

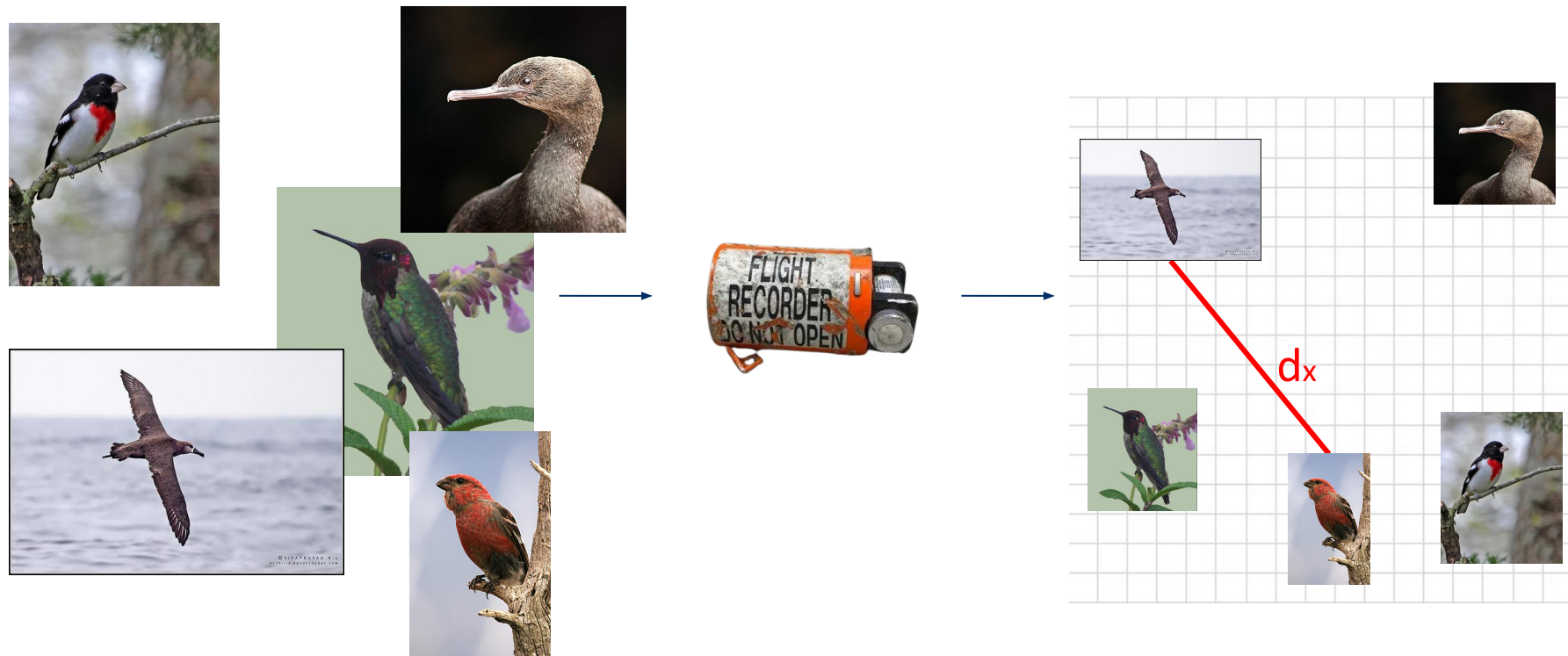


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Neural Prototype Trees for Interpretable Fine-grained Image Recognition

