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Bayes in the Big:

Computational Cognition, Vision, and Learning

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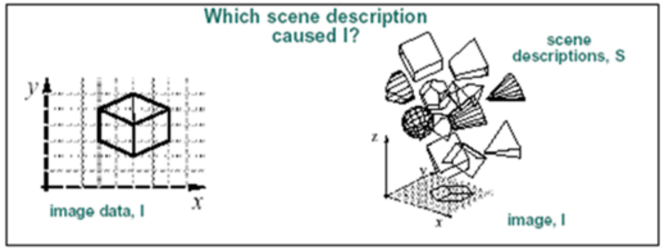
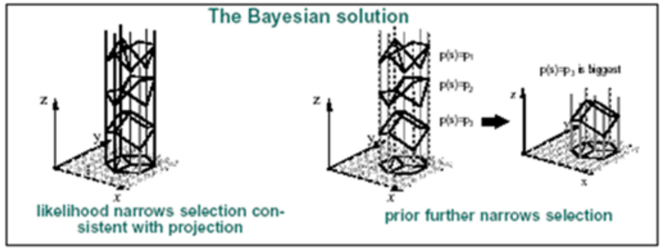
Bayes and Inverse Inference

- Helmholtz (1880's) proposed that vision could be studied as inverse inference. This requires inverting the process that generates the image.
- Inverse inference requires priors.
- There are an infinite number of ways that images can be formed.
- Why do we see a cube?
- The likelihood P(I|S) rules
- out some interpretations.
- The prior P(S) argues that cubes
- are more likely than other shapes.





Bayes and Inverse Inference

- Richard Gregory
- "Perception (vision) as hypotheses“.
- Perception is not just a passive acceptance of stimuli, but an active process involving memory and other internal processes.
- Humans have internal representations – we see images when we dream, we can imagine what animals and people will do, we can hallucinate.
- In more modern terms: “You have a physics simulator in your head”. J.B. Tenenbaum.

Vision as Inverse Inference.

- Inverse inference: optical illusions caused by incorrect inference.
- Think that the shadow is cast by the beach towel (left) or a levitating man (right).
- Ball in the box (D. Kersten).

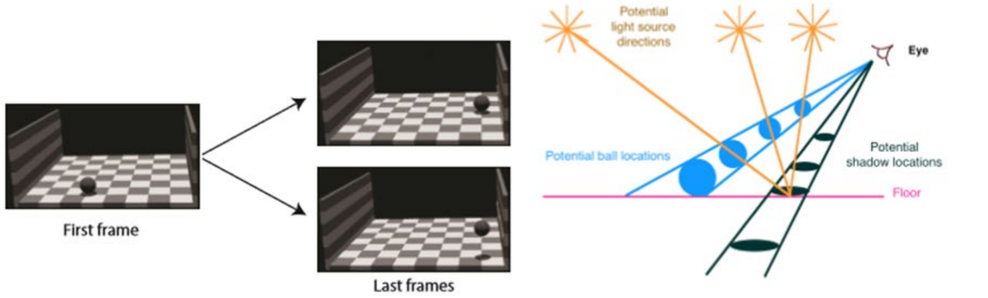
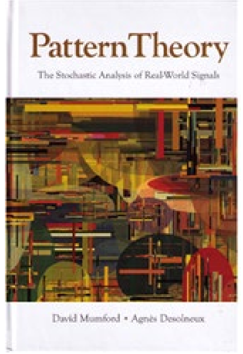


Fig. 36. In the "ball-in-a-box" experiments the motion of the shadow affects the perceived motion of the ball. The ball is perceived to rise from the ground if the shadow follows a horizontal trajectory in the image; but is perceived to move towards the back of the box if the shadow follows a diagonal trajectory. See `http://youtu.be/hdFCJepvJXU`. Left panel shows the first frame and the last frames for the two movies. Right panel. The explanation is that the observer resolves the ambiguities in the projection of a three-dimensional scene to perceive the 3D trajectory of the ball ([?].

Analysis by Synthesis: Mumford & Grenander

- Grenander (1960's) had proposed that vision could be formulated as pattern theory and proposed the idea of "analysis by synthesis". This is naturally expressed in Bayesian terms. (S. Geman was a student of Grenander).



