

## Identifying likely voters in pre-election surveys

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American Association for Public Opinion Research  
Webinar  
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### Learning objectives

- Understand **why likely voter models** are necessary in election polling
- List a variety of **sampling methods**, including **voter file options** and why they can be useful for election research
- Identify **typical questions included** in likely voter models
- Understand the **types of likely voter models** typically used, including probabilistic and deterministic (cut-off) methods

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2

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### The problem, simply stated: Not everyone votes



Democrats are usually less likely than Republicans to vote, but often equally likely to say they will

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### The challenge

*"Likely voter models are asked to produce a model of a population that does not yet exist at the time the poll is conducted, the future electorate."*

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### Different elections, different considerations

- Different elections feature different electorates:
  - Presidential-year vs. off-year
  - general vs. primary
- We want a method that works in high-turnout and in low-turnout elections
- Important to note if a particular election:
  - Has lots of early or absentee voting
  - Is drawing more or less interest than usual
- Wild cards:
  - mobilization, demobilization, new barriers to voting

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### Case study

Two waves of the American Trends Panel conducted by Pew Research Center in a midterm election

Pre-Election: Sep. 9 – Oct. 3, 2014

Post-Election: Nov. 17 – Dec. 15, 2014

N = 2,424 U.S. adults who responded to both waves of the panel, were registered to vote, and were matched to a commercial voter file

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6

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### House vote choice among registered, verified voters in 2014 election

	Republican	Democrat	Other	Don't know/ refused	NET
<i>Pre-election vote choice among...</i>					
...all registered voters	38	42	6	14	<b>D +4</b>
...verified 2014 voters	44	41	4	10	<b>R +3</b>

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- ### Why election polls sometimes go wrong
- **Biased samples** that include an incorrect proportion of each candidate's supporters
  - **Change in voter preferences** between the time of the poll and the election
  - **Incorrect forecasts** about who will vote (why we need likely voter models)
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### Unbiased sample

	Republican	Democrat	Other	Don't know/ refused	NET
<i>Pre-election vote choice among...</i>					
...all registered voters	38	42	6	14	<b>D +4</b>
...verified 2014 voters	44	41	4	10	<b>R +3</b>
Post-election vote choice among verified voters	51	45	4	-	<b>R +6</b>
2014 election results	51	46	3	-	<b>R +5</b>

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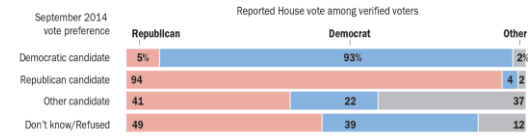
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## There was very little switching, but late deciders broke for Republicans

### Change in vote choice among panelists, pre- to post-election



Source: 2014 American Trends Panel September and November waves. Based on registered voters who participated in both waves and were matched to a national voter file.

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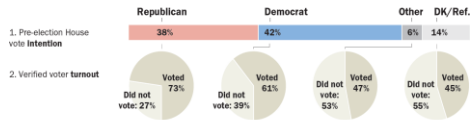
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## Republicans turned out to vote at a higher rate than Democrats

### Vote intention and turnout

Republican candidates benefited from higher turnout by their supporters. Among pre-election respondents who supported Republican candidates, 73% turned out to vote; among those who supported Democratic candidates, 61% turned out to vote.



Source: 2014 American Trends Panel September and November waves. Based on registered voters who participated in both waves and were matched to a national voter file.

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11

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## Three big choices:

- What kind of *sample*?
- What *measures* to include?
- How to *model* the data?

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12

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**Sampling**

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**Types of samples**

- **General public samples**
  - RDD samples – cellphones and landlines
  - Online samples – probability and nonprobability
- **Registration based samples (RBS)**
  - Commonly known as “the voter file”
  - List of all registered voters from every state; often stitched together by vendors
  - Used by many campaign pollsters
  - Contain information about past voting history for each individual, along with modeled partisanship and political engagement (also may include demographic and lifestyle information)

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**Some voter file vendors**

<p><b>Democratic</b></p> <p>Catalist TargetSmart</p>	<p><b>Republican</b></p> <p>TargetPoint DataTrust i360</p>
<p><b>Non-partisan</b></p> <p>Labels and Lists (L2) Aristotle NationBuilder Individual states</p>	

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### Limitations of voter files

