

The State of Natural Language Understanding

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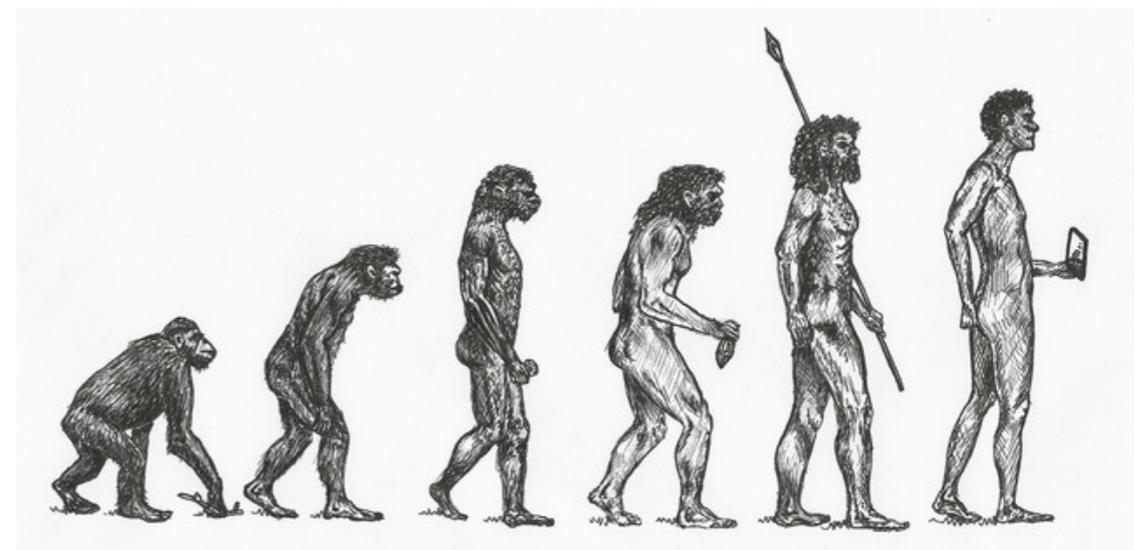
Focus is on question answering using

- Knowledge bases (Databases)
- Documents



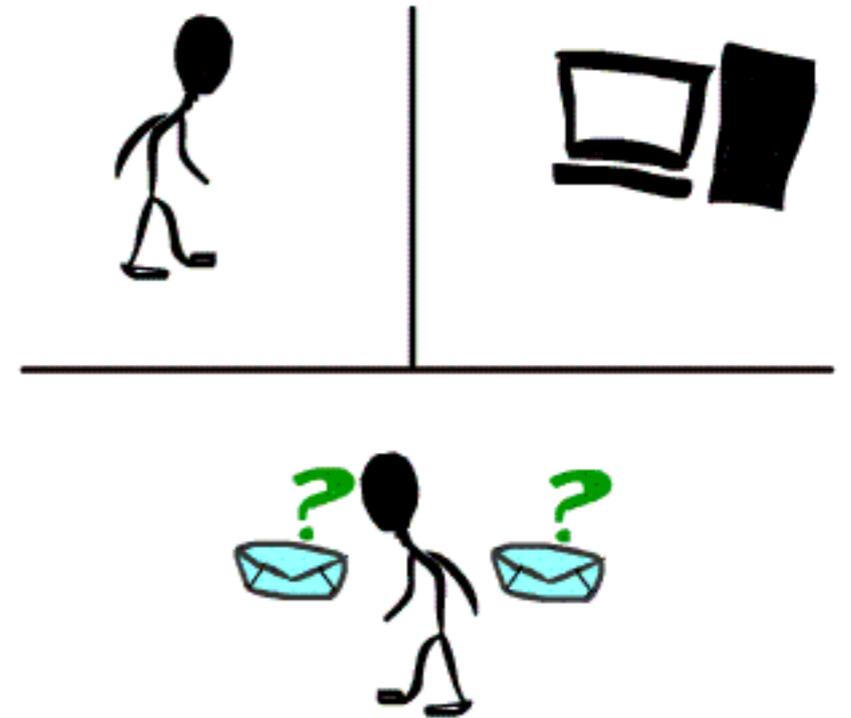
Language and Intelligence

- Distinctive characteristic of human species
- An assessment of intelligence



Intelligent Computers (1950)

Turing Test



Q: Please write me a sonnet on the subject of the Forth Bridge.

A: Count me out on this one. I never could write poetry.

Q: Add 34957 to 70764.

A: (Pause about 30 seconds and then give as answer) 105621.

Symbolic AI (1960-1990)

- Deterministic mapping of language to symbolic representations
- Pattern matching and finite state machines
- Grammars, Syntax to Logic,
- Closed-domain language interpreters

Early AI Assistants

Question Answering Systems

- Baseball (1961), LUNAR (1971)



Chatbot

- ELIZA (1966)

Most successful AI Assistant

- SHRDLU (1972)

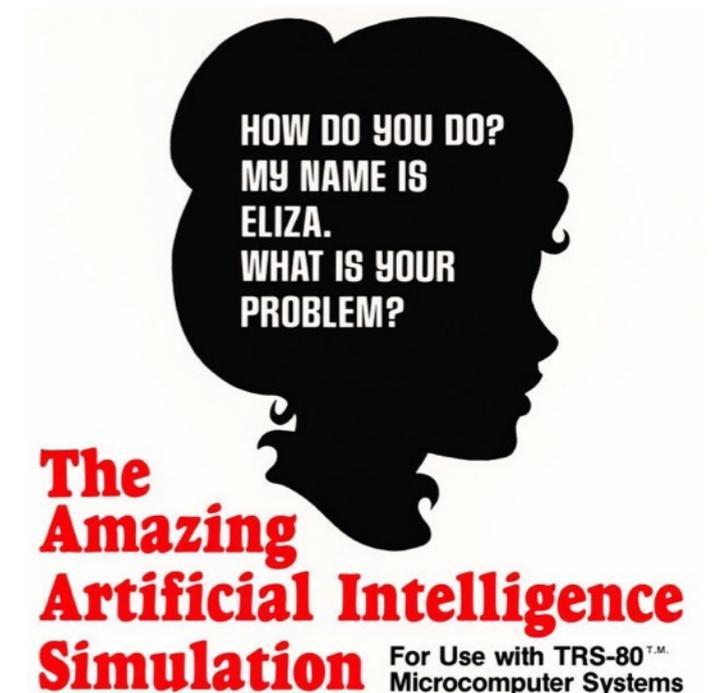
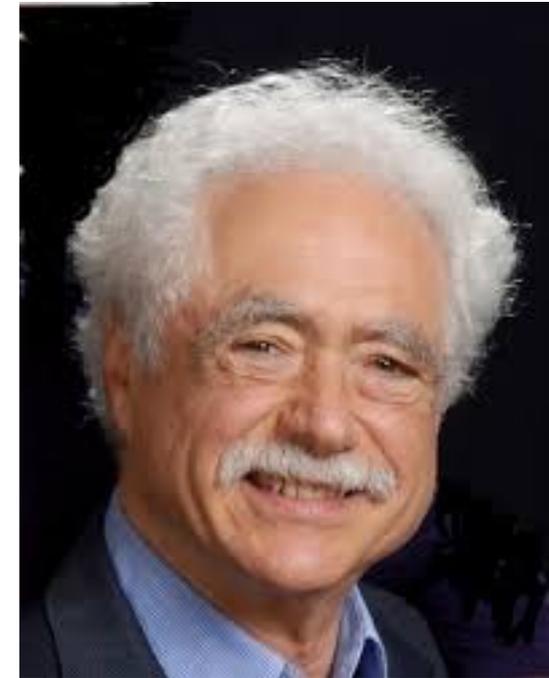


