4. Supervised Techniques II (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

March 9, 2021

Housekeeping

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HW 1 out: coming in on March 9, 2021, at 11pm (NY time).

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Naive Bayes

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Why?

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Why?

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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We can express our quantity of interest as:

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$$\Pr(c|d) \propto \underbrace{\Pr(c)}_{\text{prior}} \underbrace{\prod_{k=1}^{K} \Pr(t_k|c)}_{\text{likelihood}}$$

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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1. Why does this happen?
2. What does this imply about the relationship between estimation ('modeling') and accuracy?
3. Via the *maximum a posteriori* (map) notion, we can easily extend Naive Bayes to multiple classes. Explain how.

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A Generally encourages relaxing of spam filter: more spam.

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Actual	J	a TP	b FN	$a+b$
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Precision : $\frac{\text{number of TP}}{\text{number of TP}+\text{number of FP}} = \frac{a}{a+c}$.

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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.

Covid Testing: Ideal

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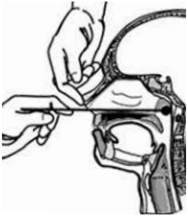

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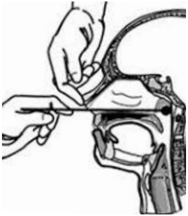

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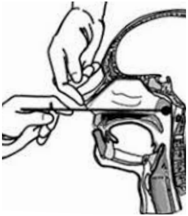

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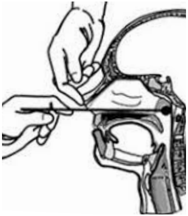

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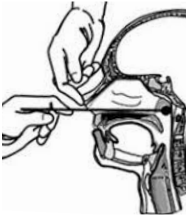

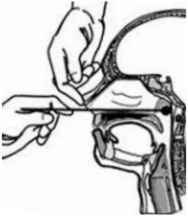

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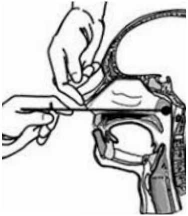

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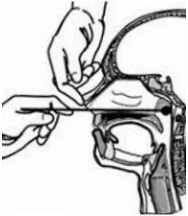

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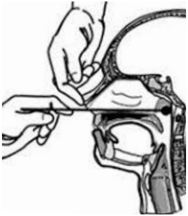

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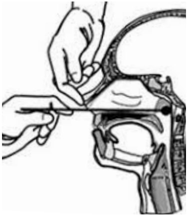

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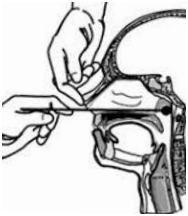

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"99% accuracy"

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Culture | Machine Learning

share this

A.I. Algorithm Recognizes Terrorist Propaganda with 99 Percent Accuracy

The war on terror goes digital.

By Kevin Litman-Navarro on February 13, 2018

Filed Under A.I., Algorithms & Data

The UK-based company ASI Data Science unveiled a machine learning algorithm Wednesday that can identify terrorist propaganda videos with 99 percent accuracy.

WordScores

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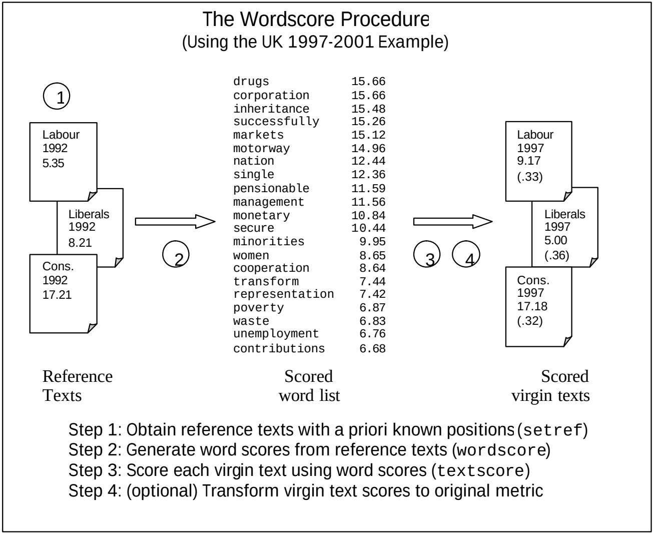
$\rightarrow$ can rescale these back to original $(-1, 1)$ dimension.

