Learning with Small Samples

Including zero-shot learning

Nour Karessli
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Bachelor in software engineering, Damascus University

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LinkedIn

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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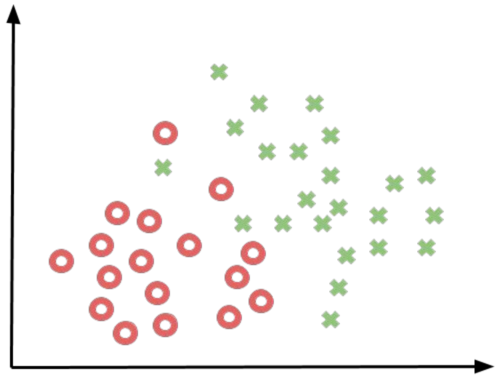
Introduction

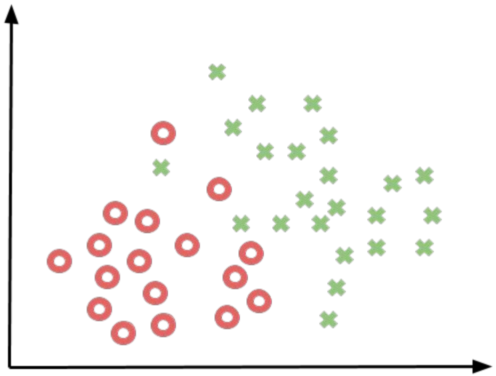
Learning

Supervised

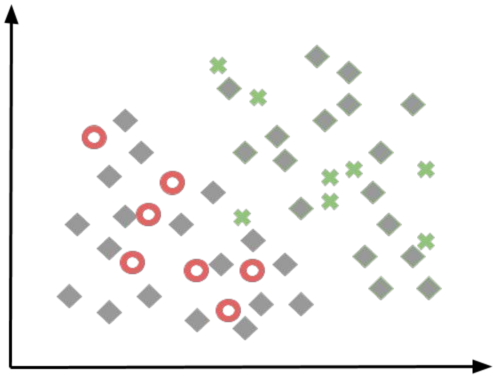


Learning

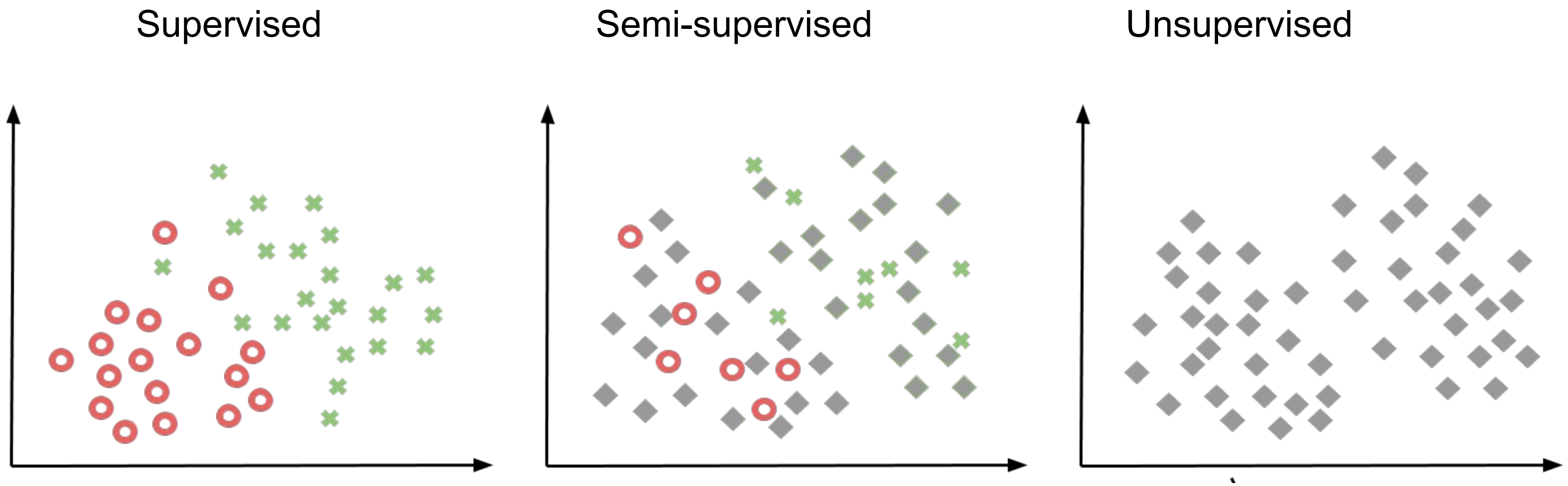
Supervised



Semi-supervised

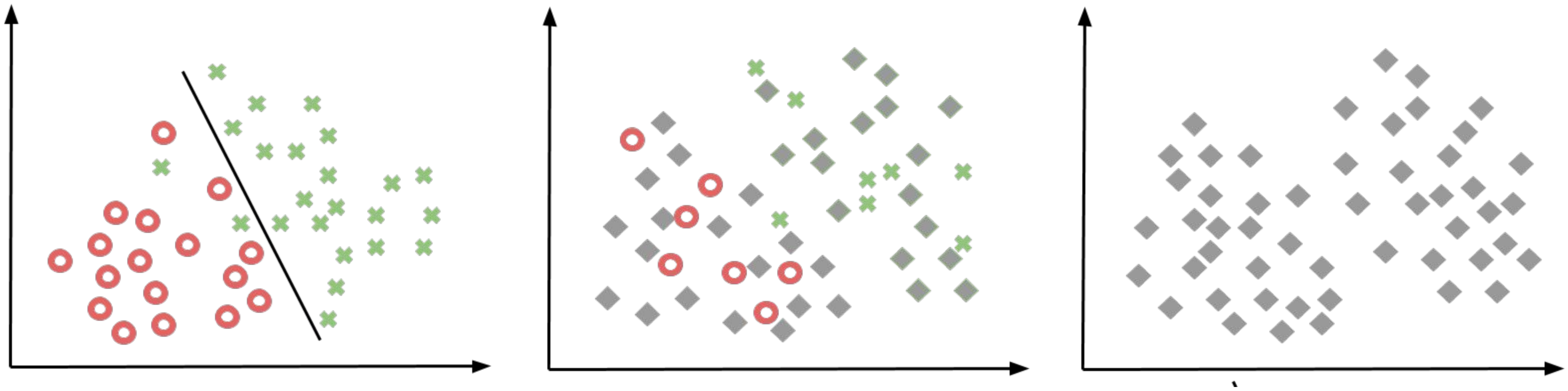


Learning



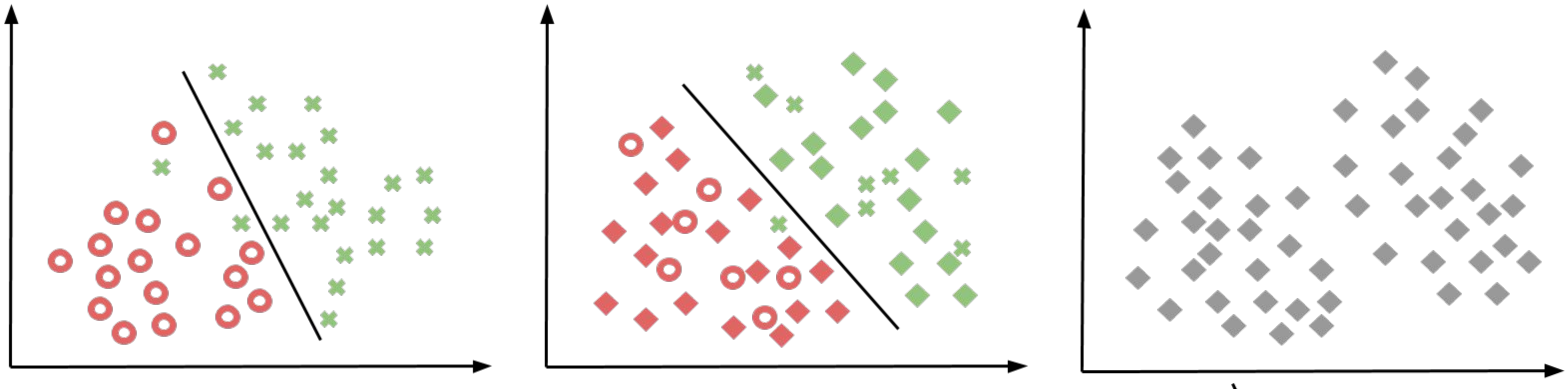
Learning

Supervised Semi-supervised Unsupervised



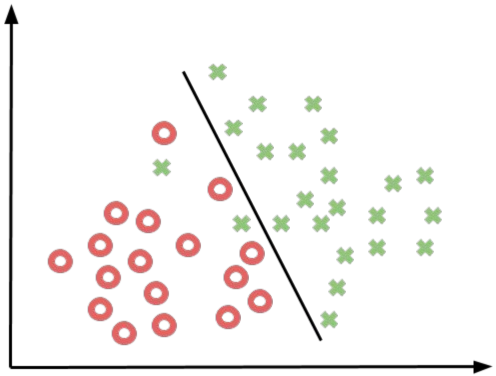
Learning

Supervised　　　Semi-supervised　　　Unsupervised

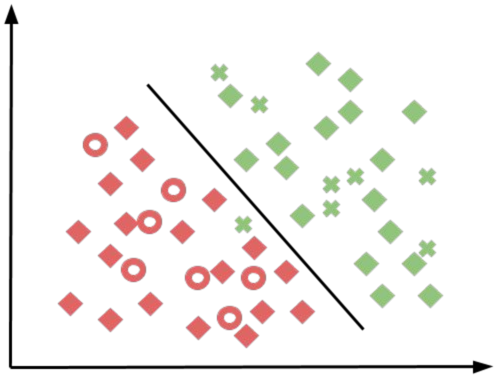


Learning

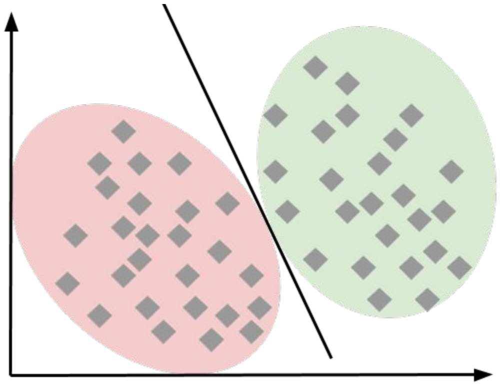
Supervised



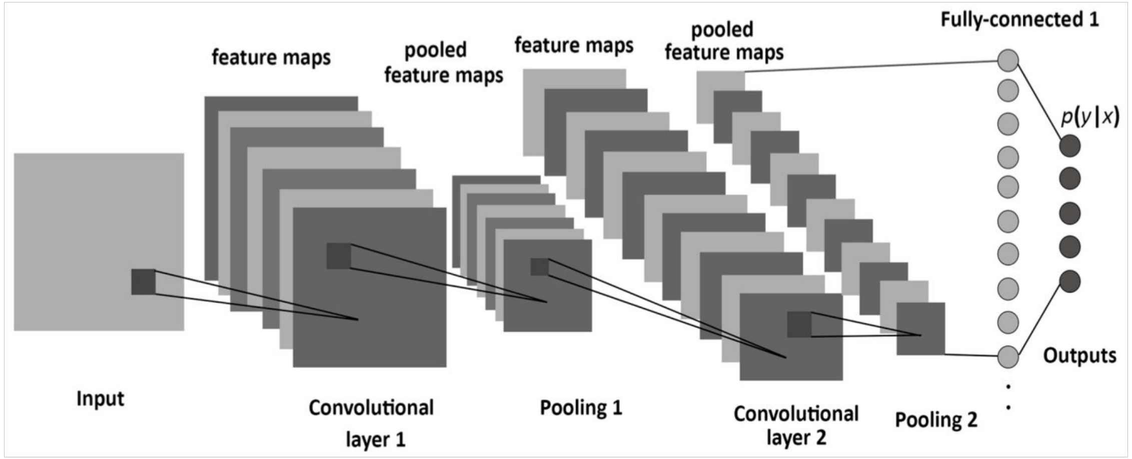
Semi-supervised



Unsupervised

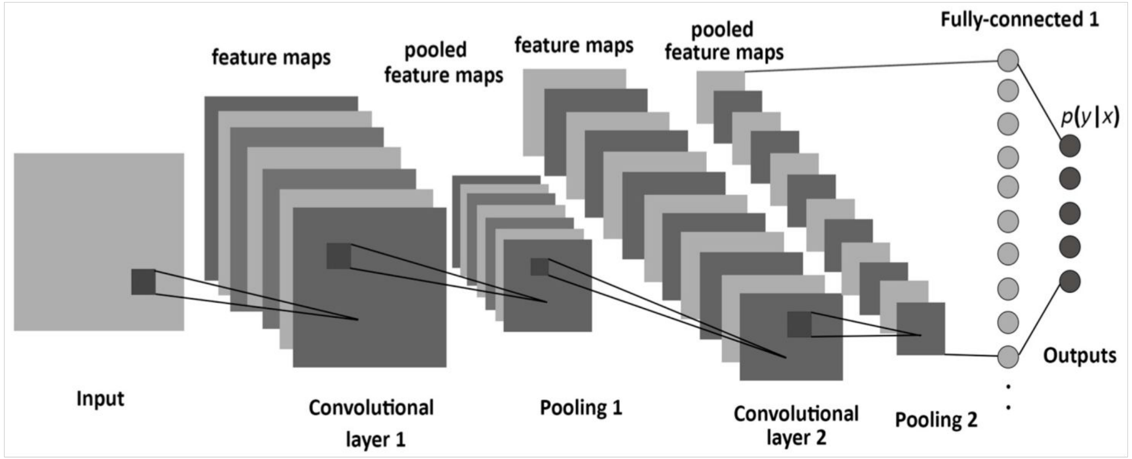


Many-shots supervised learning



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

Many-shots supervised learning



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

Annotation Effort

IMAGENET

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

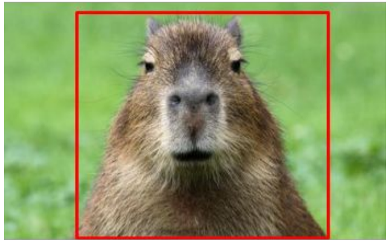
- **Classification**
  Single labeling is relatively easy

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

Task complexity

- **Classification**
  Single labeling is relatively easy

- **Localization**
  Requires precise bounding boxes



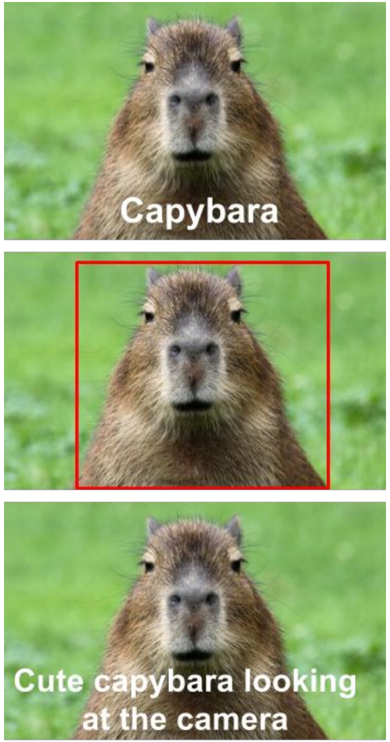
https://www.livescience.com/55223-capybara-facts.html

Task 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 ”



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Task complexity vs. annotation

- **Classification**
  ImageNet 14M labeled images

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

Task complexity vs. annotation

- **Classification**
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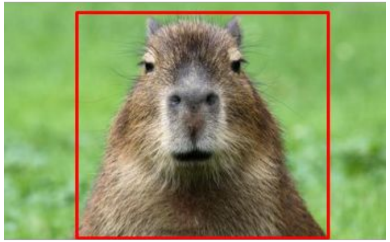
  openImages 3.6M bounding boxes



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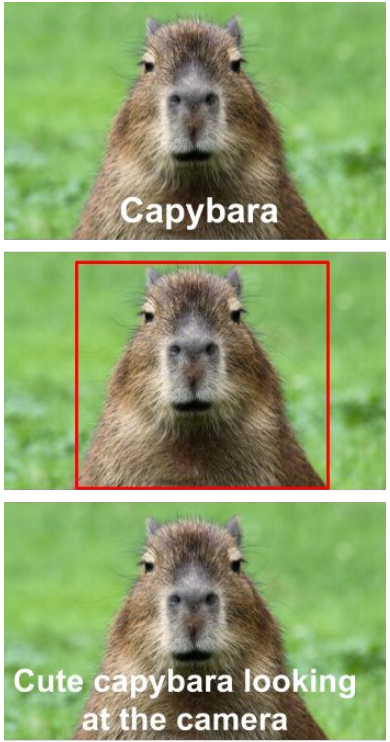
Task complexity vs. annotation

- **Classification**
  ImageNet 14M labeled images

- **Localization**
  openImages 3.6M bounding boxes

- **Captioning**
  COCO 300K captioned images



[Deng, et al CVPR2009] [Krasin, et al. 2017] [Lin, et al. 2014]
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Task complexity vs. annotation

