Learning To Detect Unseen Object Classes by Between-Class Attribute Transfer

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Visual Recognition
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Image Annotation

Koala

Tiger

Lion

Apple

Orange

30,000+ human recognizable object categories

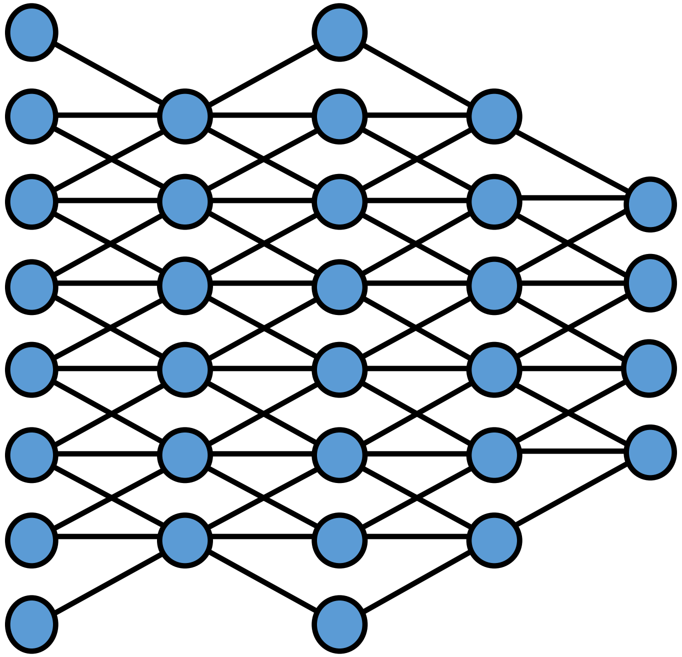
Tiger

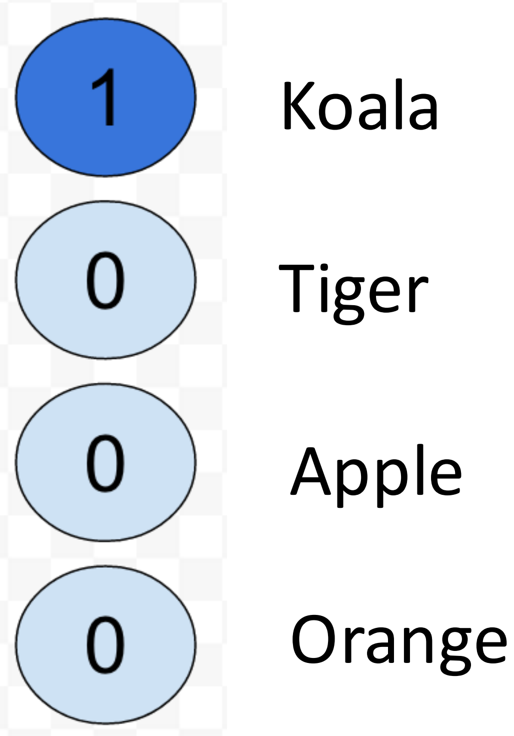
Lion

Labeled Datasets

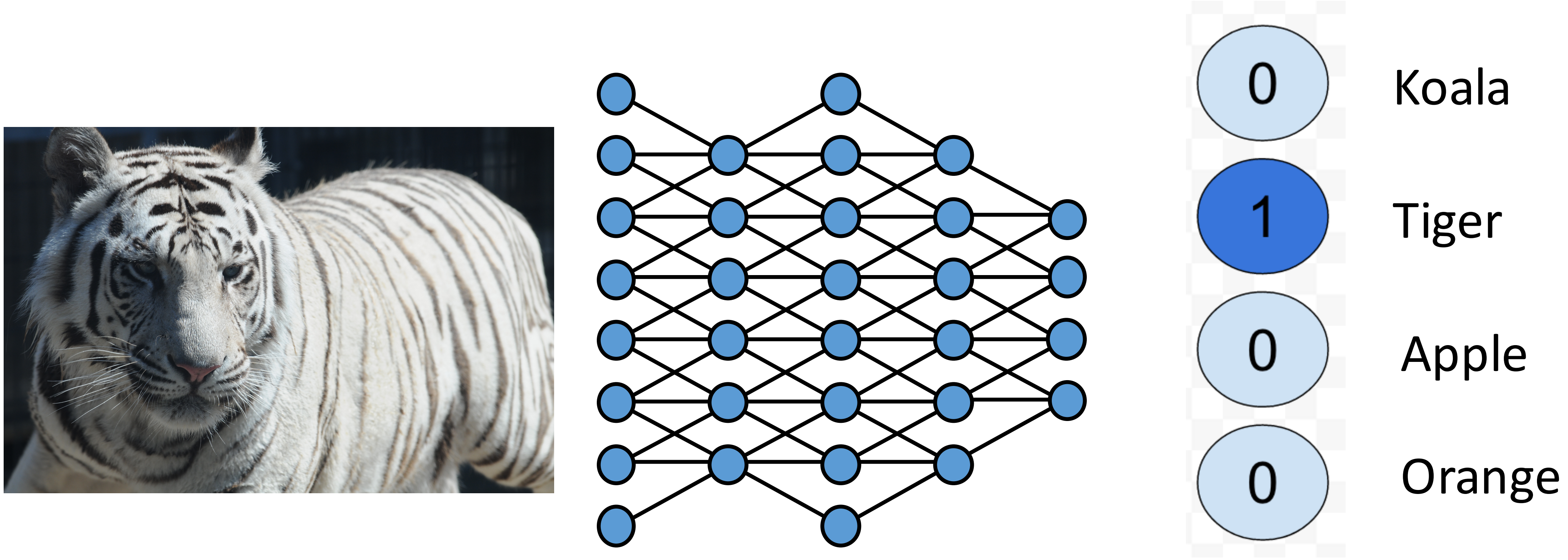
…………..

