POIR 613: Computational Social Science

Pablo Barberá

University of Southern California
pablobarbera.com

Course website:
pablobarbera.com/POIR613/

Overview of QTA (Grimmer and Stewart, 2013)

1. Acquire textual data:
   - Existing corpora; scraped data; digitized text
2. Preprocess the data:
   - Bag-of-words vs word embeddings
3. Apply method appropriate to research goal:
   - Describe and compare documents
     - Readability; similarity; keyness metrics
   - Classify documents into known categories
     - Dictionary methods
     - Supervised machine learning
   - Classify documents into unknown categories
     - Document clustering
     - Topic models
   - Scale documents on latent dimension
     - Known dimension: wordscores
     - Unknown dimensions: wordfish

Supervised machine learning

Outline

- Supervised learning overview
- Creating a labeled set and evaluating its reliability
- Classifier performance metrics
- One classifier for text
  - Regularized regression

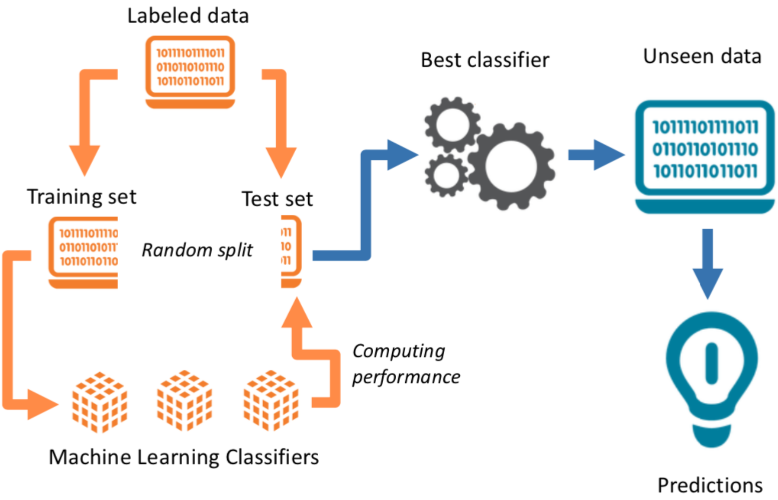
Supervised machine learning

Goal: classify documents into pre existing categories.

e.g. authors of documents, sentiment of tweets, ideological position of parties based on manifestos, tone of movie reviews...

What we need:

- Hand-coded dataset (labeled), to be split into:
  - Training set: used to train the classifier
  - Validation/Test set: used to validate the classifier
- Method to extrapolate from hand coding to unlabeled documents (classifier):
  - Naive Bayes, regularized regression, SVM, K-nearest neighbors, BART, ensemble methods...
- Performance metric to choose best classifier and avoid overfitting: confusion matrix, accuracy, precision, recall...


Labeled data
Best classifier
Unseen data
Training set
Test set
Random split
Computing performance
Machine Learning Classifiers
Predictions

Supervised learning v. dictionary methods

- Dictionary methods:
  - Advantage: not corpus-specific, cost to apply to a new corpus is trivial
  - Disadvantage: not corpus-specific, so performance on a new corpus is unknown (domain shift)
- Supervised learning can be conceptualized as a generalization of dictionary methods, where features associated with each categories (and their relative weight) are learned from the data
- By construction, they will outperform dictionary methods in classification tasks, as long as training sample is large enough

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Creating a labeled set

How do we obtain a **labeled set**?

- External sources of annotation
  - Disputed authorship of Federalist papers estimated based on known authors of other documents
  - Party labels for election manifestos
  - Legislative proposals by think tanks (text reuse)
- Expert annotation
  - “Canonical” dataset in Comparative Manifesto Project
  - In most projects, undergraduate students (expertise comes from training)
- Crowd-sourced coding
  - **Wisdom of crowds**: aggregated judgments of non-experts converge to judgments of experts at much lower cost (Benoit et al, 2016)
  - Easy to implement with FigureEight or MTurk

Code the Content of a Sample of Tweets

Instructions ▴

In this job, you will be presented with tweets about the recent protests related to race and law enforcement in the U.S.

You will have to read the tweet and answer a set of questions about its content.

Read the tweet below paying close attention to detail:

Tweet ID: **447**

El Cid
@JohnGalt2112

Follow

#BlackLivesMatter don't matter unless they are taken by a white cop.