- **Classification**
  ImageNet 14M labeled images
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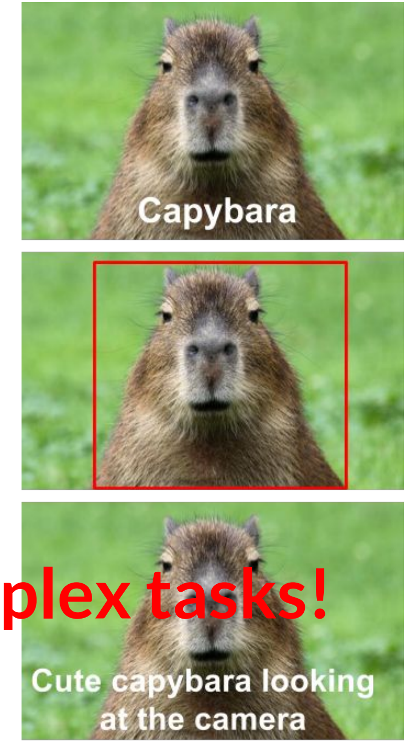
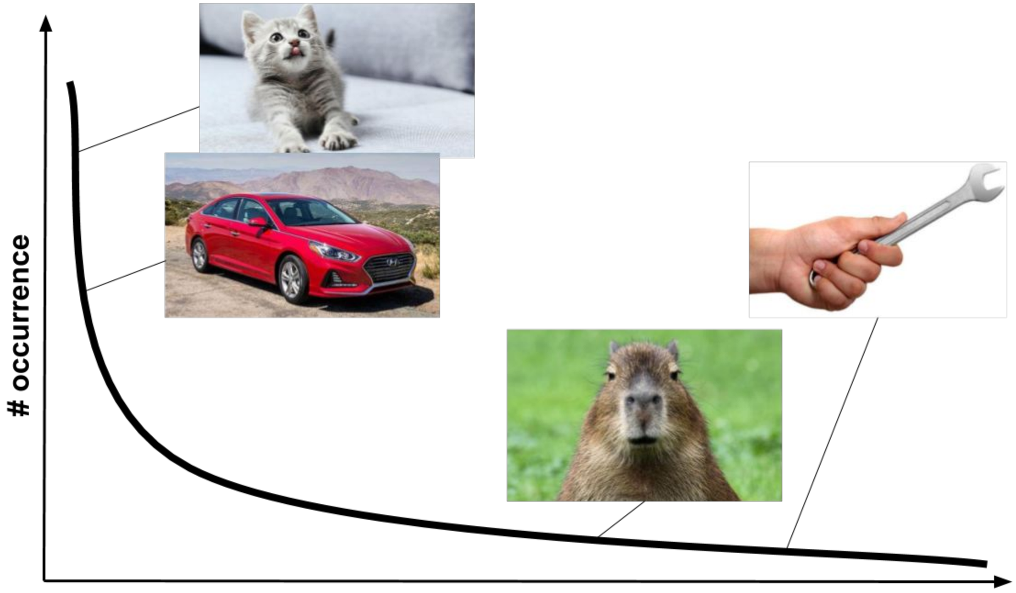
  COCO 300K captioned images



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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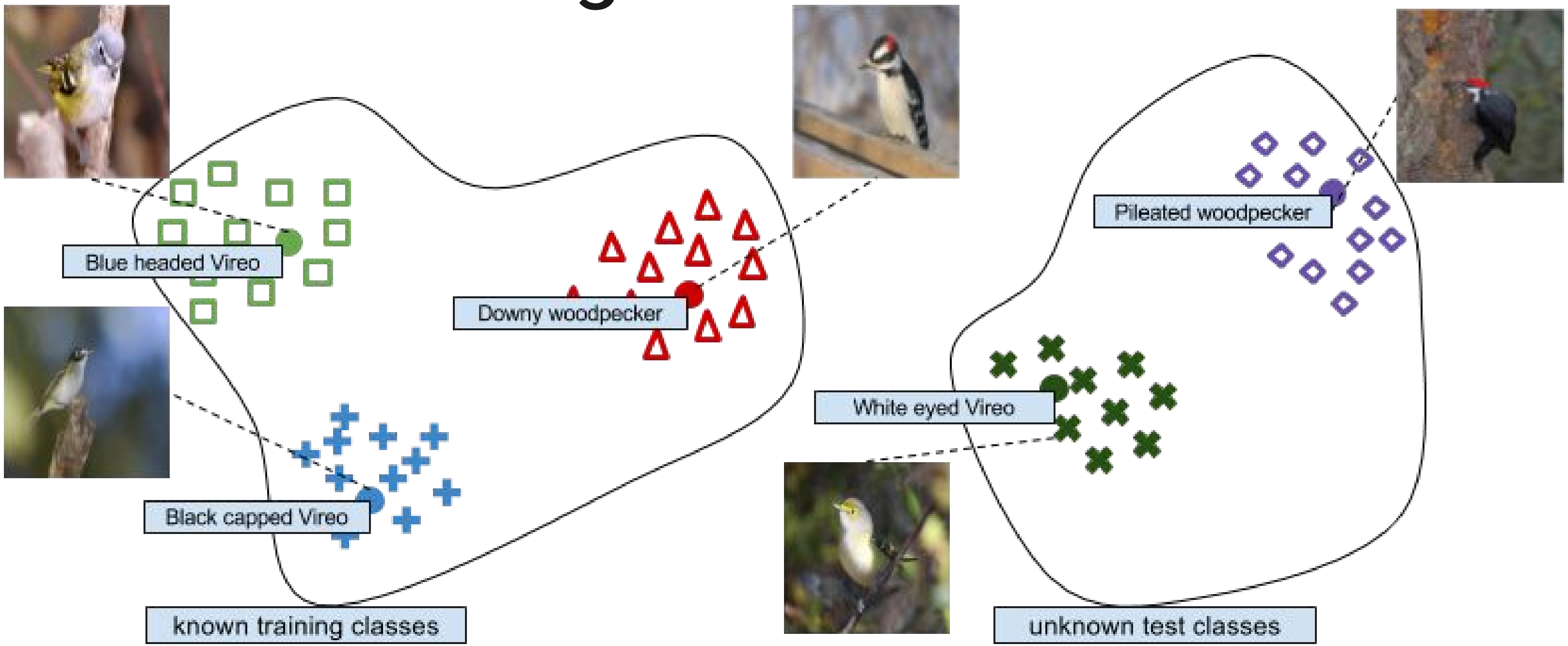
Zero-shot learning

- Extreme case of scarce training data
- Disjoint sets of training and test classes
- New class examples appear after training stage

Zero-shot learning



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

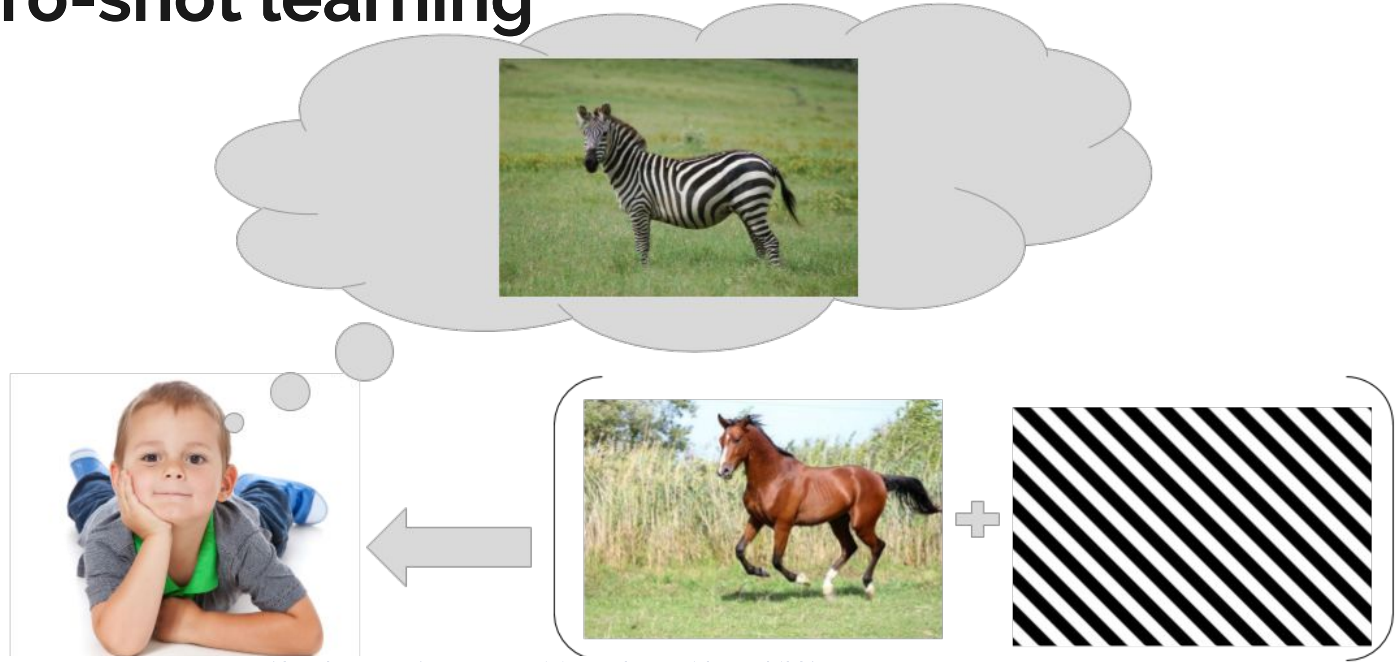
Zero-shot learning

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



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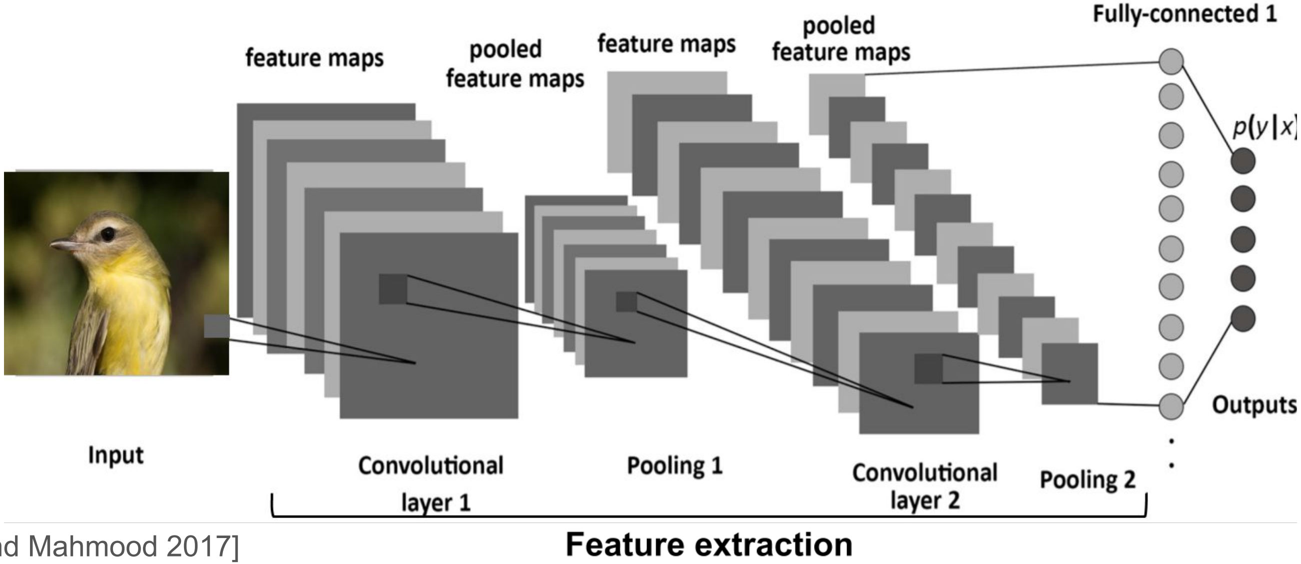
http://earlylearningtoys.org/stripes/ https://pt.wikipedia.org/wiki/Zebra-de-grant

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 - Attributes embedding

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

[0 1 0 0 1 1]

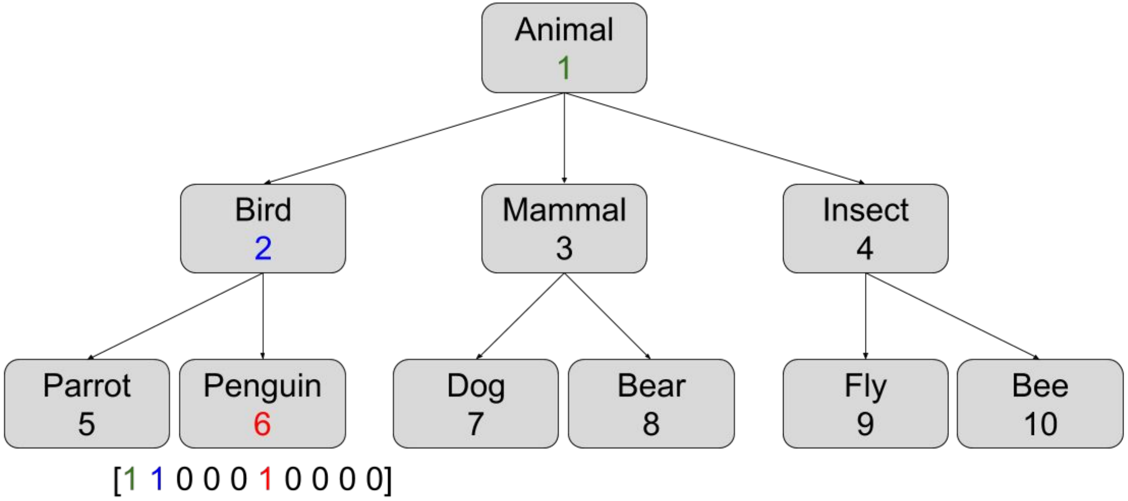
Otter
black: yes
white: no
brown: yes
stripes: no
water: yes
eats fish: yes

[1 0 1 0 1 1]

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

Side information - Hierarchical embedding

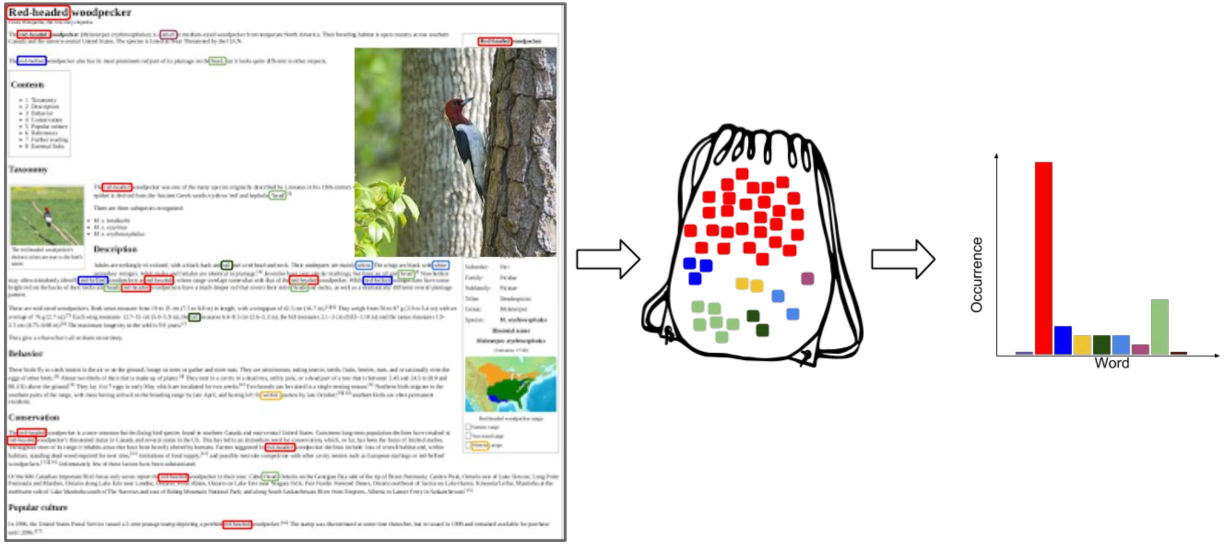
Hierarchical Label Embedding (HLE) extracted from Wordnet



[Tsochantaridis, et al. 2005]

Side information - Text embedding

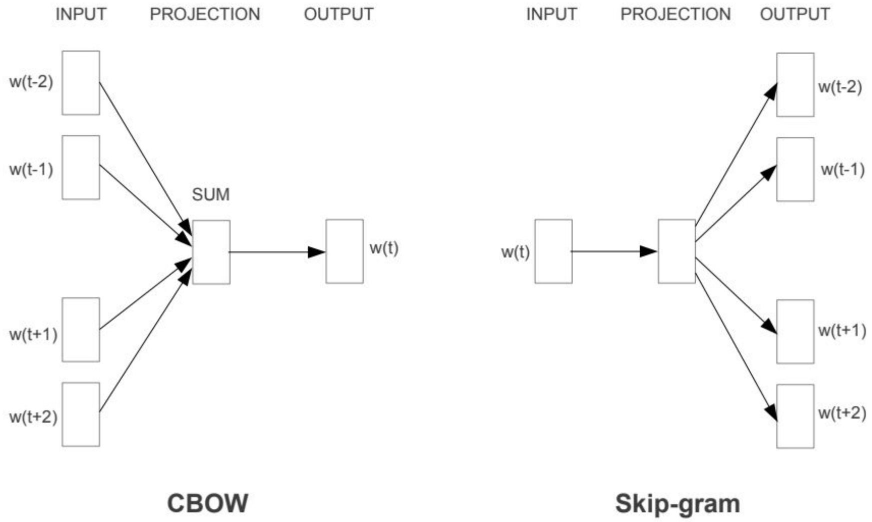
Sparse representations: Bag of Words from Wikipedia articles (BoW)



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

Side information - Text embedding

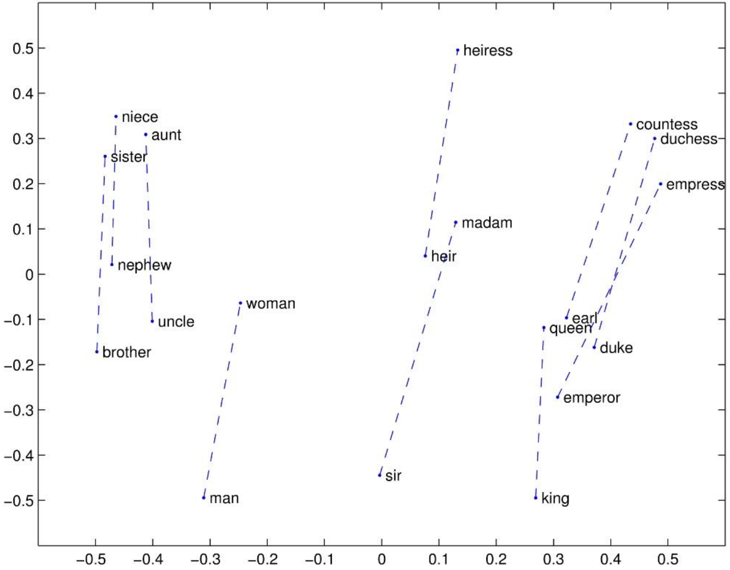
Dense representations: Word2vec



[Mikolov, et al. NIPS2013]

Side information - Text embedding

Dense representations: Global vectors for word representation (Glove)



[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.

