Symbolic AI

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Photo by Vasilyev Alexandr

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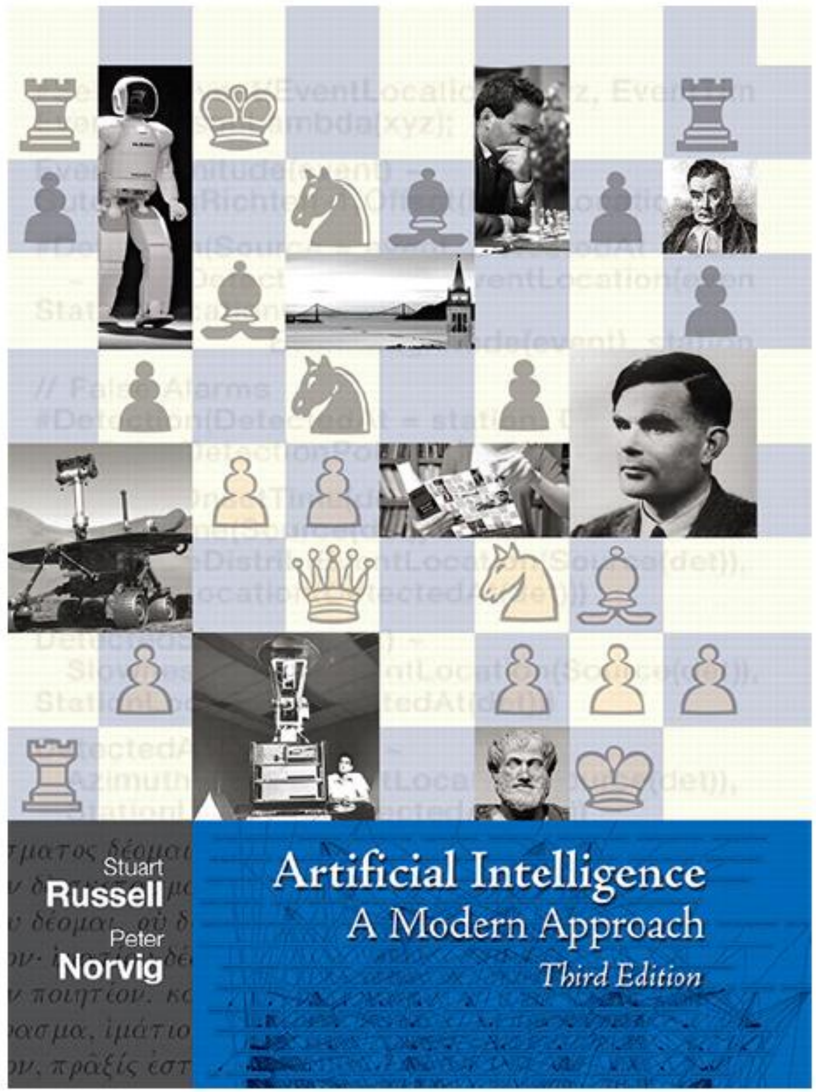
Employability Skills

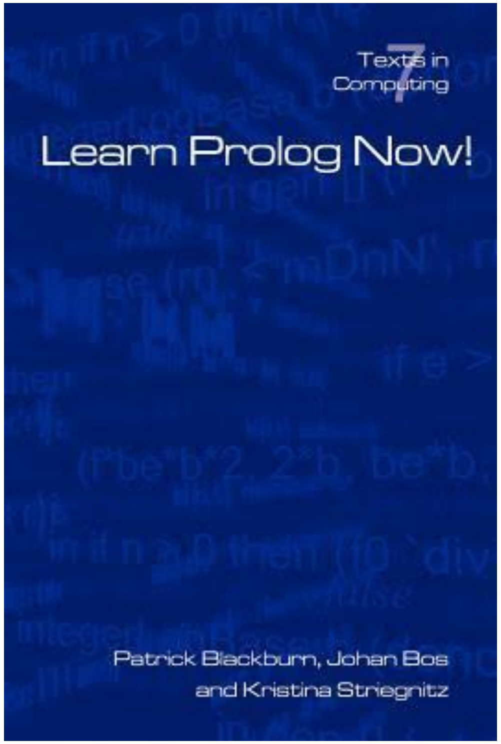
- Contemporary AI is evolving rapidly in the direction of hybrid **neuro-symbolic models**.

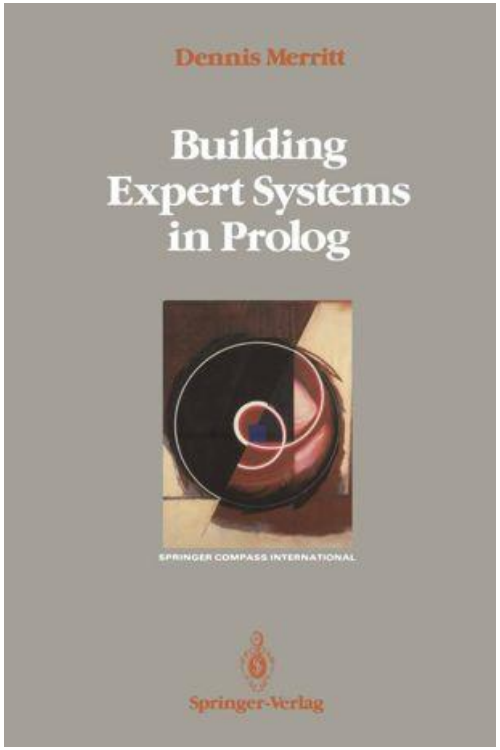
- Larger palette to build AI Systems.

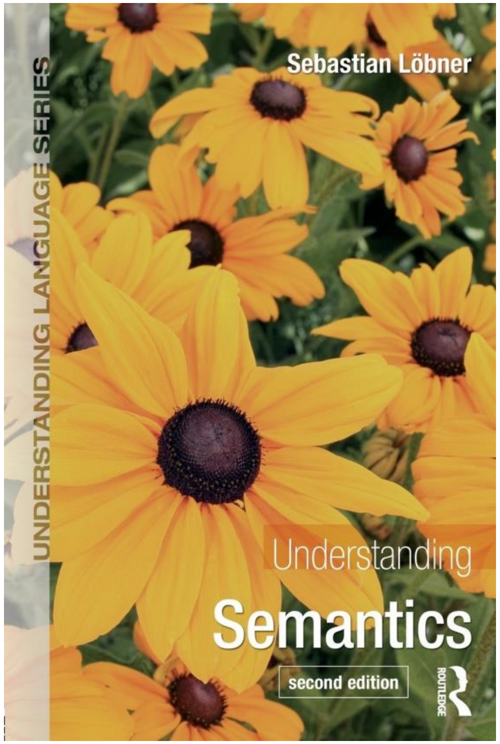
Main Suggested Reference



Complementary References







Assessment

- Labs (25%)
  - 3 exercises (1 small, 2 big)
  - 5 lab sessions.
  - Hands-on experience with tools.
- Quizzes (5%)
  - 3 Blackboard quizzes (every fortnight).
  - Purpose is to give useful feedback and preparation for exam.
- Exam (70%)
  - Hybrid (half on Blackboard, half on paper).
  - split between two parts.

Connecting to other Courses

COMP14112: Fundamentals of Artificial Intelligence

Probabilistic models, Robot Localisation, Speech Understanding

COMP11120: Mathematical Techniques for Computer Science

Introduction to logic and reasoning

COMP21111: Logic and Modelling

Propositional models and reasoning

COMP24111: Machine Learning and Optimisation

Statistical Models of the world, Classification and Clustering

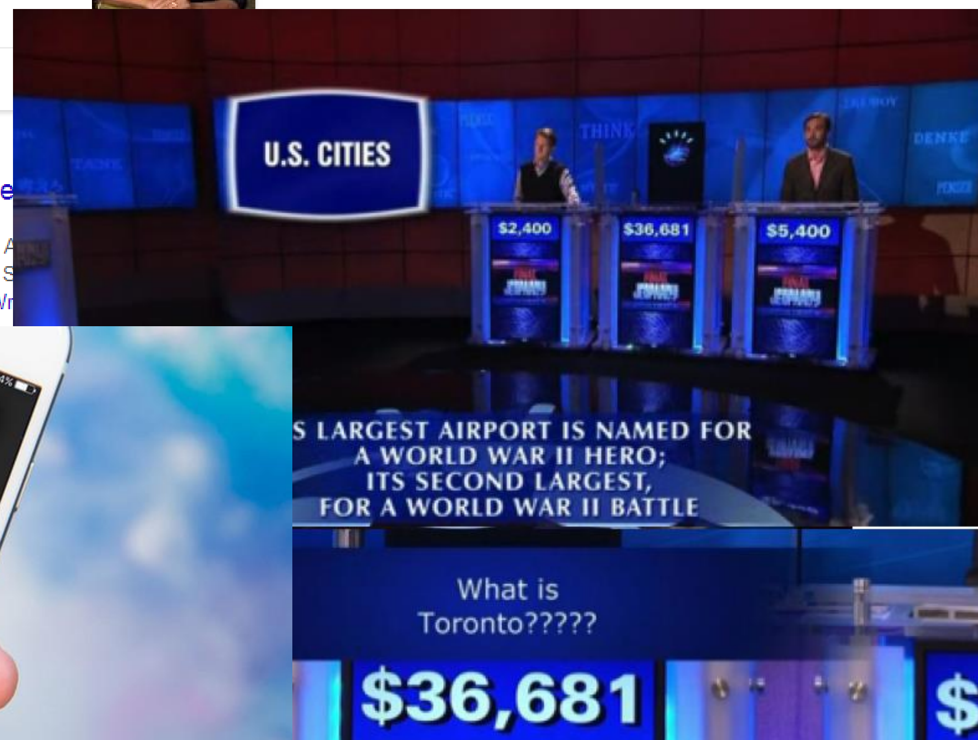
COMP34412 Natural Language Systems

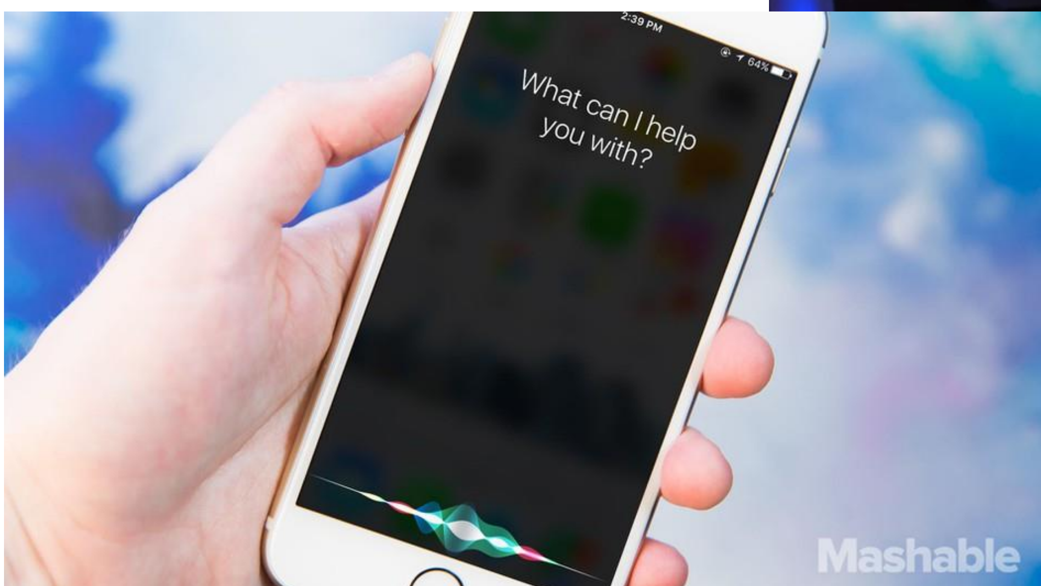
Statistical Models of language, How to build and use those models

