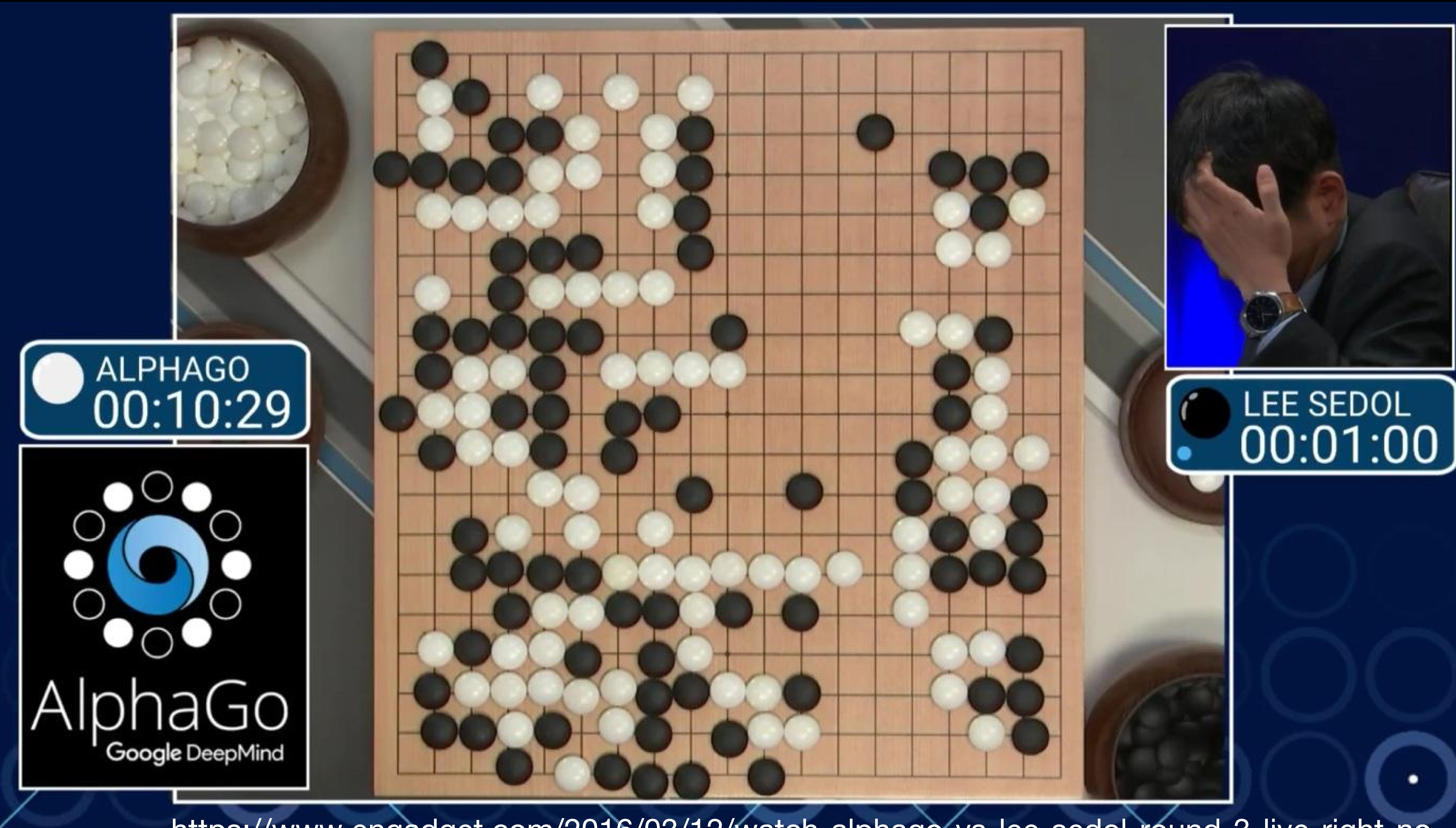
Aristo: Allen AI Challenge

Jeroen Craps
Jorik De Waen

1996: Deep Blue

VS

2016: AlphaGo



https://www.engadget.com/2016/03/12/watch-alphago-vs-lee-sedol-round-3-live-right-now/

Are these computers
smarter than humans?

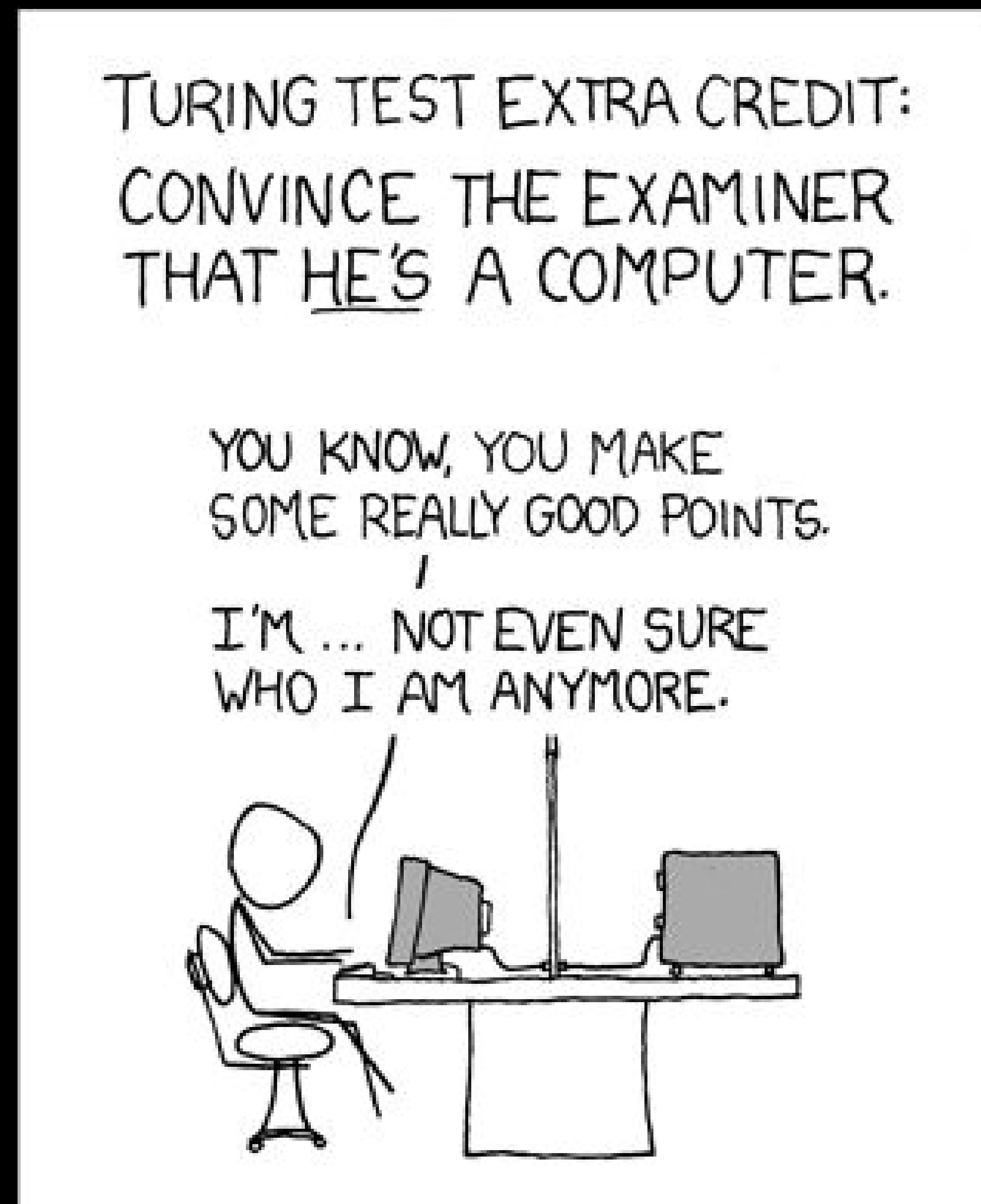
Are these computers
INTELLIGENT?