Image: analyticsindiamag.com

SHRDLU



Person: Pick up a big red block.

Computer: OK.

Person: Grasp the pyramid.

Computer: I don't understand which pyramid you mean.

Person (changing their mind): Find a block which is taller than the one you are holding and put it into the box.

Computer: By "it", I assume you mean the block which is taller than the one I am holding.

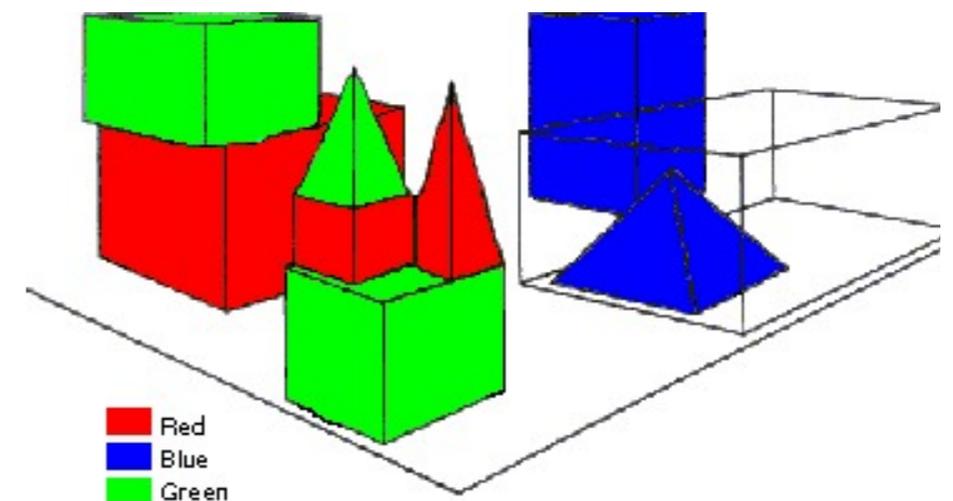
Computer: OK.

Person: What does the box contain?

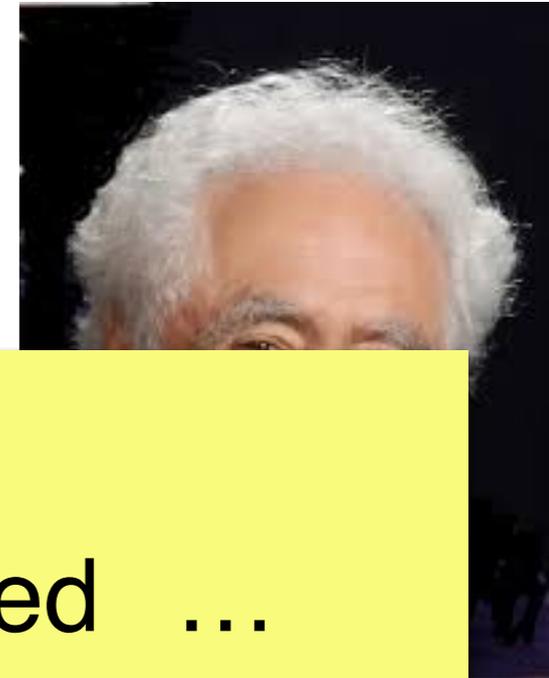
Computer: The blue pyramid and the blue block.

Person: What is the pyramid supported by?

Computer: The box.

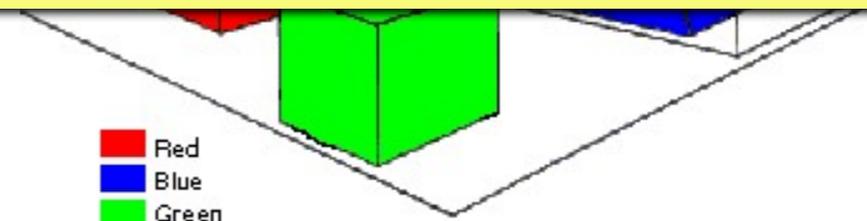


SHRDLU



A number of people have suggested ... SHRDLU program for understanding natural language represent a kind of **dead end** in AI programming.

Even having written the program, I find it near the **limit** of what I can keep in mind at once — **Terry Winograd**



Statistical NLU (1990-2010)

- Probabilistic grammars from **annotated data**
- Language paired with programs (Zelle and Mooney, 1996)

Statistical NLU (1990-2010)

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What states border Texas

$\lambda x.state(x) \wedge borders(x, texas)$

What is the largest state

$\arg \max(\lambda x.state(x), \lambda x.size(x))$

What states border the state that borders the most states

$\lambda x.state(x) \wedge borders(x, \arg \max(\lambda y.state(y), \lambda y.count(\lambda z.state(z) \wedge borders(y, z))))$

Credits: Zettlemoyer and Collins (2005)



Grammar Learning

[Zettlemoyer and Collins 2005, Liang et al. 2011]



Features are the key

- languages -> Type.HumanLanguage

Train a **ML model** to identify good and bad features based on the context

Grammar Learning

[Zettlemoyer and Collins 2005, Liang et al. 2011]

Type.HumanLanguage
Type.ProgrammingLanguage

Brazil
BrazilFootballTeam

alignment

What

language

use

- **Expensive** to annotate training data
- Domain-specific grammars
- Type.HumanLanguage