Training





Training



Intra-class Variations? ✓

Tiger

Koala

What about unseen labels?

Problem Formulation

$\mathcal{X}$: arbitrary feature space

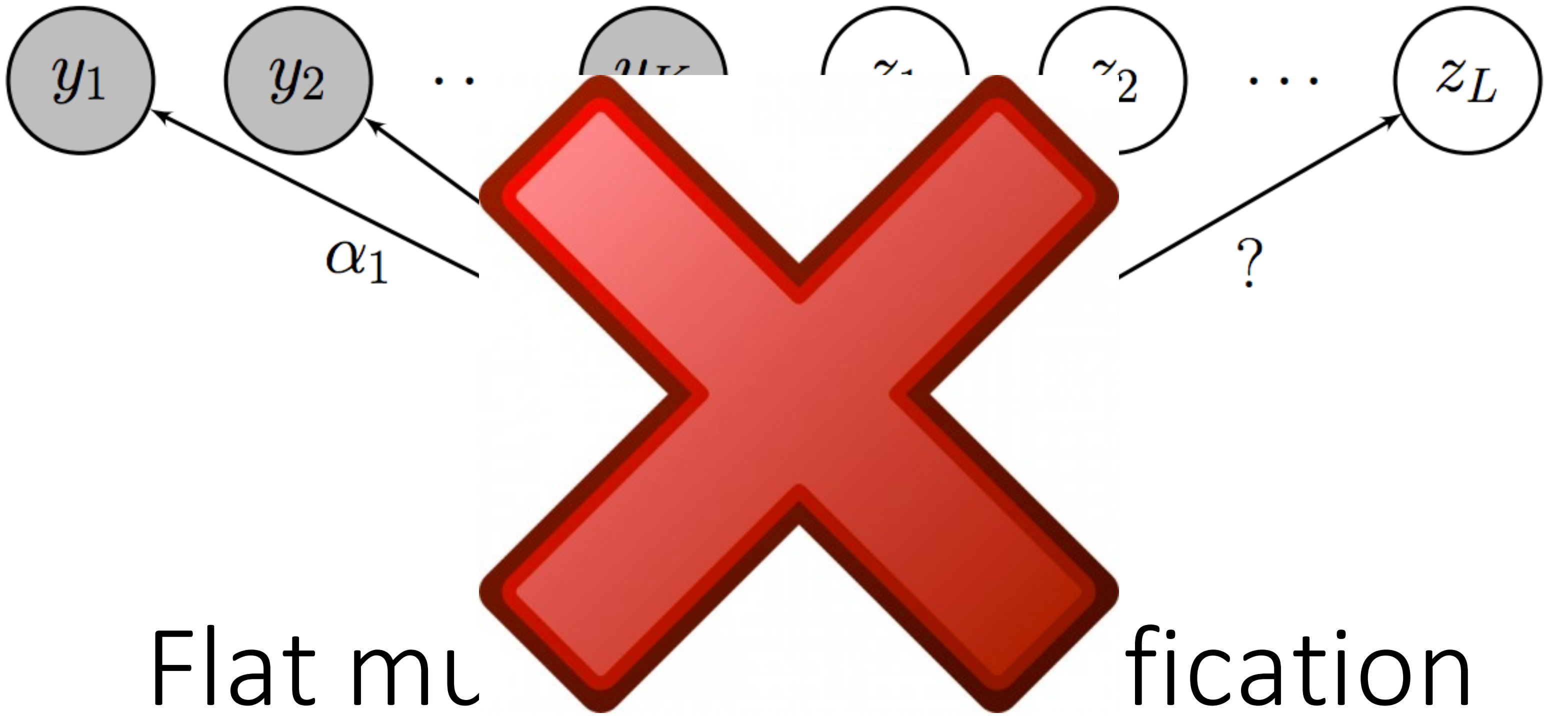
$\mathcal{Y}$: label set $\quad \mathcal{Y} = \{y_1, \ldots, y_K\}$

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

Task: learn a classifier: $f : \mathcal{X} \rightarrow \mathcal{Z}$ for a label set

$\mathcal{Z} = \{z_1, \ldots, z_L\}$ that is disjoint from $\mathcal{Y}$

Solving the Problem



Flat mu fication

Solving the Problem

Reflection: Flat multi-class classification cannot generalize to classes $(z_l)_{l=1\ldots,L}$ 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



White

Meaningful high-level concepts transcend class boundaries



Sea

Constraints on Coupling Mechanisms:

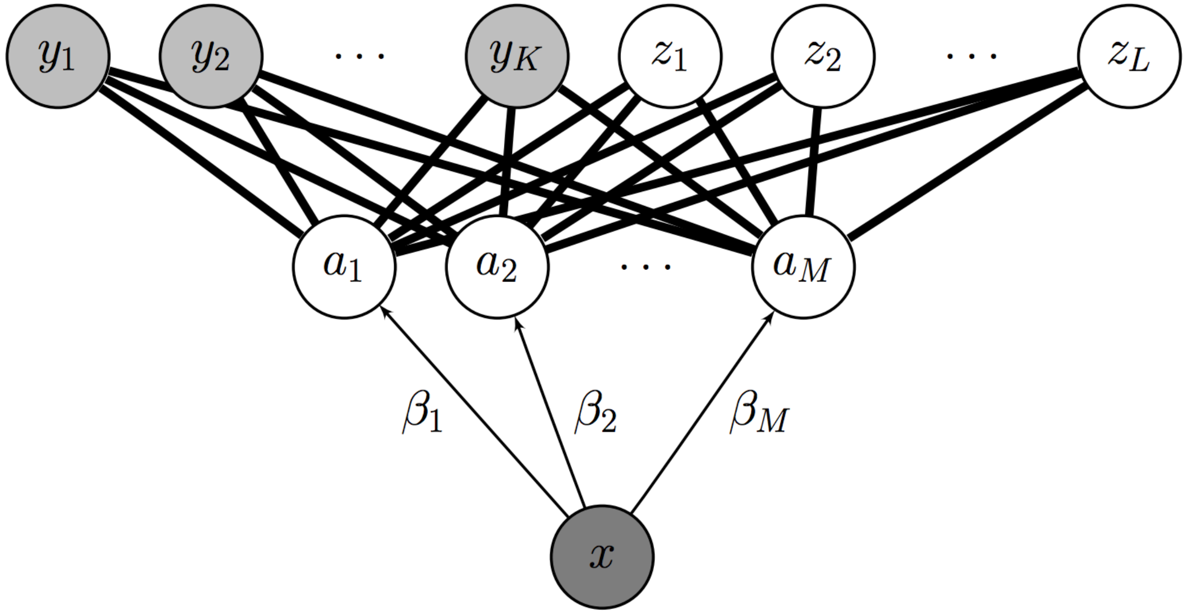
1. The amount of human effort to specify new classes should be minimal.

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

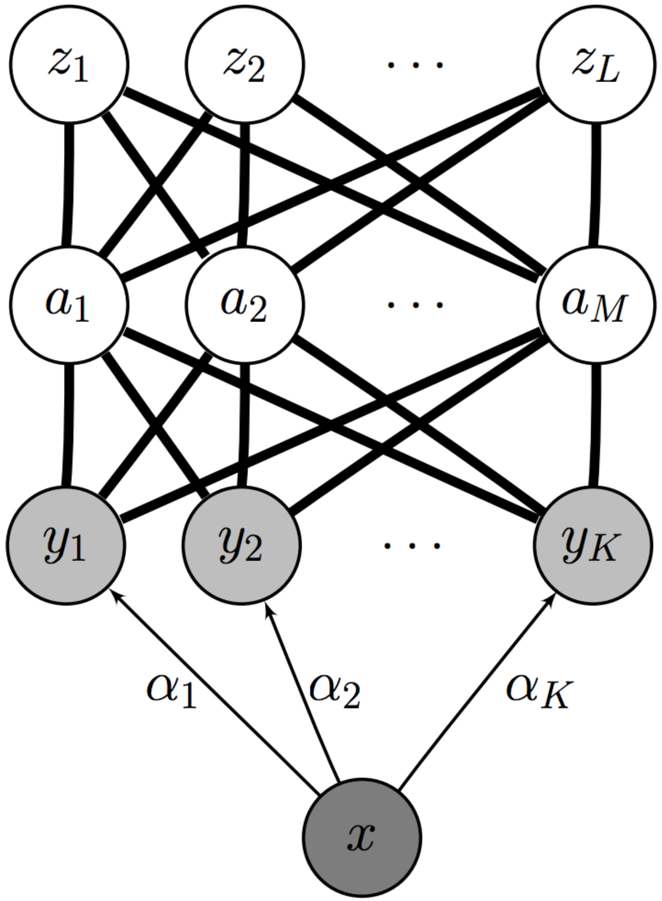
2. Coupling data that requires only common knowledge is preferable over specialized knowledge.

   → Humans are typically able to provide good prior knowledge about such attributes

