國立陽明交通大學
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Paper Tag: 3-119

NVIDIA

MCPNet: An Interpretable Classifier via Multi-Level Concept Prototypes



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What is Explainable AI (XAI)?

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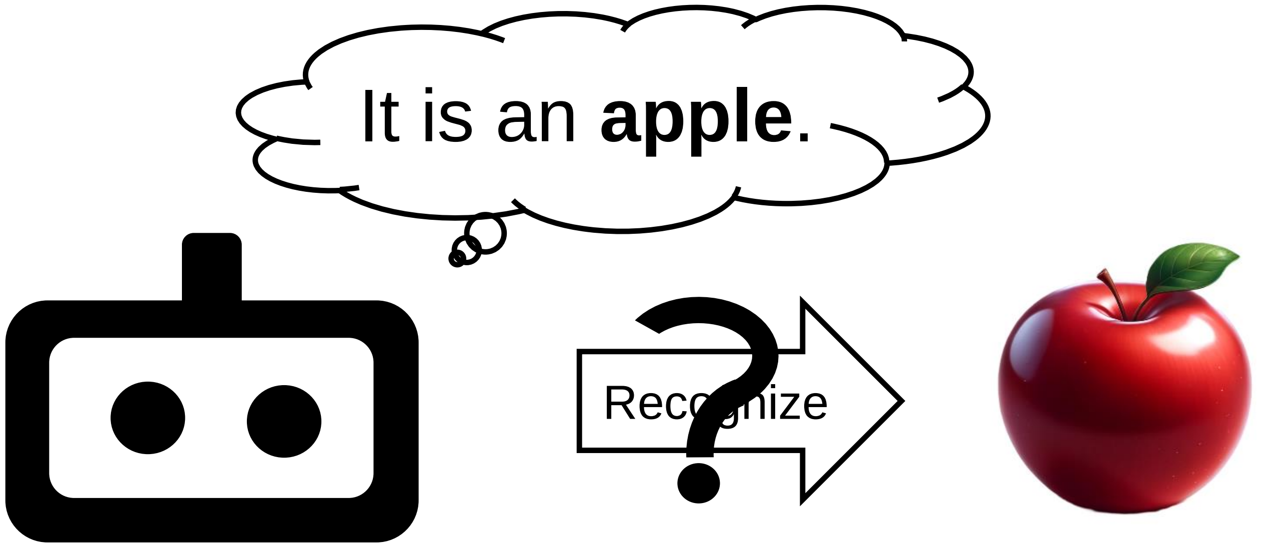

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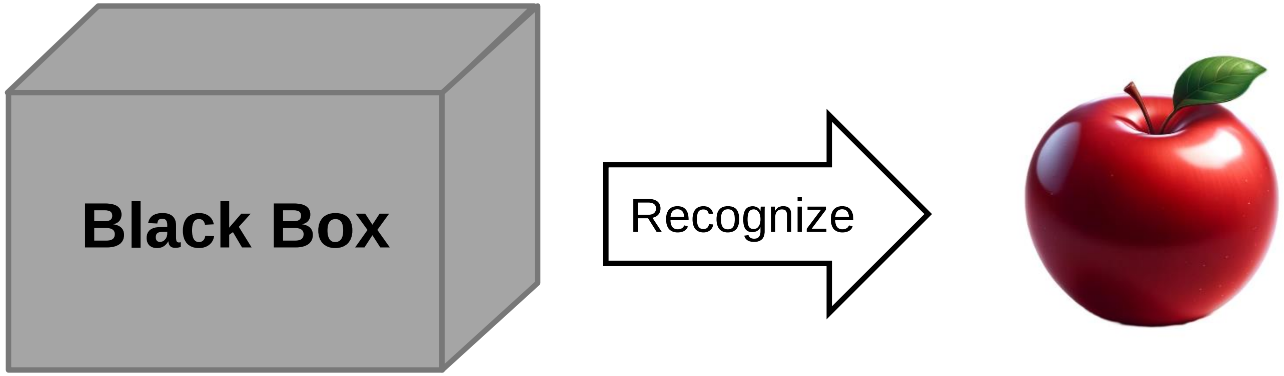

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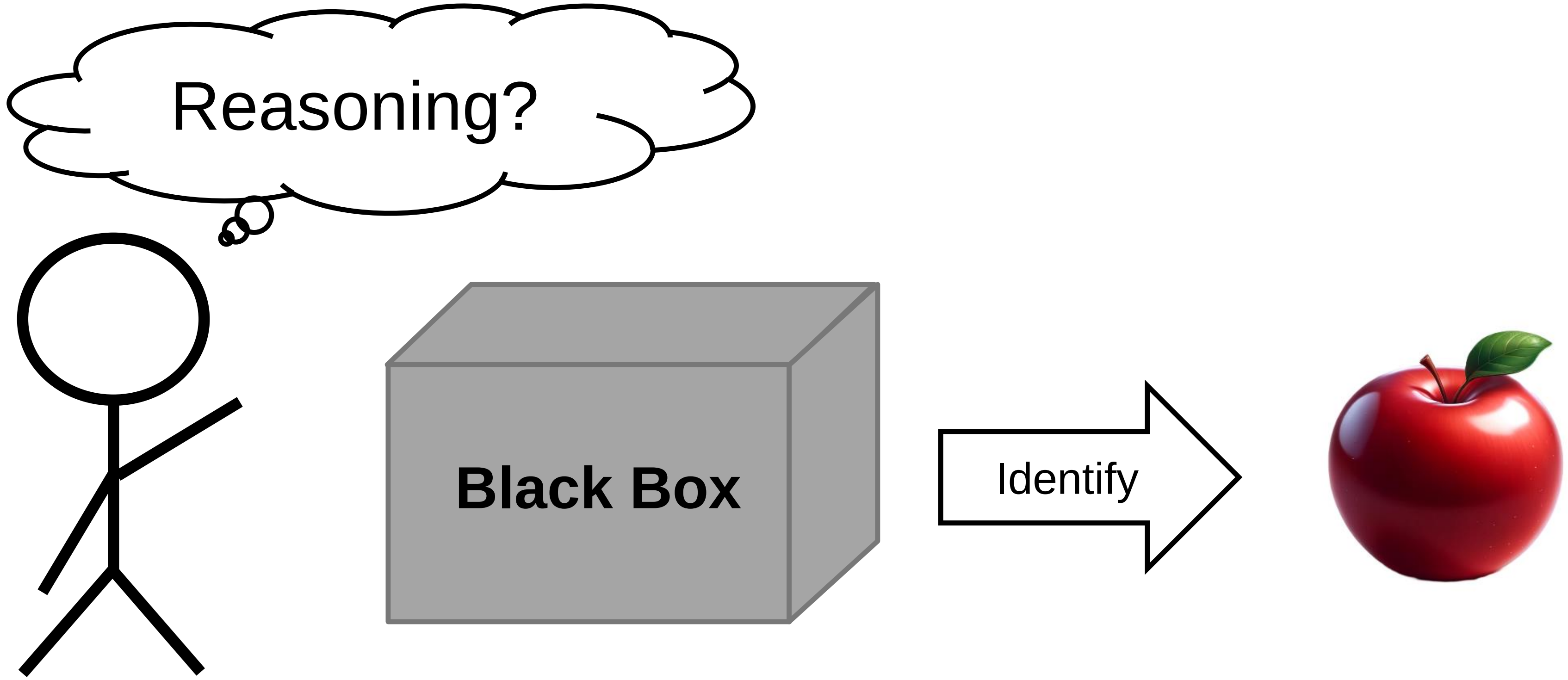

