A Formal Methods Approach Towards Deep Learning Interpretability

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Summary

Although deep neural networks have proved to be very successful at classification tasks, their intrinsic complexity makes reasoning about a classification outcome difficult. In recent work [2], statistical methods were introduced as a means to assess the influence of human-intelligible concepts in classification outcomes. We aim to assess and extend such methods by leveraging formal methods for neural network verification.

- **Question:** How important is a concept in classifying image i as label k? e.g. Is the presence of stripes relevant in the classification of an animal as a zebra?
- **Approach #1:** Use TCAV framework to provide statistical guarantees
- **Approach #2:** Use neural network verification methods [1] to provide formal guarantees

Testing with Concept Activation Vectors (TCAV) [2]

- **Idea:** Identify the region in the latent space corresponding to layer ℓ of the network in which a human-intelligible concept (e.g. blue) manifests more intensely with a vector called the Concept Activation Vector (CAV). Measure the relevance of this concept for classification of image i as class k by taking directional derivative of the layer ℓ activations for image i with the CAV.
- **Inputs:**
  - trained classification network
  - set of examples for a user-defined concept C and set of random counterexamples
  - labeled examples for the class k under consideration
- **Outputs:**
  - CAV v_c^ℓ for concept C at layer ℓ
  - TCAV score $S_{C,k}^\ell(\mathbf{x})$ of the sensitivity of the model's prediction of class k to concept C

$$S_{C,k}^\ell(\mathbf{x}) = \nabla h_k^\ell(f_\ell(\mathbf{x})) \cdot \mathbf{v}_C^\ell$$

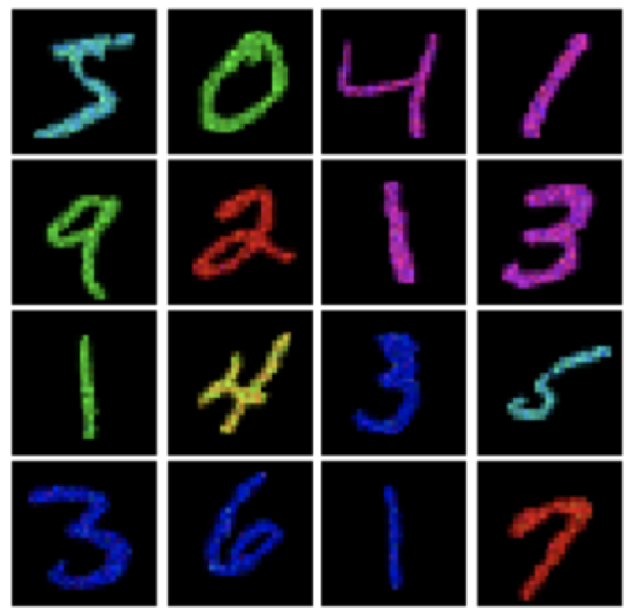
  - p-value testing the hypothesis that concept C is not relevant in classifying images of class k

Neural Network Verification

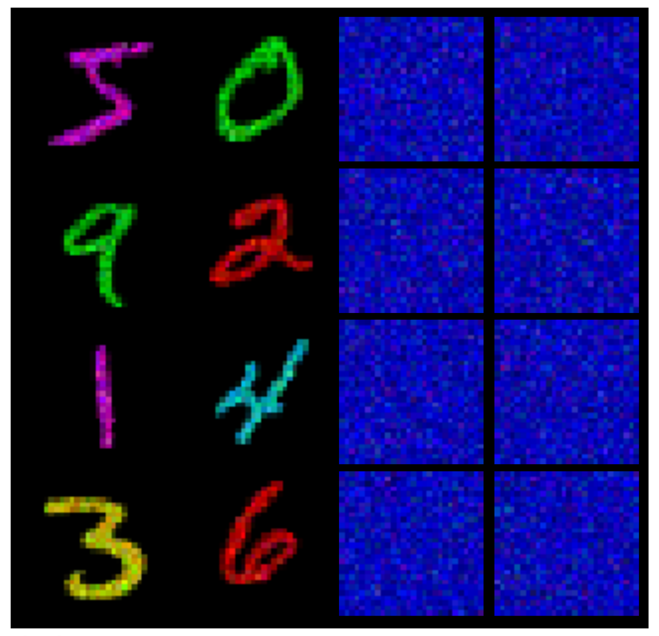
$$\vec{x} \in \mathcal{X} \Rightarrow \vec{y} = \vec{f}(\vec{x}) \in \mathcal{Y}$$

