Coding (and computing with) Uncertainty

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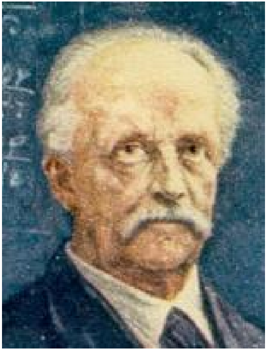
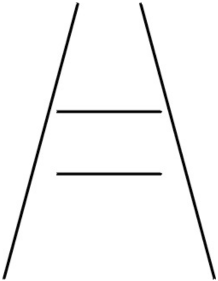
March 2017

Helmholtzian inference



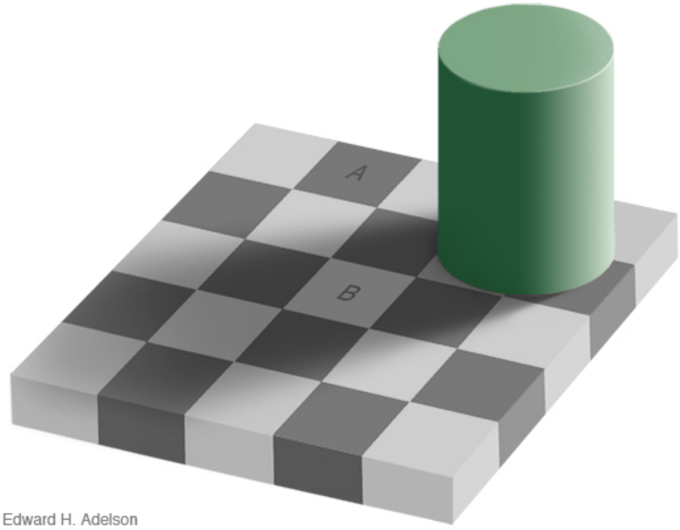
What information, then, can the qualities of such sensations give us about the characteristics of the external causes and influences which produce them? Only this: our sensations are **signs, not images***, of such characteristics.*

Illusions



Gregory 1968

Illusions



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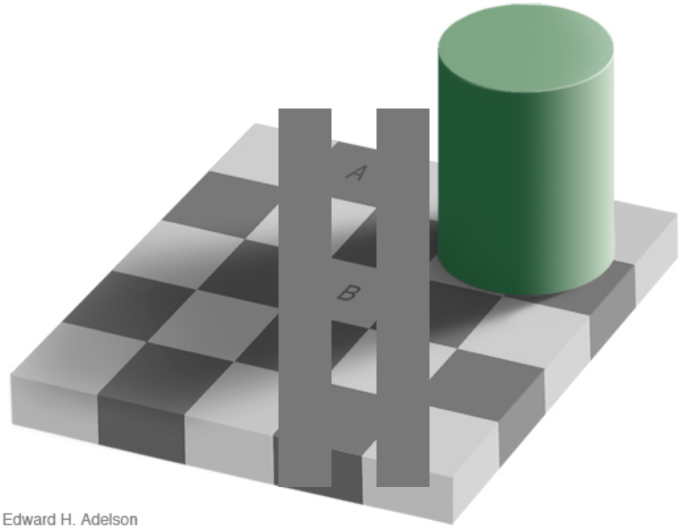
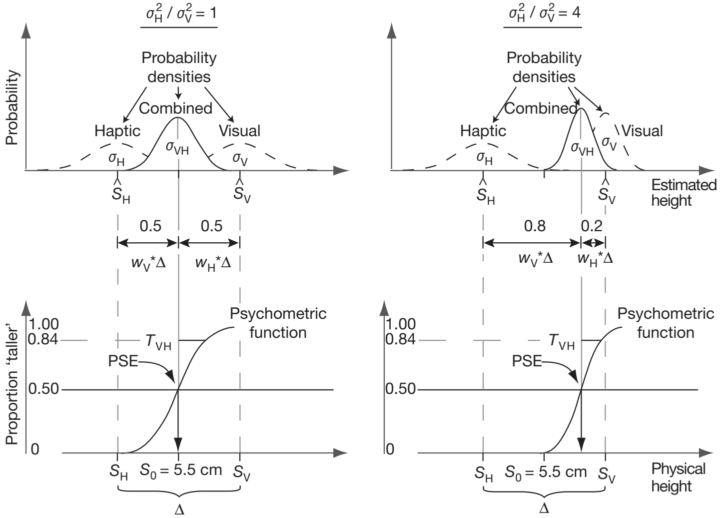


Cue combination



Ernst & Banks 2002

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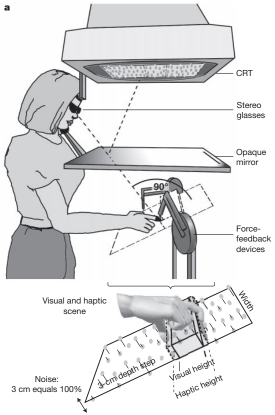

