# Open World Lifelong Learning
## A Continual Machine Learning Course

**Teacher**

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hessian.AI-DEPTH junior research group leader on Open World Lifelong Learning (OWLL)
& researcher in the Artificial Intelligence and Machine Learning (AIML) group at TU Darmstadt

**Time**

Every Tuesday 17:30 - 19:00 CEST

**Course Homepage**

http://owll-lab.com/teaching/cl_lecture

https://www.youtube.com/playlist?list=PLm6QXeaB-XkA5-lVBB-h7XeYzFzgSh6sk

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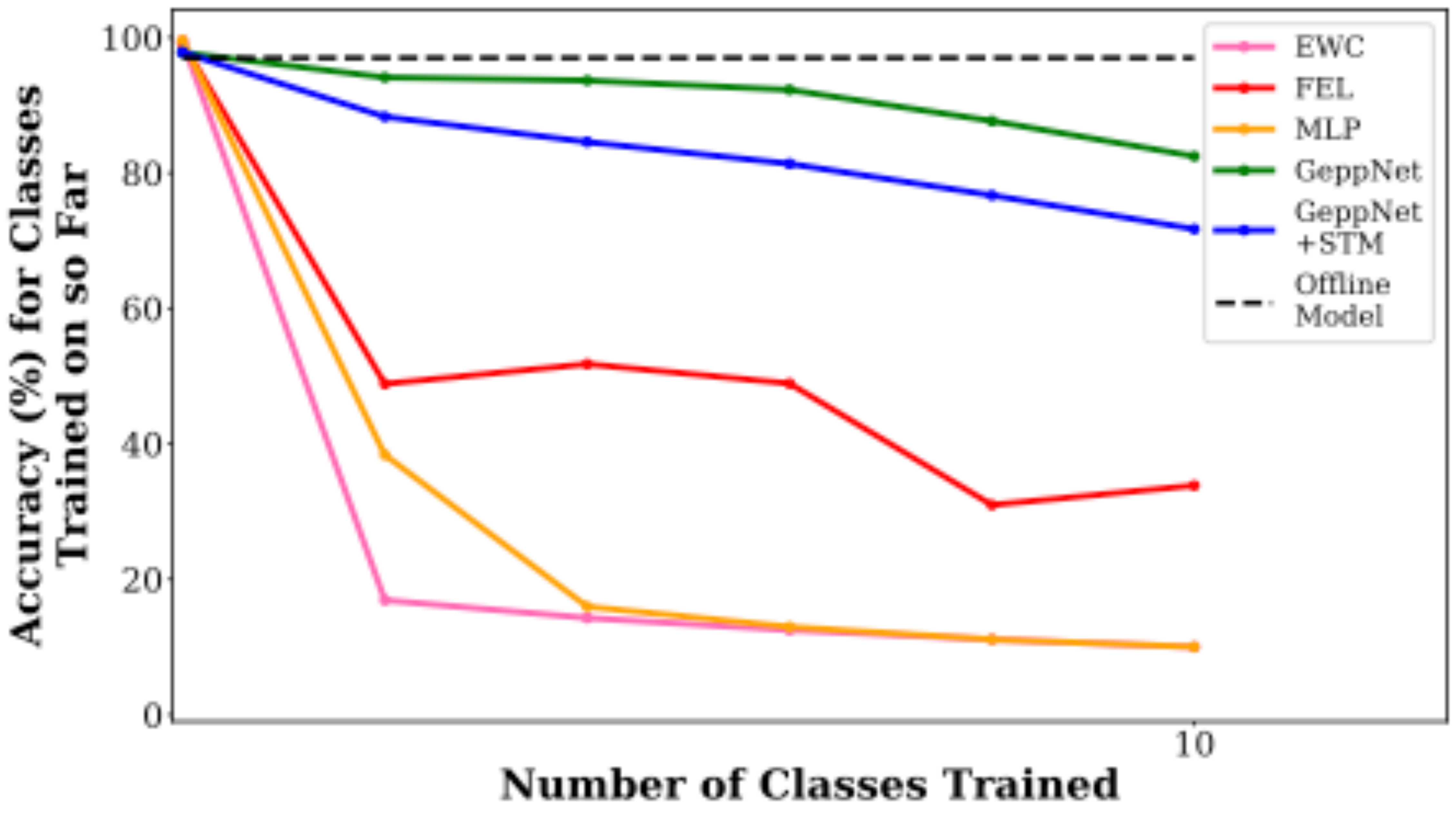
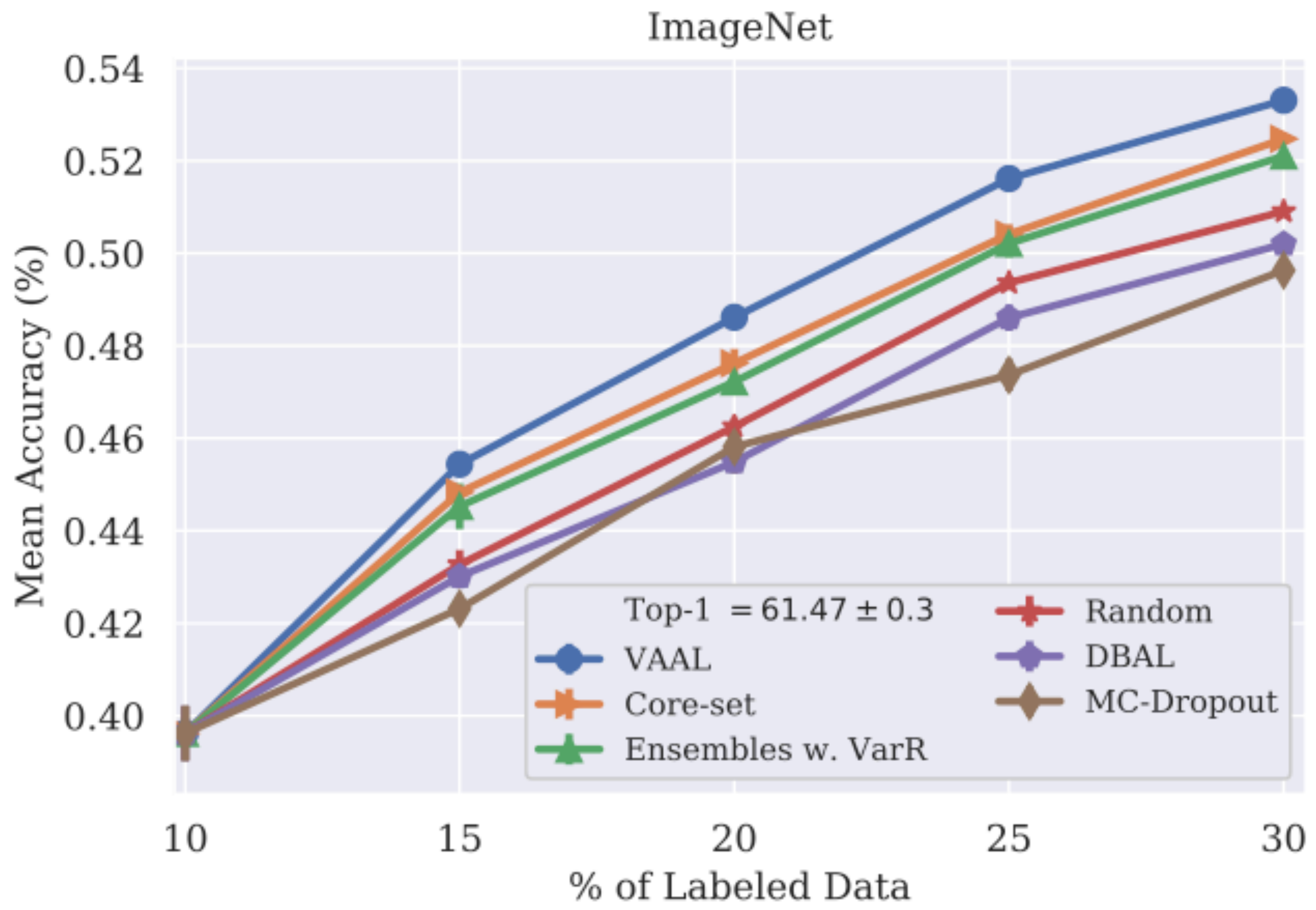
# Week 8: Open world learning - learning & prediction in the presence of the unknown

# Recall sequences so far

**We've discussed various ways to measure + assumptions, but so far it was always clear what to test on**



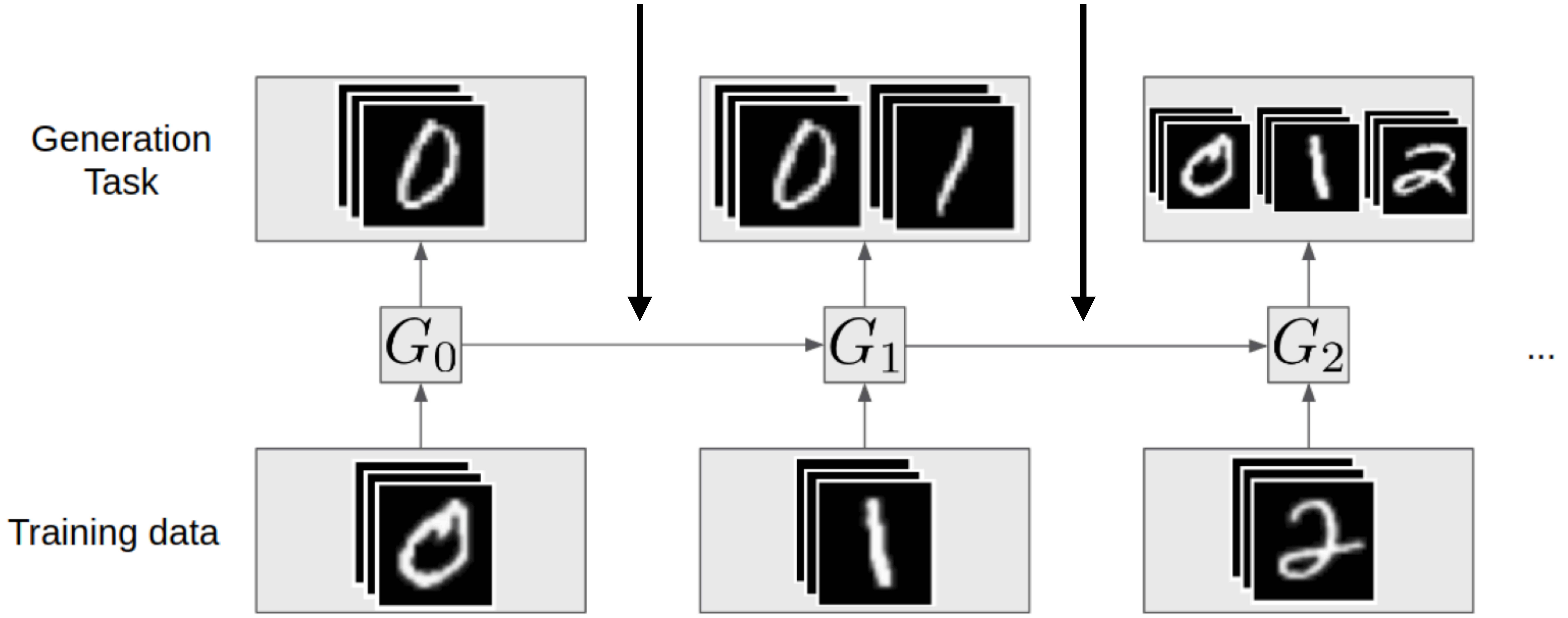

Kemker et al, "Measuring Catastrophic Forgetting in Neural Networks", AAAI 2018




Sinha et al, "Variational Adversarial Active Learning", ICCV 2019

# Recall: the tasks we considered

**What if we don't know the boundary & aren't constrained on our testing examples?**




Lesort et al, "Generative Models from the perspective of Continual Learning", IJCNN 2019

# Recall: the tasks we considered

**What if we don't know the boundary & aren't constrained on our testing examples?**

What if future or unrelated data is in the test set?

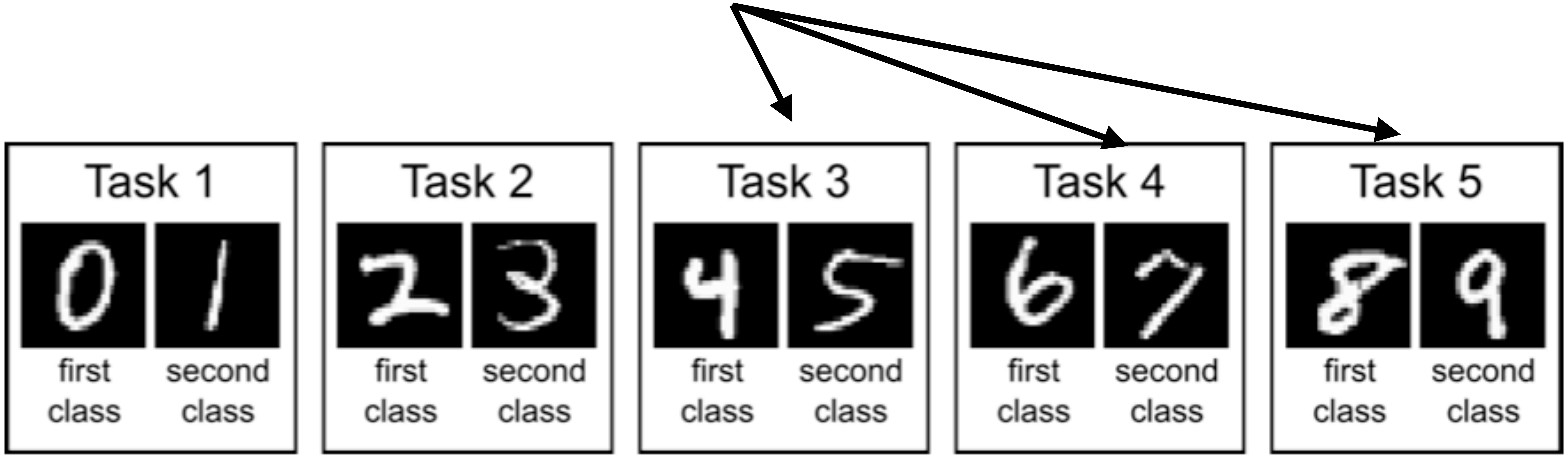
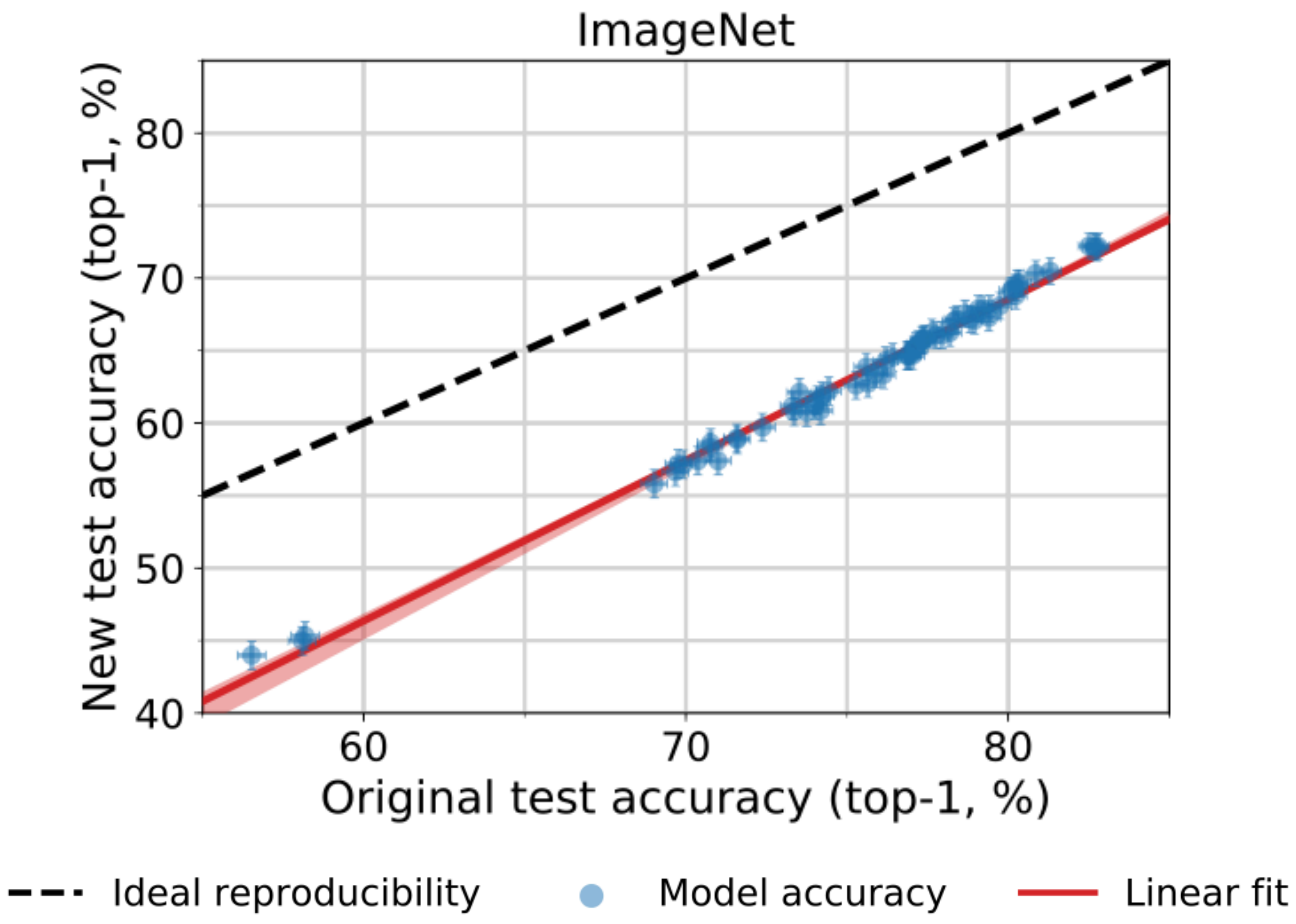



Figure 1: Schematic of split MNIST task protocol.

van de Ven & Tolias, "Three scenarios for continual learning", arXiv:1904.07734, 2019

# Recall: distribution shifts




**Recall: natural data distributions are complex & can easily shift!**

Performance loss even happens if we recollect another "test set" with the same instructions a second time!

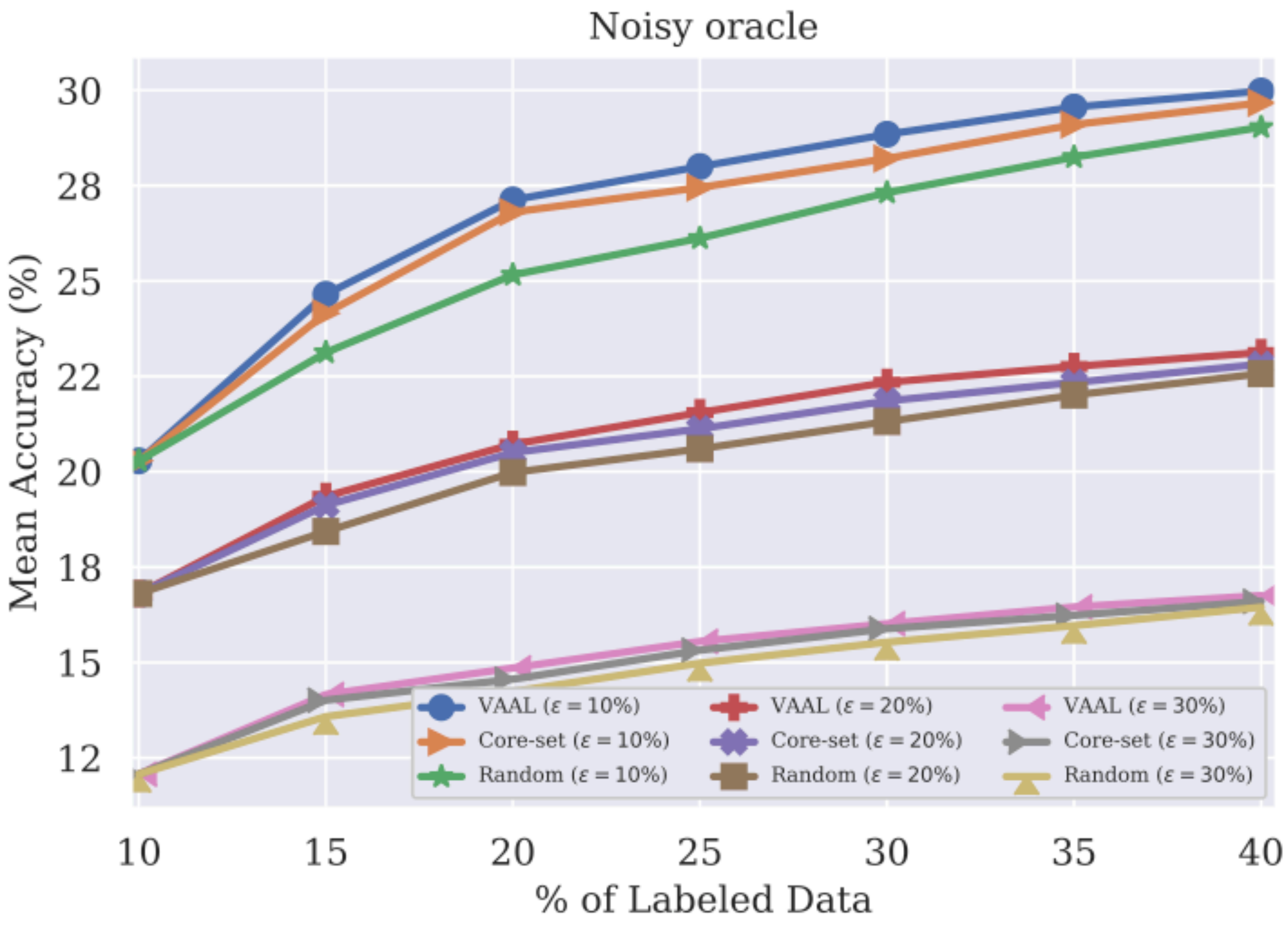
Recht et al, "Do ImageNet Classifiers Generalize to ImageNet?", ICML 2019

# Recall: noisy oracles

## Recall our active learning assumptions:

- *Oracle is infallible:*
  the teacher/labeler does not make mistakes!

- *Pool belongs to task*:
  we will cover this in our lecture on "learning and the unknown"




Sinha et al, "Variational Adversarial Active Learning", ICCV 2019

# Perspectives to address these challenges

# More than known vs. unknown

1. **Known knowns:**

    Do you have an intuition what these 4 categories could represent?

2. **Known unknowns:**

3. **Unknown unknowns:**

4. **Unknown knowns:**

# More than known vs. unknown

1. **Known knowns:**

   Examples belong to the distribution from training set was drawn. Assumption of an accurate & confident prediction.

