

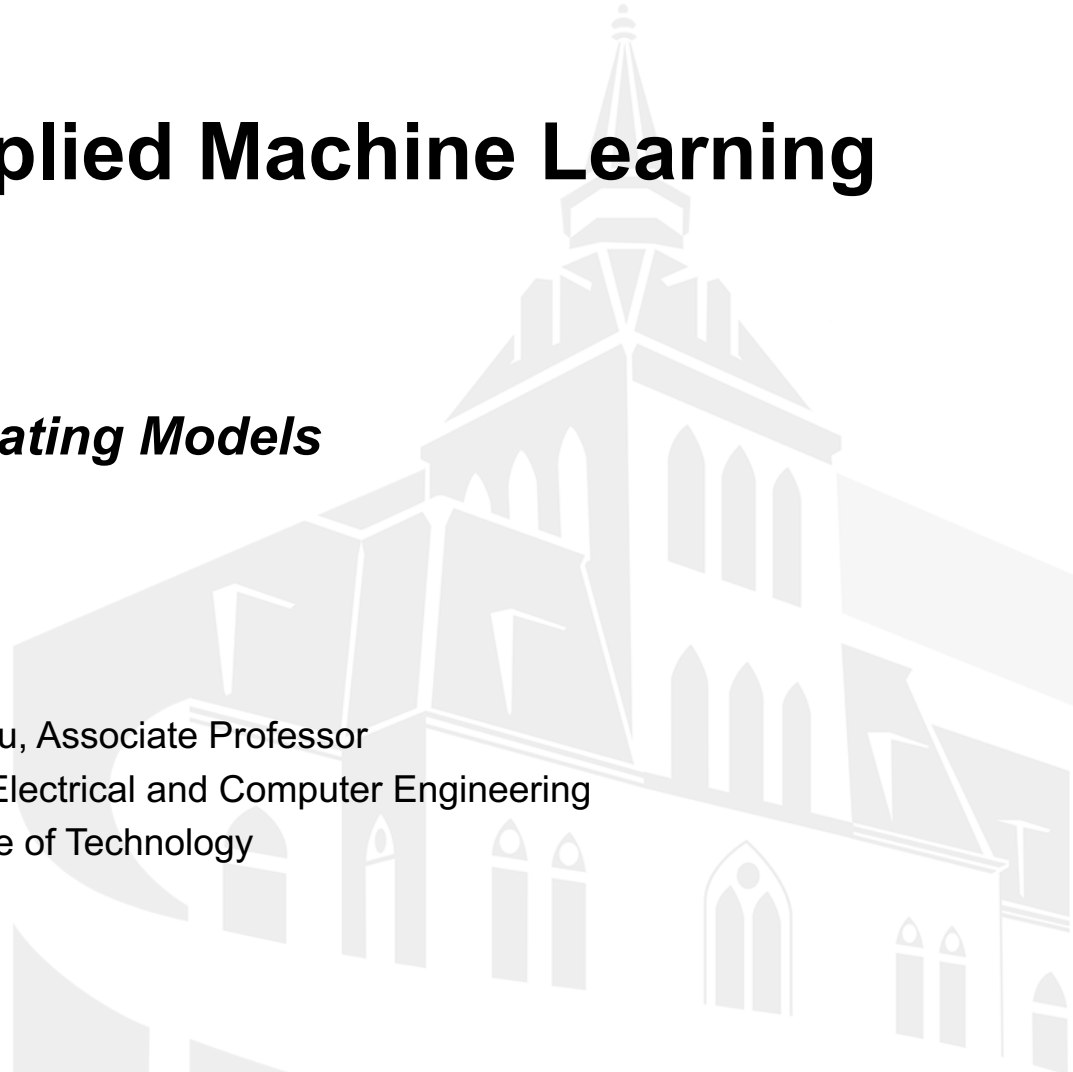


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CPE/EE 695: Applied Machine Learning

Lecture 4 - 1: Evaluating Models

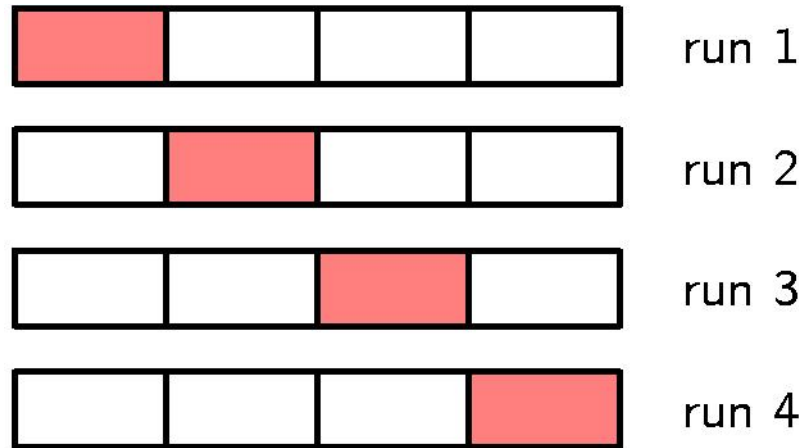
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Model Evaluation

