5. Supervised Techniques II

DS-GA 1015, Text as Data
Arthur Spirling

March 9, 2021

Where Are We?

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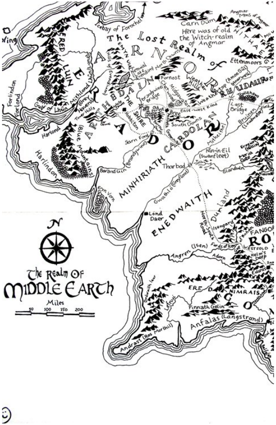
The Lost Realm of
ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Weather Hills
Fornost
North Downs
Bree
East-West Road
South Downs
Last Bridge
THE SHIRE
Sarn Ford
CARDOLAN
Mitheithel
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
MINHIRIATH
Eryn Vorn
Lond Daer
ENEDWAITH
Dunland
Isengard
Angren (Isen)
Adorn
Helm's Deep
Forlindon
Forlond
Gulf of Lhûn
Harlond
Harlindon
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
The Realm Of Middle Earth
Miles

☺

Where Are We?



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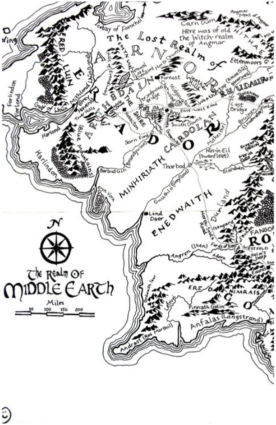

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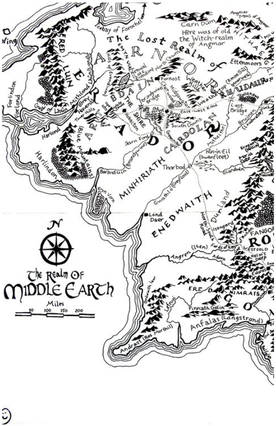

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plus opportunities for fast, reliable coding of training set.

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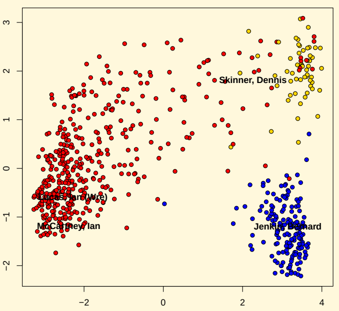

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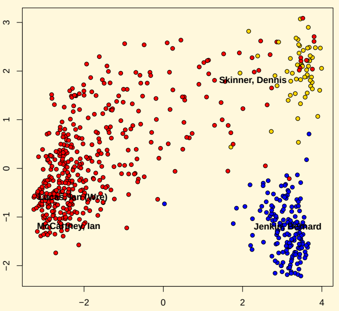

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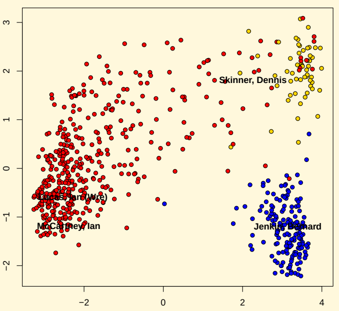

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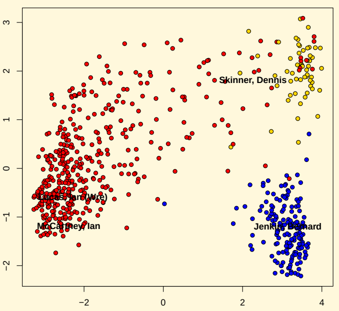

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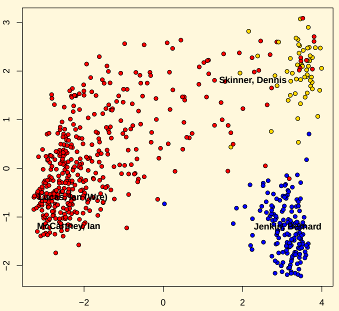

