TRANSFERLAB

Latent space prototype interpretability: Strengths and shortcomings

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Table of contents

Introduction

Interpretability, why?

- Deep Neural Networks are very powerful but **black boxes**
- Why should we trust these models for high stake decisions?
- Decision trees or linear classifiers are intrinsically **interpretable** but not very powerful

The goal is to define a form of interpretability in image processing similar to the way humans describe their thinking in classification tasks.

Interpretability, why?

- Explaining a model with *post-hoc* explanations, such as saliency maps, doesn't work [6]

- Part-based attention methods expose the parts of an input image the network focuses on when making decisions but not the relationship to prototypical cases

Prototypical Part Network

Proto P-Net [1]

- Stop explaining a black box model $\longrightarrow$ create an interpretable model!
- Focus on **fine-grained image recognition** task
- How would you classify the bird in the picture as a clay colored sparrow?

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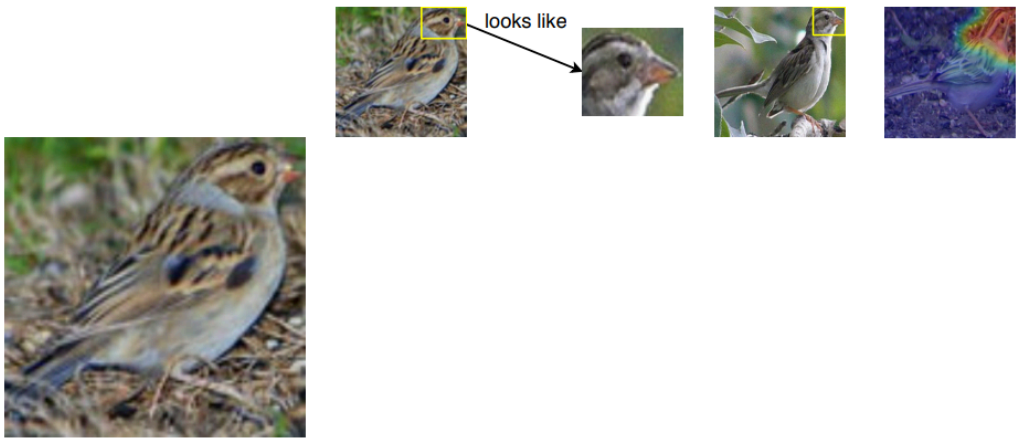

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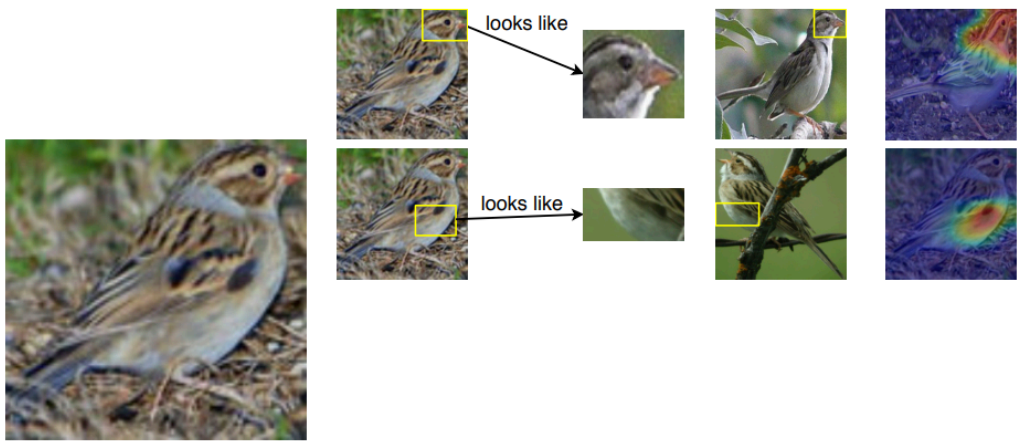

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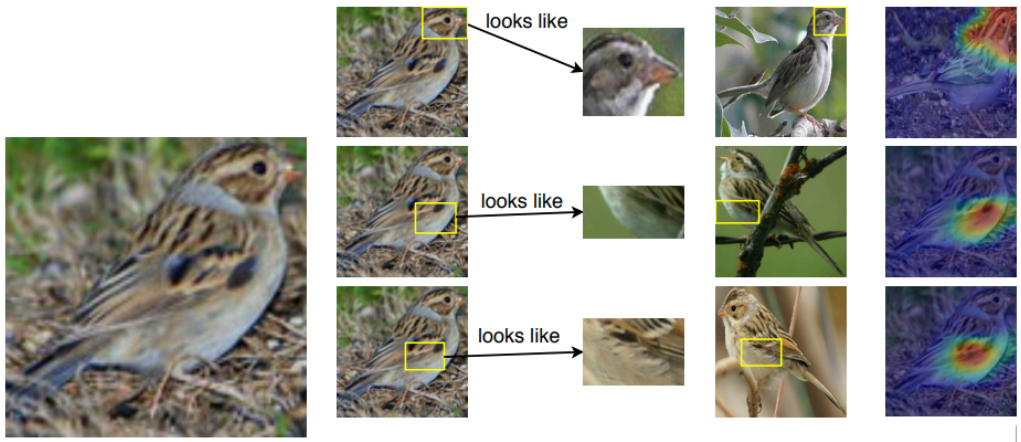

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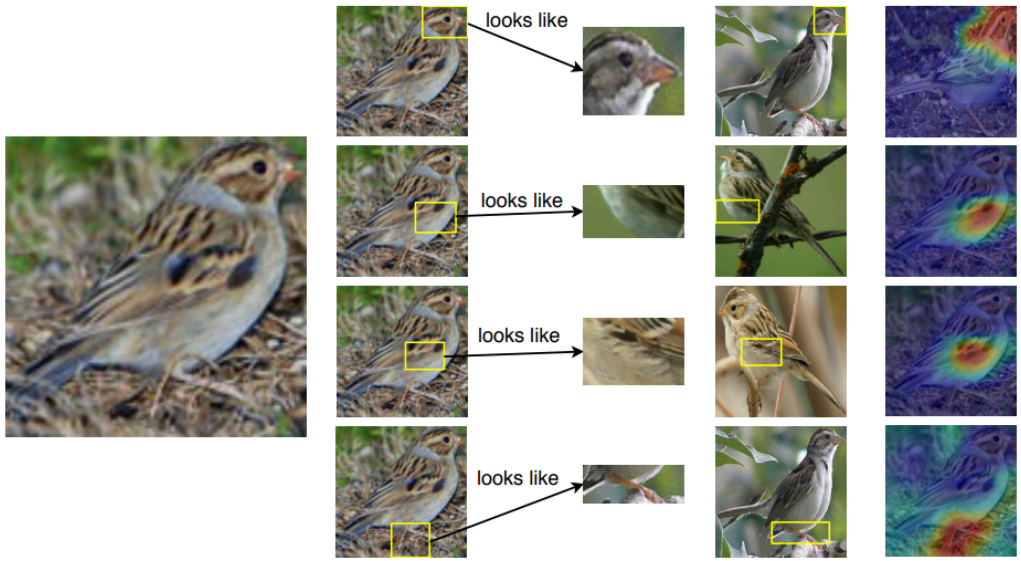
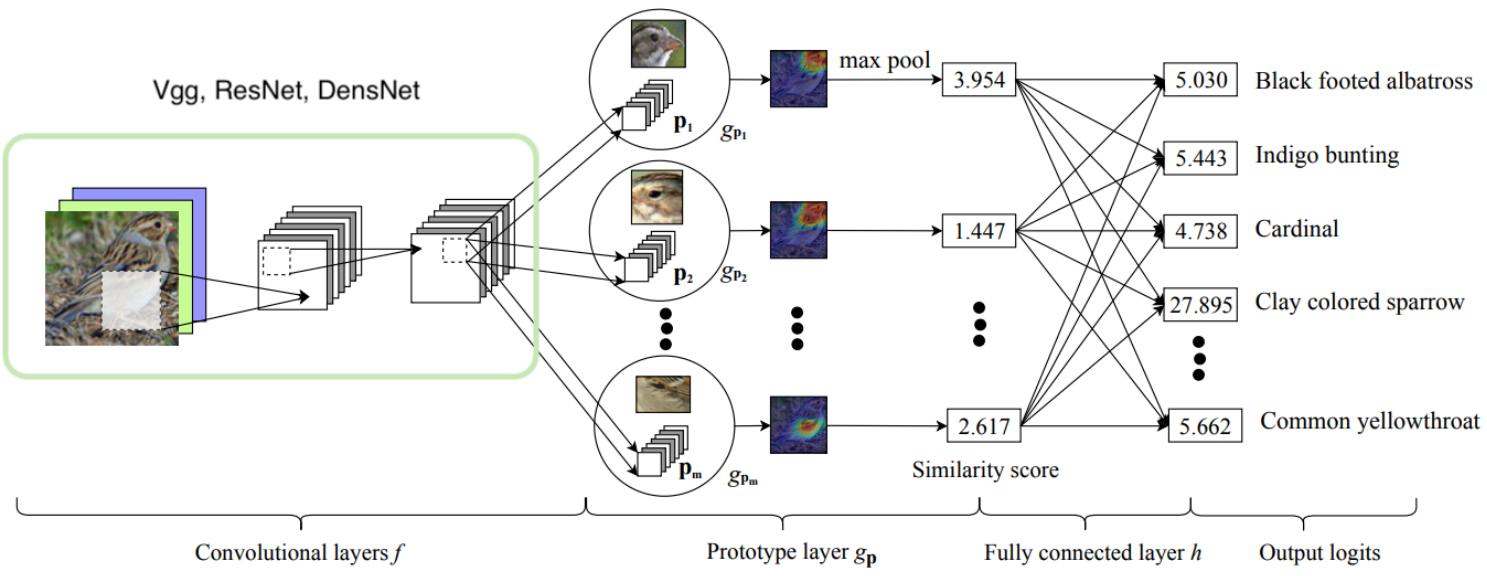