Konstantina Ellina
Pablo de Vicente Abad

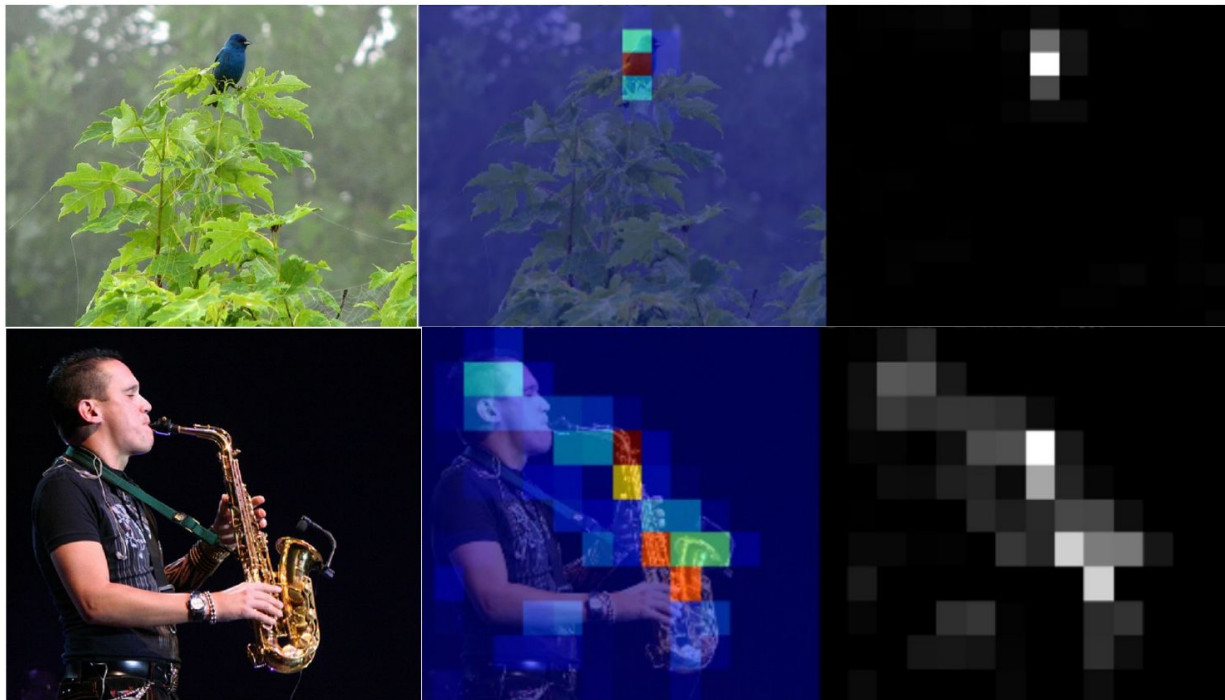
Traditional DNN's



Model Explanation

Input image

Visual Explanation

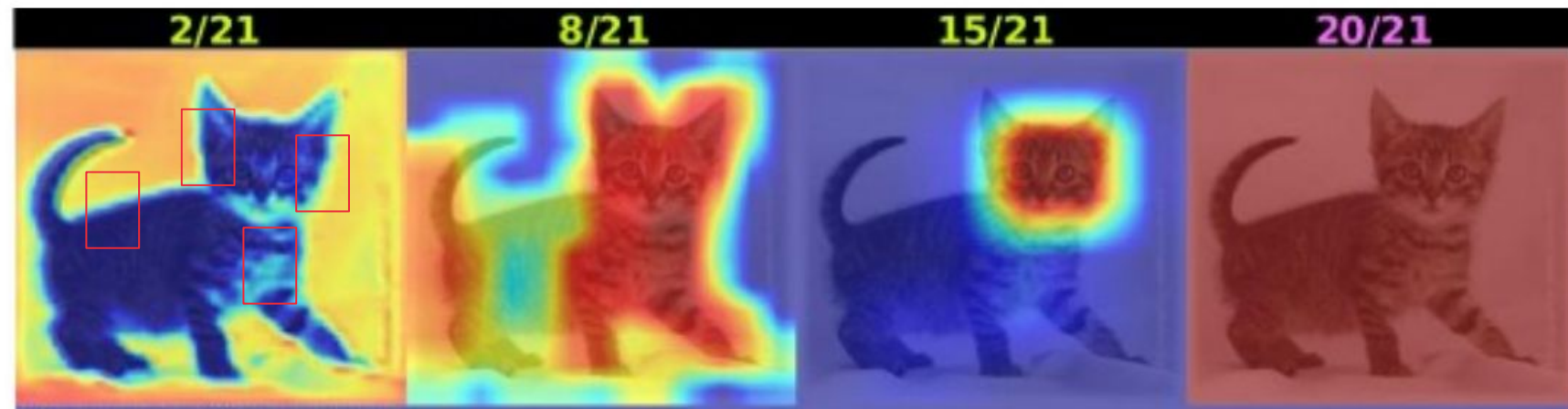


Model Interpretation

Max.