Attribute-Based Classification

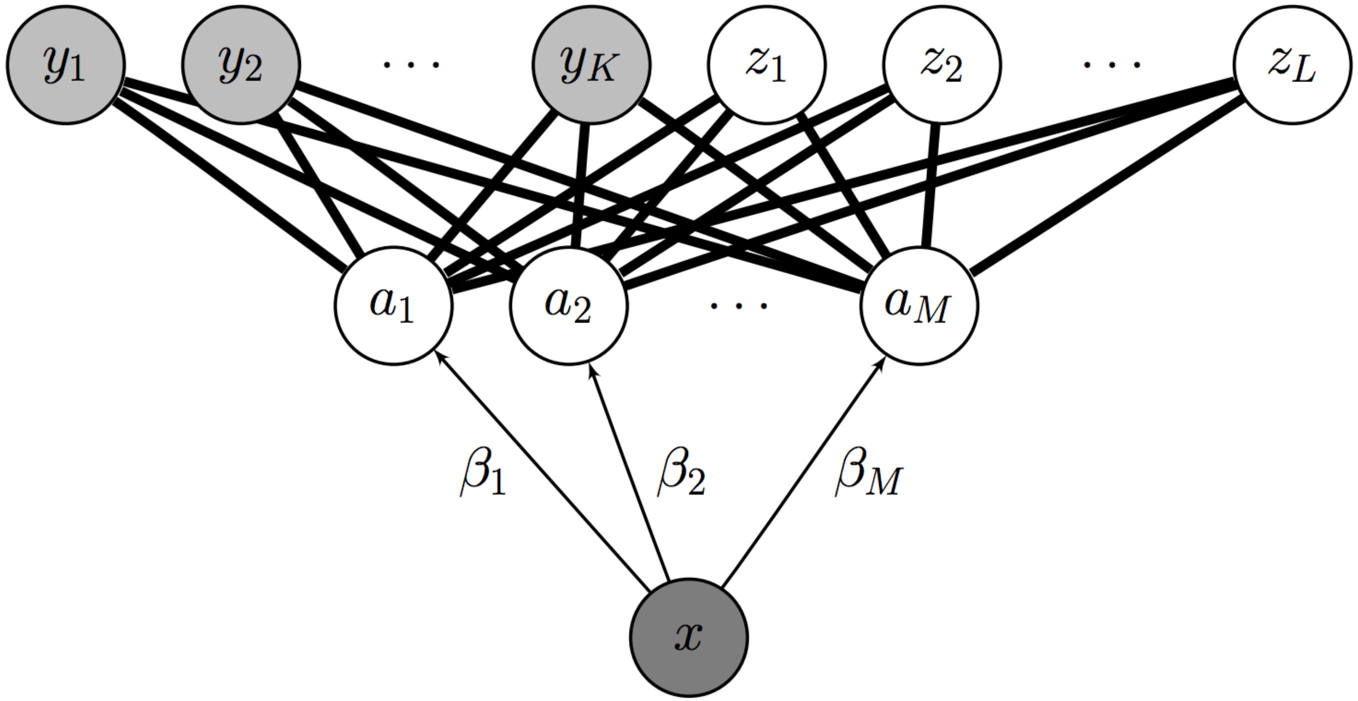


Direct Attribute Prediction (DAP)



Indirect Attribute Prediction (IAP)

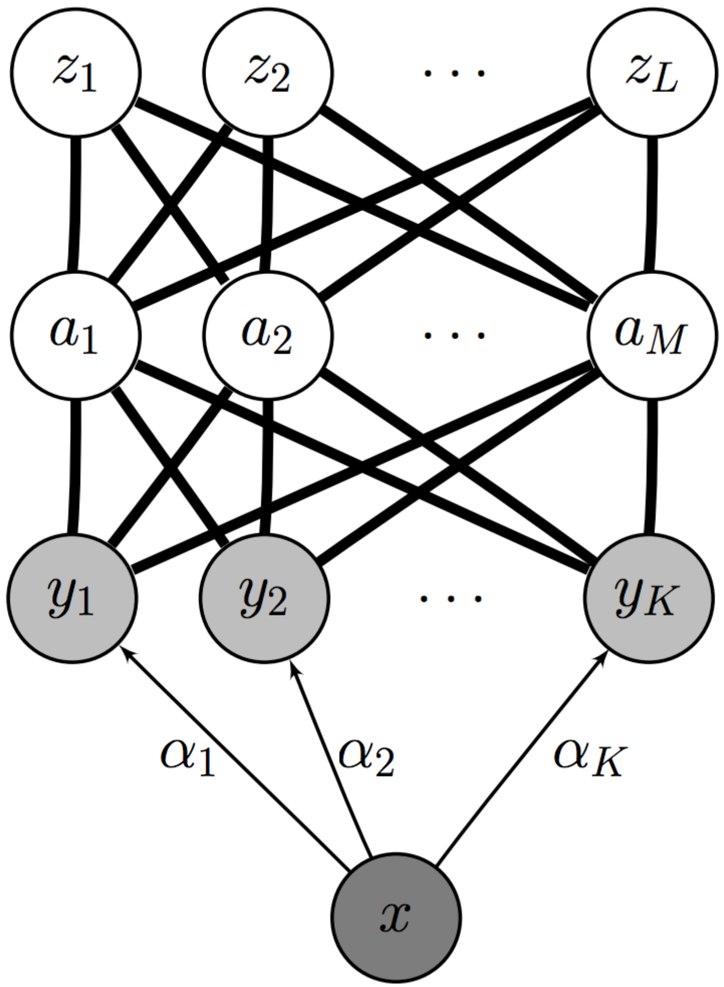
Direct attribute prediction (DAP)



training labels $(y_k)_{k=1,\ldots,K}$ imply training values for the attributes $(a_m)_{m=1,\ldots,M}$, from which parameters β_m are learned.