Train a **ML model** to identify good and bad features based on the context

NLU meets IR

TREC, IBM Watson, Google

[All](#) [News](#) [Images](#) [Shopping](#) [Videos](#) [More](#) [Settings](#) [Tools](#)

About 927,000 results (0.46 seconds)

Robert Anderson

Scottish inventor **Robert Anderson** invents the first crude electric carriage powered by non-rechargeable primary cells. American **Thomas Davenport** is credited with building the first practical electric vehicle -- a small locomotive. French physicist Gaston Planté invents the rechargeable lead-acid storage battery. Oct 30, 2009



[Timeline: History of the Electric Car . NOW on PBS](#)
www.pbs.org/now/shows/223/electric-car-timeline.html

[The History of the Electric Car | Department of Energy](#)

[Feedback](#)

<https://energy.gov/articles/history-electric-car> ▼

Sep 15, 2014 - And while **Robert Anderson**, a **British** inventor, developed the first crude electric carriage around this same time, it wasn't until the second half of the 19th century that French and English inventors built some of the first practical electric cars.

Train a **feature-based model** to identify the most similar sentence

Scaling NLU (2010-2016)

[Berant et al. 2013, Kwiatkowski et al. 2013, Reddy et al. 2014]

Google Knowledge Graph, WikiData

Alternate forms of supervision

Scaling NLU (2010-2016)

[Berant et al. 2013, Kwiatkowski et al. 2013, Reddy et al. 2014]

Google Knowledge Graph, WikiData

Alternate forms of supervision

Heavy supervision

What's Bulgaria's capital?
CapitalOf(Bulgaria)
When was Walmart started?
DateFounded(Walmart)
What movies has Tom Cruise been in?
Movies \cap Starring(TomCruise)
...

Light supervision

What's Bulgaria's capital?
Sofia
When was Walmart started?
1962
What movies has Tom Cruise been in?
TopGun, VanillaSky, ...
...



Training intuition

Where did Mozart live?

Vienna

Training intuition

Where did Mozart typress?

PlaceOfBirth(WolfgangMozart)

PlaceOfDeath(WolfgangMozart)

PlaceOfMarriage(WolfgangMozart)

Vienna

Training intuition

Where did Mozart live?

~~PlaceOfBirth(WolfgangMozart) ⇒ Salzburg~~

PlaceOfDeath(WolfgangMozart) ⇒ Vienna

PlaceOfMarriage(WolfgangMozart) ⇒ Vienna

Vienna

Training intuition

Where did Mozart live?

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PlaceOfMarriage(WolfgangMozart) ⇒ Vienna

Vienna

Where did Hogarth live?

PlaceOfBirth(WilliamHogarth) ⇒ London

PlaceOfDeath(WilliamHogarth) ⇒ London

~~PlaceOfMarriage(WilliamHogarth) ⇒ Paddington~~

London

Training intuition

Where did Mozart tupress?

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Vienna

Where did Hogarth tupress?

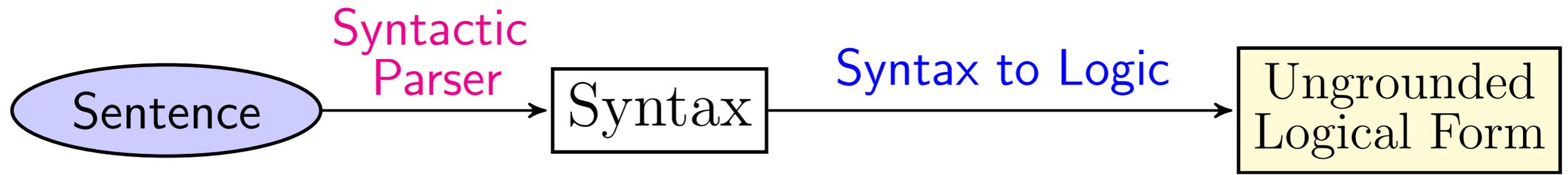
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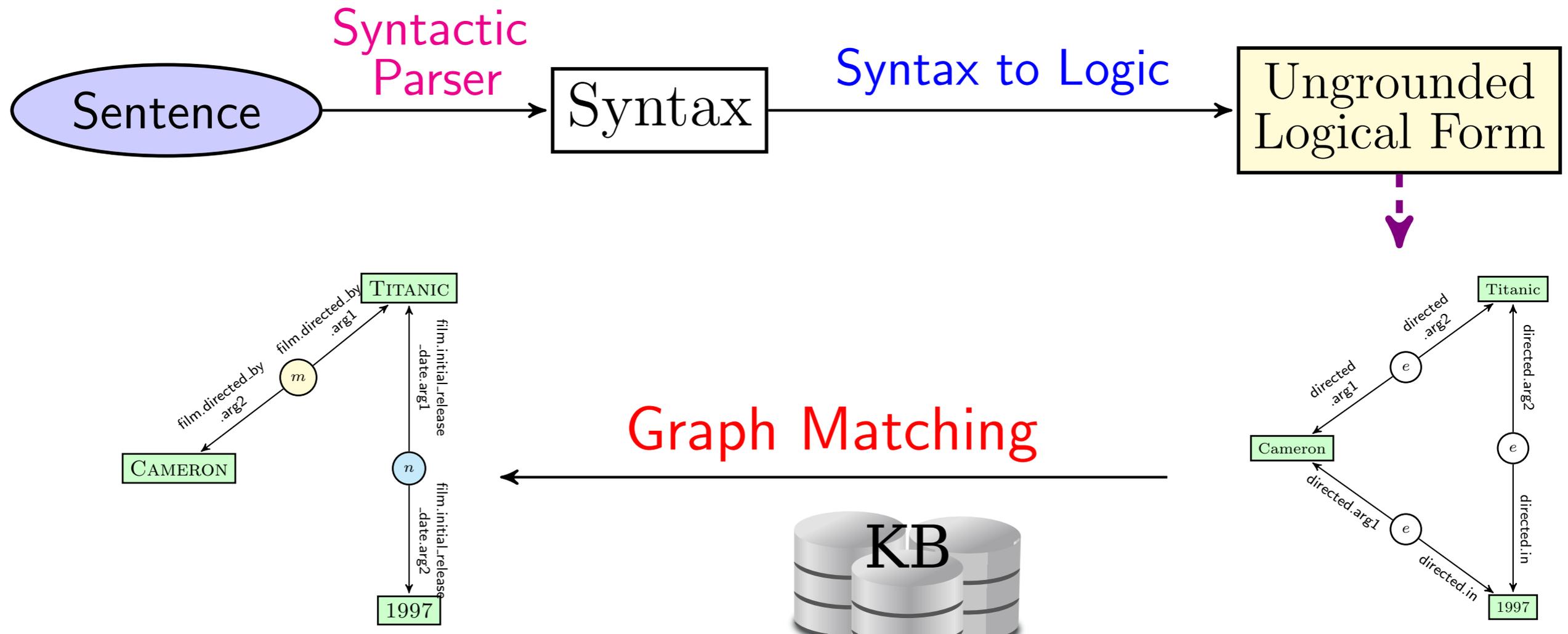
London

