

# Symbolic & Sub-Symbolic AI: Co-exist or Combine?

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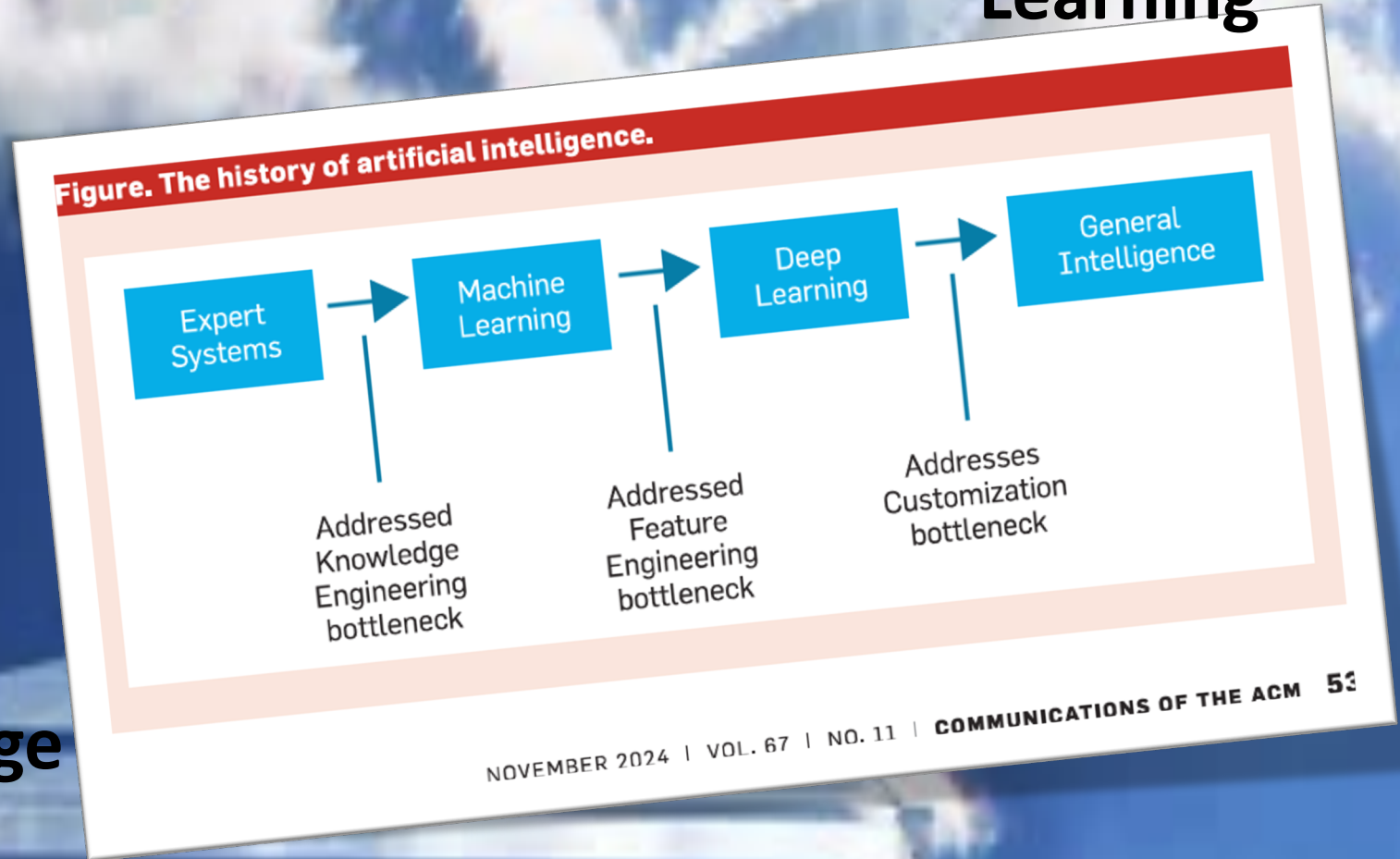
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Historical & current  
directions of travel  
in AI

