Quantitative text analysis: Machine Learning for Text

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MY 459: Quantitative Text Analysis

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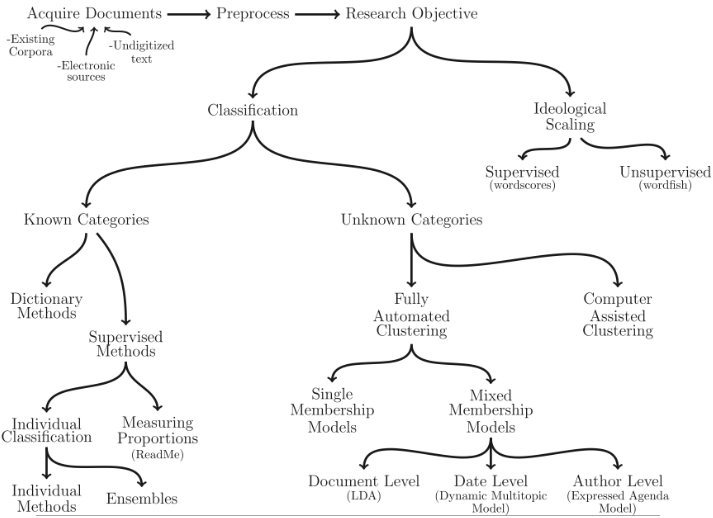
Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



Outline

- Supervised learning overview
- Creating a labeled set and evaluating its reliability
- Classifier performance metrics
- Applications of classifiers in social science research
- Examples of classifiers (next week)

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, CNN, ensemble methods, etc.
- Approach to validate classifier: cross-validation
- Performance metric to choose best classifier and avoid overfitting: confusion matrix, accuracy, precision, recall...

Classification v. scaling methods compared

- Machine learning focuses on identifying classes (classification), while social science is typically interested in locating things on latent traits (scaling)
- But the two methods overlap and can be adapted – will demonstrate later using the Naive Bayes classifier
- Applying lessons from machine learning to supervised scaling, we can
  - Apply classification methods to scaling
  - Improve it using lessons from machine learning

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* for classification require a training set that exemplifies contrasting classes, identified by the researcher
  - *Unsupervised methods* identify similarities in documents based on patterns in the term-document matrix, without requiring supervision (human annotations)
- 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

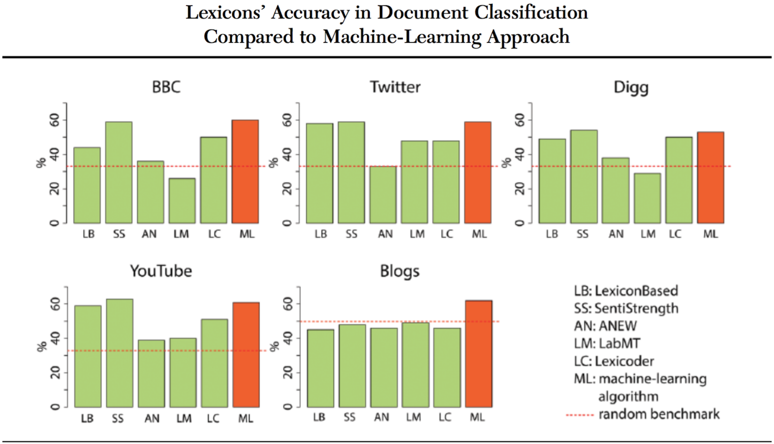
Supervised v. unsupervised methods: Examples

- General examples:
  - Supervised: Naive Bayes, regularized regression, support vector machines (SVM), convolutional neural networks (CNN)
  - Unsupervised: topic models, IRT models, correspondence analysis, factor analytic approaches
- Social science applications
  - Supervised: Wordscores (LBG 2003); SVMs (Yu, Kaufman and Diermeier 2008); Naive Bayes (Evans et al 2007)
  - Unsupervised: Structural topic model (Roberts et al 2014); "Wordfish" (Slapin and Proksch 2008); two-dimensional IRT (Monroe and Maeda 2004)

