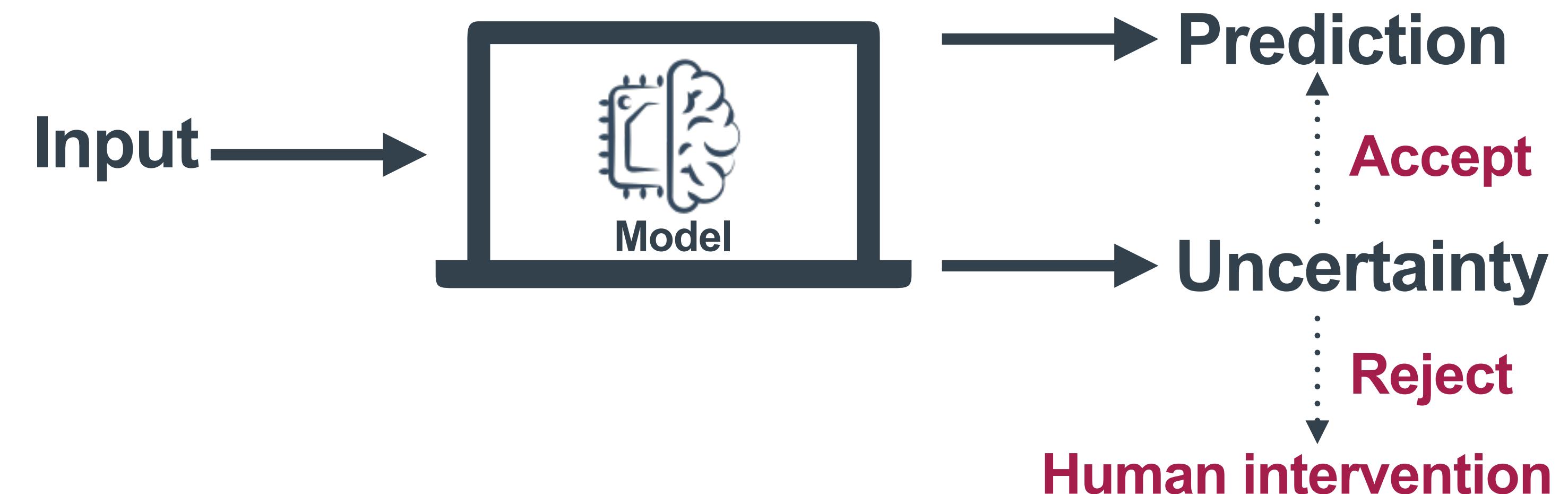




# Modelling multiple sources of uncertainty



# Scenario





# Source of uncertainty

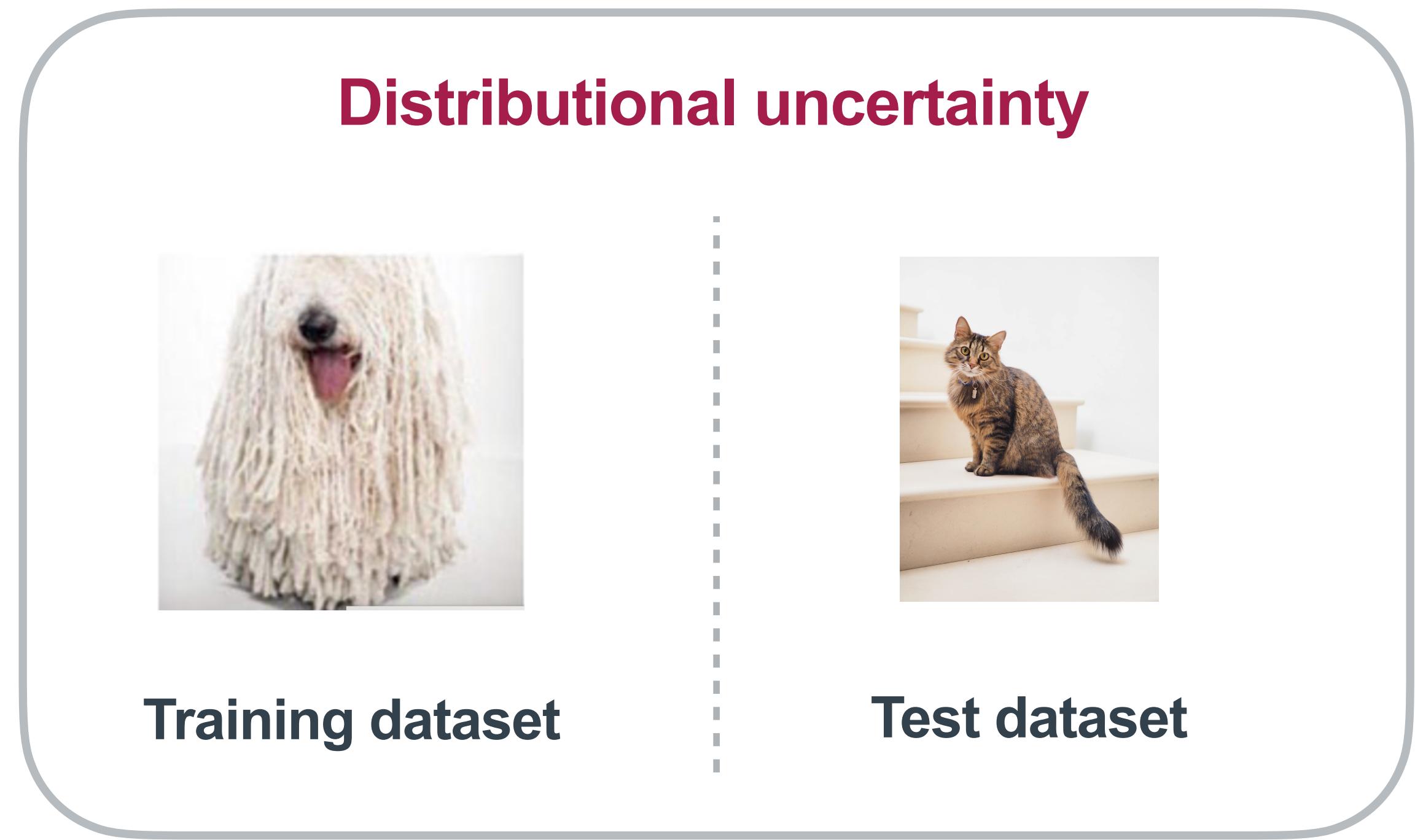


Figure from <https://www.boredpanda.com/dog-food-comparison-bagel-muffin-lookalike-teenybiscuit-karen-zack/> And Photo by Alexander London on Unsplash



# Problem:

**How to distinguish distributional uncertainty from other uncertainties?**

→ How could we distinguish between

- in-domain(distinct) data vs out-of-distribution data
- in-domain(data uncertainty) data vs out-of-distribution data

## Previous work:

- Predictive posteriors of regression or classification DNNs

[Gimpel 2016, Malinin 2017, Lee 2018, Liang 2018]

- Bayesian approaches like Monte-Carlo Dropout

[Gal 2016]

