A top-down approach for a synthetic autobiographical memory system

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Joint work with:
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Living Machines

Barcelona, 31 July 2015

Synthetic Autobiographical Memory (SAM)

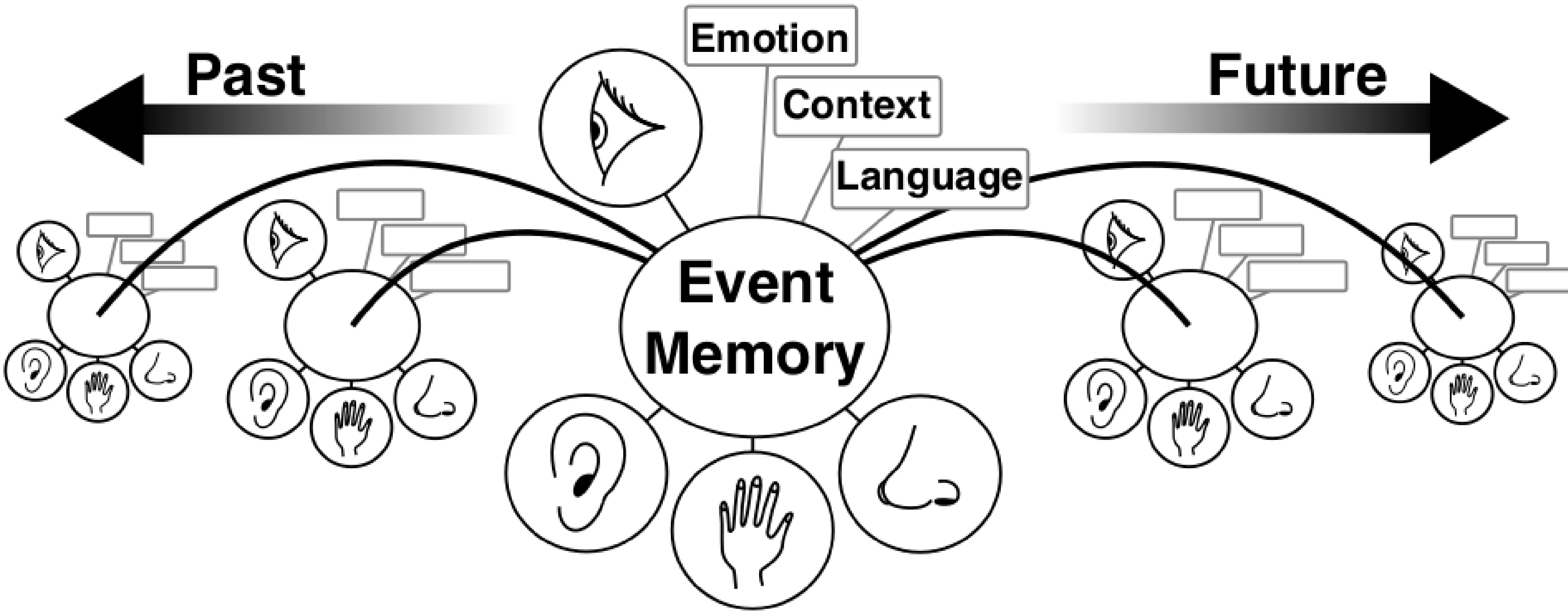
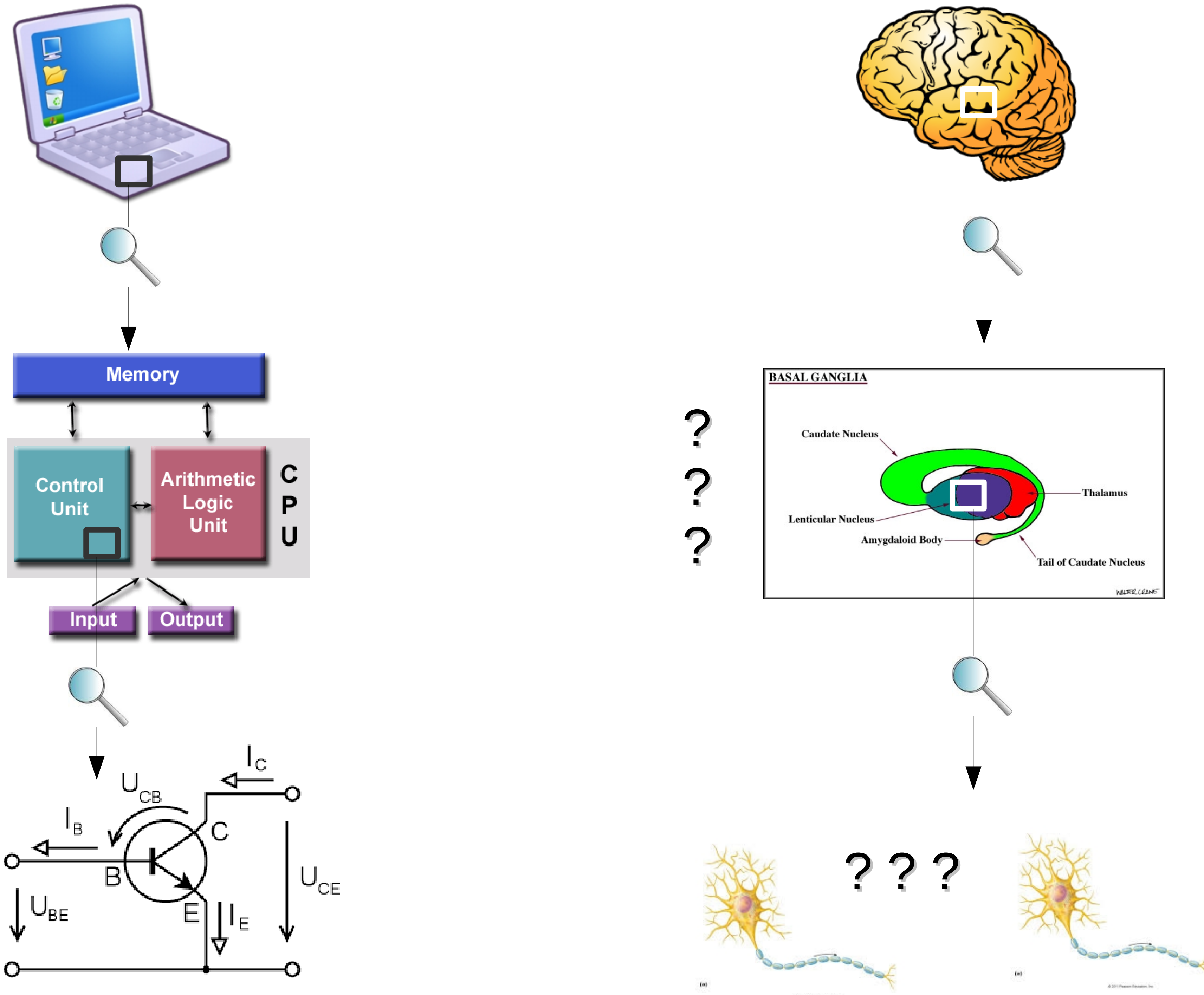


