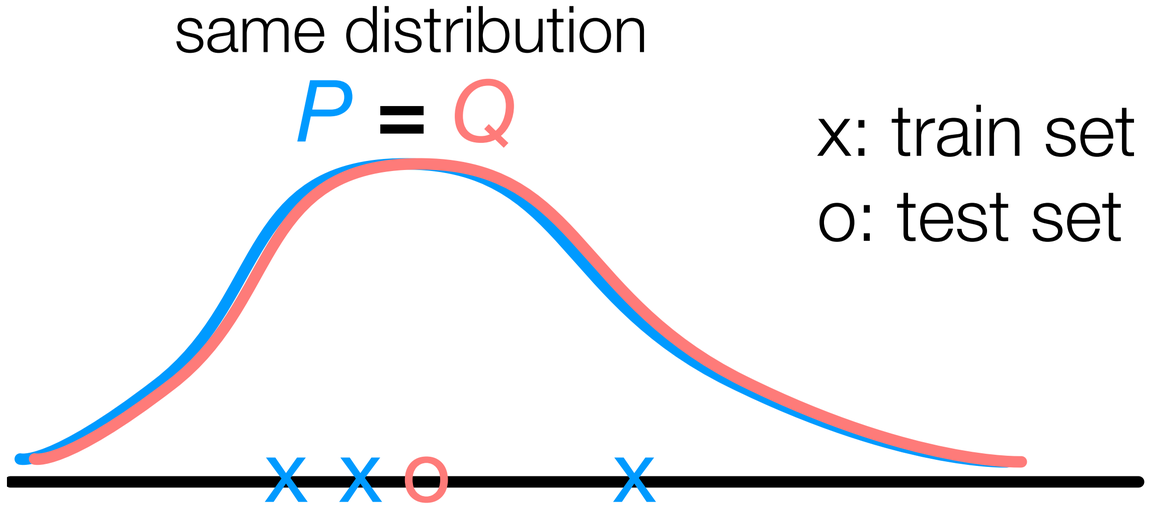
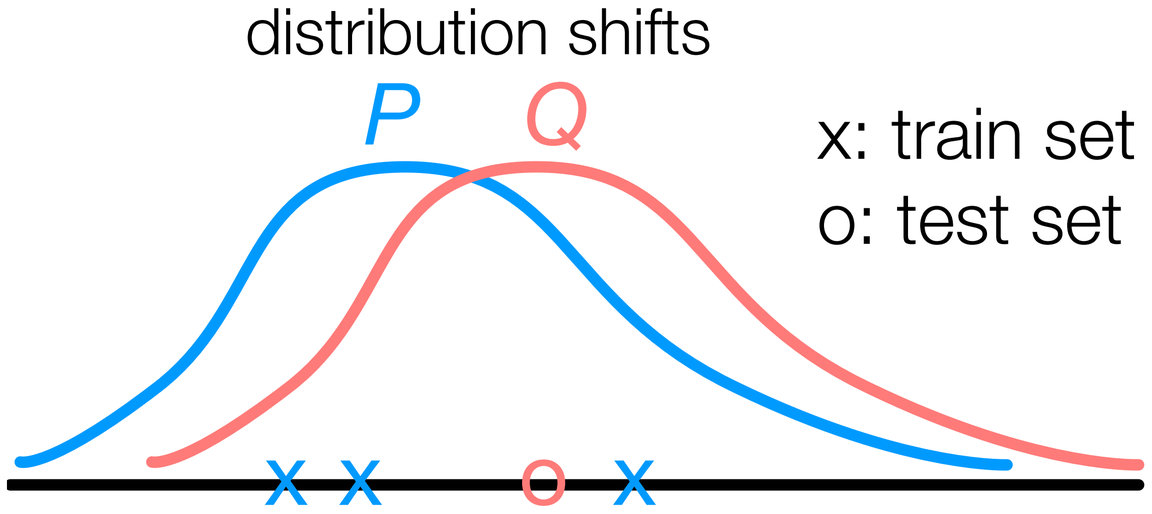
Test-Time Training with Self-Supervision for Generalization under Distribution Shifts

Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei Efros, Moritz Hardt
UC Berkeley

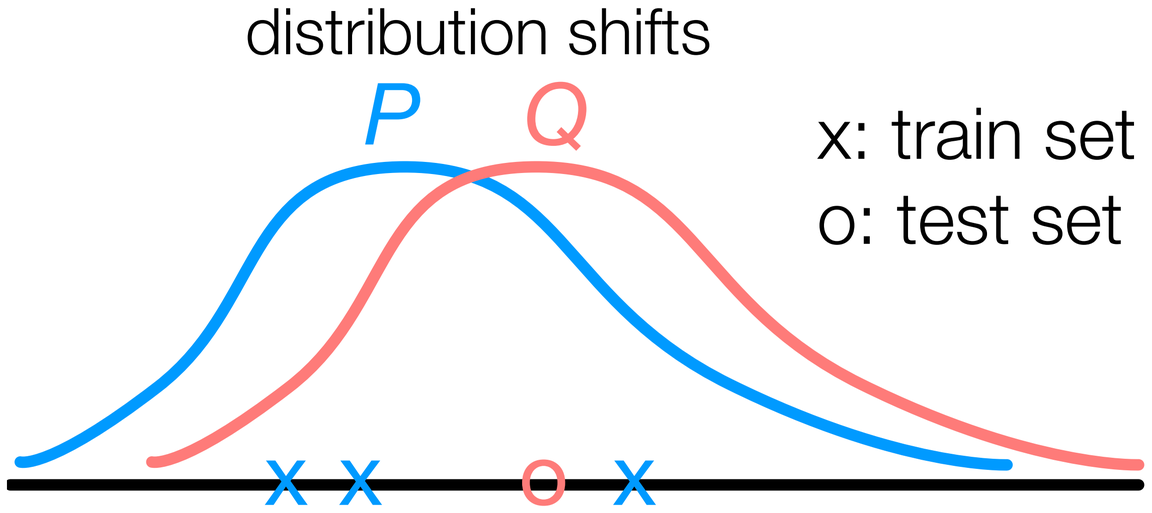
ICML 2020



- **In theory**: same distribution for training and testing



- **In theory**: same distribution for training and testing
- **In the real word**: distribution shifts are everywhere



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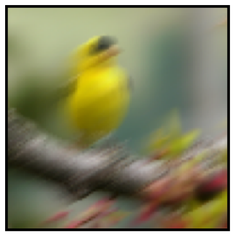
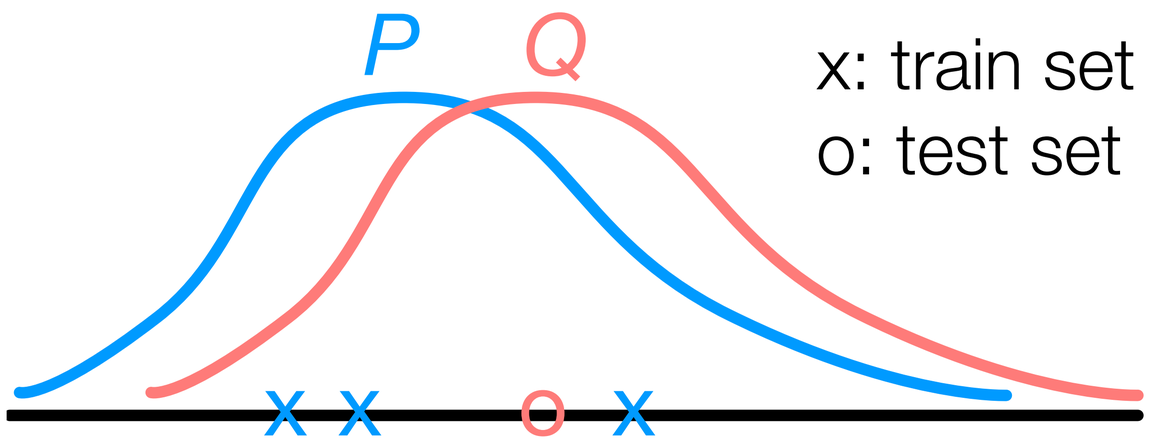


