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
Bree
South Downs
East-West Road
Last Bridge
RHUDAUR
ARTHEDAIN
CARDOLAN
THE SHIRE
Sarn Ford
Tharbad
MINHIRIATH
ENEDWAITH
Lond Daer
Dunland
Isengard
Fords of Isen
Helm's Deep
Adorn
Angren (Isen)
Pinnath Gelin
Anfalas (Langstrand)
Harlindon
Harlond
Forlindon
Forlond
Gulf of Lhûn
Eryn Vorn
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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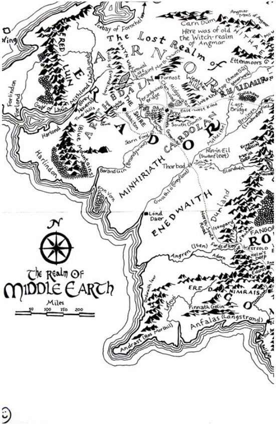

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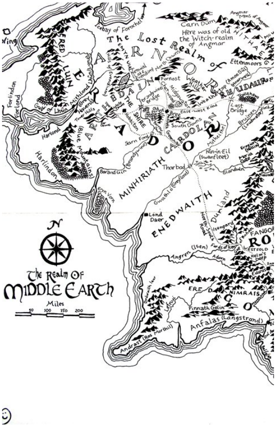

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Continue this idea, but in a more formal modeling way: Naive Bayes

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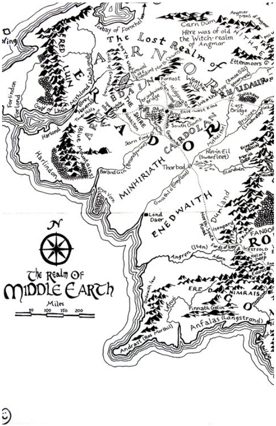

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plus opportunities for fast, reliable coding of training set.

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e.g. PCA of legislators's votes:

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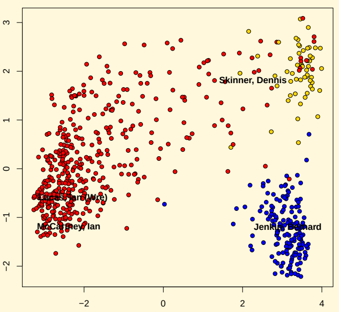

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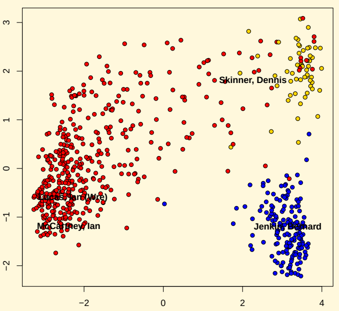

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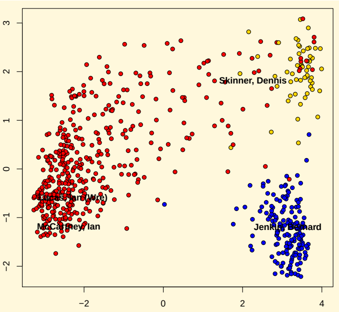

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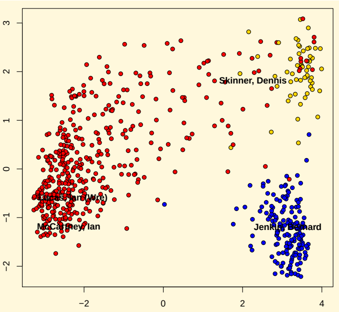

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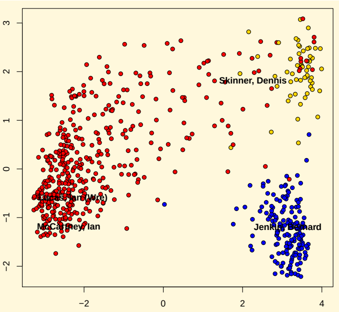

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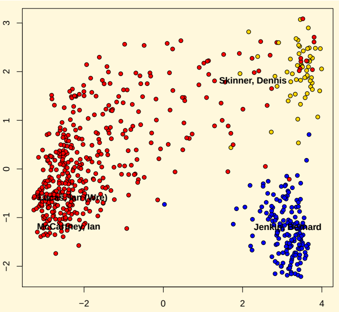