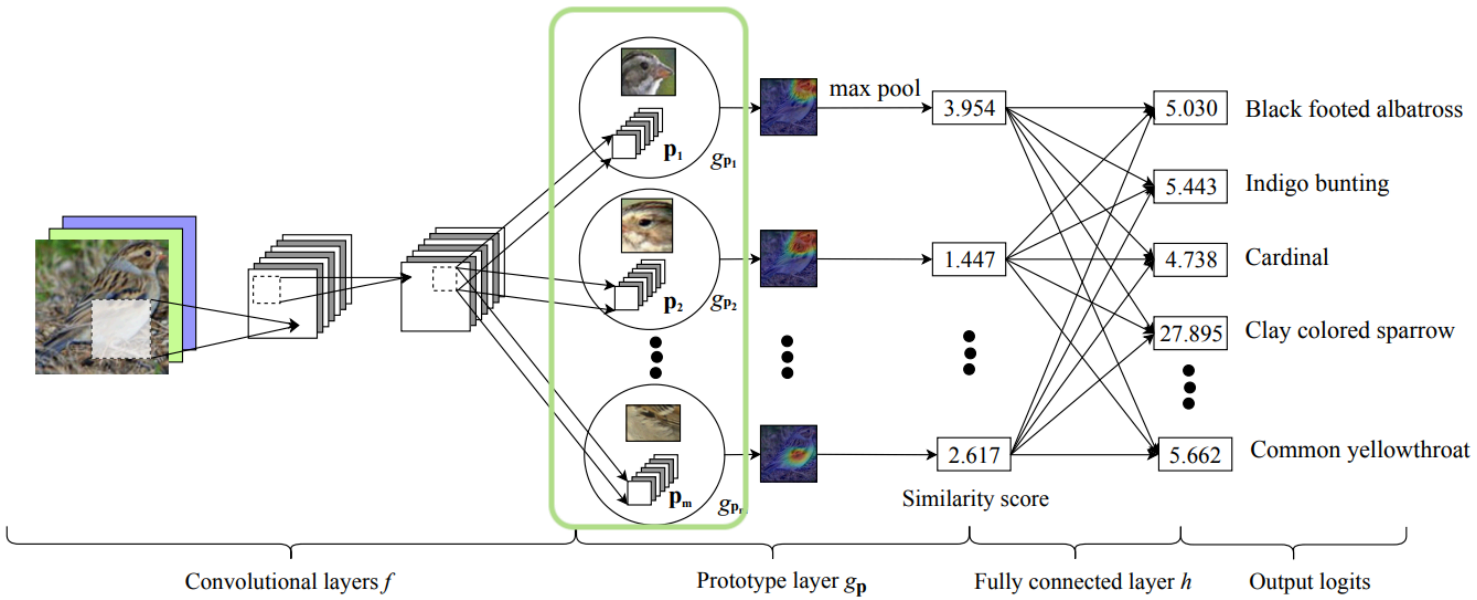
Proto P-Net

- A **regular CNN** with an additional 1x1 convolutional layer on top to extract a latent representation $\mathbf{z} \in \mathbb{R}^{HxWxD}$



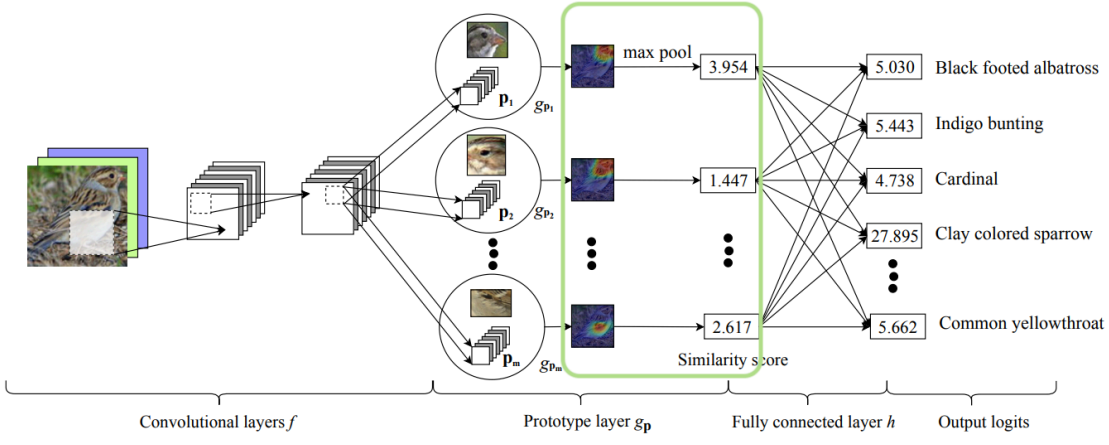
Proto P-Net

- A **prototype layer** g_p is added for interpretability.
- The network learns m prototypes per class of dimensions $H_1 x W_1 x D$, where D is the same dimension as the convolutional output
- A prototype can be seen as the latent representation of an image patch



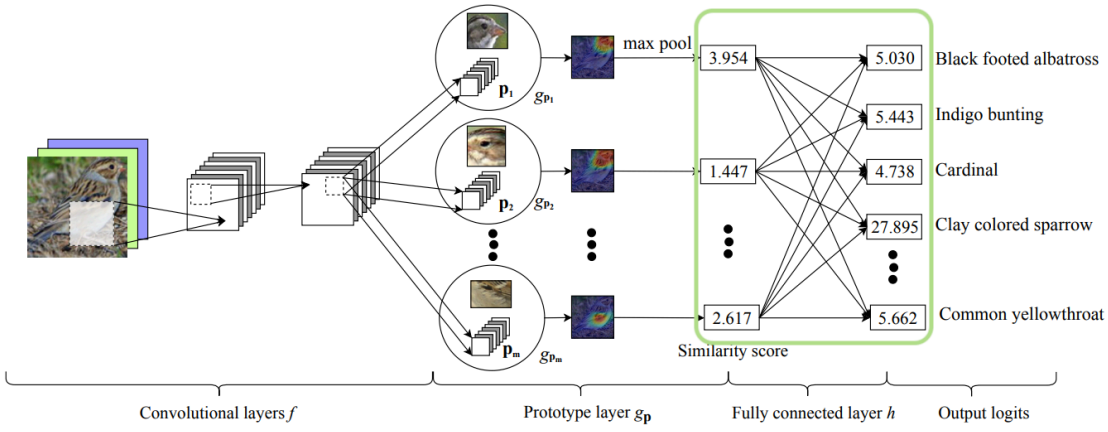
Proto P-Net

- Each unit g_{p_j} in the prototype layer computes the **L2 distances** between all latent patches and prototype $\mathbf{p}_j$ and inverts the distances in similarity scores
- An **activation map of similarity scores** is obtained for each prototype and it indicates how strong a prototypical part is present in the image
- The activation maps are reduced to a single similarity score by max pooling