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

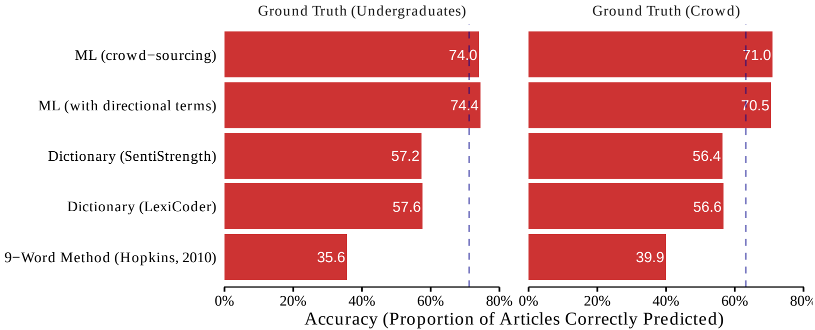
Dictionaries vs supervised learning



Source: González-Bailón and Paltoglou (2015)

Dictionaries vs supervised learning

Application: sentiment analysis of NYTimes articles



Source: Barberá et al (2017)

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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 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.

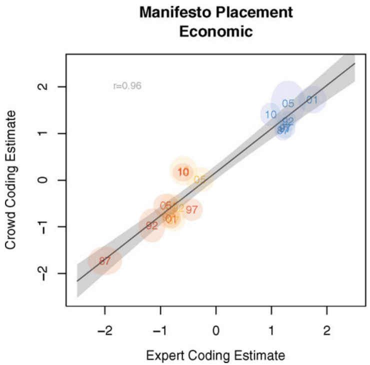
4:23 PM - 13 Dec 2014

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

- ◯ Yes
- ◯ No
- ◯ Don't Know

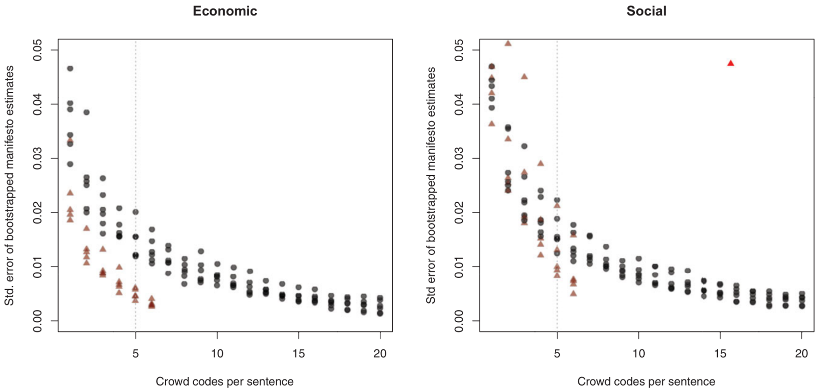
Crowd-sourced text analysis (Benoit et al, 2016 APSR)

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



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

Any labeled set should be tested and reported for its inter-rater reliability, also sometimes called inter-coder reliability, at three different standards:

Type	Test Design	Causes of Disagreements	Strength
Stability	test-retest	intraobserver inconsistencies	weakest
Reproducibility	test-test	intraobserver inconsistencies + interobserver disagreements	medium
Accuracy	test-standard	intraobserver inconsistencies + interobserver disagreements + deviations from a standard	strongest

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 occured by chance*
  - Cohen's κ is most common
  - Krippendorf's α is a generalization of Cohen's κ
  - Both range from [0,1]

Reliability data matrixes

Example here used binary data (from Krippendorff)

Article:	1	2	3	4	5	6	7	8	9	10
Coder A	1	1	0	0	0	0	0	0	0	0
Coder B	0	1	1	0	0	1	0	1	0	0