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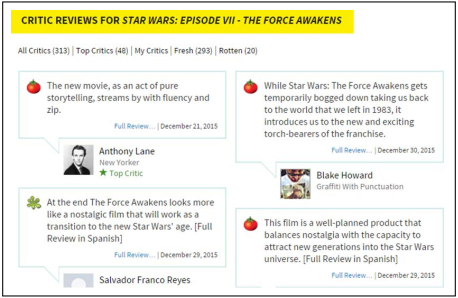

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$$\Pr(A|B) \propto \Pr(A)\Pr(B|A)$$

  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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Can assign a *Jihad Score* to each document: basically the logged likelihood ratio, $\sum_i \log \frac{\Pr(t_k|\text{Jihad})}{\Pr(t_k|\neg \text{ Jihad})}$ (note: doesn't know what 'real world' priors are, so drops them here)

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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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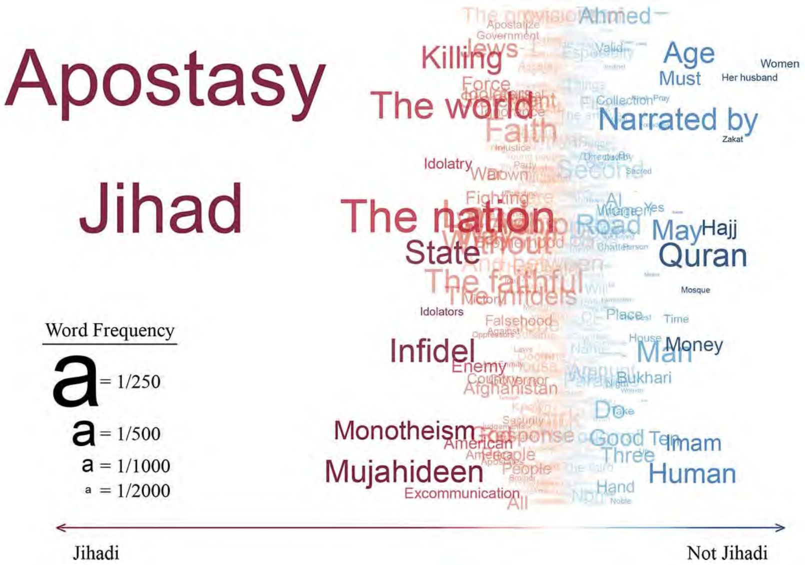

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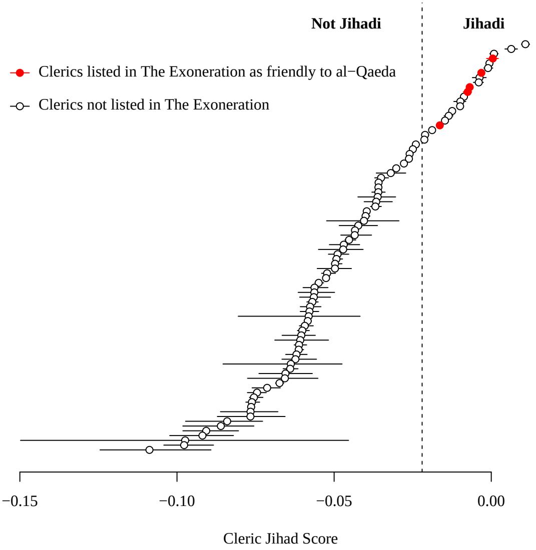

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*

Scoring and Scaling Political Texts

Wordscores (Laver, Benoit & Garry, 2003)

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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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2. Generate word scores from these reference texts

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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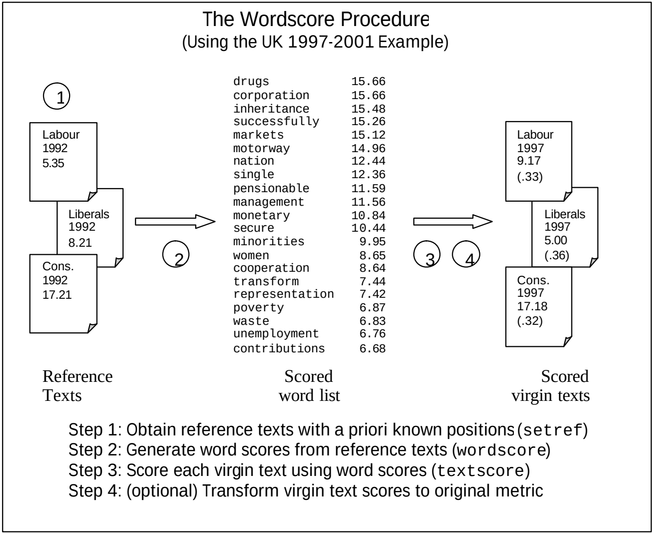

