Introduction to Machine Learning Applications Spring 2021

Lecture-10

Lydia Manikonda

manikl@rpi.edu



Today's agenda

- Accuracy metrics
- Features and Dimensionality Reduction

Announcements

- Homework-4 due on March 4th 2021, 11:59 pm ET via LMS
- We will look at how to compute precision and recall values in a dynamic fashion.

Accuracy Metrics

| | | Actual Class | |
|-----------------|-----------|--------------|------------------------|
| | | Class = 1 | Class = 0 |
| Predicted Class | Class = 1 | f_{11} | <i>f</i> ₁₀ |
| | Class = 0 | f_{01} | f_{00} |

- f_{11} True Positive
- f_{10} False Positive Type I error
- f_{01}^{-} False Negative Type II error
- f_{00}^{-} True Negative

Precision: How many selected

items are relevant?

Recall: How many relevant items are selected?



How many selected items are relevant?

 $Precision = \frac{|\{relevant \ documents\} \cap \{retrieved \ documents\}|}{|\{retrieved \ documents\}|}$

$$Precision = \frac{f_{11}}{(f_{10} + f_{11})}$$

Recall

How many relevant items are selected?

 $Recall = \frac{|\{relevant \ documents\} \cap \{retrieved \ documents\}|}{|\{relevant \ documents\}|}$

$$Recall = \frac{f_{11}}{(f_{01} + f_{11})}$$



Better measure that considers the harmonic mean of *precision* and *recall*

$$f - measure = \frac{2*(precision*recall)}{(precision+recall)}$$

$$f1score = \frac{2*precision*recall}{(precision+recall)}$$

Compute precision, recall and f-measure

tp = 8 fp = 4 fn = 2 tn = 6

| | | Actual Class | | |
|--------------------|-------|--------------|-------|--|
| | | True | False | |
| Predicted class | True | 8 | 4 | |
| | False | 2 | 6 | |

Precision = tp/(tp+fp) = 8/(8+4) = 8/12Recall = 8/(8+2) = 8/10F-score = (2*precision*recall)/(precision+recall) = (2*8*8/120)/(8/10 + 8/12) =

Plot a precision recall graph

- True_labels = $[t_1, t_2, t_3, t_4, ..., t_k]$
- Pred_labels = $[p_1, p_2, p_3, p_4, ..., p_k]$
- At each point we compute the precision-recall values and dynamically compute them as we keep looking at all the labels consequently.

- Y_true = [1, 0, 0, 1, 1]
- Y_false = [1, 1, 1, 0, 0]
- i=2: precision, recall values Actual = [1, 0, 0]Pred = [1, 1, 1] Tp=1 tn=0 Fp=2 Fn=0 Precision = 1/3 = 0.334Recall = 1/1 = 1

- Y_true = [1, 0, 1, 0, 1]
- Y_false = [0, 1, 0, 1, 1]
- i=2: precision, recall values Actual = [1, 0, 1]Pred = [0, 1, 0] Tp=0 tn=0 Fp=1 Fn=2 Precision = 0/1 = 0Recall = 0/2 = 0

Sensitivity

Also considered as the True positive rate or equivalent to recall

 $Sensitivity = \frac{|\{relevant \ documents\} \cap \{retrieved \ documents\}|}{|\{relevant \ documents\}|}$

Specificity

Also known as True Negative Rate (actual negatives that are correctly identified)

 $Specificity = \frac{True \ Negative}{(True \ Negative + False \ Positive)}$

Specificity =
$$\frac{f_{00}}{(f_{00} + f_{10})}$$

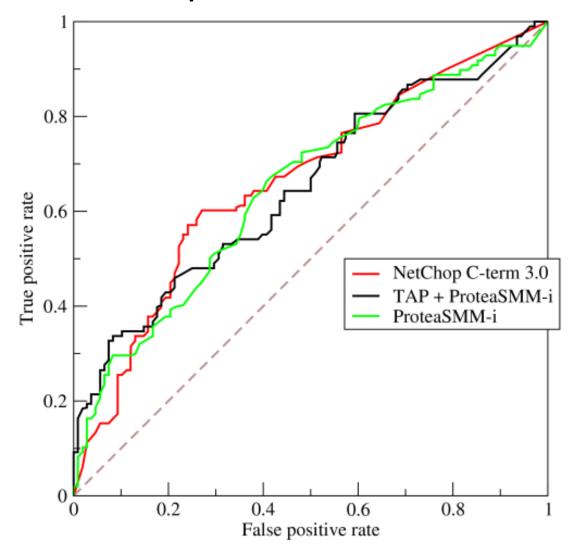


- Receiver operating characteristic curve
- Created by plotting True-positive rate vs False positive rate

