11.01.2019

Statistical Methods in AI (CSE/ECE 471)

Lecture-4: Intro to Performance Measures, Benchmarking

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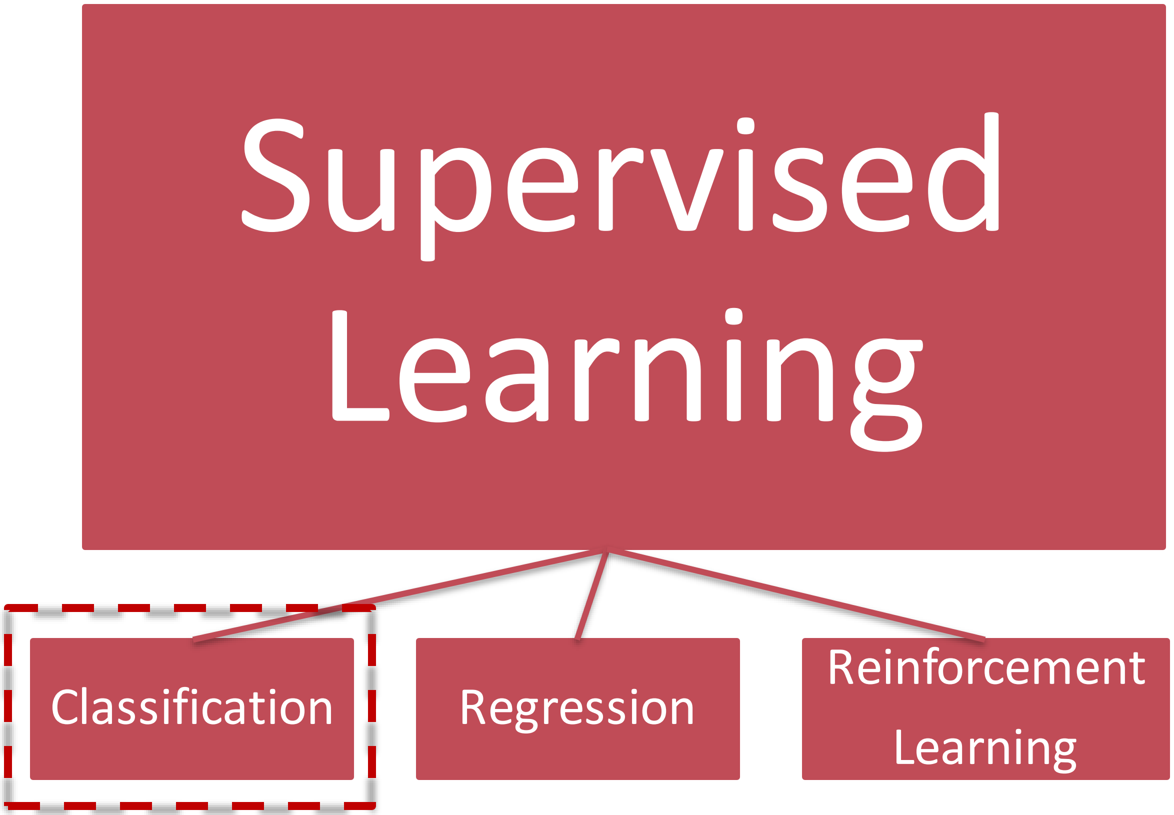
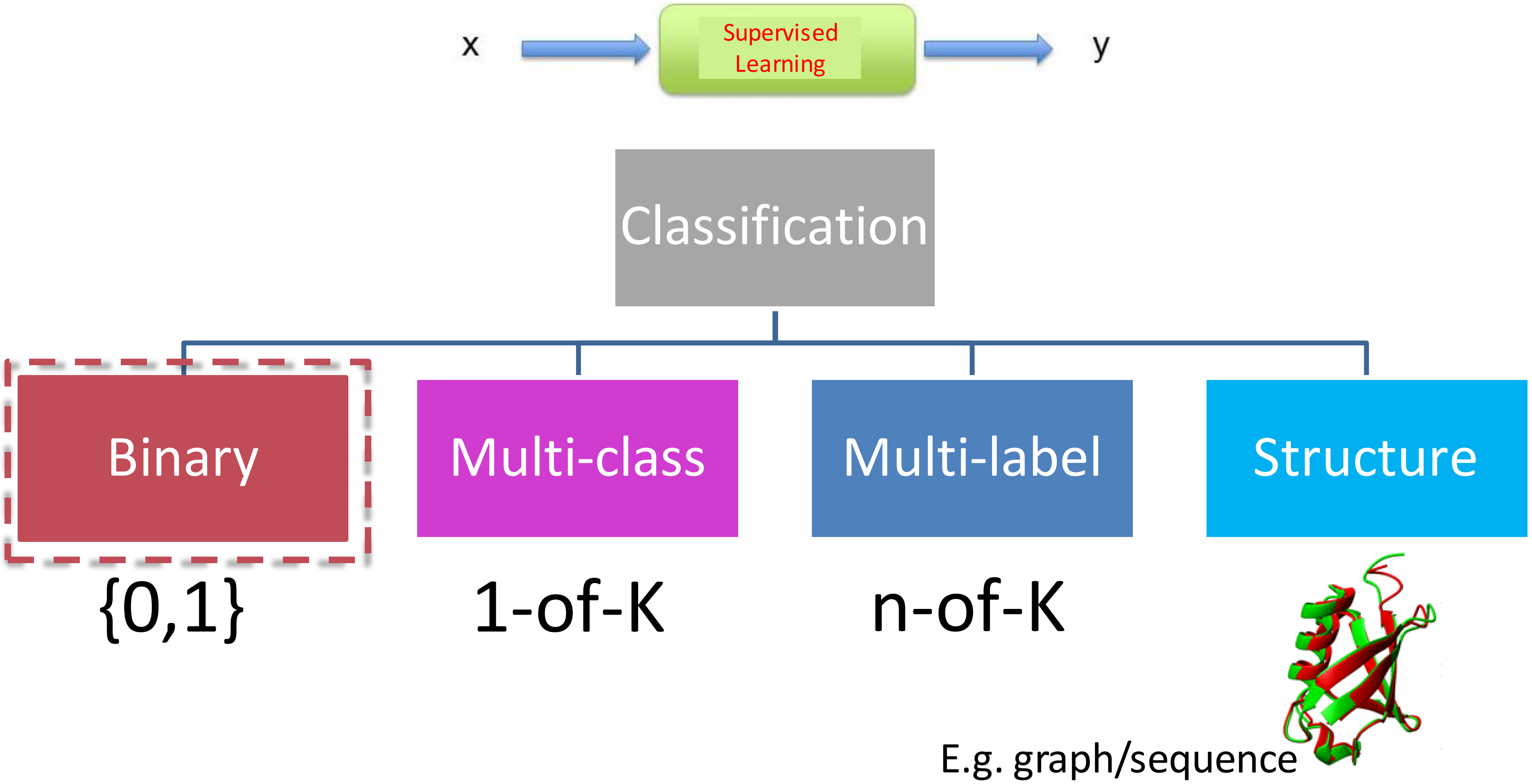
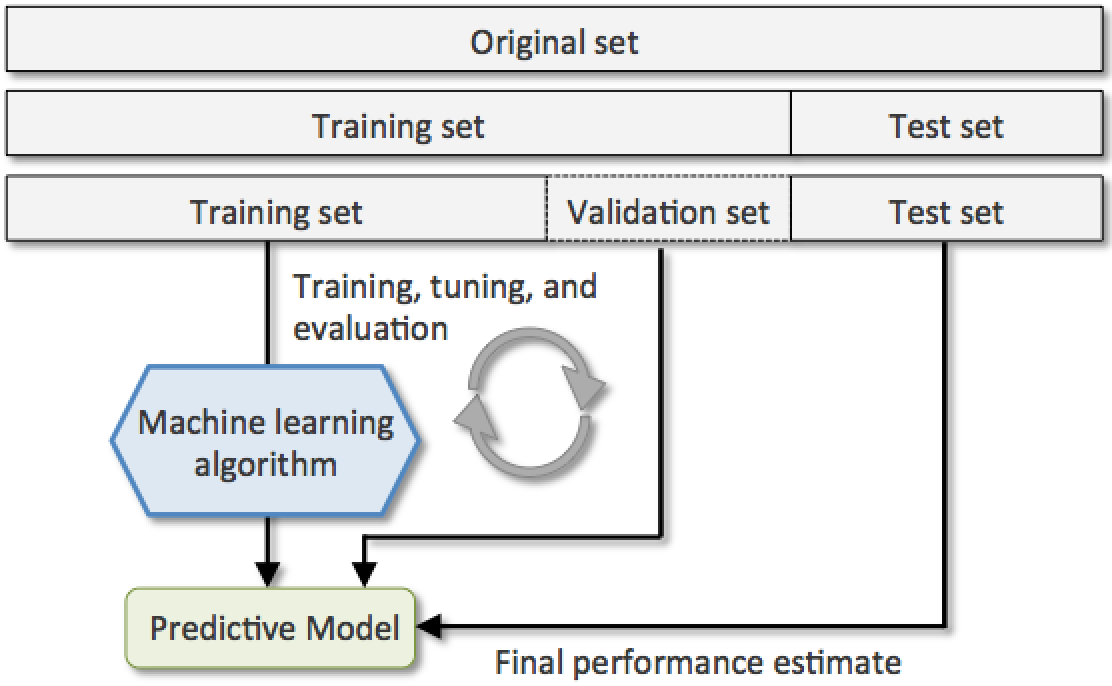
Announcements