2. **Known unknowns:**

3. **Unknown unknowns:**

4. **Unknown knowns:**

# More than known vs. unknown

1. **Known knowns:**

   Examples belong to the distribution from training set was drawn. Assumption of an accurate & confident prediction.

2. **Known unknowns:**

   Unknown examples where models are not confident or uncertainty is high. Can be optionally "negatively" labelled examples used in training.

3. **Unknown unknowns:**

4. **Unknown knowns:**

# More than known vs. unknown

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2. **Known unknowns:**

   Unknown examples where models are not confident or uncertainty is high. Can be optionally “negatively” labelled examples used in training.

3. **Unknown unknowns:**

   Unseen instances belonging to unexplored & unknown data distributions. Predictions generally overconfident & by definition false.

4. **Unknown knowns:**

# More than known vs. unknown

1. **Known knowns (*or simply knowns*):**

   Examples belong to the distribution from training set was drawn. Assumption of an accurate & confident prediction.

2. **Known unknowns:**

   Unknown examples where models are not confident or uncertainty is high. Can be optionally “negatively” labelled examples used in training.

3. **Unknown unknowns:**

   Unseen instances belonging to unexplored & unknown data distributions. Predictions generally overconfident & by definition false.

4. **Unknown knowns:**

   Usually not considered: we know the concept but choose to treat it as unknown (willful ignorance?) or our ML system cannot represent the concept + structure altogether

# Three types of approaches

**What do you think: how can we solve our challenge?**

# Three types of approaches

**Anomalies in predictions:**
The *unsuspecting angle*, where out-of-distribution are hopefully separable through anomalous output values.

**Incorporating prior knowledge:**
The *intuitive idea* to include “background” or “non-example” data population explicitly.

**Open Set recognition:**
The more *formal approach* ensures that we only rely on predictions from our “covered space”; we create bounds.

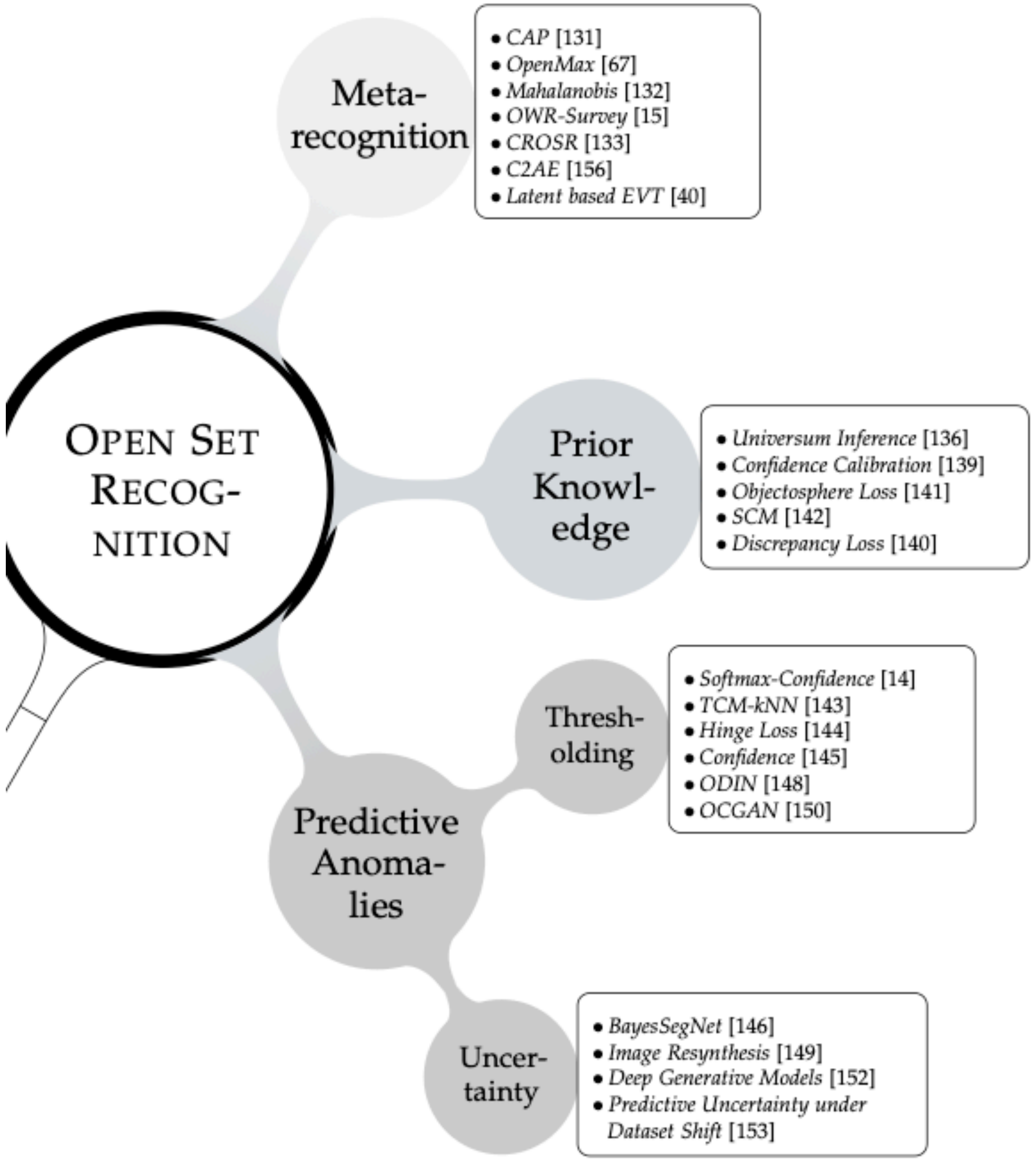
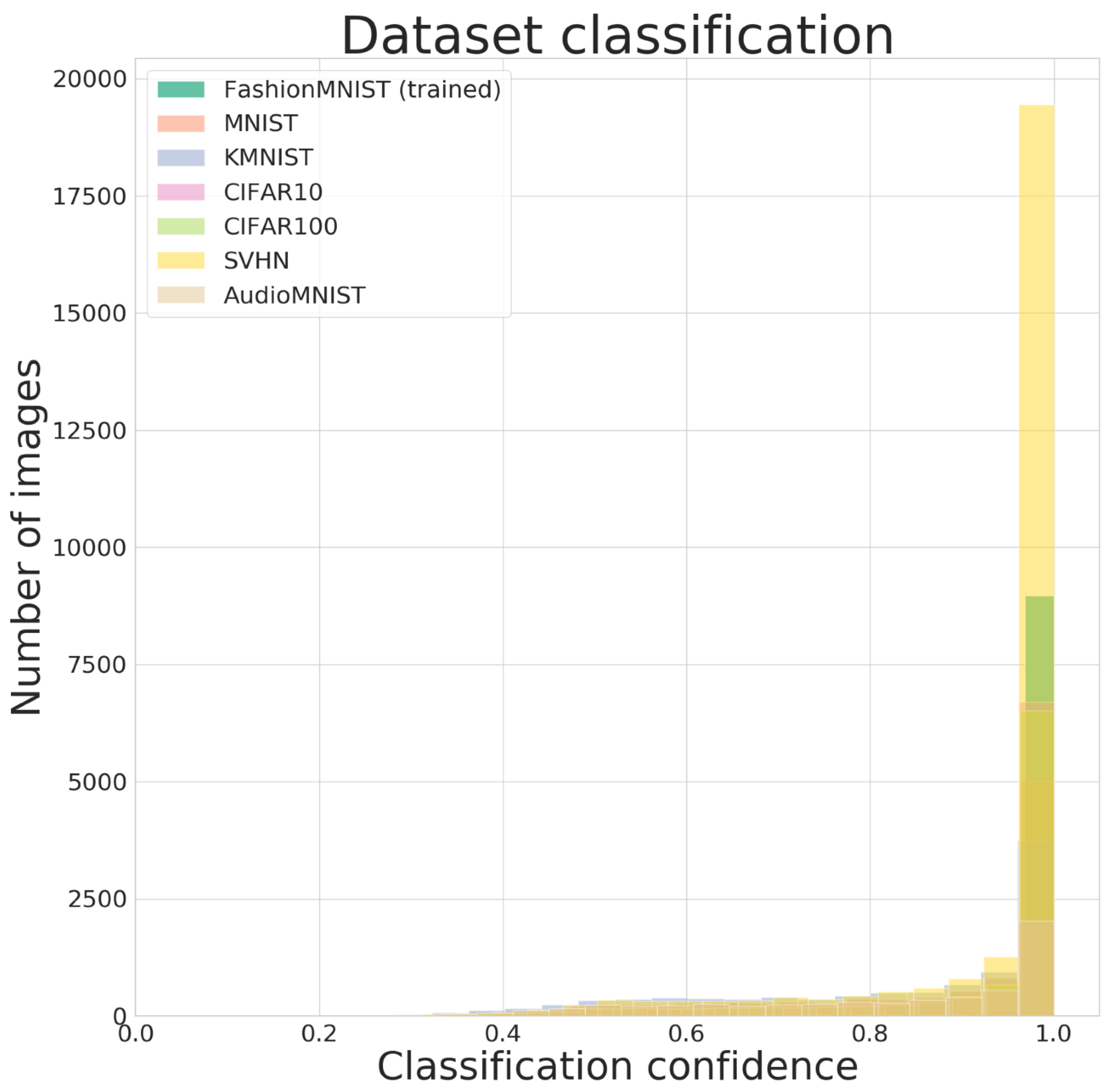



Figure from “A Wholistic View of Deep Neural Networks: Forgotten Lessons and the Bridge to Active and Open World Learning”, Mundt et al 2020

# Predictive anomalies:
# the unfortunate part of the story

**Disclaimer: I'll use my many figures from our papers for convenience, without trying to imply that we discovered these phenomena**

# Recall lecture 1: overconfidence




**Recall the quantitative example**:

1. Train a neural network classifier on a dataset (here fashion items)
2. Log predictions for arbitrary other datasets
3. Observe that majority of misclassifications happen with large output "probability"

# Overconfidence & uncertainty

**Unfortunately uncertainty is not a necessarily a “fix”**

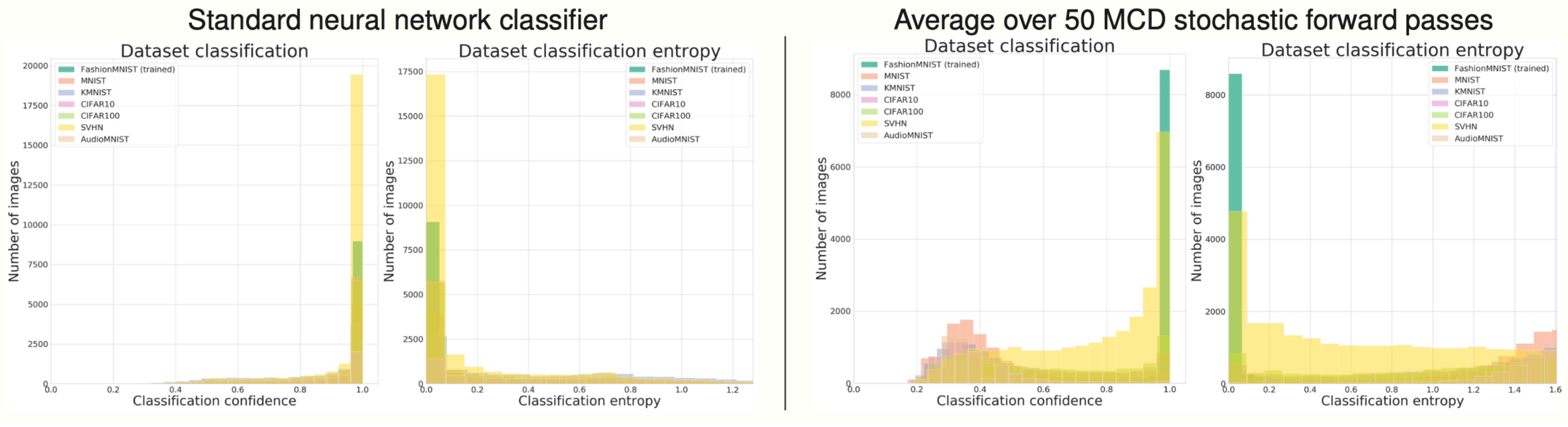
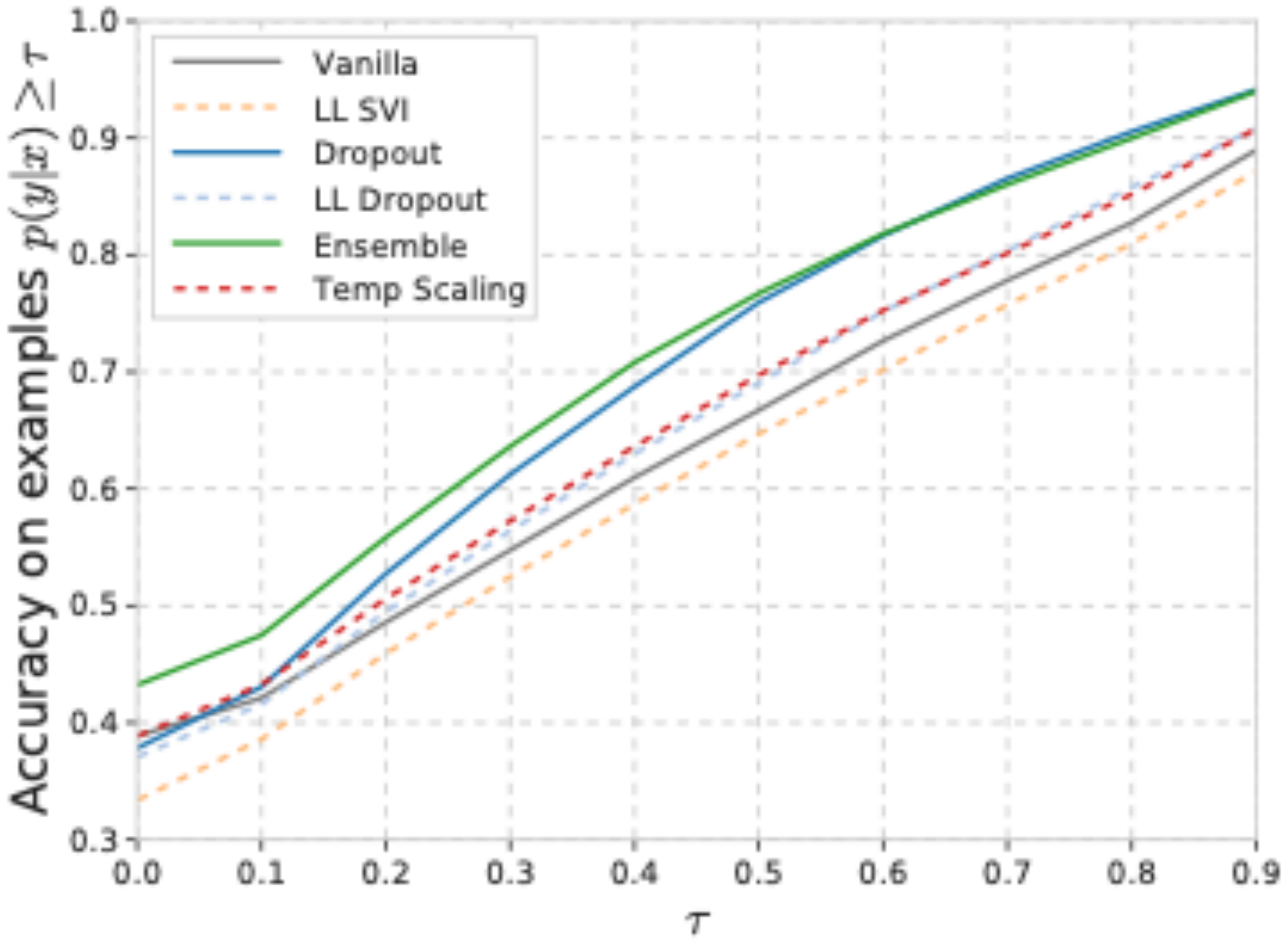


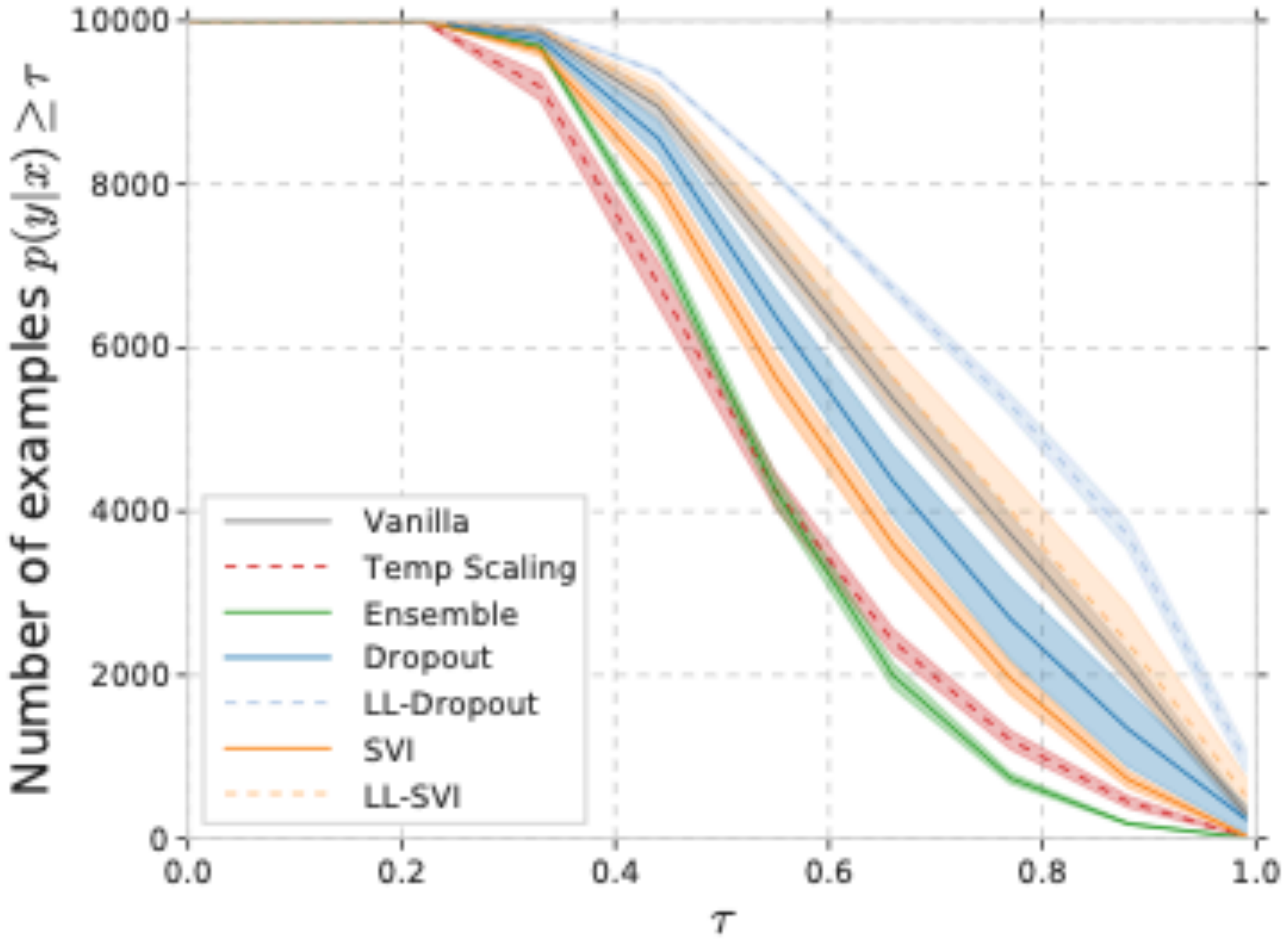

Figure from Mundt et al “Open Set Recognition Through Deep Neural Network Uncertainty, Does Out-of-Distribution Detection Require Generative Classifiers?”, ICCVW 2019

# Overconfidence & uncertainty

**Unfortunately uncertainty is not a necessarily a “fix”**
**& it get’s even harder when we try to select a threshold**




(d) ImageNet: Confidence vs Acc




(f) CIFAR: Confidence on OOD

Ovadia & Fertig et al, “Can you trust your model’s uncertainty?” Evaluating predictive uncertainty under dataset shift”, NeurIPS 2019

# Overconfidence & gen. models

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**& it get's even harder when we try to select a threshold**

