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SIC Saarland Informatics Campus

High Level Computer Vision

Some Recent Trends: B-Cos Networks & Segment Anything Model

@ July 17, 2024

Bernt Schiele

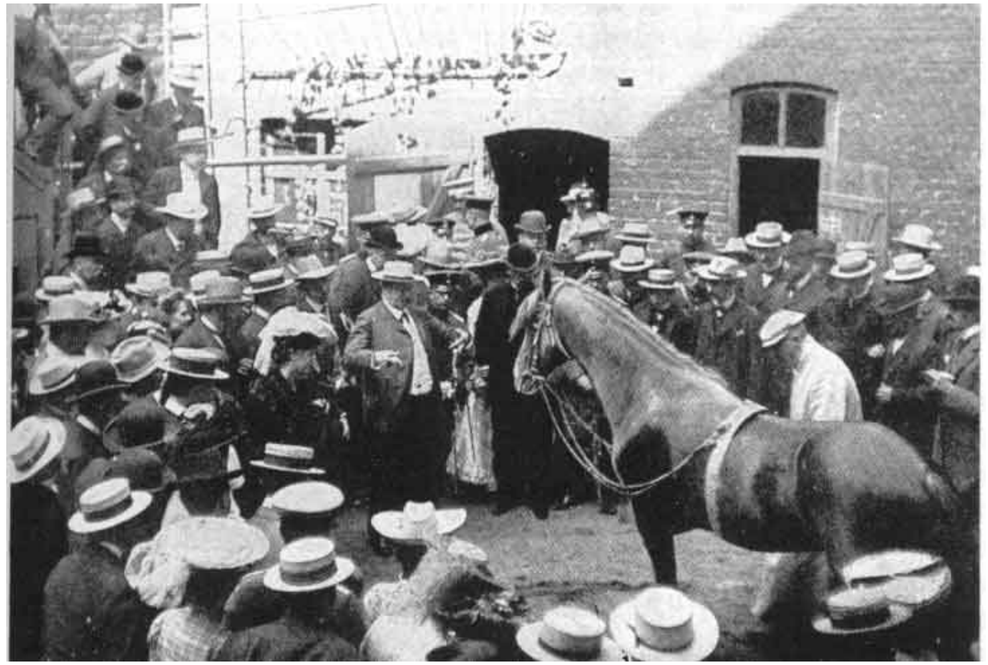
cms.sic.saarland/hlcvss24/

Max Planck Institute for Informatics & Saarland University,
Saarland Informatics Campus Saarbrücken

Overview of Today's Lecture

- Inherently Interpretable Neural Network
  - B-cos CNN [cvpr'22] - https://arxiv.org/abs/2205.10268
  - B-cos CNN & Vision transformers [pami'24] - https://arxiv.org/abs/2306.10898

- Segment Anything Model (SAM)
  - [iccv'23] - https://arxiv.org/abs/2304.02643
  - https://segment-anything.com/

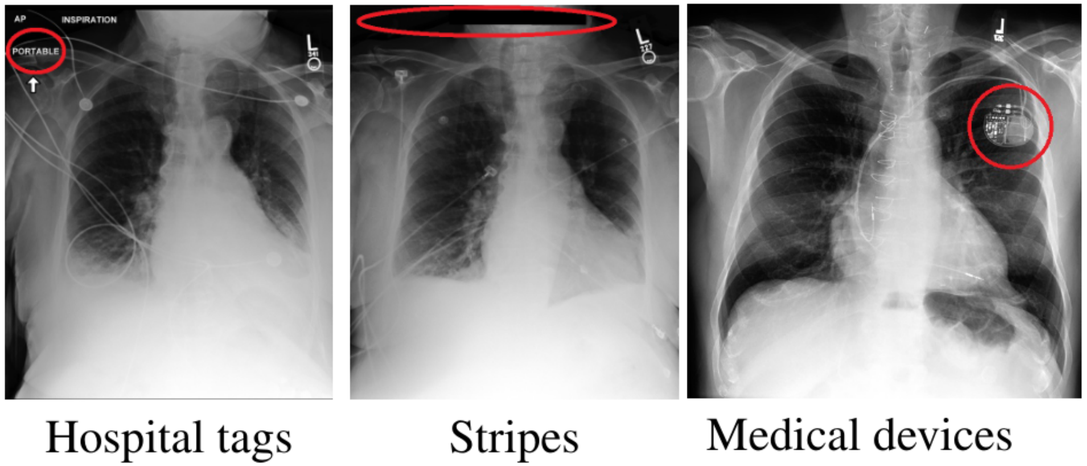


Images taken from wikipedia

We often may want to inspect how a model arrives at a prediction!

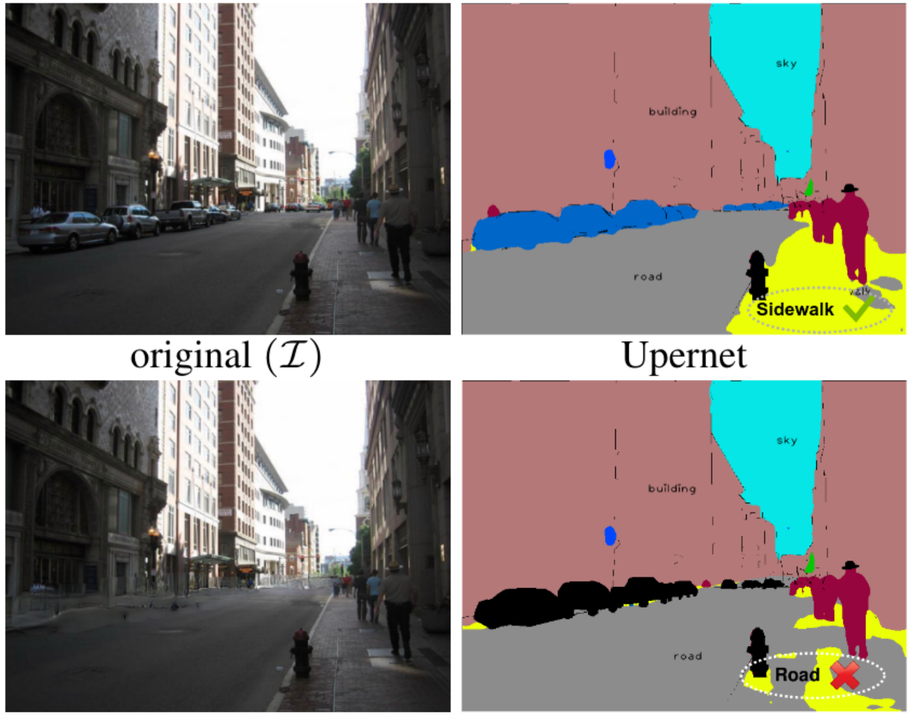
For example, to make sure the model is not relying on spurious correlations.

Source



Spurious correlations in the medical context

Source



A model relying on the context for its prediction

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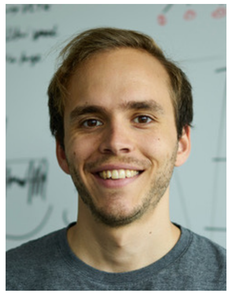
B-cos Networks: Alignment is All We Need for Interpretability

Moritz Böhle[1], Mario Fritz[2] and Bernt Schiele[1]
[1]Max Planck Institute for Informatics, [2]CISPA Helmholtz Center for Information Security

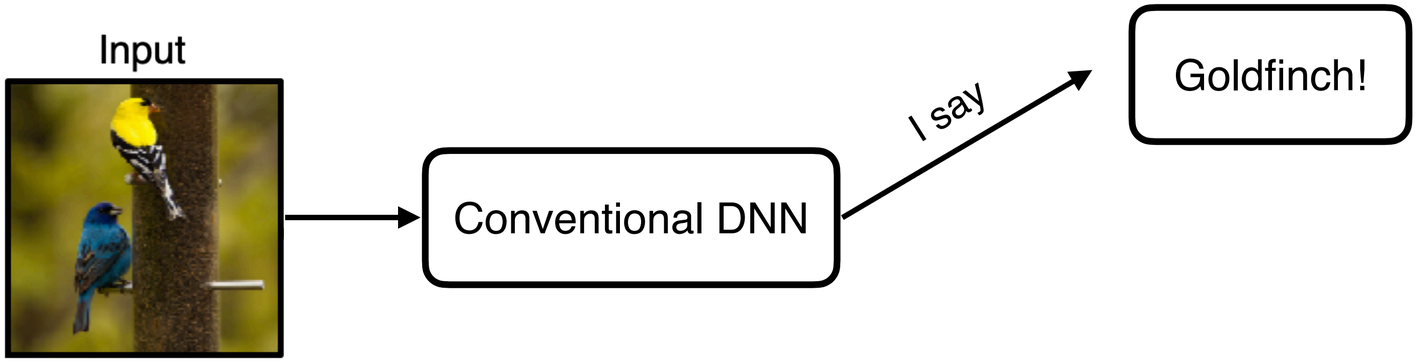


Motivation

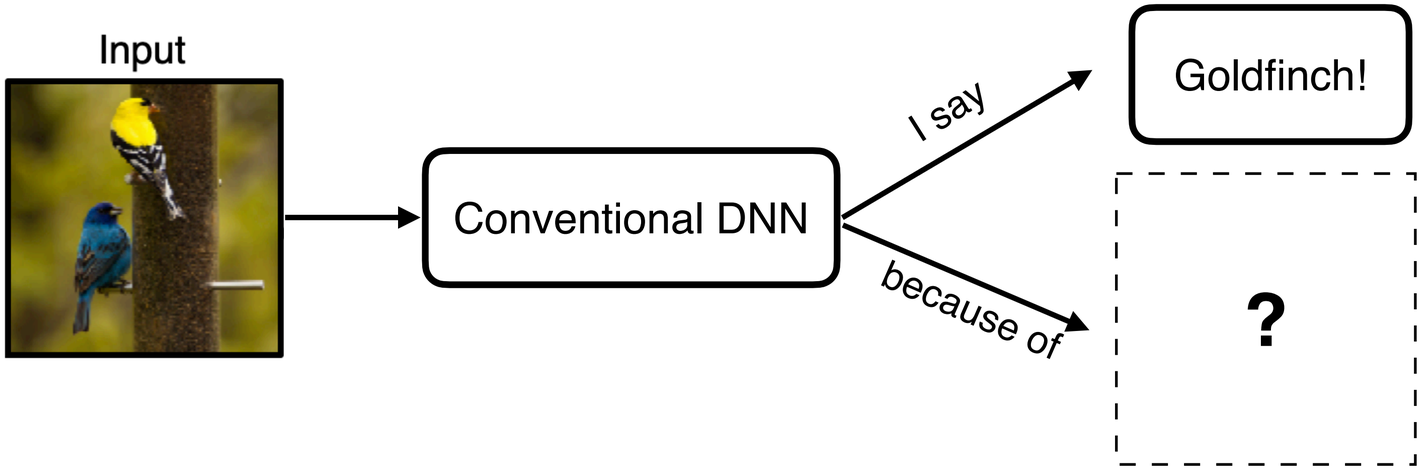
Input

Conventional DNN

Motivation



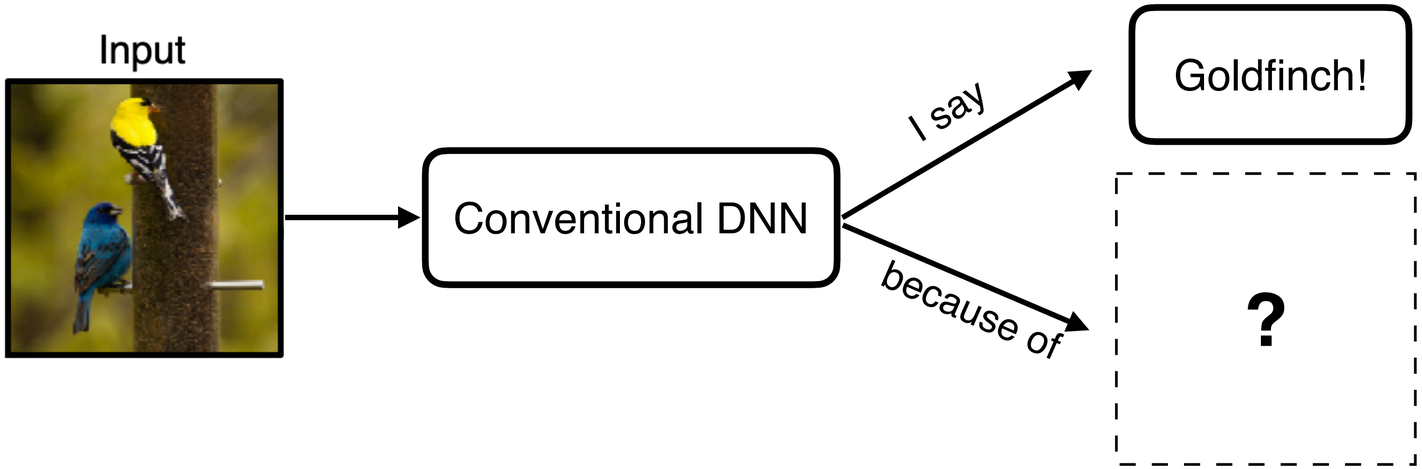
Motivation



Motivation

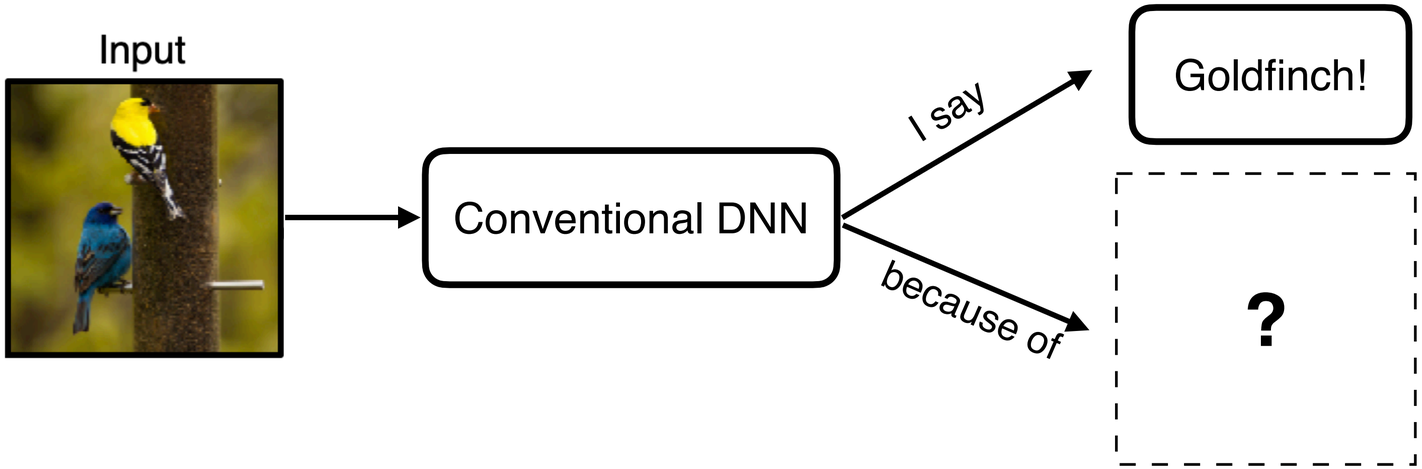
Want

Explanation



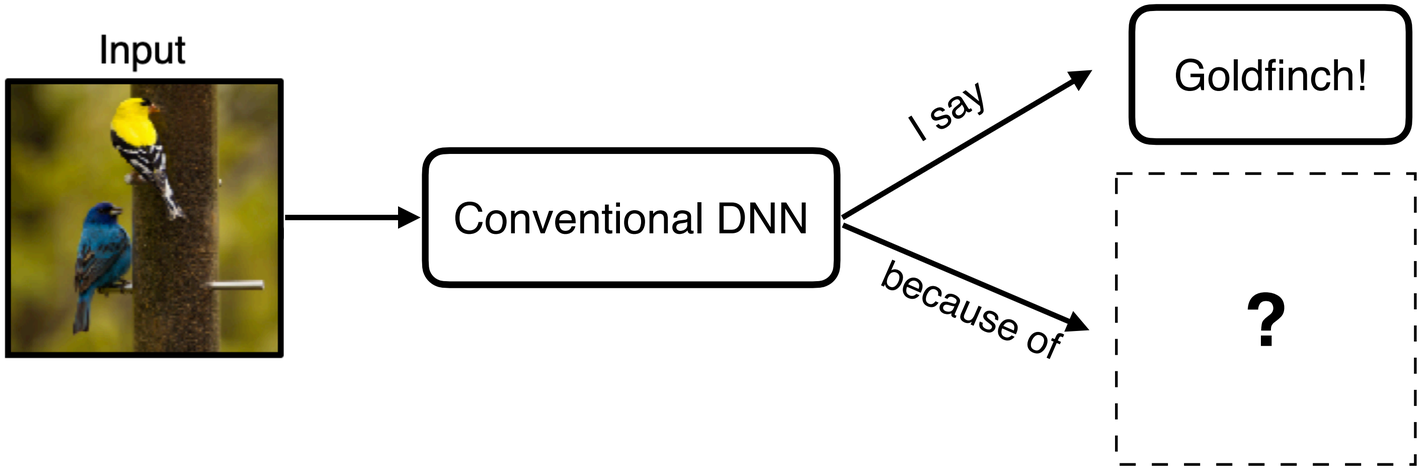
Motivation

Want Explanation to gain trust



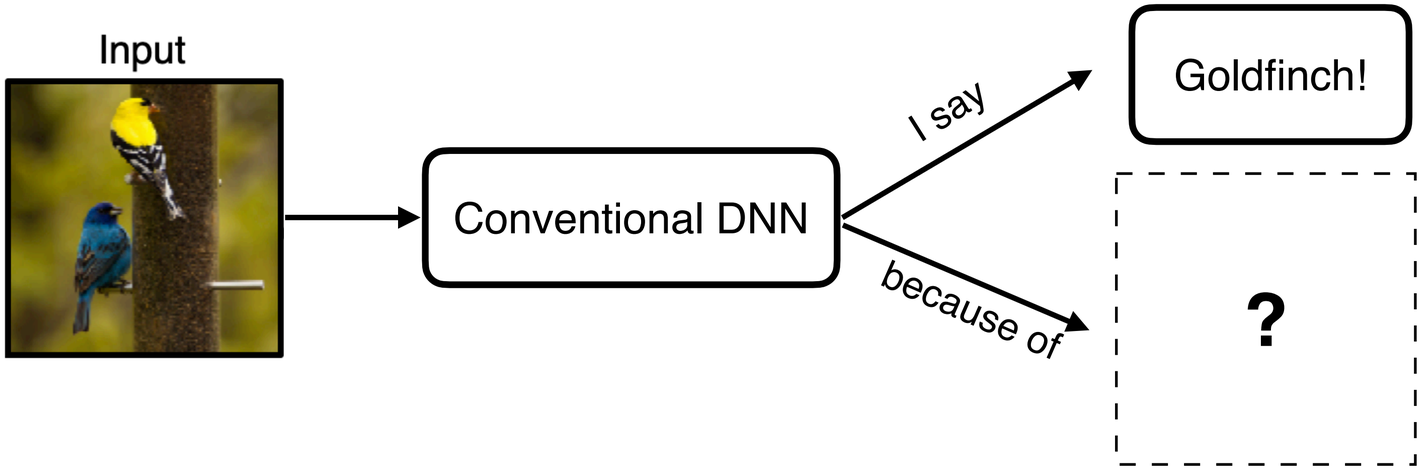
Motivation

Want Explanation to detect biases



Motivation

Want | Explanation | to | understand better

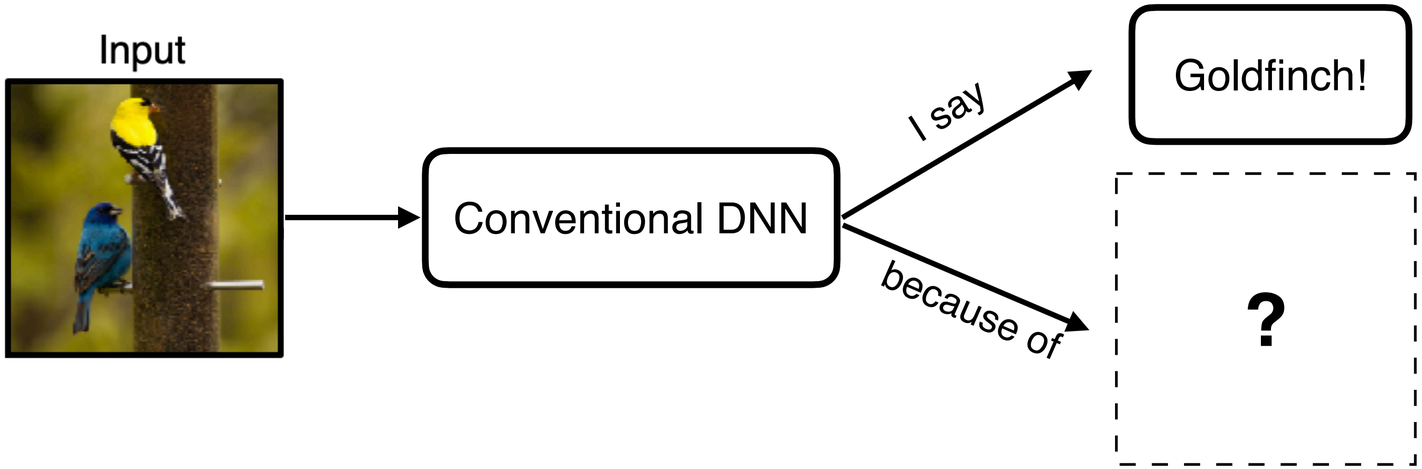


Motivation

Want

Explanation

Requirements



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Motivation

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Explanation

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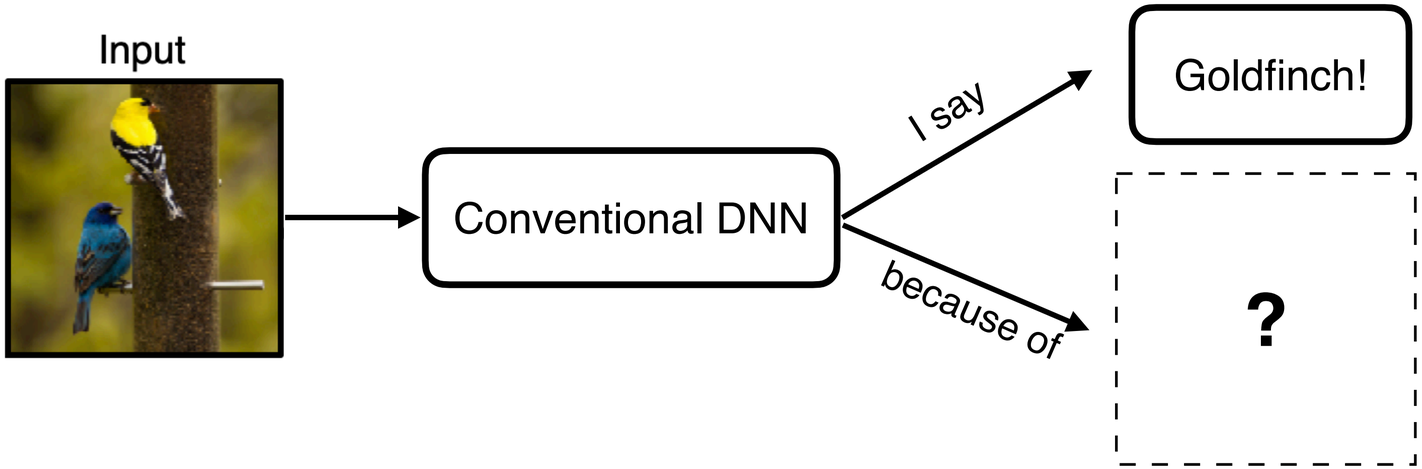
Faithful



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Motivation

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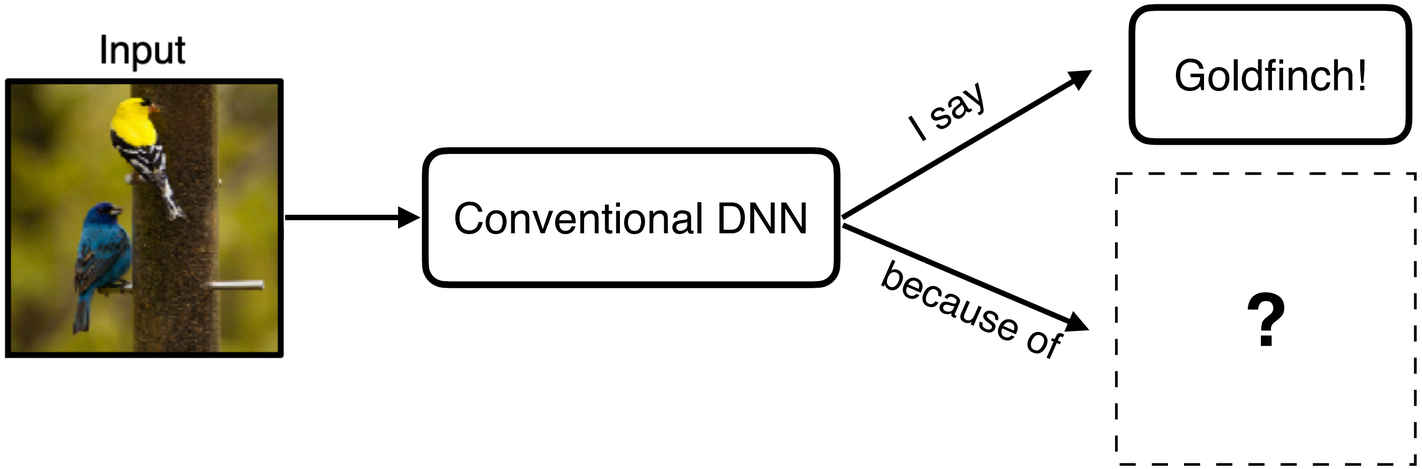
Explanation

Requirements

Faithful

Interpretable



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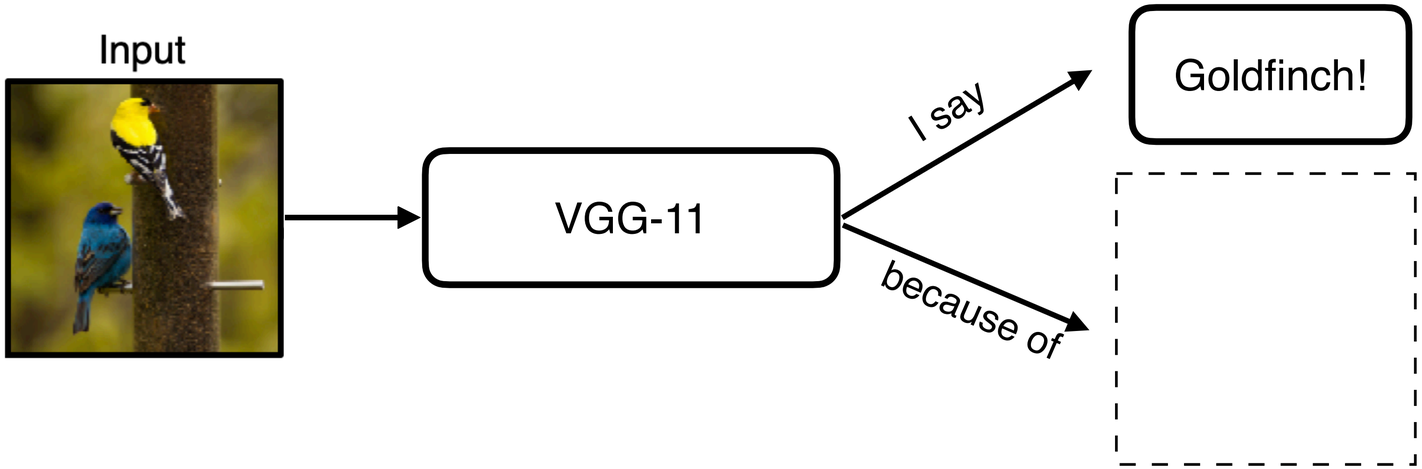

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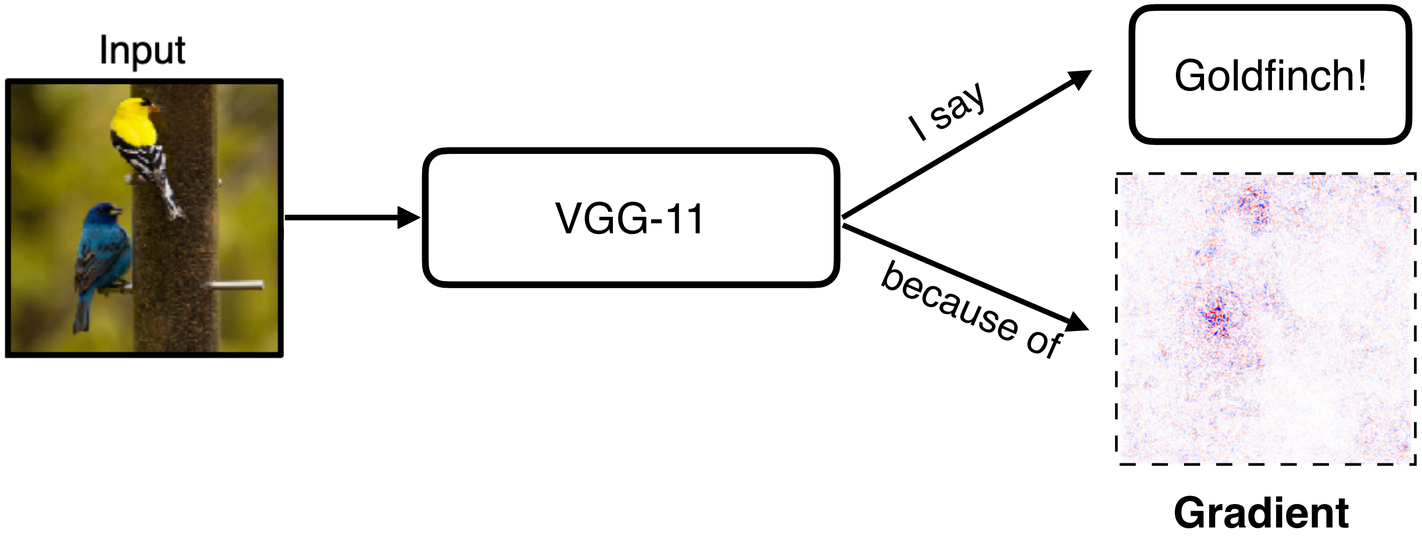

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Motivation

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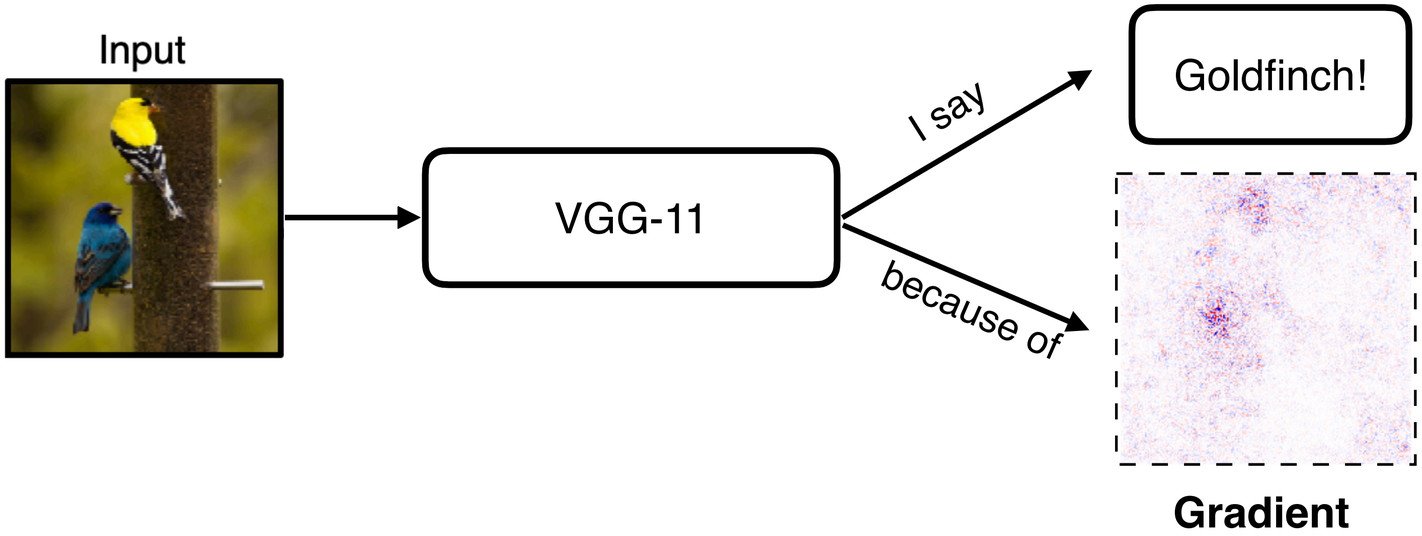
Explanation