 $FalsePositiveRate = \frac{FalsePositive}{(TrueNegative+FalsePositive)}$

 $TruePositiveRate = \frac{TruePositive}{(FalseNegative+TruePositive)}$

ROC curve – Example



https://upload.wikimedia.org/wikipedia/commons/6/6b/Roccurves.png

Class Exercises

| | | | Actual Class | | |
|--|---|--------------|---------------------------|--------------|--|
| | | | Cat (true) | ~Cat (false) | |
| Compute Accuracy Precision, Recall, f-measure, Specificity False positive ra | Predicted Class | Cat (true) | 5 | 2 | |
| | | ~Cat (false) | 3 | 3 | |
| | Accuracy = (5+3)/13 Precision = (5/5+2) | | | | |
| | Tp=5 Re | | ecall = 5/(5+3) | | |
| | Fp = 2 | | | | |
| | 111 – J | | -measure = 2*p*r/(p+r) | | |
| | atetn = 3 2* | | | | |

$$A(curacy = \frac{TP + TN}{\#Tohal} = \frac{S + 3}{S + 2 + 3 + 3} = \frac{8}{13}$$

$$Precision = \frac{TP}{TP + FP} = \frac{5}{S + 2} = \frac{5}{7} = 71.42\%$$

$$Recall = \frac{TP}{TP + FN} = \frac{5}{S + 3} = \frac{5}{8} = 62.5\%$$

$$FScore = \frac{2 \times Pre \times Rec}{(Pre + Rec)} = \frac{2 \times \frac{5}{7} \times \frac{5}{8}}{(\frac{5}{7} + \frac{5}{8})} = \frac{2}{(\frac{5}{7} + \frac{5}{8})} = \frac{2}{9} + \frac{5}{8} + \frac{5}{3} = \frac{2}{3} = 66.7\%$$

$$Specificitly = \frac{TN}{TN + FP} = \frac{3}{3 + 2} = \frac{3}{5} = 60\%$$

$$FPR = \frac{FP}{FP + TN} = \frac{2}{2 + 3} = \frac{2}{5} = 40\%$$

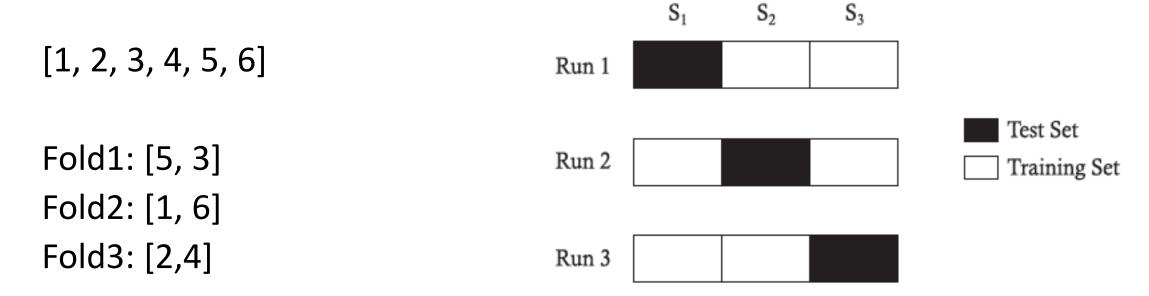
k-fold Cross-validation

- Resampling procedure to evaluate machine learning models on a given data sample.
- The parameter k refers to the number of groups that a given data sample is to be split into.
- If k=10, it is 10-fold cross-validation where the sample data is divided into 10 groups.

