Learning Distributed Representations of Large-Scale Knowledge Graphs

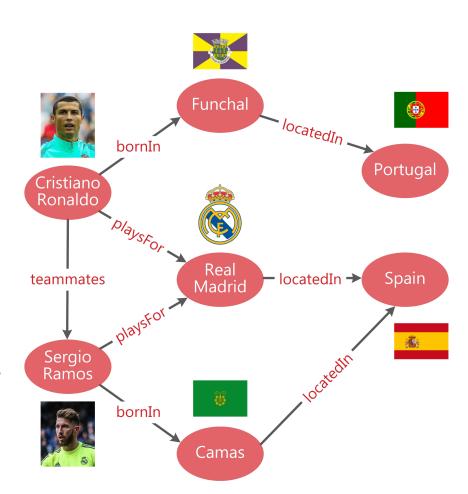
Quan Wang, Bin Wang

Institute of Information Engineering Chinese Academy of Sciences

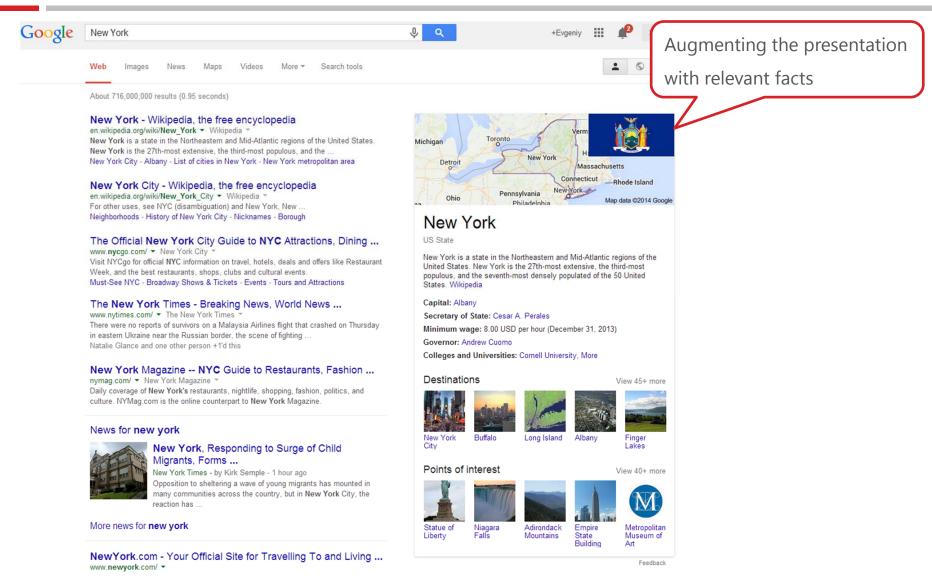
{wangquan,wangbin}@iie.ac.cn

Knowledge graphs

- Knowledge stored in graphs
- Describing entities and their relationships
- Nodes stand for entities
- Typed edges between nodes indicate various relationships between entities

