Introduction to Machine Learning for Social Scientists

Class 8: Re-sampling and intro to regularization

Edgar Franco Vivanco

Stanford University
Department of Political Science

edgarf1@stanford.edu

Summer 2018

Group project

Lottery: Monday July 30th

15% of your grade

Submit your team by tomorrow

On Group Project

- Detailed instructions on Monday.
- Final presentation and a final memo (due Aug 15th).
- Topics: **Random Forest, Neural Networks, Support Vector Machines, Bagging and boosting, Topic Modeling**

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So far:

- Supervised learning.
- Regression and classification.
- Performance.
- In sample and out of sample.

Next weeks:

- Today: Re-sampling, text analysis ($p \geq n$).
- Next week: Regularization.
- ggplot and data manipulation workshop (Friday August 3rd)
- Supervised learning.
- Cluster analysis.
- Guest speakers.

Today:

- Key concepts:
  - Validation approach
  - LOOCV
  - K-fold
  - Document-term matrix and the problem of high dimensional data
- Key R methods:
  - cv.glm()

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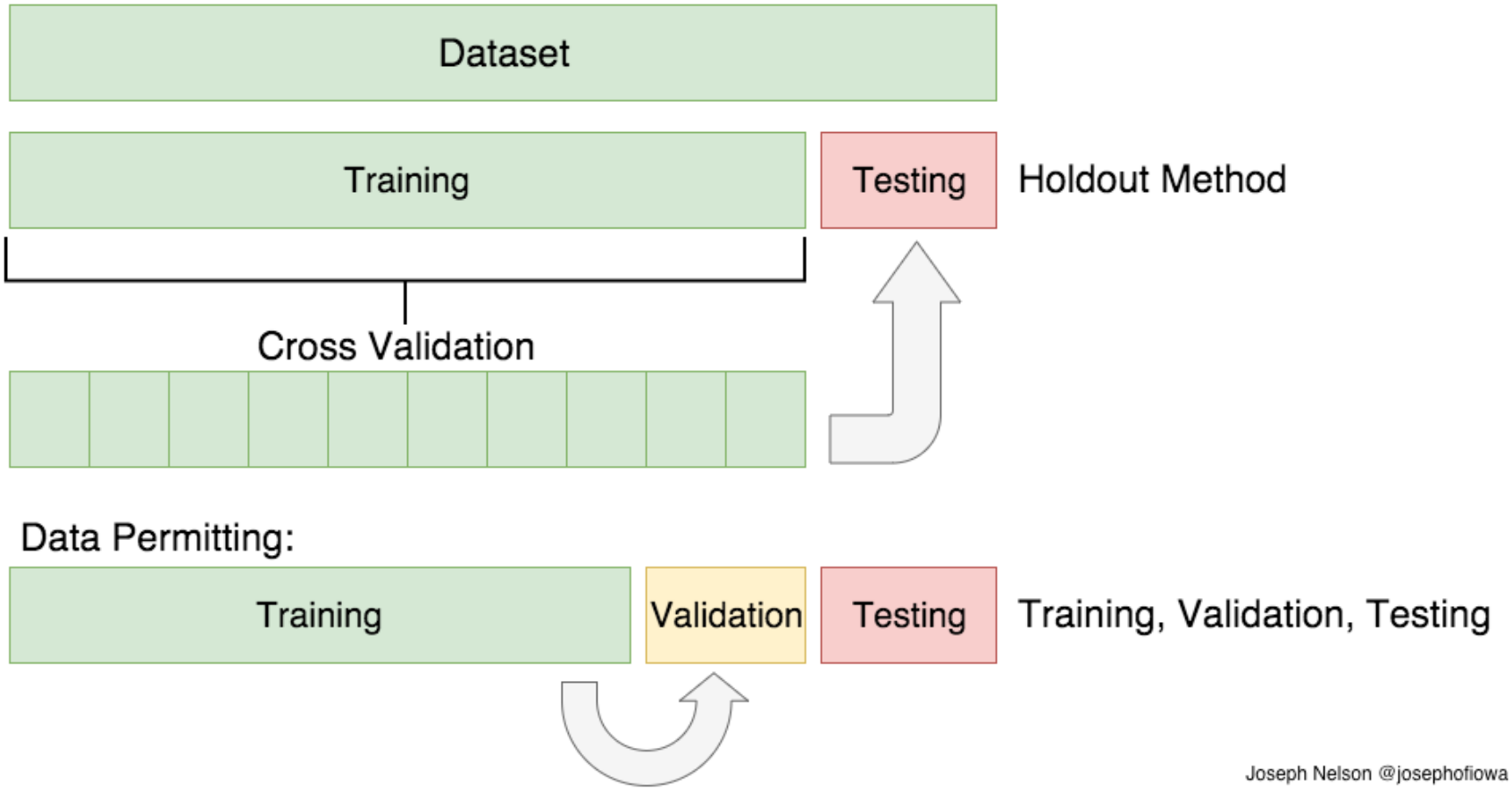
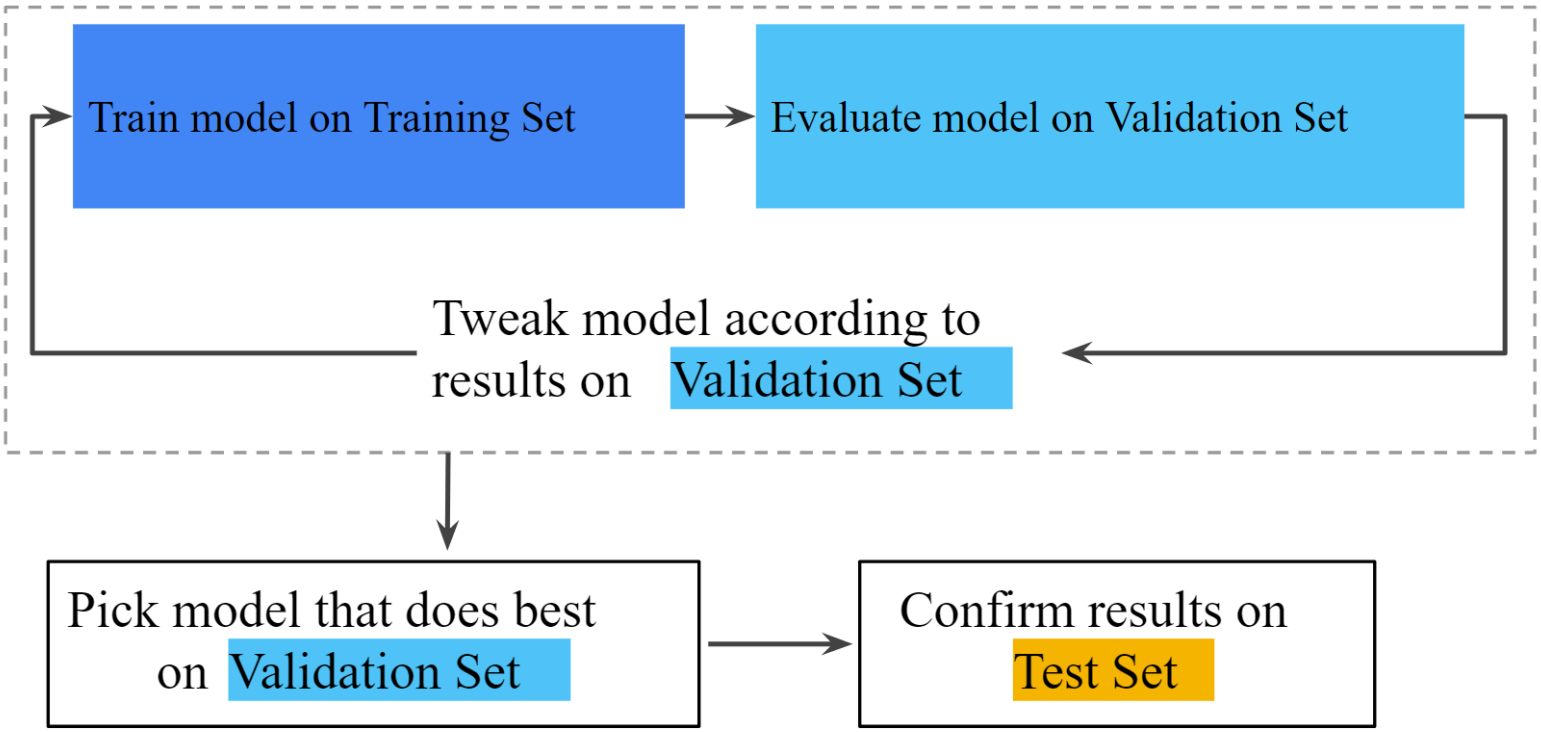
- Out of sample: held out data, test data
- Best practice: evaluate t with gold standard data


