

PREDICTIVE ELECTION MODELS

Data Analysis for Journalism and Political Communication
(Spring 2025)

Prof. Bell

DART-THROWING CHIMPANZEES



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- By design, the **prediction interval** is wider than the confidence interval (e.g., MOE)

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 - ▶ **Supervised learning:** The researcher provides the machine with a target (e.g., an election outcome) and the machine determines the features of the test data that best predict the target
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- Because computation replaces some researcher decisions, many machine learning/AI models are considered “black boxes” where it is difficult to decipher why the machine makes the predictions that it does (called **explainability**)

EXPERT POLITICAL JUDGMENT



VS.



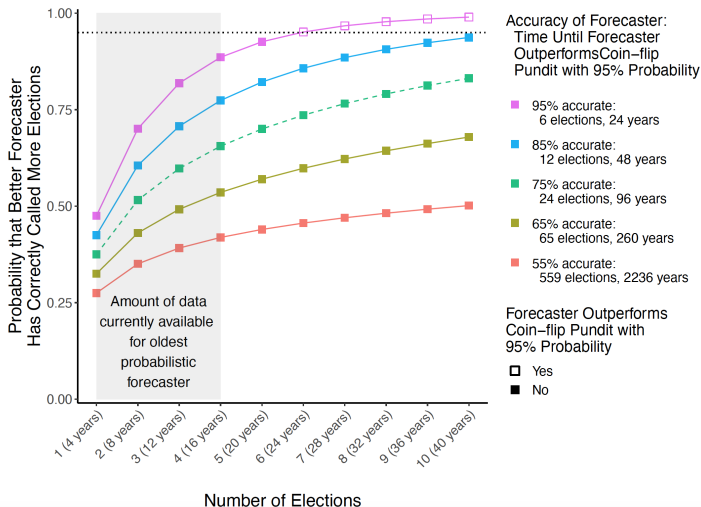
WISDOM OF THE CROWDS



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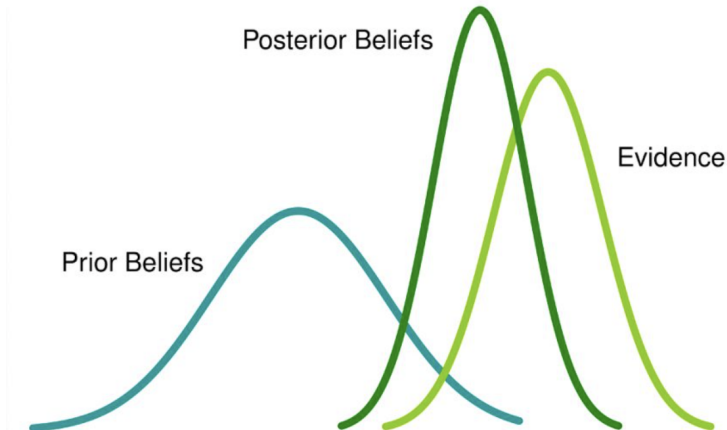
Polling aggregation	Clinton	Trump	Clinton	Trump	Clinton	Trump
	Probabilities		Electoral college		Vote share	
FiveThirtyEight	70.3	29.6	299	238	48.6	45.1
The Upshot	84.0	16.0	322	216		
RCP average of polls			301	237	47.2	44.3
The Daily Kos	88.0	12.0	313	225		
Princeton EC	99.0	1.0	312	226	51.3	48.8
HuffPost	98.1	1.6	323	215		
PollyVote			323	215	52.6	47.4
Mean	87.9	12.0	313.3	224.6	49.0	46.1

WISDOM OF THE CROWDS



Source: Grimmer, Justin, Dean Knox, and Sean Westwood. 2024. "Assessing the Reliability of Probabilistic US Presidential Election Forecasts May Take Decades." OSF Preprints. August 26. doi:10.31219/osf.io/6g5zq.

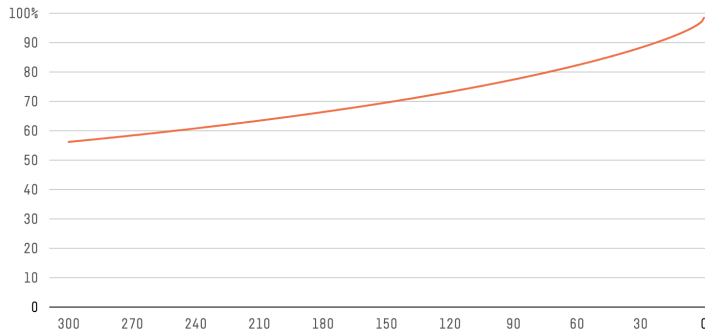
HOW PREDICTION MODELS WORK



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We put more weight on the polls as Election Day approaches

Estimated* share of the overall 538 presidential forecast that is based on polls (as opposed to non-polling historical "fundamentals"), by day before the election



*As of Aug. 23, this estimate uses a standard deviation of 9 percentage points in 538's fundamentals model and a daily standard deviation of 0.35 points in polls, plus overall uncertainty of 1 point about the polling average. Real values will depend on how many polls we have and can differ from this estimate by a few points.