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

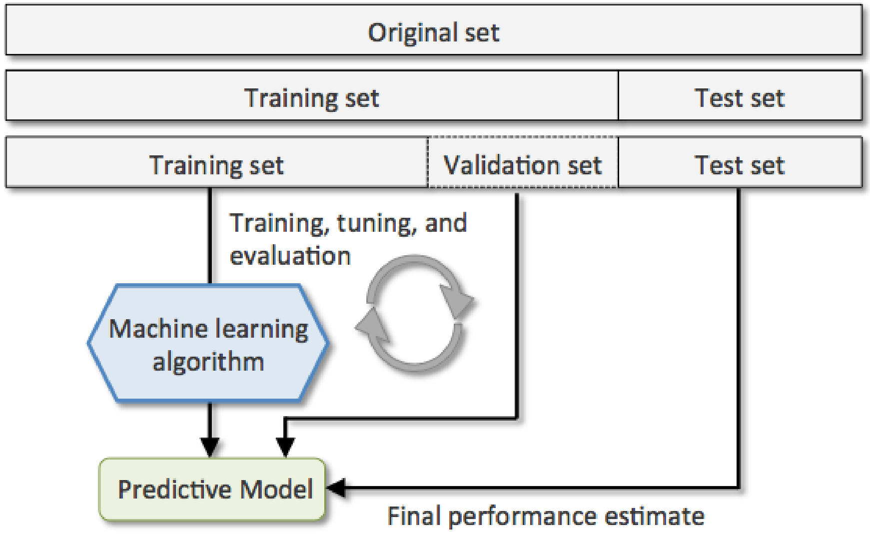

Supervised Learning
Classification
Regression
Reinforcement Learning

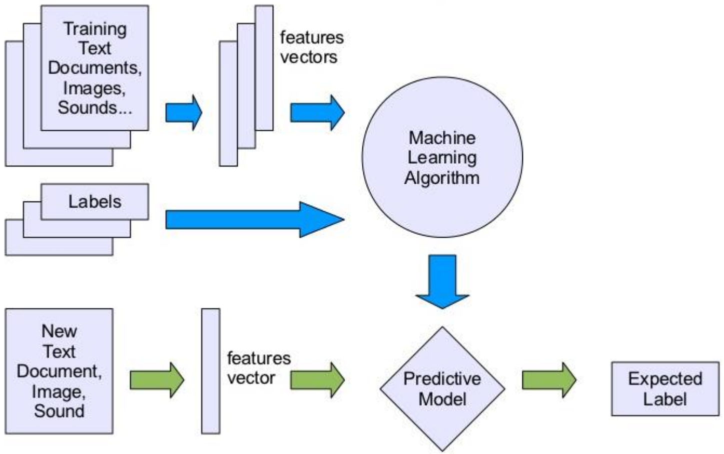

x
Supervised Learning
y
Classification
Binary
Multi-class
Multi-label
Structure
{0,1}
1-of-K
n-of-K
E.g. graph/sequence

