Research and Implementation of Multi-Dataset Training for Image Classification with Discrepant Taxonomies

Master Thesis Presentation

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Outline

The Challenge: Limited Scope of Traditional Models

- Traditional image classification models are trained on specific datasets
- Each model recognizes only a predefined set of categories
- Multiple models needed for different domains = inefficient storage and deployment

Current Approaches:

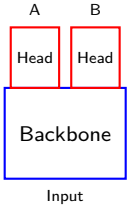
- **Transfer Learning**: Adapt pre-trained models to new tasks
- **Multi-head Architecture**: Shared backbone + task-specific heads

Problem: Still requires separate models or heads for each domain

Our Idea: Universal Model vs. Multi-Head

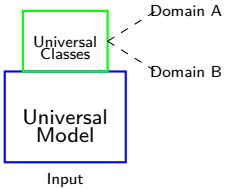
Multi-Head Approach

- Shared backbone
- Task-specific heads
- Automatic feature distillation
- Domain alignment challenges



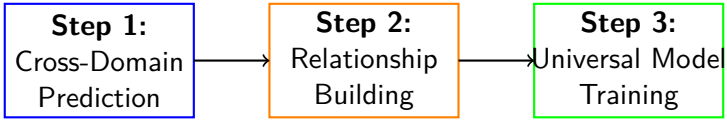
Universal Model Approach

- Single shared model
- Universal output layer
- Predefined concept mapping
- Static domain conversion



Key Insight: Build explicit concept-to-domain mappings to train a single universal model

Our Method in 3 Steps



1. **Cross-Domain Prediction**: Train domain-specific models, run inference on other domains
2. **Relationship Building**: Extract meaningful relationships from cross-domain predictions and create universal taxonomy
3. **Universal Model Training**: Create and train a single model using universal taxonomy

Changes to Method of Bevandic et al.

1. **Weighted Relationships:** Instead of binary, unweighted relationships, we use weighted relationships to capture the strength of associations between classes.
2. **Relationship Selection Methods:** We try multiple methods to select the most relevant relationships from noisy cross-domain predictions.
3. **Synthetic Ground Truth:** We develop a synthetic ground truth generation method to be able to evaluate relationship selection methods in a controlled manner.
4. **Discrete Probability Loss Function:** We use a loss function that allows training with probability distributions as targets, enabling the model to learn from the uncertainty in class relationships.

Cross-Domain Prediction Process

Goal: Discover relationships between classes from different datasets

Process:

1. Train domain-specific models
2. Run each model on images from *all other* domains, building prediction matrices $M_{ab}(i,j)$ = number of times class c_i^a predicted as class c_j^b
3. Create probability matrices $P_{ab}(i,j)$ = probability of classifying class c_i^a as class c_j^b

$$P_{ab}(i,j) = \frac{M_{ab}(i,j)}{\sum_{k=1}^{|C_a|} M_{ab}(i,k)} \tag{1}$$

Example: Caltech-256 class "car" predicated by CIFAR-100 model as "vehicle" (80%), "bike" (18%), "butterfly" (2%)

Challenge: Selecting Relevant Relationships

Problems with raw probability matrices:

- Noisy predictions from imperfect models
- Unknown number of true relationships
- Different datasets have different scales of similarity

Solution: Develop multiple relationship selection methods and evaluate them using a synthetic ground truth with custom metrics

Relationship Selection Methods Explained

1. **Most Common Foreign Prediction (MCFP) by Bevandic et al.**:

$$\text{select\_relationships}(P_{ab}) = \{(i,j) \mid j = \text{argmax}_{j'} P_{ab}(i,j')\} \tag{2}$$

2. **Naive Thresholding**:

$$\text{select\_relationships}(P_{ab}) = \{(i,j) \mid P_{ab}(i,j) \geq t\} \tag{3}$$

3. **Density Thresholding**: Select minimum relationships covering $p\%$ of probability mass
4. **Relationship Hypothesis**: Assumes relationships based on shared concepts should have equal probabilities. For each class, find optimal k relationships by minimizing:

$$\sum_{j=1}^{k} \left| X_i(j) - \frac{1}{k} \right| + \sum_{j=k+1}^{|C_b|} X_i(j) \tag{4}$$

where $X_i(j)$ are sorted probabilities in descending order.

The Need for Controlled Ground Truth

Problem: No existing datasets with known inter-dataset, *weighted* class relationships

Solution: Merge classes from a single dataset into different variants with controlled relationships.

