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 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.
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?
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

Central task: same or different?

Perceptual Mask

Stimulus

Peripheral task: threshold measurement

200 ms
Attentional Manipulation Paradigm

Central task: same or different?

A

Peripheral task: threshold measurement
“poorly attended”

B

Ignore central task

Peripheral task
“fully attended”
Attention changes thresholds

Contrast discrimination

Spatial freq. discrimination

Orientation discrimination

Contrast masking 1

Contrast masking 2
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

Stimulus → Linear filters → Non-linear interactions → Decision

- Linear filters: 3 parameters
- Non-linear interactions: 5 parameters
- Decision: 2 parameters
- Statistically Efficient Decision: no parameter
Linear filters

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

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

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

$$E_{\theta,\lambda} = \sqrt{(Im \ast Even_{\theta,\lambda})^2 + (Im \ast Odd_{\theta,\lambda})^2}$$
Non-linear interactions

Power law and divisive inhibition:

\[ R_{\theta, \lambda} = \frac{E^G_{\theta, \lambda}}{S_\lambda + \sum_{\theta', \lambda'} W_{\theta', \lambda'} E^{H}_{\theta', \lambda'}} \]
Properties

**no pooling**

- Non-linear transducer function

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**pooling**

- Contrast-independent tuning
Decision strategy

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

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

then, \[ \text{mean}(T) = \gamma \quad \text{and} \quad \text{var}(T) = \frac{1}{J_{\theta,\lambda}} \]

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

$J_{\lambda,\theta}$

contrast

$J_{\lambda,\theta}$

spatial period

$J_{\lambda,\theta}$

orientation

= stimulus
Threshold prediction

\[ J_{\text{total}}(\gamma_1) \]

\[ J_{\text{total}}(\gamma_2) \]

78\% correct discrimination
Ideal observer discrimination

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

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

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

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

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

![Graph showing decision criterion](image)

**Decision criterion:**

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

**Performance Yes/No task:**

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