The Promises and Pitfalls of Black-Box Concept Learning Models

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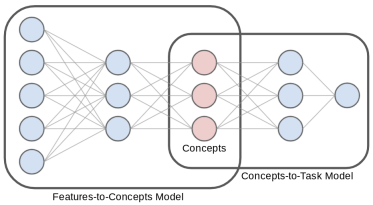
The Promises of Concept Learning Models

Concept learning models (CLMs) help us understand how models make decisions by inserting **human-interpretable concepts**. They contain two parts: a *feature-to-concept* model and a *concept-to-task* model.



Main Contributions

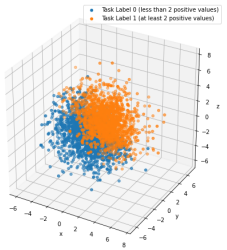
Contribution 1: We show how and when concept representations capture task-relevant info unrelated to the concepts. This informational leakage can create **misleading interpretations**.

Contribution 2: Natural mitigation techniques like adding extra dimensions, concept whitening [1], and sequential training [2, 3] do not prevent leakage.

Contribution 3: We suggest strategies to mitigate the effect of information leakage in CLMs.

Toy Task for Concept Learning

We setup a dataset of points with coordinates X, Y, and $Z \sim \mathcal{N}(0, 4)$.



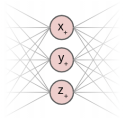
Input Features: Set of 7 non-linear, non-invertible function transformations of the coordinate values.

Concepts: x_+, y_+, and z_+ specifying if their corresponding coordinates are positive.

Labels: True (orange) if at least 2 coordinate values are positive.

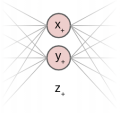
Information Leakage in CLMs

Take-away 1: Concepts are entangled in soft concept representations.



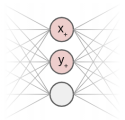
	Bottleneck Dimension		
	1	2	3
x_+	0.9999 ± 0.0001	0.65 ± 0.03	0.63 ± 0.03
y_+	0.65 ± 0.02	0.9995 ± 0.0001	0.67 ± 0.04
z_+	0.64 ± 0.02	0.66 ± 0.02	0.9995 ± 0.001

Take-away 2: Presence of unobserved concepts exacerbate information leakage.



	Bottleneck Dimension	
	1	2
x_+	0.97 ± 0.01	0.64 ± 0.01
y_+	0.66 ± 0.01	0.98 ± 0.01
z_+	0.75 ± 0.01	0.74 ± 0.01

Take-away 3: Adding extra capacity to capture unobserved concepts does not prevent leakage.



	Bottleneck Dimension		
	1	2	3
x_+	0.99998 ± 0.00001	0.59 ± 0.02	0.5 ± 0.2
y_+	0.60 ± 0.01	0.99973 ± 0.00002	0.5 ± 0.3
z_+	0.68 ± 0.02	0.693 ± 0.005	0.4 ± 0.4

Tables present AUC scores when predicting concepts from bottleneck node activations.

Concept Whitening is Not Enough

Concept Whitening [1] decorrelates soft concept representations.

Task: Predict if a subset of MNIST images (digits 1-6) display numbers smaller than 4 using an incomplete set of task relevant concepts.

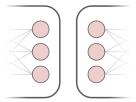
Result: Since the CW dimensions are full activation maps, we can predict all the concepts from any of the CW dimensions (aligned and unaligned) with $95 - 100\%$ accuracy.

Take-away 4: Concept Whitening does not prevent information leakage.

Task-Blind Training is Not Enough

Take-away 5: Task-blind training of concept representations does not prevent leakage.

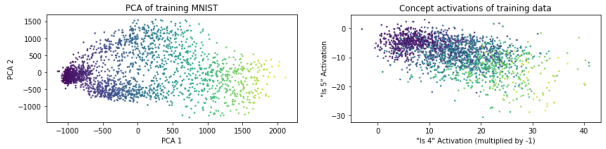
Task: Predict parity of MNIST images using ***task-irrelevant concepts***. Expect **50%** accuracy.



Model: First train pixels-to-concepts model for concept representations. Then train concepts-to-parity model. Representations are not aware of task.

Result: Model achieves **69%** on test set – much greater than 50%.

Cause: Concept representations, though task-unaware, encode first PCA dimension of MNIST data.



Furthermore

- Information leakage is sensitive to modeling choices.
- Even random concepts can improve task performance, so distinguishing between task-related concepts and random concepts can be difficult.
- Mitigation: Minimize mutual information
- Mitigation: Use human experts to refine concepts

Acknowledgements

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References

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