

Detecting Rare Events in Cognitive Systems

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Hynek Hermansky, Holly Jimison and partners

Outline

- DIRAC
- Background: Novelty is old
- Oddballs vs. rare
- Categorization framework
- Rare definition
- Role of utilities
- Examples

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DIRAC Preview: Problem Statement

- Detect and interpret (respond appropriately) to “rare” events
- Initial definition of rare:

  Clear but unexpected inputs in a given context
- Humans can do this usually very well, but machines fail
- Approach:
  - Detection based on comparison of inputs to expectations
  - Recognition based on fusion of multimodal inputs

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DIRAC Circle of Partners

Leibnitz Inst Neurobiology



KATHOLIEKE UNIVERSITEIT LEUVEN



HUJI

CTU



CARL VON OSSIETZKY universität OLDENBURG

DIRAC
Detection and Identification of Rare Audiovisual Cues

BRNO UNIVERSITY OF TECHNOLOGY
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Neural Systems Laboratory

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Workpackages

- WP1: Signal Acquisition and Associated Processing
- WP2: Auditory Representation
- WP3: Visual Representations
- WP4: Learning and Categorization
- WP5: Multi-sensory Information Fusion
- WP6: Integration and Applications
- WP7: Training and Education
- WP8: Management, Planning and Dissemination

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Intelligence: Response to the Unknown

- Ubiquity of the problem: Response to the unexpected (fight or flight)
- Long history in philosophy and science from Aristotle to modern philosophers

- Psychology and Cognitive Science
  - Cognitive functions and intelligence
  - Discrimination
  - Categorization
  - Generalization
- Informatics Examples
  - Information Theory: Quantification of surprise
  - Statistical pattern recognition, classification
  - Machine Learning
  - Data Compression

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Engineering Problem

- Given: A classification system designed to respond optimally to examples in a training & validation sets
- System is confronted with a stimulus that is different from those in the training set sample distribution
- Possible responses:
  - Fixed Response: Best fitting class
  - Adaptive Response: Modify the best fitting class – adapt the most probable category
  - Adaptive Response: Create a new category with a temporary label
  - Adaptive Response: Run ☺

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Basic Premise

- Observation: Humans and animals are usually good at responding appropriately* to the detection of "rare" stimuli and events

- Violations of this observation are striking

- Can we build robots with these capabilities?
- Can we refine neuroscience paradigms to determine the neural substrate of this capability?

* Optimally with respect to given utility function

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Determinants of Intelligent (Objective) Response

- Is there an explicable reason for the stimulus interpretation?
  - Noise
  - Distortion
  - Occlusion
  - Context
- Is the response to the rare event important?
  - Context
  - Task
  - Consequences

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Psychology: Paradigms and Approaches

Paradigms used to study of humans and animal responses to novel stimuli

- Discrimination
  - Sensitivity of the sensory system
- Categorization
  - Search
  - Oddball detection
- Generalization

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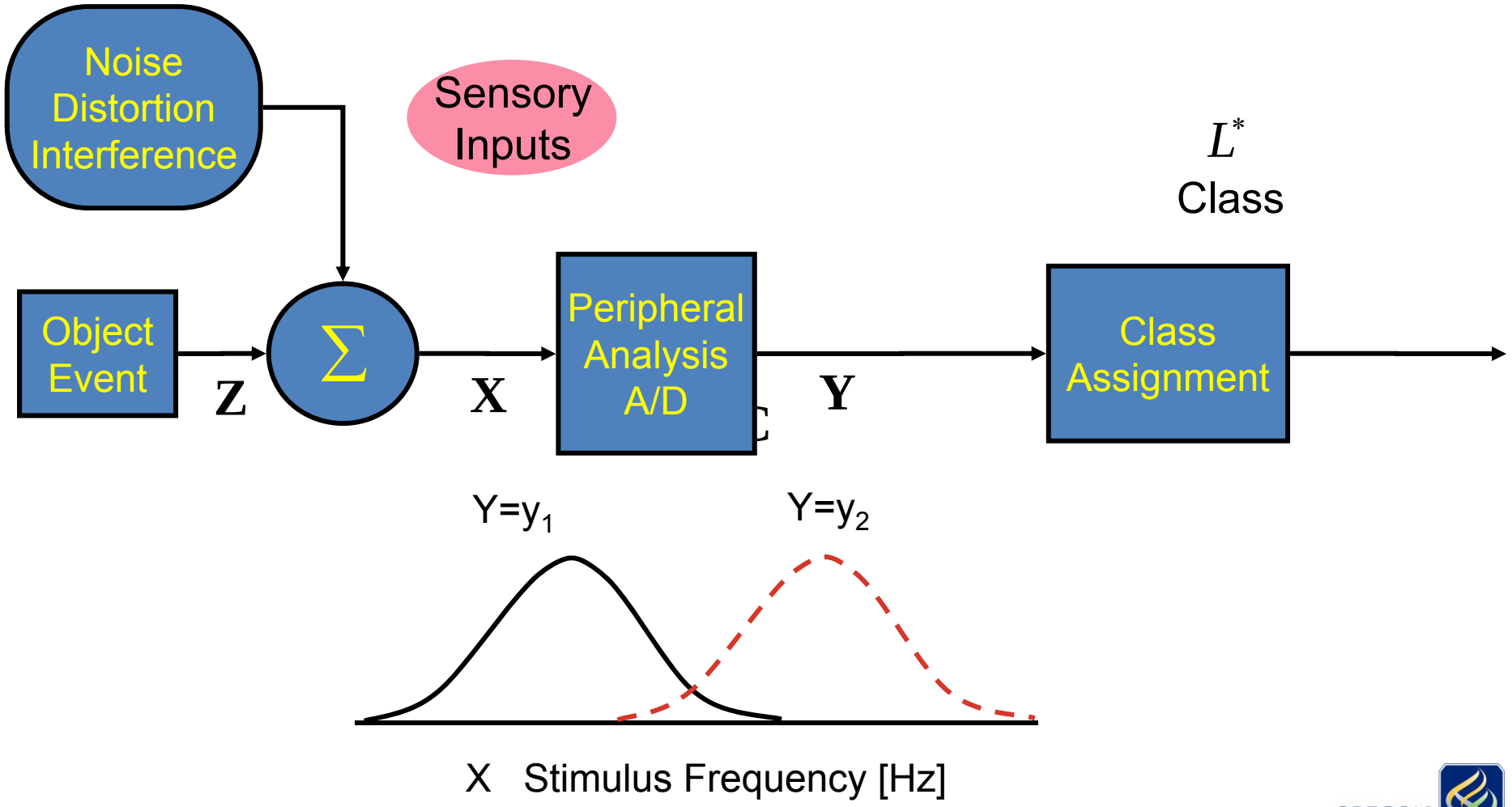
Framework for Discrimination and Categorization



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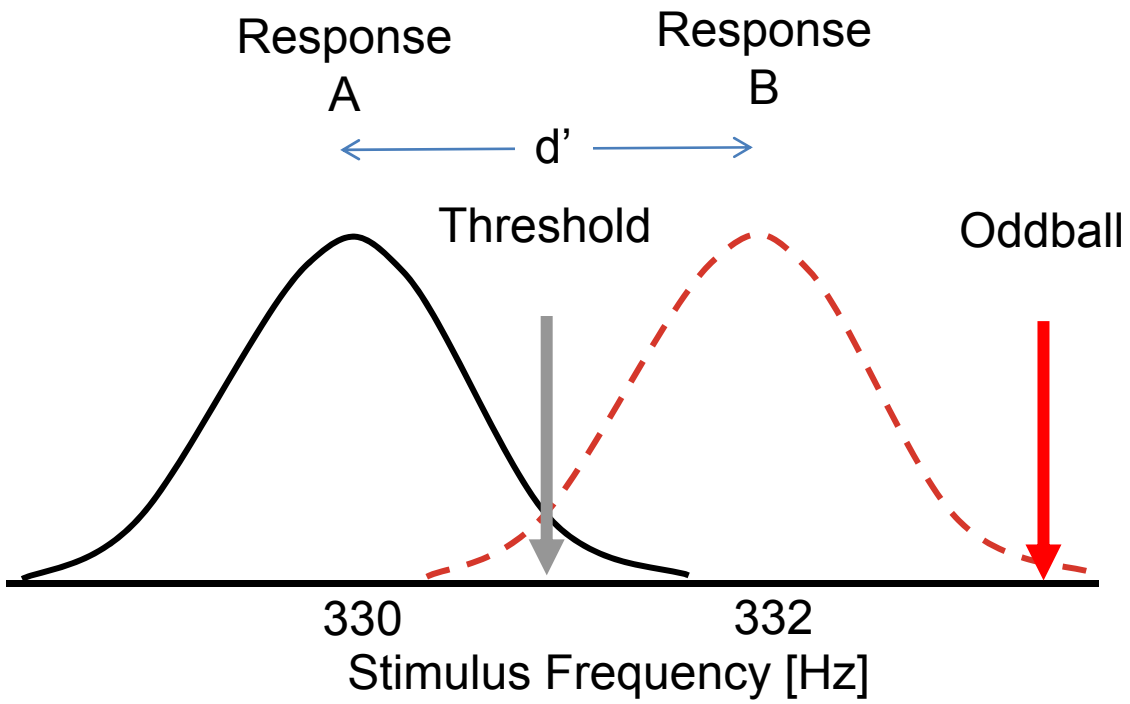
Perceptual Discrimination

Example: Discrimination between two tones, f_1 and f_2



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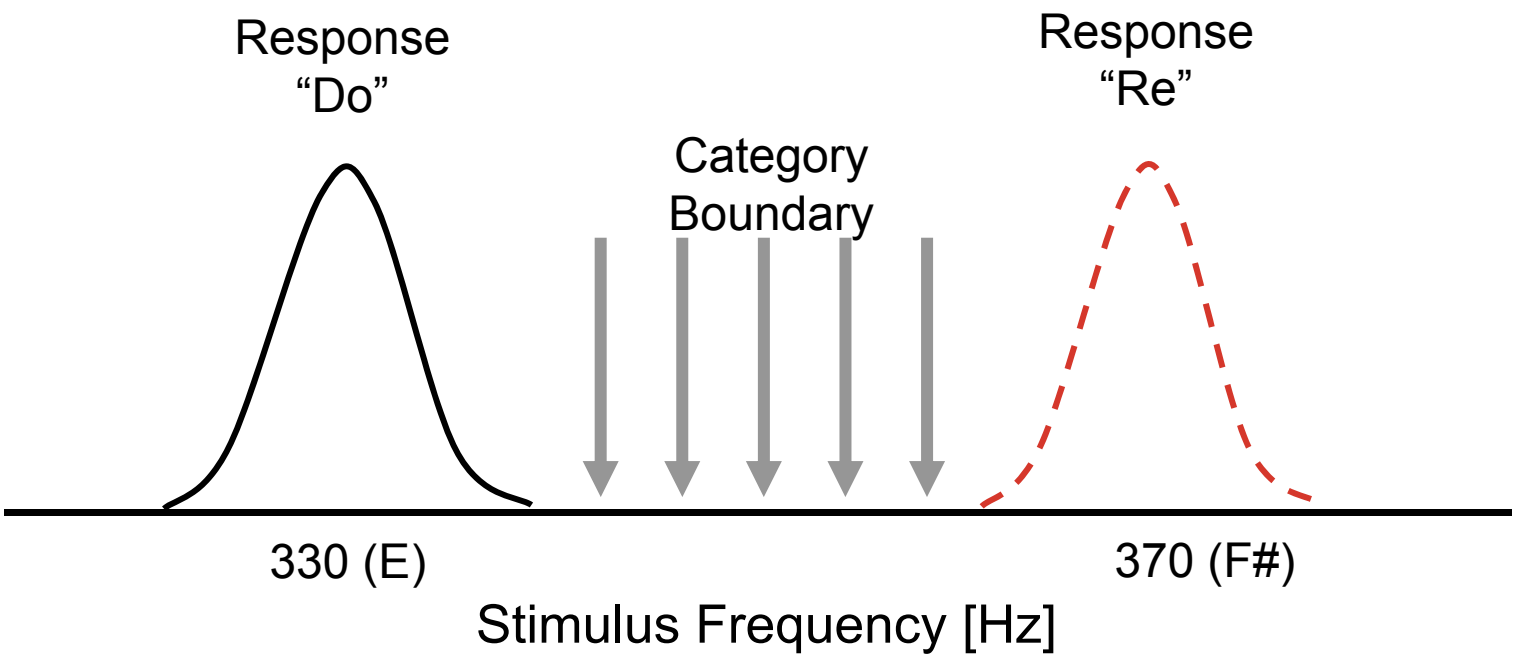
Perceptual Categorization

Example: Categorization of tones, f_1 and f_2



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Perceptual Categorization

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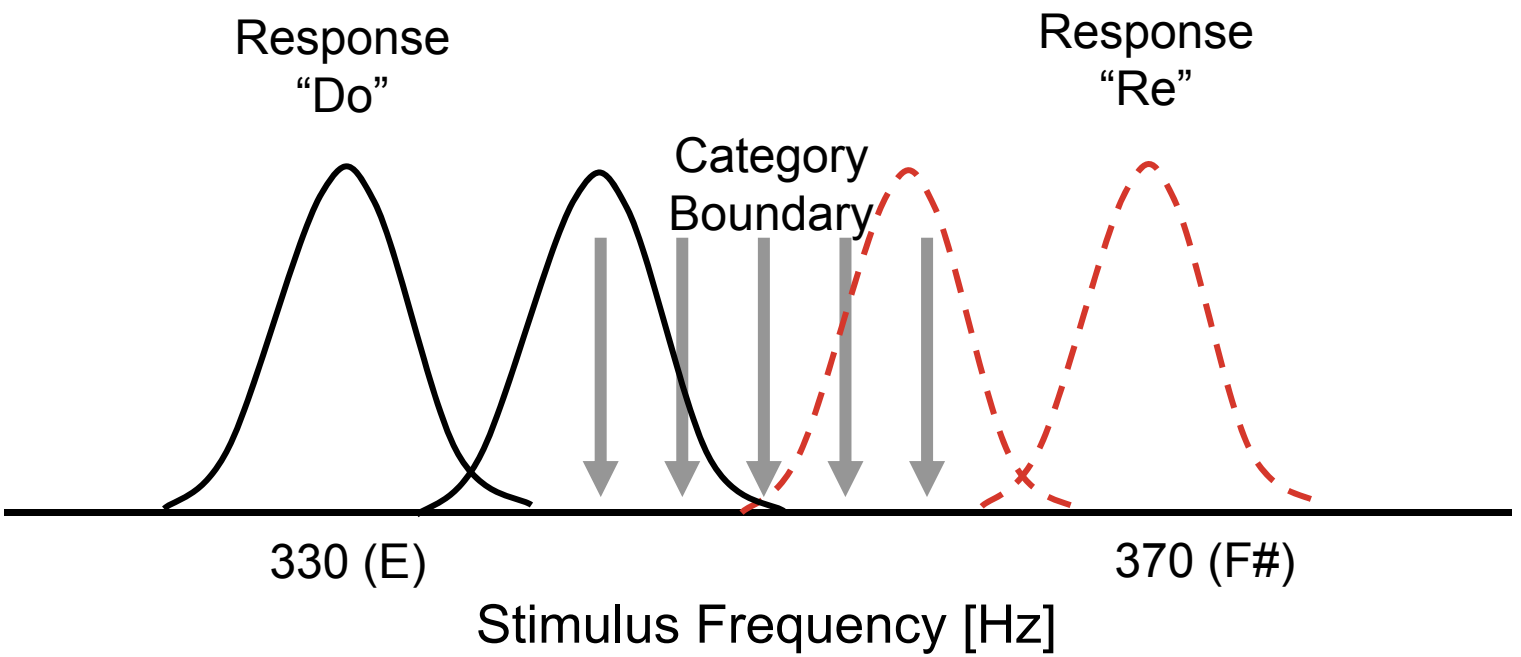

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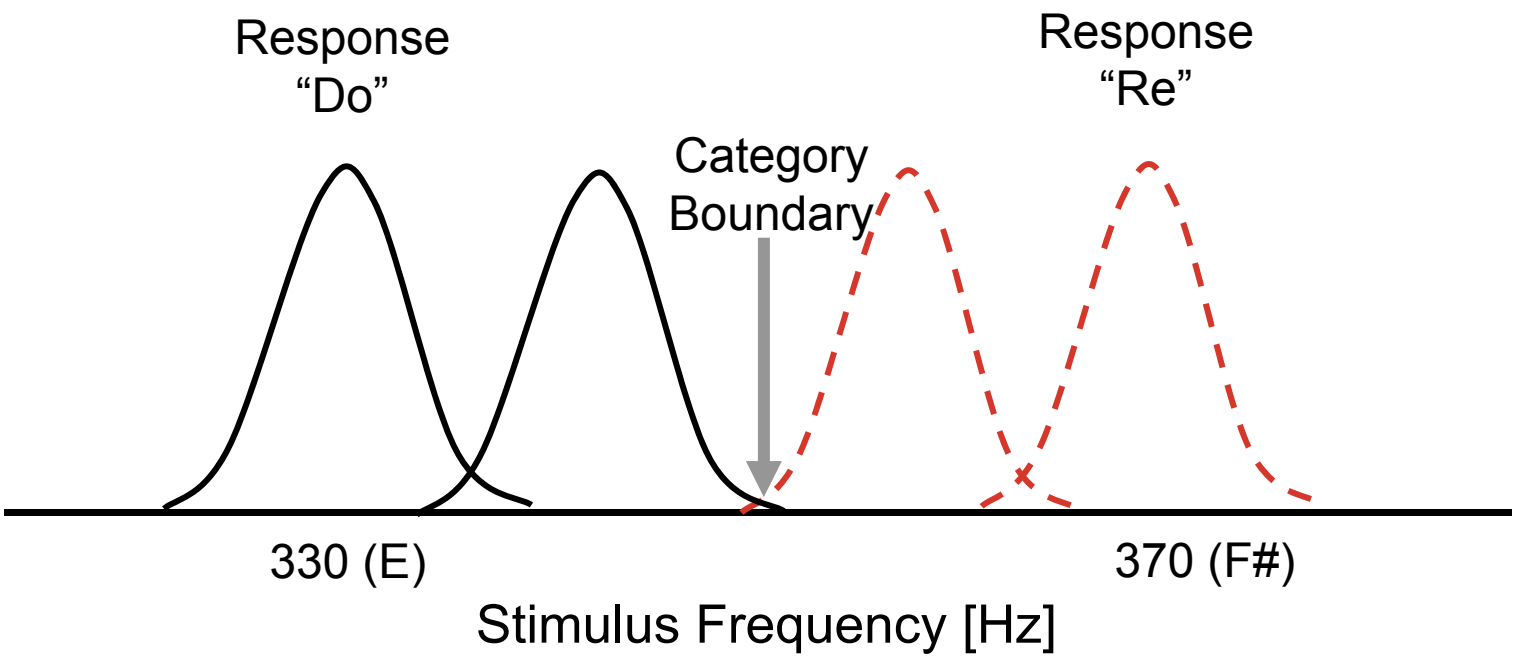

