# The Devil is in the Details: How Data Powers the Modern Campaign

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AMERICAN CONSERVATIVE UNION
CPAC 2019

# Evolution of Data

Overview

# History of Campaigning

- Polling and tracking the electorate is an older profession than most people think, evolving to fit the technology and political atmosphere of the time period.

**1890**

William Jennings Bryan compiles a rudimentary database with an alphabetical set of index cards tracking the characteristics of each individual supporter.

The very beginning.

**Mid 20th Century**

The invention and rising popularity of television led candidates away from appealing to party elites towards a more direct approach, appealing directly to voters. This medium became more complex as TV went from three networks to hundreds of channels, each with unique viewership.

The rise of traditional campaign polling.

**1980's**

Direct mail, pioneered mostly by the GOP, becomes the top mode for campaigners to galvanize voter bases. Although, this process was considered to be fairly disorganized, with no standardized industry practices.

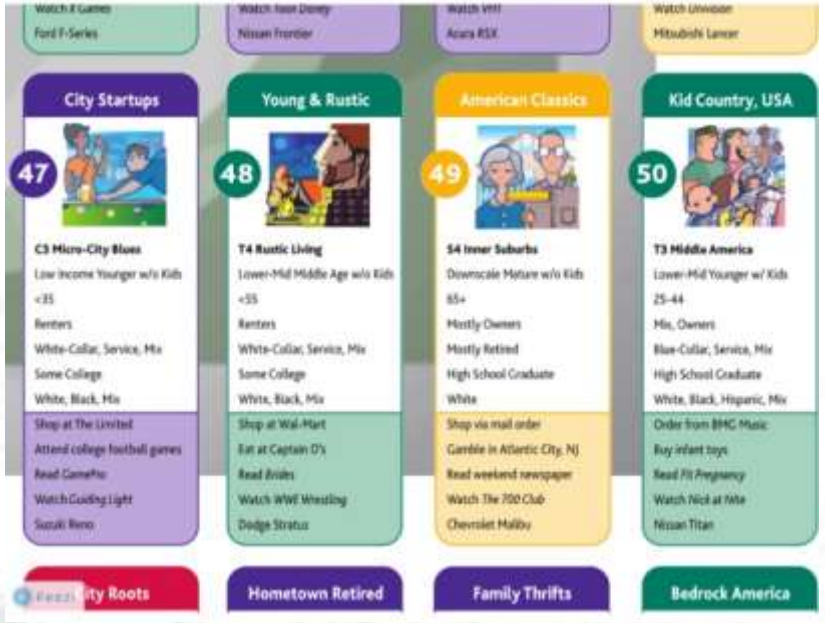
The beginning of keeping political lists and databases.

# Origins of Data

W.E.B. Du Bois Data Visualizations (1900)

# The 1990s

- Voter targeting was based on a short list of four to six segments, usually based on the analysts' judgment or through simple statistical tools like CHAID.
- Segments were generally based on one to three demographic characteristics.
- The segments were based on a single demographic or up to a max of three combined.




# 2004: Micro-Targeting

- In the early 2000s “micro-targeting” was developed and widely deployed for Former President George Bush’s re-election campaign.
- This brought about a more sophisticated segmentation of the electorate in the digital age (though it still relied on CHAID).
- This allowed an increase of up to 20 segments, but massive amounts of data was needed.
- A single micro-targeting survey to start a campaign was a $100k proposition, with no refreshes.

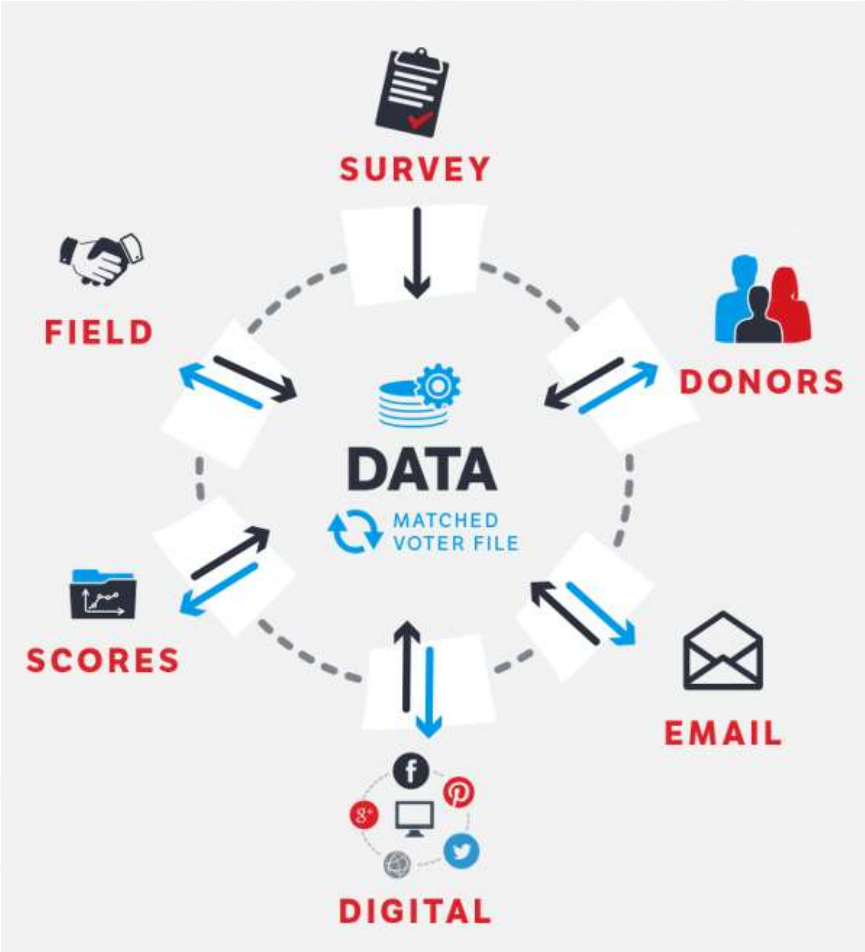
| TIP # | SCORE | # OF VOTERS | % OF FILE | Land Favorability | | | Snyder Approval | | | | Snyder Reelect | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Favorable | No Opinion | Unfavorable | Strongly Approve | Total Approve | Total Disapprove | Strongly Disapprove | Yes | No |
| STRONG SUPPORT | | | | | | | | | | | | |
| 1 | 97.96 | 7,537 | 0.1% | 76% | 20% | 4% | 89% | 100% | 0% | 0% | 100% | 0% |
| 2 | 93.10 | 15,321 | 0.2% | 76% | 20% | 5% | 76% | 98% | 2% | 0% | 94% | 6% |
| 3 | 92.50 | 53,990 | 0.7% | 74% | 18% | 9% | 69% | 99% | 1% | 1% | 96% | 4% |
| 4 | 91.47 | 14,310 | 0.2% | 70% | 22% | 8% | 72% | 99% | 1% | 0% | 89% | 11% |
| 5 | 89.35 | 50,945 | 0.7% | 74% | 17% | 9% | 65% | 94% | 6% | 1% | 93% | 7% |
| 6 | 85.60 | 25,447 | 0.3% | 71% | 21% | 8% | 61% | 90% | 10% | 0% | 87% | 13% |
| 7 | 85.36 | 51,411 | 0.7% | 58% | 32% | 11% | 63% | 92% | 8% | 1% | 82% | 18% |
| 8 | 82.71 | 211,146 | 2.8% | 52% | 31% | 17% | 58% | 90% | 10% | 4% | 81% | 19% |
| 9 | 82.36 | 11,454 | 0.2% | 66% | 24% | 10% | 56% | 89% | 11% | 0% | 79% | 21% |
| 10 | 80.26 | 13,439 | 0.2% | 52% | 30% | 17% | 56% | 86% | 14% | 5% | 79% | 21% |
| 11 | 78.24 | 31,730 | 0.4% | 74% | 11% | 15% | 46% | 87% | 13% | 9% | 80% | 20% |
| 12 | 77.13 | 43,977 | 0.6% | 61% | 25% | 14% | 51% | 81% | 19% | 8% | 80% | 20% |
| 13 | 76.01 | 22,137 | 0.3% | 66% | 24% | 10% | 49% | 85% | 15% | 6% | 70% | 30% |
| 14 | 75.52 | 67,447 | 0.9% | 60% | 22% | 17% | 45% | 82% | 18% | 7% | 75% | 25% |
| 15 | 75.36 | 23,537 | 0.3% | 43% | 33% | 24% | 47% | 83% | 17% | 4% | 70% | 30% |
| 16 | 74.23 | 98,657 | 1.3% | 57% | 23% | 21% | 49% | 81% | 19% | 12% | 73% | 27% |
| | 83.57 | 742,485 | 10.0% | 64% | 23% | 12% | 59% | 90% | 10% | 4% | 83% | 17% |
| SUPPORT | | | | | | | | | | | | |

# 2008 and Obama

- Former President Barack Obama's data team was the first to bring modern predictive analytics to politics.
- 2008: The Obama team conducts a nationwide grassroots digital campaign.
  - Collected massive amounts of data on voter perception and maintaining dynamic models.
- 2012: Obama for America's Chicago headquarters housed the campaign's Analytics team.
  - More than 50 data analysts used Big Data to predict the individual behavior of tens of millions of American voters.
  - Comparatively, the Romney campaign had six.

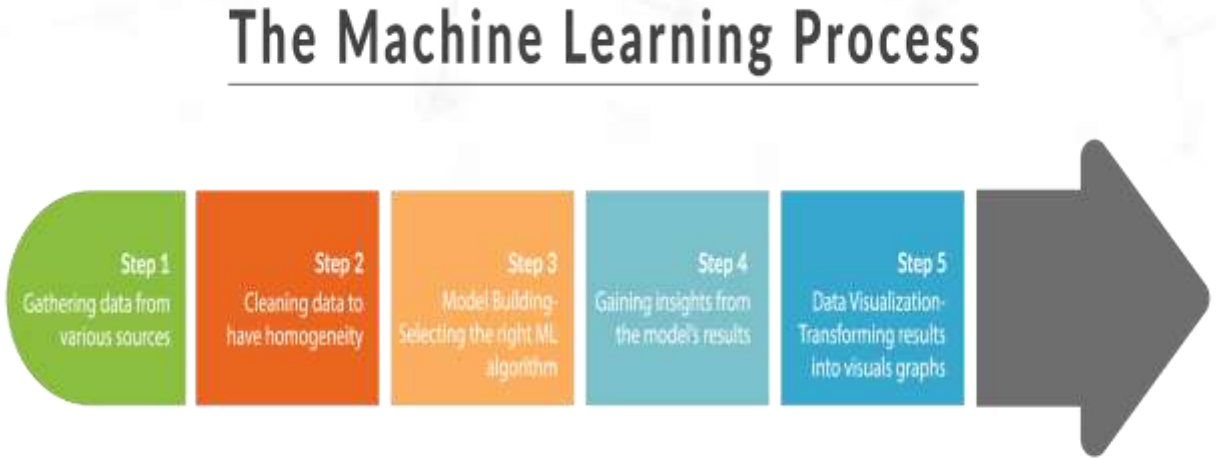
# 2014: The Republican Data Resurgence

- The post-2012 RNC Growth And Opportunity Project (aka the "Autopsy") laid out ambitious goals for Republican data, and the RNC largely accomplished them.
- The Data Trust, a private entity that could work with parties, campaigns, and PAC's, and share data between them, became the hub of the Republican Data Ecosystem.
  - Campaigns and PACs could share door results, scores, and even (with certain limitations), targets, and free data became common.
  - i360, a Koch Network-affiliated competitor, caused some level of fragmentation, but eventually was largely marginalized.
- The RNC and state parties ensured all GOP Campaigns had access to free, regularly updated analytics on every voter.
- The DNC still does not fully control its data or provide it all for free. State parties control it, and sell it to candidates. The DNC recently announced a plan to build a Data Trust of its own.