The Train-Validation-Test paradigm

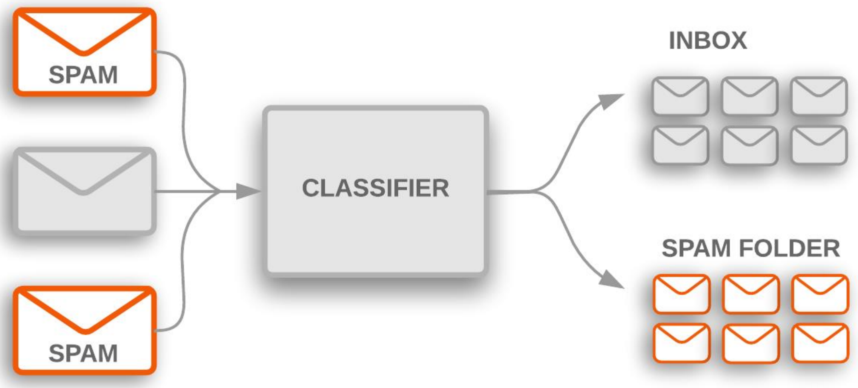


The Train-Validation-Test paradigm



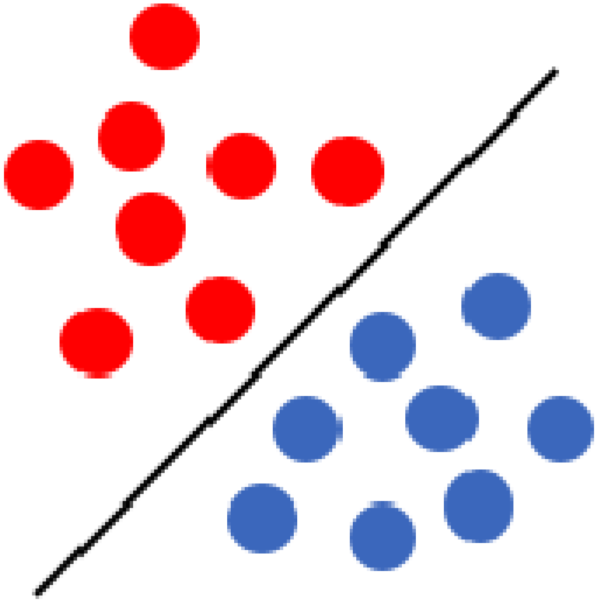


Binary Classification



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

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

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

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

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

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

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

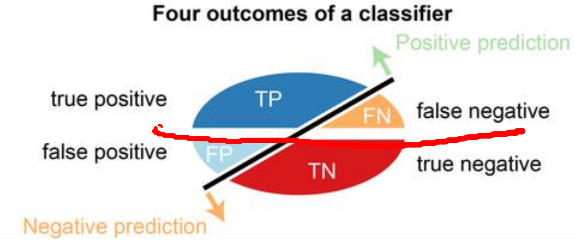
$$\frac{TP}{TP+FN}$$

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

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

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

Summary of Measures



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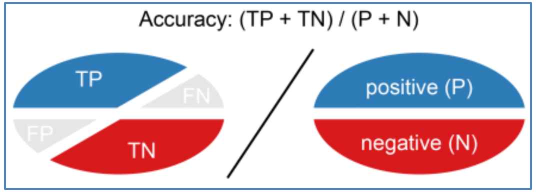
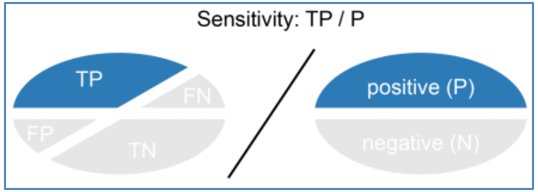
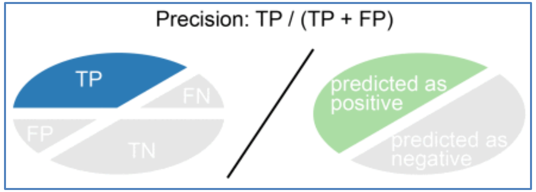


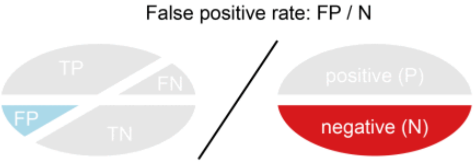
% of correct predictions



% 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)
    - $F_1 = \dfrac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$

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)
    - $F_1 = \dfrac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$