# History?

Connectionist  
Data  
Statistics  
Learning



Symbolic  
Knowledge  
Logic  
Reasoning

# The AI pendulum!

Neural  
Data  
Statistics  
Learning

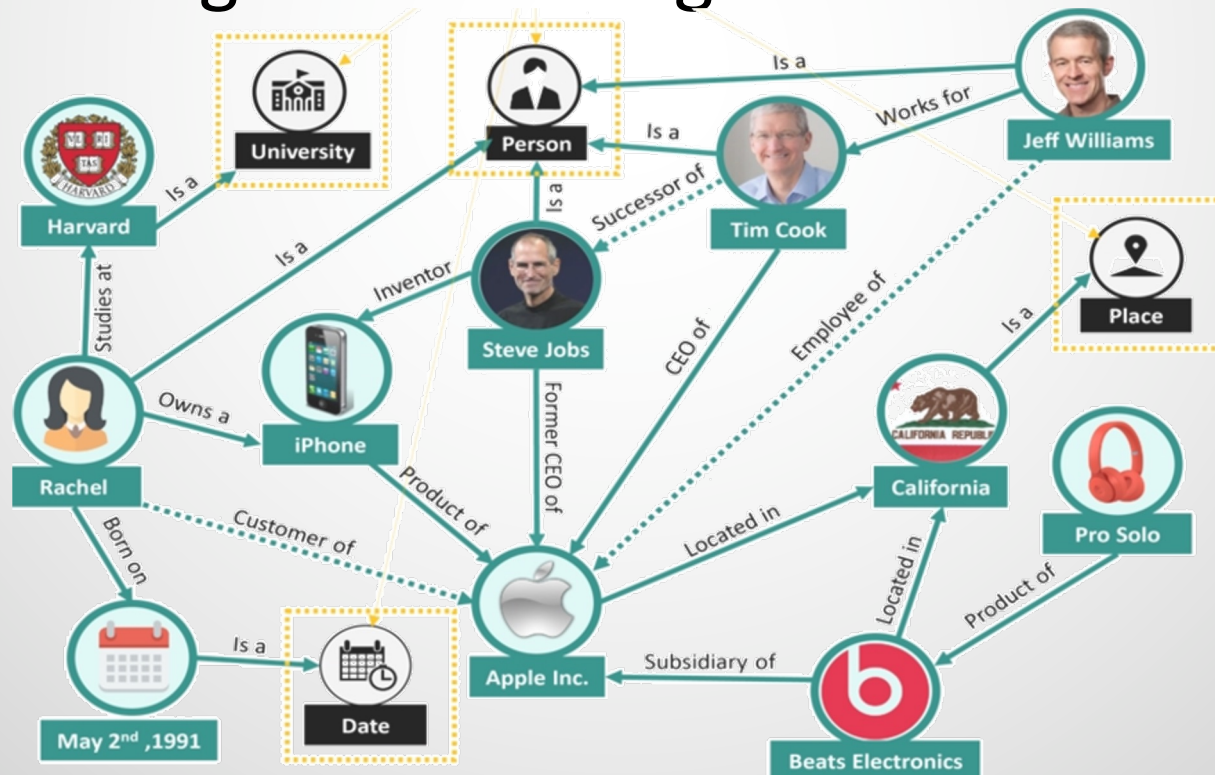
Symbolic  
Knowledge  
Logic  
Reasoning

# Direction of travel in modern AI

1. Major *breakthroughs* in machine learning
2. Major *scale-up* in **knowledge representation**
3. **Complementary** strengths & weaknesses

## 2. Major *scale-up* in knowledge representation

- Knowledge graphs as networks of relations between things
- Enables logical reasoning



## 2. Major *scale-up* in knowledge representation

- Efficient querying and reasoning
- Scales to  $10^{10}$  relations between  $10^9$  things
- In use at major industries





# Direction of travel in modern AI

1. Major *breakthroughs* in **machine learning**
2. Major *scale-up* in **knowledge representation**
3. **Complementary** strengths & weaknesses

	<b>Symbolic</b>	<b>Statistical</b>
<b>Construction cost</b>	Human effort	Data hunger
<b>Scalable</b>	Worse with more data	Worse with less data
<b>Explainable</b>	+	-
<b>Generalisable</b>	Performance cliff	Out of sample

# Strengths & Weaknesses

	Symbolic	Statistical
Construction	Human effort	Data hunger
Scaleable	Worse with more	Worse with less
Explainable	+	-
Generalisable	Performance cliff	OOD data

- Knowledge acquisition bottleneck  
vs. data acquisition bottleneck
- Combinatorial explosion  
vs. sampling inefficiency
- Explainability  
vs. black box
- Brittleness  
vs. out-of-distribution data



Neuro-symbolic AI:  
a glimpse from the  
factory floor

# Working hypothesis of neuro-symbolic AI

- Knowledge-driven & data-driven systems each have their strengths and weaknesses
- These are complementary
- We need combinations of both

# This is not a new idea



“20 years”  
[Artur d’Avila Garcez  
& Luis Lamb]

“30 years”  
[Pascal Hitzler]



# Context aware Machine Learning



flower  
cushion?