Proto P-Net

- **A fully connected layer** multiplies each m similarity score with the weight matrix W_h to obtain the logits
- A final softmax layer normalize the logits to get the class probabilities



Training algorithm

The training of ProtoPNet is divided into three steps:

1. **Stochastic Gradient Descend** of layers before the last one
2. **Projection of prototypes**
3. **Convex optimization** of last layer

Training algorithm - 1

- Convolutional layers w_{conv} and prototypes $\mathbf{P} = \{\mathbf{p}_j\}_{j=1}^{m}$ are trained together by optimizing:

$$\min_{\mathbf{P}, w_{conv}} \frac{1}{n} \sum_{i=1}^{n} CrsEnt(h \circ g_{\mathbf{p}} \circ f(\mathbf{x}_i), \mathbf{y}_i) + \lambda_1 Clst + \lambda_2 Sep$$

Training algorithm - 1

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- **Cluster cost**: each training image should have a latent patch similar to at least one prototype of its own class

$$Clst = \frac{1}{n} \sum_{i=1}^{n} min_{j:\mathbf{p}_j \in \mathbf{P}_{y_i}} \min_{\mathbf{z} \in patches(f(\mathbf{x}_i))} ||\mathbf{z} - \mathbf{p}_j||_2^2$$

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- **Cluster cost**:

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- **Separation cost**: each training image should have all latent patches away from the prototypes of the other classes

$$Sep = -\frac{1}{n} \sum_{i=1}^{n} min_{j:\mathbf{p}_j \notin \mathbf{P}_{y_i}} \min_{\mathbf{z} \in patches(f(\mathbf{x}_i))} ||\mathbf{z} - \mathbf{p}_j||_2^2$$

Training algorithm - 1

- Convolutional layers w_{conv} and prototypes $\mathbf{P} = \{\mathbf{p}_j\}_{j=1}^{m}$ are trained together by optimizing:

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- **Separation cost**:

$$Sep = -\frac{1}{n} \sum_{i=1}^{n} min_{j:\mathbf{p}_j \notin \mathbf{P}_{y_i}} \min_{\mathbf{z} \in patches(f(\mathbf{x}_i))} ||\mathbf{z} - \mathbf{p}_j||_2^2$$

- The last layer w_h is fixed:

$$w_h^{(k,j)} = 1 \; \forall \; j \; with \; \mathbf{p}_j \in \mathbf{P}_k \; and \; w_h^{(k,j)} = -0.5 \; \forall \; j \; with \; \mathbf{p}_j \notin \mathbf{P}_k$$

Training algorithm - 2

- Each prototype is projected into the nearest latent training patch with the following update step:

$$\mathbf{p}_j \leftarrow argmin_{\mathbf{z} \in Z_j} ||\mathbf{z} - \mathbf{p}_j||_2$$

- A prototype can be visualized as a **training patch**
- This prototype projection step doesn't change the prediction accuracy of ProtoPNet and it is done every 10 epochs during the training

Training algorithm -3

- Last linear classifier optimization:

$$\min_{w_h} \frac{1}{n} \sum_{i=1}^{n} CrsEnt(h \circ g_{\mathbf{p}} \circ f(\mathbf{x}_i), \mathbf{y}_i) + \lambda \sum_{k=1}^{K} \sum_{j:\mathbf{P}_j \notin \mathbf{P}_k} |w_h^{(k,j)}|$$

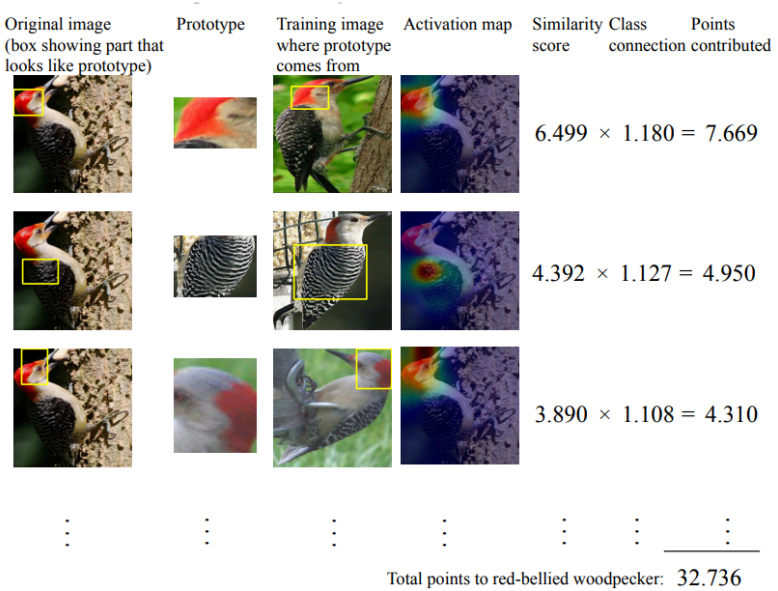
- Parameters from the convolutional layers and prototypes are fixed
- For each class, a L_1 **regularization term** penalizes the prototypes that don't belong to the class.
- The model relies less on "negative" reasoning process thanks to the sparsity property:

$$w_h^{(k,j)} \approx 0 \; for \; k \; and \; j \; with \; \mathbf{p}_j \notin \mathbf{P}_k$$

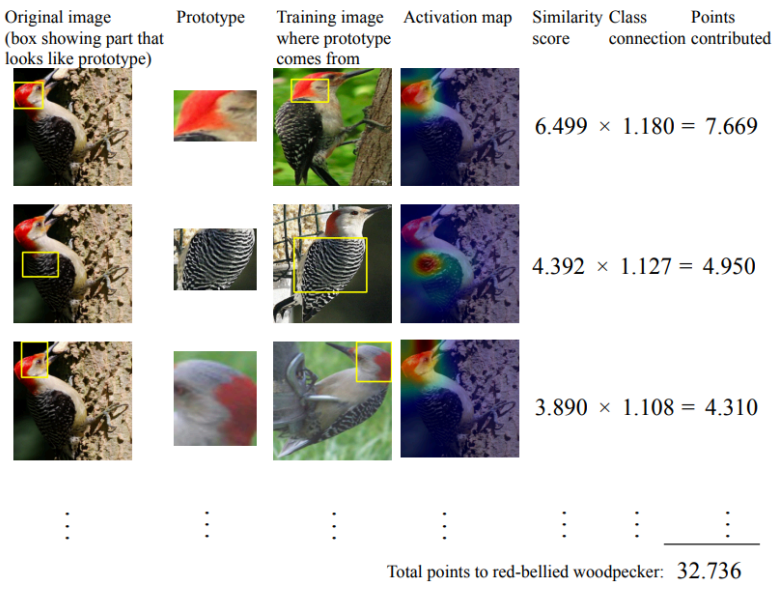
Reasoning process

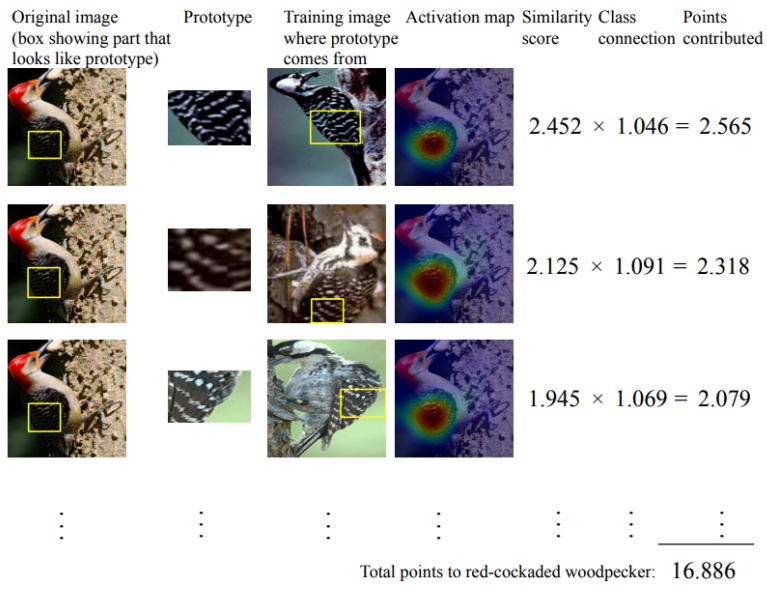
- Why is this bird classified as a red-bellied woodpecker?

