



A Formal Methods Approach Towards Deep Learning Interpretability

Kriten Kessel, Christopher Lazarus, Javier Sagastuy
Stanford University



Summary

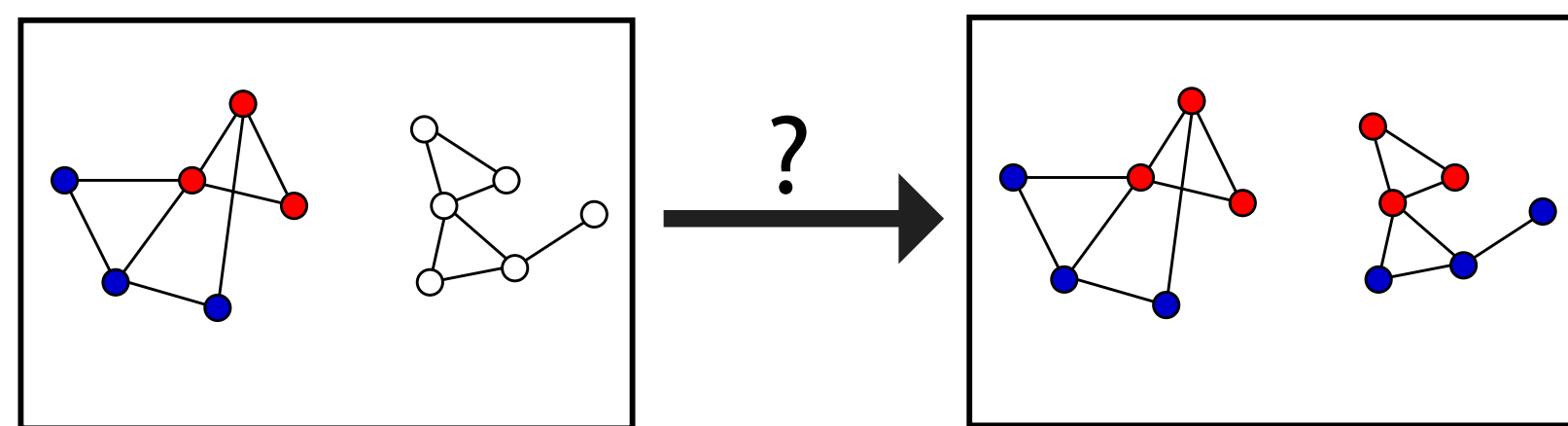
Deep Neural Networks are very useful at classifying tasks but their intrinsic complexity makes it really hard to explain the reasoning behind a classification outcome. In recent work [2], statistical methods were introduced to help assess the influence of human intelligible concepts in classification outcomes. We aim to asses and extend such methods by leveraging formal methods for Neural Network verification.

- **Problem:** Why did the network classify image γ with label k ?
- **Solution:** Come up with classes TCAV etc bla bla? or more like we tried to test the TCAV method??
- **Preliminary Results:** nothing nothing nothing.

Talk about TCAV ?

Input:

- adjacency matrices A_L and A_U for the two sets of nodes;
- features vectors X_L and X_U ;
- labels y_L

