Detecting Rare Events in Cognitive Systems

Misha Pavel, Holly Jimison,
Hynek Hermansky Daphna Weinshall

DIRAC

Detection and Identification of Rare Audiovisual Cues

- EU project of the FP6, with nine partners:
  - http://www.diracproject.org/
  - IDIAP research institute (CH),
  - Eidgenossische Technische Hochschule Zuerich (CH),
  - The Hebrew University of Jerusalem (IL),
  - Czech Technical University (CS),
  - Carl von Ossietzky Universitaet Oldenburg (DE),
  - Leibniz Institute for Neurobiology (DE),
  - Katholieke Universiteit Leuven (B),
  - Oregon Health and Science University (USA).

OREGON HEALTH & SCIENCE UNIVERSITY

DIRAC

Detection and Identification of Rare Audiovisual Cues

- Objective: Detect and interpret "rare" events
- by analysis and fusion of multimodal sensory inputs

- Hynek Hermansky – PI and Coordinator

OREGON HEALTH & SCIENCE UNIVERSITY

Outline

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

OREGON HEALTH & SCIENCE UNIVERSITY

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

OREGON HEALTH & SCIENCE UNIVERSITY

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
- 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 ☺

Basic Premise

- Observation: Humans and animals are usually good at responding optimally 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?

OREGON HEALTH & SCIENCE UNIVERSITY

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

OREGON HEALTH & SCIENCE UNIVERSITY

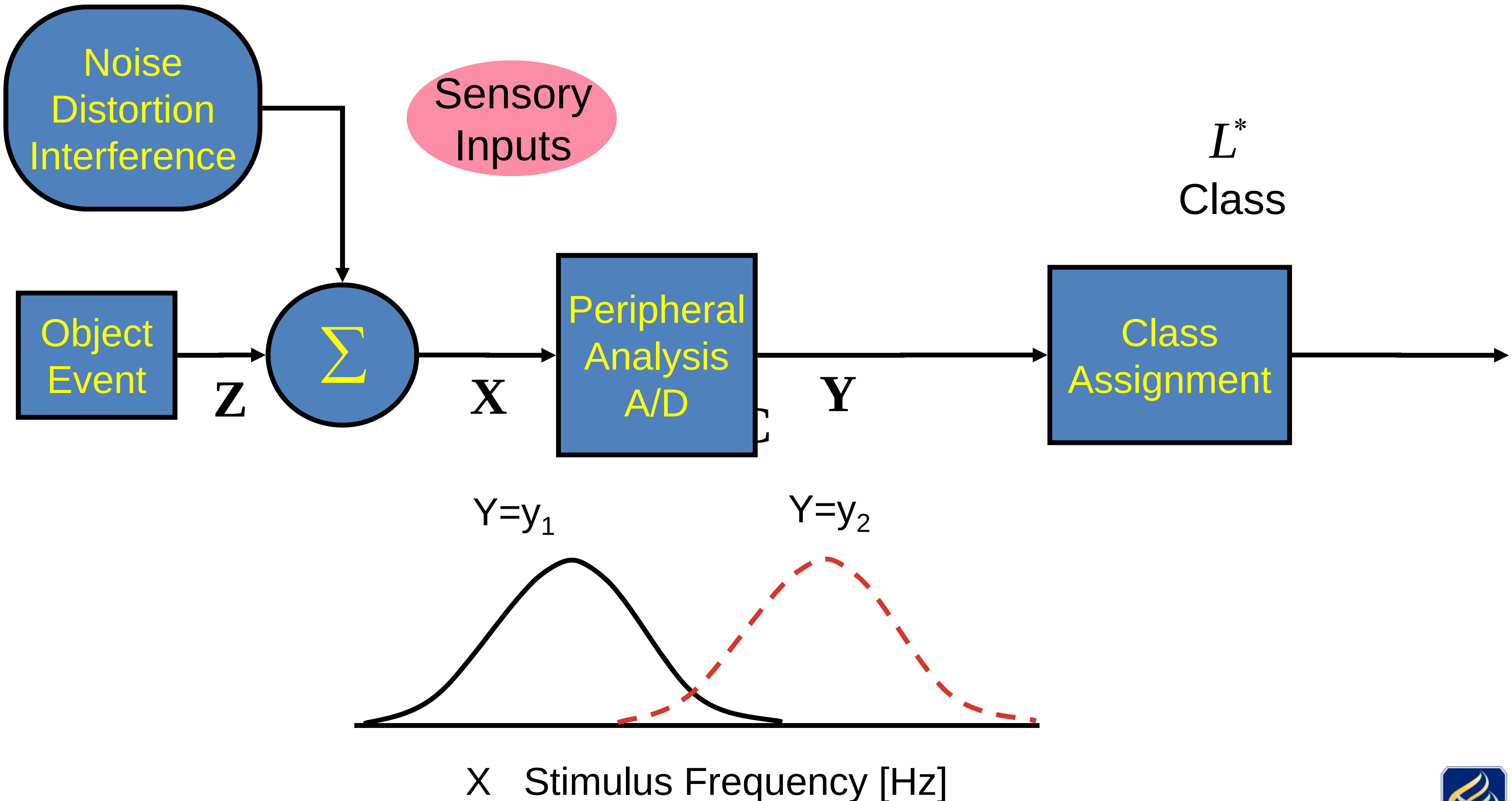
Psychology: Paradigms and Approaches

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

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

OREGON HEALTH & SCIENCE UNIVERSITY OHSU

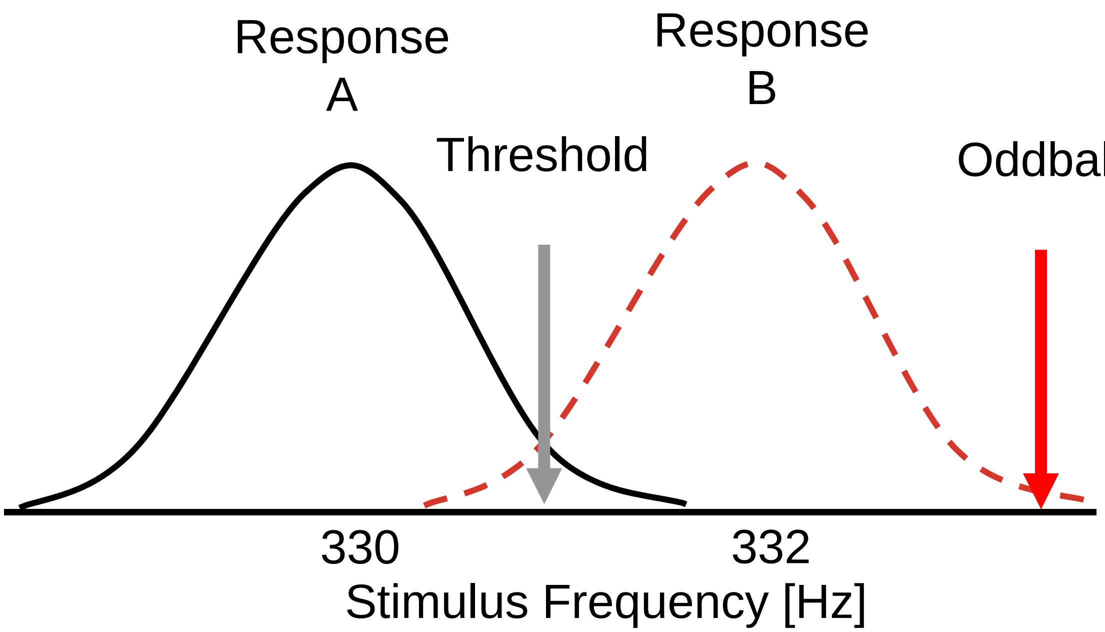
Framework for Discrimination and Categorization



OREGON HEALTH & SCIENCE UNIVERSITY

Perceptual Discrimination

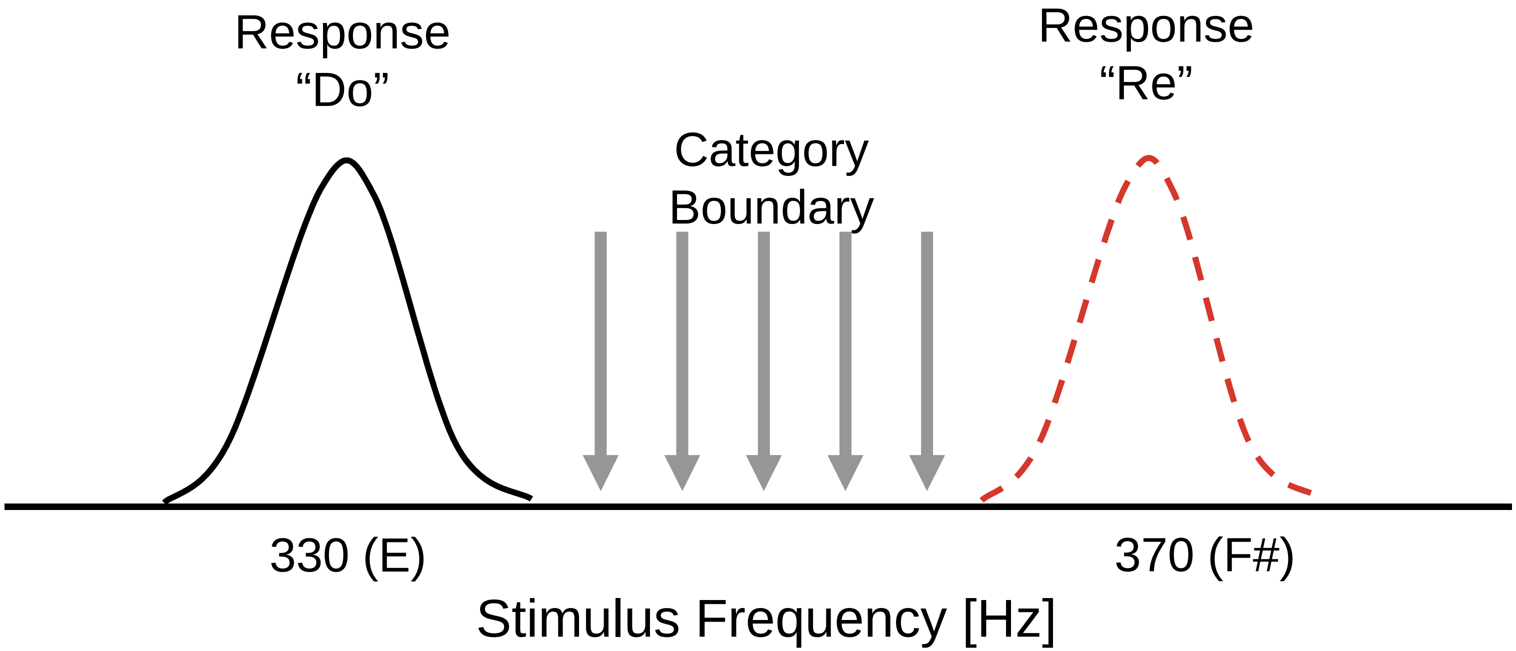
Example: Discrimination between two tones, f_1 and f_2