Reasoning process



Reasoning process





Results

- Loss of accuracy at most 3.5%

Base	ProtoPNet	Baseline	Base	ProtoPNet	Baseline
VGG16	76.1 ± 0.2	74.6 ± 0.2	VGG19	78.0 ± 0.2	75.1 ± 0.4
Res34	79.2 ± 0.1	82.3 ± 0.3	Res152	78.0 ± 0.3	81.5 ± 0.4
Dense121	80.2 ± 0.2	80.5 ± 0.1	Dense161	80.1 ± 0.3	82.2 ± 0.2

Results

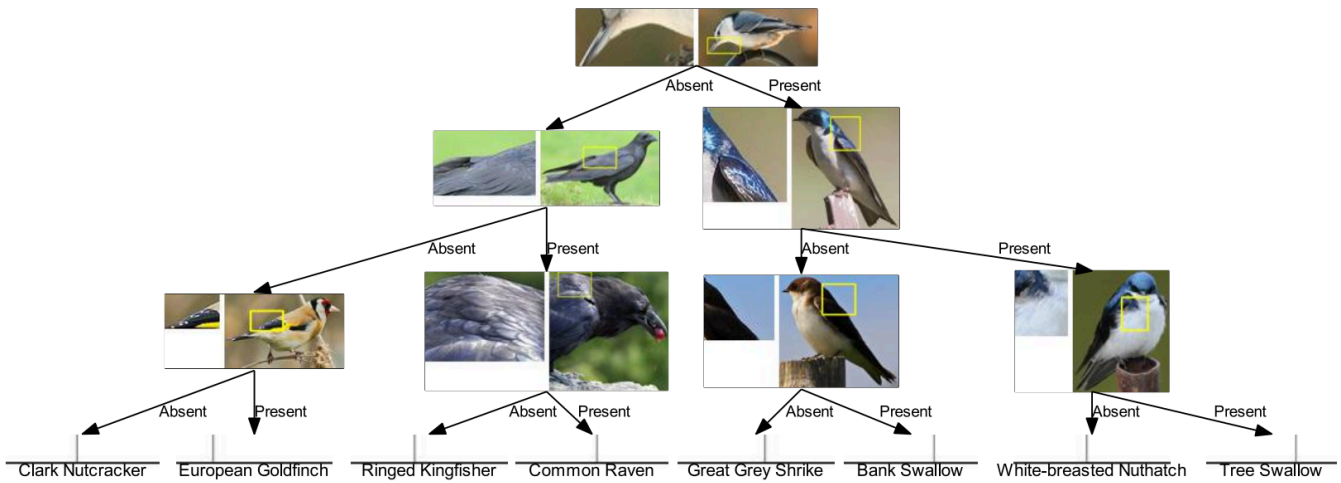
- Loss of accuracy at most 3.5%
- Accuracy can also be improved by combining multiple ProtoPNet models
- Comparison with part-level attentions methods

Interpretability	Model: accuracy
None	**B-CNN**[25]: 85.1 (bb), 84.1 (full)
Object-level attn.	**CAM**[56]: 70.5 (bb), 63.0 (full)
Part-level attention	**Part R-CNN**[53]: 76.4 (bb+anno.); **PS-CNN** [15]: 76.2 (bb+anno.); **PN-CNN** [3]: 85.4 (bb+anno.); **DeepLAC**[24]: 80.3 (anno.); **SPDA-CNN**[52]: 85.1 (bb+anno.); **PA-CNN**[19]: 82.8 (bb); **MG-CNN**[46]: 83.0 (bb), 81.7 (full); **ST-CNN**[16]: 84.1 (full); **2-level attn.**[49]: 77.9 (full); **FCAN**[26]: 82.0 (full); **Neural const.**[37]: 81.0 (full); **MA-CNN**[55]: 86.5 (full); **RA-CNN**[7]: 85.3 (full)
Part-level attn. + prototypical cases	**ProtoPNet** (ours): 80.8 (full, VGG19+Dense121+Dense161-based) 84.8 (bb, VGG19+ResNet34+DenseNet121-based)

Neural Prototype Tree

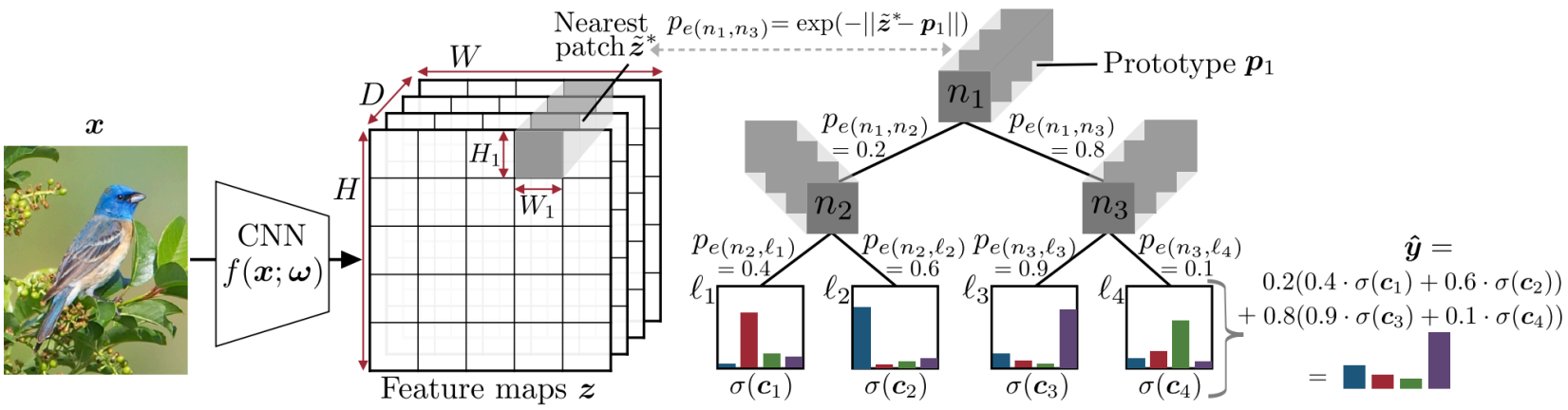
Proto Tree [5]

- A *Neural Prototype Tree* (ProtoTree) combines **prototypes learning** and a **decision binary tree**
- A single prediction is explained by outlining a decision path through the tree (**global explanation**)
- ”Guess who?” game: binary questions to underline visual properties to predict the class of the input image
- ▸ https://github.com/aai-institute/ProtoTree/tree/main



Architecture

- A CNN extracts a feature maps **z** of dimension *HxWxD*
- This latent representation **z** is the input to a ***soft* binary tree** (both children of a node are always visited)