Scaling using Linguistic Representations



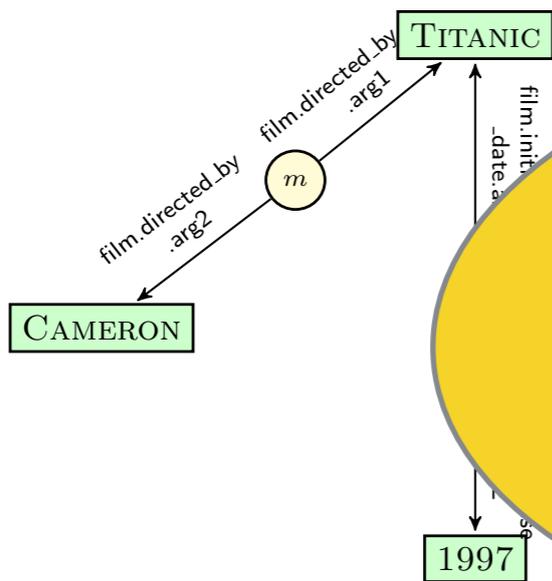
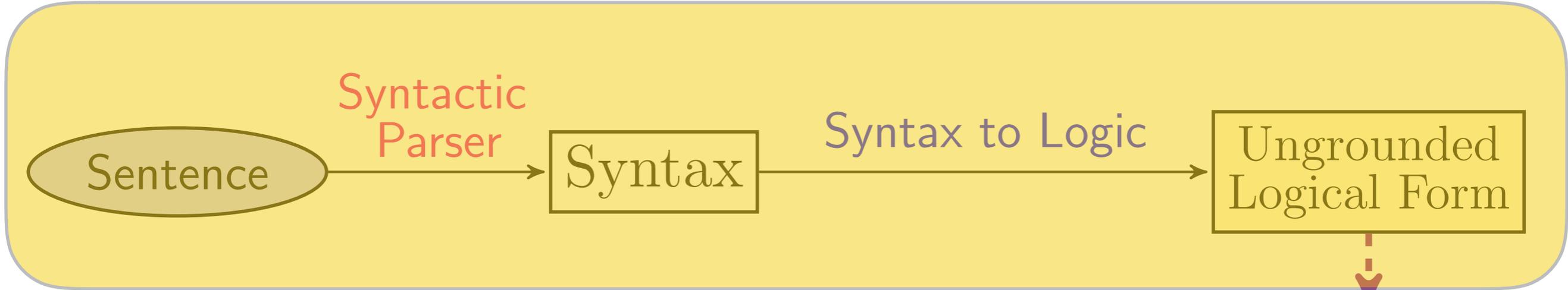
Reddy et al. (2016, 2017)

Scaling using Linguistic Representations

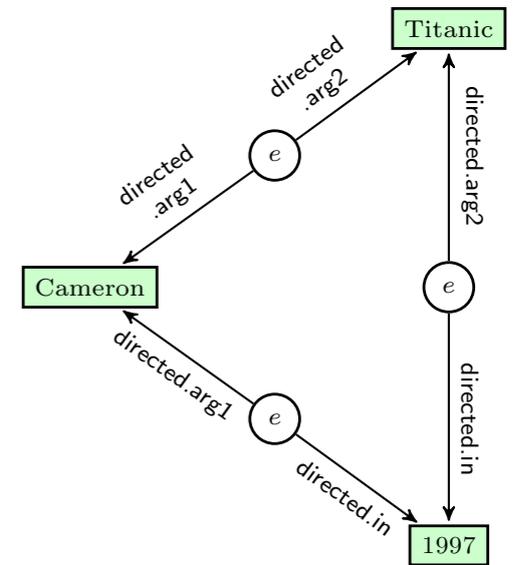


Reddy et al. (2016, 2017)