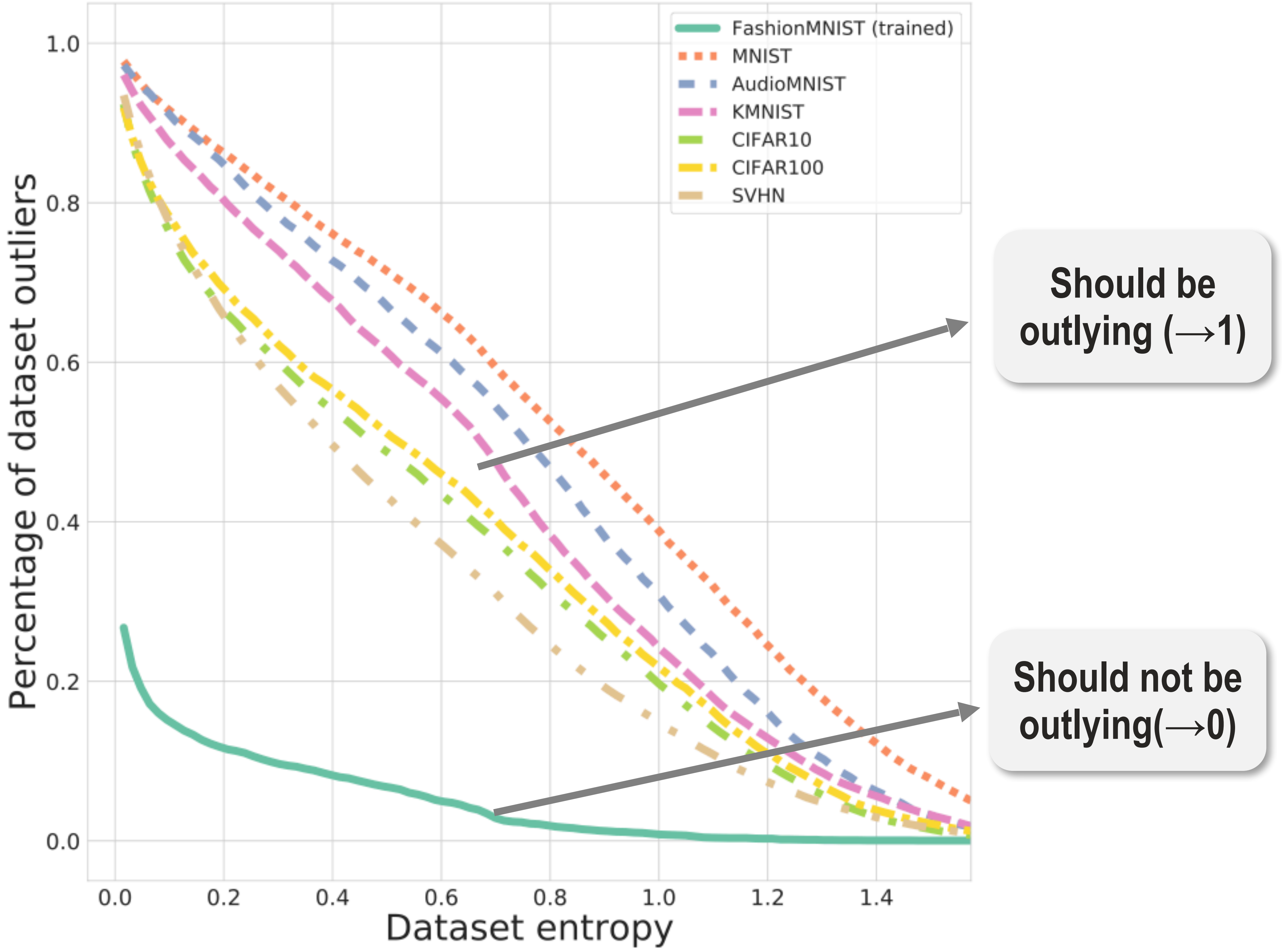
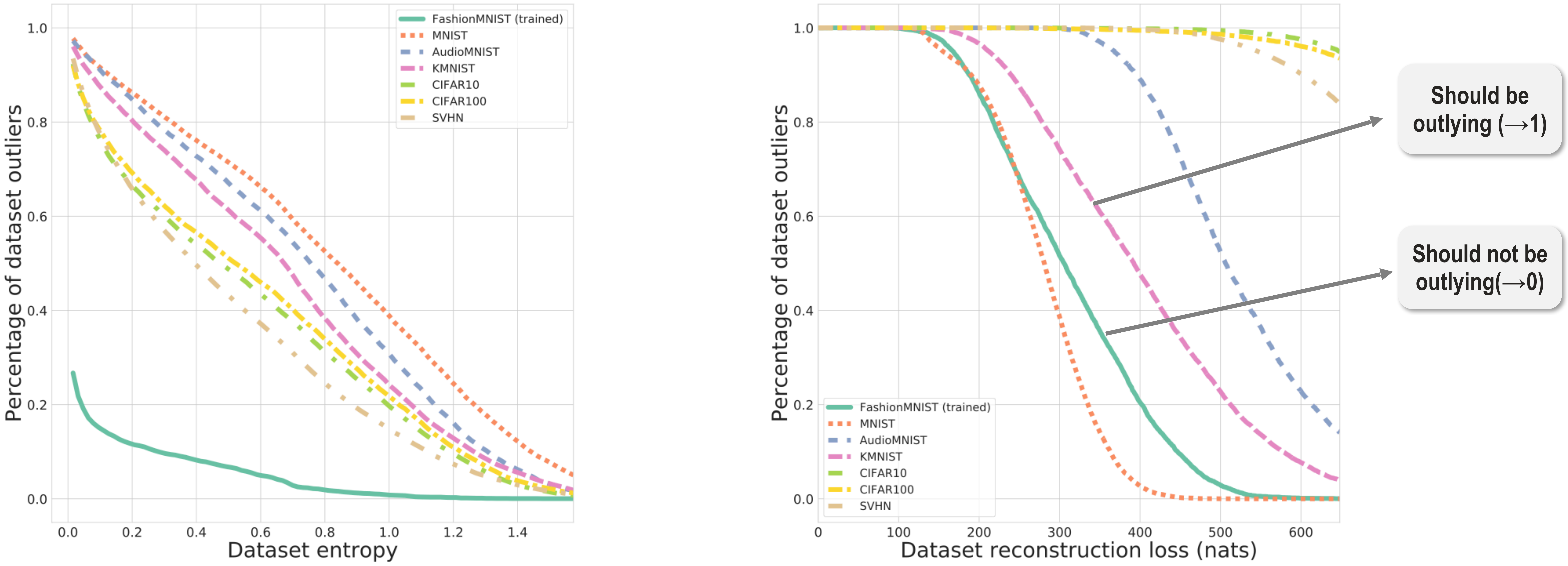



Figure from Mundt et al, "Unified Probabilistic Deep Continual Learning Through Open Set Recognition and Generative Replay", Journal of Imaging, Volume 8, Issue 4, 2022

# Overconfidence & uncertainty

## Overconfidence is not exclusive to discriminative models

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# Overconfidence & gen. models

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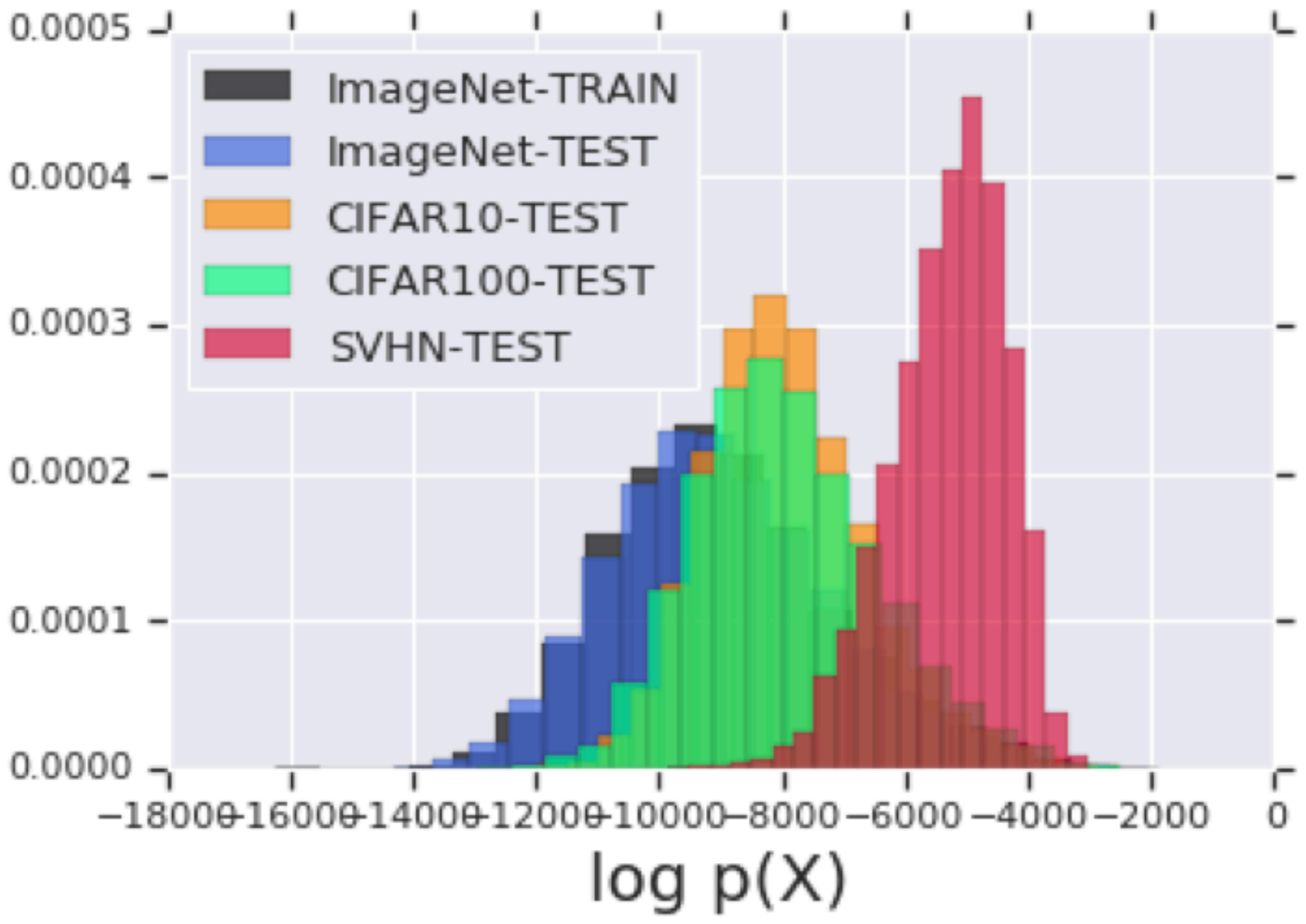
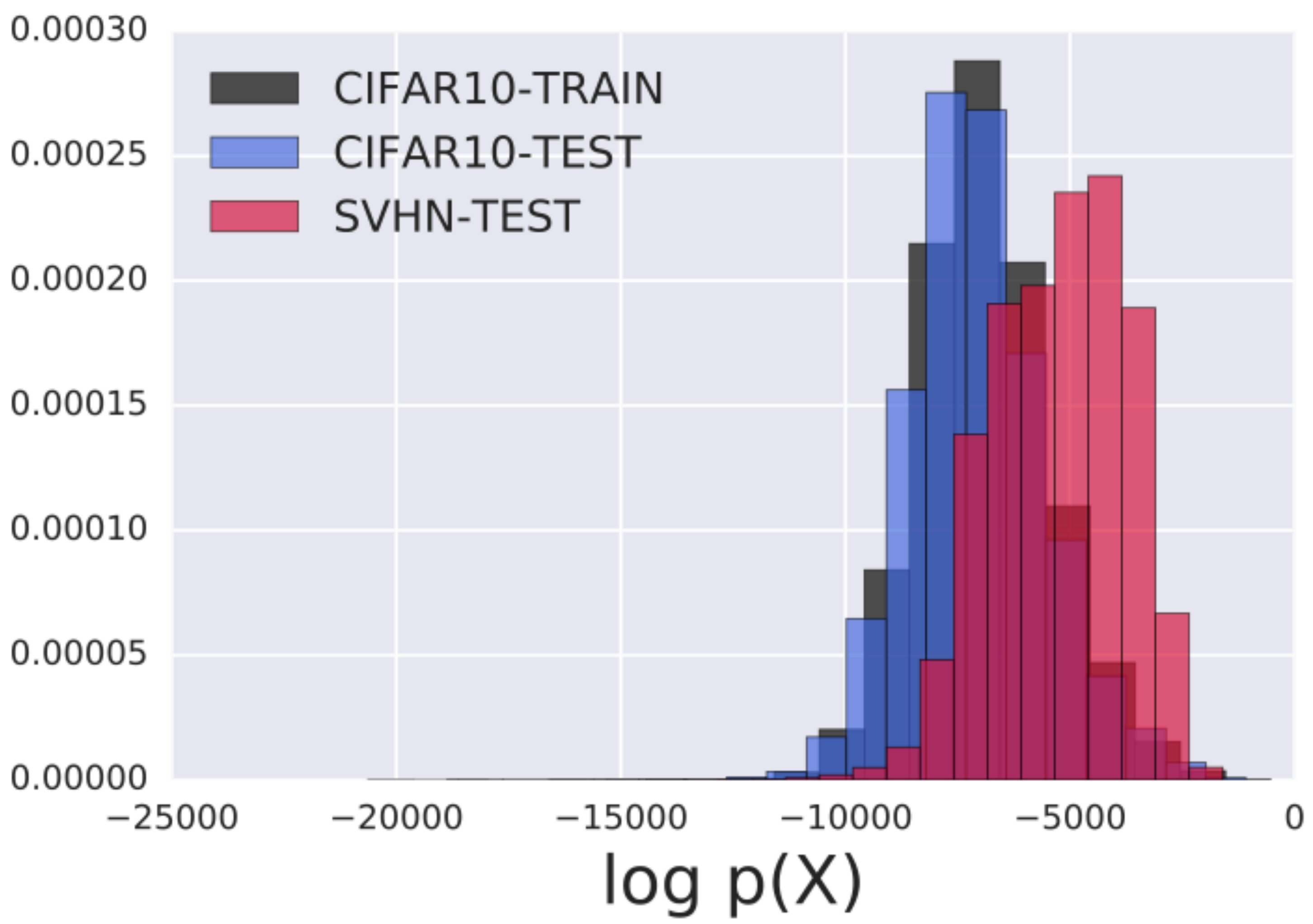
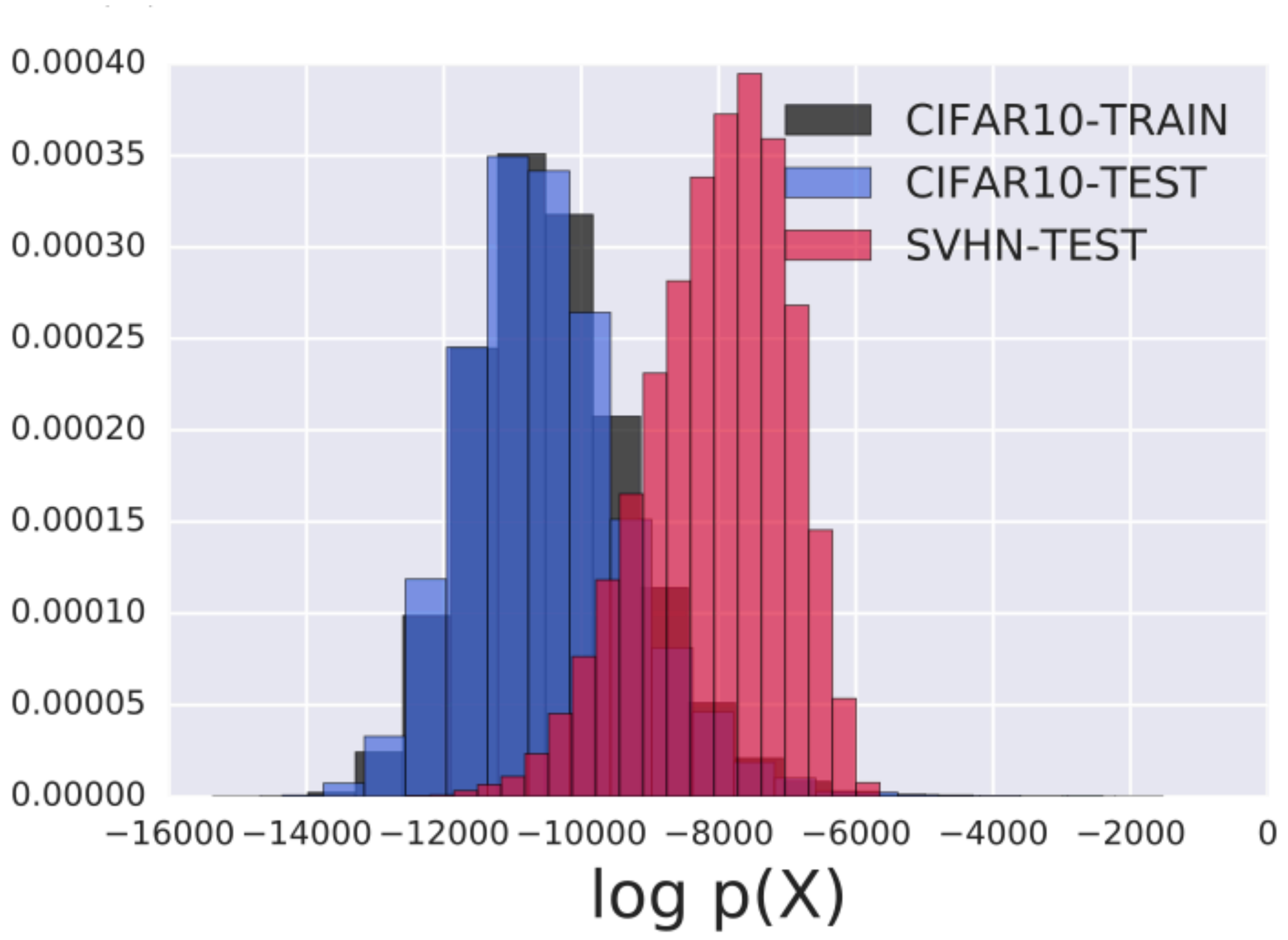



**Glow**




**PixelCNN**



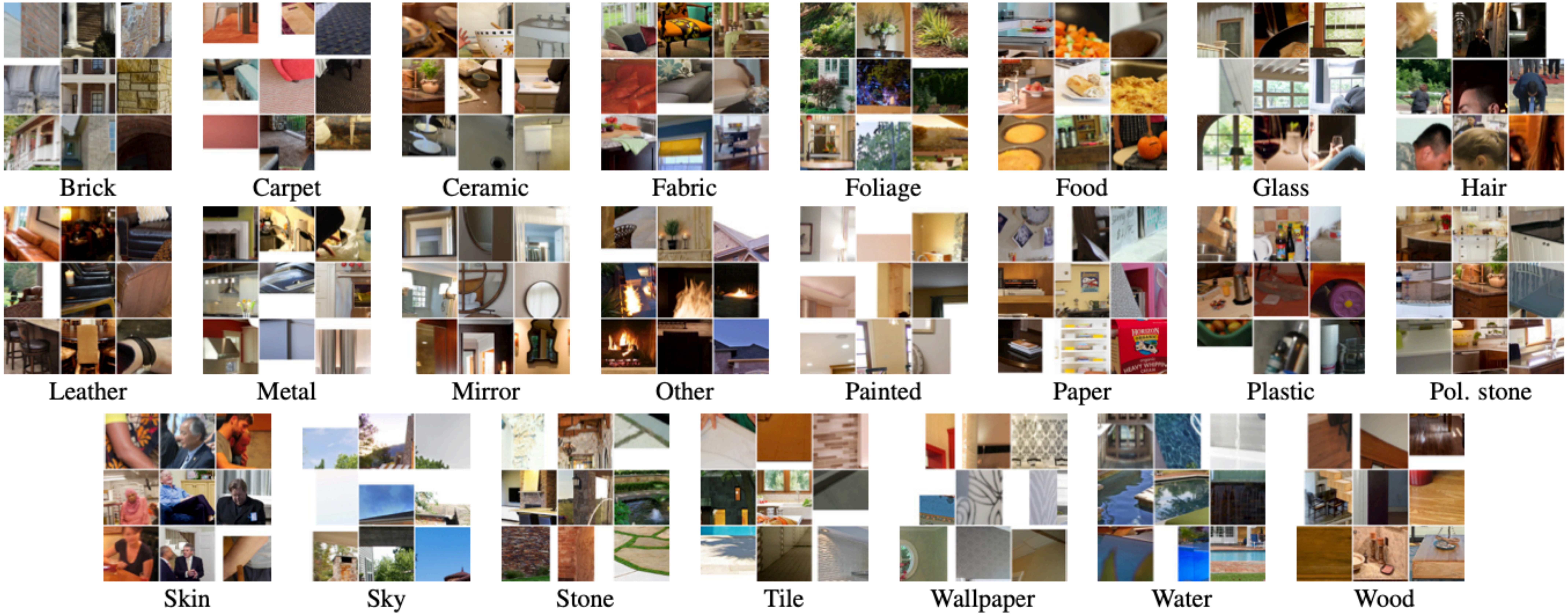

**VAE**

Nalisnick et al, “Do Deep Generative Models Know What They Don’t Know”, ICLR 2019

# Including prior knowledge: an alternative?

# The intuitive idea

**Take a look at the below Materials in Context (MINC) dataset: what do you notice?**




Bell & Upchurch et al, “Material Recognition in the Wild with the Materials in Context Database”, CVPR 2015

# The intuitive idea

**An intuitive idea is to incorporate everything we know that does not belong to our task(s)**


Bell & Upchurch et al, "Material Recognition in the Wild with the Materials in Context Database", CVPR 2015

# Inference with the universum

In essence: include **background class / "non-examples"** that aren't of interest

Key questions:

- How to implement the loss: many many conceivable conceivable
  (Disclaimer: possibly *uncountable* amount of works)
- "what part of the universum is useful" ("Inference with the universum", Weston et al, ICML 2006)
- "what are we expected to see during prediction later"? (Noise? Other concepts? Etc.)