- Non-Bayesian Ensembles like Deep Ensembles

[Lakshminarayanan 2017]

**Common problem?**



# Solution:

**Dirichlet Prior Network with KL- divergence (Malinin 2018)**

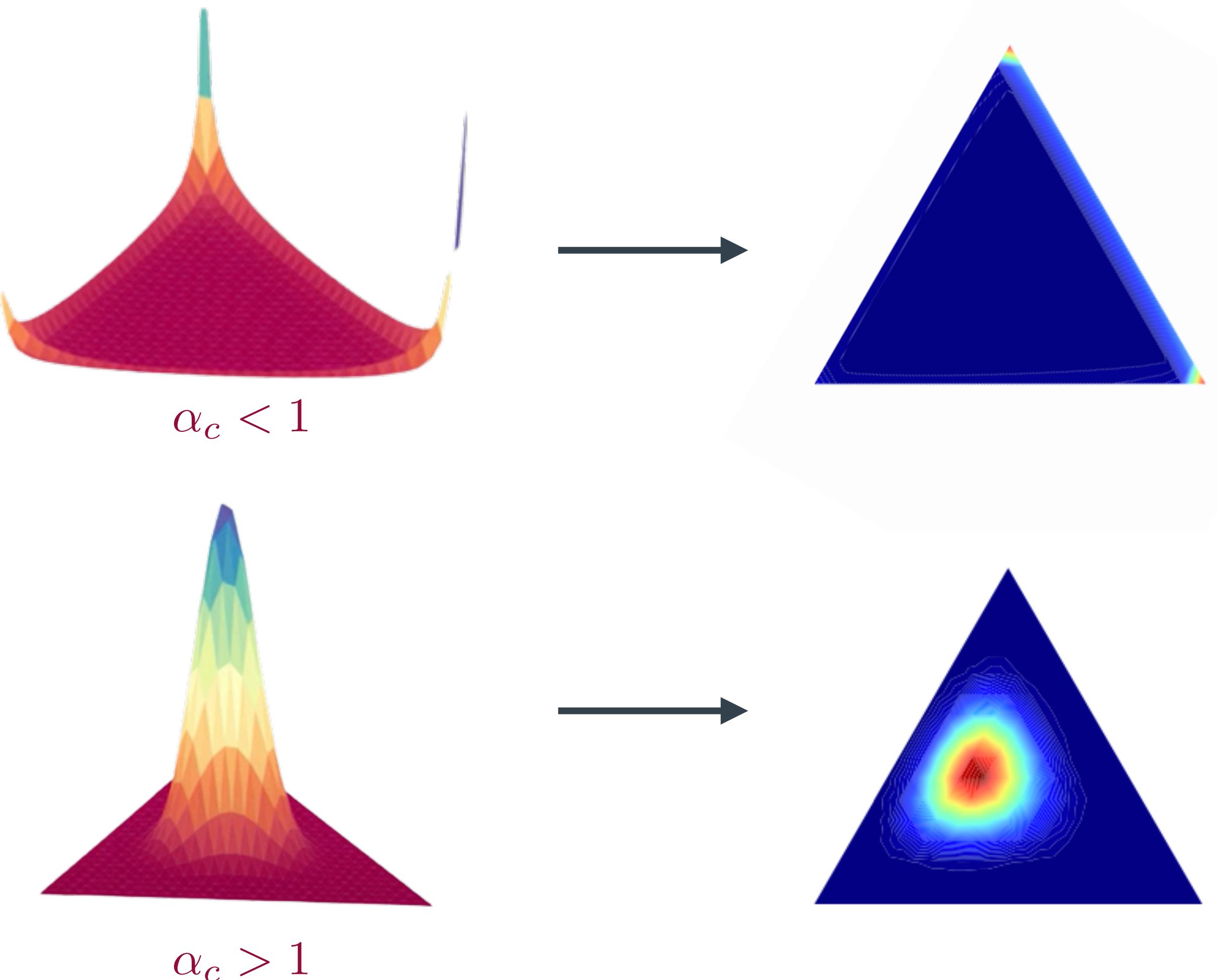
## Our contribution:

- 1. Reproduce the paper using DPN with reverse KL-divergence**
- 2. Experiments on additional dataset that we created**



# Dirichlet distribution

$$\text{Dir}(\mu|\alpha) = \frac{\Gamma(\sum_c \alpha_c)}{\prod_c \Gamma(\alpha_c)} \prod_c \mu_c^{\alpha_c-1}$$