Requirements

Faithful ✓

Interpretable



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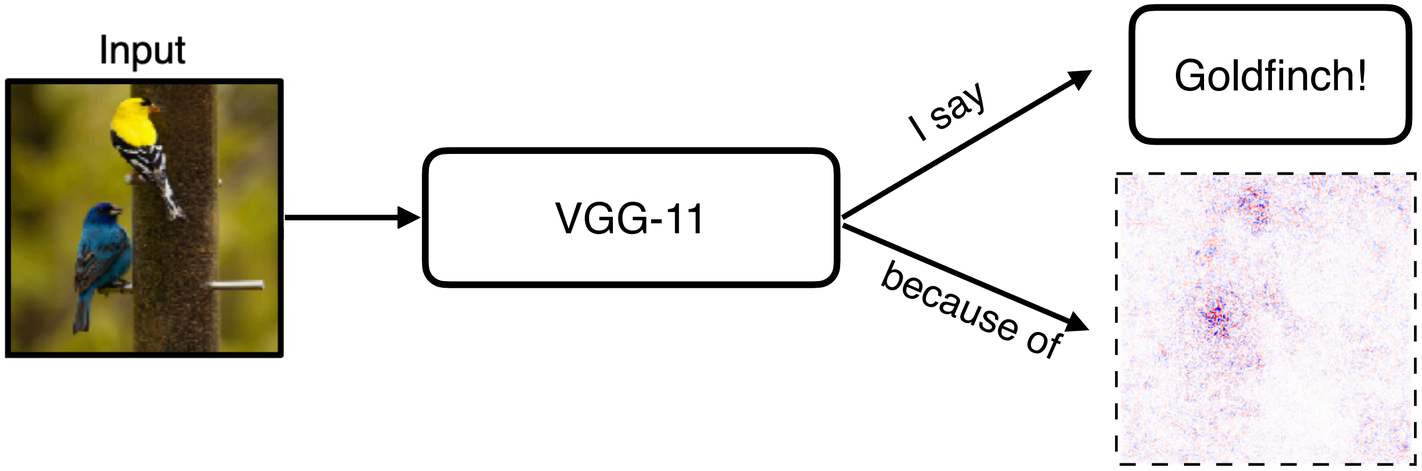
Explanation

Requirements

Faithful ✓

Interpretable ✗



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Motivation

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Explanation

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Faithful

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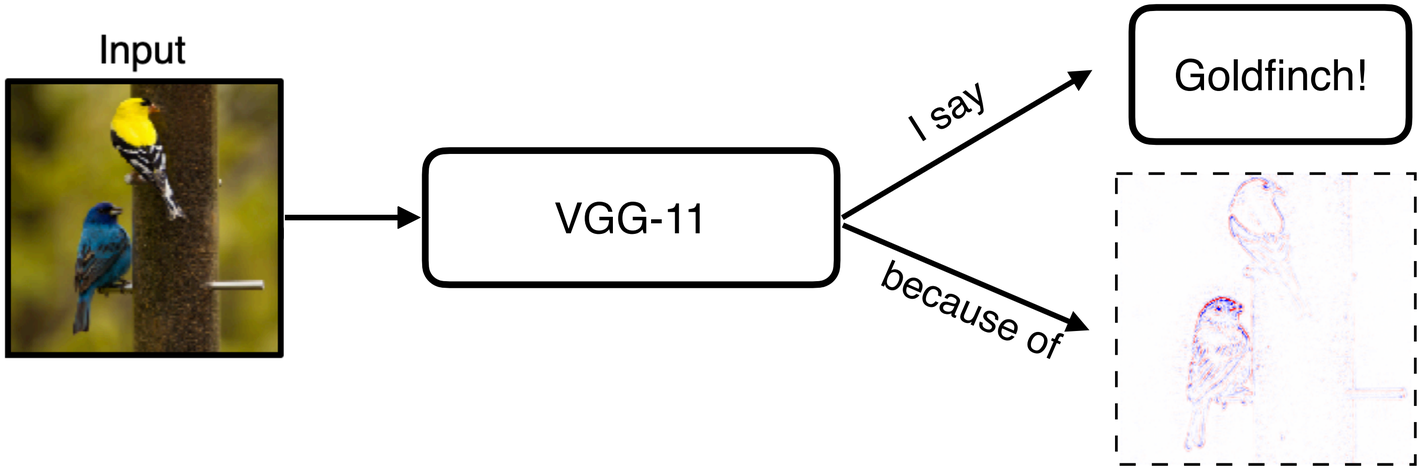

Guided Backpropagation

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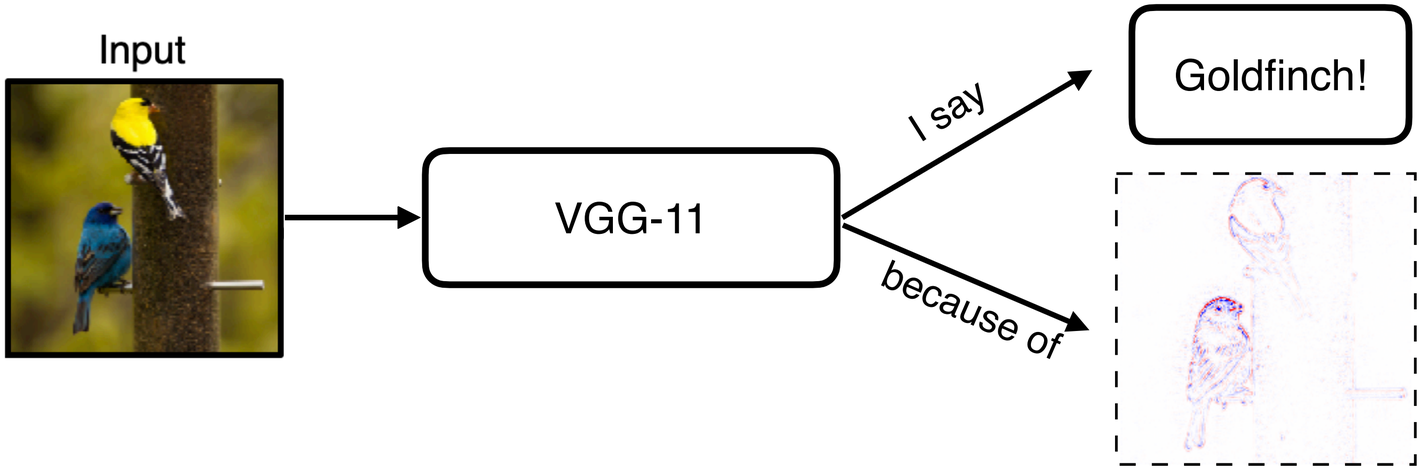
Motivation

Want: Explanation

Requirements: Faithful, Interpretable ✓



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Faithful

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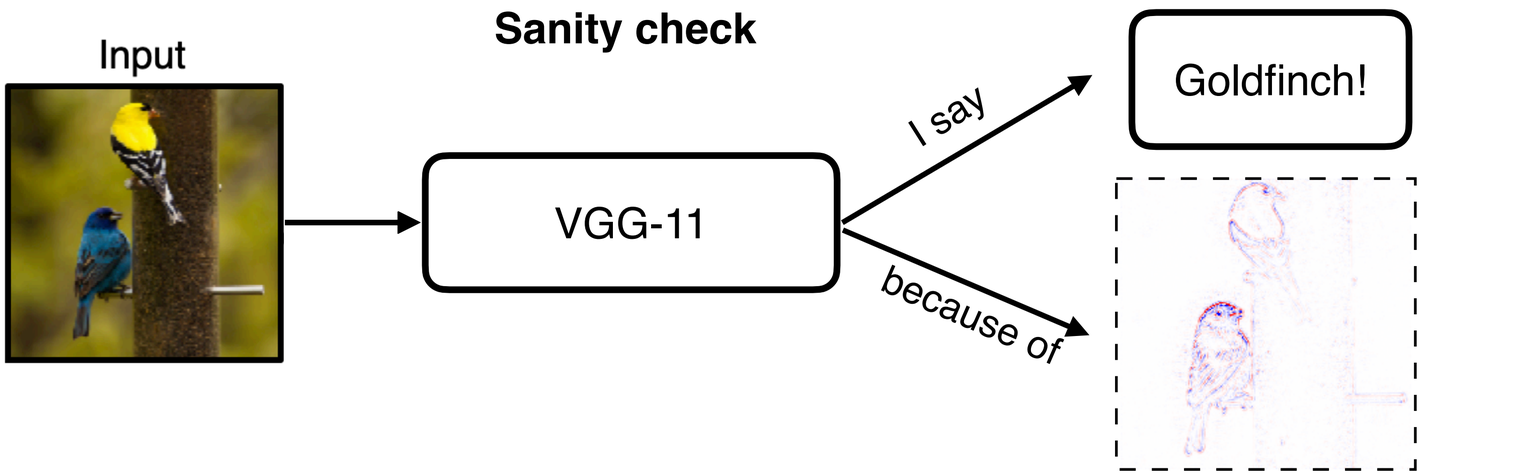

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Motivation

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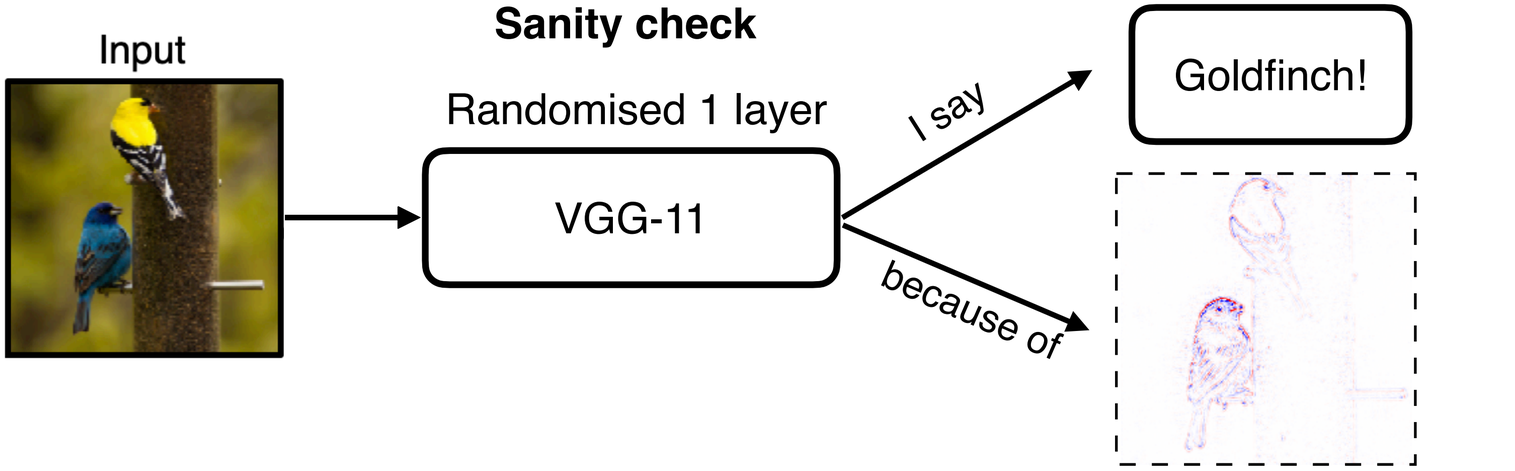
Faithful

Interpretable ?



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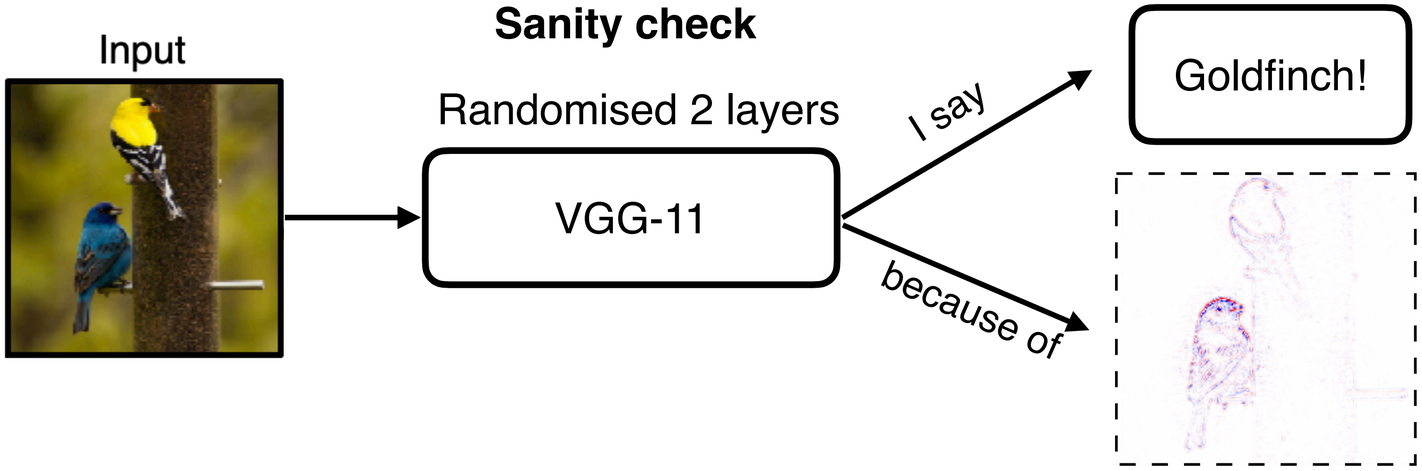

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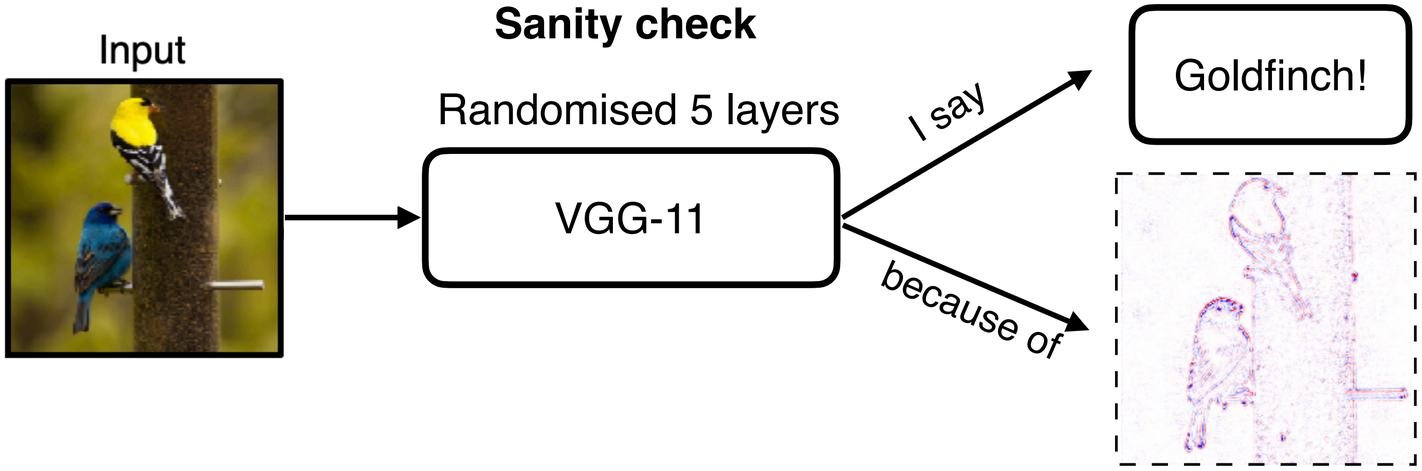

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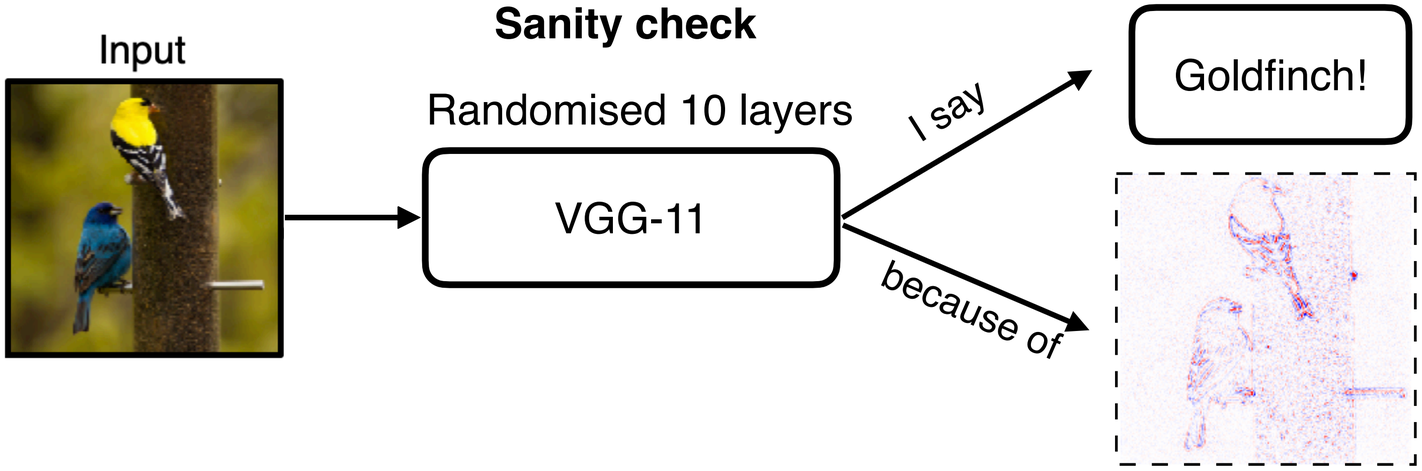
Faithful ✗

Interpretable ✓



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Motivation: we aim for Inherent Interpretability

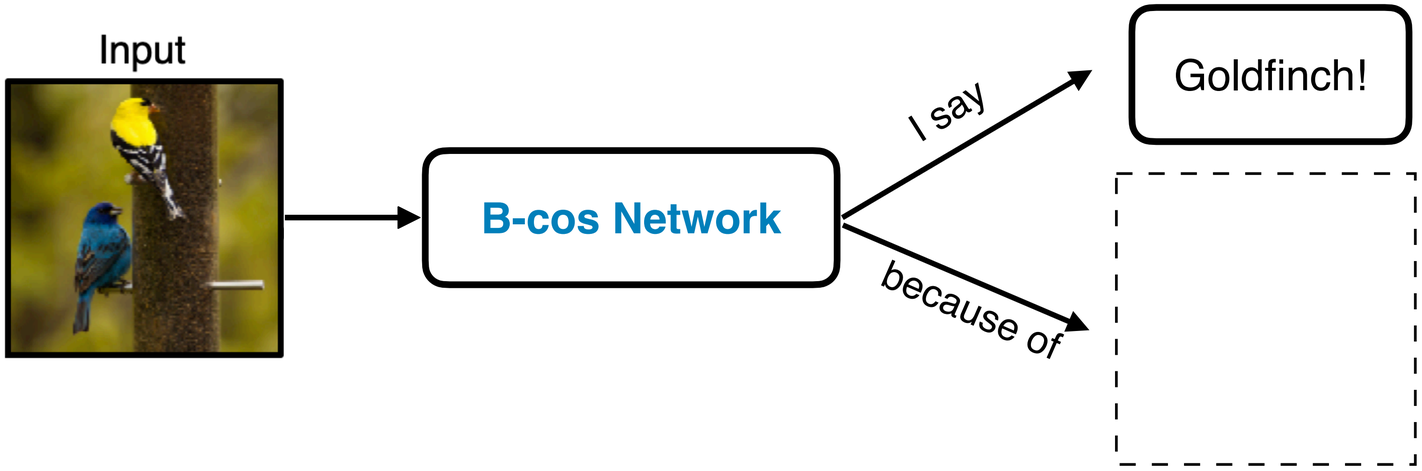
Want

Explanation

Requirements

Faithful

Interpretable



Model-inherent linear map

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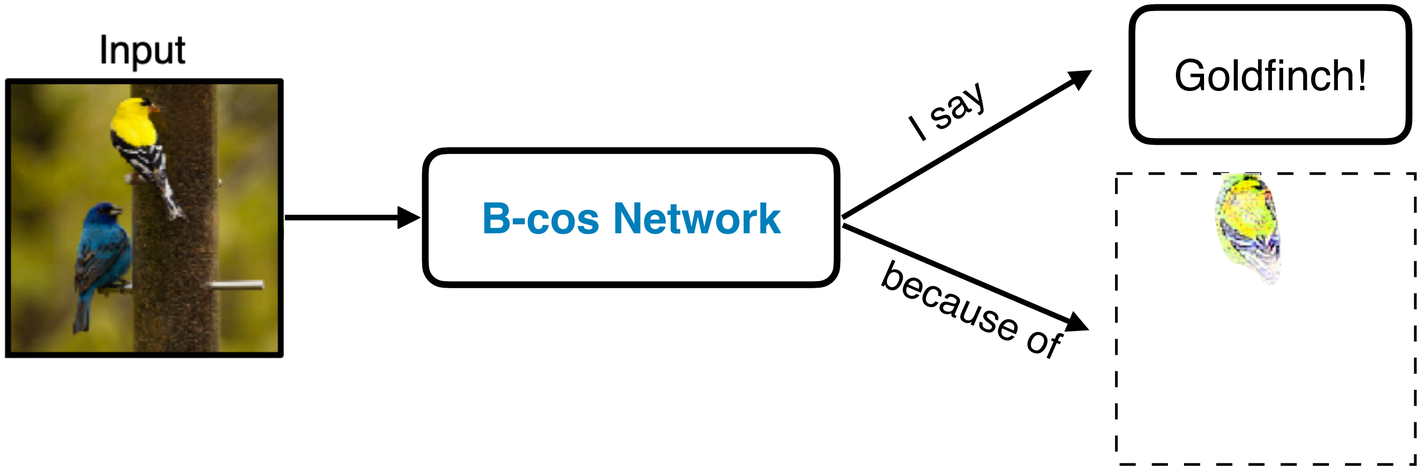

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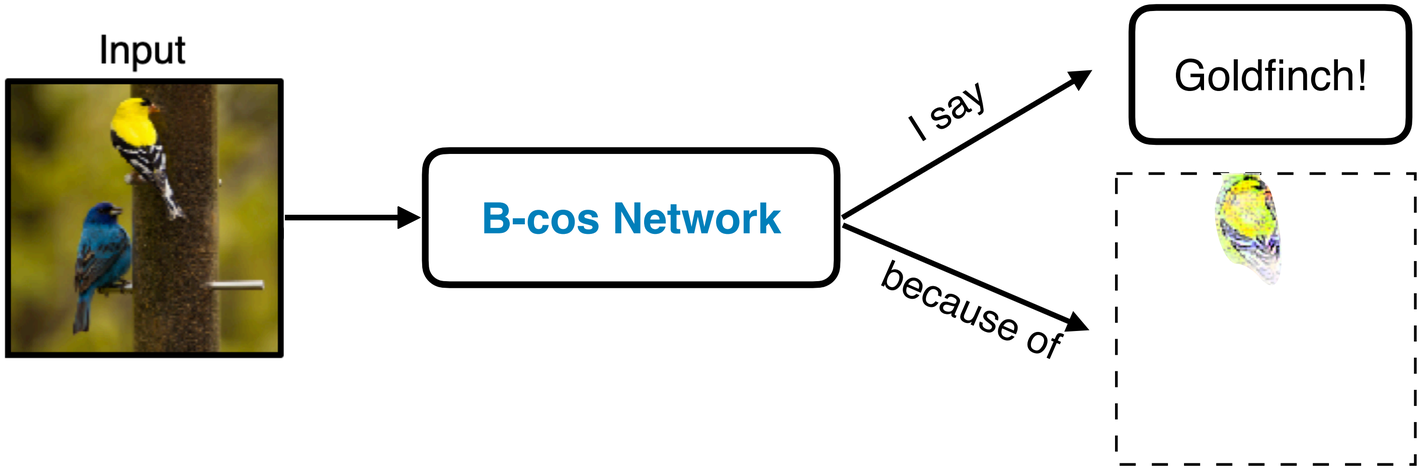
Explanation

Requirements

Faithful ✓

Interpretable

Dynamic linearity



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Motivation: we aim for Inherent Interpretability

Want

Explanation

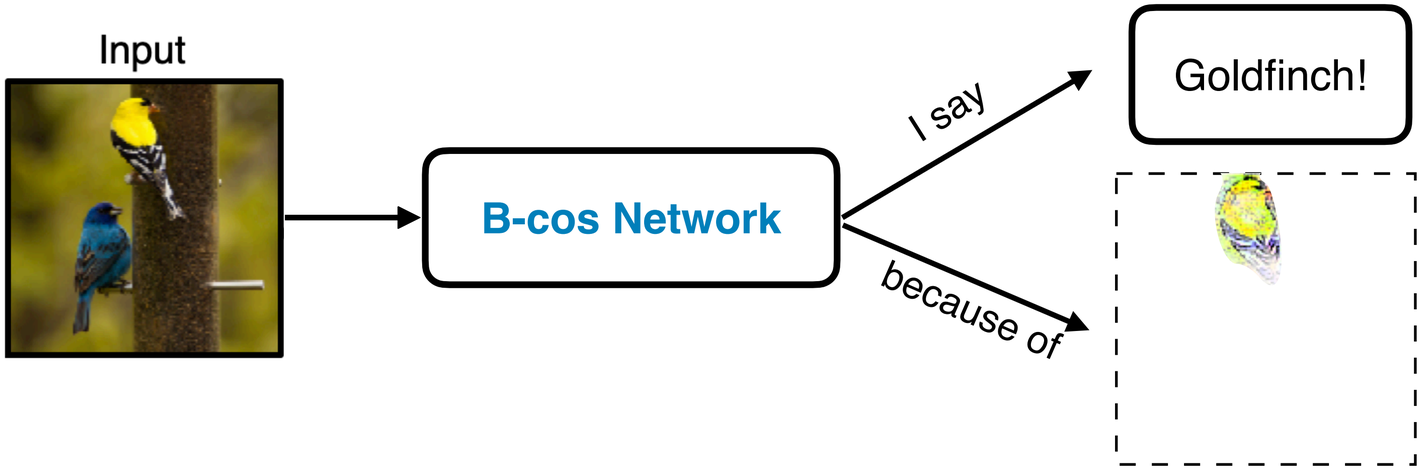
Requirements

Faithful ✓

Interpretable ✓

Dynamic linearity

Alignment pressure



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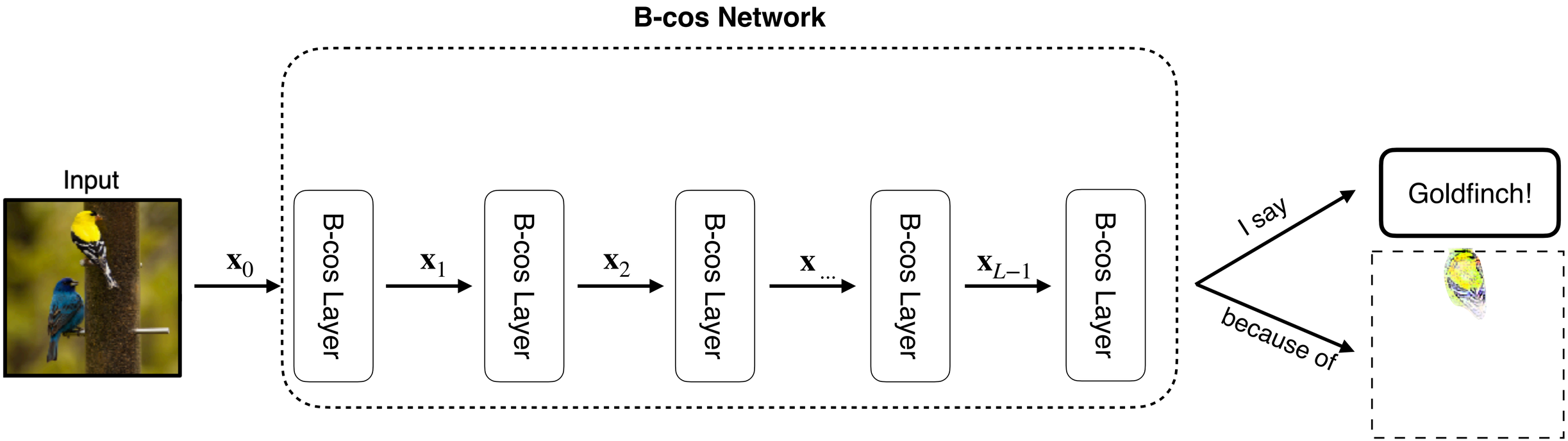
B-cos Networks: Dynamic Linearity



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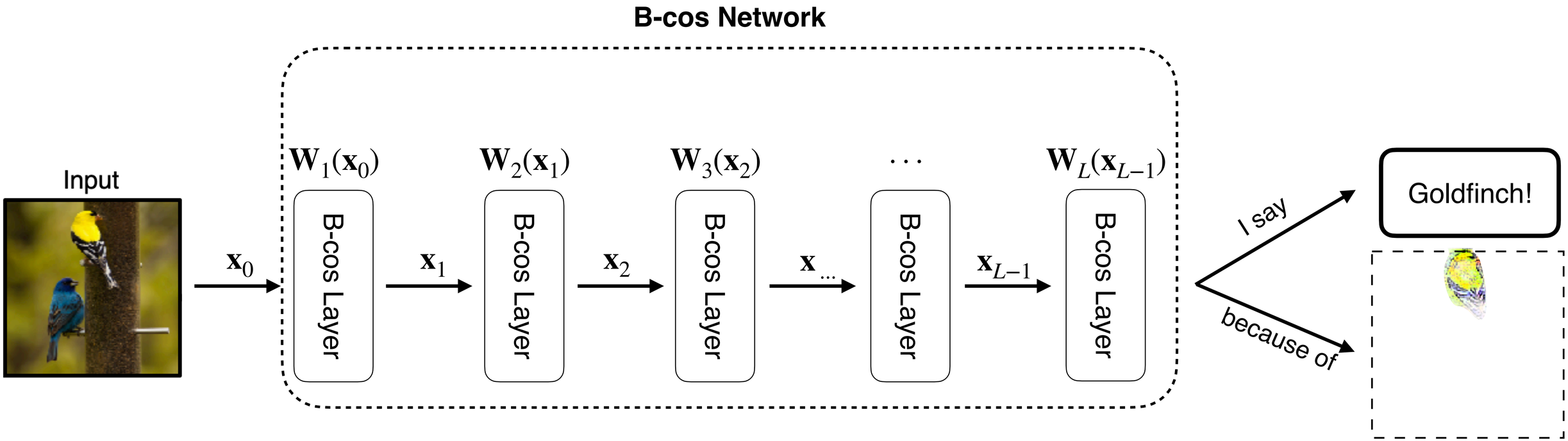