Min.

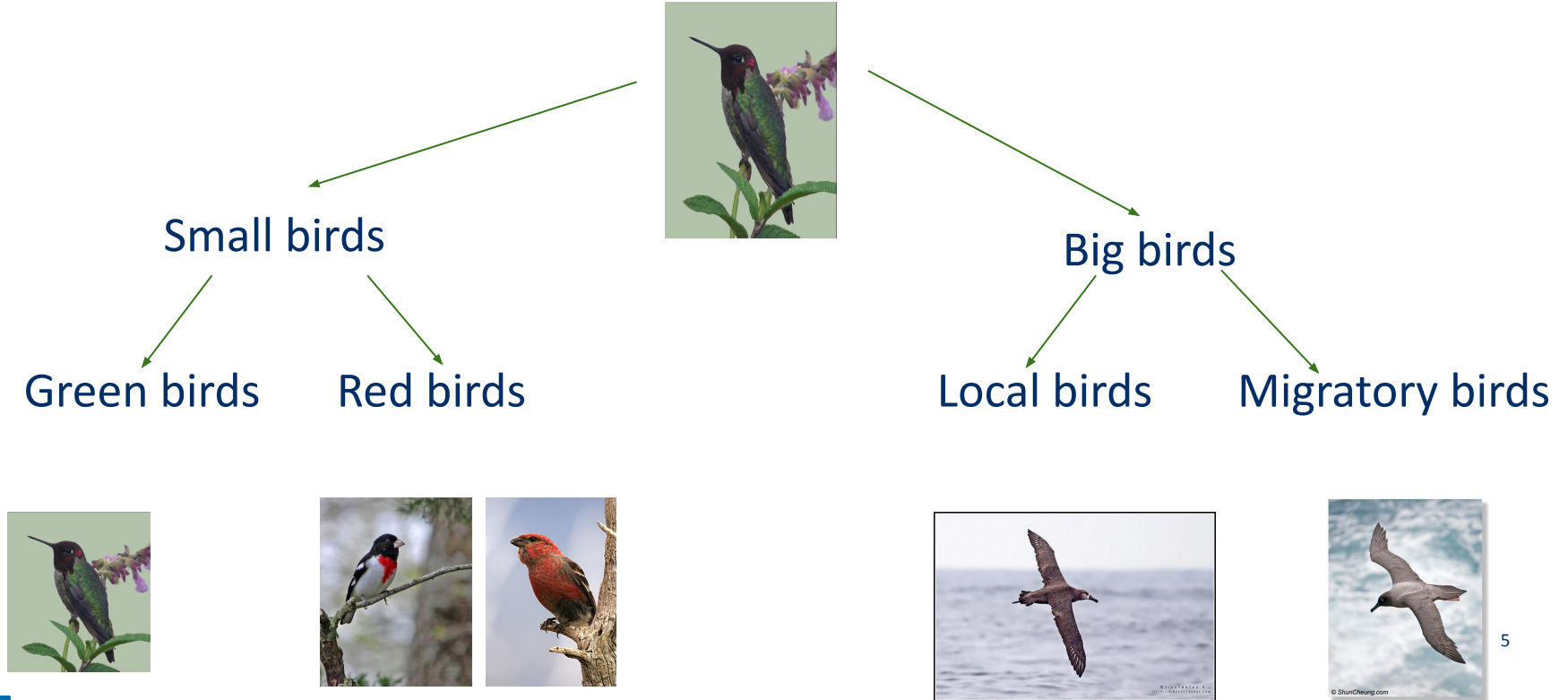


Convolutional Layers

Fully-connected Layers



Decision Trees



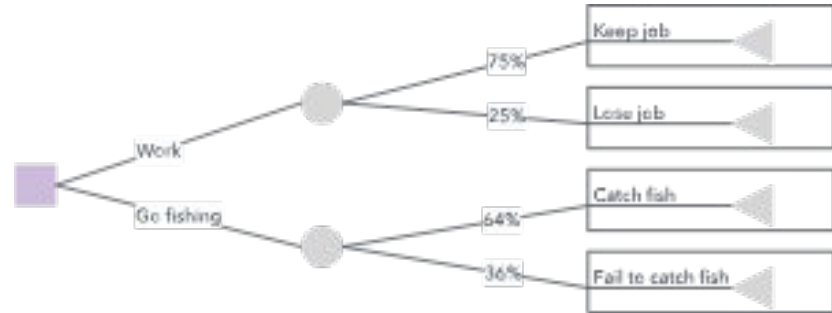
Neural Soft Decision Trees (SDTs)