# Machine Learning and Artificial Intelligence

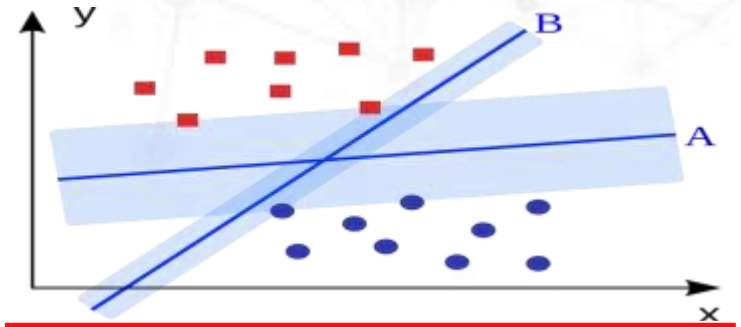
- Machine learning is a branch of artificial intelligence.
- Using the fundamental mathematic principals like probability theory, statistics, and linear algebra, machine learning is generally separated into two categories:
  - Supervised Algorithms: which apply past information registered to new data. (Prediction & Classification)
  - Unsupervised Algorithms: Generate observations and conclusions to existing datasets. (Clustering)
- Using machine learning algorithms, we can now accurately predict voter behaviors and optimize campaign operations to ensure we convey the right message to the voters we need to win a given election.



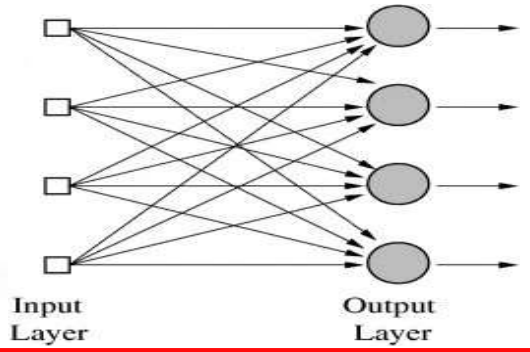
# Examples of Machine Learning Algorithms

- Learning algorithms are applied to training datasets to discover patterns and correlations to later apply to new datasets. Common types of learning algorithms include:
  - SVM algorithms, which utilize sophisticated theories of optimization and function space.
  - Artificial neural networks, modeled after the functions of the human brain.
  - Tree-based algorithms, which systematically use tree-like graphs for classifications and regressions.
- These can be used to accomplish the following goals:
  - Predict voter/consumer behavior (including election turnout).
  - Classify voters' political leanings, ideological identity, and standing on policy issues.

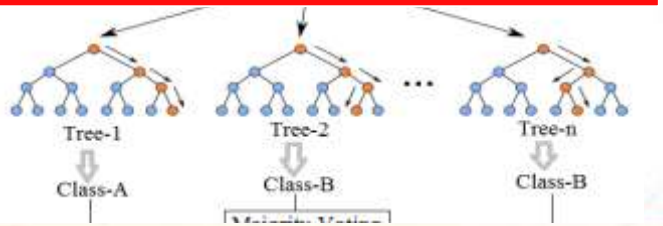
Classification/Regression Model




Deep Learning Model

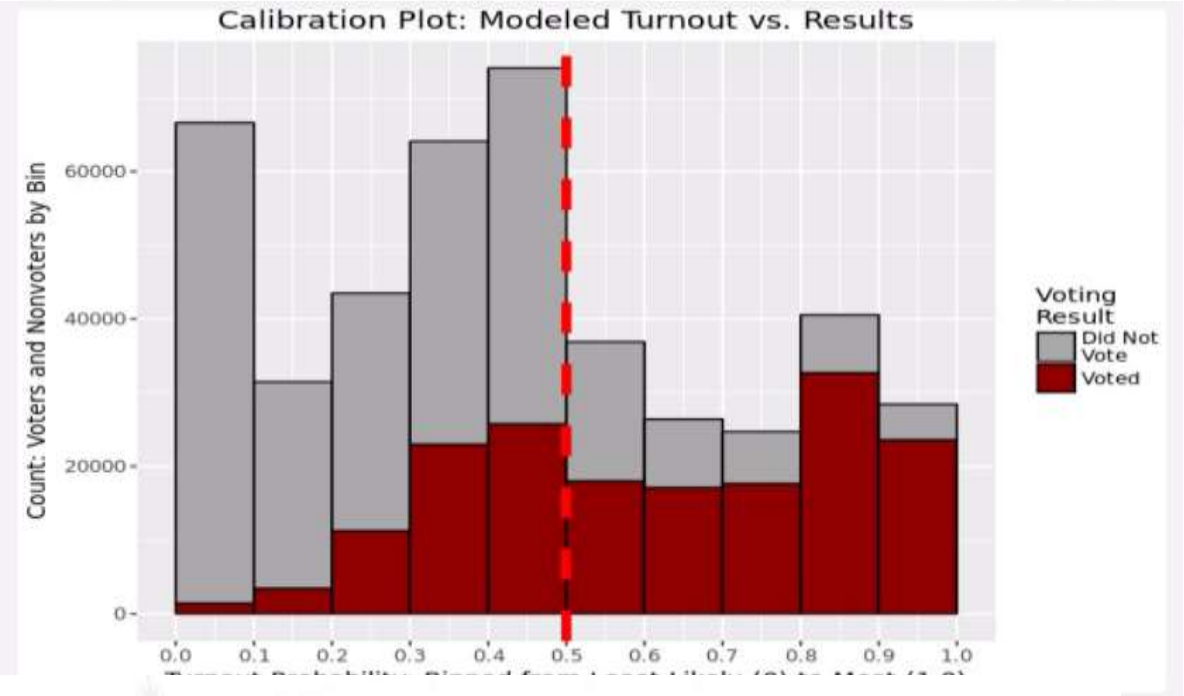


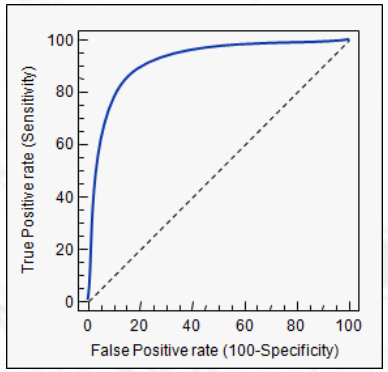

Tree based Model

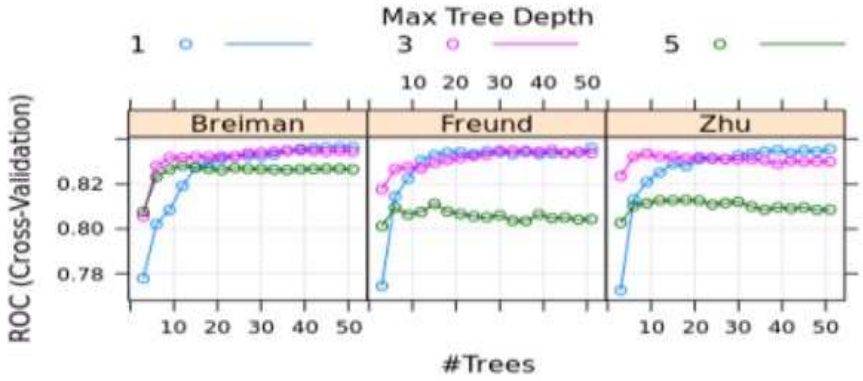


# A Real World Example

- These charts show actual outputs generated by WPAi Data Scientists.
  - Using a machine learning algorithm, WPAi's data science team accurately modeled and predicted turnout in a high-profile Congressional election.
  - The second chart shows the model training process.
    - Cross-Validations are created to ensure the models are optimally trained.
  - The ROC curve is created by plotting the true positive rate (correctly identified events) against the false positive rate (wrongly identified events) at various threshold settings.



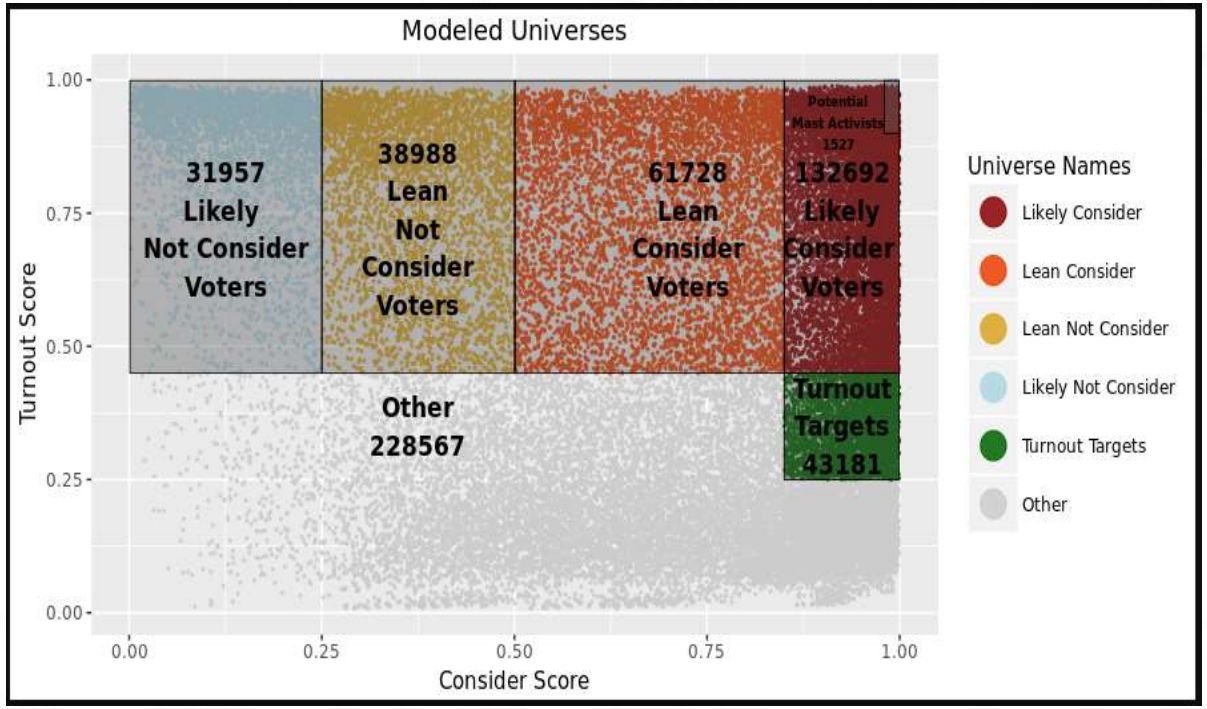



Trusted Perspective
Innovative Data
Superior Results

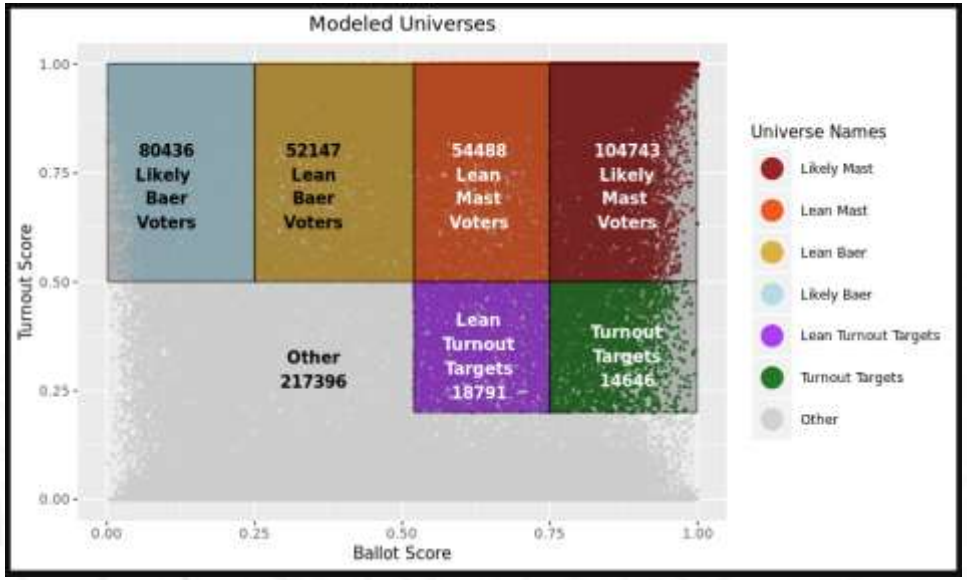
# Case Studies

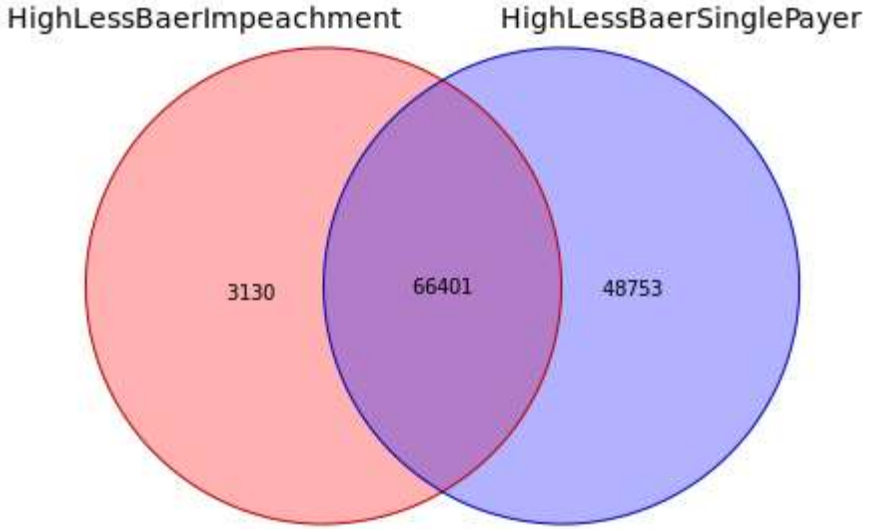
## Analytics in Practice

- WPAi's initial February 2018 analytics for Congressman Mast modeled those who would consider voting for Mast and not consider voting for Mast.
- Voters who had a probability to turnout >.48 were the campaign's Likely Voter Targets (those likely to turnout) at this point was 265,365.
  - Any voter who modeled >.48 for turnout and >.5 Consider Mast (194,420) were 73% of the Likely Voter Target universe and voters the campaign needed to secure early on.
- WPAi created custom messages addressing veterans and environmental issues.
- In July 2018, the Cook Political Report downgraded it's rating from Solid R to Likely R, indicating the district was becoming more competitive.
- Early on it was clear that Democrats saw Mast as a target.