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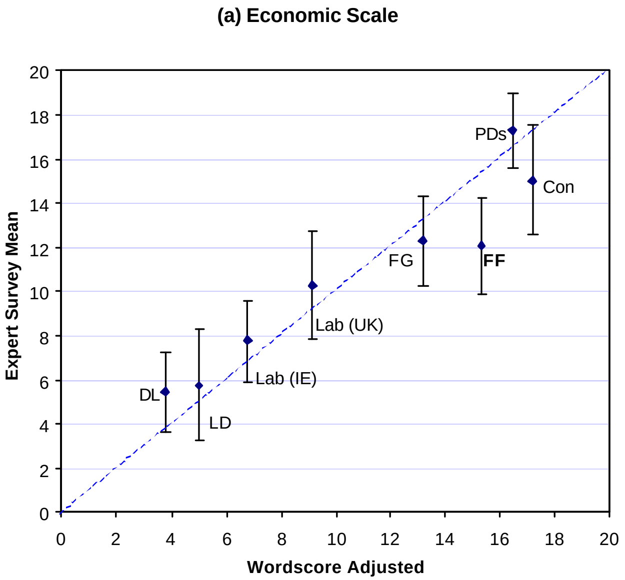

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while Beauchamp (2011) provides comparison and extension to more purely Bayesian approach.

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		J	$\neg J$	Total
Actual	J	a TP	b FN	$a + b$
	$\neg J$	c FP	d TN	$c + d$
	Total	$a + c$	$b + d$	N

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2 We may be skeptical of using accuracy as a performance indicator in this case. Explain why.

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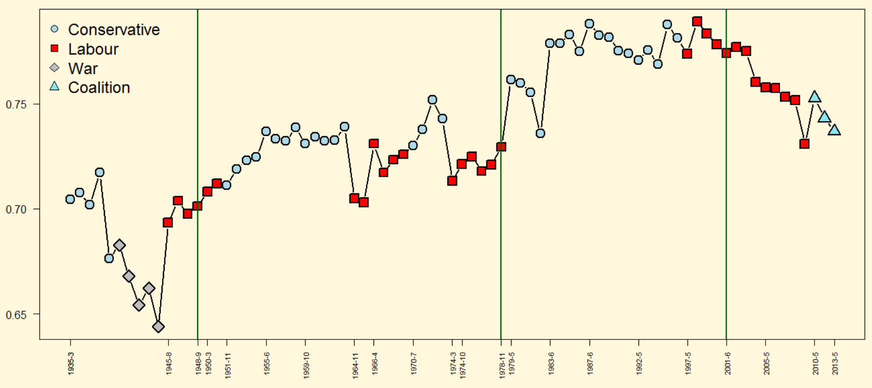

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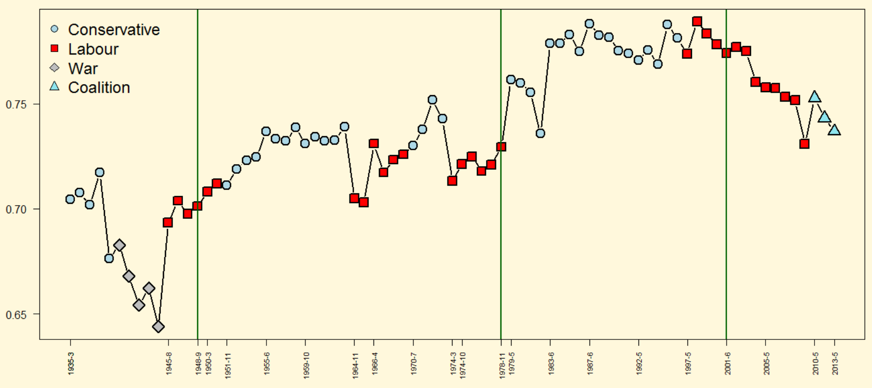

