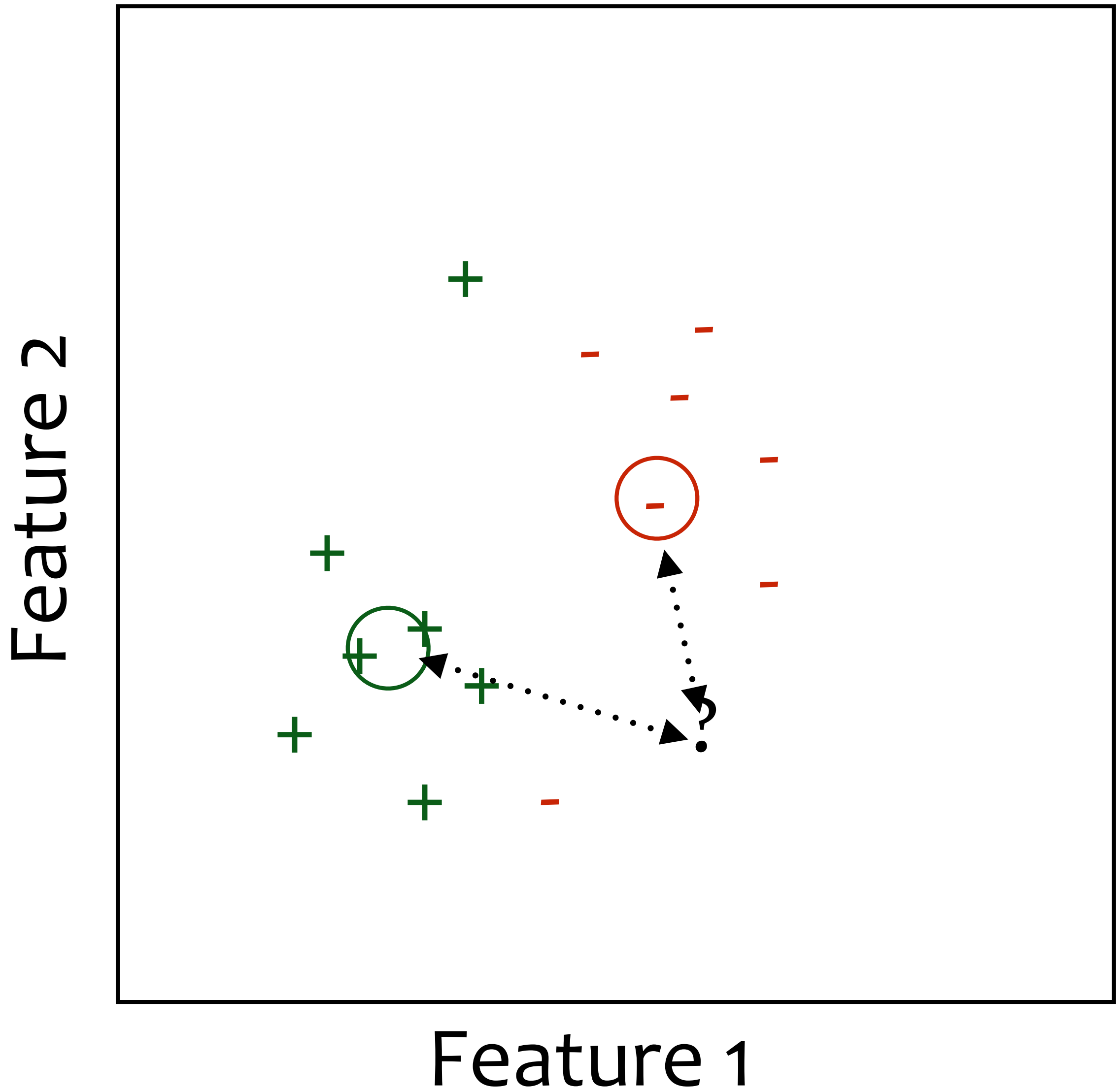
Prototype theory (in continuous feature space)



