COMP 543: Tools & Models for Data Science Intro to Supervised Learning

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"Supervised" Learning

- One of the most fundamental problems in data science
 - Given a bunch of (x_i, y_i) pairs
 - Goal: learn how to predict value of *y* from *x*
 - Called "supervised" because have examples of correct labeling

Problem Examples

- From research done at Rice:
 - Given a text clinical note, label "breast cancer" or not
 - Given a document (email) in a court case, figure which subjects pertain
 - Given information about a patient surgery, predict death
 - Given head trauma patient info, predict intracranial pressure crisis
 - Given an set of surgical vital signs, label "good surgery" or not
 - Predict location and damage from a hurricane
 - Many others!

Two Most Common Examples of Supervised Learning

- Classification and regression
- Classification:
 - \blacksquare Outcome to predict is in $\{+1,-1\}$ ("yes" or "no")
 - Ex: Given a text clinical note, label it as "breast cancer" or not
- Regression:
 - Outcome to predict is a real number
 - Ex: Given an ad, predict number of clickthrus per hour

What Models Are Used?

- Many!
 - We will cover a number of them
 - Simplest, most common: linear regression. From x_i , predict y_i as:

$$\sum_{j} x_{i,j} r_j$$

- Where $x_{i,i}$ is a matrix of rows of feature values, one for each data point
- $\langle r_1, r_2, ..., r_m \rangle$ are called regression coefficients
 - The relative magnitude of the regression coefficient tells you how important each feature is
- Other common ones: kNN (A4), support vector machines

What do we Mean by Features?

Clickthru

- Location
- Font
- Size
- Color
- ..

Patient

- Age
- History of Smoking
- History of Diabetes
- Blood pressure
- Weight
- ...

Measuring Classification Accuracy: Confusion Matrix

■ Tabular representation of results

		Actual	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN
Total		Р	N

Measuring Classification Accuracy: % Correct

- Simplest: % correct
- $\frac{\text{TP} + \text{TN}}{\text{P} + \text{N}} = 0.94$
- ? Pros and cons?

		Actual	
		Positive	Negative
Predicted	Positive	10	5
	Negative	2	95
Total		12	100

Measuring Classification Accuracy: % Correct

- Simplest: % correct
 - Pros
 - Easy to interpret
 - Easy to compute
 - Easy to compare
 - Cons
 - Certain classes may be more important than others
 - E.g. Male breast cancer
 - Can achieve high accuracy just by saying "No"
 - In this case, better to find all the cases and some that aren't

Measuring Classification Accuracy: FP & FN

	Actual		tual
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN
Total		Р	N

		Actual	
		Positive	Negative
Predicted	Positive	10	5
Fredicted	Negative	2	95
Total		12	100

■ False positive: % of those we say are "yes" that are not really "yes"

$$\frac{FP}{N} = \frac{FP}{FP + TN} = \frac{5}{5 + 95}$$

■ False negative: % of those we say are "no" that are not really "no"

$$\frac{FN}{P} = \frac{FN}{FN + TP} = \frac{2}{2 + 10}$$

- Simple concept, easy to get wrong
- Male breast cancer: 50% FP rate is okay: 3 real cases + 3 extra cases
- Alert fatigue: 72 99% of alerts are not actual causes for alert ¹

¹Sendelbach S, Funk M. Alarm fatigue: a patient safety concern. AACN advanced critical care. 2013;24(4):378-86.

Measuring Classification Accuracy: Recall & Precision

		Actual	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN
Total		Р	N

	Actual		
		Positive	Negative
Predicted	Positive	10	5
Tredicted	Negative	2	95
To	Total		100

■ Recall (Sensitivity): % of those that are really "yes" that we say are "yes"

$$\frac{TP}{P} = \frac{TP}{TP + FN} = \frac{10}{10 + 2}$$

■ Precision: % of those that we say are "yes" that are really "yes"

$$\frac{TP}{TP + FP} = \frac{10}{10 + 5}$$

? Pros and cons?

Measuring Classification Accuracy: Recall & Precision

- Recall and precision
 - Pros
 - More information than accuracy
 - Tolerance for TP and FN can be different, based on the situation
 - Cons
 - Can be confusing

Measuring Classification Accuracy F1-score

- $\blacksquare F_1$
 - Puts recall and precision into single number

$$F_1 = \frac{2 \times \text{ precision} \times \text{ recall}}{\text{precision} + \text{ recall}}$$

? Pros and cons?

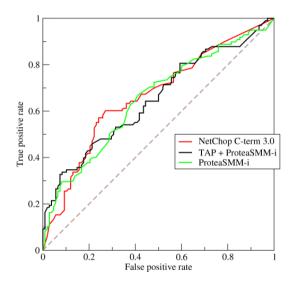
Measuring Classification Accuracy F1-score

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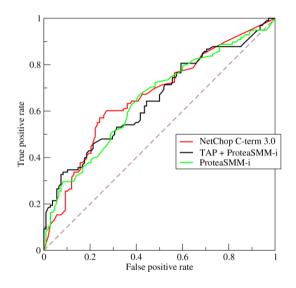
- Pros
 - Reasonable way to combine precision and recall
- Cons
 - Somewhat arbitrary
 - Could use F₂, F₃, etc.