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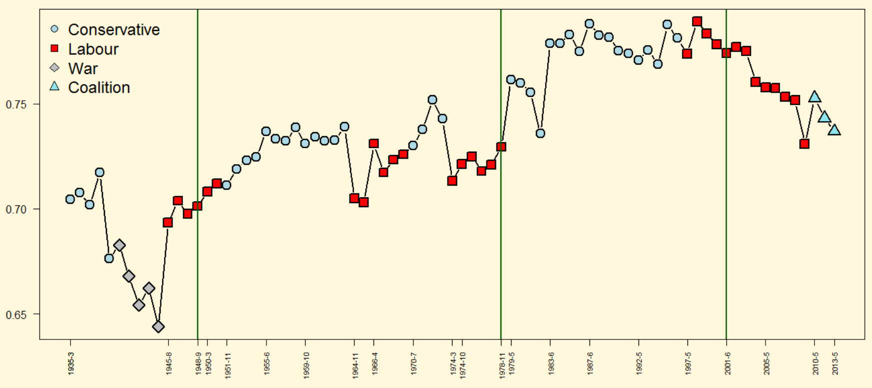

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if we had a large number of 'experts', we could (depending on the size of the problem) have everything as a 'training' set and avoid modeling at all.

Galton and the Wisdom of Crowds

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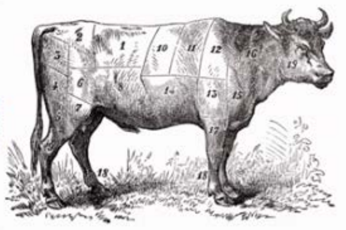

average of 800 guesses = 1,197
actual weight of the ox = 1,198

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Model allows for correcting for reader and text fixed effects,

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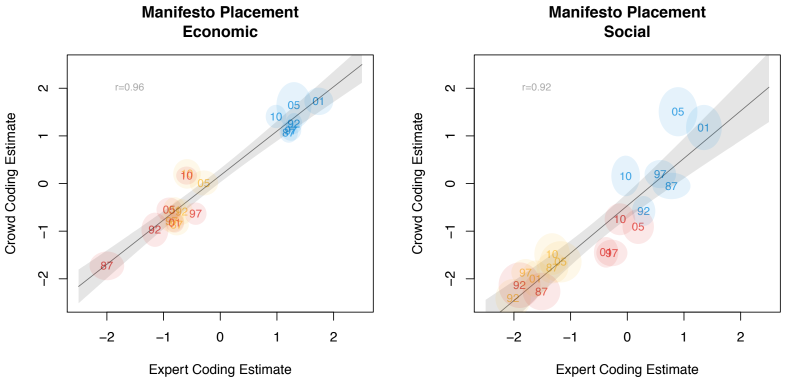

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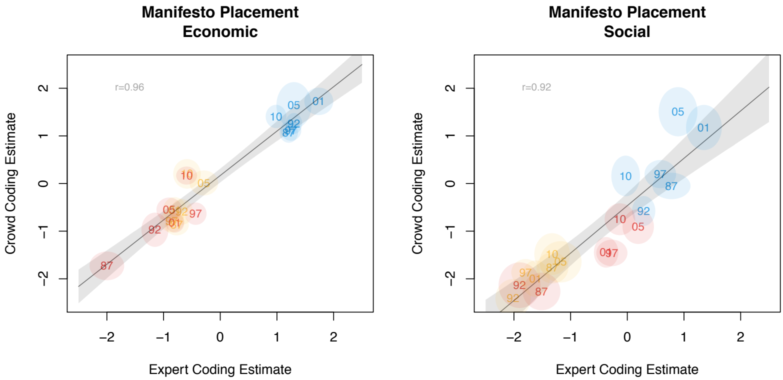

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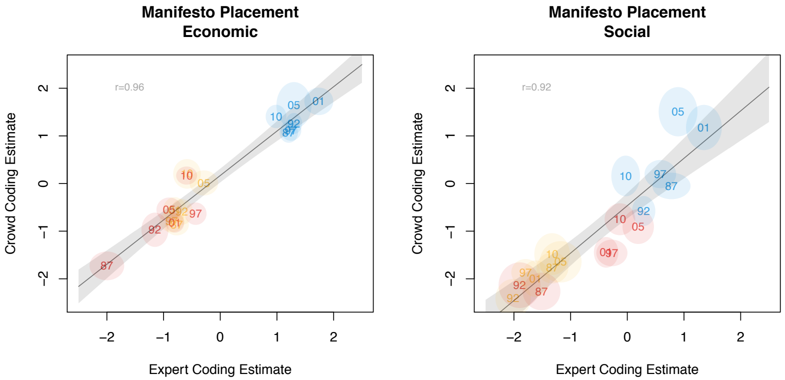

Note that this method allows replication of the data used in an analysis, not just the analysis itself!

