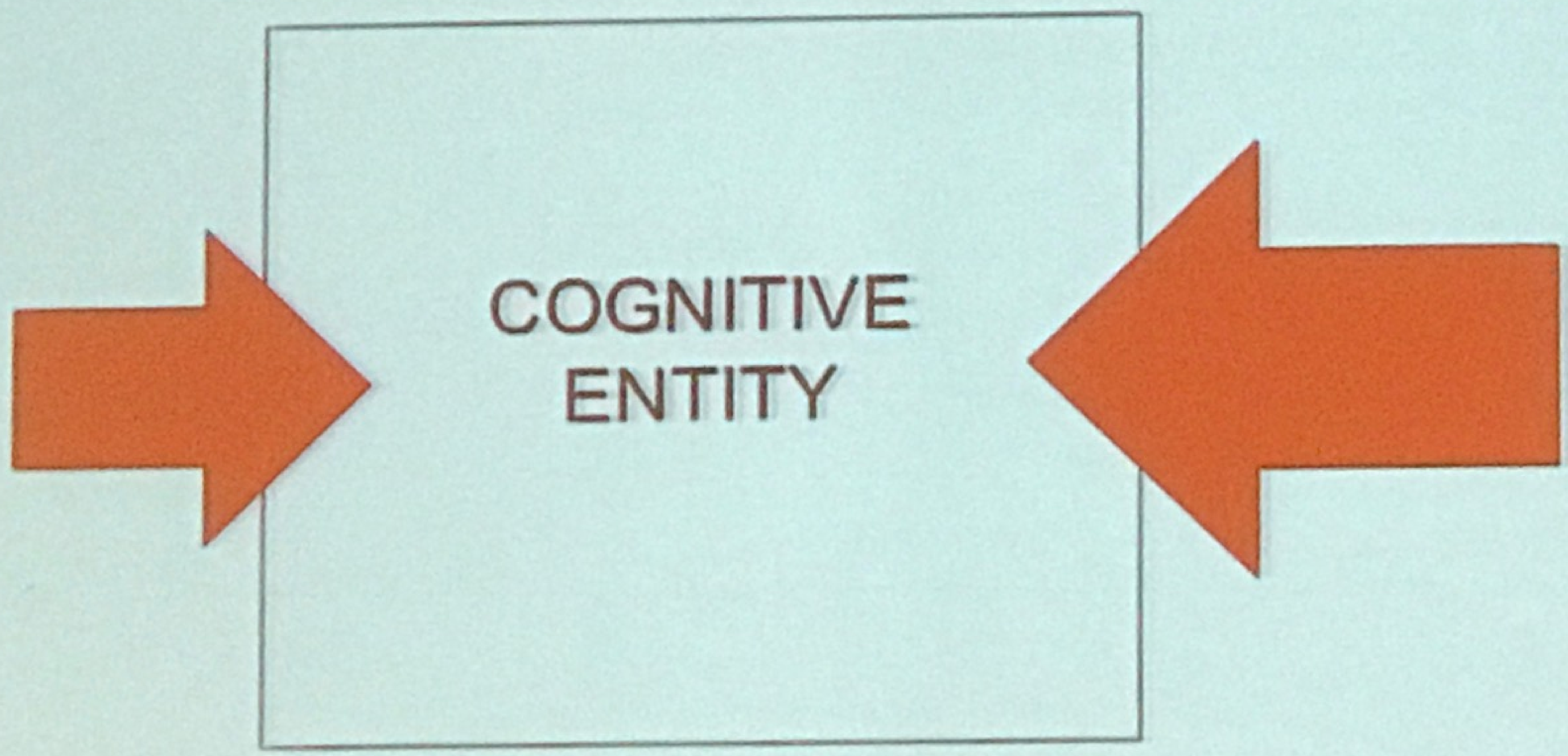
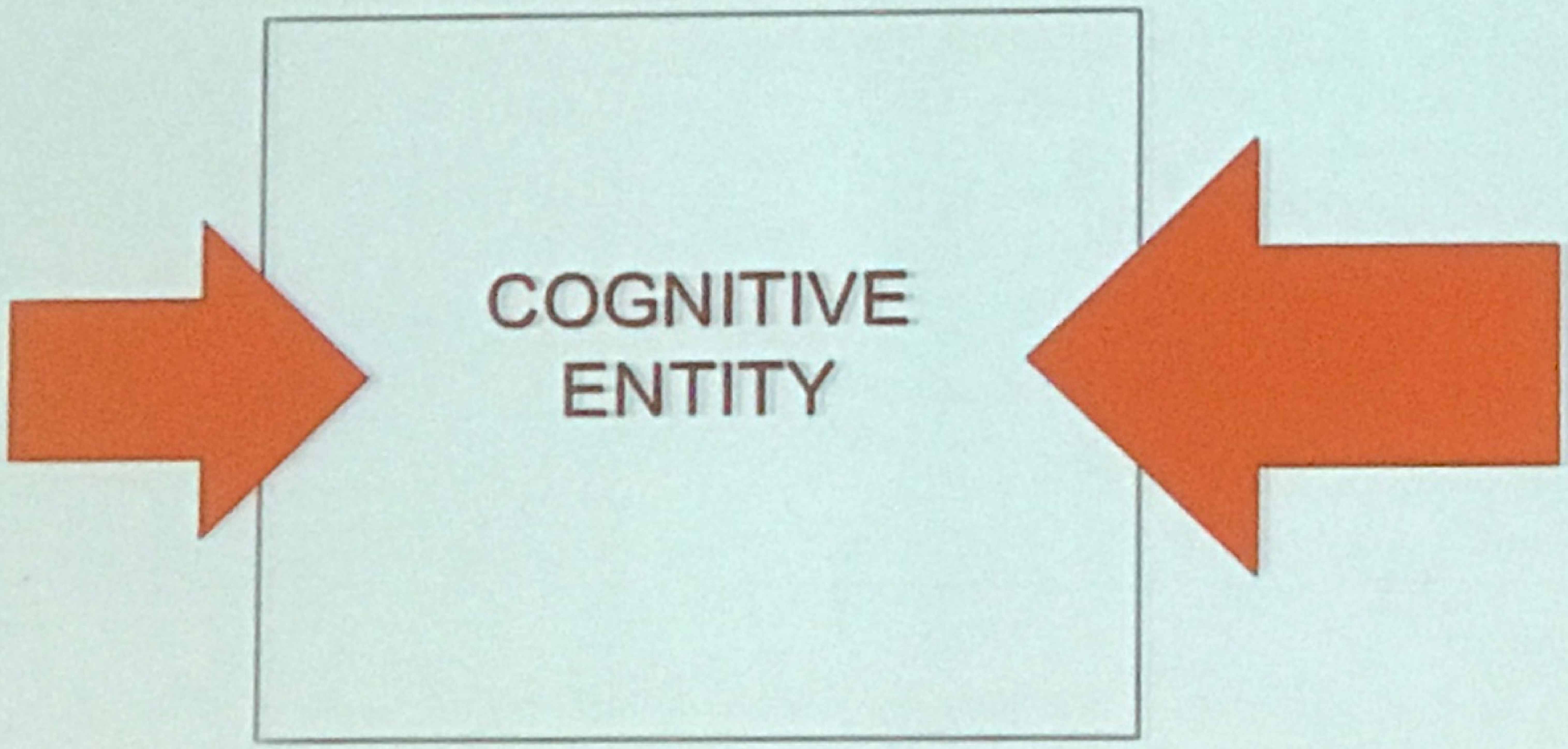
# What Needs to be Added to Machine Learning?

