$ in the embedding space of a well-populated version (e.g. English) of KG



Cross-lingual knowledge transfer can improve sparse KG completion.

Meta-learnable Knowledge Transfer Among Multiple KGs



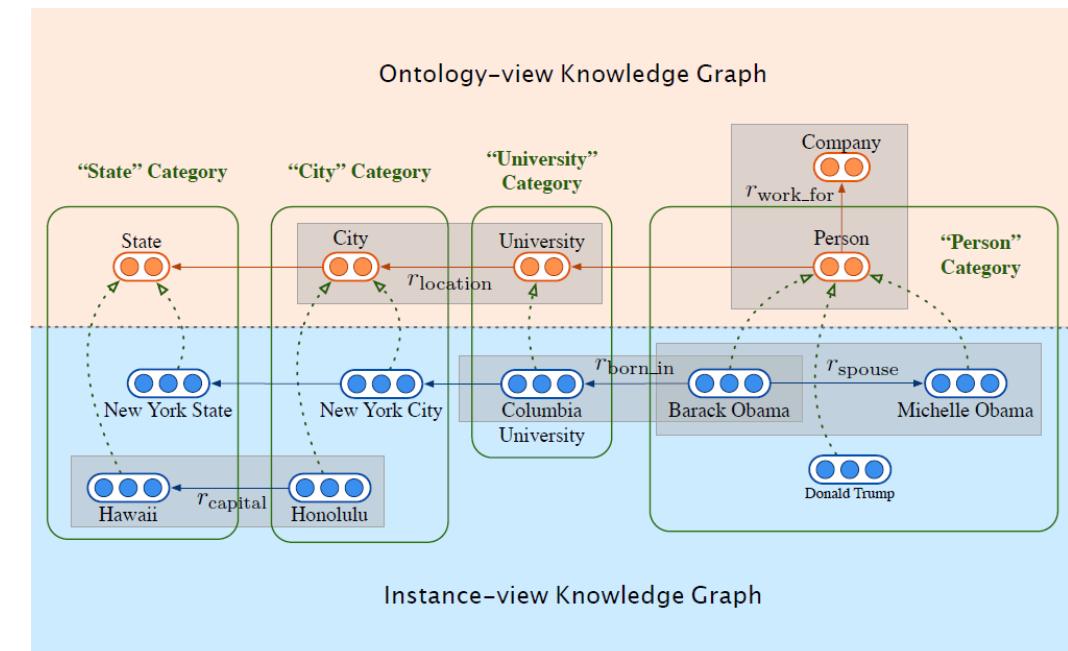
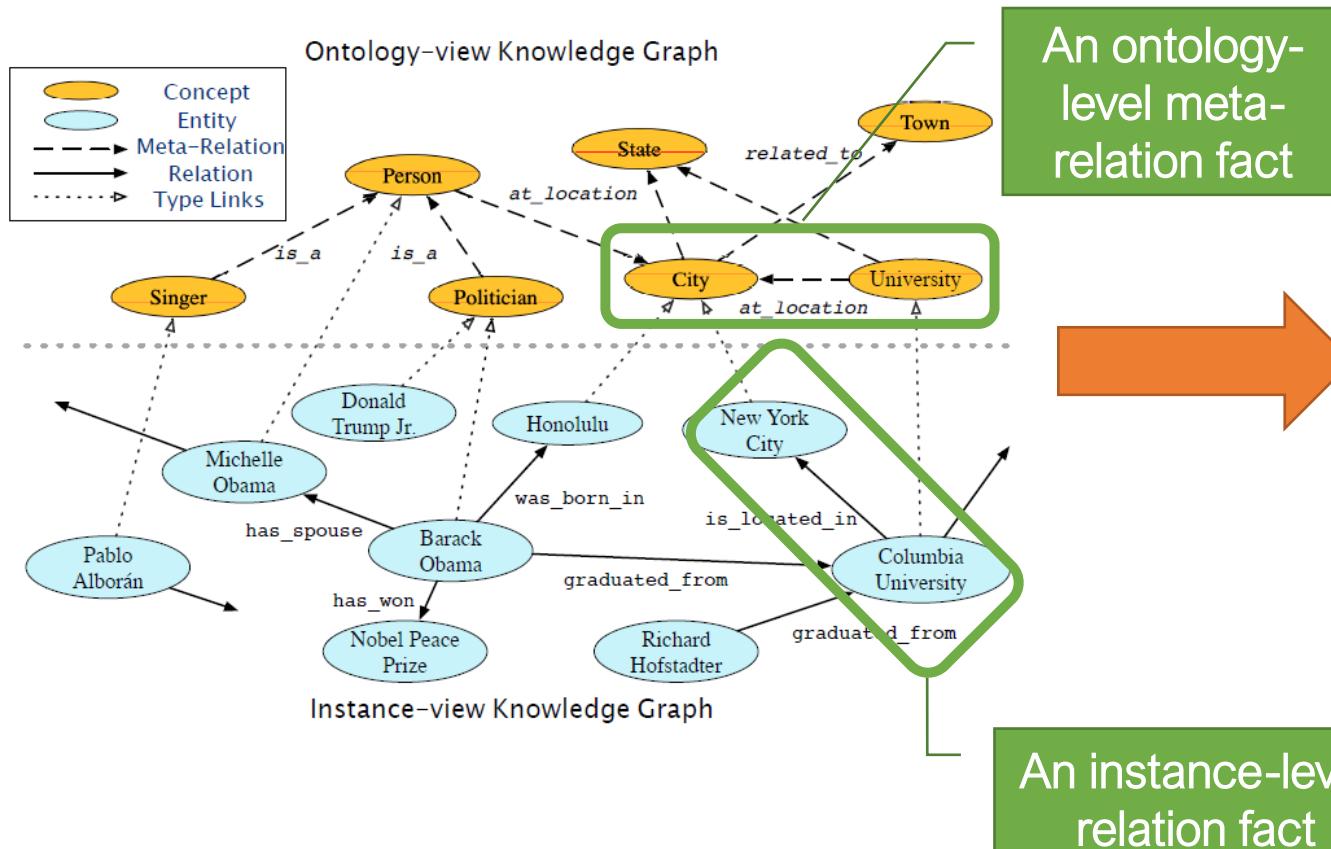
Transferable Embeddings + Meta-learning w/ RankBoost-based Model Weights

Scenario 2.a: Transferable Embedding for Instances and Abstract Concepts*

*[KDD-19]

Ontology view: meta-relations of commonsense concepts

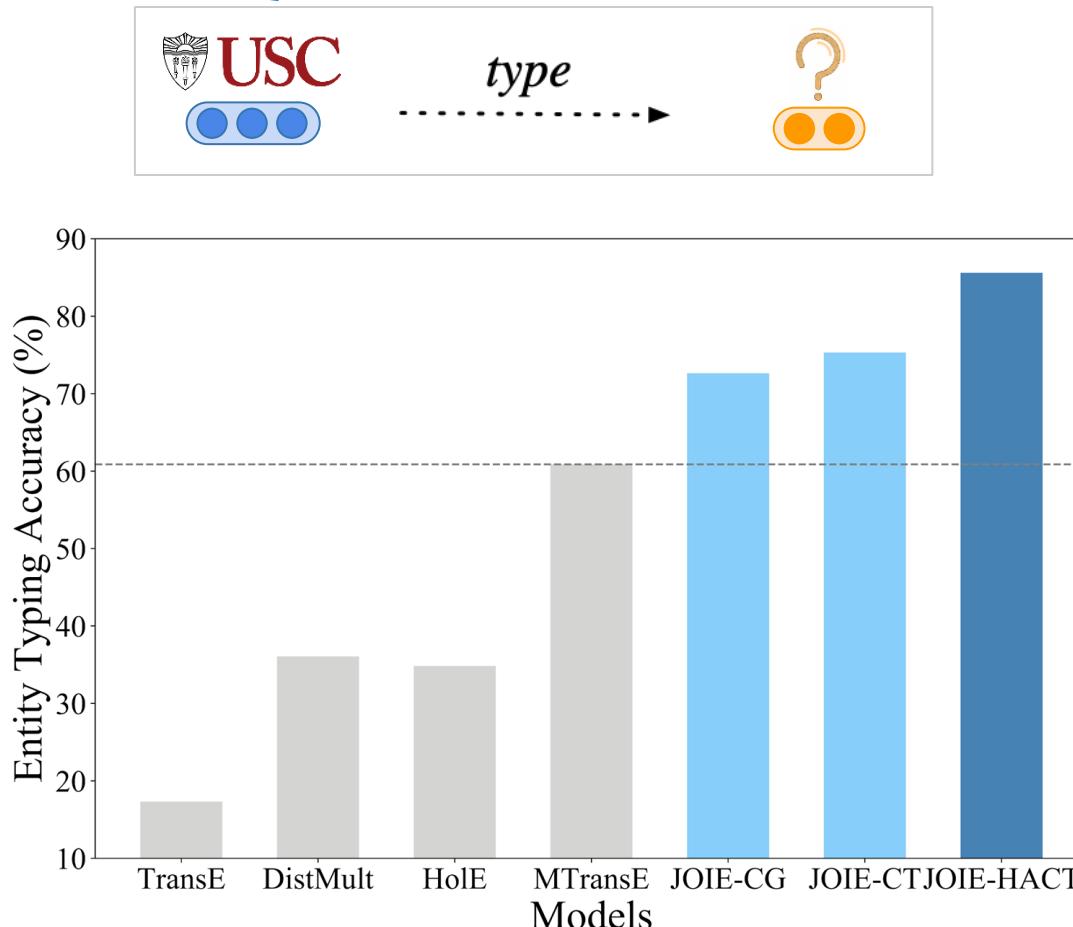
Instance view: relations of entities instantiated from concepts



Application: Entity Typing

*[KDD-19]

Type inference (906 labels) on 40% of >111k entities in YAGO.



Examples of long-tail entity typing (Least 15%)

Entity	Model	Top 3 Concept Prediction
Laurence Fishburne	DistMult MTransE JOIE	football team, club, team writer, person , artist person , artist, philosopher
Warangal City	DistMult MTransE JOIE	country, village, city administrative region, city , settlement city , town, country
Royal Victorian Order	DistMult MTransE JOIE	person, writer, administrative region election, award, order award, order , election

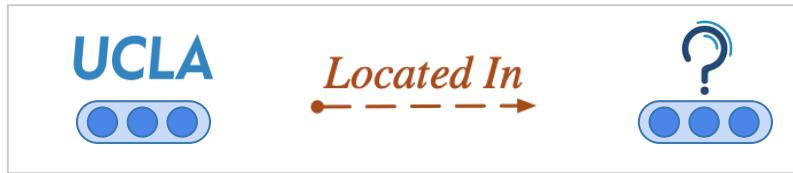
Typing accuracy on long-tail entities (Least 15%)

Metrics	Datasets		
	MRR	Acc.	Hit@3
DistMult	0.156	10.89	25.33
MTransE	0.526	46.45	67.25
JOIE-TransE-CG	0.708	59.97	79.80
JOIE-TransE-CT	0.737	62.05	82.60
JOIE-HATransE-CT	0.802	69.66	87.75