Turing test

Inventor: Alan Turing

Year: 1950

Test: Convince a human that it is chatting with another human instead of a computer



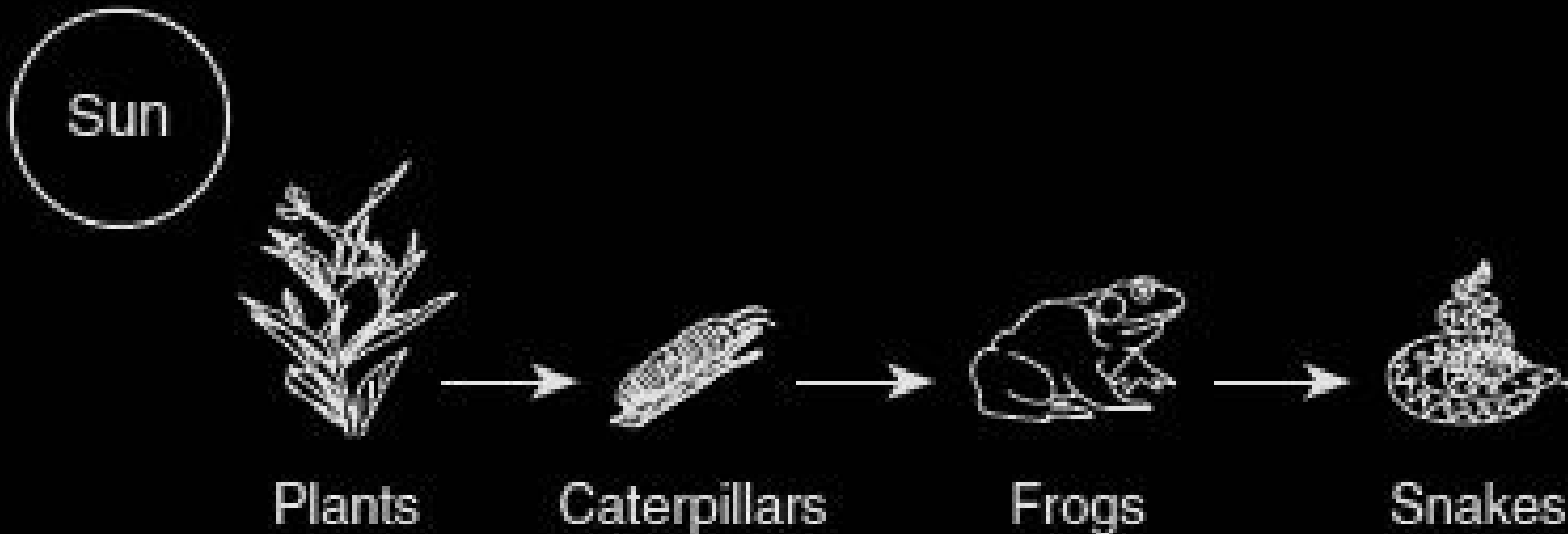
https://xkcd.com/329/

If a computer can
solve the Turing test,
is it truly intelligent?

If a computer can
solve the Turing test,
is it truly intelligent?

No.

An example



(Not drawn to scale)

If the population of snakes increases, the population of frogs will most likely

(A) decrease
(B) increase
(C) remain the same

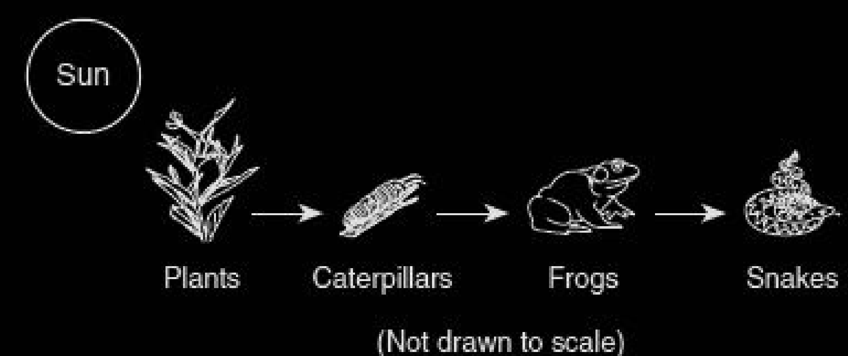
http://aristo-demo.allenai.org

An example

Target: 4th grader

Goal: Interpreting a figure and world modelling

Problem: Not factoid questions and requires language understanding



If the population of snakes increases, the population of frogs will most likely

(A) decrease
(B) increase
(C) remain the same

Expectations

Wide variety of questions	Complex questions
Commonsense and world knowledge	Acquire knowledge scalably

Why 4th grade tests?