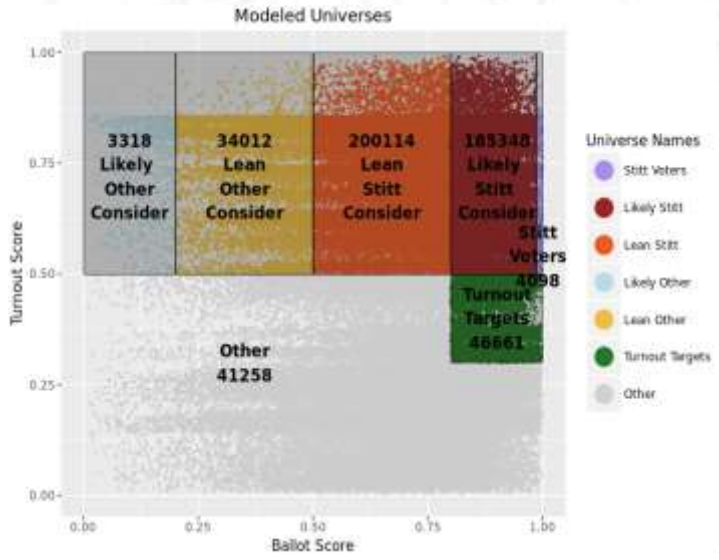
- Next, WPAi tested messages and created universes based on voter targets who were less likely, and highly less likely to vote for Democrat nominee Baer knowing she supports impeaching the president and a single payer healthcare system.
- The final prediction WPAi gave to the campaign was 55-45% in favor of Mast—precisely the result.

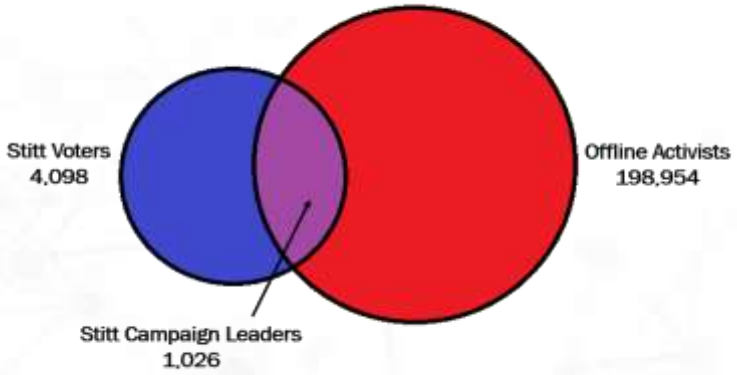


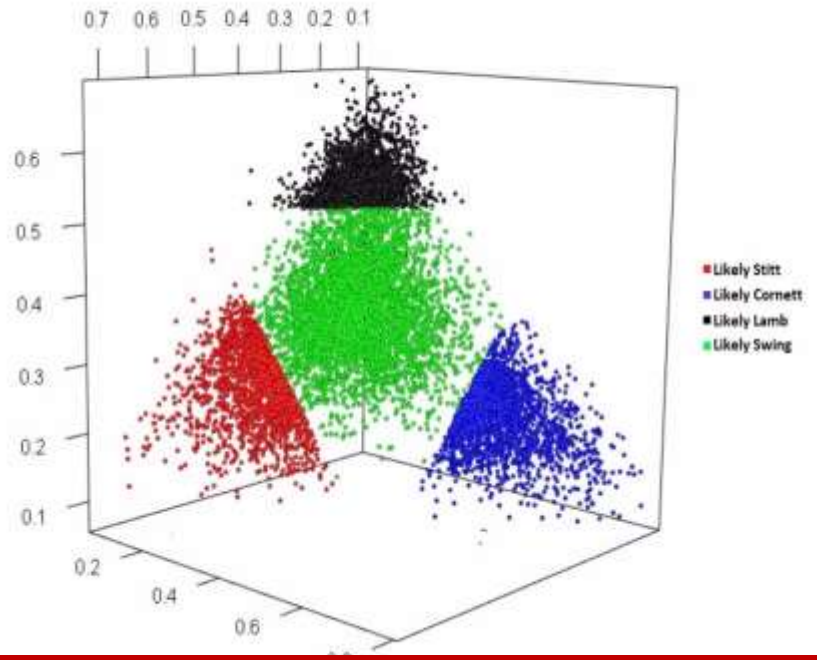

| Actual Results | Raw Data | Percentages |
|---|---|---|
| Mast | 185,905 | 54.4% |
| Baer | 156,454 | 45.6% |
| Total | 342,359 | 100% |

- In the primary, WPAi worked to help the campaign build a ground game, thus, we identified every registered Republican in Oklahoma that would consider voting for someone with Stitt's background.
- In order to develop the grassroots component of the campaign, we identified voters from around the state who would potentially be Stitt Campaign Leaders using the highest possible cutoff for Consider Stitt, which we called Stitt Voters and overlaid that on our Offline Activists.
  - This overlay resulted in 1,026 Stitt Campaign Leaders that the campaign could contact.
- Also, WPAi initially modeled 426,890 Republicans to turnout in this primary which would have been a record.
  - In the end, total turnout was 452,606.



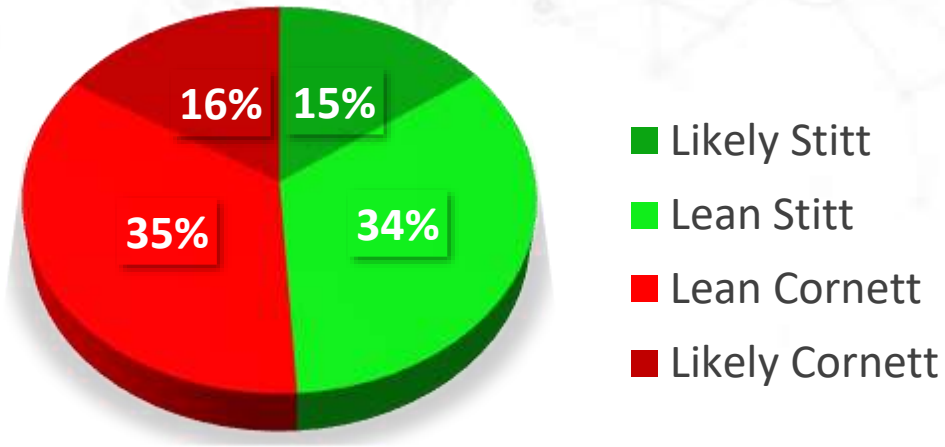



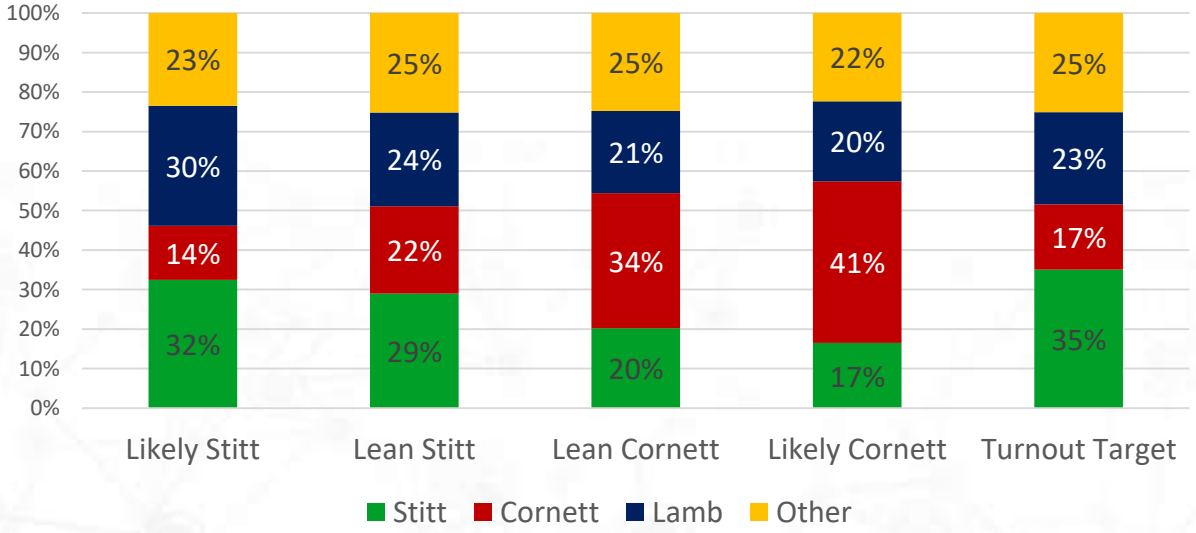
- In WPAi's April refresh, we learned that we needed to break the stalemate and that there were a lot of swing voters:
  - Likely Stitt – 15% or 51,534
  - Likely Cornett – 21% or 71,756
  - Likely Lamb – 16% or 56,075
  - Swing – 47% or 161,430
- To break this stalemate, WPAi developed more message models that we found worked best from the polling, which we then overlaid with our Swing universe to get the following targets:
  - Oppose Tax Increase – 127,110
  - Balance Budget – 121,668
  - Conservative Political Outsider – 120,042
- In the end, Stitt made the runoff by just 0.55%.




| Actual Results | Raw Data | Percentages |
|---|---|---|
| Stitt | 110,479 | 24.41% |
| Cornett | 132,806 | 29.34% |
| Lamb | 107,985 | 23.86% |
| Else | 101,336 | 22.39% |
| Total | 452,606 | 100% |

- Immediately after the primary, WPAi began runoff modeling. The findings suggested that Stitt slightly trailed Mayor Cornett, but it was essentially a tie.
- In this initial model, it was important to identify the movement of support from the primary to the runoff; where did Lamb and Other voters go?
  - Most Likely Stitt voters (53%) came from Lamb and Other while 49% of Lean Stitt did too.
- These initial findings also suggested a need to change the runoff electorate as a plurality (35%) of turnout Targets were modeled as Stitt supporters in the primary.



