

Visualization for Classification

ROC, AUC, Confusion Matrix

Visualizing Classification Performance

Confusion matrix

| | | Predicted class | | |
|--------------|--------|-----------------|-----|--------|
| | | Cat | Dog | Rabbit |
| Actual class | Cat | 5 | 3 | 0 |
| | Dog | 2 | 3 | 1 |
| | Rabbit | 0 | 2 | 11 |

Very important: Find out what “positive” means

| | | Predicted class | | |
|--------------|--------|-----------------|-----|--------|
| | | Cat | Dog | Rabbit |
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| | Rabbit | 0 | 2 | 11 |

| | |
|---|---|
| 5 true positives (actual cats that were correctly classified as cats) | 3 false negatives (cats that were incorrectly marked as dogs) |
| 2 false positives (dogs that were incorrectly labeled as cats) | 17 true negatives (all the remaining animals, correctly classified as non-cats) |

Very important:
Find out what
“positive” means

true positive (TP)

eqv. with hit

true negative (TN)

eqv. with correct rejection

false positive (FP)

eqv. with false alarm, Type I error

false negative (FN)

eqv. with miss, Type II error

sensitivity or true positive rate (TPR)

eqv. with hit rate, recall

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

specificity (SPC) or true negative rate (TNR)

$$SPC = \frac{TN}{N} = \frac{TN}{FP + TN}$$

precision or positive predictive value (PPV)

$$PPV = \frac{TP}{TP + FP}$$

recall (recall)

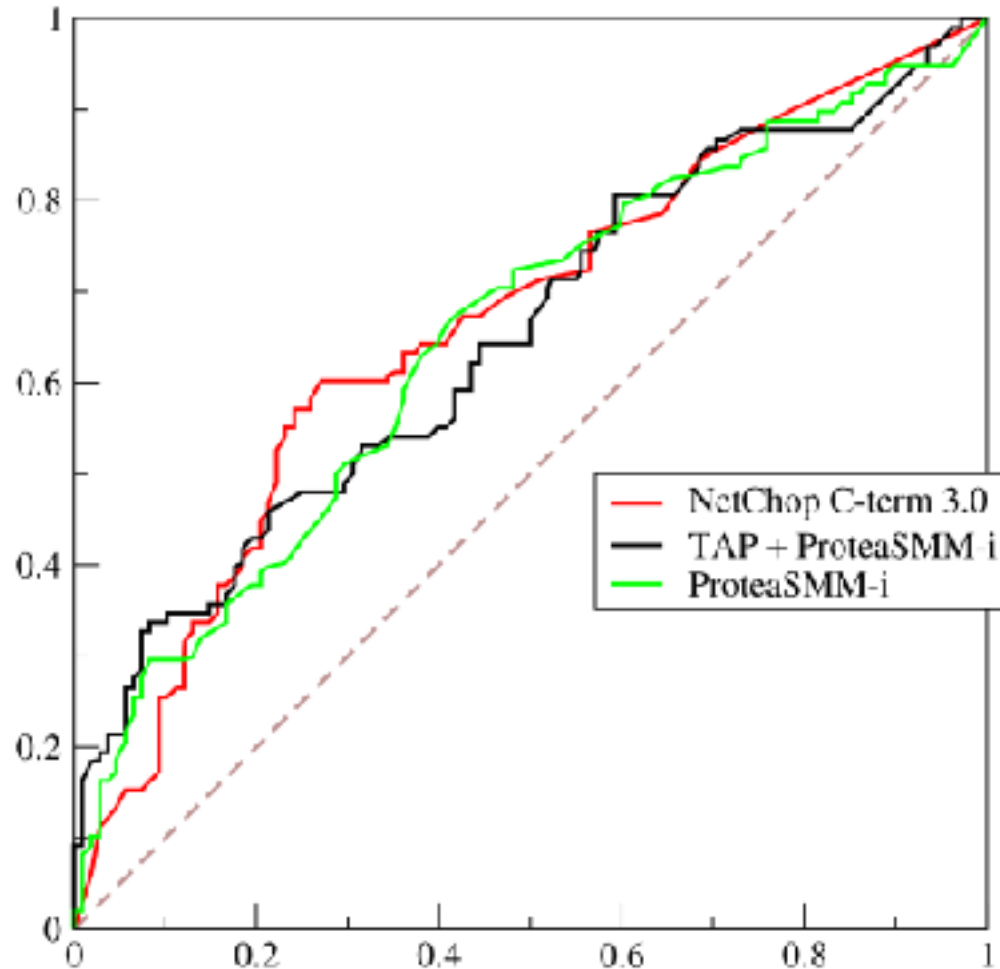
$$recall = \frac{TP}{TP + FN}$$

negative predictive value (NPV)

