POIR 613: Computational Social Science

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Supervised machine learning

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

Outline

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

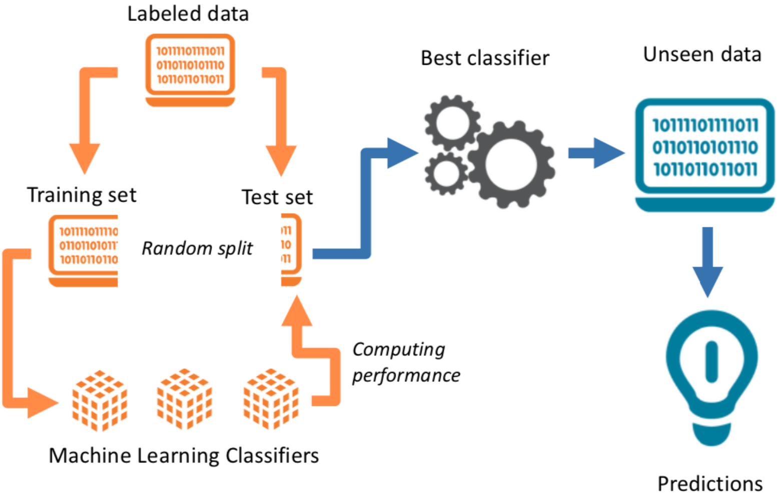
Supervised machine learning

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

Basic principles of supervised learning

- Generalization: A classifier or a regression algorithm learns to correctly predict output from given inputs not only in previously seen samples but also in previously unseen samples
- Overfitting: A classifier or a regression algorithm learns to correctly predict output from given inputs in previously seen samples but fails to do so in previously unseen samples. This causes poor prediction/generalization.

Supervised v. unsupervised methods compared

- The goal (in text analysis) is to differentiate *documents* from one another, treating them as "bags of words"
- Different approaches:
  - *Supervised methods* require a training set that exemplify contrasting classes, identified by the researcher
  - *Unsupervised methods* scale documents based on patterns of similarity from the term-document matrix, without requiring a training step
- Relative advantage of supervised methods:

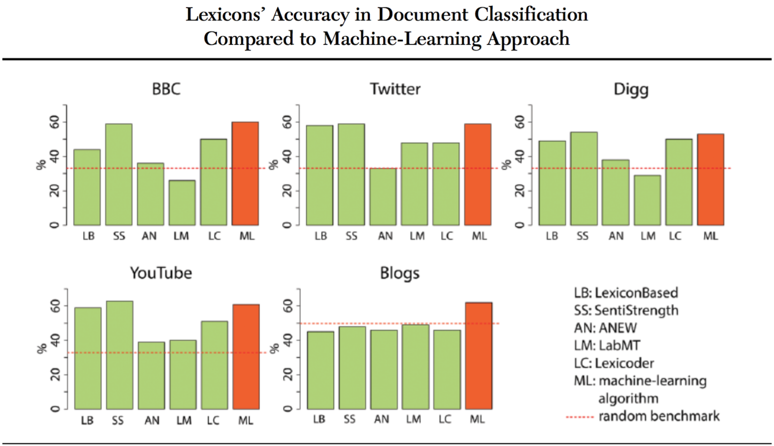
  You already know the dimension being scaled, because you set it in the training stage
- Relative disadvantage of supervised methods:

  You *must* already know the dimension being scaled, because you have to feed it good sample documents in the training stage

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

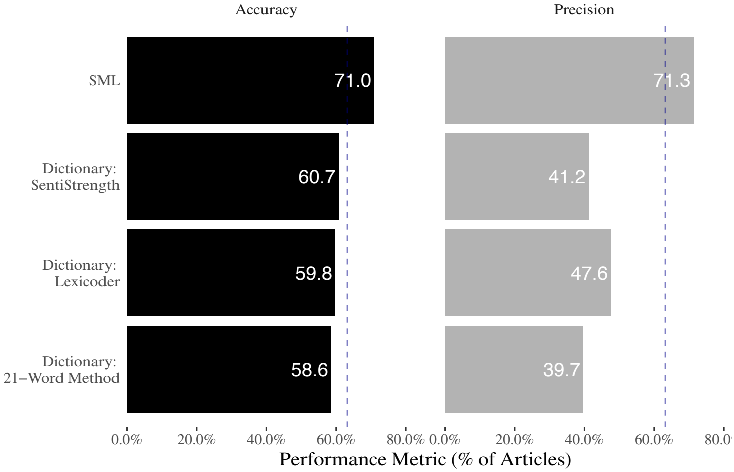
Dictionaries vs supervised learning



Source: González-Bailón and Paltoglou (2015)