Measurable ✓

Graduated ✓

Not game-able ✓

Ambitious but realistic ✓

Motivating ✓

Tackling the problem

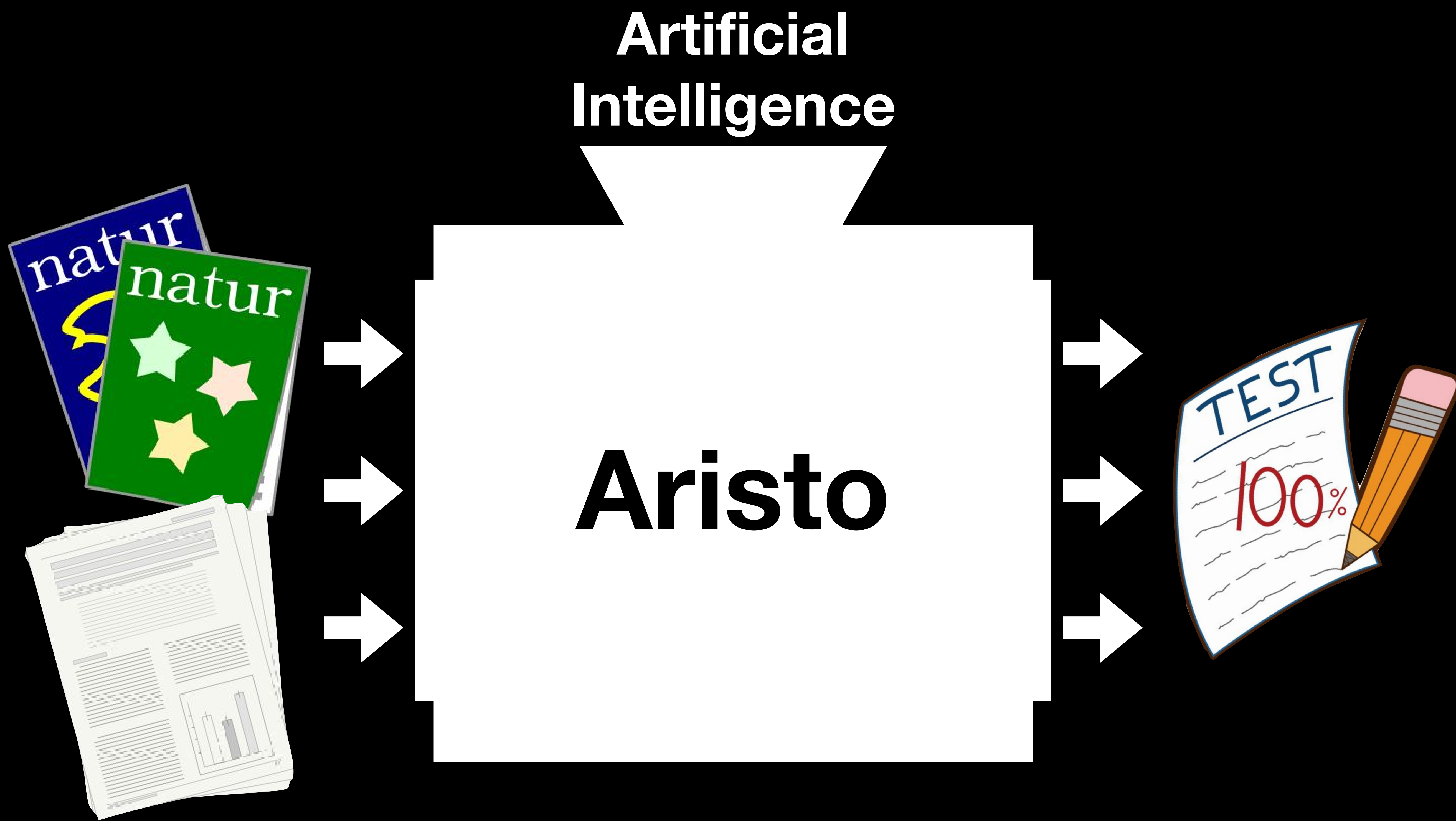


IMAGE RETRIEVAL

TEXT-BASED KNOWLEDGE EXTRACTION

PDFFigures2.0

Input: Scientific papers

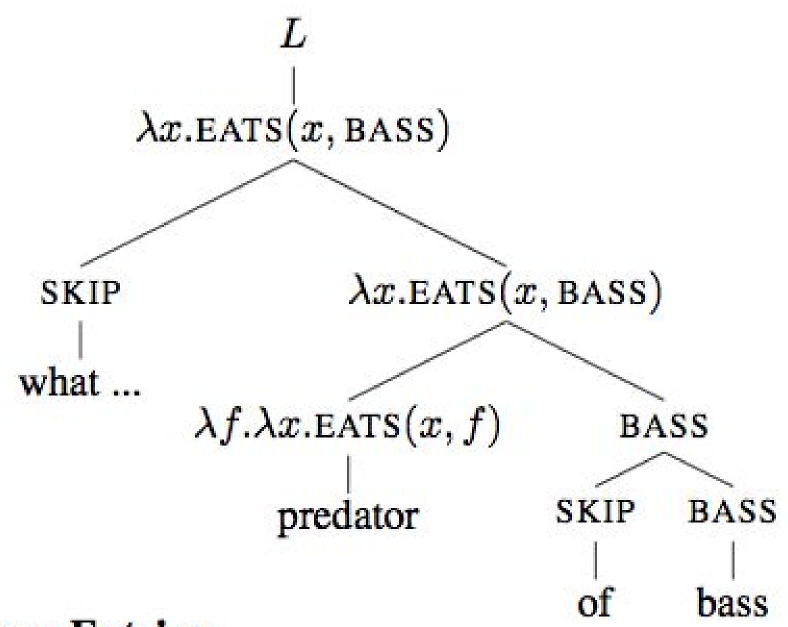
Step 1: Find the caption (keywords)
↳ Removing false positives (filters)

PDFFigures2.0

Removing false positives (filters)

1. All caps
2. Abbreviated
3. Occupy a single line
4. Uncommon font
5. Left aligned to the text beneath them

PDFFigures2.0



Lexicon Entries:
predator := N/NP : $\lambda f.\lambda x.\text{EATS}(x, f)$
bass := NP : BASS

Figure 1: Parse tree of a training example and the lexicon entries derived from it.

the parser and thereby determines the set of meaning representations that can be produced for any given sentence. Therefore, a good lexicon is necessary to achieve both high accuracy and parsing speed. However, the lexicon is unobserved in real semantic parsing applications, leading us to ask: *how do we learn a lexicon for a semantic parser?*

PDFFigures2.0

Input: Scientific papers

Step 1: Find the caption (keywords)

Step 2: Classify regions
↳ Text on position (filters)
↳ Images on tags in metadata

PDFFigures2.0

Classify figure text:

1. Graphic Overlap
2. Vertical Text
3. Wide-Spaced Text (Tables)
4. Line Width
5. Small Font
6. Margin Alignment

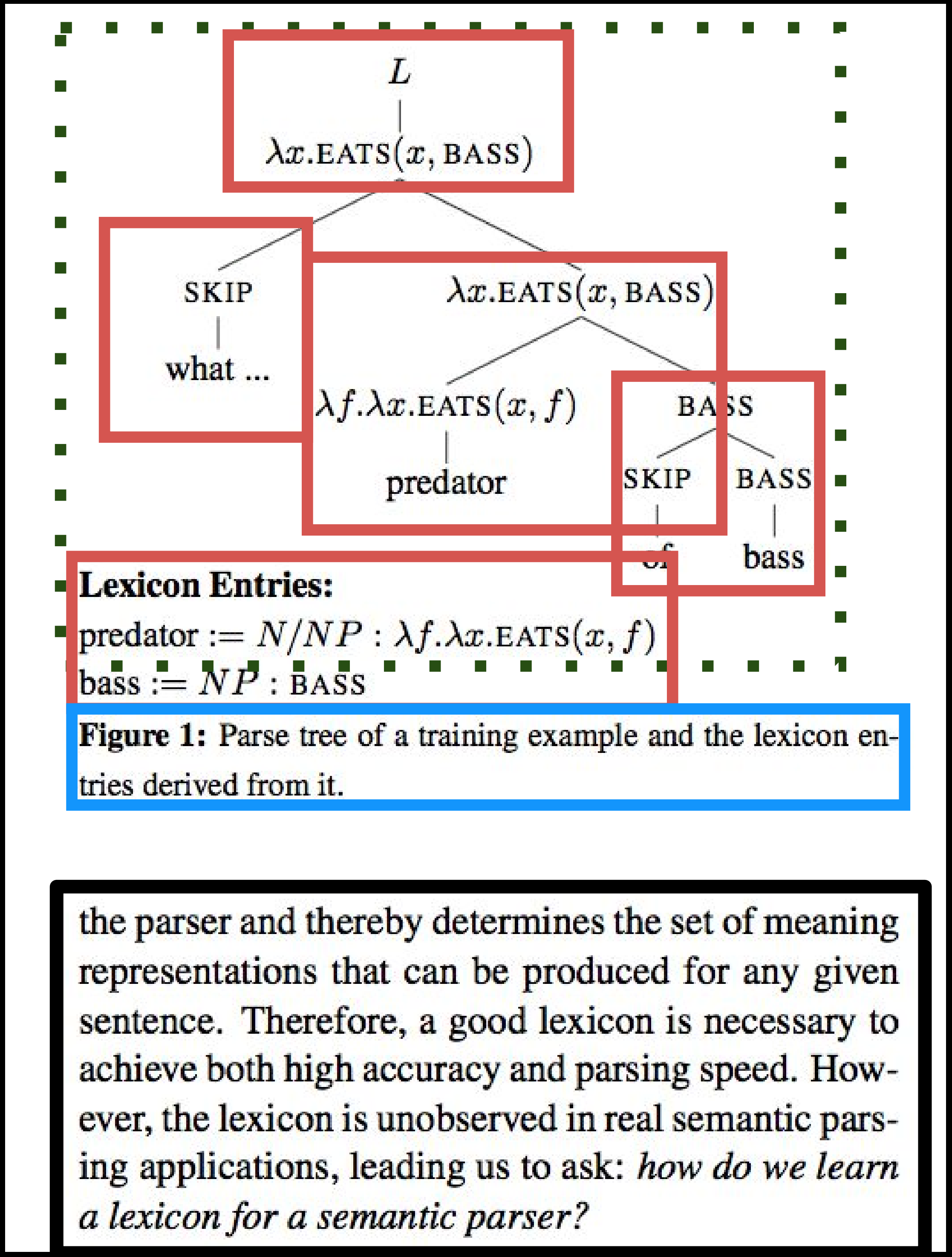
PDFFigures2.0

Input: Scientific papers

Step 1: Find the caption (keywords)

Step 2: Classify regions
↳ Text on position (filters)
↳ Images on tags in metadata