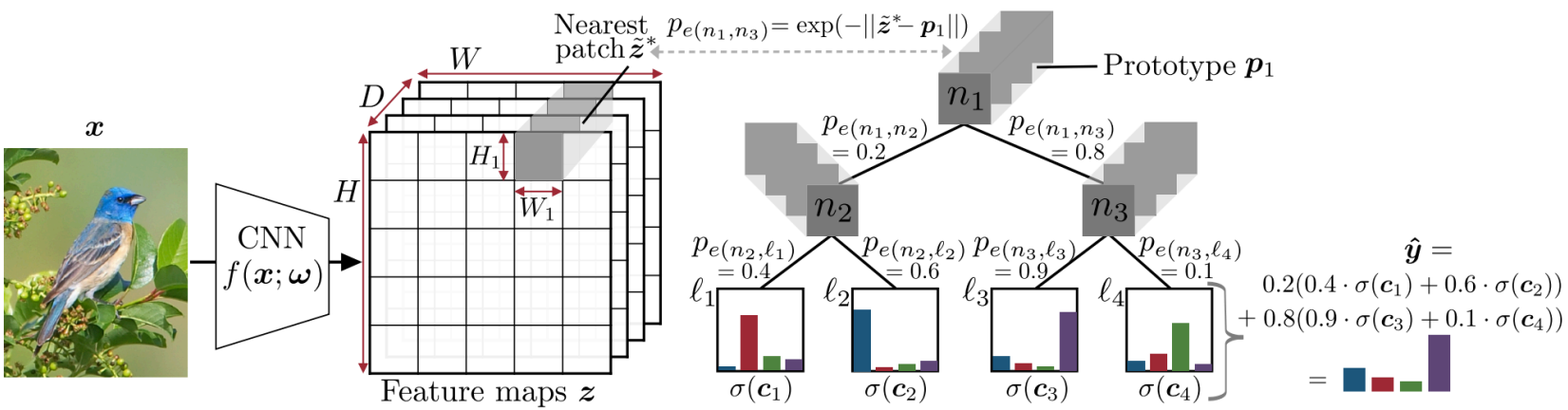


Architecture

- Each **node** of the tree is a **trainable prototype** $\mathbf{p}_n$ of dimension $H_1 x W_1 x D$
- The L_2 **distance** is computed between each prototype and all the patches $\tilde{\mathbf{z}}$ of the latent representation.
- Min pooling operation to select the closest latent patch $\tilde{\mathbf{z}}^*$
- $\mathbf{z}$ is routed through both children with probabilities:

$$p_{e(n,n.right)}(z) = exp(-||\tilde{\mathbf{z}}^* - \mathbf{p}_n||)$$

$$p_{e(n,n_left)} = 1 - p_{e(n,n.right)}$$



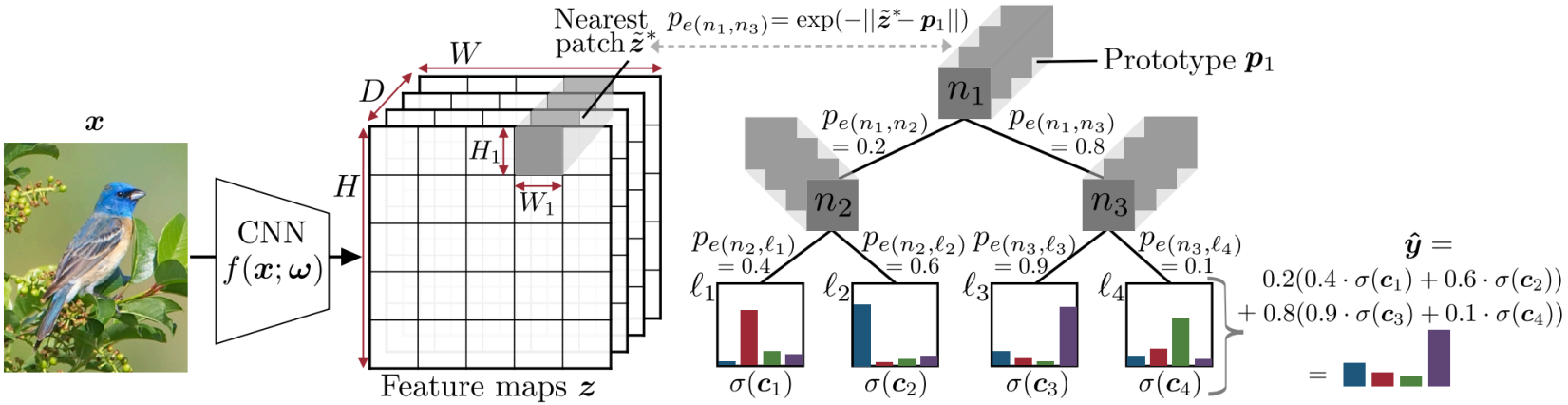
Architecture

- Each leaf is reached with probability equals to the product of probabilities of the edges of the followed path:

$$\pi_l(z) = \Pi_{e \in P_l} p_e((z))$$

- A sigmoid function is applied to the trainable parameter of each leaf to get the final class distribution:

$$\hat{y}(x) = \sum_{l \in L} \sigma(c_l) \cdot \pi(f(x; w))$$



Proto Tree Training

The training of a ProtoTree follows these steps:

- Prototypes $\mathbf{P}$ and parameters w of the CNN are trained together by minimizing the **cross entropy loss** between the class probability distribution $\tilde{\mathbf{y}}$ and the ground-truth $\mathbf{y}$
- $\mathbf{P}$ and w are then updated with gradient descent
- We update leaves distribution with a **derivative-free strategy**:

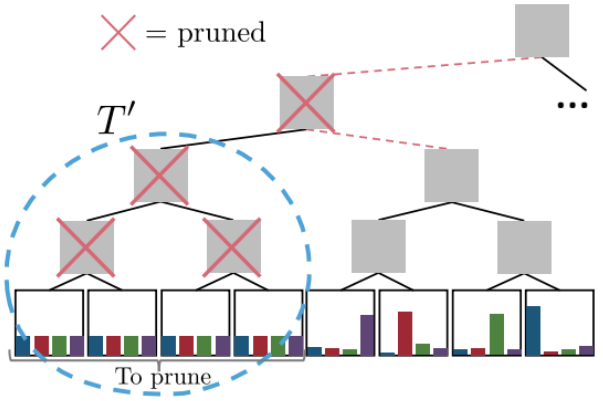
$$\mathbf{c}_l^{(t+1)} = \sum_{\mathbf{x},\mathbf{y} \in T} (\sigma(\mathbf{c}_l^{(t)}) \odot \mathbf{y} \odot \pi_l) \oslash \hat{\mathbf{y}}$$

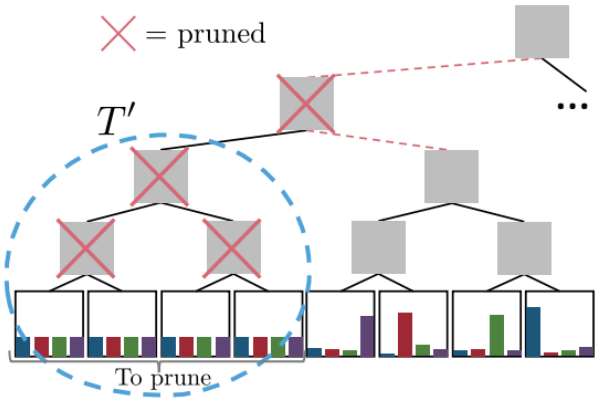
Pruning

- **Pruning operation** to reduce the number of prototypes and augment interpretability
- All leaves with a distribution similar to a uniform one are removed

$$max(\sigma(\mathbf{c}_l)) \leq \tau$$

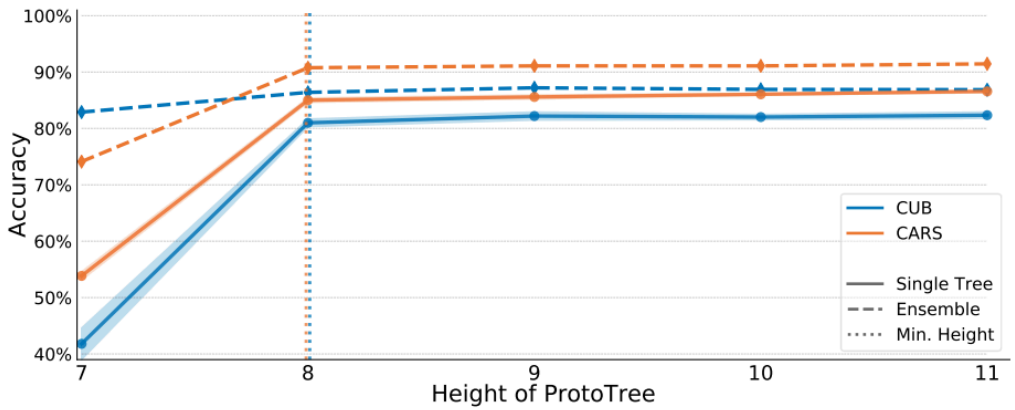
- If all leaves of a subtree are pruned, then the subtree is removed
- The tree is then reorganized by removing the superflous parent of the removed subtree