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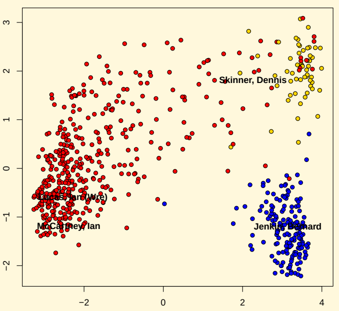

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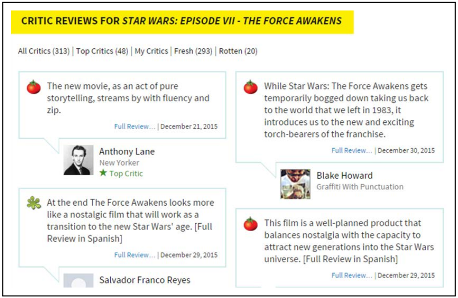

CRITIC REVIEWS FOR *STAR WARS: EPISODE VII - THE FORCE AWAKENS*

All Critics (313) | Top Critics (48) | My Critics | Fresh (293) | Rotten (20)

The new movie, as an act of pure storytelling, streams by with fluency and zip.

Full Review... | December 21, 2015

Anthony Lane
New Yorker
★ Top Critic

While Star Wars: The Force Awakens gets temporarily bogged down taking us back to the world that we left in 1983, it introduces us to the new and exciting torch-bearers of the franchise.

Full Review... | December 30, 2015

Blake Howard
Graffiti With Punctuation

At the end The Force Awakens looks more like a nostalgic film that will work as a transition to the new Star Wars' age. [Full Review in Spanish]

Full Review... | December 29, 2015

Salvador Franco Reyes

This film is a well-planned product that balances nostalgia with the capacity to attract new generations into the Star Wars universe. [Full Review in Spanish]

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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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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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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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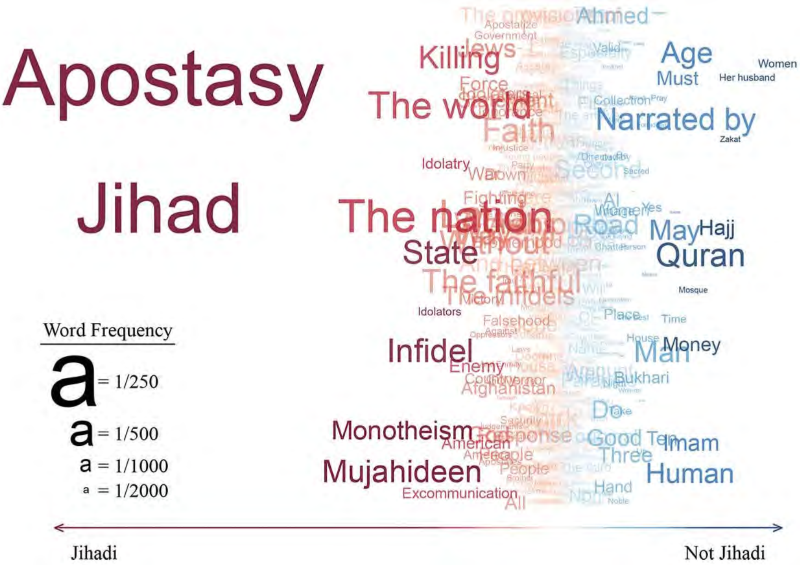

