# RECSM Summer School: Social Media and Big Data Research

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Course website:

pablobarbera.com/social-media-upf

# Supervised Machine Learning Applied to Social Media Text

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- Performance metric to choose best classifier and avoid overfitting: confusion matrix, accuracy, precision, recall...

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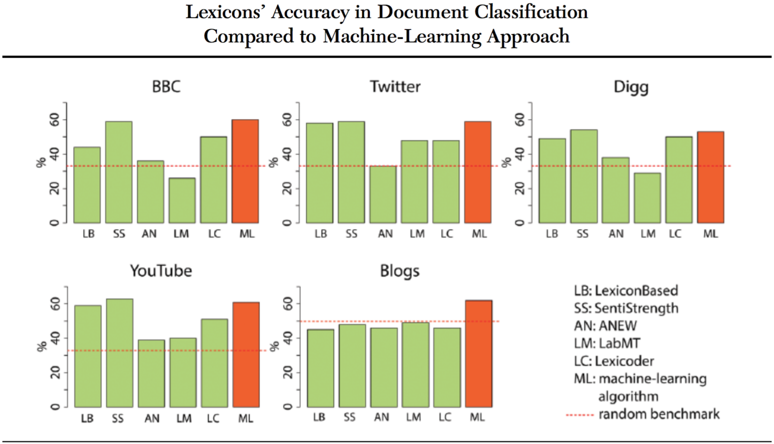
- Supervised learning can be conceptualized as a generalization of dictionary methods, where features associated with each categories (and their relative weight) are learned from the data
- By construction, they will outperform dictionary methods in classification tasks, as long as training sample is large enough

# Dictionaries vs supervised learning




**Source**: González-Bailón and Paltoglou (2015)

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- 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 CrowdFlower 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**

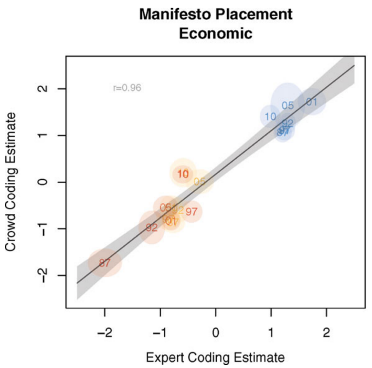

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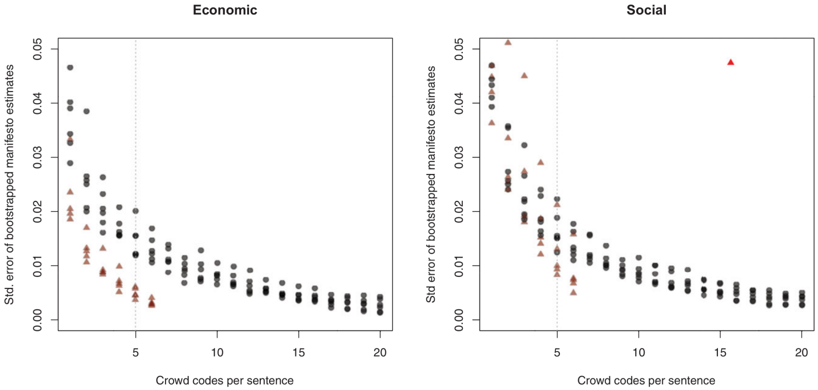
**FIGURE 5. Standard Errors of Manifesto-level Policy Estimates as a Function of the Number of Workers, for the Oversampled 1987 and 1997 Manifestos**




*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.

# Performance metrics

Confusion matrix:

| | Actual label | |
|---|---|---|
| Classification (algorithm) | Negative | Positive |
| Negative | True negative | False negative |
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$$\text{Accuracy} = \frac{\text{TrueNeg} + \text{TruePos}}{\text{TrueNeg} + \text{TruePos} + \text{FalseNeg} + \text{FalsePos}}$$

$$\text{Precision}_{\text{positive}} = \frac{\text{TruePos}}{\text{TruePos} + \text{FalsePos}}$$

$$\text{Recall}_{\text{positive}} = \frac{\text{TruePos}}{\text{TruePos} + \text{FalseNeg}}$$