How to Study

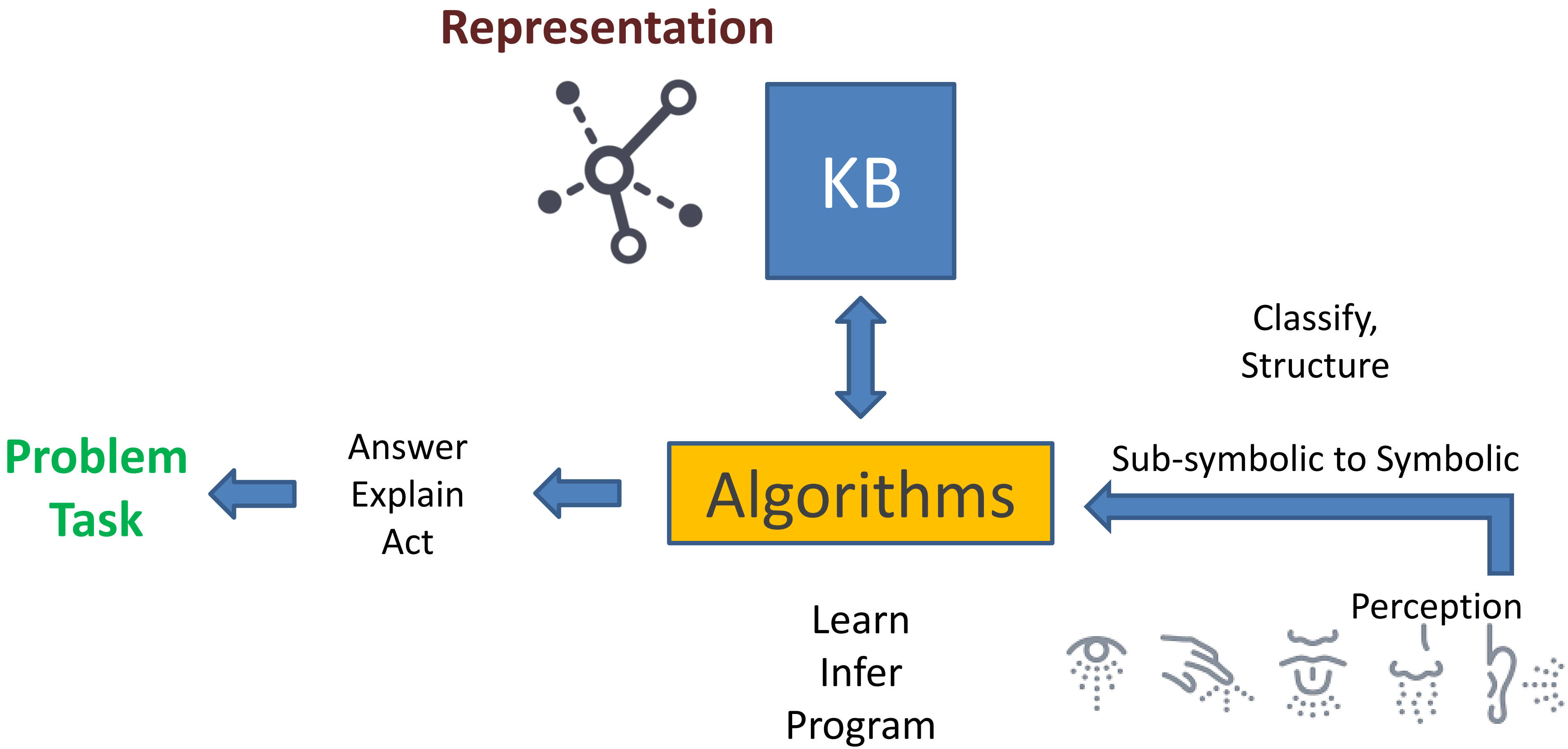
- Understanding formalisms and principles.
- Be in a position to define and explain:
  - The core concepts and algorithms.
  - Why they are relevant?
  - When you should use/not use them?
- Basic application of the core algorithms.

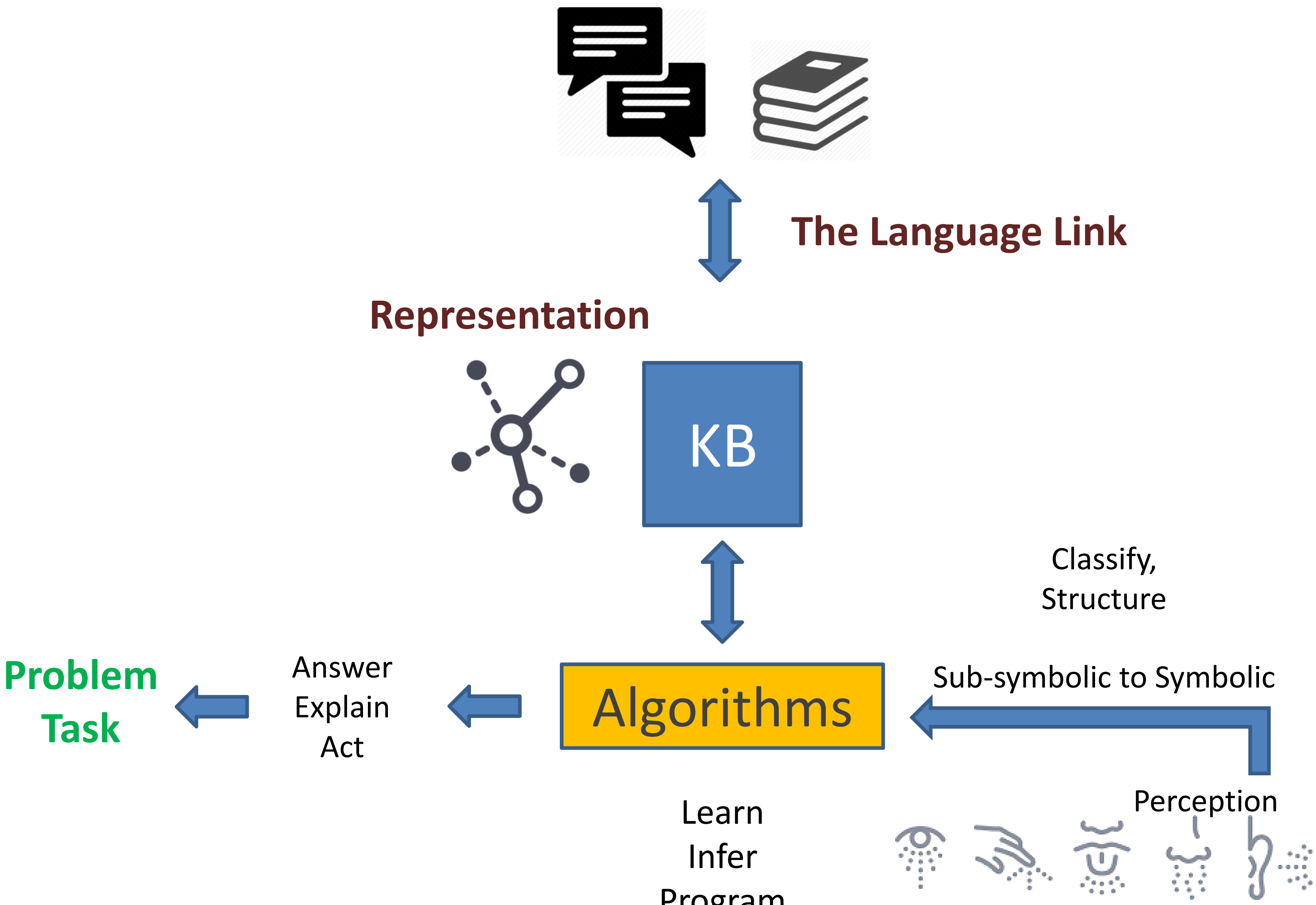

Google
who is the wife of barack obama
Web
News
Images
Shopping
Videos
More
Search tools
About 186,000,000 results (0.53 seconds)
Michelle Obama (m. 1992)
Barack Obama, Spouse
Michelle Obama - Wikipedia, the free encyclope
en.wikipedia.org/wiki/Michelle_Obama
Wikipedia
Michelle LaVaughn Robinson Obama (born January 17, 1964), an A
writer, is the wife of the 44th and current President of the United S
Capers Funnye - Sidley Austin - Hyde Park, Chicago - Jeremiah Wr


U.S. CITIES
$2,400
$36,681
$5,400
S LARGEST AIRPORT IS NAMED FOR
A WORLD WAR II HERO;
ITS SECOND LARGEST,
FOR A WORLD WAR II BATTLE
What is
Toronto?????
$36,681


2:39 PM
What can I help
you with?
Mashable


NOBEL
NAT. MDCCCXXXIII
OB. MDCCCXCVI


Representation
KB
Classify,
Structure
Problem
Task
Answer
Explain
Act
Algorithms
Sub-symbolic to Symbolic
Learn
Infer
Program
Perception

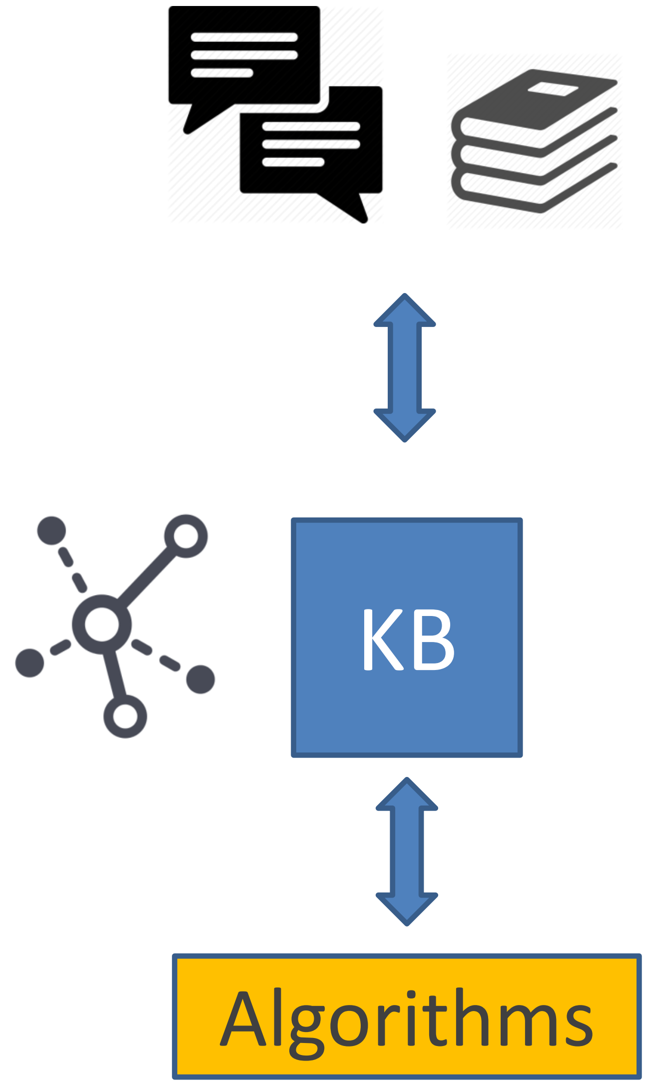

The Language Link
Representation
KB
Classify,
Structure
Problem
Task
Answer
Explain
Act
Algorithms
Sub-symbolic to Symbolic
Perception
Learn
Infer
Program

Syllabus - Nexus

3. Syntactic & Semantic Parsing

1. Knowledge Representation

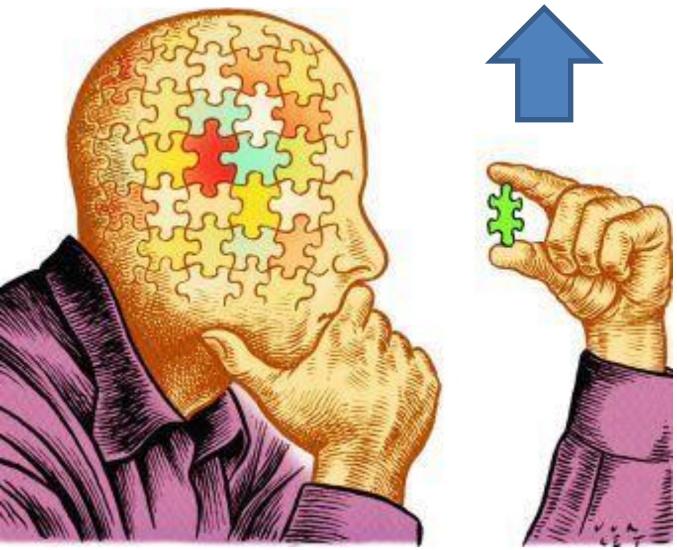
4. First-order logics & Reasoning
5. Abductive Reasoning
6. Inductive Logic Programming