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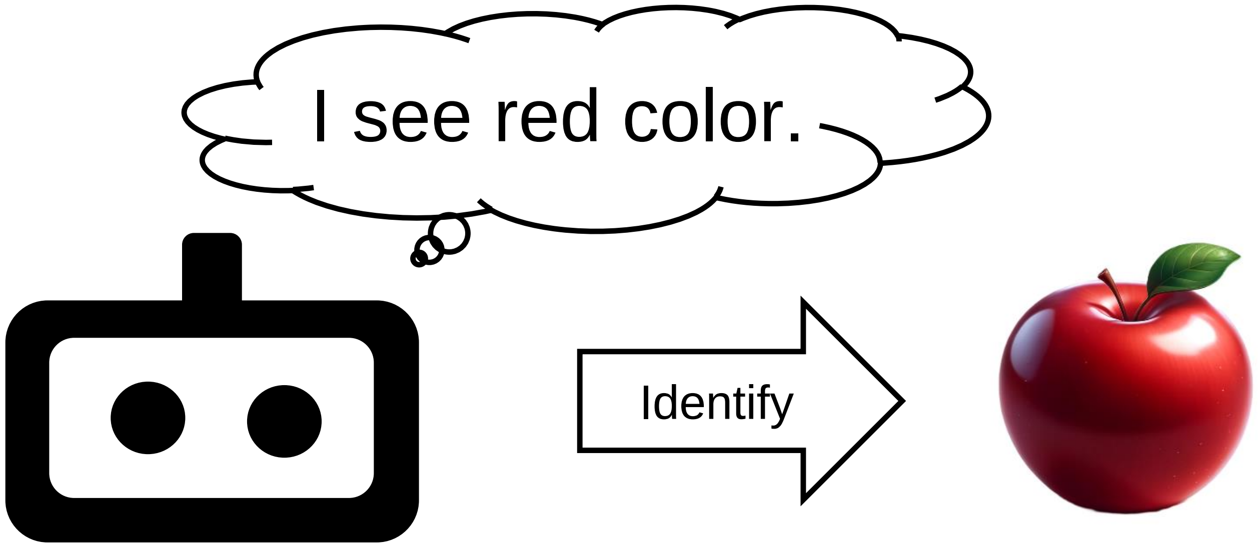

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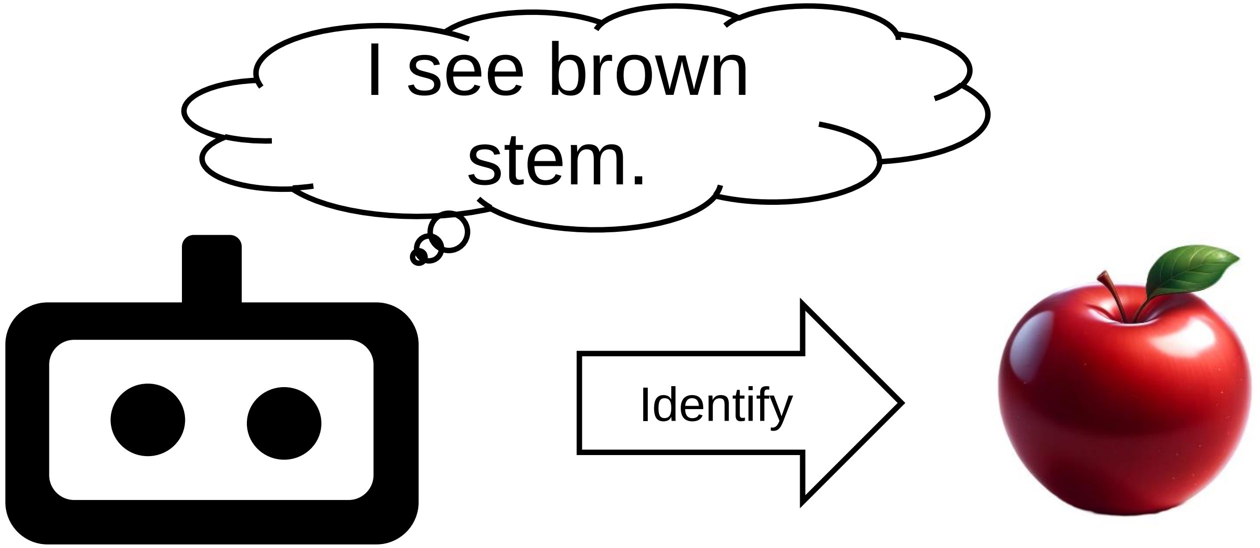