Fig. 2. Episodic memory in our model functions by combining disparate information across modalities into a single coherent percept from moment to moment. These transient percepts are monitored and coordinated over time into event sequences and episodic memories through iterative pattern completion and separation operations.

Figure from: Evans et al. 2014: Machines learning - towards a new synthetic autobiographical memory



Memory
Control Unit
Arithmetic Logic Unit
CPU
Input
Output
I C
U CB
I B
C
B
E
U BE
I E
U CE
BASAL GANGLIA
Caudate Nucleus
Thalamus
Lenticular Nucleus
Amygdaloid Body
Tail of Caudate Nucleus
?
?
?
? ? ?

Motivation

- Recall Roger Quinn's talk: traditional mechanics were used together with bio-inspired mechanical components
- Here we will use machine learning algorithms together with bio-inspired algorithms
- R. Quinn: “Work from both ends”. Here concerned with top-down approach. See Boorman et al.'s paper for “bottom-up”
- Top-down: Mimic functionality, abstract low-level details...
- … but preserve transparency: make assumptions explicit

Main idea / target

	1	2	…	10000
1	0.81472	0.27603	…	0.58225
2	0.90579	0.6797		0.54074
3	0.12699	0.6551		0.86994
4	0.91338	0.16261		0.26478
5	0.63236	0.119		0.31807
	⋮			⋮
50	0.75469	0.33712	…	0.64555

= Y

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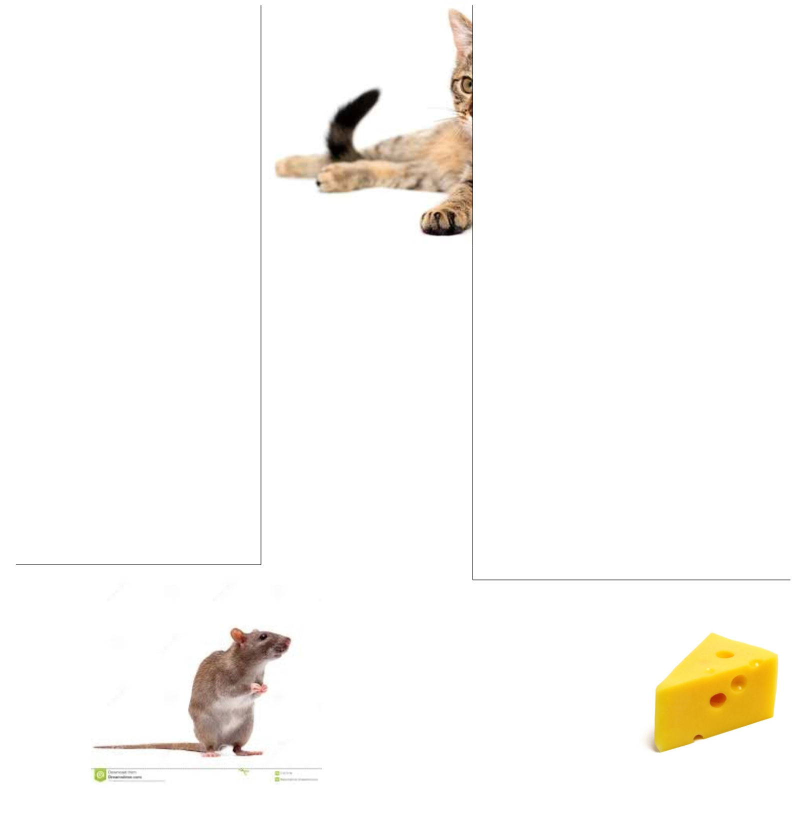
= Y

- Current approach: SQL storage
- SAM: Move towards a more realistic “remembering & forgetting” (storage is not unlimited)
- Use probability. e.g. p(Y) = ?
- Bio-inspired at *functional level*

