

11.01.2019

Statistical Methods in AI (CSE/ECE 471)

Lecture-4: Intro to Performance Measures, Benchmarking

Ravi Kiran

Center for Visual Information Technology (CVIT), IIIT Hyderabad



Announcements

- A1 has been posted. Due: **20/1, 11.59 PM**
- This week's tutorial: Probability recap, ML datasets, visualization approaches. **Bring your laptops.**

Supervised Learning

```
graph TD; A[Supervised Learning] --> B[Classification]; A --> C[Regression]; A --> D[Reinforcement Learning];
```

Classification

Regression

Reinforcement
Learning



Classification

Binary

$\{0,1\}$

Multi-class

1-of-K

Multi-label

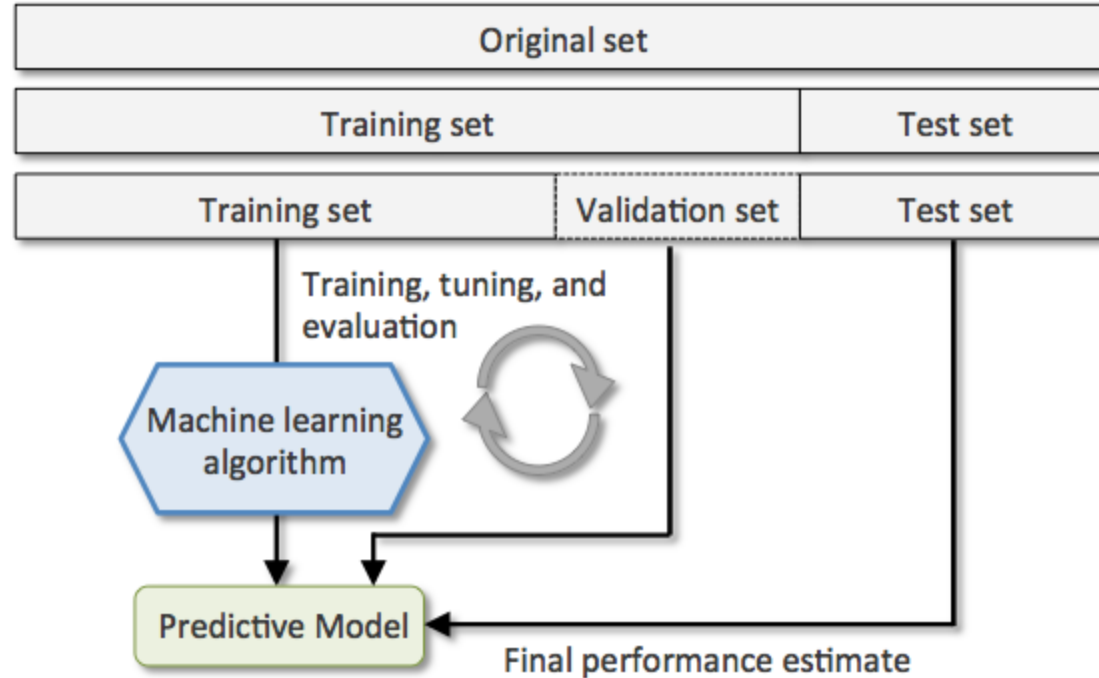
n-of-K

Structure

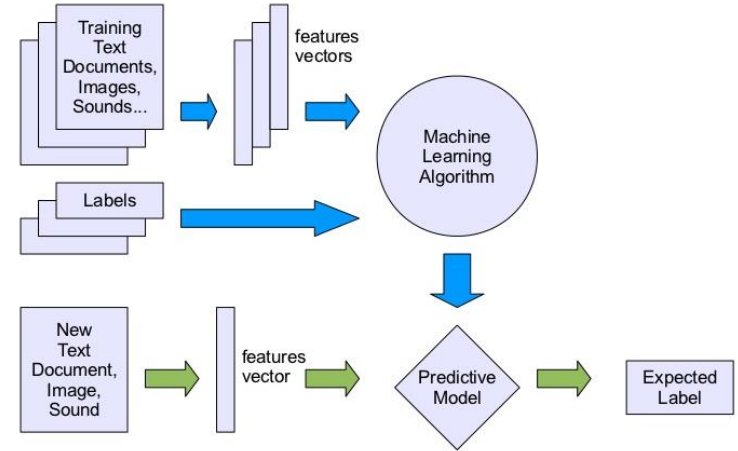
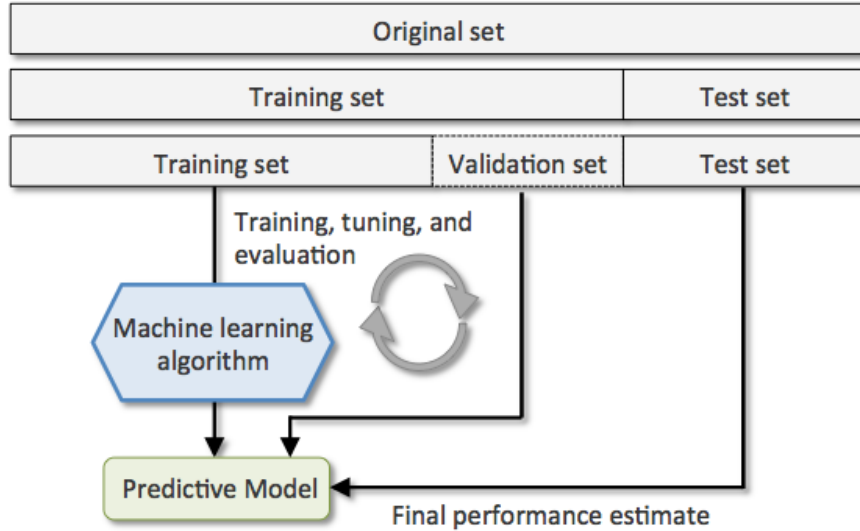
E.g. graph/sequence