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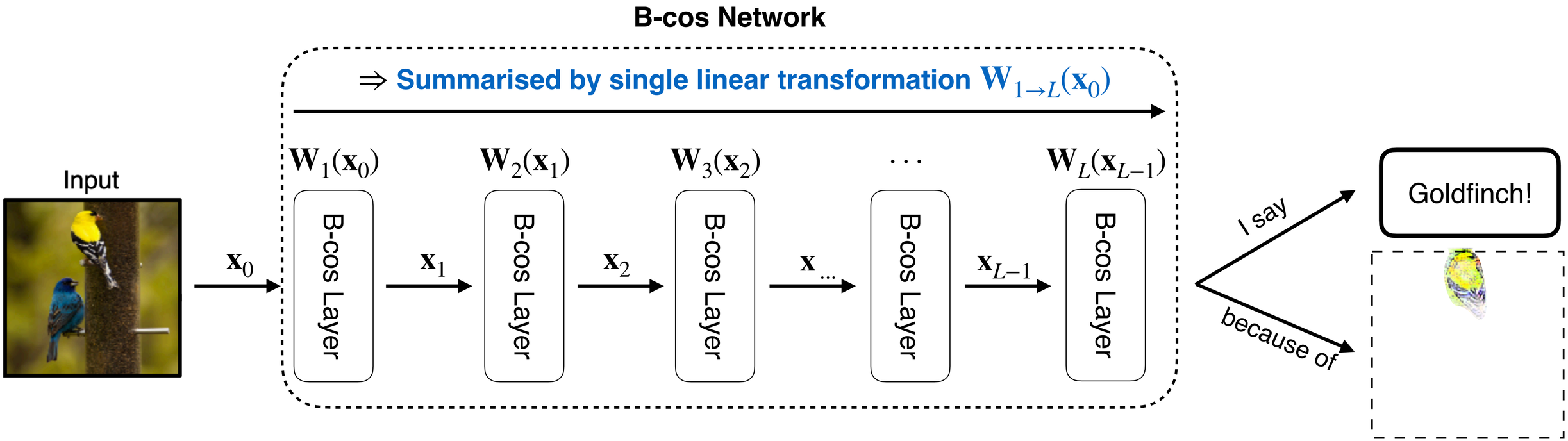
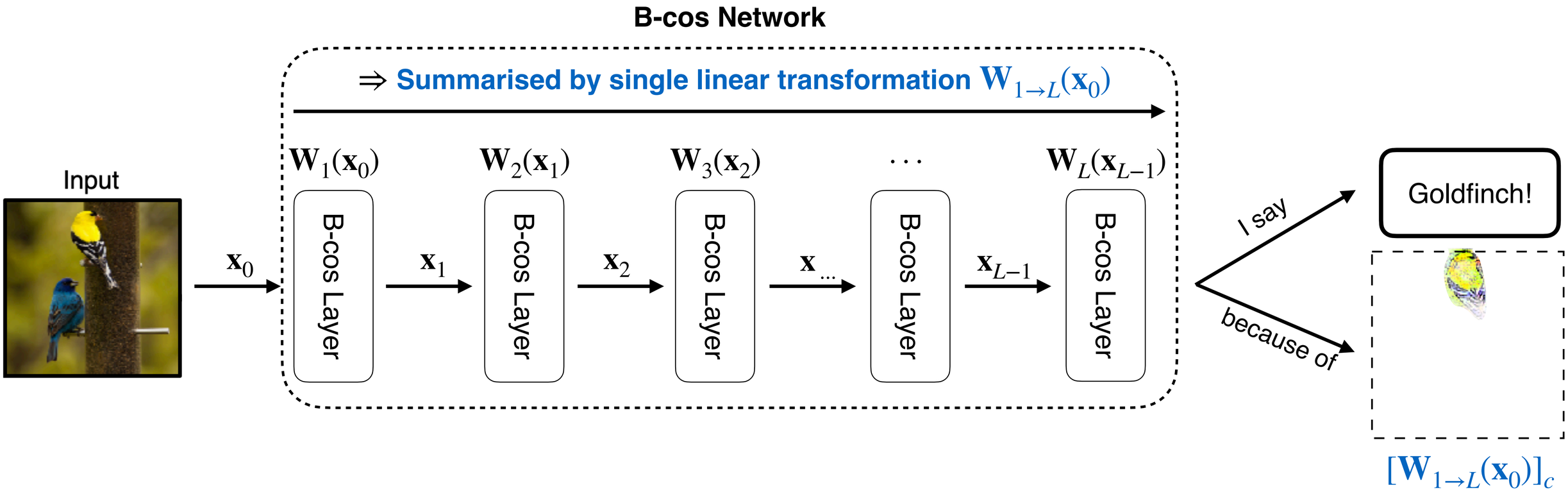


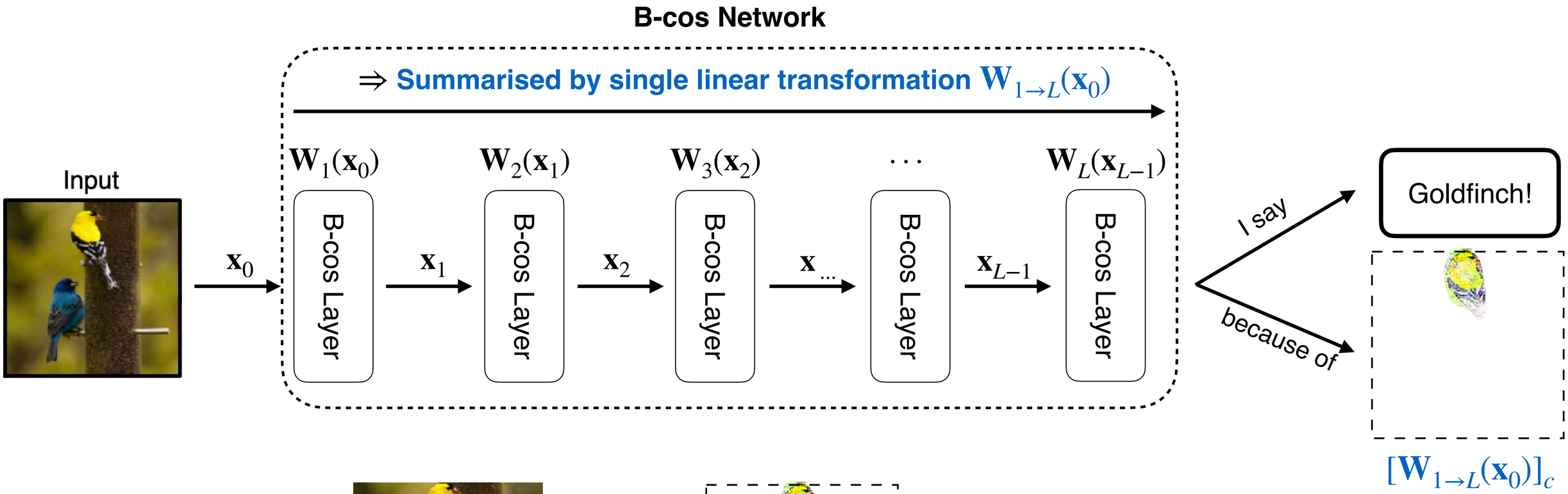
W changes with input

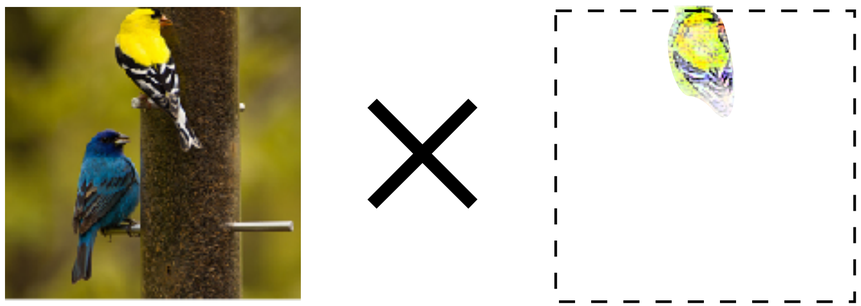
B-cos Networks: Dynamic Linearity



explanation based on W

B-cos Networks: Dynamic Linearity

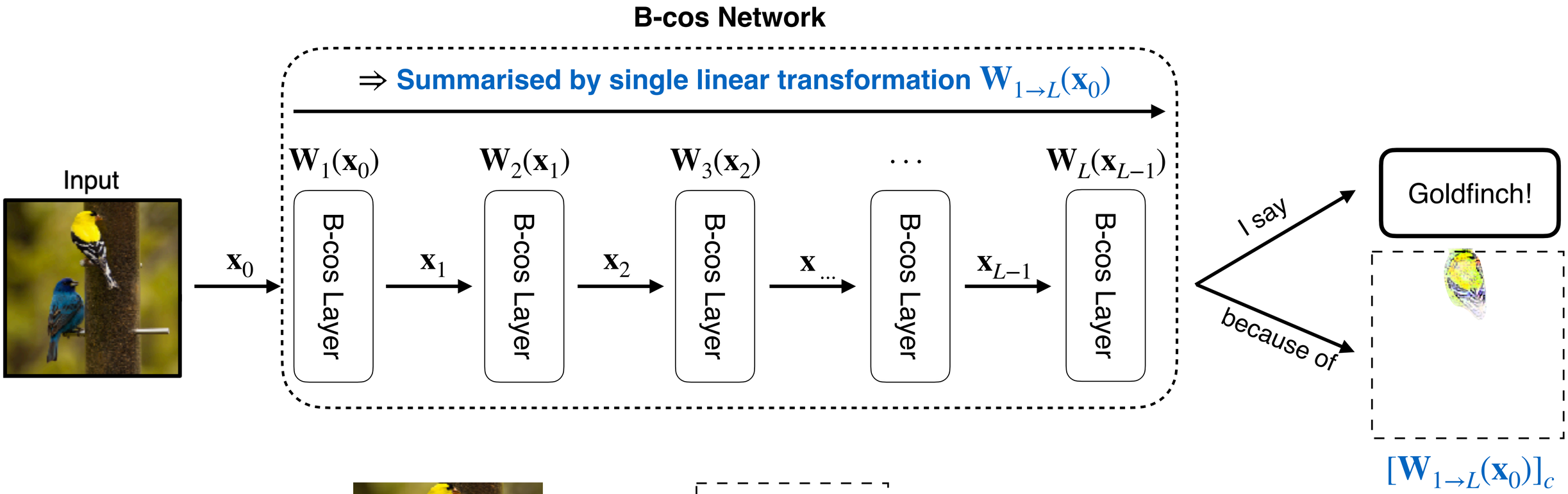


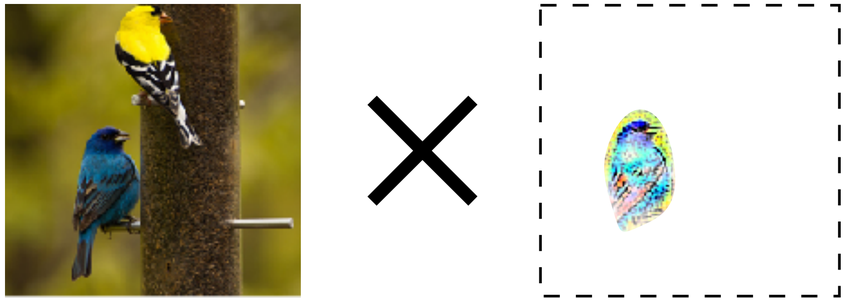


Goldfinch

48.8%

B-cos Networks: Dynamic Linearity

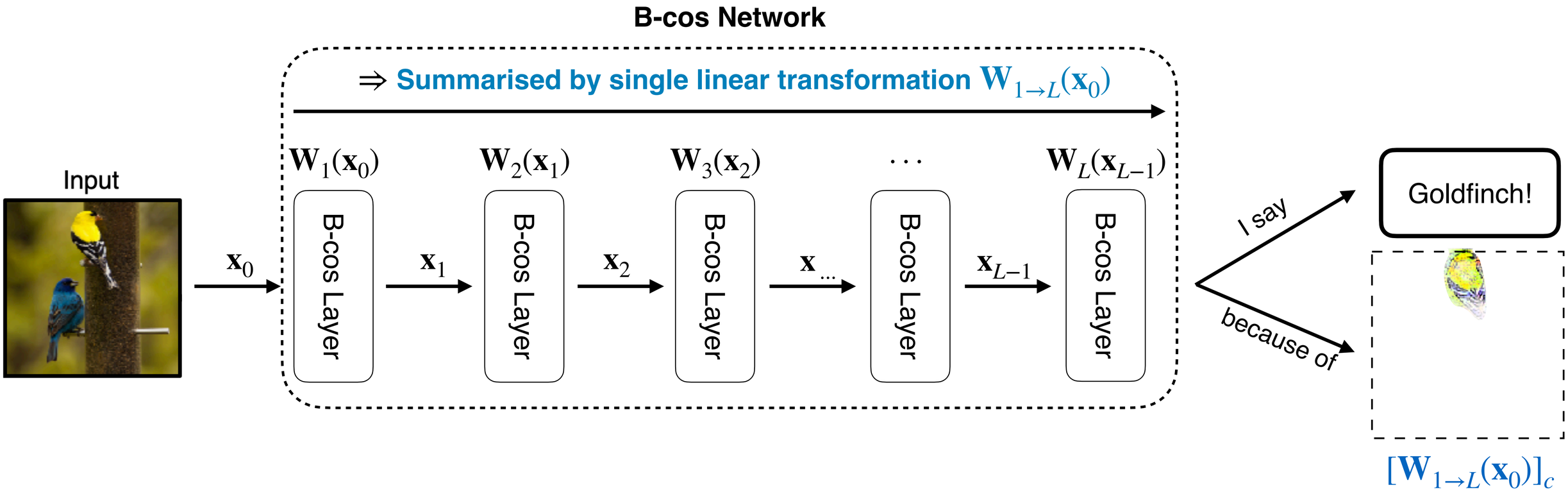




Bunting

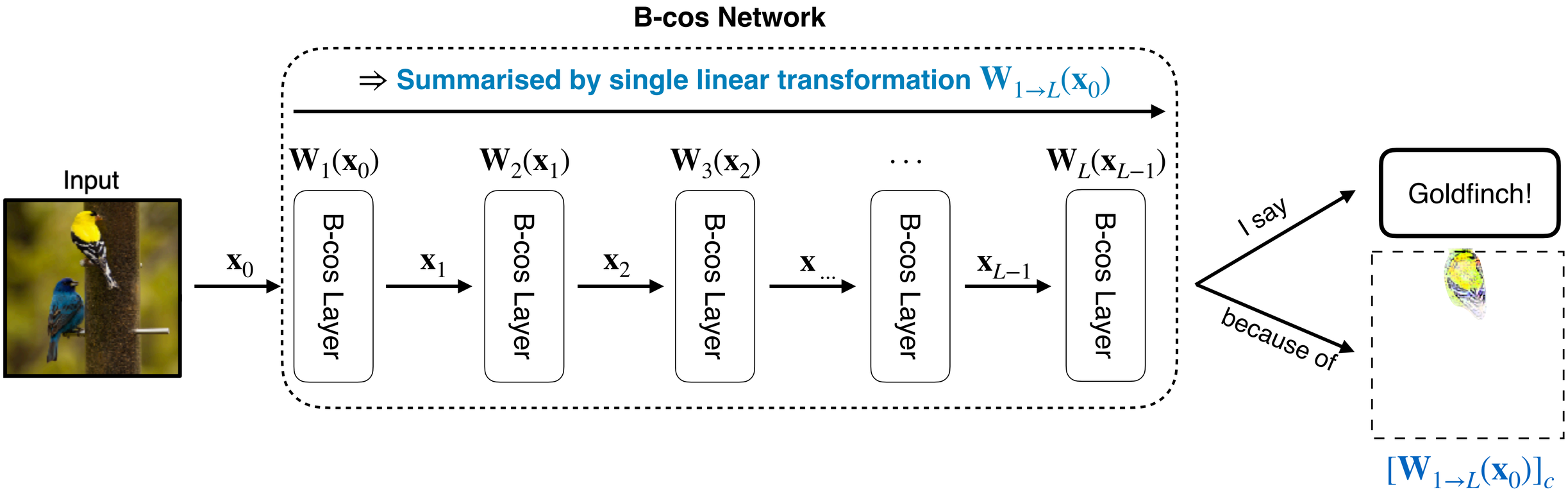
47.0%

B-cos Networks: Dynamic Linearity



Dynamic linearity allows us to faithfully summarise the model.

B-cos Networks: Dynamic Linearity



Dynamic linearity allows us to faithfully summarise the model.

But why should $\mathbf{W}_{1\to L}(\mathbf{x}_0)$ align with relevant features?

Alignment pressure

B-cos transformation vs. linear transformation

Linear transformation $f(\mathbf{x};\ \mathbf{w}) = \mathbf{w}^T\ \mathbf{x} = ||\mathbf{w}||\ ||\mathbf{x}||\ \cos(\mathbf{x}, \mathbf{w})$

B-cos transformation vs. linear transformation

Linear transformation $f(\mathbf{x};\ \mathbf{w}) = \mathbf{w}^T\ \mathbf{x} = ||\mathbf{w}||\ ||\mathbf{x}||\ \cos(\mathbf{x}, \mathbf{w})$

$= ||\mathbf{w}||\ ||\mathbf{x}||\ |\cos(\mathbf{x}, \mathbf{w})| \times \text{sgn}\left(\cos(\mathbf{w}, \mathbf{x})\right)$

B-cos transformation vs. linear transformation

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$= ||\mathbf{w}||\ ||\mathbf{x}||\ |\cos(\mathbf{x}, \mathbf{w})| \times \text{sgn}\left(\cos(\mathbf{w}, \mathbf{x})\right)$

New transformation B-cos$(\mathbf{x};\ \mathbf{w}) = \underbrace{||\ \widehat{\mathbf{w}}\ ||}_{=1}\ ||\mathbf{x}||\ |\cos(\mathbf{x}, \mathbf{w})|^{B} \times \text{sgn}\left(\cos(\mathbf{x}, \mathbf{w})\right)$

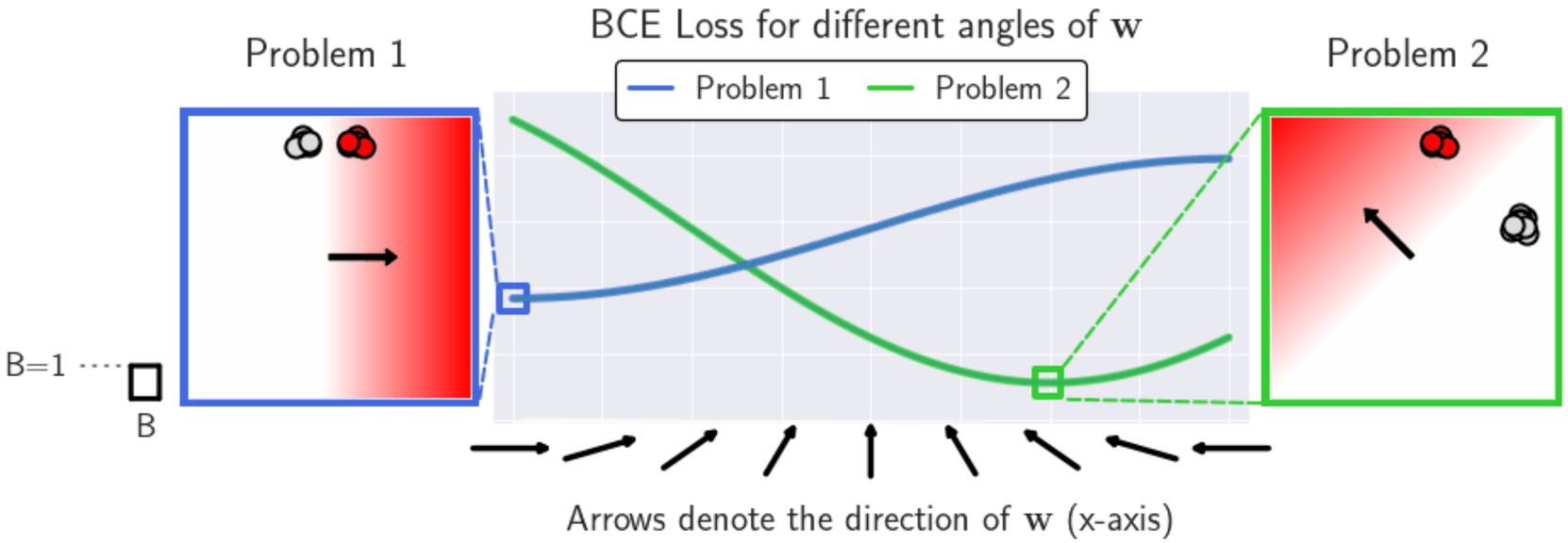
high cosine to the input
B: increase the importance of cosine term

B-cos transformation vs. linear transformation

Linear transformation $f(\mathbf{x};\ \mathbf{w}) = \mathbf{w}^T\ \mathbf{x} = ||\mathbf{w}||\ ||\mathbf{x}||\ \cos(\mathbf{x}, \mathbf{w})$

$= ||\mathbf{w}||\ ||\mathbf{x}||\ |\cos(\mathbf{x}, \mathbf{w})| \times \text{sgn}\left(\cos(\mathbf{w}, \mathbf{x})\right)$

New transformation B-cos$(\mathbf{x};\ \mathbf{w}) = \underbrace{||\ \widehat{\mathbf{w}}\ ||}_{=1}\ ||\mathbf{x}||\ |\cos(\mathbf{x}, \mathbf{w})|^{B} \times \text{sgn}\left(\cos(\mathbf{x}, \mathbf{w})\right)$



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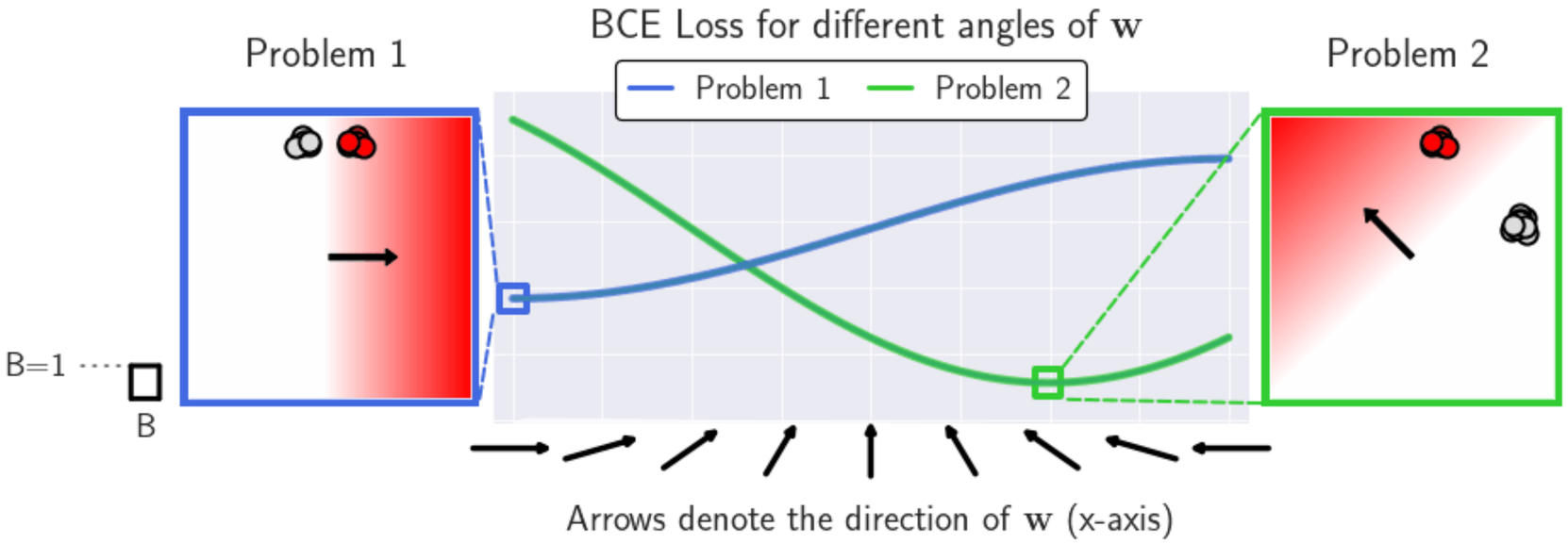
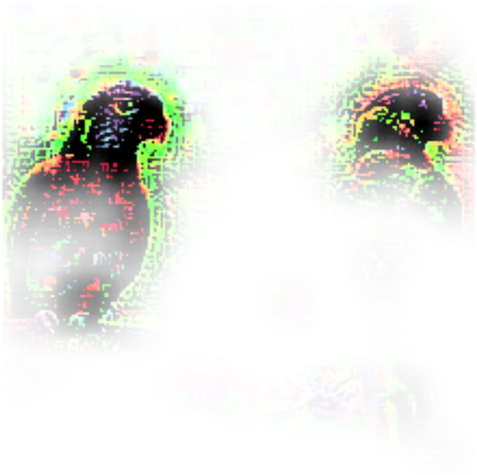


Results

- Quantitative results on ImageNet
  - Classification accuracy
  - Interpretability scores

- Some qualitative results on ImageNet
  - Explaining class logits
  - explaining intermediate neurons



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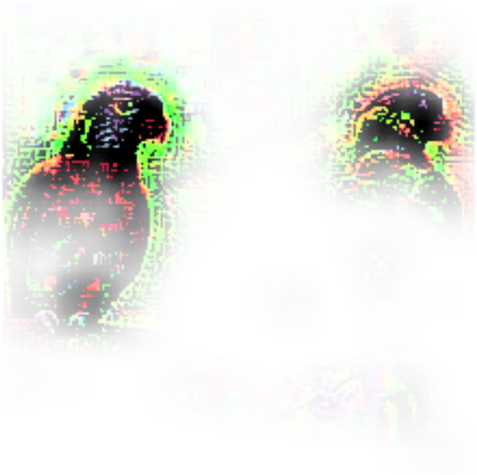
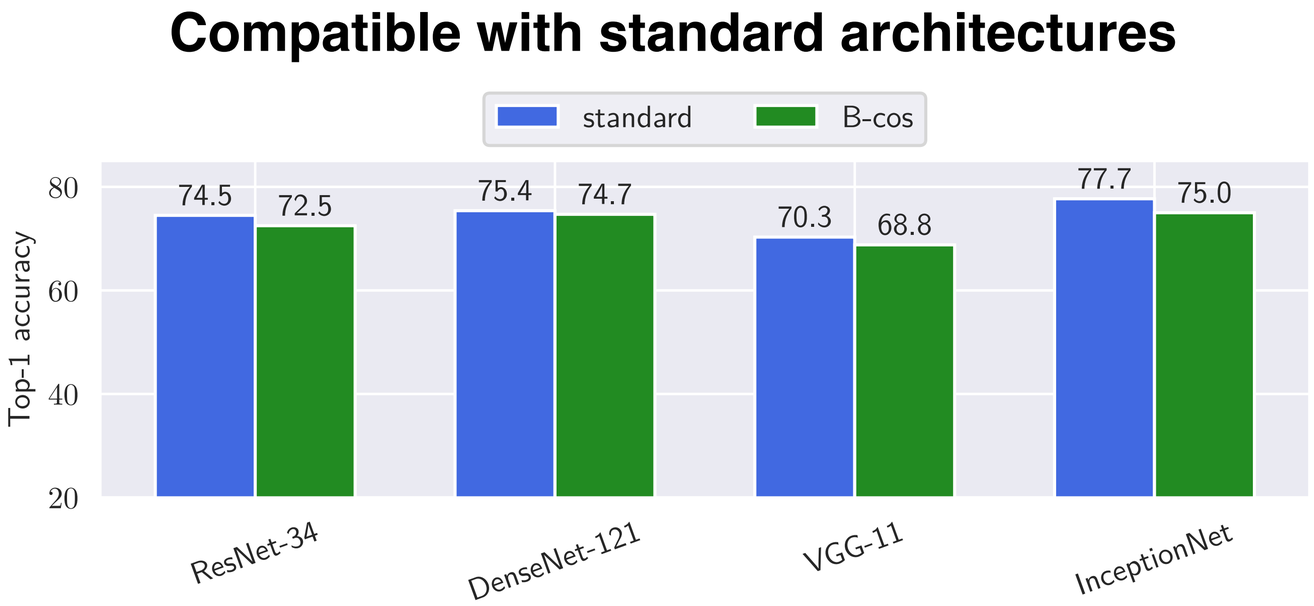


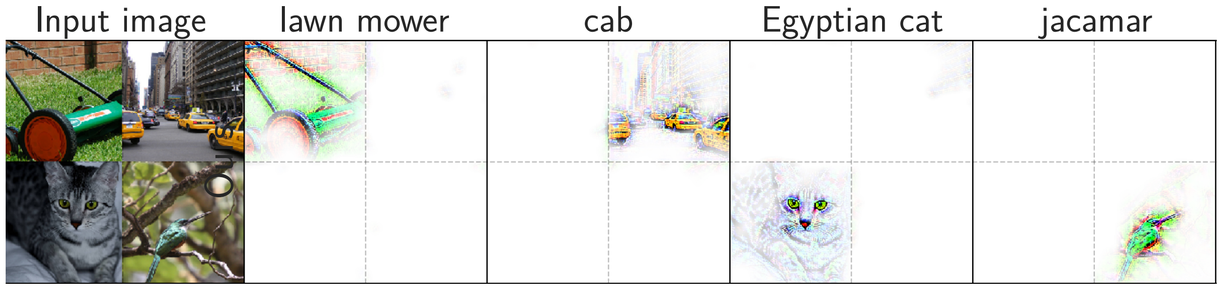
ImageNet results

- B-cos networks show competitive performance
- Importantly, they exhibit significantly higher interpretability



Measuring Interpretability via Grid Pointing Game

- To measure interpretability, we employ the *grid pointing game*

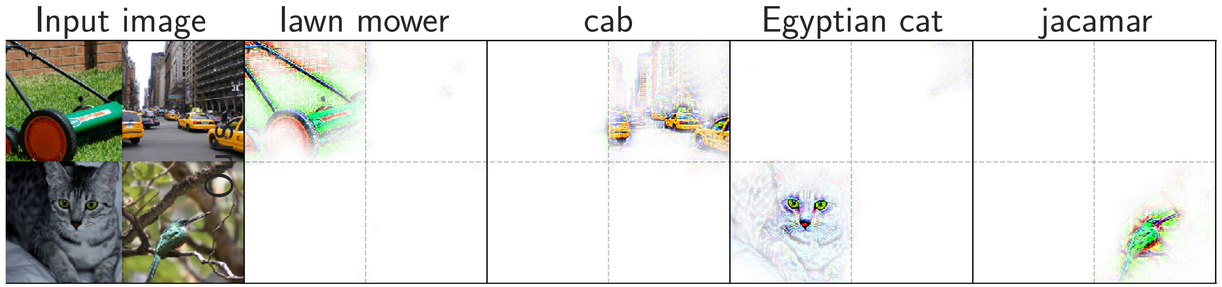


Measuring Interpretability via Grid Pointing Game

- To measure interpretability, we employ the *grid pointing game*

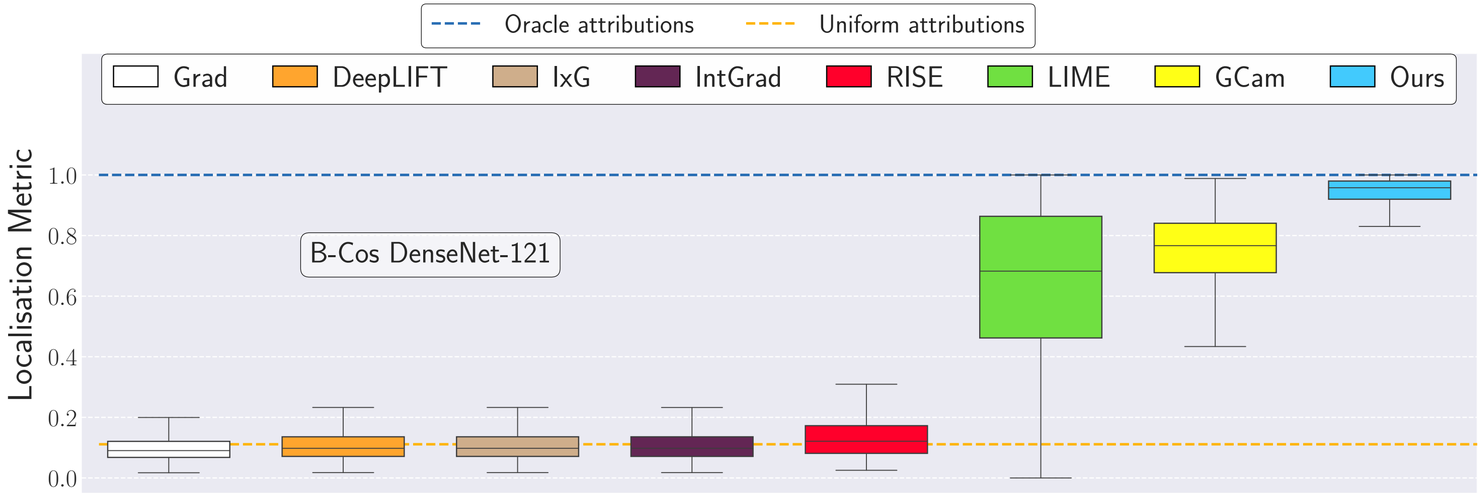
- In particular:
  - evaluate models on synthetic image grid
  - measure how well an explanation *localises* the correct image grid