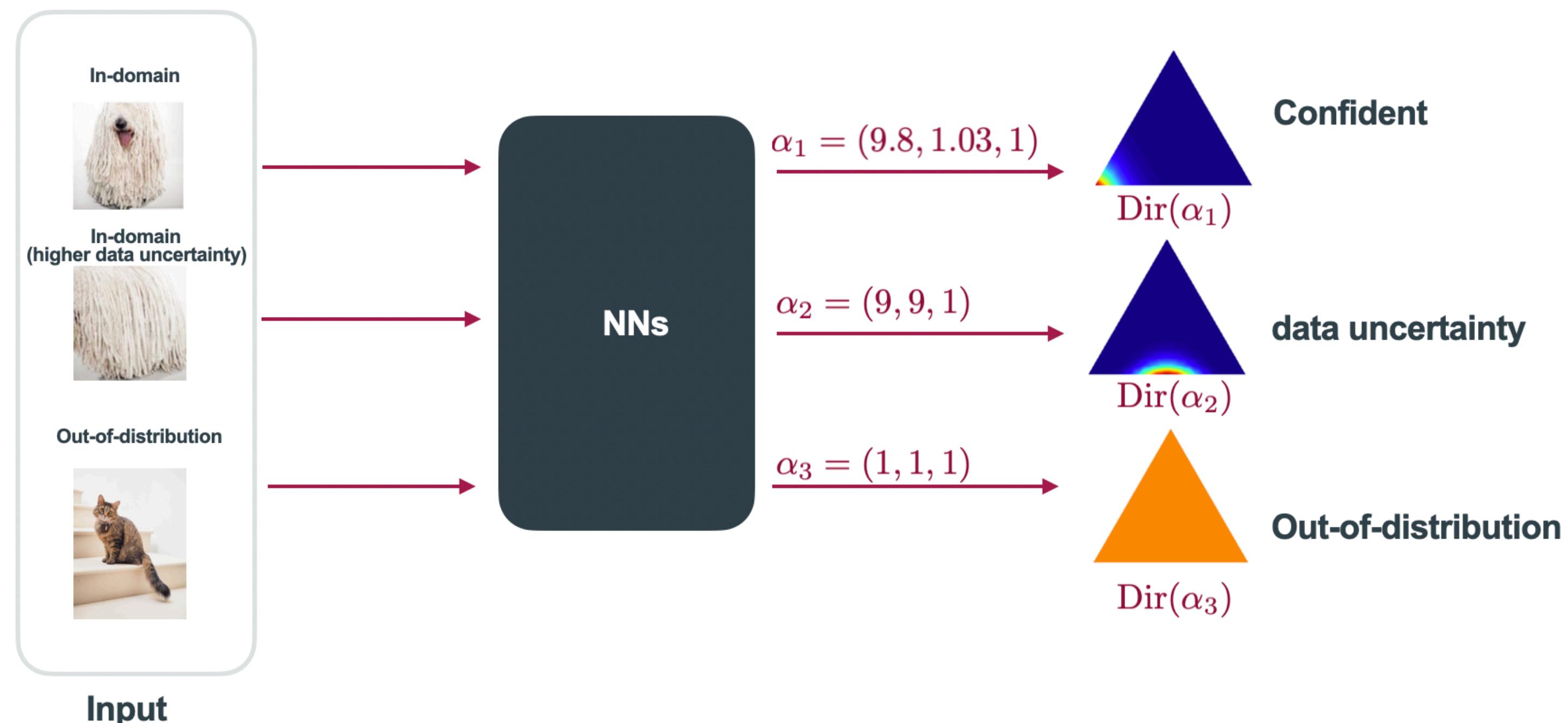


Red figures from <https://www.youtube.com/watch?v=DpGkAKdLjdo>



# Dirichlet Prior Network

It parameterises Dirichlet distribution as prior to the predictive distribution over simplex



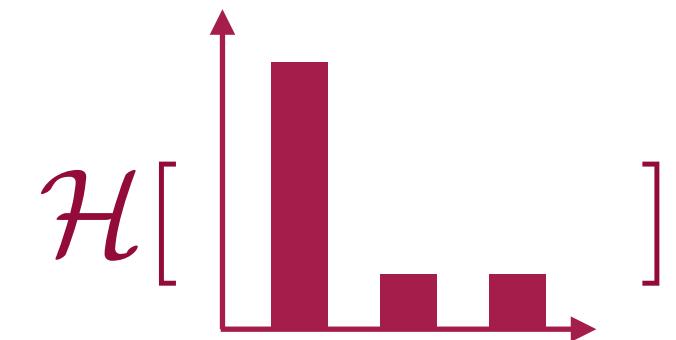
$$P(y = w_c | x^*, \hat{\theta}) = \hat{\mu}_c = \frac{\alpha_c}{\sum \alpha_c}$$



# Uncertainty Measures

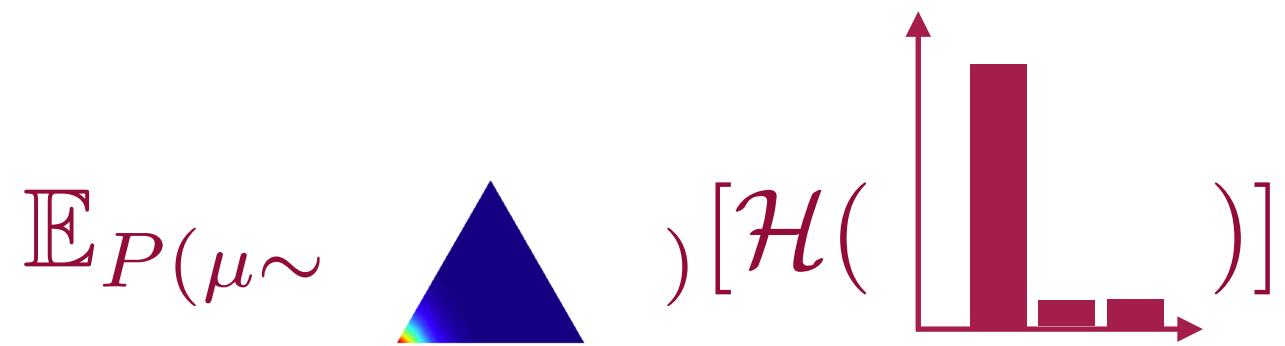
**Entropy of y:**

$$\mathcal{H}[P(y|x^*; \mathcal{D})] \longrightarrow$$



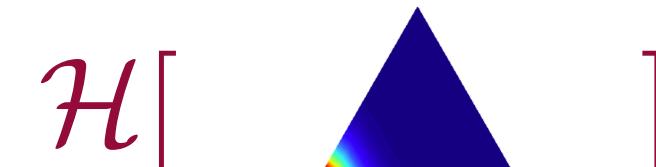
**Expected data uncertainty(D.C.):**

$$\mathbb{E}_{P(\mu|x^*; \mathcal{D})}[\mathcal{H}(P(y|\mu))] \longrightarrow$$



**Entropy of mu:**

$$\mathcal{H}[P(\mu|x^*; \mathcal{D})] \longrightarrow$$



**Mutual Information(M.I.):**

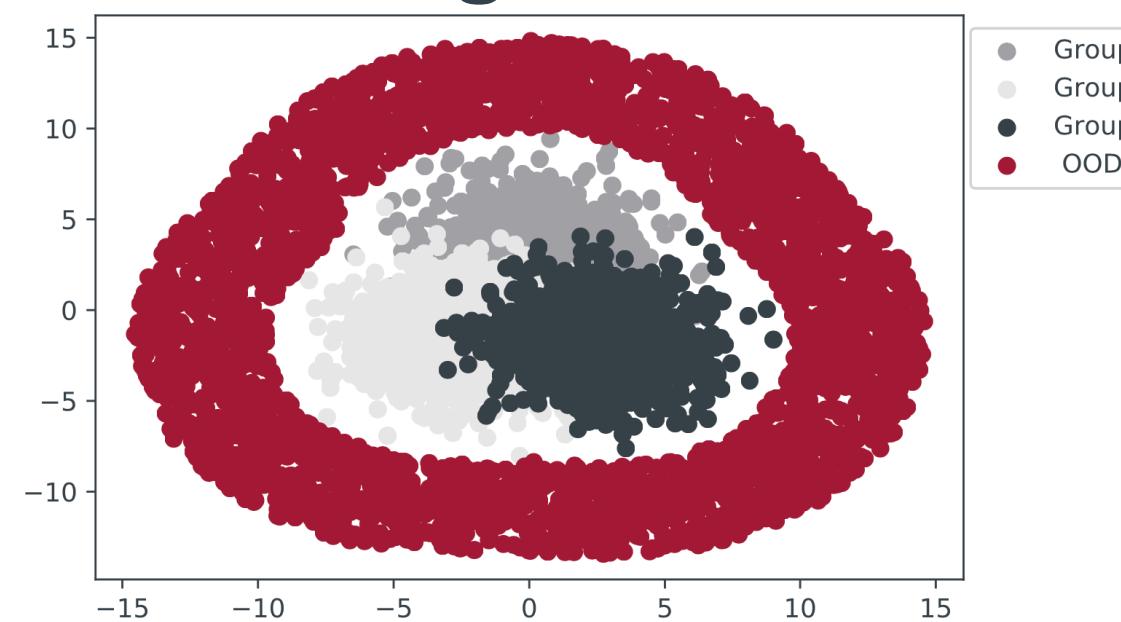
$$\mathcal{H}[P(y|x^*; \mathcal{D})] - \mathbb{E}_{P(\mu|x^*; \mathcal{D})}[\mathcal{H}(P(y|\mu))] \longrightarrow$$