Dataset
Training
Testing
Holdout Method
Cross Validation
Data Permitting:
Training
Validation
Testing
Training, Validation, Testing
Joseph Nelson @josephofiowa


Train model on Training Set
Evaluate model on Validation Set
Tweak model according to results on Validation Set
Pick model that does best on Validation Set
Confirm results on Test Set

Training error vs Test error

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- Test error: is the average error that results from using a statistical learning method to predict the response on a new observation, one that was not used in training the method.
- Training error:can be easily calculated by applying the statistical learning method to the observations used in its training.
- But the training error rate often is quite different from the test error rate, and in particular the former can dramatically underestimate the latter.

Re-sampling: Steps

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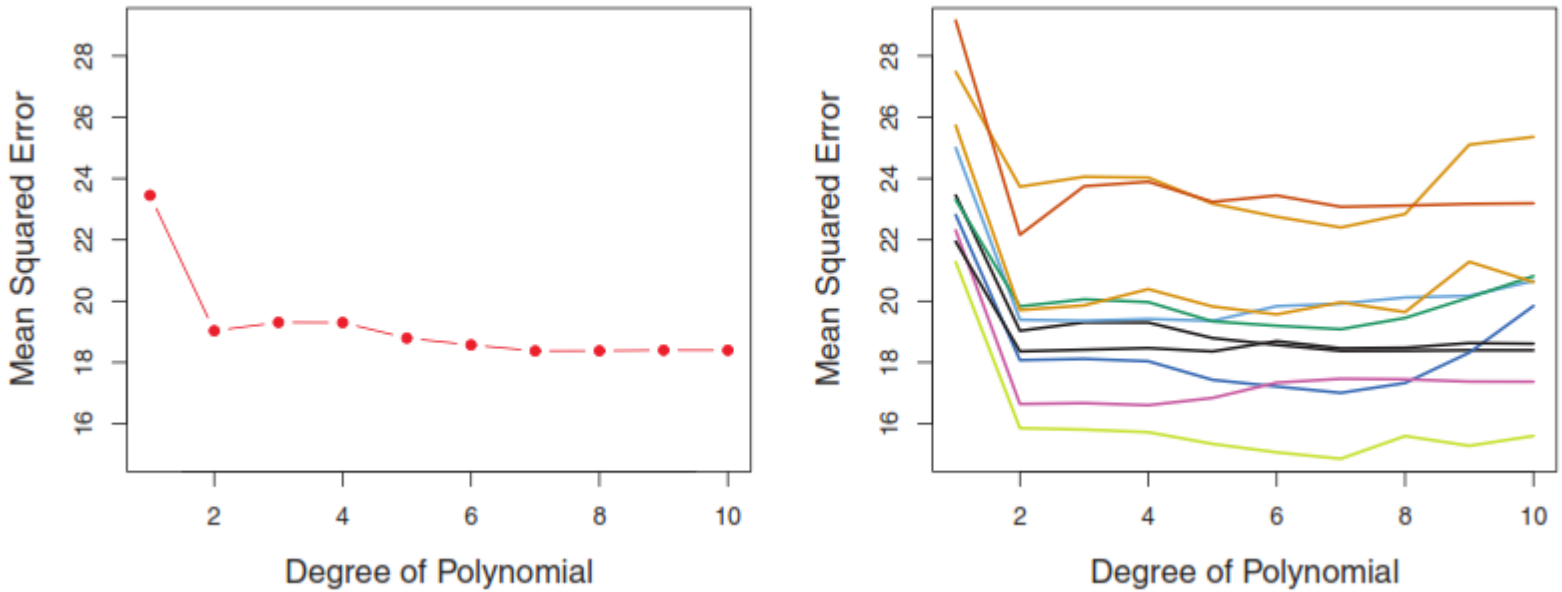
3. The fitted model is used to predict the observations in the validation set
4. The resulting validation set error rate typically assessed using MSE in the case of a quantitative responseprovides an estimate of the test error rate.