2. Prolog

Knowledge Representation

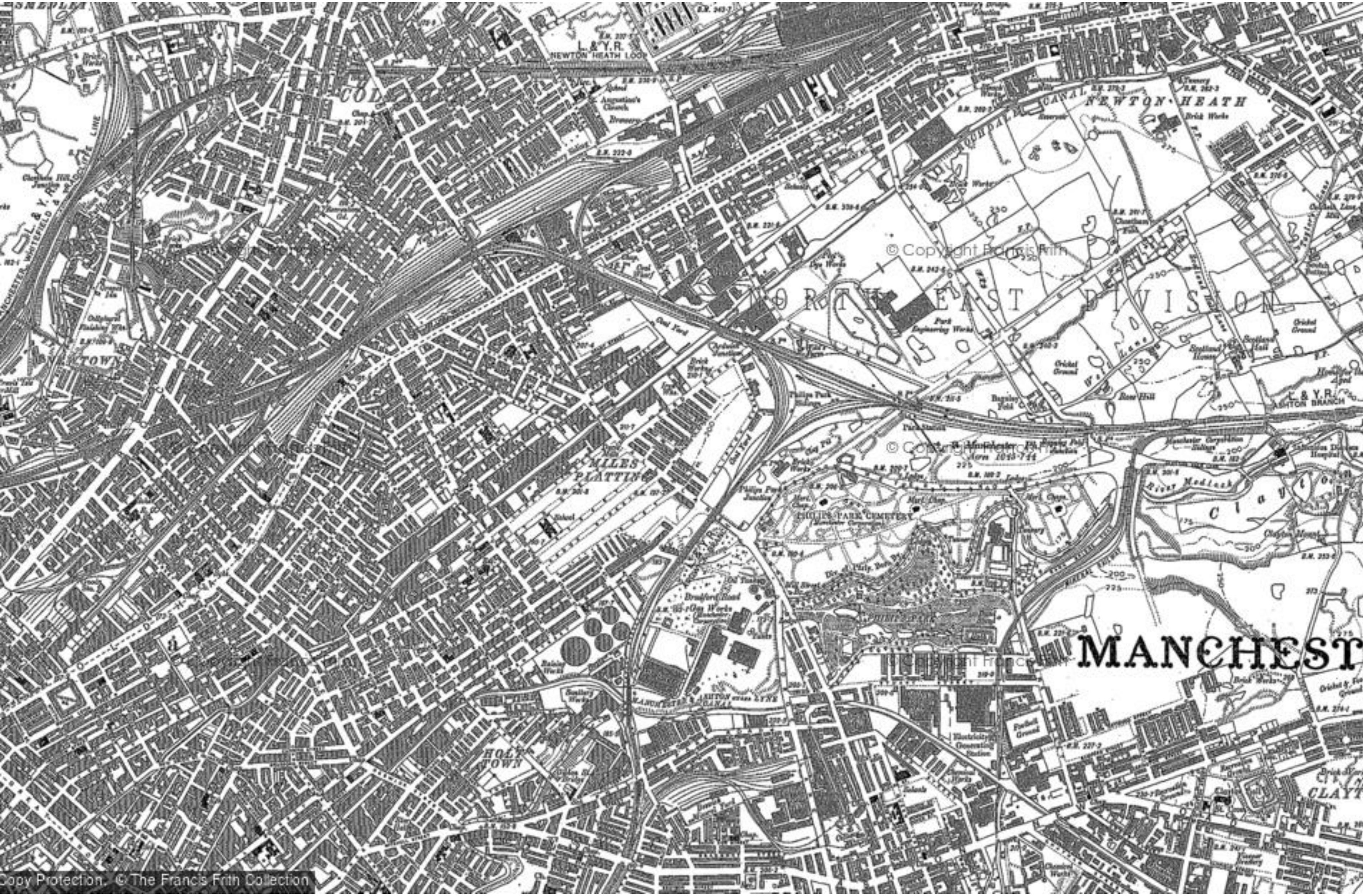
Communication of the Representation

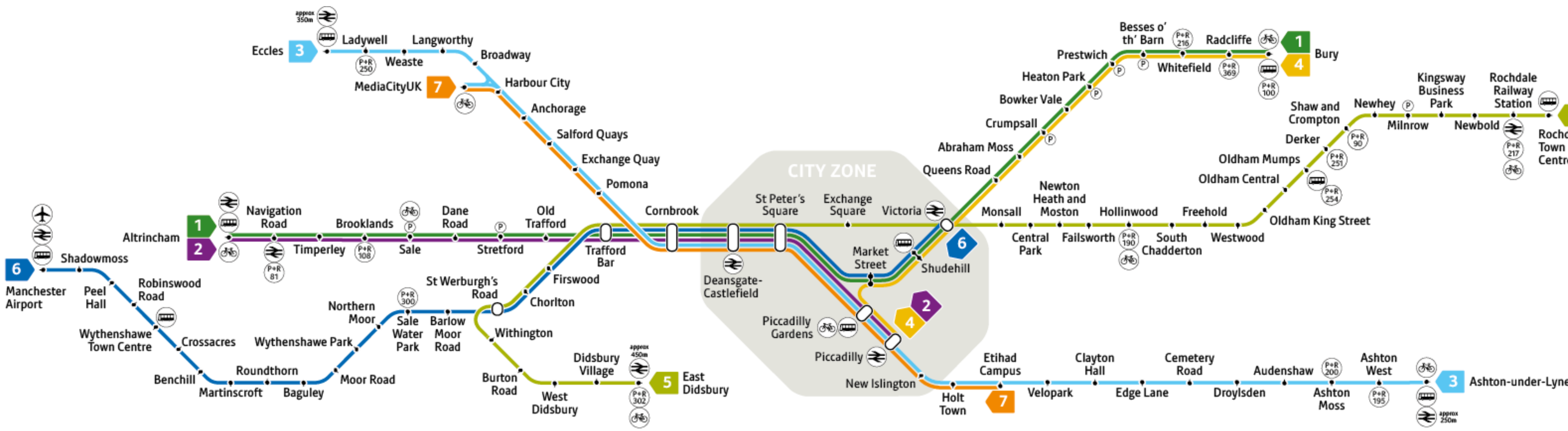


Representation of the Reality

Structure of the Reality


MANCHESTER
City Centre
Manchester Victoria
Victoria
Shudehill
Market Street
Piccadilly Gardens
St Peter's Square
Manchester Piccadilly
G-Mex
Deansgate
Manchester Oxford Road
Salford Central
Cornbrook
Wallness
New Windsor
Ancoats
Brunswick
University
Hulme
Ardwick
Silk Street
Blackfriars Road
Chapel Street
Deansgate
Oldfield Road
Liverpool Road
Water Street
Lever Street
Oldham Road
Pollard Street
Old Mill Street
Ducie Street
Store Street
Whitworth Street
Every Street
Butler Street
Livesey Street
Dantzic Street
Metrolink
St Stephen Street
E Ordsall La
Ordsall La
Elton Street
River Irwell
River Medlock
Corn Brook
Bridgewater Way
Royce Road
Stretford Road
City Road
Higher Ardwick
Brunswick Street
A664
A6042
A6
A57
A57(M)
A5067
A34
A635
A665
A57


L.&Y.R.
NEWTON HEATH LOCO
NEWTON HEATH
ROCHDALE CANAL
NORTH EAST DIVISION
MILES PLATTING
L.&Y.R.
ASHTON BRANCH
PHILLIPS PARK CEMETERY
River Medlock
Brick Works
Cricket Ground
Rose Hill
HOLT TOWN
MANCHESTER & ASHTON under LYNE CANAL
MANCHEST
CLAYTON



Services

1 Altrincham – Bury
2 Altrincham – Piccadilly
3 Ashton-under-Lyne – Eccles
4 Bury – Piccadilly
5 East Didsbury – Rochdale Town Centre
6 Manchester Airport – Victoria*
7 MediaCityUK – Etihad Campus

* Early services operate on a 20 minute frequency between Manchester Airport and Deansgate-Castlefield. Please check journey planning posters or **tfgm.com** before travelling.

Key

Metrolink stop
Change with other servic
Bus interchange
Park + Ride
with number of spaces
P+R 302
Car park
fewer than 50 spac
Rail interchange
Cycle Hub
membership required


Ceci n'est pas une pipe.
Magritte

"Human knowledge is a process of approximation. In the focus of experience, there is comparative clarity. But the discrimination of this clarity leads into the penumbral background. There are always questions left over. The problem is to discriminate exactly what we know vaguely."

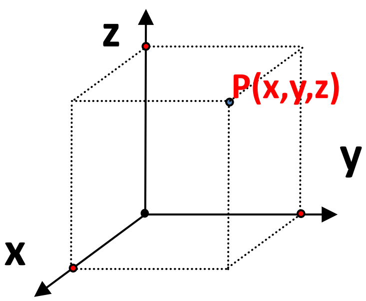
Alfred North Whitehead

KR: Five Roles

- 1. Surrogate
  - That is, a representation
- 2. Expression of ontological commitment
  - of the world
- 3. Theory of intelligent reasoning
  - and our knowledge of it
- 4. Medium of efficient computation
  - that is accessible to programs
- 5. Medium of human expression
  - and usable

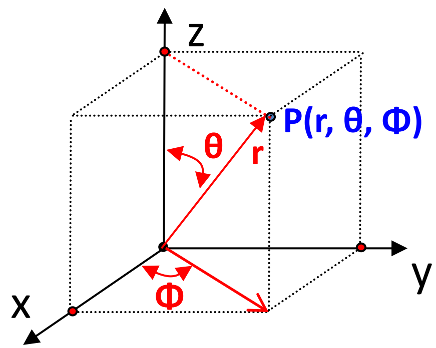
Cartesian Coordinates

P(x,y,z)



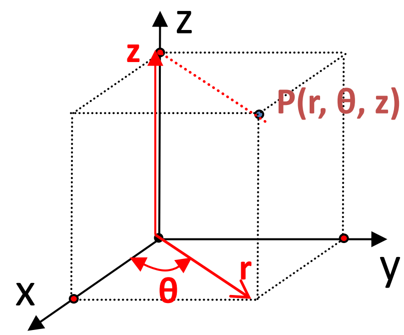
Spherical Coordinates

P(r, θ, Φ)



Cylindrical Coordinates

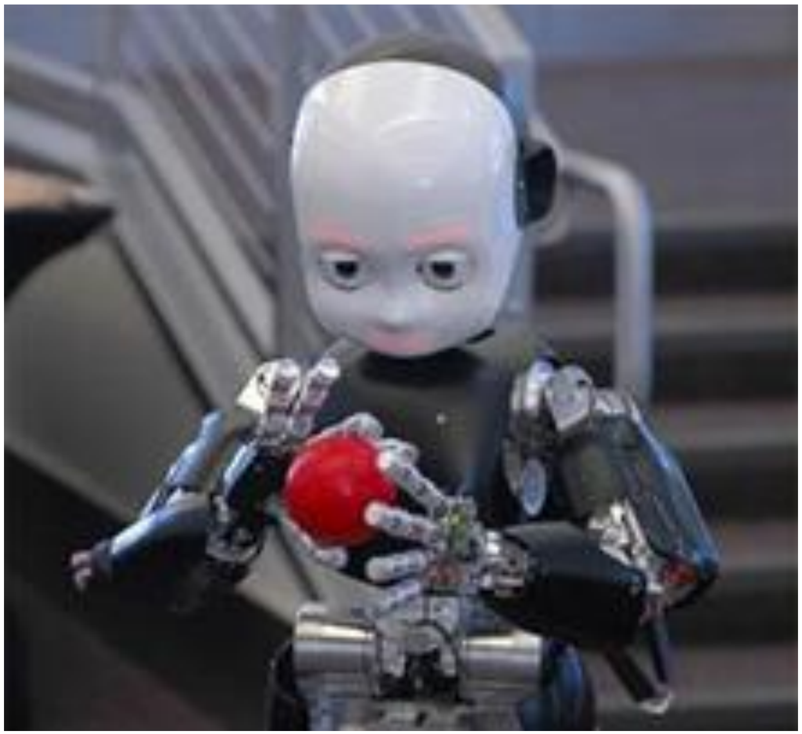
P(r, θ, z)



$$ds^2 = \left(1 - \frac{2m}{r}\right) dt^2 - \frac{1}{\left(1 - \frac{2m}{r}\right)} dr^2$$

$$-(r)^2 (d\theta^2 + \sin^2(\theta) d\phi^2)$$

Representations **deeply** impact on learning and inference



An **apple** is a sweet, edible fruit produced by an **apple tree** (***Malus pumila***). Apple trees are cultivated worldwide and are the most widely grown species in the genus *Malus*. The tree originated in Central Asia, where its wild ancestor, *Malus sieversii*, is still found today. Apples have been grown for thousands of years in Asia and Europe and were brought to North America by European colonists. Apples have religious and mythological significance in many cultures, including Norse, Greek and European Christian traditions.