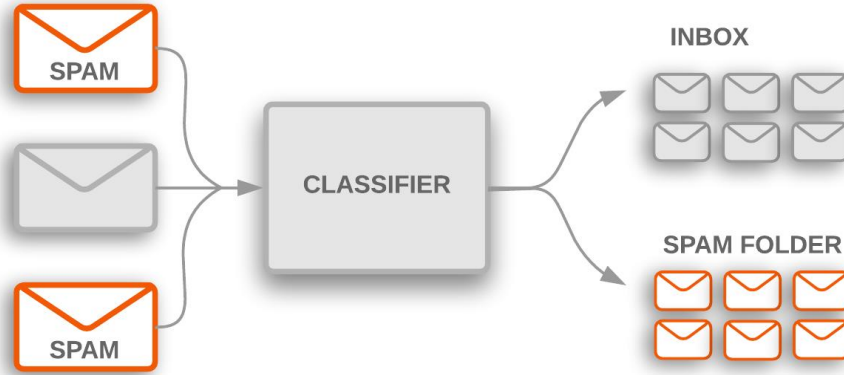
The Train-Validation-Test paradigm



The Train-Validation-Test paradigm

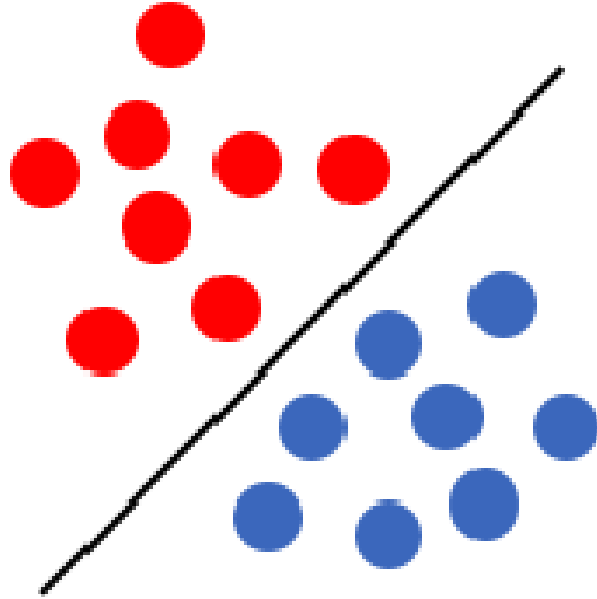


Binary Classification



Binary classification

Positive → E.g. Spam = YES



Negative → E.g. Spam = NO

Binary case...

$$Accuracy = \frac{(100 + 50)}{165} = 0.91$$

$$Misclassification = \frac{(10 + 5)}{165} = 0.09$$

$$TruePositiveRate(TP) = \frac{(100)}{105} = 0.95$$

$$FalsePositiveRate(FP) = \frac{(10)}{60} = 0.17$$

n=165		Predicted: NO	Predicted: YES	
Actual: NO		TN = 50	FP = 10	60
Actual: YES		FN = 5	TP = 100	105
		55	110	

Binary case...

$$TrueNegativeRate(TN) = \frac{(50)}{60} = 0.833$$

$$FalseNegativeRate(FN) = \frac{(5)}{105} = 0.048$$

	n=165		
	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Key accuracy measures and terminologies

- Classification Error = $\frac{\text{errors}}{\text{total}}$

$$= \frac{FP + FN}{TP + TN + FP + FN}$$

- Accuracy = $1 - \text{Error} = \frac{\text{correct}}{\text{Total}}$

$$= \frac{TP + TN}{TP + TN + FP + FN}$$

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
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Precision and Recall

- **Cancer-Prediction System**
- **Pool of 100 patients' data**
