Unified Probabilistic Deep Continual Learning Through Generative Replay and Open Set Recognition

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Introduction

- Based on Extreme Value Theory (EVT)
- Probabilistic open set recognition
- Allows for continual learning
- Prevents catastrophic forgetting
- Does not store entire data set
- Model:
  - Combines joint probabilistic encoder with a GAN
  - Tight classification bound on high-density learned parameter regions
  - Only use high-density data points in regenerative model training

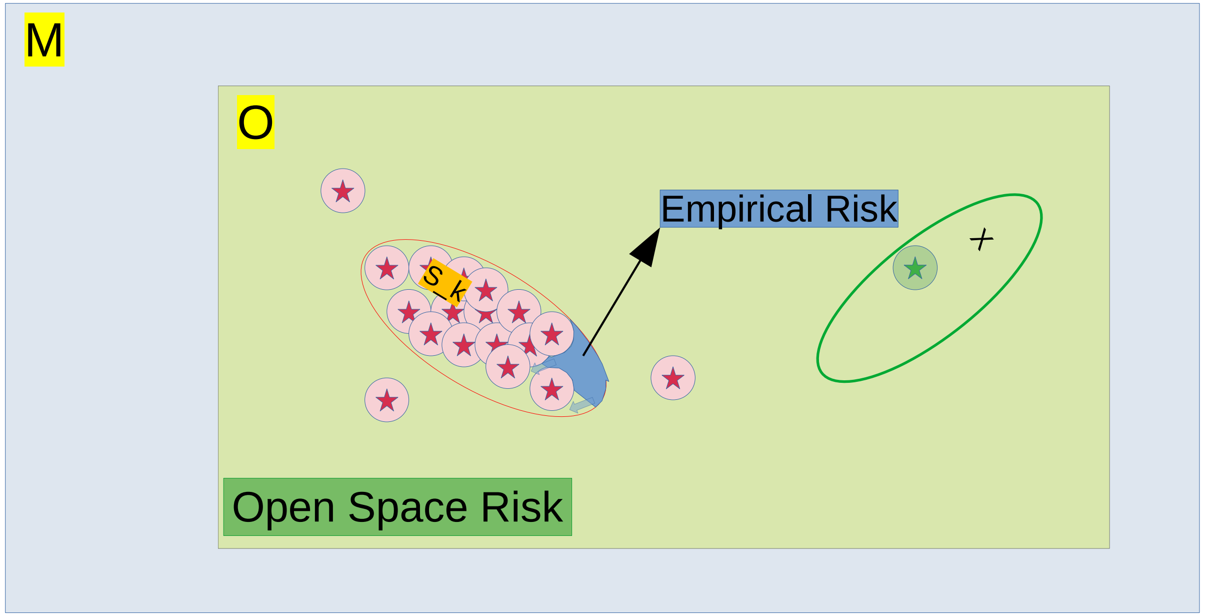
Variational Bayesian Inference

- Inference hidden variables
- Deterministic
- Easy to gauge convergence
- Requires dozens of iterations
- No conjugacy requirement
- More complicated math (slightly)

Open Set Recognition

› Definition per Scheirer et al. [31]:

- *“For any recognition function f over an input space* X*, the open set* O *is defines as* $O \subseteq X - S_K$*, where* S_K *is a union of balls of radius* r_o *including all of the training examples for known classes* $x \in K$*“.*