Hendrycks and Dietterich, 2018

Recht, Roelofs, Schmidt and Shankar, 2019

Existing paradigms



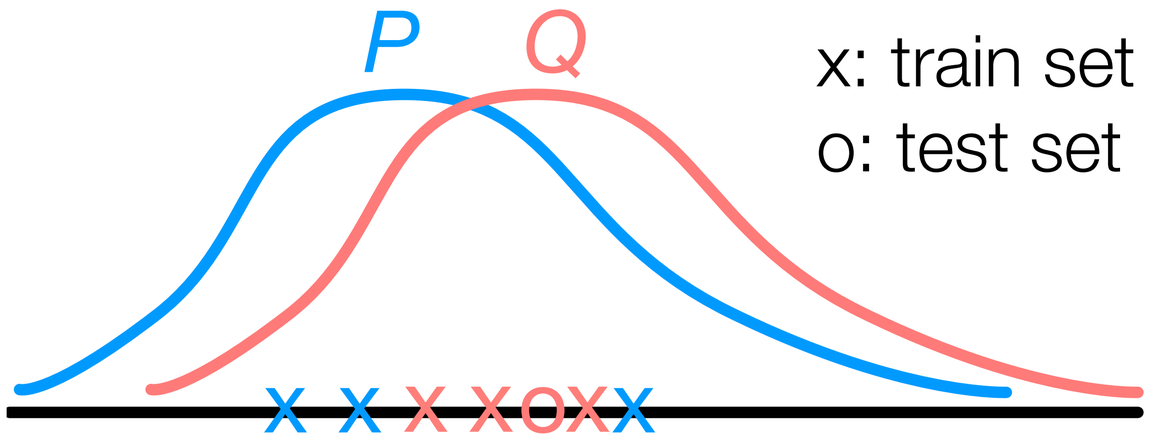
A Theory of Learning from Different Domains
Ben-David, Blitzer, Crammer, Kulesza, Pereira and Vaughan, 2009

Adversarial Discriminative Domain Adaptation
Tzeng, Hoffman, Saenko and Darrell, 2017

Unsupervised Domain Adaptation through Self-Supervision
Sun, Tzeng, Darrell and Efros, 2019

Existing paradigms

- **Domain adaptation**
  - Data from the test distribution



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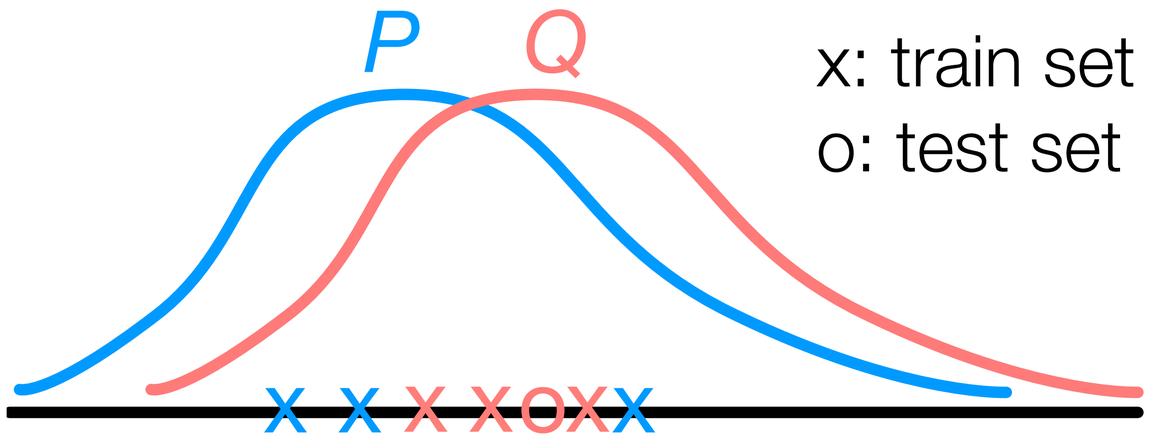
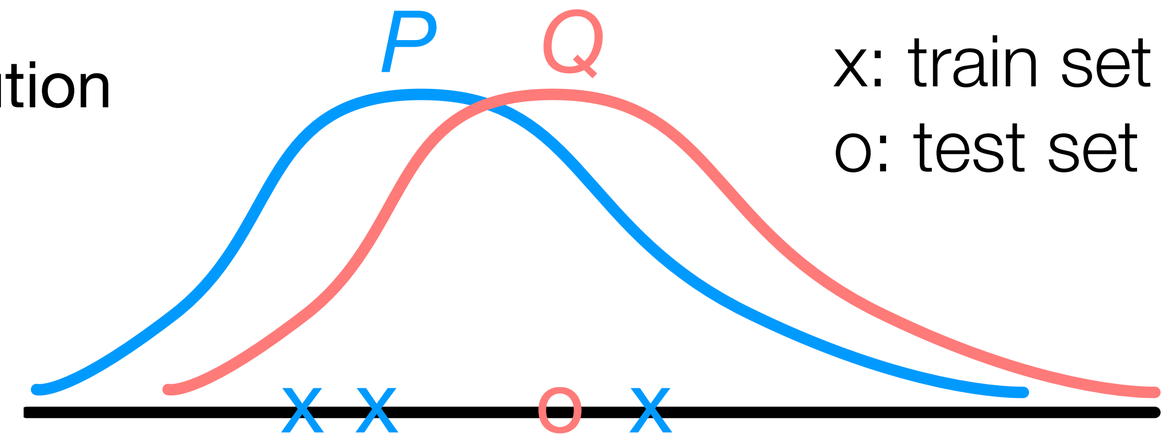
Existing paradigms

- **Domain adaptation**
  - Data from the test distribution (maybe unlabeled)
  - Hard to know the test distribution



Existing paradigms

- **Domain adaptation**
  - Data from the test distribution
  - Hard to know the test distribution
- **Domain generalization**
  - Data from the meta distribution



Domain generalization via invariant feature representation
Muandet, Balduzzi and Scholkopf, 2013

Domain generalization for object recognition with multi-task autoencoders
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Domain Generalization by Solving Jigsaw Puzzles
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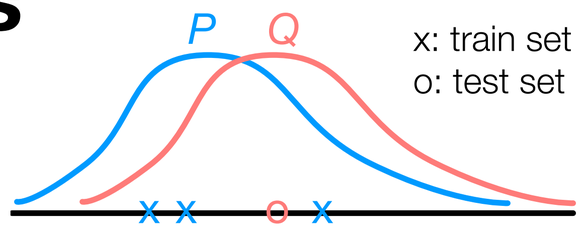
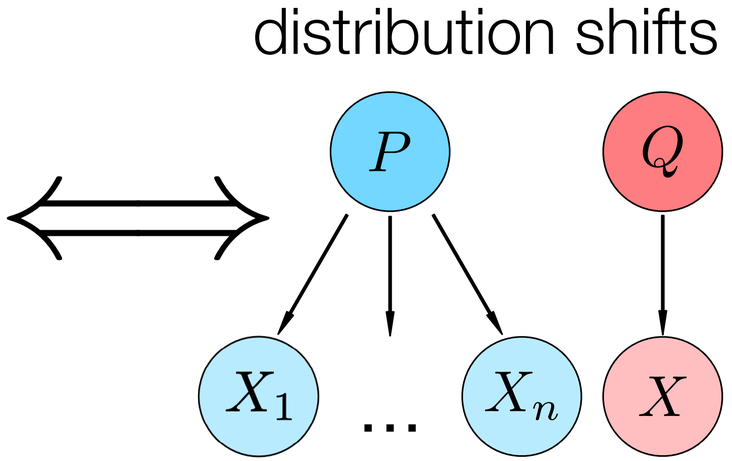
Existing paradigms





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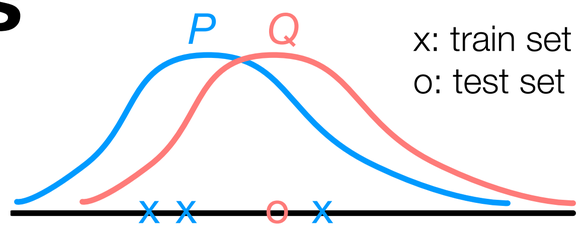
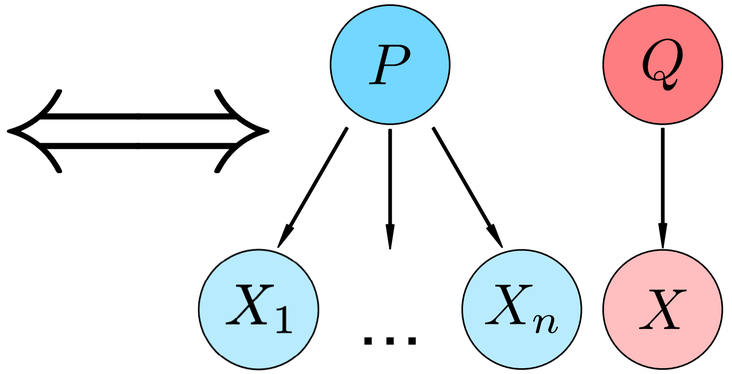


distribution shifts



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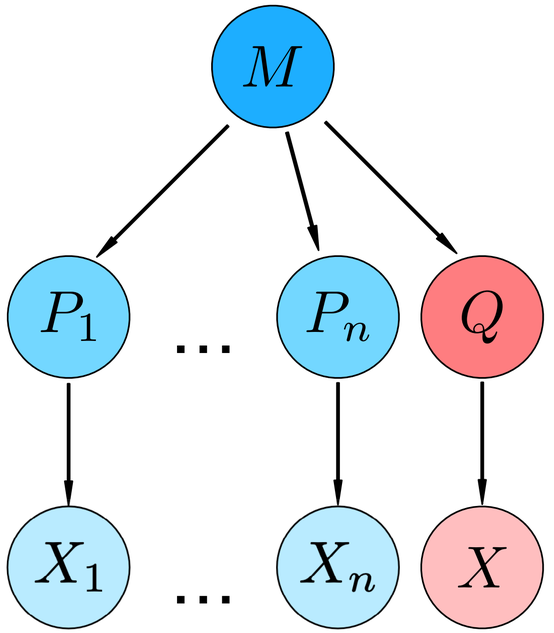