Hard decision tree

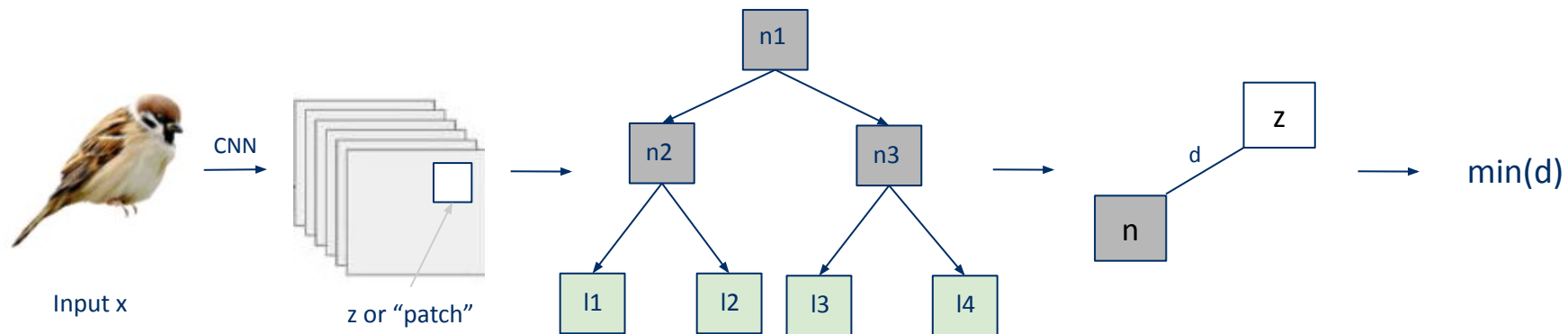


Soft decision tree

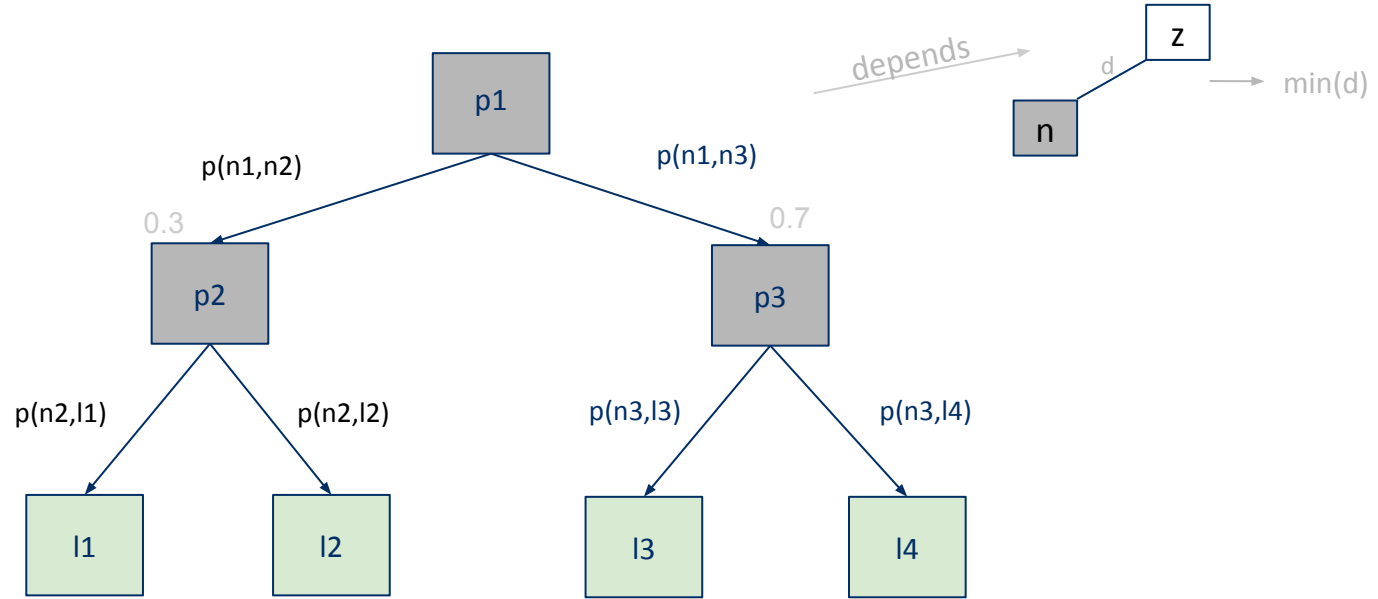
- More flexible
- Complex relationships



Model architecture



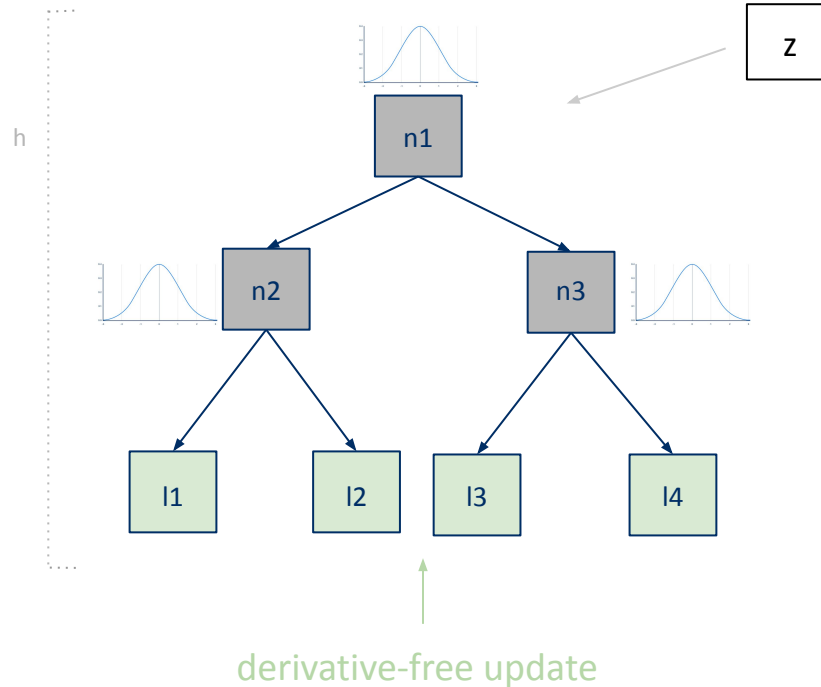
Model architecture



$$\pi(l1) * \sigma(c1) + \pi(l2) * \sigma(c2) + \pi(l3) * \sigma(c3) + \pi(l4) * \sigma(c4) = \text{final