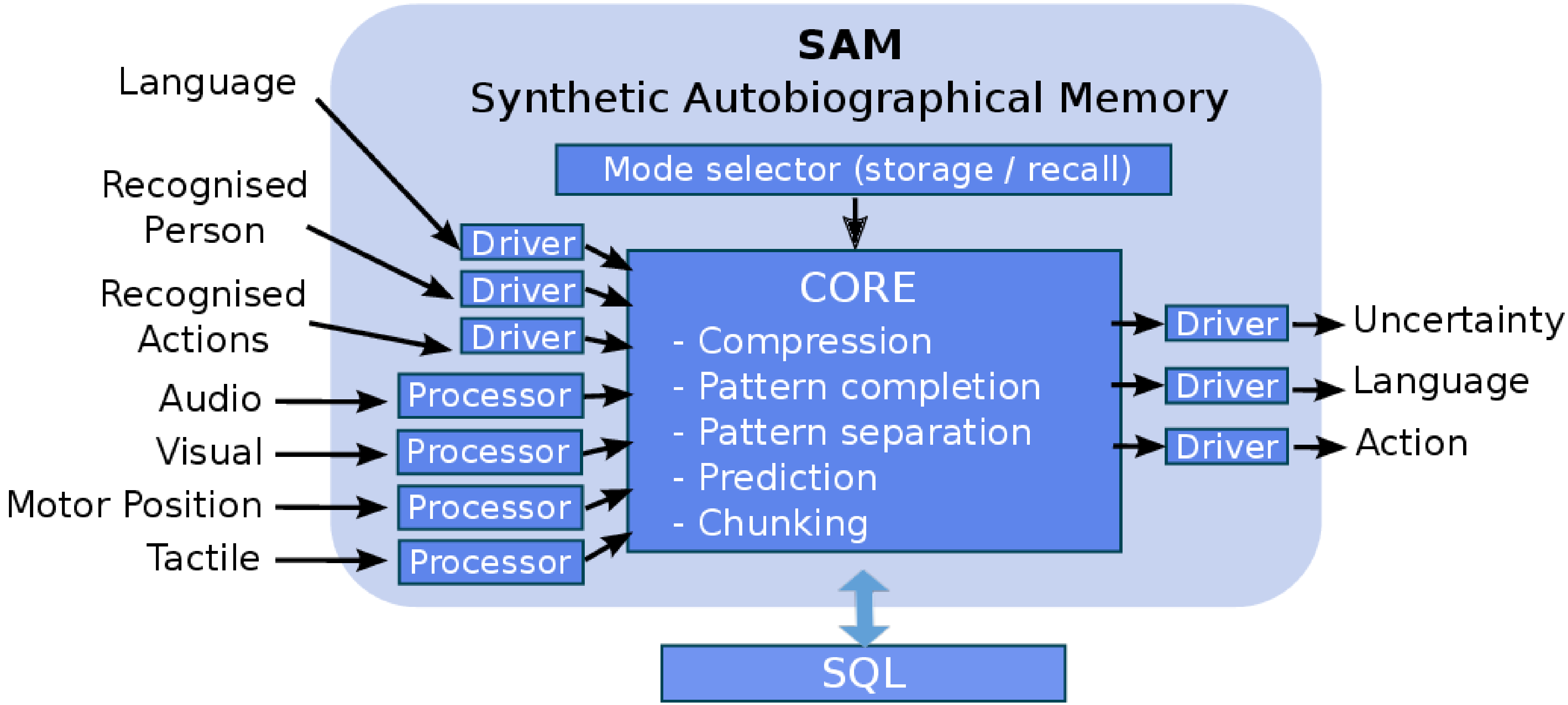
Functionality / requirements for ABM

- Evans et al. 2014:
  - Multi-sensory compression
  - Pattern separation
  - Pattern completion

- Additionally for top-down SAM:
  - Deterministic inference
  - Encoding consistency
  - Transparency



Our SAM architecture



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Top-down SAM properties:

- Probabilistic Bayesian
- Non-parametric
- Latent variable

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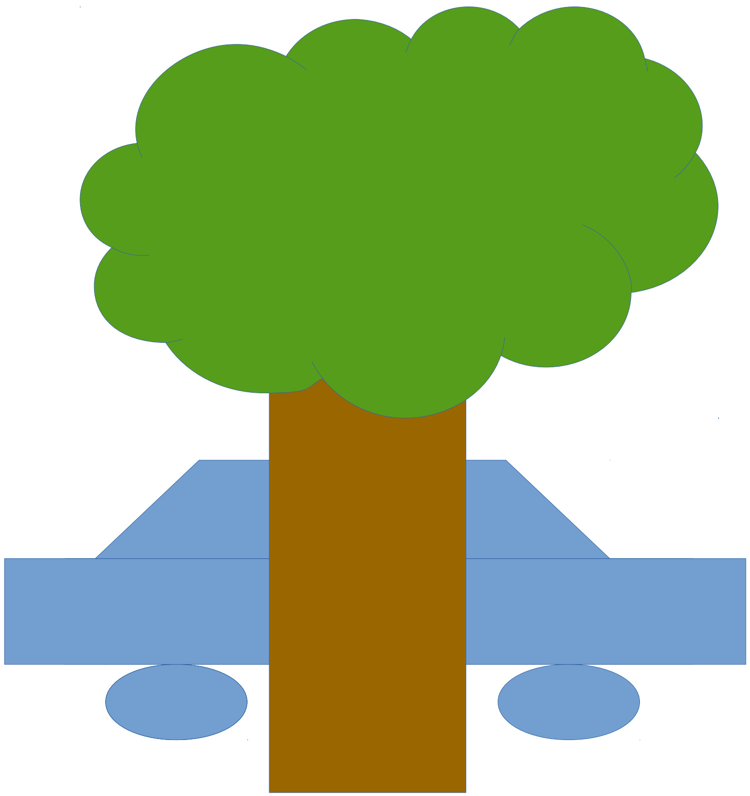
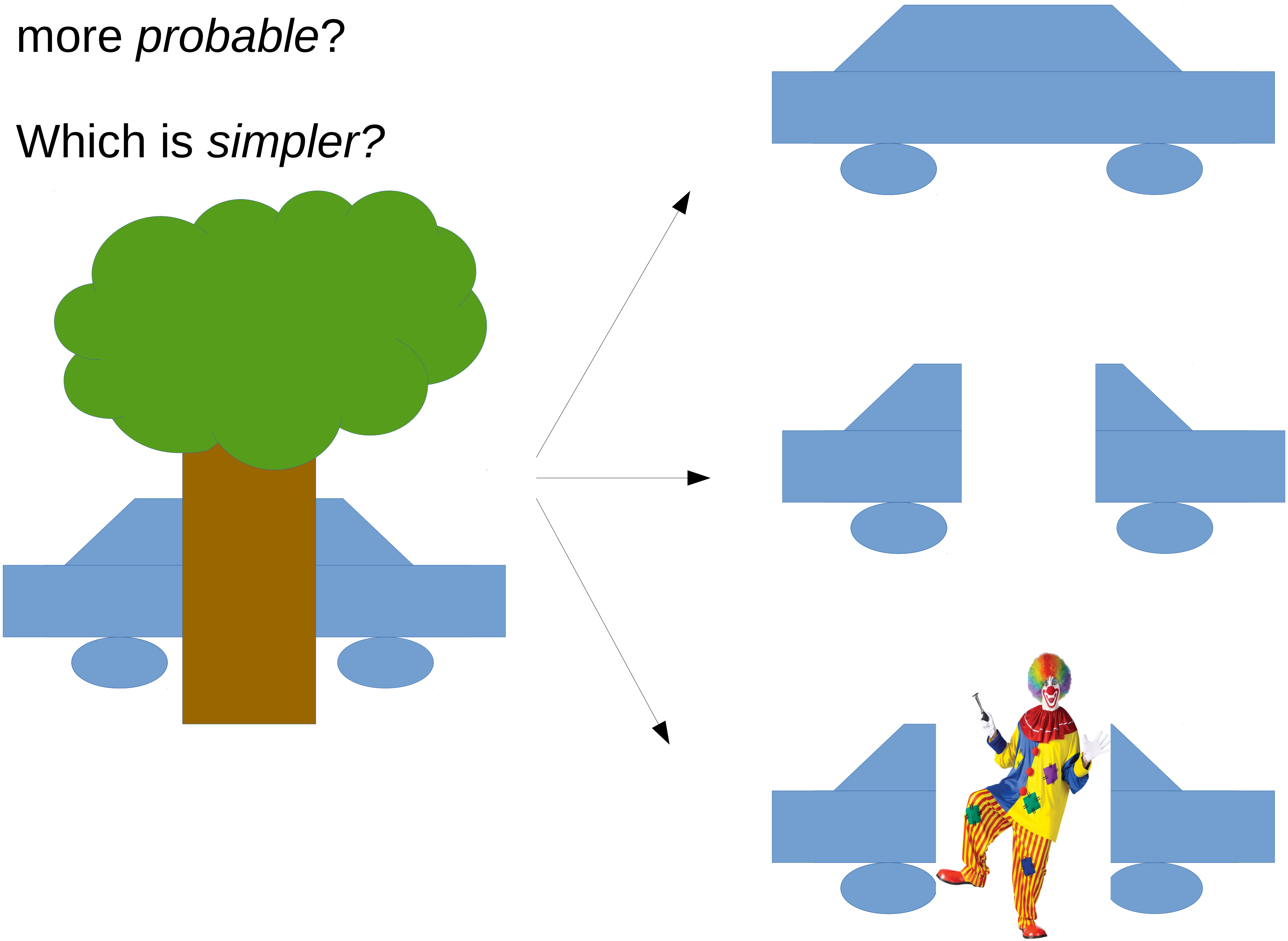
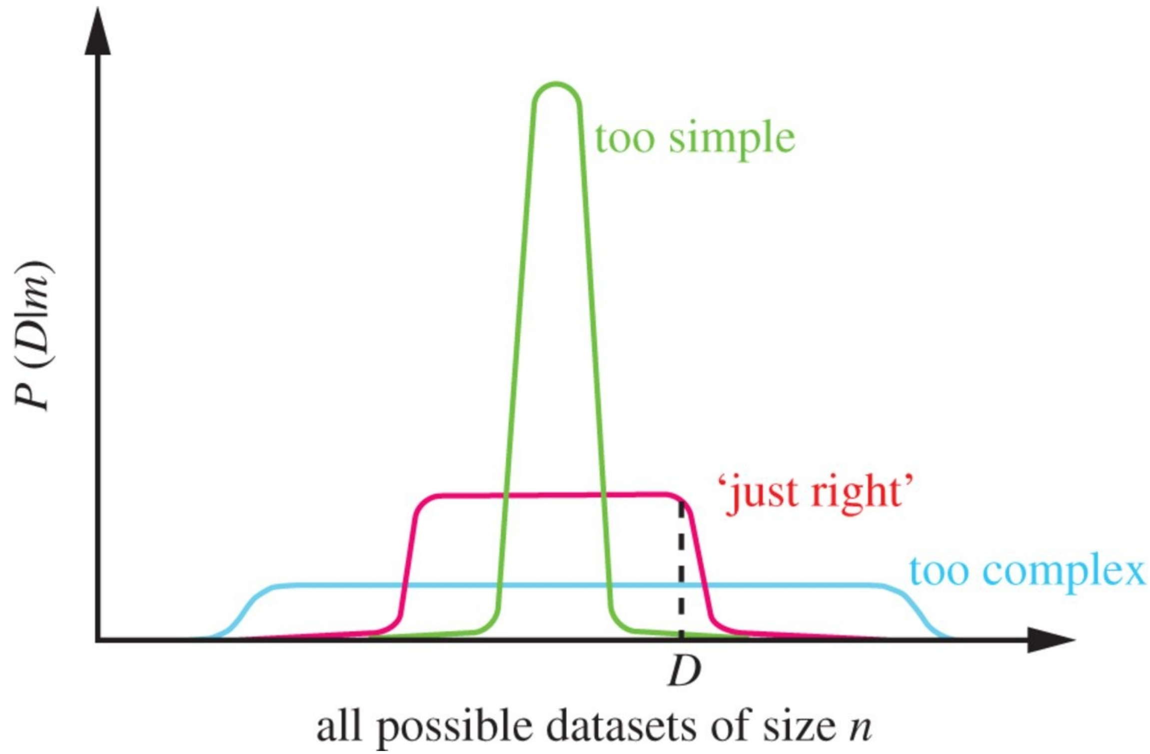


- Which of the three inferences is more *probable*?