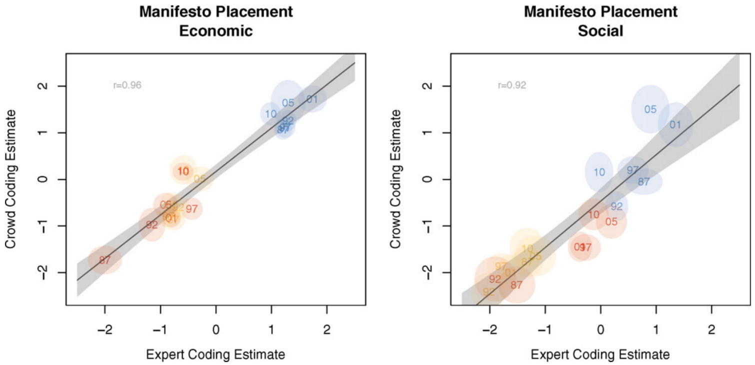
4:23 PM - 13 Dec 2014

Is this tweet related to the ongoing debate about law enforcement and race in the United States?

- ○ Yes
- ○ No
- ○ Don't Know

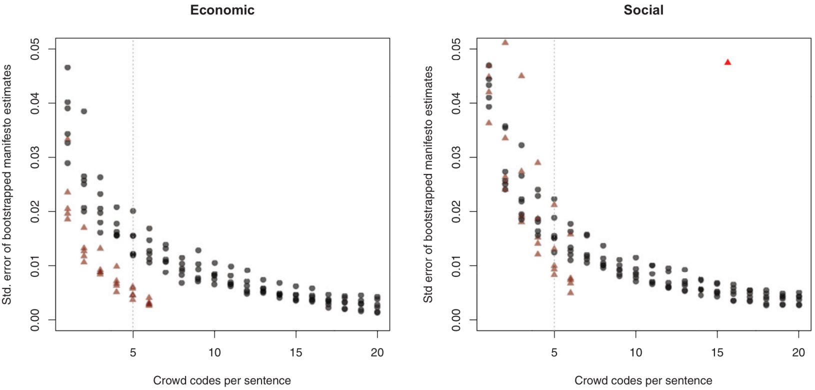
Crowd-sourced text analysis (Benoit et al, 2016 APSR)

FIGURE 3. Expert and Crowd-sourced Estimates of Economic and Social Policy Positions



Crowd-sourced text analysis (Benoit et al, 2016 APSR)

FIGURE 5. Standard Errors of Manifesto-level Policy Estimates as a Function of the Number of Workers, for the Oversampled 1987 and 1997 Manifestos



Note: Each point is the bootstrapped standard deviation of the mean of means aggregate manifesto scores, computed from sentence-level random n subsamples from the codes.

Evaluating the quality of a labeled set

Measures of agreement:

- Percent agreement Very simple:

  (number of agreeing ratings) / (total ratings) * 100%
- Correlation
  - (usually) Pearson's *r*
  - May also be ordinal, such as Spearman's rho or Kendall's tau-b
  - Range is [-1,1]
- Agreement measures
  - Take into account not only observed agreement, but also *agreement that would have occurred by chance*
  - Cohen's κ is most common
  - Krippendorf's α is a generalization of Cohen's κ
  - Both range from [0,1]

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Computing performance

Binary outcome variables:

	Actual value	
Classification	Ham	Spam
Ham	True negative	False negative
Spam	False positive	True positive

Confusion matrix:

- True negatives and true positives are **correct** predictions (to maximize)
- False positives and false negatives are **incorrect** predictions (to minimize)

Computing performance: an example

- Performance **metrics**

	Actual value	
Classification	Ham	Spam
Ham	True negative	False negative
Spam	False positive	True positive

  - **Accuracy**: correct predictions / total of predictions
    - % of units that are correctly predicted
  - **Precision** for positive labels: (true positive) / (false positive + true positive)
    - % of units predicted to be positive that are indeed positive
  - **Recall** for positive labels: (true positive) / (true positive + false negative)
    - % of units that are positive and are predicted as such

Computing performance: an example

Classification	**Actual value** Ham	Spam
Ham	600	300
Spam	200	900

Accuracy = (600 + 900) / (600 + 900 + 200 + 300)
= 0.75

75% of all emails are correctly classified

Computing performance: an example

	Actual value	
Classification	Ham	Spam
Ham	600	300
Spam	200	900

Precision = (900) / (900 + 200)
= 0.82

83% of all emails predicted to be spam are indeed **spam**

Computing performance: an example

Classification	**Actual value** Ham	Spam
Ham	600	300
Spam	200	900

Recall = (900) / (900 + 300)

= 0.75

75% of all **spam** emails are correctly classified

Computing performance: an example

	Actual value	
Classification	Ham	Spam
Ham	1700	50
Spam	150	100

Total emails:
Ham = 1850
Spam = 150

Accuracy = (1700+100) / (1700+50+150+100) = 0.90
Precision (spam) = (100) / (150+100) = 0.40
Recall (spam) = (100) / (50+100) = 0.67

Accuracy can be misleadingly high!