- A and B agree on 60% of the articles: 60% agreement
- Correlation is (approximately) 0.10
- Observed *dis*agreement: 4
- Expected *dis*agreement (by chance): 4.4211
- Krippendorff's $\alpha = 1 - \frac{D_o}{D_e} = 1 - \frac{4}{4.4211} = 0.095$
- Cohen's κ (nearly) identical

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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.
- Goal is to maximize the frontier of precise identification of true condition with accurate recall

Performance metrics

- Accuracy: How correctly is the classifier's identifications?
  - % of documents that are correctly predicted.
- Precision: Does the classifier identify *only* my content?
  - % of documents that are predicted positive that are indeed positive.
- Recall: Does the classifier identify *all* my content?
  - % of positive documents that are predicted positive.

Performance metrics

- Confusion matrix:

		True condition	
		Positive	Negative
Prediction	Positive	True Positive	False Positive (Type I error)
	Negative	False Negative (Type II error)	True Negative

		True condition	
		Positive	Negative
Prediction	Positive	True Positive	False Positive (Type I error)

Example: measuring performance

Assume:

- We have a corpus where 80 documents are really positive (as opposed to negative, as in sentiment)
- Our method declares that 60 are positive
- Of the 60 declared positive, 45 are actually positive

Solution:

$$\text{Precision} = (45/(45+15)) = 45/60 = 0.75$$
$$\text{Recall} = (45/(45+35)) = 45/80 = 0.56$$

Accuracy?

		True condition		
		Positive	Negative	
Prediction	Positive	45		60
	Negative			
		80		

add in the cells we can compute

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*		
		80		

but need True Negatives and N to compute accuracy

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	**???**	
		80		

assume 10 True Negatives:

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	***10***	***45***
		80	***25***	***105***

$$\text{Accuracy} = (45 + 10)/105 \qquad = 0.52$$
$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

now assume 100 True Negatives:

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	***100***	***135***
		80	***115***	***195***

$$\text{Accuracy} = (45 + 100)/195 \qquad = 0.74$$

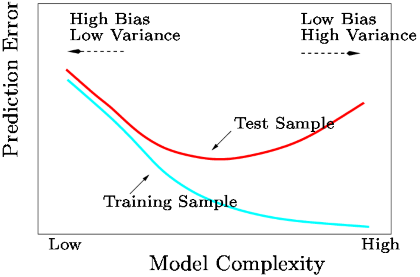
$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

Measuring performance

- Precision and recall can be reported separately for each category
- Precision and recall (or F1) should be reported alongside accuracy. Why?
- There is generally a trade-off between precision and recall. Why?

Measuring performance

- Classifier is trained to maximize in-sample performance
- But generally we want to apply method to new data
- Danger: overfitting



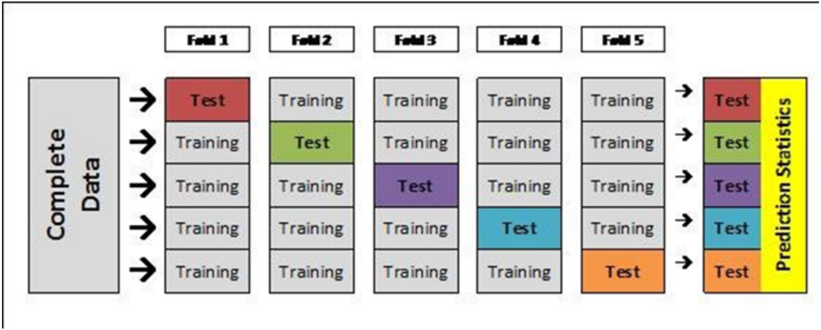
- Model is too complex, describes noise rather than signal (Bias-Variance trade-off)
- Focus on features that perform well in labeled data but may not generalize (e.g. "inflation" in 1980s)
- In-sample performance better than out-of-sample performance

- 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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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%)
- Collaboration with TNS Opinion to collect all tweets by candidates *and* tweets mentioning candidates (tweets, retweets, @-replies), May 5th to June 1st 2014.