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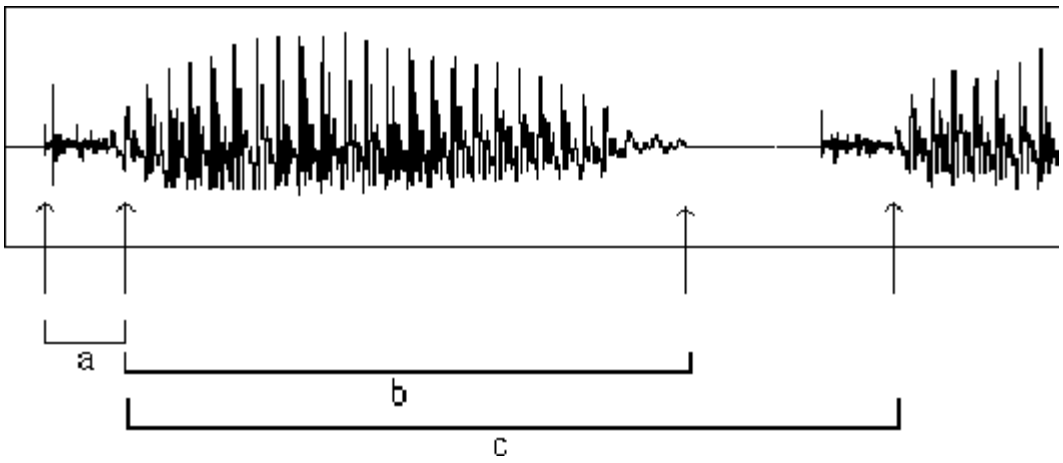
Example: Speech Sounds Discrimination



a. VOT (voice onset time), b. voicing duration, c. voice onset interval

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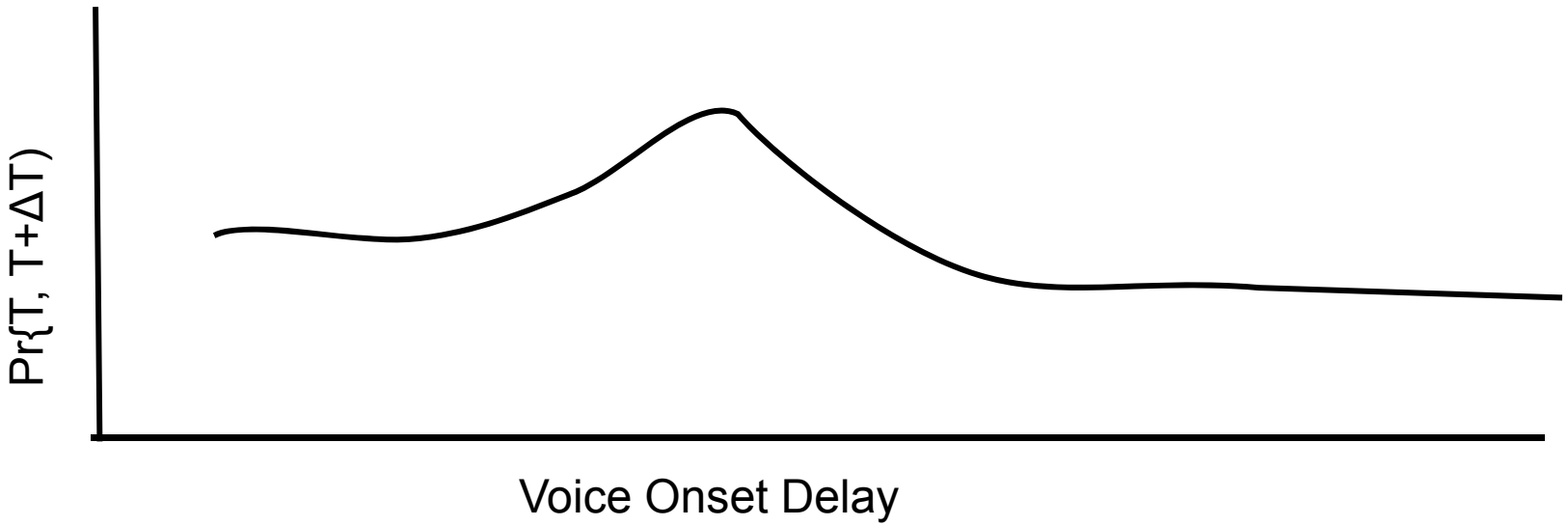
Categorical Perception?

- Speech sound perception – discrimination
- Discrimination of Pr{T, T+ΔT) (b vs. p)



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Categorical Perception?

- Speech sound perception – discrimination
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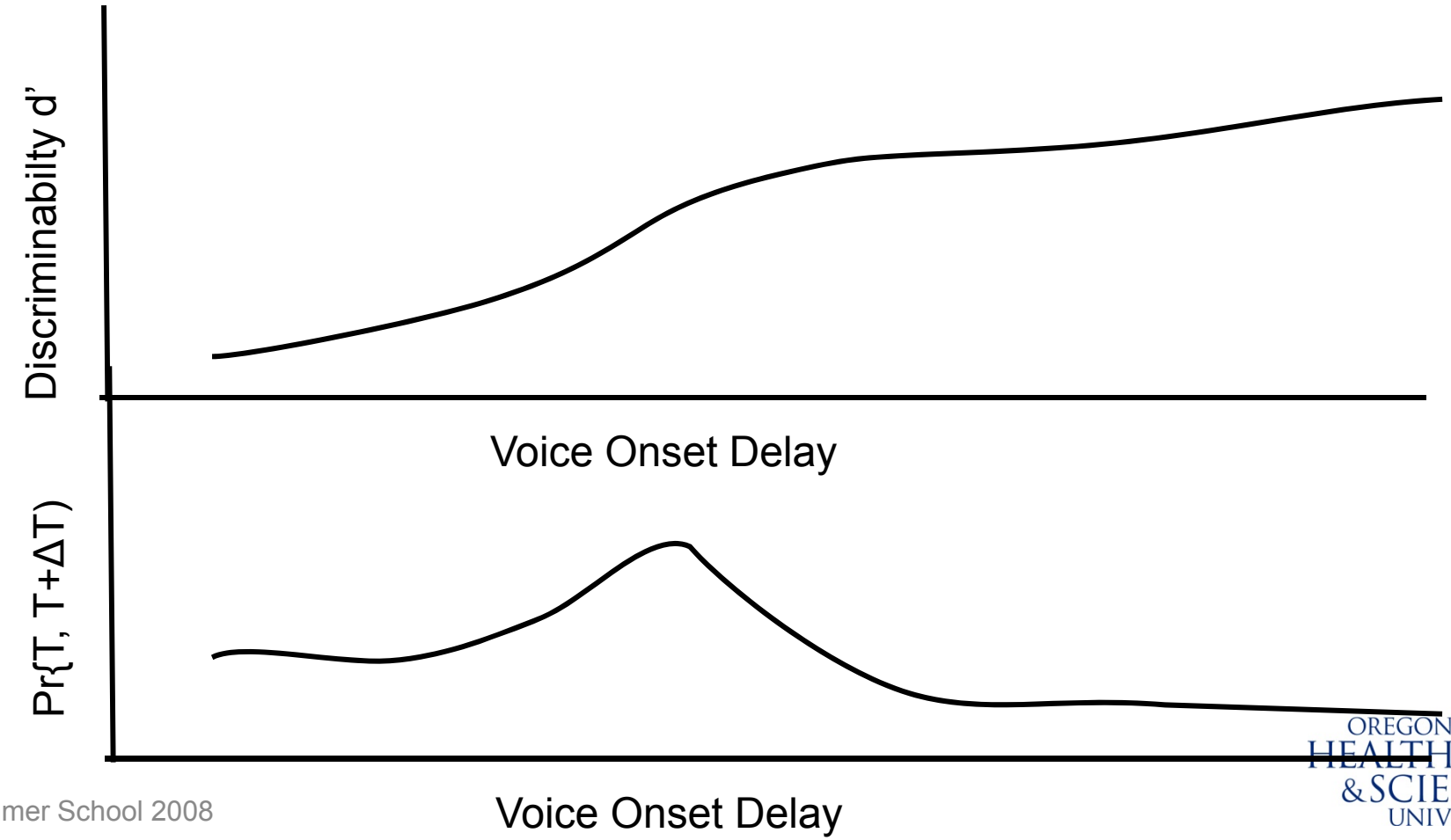

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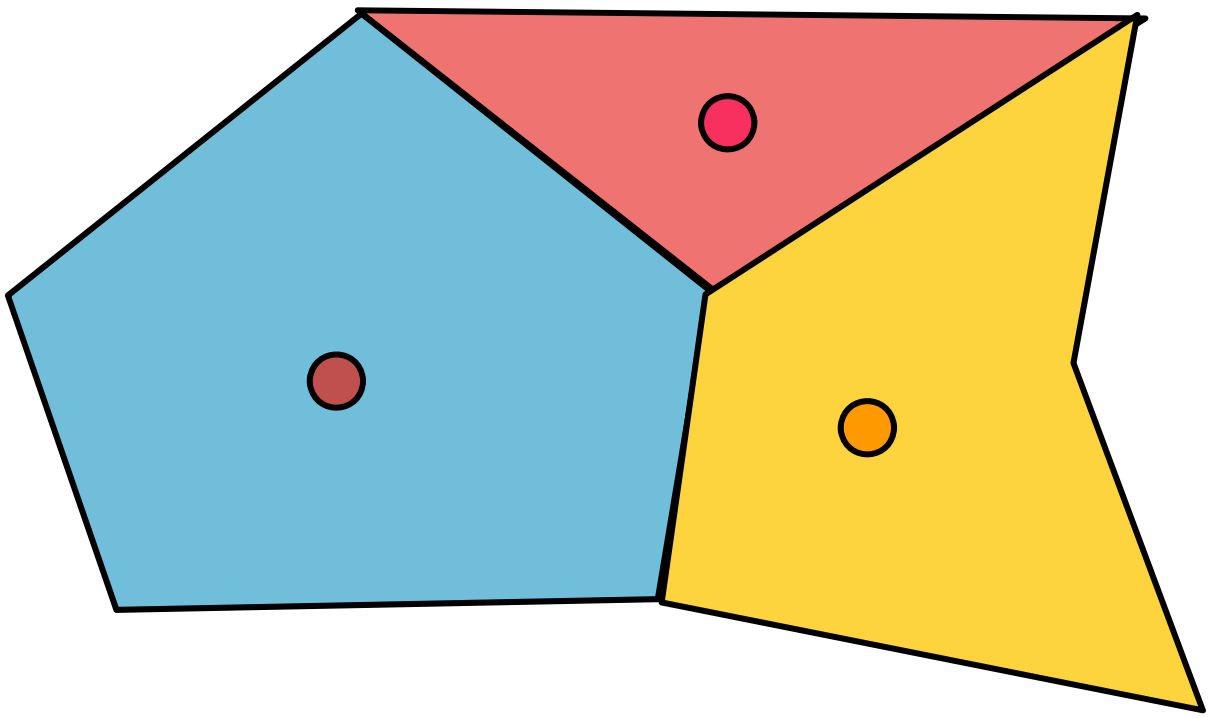
Multidimensional Categorization

Example: Categorization Regions



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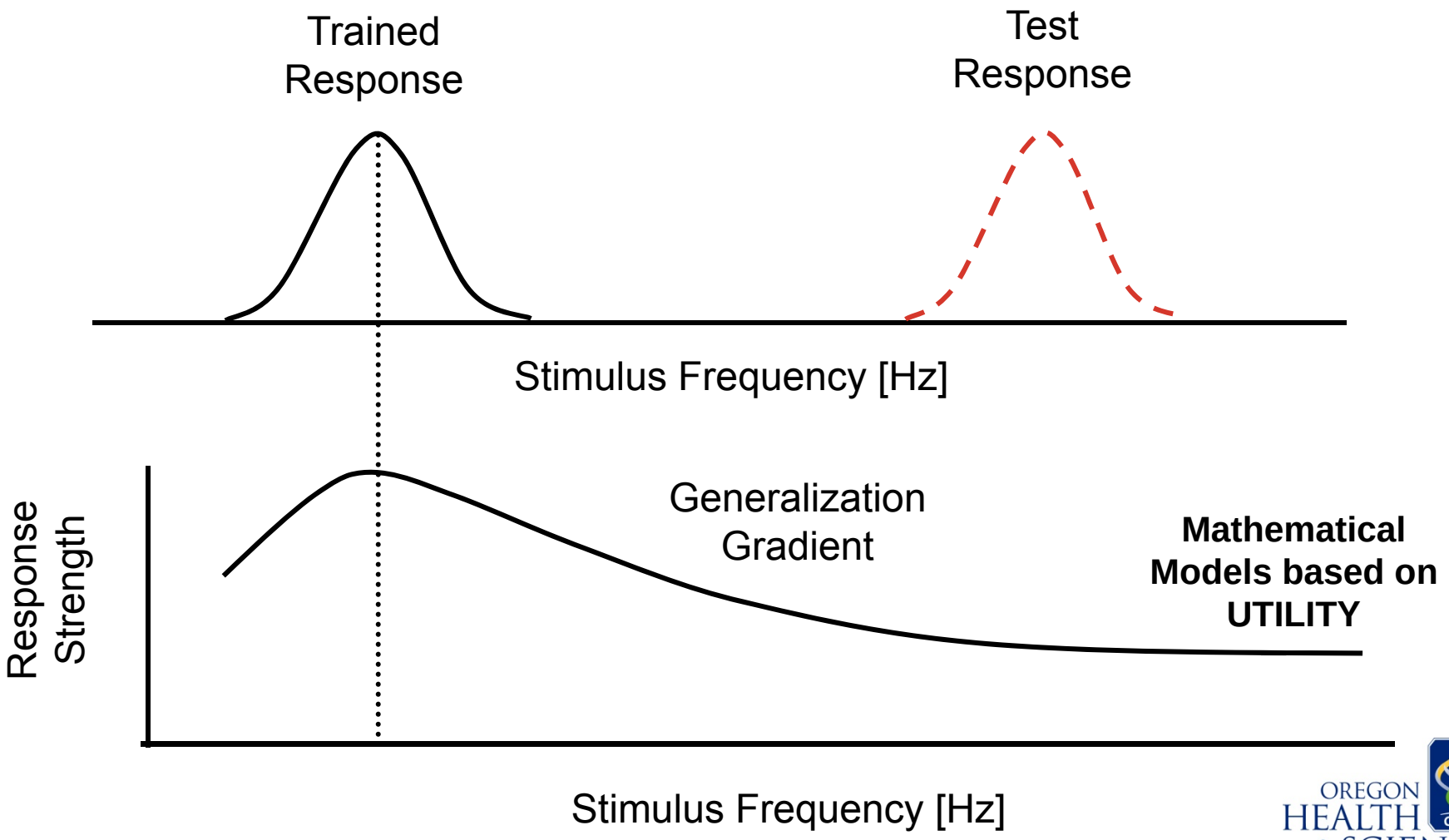
Psychological Generalization

Example: Salivation response to tones



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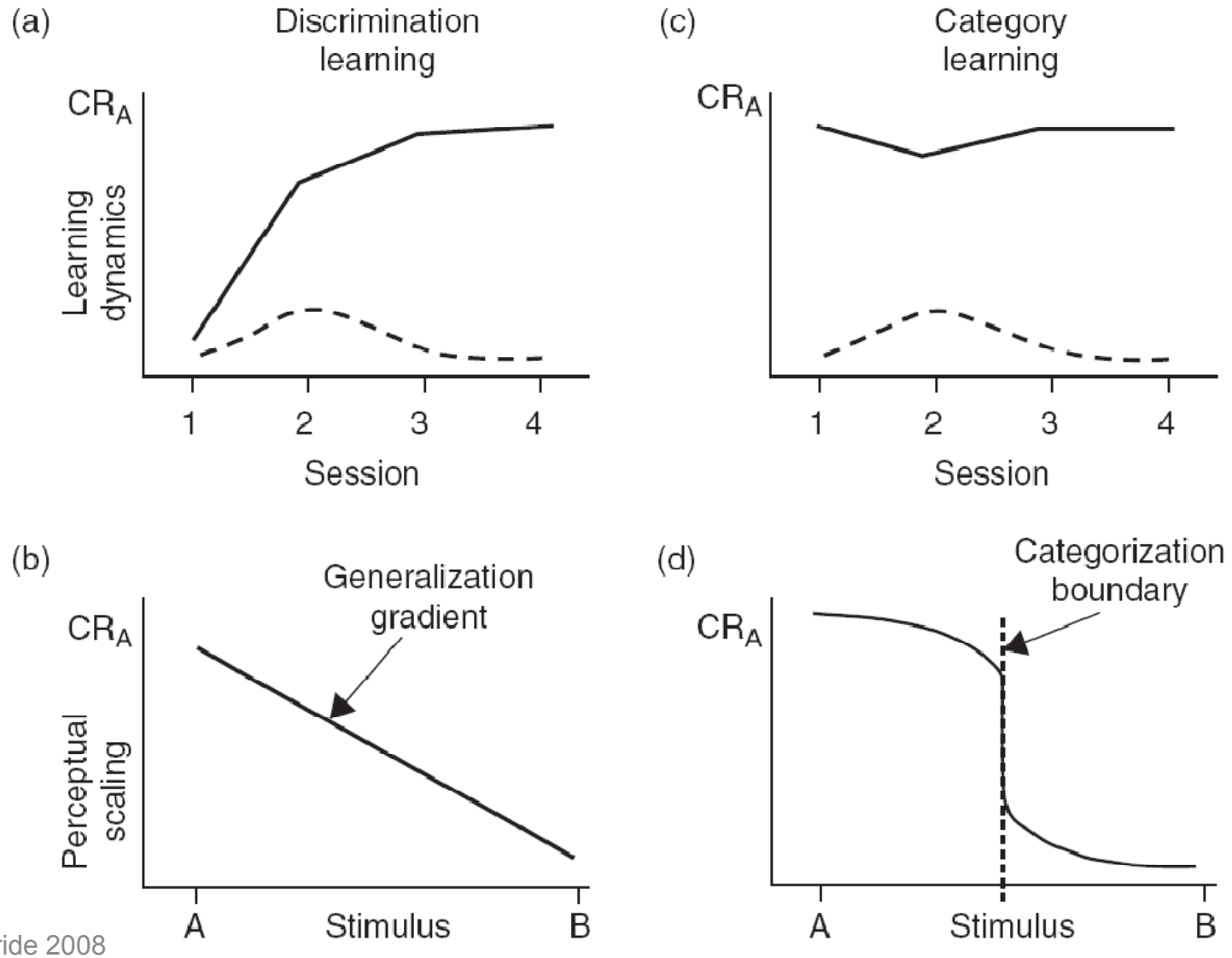
Generalization vs. Categorization



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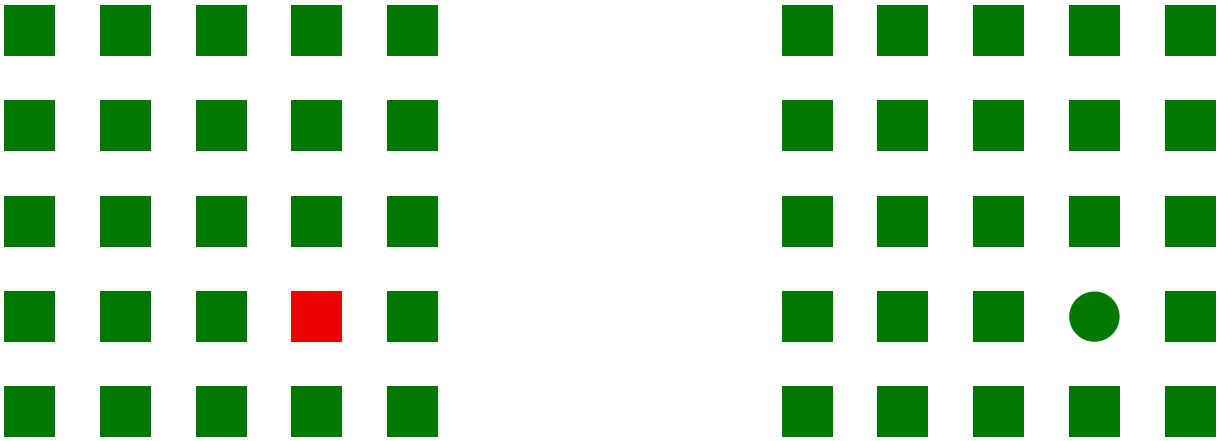
Classical Definition of "Novel" Stimuli

Spatial Oddball Detection: Color or Shape



Temporal Oddball Detection: Color or Shape



Bottom-up, outlier detection

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Intuitive Notion of Rare, Unexpected Events

- Low **class** posterior probability can be caused by
  - Low prior probability
  - Uncertain, ambiguous measurement
  - Unexpected combination of observations
  - New class – to be added?
  - Low class prior probability in context
- Most current systems' response to Low probability stimuli
  - System finds the response with maximum a posteriori probability (MAP)
  - The output is the MAP response
  - System may provide confidence metrics
- Can system recognize its ignorance?
  Feature – class incongruence + high importance (utility)

Summary of Intuitive Description

- Low posterior probability due to conflicts among different interpretations of the same object or concept
- More generic interpretation has high posterior while the less generic has low posterior probability
- To make this intuition precise we need a formal structure