# Calibration: some examples

1. We could let our predictions (classifier) explicitly follow a uniform distribution for “out” data

(Kimin Lee et al, “Training confidence-calibrated classifiers for detecting out-of-distribution samples”, ICLR 2018)

$$\min_{\theta} \mathbb{E}_{P_{\text{in}}(\widehat{\mathbf{x}},\widehat{y})}\left[-\log P_{\theta}\left(y=\widehat{y}|\widehat{\mathbf{x}}\right)\right]+\beta\mathbb{E}_{P_{\text{out}}(\mathbf{x})}\left[KL\left(\mathcal{U}\left(y\right)\parallel P_{\theta}\left(y|\mathbf{x}\right)\right)\right]$$

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2. We could calibrate our outputs, e.g. by scaling a temperature parameter later

(Liang et al, "Enhancing the reliability of out-of-distribution image detection in neural networks", ICLR 2018)

$$S_i(\boldsymbol{x}; T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})/T\right)}$$

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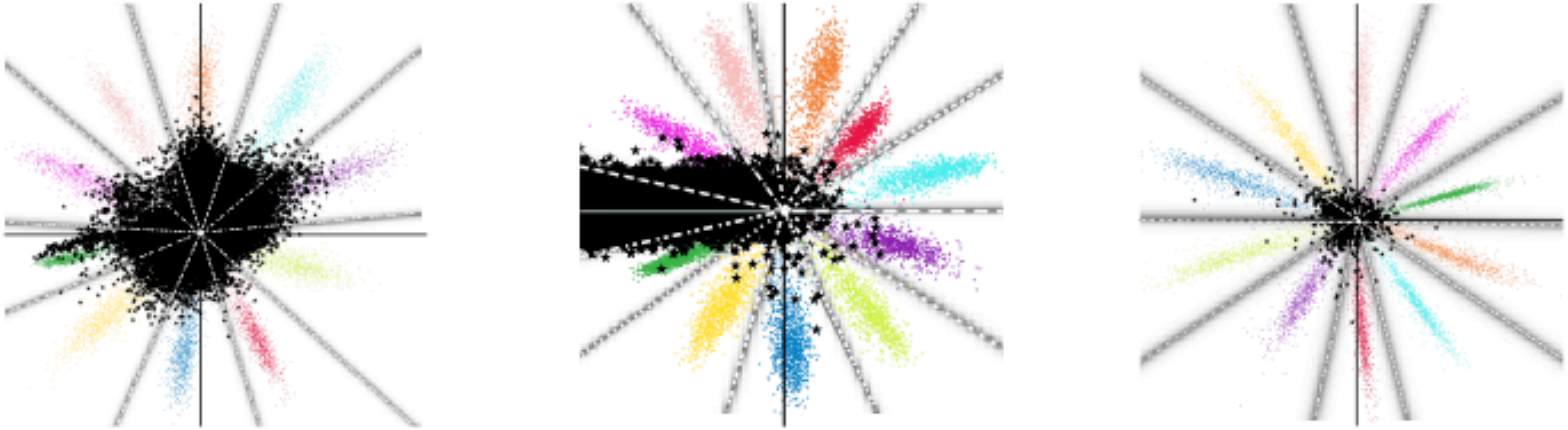
3. And many other versions to modify our loss, e.g.:

$$J_E(x)=\begin{cases}-\log S_c(x) & \text{if } x\in\mathcal{D}'_c \text{ is from class } c\\ -\frac{1}{C}\sum\limits_{c=1}^{C}\log S_c(x) & \text{if } x\in\mathcal{D}'_b\end{cases}$$

(Dhamija et al, “Reducing network agnostophobia”, NeurIPS 2018)

# Background & Objectosphere

**We could also think about encouraging features to be zero for OOD data**



(a) Softmax (b) Background (c) Objectosphere

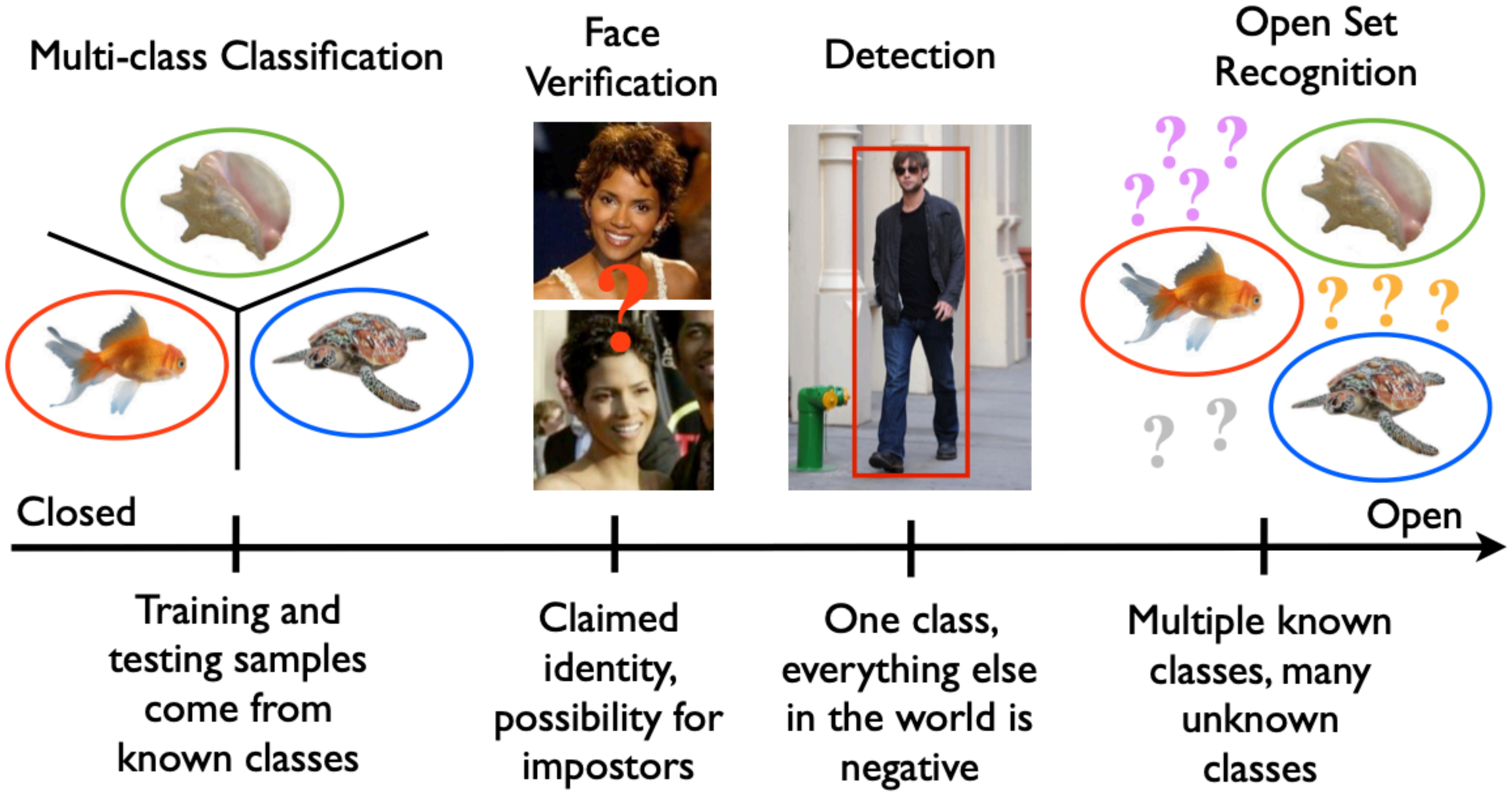
Figure 1: LENET++ RESPONSES TO KNOWNS AND UNKNOWNS. *The network in (a) was only trained to classify the 10 MNIST classes ($\mathcal{D}'_c$) using softmax, while the networks in (b) and (c) added NIST letters [15] as known unknowns ($\mathcal{D}'_b$) trained with softmax or our novel Objectosphere loss.*

Dhamija et al, “Reducing Network Agnostophobia”, NeurIPS 2018

**What do you think are the up & downsides so far?**

# Closed -open world assumption

**We may need a different approach: as the world grows more "open" we move from known unknowns to unknown unknowns. Our two perspectives only handle the former**

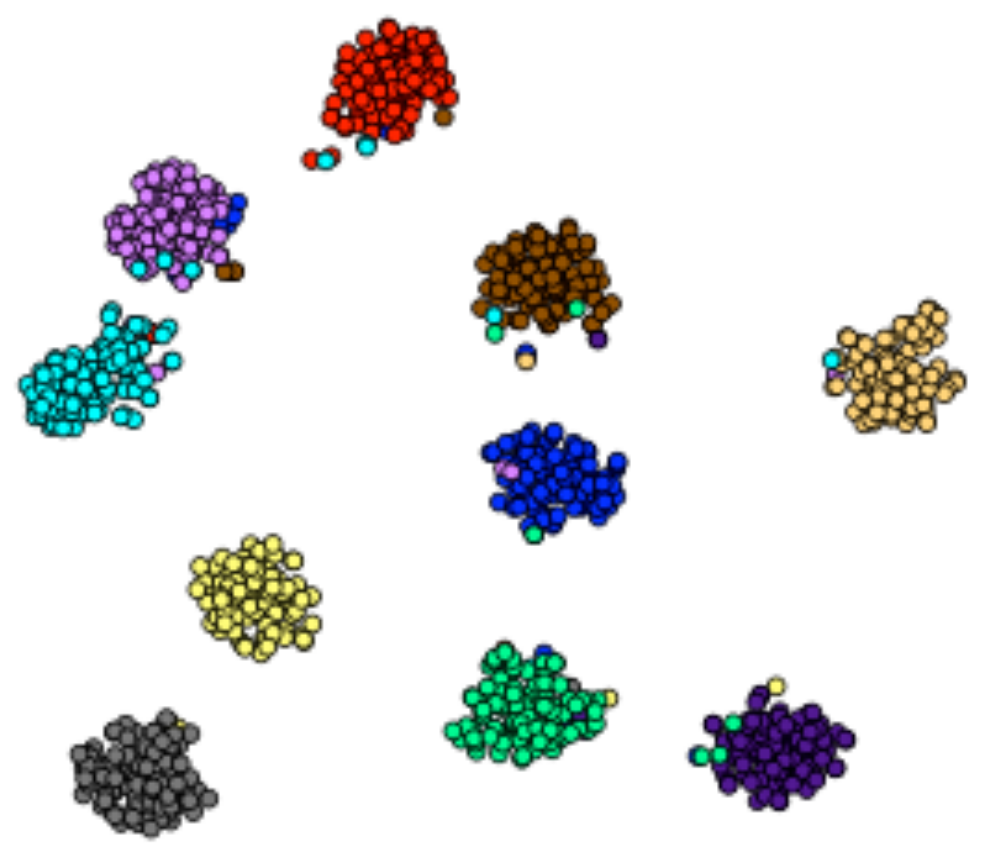



Scheirer et al, "Towards Open Set Recognition", TPAMI 2012

# Open set recognition & explicit bounds

# Intuition behind open space

Intuitively: we could take into account
distances from the known data points



# Intuition behind open space

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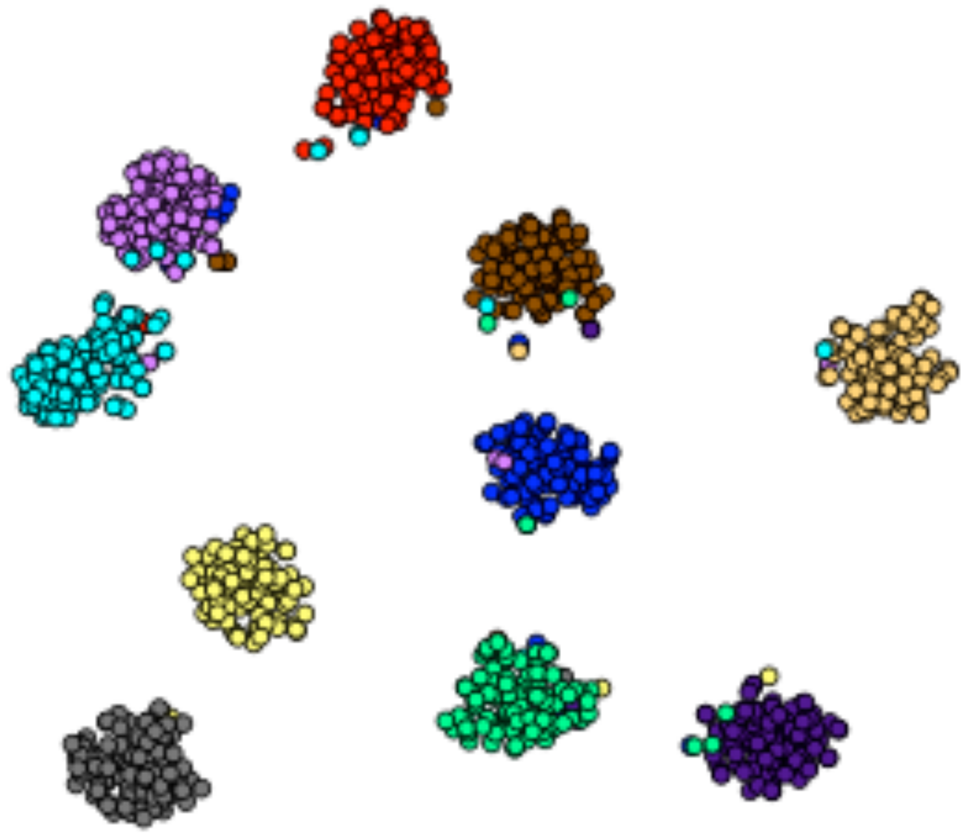
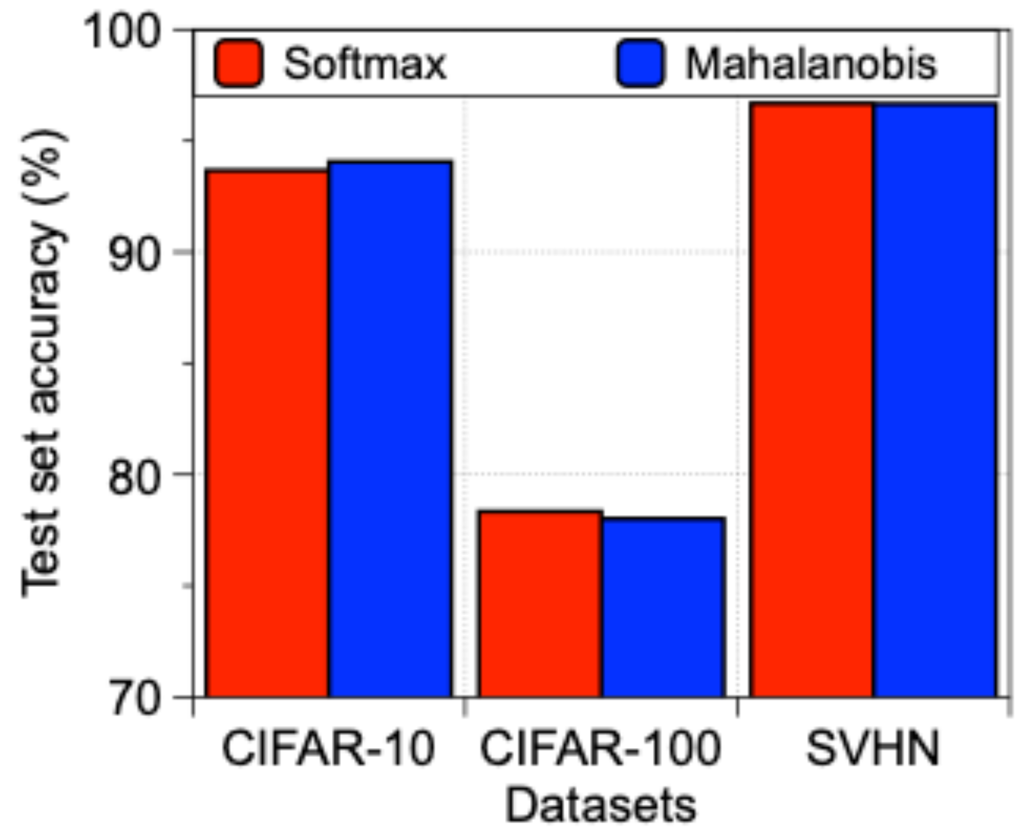
Intuitively: we could take into account distances from the known data points

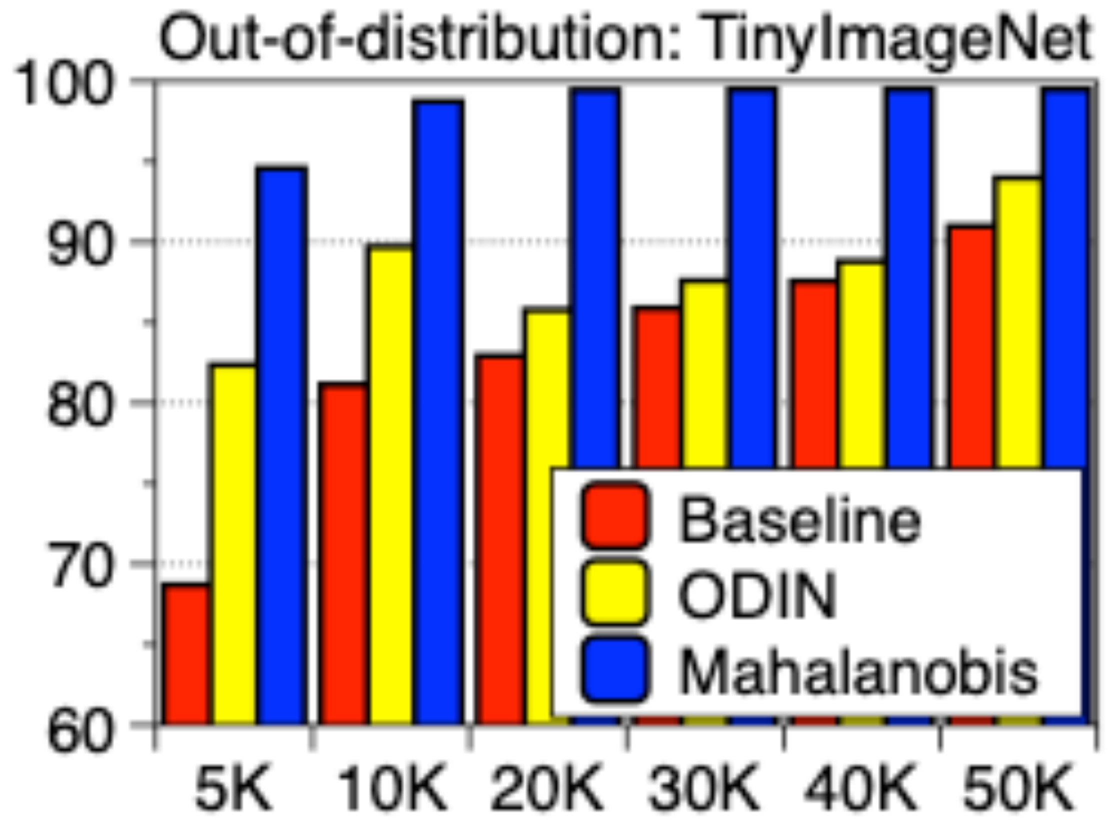
Example 1 : we could make assumptions like every class being Normal distributed & then calculate distances to our existing data points, e.g. Mahalanobis distance

$$\widehat{\mu}_c = \frac{1}{N_c} \sum_{i:y_i=c} f(\mathbf{x}_i), \quad \widehat{\mathbf{\Sigma}} = \frac{1}{N} \sum_c \sum_{i:y_i=c} \left(f(\mathbf{x}_i) - \widehat{\mu}_c\right)\left(f(\mathbf{x}_i) - \widehat{\mu}_c\right)^\top$$

$$M(\mathbf{x}) = \max_c \; -\left(f(\mathbf{x}) - \widehat{\mu}_c\right)^\top \widehat{\mathbf{\Sigma}}^{-1} \left(f(\mathbf{x}) - \widehat{\mu}_c\right)$$





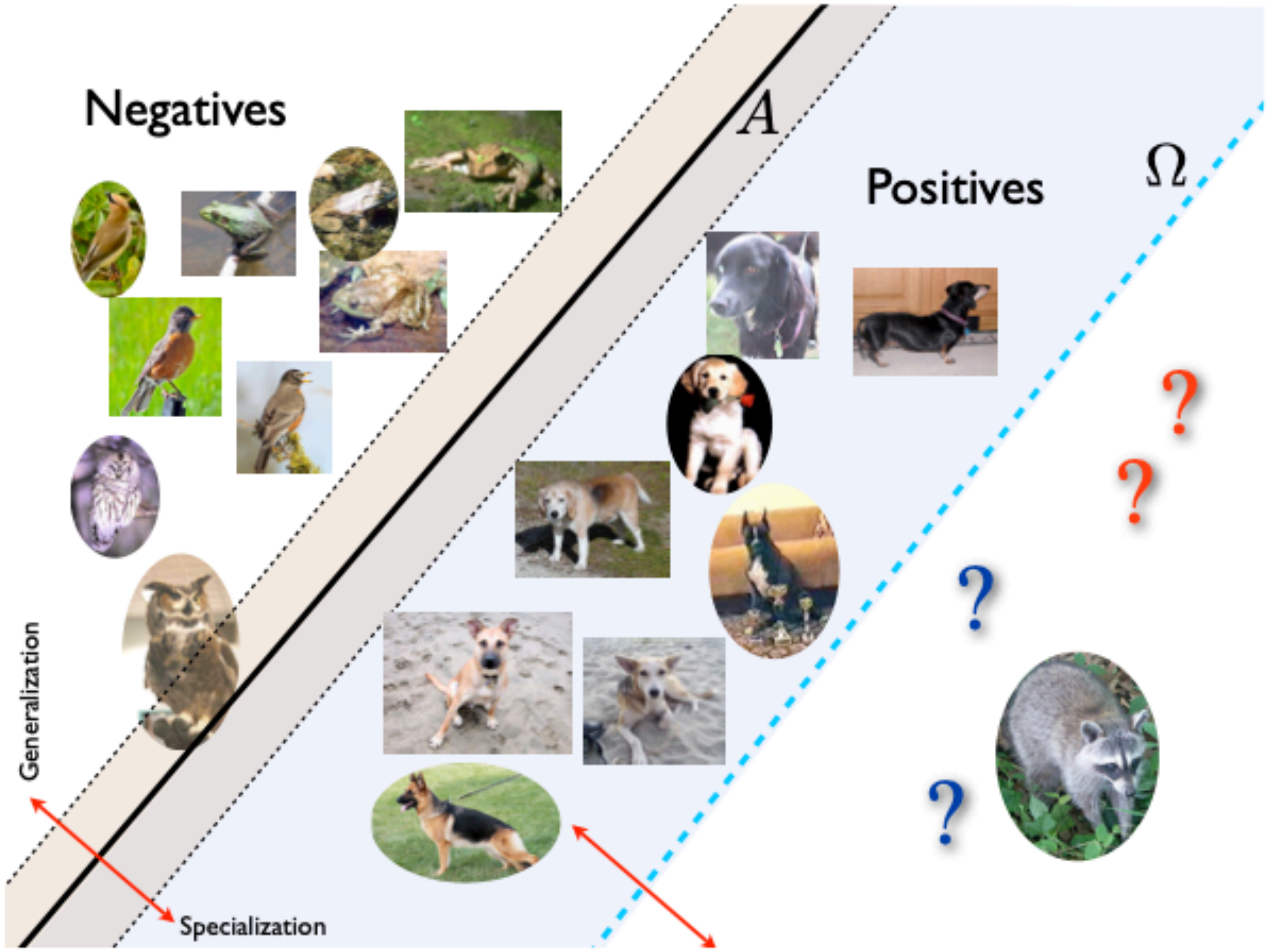




(E.g. Kimin Lee et al, “A Simple Unified Framework for Detecting Out-of-Distribution Samples and Adversarial Attacks”, NeurIPS 2018)

# Intuition behind open space

Intuitively: we could take into account distances from the known data points

Example 2: we could fit another parallel plane in an SVM, for a reject option, based on the support set with large distances