Bayesian Probability

- Observations – x
- Hidden variable – z
- Fixed (learned) parameters – alpha

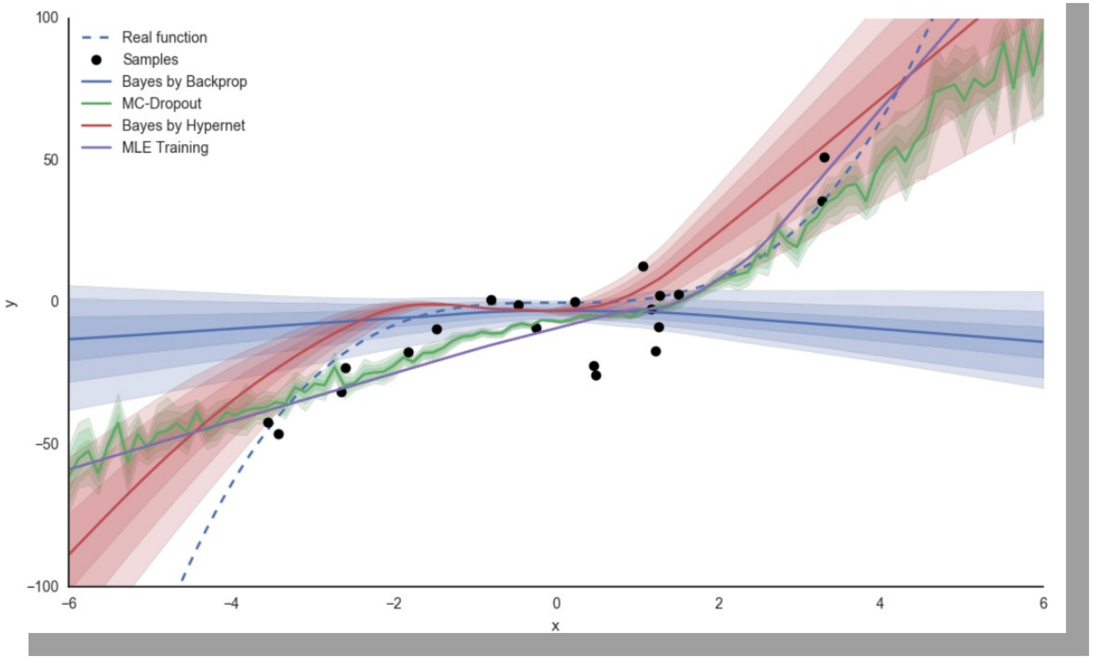
$$P(z|x,\alpha) = \frac{P(z,x|\alpha)}{\int_z P(z,x|\alpha)}$$

- Bayesian Inference:
  - Posterior requires calculating over all means and cluster assignments

$$p(\mu_{1:K}, z_{1:n} \mid x_{1:n}) = \frac{\prod_{k=1}^{K} p(\mu_k) \prod_{i=1}^{n} p(z_i) p(x_i \mid z_i, \mu_{1:K})}{\int_{\mu_{1:K}} \sum_{z_{1:n}} \prod_{k=1}^{K} p(\mu_k) \prod_{i=1}^{n} p(z_i) p(x_i \mid z_i, \mu_{1:K})}$$

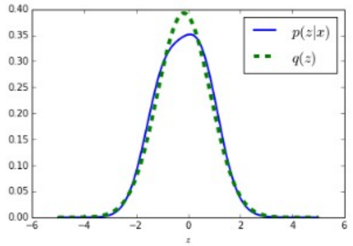
Bayesian Uncertainty

- Naturally rejects statistical outlier by dilution
- 100s to 1000s of forward passes with MCMC (Bayesian approx.)
- Fewer but many forward passes with MC Dropout (Bayesian approx.)
- Direct calculation not feasible
- Relies on the max entropy principle assumption
  - Directly contradicts with the Open Set Recognition definition



Source:Implicit Weight Uncertainty in Neural Networks - http://bayesiandeeplearning.org/2017/papers/36.pdf

Variational Inference



A variational Gaussian approximation to a scalar posterior.

A natural approach to fitting the approximation parameters λ is to minimize the KL divergence between our approximation $q(z;\lambda)$ and the posterior $p(z|x)$.[2] Writing this out,

$$KL\left[q(z;\lambda)\|p(z|x)\right] = \int q(z;\lambda)\log\frac{q(z;\lambda)}{p(z|x)}dz,$$

we see that it depends on the posterior density $p(z|x)$ which we don't know. However, we do have access to the joint distribution $p(x,z)$, which is proportional to the posterior, so we can just apply simple algebra to unpack the normalizing constant:

$$\begin{aligned}
KL\left[q(z;\lambda)\|p(z|x)\right] &= \int q(z;\lambda)\log\frac{q(z;\lambda)}{p(z|x)}dz \\
&= \int q(z;\lambda)\left[\log q(z;\lambda) - \log p(z|x)\right]dz \\
&= \int q(z;\lambda)\left[\log q(z;\lambda) - \log\frac{p(x,z)}{p(x)}\right]dz \\
&= \log p(x) + \int q(z;\lambda)\left[\log q(z;\lambda) - \log p(x,z)\right]dz \\
&= \log p(x) - \mathcal{F}(\lambda;x).
\end{aligned}$$

