



# Hierarchical Image Classification over Concept Ontology

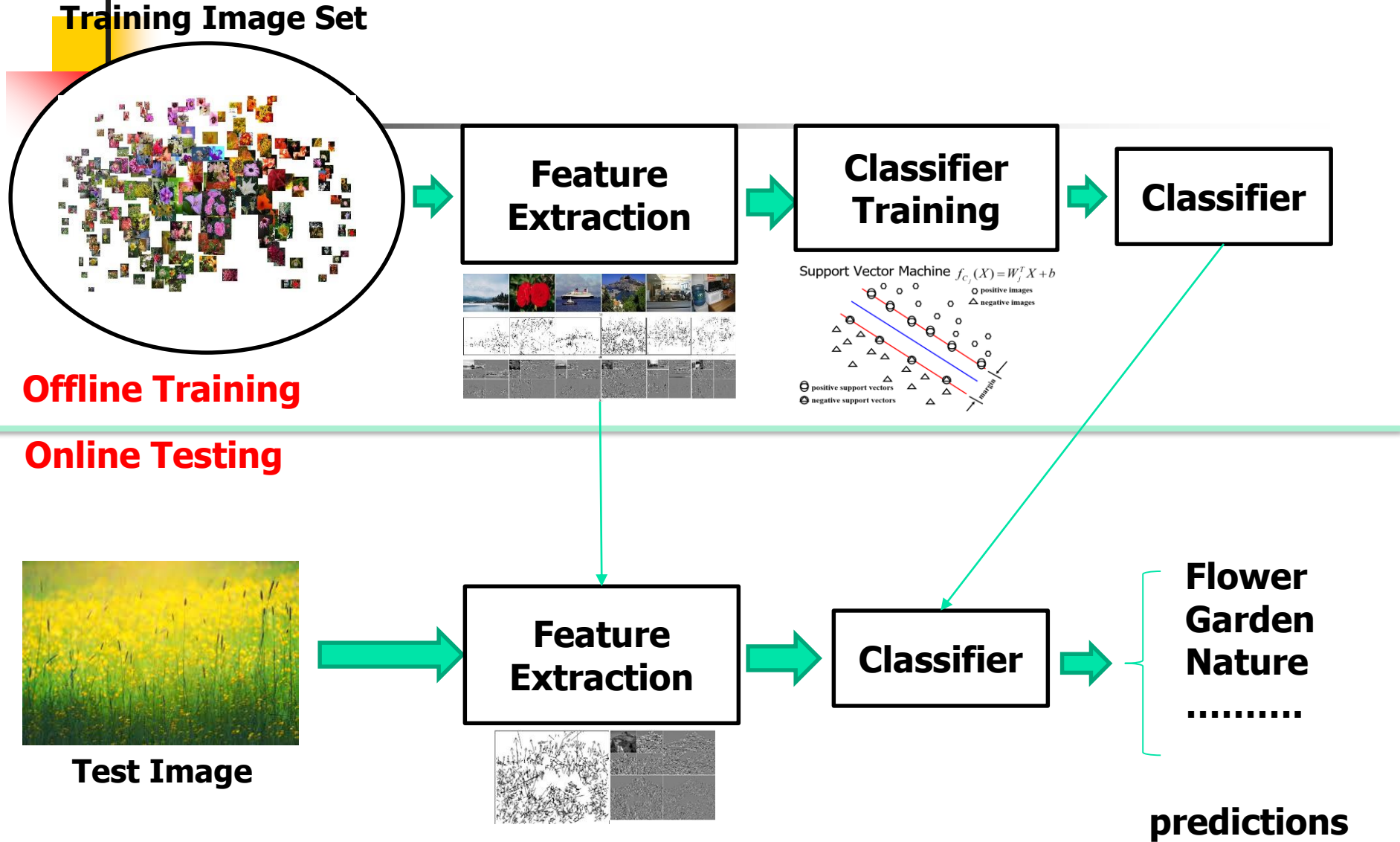
---

**Jianping Fan**  
**Dept of Computer Science**  
**UNC-Charlotte**

**Course Website:**

**<http://webpages.uncc.edu/jfan/itcs5152.html>**

# Pipeline for Traditional Image Classification System





# Feature Extraction

---

- Image-based approach
- Grid-based approach
- Object-based approach
- Bag-of-Visual-Word
- Deep Networks

# Feature Extraction

## Object-Based Approach

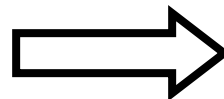
Input Image



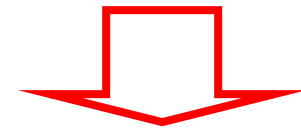
Salient Objects



Color histogram, Tamura texture,  
Locations .....



**Visual Features**

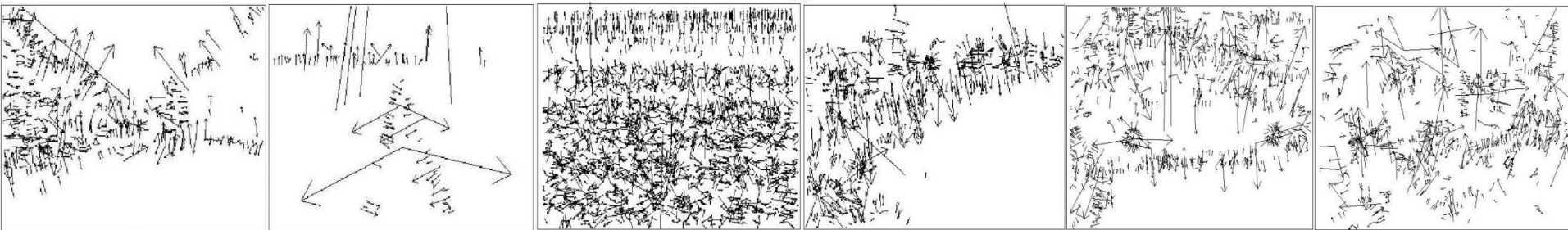


# Feature Extraction

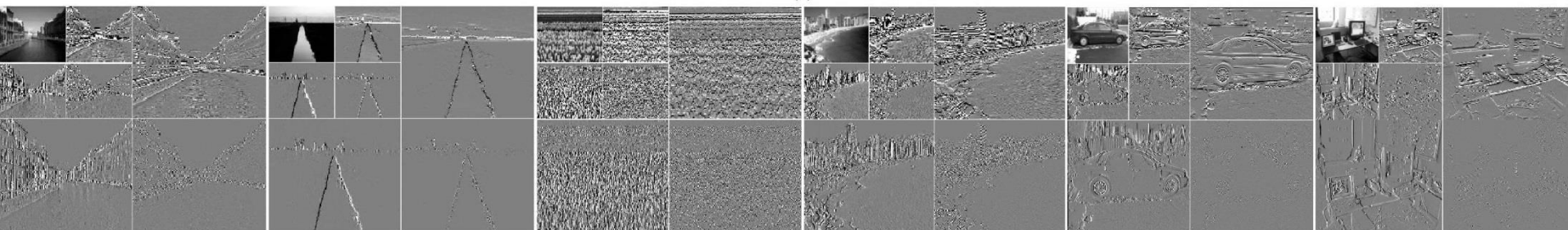
## ■ Image-Based Approach



(a)



(b)



(c)



