

Applications of multi-class machine learning models to drug design

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Overview

Applications of multi-class machine learning models to ADMET

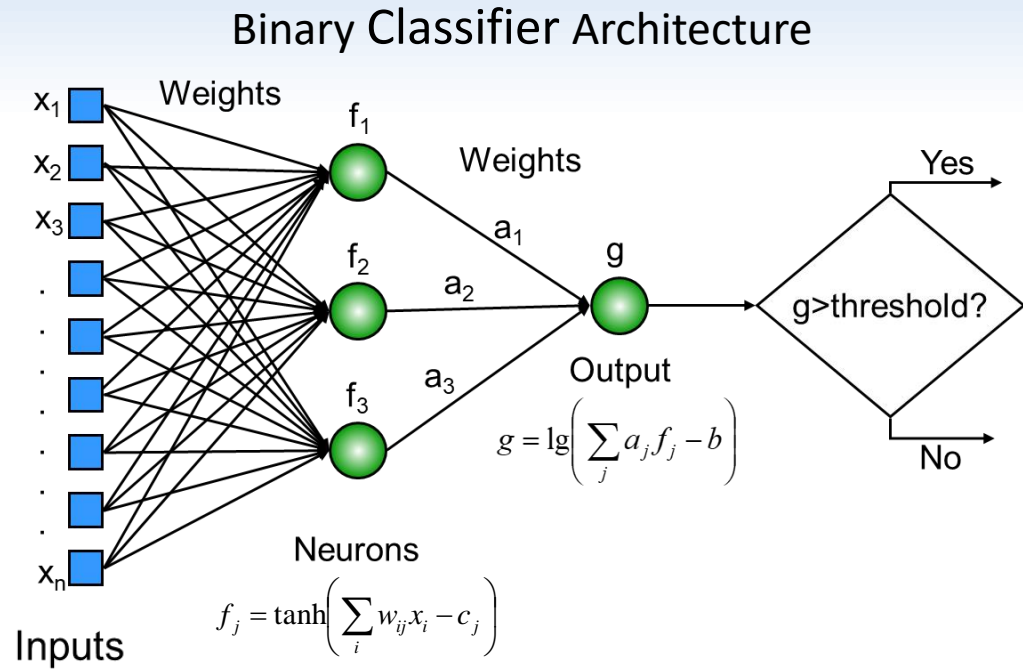
- Motivation
- Approaches/Methodology
- Application
- Comparison
- Summary/Conclusions

Motivation

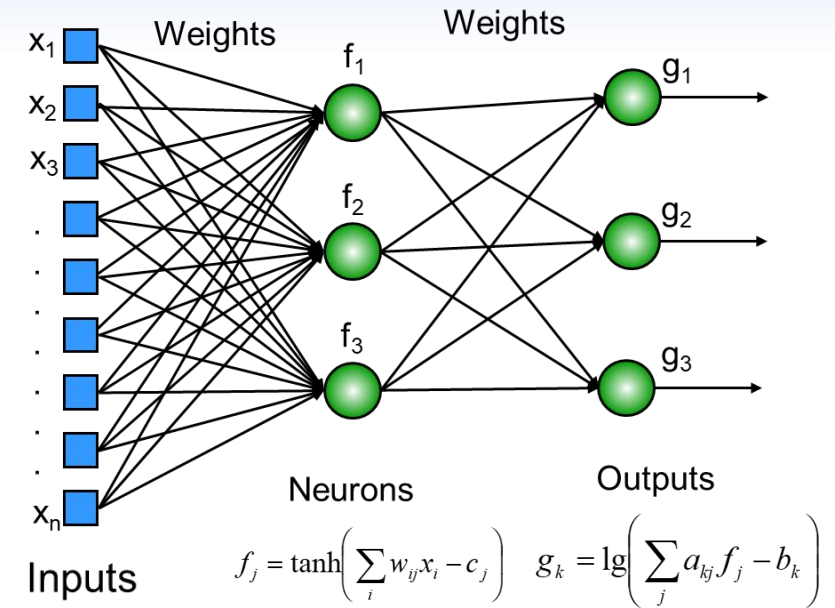
- Until recently, machine learning classification models in Cheminformatics literature have generally modeled binary endpoints (active/inactive, substrate/non-substrate, toxic/non-toxic, etc.)
- Recent examples of multi-class models and/or endpoints relevant to drug discovery
 - Mode of Action of 220 phenols in *T. pyriformis* toxicity assay (4 class decision tree model)
 - Schüürmann et al, Chem Res Tox, **16**, 974 (2003)
 - Extended Clearance Classification System
 - Predicts 1 of 3 dominant clearance mechanisms via a 6 class decision tree scheme
 - Varma et al, Pharm Res, **32**, 3785 (2015) and subsequent publications
 - Acute Rat Toxicity based on LD50
 - GHS (Globally Harmonized System of Classification and Labelling of Chemicals)
 - 5 toxic classes
 - https://en.wikipedia.org/wiki/Globally_Harmonized_System_of_Classification_and_Labelling_of_Chemicals
 - EPA uses 4 toxicity classes derived from essentially the same data
 - https://en.wikipedia.org/wiki/Toxicity_category_rating
 - AMES Mutagenicity
 - NIHS Japan uses 3 categories, strongly positive, positive, negative

Approach

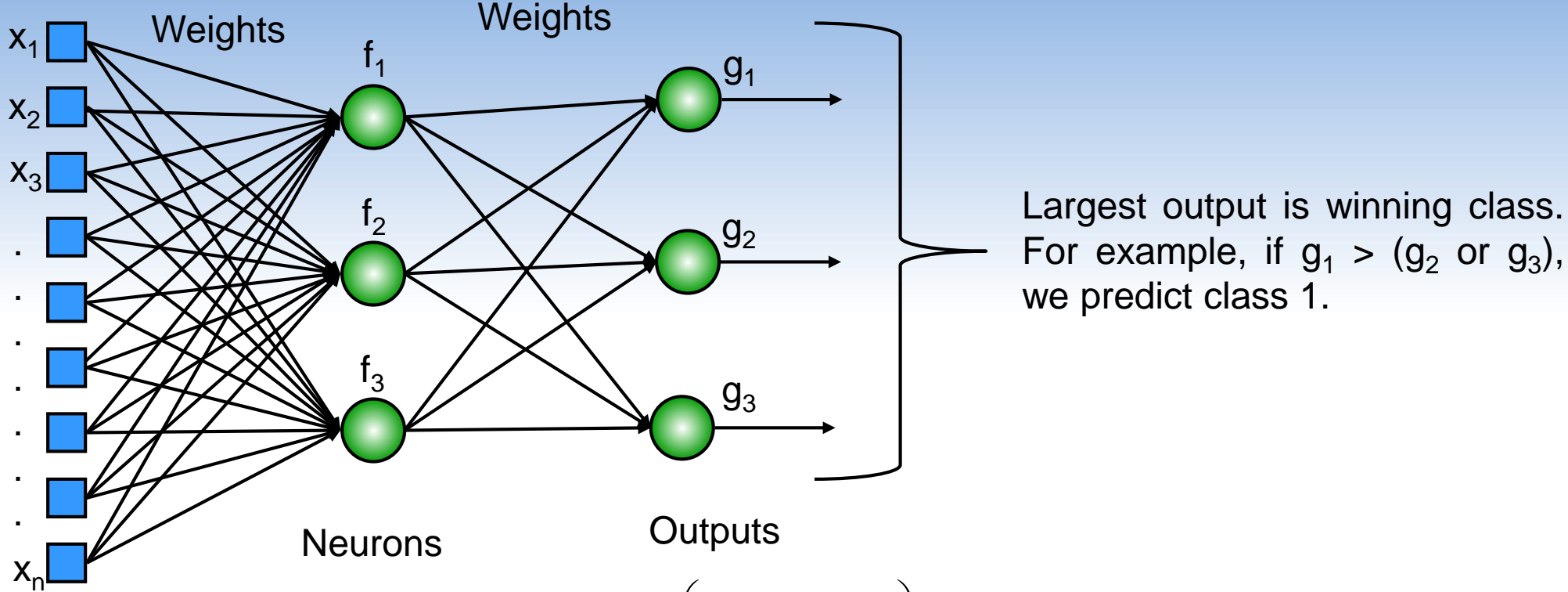
- Extend the machine learning algorithms of ADMET Modeler™ and ADMET Predictor™ to train and deploy Artificial Neural Network Ensemble (ANNE) models for predicting multi-class endpoints



Multi-Class Architecture



Multi-Classifer ANN Architecture - Deployment



Largest output is winning class. For example, if $g_1 > (g_2 \text{ or } g_3)$, we predict class 1.