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Notation

- Observations $\mathbf{X} = \{X_1, X_2, ..., X_n\}$
- Features $\mathbf{Y} = \{Y_1, Y_2, ..., Y_m\}$
- Classes/Labels $\mathbf{L} = \{l_1, l_2, ..., l_k\}$
- Prior Class Probability $P\{L \mid C\}$
- Set of Utilities: $U = \{u_{00}, u_{01}, u_{10}.u_{11}\}$
- Context $C, \quad P\{C\}$
- Probability of new category $P\{L_{n+1} \mid C\}$

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Classification in Context

- Maximum a Posteriori --$P\{L \mid \mathbf{Y}, C\} = P\{\mathbf{Y} \mid L, C\} \dfrac{P\{L \mid C\}}{P\{\mathbf{Y} \mid C\}}$

  - Mode of posterior probability distribution

$$L^* = \arg\max_{\forall l} \left\{ P\{L \mid \mathbf{Y}, C\} \right\}$$

- Maximum Expected Utility:

$$L^* = \arg\max_{\forall L} \left\{ \sum_K u_{LK} P\{L \mid K, \mathbf{X}, C\} \right\}$$

Need a framework for classification

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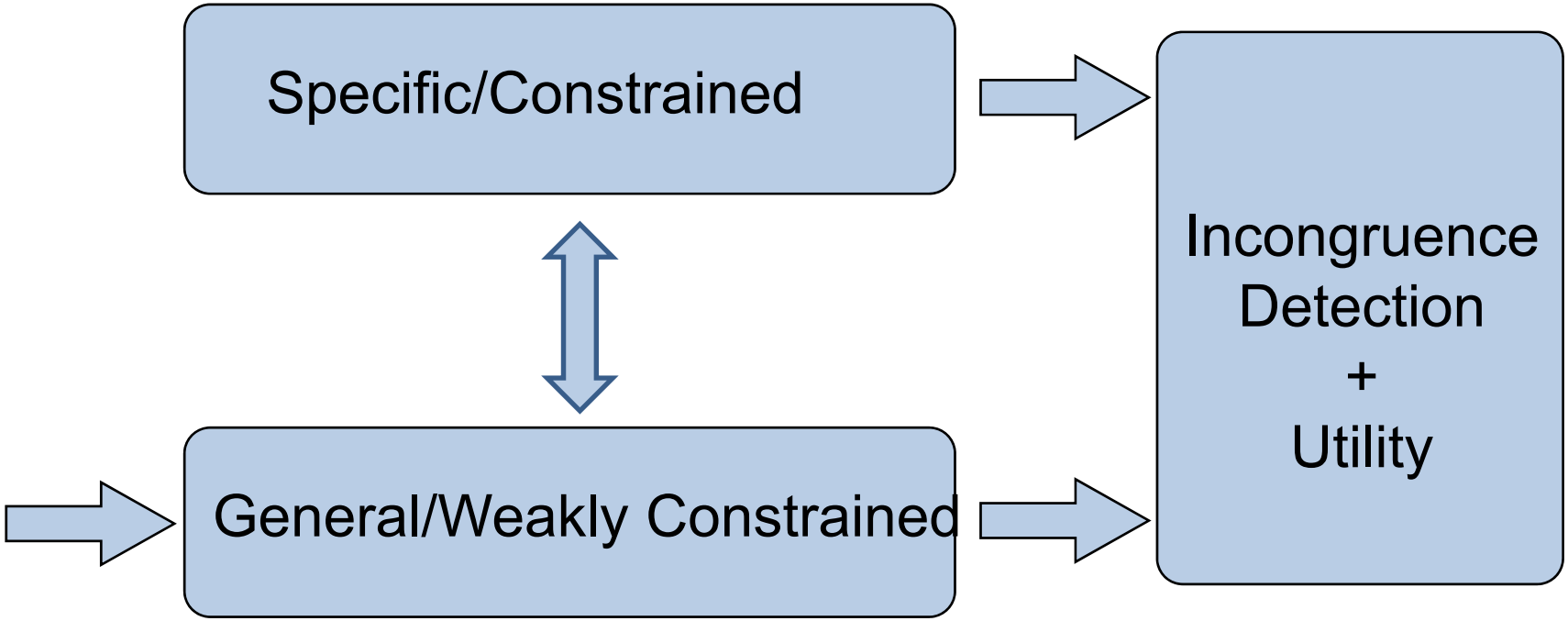
Framework: Detection of Conflict in Probabilities



Need a framework for the models and their relationships

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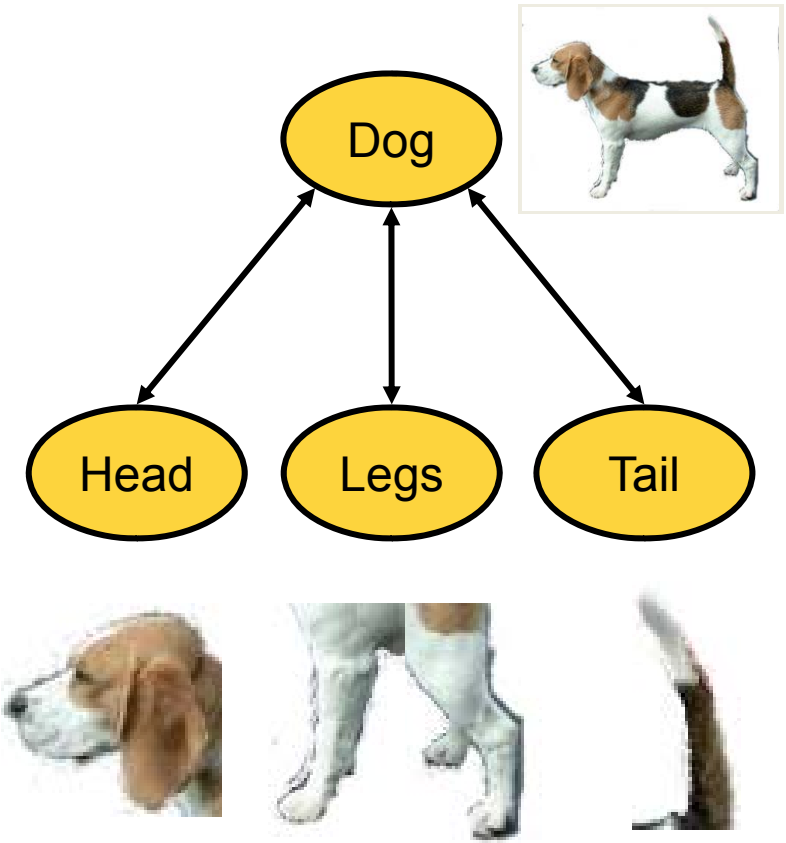
Part-Membership Hierarchy of Categories



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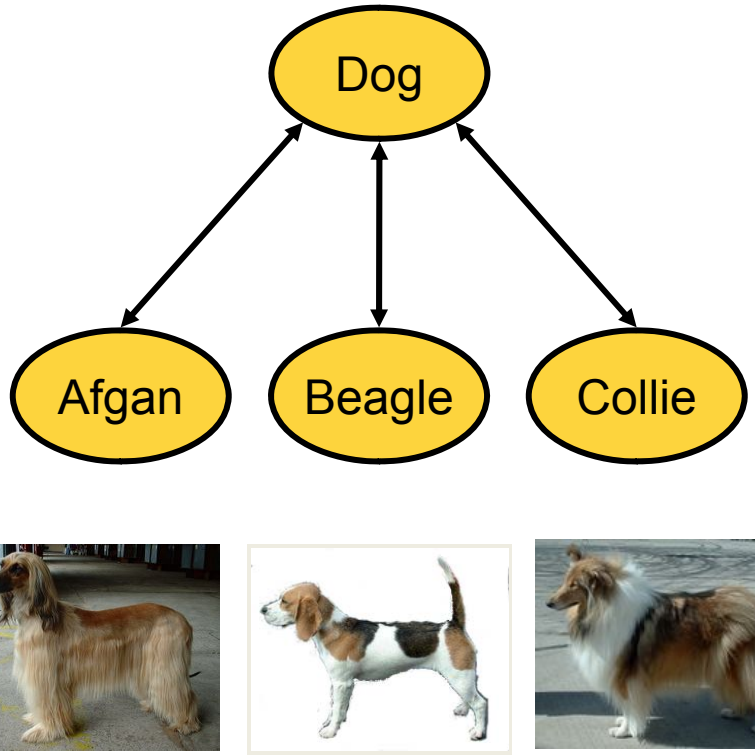
Class-Membership Categories



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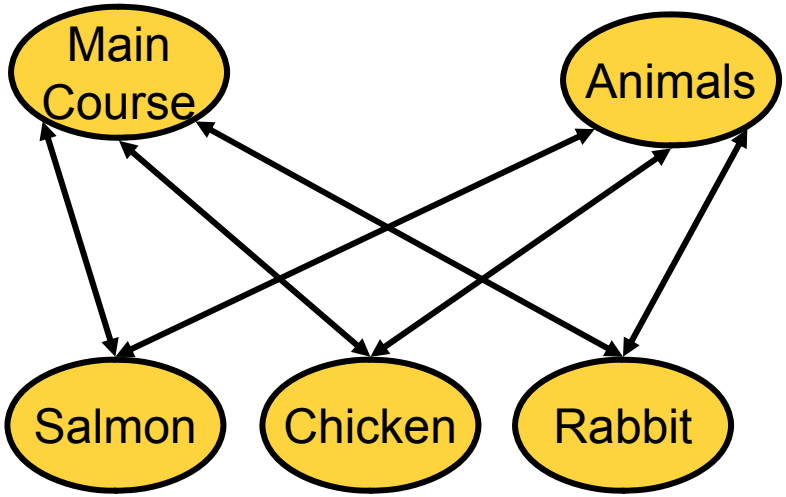
Shortcomings of a-priori Hierarchical Structures

- Strict hierarchy (tree-based representation) is violated
- Infinite number of levels – What level is appropriate?
  - Basic categories????
  - Well-defined hierarchy level???

Depends on Context and Task



Can we develop a structure that captures the advantages hierarchy and overcomes
Incorporate context

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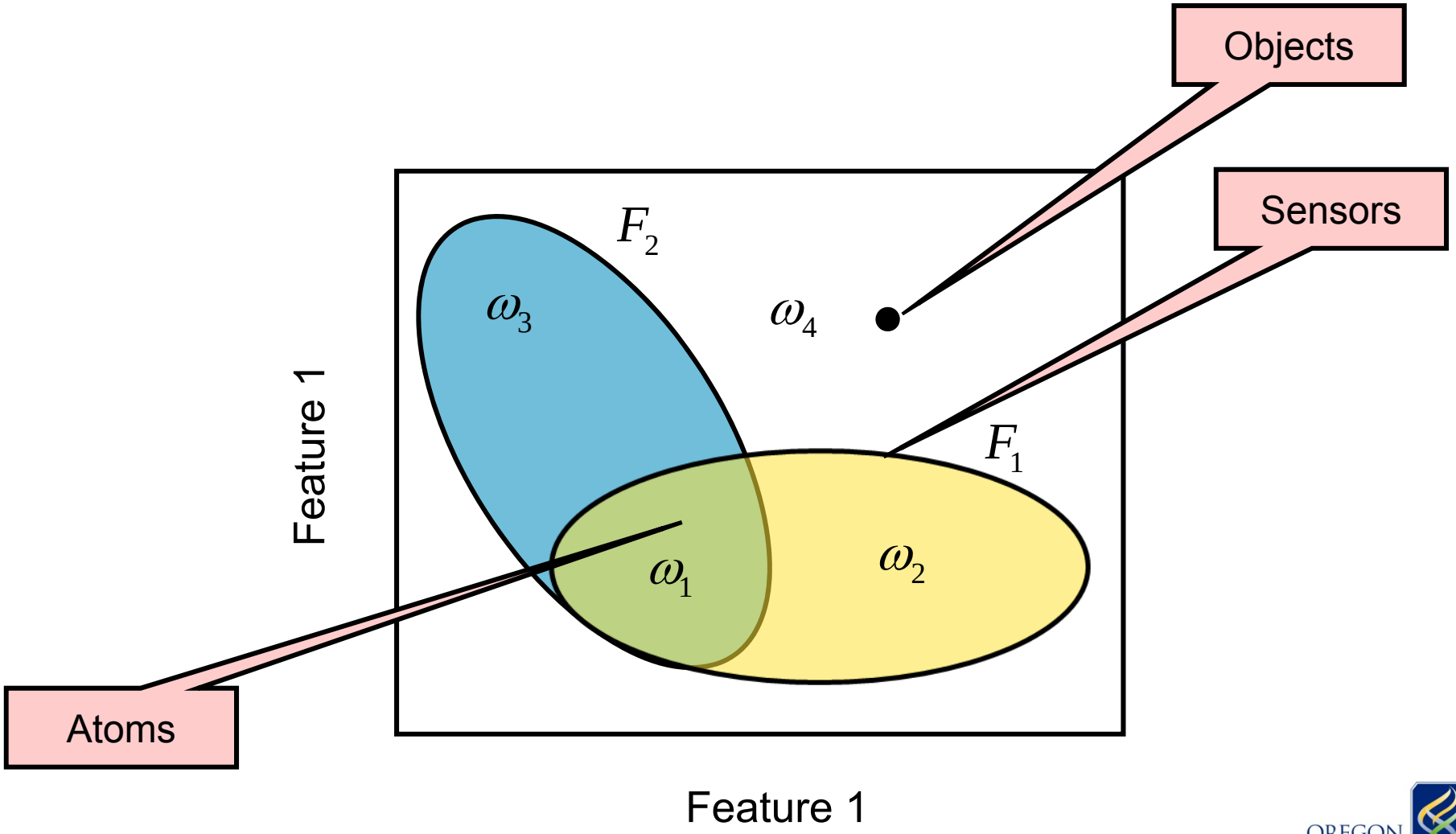
An Alternative: Object – Feature Space



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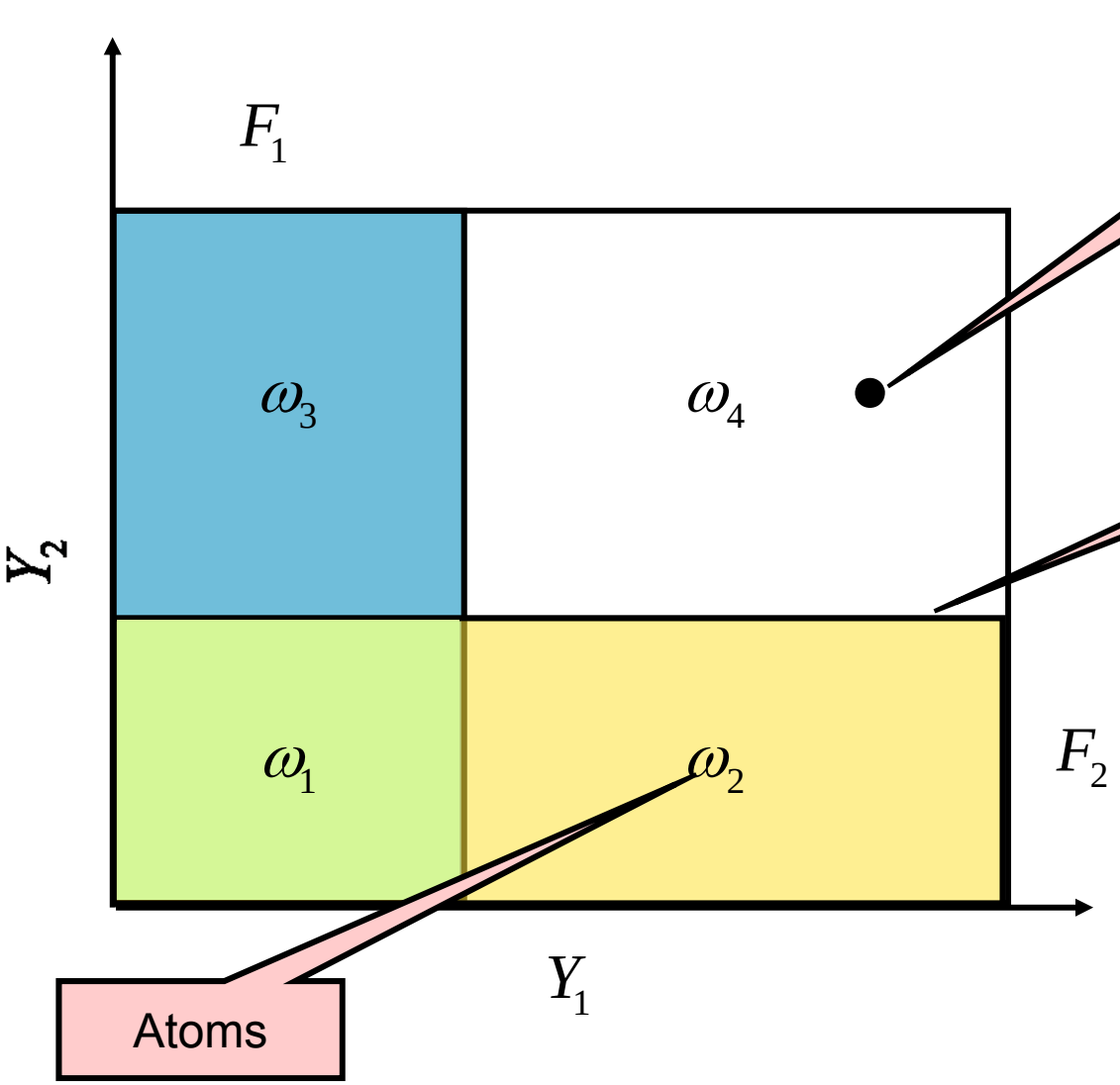
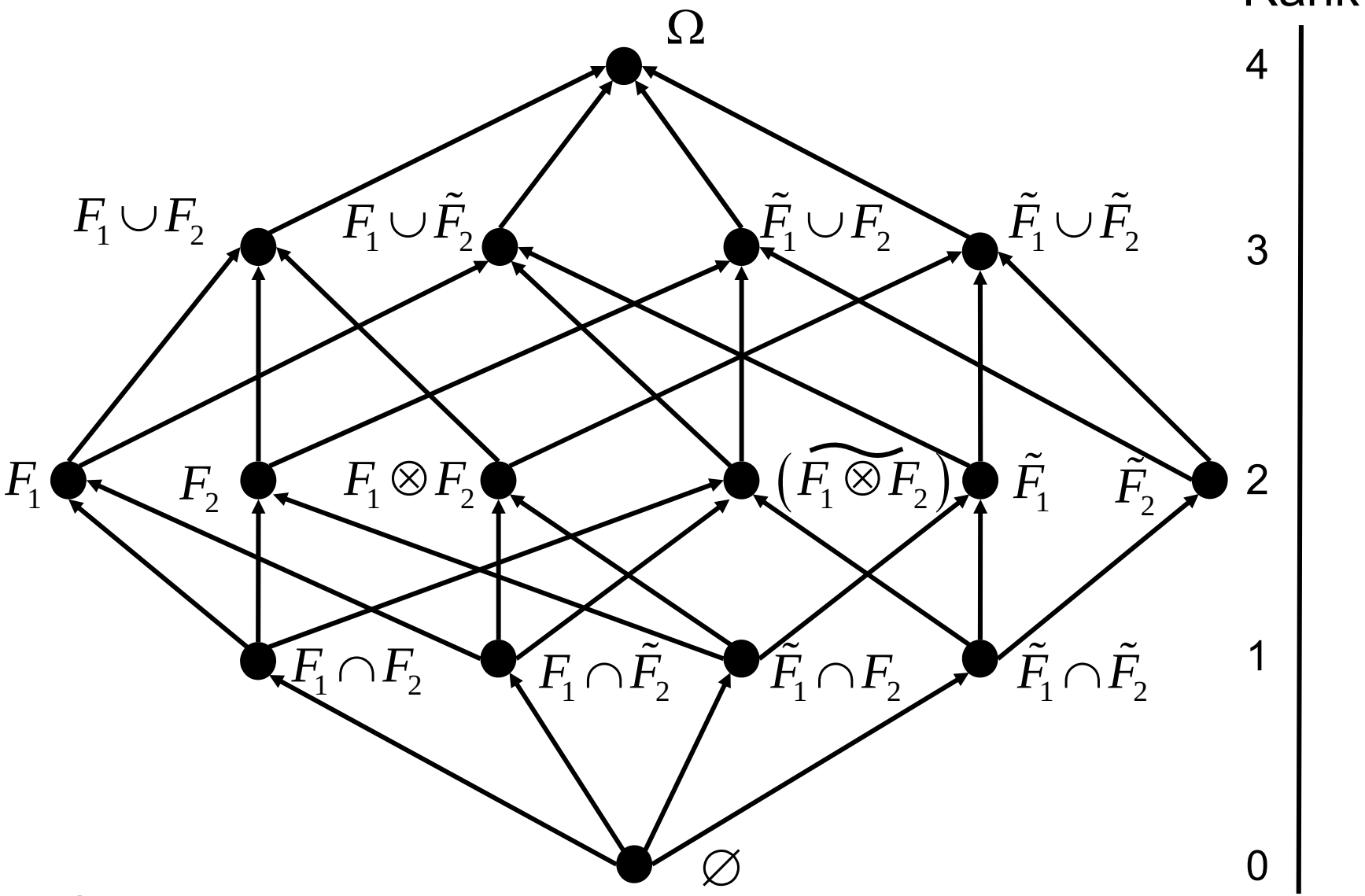
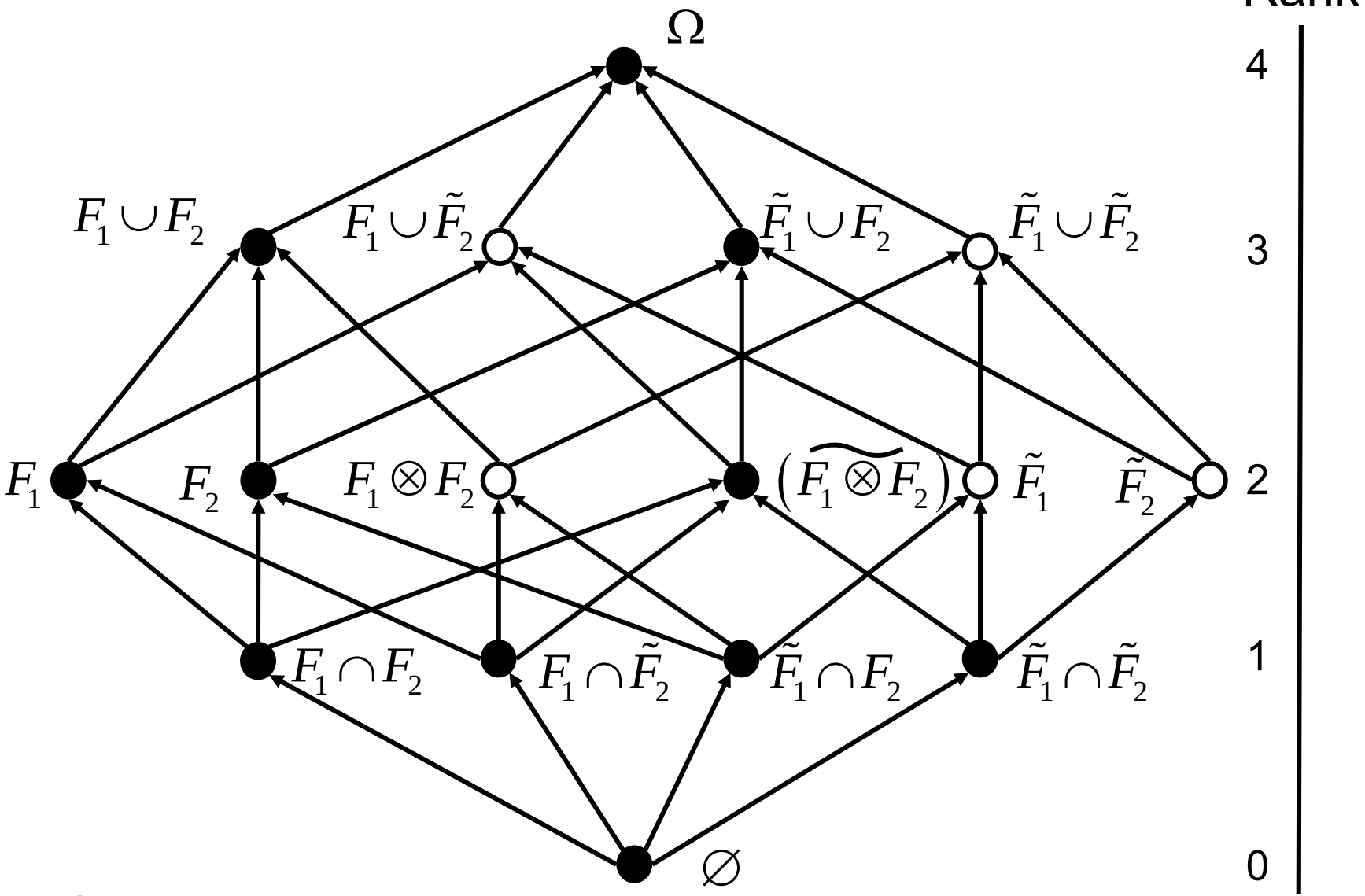
Object – Feature Space – Sensors as Predicates