- 3 patients' data from the pool are selected for chemotherapy ;
Rest $(100-3=97)$ are declared healthy !
- 1 year later ...
- 1 of them did not actually have cancer ! (FP)
- Precision = $2/(2+1) = 67\%$
- 3 from the 97 healthy declared ones have cancer (FN)
- Recall = $2/(2+3) = 40\%$
- Accuracy = $(94+2)/100 = 96\%$

Precision and Recall – examples

- A system which needs to launch a missile at a terrorist hideout located in a dense urban area.
- Precision not 100% → civilian casualties
- A system which needs to identify cancer-risk patients
- Recall not 100% → some patients will die of cancer

Precision and Recall – a probabilistic perspective

- n = # of patients who underwent a new cancer screening test
- Recall = Probability of test result + given a patient actually has cancer

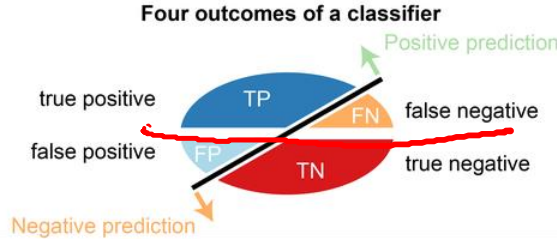
$$\frac{TP}{TP + FN}$$

- Precision = Probability of actually having cancer given the test result is +

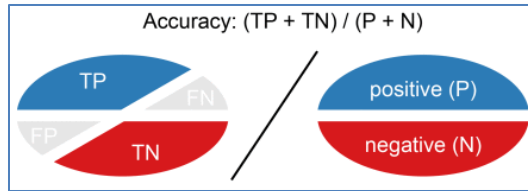
$$\frac{TP}{TP + FP}$$

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

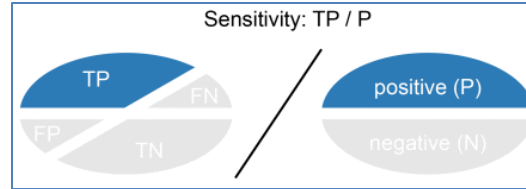
Summary of Measures



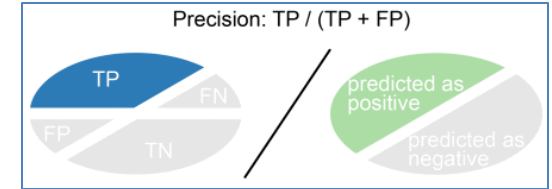
	Predicted: NO	Predicted: YES	
n=165			
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	



