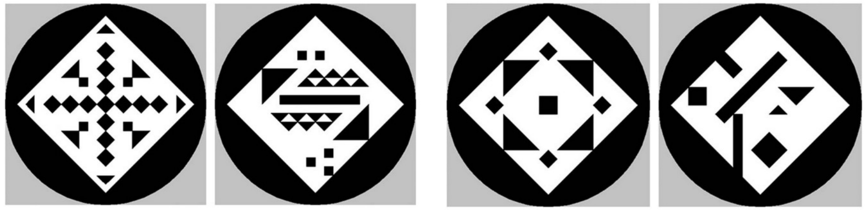
A computational model of aesthetic value

Aenne Brielmann & Peter Dayan

Aesthetic value judgments



How beautiful is this pattern? (1-7)

Tinio & Leder (2009)

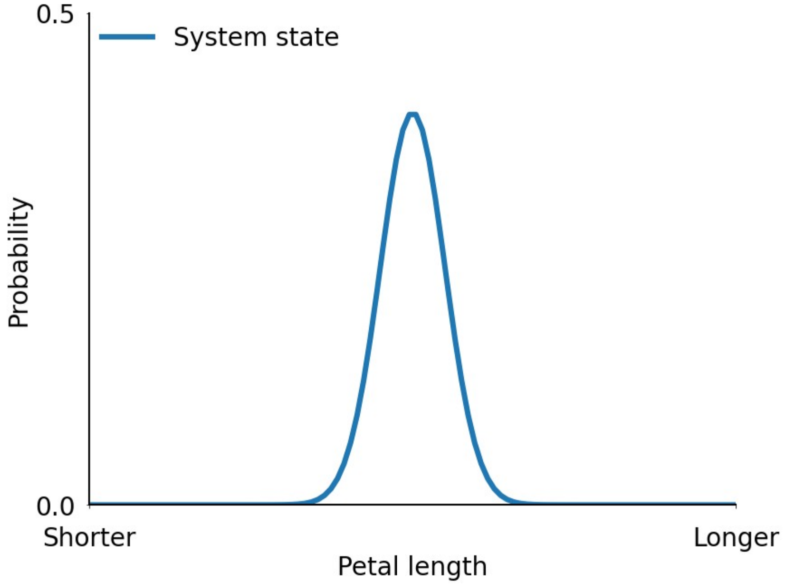
Lili Elbe by Gerda Wegener

What is the task?

We want to perceive and predict the world well (good generative model).

This dates back to Helmholtz‘ idea of perception as mental representation of the object that most likely causes the sensory input.

Flower →



Aesthetic value is the indicator of progress towards that goal.

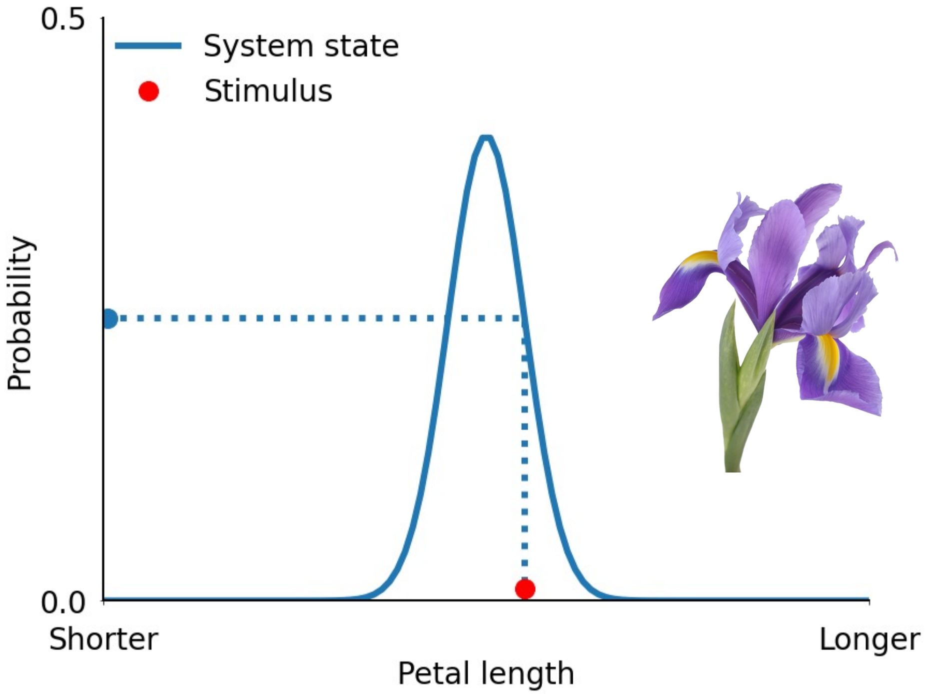
Some things we do know about aesthetic value