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

Indirect attribute prediction (IAP)

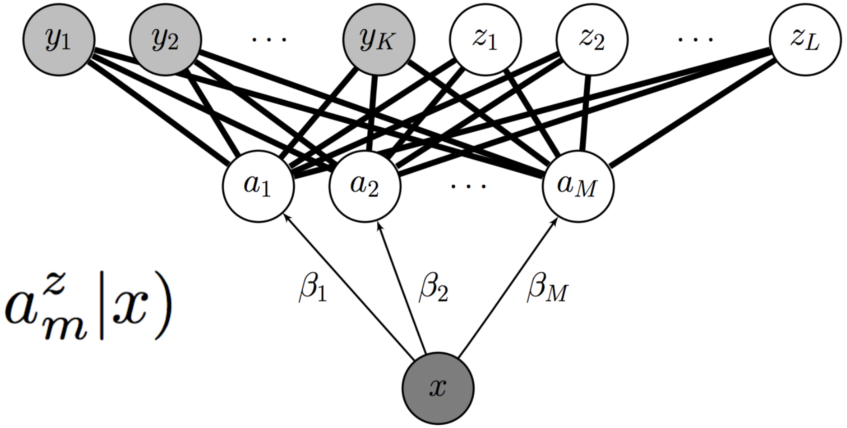


Multi-class parameters α_K are learned for each training class. At test time, the predictions for all training classes induce a labeling of the attribute layer, from which a labeling over the test classes can be inferred.

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: $p(z|a) = \frac{p(z)}{p(a^z)}[\![a = a^z]\!]$
- Posterior of a test class:

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



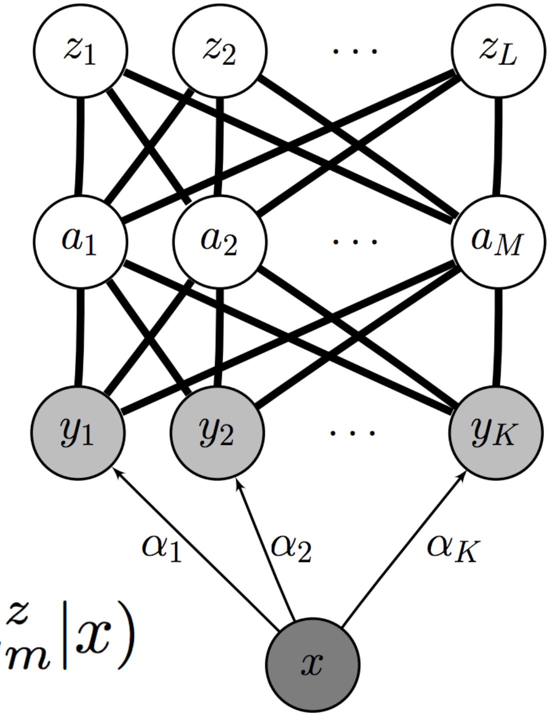
Implementation - IAP

- Learn a probabilistic multi-class classifier estimating $p(y_k|x)$
- Deterministic Assumption: $p(a_m|y) = [\![a_m = a_m^y]\!]$
- Combining above two steps:

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

- Similar to DAP:

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



Prediction Decision: MAP Prediction

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

- Class priors: assume identity, ignore $p(z)$
- Attribute priors: assume to be empirical means:

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

- Decision rule $f : \mathcal{X} \rightarrow \mathcal{Z}$:

$$f(x) = \operatorname*{argmax}_{l=1,\ldots,L} \prod_{m=1}^{M} \frac{p(a_m^{z_l}|x)}{p(a_m^{z_l})}$$