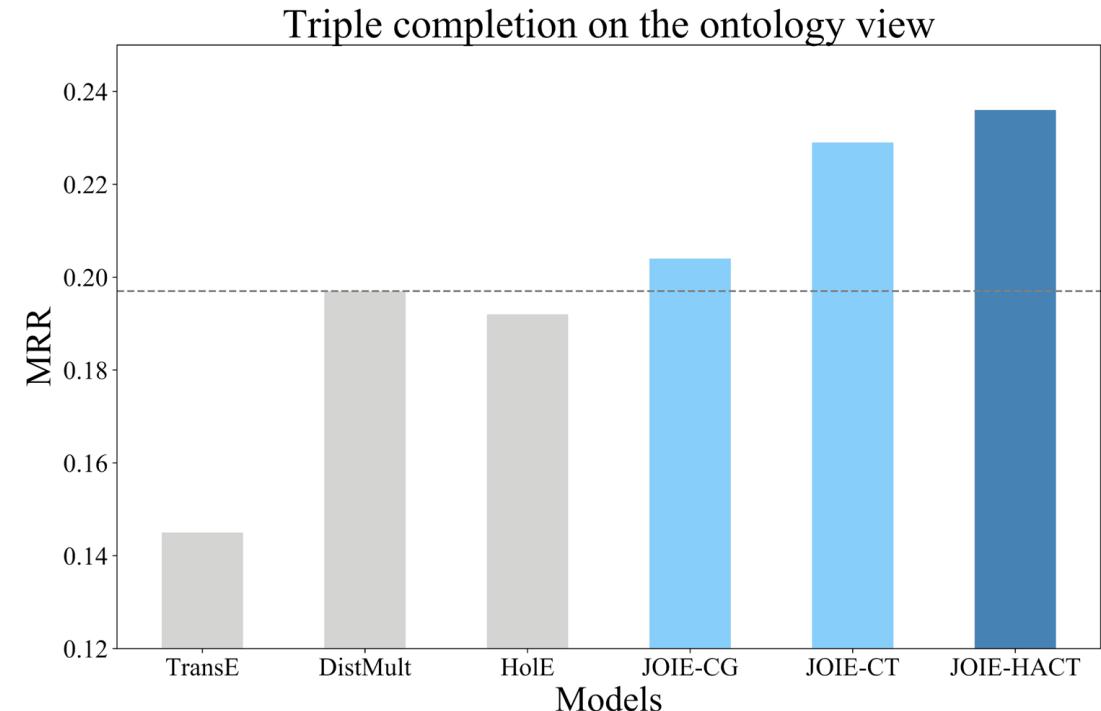
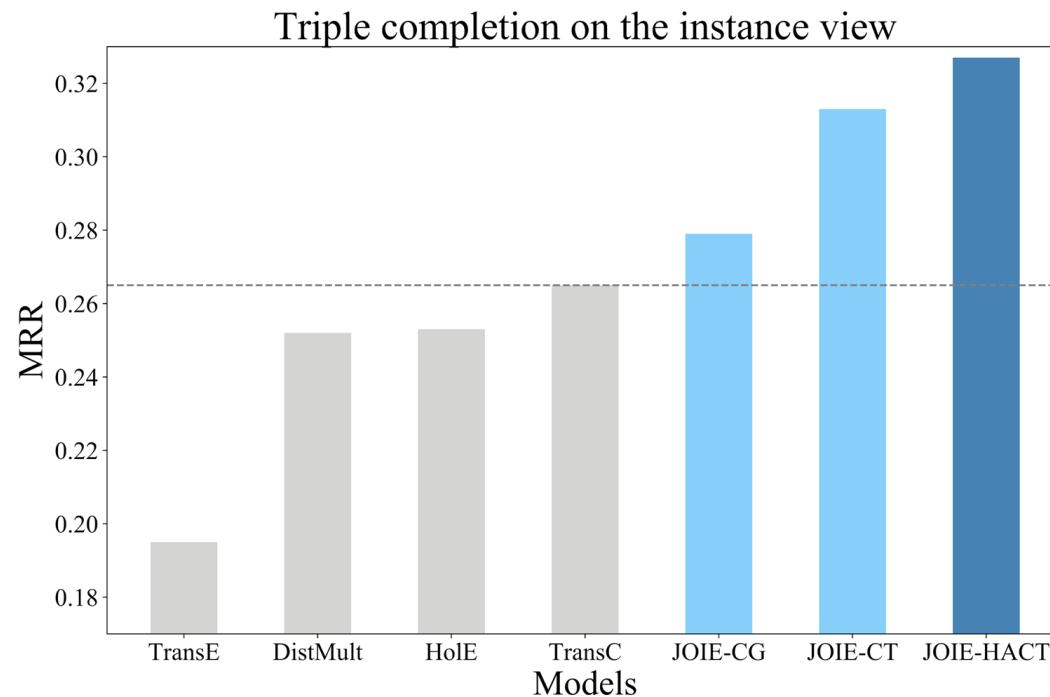
Application: KG Completion

*[KDD-19]

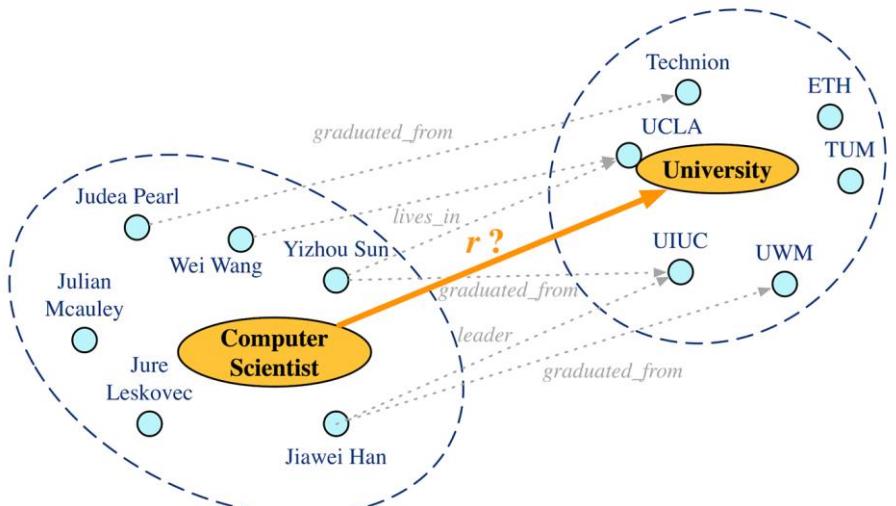
Predicting the 10% held-out relation facts on both views.



Joint representation improves the task on both views.



Transfer Instance-level Knowledge for Ontology Population



Populating unseen ontological facts by transferring knowledge from instance-view facts.

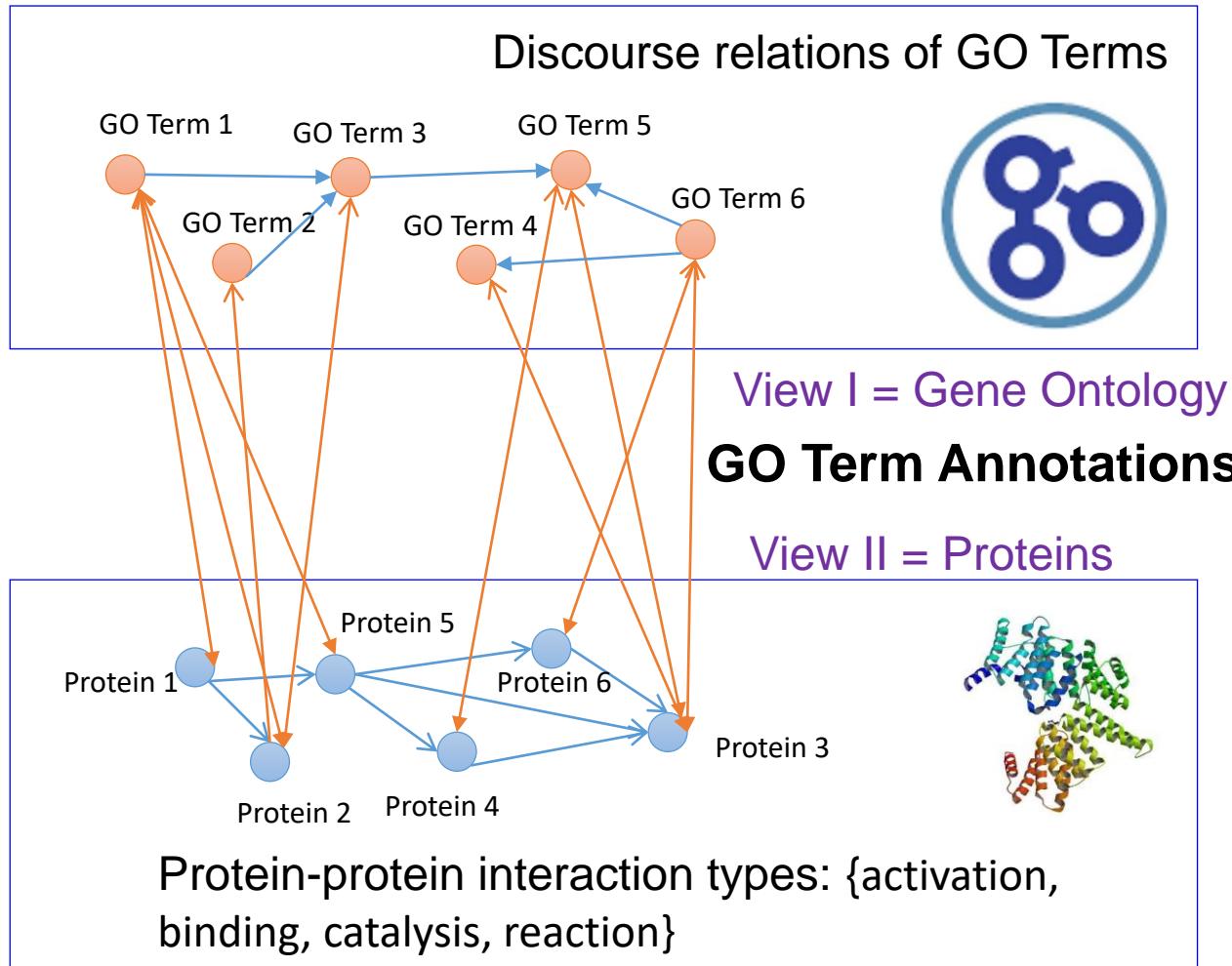
Examples of ontology population

Query	Top 3 Populated Triples with distances
(scientist, ?r, university)	scientist, <i>graduated_from</i> , university (0.499) scientist, <i>isLeaderOf</i> , university (1.082) scientist, <i>isKnownFor</i> , university (1.098)
(boxer, ?r, club)	boxer, <i>playsFor</i> , club (1.467) boxer, <i>isAffiliatedTo</i> , club (1.474) boxer, <i>worksAt</i> , club (1.479)
(scientist, ?r, scientist)	scientist, <i>doctoralAdvisor</i> , scientist (0.204) scientist, <i>doctoralStudent</i> , scientist (0.221) scientist, <i>relative</i> , scientist (0.228)

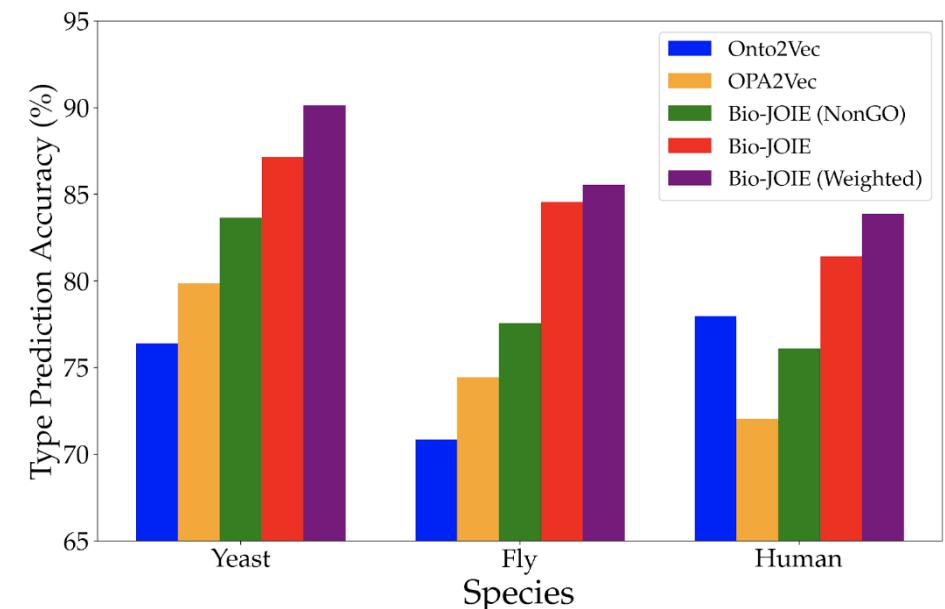
Scenario 3.a: Proteomics and Gene Ontologies

*[ACM BCB-20]
(Best Student Paper)

Transferring knowledge from the gene ontology improves typed protein-protein interaction prediction.



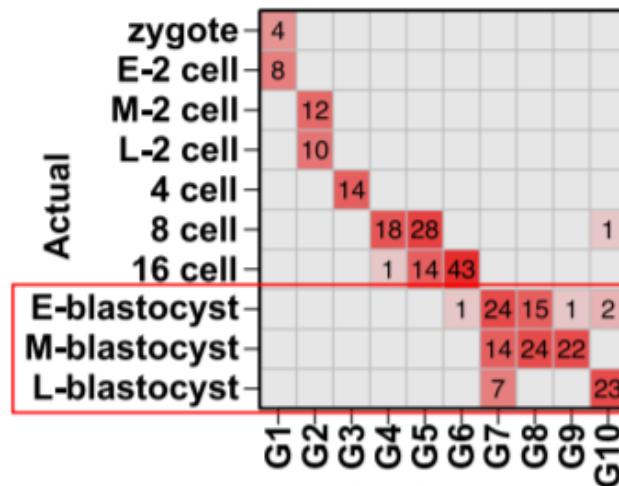
~10% of ACC improvement over SOTA
(Opa2Vec, *Bioinformatics* [J] 2019).