OREGON HEALTH & SCIENCE UNIVERSITY

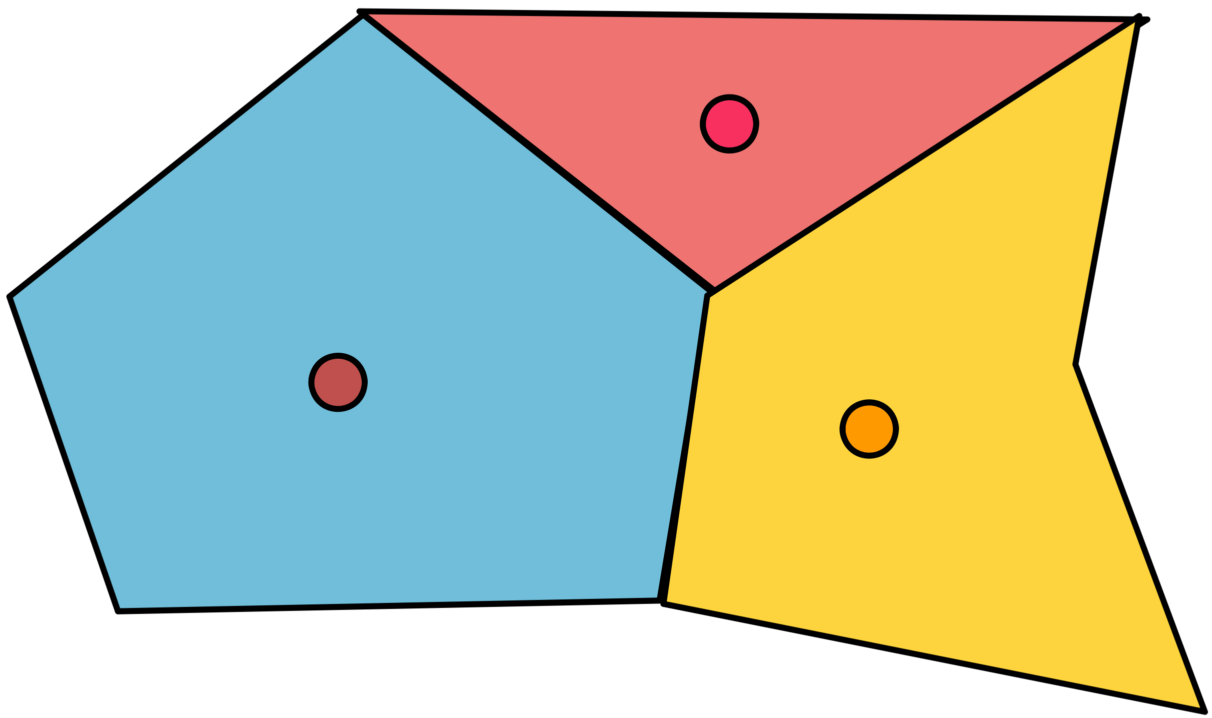
Perceptual Categorization

Example: Categorization of tones, f_1 and f_2



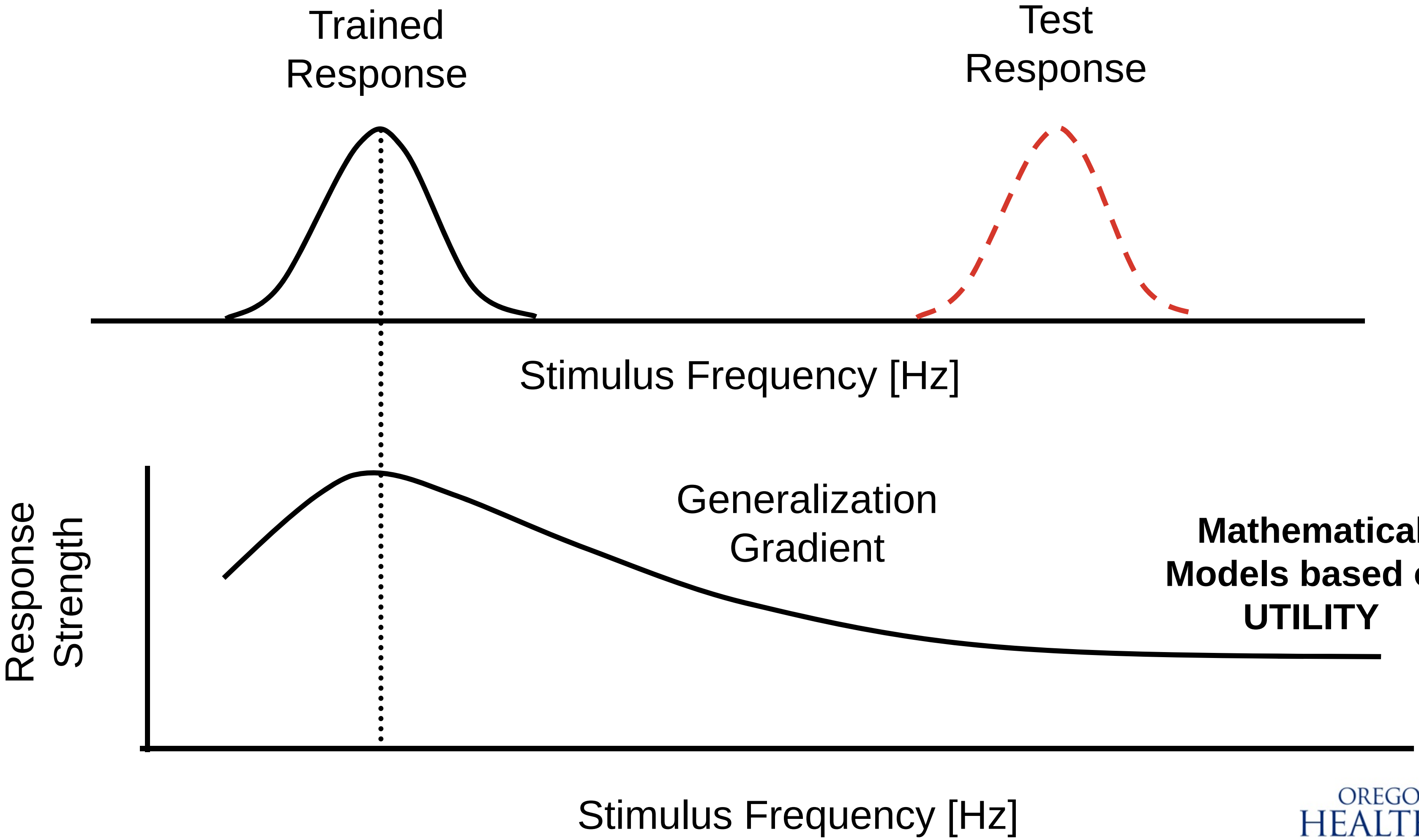
Multidimensional Categorization

Example: Categorization Regions



Psychological Generalization

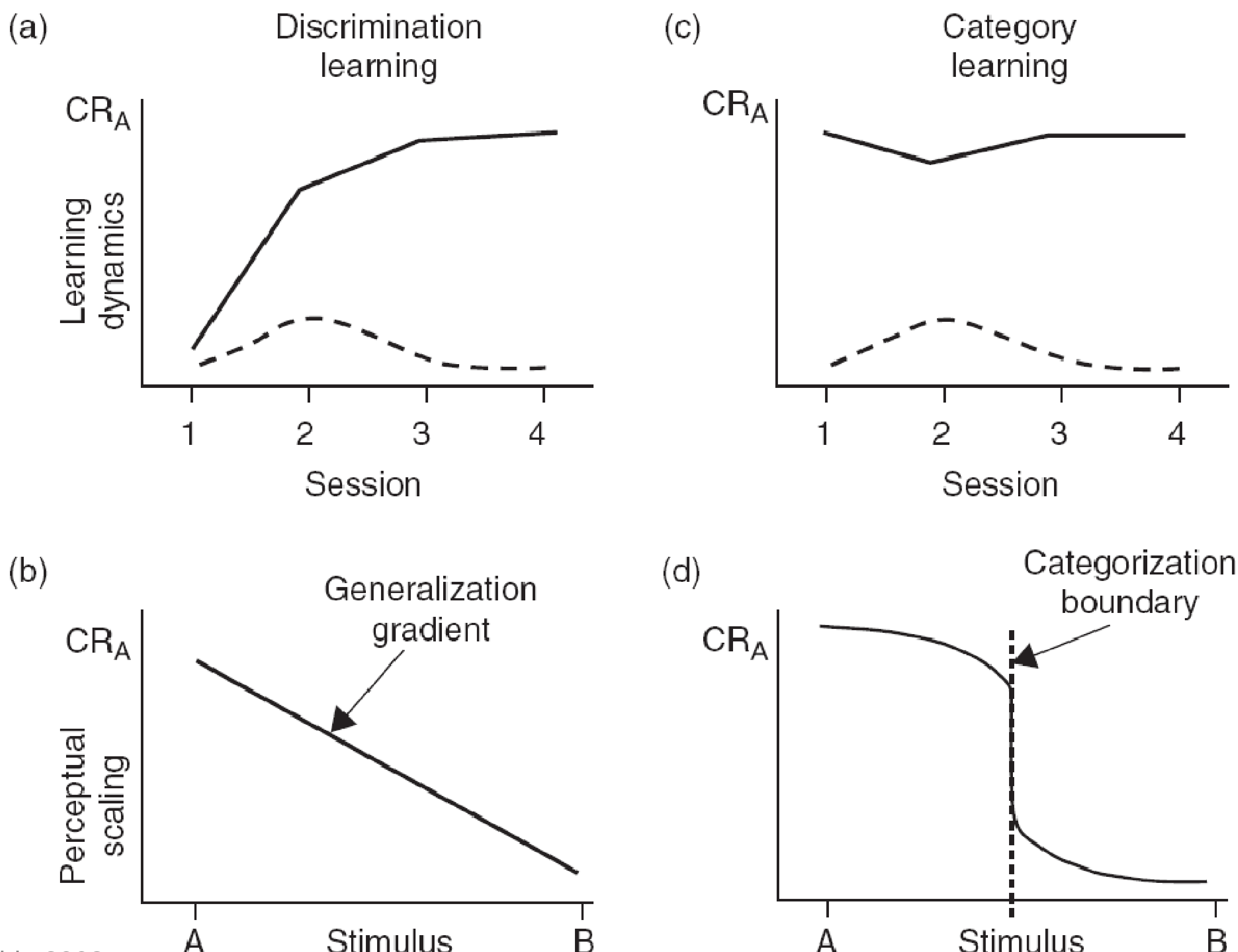
Example: Salivation response to tones



Mathematical Models based on UTILITY

OREGON HEALTH & SCIENCE UNIVERSITY

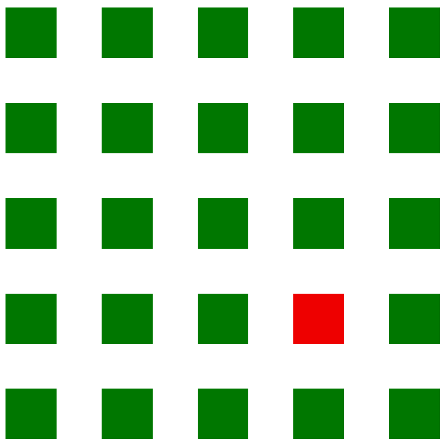
Generalization vs. Categorization

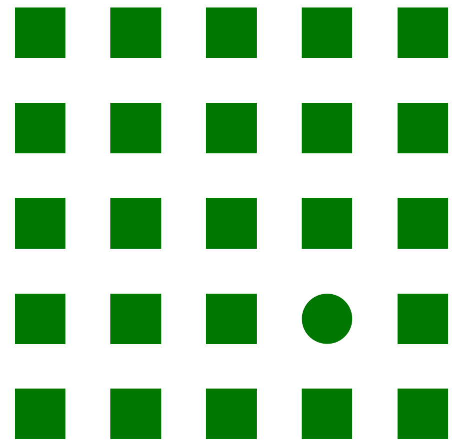


Ohl, 2008

Classical Detection of "Novel" Stimuli

Spatial Oddball Detection: Color or Shape





Temporal Oddball Detection: Color or Shape

Bottom-up, outlier detection

OREGON HEALTH & SCIENCE UNIVERSITY

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

OREGON HEALTH & SCIENCE UNIVERSITY

Notation

- Observations $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$
- Features $\mathbf{Y} = \{Y_1, Y_2, \ldots, Y_m\}$
- Classes/Labels $\mathbf{L} = \{l_1, l_2, \ldots, l_k\}$
- 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 $P\{L_{n+1} \mid C\}$

OREGON HEALTH & SCIENCE UNIVERSITY

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

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

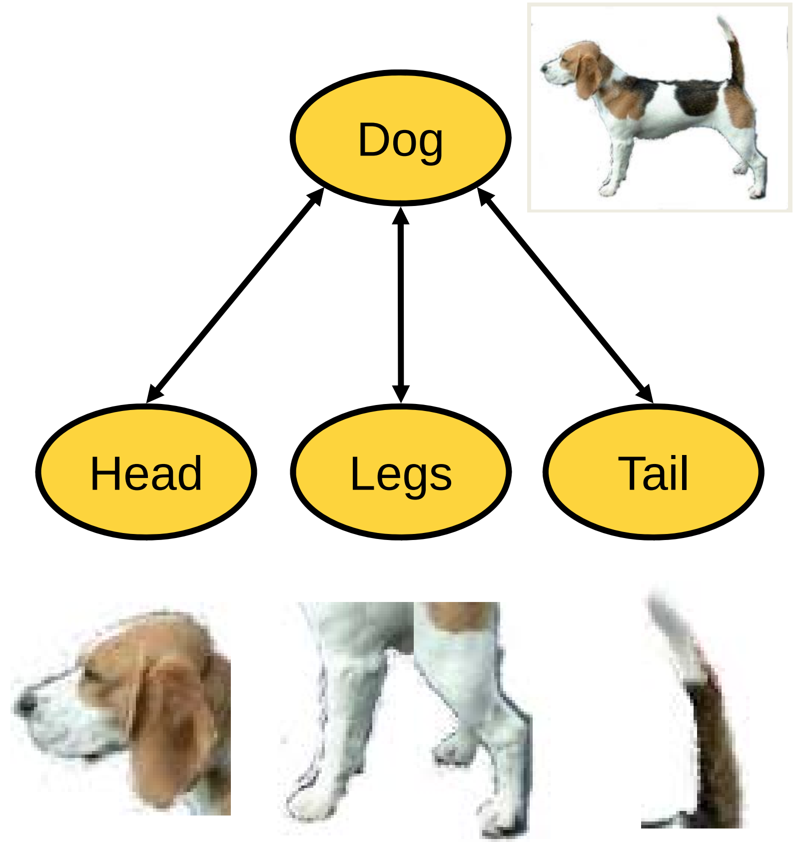
- Maximum Expected Utility:

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

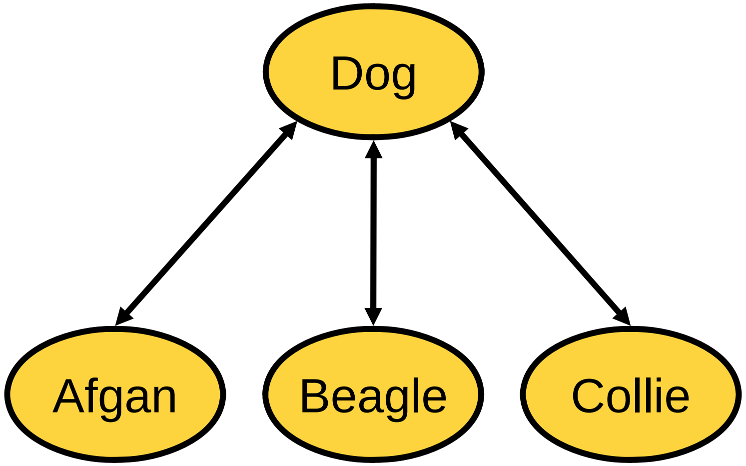
Need a framework for classification

OREGON HEALTH & SCIENCE UNIVERSITY

Part-Membership Hierarchy of Categories



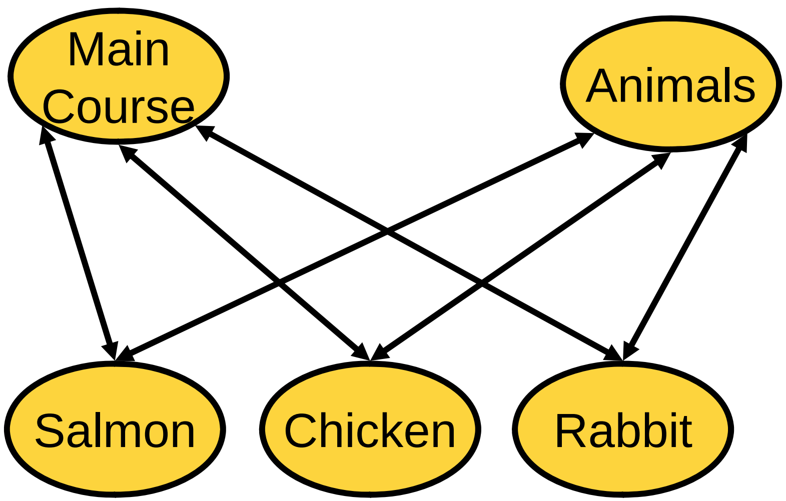
Class-Membership Categories



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???

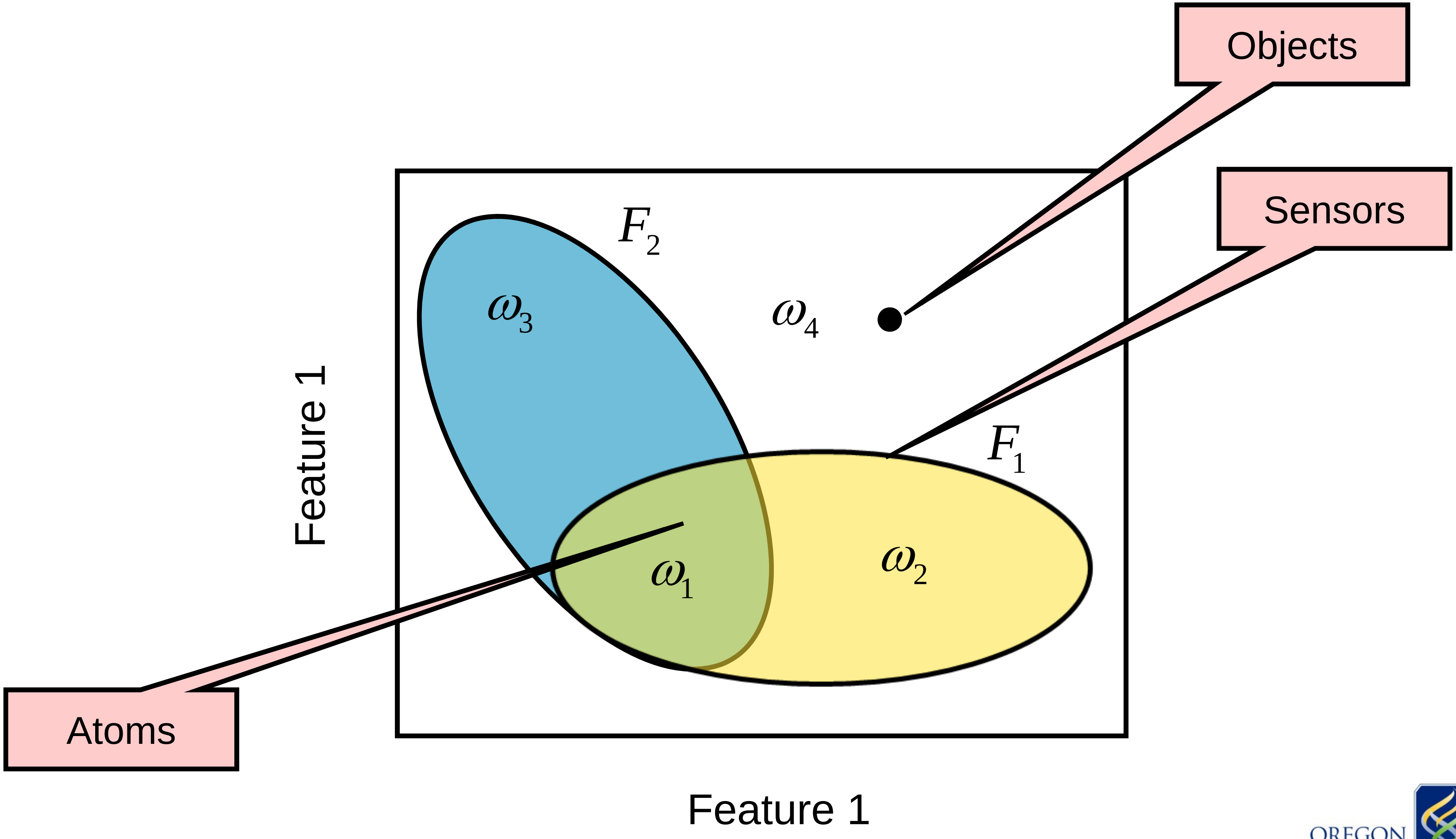
Depends on
Context and Task



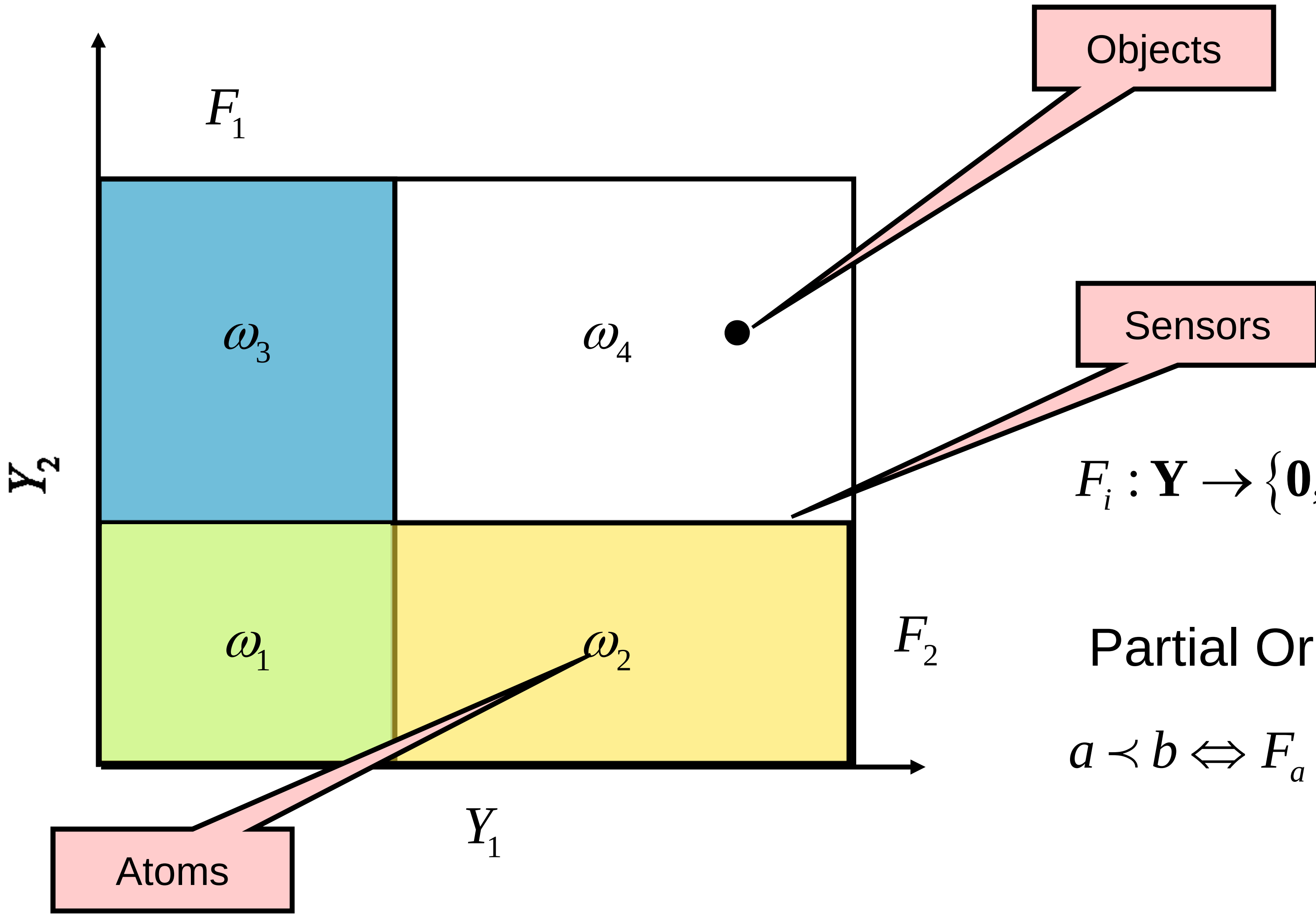
Can we develop a structure that captures the advantages hierarchy and overcomes Incorporate context