- Which is *simpler?*



Bayesian Occam's razor



Copyright: David MacKay

Bayes' rule:

$$p(? \mid D, m) = \frac{p(D \mid ?, m)\, p(? \mid m)}{p(D \mid m)}$$

Allows us to be clear about our assumptions

Transparency

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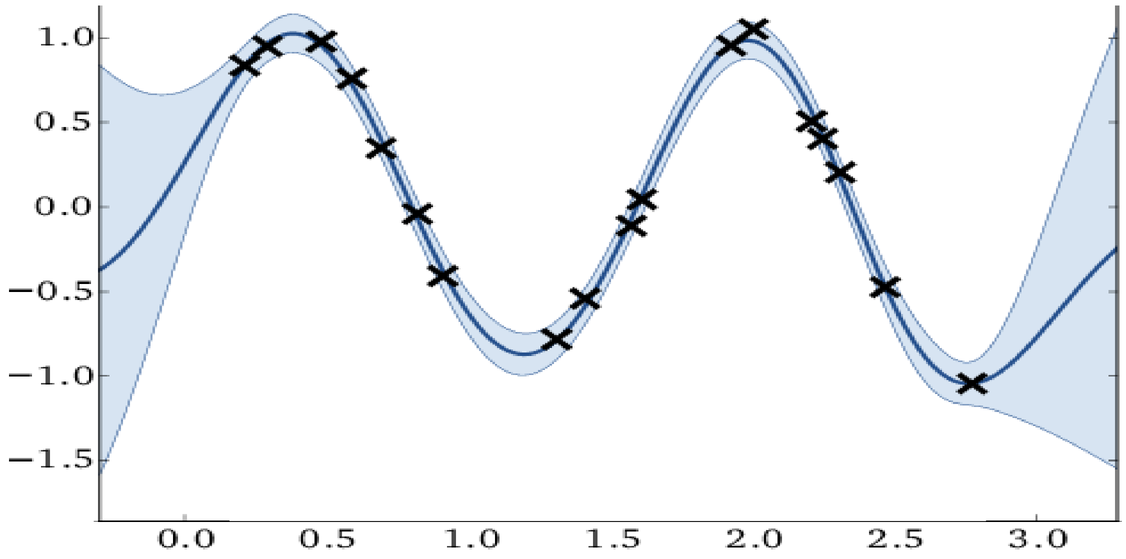
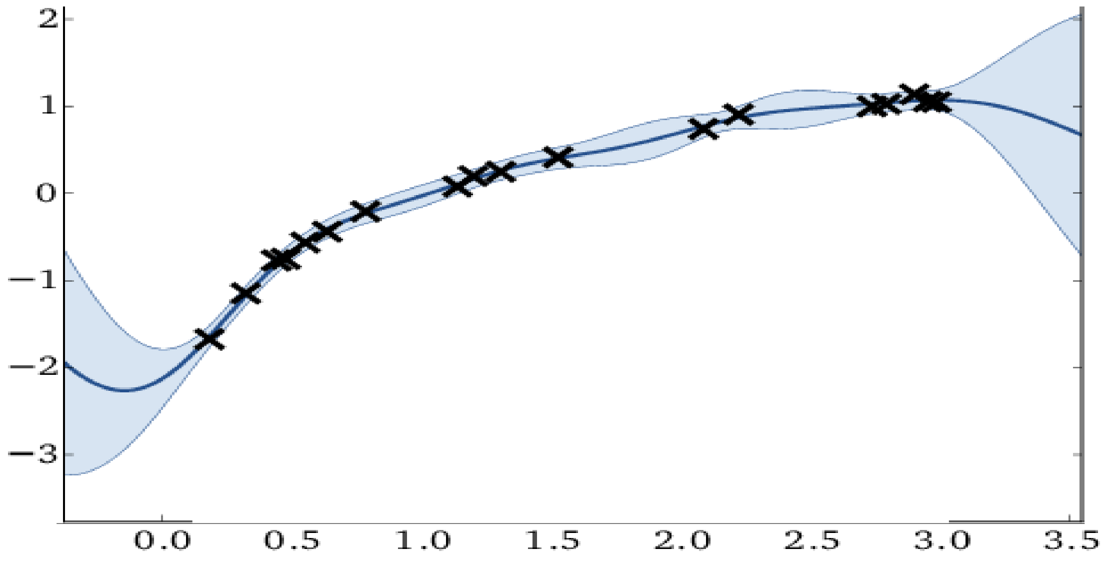
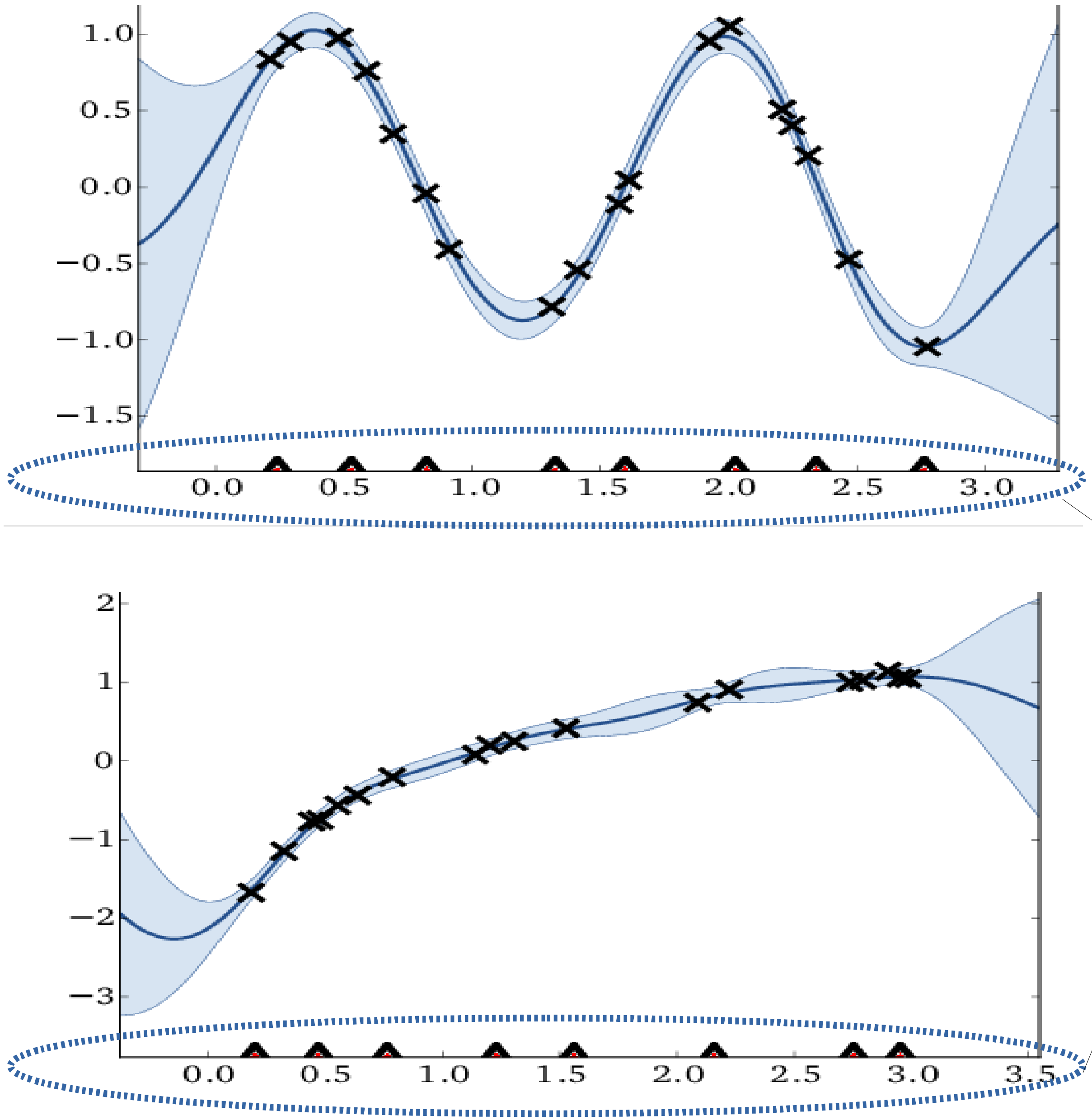
Gaussian process framework





