5. Supervised Techniques II

DS-GA 1015, Text as Data
Arthur Spirling

March 5, 2019

Housekeeping: Final Paper Details

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83% of freq counts of Diction 'optimistic' words don't appear on L&M list. For 'pessimistic' words, 70% of Diction word frequencies don't appear on L&M. Also show that L&M word lists (from company filings) are statistically significant predictor of volatility and direction makes sense (not so for Diction).

Where Are We?

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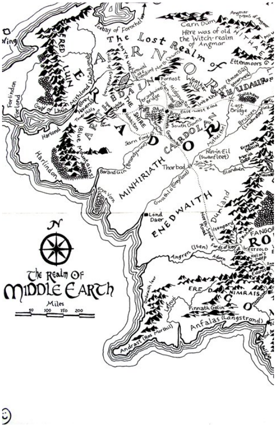
The Lost Realm of ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Trollshaws
Last Bridge
East-West Road
Bree
South Downs
THE SHIRE
CARDOLAN
Mitheithel
Sarn Ford
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
MINHIRIATH
Gwathlo (Greyflood)
Lond Daer
ENEDWAITH
Dunland
Isengard
FANGORN
Helm's Deep
Angren (Isen)
Adorn
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Forlindon
Gulf of Lhûn
Harlond
Harlindon
Blue Mountains
N
The Realm of Middle Earth
Miles
50 100 150 200

Where Are We?



Covered dictionary and related approaches to document classifications

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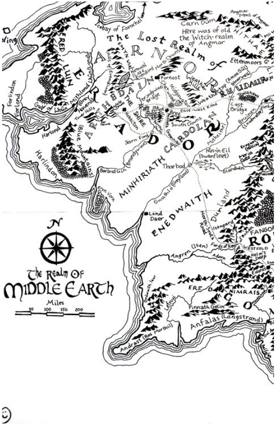

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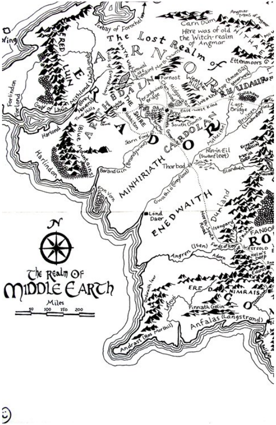

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plus opportunities for fast, reliable coding of training set.

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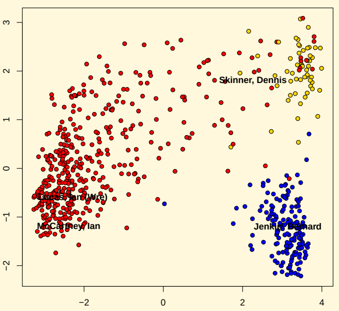

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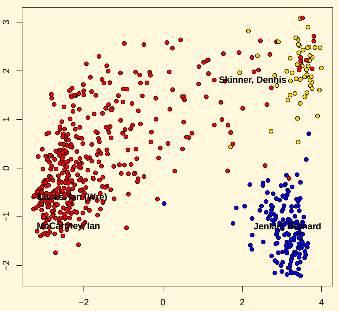

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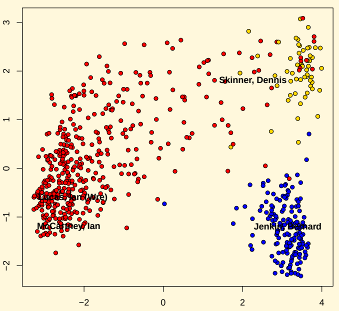

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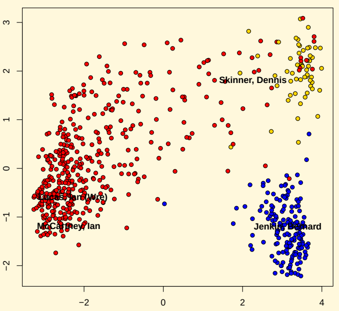

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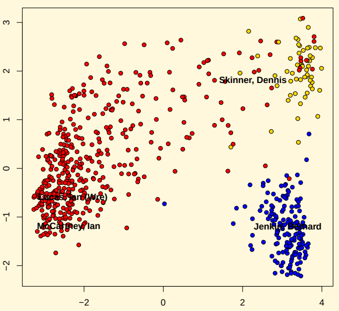

