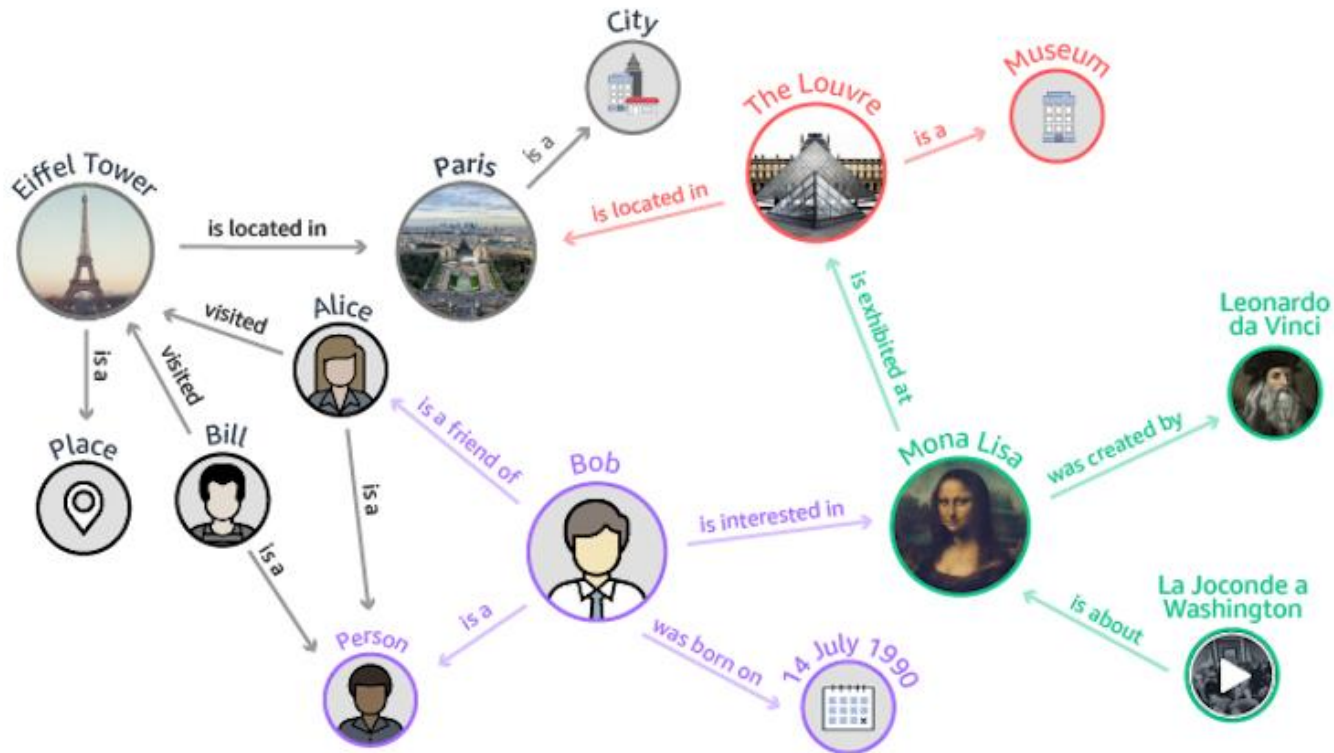


# Injecting Prior Information and Multiple Modalities into Knowledge Base Embeddings

**Sameer Singh**

University of California, Irvine

# Knowledge Graphs



# What is a knowledge graph?

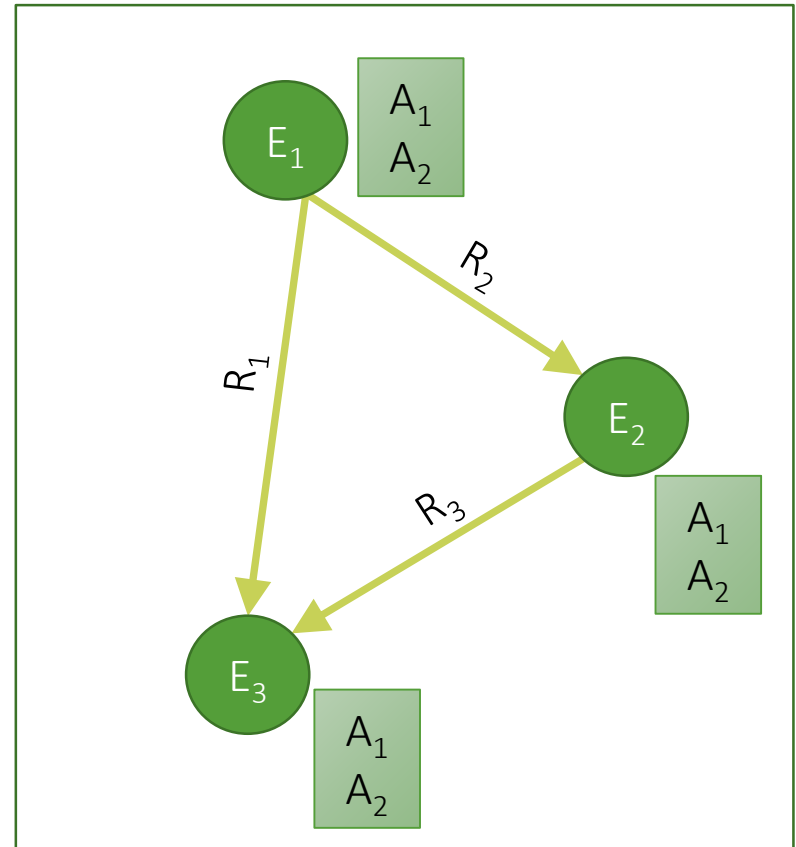
Knowledge in graph form!

Captures entities, attributes, and relationships

Nodes are entities

Nodes are labeled with attributes (e.g., types)

Typed edges between two nodes capture a relationship between entities



# Why knowledge graphs?

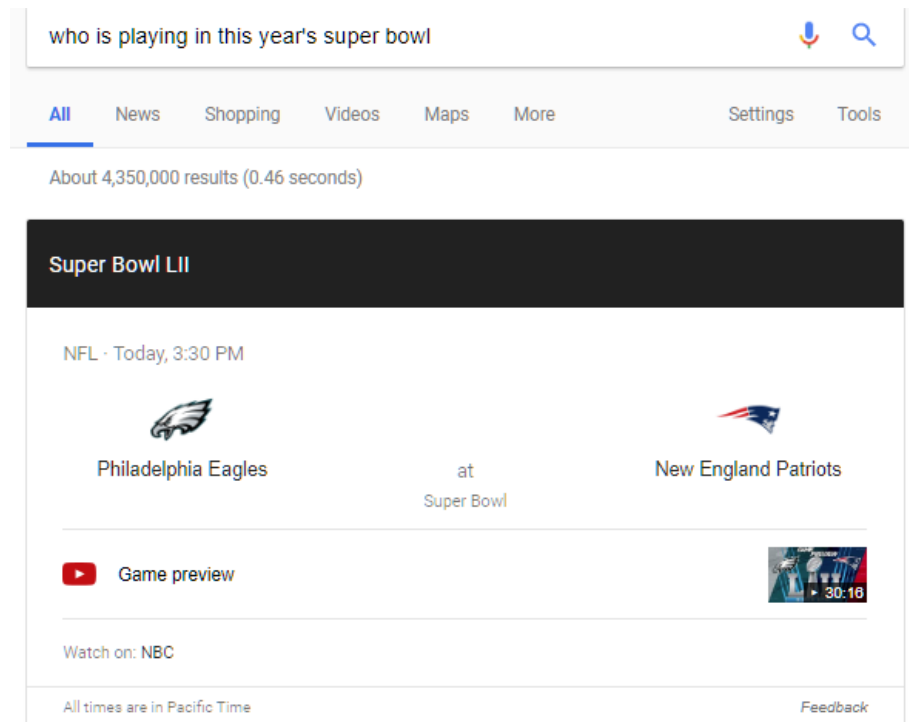
## Humans:

- Combat information overload
- Explore via intuitive structure
- Tool for supporting knowledge-driven tasks

## Als:

- Key ingredient for many AI tasks
- Bridge from data to human semantics
- Use decades of work on graph analysis

# Applications 1: QA/Agents



IBM Watson Knowledge Studio

View Guidelines | Completed 2 | Close

Alpha... | 14pt | 1

Mention

Notes

Conference

### 2004-49-168A.txt

- V1** a 1999 **Toyota** Carry, was traveling southbound in the second **lane** of a four-lane divided (seven **lanes** overall, divided by raised median), concrete **roadway**, approaching an **intersection**.
- V2**, a 2004 Mercedes S430, was northbound in the fourth **lane** of a four-lane, divided (seven **lanes** overall, divided by raised median), concrete **roadway**, about to turn left into westbound traffic at the same **intersection**.
- As both **vehicles** entered the **intersection**, the **front** of **V1** impacted the **back** of **V2**.
- V1** rotated clockwise as **V2** rotated counter-clockwise, and the left side of **V1** impacted the right side of **V2** in a sideslap configuration.
- Both **vehicles** moved southwest to final rest.
- Both **vehicles** were towed due to damage.
- The unrestrained **driver** of **V1** was hospitalized with foot and rib fractures as well as a liver laceration.
- The restrained **driver** of **V2** was treated and released with minor abrasion and contusion as well as a finger fracture.
- The restrained **rear** right passenger in **V2** was pronounced brain dead two days later from multiple brain injuries.
- V2** were equipped with enhanced dual frontal **airbags**, which deployed.