- Mumford embraced Analysis by Synthesis and Pattern Theory.
- Analysis by Synthesis emphasizes pattern synthesis as well as pattern analysis. Bayesian inference requires you construct a prior probability model of whatever signals or situations you are modeling and you should always test your prior by sampling to see which features it models accurately and which it does not.

Mumford’s Bold Hypothesis.

- Mumford (1991) boldly proposed a model for how a primate brain could perform analysis by synthesis using bottom-up and top-down processing.
- He proposed that each area of the cortex carries on its calculations with the active participation of a nucleus in the thalamus with which it is reciprocally and topographically connected. This nucleus plays the role of an 'active blackboard‘ on which the current best reconstruction of some aspect of the world is always displayed
- Each cortical area maintains and updates the organism's knowledge of a specific aspect of the world, ranging from low level raw data to high level abstract representations, and involving interpreting stimuli and generating actions.
- It draws on multiple sources of expertise, learned from experience, creating multiple, often conflicting, hypotheses which are integrated by the action of the thalamic neurons and then sent back to the standard input layer of the cortex.
- .

Mumford's bold hypothesis for the architecture of the neocortex

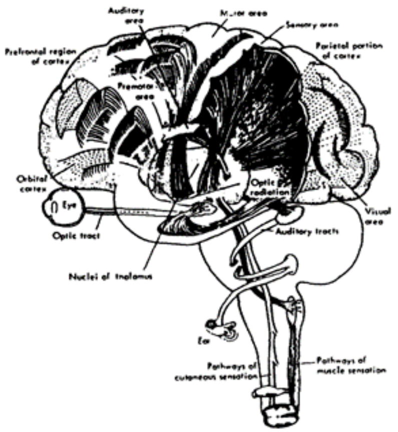


Fig. 2. The location of the thalamus within the cortex (from Luria 1969)

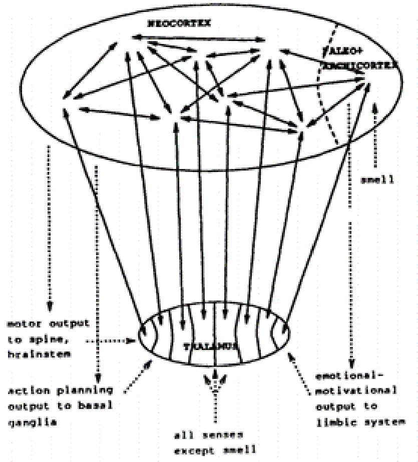


Fig. 3. Simplified schematic of cortical connections

- The higher areas of the neocortex attempts to fit its abstractions to the data it receives from lower areas by sending back to them from its deep pyramidal cells a template reconstruction best fitting the lower level view.
- The lower areas attempts to reconcile the reconstruction of its view that it receives from higher areas with what it knows, sending back from its superficial pyramidal cells the features in its data which are not predicted by the higher area.
- The whole calculation is done with all areas working simultaneously, but with order imposed by synchronous activity in the various top-down, bottom-up loops.
- *Neuroscience experiments give increasing support for top-down models and maybe for analysis by synthesis.*

Vision as Bayesian Inference: Yuille & Kersten.

- A. Yuille & D. Kersten. Trends in Cognitive Science. 2006.