People value experiences that are

- easy to process e.g. Reber et al., 2004
  - prototypical for their category e.g., Martindale et al., 1988; Rhodes et al., 2001
  - experienced several times before e.g., Zajonc, 1968

Intuition 1: **immediate sensory reward**

Formalizes processing fluency.



Aesthetic value increases with the probability of the object given the generative model.

Indicates our model of the world is right, applicable.

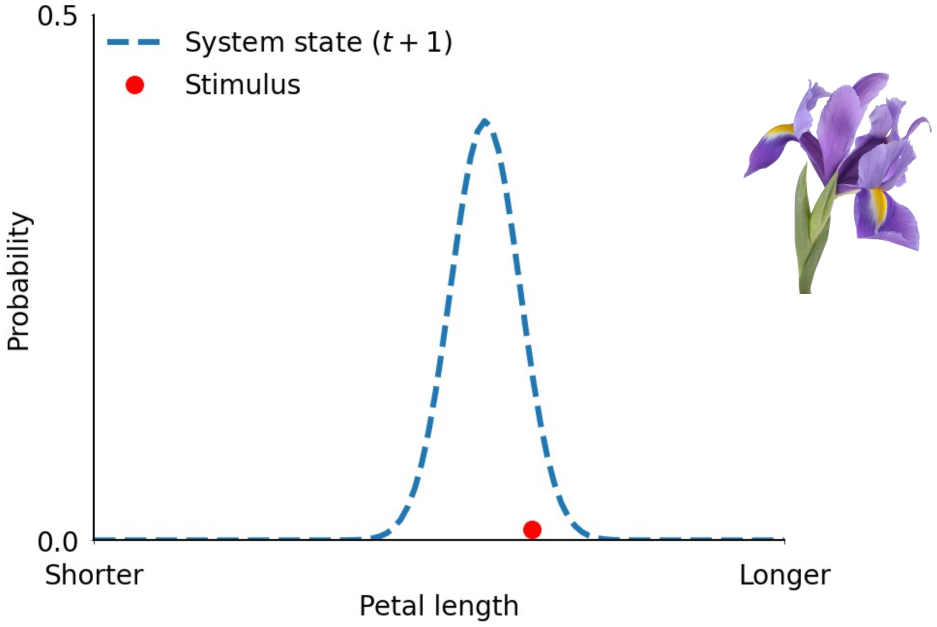
Some things we do know about aesthetic value

