An Improved Method of Automated Nonparametric Content Analysis for Social Science[1]

Gary King[2]

Institute for Quantitative Social Science
Harvard University

New York University, Text as Data Speaker Series, 12/1/2016

[1]Based on joint work with Connor Jerzak and Anton Strezhnev (building on earlier work with Dan Hopkins and Ying Lu)

[2]GaryKing.org

Mortality Data, Developed Countries:

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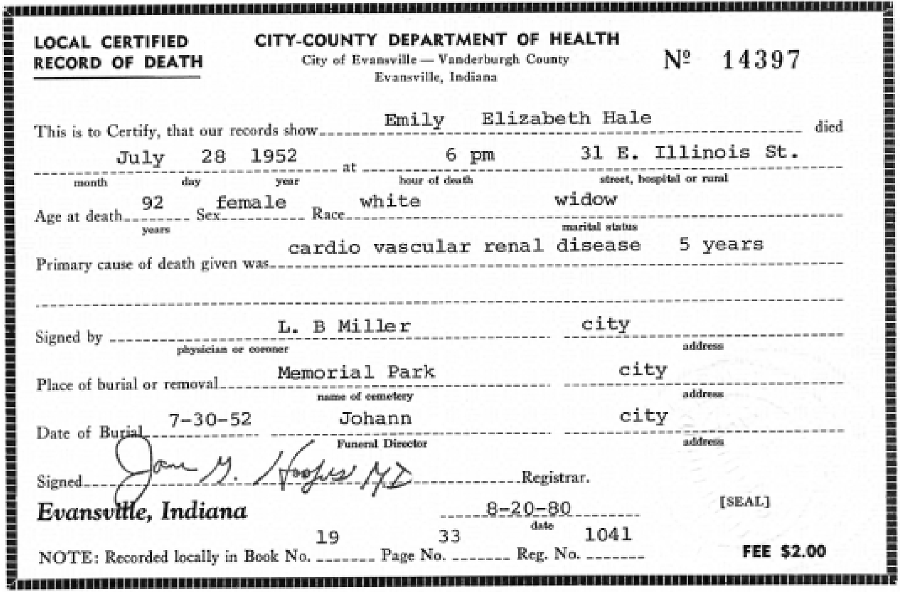

LOCAL CERTIFIED RECORD OF DEATH

CITY-COUNTY DEPARTMENT OF HEALTH
City of Evansville — Vanderburgh County
Evansville, Indiana

№ 14397

This is to Certify, that our records show Emily Elizabeth Hale died July 28 1952 (month, day, year) at 6 pm (hour of death) 31 E. Illinois St. (street, hospital or rural)

Age at death 92 (years) Sex female Race white widow (marital status)

Primary cause of death given was cardio vascular renal disease 5 years

Signed by L. B Miller (physician or coroner) city (address)

Place of burial or removal Memorial Park (name of cemetery) city (address)

Date of Burial 7-30-52 Johann (Funeral Director) city (address)

Signed Jame G. Hoofus MD Registrar.

Evansville, Indiana 8-20-80 (date) [SEAL]

NOTE: Recorded locally in Book No. 19 Page No. 33 Reg. No. 1041 FEE $2.00

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Mortality Data, Most of the World: Verbal Autopsy

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Fast Company Names Crimson Hexagon Number Seven on "The 10 Most Innovative Companies in Web" List Leading Social Intelligence Firm Recognized For Revolutionary Measurement of Consumer Opinions in Social Media

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- Solve for "truth" to correct estimate:

$$P(D=1) = \frac{\widehat{P(D=1)} - (1-\text{spec})}{\text{sens} - (1-\text{spec})}$$