Embodied representations

Symbolic representations

"The distinctive feature of brains such as the one we own is <u>their uncanny ability to create maps</u>... But when brains make maps, they are also creating images, the main currency of our minds. Ultimately consciousness allows us to experience maps as images, to manipulate those images, and to apply reasoning to them."

Antonio Damasio (2010)

Semantics

=

Formal meaning representation model (lots of data)

+

inference model

This behaves a lot like intelligence!

> 2000 years of tradition!

Semantics

Logics, linguistics, philosophy, cognitive sciences, computer science

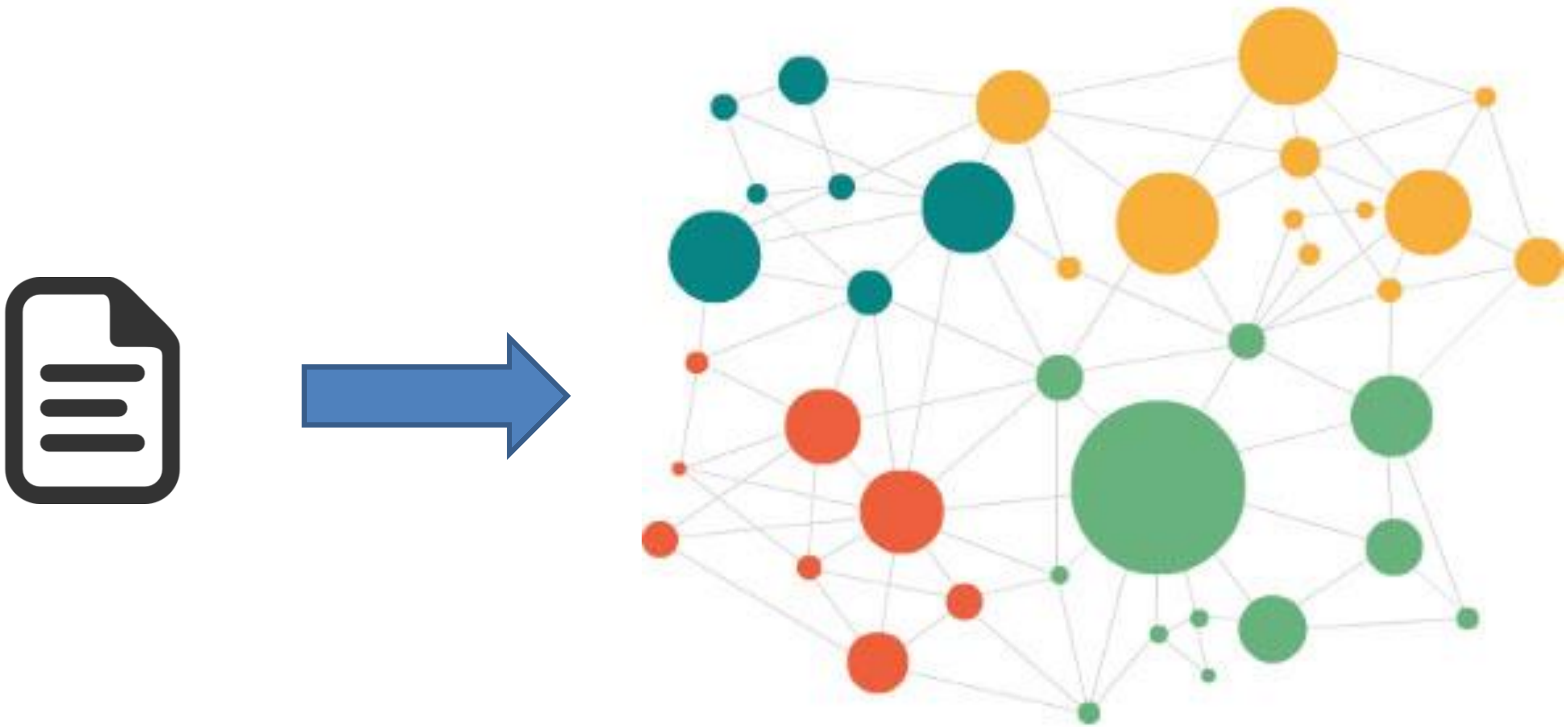
=

Formal meaning representation model (lots of data)

+

inference model

This behaves a lot like intelligence!



Building Knowledge Bases

Data **Intelligence**

Structure/Semantics

Unstructured Data

KB Construction

Structured Data

Easy to generate

Easy to analyze (computationally)

Consistent
Comparable
Processable

From Text to Structure

...
Barack Obama went with his daughter Malia to the baseball game.
...

...
Today, during an official visit, Natasha called to her father, the president of the United States.
...

From Text to Structure

...

Barack Obama went with his daughter **Malia** to the baseball game.

...

...

Today, during an official visit, **Natasha** called to her father, the president of the United States.

...

Named Entity recognition, disambiguation

From Text to Structure

…

Barack Obama went with his daughter **Malia** to the baseball game.

…

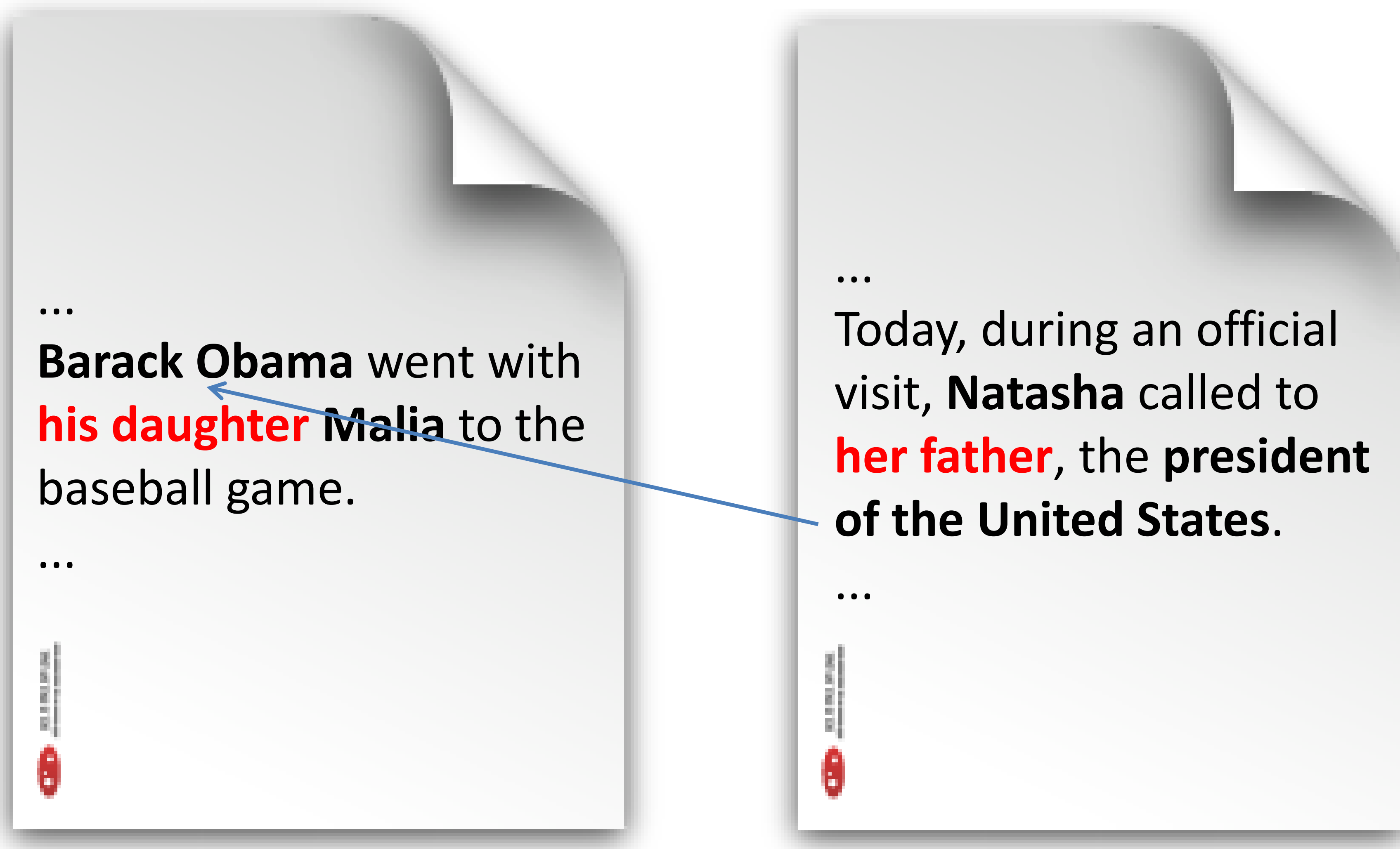
…

Today, during an official visit, **Natasha** called to her father, the **president of the United States**.

…

Co-reference resolution

From Text to Structure



Relation extraction

Regularities in Natural Language

Barack Obama went with his daughter Malia to the baseball game.

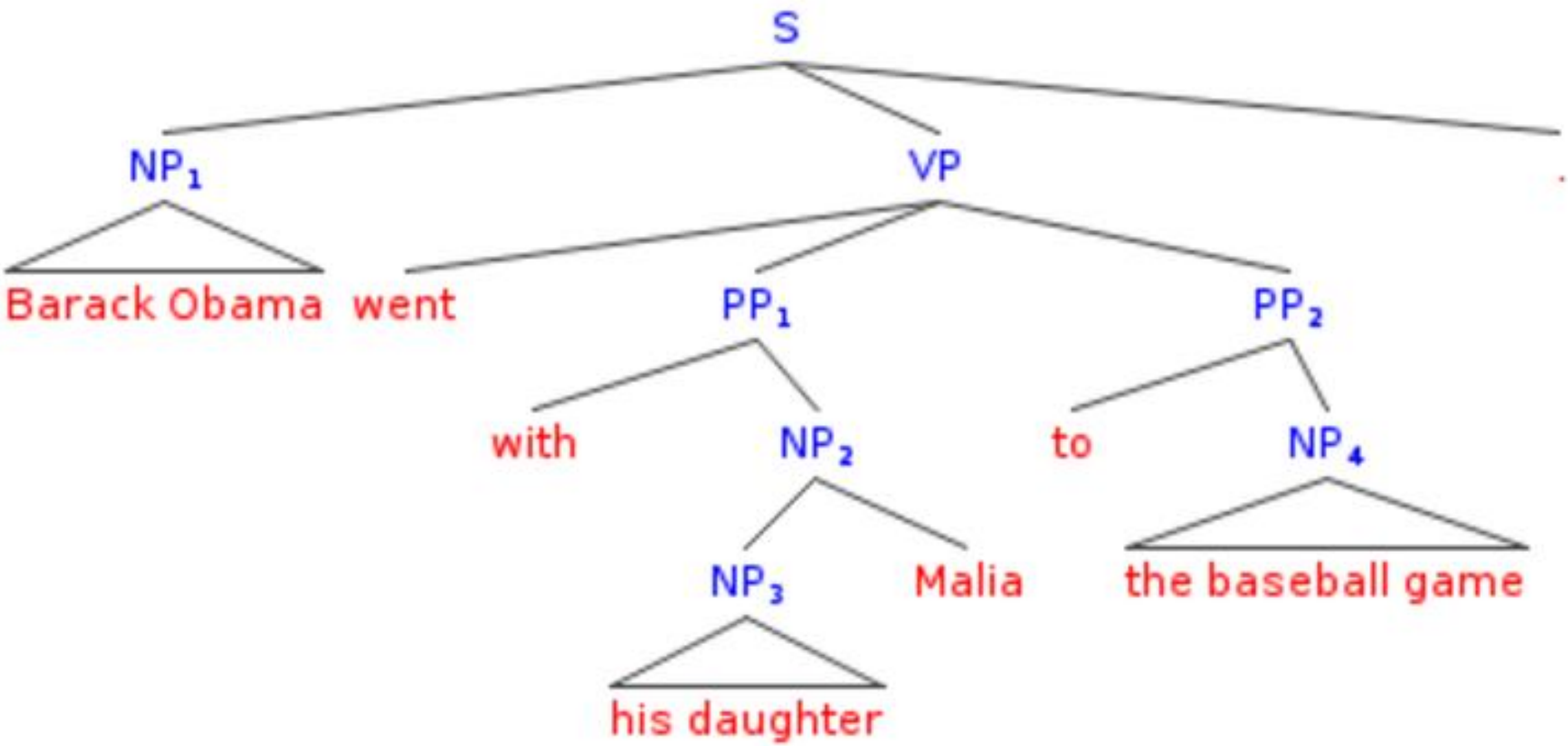
Barack/NNP
Obama/NNP
went/VBD
with/IN
his/PRP$
daughter/NN
Malia/NN
to/TO
the/DT
baseball/NN
game/NN
./.