Also: semantic loss-function

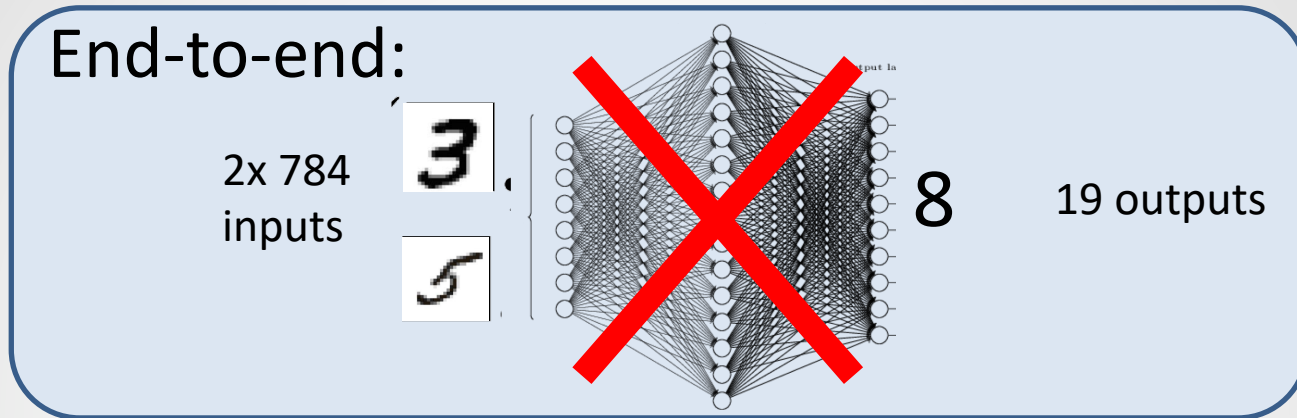
$P(\text{cushion} | \text{chair}) \gg P(\text{flower} | \text{chair})$

“Given the context of chair,  
a **cushion** is much more likely  
than a **flower**”

$\forall x, y \text{ chair}(x) \wedge \text{partOf}(y, x) \rightarrow$   
 $\text{cushion}(y) \vee \text{armRest}(y)$

“Parts of a chair are:  
cushion and armrest”