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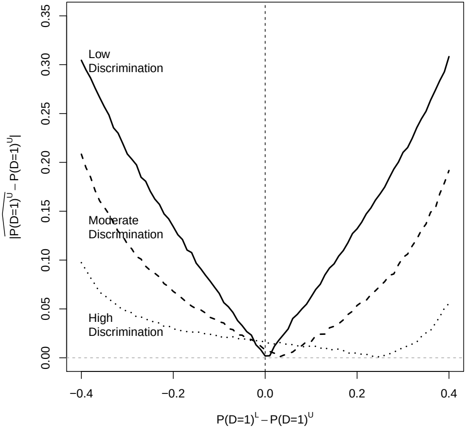

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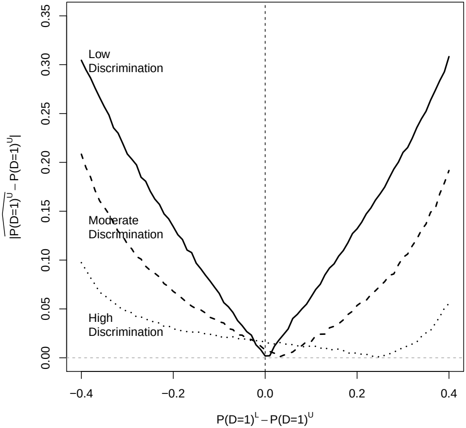

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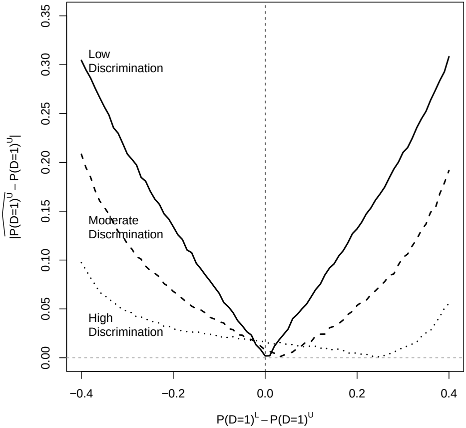

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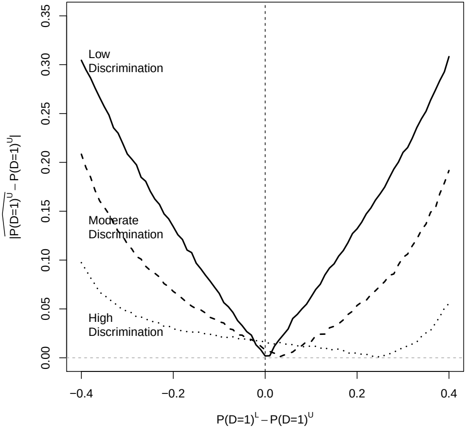

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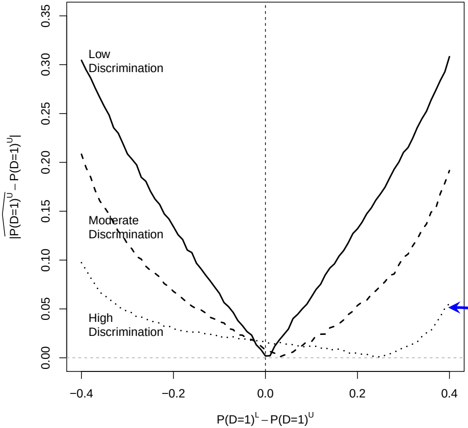

Try to: Reduce $P(D)$ divergence; Increase $P(S|D)$ discrimination

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- Overall method: weighted bagging + PScore + Bayesian shrinkage

A Proposed Readme2: Part 2 (of 2)

- Form $P(S|D)$ by tabulating weighted bootstrap labeled set
- But $P(S|D)$ is sparse (for each bootstrapped sample)
- Use Bayesian model: mitigate sparseness, increase efficiency
  - Most words have little effect
  - If no effect, $P(S|D) = P(S)$
  - $\rightsquigarrow$ Shrink $P(S|D)$ toward prior of $P(S)$[U]
  - (Details: Beta-binomial Bayesian model for cell counts)
- Overall method: weighted bagging + PScore + Bayesian shrinkage
- Refinements: alternative numeric representations of text