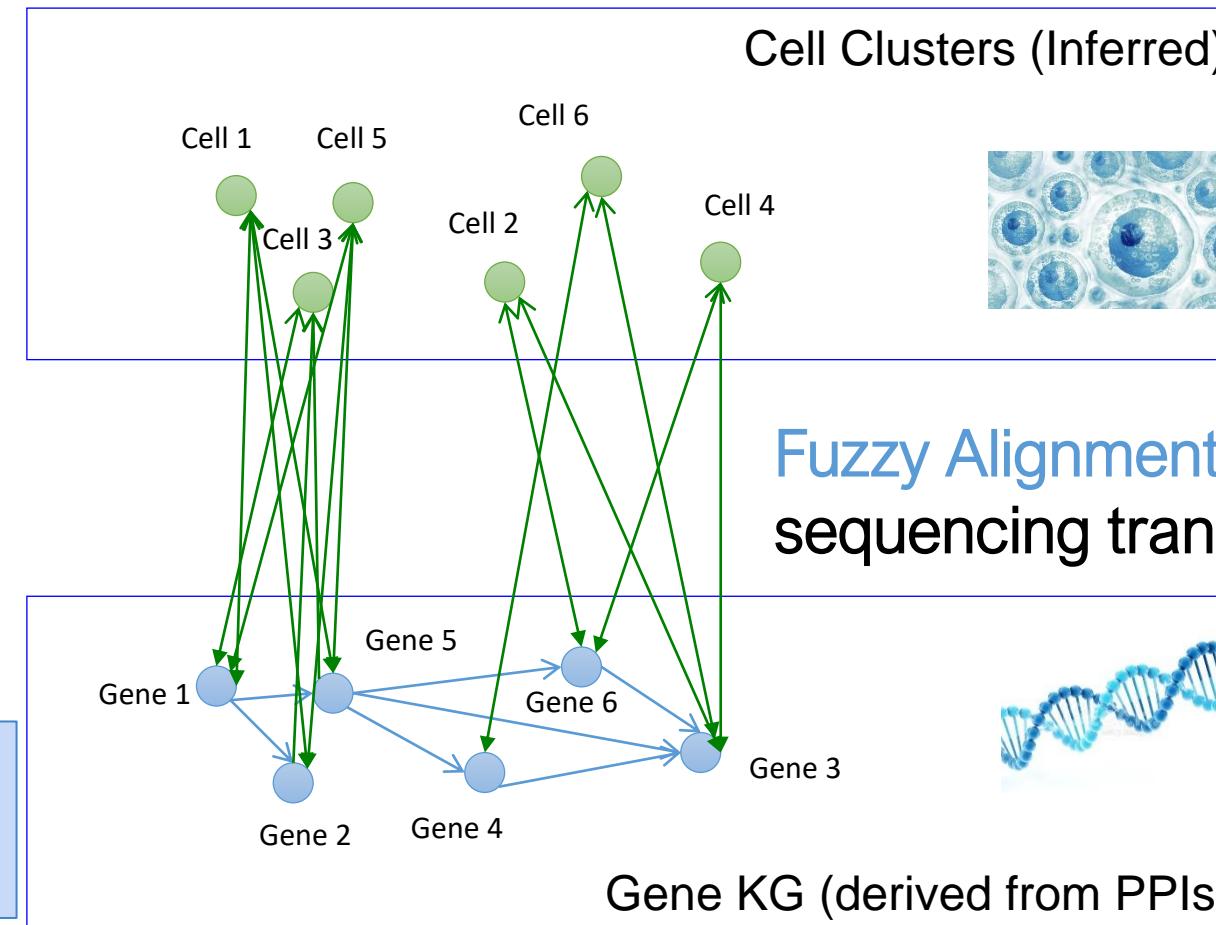
and helps disease target prediction for COVID-19 related viral proteins.

Scenario 3.b: Cell Clustering

At least 10-15% of ARI improvement over pCMF [Durif+, *Bioinform.* 2019] and others.

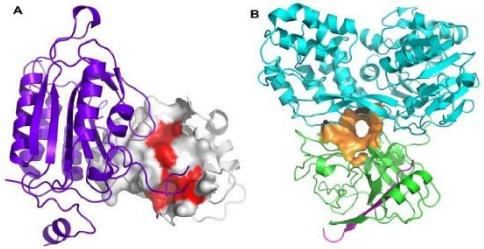


Non-negative Tri-Factorization
 $\operatorname{argmin}_{\theta} \|S - E_1 U E_2^T\|$

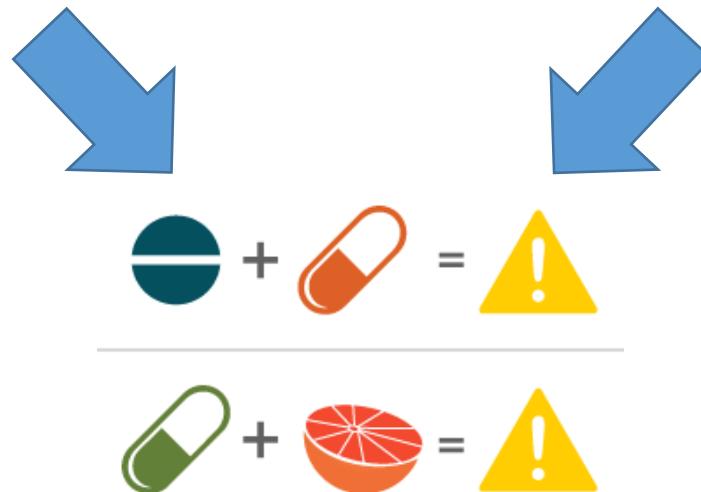


Experiment done on the Zeisel dataset [Zeisel+, *Science* 2015]

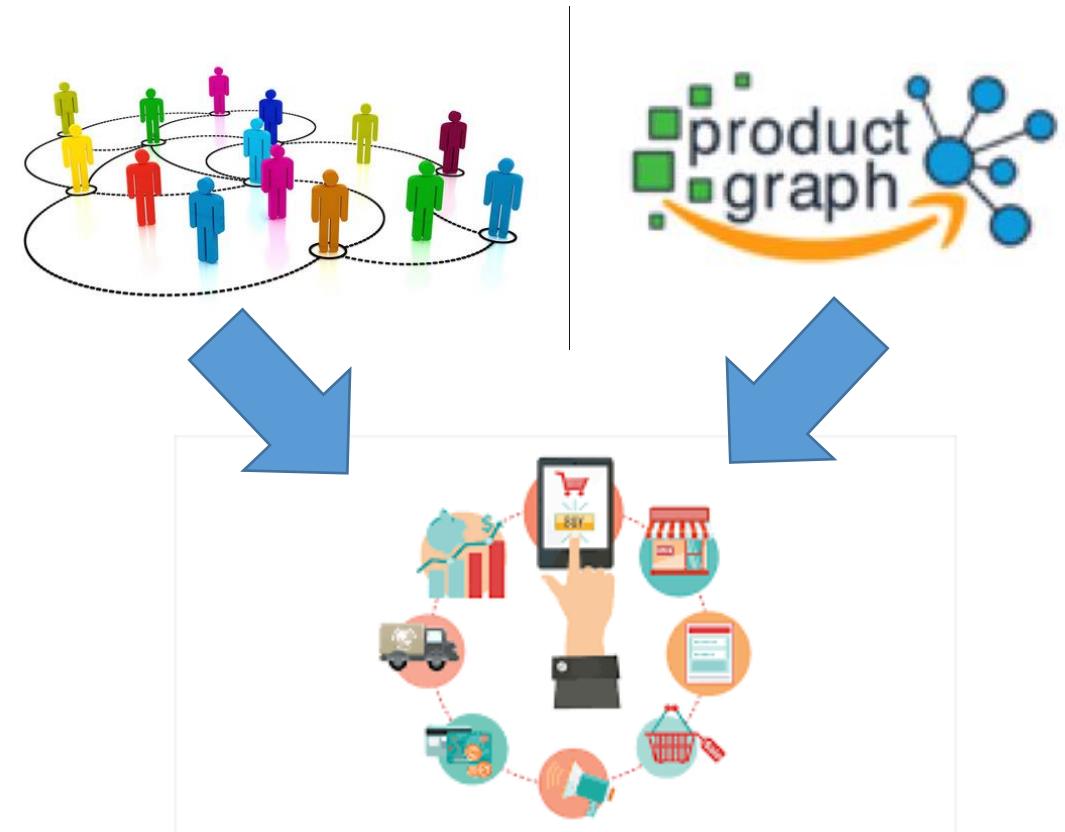
More Applications To Be Explored



UMLS
DISEASE
ONTOLOGY



Polypharmacy (drug-drug) interaction
or drug-target prediction



Product recommendation

Outline

Transferable Representation Learning of Multi-relational Data

Knowledge Acquisition from Unstructured Data

Future research agenda

Knowledge Acquisition for Events

DARPA & IARPA projects: KAIROS, BETTER, AIDA

Human language always communicates about events.



How to earn a PhD?



Subevents of **earning a PhD**

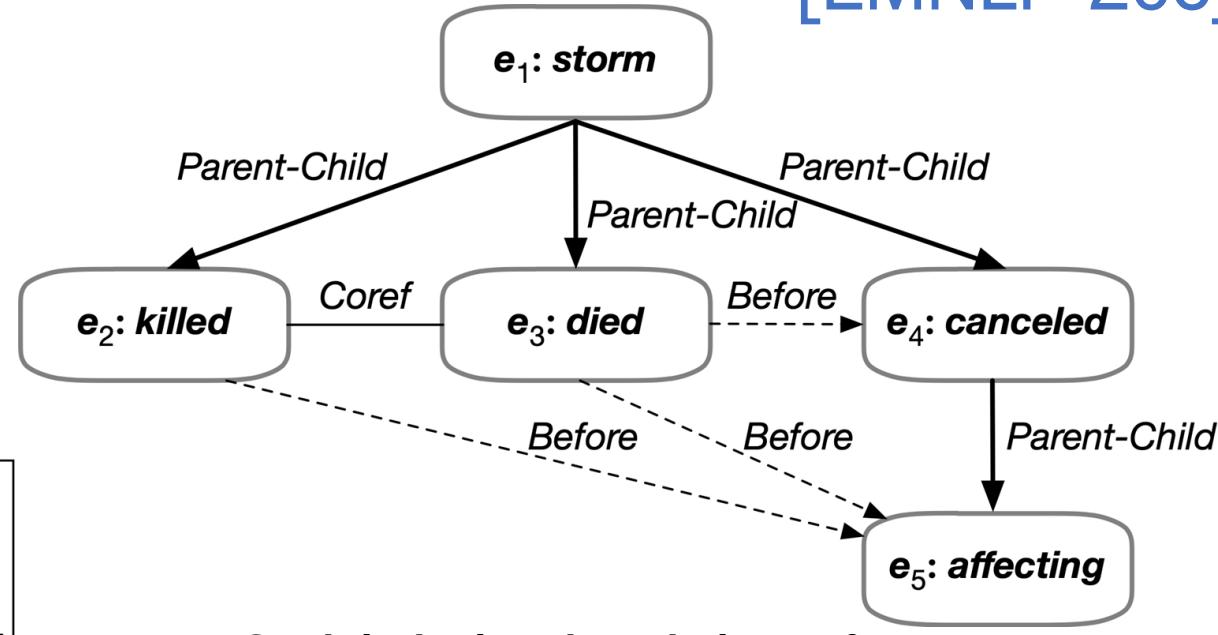
- What should be the right process?
- What contains others?
- What are depending on others?
- What are essential?

Logically Constrained Learning for Event Relation Extraction

*[EMNLP-20c]

- Temporal Relations
- Subevent Relations (Memberships)
- Event Coreference

On Tuesday, there was a typhoon-strength ($e_1:\text{storm}$) in Japan. One man got ($e_2:\text{killed}$) and thousands of people were left stranded. Police said an 81-year-old man ($e_3:\text{died}$) in central Toyama when the wind blew over a shed, trapping him underneath. Later this afternoon, with the agency warning of possible tornadoes, Japan Airlines ($e_4:\text{canceled}$) 230 domestic flights, ($e_5:\text{affecting}$) 31,600 passengers.