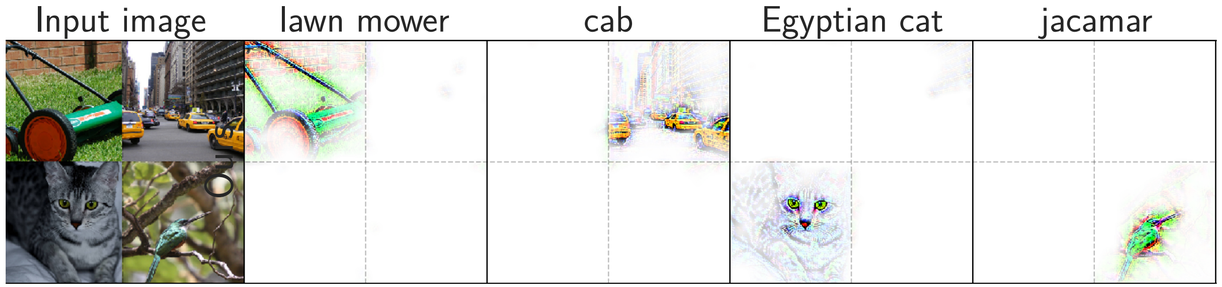
    (score $s = \frac{A_i^+}{\sum_j A_j^+}$ with A_i^+ the positive attribution to subimage i)



ImageNet results

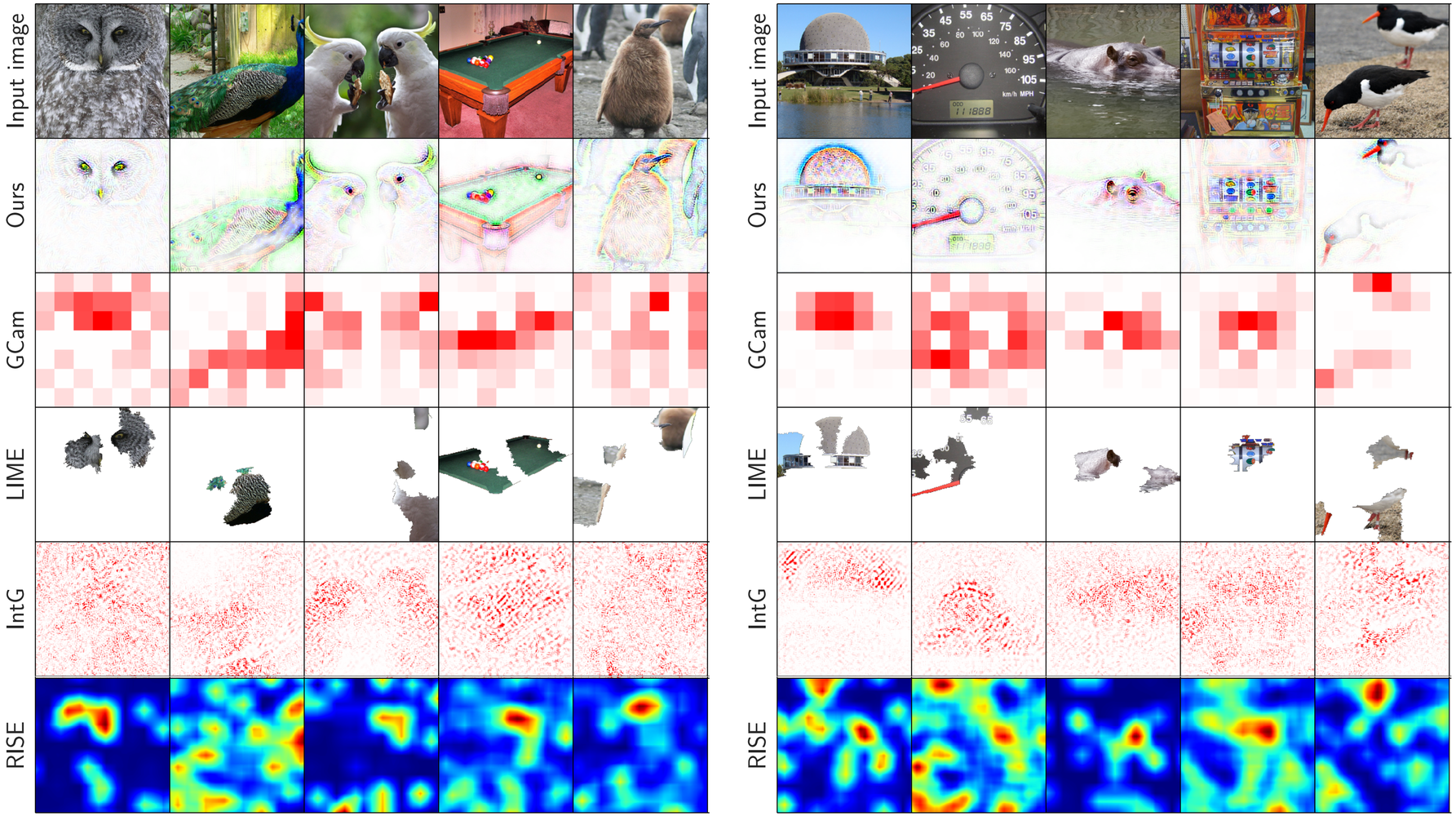
High interpretability





Gradient (Baehrens (2010)), DeepLIFT (Shrikumar (2017)), Input x Gradient (cf. Adebayo (2018)), IntGrad (Sundararajan (2017)), RISE (Petsiuk, 2018), LIME (Ribeiro, 2016), GradCam (Ramprasaath et al. (2017))

Visualisations of $\mathbf{W}_{1\to L}(\mathbf{x})$



Visualisations: intermediate neurons

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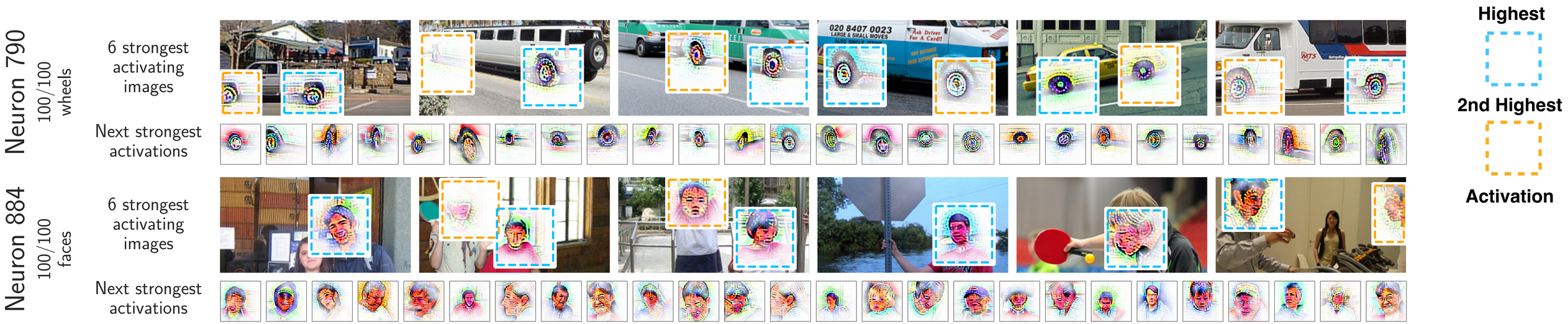
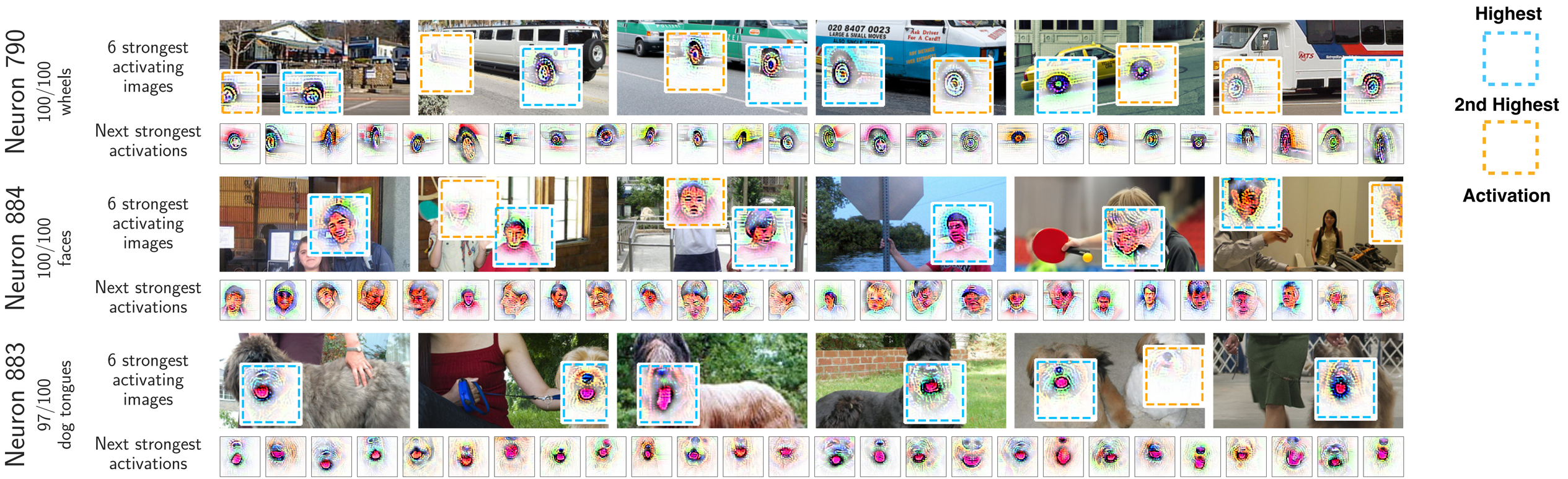


Visualisations: intermediate neurons



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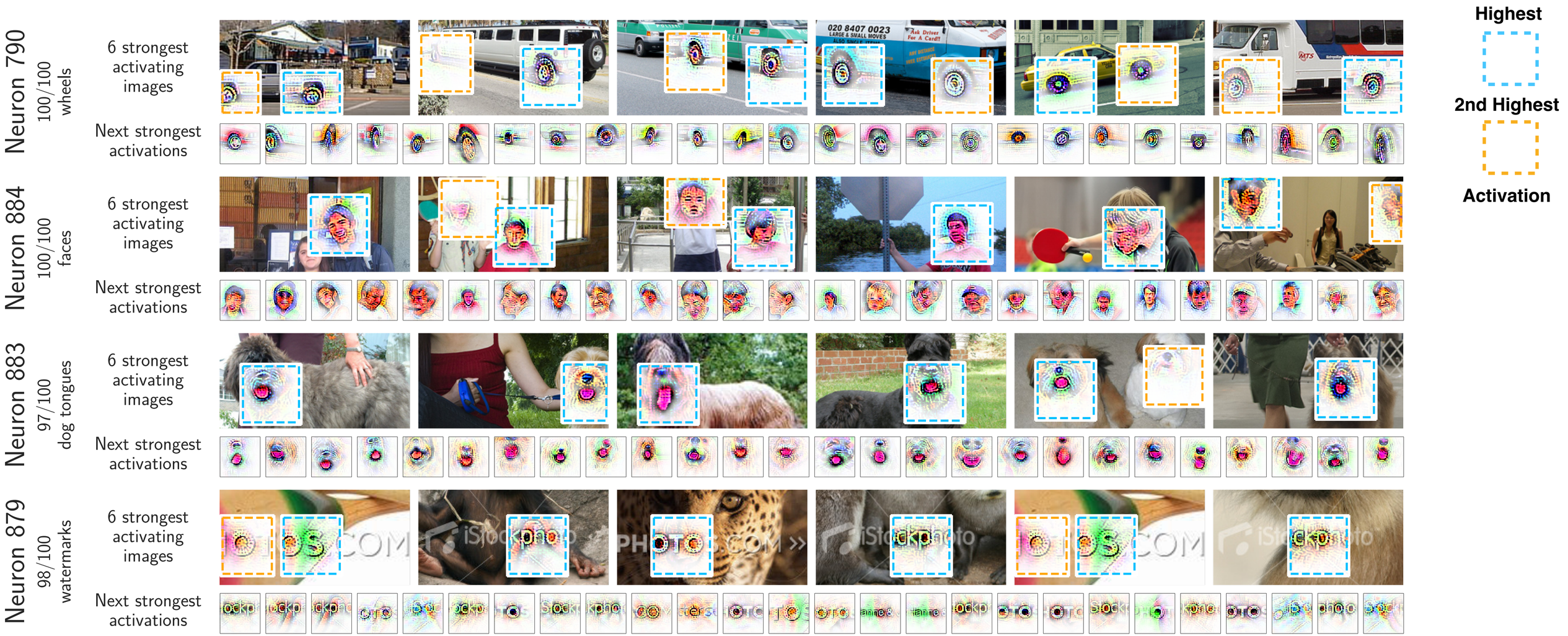


Interim Summary

- Deep Neural Network explanations need to be **faithful & interpretable**
  - for faithfulness: B-cos is designed to be **dynamic linear**
  - for interpretability: B-cos induces **alignment pressure**

- The resulting networks are **competitive classifiers**...

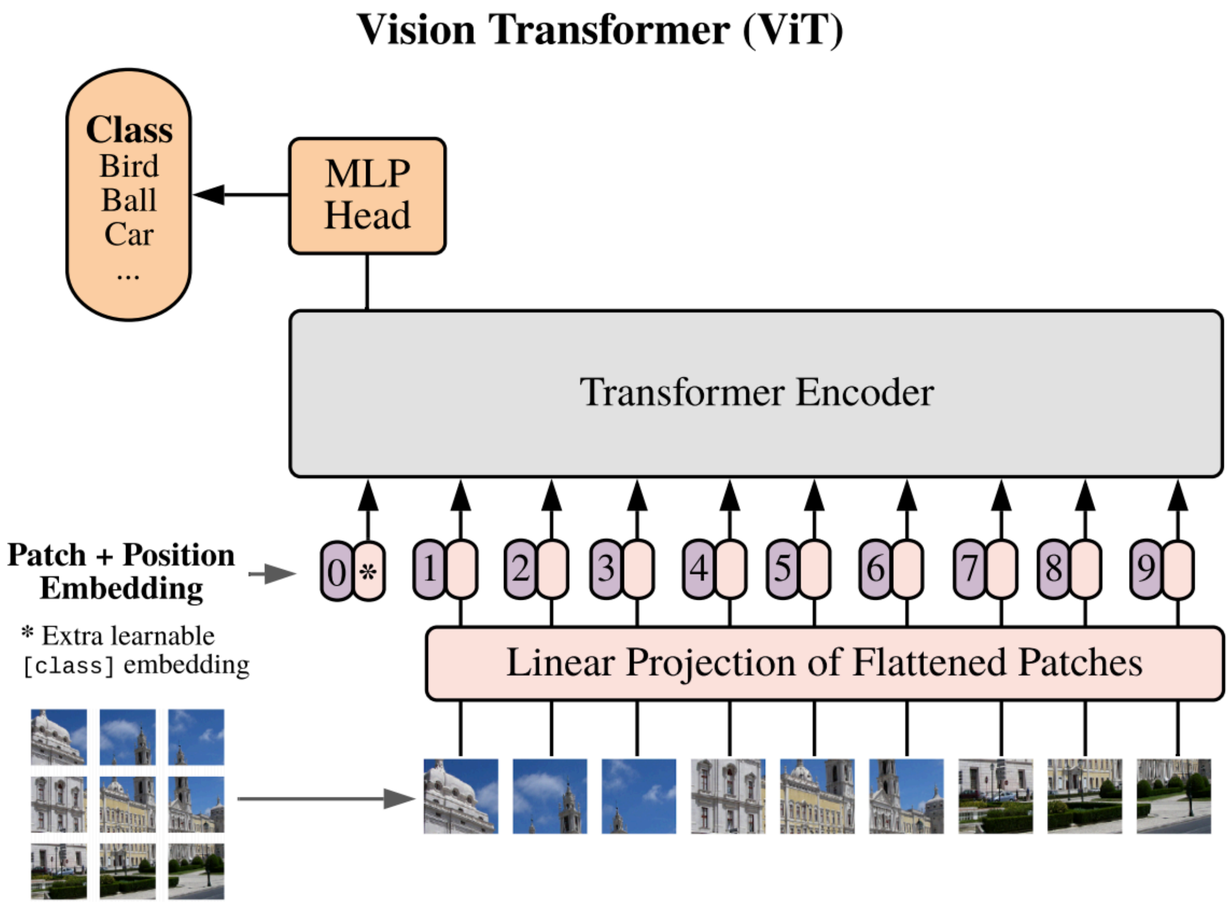
- ... and **provide interpretable explanations** for their decisions

Overview of Today's Lecture

- Inherently Interpretable Neural Network
  - B-cos CNN [cvpr'22] - https://arxiv.org/abs/2205.10268
  - B-cos CNN & Vision transformers [pami'24] - https://arxiv.org/abs/2306.10898

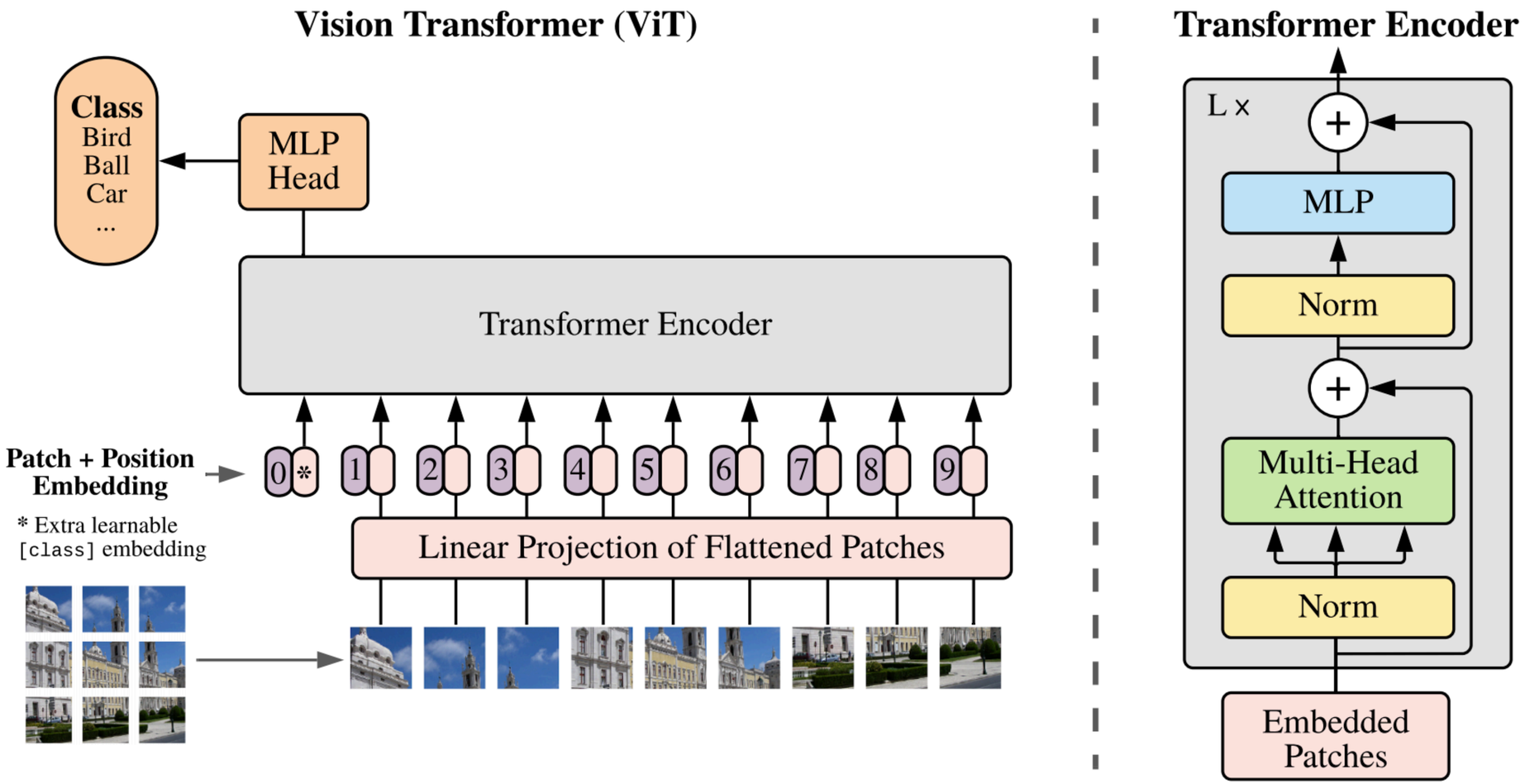
- Segment Anything Model (SAM)
  - [iccv'23] - https://arxiv.org/abs/2304.02643
  - https://segment-anything.com/

Vision Transformer (ViT)



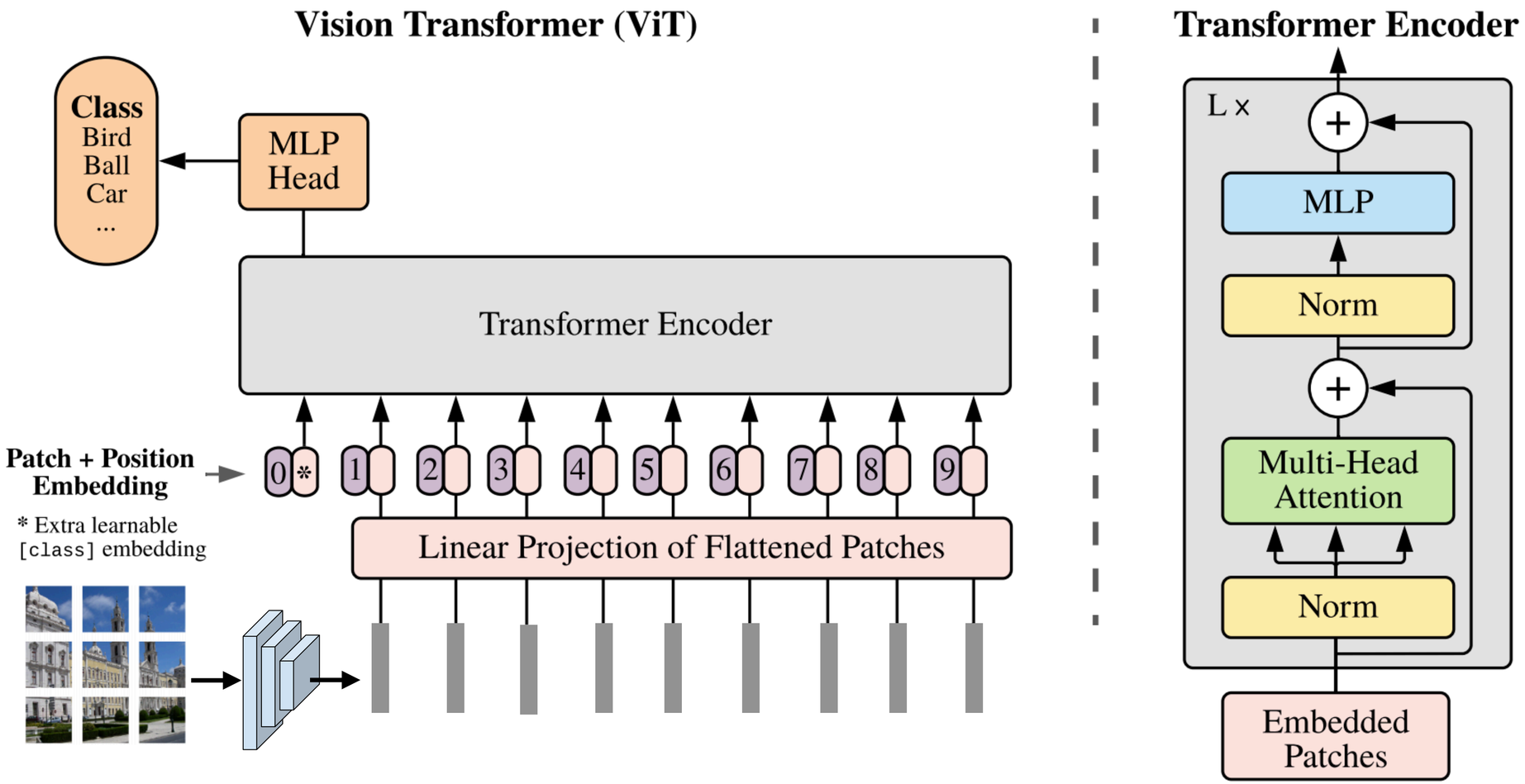
An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021

Vision Transformer (ViT)



An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021

Hybrid ViT Architecture (with CNN-embedding of image patches)



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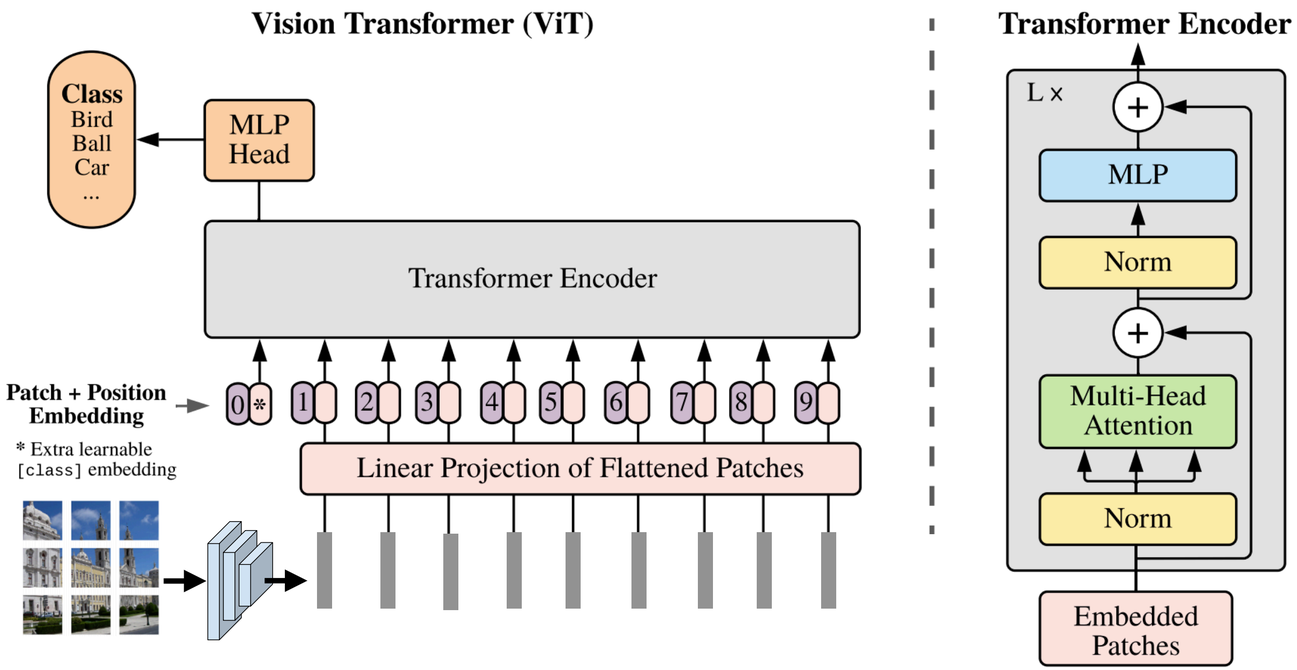
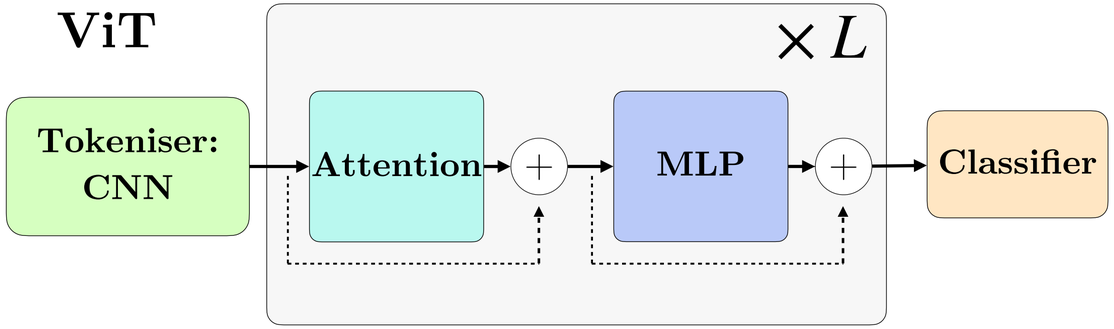
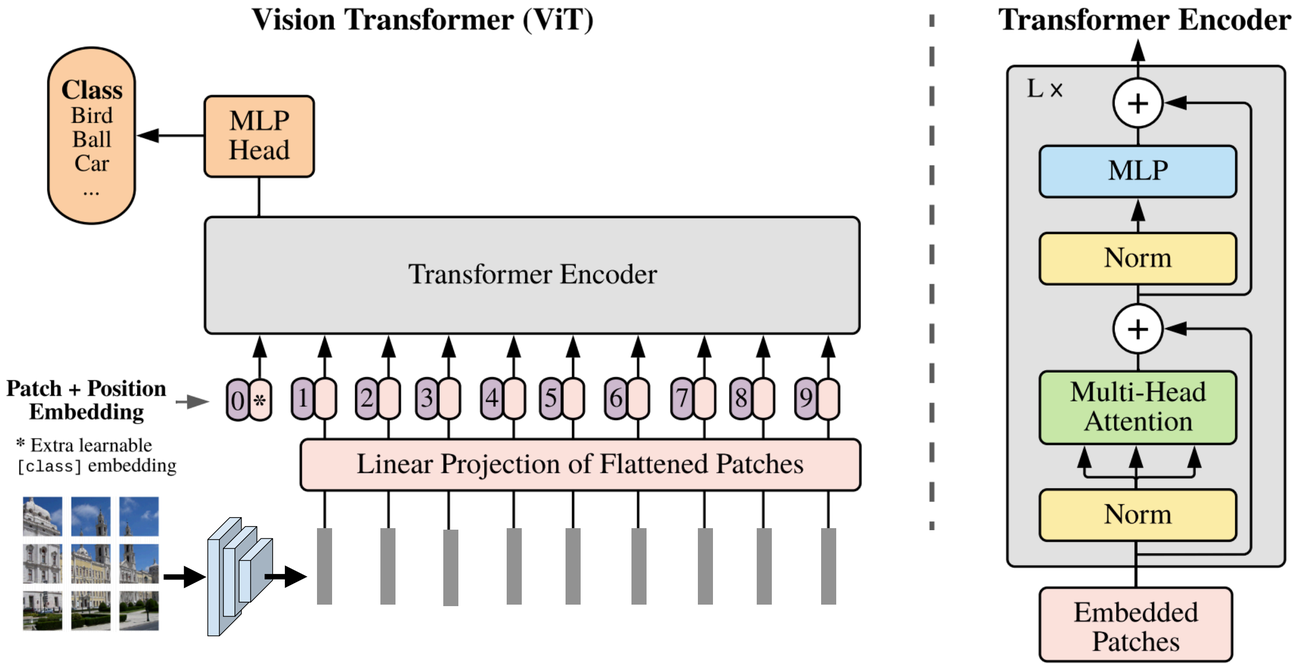
Attention is not All You Need (for XAI)



Dosovitskiy et al. 2021

Attention is not All You Need (for XAI) XAI: explainable ai





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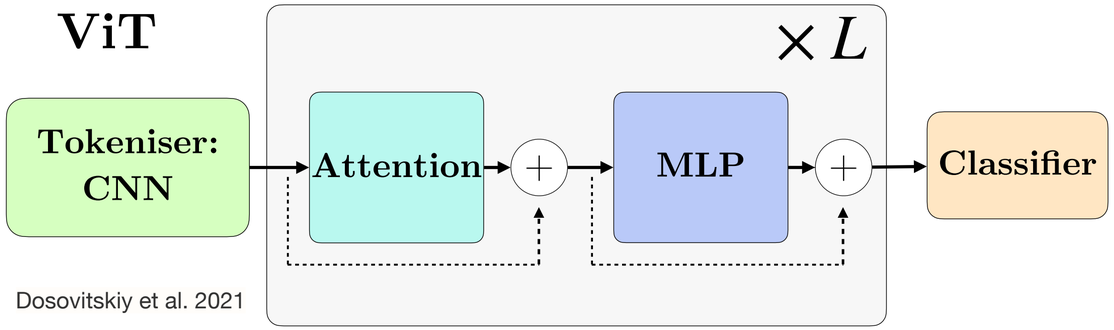