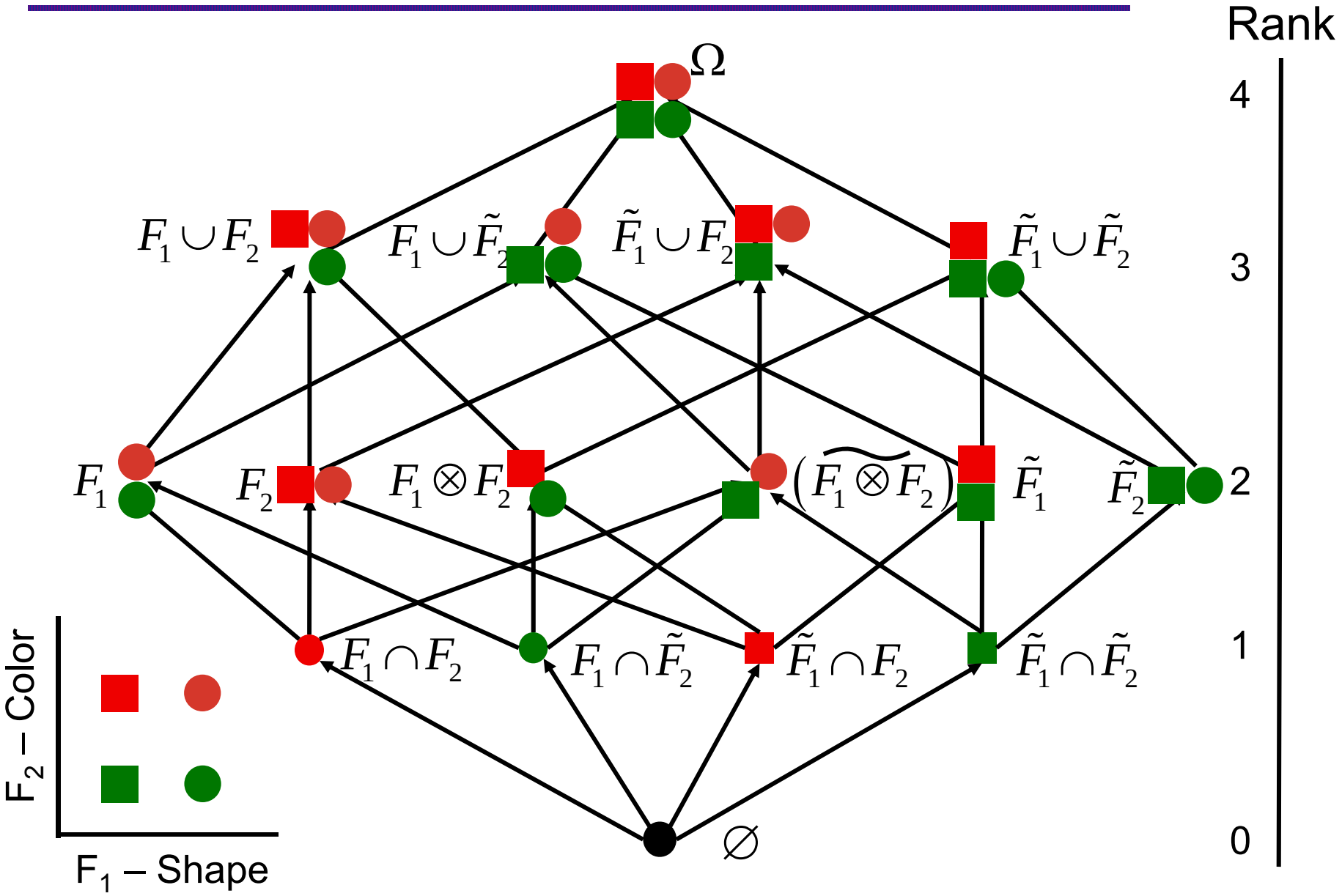
Complete Partial Order



Class-Specific Partial Order



Example: Partial Order in Visual Search



Object – Feature Space – Sensors as Predicates

Objects $y \in \mathbf{Y}$

Predicates $F_i : \mathbf{Y} \rightarrow \{\mathbf{0},\mathbf{1}\}$

Partial Order $a \prec b \Leftrightarrow F_a \subseteq F_b$

Stronger
More Specific
Model

Weaker
More General
Model

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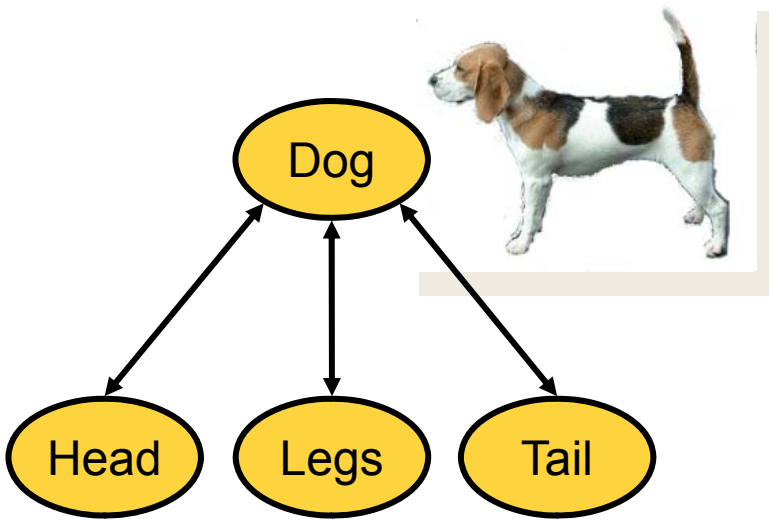
Example: Part – Membership Category



$$F_{dog} = F_{legs} \cap F_{head} \cap F_{tail}$$

$$F_{dog} \subset F_{legs} \Rightarrow dog \prec legs$$

Dog is more specific (stronger) model then parts

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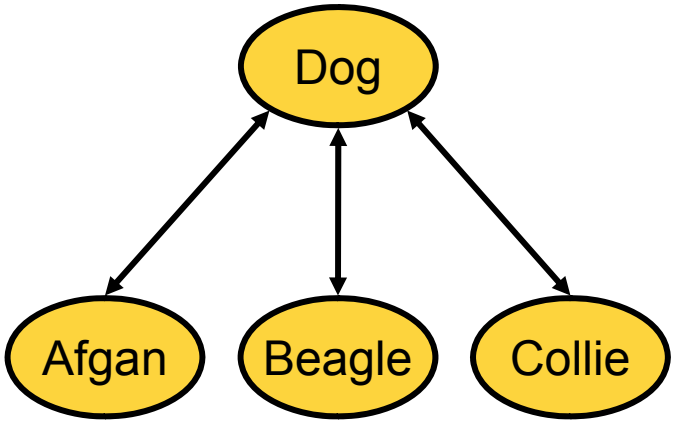
Example: Class – Membership



$$F_{dog} = F_{Afgan} \cup F_{Beagel} \cup F_{Collie}$$

$$F_{dog} \supset F_{legs} \Rightarrow dog \succ Afgan$$







Dog is more general (weaker) model then the breeds

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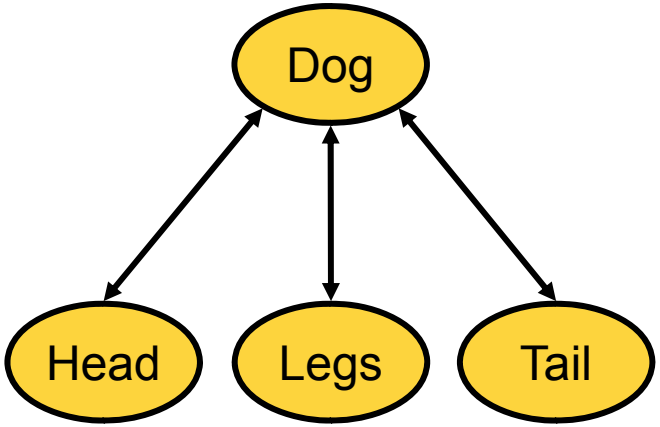
Incongruent Part – Whole Category



Incongruent

$$F_{dog} = F_{legs} \cap F_{head} \cap F_{tail}$$

$$F_{dog} \subset F_{legs} \Rightarrow dog \prec legs$$

$$P^{s}_{dog} = \prod_{b \in A^{l}} P_b = P_{legs} P_{head} P_{tail}$$

$$\mathrm{P}^{s}_{dog}(\mathbf{X}) \gg \mathrm{P}_{dog}(\mathbf{X})$$

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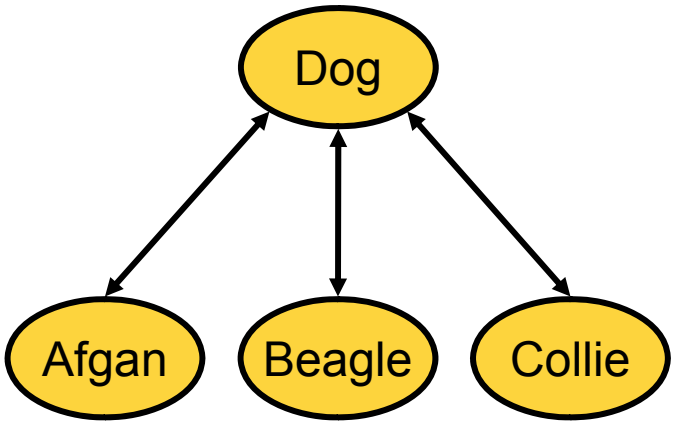
Example: Class – Membership





Incongruent

$$F_{dog} = F_{Afgan} \cup F_{Beagel} \cup F_{Collie}$$

$$F_{dog} \supset F_{legs} \Rightarrow dog \succ Afgan$$

$$F_{dog} = F_{Afgan} \cup F_{Beagel} \cup F_{Collie}$$

$$\mathrm{P}_{dog}^{g} = \sum_{b \in A^{s}} P_{b} = P_{Afgan} + P_{Beagle} + P_{Collie}$$

$$\mathrm{P}_{dog}^{g}(\mathbf{X}) \ll \mathrm{P}_{dog}(\mathbf{X})$$

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Rare – Incongruent Events

	Specific	General
"Noise" or oddball	Low	Low
Incongruent	Low	High
Incorrect Model	High	Low
Expected	High	High

$$D\left[\mathrm{P}_a^l(\mathbf{X}) \,|\, \mathrm{P}_a(\mathbf{X})\right] = \int \mathrm{P}_a^l(x) \log \frac{\mathrm{P}_a(x)}{\mathrm{P}_a^l(x)} dx$$

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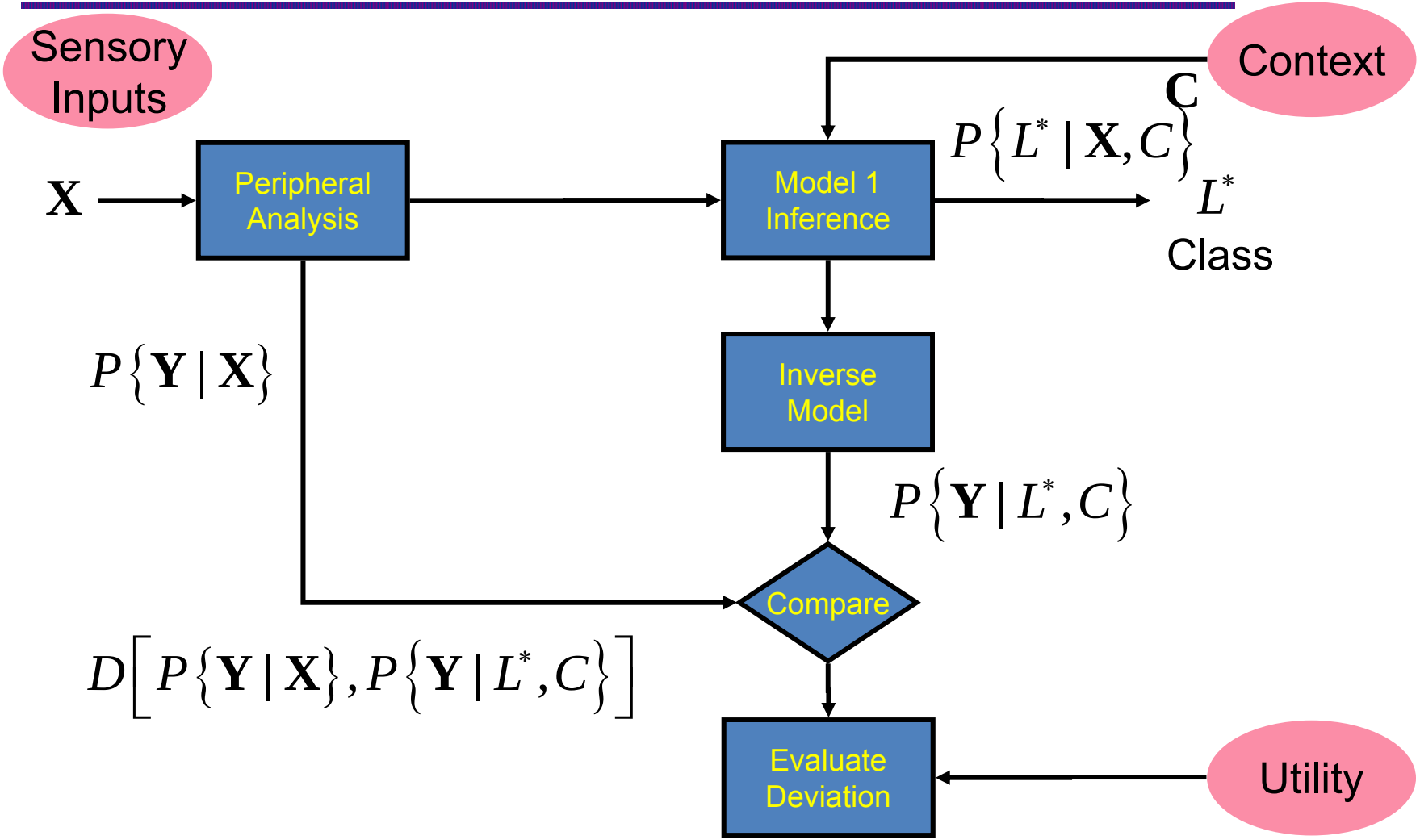
Algorithms for Detection of Rare Events



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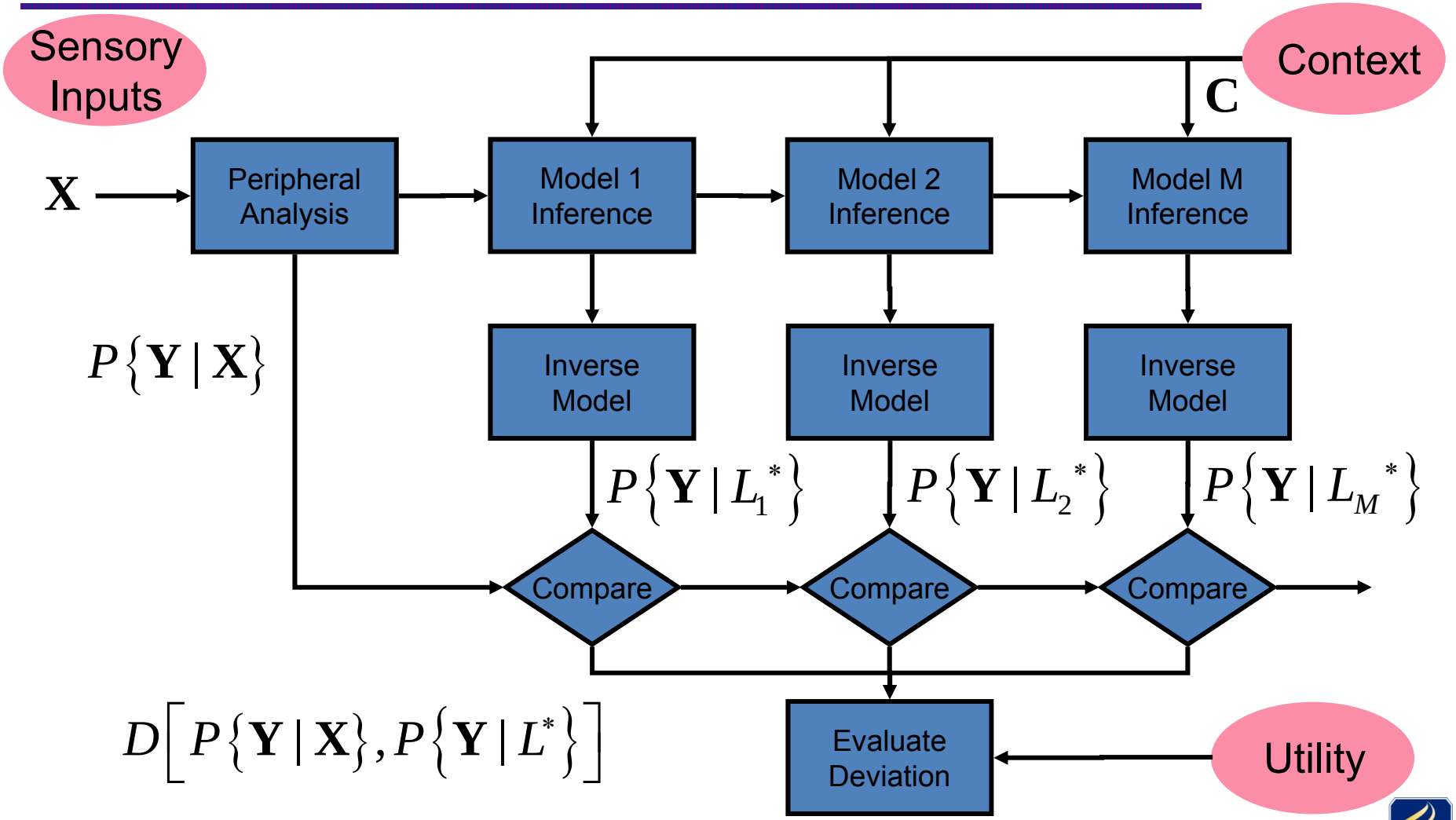
Hierarchical Models of Rare Events



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Context

- Task
- Environmental setting
- Hierarchy of models
- Prior probabilities
- Utilities

Examples of Human Failures to Consider Utilities

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How to Get Utility Estimates?