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

Experimental Evaluation Results

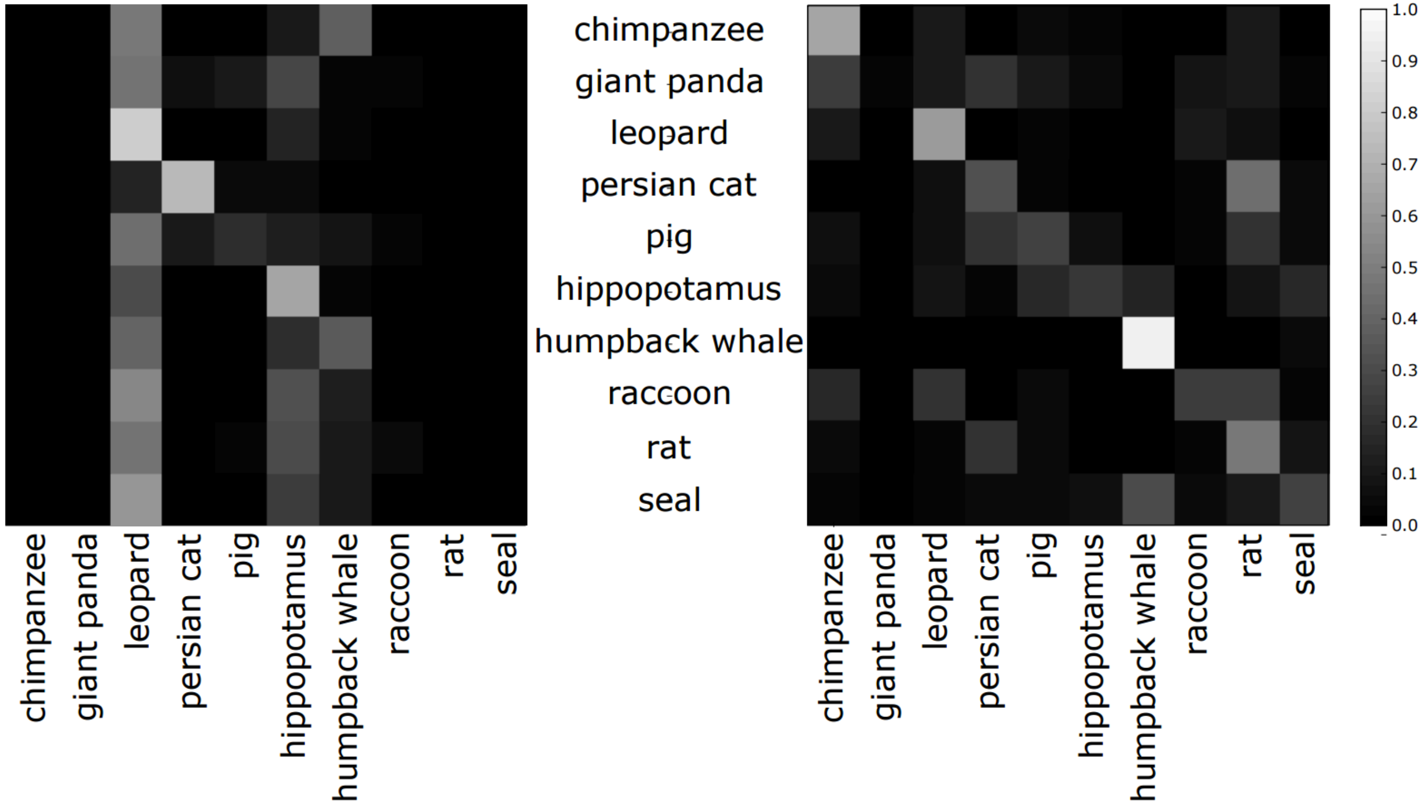


Figure 4. Confusion matrices between 10 test classes of the *Animals with Attributes* dataset (best viewed in color). Left: indirect attribute prediction (IAP), right: direct attributes prediction (DAP).

Multi-class accuracy for DAP:
40.5%

Multi-class accuracy for IAP:
27.8%

Chance level accuracy:
10%

Ordinary multi-class classification accuracy:
65.9%

Experimental Evaluation Results

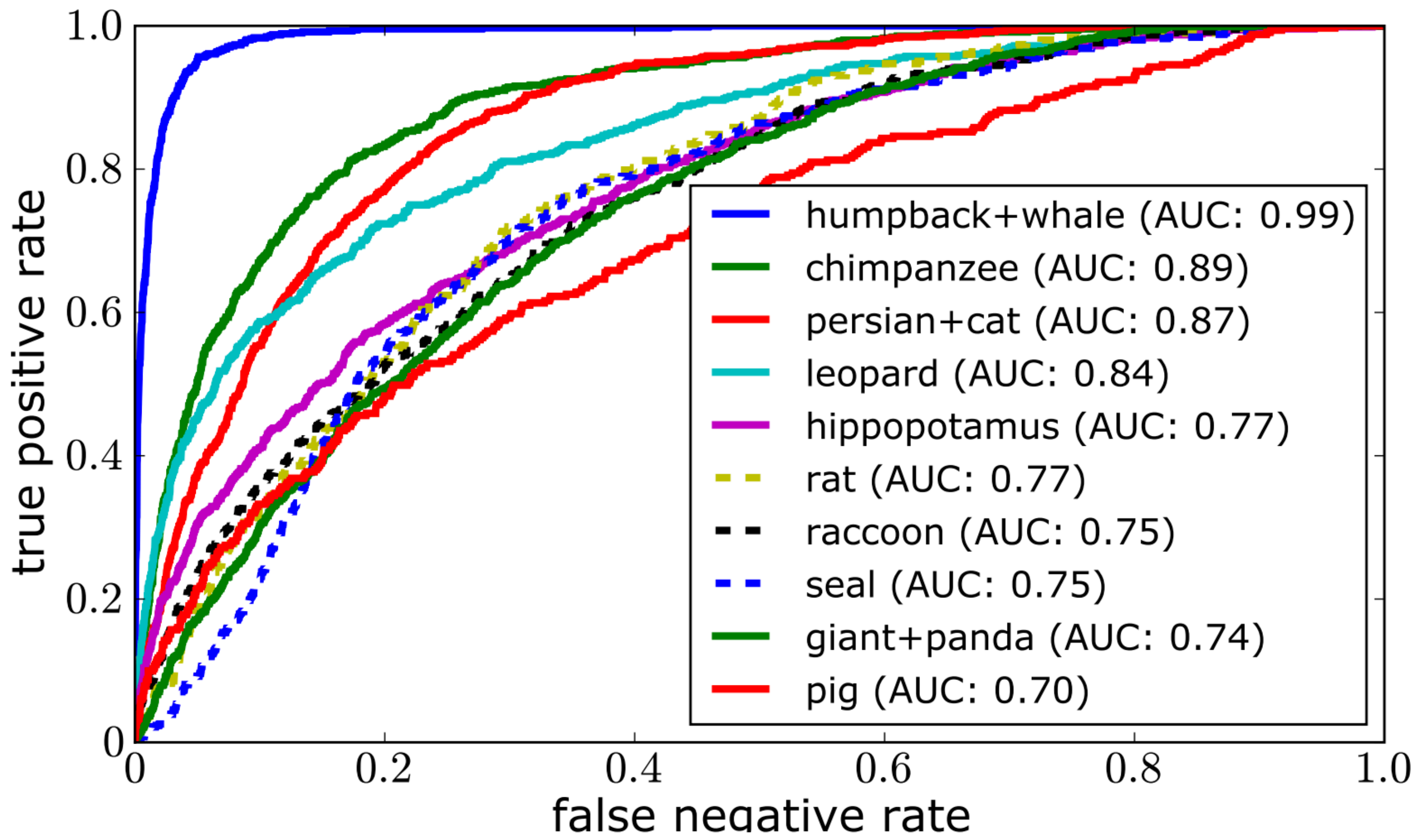
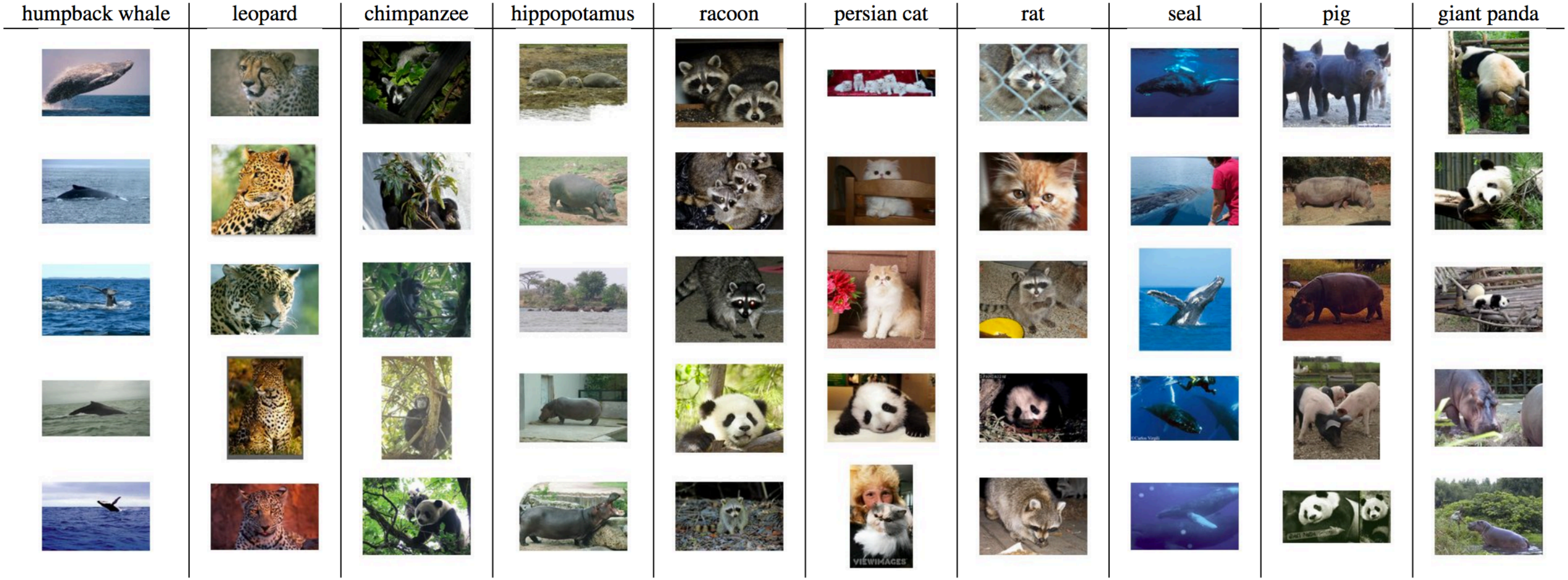


