Learning with Small Samples

Including zero-shot learning

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Bachelor in software engineering, Damascus University

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About this tutorial

- A basic understanding of zero-shot and low-shot learning
- Get to know state of the art approaches
- Hands-on experience with zero-shot image classification
- Hands-on experience with training image classifier with small set

Prerequisites

- Basic math e.g. matrix operations, derivatives,.., etc
- Basic understanding of ML concepts e.g. classifier, loss function,.., etc.
- Basic DL concepts e.g. MLP, CNN, LSTM, ..,etc
- Python, Keras

Structure

- Introduction & motivation
- Zero-shot learning
  - Definition
  - Side information
  - Zero-shot learning models
  - Exercise
- Low-shot learning
  - Definition
  - Low-shot learning models
- Tips & tricks
- Exercises

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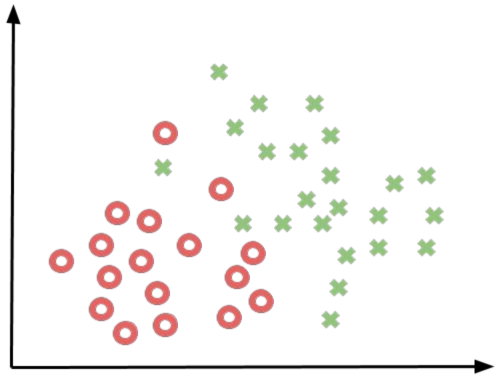
Introduction & Motivation

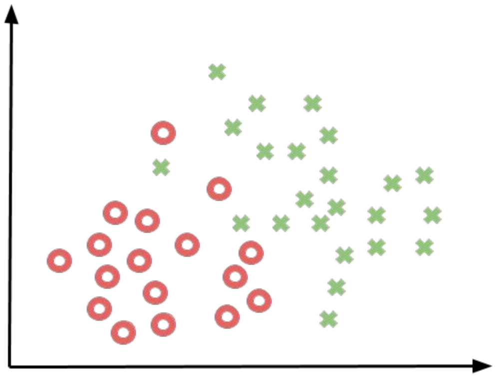
Learning

Supervised

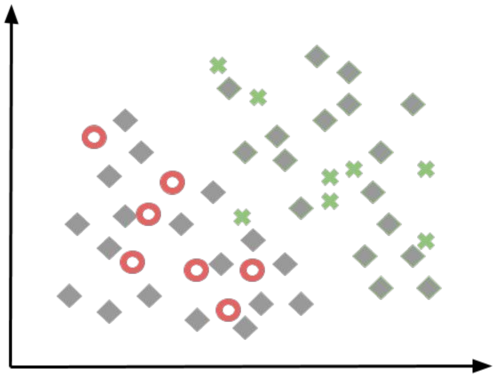


Learning

Supervised

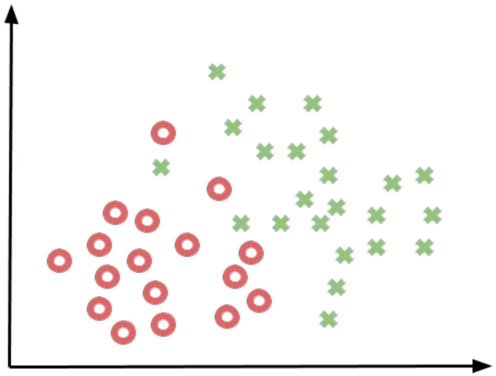


Semi-supervised



Learning

Supervised



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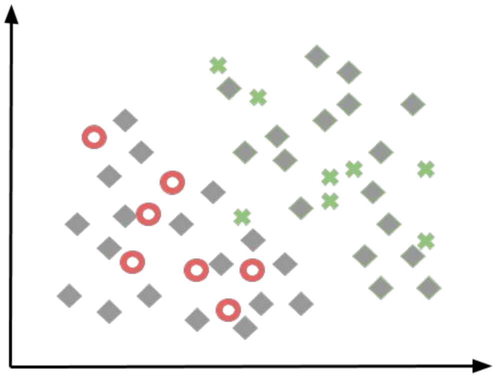
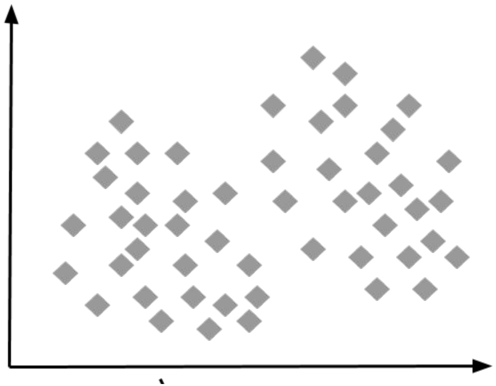
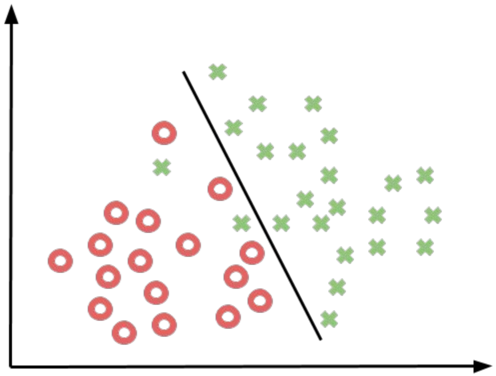


Unsupervised



Learning

Supervised



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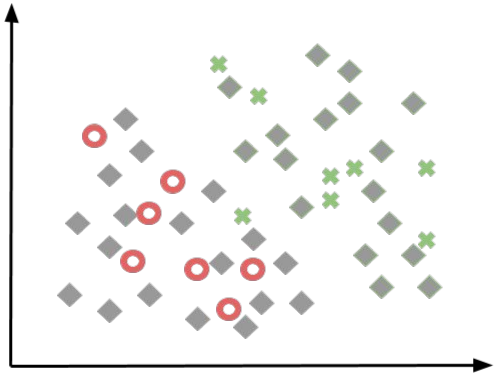

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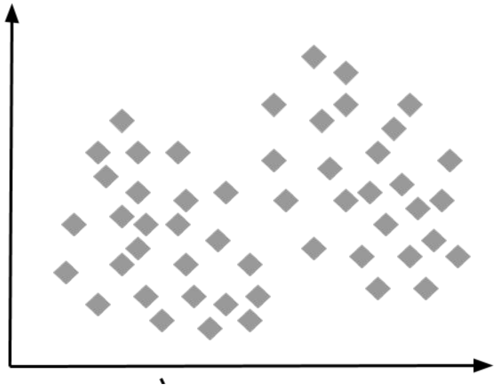

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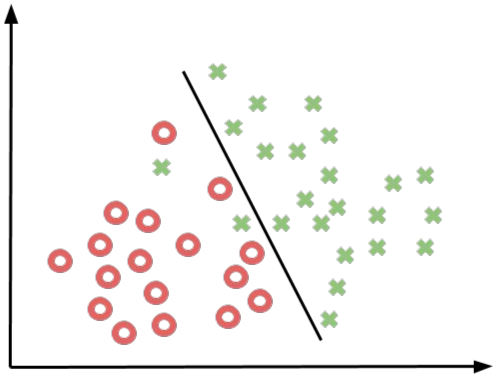

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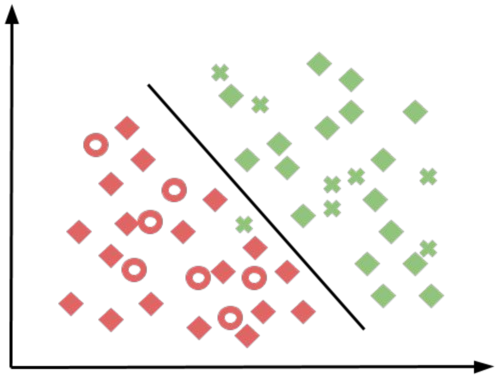

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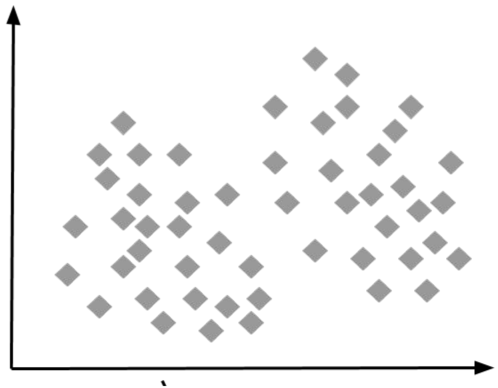

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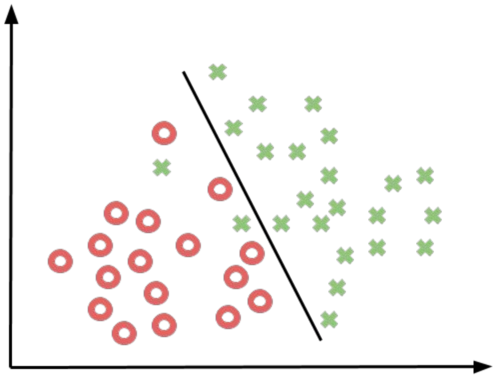

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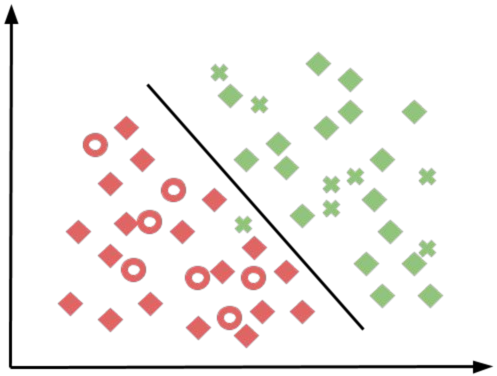

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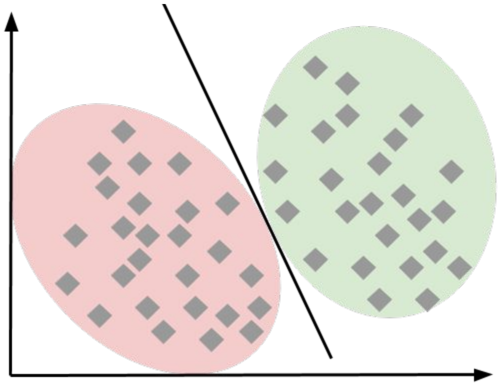
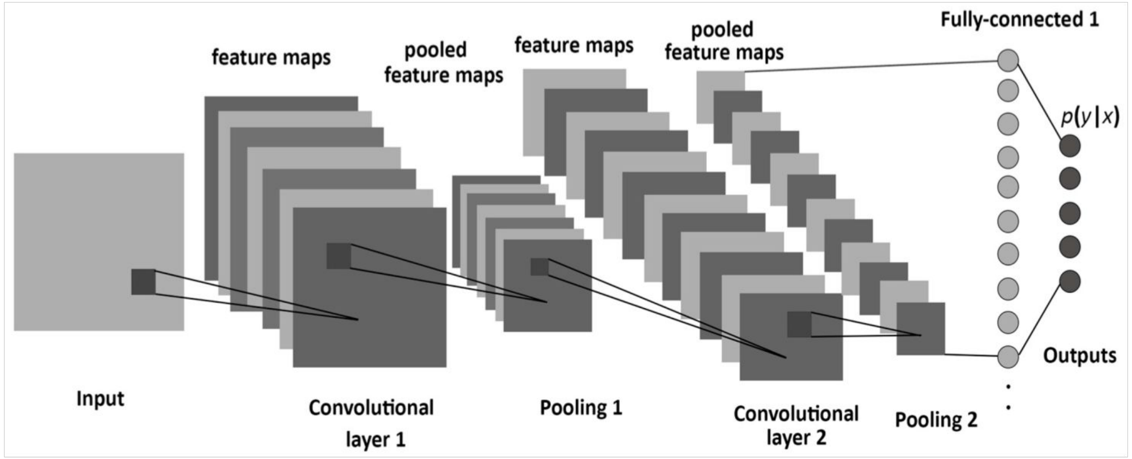
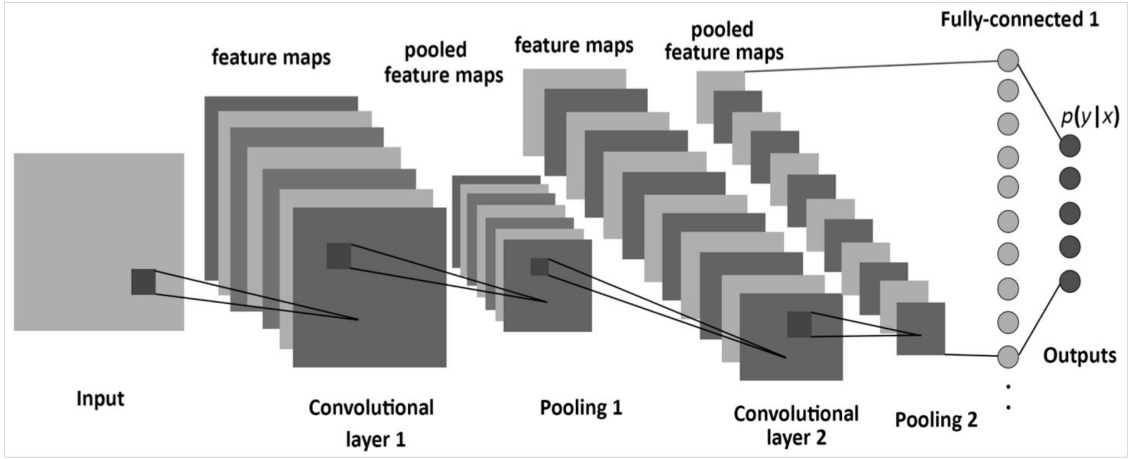