# Performance metrics: an example

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$$\text{Accuracy} = \frac{800 + 50}{700 + 50 + 100 + 50} = 0.85$$

$$\text{Precision}_{\text{positive}} = \frac{50}{50 + 50} = 0.50$$

$$\text{Recall}_{\text{positive}} = \frac{50}{50 + 100} = 0.33$$

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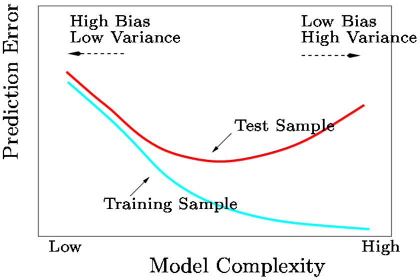

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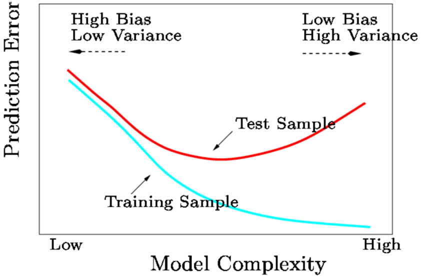

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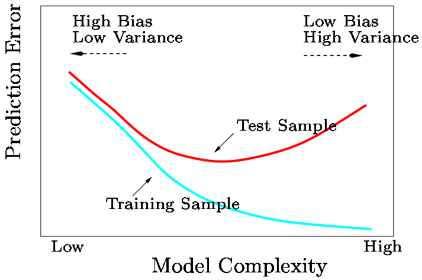


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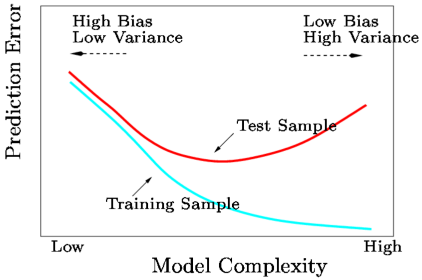


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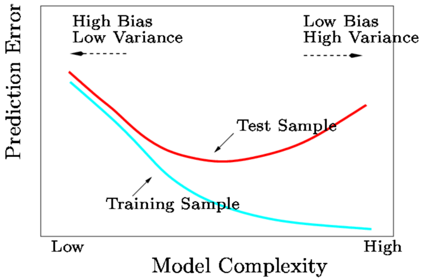


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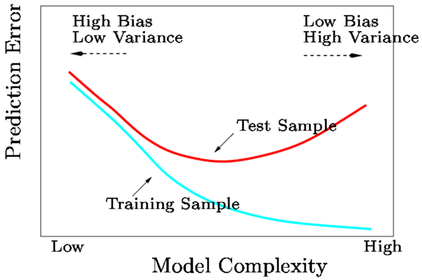


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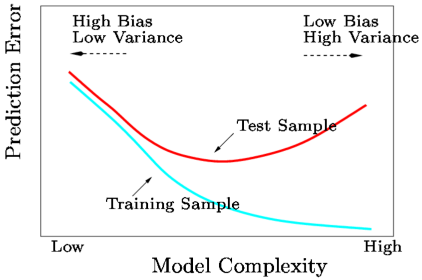


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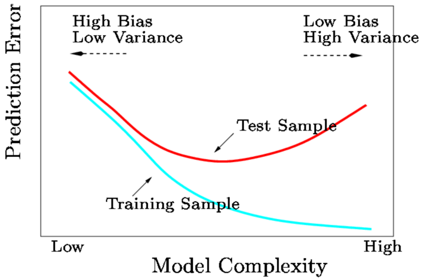


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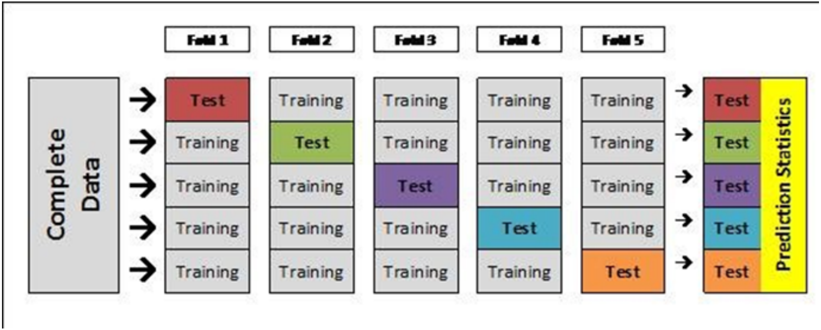
  - Cross-validation

# 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



# Example: Theocharis et al (2016 JOC)

Why do politicians not take full advantage of interactive affordances of social media?

