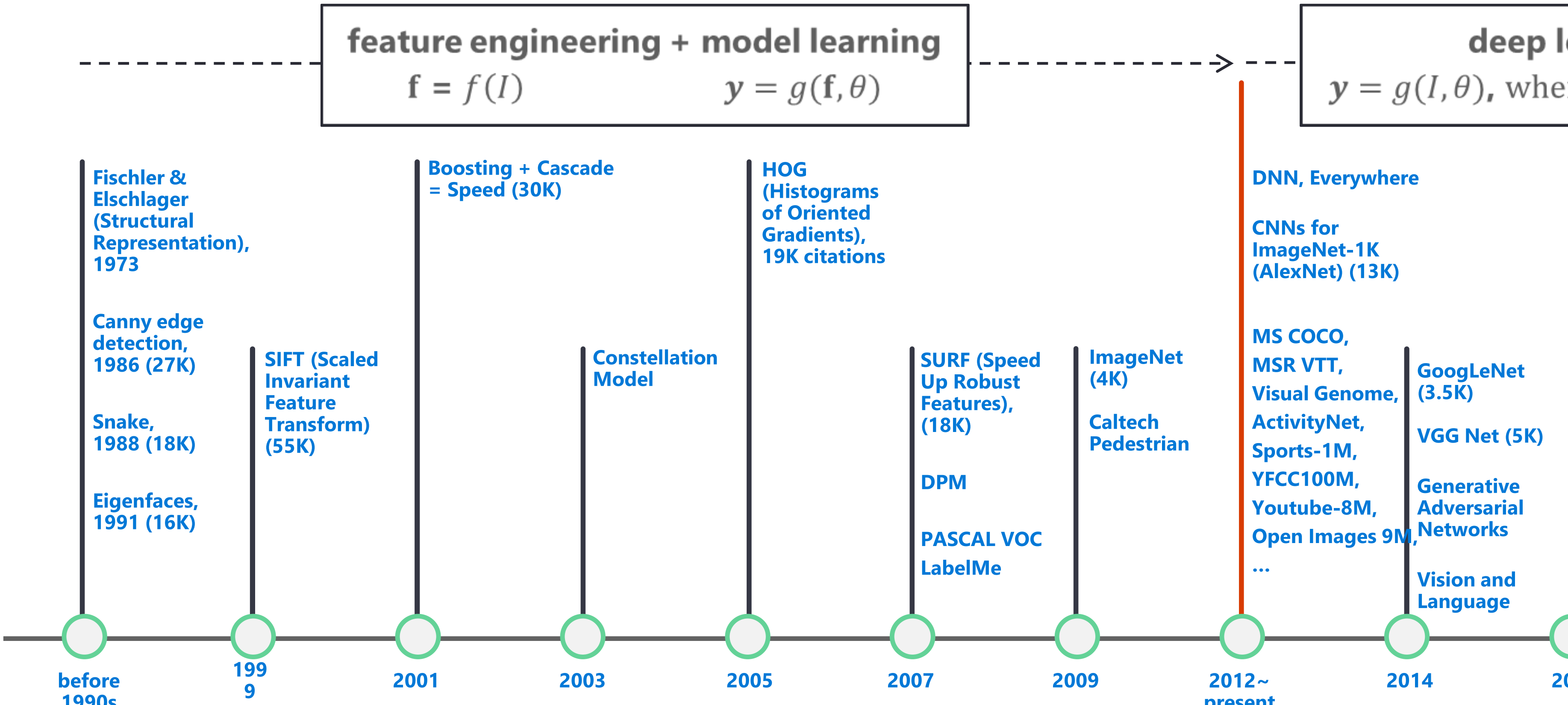
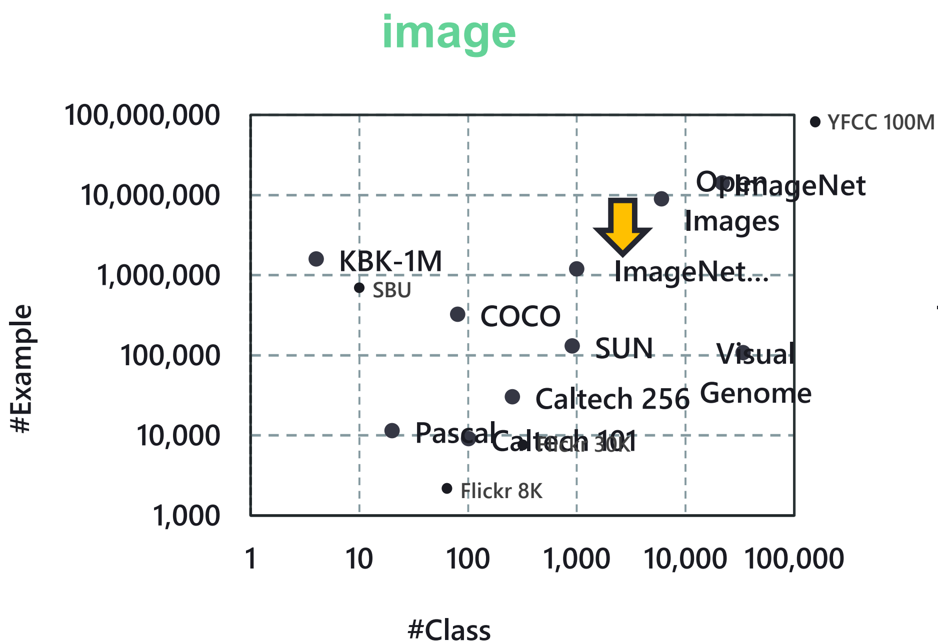
Advances in Few-shot Learning

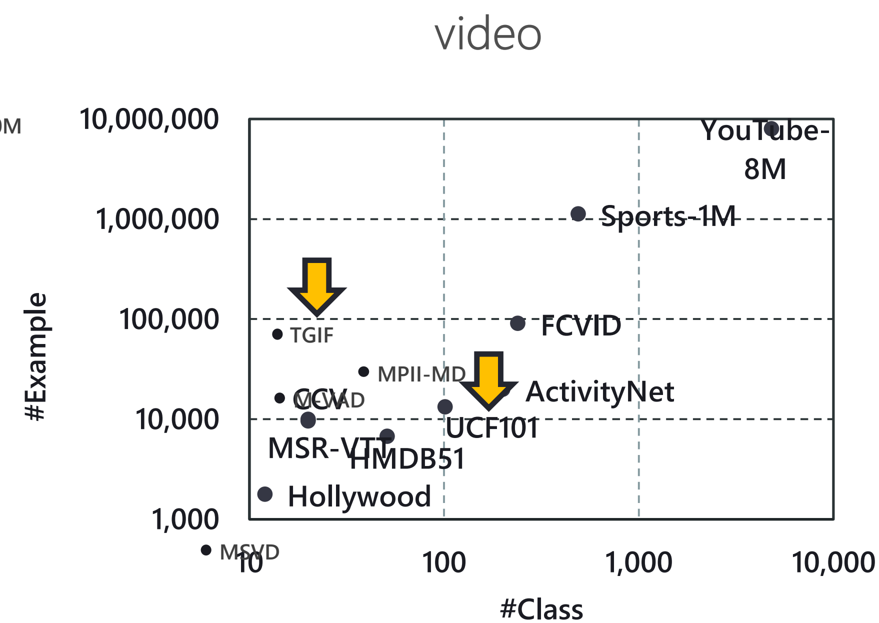
Jiebo Luo
University of Rochester

Computer vision: 50 years of progress



Computer vision: 50 years of progress





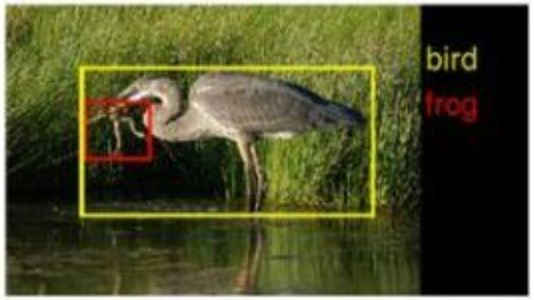
Note: The class information is unknown for Flickr 8K/30K, SBU, and MSVD, MPII-MD, M-VAD, TGIF.

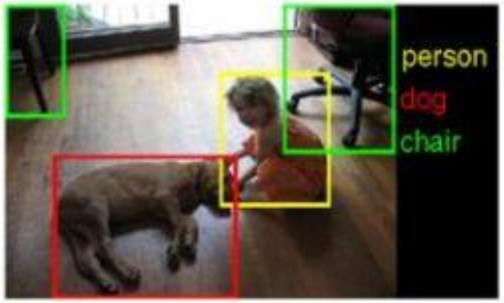
What Factors Propelled the Advances?

- Sensor technologies and numbers
- Big data
- Computing power
- Human power!

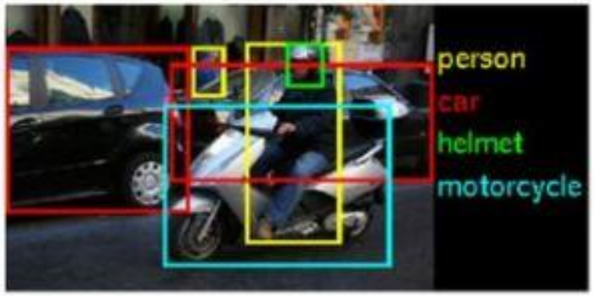
The Amount of Human Labor in AI

- Data labeling has become an industry!





DATATANG



The Spectrum of Machine Learning

Cost: delay, dollars, manpower

Low cost → High cost

Unsupervised Learning

Learning From Noisy Labels

e.g., Facebook
1 billion images with hashtags

Semi Supervised Learning

Supervised Learning

Few Shot Learning ?

Outline

- **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusions**

Introduction

- **Origin…**

[1] Miller, Matsakis, and Viola, "Learning from *One Example* through Shared Densities on Transforms," *CVPR* 2000.

[2] Fei-Fei, Fergus and Perona, "A Bayesian approach to unsupervised *one-shot learning* of object categories," *ICCV* 2003.

Introduction

- ## Definition

One-shot learning is an object categorization problem in computer vision. Whereas most machine learning based object categorization algorithms require training on hundreds or thousands of images and very large datasets, one-shot learning aims to learn information about object categories from one, or only a few, training images.