Gaussian process framework



Compression via a finite set of pseudo-inputs (fantasy data).

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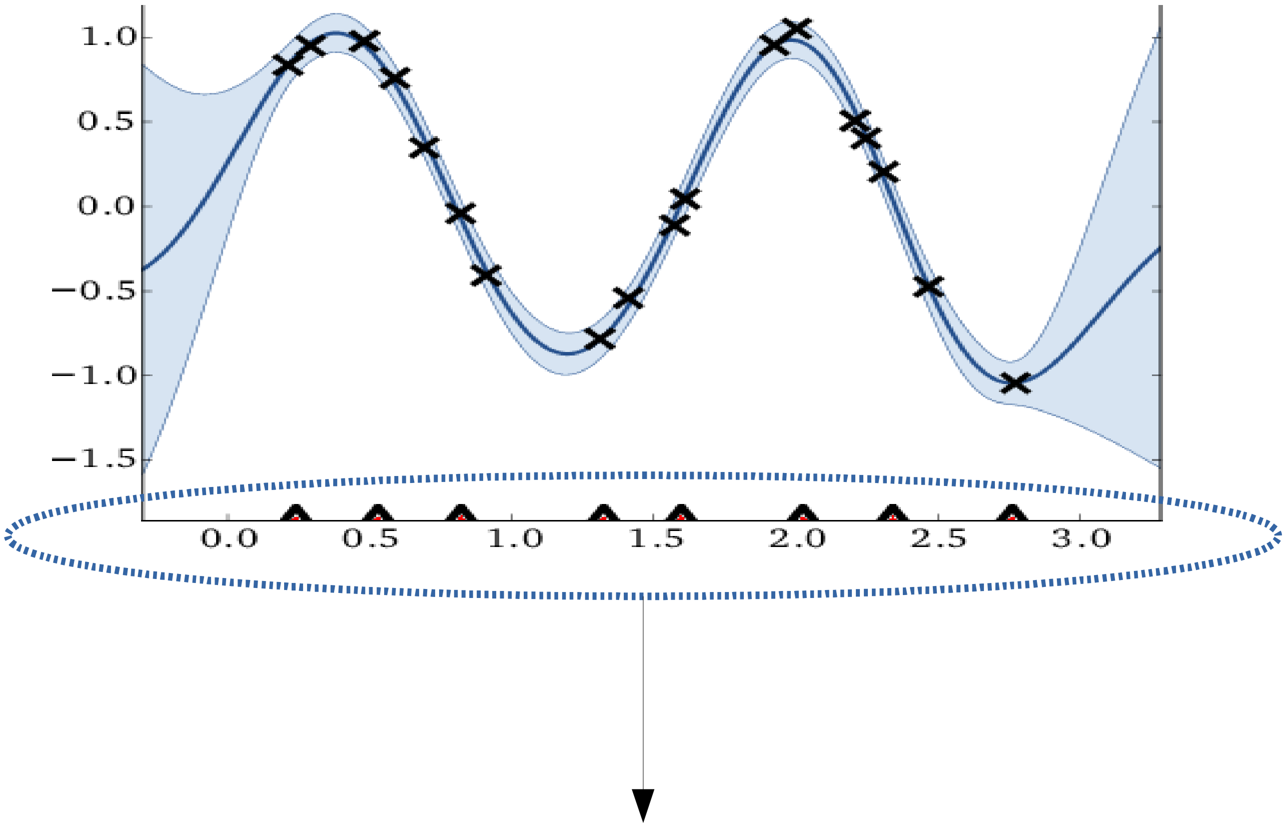


Abstracted / unknown underlying causes:
=> Treat inputs as latent & learn a distribution over them

Latent Variables

- What are the *latent* features of “cuteness”?