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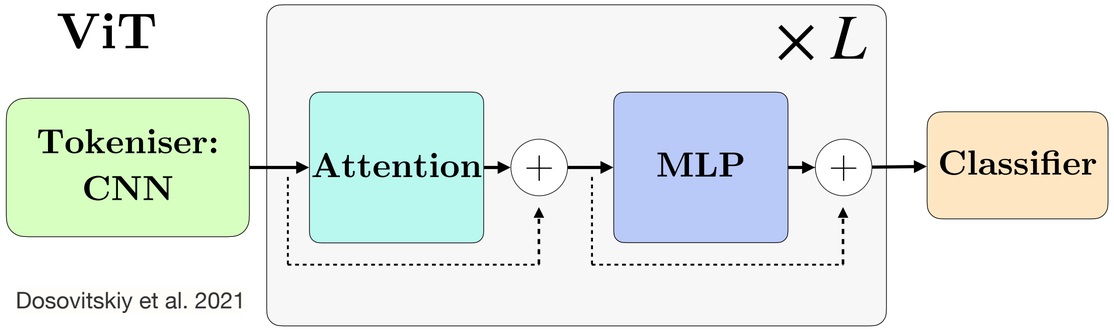

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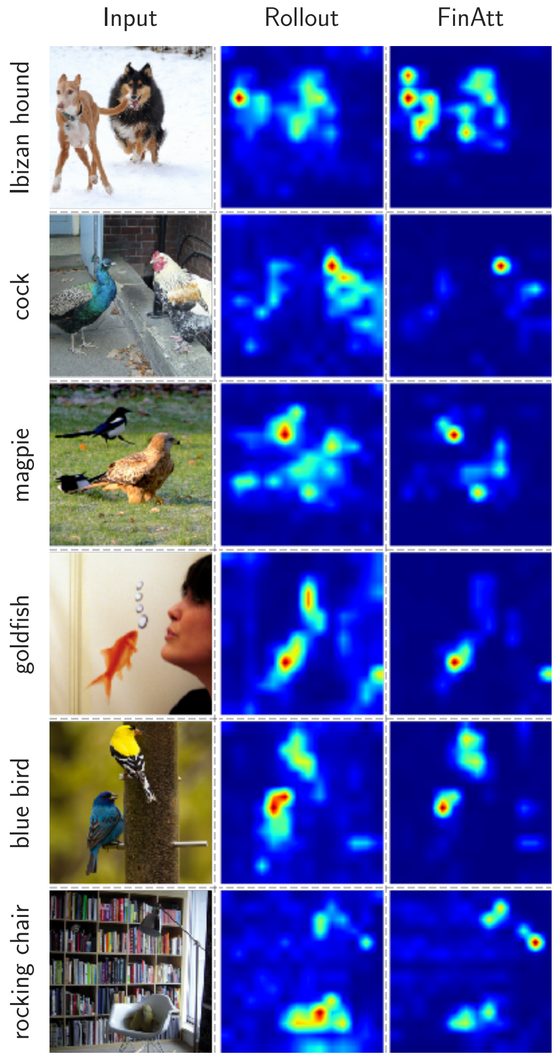

Attention Rollout: Abnar & Zuidema, ACL 2020

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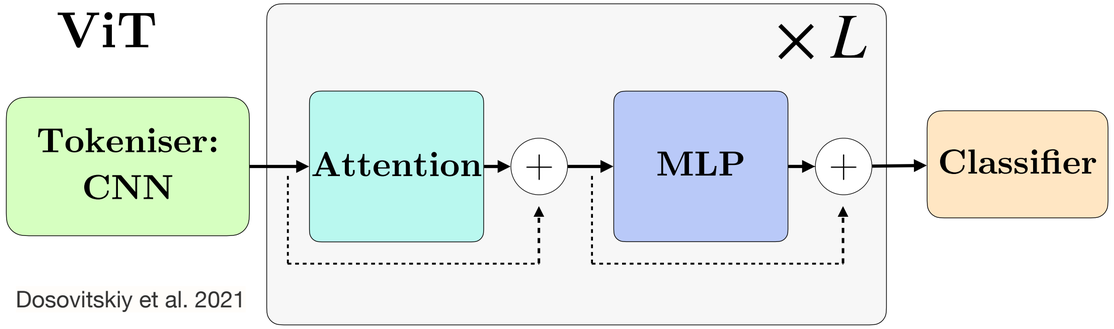
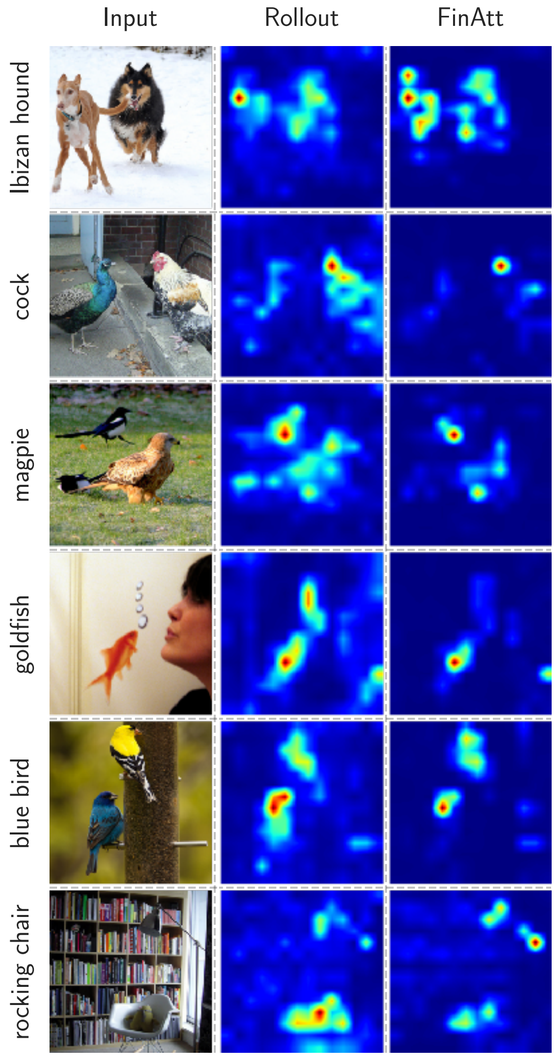


Dosovitskiy et al. 2021

High resolution



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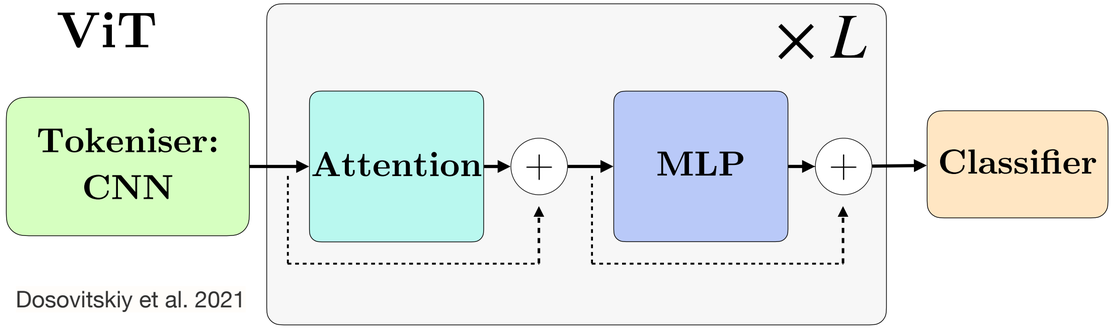
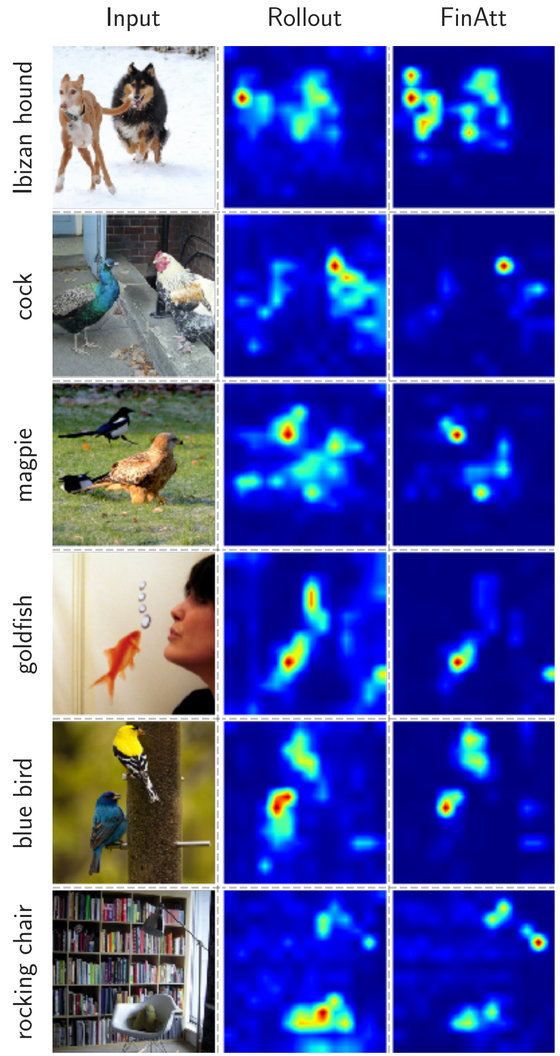


Dosovitskiy et al. 2021

- High resolution
- Holistic explanation



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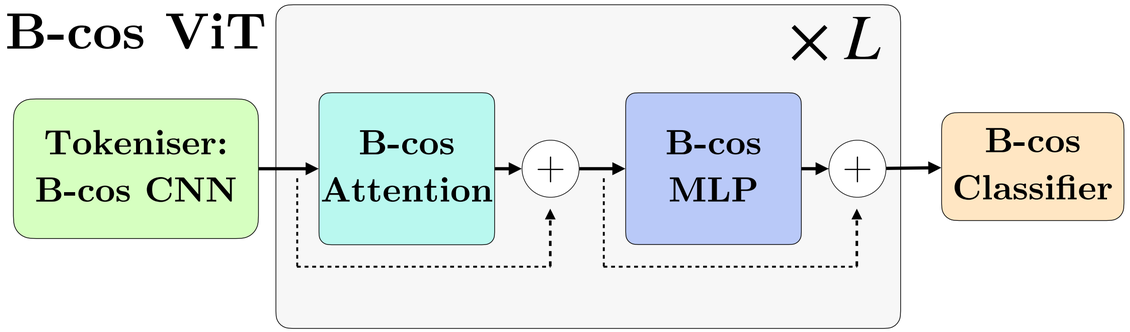
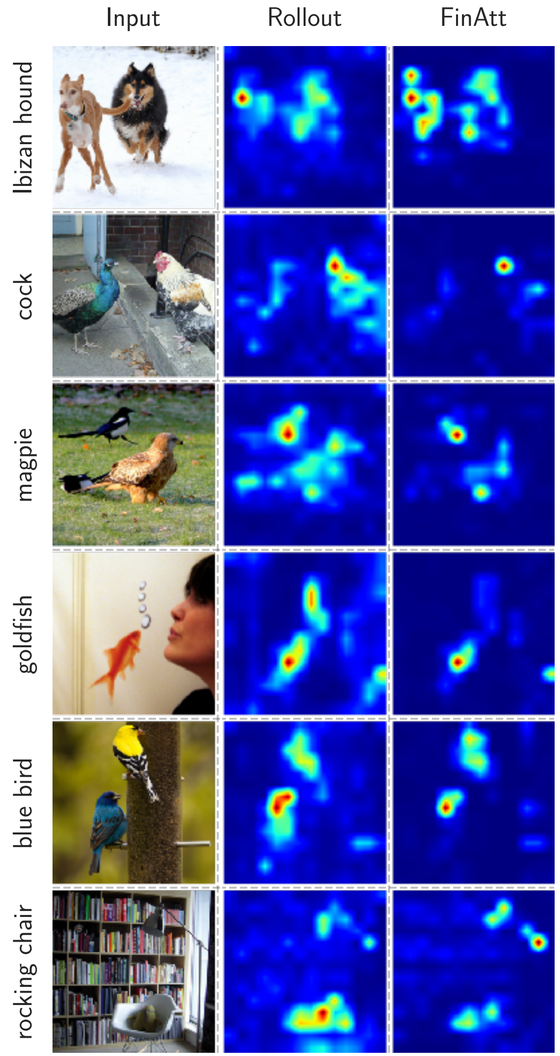


- ✓ High resolution
- ✓ Holistic explanation



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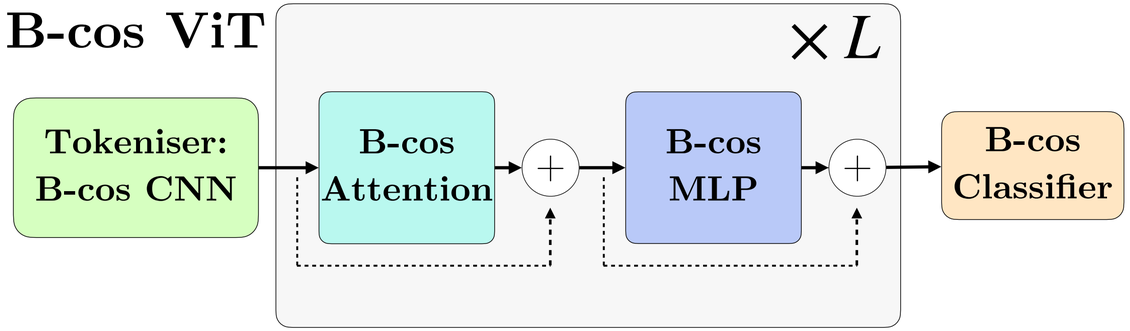

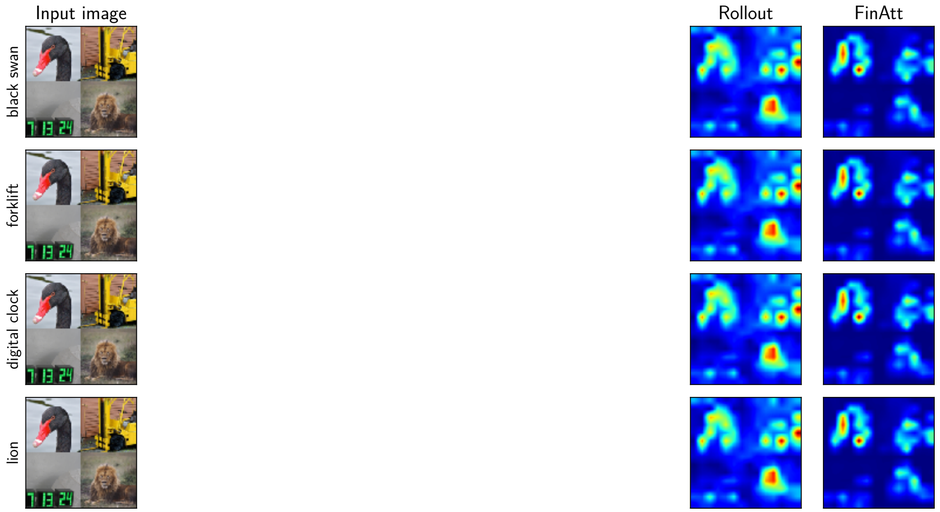

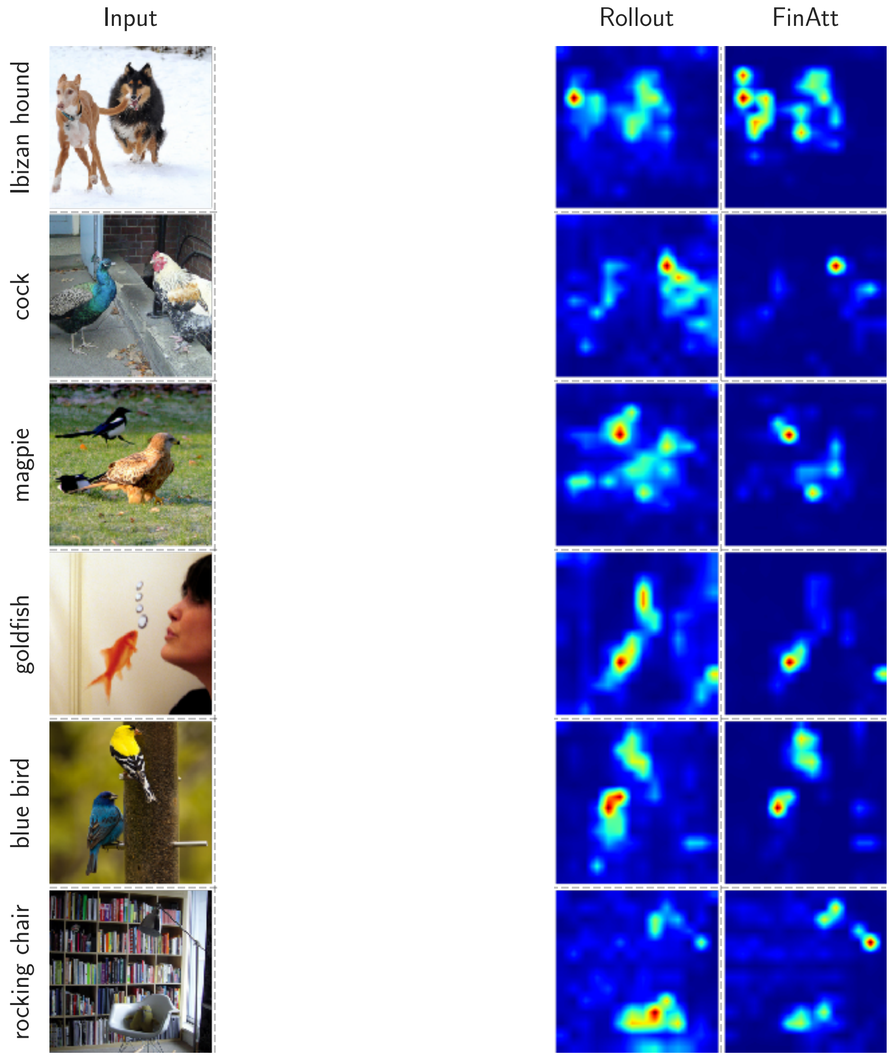

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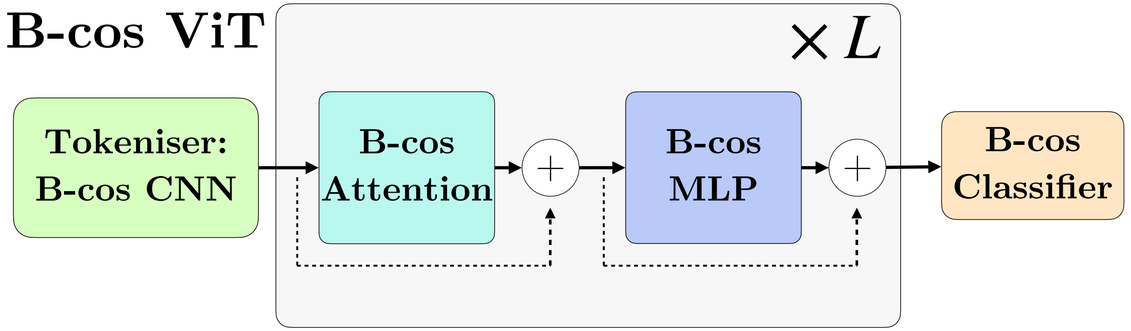

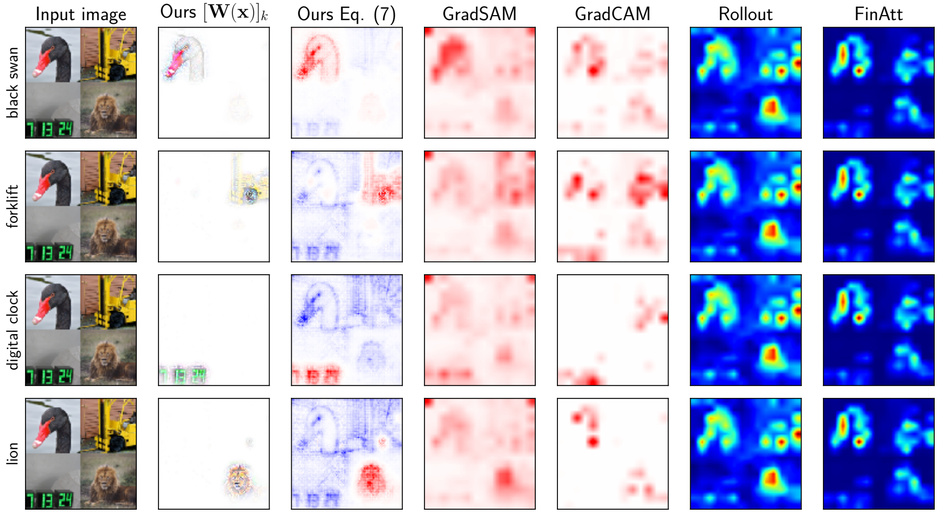

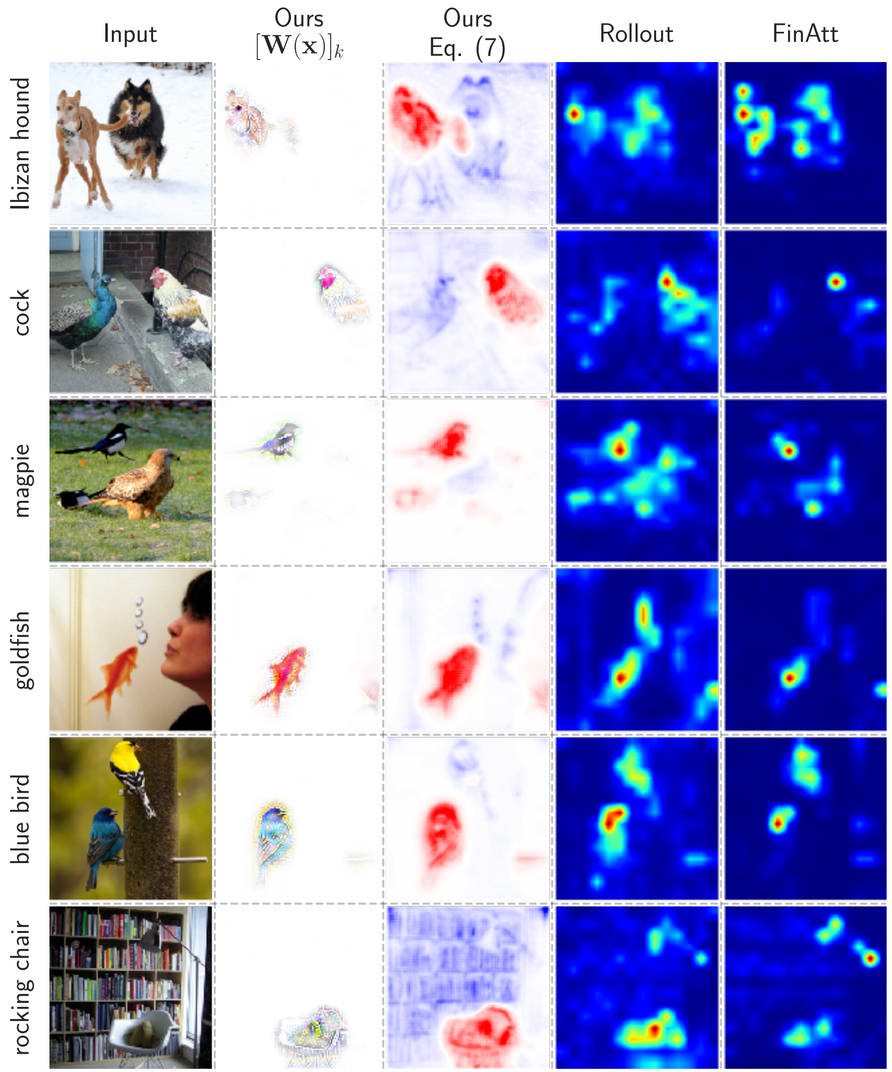

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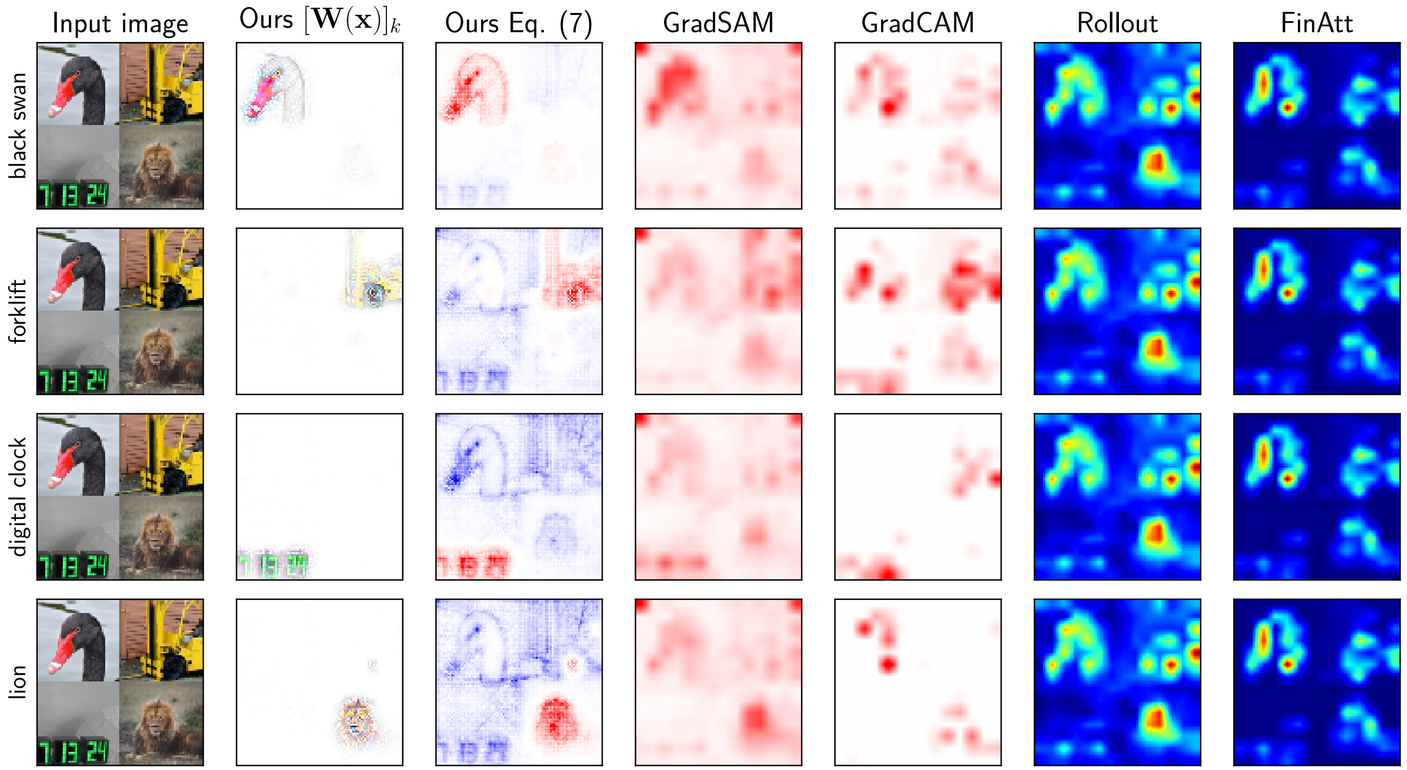

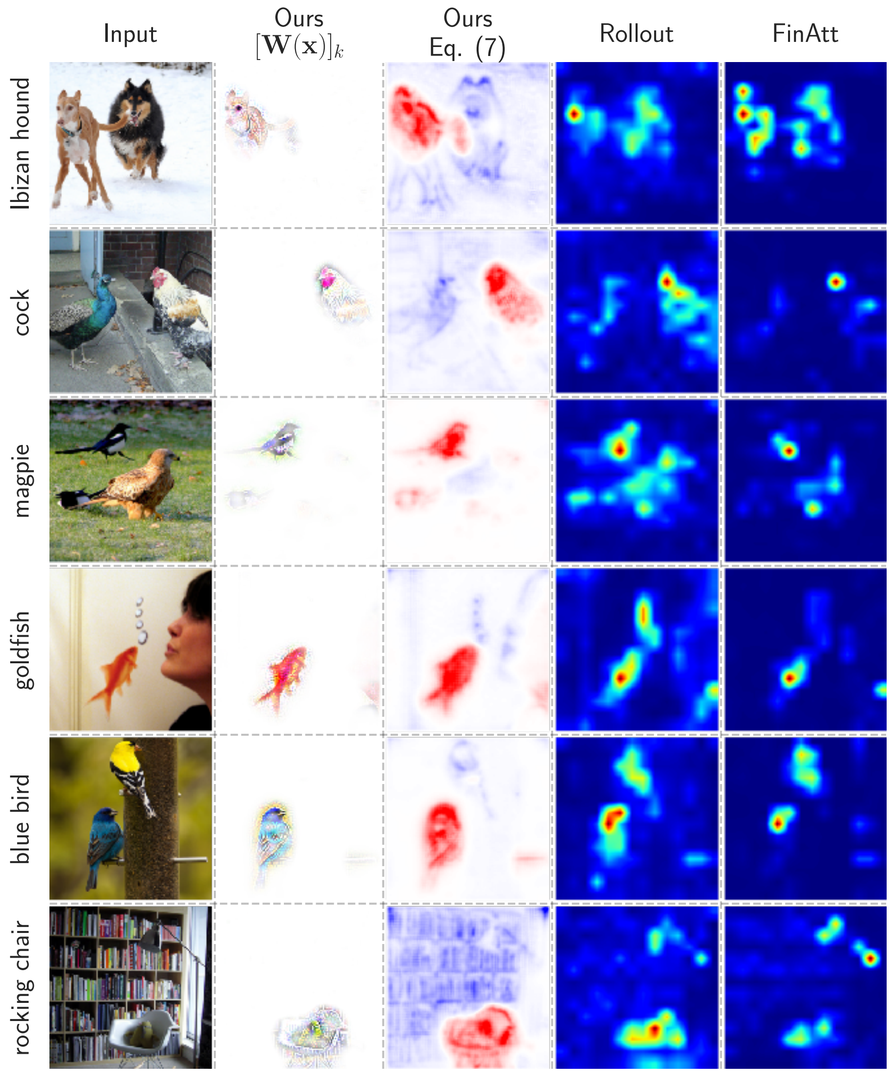

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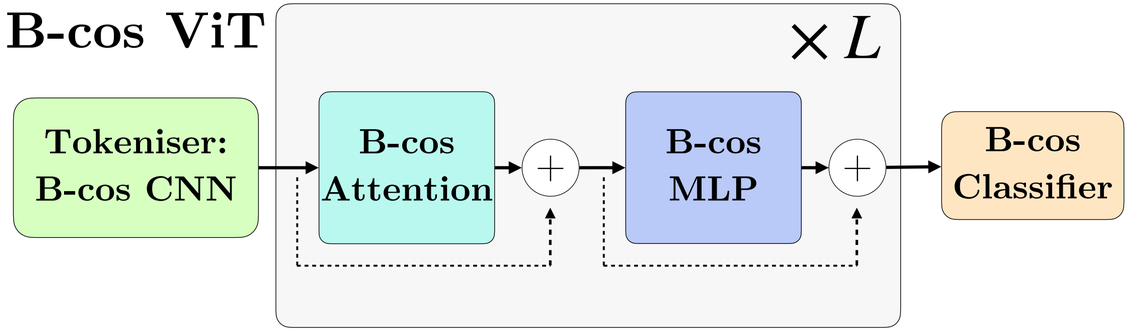