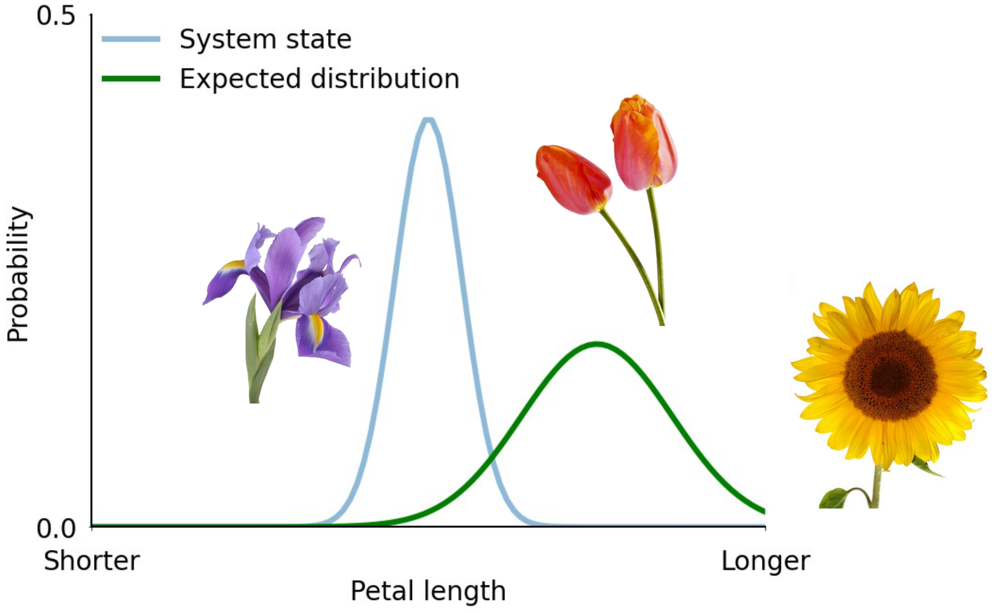
People value experiences that are

- easy to process e.g. Reber et al., 2004
  - prototypical for their category e.g., Martindale et al., 1988; Rhodes et al., 2001
  - experienced several times before e.g., Zajonc, 1968
  - BUT people get bored e.g., Bornstein & D'Agostino, 1992
- afford learning e.g., . Van de Cruys & Wagemans, 2011
  - intermediate complexity e.g., Berlyne, 1971
  - unity in variety e.g., Van Geert & Wagemans, 2020

Intuition 2: **Expected long-term reward**

Operationalizes the reward of learning





Aesthetic value increases as the value of the system state increases, i.e., proportional to the change in the expected future reward.

Indicates that our model will be better suited for the future.

Some things we do know about aesthetic value

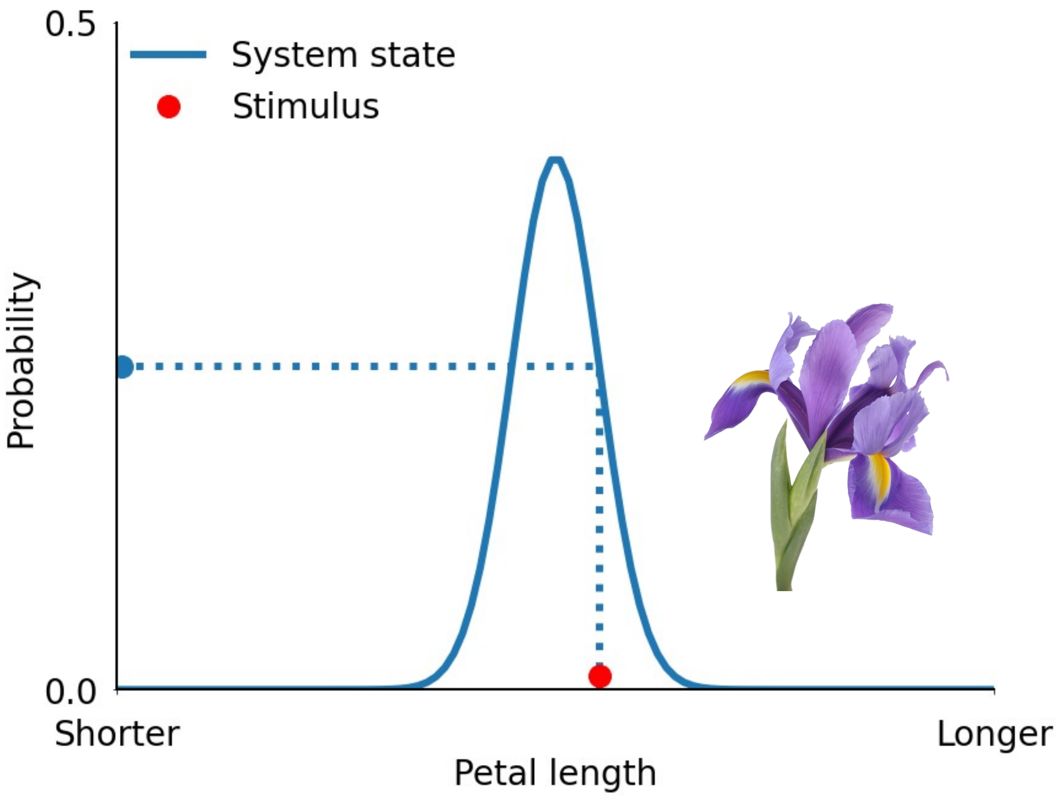
People value experiences that are

- easy to process — e.g. Reber et al., 2004
  - BUT people get bored — e.g., Bornstein & D'Agostino, 1992