Scaling using Linguistic Representations

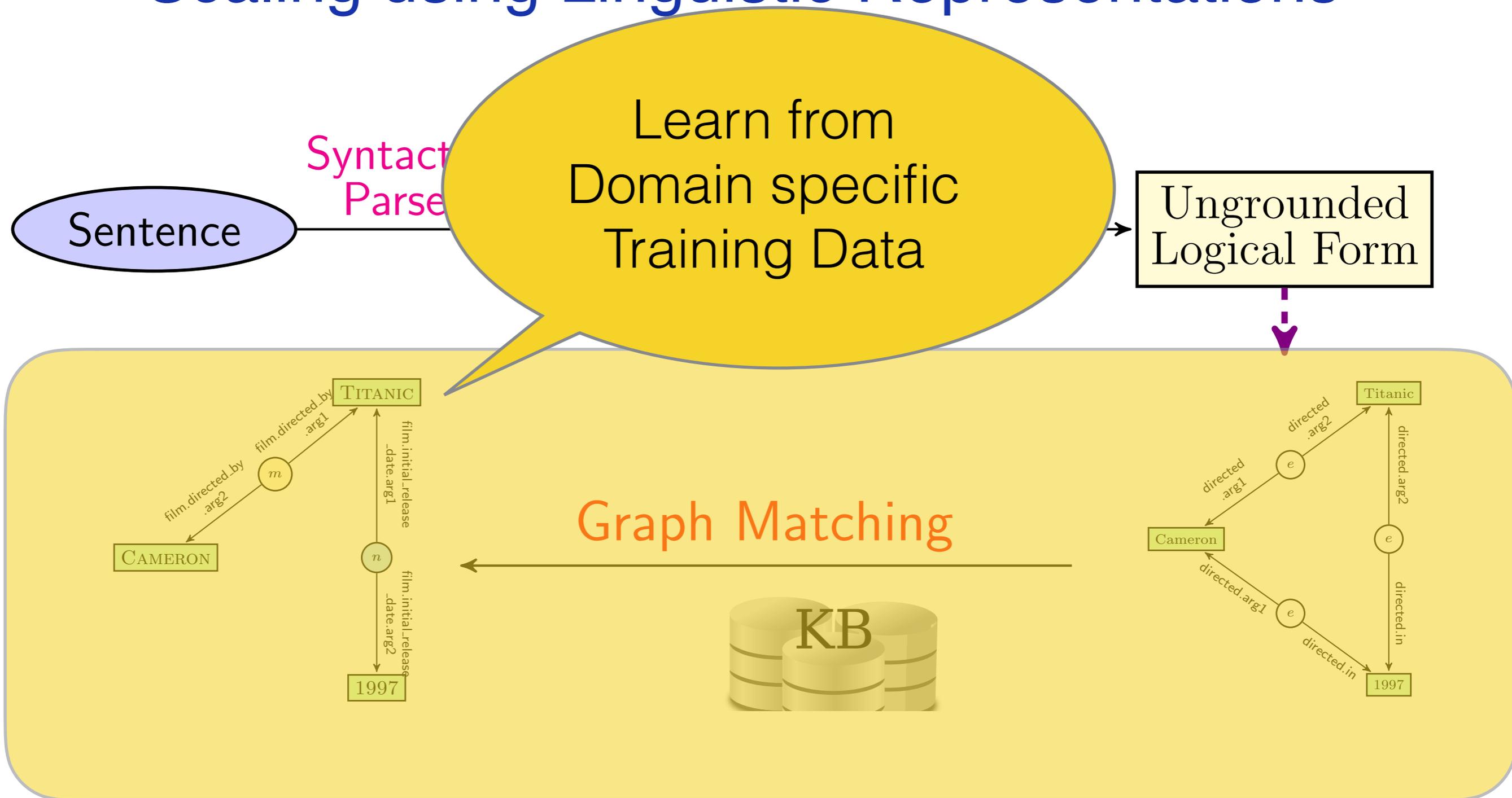


Domain Agnostic and handles long tail language



Reddy et al. (2016, 2017)

Scaling using Linguistic Representations



Reddy et al. (2016, 2017)

Deep Learning



The general approach to building Deep Learning systems is compelling and powerful: The researcher defines a **model architecture** and a **top-level loss function** and then both the **parameters** and the **representations** of the model **self-organize** so as to minimize this loss, in an end-to-end learning framework. — **Chris Manning (2015)**

Word Embeddings

[Mikolov et al. 2013, Pennington et al. 2014]

Symbols to numerical representations

How similar are **hotel** and **lodge**?

- **Traditional:** character overlap, dictionary
- **Embeddings:** hotel = [0.5 0.3 0.2 0.9]
lodge = [0.9 0.2 0.4 0.1]

Entity and Relation Embeddings

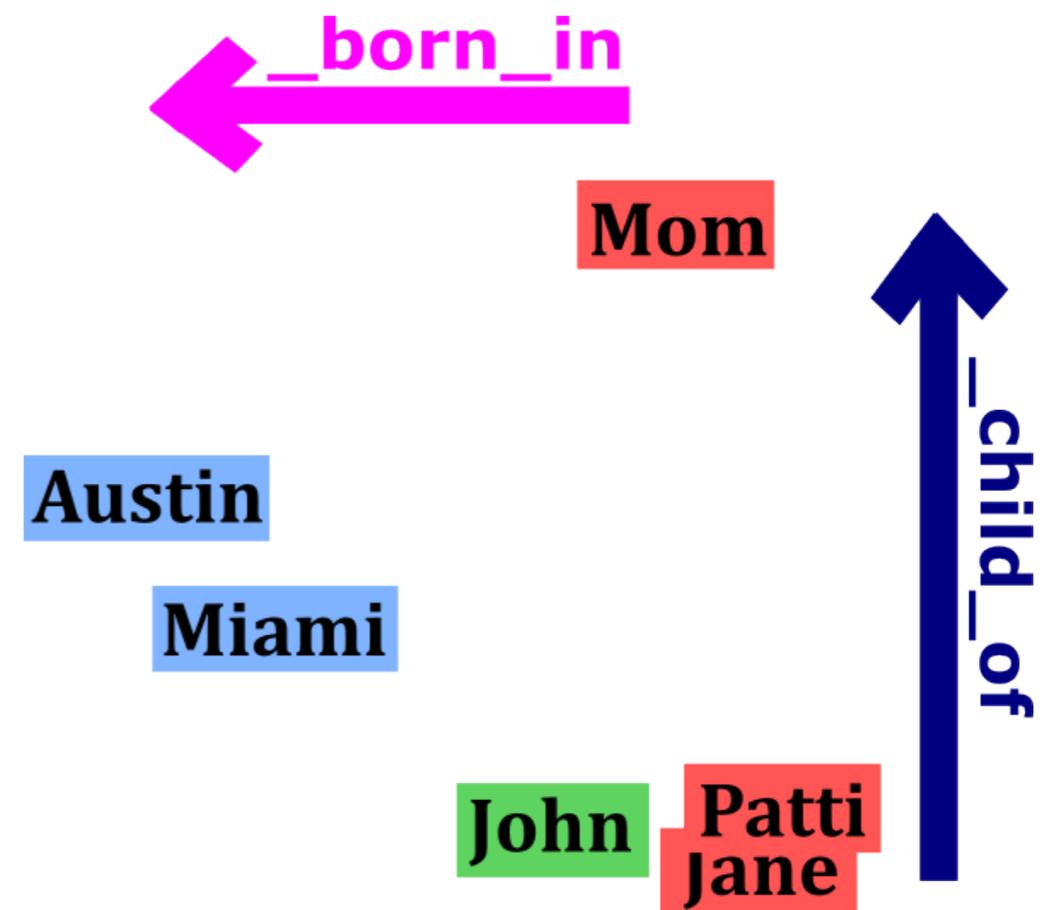
[Bordes et al. 2013]

Intuition: we want $\mathbf{s} + \mathbf{r} \approx \mathbf{o}$.

The similarity measure is defined as:

$$d(sub, rel, obj) = \|\mathbf{s} + \mathbf{r} - \mathbf{o}\|_2^2$$

\mathbf{s}, \mathbf{r} and \mathbf{o} are learned to verify that.