Example:

- We have classes "car", "eye", "dog", "butterfly"
- Create Variant A: "{car, eye}", "{butterfly}"
- Create Variant B: "{car, butterfly}", "{dog, eye}"
- "A:{car, eye}" → "B:{car, butterfly}" (50%)
- "B:{car, butterfly}" → "A:{car, eye}" (50%)
- "A:{butterfly}" → "B:{car, butterfly}" (100%)
- "B:{car, butterfly}" → "A:{butterfly}" (50%)

Domain-Shifted Synthetic Datasets

Problem: Original synthetic variants too easy (same underlying images)

Solution: Apply domain transformations to create realistic challenges

Transformations Applied:

- **Variant A**: Noisy grayscale
- **Variant B**: Rotation + blur
- **Variant C**: Random erasing + color jitter + perspective shifts

Example images from domain-shifted variants

Results:

- Model accuracy drops by 10%
- More realistic cross-domain predictions
- Better evaluation of relationship selection methods

Evaluation Metrics for Relationship Selection

How do we measure the quality of selected relationships?

1. **Edge Difference Ratio (EDR)**: Measures difference in edge weights between predicted and ground truth graphs

$$\text{EDR}(G_1, G_2) = \frac{\sum_{i,j} |A_1(i,j) - A_2(i,j)|}{\sum_{i,j} \max(A_1(i,j), A_2(i,j))} \tag{5}$$

   Range: [0,1], where 0 = identical graphs, 1 = no common edges

2. **Precision & Recall**: Binary evaluation of relationship presence
   - Convert adjacency matrices to binary: $B(i,j) = 1$ if $A(i,j) > 0$
   - **Precision** = $\frac{TP}{TP+FP}$ (correctness of selected relationships)
   - **Recall** = $\frac{TP}{TP+FN}$ (coverage of true relationships)
   - **F1 Score** = Harmonic mean of precision and recall

Relationship Selection Results: Domain-Shifted Evaluation

Evaluation on domain-shifted synthetic datasets (more realistic)

Method	Parameter	EDR	Precision	Recall	F1 Score
Relationship Hypothesis	5	**0.759**	0.390	0.543	0.444
Naive Thresholding	0.10	0.761	0.418	0.519	**0.450**
Density Thresholding	0.60	0.766	0.349	**0.582**	0.426
MCFP	N/A	0.842	**0.490**	0.226	0.305

Table: Performance on domain-shifted synthetic datasets (Caltech-101, Caltech-256, CIFAR-100) with globally optimal parameters

Key Observations:

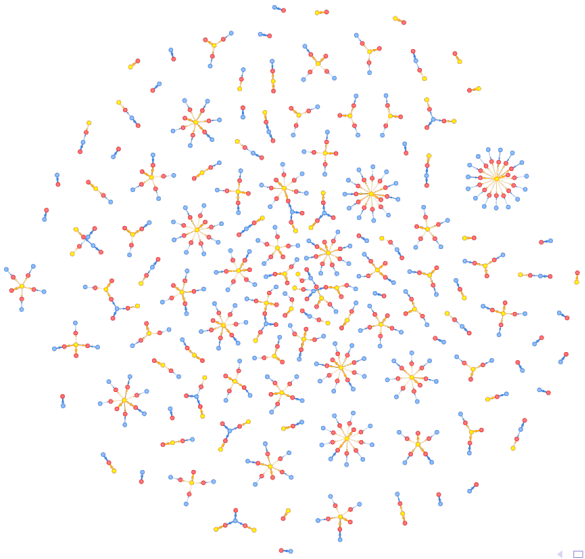
- **Relationship Hypothesis** achieves best EDR 0.759
- **MCFP** maintains highest precision but lowest recall
- Maybe still not realistic enough, but suitable for getting method parameters

Universal Taxonomy Building Rules

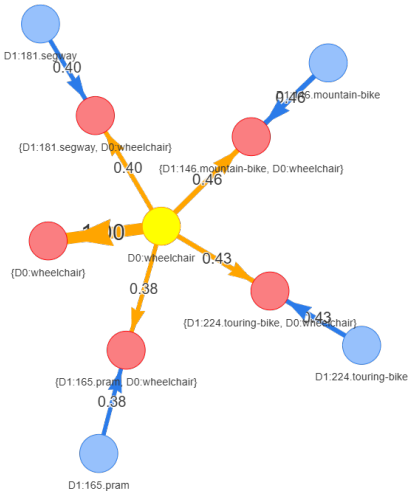
How do we convert relationship graphs into universal taxonomies?