Another example: latent *process*

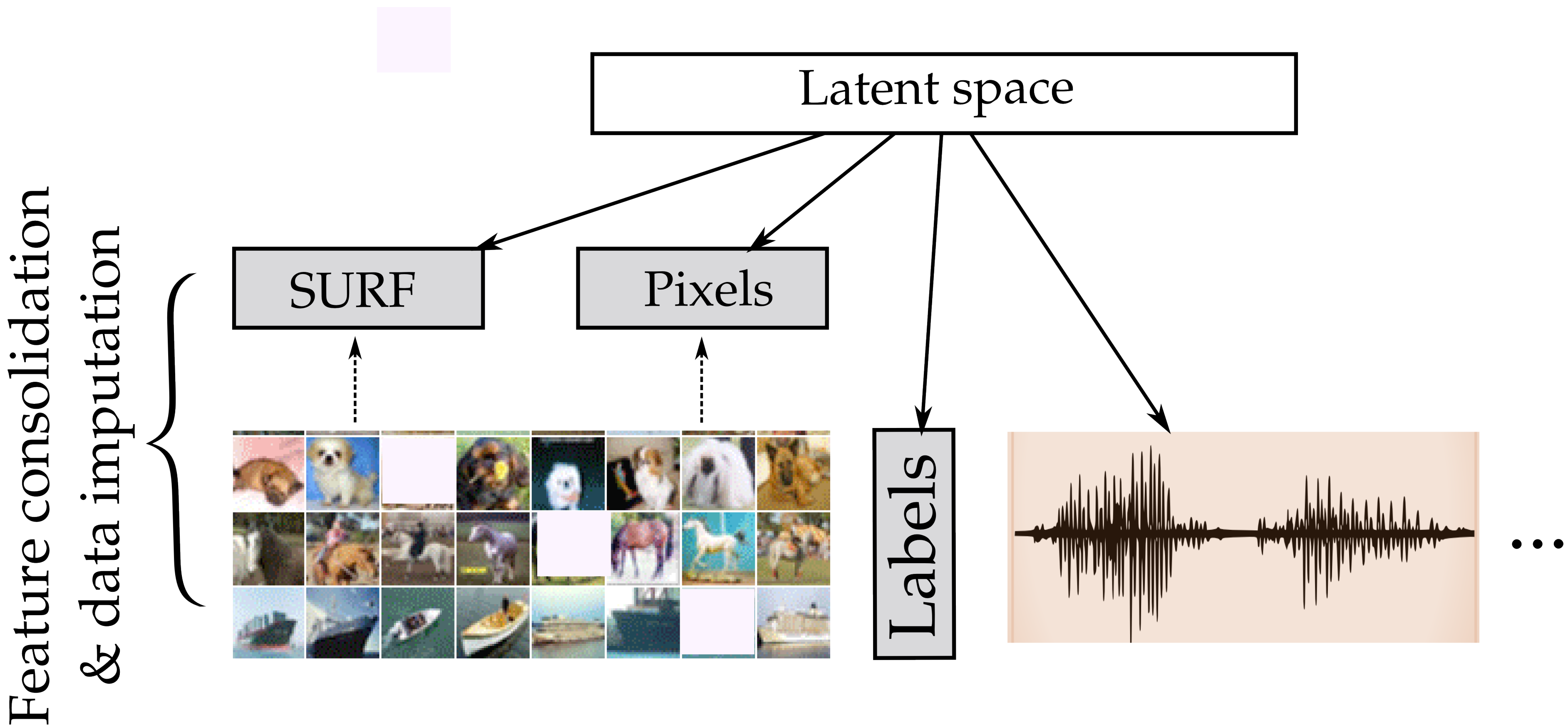
Is Beckam an expert in Newtonian & trajectory mechanics?

$$m\frac{\mathrm{d}^2\vec{x}(t)}{\mathrm{d}t^2} = -\nabla V(\vec{x}(t)), \quad \vec{x} = (x, y, z)$$

$$R_s = \sqrt{x^2 + y^2}$$

$$= \sqrt{\left(\frac{2v^2\cos^2\theta}{g}\left(\frac{\sin\theta}{\cos\theta} - m\right)\right)^2 + \left(m\frac{2v^2\cos^2\theta}{g}\left(\frac{\sin\theta}{\cos\theta} - m\right)\right)^2}$$

Latent underlying machinery



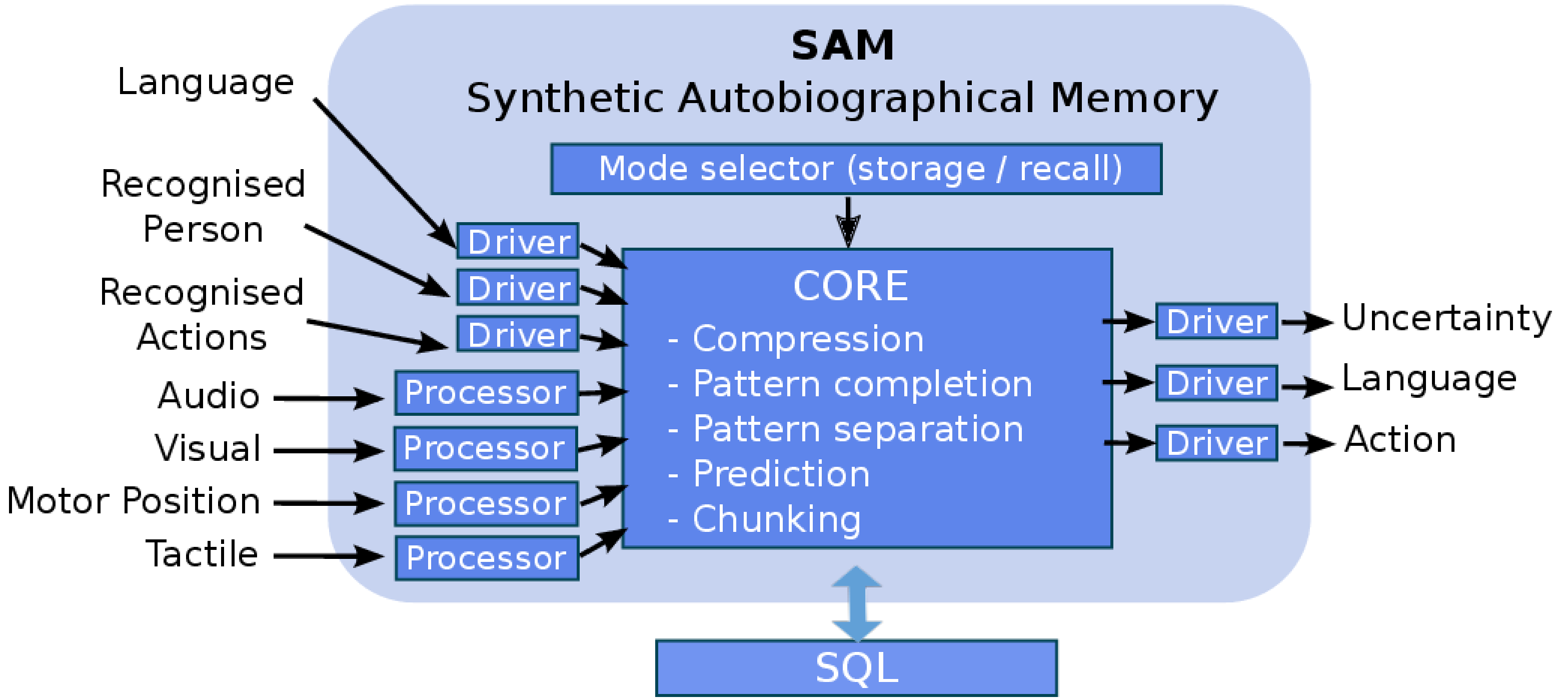
Results 1 (Demonstration)

