

Logical Neural Networks

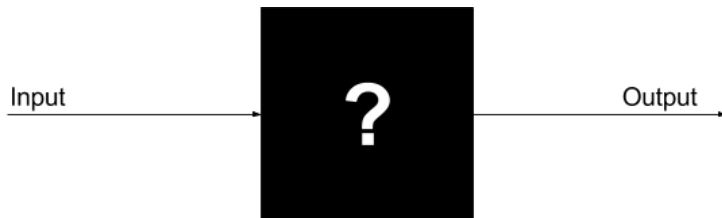
Opening The Black Box

COMP 489 Project

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Introduction + Motivation



Difficult to interpret Artificial Neural Networks using standard activations, e.g., Sigmoid, TanH.

Why Interpretable Systems?

- Safety Critical Systems
- Ensuring systems make Ethical decisions
- European Union General Data Protection Regulation

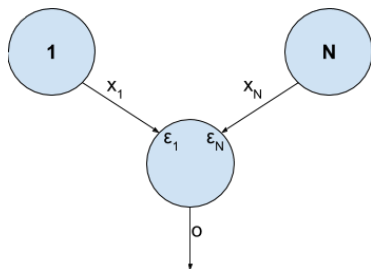
Problem Statement

Want ANNs which not only achieve high accuracy but have logic that can be defended.

Idea

- Some problems appear to have a logic decomposition
- Logical functions are easy for humans to interpret
- **Goal:** Learn these logical decompositions using backpropagation
- **Problem:** Standard Boolean Logic Gates are not continuous.

Noisy Neurons



- They represent a continuous parameterisation of discrete logic gates.
- x_i is probability the i 'th input is on.
- ϵ_i is the probability that input i is irrelevant. The ϵ 's are the learned weights
- There exists Noisy-AND and Noisy-OR Neurons.

Approach: Logical Neural Networks

Logical Neural Networks have layers consisting of Noisy Neurons. Can be trained with backpropagation.

Problem: Weight Initialization

- Even small networks wouldn't train.
- Derived a distribution from which to sample weights.
- Now large networks can be trained, including deep Logical Networks. Up-to 10 layers deep!

Experimental Approach

- Want to evaluate accuracy and performance of Logical Neural Networks
- Will use MNIST problem.
- **Performance:** Networks trained from 30 different initial conditions, performance compared using confidence intervals from evaluation of network on testing set.
- **Interpretability:** Difficult to establish. Results are obtained by visually comparing interpretations of the weights from different networks.

Experimental Results: Performance

- Logical Neural Networks have statistically equivalent performance to Multi-Layer Perceptron Networks.

Experimental Results: Interpretability

- Logical Neural Networks are potentially more interpretable than Multi-Layer Perceptron Networks.
- Interpretability of Logical Neural Networks depends on activations used.

Experimental Results: Interpretability - No Hidden

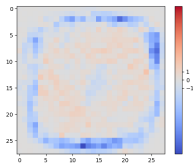


Figure: Features for a perceptron network

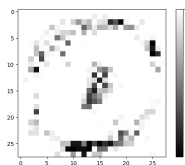
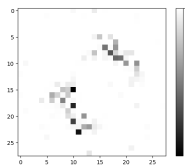


Figure: Features for a logical neural network using an AND activation

Experimental Results: Interpretability - Hidden Layers

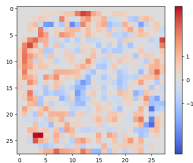


Figure: Features that positively contribute to the classification as a 1.

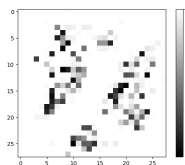
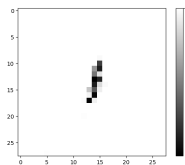


Figure: Features contributing to classification of a 1 in an AND
→ OR Model

Conclusion

Did we succeed in solving the problem? Well... Yes and No

- Logical Neural Networks are a promising alternative to Multi-Layer Perceptron Networks.
- Interpretability on MNIST was "better". But again, difficult to establish.
- Was found that interpreting Logical Neural Networks became difficult with multiple layers.

Questions