% of correct predictions



% of + class correctly predicted
[aka Recall / TPR]



correct prediction of + class



% of - class incorrectly predicted

F1-score: A unified measure

- What to do when one classifier has better Precision but worse Recall, while other classifier behaves exactly opposite?
 - F-measure (Information Retrieval)

$$\blacksquare F_1 = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

Utility and Cost

- What to do when one classifier has better Precision but worse Recall, while other classifier behaves exactly opposite?

○ F-measure (Information Retrieval)

$$\blacksquare F_1 = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$$

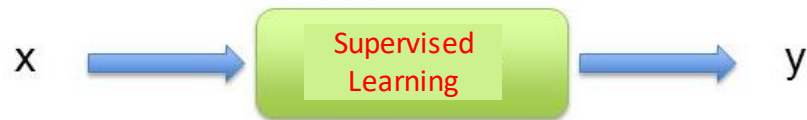
$$\text{Recall} = \frac{TP}{TP + FN}$$
$$\text{Precision} = \frac{TP}{TP + FP}$$

→ F1 measure punishes extreme values more !

→ Definition of Recall and Precision have same numerator, different denominators. A sensible way to combine them is harmonic mean.

Utility and Cost

- Sometimes, there is a cost for each error
 - E.g. Earthquake prediction
 - False positive: Cost of preventive measures
 - False negative: Cost of recovery
- Detection Cost (Event detection)
 - $\text{Cost} = C_{\text{FP}} * \text{FP} + C_{\text{FN}} * \text{FN}$



