Counting on the most reliable pollworkers

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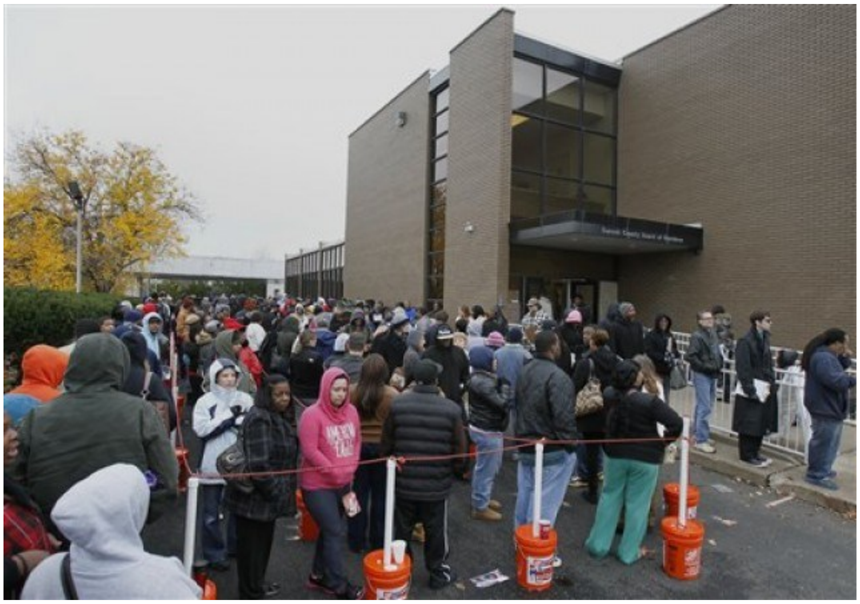
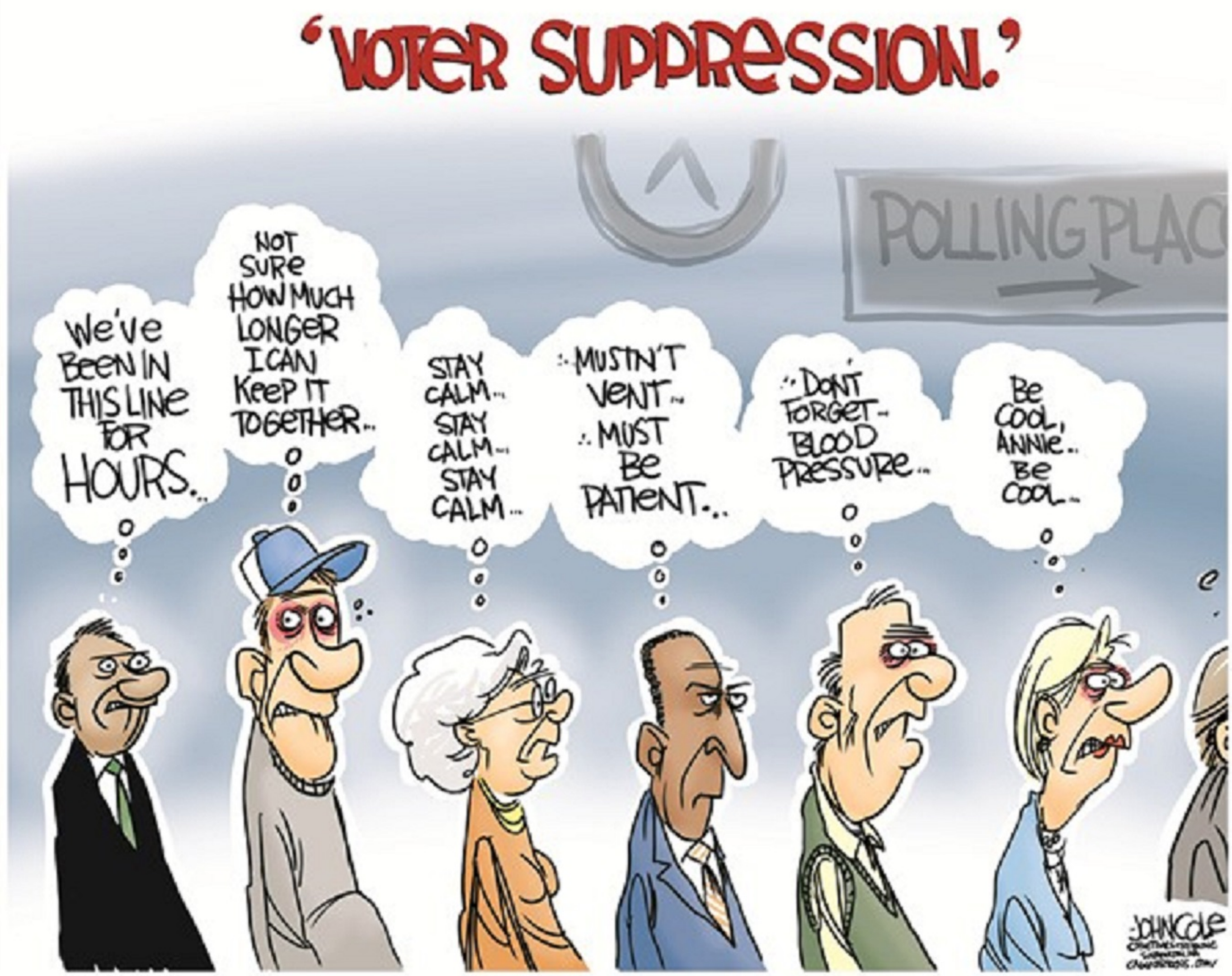
Poll Worker (PW) Recruitment

