# A typical weak paper

- Short and naïve introduction – demonstrates lack of background research and of expertise from the authors
- Methods / algorithms not very original – demonstrates lack of understanding of the state-of-the-art in the field
- Results show operation of system on one example case – lack of systematic study demonstrates laziness and greatly reduces belief that research described is generally applicable
- Short discussion limited to own research rather than putting work into perspective by comparing to previous studies – shows lack of knowledge of others’ work and reduces credibility

# A typical weak paper: summary

A weak paper is one where the authors describe work that is not very new, is not thoroughly validated, and is not properly placed in perspective with respect to previous work.

Mostly, it is weak because... the authors have been lazy and have not done proper background research.

# A typical strong paper

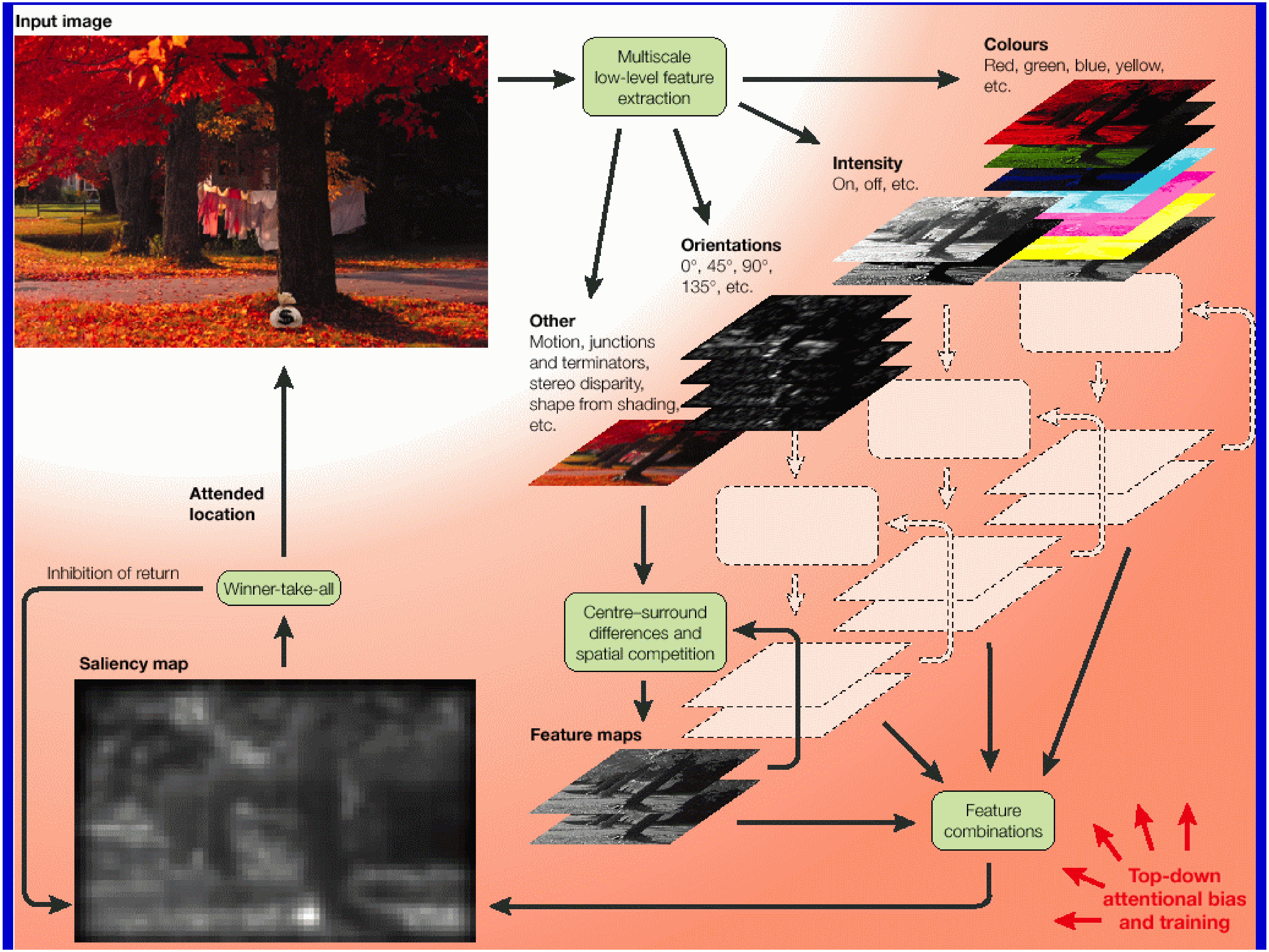
- Comprehensive expert introduction – demonstrates extensive background research, mastery of the whole field, understanding of the important issues, and clear positioning of the research as new
- Methods / algorithms are original – demonstrates good understanding of the state-of-the-art in the field, and expertise
- Results include thorough quantitative validation – the authors seriously stand behind their research and make efforts to prove how it is new / different / better
- Discussion puts work into perspective by comparing to previous studies – shows expertise and credibility by not being shy about comparing to other research

# A typical strong paper: summary

A strong paper is one where the authors demonstrate that they have complete expert understanding of the major open research issues in the field, and where they provide a convincing argument that they just professionally cleaned up one of those issues.

Mostly, it is strong because the authors know what they are doing!