# Learning that is robust to change (through intermediate abstractions)

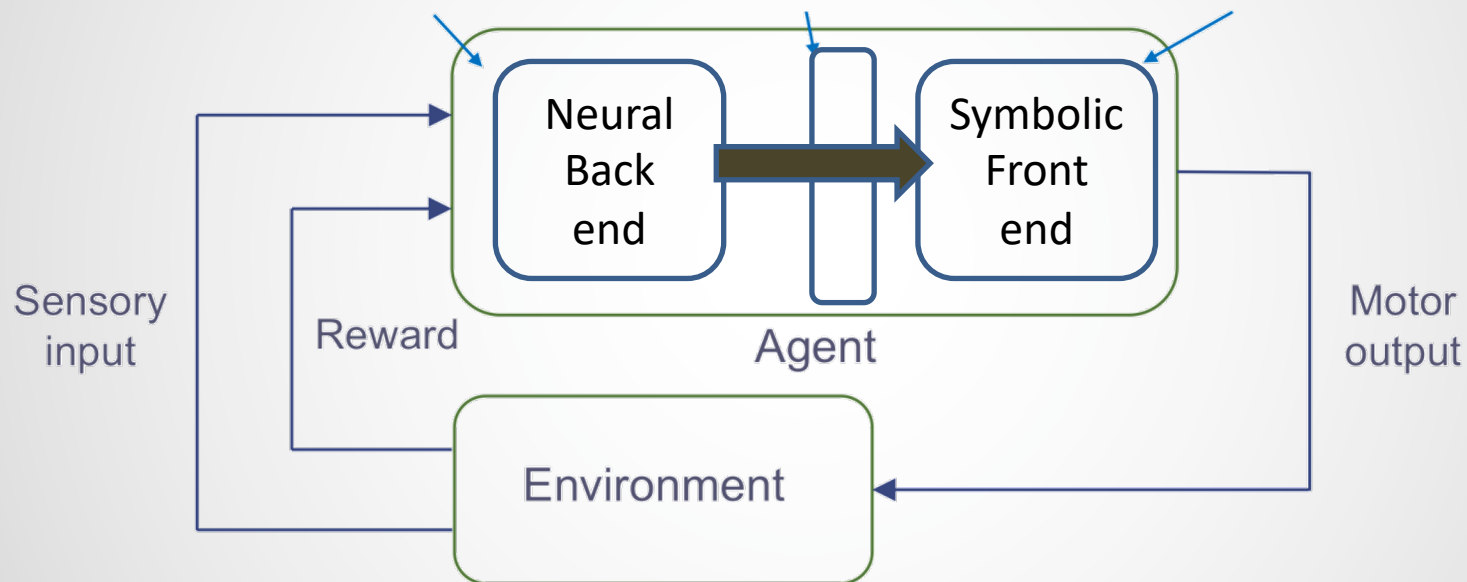


see(**3**)=3, see(**5**)=5, 3+5=8

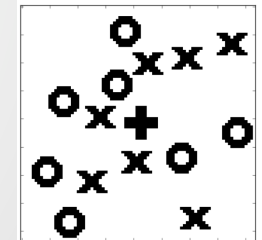
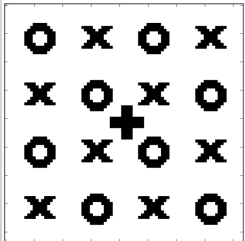
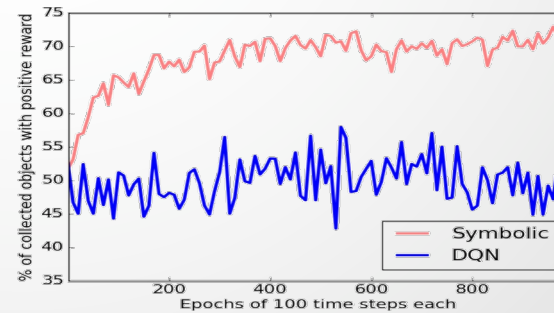
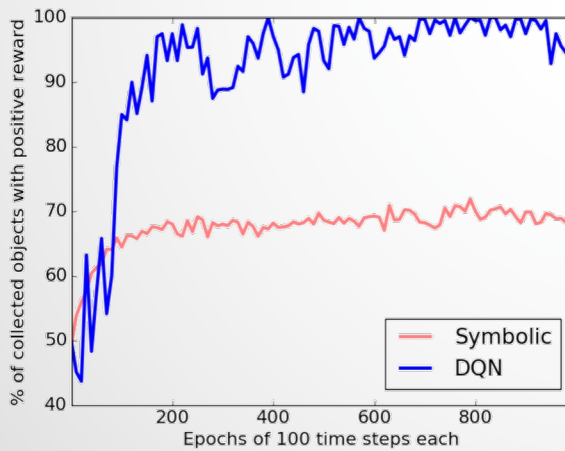
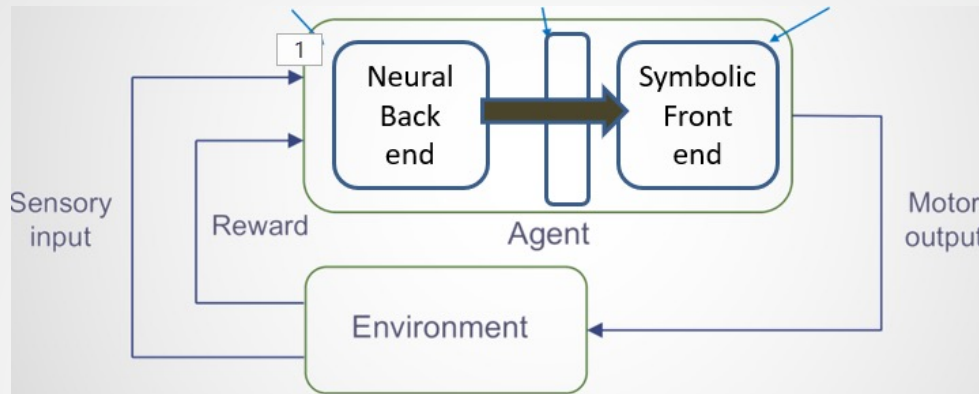
see(**3**)=3, see(**5**)=5, 3+5=8



