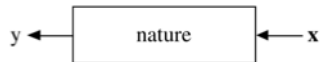
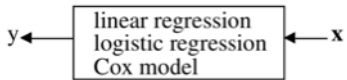


Class slides for Thursday, Sept 24:
Armed conflict, part 2

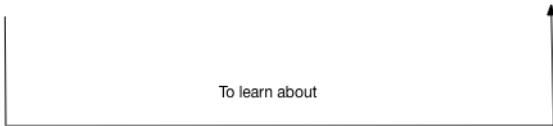
Matthew J. Salganik

COS 597E/SOC 555 Limits to prediction
Fall 2020, Princeton University

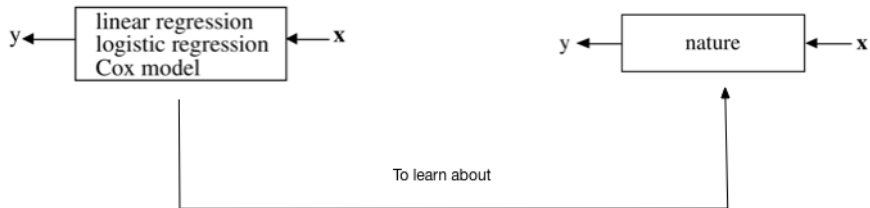
Social science (Data modeling)



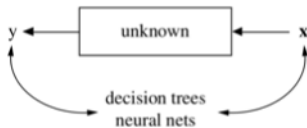
To learn about



Social science (Data modeling)

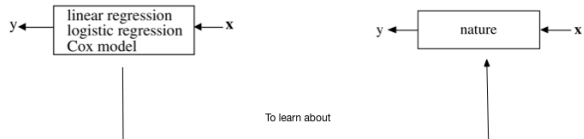


Computer science (Algorithmic modeling)



Compare \hat{y} and y to learn about algorithm

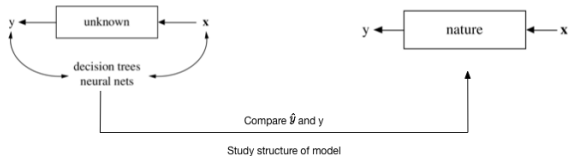
Social science (Data modeling)



Computer science (Algorithmic modeling)



Third way (Prediction for understanding)



Civil wars and internal armed conflicts, 1946-2012

Civil wars and internal armed conflicts, 1946-2012



Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data

David Muchlinski

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David Siroky

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Matthew Kocher

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 - ▶ Notice that models did not maximize scoring function (AUC)

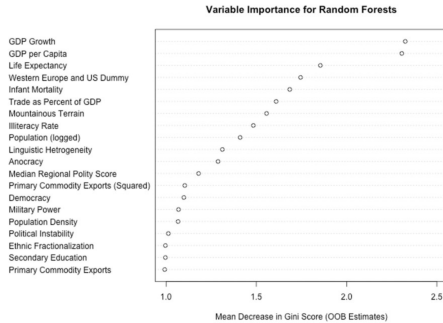


Fig. 4 Plot of variable importance by mean decrease in Gini Score.

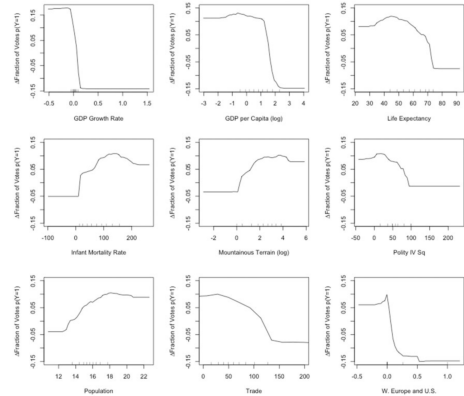


Fig. 5 Partial dependence plots.

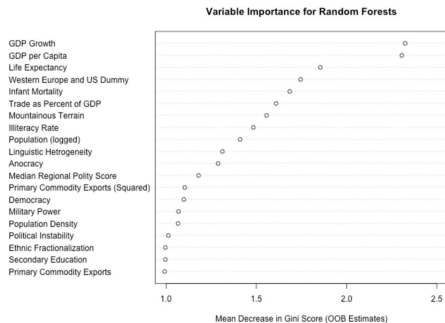


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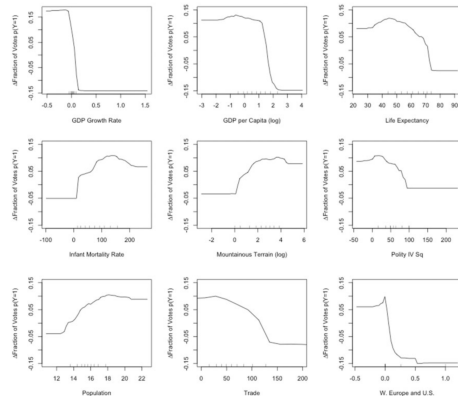