Leslie Valiant
Harvard University

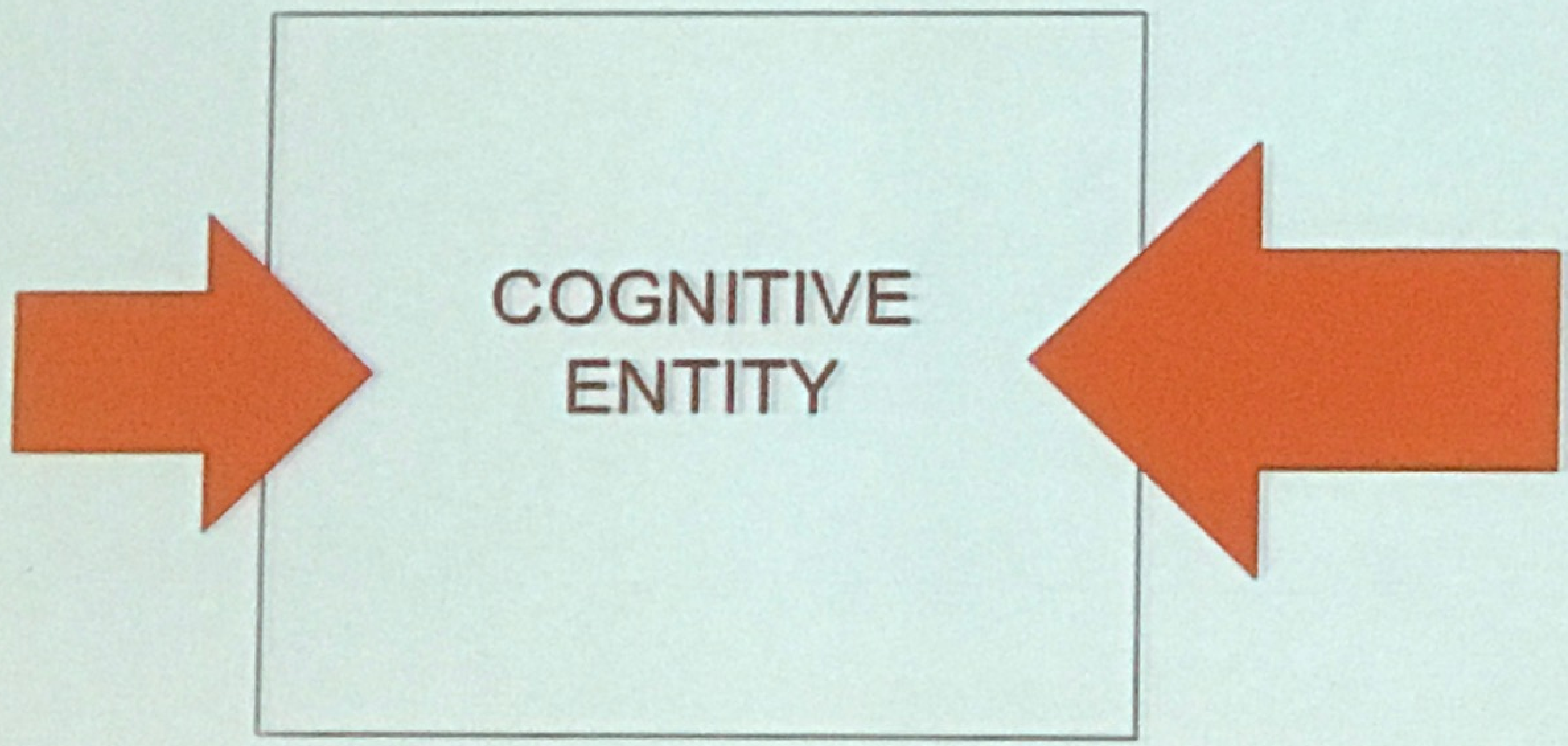
WCC, Poznan, September, 2018


COGNITIVE
ENTITY




# COGNITION MUST HAVE A THEORY.

SEMANTICS: Correspondence between **State of Cognitive Entity** and **World**

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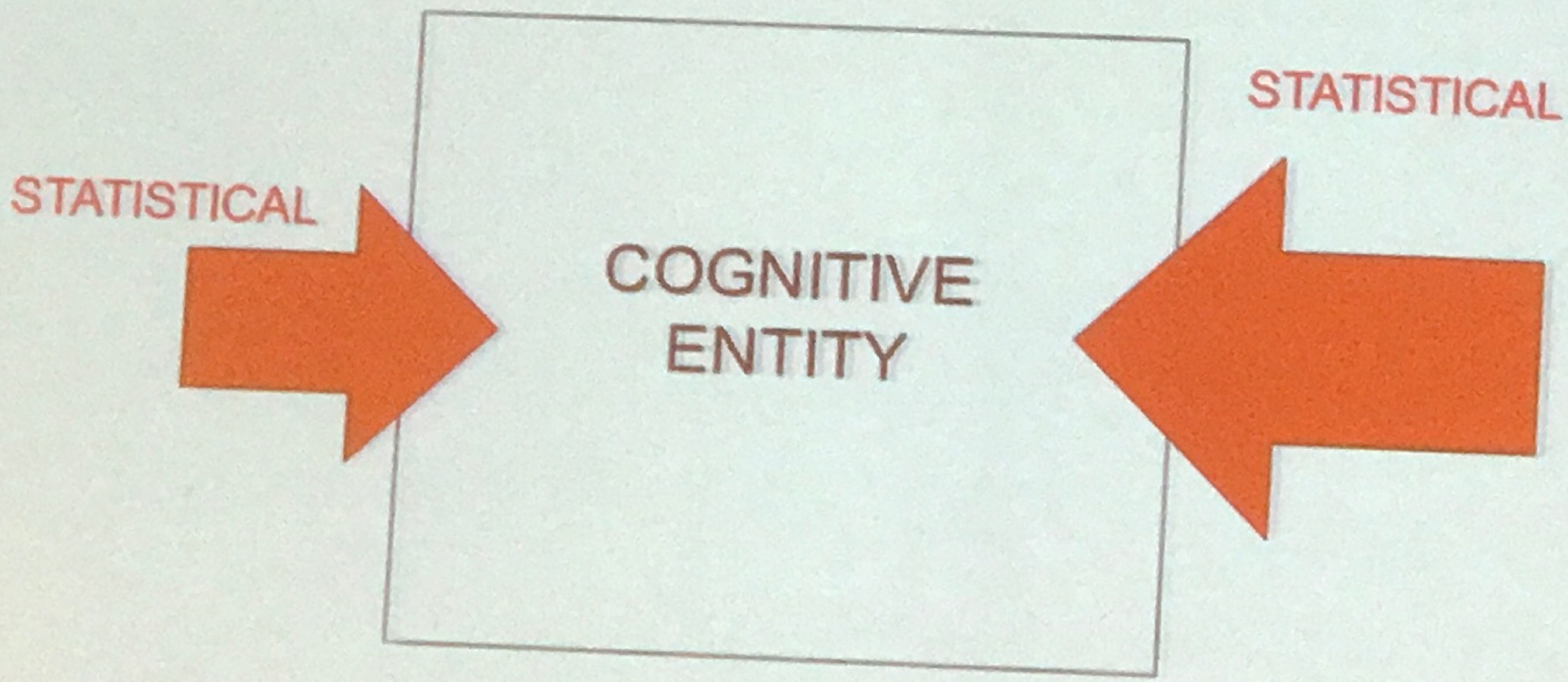


