Prediction and cross validation

Soc Stats Reading Group

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Outline

1. Civil war
2. Cross validation
3. Back to civil war
4. Why care about prediction?

Ward, Greenhill & Bakke (2010)

- "The perils of policy by p-value: Predicting civil conflicts." *Journal of Peace Research* 47(4), 363-75.
- "…basing policy prescriptions on statistical summaries of probabilistic models (which are predictions) can lead to misleading policy prescriptions if out-of-sample predictive heuristics are ignored."
    - In a word: overfitting

Civil wars

Table I. Variables included in the Fearon & Laitin model

Variable	*Statistically significant at 0.05 level*
Prior War	Yes
GDP per capita	Yes
Population	Yes
Mountainous Terrain	Yes
Non-contiguous State	No
Oil Exporter	Yes
New State	Yes
Instability	Yes
Democracy	No
Ethnic Fractionalization	No
Religious Fractionalization	No

* based on Fearon and Laitin, 2003: Table 1, Column 1.

Table II. Variables included in the Collier & Hoeffler model

Variable	*Statistically significant at 0.05 level*
Commodity Dependence	Yes
Squared Commodity Dependence	Yes
Male Secondary Schooling	Yes
GDP Growth	Yes
Peace Duration	Yes
Geographic Dispersion	Yes
Population	Yes
Social Fractionalization	Yes
Ethnic Dominance	No

*based on Collier and Hoeffler, 2004: Table 5, column 5.

- Based on logistic regression
- Widely used to guide policy
  - World Bank, House of Representatives
  - *The New Yorker*, *The New York Times*, etc.

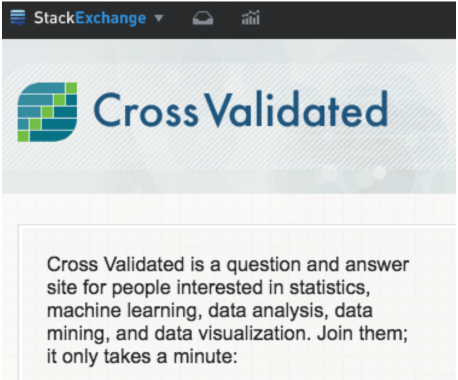
Civil wars

- But: Strikingly poor performance on in-sample prediction

Table III. Number of correctly predicted onsets and false positives at varying cut-points

	Fearon & Laitin model	
Threshold	*Correctly predicted*	*False positives*
0.5	0/107	0
0.3	1/107	3
0.1	15/107	66
	Collier & Hoeffler model	
Threshold	*Correctly predicted*	*False positives*
0.5	3/46	5
0.3	10/46	20
0.1	34/46	110

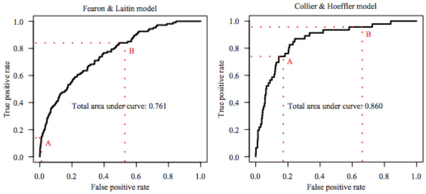
Cross validation



Procedure

1. Split data into k "folds" (equally sized groups)
2. Withholding one fold, re-estimate model
3. Test predictive power of model on withheld group (AUC)

Receiver operating characteristic (ROC) curve



- We use area under the ROC curve (AUC) as a heuristic measure of predictiveness
  - Intuitively, increasing AUC implies TPR $>$ FPR
- (From the people who brought you instructional television. . .)

Tricks and missteps

- Bias-variance tradeoff
  - k = n (LOOCV): higher variance (low variance among training sets), but lower bias
  - k $<$ n (*k*-fold): lower variance, but higher bias (*overestimating* prediction error)
- General consensus is that it might be better to overestimate prediction error (conservative bias)
  - Also, LOOCV is "more expensive"
- **Don't do (supervised) feature selection before model validation!**
  - Will overestimate AUC (drastically)

Cross validation: pretty easy to implement!

```
# Function to divide data into folds randomly
fold <- function(data, k) {
  data <- data[sample(nrow(data)),]  # Shuffle data
  data %<>% mutate(fold = cut(seq(1:nrow(data)), breaks = k, labels=FALSE))
  return(data)
}

# Function to cross-validate data on given model (curried)
cv.predict.logit <- function(data, dv, model.fx, k) {
  data %<>% fold(k)  # Fold data
  aucs <- c()
  for(i in 1:k) {
    # Divide data into train and test sets
    train <- data %>% filter(fold != i)
    test <- data %>% filter(fold == i)

    # Estimate model on training data
    mx <- model.fx(data=train)

    # Predict on test data and calculate AUC
    preds <- predict(mx, newdata=test, type="response")
    AUC <- somers2(preds, test[[dv]])[1]
    aucs[i] <- AUC
  }
  return(mean(aucs, na.rm=TRUE))  # Yield mean AUC
}

# Function to rerun CV results n times and average AUCs
crossval <- function(data, dv, model.fx, k, n) {
  aucs <- replicate(n, cv.predict.logit(data, dv, model.fx, k))
  return(aucs)
}
```