Entity

Mention

Type	Subtype	Role
a	ACCIDENT_CAUSE	
o	ACCIDENT_OUTCOME	
-	CONDITION	
i	IMPACT	
f	MANUFACTURER	
m	MODEL	
y	MODEL_YEAR	
u	PART_OF_CAR	
p	PERSON	
s	STRUCTURE	
h	VEHICLE	



# Applications 3: Fueling Discovery

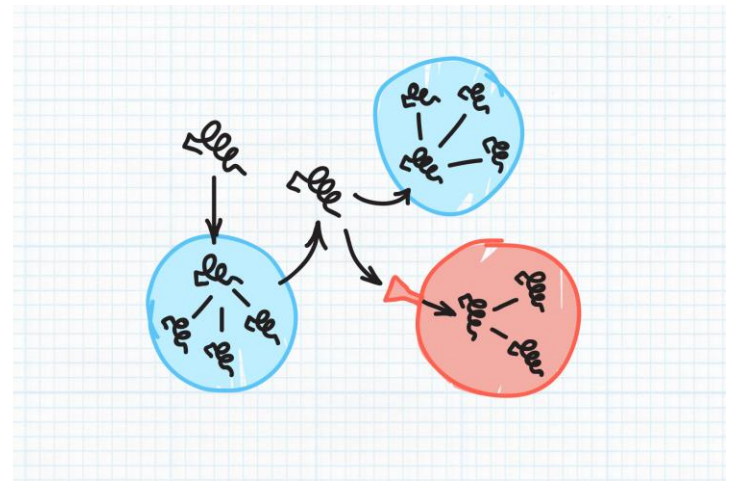
## beatles (musicartist)

literal strings: [BEATLES](#), [Beatles](#), [beatles](#)

### Help NELL Learn!

NELL wants to know if these be  
If they are or ever were, click thumbs-up. Or

- [beatles](#) is a [musical artist](#) 👍 🗑️
- [beatles](#) is a musician in the [genre classic pop](#) (musicgenre) 👍 🗑️
- [beatles](#) is a musician in the [genre pop](#) (musicgenre) 👍 🗑️
- [beatles](#) is a musician in the [genre rock](#) (musicgenre) 👍 🗑️
- [beatles](#) is a musician in the [genre classic rock](#) (musicgenre) 👍 🗑️



# Knowledge Graphs & Industry

Google Knowledge Graph

Google Knowledge Vault

Amazon Product Graph

Facebook Graph API

IBM Watson

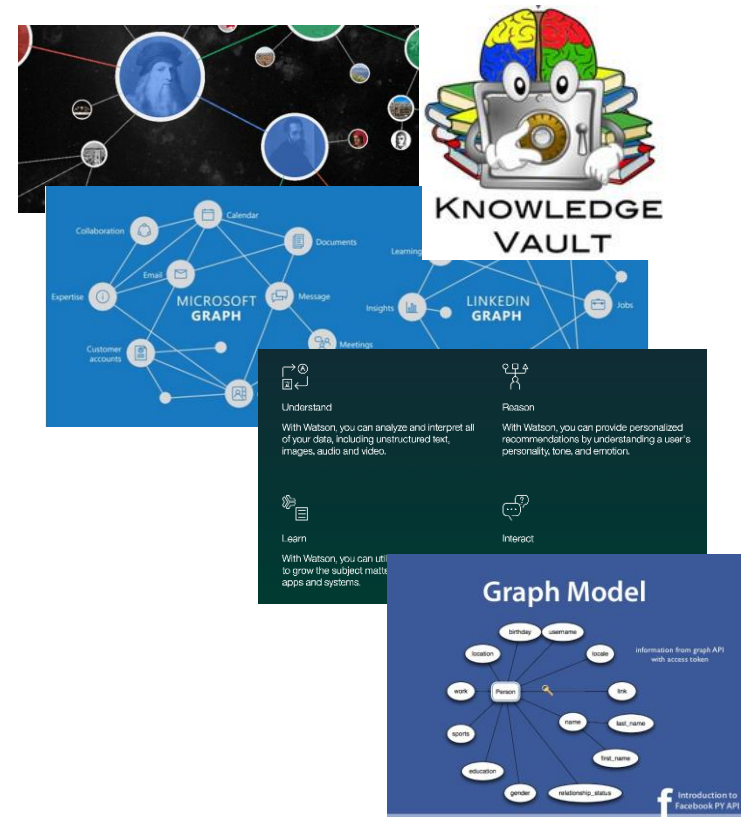
Microsoft Satori

Project Hanover/Literome

LinkedIn Knowledge Graph

Yandex Object Answer

Diffbot, GraphIQ, Maana, ParseHub, Reactor Labs, SpazioDati





Where do knowledge graphs come from?

# Where do knowledge graphs come from?

## Structured Text

Wikipedia Infoboxes, tables,  
databases, social nets

The "Fab Four" Beatles lineup in 1964.  
Clockwise from top left: John Lennon, Paul McCartney, Ringo Starr and George Harrison

Background information	
Origin	L
Genres	K
Years active	F
Labels	1
Associated acts	E
Website	£
Past members	£

eography Centre, Liverpool			
00:18	07:06	12:36	19:32
9.15m H	1.34m L	9.50m H	1.20m L
00:55	07:43	13:14	20:10
9.18m H	1.36m L	9.49m H	1.25m L
01:33	08:21	13:53	20:47
9.10m H	1.51m L	9.37m H	1.42m L
02:14	08:59	14:36	21:27
8.91m H	1.76m L	9.15m H	1.70m L
03:00	09:42	15:24	22:12
8.63m H	2.08m L	8.84m H	2.04m L
03:52	10:34	16:21	23:09
8.27m H	2.43m L	8.45m H	2.39m L
04:59	11:42	17:34	
7.95m H	2.71m L	8.13m H	
00:24	09:20	13:09	18:57
2.63m L	7.82m H	2.73m L	8.06m H
01:49	07:39	14:31	20:13
2.56m L	8.03m H	2.42m L	8.29m H
03:03	08:49	15:43	21:18
2.23m L	8.46m H	1.93m L	8.59m H
04:08	09:47	16:45	22:14
1.82m L	8.94m H	1.41m L	9.07m H
05:03	10:36	17:38	23:01
1.44m L	9.34m H	0.99m L	9.35m H

The Beatles Total Album Sales Statistics		Data
Total number of Beatles albums sold		2,303,500,000
Total Albums Sold on iTunes		785,000
Total Singles Sold on iTunes		3,800,000
Sales By Available Markets		
United States		209.1 Million
Canada		13.8 Million
United Kingdom		7.5 Million
Germany		7.3 Million
France		3.1 Million
Australia		2.8 Million
Japan		1.9 Million
Argentina		1.6 Million
Brazil		600,000
Sweden		584,000
Austria		570,000
Switzerland		450,000

Billboard Chart Statistics	
Total weeks on chart	1,278 weeks
Total number ones	15
Total weeks at number one	175 weeks
Album with longest time spent at number one ("Please Please Me")	30 weeks

PREV DATA SET

NEXT DATA SET

# Where do knowledge graphs come from?

## Structured Text

Wikipedia Infoboxes, tables,  
databases, social nets

## Unstructured Text

WWW, news, social media,  
reference articles

## Beatles last live performance

Published: Thursday, January 26th 2017, 5:24 am PST

Updated: Monday, January 30th 2017, 4:06 am PST

Written by Jim Eftink, Producer [CONNECT](#)

### Allan Williams, First Manager of the Beatles, Dies at 86

By ALLAN KOZINN DEC. 31, 2016



(Source)

**The Beatles**  
January 17 at 10:00am · [📍](#)  
The Harrison family is proud to announce the release of George Harrison – The Vinyl Collection box set featuring all of George Harrison's solo studio albums in one collection for the first time.  
**GEORGE HARRISON - THE VINYL COLLECTION**  
Released on 24th February, 2017, the vinyl box set includes all twelve of George's studio albums with exact replicas of the original release track listing and artwork. Also included in the box set are George's classic live album Live in Japan (2L ... [See More](#)

ourselves

Little did  
would po



[Like](#) [Comment](#) [Share](#)

[like](#) love would 3K [Top Comments](#)

908 shares

[Write a comment...](#)

[Jeffrey Smith](#) What I would really be interested in is an "All Things Must Pass...Stripped Down" with just the basic tracks without Phil Spector's wall of Sound. I'll bet it would sound really good and I would buy it in a heartbeat.  
[Like](#) · [Reply](#) · [jkp31](#) · January 17 at 10:20am

[17 Replies](#)

[Dave Standing](#) I can just see the greedy Harrison family and the greedy music industry multi-millionaire big wigs rubbing their hands with glee once more whilst discussing various methods to make people buy their already bought and paid for record collections all... [See More](#)  
[Like](#) · [Reply](#) · [jkp26](#) · January 17 at 10:19am · [Edited](#)

[30 Replies](#)

[View more comments](#)



he manager of the Beatles in 1960, he sent them on a stint in Germany  
e its stagecraft. Press Association, via Associated Press

**The Beatles**  
January 17 at 6:58am · [📍](#)  
"Of very few individual songs can it be said, 'This changed the course of popular music.' 'A Day in The Life' is one such song." - Richard Havers

