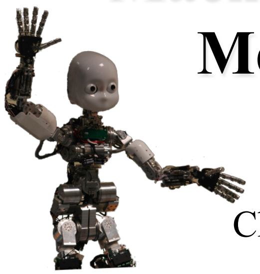
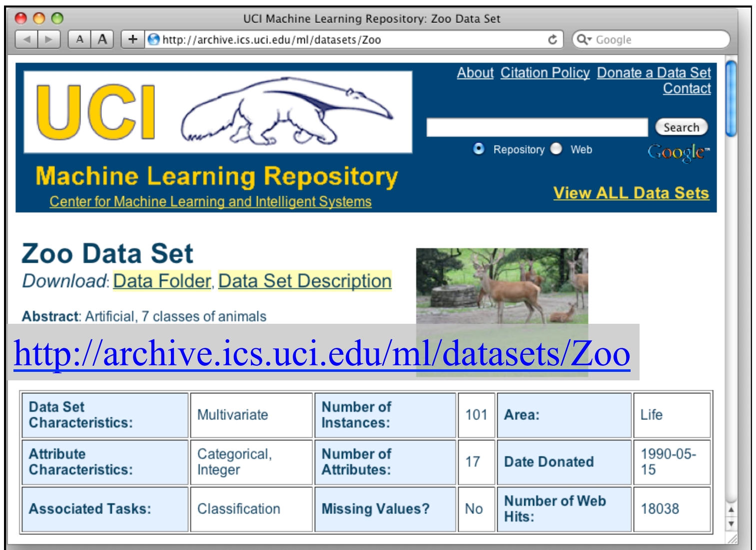
Machine Learning: Methodology



Chapter 18.1-18.3

Some material adopted from notes
by Chuck Dyer



Zoo data

animal name: string
hair: Boolean
feathers: Boolean
eggs: Boolean
milk: Boolean
airborne: Boolean
aquatic: Boolean
predator: Boolean
toothed: Boolean
backbone: Boolean
breathes: Boolean
venomous: Boolean
fins: Boolean
legs: {0,2,4,5,6,8}
tail: Boolean
domestic: Boolean
catsize: Boolean
type: {mammal, fish, bird, shellfish, insect, reptile, amphibian}

101 examples

aardvark,1,0,0,1,0,0,1,1,1,1,0,0,4,0,0,1,mammal
antelope,1,0,0,1,0,0,0,1,1,1,0,0,4,1,0,1,mammal
bass,0,0,1,0,0,1,1,1,1,0,0,1,0,1,0,0,fish
bear,1,0,0,1,0,0,1,1,1,1,0,0,4,0,0,1,mammal
boar,1,0,0,1,0,0,1,1,1,1,0,0,4,1,0,1,mammal
buffalo,1,0,0,1,0,0,0,1,1,1,0,0,4,1,0,1,mammal
calf,1,0,0,1,0,0,0,1,1,1,0,0,4,1,1,1,mammal
carp,0,0,1,0,0,1,0,1,1,0,0,1,0,1,1,0,fish
catfish,0,0,1,0,0,1,1,1,1,0,0,1,0,1,0,0,fish
cavy,1,0,0,1,0,0,0,1,1,1,0,0,4,0,1,0,mammal
cheetah,1,0,0,1,0,0,1,1,1,1,0,0,4,1,0,1,mammal
chicken,0,1,1,0,1,0,0,0,1,1,0,0,2,1,1,0,bird
chub,0,0,1,0,0,1,1,1,1,0,0,1,0,1,0,0,fish
clam,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,shellfish
crab,0,0,1,0,0,1,1,0,0,0,0,0,4,0,0,0,shellfish
…

Zoo example

```
aima-python> python
>>> from learning import *
>>> zoo
<DataSet(zoo): 101 examples, 18 attributes>
>>> dt = DecisionTreeLearner()
>>> dt.train(zoo)
>>> dt.predict(['shark',0,0,1,0,0,1,1,1,1,0,0,1,0,1,0,0])
'fish'
>>> dt.predict(['shark',0,0,0,0,0,1,1,1,1,0,0,1,0,1,0,0])
'mammal'
```

Evaluation methodology (1)

Standard methodology:

1. Collect large set of examples with correct classifications
2. Randomly divide collection into two disjoint sets: *training* and *test*
3. Apply learning algorithm to training set giving hypothesis H
4. Measure performance of H w.r.t. test set

Evaluation methodology (2)

- Important: keep the training and test sets disjoint!
- Study efficiency & robustness of algorithm: repeat steps 2-4 for different training sets & training set sizes
- On modifying algorithm, restart with step 1 to avoid evolving algorithm to work well on just this collection

Evaluation methodology (3)

Common variation on methodology:

1. Collect large set of examples with correct classifications
2. Randomly divide collection into two disjoint sets: *developmen*t and *test,* and further divide development into *devtrain* and *devtest*
3. Apply learning algorithm to *devtrain* set giving hypothesis H
4. Measure performance of H w.r.t. *devtest* set
5. Modify approach, repeat 3-4 ad needed
6. Final test on *test* data

Zoo evaluation

train_and_test(learner, data, start, end) uses data[start:end] for test and the rest for train

```
>>> dtl = DecisionTreeLearner
>>> train_and_test(dtl(), zoo, 0, 10)
1.0
>>> train_and_test(dtl(), zoo, 90, 100)
0.80000000000000004
>>> train_and_test(dtl(), zoo, 90, 101)
0.81818181818181823
>>> train_and_test(dtl(), zoo, 80, 90)
0.90000000000000002
```

K-fold Cross Validation

- Problem: getting "ground truth" data can be expensive
- Problem: ideally need different test data each time we test
- Problem: experimentation is needed to find right "feature space" and parameters for ML algorithm
- Goal: minimize amount of training+test data needed
- Idea: split training data into K subsets, use K-1 for *training*, and one for *development testing*
- Common K values are 5 and 10

Zoo evaluation

cross_validation(learner, data, K, N) does N iterations, each time randomly selecting 1/K data points for test, rest for train

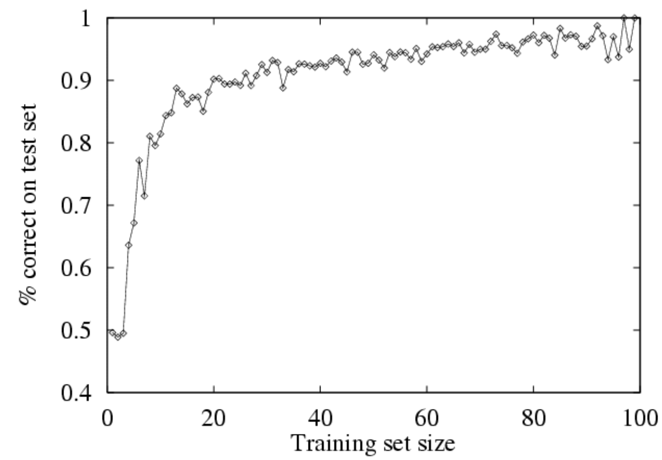
```
>>> cross_validation(dtl(), zoo, 10, 20)
0.95500000000000007
```

leave1out(learner, data) does len(data) trials, each using one element for test, rest for train

```
>>> leave1out(dtl(), zoo)
0.97029702970297027
```

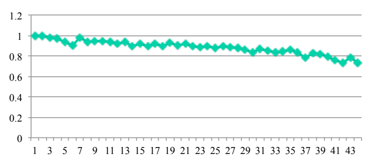
Learning curve

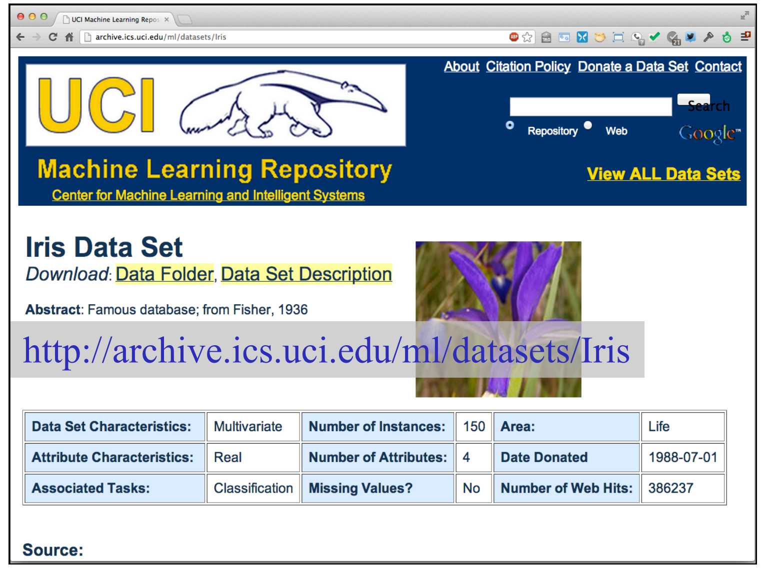
Learning curve = % correct on test set as a function of training set size