This shows that the KL divergence is equal to the model evidence $\log p(x)$, which is an (unknown) normalizing constant, minus a term $\mathcal{F}$ given by

$$\mathcal{F}(\lambda;x) = \int q(z;\lambda)\left[\log p(x,z) - \log q(z;\lambda)\right]dz.$$

This term is alternately referred to as (negative) variational free energy or the evidence lower bound (ELBO). It is a lower bound on $\log p(x)$

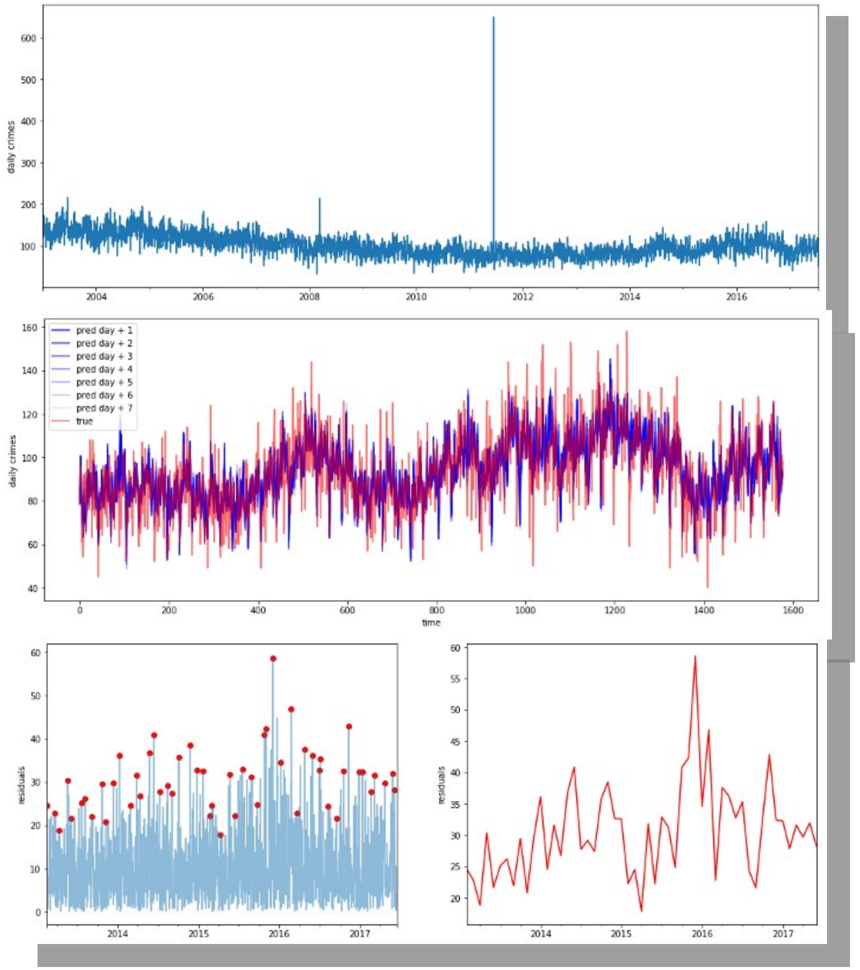
Source: Variational Inference in 5 Minutes - http://davmre.github.io/blog/inference/2015/11/13/elbo-in-5min

Calibration

- What to do with outliers?
  - [38] uses perturbation and temperature scaling
  - [39] uses a separate GAN with additional loss term for outliers
  - [40] uses unknown class label and true negative samples
- They use a GAN and outlier rejection using EVT (ELBO)

Extreme Value Theory (EVT)

- Consider training residual absolute values, Extreme Values
- Model Extreme Values and assign distribution, Dirichlet distribution
- Compare empirical and estimated distribution
- Expect similar number of anomalies



Source: https://towardsdatascience.com/anomaly-detection-with-extreme-value-analysis-b11ad19b601f