Goal: inducing the relations of events

A resource hungry task with limited labeled data:

- No resource annotates all types of relations
 - TempRel data: TBDense and MATRES
 - Subevent and Coref: HiEve
- Annotations are on ~100 documents

Logical Constraints of Relations

Symmetry

$e3:\text{died}$ is BEFORE $e4:\text{canceled}$
 $\Rightarrow e4:\text{canceled}$ is AFTER $e3:\text{died}$

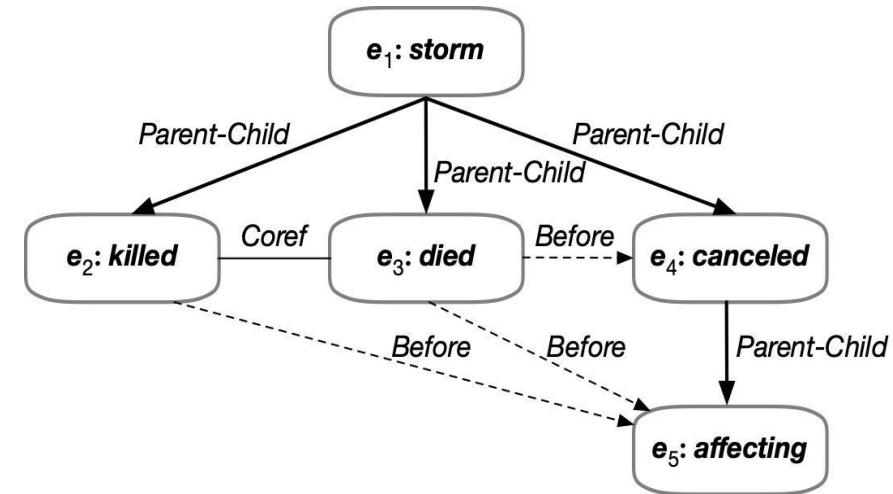
Conjunction

$e3:\text{died}$ is BEFORE $e4:\text{canceled}$
 $\wedge e4:\text{canceled}$ is a PARENT of $e5:\text{affecting}$
 $\Rightarrow e3:\text{died}$ BEFORE $e5:\text{affecting}$

(we also consider **Implication** and **Negation**)

Transitivity

$e1:\text{storm}$ is PARENT of $e4:\text{canceled}$
 $\wedge e4:\text{canceled}$ is a PARENT of $e5:\text{affecting}$
 $\Rightarrow e1:\text{storm}$ is a PARENT of $e5:\text{affecting}$



Why logical constraints in learning?

- Learning to provide **globally consistent** predictions
- Providing **indirect supervision** across tasks/learning resources

Incorporating Logical Constraints in A Neural Architecture

From logical constraints to differentiable functions

- L_A Annotation Loss: $\top \rightarrow r(e_1, e_2) \rightarrow -w_r \log r_{(e_1, e_2)}$
- L_S Implication Loss: $\alpha(e_1, e_2) \leftrightarrow \bar{\alpha}(e_2, e_1) \rightarrow |\log \alpha_{(e_1, e_2)} - \log \bar{\alpha}_{(e_2, e_1)}|$
- L_C Conjunction Loss: $\alpha(e_1, e_2) \wedge \beta(e_2, e_3) \rightarrow \gamma(e_1, e_3) \rightarrow \log \alpha_{(e_1, e_2)} + \log \beta_{(e_2, e_3)} - \log \gamma_{(e_1, e_3)}$
 $\alpha(e_1, e_2) \wedge \beta(e_2, e_3) \rightarrow \neg\delta(e_1, e_3) \rightarrow \log \alpha_{(e_1, e_2)} + \log \beta_{(e_2, e_3)} - \log(1 - \delta_{(e_1, e_3)})$
- Training Objective: $L = L_A + \lambda_S L_S + \lambda_C L_C$

Symmetry and negation are subsumed within implication loss; Transitivity is subsumed within conjunction loss.

$\alpha \setminus \beta$	PC	CP	CR	NR	BF	AF	EQ	VG
α	PC, \neg AF	-	PC, \neg AF	\neg CP, \neg CR	BF, \neg CP, \neg CR	-	BF, \neg CP, \neg CR	-
PC	PC, \neg AF	-	PC, \neg AF	\neg CP, \neg CR	BF, \neg CP, \neg CR	-	BF, \neg CP, \neg CR	-
CP	-	CP, \neg BF	CP, \neg BF	\neg PC, \neg CR	-	AF, \neg PC, \neg CR	AF, \neg PC, \neg CR	-
CR	PC, \neg AF	CP, \neg BF	CR, EQ	NR	BF, \neg CP, \neg CR	AF, \neg PC, \neg CR	EQ	VG
NR	\neg CP, \neg CR	\neg PC, \neg CR	NR	-	-	-	-	-
BF	BF, \neg CP, \neg CR	-	BF, \neg CP, \neg CR	-	BF, \neg CP, \neg CR	-	BF, \neg CP, \neg CR	\neg AF, \neg EQ
AF	-	AF, \neg PC, \neg CR	AF, \neg PC, \neg CR	-	-	AF, \neg PC, \neg CR	AF, \neg PC, \neg CR	\neg BF, \neg EQ
EQ	\neg AF	\neg BF	EQ	-	BF, \neg CP, \neg CR	AF, \neg PC, \neg CR	EQ	VG, \neg CR
VG	-	-	VG, \neg CR	-	\neg AF, \neg EQ	\neg BF, \neg EQ	VG	-

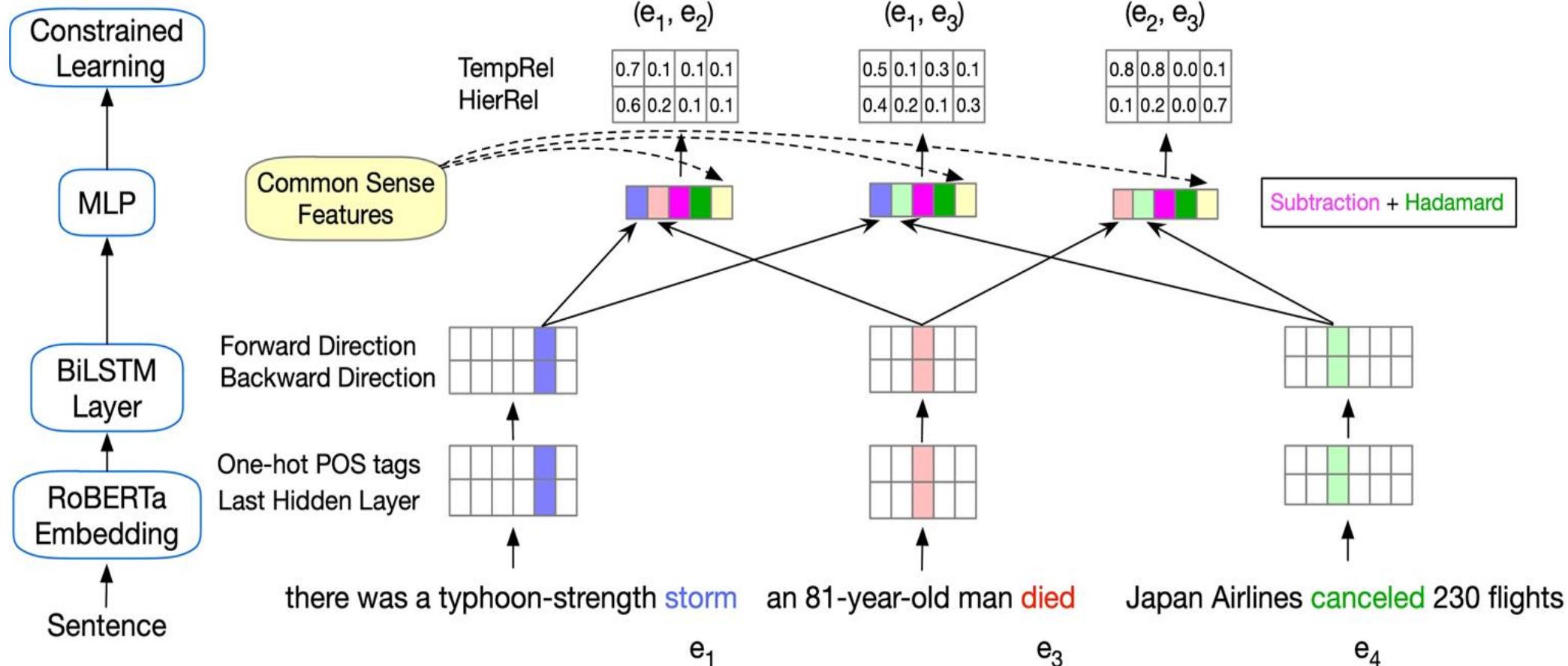
The Joint Constrained Learning Architecture

- Temporal Relations
- Subevent Relations (Memberships)
- Event Coreference

Logical constraints

- Symmetry, transitivity, conjunction, implication.
- Converting constraints into differentiable learning objectives

$$\text{Loss Function: } L = L_A + \lambda_S L_S + \lambda_C L_C$$



Logically Constrained Learning for Event Relation Extraction

*[EMNLP-20c]

Constrained learning surpasses SOTA TempRel extraction on MATRES [Ning+, ACL-18] by relatively 3.27% in F_1 .

Model	P	R	F_1
CogCompTime (Ning et al., 2018c)	0.616	0.725	0.666
Perceptron (Ning et al., 2018b)	0.660	0.723	0.690
BiLSTM+MAP (Han et al., 2019b)	-	-	0.755
LSTM+CSE+ILP (Ning et al., 2019)	0.713	0.821	0.763
Joint Constrained Learning (ours)	0.734	0.850	0.788

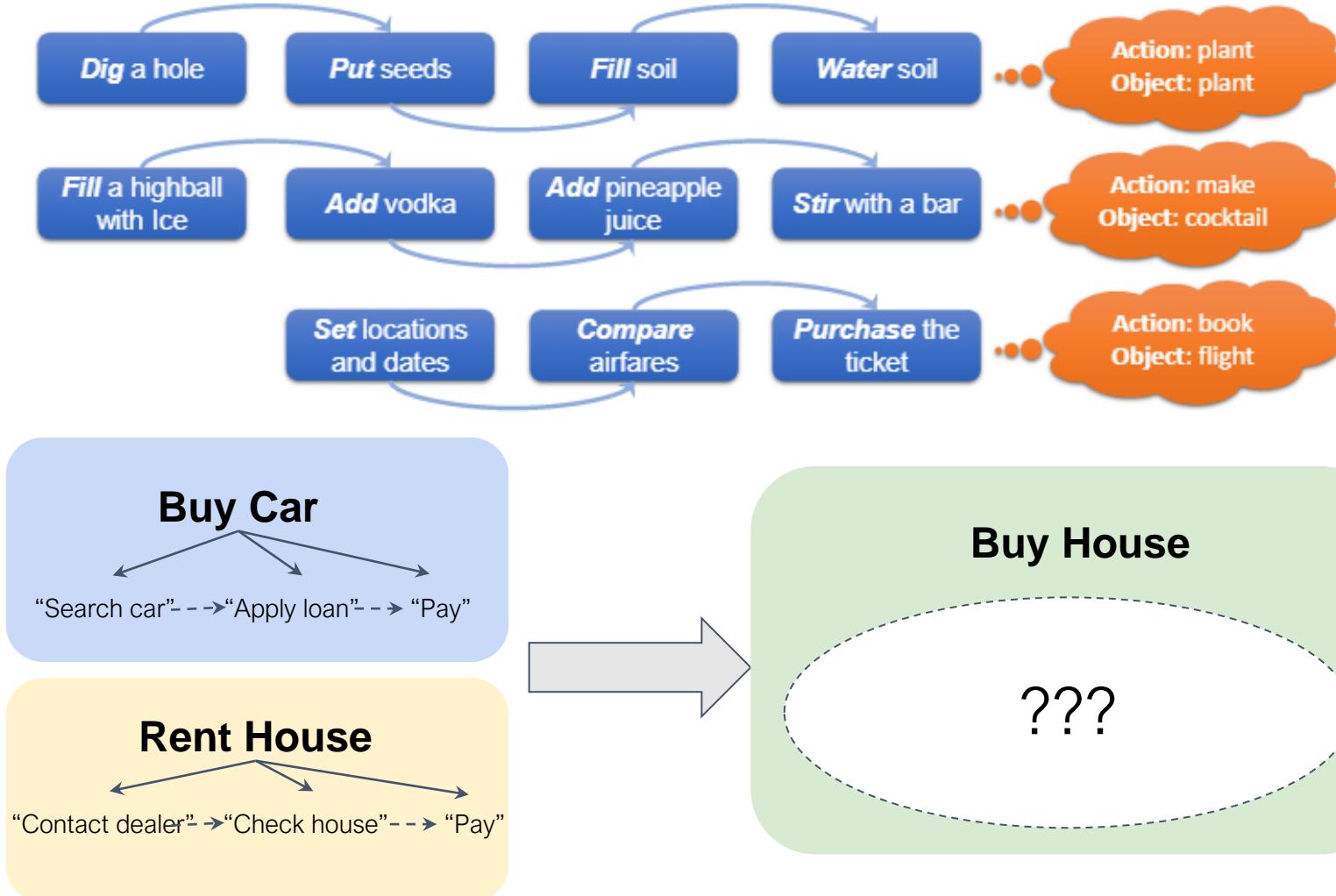
On HiEve [Glavaš+, LREC-14] for subevent extraction, it relatively surpasses previous methods by at least 3.12% in F_1 .