Example with Large $P(D)$ Divergence: Enron Emails

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California energy crisis dramatically changes content

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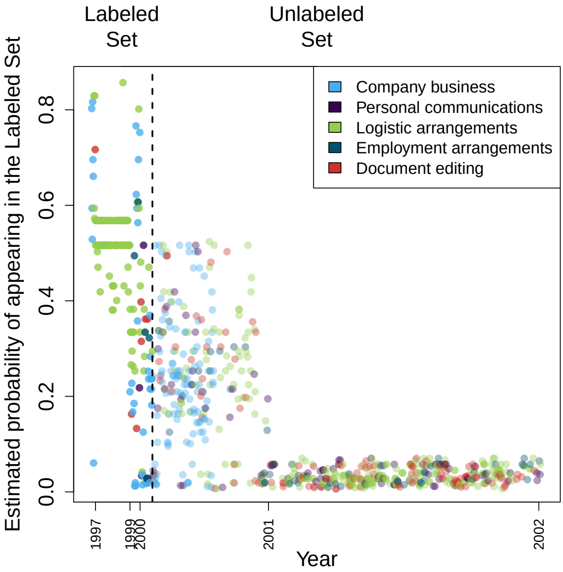

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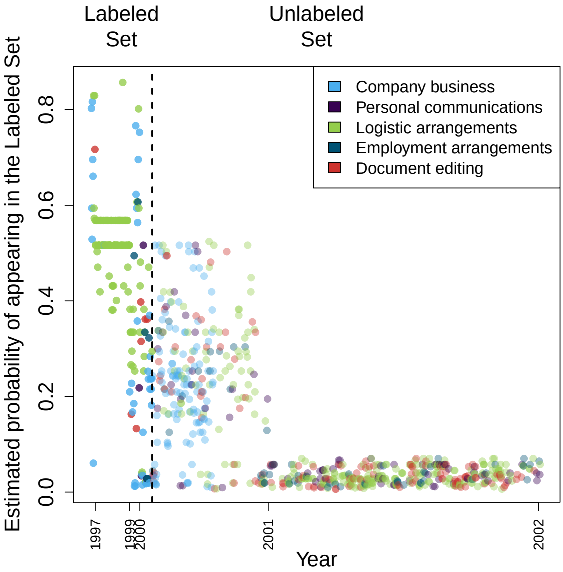

- Pscores vary considerably over time by category

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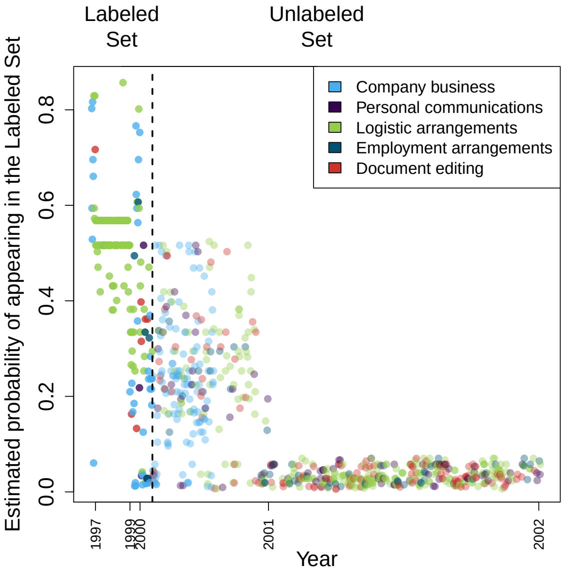

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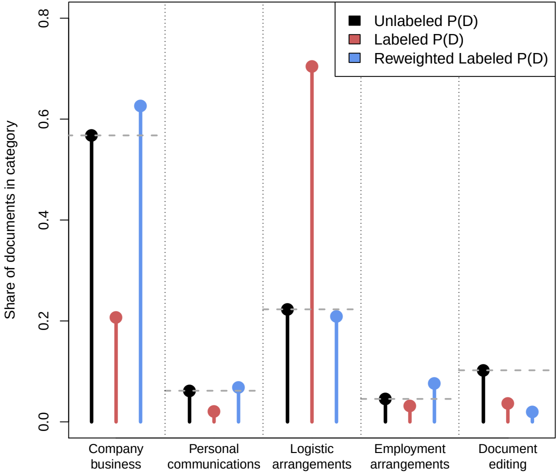