Compute central tendency (e.g. mean) for each category

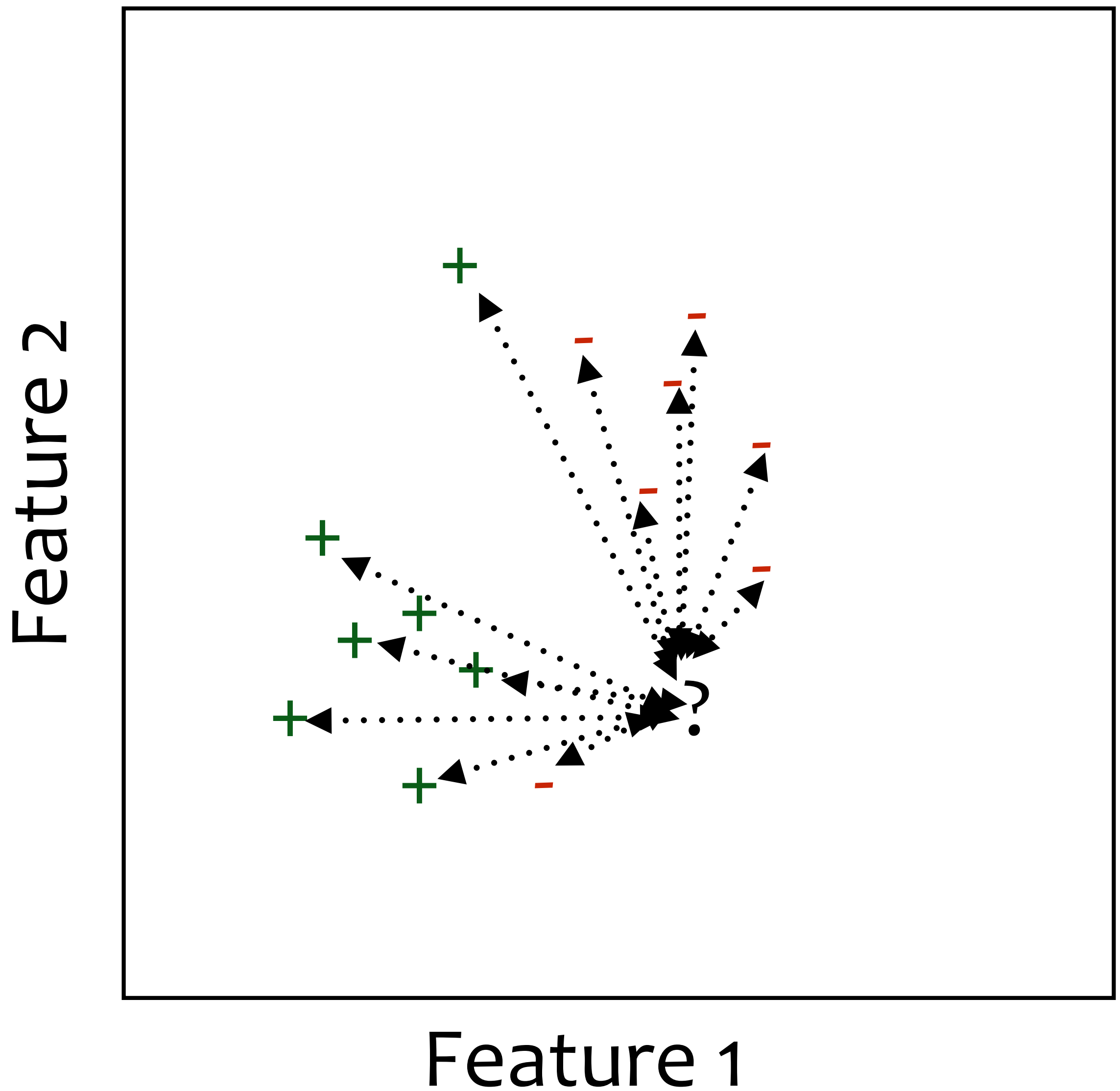
Compute distance between new instance and each category mean