OREGON HEALTH & SCIENCE UNIVERSITY

An Alternative: Object – Feature Space



Object – Feature Space – Sensors as Predicates

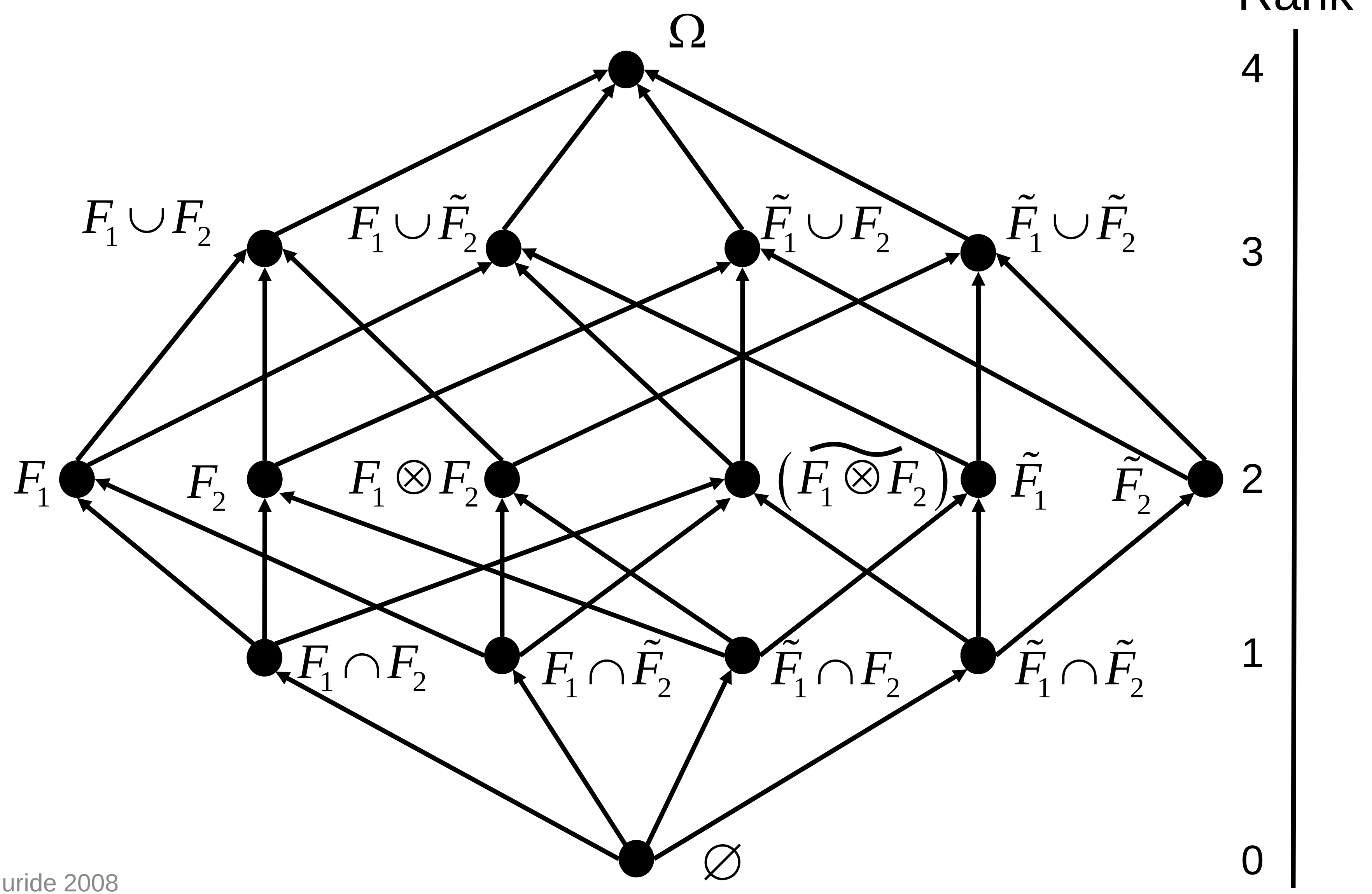


$$F_i : \mathbf{Y} \to \{\mathbf{0},\mathbf{1}\}$$

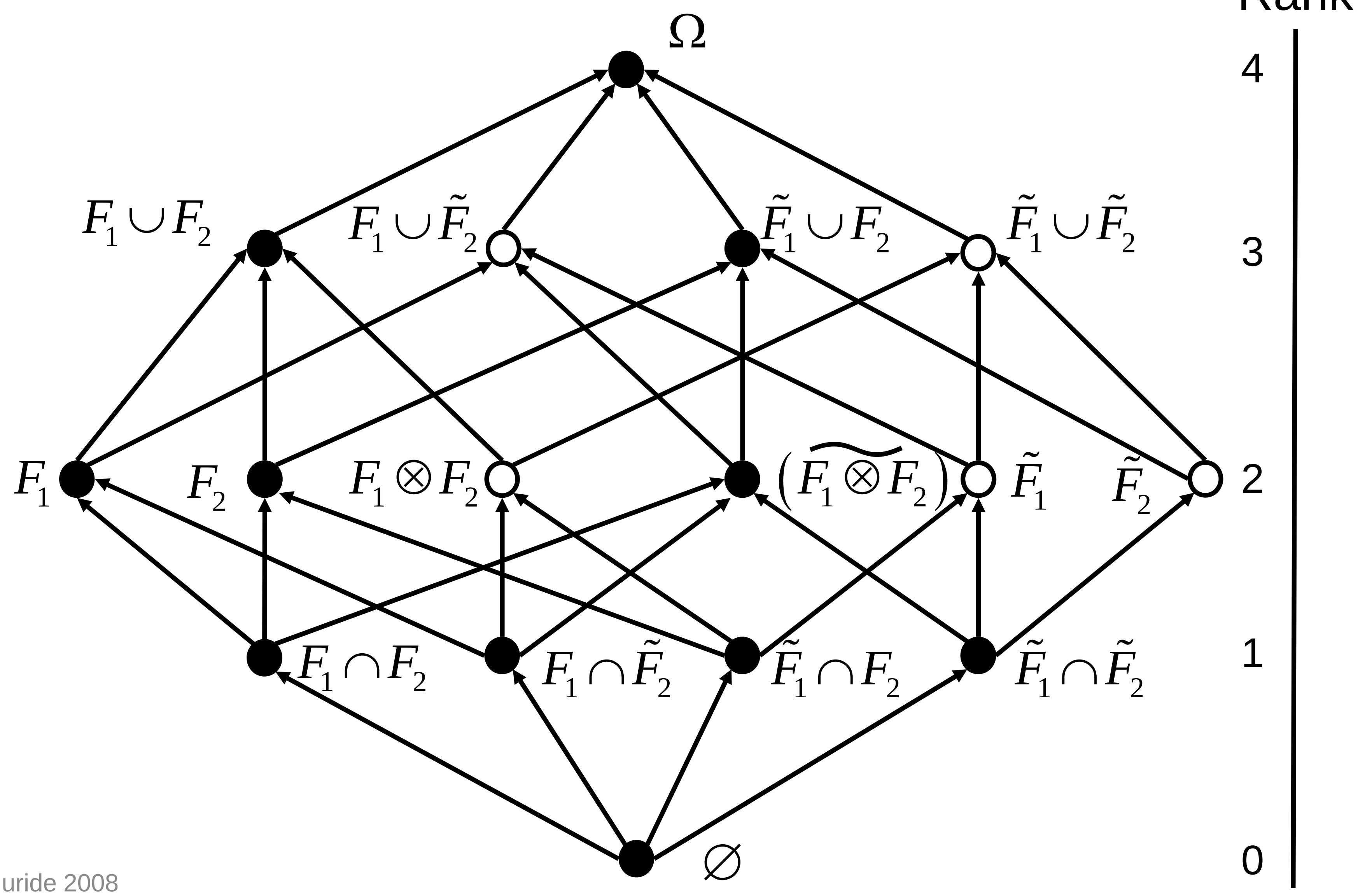
Partial Order

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

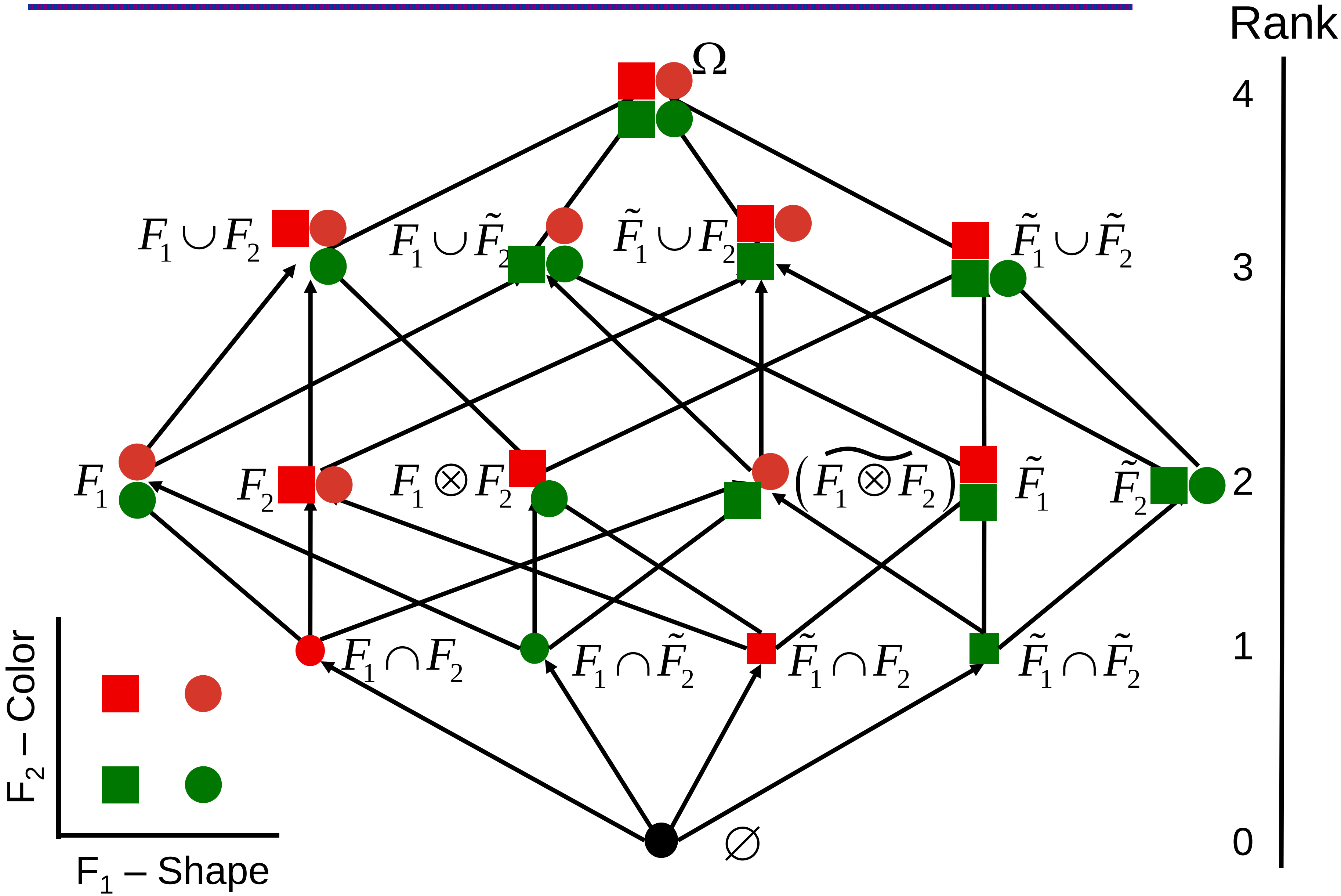
Complete Partial Order



Class-Specific Partial Order



Example: Partial Order in Visual Search



Object – Feature Space – Sensors as Predicates

Objects $y \in \mathbf{Y}$

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

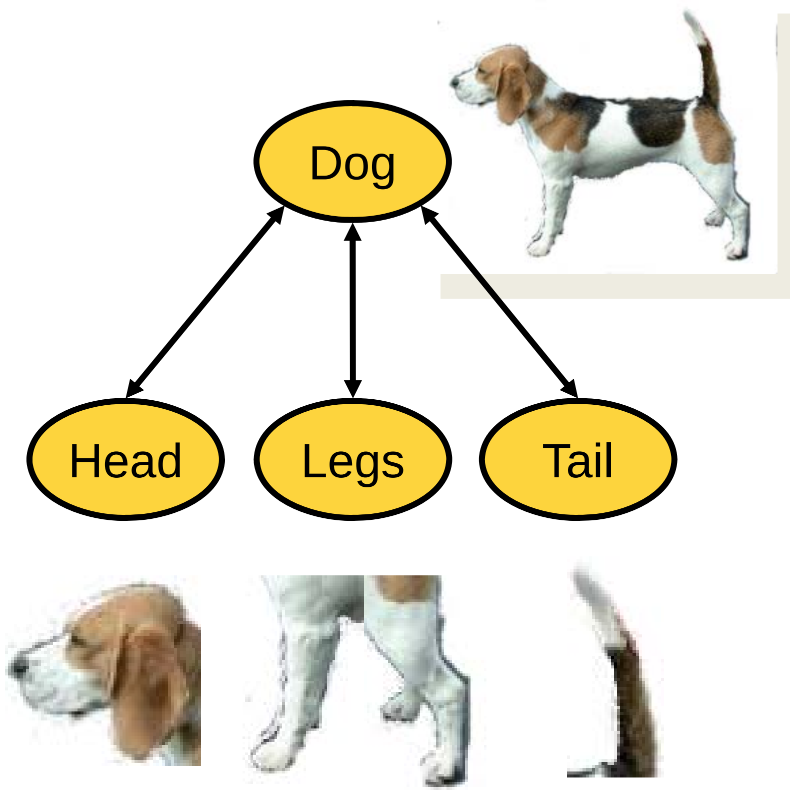
Partial Order $a \prec b \Leftrightarrow F_a \subseteq F_b$

Stronger
More Specific
Model

Weaker
More General
Model

OREGON HEALTH & SCIENCE UNIVERSITY OHSU

Example: Part – Membership Category

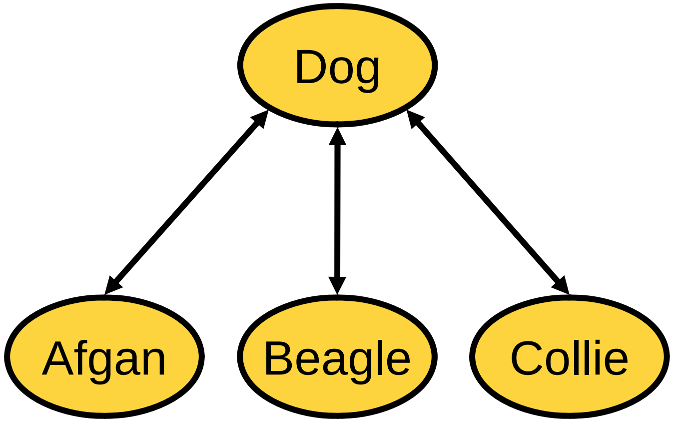


$$F_{dog} = F_{legs} \cap F_{head} \cap F_{tail}$$

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

Dog is more specific (stronger) model then parts

Example: Class – Membership





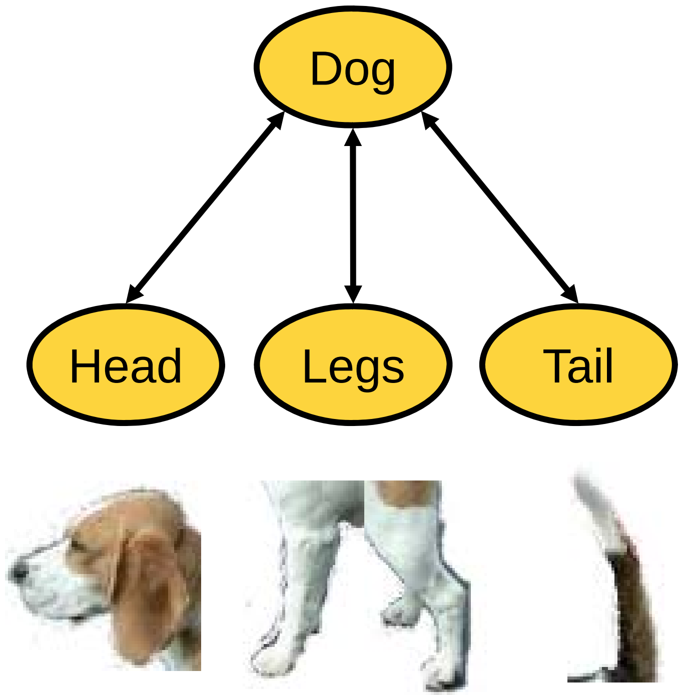
$$F_{dog} = F_{Afgan} \cup F_{Beagel} \cup F_{Collie}$$