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

Coding tweets

Coded data: random sample of ~7,000 tweets from each country, labeled by undergraduate students:

1. **Politeness**
   - Polite: tweet adheres to politeness standards.
   - Impolite: ill-mannered, disrespectful, offensive language...
2. **Communication style**
   - Broadcasting: statement, expression of opinion
   - Engaging: directed to someone else/another user
3. **Political content: moral and democracy**
   - Tweets make reference to: freedom and human rights, traditional morality, law and order, social harmony, democracy...

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%.
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)

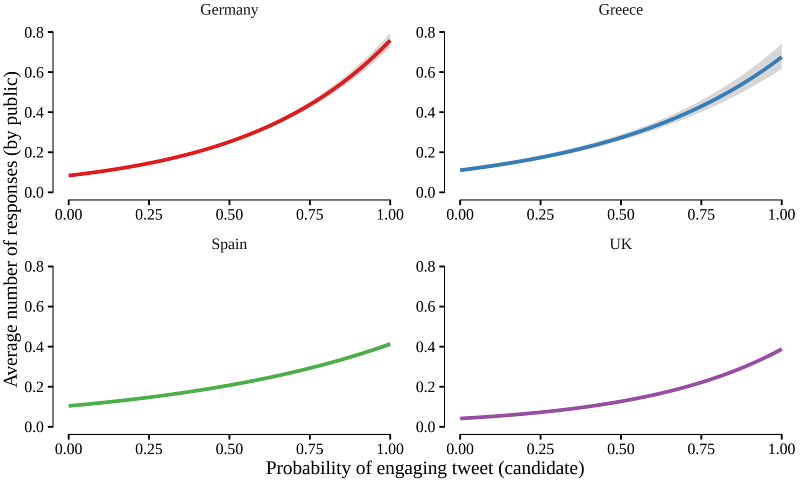
		UK	Spain	Greece	Germany
Communication Style	Accuracy	0.821	0.775	0.863	0.806
	Precision	0.837	0.795	0.838	0.818
	Recall	0.946	0.890	0.894	0.832
Polite vs. impolite	Accuracy	0.954	0.976	0.821	0.935
	Precision	0.955	0.977	0.849	0.938
	Recall	0.998	1.000	0.953	0.997
Morality and Democracy	Accuracy	0.895	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

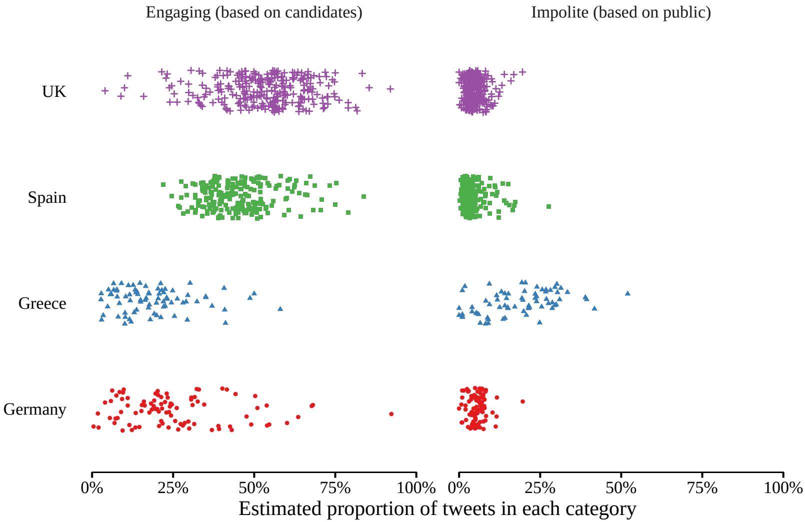
Predictive validity

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:

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