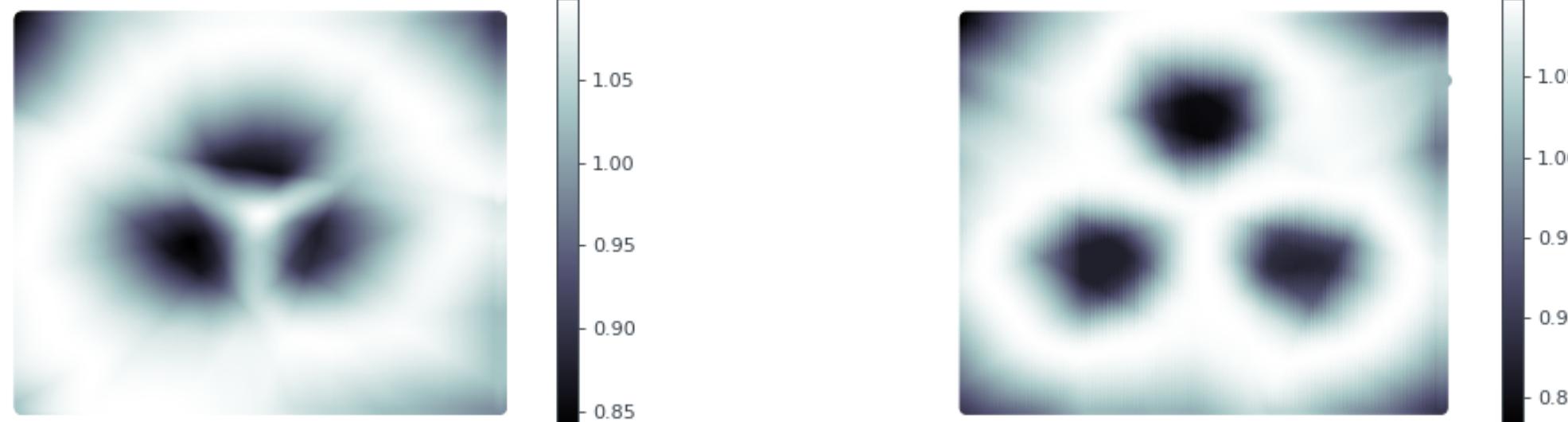


# Synthetic Experiments

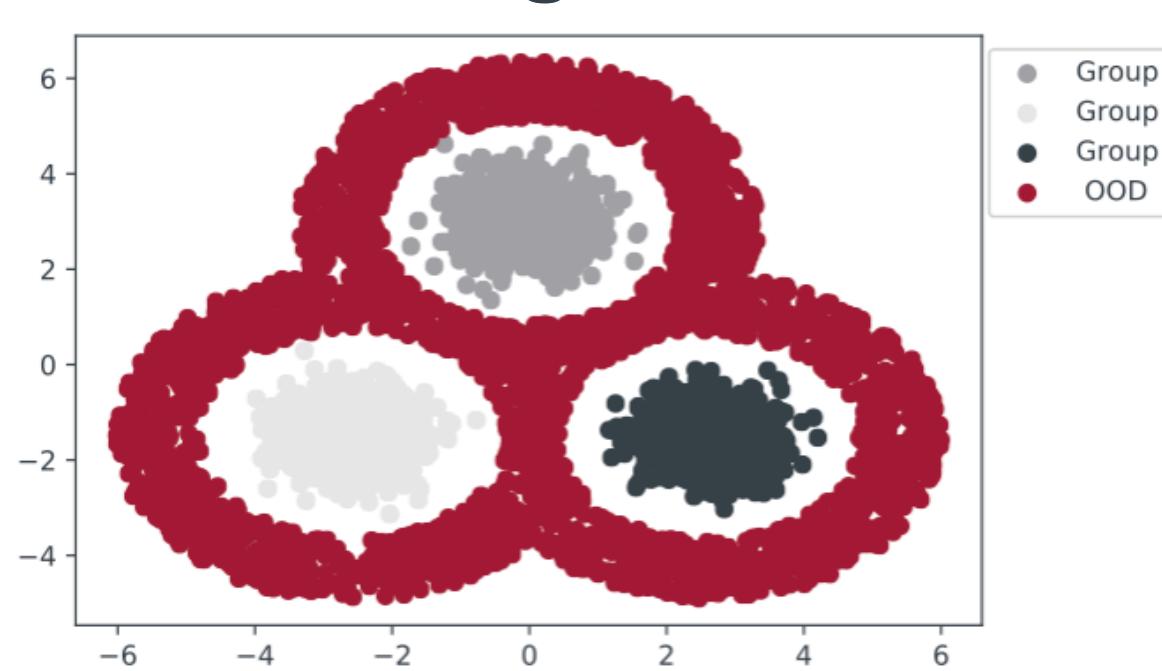
**Training Dataset**



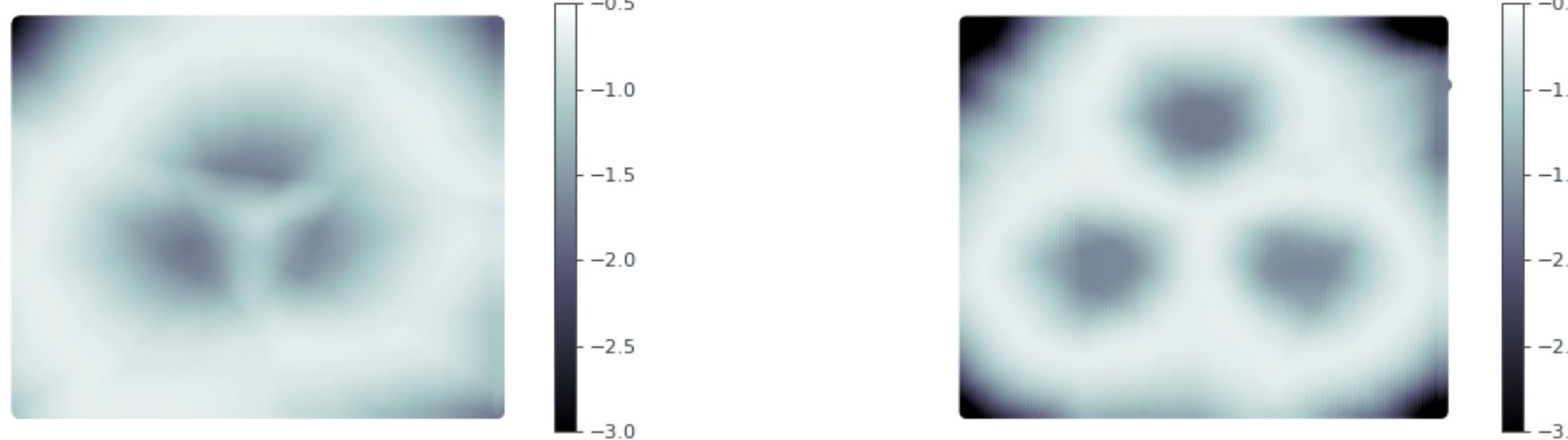
**Entropy of  $y$**



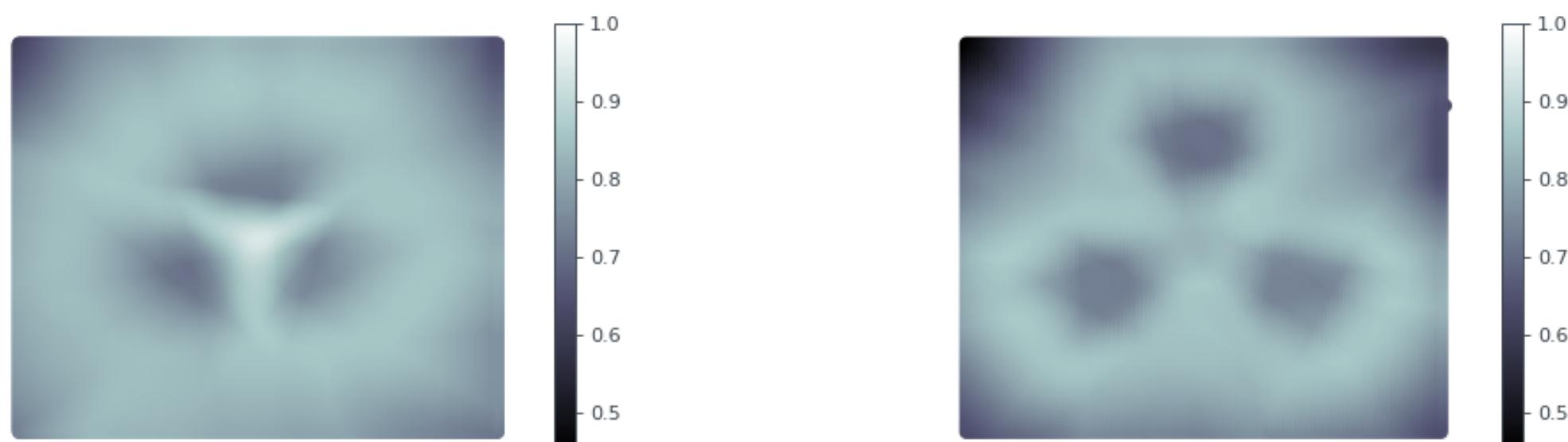
**Training Dataset**



**Entropy of  $\mu$**



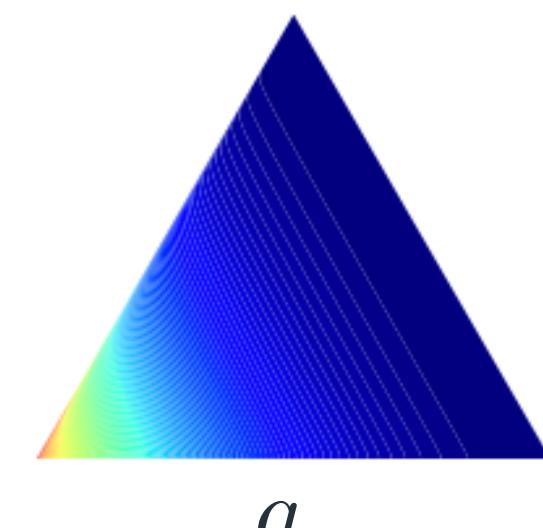