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

Dog is more general (weaker) model then the breeds

OREGON HEALTH & SCIENCE UNIVERSITY

Incongruent Part – Whole Category



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

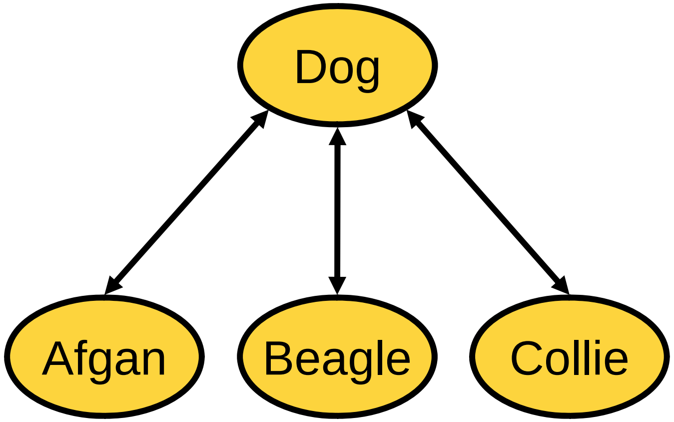
$$F_{dog} \subset F_{legs} \Rightarrow dog \prec legs$$

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

Incongruent

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

Example: Class – Membership



Incongruent

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

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

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

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

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

OREGON HEALTH & SCIENCE UNIVERSITY

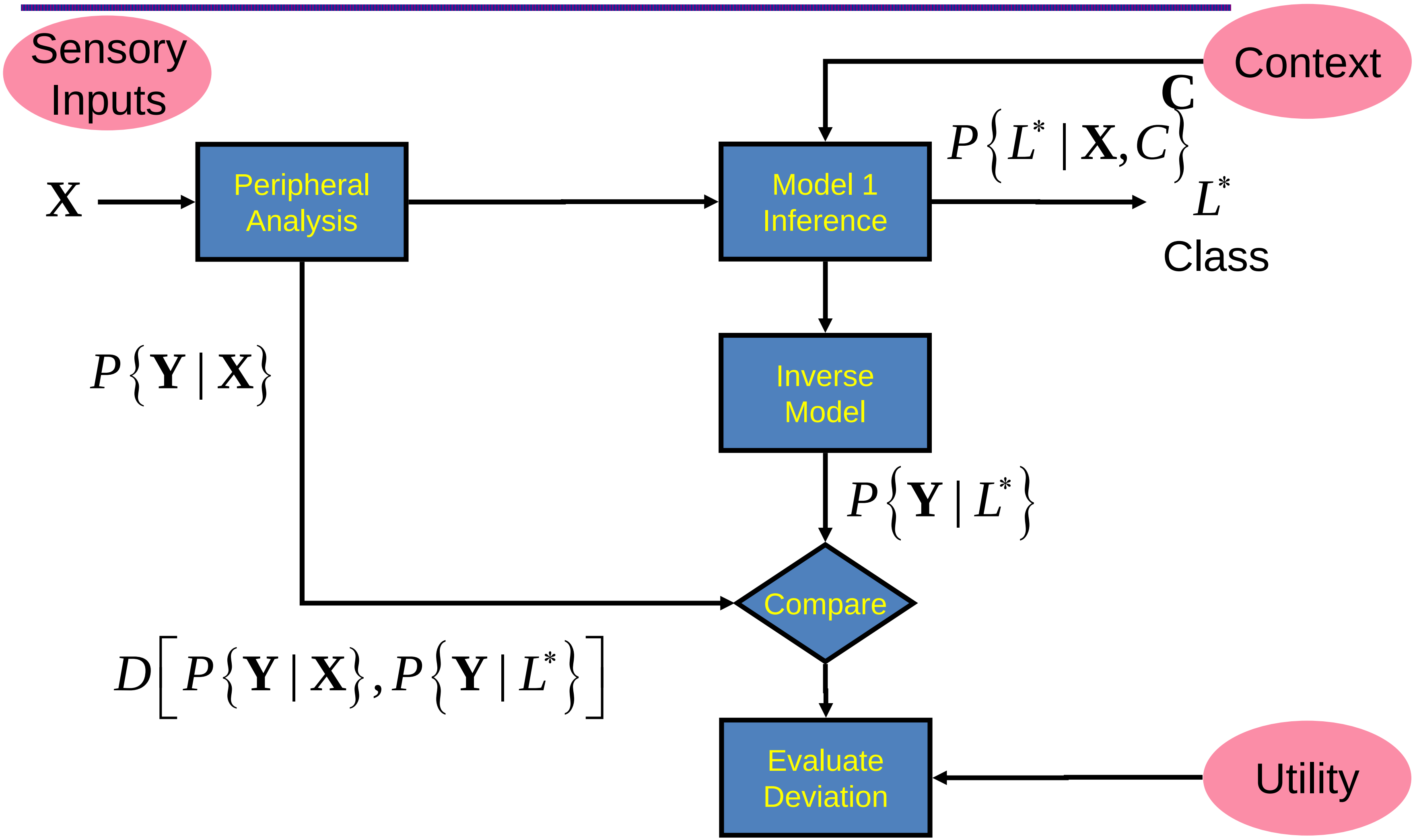
Rare – Incongruent Events

	Specific	General
"Noise" or oddball	Low	Low
Incongruent	Low	High
Incorrect Model	High	Low
Not rare or incongruent	High	High

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

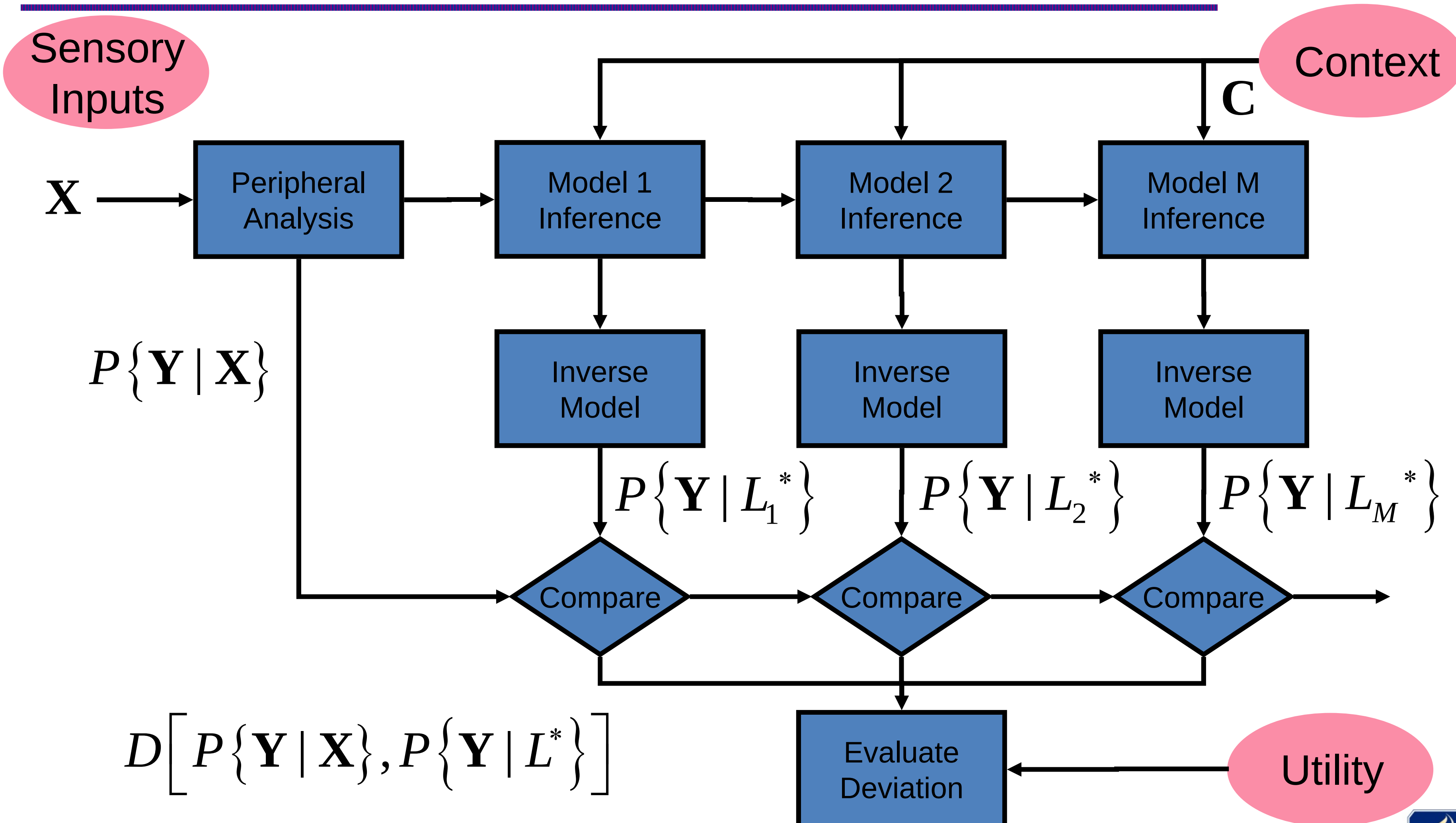
OREGON HEALTH & SCIENCE UNIVERSITY

Algorithms for Detection of Rare Events



OREGON HEALTH & SCIENCE UNIVERSITY

Hierarchical Models of Rare Events



OREGON HEALTH & SCIENCE UNIVERSITY

Context

- Task
- Environmental setting
- Hierarchy of models

- Prior probabilities
- Utilities

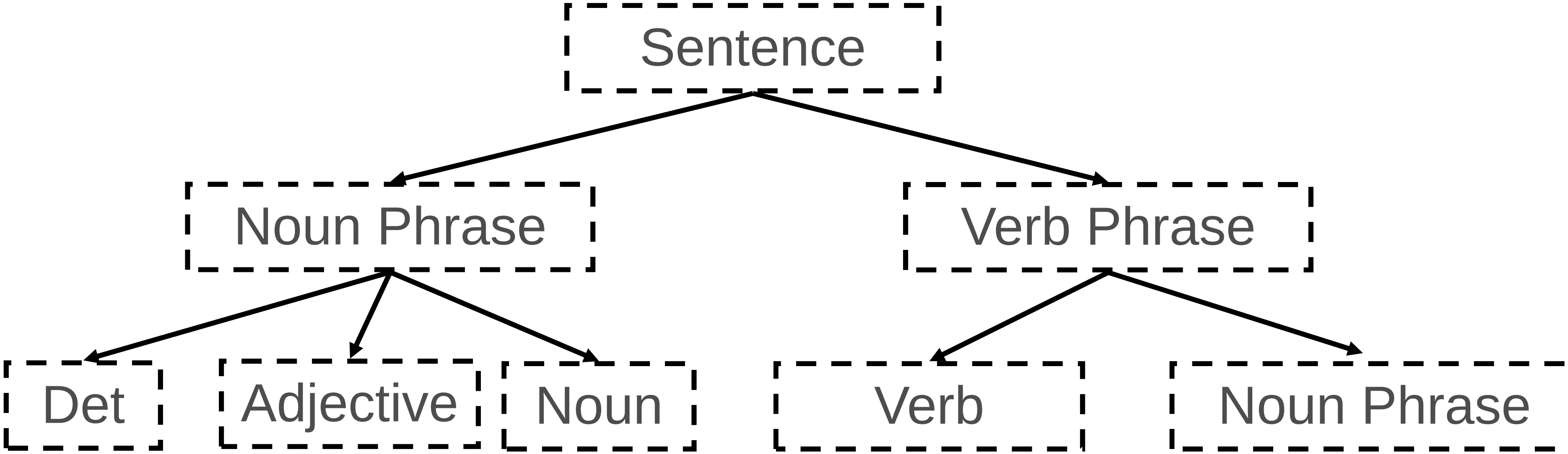
OREGON HEALTH & SCIENCE UNIVERSITY

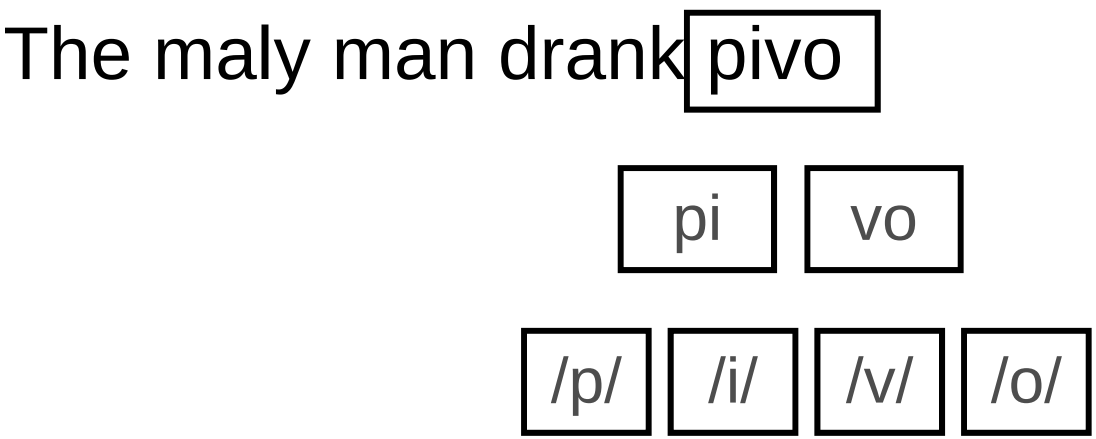
How to Get Utility Estimates?