**COGNITION MUST HAVE A THEORY.**

"All belief comes from Syllogism or Induction" - *Aristotle*

Syllogism ~ Mathematical Logic, Reasoning

Induction ~ Machine Learning Theory

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**Goals for our Time**

1. Give Learning and Reasoning a common semantics.

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**Goals for our Time**

1. Give Learning and Reasoning a common semantics.

2. Enable a robust database of commonsense knowledge to be acquired by learning for AI.

Did Aristotle own
a cell phone?

# Word Completion

(From China Daily, 2018)

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China rises as a maritime powerhouse after snapping up profitable seaport terminals across the world.

Google: "maritime powerhouse" "seaport terminals" 6

Macao's retail sale up by 23.7 pct in Q2.

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1. Performance measured quantitatively.
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Learning Theory approach:

3. Performance relative to particular world (i.e. distribution *D* of natural inputs.)
4. Insists on feasible computation and error control.

# Robust Logic

(Semantics for unifying learning and reasoning.)
(Can test on word completion.)

*An Idea From Cognitive Science:*

Working Memory ≈ Mind's eye

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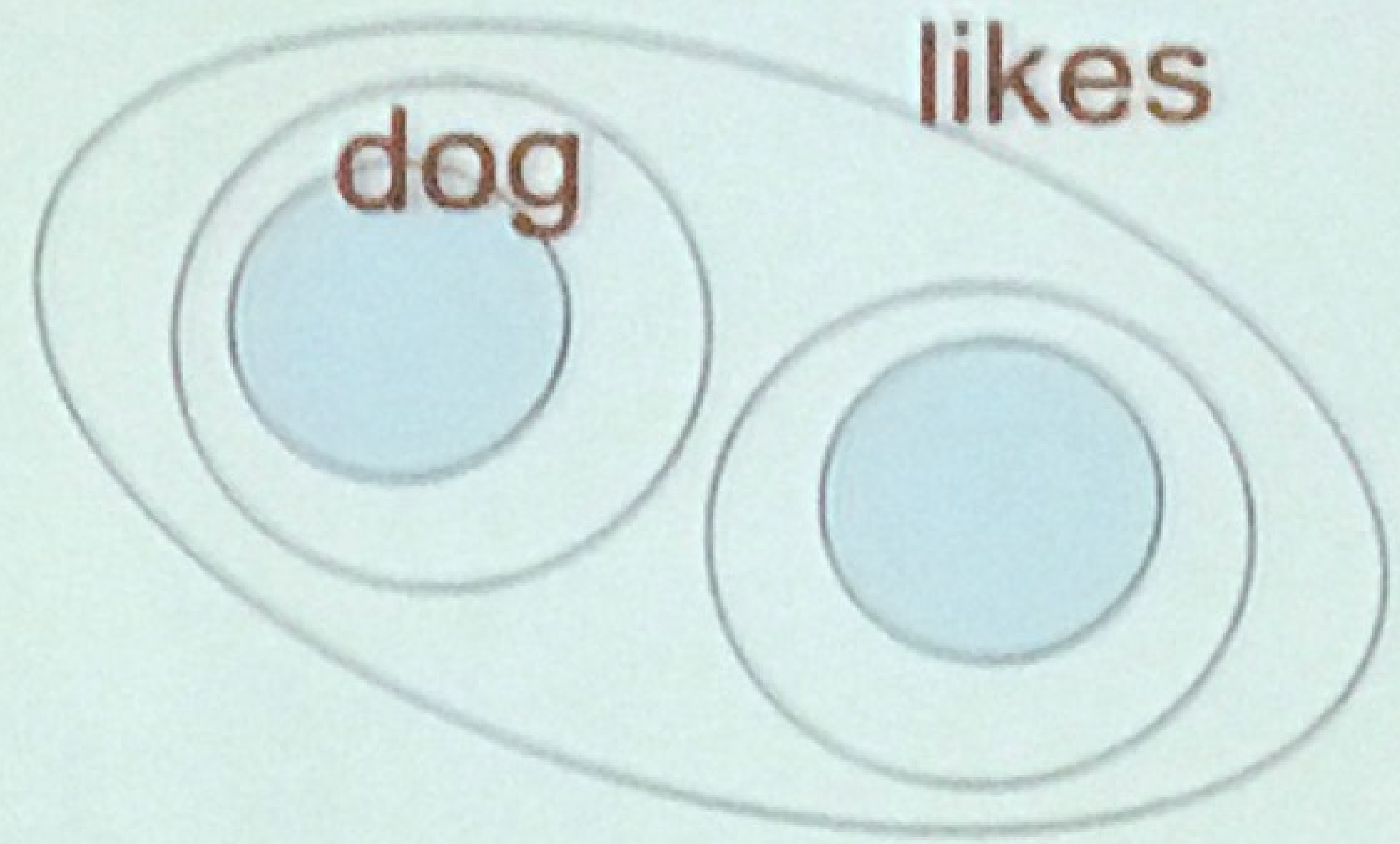
# A Scene