PDFFigures2.0



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PDFFigures2.0

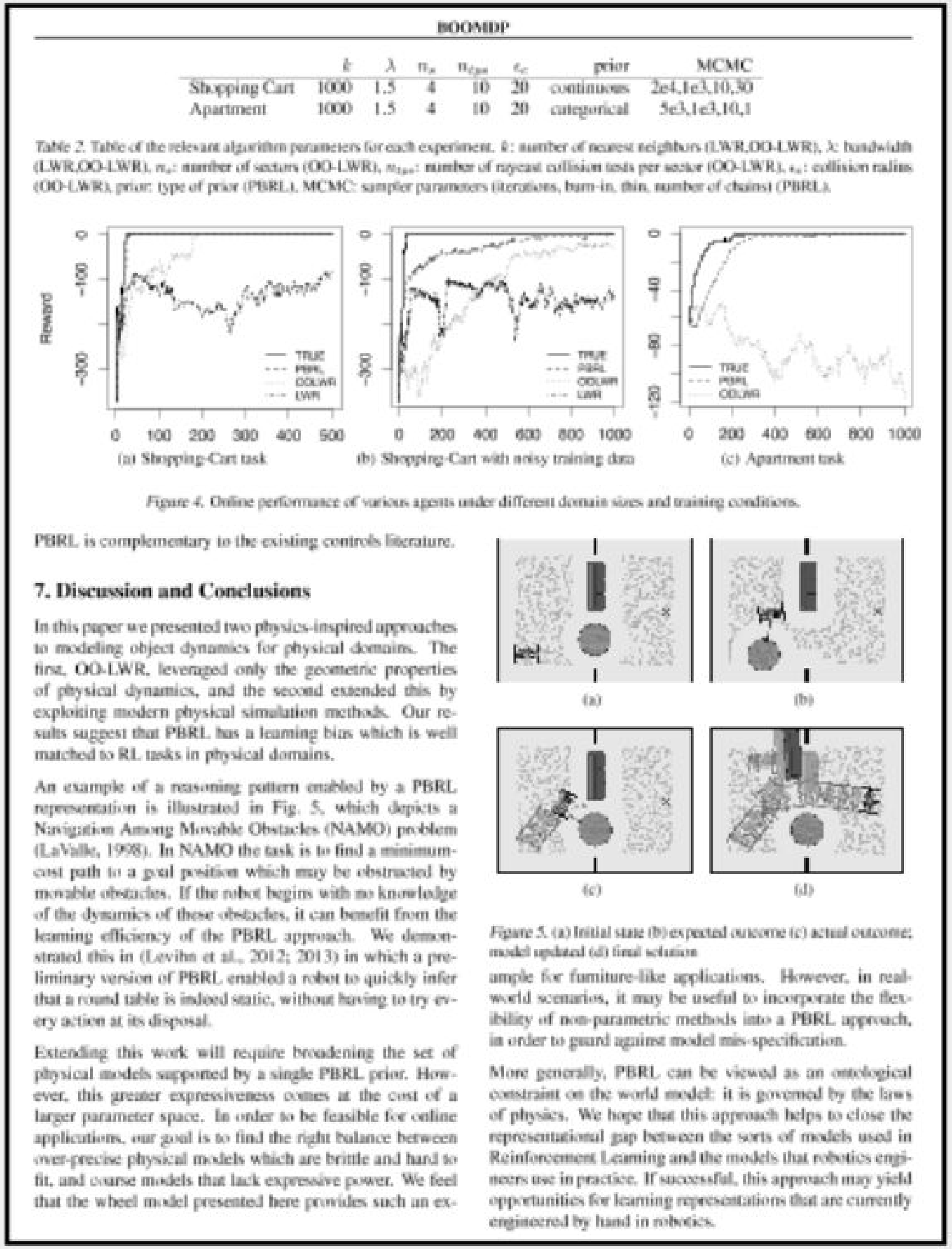
Input: Scientific papers

Step 1: Find the caption (keywords)

Step 2: Classify regions and text

Step 3: Assign captions with titles
through clustering to images

PDFFigures2.0 (Result)



BOOMDP

	k	λ	n_s	n_{tps}	ϵ_c	prior	MCMC
Shopping Cart	1000	1.5	4	10	20	continuous	2e4,1e3,10,30
Apartment	1000	1.5	4	10	20	categorical	5e3,1e3,10,1

Table 2. Table of the relevant algorithm parameters for each experiment. k: number of nearest neighbors (LWR,OO-LWR), λ: bandwidth (LWR,OO-LWR), n_s: number of sectors (OO-LWR), n_{tps}: number of raycast collision tests per sector (OO-LWR), ϵ_c: collision radius (OO-LWR), prior: type of prior (PBRL), MCMC: sampler parameters (iterations, burn-in, thin, number of chains) (PBRL).

(a) Shopping-Cart task (b) Shopping-Cart with noisy training data (c) Apartment task

Figure 4. Online performance of various agents under different domain sizes and training conditions.

PBRL is complementary to the existing controls literature.

7. Discussion and Conclusions

In this paper we presented two physics-inspired approaches to modeling object dynamics for physical domains. The first, OO-LWR, leveraged only the geometric properties of physical dynamics, and the second extended this by exploiting modern physical simulation methods. Our results suggest that PBRL has a learning bias which is well matched to RL tasks in physical domains.

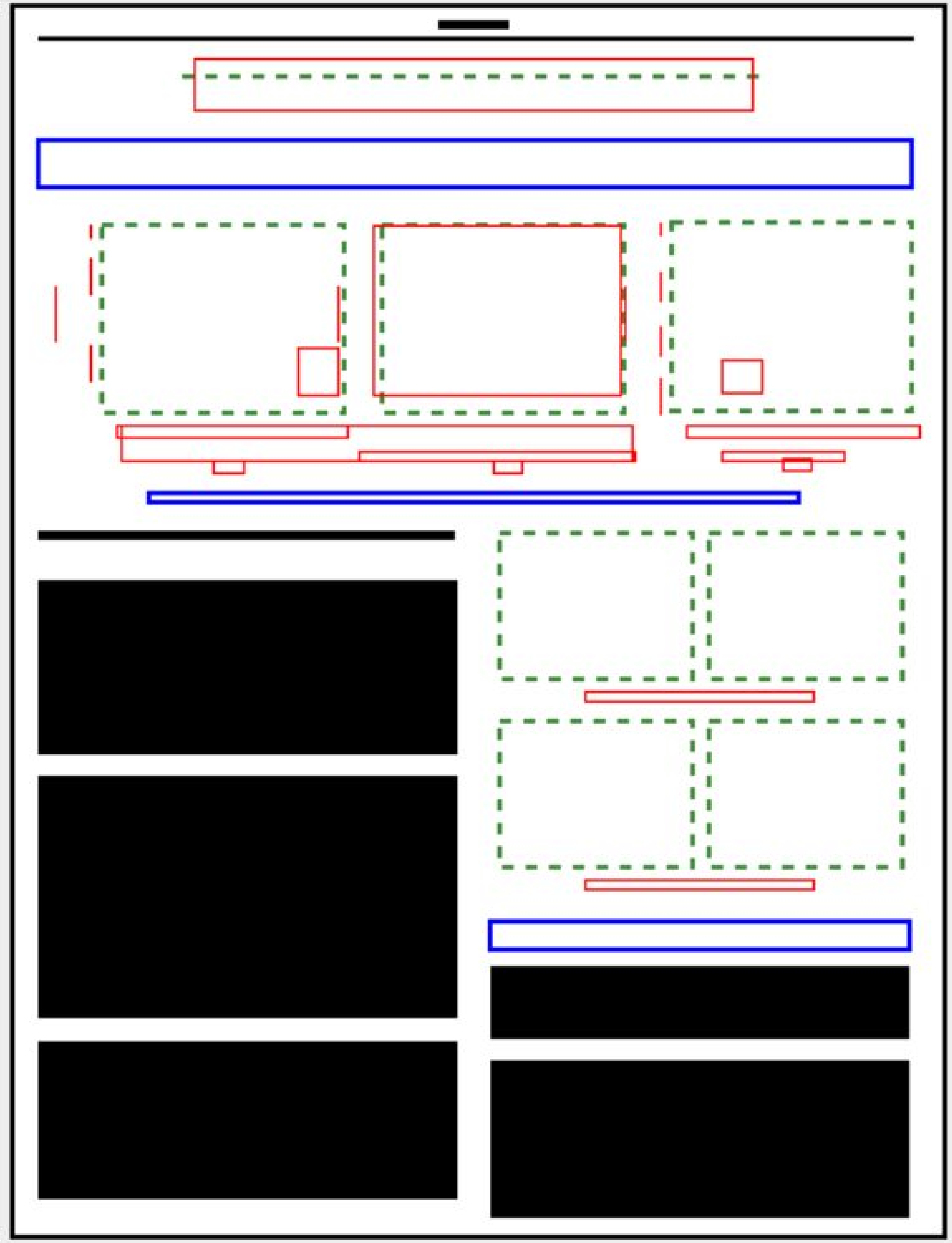
An example of a reasoning pattern enabled by a PBRL representation is illustrated in Fig. 5, which depicts a Navigation Among Movable Obstacles (NAMO) problem (LaValle, 1998). In NAMO the task is to find a minimum-cost path to a goal position which may be obstructed by movable obstacles. If the robot begins with no knowledge of the dynamics of these obstacles, it can benefit from the learning efficiency of the PBRL approach. We demonstrated this in (Levihn et al., 2012; 2013) in which a preliminary version of PBRL enabled a robot to quickly infer that a round table is indeed static, without having to try every action at its disposal.