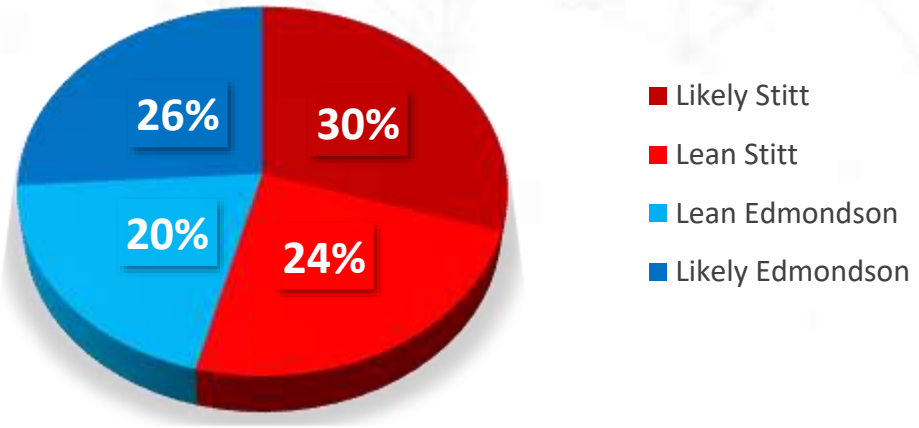



- By targeting only those that voted in the primary and knowing the probability for whom they voted, WPAi was able to increase Likely Stitt by more than 30,000 voters AND help the campaign change the electorate in targeting another 55k Republicans who were unlikely to turnout but would vote for Stitt.
- Stitt also now, for the first time, had a lead in the race.
- From the message testing, WPAi was able to identify what is as close to a silver bullet in political messaging: Illegal Immigration.
  - The regression test indicated a coefficient far greater than any other message.
- WPAi modeled this message and then created several digital and mail targets that the campaign could use.
- The result was a 55-45 win for Stitt.

| Month | Likely Stitt | Lean Stitt | Lean Cornett | Likely Cornett | Turnout Targets |
|---|---|---|---|---|---|
| July | 59,780 | 130,917 | 138,014 | 61,518 | 20,199 |
| August | 91,869 | 128,575 | 115,783 | 67,434 | 74,659 |

| Universe | Universe Description |
|---|---|
| Strong Immigration | 197,004 |
| Strong Immigration and LikelyTurnout | 84,249 |
| Strong Immigration and TurnoutTarget | 16,706 |
| Strong Immigration and LikelyTurnout households | 70,071 |
| Strong Immigration and LikelyTurnout | 84,249 |
| Strong Immigration and LikelyTurnout households | 70,071 |
| Strong Immigration and LikelyTurnout OKC DMA | 44,151 |
| Strong Immigration and TurnoutTarget | 16,706 |
| Strong Immigration and LikelyTurnout sex=F & age<50 | 12,798 |

- To begin the general election (as the GOP nominee), Kevin Stitt lead Drew Edmondson 54-46.
- Even with a lead it is important to identify different segments to break out the electorate for targeting.
  - In September, WPAi was predicting just over one million voters to turnout.
  - Almost all Likely Voters in Oklahoma disapproved of Fallin.
  - Almost 60% of Likely Voters approved of Trump.
  - Almost 70% of Likely Voters believed Oklahoma was on the Wrong Track.




| Universe | Universe Count | Universe Score |
|---|---|---|
| Likely Trump Approval | 655,525 | Turnout Score >=.5 & Trump Approve Score >=.5 |
| Likely Fallin Disapprove | 856,990 | Turnout Score >=.5 & Fallin Approve Score <.5 |
| Likely Wrong Track | 735,037 | Turnout Score >=.5 & Direction Score >=.5 |

- WPAi needed to identify our early messaging universes but unlike the runoff, there wasn't a Silver Bullet.
- The campaign decided to target Lean Edmondson with the Wrong Track and Stitt Outsider message but continued to feed Likely Stitt voters pro-Trump, Immigration, and Budget messaging.
- It was equally important to identify which messages would motivate voters who supported either Cornett or Lamb in the primary.
- The result was a 54-42% victory for Stitt.

| Universe | Likely Stitt | Lean Stitt | Lean Edmondson | Likely Edmondson | Lean Turnout Target | Turnout Target |
|---|---|---|---|---|---|---|
| Likely Wrong Track | 145,704 | 135,020 | 176,455 | 277,858 | 34,596 | 15,524 |
| Likely Trump Approve | 336,326 | 256,183 | 57,057 | 5,959 | 92,576 | 58,386 |
| More Likely Stitt Budget | 336,893 | 263,591 | 87,156 | 8,625 | 96,059 | 58,421 |
| More Likely Stitt Outsider | 334,607 | 248,386 | 102,311 | 12,876 | 94,039 | 58,291 |
| More Likely Stitt Immigration | 336,439 | 254,772 | 73,269 | 11,227 | 94,023 | 58,403 |

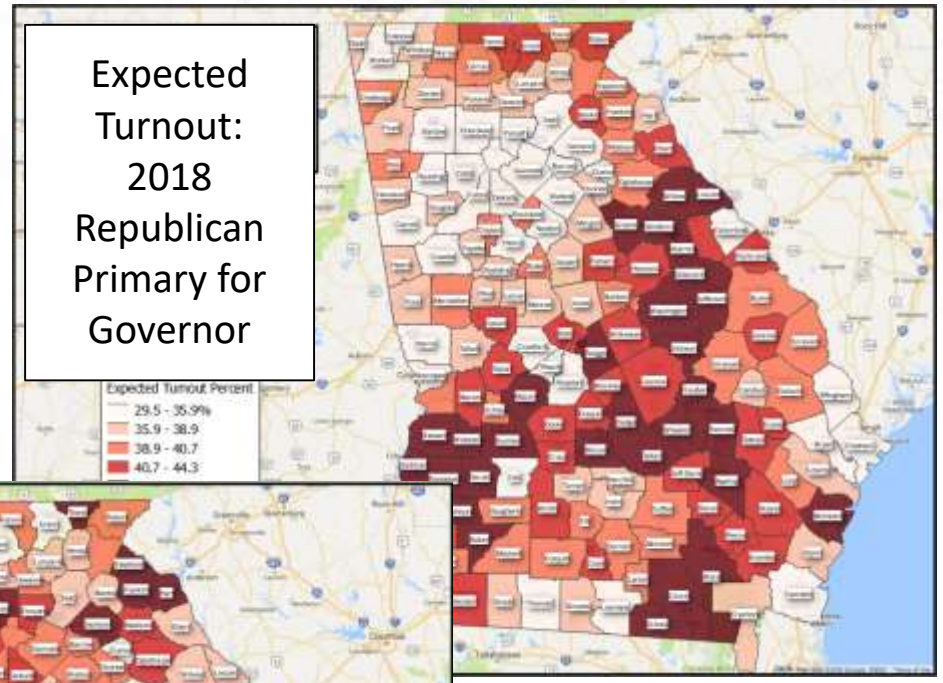
| Universe | Modeled Cornett | Modeled Lamb |
|---|---|---|
| Likely Wrong Track | 39,452 | 21,154 |
| Likely Trump Approve | 84,184 | 50,799 |
| High More Likely Stitt Budget | 78,103 | 48,286 |
| High More Likely Stitt Outsider | 58,129 | 38,549 |
| High More Likely Stitt Immigration | 67,030 | 44,745 |
| High More Likely Stitt Teachers | 19,197 | 14,017 |

KEMP

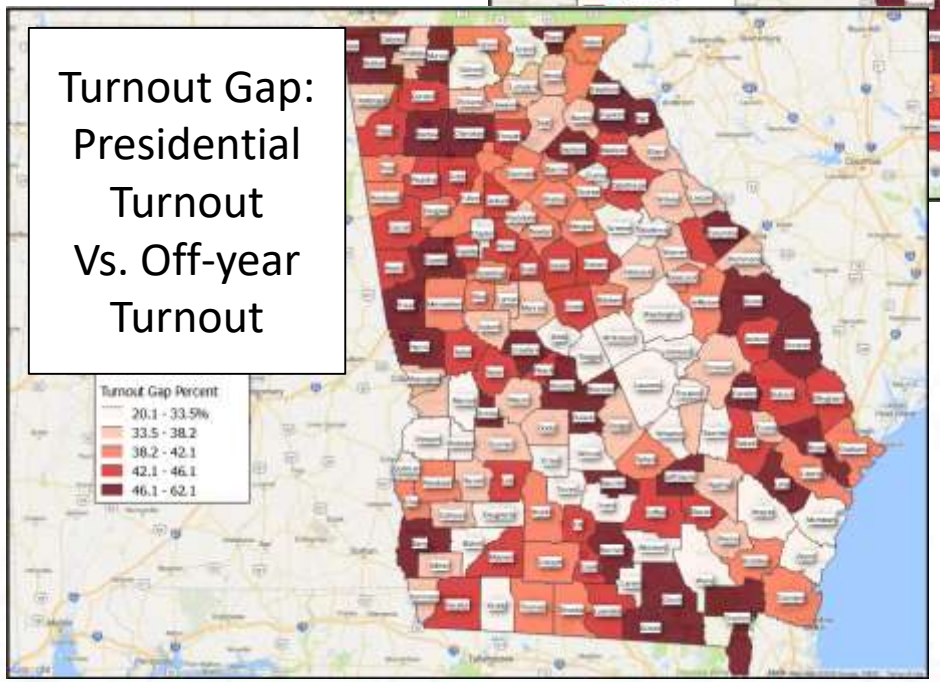
GOVERNOR

WPAi intelligence

- In the primary, WPAi built a turnout model which allowed the campaign to optimally allocate resources and understand how even a high turnout Midterm primary would differ from a Presidential year primary.
- The predictive analytics turnout model informed everything: campaign resource allocation, targeting, polling samples, etc.




Expected Turnout: 2018 Republican Primary for Governor




Turnout Gap: Presidential Turnout Vs. Off-year Turnout

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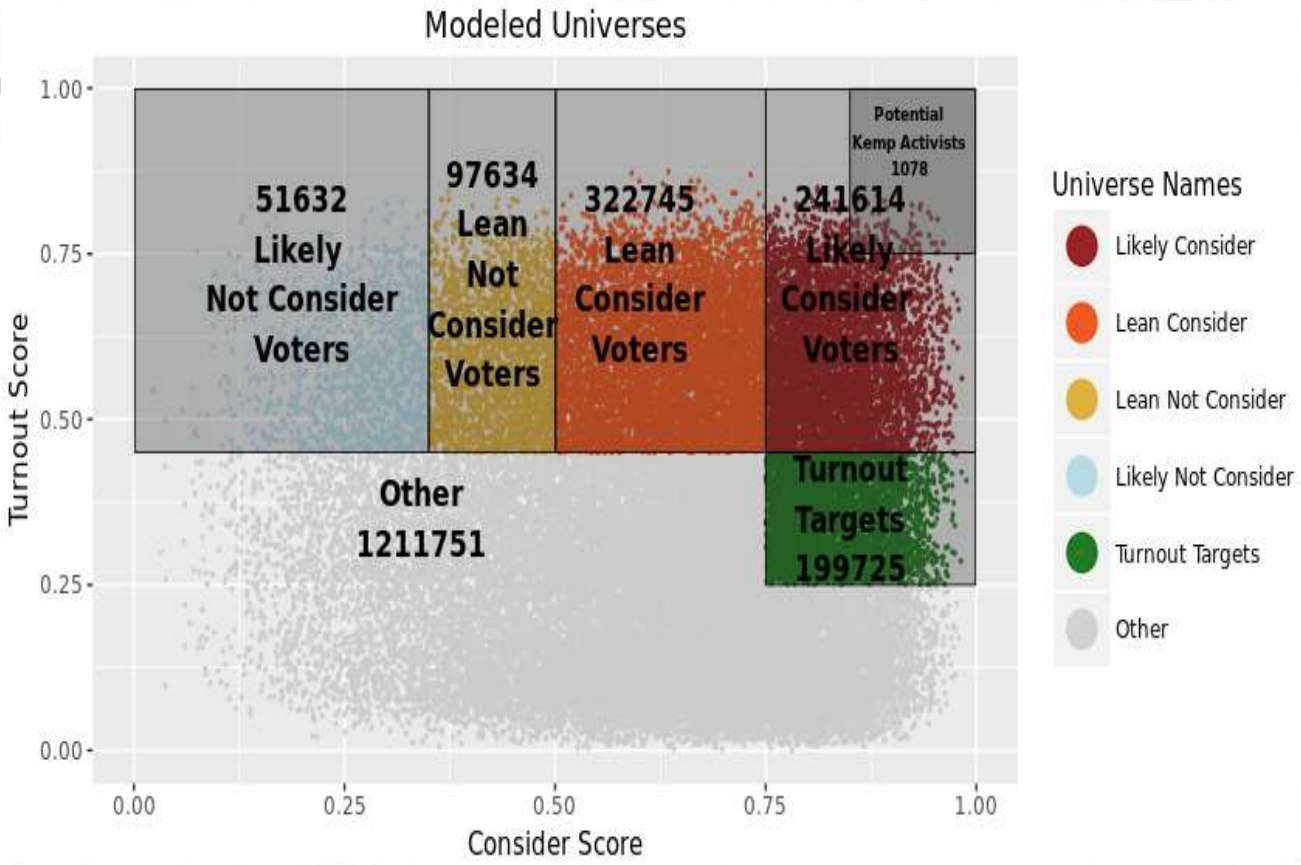
- WPA's data scientists then paired the turnout model with a "consideration model"— a model of whether each primary voter was open to voting for Kemp to build a full set of campaign targets.
- Which voters were available and how many additional votes could be gained via turnout efforts helped the campaign better set its messaging strategy.
- WPAi also identified those voters who were drawn to Kemp's bio and which would move to him if he were closely aligned with President Trump.