k-fold Cross-validation

- > Shuffle the dataset (better)
- > Split the dataset into *k* disjoint groups
- > For each unique group:
 - > Take the group as a hold out or test (validation) data set
 - > Take the remaining groups as a training data set
 - > Fit a model on the training set and evaluate it on the test set
 - > Record the evaluation score
- > Find the mean of all the sample of model evaluation scores

k-fold Cross-validation

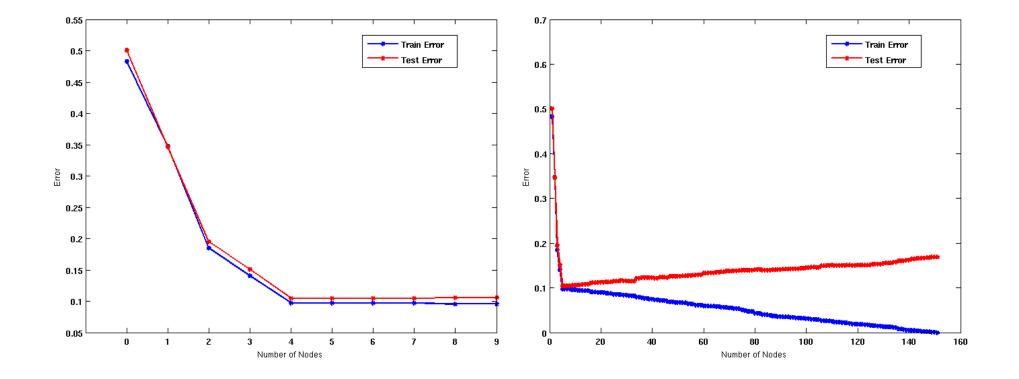


Model1: Trained on Fold2 + Fold3, Tested on Fold1 Model2: Trained on Fold1 + Fold3, Tested on Fold2 Model3: Trained on Fold1 + Fold2, Tested on Fold3

Example

- Given a set of data points {a, b, c, d, e, f, g, h}
 - Perform 4-fold cross validation
 - Explain it in your own terms what are the folds and how do you use them?

Model Overfitting & Underfitting



Underfitting: when model is too simple, both training and test errors are large **Overfitting**: when model is too complex, training error is small but test error is large

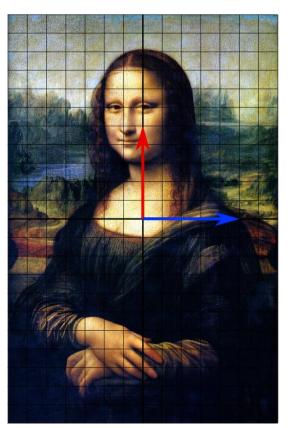
How do we convert ground truth data and predictions to a confusion matrix?

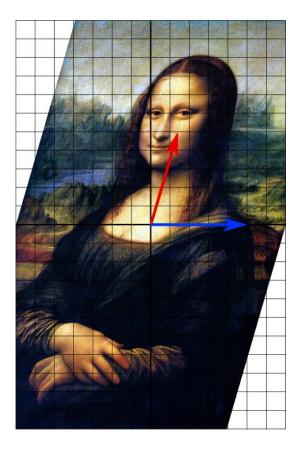
• Notebook example

• Exercises in the notebook to follow..

Eigenvalues and Eigenvectors

- In the image on the right, when the image is transformed, red arrow changed the direction. But the blue arrow didn't – this is the eigenvector.
- Eigenvector does not change its direction.





Picture credits: By TreyGreer62 - Image:Mona Lisa-restored.jpg, CC0, https://commons.wikimedia.org/w/index.php?curid=12768508

Eigenvalues and Eigenvectors

• Eigenvectors are the **characteristic vectors** that are nonzero vectors.

- Eigenvalues are the scalar values or **factors** with which corresponding eigenvectors are scaled.
- But how do we compute them?

Computing eigenvalues and eigenvectors

• We multiply a matrix with a vector and get the same result when we multiply a scalar by that vector.

we start by Finding eigenvalue. $AV = \lambda V$ AV = AIV V is the non-zero Cigenvector corresponding to the eigenvalue A. AV - AIV = O $|A - \lambda I| v = 0$

Example: Computing eigenvalues and eigenvectors

If
$$A = \begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix}$$
, compute eigenvalues and their
corresponding eigenvector.
Shart with: $|A - \lambda T| = 0 \longrightarrow \text{Finding the determinant.}$
 $\left| \begin{bmatrix} 6 & 3 \\ 4 & 5 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right| = \left| \begin{bmatrix} -6 -\lambda & 3 - 0 \\ 4 - 0 & 5 - \lambda \end{bmatrix} = 0$
 $\left| -6 - \lambda & 3 \\ 4 & 5 - \lambda \end{bmatrix} = 0 = 0$
 $\left| -6 - \lambda & 3 \\ 4 & 5 - \lambda \end{bmatrix} = 0 = 0$
 $\left(-6 - \lambda (5 - \lambda) - (3)(4) = 0 = 0$
 $\left(-30 + 6\lambda - 5\lambda + \lambda^{\gamma} - 12 = 0 = 0$
 $\lambda^{\gamma} + \lambda - 42 = 0$
 $\left(\lambda + T \right) \left(\lambda = 6 \right) = 0$
 $\lambda = -7 \text{ or } 6$.