# Feature Extraction

## ■ Grid-Based Approach



















# Feature Extraction

## ■ Bag-of-Visual-Word Approach

Examples for visual words

Airplanes		
Motorbikes		
Faces		
Wild Cats		
Leaves		
People		
Bikes		



# Image Representation

---

## Salient Objects

Color histogram

Tamura Texture

Shape

⋮

## Images

Color  
histogram

Wavelet

Texture

histogram

⋮





# Image Representation

---

## Bag-of-Visual-Word

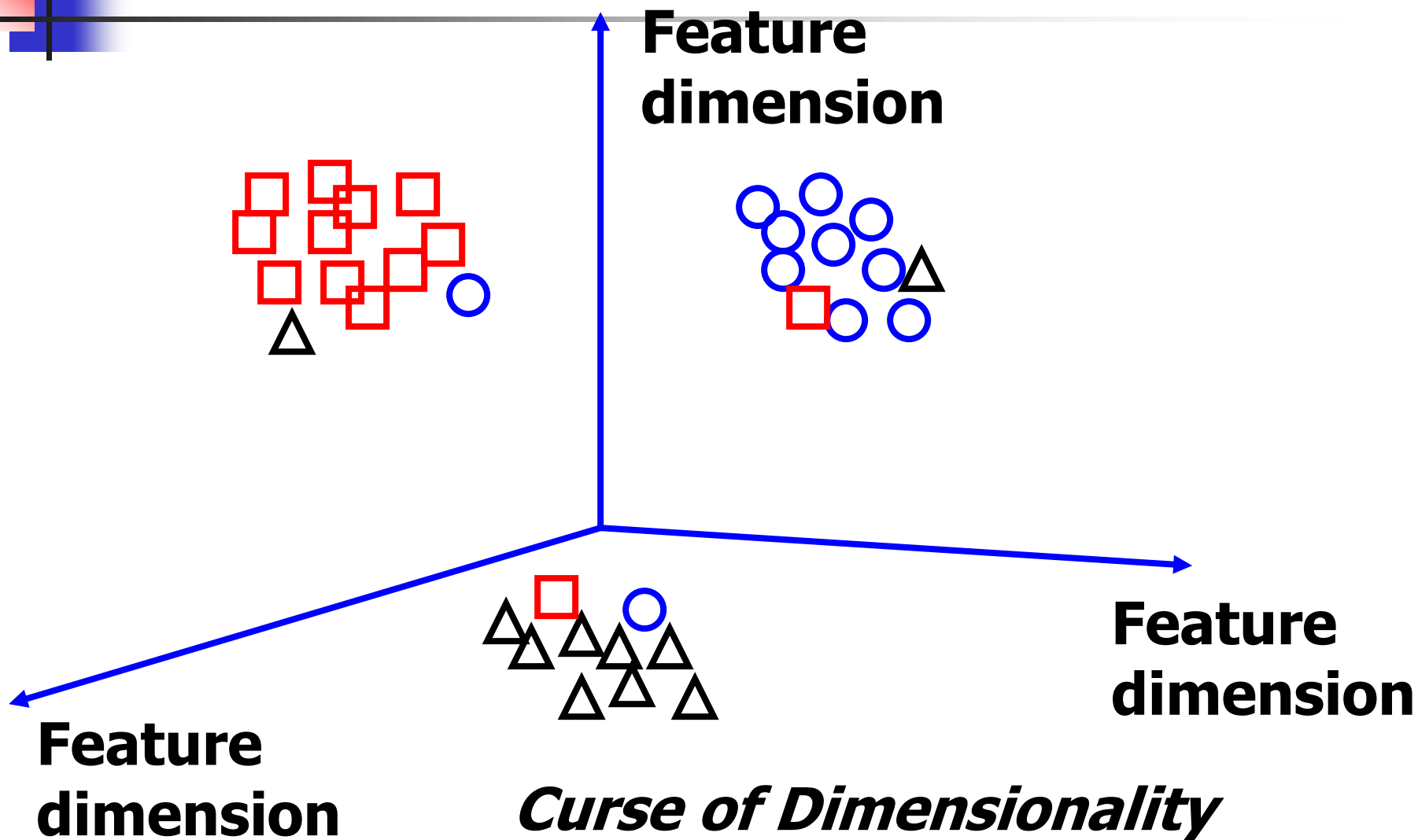
Histogram of  
Visual Words

## Image Grids

Color  
histogram  
Wavelet  
Texture  
histogram

⋮

# Feature-Based Image Representation

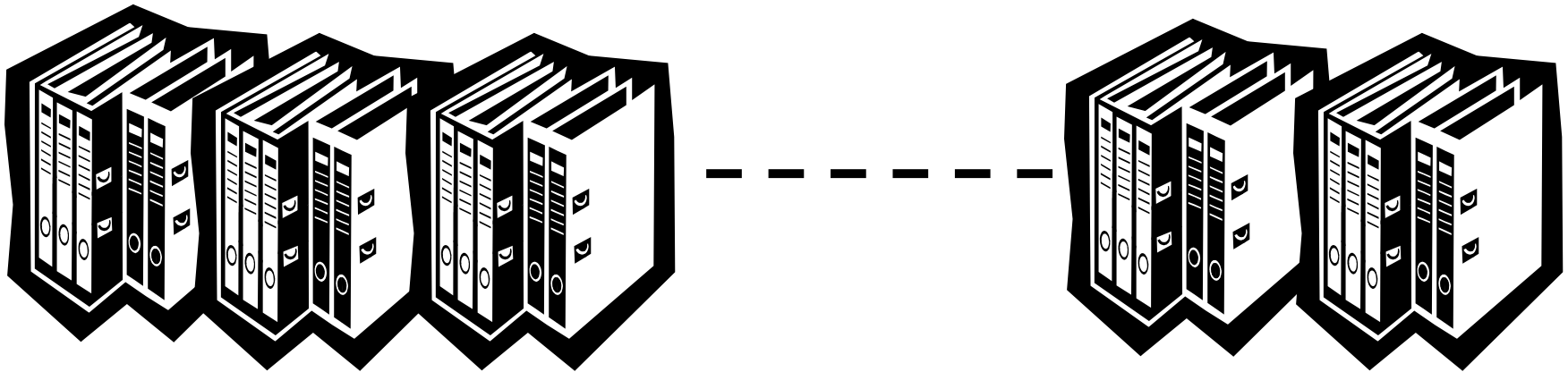




# Organization of Large-Scale Categories

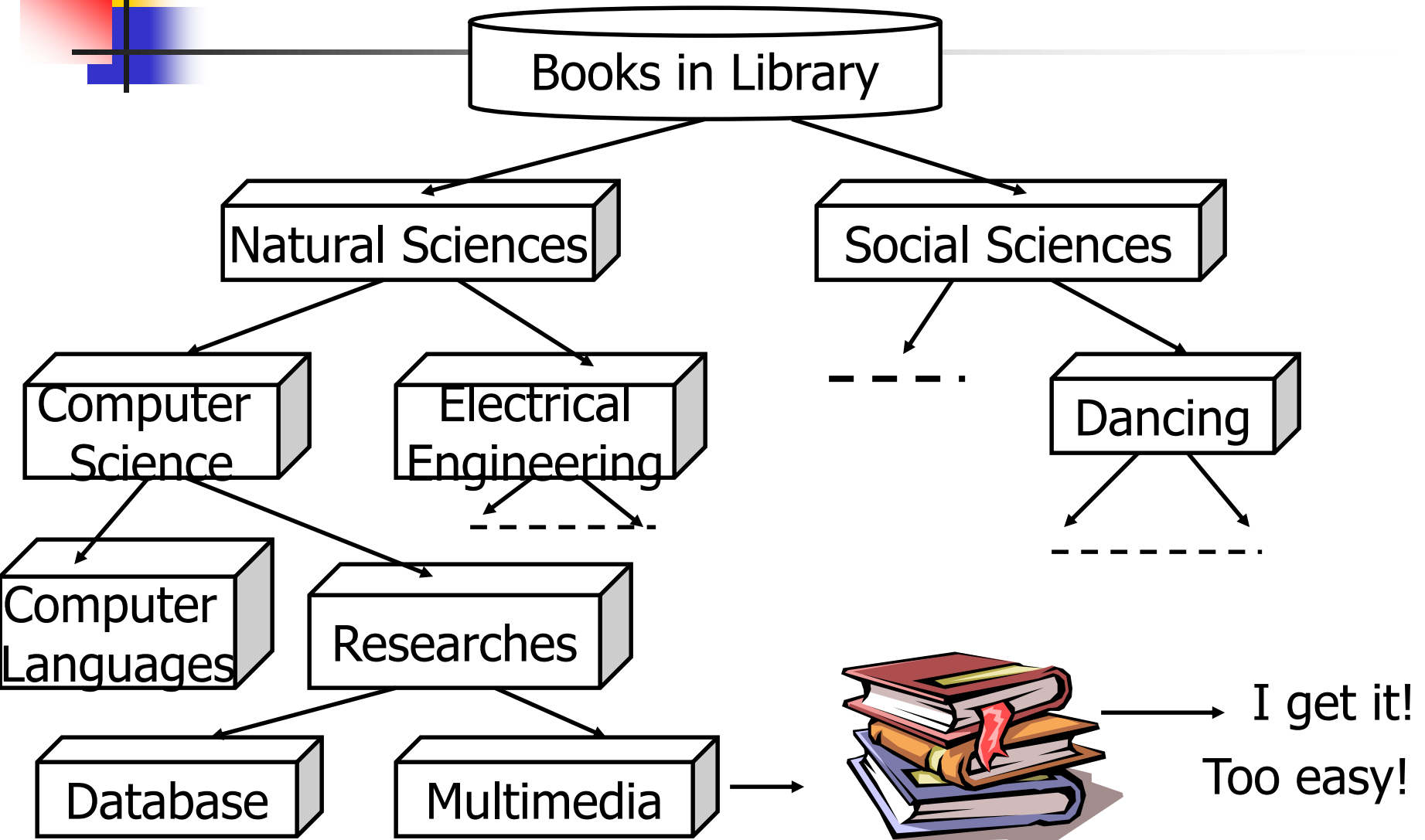
---

**Library:** 12,000,000 books





# Organization of Large-Scale Categories





# Organization of Large-Scale Categories

---

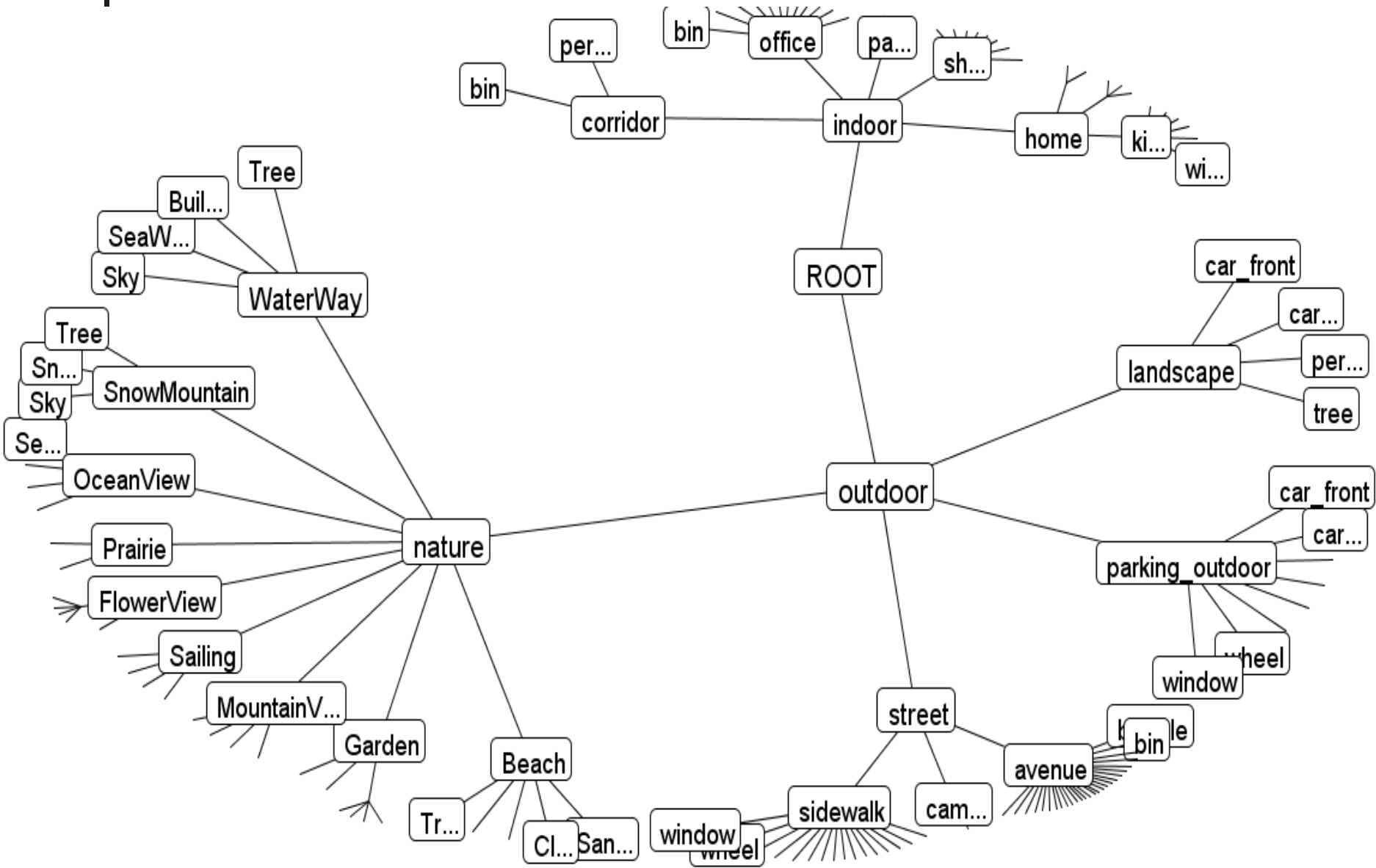
- **What is the solution?**

**Let's go back to principle!**

**Concept Hierarchy or Ontology**

# Hierarchical Concept Organization

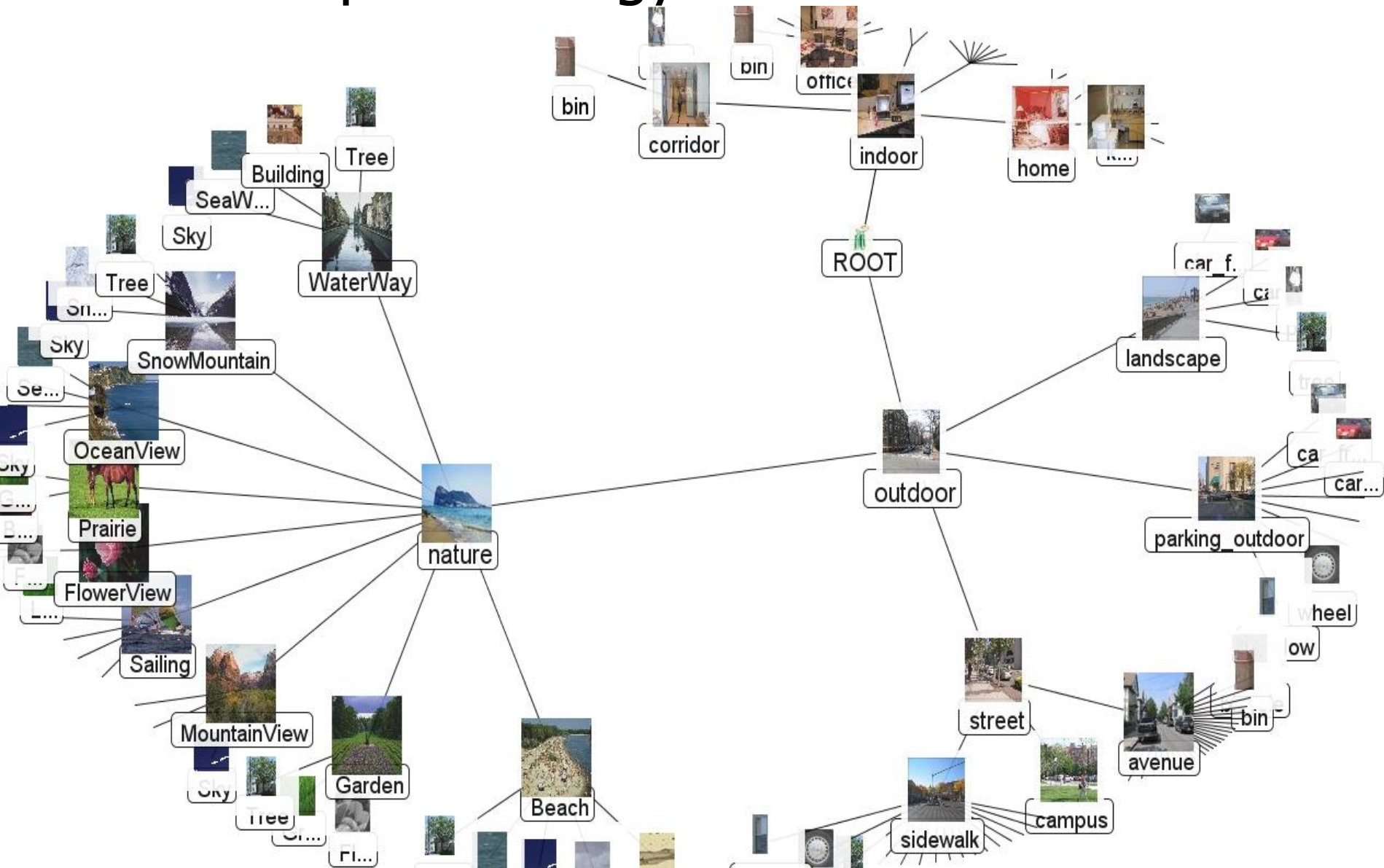
## ■ Concept Ontology



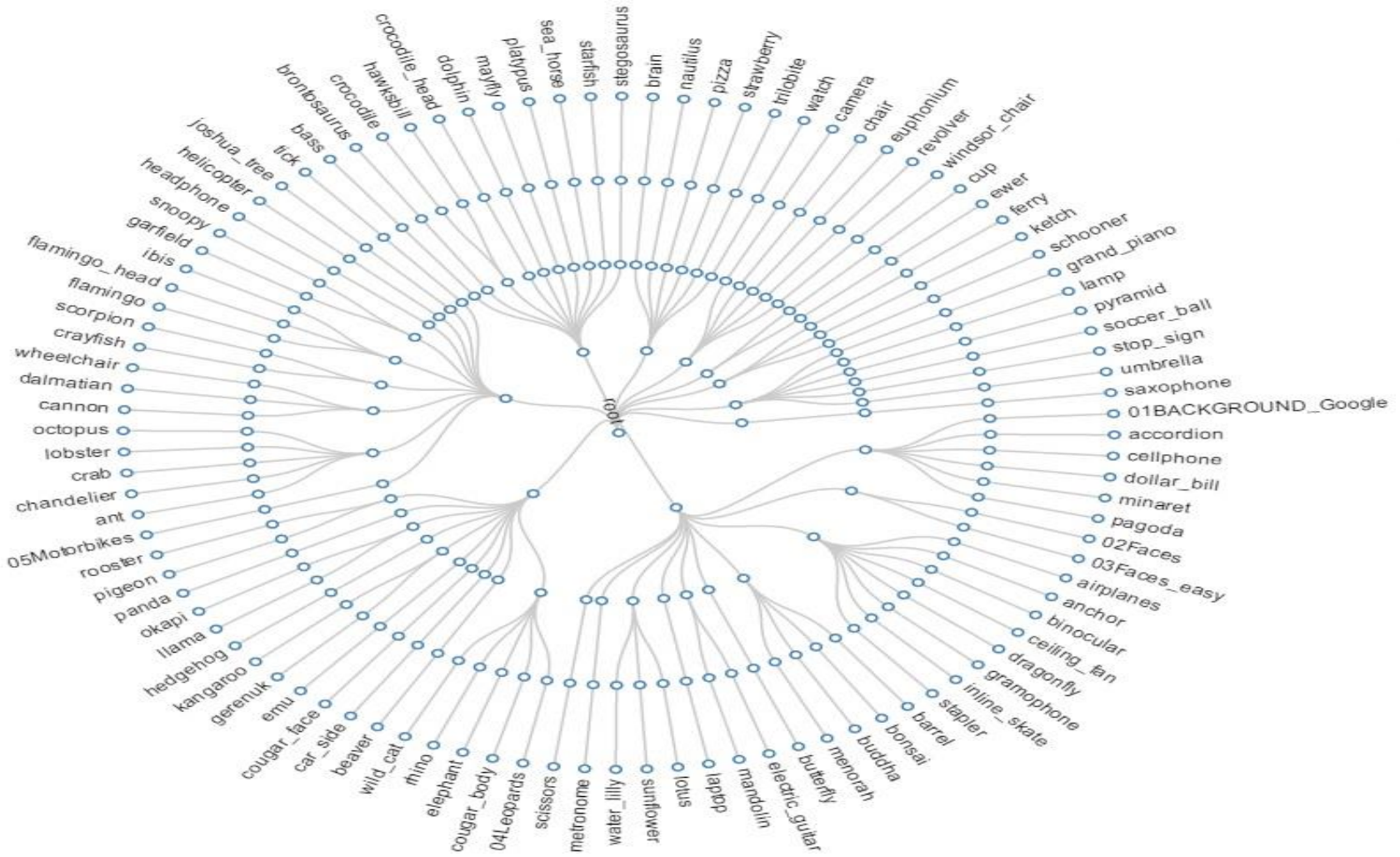


# Hierarchical Concept Organization

## ■ Concept Ontology

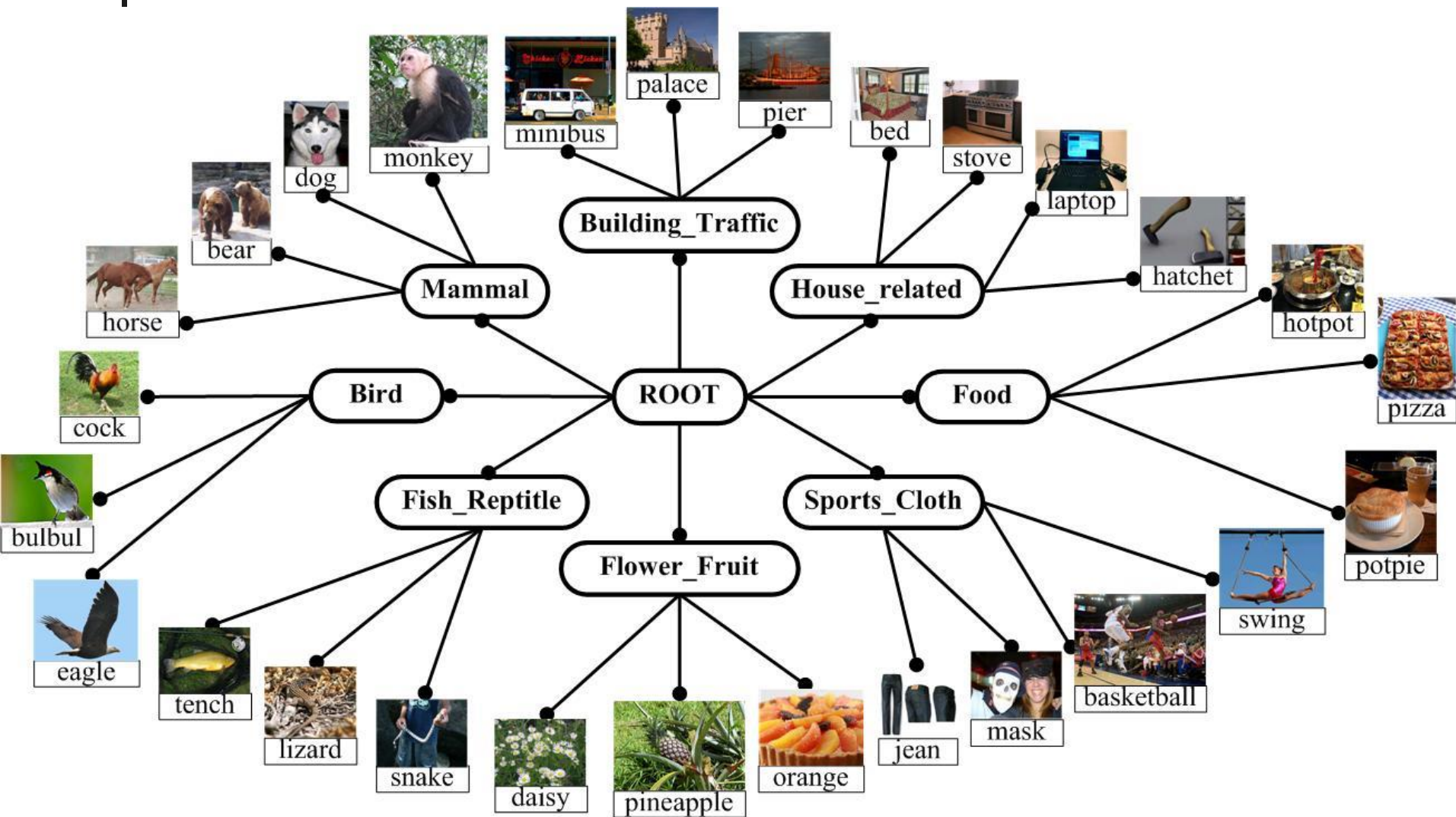


# Hierarchical Concept Organization



**CalTech101**

# Hierarchical Concept Organization



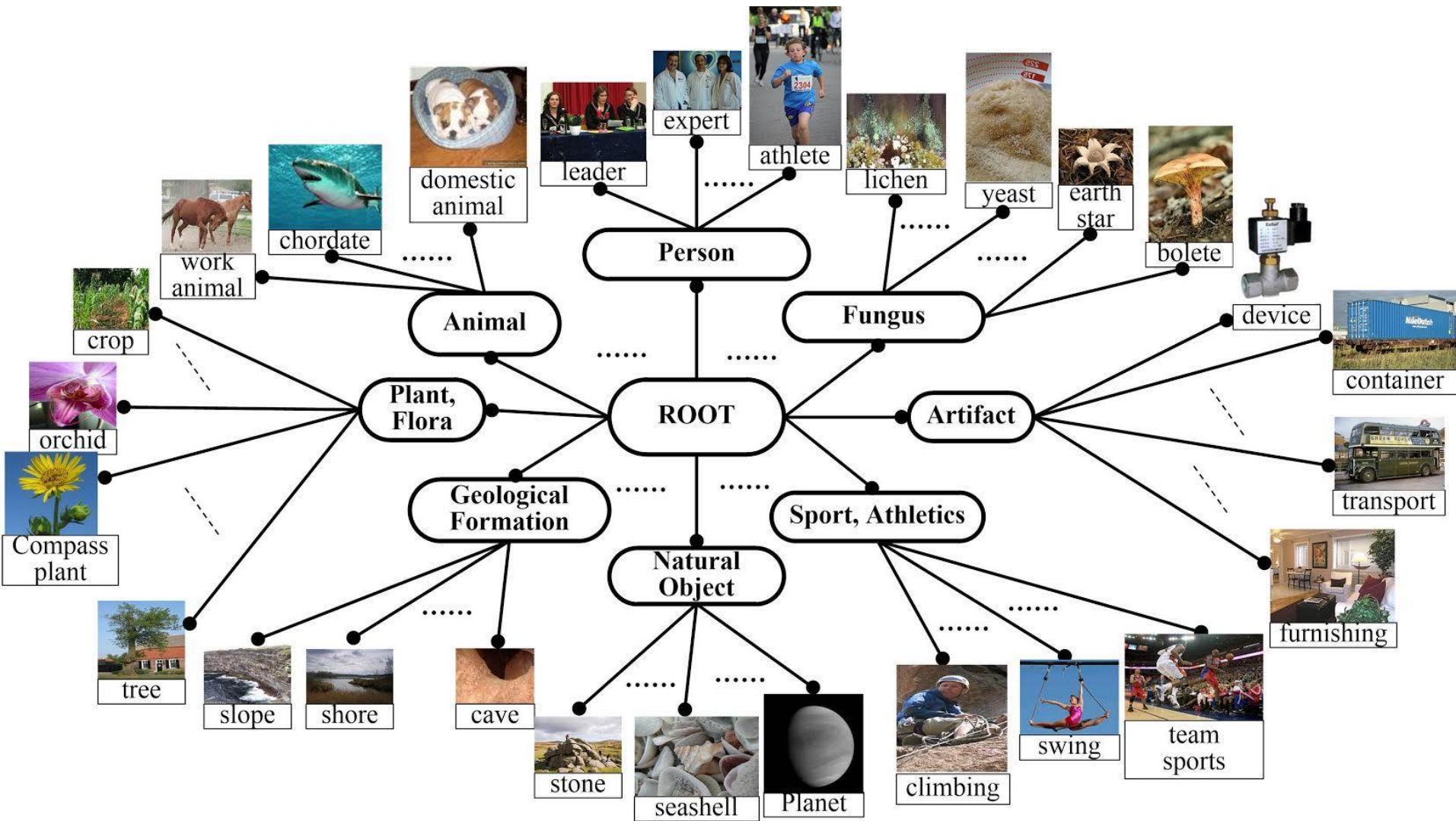
**Two-Layer Ontology for ImageNet1K**



# Hierarchical Concept Organization

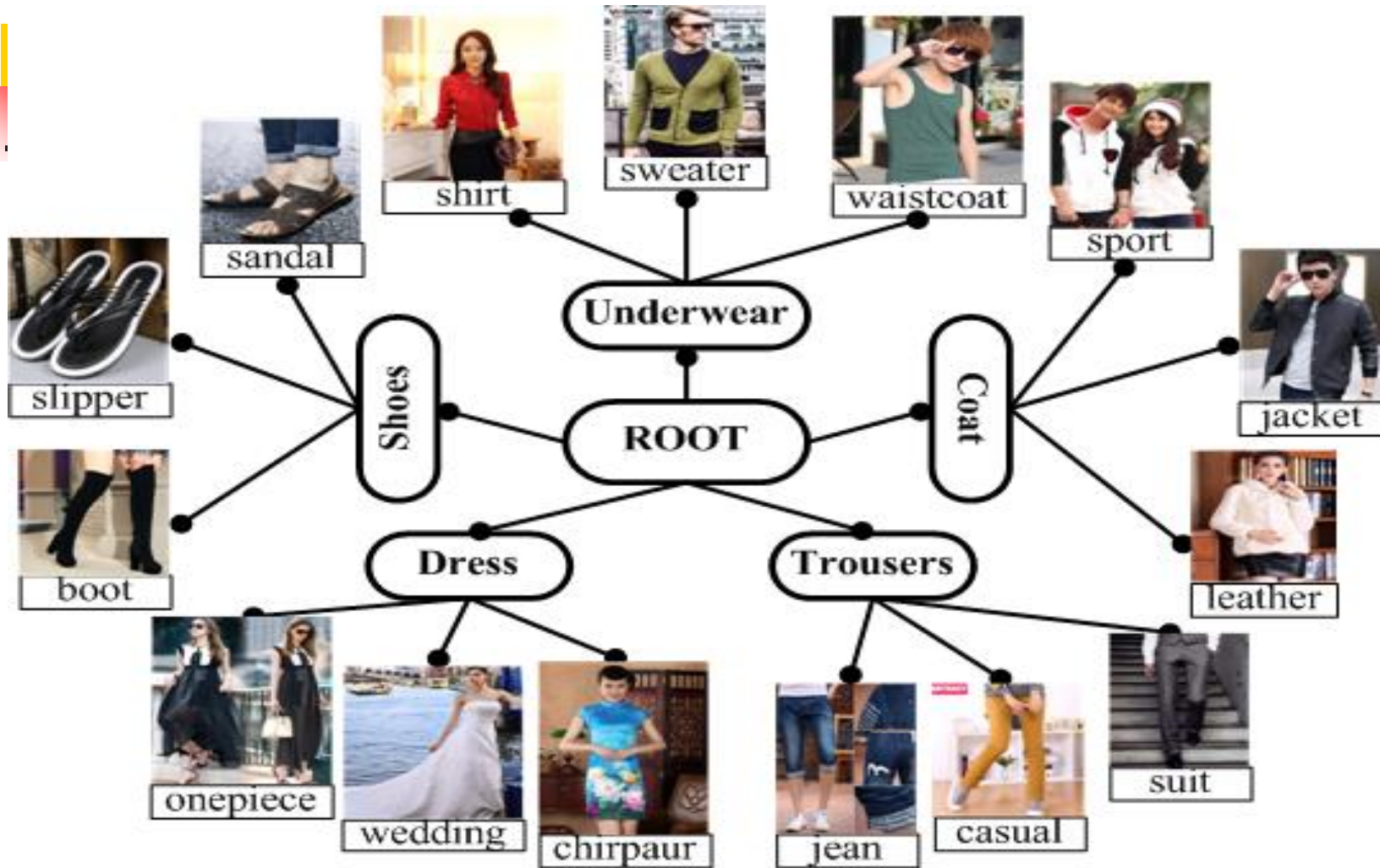


# Hierarchical Concept Organization



**Two-Layer Ontology for ImageNet10K**

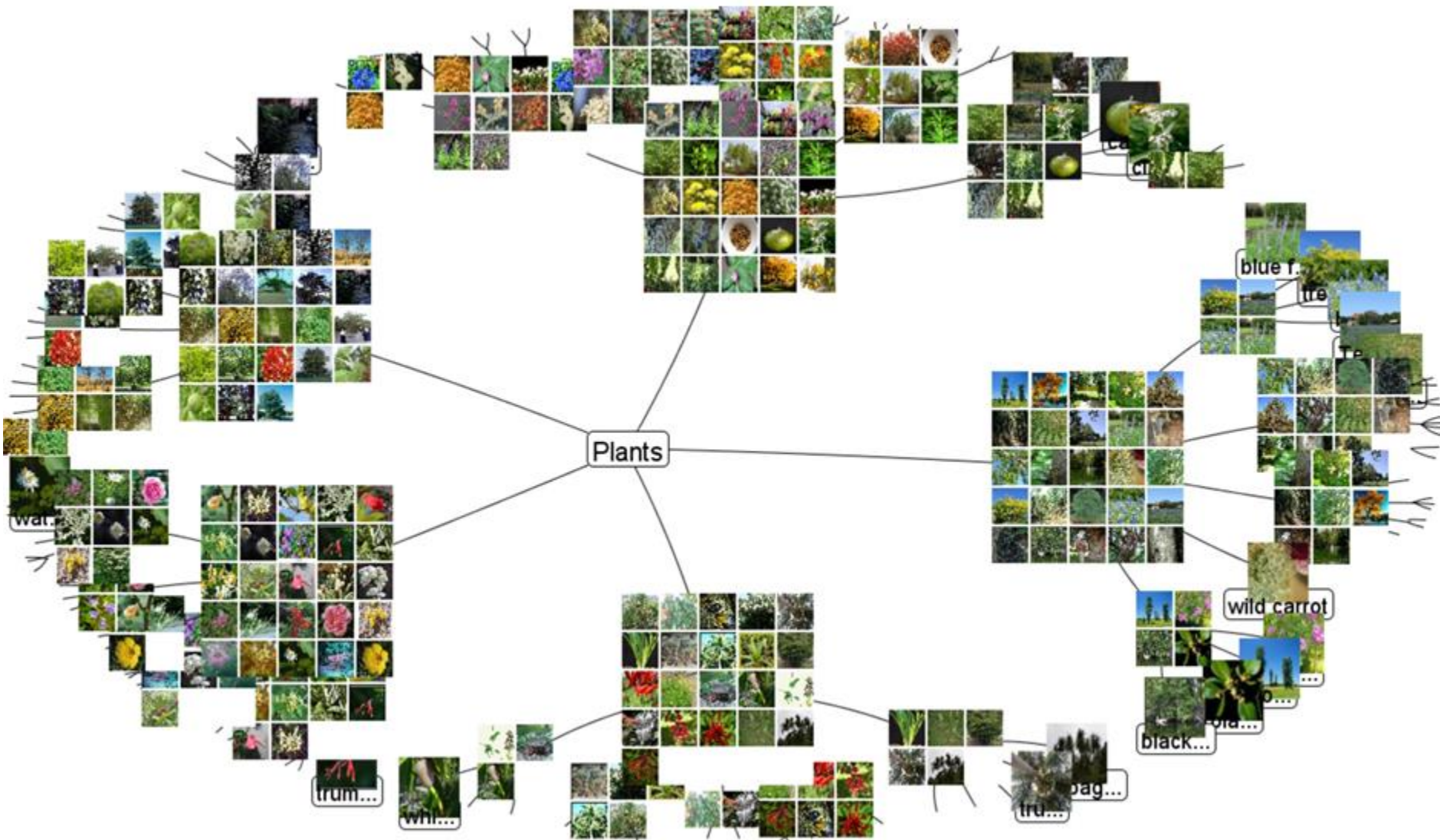
# Hierarchical Concept Organization



**Two-Layer Ontology for Taobao Products**

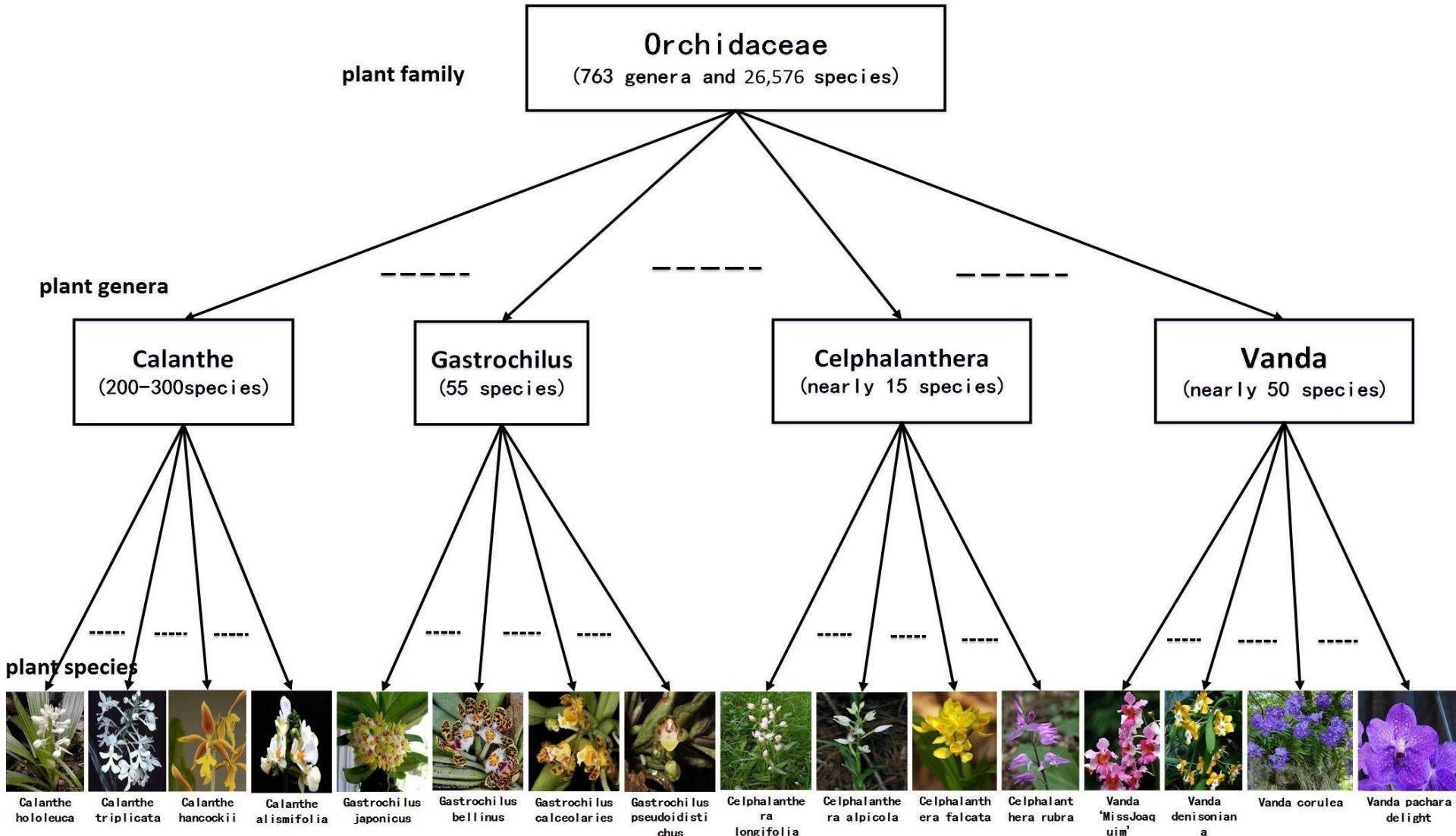


# Hierarchical Concept Organization



**Plant Ontology**

# Hierarchical Concept Organization



**Two-Layer Ontology for Orchidaceae**





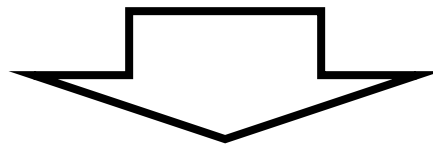
# Hierarchical Concept Organization

---

- **Multi-Modal Features**

- **Concept Ontology**

- 1. How to integrate multiple multi-modal features for classifier training?**
- 2. How to support hierarchical classifier training over concept ontology?**