1 2 3
n
7 22 13
91

Validation set approach:

- Linear vs Polynomial
- Split observations into two sets of same size.

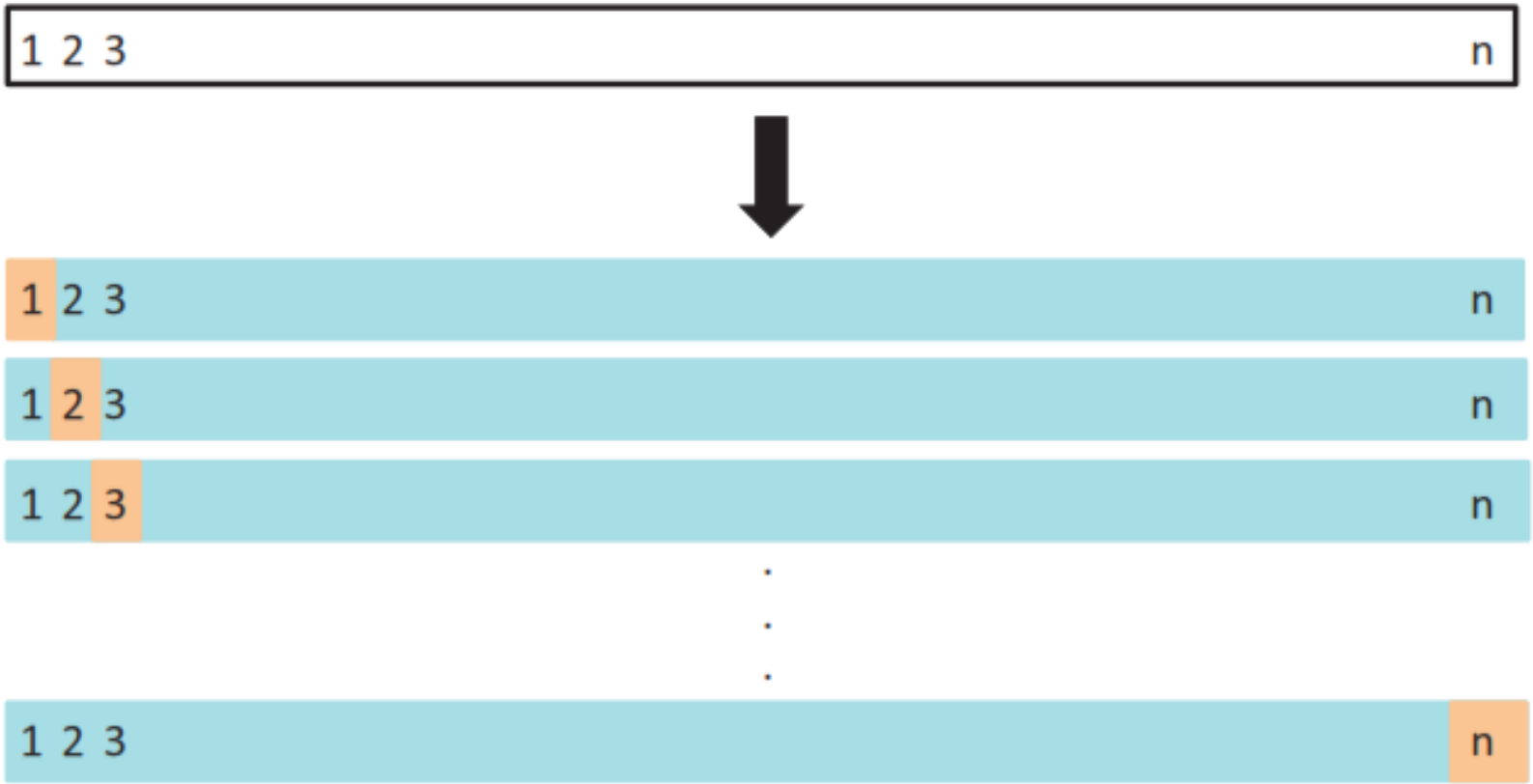


Two potential drawbacks:

- The validation estimate of the test error can be highly variable.
- *Overestimates* the test error for the model fit on the entire dataset (because we use few observations in training set).

Leave-One-Out Cross-Validation

- Like the validation set approach, LOOCV involves splitting the set of observations into two parts.
- However, instead of creating two subsets of comparable size, a single observation (x1,y1) is used for the validation set, and the remaining observations (x2,y2),...,(xn,yn) make up the training set.
- The statistical learning method is t on the n 1 training observations, and a prediction $\hat{y_1}$ is made for the excluded observation, calculating the error $(y_1 - \hat{y_1})^2$
- We repeat the process n times
- We estimate a mean-cross validation error.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n

The LOOCV estimate for the test MSE is the average of these n test error estimates.