prediction}$$

Training

Pretrained CNN



Backpropagation in
mini batches

Deterministic reasoning

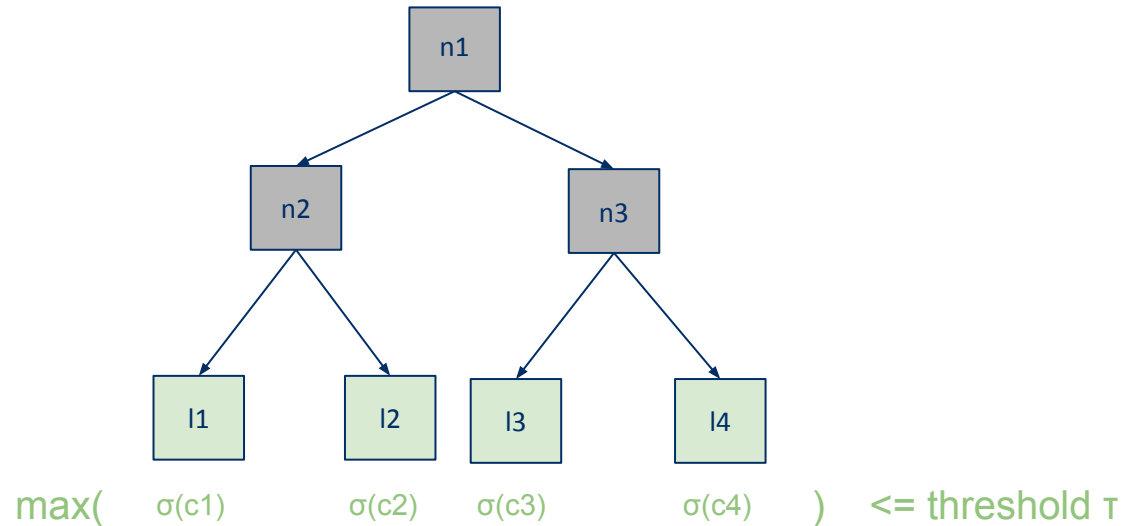
- From soft decision tree to hard decision tree at test time
- Each input gets the same prediction every time
- Same accuracy