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

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

→ **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)
  - $Cost = C_{FP} * FP + C_{FN} * FN$

x → Supervised Learning → y

Classification

Binary

{0,1}

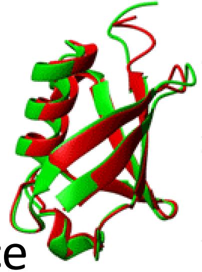
Multi-class

1-of-K

Multi-label

n-of-K

Structure

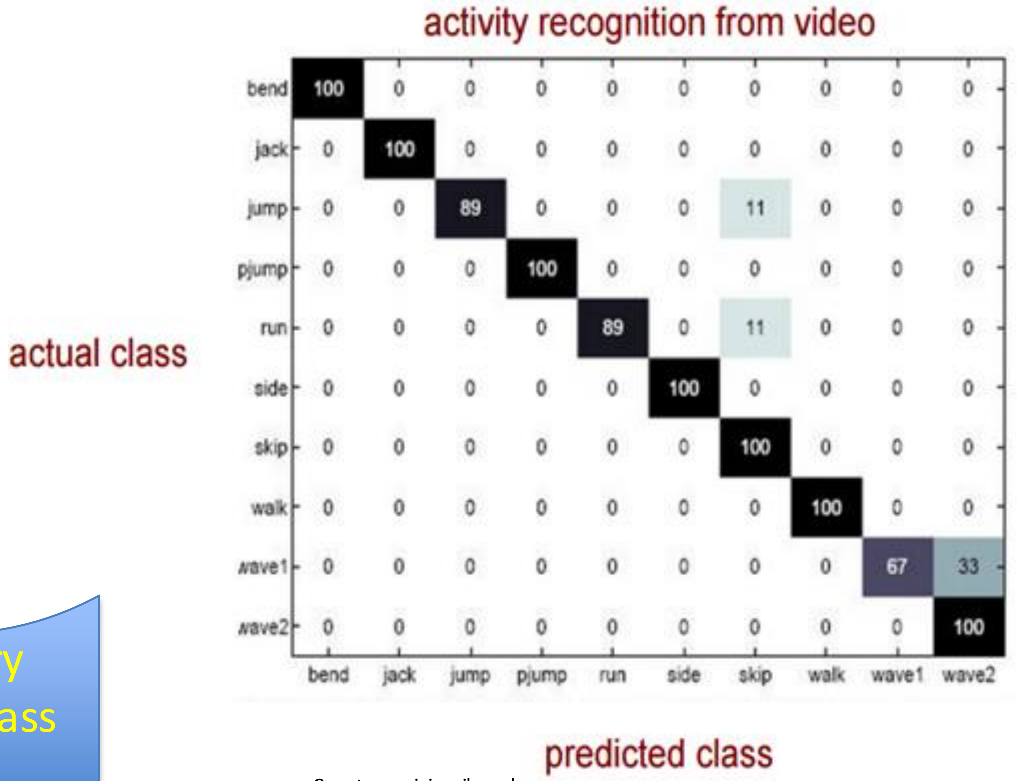


E.g. graph/sequence

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	

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

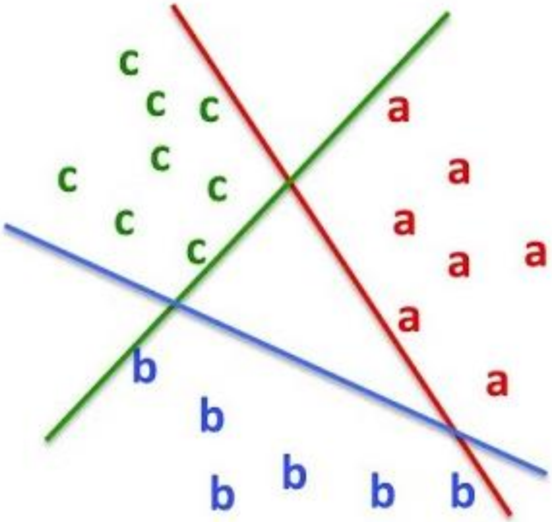


	bend	jack	jump	pjump	run	side	skip	walk	wave1	wave2
bend	100	0	0	0	0	0	0	0	0	0
jack	0	100	0	0	0	0	0	0	0	0
jump	0	0	89	0	0	0	11	0	0	0
pjump	0	0	0	100	0	0	0	0	0	0
run	0	0	0	0	89	0	11	0	0	0
side	0	0	0	0	0	100	0	0	0	0
skip	0	0	0	0	0	0	100	0	0	0
walk	0	0	0	0	0	0	0	100	0	0
wave1	0	0	0	0	0	0	0	0	67	33
wave2	0	0	0	0	0	0	0	0	0	100