We found eigenvalues.

Now compute corresponding eigenvectors

If
$$A = \begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix}$$
, compute eigenvalues and their
corresponding eigenvector.
Start with: $|A - \lambda I| = 0 \quad \longrightarrow$ Finding the detorminant.
 $\left| \begin{bmatrix} 6 & 3 \\ 4 & 5 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right| = \left| \begin{bmatrix} -6 - \lambda & 3 - 0 \\ 4 - 0 & 5 - \lambda \end{bmatrix} \right| = 0$
 $\left| -6 - \lambda & 3 \\ 4 & 5 - \lambda \end{bmatrix} = 0 \quad = 0$
 $\left(-6 - \lambda \right) (5 - \lambda) - (3)(4) = 0 \quad = 3$
 $\left(-6 - \lambda \right) (5 - \lambda) - (3)(4) = 0 \quad = 3$
 $-30 + 6\lambda - 5\lambda + \lambda^{\gamma} - 12 = 0 \quad = 4$
 $\lambda^{\gamma} + \lambda - 42 = 0$
 $\left(\lambda + T \right) \left(\lambda = 6 \right) = 0$
 $\lambda = -7 \quad \text{or} \quad 6$.

Case-1: eigenvalue=6

Case 1:
$$\lambda = 6$$
: $AV = \lambda V$

$$\begin{pmatrix} -6 & 3 \\ 4 & 5 \end{pmatrix} \begin{pmatrix} \pi \\ 9 \end{pmatrix} = 6 \begin{pmatrix} \pi \\ 9 \end{pmatrix} \begin{pmatrix} -6\pi + 3y \\ 4x + 5y = 6x \\ 4x + 5y = 6y \end{pmatrix} - 0$$

$$-12x + 3y = 0$$

$$4x - y = 0$$

$$4y$$

$$4x = y \text{ or } y = 4x.$$
So, eigenvector is any non-zero multiple of
$$\begin{bmatrix} 1 \\ 4 \end{bmatrix}.$$

Case-2: eigenvalue=-7

ane-2:
$$\lambda = -7$$
: $AV = \lambda V$
 $\begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = (-7) \begin{bmatrix} x \\ y \end{bmatrix}$
Multiplying these matrices:
 $-6x+3y = -7x$ 0
 $4x + 5y = -7y$
 $x + 3y = 0$ 0 .
 $4x + 12y = 0$
 1
 $x = -3y$ or $y = (-\frac{1}{3})x$
 $\begin{bmatrix} -3 \\ 1 \end{bmatrix} \rightarrow$ Gigenvector is any non-serve multiple of this vector.

Lets case-2's eigenvector and multiply with the original matrix

Replace (anc-2's eigenvector to multiply with the original matrix.

$$\begin{bmatrix}
-6 & 3 \\
-4 & 5
\end{bmatrix}
\begin{bmatrix}
-3 \\
1
\end{bmatrix} =
\begin{bmatrix}
(-6)(-3) + (3)(1) \\
(+)(-3) + (3)(1)
\end{bmatrix}$$

$$=
\begin{bmatrix}
18 + 3 \\
-12 + 5
\end{bmatrix} =
\begin{bmatrix}
21 \\
-7
\end{bmatrix}$$

$$\begin{bmatrix}
21 \\
-7
\end{bmatrix}$$

$$\begin{bmatrix}
1 \\
-7
\end{bmatrix}$$

$$\begin{bmatrix}
-7 \\
-3 \\
1
\end{bmatrix}$$

$$\begin{bmatrix}
(-7) \\
-3 \\
1
\end{bmatrix}$$

$$Gigenvector.$$

Example-2: eigenvalues and eigenvectors

Matrix is:

$$A = \left(\begin{array}{cc} 2 & 2 \\ 5 & -1 \end{array}\right)$$

Principal Component Analysis

- Step-1: Standardization
- Step-2: Compute covariance matrix
- Step-3: Compute the eigenvalues and eigenvectors of the covariance matrix
- Step-4: Sort the eigenvalues in a decreasing order
- Step-5: Choose the top-k eigenvectors which are the principal components – these will be the transformed feature vectors (reorient the data is the common approach)