Concept-Based Methods for Neural Network Interpretation

Riccardo Massidda

https://pages.di.unipi.it/massidda/

Università di Pisa

Abstract

Concept-based methods attempt to interpret existing neural networks or to design inherently interpretable models by exploiting human-comprehensible concepts. In the current talk, I will present few significant examples of such methods, discussing their commonalities, their underlying assumptions, and their applications. More in detail, I will focus on the semantic alignment of neural directions and visual concepts in CNNs for computer vision. In this context, different existing approaches might be understood in terms of a unified general framework. Furthermore, I will show the impact of acknowledging semantic relations on such framework. Finally, the talk discusses the main issues affecting concept-based methods and hints to possible research strategies to tackle them.

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Motivation

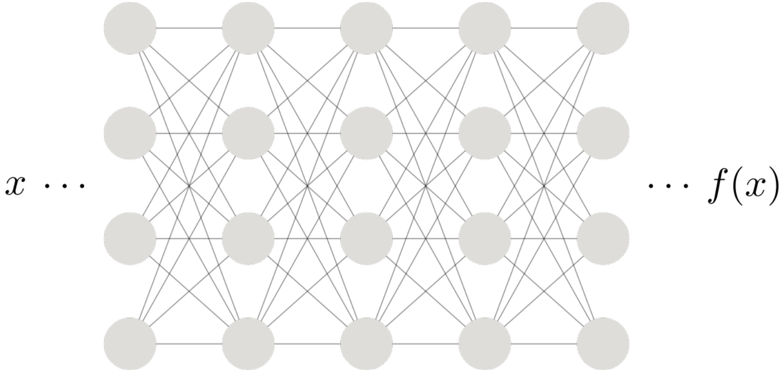

Figure 1: An Artificial Neural Network f is composed of a set of neural units U which are displaced into consecutive and interconnected layers.

Function and Concept

Frege (1891)

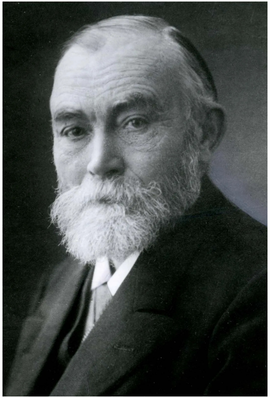

Figure 2: Gottlob Frege

"We thus see how closely that which is called a concept in logic is connected with what we call a function. Indeed, we may say at once: a *concept* is a *function* whose value is always a *truth-value*."

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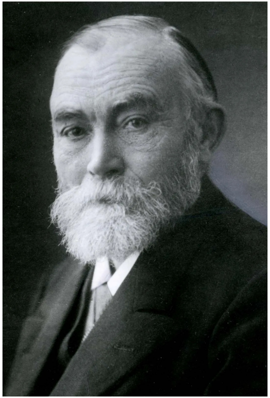

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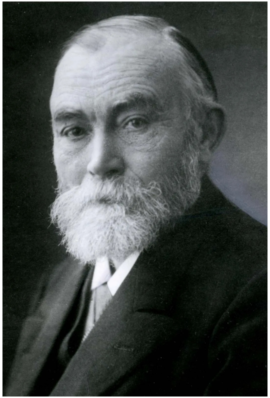

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$$E_c = \{o \in W : I_c(o)\} \tag{2}$$

Concept-Based Methods

Posthoc analysis:

- Latent Object Detectors (Zhou, Khosla, et al. 2014)
- Feature Visualization (Olah, Mordvintsev, and Schubert 2017)
- Network Dissection (Zhou, Bau, et al. 2019)
- TCAV (Kim et al. 2018)
- CaCe (Goyal et al. 2020)
- Interpretable Basis Decomposition (Zhou, Sun, et al. 2018)
- Net2Vec (Fong and Vedaldi 2018)
- ConceptSHAP (Yeh et al. 2020)

Inherently interpretable:

- Concept Bottleneck Models (Koh et al. 2020)
- Debiased CBMs (Bahadori and Heckerman 2021)
- Graph CBMs for algorithmic reasoning (Georgiev et al. 2021)
- ProtoPNet (C. Chen et al. 2019)
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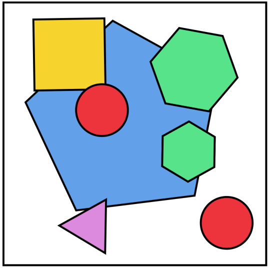
Network Dissection