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

OREGON HEALTH & SCIENCE UNIVERSITY

Example of Utility Assessment: Linguistic Analysis





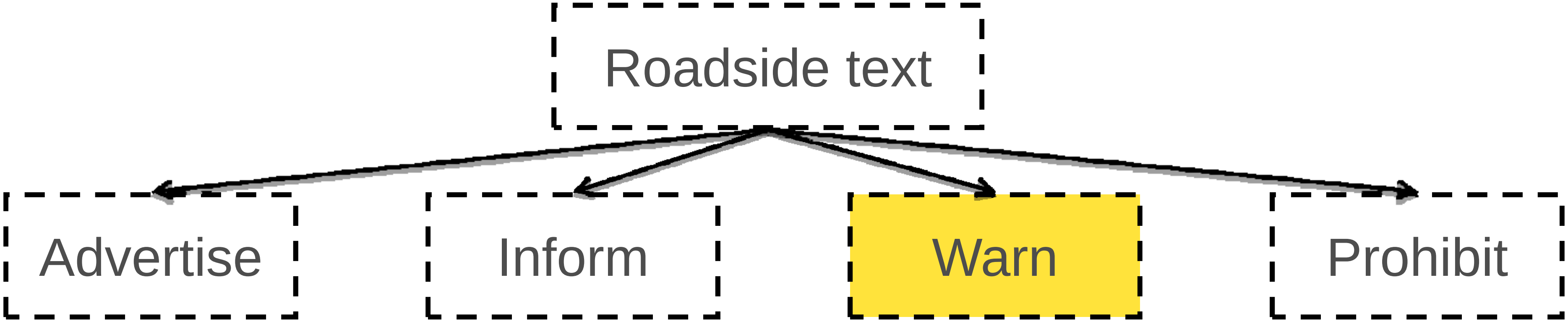
Example of Utility Application: Roadside Text/Graphics

Roadside signs

Advertise | Inform | Warn | Prohibit

← Lower Utility —— Higher Utility →

Example of Utility Application: Roadside Text/Graphics



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

OREGON HEALTH & SCIENCE UNIVERSITY

Example of Utility Application: Roadside Text/Graphics

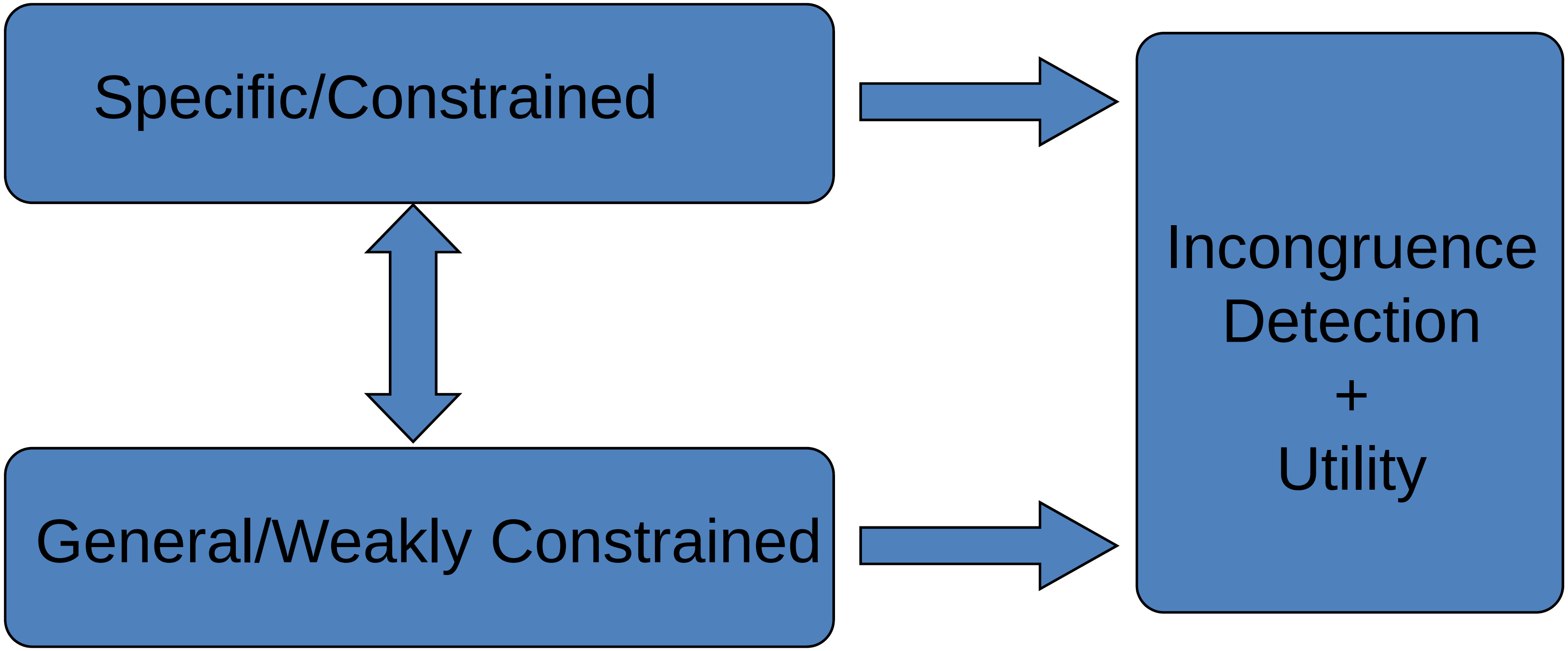
Roadside text

- Advertise
- Inform
- Warn
- Prohibit

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

Framework: Detection of Conflict in Probabilities

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



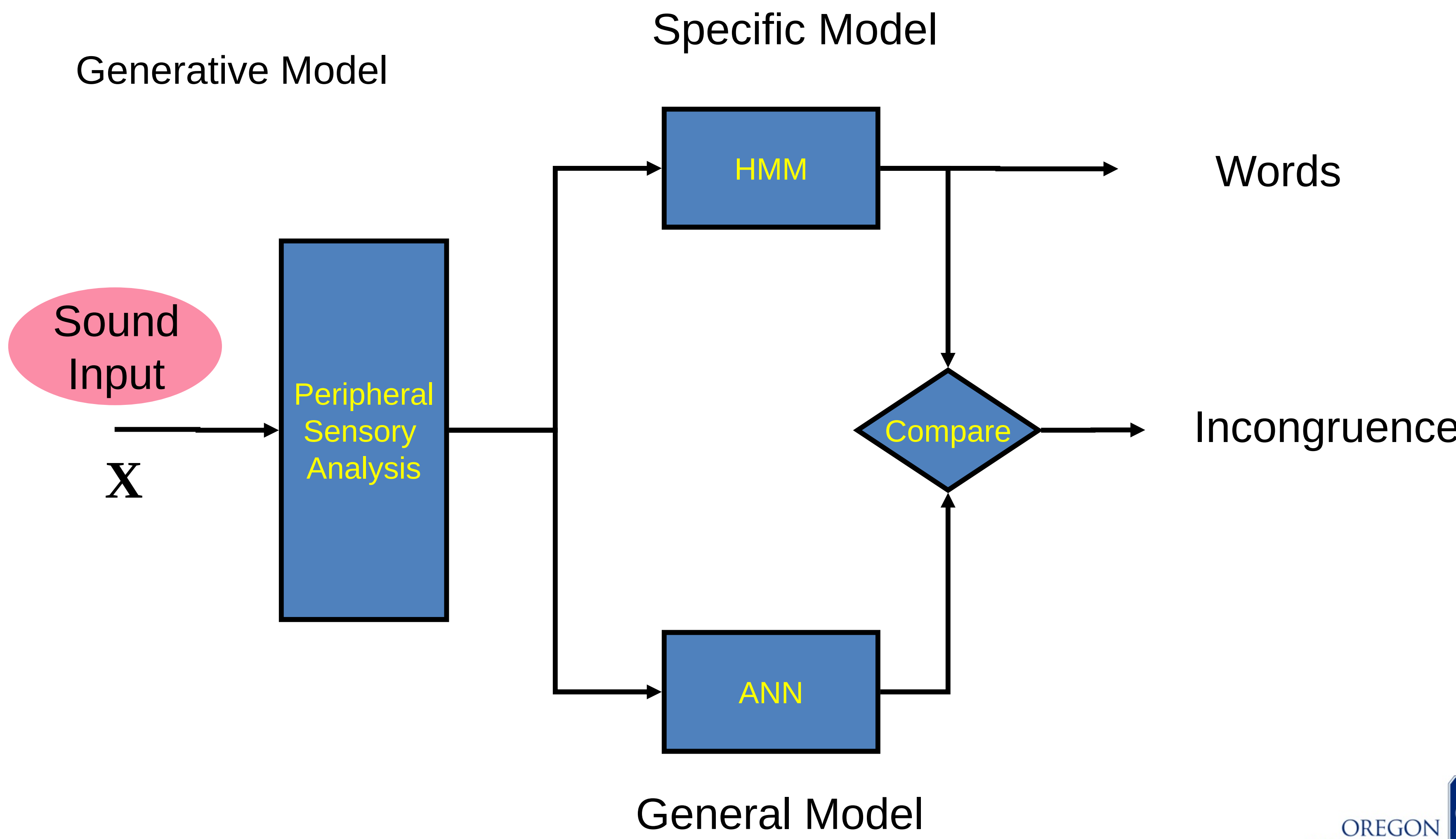
Example: Digit Recognition

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 ”