Zoo

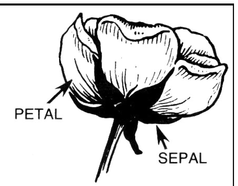
>>> learningcurve(DecisionTreeLearner(), zoo)
[(2, 1.0), (4, 1.0), (6, 0.98333333333333339), (8, 0.97499999999999998), (10, 0.94000000000000006), (12, 0.90833333333333321), (14, 0.98571428571428577), (16, 0.9375), (18, 0.94999999999999996), (20, 0.94499999999999995), … (86, 0.78255813953488373), (88, 0.73636363636363644), (90, 0.70777777777777795)]





http://archive.ics.uci.edu/ml/datasets/Iris

Iris Data



- Three classes: Iris Setosa, Iris Versicolour, Iris Virginica
- Four features: sepal length and width, petal length and width
- 150 data elements (50 of each)

```
aima-python> more data/iris.csv
5.1,3.5,1.4,0.2,setosa
4.9,3.0,1.4,0.2,setosa
4.7,3.2,1.3,0.2,setosa
4.6,3.1,1.5,0.2,setosa
5.0,3.6,1.4,0.2,setosa
```

http://code.google.com/p/aima-data/source/browse/trunk/iris.csv

Comparing ML Approaches

- The effectiveness of ML algorithms varies depending on the problem, data and features used
- You may have institutions, but run experiments
- Average accuracy (% correct) is a standard metric

>>> compare([DecisionTreeLearner, NaiveBayesLearner, NearestNeighborLearner], datasets=[iris, zoo], k=10, trials=5)

	iris	zoo
DecisionTree	0.86	0.94
NaiveBayes	0.92	0.92
NearestNeighbor	0.85	0.96

Confusion Matrix (1)

- A confusion matrix can be a better way to show results
- For binary classifiers it's simple and is related to type I and type II errors (i.e., false positives and false negatives)
- There may be different costs for each kind of error
- So we need to understand their frequencies

predicted

a/c	C	~C
C	True positive	False negative
~C	False positive	True negative

actual

Confusion Matrix (2)

- For multi-way classifiers, a confusion matrix is even more useful
- It lets you focus in on where the errors are

predicted

	Cat	Dog	rabbit
Cat	5	3	0
Dog	2	3	1
Rabbit	0	2	11

actual

Accuracy, Error Rate, Sensitivity and Specificity

A\P	C	¬C	
C	TP	FN	P
¬C	FP	TN	N
	P'	N'	All

- **Classifier Accuracy,** or recognition rate: percentage of test set tuples that are correctly classified

  Accuracy = (TP + TN)/All
- **Error rate:** *1 – accuracy*, or

  Error rate = (FP + FN)/All

- **Class Imbalance Problem**:
  - One class may be *rare*, e.g. fraud, or HIV-positive
  - Significant *majority of the negative class* and minority of the positive class
  - **Sensitivity**: True Positive recognition rate
    - **Sensitivity = TP/P**
  - **Specificity**: True Negative recognition rate
    - **Specificity = TN/N**

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Precision and Recall

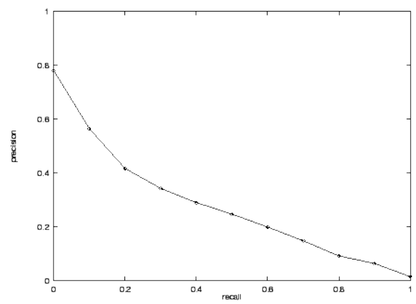
- Information retrieval uses precision and recall to characterize retrieval effectiveness
  - **Precision**: exactness – what % of tuples that the classifier labeled as positive are actually positive
  - **Recall:** completeness – what % of positive tuples did the classifier label as positive?