**Expected Data Uncertainty**



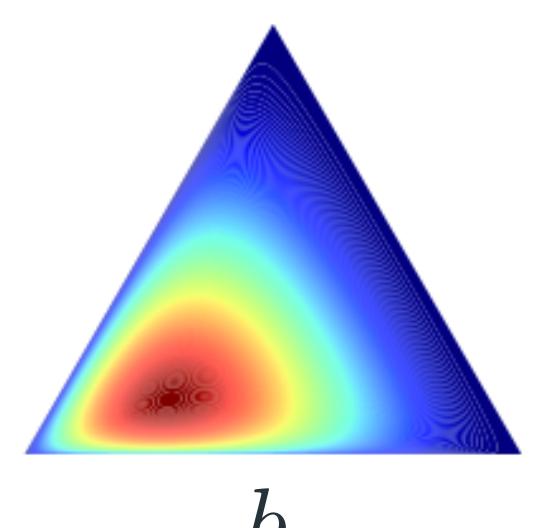


# Synthetic Experiments

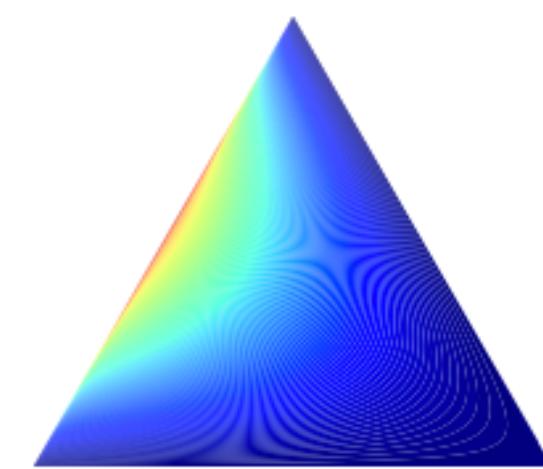
Points	Entropy of $y$	Entropy of $\mu$	Data Uncertainty
$a$ In domain	0.9071	-1.4869	0.7523
$b$ High class overlap	1.0439	-1.0974	0.8985
$c$ weak class overlap	1.0402	-1.0914	0.8739
$d$ Out-of-distribution	1.0951	-0.7129	0.8441