## A Logical Rule:

$\exists x_1 Dog(x_1) \wedge Likes(x_1,x_2) \rightarrow Bone(x_2)$

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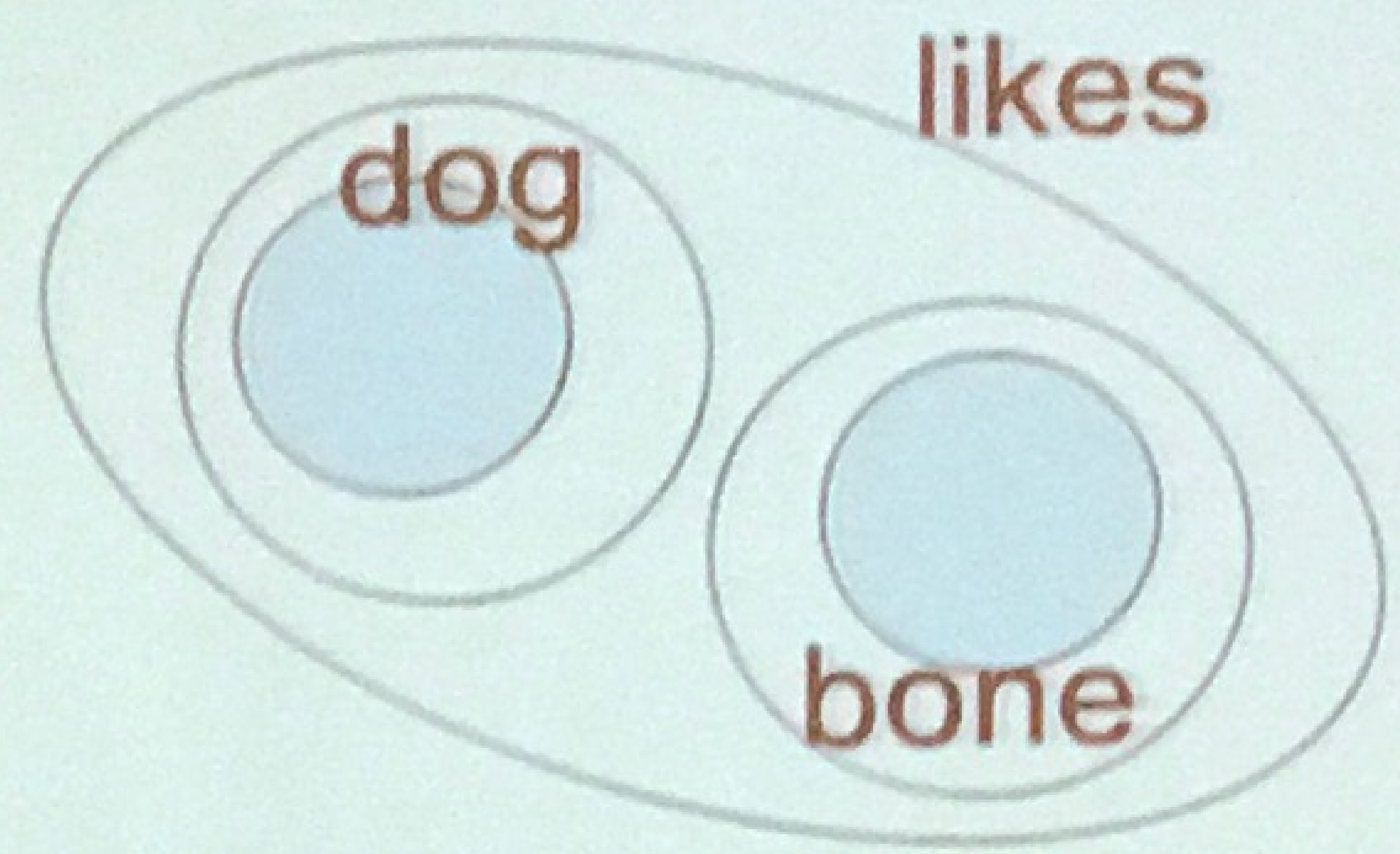


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$$\exists x_1 \mathrm{Dog}(x_1) \wedge \mathrm{Likes}(x_1, x_2) \rightarrow \mathrm{Bone}(x_2)$$

## A Learned Rule:

"Expression from learnable class" $\equiv \mathrm{Bone}(x_2)$


Computers have to ACQUIRE knowledge, and then ACT on it.
Type A
Type B
Accept
Labeled
Examples
?
Classifies
Unlabeled
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# SUPERVISED LEARNING

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Type A 

Type B 

Accept Labeled Examples

? 