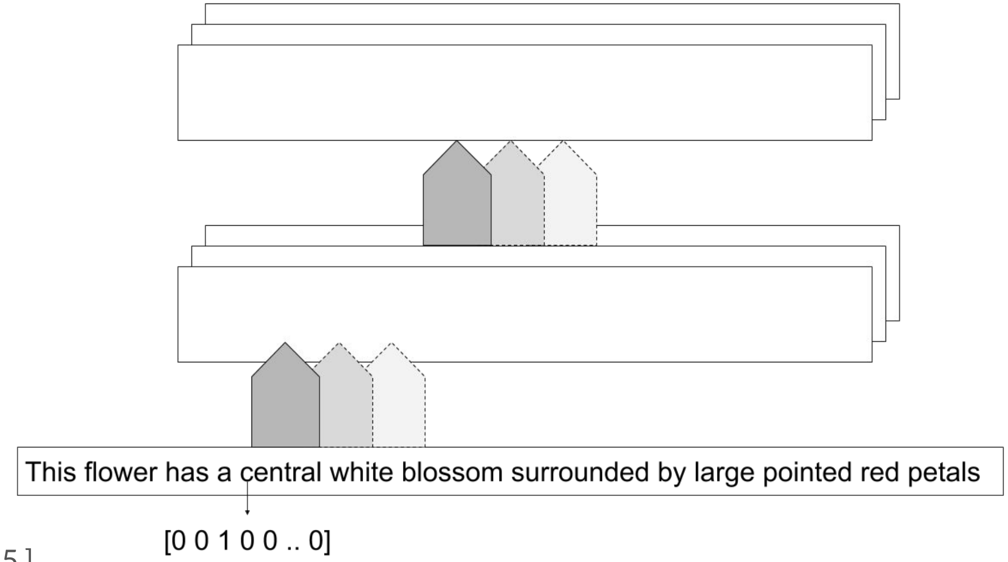
This flower has a central white blossom surrounded by large pointed red petals which are veined and leaflike.

Light purple petals with orange and black middle green leaves

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

Side information - Visual descriptions

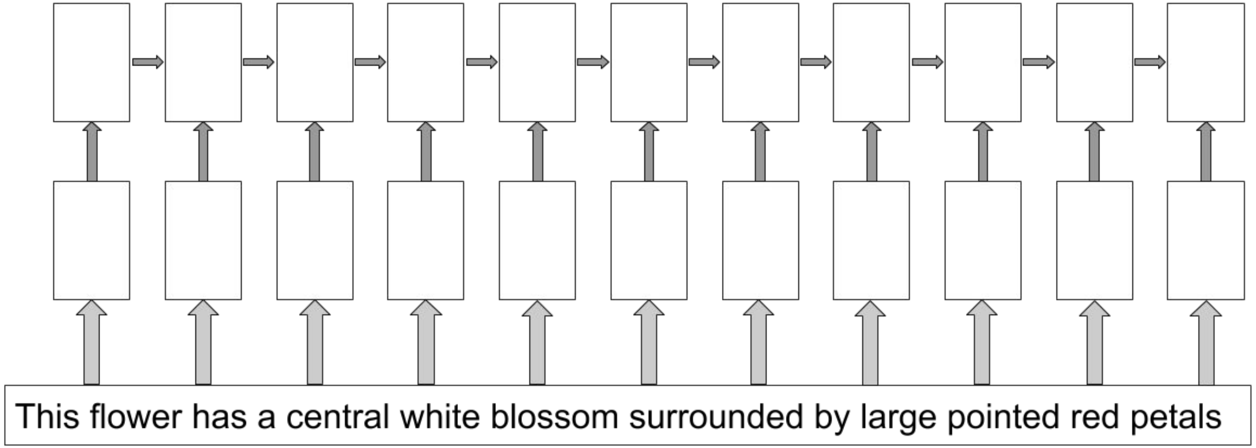
- Character level CNN



[Zhang, et al. NIPS2015]

Side information - Visual descriptions

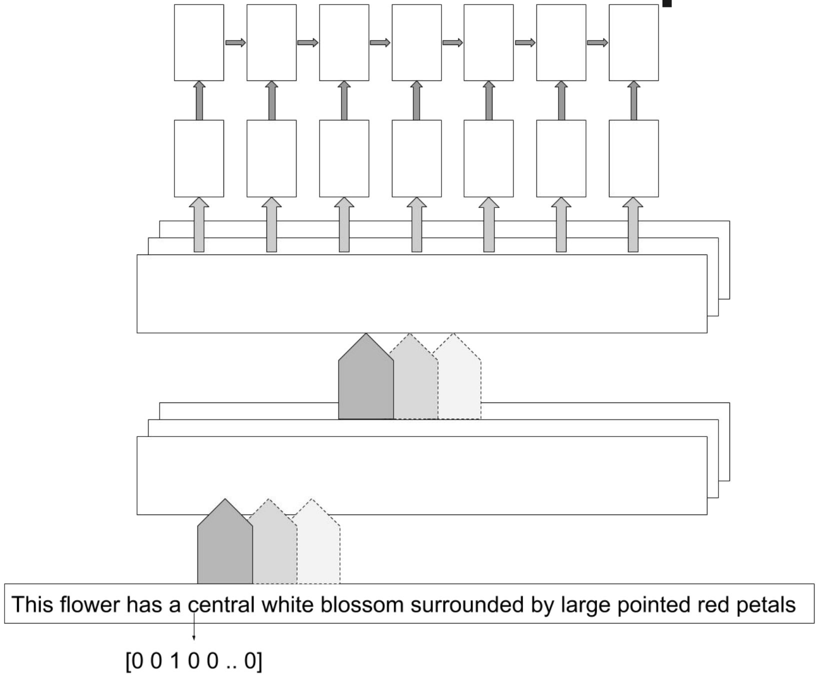
- LSTM



[Hochreiter and Schmidhuber 1998]

Side information - Visual descriptions

- CNN + RNN



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

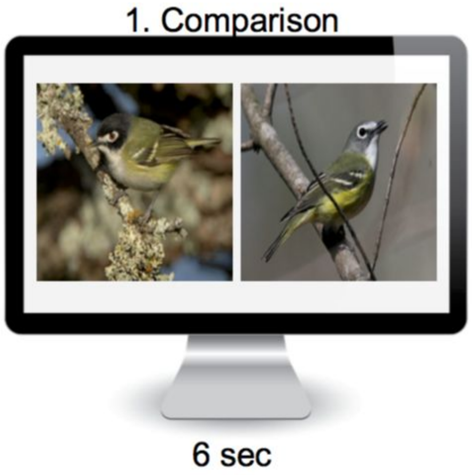
Side information - Gaze embedding

- 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

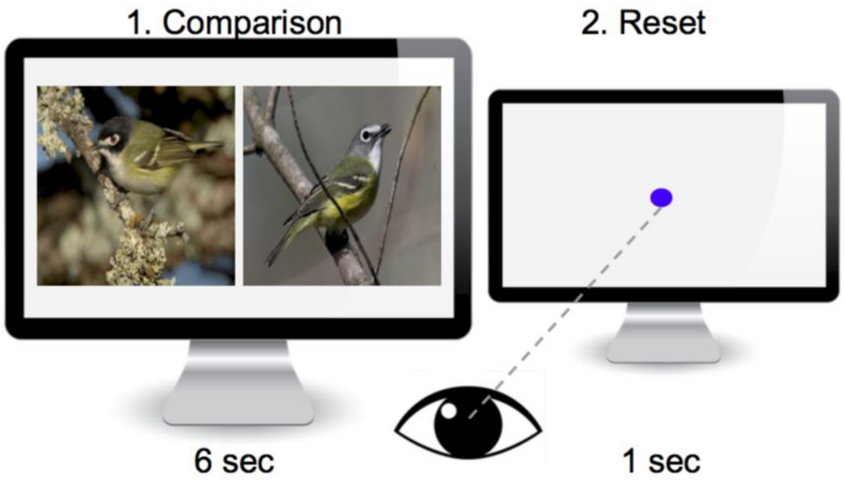
Experiment



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

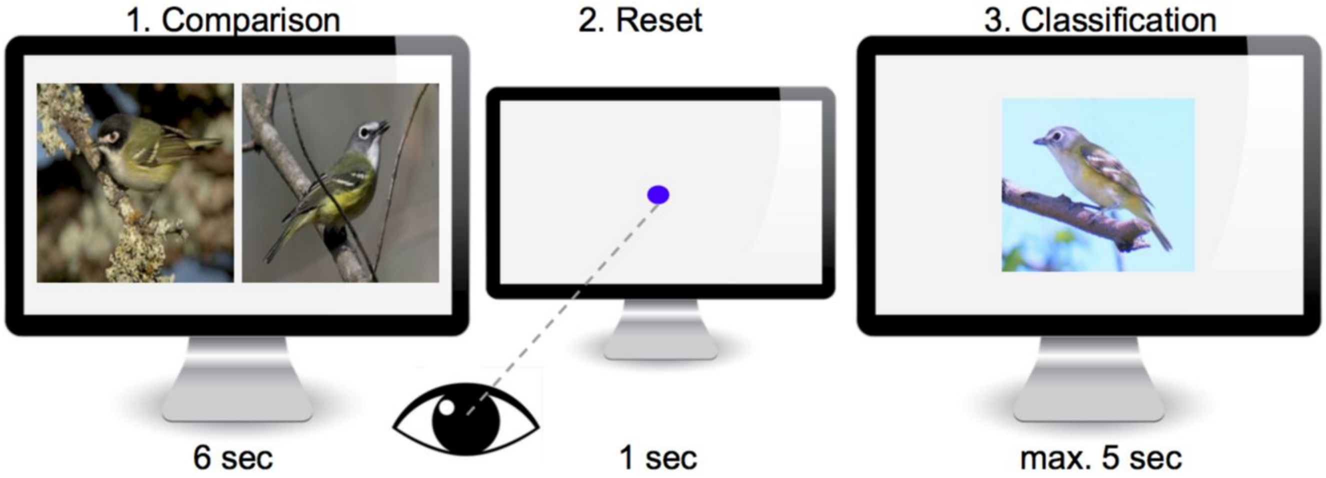
Experiment



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

Experiment



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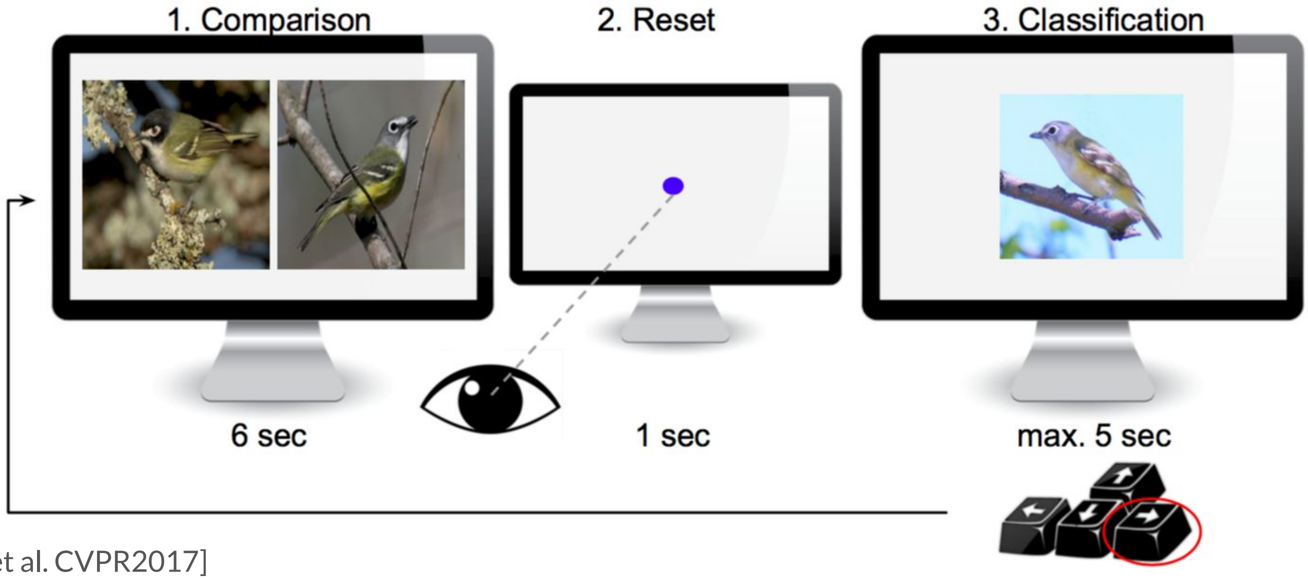
Side information - Gaze embedding

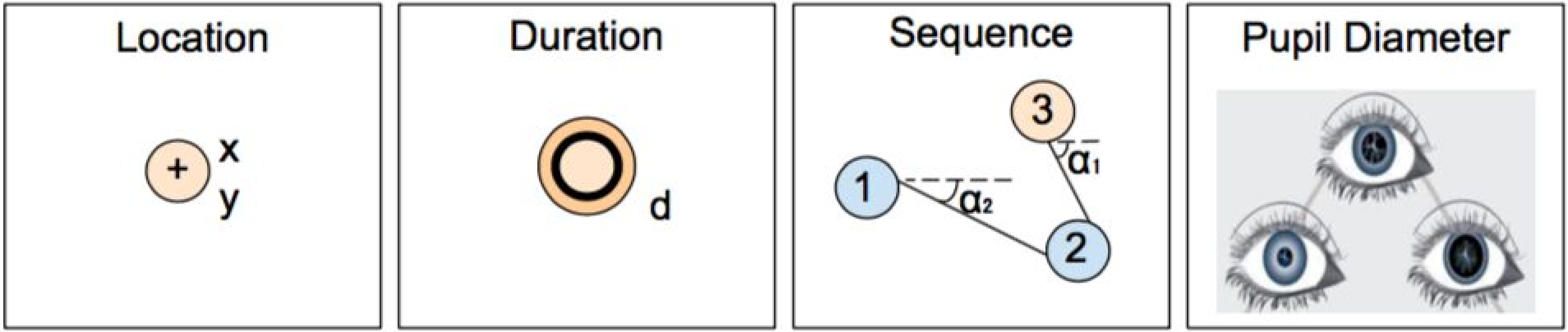
Experiment



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

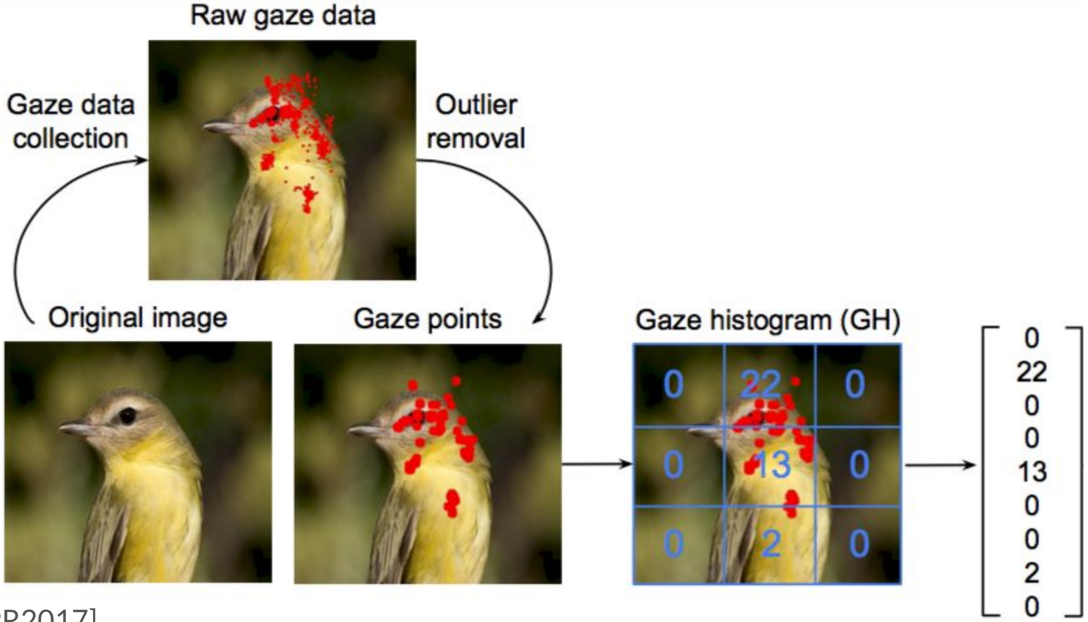
Features



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

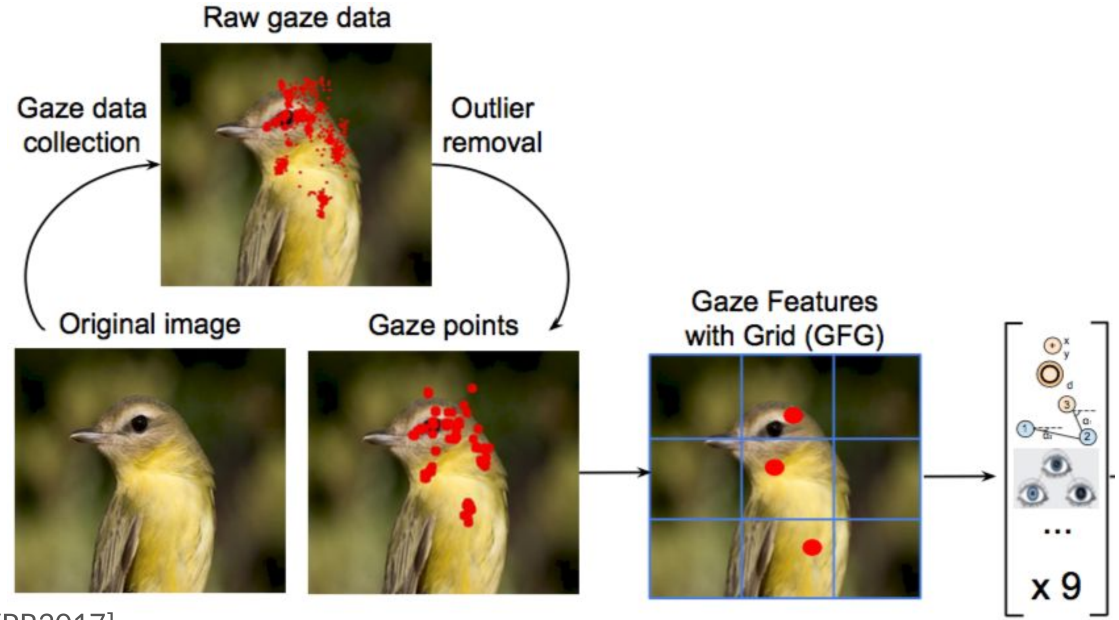
Embeddings



[Karessli, et al. CVPR2017]

