Outline

Election modeling

Electoral modeling in practice

Electoral modeling: good, bad, and ugly

Weapons of Math Destruction
Analytics for presidential campaigns

**goal:** allocate limited resources to optimize electoral vote

▶ each state gets votes proportional to population (about 1 vote / 600K residents) + $k$
▶ most states allocate all votes to winner of statewide popular vote

where $k =$

- A. 0
- B. 1
- C. 2
- D. 5
- E. 10
Why an electoral college?

the electoral college

▶ is a compromise from the constitutional convention of 1787 to get small states to join the United States
▶ increases power of rural states
▶ concentrates campaign attention in very few “battleground” states
▶ decides the winner of the election
  ▶ ≠ popular vote winner in 1876, 1888, 2000, 2016
Why an electoral college?

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  - ≠ popular vote winner in 1876, 1888, 2000, 2016

can we get rid of the electoral college?

- via constitutional amendment: need 2/3 of states to agree
- via state compact: need 105 more electoral votes
Optimization on the Obama campaign
Optimization on the Obama campaign

Election votes vs Margin

-30 -20 -10 0 10 20 30

-30 -20 -10 0 10 20 30

Marg

0
10
20
30
40
50
60
70

Electoral votes

wasted effort

won by just enough...
2016 electoral map
Not much (effective) optimization on the Clinton campaign

2016 Electoral Votes Histogram (source: RCP Th. 11/10 10p)
Biden campaign: ???

...gotta count the votes...

big questions:

► is the US electoral system democratic? (good/bad?)
  ► first-past-the-post
  ► electoral college
  ► senate
  ► supreme court
  ► relevant reading: They Don’t Represent Us, by Lawrence Lessig

► polls were quite wrong (a bit less than 2016):
  9% predicted margin $\rightarrow$ around 4–5% actual margin
  (national popular vote)
2016 electoral optimization (in hindsight)

Hamdan Azhar (2012 Ron Paul Data Guru; guest speaker in December):

▶ Hillary would have won the election if she had gotten just 224K more votes.
▶ How? She’s currently at 218 electoral votes.
▶ The easiest way she could have gotten 52 more electoral votes is by having won PA, WI, and FL.
▶ The combined Trump margin of victory in these three states was 224K.
▶ 224K votes divided by 124M votes cast yields 0.19%.

The election was decided by 0.19% of the electorate.
What choices can a campaign make?

campaigns can control

▶ which states the candidate visits
▶ how many ads for the candidate are produced
   ▶ TV
   ▶ yard sign
   ▶ internet
   ▶ facebook
   ▶ merchandise
▶ voter registration targeting
▶ get-out-the-vote (GOTV) targeting
▶ candidate policy statements

to maximize probability of electoral win
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Data for political campaigns

data sources:

- (public) voter files
- (private) purchased information
- polling data
  - previous years
  - primary election
  - surveys (phone, internet, in-person, . . . )
  - exit polls
- economic data
Analytics for political campaigns

**goal:** allocate limited resources to optimize electoral vote

**three key components:**

- support
- persuasion
- turnout
Levels of modeling

three kinds of models:

- agent level predictive model (Obama 2012)
- demographic level predictive model (NYT turnout model)
- aggregated polls-based model (Nate Silver and 538)
Agent level predictive model

<table>
<thead>
<tr>
<th>age</th>
<th>gender</th>
<th>state</th>
<th>income</th>
<th>education</th>
<th>voted?</th>
<th>support</th>
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<td>$53,000</td>
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<td>Biden</td>
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<td>$19,000</td>
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<td>M</td>
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<tr>
<td>41</td>
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<td>NV</td>
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<td>?</td>
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</table>
## Demographic level predictive model

<table>
<thead>
<tr>
<th>county</th>
<th>demographics</th>
<th>vote %</th>
<th>support %</th>
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</tr>
</thead>
<tbody>
<tr>
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<td>white male</td>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>tompkins</td>
<td>asian female</td>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>tompkins</td>
<td></td>
<td>:</td>
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Aggregated polls-based model

weighted average predictor:

- poll people from each demographic group $i$ to measure average support $\bar{v}_i$
- predict turnout $t_i$ for each group $i$ using historical data
- compute weighted average

\[
\text{predicted vote share} = \frac{1}{\sum_i t_i} \sum_i t_i \bar{v}_i
\]
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\]

sources of error:

- statistical error
- systematic error
- non-response bias
How to choose the weights?

two ingredients produce weights:

- definition of demographic group
- turnout prediction per group
The trouble with polls

Q: do you pick up your phone when an unknown number calls?