Visualizing Classification Performance

ROC curve / cost curves

True Positive Rate

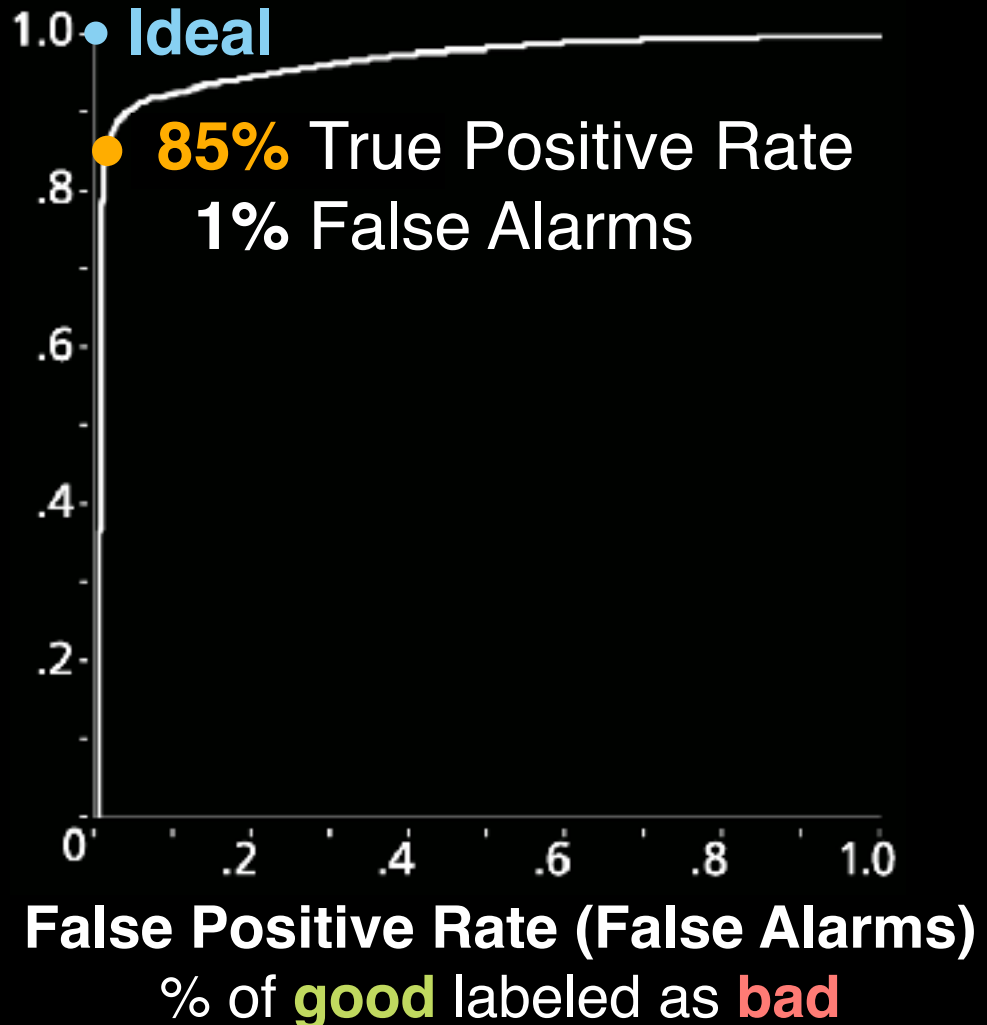


Polonium's ROC Curve

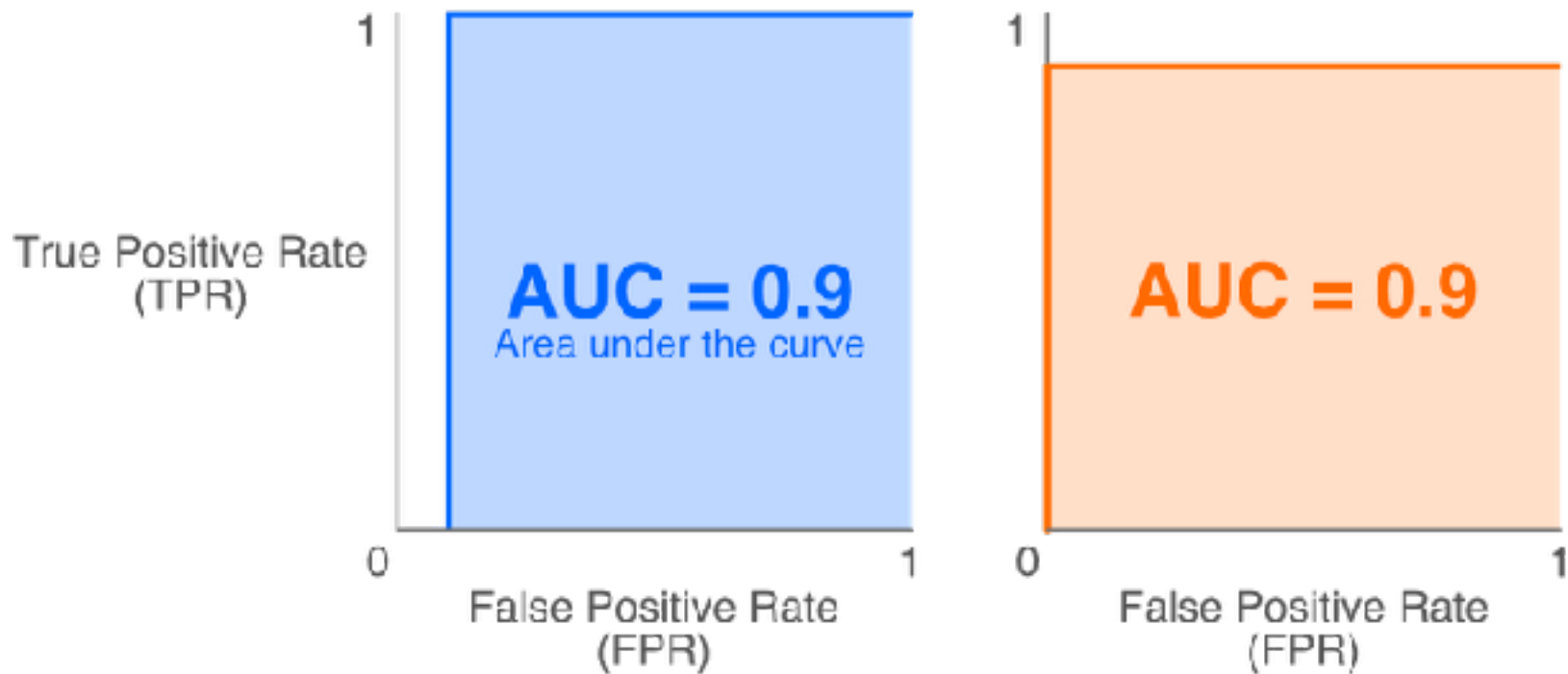
Positive class: malware

Negative class: benign

True Positive Rate
% of **bad** correctly labeled



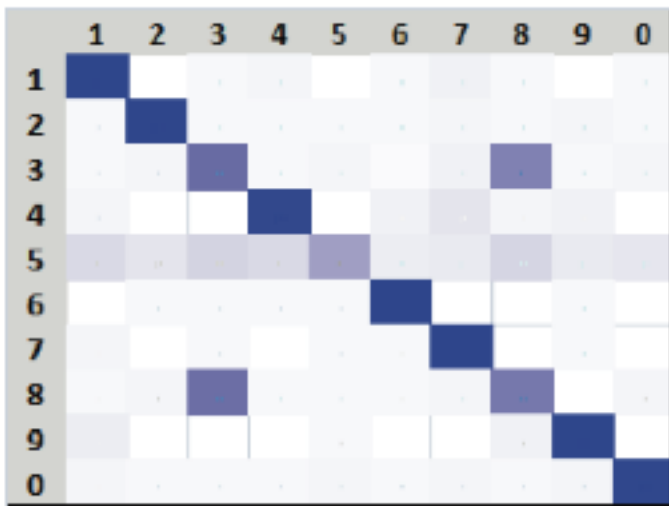
Area Under the Curve (AUC)



| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 |
|---|----|----|----|----|----|----|----|----|----|----|
| 1 | 91 | 0 | 1 | 2 | 0 | 1 | 3 | 1 | 0 | 1 |
| 2 | 1 | 89 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 1 |
| 3 | 1 | 2 | 48 | 1 | 2 | 0 | 3 | 40 | 1 | 2 |
| 4 | 2 | 0 | 0 | 83 | 0 | 3 | 7 | 2 | 3 | 0 |
| 5 | 10 | 7 | 12 | 10 | 30 | 4 | 5 | 11 | 5 | 6 |
| 6 | 0 | 1 | 1 | 1 | 1 | 95 | 0 | 0 | 1 | 0 |
| 7 | 2 | 0 | 1 | 0 | 1 | 1 | 94 | 0 | 1 | 0 |
| 8 | 1 | 2 | 47 | 1 | 1 | 1 | 2 | 43 | 0 | 2 |
| 9 | 4 | 0 | 0 | 0 | 1 | 0 | 0 | 3 | 92 | 0 |
| 0 | 2 | 1 | 1 | 1 | 2 | 1 | 2 | 1 | 2 | 87 |



Hard to spot trends and patterns



Easier

Figure 2. Representations of confusion matrix for a handwritten digit classification task. (top) standard confusion matrix; (bottom) heat-map confusion matrix. It is much easier to identify underlying patterns in the visual representation; 3 and 8 are often misclassified as each other and 5 is misclassified as many different numbers.

Weights in combined models

Bagging / Random forests

- Majority voting

Let people play with the weights?