Side information - Gaze embedding

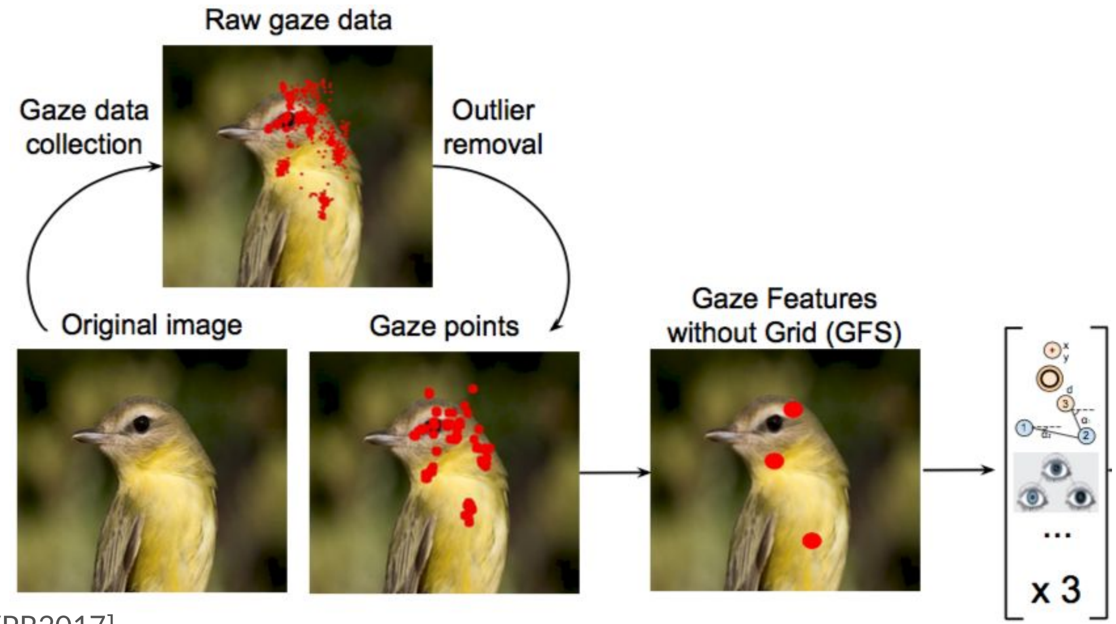
Embeddings



[Karessli, et al. CVPR2017]

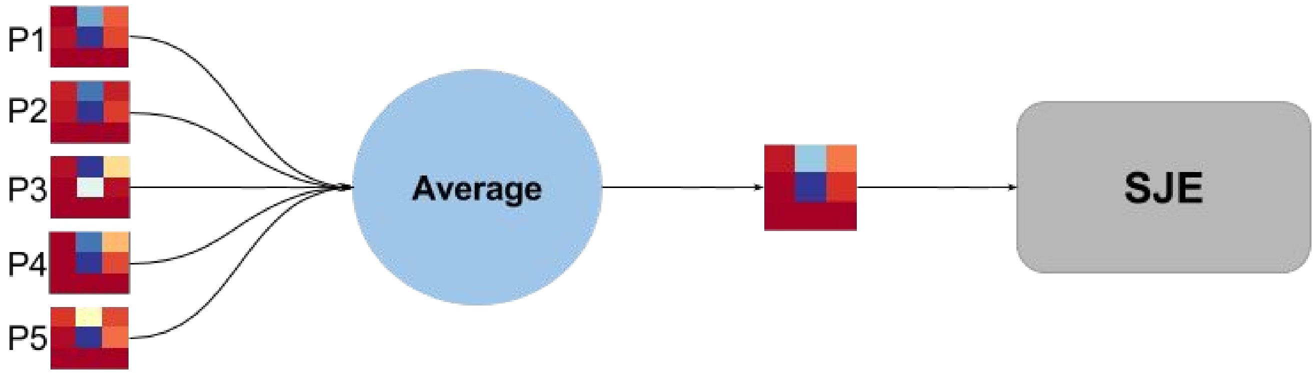
Side information - Gaze embedding

Embeddings



[Karessli, et al. CVPR2017]

Side information - Gaze embedding



[Karessli, et al. CVPR2017]

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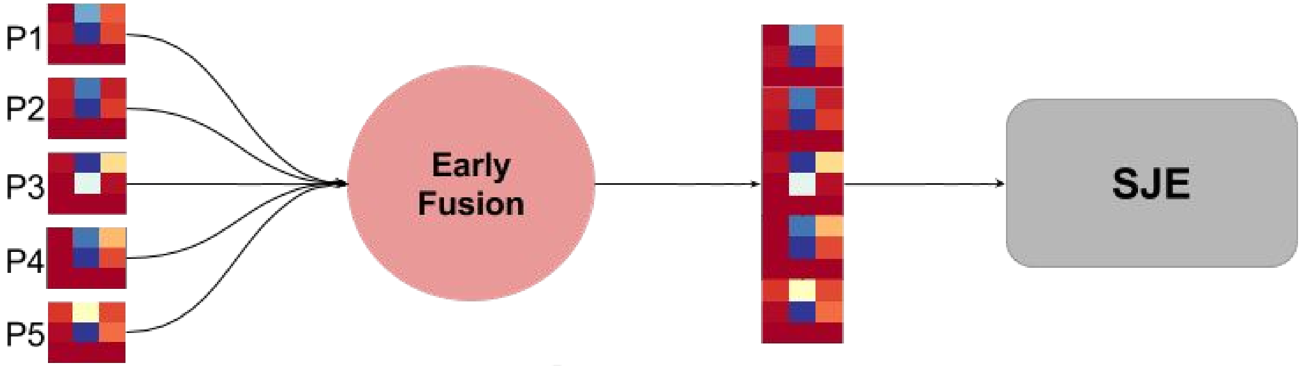

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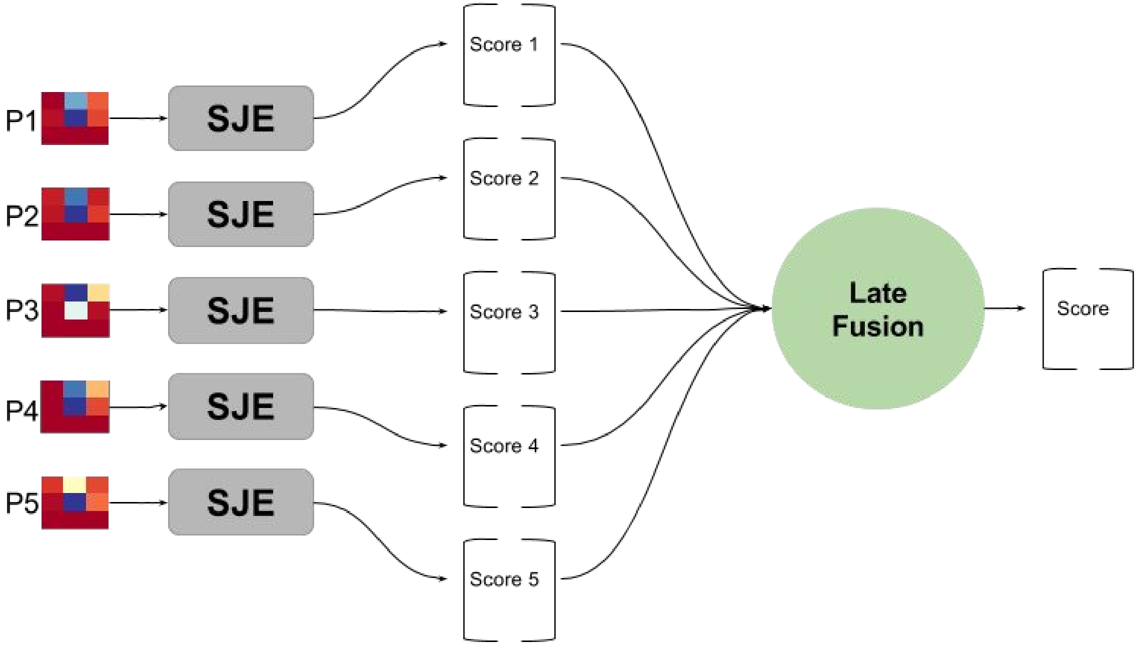


[Karessli, et al. CVPR2017]

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**

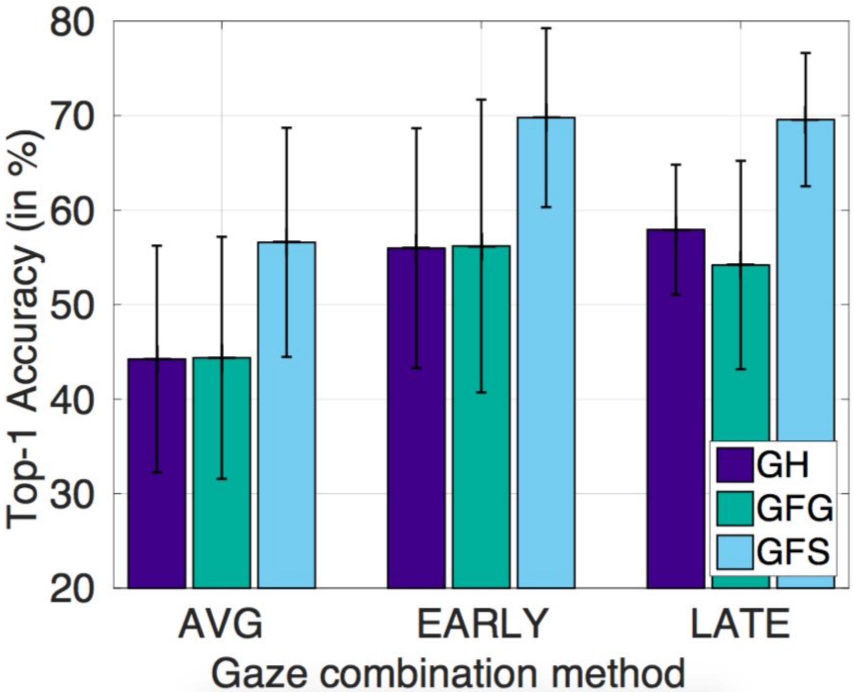
[Reed, et al. CVPR16, ICML16, NIPS16] [Akata, et al. CVPR2015]

Mini-CUB birds

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

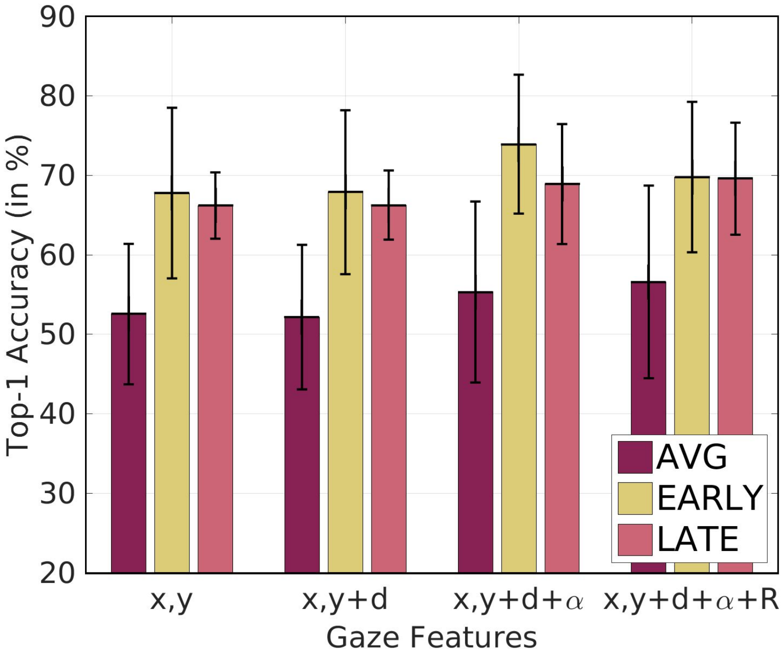
[Welinder, et al. 2010]

Results



[Karessli, et al. CVPR2017]

Results



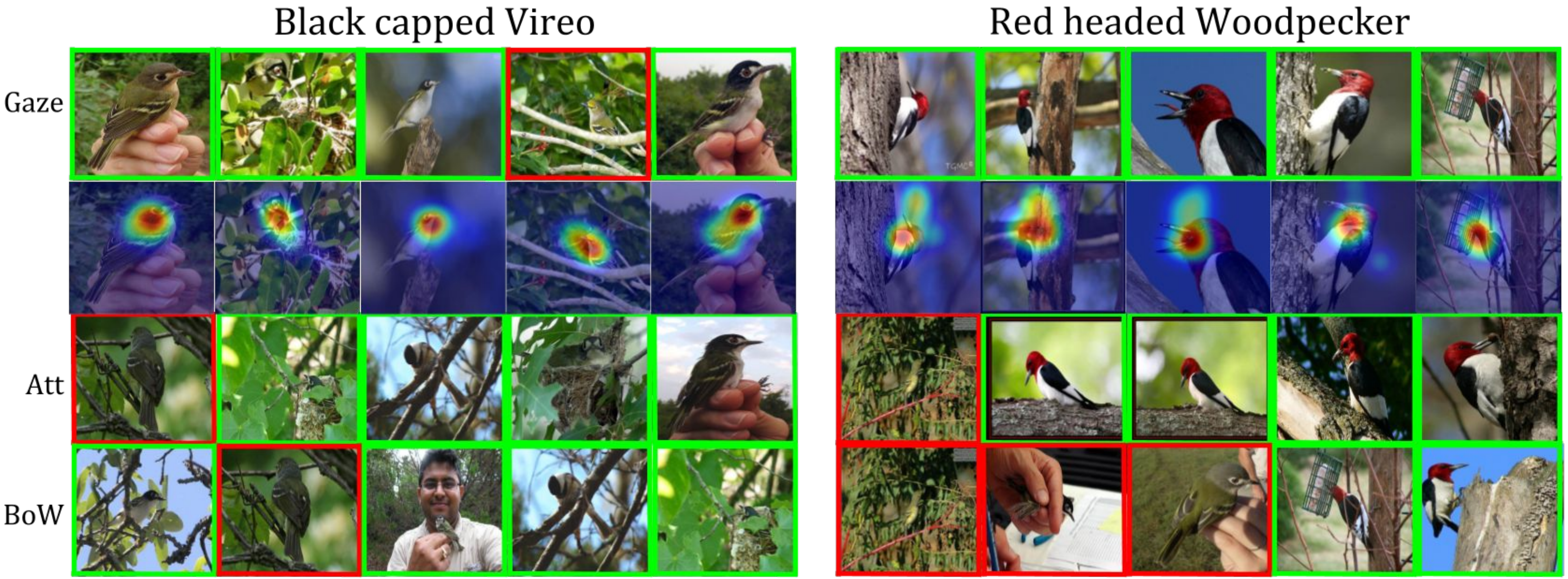
[Karessli, et al. CVPR2017]

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]