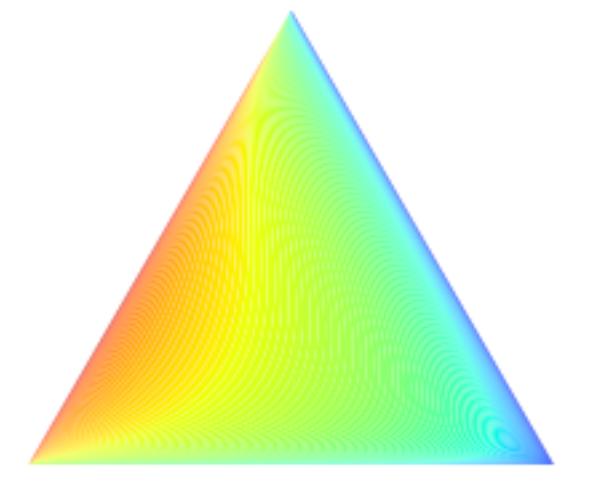
$a$



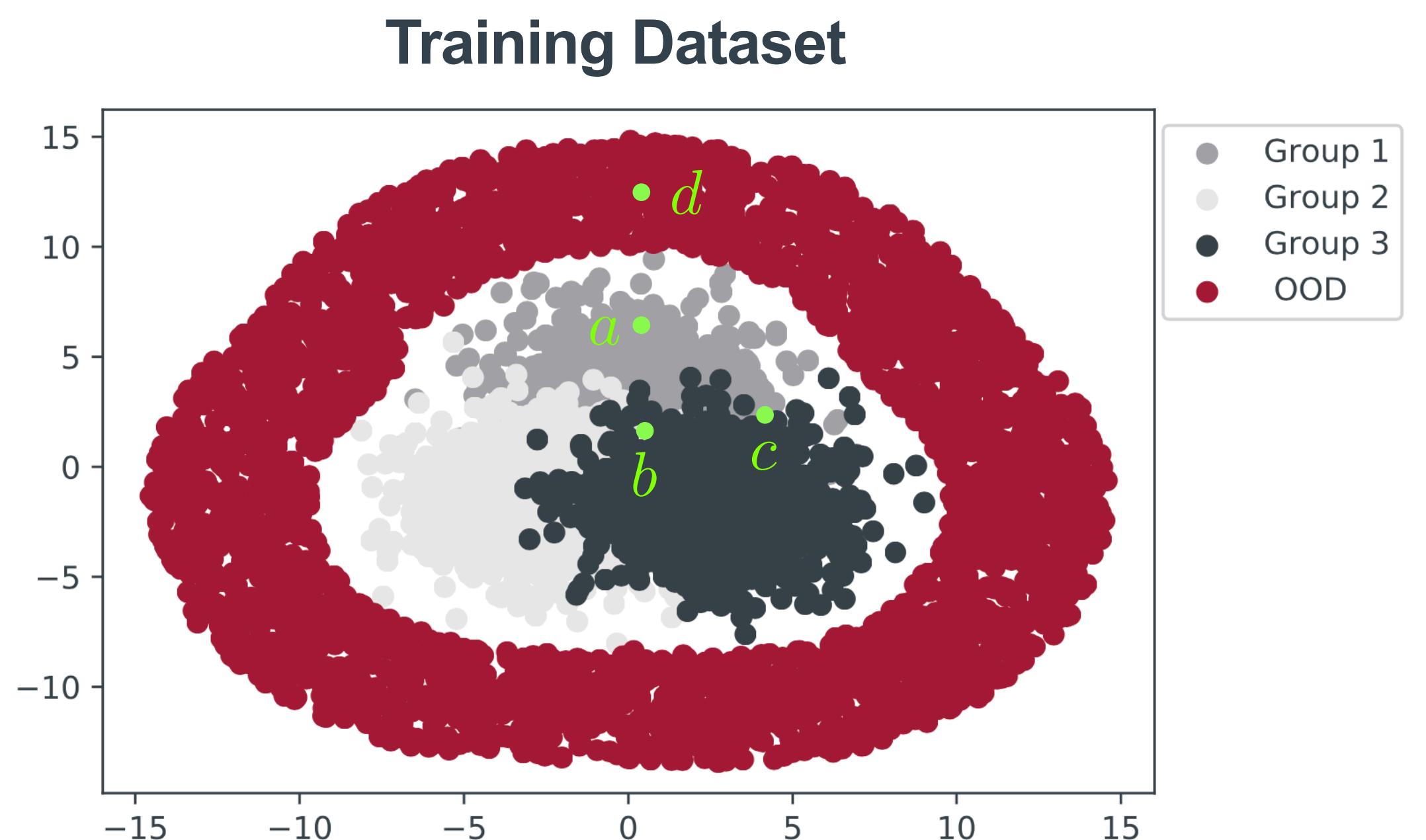
$b$



$c$



$d$

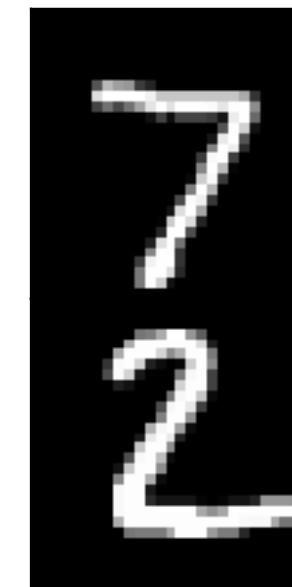




# Reproduction (MNIST+FashionMNIST)

## Setup

In-domain Dataset



Out-of-distribution Dataset



## Results

Detections	AUROC				AUPR			
	Ent. y	Ent. $\mu$	M.I.	D.U.	Ent. y	Ent. $\mu$	M.I.	D.U.
Misclassification	92.3	89.7	89.9	92.4	33.9	29.2	29.7	34.3
OOD	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.9
Misclass. vs OOD	100.0	100.0	100.0	99.3	100.0	100.0	100.0	100.0