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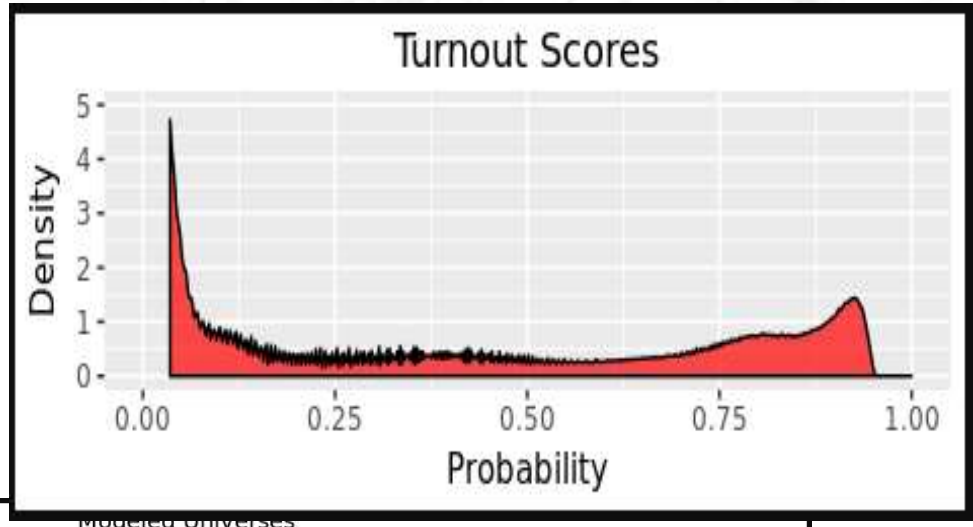
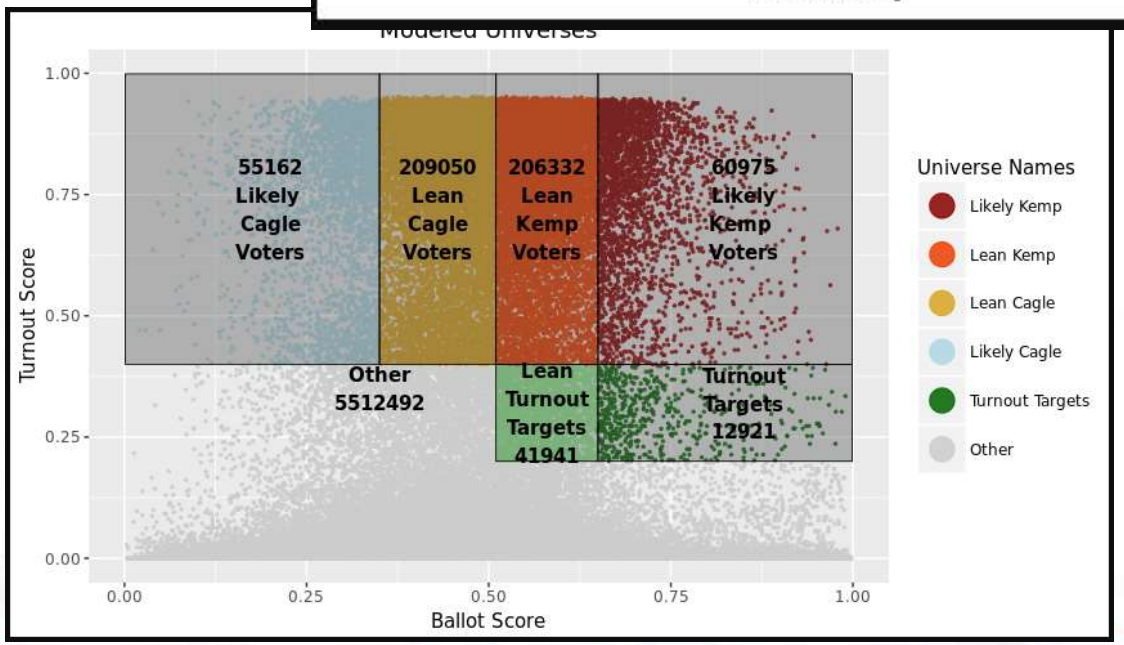
- Much like Stitt, in the run-off WPAi built a quick and responsive turnout update and identified Kemp voters, Cagle voters, and those for whose votes we were competing.



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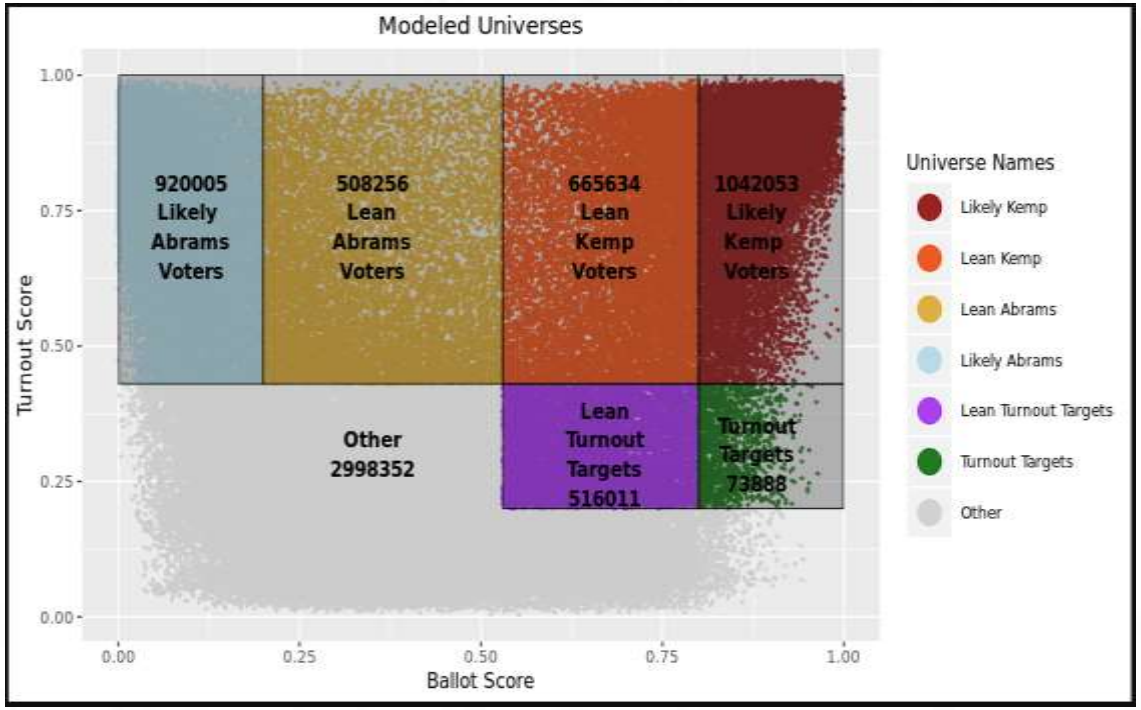
- Initial General Election models were created in August of 2018. While this is still too early to accurately predict turnout it does allow us to identify base voters, turnout targets and “leans” with specific messaging.
- The Kemp campaign’s likely voter targets (those likely to turnout) was 3,135,948. Already, this was 600,000 more than in 2014.
- A majority (54%) of voters were modeled to support Kemp but note the large range of Lean Abrams voters; >=.53 & <=.20 compared to Lean Kemp from <.8 & >=.53.
    - And second, note the heavy concentration of voters <0.50 on the x-axis.
- These two data points alone indicate that if Abrams was able to change the electorate, there would be a swing toward her.



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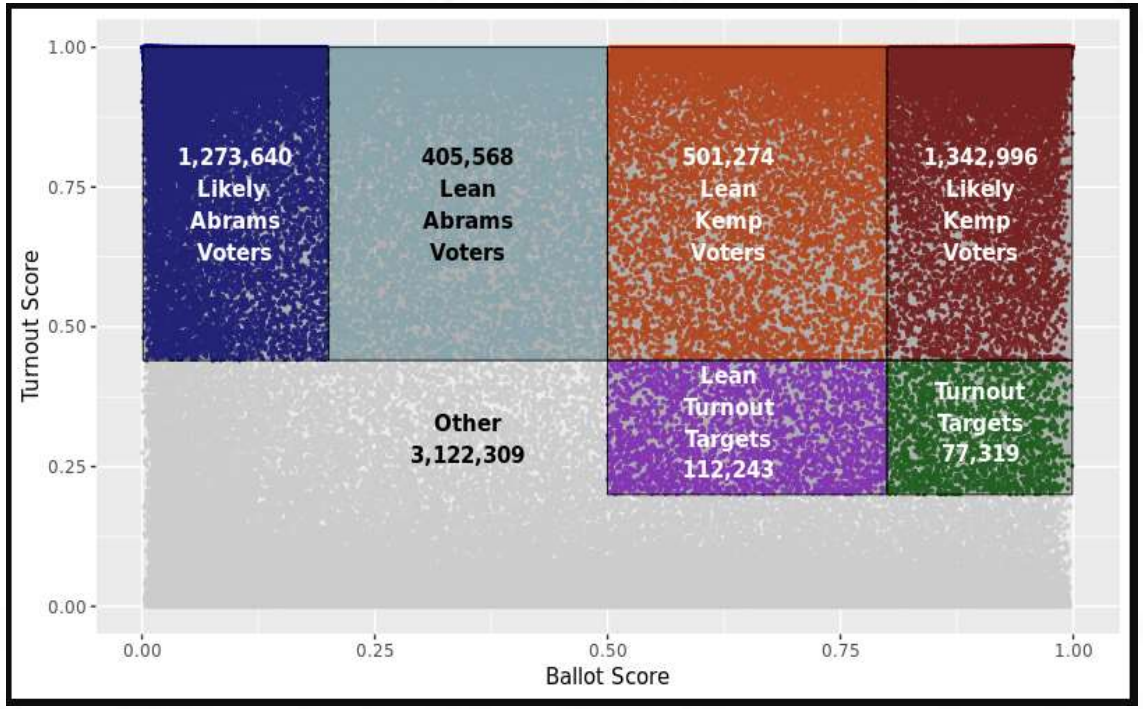
WPA intelligence

- These models allowed us to assess how each individual voter would be affected by messaging about Trump, Kemp's bio, and contrasting with Abrams.
- Deploying digital and direct mail based on these messages and the universes created by our turnout and ballot models allowed each voter to see the message from the campaign that would best persuade them and was a key element of the campaign's messaging strategy.

| Message | Lean Kemp | Turnout Target | Lean Turnout Target | Lean Abrams |
|---|---|---|---|---|
| Likely Trump Approve | 390,197 | 85,127 | 140,349 | 132,547 |
| Highly likely Trump Approve | 191,336 | 32,756 | 30,072 | 31,845 |
| More Likely Kemp Businessman | 426,044 | 89,844 | 179,499 | 186,474 |
| Highly More Likely Kemp Businessman | 247,170 | 60,049 | 50,003 | 40,399 |
| Less Likely Abrams Sanctuary Cities | 479,121 | 100,583 | 237,413 | 263,706 |
| Highly Less Likely Abrams Sanctuary Cities | 252,110 | 60,714 | 74,650 | 40,112 |
| Less Likely Abrams Taxes | 487,320 | 102,755 | 255,133 | 319,777 |
| Highly Less Likely Abrams Taxes | 246,366 | 47,831 | 62,729 | 51,647 |
| Less Likely Abrams Offenders DNA | 495,603 | 101,320 | 256,845 | 357,886 |
| Highly Less Likely Abrams Offenders DNA | 254,784 | 61,332 | 84,826 | 48,971 |

# KEMP GOVERNOR

- While WPAi was able to target based on messaging, we were also able to help the campaign in preparing for this eventual change in the electorate, which is precisely what happened.
- In the plot to the right, the likely voter targets increased almost 400,000 voters and the electorate had shifted to 3,523,478 in late October.
- There were more registered voters as indicated by the increased Other grouping.
  - This Other group also thinned out in the Lean Abrams range and was heavily concentrated on the far left of the x-axis.
  - This indicated that this new crop of voters--who were not falling within the model--were likely to be Abrams voters even though they did not have a turnout history or did not match the stated responses from the survey and were unable to be picked up by the turnout model.
- While Kemp maintained a lead with voters the model was able to identify, it did indicate a shift towards Abrams as the election neared.