Approach: TCAV + Verification

Custom data sets

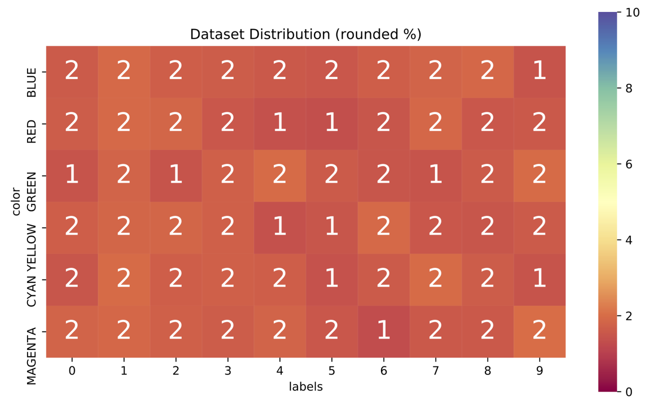


(a) Colorized MNIST training set for classification of hand-written digits

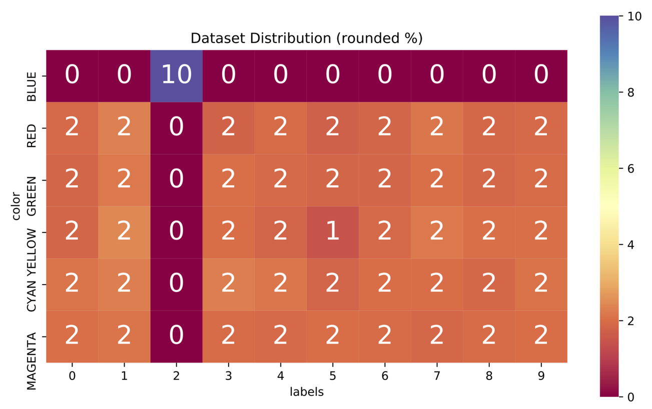


(b) Blue concept training set and non-blue training set to learn CAVs for concept blue

Maybe talk about classe sand support vector LALALALALAL



(c) label 1



(d) label 2

2 Figures side by side

$$\mathcal{L}_{LP} = -\mathbb{E}_{Z\sim q(Z|A,X)}[A_{ij}\log\tilde{A}_{ij} + (1-A_{ij})\log(1-\tilde{A}_{i,j})] + \mathrm{KL}(q(Z|A,X)||p(Z)).$$

2. Edge hallucination produces $\hat{A}$:

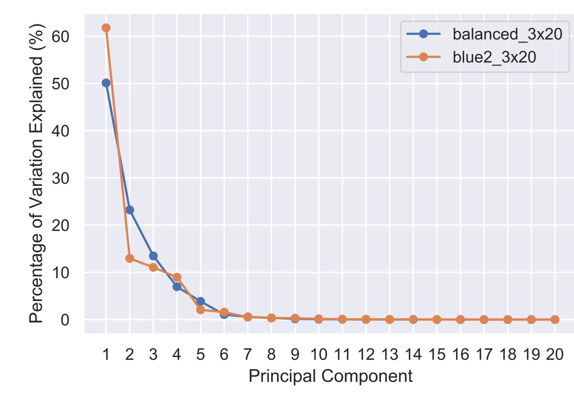
- top$K$ (K hyper-parameter)
- sampling using gumbel softmax [4] trick (allows gradients to flow)

3. Node classification

- $\hat{y} = \mathrm{GCN}(\hat{A}, X)$

Results

Need to talk about significant CAVs Then talk about the avenues and boulevards.