Inputs $f_j = \tanh\left(\sum_i w_{ij}x_i - c_j\right)$ $g_k = \text{lg}\left(\sum_j a_{kj}f_j - b_k\right)$ ← Logistic Output

Weights optimized to improve training set model performance

Multi-Class ANN Objective Function - Training

- Let g_{ij} be the i 'th output for observation j of the training set. Let observation j belong to class k . Let the number of observations in class k be N_k . Let the number of classes be K . Then:

$$F = \sum_{k=1}^K \left\{ \frac{1}{N_k} \sum_{j \in k} \left[(1 - g_{kj})^2 + \sum_{i \neq k} g_{ij}^2 \right] \right\}$$

Squared Error Loss

↑
Sum over classes

↑
Sum over Observations in class k

↑
Output of correct class should approach 1

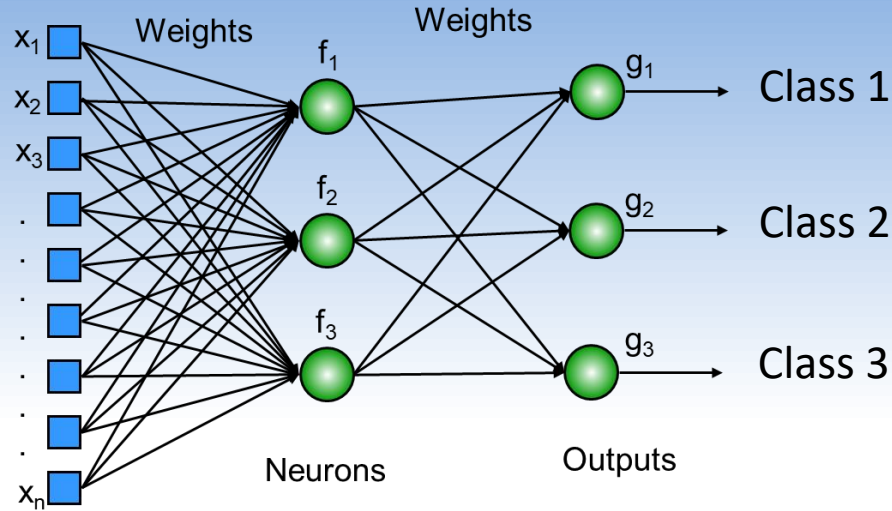
↑
Outputs of incorrect classes should approach 0

Combining Individual Network Predictions

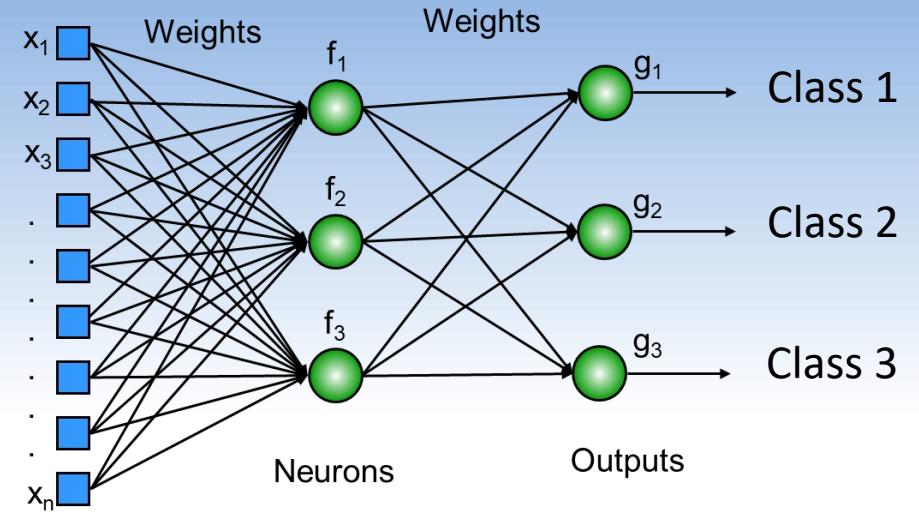
- Averaging

$$G_i = \frac{1}{N_{nets}} \sum_{j=1}^{N_{nets}} g_{ij}$$

Largest G_i is winning class



Network 1



Network 2

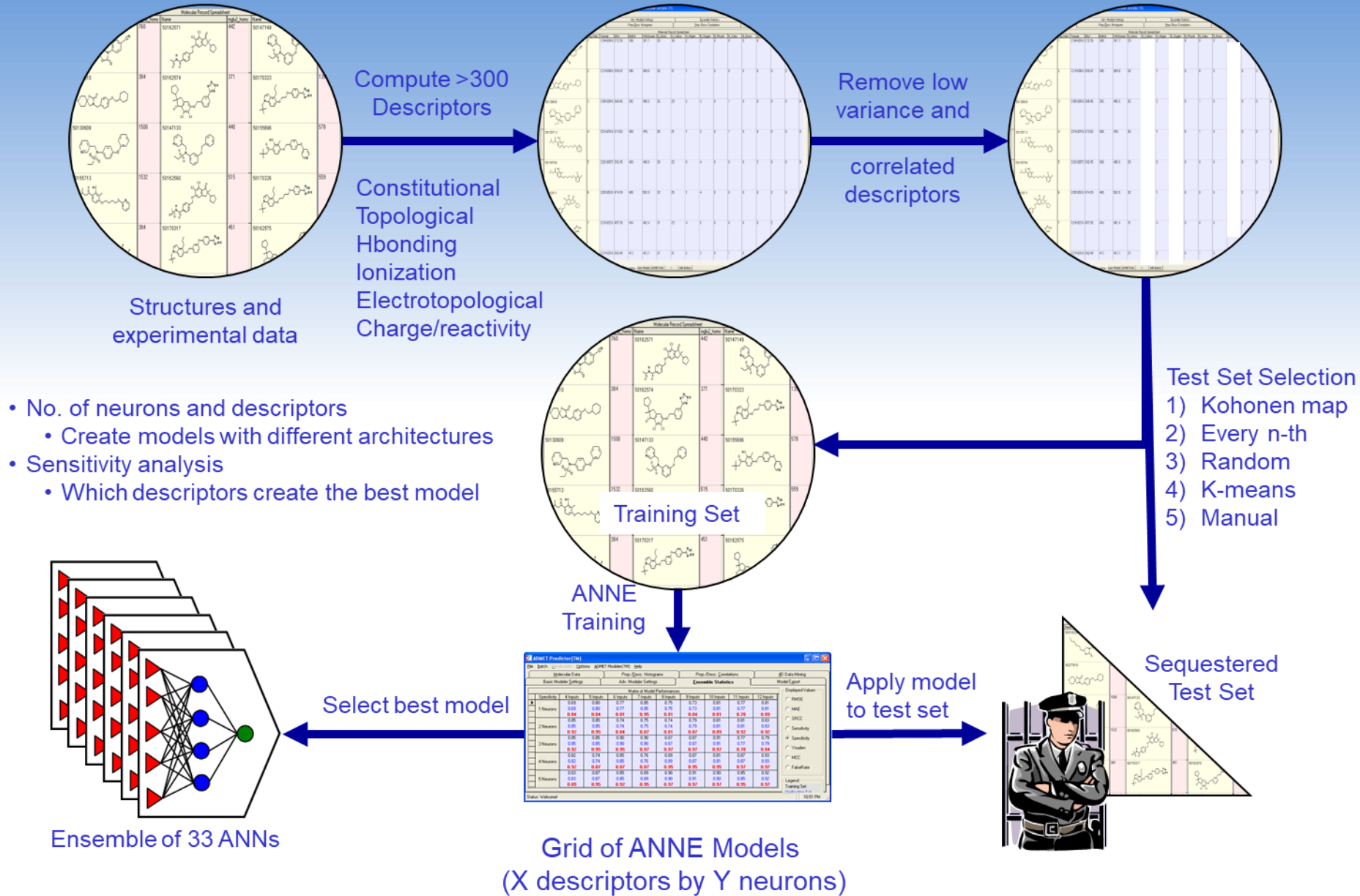
- Voting

- Plurality with elimination (also known as instant runoff voting)
 - https://en.wikipedia.org/wiki/Instant-runoff_voting

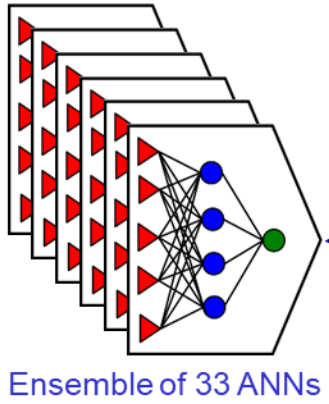
Some Alternative ANN Approaches

- Softmax Output
 - https://en.wikipedia.org/wiki/Softmax_function
- Cross-Entropy Loss function
 - https://en.wikipedia.org/wiki/Cross_entropy
- Did not offer any improvement over logistic output and squared error loss on data sets we investigated

Model Building - Overview



- No. of neurons and descriptors
 - Create models with different architectures
- Sensitivity analysis
 - Which descriptors create the best model

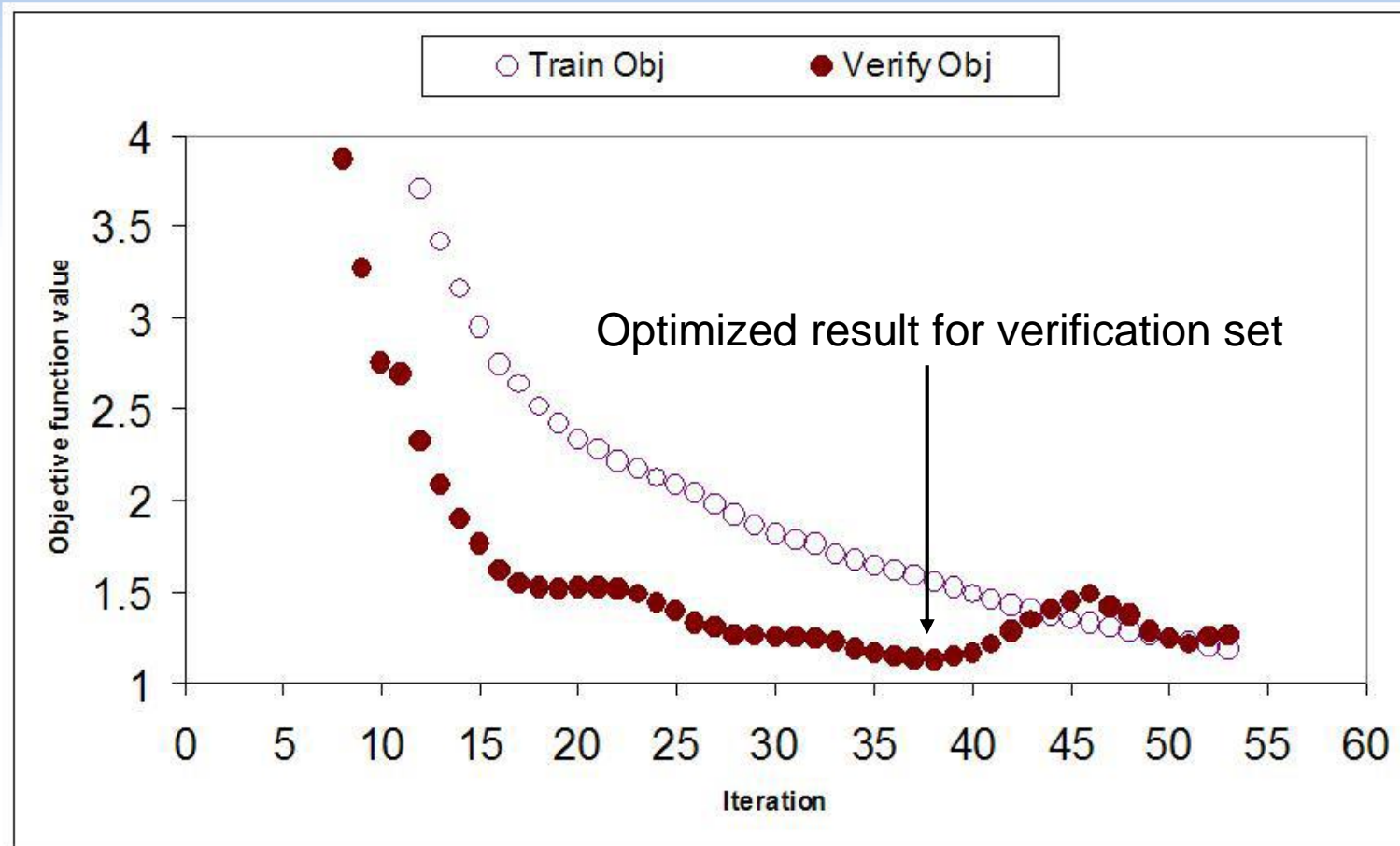


| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
|-------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Specificity | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| Sensitivity | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| AUC | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| RMSE | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| MAE | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