Imagine extreme scenario: we classify everything as ham – accuracy would be 92.5%

The trade-off between precision and recall

Two extreme scenarios (but same underlying data):

1) Model predicts *always spam*

	Actual value	
Classif.	Ham	Spam
Ham	0	0
Spam	800	1200

Accuracy = 1200 / 2000 = 0.60
Precision (spam) = 1200 / (800 + 1200) = 0.60
Recall (spam) = 1200 / 1200 = 1.00

High recall but low precision.

2) Model predicts *(almost) always ham*
(e.g. only emails with 10+ links as spam)

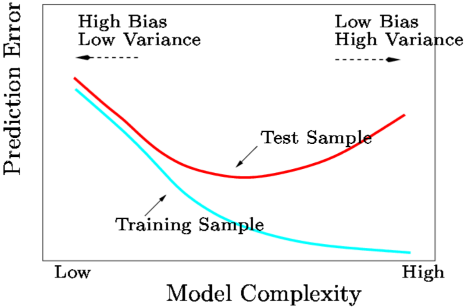
	Actual value	
Classif.	Ham	Spam
Ham	800	1190
Spam	0	10

Accuracy = (800 + 10) / 2000 = 0.40
Precision (spam) = 10 / 10 = 1.0
Recall (spam) = 10 / 1200 = 0.01

High precision but low recall.

Measuring performance

- Classifier is trained to maximize in-sample performance
- But generally we want to apply method to new data
- Danger – overfitting: In-sample performance better than out-of-sample performance (low generalizability)

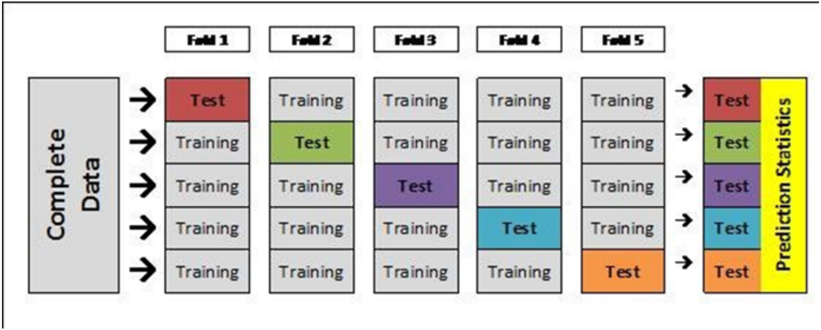


- Solutions?
  - Randomly split dataset into training and test set
  - Cross-validation

Cross-validation

Intuition:

- Create K training and test sets ("folds") within training set.
- For each k in K, run classifier and estimate performance in test set within fold.
- Choose best classifier based on cross-validated performance



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Types of classifiers

General thoughts:

- Trade-off between accuracy and interpretability
- Parameters need to be cross-validated

Frequently used classifiers:

- Naive Bayes
- Regularized regression
- SVM
- Others: k-nearest neighbors, tree-based methods, etc.
- Ensemble methods

Regularized regression

Assume we have:

- $i = 1, 2, \ldots, N$ documents
- Each document i is in class $y_i = 0$ or $y_i = 1$
- $j = 1, 2, \ldots, J$ unique features
- And x_{ij} as the count of feature j in document i

We could build a linear regression model as a classifier, using the values of β_0, β_1, ..., β_J that minimize:

$$RSS = \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2$$

But can we?

- If $J > N$, OLS does not have a unique solution
- Even with $N > J$, OLS has low bias/high variance (overfitting)

Regularized regression

What can we do? Add a penalty for model complexity, such that we now minimize:

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{J}\beta_j^2 \rightarrow \text{ridge regression}$$

or

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{J}|\beta_j| \rightarrow \text{lasso regression}$$

where λ is the **penalty parameter** (to be estimated)

Regularized regression

Why the penalty (shrinkage)?

- Reduces the variance
- Identifies the model if J $>$ N
- Some coefficients become zero (feature selection)

The penalty can take different forms:

- Ridge regression: $\lambda \sum_{j=1}^{J} \beta_j^2$ with $\lambda > 0$; and when $\lambda = 0$ becomes OLS
- Lasso $\lambda \sum_{j=1}^{J} |\beta_j|$ where some coefficients become zero.
- Elastic Net: $\lambda_1 \sum_{j=1}^{J} \beta_j^2 + \lambda_2 \sum_{j=1}^{J} |\beta_j|$ (best of both worlds?)

How to find best value of λ? Cross-validation.
Evaluation: regularized regression is easy to interpret, but often outperformed by more complex methods.

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