Dictionaries vs supervised learning

Application: sentiment analysis of NYTimes articles



Source: Barberá et al (2019)

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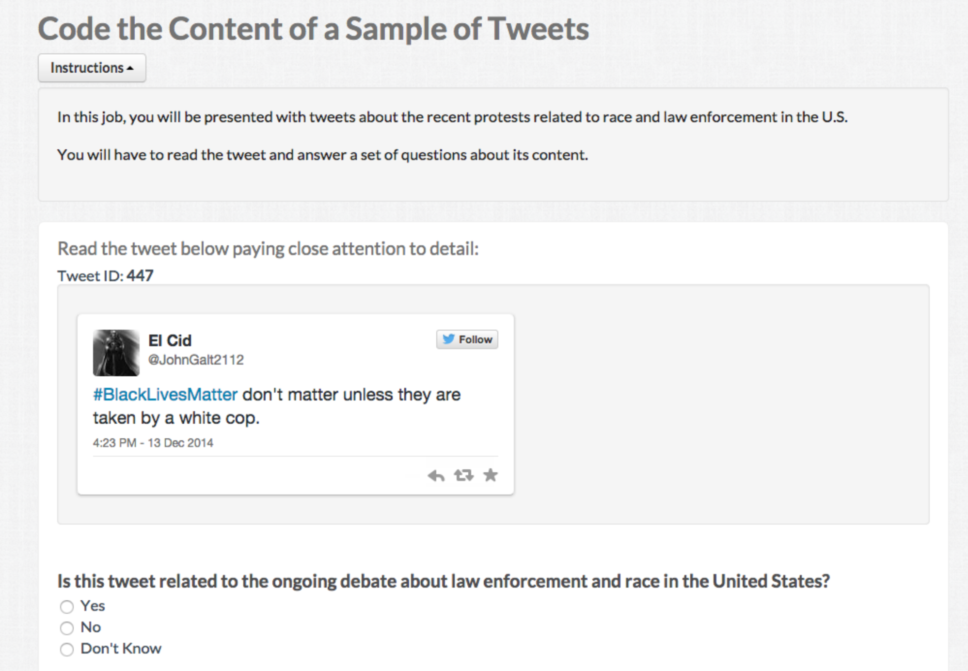
Creating a labeled set

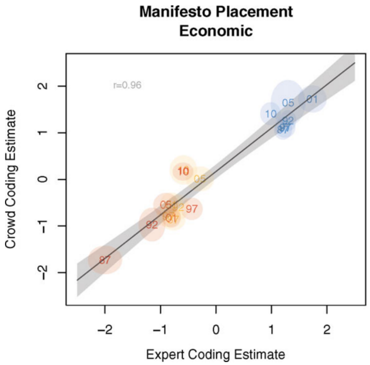
How do we obtain a **labeled set**?

- 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

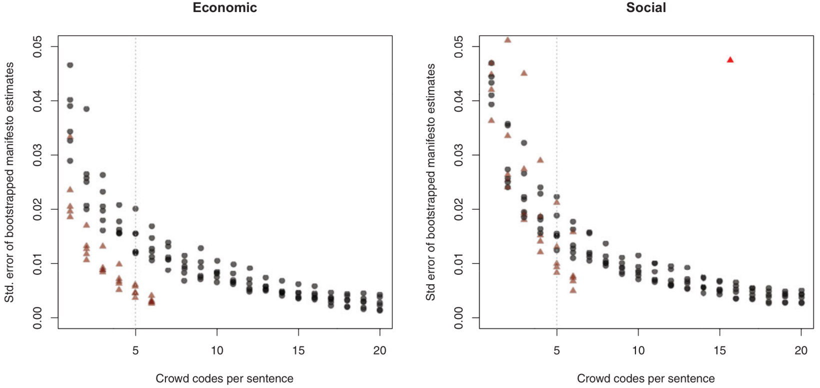
Crowd-sourced text analysis (Benoit et al, 2016 APSR)