- Utility estimation from context and background
  - Linguistic analysis
  - Multimodal inputs
  - Contextual cues
  - Task objectives

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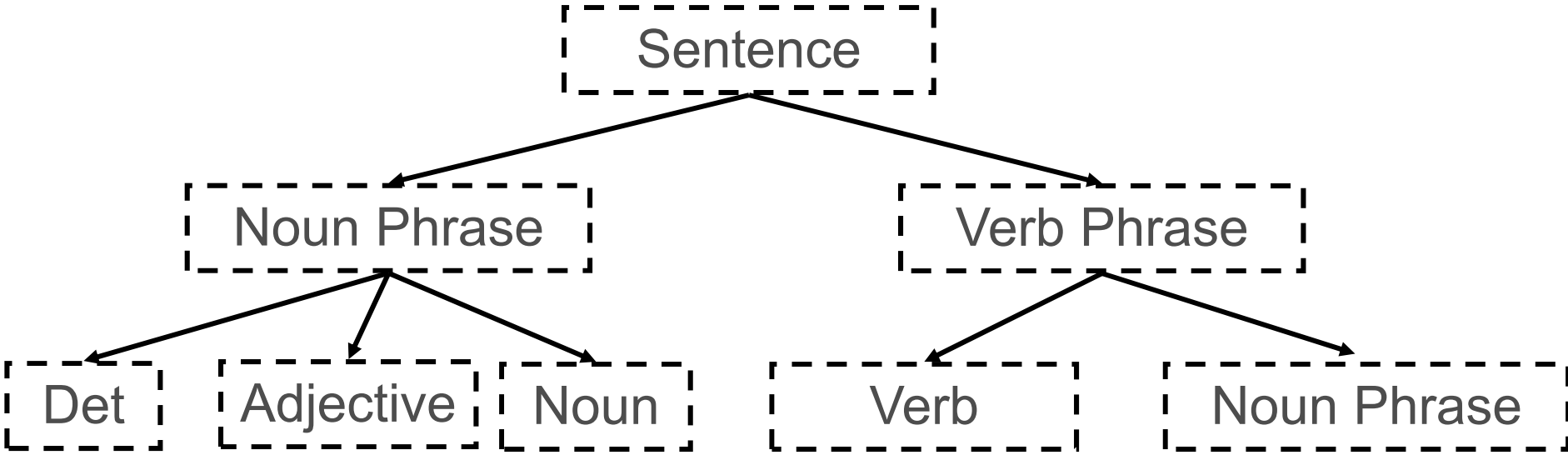
Example of Utility Assessment: Linguistic Analysis



The maly man drank pivo

pi vo

/p/ /i/ /v/ /o/

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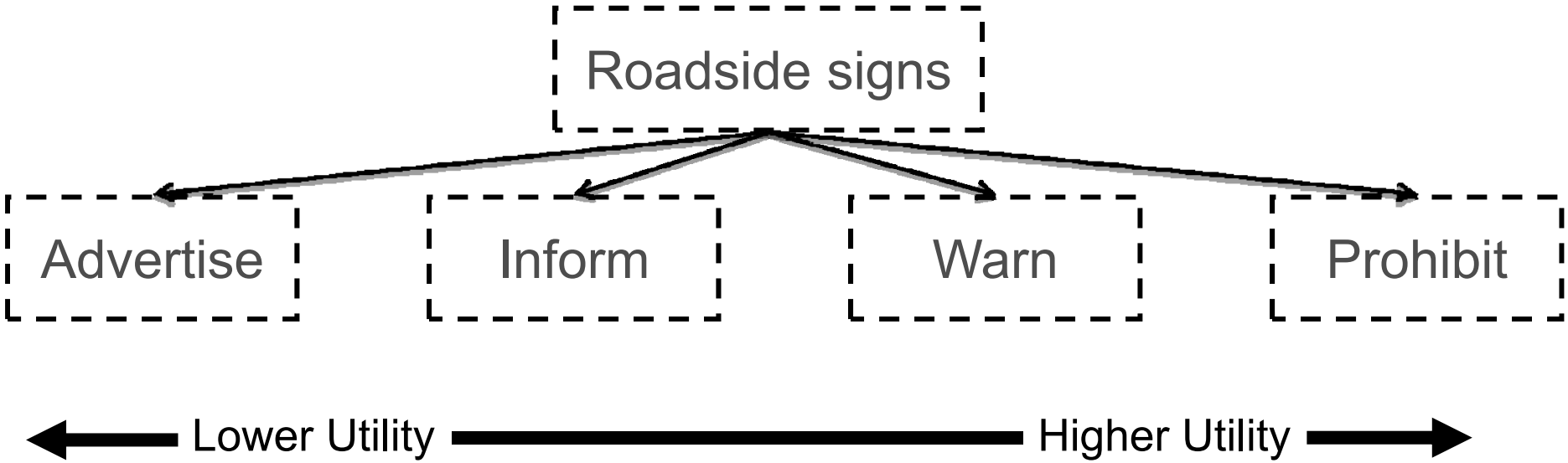
Example of Utility Application: Roadside Text/Graphics



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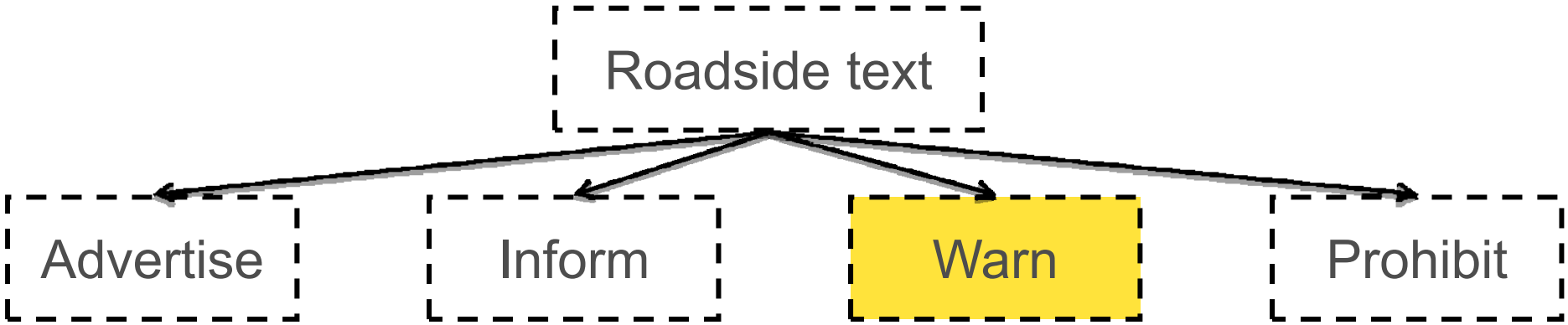



Diamond shape gives the context of the sign
Warning has a high utility

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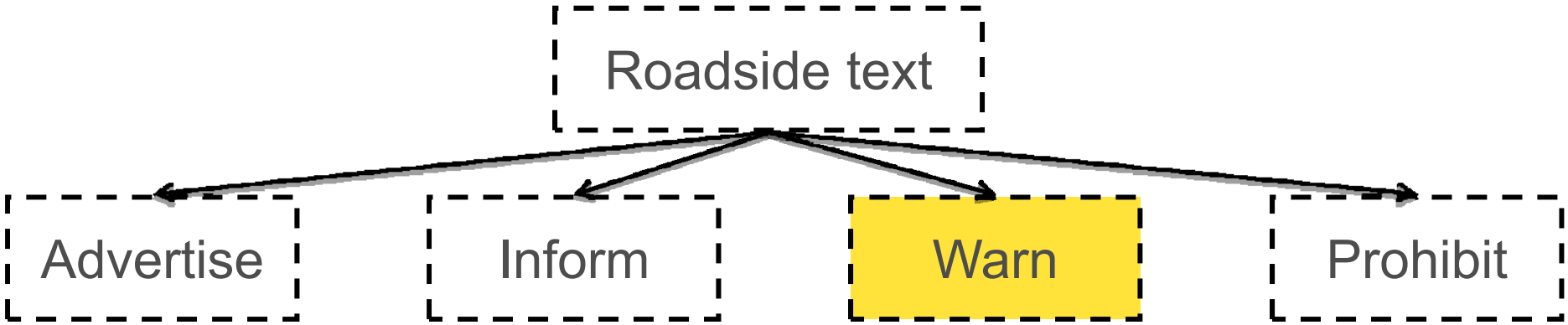
Example of Utility Application: Roadside Text/Graphics





Novel symbol (at some point)
(junction at a bend)

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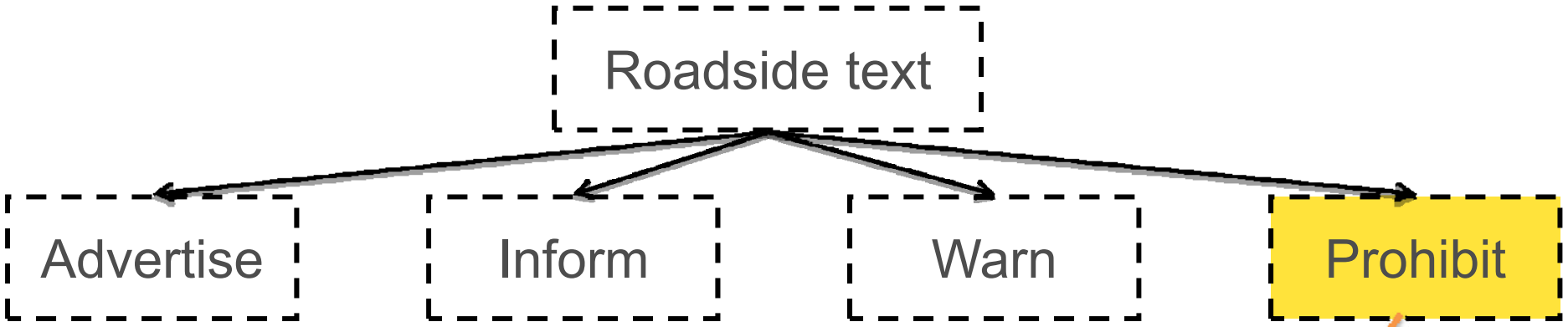
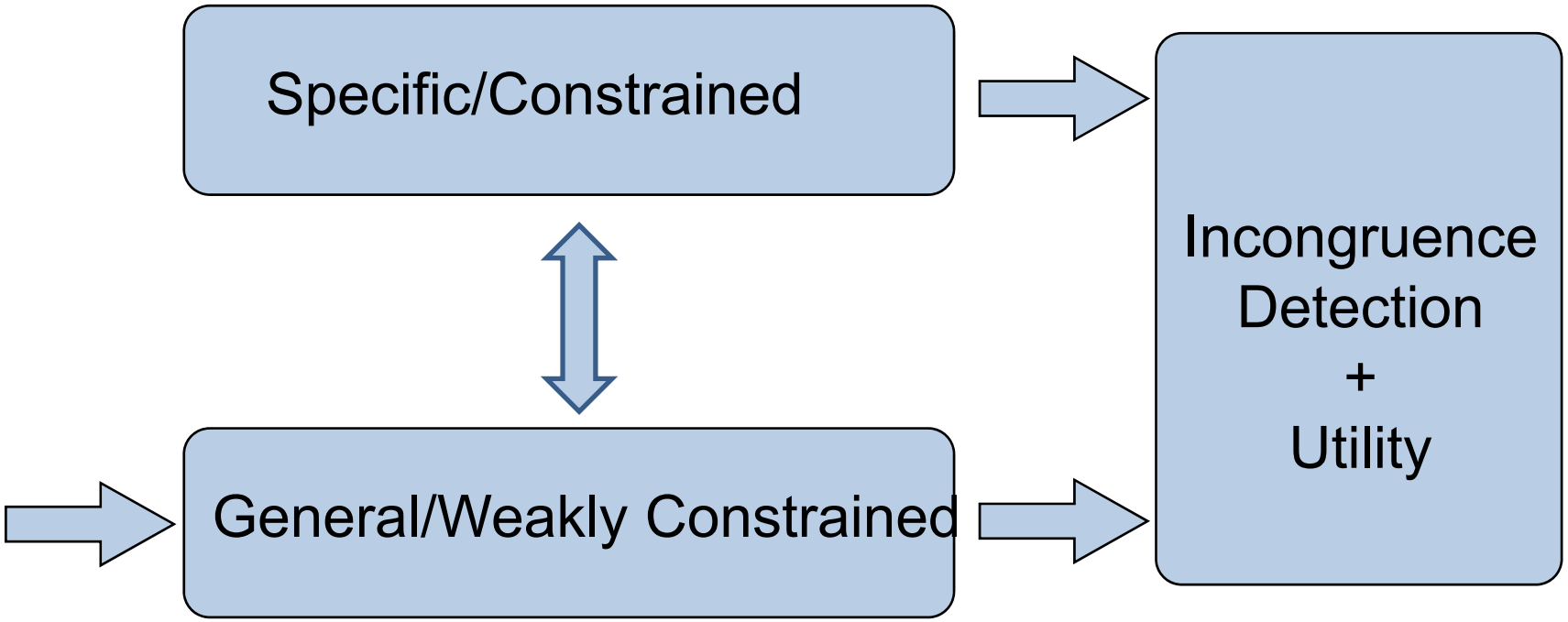
Example of Utility Application: Roadside Text/Graphics





Framework: Detection of Conflict in Probabilities

- Generative approach (a speech example)
- Discriminative approach (a vision example)



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Example: Digit Recognition

Context: “Please say your ten digit account number”

- Expected: Sequence of 10 digits:
- Possible “unexpected” inputs:
  - “O”
  - “Not”
  - “Three hundred twenty”
- Context: “Please say your address”
- Expected: “One six zero zero pennsylvania avenue”
- Possible “unexpected” inputs:
  - “Sixteen hundred pennsylvania avenue”
  - “Pennsylvania avenue sixteen hundred ”

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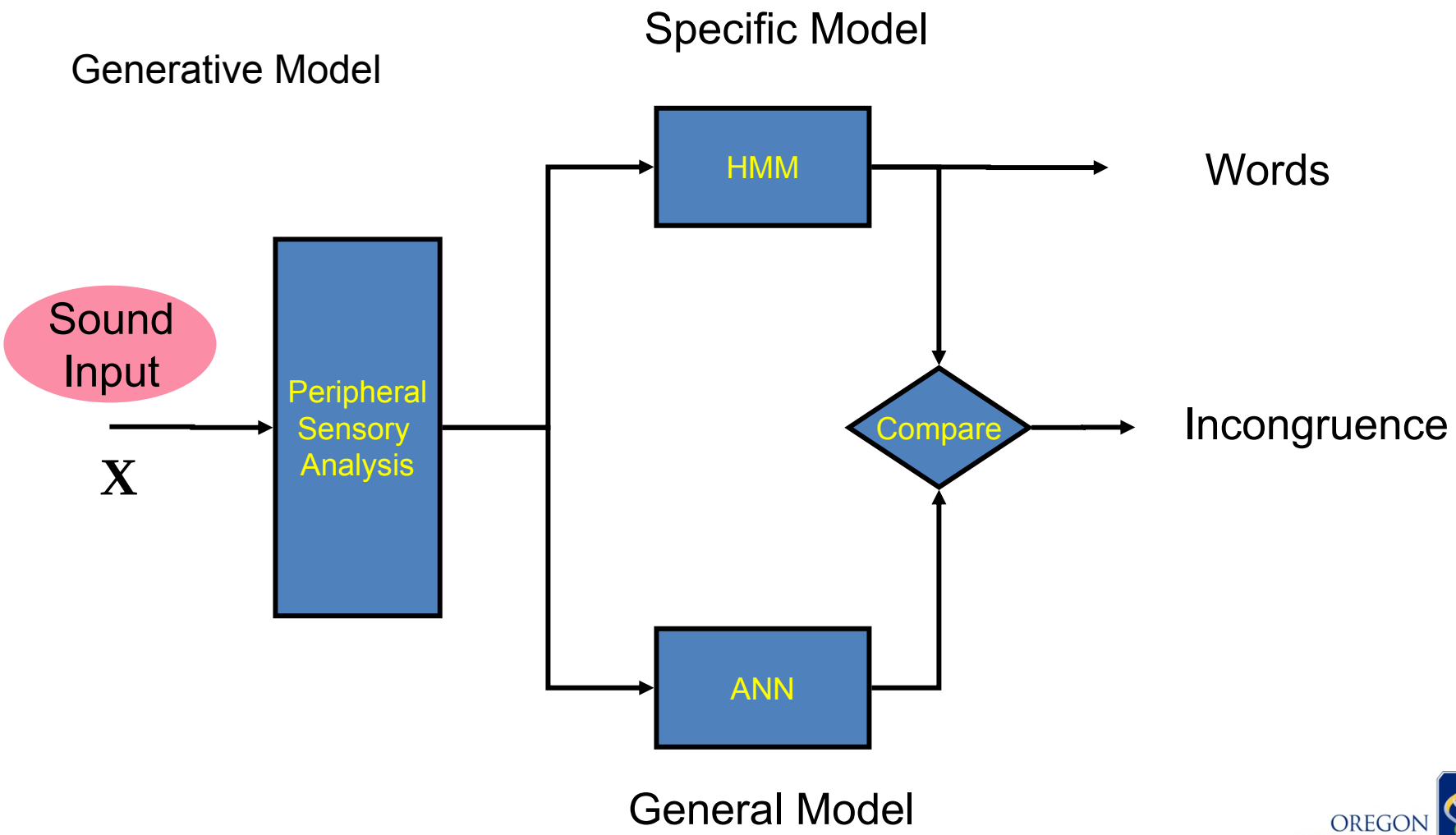
Example: Detection of out-of-vocabulary (OOV) Words