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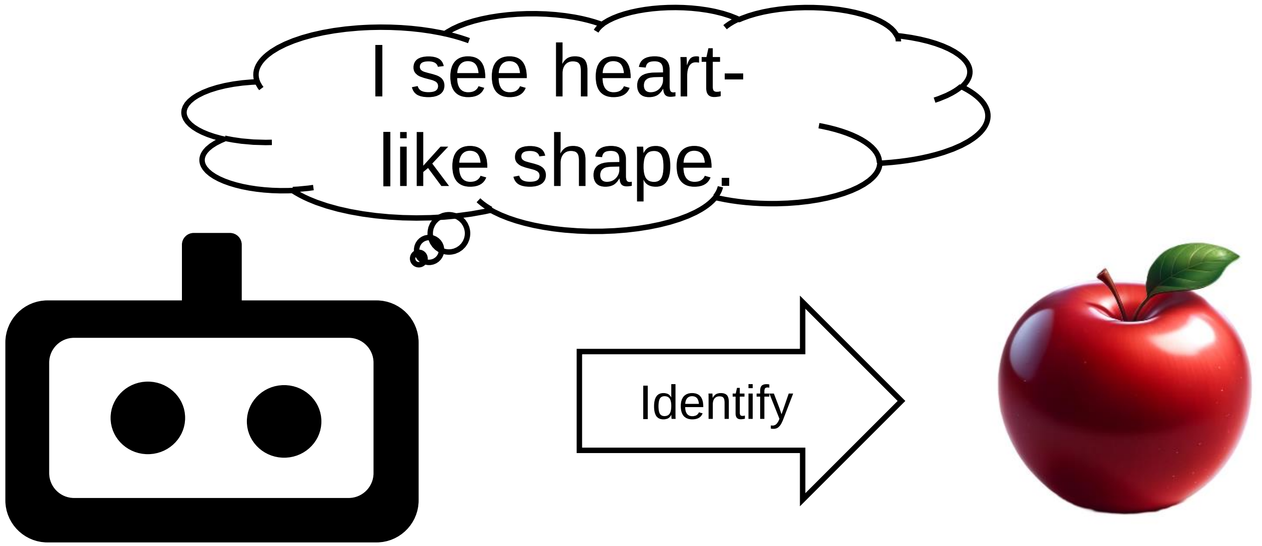

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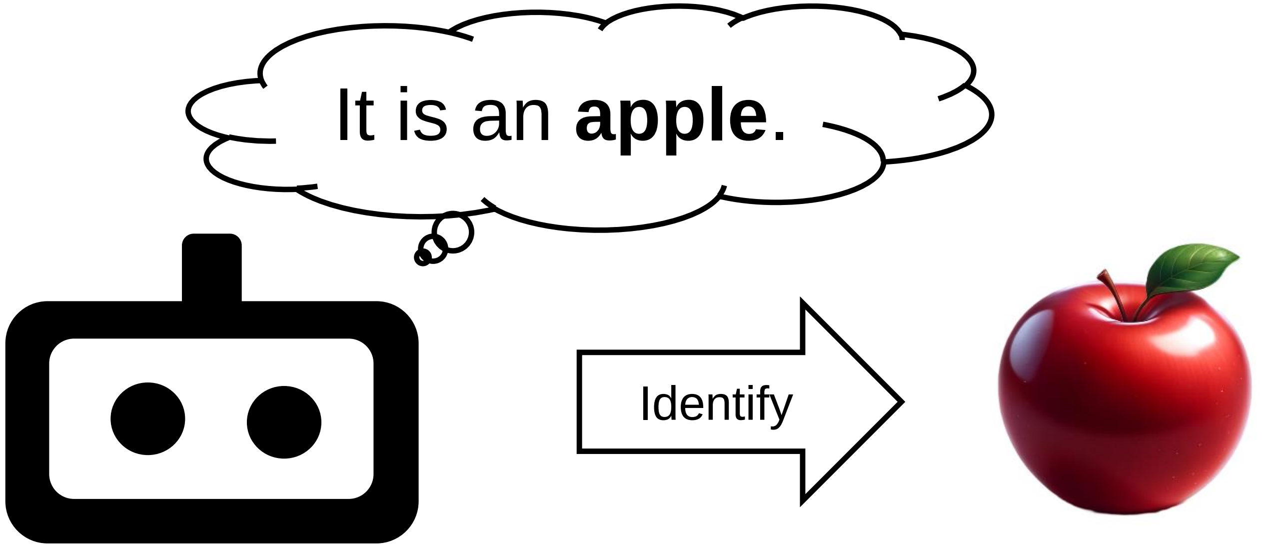

Types of Explainable AI Methods

- Two types of explainable AI methods
  - Post-hoc method
    - Explainable the model after the training
    - Inconsistent to prediction
  - Inherent method
    - Model is designed with interpretability built into their structure
    - Performance trade-offs between accuracy and interpretability