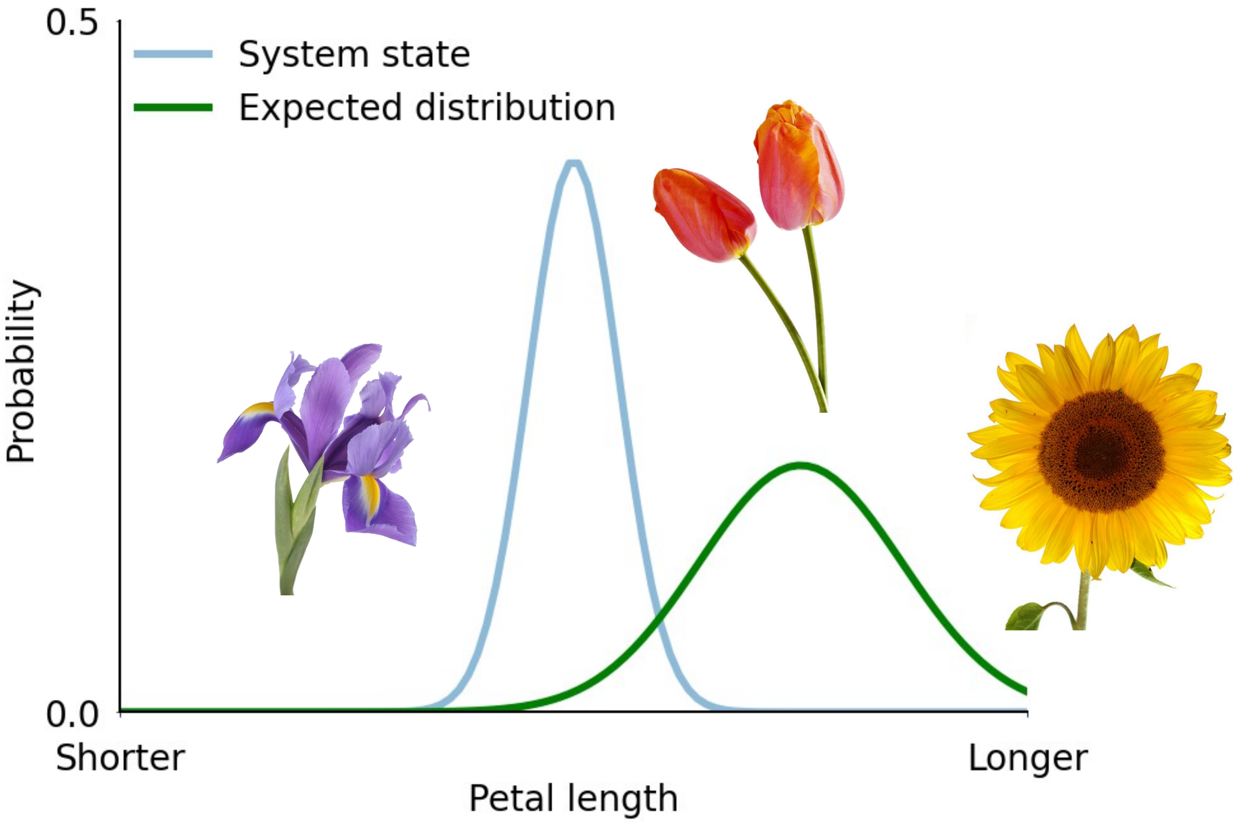
- of intermediate complexity — e.g., Berlyne, 1971
  - BUT people choose to experience the same things over and over