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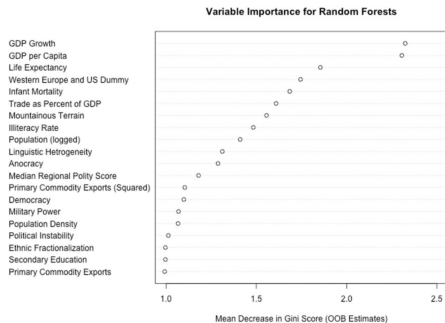


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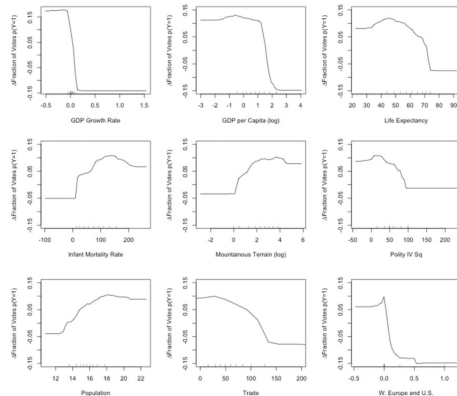


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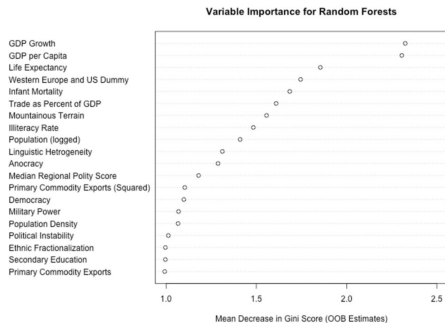


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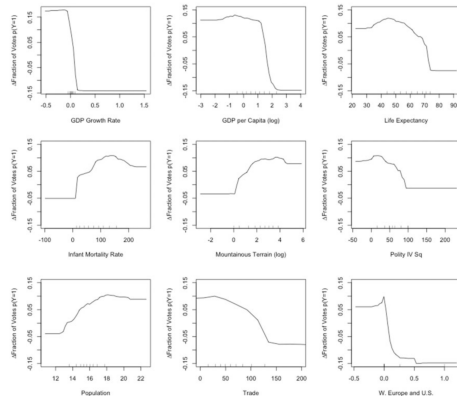


Fig. 5 Partial dependence plots.

- ▶ I'm not sure I believe this. What are the units?
- ▶ Recall Arvind's concerns about correlated predictors
- ▶ If we did this with a slightly different implementation of random forest would we get the same results? What about another ML method?

Assignment 2

- ▶ It is very hard to tell what is happening in the comments and replies without digging in, hence your assignment. But imagine what we happen if the code was not available!

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- ▶ Can we use predictive models to learn about the data generating process?
- ▶ What is a good way to measure generalization performance when there is measurement uncertainty?

What Is Civil War?

CONCEPTUAL AND EMPIRICAL COMPLEXITIES OF AN OPERATIONAL DEFINITION

NICHOLAS SAMBANIS

Department of Political Science

Yale University

The empirical literature on civil war has seen tremendous growth because of the compilation of quantitative data sets, but there is no consensus on the measurement of civil war. This increases the risk of making inferences from unstable empirical results. Without ad hoc rules to code its start and end and differentiate it from other violence, it is difficult, if not impossible, to define and measure civil war. A wide range of variation in parameter estimates makes accurate predictions of war onset difficult, and differences in empirical results are greater with respect to war continuation.

Keywords: *civil war; Correlates of War; data sets; coding rules*

Significant differences across civil war lists are mainly due to disagreement on three questions: What threshold of violence distinguishes civil war from other forms of internal armed conflict? How do we know when a civil war starts and ends? How can we distinguish between intrastate, interstate, and extrastate wars? Answers to these questions are not only relevant for the purposes of accurate coding, but they also reveal the degree to which we share a common understanding of the concept of civil war.

12 different measures of civil wars. Does this matter? Should we standardize on one definition? Think back to ImageNet.



- ▶ What is a good way to measure generalization performance when the data has structure (focus on time)?

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- ▶ Should we use the future to predict the past? Should we use the present to predict the present?