OREGON HEALTH & SCIENCE UNIVERSITY

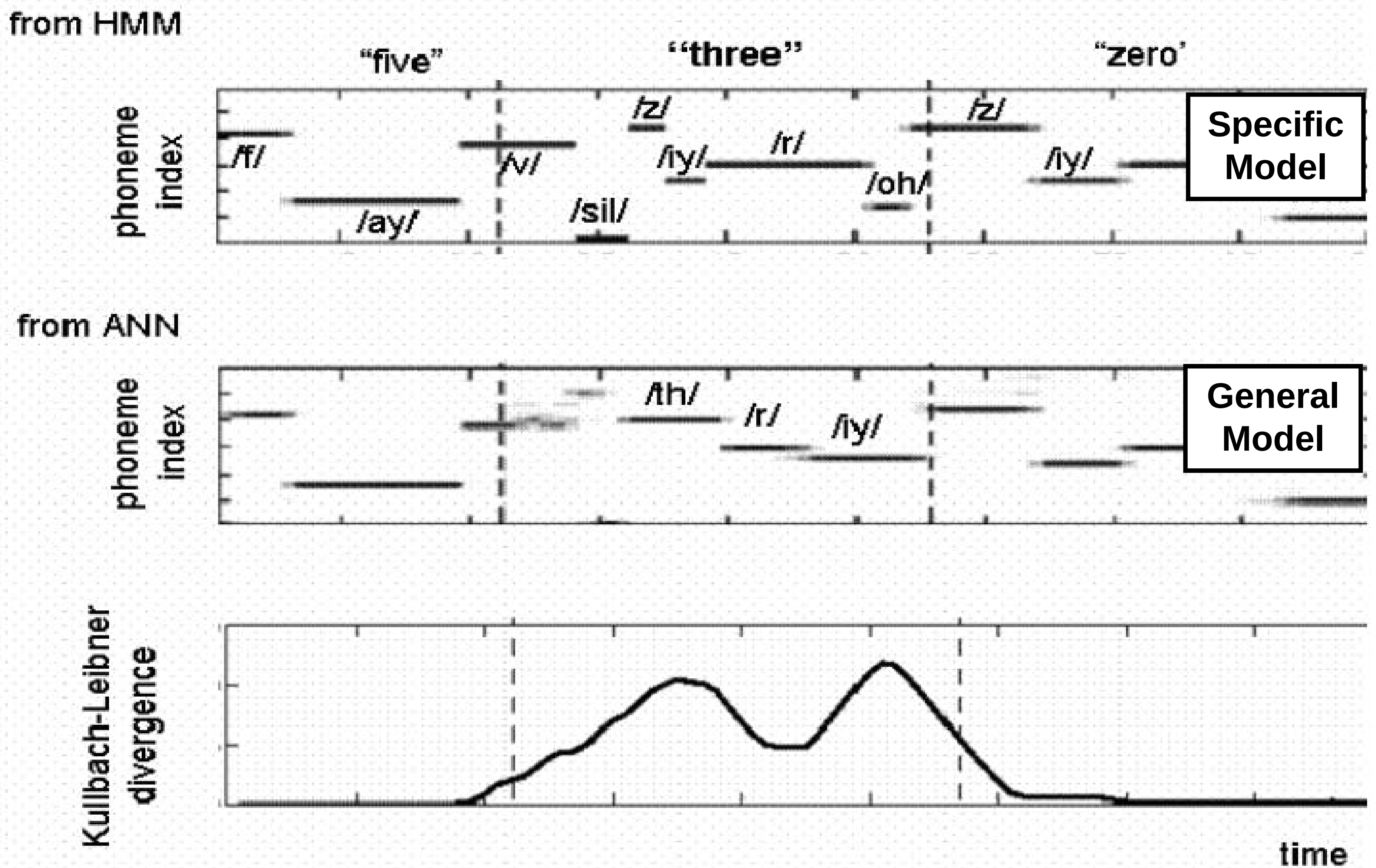
Example: Detection of out-of-vocabulary (OOV) Words



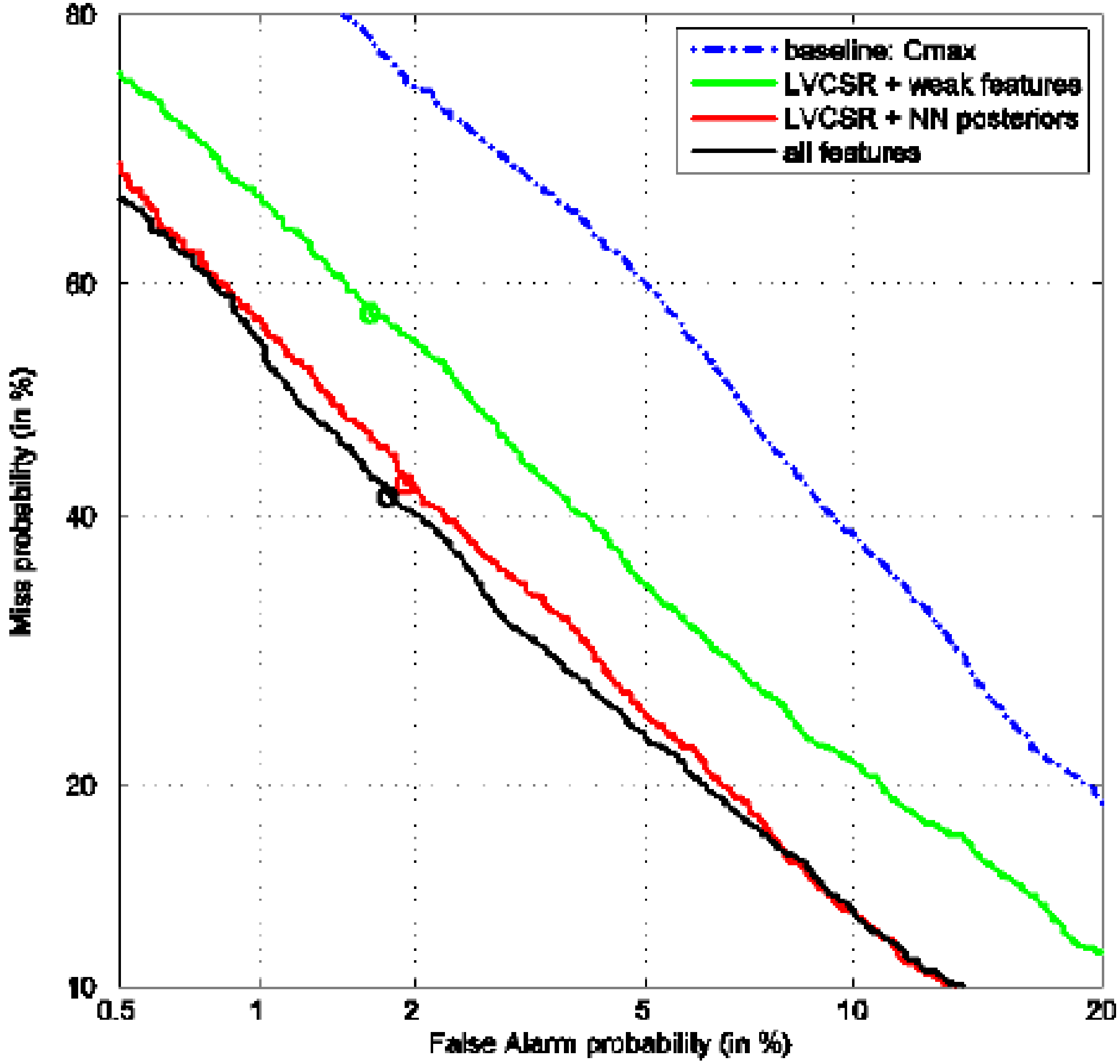
Example: Out-of-Vocabulary Word Detection

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

Example: Out-of-Vocabulary Word Detection



Detection Results (without Utility)



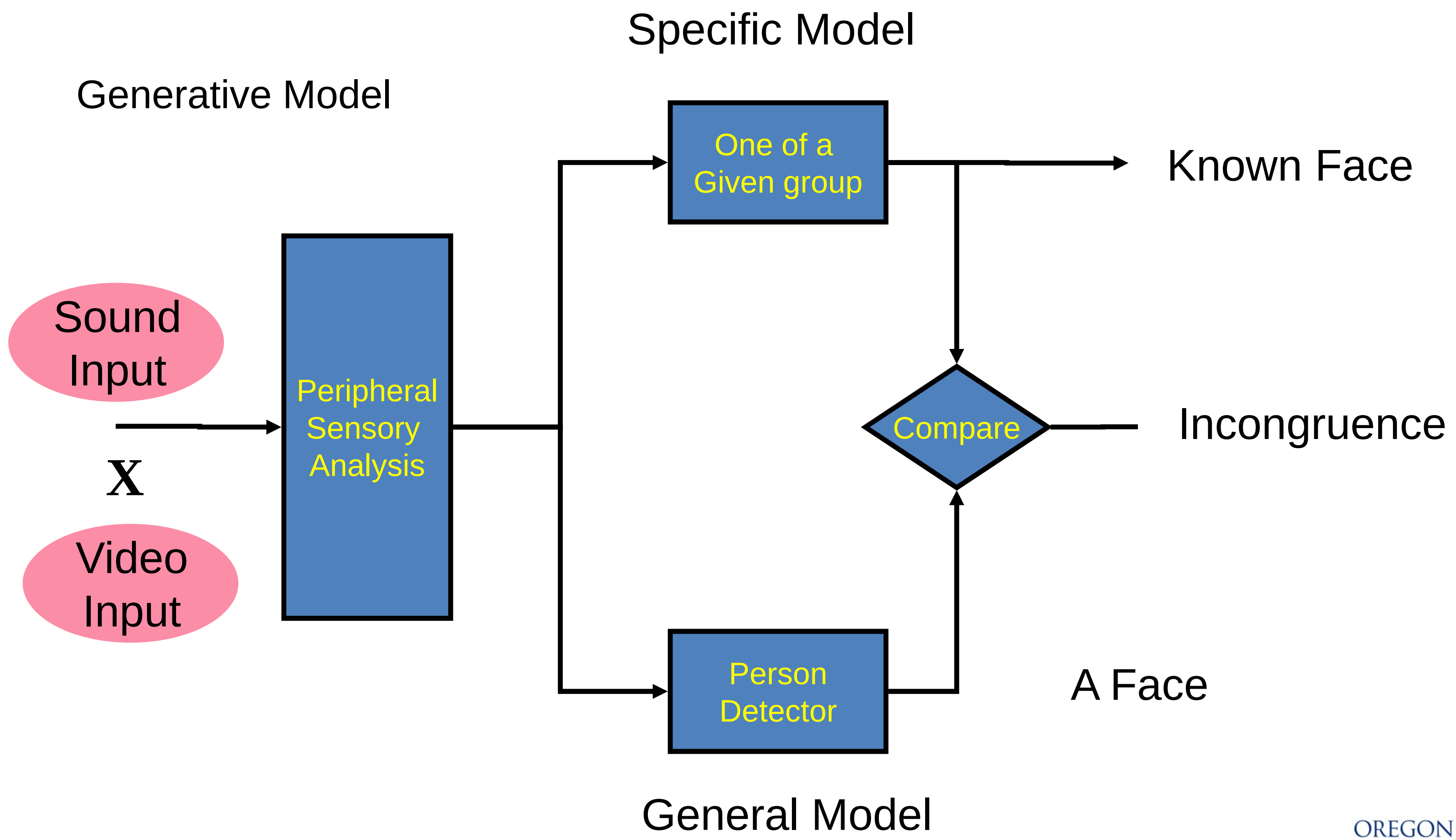
Audio-Visual Detection of New Individual