**The Beatles - A Day in The Life**  
A Day in The Life The Beatles 1 Video Collection is  
Out Now. Get your copy here.

# Where do knowledge graphs come from?

## Structured Text

Wikipedia Infoboxes, tables, databases, social nets

## Unstructured Text

WWW, news, social media, reference articles

## Images

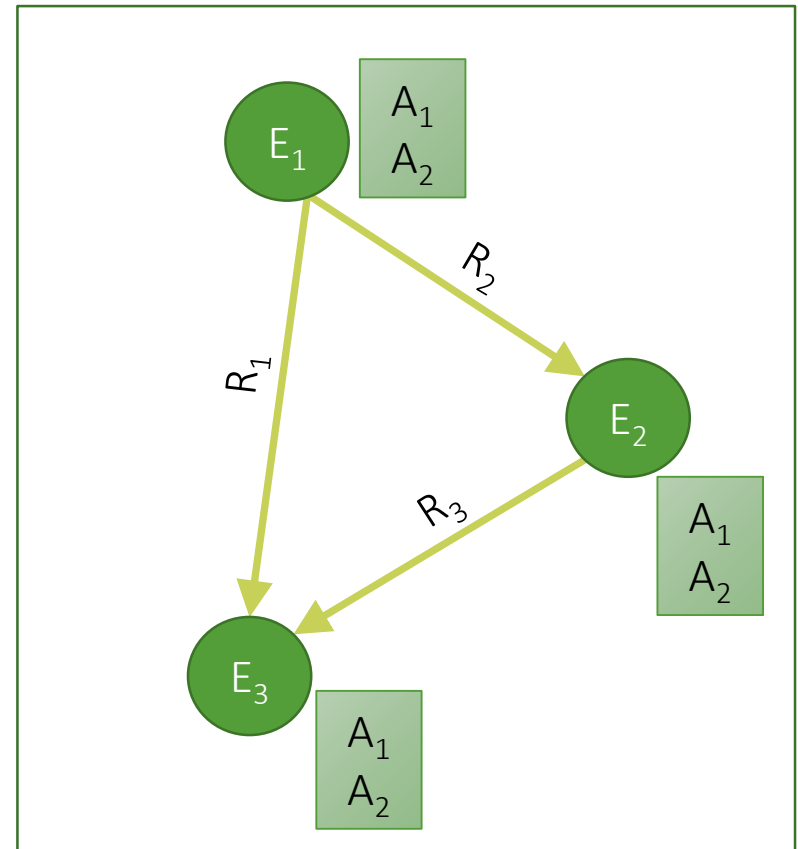


# Basic problems

**Who** are the entities (nodes) in the graph?

**What** are their attributes and types (labels)?

**How** are they related (edges)?



# Outline

Knowledge Graph Embeddings

Injecting Prior Information

Injecting Multiple Modalities

# Outline

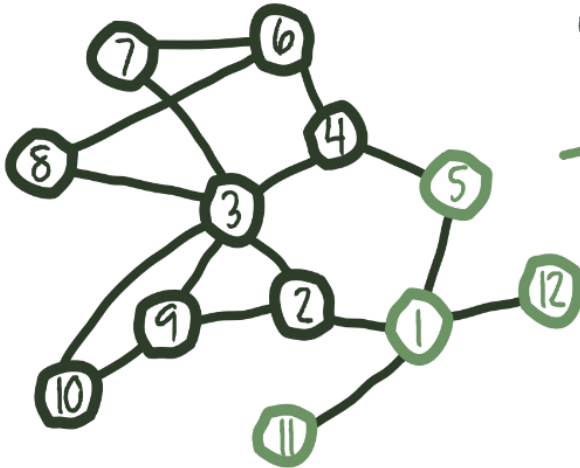
Knowledge Graph Embeddings

Injecting Prior Information

Injecting Multiple Modalities

# Graph Embeddings

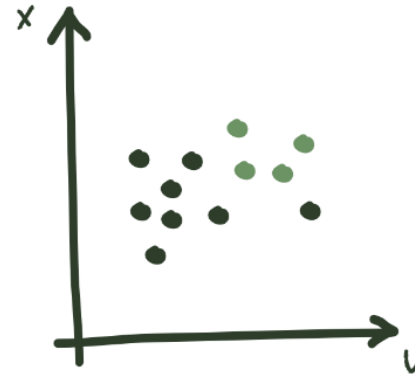
from a graph representation ...



embedding  
algorithm



to real vector representation

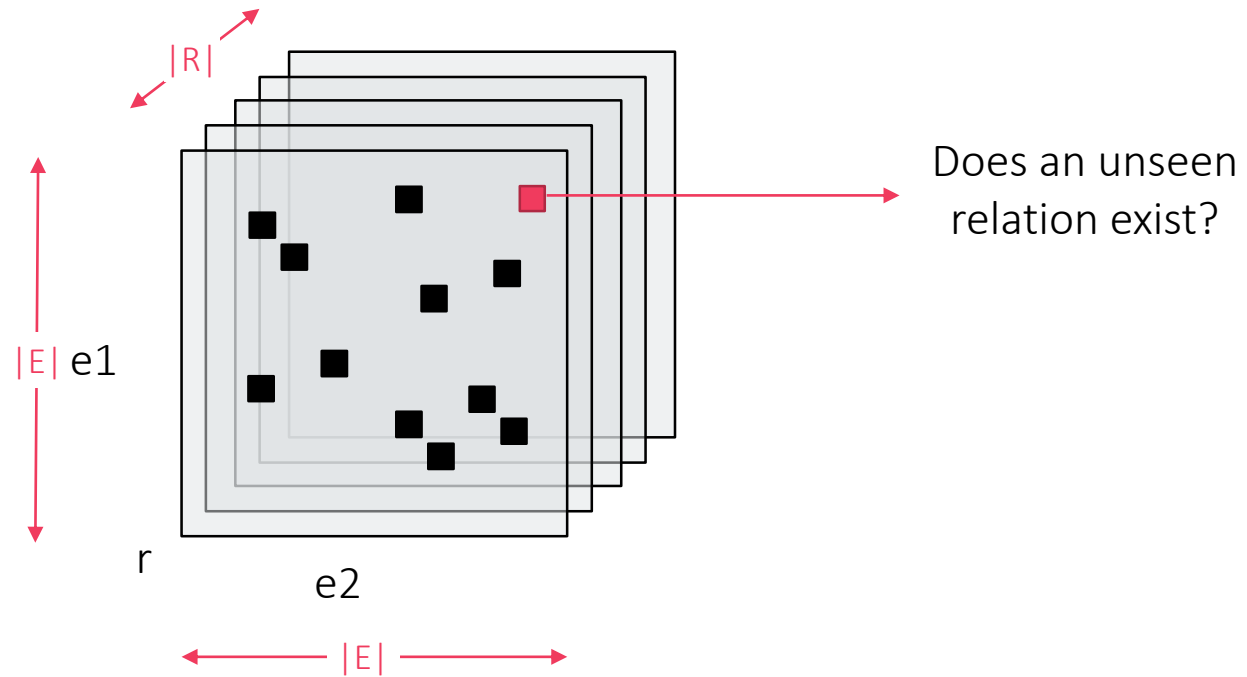


1. Encodes all the information about entities
2. Predict missing relations/facts
3. Clean up incorrect (inconsistent) information

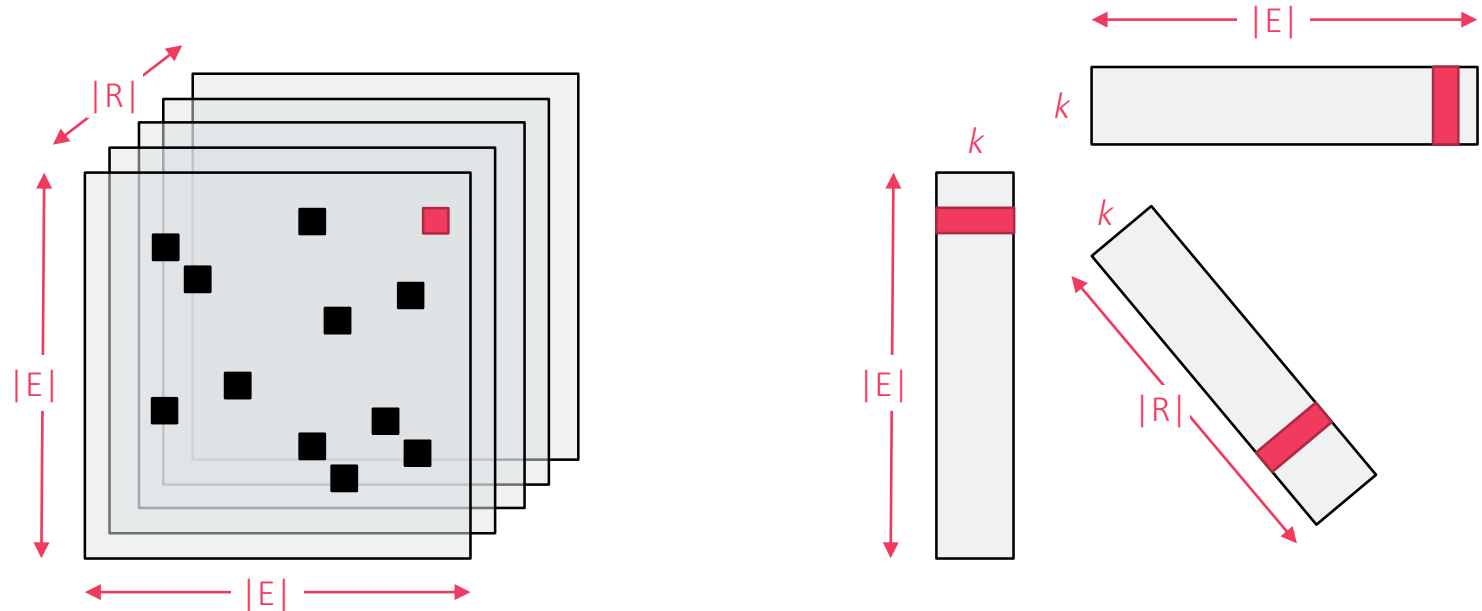
Generate from  
Graph Embeddings!



# Tensor Formulation of KG



# Factorize that Tensor



$$S(r(a, b)) = f(\mathbf{v}_r, \mathbf{v}_a, \mathbf{v}_b)$$

# Knowledge Base Completion

## Scoring Function

Model	Score $\psi_r(\mathbf{e}_s, \mathbf{e}_o)$
RESCAL [21]	$\mathbf{e}_s^T \mathbf{W}_r \mathbf{e}_o$
SE [3]	$\ \mathbf{W}_r^L \mathbf{e}_s - \mathbf{W}_r^R \mathbf{e}_o\ _p$
TransE [1]	$\ \mathbf{e}_s + \mathbf{r}_r - \mathbf{e}_o\ _p$
DistMult [34]	$\langle \mathbf{e}_s, \mathbf{r}_r, \mathbf{e}_o \rangle$
ComplEx [33]	$\langle \mathbf{e}_s, \mathbf{r}_r, \mathbf{e}_o \rangle$
ConvE	$f(\text{vec}(f([\overline{\mathbf{e}}_s; \overline{\mathbf{r}}_r] * \omega))) \mathbf{W}) \mathbf{e}_o$

Table from Dettmers, et al. (2017)

# Many Different Factorizations

CANDECOMP/PARAFAC-Decomposition

$$S(r(a, b)) = \sum_k R_{r,k} \cdot e_{a,k} \cdot e_{b,k}$$

Tucker2 and RESCAL Decompositions

$$S(r(a, b)) = (\mathbf{R}_r \times \mathbf{e}_a) \times \mathbf{e}_b$$

Model E

$$S(r(a, b)) = \mathbf{R}_{r,1} \cdot \mathbf{e}_a + \mathbf{R}_{r,2} \cdot \mathbf{e}_b$$

Holographic Embeddings

$$S(r(a, b)) = \mathbf{R}_r \times (\mathbf{e}_a \star \mathbf{e}_b)$$

Not tensor  
factorization  
(per se)