1. **Isolated Node Rule**: Classes with no relationships
   - Create new universal class for standalone domain classes
   - Ensures all classes are represented in universal taxonomy
2. **Bidirectional Relationship Rule**: Classes with mutual relationships ($A \leftrightarrow B$)
   - Create single universal class C with relationships $A \rightarrow C$, $B \rightarrow C$
   - Indicates classes likely represent the same concept
3. **Transitive Cycle Rule**: Prevent invalid cycles ($A \rightarrow B \rightarrow C$ where A, C same domain)
   - Remove relationship with lower probability
   - Classes within same domain should be disjoint
4. **Unilateral Relationship Rule**: Handle subset relationships ($A \rightarrow B$)
   - Create universal class for shared concepts ($A \cup B$)
   - Create universal class for unique concepts (B only)

Taxonomy Visualization (Caltech-101 + Caltech-256)



Good Cluster



Bad Cluster


D1:194.socks
D1:223.top-hat
D1:243.welding-mask
D1:226.traffic-light
D1:141.microscope
D1:003.backpack
D1:012.binoculars
D1:161.photocopier
D1:183.sextant
D1:219.theodolite
D1:019.boxing-glove
D1:070.fire-extinguisher
D1:215.telephone-box
D1:120.joy-stick
D1:176.saddle
D0:binocular
{D1:194.socks, D0:binocular}
{D1:223.top-hat, D0:binocular}
{D1:243.welding-mask, D0:binocular}
{D1:226.traffic-light, D0:binocular}
{D0:binocular, D1:141.microscope}
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{D1:183.sextant, D0:binocular}
{D1:219.theodolite, D0:binocular}
{D1:019.boxing-glove, D0:binocular}
{D1:070.fire-extinguisher, D0:binocular}
{D1:215.telephone-box, D0:binocular}
{D1:120.joy-stick, D0:binocular}
{D1:176.saddle, D0:binocular}

Building the Universal Model

- Every universal class corresponds to one output neuron
- Each domain class maps to one or more universal classes
- Matrix M_i maps domain i classes to universal classes

Target Generation: Convert domain labels to universal class distributions

$$\mathbf{t} = \hat{M}_i[j, :] \quad \text{where } \hat{M}_i(j, u) = \frac{M_i(j, u)}{\sum_{u'} M_i(j, u')} \tag{6}$$

Loss Function:

$$\mathcal{L} = -\sum_{u=1}^{|U|} \mathbf{t}(u) \log(\mathbf{p}(u)) \tag{7}$$

Multi-Domain Training Process

Training Procedure:

1. Concatenate domain datasets
2. Each sample: $(\text{image}, (\text{domain\_id}, \text{label})) \rightarrow (\text{image}, \text{universal\_target})$
3. Train universal model on unified dataset

Inference:

$$\mathbf{d}_i = M_i^T \mathbf{p} \tag{8}$$

$$\hat{c}_i = \text{argmax}(\mathbf{d}_i) \tag{9}$$

where $\mathbf{p}$ are universal class predictions and $\hat{c}_i$ is the predicted class in domain i.

Universal Model Performance

Datasets: Caltech-101, Caltech-256, CIFAR-100

Cal-101 + Cal-256 Results

Taxonomy	Cal-101	Cal-256
Hypothesis	91.81 (+0.00)	82.84 (+13.36)
MCFP	91.23 (-0.58)	80.75 (+11.27)
MCFP Binary	92.73 (+0.92)	**89.71 (+20.23)**
Density	92.96 (+1.15)	81.54 (+12.06)
Naive	**93.19 (+1.38)**	82.25 (+12.77)

Cal-101 + Cal-256 + CIFAR Results

Taxonomy	Cal-101	Cal-256	CIFAR
Hypothesis	68.74 (-23.07)	58.17 (-11.31)	69.03 (+8.55)
MCFP	83.28 (-8.53)	76.50 (+7.02)	76.10 (+15.62)
MCFP Binary	94.58 (+2.77)	85.13 (+15.65)	82.71 (+22.23)
Density	95.39 (+3.58)	83.53 (+14.05)	**83.14 (+22.66)**
Naive	**95.50 (+3.69)**	**85.36 (+15.88)**	72.56 (+12.08)

Baselines: Cal-101: 91.81%, Cal-256: 69.48%, CIFAR-100: 60.48%

Key Findings:

- Universal models **outperform** single-domain baselines
- Different relationship selection methods excel on different datasets
- No single method consistently optimal across all scenarios

Key Contributions

1. **Novel Weighted Graph Approach**: We have a *weighted* relationship graph instead of binary edges
2. **Comprehensive Relationship Selection Methods**: Four new proposed methods with detailed evaluation
3. **Synthetic Ground Truth**: Controlled evaluation environment with domain-shifted variants
4. **Reusable Taxonomy Framework**: Our code is adaptable to new taxonomy building rules, relationship selection methods, datasets and model architectures

Main Findings

Successful Aspects:

- Universal models achieve better accuracy than single-domain models
- Our relationship graphs create meaningful, weighted inter-dataset class relationships
- Synthetic datasets provide a valuable, customizable evaluation environment

Future Work & Limitations:

- No single relationship selection method works optimally for all cases
- Some bad clusters in universal taxonomy remain
- Tests were limited to 3-domain scenarios $\rightarrow$ need to scale to more datasets
- Try out for other vision tasks (e.g., object detection, segmentation)

Questions?

Thank you for your attention!

Questions?