# Corrupted MNIST

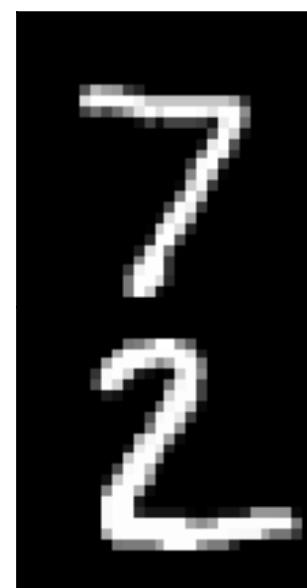
## Setup



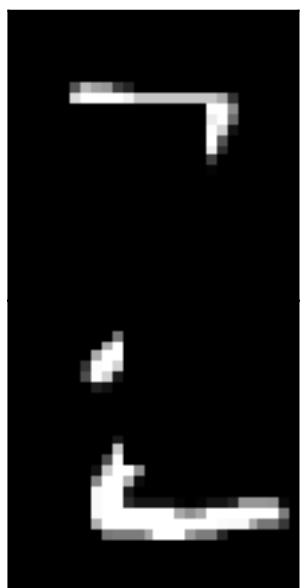
In-domain



Out-of-distribution



Test set 1

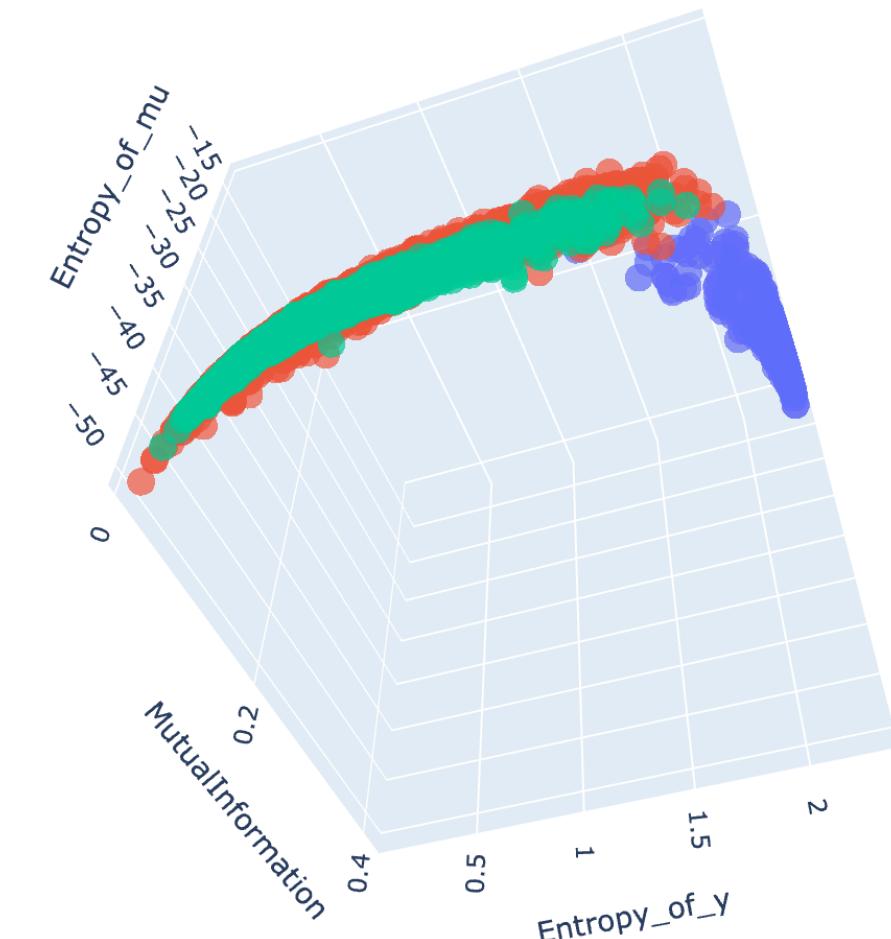


Test set 2

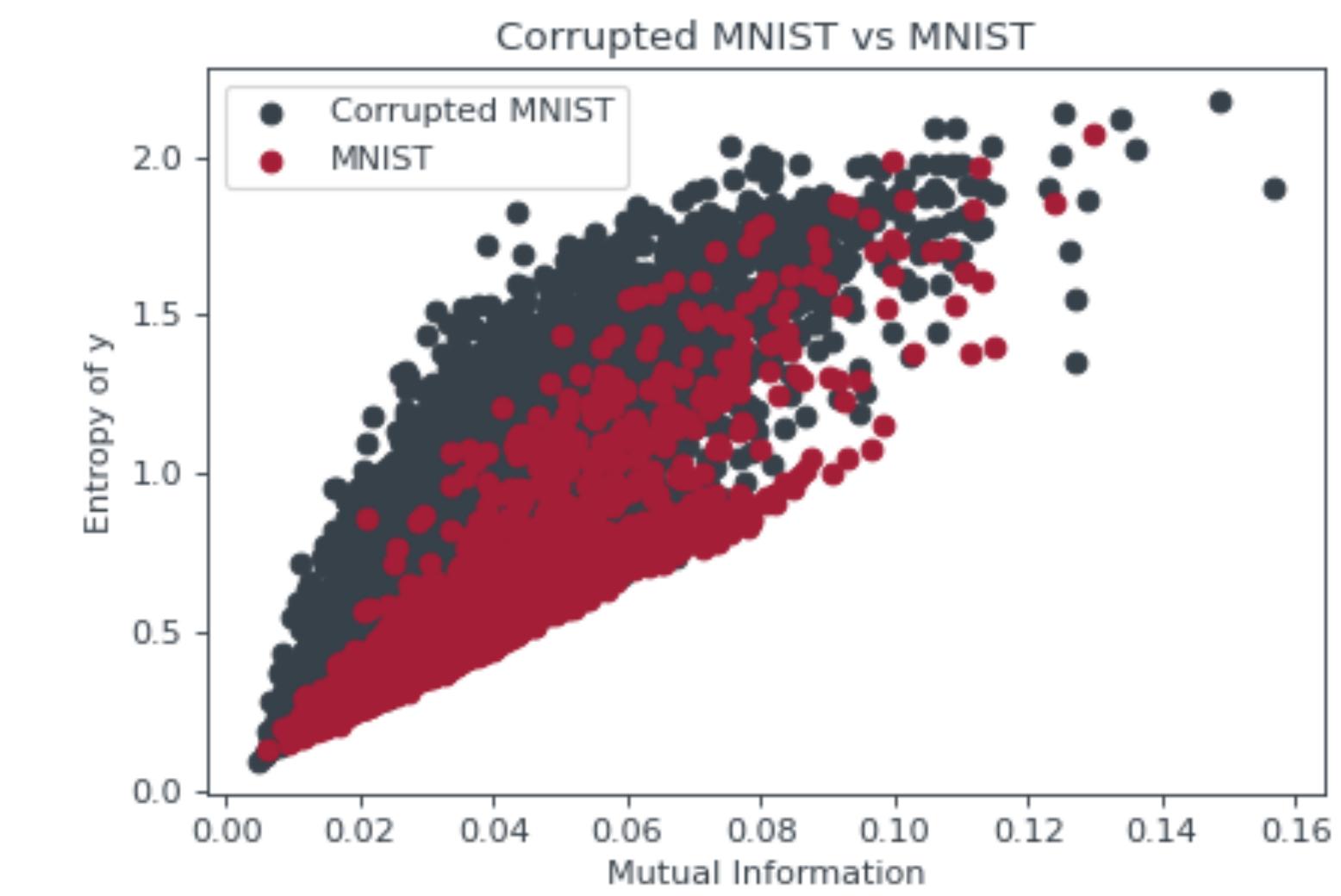
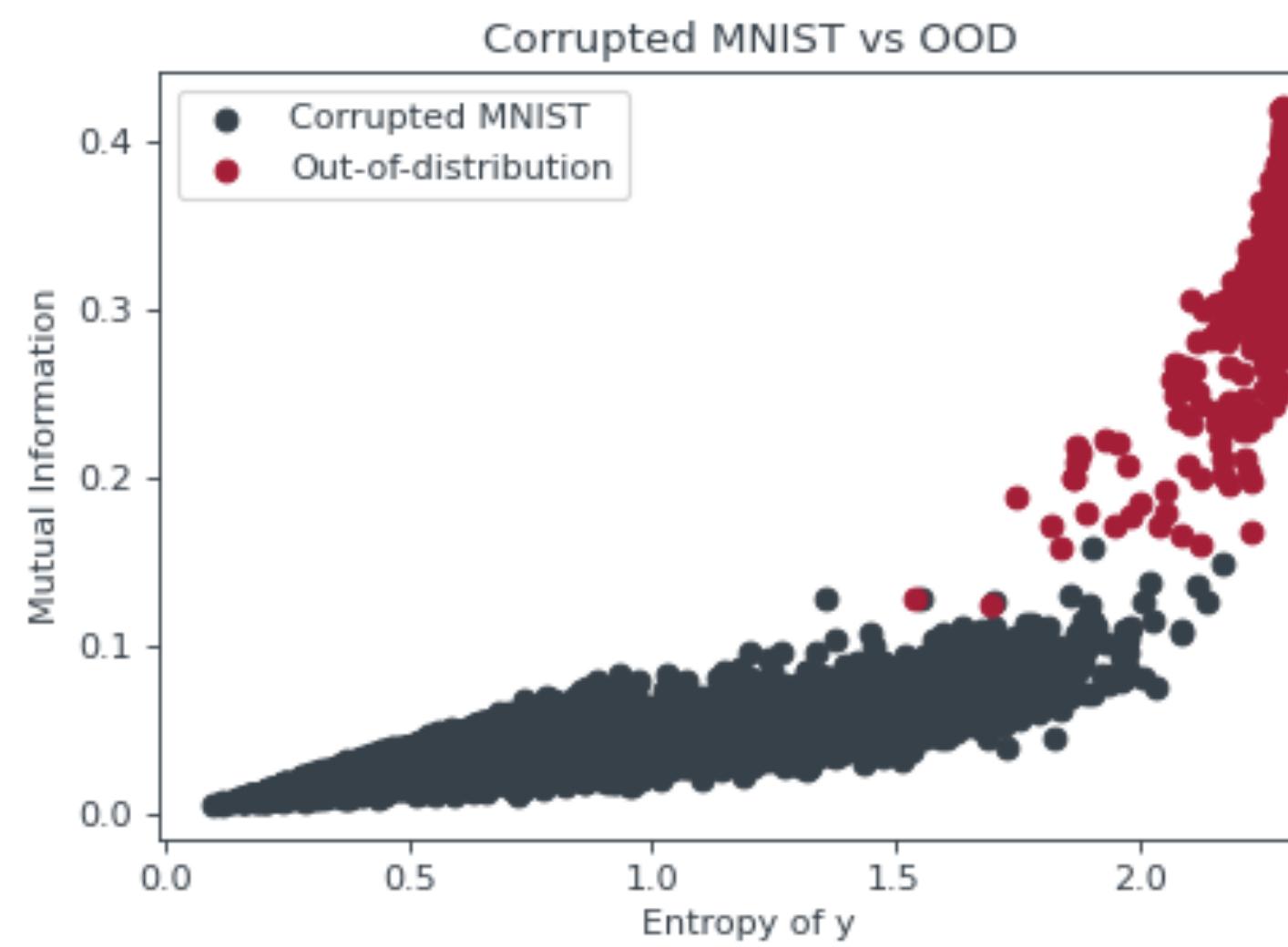
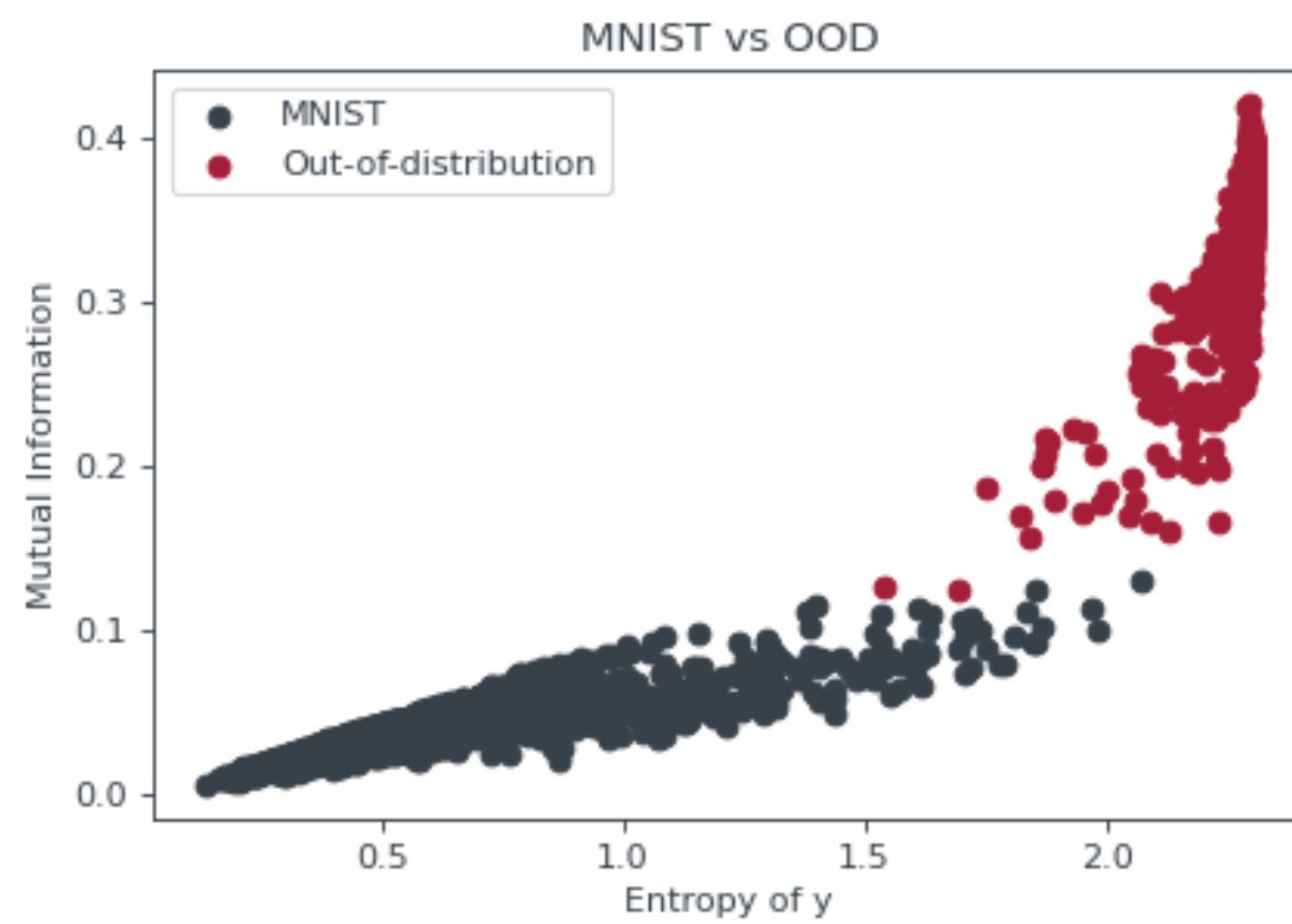
	<b>Dataset</b>	<b>Size</b>	<b>Erased regions%</b>
Training in domain	MNIST	60000	50
Training OOD	FashionMNIST	60000	0
Test set 1	MNIST	10000	0
Test set 2	MNIST	10000	100
Test set OOD	FashionMNIST	10000	0



# Results



Detections	Sets	AUROC				AUPR			
		Ent. y	Ent. $\mu$	M.I.	D.U.	Ent. y	Ent. $\mu$	M.I.	D.U.
In-domain	Corrupted vs MNIST	72.0	67.5	59.2	72.7	73.8	68.0	60.0	74.5
OOD	MNIST	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.9
	Corrupted MNIST	100.0	100.0	100.0	99.9	100.0	100.0	100.0	99.8





# Conclusion

1. Dirichlet Prior Network can distinguish distributional uncertainty from others
2. This approach can not clearly distinguish between
  - in-domain data (MNIST)
  - in-domain data with data uncertainty (Corrupted MNIST)

# Further work

1. Baseline
2. Out-of-distribution dataset

**Thank you for your attention!**