Model	F_1 score		
	PC	CP	Avg.
StructLR (Glavaš et al., 2014)	0.522	0.634	0.577
TACOLM (Zhou et al., 2020a)	0.485	0.494	0.489
Joint Constrained Learning (ours)	0.625	0.564	0.595

Key Observations

- Constraints are a natural bridge for learning resources with different sets of relations
- Adding constraints in learning is sufficient to enforce logical consistency of outputs, surpassing ILP in inference (w/ constrained learning) by 2.6-12.3% in ACC

More About Eventuality Knowledge Acquisition from Text



Few-shot *intention prediction* for event processes based on indirect supervision from gloss knowledge [CoNLL-20 Best Paper Nomination]

Open-domain event schema induction with analogy-aware inference [EMNLP-20d]

Probabilistic Constrained Knowledge Acquisition*

*[AAAI-19]

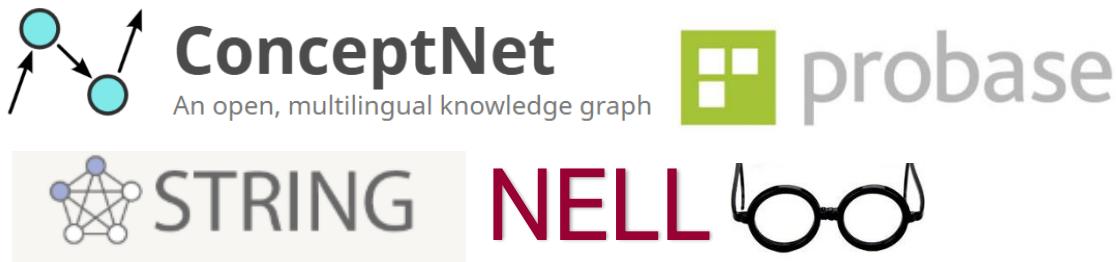
Toyota

competeswith

Honda 0.94

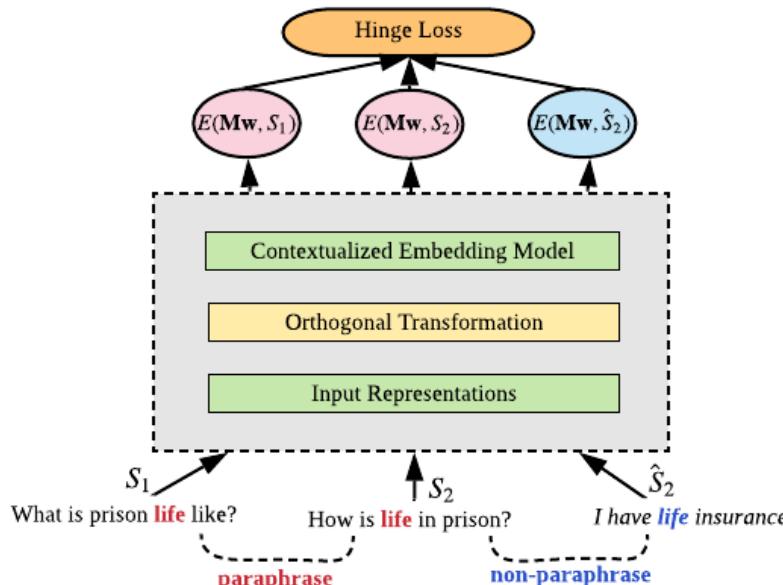
Hyundai 0.91

Chrysler 0.76



- Incorporating Probabilistic Soft Logic constraints in learning (w/ Łukasiewicz t-norm)
- Confidence prediction for unseen facts

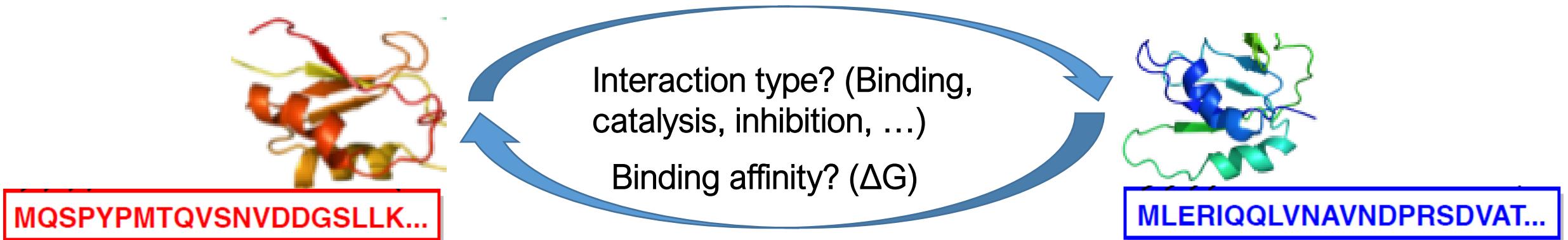
Retrofitting language models for robust discourse relation detection⁺



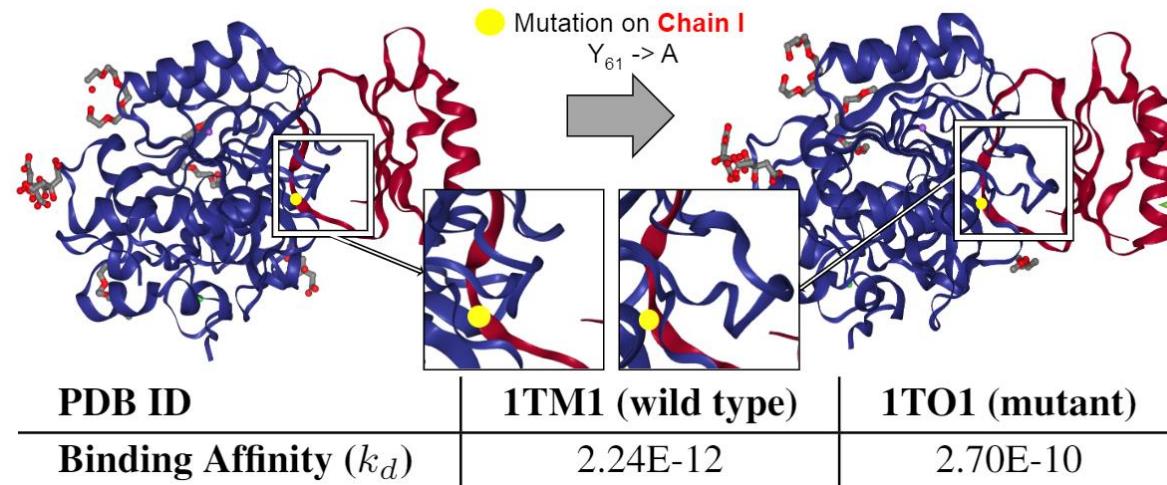
+2.60-3.30% (acc) on textual inference and +3-5% (Pearson's) in textual similarity (SentEval)
+5.4% (acc) on Adversarial SQuAD.

*[EMNLP-19]

Knowledge Acquisition Beyond Human Languages



“Entailment model” for Protein-protein interaction prediction [ISMB’19, *Bioinformatics 2019*].



$\Delta\Delta G$ estimation on SKEMPIv2 benchmark:
~20% of absolute improvement (0.69->0.88) in Pearson’s Corr over SOTA!

Pre-trained language model on wild-type protein sequences helps estimate point mutation effects on proteins [NAR: Genom. Bioinform. 2020].

Outline

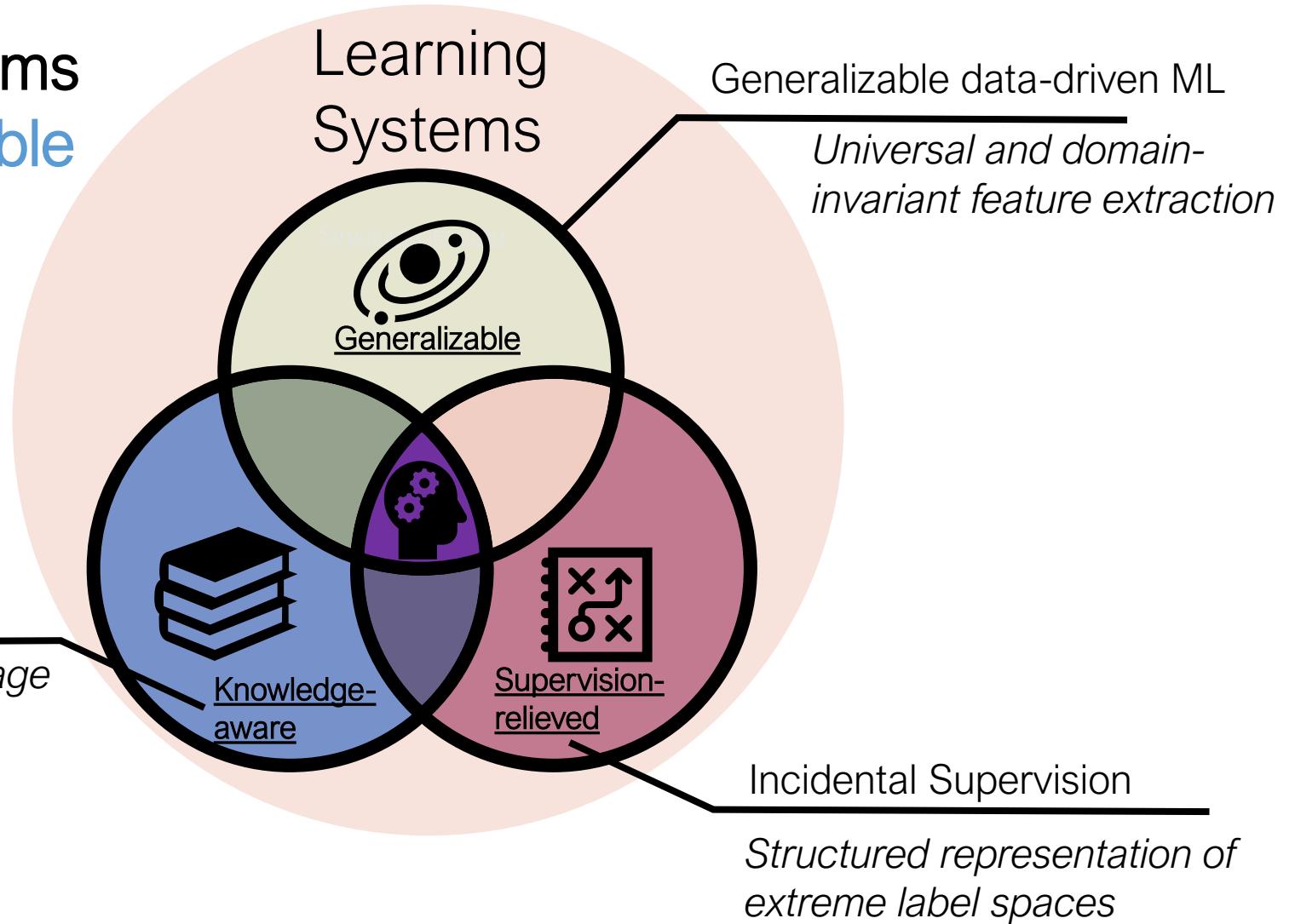
Transferable Representation Learning of Multi-relational Data