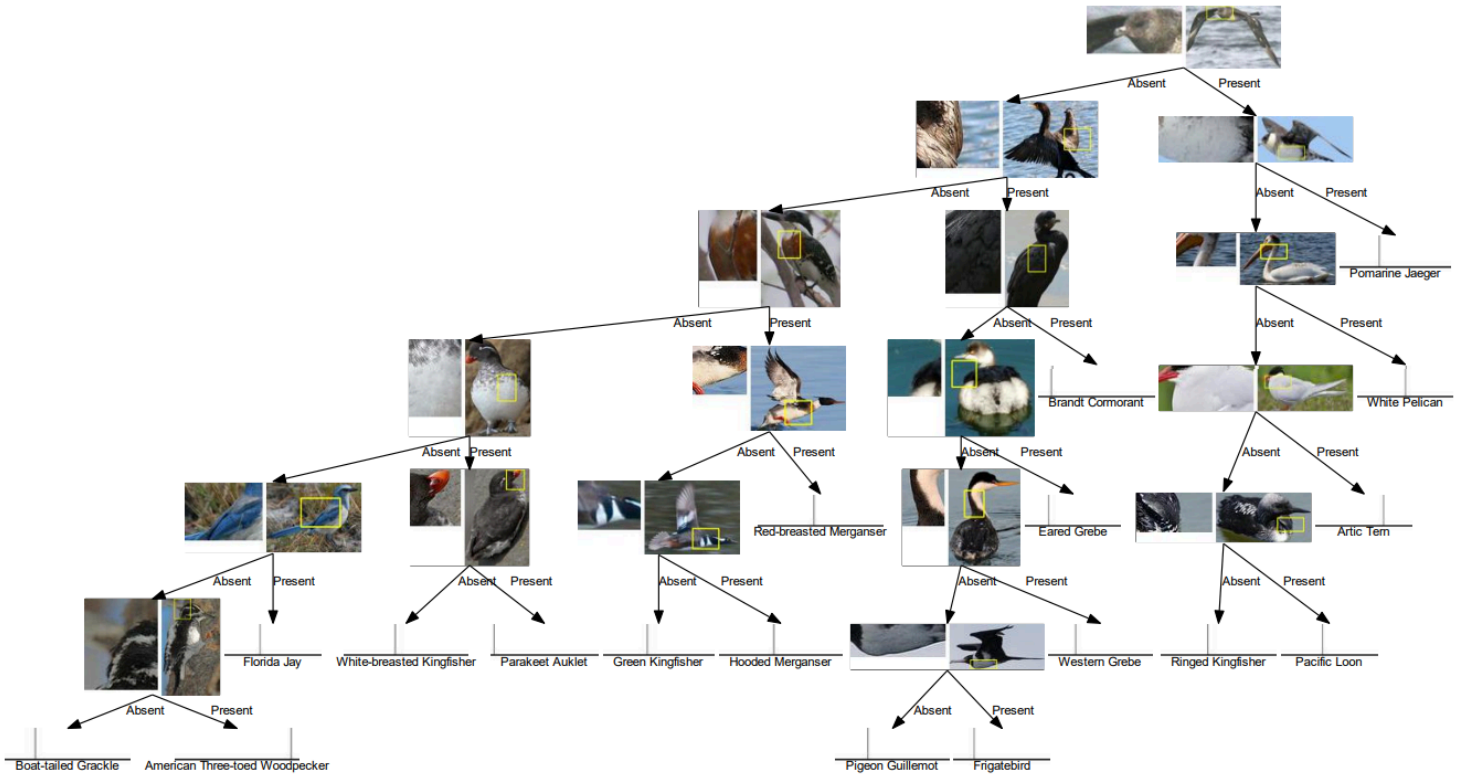
ProtoTree Height

- A model with fewer prototypes is easier to interprete but represent a less complex model with less predictive power
- Need to select a right value for *h*, the height of the tree
- The initial value for *h* such that the number of leaves is at least as large as the number of classes.



Reasoning

- Visualization of a subtree of a ProtoTree
- For each node: the prototype and the image from which the prototype is extracted

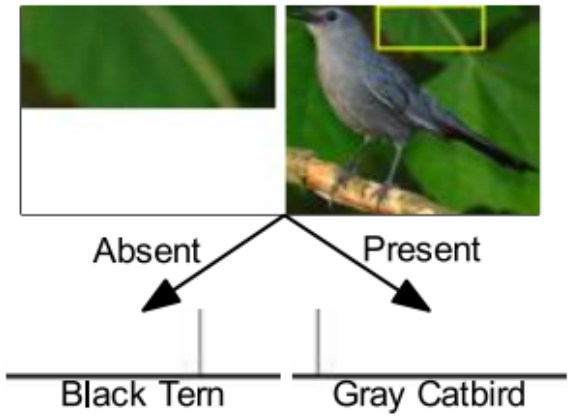


Results

- Higher accuracy then ProtoPNet
- ProtoTree is almost 90% smaller (1 prototype per class against 10 of ProtoPNet) and easier to interpret

Data set	Method	Inter-pret.	Top-1 Accuracy	#Proto types
CUB (224×224)	Triplet Model [34]	-	**87.5**	n.a.
	TranSlider [58]	-	85.8	n.a.
	TASN [57]	o	87.0	n.a.
	ProtoPNet [9]	+	79.2	2000
	ProtoTree h=9 (ours)	++	82.2±0.7	**202**
	ProtoPNet ens. (3) [9]	+	84.8	6000
	ProtoTree ens. (3)	+	86.6	605
	ProtoTree ens. (5)	+	**87.2**	1008

- ProtoTree reveals biases learned by the model, where some prototypes focus on the background.



Shortcomings

Looks like that, does it?

- For a human-interpretable model this statement must hold:

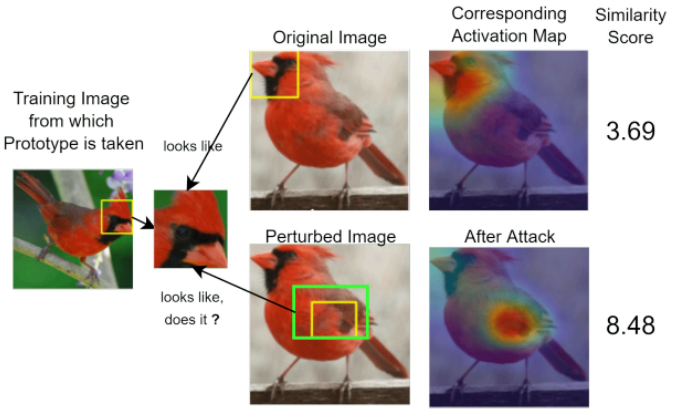
  > Two image patches look similar to a ProtoPNet $\iff$ Two image patches look similar to a human

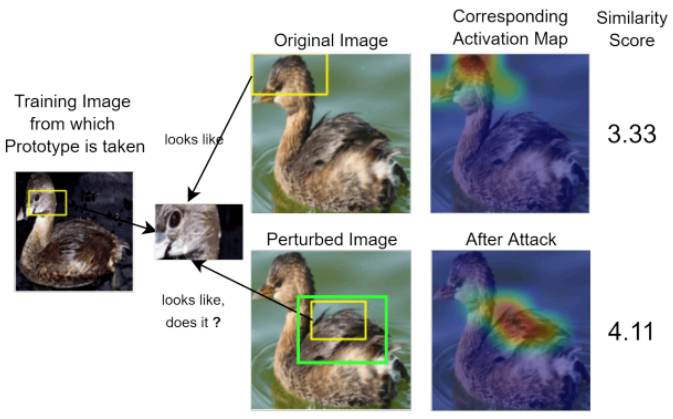
- **Semantic gap** between image space and latent space