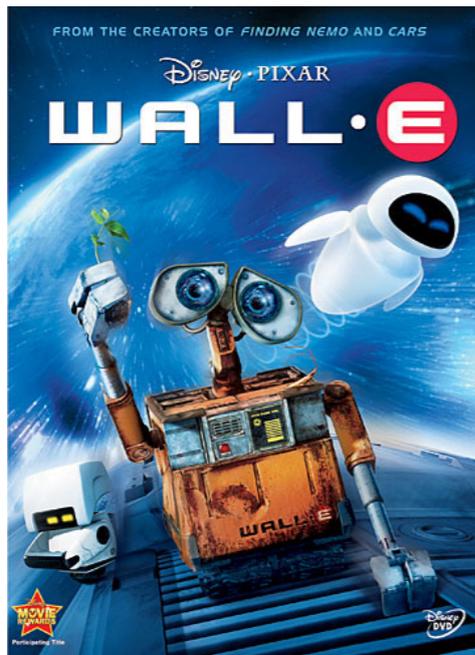


Entity and Relation Embeddings

FRANCE	JESUS	SCRATCHED
SPAIN	CHRIST	SMASHED
ITALY	GOD	RIPPED
RUSSIA	RESURRECTION	BRUSHED
POLAND	PRAYER	HURLED
ENGLAND	YAHWEH	GRABBED
DENMARK	JOSEPHUS	TOSSED
GERMANY	MOSES	SQUEEZED
PORTUGAL	SIN	BLASTED
SWEDEN	HEAVEN	TANGLED
AUSTRIA	SALVATION	SLASHED

Entity and Relation Embeddings

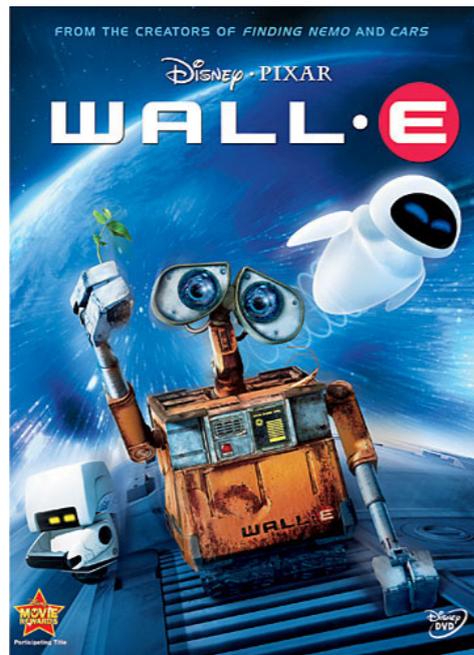
WALL-E



+ movie.genre =

Entity and Relation Embeddings

WALL-E

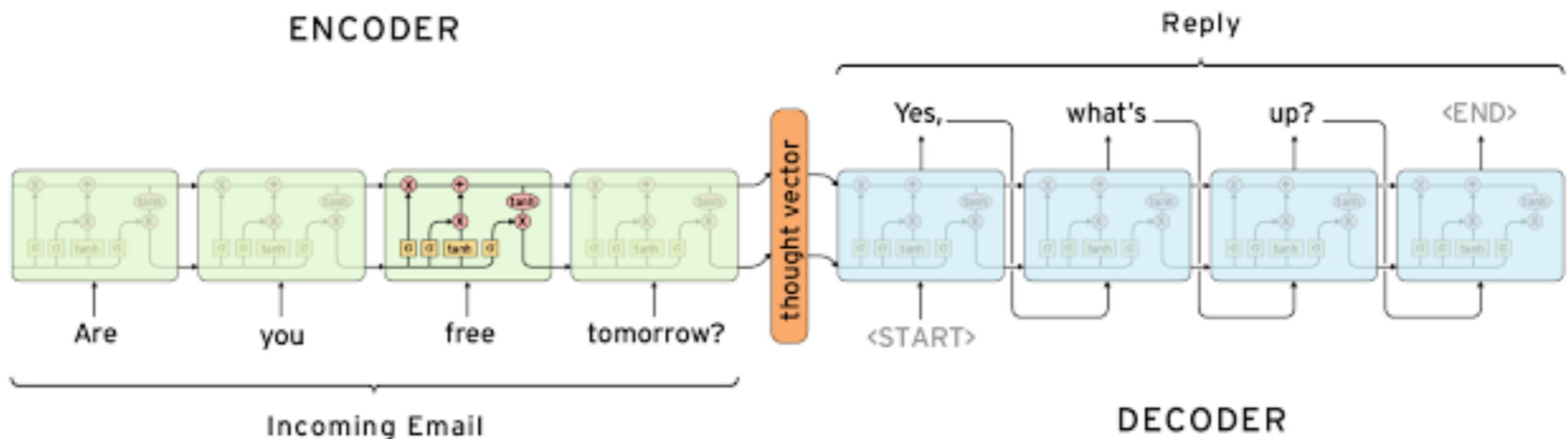


+ movie.genre =

Animation
Comedy Film
Adventure Film
Fantasy
Drama
Satire

End to End AI Assistants

- Sequence to Sequence Machine Translation (Cho et al. 2014, Sutskever et al. 2014)
- Easy to train on unstructured data



Credits: Denny Britz

Hard to control and debug

<i>message</i>	How old are you?
<i>response</i>	16 and you?
<i>message</i>	What's your age?
<i>response</i>	18.

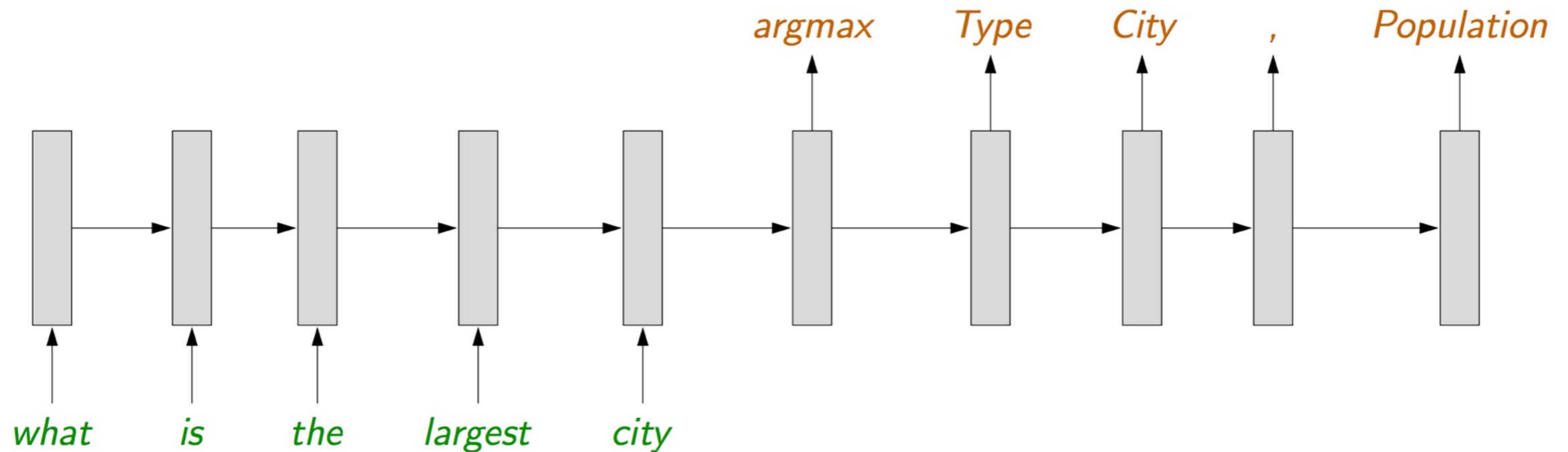
[Li et al. 2016]