# Graph Completion

Entity Prediction

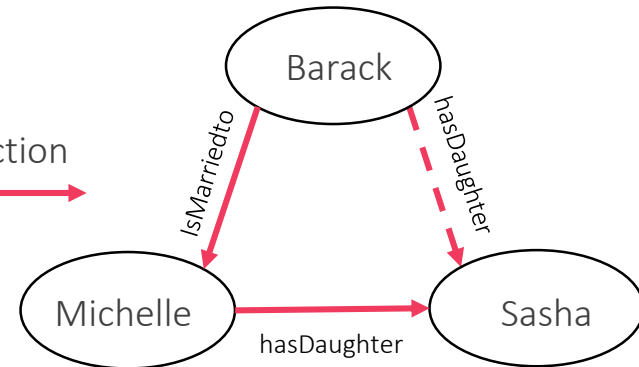
Link Prediction

<Barack, IsMarriedto, Michelle>

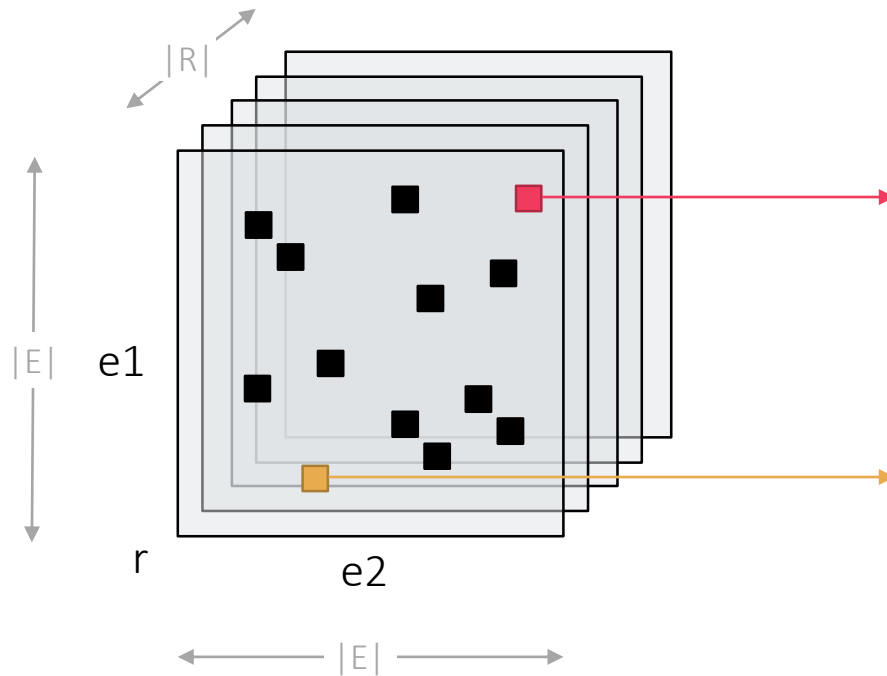
<Barack, hasDaughter, Sasha>

< Michelle, hasDaughter, ?>

Link Prediction



# Parameter Estimation



Observed cell: increase score

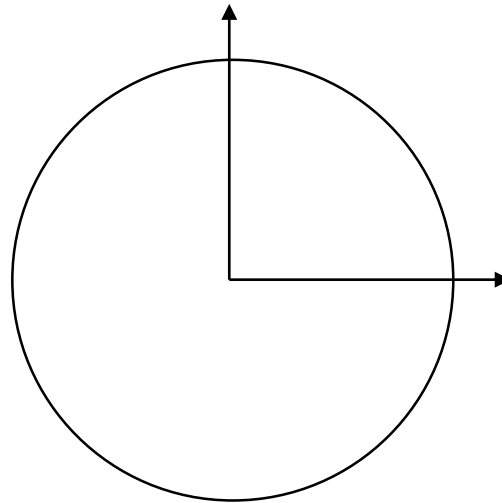
$$S(r(a, b))$$

Unobserved cell: decrease score

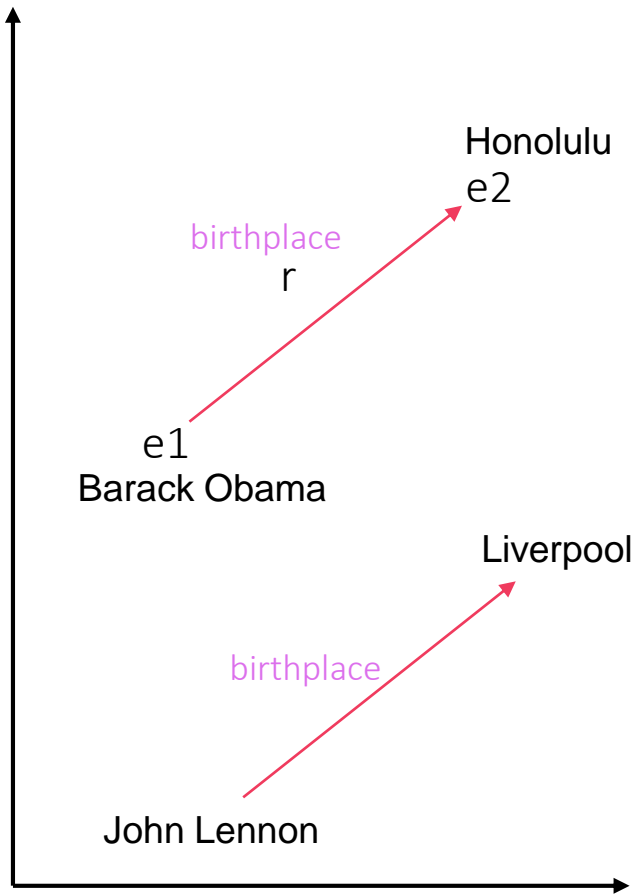
$$S(r'(x, y))$$

# Why do they work?

How can they remember one spouse from million possible ones?



# Translation Embeddings



TransE

$$S(r(a, b)) = -\|\mathbf{e}_a + \mathbf{R}_r - \mathbf{e}_b\|_2^2$$

TransH

$$S(r(a, b)) = -\|\mathbf{e}_a^\perp + \mathbf{R}_r - \mathbf{e}_b^\perp\|_2^2$$

$$\mathbf{e}_a^\perp = \mathbf{e}_a - \mathbf{w}_r^T \mathbf{e}_a \mathbf{w}_r$$

TransR

$$S(r(a, b)) = -\|\mathbf{e}_a \mathbf{M}_r + \mathbf{R}_r - \mathbf{e}_b \mathbf{M}_r\|_2^2$$



# Outline

Knowledge Graph Embeddings

Injecting Prior Information

Injecting Multiple Modalities

# Injecting Knowledge



Most people are married to one person.  
“is native to” is same as birthplace relation.

I don't understand. Give me labeled data.

Sigh... okay.  
Barack, spouseOf, Michelle  
Barack, spouseOf, Ann Dunham



Link Predictor



How can we make it easy for users to inject prior knowledge?

# Logical Statements as Supervision

If you see “was a native of”, it means birthplace

$$X \text{ was native of } Y \Rightarrow \text{birthplace}(X,Y)$$

If a founder of the company is employed by the company, he's the CEO

$$X \text{ is the founder of } Y \wedge \text{employee}(X,Y) \Rightarrow \text{ceoOf}(X,Y)$$

Everyone is married to at most one person

$$\text{spouse}(X, Y) \Rightarrow \forall Y' \neg \text{spouse}(X,Y')$$

# Logic Representation of Relations

Relations are binary predicates

$$\text{bornIn}(a, b) = \top \text{ or } \perp$$

$$\text{was-born-in}(a, b) = \top \text{ or } \perp$$

where  $a, b \in \{ \text{"Bernie Sanders"}, \text{"Brooklyn"}, \text{"Michelle Obama"}, \dots \}$

Facts/Triples are ground atoms:

$$\mathcal{F} = \begin{cases} \text{bornIn}(\text{Bernie Sanders}, \text{Brooklyn}) \\ \text{was-born-in}(\text{Bernie Sanders}, \text{Brooklyn}) \\ \text{spouse}(\text{Barack Obama}, \text{Michelle Obama}) \\ \vdots \end{cases}$$

Models maximize the probability of ground atoms

$$\theta^* = \operatorname{argmax}_{\theta} \sum_{f \in \mathcal{F}} \log \mathcal{P}_{\theta}(f)$$

# Model's belief in a formula $f$

For facts, we know this belief:  $\mathcal{P}_\theta(f)$

Otherwise, recurse...

Can be any model!

$$\mathcal{P}_\theta(f) = \begin{cases} R(a, b) & \text{then compute directly} \\ \neg f' & \text{then } 1 - \mathcal{P}_\theta(f') \\ f_1 \wedge f_2 & \text{then } \mathcal{P}_\theta(f_1)\mathcal{P}_\theta(f_2) \\ \forall_e f(e) & \text{then } \prod_e \mathcal{P}_\theta(f(e)) \end{cases}$$

$$\mathcal{P}_\theta(\forall_{a,b} \text{was-born-in}(a, b) \Rightarrow \text{bornIn}(a, b)) =$$

$$\prod_{a,b} 1 - \mathcal{P}_\theta(\text{was-born-in}(a, b)) (1 - \mathcal{P}_\theta(\text{bornIn}(a, b)))$$

$\text{was-born-in}(a, b) \quad \neg \text{bornIn}(a, b)$   
 $\text{was-born-in}(a, b) \Rightarrow \text{bornIn}(a, b)$   
 $\forall_{a,b} \text{was-born-in}(a, b) \Rightarrow \text{bornIn}(a, b)$

# Updating the Embeddings

Our model is maximizing probability of **ground atoms**

$$\theta^* = \operatorname{argmax}_{\theta} \sum_{f \in \mathcal{F}} \log \mathcal{P}_{\theta}(f)$$