Many-shots supervised learning



[Albelwi, Mahmood 2017]
http://www.image-net.org/

Many-shots supervised learning



[Albelwi, Mahmood 2017]
http://www.image-net.org/

Annotation Effort

14M images, **21K** categories

[Deng, et al CVPR2009]

Annotation Effort

- OpenImages
  9M images, **6K** categories

- COCO
  330K images

- MIT Places
  2.5M images

[Krasin, et al. 2017] [Lin, et al. 2014] [Zhou, et al. NIPS2014]

Task complexity

- **Classification**
  Single labeling is relatively easy task

Complexity

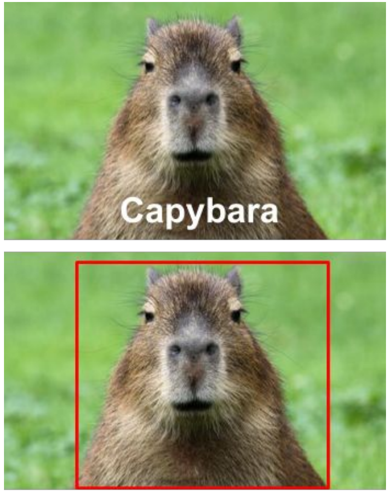
https://www.livescience.com/55223-capybara-facts.html

Task complexity

Complexity

- **Classification**
  Single labeling is relatively easy

- **Localization**
  Requires precise bounding boxes



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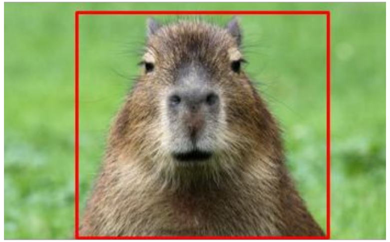
Task complexity

Complexity

- **Classification**
  Single labeling is relatively easy

- **Localization**
  Requires precise bounding boxes

- **Captioning**
  Many other possibilities!
  “Surprised capybara looking at the camera”
  “Portrait photo of a capybara ”



https://www.livescience.com/55223-capybara-facts.html

Task complexity vs. annotation

Complexity

- **Classification**
  ImageNet 14M labeled images

[Deng, et al CVPR2009]
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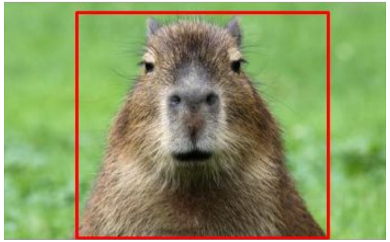
Task complexity vs. annotation

Complexity

- **Classification**
  ImageNet 14M labeled images

- **Localization**
  openImages 3.6M bounding boxes



[Deng, et al CVPR2009] [Krasin, et al. 2017]
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Task complexity vs. annotation

Complexity

- **Classification**
  ImageNet 14M labeled images

- **Localization**
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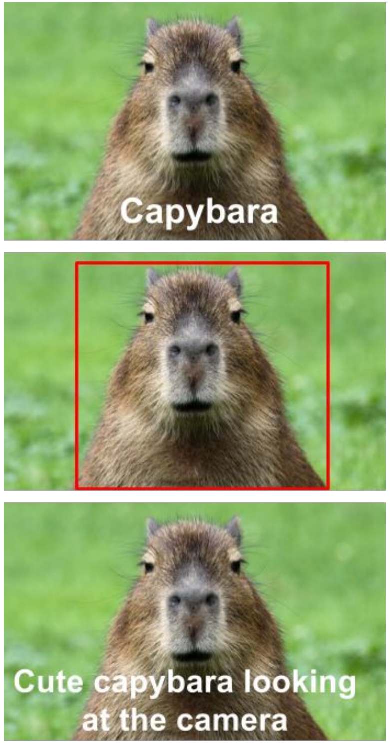
- **Captioning**
  COCO 300K captioned images



[Deng, et al CVPR2009] [Krasin, et al. 2017] [Lin, et al. 2014]
https://www.livescience.com/55223-capybara-facts.html

Task complexity vs. annotation

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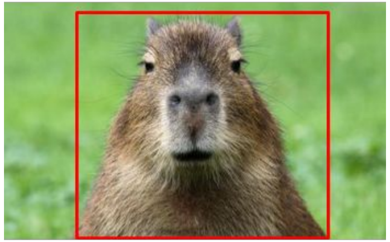
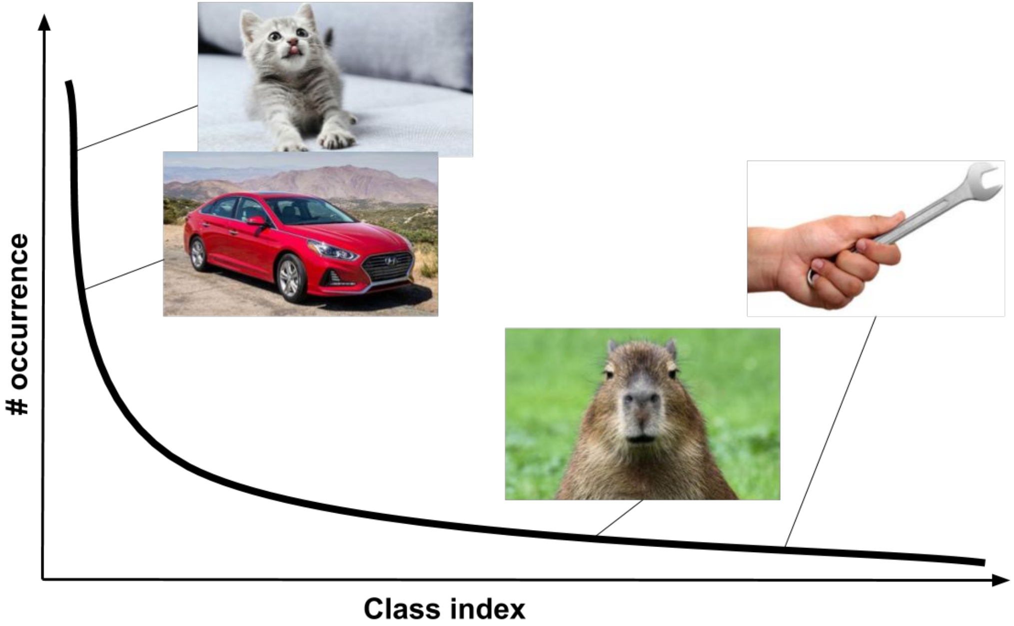


Less annotations for more complex tasks!

[Deng, et al CVPR2009] [Krasin, et al. 2017] [Lin, et al. 2014]
https://www.livescience.com/55223-capybara-facts.html

Tail distribution



https://www.cars.com/
http://www.foxnews.com/lifestyle/2017/11/09/how-to-keep-cat-from-scratching-your-sofa-to-shreds.html
https://www.livescience.com/55223-capybara-facts.html
https://www.indiamart.com/proddetail/hand-wrench-13045857897.html

Fine-grained categories

Hard: subtle differences

Oxford Pet dataset

[Parkhi, et al. CVPR2012]

Fine-grained categories

Hard: subtle differences

Cars dataset

[Krause, et al. ICCV2013]

Fine-grained categories

Hard: subtle differences

FGVC-Aircraft dataset

[Maji, et al. 2013]

Fine-grained categories

Hard: subtle differences

60 classes of Caltech Birds dataset

[Welinder, et al. 2010]

Fine-grained categories

Novice annotator

[Welinder, et al. 2010]

Fine-grained categories

Bird expert → expensive

[Welinder, et al. 2010]

Zero-shot Learning

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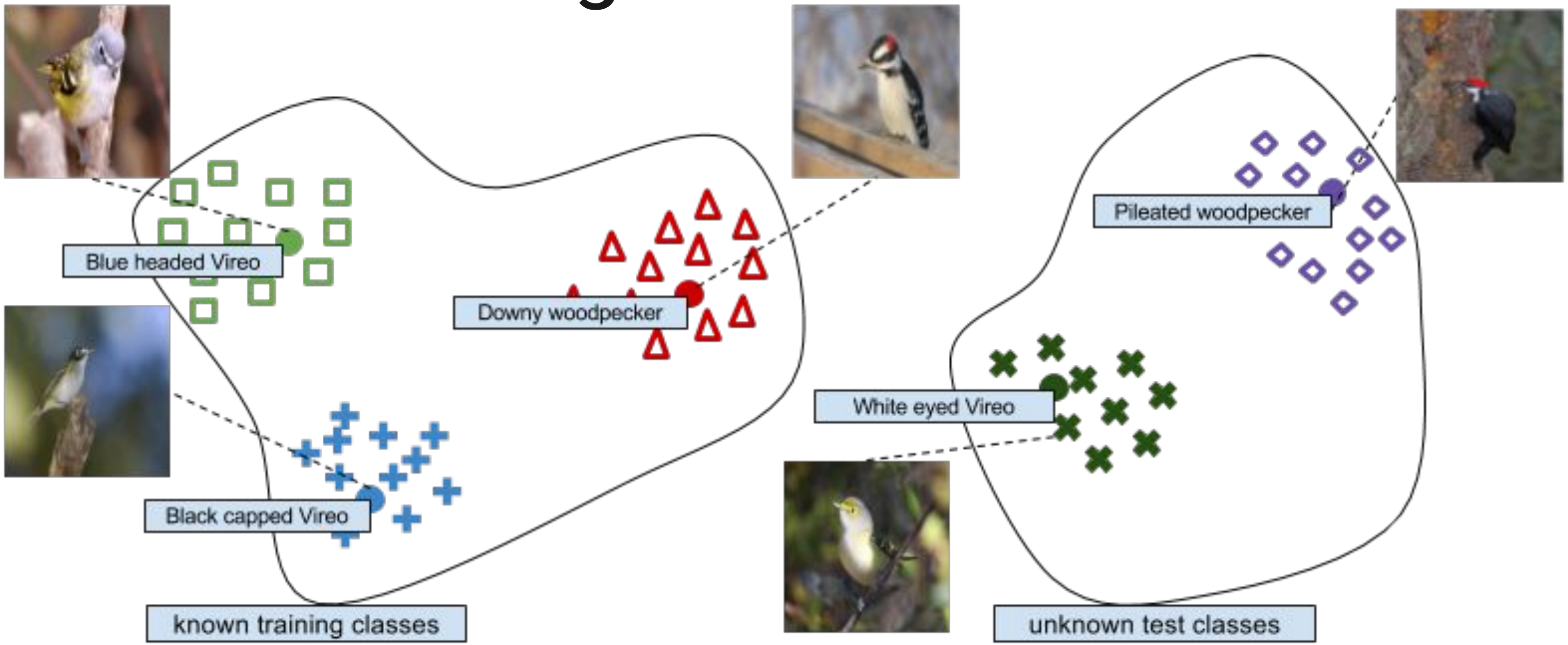
Zero-shot learning

- Extreme case of scarce training data for some categories
- Disjoint sets of training and test classes
- New class examples appear only after training stage (at test time)

Animals classifier: **No** panda images at training time → panda images in testset