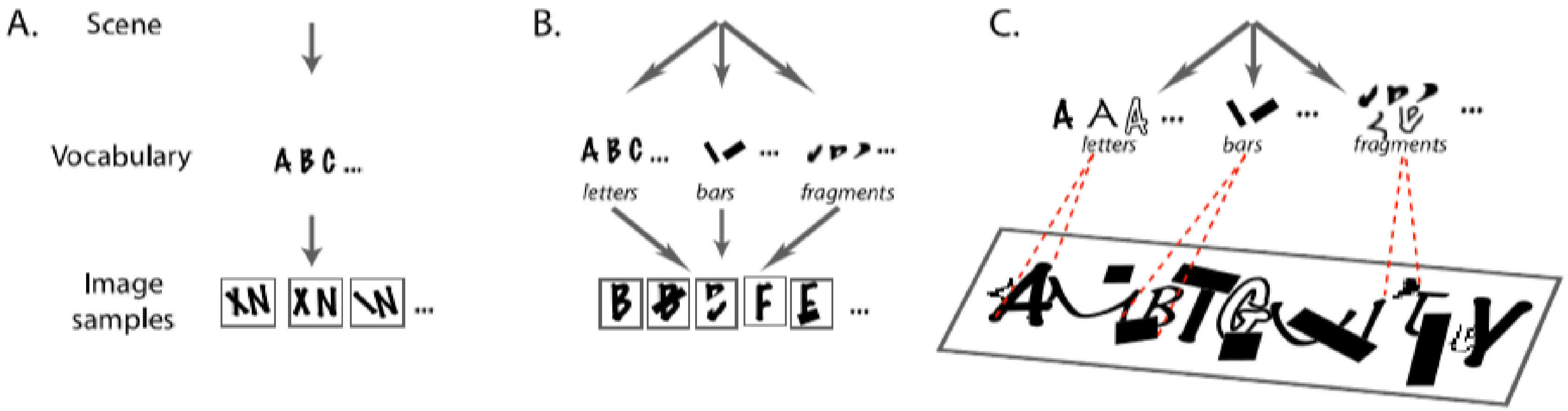


Figure 1: Left Panel (A). A simple vocabulary for generating the image. There is little, or no, ambiguity in interpreting images. At worst, the letter X may be confused with a slanted I partially occluding a vertical I. Centre Panel (B). A richer vocabulary. A given cause, such as a particular letter, can be manifest in many different images. But there are now multiple ways to generate identical images, see text. Right Panel (C). The richer the vocabulary, the greater the image ambiguity, and the harder it is to interpret the image. This leads to a formidable inference problem.