Classification

Binary

$\{0,1\}$

Multi-class

1-of-K

Multi-label

n-of-K

Structure

E.g. graph/sequence



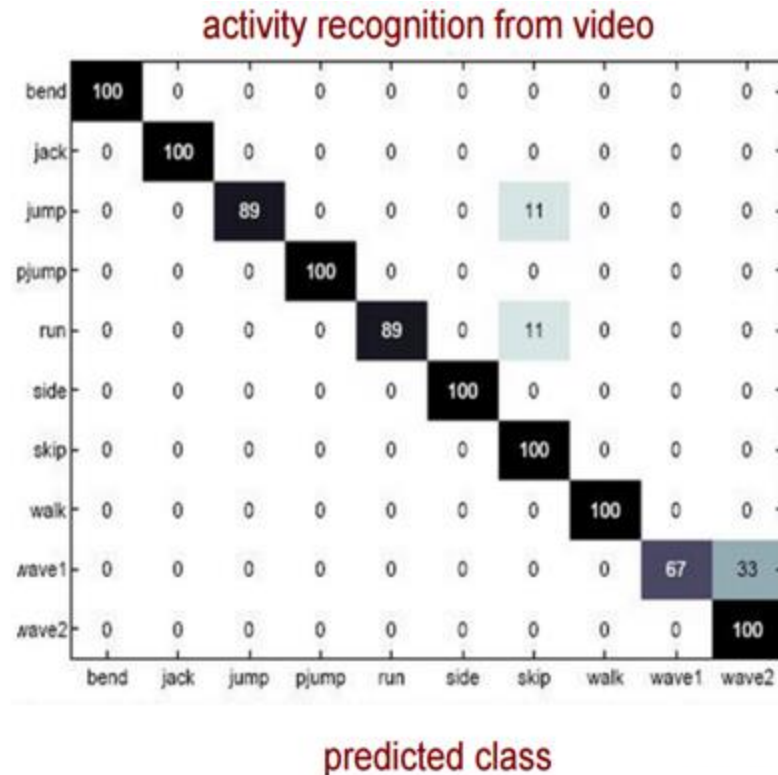
Multi-class problems - Confusion matrix

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

actual class



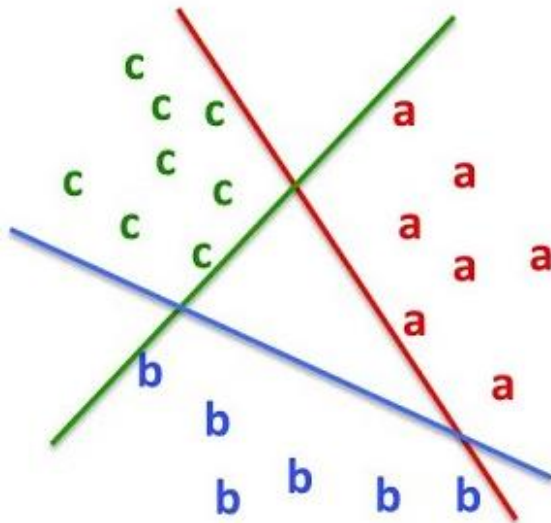
Avg. accuracy may not be very meaningful with imbalanced class label distribution



Courtesy: vision.jhu.edu

How to use 2-class measures for multi-class ?

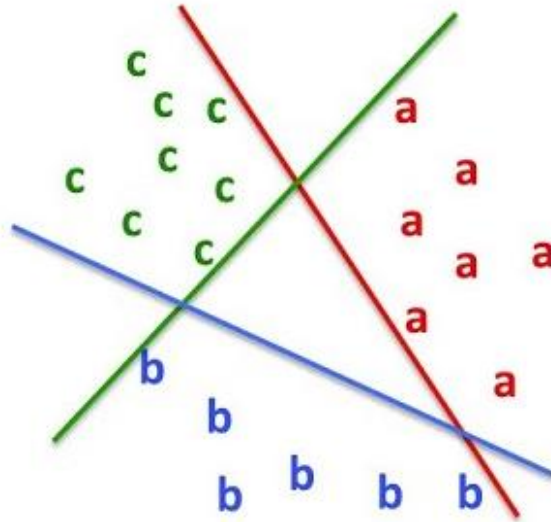
- The 'Cow-Essay' strategy
 - Convert into 2-class problem(s) !



P	R
P_1	R_1
P_2	
P_{10}	R_{10}

How to use 2-class measures for multi-class ?

- The 'Cow-Essay' strategy
 - Convert into 2-class problem(s) !



- Average Precision, Recall etc.



Classification

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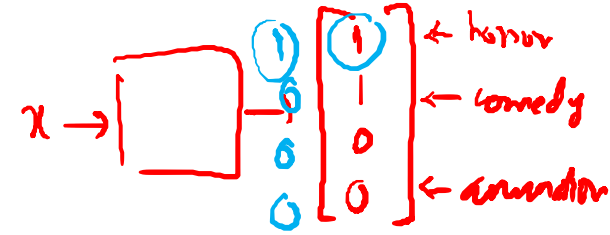
n-of-K

Structure



E.g. graph/sequence

Example-based



- $\frac{1}{n}$ is the number of examples.
- Y_i is the ground truth label assignment of the i^{th} example..
- x_i is the i^{th} example.
- $h(x_i)$ is the predicted labels for the i^{th} example.

$$\text{Precision} = \frac{1}{n} \sum_{i=1}^n \frac{|Y_i \cap h(x_i)|}{|h(x_i)|}$$

What fraction of labels are predicted correctly?

$$\text{Recall} = \frac{1}{n} \sum_{i=1}^n \frac{|Y_i \cap h(x_i)|}{|Y_i|}$$

What % of correct labels were predicted?