EnsembleMatrix

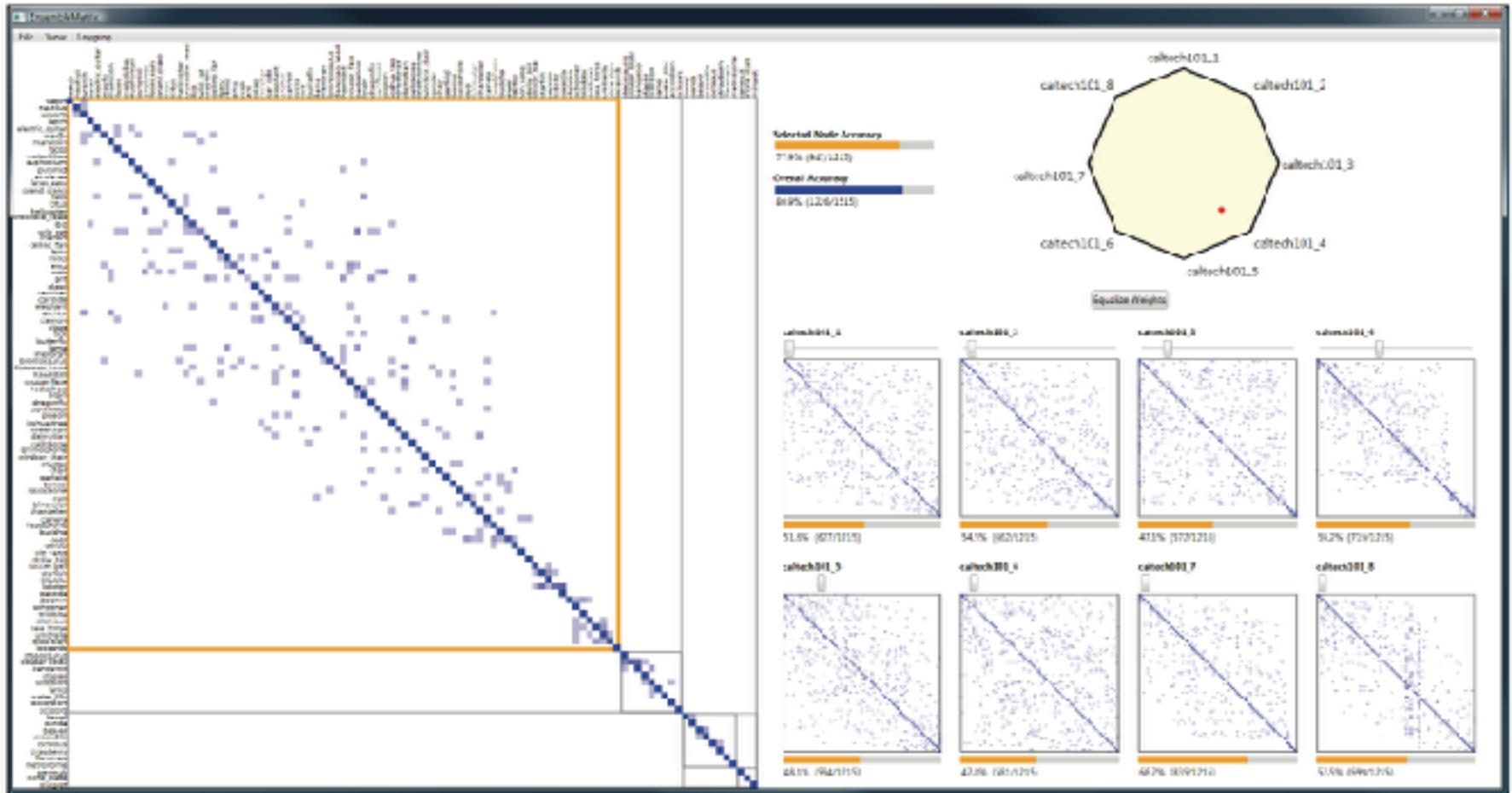


Figure 1. Primary view in EnsembleMatrix. Confusion matrices of component classifiers are shown in thumbnails on the right. The matrix on the left shows the confusion matrix of the current ensemble classifier built by the user.

<http://research.microsoft.com/en-us/um/redmond/groups/cue/publications/CHI2009-EnsembleMatrix.pdf>

Improving performance

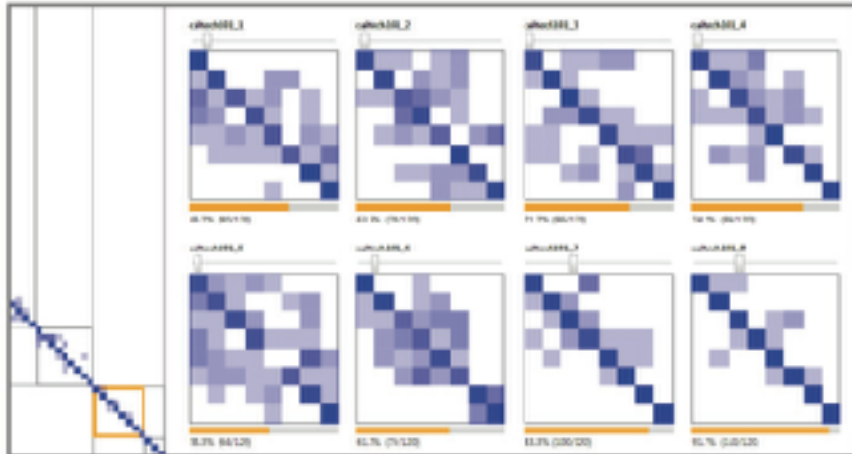


Figure 3. After partitioning the matrix, selecting a partition, outlined in orange, causes the thumbnails to display only the data instances in that partition. The component classifiers demonstrate very different behavior in this partition, including clustering and large differences in accuracy.

- Adjust the weights of the individual classifiers
- Data partition to separate problem areas
 - Adjust weights just for these individual parts
- State-of-the-art performance, on one dataset

<http://research.microsoft.com/en-us/um/redmond/groups/cue/publications/CHI2009-EnsembleMatrix.pdf>