Scheirer et al, “Towards Open Set Recognition”, TPAMI 2012

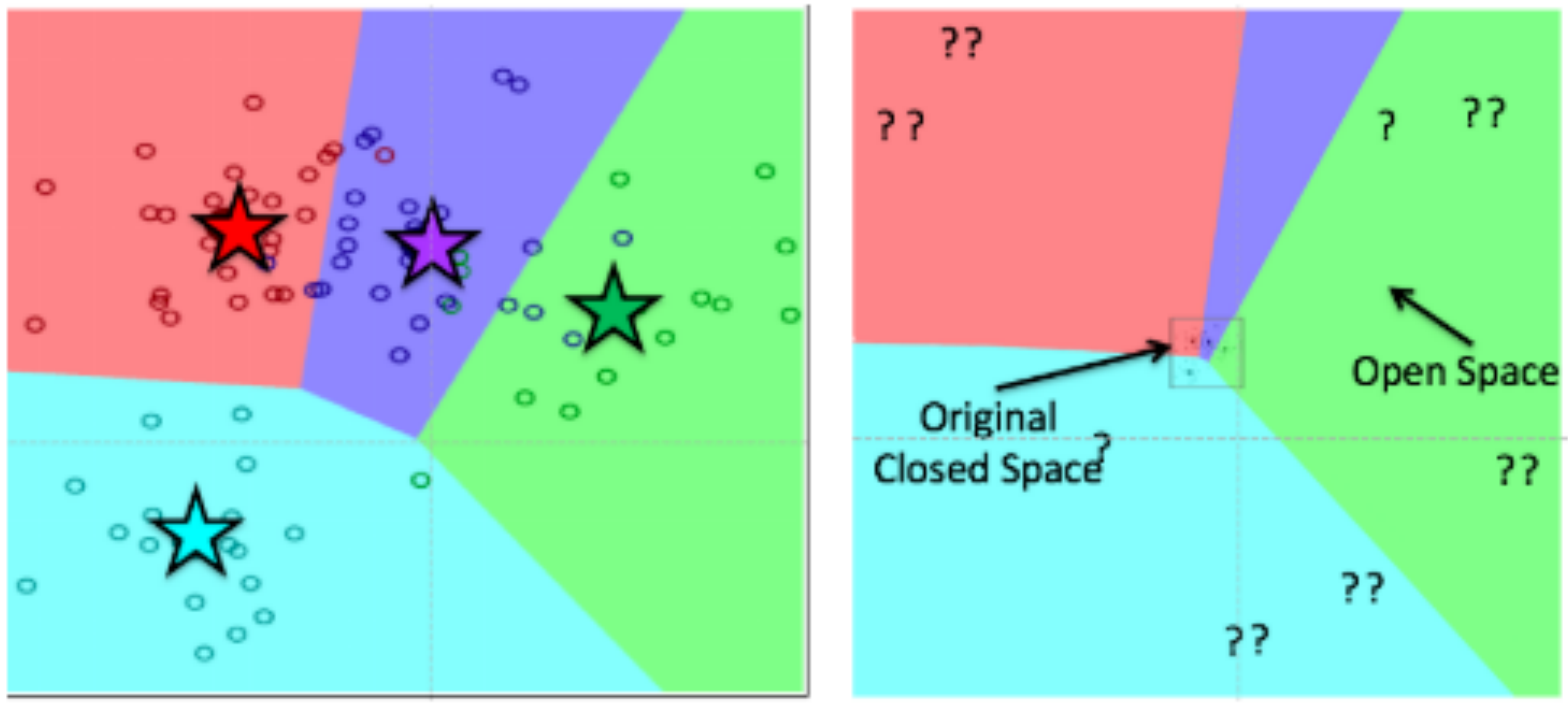
# Formalizing open space/sets

Intuitively: open space is what we have not covered with known data

Formally: (see e.g. “Learning and the Unknown”, Boult et al, AAAI 2019)

For a recognition function function f over space $\mathscr{X}$ & a union of balls with radius r that includes all known training examples:

$$\mathcal{O} = \mathscr{X} - \cup_{i \in N} B_r(x_i)$$

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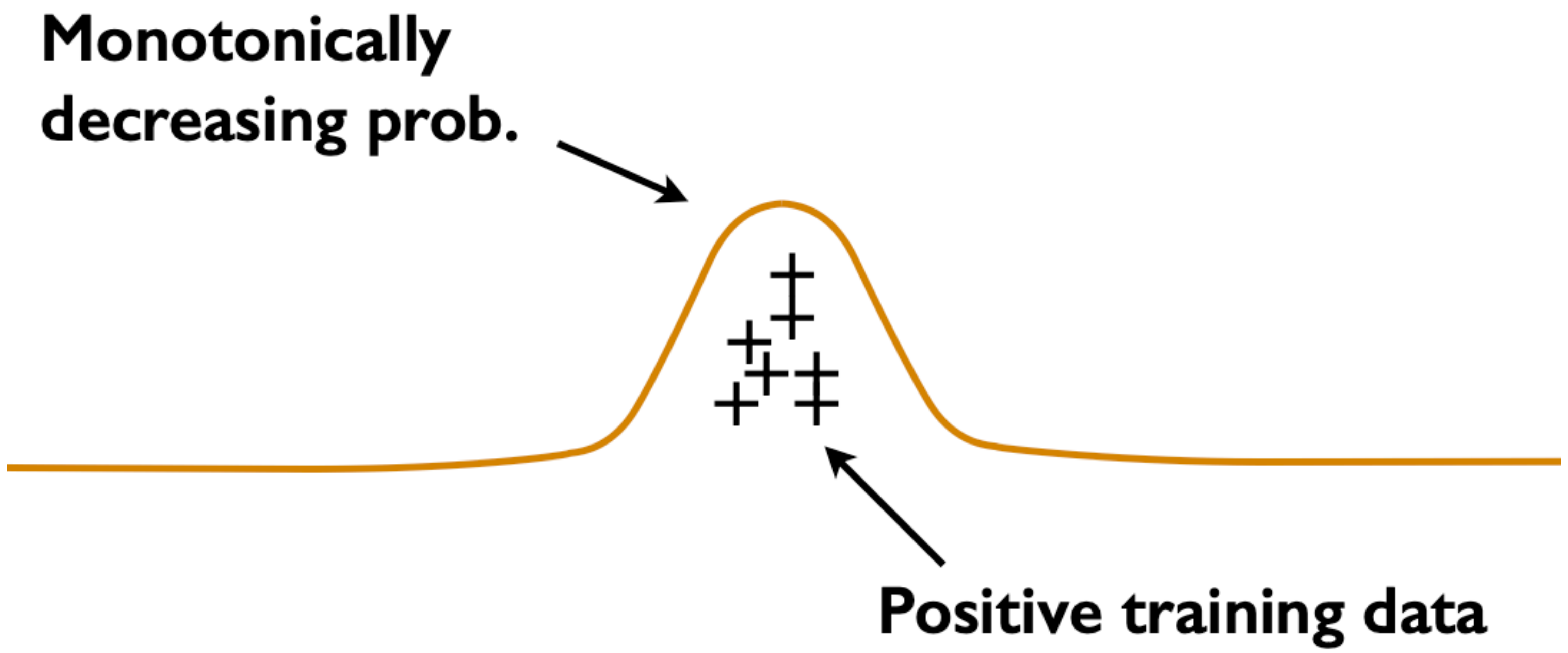
Can now define open space risk as a relative measure of open space to the full space, but see the survey for the full math

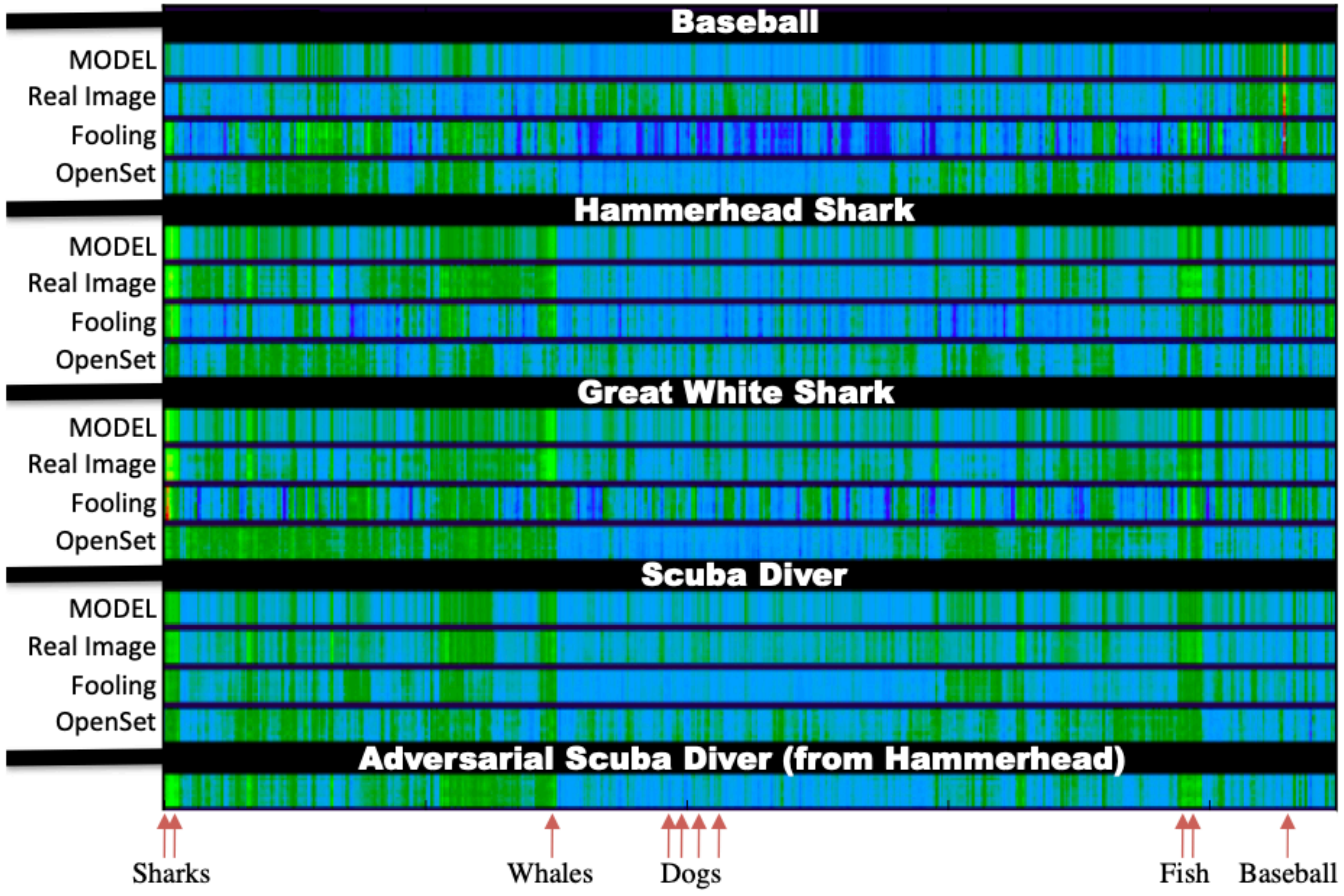
For now: the aim would be to decay the probability away from supporting evidence




Scheirer et al, "Probability Models for Open Set Recognition", TPAMI 2014

# Bounds with extreme values

**In other words, we could fit a distance based model (following the radius idea), e.g. here based on the mean activations of training data in a deep net**




Bendale & Boult et al, "Towards Open Set Deep Networks", CVPR 2016

# Bounds with extreme values

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**Algorithm 1** EVT Meta-Recognition Calibration for Open Set Deep Networks, with per class Weibull fit to $\eta$ largest distance to mean activation vector. Returns libMR models $\rho_j$ which includes parameters $\tau_i$ for shifting the data as well as the Weibull shape and scale parameters:$\kappa_i$, $\lambda_i$.

**Require:** FitHigh function from libMR
**Require:** Activation levels in the penultimate network layer $\mathbf{v}(\mathbf{x}) = v_1(x) \dots v_N(x)$
**Require:** For each class $j$ let $S_{i,j} = v_j(x_{i,j})$ for each correctly classified training example $x_{i,j}$.
1: **for** $j = 1 \dots N$ **do**
2: **Compute mean AV**, $\mu_j = mean_i(S_{i,j})$
3: **EVT Fit** $\rho_j = (\tau_j, \kappa_j, \lambda_j) = \text{FitHigh}(\|\hat{S}_j - \mu_j\|, \eta)$
4: **end for**
5: **Return** means $\mu_j$ and libMR models $\rho_j$

Bendale & Boult et al, “Towards Open Set Deep Networks”, CVPR 2016

# Bounds with extreme values

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**In other words, we could fit a distance based model (following the radius idea), e.g. here based on the mean activations of training data in a deep net**

But which distribution should we choose?

- We are mainly interested in the extreme distances, as we want to make a decision of when to reject
- Extreme value theory may provide an answer for us

**Algorithm 1** EVT Meta-Recognition Calibration for Open Set Deep Networks, with per class Weibull fit to $\eta$ largest distance to mean activation vector. Returns libMR models $\rho_j$ which includes parameters $\tau_i$ for shifting the data as well as the Weibull shape and scale parameters: $\kappa_i$, $\lambda_i$.