Classifies Unlabeled Examples

There is a science of this.


Prediciton
Error
Decreases as fast as $N^{-\beta}$
$N$ = #computational steps
To learn to error 1/100 need only $N = 100^{1/\beta}$
for *some* constant, such as $\beta = 0.5$.
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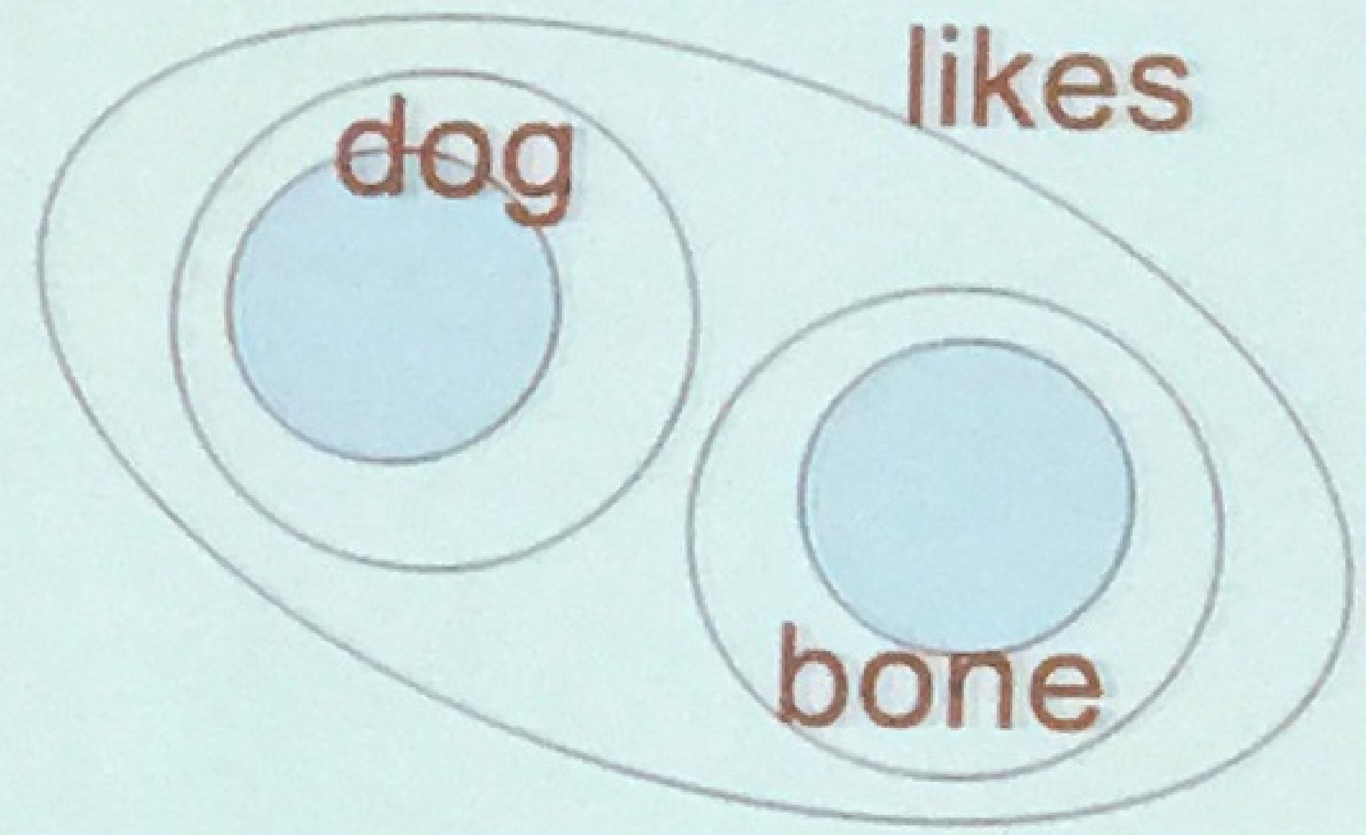
# Robust Logic Feature 2:
## Quantifiers are Local