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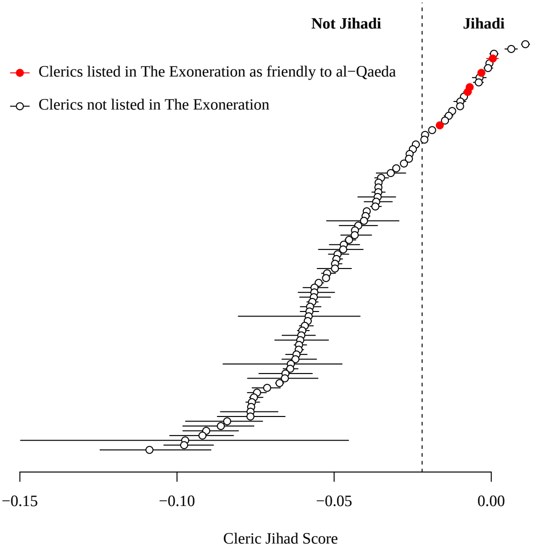

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*

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.

Basics

1. Begin with a reference set (training set) of texts that have known positions.

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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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$\rightarrow$ can rescale these back to original $(-1, 1)$ dimension.

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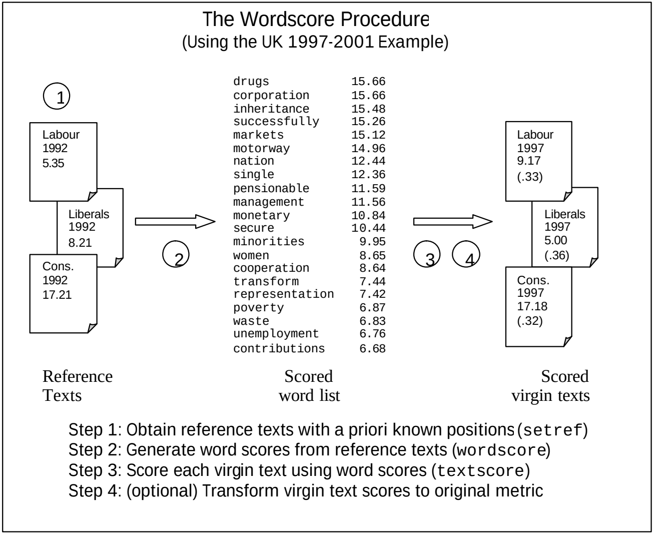

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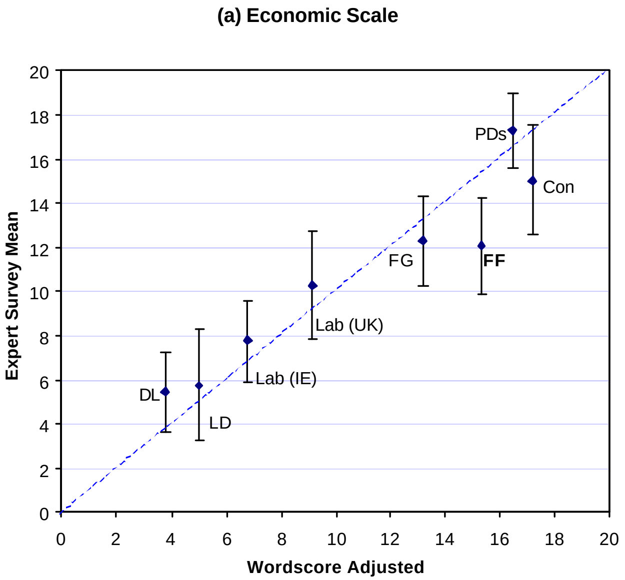

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while Beauchamp (2011) provides comparison and extension to more purely Bayesian approach.