Extending this work will require broadening the set of physical models supported by a single PBRL prior. However, this greater expressiveness comes at the cost of a larger parameter space. In order to be feasible for online applications, our goal is to find the right balance between over-precise physical models which are brittle and hard to fit, and coarse models that lack expressive power. We feel that the wheel model presented here provides such an example for furniture-like applications. However, in real-world scenarios, it may be useful to incorporate the flexibility of non-parametric methods into a PBRL approach, in order to guard against model mis-specification.

(a) (b) (c) (d)

Figure 5. (a) Initial state (b) expected outcome (c) actual outcome; model updated (d) final solution

More generally, PBRL can be viewed as an ontological constraint on the world model: it is governed by the laws of physics. We hope that this approach helps to close the representational gap between the sorts of models used in Reinforcement Learning and the models that robotics engineers use in practice. If successful, this approach may yield opportunities for learning representations that are currently engineered by hand in robotics.



Text-based knowledge extraction

Possible approach:

Input: 4^{th} grade textbooks

Step 1: Match patterns with text to find relations between concepts

Step 2: Translate matched patterns (+ variants) to formal logic language

Step 3: Store knowledge as logical statements in knowledge base

Peter Clark, Niranjan Balasubramanian, Sumithra Bhakthavatsalam, Kevin Humphreys, and Kinkead.
Automatic construction of inference-supporting knowledge bases. In 4th Workshop on Automated Knowledge Base Construction(AKBC), 2014.

Text-based knowledge extraction

Input: 4^{th} grade textbooks

Step 1: Match patterns with text to find relations between concepts

“Mechanical energy is produced when two objects move together.”

⬇

("two objects"/?x "produce" "Mechanical energy")
"when“ /CONDITION
("two objects"/?x "move" "" ["together"])

Peter Clark, Niranjan Balasubramanian, Sumithra Bhakthavatsalam, Kevin Humphreys, and Kinkead.
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Text-based knowledge extraction

Step 2: Translate matched patterns (+ variants) to formal logic language

("two objects"/?x "produce" "Mechanical energy")
"when“ /CONDITION
("two objects"/?x "move" "" ["together"])

⬇

forall m, t, o
isa(m,"move"), isa(t,"together"), isa(o,"two objects"), agent(m,o), arg(m,t)
-> exists p, e
isa(p,"produce"),isa(e,"Mechanical energy"), agent(p,o), object(p,e), condition(p,m).

Peter Clark, Niranjan Balasubramanian, Sumithra Bhakthavatsalam, Kevin Humphreys, and Kinkead.
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forall m, t, o
isa(m,"move"), isa(t,"together"), isa(o,"two objects"), agent(m,o), arg(m,t)
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condition(p,m).

⬇

Knowledge Base

Peter Clark, Niranjan Balasubramanian, Sumithra Bhakthavatsalam, Kevin Humphreys, and Kinkead.
Automatic construction of inference-supporting knowledge bases. In 4th Workshop on Automated Knowledge Base Construction(AKBC), 2014.

Answering questions

1

What is the meaning of the question?

2

What is the answer?

1. What is the meaning?

- A question == A query for some piece of data
- Goal: Construct a logical query that matches the question
- One approach: Use a probabilistic context-free grammar

Refresher: CFG

Production rules:

(1) [S] -> [Subject] [Verb] [Object]
(2) [Subject] -> My dog
(3) [Subject] -> Arnold Schwarzenegger
(4) [Verb] -> likes
(5) [Verb] -> hates
(6) [Object] -> treats
(7) [Object] -> Sarah Connor

Constructing a sentence:

[S]
↓ (1)
[Subject] [Verb] [Object]
↓ (2)
My dog [Verb] [Object]
↓ (4)
My dog likes [Object]
↓ (7)
My dog likes Sarah Connor

Training the model

Training Example:

$$\mathbf{w} = \text{What is the predator of bass ?}$$

$$L = \{\lambda x.\text{EATS}(x, \text{BASS}),\ \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x)),\ \ldots\}$$

1. **Model weak supervision.** Add L to the grammar as a nonterminal and add a unary rule $L \to \ell$ for all $\ell \in L$.

Generated Grammar:

Unary rules:

$L \to \lambda x.\text{EATS}(x, \text{BASS})$

$L \to \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x))$

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Training the model

Training Example:

$$\mathbf{w} = \text{What is the predator of bass ?}$$

$$\begin{aligned} L = \{&\lambda x.\text{EATS}(x, \text{BASS}),\\ &\lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x)),\\ &\ldots\} \end{aligned}$$

2. **Enumerate logical form splits.** For all $\ell \in L$, perform a depth-first search over logical forms starting at ℓ. To explore a logical form f during the search, use $\text{SPLIT}(f)$ to produce a collection of g, h pairs. For each g, h pair, add the binary rules $f \rightarrow g\ h$ and $f \rightarrow h\ g$ to the grammar, then add g and h to the search queue for later exploration.

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

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$$L = \{\lambda x.\text{EATS}(x, \text{BASS}), \\ \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x)), \\ ...\}$$

Generated Grammar:

Nonterminal rules:

$$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow \text{BASS} \;\; \lambda f.\lambda x.\text{EATS}(x, f)$$

$$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow \lambda f.\lambda x.\text{EATS}(x, f) \;\; \text{BASS}$$

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Training the model

Training Example:

$$\mathbf{w} = \text{What is the predator of bass ?}$$

$$L = \{\lambda x.\text{EATS}(x, \text{BASS}), \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x)), \ldots\}$$

3. **Create lexicon entries.** Add a terminal rule $f \rightarrow w$ to G for every word in the question, $w \in \mathbf{w}$, and logical form f encountered during the search above.

Generated Grammar:

Terminal rules:

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ what

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ is

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Training the model

Training Example:

$$\mathbf{w} = \text{What is the predator of bass ?}$$

$$L = \{\lambda x.\text{EATS}(x, \text{BASS}), \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x)), \ldots\}$$

4. **Allow word skipping.** Add a special SKIP non-terminal, along with the rules $f \rightarrow f$ SKIP, $f \rightarrow$ SKIP f and SKIP $\rightarrow w$ for all logical forms f and words $w \in \mathbf{w}$.

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Training the model

Generated Grammar:

Unary rules:

$L \rightarrow \lambda x.\text{EATS}(x, \text{BASS})$

$L \rightarrow \lambda x.\text{CAUSE}(\text{INCREASE}(\text{BASS}), \text{INCREASE}(x))$

Nonterminal rules:

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow \text{BASS} \;\; \lambda f.\lambda x.\text{EATS}(x, f)$

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow \lambda f.\lambda x.\text{EATS}(x, f) \;\; \text{BASS}$

$\text{BASS} \rightarrow \text{SKIP} \;\; \text{BASS}$

...