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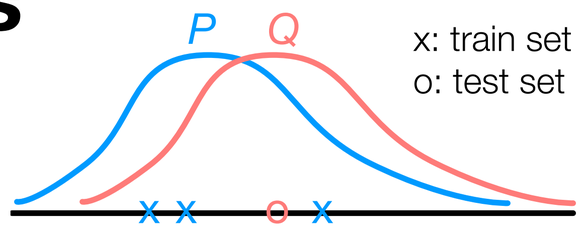

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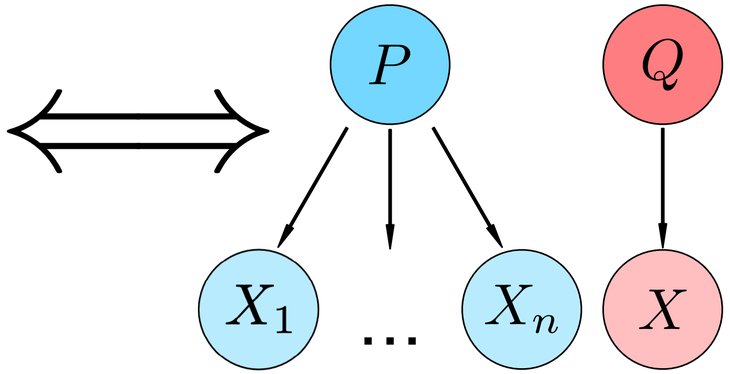
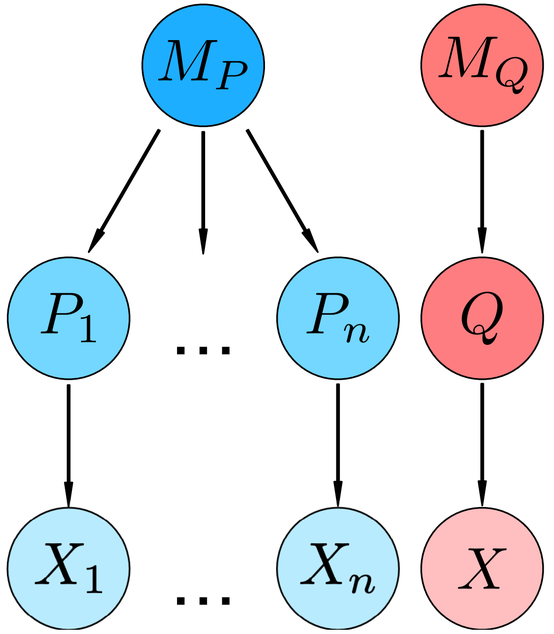


meta distribution shifts



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  - Topological structure of the test distribution

Certifying some distributional robustness with principled adversarial training
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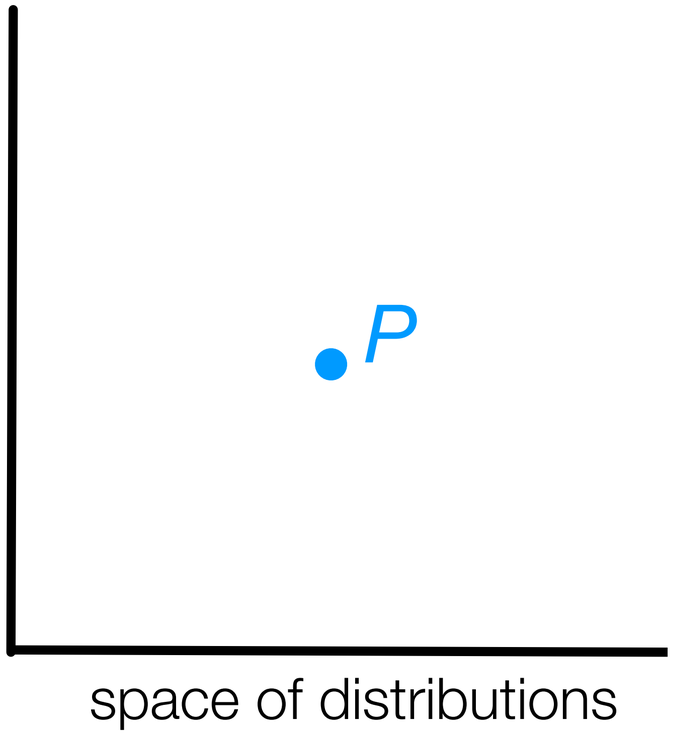

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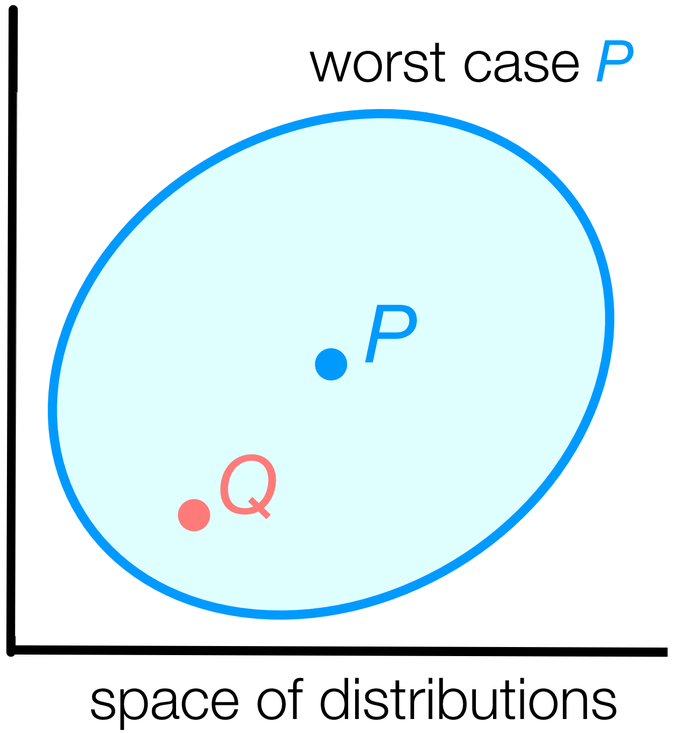

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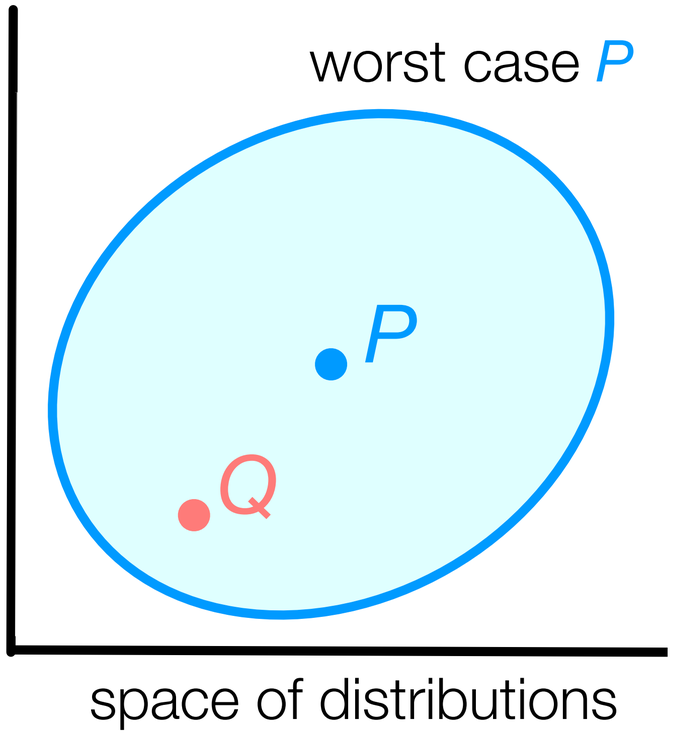

Existing paradigms anticipate the distribution shifts

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Test-Time Training (TTT)

- Does not anticipate the test distribution

Test-Time Training (TTT)

$$\text{standard test error} = \mathbb{E}_Q[\ell(x, y);\ \theta]$$

- Does not anticipate the test distribution
- The test sample x gives us a hint about Q

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- Does not anticipate the test distribution
- The test sample x gives us a hint about Q
- No fixed model, but adapt at test time
- One sample learning problem
- No label? Self-supervision!