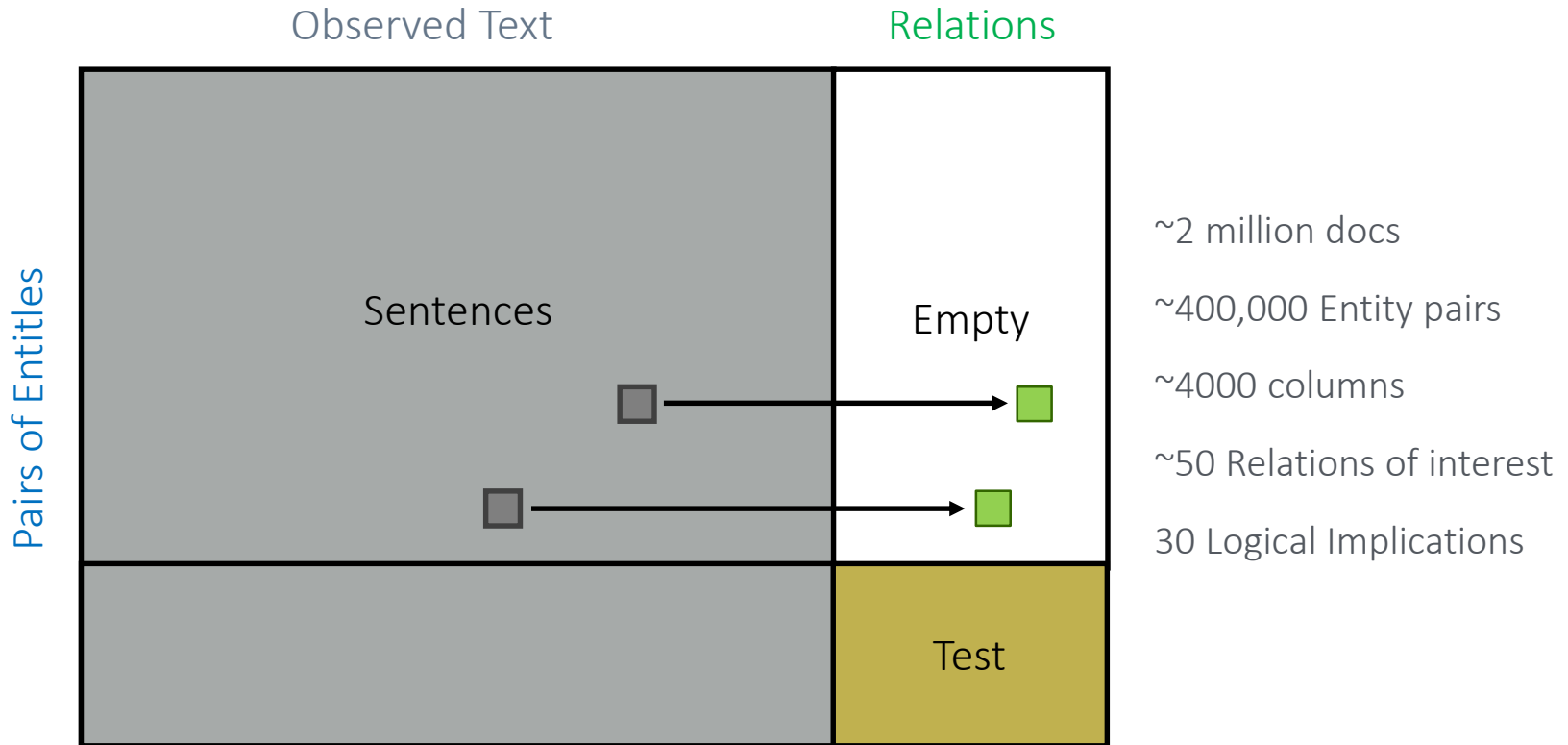
But now we have a set of formulae, ground or otherwise

$$\mathcal{F} = \left\{ \begin{array}{l} \text{bornIn}(\text{Bernie Sanders}, \text{Brooklyn}) \\ \text{was-born-in}(\text{Bernie Sanders}, \text{Brooklyn}) \\ \text{spouse}(\text{Barack Obama}, \text{Michelle Obama}) \\ \forall_{a,b} \text{ was-born-in}(a, b) \Rightarrow \text{bornIn}(a, b) \\ \vdots \end{array} \right.$$

Still maximizing the probability:  $\theta^* = \operatorname{argmax}_{\theta} \sum_{f \in \mathcal{F}} \log \mathcal{P}_{\theta}(f)$

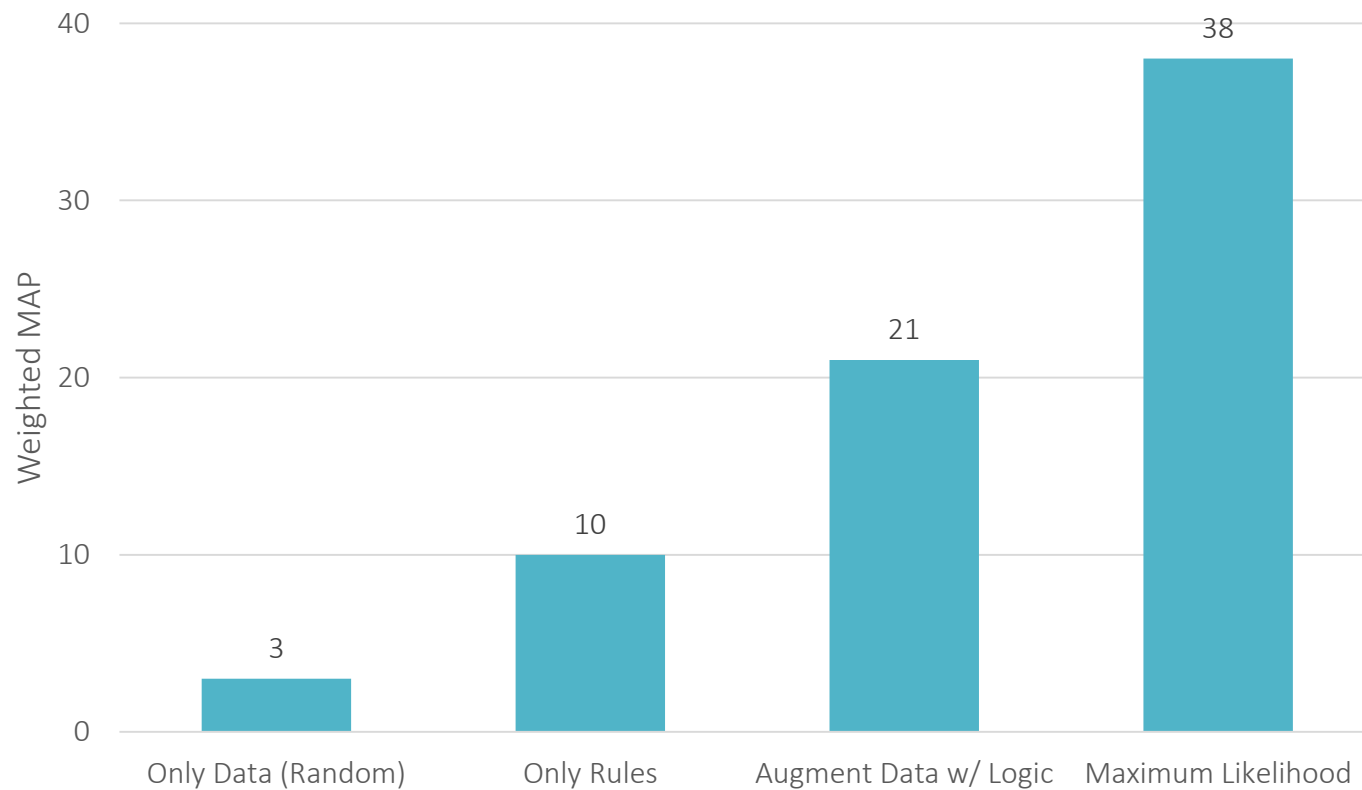
Optimized using gradient descent  
works for most models!

# Zero-Shot Learning



We're evaluating whether formulae can be used instead of labeled data.

# Zero-Shot Learning





# Outline

Knowledge Graph Embeddings

Injecting Prior Information

Injecting Multiple Modalities

Carles\_Puyol

isAffiliatedTo Spain\_national\_under-18\_football\_team

isAffiliatedTo Spain\_national\_under-21\_football\_team

isAffiliatedTo Spain\_national\_under-23\_football\_team

isAffiliatedTo Catalonia\_national\_football\_team

Carles\_Puyol, isAffiliatedTo, ??

Spain\_national\_football\_team

Italy\_national\_football\_team

Carles\_Puyol

isAffiliatedTo Spain\_national\_under-18\_football\_team

isAffiliatedTo Spain\_national\_under-21\_football\_team

isAffiliatedTo Spain\_national\_under-23\_football\_team

isAffiliatedTo Catalonia\_national\_football\_team

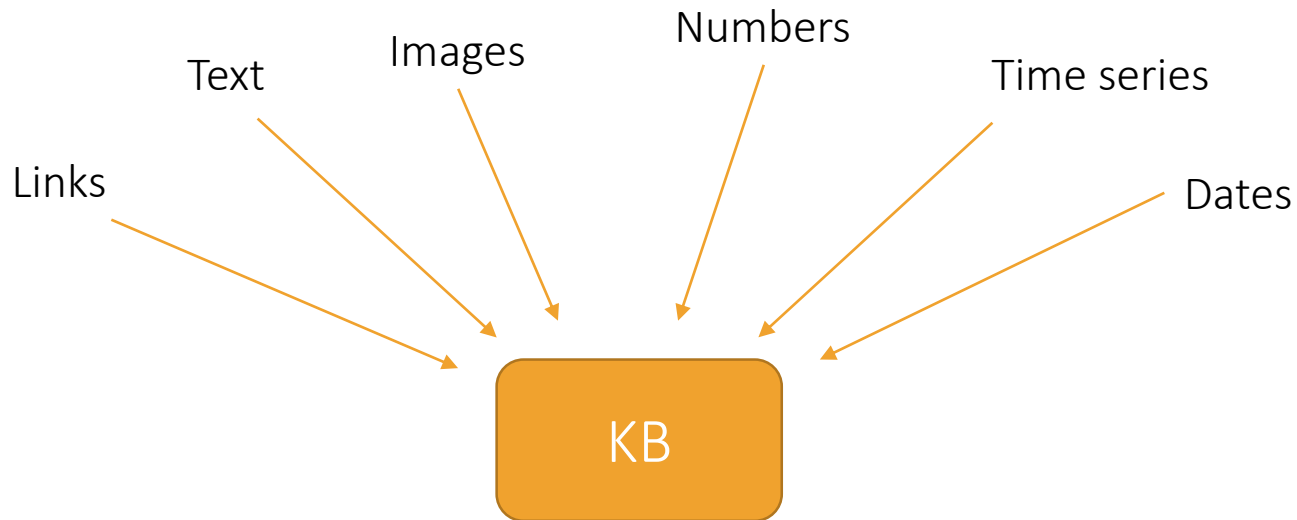
Carles\_Puyol, playsFor, ??

FC\_Barcelona



Real\_Madrid\_CF

# Information is in many modalities



Maybe we should be reasoning about all of these?