Microsoft Tay

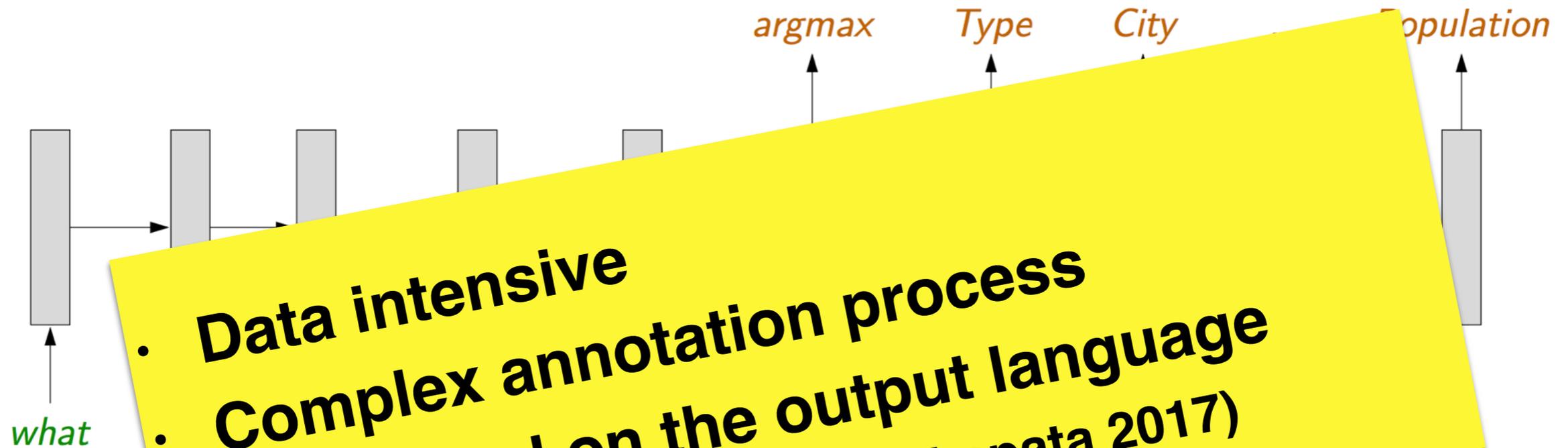
QA on Knowledge Bases

[Jia and Liang 2016, Dong and Lapata 2016]



QA on Knowledge Bases

[Jia and Liang 2016, Dong and Lapata 2016]



Reading Comprehension

Question: *“The number of new Huguenot colonists declined after what year?”*

Paragraph: *“The largest portion of the Huguenots to settle in the Cape arrived between 1688 and 1689...but quite a few arrived as late as **1700**; thereafter, the numbers declined...”*

Correct Answer: **“1700”**

Tremendous gains using Deep Learning

Reading Comprehension

Rank	Model	EM	F1
	Human Performance <i>Stanford University</i> <i>(Rajpurkar et al. '16)</i>	82.304	91.221
1 Jan 22, 2018	Hybrid AoA Reader (ensemble) <i>Joint Laboratory of HIT and iFLYTEK Research</i>	82.482	89.281
2 Jan 05, 2018	SLQA+ (ensemble) <i>Alibaba iDST NLP</i>	82.440	88.607
2 Jan 03, 2018	r-net+ (ensemble) <i>Microsoft Research Asia</i>	82.650	88.493

SQuAD leaderboard

Reading Comprehension

Rank	Model	EM	F1
	Human Performance Stanford University (Rainurk)	89.281	91.221
1			89.281
Jan 2, 2019			
2			88.607
Jan 05, 2019			
2		82.650	88.493
Jan 03, 2019			

Do these models actually understand?

SQuAD leaderboard

Adversarial attacks

[Jia and Liang 2016]

Question: *“The number of new Huguenot colonists declined after what year?”*

Paragraph: *“The largest portion of the Huguenots to settle in the Cape arrived between 1688 and 1689...but quite a few arrived as late as **1700**; thereafter, the numbers declined. The number of old Acadian colonists declined after the year of **1675**.”*