- What happens when we can’t recruit enough PW’s
- Or cancel last minute
- Or even worse… no show on election day

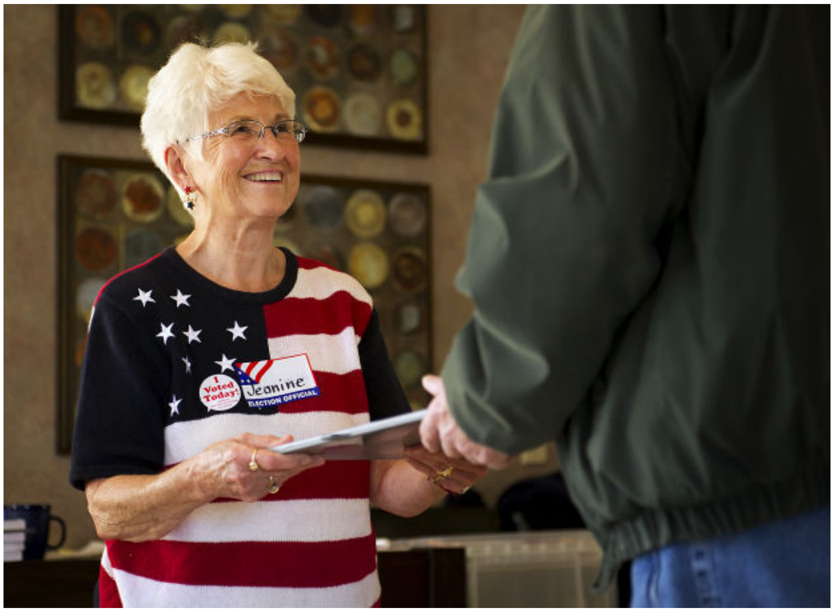
We may end up with…



Which may lead to…



Optimal Selection



So how do we find the reliable pollworker candidates?

ROOM FOR IMPROVEMENT

- Given success rates of 67% for our November 2014 election and 78% for our June 2014 election, clearly room for improvement (less so for our primary elections)
- Can begin better differentiating between commited versus uncommitted PW's
- How do we model the very intuitions that our recruiters are attempting to access
- And find additional patterns that are derived mathematically

GOAL OF THIS PROJECT

- Minimize negative outcomes (PW said no thanks, cancelled last minute, no showed on election day) while still identifying sufficient numbers of PW candidates to actually work
- Costs of incorrectly identifying a negative outcome as a positive outcome: potential late openings of certain polls, last minute shuffling of resources, many more phone calls required

What do we know about our pollworkers

- Some demographic data (gender, age)
- Voting history= civic participation?
- Previous pollworker history predicts future pollworker participation?
- Distance travelled from home to poll site matters?
- Specific outcomes (response)
- PW’s can be split into 6 distinct clusters using unsupervised K means clustering

What is the prediction algorithm doing?

- For each record being predicted on, assigning a class probability (between 0 and 1) to the outcome variable
- Under normal circumstances, anything with a probability >.5 will be predicted as a successful outcome ("A"), anything less will be considered an unsuccessful outcome ("U")
- Setting the threshold higher makes the algorithm more discriminating in its predictions, allowing us to shed our unsuccessful outcomes
- Ended up using a mix of GBM and ADA Boost algorithms

June 2016 Primary

```
##
##     A     C     I     L     O     U
## 22503  3404    75   117  3925   368
```

- We saw a recruitment success rate of 73.6%
- No show rate of nearly 13%
- Cancellation rate of 11.1%

Prediction Algorithm Performance for June 2016 Primary

```
##
##    A    C    I    L    O    U
## 6009  628    9   42  281  110
```

- Algorithm generated a list 25,060 high probability candidates
- Only 7,145 received assignments
- Excellent recruitment success rate of 85%
- Super low no show rate of 3.9%
- Low cancellation rate of 8.8%

November 2016 General

```
##
##     A     B     C     D     E     I     L     N     O     P     R     T
## 27260    28  2371    14     1  4382    68    11  2450   217     4    77
##     U     X
##  1085    43
```

- We saw a recruitment success rate of 71.7%
- No show rate of nearly 6.4%
- Cancellation rate of 6.2%

Prediction Algorithm Performance for November 2016 General

```
##
##    A    C    I    L    O    U
## 9440  561  700   24  215  356
```

- Algorithm generated a list 33,193 high probability candidates
- 11,296 received assignments
- Excellent recruitment success rate of 83.6%
- Low no show rate of 1.9%
- Low cancellation rate of 4.9%

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