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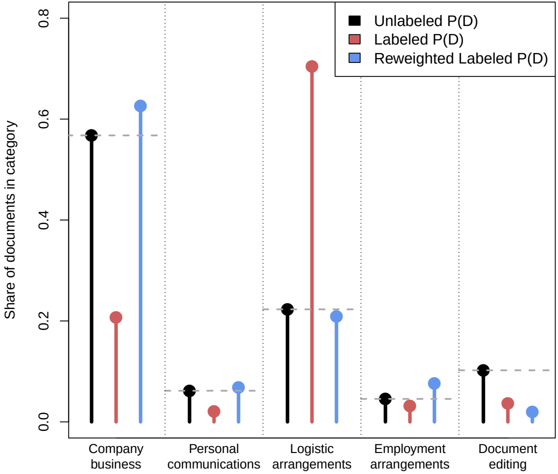

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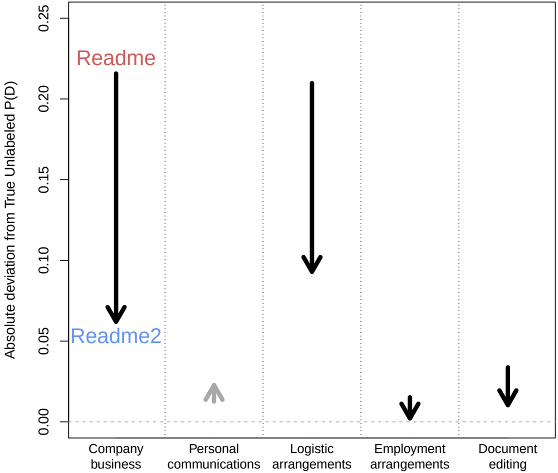

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- Weighted bootstrapping eliminates most $P(D)$ divergence
- Large reduction in estimation error

Validation in 72 Data Sets

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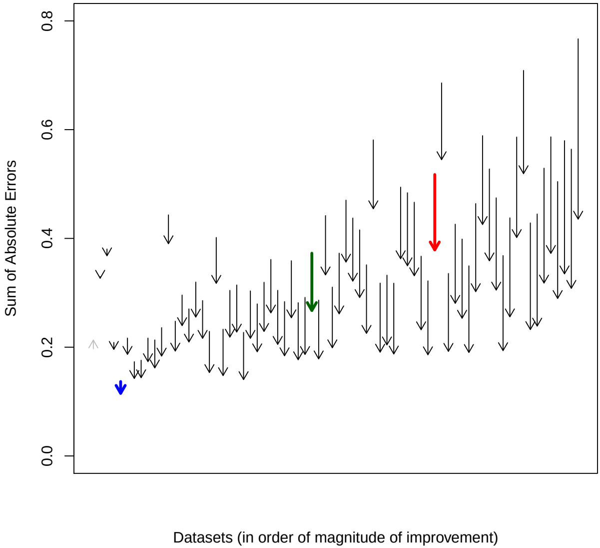

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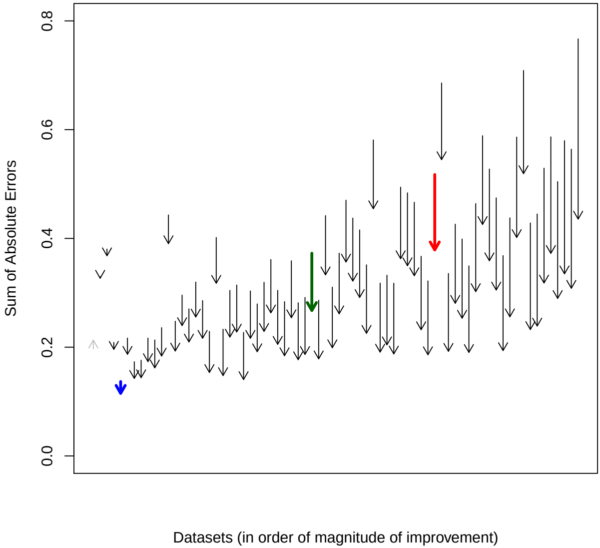