Grid of ANNE Models
(X descriptors by Y neurons)

Early Stopping Avoids Overtraining

1. Split training set into training and verification sets
2. Optimize network weights to improve training set performance
3. Monitor performance of verification set – determines stopping point



Some Metrics for Two-Class models

- Accuracy

$$Acc = N_{correct} / N_{total}$$

- Matthews Correlation Coefficient (perfect = 1, random = 0, worst = -1)
 - Matthews, *Biochem Biophys Acta*, **405**, 442, (1975)

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

- Youden's Index (perfect = 1, random = 0, worst = -1)
 - Youden, *Cancer*, **3**, 32 (1950)

$$Y = \frac{TP}{TP + FN} + \frac{TN}{TN + FP} = \text{sensitivity} + \text{specificity} - 1$$

$$\text{Note: Balanced Accuracy (BA)} = \frac{Y + 1}{2}$$

Some Metrics for Multi-Class models

- Accuracy

$$Acc = N_{correct}/N_{total}$$

- Generalized Matthews Correlation Coefficient (perfect = 1, random = 0)
 - Gorodkin, Comp. Biol. Chem., **28**, 367 (2004)

$$MCC = \frac{N_{tot}N_{corr} - \sum o_k p_k}{\sqrt{(N_{tot}^2 - \sum o_k o_k)(N_{tot}^2 - \sum p_k p_k)}}$$

o_k, p_k : Number observed, predicted in class k

- Generalized Youden's Index (perfect = 1, random = 0)

$$Y = \frac{N_{tot}N_{corr} - \sum o_k p_k}{N_{tot}^2 - \sum o_k o_k}$$

Evaluate Performance of ANNE Models

ADMET Modeler(TM): EPACat_Avg_TS1_IG.dat (D:/Marv/Documents/AllMyData/Presentations/ACS-Fall2018/EPACat_Avg_TS1_IG)

File Edit View Tools Help

| Model Performance Grid | | | | | | | | | | | | | | | | |
|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------------|------------|--|
| Youden | 14 Inputs | 21 Inputs | 28 Inputs | 35 Inputs | 42 Inputs | 49 Inputs | 56 Inputs | 63 Inputs | 70 Inputs | 77 Inputs | 84 Inputs | 91 Inputs | 98 Inputs | 105 Inputs | 112 Inputs | |
| 3 Neurons | 0.32 | 0.33 | 0.33 | 0.33 | 0.33 | 0.34 | 0.34 | 0.34 | 0.37 | 0.36 | 0.36 | 0.35 | 0.35 | 0.36 | 0.35 | |
| 4 Neurons | 0.34 | 0.34 | 0.33 | 0.36 | 0.35 | 0.36 | 0.36 | 0.35 | 0.36 | 0.36 | 0.37 | 0.37 | 0.36 | 0.36 | 0.37 | |
| 5 Neurons | 0.33 | 0.35 | 0.35 | 0.34 | 0.35 | 0.38 | 0.36 | 0.38 | 0.37 | 0.38 | 0.38 | 0.37 | 0.38 | 0.36 | 0.36 | |
| 6 Neurons | 0.33 | 0.34 | 0.35 | 0.35 | 0.37 | 0.38 | 0.39 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.36 | |
| 7 Neurons | 0.34 | 0.34 | 0.35 | 0.36 | 0.39 | 0.39 | 0.37 | 0.38 | 0.38 | 0.37 | 0.38 | 0.37 | 0.38 | 0.36 | 0.37 | |
| 8 Neurons | 0.34 | 0.34 | 0.36 | 0.37 | 0.38 | 0.38 | 0.37 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | |
| 9 Neurons | 0.34 | 0.35 | 0.35 | 0.36 | 0.38 | 0.38 | 0.38 | 0.39 | 0.39 | 0.39 | 0.37 | 0.37 | 0.38 | 0.37 | 0.38 | |
| 10 Neurons | 0.35 | 0.35 | 0.36 | 0.37 | 0.38 | 0.39 | 0.38 | 0.38 | 0.37 | 0.38 | 0.38 | 0.37 | 0.38 | 0.38 | 0.38 | |
| 11 Neurons | 0.34 | 0.34 | 0.35 | 0.37 | 0.38 | 0.38 | 0.38 | 0.38 | 0.39 | 0.38 | 0.37 | 0.39 | 0.38 | 0.38 | 0.38 | |
| 12 Neurons | 0.34 | 0.35 | 0.35 | 0.36 | 0.37 | 0.38 | 0.38 | 0.40 | 0.38 | 0.39 | 0.38 | 0.39 | 0.38 | 0.38 | 0.38 | |

Metric

- Sensitivity
- Specificity
- Youden
- MCC
- Min Confidence
- False Rate

Legend

- Train
- Verify
- Test

Good Best

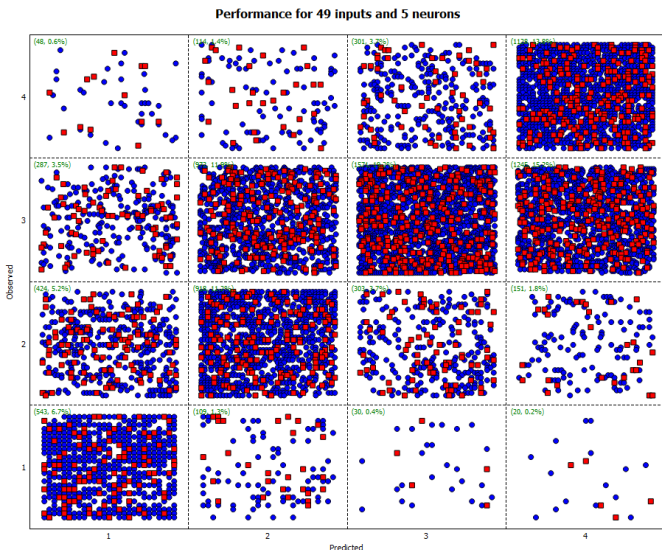
STOP Process

View Log File

Model Settings

Save project

8164 observations



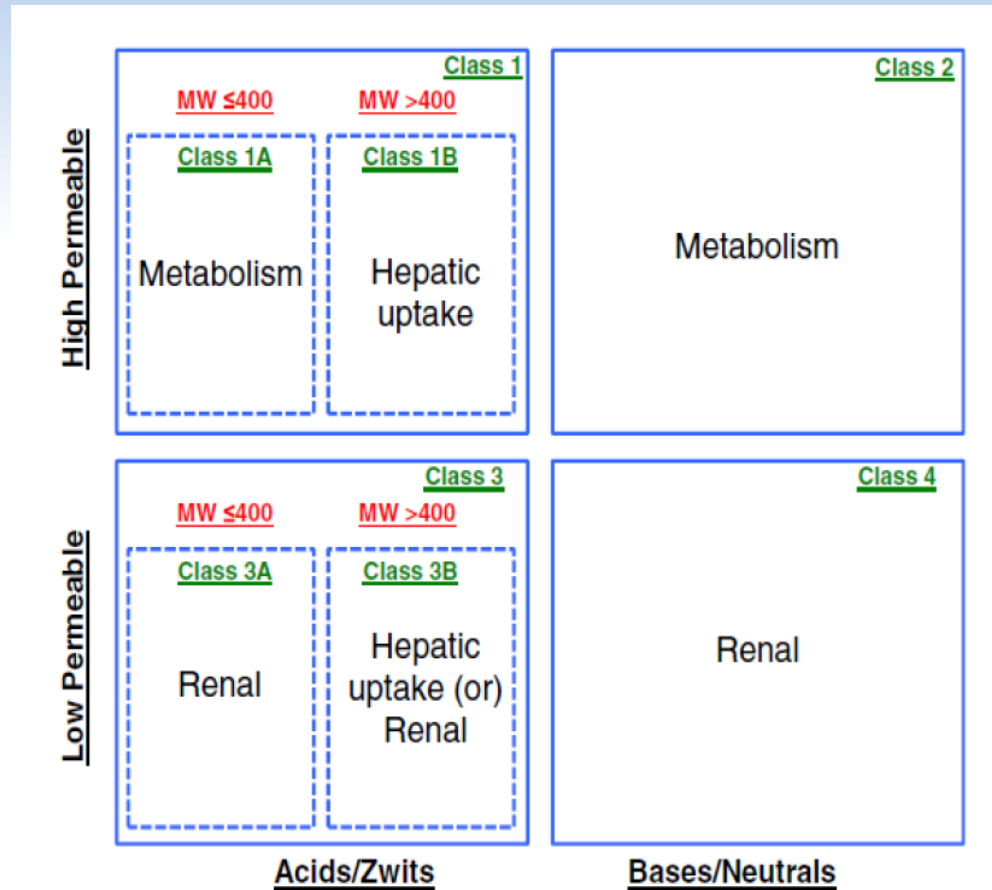
ALL: Youden=0.370 MCC=0.350 False Rate=0.490
 TRAIN: Youden=0.383 MCC=0.362 False Rate=0.481
 TEST: Youden=0.319 MCC=0.300 False Rate=0.529