Back to civil war

```
# Define Collier & Hoeffler model
ch.form <- as.factor(warsa) ~ sxp + sxp2 + secm + gy1 + peace + geog
ch.mx <- Curry(glm, formula=ch.form, family=binomial(link=logit))

# Define Fearon & Laitin model
fl.form <- as.factor(onset) ~ warl + gdpenl + lpopl1 + lmtnest + ncc
fl.mx <- Curry(glm, formula=fl.form, family=binomial(link=logit))

# Perform cross-validation
k <- 4  # Set k folds
ch.auc <- cv.predict.logit(ch, "warsa", ch.mx, k)
fl.auc <- cv.predict.logit(fl, "onset", fl.mx, k)

c(ch.auc, fl.auc)
```

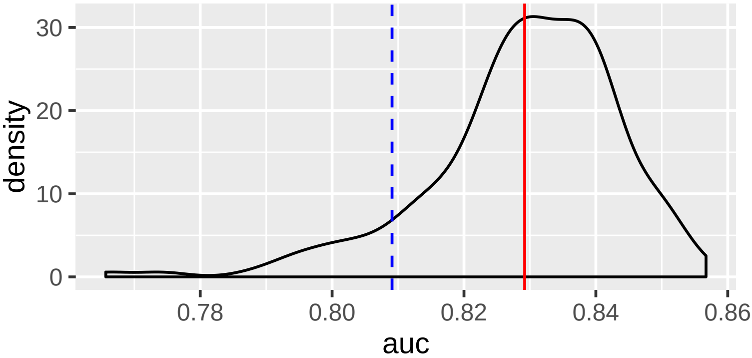
```
## [1] 0.8090876 0.7423249
```

Calculating a stable AUC

- Sensitive to dataset randomization during “folding”
  - Not too much to worry about here (usually)
- Sensitive to choice of k
  - Low k: upward bias in AUC
  - High k: higher variance in AUC

Sensitivity to randomization: F&L

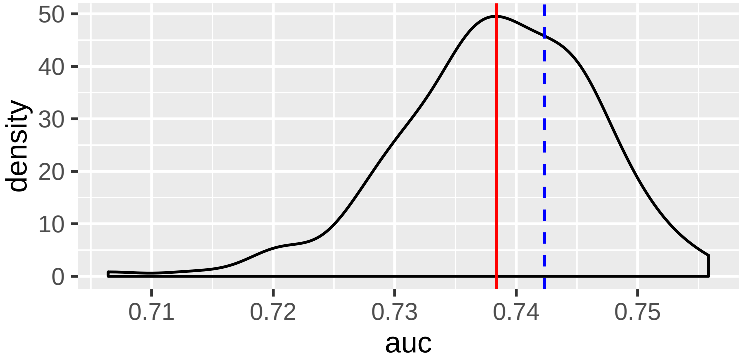
```r
k <- 4
n <- 200  # Set n CV cycles
ch.aucs <- crossval(ch, "warsa", ch.mx, k, n)
```



- mean over N cycles
- AUC in first cycle

Sensitivity to randomization: C&H

```
k <- 4
n <- 200  # Set n CV cycles
fl.aucs <- crossval(fl, "onset", fl.mx, k, n)
```



- mean over N cycles
- AUC in first cycle

Sensitivity to choice of k: F&L

```r
n <- 100
list(k4 = crossval(fl, "onset", fl.mx, 4, n),
     k10 = crossval(fl, "onset", fl.mx, 10, n),
     k20 = crossval(fl, "onset", fl.mx, 20, n),
     k100 = crossval(fl, "onset", fl.mx, 100, n),
     k500 = crossval(fl, "onset", fl.mx, 500, n)) ->
  fl.aucs.ks
```

Sensitivity to choice of k: F&L

```
## Using  as id variables
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```

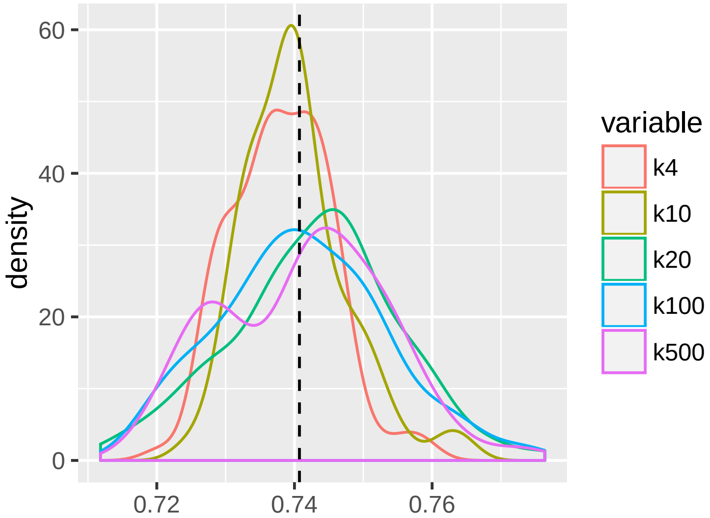

Conclusion: why might we care?

- Technical tradeoff between variable significance vs. model predictiveness (Ward et al. 2010; Lo et al. 2015)
- If we really think our models explain causal effects, shouldn't they be predictive? (Watts 2014)
  - Especially if we're basing policy on our findings
- Distinguishing origins from effects (Sewell 1996; Pierson 2000; Clemens 2007)