Looks like that, Does it? [2]

Head on Stomach experiment

- One of the most activated prototype $\mathbf{p}_l$ is taken into consideration
- The image is perturbed (with very small noise) such that the network finds $\mathbf{p}_l$ in a different location with **high similarity** in a **non-sensical place**

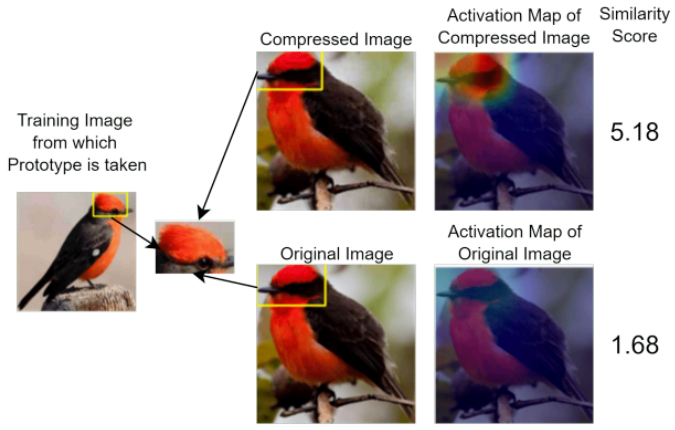


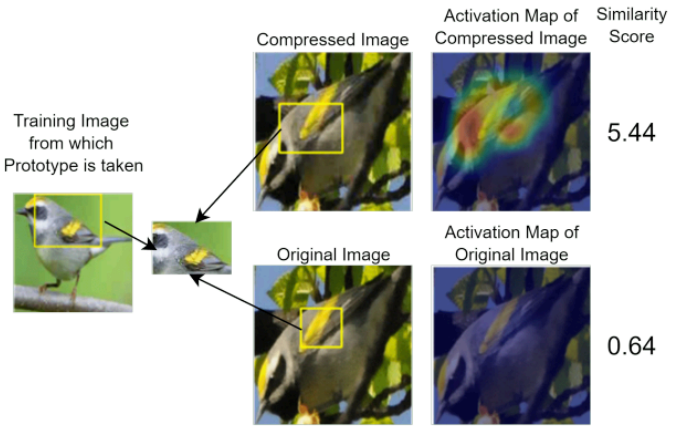


Looks like that, Does it? [2]

JPEG compression experiment

- Training images of half of the classes are compressed
- The similarity score of the compressed version of an image ($\bar{x}$) from a compressed class that is classified correctly by ProtoPNet is recorded
- This score is then compared with the one obtained by passing the original image (x) to ProtoPNet
- If the scores are very different, it means ProtoPNet doesn't consider x and $\bar{x}$ similar as humans would



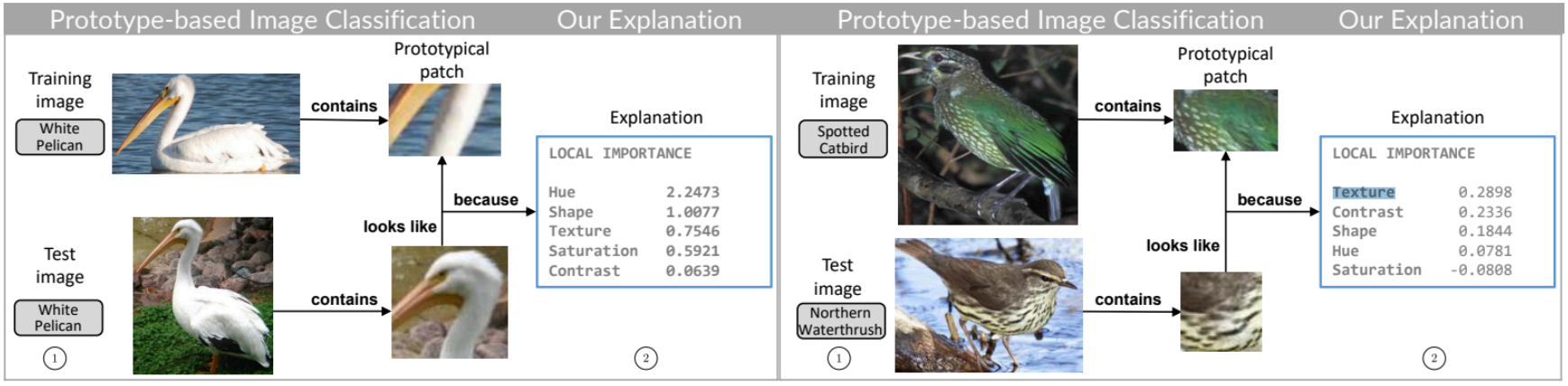


Looks like that, Because... [4]

- Prototypes alone are not enough, they need to be **explained**
- Visual textual information is added to each prototype regarding visual features:

> **hue**, **contrast**, **saturation**, **shape**, **texture**

- Useful to understand misleading prototypes and redundancy



Looks like that, Because... [4]

- A set of modified images is created for each visual feature
- **Local score** for test image k, prototype j and transformation i:

$$\phi_{local}^{i,j,k} = g_{j,k} - \hat{g}_{i,j,k}$$

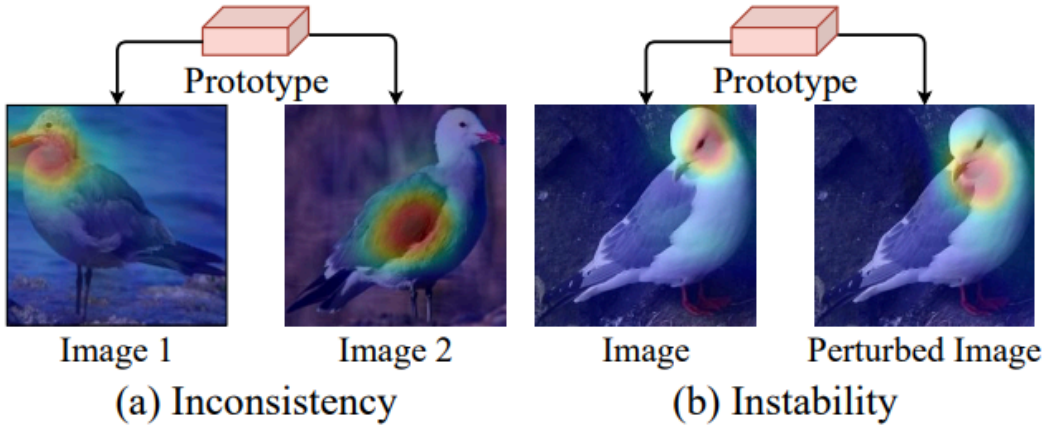
- **Global score** for a prototype j and transformation i (obtained from the training dataset)

$$\phi_{global}^{i,j} = \frac{\sum_{k=1}^{|S_{train}|} \phi_{local}^{i,j,k} \cdot g_{j,k}}{\sum_{k=1}^{|S_{train}|} g_{j,k}}$$

Recent improvement

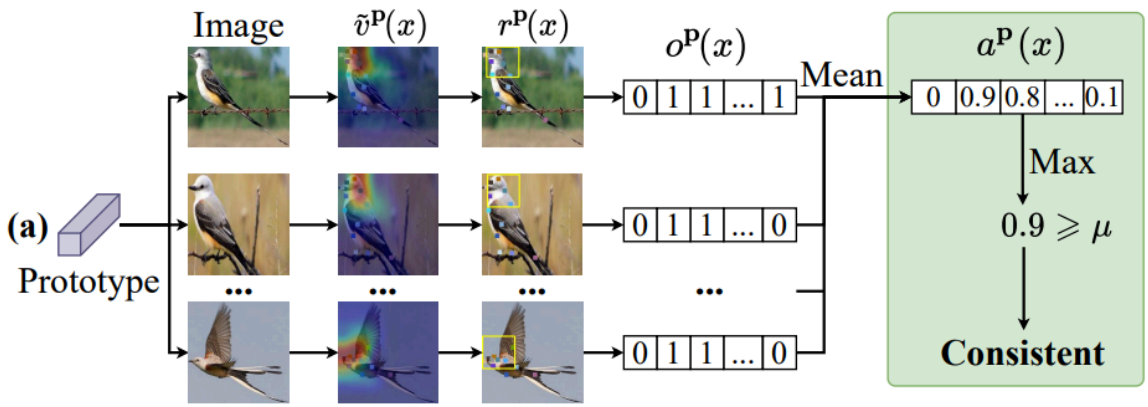
Improvement of Interpretability with SA and SDFA [3]