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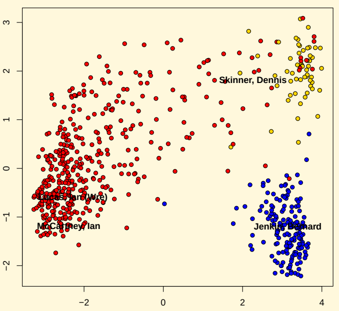

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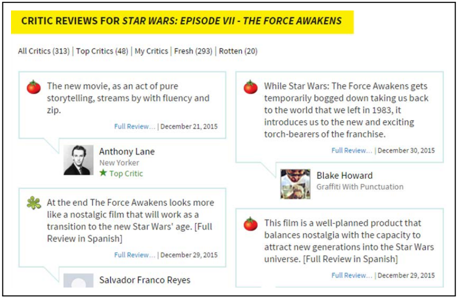

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$$\Pr(A|B) \propto \Pr(A)\Pr(B|A)$$

Here, $\Pr(A)$ is our prior for A, while $\Pr(B|A)$ will be the likelihood for the data we saw.

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3 A subject claims to have psychic abilities—he can tell you how a (fair) coin will come down in nine tosses. He has less than a $\frac{1}{500}$ chance of being correct by chance, but he succeeds in the task! Do you 'update' that he has psychic abilities? Why or why not?

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where $\Pr(c)$ is the prior probability of a document occurring in class c; and $\Pr(t_k|c)$ is interpreted as "measure of the how much evidence t_k contributes that c is the correct class"

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2 What does this imply about the relationship between estimation ('modeling') and accuracy?

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July 20, 2014 10.14pm EDT

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Then for each cleric, concatenate all works into one and give this 'document'/cleric a score.

Discriminating Words

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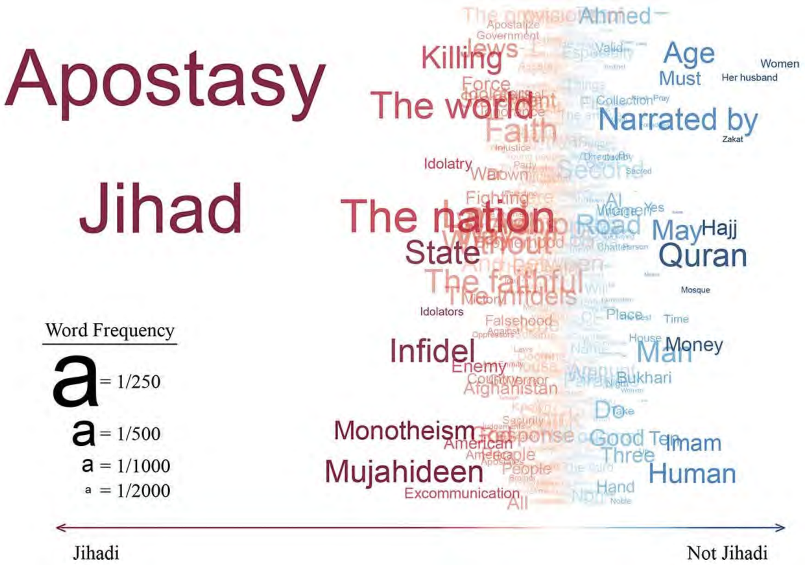

Validation: *Exoneration*

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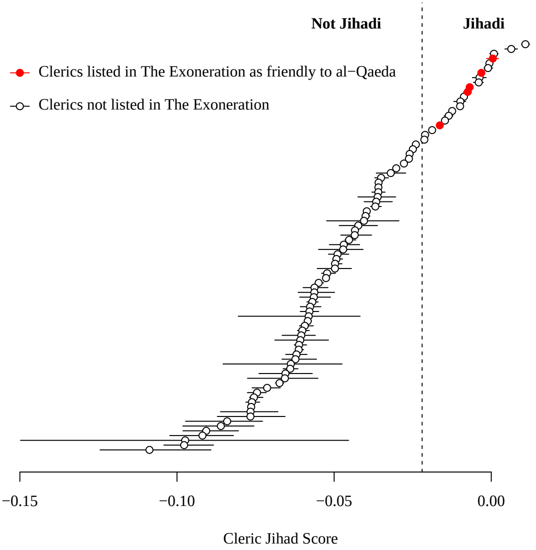

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*

Scoring and Scaling Political Texts

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→ LBG suggest a way of scoring documents in a NB style, so that we can answer such questions.