A. always
B. usually
C. sometimes
D. nver
The trouble with polls

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A: ... varies by demographic; eg, older americans are more likely to answer
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Q: are people who respond to polls like people who don’t?
The trouble with polls

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A. always  
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D. never

**A:** ... varies by demographic; eg, older americans are more likely to answer

**Q:** could we build a model to predict which of you picks up?

**Q:** are people who respond to polls like people who don’t?

**A:** no:

*There is a 19-year-old black man in Illinois who has no idea of the role he is playing in this election. He is sure he is going to vote for Donald J. Trump. In some polls, he’s weighted as much as 30 times more than the average respondent, and as much as 300 times more than the least-weighted respondent.*
Correct biased sample

two types of people

- type A always fill out all questions
- type B leave question 3 blank half the time

<table>
<thead>
<tr>
<th>question 1</th>
<th>question 2</th>
<th>question 3</th>
<th>question 4</th>
<th>...</th>
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<tr>
<td>2.7</td>
<td>yes</td>
<td>4</td>
<td>yes</td>
<td>...</td>
</tr>
<tr>
<td>9.2</td>
<td>no</td>
<td>?</td>
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estimate population mean of question 3

- excluding missing entries: 2.5
- imputing missing entries: 2
Correct biased sample

two types of people

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▶ type B leave question 3 blank half the time

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<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
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estimate population mean of question 3 if the type B people have two subtypes:

▶ one that answers “1” to question 3
▶ another that doesn’t answer, but whose true answer is “27”
How does this apply to election models?

**simple model:** suppose that in each demographic group,

- there are some Trump and some Biden supporters
- the Trump supporters respond to pollsters at lower rates (or lie about their support)

there is **no way** to detect this from polling data!
How does this apply to election models?

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**confidence intervals:** (computed eg via bootstrap or analytical methods)

- account for **statistical** error
- do not account for **systematic** error
Conditions for unbiased estimation

to ensure that estimate is unbiased, need outcome to be independent of missingness conditional on covariates

e.g., estimate for predicted vote share is unbiased if (turnout model is correct and)

  support for Trump \perp\text{ non-response} \mid\text{ demographics}
Dealing with systematic bias

problem with systematic bias:

▶ even if you know it exists, you don’t know how much!

modeling systemic bias?

▶ use the bias from previous years to infer bias this year
▶ problem: level of bias may vary with other (never-before-seen) factors, e.g.
  ▶ female candidate
  ▶ candidate with no experience
  ▶ candidate who endorses unconstitutional policies
  ▶ COVID
  ▶ shutdowns

we have no data to estimate these effects!
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NYT 5 month prediction

The graph shows a prediction for Clinton and Trump's chances from June to November 8. Clinton's line starts high and drops slightly, ending at 85%. Trump's line is significantly lower, starting high and dropping to 15% by November 8.
NYT night-of prediction

Chance of Winning Presidency

>95% Trump

<5% Clinton
Assessing the quality of analytics

as of Monday night 11/8/16,

- **good.** Nate Silver and 538: 65% Clinton to 35% Trump
- **bad.** New York Times: 84% Clinton to 16% Trump
- **ugly.** Princeton Election Consortium: 99% Clinton to 1% Trump (!)
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why did we predict the 2016 election so poorly?
http://fivethirtyeight.com/features/
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from the data we have, can we conclude predictions did poorly?

need to **calibrate** prediction accuracy
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Weapons of Math Destruction
what is a WMD? a predictive model

- whose outcome is not easily measurable
- whose predictions can have negative consequences
- that creates self-fulfilling (or defeating) feedback loops
CERN is not a WMD
CERN is not a WMD

why are predictive models from CERN ok?

▸ they are running an experiment
▸ they rigorously separate train and test sets
▸ they have a lot of data and can get more
▸ they have generative models that quantitatively agree with experimental measurements
▸ they have multiple experiments that measure the same phenomenon of interest using completely different tools
College rankings are a WMD

why are college rankings a WMD?
College rankings are a WMD

why are college rankings a WMD?

- can’t measure “test error” for college rankings
- high rankings **cause** college “quality” to increase: attracts
  - students
  - faculty
  - donors
- college rankings shape behaviour and pervert incentives
  - tuition increases
  - spending on sports
Parole models are a WMD

- parole models predict **recidivism** (probability of committing another crime)
- automatically decide if a prisoner can be released early
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- parole models predict recidivism (probability of committing another crime)
- automatically decide if a prisoner can be released early

why are parole models a WMD?

- what data do they use? race? neighborhood?
- keeping people in prison longer may cause them to recidivate
  - hard to find a job
  - increase familiarity with crime
  - effects may spread within neighborhoods or communities
Are election models a WMD?

are (presidential) election models a WMD?

▶ is the outcome measurable?
  ▶ yes, but only every four years!
  ▶ or more frequently, but with unquantifiable systematic error

▶ do predictions affect results?
  ▶ via turnout: yes
  ▶ via support: ?
  ▶ via persuasion: ?

▶ do predictions create negative feedback cycles?
  ▶ yes: contacting only people likely to be on your side deepens extremism
  ▶ using race as a feature thus deepens racial divides
Don’t create WMDs

is your project a WMD?

- are outcomes hard to measure?
- could its predictions harm anyone?
- could it create a feedback loop?