Zero-shot learning



Images: http://www.vision.caltech.edu/visipedia/CUB-200.html

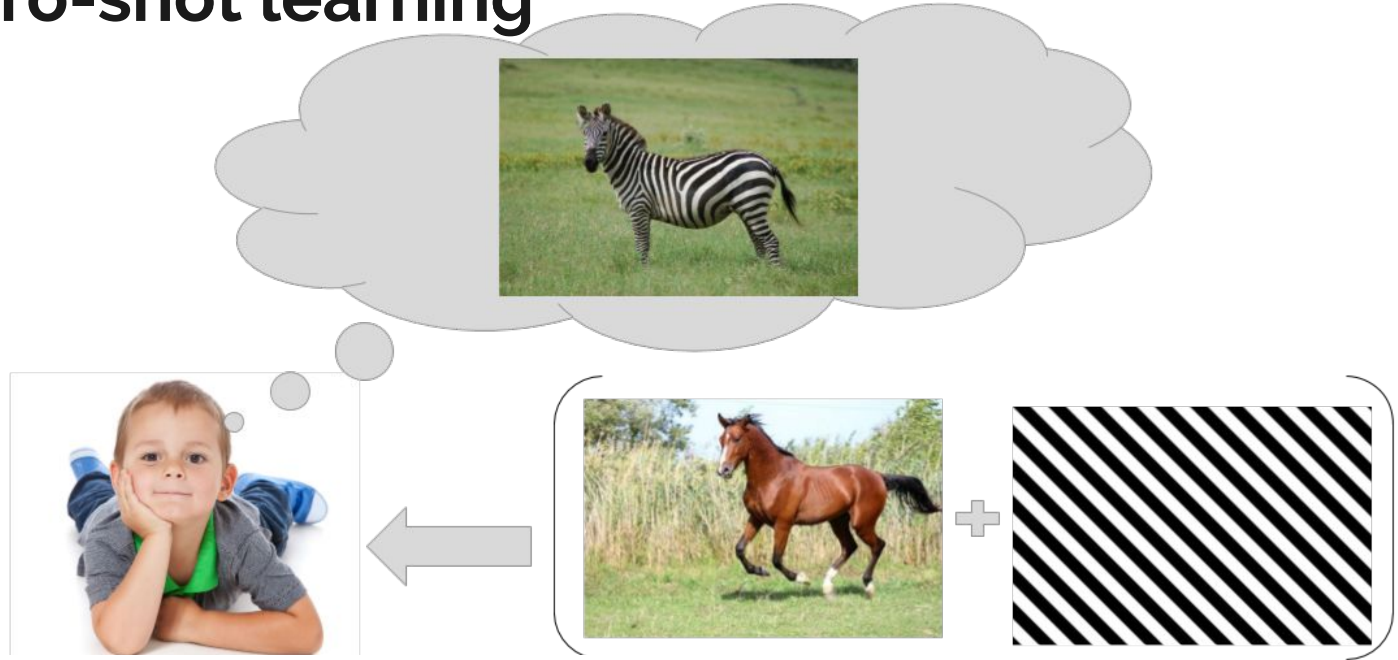
Zero-shot learning

How?

Zero-shot learning

http://www.youngparents.com.sg/development/10-steps-raising-self-confident-child/
http://www.thehorse.com/articles/33568/5-tips-for-packing-the-pounds-on-performance-horses
http://earlylearningtoys.org/stripes/

Zero-shot learning



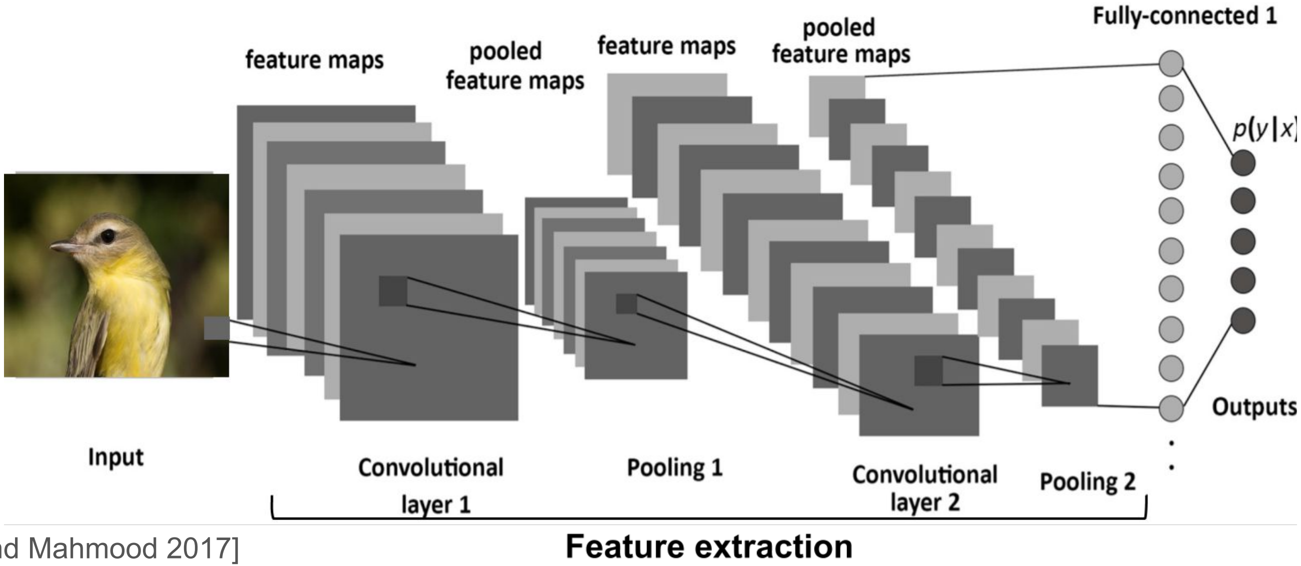
http://www.youngparents.com.sg/development/10-steps-raising-self-confident-child/
http://www.thehorse.com/articles/33568/5-tips-for-packing-the-pounds-on-performance-horses
http://earlylearningtoys.org/stripes/ https://pt.wikipedia.org/wiki/Zebra-de-grant

Zero-shot learning

Knowledge transfer & Side information

Knowledge transfer

Use bottleneck image features of pre-trained model



[Albelwi and Mahmood 2017]

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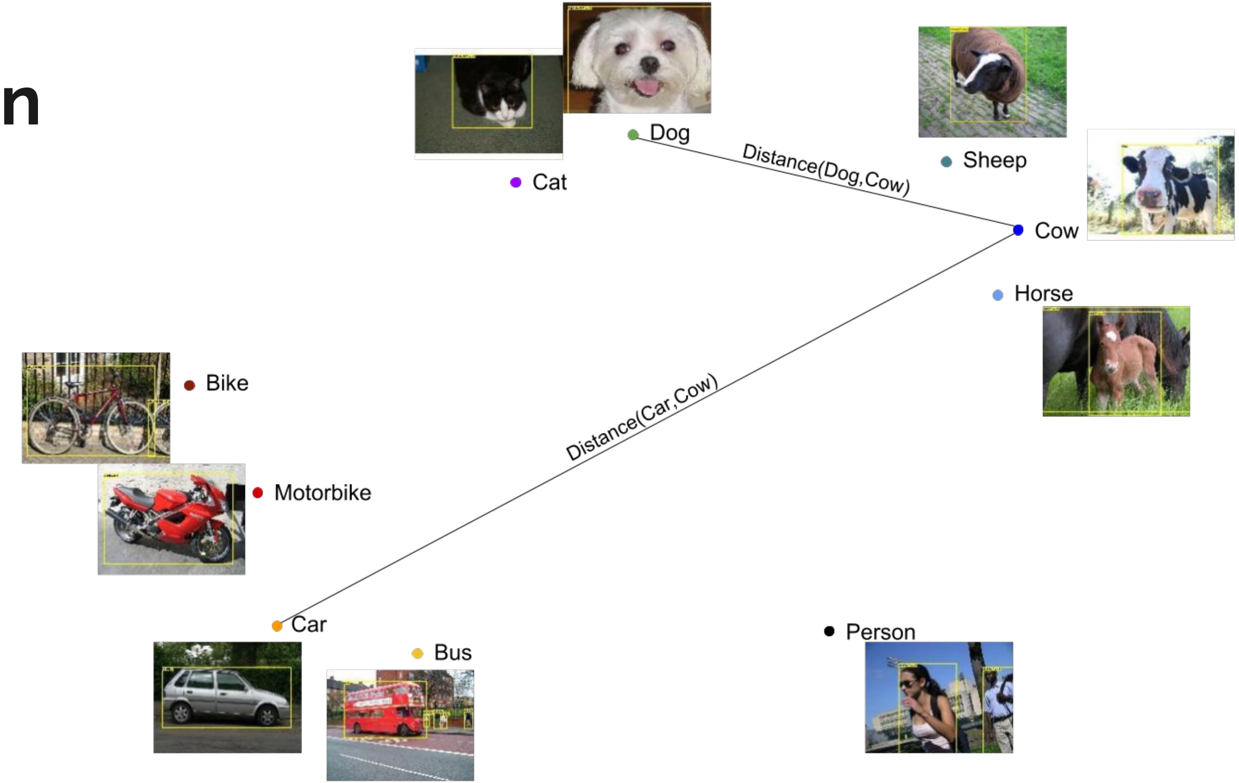
Side information

Use side information to get a better representation for classes (categories).

Labels → Vector representations



PASCAL VOC 2006 http://host.robots.ox.ac.uk/pascal/VOC/voc2006/examples/index.html

Side information - Attributes embedding

Polar bear
black: no
white: yes
brown: no
stripes: no
water: yes
eats fish: yes

[0 1 0 0 1 1]

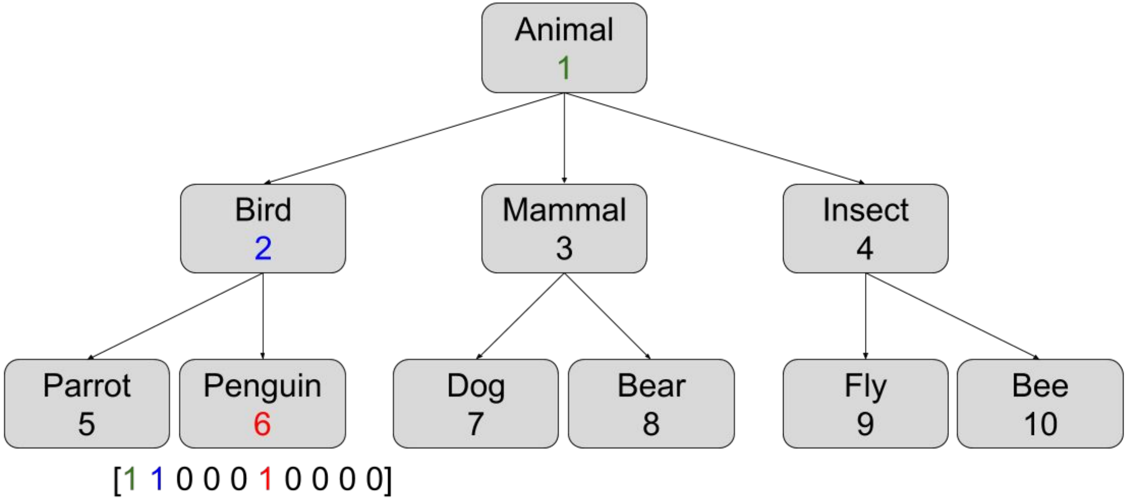
Otter
black: yes
white: no
brown: yes
stripes: no
water: yes
eats fish: yes

[1 0 1 0 1 1]

[Lampert, et al. CVPR2009]
http://www.image-net.org/

Side information - Hierarchical embedding

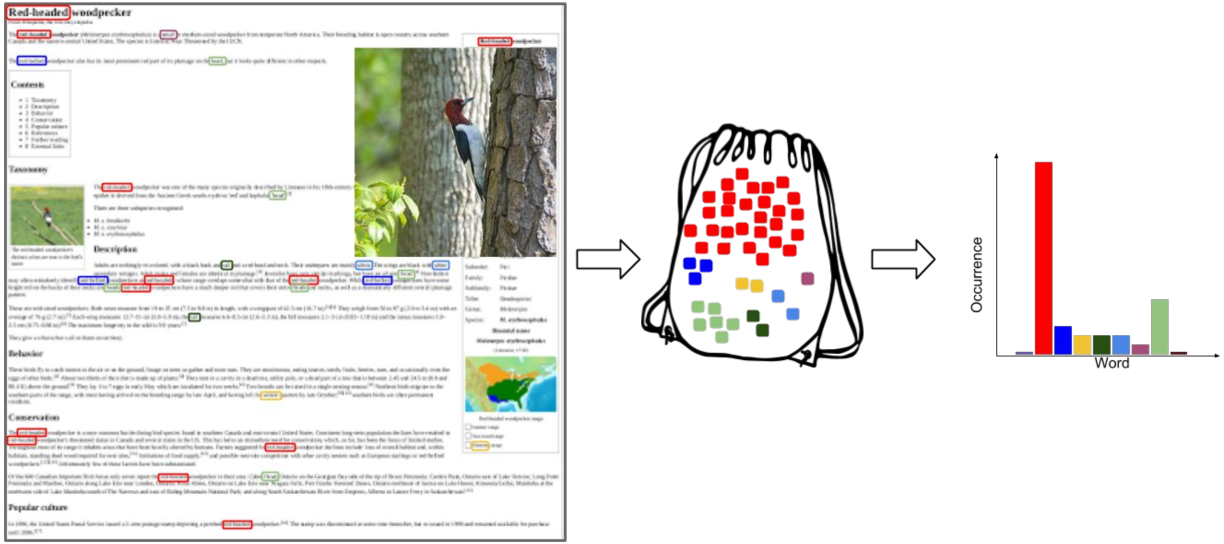
HLE Hierarchical Label Embedding extracted from Wordnet