$$CV_{(n)} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

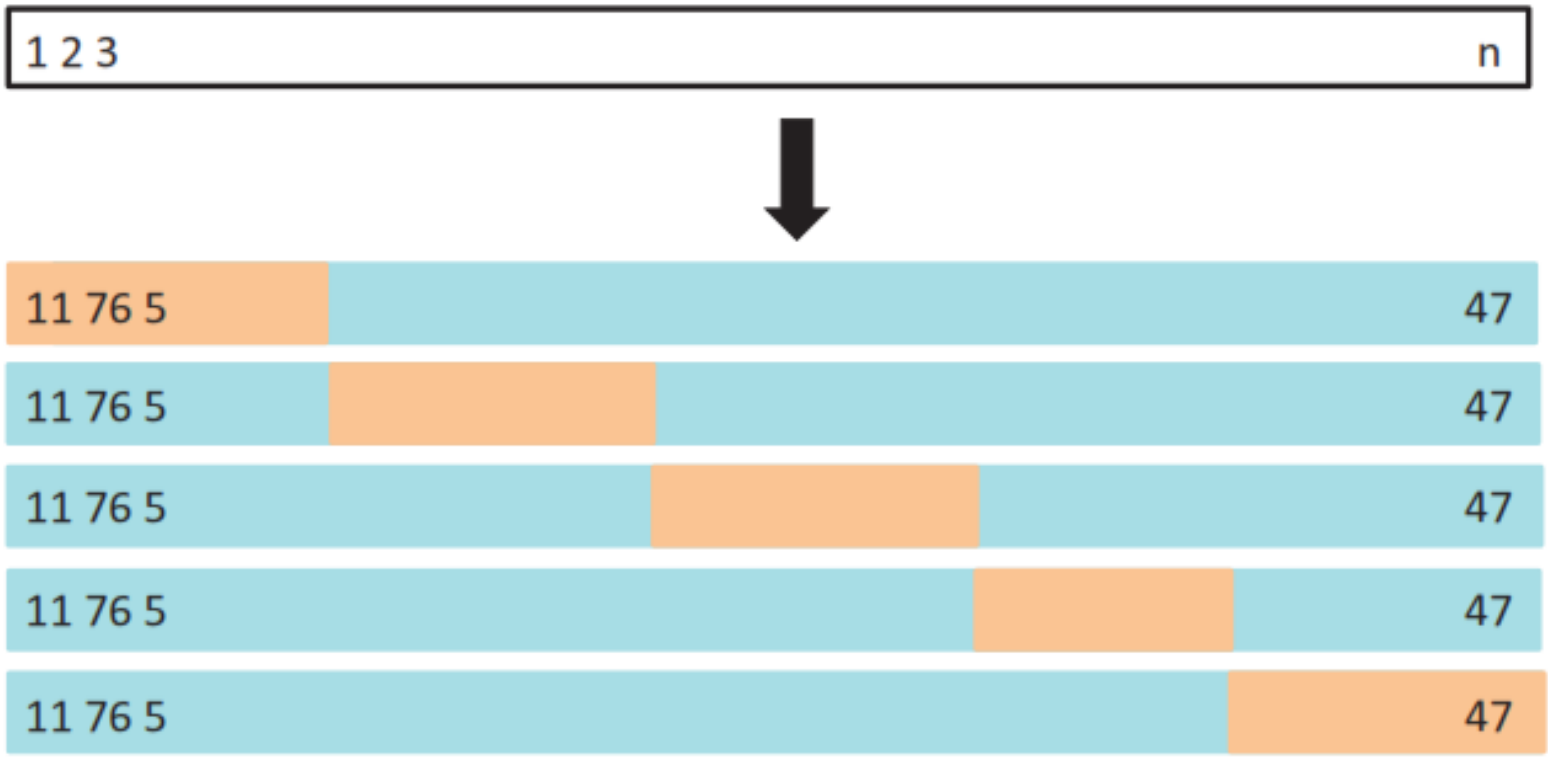
LOOCV

Advantages:

- Less bias: Because we use n-1 observations, the LOOCV tends not to overestimated the test error rate.
- Since there is no randomness in the training/validation set splits, LOOCV will always yield the same results.

K-fold Cross Validation

- This approach involves randomly dividing the set of observations into k groups, or folds of approximately equal size.
- The first fold is treated as the validation set and the method is fit on the remaining k-1 folds.
- The mean squared error is then computed on the observations in the held-out fold (MSE_1)
- The procedure is repeated k times; each time, a different group of observations is treated as a validation set.
- This process results in k estimates of the test error MSE_1, MSE_2,...,MSE_k


1 2 3
n
11 76 5
47
11 76 5
47
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47
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47
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47