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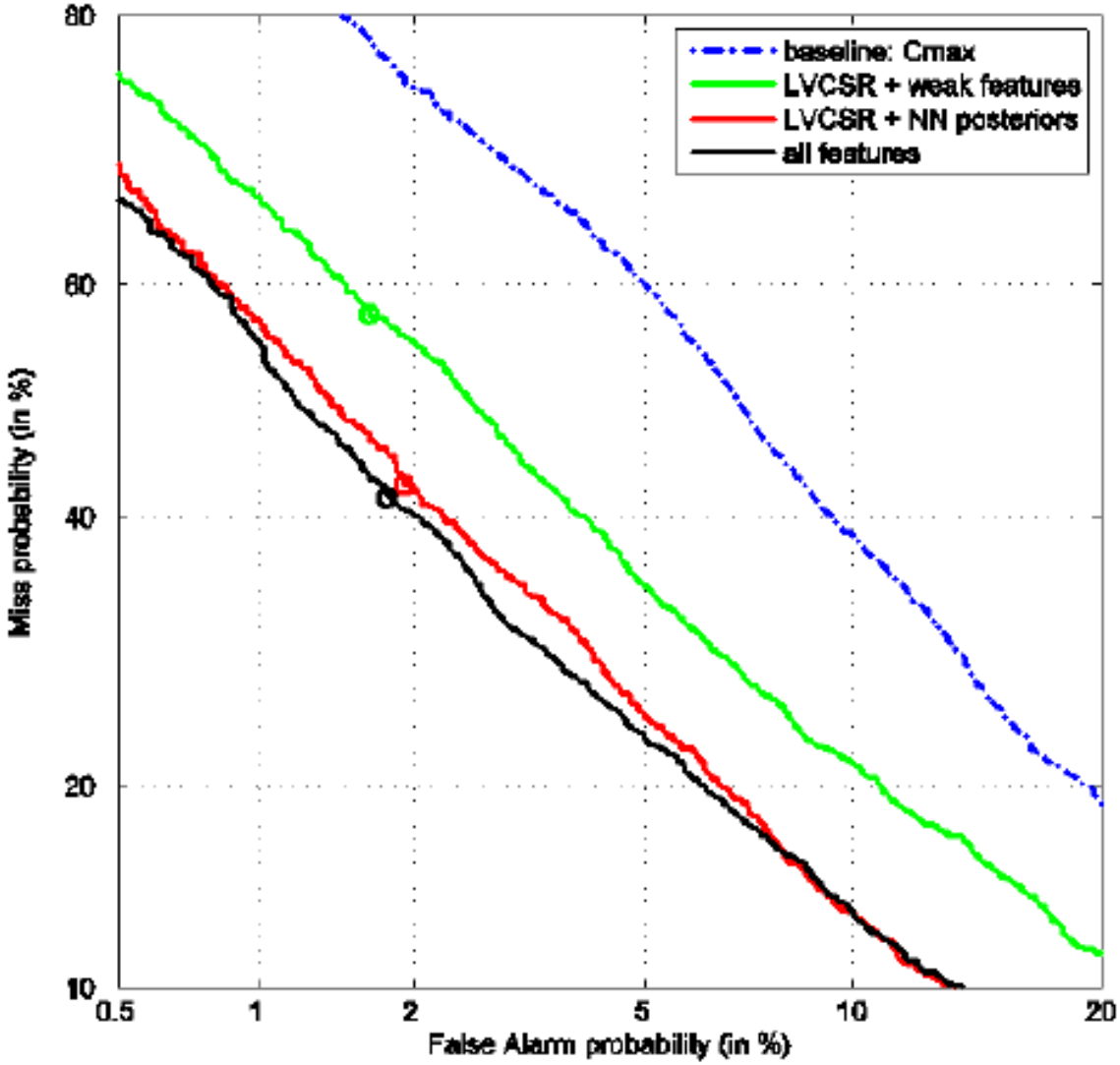
Example: Out-of-Vocabulary Word Detection

- Train a spoken digit recognizer on all but one digits
- Test with all digits

Detection Results (without Utility)



Audio-Visual Detection of New Individual

Known Training Identities



Known Testing Identities

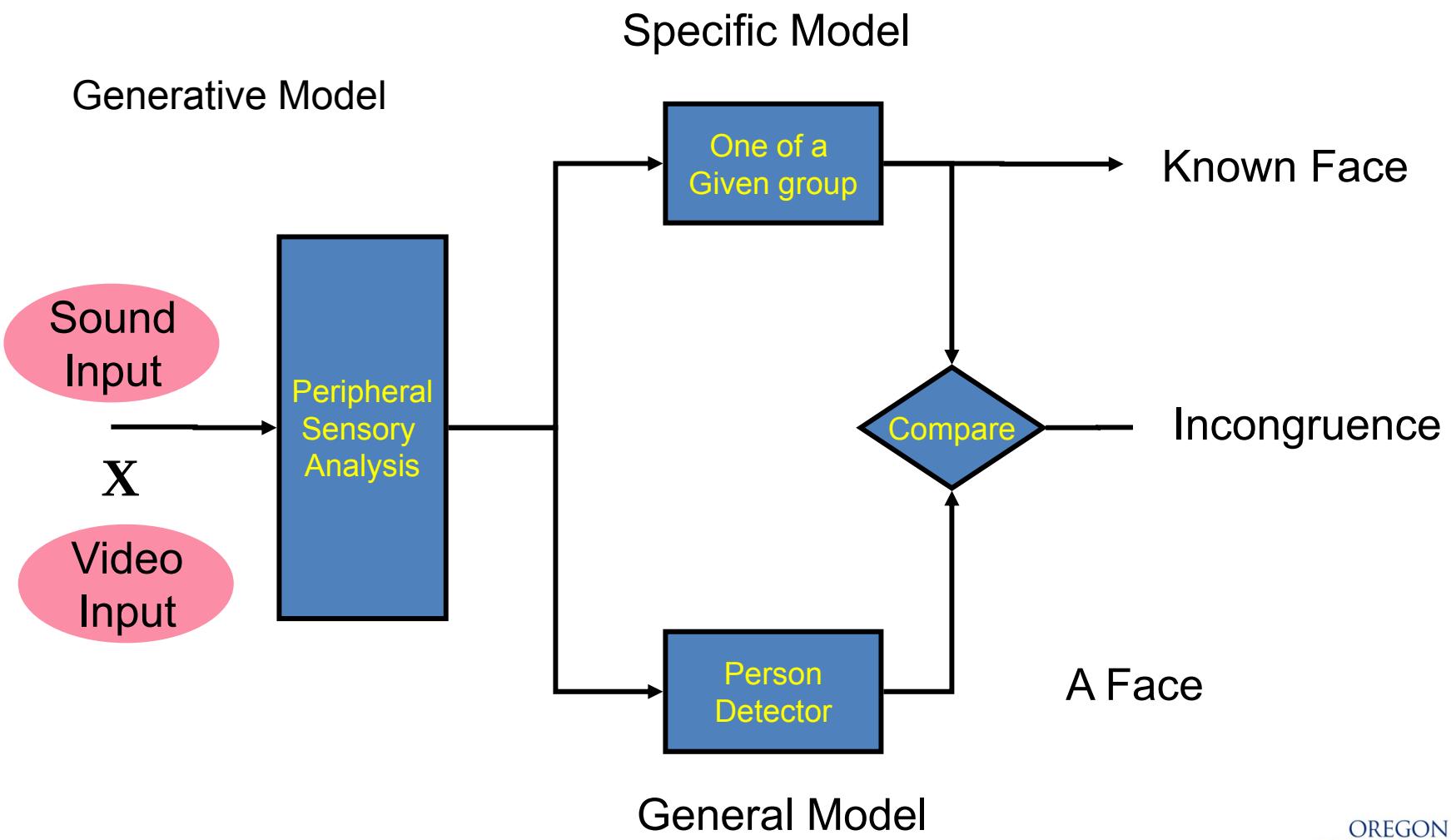


Unknown Identities





Example: Detection of out-of-vocabulary (OOV) Words



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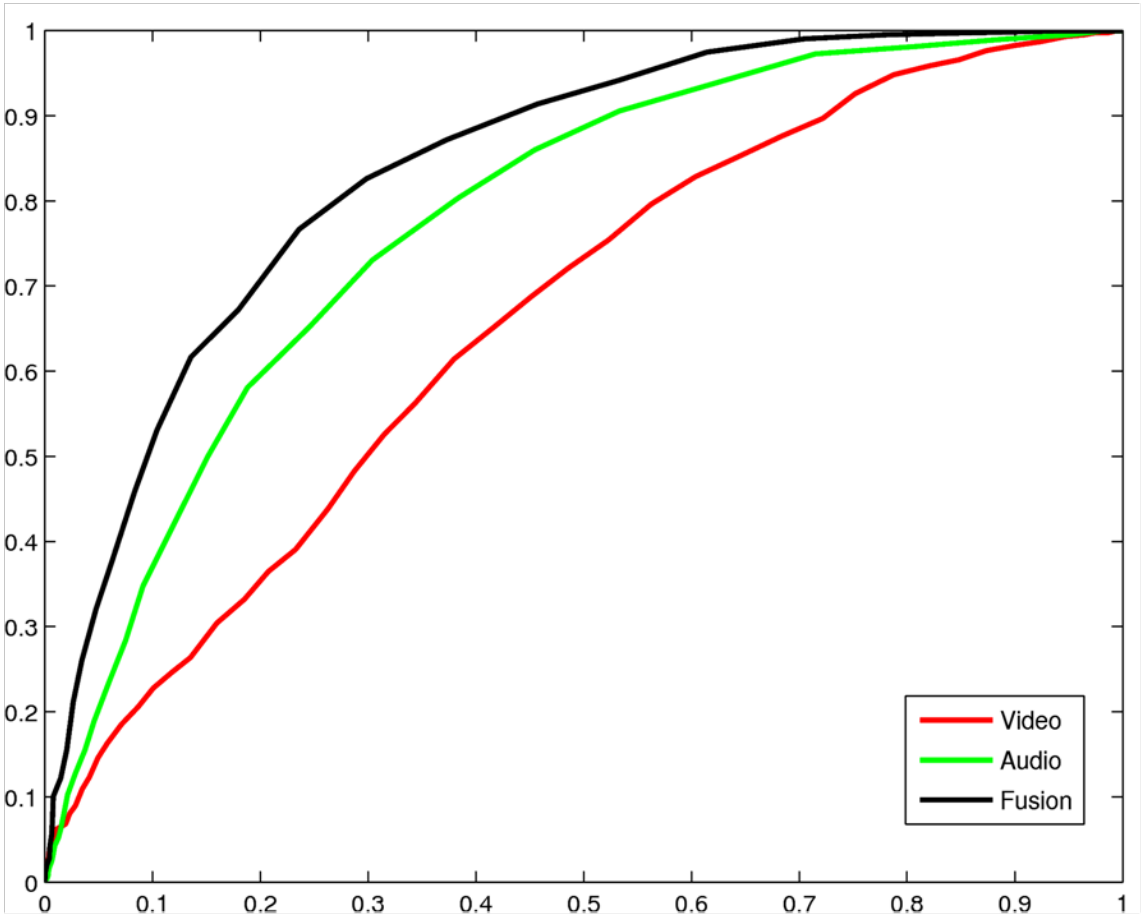
Results



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Audio-Visual Authentication

- Classify individuals using A/V inputs
- Categories were
  - Face
  - PLP Speech representation



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Rare – Incongruent Events

	Specific Afgan	General Dog
"Noise" or oddball	Reject	Reject
Incongruent	Reject	Accept
Incorrect Model	Accept	Reject
Not rare or incongruent	Accept	Accept

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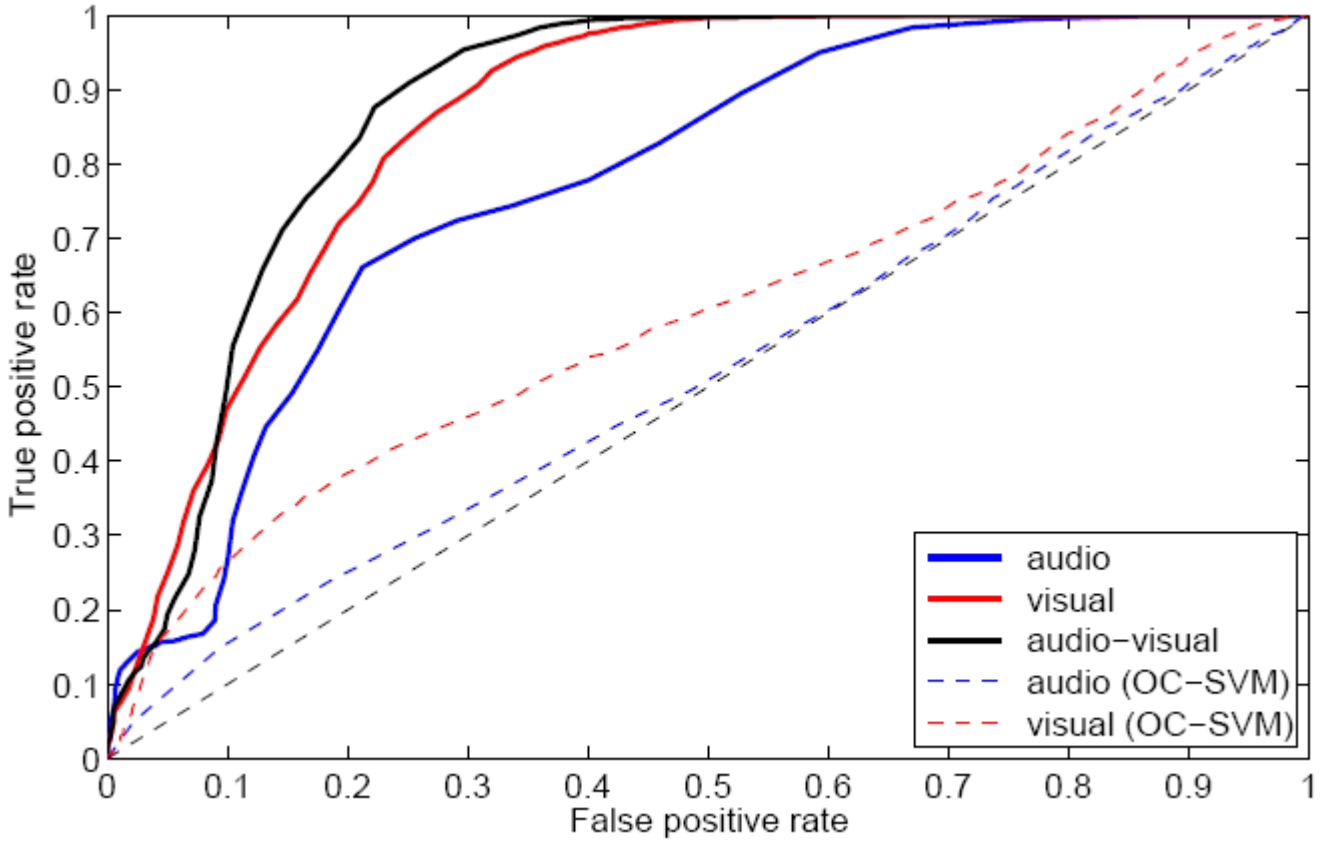
ROC for Imposter Classification



Work in Progress

- Using learning by generation (Hinton)
- Generative model of stimulus features
- Leave a digit out

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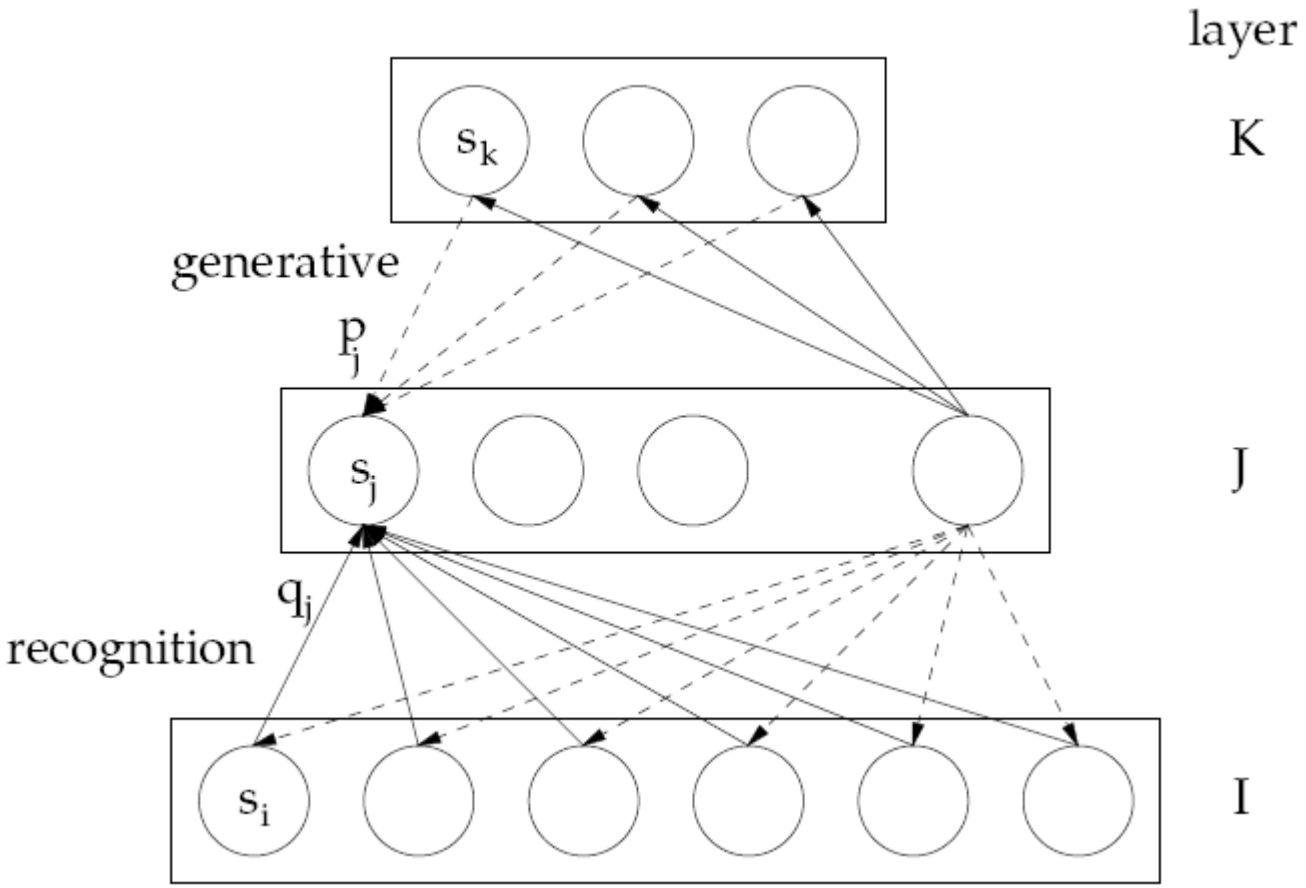
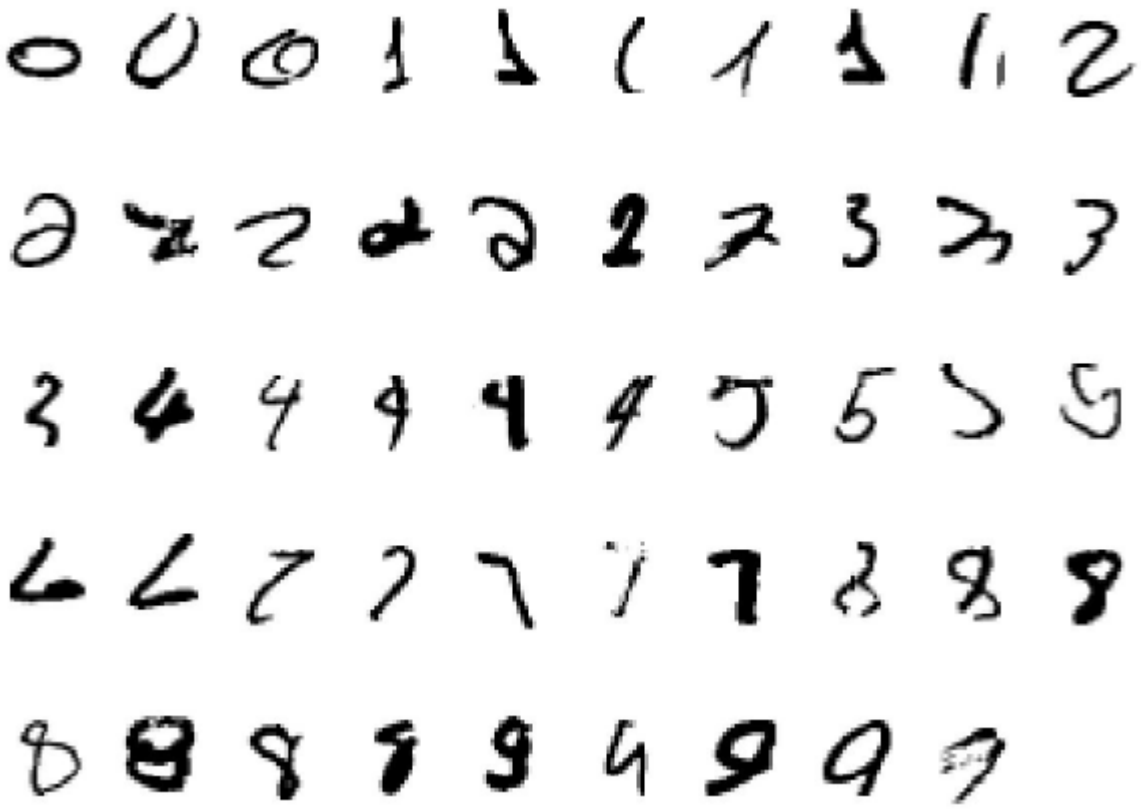
Learning by Generation (Hinton)



Recognition of Written Digits



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Multimodal Fusion

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A Number of Mathematical Techniques

- Bayesian
- Mixture of experts
- Bagging, boosting,…
- Theory of evidence (Dempster Schafer)
- Fuzzy set theory

Bayesian Fusion

- Given input X_1, X_2, maximize probability of class C

$$P\{C \mid X_1, X_2\} = P\{X_1, X_2 \mid C\} \frac{P\{C\}}{P\{X_1, X_2\}}$$

- Independence

$$P\{X_1, X_2 \mid C\} = P\{X_1 \mid C\} P\{X_2 \mid C\}$$

- Find class C that maximizes

$$\log\left[\hat{P}\{X_1, X_2 \mid C\}\right] = w_1 f_C(X_1) + w_2 f_C(X_2)$$

- When and how to choose w_i?