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3 Score the virgin texts (test set) of texts using those word scores, possibly transform virgin scores to original metric.

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NB any new words in the virgin document that were *not* in the reference texts are ignored: the sum is only over the words we've seen in the reference texts.

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New Labour Moderates its Economic Policy

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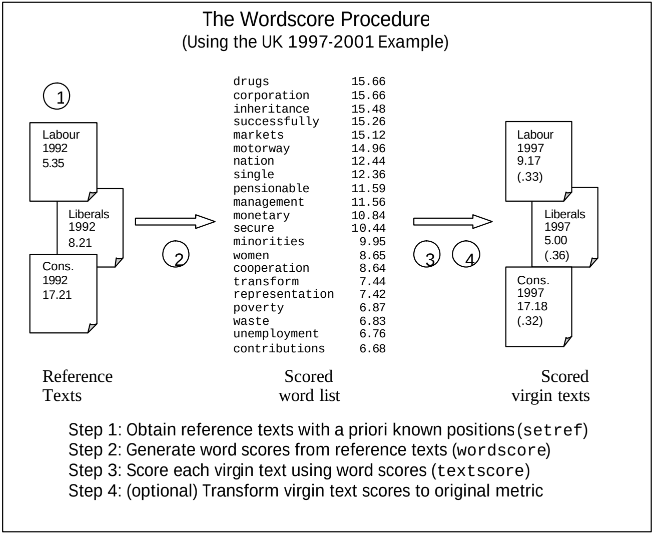

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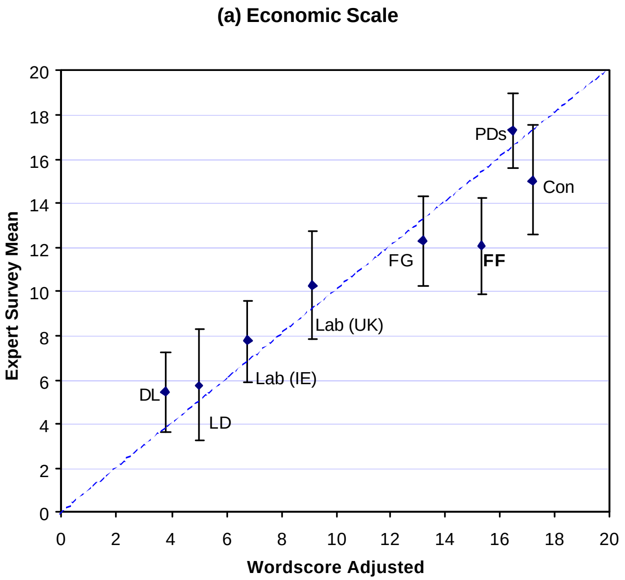

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while Beauchamp (2011) provides comparison and extension to more purely Bayesian approach.

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		Predicted		
		J	$\neg J$	Total
Actual	J	a TP	b FN	$a+b$
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1. For such a task, there's probably a trade-off between precision and recall. Explain why.
2. We may be skeptical of using accuracy as a performance indicator in this case. Explain why.