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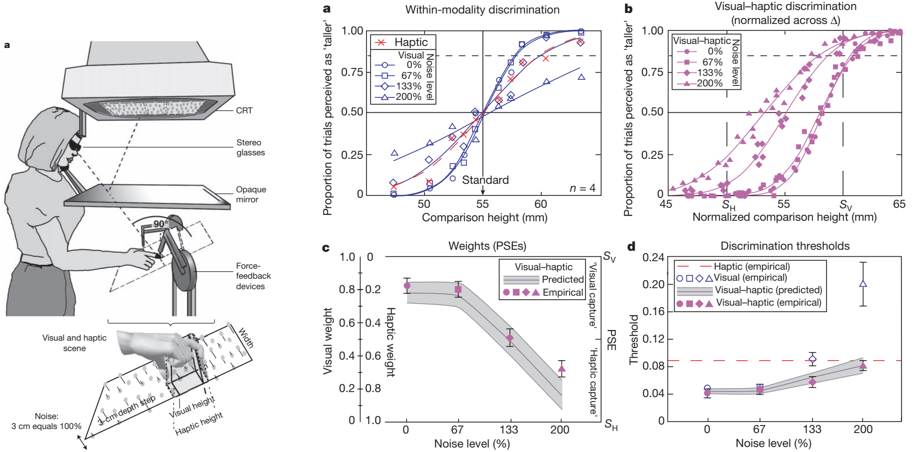

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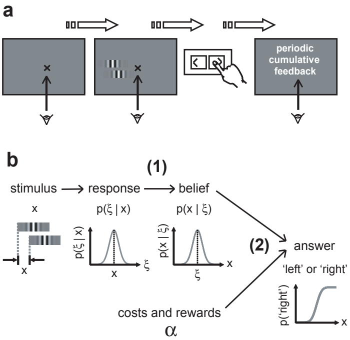
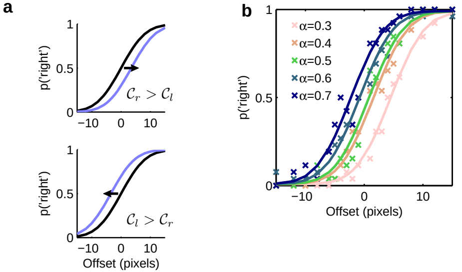
Bayesian Decisions

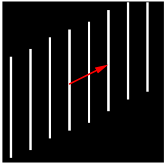




Sahani & Whiteley 2008

Motion Uncertainty

Given only local information about a moving edge, its velocity cannot be estimated. This is known as the aperture problem.



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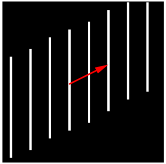

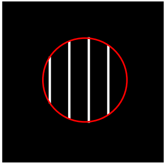

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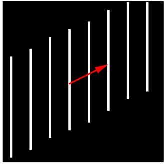

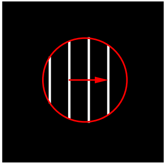

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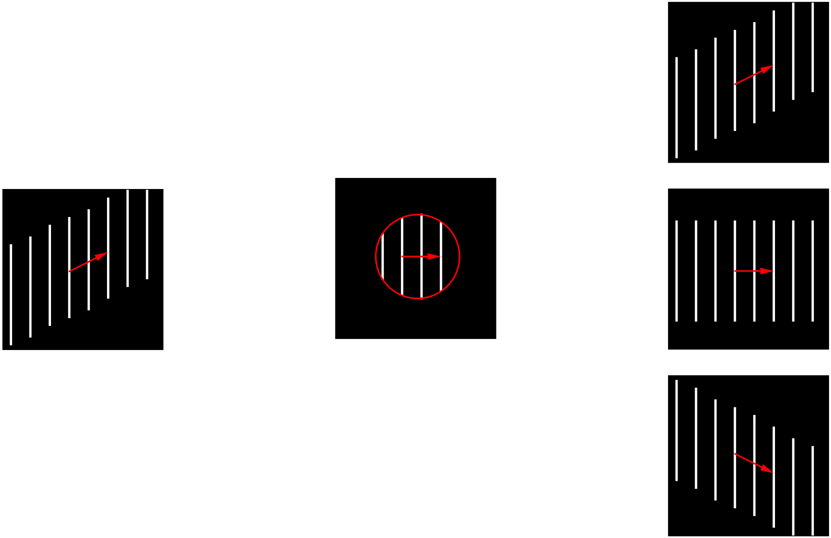
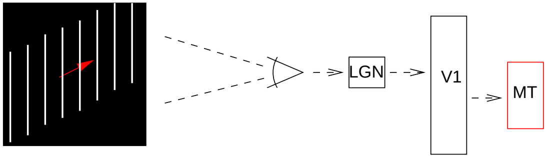


The Aperture Problem in V1 and MT

The aperture problem is relevant to the visual system because motion sensitive cells early in the visual pathway have small receptive fields. (Pack and Born 2001)



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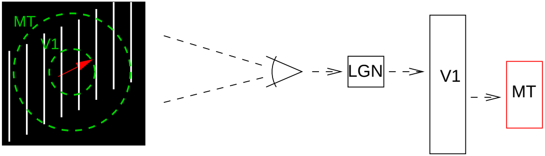