- Need of a benchmark to quantitatively evaluate the interpretability of prototypes
- Evalutation metrics based on two problems:
  - inconsistency: a prototype may mistakenly correspond to different object parts in different images
  - instability: a prototype may mistakenly correspond to different object parts in the original image and the slightly perturbed image



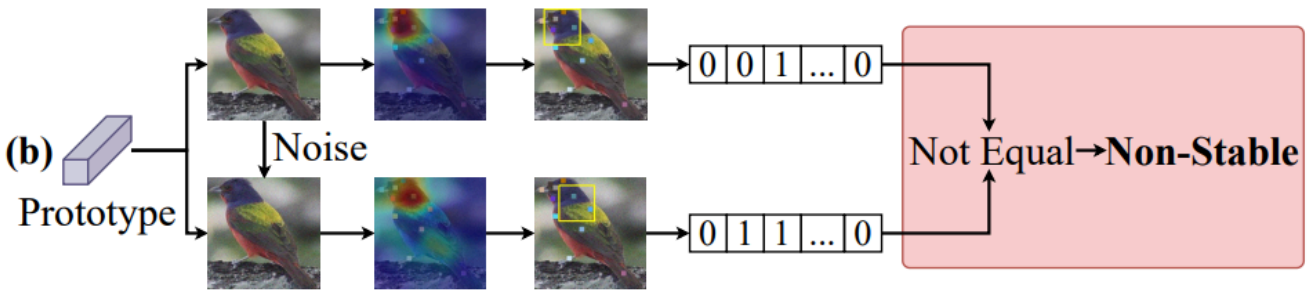
Improvement of Interpretability with SA and SDFA [3]

- The dataset needs to have object parts annotations
- **Consistency score**:
  - Consider a prototype of class k and all the test images of that class
  - For each image, compute a binary vector: 1 if an object part is inside the prototype activation region, 0 otherwise
  - Take the average of all these binary vectors
  - If the maximum element is higher than a threshold the prototype is consistent
  - Take the ratio between the number of consistent prototypes and the total number of prototypes as the consistency score



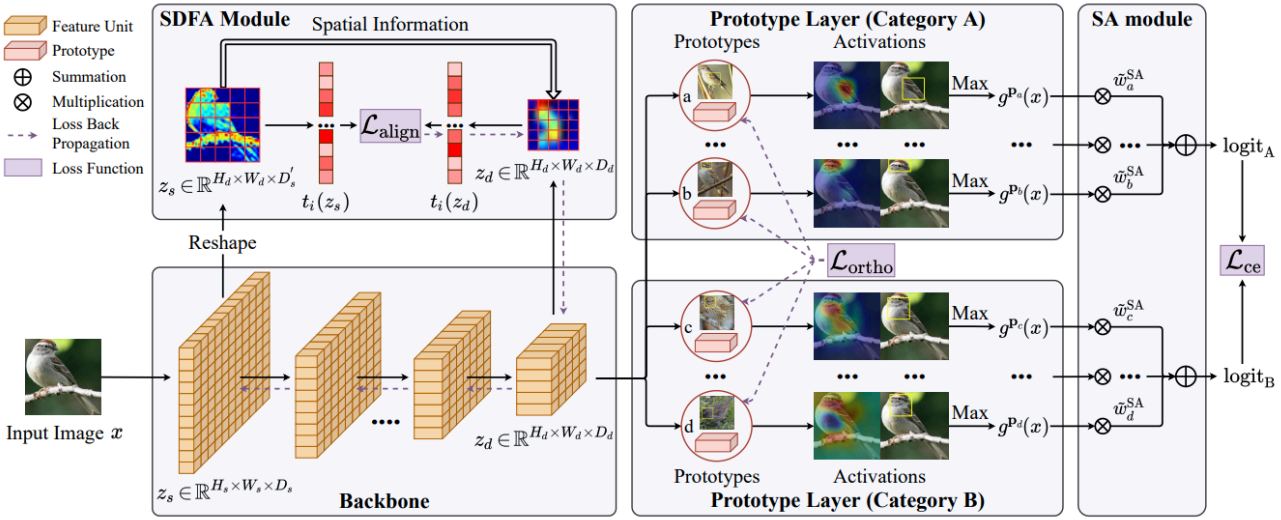
Improvement of Interpretability with SA and SDFA [3]

- **Stability score**:
  - Consider a prototype of class k and all the test images of that class
  - For each image, compute the binary vector for the original version and the perturbeted one
  - If these binary vector are equals, the prototype is stable
  - Take the ratio between the number of stable prototypes and the total number of prototypes as the stability score



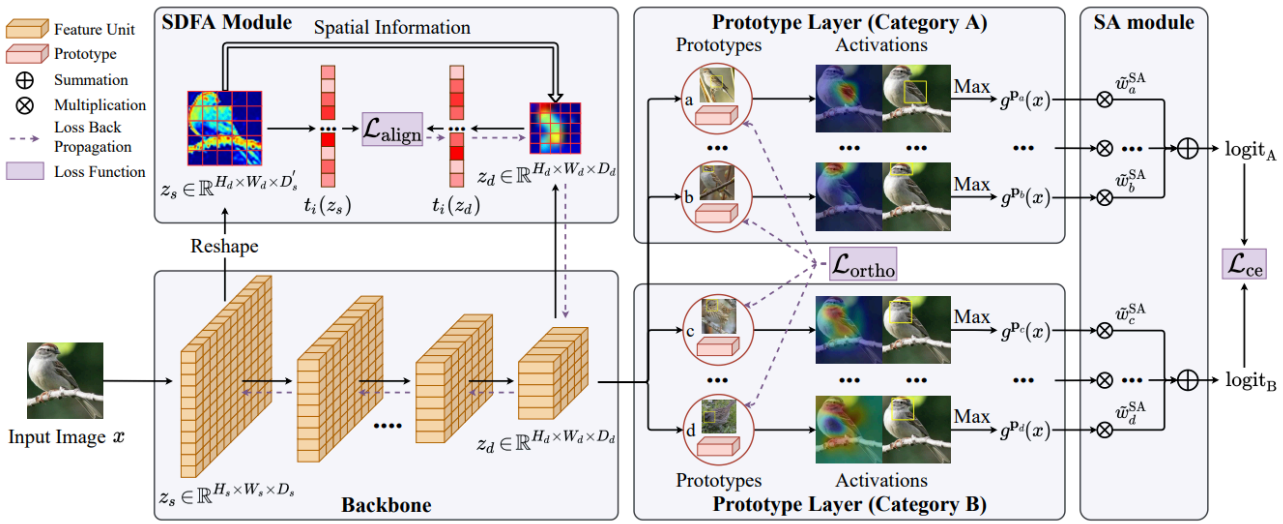
Improvement of Interpretability with SA and SDFA [3]

- **Shallow Deep Features Alignement** (SDFA) module: incorporated **spatial information** from shallow layers is in the deep feature maps
- Similarity structure $t \in \mathbb{R}^{HWxHW}$ of a feature map $z \in \mathbb{R}^{HxWxD}$ can be used to compare two representations
- A loss term is added during the training to enforce these spatial structures to be similar



Improvement of Interpretability with SA and SDFA [3]

- **Score Aggregation** (SA) module: the activation values of prototypes are allocated into their categories
- Because of the last fully connected layer of ProtoPNet, the classification score depends also on the prototypes of other classes
- The similarity scores of the prototypes are aggregated into their classes
- A learnable layer adjust the importance of each prototypes for each class prototypes.



Conclusions

- Start using interpretable models for high stake decisions instead of black boxes!
- Prototypical learning gives a form of interpretability, ***this part looks like that!***
- There still are some shortcomings
- Recent improvement of ProtoPNet and first attempt to create a benchmark for interpretability

Thank you!

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