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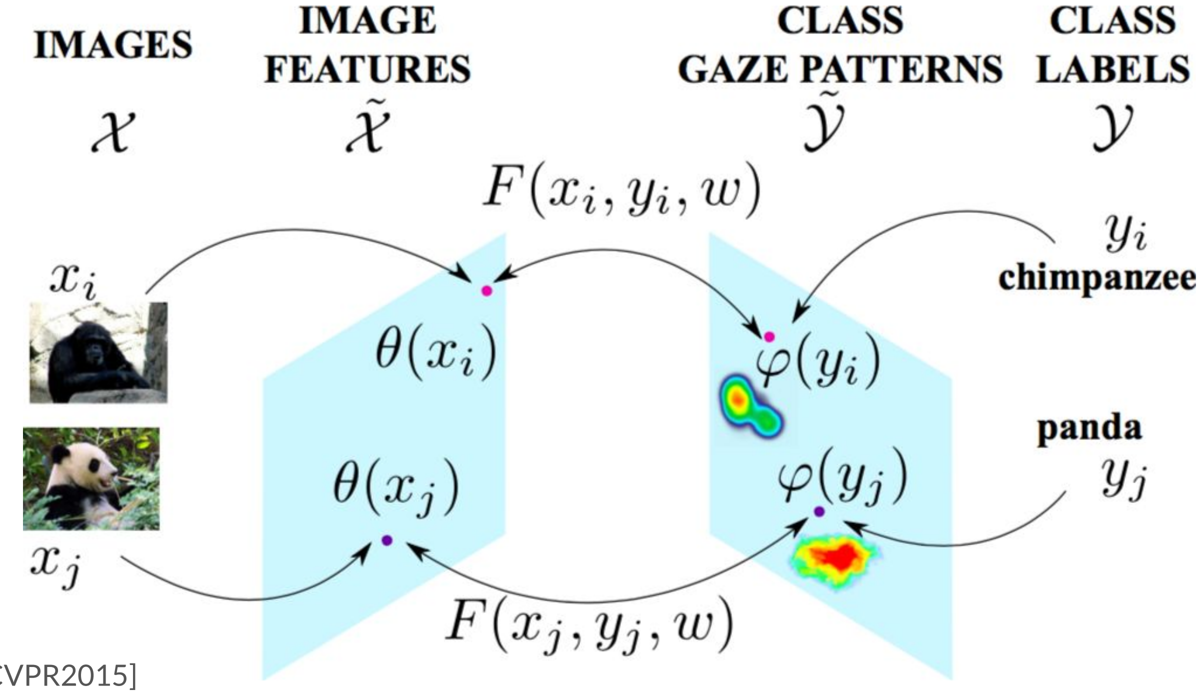
Zero-shot models



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

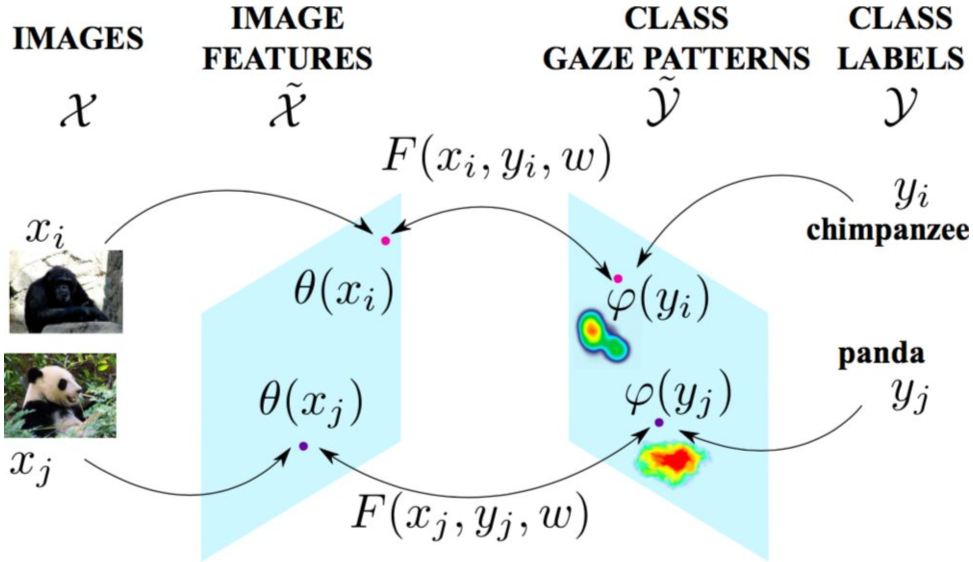
Maximizing the compatibility:

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

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]

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]

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

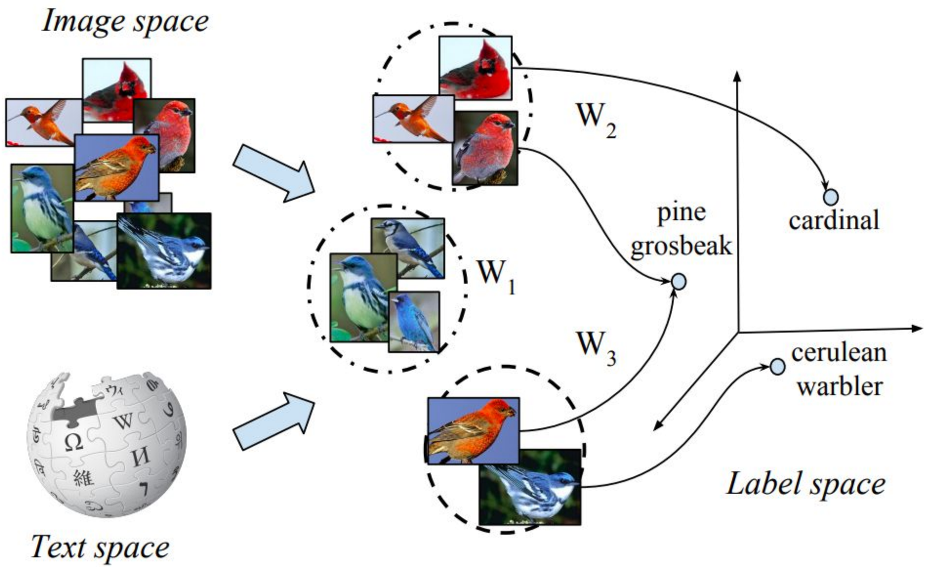
Semantic autoencoder, linear objective

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

- 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]

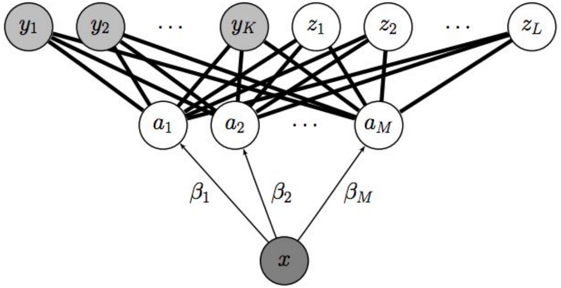
Intermediate Classifier - DAP

Direct attribute prediction

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

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

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



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

Intermediate Classifier - CONSE

Convex combination of semantic embedding

$$f(x,t) = \underset{y \in \mathcal{Y}^{tr}}{\operatorname{argmax}}\, p_{tr}(y|x)$$

At test time, uses combination of semantic embeddings

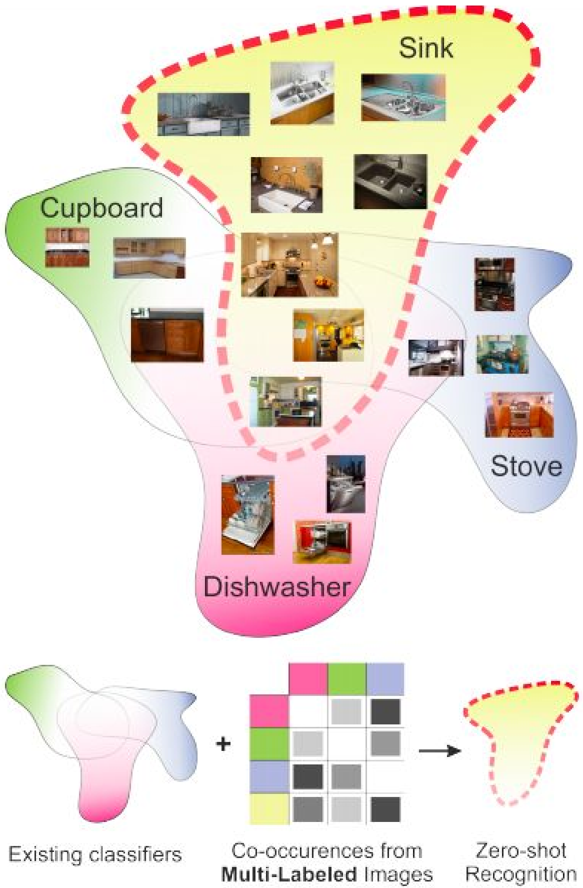
$$\frac{1}{Z}\sum_{i=1}^{T} p_{tr}(f(x,t)|x).s(f(x,t))$$

[Norouzi, et al. ICLR2014]

Intermediate Classifier - COSTA

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

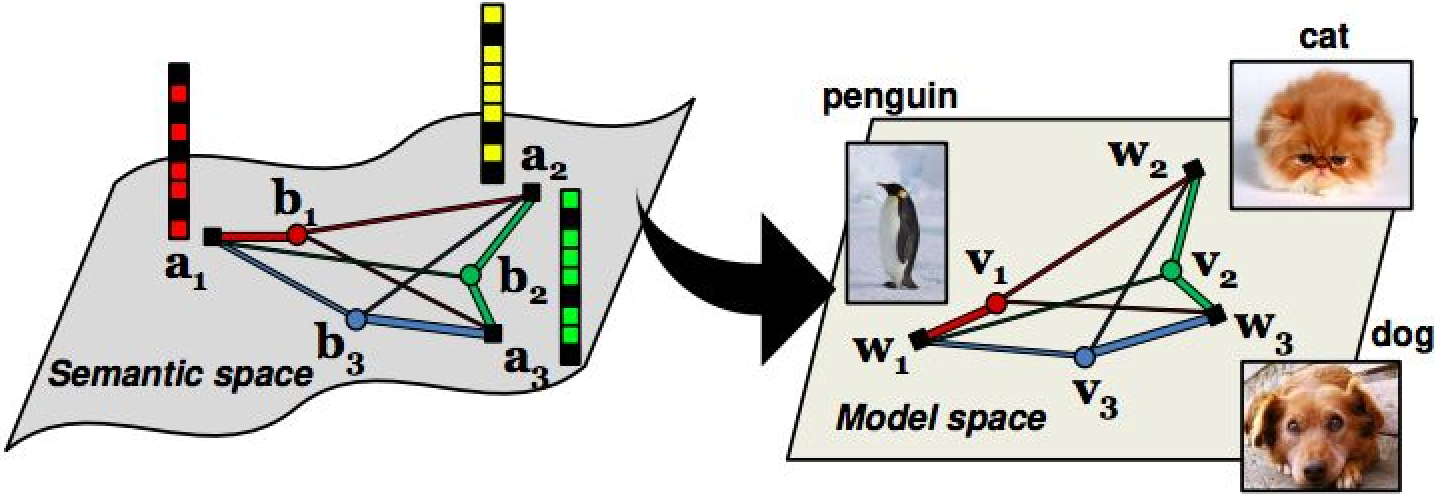
$$\hat{w}_l = \sum_k w_k \, s_{lk}$$



[Mensink, et al. CVPR2014]

Hybrid models - SYNC

Synthesized classifier, minimize distortion error



[Changpinyo, et al. CVPR2016]

Hybrid models - SYNC

Synthesized classifier, minimize distortion error

$$\min_{w_c, v_r} \|w_c - \sum_{r=1}^{R} s_{cr} v_r\|_2^2$$

[Changpinyo, et al. CVPR2016]

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], CONSE [Norouzi, et al. ICLR2014], COSTA [Mensink, et al. CVPR2014]

4. **Hybrid models**
   SYNC [Changpinyo, et al. CVPR2016]

AWA dataset

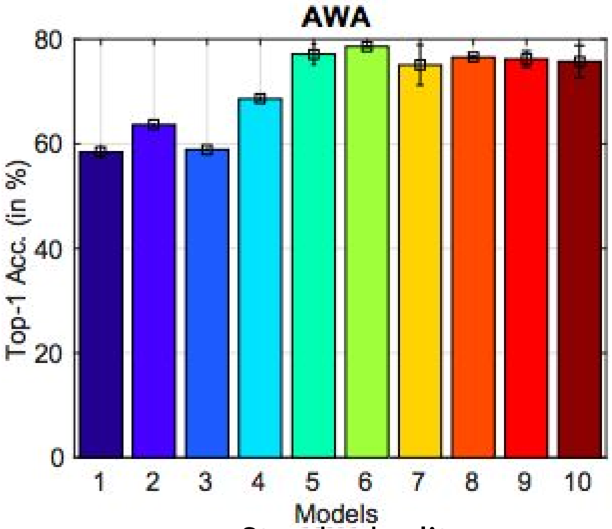
Animal with attributes dataset

- 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

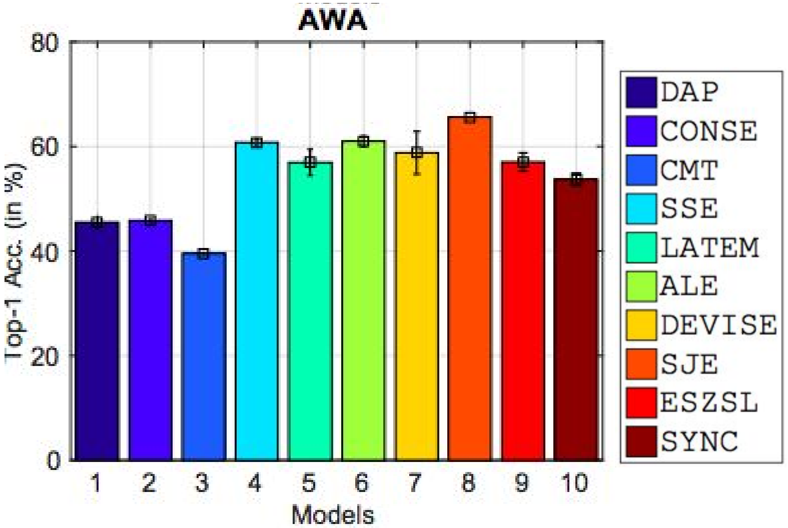
[Lampert, et al. TPAMI2013]

Results

Evaluation on Animals with Attributes AWA



Standard split



Proposed split

[Xian, et al. CVPR2017]

Q & A

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

Zero-shot learning exercise

SJE implementation

- Select dataset (AWA)
- Download data (image features & class embeddings)
- Implement zero-shot algorithm SJE

Low-shot Learning

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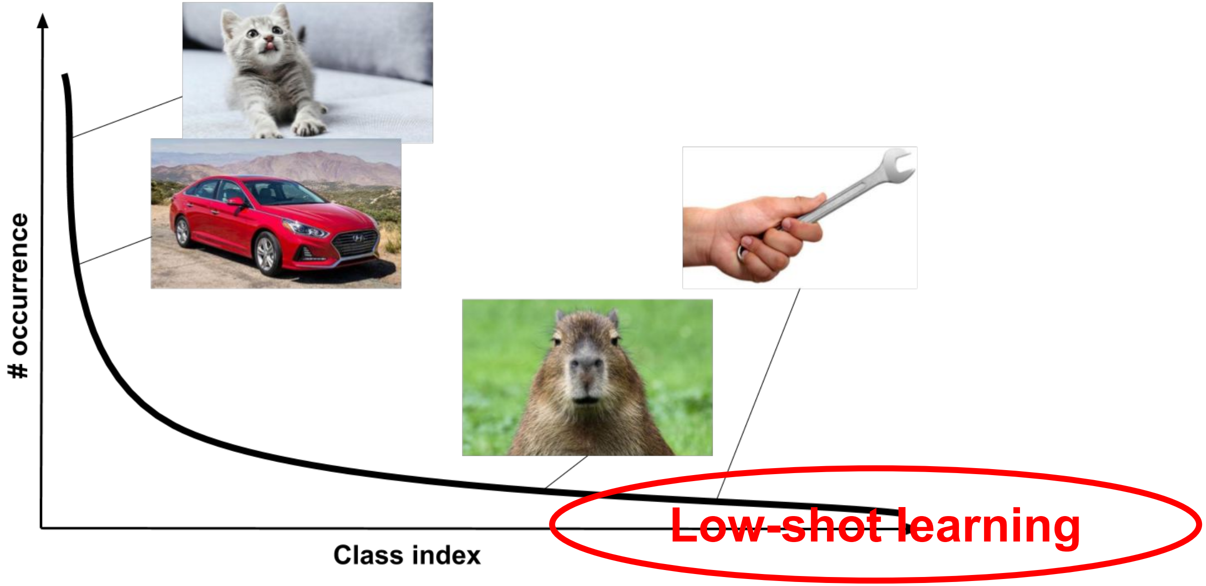
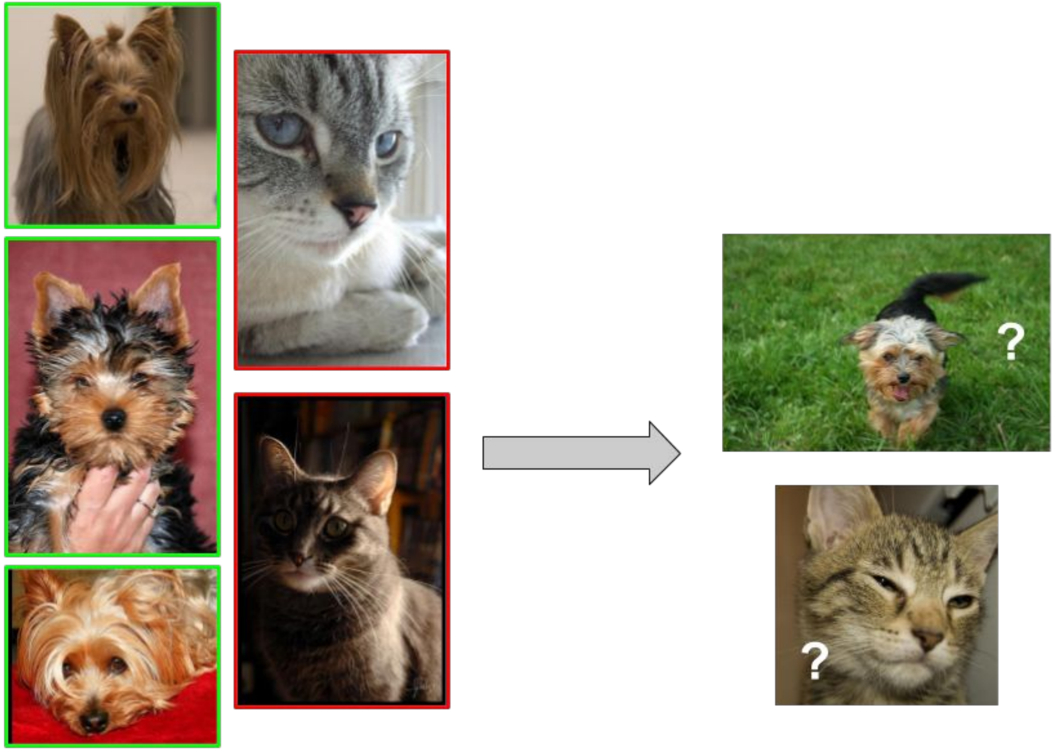
Go back to tail distribution..



