Rule induction for global explanation of neural nets

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EXISTING APPROACHES

Existing techniques for interpreting DNN in NLP:

- Input deletion
- Gradient computation
- Layerwise relevance propagation (LRP)
- Backpropagation using reference value (DeepLIFT)





• Learning explanation models: LIME, SHAP Attention weights



Open question:

How do we find the feature interactions that have been learned by a model for a certain class?

PROPOSED TECHNIQUE AND RESULTS: INDUCING RULES FOR INTERPRETING NEURAL NETS



Learned Rules (unordered):

government = high and launch = absent and medical = absent and nasa = absent \rightarrow Cryptography (\checkmark 45/46)

Text classification: medicine vs. space vs. electronics vs. cryptography (20 newsgroups data)

Reweigh input features with their saliency scores in the network

Product of feature values and saliency scores

Select top reweighed features

Sensitivity Analysis / Mutual Information

Simplify the selected reweighed features to sign Provides correlations b/w feature values and predicted output probabilities

+1: positive correlation (high feature value: high prob.)

-1: negative correlation (low feature value: high prob.) 0: absent feature value

Induce if-then-else rules using RIPPER-k on the

Primary diagnostic category and in-hospital mortality prediction using EHR notes (MIMIC-III corpus)

Take blood pressure (treatment) = high and Nothing by mouth = absent and **Coronary heart disease = high and** Flagyl = absent

 \rightarrow Diseases of the circulatory system (\checkmark 84/90)

Dilantin = high and Thalamus, posterior lateral nucleus = high \rightarrow Diseases of the nervous system (\checkmark 5/6)

correlation data to fit neural classifier predictions (one-vs-rest)

Feature-class associations that explain model predictions

Results:

• Rule fidelity score to explain neural predictions: • 0.8 macro F1, high precision, lower recall. Interdependence between features plays an important role for classification.

Pneumonia = high and Lung opacity = high and Non-specific ST-T changes by ECG = low and CT of pelvis w/o contrast = absent \rightarrow Diseases of the respiratory system (\checkmark 7/7)

Physical examination = high and Pregnancy with medical condition = high \rightarrow Dies within hospital (\checkmark 221/222)

Code available at: http://github.com/clips/interpret_with_rules/