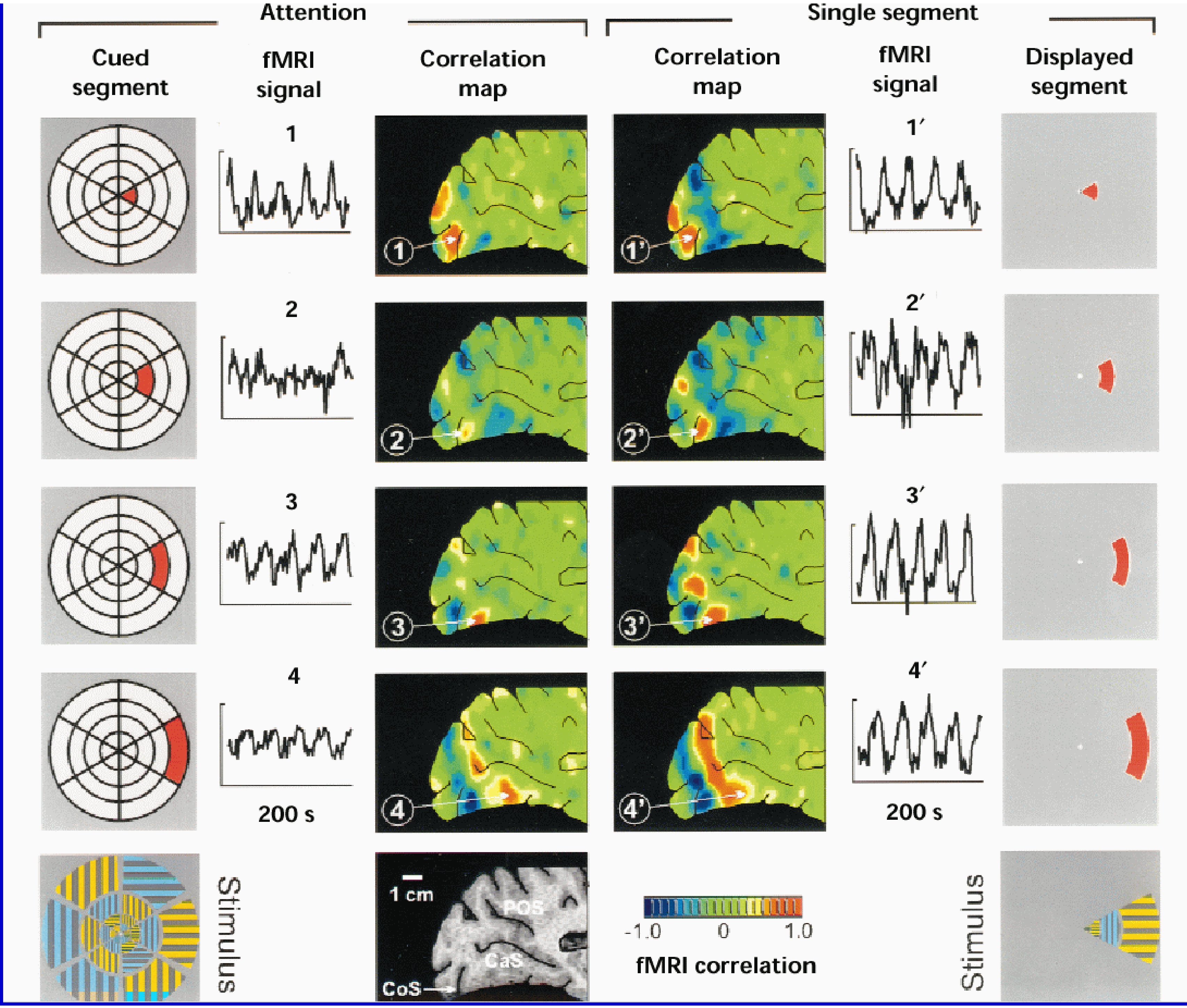
And because they worked extremely hard on their research.


Input image
Multiscale low-level feature extraction
Colours
Red, green, blue, yellow, etc.
Intensity
On, off, etc.
Orientations
0°, 45°, 90°, 135°, etc.
Other
Motion, junctions and terminators, stereo disparity, shape from shading, etc.
Attended location
Inhibition of return
Winner-take-all
Centre–surround differences and spatial competition
Feature maps
Feature combinations
Saliency map
Top-down attentional bias and training