Known Training Identities

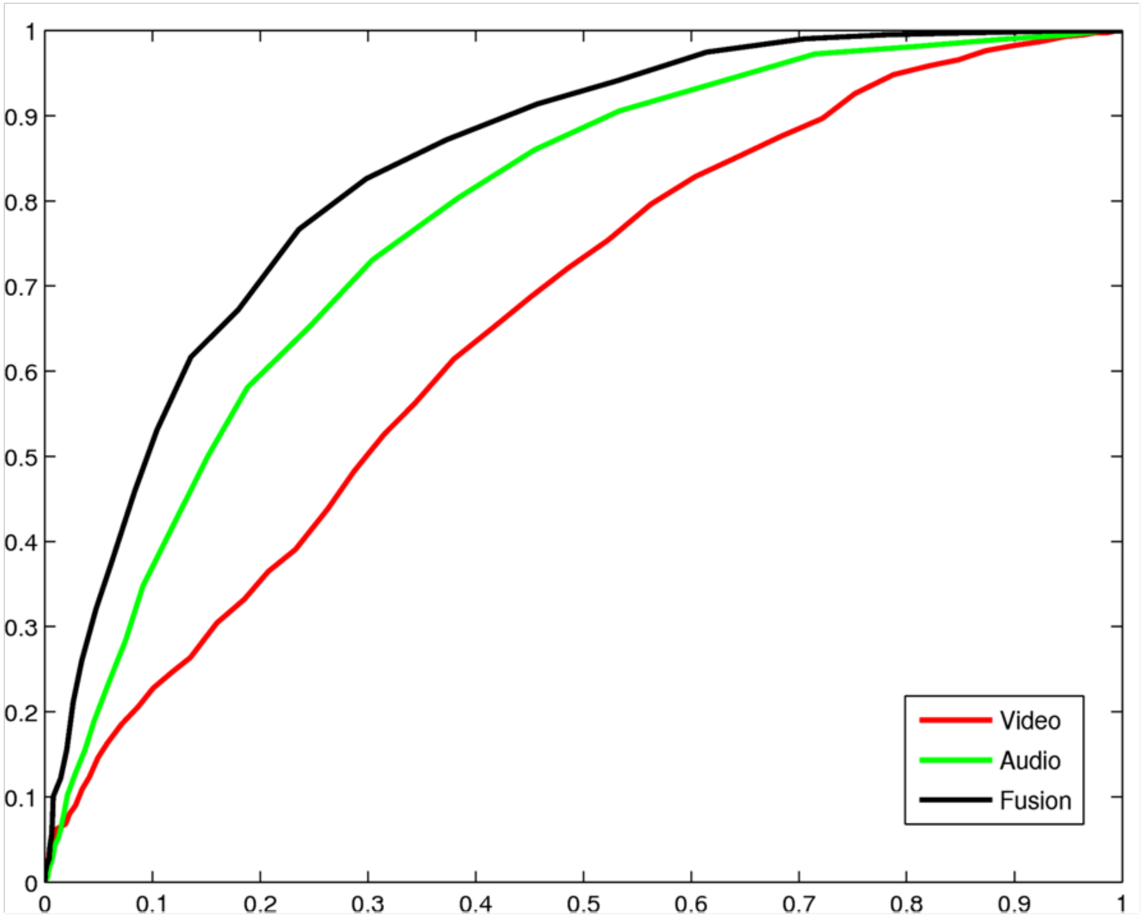
Known Testing Identities

Unknown Identities

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



Results



1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Video
Audio
Fusion

Audio-Visual Authentication

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

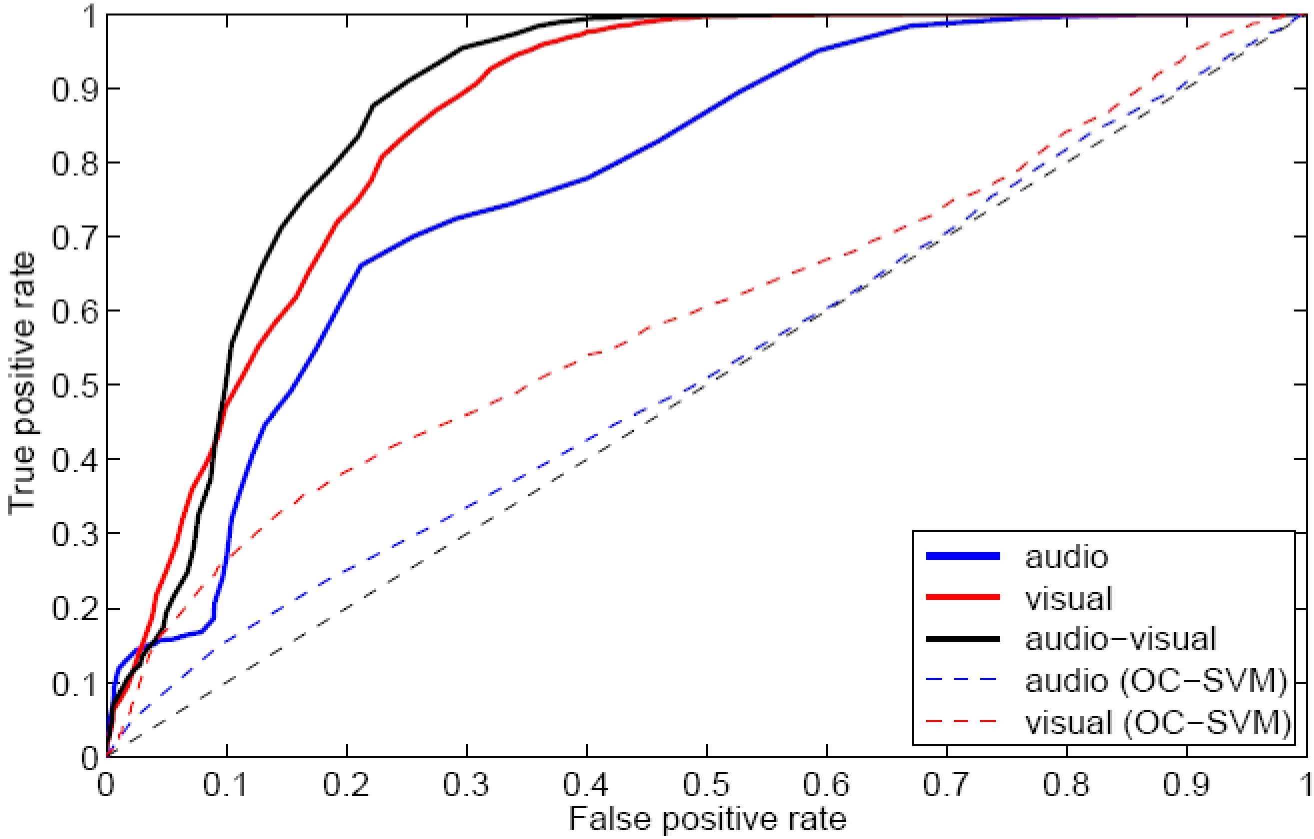
OREGON HEALTH & SCIENCE UNIVERSITY

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

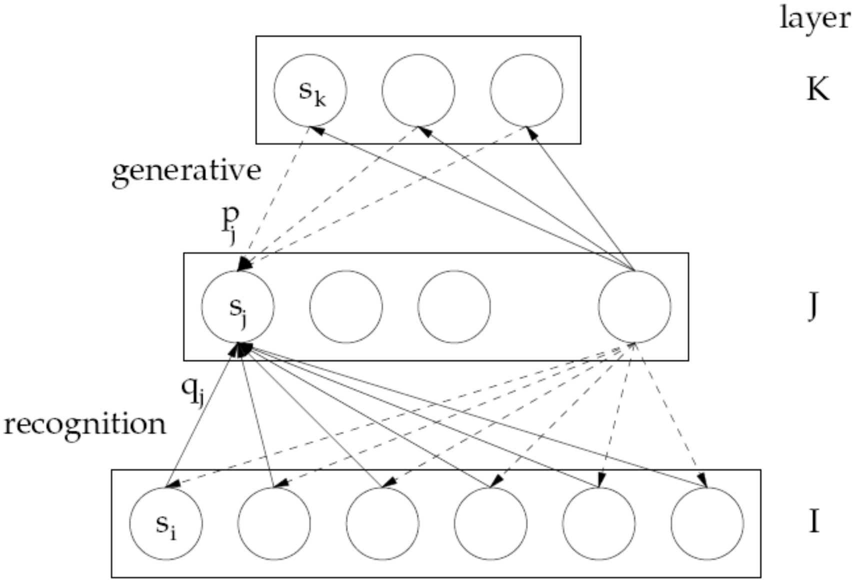
OREGON HEALTH & SCIENCE UNIVERSITY OHSU

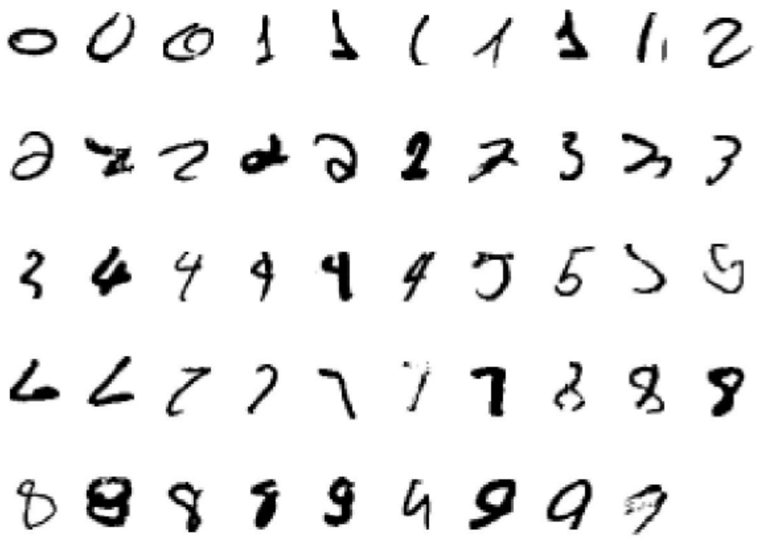
ROC for Imposter Classification



Work in Progress

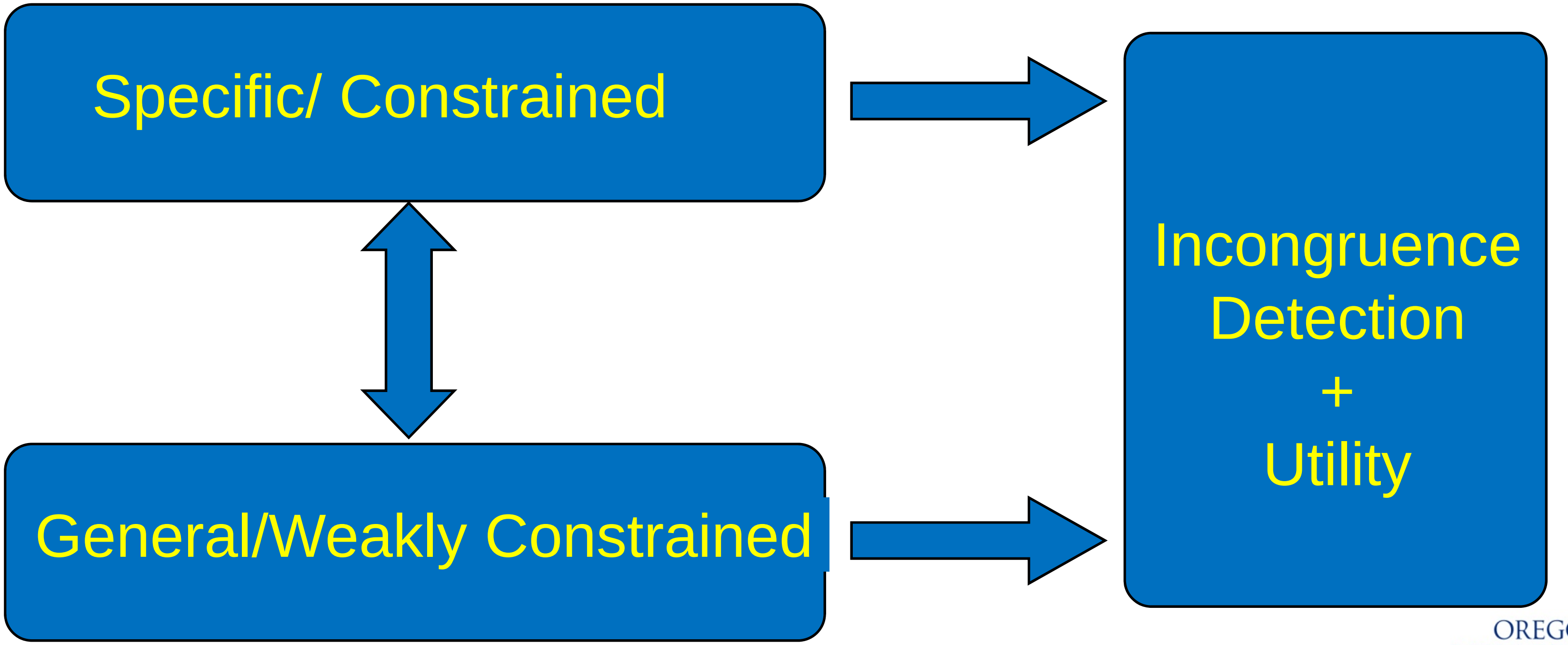
- Using learning by generation (Hinton)
- Generative model of stimulus features
- Leave a digit out





Summary:

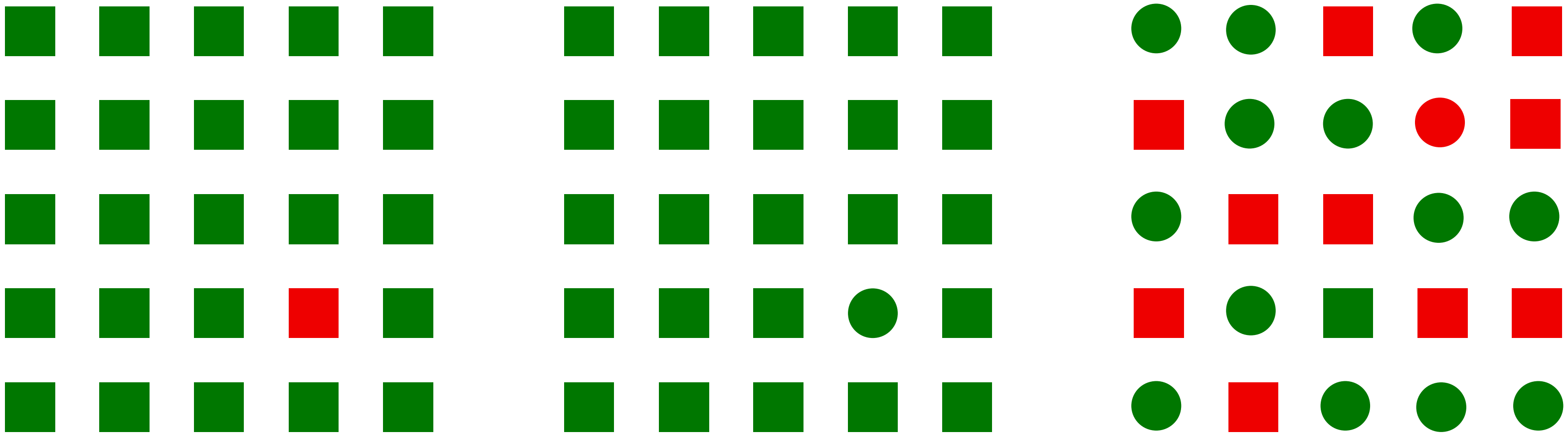
- Detection of Conflict in Probabilities
- Utility of Responses



OREGON HEALTH & SCIENCE UNIVERSITY

Human is not Perfect: Disjunction of Features

Search for Color and Shape



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

The Ultimate Goal

- Incongruence detection is the basic component of humor

- Robot that can tell jokes
- Robot that can laugh at good jokes
- Robot that will laugh at my jokes

Acknowledgements

- Colleagues and partners in DIRAC

- European Commission Funding of DIRAC
- NIH
- DARPA

OREGON HEALTH & SCIENCE UNIVERSITY

Thank You

END

OREGON HEALTH & SCIENCE UNIVERSITY