Courtesy: vision.jhu.edu

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

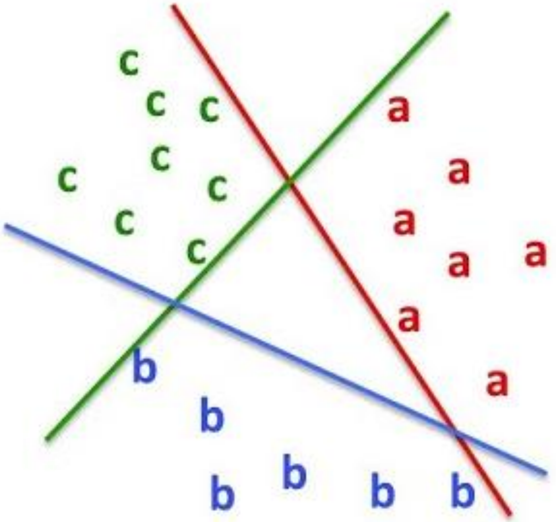
- The `Cow-Essay’ strategy
  - Convert into 2-class problem(s) !



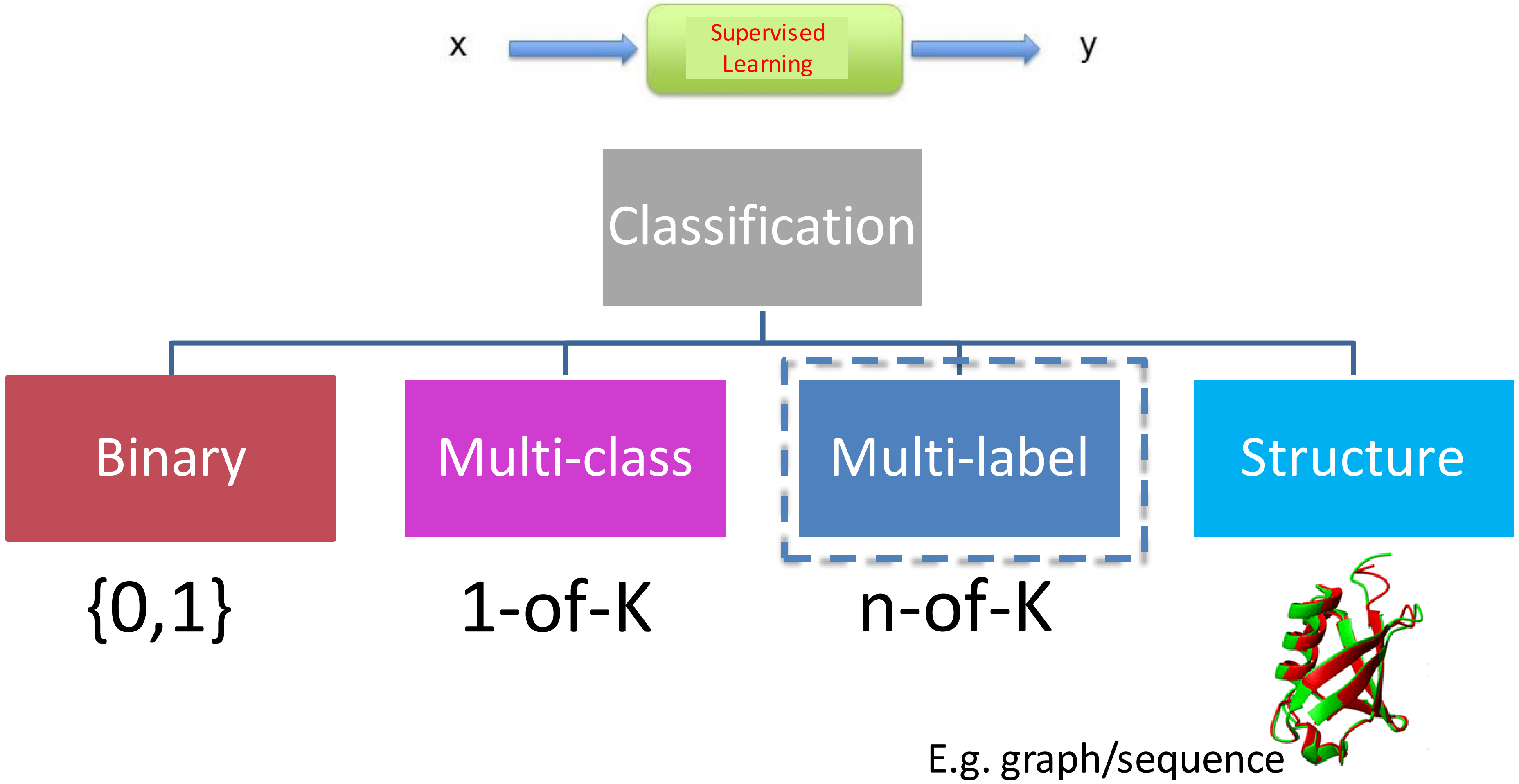
P	R
P_1	R_1
P_2	
P_{10}	R_{10}

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

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



