

the History of the Future of the Bayesian Brain

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Author



Karl J. Friston

- ▶ British neuroscientist
 - ▶ Major in brain imaging
 - ▶ Famous for Statistical parametric mapping (SPM)
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Contents of paper

- ▶ Introduction
- ▶ The Bayesian brain
- ▶ Prehistory: functional integration club
- ▶ History: optimality, natural selection and value
- ▶ The Bayesian paradigm
- ▶ Bayesian brain & optimization
- ▶ Epilogue



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- ▶ Introduction
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 - ▶ Epilogue
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(1967)

(1990)

(1991)

(1994)



Characters



Samir Zeki



Horace Barlow



Gerry Edelman



Graeme Mitchison



*Peter Foldiak
Peter Dayan
Giulio Tononi
Olaf Sporns
Tim Shallice
Gerffrey Hinton*

....



Wooldice



Contents of presentation

- ▶ **About paper**
 - ▶ Author
 - ▶ Contents of paper
 - ▶ Character
- ▶ **Background knowledge**
 - ▶ Bayesian statistics
 - ▶ Bayesian optimal classifier
- ▶ **Part I: The rise of Bayesian thinking**
 - ▶ Functional segregation and integration of brain
 - ▶ The notion of optimality
- ▶ **Part II: The Bayesian Brain**
 - ▶ Optimal decision
 - ▶ Value learning



Background knowledge:

Bayesian statistics



Bayesian statistics

- ▶ Classical definition of probability

- ▶ Frequency

- ▶ $P(event) = \lim_{n \rightarrow \infty} \frac{\text{number of the event}}{\text{number of trial}}$

- ▶ How to get $P(event)$ when $n = 1$?

- ▶ Bayesian probability

- ▶ Calculate the probability using data, logic, and hypothesis

- ▶ Bayes' theorem

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}.$$



Bayesian optimal classifier

$$y = \operatorname{argmax}_{c_j \in C} \sum_{h_i \in H} P(c_j | h_i) P(T | h_i) P(h_i)$$

- ▶ C_j = class, h_i = Hypothesis, T : training set
- ▶ No other classifier can overcome Bayesian optimal classifier.

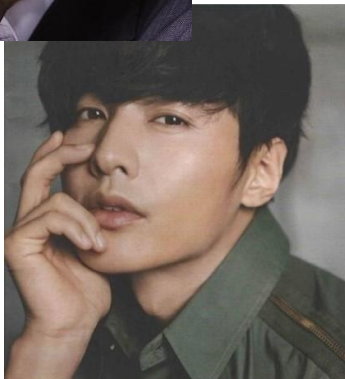
Bayesian optimal classifier

$$y = \operatorname{argmax}_{c_j \in C} \sum_{h_i \in H} P(c_j | h_i) P(T | h_i) P(h_i)$$

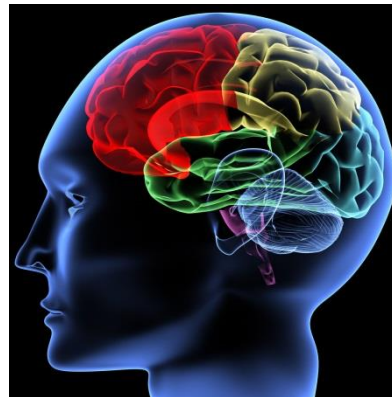
- ▶ C_j = class, h_i = Hypothesis, T : training set

Prior probability: $P(h)$

$y = \operatorname{arg max} P(.)$



Brain



B. Won

JS. Jung

Bayesian optimal classifier



Part I:

The rise of Bayesian thinking



Functional segregation / integration

- ▶ Regionally specific activations
 - ▶ Statistical parametric mapping
- ▶ Interactions mediated by effective connectivity
 - ▶ Dynamic causal modeling



Notion of optimality

- ▶ **Brain is optimal in some sense.**
 - ▶ What is optimized?
 - ▶ Information theory: Bayes optimal

- ▶ **Bayes brain**
 - ▶ Optimal decision theory
 - ▶ Value learning



Part II:

The Bayesian brain



Bayesian brain

- ▶ **Information theory**
 - ▶ maximize the mutual information between sensory input & internal representations
- ▶ **Value learning /selection**
 - ▶ value or adaptive fitness
- ▶ **Free energy minimization**
 - ▶ marginal likelihood of a model

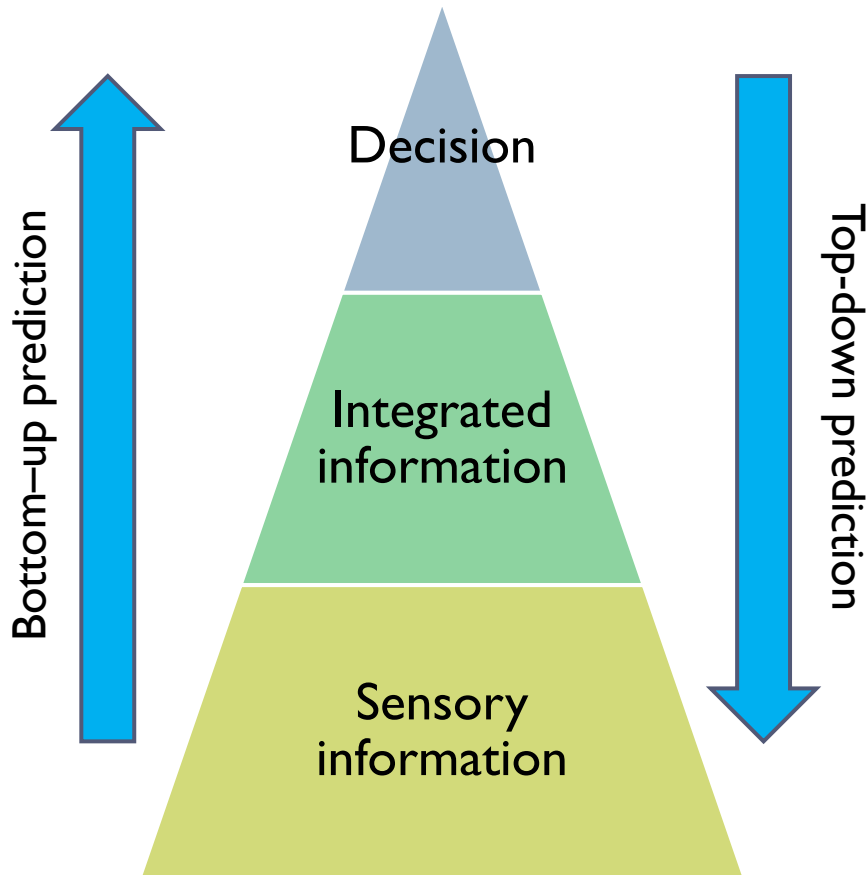
- ▶ All 3 processes are same thing

- ▶ Self organizing system (brain) minimize entropy



Epilogue

► Further research of Bayesian brain



- *Top-down predictions suppress errors of bottom-up prediction :*
example of minimizing free energy

Research of neuronal infrastructures :
functional integration
effective connectivity
dynamic causal modeling
Bayesian evidence based modeling