Knowledge Acquisition from Unstructured Data

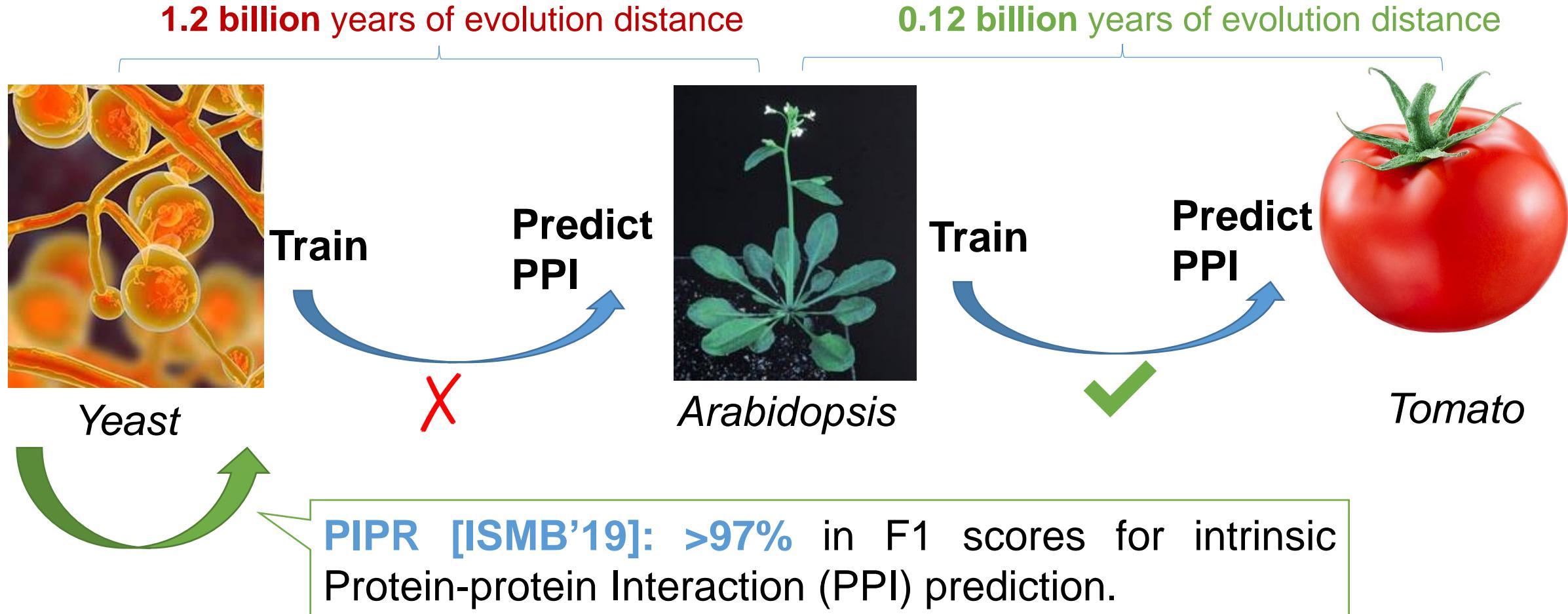
Future research agenda

What's Next

Data-driven learning systems should become more **reliable** and **adaptive**.

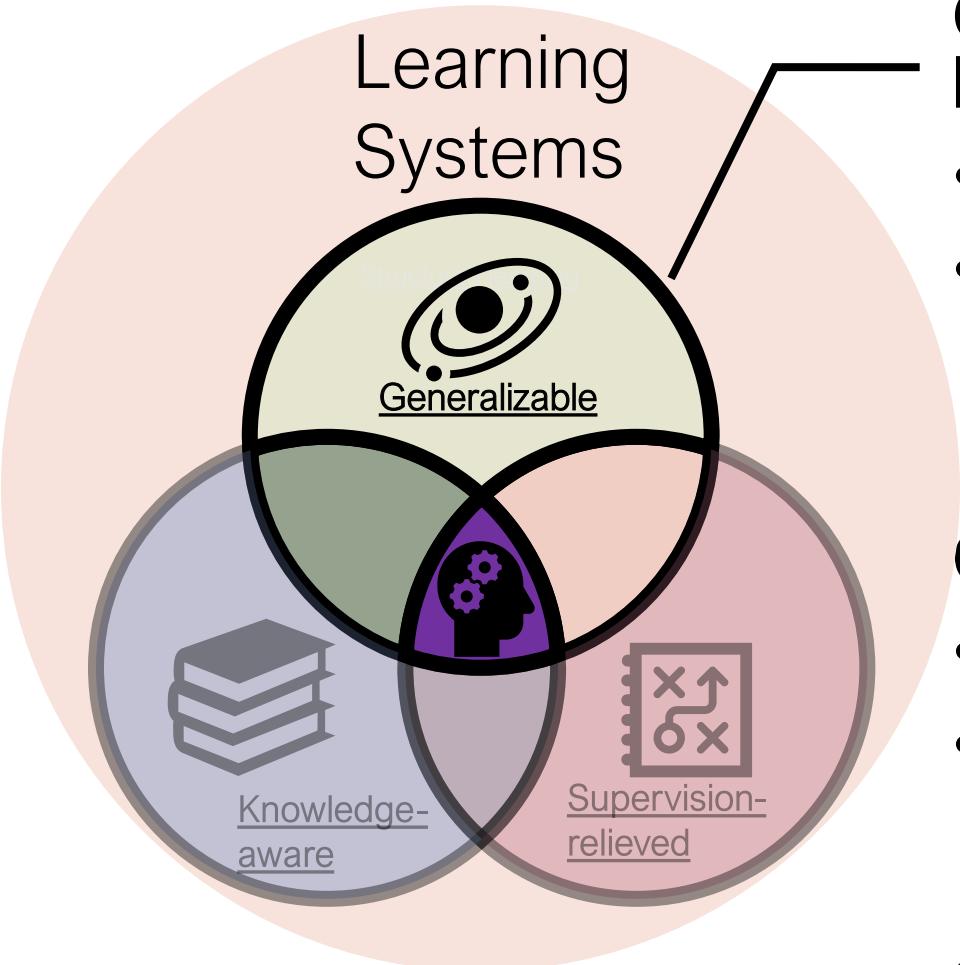


Robust Learning Systems with Generalizability



Future direction: using transfer learning to predict PPI for > 1.3 million low-resource species.

Robust Learning Systems with Generalizability



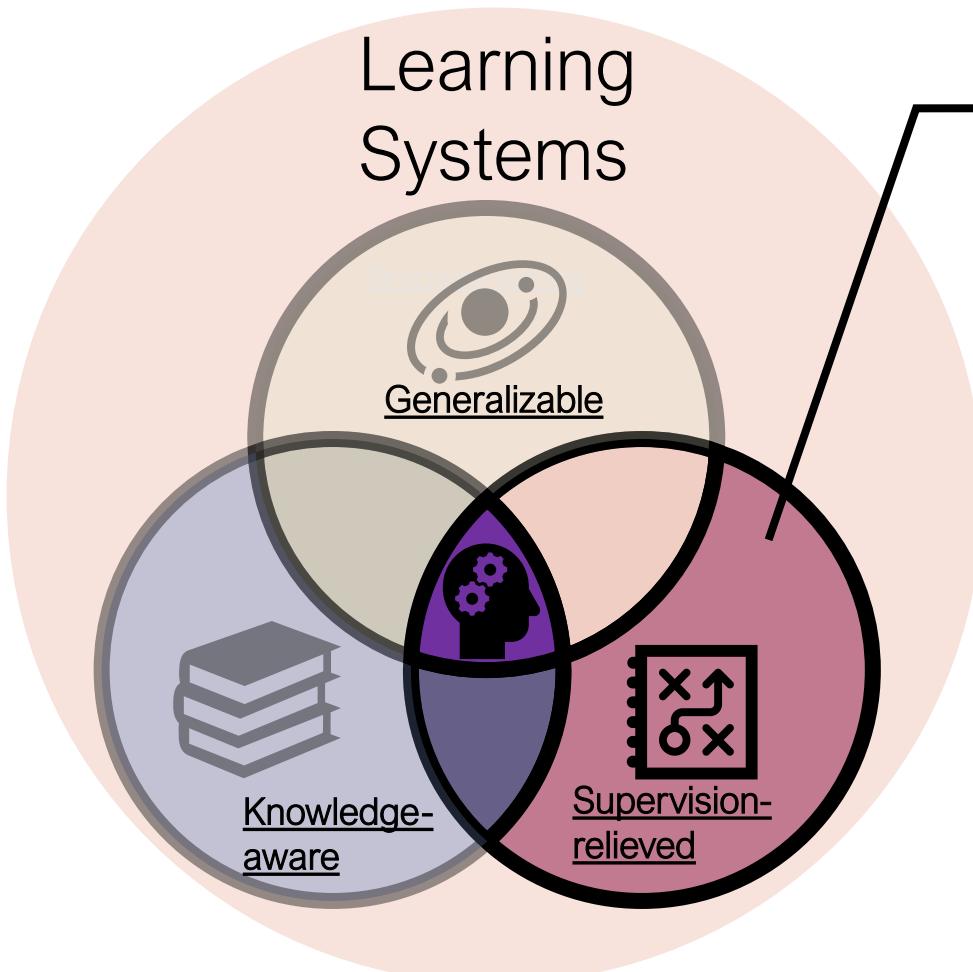
General methodologies for domain-adaptive learning/inference

- Domain-invariant feature extraction
- Massively pre-training
 - Language- and domain-invariant KG embedding (ongoing)
 - Pre-training language models on thousand-species genomic/proteomic data

Cross-domain tasks

- NLP tasks on >6000 **low-resource languages**
- PPI, folding energy, 3D structure prediction, functional annotation ... for > 1.3 million **low-resource species**
- Clinical data processing **[AIME-20]** (low-resource due to **privacy**)

Support Learning With Minimal Supervision



Representing Structures of Feature and Label Spaces

- Non-Euclidean representation learning
- *Set learning* for order-invariant data
 - Concurrent clinical events [\[AIME-20\]](#)

Indirect supervision

- Leverage cheap supervision signals from auxiliary data / tasks
- Learning with noisy labels (ongoing direction)
- Learning/inference with dependency of labels

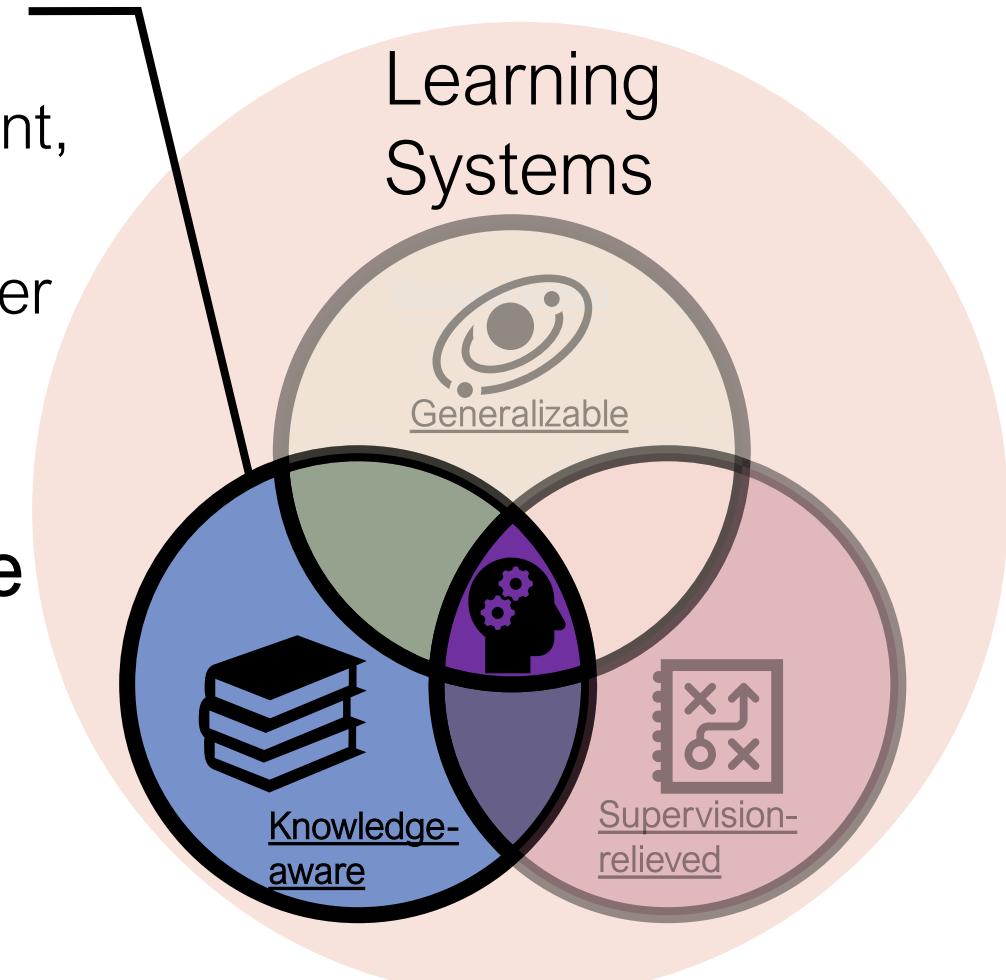
Reliable and Knowledge-aware Learning Systems

Null prediction problem

- Lots of NLU models for entity typing, entity alignment, entity linking, semantic IR, QA, ...
- How to let them understand when there is no answer to a query?