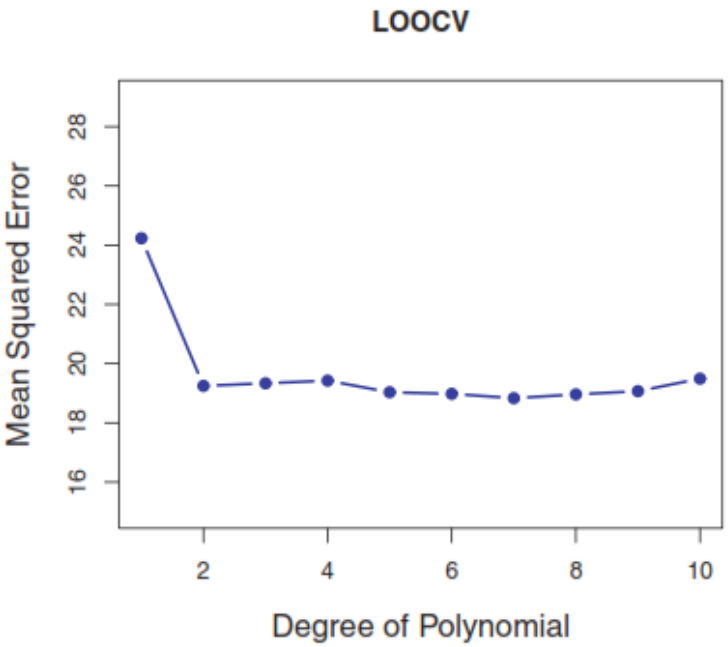
K-fold Cross Validation

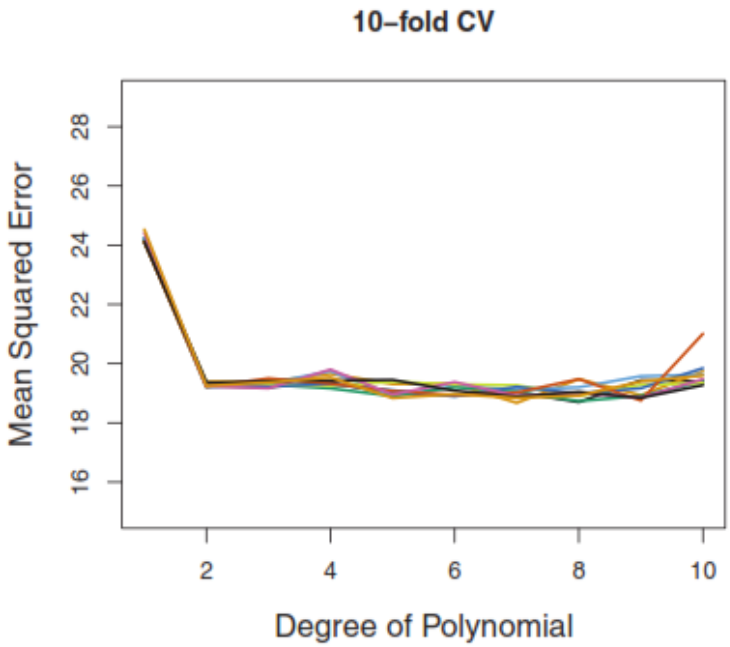
The k-fold CV estimate is computed by averaging these values:

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^{k} MSE_i$$

K-fold Cross Validation

- LOOCV is a special case of k-fold in which k is set equal n.
- Advantages of K-fold:
  - Computational speed
  - Intermediate level of bias and variance.
  - More bias than LOOCV but less than validation approach
  - Lower variance than LOOCV.


LOOCV
Mean Squared Error
16
18
20
22
24
26
28
2
4
6
8
10
Degree of Polynomial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16
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10
Degree of Polynomial

Cross Validation on classification problems

- We can use cross-validation when Y is qualitative/
- We use the number of misclassified observations:

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^{n} I(y_i \neq \hat{y}_i)$$

R!

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,
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- Pre 2000's social scientists avoided using texts/speech.
- 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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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