[Tsochantaridis, et al. 2005]

Side information - Text embedding

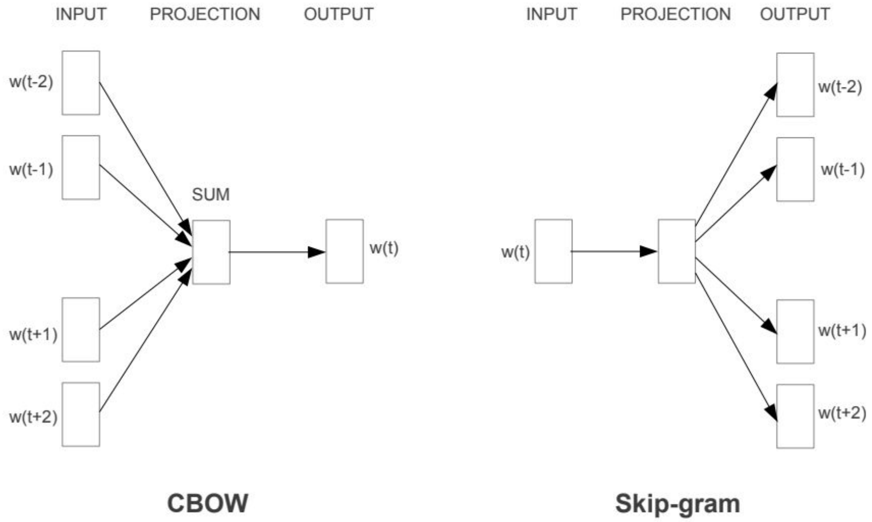
Sparse representations: **BoW** Bag of Words from Wikipedia articles



https://en.wikipedia.org/wiki/Red-headed_woodpecker

Side information - Text embedding

Dense representations: **Word2vec**

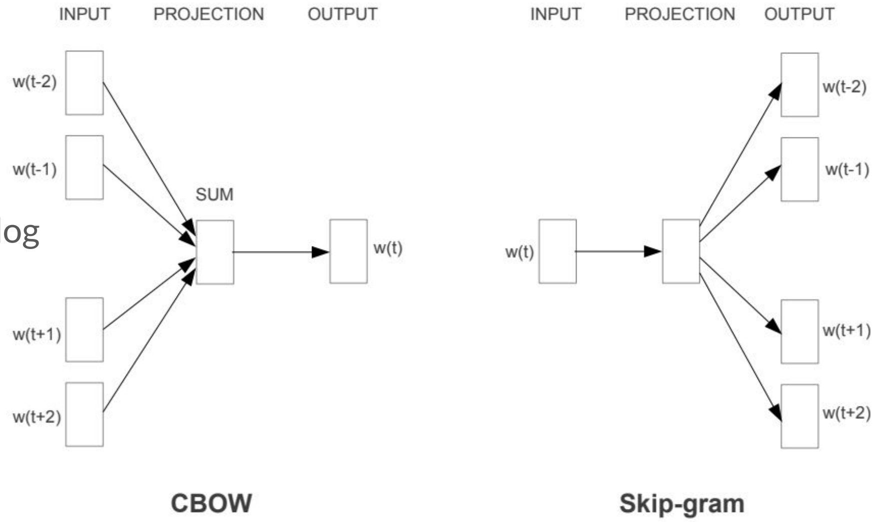


[Mikolov, et al. NIPS2013]

Side information - Text embedding

Dense representations: **Word2vec**

The fox __?__ over the lazy dog



[Mikolov, et al. NIPS2013]

Side information - Text embedding

Dense representations: **Word2vec**

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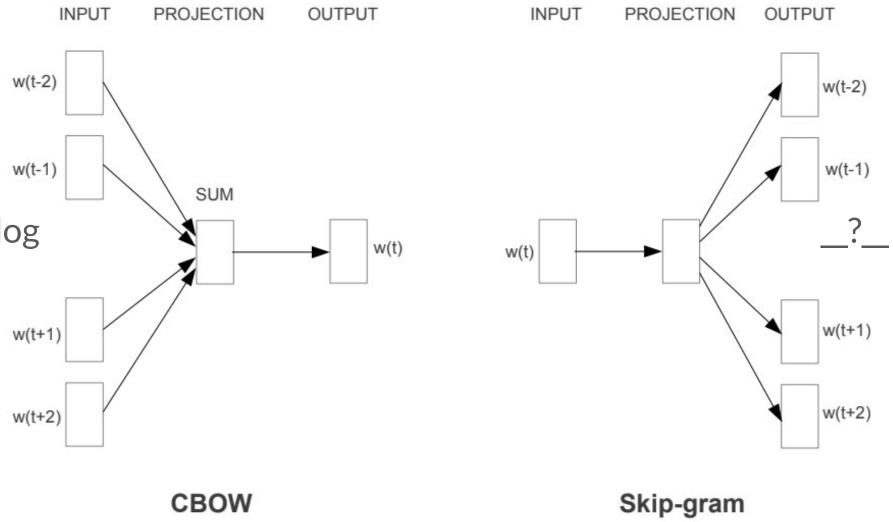
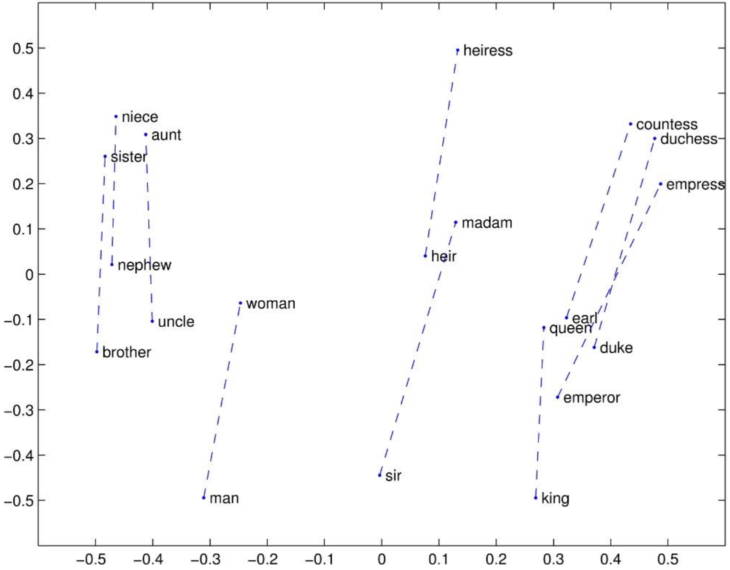


__?__ __?__ jumps __?__ _?_ __?__ __?__

[Mikolov, et al. NIPS2013]

Side information - Text embedding

Dense representations: **Glove** Global vectors for word representation



[Pennington, et al. EMNLP2014]

Side information - Visual descriptions

The bird has a white underbelly, black feathers in the wings, a large wingspan, and a white beak.

This bird has distinctive-looking brown and white stripes all over its body, and its brown tail sticks up.

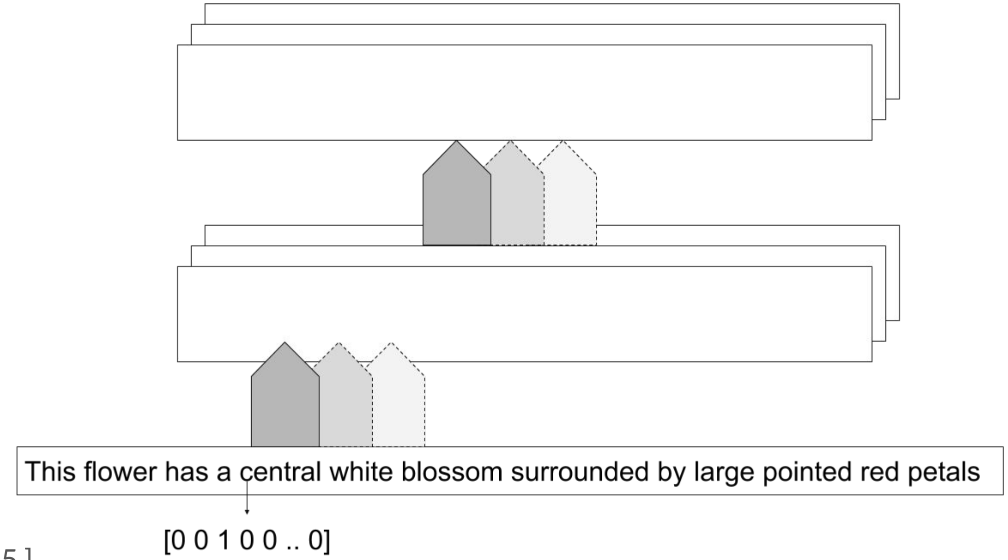
This flower has a central white blossom surrounded by large pointed red petals which are veined and leaflike.

Light purple petals with orange and black middle green leaves

[Reed, et al. CVPR16, ICML16, NIPS16]

Side information - Visual descriptions

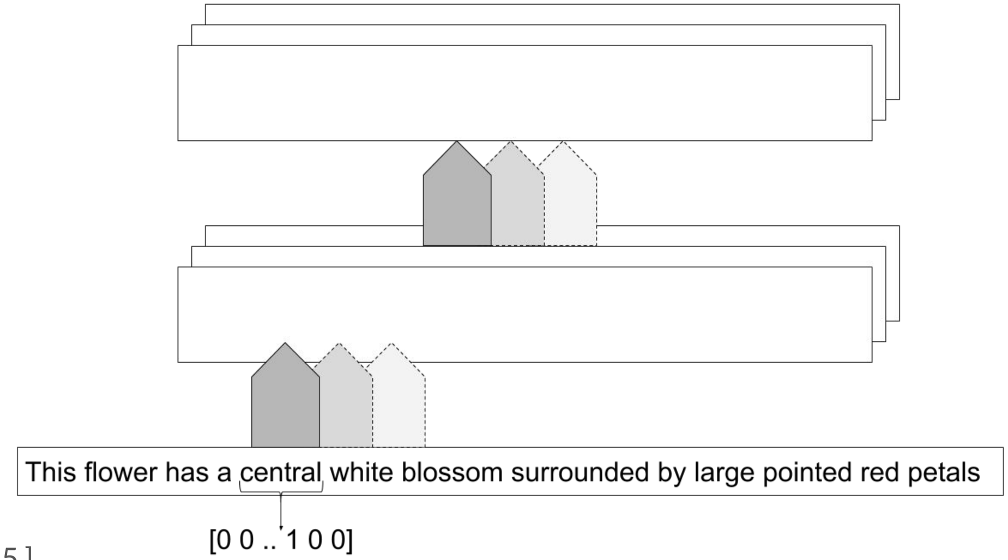
- Character level CNN



[Zhang, et al. NIPS2015]

Side information - Visual descriptions

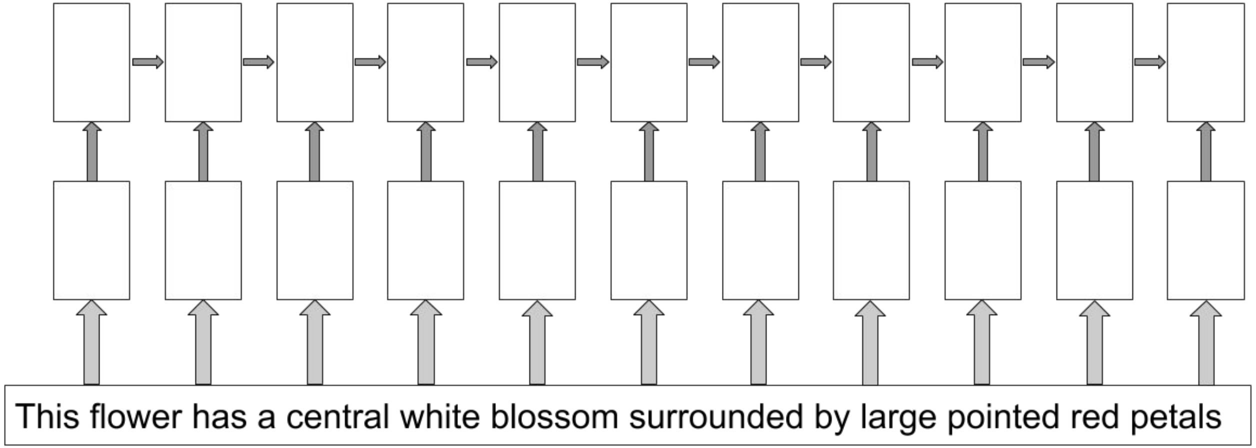
- Word level CNN



[Zhang, et al. NIPS2015]