# Learning that is robust to change (through intermediate abstractions)



# Learning that is robust to change (through intermediate abstractions)



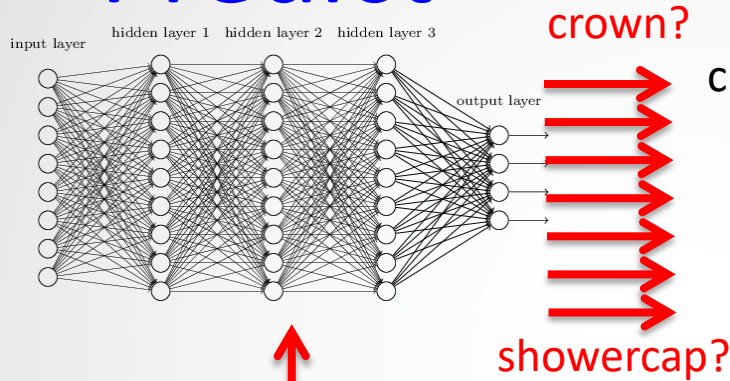
# out-of-distribution data

class: 793  
label: n04209133 shower cap  
certainty: 99.7%

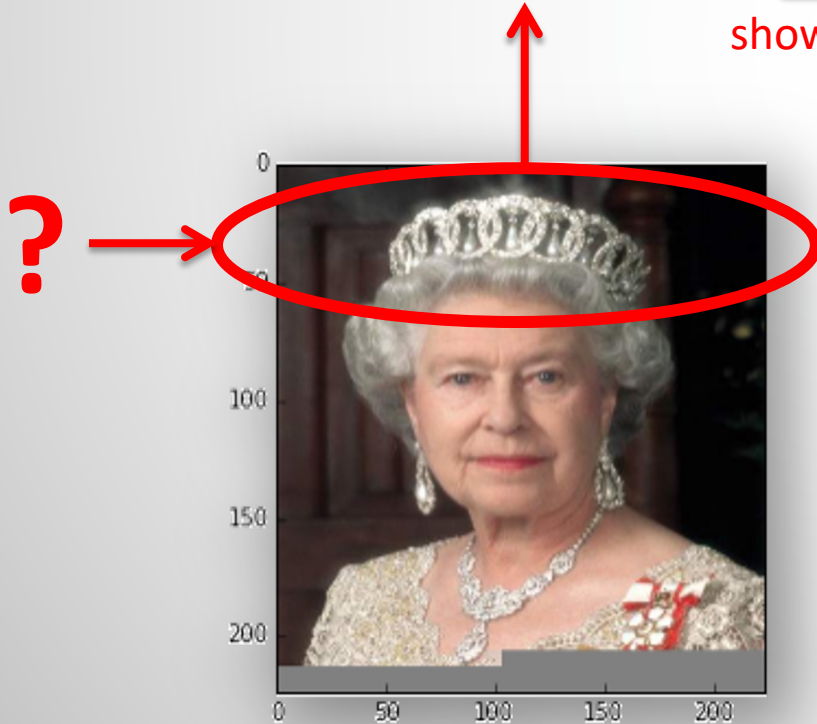
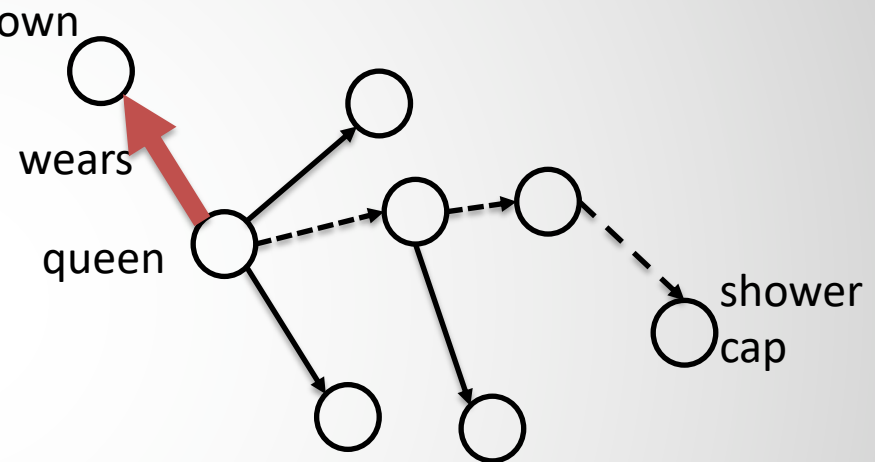