Bau et al. (2020)



(a) $x \in X$

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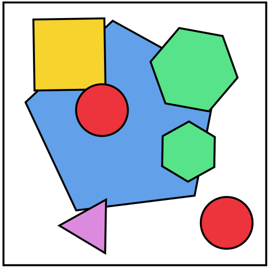

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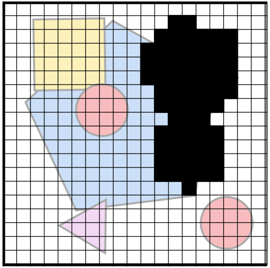

(b) $L_c(x)$

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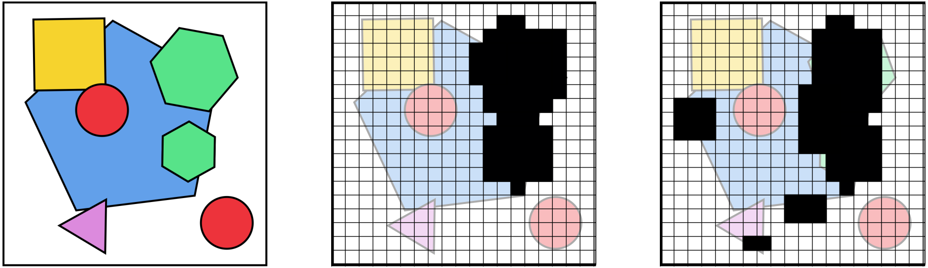

(a) $x \in X$ (b) $L_c(x)$ (c) $M_u(x)$

Figure 3: Decomposition of an image example x for a specific concept c and a given unit u according to the Network Dissection approach.

Network Dissection

Bau et al. (2020)

$$\mathrm{IoU}(u, c) = \frac{\sum_{x \in X} |M_u(x) \wedge L_c(x)|}{\sum_{x \in X} |M_u(x) \vee L_c(x)|} \tag{3}$$

Concept Activation Vectors (CAVs)

Kim et al. (2018)

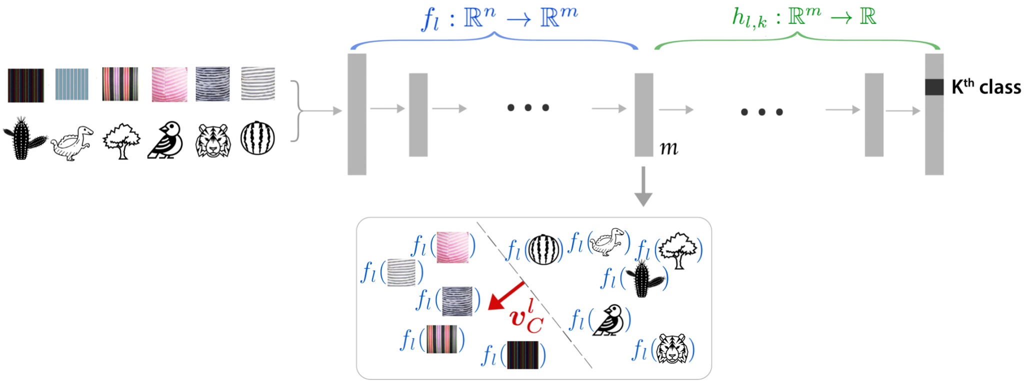

Figure 4: Schema of the learning procedure for a Concept Activation Vector.

Testing with CAVs (TCAV)

Kim et al. (2018)

$$
\begin{aligned}
S_{C,k,l}(x) &= \lim_{\epsilon \to 0} \frac{h_{l,k}(f_l(x) + \epsilon v_C^l) - h_{l,k}(f_l(x))}{\epsilon} \\
&= \nabla h_{l,k}(f_l(x)) \cdot v_C^l
\end{aligned} \tag{4}
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\mathrm{TCAV}_{C,k,l} = \frac{|\{x \in X_k : S_{C,k,l}(x) > 0\}|}{|X_k|} \tag{5}
$$

