Performance Measures in Data Mining
Common Performance Measures used in Data Mining and Machine Learning Approaches

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Outline

Item Set and Association Rule Weights
  Simple Measures
  Complex Measures

Classification
  Basic Performance Measures
  Complex Measures – Performance Curves

Regression

Assessment Strategies
Measures for Item Sets

Various algorithms can yield frequent item sets. From frequent item sets $c$ and $c \cup \{i\}$ you can derive if $c$ then $\{i\}$. Typically there is only one item in the RHS (right hand side of the rule).

- **Support (of an item set):**
  $$sup(X \rightarrow Y) = sup(Y \rightarrow X) = P(X \wedge Y)$$
  how many times the item set is found in the database

- **Confidence (of a rule):**
  $$conf(X \rightarrow Y) = P(Y|X) = \frac{P(X and Y)}{P(X)} = \frac{sup(X \rightarrow Y)}{sup(X)}$$
Measures for Item Sets cont.’d

Measures how frequent an item set / how interesting a rule is in comparison to the expected occurrence (interesting):

- **Leverage (of an item set):**
  \[ \text{lev}(X \rightarrow Y) = P(X \text{ and } Y) - (P(X)P(Y)) \]

- **Lift (of a rule):**
  \[ \text{lift}(X \rightarrow Y) = \frac{P(X \wedge Y)}{P(X)P(Y)} = \frac{\text{conf}(X \rightarrow Y)/\text{sup}(Y)}{\text{conf}(Y \rightarrow X)/\text{sup}(X)} \]

- **Conviction (of a rule):** Similar to Lift, but directed
  Compares the probability that X appears without Y, if they were independent with the observed frequency of X and Y.
  \[ \text{conviction}(X \rightarrow Y) = P(X)P(\neg Y)/P(X \wedge \neg Y) = (1 - \text{sup}(Y))/(1 - \text{conf}(X \rightarrow Y)) \]
Supplementary Material

J-Measure

- empirically observed accuracy of rule
- Cross-entropy (measuring how good a distribution approximates another distribution) between the binary variables $\phi$ and $\theta$ with vs. without conditioning on event $\theta$

\[
J(\theta \Rightarrow \phi) = p(\theta) \left( p(\phi|\theta) \log \frac{p(\phi|\theta)}{p(\phi)} + (1 - p(\phi|\theta)) \log \frac{1 - p(\phi|\theta)}{1 - p(\phi)} \right)
\]
Basic Building Blocks for Performance Measures

- True Positive (TP): positive instances predicted as positive
- True Negative (TN): negative instances predicted as negative
- False Positive (FP): negative instances predicted as positive
- False Negative (FN): positive instances predicted as negative

Confusion Matrix:

<table>
<thead>
<tr>
<th></th>
<th>Predicted a</th>
<th>Predicted b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real a</td>
<td>TP</td>
<td>FN</td>
</tr>
<tr>
<td>Real b</td>
<td>FP</td>
<td>TN</td>
</tr>
</tbody>
</table>
Performance Measures

Accuracy, \( acc = \frac{TP + TN}{TP + FN + FP + TN} \)

\( = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \)

Error rate, \( err = \frac{FN + FP}{TP + FN + FP + TN} = 1 - acc \)

\( = \frac{\text{Number of wrong predictions}}{\text{Total number of predictions}} \)
Performance Measures cont’d

True Positive Rate, $TPR$, Sensitivity $= \frac{TP}{TP + FN}$

True Negative Rate, $TNR$, Specificity $= \frac{TN}{TN + FP}$

False Positive Rate, $FPR = \frac{FP}{TN + FP}$

False Negative Rate, $FNR = \frac{FN}{TP + FN}$
Performance Measures cont’d

Precision, \( p = \frac{TP}{TP + FP} \)

Recall, \( r = \frac{TP}{TP + FN} \)

\( F_1 \) measure = \( \frac{2rp}{r + p} = \frac{2 \times TP}{2 \times TP + FP + FN} \)
Performance Curves

- "costs" of different error types are different
- prediction behaviour changes over the test set
- performance display in 2D
- different domains prefer different chart types
Lift Charts

- from marketing area to evaluate mailing success
- y-axis: number or percentage of responders
- x-axis: sample
- red diagonal: random lift
- green line: optimum lift

Taken from http://www.dmg.org/rfc/pmml-3.2/ModelExplanation.html
ROC Curves

- Receiver Operator Characteristics
- $y$-axis: TPR
- $x$-axis: FPR
- diagonal: random guessing (TPR=FPR)

Taken from http://en.wikipedia.org/wiki/File:Roccurves.png
Sensitivity vs. Specificity

- preferred in medicine
- \( y \)-axis: TPR
- \( x \)-axis: TNR (specificity)
- also frequently as ROC curve with 1 - specificity

Taken from http://i.stack.imgur.com/fnUd2.png
Recall Precision Curves

- preferred in information retrieval
- positives are the documents retrieved in response to a query
- true positives are documents really relevant to the query
- $y$-axis: precision
- $x$-axis: recall

Taken from http://scikit-learn.github.io/scikit-learn.org/
Error Measures for Regression

Mean – squared error, $MSE = \frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}$

Root mean–squared error, $RMSE = \sqrt{\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}}$

Mean – absolute error, $MAE = \frac{|p_1 - a_1| + \cdots + |p_n - a_n|}{n}$
Relative Error Measures

Relative squared error = \[ \frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \cdots + (a_n - \bar{a})^2} \]

Root relative squared error = \[ \sqrt{\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \cdots + (a_n - \bar{a})^2}} \]

Relative absolute error = \[ \frac{|p_1 - a_1| + \cdots + |p_n - a_n|}{|a_1 - \bar{a}| + \cdots + |a_n - \bar{a}|} \]
General Problem

- each algorithm abstracts from observations (instances)
- the aspects kept and the aspect discarded differ between the learning scheme (inductive bias)
- this means also: information about individual instances are contained in the model, too
- individual instance information leads to overfitting
Solution Strategies

- use fresh data, i.e., instances not used for the training
- for very large numbers of instances: simple split in test and training set
- most common: 10-fold cross validation
- LOOCV: Leave one out cross validation