# Robust for out-of-distribution data (by using background knowledge)

## Predict

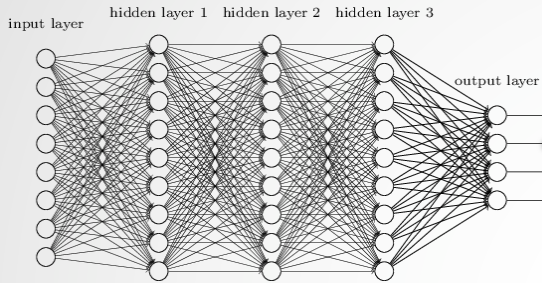


## Select

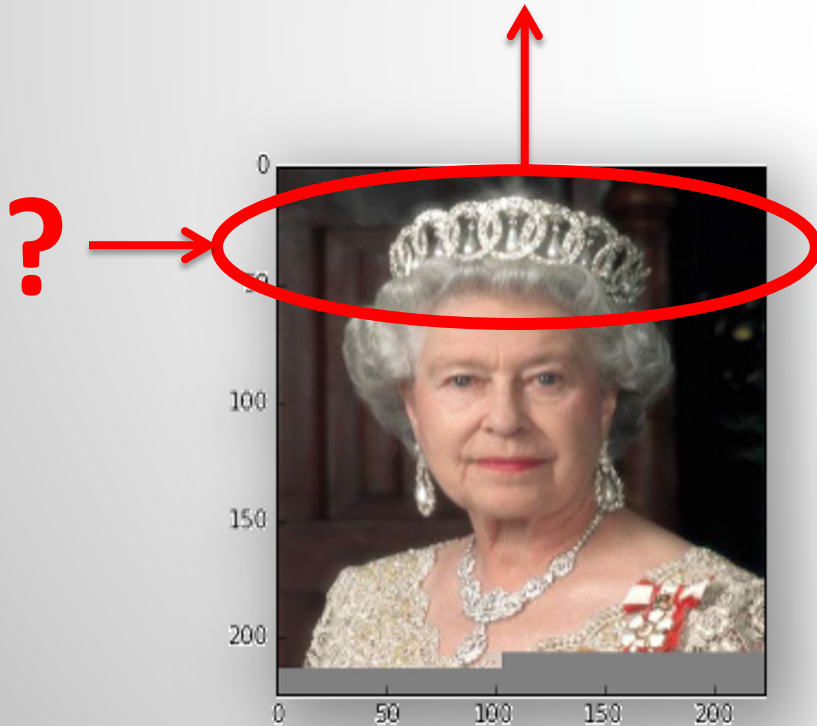
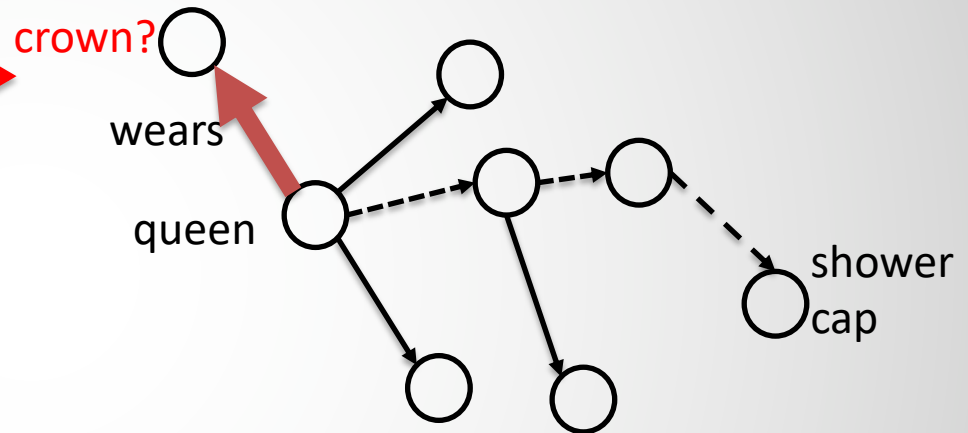