Results and fine tuning

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
CARS (224×224)	RAU [36]	-	93.8	n.a.
	Triplet Model [34]	-	93.6	n.a.
	TASN [57]	o	93.8	n.a.
	ProtoPNet [9]	+	86.1	1960
	ProtoTree $h=11$ (ours)	++	86.6 ± 0.2	195
	ProtoPNet ens. (3) [9]	+	91.4	5880
	ProtoTree ens. (3)	+	90.3	586
	ProtoTree ens. (5)	+	91.5	977

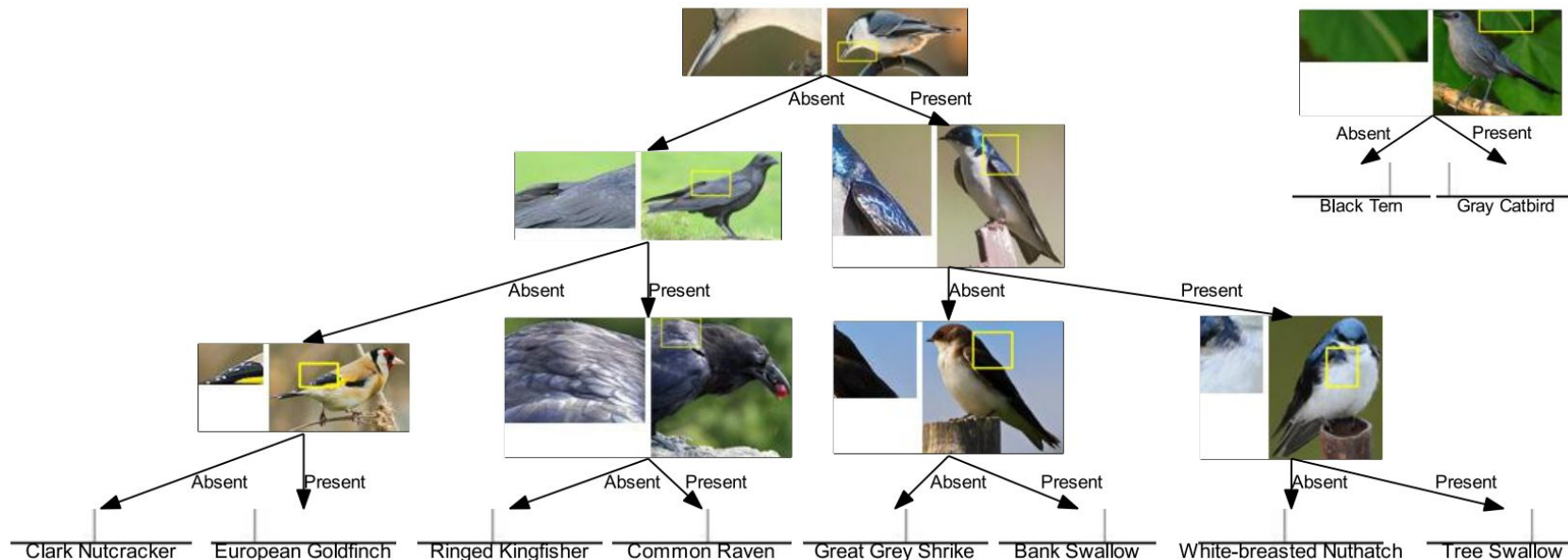
Pruning

- Reduce complexity
- Enhance interpretability without losing significant accuracy



Summarizing

- Need to create interpretable models by design
- Accuracy-Interpretability trade-off





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