Week 11

July 27, 2021

Prioritizing what to work on - spam classification example

- Building a spam classifier.
- Misspelled word => Spam (1).
- Real content => Not spam (0).

From: cheapsales@buystufffromme.com
To: ang@cs.stanford.edu

Subject: Buy now!

Deal of the week! Buy now!
Rolex w4tchs - \$100
Medicine (any kind) - \$50
Also low cost M0rgages
available.

Span

From: Alfred Ng

To: ang@cs.stanford.edu Subject: Christmas dates?

Hey Andrew,

Was talking to Mom about plans for Xmas. When do you get off work. Meet Dec 22?

Alf

Non-spom

Select your own features

- Choose 100 words that indicate if an email is spam or not.
- Buy, discount, and deal are examples of spam.
- Andrew and now are examples of non-spam.
- All these words go into one long vector.
- If a matching word does not appear in the email, store 0 in the vector; otherwise, store 1.
- Check which word category has the most occurrences.

How to improve system accuracy?

- Collect more data.
- Develop sophisticated features based on email routing data.
- Create a powerful algorithm for detecting misspellings.
- Plot learning curves to see whether extra data, features, and so on will help algorithmic optimization.

Error analysis

- Examine the samples (in the cross validation set) on which your algorithm made errors manually.
- Try to figure out why.
- For example, you may find out that the most prevalent types of spam emails are pharmaceutical emails and phishing emails.
- What features would have helped classify them correctly?

Error metrics for skewed analysis

- Suppose we're attempting to categorize cancer patients.
- We have 1% error. Looks good?
- But only 0.5% of people have cancer.
- Now, 1% error looks very bad!

Precision and recall

Classification	Guessed	Real
True positive	1	1
False positive	1	0
True negative	0	0
False negative	0	1

• Precision: How often does our algorithm cause a false alarm?

$$\frac{true\ positives}{true\ positives\ +\ false\ positives}$$

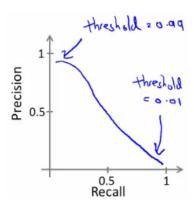
• Recall: How sensitive is our algorithm?

$$\frac{true\ positives}{true\ positives\ +\ false\ negative}$$

Trading off precision and recall

- Trained a logistic regression classifier
 - Predict 1 if $h_{\theta}(x) >= 0.5$
 - Predict 0 if $h_{\theta}(x) < 0.5$

- We might change the prediction threshold such that we are more sure that a 1 is a true positive.
 - Predict 1 if $h_{\theta}(x) >= 0.8$
 - Predict 0 if $h_{\theta}(x) < 0.2$
- \bullet But classifier has lower recall predict y = 1 for a smaller number of patients.



 F_{score} is calculated by averaging precision and recall and assigning a larger weight to the lower number.

$$F_{score} = 2\frac{PR}{P+R}$$

If you're attempting to establish the threshold automatically, one method is to test a variety of threshold values and assess them on your cross validation set. Then select the threshold that yields the highest F_{score} .