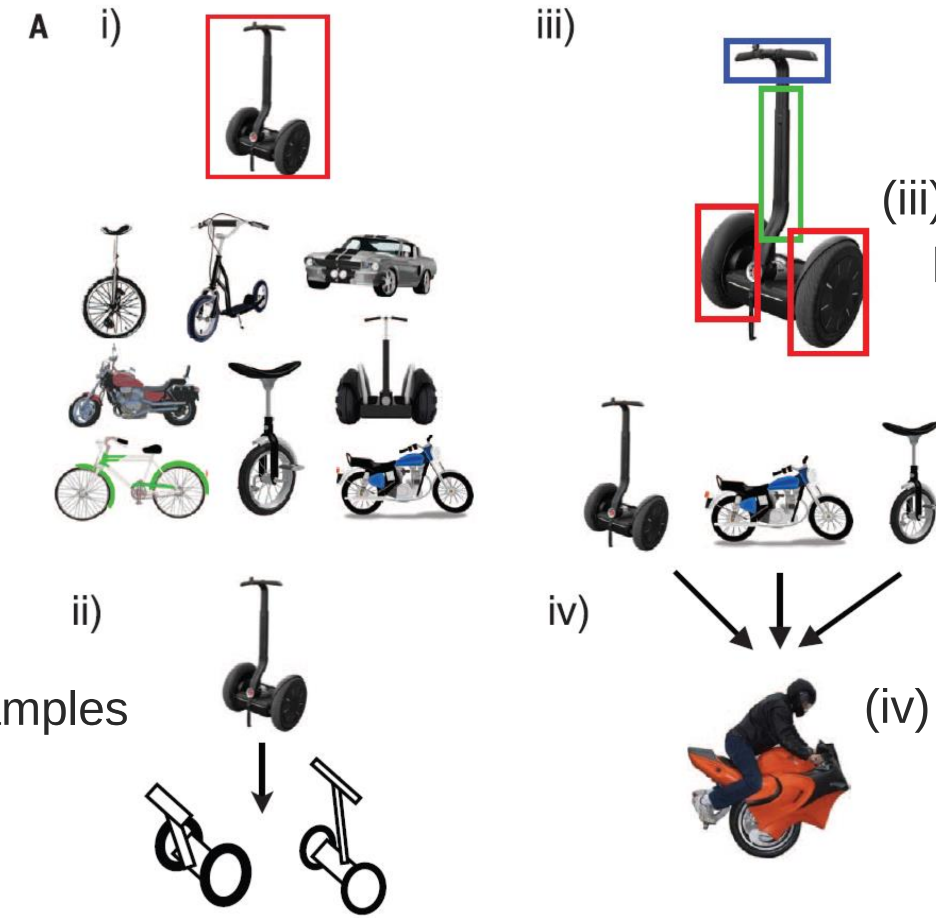
(https://www.wikipedia.org/)

Introduction

- **Humans versus Algorithms**

(i) Generalization to new examples

(ii) Create new examples



(iii) Parsing objects into parts and relations

(iv) Create new concepts

(M. Lake et al. *Science* 2015)

Introduction

- **Goals of Algorithms**

Good generalization ability to new examples

Good transfer ability from different concepts

High classification accuracy with limited data

Introduction

- ## Terminologies

Three kinds of datasets:

- A **support** set (few-shot training set)
- A **query** set (test set)
- An **auxiliary** set (additional set)

  It has its own label space that is disjoint with the support/query set.

If the support set contains ***K*** labeled samples for each of ***C*** categories, the target few-shot task is called as a ***C***-way ***K***-shot task.

Outline

- ✓ **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

Few-shot Methods

- **Hallucination based methods (*learn to augment*)**

Key Idea: Learn rules to augment data.

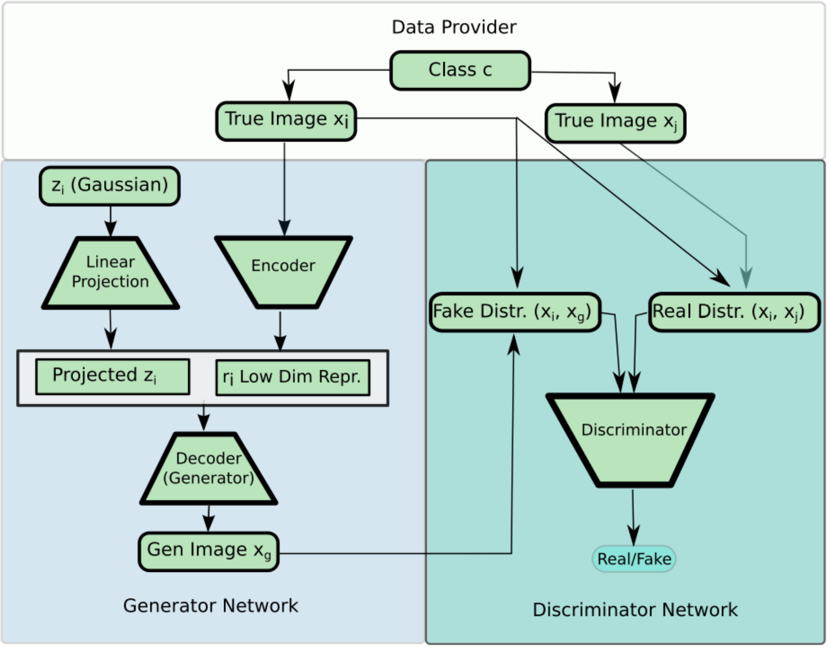
Humans are good at imagination

(Wang et al. *CVPR* 2018)

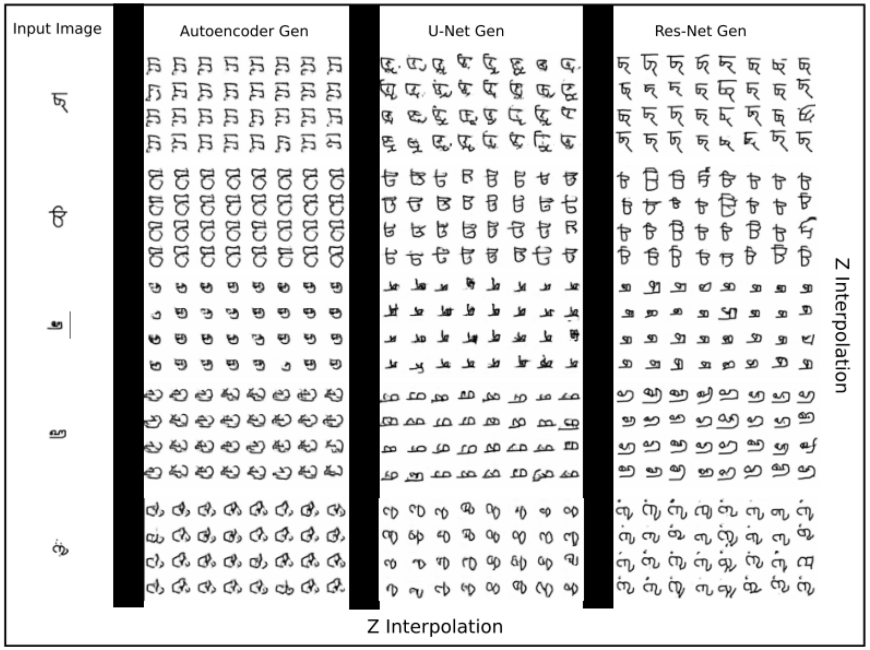
Hallucination based Methods

- **Data Augmentation GAN** [*arXiv'17*]

Design and train a generative model to perform data augmentation



GAN framework



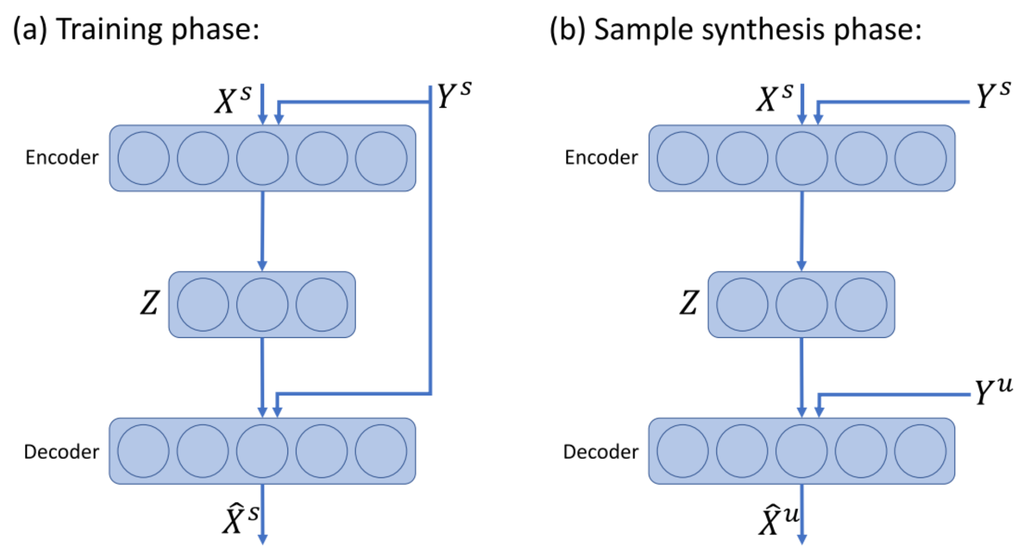
Generated examples

(Antoniou et al. *arXiv* 2017)

Hallucination based Methods

- **Δ-encoder: Effective Sample Synthesis** [*NIPS'18*]

Use an encoder to learn *transferable deformations* between pairs of examples and apply these deformations to other unseen examples



$\hat{X}^S$ is the reconstruction of X^S

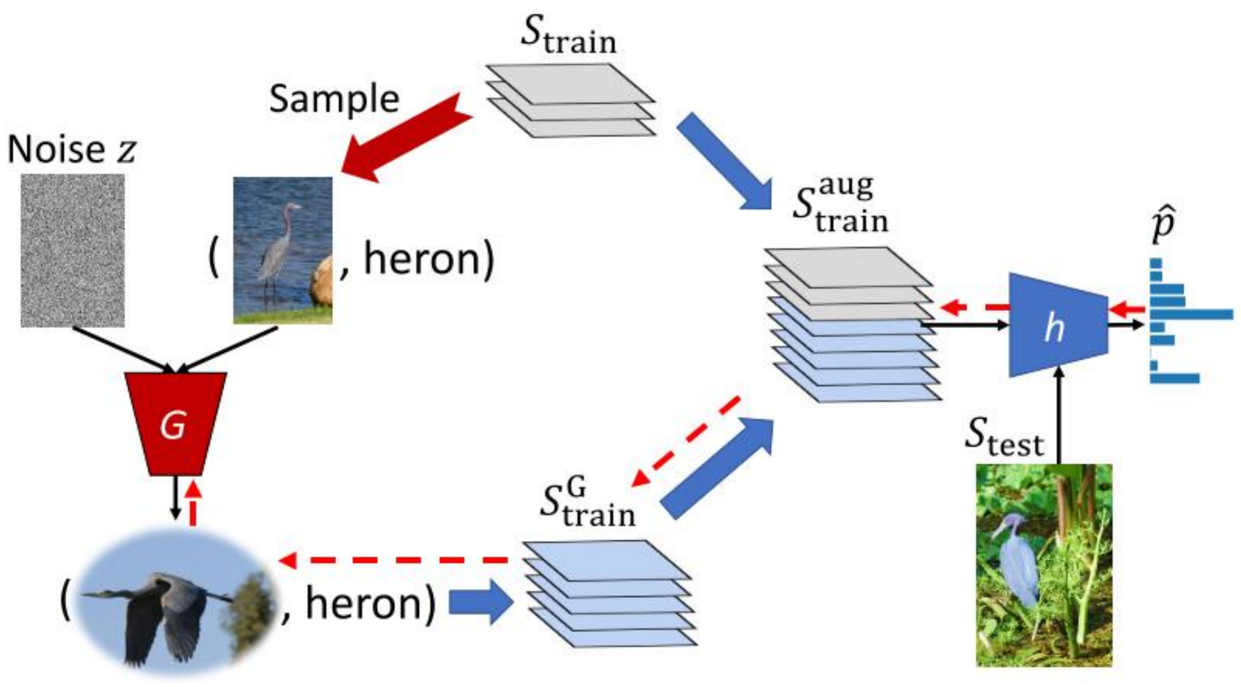
$\hat{X}^u$ is the synthesized sample conditioned by Y^u

(Schwartz et al. *NIPS* 2018)

Hallucination based Methods

- **Meta-Learning with Learned Hallucination** [*CVPR'18*]