# Construct justifications

## Predict

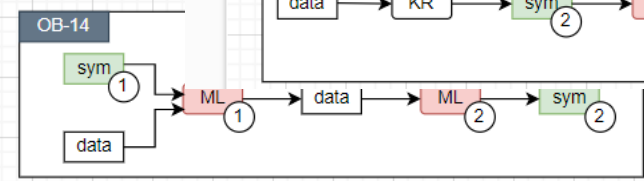
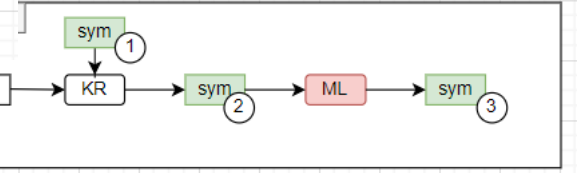
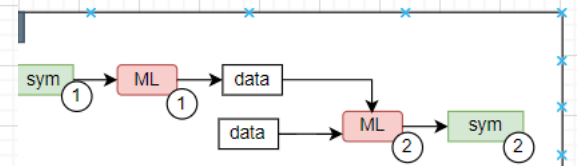
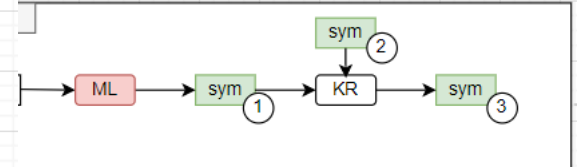
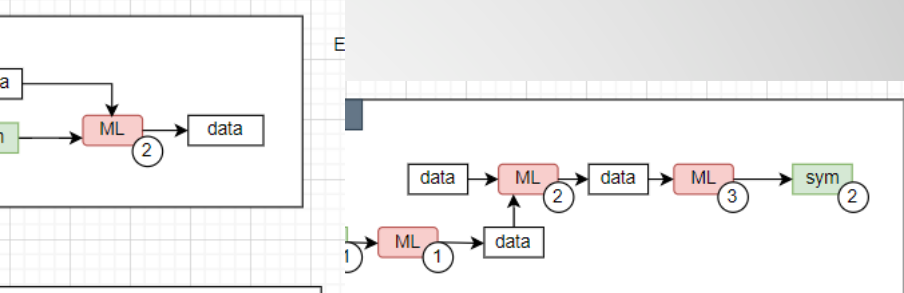
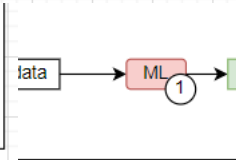
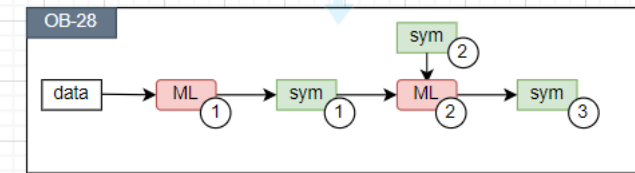
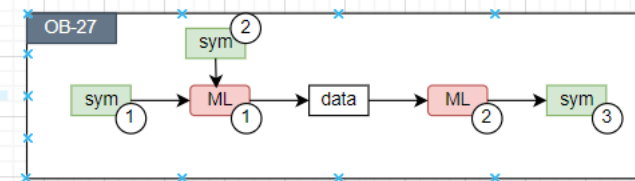
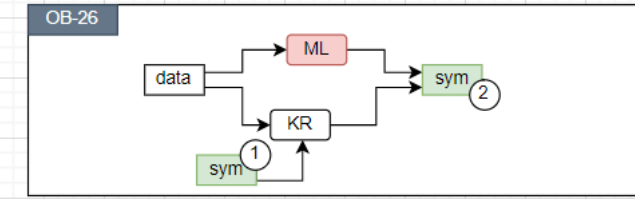
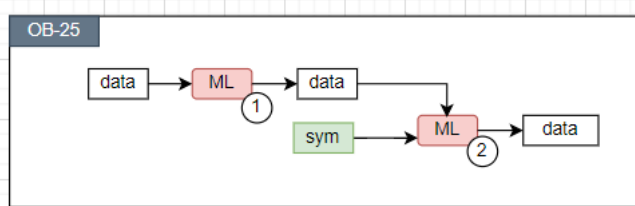
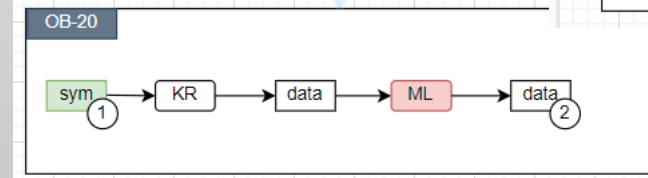
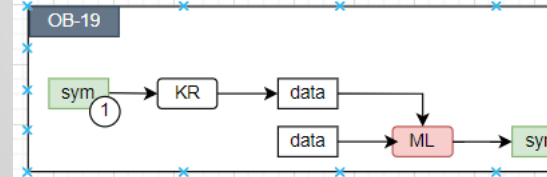
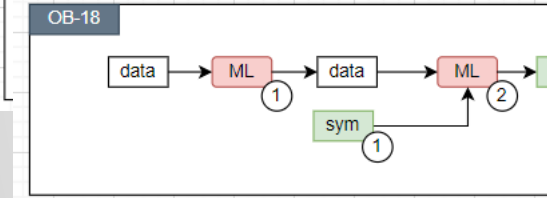
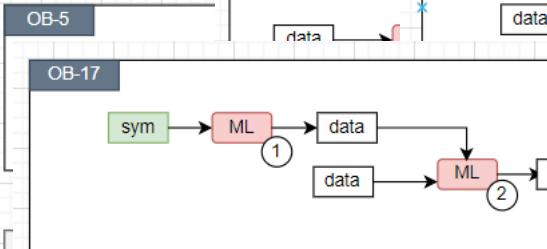
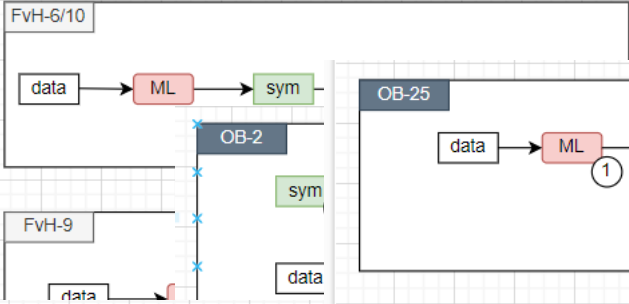
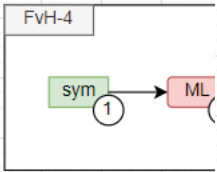
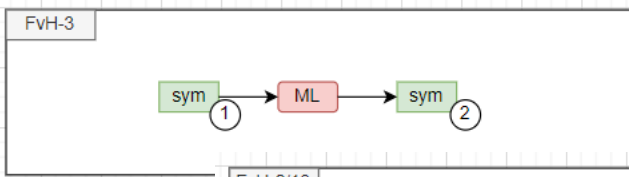