A comprehensive theory of aesthetic value

immediate sensory reward



change in expected future reward

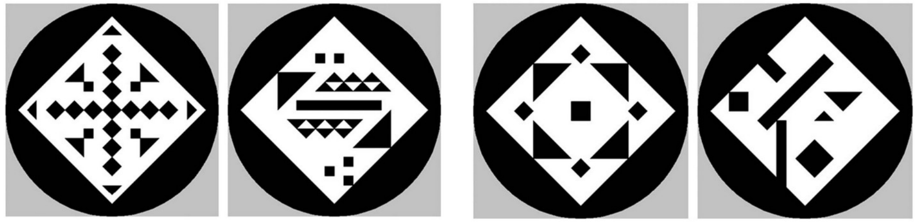


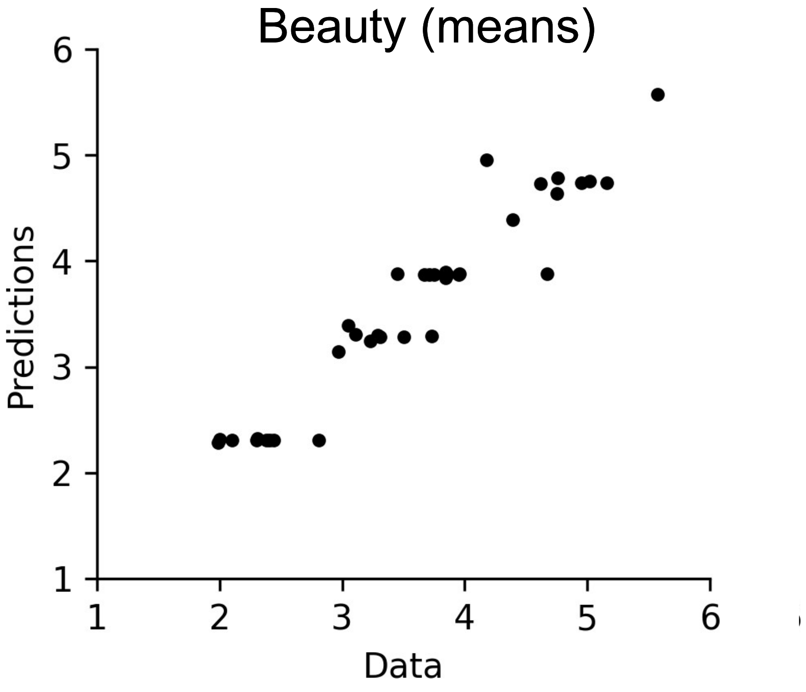
cf. Rutledge et al., 2014

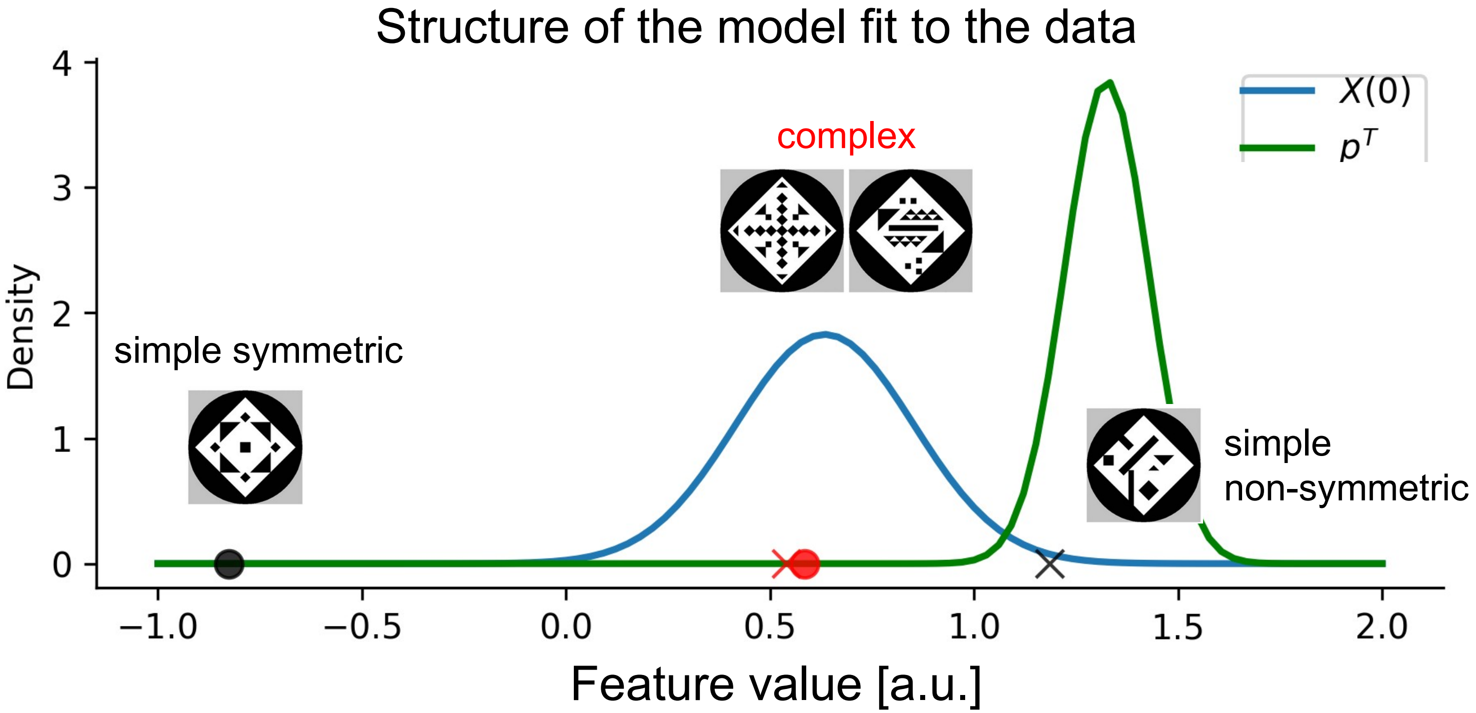
A simple model can fit empirical data

Tinio & Leder (2009).