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, aka product-moment correlation
  - Formula: $r_{AB} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{A_i - \bar{A}}{s_A}\right) \left(\frac{B_i - \bar{B}}{s_B}\right)$
  - May also be ordinal, such as Spearman's rho or Kendall's tau-b
  - Range is [0,1]
- 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

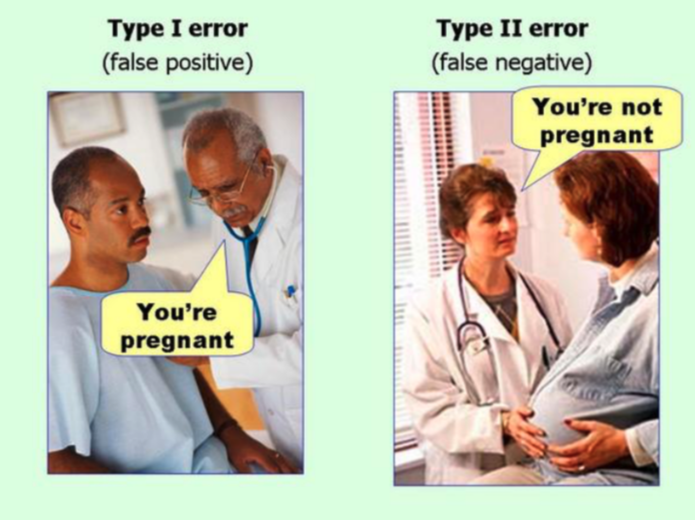
Binary outcome variables:

	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



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

	Actual value	
Classification	Ham	Spam
Ham	$\boxed{600}$	300
Spam	200	$\boxed{900}$

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

75% of all emails are correctly classified

Computing performance: an example

Classification	Actual value: Ham	Spam
Ham	600	300
Spam	200	$\boxed{900}$

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

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

Computing performance: an example

	Actual value	
Classification	Ham	Spam
Ham	600	300
Spam	200	$\boxed{900}$

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)

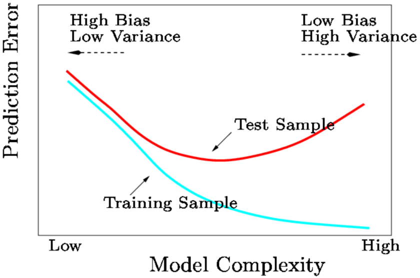
	Actual value	
Classif.	Ham	Spam
Ham	800	1190
Spam	0	10

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



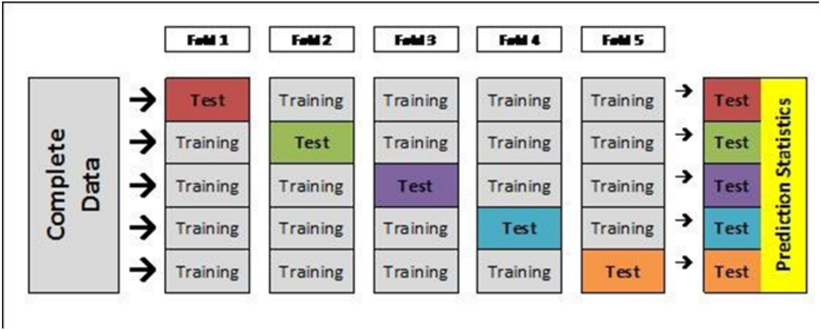
- Model is too complex, describes noise rather than signal
- Focus on features that perform well in labeled data but may not generalize (e.g. “inflation” in 1980s)
- In-sample performance better than out-of-sample performance

- 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.