**Multi-Level Image Annotation:  
Annotating Images at Different Semantic Levels**

# Classifier Training for Atomic Image Concepts

Atomic Image Concept

**Beach**

Different Patterns  
of Co-Apearances  
of Salient Objects

**Water & Sky**

**Water & Sand**

**Water, Sand, Sky, ...**

Feature Subsets

**Feature  
Subset 1**

**Feature  
Subset 2**

**Feature  
Subset 9**

$$M = \sum_{i=2}^n C_n^i = 2^n - n - 1$$

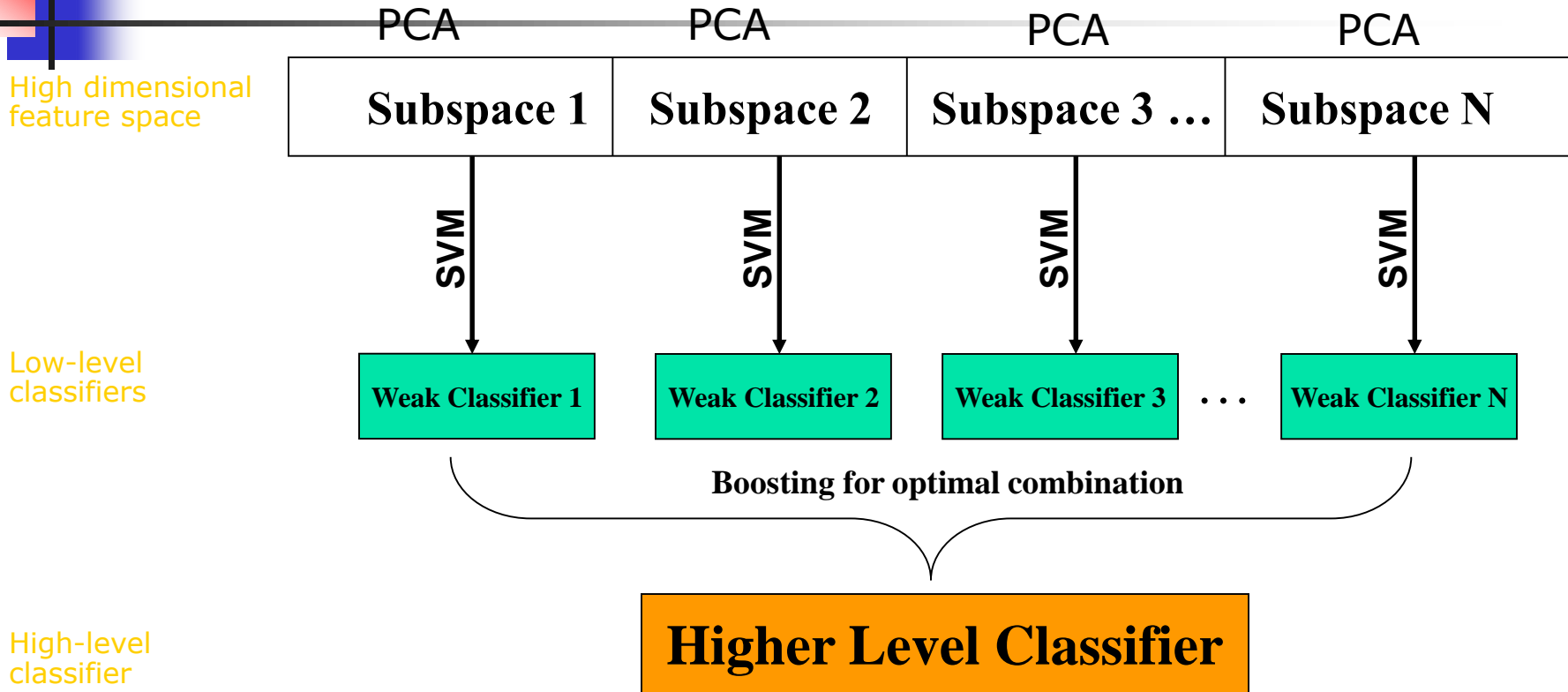


# Classifier Training for Atomic Image Concepts

---

- Curse of Dimensionality
  - # samples needed increase with # dimensions (generally exponentially) .
  - Human labeling is expensive
  - Some features are redundant
- Proposal
  - **Joint SVM boosting and feature selection**

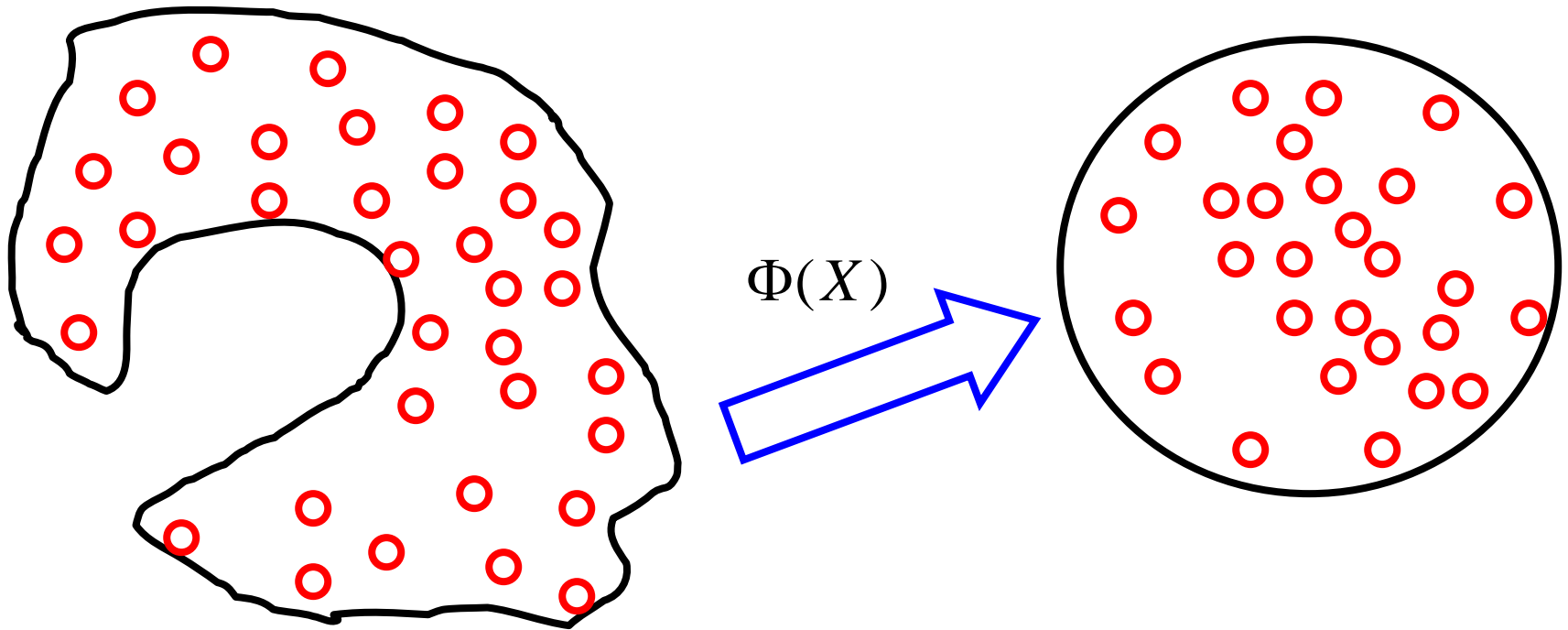
# Boosting SVM Classifier Training



- Less training samples due to dimension reduction
- Reuse training results on low-level concepts
- More selection opportunities compared to filter and wrapper

# Classifier Training for Atomic Image Concepts

- Kernel-Based Data Warping



**Kernel Function:**  $K(X_i, X_j) = \Phi(X_i)^T \Phi(X_j)$





# Classifier Training for Atomic Image Concepts

---

- **Kernel for Color Histogram**
  - **Statistical Image Similarity**

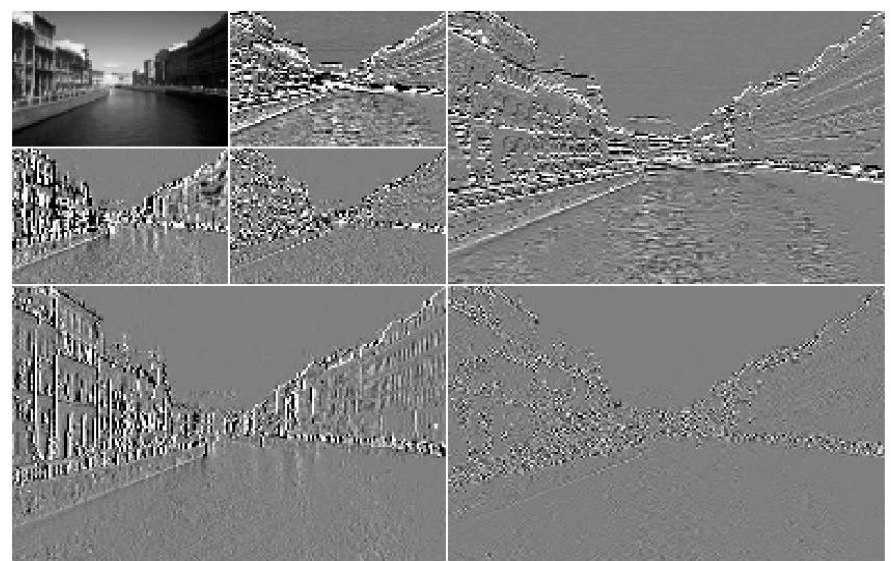
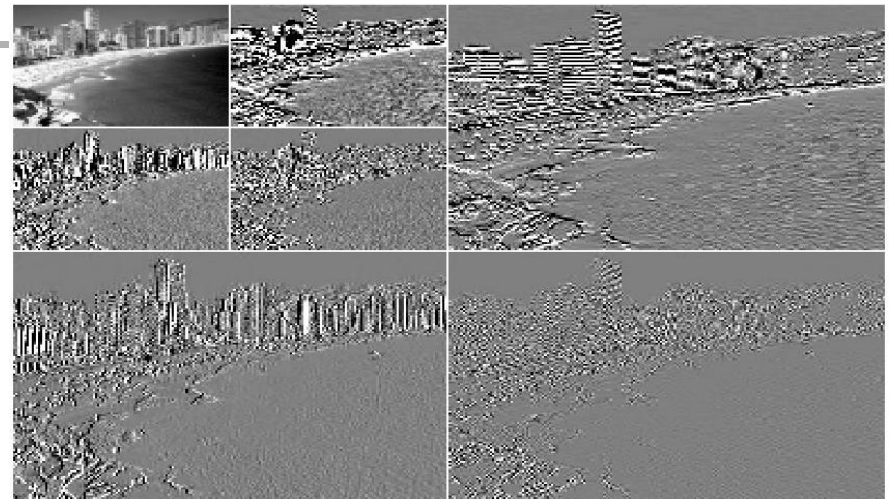
$$\chi^2(u, v) = \frac{1}{2} \sum_{i=1}^N \frac{(u_i - v_i)^2}{u_i + v_i}$$

- **Kernel**

$$K(u, v) = e^{-\chi^2(u, v) / \sigma}$$

# Classifier Training for Atomic Image Concepts

## Wavelet Filter Bank Kernel





# Classifier Training for Atomic Image Concepts

---

- **Wavelet Filter Bank Kernel**

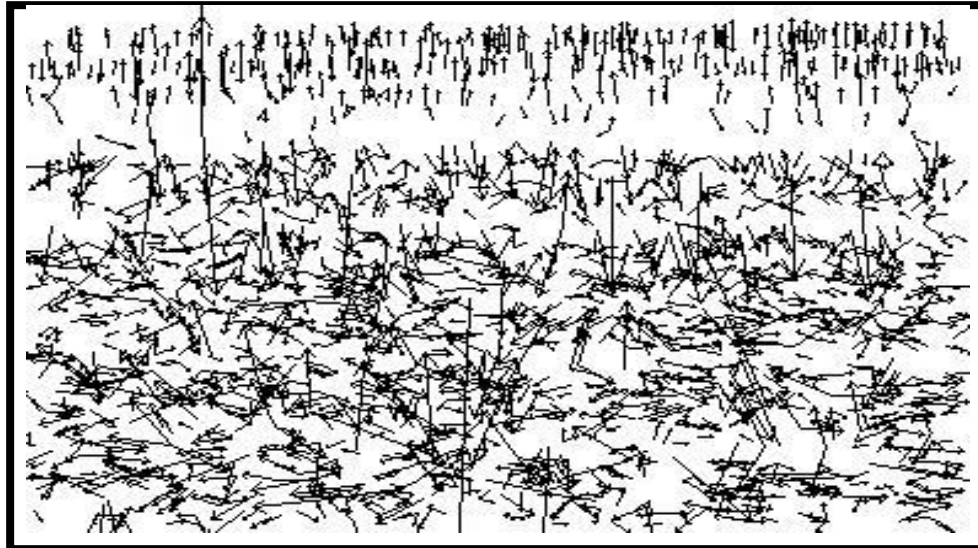
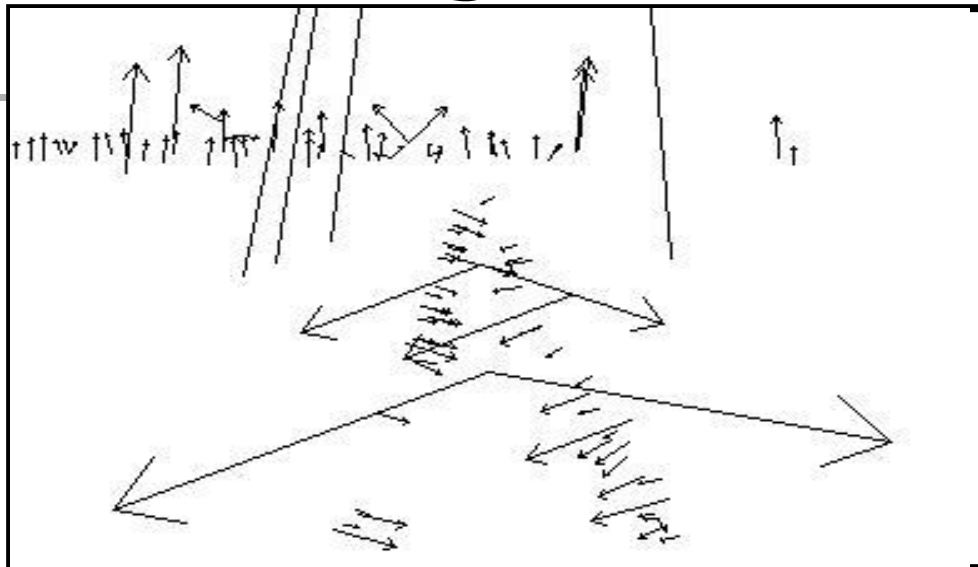
$$K(x, y) = e^{-\sum_{i=1}^n \chi_i^2 (h_i(x), h_i(y)) / \sigma_i}$$

$$= \prod_{i=1}^n e^{-\chi_i^2 (h_i(x), h_i(y)) / \sigma_i}$$



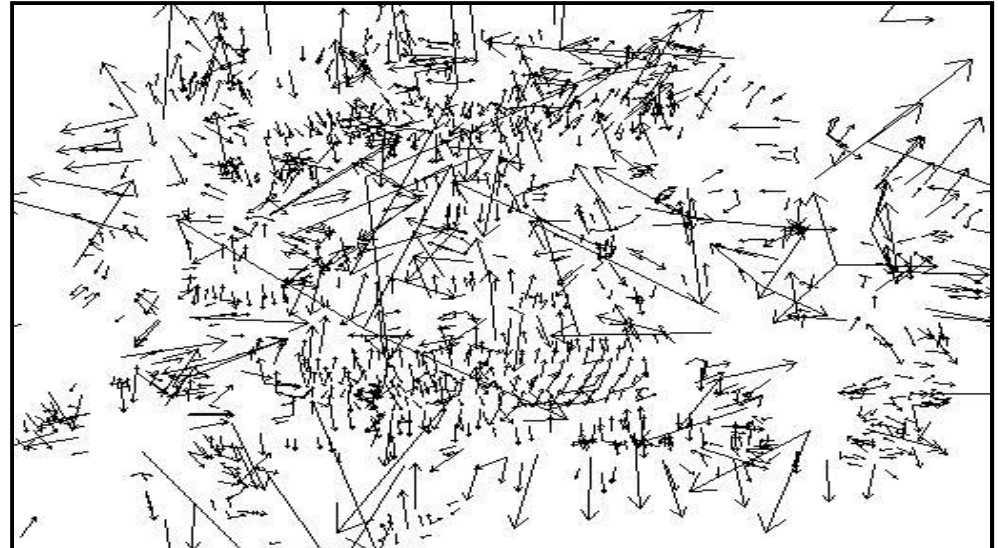
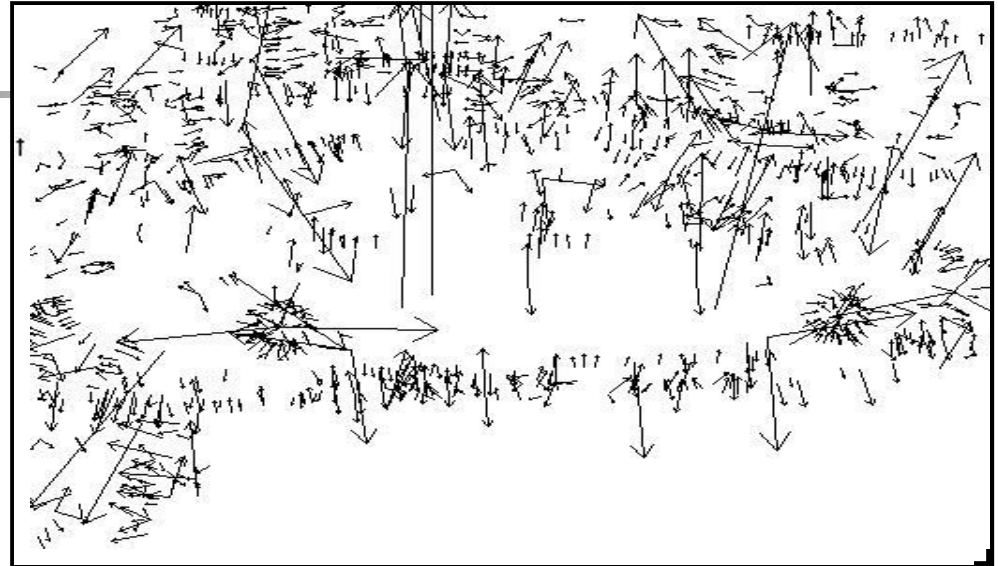
# Classifier Training for Atomic Image Concepts

- **Interest Point Matching Kernel**



# Classifier Training for Atomic Image Concepts

## ■ Interest Point Matching Kernel







# Classifier Training for Atomic Image Concepts

---

- **Multiple Kernel Learning**

$$\hat{K}(x, y) = \sum_{i=1}^{\kappa} \alpha_i K_i(x, y) \quad \sum_{i=1}^{\kappa} \alpha_i = 1$$

- **SVM Image Classifier**

$$f(X) = \text{sign} \left( g \left( \sum_{l=1}^M \beta_l Y_l \hat{K}(X_l, X) + b \right) \right)$$



# Classifier Training for Atomic Image Concepts

---

## ■ Dual Problem

$$\min \frac{1}{2} \left( \sum_{h=1}^K \|w_h\|_2 \right)^2 + c \sum_{l=1}^M \xi_l$$

**Subject to:**

$$\forall_{l=1}^M : \xi_l \geq 0, Y_i \left( \sum_{h=1}^K \left\langle w_k, \Phi(X_l) \right\rangle + b \right) \geq 1 - \xi_l$$

# Classifier Training for Atomic Image Concepts



Original Image

Automatic Salient



Object Detection



Salient Objects

Semantic Image



Classification



Semantic Image  
Concept: Garden

# Classifier Training for Atomic Image Concepts

## ■ Some Results

Beach Scene

**Image Semantic Representation**

View  
Original Image  ShowBoundary  ShowSalientObject

Salient Image

Image Scene **Beach**

The beach scene analysis consists of three panels. The first panel, 'Original Image', shows a photograph of a beach with labels for 'Sky', 'Building', 'Unknown', 'SeaWater', 'SandField', 'Grass', and another 'Unknown'. The second panel, 'Salient Image', is a color-coded map where different regions are highlighted in blue, brown, yellow, cyan, and green. The third panel, 'Image Scene', is a similar color-coded map but with the scene identified as 'Beach' in yellow text. The labels in this panel are 'Sky', 'Building', 'Unknown', 'SeaWater', 'SandField', 'Grass', and 'Unknown'.