Regularities in Natural Language

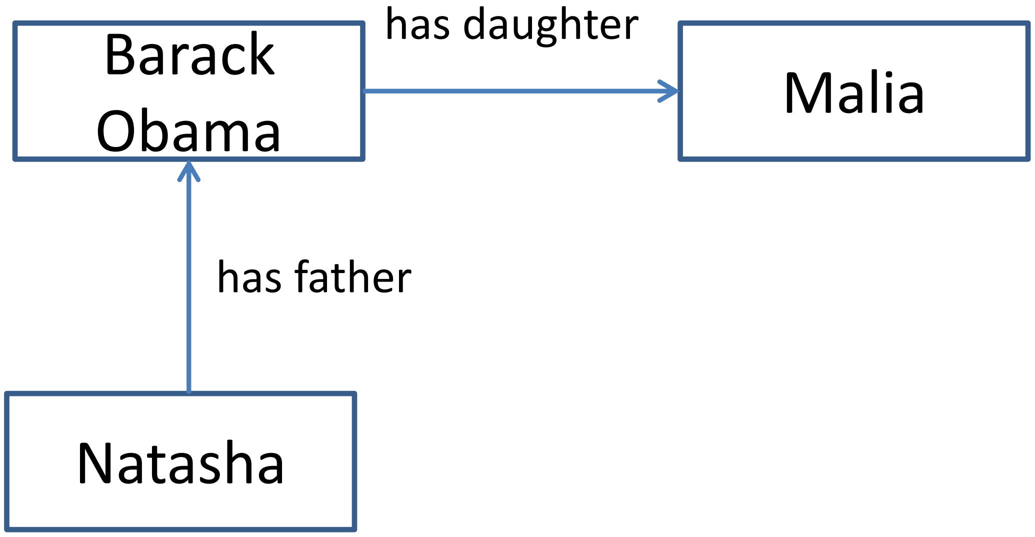
Barack Obama went with his daughter Malia to the baseball game.

Barack/**NNP** → Proper noun
Obama/**NNP**
went/VBD
with/IN
his/PRP$
daughter/NN
Malia/NN
to/TO
the/DT
baseball/NN
game/NN
./.

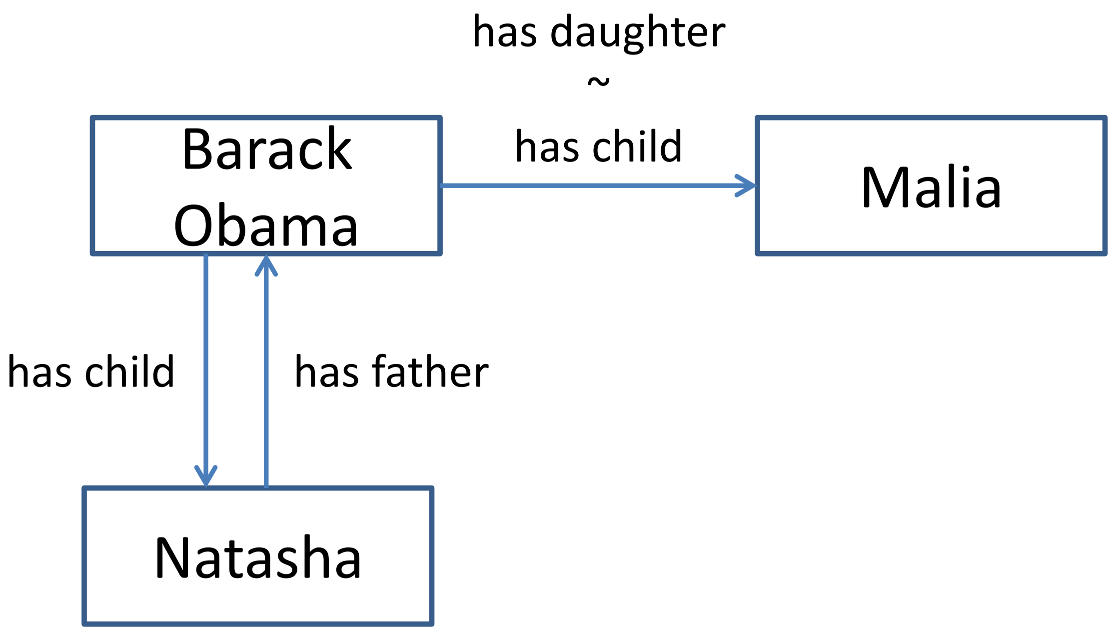
Regularities in Natural Language



Structural/Logical Form



Structural/Logical Form



Applying some logical or corpus-based inference we get ....

Rephrasing it

- has_child(Barack_Obama, Malia)
- has_child(Barack_Obama, Natasha)
- …

Now we can answer this query

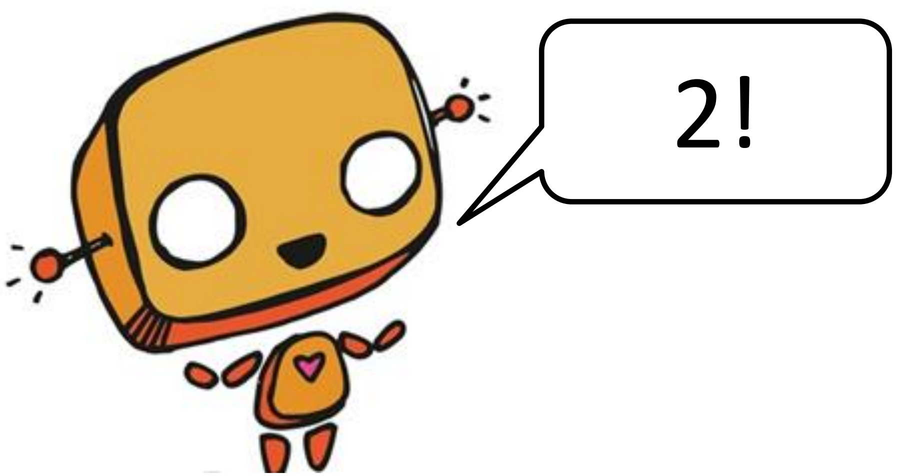
- *How many children does Barack Obama have?*

some magic called **semantic parsing** goes on ...

- count(has_child(Barack_Obama, ?x))

It computes!

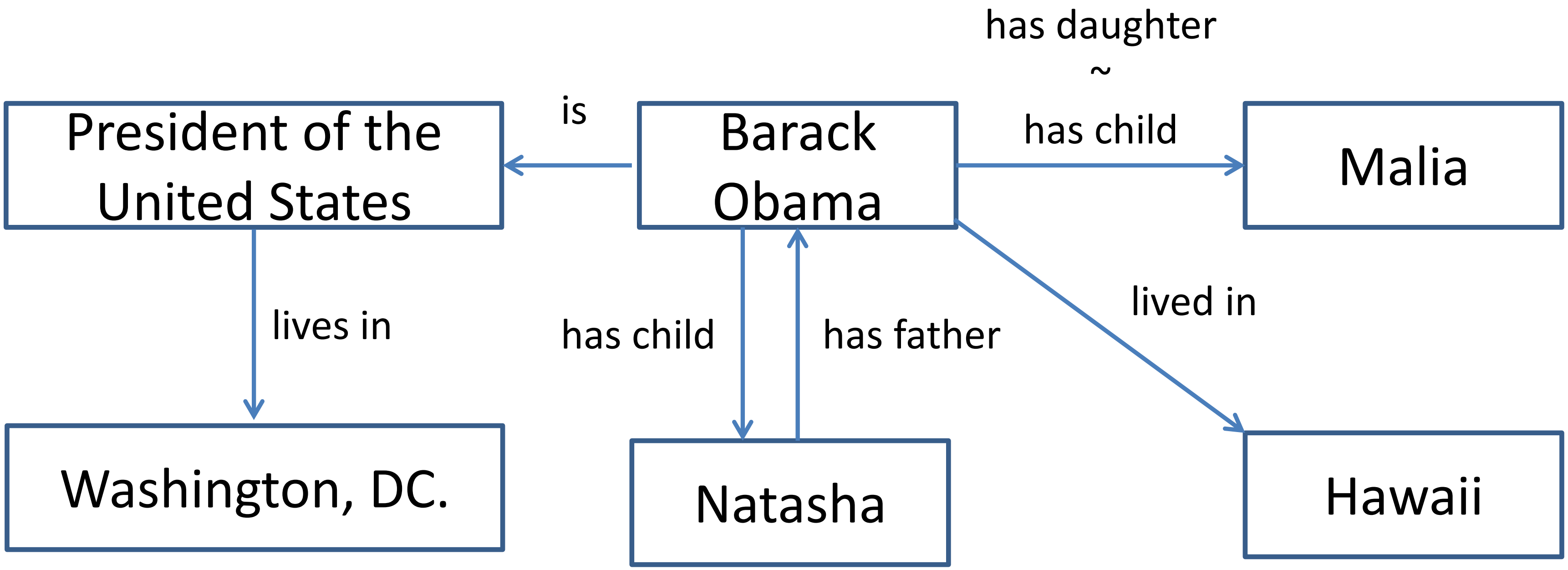
Query: count(has_child(Barack_Obama, ?x))



KB:

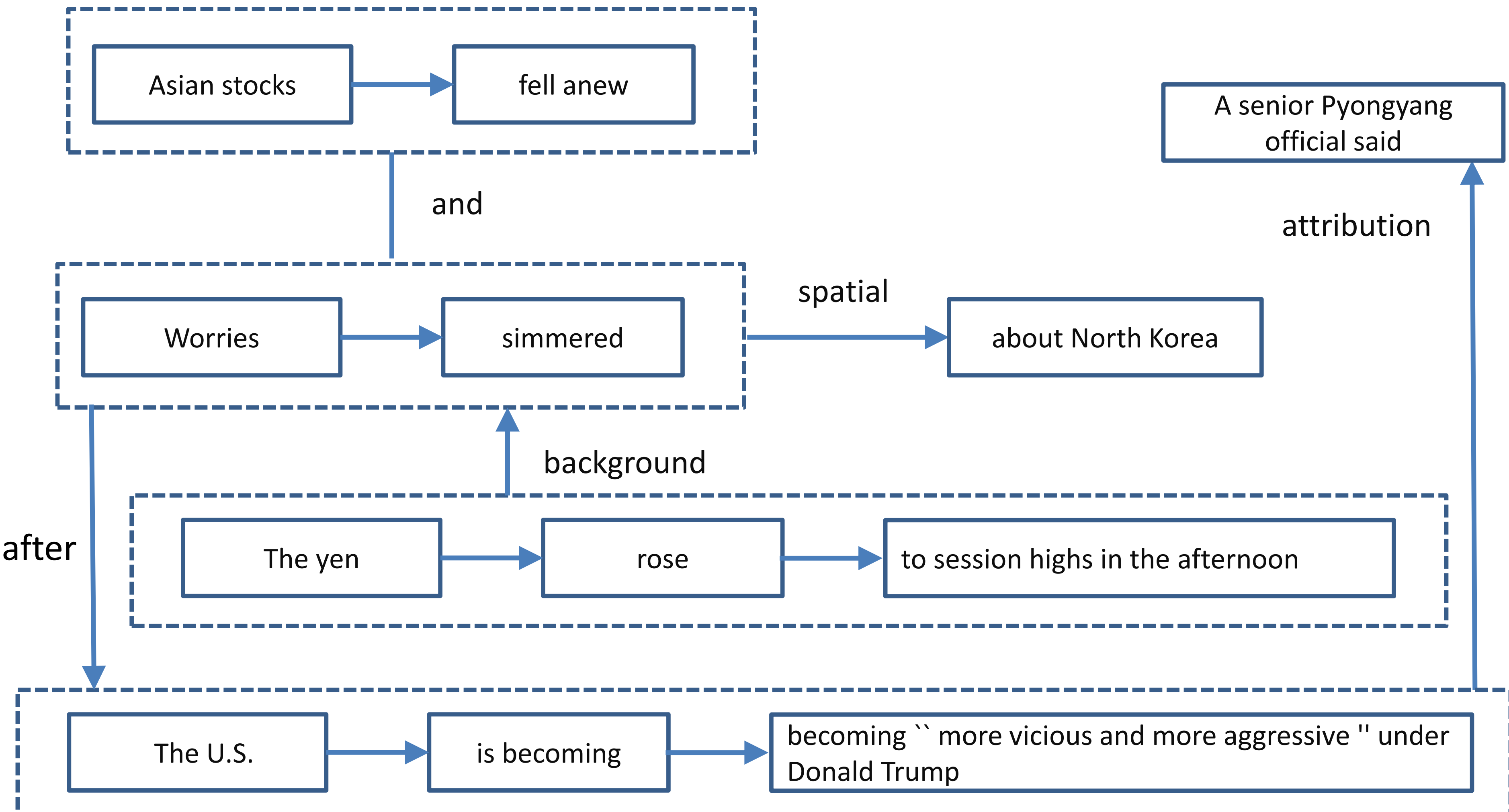
- has_child(Barack_Obama, Malia)
- has_child(Barack_Obama, Natasha)
- …

Extrapolating



Semantic representation

Asian stocks fell anew and the yen rose to session highs in the afternoon as worries about North Korea simmered, after a senior Pyongyang official said the U.S. is becoming ``more vicious and more aggressive'' under President Donald Trump .