Rotation prediction as self-supervision

(Gidaris et al. 2018)

x

- Create labels from unlabeled input

Unsupervised Representation Learning by Predicting Image Rotations
Gidaris, Singh and Komodakis, 2018

Rotation prediction as self-supervision

(Gidaris et al. 2018)

x y_{s}

0°

90°

180°

270°

- Create labels from unlabeled input
- Rotate input image by multiples of 90°

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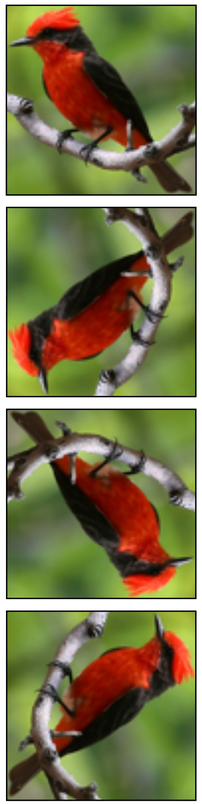
x



CNN

θ

y_s

0°

90°

180°

270°

- Create labels from unlabeled input
- Rotate input image by multiples of 90°
- Produce a four-way classification problem

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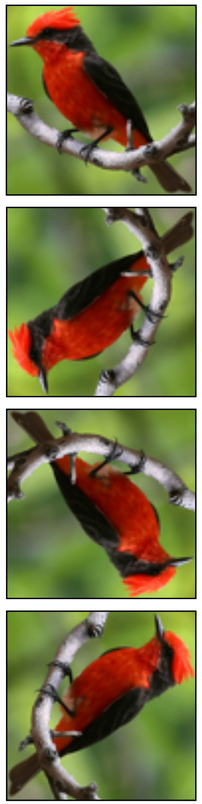
x



θ_{e} θ_{s}

y_{s}

0°

90°

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- Create labels from unlabeled input
- Rotate input image by multiples of 90°
- Produce a four-way classification problem
- Usually a pre-training step

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θ_{e}

- Create labels from unlabeled input
- Rotate input image by multiples of 90º
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  - After training, take feature extractor

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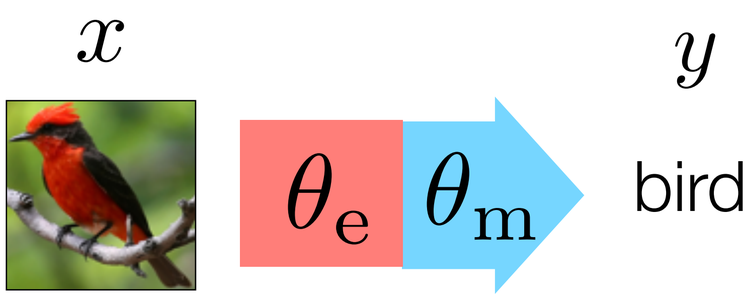

- Create labels from unlabeled input
- Rotate input image by multiples of 90°
- Produce a four-way classification problem
- Usually a pre-training step
  - After training, take feature extractor
  - Use it for a downstream main task

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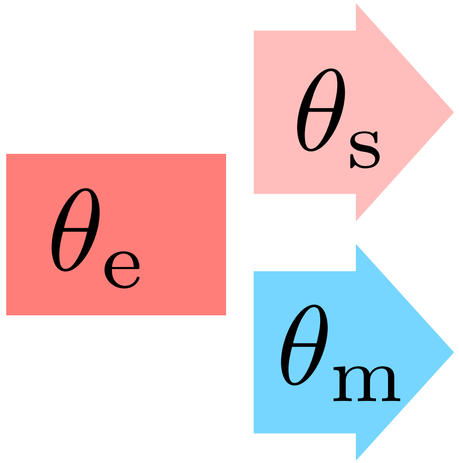
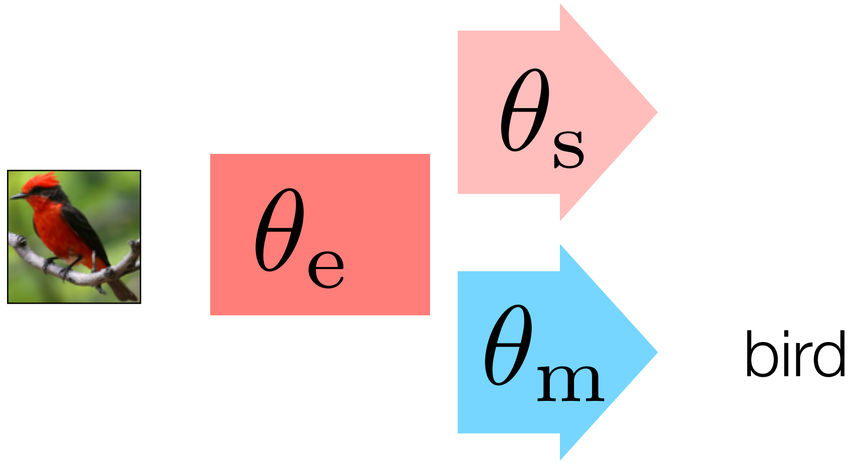
Algorithm for TTT