Garden Scene

**Image Semantic Representation**

View  
Original Image  ShowBoundary  ShowSalientObject

Salient Image

Image Scene **Garden**

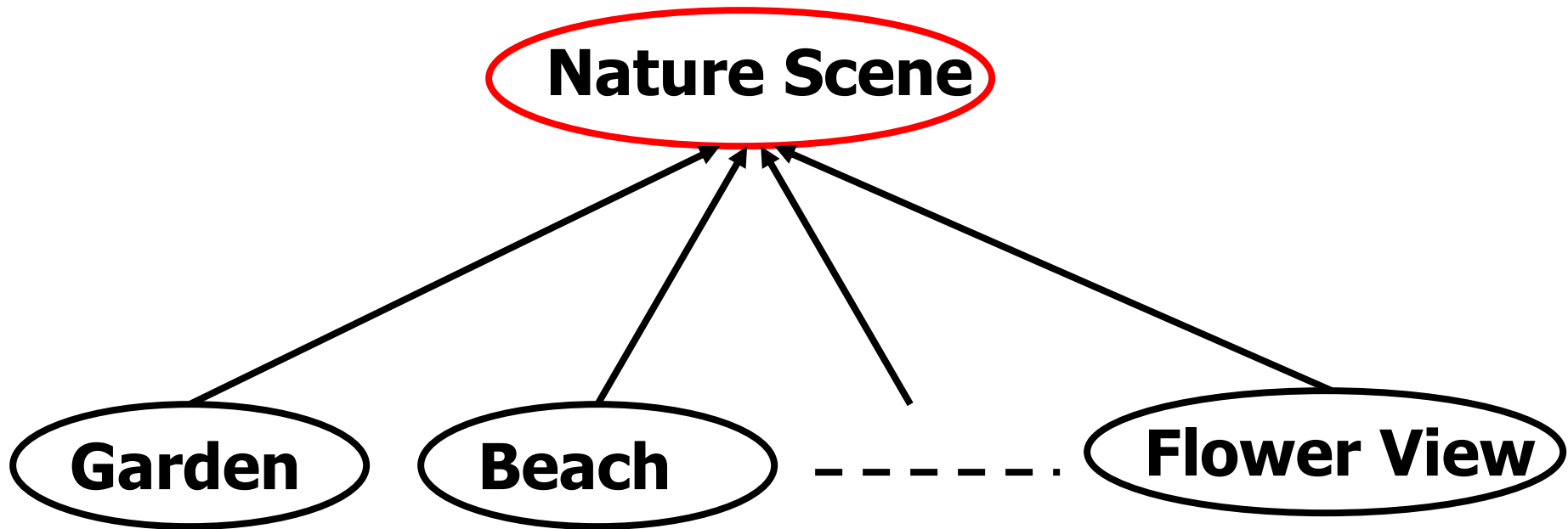
The garden scene analysis consists of three panels. The first panel, 'Original Image', shows a photograph of a garden with labels for 'Sky', 'Unknown', 'Tree', 'Grass', 'Unknown', 'PurpleFlower', and another 'Unknown'. The second panel, 'Salient Image', is a color-coded map with regions in blue, green, and purple. The third panel, 'Image Scene', is a similar color-coded map with the scene identified as 'Garden' in green text. The labels in this panel are 'Sky', 'Unknown', 'Tree', 'Grass', 'Unknown', 'PurpleFlower', and 'Unknown'.



# High-Level Image Concept Modeling

---

- Inter-Concept Similarity Modeling



**Nature Scene: Larger Hypothesis Space & Large Variations of Visual Properties!**

**Garden, Beach, Flower view: Different but share common visual properties!**





# Classifier Training for High-Level Image Concepts

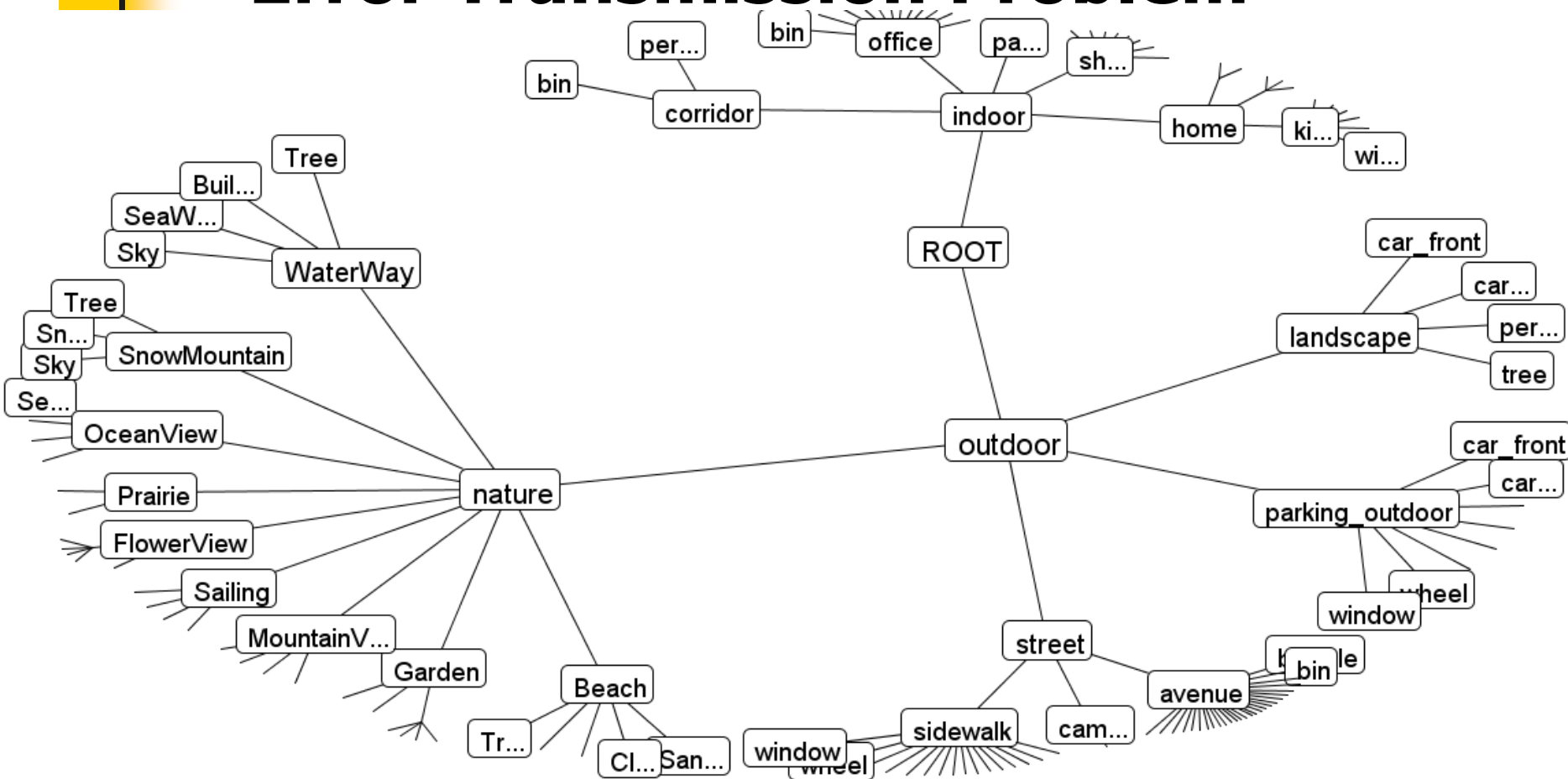
---

- **Challenging Problems**

- Error Transmission Problems
- Training Cost Issue
- Knowledge Transferability and Task Relatedness Exploitation

# Classifier Training for High-Level Image Concepts

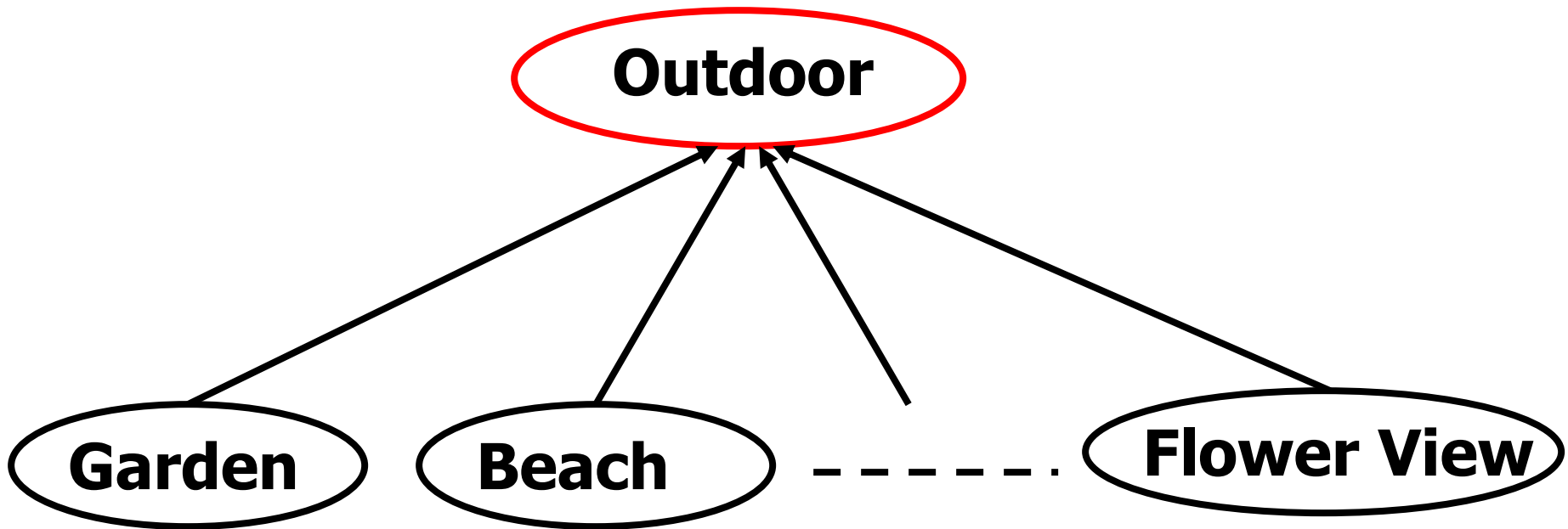
## ■ ■ Error Transmission Problem



**The classifiers for low-level image concepts cannot recover the errors for the classifiers of high-level image concepts!**

# Classifier Training for High-Level Image Concepts

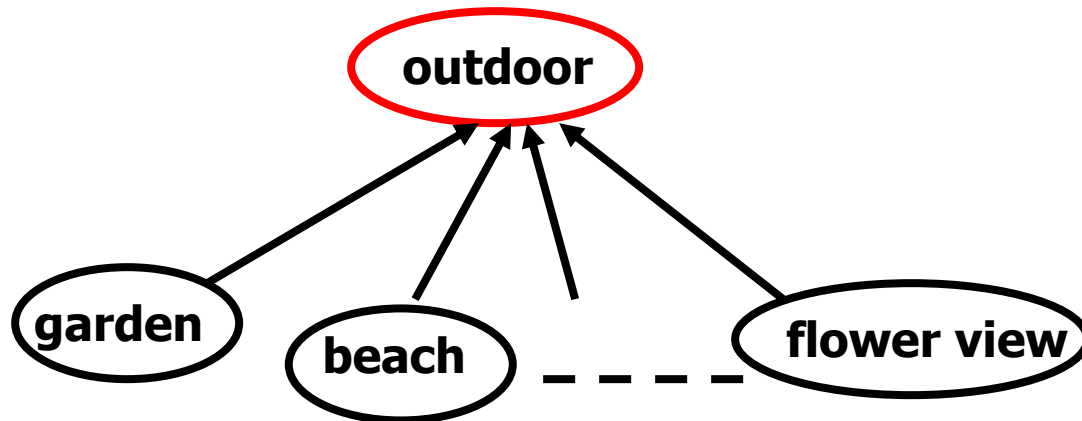
- **Error Transmission Problem**



**Errors for the classifiers of atomic image concepts may be transmitted to the classifiers for the high-level image concepts!**

# Classifier Training for High-Level Image Concepts

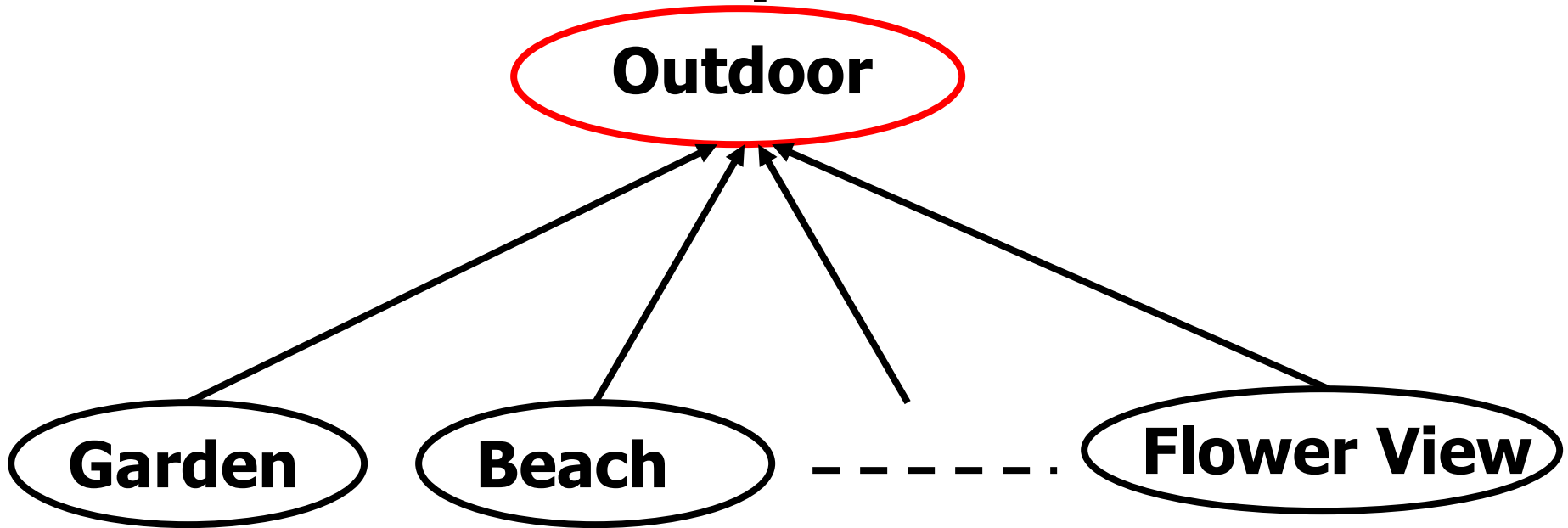
- **Training Cost Issue**
  - Multiple Hypotheses



- Large Diversity of Contents

# Classifier Training for High-Level Image Concepts

- **Knowledge Transferability & Task Relatedness Exploitation**



**They are different but strongly related!**





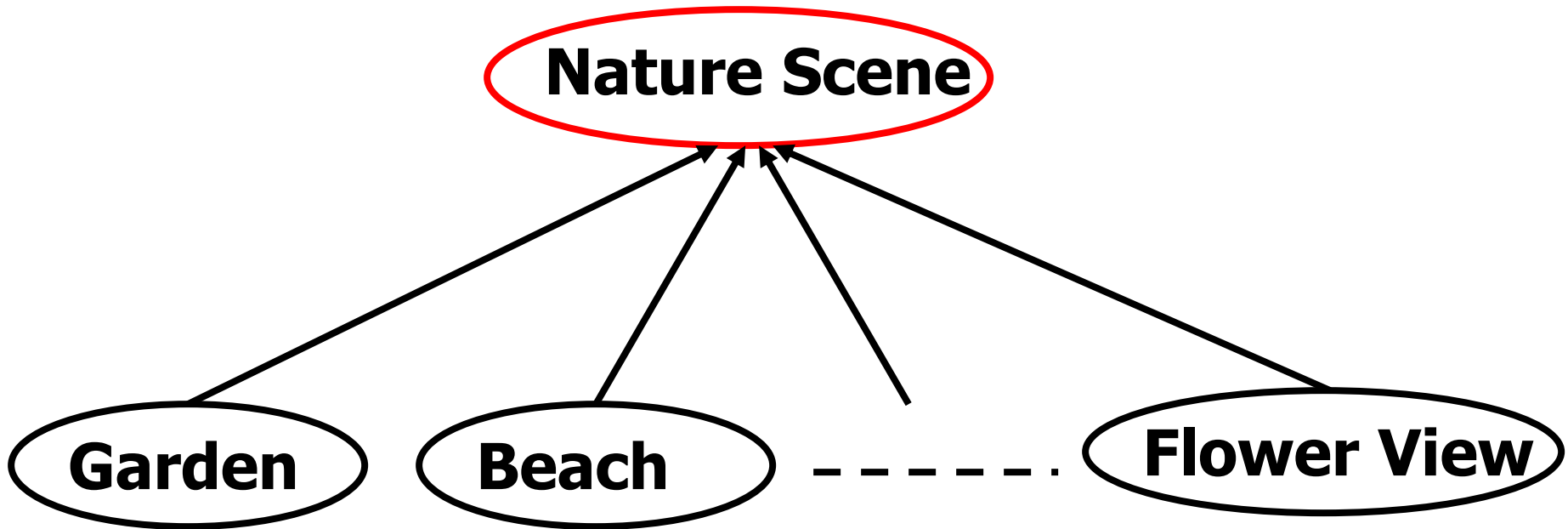
# Classifier Training for High-Level Image Concepts

---

- Multi-Task Learning
  - **Which tasks are strongly related?**
  - **How to quantify the task relatedness?**
  - **How to integrate such task relatedness for training large-scale related image classifiers?**

# Classifier Training for High-Level Image Concepts

- Related Learning Tasks

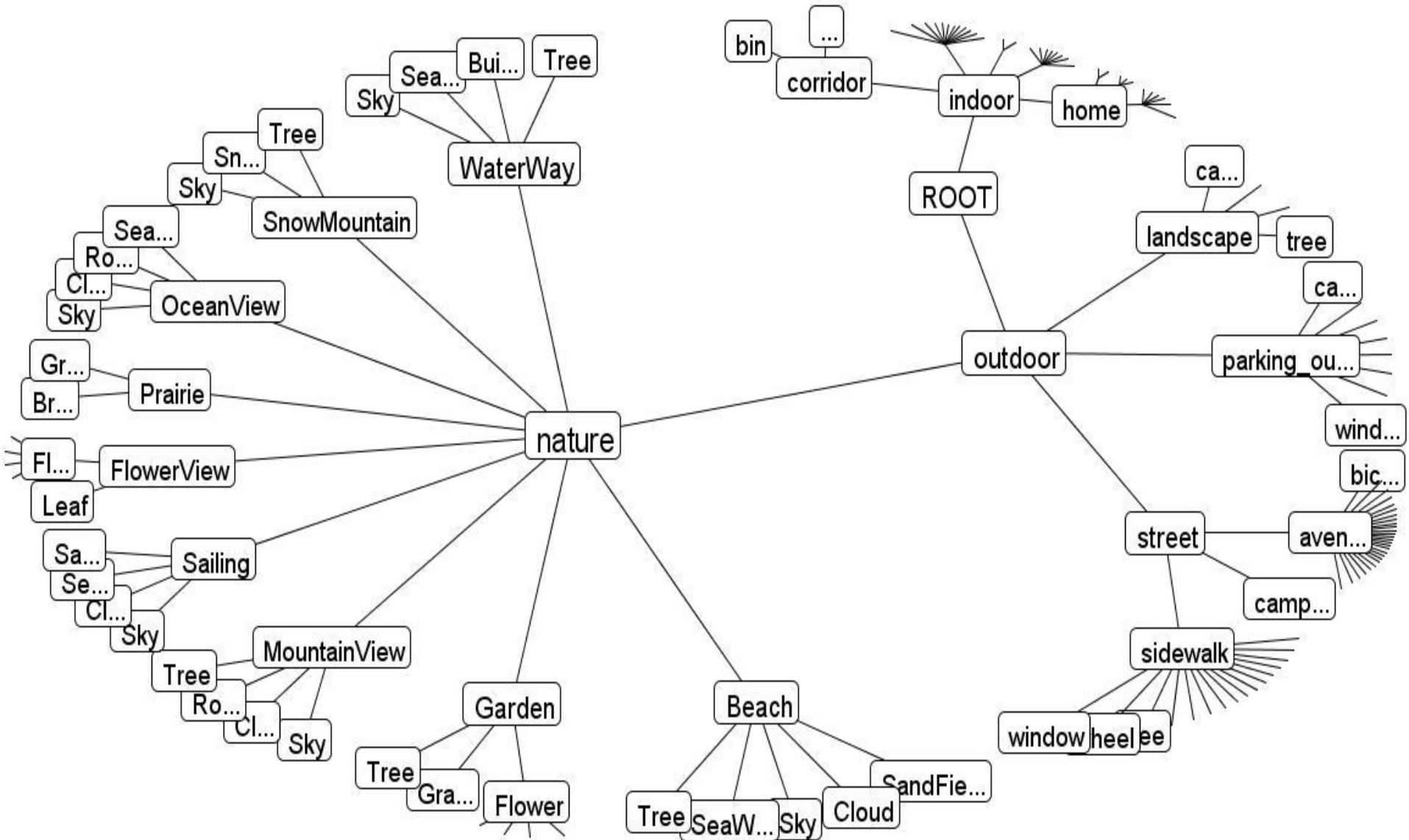


**They are different but strongly related!**

**Concept Ontology can provide a good environment for multi-task learning!**

# Classifier Training for High-Level Image Concepts

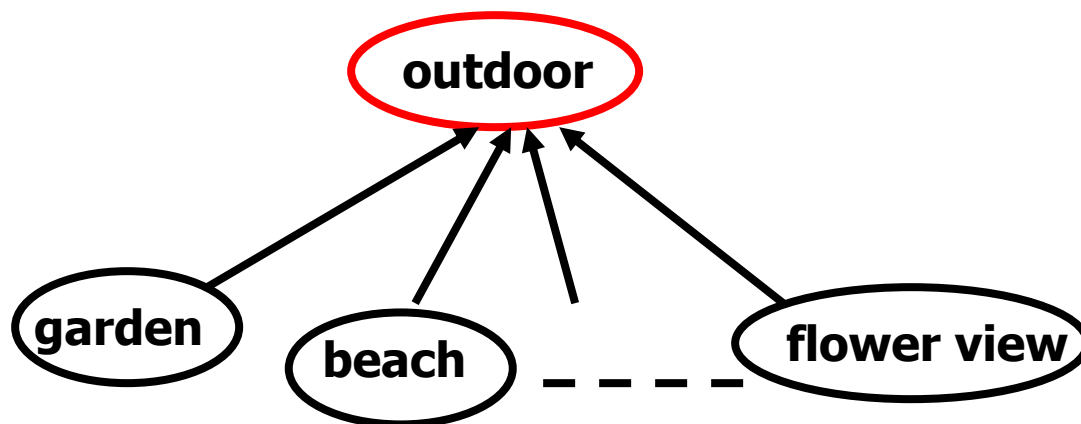
## ■ Related Learning Tasks



# Classifier Training for High-Level Image Concepts

## ■ Relatedness Modelling

$$f_{C_j}(X) = W_j^T X + b \quad W_j = W_0 + V_j$$



$W_0$ : **Common Prediction Structure**



# Classifier Training for High-Level Image Concepts

---

## ■ Joint Objective Function

$$\min \left\{ \sum_{j=1}^C \sum_{i=1}^N \xi_{ij} + \frac{\beta_1}{C} \sum_{j=1}^C \|V_j\|^2 + \beta_2 C \|W_0\|^2 \right\}$$

**Subject to:**

$$\forall_{j=1}^C \forall_{i=1}^N : Y_{ij} (W_0 + V_j) \bullet X_{ij} + b \geq 1 - \xi_{ij}$$





# Classifier Training for High-Level Image Concepts

---

## ■ Dual Problem

$$\max \left\{ \sum_{j=1}^C \sum_{i=1}^N \alpha_{ij} - \frac{1}{2} \sum_{j=1}^C \sum_{i=1}^N \sum_{h=1}^C \sum_{l=1}^N \alpha_{ih} Y_{ih} \alpha_{jl} Y_{jl} K_{jh}(X_{ih}, X_{jl}) \right\}$$