Figure 5. Detection performance of object classification with disjoint training and test classes (DAP method): ROC-curves and area under curve (AUC) for the 10 *Animals with Attributes* test classes.

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

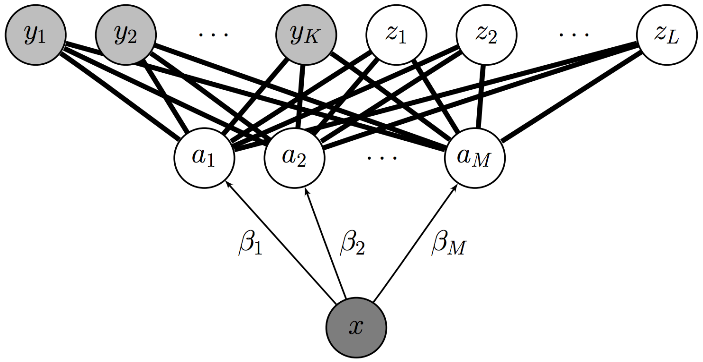
Random AUC: 0.5

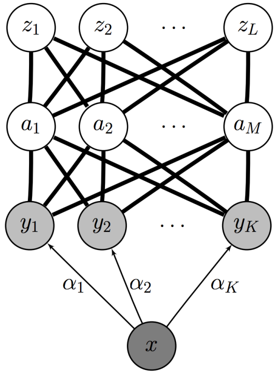
Experimental Evaluation Results



Summary

- A framework of learning for disjoint training and test classes
- Two methods for attribute-based classification: DAP and IAP