Data Sets

- Dominant Clearance Mechanism
 - Compare to ECCS scheme (Extended Clearance Classification System)
- Acute Rat Toxicity Class
 - Based on LD50 cutoffs
 - 4 class scheme used by EPA
 - 5 class scheme used by GHS (Globally Harmonized System)
 - https://en.wikipedia.org/wiki/Globally_Harmonized_System_of_Classification_and_Labeling_of_Chemicals
- AMES Mutagenicity (provided by NIHS Japan)
 - 3 class model (strongly positive, positive, negative)

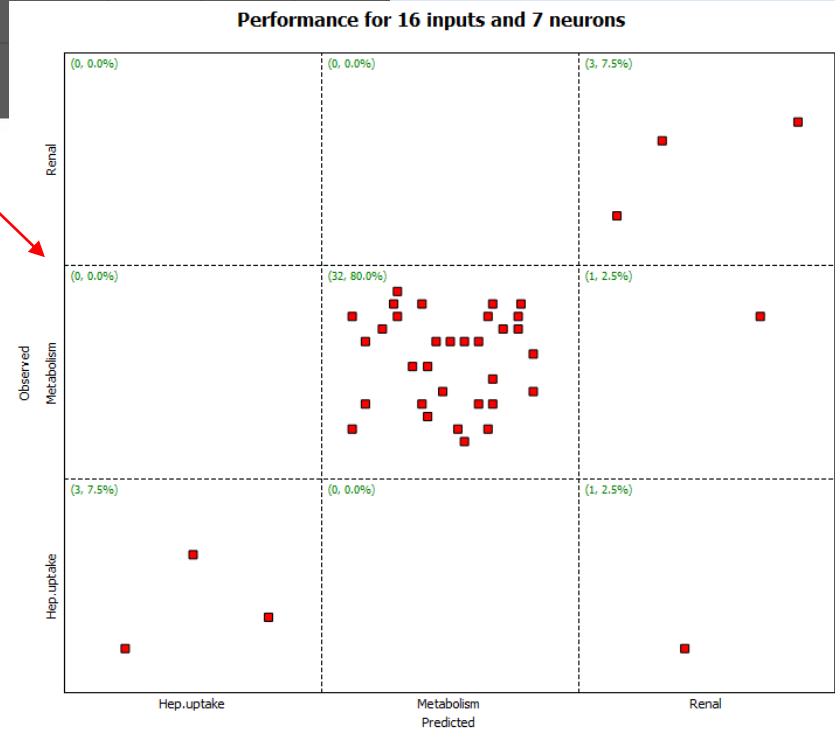
Extended Clearance Classification System

- Predicts dominant clearance mechanism of drugs
 - Varma et al, Pharm Res, 32, 3785 (2015) and subsequent publications
 - ~300 compounds

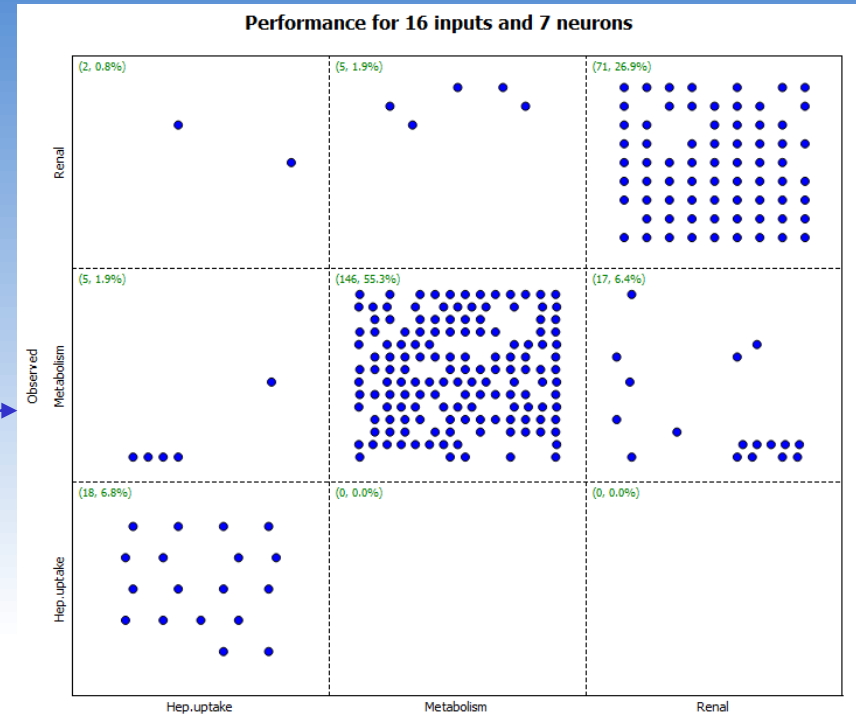


ECCS – ANNE Model

| Model Performance Grid | | | | | | | | | | | |
|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Youden | 10 Inputs | 12 Inputs | 14 Inputs | 16 Inputs | 18 Inputs | 20 Inputs | 22 Inputs | 24 Inputs | 26 Inputs | 28 Inputs | 30 Inputs |
| 3 Neurons | 0.76 | 0.78 | 0.82 | 0.83 | 0.83 | 0.80 | 0.80 | 0.82 | 0.81 | 0.81 | 0.81 |
| | 0.79 | 0.83 | 0.79 | 0.81 | 0.79 | 0.79 | 0.81 | 0.81 | 0.90 | 0.81 | 0.81 |
| 5 Neurons | 0.78 | 0.79 | 0.82 | 0.83 | 0.82 | 0.82 | 0.83 | 0.83 | 0.84 | 0.81 | 0.81 |
| | 0.85 | 0.83 | 0.77 | 0.88 | 0.88 | 0.86 | 0.90 | 0.90 | 0.90 | 0.90 | 0.90 |
| 7 Neurons | 0.81 | 0.80 | 0.81 | 0.84 | 0.80 | 0.80 | 0.80 | 0.80 | 0.81 | 0.80 | |
| | 0.90 | 0.81 | 0.90 | 0.90 | 0.81 | 0.81 | 0.79 | 0.79 | 0.79 | 0.79 | |
| 9 Neurons | 0.82 | 0.82 | 0.80 | 0.81 | 0.81 | | | | | | |
| | 0.88 | 0.79 | 0.88 | 0.88 | 0.79 | 0.86 | | | | | |
| 11 Neurons | 0.71 | 0.71 | 0.77 | 0.78 | | | | | | | |
| | 0.51 | 0.61 | 0.77 | 0.77 | | | | | | | |



Test Set



Training Set

ECCS Comparisons

| Statistic | ECCS | ANNE-Train | ANNE-Test | ANNE-All | SVME-Train | SVME-Test | SVME-All |
|-----------|------|------------|-----------|----------|------------|-----------|----------|
| Youden | 0.83 | 0.84 | 0.90 | 0.85 | 0.98 | 0.90 | 0.97 |
| MCC | 0.82 | 0.80 | 0.85 | 0.81 | 0.98 | 0.85 | 0.97 |
| Accuracy | 91% | 89% | 95% | 90% | 99% | 95% | 99% |

ECCS : Benefit of the doubt for Class 3B (Hep. Uptake or Renal)

ANNE Model: 7 neurons, 16 descriptors

Descriptors selected by Input Gradient method

Some Key Descriptors: FAnion, S+logP, FZwitter, QAvgNeg, QAvgPos

SVME Model: 23 Descriptors selected by Genetic Algorithm

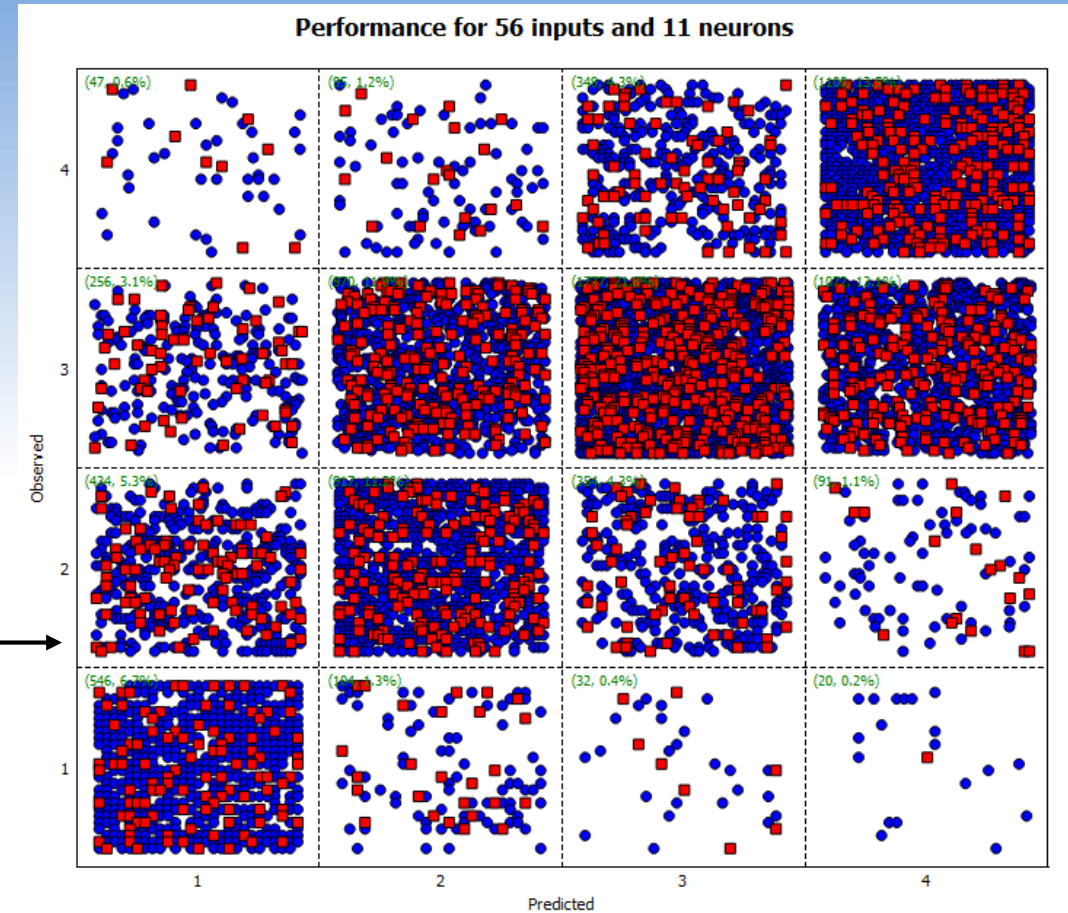
Some Key Descriptors: S+logP, No. Pi systems, T_Dipole, E-states, No. acidic atoms