**Subject to:**

$$\forall_{i=1}^N \forall_{j=1}^C : 0 \leq \alpha_{ij} \leq C, \sum_{j=1}^C \sum_{i=1}^N \alpha_{ij} Y_{ij} = 0$$



# Classifier Training for High-Level Image Concepts

---

## ■ Biased Classifier Training

$$\min \left\{ \frac{1}{2} \|W - W_0\|^2 + \alpha \sum_{l=1}^m [1 - Y_l (W^T \bullet X_l + b)] \right\}$$

## ■ Dual Problem

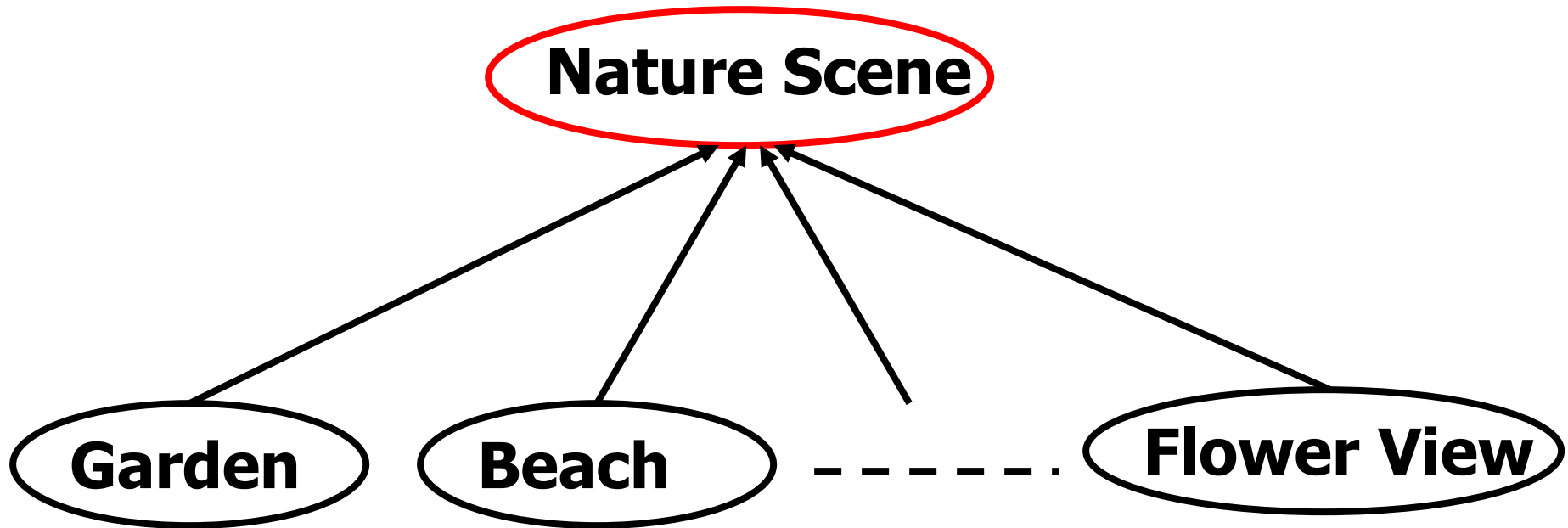
$$\min \left\{ \frac{1}{2} \sum_{l=1}^m \sum_{h=1}^m \alpha_l \alpha_h Y_l Y_h X_l^T X_h - \sum_{l=1}^m \alpha_l (1 - Y_l W_0^T X_l) \right\}$$

**Subject to:**

$$\forall_{l=1}^m : 0 \leq \alpha_l \leq C, \sum_{l=1}^m \alpha_l Y_l = 0$$

# Classifier Training for High-Level Image Concepts

- Common Prediction Structure



**Common Visual Properties**



# Classifier Training for High-Level Image Concepts

---

- **Hierarchical Boosting**

$$H_{C_k}(X) = \sum_{j=1}^{C+1} p_j(X) f_{C_j}(X)$$

$$p_j(X) = \frac{\exp(f_{C_j}(X))}{\sum_{j=1}^{C+1} \exp(f_{C_j}(X))}$$



# Classifier Training for High-Level Image Concepts

---

- **Biased Classifier for Parent Node**

$$W = W_0 + \sum_{l=1}^m \alpha_l Y_l X_l$$

$$f_{C_k}(X) = W^T X + b$$





# Classifier Training for High-Level Image Concepts

---

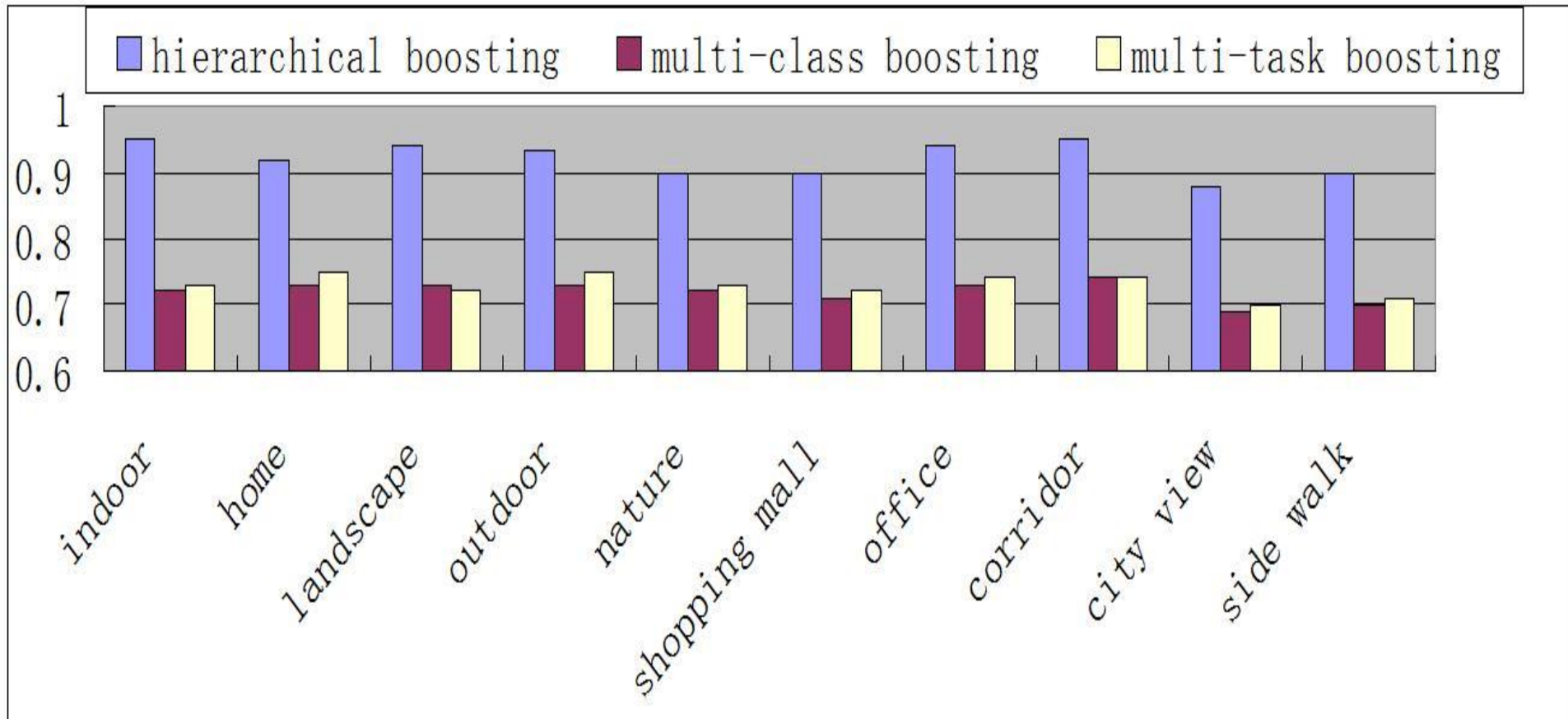
- **Hierarchical Boosting to Generate Classifier for Parent Node**

$$H_{C_k}(X) = \sum_{j=1}^{C+1} p_j(X) f_{C_j}(X)$$

$$p_j(X) = \frac{\exp(f_{C_j}(X))}{\sum_{j=1}^{C+1} \exp(f_{C_j}(X))}$$

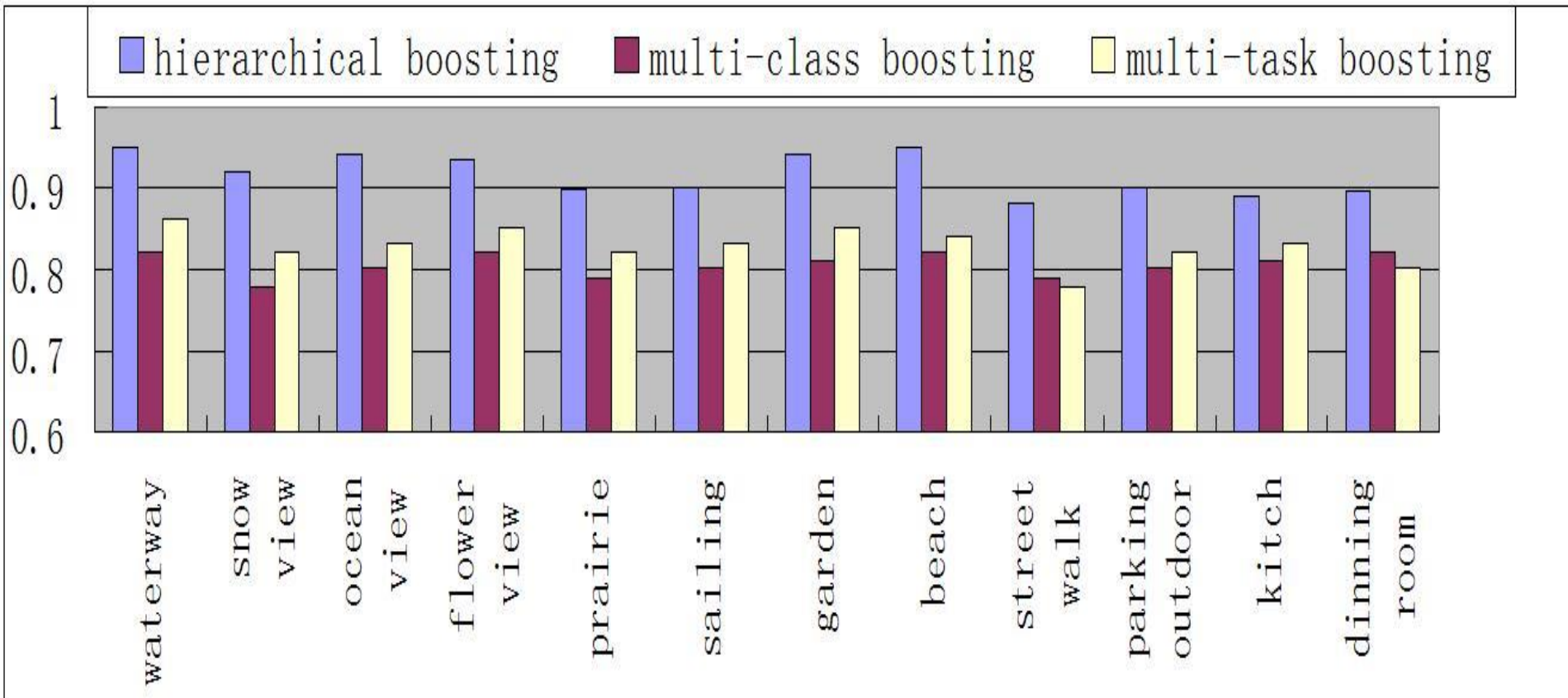
# Classifier Training for High-Level Image Concepts

## ■ Performance Evaluation



# Classifier Training for High-Level Image Concepts

## ■ Performance Evaluation





# Classifier Training for High-Level Image Concepts

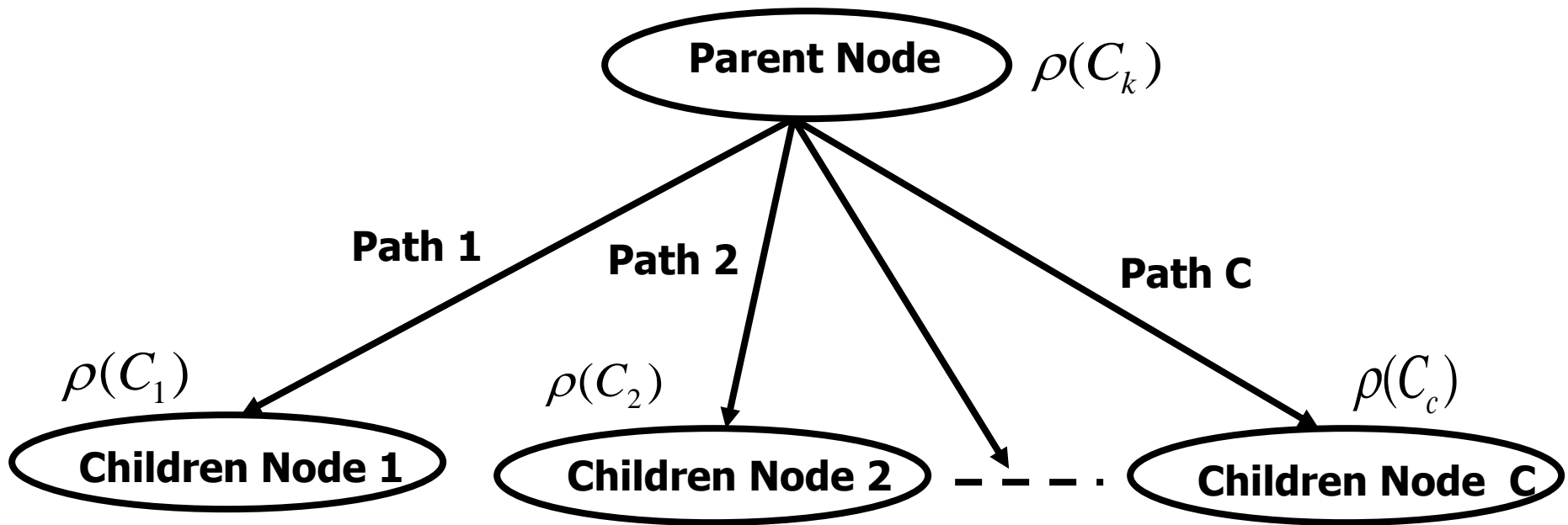
---

- **Advantages of Hierarchical Boosting**
  - **Handling inter-concept similarity via multi-task learning**
  - **Reducing training cost**
  - **Enhancing discrimination power of the classifiers**



# Hierarchical Image Classification

- Overall Probability  $\varphi(C_k)$



$$\varphi(C_k) = \rho(C_k) + \max \{ \rho(C_j) \mid j = 1, \dots, C \}$$



# Hierarchical Image Classification

## ■ Some Results



Multi-Level Concepts: office => indoor

Salient Objects: screen; keyboard; speaker;  
mouse\_pad;

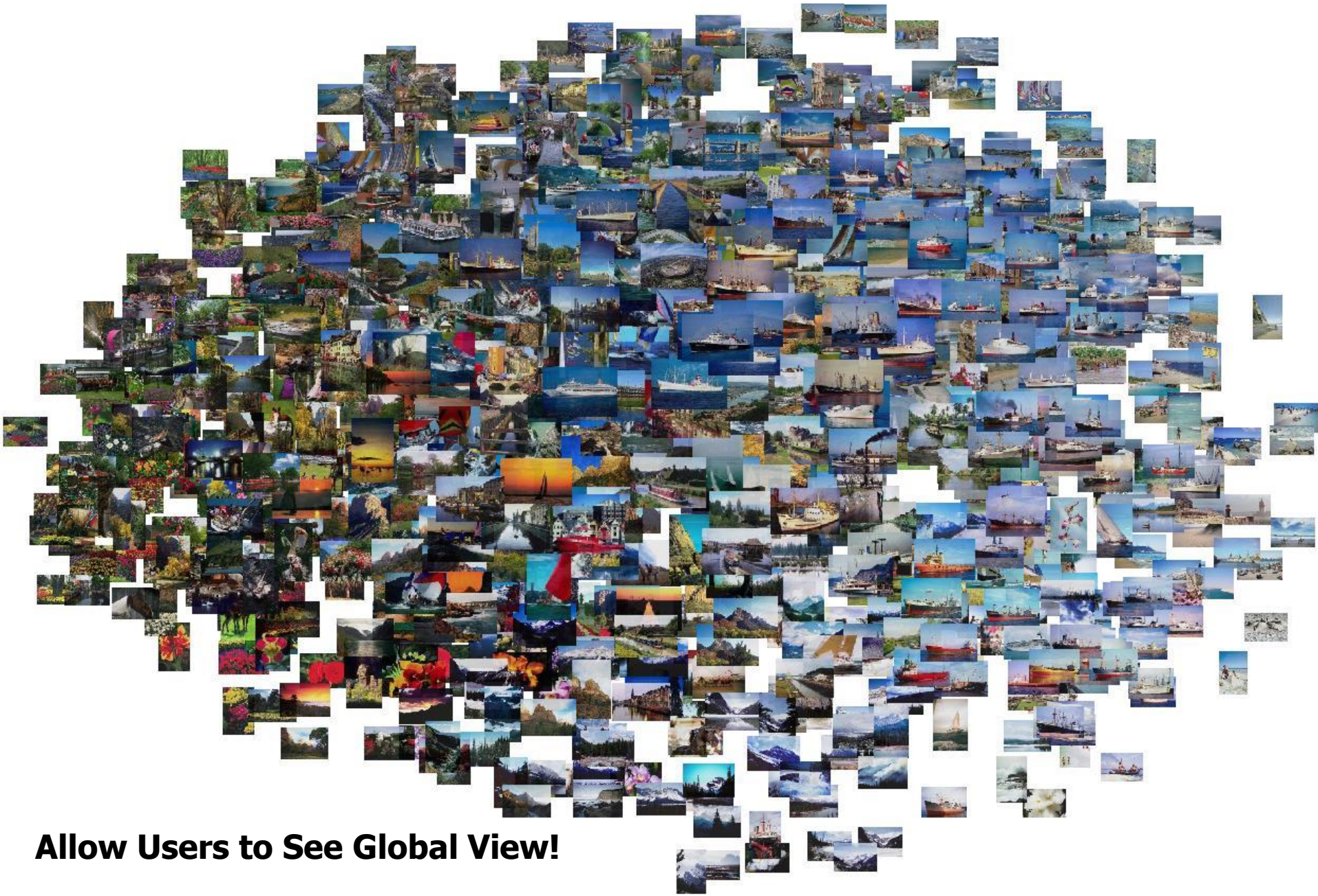


Multi-Level Concepts: sidewalk => street => outdoor

Salient Objects: person; car\_left; wheel;



# Classification Result Evaluation



**Allow Users to See Global View!**



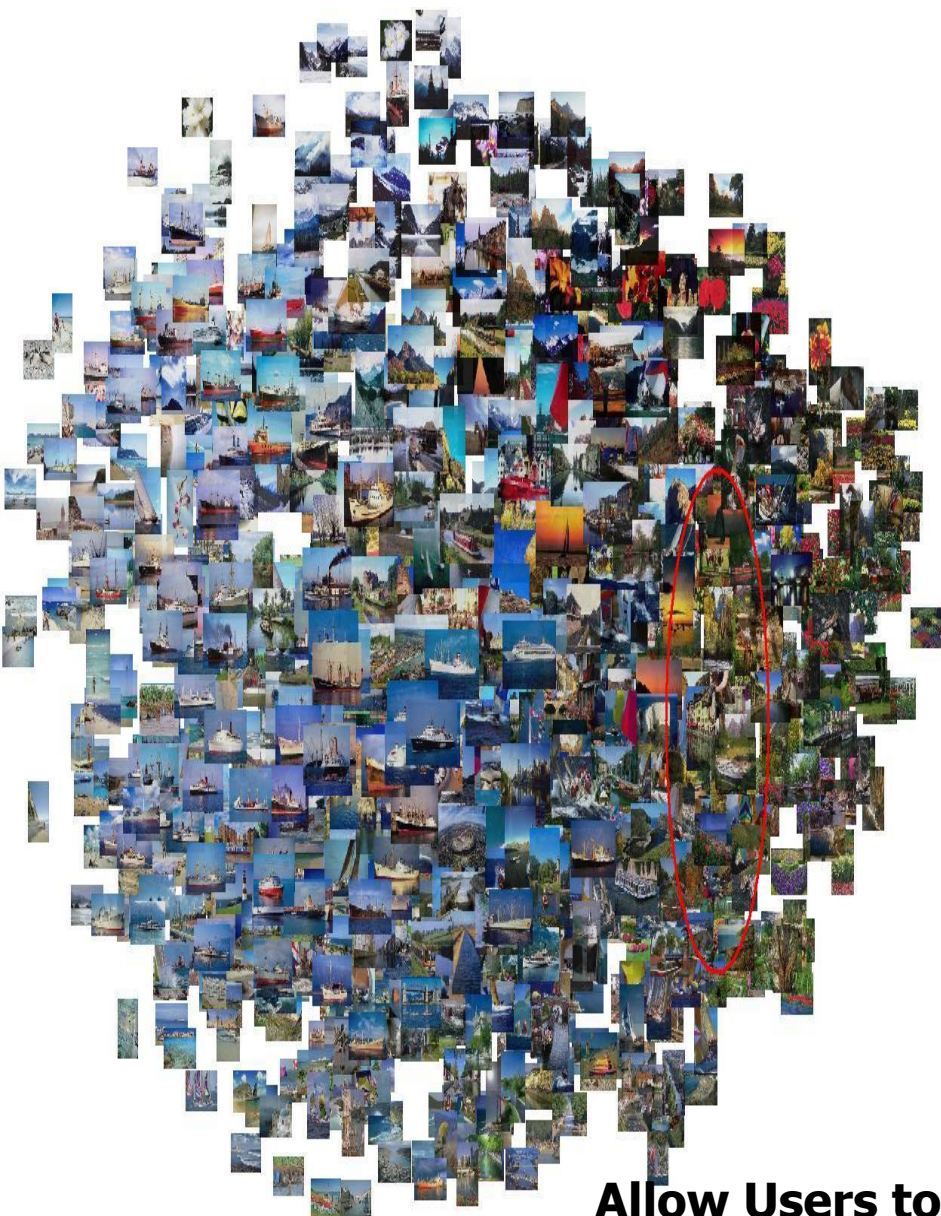
# Classification Result Evaluation

**Allow Users to See Similarity Direction!**





# Classification Result Evaluation



(a)



(b)