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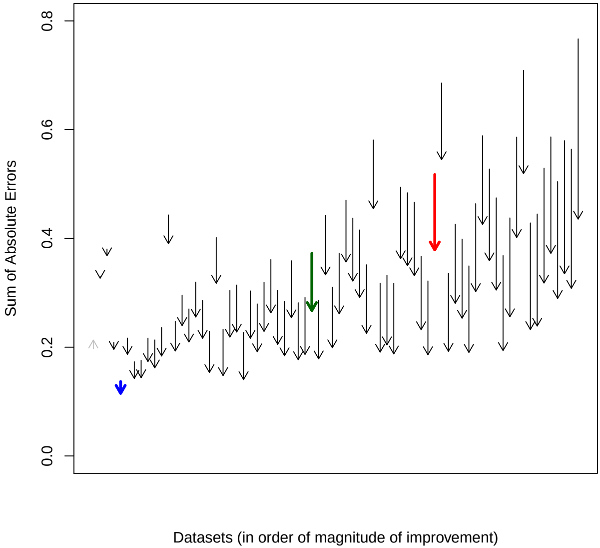

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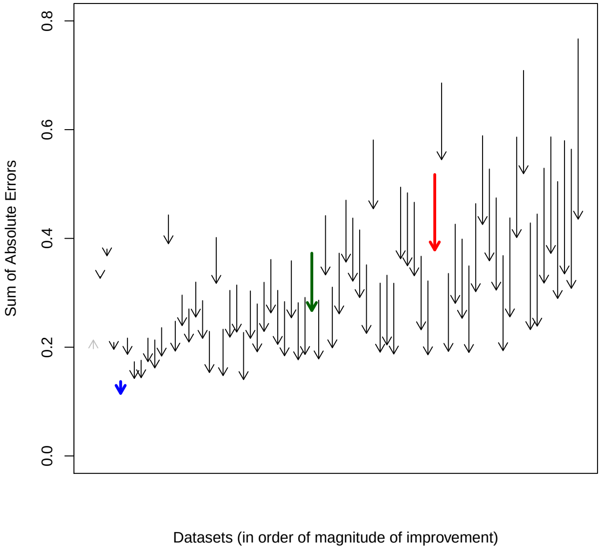

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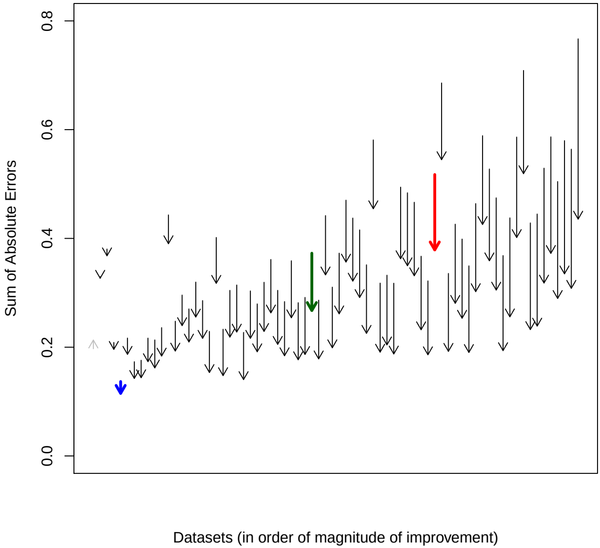

- Enron
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- Immigration blogs
- 69 Twitter data sets created by firms, governments, candidates, nonprofits, etc.

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For more information:
GaryKing.org