Terminal rules:

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ what

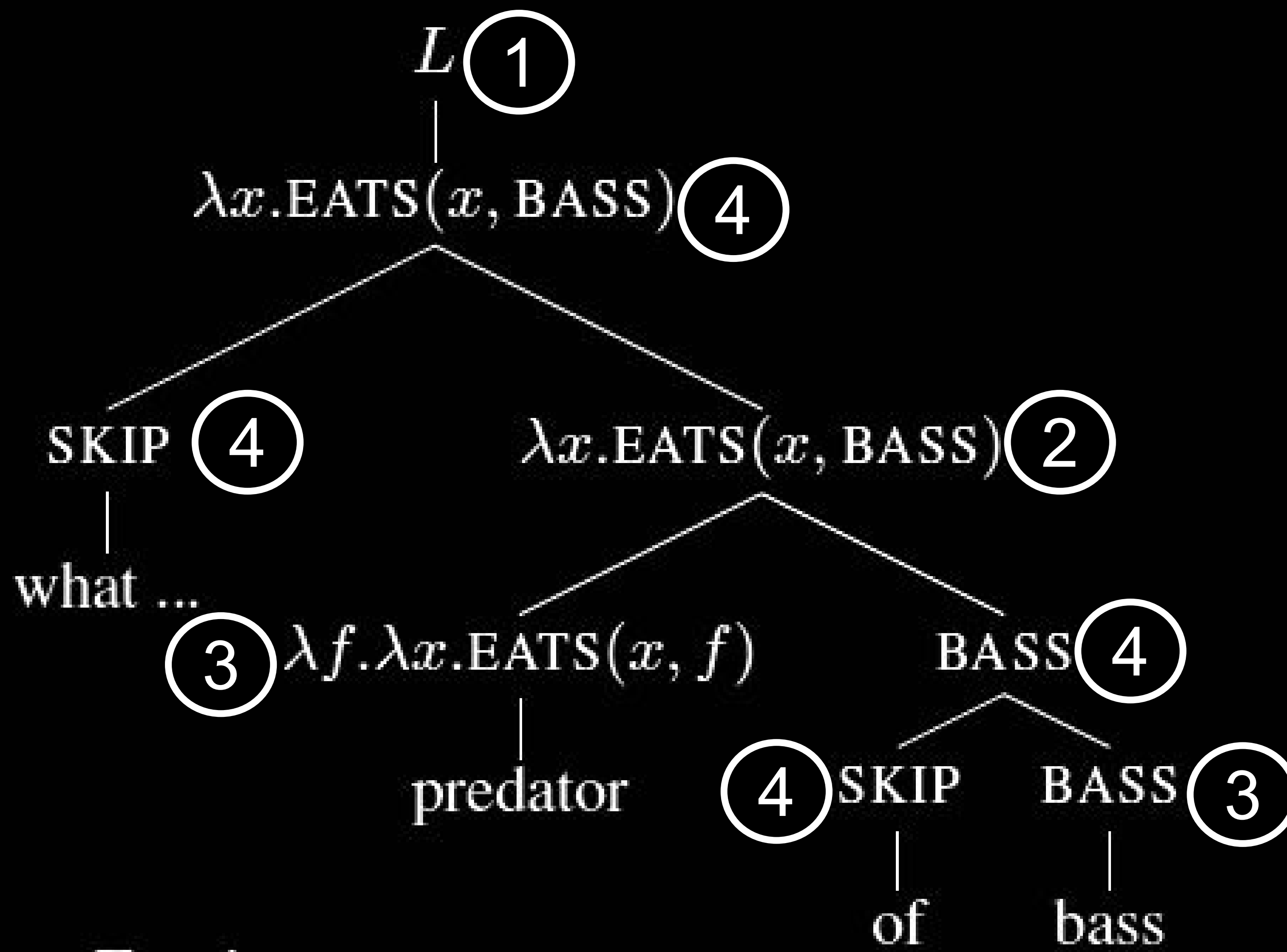
$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ is

$\text{SKIP} \rightarrow$ what

...

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Training the model



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$\text{BASS} \rightarrow \text{SKIP} \;\; \text{BASS}$

$$P(t|L;\theta) = \prod_{(f \rightarrow g\ h) \in t} P(f \rightarrow g\ h;\theta) \times \prod_{(f \rightarrow w) \in t} P(f \rightarrow w;\theta)$$

Terminal rules:

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ what

$\lambda x.\text{EATS}(x, \text{BASS}) \rightarrow$ is

$\text{SKIP} \rightarrow$ what

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Training the model

$$P(\mathbf{w}|L;\theta) = \sum_t P(\mathbf{w}, t|L;\theta)$$

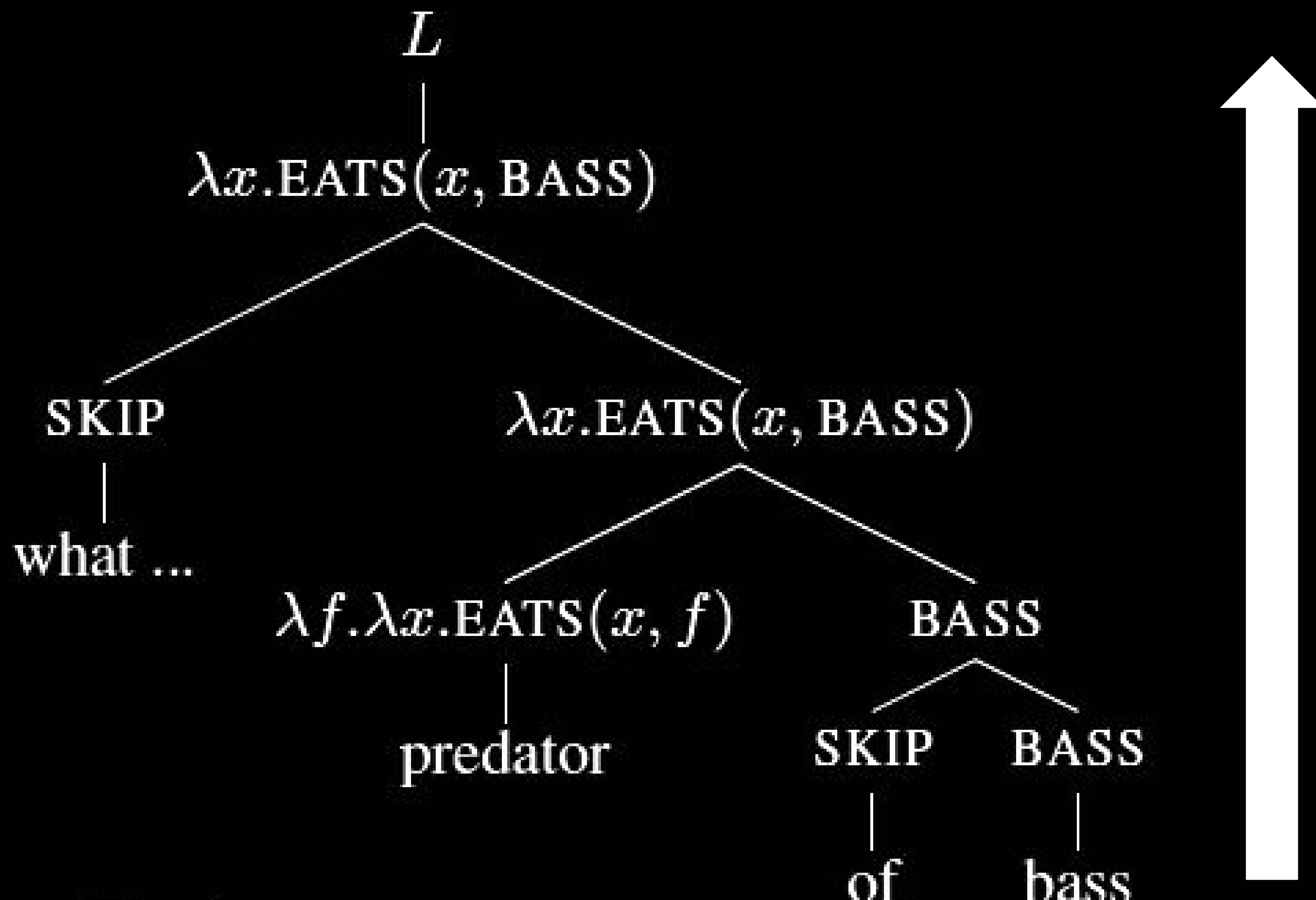
= The probability of generating a question from the given label

Goal: Optimise probabilities of applying each rule to maximise this for each training example

Method: Expectation Maximisation

Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

Applying the model



Jayant Krishnamurthy. Probabilistic models for learning a semantic parser lexicon. InProceedings of NAACL-HLT, pages 606–616,2016.