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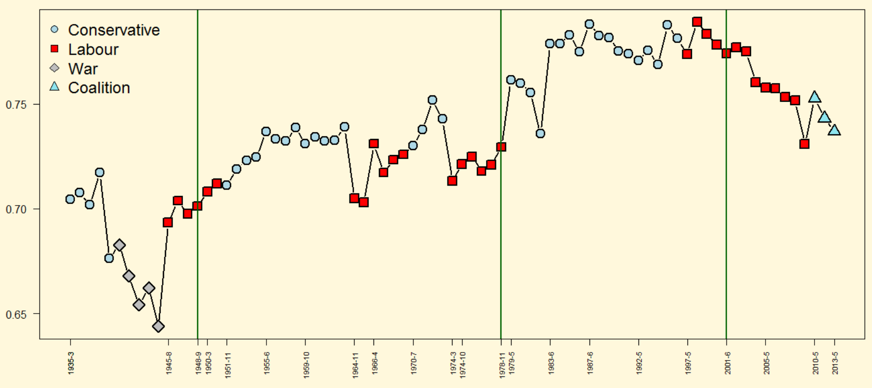

Use machine to classify left (-1) vs right ($+1$) MPs in UK and record classification accuracy.

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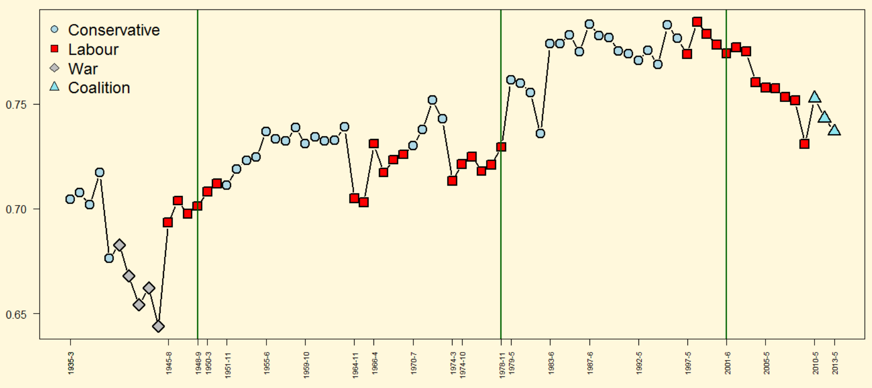

Use machine to classify left (-1) vs right ($+1$) MPs in UK and record classification accuracy. When high, parties are more polarized.

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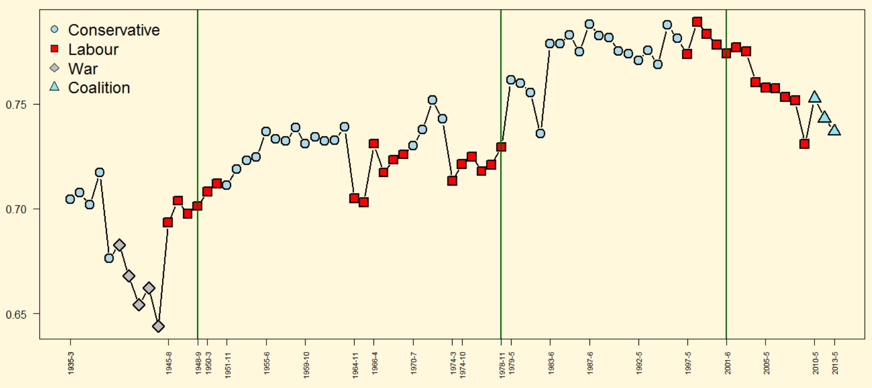

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Makes sense in terms of historical record!

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→ would like unbiased approach (and be nice if non-parametric), that avoids the intermediate step of document classification.

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NB "*among all documents in a given category, the prevalence of particular word profiles in the labeled set should be the same in expectation as in the population set*". This is key assumption. btw, what happened to the danger of drift?!

Performance: Congress, Editorials, Enron

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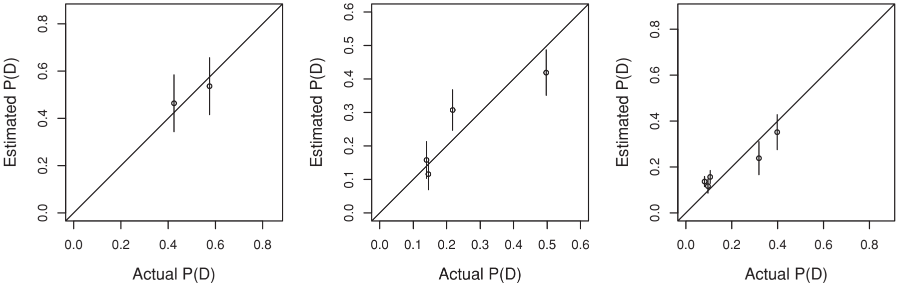
FIGURE 4 Additional Out-of-Sample Validation