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```
for j = 1 ... N do
    Compute mean AV, μ_j = mean_i(S_{i,j})
    EVT Fit ρ_j = (τ_j, κ_j, λ_j) = FitHigh(‖Ŝ_j − μ_j‖, η)
end for
Return means μ_j and libMR models ρ_j
```

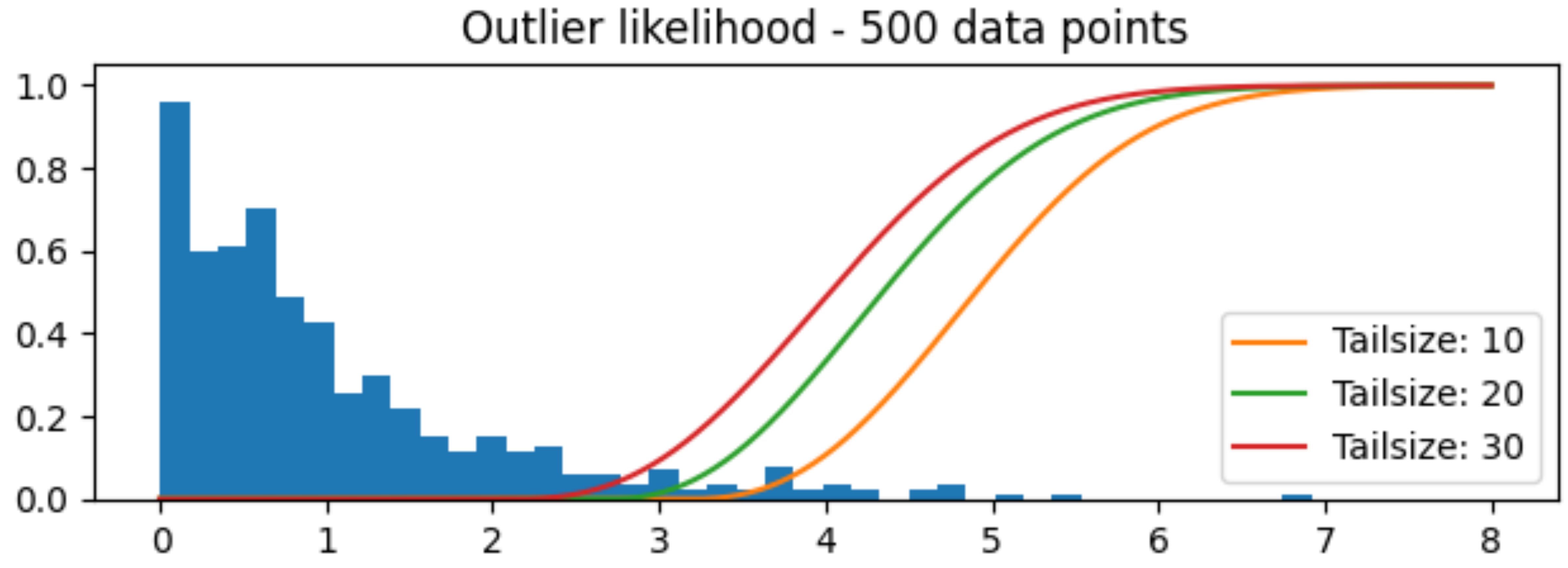
Bendale & Boult et al, “Towards Open Set Deep Networks”, CVPR 2016

# Bounds with extreme values

Extreme value theory is interested in the probability of events that are more extreme than any previously observed

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Regardless of the overall distribution, if the data is bounded, EVT tells us that sampling the tail/the extrema away from the median of our distribution results in an EVT distribution: Weibull, Gumbel or Fréchet



# Bounds with extreme values

We can use the cumulative distribution function (CDF) to either reject right away, because we exceed our extremely observed distances, or use the value to modify our prediction score (Referred to as OpenMax here)

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**Algorithm 2** OpenMax probability estimation with rejection of unknown or uncertain inputs.

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**Require:** Activation vector for $\mathbf{v}(\mathbf{x}) = v_1(x), \ldots, v_N(x)$
**Require:** **means** $\mu_j$ and libMR models $\rho_j = (\tau_i, \lambda_i, \kappa_i)$
**Require:** $\alpha$, the numer of "top" classes to revise

Let $s(i) = \text{argsort}(v_j(x))$; Let $\omega_j = 1$
**for** $i = 1, \ldots, \alpha$ **do**
$\quad \omega_{s(i)}(x) = 1 - \frac{\alpha - i}{\alpha} e^{-\left(\frac{\|x - \tau_{s(i)}\|}{\lambda_{s(i)}}\right)^{\kappa_{s(i)}}}$
**end for**
Revise activation vector $\hat{v}(x) = \mathbf{v}(\mathbf{x}) \circ \omega(\mathbf{x})$
Define $\hat{v}_0(x) = \sum_i v_i(x)(1 - \omega_i(x))$.

$$\hat{P}(y = j|\mathbf{x}) = \frac{e^{\hat{\mathbf{v}}_\mathbf{j}(\mathbf{x})}}{\sum_{i=0}^{N} e^{\hat{\mathbf{v}}_\mathbf{i}(\mathbf{x})}}$$

Let $y^* = \text{argmax}_j P(y = j|\mathbf{x})$
Reject input if $y^* == 0$ or $P(y = y^*|\mathbf{x}) < \epsilon$

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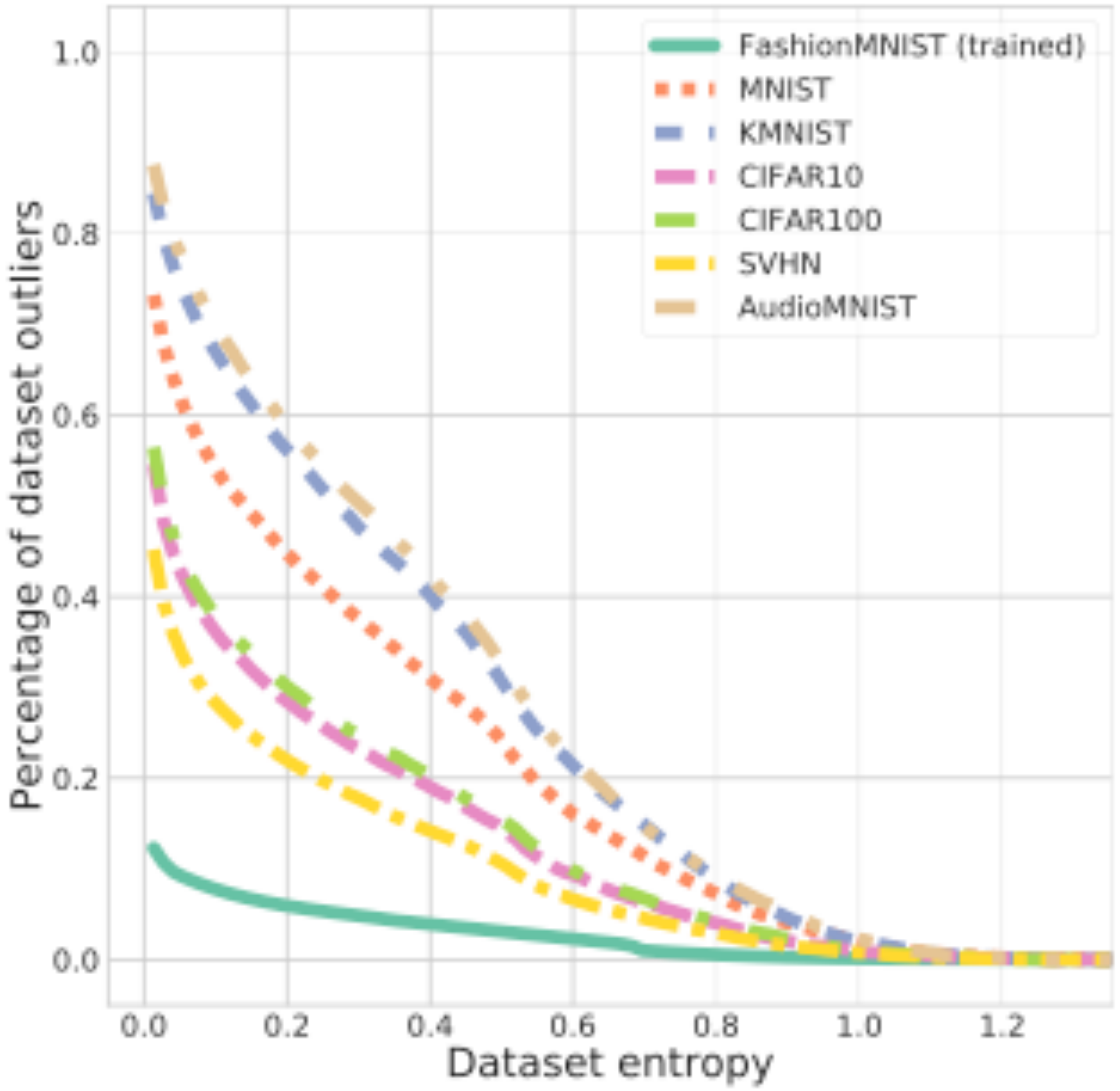
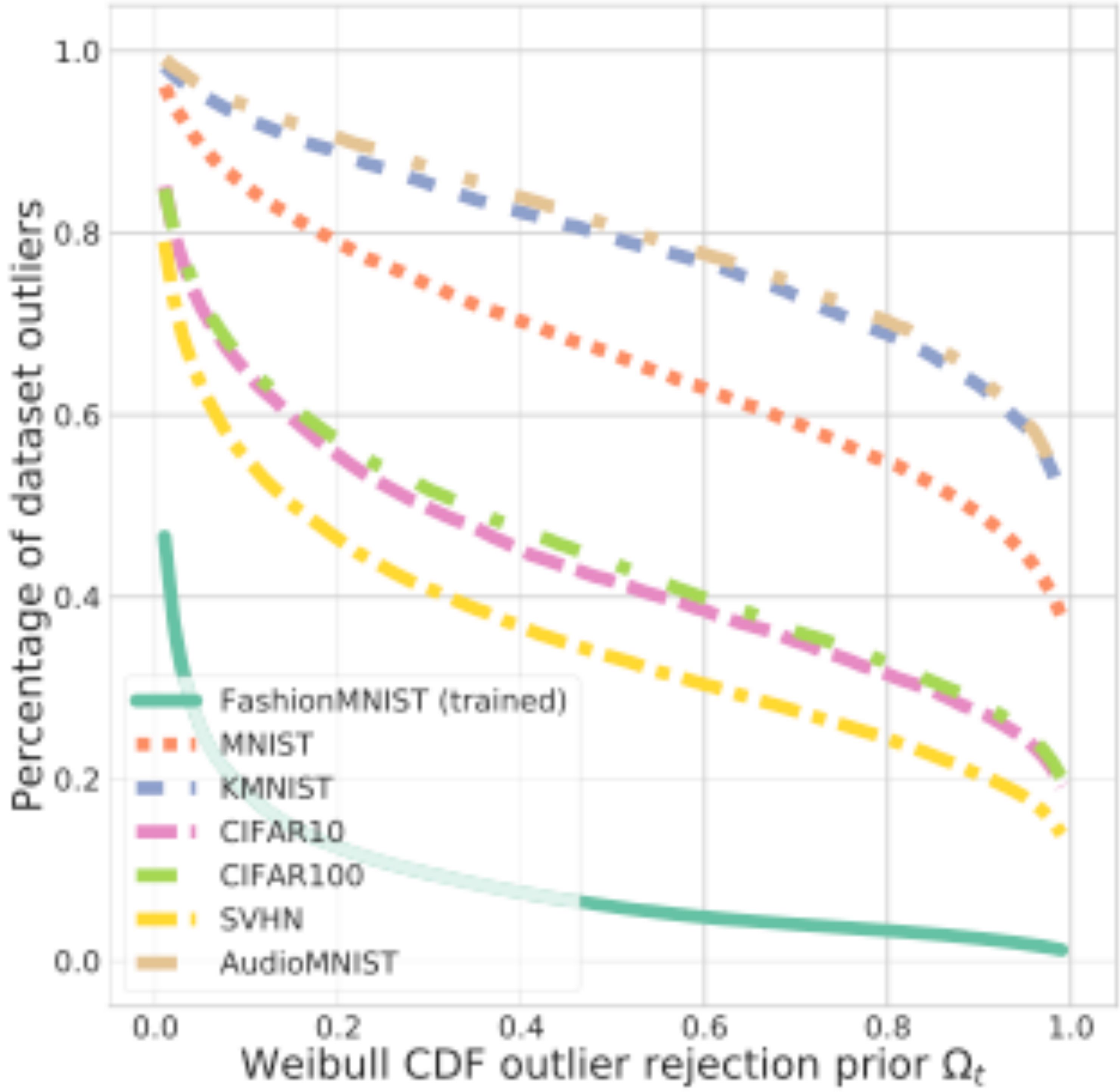
Bendale & Boult et al, "Towards Open Set Deep Networks", CVPR 2016

# OpenMax in a generative variant

**OpenMax seem to improve a lot!**

**But why is there still so much room for improvement?**

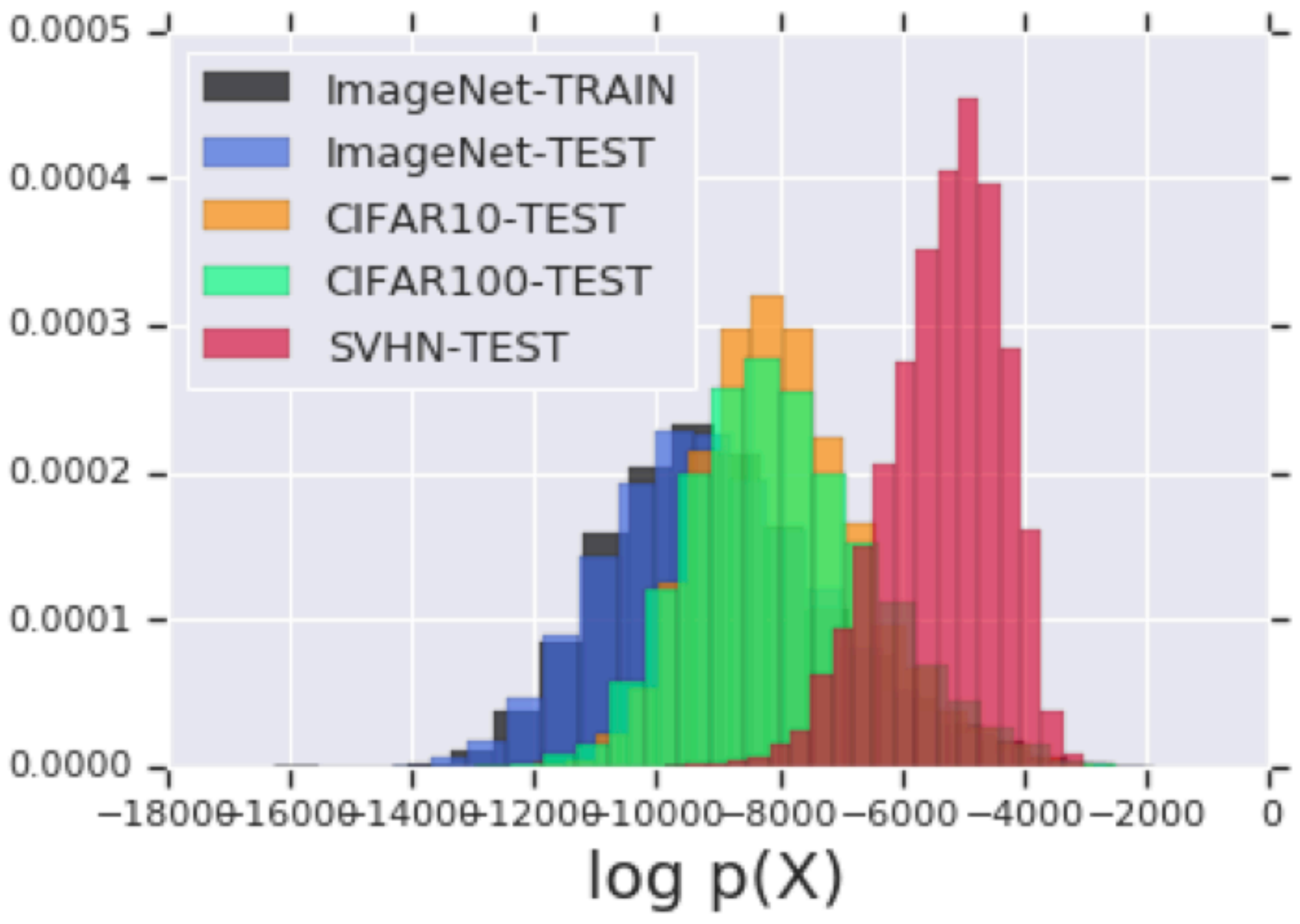


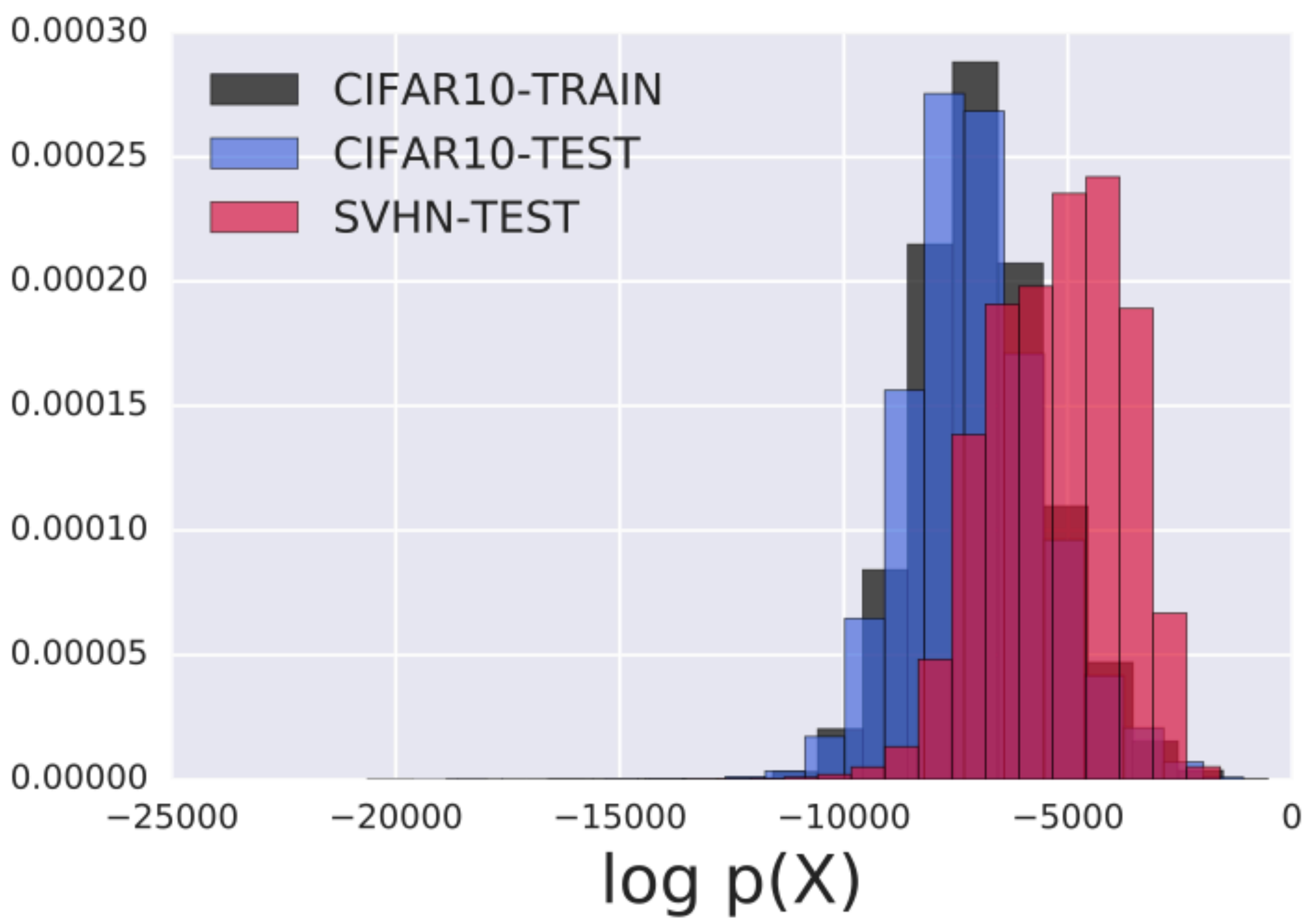
# Do we need generative models on top?

# Overconfidence & gen. models

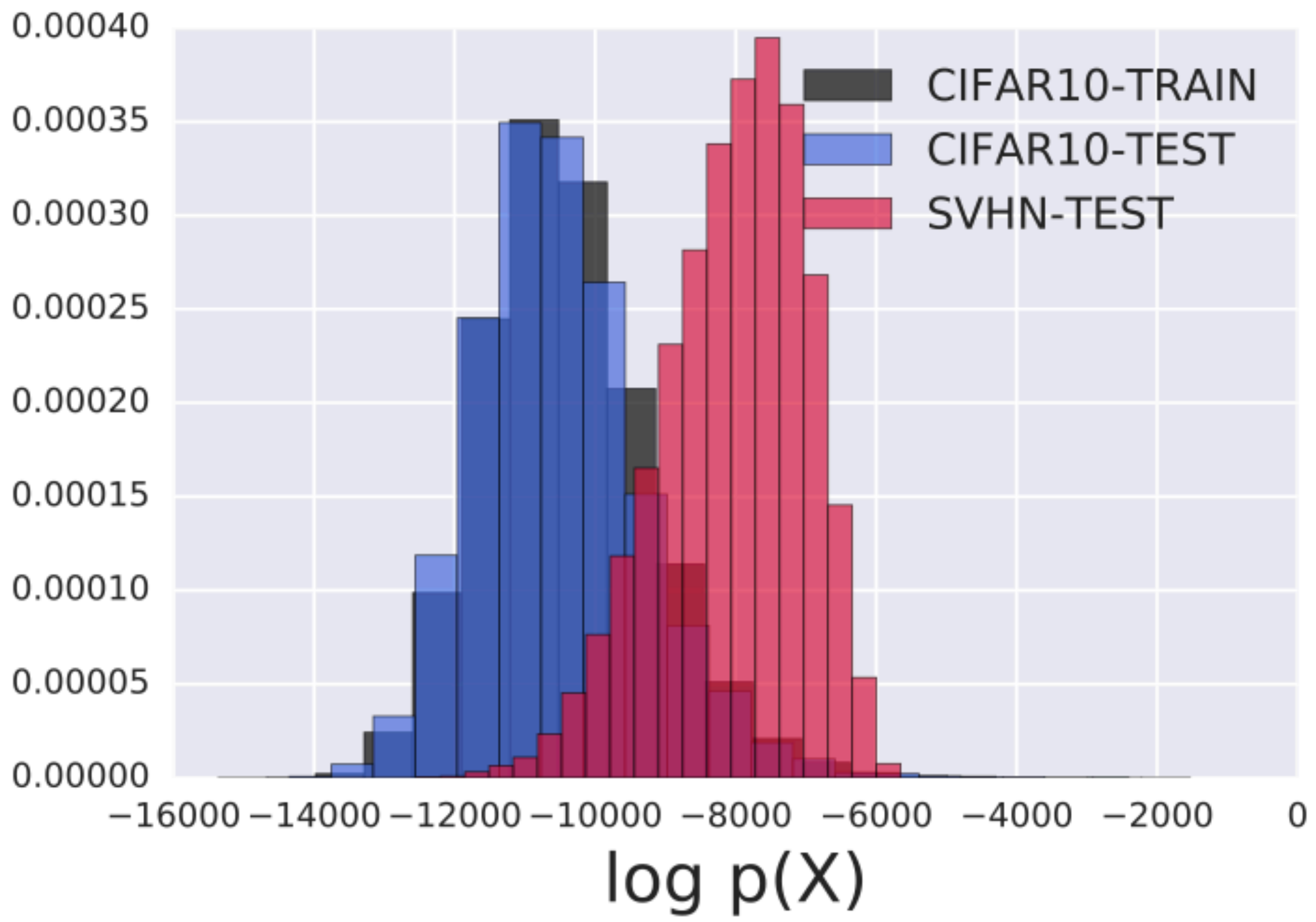
**Recall earlier: overconfidence is not exclusive to discriminative models, but what if it's only about predictive values again?**




**Glow**




**PixelCNN**

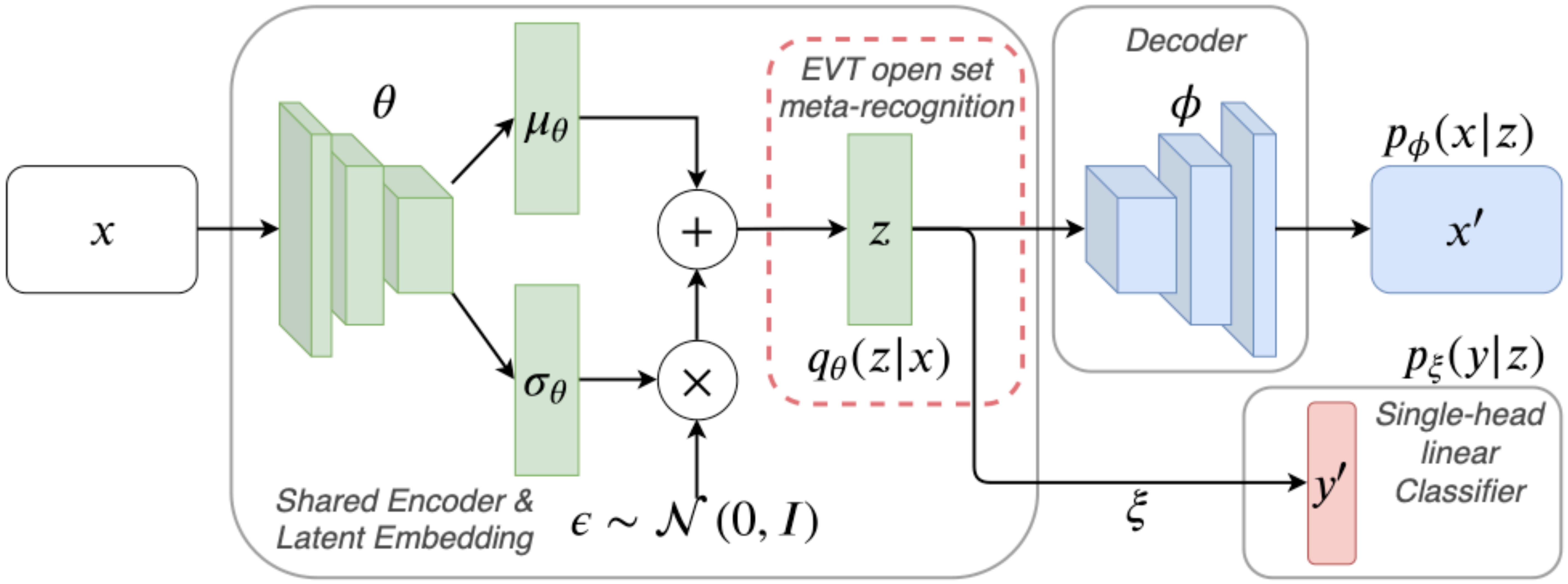



**VAE**

Nalisnick et al, "Do Deep Generative Models Know What They Don't Know", ICLR 2019