Examples of Fusion in Vision

- Color vision
- Binocular vision and depth perception
- Integration of motion information
- Spatial frequency analysis: multi-scale representation and integration of scales:
  edge location/orientation
- Visual search and object detection

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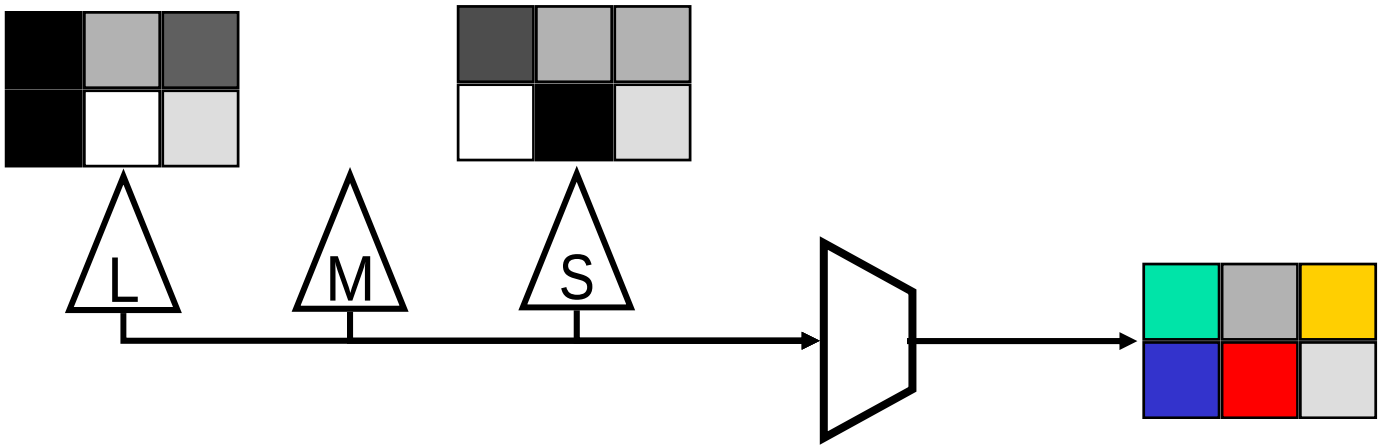
Color Vision

- Individual sensors (cones) do not see color – How are the sensors combined to form color image?



- Color constancy - Integration of color information over space

Robustness: Use context information to perform "white balance" computation

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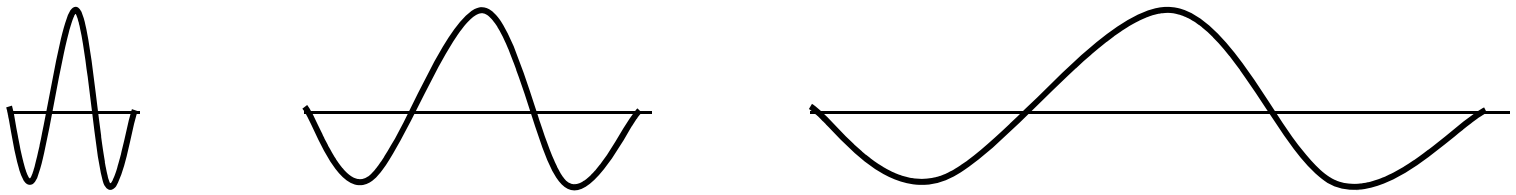
Spatial Frequency (Scale) Analysis in Vision

- Multi-resolution representation
- Fusion of information from different scale streams – combination of edges



Receptive Fields

- Robustness: Approximate scale invariance
  The impact of a given scale depends on cue reliability

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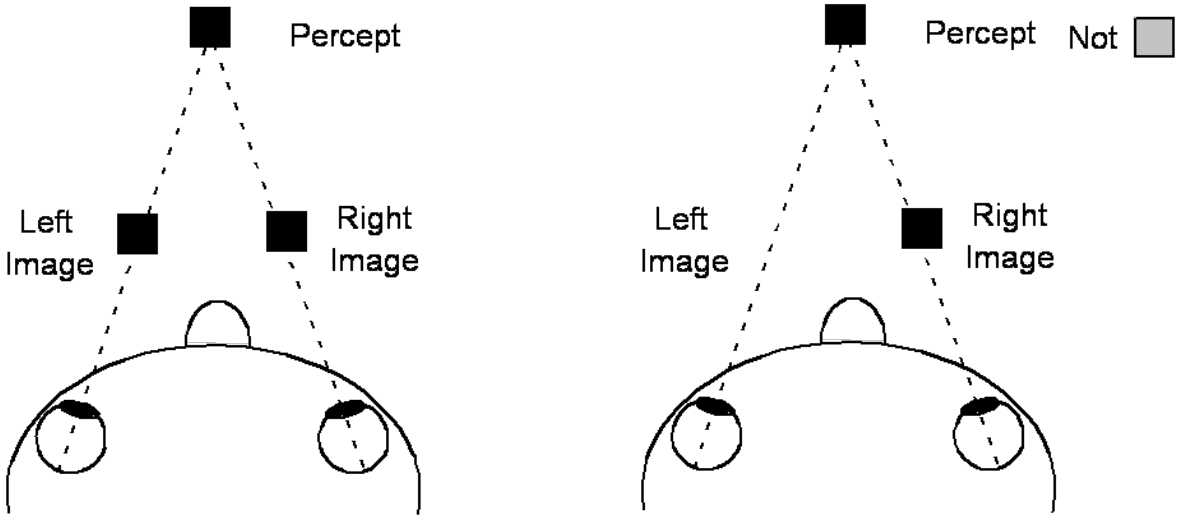
Fusing Multiple Cues in Binocular Perception (Stereo)



Fusion enables stereo and improves S/N ratio

Fusion is not just linear combination or averaging

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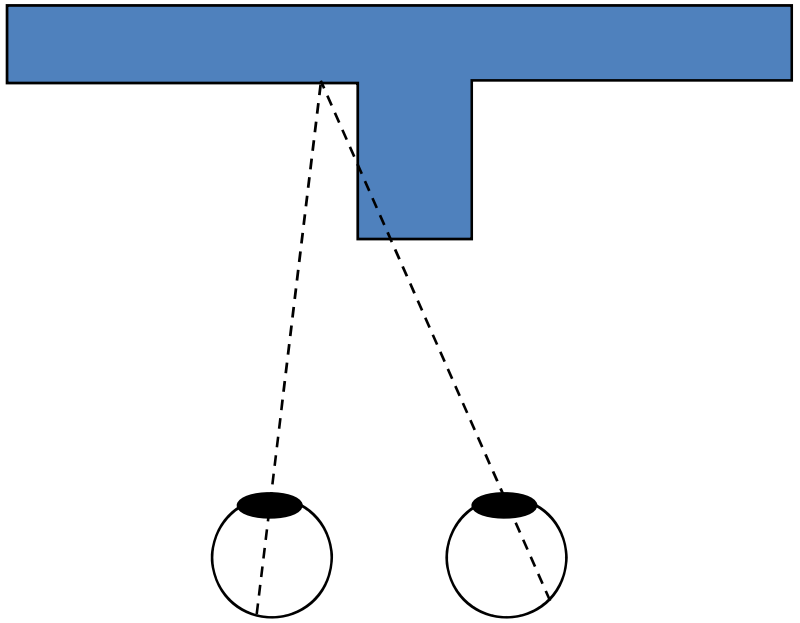
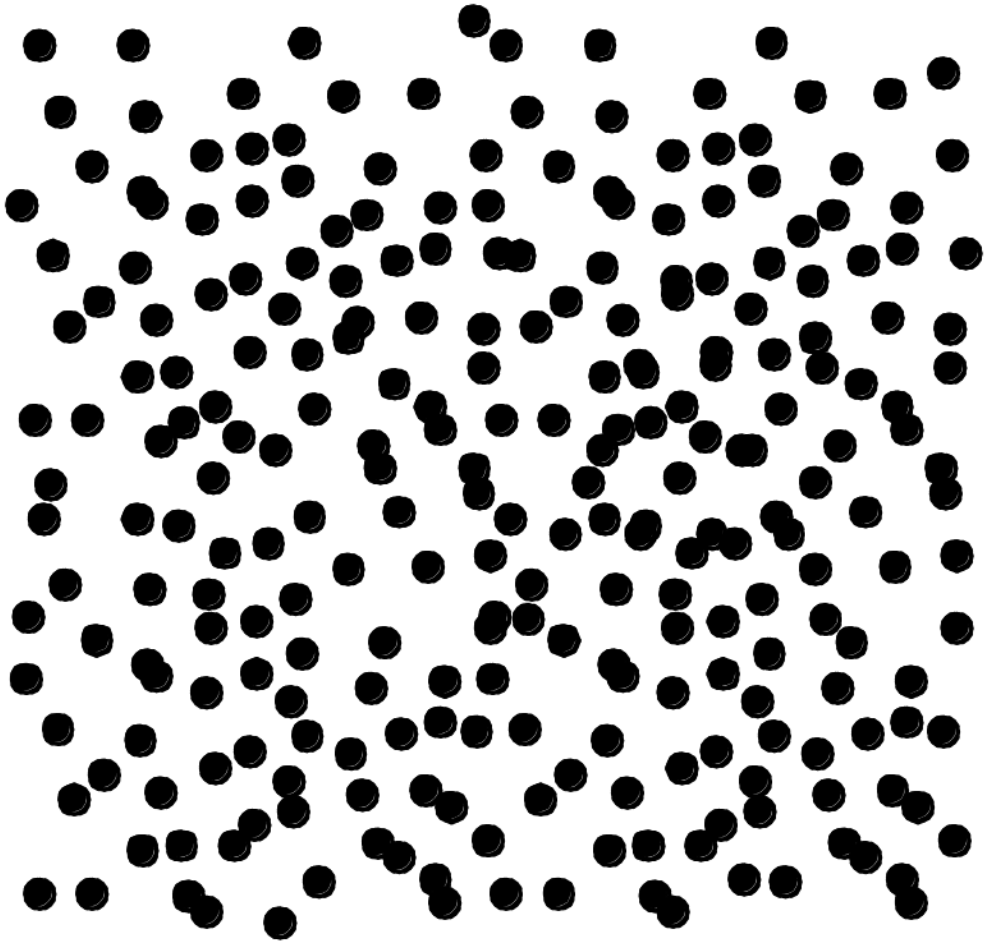
Binocular Rivalry and Da Vinci Stereopsis

- Monocular view due to occlusion
- The “occluded” eye is attenuated



Rapid adaptation – ignore input that is not relevant to a task

Grouping – Motion Integration



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Multiple Cues to Depth Perception

- Perspective
- **Texture**
- Shading
- Stereo by binocular vision
- **Parallax motion** – "Kinetic depth effect"
- Arial perspective (fog, haze)

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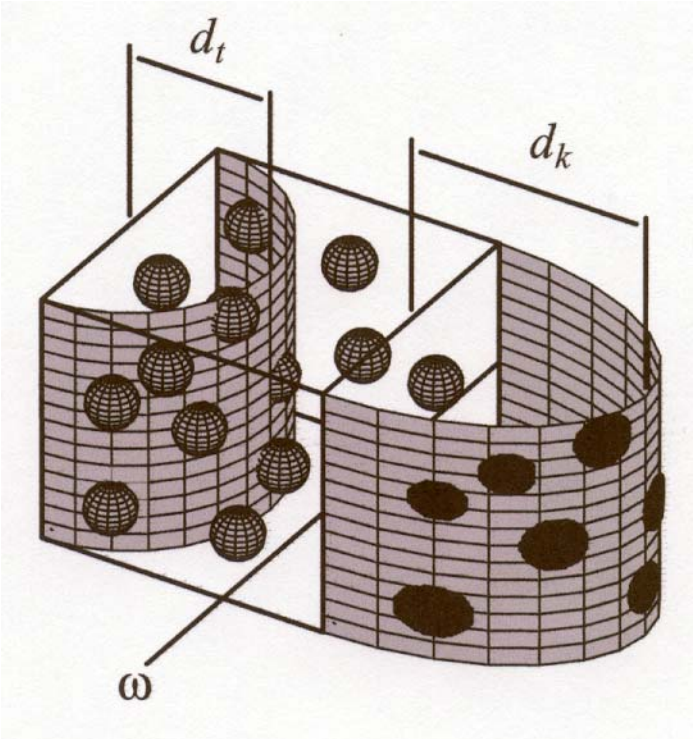
Depth Perception: Fusion of Multiple Cues

- Binocular stereo
- Kinetic depth effect
- Perspective cues

Experiment:



From Landy and Maloney, VR, 1995

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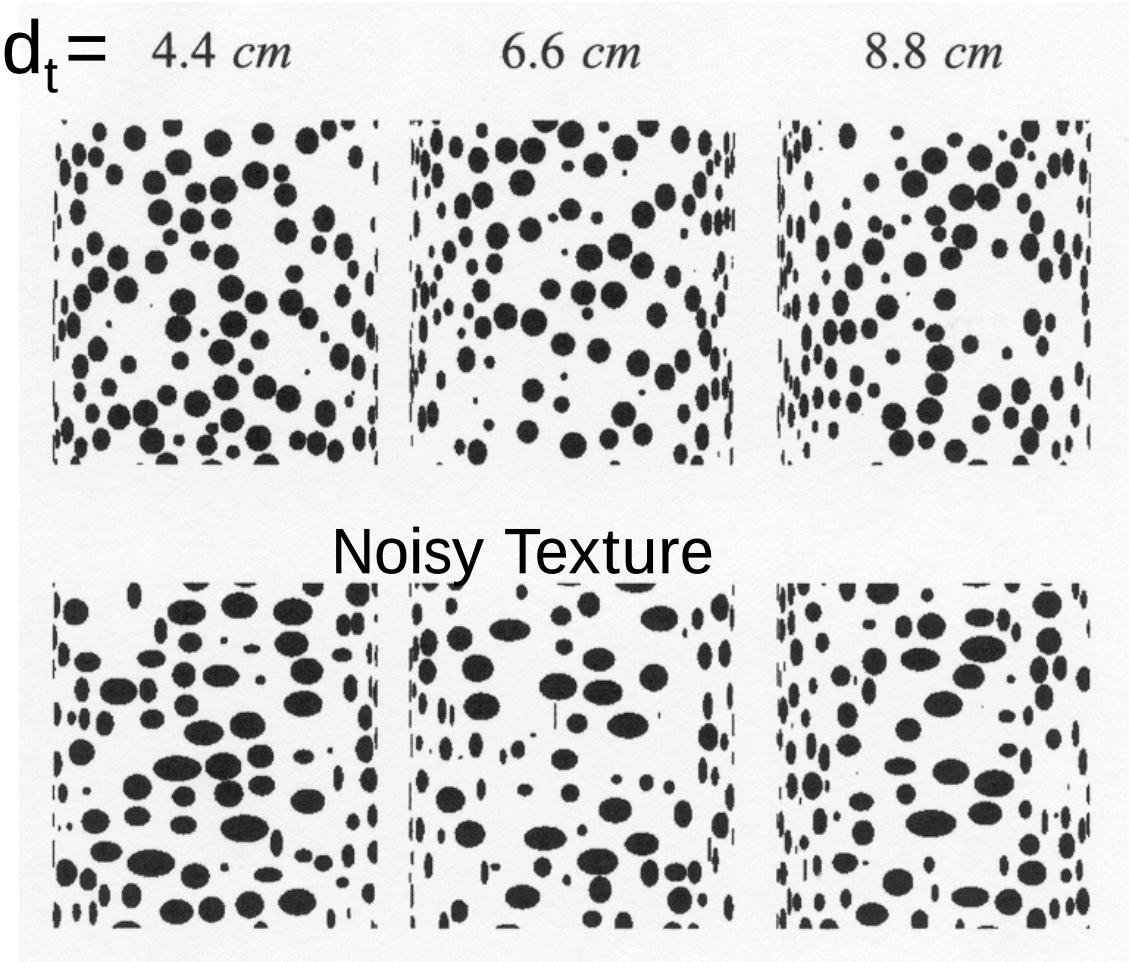
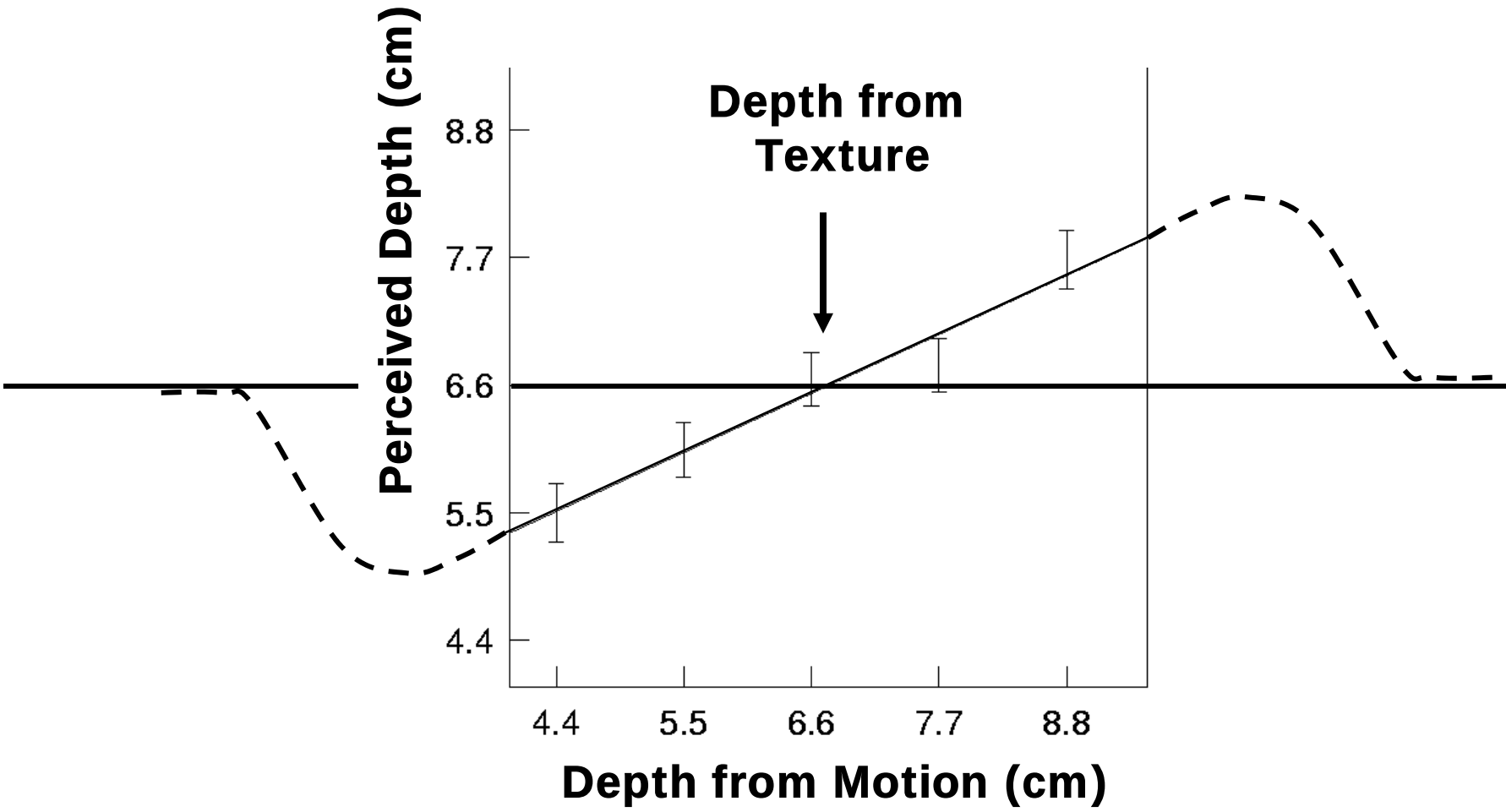
Perspective cues