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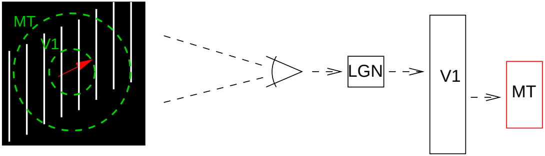

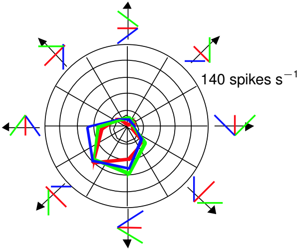

Late

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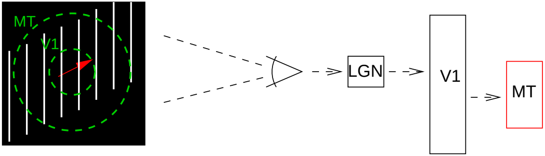

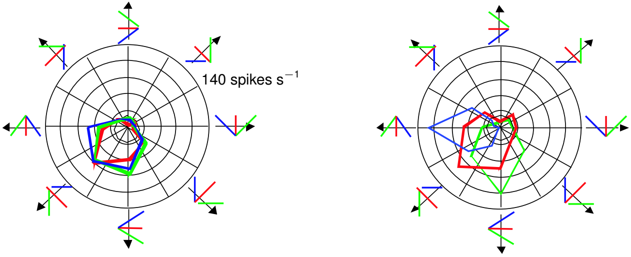

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Solving the Aperture Problem

The visual system appears to resolve the aperture problem. How does it do it?

- Local (aperture constrained) measurements must be combined with object form cues to estimate global object motion.

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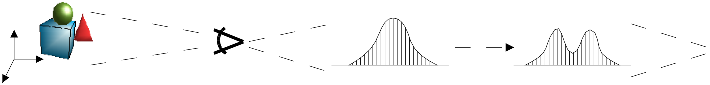
- Weiss and Adleson showed that the psychophysical evidence could be well modelled if observers were assumed to retain uncertainty about local estimates, and combine them, along with an *a priori* expectation, in a probabilistically appropriate fashion.

Uncertainty in Perception



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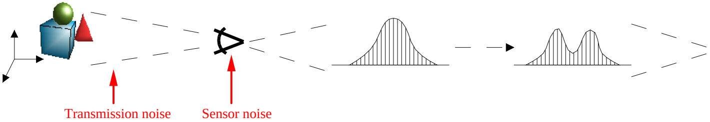

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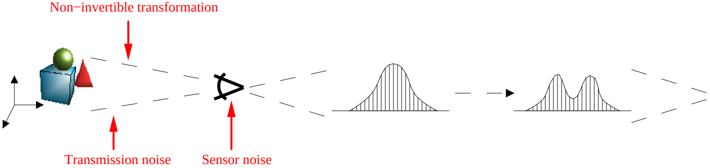

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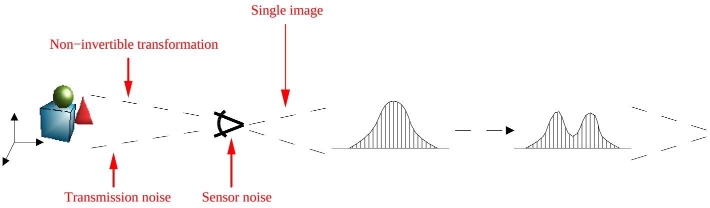

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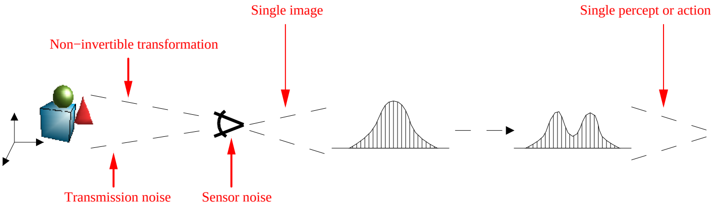

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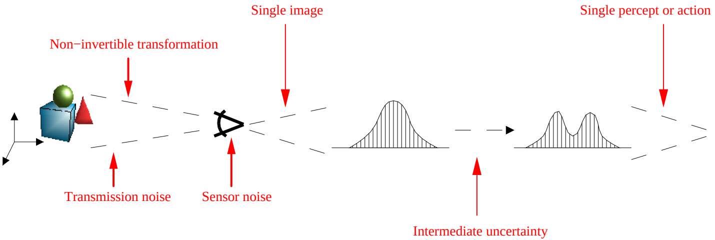