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

Low-shot learning

- Ability to generalize only with a few examples
- Exploits prior learning on other classes



http://www.image-net.org/

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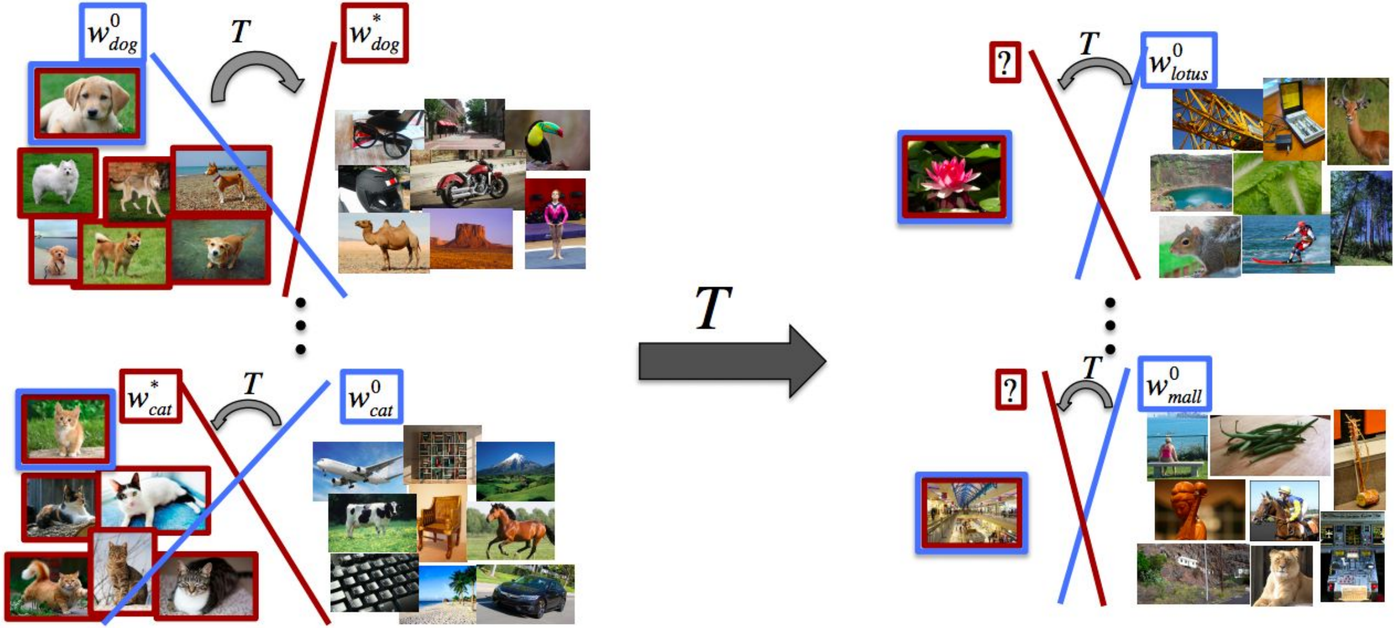
Low-shot learning approaches

We will overview three recent works on the problem of low-shot image classification

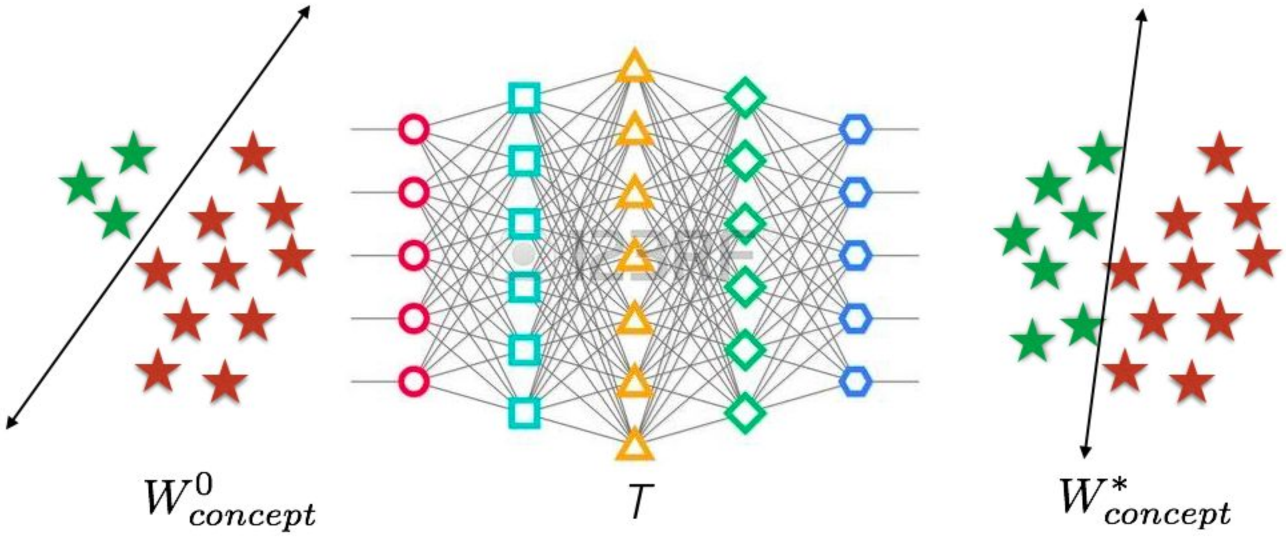
- Learning to learn
- Matching nets
- Shrinking and Hallucinating Features

Learning to learn



[Wang and Hebert ECCV2016]

Learning to learn



[Wang and Hebert ECCV2016]

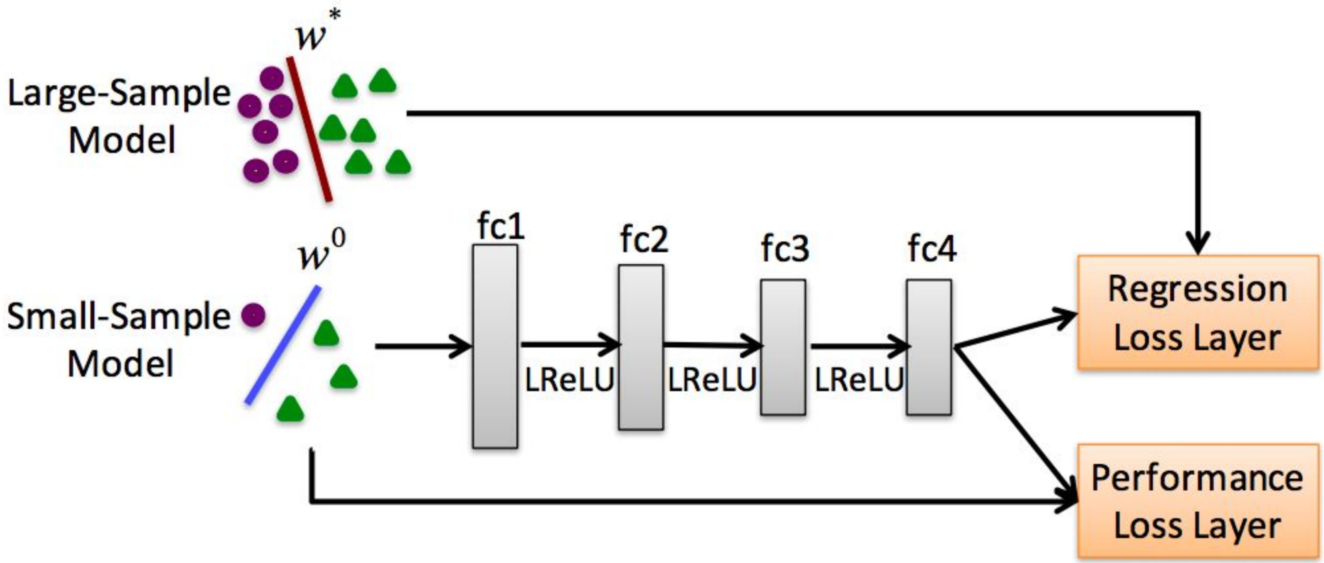
Learning to learn

Loss function

$$L(\Theta) = \sum_{j=1}^{J} \left\{ \underbrace{\frac{1}{2} \left\| \mathbf{w}_j^* - T\left(\mathbf{w}_j^0, \Theta\right) \right\|_2^2}_{\substack{\text{Model regression term} \\ \text{Euclidean distance}}} + \lambda \sum_{i=1}^{M+N} \underbrace{\left[1 - y_i^j \left(T\left(\mathbf{w}_j^0, \Theta\right)^T \mathbf{x}_i^j \right) \right]_+}_{\substack{\text{Data fitting term} \\ \text{Hinge loss}}} \right\}$$

[Wang and Hebert ECCV2016]

Learning to learn



[Wang and Hebert ECCV2016]

Learning to learn

Novel categories:

- **Initialization**
  learn model from small set of K (image,label) pairs
- **Transformation**
  perform the learned transformation T
- **Refinement**
  retrain SVM using the transformed model as regularizer

$$R(\mathbf{w}) = \frac{1}{2}\left\|\mathbf{w} - T\left(\mathbf{w}^0, \Theta\right)\right\|_2^2 + \eta \sum_{i=1}^{K} \left[1 - y_i\left(\mathbf{w}^T \mathbf{x}_i\right)\right]_+$$

[Wang and Hebert ECCV2016]

Matching Networks

Given a support set $S = \{(x_i, y_i)\}_{i=1}^{k}$ learns the mapping $S \rightarrow C_S(x)$

The classifier defines the probability distribution, P is parameterized by a neural network:

$$C(x^{test}) = P(y^{test}|x^{test}, S)$$

Prediction:

$$argmax_y P(y|x^{test}, S)$$

[Vinyals, et al. NIPS2016]

Matching Networks

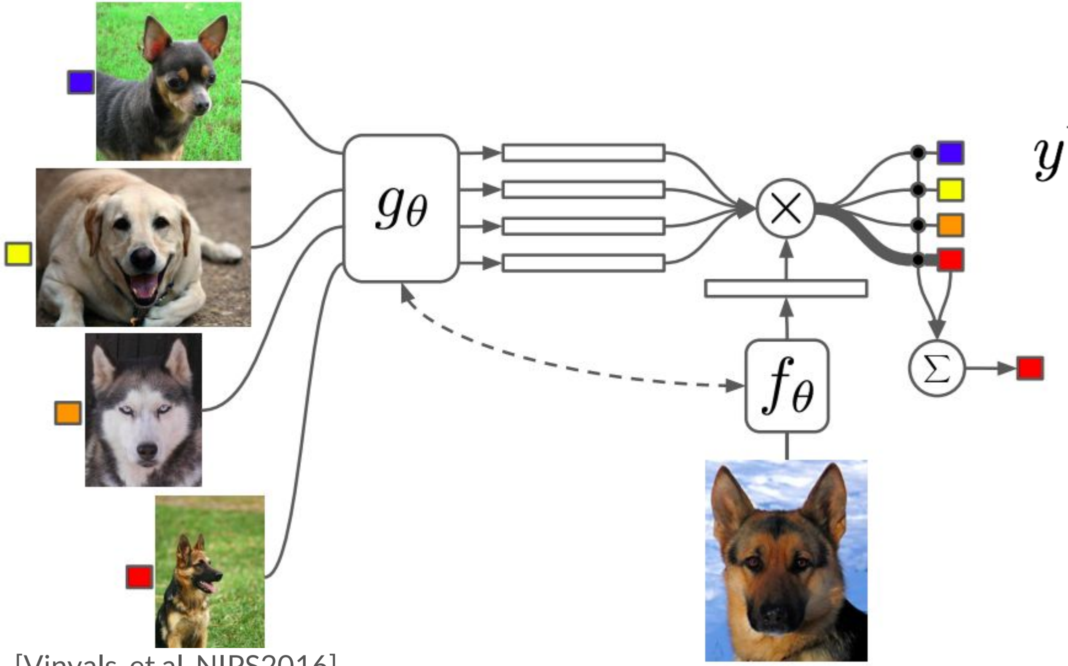
Prediction

$$y^{test} = \sum_{i=1}^{k} a(x^{test}, x_i)y_i$$

- Attention mechanism
- Linear combination of support set labels

[Vinyals, et al. NIPS2016]

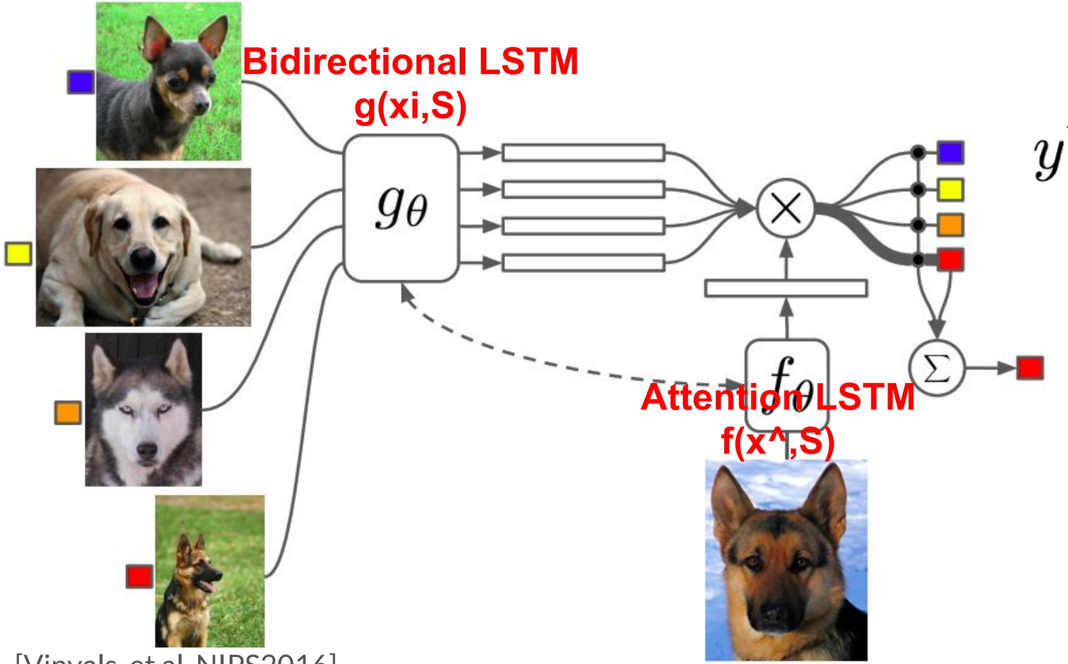
Matching Networks



$$y^{test} = \sum_{i=1}^{k} a(x^{test}, x_i) y_i$$

[Vinyals, et al. NIPS2016]

Matching Networks



$$y^{test} = \sum_{i=1}^{k} a(x^{test}, x_i) y_i$$

0.1*Chihuahua
0.1*Labrador Retriever
0.5*German Shepherd
0.3*Siberian Husky

[Vinyals, et al. NIPS2016]