**Allow Users to Zoom into Images of Interest!**

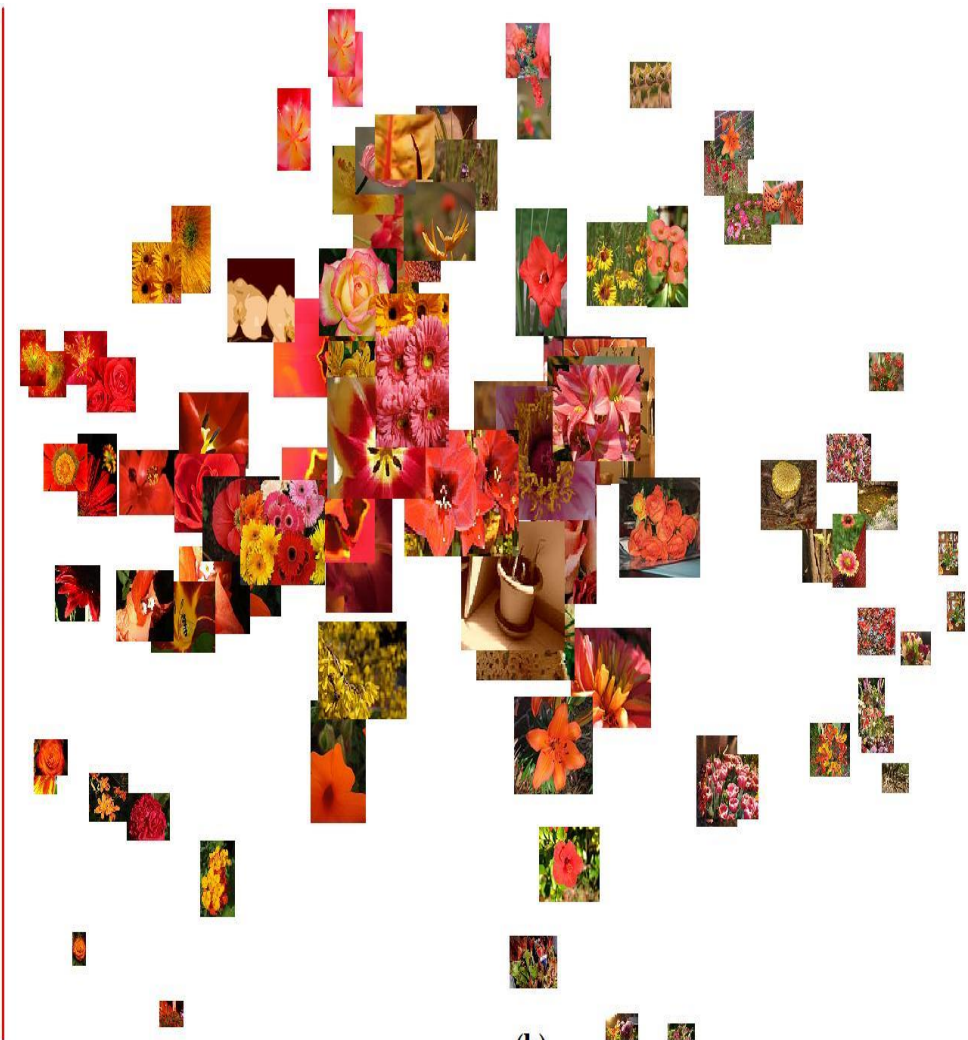


# Classification Result Evaluation: **Red Flower**

**Allow Users to Select Query Example Interactively!**



(a)



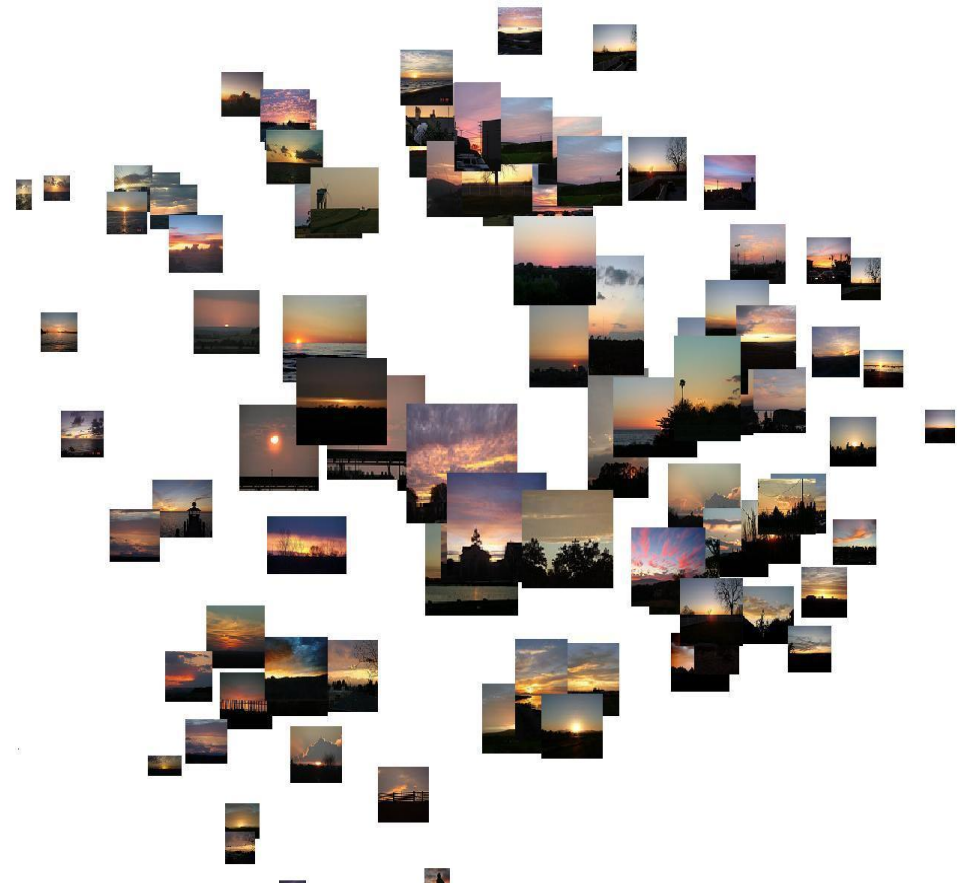
(b)

# Classification Result Evaluation: **Sunset**

**Allow Users to Look for Particular Images!**



(a)



(b)





# **Some Interesting Observations**

---

- **Concept Ontology for identifying inter-related learning tasks**
- **Multi-task learning for inter-related tasks**
- **Hierarchical learning over concept ontology**

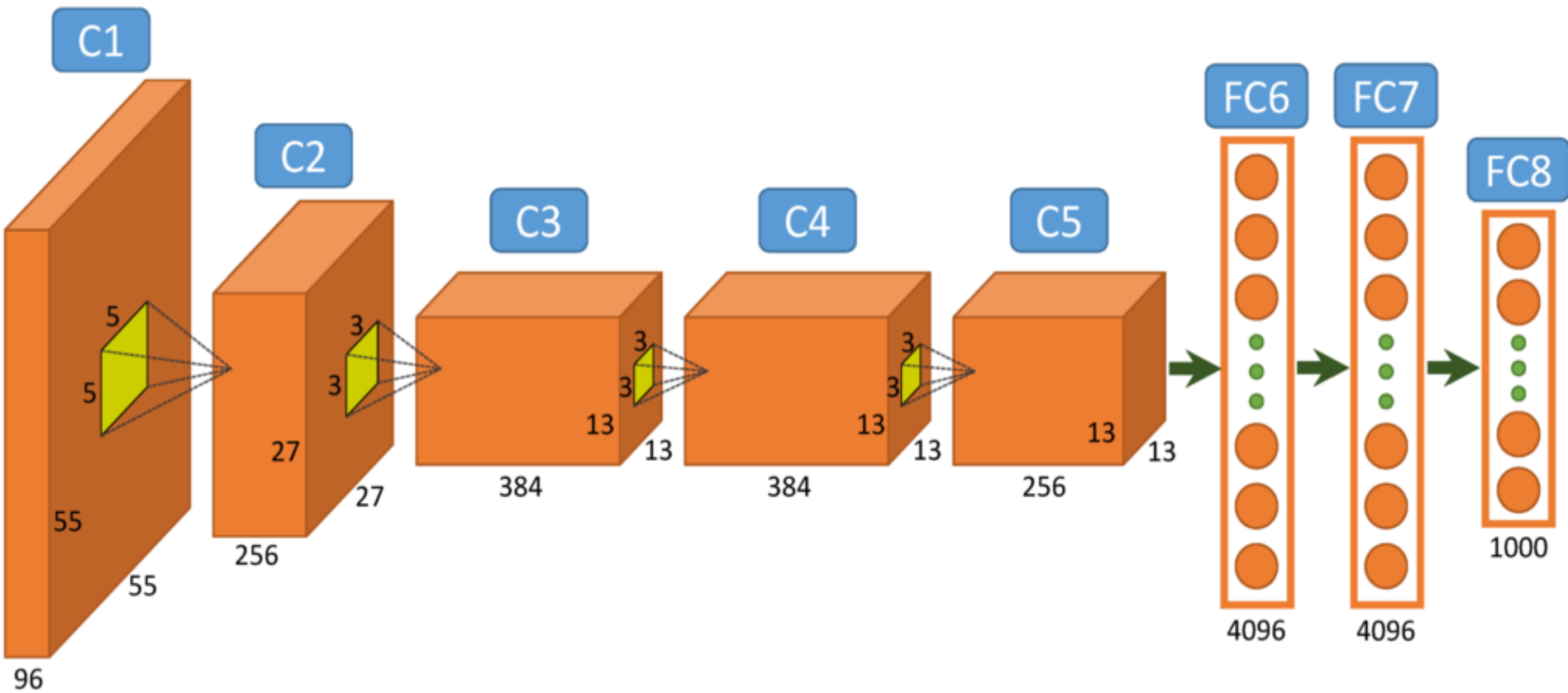


# **Deep Multi-Task Learning over Concept Ontology**

---

- **Ontology-driven task group generation**
- **Deep multi-task learning for each task group**
- **Hierarchical deep multi-task learning over concept ontology**

# Traditional Deep Learning



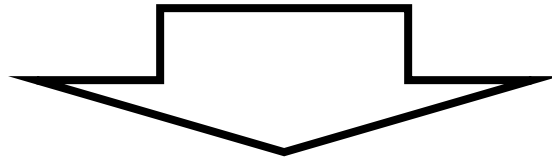


# Traditional Deep Learning

---

## ■ Problem of AlexNet

- Inter-class visual correlations are completely ignored! They are assumed to be independent!
- The differences of their learning complexities are completely ignored!



- Back-propagation for optimization may pay more attentions on hard ones!