2. What is the answer?

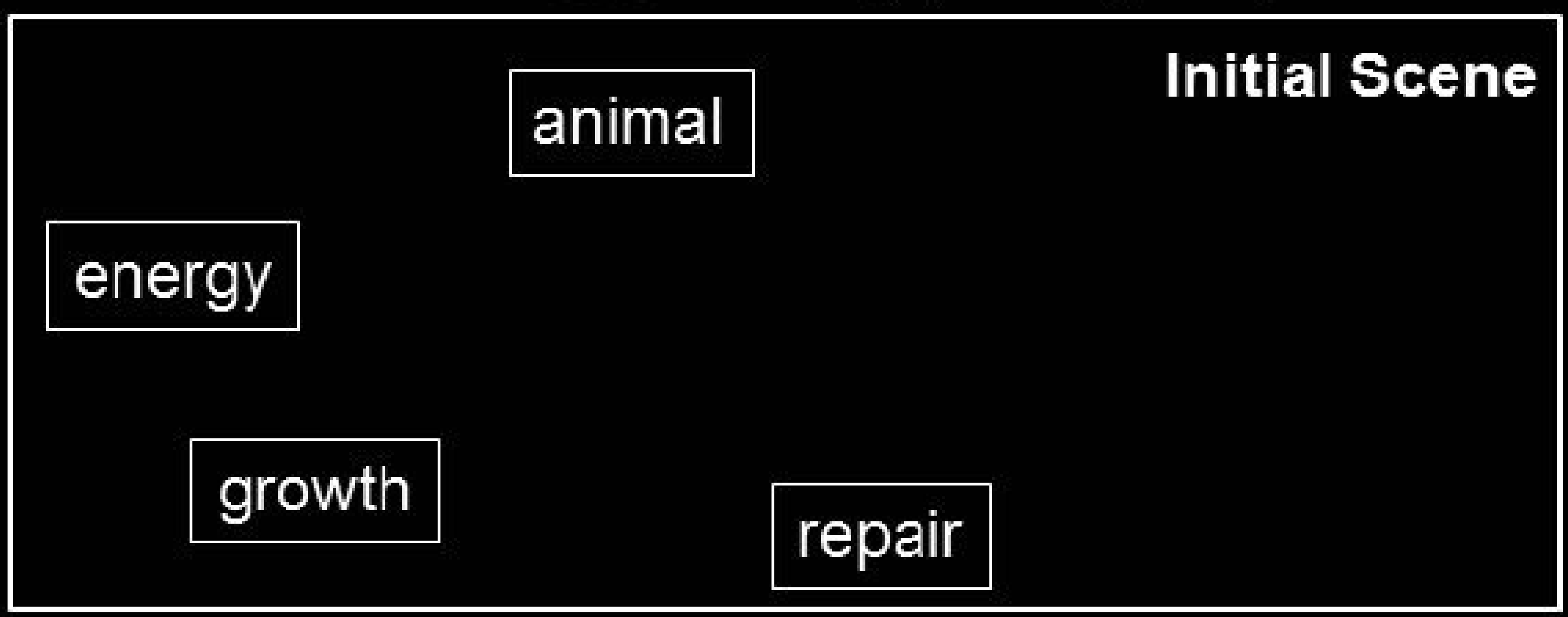
Input: A multiple-choice question

Example: “Animals get energy for growth and repair from (A) food, (B) water (C) ... “

Yang Li and Peter Clark. Answering elementary science questions by constructing coherent scenes using background knowledge.In EMNLP, pages 2007–2012, 2015.

2. What is the answer?

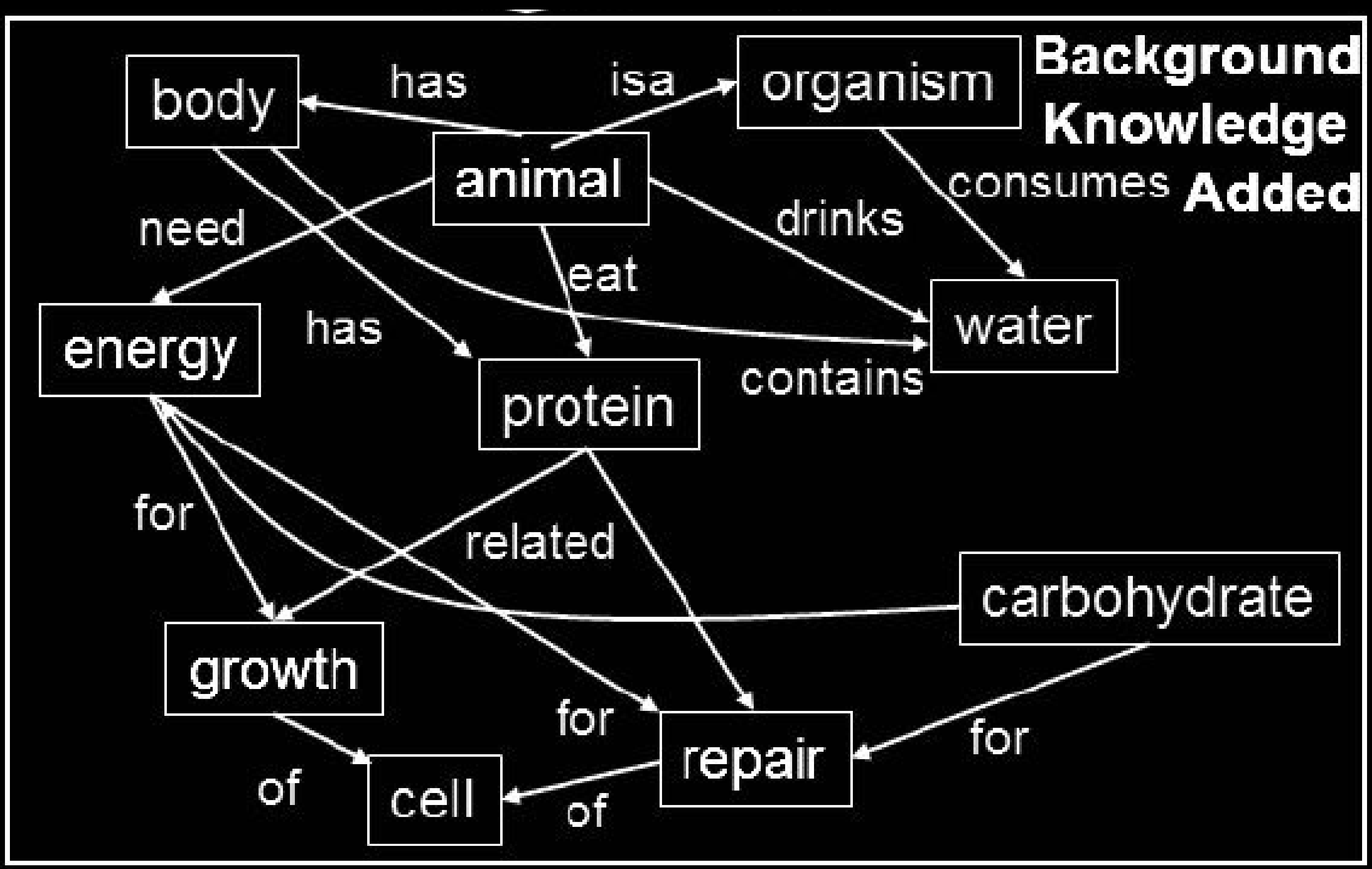
Step 1: Analyse the question and find important concepts (see previous algorithm)



Yang Li and Peter Clark. Answering elementary science questions by constructing coherent scenes using background knowledge.In EMNLP, pages 2007–2012, 2015.