Train a hallucinator G along with the classifier h ***end-to-end***



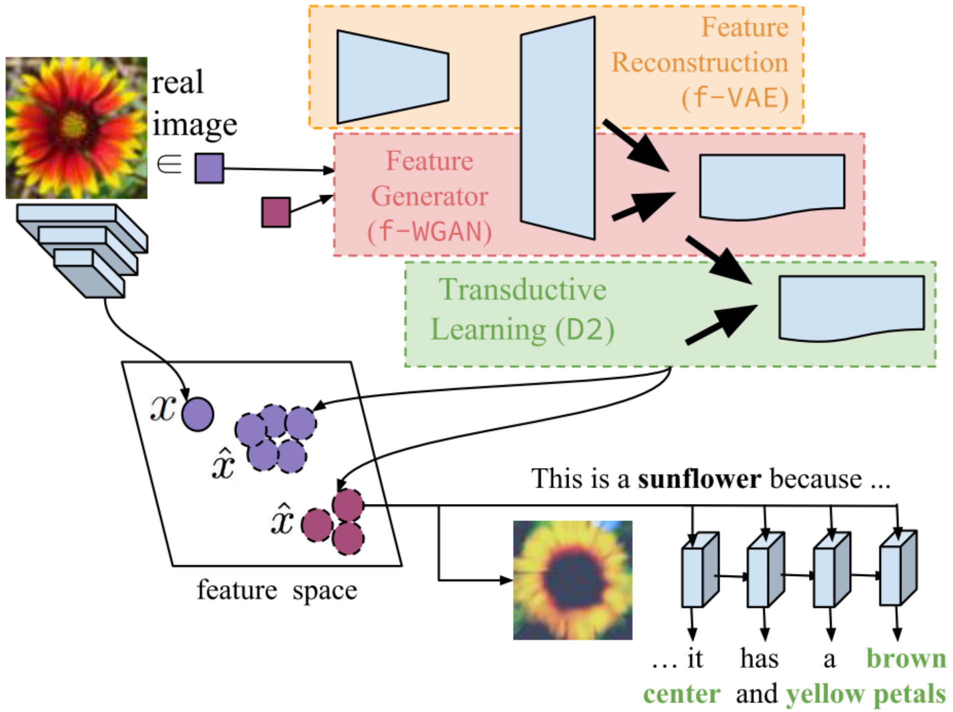
An end-to-end framework

(Wang et al. *CVPR* 2018)

Hallucination based Methods

- **A Unified Feature Generating Framework** [*CVPR'19*]

Develop a generative model by combining the strength of VAE and GANs



Data augmentation in the ***feature space***

(Xian et al. *CVPR* 2019)

Hallucination based Methods

Many Algorithms…

- Shrink and hallucinate features [Hariharan et al. ICCV 2017]
- Feature space transfer for variations in pose [Liu et al. CVPR 2018]
- Multi-level semantic feature augmentation [Chen et al. TIP 2019]
- Task-Adaptive Projection of features [Yoon et al. ICML 2019]
- ……

Summary

- Image-level augmentation to *feature-level* augmentation
- Task-independent augmentation to *Task-dependent* augmentation
- Two-stage augmentation to *end-to-end* augmentation
- ……

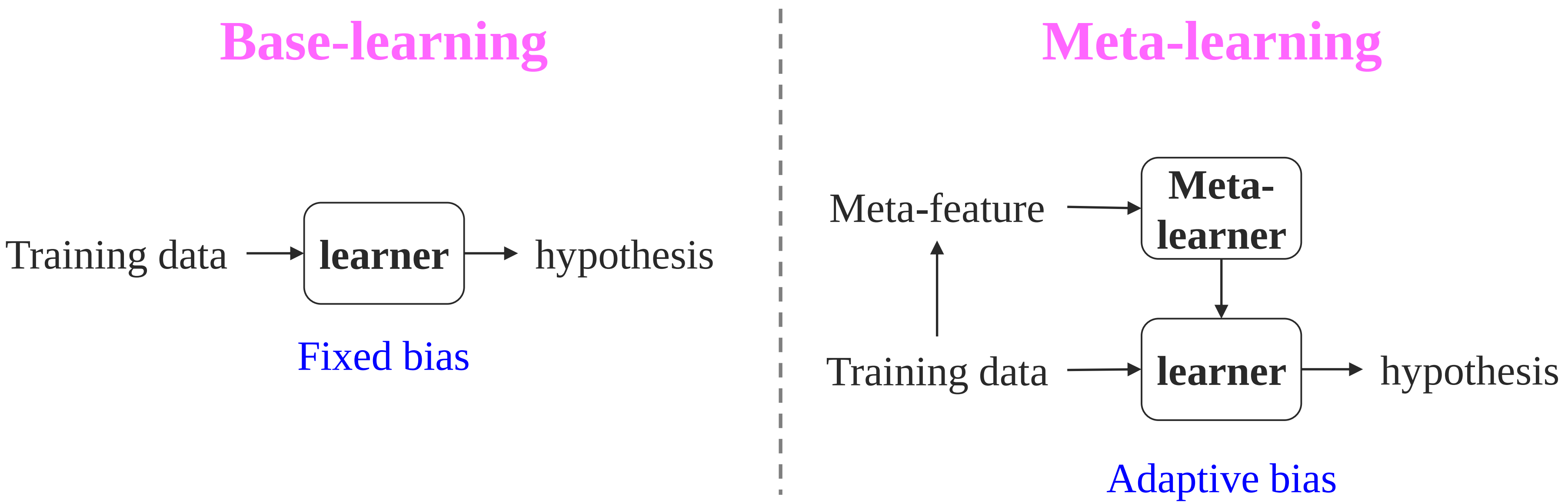
Outline

- **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

Few-shot Methods

- **Meta-learning based methods (*learn to learn*)**

Definition: what is meta-learning?



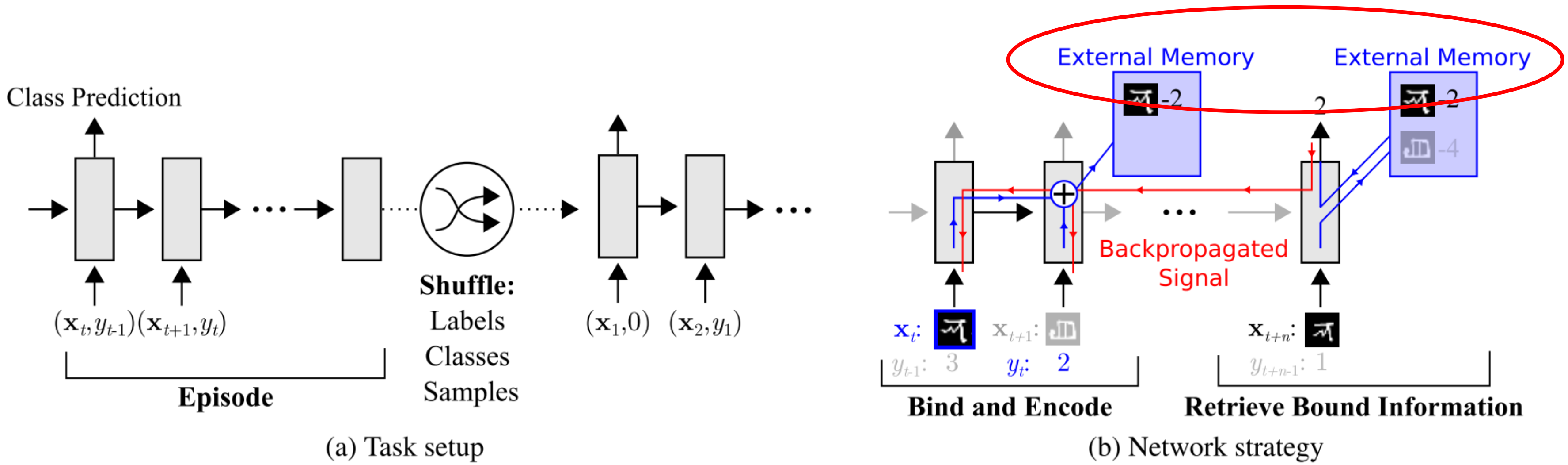
Key Idea: Use a meta-learner to learn a task-adaptive learner.

(Vilalta et al. *AI Review* **2002**)

Meta-learning based Methods

- **MANN: Memory-augmented Neural Network** [*ICML'16*]

  Use a controller (e.g., *LSTM*) to interact with an *external memory module* that stores sample representation-class label information.



(Santoro et al. *ICML* 2016)

Meta-learning based Methods

- **MAML: Model-Agnostic Meta-Learning** [*ICML'17*]

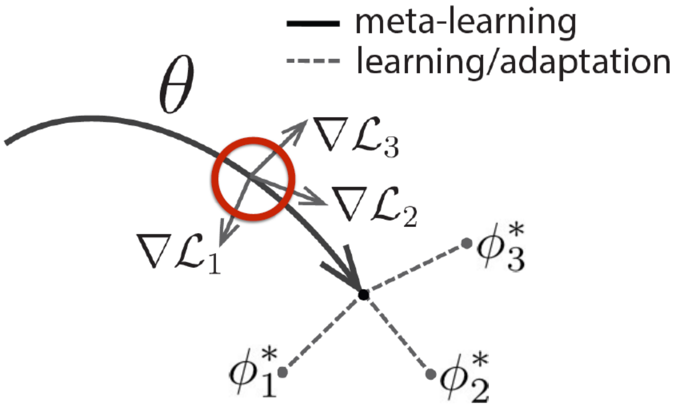
Train a model with a small number of gradient updates, leading to fast learning on a new task. (*involve a gradient through a gradient*)

$$\min_{\theta} \sum_{\text{task } i} \mathcal{L}(\theta - \alpha \nabla_{\theta} \mathcal{L}(\theta, \boxed{\mathcal{D}_i^{\text{tr}}}), \boxed{\mathcal{D}_i^{\text{ts}}})$$

training and test data for task i

θ parameter vector being *meta-learned*

ϕ_i^* optimal parameter vector for task i



(Finn et al. *ICML* 2017)
(Meta-learning tutorial ICML'19)

Meta-learning based Methods

- **MAML: Model-Agnostic Meta-Learning** [*ICML'17*]

$$\min_{\theta} \sum_{\text{task } i} \mathcal{L}(\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \boxed{\mathcal{D}_i^{\text{tr}}}), \boxed{\mathcal{D}_i^{\text{ts}}})$$

training and test data for task *i*

General Algorithm:

~~Amortized approach~~ Optimization-based approach

1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$
3. ~~Compute $\phi_i \leftarrow f_\theta(\mathcal{D}_i^{\text{tr}})$~~ Optimize $\phi_i \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})$