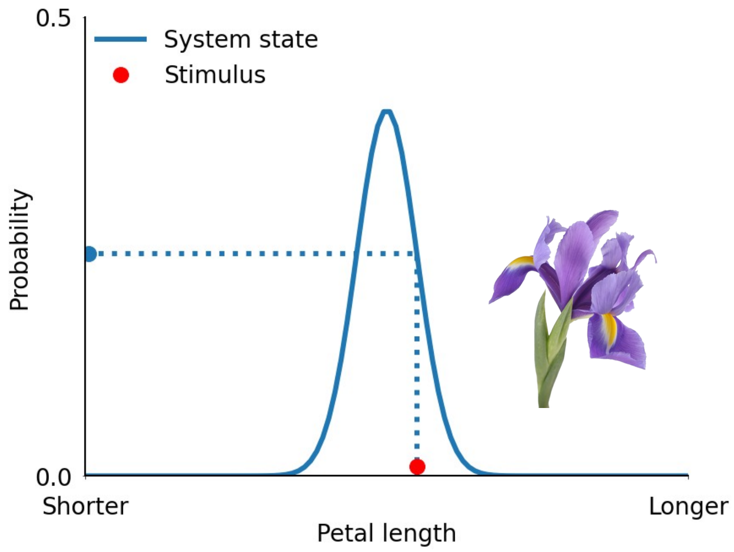
Just how stable are stable aesthetic features? Symmetry, complexity, and the jaws of massive familiarization.

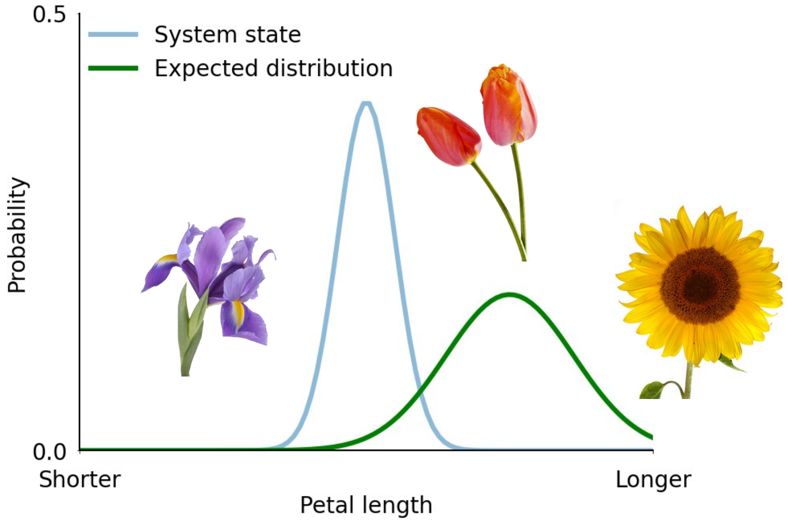






Aesthetic value is…





... derived from the task of developing an efficient sensory system.

… fundamentally similar to primary and secondary rewards.

... comprised of two linked components:
immediate sensory reward &
change in expected future reward.

… precisely quantifiable using the same approach as reinforcement learning frameworks.

Thank you!

Peter Dayan

Max Berentelg

the Computational Neuroscience Group @MPI-BC

MAX-PLANCK-GESELLSCHAFT

Alexander von Humboldt
Stiftung / Foundation

Walter Benjamin-Programm
DFG Deutsche Forschungsgemeinschaft

Feeling inspired?