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Motivation

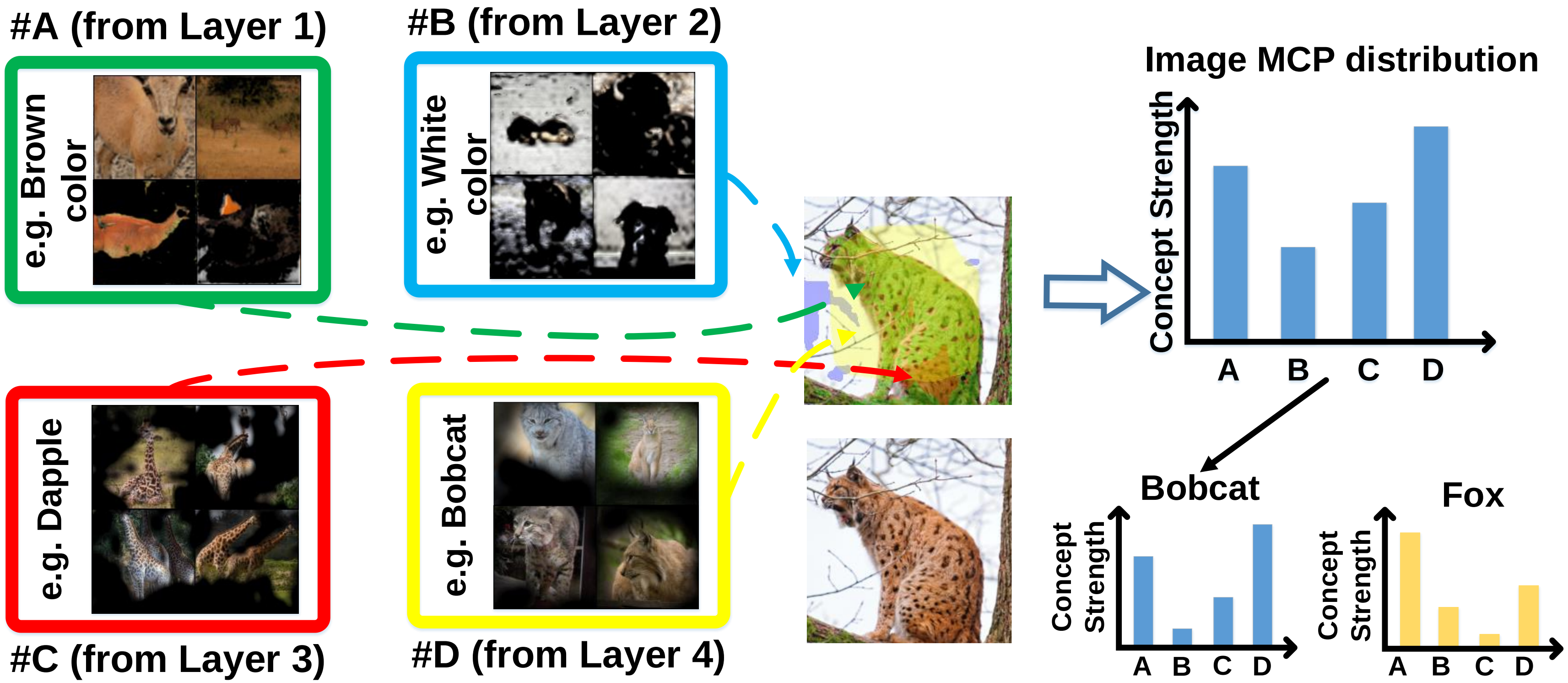
- Providing low and mid-level explanations:
  - A more comprehensive aspect to unveil the model
  - Seamlessly integrated into various model (CNN-based)

	MCPNet(Ours)	ProtoPNet [1,2,3]	Concept Bottleneck [4]	TCAV [5]	CRAFT [6]
Explanation Type	Inherent	Inherent	Inherent	Post-hoc	Post-hoc
Explanation Scale	Multi-Level	Single-Level	Single-Level	Single-Level	Single-Level
w/o Concept Labels	✓	✓	✗	✗	✓
w/o Modifying Models	✓	✗	✗	✓	✓

[1] CHEN, Chaofan, et al. This looks like that: deep learning for interpretable image recognition.
[2] DONNELLY, Jon, et al. Deformable protopnet: An interpretable image classifier using deformable prototypes.
[3] NAUTA, Meike, et al. Pip-net: Patch-based intuitive prototypes for interpretable image classification.
[4] KOH, Pang Wei, et al. Concept bottleneck models. In: *International conference on machine learning*.
[5] KIM, Been, et al. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav).
[6] FEL, Thomas, et al. Craft: Concept recursive activation factorization for explainability.

Target

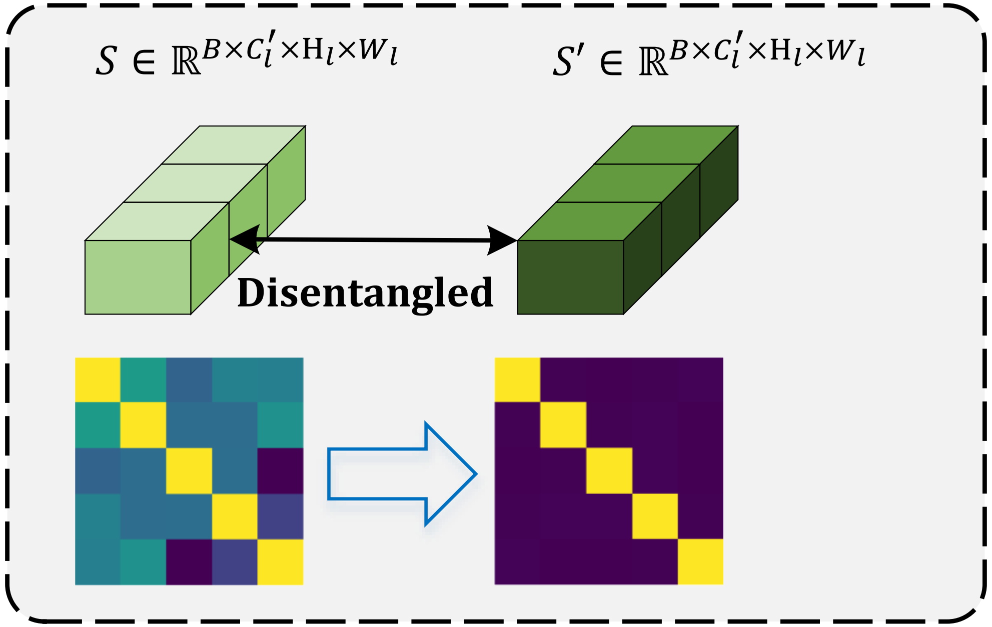
- An <u>inherently hierarchical explanation method</u> to unveil the model
  - Providing multi-scale explanations
  - Without compromising the performance
  - Seamlessly integrate with various backbone (CNN-based)