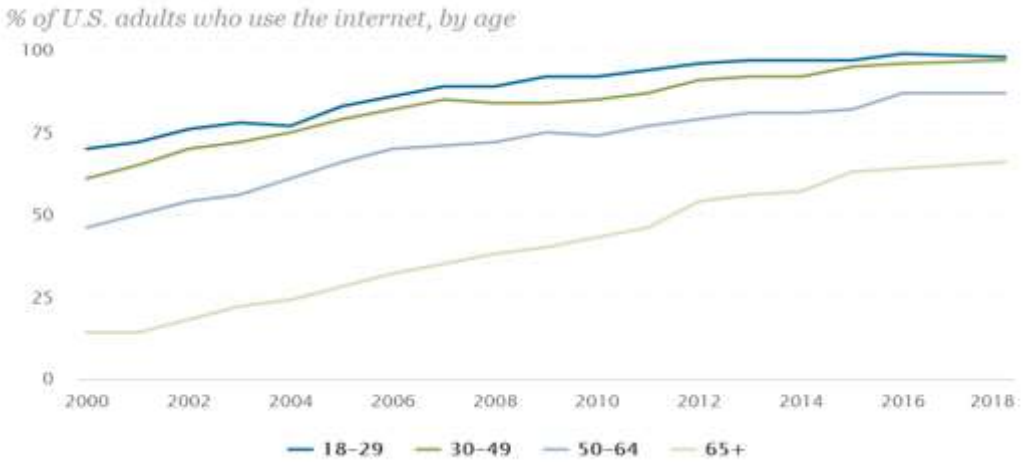


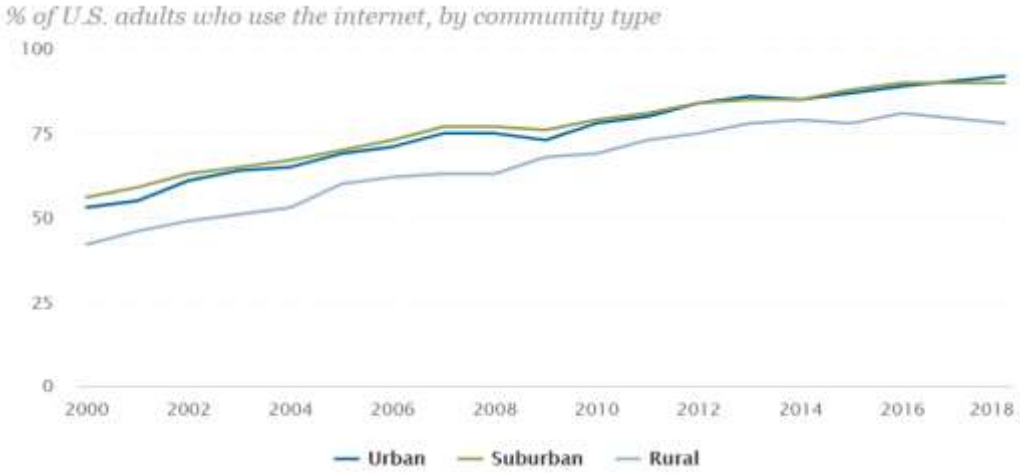

| Actual Results | Raw Data | Percentages |
|---|---|---|
| Kemp | 1,978,408 | 50.22% |
| Abrams | 1,923,685 | 48.83% |
| Metz | 37,235 | 0.95% |
| Total | 3,939,328 | 100% |

# Big Data

# Internet Usage and facebook

- Internet use is ubiquitous across all age groups, income levels, and races, with the rate of increase being greatest among seniors.
- In each year since 2016, Facebook growth has stagnated with a steady 68% of adults reporting they use Facebook.
- However, ad revenue continues to grow at 33% per year.

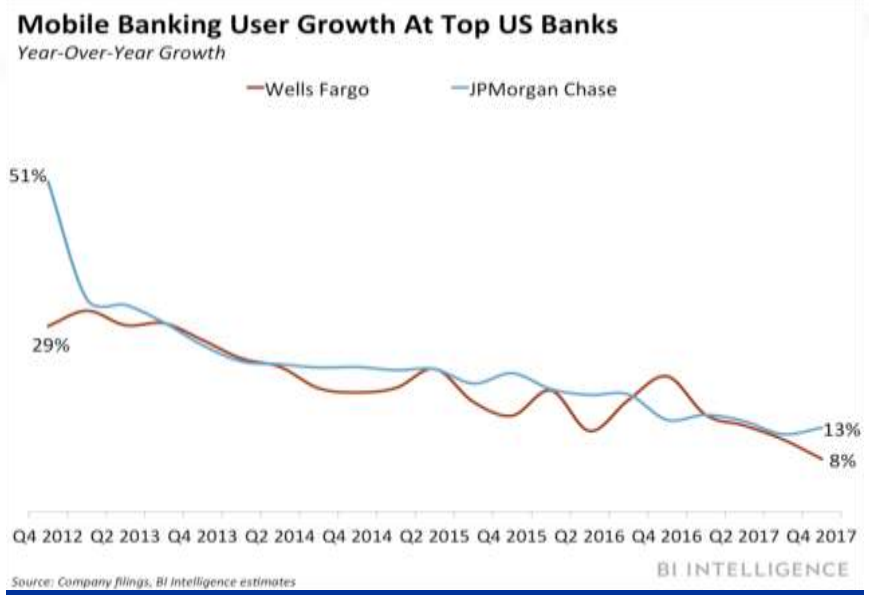



*Source: Pew Research*

# Big Data

- Everyone is doing something that produces data.
- According to a Business Insider study, 83% of respondents use mobile banking.
  - Because mobile banking is becoming ubiquitous the percentage is plateauing.
- In 2017, global e-retail sales amounted to 2.3 trillion dollars with projections of 4.48 trillion by 2021.
- In May 2018, the EU enacted the General Data Protection Regulation (GDPR).
  - The goal was to limit data collection requiring companies to ask for user consent before collecting data, and to allow users to ask data collecting companies to delete their data.

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# Big Data

## How Data Powers a Modern Campaign

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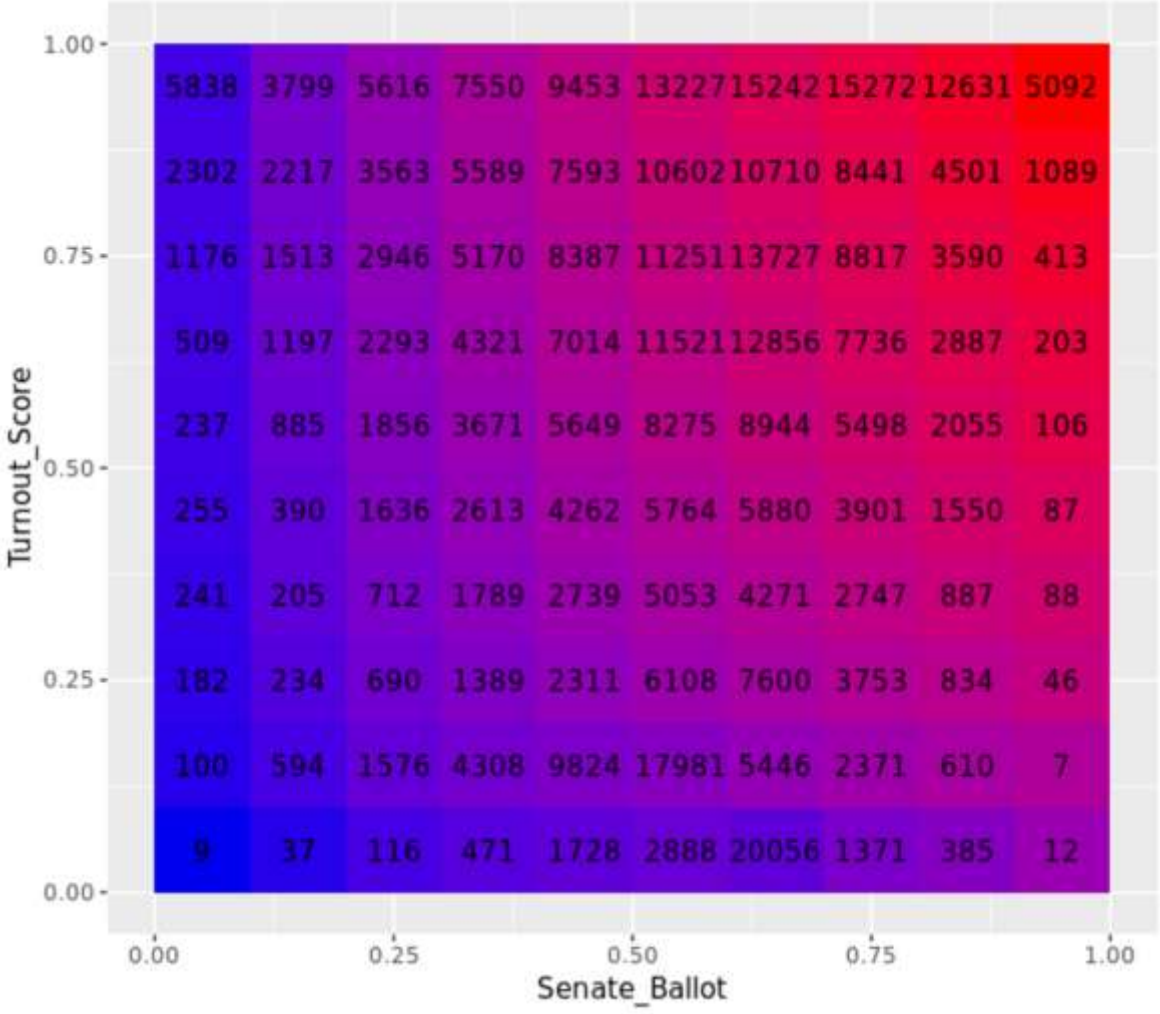
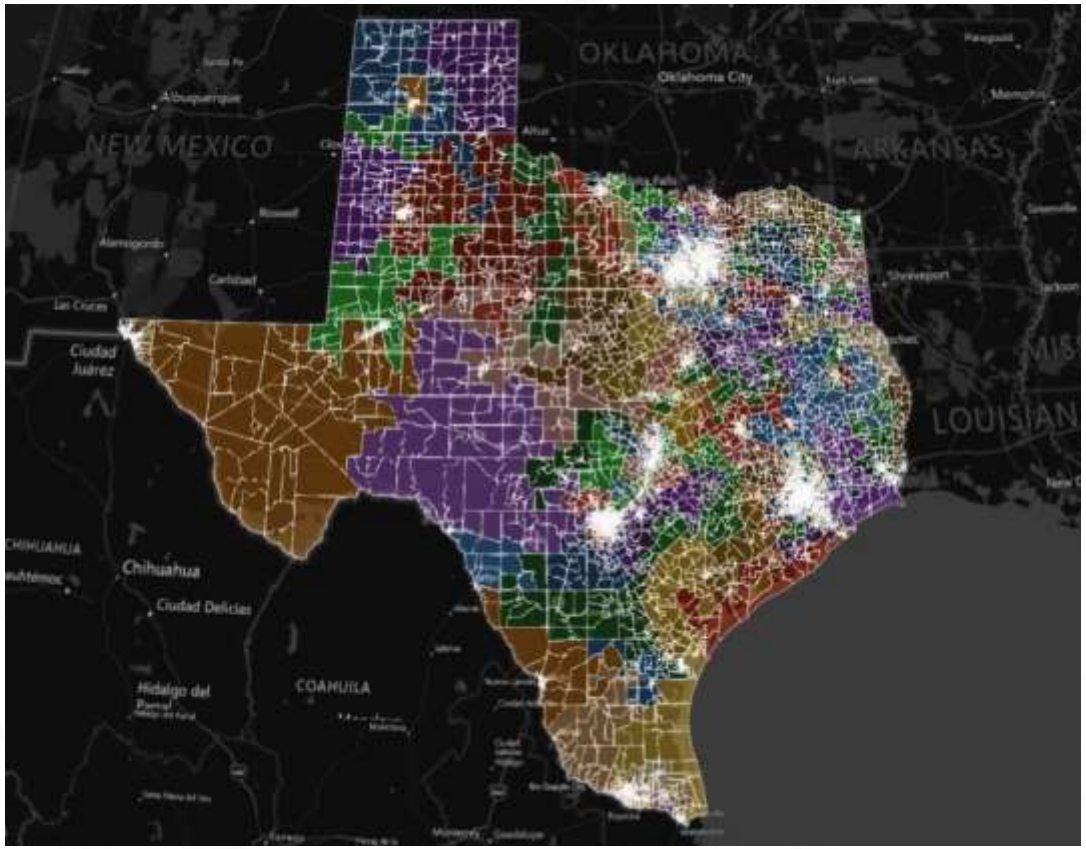
# Polling and Campaign Strategy

- If the turnout model is correct, then sampling using PPS (proportional probability sampling) can help make your poll even more accurate.
  - PPS does not exclude non-voters from being a sampling unit as they still can to be included, rather, it refines the sample to something more reflective of reality.
- We also use the model to understand the voter universe, build a set of vote goals, and identify who we will need to message.
- This example to the right shows exact counts of voters in each combination of turnout likelihood and candidate support likelihood allowing the campaign to identify our base, turnout targets, and swing voters we will need to persuade.