Side information - Visual descriptions

- LSTM



[Hochreiter and Schmidhuber 1998]

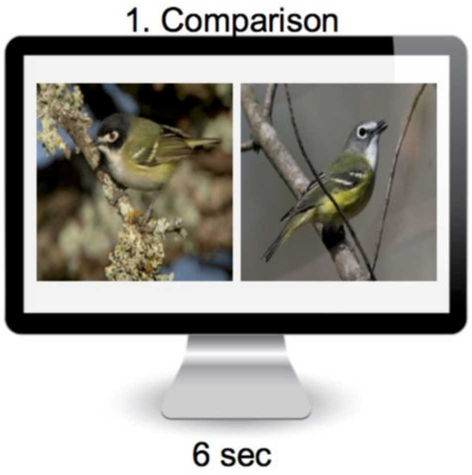
Side information - Gaze embedding

- Discrimination of objects by novice
- Data collection is fast
- Implicit annotation,
  you don't need to name the object

[Karessli, et al. CVPR2017]

Side information - Gaze embedding

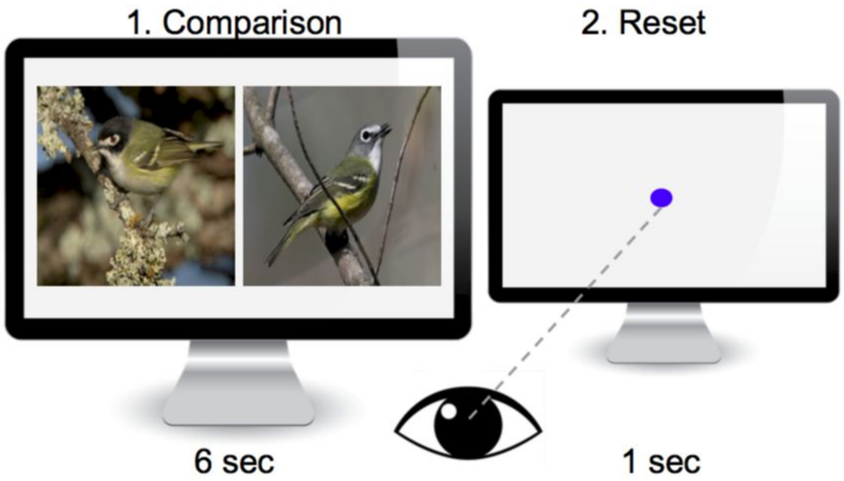
Experiment



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

Experiment



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

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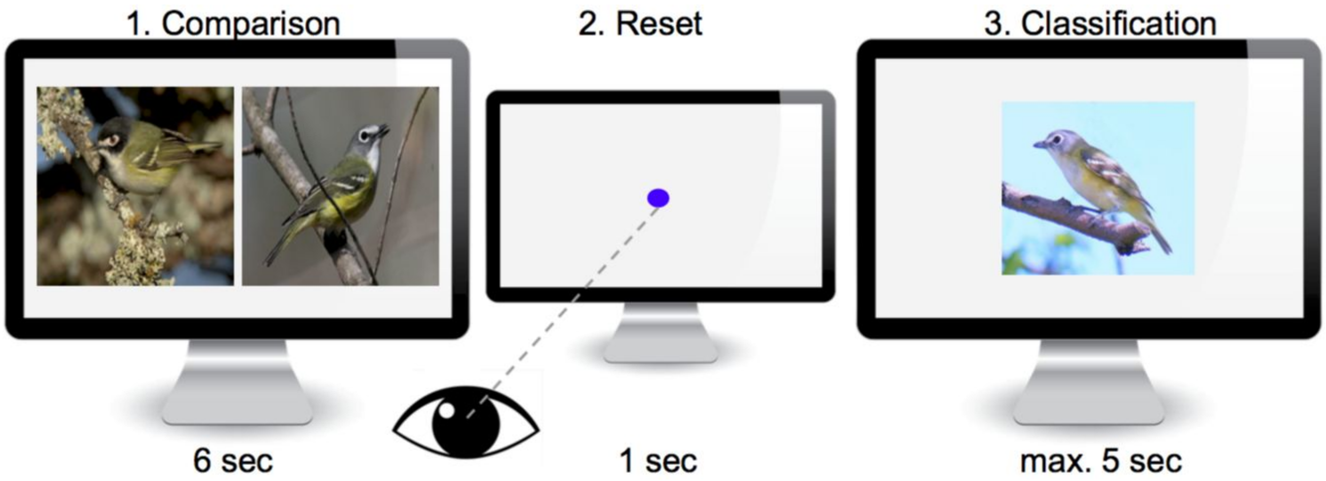

[Karessli, et al. CVPR2017]

Side information - Gaze embedding

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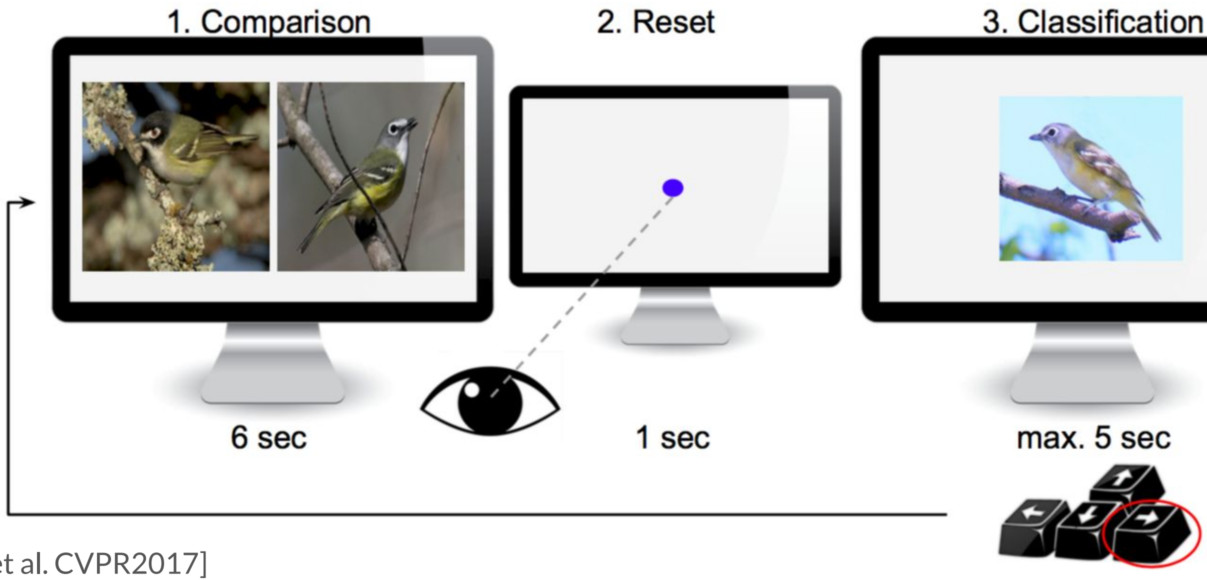
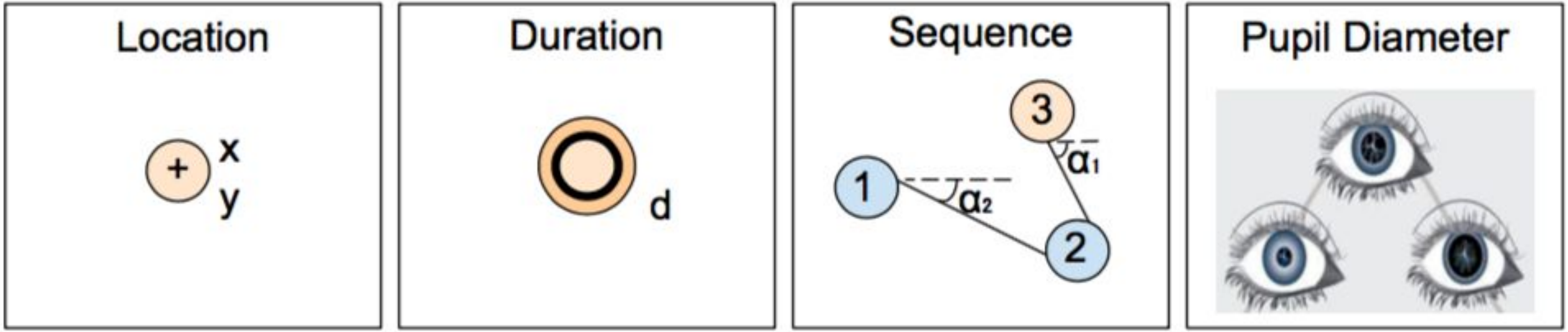


[Karessli, et al. CVPR2017]

Side information - Gaze embedding

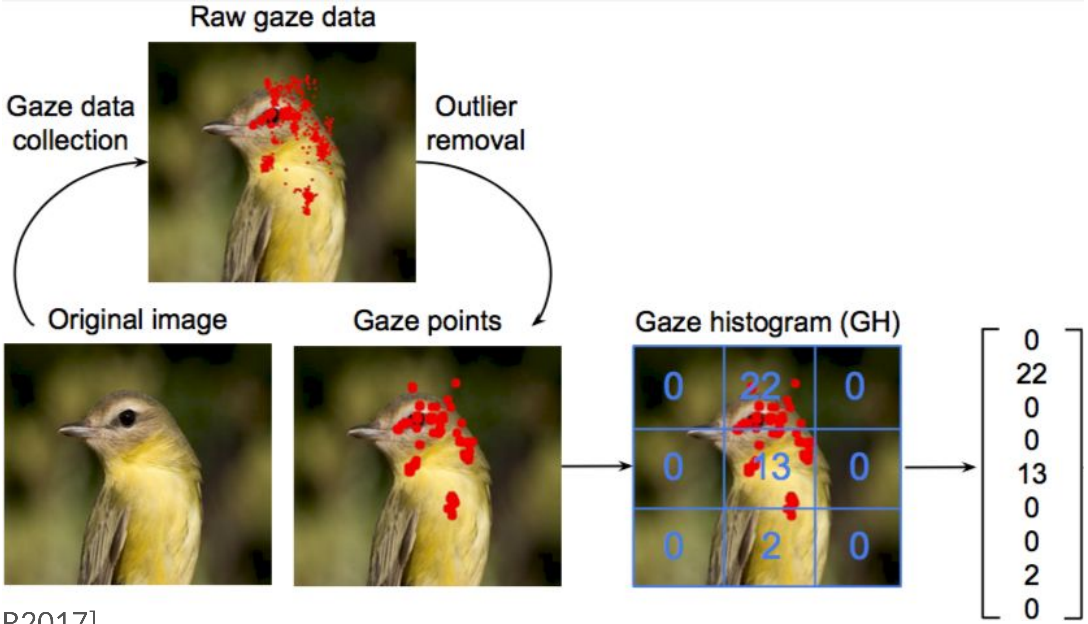
Features



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

Embeddings



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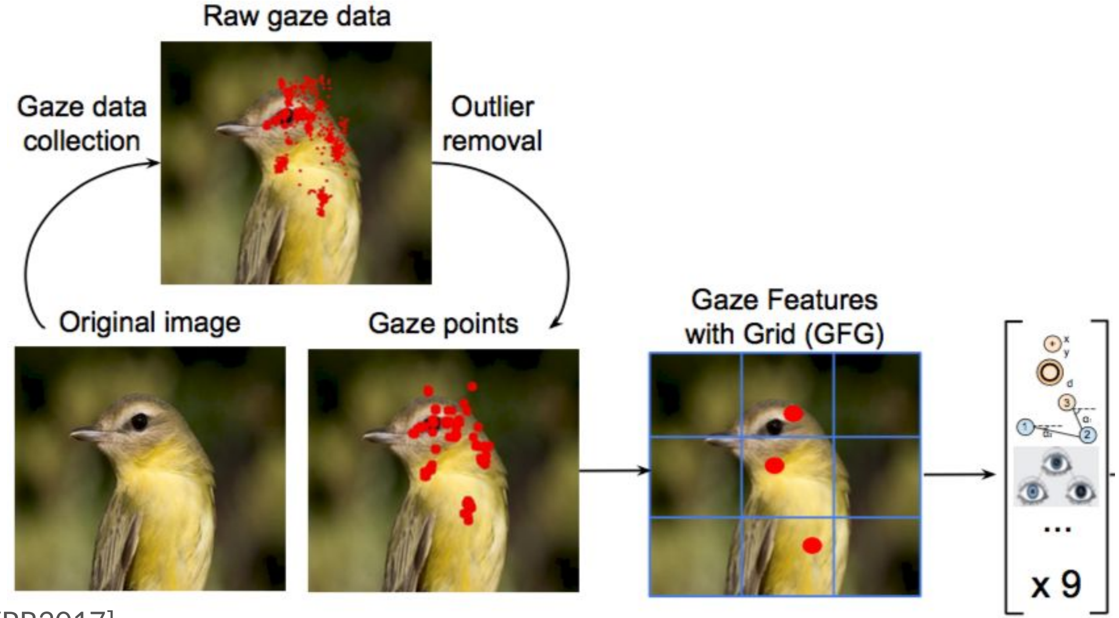
Side information - Gaze embedding