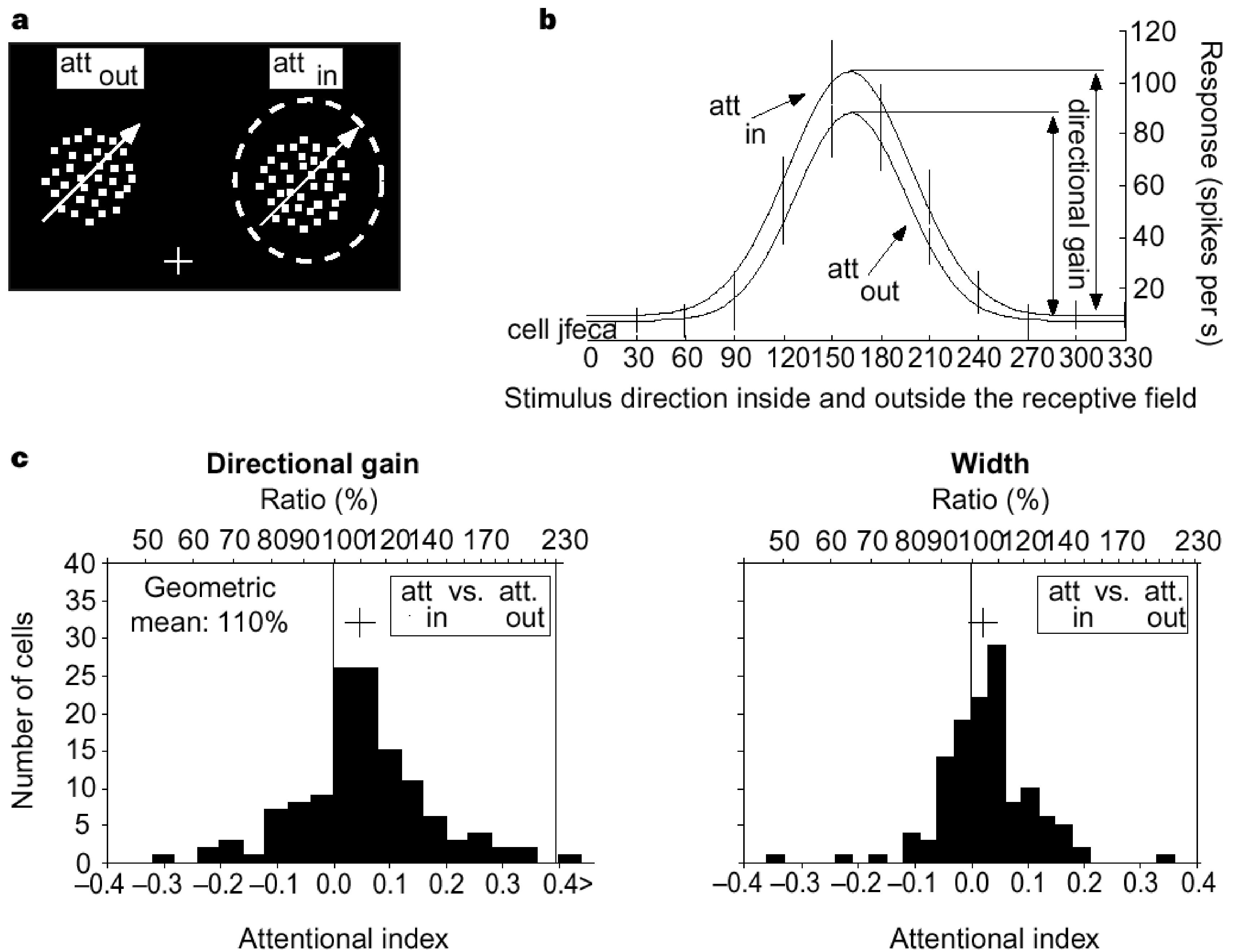
# Step 1: motivation

- Evaluate state of the art
- Find important yet unanswered questions

- E.g., here:
  - Attention has been shown to modulate visual cortical representation
  - But exactly what functional form does this modulation take?