New Labour Moderates its Economic Policy



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Attempts to rescale not always very convincing.

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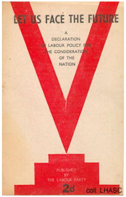

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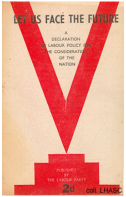

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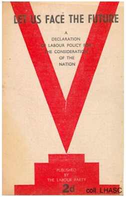

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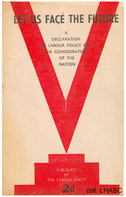

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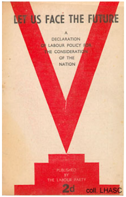

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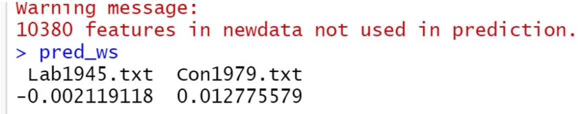

```
Warning message:
10380 features in newdata not used in prediction.
> pred_ws
 Lab1945.txt   Con1979.txt
-0.002119118  0.012775579
```

Crowdsourcing

Galton and the Wisdom of Crowds

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→ "sixpenny fee deterred practical joking, and the hope of a prize and the joy of competition prompted each competitor to do his best."

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Identify Which Of Two Text Segments Contains Easier Language

Instructions ▾

Text A	Text B
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Which text is easier to read and understand?

Text A easier	Text B easier
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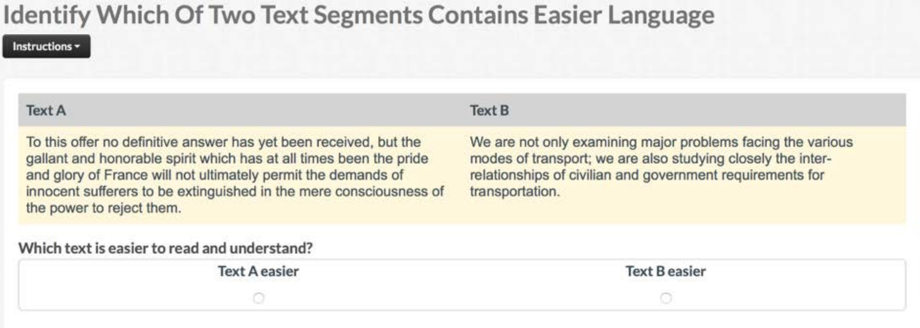

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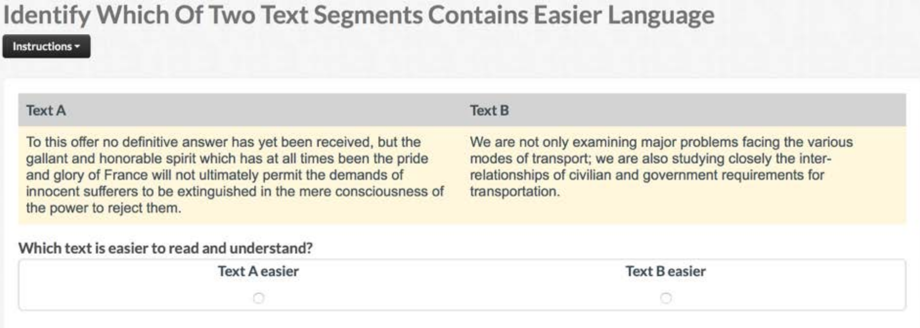

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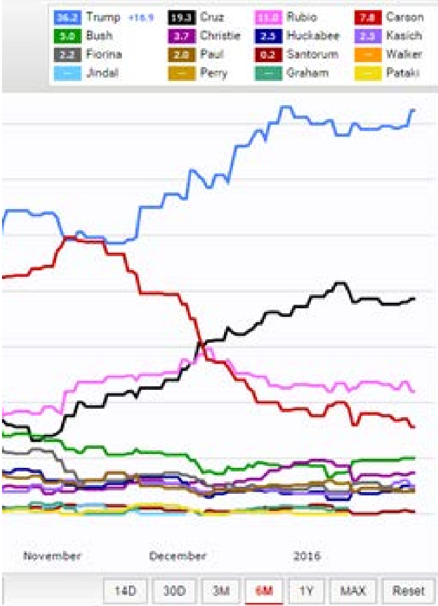