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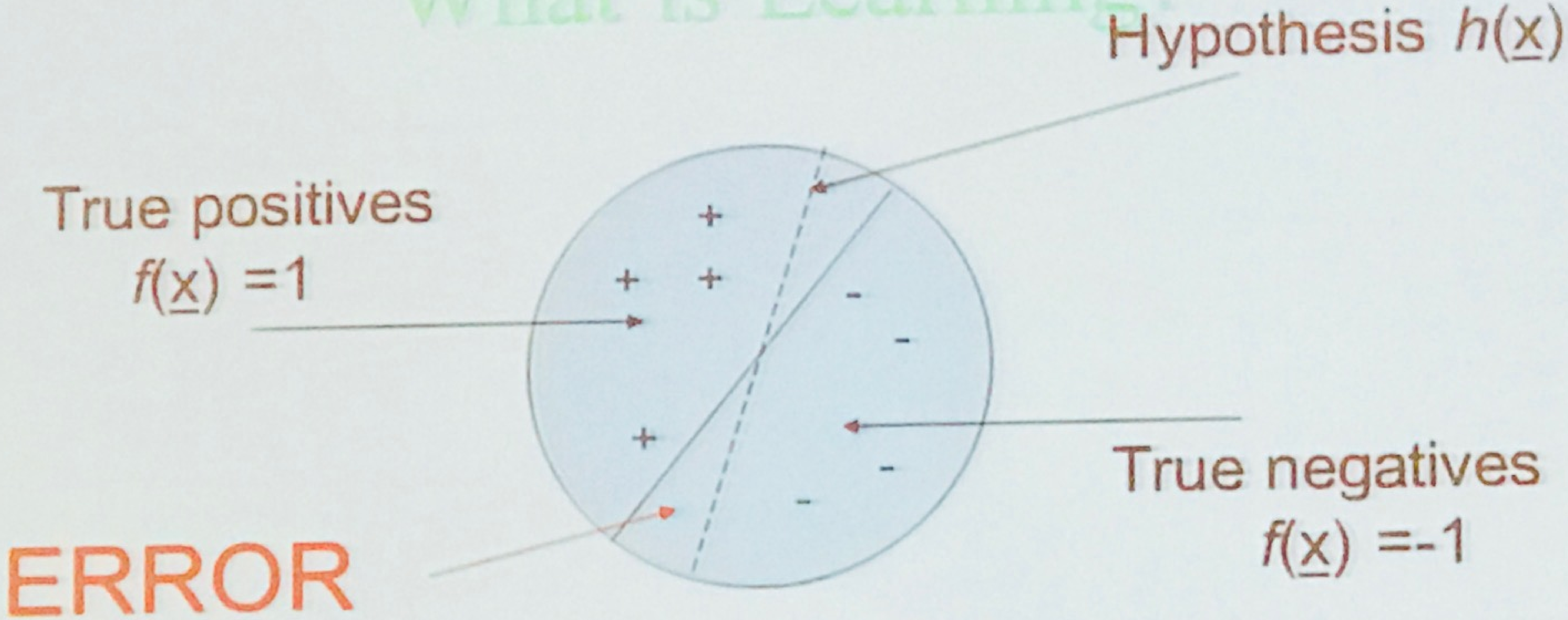
# Robust Logic Feature 4:

## What is Learning?




PAC Learning

1. Examples from *arbitrary distribution D*, but testing from same.
2. Errors can be reduced *arbitrarily* with more examples and more computation, and with only polynomial cost in these.

Robust Logic Feature 5:
What is world D?
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# Robust Logic Feature 5:

## What is world D?

Examples in Mind's Eye!

# Robust Logic Feature 5:

## What is world D?

Examples arise from ground truth vectors:

$(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, \ldots\ldots, x_{1000})$.

But this is about **incomplete specification**.

An example is (1,*,0,0,*,1,0,*,*,*, ….. ,*)

D over {0,1,*}.

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To predict $x_6$ apply rules with entry $x_6$ **obscured**:

e.g. (1,*,0,0,*,?,0,*,*,*, ….. ,*).

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# Robust Logic Feature 6: Is Not Hierarchical Learning Difficult?

e.g. to learn $F(x_1, x_2)$, and $G(F(x_1, x_2), x_3)$ while F is inaccurately known.

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Consider that examples come with correct labels. (As in learning math from teacher.)

# Upshot

Will learn rules like

# Upshot

# Upshot

Will learn rules like:

[illegible]

using the most appropriate supervised learning algorithm, [illegible] [illegible] each word in dictionary or [illegible], and chain these for reasoning.

# The Experiment (L. Michael & L.V.)

500,000 sentences from Wall Street Journal

Use mechanical parser to find subject/object etc.