Compute similarity of each instance to each category mean

Classify based on similarity:

$$P(x \text{ in } C_i) = \frac{\text{sim}(x, C_i)}{\sum_j \text{sim}(x, C_i)}$$

Exemplar theory



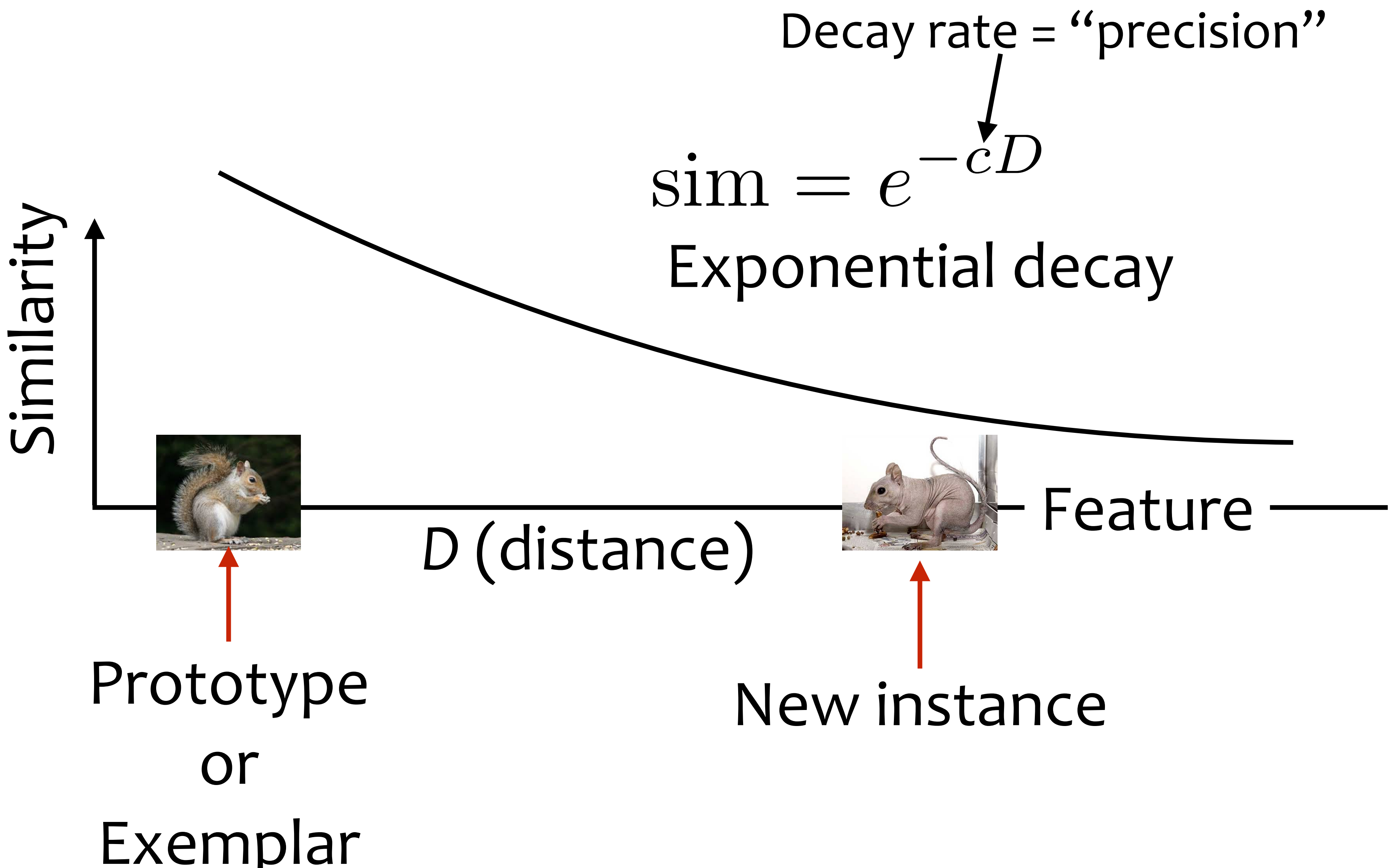
Compute distance between new instance and each stored exemplar