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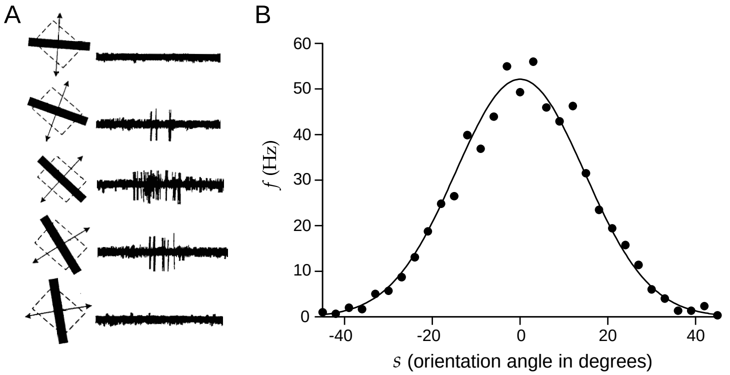
- The sensor experiences only a single image.
- In general, the eventual percept or action is also unitary.
- Intermediate stages of computation require representation of distributions over various inferred "features".

Information Representation

Individual neurons are broadly tuned and noisy. Information appears to be conveyed by neuronal populations.



Population Codes

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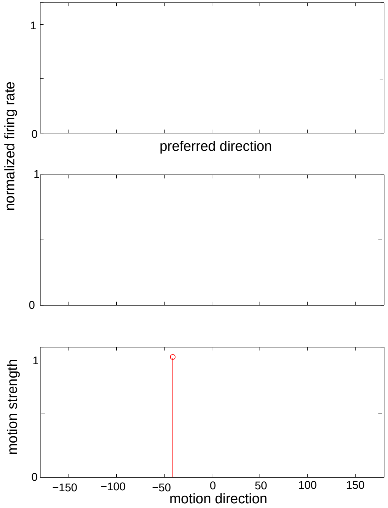
  input = x



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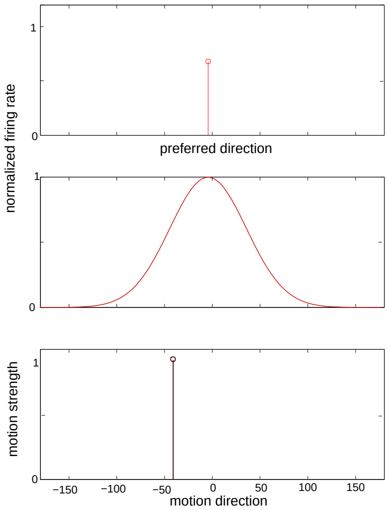

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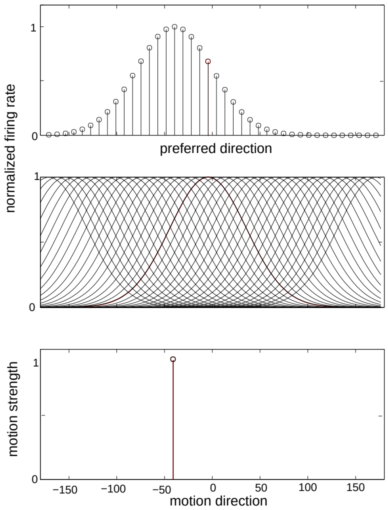

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$$r_i(x) = f_i(x)$$
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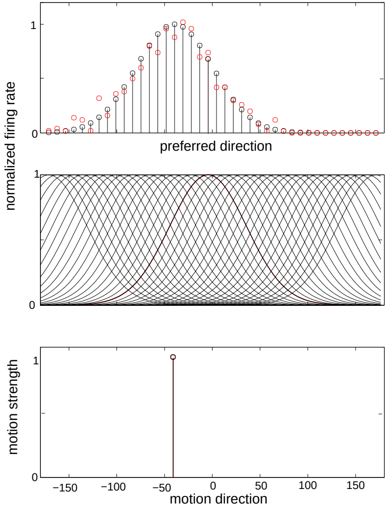

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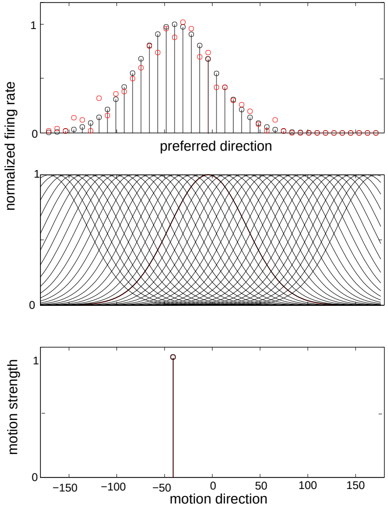

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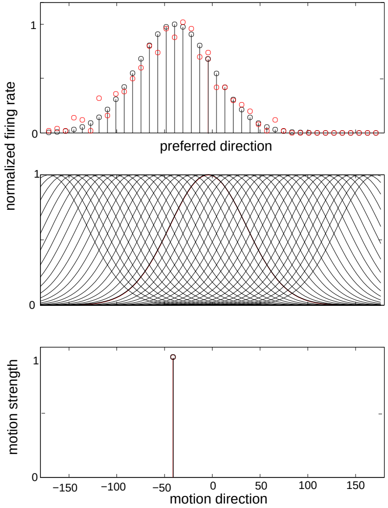