# OpenMax in a generative variant

## We could formulate an OpenMax variant based on a VAE, based on generative factors




**Algorithm 1 Open set recognition calibration for deep variational neural networks.** A Weibull model fit of tail-size $\eta$ is conducted to bound the per class approximate posterior. Per class $c$ Weibull models $\boldsymbol{\rho}_c$ with their respective shift $\tau_c$, shape $\kappa_c$ and scale $\lambda_c$ parameters are returned.

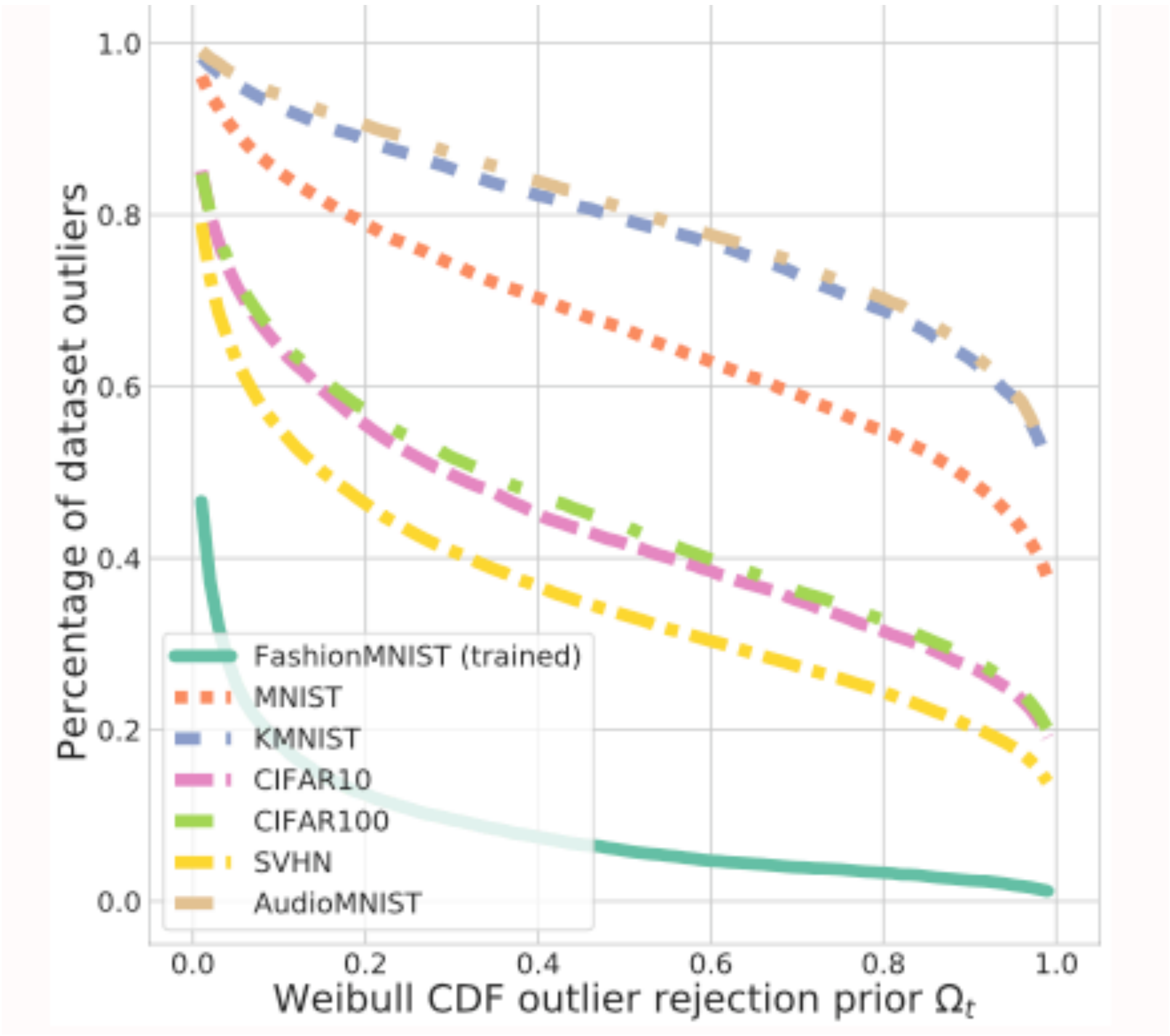
**Require:** Trained encoder $q_{\boldsymbol{\theta}}(\boldsymbol{z}|\boldsymbol{x})$ and classifier $p_{\boldsymbol{\xi}}(\boldsymbol{y}|\boldsymbol{z})$
**Require:** Classifier probabilities $p_{\boldsymbol{\xi}}(\boldsymbol{y}|\boldsymbol{z})$ and samples from the approximate posterior $\boldsymbol{z}(\boldsymbol{x}^{(i)}) \sim q_{\boldsymbol{\theta}}(\boldsymbol{z}|\boldsymbol{x}^{(i)})$ for each training dataset example $\boldsymbol{x}^{(i)}$
**Require:** For each class $c$, let $\boldsymbol{S}_c^{(i)} = \boldsymbol{z}(\boldsymbol{x}_c'^{(i)})$ for each correctly classified training example $\boldsymbol{x}_c'^{(i)}$
1: **for** $c = 1 \dots C$ **do**
2: **Get per class latent mean** $\bar{\boldsymbol{S}}_c = mean(\boldsymbol{S}_c^{(i)})$
3: **Weibull model** $\boldsymbol{\rho}_c = \text{Fit Weibull}\left(||\boldsymbol{S}_c - \bar{\boldsymbol{S}}_c||, \eta\right)$
4: **Return** means $\bar{\boldsymbol{S}}$ and Weibull models $\boldsymbol{\rho}$

Mundt et al "Open Set Recognition Through Deep Neural Network Uncertainty, Does Out-of-Distribution Detection Require Generative Classifiers?", ICCV Statistical Deep Learning Workshop 2019
& Mundt et al, "Unified Probabilistic Deep Continual Learning Through Open Set Recognition and Generative Replay", Journal of Imaging, Volume 8, Issue 4, 2022

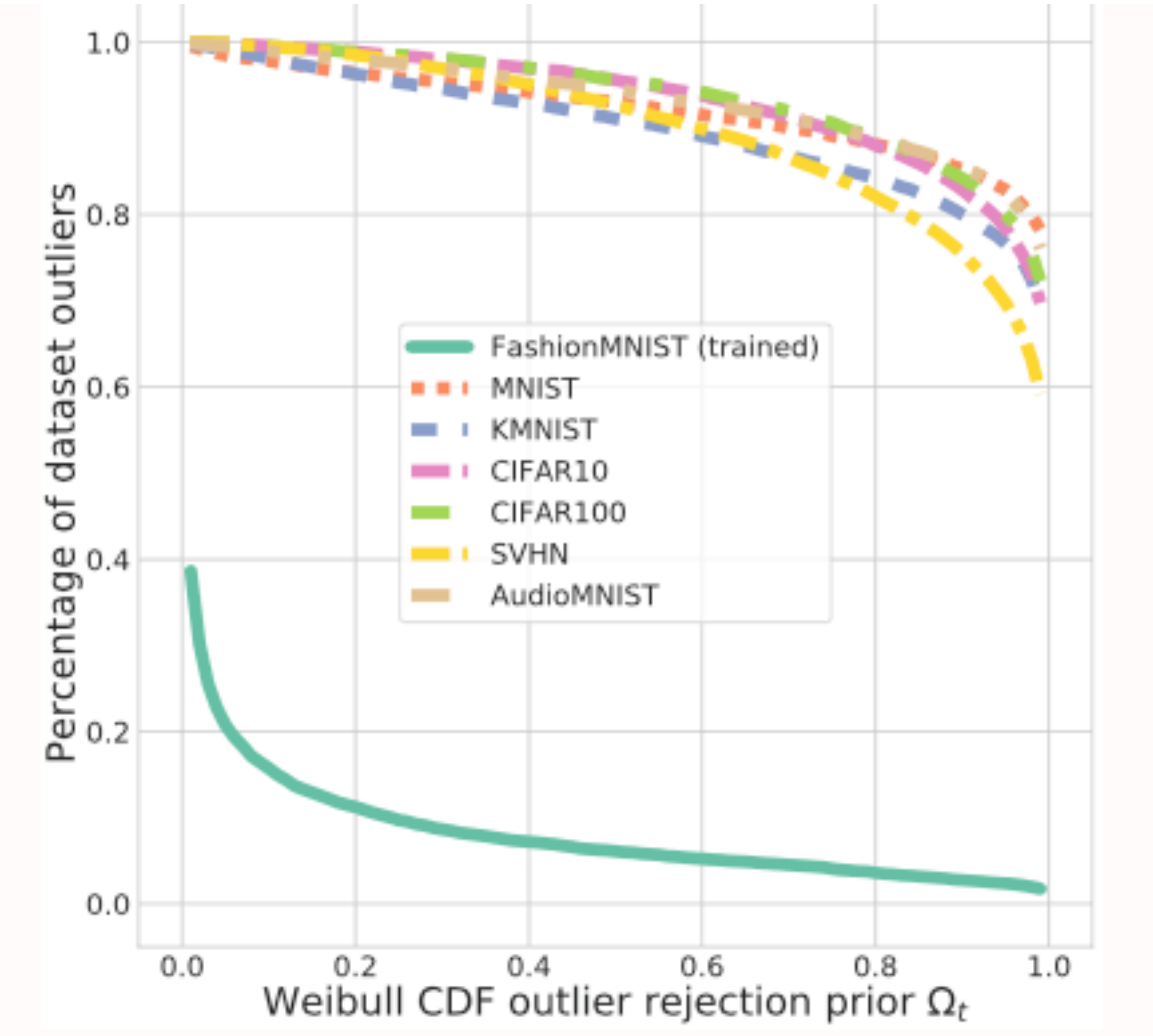
# OpenMax in a generative variant

## It may indeed be a question of the learned representations

Standard classifier p(y|x) with OpenMax




“Open”VAE approach: p(x,y)

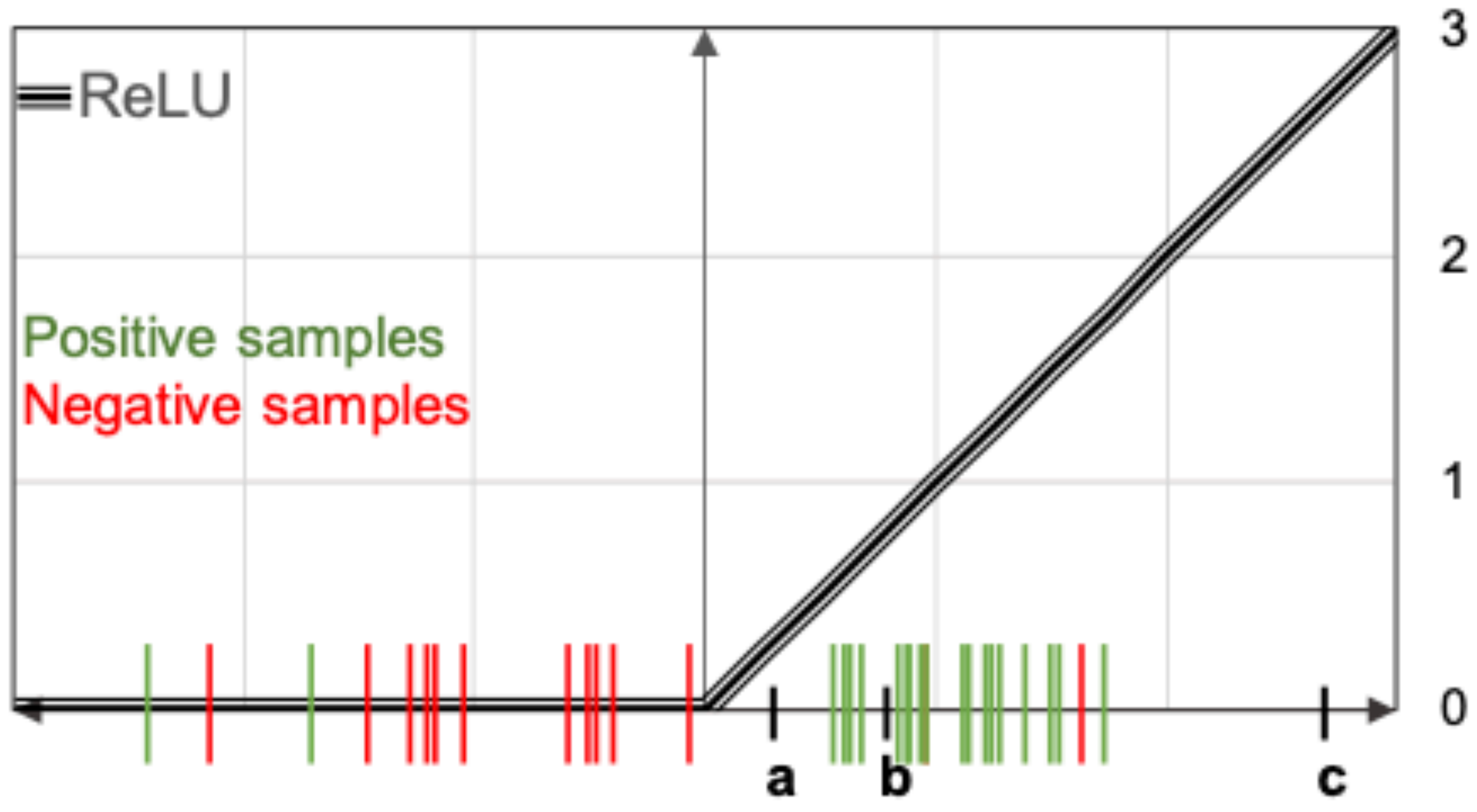



Mundt et al “Open Set Recognition Through Deep Neural Network Uncertainty, Does Out-of-Distribution Detection Require Generative Classifiers?”, ICCV Statistical Deep Learning Workshop 2019
& Mundt et al, “Unified Probabilistic Deep Continual Learning Through Open Set Recognition and Generative Replay”, Journal of Imaging, Volume 8, Issue 4, 2022

**As an alternative/auxiliary approach, we could also take a direct look at the functions that we use in our model**

# An alternative/auxiliary view

Hypothesis: specific functions in our ML models, like ReLU in NNs are (at least in parts) the culprit - they always produce high confidence far away from the data (Hein et al, “Why ReLU networks yield high confidence predictions far away from the training data and how to mitigate the problem”, CVPR 2019)



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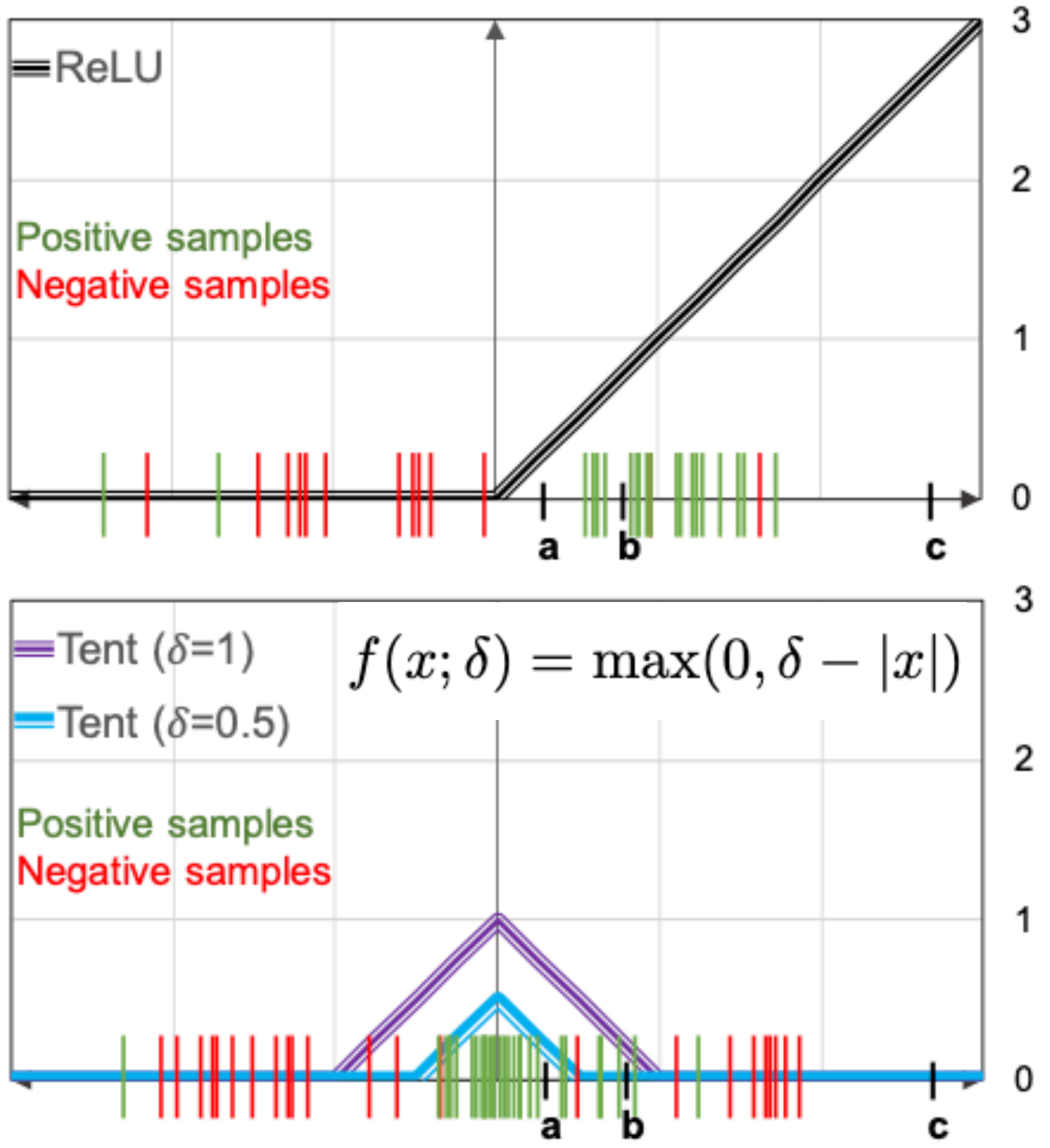
Alternative idea: use functions that are bounded and try to determine their "extent" based on the observed data (Rozsa & Boult, "Improved Adversarial Robustness by Reducing Open Space Risk via Tent Activations", 2019)



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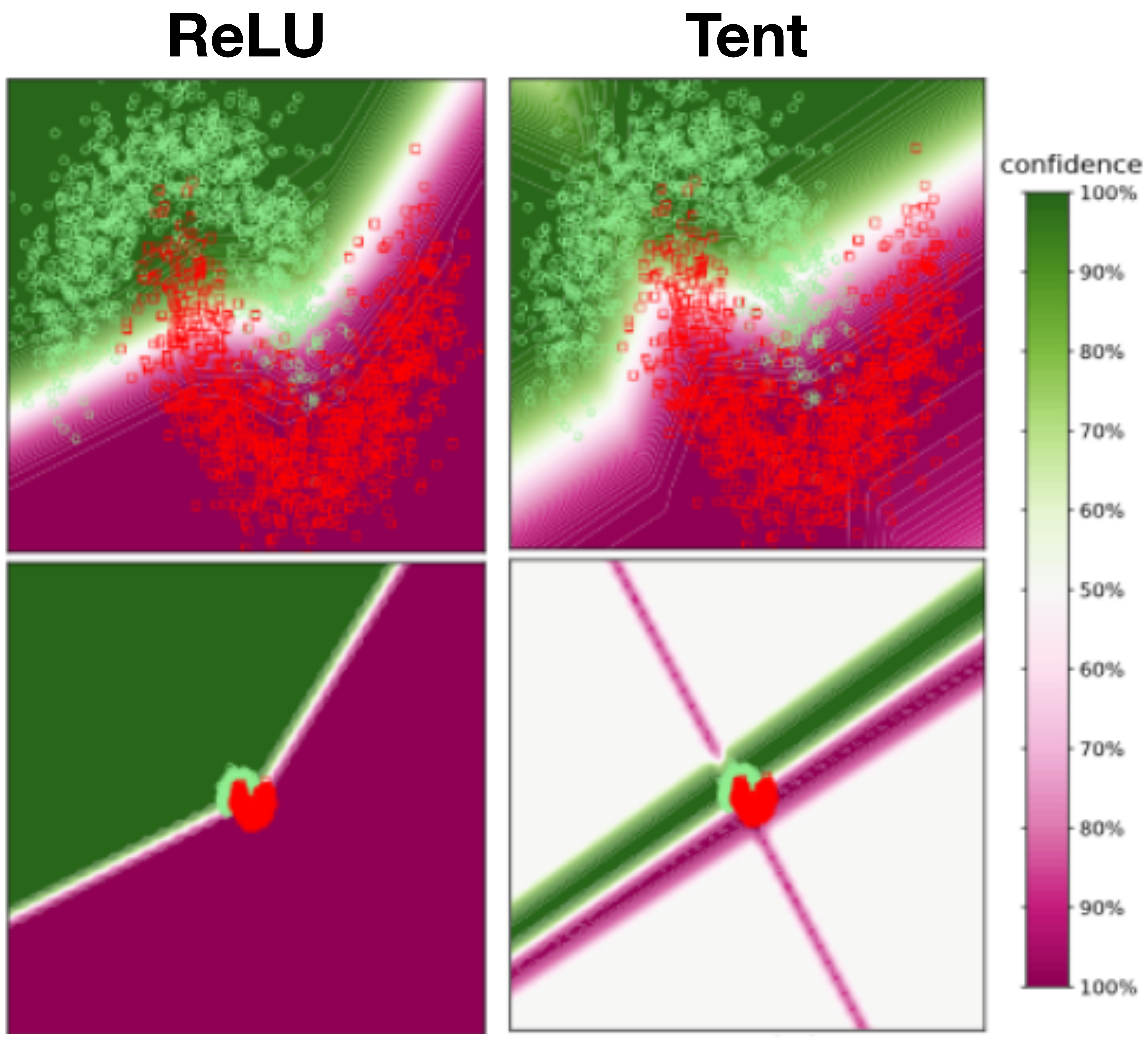



Figure produced by Quentin Delfosse, illustrating ReLU vs Tent activations