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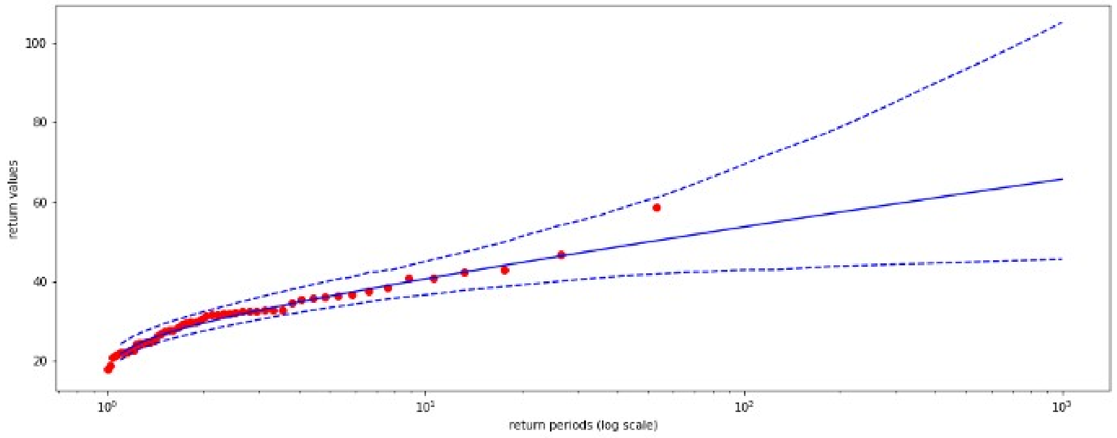