Semantic Parsing using CCGs

Language

$$
\begin{array}{ccccc}
\text{show} \quad \text{me} & \text{flights} & \text{to} & \text{Boston} \\
\hline
S/N & N & PP/NP & NP \\
\lambda f.f & \lambda x.flight(x) & \lambda y.\lambda x.to(x,y) & BOSTON \\
\end{array}
$$

$$
\frac{PP/NP \quad NP}{PP} > \qquad \lambda x.to(x, BOSTON)
$$

$$
\frac{PP}{N\backslash N} \qquad \lambda f.\lambda x.f(x) \wedge to(x, BOSTON)
$$

$$
\frac{N \quad N\backslash N}{N} < \qquad \lambda x.flight(x) \wedge to(x, BOSTON)
$$

$$
\frac{S/N \quad N}{S} > \qquad \lambda x.flight(x) \wedge to(x, BOSTON)
$$

Structure

Artzi

Symbol

Tree

Tree is the name of a set

Tree is a noun

Any cognitive representation for long, vertical, usually green with a wood basis

Some Goal

Similarity, discrimination

Representation

Structure of the Reality

Symbol

Tree

Extension
of the set

Any cognitive
representation
for long,
vertical,
usually green
with a wood
basis

**Some
Goal**

Similarity,
discrimination

Representation

Structure of the Reality

Operating on the Representation

Symbol

Tree

The tallest tree

Some Goal

Similarity, discrimination

Any cognitive representation for long, vertical, usually green with a wood basis

Representation

Structure of the Reality

Operating on the Representation

Definite article: "get me one"

Symbol

Tree

The tallest tree

Some Goal

Any cognitive representation for long, vertical, usually green with a wood basis

Similarity, discrimination

Representation

Structure of the Reality

Operating on the Representation

Superlative adjective : “top most”

Symbol

Tree

The **tallest** tree

Any cognitive representation for long, vertical, usually green with a wood basis

Some Goal

Similarity, discrimination

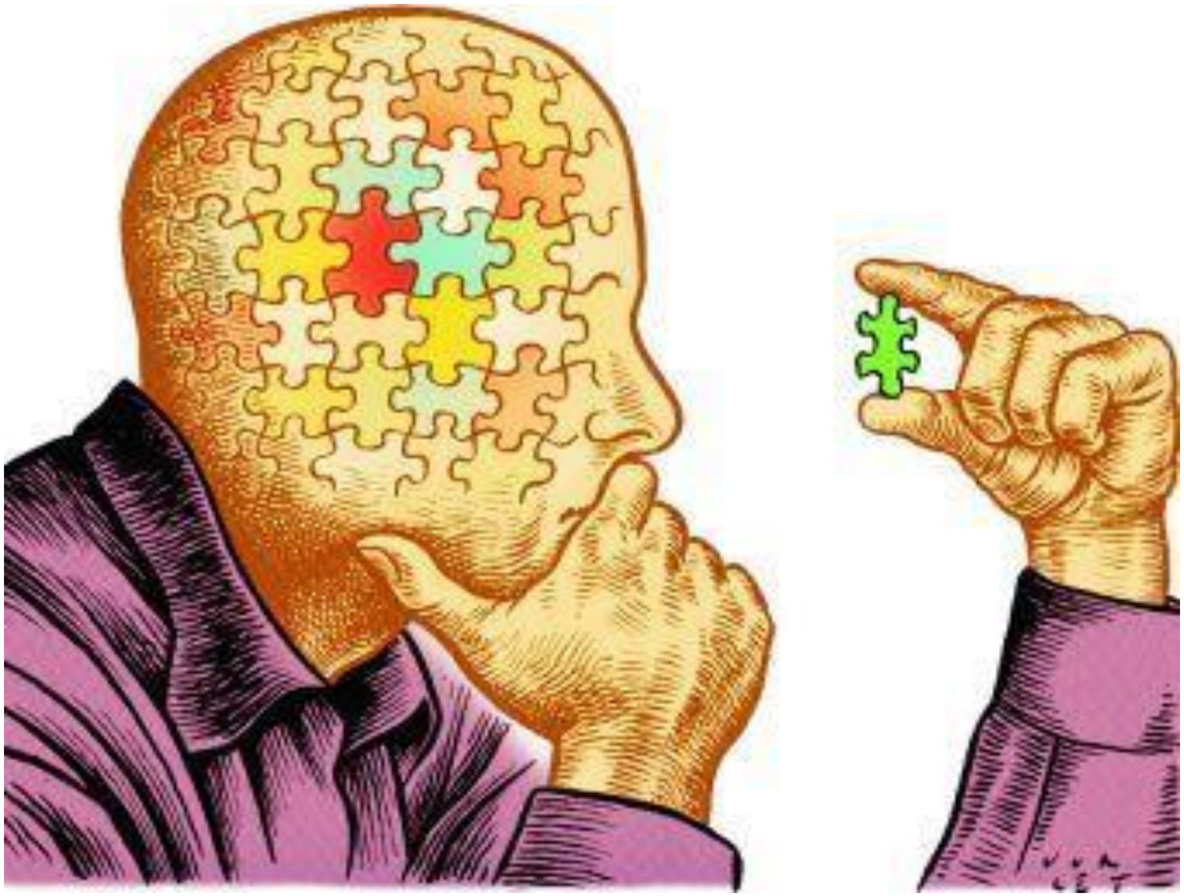
Representation

Structure of the Reality

Natural Language ⟺ Representation

- There is a mapping between natural language and knowledge representation.

- Looking at natural language is looking at the representation (constrained by the communication medium).



Knowledge & Inference

Reasoning

Should you take COMP24412?...

Let us represent the knowledge we have about the course and then see what follows (logically).

Representing some Knowledge

The Facts

COMP24412 teaches Logic
COMP24412 is about AI
Prolog is a programming language
COMP24412 teaches Prolog
AI is cool
Yachts cost lots of money

The Rules

If you take a course and it teaches X then you know X
If you take a course about X and X is cool then you are cool
If you know a programming language then you can program
If you can program and know logic you can get a good job
If you have a good job you get lots of money
If you have X and Y costs X then you can have Y

Reger

Representing some Knowledge

The Facts

teaches(COMP24412, Logic)	COMP24412 teaches Prolog
COMP24412 is about AI	AI is cool
Prolog is a programming language	Yachts cost lots of money

The Rules

If you take a course and it teaches X then you know X
If you take a course about X and X is cool then you are cool
If you know a programming language then you can program
If you can program and know logic you can get a good job
If you have a good job you get lots of money
If you have X and Y costs X then you can have Y

Reger

Representing some Knowledge

The Facts

teaches(COMP24412, Logic) teaches(COMP24412, Prolog)
about(COMP24412, AI) cool(AI)
language(Prolog) costs(Yacht, LotsOfMoney)

The Rules

If you take a course and it teaches X then you know X
If you take a course about X and X is cool then you are cool
If you know a programming language then you can program
If you can program and know logic you can get a good job
If you have a good job you get lots of money
If you have X and Y costs X then you can have Y

Reger

Representing some Knowledge

The Facts

$$\text{teaches}(\text{COMP24412}, \text{Logic}) \quad \text{teaches}(\text{COMP24412}, \text{Prolog})$$
$$\text{about}(\text{COMP24412}, \text{AI}) \quad \text{cool}(\text{AI})$$
$$\text{language}(\text{Prolog}) \quad \text{costs}(\text{Yacht}, \text{LotsOfMoney})$$

The Rules

$$\text{take}(U, C) \land \text{teaches}(C, X) \Rightarrow \text{know}(U, X)$$

If you take a course about X and X is cool then you are cool

If you know a programming language then you can program

If you can program and know logic you can get a good job

If you have a good job you get lots of money

If you have X and Y costs X then you can have Y

Reger

Inferring some more Knowledge

The Facts

$$\text{teaches}(\text{COMP24412}, \text{Logic}) \quad \text{teaches}(\text{COMP24412}, \text{Prolog})$$
$$\text{about}(\text{COMP24412}, \text{AI}) \quad \text{cool}(\text{AI})$$
$$\text{language}(\text{Prolog}) \quad \text{costs}(\text{Yacht}, \text{LotsOfMoney})$$

The Rules

$$\text{take}(U, C) \land \text{teaches}(C, X) \Rightarrow \text{know}(U, X)$$
$$\text{take}(U, C) \land \text{about}(C, X) \land \text{cool}(X) \Rightarrow \text{cool}(U)$$
$$\text{know}(U, X) \land \text{language}(X) \Rightarrow \text{canProgram}(U)$$
$$\text{canProgram}(U) \land \text{know}(U, \text{Logic}) \Rightarrow \text{hasGoodJob}(U)$$
$$\text{hasGoodJob}(U) \Rightarrow \text{has}(U, \text{LotsOfMoney})$$
$$\text{has}(U, X) \land \text{costs}(Y, X) \Rightarrow \text{has}(U, Y)$$

Reger

Inferring some more Knowledge

$$\text{teaches}(\text{COMP24412}, \text{Logic}) \quad \text{teaches}(\text{COMP24412}, \text{Prolog})$$
$$\text{about}(\text{COMP24412}, \text{AI}) \quad \text{cool}(\text{AI})$$
$$\text{language}(\text{Prolog}) \quad \text{costs}(\text{Yacht}, \text{LotsOfMoney})$$

$$\text{take}(U, C) \wedge \text{teaches}(C, X) \Rightarrow \text{know}(U, X)$$
$$\text{take}(U, C) \wedge \text{about}(C, X) \wedge \text{cool}(X) \Rightarrow \text{cool}(U)$$
$$\text{know}(U, X) \wedge \text{language}(X) \Rightarrow \text{canProgram}(U)$$
$$\text{canProgram}(U) \wedge \text{know}(U, \text{Logic}) \Rightarrow \text{hasGoodJob}(U)$$
$$\text{hasGoodJob}(U) \Rightarrow \text{has}(U, \text{LotsOfMoney})$$
$$\text{has}(U, X) \wedge \text{costs}(Y, X) \Rightarrow \text{has}(U, Y)$$

$$\text{take}(\text{you}, \text{COMP24412})$$

Reger

Inferring some more Knowledge

$\text{teaches}(\text{COMP24412}, \text{Logic})$ $\text{teaches}(\text{COMP24412}, \text{Prolog})$

$\text{about}(\text{COMP24412}, \text{AI})$ $\text{cool}(\text{AI})$

$\text{language}(\text{Prolog})$ $\text{costs}(\text{Yacht}, \text{LotsOfMoney})$

$$\text{take}(U, C) \wedge \text{teaches}(C, X) \Rightarrow \text{know}(U, X)$$
$$\text{take}(U, C) \wedge \text{about}(C, X) \wedge \text{cool}(X) \Rightarrow \text{cool}(U)$$
$$\text{know}(U, X) \wedge \text{language}(X) \Rightarrow \text{canProgram}(U)$$
$$\text{canProgram}(U) \wedge \text{know}(U, \text{Logic}) \Rightarrow \text{hasGoodJob}(U)$$
$$\text{hasGoodJob}(U) \Rightarrow \text{has}(U, \text{LotsOfMoney})$$
$$\text{has}(U, X) \wedge \text{costs}(Y, X) \Rightarrow \text{has}(U, Y)$$