- Many are missed by voter files:
  - People **not listed in voter files**
  - At least 11% of the adult citizenry is not listed
    - Disproportionately affects blacks, Hispanics and the highly mobile
  - Little digital fingerprint
  - New voters and **new registrants**
- Even among people who are listed in the voter file, information may not be up to date or accurate
  - **In our case study, 16% say they voted in 2014 but have no record of voting** (on voter file)
  - Some of this is **over-reporting**, but its also plausible that the **absence of a record is an error**
- Differs by state

1. Jackman, Simon and Bradley Spahn. 2015b. "Unlisted in America." Unpublished paper. Accessed Dec. 22, 2015, at <https://www.dropbox.com/s/9v511y9k422aw/jackman%20spahn%20-%20Unlisted%20in%20America.pdf?dl=0>

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16

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### Measures for identifying likely voters

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17

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### Perry scale method

- Developed in the 1950s and 1960s by Paul Perry of Gallup
- Derives a likely voter index from questions aimed at measuring:
  - Political engagement
  - Experience with voting
  - Past vote
  - And intention to vote
- Cutoff at expected turnout
- Commonly-used method

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18

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### Self-reports of past voting predict future voting, but are not perfect

Share of registered voters	2012 vote (self-reported)	% who are verified 2014 voters	Margin
87	<b>Voted</b>	70	D +4
12	Did not vote	17	D +8
1	Too young to vote	27	D +55
<i>How often vote</i>			
45	<b>Always</b>	82	R +2
33	<b>Nearly always</b>	59	D +8
13	Part of the time	34	D +9
9	Seldom	17	D +37
<i>Ever voted in precinct or election district</i>			
83	<b>Yes</b>	70	D +2
17	No	26	D +21

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22

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### Combining the measures to form the Perry scale

Score on scale	Share of all verified voters	% who are verified voters in each group
7	63%	83%
6	15	63
5	10	59
4	4	34
3	4	41
2	2	23
1	1	13
0	1	11
100		

83% of those who scored a 7 actually voted

Source: 2014 American Trends Panel September and November waves. Based on registered voters who participated in both waves and were matched to a national voter.

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23

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### Approaches to identifying likely voters

Deterministic	
<b>WHAT:</b> • Ask of all adults/registered voters • Identify likely voters with a series of questions used in a scale. • Only include <b>most likely to vote</b> (top of scale) according to expected turnout.	<b>WHO:</b> • Gallup • Pew Research Center • ABC/Washington Post • LA Times • Quinnipiac Poll • Time • IPSOS (also uses weighting)
Probabilistic	
Model as you sample	

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24

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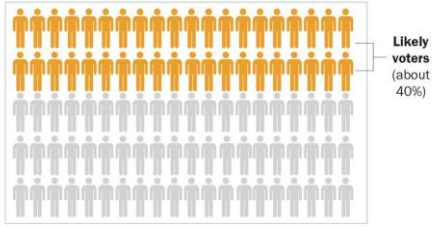
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### Approaches to identifying likely voters



**Deterministic methods**

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### Approaches to identifying likely voters

Deterministic	Probabilistic
<b>WHAT:</b> • Same questions, <b>used as a weight</b> • Include everyone, <b>weighted to their probability of voting.</b>	<b>WHO:</b> • CBS/New York Times • Marist
Model as you sample	

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### Approaches to identifying likely voters



**Probabilistic methods**

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### Approaches to identifying likely voters

Deterministic	
Probabilistic	
Model as you sample	
<p><b>WHAT:</b></p> <ul style="list-style-type: none"> <li>• Usually rely on a combination of <b>past vote from voter file</b> and <b>self-reported vote</b> on a sliding scale</li> <li>• <b>Sample using past vote</b></li> <li>• Construct sample to <b>reflect probability of voting</b></li> <li>• Goal to increase efficiency</li> </ul>	<p><b>WHO:</b></p> <p>Primarily partisan pollsters including:</p> <ul style="list-style-type: none"> <li>• Anzalone Liszt Grove Research</li> <li>• Democracy Corps</li> <li>• the Field Poll</li> </ul>

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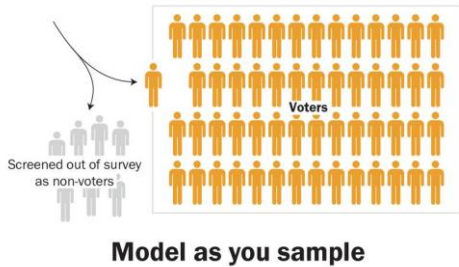
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### Approaches to identifying likely voters



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29

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### Deterministic (cut-off) methods

- One example: the Perry scale
- Categorize each survey respondent as a likely voter or nonvoter
- Uses a threshold or “cutoff” that matches the predicted rate of voter turnout in the election
- The turnout forecast matters