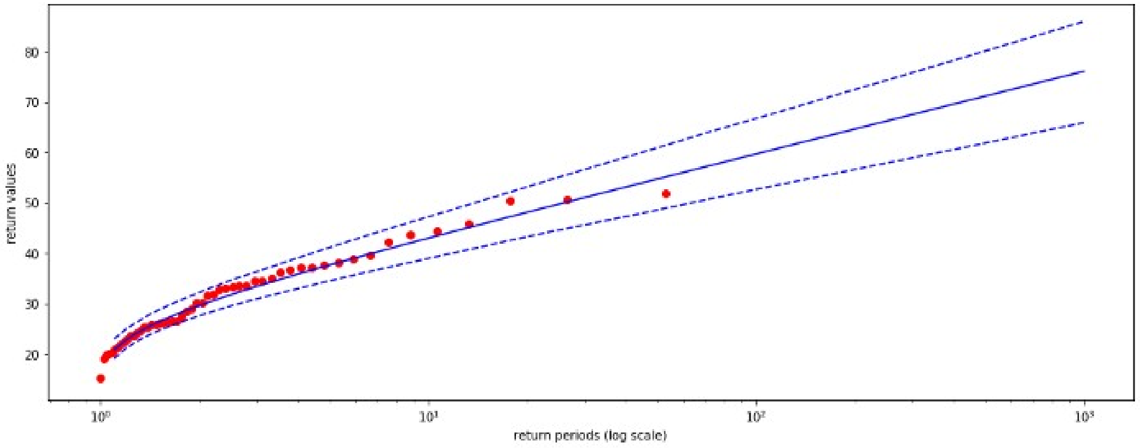

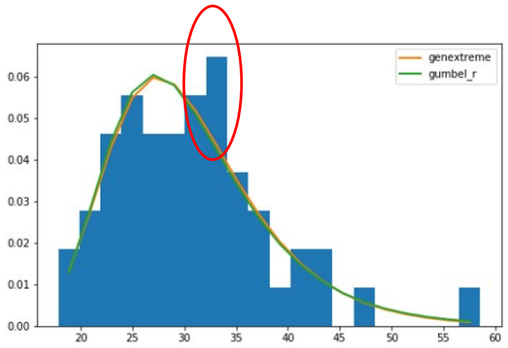

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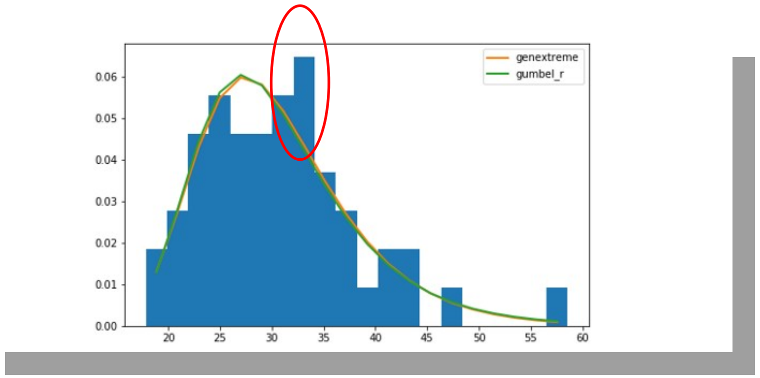
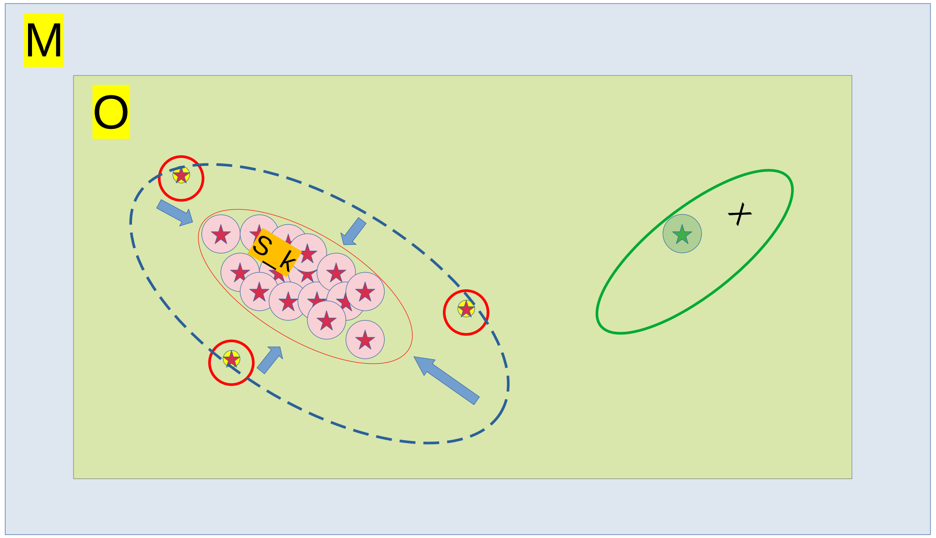
Extreme Value Theory (EVT)

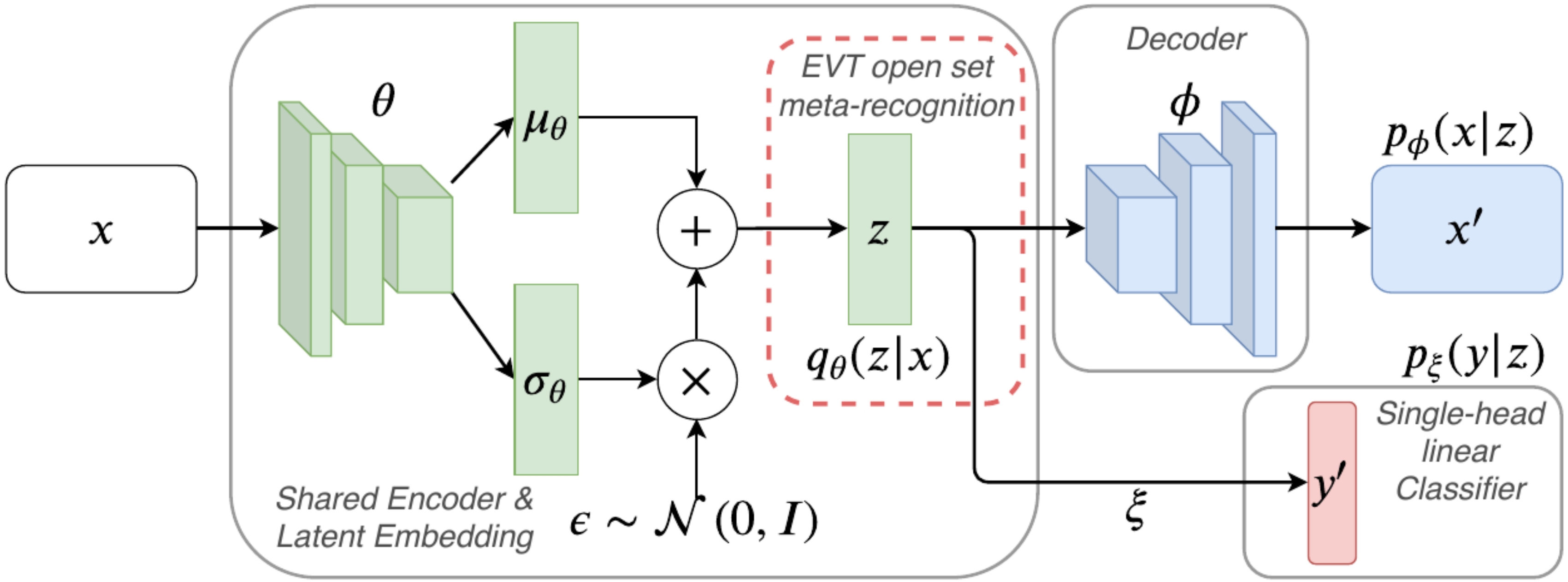
› In this paper:

- Use EVT to bound approximate posterior, instead of assigning confidence
- Use it to bound high density class distributions
- Used on each class separately





Model



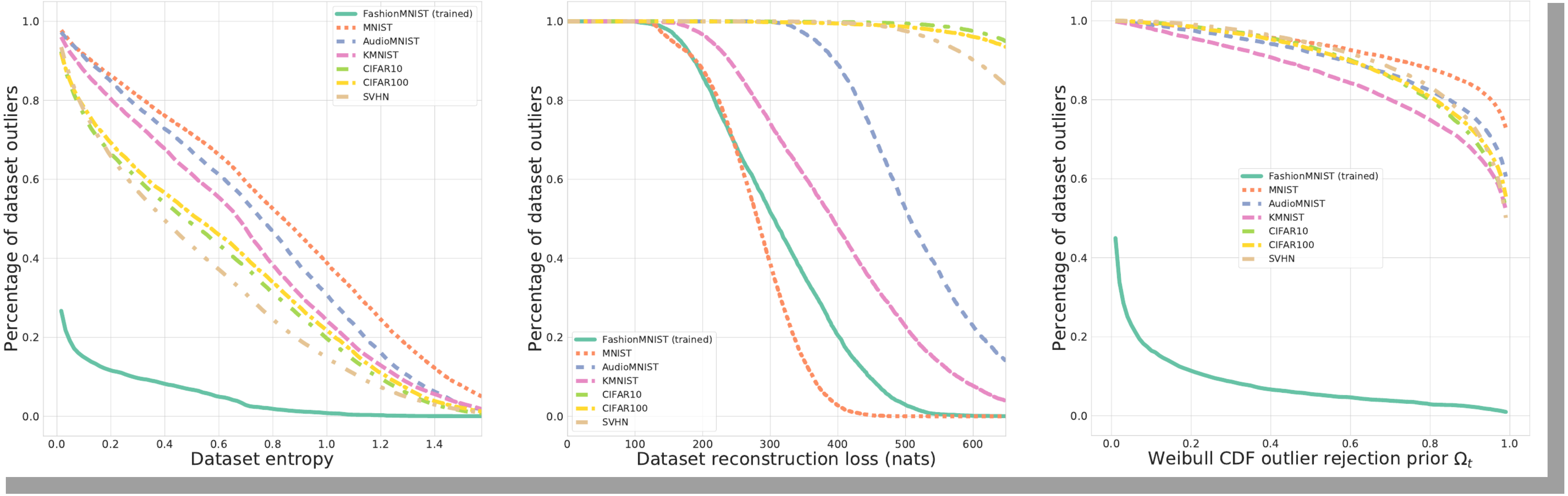
x
θ
μ_θ
σ_θ
Shared Encoder & Latent Embedding
$\epsilon \sim \mathcal{N}(0, I)$
EVT open set meta-recognition
z
$q_\theta(z|x)$
Decoder
ϕ
$p_\phi(x|z)$
x'
ξ
$p_\xi(y|z)$
y'
Single-head linear Classifier

Loss Function

$$\mathcal{L}\left(x^{(n)}, y^{(n)}; \theta\phi, \xi\right) = -\beta KL\left(q_\theta(z|x^{(n)})||p(z)\right) + \mathbb{E}_{q_\theta(z|x^{(n)})}\left[\log p_\phi(x^{(n)}|z) + \log p_\xi(y^{(n)}|z)\right] \tag{1}$$

- θ – shared encoder parameters
- φ – decoder parameters
- ξ – linear classifier parameters

Performance



- Thank you!