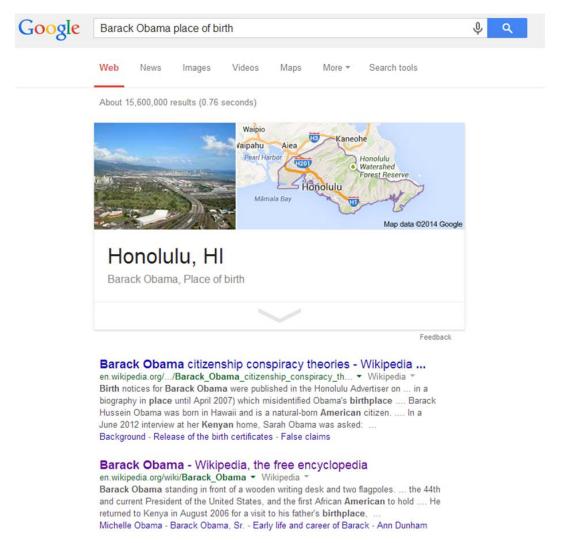


Applications: Web search



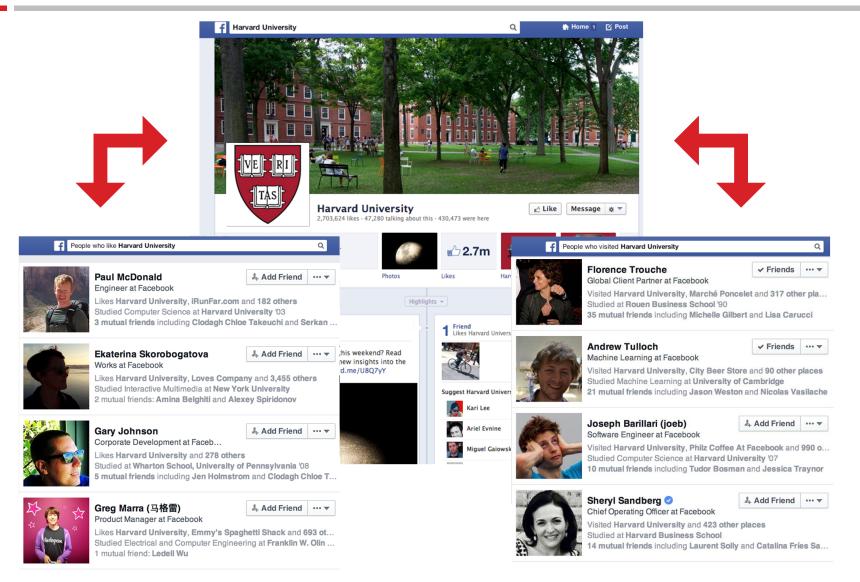
Example from: Antoine Bordes and Evgeniy Gabrilovich (2014). Constructing and mining web-scale knowledge graphs. KDD'14 tutorial.

Applications: Question answering





Applications: Social networks



Example from: Antoine Bordes and Evgeniy Gabrilovich (2014). Constructing and mining web-scale knowledge graphs. KDD'14 tutorial.

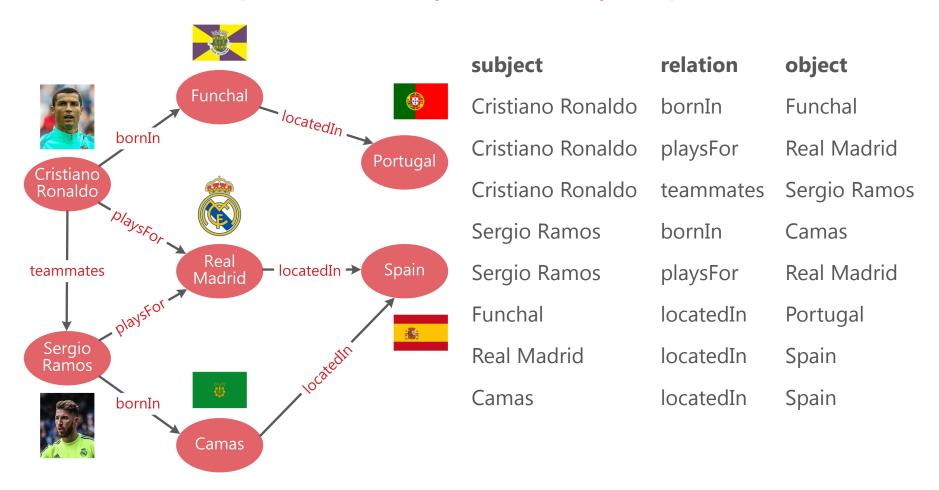
Applications: Social networks (cont.)



Example from: Antoine Bordes and Evgeniy Gabrilovich (2014). Constructing and mining web-scale knowledge graphs. KDD'14 tutorial.

