





Interpreting neural network models for toxicity prediction by extracting learned chemical features

30/06/2022 Moritz Walter

Strasbourg Summer School in Chemoinformatics 2022





Chemical feature visualisation



- ANN/DNN model: hidden layer neurons learn representation of data suitable to solve supervised task (classification/regression)
- Aim: find chemical features detected in neurons





Chemical feature visualisation

Modelled endpoint: mutagenicity



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Automatic substructure extraction



- FCA (Formal Concept Analysis) identifies combinations of compounds and FP bits (formal concepts)
- From those chemical substructures are extracted if associated with neuron activation





From substructures to atom attributions

- 1 Determine importance of neuron for individual prediction
 - Integrated gradients (IG) on hidden neurons



Neuron IG attributions:

0.32 - 0.22 - -0.12 - 0.42 - 0.07



Prediction: 0.91





From substructures to atom attributions

2 Map neuron importances onto structure:

- Find most specific matching substructure(s) in trees
- Share attribution between atoms of substructure



Integrated gradients on input features as comparison¹

1 Preuer et al. 2019: Interpretable deep learning in drug discovery





Neural network model

- Dataset on Ames mutagenicity (~8k)
 - Hansen (curated), ISSSTY, ECVAM, CGX, Snyder
- Derek expert system used to label compounds (structural alerts for mutagenicity)
- Model architecture: 1 hidden layer (512 neurons)
- Input: Morgan FP (radius=1, 2048 bits)
- High performance on test set: ACC: 0.91, ROC-AUC: 0.97, Recall: 0.91, Precision: 0.92





Evaluation

- Individual compounds: attribution AUCs for TP compounds
- Alerts: compute average AUCs for compounds matching a given alert





Explanatory performance

	Median AUC	AUC ≥0.8
IG input	0.964	255/306
IG hidden neurons	0.935	227/306









Alert performances

	Median AUC	AUC ≥0.8
IG input	0.894	36/52
IG hidden	0.903	37/52



IG input





Individual compounds

Derek Alert



Arom. nitro



AUC = 1

Contributing to toxic prediction Contributing to non-toxic prediction



Isocyanate

AUC = 1

IG hidden



AUC = 0.83

AUC = 0.5





Individual compounds

Derek Alert



IG input

IG hidden





Quinolone-3-carboxylic acid

AUC = 0.577

AUC = 0.988







Hydroxylated anthraquinone

AUC = 0.8

AUC = 1





Conclusion

- Method to visualize chemical features learned in hidden layers
- Extracted fragments can be used to interpret neural network model
- Method limited by quality of extracted fragments
- Different explanation methods have strengths and weaknesses
- \rightarrow Benchmarking required





Acknowledgement





Prof. Dr. Val Gillet

Dr. Sam Webb





- Determines importance of each input feature for given prediction
- Integration of gradients (of model output wrt feature) along straight path between baseline (bit vector of 0s) and instance

$$a_i(x) = (x_i - x'_i) \int_{a=0}^{1} \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$

Integral approximated using a sum:

$$a_i(x) \approx (x_i - x'_i) \sum_{k=1}^m \frac{\partial F(x' + \frac{k}{m} \times (x - x'))}{\partial x_i} \times \frac{1}{m}$$

 a_i : attribution for feature i x_i : feature i x'_i : feature i in baseline (0) F: NN model x_i : feature i α : path x' -> x m: number of steps k: current step





Alert performances

Alert	Proportion train set	IG input	IG hidden neurons
Aromatic nitro	0.130	0.983	0.908
Alkylating agent	0.058	0.900	0.918
PAHs	0.043	0.764	0.540
Epoxide	0.033	0.974	0.912
N-Nitroso	0.029	0.980	0.950
Isocyanate	0.002	1	0.5
Aromatic nitroso	0.007	1	0.711
Hydrox. anthraquinone	0.007	0.63	0.758
Quinolone-3-carboxylic acid	0.003	0.674	0.992





Negative prediction



Taken from model trained on experimental Ames labels Prediction: 0.41 Label: negative



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