Perception as inference
Natural scenes are full of ambiguity
Natural scenes are full of ambiguity
What do these edges mean?
What do these edges mean?
What do these edges mean?
What is this?
What do these edges mean?

Luminance, illuminance, and reflectance, are physical quantities that can be measured by physical devices. There and the illuminance image, shown below.

The block is made of a 2x2 set of cubes, each colored either or . Patches differ in brightness. Patches have the same reflectance, but different .

From a physical point of view, the problem of lightness constancy is as follows. An illuminance image, \( E(x,y) \), is applied to the checker-block image. Figure 24.8(a) shows .

Unfortunately, the different ``checker-block'' images have been proposed for understanding lightness per caused by the same reflectance, but different . Note that Land and McCann's constraints fail when the two light-dark edges. They are exactly the same in the image, and so the produced the two numbers that were multiplied to make .

Humans do it pretty well. This must mean that illuminance is counterbalanced by its higher .

Intrinsic and were arbitrary functions, then there exists an .

\[ L(x,y) = E(x,y)R(x,y). \]

These underlying pose a problem for any "checker-block" image. Figure 24.8(a) shows when shifted, the two half-rings appear quite different.

What do these edges mean? (Adelson, 2000)
Lightness perception depends on 3D scene layout

Checker-shadow illusion: The squares marked A and B are the same shade of gray.

Edward H. Adelson
What are the letters?
What letter is this?
What is this?
What is this?
How are these different percepts represented in cortex?
(Scott Murray - Ph.D. thesis)
BOLD signal: LOC vs. V1

MRI Signal

Time (s)

V1

LOC

“diamond”

“non-diamond”

“diamond”

“non-diamond”
Picket-fence effect with speech
(from Bregman ‘Auditory Scene Analysis’

![Picket-fence diagram]
Sinewave speech
Sinewave speech

Please say what this word is

sill
shook
rust
wed
pass
lark
jaw
coop
beak
Bayes’ rule

\[ P(E|D) \propto P(D|E) \times P(E) \]

- \( P(D|E) \) how data is generated by the environment
- \( P(E) \) prior beliefs about the environment

\( E \) = the actual state of the environment
\( D \) = data about the environment
You observe $y$, what is $x$?

You observe $y$, what is $x$?

$y = x + n$

$P(x|y) \propto P(y|x) P(x)$

likelihood prior

estimated value $\hat{x}$

observed value $y = 14$

Simple example
Generative models

\[ P(\alpha|D, M) \]

observed data \( D \)

model \( M \)

causes \( \alpha \)

\[ P(D|\alpha, M) \]

explanation or prediction
Inference:

\[
P(\alpha|D, M) \propto P(D|\alpha, M) \, P(\alpha|M)
\]

Explanation or prediction:

\[
P(D|\hat{\alpha}, M) \quad \text{with} \quad \hat{\alpha} = \arg \max_{\alpha} P(\alpha|D, M)
\]

Objective for learning:

\[
\hat{M} = \arg \max_{M} \langle \log P(D|M) \rangle
\]

\[
P(D|M) = \sum_{\alpha} P(D|\alpha, M) \, P(\alpha|M)
\]
Mixture of Gaussians Model
Mixture of Gaussians model

\[ p(x) = \sum_{\alpha=1}^{K} p(x|\alpha) P(\alpha) \]

\[ p(x|\alpha) = \frac{1}{Z} e^{-\frac{||x-\mu_\alpha||^2}{2\sigma_\alpha^2}} \]

\[ P(\alpha) = \frac{1}{Z_\alpha} e^{\gamma_\alpha} \]

Model parameters: \[ M = \{\mu_\alpha, \sigma_\alpha, \gamma_\alpha\} \]
Inference:

\[ P(\alpha | x) = \frac{p(x | \alpha) P(\alpha)}{p(x)} \]

Learning:

\[ \hat{\mu}_\alpha, \hat{\sigma}_\alpha, \hat{\gamma}_\alpha = \arg \min_{\mu_\alpha, \sigma_\alpha, \gamma_\alpha} \langle \log p(x) \rangle \]
\[ \mathcal{L} = \langle \log p(x) \rangle \]

\[
\Delta \mu_\alpha \propto \frac{\partial \mathcal{L}}{\partial \mu_\alpha} = \frac{1}{\sigma_\alpha^2} \langle (x - \mu_\alpha) P(\alpha|x) \rangle
\]

\[
\mu_\alpha = \frac{\langle x P(\alpha|x) \rangle}{\langle P(\alpha|x) \rangle}
\]

\[
\Delta \lambda_\alpha \propto \frac{\partial \mathcal{L}}{\partial \lambda_\alpha} = \langle \frac{1}{2} \left[ N/\lambda_\alpha - |x - \mu_\alpha|^2 \right] P(\alpha|x) \rangle
\]

\[
\sigma_\alpha^2 = \frac{\langle \frac{1}{N} |x - \mu_\alpha|^2 P(\alpha|x) \rangle}{\langle P(\alpha|x) \rangle}
\]

\[
\Delta \gamma_\alpha \propto \frac{\partial \mathcal{L}}{\partial \gamma_\alpha} = \langle P(\alpha|x) - P(\alpha) \rangle
\]

\[
P(\alpha) = \langle P(\alpha|x) \rangle
\]
Learning rules (via gradient descent)

\[ \Delta \mu_\alpha \propto \frac{1}{\sigma_\alpha^2} \left\langle (x - \mu_\alpha) P(\alpha|x) \right\rangle \]

\[ \Delta \lambda_\alpha \propto \left\langle \left[ \sigma_\alpha^2 - \frac{1}{2} |x - \mu_\alpha|^2 \right] P(\alpha|x) \right\rangle \]

\[ \Delta \gamma_\alpha \propto \left\langle P(\alpha|x) - P(\alpha) \right\rangle \]