A politician's incentive structure

Democracy $\rightarrow$ Dialogue $>$ Mobilisation $>$ Marketing

Politician $\rightarrow$ Marketing $>$ Mobilisation $>$ Dialogue*

H1: Politicians make broadcasting rather than engaging use of Twitter

H2: Engaging style of tweeting is positively related to impolite or uncivil responses

# Data collection and case selection

Data: European Election Study 2014, Social Media Study

- List of all candidates with Twitter accounts in 28 EU countries
  - 2,482 out of 15,527 identified MEP candidates (16%)
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Case selection: expected variation in politeness/civility

| | Received bailout | Did not receive bailout |
|---|---|---|
| High support for EU | Spain (55.4%) | Germany (68.5%) |
| Low support for EU | Greece (43.8%) | UK (41.4%) |

(% indicate proportion of country that considers the EU to be “a good thing”)

# Data collection and case selection

Data coverage by country

| Country | Lists | Candidates | on Twitter | Tweets |
|---|---|---|---|---|
| Germany | 9 | 501 | 123 (25%) | 86,777 |
| Greece | 9 | 359 | 99 (28%) | 18,709 |
| Spain | 11 | 648 | 221 (34%) | 463,937 |
| UK | 28 | 733 | 304 (41%) | 273,886 |

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**Incivility** = impoliteness + moral and democracy

# Coding tweets

## Coding process: summary statistics

| | Germany | Greece | Spain | UK |
|---|---|---|---|---|
| Coded by 1/by 2 | 2947/2819 | 2787/2955 | 3490/1952 | 3189/3296 |
| Total coded | 5766 | 5742 | 5442 | 6485 |
| Impolite | 399 | 1050 | 121 | 328 |
| Polite | 5367 | 4692 | 5321 | 6157 |
| % Agreement | 92 | 80 | 93 | 95 |
| Krippendorf/Maxwell | 0.30/0.85 | 0.26/0.60 | 0.17/0.87 | 0.54/0.90 |
| Broadcasting | 2755 | 2883 | 1771 | 1557 |
| Engaging | 3011 | 2859 | 3671 | 4928 |
| % Agreement | 79 | 85 | 84 | 85 |
| Krippendorf/Maxwell | 0.58/0.59 | 0.70/0.70 | 0.66/0.69 | 0.62/0.70 |
| Moral/Dem. | 265 | 204 | 437 | 531 |
| Other | 5501 | 5538 | 5005 | 5954 |
| % Agreement | 95 | 97 | 96 | 90 |
| Krippendorf/Maxwell | 0.50/0.91 | 0.53/0.93 | 0.41/0.92 | 0.39/0.81 |

# Machine learning classification of tweets

Coded tweets as training dataset for a machine learning classifier:

1. Text preprocessing: lowercase, remove stopwords and punctuation (except # and @), transliterating to ASCII, stem, tokenize into unigrams and bigrams. Keep tokens in 2+ tweets but $<$90%.

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2. Train classifier: logistic regression with L2 regularization (ridge regression), one per language and variable
3. Evaluate classifier: compute accuracy using 5-fold crossvalidation

# Machine learning classification of tweets

Classifier performance (5-fold cross-validation)

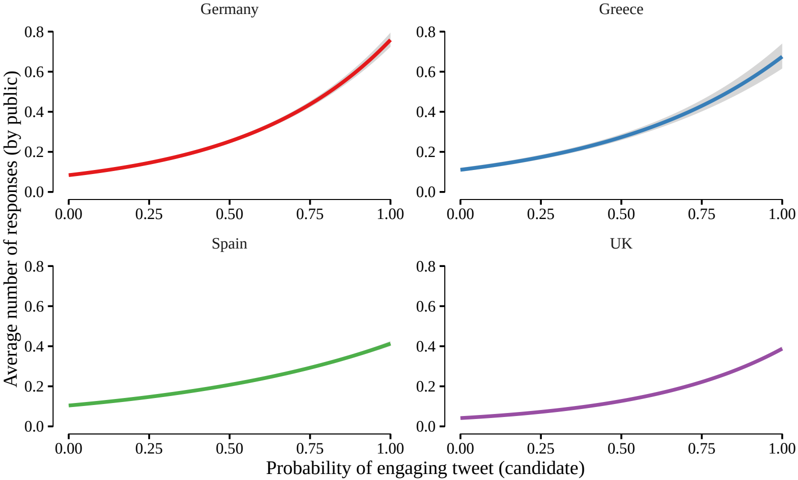
| | | UK | Spain | Greece | Germany |
|---|---|---|---|---|---|
| Communication Style | Accuracy | 0.821 | 0.775 | 0.863 | 0.806 |
| | Precision | 0.837 | 0.795 | 0.838 | 0.818 |
| | Recall | 0.946 | 0.890 | 0.894 | 0.832 |
| Polite vs. impolite | Accuracy | 0.954 | 0.976 | 0.821 | 0.935 |
| | Precision | 0.955 | 0.977 | 0.849 | 0.938 |
| | Recall | 0.998 | 1.000 | 0.953 | 0.997 |
| Morality and Democracy | Accuracy | 0.895 | 0.913 | 0.957 | 0.922 |
| | Precision | 0.734 | 0.665 | 0.851 | 0.770 |
| | Recall | 0.206 | 0.166 | 0.080 | 0.061 |