network
architecture

Algorithm for TTT

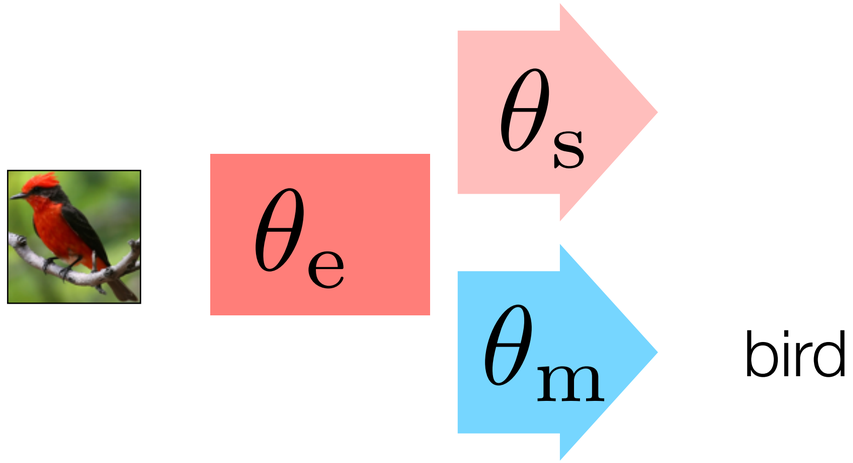
training



Algorithm for TTT

training

$\ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}})$



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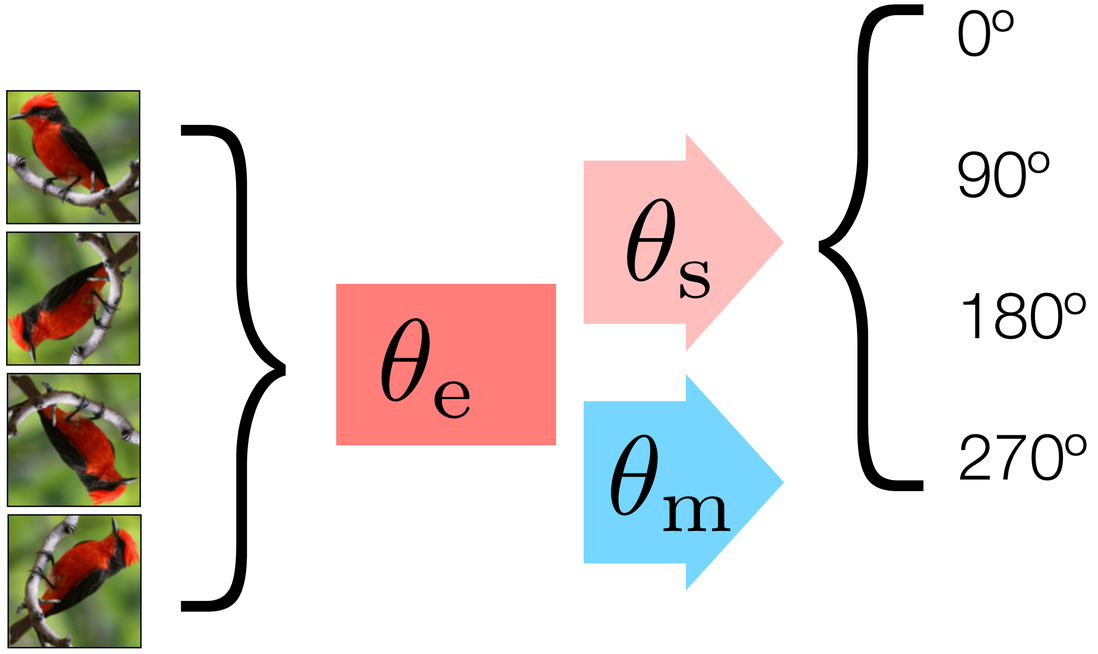
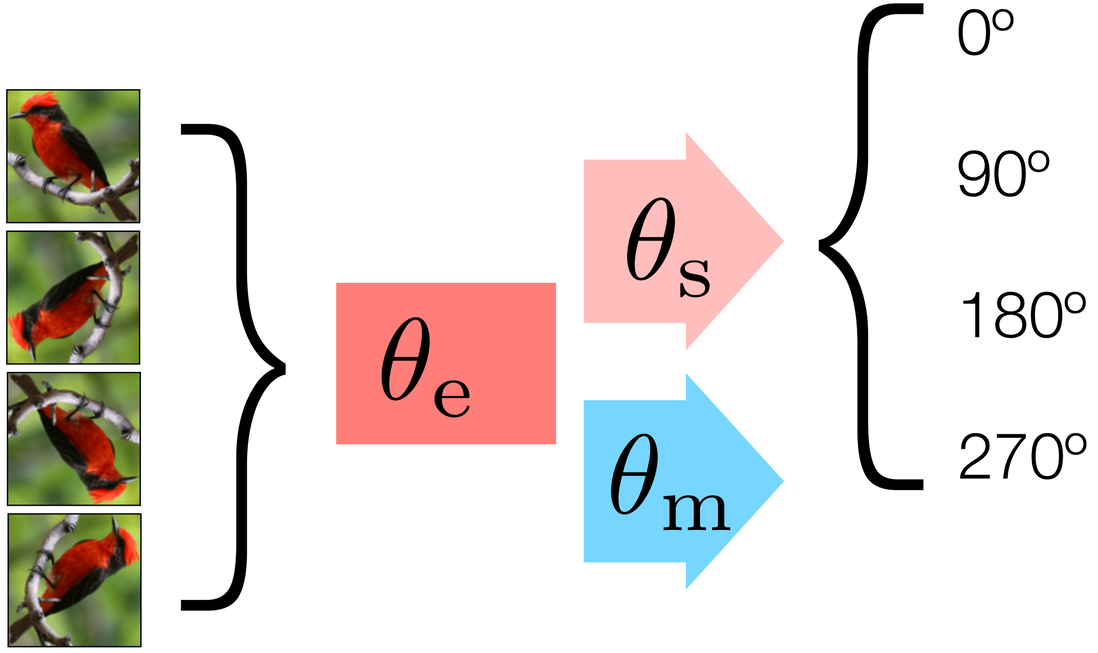


Algorithm for TTT

training

$\ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}})$

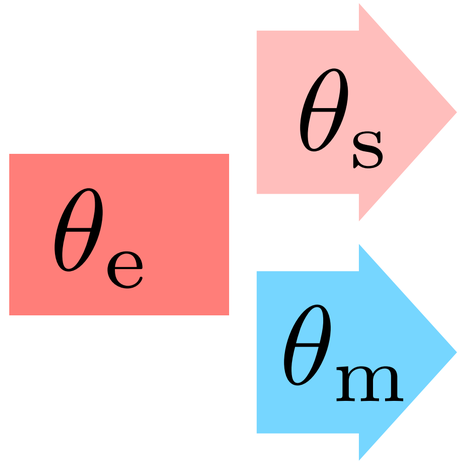
$+\ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s)$



Algorithm for TTT

training

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}},\theta_{\mathrm{m}}} \mathbb{E}_P \left[\begin{array}{l} \ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}}) \\ + \ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \end{array} \right]$$



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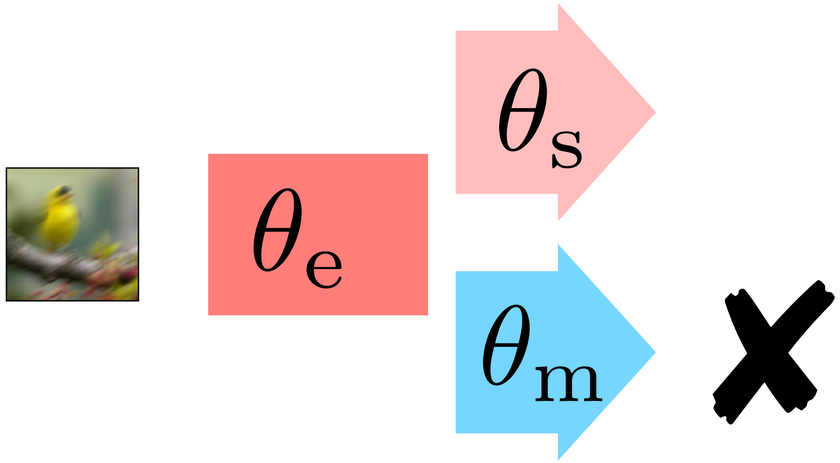
testing



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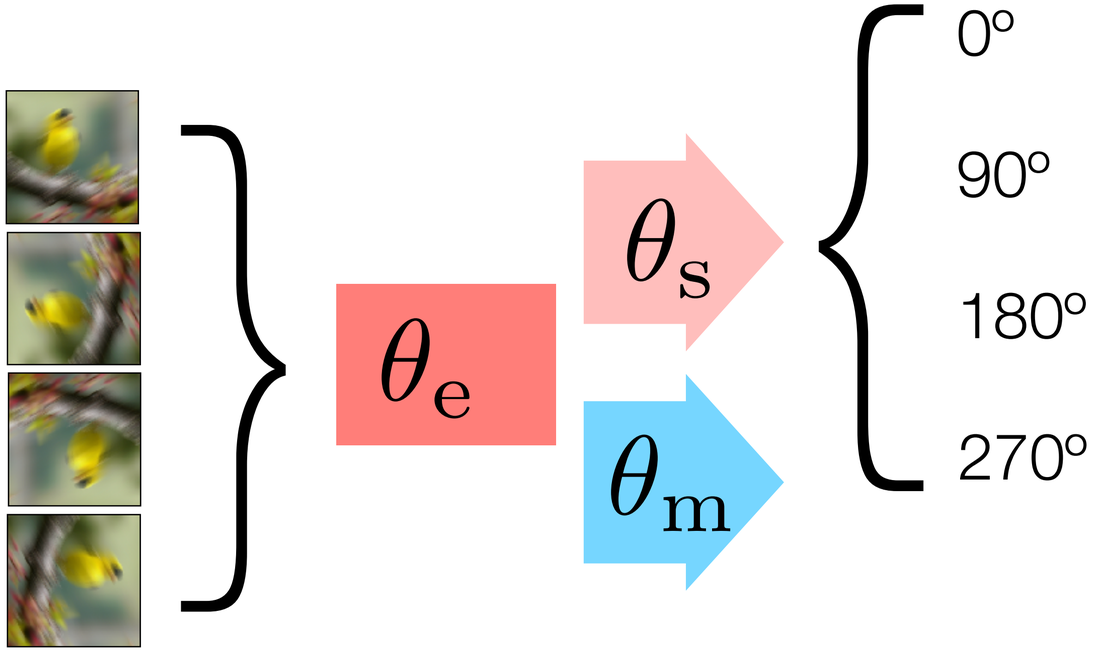

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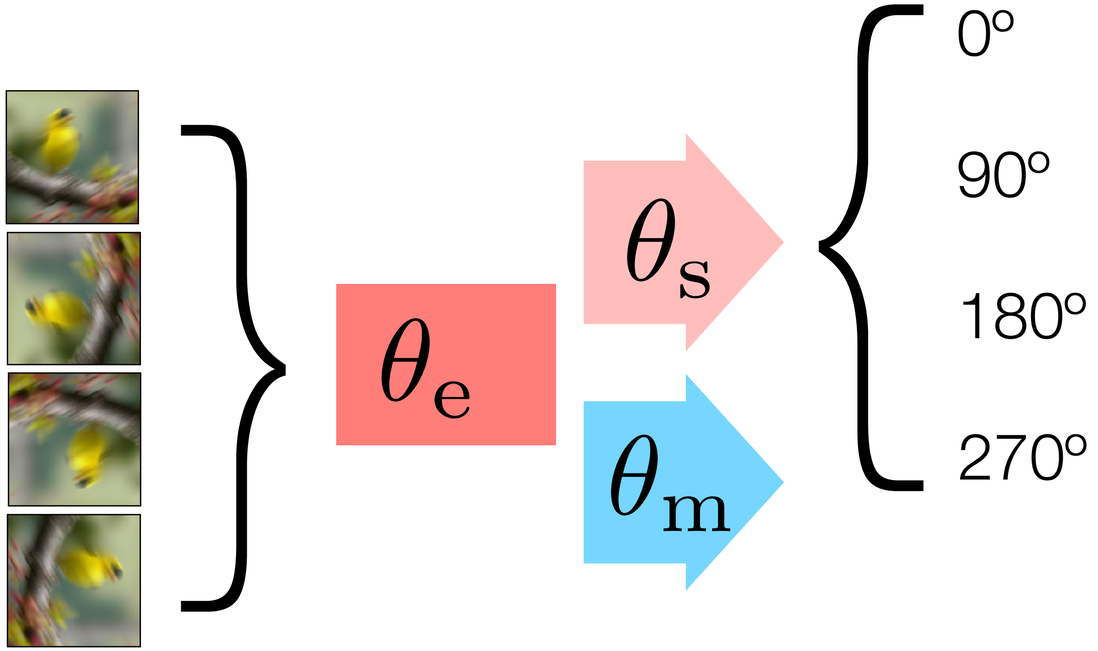
$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}}} \left[\ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \right]$$