Accuracy = Fraction of samples predicted correctly

Summary

- Many metrics:
 - Accuracy, TP, FP, Precision, Recall, AP/mAP
 - Class imbalance and decision-cost imbalance must be taken into account
- Confusion Matrix: Important to analyze and refine solution.

Baselines

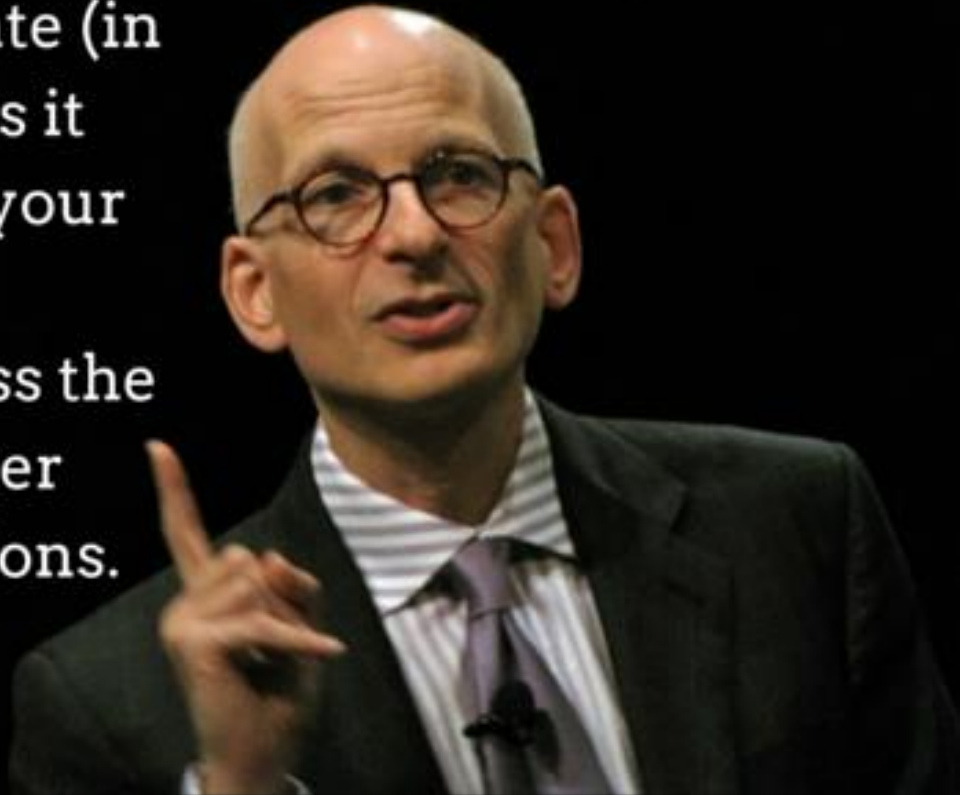
- 0 cost-to-build classifiers
- Binary
 - Equal # of samples / class → Random Guessing (50% accuracy)
 - Class imbalance
 - → Guess according to class proportion (Accuracy = $x^2 + (1-x)^2$)
 - 0-Rule: Majority class (Accuracy =) [slightly stronger baseline]



A useful metric is both accurate (in that it measures what it says it measures) and aligned with your goals.

Don't measure anything unless the data helps you make a better decision or change your actions.

~ Seth Godin



References and Reading

- <https://classeval.wordpress.com/introduction/basic-evaluation-measures/>
- <https://towardsdatascience.com/what-metrics-should-we-use-on-imbalanced-data-set-precision-recall-roc-e2e79252aeba>
- Code
 - https://scikit-learn.org/stable/modules/model_evaluation.html#classification-metrics

Type I error (false positive)



Type II error (false negative)



Figure 3.1 Type I and Type II errors

levels to .01 or even .001