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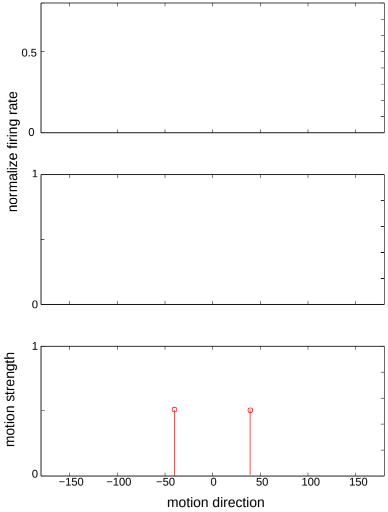

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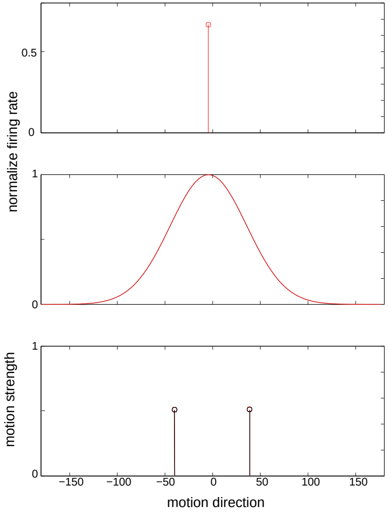

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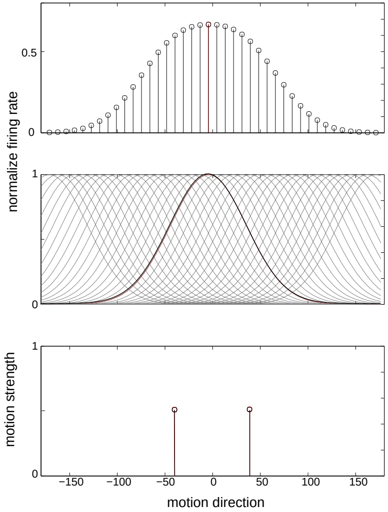

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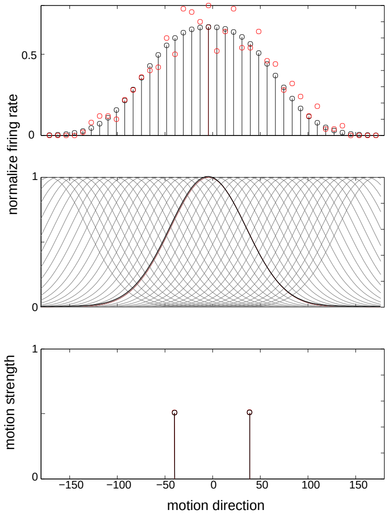

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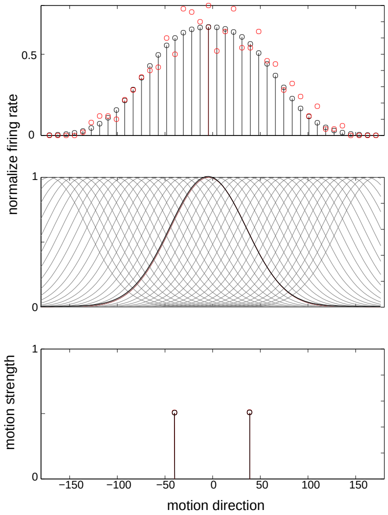

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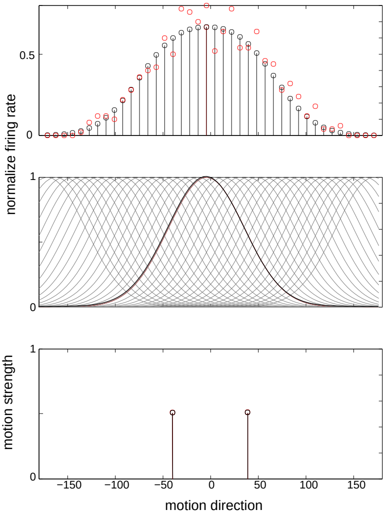

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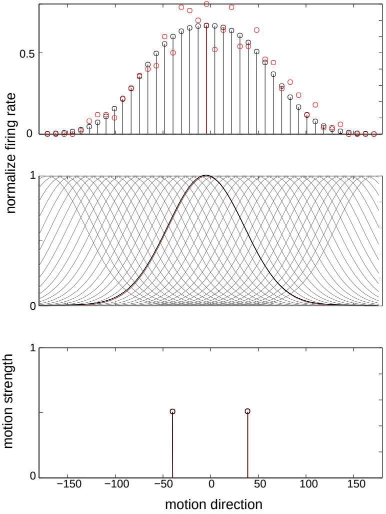
  - Maximum likelihood (Zemel *et al.*) is powerful, but expensive.