# Open world learning: combining ideas

# Open world learning

**In retrospect: although there have been increments, the types of continual learning we have seen so far were indeed in a closed world**

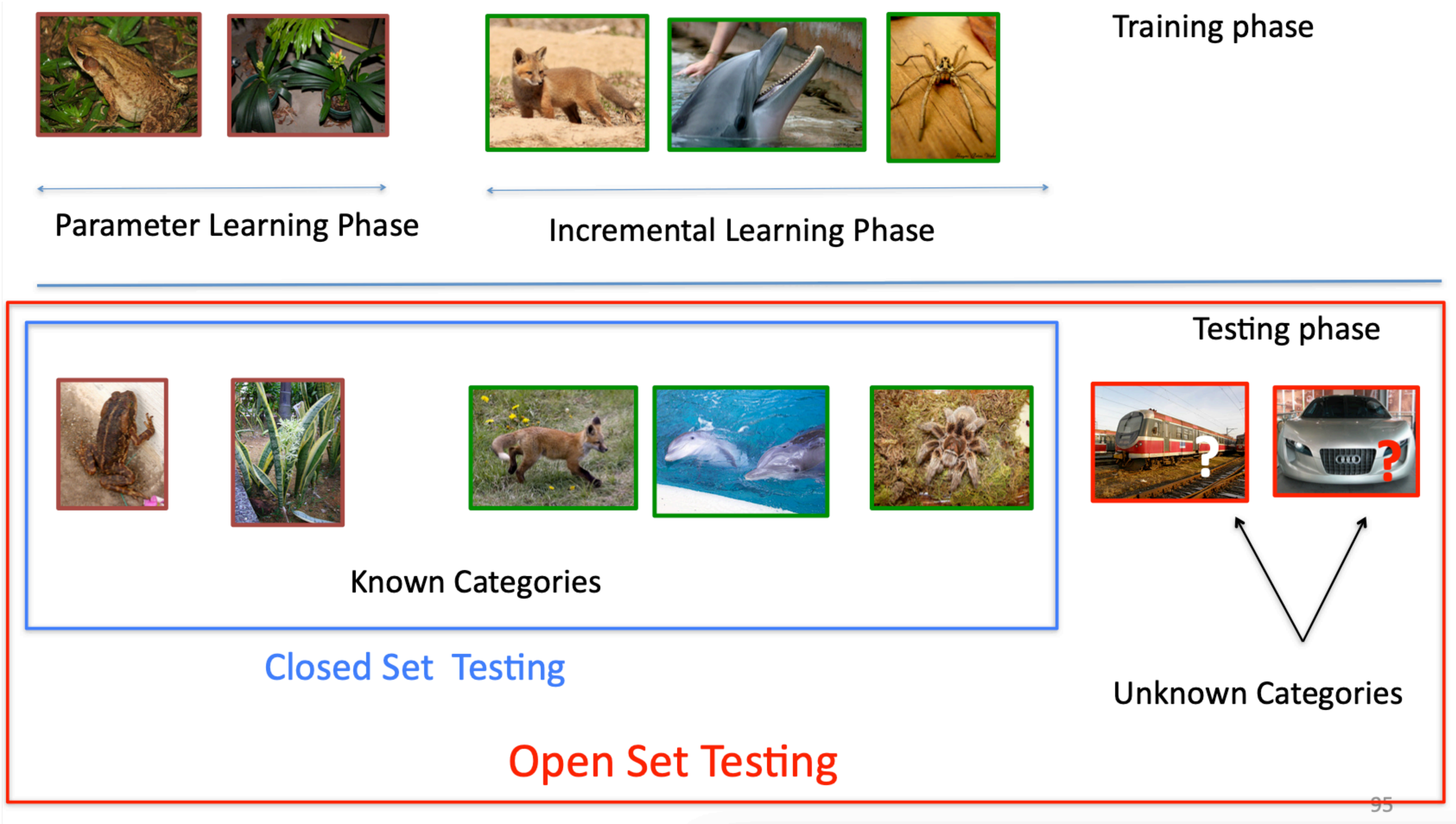
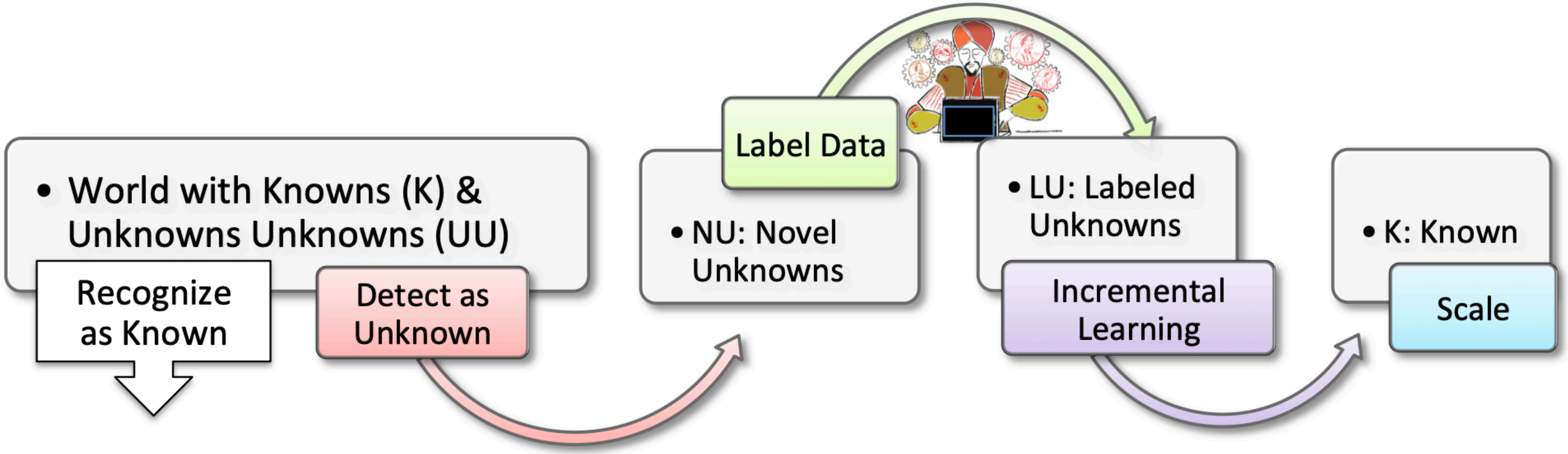



Figure from CVPR16 “Statistical Methods for Open Set Recognition” by Scheirer & Boult, https://www.wjscheirer.com/misc/openset/cvpr2016-open-set-part3.pdf

# Open world learning

**Open world learning tries to "puzzle together" the pieces we have seen so far**

"An effective open world recognition system must efficiently perform four tasks: detect unknown, choose which points to label for addition to the model, label the points, and update the model" (Boult et al, "Learning and the Unknown", AAAI 2019)




Bendale & Boult ,"Towards Open World Recognition", CVPR 2015

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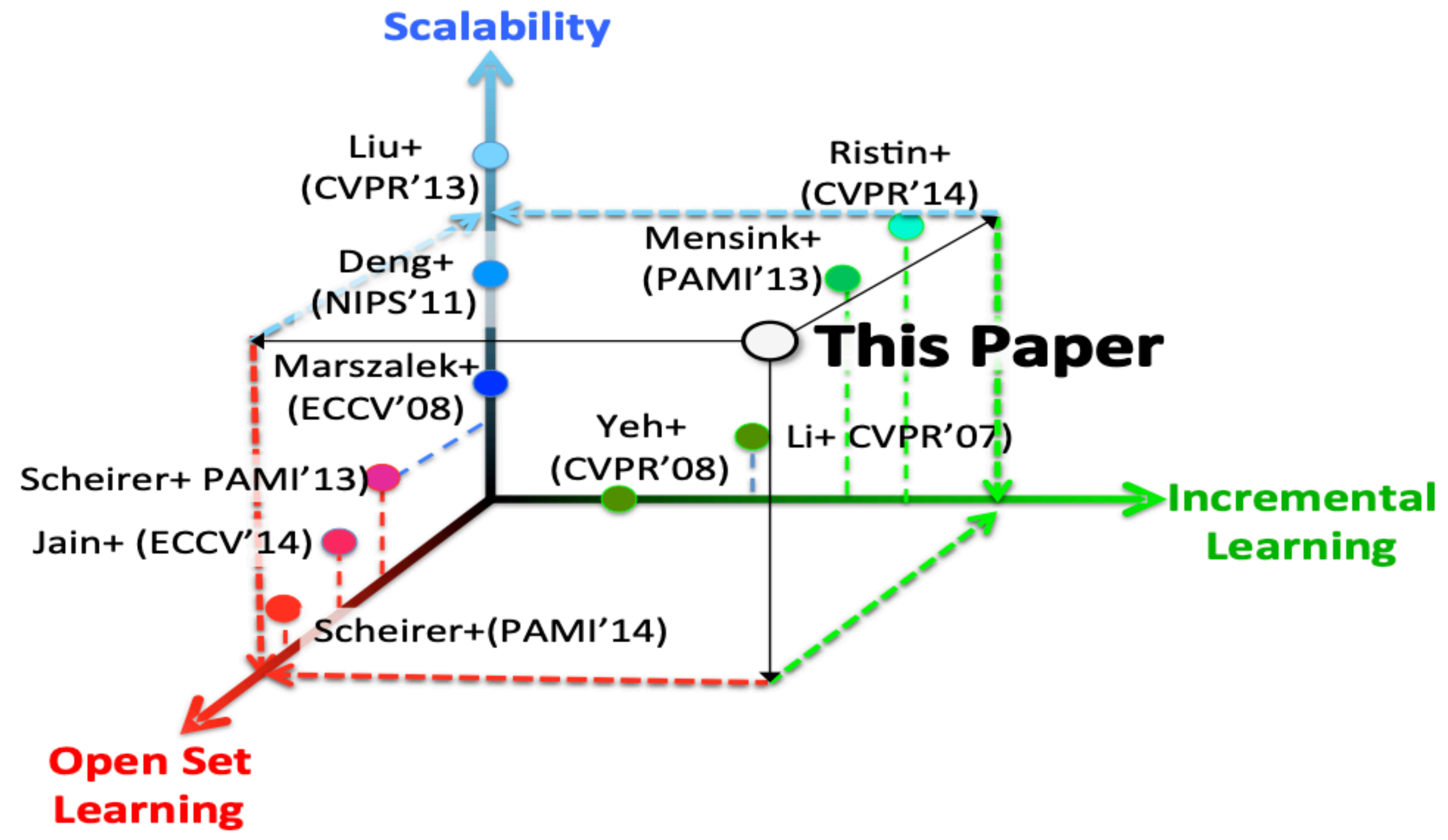
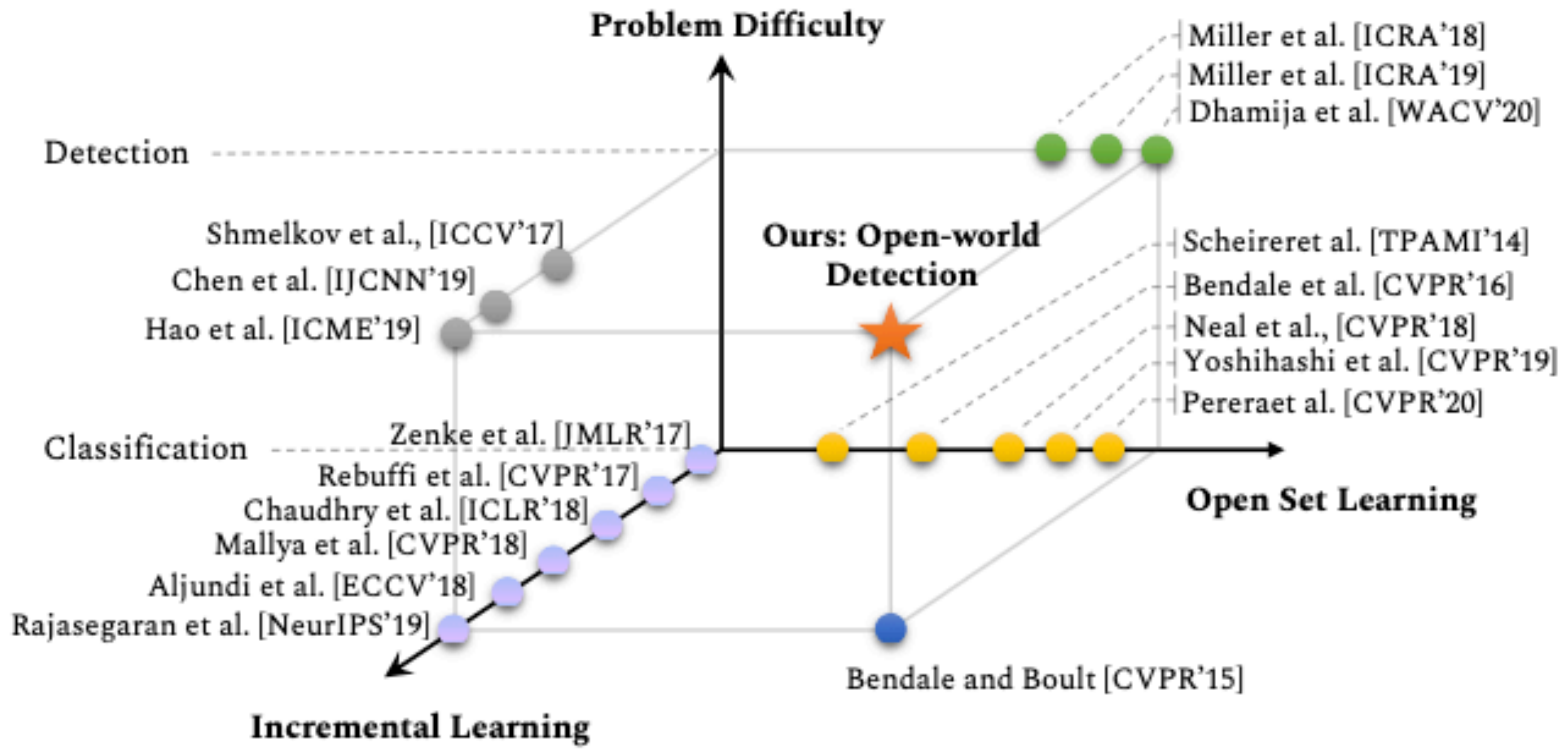



Bendale & Boult ,"Towards Open World Recognition", CVPR 2015




Joseph et al, "Towards Open World Object Detection", CVPR 2021

# Open world learning

**We can try to puzzle the pieces together now. As it is very much a cutting-edge research frontier, let's talk about it more in the "frontiers" lecture**

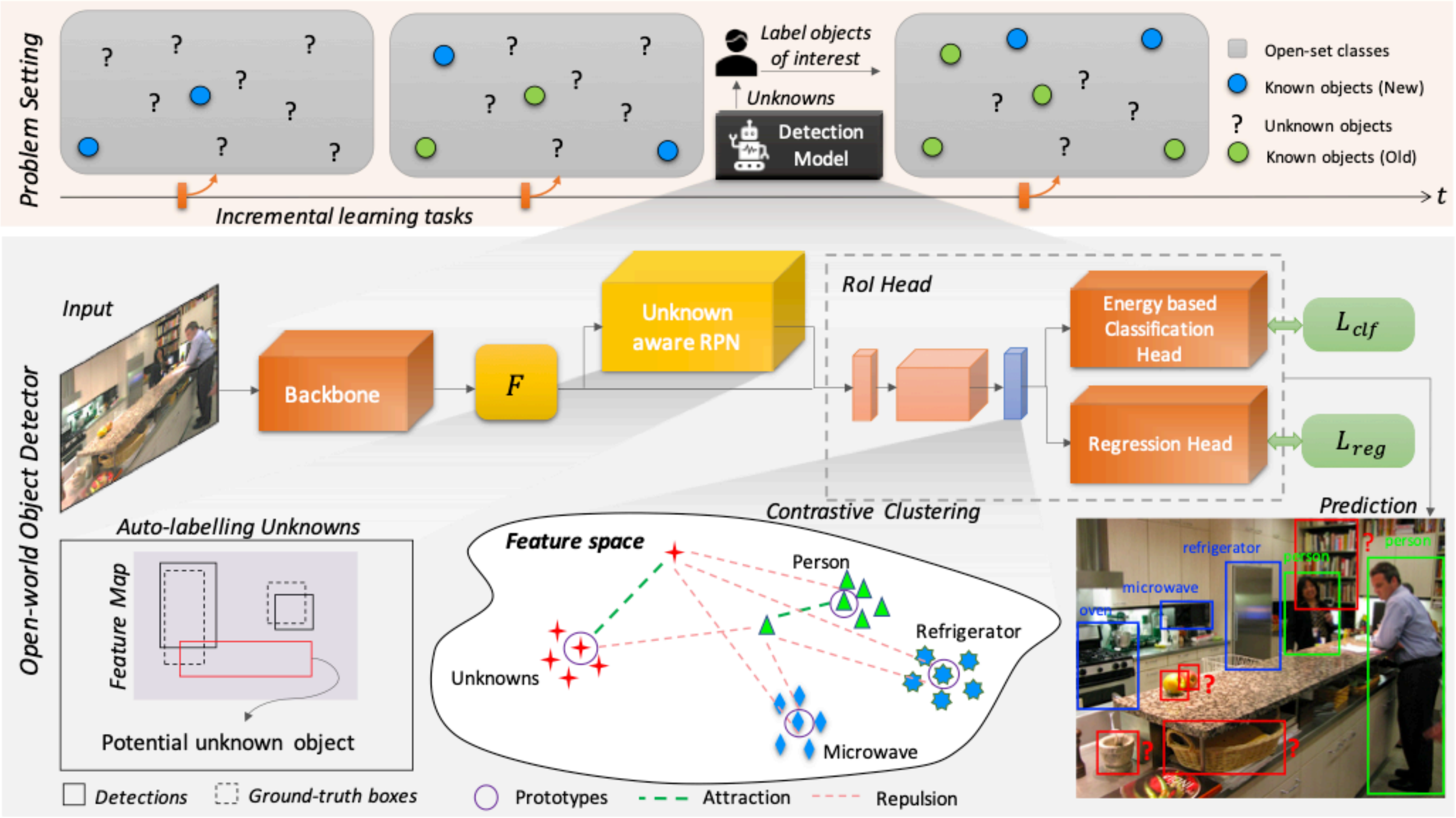



Figure 2: *Approach Overview: Top row:* At each incremental learning step, the model identifies unknown objects (denoted by '?'), which are progressively labelled (as blue circles) and added to the existing knowledge base (green circles). *Bottom row:* Our open world object detection model identifies potential unknown objects using an energy-based classification head and the unknown-aware RPN. Further, we perform contrastive learning in the feature space to learn discriminative clusters and can flexibly add new classes in a continual manner without forgetting the previous classes.

Joseph et al, "Towards Open World Object Detection", CVPR 2021

# Frontiers

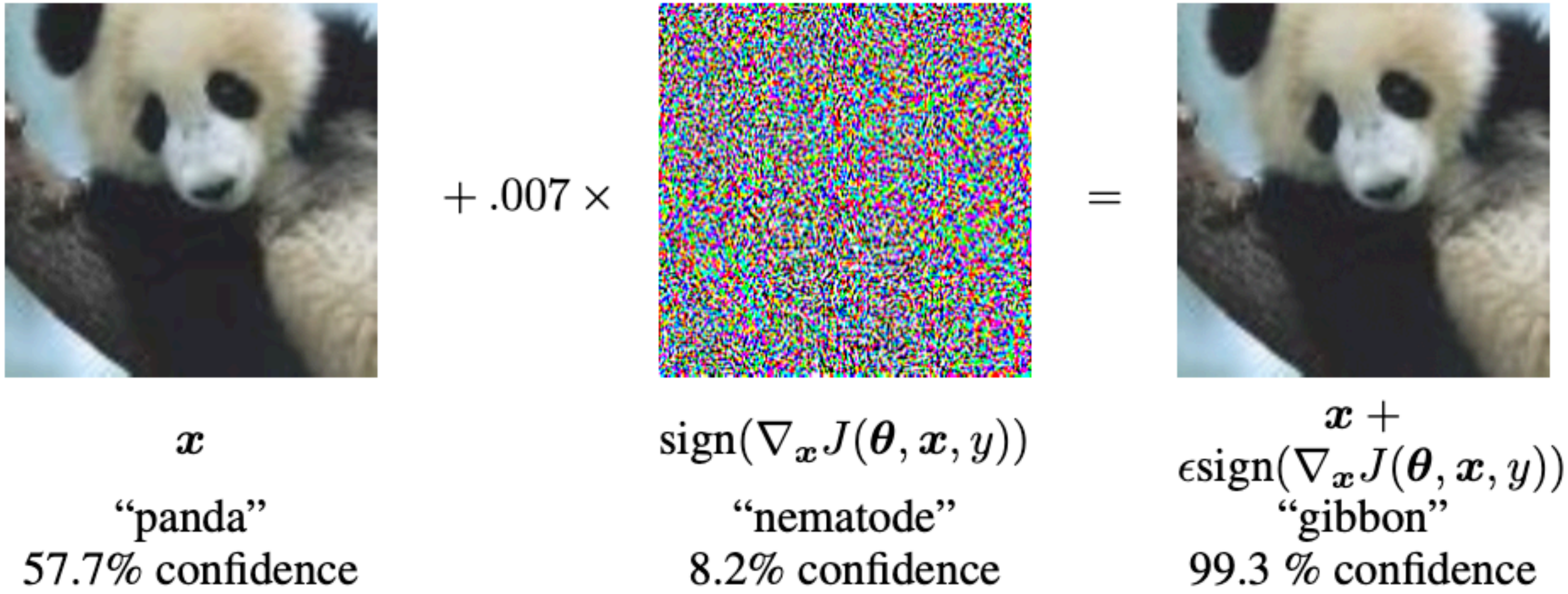
**Ending on some open questions & a disclaimer:**

- Note the “towards” in many of the paper titles
- There is much to be done still: what about avoiding forgetting in addition now?
- Naturally, evaluation gets even more complicated now!
- It’s no longer a question of ML algorithms, perhaps it already was a systems question beforehand, but now it definitely is

# Corruptions, adversarial etc.

ContinualAI hessian.AI TECHNISCHE UNIVERSITÄT DARMSTADT

## What about natural corruptions, adversarial attacks etc.?




Goodfellow et al, "Explaining and Harnessing Adversarial Examples", ICLR 2015

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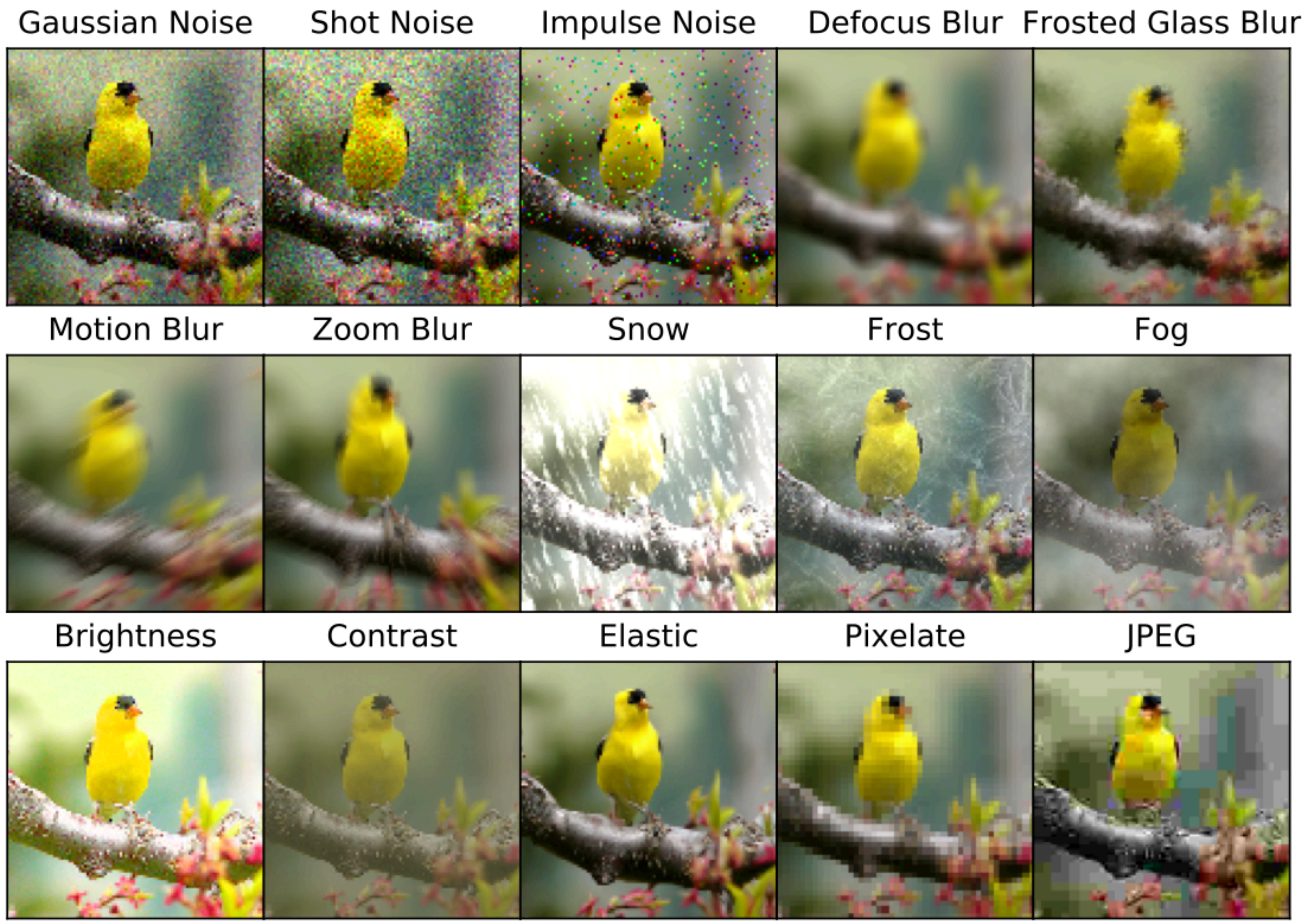


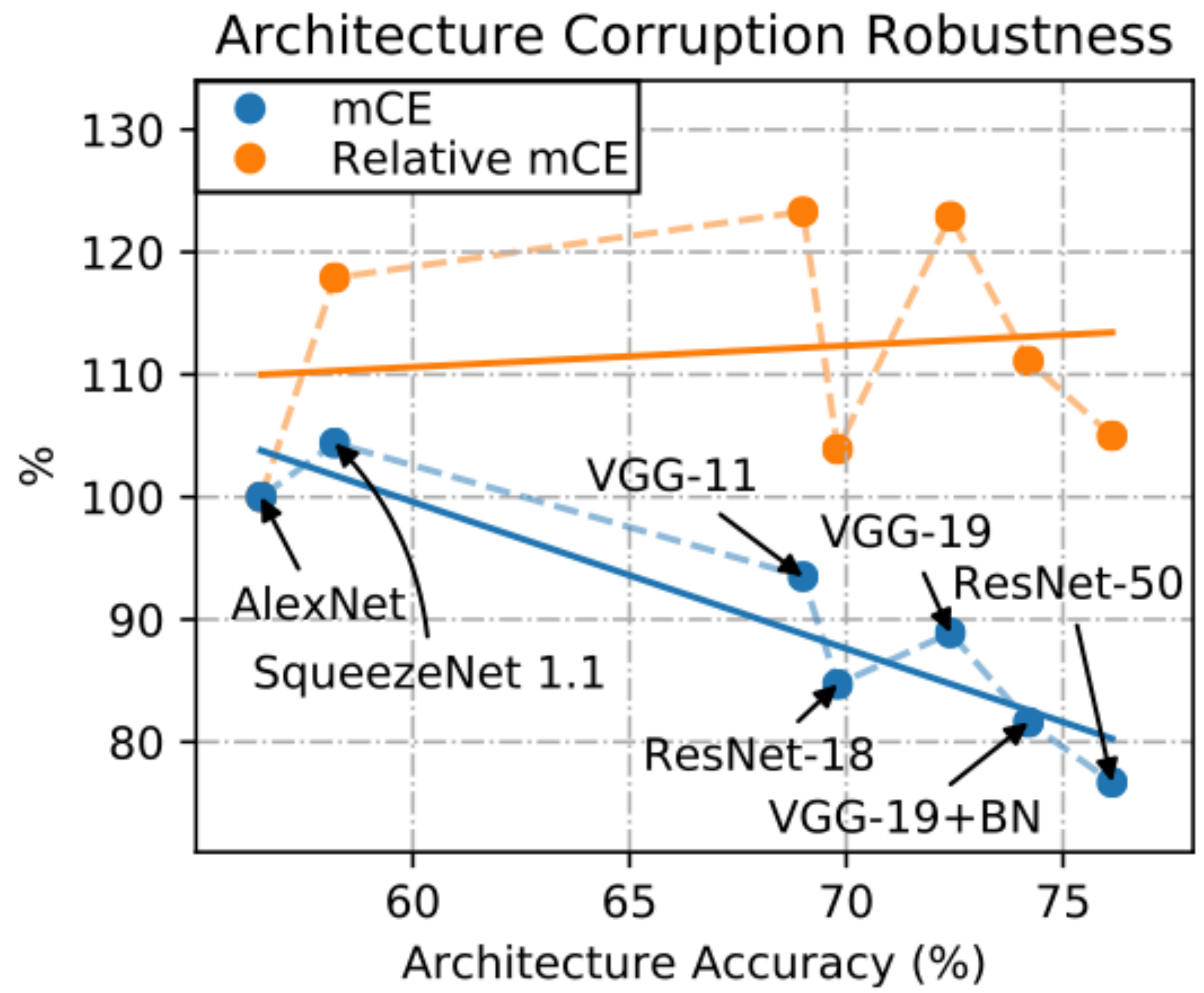


Figure 3: Robustness (mCE) and Relative mCE IMAGENET-C values. Relative mCE values suggest robustness in itself declined from AlexNet to ResNet. "BN" abbreviates Batch Normalization.

Hendricks & Dietterich, "Benchmarking Neural Network Robustness to Common Corruptions and Perturbations", ICLR 2019