Introduction to Machine Learning for Social Scientists

Class 9: Regularization 1

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Logistics

Today:

- Instructions for Group project and Lottery
- Text Analysis
- Intro to regularization

Reading between the lines

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Reading Between the Lines: Prediction of Political Violence Using Newspaper Text

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This article provides a new methodology to predict armed conflict by using newspaper text. Through machine learning, vast quantities of newspaper text are reduced to interpretable topics. These topics are then used in panel regressions to predict the onset of conflict. We propose the use of the within-country variation of these topics to predict the timing of conflict. This allows us to avoid the tendency of predicting conflict only in countries where it occurred before. We show that the within-country variation of topics is a good predictor of conflict and becomes particularly useful when risk in previously peaceful countries arises. Two aspects seem to be responsible for these features. Topics provide depth because they consist of changing, long lists of terms that make them able to capture the changing context of conflict. At the same time, topics provide width because they are summaries of the full text, including stabilizing factors.

The conflict literature has made significant progress in understanding which countries are more at risk of suffering an armed conflict.[1] However, many factors that have been identified as leading to increased risk, like mountainous terrain or ethnic polarization, are time invariant or very slow moving, and therefore not useful in predicting the timing of conflict. Other factors, like GDP levels or political institutions, still vary more between countries than within countries over time. This means it is easier to predict whether a country is at risk *in general* rather than *when* a country is particularly at risk. Yet, understanding the timing of conflict is critical for policy.

An additional problem of forecasting the timing of armed conflict is that it is rare and at the same time relatively concentrated in some countries. This is problematic because it implies that the variation between countries can dominate the analysis unless the between- and within-country variations are separated explicitly. Empirical models that are overall quite accurate can therefore be of little use on the time dimension. We show, using a simple panel regression model, that many variables commonly used in the literature indeed face this problem. This means they predict conflict where it occurred before, and therefore fail to predict conflicts in previously peaceful countries.

As a solution to this problem, we propose data generated from news sources. To this end, we implement an automated method to quantify the content of news using the latent Dirichlet allocation (LDA) model (Blei, Ng, and Jordan 2003), which we apply to over 700,000 newspaper articles from English-speaking newspapers. There are two advantages that topics have over existing methods of analyzing text. First, topics provide depth because, by design, they put words into context. The context can be useful for forecasting. Second, topics provide width because they allow us to use the whole text, including stabilizing factors, when forecasting conflict. This means we can let the data speak without losing interpretability of the results.

At the prediction stage, we rely on a simple panel regression model, which uses all generated topics as explanatory variables. The result is a model able to forecast out of sample the onset of civil war, armed conflict, and even movements of refugees a year before they occur. It relies entirely on news text and can therefore provide forecasts without the need to extrapolate or wait for other data sources. Furthermore, the procedure can be implemented with only minimal personal judg-

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Text analysis

- A large amount of social interaction occurs in texts:
  - Congressional speeches, press releases, newsletters,
  - Facebook posts, tweets. emails, cell phone records.
  - Newspapers, magazines, news broadcasts,
  - Treaties, sermons, fatwas
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- Why?

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- Why?
  - Hard to find
  - Time consuming
  - Not generalizable (each new data set ... new coding scheme)
  - Difficult to store/search
  - Idiosyncratic to coders/researchers
  - Statistical methods/algorithms, computationally intensive

Text analysis

Today:

- Massive increase in availability of unstructured text: In 2017, the number of emails sent and received per day total over 260 billion.
- Cheap storage: 1981: $ 500,000 per GB. 2017: $ 0.03 per GB
- Explosion in methods and programs to analyze texts
  - Generalizable
  - Systematic
  - Cheap

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One (of many) recipe for preprocessing: retain useful information

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Caution
`‘‘Turkey’’ = ‘‘turkey’’`

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`[a, any, are, civil, engaged, great, in, nation, now, or, testing, that, war, we, whether]`

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Trigrams [now we are, we are engaged, are engaged in, engaged in a, in a great, a great civil, great civil war, civil war testing, war testing whether, testing whether that, whether that nation, that nation or, nation or any, or any nation]

Document Term Matrix:

	T1	T2	T3	T4	T5	T6	T7	T8
Doc1	2	0	4	3	0	1	0	2
Doc2	0	2	4	0	2	3	0	0
Doc3	4	0	1	3	0	1	0	1
Doc4	0	1	0	2	0	0	1	0
Doc5	0	0	2	0	0	4	0	0
Doc6	1	1	0	2	0	1	1	3
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- What goes wrong in high dimensions?
  - There is no longer a unique least square coefficient estimate: the variance is infinite.
  - We might be including irrelevant variables.
  - Risk of overfitting.

Three methods to deal with high dimensionality:

- **Subset selection:** Identify a subset of the p predictors that we believe to be related to the response.
- **Shrinkage or regularization:** Fitting a model with all the p predictors. However, the estimated coefficients are shrunken towards zero.
- **Dimension reduction:** Projecting the p predictors into a M-dimensional subspace, where M ¡p.

Analyzing News Stories

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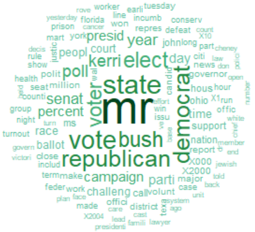
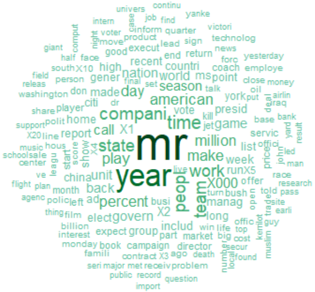
We've preprocessed the data $\rightsquigarrow$ Create a Document-Term Matrix

Analyzing News Stories





R!

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Linear regression: Choose $\beta's$ to minimize sum of squared residuals

$$\boldsymbol{\beta}_{\text{OLS}} = \text{argmin}_{\boldsymbol{\beta}} \sum_{i=1}^{N} (Y_i - \boldsymbol{\beta} \cdot \boldsymbol{x}_i)^2$$

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$$\boldsymbol{\beta}_{\text{LASSO}} = \text{argmin}_{\boldsymbol{\beta}} \sum_{i=1}^{N} (Y_i - \boldsymbol{\beta} \cdot \boldsymbol{x}_i)^2 + \lambda \underbrace{\sum_{p=1}^{P} |\beta_p|}_{\text{penalty}}$$

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What does λ do?

LASSO Penalty: Algebra

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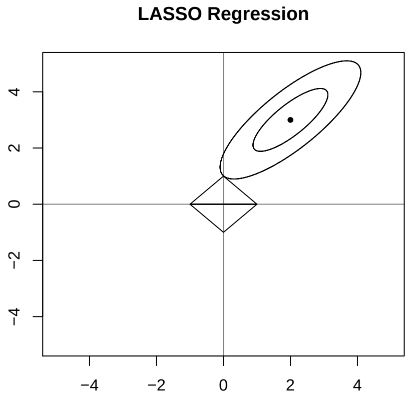
LASSO Penalty: Geometry



R!

NEXT

- More on LASSO
- Homework 4 (*available on Wed 1st due on Wed 8th*)
- ggplot and data manipulation workshop (*Friday August 3rd*)