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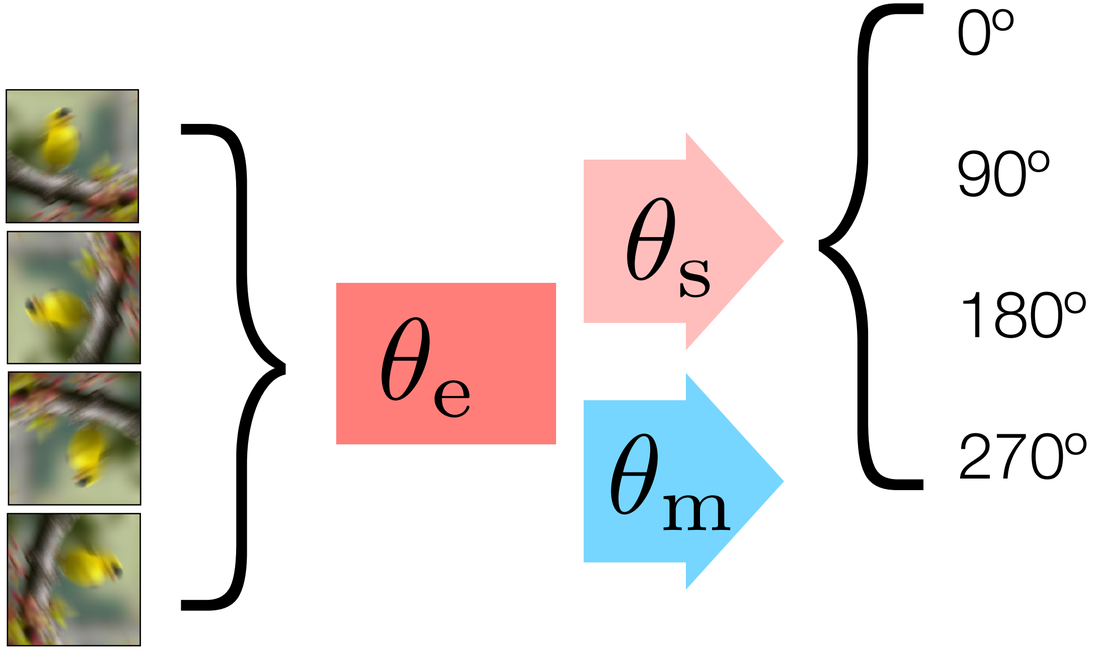
testing

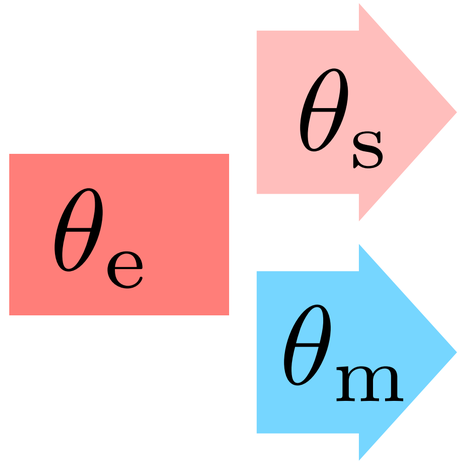
$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}}} \mathbb{E}_Q \left[\ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \right]$$



Algorithm for TTT

training

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}},\theta_{\mathrm{m}}} \mathbb{E}_P \left[\begin{array}{l} \ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}}) \\ + \ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \end{array} \right]$$



testing

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}}} \mathbb{E}_Q \left[\ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \right]$$

$\rightarrow \theta(x)$: make prediction on x

Algorithm for TTT

training

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}},\theta_{\mathrm{m}}} \mathbb{E}_P \left[\begin{array}{l} \ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}}) \\ + \ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \end{array} \right]$$

testing

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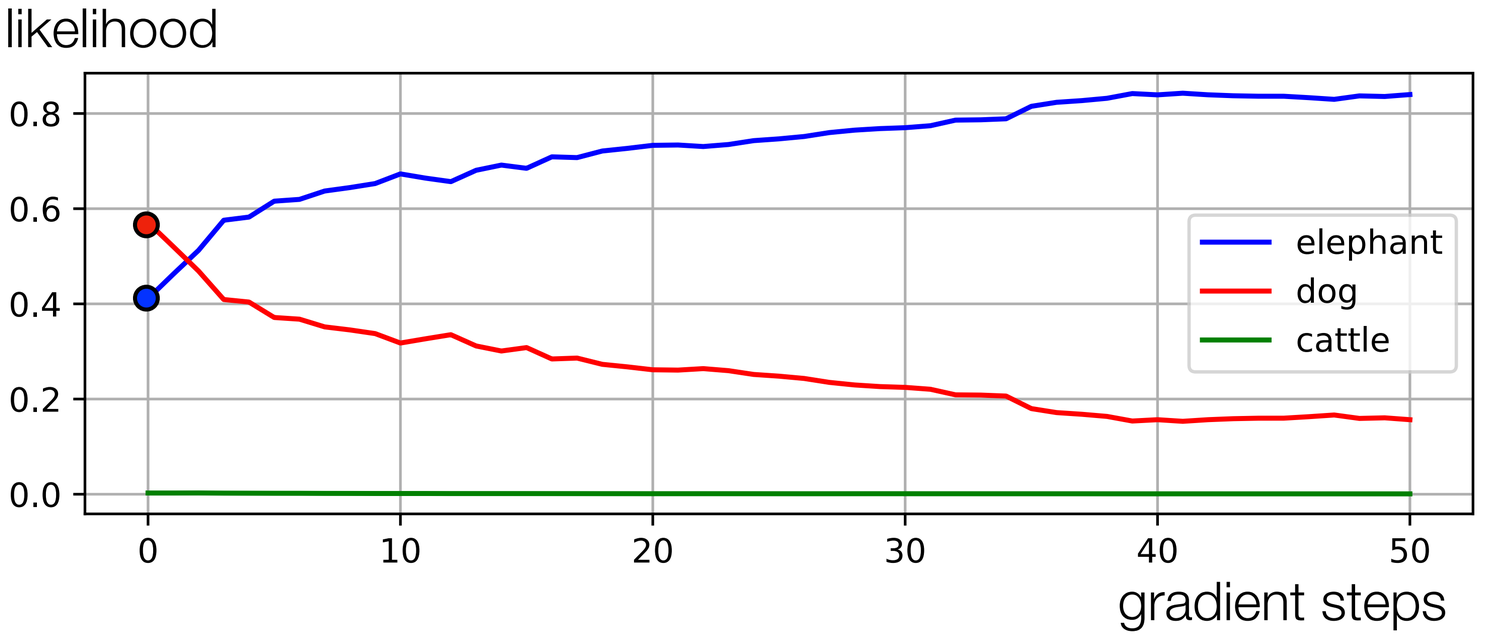

Algorithm for TTT

training

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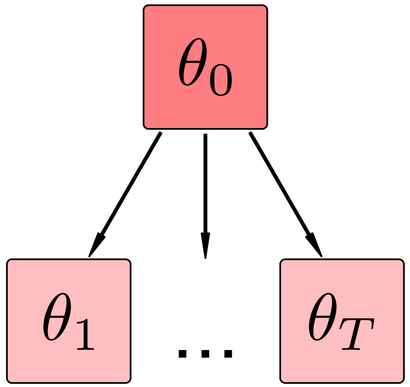
$\rightarrow \theta(x)$: make prediction on x

multiple test samples $x_1, ..., x_T$

θ_0: parameters after joint training



Algorithm for TTT

training

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}},\theta_{\mathrm{m}}} \mathbb{E}_P \left[\begin{array}{l} \ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}}) \\ + \ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \end{array} \right]$$

testing

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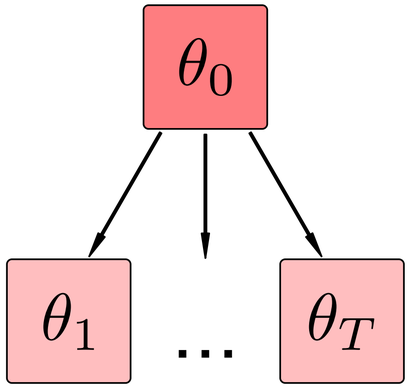
$\rightarrow \theta(x)$: make prediction on x