Symbolic representation of knowledge graphs

- Most knowledge graph implementations use RDF triples
 - Each fact represented as a subject-relation-object triple

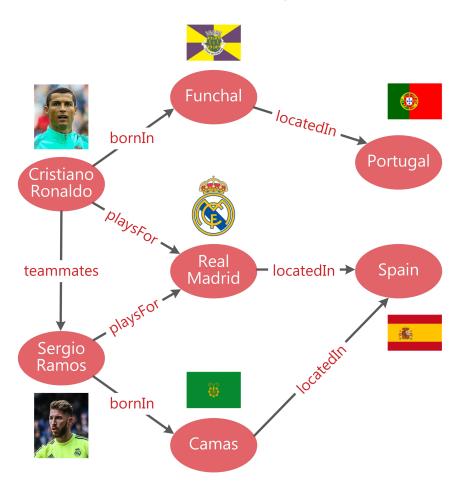


Limitations of symbolic representation

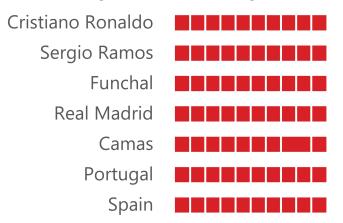
- Hard to carry out computation and inference on the graph
 - Is <u>Spain</u> more similar to <u>Camas</u> (a municipality located in Spain) or <u>Portugal</u> (both Portugal and Spain are European countries)?
 - What is the relationship between <u>Cristiano Ronaldo</u> and <u>Portugal</u>?
 - What is the <u>nationality</u> of <u>Sergio Ramos</u>?
 - •
- Computational complexity of algorithms
 - Complexity depends on explicit dimensionality (in size of data)
 - Query-time inference is sometimes NP-hard
 - Not trivial to parallelize, or use GPUs

Distributed representation of knowledge graphs

- Represent entities and relations in continuous vector spaces
 - Efficient task-independent feature learning for entities and relations



Entities as points in vector spaces (vectors)



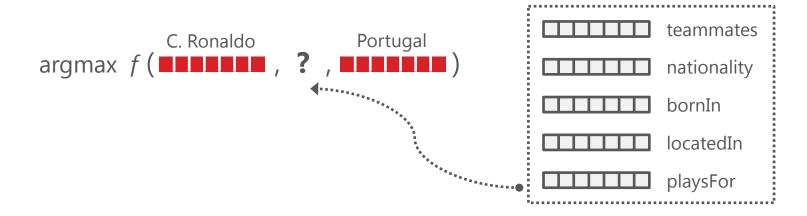
Relations as operations between entities (vectors/matrices/tensors)

teammates	or or
bornIn	or or
playsFor	or or
locatedIn	or or

- Easy computation and inference on the graph
 - Is <u>Spain</u> more similar to <u>Camas</u> (a municipality located in Spain) or <u>Portugal</u> (both Portugal and Spain are European countries)?



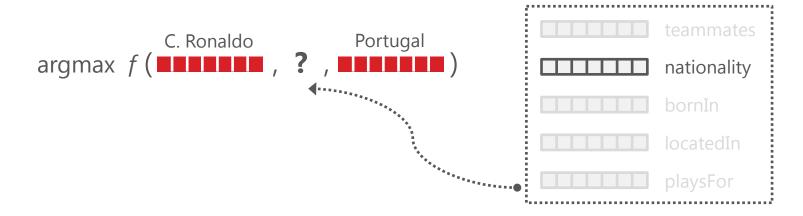
What is the relationship between <u>Cristiano Ronaldo</u> and <u>Portugal</u>?