Multi-Class Toxicity Models

- Workshop on Predictive Models for Acute Oral Systemic Toxicity (April 2018)
 - Sponsor: National Toxicology Program Interagency Center for the Evaluation of Alternative Toxicological Methods (NICEATM)
 - <https://ntp.niehs.nih.gov/pubhealth/evalatm/3rs-meetings/past-meetings/tox-models-2018/index.html>
 - Various toxicity data sets available to develop *in silico* models and present at workshop
 - 2 Multi-class toxicity datasets were included
 - Both based on acute rat LD50 data with cutoffs
 - 4 Category model using cutoffs based on EPA guidelines
 - Category 1 : $LD50 \leq 50$ mg/kg
 - Category 2 : $50 \text{ mg/kg} < LD50 \leq 500$ mg/kg
 - Category 3 : $500 \text{ mg/kg} < LD50 \leq 5000$ mg/kg
 - Category 4 : $LD50 > 5000$ mg/kg
 - 5 Category model using cutoffs based on GHS guidelines
 - Category 1 : $LD50 \leq 5$ mg/kg
 - Category 2 : $5 \text{ mg/kg} < LD50 \leq 50$ mg/kg
 - Category 3 : $50 \text{ mg/kg} < LD50 \leq 300$ mg/kg
 - Category 4 : $300 \text{ mg/kg} < LD50 \leq 2000$ mg/kg
 - Category 5 : $LD50 > 2000$ mg/kg
 - ~8000 compounds in each data set
 - ~4000 blind compounds for prediction

EPA 4 Class ANNE Model Performance

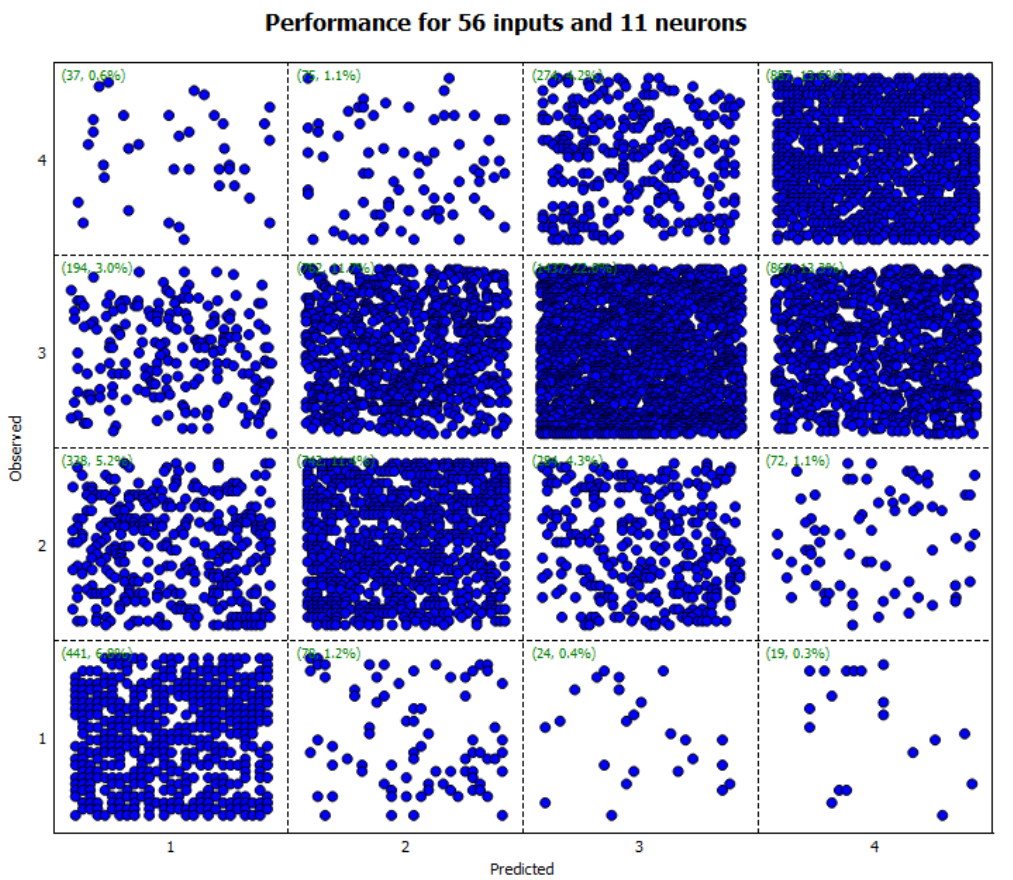
| Model Performance Grid | | | | | | | | | | | | | | | |
|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------------|------------|
| Youden | 14 Inputs | 21 Inputs | 28 Inputs | 35 Inputs | 42 Inputs | 49 Inputs | 56 Inputs | 63 Inputs | 70 Inputs | 77 Inputs | 84 Inputs | 91 Inputs | 98 Inputs | 105 Inputs | 112 Inputs |
| 3 Neurons | 0.32 | 0.33 | 0.34 | 0.34 | 0.35 | 0.34 | 0.35 | 0.35 | 0.35 | 0.36 | 0.35 | 0.35 | 0.35 | 0.36 | 0.36 |
| 4 Neurons | 0.33 | 0.34 | 0.34 | 0.34 | 0.35 | 0.35 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.37 | 0.36 | 0.36 | 0.36 |
| 5 Neurons | 0.33 | 0.35 | 0.35 | 0.36 | 0.37 | 0.37 | 0.36 | 0.37 | 0.38 | 0.37 | 0.37 | 0.37 | 0.38 | 0.37 | 0.37 |
| 6 Neurons | 0.33 | 0.36 | 0.36 | 0.35 | 0.36 | 0.37 | 0.38 | 0.38 | 0.38 | 0.37 | 0.37 | 0.38 | 0.38 | 0.37 | 0.38 |
| 7 Neurons | 0.34 | 0.36 | 0.36 | 0.36 | 0.37 | 0.37 | 0.38 | 0.38 | 0.38 | 0.38 | 0.39 | 0.38 | 0.38 | 0.38 | 0.38 |
| 8 Neurons | 0.34 | 0.36 | 0.36 | 0.36 | 0.38 | 0.38 | 0.38 | 0.38 | 0.39 | 0.39 | 0.39 | 0.38 | 0.39 | 0.38 | 0.38 |
| 9 Neurons | 0.35 | 0.37 | 0.37 | 0.36 | 0.38 | 0.38 | 0.39 | 0.39 | 0.40 | 0.39 | 0.39 | 0.40 | 0.39 | 0.39 | 0.40 |
| 10 Neurons | 0.35 | 0.36 | 0.36 | 0.37 | 0.38 | 0.38 | 0.39 | 0.39 | 0.39 | 0.40 | 0.40 | 0.40 | 0.40 | 0.39 | 0.40 |
| 11 Neurons | 0.35 | 0.37 | 0.36 | 0.37 | 0.39 | 0.38 | 0.39 | 0.39 | 0.40 | 0.40 | 0.39 | 0.40 | 0.39 | 0.40 | 0.39 |
| 12 Neurons | 0.35 | 0.37 | 0.36 | 0.37 | 0.39 | 0.40 | 0.39 | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 |



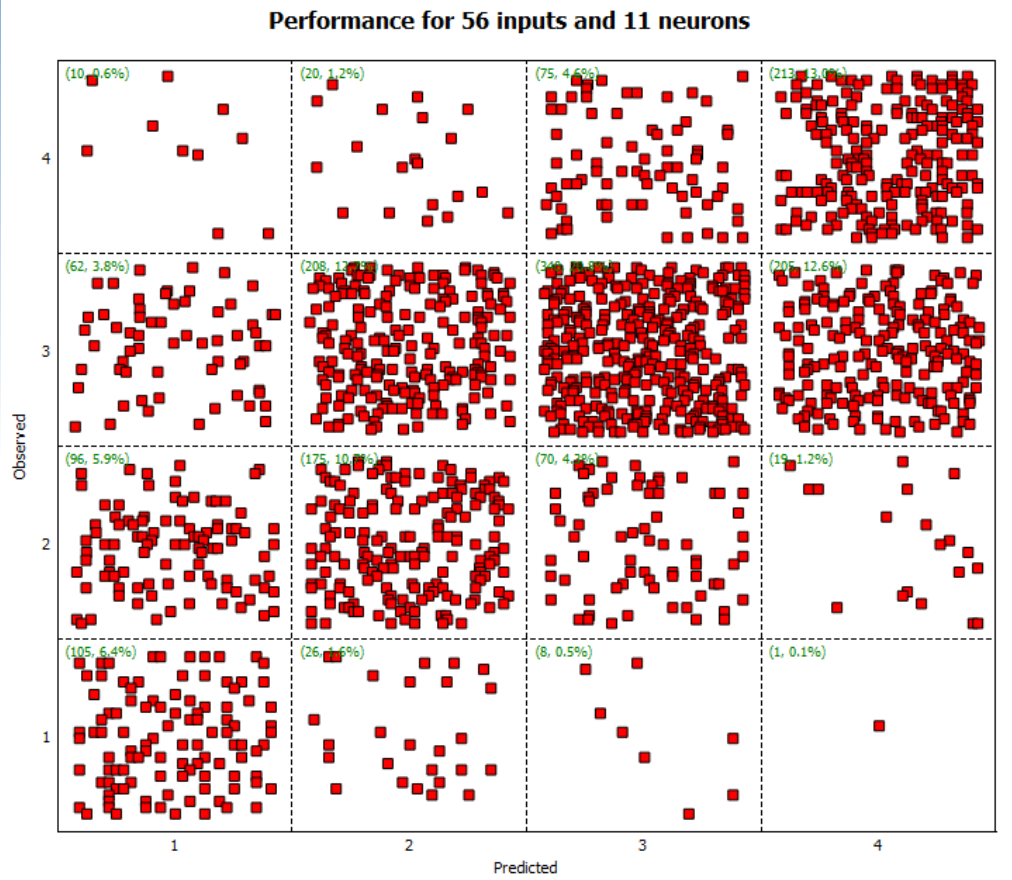
Training time for entire grid : ~3.5 hours