Representing uncertainty

- Deterministic representations
  - Linear decoding
  - Linear encoding (DPC)
  - Log-linear decoding (natural parameters)
  - 'Probabilistic encoding' / Inferential decoding (PPC)
- Stochastic (sample-based) representations

Linear decoding

$$p(x; \mathbf{r}) \propto \Big[\sum_a \phi_a(x) r_a \Big]_+$$

- Discussed by Anderson (90s); recent work by EliasSmith and others.
- Computations linear in probability / density become easy.
- Encoding may be difficult.
- Basis functions ϕ_a set a bound on possible precision.
- Noise enters decoder directly – suppressed if uncorrelated.

Linear encoding

$$r_a = \left[\int dx \, \phi_a(x) p(x) \right]_+ = [\langle \phi_a(x) \rangle]_+$$

- "Distributional Population Code" (DPC) – Pouget, Zemel, Dayan.
- Encoding easy to learn (delta rule)
- Decoding (i.e. identifying natural parameters) may be challenging – MaxEnt or EM-like algorithm if rates are noisy.
- Computation must be learnt.

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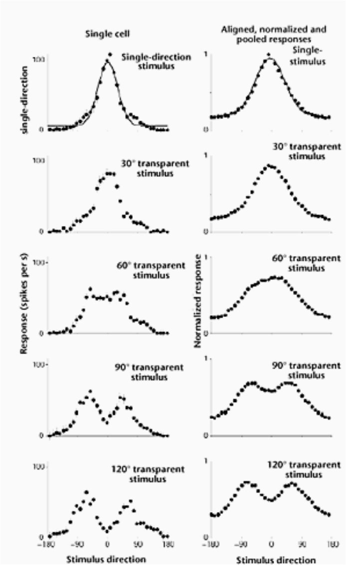

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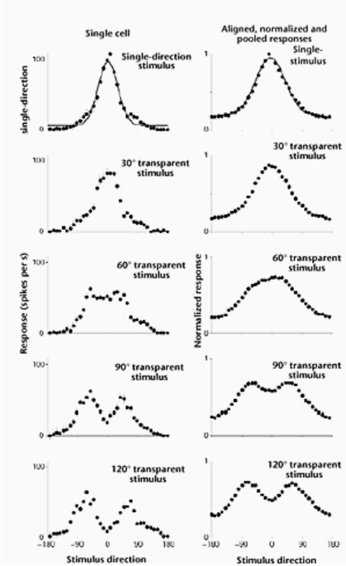

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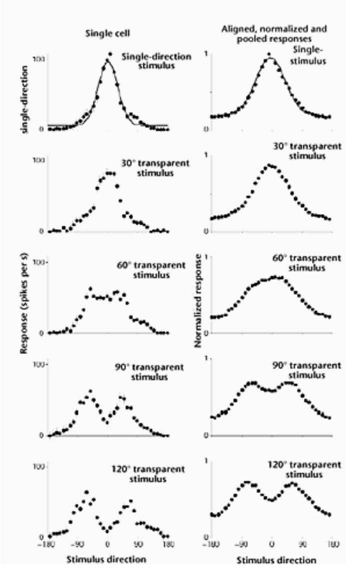

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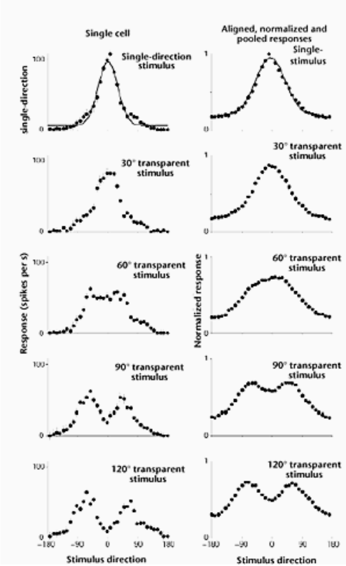

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- Cannot represent uncertainty about stimulus presence.
- Cannot represent uncertainty about a multiple stimulus.
- So then what about uncertainty?

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The solution is to encode the uncertainty about the entire feature *map* $m(x)$.
(This uncertainty is described by a probability functional, $p[m]$.)

$$r_i[\quad] = \qquad ?$$

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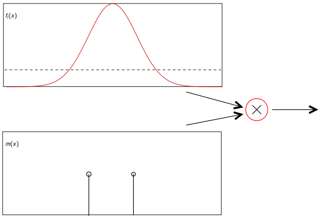

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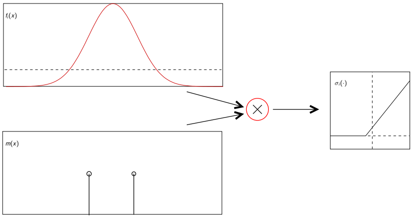

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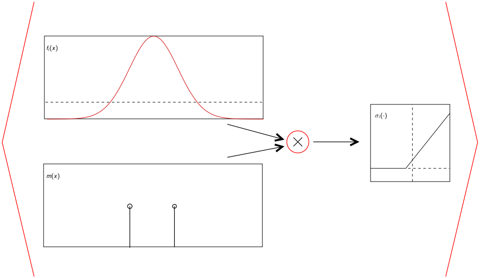

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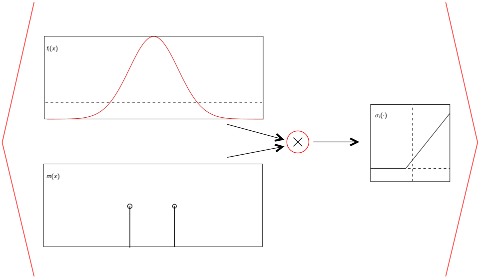

Why the Expected Firing Rate?