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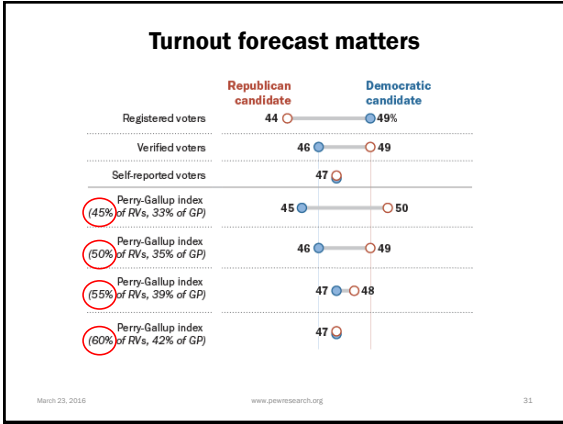
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- ### Probabilistic or modeling approaches
- Same set of questions as Perry scale
  - Calculates a probability of voting for each survey respondent
  - Variety of methods including logistic regression, random forest
  - Can include records of past turnout from the voter file
  - Models could be applied to future elections to test viability
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### Voter file measures of past voting behavior predict future voting

Share of registered voters		% who are verified 2014 voters	Margin
<i>Verified past vote</i>			
78	Voted in 2012	75	D +2
22	No record	21	D +18
100			
<i>Unverified past vote</i>			
55	Voted in 2010	84	R +6
45	No record	36	D +19
100			

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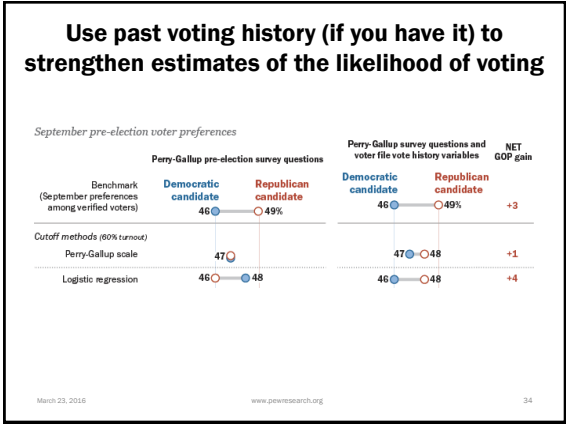
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## Machine learning approaches

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- ### Machine learning models
- **Random Forest**
    - Able to sort through large numbers of variables to find patterns
    - Typical decision tree analysis identifies various ways of splitting a dataset into separate paths or branches, based on options for each variable
    - Random forest uses large number of decision trees to split the data into similar groups
    - Probabilistic model – produces a predicted probability for each respondent
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### Optimizing your models with limited space

• Machine learning models using combinations of questions show promise if you have limited space

	Republican	Democrat	Margin
Overall machine learning model (random forest)	48	46	R +2
Ground truth	49	46	R +3
Registered voters in survey	38	42	D +4
Plan to vote in the general election	46	48	D +2
Voted in 2012	45	49	D +4
Plan to vote, voted in 2012	46	48	D +2
Plan to vote, voted in 2012, voted in your precinct before	47	48	D +2
Plan to vote, voted in 2012, how often do you vote in elections	47	48	D +2
Plan to vote, voted in 2012, thought about the election	47	47	EVEN
Plan to vote, voted in 2012, follow government and politics	47	47	EVEN

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### Applying models to future elections

- Tricks to apply models to future election data
  - Use regression coefficients to create a predictive equation – apply to new dataset
  - Using statistical software makes it simpler!
    - STATA: Run regression on old dataset, use “predict” function right away with new dataset
    - SPSS: Specify in regression parameter under SELECT which dataset you’re predicting onto
    - R: Use “predict” function and specify “new data” parameter

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### Take-home considerations

- Can’t take people at their word about voting
  - Republicans more likely than Democrats to vote
  - Over-reporting of intention, but under-reporting too
- Use multiple questions in multiple dimensions
  - Intention, past behavior, engagement
  - The specific questions may not matter
- Various models (deterministic vs. probabilistic) can work
  - Cutoff methods adjust to different election circumstances
  - Probabilistic methods use all available data
  - But harder to calibrate and implement
- Voter files can be very useful
  - Valuable in low-turnout elections
  - Useful for targeting
  - But issues of coverage remain

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**Additional resources**

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**Additional resources**

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41

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**Questions?**

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42

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