Making language models aware of knowledge

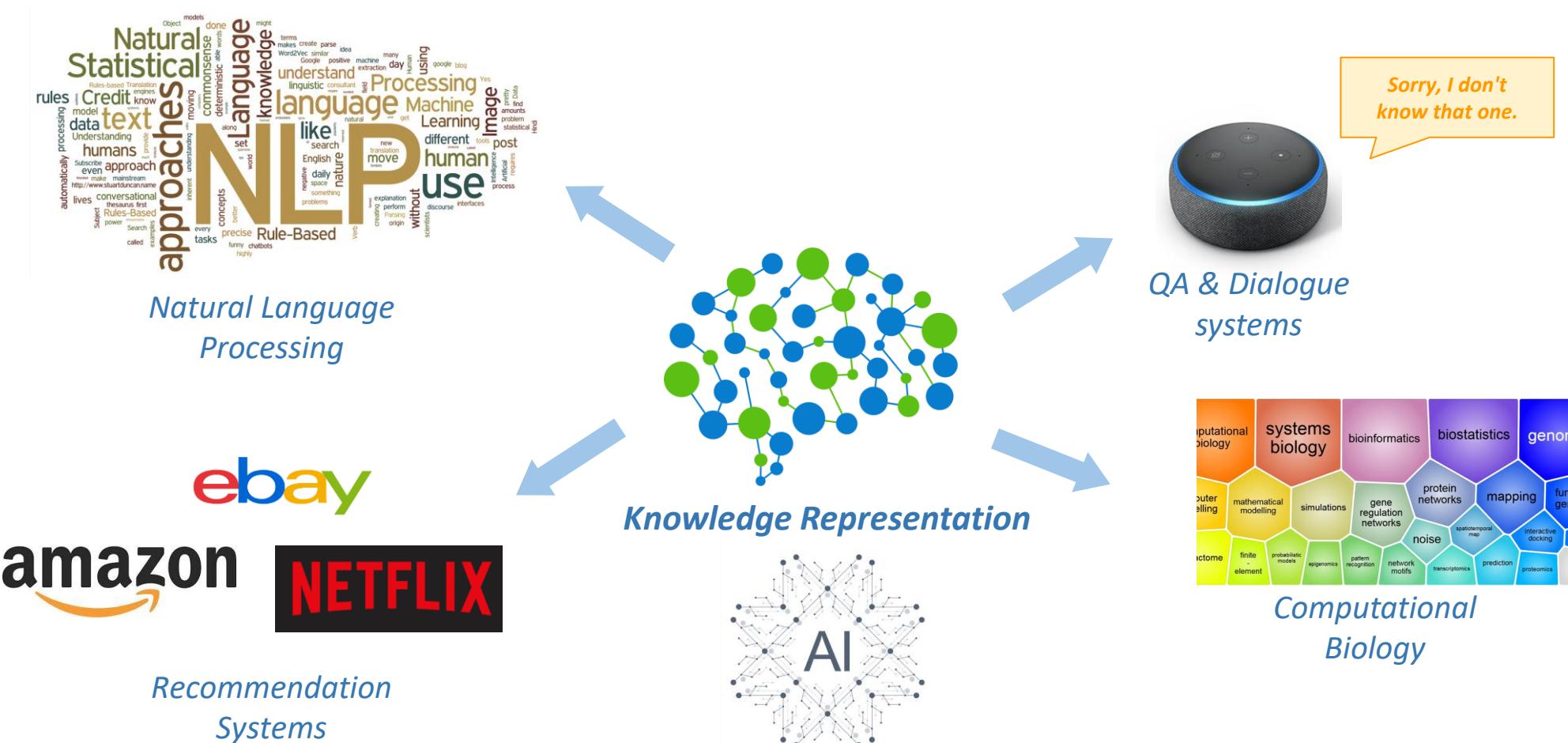
- Eventuality knowledge*
- Temporal knowledge



*Will be discussed in our AAAI-21 and ACL-21 tutorials about Event-centric NLU.

Cross-domain and Interdisciplinary Research

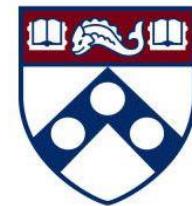
A useful technology may benefit multiple research areas and disciplines, and it is important to let it contribute to the Common Good.



Acknowledgement

My 72 coauthors from 15 institutes. We wrote 50 papers together in the past 6 years.

- Carlo Zaniolo, Kai-Wei Chang, Wei Wang, Alex Bui, Yizhou Sun, Mario Gerla, Eleazar Eskin, Jessica Li, Demetris Terzopoulos, Chelsea Ju, Dat Duong, Guangyu Zhou, Tianran Zhang, Jyun-Yu Jiang, Junheng Hao, Wenchao Yu, Weijia Shi, Shirley Chen, Jieyu Zhao, Kuan-hao Huang, Jiaqi Gu, Qi Zhao, Pengyuan Du, Tuan Le, Seunghyun Yoo, Zijun Xue, Pei Zhou, Tao Zhou, Zheng Wang, James Zhang, Ankith Uppunda ([UCLA](#))
- Dan Roth, Ben Zhou, Haoyu Wang, Hongming Zhang ([UPenn](#))
- Nigel Collier, Fangyu Liu ([Cambridge](#))
- Heng Ji, Manling Li ([UIUC](#))
- Andrew McCallum, Michael Boratko ([UMass](#))
- Kathleen McKeown ([Columbia](#))
- Bryan Perozzi, Gang Huang, Mohan Yang, Shi Gao, Jie Mao ([Google](#))
- Chris Quirk ([Microsoft](#))
- Changping Meng, Jennifer Neville ([Purdue](#))
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- X. Sean Wang, Jingheng Zhou ([Fudan](#))
- Zequn Sun, Jiacheng Huang, Wei Hu, Yuzhong Qu, Chengming Wang, Lingbing Guo, Qingheng Zhang, Jiacheng Huang ([NJU](#))
- Qiang Ning ([AI2](#))
- Changjun Fan, Li Zeng, Zhong Liu ([NUDT](#))
- Chengkai Li, Farahnaz Akrami ([U. Texas](#))



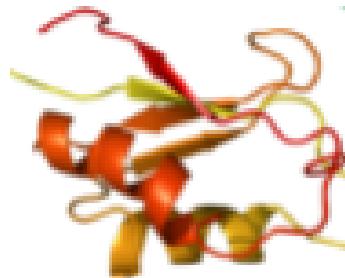
Thank You

Sequence-based Protein-Protein Interaction (PPI) Prediction*

UCLA

*[ISMB'19, Bioinformatics 2019]

Amino acid sequence 1



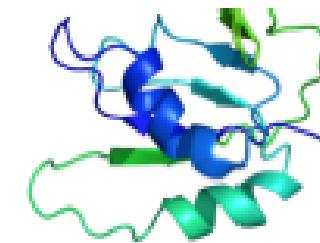
MQSPYPMTQVSNVDDGSLLK...

Interact or not?

Interaction type? (Binding, catalysis, inhibition, ...)

Binding affinity? (ΔG)

Amino acid sequence 2



MLERIQQLVNAVNDPRSDVAT...

PIPR: Multifaceted Protein-Protein Based on Only Sequences

*[ISMB'19, Bioinformatics 2019]

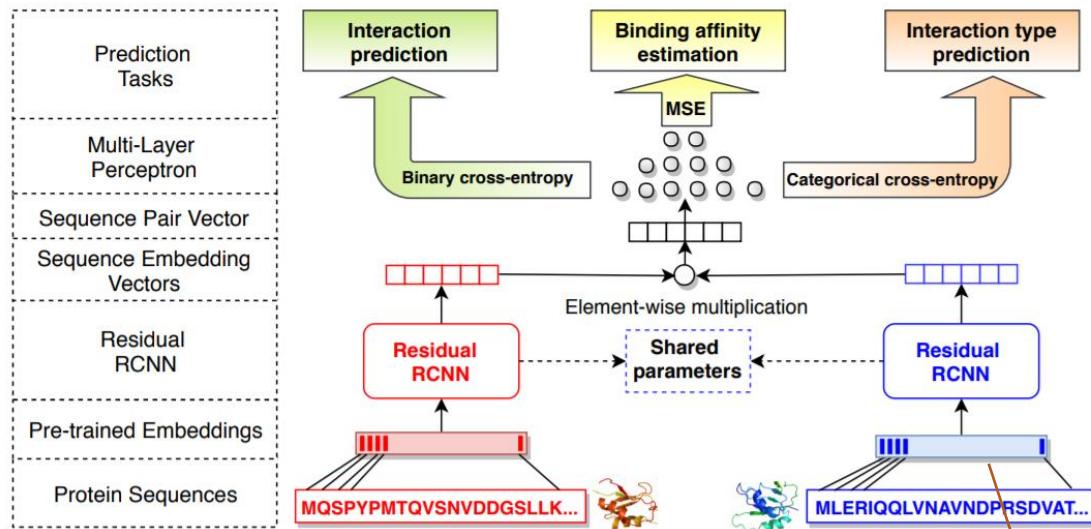
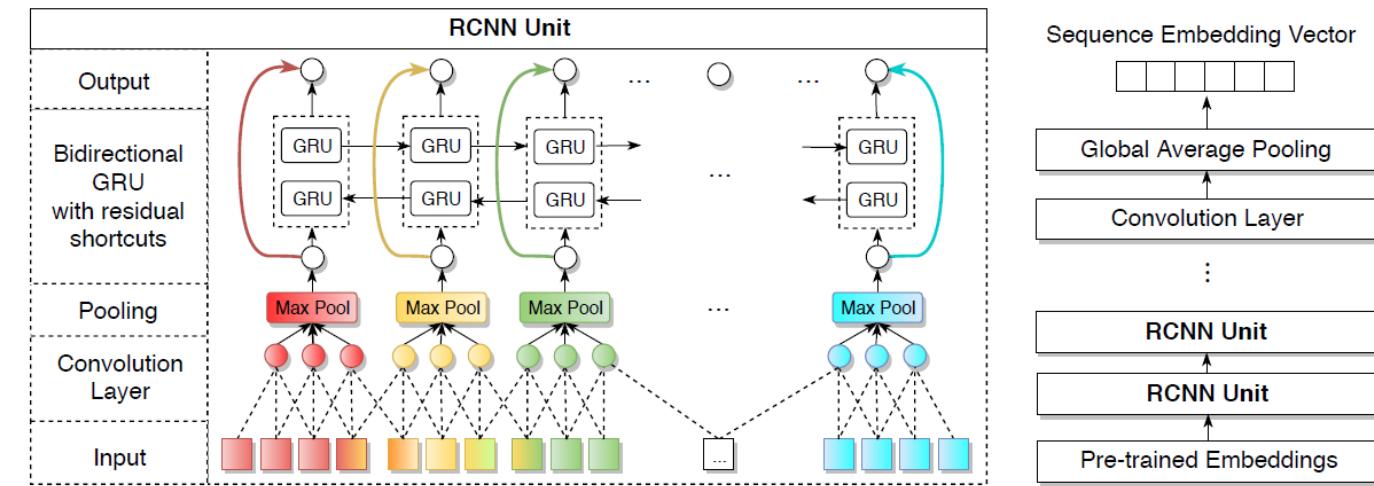


Fig. 2: The overall learning architecture of our framework.