$\text{take}(\text{you}, \text{COMP24412})$

$\text{know}(\text{you}, \text{Logic})$ $\text{know}(\text{you}, \text{Prolog})$

Reger

Inferring some more Knowledge

$\text{teaches}(\text{COMP24412}, \text{Logic})$ $\text{teaches}(\text{COMP24412}, \text{Prolog})$
$\text{about}(\text{COMP24412}, \text{AI})$ $\text{cool}(\text{AI})$
$\text{language}(\text{Prolog})$ $\text{costs}(\text{Yacht}, \text{LotsOfMoney})$

$$\text{take}(U, C) \wedge \text{teaches}(C, X) \Rightarrow \text{know}(U, X)$$
$$\text{take}(U, C) \wedge \text{about}(C, X) \wedge \text{cool}(X) \Rightarrow \text{cool}(U)$$
$$\text{know}(U, X) \wedge \text{language}(X) \Rightarrow \text{canProgram}(U)$$
$$\text{canProgram}(U) \wedge \text{know}(U, \text{Logic}) \Rightarrow \text{hasGoodJob}(U)$$
$$\text{hasGoodJob}(U) \Rightarrow \text{has}(U, \text{LotsOfMoney})$$
$$\text{has}(U, X) \wedge \text{costs}(Y, X) \Rightarrow \text{has}(U, Y)$$

$\text{take}(\text{you}, \text{COMP24412})$

$\text{know}(\text{you}, \text{Logic})$ $\text{know}(\text{you}, \text{Prolog})$

Reger

Inferring some more Knowledge

teaches(COMP24412, Logic) teaches(COMP24412, Prolog)
about(COMP24412, AI) cool(AI)
language(Prolog) costs(Yacht, LotsOfMoney)

$$\mathrm{take}(U, C) \land \mathrm{teaches}(C, X) \Rightarrow \mathrm{know}(U, X)$$
$$\mathrm{take}(U, C) \land \mathrm{about}(C, X) \land \mathrm{cool}(X) \Rightarrow \mathrm{cool}(U)$$
$$\mathrm{know}(U, X) \land \mathrm{language}(X) \Rightarrow \mathrm{canProgram}(U)$$
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take(you, COMP24412)
know(you, Logic) know(you, Prolog) cool(you)

Reger

Inferring some more Knowledge

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$\text{about}(\text{COMP24412}, \text{AI})$ $\text{cool}(\text{AI})$
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Reger

In Prolog

- Convert the previous KB into Prolog.
- Does it work?

You can use SWISH:

https://swish.swi-prolog.org/example/kb.pl

Inductive Logic Programming

- ILP algorithms are constructive induction algorithms
  - Able to create new predicates to facilitate the expression of explanatory hypotheses

- Express Grandparent
  - Empty background
  - Hypotheses are long and complicated

$$
\begin{aligned}
\text{Grandparent}(x, y) \Leftrightarrow\ & [\exists z\ \text{Mother}(x, z) \wedge \text{Mother}(z, y)] \\
\vee\ & [\exists z\ \text{Mother}(x, z) \wedge \text{Father}(z, y)] \\
\vee\ & [\exists z\ \text{Father}(x, z) \wedge \text{Mother}(z, y)] \\
\vee\ & [\exists z\ \text{Father}(x, z) \wedge \text{Father}(z, y)]
\end{aligned}
$$

Chu

Inductive Logic Programming

- By creating a new predicate, the definition of Grandparent can be reduced

$$\text{Parent}(x, y) \Leftrightarrow [\text{Mother}(x, y) \vee \text{Father}(x, y)]$$
$$\text{Grandparent}(x, y) \Leftrightarrow [\exists z\ \text{Parent}(x, z) \wedge \text{Parent}(z, y)]$$

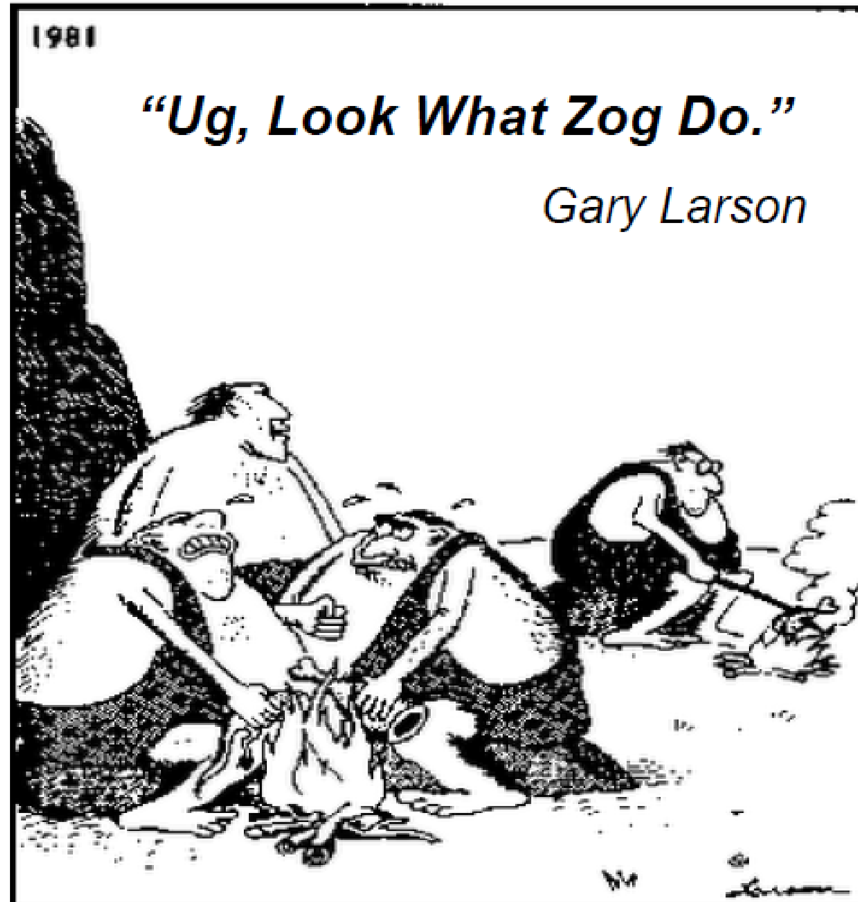
- Background knowledge can reduce the size of hypotheses required to explain the observations

- Why?

Chu

Inference & Explanation

- **Explanation-based Learning (EBL)**
  - Method for extracting rules from individual observations through an explanation.
- **Explanation**
  - Stick holds the food over the fire while keeping hands safe.
- **Generalization**
  - Any long, rigid, sharp object can be used to toast food over the fire.
  - General rule follows logically from the background knowledge of the cavemen's usual cooking process.



Chu

Inference & Explanation

Q: A student climbs up a rocky mountain trail in Maine. She sees many small pieces of rock on the path. <u>Which action most likely made the small pieces of rock?</u>

[0]: sand blowing into cracks

[1]: leaves pressing down tightly

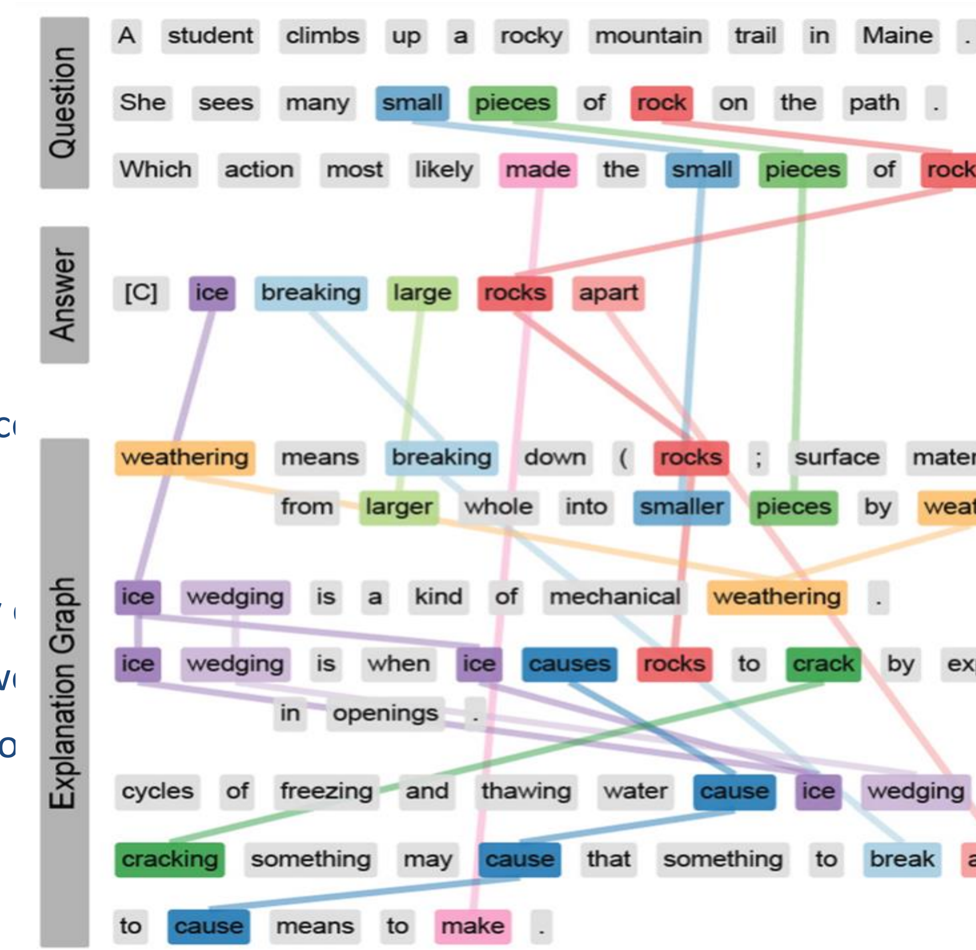
[2]: ice breaking large rocks apart

[3]: shells and bones sticking together

A: ice breaking large rocks apart

Explanation:

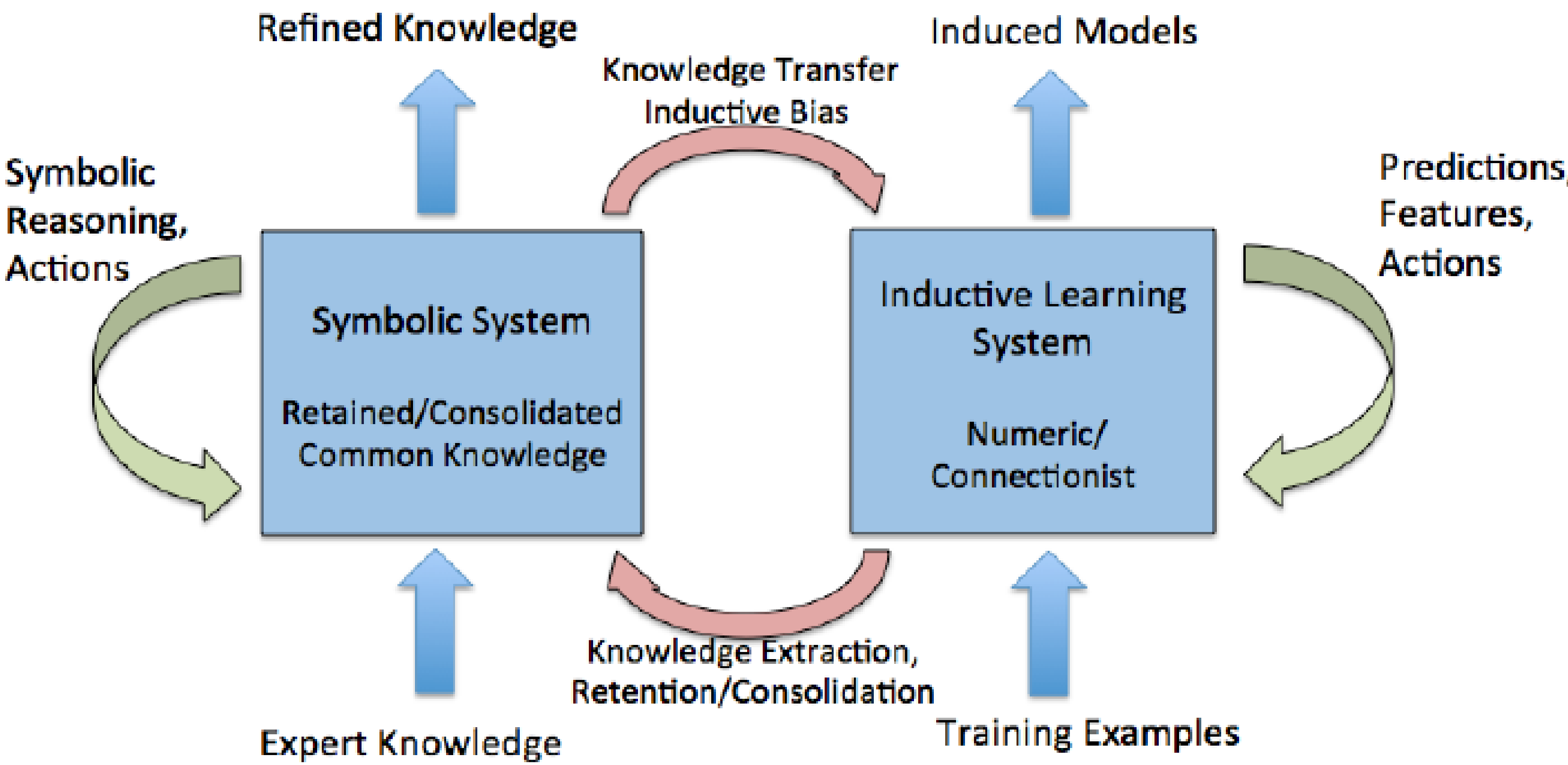
- weathering means breaking down (rocks ; surfac
weather
- ice wedging is a kind of mechanical weathering
- ice wedging is when ice causes rocks to crack by
- cycles of freezing and thawing water cause ice w
- cracking something may cause that something to
- to cause means to make



Jansen, Peter A., et al. "Worldtree: A corpus of explanation graphs for elementary science questions supporting multi-hop inference." *arXiv preprint arXiv:1802.03052* (2018).