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

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

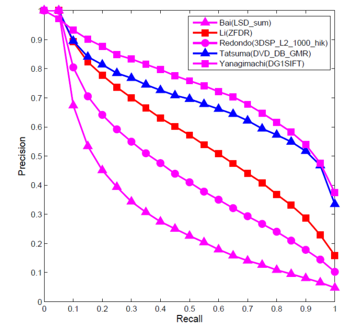
Precision and Recall

- In general, increasing one causes the other to decrease
- Studying the precision recall curve is informative



Precision and Recall

If one system's curve is always above the other, it's better



F measure

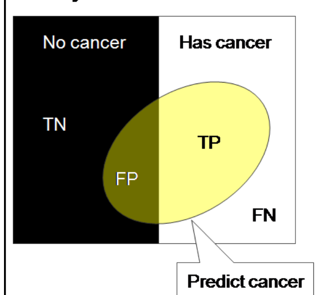
The F measure combines the two into a useful single metric

$$F = \frac{2 \times precision \times recall}{precision + recall}$$

Actual\Predicted class	cancer = yes	cancer = no	Total	Recognition(%)
cancer = yes	**90**	**210**	300	30.00 (*sensitivity*
cancer = no	**140**	**9560**	9700	98.56 (*specificity*)
Total	230	9770	10000	96.40 (*accuracy*)

ROC Curve (1)

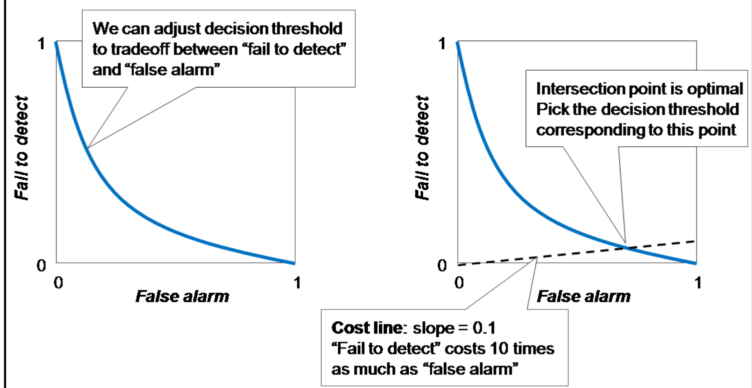
Binary Classification Problem



	Has cancer	No cancer
Predict cancer	**TP**	**FP**
Predict No cancer	**FN**	**TN**

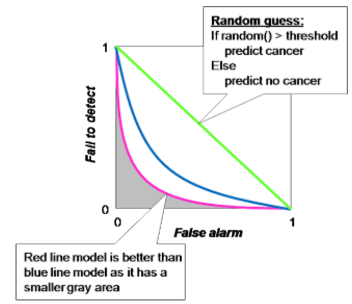
Fail to detect
P (Miss | Cancer) = FN / (TP + FN)
False alarm
P (Alarm | NoCancer) = FP / (FP + TN)

ROC Curve (2)



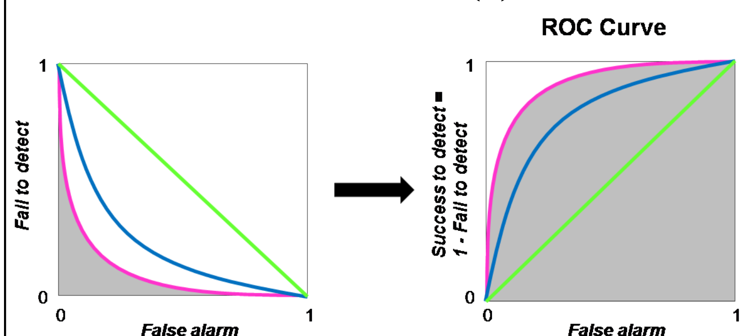
There is always a tradeoff between the false negative rate and the false positive rate.

ROC Curve (3)



"Random guess" is worst prediction model and is used as a baseline. The decision threshold of a random guess is a number between 0 to 1 in order to determine between positive and negative prediction.

ROC Curve (4)



ROC Curve transforms the y-axis from "fail to detect" to 1 - "fail to detect”, i.e., "success to detect”