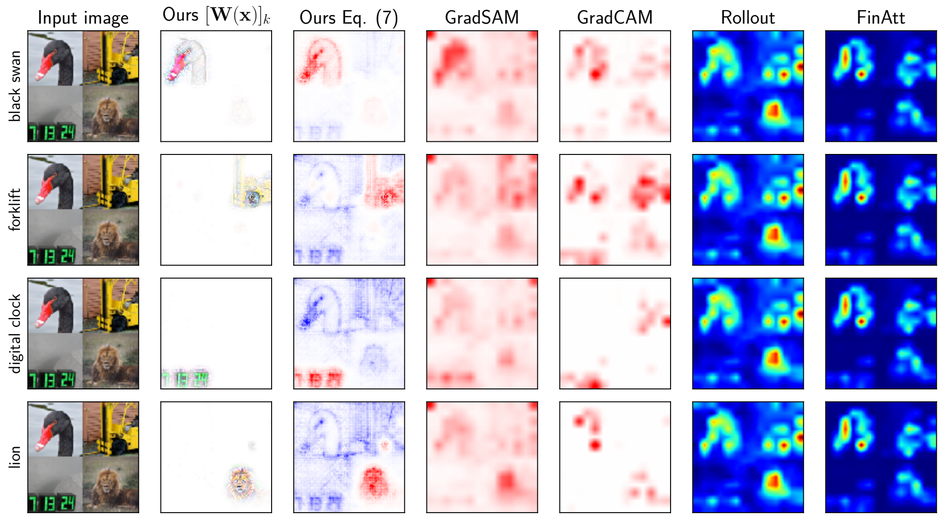

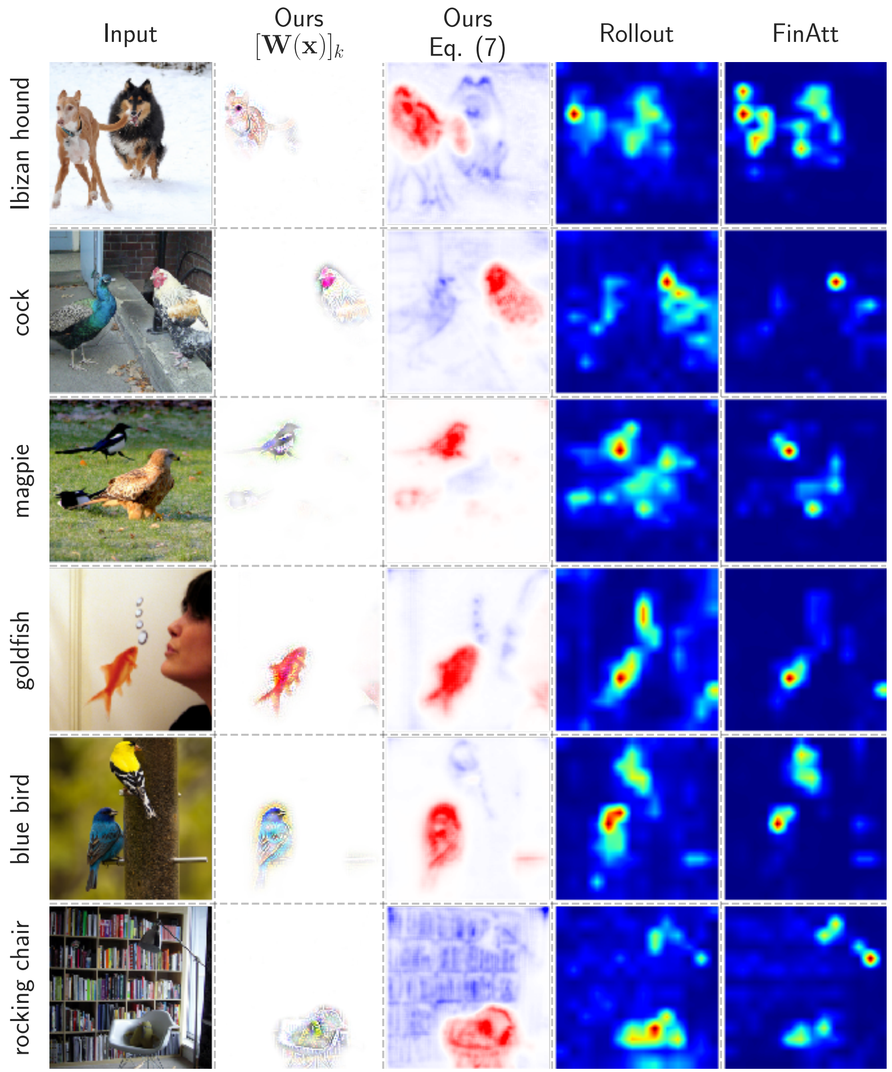

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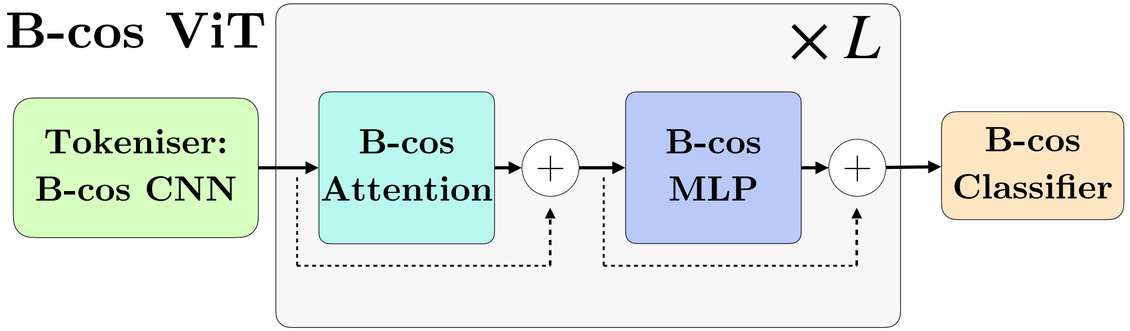

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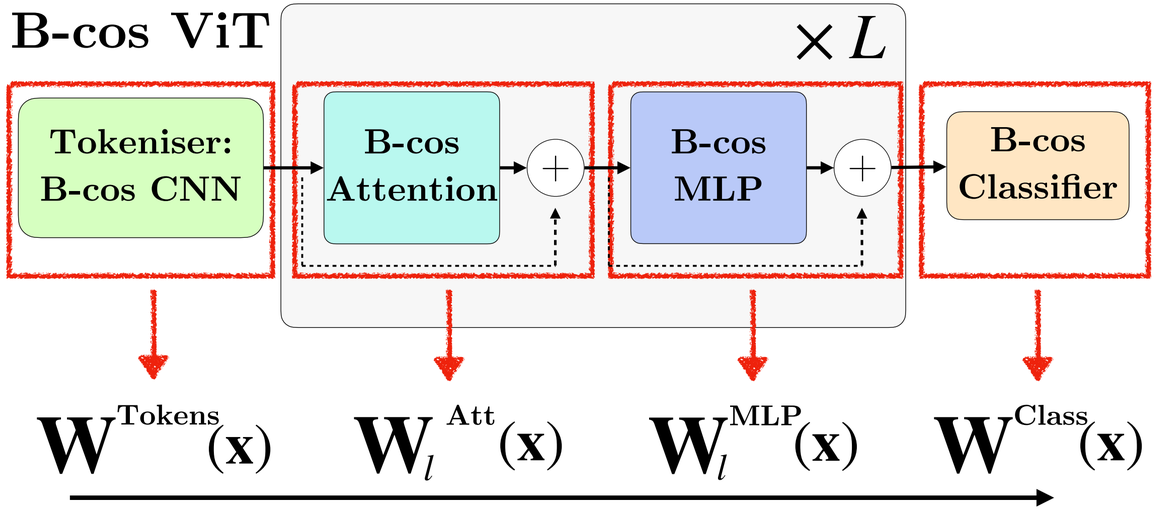
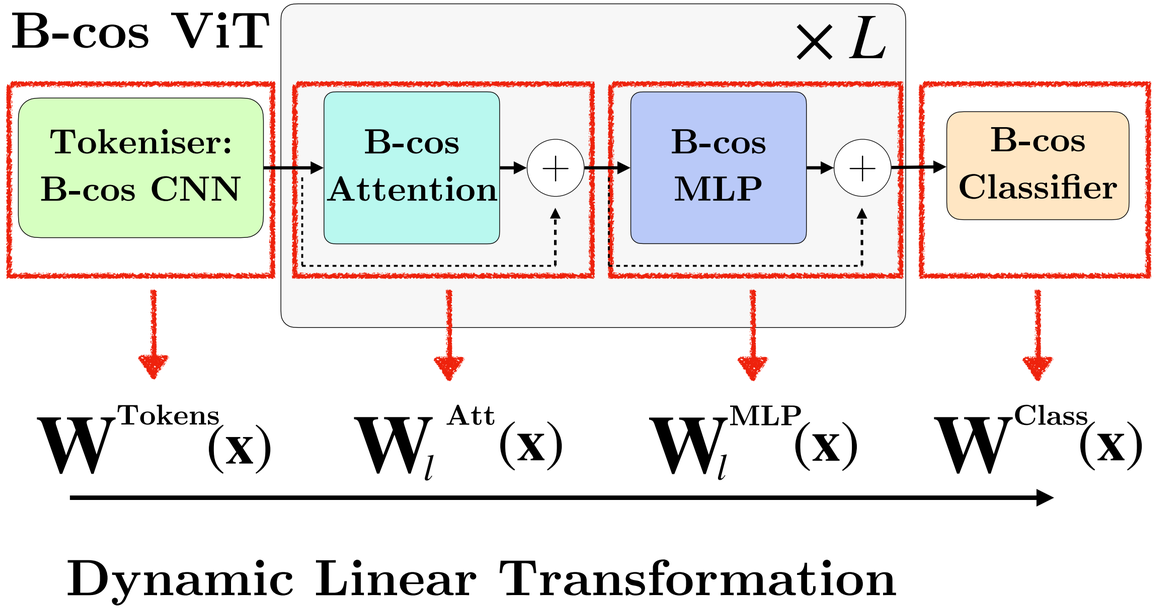


Dynamic Linear Transformation

$$\mathbf{W}(\mathbf{x}) = \mathbf{W}^{\text{Class}}(\mathbf{x}) \prod_{l=1}^{L} \left(\mathbf{W}_l^{\text{MLP}}(\mathbf{x}) \, \mathbf{W}_l^{\text{Att}}(\mathbf{x}) \right) \, \mathbf{W}^{\text{Tokens}}(\mathbf{x})$$

Attention is not All You Need (for XAI)

- Tokeniser + MLP + Classifier
  - interpret as CNNs,
    convert to B-cos CNNs



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Attention is not All You Need (for XAI)

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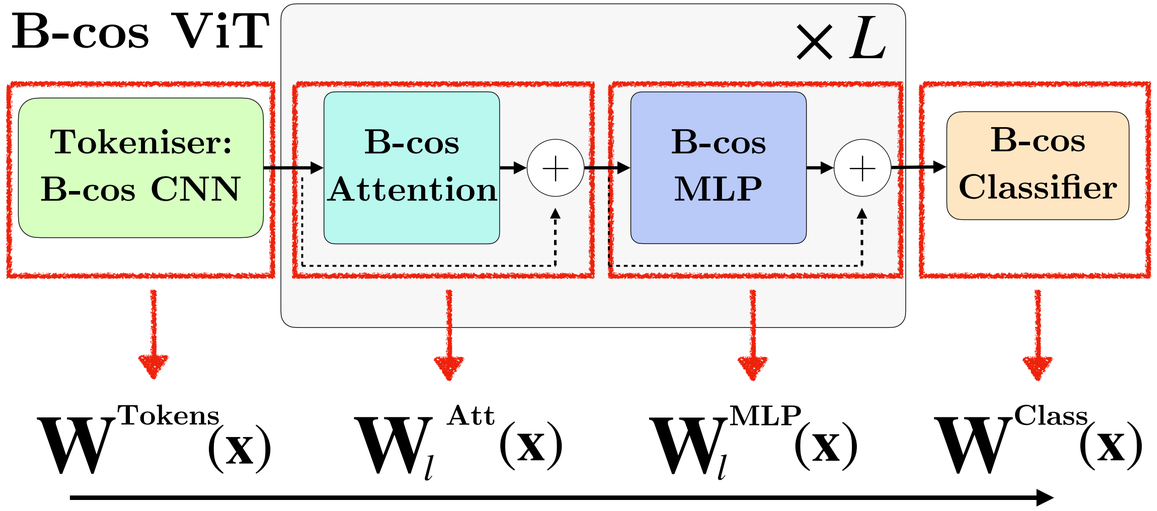
- Self-Attention (SA) is dynamic linear
  - $$SA(\mathbf{X}) = \underbrace{\mathbf{A}(\mathbf{X})\,\mathbf{V}}_{\mathbf{W}(\mathbf{X})}\,\mathbf{X} = \mathbf{W}(\mathbf{X})\,\mathbf{X}$$



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Attention is not All You Need (for XAI)

- Tokeniser + MLP + Classifier
  - interpret as CNNs,
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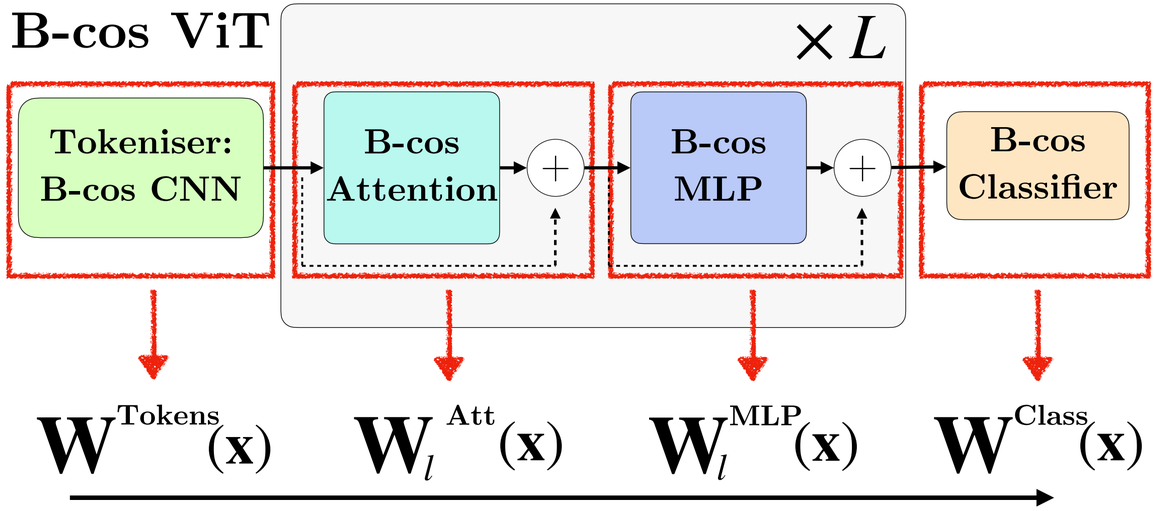
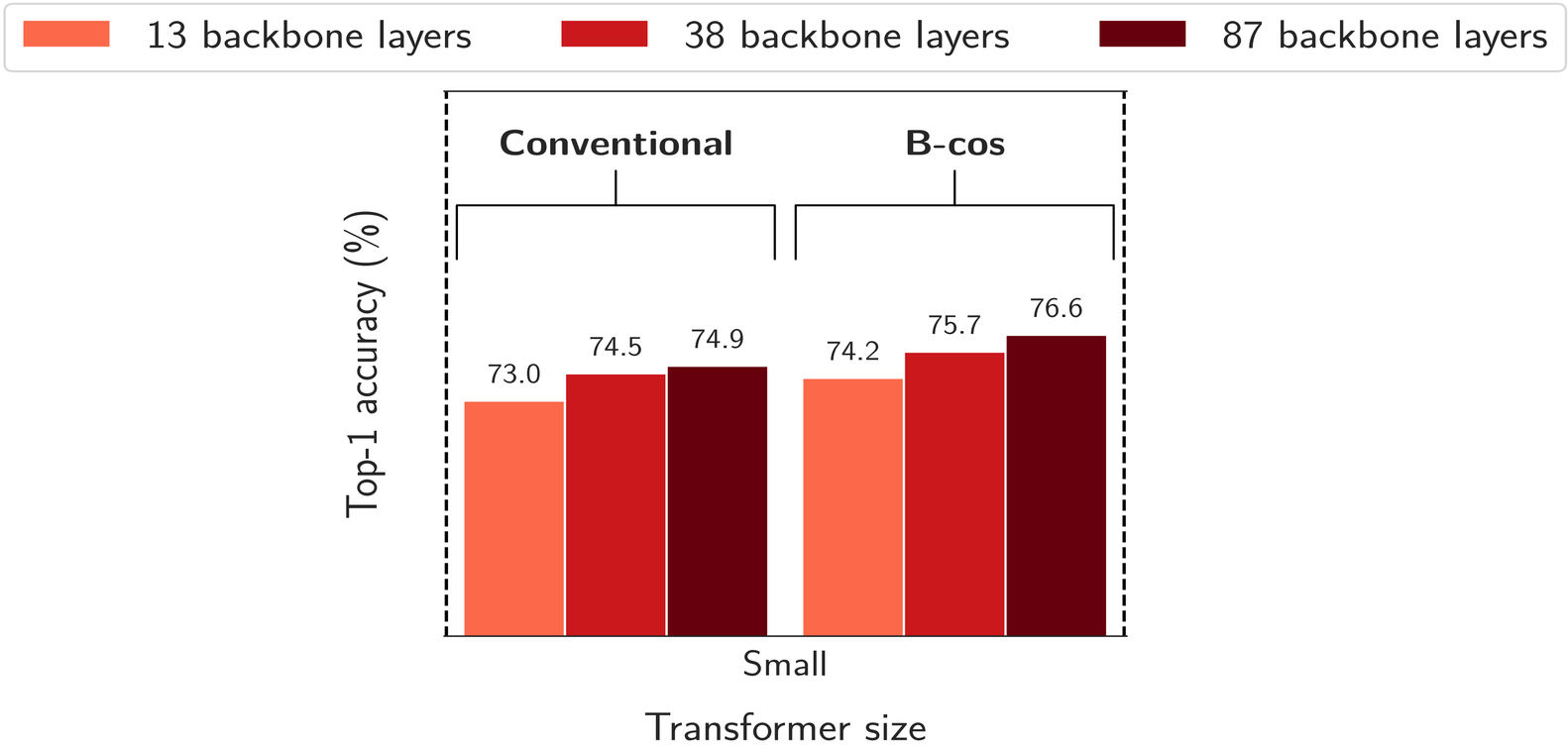
- Self-Attention (SA) is dynamic linear
  - $$SA(\mathbf{X}) = \underbrace{\mathbf{A}(\mathbf{X})\,\mathbf{V}}_{\mathbf{W}(\mathbf{X})}\,\mathbf{X} = \mathbf{W}(\mathbf{X})\,\mathbf{X}$$
- Side note:
  - for Tokenisation, use L layers of pretrained+frozen B-cos DenseNet-121



$$\mathbf{W}(\mathbf{x}) = \mathbf{W}^{\text{Class}}(\mathbf{x}) \prod_{l=1}^{L} \left(\mathbf{W}_l^{\text{MLP}}(\mathbf{x})\, \mathbf{W}_l^{\text{Att}}(\mathbf{x}) \right) \mathbf{W}^{\text{Tokens}}(\mathbf{x})$$

Attention is not All You Need (for XAI)

Results — classification accuracy



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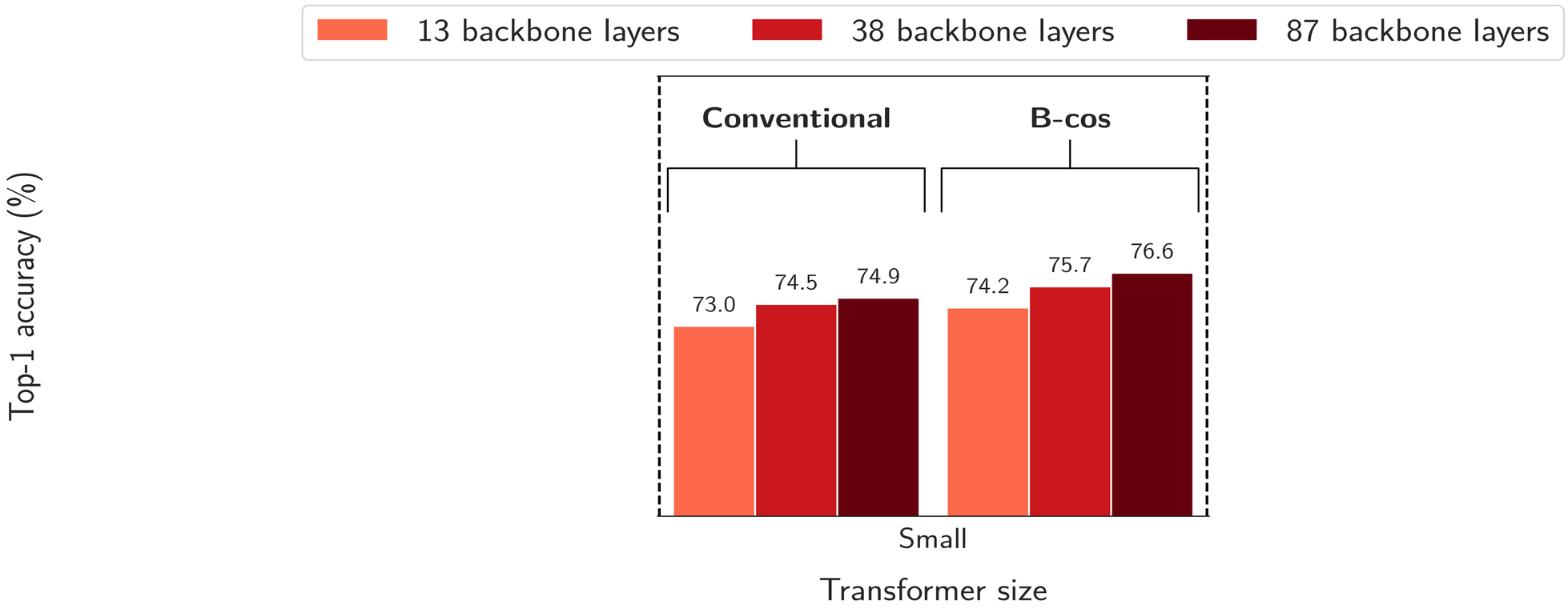

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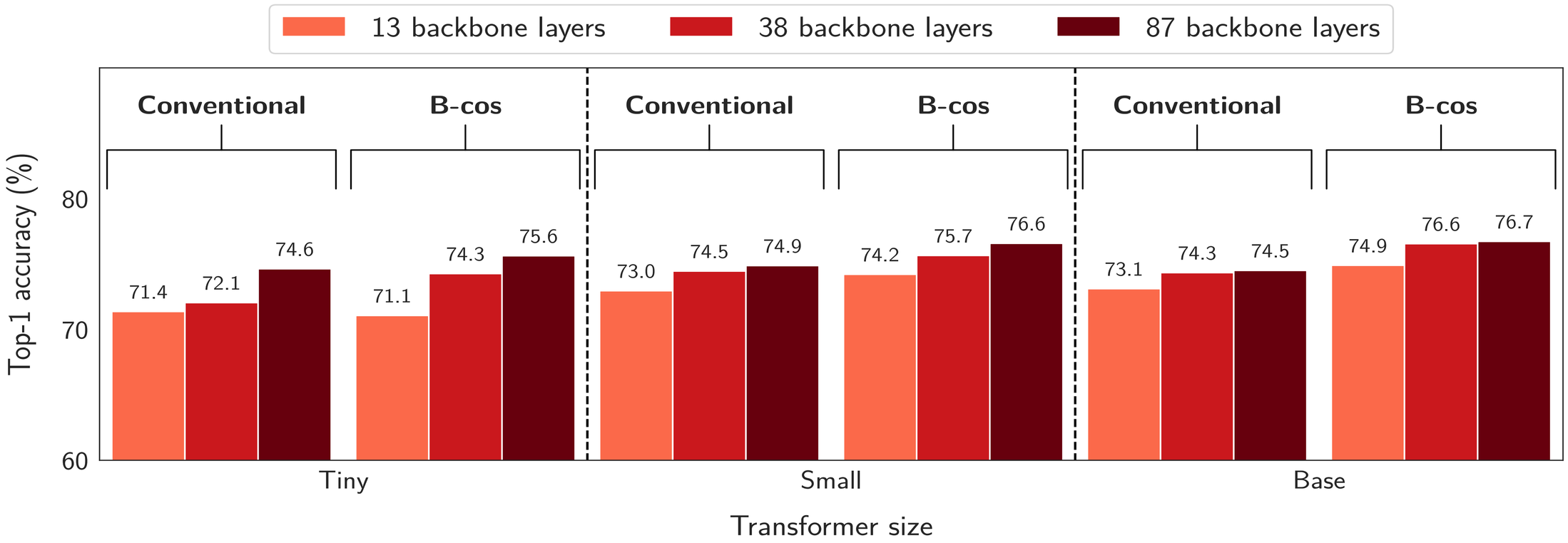
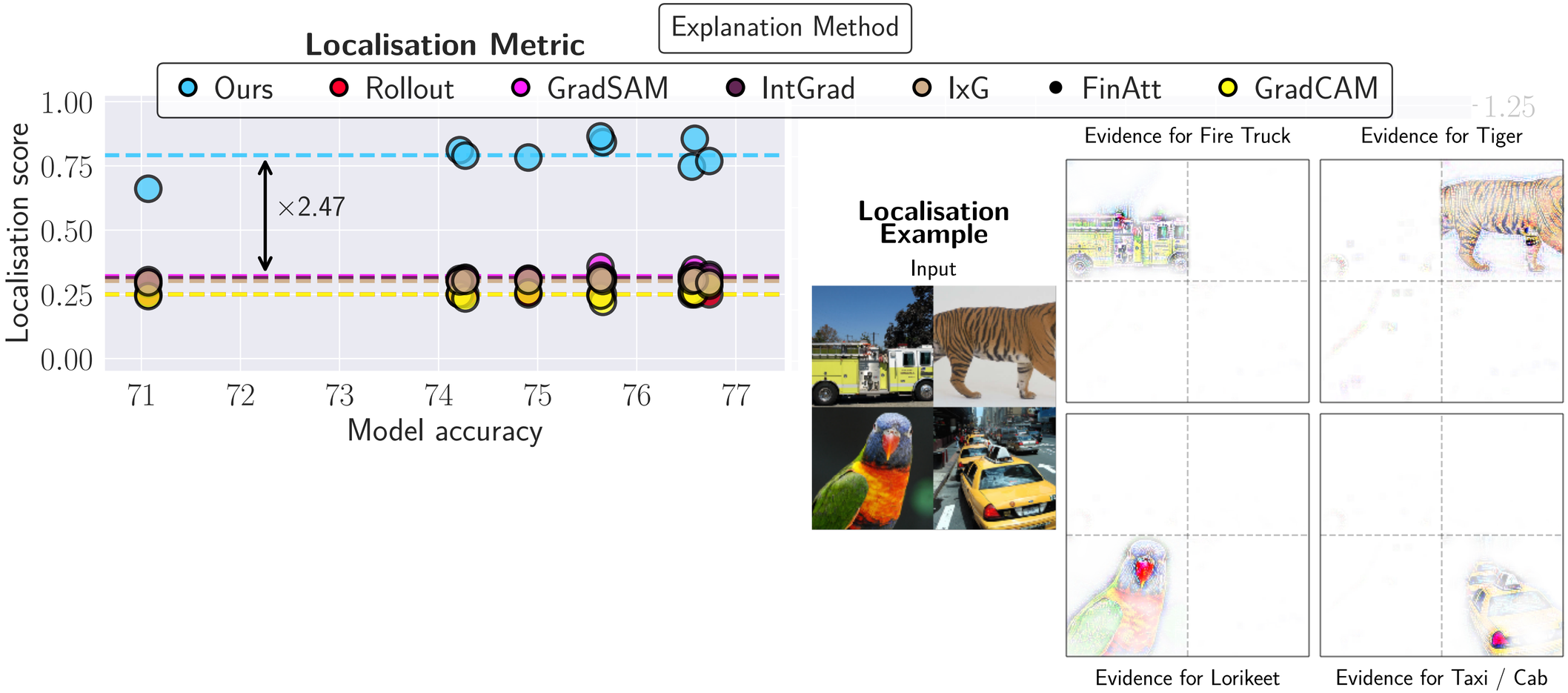
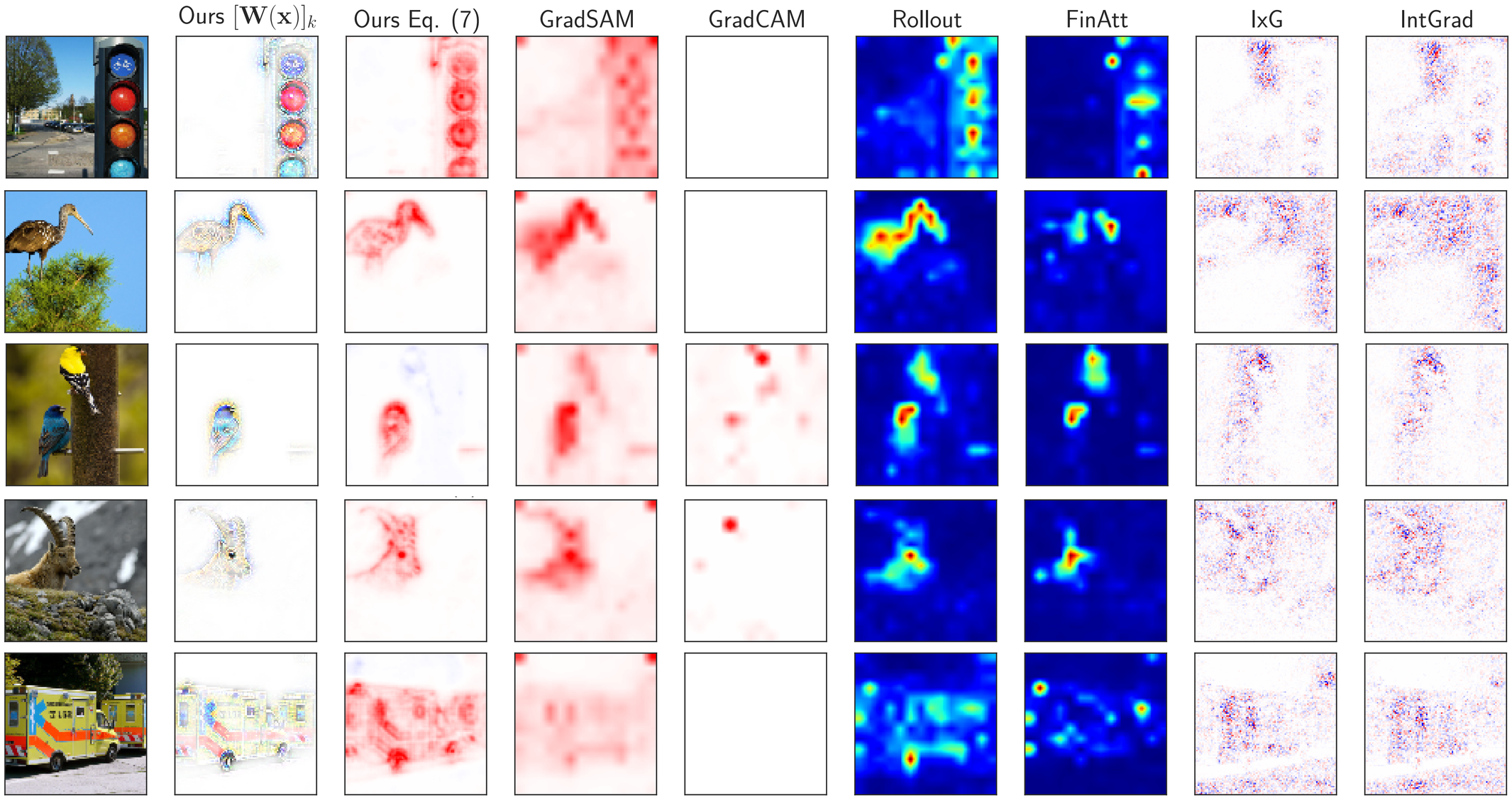


Results — interpretability metrics (grid pointing game)



Qualitative Results



Attention is not All You Need (for XAI) - Summary

- B-cos framework generally compatible with ViTs
  - Attention already dynamic linear $\mathrm{SA}(\mathbf{X}) = \mathbf{W}(\mathbf{X})\mathbf{X}$
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- B-cos ViTs can be highly performant
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- B-cos ViTs can be highly performant
  - similar results as with standard ViTs in comparable setting
- B-cos ViTs highly interpretable
  - similar interpretability as B-cos CNNs

