

## Introduction & Motivation

- deep-learning models is o Interpretability of demanded in high-stakes applications, e.g., disease diagnosis and autonomous driving.
- ProtoPNet achieves similarity-based classification by measuring how strongly parts of a test image look like the training prototypes.
- ProtoPNet tends to learn trivial prototypes, due to the co-effects of clustering and separation training losses.



• We make an analogy between the prototype learning from ProtoPNet and support vector learning from SVM, and propose to learn support prototypes that benefit classification accuracy and interpretability.



# Learning Support and Trivial Prototypes for Interpretable Image Classification

Chong Wang, Yuyuan Liu, Yuanhong Chen, Fengbei Liu, Yu Tian, Davis J. McCarthy, Helen Frazer, Gustavo Carneiro

### Method

- A support ProtoPNet branch to utilize support prototypes, capturing hard-to-learn visual patterns. (closeness)
- A trivial ProtoPNet branch to employ trivial prototypes, capturing easy-to-learn visual features. (discrimination) ST-ProtoPNet: ensemble classification interpretation by the two complementary sets of prototypes.



- Dataset
- Fine-grained image recognition tasks Stanford Cars, and Stanford Dogs.
- **Evaluation metrics:** Ο

Classification: top-1 accuracy

Interpretability: CH, OIRR, IoU, and DAUC

highly

interpretable

$$\mathbf{p}_{r} \in \mathcal{P}_{c_2} \mathbf{p}_{m}^{\mathrm{T}} \mathbf{p}_{r}$$

$$\sum_{n \in \mathcal{P}_{c_2}} \mathbf{p}_m^{\mathrm{T}} \mathbf{p}_n$$

#### **Classification Accuracy**

C

Method	CUB					Cars						
	VGG16	VGG19	ResNet34	ResNet152	Dense121	Dense161	VGG16	VGG19	ResNet34	ResNet152	Dense121	Dense 161
Baseline	$73.3 \pm 0.2$	$74.7\pm0.4$	$82.2\pm0.3$	$80.8 \pm 0.4$	$81.8 \pm 0.1$	$82.1\pm0.2$	$87.3 \pm 0.4$	$88.5\pm0.3$	$92.6\pm0.3$	$92.8 \pm 0.4$	$92.0 \pm 0.3$	$92.5\pm0.3$
ProtoPNet [4]	$77.2 \pm 0.2$	$77.6\pm0.2$	$78.6\pm0.1$	$79.2 \pm 0.3$	$79.0\pm0.2$	$80.8\pm0.3$	$88.3 \pm 0.2$	$89.4\pm0.2$	$88.8\pm0.1$	$88.5 \pm 0.3$	$87.7 \pm 0.1$	$89.5\pm0.2$
TesNet [53]	$81.3 \pm 0.2$	$81.4\pm0.1$	$82.8\pm0.1$	$82.7 \pm 0.2$	$84.8\pm0.2$	$84.6\pm0.3$	$90.3 \pm 0.2$	$90.6\pm0.2$	$90.9\pm0.2$	$92.0 \pm 0.2$	$91.9\pm0.3$	$92.6\pm0.3$
Trivial ProtoPNet	$80.8 \pm 0.2$	$81.2\pm0.2$	$82.5\pm0.2$	$83.1 \pm 0.3$	$83.9\pm0.3$	$84.6\pm0.3$	$90.1 \pm 0.2$	$90.7\pm0.2$	$91.1\pm0.2$	$91.5 \pm 0.2$	$91.4\pm0.3$	$92.4\pm0.3$
Support ProtoPNet	$81.7 \pm 0.2$	$81.8\pm0.3$	$83.0\pm0.1$	$83.6 \pm 0.2$	$84.7\pm0.2$	$85.2\pm0.3$	$90.9 \pm 0.2$	$90.8\pm0.2$	$91.0\pm0.2$	$91.8 \pm 0.2$	$91.7 \pm 0.2$	$92.7\pm0.3$
ST-ProtoPNet (ours)	$82.9 \pm 0.2$	$83.2\pm0.2$	$83.5\pm0.1$	$84.1\pm0.2$	$85.4\pm0.2$	$86.1\pm0.2$	91.1 ± 0.2	$91.7\pm0.2$	$91.4\pm0.1$	$92.0\pm0.2$	$92.3\pm0.3$	$92.7\pm0.2$

## **Prototype Visualization and Analysis**



## Interpretable Reasoning of ST-ProtoPNet

Testing image	Prototype	Training image with prototype	Activation map	Similarity score
				5.142
			i	4.901 :
				4.368
	A STATISTICS	Curvidu 2		4.206

## **Measuring Interpretability based on Localisation**

Metric GradCAM [43] ProtoPNet [4] TesNet [53] DefProto [11] TrvProto SptProto ST-Pr	
	oto
CH $(\%, \uparrow)$ 52.46 48.66 59.38 52.09 63.05 63.87 66.4	3
IoU (%, ↑) 39.91 38.03 36.92 40.77 37.74 <b>42.04</b> 41.0	5
OIRR (%, ↓) 37.01 37.26 38.97 28.68 34.48 28.69 <b>28.0</b>	9
DAUC $(\%, \downarrow)$ 7.01 7.39 5.86 5.99 6.06 5.80 5.74	1



### **Experimental Results**





#### Findings

- Support prototypes tend to only focus on relevant and share bird parts visually similar features among classes.
- Trivial porotypes focus not only on the relevant bird parts but also the background regions.

Acknowledgement: BRAIx (MRFAI000090) • ARC (FT190100525)