- Average Precision, Recall etc.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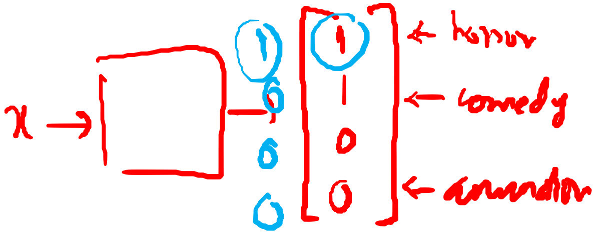
Example-based



- 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.

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 ?

1/2

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

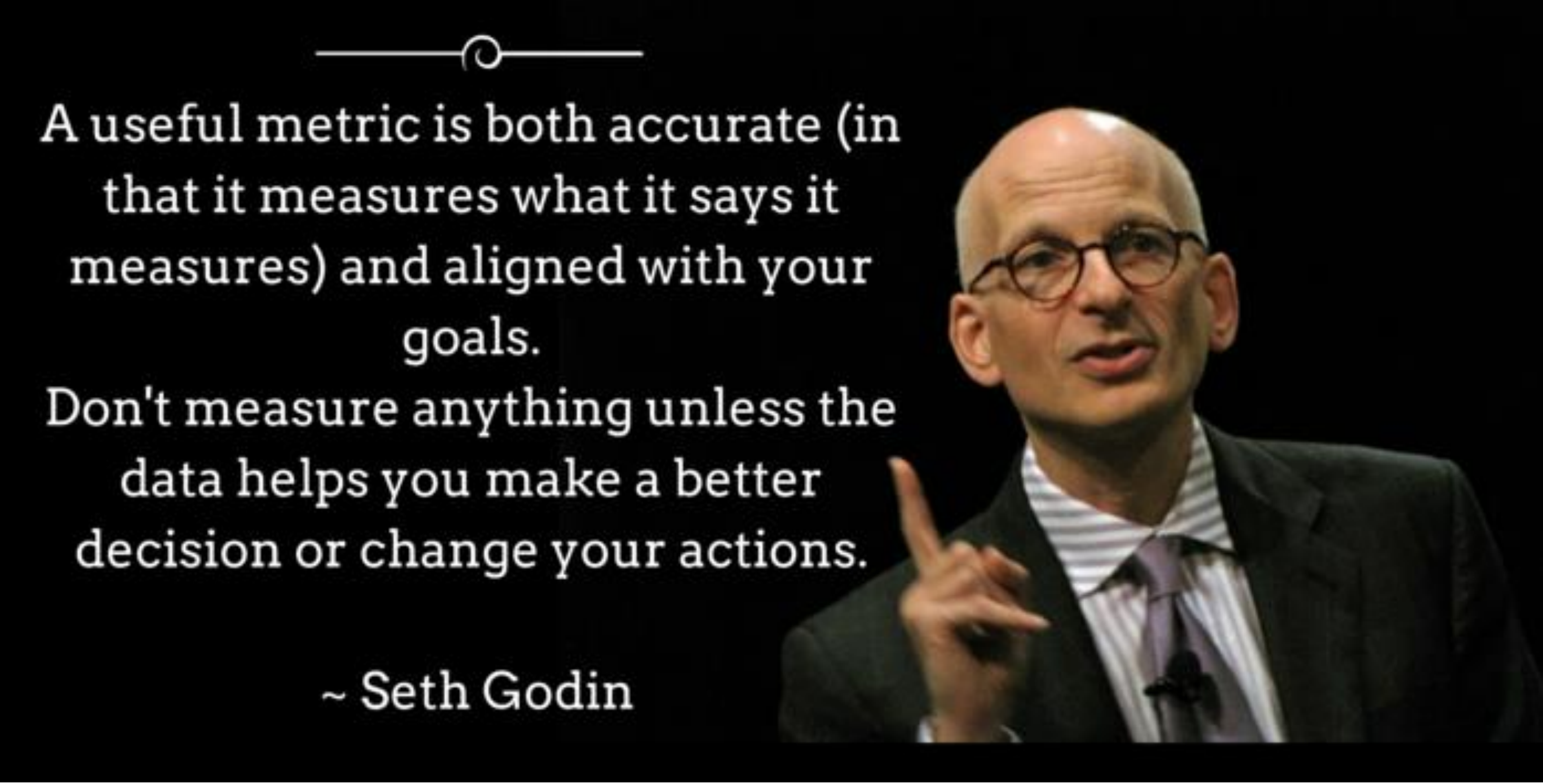
http://ieeexplore.ieee.org/document/6471714/