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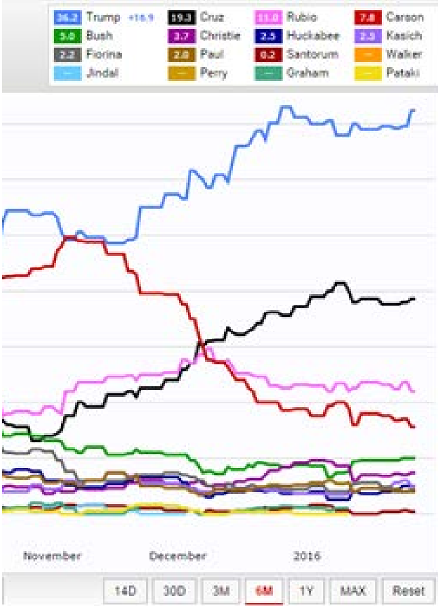

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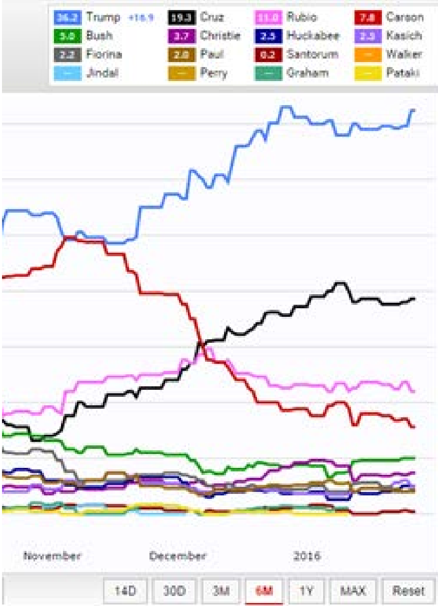

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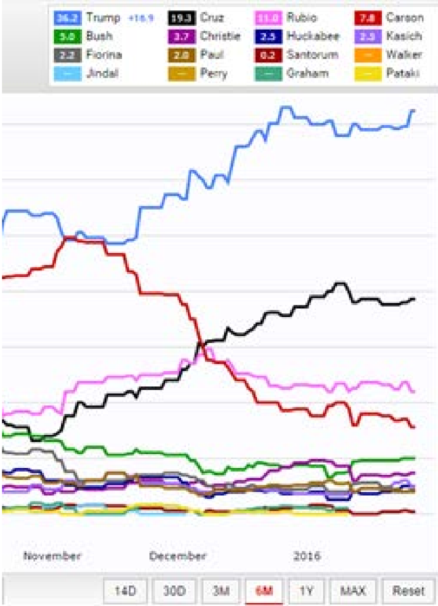

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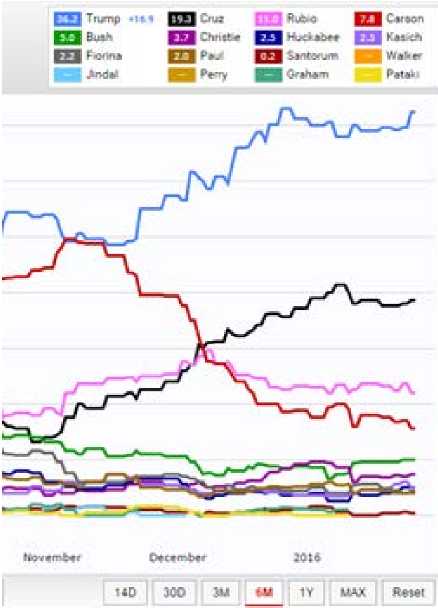

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Q What are analogies to these in crowdsourcing tasks in text coding?

Extra Material

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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?!