Brefczynski & DeYoe, Nature Neuroscience 1999

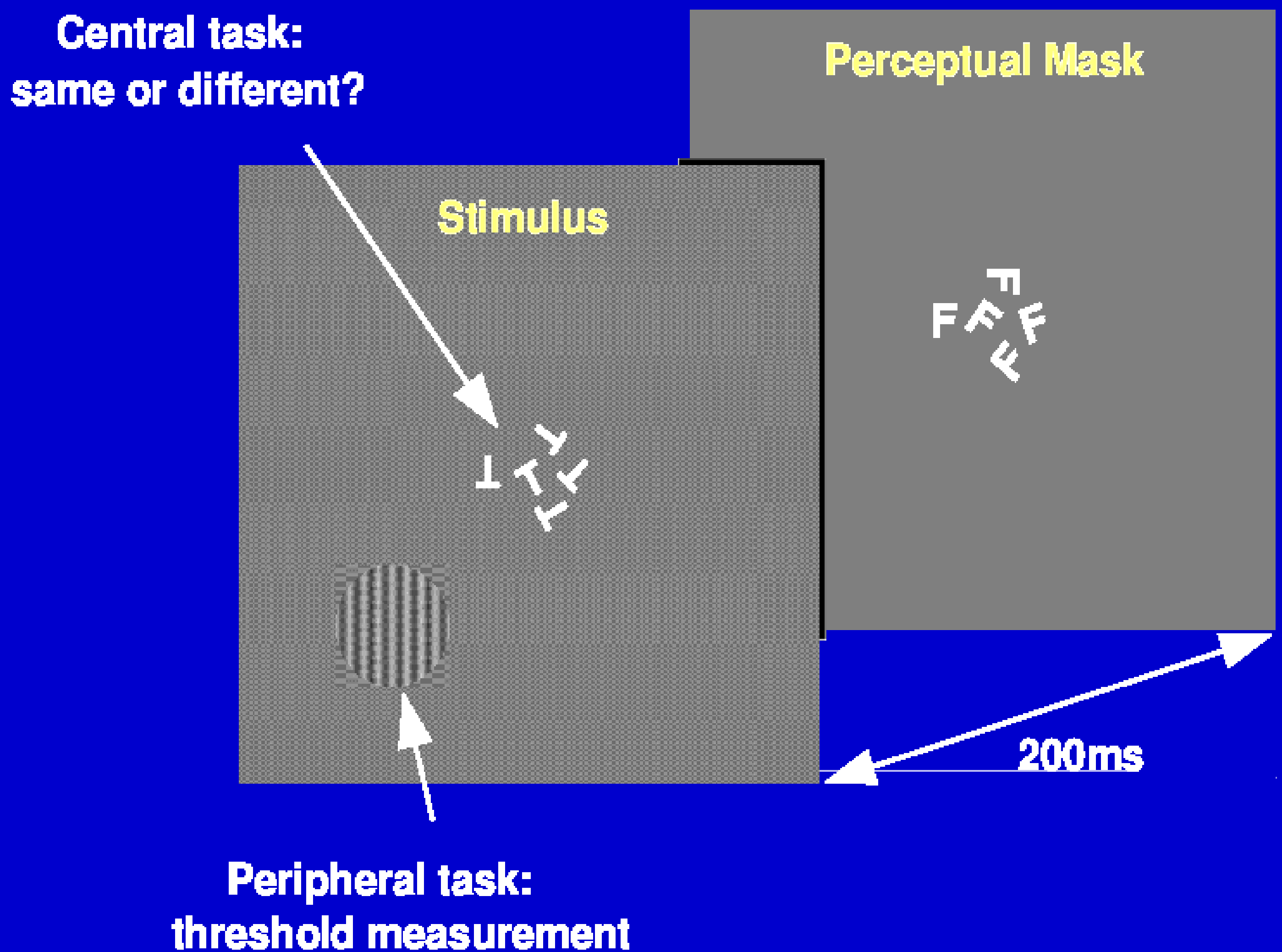



Treue & Martinez-Trujillo, Nature 1999

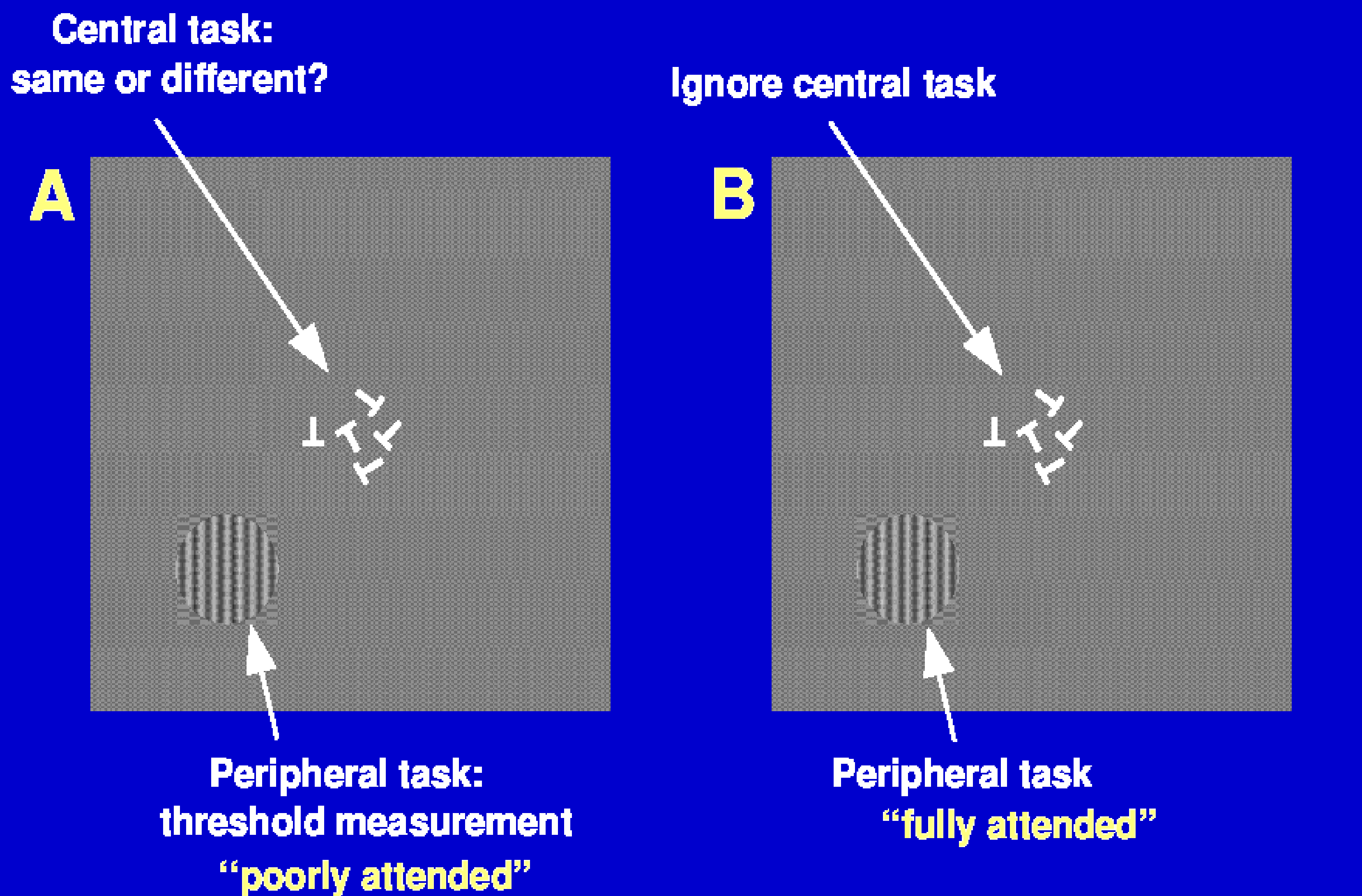
# Step 2: Design

- Here, we design an experiment, but could be an algorithm as well.
- The important part is that it must provide a clear, unambiguous answer to the question