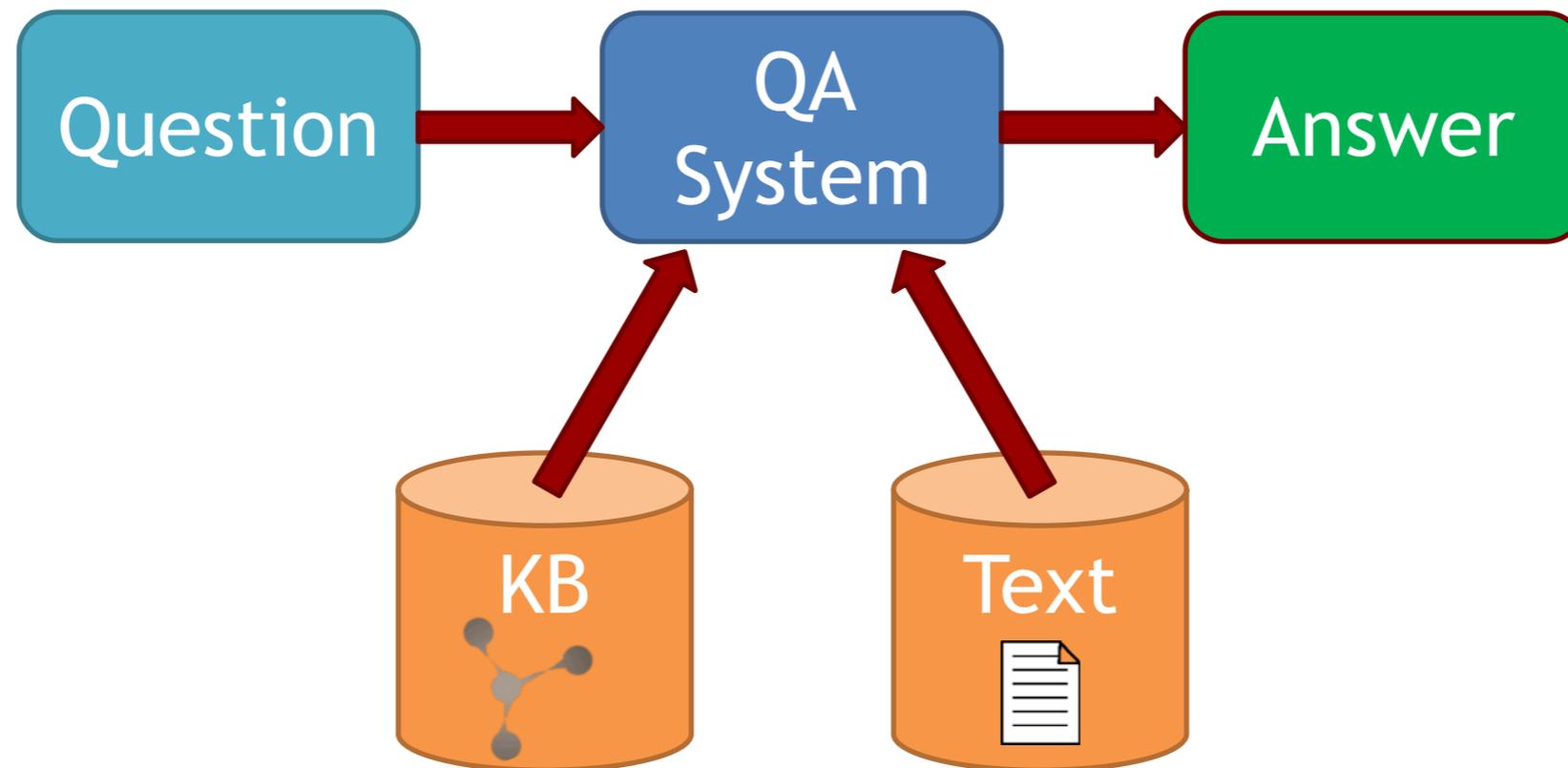
Correct Answer: ***“1700”***

Predicted Answer: ***“1675”***

Performance drops from 80s to 30s.

Multiple Knowledge Sources

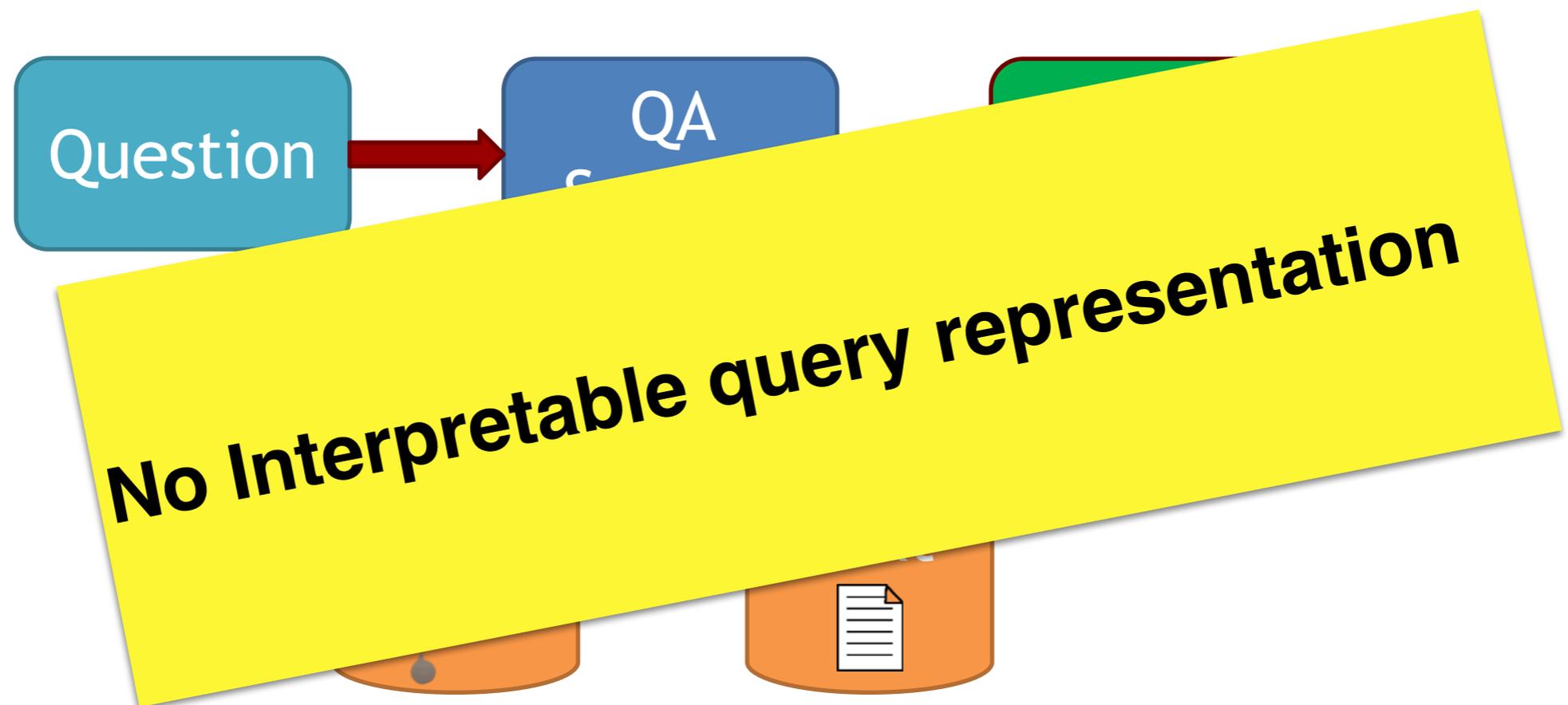
[Das, Zaheer, Reddy, McCallum 2017]



Who is the first African-american president of US?

Multiple Knowledge Sources

[Das, Zaheer, Reddy, McCallum 2017]



Who is the first African-american president of US?

Winners

Could be deployed with care

- Reading comprehension
- Simple QA on knowledge bases
- Chit chat bots
- Human assisted auto reply

Losers

Multi relational QA on knowledge bases

Goal oriented dialog

Summary

Don't buy the Deep Learning hype for AI Assistants

NLU is harder than signal processing tasks

Data intensive and expensive

Limited control and low interpretability

Sensitive to adversarial attacks

Thank you

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