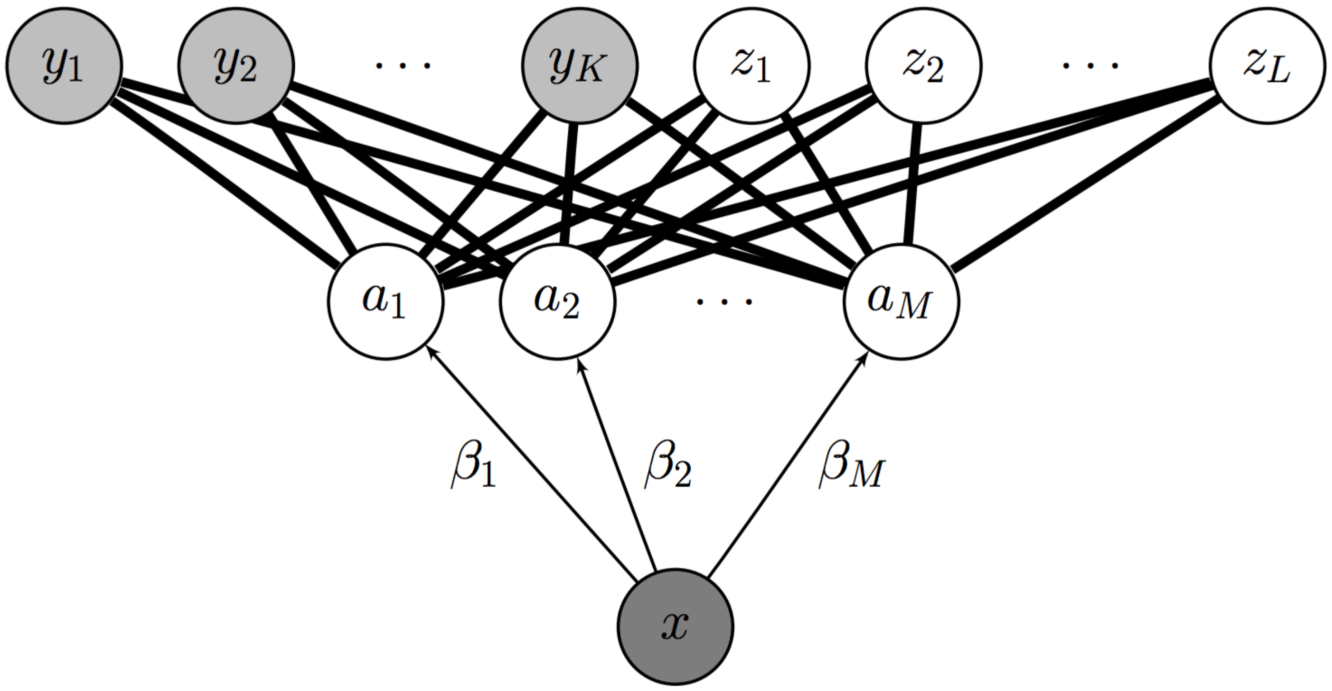


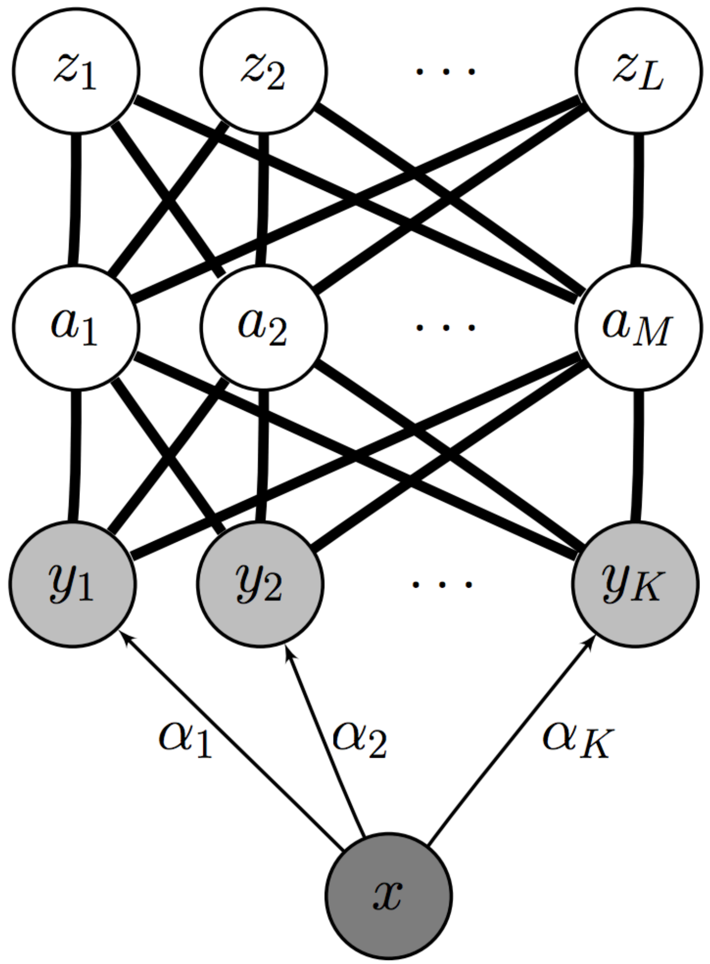


- A new dataset: Animals with Attributes with attribute annotation

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


y_1
y_2
$\cdots$
y_K
z_1
z_2
$\cdots$
z_L
a_1
a_2
$\cdots$
a_M
β_1
β_2
β_M
x


z_1
z_2
$\cdots$
z_L
a_1
a_2
$\cdots$
a_M
y_1
y_2
$\cdots$
y_K
α_1
α_2
α_K
x

Reference

- Lampert, Christoph H., Hannes Nickisch, and Stefan Harmeling. "Learning to detect unseen object classes by between-class attribute transfer." *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 2009.
- animals with attributes: *A dataset for Attribute Based Classification*