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- Matches the intuitive notion that the firing rate of an “indicator” neuron signals confidence.
- Reduces to conventional single feature and function encoding schemes in the appropriate limits.

Why a Nonlinear Transfer Function?

$$r_i[\,p\,] = \left\langle \sigma_i\left(\int dx \ f_i(x) m(x) \right) \right\rangle_{p[m]}$$

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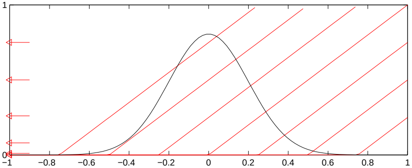

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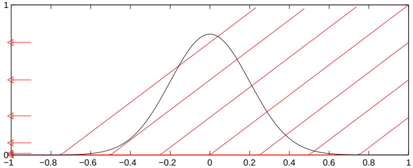

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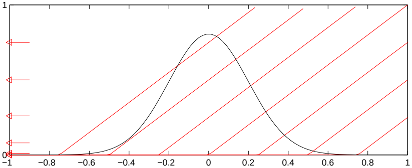

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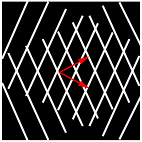
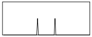
- For additional theoretical reasons, it is likely that some variation in transfer function between neurons is important.

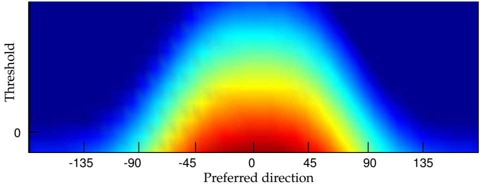
Representing Transparency and Uncertainty

Transparency:

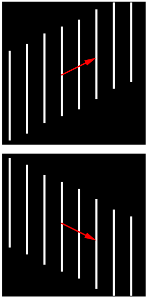


$$p[m_{12}] = 1$$

$m_{12} =$ 



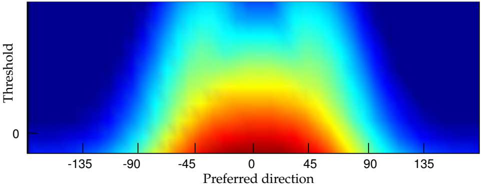
Uncertainty:



$$p[m_1] = p[m_2] = \frac{1}{2}$$

$m_1 =$ 

$m_2 =$ 



Decoding

Transparent and uncertain motion lead to visually different codes, but can they be recovered from the population?

- We decode by finding an estimated distribution $q[m]$ that best explains the observed firing rates.

NB: decoding (unlike computation) is not an operation of intrinsic biological interest; it merely demonstrates that the encoded information can be recovered in principle.

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  - Well known problem solved by “generalized iterative scaling”.
- Realistically, only a noisy estimate of the rate will be available.
  - Constraints cannot be satisfied exactly.
  - Find $q[m]$ for which the observed spike counts are most likely.
  - Decoding in this case tests the robustness of the code to noise.

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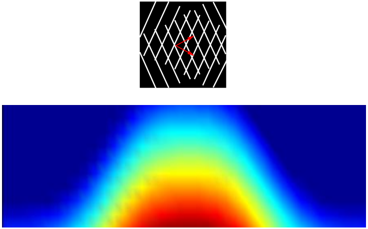
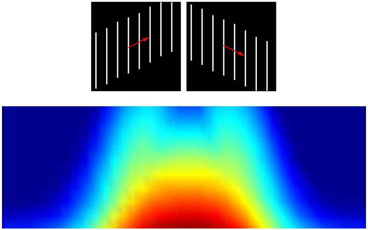
Transparency vs. Uncertainty





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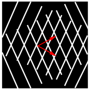

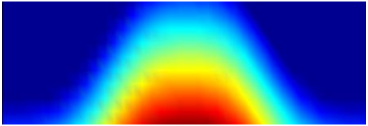

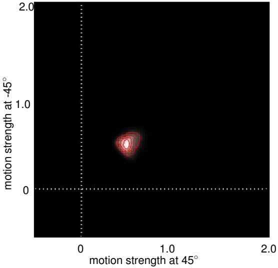

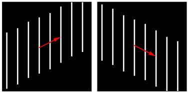

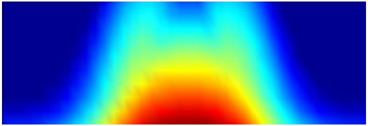

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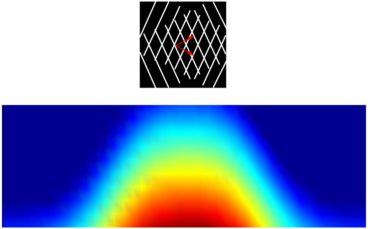