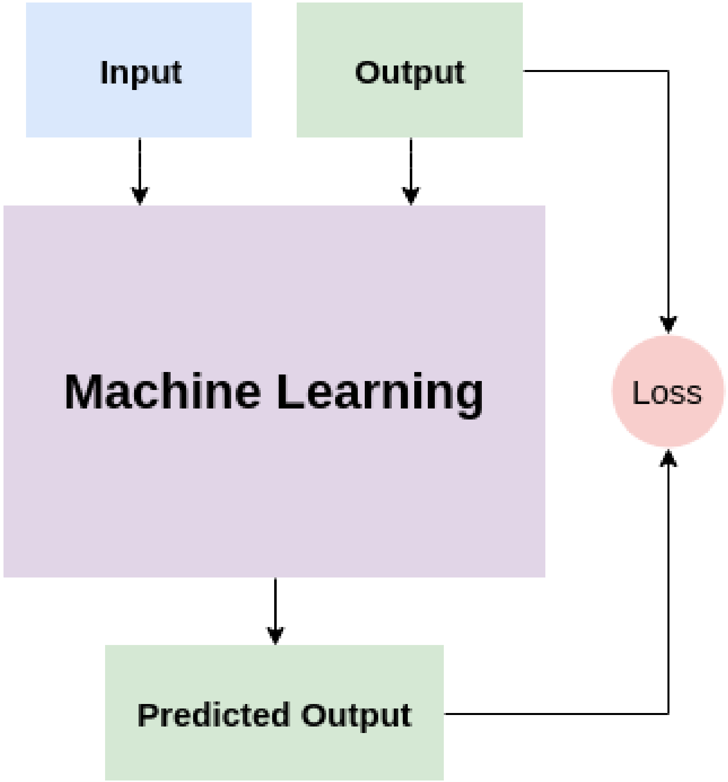
Going Beyond

Neuro-Symbolic Models



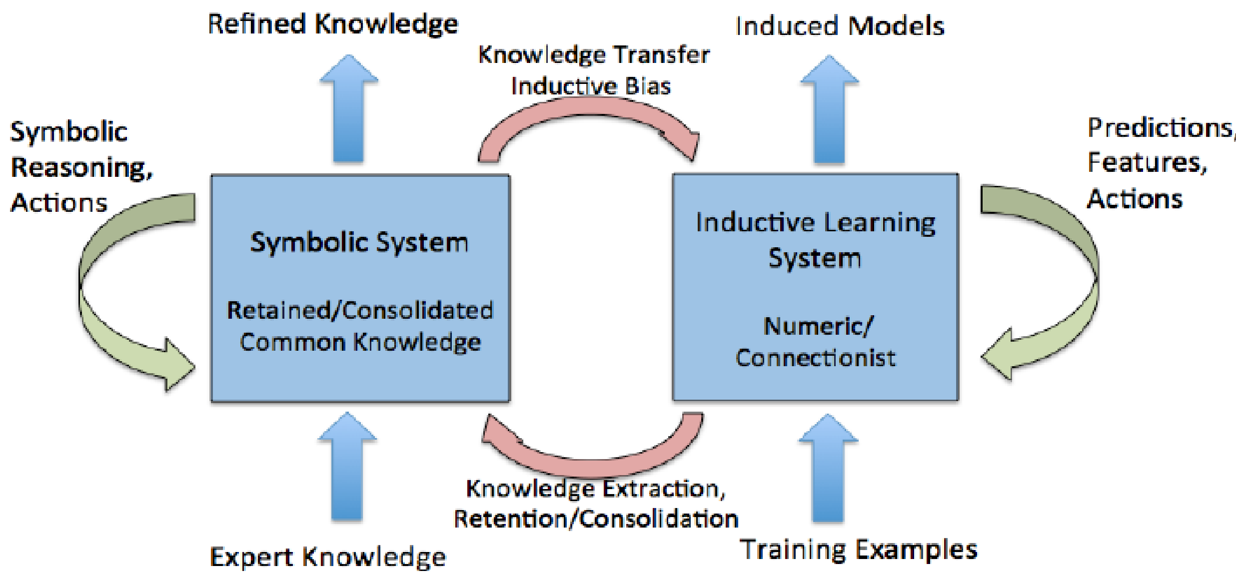
Current Limits of Deep Learning

1. Deep learning thus far is data hungry
2. Deep learning thus far is shallow and has limited capacity for transfer
3. Deep learning thus far has no natural way to deal with hierarchical structure
4. Deep learning thus far is not sufficiently transparent
5. Deep learning thus far has not been well integrated with prior knowledge
6. Deep learning thus far cannot inherently distinguish causation from correlation
7. Deep learning presumes a largely stable world, in ways that may be problematic
8. Deep learning thus far works well as an approximation, but its answers often cannot be fully trusted
9. Deep learning thus far is difficult to engineer with



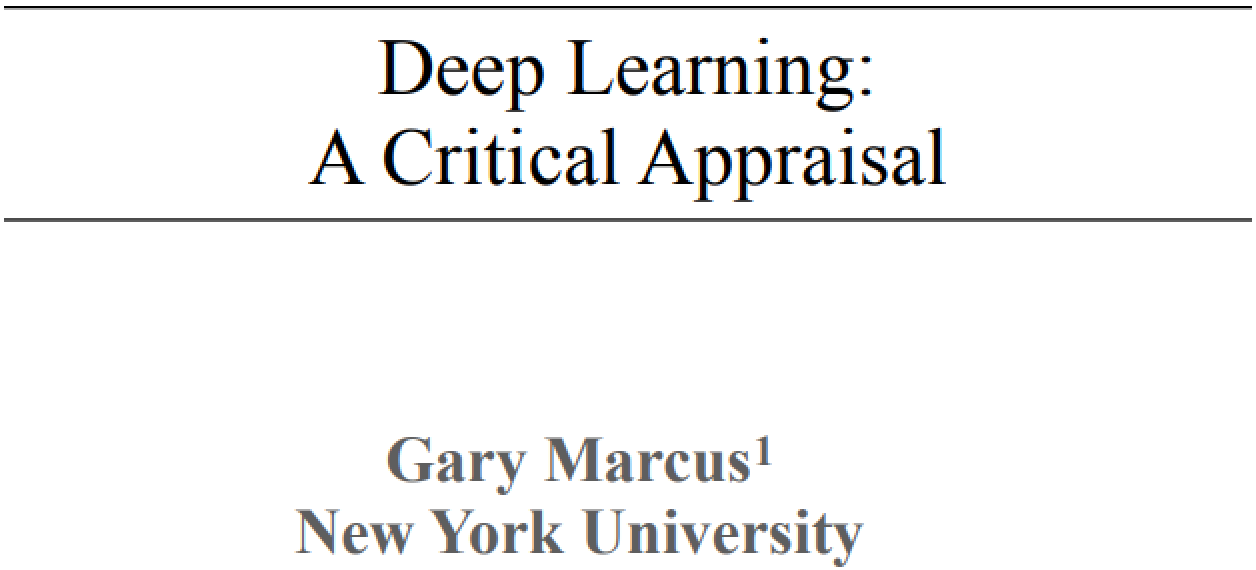
Marcus, Gary. "Deep learning: A critical appraisal." *arXiv preprint arXiv:1801.00631* (2018).

Statistical vs Symbolic AI Systems



	Statistical	Symbolic
Explainability	Hard	Easy
Generalizing algebraic operations	Hard	Easy
Robustness to noise	Easy	Hard
Robustness to ambiguity	Easy	Hard
Robustness to mislabeling	Easy	Hard

Recommended Reading


Deep Learning:
A Critical Appraisal

Gary Marcus[1]
New York University

https://arxiv.org/ftp/arxiv/papers/1801/1801.00631.pdf

Summary of Today

- Motivation behind Symbolic AI.
- Link between Language, Representation and Inference.
- End-to-end overview of the components of the course.

Complementary Reference Slides

Knowledge in Learning

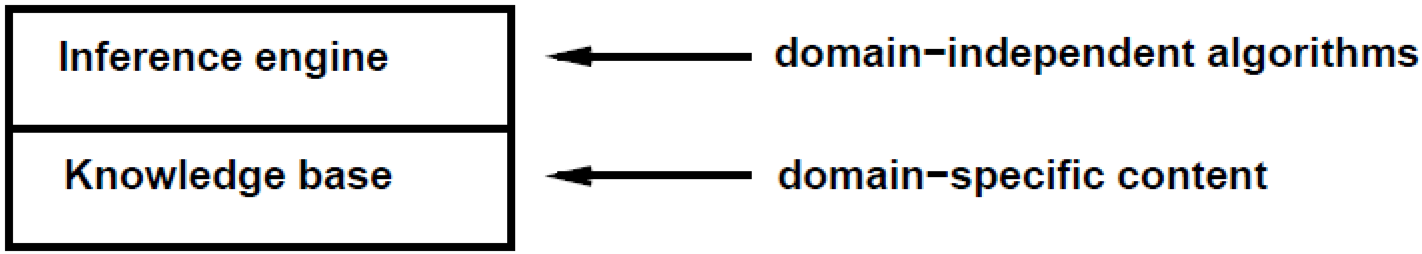
- Task: to design agents that already know something, and are trying to learn more.

- Agents must have a learning process to gain the background knowledge in the first place
  – Learning taken place afterwards define the agent's incremental/cumulative development

- Agents can start off like normal agents
  – Gain initial knowledge through inductive learning
  – After, uses background knowledge to learn more effectively

Russell & Norvig

Knowledge Bases



- Knowledge base = set of sentences in a formal language
- Declarative approach to building an agent (or other system):
  – Tell it what it needs to know
- Then it can Ask itself what to do|answers should follow from the KB
- Agents can be viewed at the knowledge level
  – i.e., what they know, regardless of how implemented
- Or at the implementation level
  – i.e., data structures in KB and algorithms that manipulate them

Russell & Norvig

KB Agent

function KB-AGENT(*percept*) **returns** an *action*
  static: *KB*, a knowledge base
    t, a counter, initially 0, indicating time

  TELL(*KB*, MAKE-PERCEPT-SENTENCE(*percept*, *t*))
  action ← ASK(*KB*, MAKE-ACTION-QUERY(*t*))
  TELL(*KB*, MAKE-ACTION-SENTENCE(*action*, *t*))
  $t \leftarrow t + 1$
  return *action*

Russell & Norvig

A simple knowledge-based agent

- The agent must be able to:
  - Represent states, actions, etc.
  - Incorporate new percepts
  - Update internal representations of the world
  - Deduce hidden properties of the world
  - Deduce appropriate actions

- => sound and complete reasoning with partial information states

Russell & Norvig