# Grassroots Optimization: Texas Example

- The Abbott re-elect campaign built aggressive vote goals and an objective of generating Republican-leaning turnout to help Republicans down the ballot.
- The unique structure of Texas politics, where mid-term turnouts are usually extremely low (averaging 35% over the previous three mid-terms) provided an opportunity to identify and turnout a large number of Republican-leaning votes.
- WPAi began our effort to assist the Abbott campaign by building a predictive model of likelihood to vote in the mid-terms and likelihood to support Abbott.
    - This yielded approximately 4.5 million targets for turnout efforts.

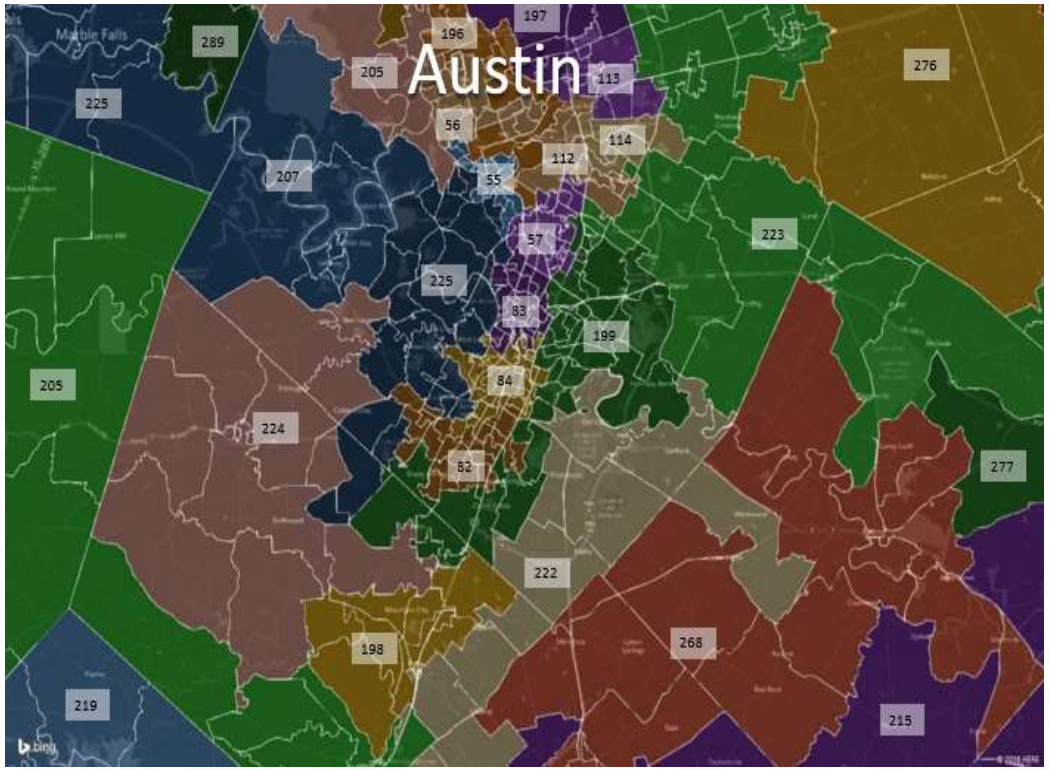


# Grassroots Optimization: Texas Example

- WPAi then helped the campaign plan the location of 180 field operatives who were responsible for mobilizing volunteers to contact these targets by using a vertex-covering optimization algorithm.
- The algorithm made it possible to relatively quickly build field turfs for all 180 operatives across Texas that were both:

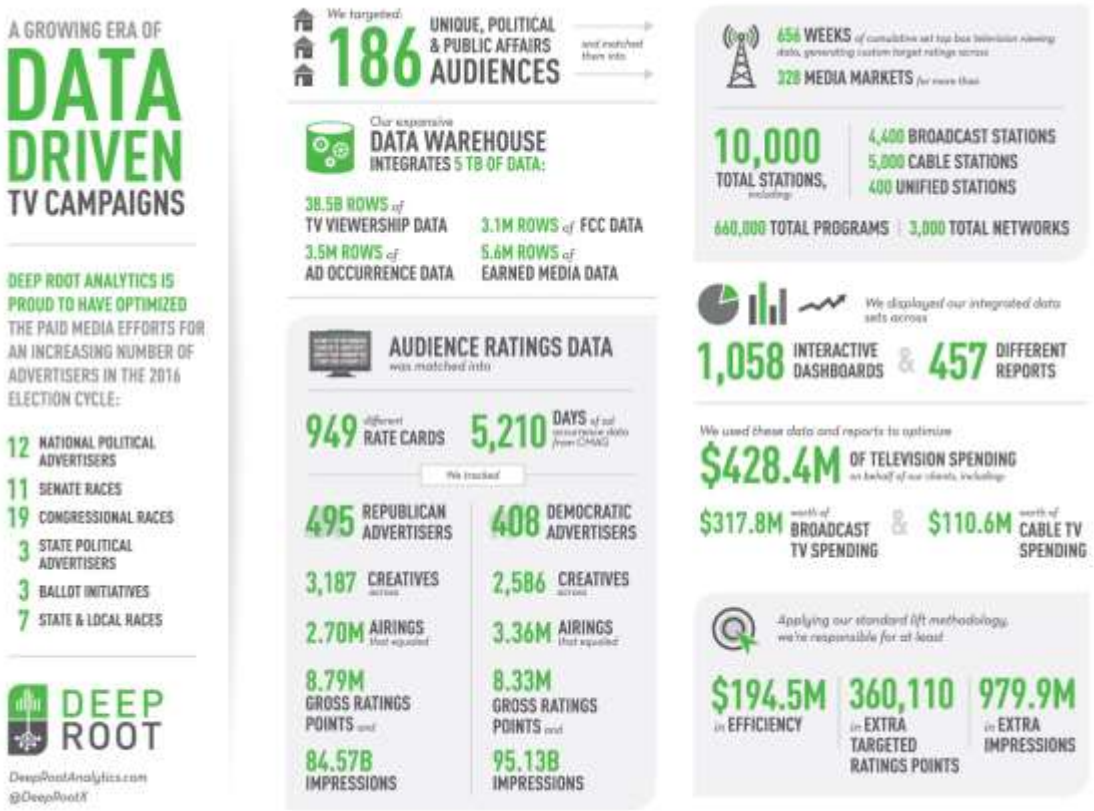
  1) Geographically contiguous and compact

  2) Scaled so a field operative hired 18 months from the election would have almost exactly three times the targets as one hired six months from the election, so that all targets have the highest likelihood of contact.



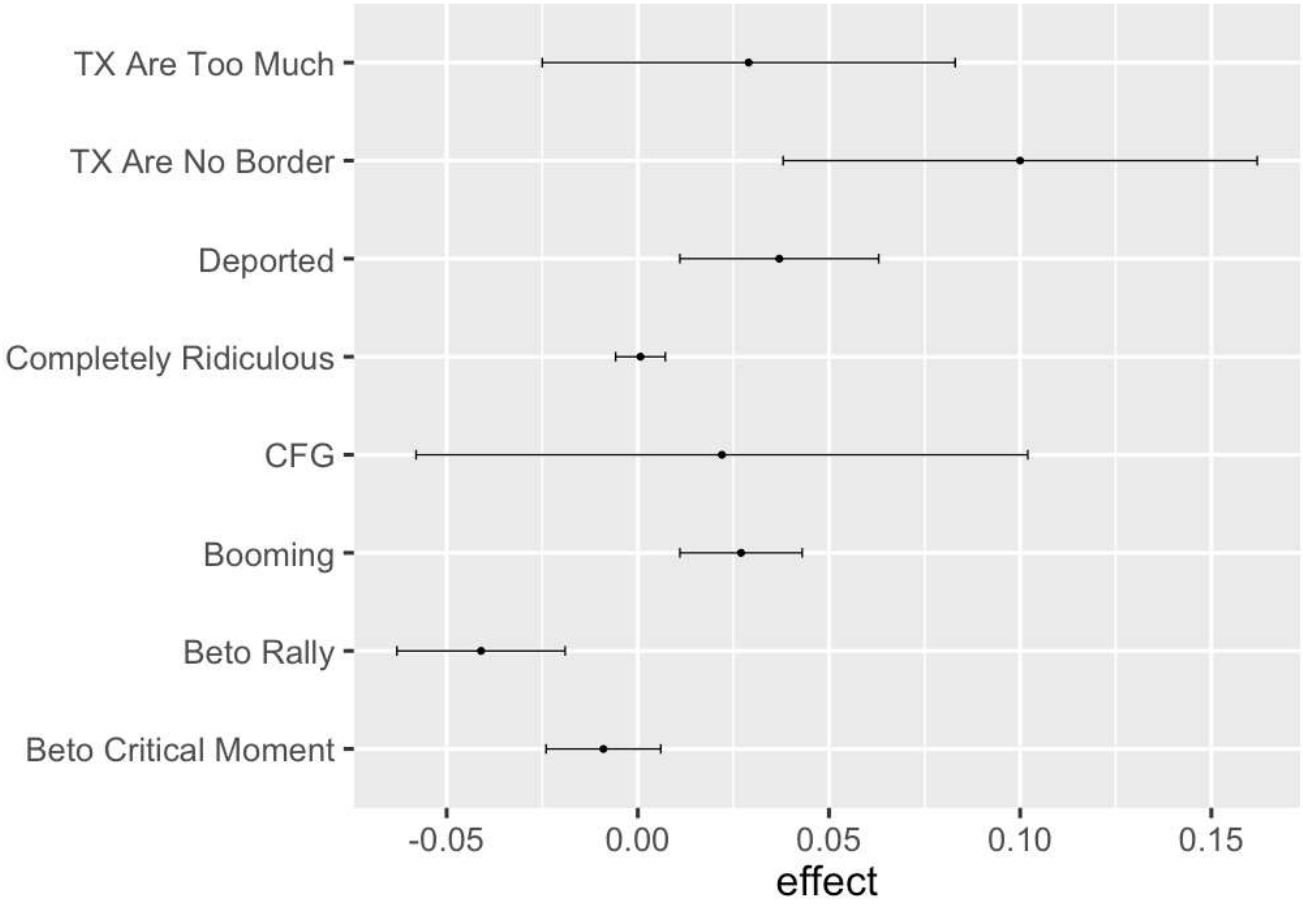
# TV Targeting

- When a campaign targets on TV, models are used to create targeting based on custom TV ratings.
- First, models are utilized to design a target universe to target with television based on factors such as persuadability and receptibility.
- Then, this universe is matched to TV watching habits and ratings/indices are created to allow TV ad buyers to buy the shows that most cost effectively reach this audience.
- Some TV, mostly satellite, is individually addressable; such that a campaign should send TV ads to specific households.