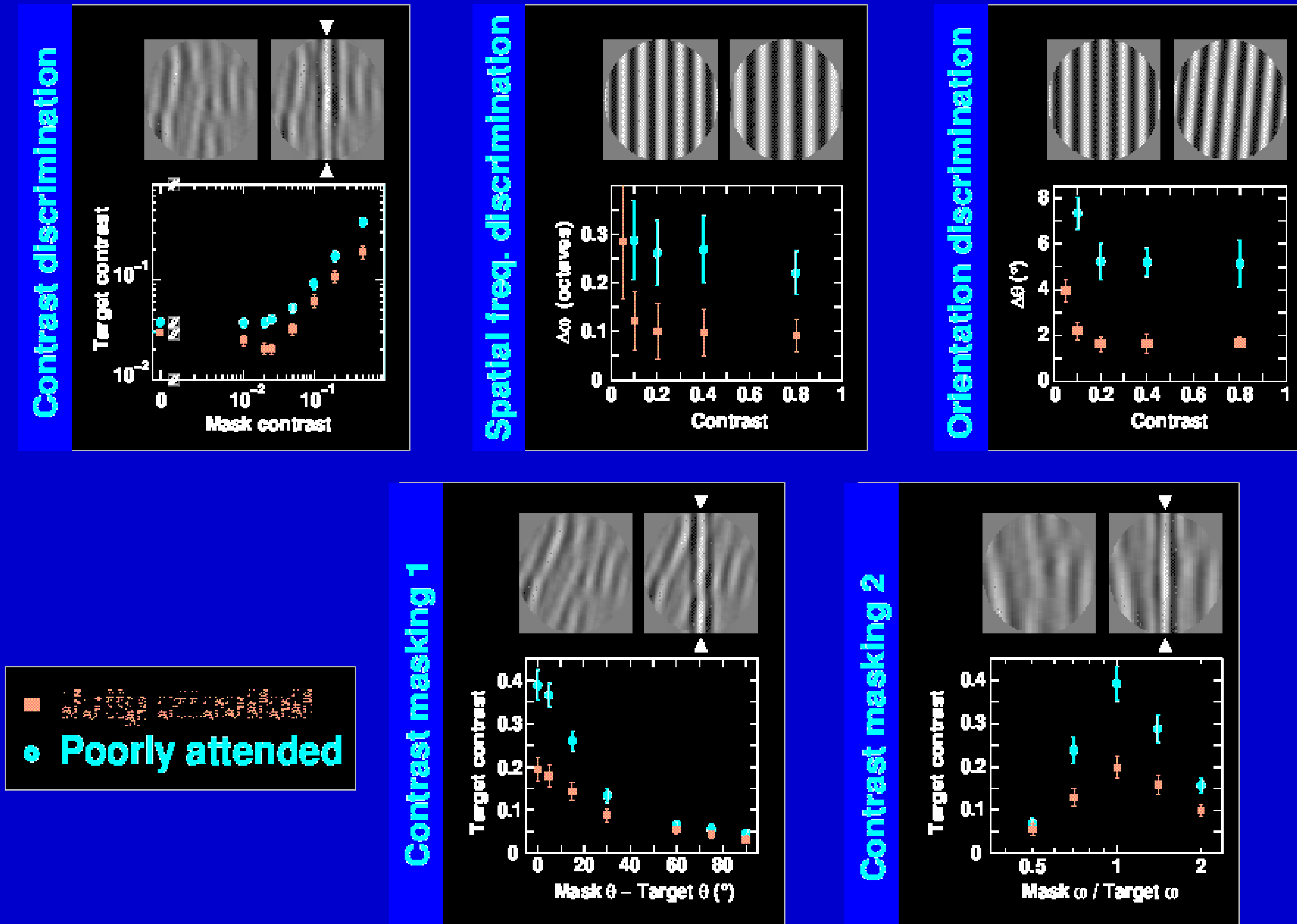
# Attentional Manipulation Paradigm



# Attentional Manipulation Paradigm



# Attention changes thresholds

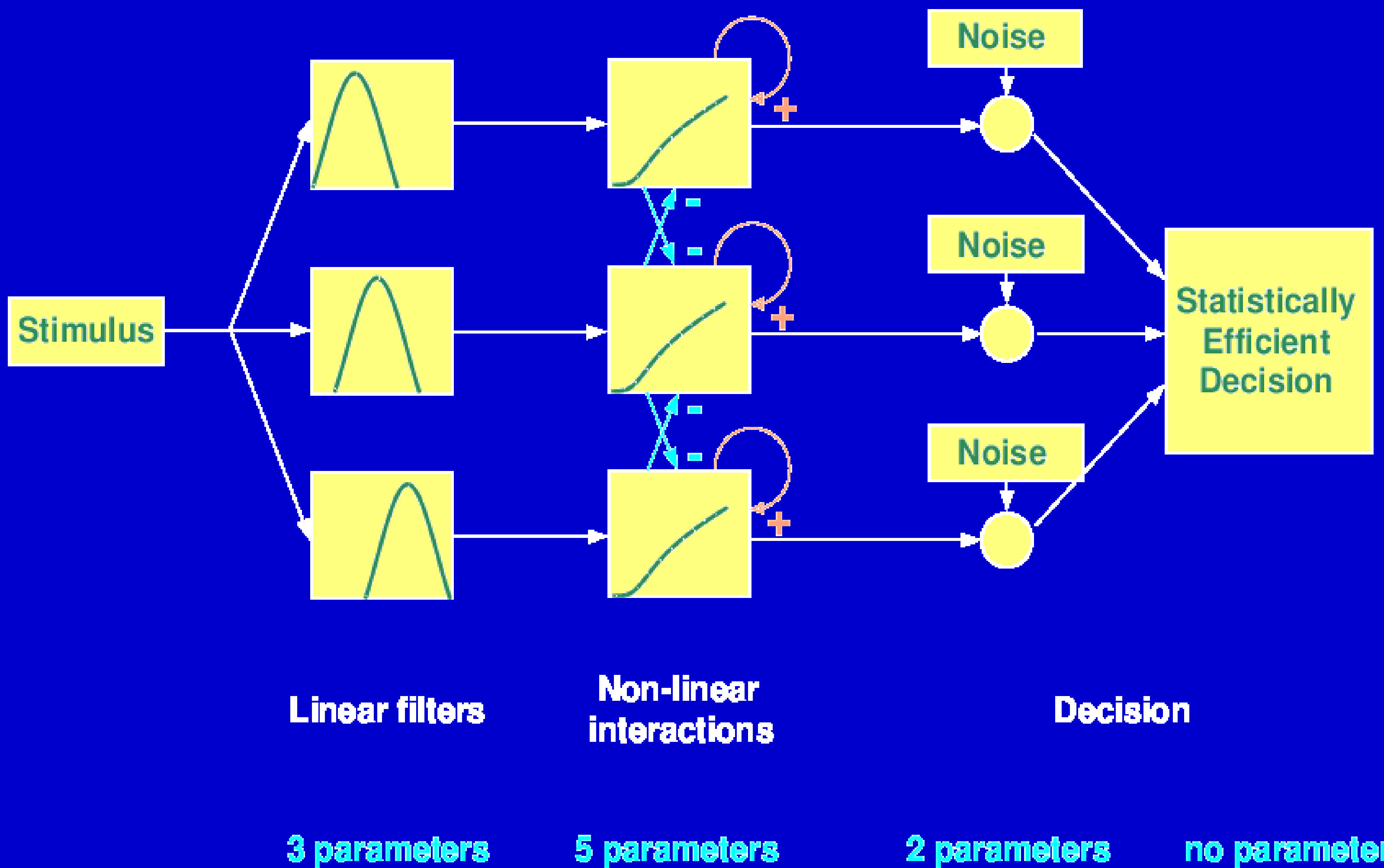


# Step 3: analyze in details

- Here, we develop a new theory to establish a quantitative linkage between neural activity in a simple model and behavioral performance in humans.