Siamese architecture
for capturing multi-faceted PPI information.



Physicochemical property-aware embeddings of amino acids.

Residual RCNN for multi-granular feature aggregation.

Multi-faceted PPI Prediction

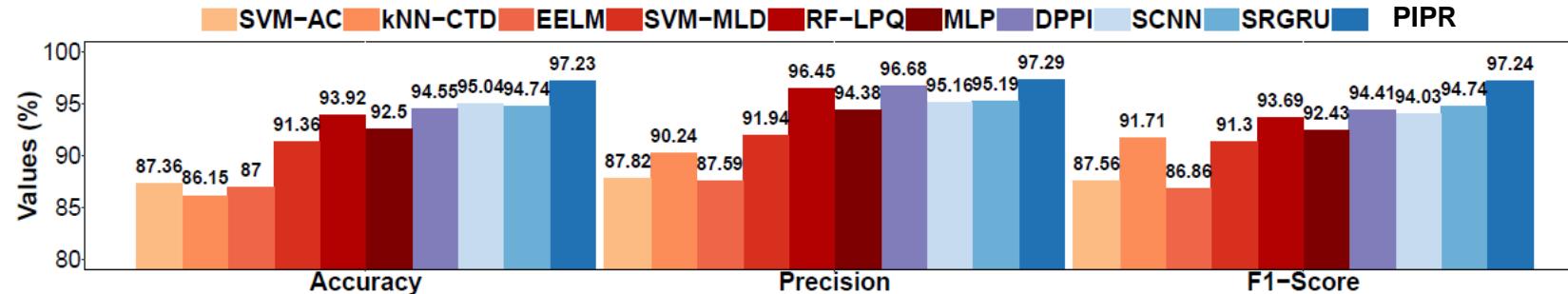


Fig. 3: Evaluation of binary PPI prediction on the Yeast dataset.

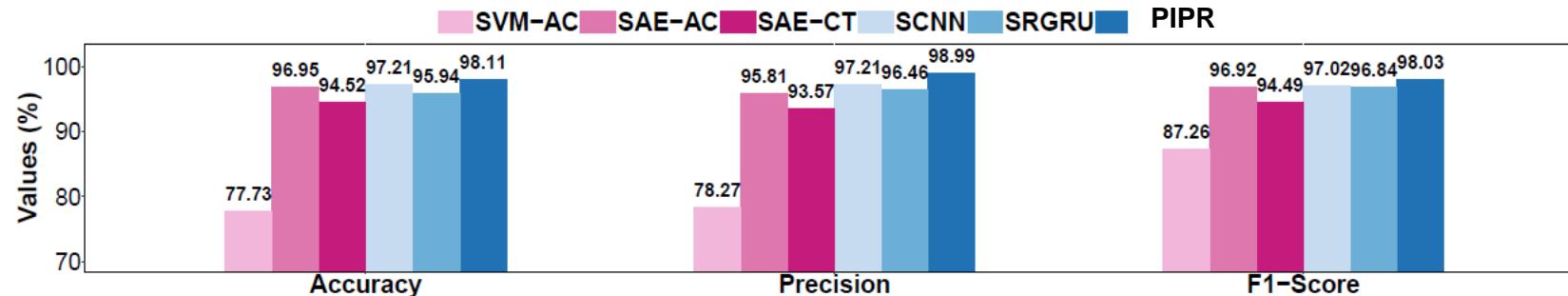
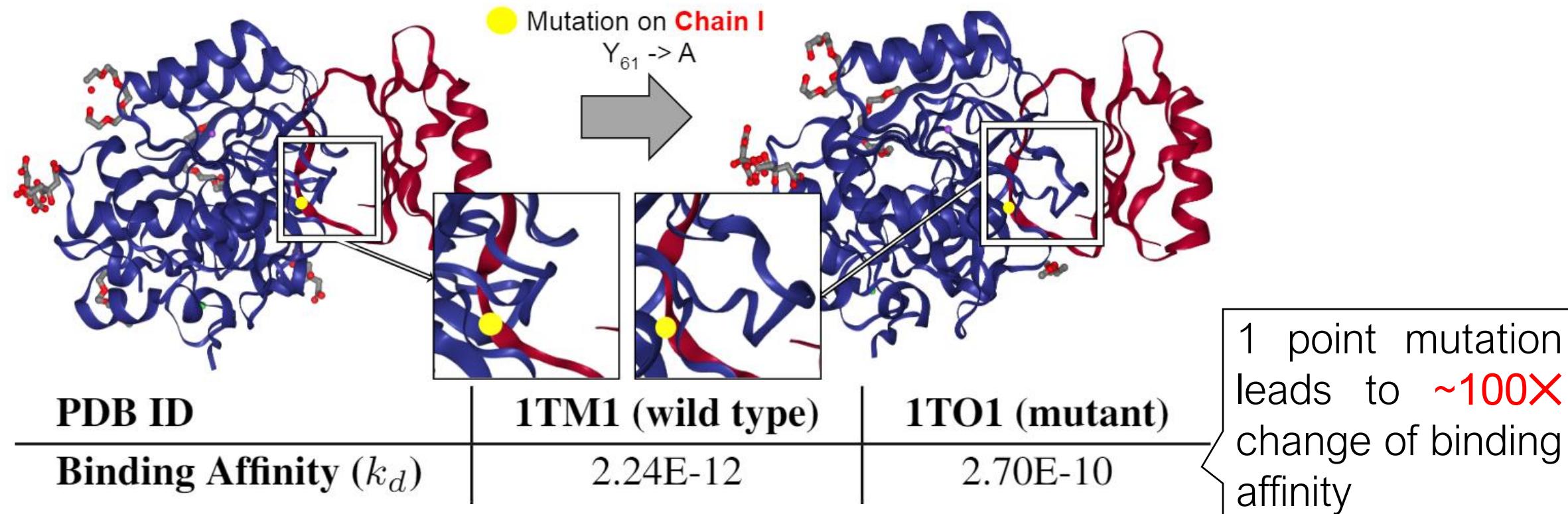


Fig. 4: Evaluation of binary PPI prediction on the Human dataset.

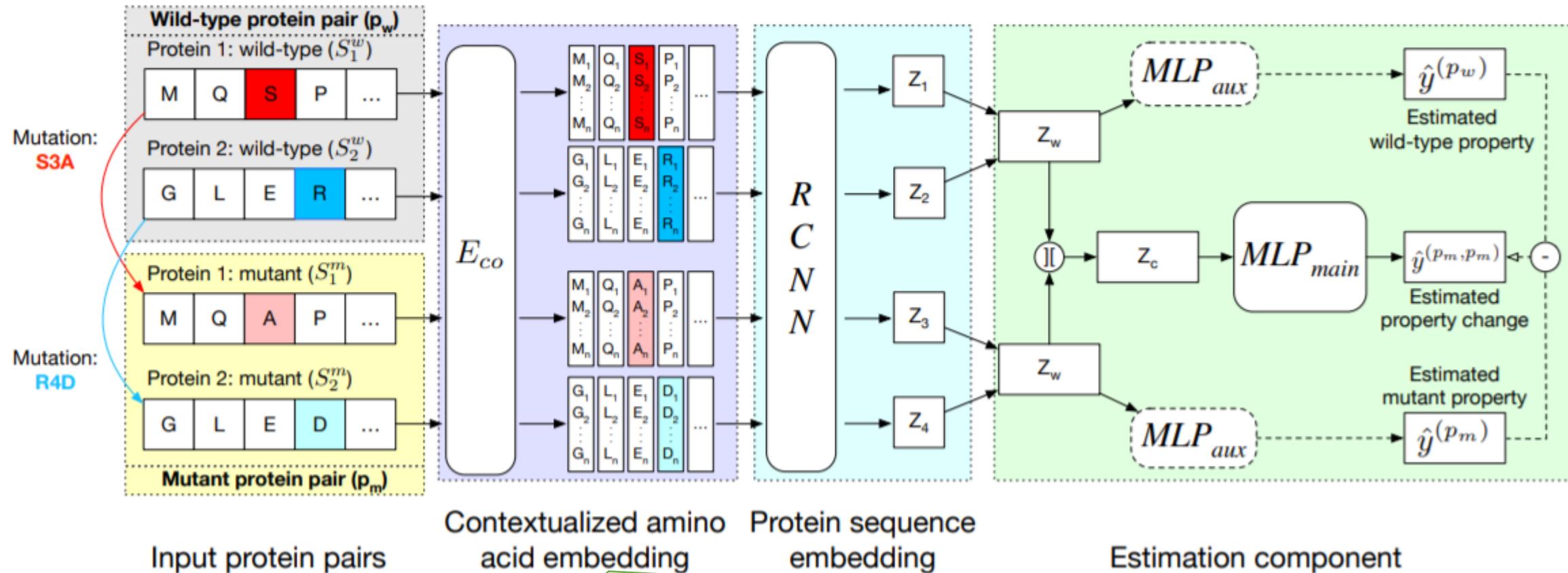
- Also reaches SotA performance on **PPI type prediction** and **binding affinity estimation** on three other benchmark datasets

Point Mutation Effect Estimation



- Mutations (very slight changes) are very difficult to be captured
- 1 or 2 point mutations may cause a significant change to a PPI property

MuPIPR: Pre-trained Amino Acid Language Model + Multi-task Learning

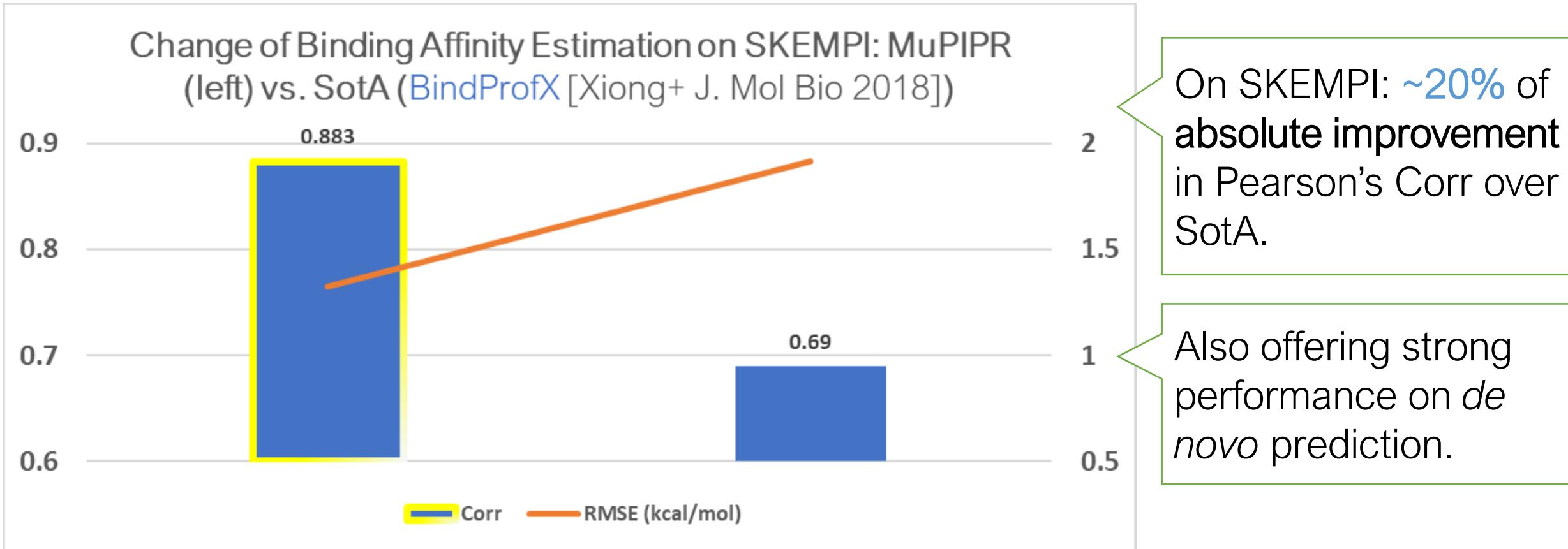


Pre-trained BiLSTM language model on wild-type proteins help propagating point mutation effects

*[NAR Genom. Bioinform. 2020]

Estimation of PPI Property Changes

*[NAR Genom. Bioinform. 2020]



Also significantly better in estimating change of buried surface area (Δ BSA)

- MuPIPR 0.695 vs. SotA 0.329 in Corr