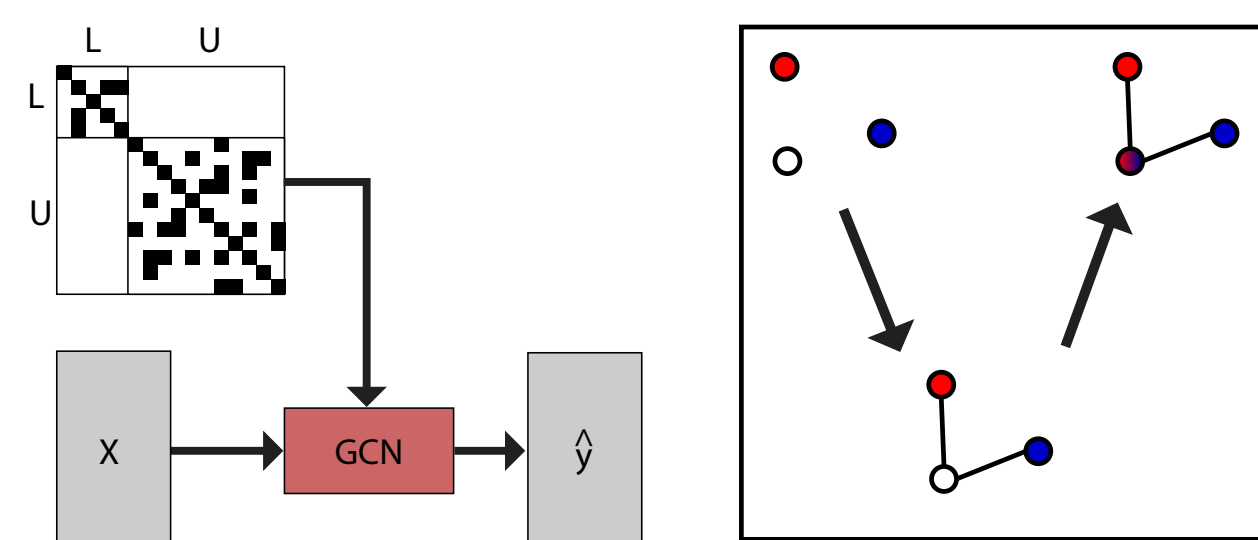


Output:

- predictions for the unlabelled nodes \hat{y}_L

Neural Network Verification

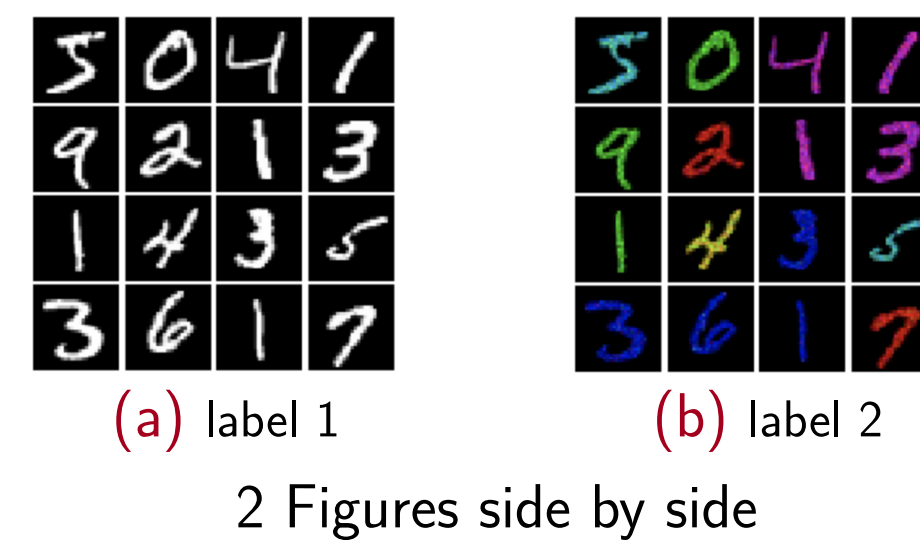
GCN [1] for node classification: $\hat{y} = h(Ah(AXW_1)W_2)$