AUC ROC



- ROC = "Receiver operating characteristic"
- AUC = "Area under curve"
- Measure of how well the classes are separated
- Use for "tunable" classifiers (with cut-offs, like Logistic Regression)
- Gives single number ≤ 1.0
- Less than 0.5 means "actively bad"
- ? What does it mean if you have an AUC < 0.5?
- ? Pros and cons?

AUC ROC



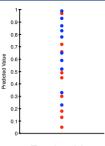
Pros

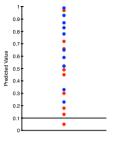
- Single number
- Well known
- Immune to classification threshold

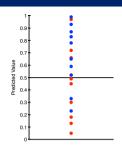
Cons

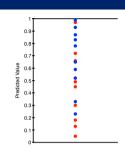
Only works on binary classification

AUC ROC









- Red = Negative cases
- Blue = Positive cases
- Start at the bottom (or top)
- Sweep up (down)
- Compute the TPR and FPR at each step
- Plot on ROC
- Compute AUC

Measuring Regression Accuracy

- View the list of prediction errors as a vector
- Can have many loss functions, corresponding to norms
- Given a vector of errors $\langle \varepsilon_1, \varepsilon_2, ..., \varepsilon_n \rangle$, l_p norm defined as:

$$\left(\sum_{i=1}^n |\varepsilon_i|^p\right)^{1/p}$$

- Common loss functions correspond to various norms:
 - *l*₁ corresponds to mean absolute error
 - \blacksquare l_2 to mean squared error/least squares
 - Most commonly used
 - Convex
 - Easy to compute
 - $lacktriangleq l_{\infty}$ corresponds to minimax

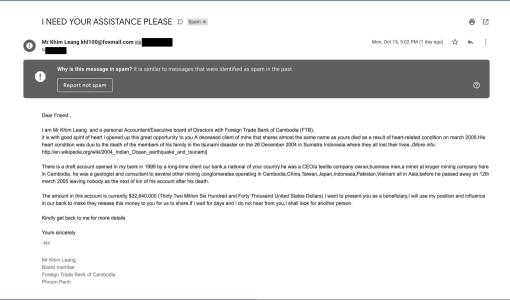
Feature Selection

- Lots of focus in supervised learning on models
 - Linear regression, SVM, kNN, etc.
- Almost always **less** important than feature engineering
 - That is, most simple models accept $x_i = \langle x_{i,1}, x_{i,2}, ..., x_{i,m} \rangle$
 - Do not accept your raw data!
 - How you "vectorize" is often the most important question!
- Let's consider feature engineering thru an example...

Web Page Link Feature Selection

- Web page link
 - Location
 - Font
 - Size
 - Color
 - ...
- vs. Deep learning
 - Use the raw data
 - E.g. Take a screen shot of the web page
 - Skip the feature engineering phase

Feature Selection Email



"Bag of Words"

- Might build a dictionary
 - That is, map from each of *m* unique words in corpus
 - To a number from $\{1...m\}$
 - Then, each email is a vector $\langle 1,0,2,1,0,0,... \rangle$
 - \blacksquare jth entry is num occurrences of word j
 - Latent Dirichlet Allocation (LDA) uses this approach
 - ? Are there issues with this approach?

"Bag of Words Issues"

- Lose sequence information
 - Use N-grams
 - # of combinations explodes
 - The data dimensionality can get to billions
 - But the feature vector is typically sparse
- Word importance is lost

TF-IDF

- "Term Frequency" frequency of each word in the document
 - Defined as:

$$TF = \frac{\text{num occurs of word in doc}}{\text{num words in doc}}$$

- "Inverse Document Frequency" rareness of the word in the corpus
 - Defined as:

$$IDF = \log \frac{\text{num of docs}}{\text{num of docs having the word}}$$

■ TD-IDF defined as $TF \times IDF$

N-Grams

- Words in this doc might not be suspicious
- Might be how they are put together
 - "great sorrow"
 - "heavy tears"
 - "financial institution"
 - "fear ness"
- Idea: also include all 2-grams, 3-grams, 4-grams, etc. as features

RICE 2:

What Else?

- Country of sender
- Number of words in email
- Time of day sent
- Was the email sent previously? Does it include an email I sent?
- Recipient list disclosed? If not, indicative of spam

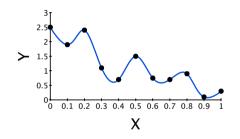
Supervised Learning Methodology

- Important to divide available data into
 - Training—used to learn model
 - Validation—used to see if model useful
 - Repeat these two, experimenting
 - Testing-used to evaluate useful models
- Don't touch testing until ready to eval
 - Evaluation on testing must be very last step!
 - ? Why?

Why Test Only Once?

Overfitting

- It's easy to build a model that exactly fits your data
- But doesn't work on new data
- Maybe the world has changed
 - Can't do much about this
- Overfitting
 - You don't want to engineer something that only works on your test data



How To Perform Testing

- One-off
 - Apply validated model(s), get results
 - ? Problems?

How To Perform Testing

- One-off
 - Apply validated model(s), get results
 - Problems?
 - You're done
 - You've used up your test set

k-Fold Cross-Validation

■ Break into *k* random subsets ("folds")

```
For i = 1 to k do:
   Train on all folds except i;
   Eval learned model on fold i;
Report average results;
```

- Benefits
 - Works for small test sets
 - k can be large

Other techniques for Generating Test Sets

- Jackknife resampling (Leave out one)
- Bootstrap random sampling with replacement

Questions?