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

mboehle@mpi-inf.mpg.de
github.com/moboehle/B-cos

max planck institut informatik

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Summary: B-cos Networks to go

- ◇ DNNs typically explained by post-hoc methods
- ◇ Instead, we make DNNs **inherently interpretable**
- ◇ For this, we introduce **B-cos**$(\mathbf{x}) = \mathbf{w}^T(\mathbf{x})\,\mathbf{x}$

  ⇒ B-cos networks are dynamic linear $\mathbf{y}(\mathbf{x}) = \mathbf{W}_{1\to L}(\mathbf{x})\,\mathbf{x}$
- ◇ $\mathbf{W}_{1\to L}(\mathbf{x})$ optimised to align with $\mathbf{x}$ ⇒ **easy to interpret**
- ◇ **Compatible with standard CNN architectures**

Method: The B-cos Transformation

B-cos Transformation

$$\text{B-cos}(\mathbf{x}) = \underbrace{\|\widehat{\mathbf{w}}\|}_{=1}\,\|\mathbf{x}\|\,|\cos(\mathbf{x},\mathbf{w})|^{\mathrm{B}} \times \operatorname{sgn}\big(\cos(\mathbf{x},\mathbf{w})\big)$$

B-cos Properties

Dynamic linear	Bounded	Maximal if aligned
$\text{B-cos}(\mathbf{x}) = \mathbf{w}^T(\mathbf{x})\,\mathbf{x}$	$\text{B-cos}(\mathbf{x}) \le \|\mathbf{x}\|$	$\text{B-cos}(\mathbf{x}) = \|\mathbf{x}\| \Leftrightarrow \mathbf{x} \parallel \mathbf{w}$

- ◇ B-cos$(\mathbf{x})$ is a **modified** linear transformation

  that **suppresses outputs for badly aligned weights**

  ⇒ can **replace linear transformations** in CNNs!
- ◇ During optimisation, B-cos induces **weight alignment**

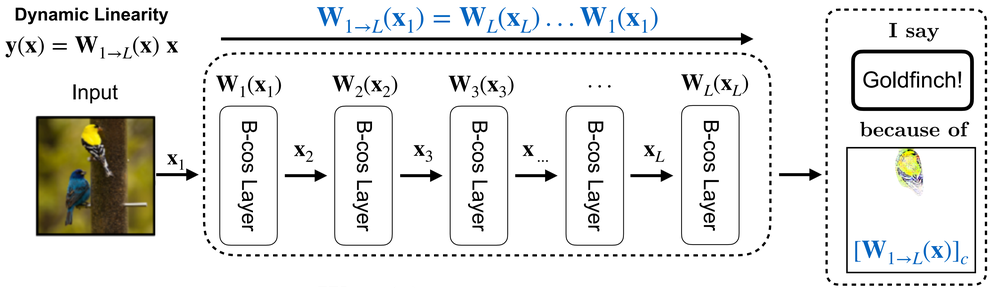
Higher B → higher weight alignment

High-level Overview: Dynamic Linearity + Input Alignment

Dynamic Linearity

$$\mathbf{y}(\mathbf{x}) = \mathbf{W}_{1\to L}(\mathbf{x})\,\mathbf{x}$$

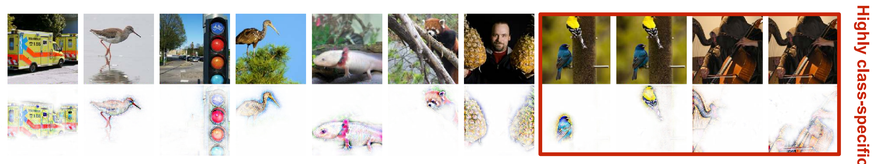
$$\mathbf{W}_{1\to L}(\mathbf{x}_1) = \mathbf{W}_L(\mathbf{x}_L)\ldots\mathbf{W}_1(\mathbf{x}_1)$$



Given the **dynamic linearity,** $\mathbf{W}_{1\to L}(\mathbf{x})$ **faithfully summarises the model**

By promoting **weight-input alignment,** we make $\mathbf{W}_{1\to L}(\mathbf{x})$ **interpretable** (see B-cos, left)

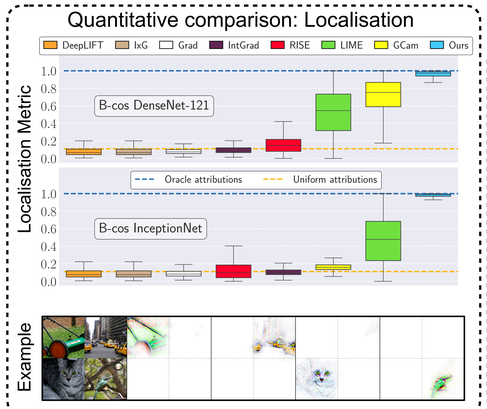
Model-inherent explanations $\mathbf{W}_{1\to L}(\mathbf{x})$ can directly be visualised in colour (no overlay)!

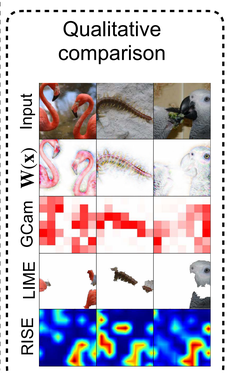


We can also compute linear contributions $\mathbf{s}_c = [\mathbf{W}_{1\to L}]_c^T \odot \mathbf{x}$. E.g., here, we show $\Delta = \mathbf{s}_{c_1} - \mathbf{s}_{c_2}$.

References: DeepLIFT (Shrikumar, '17), IntGrad (Sundararajan, '17), RISE (Petsiuk, '18), LIME (Ribeiro, '16), GCam (Selvaraju, '17), ResNet (He, '16), DenseNet (Huang, '17), Inception (Szegedy, '16), VGG (Simonyan, '15)), ImageNet (Deng, '09)

Results: interpretable *and* accurate





In contrast to post-hoc methods **inherent explanations** are
(1) model-faithful (2) highly detailed (3) parameter-free

We can explain any neuron in layer l in the same way via $\mathbf{W}_{1\to l}(\mathbf{x})$:

"Wheel Neuron" Explanations for highest actvts. of neuron 739 in layer 87

B-cos CNNs achieve **comparable accuracy** on ImageNet as baselines

pre: pretrained models
B-cos: converted models
training$^+$: more epochs

VGG-11		ResNet-34		DenseNet-121		InceptionNet	
pre	B-cos	pre	B-cos	pre	B-cos	pre	B-cos
69.0	69.6	73.3	71.7	74.4	73.3	77.3	75.4
$\Delta = +0.6$		$\Delta = -1.6$		$\Delta = -1.1$		$\Delta = -1.9$	
B-cos DenseNet-121 training$^+$				74.4 ($\Delta = 0.0$)			