## Top predictive n-grams

| | |
|---|---|
| Broadcasting | just, hack, #votegreen2014, :, and, @ ', tonight, candid, up, tonbridg, vote @, im @, follow ukip, ukip @, #telleurop, angri, #ep2014, password, stori, #vote2014, team, #labourdoorstep, crimin, bbc news |
| Engaging | @ thank, @ ye, you'r, @ it', @ mani, @ pleas, u, @ hi, @ congratul, :), index, vote # skip, @ good, fear, cheer, haven't, lol, @ i'v, you'v, @ that', choice, @ wa, @ who, @ hope |
| Impolite | cunt, fuck, twat, stupid, shit, dick, tit, wanker, scumbag, moron, cock, foot, racist, fascist, sicken, fart, @ fuck, ars, suck, nigga, nigga ?, smug, idiot, @arsehol, arsehol |
| Polite | @ thank, eu, #ep2014, thank, know, candid, veri, politician, today, way, differ, europ, democraci, interview, time, tonight, @ think, news, european, sorri, congratul, good, :, democrat, seat |
| Moral/Dem. | democraci, polic, freedom, media, racist, gay, peac, fraud, discrimin, homosexu, muslim, equal, right, crime, law, violenc, constitut, faith, bbc, christian, marriag, god, cp, racism, sexist |
| Others | @ ha, 2, snp, nice, tell, eu, congratul, campaign, leav, alreadi, wonder, vote @, ;), hust, nh, brit, tori, deliv, bad, immigr, #ukip, live, count, got, roma |

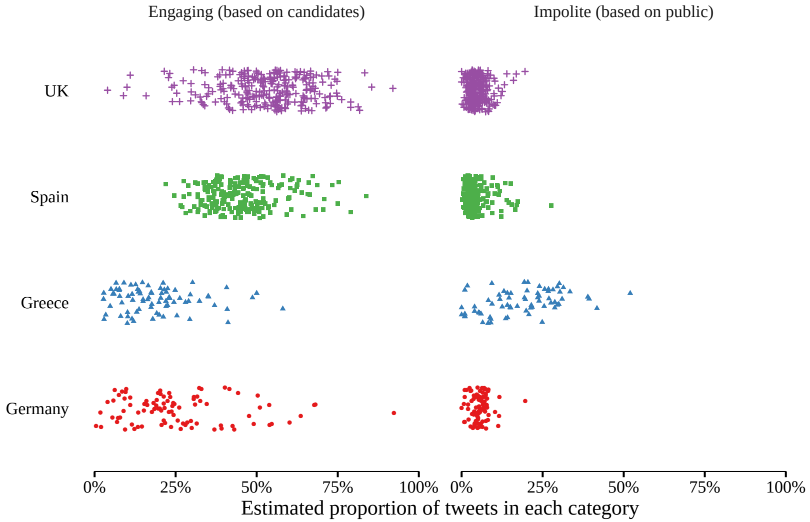
# Predictive validity

## Citizens are more likely to respond to candidates when they adopt an engaging style



# Results: H1

## Proportion of engaging tweets sent and impolite tweets received, by candidate and country



# Results: H2

Is engaging style positively related to impolite responses?

Three levels of analysis:

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1. **Across candidates**: candidates who send more engaging tweets receive more impolite responses.

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1. **Across candidates**: candidates who send more engaging tweets receive more impolite responses.
2. **Within candidates, over time**: the number of impolite responses increases during the campaign for candidates who send more engaging tweets
3. **Across tweets**: tweets that are classified as engaging tend to receive more impolite responses

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General thoughts:

- Trade-off between accuracy and interpretability

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- 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 $\beta_0$, $\beta_1$, ..., $\beta_J$ 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 $\lambda$ is the **penalty parameter** (to be estimated)

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