Compute similarity based on distance

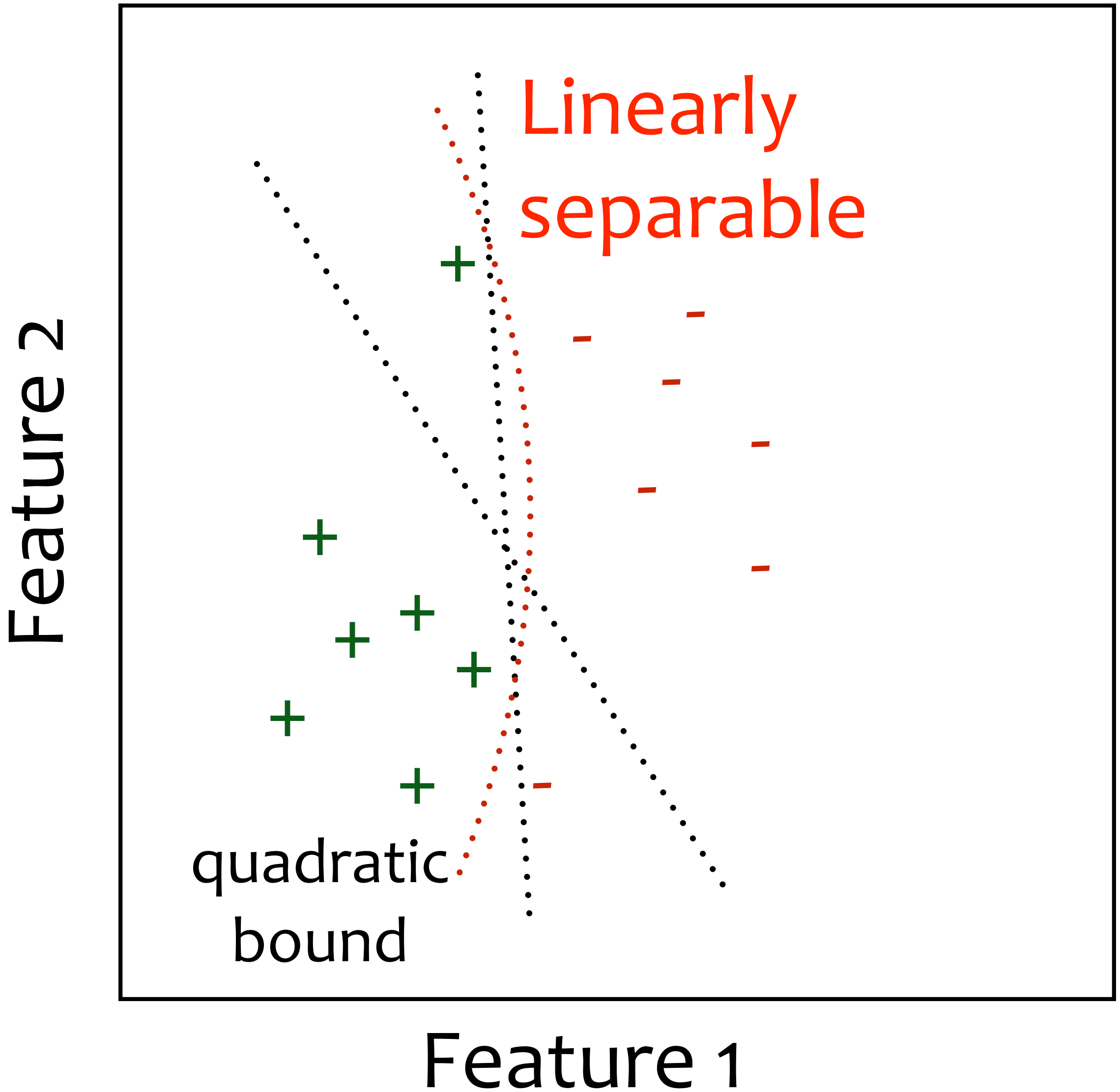
Classify based on similarity:

$$P(x \text{ in } C_i) = \frac{\sum_{e \in C_i} \mathrm{sim}(x, e)}{\sum_i \sum_{e \in C_i} \mathrm{sim}(x, e)}$$

Computing similarity from distance



Classification bound models



- Learn a classification boundary between categories
- Classify by applying bound
- Linear bounds are particularly easy
- Hypothesis: humans can handle quadratic bounds (linear bounds are a special case)

Induction as Bayesian inference

- Hume (1748) argued that inductive conclusions are not definite
- Thomas Bayes (1763) argued that they are, however, probable to various degrees
- That is, induction can be understood as a form of probabilistic inference
- He proposed an equation, now called Bayes' rule, to quantify the strength of an induction
- In modern cognitive science, many researchers have shown that human inductive judgments (in many domains) correspond closely to the predictions of this framework; they are nearly optimal

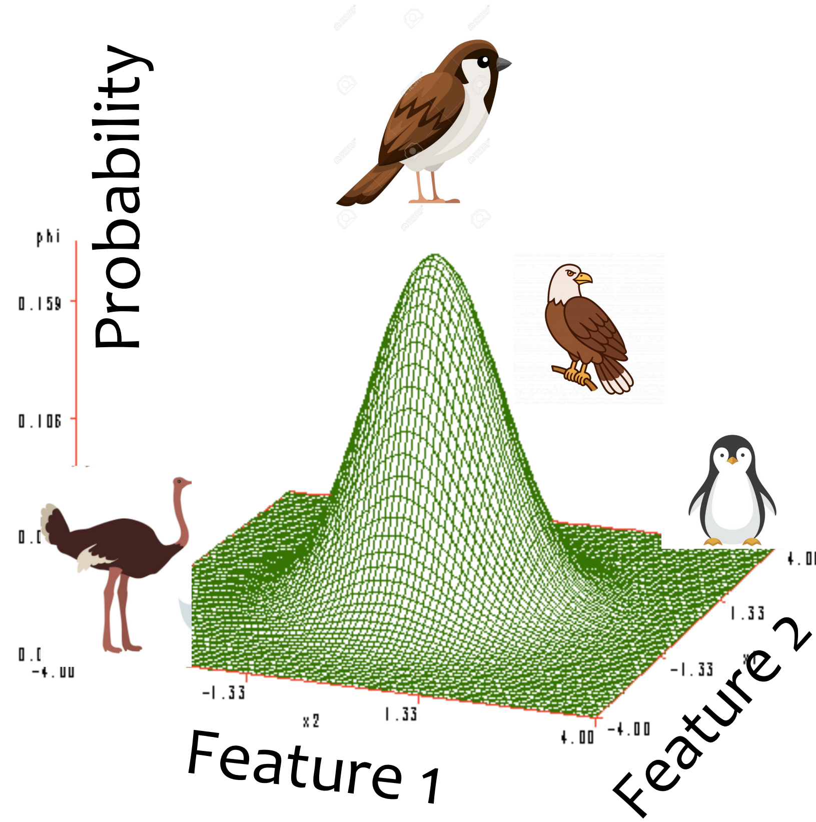
Bayesian models of categorization

- Some recent models of categorization frame it as a probabilistic inference problem

  - A category is a probability distribution over feature space

  - We learn categories by inducing the most plausible distributions to explain the world

  - We classify objects by assigning them to the most likely distribution to which they might be long.



These models are called Bayesian models because rational probabilistic classification follows Bayes’ rule