# 10 Automating interpretation systems

**Interpretation**

Plausible inference of hidden semantic structure from observable inputs

**E.g.**

| input | | hidden structure |
|---|---|---|
| word sequence | → | meaning |
| pixel matrix | → | object, relations |
| speech signal | → | phonemes, words |
| words in e-mail Subject: | → | Is message spam? Yes/No |
| symptoms | → | illness |

How to combine ambiguous, incomplete and conflicting evidence to draw reasonable conclusions?

**Distinct from logical reasoning**

- plausible inference:
  - non-monotonic: might change conclusions given more evidence
  - uncertain: conclusions are not guaranteed to be correct
    (but still want to do as well as possible)
- logical inference:
  - monotonic: once a conclusion is drawn it can never be retracted
  - certain: conclusions are certain given assumptions

## 10.1 How to build an interpretation system?

$$\text{observables} \rightarrow \boxed{\ ?\ } \rightarrow \text{hidden semantic structure}$$

Two key problems

1. need to represent facts about process that connects evidence to truth
2. need principles of evidence combination

**In this course**

We will represent uncertain knowledge using *probability theory*

Some alternatives we will not cover are

- fuzzy logic, fuzzy sets
- default logic
- rule-based systems
- Dempster-Shafer theory
- rough sets, ...

## 10.2 Probability theory

We will cover this in depth for the next several lectures. To get started, consider of some simple examples and basic properties of probability

- example: rolling a dice
- example: random variable

***Independent random variables***

$$\mathrm{P}(X_1 = x_1, X_2 = x_2) \quad = \quad \mathrm{P}(X_1 = x_1)\,\mathrm{P}(X_2 = x_2)$$

Alternative definition

$$\mathrm{P}(X_1 = x_1 | X_2 = x_2) \quad = \quad \mathrm{P}(X_1 = x_1)$$

It is easy to prove these two definitions are equivalent (prove it!)

***Conditional probability***

$$\mathrm{P}(A|B) \quad = \quad \frac{\mathrm{P}(A, B)}{\mathrm{P}(B)}$$

***Bayes' Theorem***

$$\mathrm{P}(A|B) \quad = \quad \frac{\mathrm{P}(B|A)\,\mathrm{P}(A)}{\mathrm{P}(B)}$$

***Conditionally independent random variables***

$X_1$ and $X_2$ are *conditionally independent given* $X_3$ if

$$\begin{aligned} & \mathrm{P}(X_1\!=\!x_1, X_2\!=\!x_2 | X_3\!=\!x_3) \\ = \;\; & \mathrm{P}(X_1\!=\!x_1 | X_3\!=\!x_3)\mathrm{P}(X_2\!=\!x_2 | X_3\!=\!x_3) \quad \text{for all } x_1, x_2, x_3 \end{aligned}$$

Equivalently, if

$$\begin{aligned} & \mathrm{P}(X_1\!=\!x_1 | X_2\!=\!x_2, X_3\!=\!x_3) \\ = \;\; & \mathrm{P}(X_1\!=\!x_1 | X_3\!=\!x_3) \quad \text{for all } x_1, x_2, x_3 \end{aligned}$$

Prove these definitions are equivalent

## 10.3 Forward generative models

Now, to apply this to building interpretation systems

1. Represent knowledge with probability: forward generative models

$$\begin{array}{ccc} \downarrow & & \text{world} \\ \boxed{\text{truth}} & & \downarrow \\ \downarrow & & \text{sensor} \\ \boxed{\text{evidence}} & & \downarrow \\ & & \text{observed measurement} \end{array}$$

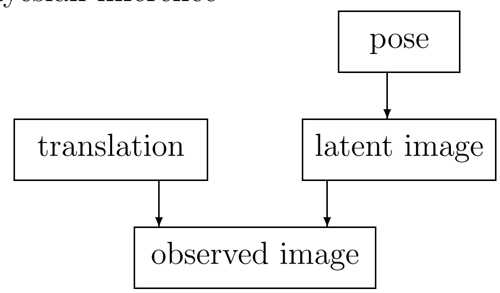
2. Principle of evidence combination: Bayesian inference

$$\begin{aligned} \text{conclusion} &= \arg \max_{\text{possible truth}} P(\text{possible truth}|\text{evidence}) \\ &= \arg \max_{\text{possible truth}} \frac{P(\text{evidence}|\text{possible truth})P(\text{possible truth})}{P(\text{evidence})} \\ &= \arg \max_{\text{possible truth}} P(\text{evidence}|\text{possible truth})P(\text{possible truth}) \end{aligned}$$

## 10.4 Demos

**Demo 1: Image normalization**

Bayesian inference



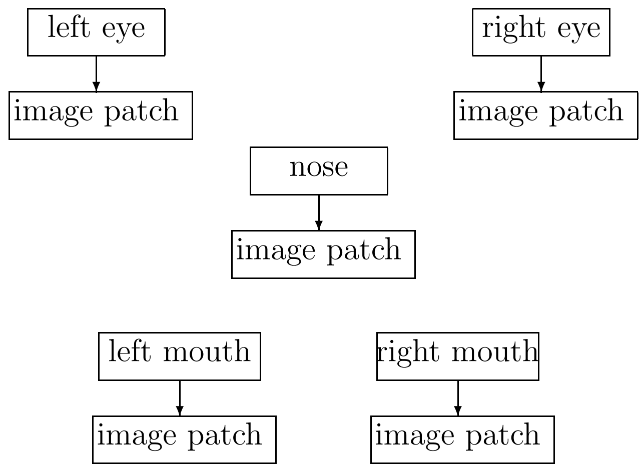

A time component is included to model image stabilization

**Demo 2: Independent object tracking**

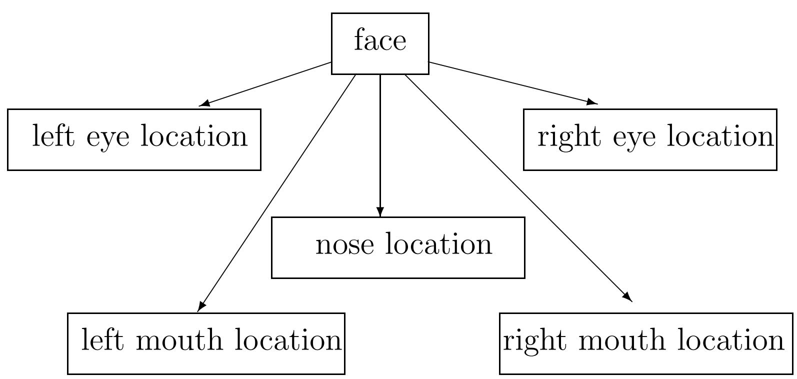
**Demo 3: Independent object tracking and object removal**

**Demo 4: Face tracking**

Two models combined: low-level model




High-level model




## Readings

Dean, Allen, Aloimonos: Section 3.7
Russell and Norvig 2nd Ed.: Section 14.7