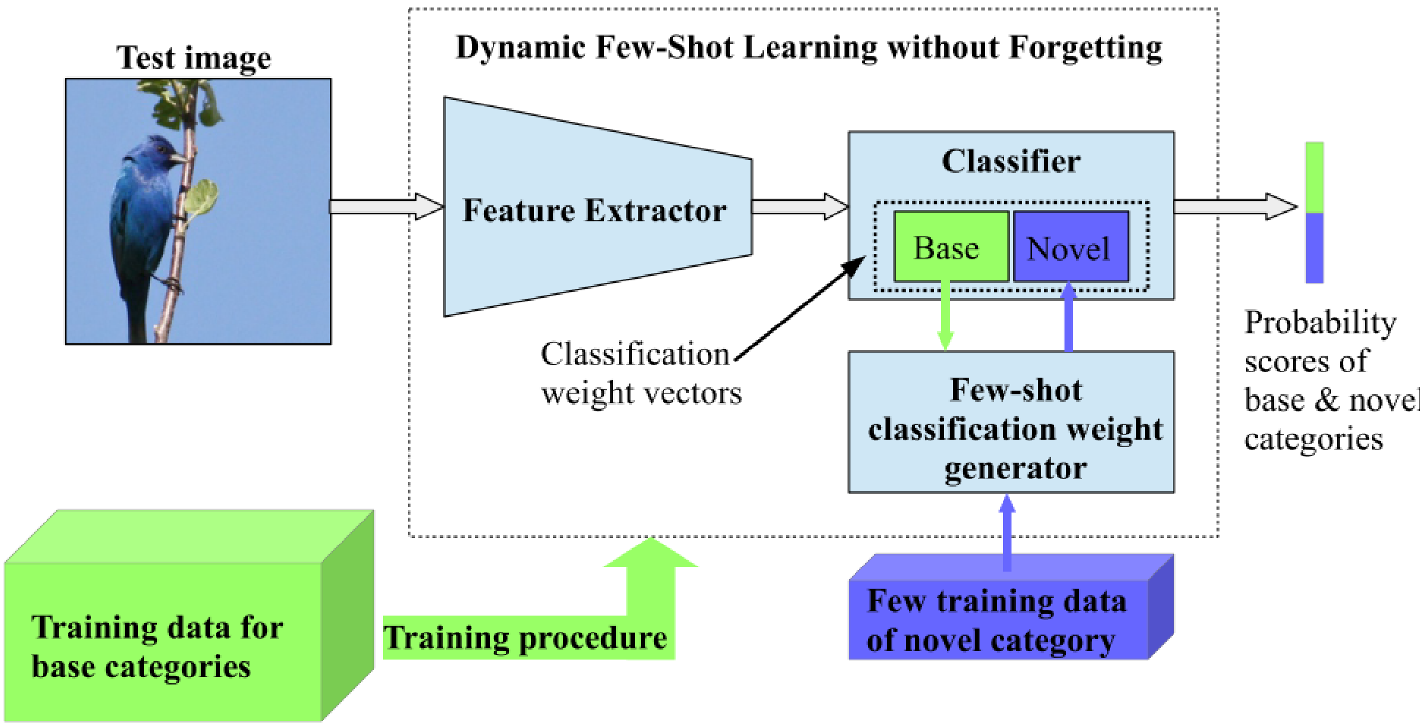
—> brings up **second-order** derivatives (more on this later)

(Finn et al. *ICML* 2017)
(Meta-learning tutorial ICML'19)

Meta-learning based Methods

Dynamic Few-shot Learning [CVPR'18]

- Recognize both base and novel categories
- Design an *attention-based weight generator* for novel categories

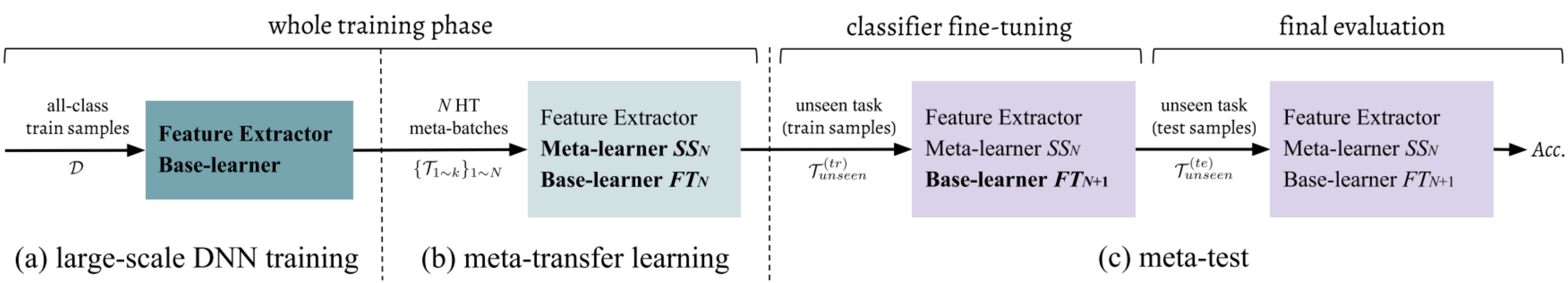


(Gidaris et al. *CVPR* 2018)

Meta-learning based Methods

MTL: Meta-transfer Learning *[CVPR'19]*

- *Pre-train* on a large-scale dataset to obtain a fixed feature extractor
- Fine tune the *base-learner* using the meta-train samples
- Learn *Scaling and Shifting (SS)* parameters (*meta-learner*) for novel tasks
- Perform hard task mining



(Sun et al. *CVPR* 2019)

Meta-learning based Methods

Many Algorithms…

- Task-Agnostic Meta-Learning [Jamal et al. CVPR 2019]
- Task-Aware Feature Embeddings [Wang et al. CVPR 2019]
- Use linear classifiers (SVM) as the base learner [Lee et al. CVPR 2019]
- Generate functional weights of the base learner [Li et al. ICML 2019]
- Amortized Bayesian meta-learning [Ravi et al. ICLR 2019]
- ……

Summary

- How to design the meta-learner (black-box or optimization-based)?
- How to affect or learn the base-learner using the meta-learner?
- The pre-training and initialization of the base-learner are important
- ……

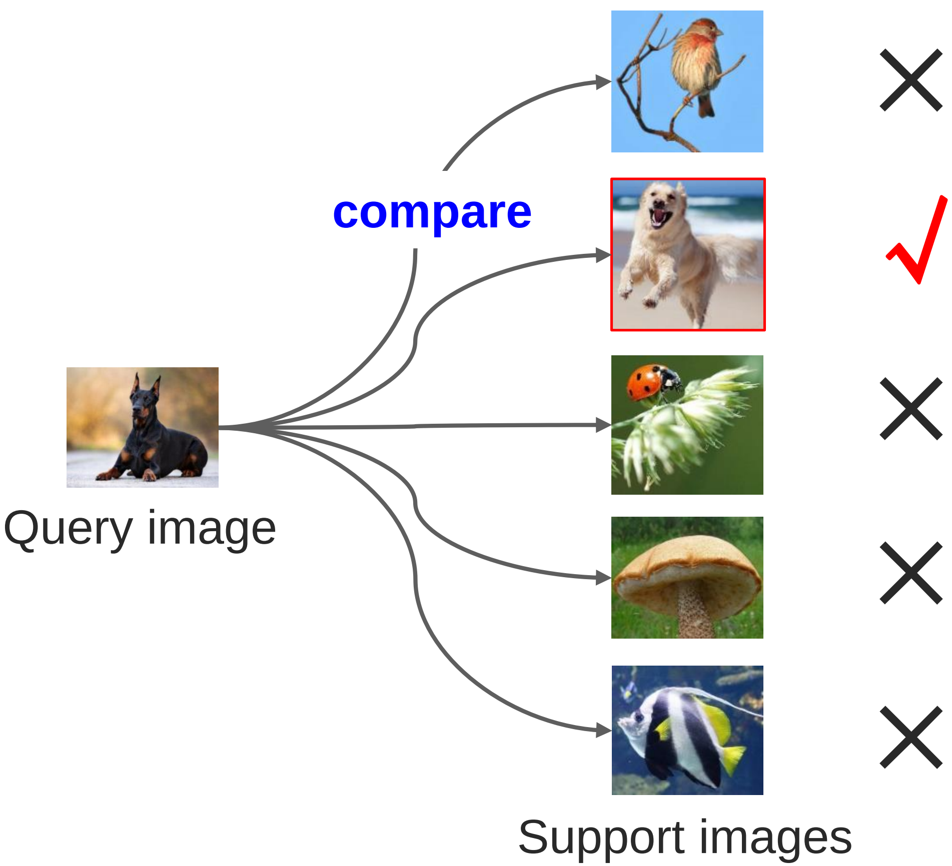
Outline

- **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

Few-shot Methods

- **Metric-learning based methods (*learn to compare*)**

Key Idea: Learn transferable representations

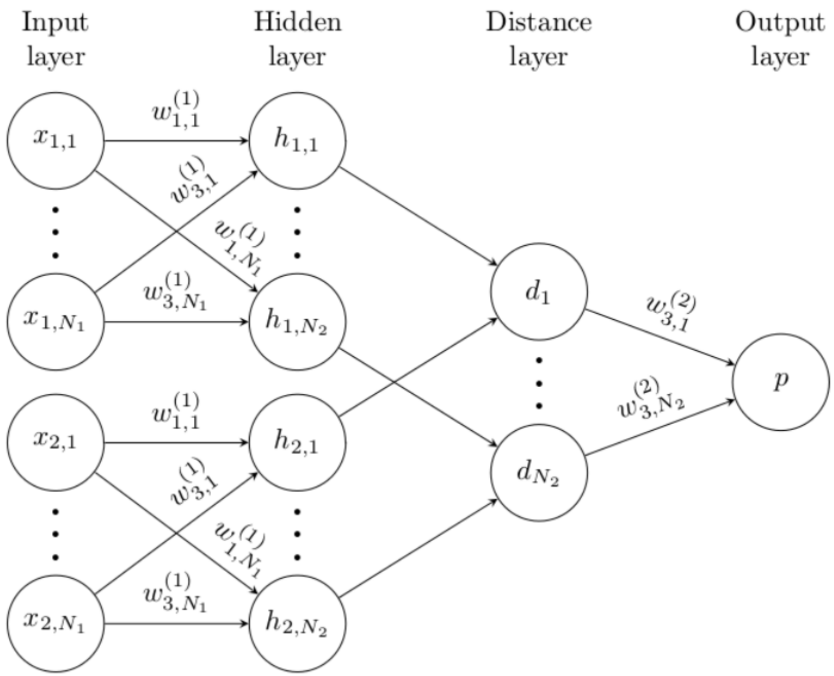


Learn to compare query images with support images

Metric-learning based Methods

Siamese Neural Networks [*ICML'15*]

- Learn a Siamese network by metric-learning losses from a source data
- Reuse the network's features for the target one-shot learning task



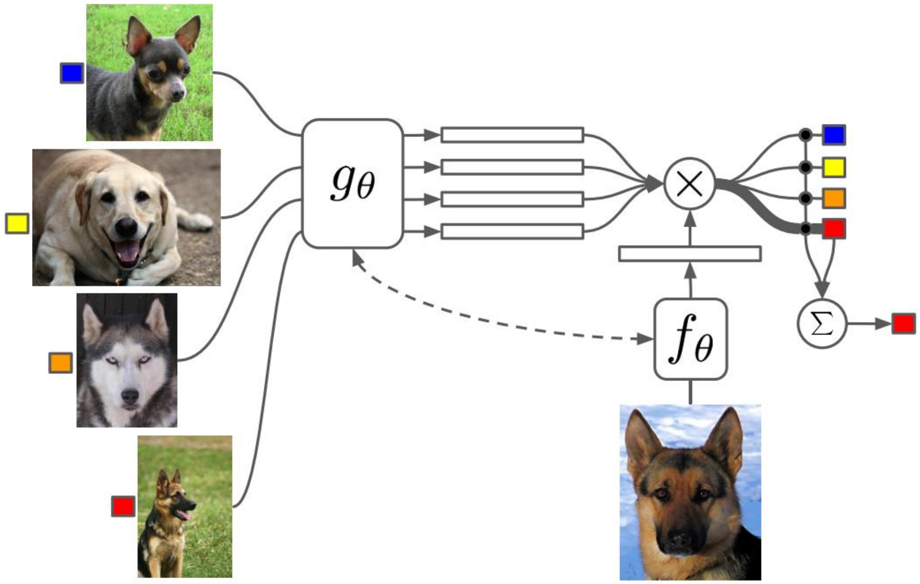
Mismatch
0

(Koch et al. *ICML* 2015)

Metric-learning based Methods

Matching Networks [*NIPS'16*]