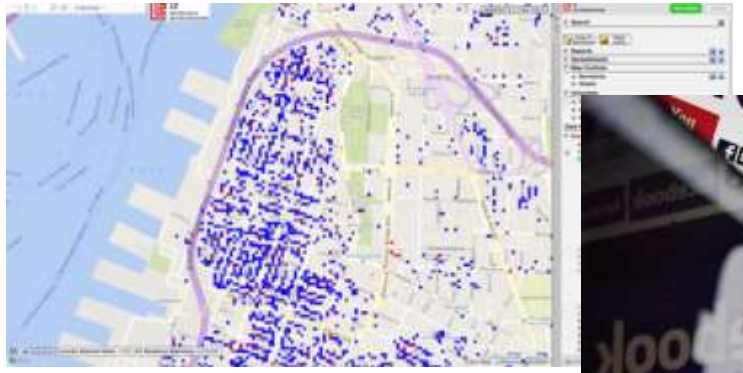
# Ad Effects

- Campaigns can now pull data from tracking, especially ballot movement and run a regression against when the ads were run.
- In the example to the right from several ads in the Texas senate race, we see that the Texans Are “No Border” ad has the greatest impact.

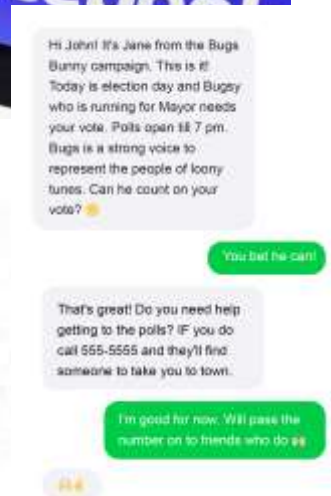


# Other Uses

- Door to Door
- Digital
- Direct Mail
- Texting
- GOTV





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**Big Data**

# How the Parties are Doing Data Heading Into 2020

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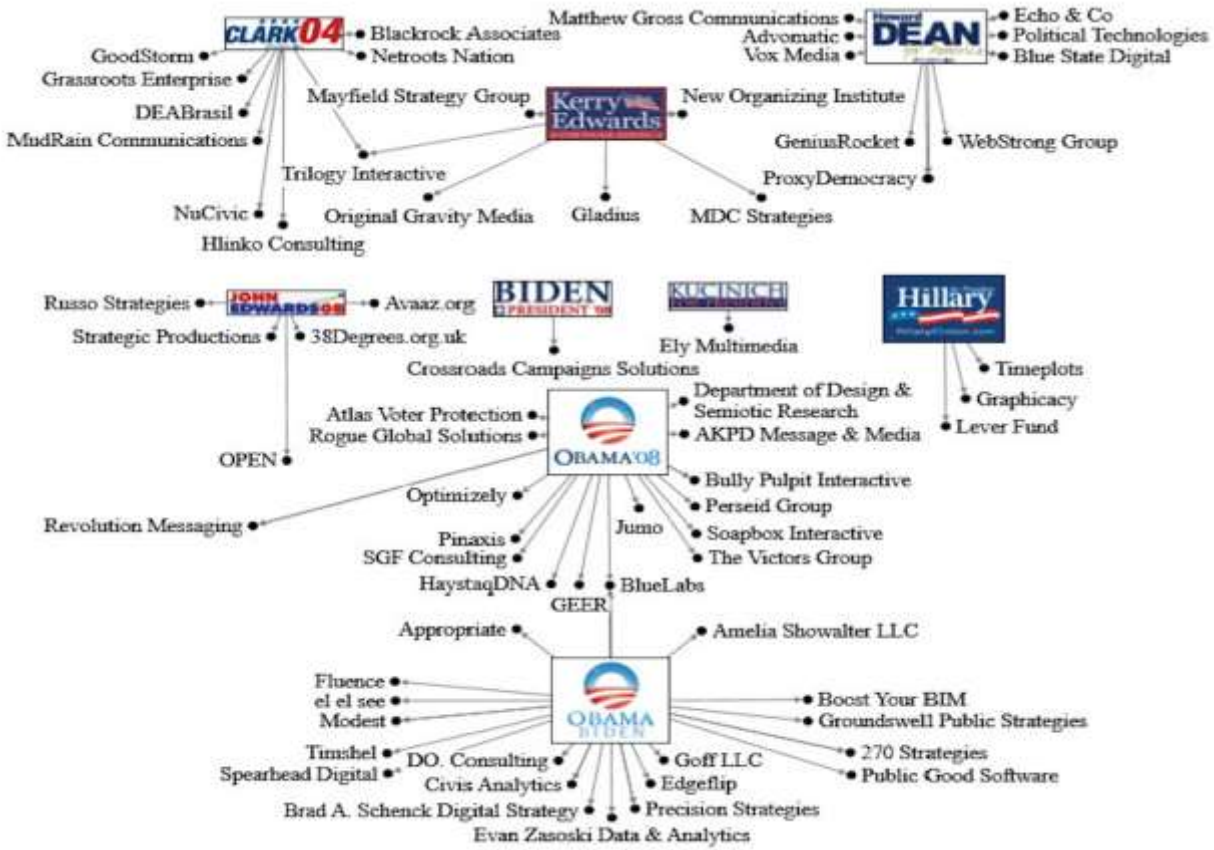
# 2016 Data: According To HRC

- "I set up my campaign and we have our own data operation…I inherit nothing from the Democratic Party…I mean it was bankrupt, it was on the verge of insolvency, its data was mediocre to poor, nonexistent, wrong…
- Trump…inherits an RNC data foundation that, after the Republicans lost in 2012…they brought in their main vendors, they basically said, "We will never be behind the Democrats again," and they invested between 2012 and 2016 this hundred million dollars to build this data foundation.
- So Trump becomes the nominee and he is basically handed this tried and true, effective foundation." - Hillary Clinton, Code 2017, May 21,2017

# Data and the Left

- The DNC is poorly-funded and weak compared to Leftist groups, individual campaigns, and state parties, so data is less centralized, with state parties in control.
- Democrats, however, still have a significant edge in the number of data-centric firms and organizations, aided by much stronger Silicon Valley support.
- ActBlue, the left's fundraising platform, which allows one-click donations across races, is far ahead of the GOP and fueled the Democrats' massive individual-campaign fundraising advantage in 2018.




*Kreiss, Daniel. "Prototype Politics: Technology-Intensive Campaigning And The Data Of Democracy."

# Data and the Left in 2020

- On Feb 13th, the DNC announced a deal among stakeholders to build a Data Trust of their own, headed by Howard Dean.
- The huge amount of money that will be spent in the likely-chaotic presidential primary, combined with their easy access to tech talent and start-up culture, provides strong opportunities for Democratic innovation in 2020.
- Michael Bloomberg says he will spend at least $500 million dollars focused on data and technology, whether he personally runs or not.

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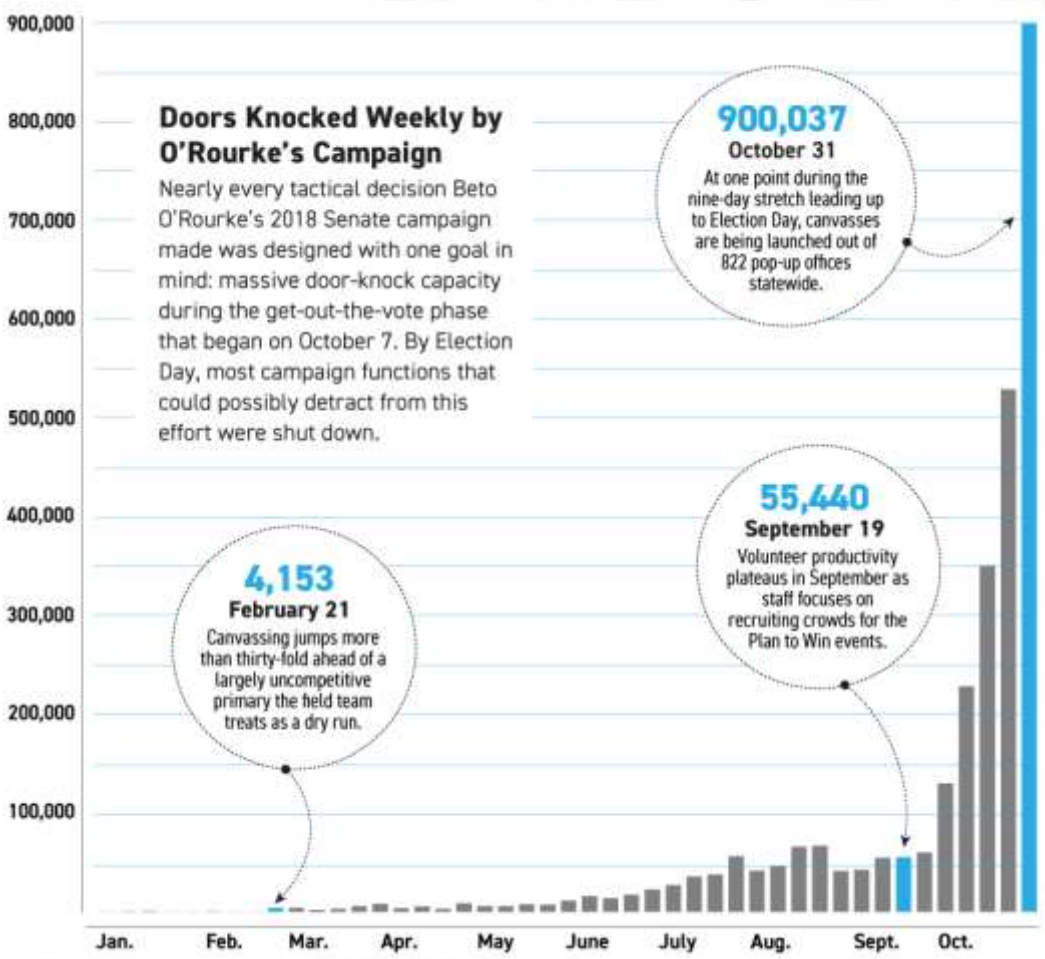
# Data and the Left – Texas (2018)

- The 2018 Beto O'Rourke Campaign for Texas Senate had a mostly untargeted field campaign.
- The goal was to knock on as many doors as possible, not follow a data – driven plan.




*Source: Politico*

# Data and the Right

- The GOP Data Ecosystem is centered on the Data Trust and the RNC Voter Scores, though a few still use the i360 sytstem.
- The RNC Voter Scores and the voter file and consumer data that go with them are available to most Republican campaigns.
- The GOP Analytics and Digital firms are strong, as is the Trump and RNC fundraising infrastructure, but individual campaign fundraising tech lags behind the Democrats.
- However, there are fewer data firms on the right engaging in original R&D than the left.

# The Sleeping Giant

| | 2016 | | | 2018* | | |
|---|---|---|---|---|---|---|
| Age | Didn't Vote (Millions) | Did Vote (Millions) | Percentage Voting | Didn't Vote (Millions) | Did Vote (Millions) | Percentage Voting |
| 18-29 | 31 | 23 | 43% | 39 | 15 | 28% |
| 30-44 | 28 | 35 | 56% | 37 | 26 | 41% |
| 45-64 | 28 | 56 | 67% | 39 | 46 | 54% |
| 65+ | 14 | 34 | 71% | 17 | 30 | 64% |
| Gender | | | | | | |
| Male | 49 | 71 | 59% | 64 | 56 | 47% |
| Female | 47 | 80 | 63% | 66 | 61 | 48% |
| Race | | | | | | |
| White | 55 | 101 | 65% | 72 | 84 | 54% |
| Black | 12 | 17 | 59% | 16 | 13 | 45% |
| Hispanic | 14 | 13 | 48% | 14 | 13 | 48% |
| Asian | 5 | 5 | 49% | 6 | 3 | 37% |
| Education | | | | | | |
| High School or Less | 53 | 47 | 47% | 58 | 42 | 43% |
| Some College | 28 | 48 | 63% | 42 | 35 | 46% |
| Bachelor's Degree | 12 | 33 | 74% | 17 | 28 | 63% |
| Advanced Degree | 5 | 20 | 80% | 6 | 20 | 78% |

*Estimates only, likely to adjust when Census releases findings.

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