Overview of Today's Lecture

- Inherently Interpretable Neural Network
  - B-cos CNN [cvpr'22] - https://arxiv.org/abs/2205.10268
  - B-cos CNN & Vision transformers [pami'24] - https://arxiv.org/abs/2306.10898

- Segment Anything Model (SAM)
  - [iccv'23] - https://arxiv.org/abs/2304.02643
  - https://segment-anything.com/

Segment Anything

slides credit:

Alexander Kirillov @ Meta AI

slide credit: Alexander Kirillov

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slide credit: Alexander Kirillov

Deep learning paradigm shift

[2012 – 2022]

- **Apply DL to task X**
- End-to-end
- Step change on **specific tasks** and **specific data** distributions
- Adaptation via **fine-tuning only**

slide credit: Alexander Kirillov

Deep learning paradigm shift

[2012 – 2022] → [2022 – present]

- **Apply DL to task X**
- End-to-end
- Step change on **specific tasks** and **specific data** distributions
- Adaptation via **fine-tuning only**

- **Combine foundation/base models for X, Y, Z to do tasks Q, R, S**
- Powerful **components** (LLMs, CLIP …)
- Step change on **broad tasks** and **broad data** distributions
- Adaptation without parameter updates (**prompting**)

slide credit: Alexander Kirillov

Broadly applicable solution for segmentation

- The Segment Anything project / Segment Anything Model (SAM)
  - A component (SAM) that broadly solves segmentation
  - Useful to both humans and machines (i.e., a component in a system)
  - Broad generalization to new domains and use cases / tasks
  - Adaptation primarily via prompting

slide credit: Alexander Kirillov

Segment Anything Project Goal

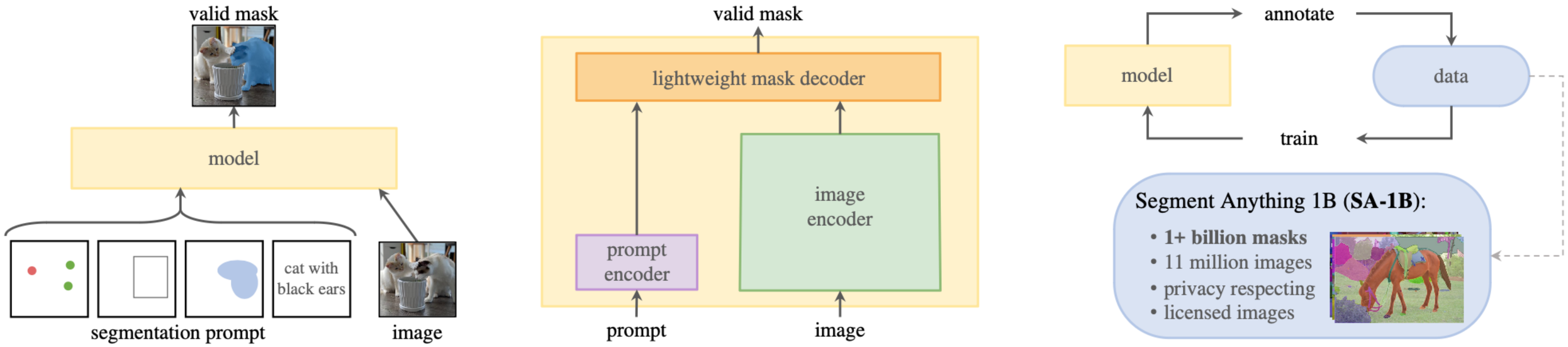
- Develop a **promptable model** and pre-train it on a broad **dataset** using a **task** that enables powerful generalization
  - Model: *Doesn't exist!*
  - Dataset: *Doesn't exist!*
  - Task: *Doesn't exist!*

- Model/data/task are highly coupled

- We need a comprehensive solution

slide credit: Alexander Kirillov

Segment Anything: Task, Model, Data



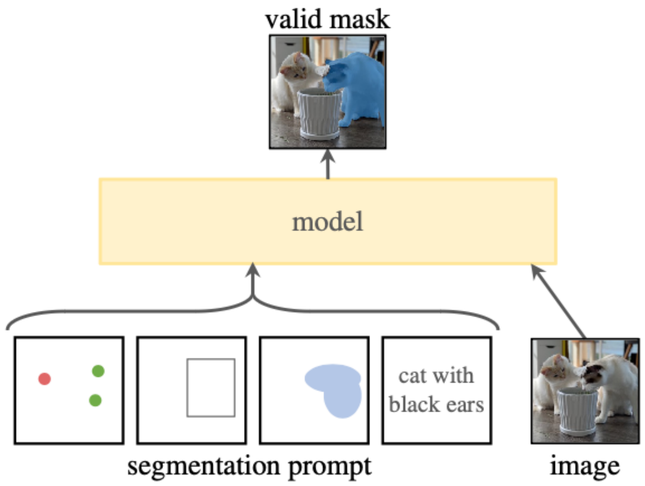
(a) **Task**: promptable segmentation (b) **Model**: Segment Anything Model (**SAM**) (c) **Data**: data engine (top) & dataset (bottom)

slide credit: Alexander Kirillov

Task: Promptable Segmentation

- Translate “prompt” from NLP to segmentation
  - Segmentation prompt: anything that specifies *what* to segment
  - E.g., foreground/background points, boxes, masks, text

- The task: Return a *valid* segmentation mask given *any prompt*



(a) **Task**: promptable segmentation

slide credit: Alexander Kirillov

Example: AR gaze-to-mask

slide credit: Alexander Kirillov

Example: AR gaze-to-mask

slide credit: Alexander Kirillov

slide credit: Alexander Kirillov

Why Promptable Segmentation?

- Composable with other models.

- Prompts easy to simulate at training.

- Enables human-in-loop annotation.

fast annotation

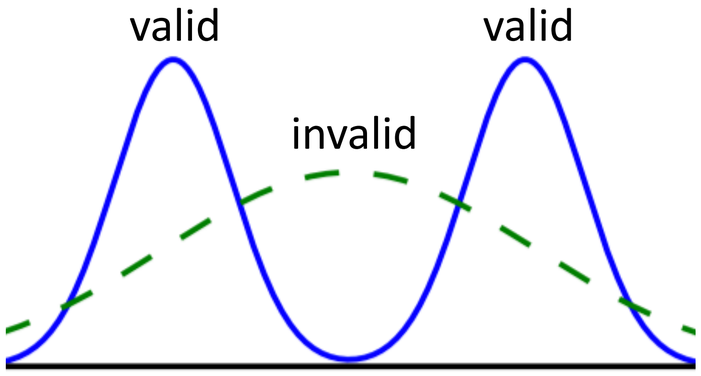
1 click 2 clicks

slide credit: Alexander Kirillov

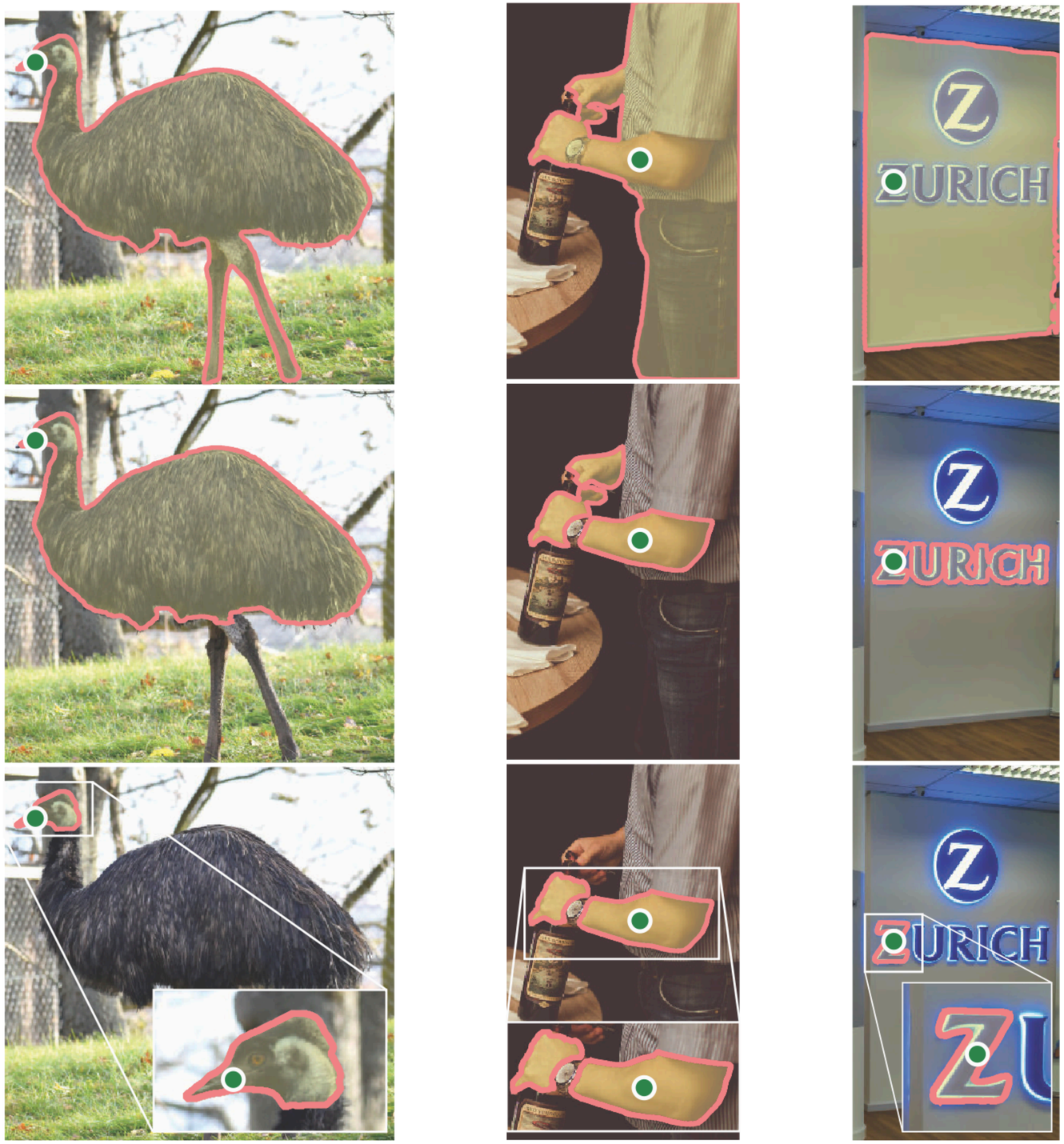
A “Valid” Mask?

- Prompts can be *ambiguous*
- Segmentation is *ambiguous*
- The task should train a model that handles ambiguity

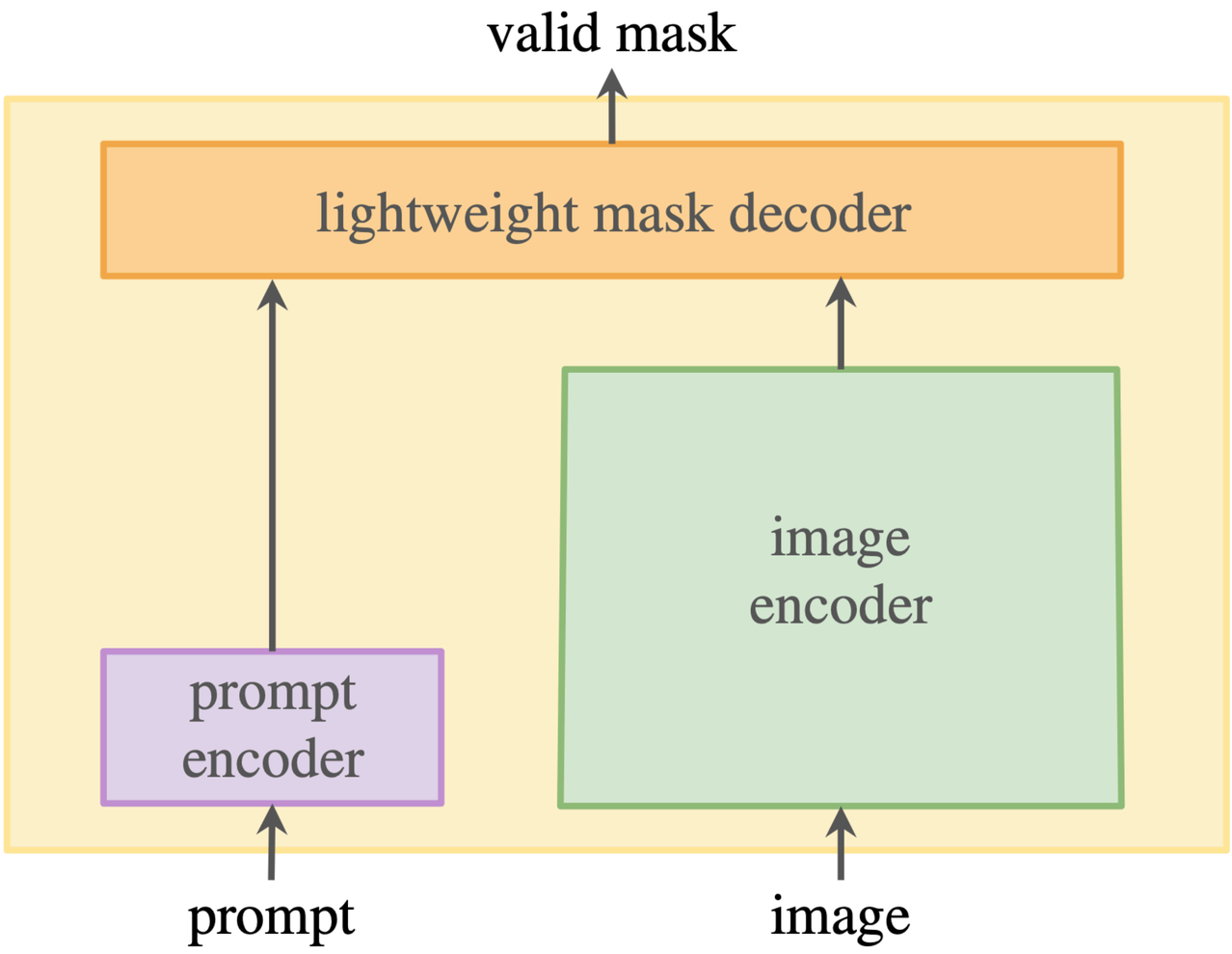
- Avoid “mode averaging”



Adapted from NIPS 2016 Tutorial: “Generative Adversarial Networks" by Ian Goodfellow

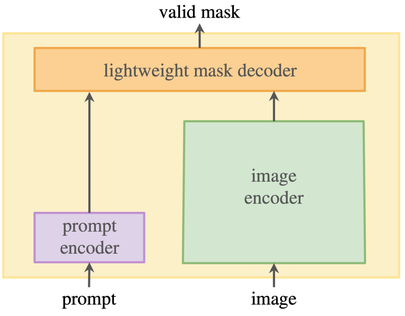


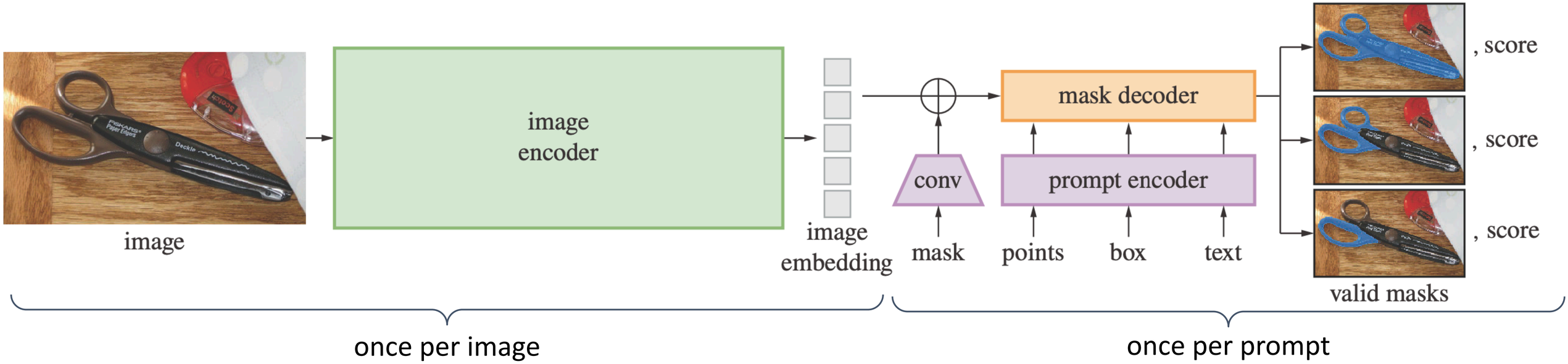
SAM: Model Overview



slide credit: Alexander Kirillov

SAM in More Detail

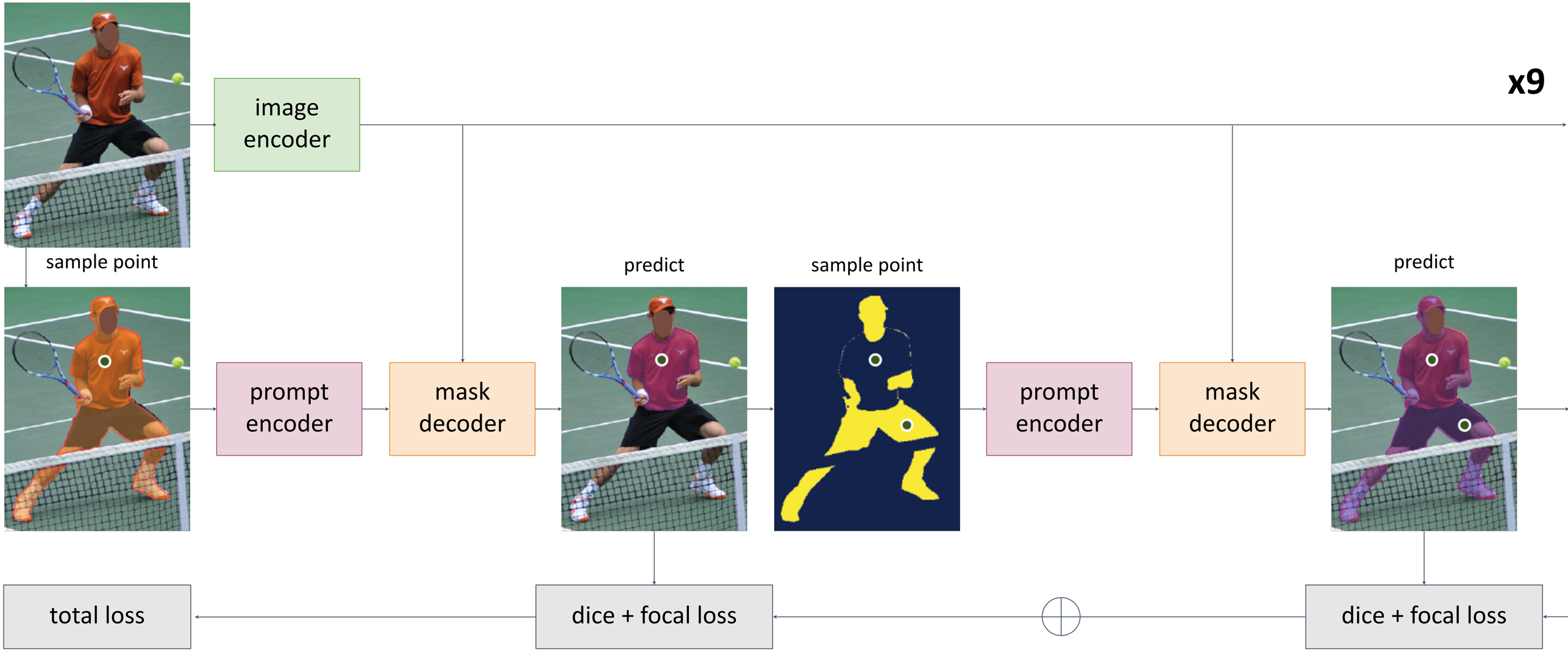




- **Image encoder:** ViT-H adapted for 1024x1024 input resolution
- **Prompt encoder:** Positional and label embeddings for points/boxes; CLIP for text
- **Mask decoder:** Lightweight transformer (~50ms on CPU)
- **Output:** 1 or 3 masks + model's prediction of mask quality

slide credit: Alexander Kirillov

SAM training



slide credit: Alexander Kirillov

Transformer details

- Image encoder is ViT-H modified for large resolution (ViTDet):
  - initialized with MAE weights
  - Patch size 16
  - Size 14 windowed attention in all but three layers
  - Final 1x1 conv mapping ViT-H channel dim. (1280) to mask decoder dim. (256)
  - For 1024x1024 input image, output embeddings is 256x64x64
- Mask decoder
  - Large internal MLP dimension of 2048
  - Down-sampled q/k/v dimension of 128 in cross attention
  - Entire prompt token added as positional encoding to q/k in attention every layer (DETR style)
  - After transformer, embeddings upscaled to 256x256 by 2 conv transposes of dim 64 and 32

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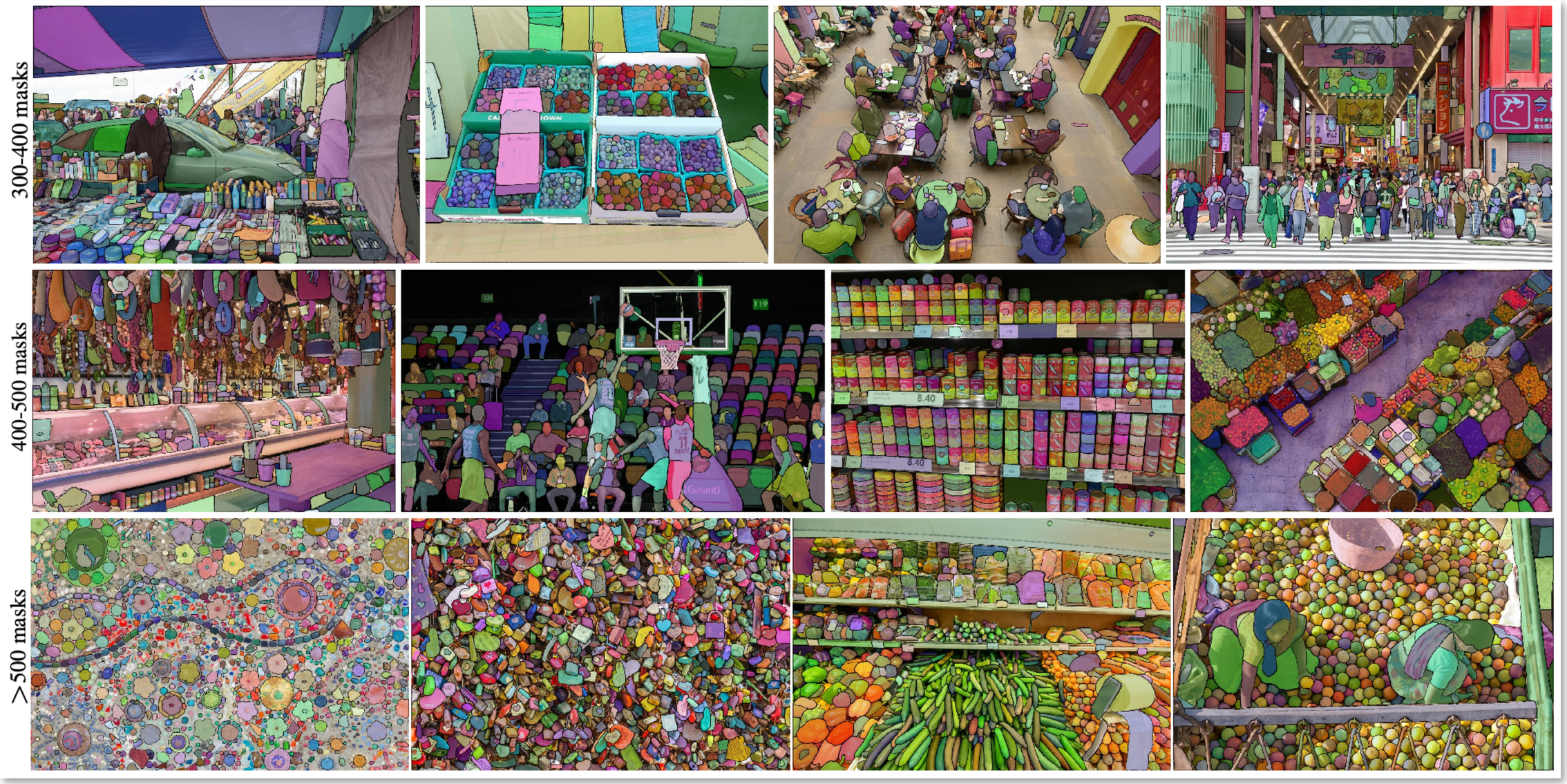
slide credit: Alexander Kirillov

Dataset Construction

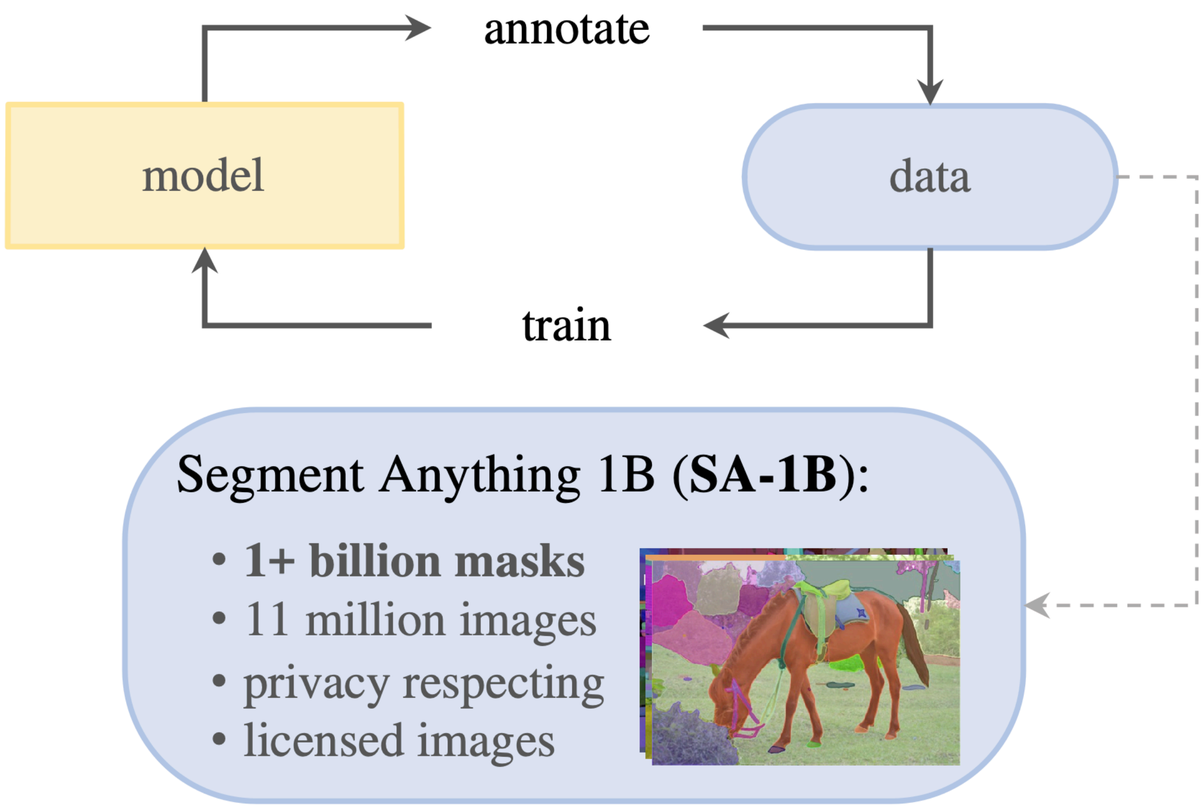


Data Engine

- Model-in-the-loop dataset construction

- Requires SAM to run in (amortized) real-time on CPU in a browser

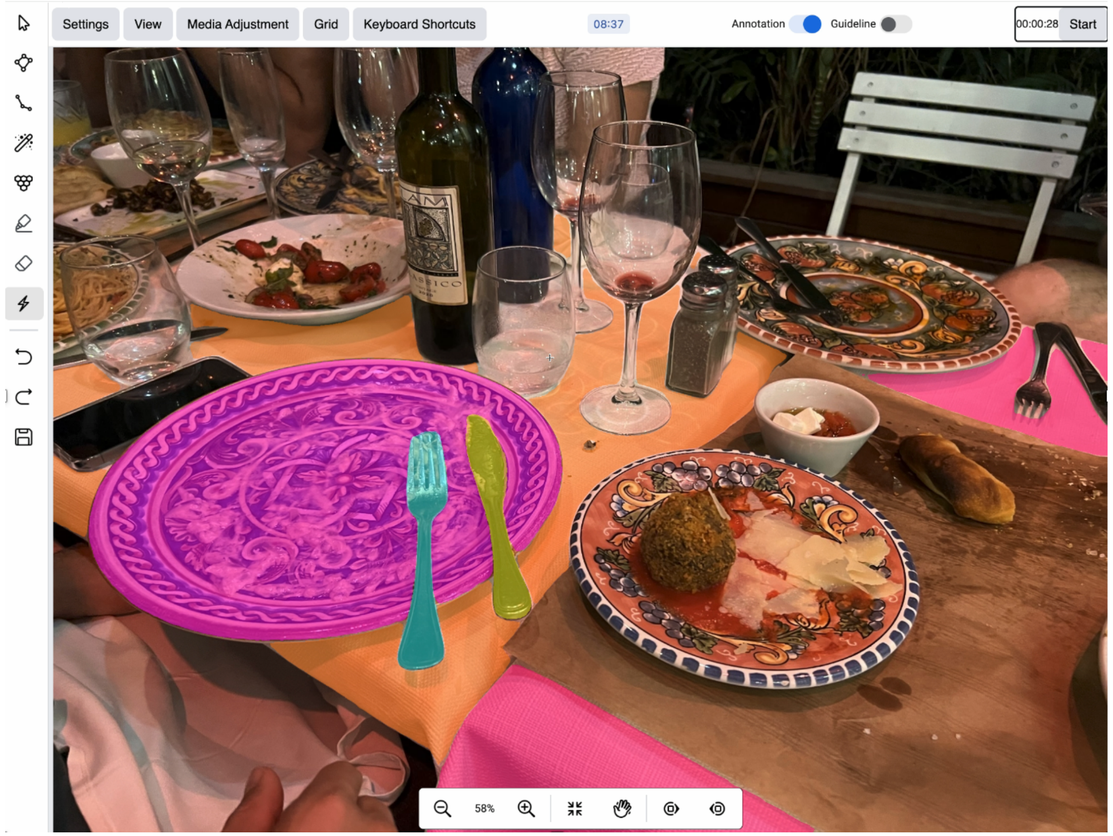
- Three stages
  - *Assisted manual,*
  - *semi-manual,*
  - *fully automatic*



slide credit: Alexander Kirillov

Data Engine: Assisted Manual Stage

- SAM in a web-browser
  - Interactive segmentation tool
- 4.3 million masks (120k images)
- 6.5x faster than COCO masks
  - 2x slower than box annotation
- Retrained SAM 6 times
  - Scaled model size
  - Other improvements



slide credit: Alexander Kirillov

slide credit: Alexander Kirillov

Data Engine: Semi-Manual Stage

- Goal: increase diversity beyond most prominent objects
- Automatically segment many objects using detector + SAM
- Added 5.9 million more masks (180k more images)
- Retrained SAM 5 more times

Automatic masks + Manually annotated on top = Automatic + Manual

Data Engine: Fully Automatic Stage

- We ran SAM in “segment everything” mode on 11 million images
- Generated 1.1 billion masks

slide credit: Alexander Kirillov

SA-1B Dataset

- 11 million images
- 1.1 **billion** masks
- All automatically generated by SAM
- 400x larger than previous largest segmentation dataset
- Quality evaluation
  - Estimated 94% have at least 90% IoU with professional masks
  - Prior work estimates human inter-annotator IoU at 85-91%

slide credit: Alexander Kirillov

SA-1B Examples (Automatically Labelled)

slide credit: Alexander Kirillov

SA-1B Examples (Automatically Labelled)

slide credit: Alexander Kirillov

SA-1B Examples (Automatically Labelled)