Exercise

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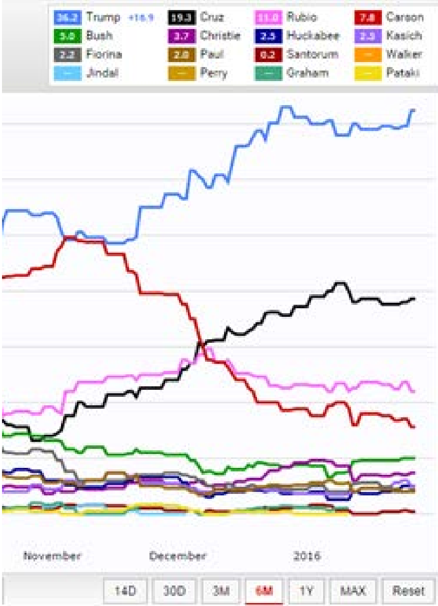

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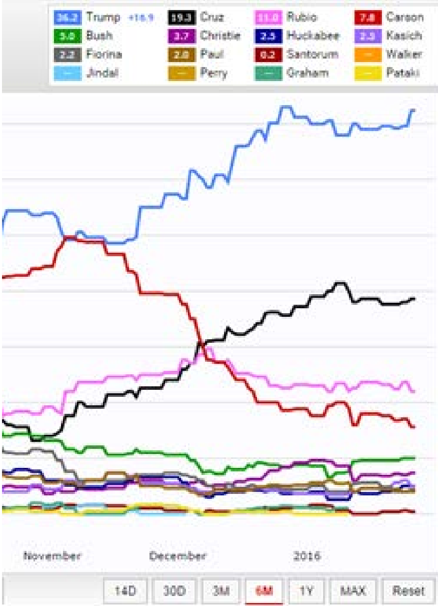

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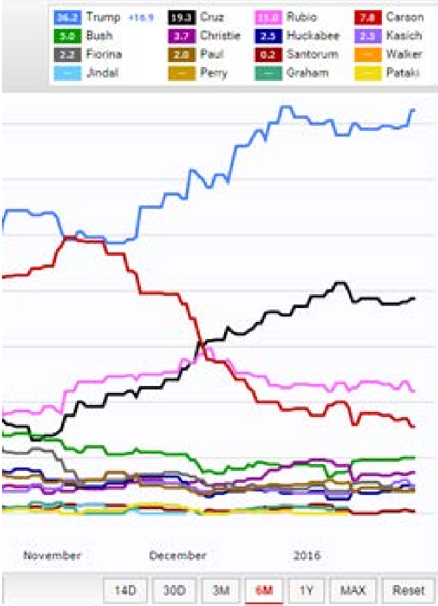

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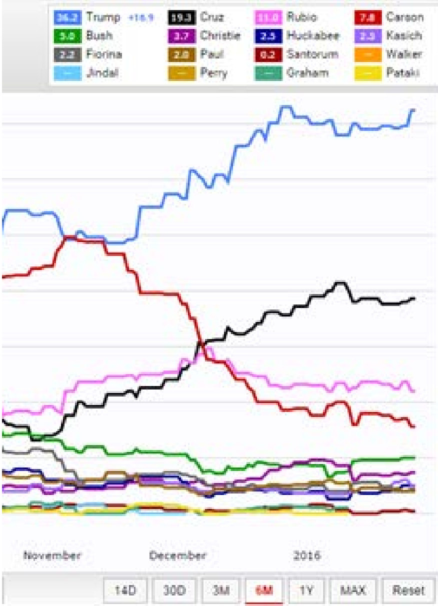

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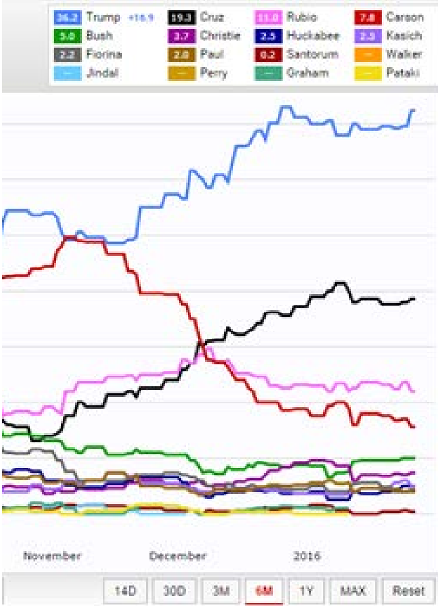

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