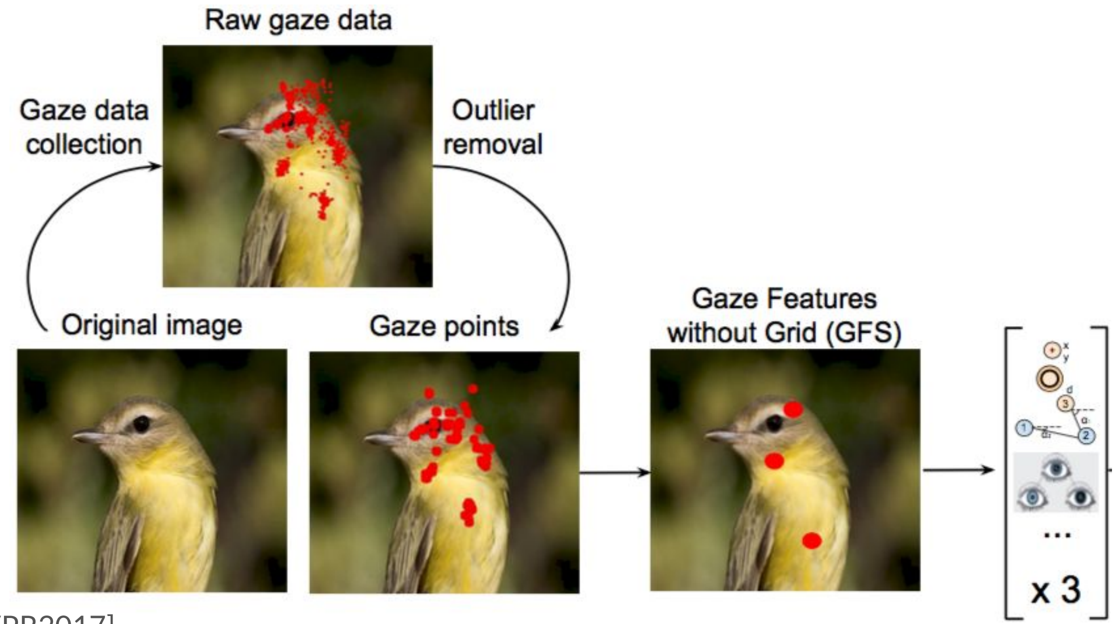
Embeddings



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

Embeddings



[Karessli, et al. CVPR2017]

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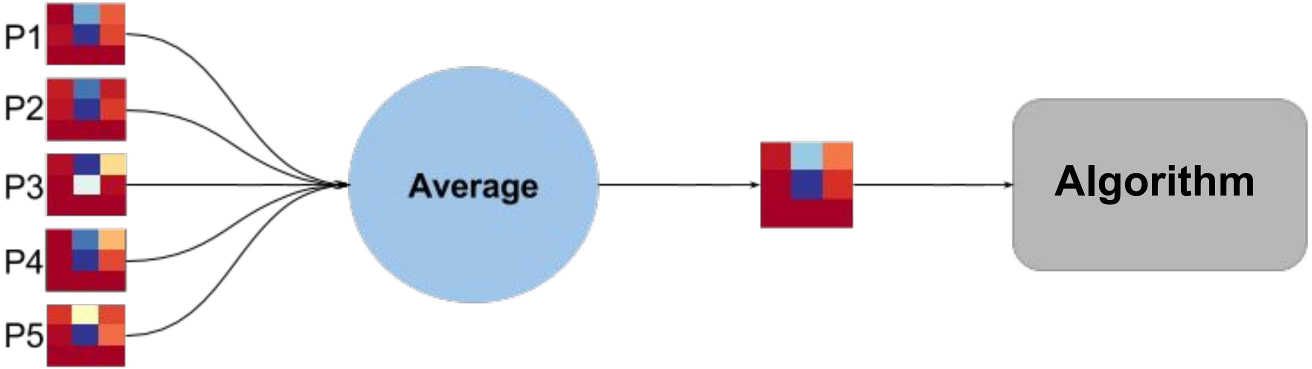

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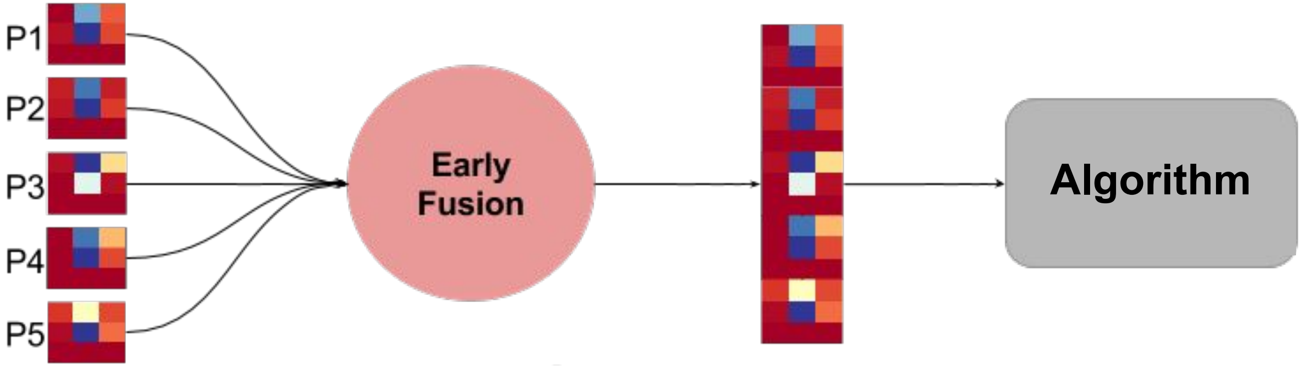

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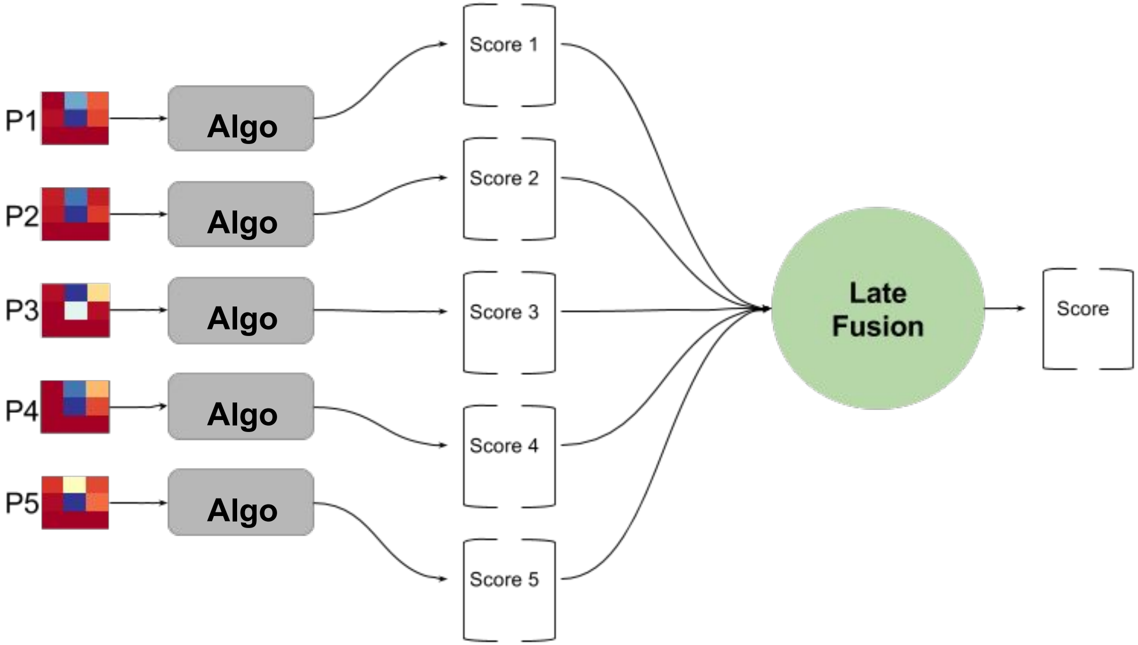


[Karessli, et al. CVPR2017]

Side information summary

- **Supervised**
    - Expert
        - Class attributes
    - Novice
        - Detailed visual descriptions (deep representations of visual descriptions)
        - Human gaze

- **Unsupervised**
    - Hierarchical similarity
    - Text embeddings

CUB birds

- 11,788 images
- 200 bird species, 150 train+val set and 50 test classes

[Welinder, et al. 2010]

Results

Source	Side information	Accuracy
Text	Hierarchical	20.6
	Bag of Words	22.1
	Word2vec	28.4
	Glove	24.2
Expert annotator	Attributes	50.1
Novice annotator	Detailed visual descriptions	**56.8**

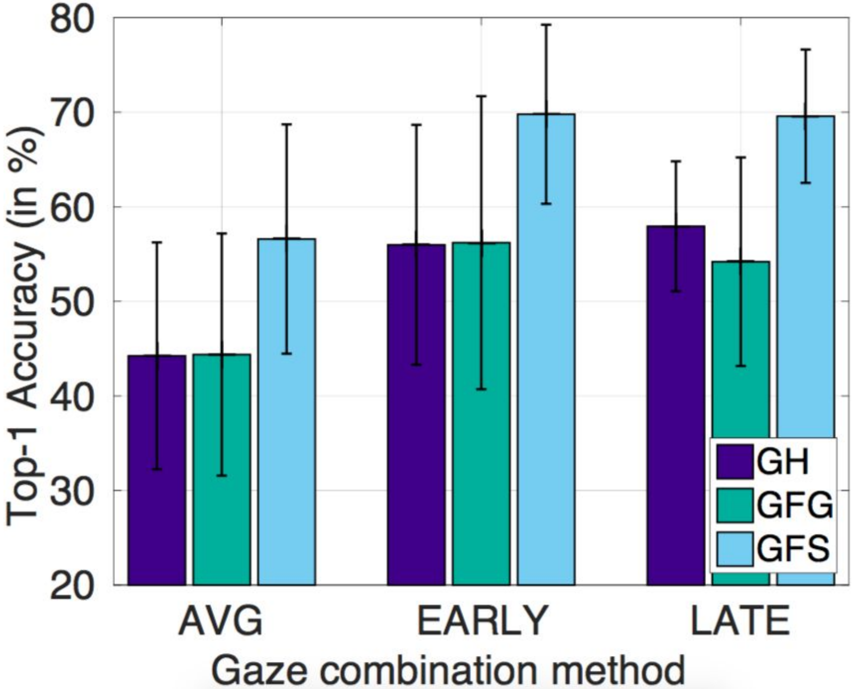
[Reed, et al. CVPR16, ICML16, NIPS16] [Akata, et al. CVPR2015]

Mini-CUB birds

- 464 images
- 14 bird species, 11 train+val set and 3 test classes

[Welinder, et al. 2010]

Results



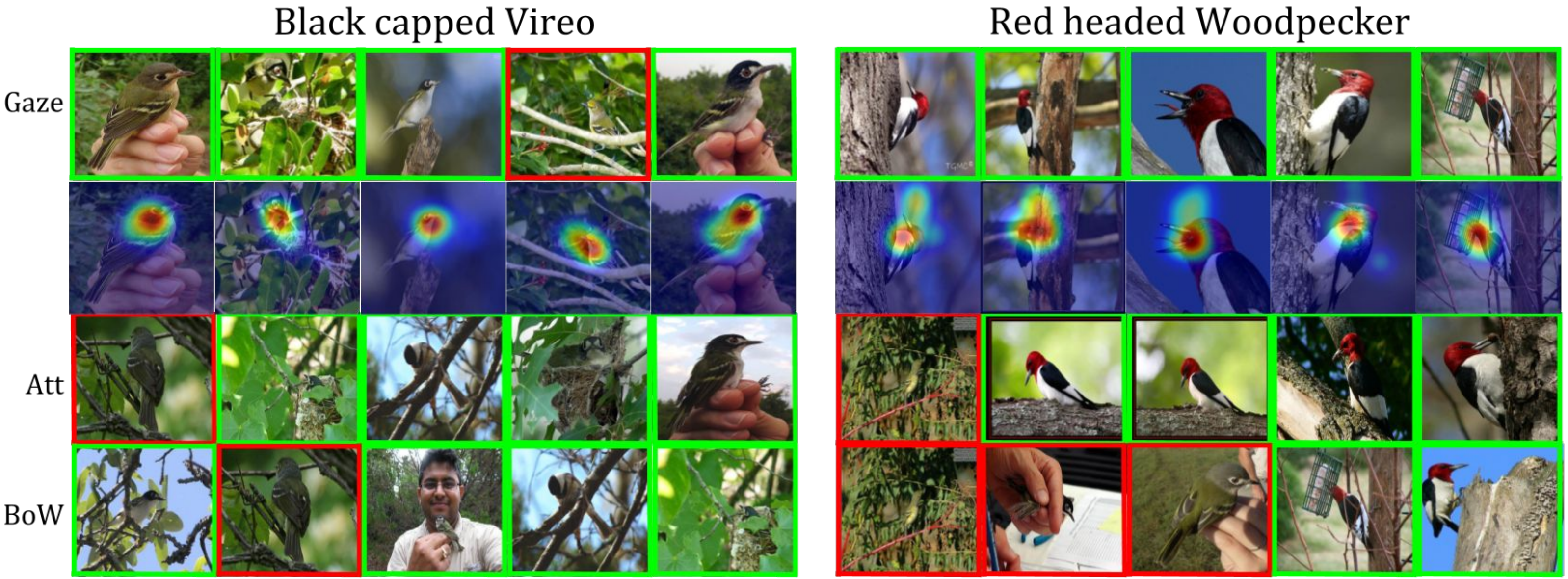
[Karessli, et al. CVPR2017]