Video: https://youtu.be/rIPX3CIOhKY

“Eigenfaces”

“Fantasy memories”
used as a
compressed basis
(inducing points)

Results 2



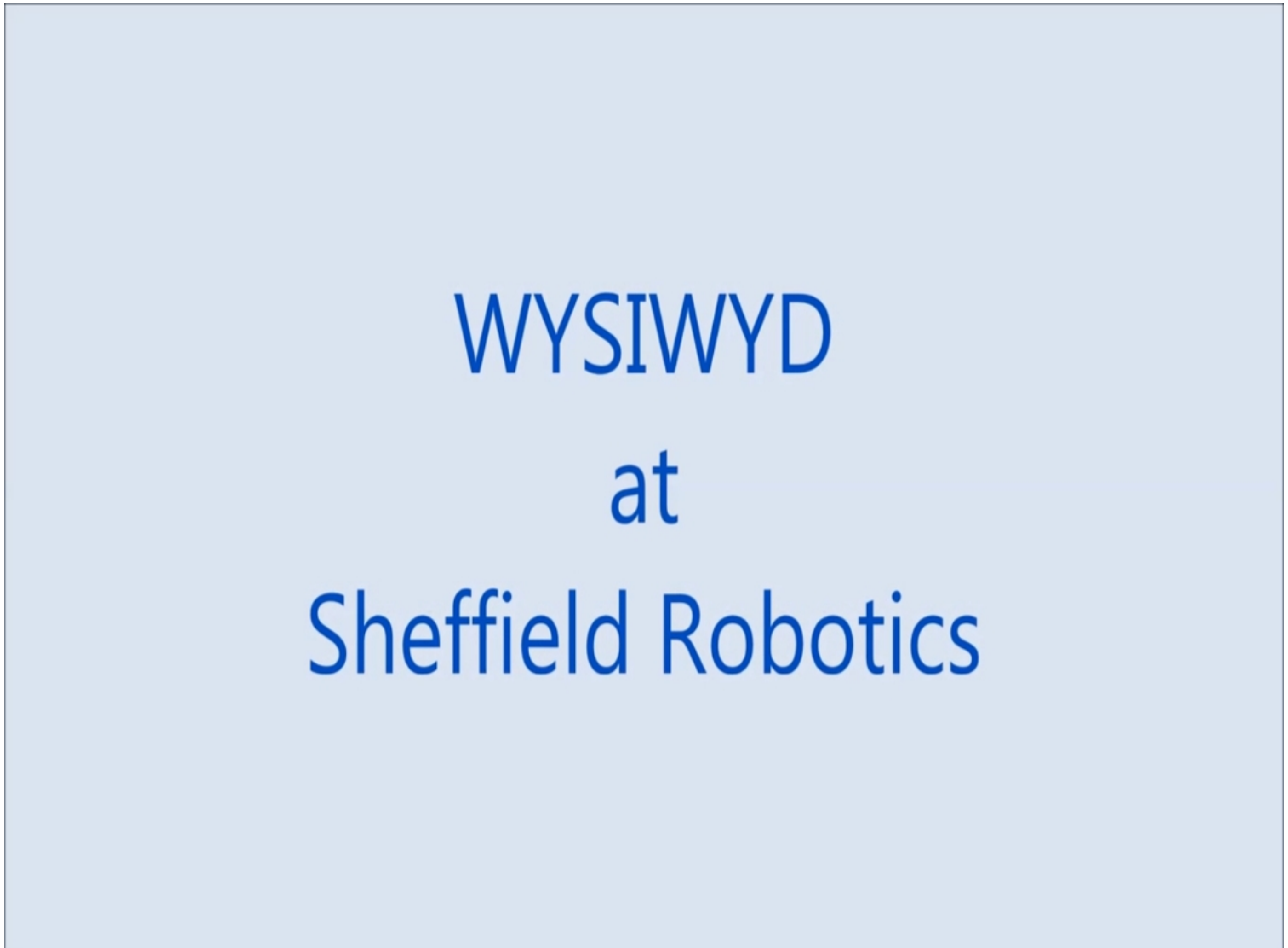
GPy Dev. Team

Luke Boorman

Uriel Martinez-Hernandez

Daniel Camilleri

WYSIWYD Team



Video: https://youtu.be/Z5K0csC5gZ4

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- Daniel Camilleri
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