Descriptors: Standard + ANNE regression model of LD50 using NICEATM data

EPA 4 Class ANNE Model Performance



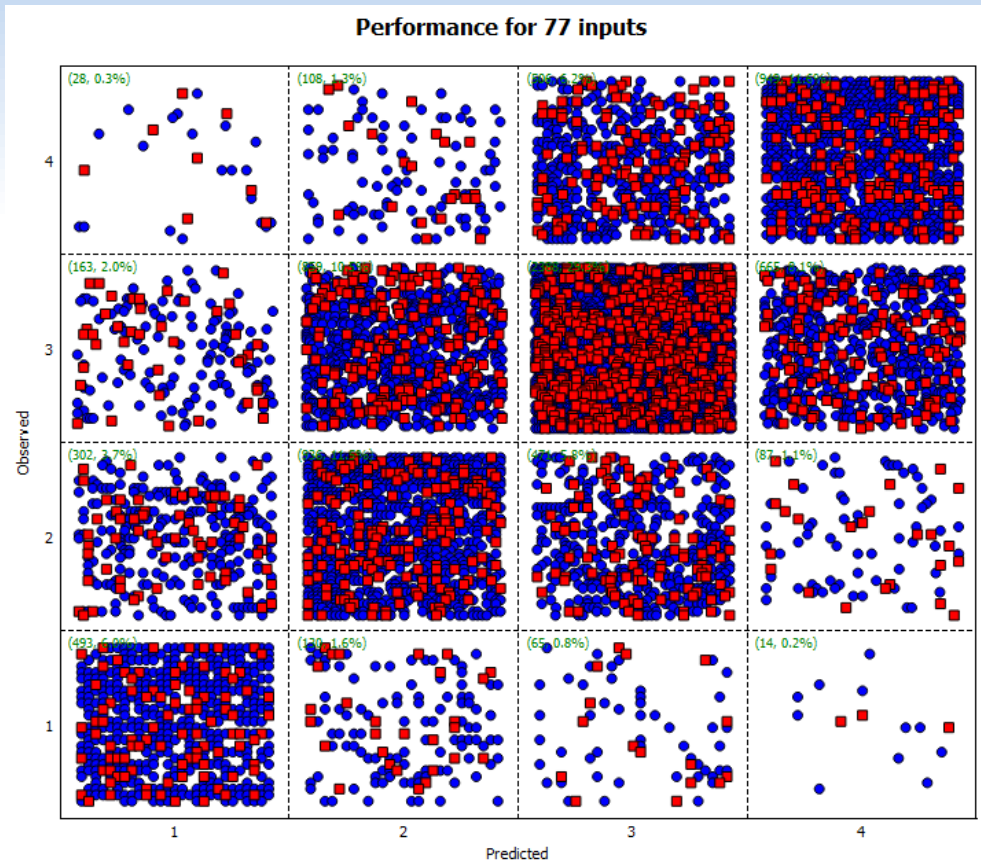
Training Set



Test Set

SVM Model Performance

| Model Performance Grid | | | | | | | | | | | | | | | |
|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------------|------------|
| Youden | 14 Inputs | 21 Inputs | 28 Inputs | 35 Inputs | 42 Inputs | 49 Inputs | 56 Inputs | 63 Inputs | 70 Inputs | 77 Inputs | 84 Inputs | 91 Inputs | 98 Inputs | 105 Inputs | 112 Inputs |
| CSVM | 0.34 | 0.36 | 0.39 | 0.40 | 0.41 | 0.40 | 0.42 | 0.41 | 0.40 | 0.42 | 0.43 | 0.42 | 0.45 | 0.45 | 0.47 |
| | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| | 0.30 | 0.29 | 0.28 | 0.31 | 0.32 | 0.30 | 0.32 | 0.33 | 0.33 | 0.34 | 0.32 | 0.33 | 0.32 | 0.31 | 0.33 |



Training time: ~11 hours

EPA 4 Class Model Performance

ANNE Training Set

| Obs/Pred | 1 | 2 | 3 | 4 |
|----------|-----|-----|------|-----|
| 1 | 441 | 78 | 24 | 19 |
| 2 | 338 | 742 | 284 | 72 |
| 3 | 194 | 762 | 1427 | 867 |
| 4 | 37 | 75 | 274 | 887 |

ANNE Test Set

| Obs/Pred | 1 | 2 | 3 | 4 |
|----------|-----|-----|-----|-----|
| 1 | 105 | 26 | 8 | 1 |
| 2 | 96 | 175 | 70 | 19 |
| 3 | 62 | 280 | 340 | 205 |
| 4 | 10 | 20 | 75 | 213 |

SVM Training Set

| Obs/Pred | 1 | 2 | 3 | 4 |
|----------|-----|-----|------|-----|
| 1 | 400 | 102 | 49 | 11 |
| 2 | 239 | 768 | 366 | 63 |
| 3 | 122 | 681 | 1927 | 530 |
| 4 | 20 | 87 | 383 | 783 |

SVM Test Set

| Obs/Pred | 1 | 2 | 3 | 4 |
|----------|----|-----|-----|-----|
| 1 | 93 | 28 | 16 | 3 |
| 2 | 63 | 168 | 105 | 24 |
| 3 | 41 | 178 | 461 | 135 |
| 4 | 8 | 21 | 123 | 166 |

EPA 4 Class Model Performance Metrics

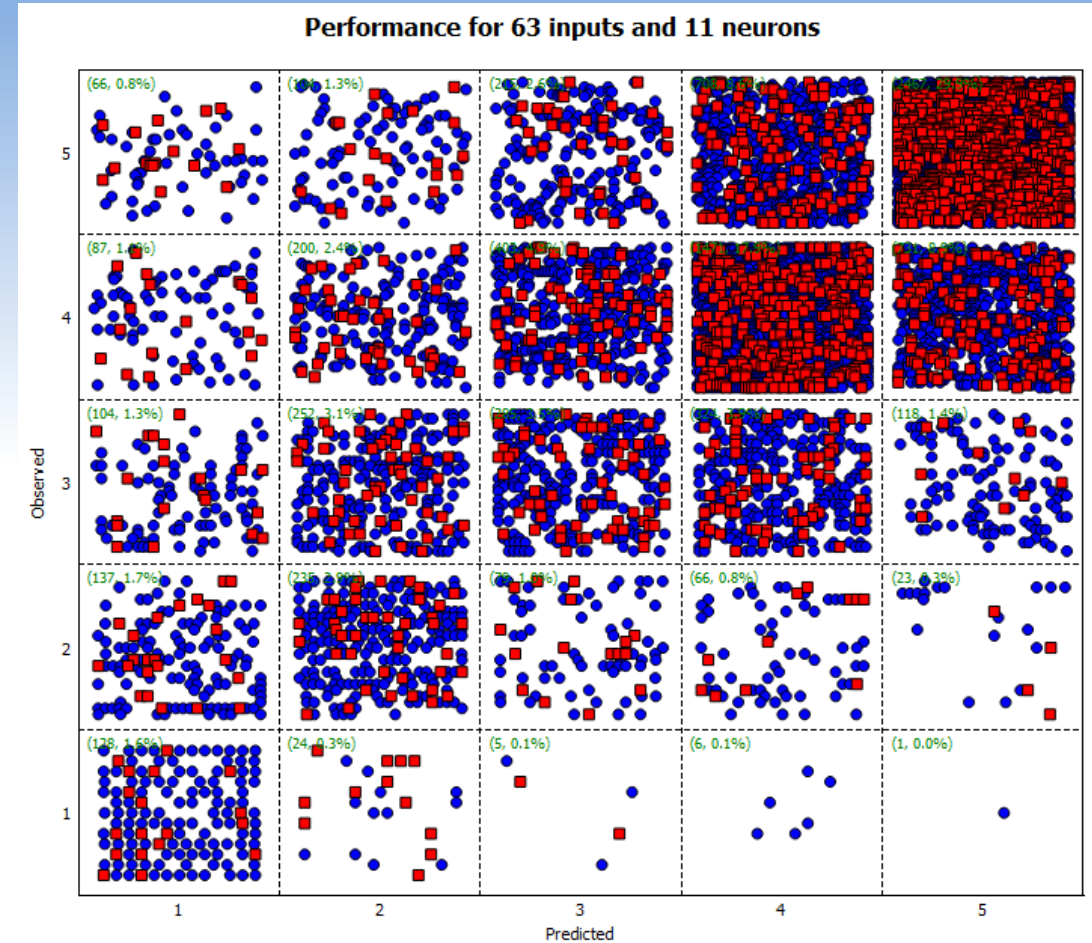
| | ANNE Train | ANNE Test | ANNE All | SVM Train | SVM Test | SVM All |
|--------|------------|-----------|----------|-----------|----------|---------|
| Youden | 0.39 | 0.39 | 0.37 | 0.42 | 0.34 | 0.41 |
| MCC | 0.36 | 0.38 | 0.36 | 0.41 | 0.33 | 0.39 |
| Acc | 54% | 52% | 53% | 59% | 54% | 58% |