- We then apply it to the interpretation of the data

# Model architecture

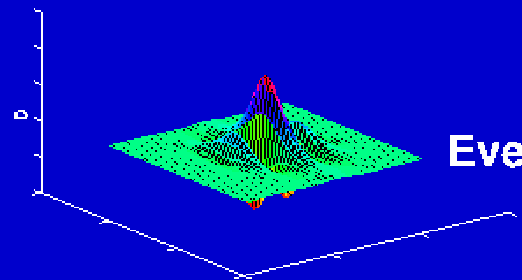


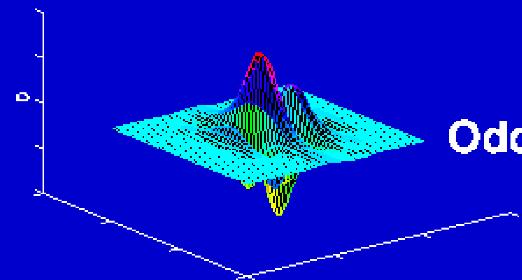
# Linear filters

Separable in spatial period $\lambda$
and orientation $\theta$

Gaussian tuning curves $(\sigma_\lambda, \sigma_\theta)$

Quadrature pairs $Even_{\theta,\lambda}$ , $Odd_{\theta,\lambda}$



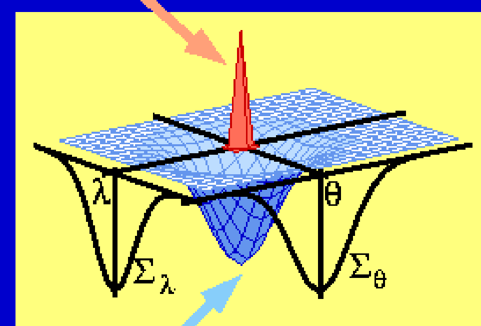




$$E_{\theta,\lambda} = \sqrt{\left(Im \star Even_{\theta,\lambda}\right)^2 + \left(Im \star Odd_{\theta,\lambda}\right)^2}$$

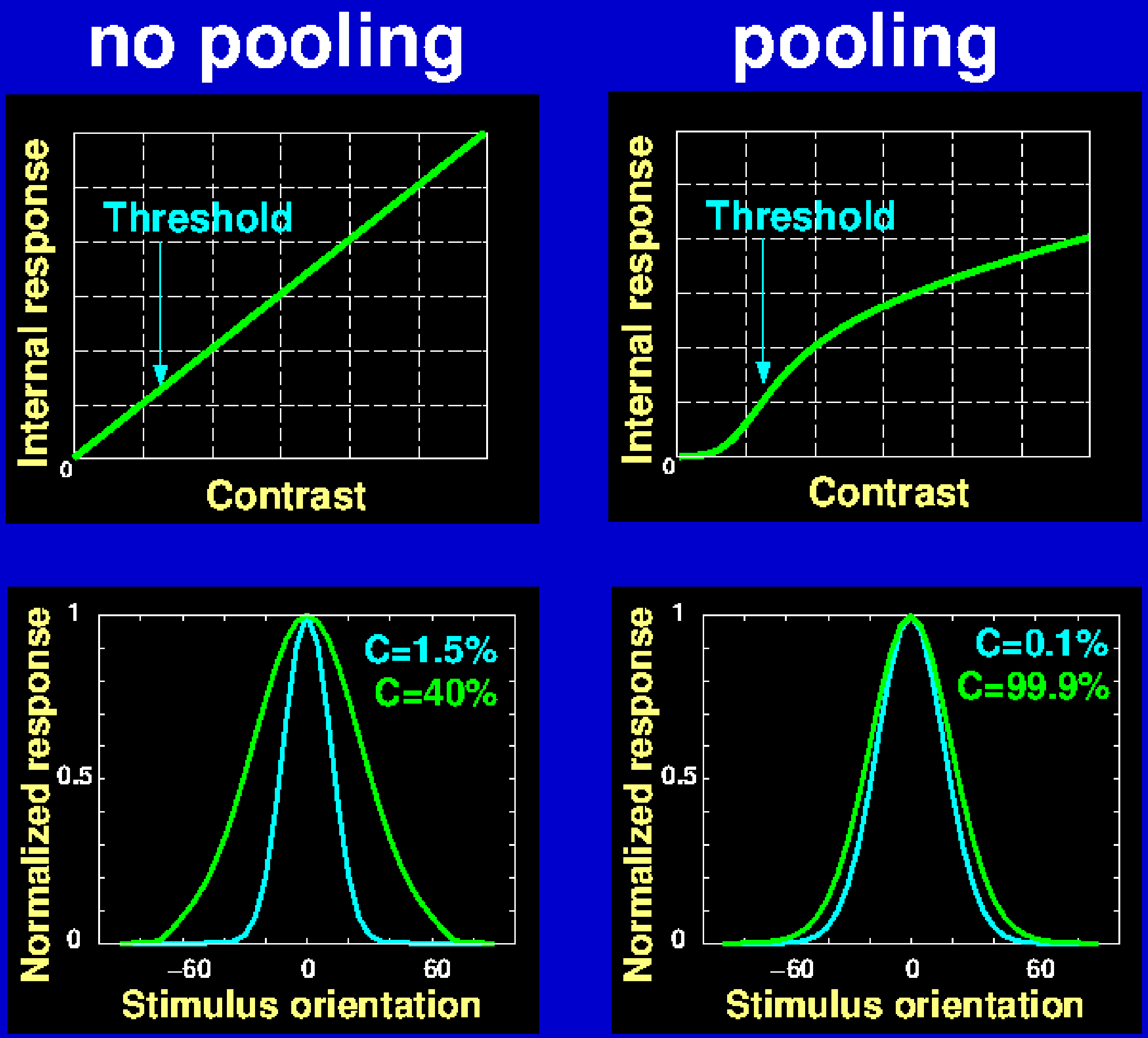
# Non-linear interactions

**Power law and divisive inhibition:**

$$R_{\theta,\lambda} = \frac{E_{\theta,\lambda}^{G}}{S_\lambda + \sum_{\theta',\lambda'} W_{\theta',\lambda'} E_{\theta',\lambda'}^{H}}$$