- Directly compare the unlabeled query image with the support images
- Propose the popular ***episodic training mechanism***



$$P(\hat{y}|\hat{x}, S) = \sum_{i=1}^{k} a(\hat{x}, x_i) y_i$$

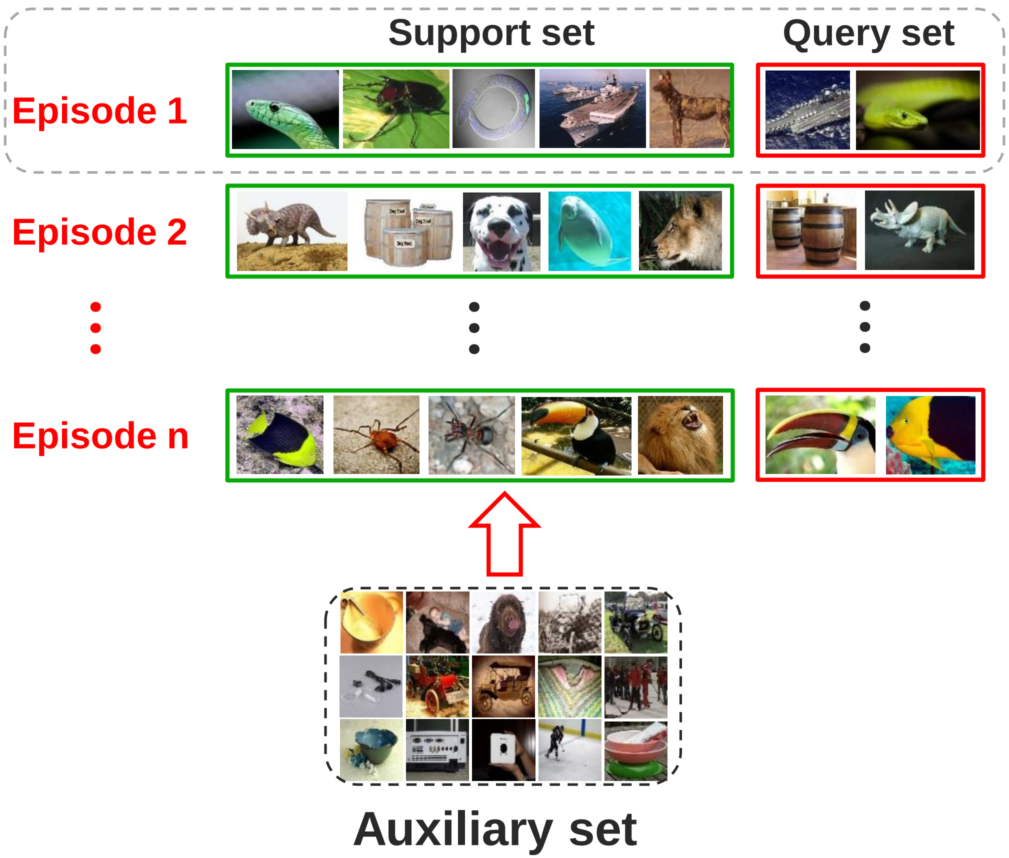
- **Query image**: $(\hat{x}, \hat{y})$
- **Support set**: $S = \{(x_i, y_i)\}_{i=1}^{k}$
- $a(\cdot,\cdot)$: LSTM based attention

(Vinyals et al. *NIPS* 2016)

Metric-learning based Methods

- **What is the episodic training?**

Principle: test and train conditions must match!
(Specifically, using the training data to mimic the target few-shot task)

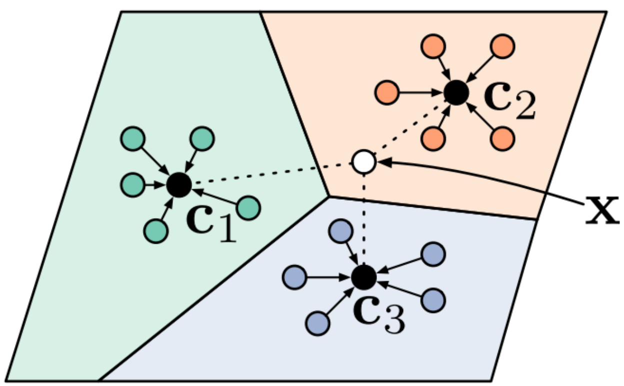


(Vinyals et al. *NIPS* 2016)

Metric-learning based Methods

Prototypical Networks [*NIPS'17*]

- Take the mean vector as a prototype for each support class
- Find the nearest prototype for each query image
- Adopt the squared Euclidean distance



(a) Few-shot

$$p_{\phi}(y = k \mid \mathbf{x}) = \frac{\exp(-d(f_{\phi}(\mathbf{x}), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_{\phi}(\mathbf{x}), \mathbf{c}_{k'}))}$$

- **Query image**: (x, y)
- **Support prototypes**: $\boldsymbol{c}_k|_{k=1}^{3}$
- $\mathbf{d}(\cdot,\cdot)$: squared Euclidean distance

(Snell et al. *NIPS* 2017)

Metric-learning based Methods

Relation Network [*CVPR'18*]

- Concatenate the feature maps between query image and each class
- Use a mean vector to represent each class
- Use a deep neural network to *learn* a deep distance metric instead of a fixed metric function

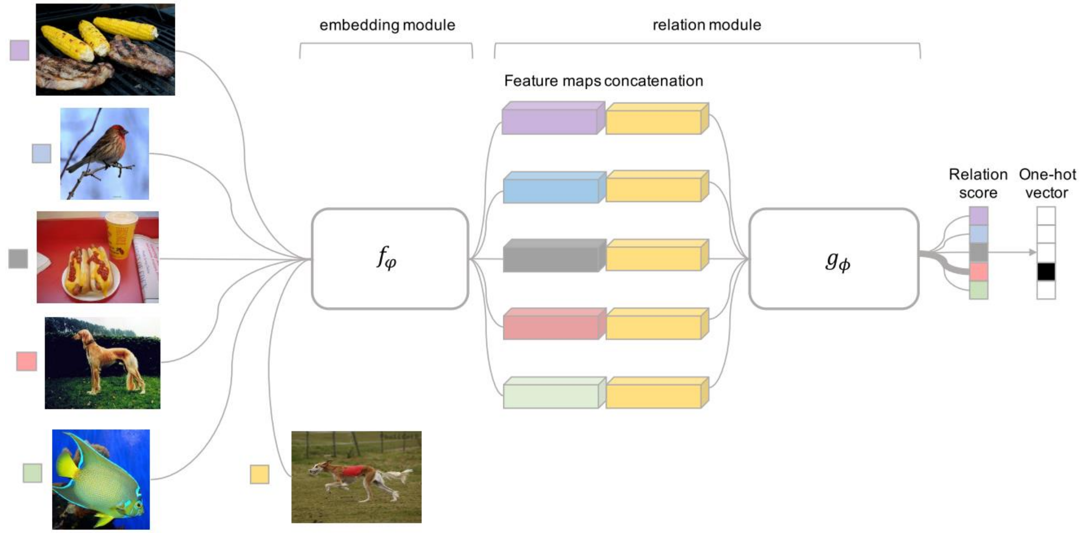


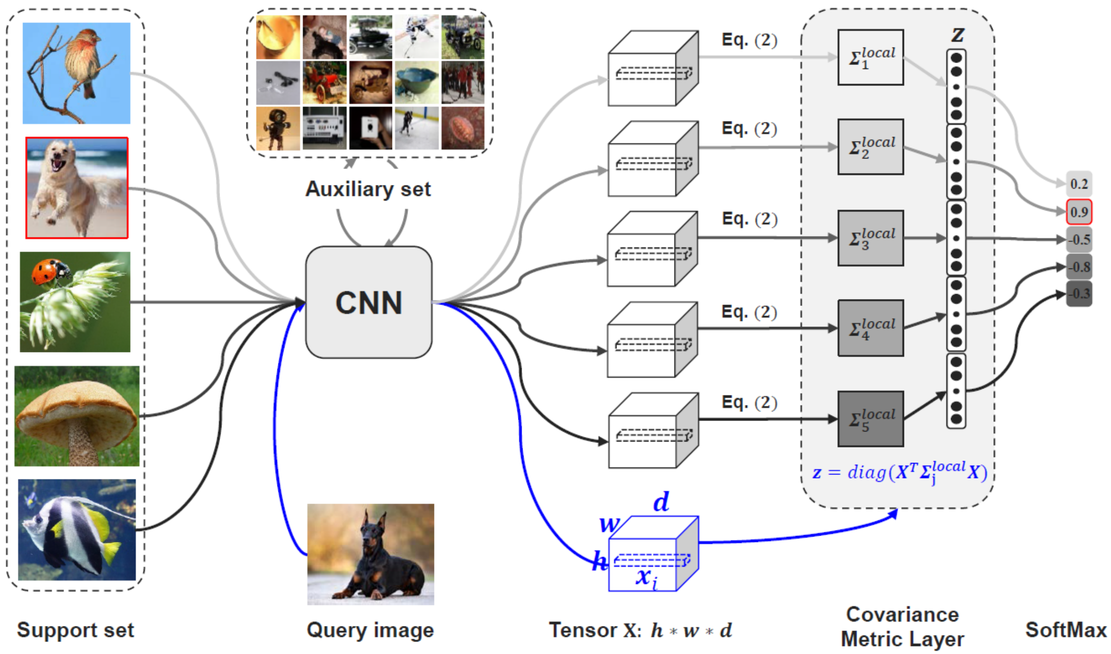
Figure 1: Relation Network architecture for a 5-way 1-shot problem with one query example.

(Sung et al. *CVPR* 2018)

Metric-learning based Methods

Covariance Metric Network *[AAAI'19*]*

- Use richer *local descriptors* to represent each image
- Propose a novel *local covariance representation* for each class
- Define a new *covariance metric function*



(Li et al. *AAAI* 2019)

Covariance Metric Network

Local Covariance Representation

Given an image set of the c-th class $\boldsymbol{D}_c = \{\boldsymbol{X}_1, \dots, \boldsymbol{X}_K\}, \boldsymbol{X}_i|_{i=1}^{K} \in R^{d*M}$ (d is the local descriptor dimensionality), which contains *K* images with *M* local deep local descriptors per image, the local covariance metric can be defined as follows,

$$\boldsymbol{\Sigma}_c^{local} = \frac{1}{MK-1}\sum_{i=1}^{K}(\boldsymbol{X}_i - \boldsymbol{\tau})(\boldsymbol{X}_i - \boldsymbol{\tau})^\top$$

For example:
For a 5-way 5-shot task, there are $M = 400$ deep local descriptors for each image $\boldsymbol{X}_i$. It means that we have $MK = 400 * 5$ samples for one class in total. Then we use all these 2000 samples to calculate a covariance matrix as the representation.