(a) label 1

model	layer	TCAV Score	signif cant
balanced_5x50	fc1	0.15 ± 0.10	yes
	fc4	0.14 ± 0.13	yes
blue2_5x50	fc1	1.00 ± 0.00	yes
	fc4	1.00 ± 0.00	yes
balanced_3x50	fc1	0.14 ± 0.13	yes
	fc2	0.08 ± 0.05	yes
blue2_3x50	fc1	0.80 ± 0.08	yes
	fc2	0.78 ± 0.11	yes
balanced_3x20	fc1	0.20 ± 0.06	yes
	fc2	0.14 ± 0.05	yes
blue2_3x20	fc1	1.00 ± 0.01	yes
	fc2	0.98 ± 0.01	yes

(b) label 2

2 Figures side by side

Node classification results

#	network	in/out sets	algorithm	result
1	blue2_5x50	$\mathcal{X}_1/\mathcal{Y}_{+\text{PC1,fc4}}$	NSVerify	violated
	bal2_5x50	$\mathcal{X}_1/\mathcal{Y}_{+\text{PC1,fc4}}$	NSVerify	violated
1.1	blue2_5x50	$\mathcal{X}_1/\mathcal{Y}_{+\text{mean,fc4}}$	NSVerify	violated
	bal2_5x50	$\mathcal{X}_1/\mathcal{Y}_{+\text{mean,fc4}}$	NSVerify	violated
2	blue2_3x20	$\mathcal{X}_1/\mathcal{Y}_{+\text{PC1,fc2}}$	Reluplex	violated
	bal2_3x20	$\mathcal{X}_1/\mathcal{Y}_{+\text{PC1,fc2}}$	Reluplex	violated
2.1	blue2_3x20	$\mathcal{X}_1/\mathcal{Y}_{+\text{mean,fc2}}$	Reluplex	violated
	bal2_3x20	$\mathcal{X}_1/\mathcal{Y}_{+\text{mean,fc2}}$	Reluplex	violated
3	blue2_5x50	$\mathcal{X}_{2,5}/\mathcal{Y}_{+\text{PC1,fc4}}$	NSVerify	unknown
	bal2_5x50	$\mathcal{X}_{2,5}/\mathcal{Y}_{+\text{PC1,fc4}}$	NSVerify	unknown
3.1	blue2_3x20	$\mathcal{X}_{2,5}/\mathcal{Y}_{+\text{PC1,fc2}}$	NSVerify	holds
	bal2_3x20	$\mathcal{X}_{2,5}/\mathcal{Y}_{+\text{PC1,fc2}}$	NSVerify	violated

Table: Results of formal verification experiments for various networks, input and output sets, and algorithms. If the result is violated, this indicates that $\vec{x} \in \mathcal{X} \not\Rightarrow \vec{y} = \vec{f}(\vec{x}) \in \mathcal{Y}$.

- Try to salvage somethibg
- Nothing worked :)

References

[1] G. Katz, C. Barrett, D. L. Dill, K. Julian, and M. J. Kochenderfer. Reluplex: An efficient smt solver for verifying deep neural networks. In International Conference on Computer Aided Verification, pages 97–117. Springer, 2017
[2] B. Kim, M. Wattenberg, J. Gilmer, C. J. Cai, J. Wexler, F. B. Viegas, and R. Sayres. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav). In ICML, 2018
[3] Y. LeCun, C. Cortes, and C. Burges. Mnist handwritten digit database. ATT Labs [Online]. Available: http://yann. lecun. com/exdb/mnist, 2:18, 2010
[4] C. Liu, T. Arnon, C. Lazarus, C. Barrett, and M. J. Kochenderfer. Algorithms for verifying deep neural networks. CoRR, abs/1903.06758, 2019

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