multiple test samples $x_1, ..., x_T$

θ_0: parameters after joint training

standard version

no assumption on the test samples



Algorithm for TTT

training

$$\min_{\theta_{\mathrm{e}},\theta_{\mathrm{s}},\theta_{\mathrm{m}}} \mathbb{E}_P \left[\begin{array}{l} \ell_{\mathrm{m}}(x, y; \theta_{\mathrm{e}}, \theta_{\mathrm{m}}) \\ + \ell_s(x, y_{\mathrm{s}}; \theta_e, \theta_s) \end{array} \right]$$

testing

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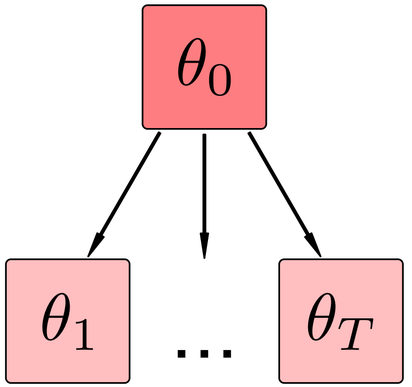
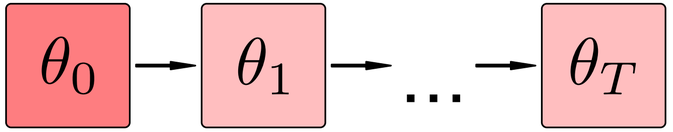


online version

$x_1, ..., x_T$ come from the same Q

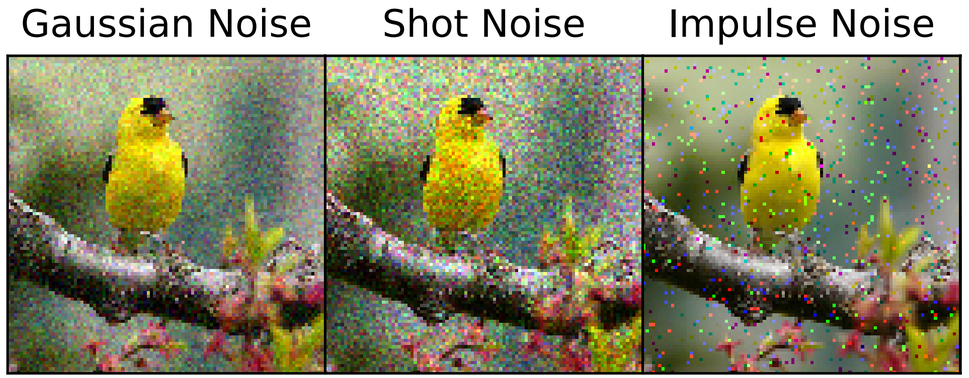
or smoothly changing $Q_1, ..., Q_T$



Results

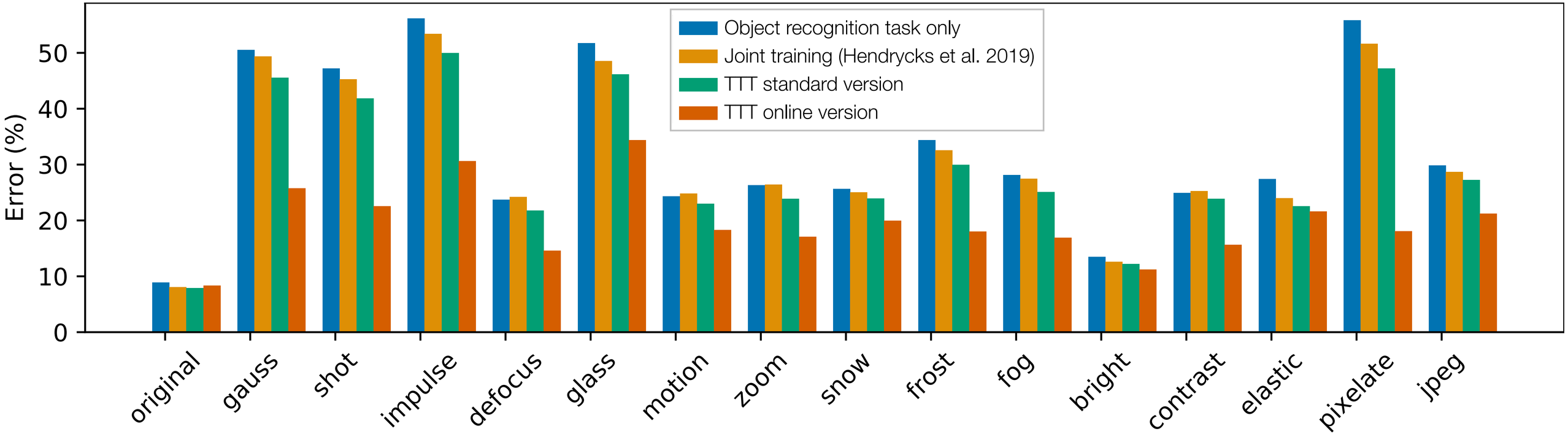
Object recognition with corruptions

- 15 corruptions
- CIFAR-10: 10 classes
- ImageNet: 1000 classes
- No knowledge of the corruptions during training



Benchmarking Neural Network Robustness to Common Corruptions and Perturbations
Hendrycks and Dietterich, 2018

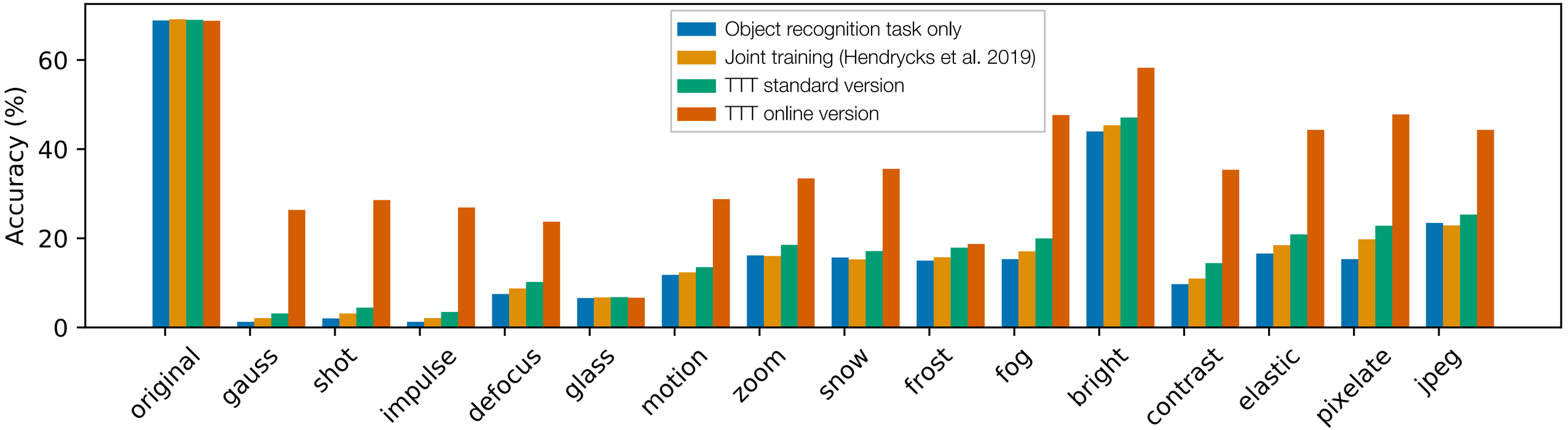
Results on CIFAR-10-C



Joint training reported here is our improved implementation of their method. Please see our paper for clarification, and their paper for their original results.