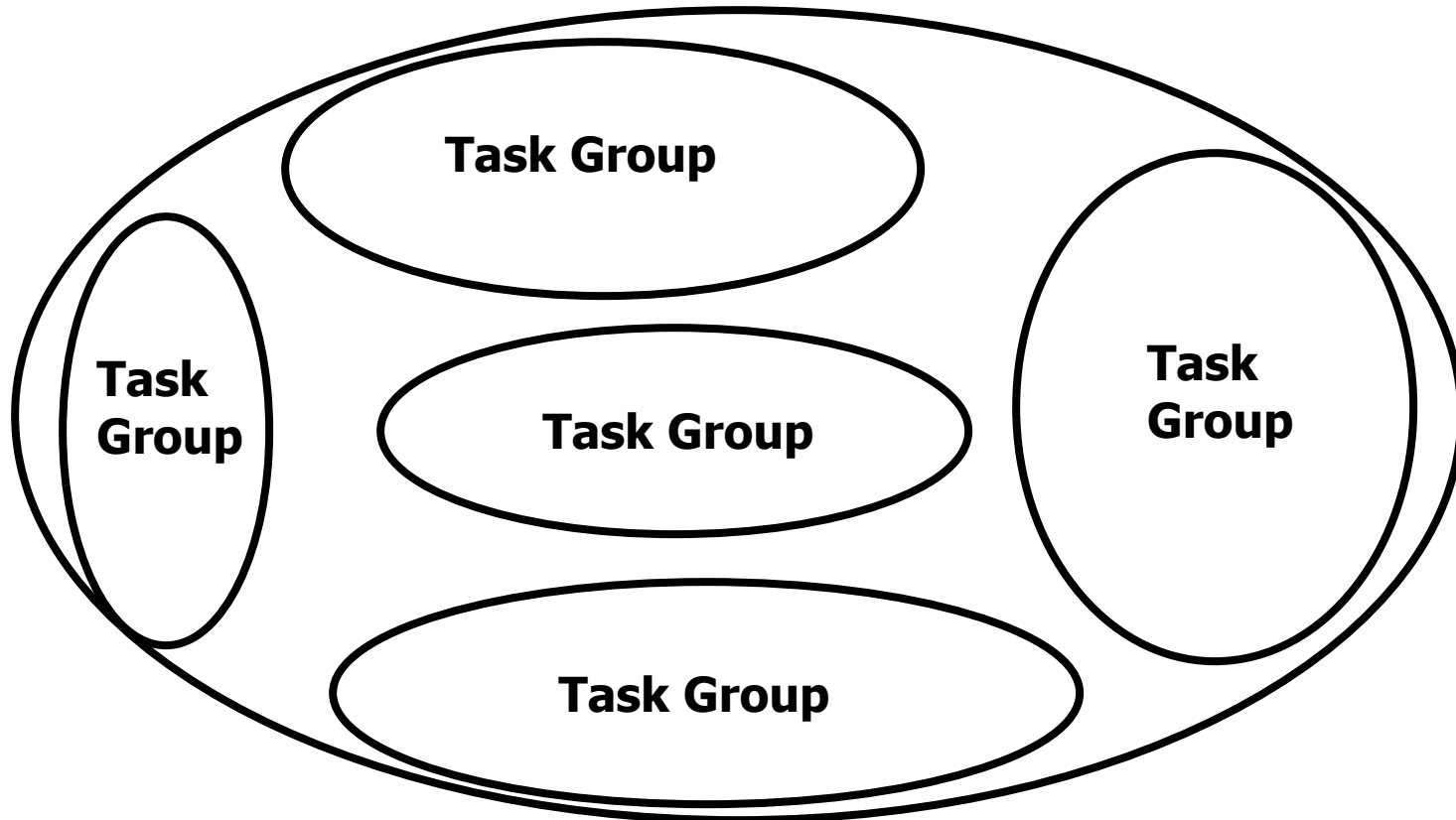


# Traditional Deep Learning

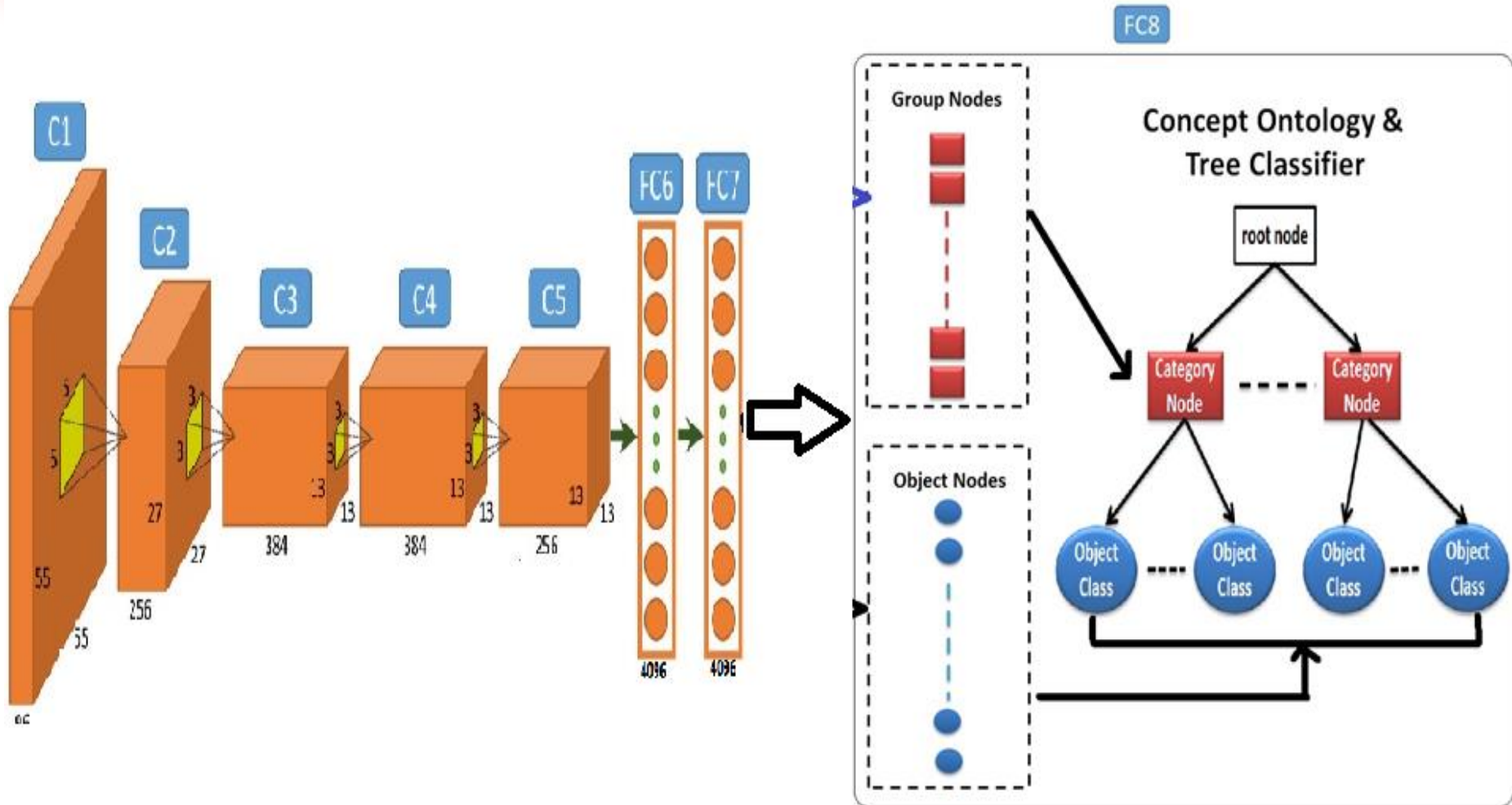
---

- **Wish List**

1,000 image categories

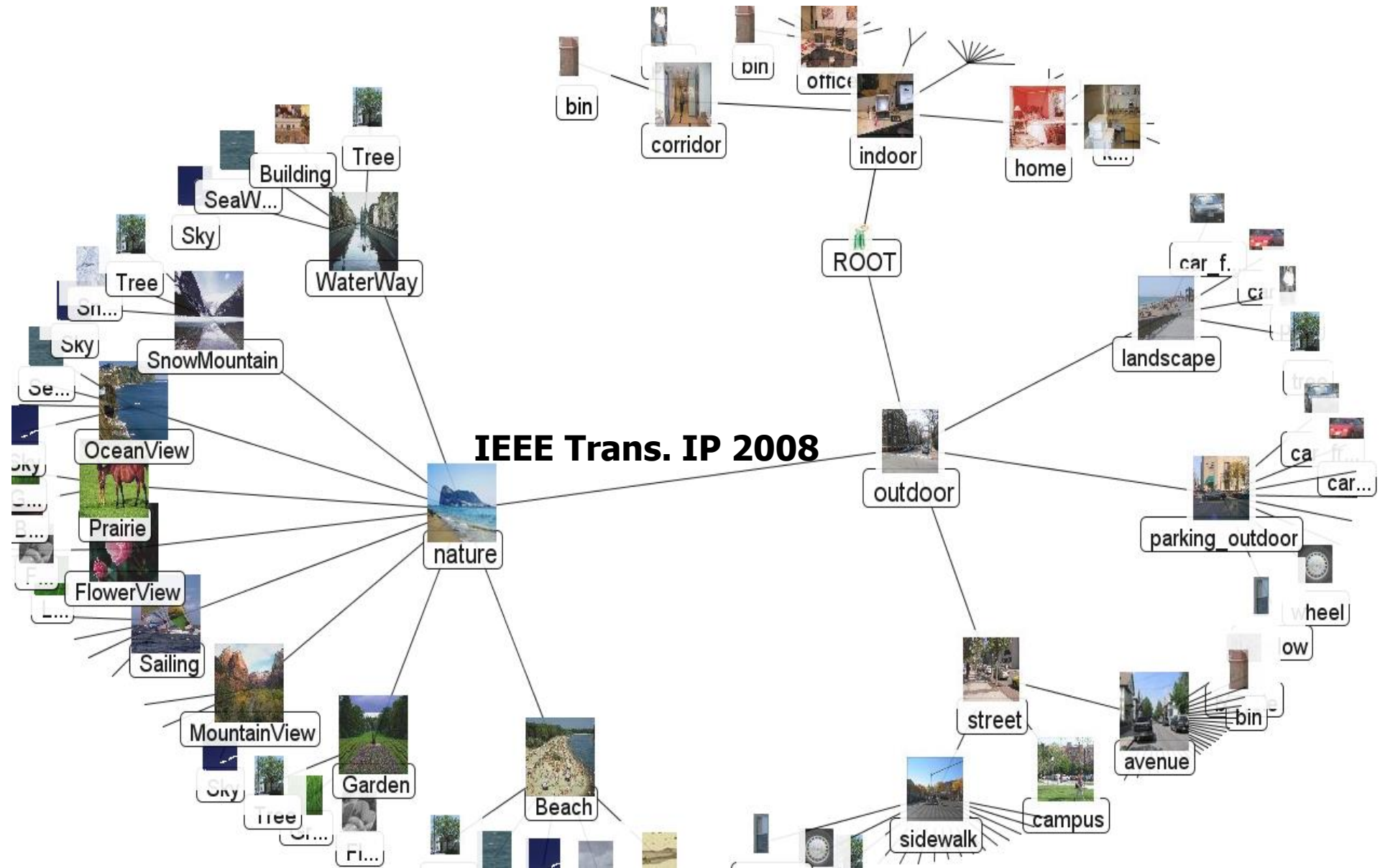


# Deep Multi-Task Learning over Concept Ontology



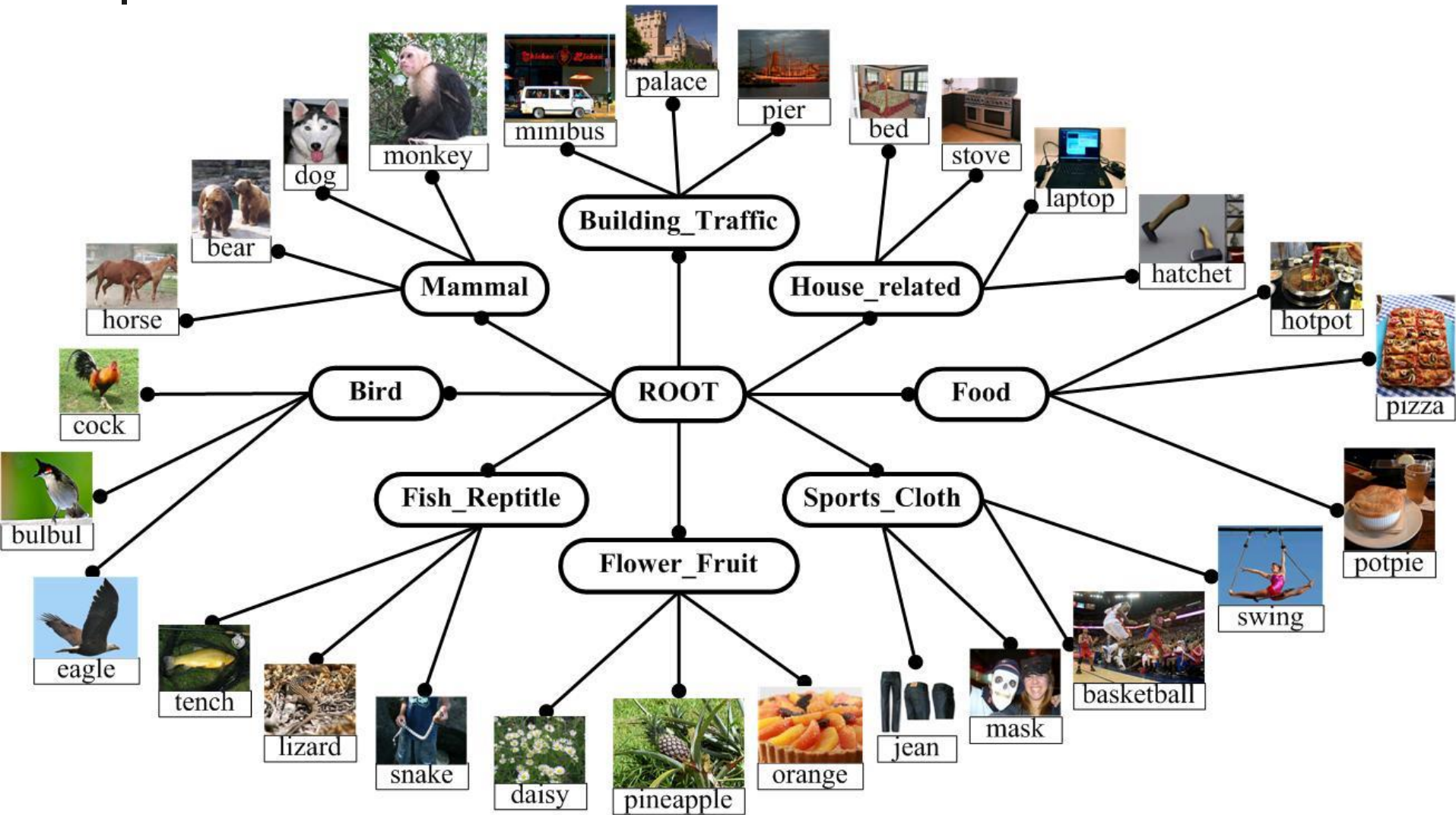


# Ontology for Task Group Generation





# Ontology for Task Group Generation



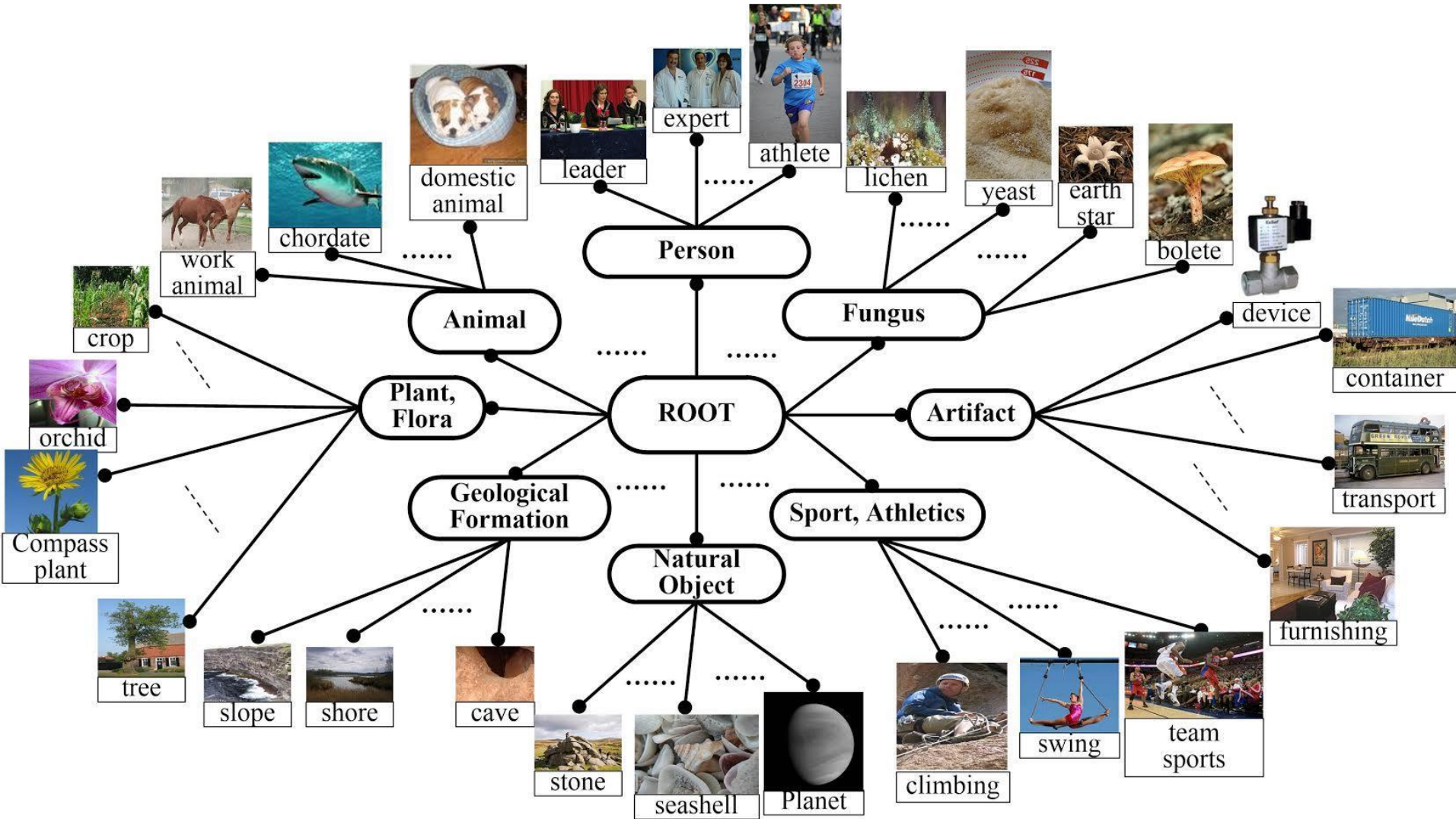
**Two-Layer Ontology for ImageNet1K**

# Ontology for Task Group Generation



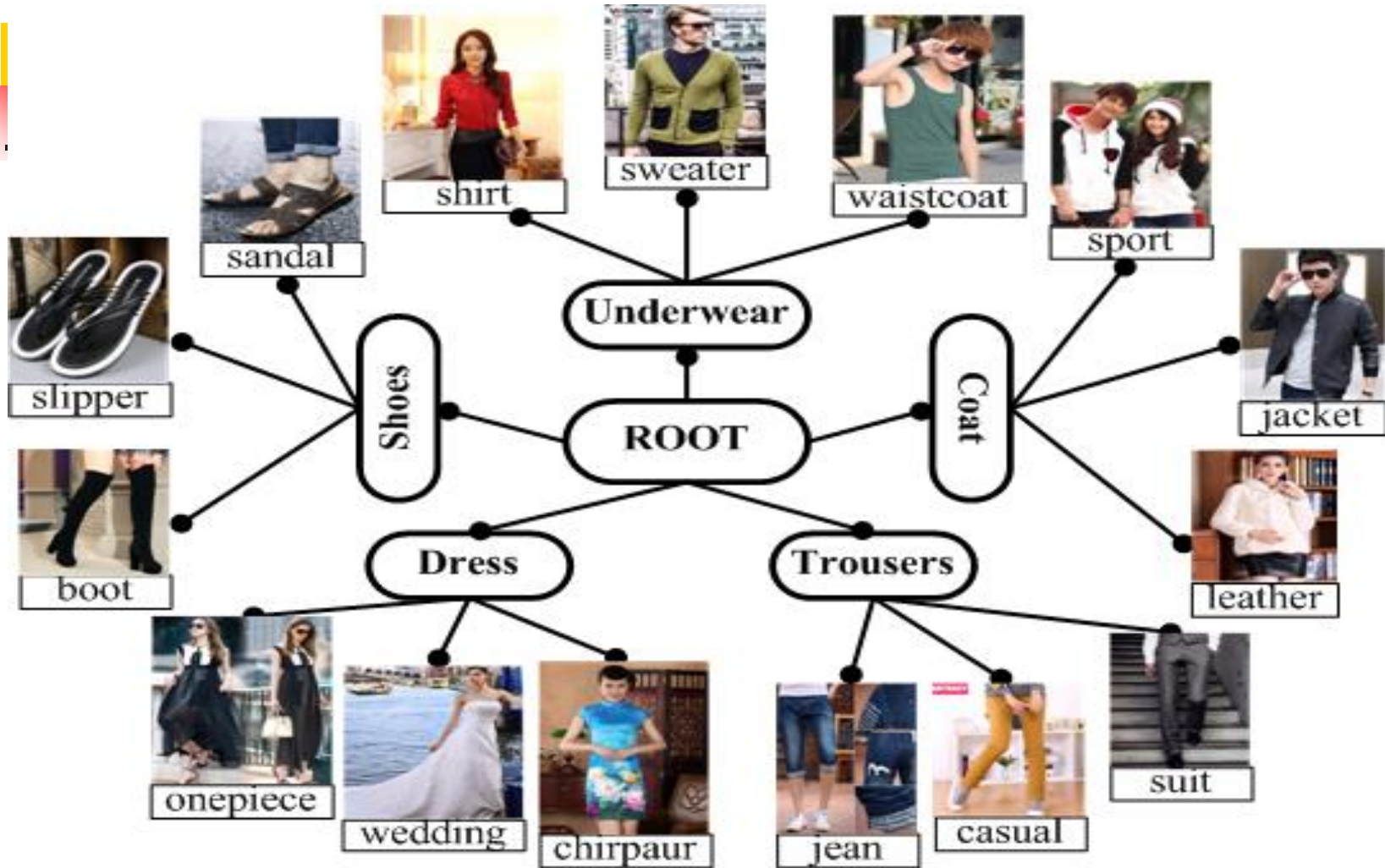


# Ontology for Task Group Generation



**Two-Layer Ontology for ImageNet10K**

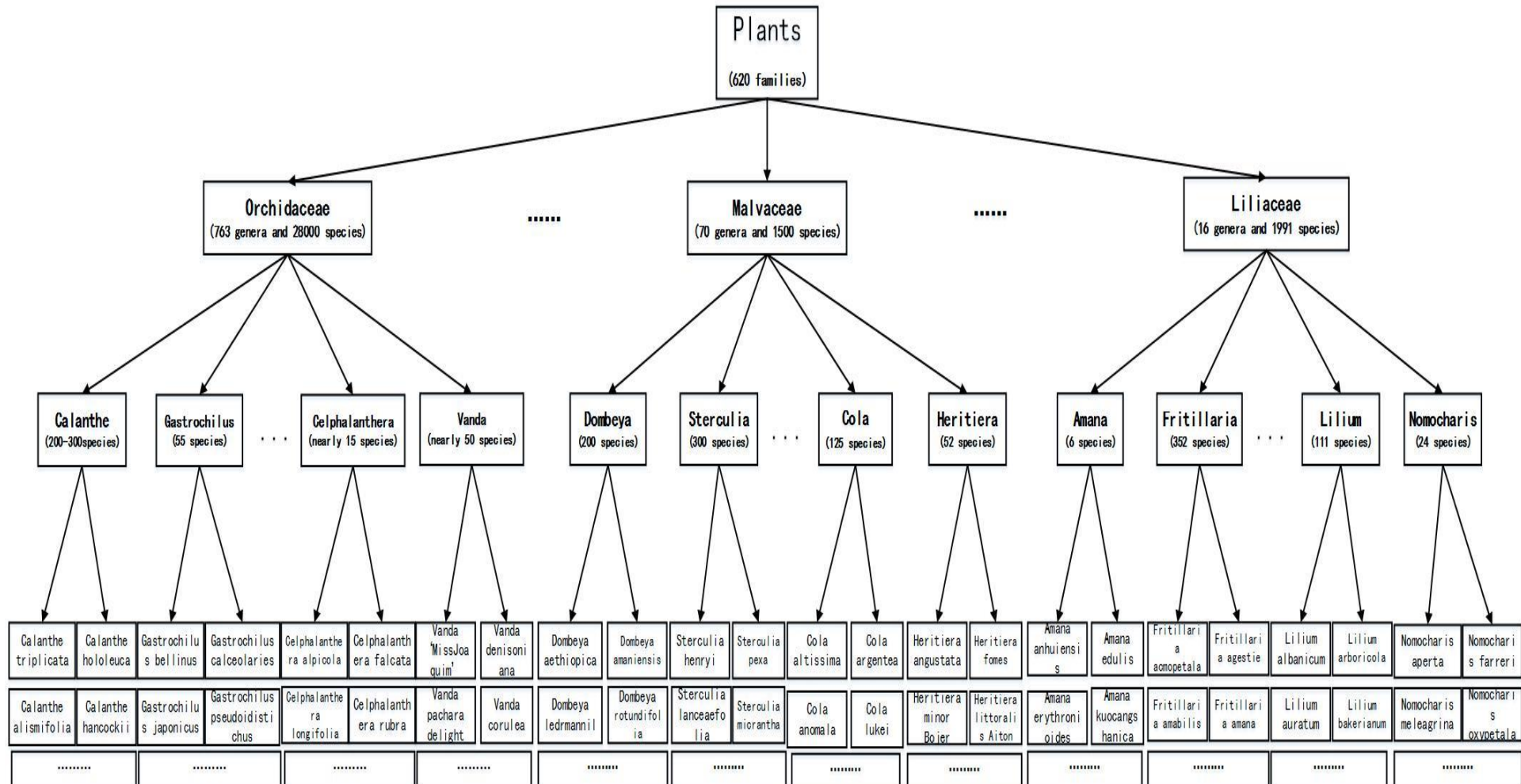
# Ontology for Task Group Generation



**Two-Layer Ontology for Taobao Products**

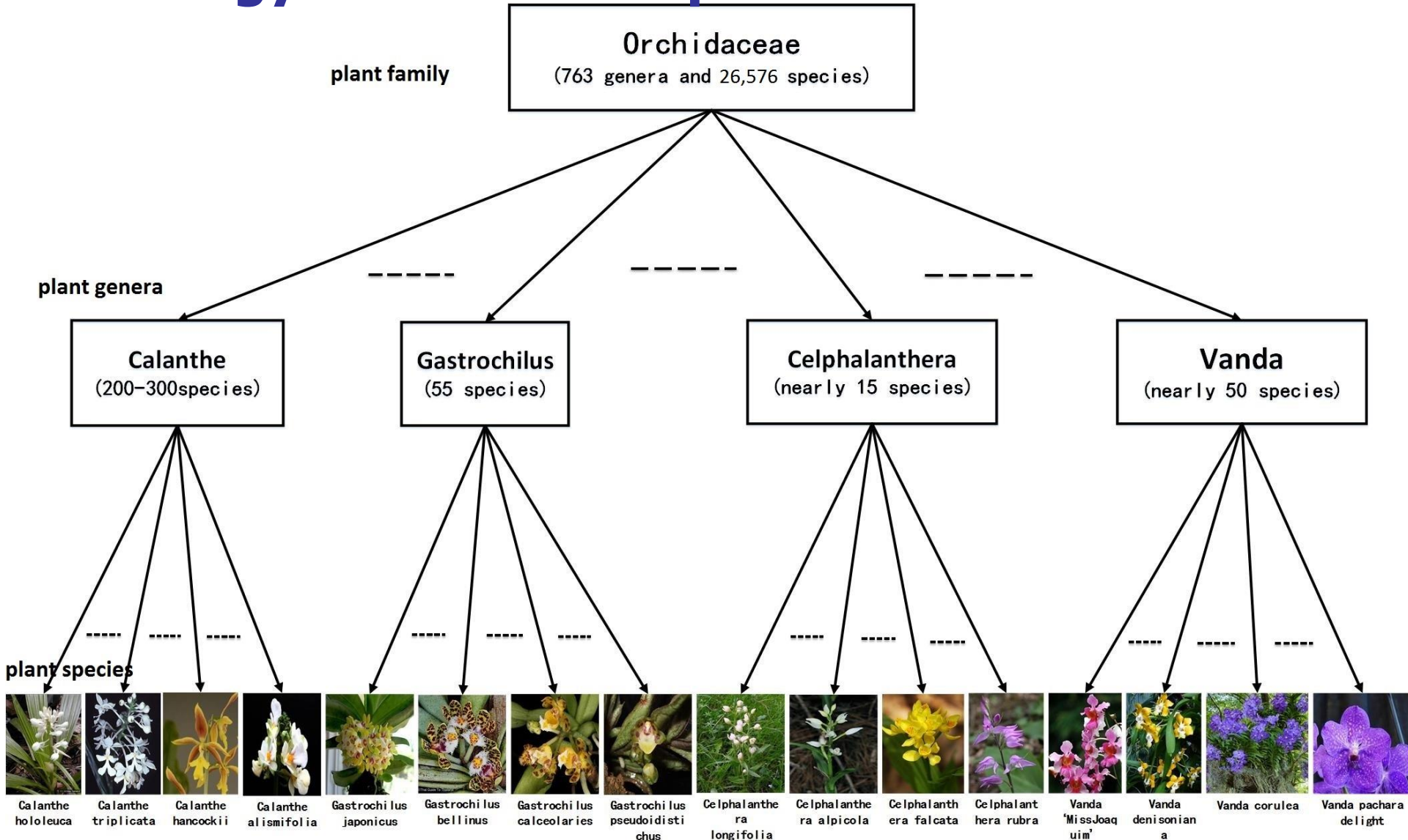


# Ontology for Task Group Generation



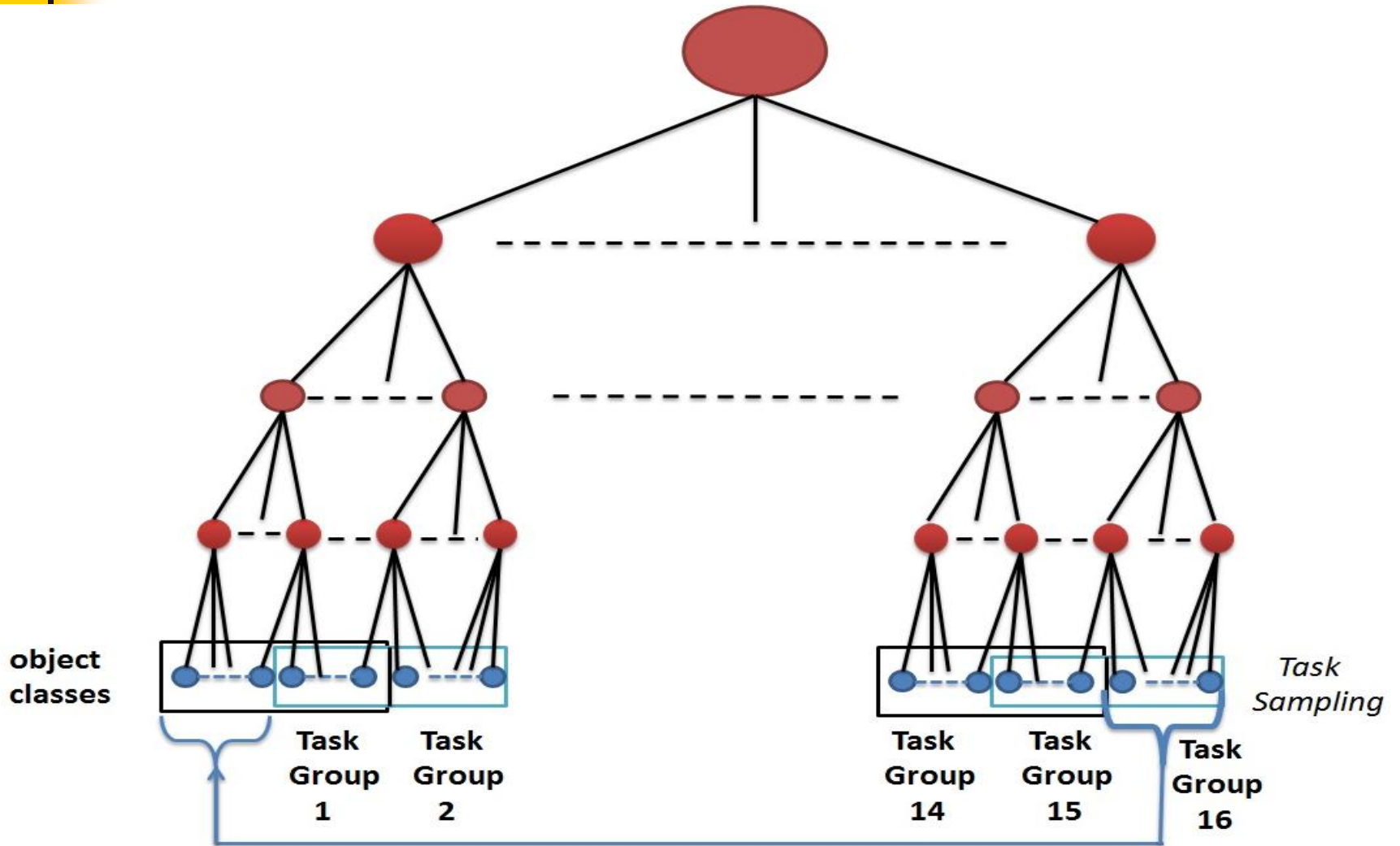
## Plant Species Ontology

# Ontology for Task Group Generation

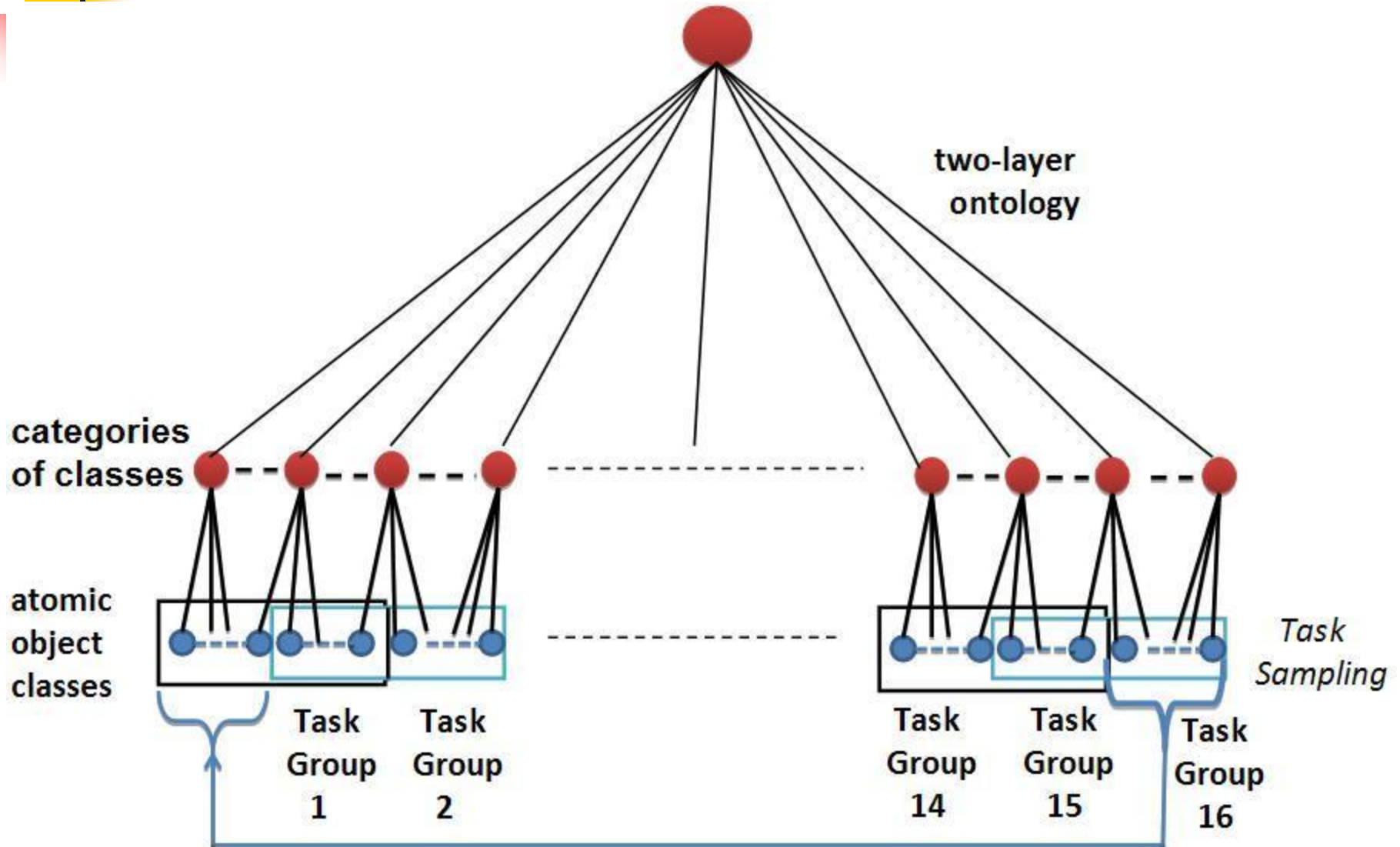


## Two-Layer Ontology for Orchidaceae

# Ontology-Driven Task Group Generation



# Ontology-Driven Task Group Generation





# Ontology-Driven Task Group Generation

root

Level 1



Level 2

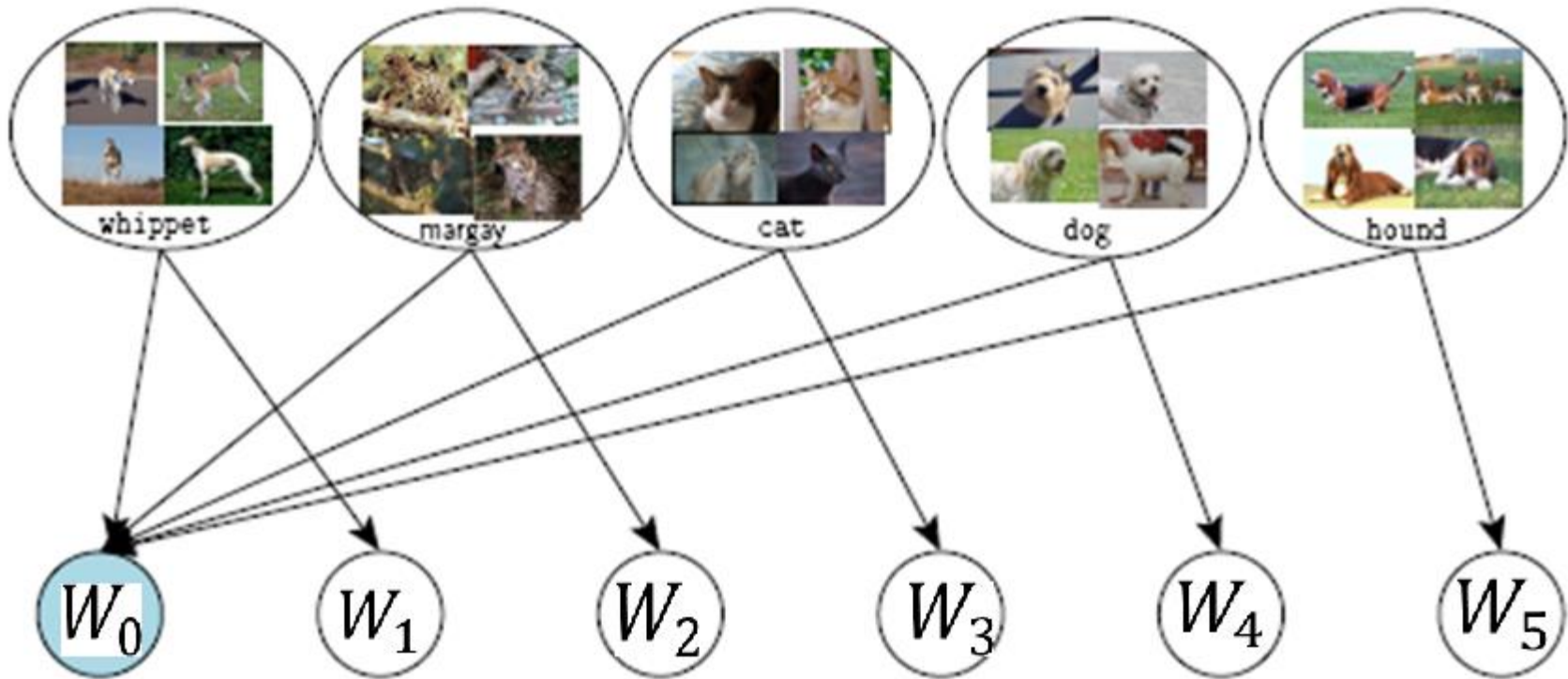


Level 3



# Learning Base CNNs for Each Task Group

- **Deep Multi-Task Learning:**  $F_j(\mathbf{x}) = (W_0 + W_j)^T \mathbf{x} + \mathbf{b}$







# Learning Base CNNs for Each Task Group

---

## ■ Deep Multi-Task Learning

$$\min \left\{ C \sum_{l=1}^R \sum_{j=1}^B \xi_j^l + \delta_1 \text{Tr} \left( WW^T \right) + \frac{\delta_2}{2} \text{Tr} \left( WLW^T \right) \right\}$$

*subject to:*

$$\forall_{l=1}^R \forall_{j=1}^B : y_j^l \left( W_j^T \cdot x_j^l + b \right) \geq 1 - \xi_j^l, \quad \xi_j^l \geq 0$$



# Learning Base CNNs for Each Task Group

---