(Li et al. *AAAI* 2019)

Covariance Metric Network

Local Covariance Representation

Advantages:

- **Using local descriptors**
  - Data augmentation (***vs.*** Few-shot)
  - Capture the local details (***vs.*** Global feature)
- **Using covariance matrix**
  - Capture the second-order information (***vs.*** First-order)
  - Describe the underlying concept distribution (***vs.*** No-distribution)

(Li et al. *AAAI* 2019)

Covariance Metric Network

- **Covariance Metric Function**

Measure the ***distribution consistency*** between a sample and a class:

$$d(\boldsymbol{x}, \boldsymbol{\Sigma}) = \boldsymbol{x}^\top \boxed{\boldsymbol{\Sigma}} \boldsymbol{x}$$

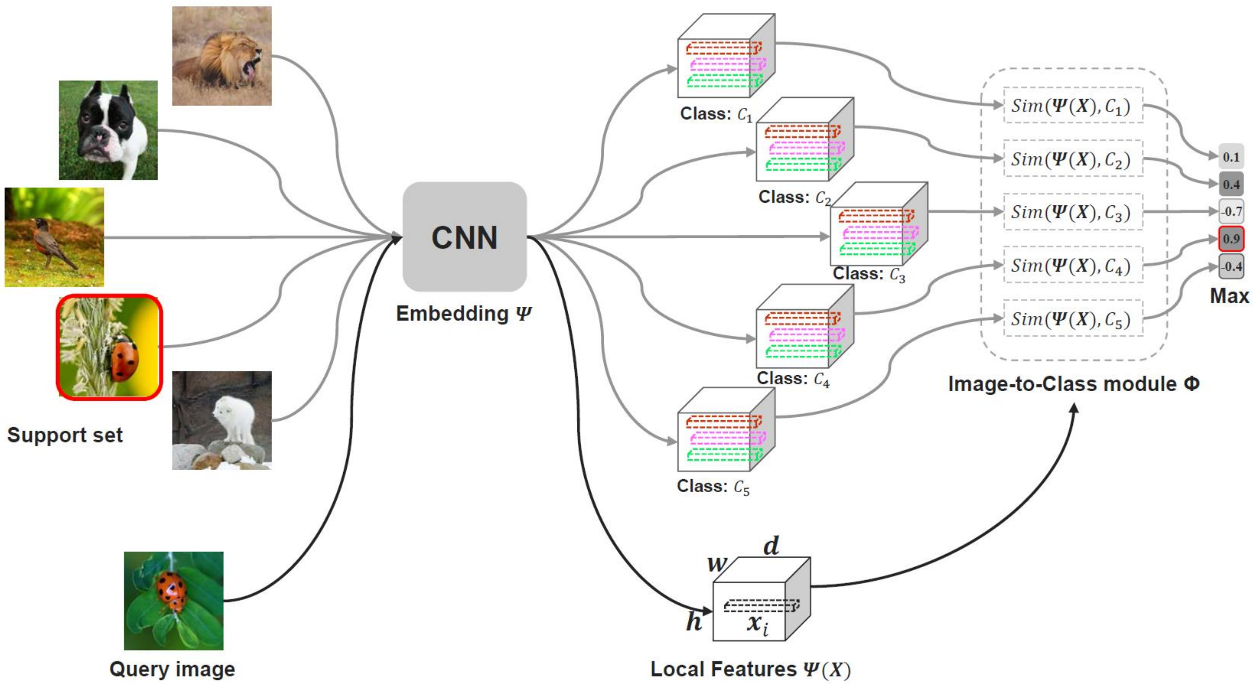
Describes the underlying distribution of one concept (class)

(Li et al. *AAAI* 2019)

Metric-learning based Methods

Deep Nearest Neighbor Neural Network *[CVPR'19*]*

- Use *rich* and *non-summarized local descriptors* for each image
- Use *a mixed local descriptors pool* for each class
- Use *an image-to-class* measure via a k-NN search



(Li et al. *CVPR* 2019)

Deep Nearest Neighbor Net

Reference Work

In Defense of Nearest-Neighbor Based Image Classification (*CVPR'08*)

It gives us two insights:

- Descriptor quantization (e.g., bags-of-words) will give rise to a significant degradation in the discriminative power of descriptors;
- Image-to-Class measure is better than Image-to-Image measure.

Deep Nearest Neighbor Net

Motivation

Conventional Methods:

- Use **image-level pooled feature** to represent each image
- Use an **Image-to-Image measure** function

(*lose considerable discriminative information*)

The Proposed Method:

- Use raw, rich **local descriptors** to represent each image
- Use an **Image-to-Class measure** function

(*enjoy an exchangeability of visual patterns across images in the same class*)

Deep Nearest Neighbor Net

Image-to-Class Measure

Given a query image q and a support class c, the image-to-class similarity between q and c can be formulated as

$$\Phi\big(\Psi(q), c\big) = \sum_{i=1}^{m} \sum_{j=1}^{k} \cos(\boldsymbol{x}_i, \hat{\boldsymbol{x}}_i^j)$$

$$\cos(\boldsymbol{x}_i, \hat{\boldsymbol{x}}_i) = \frac{\boldsymbol{x}_i^\top \hat{\boldsymbol{x}}_i}{\|\boldsymbol{x}_i\| \cdot \|\hat{\boldsymbol{x}}_i\|},$$

Where q is embedded as m local descriptors $\Psi(q) = [\boldsymbol{x}_1, \ldots, \boldsymbol{x}_m] \in \mathbb{R}^{d \times m}$, and for each descriptor $\boldsymbol{x}_i$, we find its *k*-nearest neighbors $\hat{\boldsymbol{x}}_i^j|_{j=1}^k$.

Metric-learning based Methods

Many Algorithms…

- Infinite mixture prototypes for each class [Allen et al. ICML 2019]
- Localize objects using bounding box [Wertheimer et al. CVPR 2019]
- Use Graph Neural Network [Garcia et al. CVPR'18, Kim et al. CVPR'19]
- Dense Classification and Implanting [Lifchitz et al. CVPR 2019]
- ……

Summary

- Global feature to local descriptors
- First-order information to second-order information
- The design of the metric function is important
- The relation between support classes is important
- ……

Comparison

Hallucination-based

- Can be combined with other kinds of methods
- Can perform any-shot tasks

- Hard to approximate the data distribution
- Challenging optimization

Meta-based

- Good at out-of-distribution tasks
- Can handle varying & large shots well

- Model & architecture intertwined
- Challenging optimization

Metric-based

- Simple
- Entirely feedforward
- Computationally fast & easy to optimize

- Harder to generalize to varying shots
- Hard to scale to very large shots

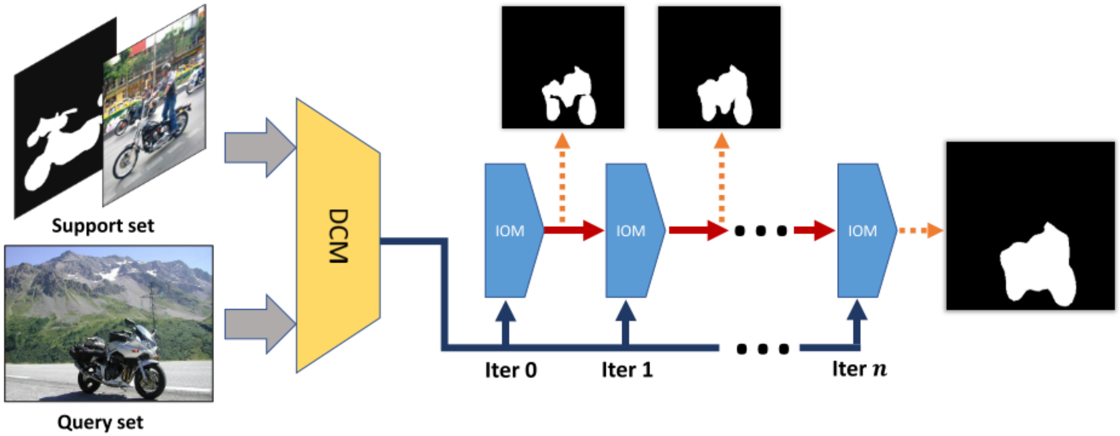
(Meta-learning tutorial ICML'19)

Outline

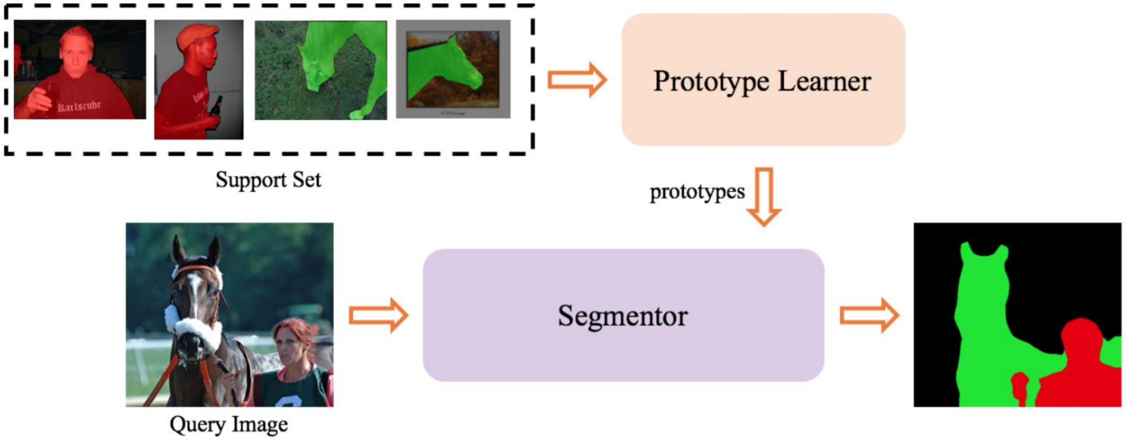
- ✓ **Introduction**
  - Few-shot learning
- ✓ **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - Medical image analysis
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

New Few-shot Applications

- **Image Segmentation** [Zhang et al. *CVPR'19*]

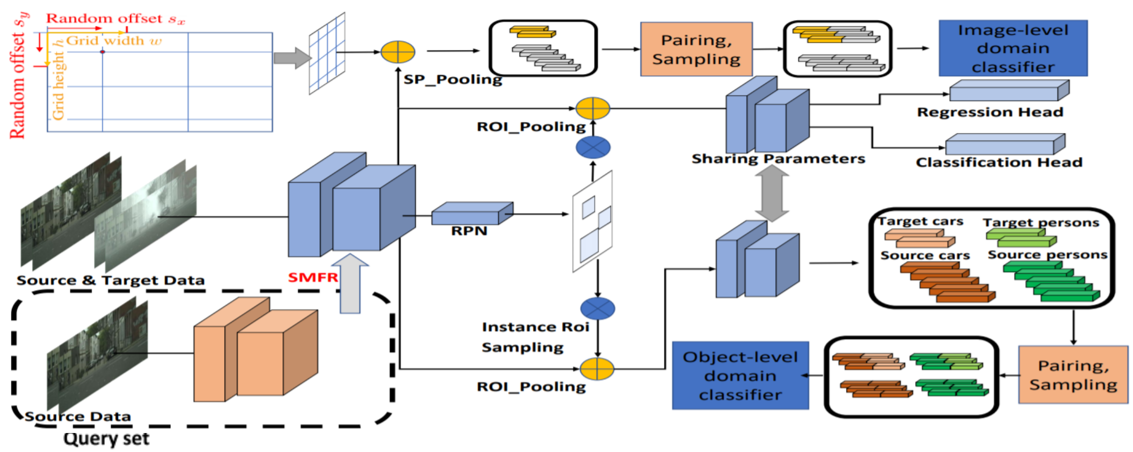


- **Semantic Segmentation** [Dong et al. *BMVC'18*]

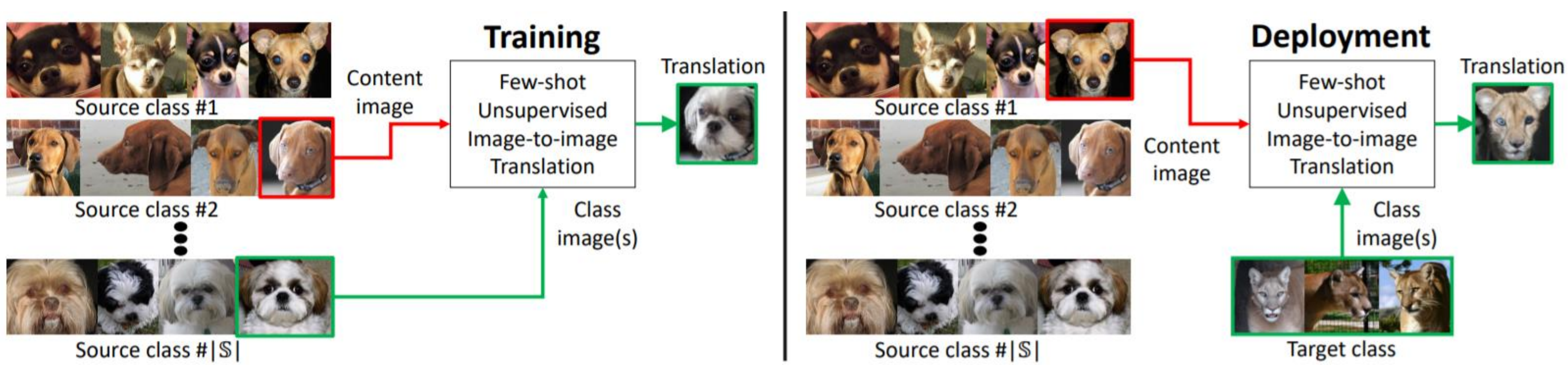


New Few-shot Applications

- **Object Detection** [Wang et al. *CVPR'19*]