Classifier Performance and Comparison

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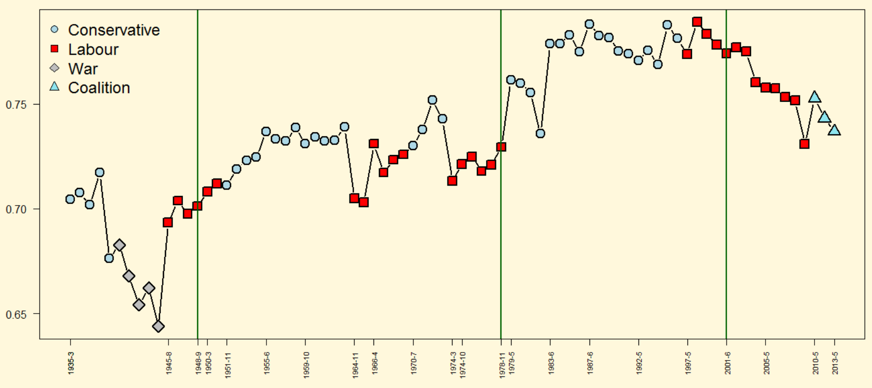

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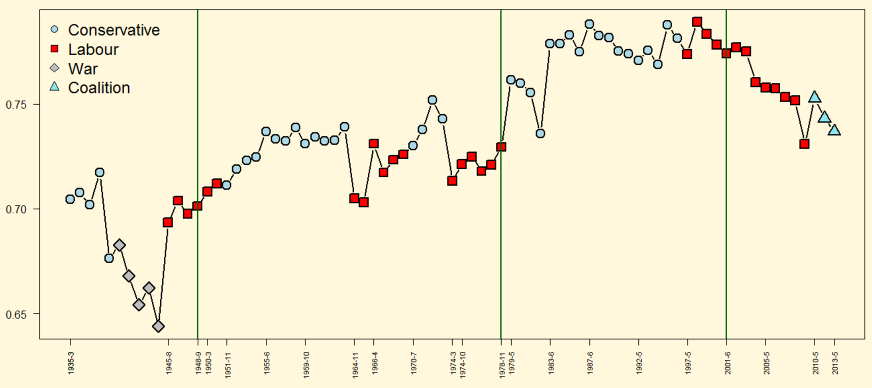

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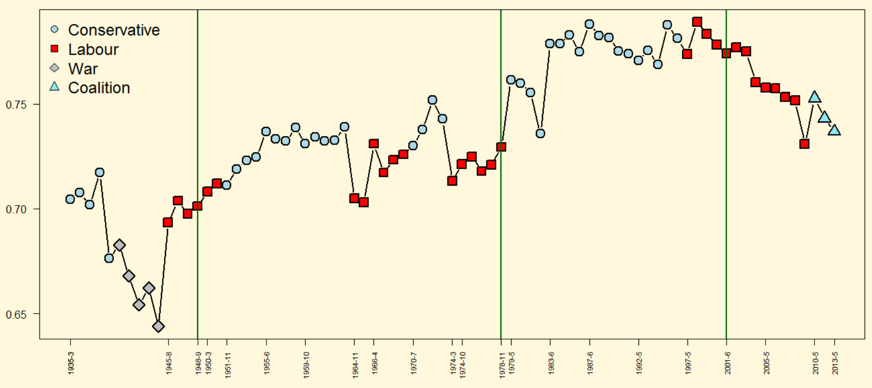

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Makes sense in terms of historical record!

Proportions

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

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where $\Pr(\mathbf{S})$ is the probability of each of the word stem (binary) combinations occurring, which we can tabulate from the target texts (test set).

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Performance: Congress, Editorials, Enron

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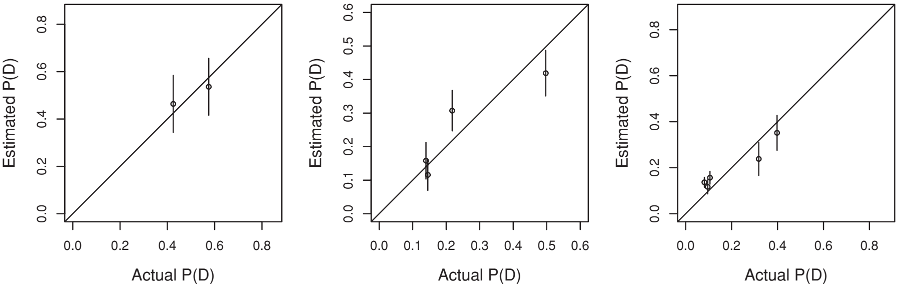
▸ Estimation details