# Properties




**Non-linear transducer function**

**Contrast-independent tuning**

# Decision strategy

Stimulus parameter $\gamma$ (contrast, orient., s.f.)

Assume unbiased efficient statistic $T(R_{\theta,\lambda}, \gamma)$

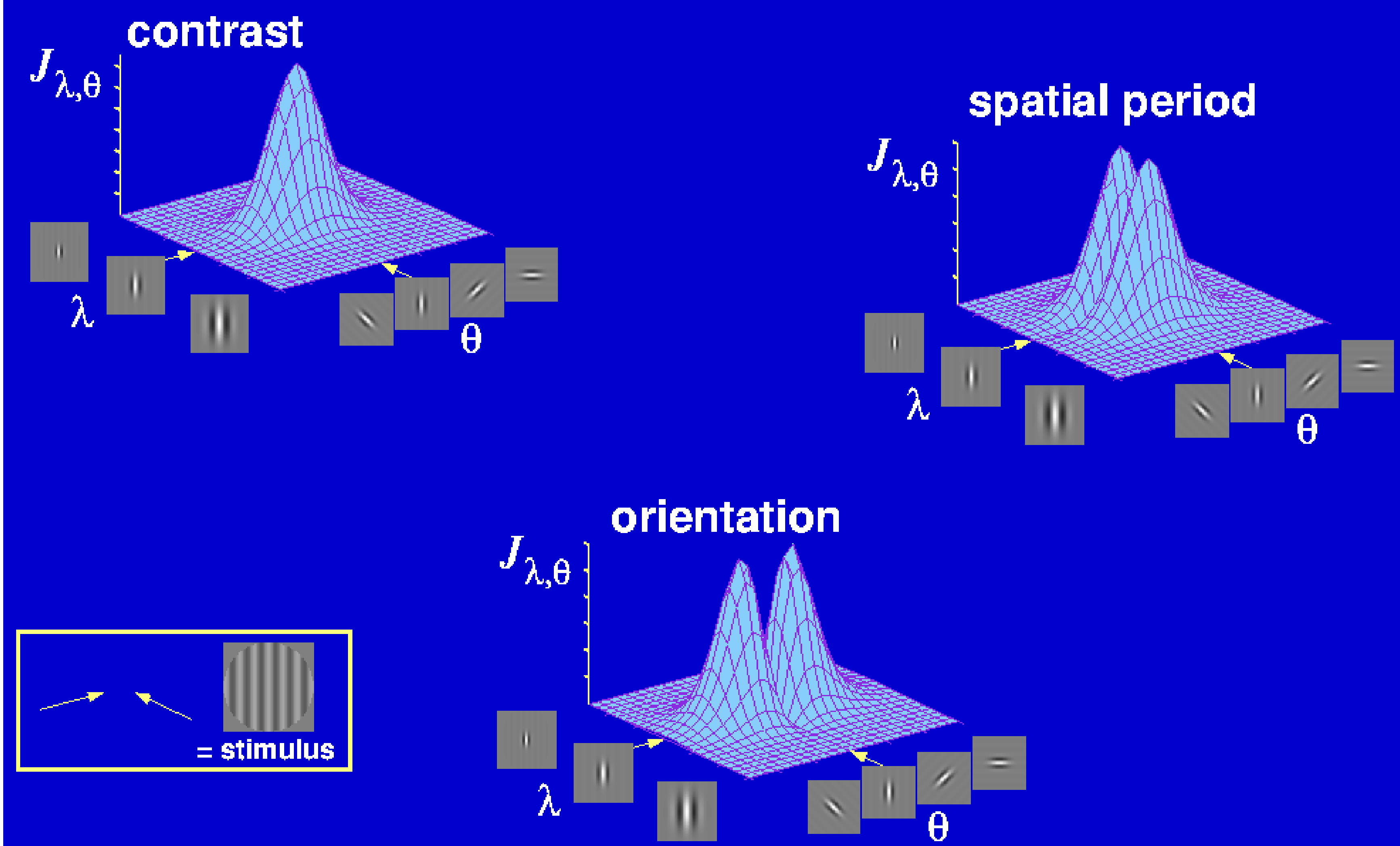
then, $\text{mean}(T) = \gamma$ and $\text{var}(T) = 1/J_{\theta,\lambda}$

with:

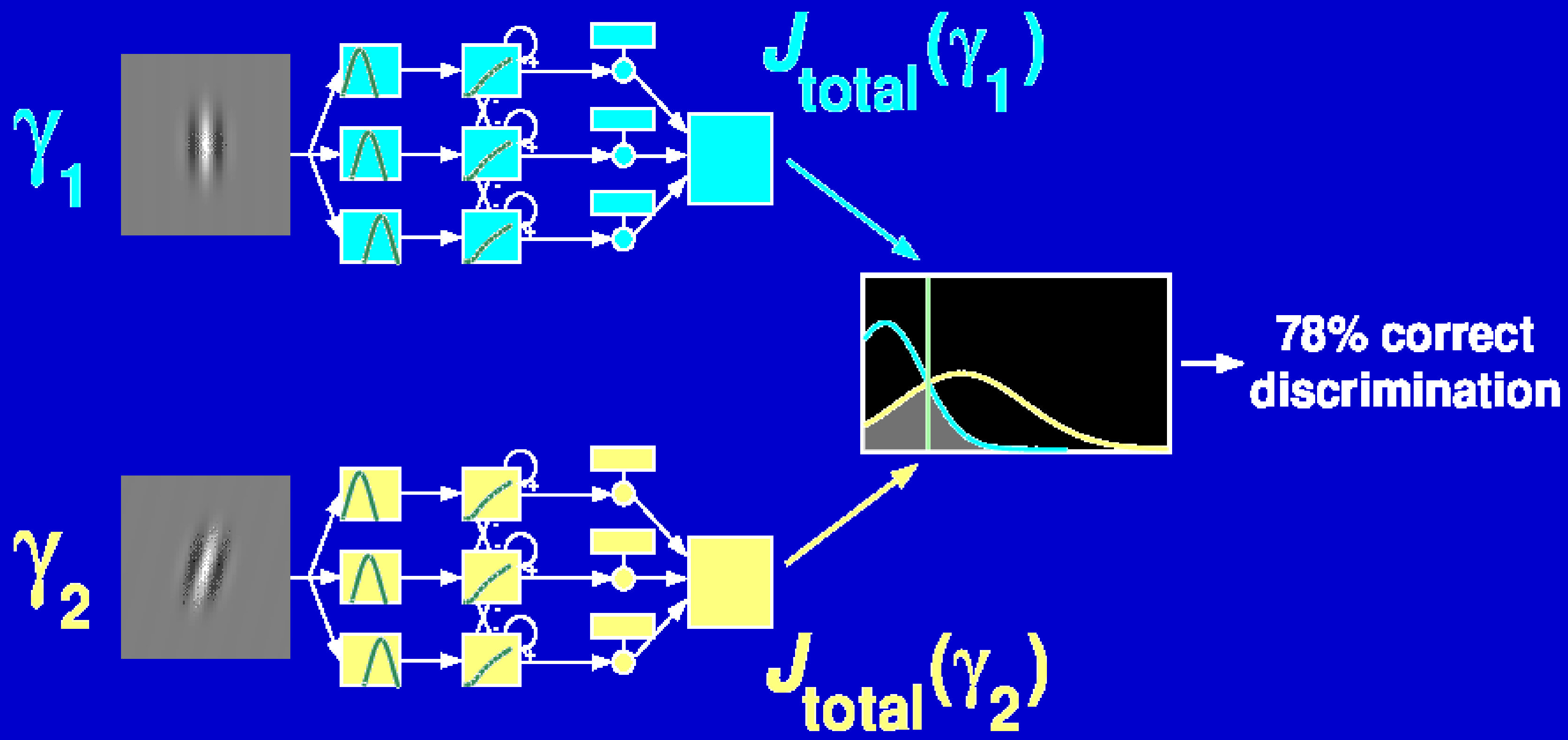
$$J_{\theta,\lambda} = \frac{1}{V_{\theta,\lambda}^2}\left[\left(\frac{\delta R_{\theta,\lambda}}{\delta\gamma}\right)^2 + 2\left(\frac{\delta V_{\theta,\lambda}}{\delta\gamma}\right)^2\right]$$

Fisher information

# Fisher information



# Threshold prediction



# Ideal observer discrimination

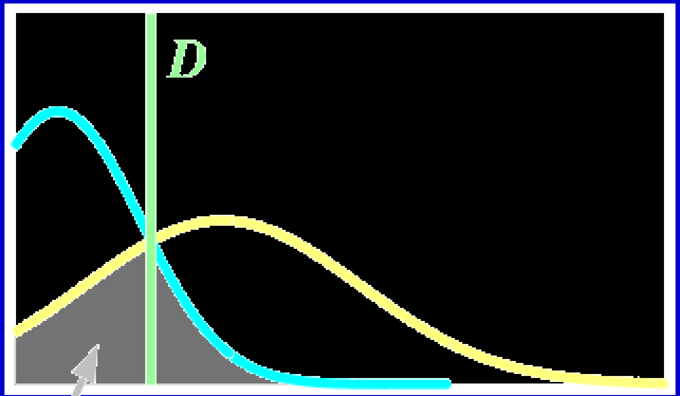
## Discriminate between stimulus 1 ($\gamma_1$) and stimulus 2 ($\gamma_2$)

**Stimulus 1:** $\mu_1 = \gamma_1$,

$\sigma_1^2 = 1/J_{total}(\gamma_1)$

**Stimulus 2:** $\mu_2 = \gamma_2$,

$\sigma_2^2 = 1/J_{total}(\gamma_2)$




Prob(error) = 1-Performance

**Decision criterion:**

$$D = \frac{2\mu_2\sigma_1^2 - 2\mu_1\sigma_2^2 - \sqrt{(2\mu_1\sigma_2^2 - 2\mu_2\sigma_1^2)^2 - 4(\sigma_1^2 - \sigma_2^2)(\mu_2^2\sigma_1^2 - \mu_1^2\sigma_2^2 - 2\sigma_1^2\sigma_2^2 \log\frac{\sigma_1}{\sigma_2})}}{2(\sigma_1^2 - \sigma_2^2)}$$

**Performance Yes/No task:**

$$Performance = 1 - \frac{1}{4} erfc\left(\frac{\mu_2 - D}{\sigma_2\sqrt{2}}\right) - \frac{1}{4} erfc\left(\frac{D - \mu_1}{\sigma_1\sqrt{2}}\right)$$

# But what was the conclusion?

- Haha, you will need to read the paper.

- Here we focused on the approach and general methods

- See the paper at http://ilab.usc.edu/publications/Lee_etal99nn.html (click on the PDF icon in front of the author names to download the full paper)