- Texture vs Motion
- Estimate perceived distance
- Result
  $d = w_t d_t + w_k d_k$



Combining Perspective and Motion Cues for Depth Perception



Reliability of information determines the cue weight and ignore input that is not relevant to a task

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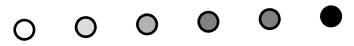
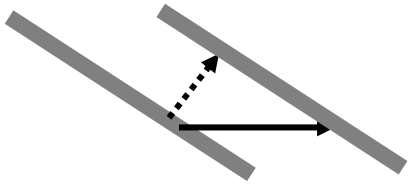
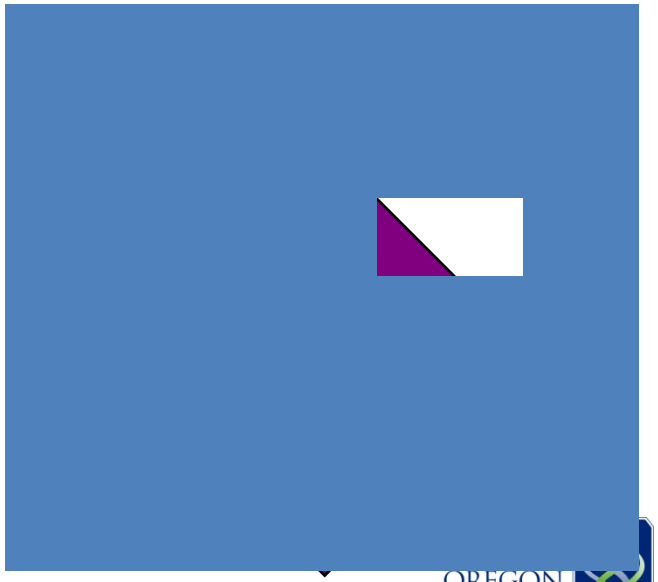
Integration of Motion Information

- Object velocity perception
- "Aperture problem"
- Multiple apertures
- Grouping - Affine representation







Reliability of local measurements determine their impact on the global estimates

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Integration of Motion Information

- Object velocity perception
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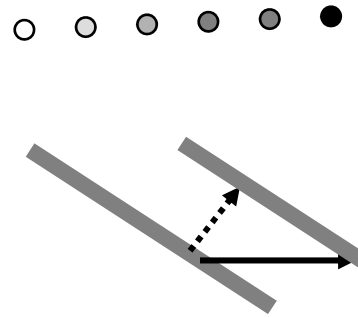
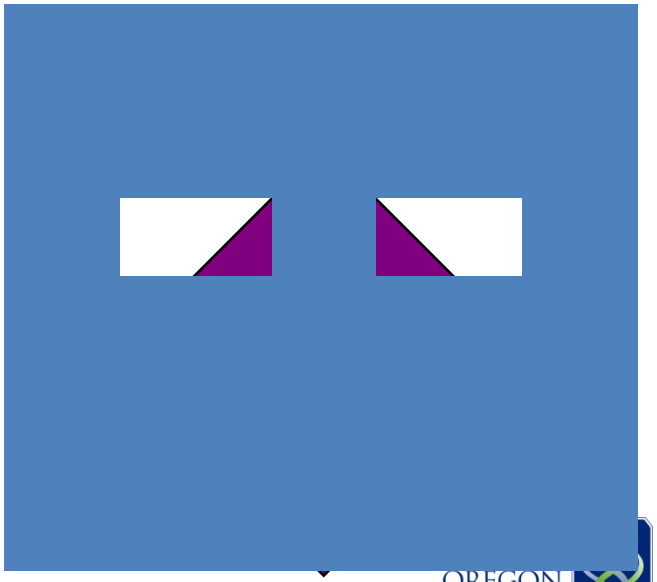




Reliability of local measurements determine their impact on the global estimates

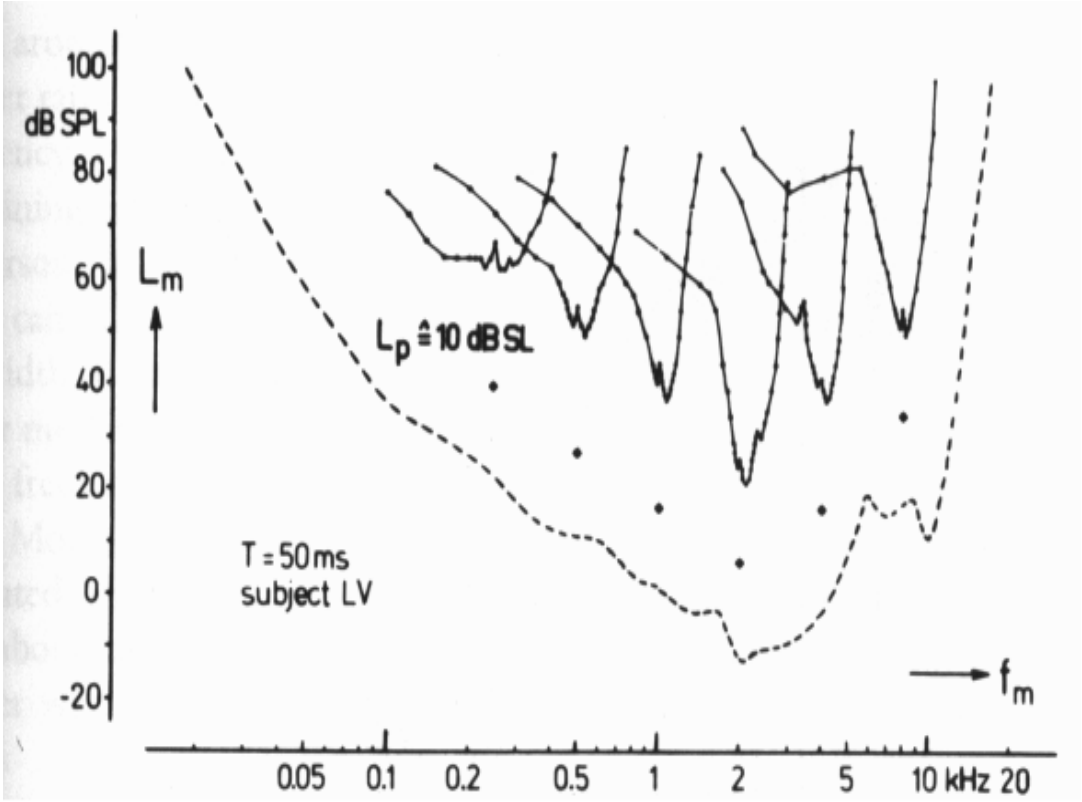
Incorporating Context

- Context ~ Information not directly useful for the classification task, but can modulate performance
- Examples
  - Accent in speech, speaker identity,…
  - Language model X -> {Yes,No}
  - Context in search for objects

Fusion in Audition

- Binaural Hearing
  - Binaural summation – signal detection
  - Binaural release from masking
  - Localization: Source location estimation by cue combination
- Frequency analysis in audition
- Temporal fusion and acoustic stream segregation

Fusing Multiple Streams: Critical Bands Decomposition & Fusion



H. Fletcher's articulation index: Frequency bands appear to provide independent "looks"

$$P\{Error\} = \prod_B P_B\{Error\}$$

Human speech recognition system ignores unreliable bands?

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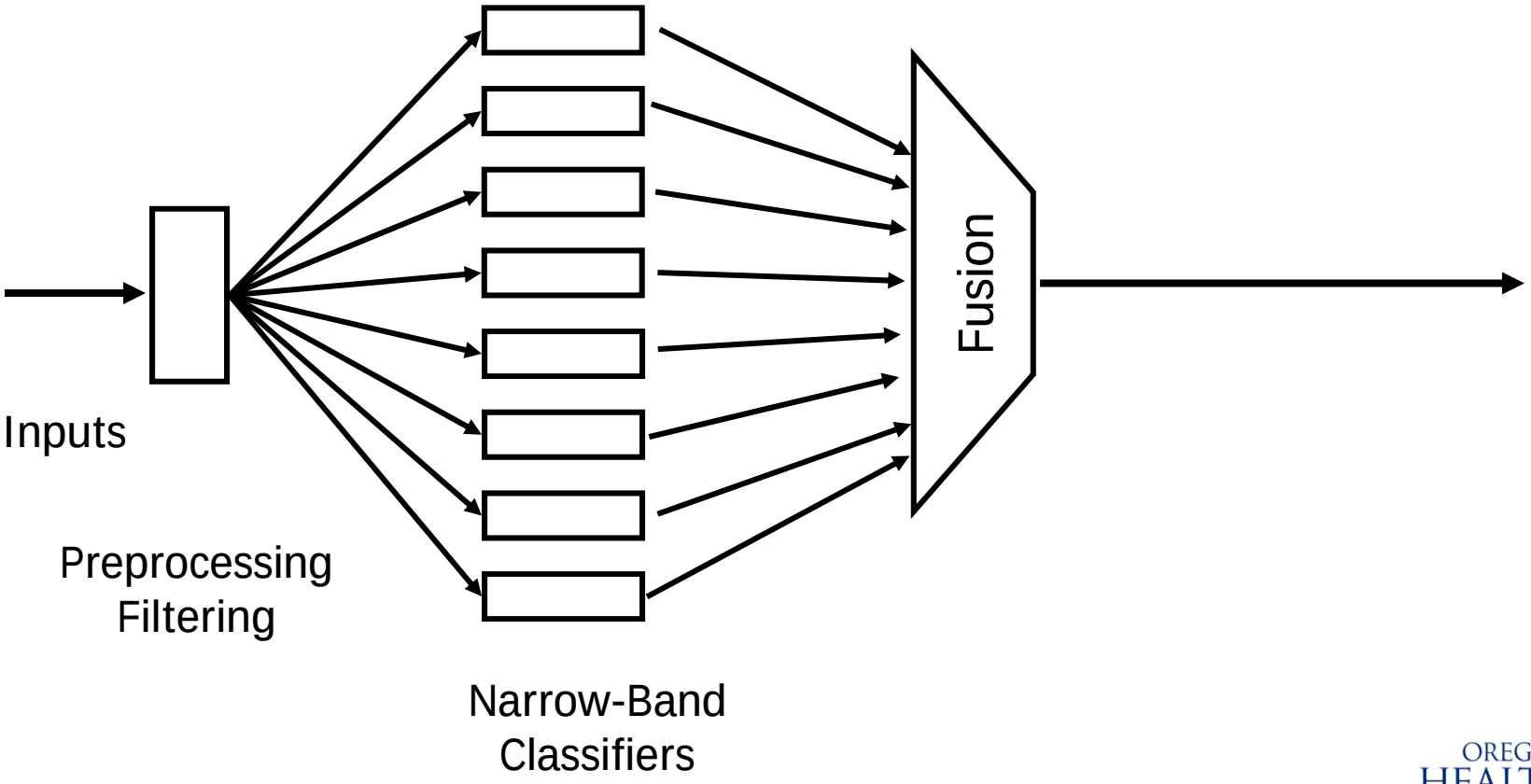
Implications of Fletcher's Findings

- Independence => No false positives



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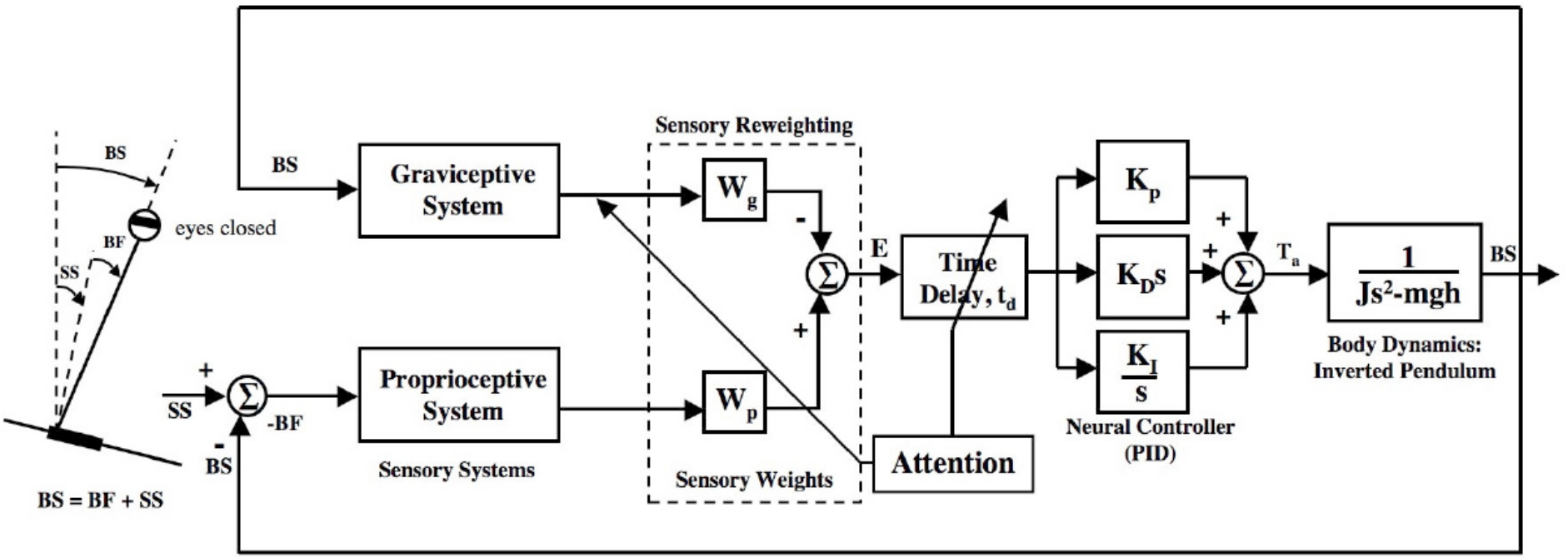
Balance and Posture Control

Fusio vestibular, proprioceptive and visual information



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Fusion in Multimodal Perception

- Visual + auditory speech recognition
  - Complementary information
  - Visual cues override auditory cues
- Gesture + language
  - Dynamic context manipulation
- Synchrony and simultaneity
  - Similar to image registration
  - Tennis game (78 feet)

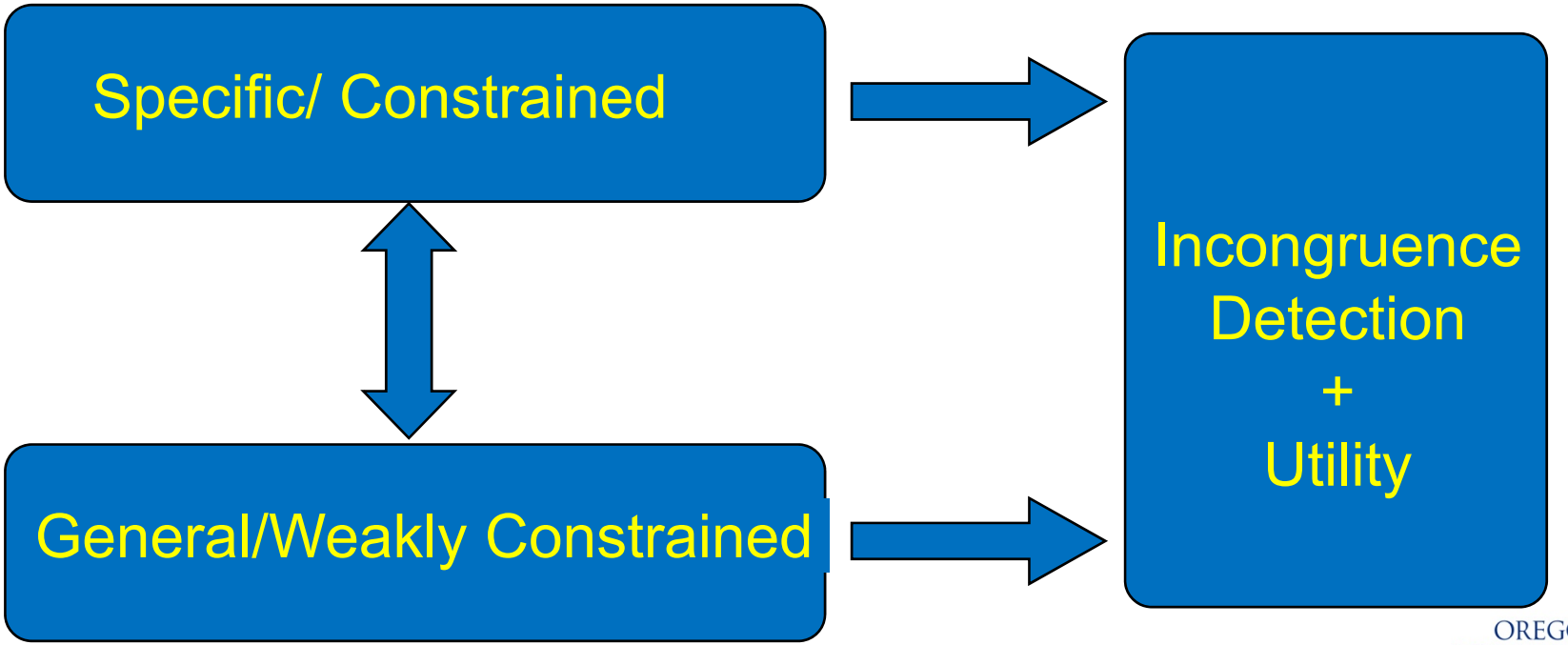
Summary: Benefits of Fusion

Performance enhancements due to

- Improved signal–to-noise ratio
  - Reduction of noise (Registration-conformal mapping)
- Complementary information
  - Visual – auditory recognition (“da” vs. “ba”)
  - Context-aware classification (color vs illumination)
- Higher order features and dimensions
  - Stereo, depth perception (Correspondence)

Summary:

- Detection of Conflict in Probabilities
- Utility of Responses



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Application Areas

1. Elder Monitoring
    1. Elders inside/outside activities (falls, near falls, mishaps)
    2. Elders social interactions anomalies
    3. Elders adherence to regiments (medication taking)
2. Surveillance and Security
    1. Analysis of audio/video transmissions
    2. Analysis of interviews
3. Navigation Aids
    1. Navigation in unknown environments
    2. Navigation in support of people with cognitive deficits
4. A/V Appearance Training
5. Deception Detection

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- DARPA

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Thank You

END