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Schematic representation

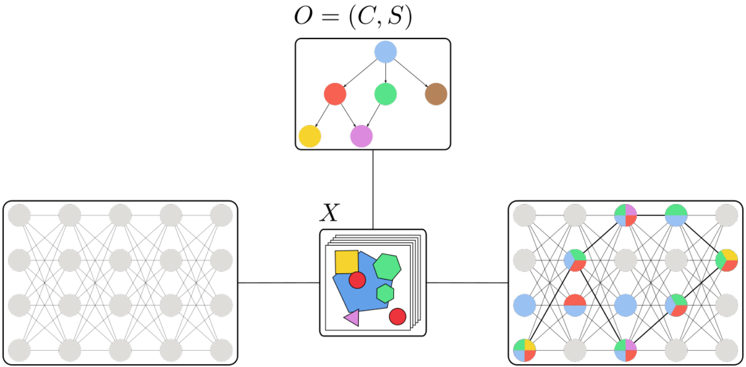

Figure 5: Overview of the proposed methodology. A set of neural directions D is semantically aligned with an ontology O through a pixel-level annotated dataset X, whose labels are in a two-way relationship with the ontology concepts C. Semantic relations S enable the retrieval of subgraphs composed of architecturally connected and semantically related directions.

Higher-Level Concepts

(a) Induced taxonomy (b) $x \in X$ (c) $L_c(x)$

Figure 6: Given the taxonomy induced by the specialisation relation, it is possible to analyze concept masks not directly annotated in the input.

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Neural Directions

A neural direction

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$\approx$ as in NetDissect!

Semantic Alignment

Given a set of neural directions D and an ontology $O = (C, S)$, the semantic alignment is estimated by an arbitrary performance metric

$$\sigma : D \times C \to [0, 1] \tag{8}$$

over the classification boundary defined by the direction.

Candidate σ

The Jaccard similarity, also known as Intersection over Union (IoU),

$$\sigma_{\mathrm{IoU}}(d, c) = \frac{\sum_{x \in X} |M_d(x) \wedge L_c(x)|}{\sum_{x \in X} |M_d(x) \vee L_c(x)|}, \tag{9}$$

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or the Sørensen–Dice coefficient, also known as F1 score,

$$\sigma_{\mathrm{F1}}(d, c) = \frac{\sum_{x \in X} 2|M_u(x) \wedge L_c(x)|}{\sum_{x \in X} |M_u(x)| + |L_c(x)|}, \tag{10}$$

consitute insightful measures of semantic alignment.

Acknowledging Polysemanticity

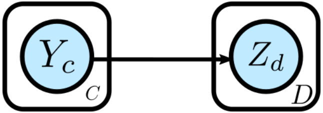

Figure 7: Ideal interaction between visual concepts C and neural directions D.

$$\begin{aligned}\sigma_{\mathcal{L}}(d, c) &= \mathcal{L}(Y_c = 1 \mid Z_d = 1) \\ &= \frac{\sum_x |L_c(x) \wedge M_d(x)|}{\sum_x |L_c(x)|}\end{aligned} \tag{11}$$

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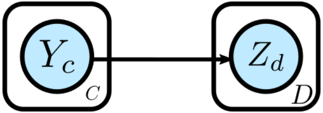

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Unit-alignment comparison

(a) Examples with maximal activations

Synset	$\sigma(u, c)$
hovel.n.01	0.021
roof.n.03	0.025
building.n.01	0.031
shelter.n.01	0.035
house.n.01	0.098

(b) $\mathrm{IoU}(u, c)$

Synset	$\sigma(u, c)$
circus_tent.n.01	0.401
greenhouse.n.01	0.403
shed.n.01	0.469
pavilion.n.01	0.568
bandstand.n.01	0.631

(c) $\mathcal{L}(c \mid u)$

Figure 8: Semantic alignment of unit 196 in the last residual block of ResNet-18.

Network Alignment Ψ

We define the set of τ-sufficiently aligned direction-concept pairs as

$$\Psi_\tau = \{(d, c) \mid \sigma(d, c) \geq \tau\} \subseteq D \times C. \tag{12}$$

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By extracting each non-trivial connected component, we obtain a set

$$T = \{t \mid t \subseteq \Psi, |t| > 1, G[t] \text{ is connected}\}, \tag{14}$$

where each $t \in T$ is a semantically related and architecturally connected neural circuit.