## Justify



**Etc...**

# The Vienna study (group of Marta Sabout at WU)

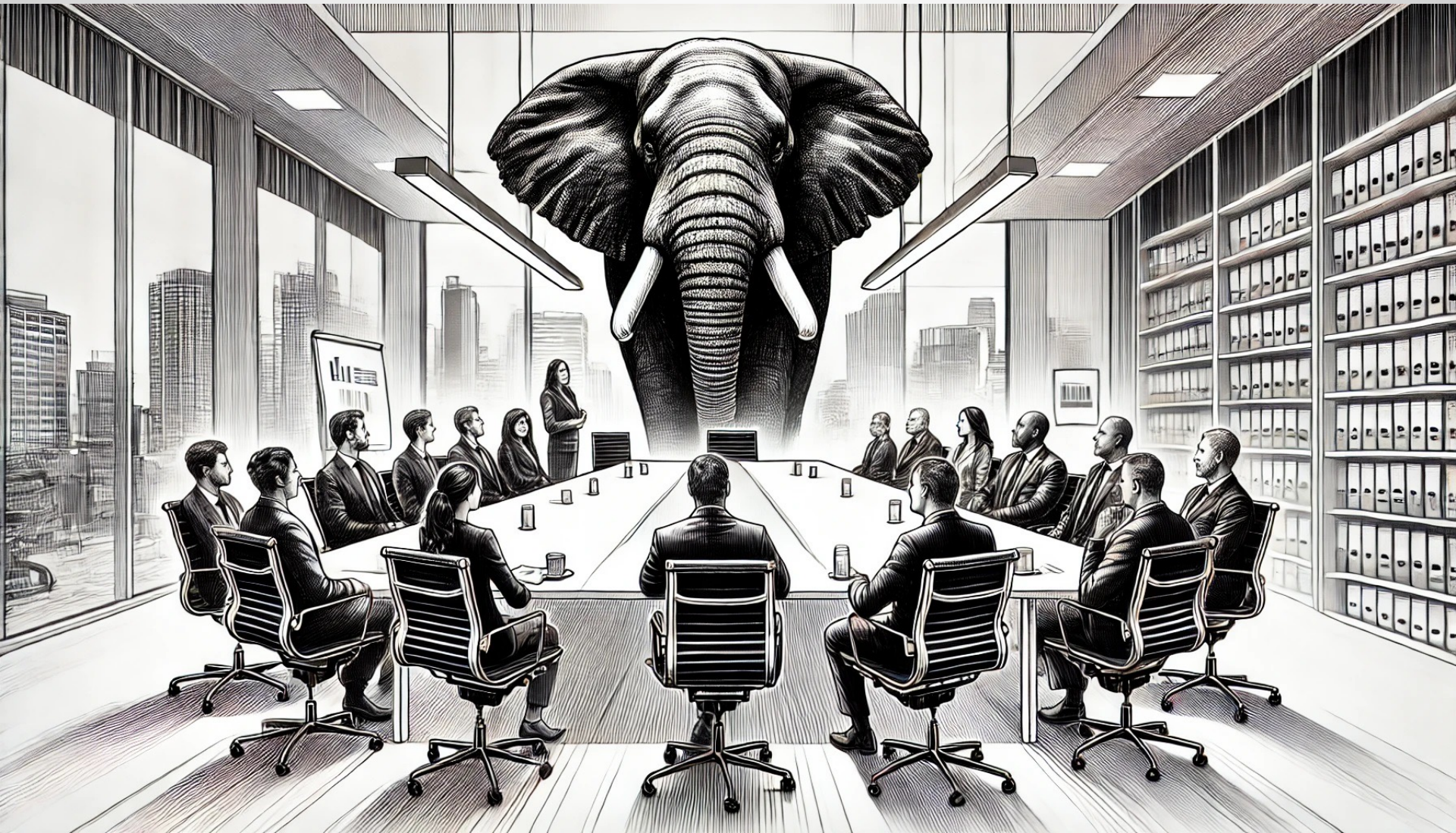


# So the neuro-symbolic paradigm enables AI systems that are

- Explainable
- Guaranteed safe
- Aware of context
- Robust against data drift
- Robust against out-of-distribution data
- Effective on a weak signal from small data



# The LLM in the room...



# The LLM in the room would say:

- ~~1. LLMs are the new paradigm in AI~~
2. LLMs don't need any symbols  
(they have purely neural representations)
3. Therefore we can happily stay  
in the neural paradigm

# LLMs are *language* models...

... they are not *world* models

Representational hypothesis in cognitive science:

*“cognitive processes are mediated by  
internal representations of information.*

*The mind operates by creating, storing, and manipulating  
**mental representations of the external world**  
to guide perception, reasoning,  
decision-making, and action.”*

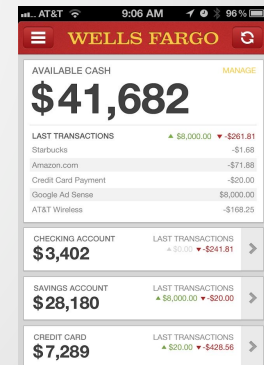
# Neuro-symbolic synthesis:

AI systems will need world models,  
and these world models will be

**Partially** subsymbolic/neural/distributed  
(& reasoning = network activations)



**Partially** symbolic/propositional/discrete  
(& reasoning = symbol manipulations)



But:

**reasoning about the world  $\neq$  reproducing linguistic patterns**

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