Vision as Bayesian Inference: Yuille & Kersten

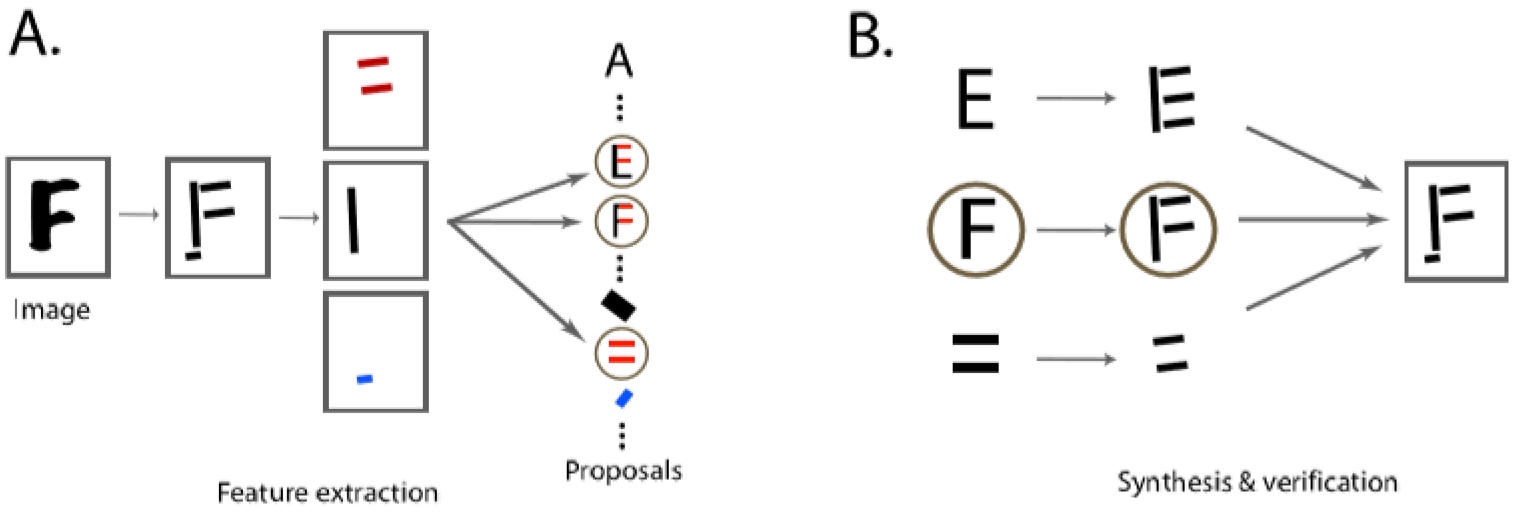


Figure 2: Analysis by synthesis. A. Low-level processing (left panel) can extract edge features, such as bars, and use conjunctions of these features to make bottom-up proposals to access the higher-level models of objects. B. The high-level objects access the image top-down to validate or reject the bottom-up proposals (right panel). In this example, the low-level cues propose that the image can be interpreted as an E, an F, or a set of parallel bars. But interpreting it as an F explains almost all the features in the image and is preferred.

Vision as Bayesian Inference: Yuille & Kersten

- Adding more realism building on work by Z. Tu & S.C. Zhu 2002, Z. Tu et al. 2006.

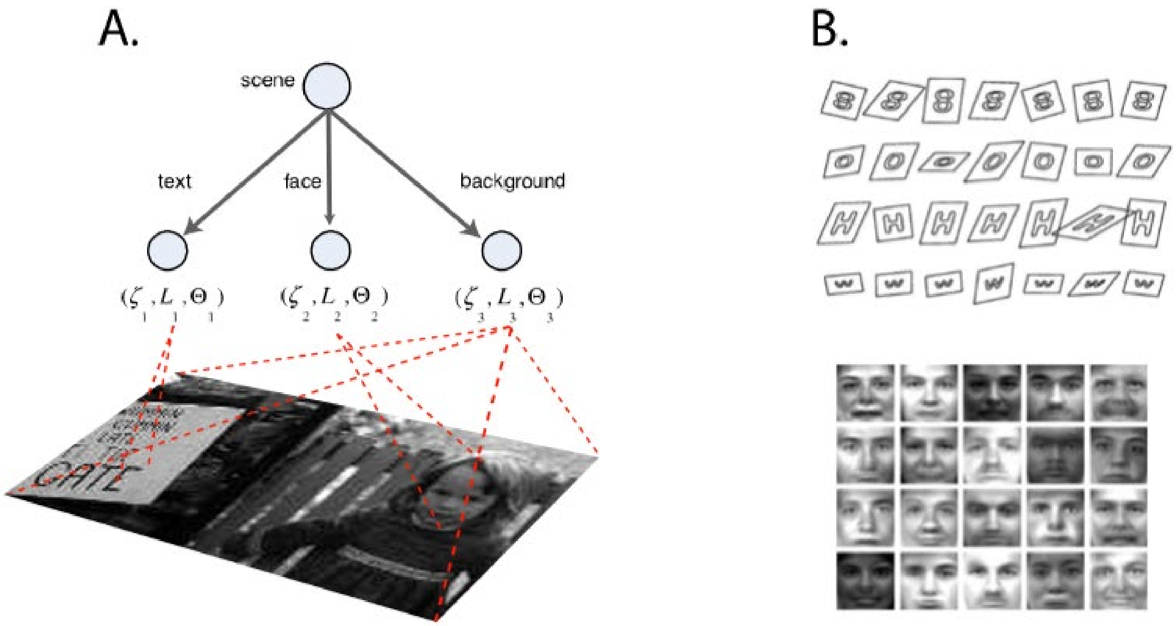


Figure 3: A. The image is generated (left panel) by a probabilistic context free grammar shown by a two layer graph with nodes with properties (ζ, l, θ) corresponding to regions L_i in the image. B. The right panel shows samples from the face model and the letter model – i.e. from $p(I_{R(L)}|\zeta, L, \Theta)$.

Reference Papers.

- D. Mumford. On the Computational Architecture of the Neocortex. 1991.
- D.K. Knill and W. Richards. Perception as Bayesian Inference. 1996.
- T.S. Lee. Computations in the Early Visual Cortex. 2003.
- A.L. Yuille and D.K. Kersten. Vision as Bayesian Inference. TICS. 2006.
- A.L. Yuille and D.K. Kersten. Early Vision. In From Neuron to Cognition via Computational Neuroscience. Eds. M. Arbib, J.J. Bonaiuto. 2016.