FIGURE 4 Additional Out-of-Sample Validation



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Galton and the Wisdom of Crowds

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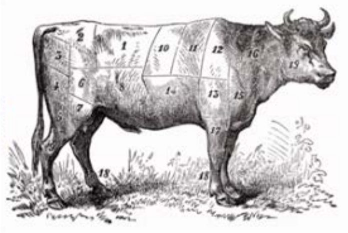

average of 800 guesses = 1,197

actual weight of the ox = 1,198

Crowdsourcing as Concept

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Benoit, Conway, Lauderdale, Laver and Mikhaylov (2016)

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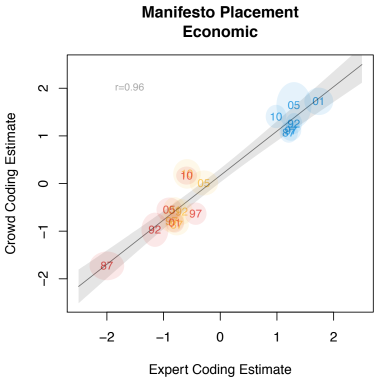

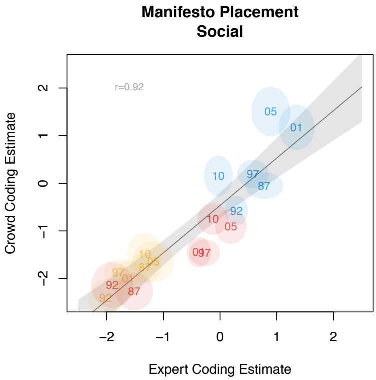

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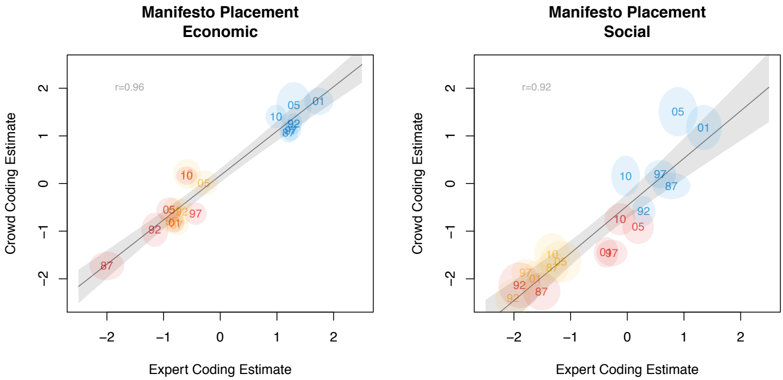

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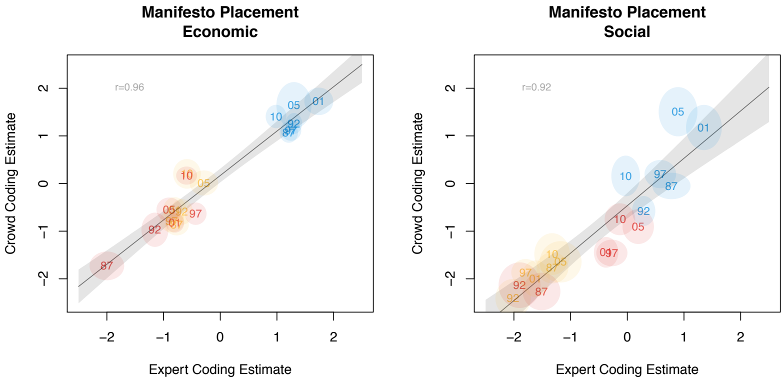

Note that this method allows replication of the data used in an analysis, not just the analysis itself!