## ■ Deep Multi-Task Learning

$$\min \left\{ \sum_{j=1}^B \sum_{l=1}^R \beta_l^j - \frac{1}{2\delta_1} \beta^T Y \Re \left( \Re + \frac{\delta_2}{\delta_1} \Re (L \otimes I) \Re \right)^{-1} \Re Y \beta \right\}$$

*subject to:*

$$\forall_{l=1}^R \forall_{j=1}^B : \sum_{l=1}^R \beta_l^j \cdot y_l^j = 0, \quad 0 \leq \beta_l^j \leq 1$$



## Learning Base CNNs for Each Task Group

---

### ■ Deep Multi-Task Learning

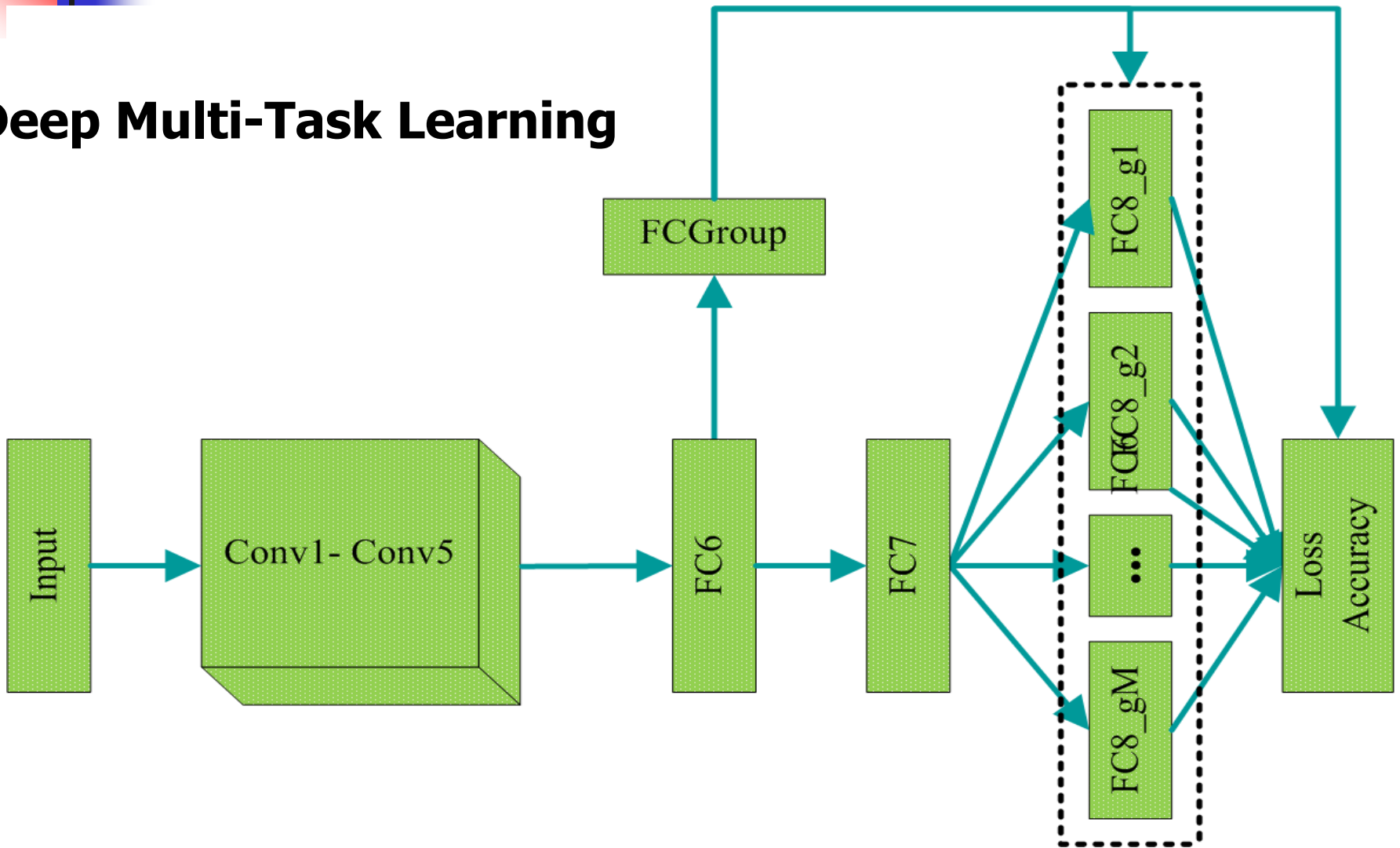
$$\alpha^* = \frac{1}{2\delta_1} \left( \mathfrak{R} + \frac{\delta_2}{\delta_1} \left( \mathfrak{R} \left( L \otimes I \right) \mathfrak{R} \right)^{-1} \mathfrak{R} Y \beta^* \right)$$

### Multi-Task Classifiers at Sibling Leaf Nodes

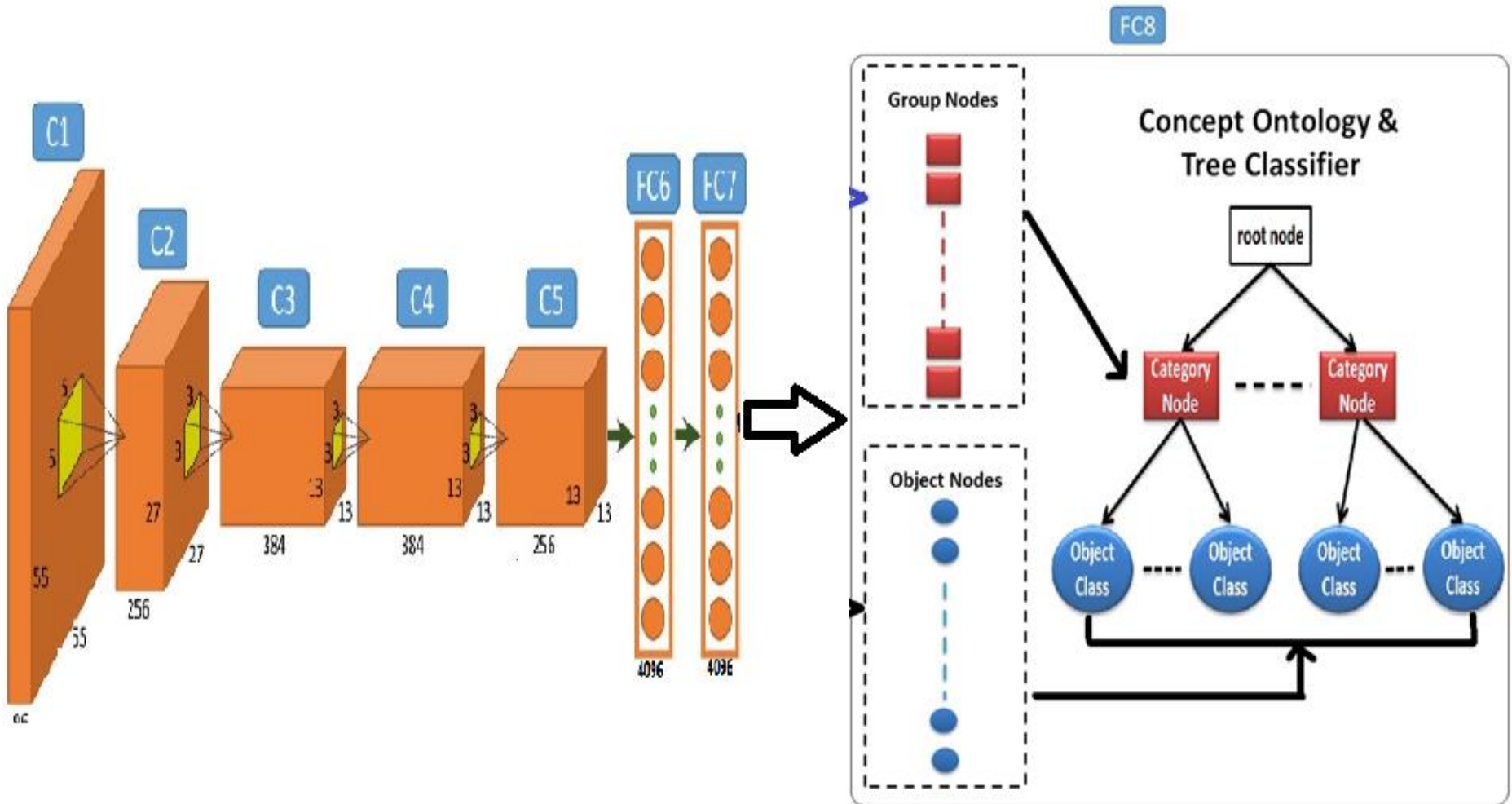
$$\forall_{j=1}^B : f_{c_j}^1(x) |_{F_{c_j}^1} = \sum_{l=1}^R \alpha_j^{l*} \kappa(x_j^l, x) + b_j^*, \quad c_j \in c_h$$

# Learning Base CNNs for Each Task Group

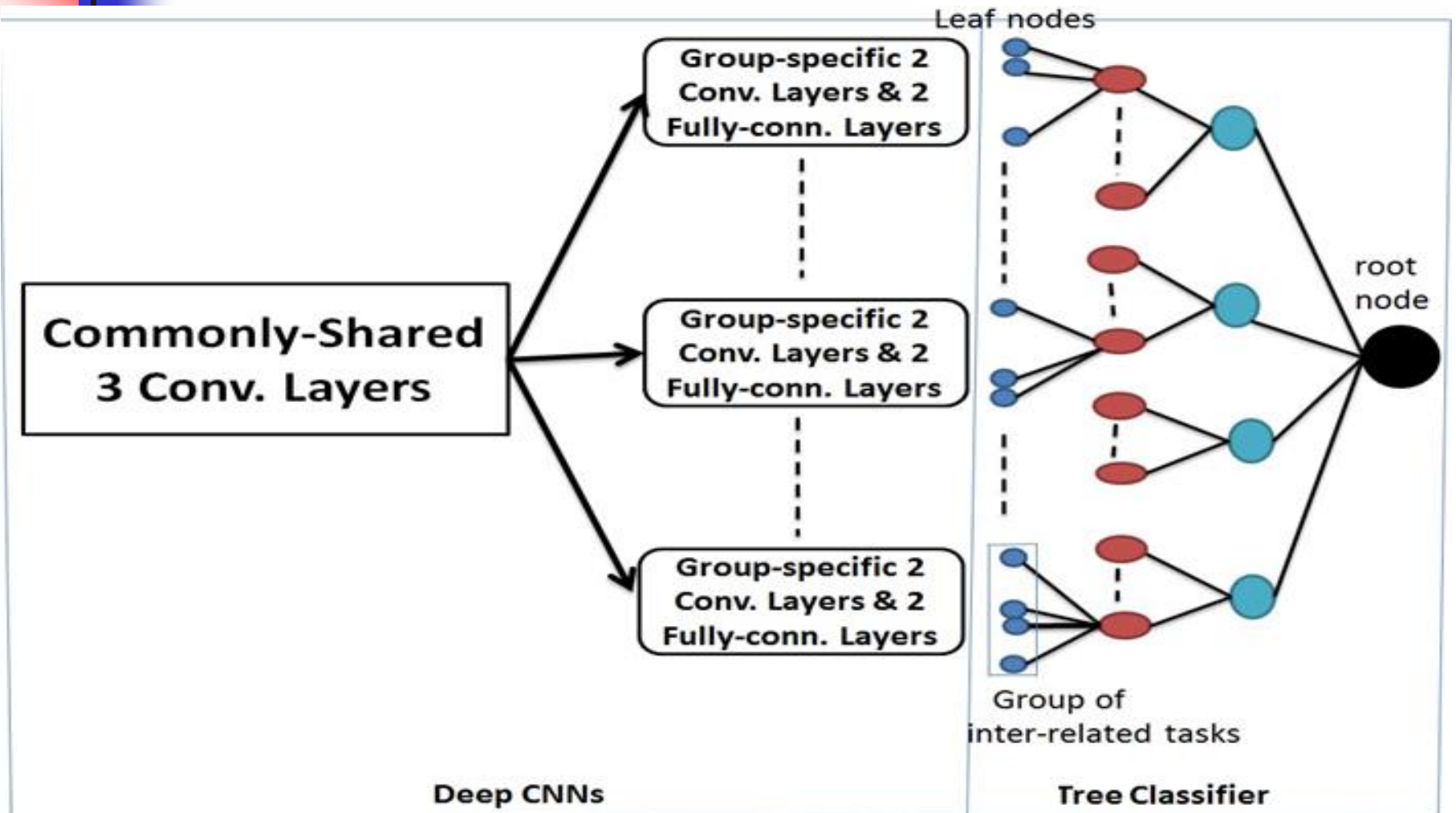
## Deep Multi-Task Learning



# Hierarchical Deep Multi-Task Learning

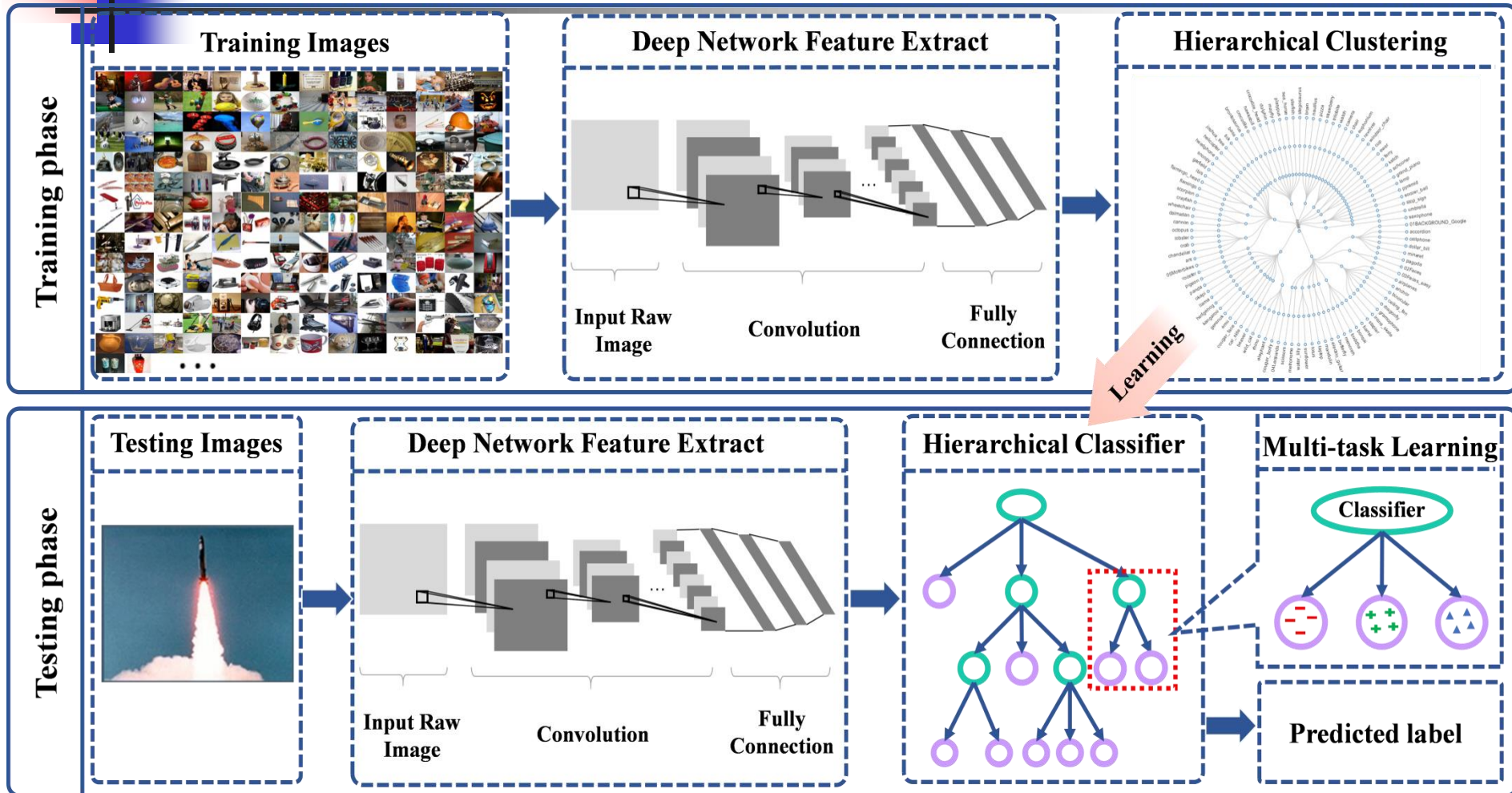


# Hierarchical Deep Multi-Task Learning





# Hierarchical Deep Multi-Task Learning





# Hierarchical Deep Multi-Task Learning

## ■ Controlling Inter-Level Error Propagation

$$\min \left\{ C \sum_{m=1}^R \sum_{h=1}^B \xi_j^m + \gamma_1 \text{Tr} (W W^T) + \frac{\gamma_2}{2} \text{Tr} (W L W^T) \right\}$$

*subject to:*

$$\forall_{m=1}^R \forall_{h=1}^B : y_h^m (W_h^T \cdot x_h^m + b) \geq 1 - \xi_h^m, \xi_h^m \geq 0, c_h \in c_k$$

$$\forall_{h=1}^B : f_{c_h}^{l+1}(x) |_{F_{c_h}^{l+1}} - f_{c_j}^l(x) |_{F_{c_j}^l} \geq 0$$

$$\forall_{h=1}^B : f_{c_h}^{l+1}(x) |_{F_{c_h}^{l+1}} = \sum_{j=1}^B \eta_j f_{c_j}^l(x) |_{F_{c_j}^l}$$

# Hierarchical Deep Multi-Task Learning