Cross-validation





Evaluation methods

- **Leave-one-out cross-validation:** This method is used when the data set is very small.
 - It is a special case of cross-validation
- Each fold of the cross validation has only **a single test example** and all the rest of the data is used in training.
- If the original data has m examples, this is **m -fold cross-validation**

Classification measures

- Accuracy is only one measure (error = 1-accuracy).

Accuracy is not always suitable

- In text mining, we may only be interested in the documents of a particular topic, which are only a small portion of a big document collection.
- In classification involving skewed or highly imbalanced data, e.g., network intrusion and financial fraud detections, **we are interested only in the minority class**.
 - High accuracy does not mean any intrusion is detected.
 - E.g., 1% intrusion. Achieve 99% accuracy by doing nothing.
- The class of interest is commonly called the **positive class**, and the rest **negative classes**.

Precision and recall measures

confusion matrix

| | Classified Positive | Classified Negative |
|-----------------|---------------------|---------------------|
| Actual Positive | TP | FN |
| Actual Negative | FP | TN |

where

TP: the number of correct classifications of the positive examples (**true positive**),

FN: the number of incorrect classifications of positive examples (**false negative**),

FP: the number of incorrect classifications of negative examples (**false positive**), and

TN: the number of correct classifications of negative examples (**true negative**).

FP: Type I error , false alarm

FN: Type II error

Precision and recall measures (cont...)

| | Classified Positive | Classified Negative |
|-----------------|---------------------|---------------------|
| Actual Positive | TP | FN |
| Actual Negative | FP | TN |

$$p = \frac{TP}{TP + FP} \quad r = \frac{TP}{TP + FN}$$

Precision p is the number of **correctly classified positive examples** divided by the total number of examples that are classified as positive.

Recall r is the number of **correctly classified positive examples** divided by the total number of actual positive examples in the test set.

An example

| | Classified Positive | Classified Negative |
|-----------------|---------------------|---------------------|
| Actual Positive | 1 | 99 |
| Actual Negative | 0 | 1000 |

- This confusion matrix gives

- precision $p = 100\%$ and
- recall $r = 1\%$

because we only classified one positive example correctly and no negative examples wrongly.

- **Note:** precision and recall only measure classification on the positive class.

F_1 -value (also called F_1 -score)

- It is hard to compare two classifiers using two measures. F_1 score combines precision and recall into one measure

$$F_1 = \frac{2pr}{p+r}$$

F_1 -score is the harmonic mean of precision and recall.

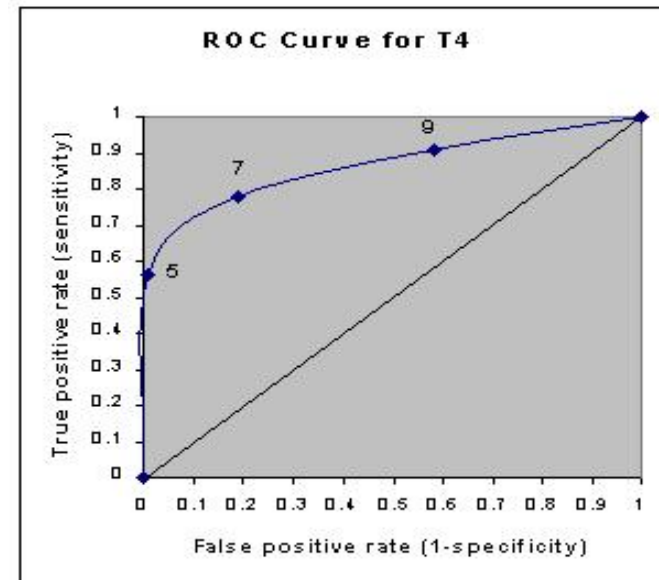
$$F_1 = \frac{2}{\frac{1}{p} + \frac{1}{r}}$$

- The harmonic mean of two numbers tends to be closer to the smaller of the two.
- For F_1 -value to be large, both p and r must be large.

ROC(Receiver Operating Characteristic) curve

Sensitivity: the proportion of positives which are correctly identified . recall rate, True Positive Rate

specificity : the proportion of negatives which are correctly identified . True Negative Rate



- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.
- The area under the curve (AUC) is a measure of accuracy.



Acknowledgement

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