538

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- How to quantify the uncertainty in poll results

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Support_{t+} = $N(\mu_t, \sigma)$ where $\mu_t \sim N(\mu_{t-1}, \tau_t)$ & $\tau_t = N(\tau_{t-1}, \sigma_{\tau})$
or $I_t \sim N(0, \sigma_{\tau})$

AND "X."

AND "X..."

Poll obs. $\sim N(\mu_x + (\text{pollster} + \text{mode} + \text{population} + \text{third party} + \text{bullet}), \text{obs} - \text{sig} + \sigma_{NS})$

where
 $X_i \sim N(\mu, \sigma^2)$ and $\sigma^2 \sim N_{1/2}(0, 1)$
 obs sigma = $\sqrt{\frac{1 + \mu^2}{N}}$

M.U. Signu, δ is derived
indirectly off the posterior
flange.

One party, \uparrow obs sigma: $\frac{1}{\sqrt{N}}$
 obs $\sim N_{\mu}(0,1), [0,2]$

And with the following trend
expansion for states $p_1 \dots p_n$
and parties $p_1 \dots p_n$

$$M(P_1, \dots, P_r, S) \sim MN(\mu, t, s, \Omega^P) \sim \Omega^P$$

& $\mu_{P_i} \in S$ for P_1, \dots, P_r

For policy eval, medo, Ω model Ω as a part of a global Ω and random Ω PS, with Ω PS with (3)

P1	P2	P3	
1	0.5	0.1	P1
0.5	1	0.1	P2
0.1	0.1	1	P3

$$S = 1.5$$

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- How to adjust polls for house effects and/or mode effects
- How to quantify the uncertainty in poll results
- How to model election outcomes (e.g, intra-state correlation)

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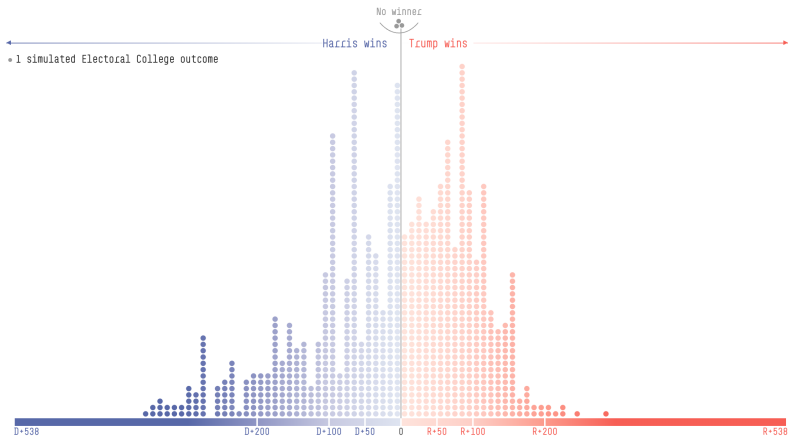
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- How to communicate probabilities

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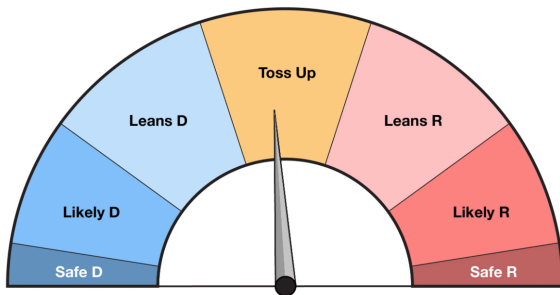


Trump	509
Harris	488
No winner	3
<hr/>	
1,000 simulations	



HOW PREDICTION MODELS WORK

2024 Presidential Forecast

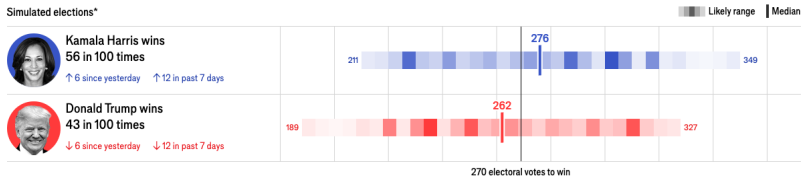


President

Harris 52%

241 Harris, 246 Trump, 51 Toss Up

How PREDICTION MODELS WORK



*The number of simulations each candidate wins approximates their chance of winning the election

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