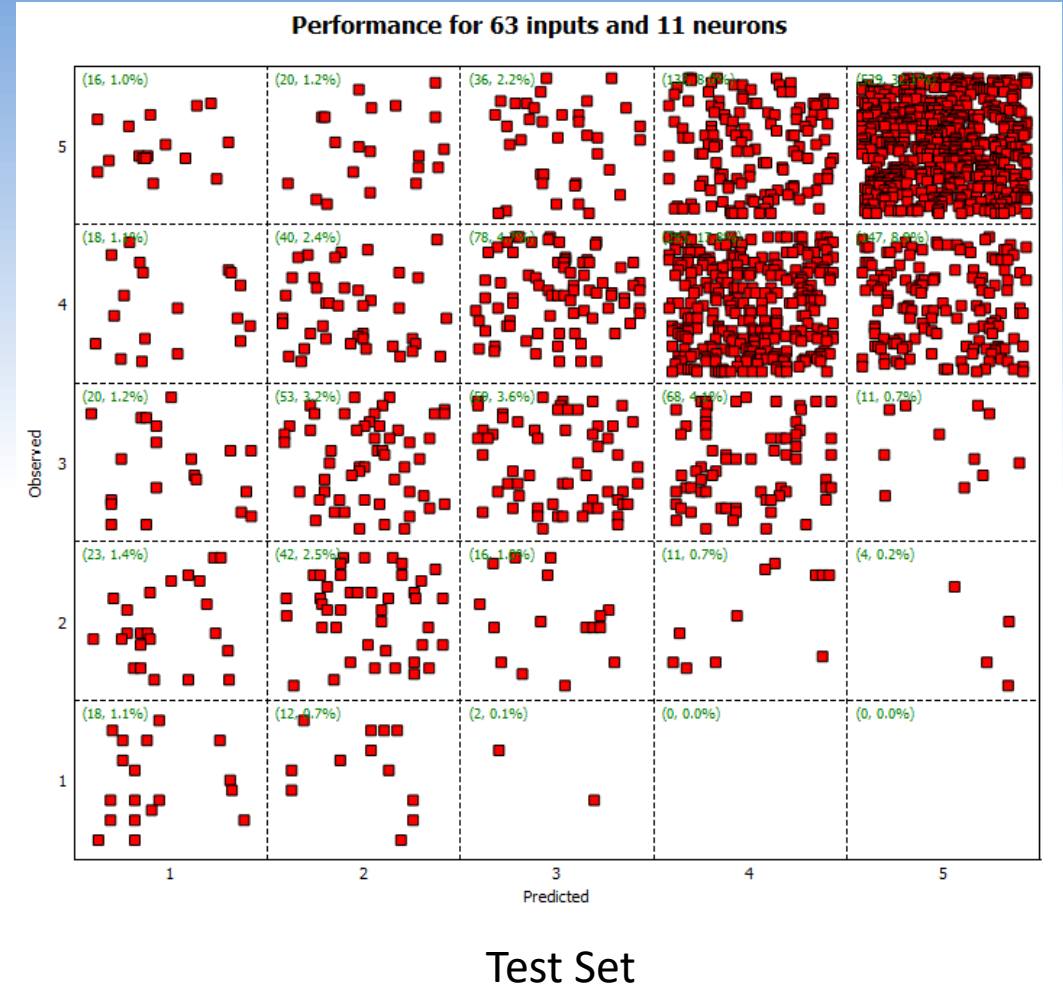
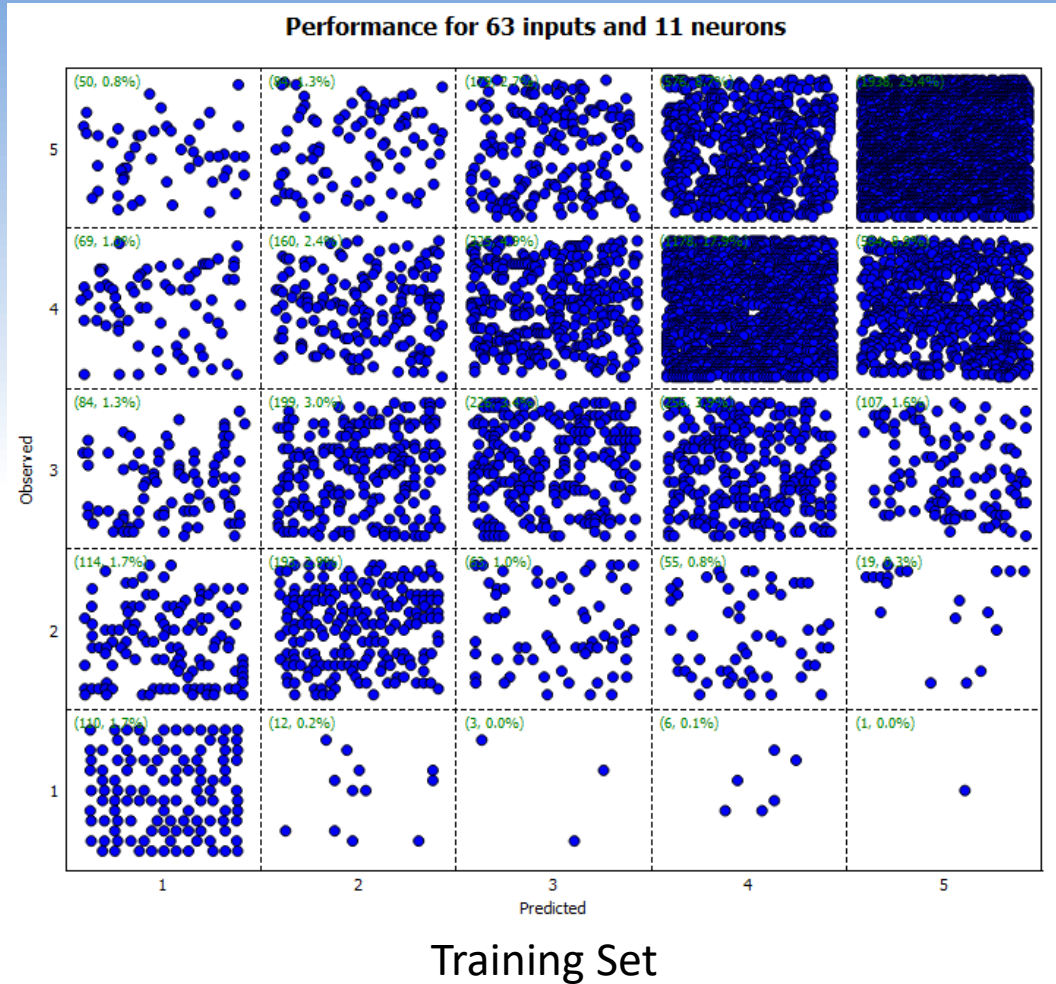
Overtrained

GHS 5 Class Model Performance

| Model Performance Grid | | | | | | | | | | | | | |
|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Youden | 14 Inputs | 21 Inputs | 28 Inputs | 35 Inputs | 42 Inputs | 49 Inputs | 56 Inputs | 63 Inputs | 70 Inputs | 77 Inputs | 84 Inputs | 91 Inputs | 98 Inputs |
| 3 Neurons | 0.31 | 0.32 | 0.32 | 0.33 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | 0.35 | 0.35 | 0.35 | 0.36 |
| | 0.33 | 0.34 | 0.36 | 0.36 | 0.36 | 0.34 | 0.34 | 0.35 | 0.37 | 0.35 | 0.36 | 0.35 | 0.37 |
| 5 Neurons | 0.32 | 0.33 | 0.33 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | 0.35 | 0.36 | 0.36 | 0.36 | 0.35 |
| | 0.32 | 0.35 | 0.37 | 0.36 | 0.36 | 0.36 | 0.34 | 0.36 | 0.37 | 0.37 | 0.37 | 0.37 | 0.36 |
| 7 Neurons | 0.32 | 0.33 | 0.34 | 0.34 | 0.34 | 0.35 | 0.35 | 0.35 | 0.35 | 0.36 | 0.36 | 0.36 | 0.37 |
| | 0.33 | 0.34 | 0.36 | 0.37 | 0.37 | 0.35 | 0.35 | 0.38 | 0.37 | 0.36 | 0.36 | 0.37 | 0.37 |
| 9 Neurons | 0.33 | 0.34 | 0.34 | 0.34 | 0.35 | 0.35 | 0.35 | 0.36 | 0.36 | 0.37 | 0.37 | 0.38 | 0.37 |
| | 0.34 | 0.35 | 0.35 | 0.37 | 0.35 | 0.35 | 0.36 | 0.37 | 0.37 | 0.36 | 0.36 | 0.36 | 0.36 |
| 11 Neurons | 0.33 | 0.33 | 0.34 | 0.34 | 0.34 | 0.35 | 0.36 | 0.37 | 0.36 | 0.37 | 0.37 | 0.37 | 0.37 |
| | 0.34 | 0.36 | 0.36 | 0.35 | 0.36 | 0.36 | 0.36 | 0.39 | 0.37 | 0.37 | 0.36 | 0.37 | 0.36 |
| 13 Neurons | 0.33 | 0.34 | 0.34 | 0.34 | 0.35 | 0.35 | 0.36 | 0.36 | 0.36 | 0.37 | 0.36 | 0.38 | 0.36 |
| | 0.35 | 0.35 | 0.37 | 0.35 | 0.36 | 0.35 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.37 | 0.37 |
| 15 Neurons | 0.33 | 0.34 | 0.34 | 0.35 | 0.35 | 0.35 | 0.35 | 0.36 | 0.37 | 0.37 | 0.38 | 0.36 | 0.36 |
| | 0.34 | 0.35 | 0.37 | 0.36 | 0.36 | 0.37 | 0.35 | 0.37 | 0.38 | 0.37 | 0.36 | 0.36 | 0.36 |
| 17 Neurons | 0.32 | 0.33 | 0.35 | 0.34 | 0.35 | 0.35 | 0.35 | 0.36 | 0.36 | | | | |
| | 0.34 | 0.36 | 0.36 | 0.35 | 0.35 | 0.35 | 0.35 | 0.38 | 0.38 | | | | |



GHS 5 Class Model Performance



GHS 5 Class Model Performance

| Obs/Pred | 1 | 2 | 3 | 4 | 5 |
|----------|-----|-----|-----|------|------|
| 1 | 110 | 12 | 3 | 6 | 1 |
| 2 | 114 | 193 | 63 | 55 | 19 |
| 3 | 84 | 199 | 226 | 256 | 107 |
| 4 | 69 | 160 | 325 | 1178 | 584 |
| 5 | 50 | 84 | 179 | 576 | 1938 |