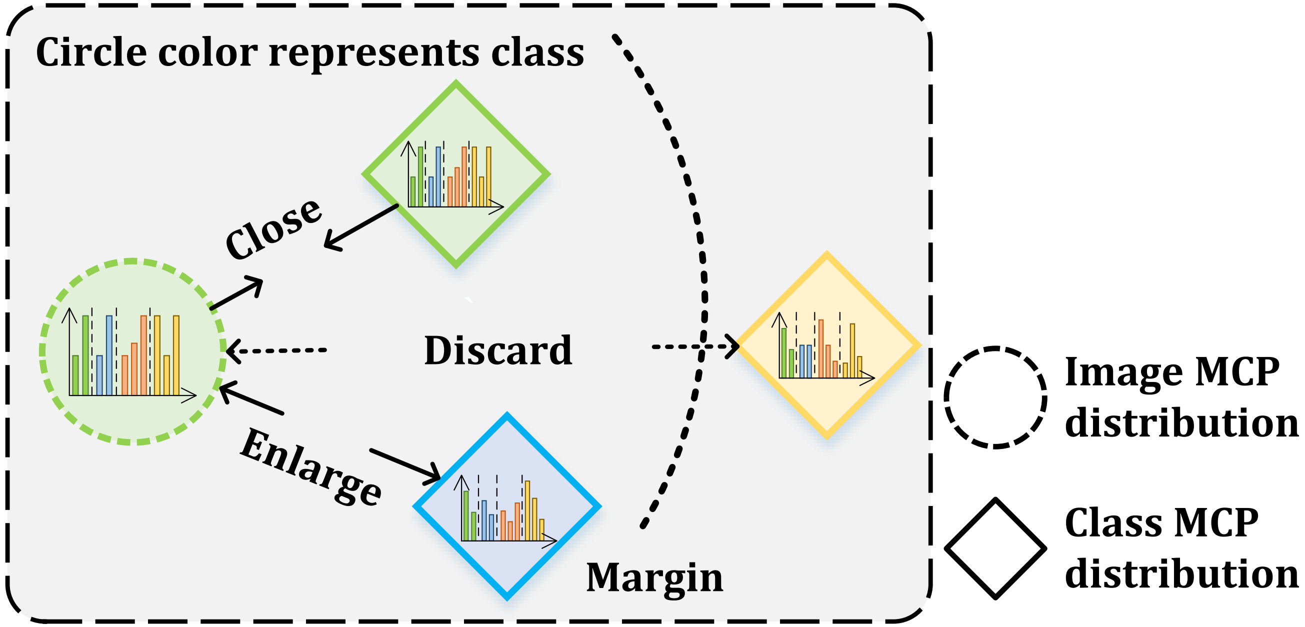
Proposed Method

- Proposed constraints
  - Centered Kernel Alignment (CKA) loss
  - Class-aware Concept Distribution (CCD) loss

