Learning To Detect Unseen Object Classes by Between-Class Attribute Transfer
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Presented by Ruohan Gao
UTCS CS381V
Visual Recognition
2016 Spring
Image Annotation

Koala

Tiger

Lion

Apple

Orange
30,000+ human recognizable object categories

Tiger

Lion

Labeled Datasets
Training

Koala

Tiger

Apple

Orange
Training
Intra-class Variations? 

Tiger

Koala
What about unseen labels?
Problem Formulation

\( \mathcal{X} \) : arbitrary feature space

\( \mathcal{Y} \) : label set \( \mathcal{Y} = \{ y_1, \ldots, y_K \} \)

Training Samples: \( (x_1, l_1), \ldots, (x_n, l_n) \subset \mathcal{X} \times \mathcal{Y} \)

Task: learn a classifier: \( f : \mathcal{X} \to \mathcal{Z} \) for a label set \( \mathcal{Z} = \{ z_1, \ldots, z_L \} \) that is disjoint from \( \mathcal{Y} \)
Solving the Problem

Flat classification
Solving the Problem

Reflection: Flat multi-class classification cannot generalize to classes \((z_l)_{l=1,...,L}\) that are not part of the training set.

We need to introduce a coupling between classes in \(\mathcal{Y}\) and \(\mathcal{Z}\).

Inserted by human efforts.
Constraints on Coupling Mechanisms:

1. The amount of human effort to specify new classes should be minimal.

2. Coupling data that requires only common knowledge is preferable over specialized knowledge.
What’s this animal?

Furry:
Black:
White:
Water:
Eats Bamboo:
Semantic Attributes

• Shape
• Color
• Life Habits
• Organs
• Geographic Information
• ............
Semantic Attributes

Meaningful high-level concepts transcend class boundaries

White

Sea
Constraints on Coupling Mechanisms:

1. The amount of human effort to specify new classes should be minimal.

2. Coupling data that requires only common knowledge is preferable over specialized knowledge.

Attributes are assigned on a per-class basis instead of a per-image basis.

Humans are typically able to provide good prior knowledge about such attributes.
Attribute-Based Classification

Direct Attribute Prediction (DAP)

Indirect Attribute Prediction (IAP)
Direct attribute prediction (DAP)

At test time, attribute values can directly be inferred, and these imply output class label even for previously unseen classes.

Training labels \((y_k)_{k=1,...,K}\) imply training values for the attributes \((a_m)_{m=1,...,M}\), from which parameters \(\beta_m\) are learned.
Indirect attribute prediction (IAP)

Multi-class parameters $\alpha_K$ are learned for each training class. At test time, the predictions for all training classes induce a labeling of the attribute layer, from which a labeling over the test classes can be inferred.
Implementation - DAP

- The trained classifiers provide: \( p(a_m|x) \)
- Complete Image-Attribute Layer: \( p(a|x) = \prod_{m=1}^{M} p(a_m|x) \)
- Deterministic Assumption: \( p(a|z) = [a = a^z] \)
- Bayes’ Rule: \( p(z|a) = \frac{p(z|a)}{p(a^z)} [a = a^z] \)
- Posterior of a test class:

\[
p(z|x) = \sum_{a \in \{0,1\}^M} p(z|a)p(a|x) = \frac{p(z)}{p(a^z)} \prod_{m=1}^{M} p(a^z_m|x)
\]
Implementation - IAP

• Learn a probabilistic multi-class classifier estimating $p(y_k|x)$

• Deterministic Assumption: $p(a_m|y) = [a_m = a^y_m]$

• Combining above two steps:

$$p(a_m|x) = \sum_{k=1}^{K} p(a_m|y_k)p(y_k|x)$$

• Similar to DAP:

$$p(z|x) = \sum_{a \in \{0,1\}^M} p(z|a)p(a|x) = \frac{p(z)}{p(a^z)} \prod_{m=1}^{M} p(a^z_m|x)$$
Prediction Decision: MAP Prediction

\[ p(z|x) = \sum_{a \in \{0,1\}^M} p(z|a)p(a|x) = \frac{p(z)}{p(a^z)} \prod_{m=1}^{M} p(a^z_m|x) \]

- Class priors: assume identity, ignore \( p(z) \)
- Attribute priors: assume to be empirical means:
  \[ p(a_m) = \frac{1}{K} \sum_{k=1}^{K} a^{y_k}_m \]
- Decision rule \( f : \mathcal{X} \rightarrow \mathcal{Z} : \)
  \[ f(x) = \text{argmax} \prod_{l=1}^{L} \frac{p(a^z_l|x)}{p(a^z_l)} \]
Experimental Evaluation Results

- New dataset: Animals with Attributes
- 30,475 images with at minimum of 92 images for any class
- Animals are uniquely characterized by their attribute vector

<table>
<thead>
<tr>
<th>Animal</th>
<th>black</th>
<th>white</th>
<th>brown</th>
<th>stripes</th>
<th>water</th>
<th>eats fish</th>
</tr>
</thead>
<tbody>
<tr>
<td>otter</td>
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<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
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</tr>
<tr>
<td>polar bear</td>
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<td>yes</td>
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<tr>
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<td>no</td>
<td>yes</td>
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</table>
Experimental Evaluation Results

<table>
<thead>
<tr>
<th>Class</th>
<th>Multi-class accuracy for DAP: 40.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Multi-class accuracy for IAP: 27.8%</td>
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<tr>
<td></td>
<td>Chance level accuracy: 10%</td>
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<td></td>
<td>Ordinary multi-class classification accuracy: 65.9%</td>
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</tbody>
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Figure 4. Confusion matrices between 10 test classes of the *Animals with Attributes* dataset (best viewed in color). Left: indirect attribute prediction (IAP), right: direct attributes prediction (DAP).
Experimental Evaluation Results

Figure 5. Detection performance of object classification with disjoint training and test classes (DAP method): ROC-curves and area under curve (AUC) for the 10 Animals with Attributes test classes.

Quality of the individual attribute predictors on the test set using DAP

Random AUC: 0.5
Experimental Evaluation Results

<table>
<thead>
<tr>
<th>humpback whale</th>
<th>leopard</th>
<th>chimpanzee</th>
<th>hippopotamus</th>
<th>racoon</th>
<th>persian cat</th>
<th>rat</th>
<th>seal</th>
<th>pig</th>
<th>giant panda</th>
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<tbody>
<tr>
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<td><img src="image3" alt="Image" /></td>
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<td><img src="image20" alt="Image" /></td>
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Summary

• A framework of learning for disjoint training and test classes

• Two methods for attribute-based classification: DAP and IAP

• A new dataset: Animals with Attributes with attribute annotation
Interesting Discussion Points and Future Extensions

• Why DAP outperforms IAP by so much?
• Some attributes might be easy to learn than the others. What is the best way to learn attributes?
• Develop adaptive system to grow to include new classes
• Remove the amount of human effort
• Develop a system that automatically figures out attributes from images based on a fixed set of human defined attributes?
• Merged with supervised classification with scarce training examples
• Multi-layer attributes? Interrelationship among attributes?
• Attribute specific queries
Reference


• **animals with attributes**: *A dataset for Attribute Based Classification*