Results

Method	Accuracy
Bag-of-Words from Wiki	55.2
Human annotated attributes	72.9
Gaze embeddings	73.9
Attributes + Gaze	**78.2**

[Karessli, et al. CVPR2017]

Results

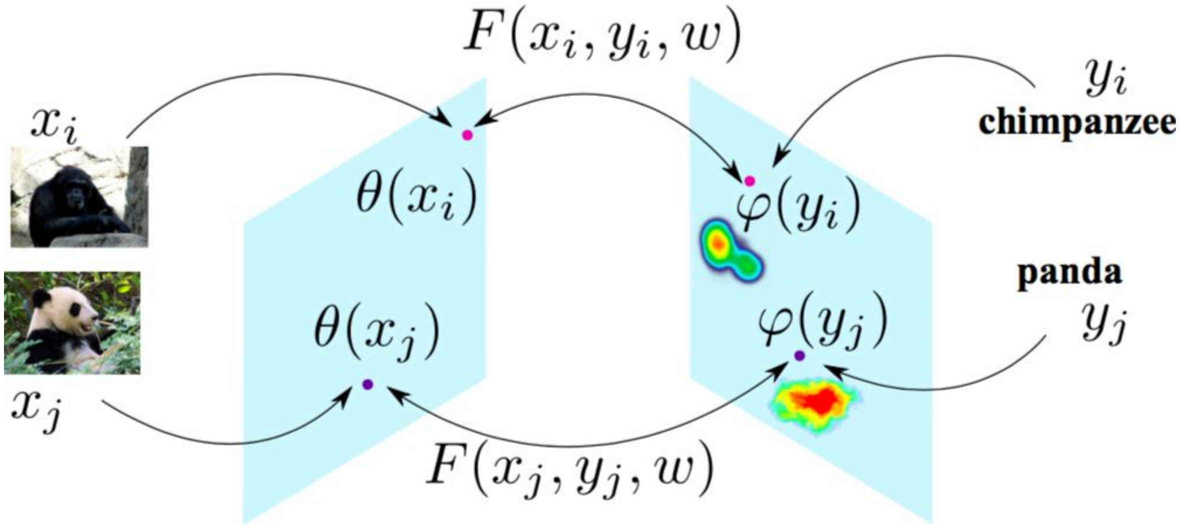


[Karessli, et al. CVPR2017]

Structure

- Introduction & motivation
- Zero-shot learning
  - Definition
  - Side information
  - Zero-shot learning models
  - Exercise
- Low-shot learning
  - Definition
  - Low-shot learning models
- Tips & tricks
- Exercises

Zero-shot models



[Akata, et al. CVPR2015]

Task formulation

Training set $S = \{(x_n, y_n), n = 1..N\}, y_n \in Y^{train}$

We want to learn a function $f : X \to Y$ by minimize the empirical risk:

$$\frac{1}{N} \sum_{n=1}^{N} L(y_n, f(x_n; W)) + \Omega(W)$$

- Loss function
- Regularization term

[Akata, et al. CVPR2015]

Task formulation

Training set $S = \{(x_n, y_n), n = 1..N\}, y_n \in Y^{train}$

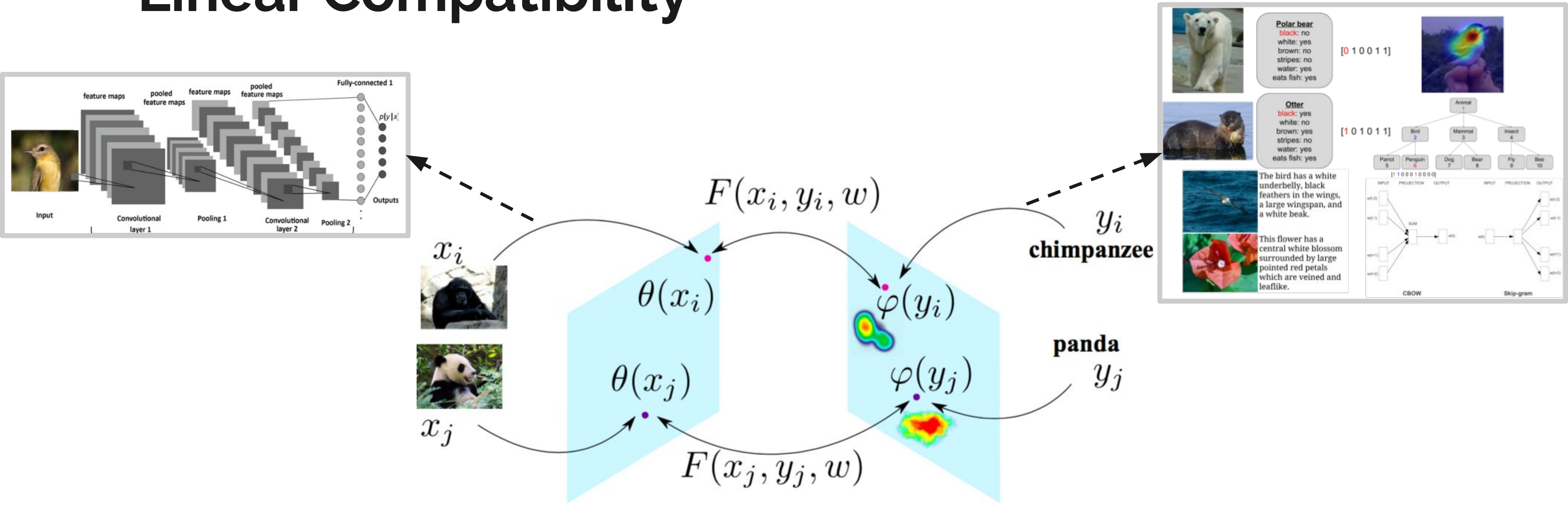
Maximizing the compatibility (score):

$$f(x_n; W) = \underset{y \in Y}{\operatorname{argmax}}\, F(x, y; W)$$

At test time we predict $y \in Y^{test}$ that gives the highest compatibility $Y^{test} \subset Y$

[Akata, et al. CVPR2015]

Linear Compatibility

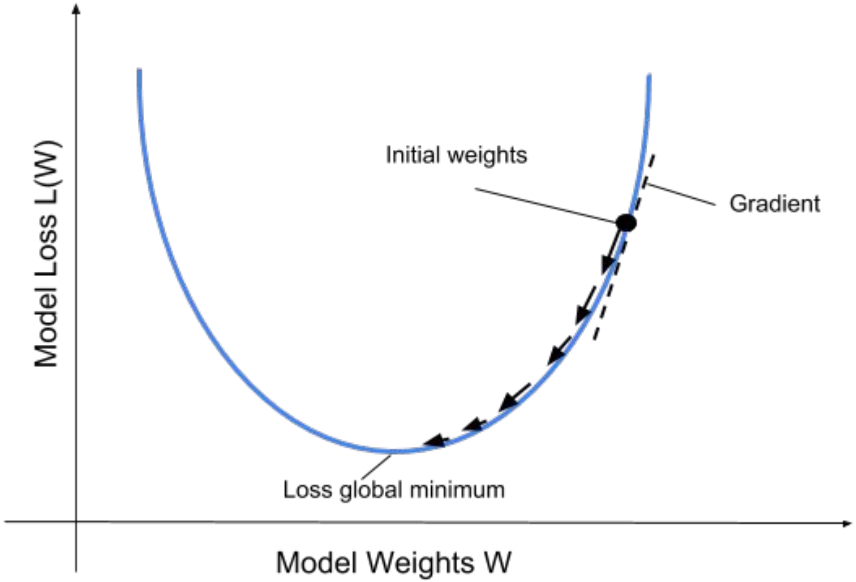


$$F(x, y; W) = \theta(x)^T W \phi(y)$$

[Akata, et al. CVPR2015]

Recap - Gradient Descent

Minimize the loss function by updating the weights with respect to the gradient.



Gradient descent
updates weights only after **each epoch**

Stochastic gradient descent
updates weights on **each sample**

https://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/

Linear Compatibility - DEVISE

Deep visual semantic embedding, pairwise ranking

$$\sum_{y \in \mathcal{Y}^{tr}} [\Delta(y_n, y) + F(x_n, y; W) - F(x_n, y_n; W)]_+$$

$$\Delta(y_n, y) = \begin{cases} 0, & \text{if } y_n = y. \\ 1, & \text{otherwise.} \end{cases}$$

[Frome, et al. NIPS2013]

Linear Compatibility - ALE

Attribute label embedding, weighted pairwise ranking

$$\sum_{y \in y^{tr}} l_k[\Delta(y_n, y) + F(x_n, y; W) - F(x_n, y_n; W)]_+$$

$l_k = \sum_{i=1}^{k} \alpha_i$ where $\alpha_i = 1/i$

[Akata, et al. CVPR2015]

Linear Compatibility - SJE

Structured joint embedding, multiclass objective

$$[\max_{y \in \mathcal{Y}^{tr}} (\Delta(y_n, y) + F(x_n, y; W)) - F(x_n, y_n; W)]_+$$

[Akata, et al. CVPR2015]

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Zero-shot learning exercise

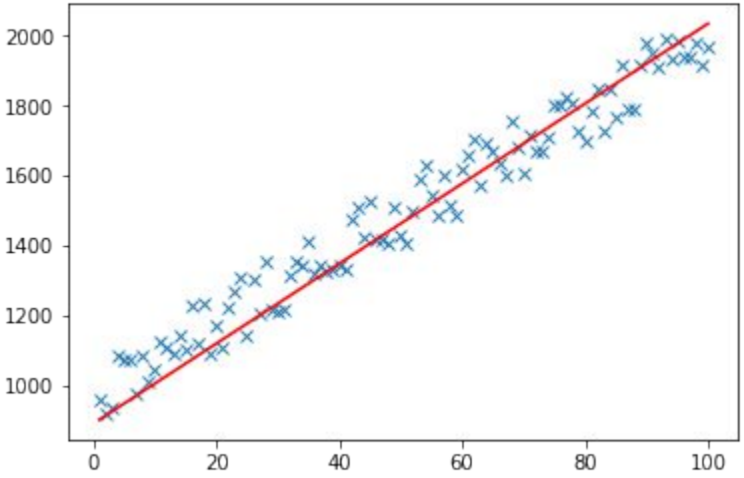
Recap Exercise - Linear Regression & Gradient Descent

Linear regression - implementation

- Clone [repo]
- Generate data for linear regression
- Implement optimisation GD and SGD

Linear regression

$y = w_0 x_0 + w_1 x_1$; $x_0 = 1$



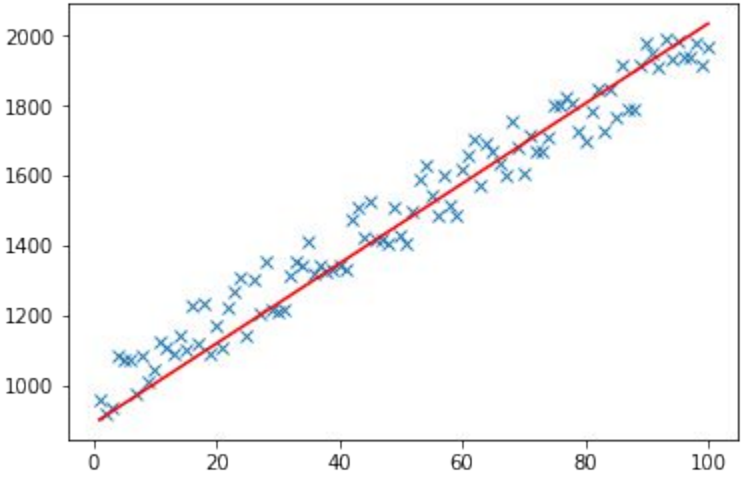
https://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/