Centered Kernel Alignment loss

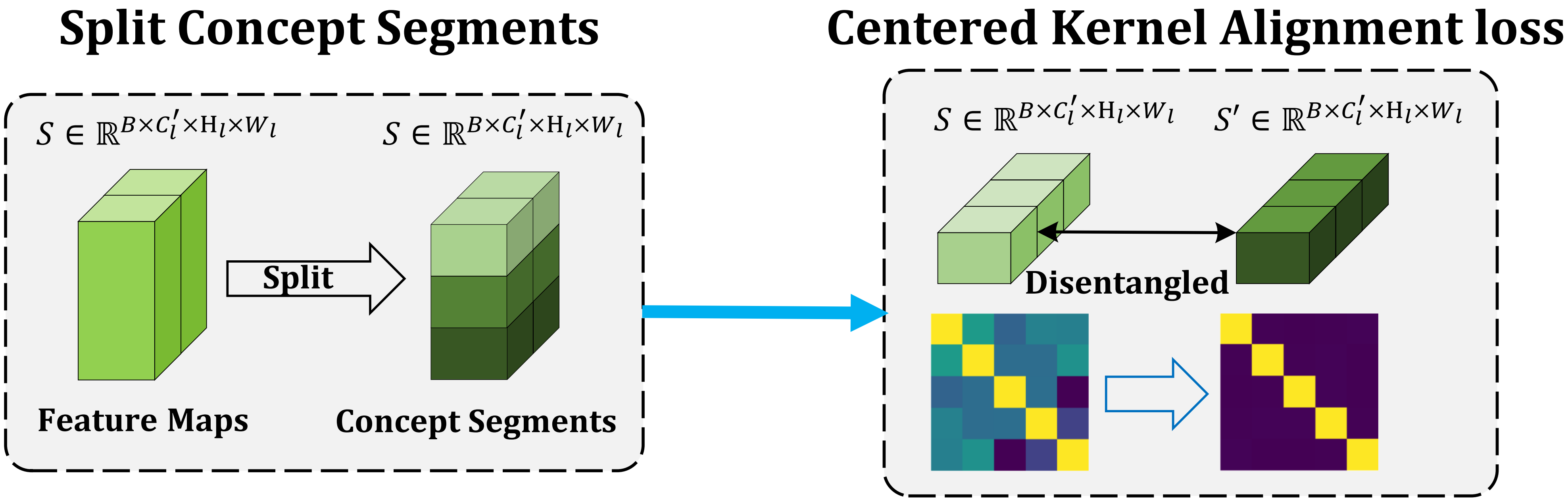


Class-aware Concept Distribution loss



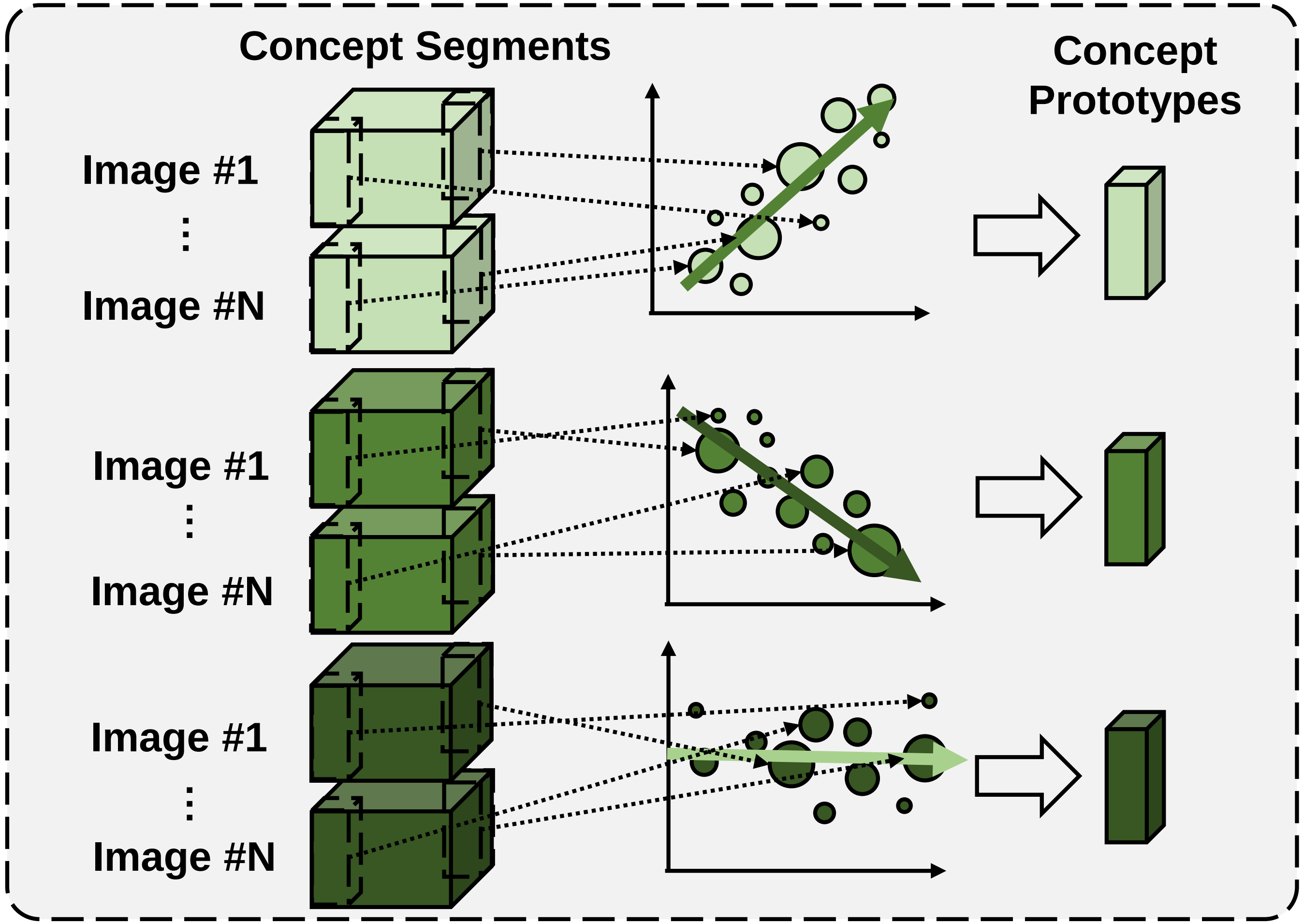
Proposed Method

- Centered Kernel Alignment (CKA) loss
  - Disentangling segment semantics



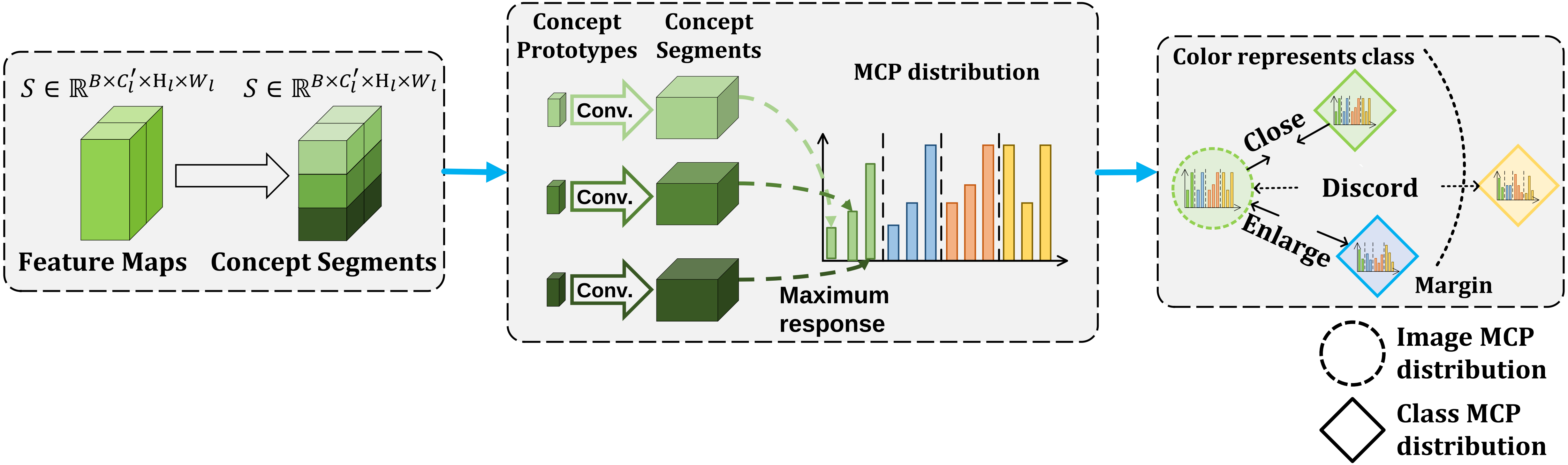
Proposed Method

- Concept prototypes extraction



Proposed Method

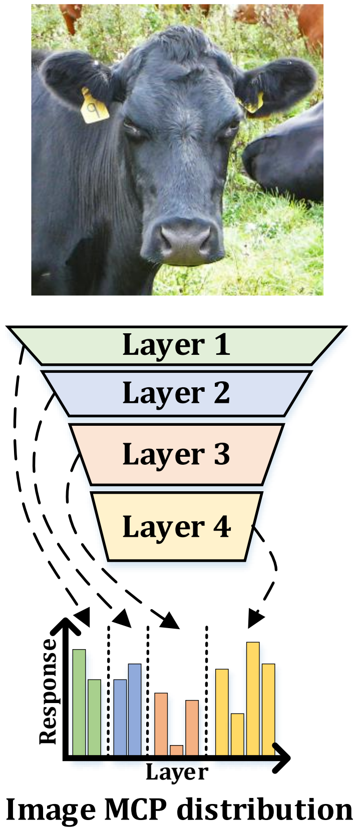
- Class-aware Concept Distribution (CCD) loss
  - Classifying via Multi-level Concept Prototypes distributions (MCP distribution)