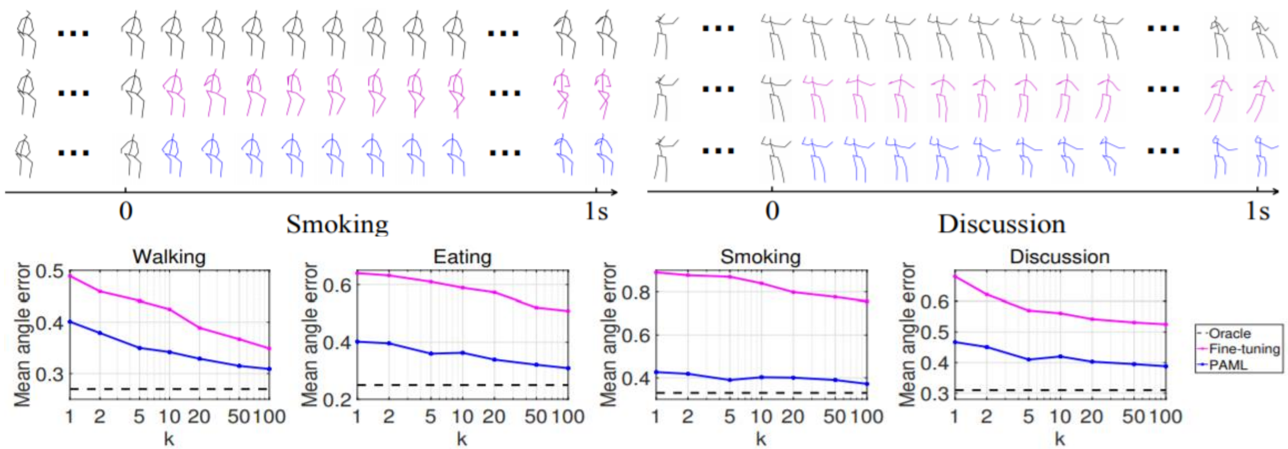


- **Image-to-Image Translation** [Liu et al. *CVPR'19*]

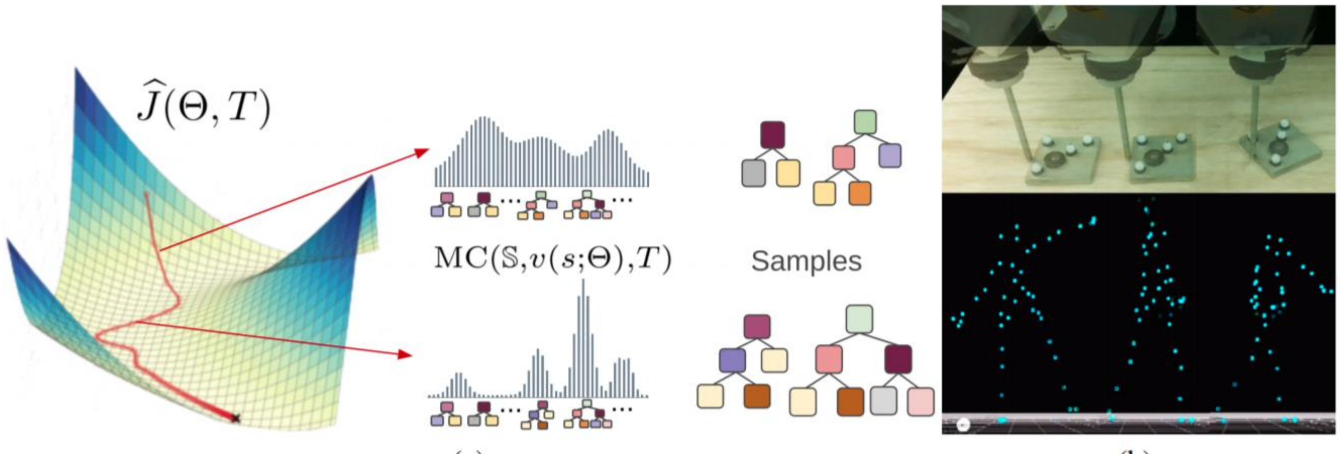


New Few-shot Applications

- **Human Motion Prediction** [Gui et al. *ECCV'18*]



- **Human Pose Prediction** [Alet et al. *CoRL'18*]

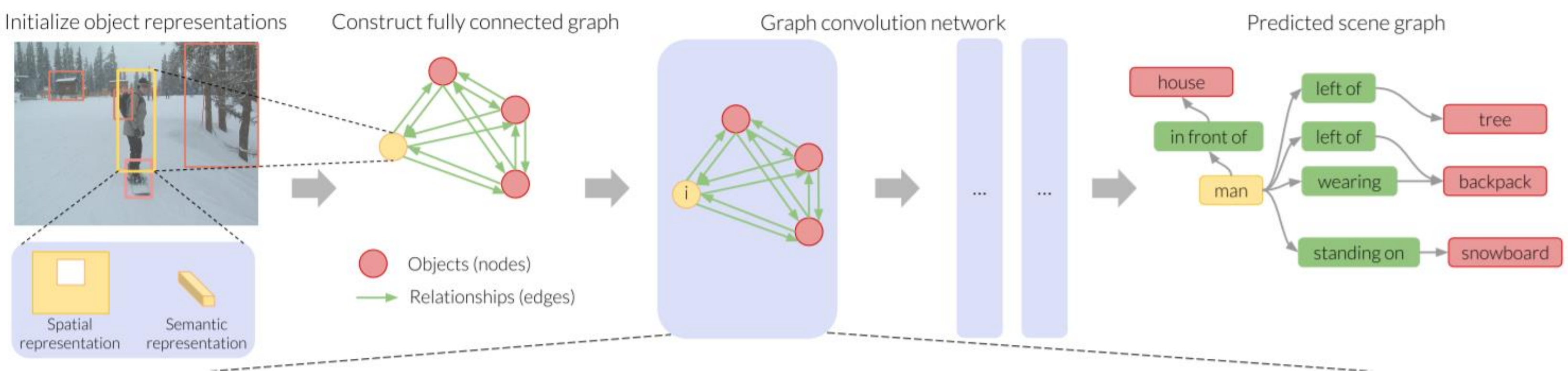


(a)

(b)

New Few-shot Applications

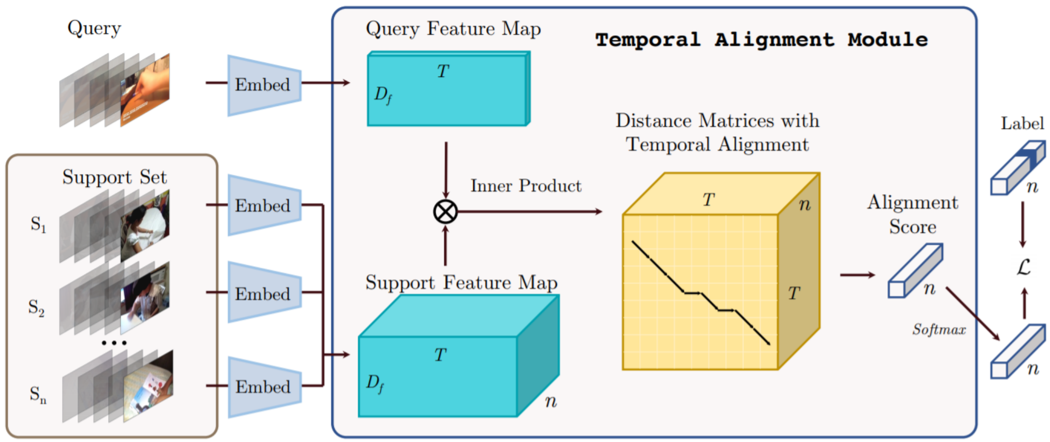
- **Scene Graph Prediction** [Dornadula et al. *arXiv'19*]



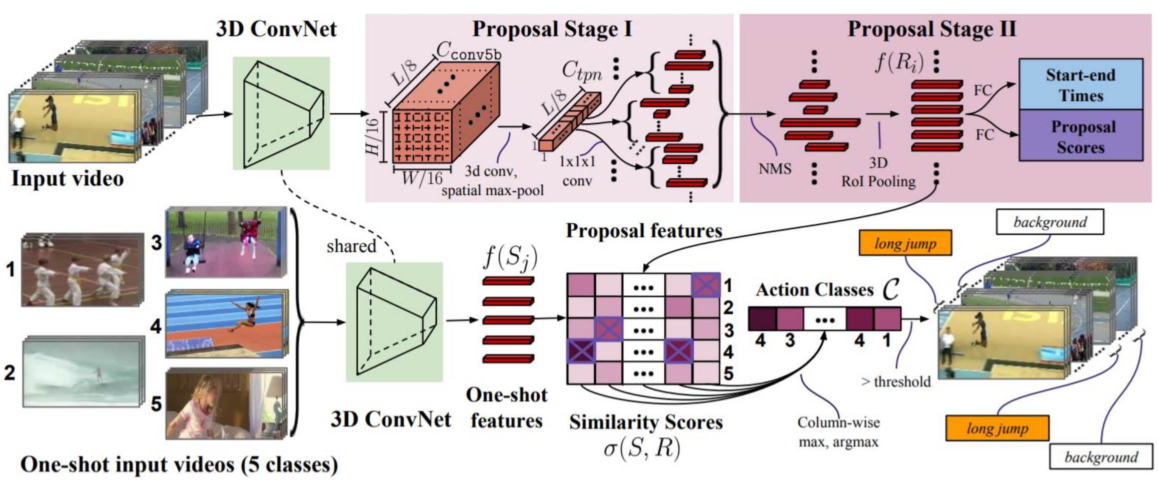
- **Talking Head Synthesis** [Zakharov et al. *arXiv'19*]

New Few-shot Applications

- **Video Classification** [Cao et al. *arXiv'19*]



- **Temporal Activity Detection**[Xu et al. *arXiv'18*]



Outline

- **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - Medical image analysis
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

Open Problems

General Few-shot Learning

Existing Few-shot Methods:

- Base and novel classes are sampled from *the same dataset*

  (*The training and test data come from the same distribution*)

General Few-shot Methods:

- Base and novel classes come from *different datasets*

  (*The training and test data have domain shift*)