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Galton and the Wisdom of Crowds

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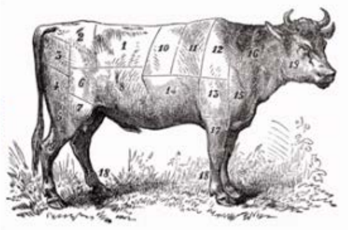

average of 800 guesses = 1,197
actual weight of the ox = 1,198

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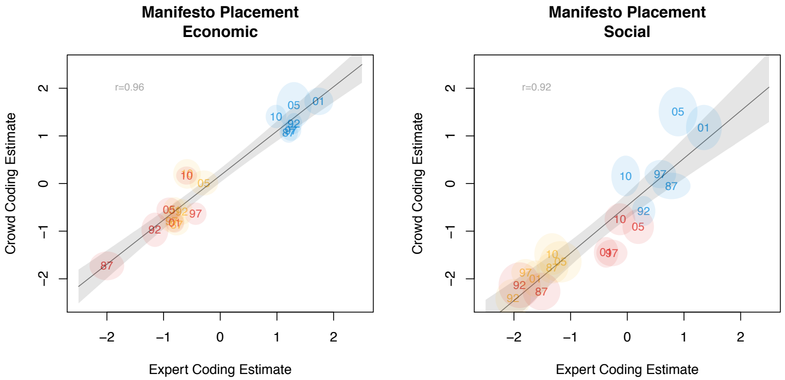

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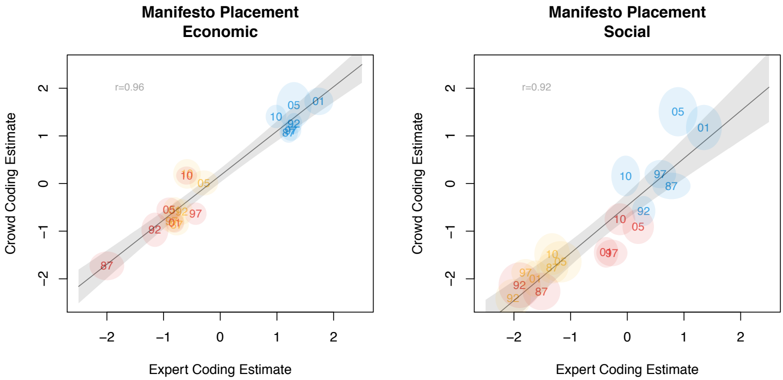

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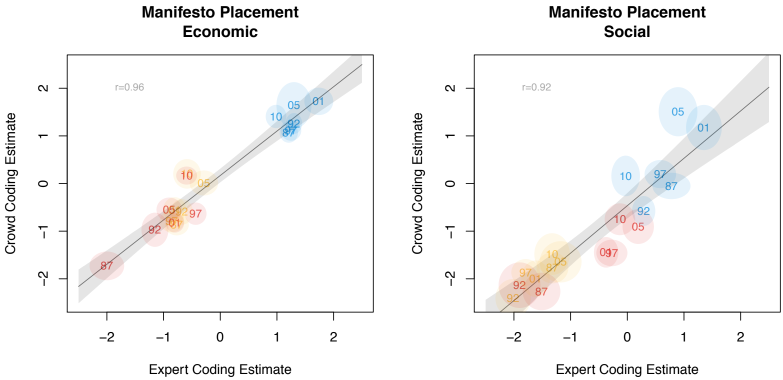

Note that this method allows replication of the data used in an analysis, not just the analysis itself!