Using Self-Supervised Learning Can Improve Model Robustness and Uncertainty
Hendrycks, Mazeika, Kadavath and Song, 2019

Results on ImageNet-C



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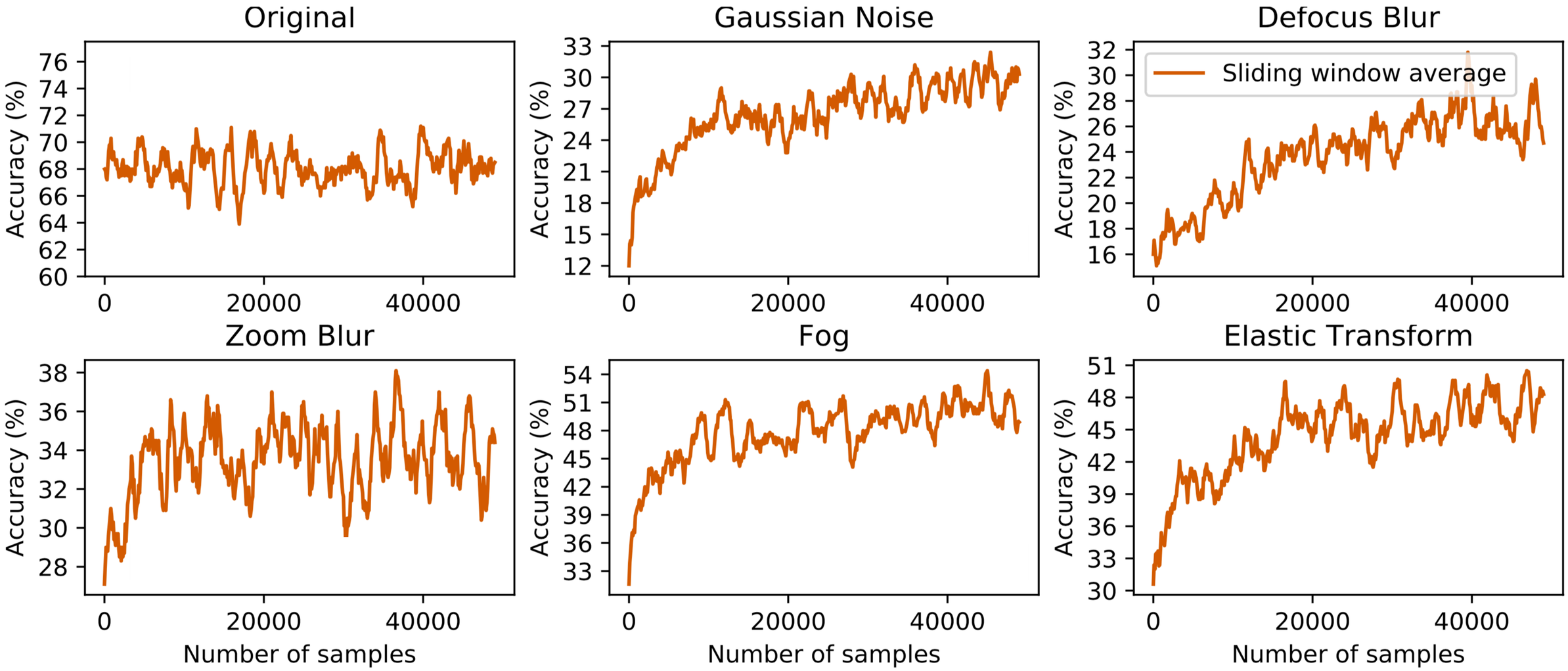
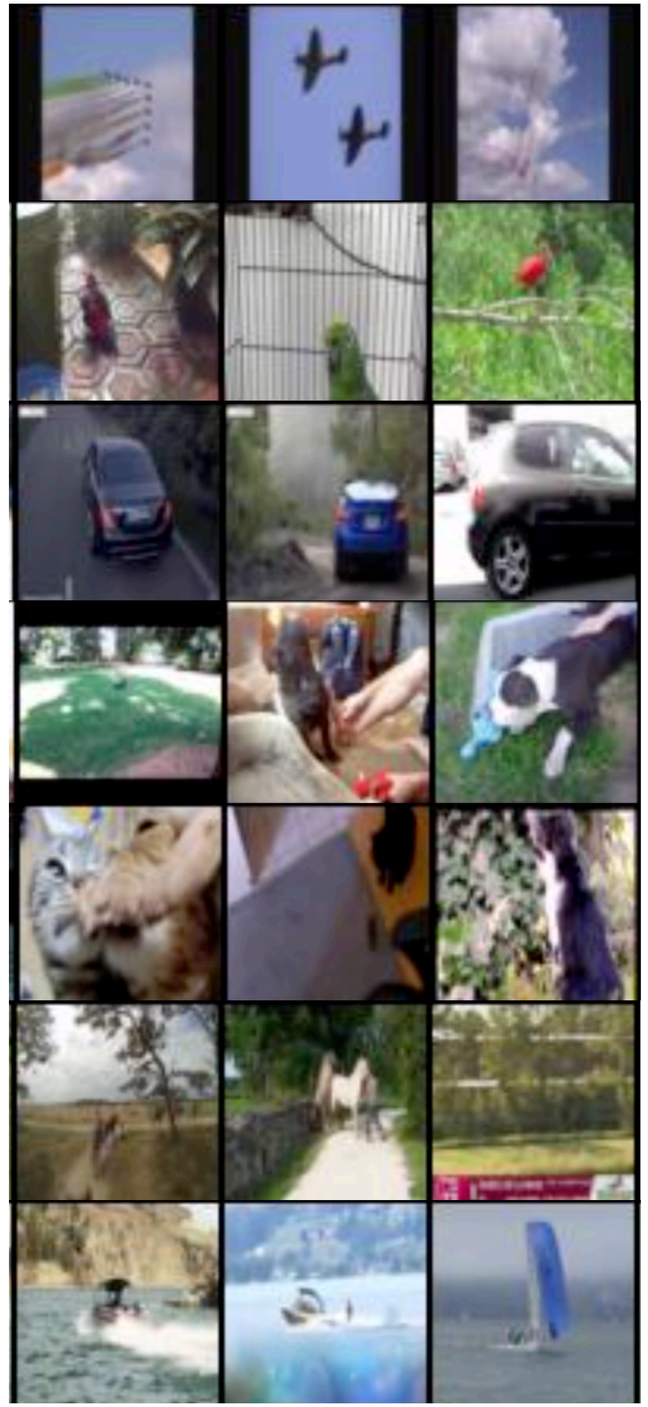
Using Self-Supervised Learning Can Improve Model Robustness and Uncertainty
Hendrycks, Mazeika, Kadavath and Song, 2019

The online version on ImageNet-C



From still images to videos

- Videos of objects in motion
- 7 classes from CIFAR-10
- 30 classes from ImageNet
- Train on CIFAR-10 / ImageNet
- Test on video frames



A systematic framework for natural perturbations from videos
Shankar, Dave, Roelofs, Ramanan, Recht and Schmidt, 2019

Results

Method	CIFAR-10 accuracy (%)	ImageNet accuracy (%)
Object recognition task only	41.4	62.7
Joint training (Hendrycks et al. 2019)	42.4	63.5
TTT standard	45.2	63.8
TTT online	45.4	64.3

Positive examples

Join training: dog
TTT: elephant

Join training: dog
TTT: cattle

Join training: car
TTT: bus

Results

Method	CIFAR-10 accuracy (%)	ImageNet accuracy (%)
Object recognition task only	41.4	62.7
Joint training (Hendrycks et al. 2019)	42.4	63.5
TTT standard	45.2	63.8
TTT online	45.4	64.3

Negative examples

Join training: hamster

TTT: cat

Join training: snake

TTT: lizard

Join training: turtle

TTT: lizard

Results

Method	CIFAR-10 accuracy (%)	ImageNet accuracy (%)
Object recognition task only	41.4	62.7
Joint training (Hendrycks et al. 2019)	42.4	63.5
TTT standard	45.2	63.8
TTT online	45.4	64.3

Negative examples

Join training: airplane

TTT: bird

Join training: airplane

TTT: watercraft

Rotation prediction is quite limiting!

CIFAR-10.1

- New test set on CIFAR-10
- Cannot notice the distribution shifts
- Still an open problem

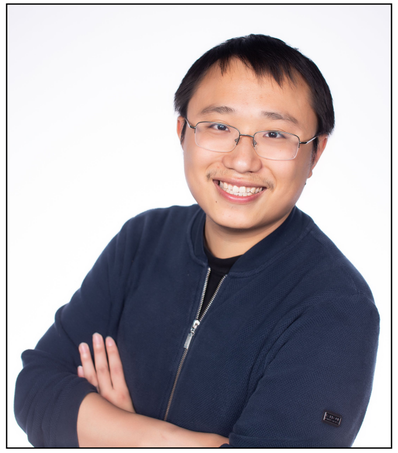
Results

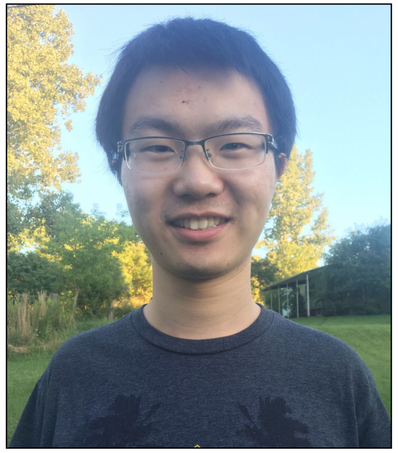
Method	Error (%)
Object recognition task only	17.4
Joint training (Hendrycks et al. 2019)	16.7
TTT standard	15.9

Do CIFAR-10 Classifiers Generalize to CIFAR-10?
Recht, Roelofs, Schmidt and Shankar, 2019

Conclusion

- Boundary between labeled and unlabeled samples
  - Broken down by self-supervision
- Boundary between training and testing
  - We are trying to break this down


Xiaolong Wang


Zhuang Liu


John Miller


Alyosha Efros


Moritz Hardt