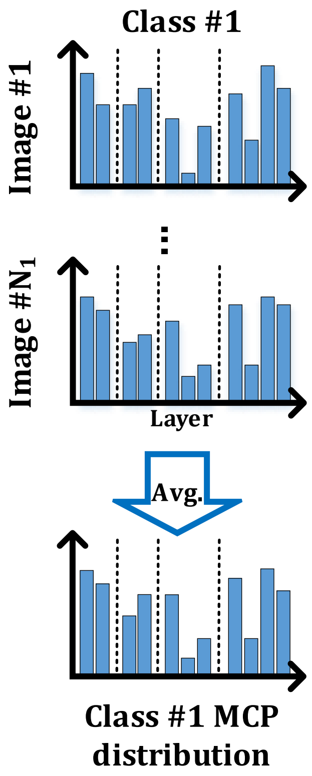
Proposed Method

- Our new classify paradigm

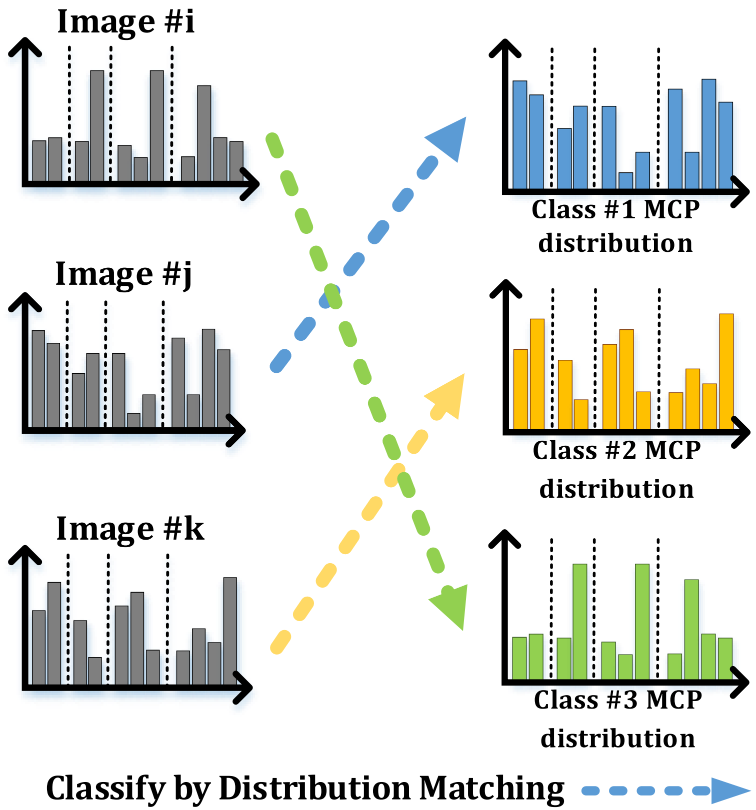
For each image:



For each class:



Classify images:



Experiments – Quantitative Results

- Main quantitative results:

Backbone	Methods	Explanation	Accuracy AWA2	Accuracy Caltech101	Accuracy CUB_200_2011
ResNet50	Baseline	N/A	94.92%	94.21%	77.94%
	ProtoTree [14]	Single-Scale	90.60%	72.19%	18.00%†
	Deformable ProtoPNet [2]	Single-Scale	85.51%	93.88%	73.42%†
	ST-ProtoPNet [28]	Single-Scale	93.76%	95.95%	76.34%†
	PIP-Net [15]	Single-Scale	85.99%	87.86%	70.99%†
	MCPNet (Ours)	Multi-Scale	93.92%	93.88%	80.15%
Inception V3	Baseline	N/A	95.47%	96.42%	79.43%
	ProtoTree [14]	Single-Scale	92.29%	86.02%	13.03%
	Deformable ProtoPNet [2]	Single-Scale	92.68%	97.22%	72.99%
	ST-ProtoPNet [28]	Single-Scale	93.60%	96.99%	75.25%
	PIP-Net [15]	Single-Scale	43.82%	45.04%	6.76%
	MCPNet (Ours)	Multi-Scale	94.62%	95.76%	78.94%
ConvNeXt-tiny	Baseline	N/A	96.55%	96.56%	84.55%
	ProtoTree [14]	Single-Scale	94.00%	78.82%	21.57%
	Deformable ProtoPNet [2]	Single-Scale	91.94%	93.65%	35.05%
	ST-ProtoPNet [28]	Single-Scale	94.22%	97.17%	81.84%
	PIP-Net [15]	Single-Scale	93.80%	96.61%	82.74%
	MCPNet (Ours)	Multi-Scale	95.61%	95.95%	83.45%

Experiments – 5-shot Classification

- 5-shot for unseen class images classification:

Dataset	Method	Accuracy
AWA2	Baseline	60.55%
	ProtoTree [14]	33.68%
	Deformable ProtoPNet [2]	19.71%
	ST-ProtoPNet [28]	30.15%
	PIP-Net [15]	26.17%
	MCPNet (Ours)	**73.79%**