Partner Exercise

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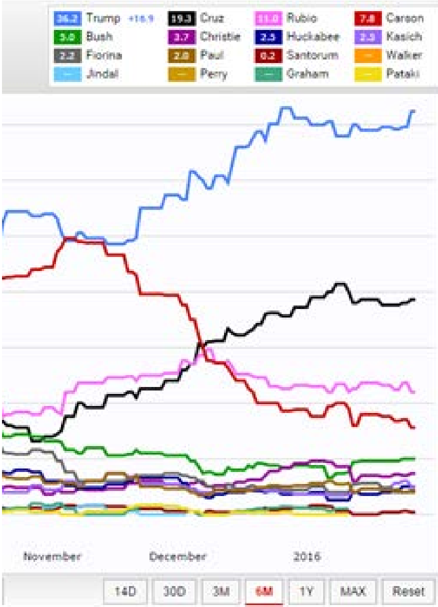

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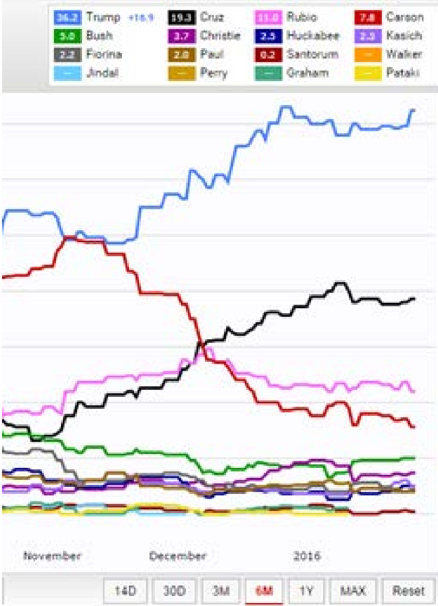

You work for a polling company and have access to a crowdsourcing service, and want to know who will win the US Presidential election.

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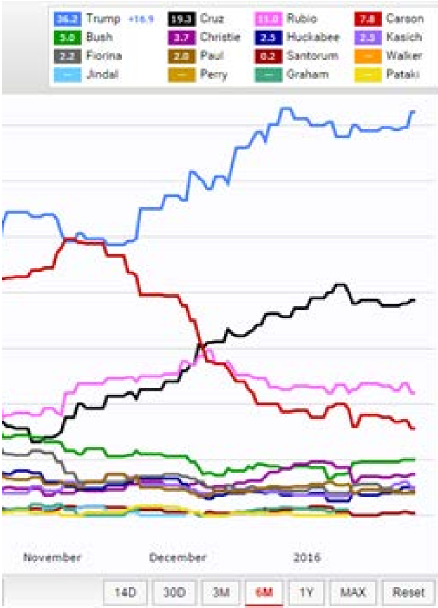

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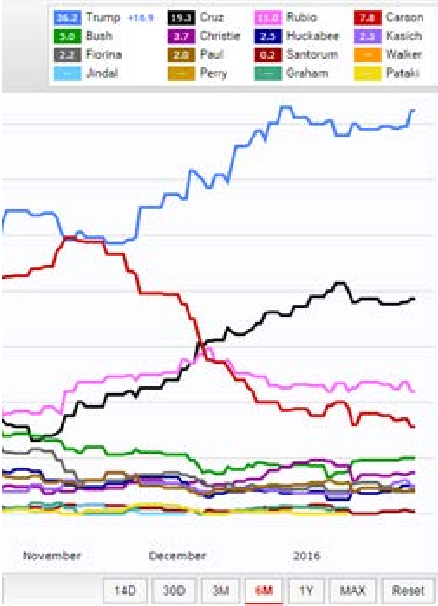

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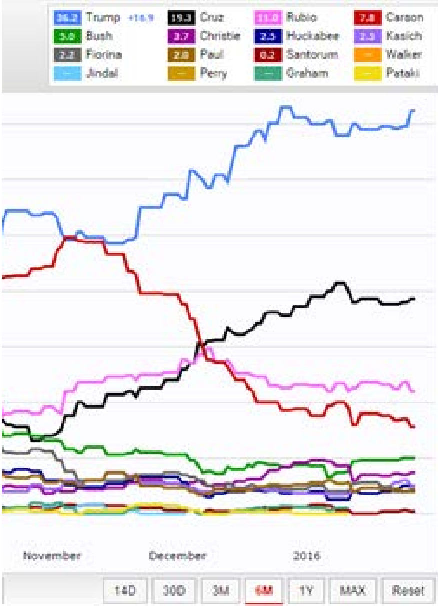

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