Matching Networks

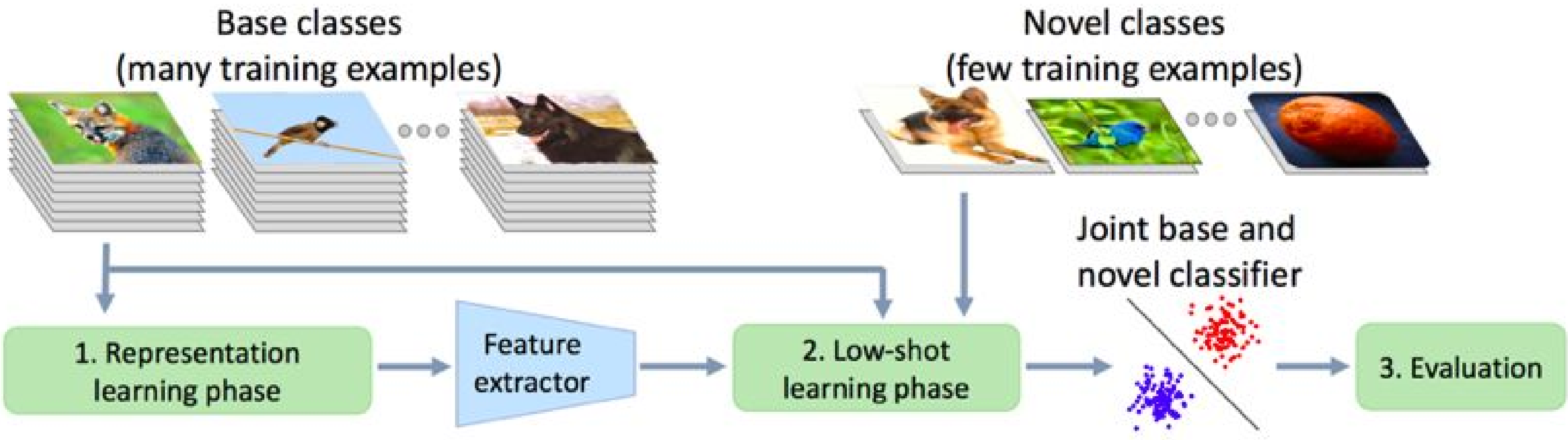
Training strategy

1. Sample task **T** (5 labels, up to 5 examples per label)
2. Sample a label set **L** from T e.g. {cats, dogs}
3. Sample a support set **S** examples from L
4. Sample batch **B** examples from L
5. Evaluate loss on **B** using **S**

$$\theta = \underset{\theta}{argmax} E_{L\sim T}[E_{S\sim L, B\sim L}[\sum_{(x,y)\in B} log P_\theta(y|x, S)]]$$

[Vinyals, et al. NIPS2016]

Shrinking and Hallucinating Features



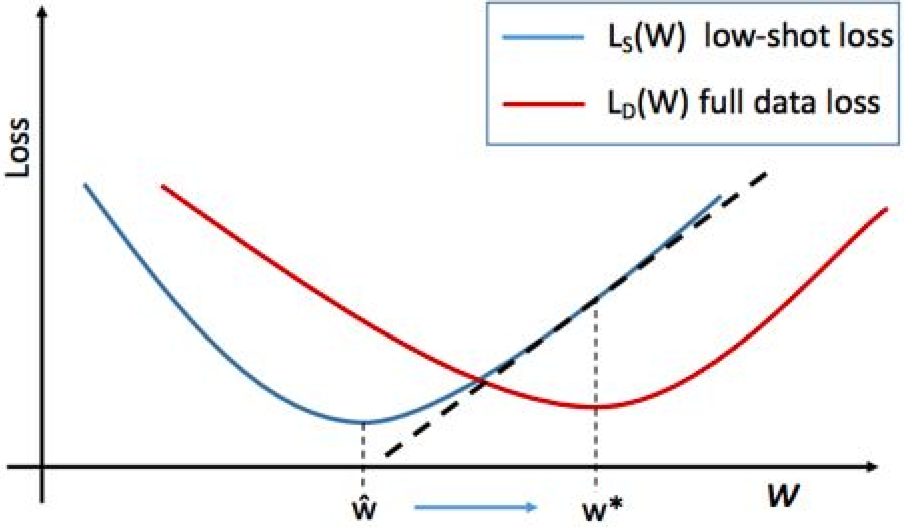
[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Introduces Squared Gradient Magnitude loss

- Minimise the loss of low-shot during representation learning

→ better representation for low-shot learning



[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Train feature extractor and classifier on D (all data) has the objective

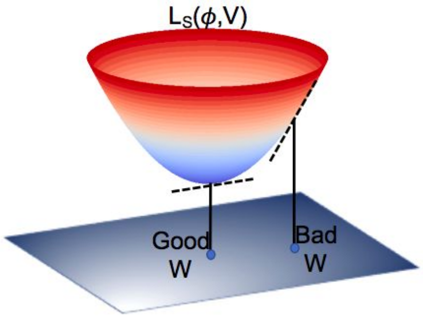
$$\min_{W,\phi} L_D(\phi, W) = \min_{W,\phi} \frac{1}{|D|} \sum_{(x,y)\in D} L_{cls}(W, \phi(x), y)$$

For small set S, the objective

$$\min_{V} L_S(\phi, V) = \min_{V} \frac{1}{|S|} \sum_{(x,y)\in S} L_{cls}(V, \phi(x), y)$$

Minimise

$$\tilde{L}_S(\phi, W) = \|\nabla_V L_S(\phi, V)|_{V=W}\|^2$$



[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

$$\begin{aligned}\tilde{L}_S(\phi, W) &= \sum_{k=1}^{K}(p_k(W, \phi(x)) - \delta_{yk})^2 \|\phi(x)\|^2 \\ &= \alpha(W, \phi(x), y)\|\phi(x)\|^2.\end{aligned}$$

$\alpha(W, \phi(x), y)$ Per example weight that is higher for misclassified data points

Final SGM loss

$$L_D^{SGM}(\phi, W) = \frac{1}{|D|}\sum_{(x,y)\in D}\alpha(W, \phi(x), y)\|\phi(x)\|^2$$

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Train feature representation by minimizing a linear combination of the SGM loss and the original classification objective

$$\min_{W,\phi} L_D(\phi, W) + \lambda L_D^{SGM}(\phi, W)$$

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Hallucinate samples

perched bird with sky background

perched bird with green background

Assumption

Any two examples z1 and z2 belonging to the same category represent a plausible transformation.

→ Given a novel category example x, apply to x the transformation that sent z1 to z2.

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

1. Cluster feature vectors in each category into 100 clusters.

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

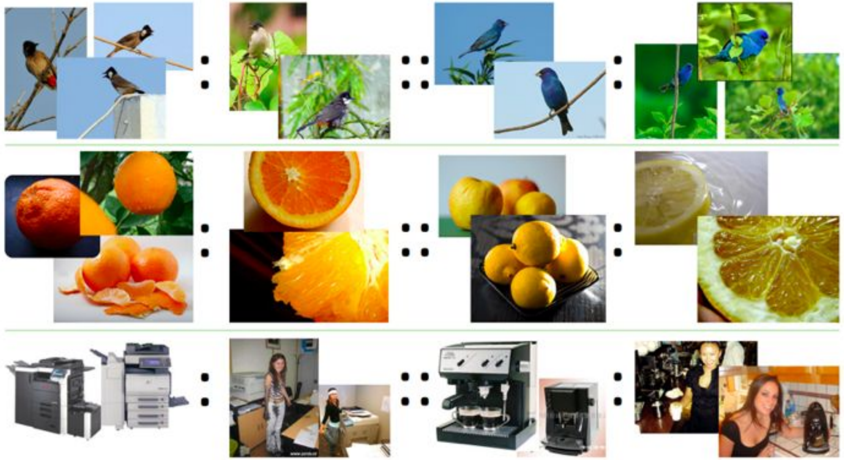
1. Cluster feature vectors in each category into 100 clusters.
2. Form quadruple of centroids

[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

1. Cluster feature vectors in each category into 100 clusters.
2. Form quadruple of centroids
3. Feed 3 centroids and predict the forth

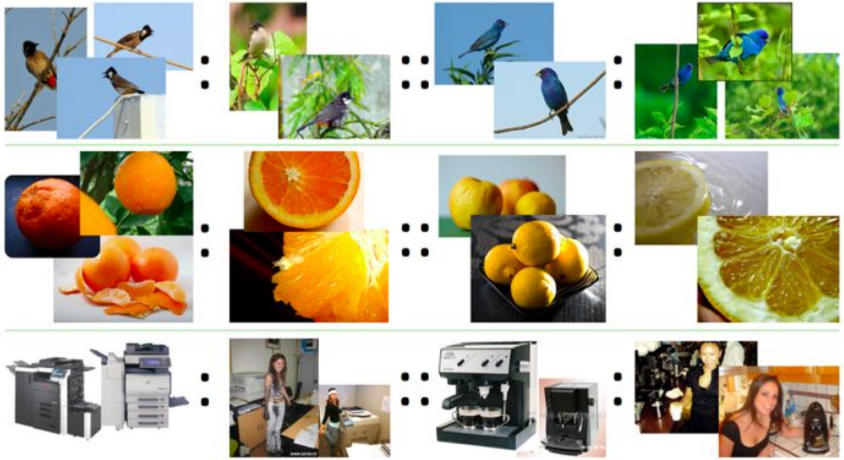


[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

1. Cluster feature vectors in each category into 100 clusters.
2. Form quadruple of centroids
3. Feed 3 centroids and predict the forth
4. Minimize the weighted sum of two losses

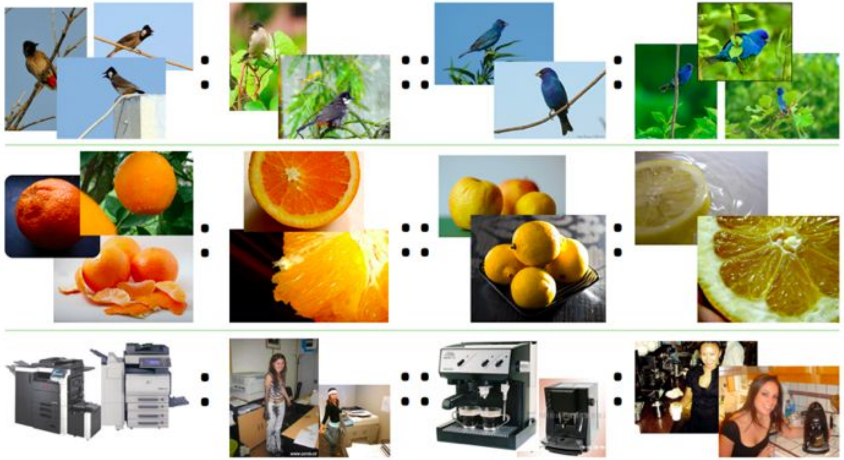


[Hariharan and Girshick arXiv2016]

Shrinking and Hallucinating Features

Fully supervised regression using MLP of 3 fully connected layers

1. Cluster feature vectors in each category into 100 clusters.
2. Form quadruple of centroids
3. Feed 3 centroids and predict the forth
4. Minimize the weighted sum of two losses
    - Classification loss
    - Mean squared error



[Hariharan and Girshick arXiv2016]

Results

Representation	Lowshot phase	n=1	2	5	10	20
ResNet-10						
Baseline	Classifier	14.1	33.3	56.2	66.2	71.5
Baseline	Generation* + Classifier	29.7	42.2	56.1	64.5	70.0
SGM*	Classifier	23.1	42.4	*61.7*	69.6	*73.8*
SGM*	Generation* + Classifier	*32.8*	46.4	*61.7*	*69.7*	*73.8*
L2*	Classifier	29.1	*47.4*	**62.3**	68.0	70.6
Baseline	Model Regression [47]	20.7	39.4	59.6	68.5	73.5
Baseline	Matching Network [46]	**41.3**	**51.3**	*62.1*	67.8	71.8

Top-5 accuracy on Imagenet1K for novel classes only

[Hariharan and Girshick arXiv2016]

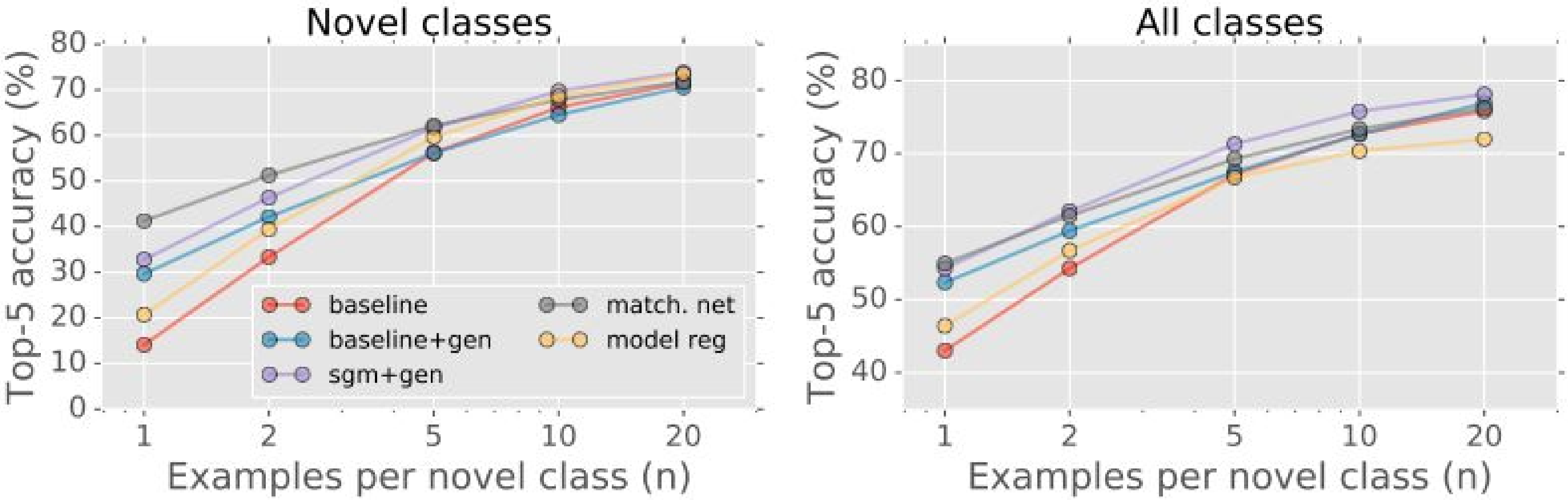
Results

Representation	Lowshot phase	n=1	2	5	10	20
ResNet-10						
Baseline	Classifier	43.0	54.3	67.2	72.8	75.9
Baseline	Generation* + Classifier	52.4	59.4	67.5	72.6	76.9
SGM*	Classifier	49.4	60.5	*71.3*	**75.8**	*78.1*
SGM*	Generation* + Classifier	*54.3*	*62.1*	*71.3*	**75.8**	*78.1*
L2*	Classifier	52.7	**63.0**	**71.5**	74.8	76.4
Baseline	Model Regression [47]	46.4	56.7	66.8	70.4	72.0
Baseline	Matching Network [46]	**55.0**	61.5	69.3	73.4	76.2

Top-5 accuracy on Imagenet1K for all classes

[Hariharan and Girshick arXiv2016]

Results



[Hariharan and Girshick arXiv2016]

Tips & Tricks

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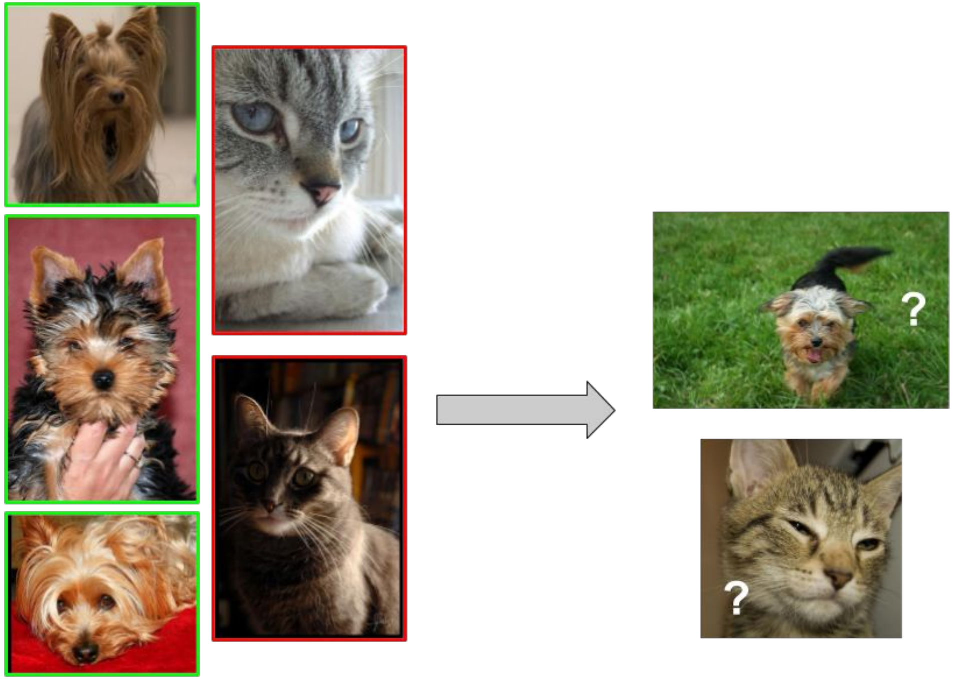
Generalization from small training set