**Time is ripe for doing multimodal stuff**

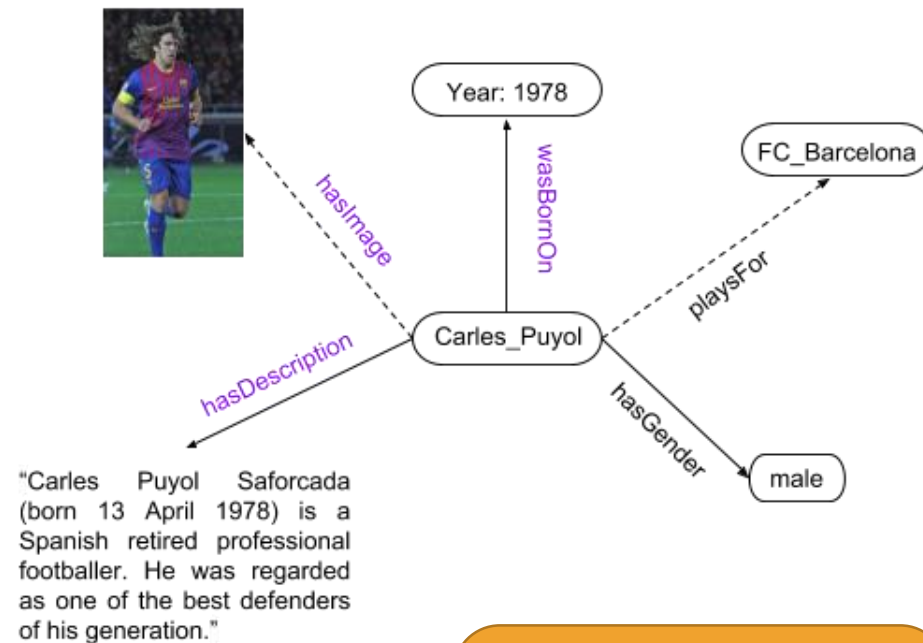
# Link Prediction with Text/Images

Knowledge  
Graphs

Text/Images

Entity and Relation  
Embeddings

# Multimodal Knowledge Graph



Entity

Text

Images

Numbers, etc.

How do we get embeddings for these new relations and "objects"?

# Multimodal KB Embeddings

Scoring  
Function

Object

Encoder

Everything else remains the same!

# Multimodal KB Embeddings

Object

Encoder

Entity

Lookup

Images

CNN

Text

LSTM

Numbers, etc.

FeedFwd

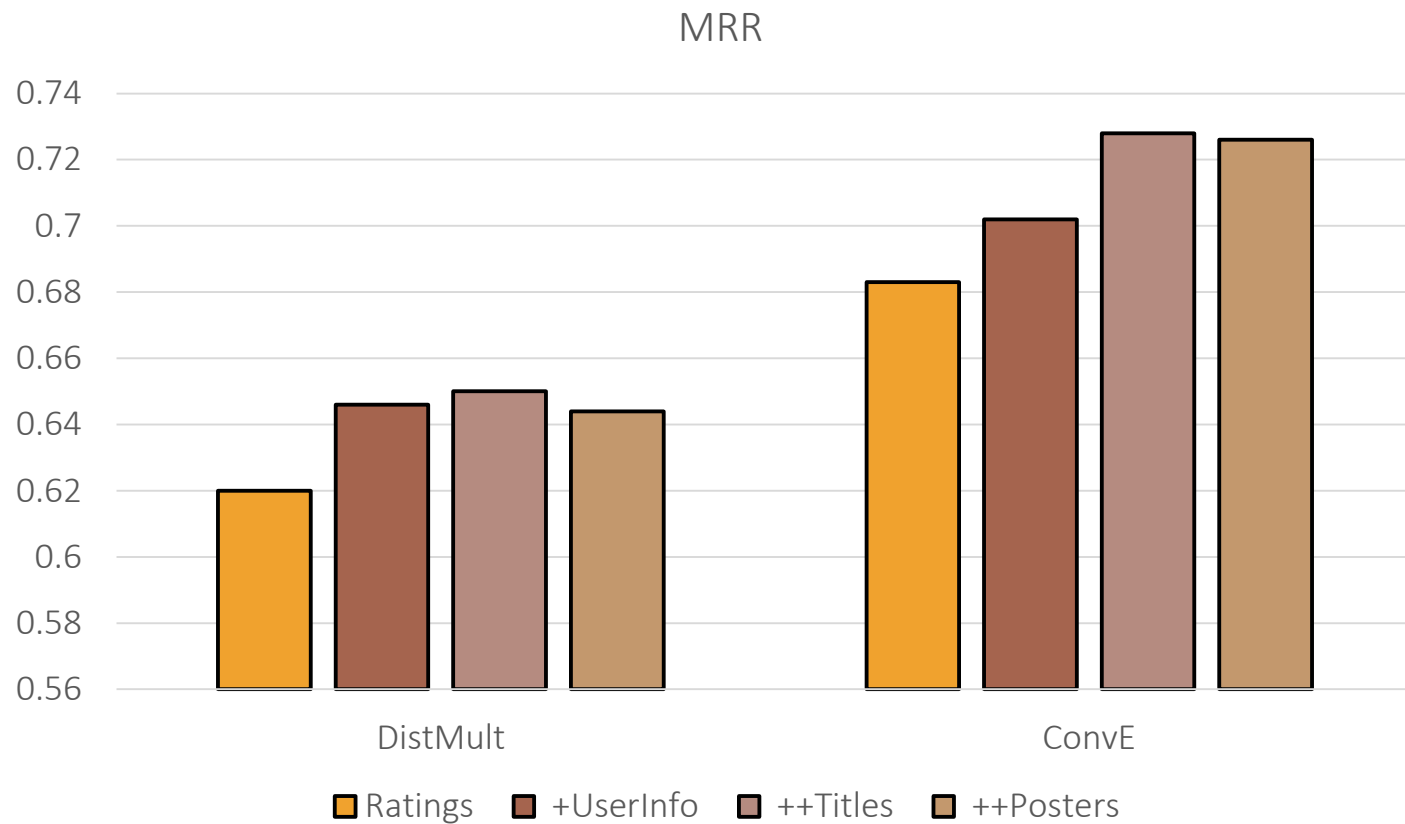


# Augmenting Existing Graphs

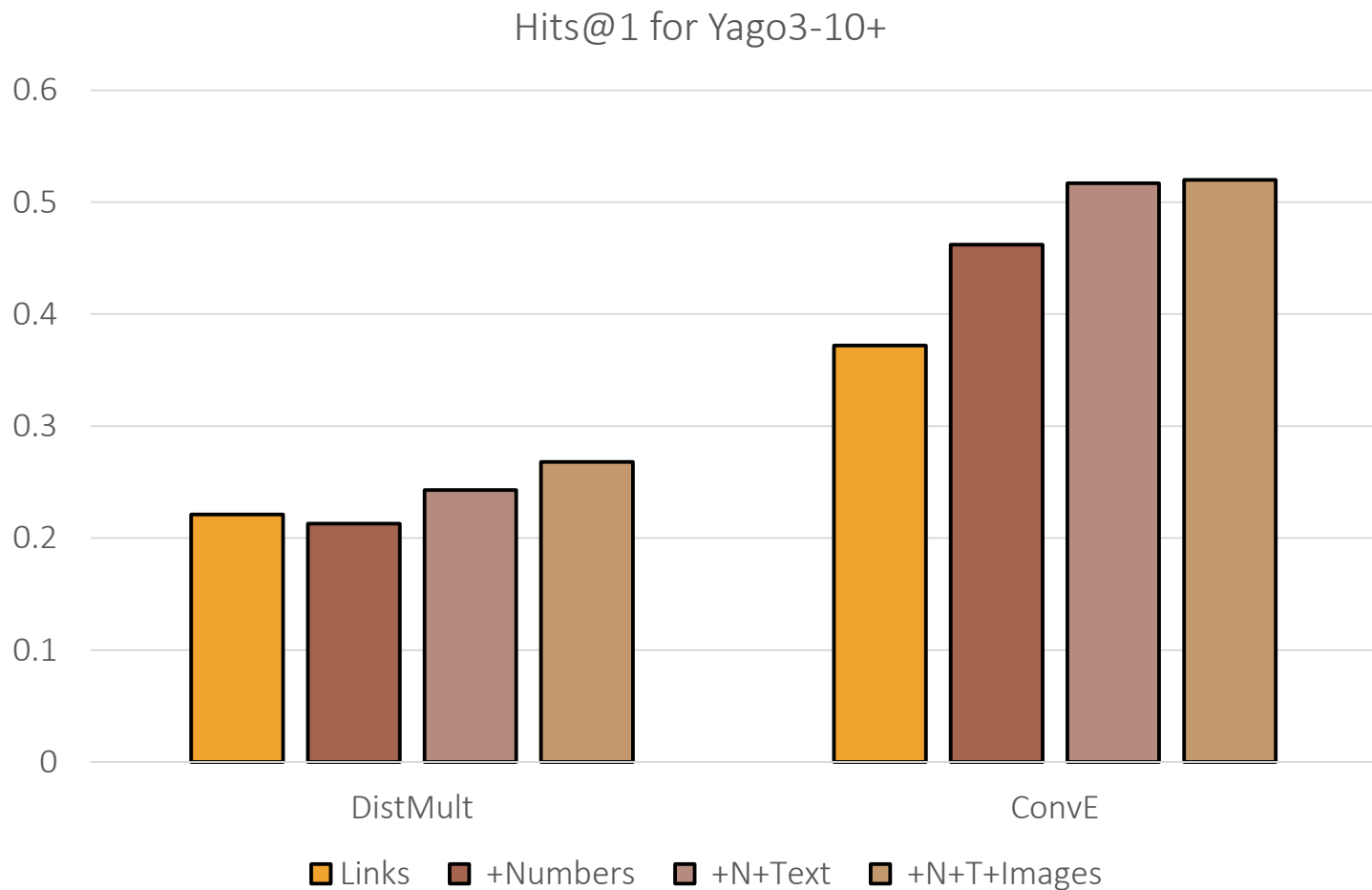
MovieLens-100k	
Relations	13
Users	943
Movies	1682
Posters	1651
Ratings	100,000

YAGO3-10	
Relations	37 → 45
Entities	123,182
Structure Triples	1,079,040
Numbers (Years)	1651
Descriptions	107,326
Images	61,246

# MovieLens “Link Prediction”



# YAGO Link Prediction Results



# YAGO Relation Breakdown:

Relations	Links	+Numbers	+Text	+Images
isAffiliatedTo	0.401	0.467	<b>0.481</b>	0.478
playsFor	0.413	0.471	<b>0.486</b>	0.476
hasGender	0.596	0.599	0.627	<b>0.683</b>
isConnectedTo	0.367	0.379	<b>0.384</b>	0.372
isMarriedTo	0.207	0.221	0.296	<b>0.326</b>

# Generation and Link Prediction

Knowledge  
Graphs

Text/Images

Entity and Relation  
Embeddings

# Generating Multimodal Information

Neural  
Regressor

Numbers, etc.