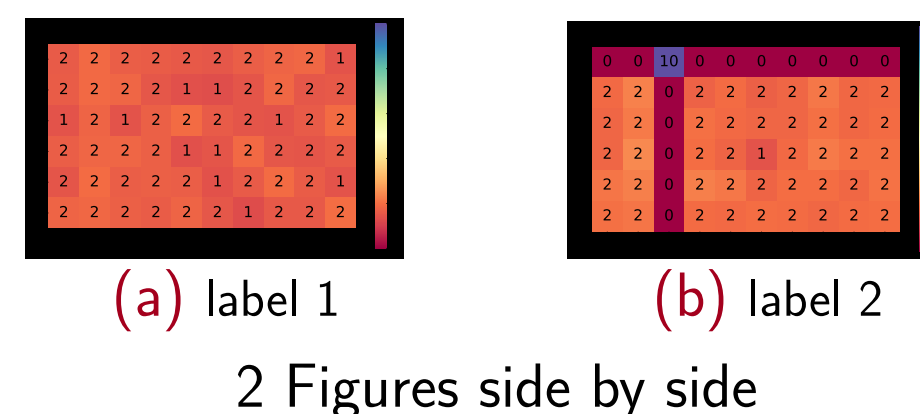
Approach: TCAV + Verification

Data bla bla

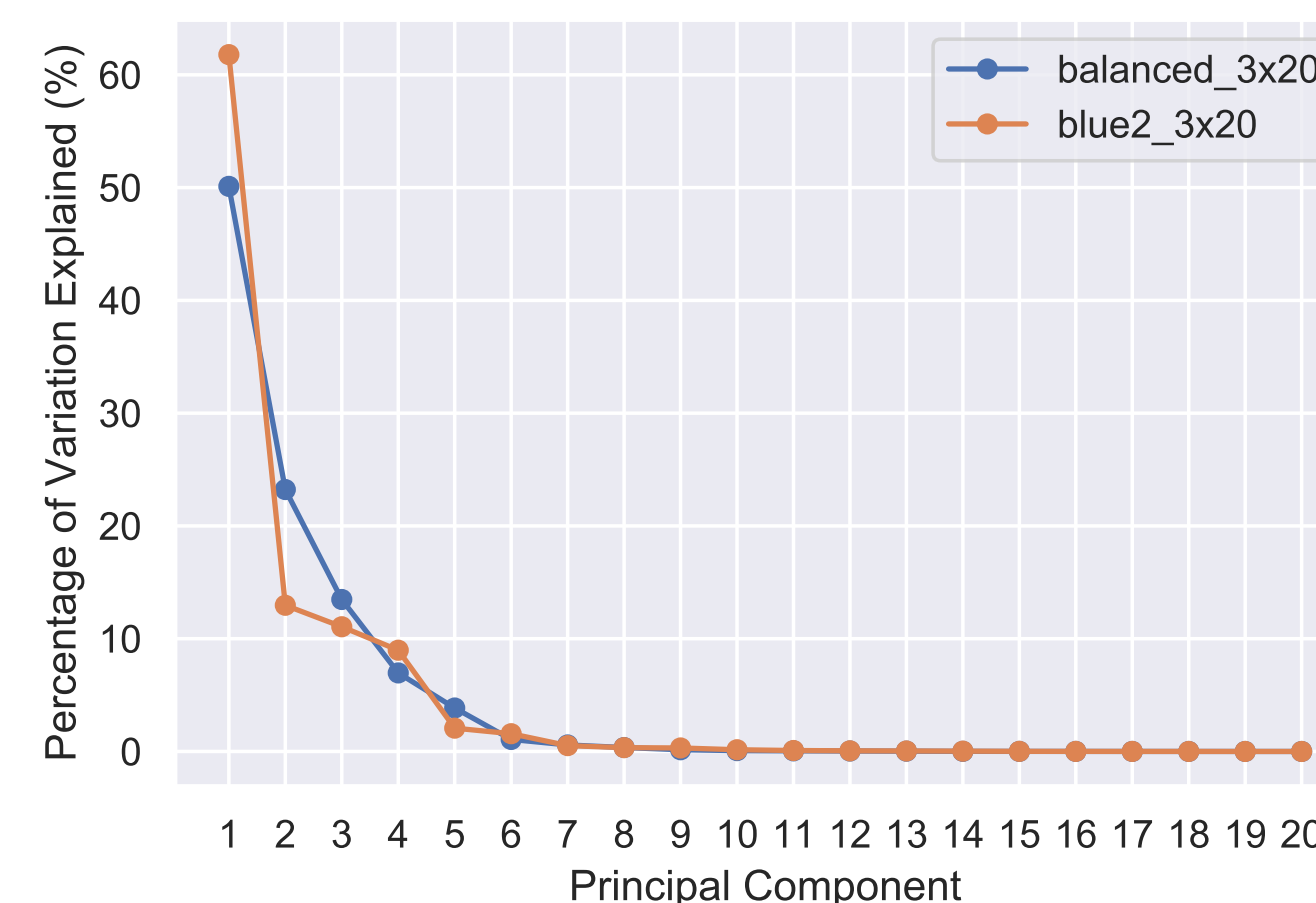
- talk about data



Maybe talk about classe sand support vector LALALALALAL



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



2. Edge hallucination produces \hat{A} :

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

Results

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

Node classification results

| model | balanced | blue 2 | red 2 | green 2 |
|---------------|----------|--------|-------|---------|
| balanced_5x50 | 0.942 | 0.942 | 0.941 | 0.944 |
| blue2_5x50 | 0.780 | 0.952 | 0.682 | 0.689 |
| balanced_3x50 | 0.942 | 0.940 | 0.942 | 0.941 |
| blue2_3x50 | 0.724 | 0.954 | 0.675 | 0.684 |
| balanced_3x20 | 0.890 | 0.890 | 0.891 | 0.888 |
| blue2_3x20 | 0.708 | 0.923 | 0.663 | 0.672 |

- 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