2. What is the answer?

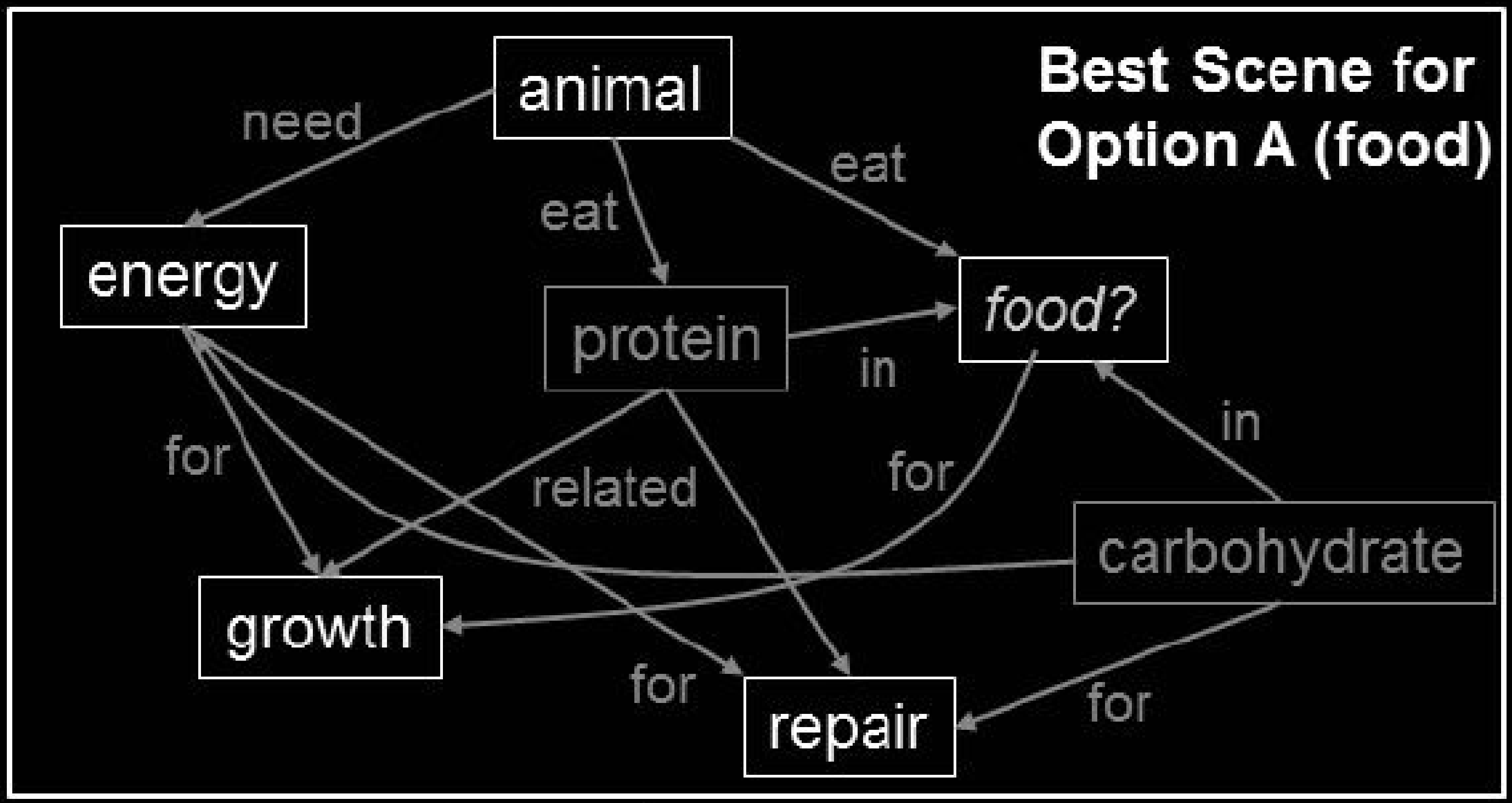
Step 2: Add background knowledge from knowledge base to form a graph



Yang Li and Peter Clark. Answering elementary science questions by constructing coherent scenes using background knowledge.In EMNLP, pages 2007–2012, 2015.

2. What is the answer?

Step 3: Add option and prune graph



$$score(w) = \sum_{kw \in K} IS(kw) * rel(kw, w)$$

Yang Li and Peter Clark. Answering elementary science questions by constructing coherent scenes using background knowledge.In EMNLP, pages 2007–2012, 2015.

2. What is the answer?

Step 4: Score option based on coherence within knowledge graph

$$coherence(w) = \sum_{w' \in \{(w,r,w')\}} rel(w, w')$$

The chosen answer with the highest coherence value is chosen

Yang Li and Peter Clark. Answering elementary science questions by constructing coherent scenes using background knowledge.In EMNLP, pages 2007–2012, 2015.

DEMO

http://aristo-demo.allenai.org

https://github.com/allenai/aristo-mini

Elasticsearch

What? Commercial search engine

Scalable, near real-time and multitenancy

How? JSON and Java API

Stemming

Domain: Natural Language Processing

What?

1. Removes stopwords
2. Removes Morphological affixes

Imports the remainder to
Information Retrieval index

Stemming (Example)

Once a player commits five fouls,
he is no longer allowed to play in the game,
and a player on the bench must go in the
game immediately.

Stemming (Example)

player commits five fouls,
no longer allowed play game,
player on bench must go
game immediately.

Stemming (Example)

player commit five foul,
no longer allow play game,
player on bench must go
game immedi.

Querying

“What color is the sky? red”

“What color is the sky? green”

“What color is the sky? blue”

Querying

"What color is the sky? red" Score: 0.3

"What color is the sky? green" Score: 0.1

"What color is the sky? blue" Score: 0.6

Score function

```
score(q,d)  =  1
            queryNorm(q)      2
          · coord(q,d)        3
          · ∑ (               4
                tf(t in d)      5
              · idf(t)²         6
              · t.getBoost()    7
              · norm(t,d)       8
            ) (t in q)        9
```

-> Score =< 1
-> Large overlap

-> Frequency
-> Inverse frequency

-> Score =< 1

https://www.elastic.co/guide/en/elasticsearch/guide/current/practical-scoring-function.html

Recent developments

dS De Standaard

Meest recent Binnenland Buitenland Opinie Biz Cultuur Sport Life&Style Beroemd&Bizar Niet te missen

HOME > BIZ > MOBILIA

Deze slimme app lost wiskundevraagstukken voor je op

Vandaag om 11:58 door Michel van der Ven

G+ Tweet Delen Mail Print

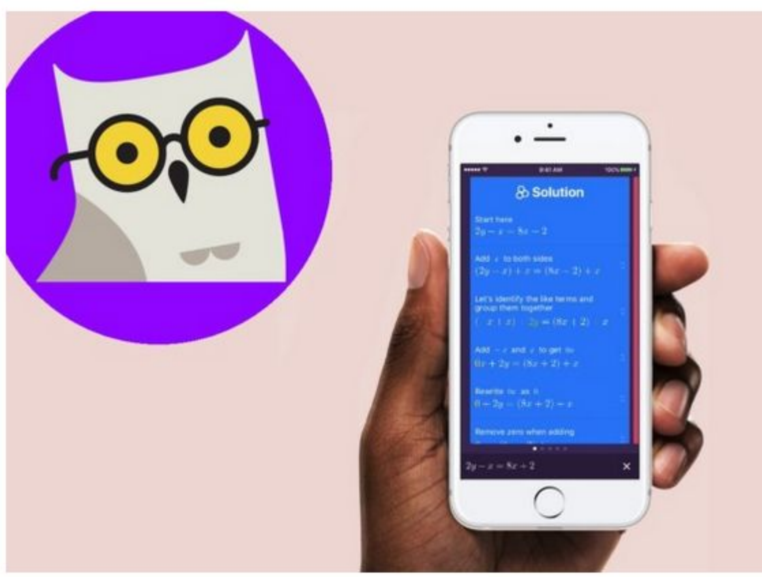


Foto: rr

Een app die kinderen helpt met hun huiswerk? Waar waren dat soort toepassingen toen ik jong was!? Beetje spijtig wel dat Socratic Engelstalig is, want daardoor vallen er bij ons flink wat vakken af. Maar voor de universele taal die wiskunde heet is dit een toppertje hoor!

Leerkrachten, ouders en pedagogen die nu uit hun stoel opveren van verbazing, kunnen we – in elk geval gedeeltelijk – geruststellen. Socratic geeft leerlingen niet zomaar de hapklare oplossing op een geschiedenisvraag of van zo'n fijne differentiaalvergelijking. De antwoorden

HOME
BIZNIEUWS
MOBILIA
TIPS
APPS
REVIEWS
BELEGGEN
MIJN GELD
EXPERTS
BEREKEN ZELF

MEEST RECENT · MEEST GELEZEN

- 11:58 Deze slimme app lost wiskundevraags
- 11:40 Netwerkproblemen bij Base
- 14:08 De Croo tegen monopolie voor ticketa
- 12:10 Ex-werknemer heeft monopolie op tic
- 08:12 Uber gebruikt software om autoriteit

NIET TE MISSEN

dS+ Achter de kook voor uw poedel of na

Vergeet Royal Canin of Whi tegenwoordig spelen baasj chef-kok voor hun hond of k

dS+ 'Knettergek we dat wachten en die

https://socratic.org/

http://www.standaard.be/cnt/dmf20170228_02755032