Doc7	2	1	3	4	0	2	0	2

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- LASSO

Document Term Matrix:

American Political Science Review (2018) 112, 2, 358–375
doi:10.1017/S0003055417000570

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

HANNES MUELLER *Institut d'Analisi Economica*
CHRISTOPHER RAUH *University of Montreal*

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-

Hannes Mueller is a tenured scientist at IAE (CSIC), Barcelona GSE Institut d'Analisi Economica, CSIC Campus UAB, 08193 Bellaterra, Spain (h.mueller.uni@gmail.com).
Christopher Rauh is an Assistant Professor at University of Montreal, Département de Sciences Économiques, Université de Montréal, C.P.6128 succ. Centre-Ville, Montréal H3C 3J7, Canada (christopher.raphael.rauh@umontreal.ca).
We thank Tim Besley, Melissa Dell, Vincenzo Galasso, Hector Galindo, Matt Gentzkow, Stephen Hansen, Ethan Kapstein, Daniel Ohayon, Akash Raja, Bernhard Reinsberg, Anand Shrivastava, Ron Smith, Jack Willis, Stephane Wolton, and the participants of the workshops and conferences ENCoRe Barcelona, Political Econ-

NEXT

- Lottery
- LASSO
- Reading on text analysis
- ggplot and data manipulation workshop (Friday August 3rd)