Circuits analysis

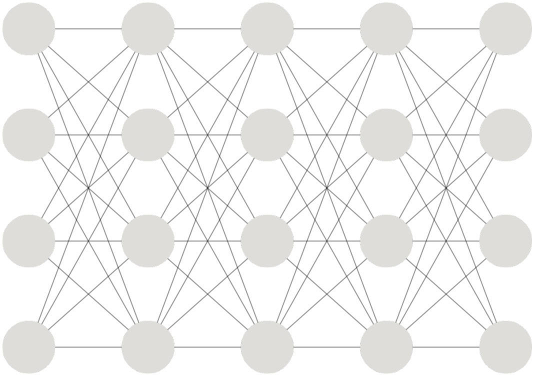

Figure 9: The ontological structure of visual concepts enables the retrieval of architecturally connected and semantically related directions.

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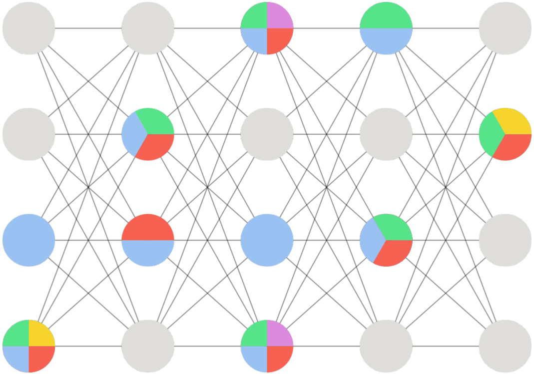

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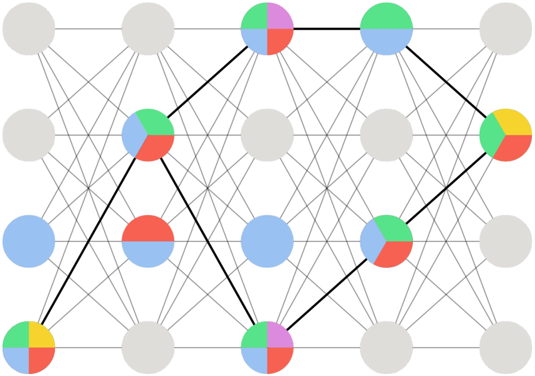

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Circuit 16

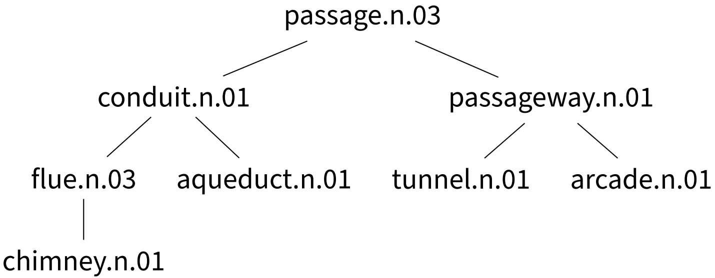

Figure 10: Hierarchy of WordNet synsets within Circuits 16 from AlexNet/Broden pretrained on Places365.

Circuit 16

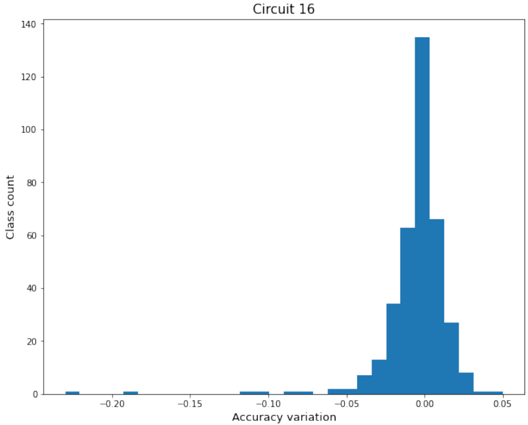

Figure 11: Accuracy drop histogram for Circuit 16 from AlexNet/Broden pretrained on Places365.

k	Description	Drop
96	/c/clothing_store	-0.05
121	/d/dining_room	-0.05
159	/g/gazebo/exterior	-0.06
91	/c/church/outdoor	-0.06
12	/a/arch	-0.08
260	/p/pavilion	-0.09
288	/r/river	-0.1
66	/b/bridge	-0.11
347	/v/viaduct	-0.19
10	/a/aqueduct	-0.23

Table 1: Class accuracy drop for Circuit 16 from AlexNet/Broden pretrained on Places365.

Implementation

Bisturi

`https://github.com/rmassidda/bisturi`

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The network has learned concept c.

The network ~~has learned~~ is able to represent concept c.

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...well, so?

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  > *If the explanation was completely faithful to what the original model computes, the explanation would equal the original model, and one would not need the original model in the first place, only the explanation.*

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