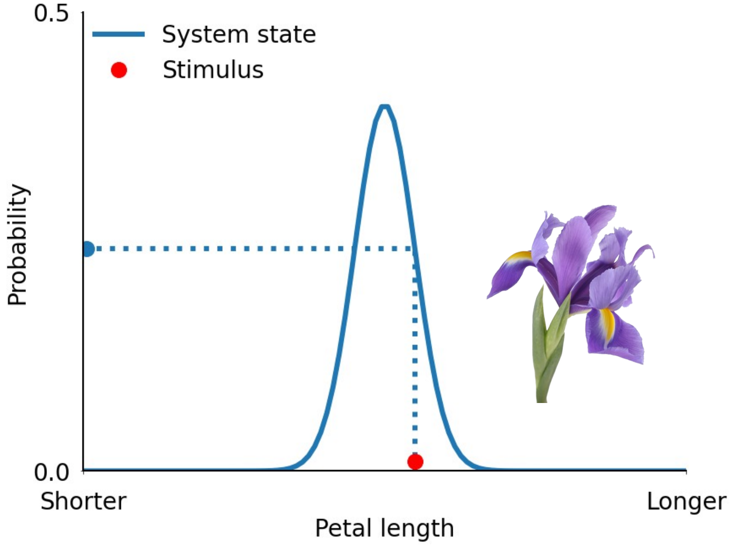
Got data?
→ Code for implementing the model is available on GitHub

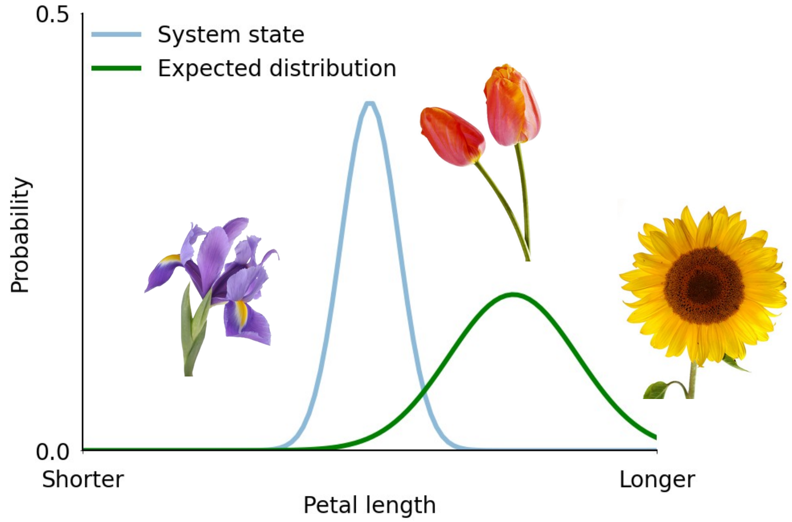
No python experience? No problem!
→ Get in touch with me: aenne.brielmann@tuebingen.mpg.de

Just want to take a look at how the model behaves?
→ Try the shiny app for simulating mere exposure effects

Want to start a (public) debate?
→ Find me on Twitter @aabrielma

Aesthetic value is…





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A formal model of aesthetic value

Component 1: **immediate sensory reward *r***

We define *r* as the log likelihood of a stimulus given the system state.

= Mahalanobis distance between ***s***(*t*) and the system state ***X***(*t*):

$$r(t) = \log[p(\mathbf{s}(t); \mathbf{X}(t))] = k - (\mathbf{s}(t) - \boldsymbol{\mu}(t))^T \Sigma^{-1} (\mathbf{s}(t) - \boldsymbol{\mu}(t))/2$$

where *k* is a constant

This represents an exact operationalization of “processing fluency”

Formal model description

Learning takes place by moving the mean of the system state towards the feature values of the stimulus

$$|\boldsymbol{\mu}(t+1) - \mathbf{s}(t)|^2 \leq |\boldsymbol{\mu}(t) - \mathbf{s}(t)|^2$$

along each feature dimension *j*:

$$\mu_j(t+1) = \mu_j(t) + \alpha(s_j(t) - \mu_j(t))$$

Component 2: **Expected long-term reward**

The system state itself has a value

= average expected future sensory reward.

$$V(\mathbf{X}(t);t) = K - KL(p^{\mathrm{T}}(\mathbf{s};t);p(\mathbf{s};\mathbf{X}(t)))$$

where p^T is expected distribution, K is a constant and KL is the Kullback-Leibler divergence

We here assume that p^T is stable.

Component 2: **Expected long-term reward**

The system state itself has a value which is equal to the average expected future sensory reward.

As in RL, the change in the value of the system state

$$\Delta V(\mathbf{X}(t);t) = V(\mathbf{X}(t+1);t+1) - V(\mathbf{X}(t);t)$$

acts as a surrogate reward.

This operationalizes the reward of learning.