300-400 masks

400-500 masks

slide credit: Alexander Kirillov

>500 masks

slide credit: Alexander Kirillov

Zero-Shot Transfer Tasks

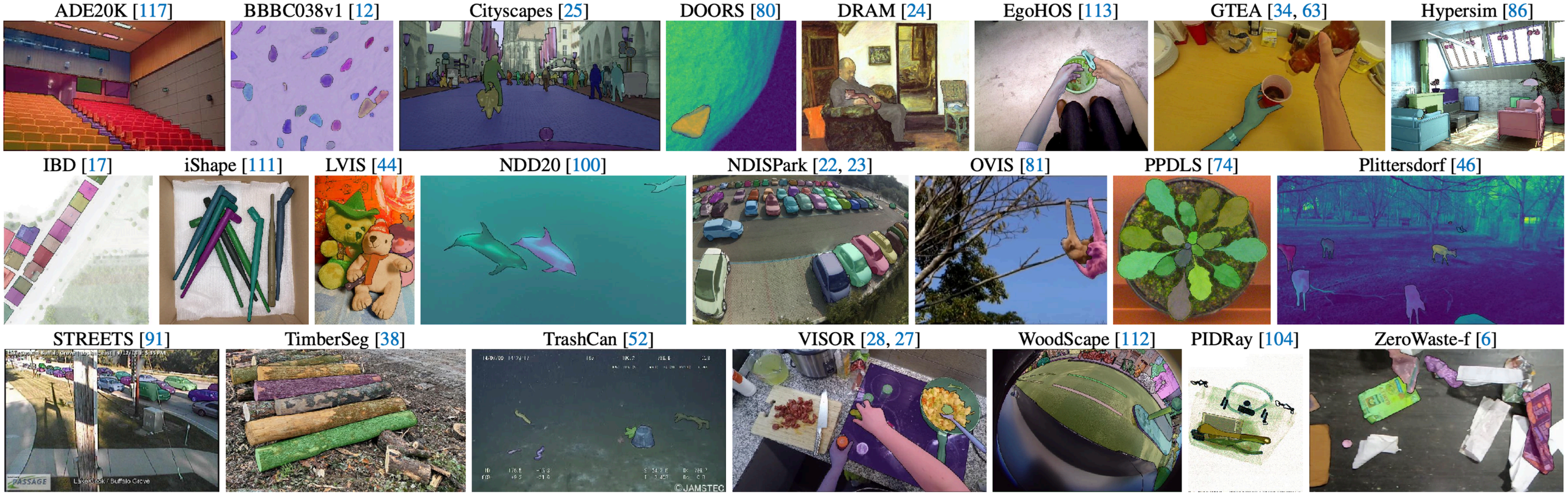
1. Single point valid mask evaluation
2. Edge detection
3. (Object proposals)
4. (Instance segmentation)
5. Text-to-mask

slide credit: Alexander Kirillov

slide credit: Alexander Kirillov

Single Point Valid Mask Evaluation

- SA-1B: mostly “scene” images (photographers walking in the world)
- 23 diverse dataset suite – mostly out-of-distribution vis-à-vis SA-1B



Single Point Valid Mask Evaluation Protocol

slide credit: Alexander Kirillov

Single Point Valid Mask Evaluation Protocol

- Select g.t. mask from dataset
  - Sample point from mask
  - Prompt model with point, model predicts mask

slide credit: Alexander Kirillov

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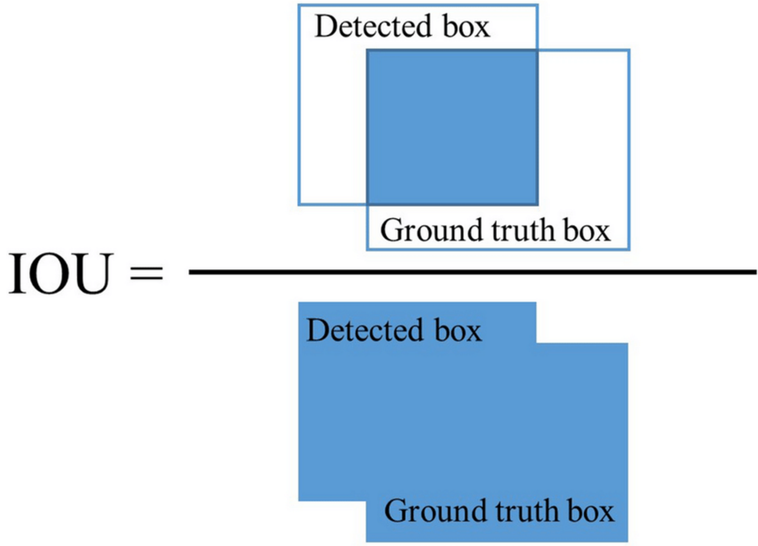
  - Metric: mean IoU (mIoU) over mask



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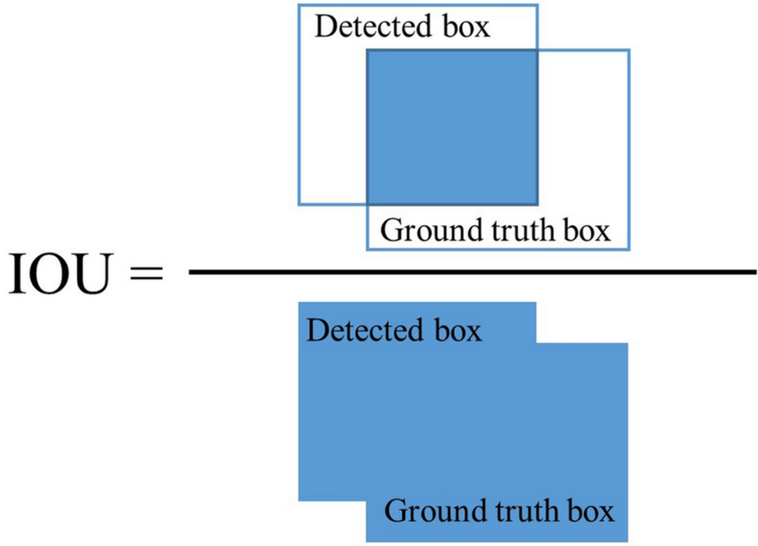
  - Recall SAM can predict 3 masks to handle ambiguity



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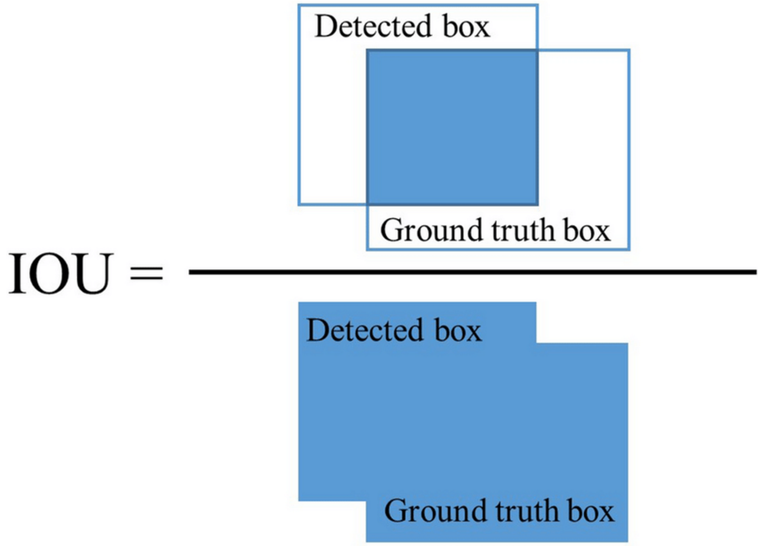

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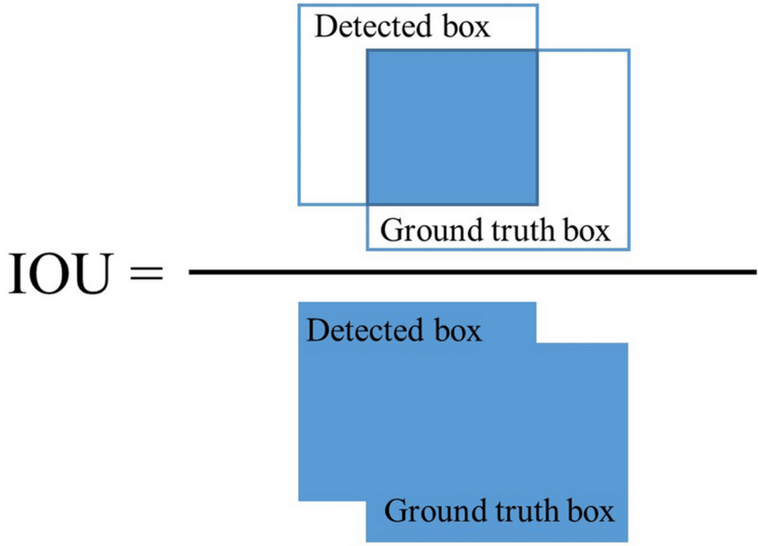
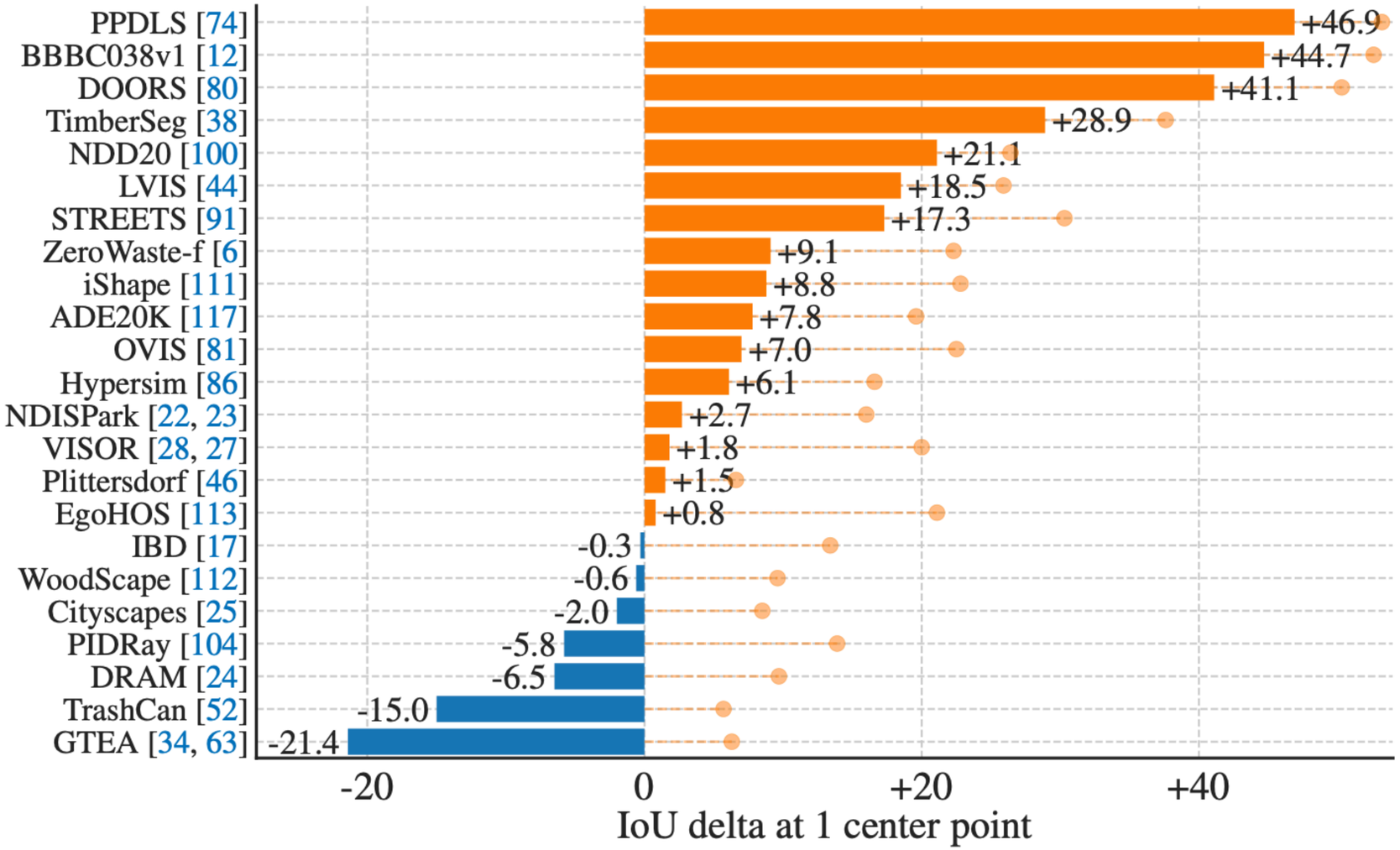
  - Regular evaluation: model puts forth most confident mask



slide credit: Alexander Kirillov

Single Point Valid Mask Evaluation

- SAM vs. RITM
- Circle = oracle



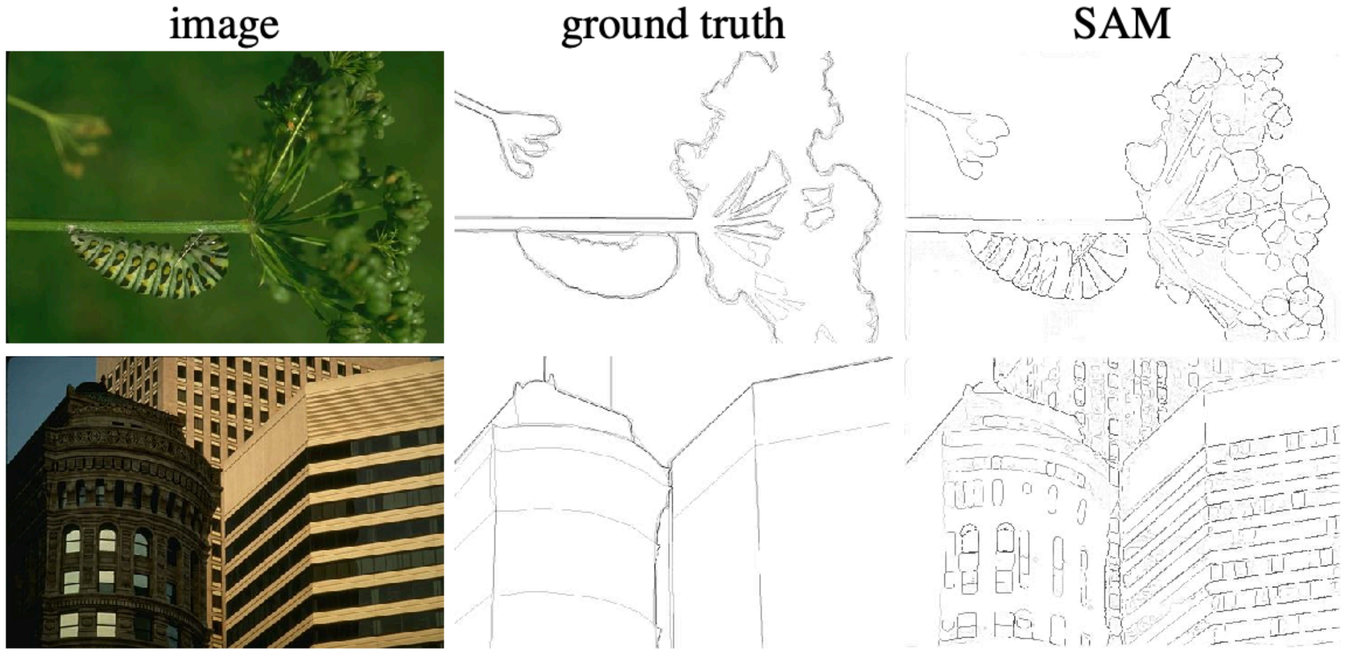
slide credit: Alexander Kirillov

RITM: Konstantin Sofiiuk, Ilya A Petrov, and Anton Konushin. Reviving iterative training with mask guidance for interactive segmentation. ICIP, 2022

Edge Detection

⇨

- BSDS500
- Segment everything (regular grid of foreground points)
  → filter edges from masks → edge NMS



method	year	ODS	OIS	AP	R50
HED [108]	2015	.788	.808	.840	.923
EDETR [79]	2022	.840	.858	.896	.930
zero-shot transfer methods:					
Sobel filter	1968	.539	-	-	-
Canny [13]	1986	.600	.640	.580	-
Felz-Hutt [35]	2004	.610	.640	.560	-
SAM	2023	.768	.786	.794	.928

slide credit: Alexander Kirillov

Text-to-Mask

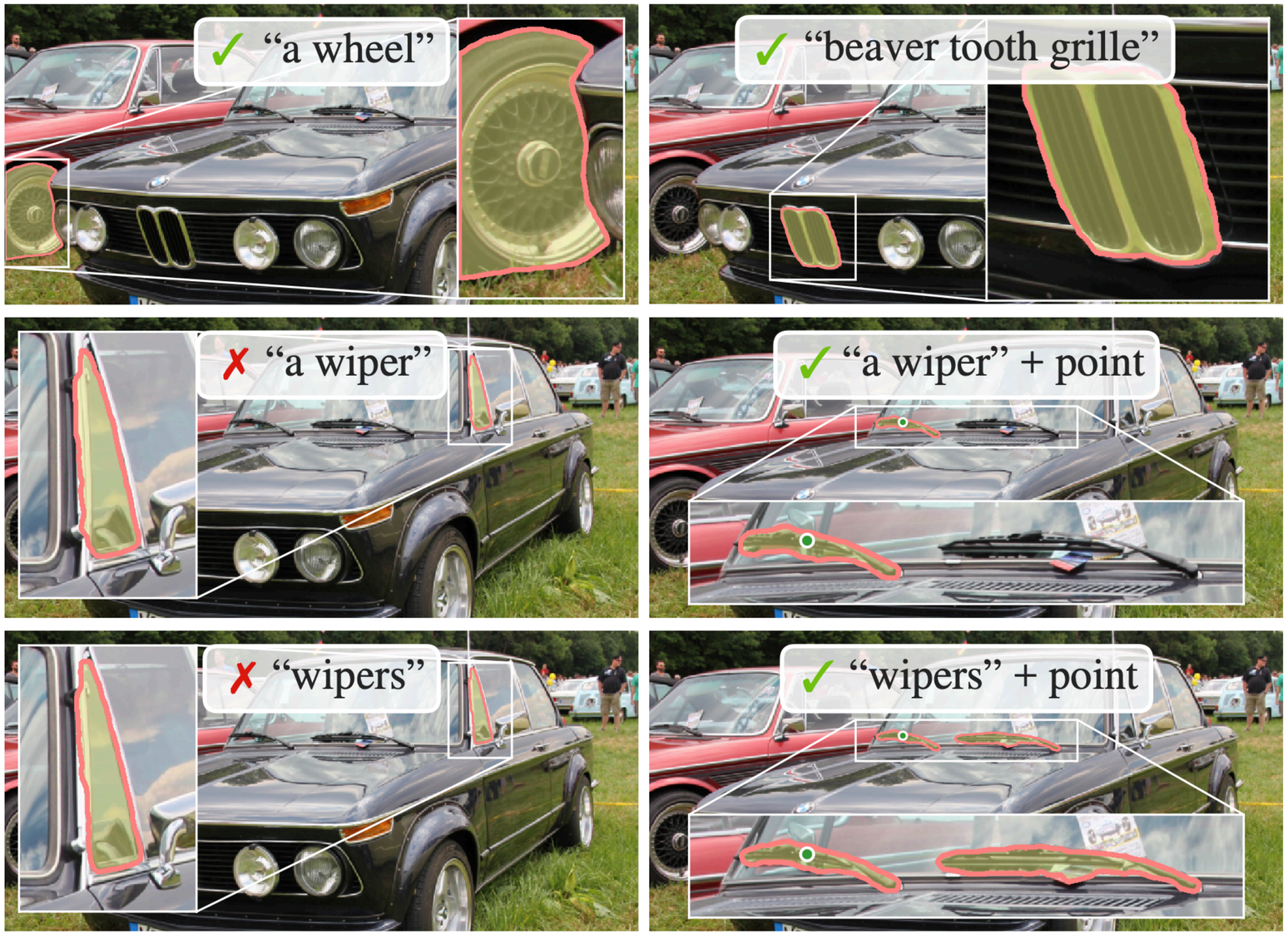
- Training:
  - For each mask (larger than 100x100), compute the CLIP image encoder embedding
  - Prompt with embedding during simulated interactions

- Recall in CLIP image and text embeddings are *aligned*

- During inference: prompt with text embedding

slide credit: Alexander Kirillov

Text-to-Mask Qualitative Examples



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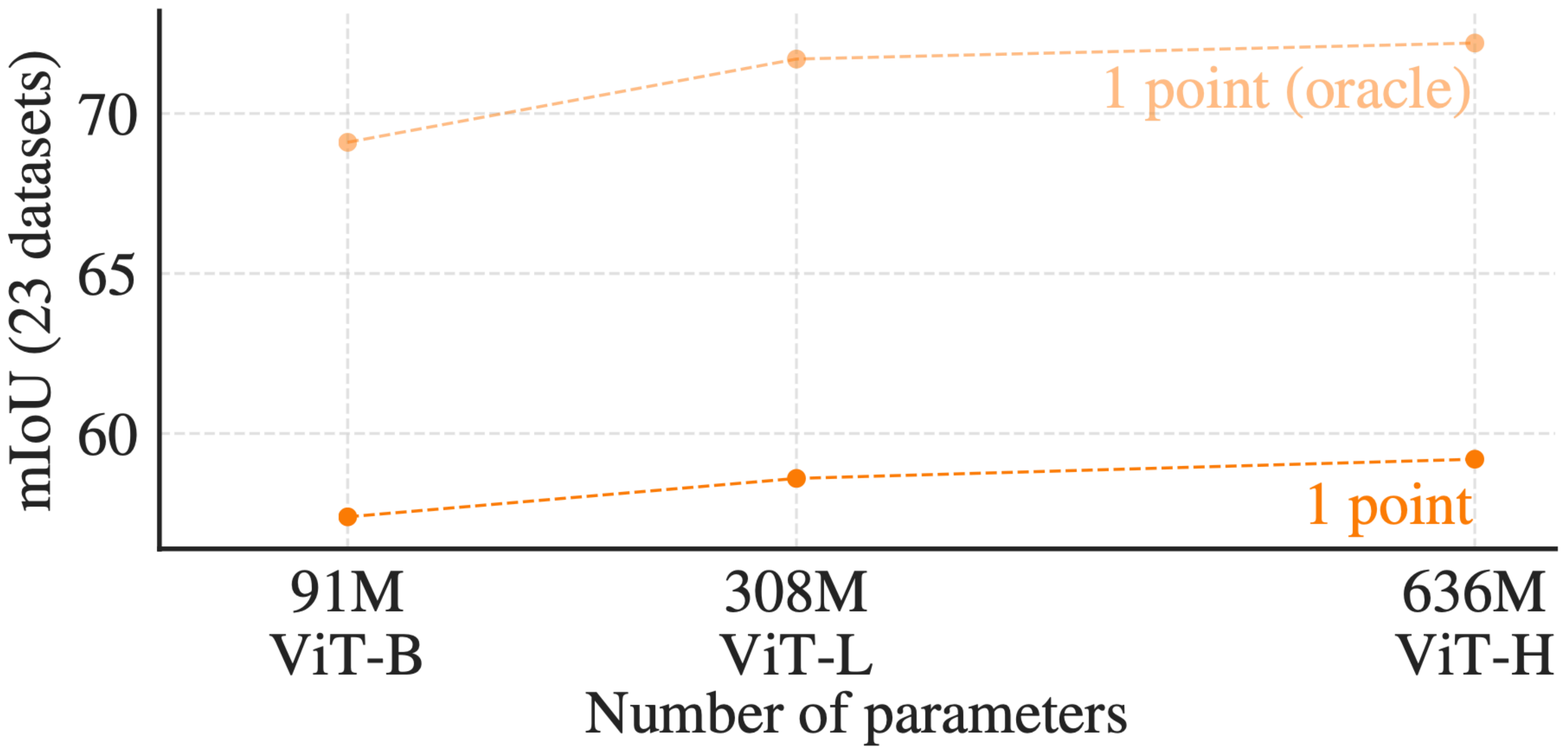
Ablations

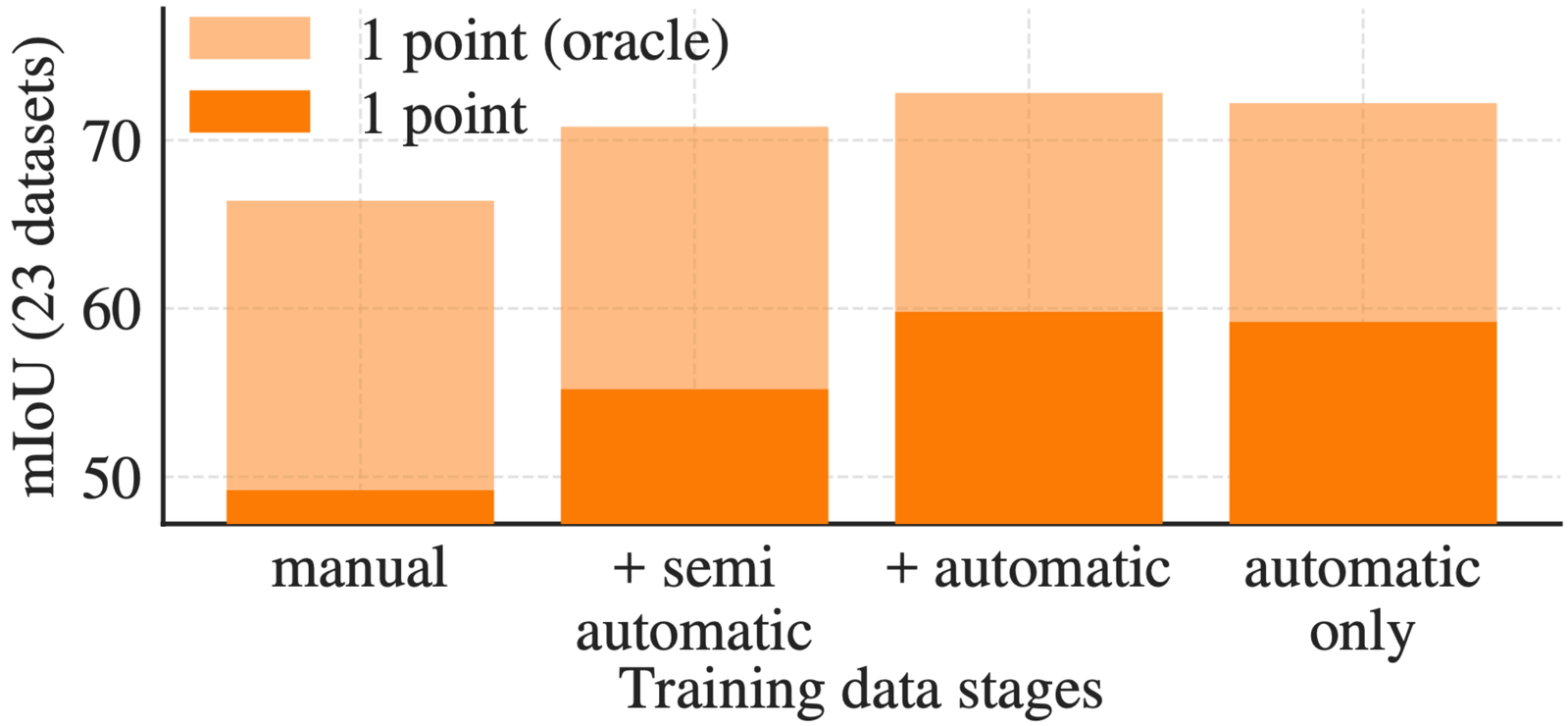
- Scaling saturation



slide credit: Alexander Kirillov

Ablations

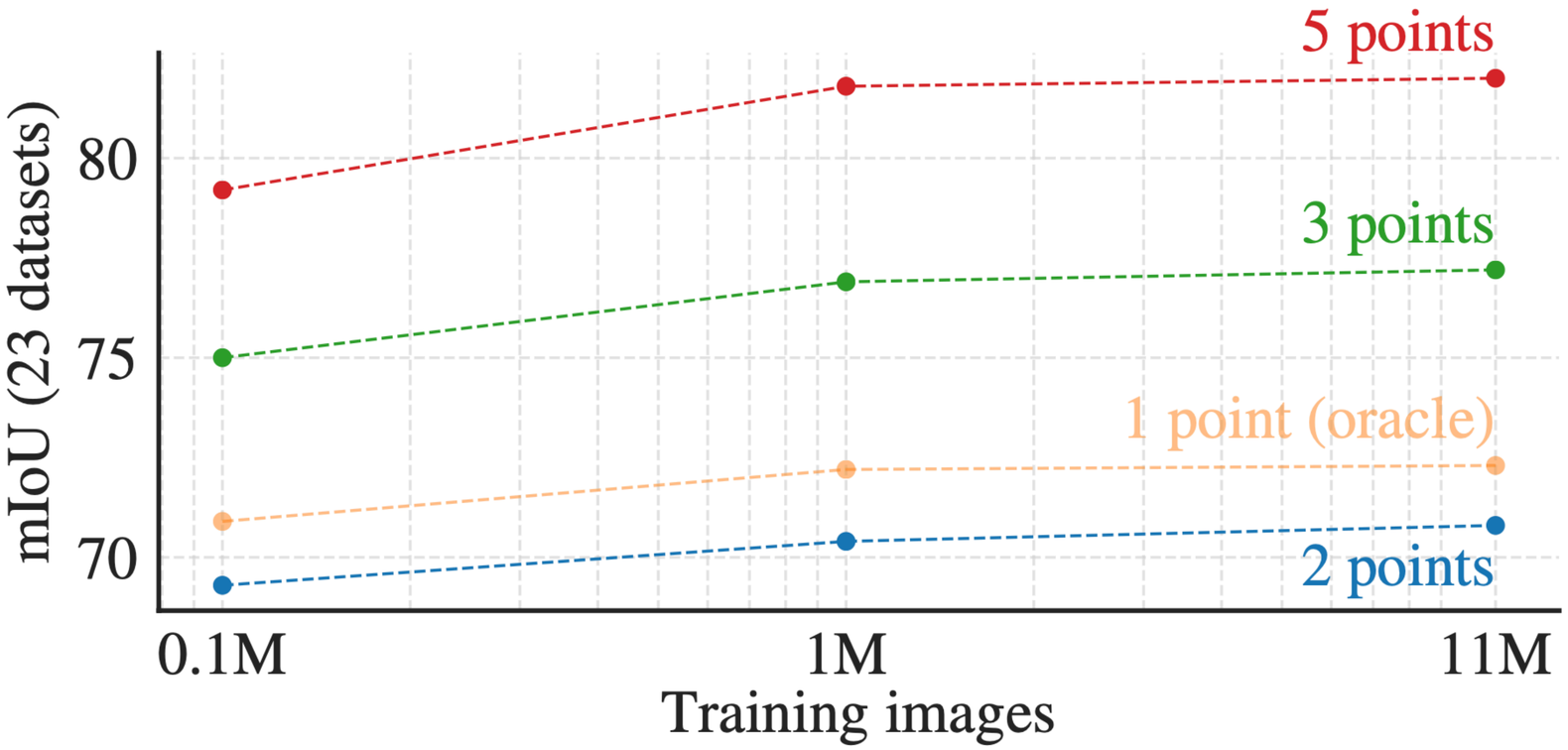
- Automatic data is good enough



slide credit: Alexander Kirillov

Ablations

- Training with 10% of the data is good



slide credit: Alexander Kirillov

Limitations

slide credit: Alexander Kirillov

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- Can miss fine structures

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- Small “sprinkles” and holes (fixed with post-processing)

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- Text-to-mask exploration is preliminary
- Domain-specialized tools may work better

slide credit: Alexander Kirillov

slide credit: Alexander Kirillov

Conclusion

- Main contributions
  - New task (yields pre-training and inference)
  - New model (SAM)
  - New dataset (SA-1B – 1 billion masks!)
- The SA Project: attempt at a base/foundation model for segmentation
  - Up to community use and evaluation to see if that is the case

- NLP:LLMs :: CV:???
  - Is there something as simple, general, and powerful for CV?

Links

- Project website: https://segment-anything.com
- Interactive demo: https://segment-anything.com/demo
- Dataset explorer: https://segment-anything.com/dataset/index.html
- Code (inference only for now): https://github.com/facebookresearch/segment-anything

slide credit: Alexander Kirillov