RStudio

data.full																			
		Filter	Cols: << 1 - 50 >>																
	warstds	ager	agexp	anoc	army85	autch98	auto4	autonomy	avgnabo	centpol3	coldwar	decade1	decade2	decade3	decade4	dem	dem4	demch98	dlan
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2	peace	34.34635	8.478997	0	129413.0	0	10.000000	0.000000000	0.0450517	1	1	0	0	0	0	0	0.000000	0	70.0
3	peace	77.00000	8.481015	0	130431.0	0	10.000000	0.000000000	0.0300345	1	1	0	0	0	0	0	0.000000	0	70.0
4	peace	78.00000	8.451628	0	126781.7	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
5	peace	79.00000	8.500172	0	130979.2	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
6	peace	80.00000	8.528873	0	130616.5	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
7	peace	81.00000	8.546965	0	129142.7	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
8	peace	82.00000	8.550921	0	129067.3	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
9	peace	83.00000	8.530715	0	130133.3	0	10.000000	0.000000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
10	peace	84.00000	8.544636	0	131839.4	0	10.000000	0.000000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
11	peace	85.00000	8.532668	0	129951.5	0	10.000000	0.000000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
12	peace	86.00000	8.488276	0	129301.5	0	10.000000	0.000000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
13	peace	87.00000	8.534172	0	130448.2	0	10.000000	0.000000000	0.2500000	1	1	0	0	0	0	0	0.000000	0	70.0
14	peace	88.00000	8.529870	0	131597.9	0	10.000000	0.000000000	0.2500000	1	1	0	0	0	0	0	0.000000	0	70.0
15	peace	89.00000	8.525314	0	131245.8	0	10.000000	0.000000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
16	peace	90.00000	8.581366	0	129057.9	0	10.000000	0.000000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
17	peace	91.00000	8.562673	0	47000.0	0	10.000000	0.000000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
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19	peace	93.00000	8.541015	0	47000.0	0	10.000000	0.000000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
20	peace	94.00000	61.100498	0	47000.0	0	10.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
21	peace	95.00000	54.437160	0	47000.0	0	7.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
22	peace	96.00000	45.760941	0	47000.0	-3	7.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
23	peace	97.00000	51.714909	0	47000.0	0	7.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
24	peace	98.00000	46.355721	0	47000.0	0	7.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
25	peace	99.00000	38.092049	0	47000.0	0	7.000000	0.000000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
26	peace	100.00000	38.050751	0	47000.0	0	7.000000	0.000000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
27	peace	101.00000	35.823952	0	47000.0	0	7.000000	0.000000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
28	peace	102.00000	45.656319	0	47000.0	0	7.000000	0.000000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
29	peace	103.00000	33.937969	0	47000.0	0	7.000000	0.000000000	0.0105231	1	1	0	1	0	0	0	0.000000	0	70.0

Drops year and country code. These are never used in the paper (as far as I can tell).

data.tbl		Filter		Cols: << 1-50 >>																		
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29	peace	103.00000	53.947964	0	47000.0	0	7.000000	0.0000000000	0.01019231	1	1	0	1	0	0	0	0	0.000000	0	70.0		

	warstds	ager	agep	asec	army85	astch98	autot	asternomy	asgnubo	contig03	colbwar	decade1	decade2	decade3	decade4	dem	dem1	demch98	dian
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9	peace	83.00000	8.530715	0	131133.3	0	10.000000	0.0090000000	0.0225258	1	1	0	0	0	0	0	0.000000	0	70.0
10	peace	84.00000	8.544036	0	131839.4	0	10.000000	0.0090000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
11	peace	85.00000	8.532968	0	129951.5	0	10.000000	0.0090000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
12	peace	86.00000	8.488276	0	129101.5	0	10.000000	0.0090000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
13	peace	87.00000	8.534172	0	130448.2	0	10.000000	0.0090000000	0.2500000	1	1	0	0	0	0	0	0.000000	0	70.0
14	peace	88.00000	8.529870	0	131597.9	0	10.000000	0.0090000000	0.2500000	1	1	0	0	0	0	0	0.000000	0	70.0
15	peace	89.00000	8.525314	0	131245.8	0	10.000000	0.0090000000	0.0000000	1	1	0	0	0	0	0	0.000000	0	70.0
16	peace	90.00000	8.581366	0	129057.9	0	10.000000	0.0090000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
17	peace	91.00000	8.562673	0	47000.0	0	10.000000	0.0090000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
18	peace	92.00000	8.560198	0	47000.0	0	10.000000	0.0090000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
19	peace	93.00000	8.541015	0	47000.0	0	10.000000	0.0090000000	0.0000000	1	1	1	0	0	0	0	0.000000	0	70.0
20	peace	94.00000	61.100498	0	47000.0	0	10.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
21	peace	95.00000	54.437190	0	47000.0	0	7.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
22	peace	96.00000	45.760941	0	47000.0	-3	7.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
23	peace	97.00000	51.714909	0	47000.0	0	7.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
24	peace	98.00000	46.357721	0	47000.0	0	7.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
25	peace	99.00000	38.092049	0	47000.0	0	7.000000	0.0090000000	0.0078924	1	1	1	0	0	0	0	0.000000	0	70.0
26	peace	100.00000	38.050751	0	47000.0	0	7.000000	0.0090000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
27	peace	101.00000	35.823952	0	47000.0	0	7.000000	0.0090000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
28	peace	102.00000	45.826519	0	47000.0	0	7.000000	0.0090000000	0.0131874	1	1	0	1	0	0	0	0.000000	0	70.0
29	peace	103.00000	53.942904	0	47000.0	0	7.000000	0.0090000000	0.0104241	1	1	0	1	0	0	0	0.000000	0	70.0

#Fearon and Laitin Model (2003) Specification###

model.fl.1<-

```
train(as.factor(warstds)~warhist+ln_gdpen+lpopns+lmtnest+ncontig+oil+nwstate
+inst3+pol4+ef+relfrac, #FL 2003 model spec
metric="ROC", method="glm", family="binomial",
trControl=tc, data=data.full)
```

Uses the present to predict the present

Assignment 2

Class slides for Thursday, Sept 24:
Armed conflict, part 2

Matthew J. Salganik

COS 597E/SOC 555 Limits to prediction
Fall 2020, Princeton University