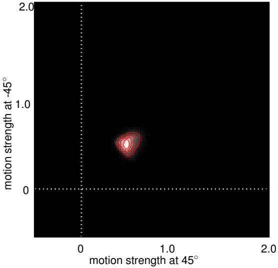

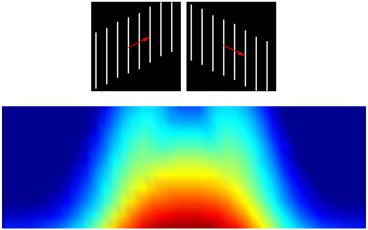

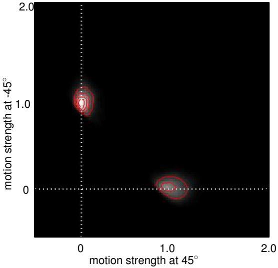

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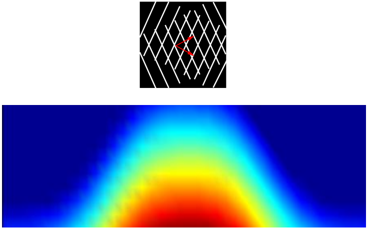

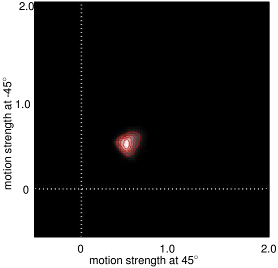

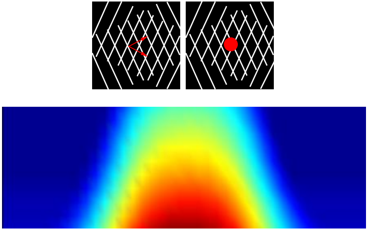

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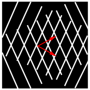

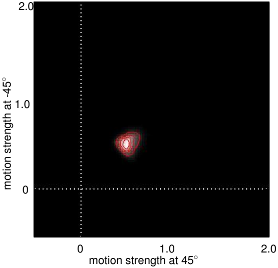

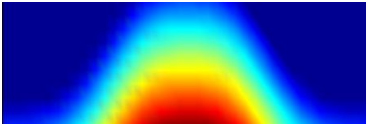

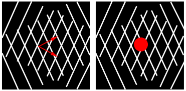

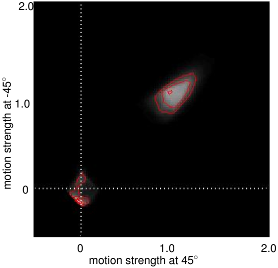

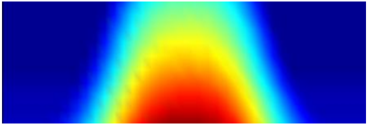

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Log-linear decoding

$$p(x; \mathbf{r}) \propto \exp\left(\sum_a \phi_a(x) r_a\right)$$

- Natural parameter encoding.
- Makes some computations (e.g. cue combination) very easy.
- Encoding may be difficult to learn.
- Uncorrelated noise in activities may average away.
- Basis functions set maximum log-precision.

PPC

$$p(x; \mathbf{r}) = p(x|\mathbf{r}) \propto p(\mathbf{r}|x)p(x)$$

- For 'Poisson-like' $p(\mathbf{r}|x)$ (linear sufficient stats) this gives log-linear decoding.
- Unclear what $p(\mathbf{r}|x)$ should be – often taken to be observed experimental noise, but this is incorrect.
- Confuses information content with encoding: does retinal activity "encode" everything about a scene?
- "Representation" depends on knowing both likelihood and prior $\Rightarrow$ will usually depend on knowledge of the external world.
- Fixing a likelihood and prior is equivalent to assuming a parametric encoding.

Computation with DDCs

- Many (even most) probabilistic computations depend on calculating expectations.
  - Conditional marginalisation (prediction, message passing):

$$p(x) = \int dy\, p(x|y)p(y) = \mathbb{E}_{p(y)}\left[p(x|y)\right]$$

  - Variational (EM) learning in latent variable models:

$$\theta^{\text{new}} = \operatorname{argmax} \mathbb{E}_{q(x^{\text{lat}})}\left[\log p(x^{\text{obs}}, x^{\text{lat}}|\theta)\right]$$

  - Action evaluation (Bayesian decision theory)

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- If the $\psi_i[m]$ form an adequate basis for the required functions of m, then these expectations can be computed as linear combinations of r_i:

$$f[m] = \sum_i \alpha_i \psi_i[m]$$

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- Cue or message combination may be complex.
- [Related to belief states, predictive state representations and RKHS mean embeddings; c.f. Kernel Belief Propagation (Song et al 2011)]

Computation with log-likelihood codes

- cue (message) combination $\Rightarrow$ addition.
- projection / marginalisation? [see work by Beck et al.]