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

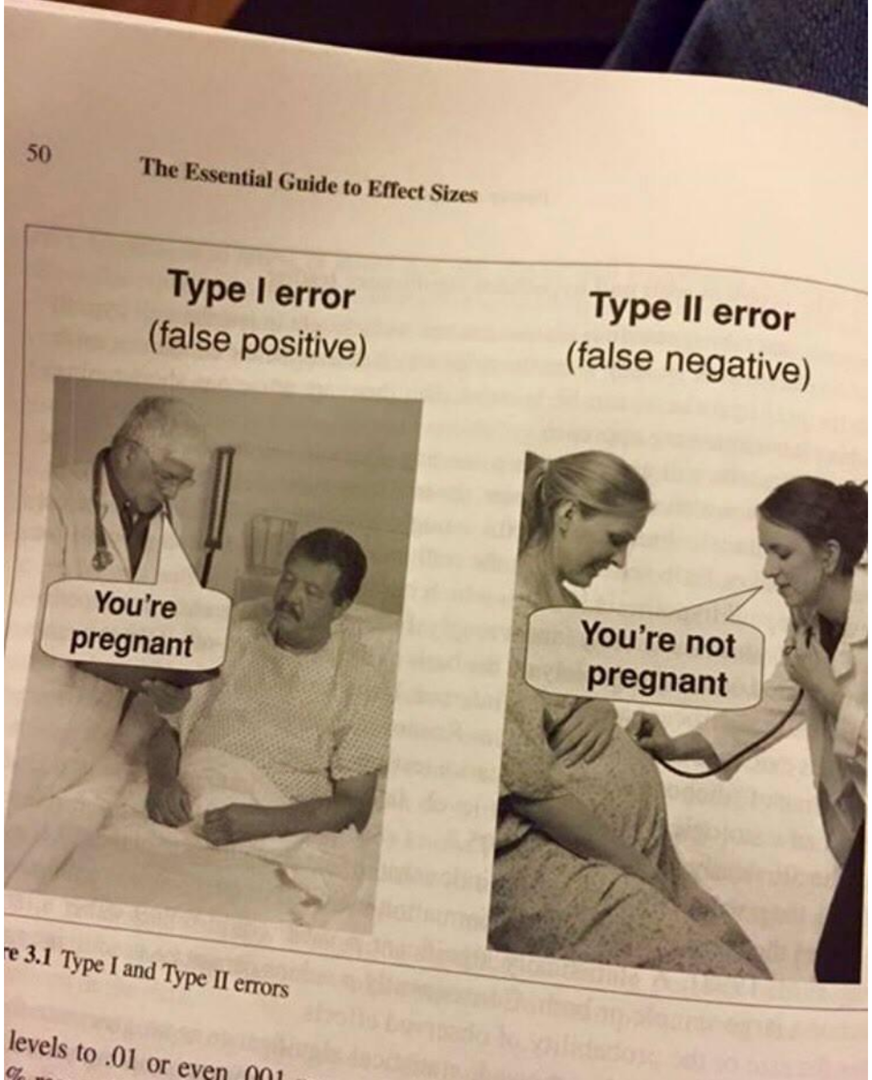
- 0 cost-to-build classifiers
- Binary
  - Equal # of samples / class → Random Guessing (50% accuracy)
  - Class imbalance x $(1-x)$
    - → Guess according to class proportion (Accuracy = $x^2+(1-x)^2$)
    - 0-Rule: Majority class (Accuracy =) [slightly stronger baseline]


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



50 The Essential Guide to Effect Sizes

Type I error
(false positive)

You're
pregnant

Type II error
(false negative)

You're not
pregnant

re 3.1 Type I and Type II errors

levels to .01 or even .001

10 3 7

3,1, 8, 4