Overfitting curse

Symptoms

- Very high training accuracy
- Very low testing accuracy

→ Model doesn't generalize to unseen data

Regularization

L_2 regularization

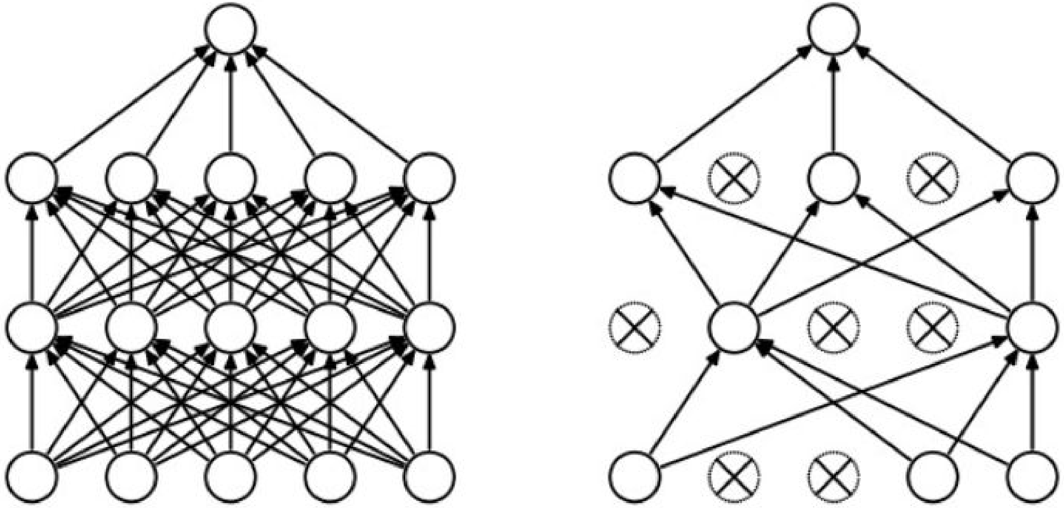
- Most common form of regularization
- Penalizing the squared magnitude of weights in the objective

L_1 regularization

- Relatively common form of regularization
- Penalizing L_1 of weights in the objective

Dropout

Removing a neuron from a designated layer during training or by dropping certain connection



[Srivastava, et al. JMLR2014]
http://cs231n.github.io/neural-networks-2/

Batch normalization

A common practice in NN, forces activiations to have unit gaussian distribution

- Insert BN layer after FC and Conv, and before non-linearities

Robust networks to bad initialization

- interpreted as doing preprocessing at every layer of the network
- Normalization is differentiable

[Ioffe and Christian Szegedy ICML2015]

Transfer learning

Problem Training a model from scratch only with small data is **challenging** and suffer from **overfitting**

Transfer learning

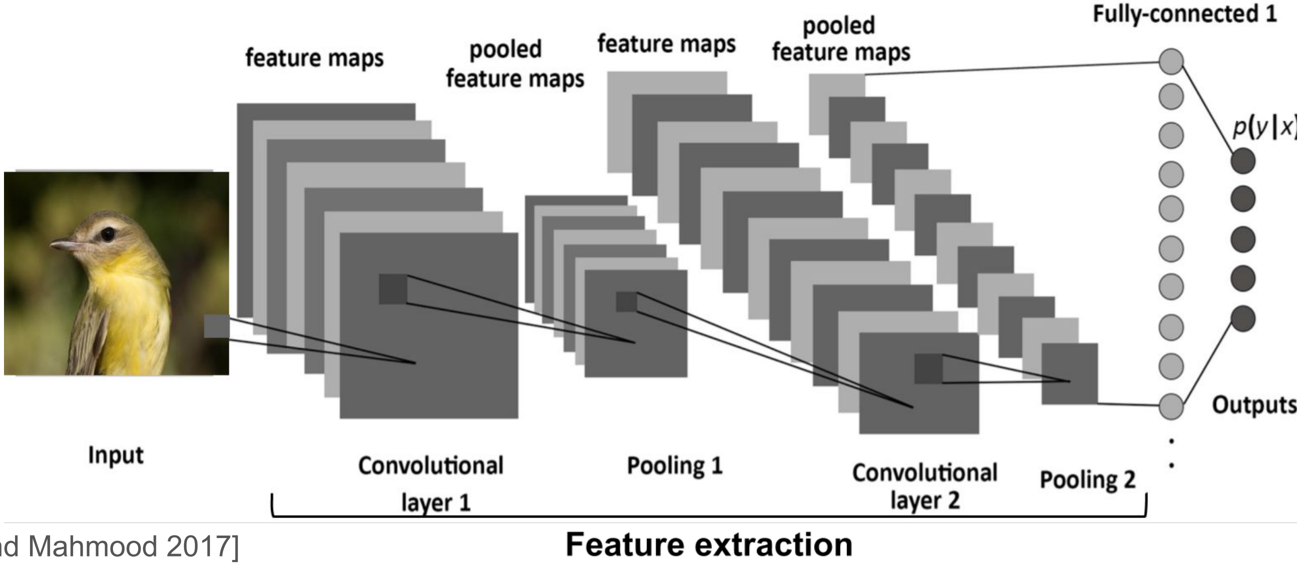
Problem Training a model from scratch only with small data is **challenging** and suffer from **overfitting**

Solution Use the knowledge of a pre-trained model on a border task to solve more specific one

- Bottle neck features
- Fine-tuning top layers

Transfer learning

Extract bottleneck features from a pre-trained network



[Albelwi and Mahmood 2017]

Transfer learning

Finetune top layers of pre-trained network

- Remove top dense layers
- Add your own classification layers on top
- Freeze bottom layers
- Fine-tune top layers on small data

Data augmentation

Increase the amount of training data using information only in our training data

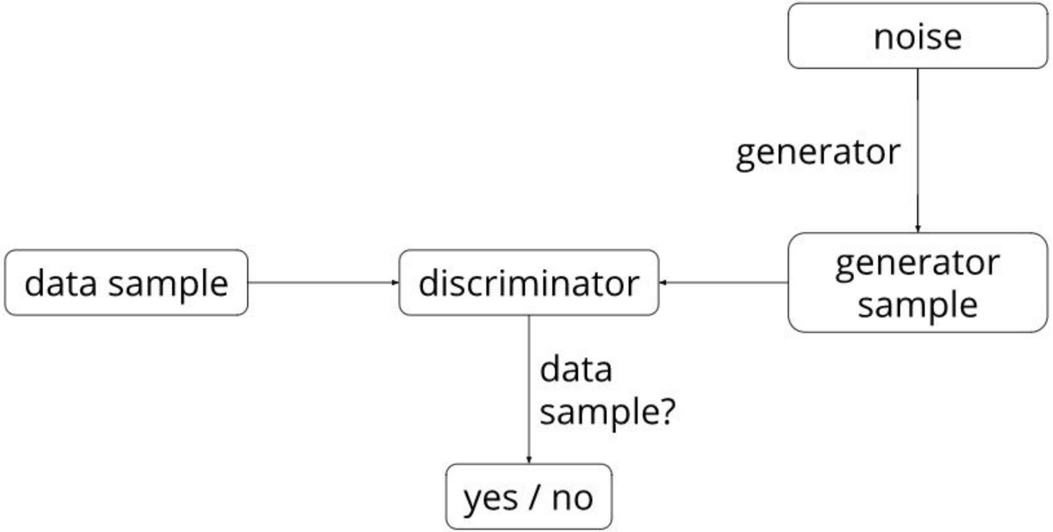
- Affine transformations
- Generative Adversarial Networks (**GANs**)

Affine transformations

https://kids.nationalgeographic.com/animals/meerkat/#meerkat-closeup-log.jpg

Generative Adversarial Networks (GANs)

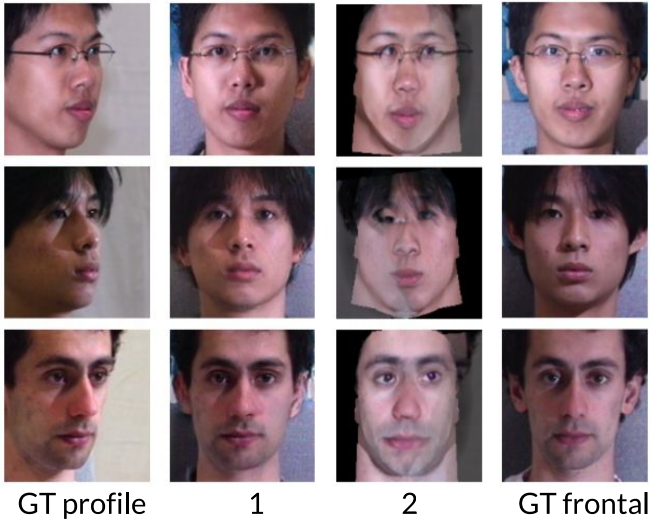
Lean data distribution



https://ishmaelbelghazi.github.io/ALI/

Generative Adversarial Networks (GANs)

Frontal face generator



[Huang, et al. ICCV2017][1] [Hassner, et al. CVPR2015][2]

Generative Adversarial Networks (GANs)

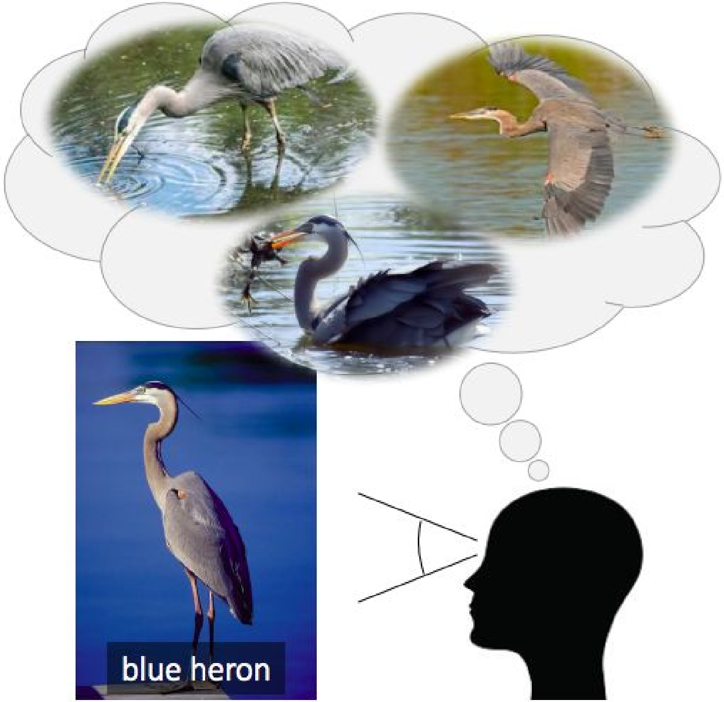
Image to image translation

[Zhu, et al. ICCV2017]
https://github.com/junyanz/CycleGAN

Low-shot learning + GANs

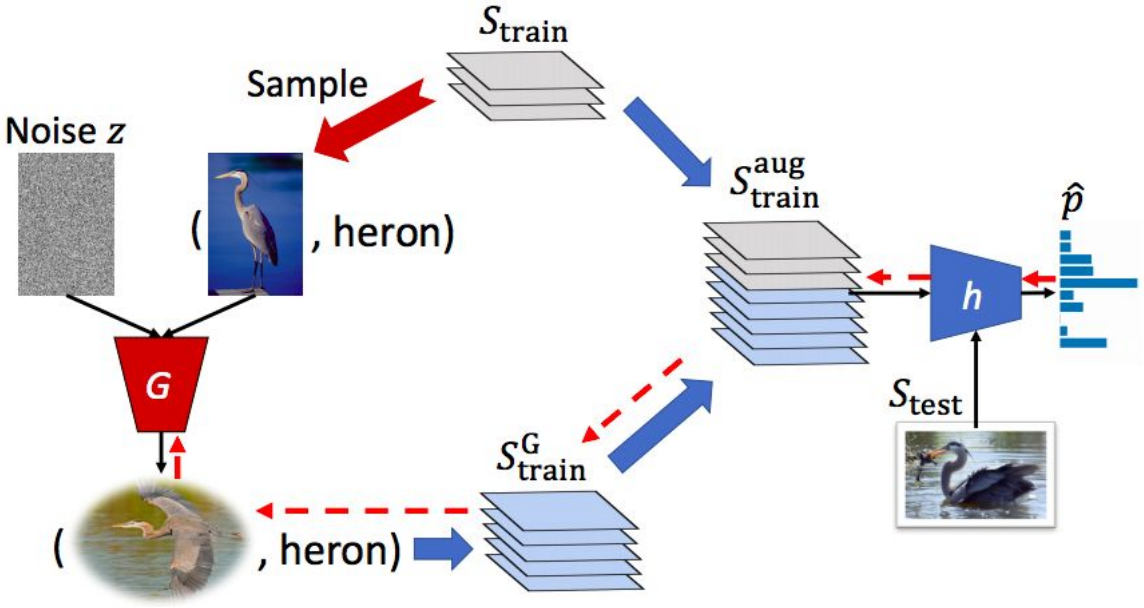
Low-Shot Learning from Imaginary Data

Meta-learning + Hallucination



[Wang, et al. arXiv2018]

Low-shot learning + GANs



[Wang, et al. arXiv2018]

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Image augmentation exercise

Image augmentation

- Clone git repo https://github.com/Noura-kr/DSR.git
- New notebook in DSR/notebooks/small_classifier/
- Read and plot meerkat.jpg
- Use keras keras.preprocessing.image.ImageDataGenerator to generate different images
- Plot results

Image classifier with small set exercise

Image classifier with small set

Train small network from scratch

- Clone git repo https://github.com/Noura-kr/DSR.git
- New notebook in DSR/notebooks/small_classifier/
- Define small conv net: 3 conv blocks (2Dconv,relu_activation,max_pooling) + 2 dense layers (don't forget flatten!)
- Compile network with binary_crossentropy loss and rmsprop
- Define image generator
- Train using generator
- Bonus: plot loss & accuracy

Image classifier with small set

Cheatsheet

Train image 2000
Validation images 800
Input size 150x150x3 (w,h,RGB)
Conv_1: filters 32, kernel size(3,3)
Conv_2: filters 32, kernel size(3,3)
Conv_3: filters 64, kernel size(3,3)
Dense_1: 64, relu
Dense_2: ? , sigmoid

Train small network from scratch

- Clone git repo https://github.com/Noura-kr/DSR.git
- New notebook in DSR/notebooks/small_classifier/
- Define small conv net: 3 conv blocks (2Dconv,relu_activation,max_pooling) + 2 dense layers (don't forget flatten!)
- Compile network with binary_crossentropy loss and rmsprop
- Define image generator
- Train using generator
- Bonus: plot loss & accuracy

Image classifier with small set

Extract features from pre-trained model

- from keras.applications import vgg16
- Define image generator
- Use model.predict_generator to get features
- Save features in .npy file

Image classifier with small set

Train small MLP on bottleneck features

- Define network with two dense layers (don’t forget activations and dropout)
- Compile with binary_crossentropy loss and rmsprop
- Train with bottleneck features
- Bonus: plot loss & accuracy

Image classifier with small set

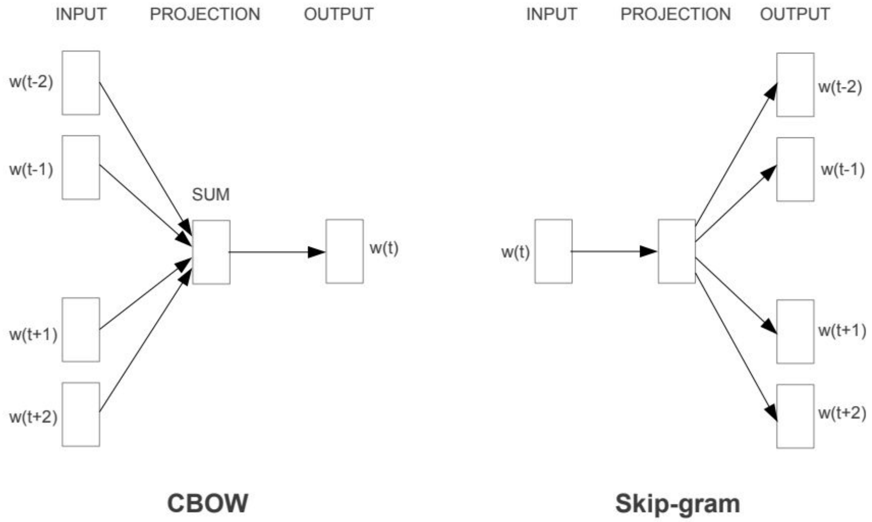
Fine-tune pre-trained network

- Load pre-trained model + weights, specify input size according to our images
- New model (vgg + mlp)
- Freeze first 15 layers of the new model
- Compile new model with binary_crossentropy loss and SGD with low learning rate (finetuning)
- Train with images

Word Embedding

Word embedding

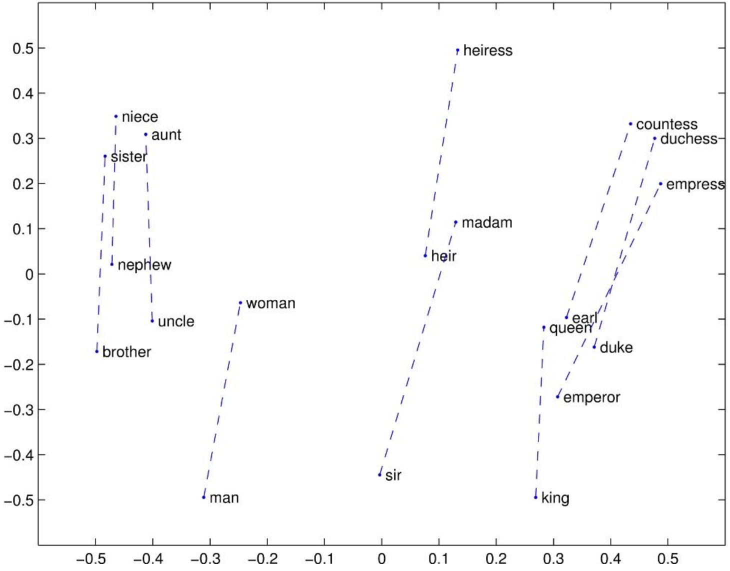
Dense representations: Word2vec



[Mikolov, et al. NIPS2013]

Word embedding

Dense representations: Global vectors for word representation (Glove)



[Pennington, et al. EMNLP2014]

Word embedding exercise

Thanks!