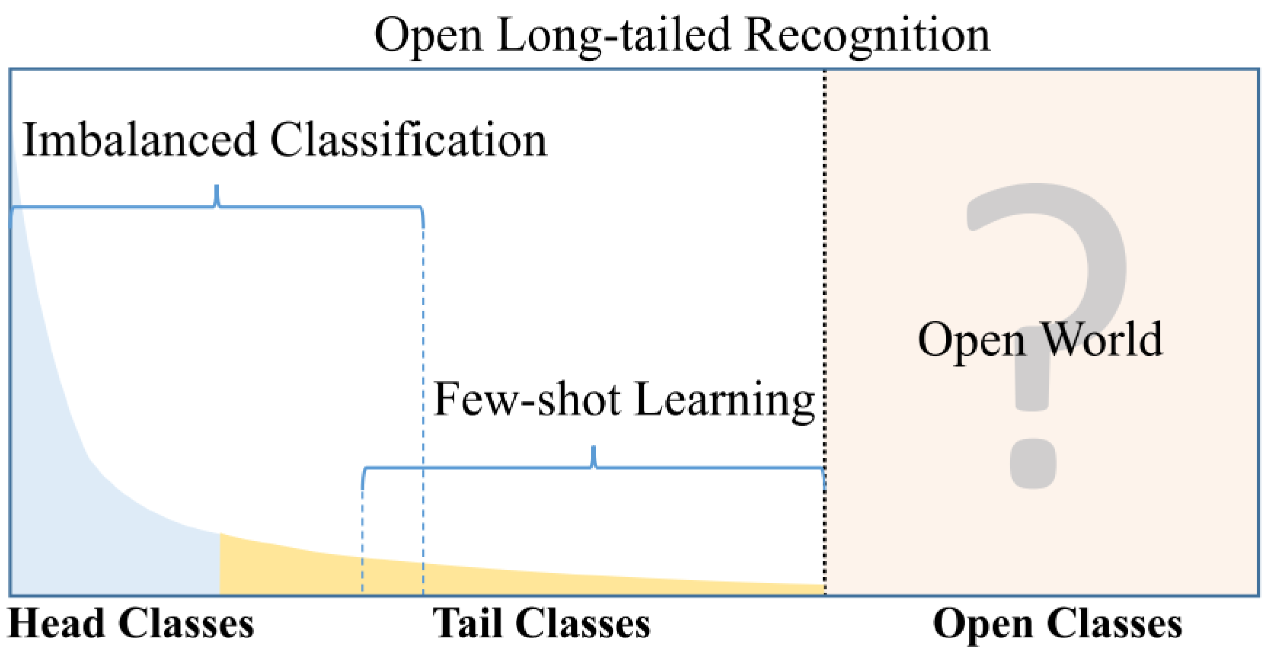
(Chen et al. *ICLR* 2019)

Open Problems

Real Long-tail Problems

Existing Few-shot problems:

- Strictly constructed few-shot setting (*not realistic problems*)



(Liu et al. *CVPR* 2019)

Conclusions

- **Key Issues in Few-shot Learning (*Image Classification*)**

  - **Transferable Knowledge**
    How to learn and transfer knowledge or representations from the auxiliary dataset?

  - **Image Representation**
    How to represent an image?

  - **Concept Representation**
    How to precisely represent a class (concept)?

  - **Relation Measure**
    How to robustly measure the relationship between a concept and a query image?

Outline

- **Introduction**
  - Few-shot learning
- **Few-shot Methods**
  - Hallucination based methods
  - Meta-learning based methods
  - Metric-learning based methods
- **New Few-shot Applications**
  - Object Detection
  - Image Segmentation
  - Image-to-Image translation
  - Medical image analysis
  - ……
- **Open Problems**
  - General few-shot learning
  - Real long-tail problems
- **Conclusion**

References

[1] Miller, Matsakis, and Viola, Learning from *One Example* through Shared Densities on Transforms. *CVPR* 2000.
[2] L. Fei-Fei, R. Fergus and P. Perona. A Bayesian approach to unsupervised *one-shot learning* of object categories. *ICCV* 2003.
[3] L. Fei-Fei, R. Fergus and P. Perona. *One-Shot learning* of object categories. *TPAMI* 2006.
[4] Lake, Brenden M., Ruslan Salakhutdinov, and Joshua B. Tenenbaum. Human-level concept learning through probabilistic program induction. *Science* 2015.
[5] Wang Y X, Girshick R, Hebert M, et al. Low-shot learning from imaginary data. *CVPR* 2018.
[6] Xian Y, Sharma S, Schiele B, et al. f-VAEGAN-D2: A feature generating framework for any-shot learning. *CVPR* 2019.
[7] Schwartz E, Karlinsky L, Shtok J, et al. Delta-encoder: an effective sample synthesis method for few-shot object recognition. *NIPS* 2018.
[8] Cheny Z, Fuy Y, Zhang Y, et al. Multi-level Semantic Feature Augmentation for One-shot Learning. *TIP* 2019.
[9] Hariharan B, Girshick R. Low-shot visual recognition by shrinking and hallucinating features. *ICCV* 2017.
[10] Liu B, Wang X, Dixit M, et al. Feature space transfer for data augmentation. *CVPR* 2018.
[11] Yoon S W, Seo J, Moon J. TapNet: Neural Network Augmented with Task-Adaptive Projection for Few-Shot Learning. *ICML* 2019.
[12] Vilalta R, Drissi Y. A perspective view and survey of meta-learning. *Artificial intelligence review* 2002.
[13] Santoro A, Bartunov S, Botvinick M, et al. Meta-learning with memory-augmented neural networks. *ICML* 2016.
[14] Finn C, Abbeel P, Levine S. Model-agnostic meta-learning for fast adaptation of deep networks. *ICML* 2017.
[15] Gidaris, Spyros, and Nikos Komodakis. Dynamic few-shot visual learning without forgetting. *CVPR* 2018.
[16] Sun, Qianru, et al. Meta-transfer learning for few-shot learning. *CVPR* 2019.
[17] Jamal, Muhammad Abdullah, and Guo-Jun Qi. Task Agnostic Meta-Learning for Few-Shot Learning. *CVPR* 2019.
[18] Lee, Kwonjoon, et al. Meta-learning with differentiable convex optimization. *CVPR* 2019.
[19] Wang, Xin, et al. TAFE-Net: Task-Aware Feature Embeddings for Low Shot Learning. *CVPR* 2019.
[20] Li, Huaiyu, et al. LGM-Net: Learning to Generate Matching Networks for Few-Shot Learning. *ICML 2019*.
[21] Ravi, Sachin, and Alex Beatson. Amortized bayesian meta-learning. *ICLR* 2019.
[22] Koch, Gregory, Richard Zemel, and Ruslan Salakhutdinov. Siamese neural networks for one-shot image recognition. *ICML* 2015.
[23] Vinyals, O., Blundell, C., Lillicrap, T., & Wierstra, D. Matching networks for one shot learning. *NIPS 2016*.
[24] Snell, Jake, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. *NIPS* 2017.
[25] Sung, F., Yang, Y., Zhang, L., Xiang, T., Torr, P. H., & Hospedales, T. M. Learning to compare: Relation network for few-shot learning. CV*PR 2018*.

References

[26] Li, W., Xu, J., Huo, J., Wang, L., Yang, G., & Luo, J. Distribution consistency based covariance metric networks for few-shot learning. *AAAI* 2019.

[27] Li, W., Wang, L., Xu, J., Huo, J., Gao, Y., & Luo, J. Revisiting Local Descriptor based Image-to-Class Measure for Few-shot Learning. CV*PR 2019.*

[28] Boiman, O., Shechtman, E., & Irani, M. In defense of nearest-neighbor based image classification. *CVPR* 2008.

[29] Allen, K. R., Shelhamer, E., Shin, H., & Tenenbaum, J. B. Infinite Mixture Prototypes for Few-Shot Learning. *ICML 2019*.

[30] Wertheimer, Davis, and Bharath Hariharan. Few-Shot Learning with Localization in Realistic Settings. *CVPR* 2019.

[31] Garcia, Victor, and Joan Bruna. Few-shot learning with graph neural networks. *ICLR 2018*.

[32] Kim, J., Kim, T., Kim, S., & Yoo, C. D. Edge-Labeling Graph Neural Network for Few-shot Learning. *CVPR* 2019.

[33] Lifchitz, Y., Avrithis, Y., Picard, S., & Bursuc, A. Dense Classification and Implanting for Few-Shot Learning. *CVPR 2019*.

[34] Zhang, C., Lin, G., Liu, F., Yao, R., & Shen, C. CANet: Class-Agnostic Segmentation Networks with Iterative Refinement and Attentive Few-Shot Learning. *CVPR 2019*.

[35] Dong, N., & Xing, E. Few-Shot Semantic Segmentation with Prototype Learning. *BMVC* 2018.

[36] Tao Wang et al. Few-shot Adaptive Faster R-CNN. *CVPR* 2019.

[37] Gui, L. Y., Wang, Y. X., Ramanan, D., & Moura, J. M. Few-shot human motion prediction via meta-learning. *ECCV 2018*.

[38] Liu, M. Y., Huang, X., Mallya, A., Karras, T., Aila, T., Lehtinen, J., & Kautz, J. Few-shot unsupervised image-to-image translation. *CVPR 2019*.

[39] Alet, F., Lozano-Pérez, T., & Kaelbling, L. P. Modular meta-learning. *CoRL 2018*.

[40] Dornadula, A., Narcomey, A., Krishna, R., Bernstein, M., & Fei-Fei, L. Visual Relationships as Functions: Enabling Few-Shot Scene Graph Prediction. *arXiv 2019*.

[41] Zakharov, E., Shysheya, A., Burkov, E., & Lempitsky, V. Few-Shot Adversarial Learning of Realistic Neural Talking Head Models. *arXiv 2019*.

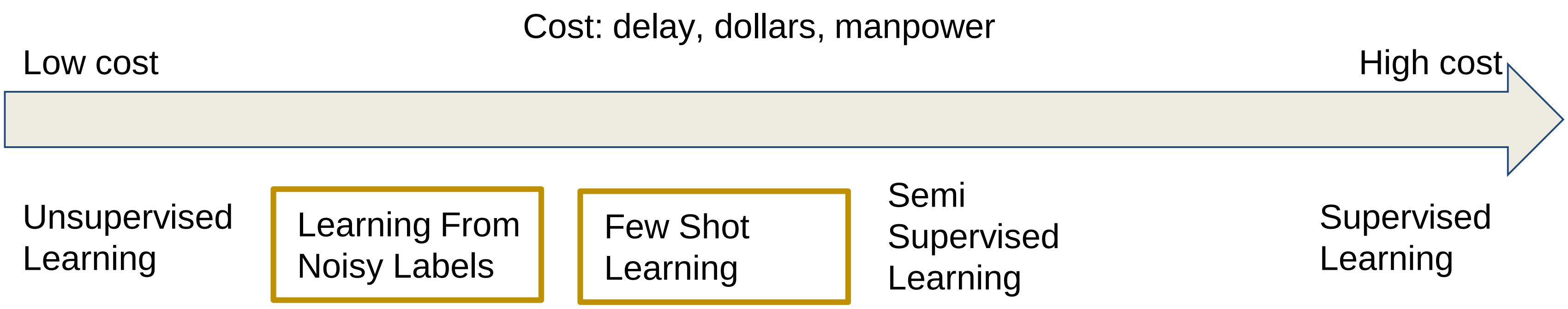
[42] Cao, K., Ji, J., Cao, Z., Chang, C. Y., & Niebles, J. C. Few-Shot Video Classification via Temporal Alignment. *arXiv 2019*.

[43] Xu, H., Kang, B., Sun, X., Feng, J., Saenko, K., & Darrell, T. Similarity R-C3D for Few-shot Temporal Activity Detection. *arXiv 2018*.

[44] Wei-Yu Chen, Yen-Cheng Liu, Zsolt Kira, Yu-Chiang Frank Wang, Jia-BinHuang: A Closer Look at Few-shot Classification. ICLR 2019.

[45] Liu, Z., Miao, Z., Zhan, X., Wang, J., Gong, B., & Yu, S. X. Large-Scale Long-Tailed Recognition in an Open World. *CVPR* 2019.

The Spectrum of Machine Learning




Questions?