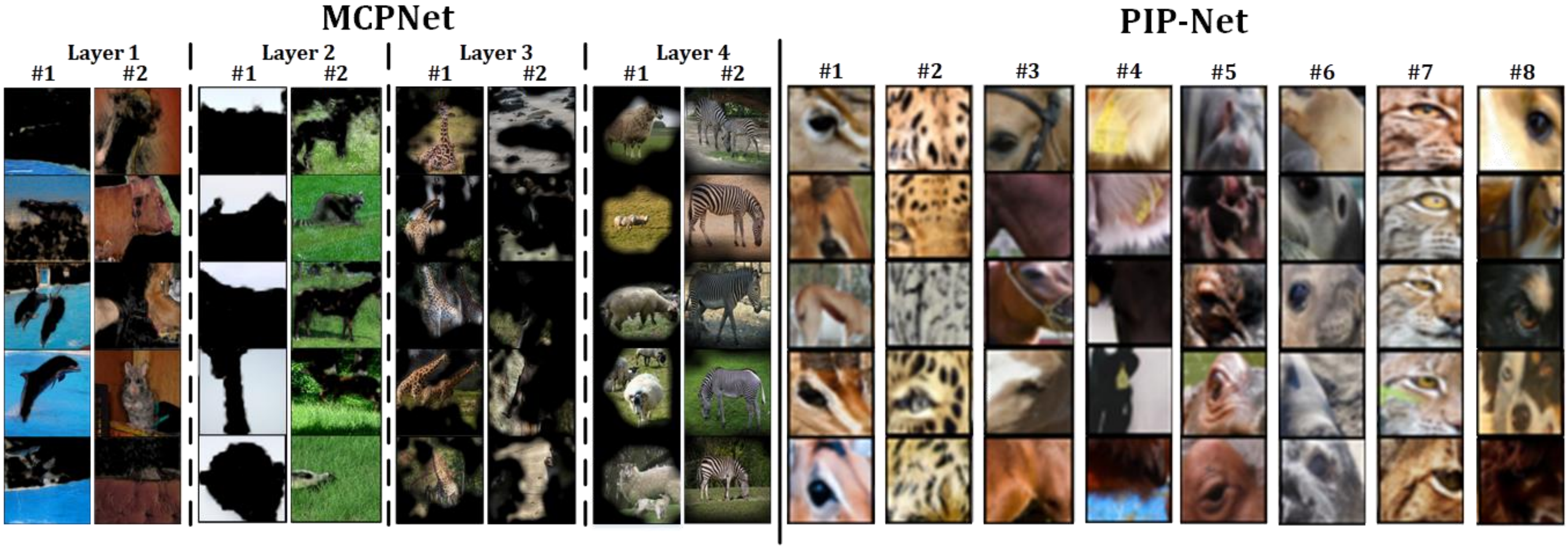
Experiments – Ablation Study

- The effect of different number of channel per segment:

Dataset	Channel	Accuracy
AWA2	32	93.92%
	16	93.95%
	8	93.58%
Caltech101	32	93.88%
	16	93.79%
	8	93.51%
CUB_200_2011	32	80.15%
	16	80.19%
	8	81.22%

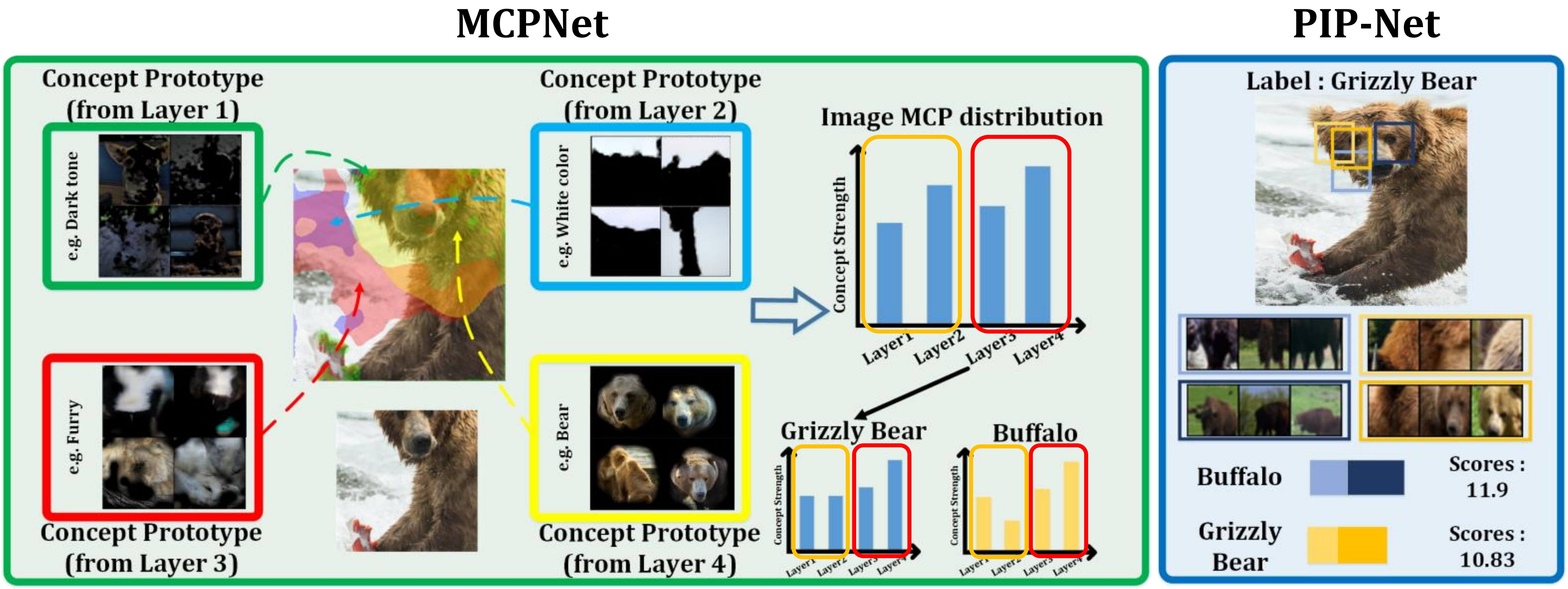
Experiments – Concept Visualizations

- MCPNet (Ours) provides different scales concepts.
- Previous methods (e.g. PIP-Net) only provides single scale concepts.



NAUTA, Meike, et al. Pip-net: Patch-based intuitive prototypes for interpretable image classification.

Experiments - Explanations



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