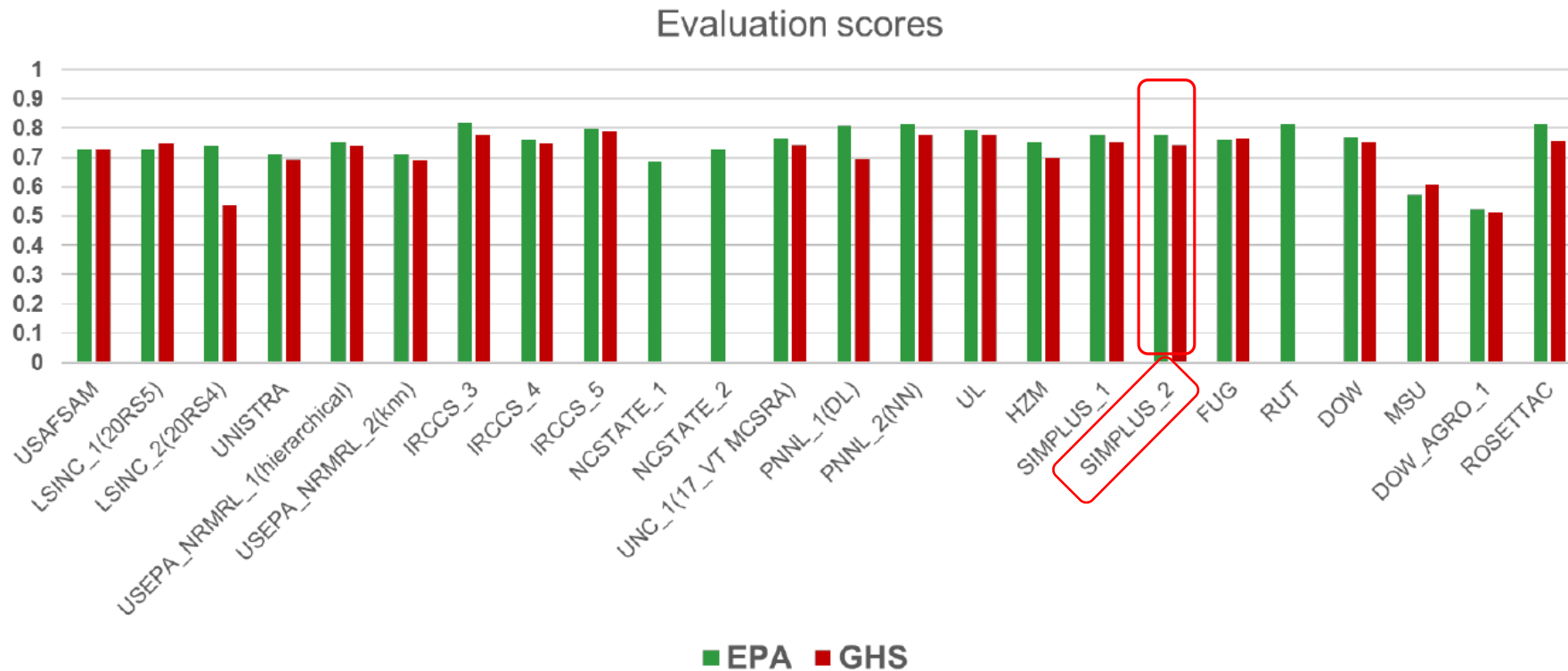
Training Set

| Obs/Pred | 1 | 2 | 3 | 4 | 5 |
|----------|----|----|----|-----|-----|
| 1 | 18 | 12 | 2 | 0 | 0 |
| 2 | 23 | 42 | 16 | 11 | 4 |
| 3 | 20 | 53 | 59 | 68 | 11 |
| 4 | 18 | 40 | 78 | 293 | 147 |
| 5 | 16 | 20 | 36 | 132 | 529 |

Test Set

| | Train | Test | All |
|--------|-------|------|------|
| Youden | 0.37 | 0.39 | 0.37 |
| MCC | 0.36 | 0.38 | 0.36 |
| Acc | 55% | 57% | 56% |

Comparison with other Participants



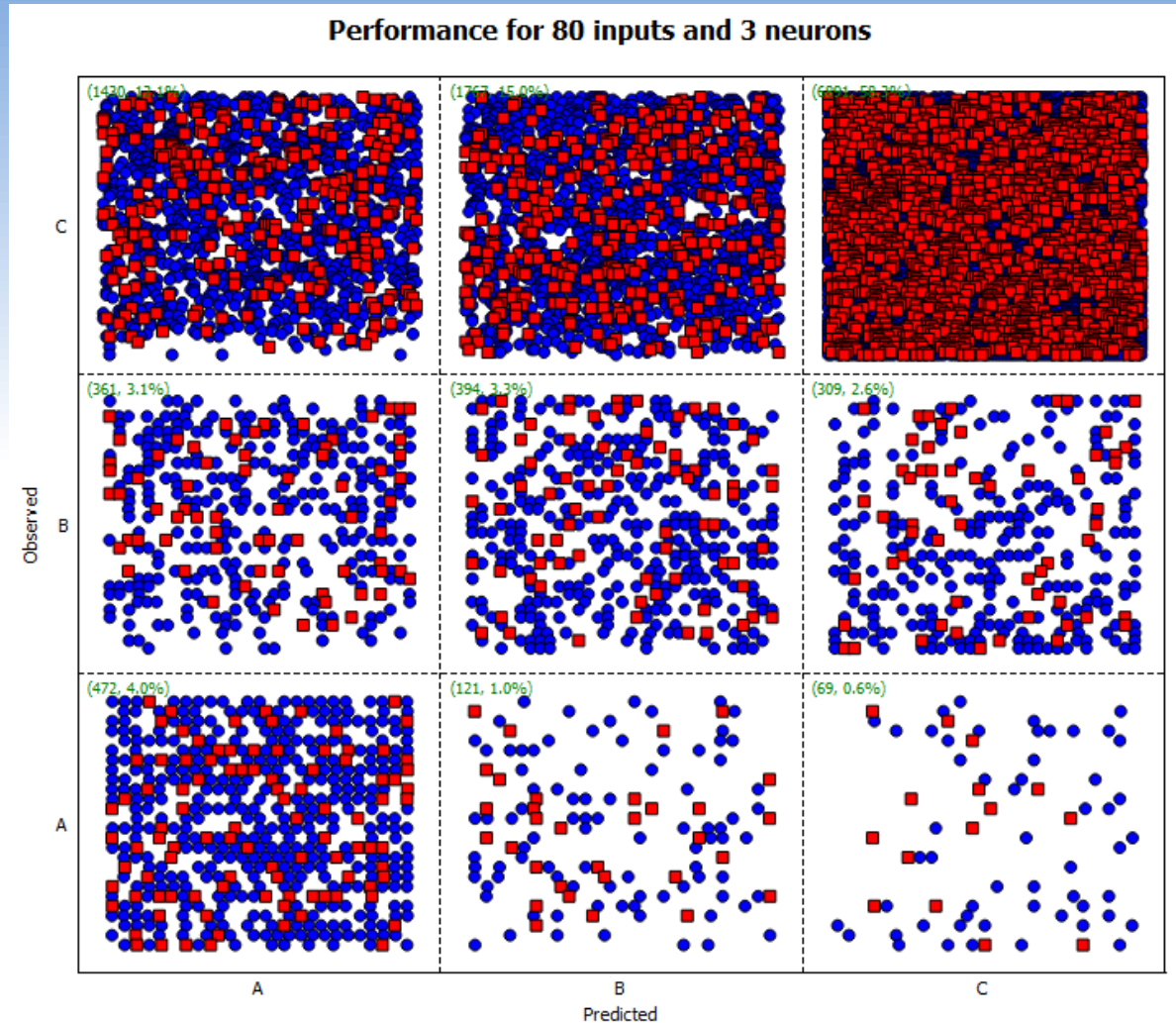
<https://ntp.niehs.nih.gov/iccvam/meetings/at-models-2018/ppt/5-mansouri.pdf>

AMES Mutagenicity 3 class model

- Data from NIHS Japan

- <http://www.nihs.go.jp/dgm/index-e.html>
- <http://www.nihs.go.jp/dgm/amesqsar.html>
- ~12000 data points
- 3 classes
 - Class A : Strongly positive
 - Induces >1000 mutated colonies/mg in at least one AMES strain (+/- rat S9)
 - Class B : Positive
 - Induces >2-fold increase in mutated colonies relative to negative control in at least one AMES strain
 - Class C : Negative
 - Not A or B

Mut 3 Class Model Performance



| Obs/Pred | A | B | C |
|----------|------|------|------|
| A | 373 | 89 | 54 |
| B | 292 | 319 | 251 |
| C | 1161 | 1424 | 5488 |

Training Set

| Obs/Pred | A | B | C |
|----------|-----|-----|------|
| A | 99 | 32 | 15 |
| B | 69 | 75 | 58 |
| C | 269 | 343 | 1403 |

Test Set

| Obs/Pred | A | B | C |
|----------|---|---|-------|
| A | 0 | 0 | 662 |
| B | 0 | 0 | 1064 |
| C | 0 | 0 | 10088 |

Brain Dead
All Predictions =
Class C, Negative

Mut 3 Class Model Performance Comparison

| | Train | Test | All | Brain Dead |
|--------|-------|------|------|---------------|
| Youden | 0.39 | 0.41 | 0.40 | 0 |
| MCC | 0.27 | 0.28 | 0.27 | 0/0 |
| Acc | 65% | 67% | 66% | 85% |

Summary

- ADMET Multi-Class models are seeing increased usage in industry and government
- ANNE Multi-Class methodology provides good model performance and training time performance compared to SVM and other approaches
- Use of proper metrics is critical in assessing quality of multi-class models, especially for heavily imbalanced data sets

Acknowledgements

- Co-authors
 - Pankaj Daga
 - Michael Lawless
 - Robert D. Clark
- David Miller
- Michael Bolger