Conditional  
Text GAN

Text

Conditional  
Image GAN

Images

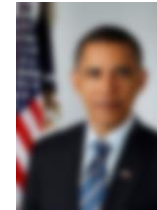
# Conditional GAN Structure

Generator

Discriminator

# Conditional GAN Structure

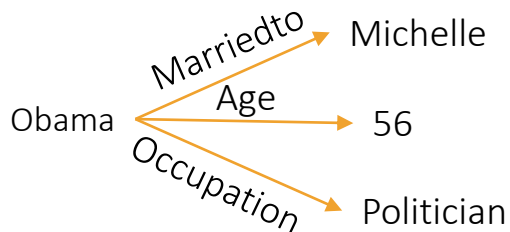
Generator



**Barack Hussein Obama II is an American politician who served as the 44th President of the United States from 2009 to 2017.**

Barack Hussein Obama II is an American politician who served as the 44th President of the United States from 2009 to 2017.

Obama

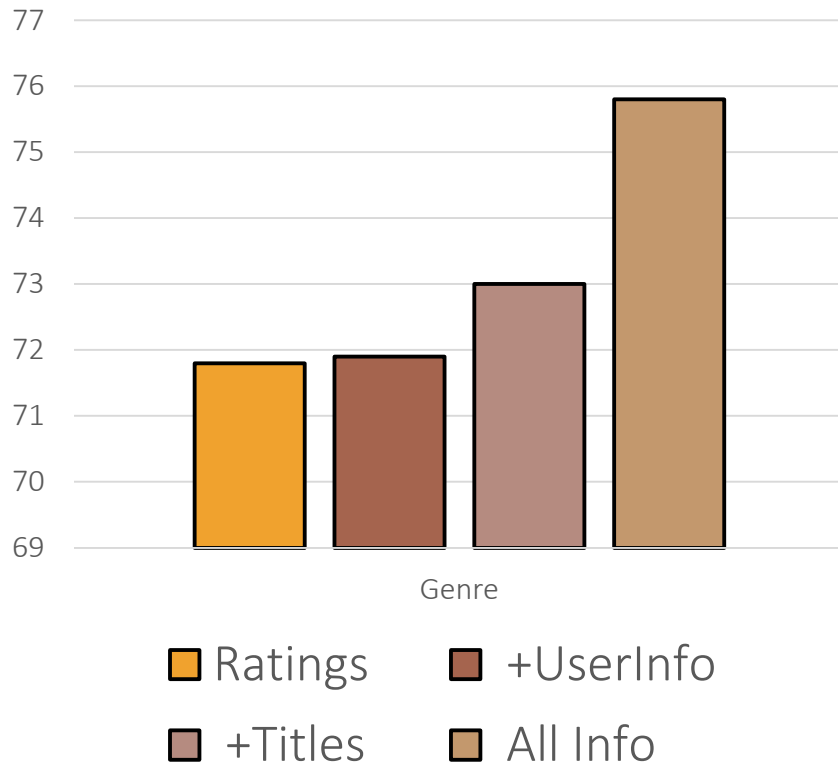


Discriminator

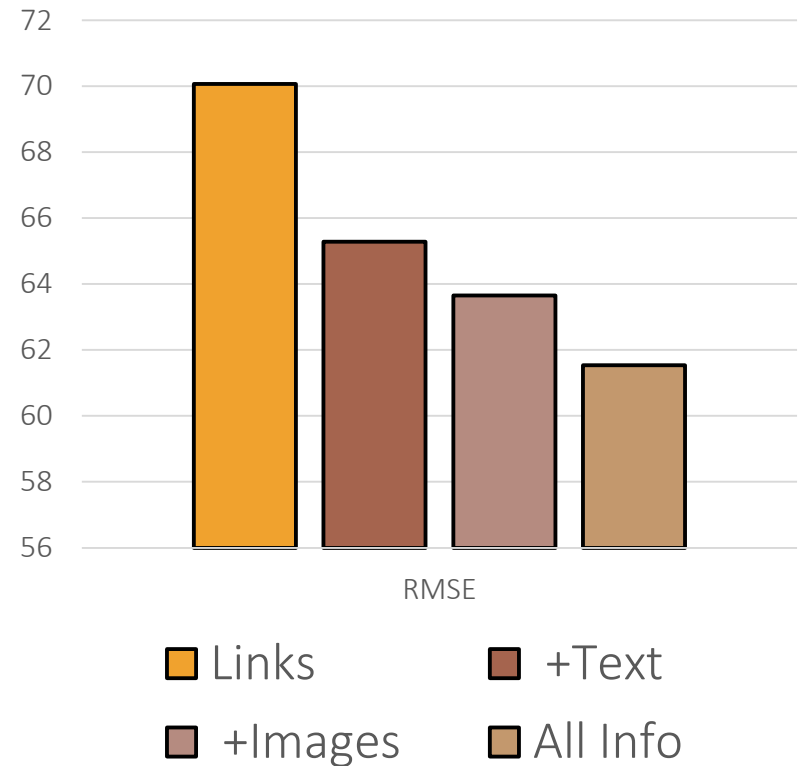


# “Generating” Attributes

Genre Prediction (Accuracy)



Birth and Death Years (RMSE)



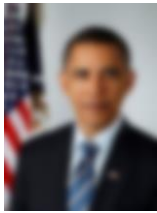
# Generated Movie Titles

Reference	From Embeddings
Amityville 3-D (Horror)	Creatures
The Gay Divorcee (Romance/Musical)	Taste Condition
Jury Duty (Comedy)	Nixon World
Turbulence (Thriller)	Assignment
Mortal Kombat: Annihilation (Action/thriller)	The Cop Witness
Balto (Children's/Comedy)	Innocent Army
Jason's Lyric (Crime/Drama)	Wooden Beast

# Generated Entity Descriptions

Reference	From Embeddings
Dean Sinclair (born 17 December 1984) is an English professional footballer who plays as a midfielder for Hampton & Richmond Borough.	Dean Sinclair (born 19 January 1981) is a professional footballer who plays as a left midfielder for <oov> in the England of England B.
Kelly LeBrock (born March 24, 1960) is an American actress and model.	Kelly LeBrock (born May 5, 1953) is an American composer music actress and singer.
The Lawnmower Man is a 1992 American science fiction action horror film directed by Brett Leonard and written by Brett Leonard and Gimel Everett.	The Lawnmower Man (born 10 October <oov> 1966) is a British science fiction and voice artist who had <oov> California.
Kungälv Municipality is a municipality in Västra Götaland County in western Sweden.	Kungälv Municipality is a city in Parish, Texas, Valley and Quebec. County.

# What do people think?

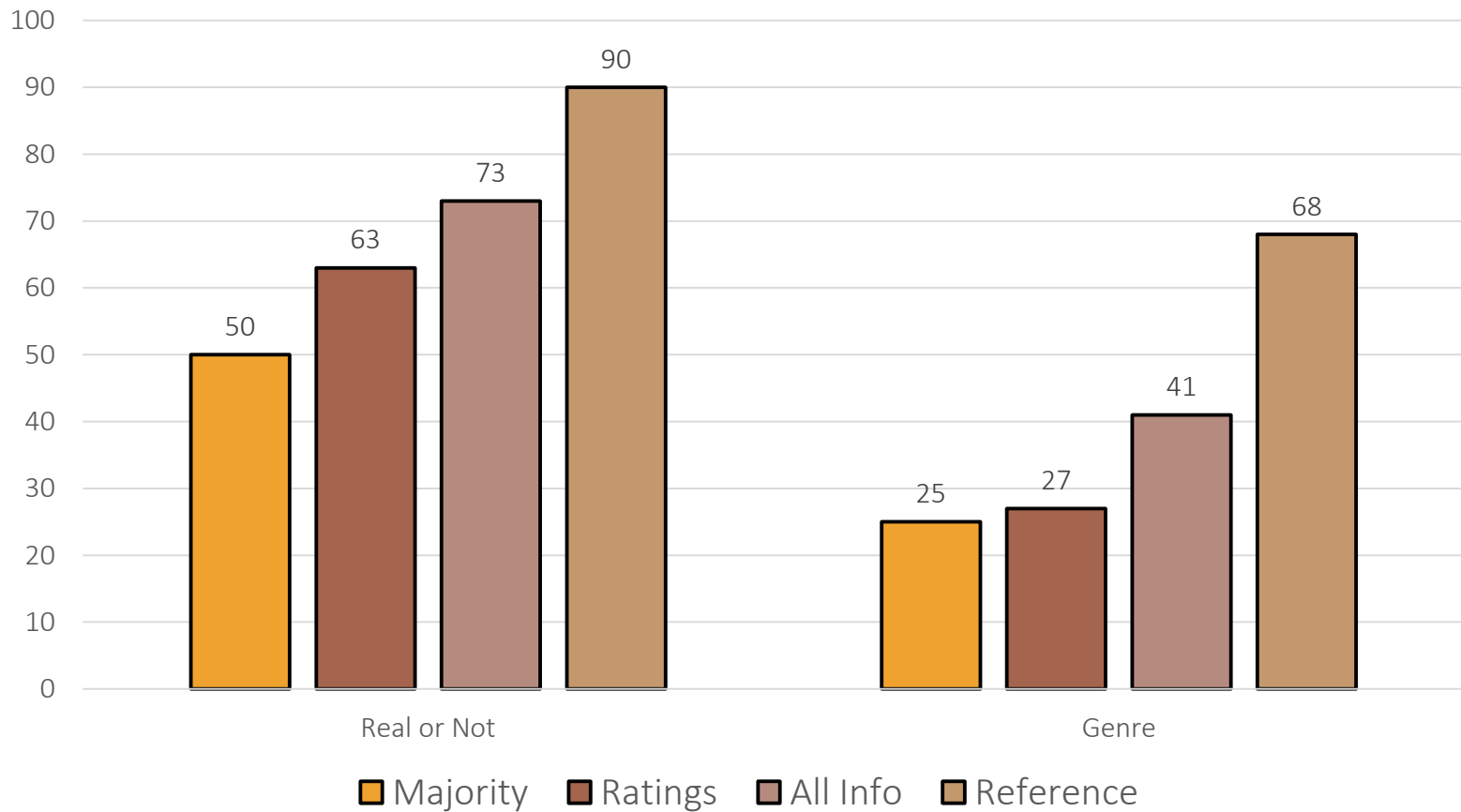


**Barack Hussein Obama II is an American politician who served as the 44th President of the United States from 2009 to 2017.**