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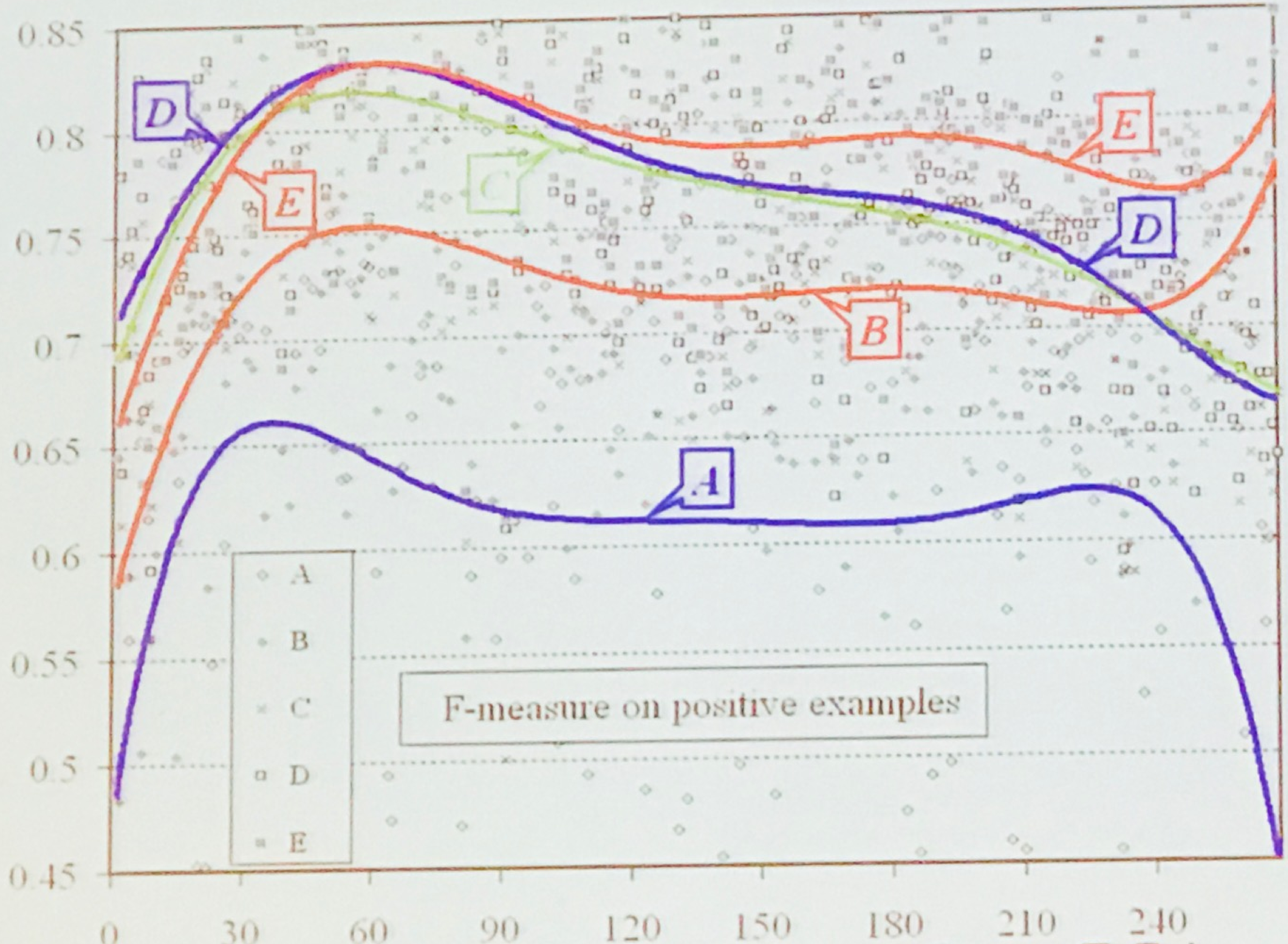
Learn rules from single sentences to predict unstated things.

See how much better chaining these is in predicting missing word, than a baseline "syntactic" method.

# The Experiment (L. Michael & L.V.)

Learned rule are *linear inequalities on compound features*: e.g.

"1.09 * (∃ x: (x lowers y) ∧ (bargain x)) +
0.99 * (∃ x: (x lowers y) ∧ (competition x)) + 0.51 *
(∃ x: (y lowers x) ∧ (demand x)) +
………… > 1"  ≡  (price y).




D = without chaining. E = with chaining. Order E-D increasing

# Robust Logic

**Examples**: Scenes on $t$ objects.

**RHS of rule**: e.g. $R(x_3, x_4)$.

**LHS of rule**: Linear inequality over compound features. (or any other learnable class.)

**Compound features**, local quantifiers

e.g. $\exists x_1 \forall x_2 A(x_1, x_2, x_3) B(x_1, x_4)$.

**Propositional learning algorithm**: to inherit good quantitative characteristics, such as error resilience, attribute efficiency.

e.g. Winnow (Littlestone), deep learning.

# Desirable Properties of Robust Logic

**Theorems**: Rules learnable; chaining of rules applied to one example is polynomial time, sound and complete. (All in pac-semantics.)

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**Restriction:** relations of constant arity.

**Otherwise:** run time, error bounds polynomial in rule sizes, rule numbers, number *t* of objects in scenes.

**Here all of:** learning, reasoning, multi-objec

# A Challenge: Developing Good Teaching Materials

"grey elephant":

"pink elephant":

"white elephant":

# A Challenge: Developing Good Teaching Materials

| | (Google 5-11-18) |
|---|---|
| "grey elephant": | 1,370,000 |
| "pink elephant": | 546,000 |
| "white elephant": | 707,000 |

# Challenges for AI that are addressed by Robust Logic

**Infusing machines with general knowledge so that robust reasoning on it is possible.**

- Learning enables system to stay "approximately consistent".
- Learning as method of choice for knowledge that is nowhere defined.
- Principled reasoning on learned knowledge.