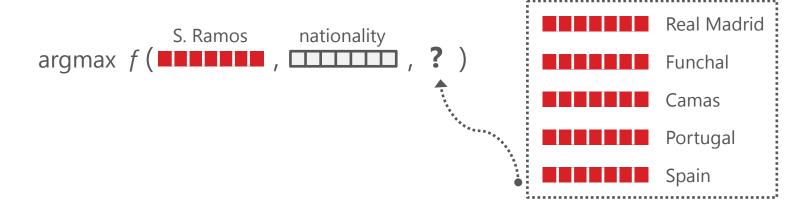
- Easy computation and inference on the graph
 - Is <u>Spain</u> more similar to <u>Camas</u> (a municipality located in Spain) or <u>Portugal</u> (both Portugal and Spain are European countries)?



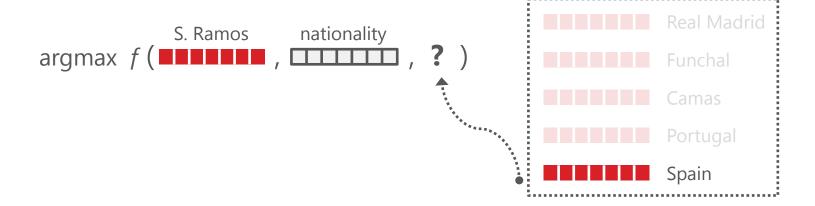
What is the relationship between <u>Cristiano Ronaldo</u> and <u>Portugal</u>?



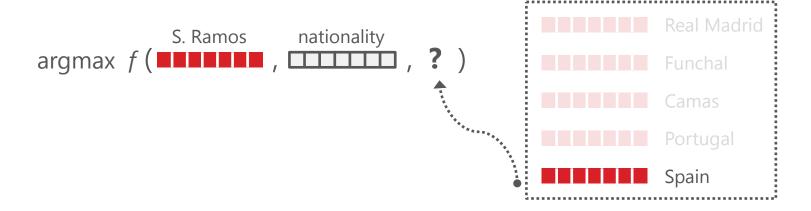
- Easy computation and inference on the graph
 - What is the <u>nationality</u> of <u>Sergio Ramos</u>?



- Easy computation and inference on the graph
 - What is the <u>nationality</u> of <u>Sergio Ramos</u>?

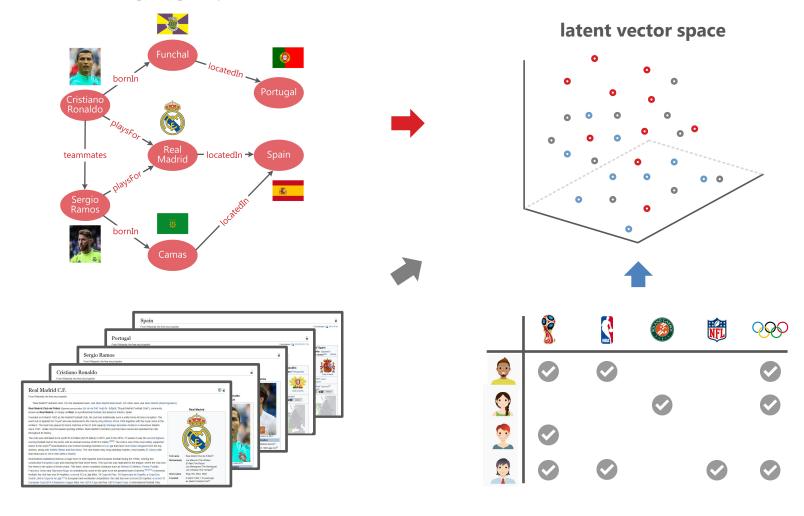


- Easy computation and inference on the graph
 - What is the <u>nationality</u> of <u>Sergio Ramos</u>?



- Computational complexity of algorithms
 - Complexity depends on latent dimensions
 - Querying is often cheap
 - GPU-parallelism friendly

 Better support for data fusion, facilitating application of knowledge graphs to various domains



This talk

- Part I: Models based on RDF triples
 - Learning distributed representations from RDF triples
- Part II: Models based on extra information
 - Learning with extra information beyond RDF triples
- Part III: Applications
 - Applying distributed representations to downstream tasks
- Part IV: Summary and concluding remarks