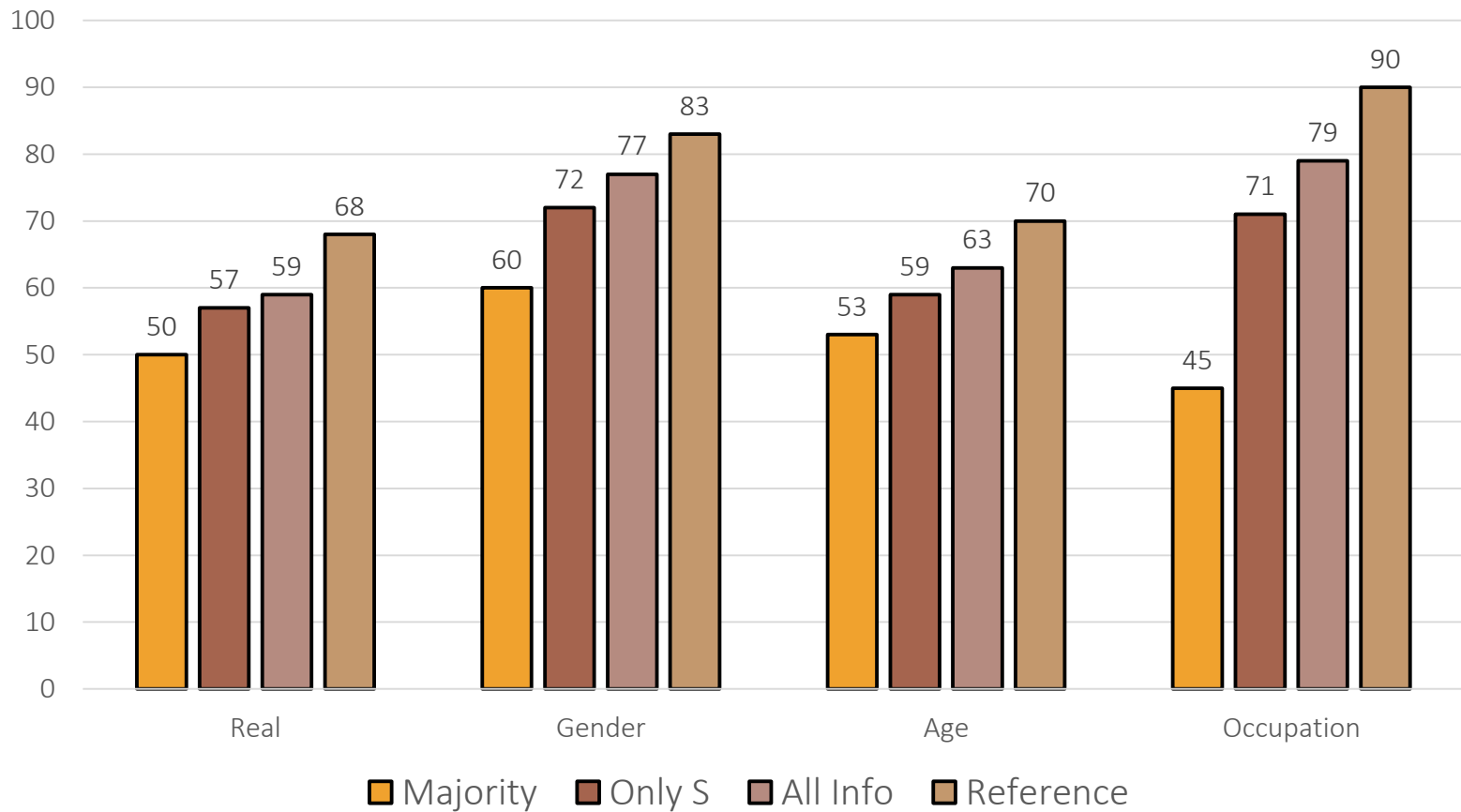
Do you think it is real or artificially generated?

Can you guess the age, gender, occupation, etc.?

# Evaluation on MovieLens Titles



# Evaluation on YAGO Descriptions



# Generated Images for YAGO

Sports



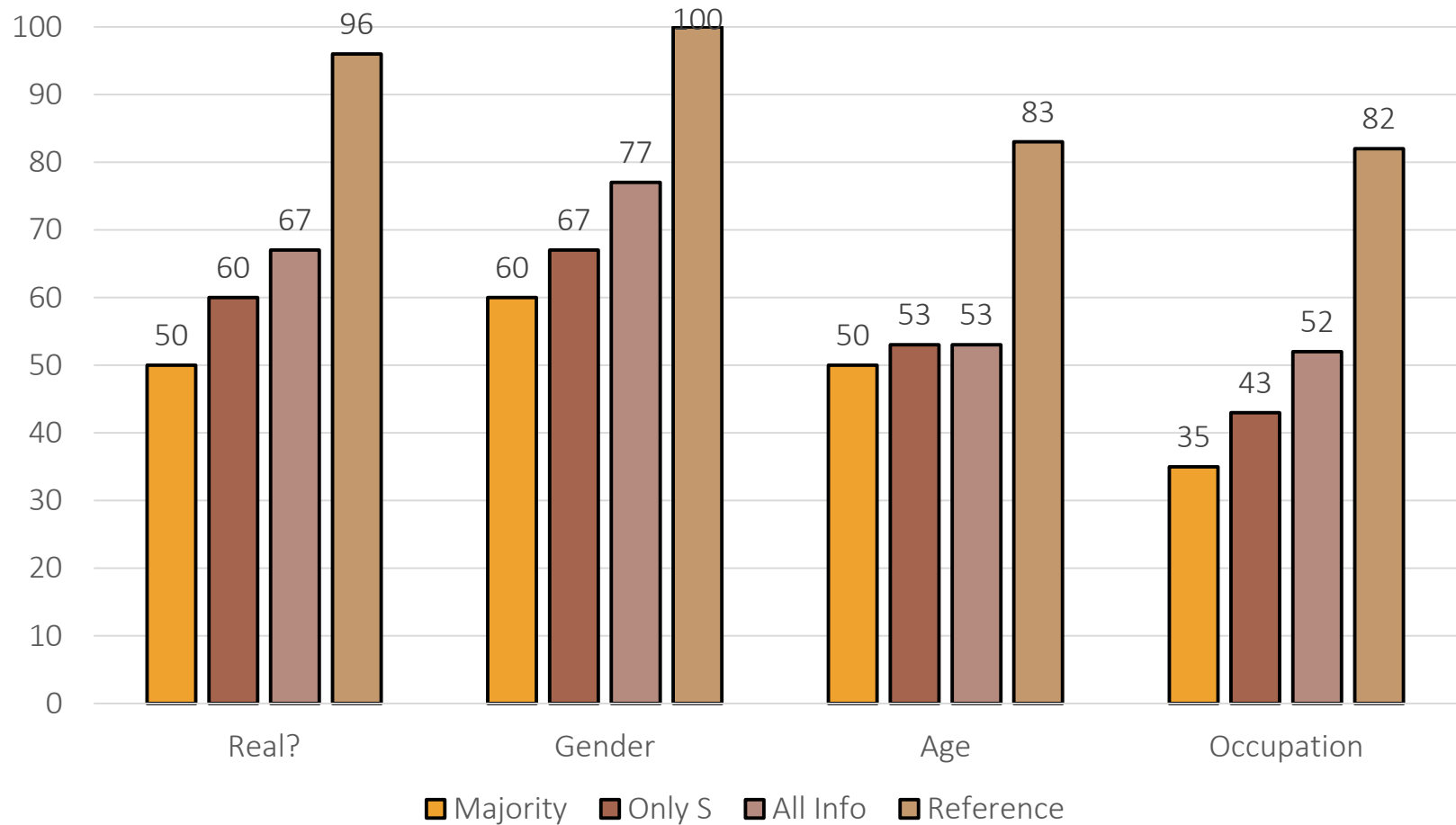
Male Celebrity



Female Celebrity



# Human Evaluation for Images





# Multimodal Attribute Extraction

## Gray Vinyl Barstool

This sleek dual purpose stool easily adjusts from counter to bar height. The backless design is casual and contemporary which allow it to seamlessly accent any area in the home. The easy to clean vinyl upholstery is perfect when being used on a regular basis. The height adjustable swivel seat adjusts from counter to bar height with the handle located below the seat....



Color Finish Gray

Style Contemporary

Adjustable Height Yes

Frame Material Metal

# MAE Dataset

Cleaned up crawl of retail products in the Diffbot Knowledge Graph

Number of Entities	2.25 million
Number of Images	4.172 million
Number of unique Attributes	2,114
Number of unique Values	15,380
Number of Attribute-Value Pairs	7.671 million



# Multimodal Attribute Extraction

**Task:** Given text and images about an entity, extract attributes

**Dataset:** Massive, diverse, open-domain dataset

**Evaluation:** Curated, small, held-out dataset

**Baseline:** Shows the challenge, and promise, of the task

<https://rloganiv.github.io/mae/>

# Take-aways

- Knowledge Graphs are a useful representation
  - But, are incomplete and noisy is a problem
- Knowledge Graph Embeddings
  - Dense representations of entities and relations
  - Easy to learn, and very powerful
- Injecting Prior Knowledge
  - Use domain information to train more efficiently
- Injecting Multiple Modalities
  - Use all types of available information: Images, text, numbers



Work with **Matt Gardner** and me

as part of

The Allen Institute for  
Artificial Intelligence  
in **Irvine**, CA



**All levels:** pre-docs, PhD interns, postdocs, and research scientists!

# Thank you!

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**Tim Rocktaschel**, **Samuel Humeau**, **Sebastian Riedel**, and **Robert Logan**