Linear regression with GD - implementation

Loss = 1/2N $(P-Y)^2$

foreach epoch

1. Calculate predictions P = X * W
2. Calculate error = P - Y
3. Calculate gradient = X.T * error / N
4. Update weights W = W - lr * gradient



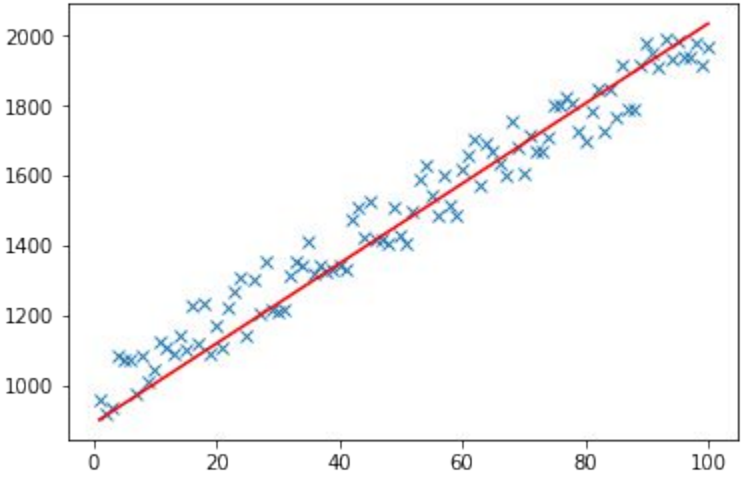
https://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/

Linear regression with SGD - implementation

Loss = $1/2N\ (P-Y)^2$

foreach epoch
Shuffle training samples
foreach sample x_i, y_i

1. Calculate sample prediction $p_i = x * W$
2. Calculate error = $p_i - y_i$
3. Calculate gradient = x_i * error
4. Update weights $W = W - lr * gradient$



https://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/

Structured Joint Embedding exercise

AWA dataset

Animal with attributes dataset

- 30K images
- 50 classes
- 85 attribute
- Standard split 40 train+val 10 test

[Lampert, et al. TPAMI2013]

SJE implementation

- Select dataset (AWA)
- Download data (image features & corresponding labels) & use class embeddings in repo
- Implement zero-shot algorithm SJE
- Evaluate Top-1 accuracy on test set

SJE implementation

Initialize W (DxE)
foreach epoch
    Shuffle training samples
    foreach sample **(x_i, y_{true})**
        $score_{true} = \Theta(x_i) * W^T * \phi(y_{true})$
        $loss_{max} = -1$, $y_{max} = -1$
        foreach training label $\mathbf{y_{tr}}$
            $score = \Theta(x_i) * W^T * \phi(y_{tr})$
            $loss = \Delta(y_{tr}, y_{true}) + score_{true} - score$
            if $loss > loss_{max}$
                update $loss_{max}$ and y_{max}
        if $y_{max} \neq y_{true}$
            $W = W - lr * \Theta(x_i) [\phi(y_{true}) - \phi(y_{max})]$
	D: x dim, E: y dim
	
	find max score
	
	violation
	update weights

More Zero-shot models

Linear Compatibility - ESZSL

Embarrassingly simple zero-shot learning, adds regularization terms

$$\gamma \parallel W\phi(y) \parallel^2 + \lambda \parallel \theta(x)^T W \parallel^2 + \beta \parallel W \parallel^2$$

γ, λ, β regularization parameters

[Romera-Paredes and Torr ICML2015]

Linear Compatibility - SAE

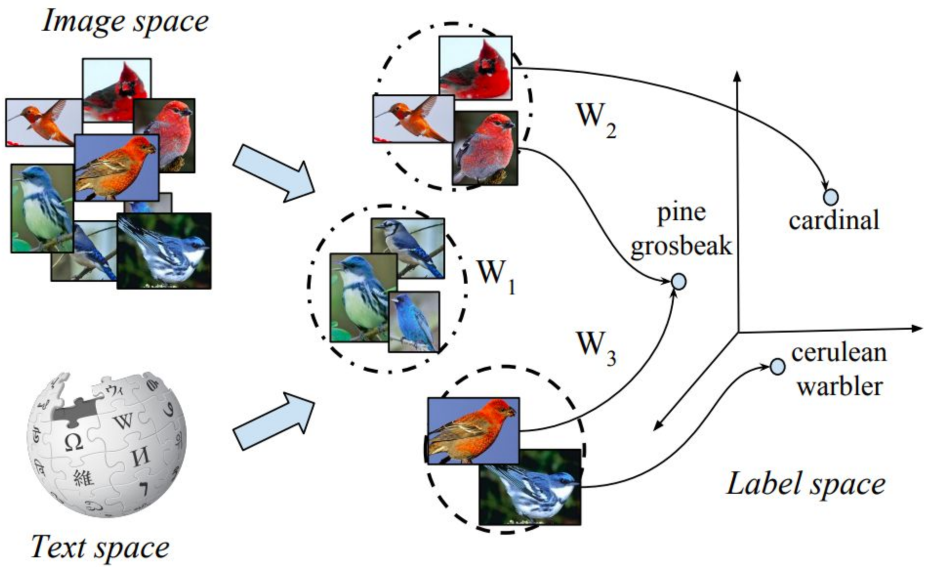
Semantic autoencoder, linear objective

$$\min_{W} \| \theta(x) - W^T \phi(y) \|^2 + \lambda \| W\theta(x) - \phi(y) \|^2$$

- Autoencoder learns projection from image features to label embedding
- The autoencoder must reconstruct original image features

[Kodirov, et al. CVPR2017]

Nonlinear Compatibility - LATEM



Latent embeddings

[Xian, et al. CVPR2016]

Nonlinear Compatibility - LATEM

Latent embeddings, piecewise linear compatibility

$$F(x, y; W_i) = \max_{1 \leq i \leq K} \theta(x)^T W_i \phi(y)$$

- Support non-linearity
- Different W encodes different characteristics

[Xian, et al. CVPR2016]

Nonlinear Compatibility - CMT

Cross modal transfer, nonlinear compatibility using two layers NN

$$\sum_{y \in \mathcal{Y}^{tr}} \sum_{x \in \mathcal{X}_y} \|\phi(y) - W_1 \tanh(W_2.\theta(x)\|$$

[Socher, et al. NIPS2013]

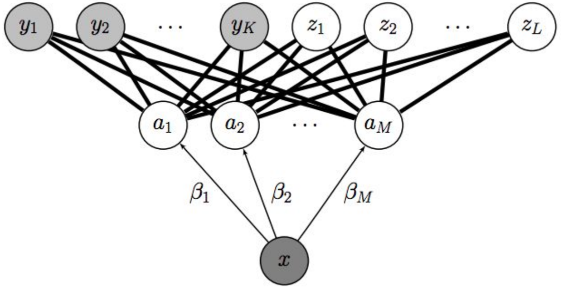
Intermediate Classifier - DAP

Direct attribute prediction

1. Learning probabilistic classifiers for each attribute
2. Combie scores

$$f(x) = \underset{c}{\operatorname{argmax}} \prod_{m=1}^{M} \frac{p(a_m^c | x)}{p(a_m^c)}$$

<u>Polar bear</u>
black: no
white: yes
brown: no
stripes: no
water: yes
eats fish: yes



[Lampert, et al. CVPR2009]
http://www.image-net.org/

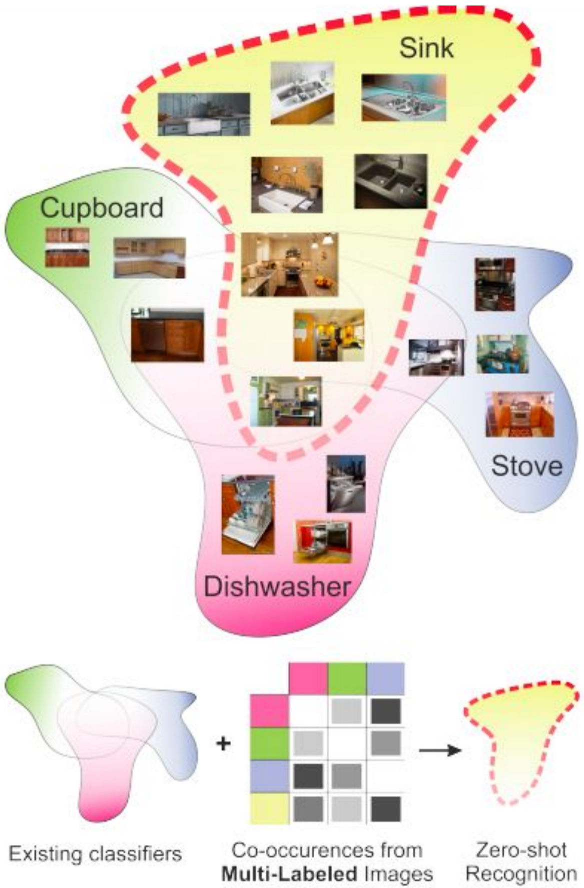
Intermediate Classifier - COSTA

Co-occurrence statistics of visual concepts
between seen and unseen classes

$$\hat{w}_l = \sum_k w_k \; s_{lk}$$

k classifier weights (svm)

Similarity between seen k and unseen l



[Mensink, et al. CVPR2014]

Models summary

1. **Linear compatibility**
   DEVISE [Frome, et al. NIPS2013], ALE [Akata, et al. CVPR2015], SJE [Akata, et al. CVPR2015], ESZSL [Romera-Paredes and Torr ICML2015], SAE [Kodirov, et al. CVPR2017]

2. **Nonlinear compatibility**
   LATEM [Xian, et al. CVPR2016], CMT [Socher, et al. NIPS2013]

3. **Intermediate classifier**
   DAP [Lampert, et al. CVPR2009], COSTA [Mensink, et al. CVPR2014]

AWA dataset

Animal with attributes dataset

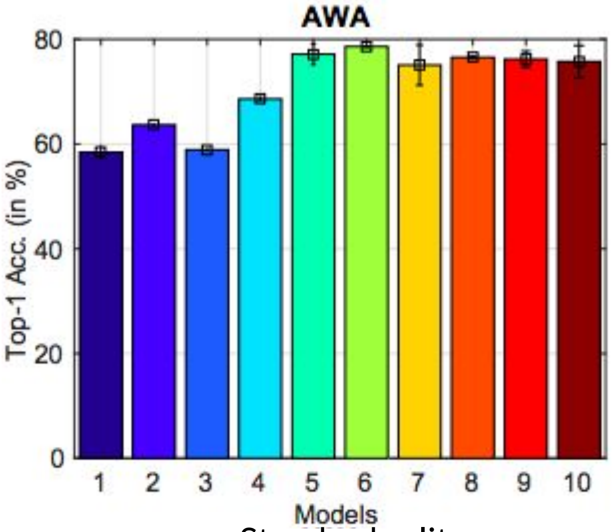
- 30K images
- 50 classes
- 85 attribute
- Standard split 40 train+val 10 test
- Suggested split

  Insures that none of the test classes is used to train the image features base model

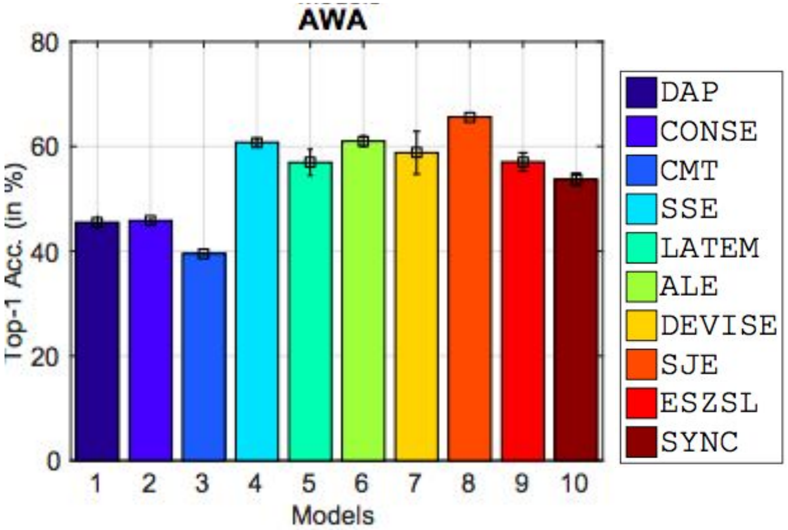
[Lampert, et al. TPAMI2013]

Results

Evaluation on Animals with Attributes AWA



Standard split



Proposed split

[Xian, et al. CVPR2017]

Q & A