# Extracting Systematic Social Science Meaning from Text (& Cause-Specific Mortality Rates from Symptom Data)

Gary King
Harvard University

March 20, 2007

# References

- Daniel Hopkins and Gary King. "Extracting Systematic Social Science Meaning from Text"

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- Copies at `http://gking.harvard.edu`

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    - E.g., classify constituents' letters to a member of congress by policy area, or estimate proportion of letters in each policy area
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- Maximizing one goal won't get you the other: high classification accuracy can coexist with huge biases in category proportions

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- Scales to large numbers of documents
- Separately: propose correction for imperfect inter-coder reliability (i.e., should work better than hand coding everything if that were feasible)

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- "We are living through the largest expansion of expressive capability in the history of the human race"

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  - Little common internal structure (no inverted pyramid)

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  - Groups infinite possible posts into "only" $2^{3{,}672}$ distinct types

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- Word Stem Profile:

$$\mathbf{S}_i = \begin{cases} S_{i1} = 1 & \text{if ``awful'' is used, 0 if not} \\ S_{i2} = 1 & \text{if ``good'' is used, 0 if not} \\ \vdots & \vdots \\ S_{iK} = 1 & \text{if ``except'' is used, 0 if not} \end{cases}$$

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    - Even optimal classification with high % correctly classified can produce biased estimates of proportions

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- Estimates of category proportions: vastly improved

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- Use this equation to correct $P(\hat{D})$

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- Drop the intermediate $\hat{D}$ calculation, since $\hat{D} = f(\mathbf{S})$:

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- Simplify to an equivalent matrix expression:

$$P(\mathbf{S}) = P(\mathbf{S}|D) P(D)$$

The matrix expression again:

$$\underset{2^K\times 1}{P(\mathbf{S})} = \underset{2^K\times J}{P(\mathbf{S}|D)}\underset{J\times 1}{P(D)}$$

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Document category proportions (quantity of interest)

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Word stem profiles, by category (estimate in *labeled* set by tabulation)

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Alternative symbols (to emphasize the linear equation)

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$$\implies Y = X\beta \quad \implies \quad \beta = (X'X)^{-1}X'y$$

Solve for quantity of interest (with no error term)

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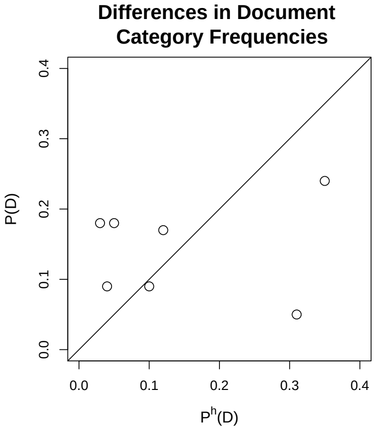
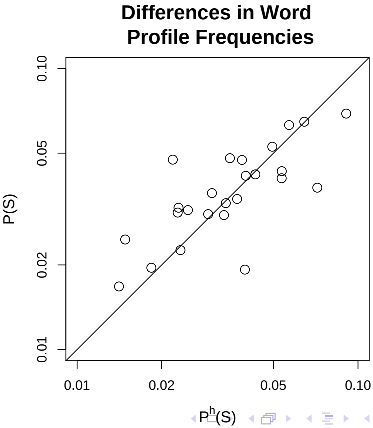
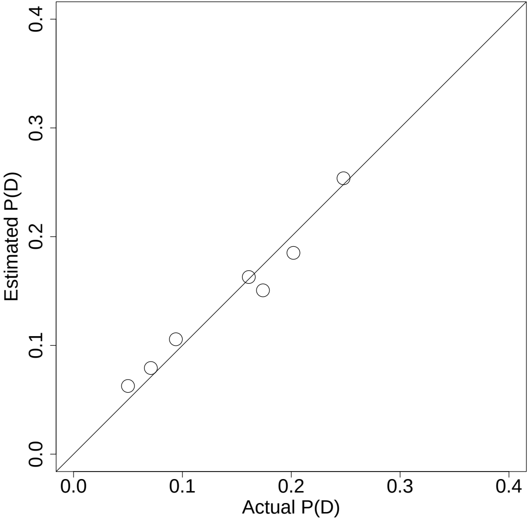
# A Simulation with a Nonrandom Hand-coded Sample

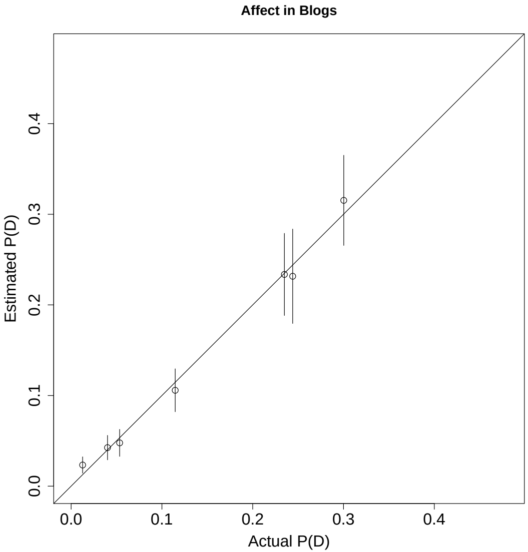


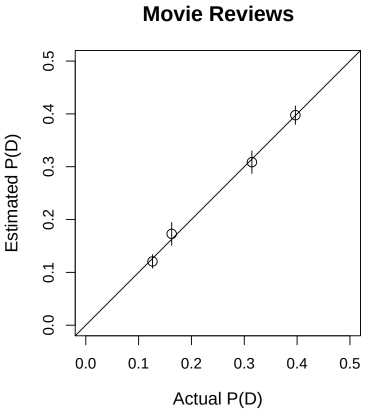
# A Simulation: Accurate Estimates

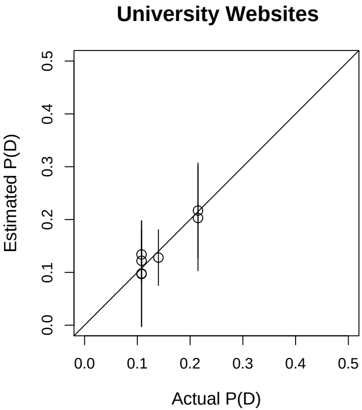


# Out of Sample Validation: Blogs

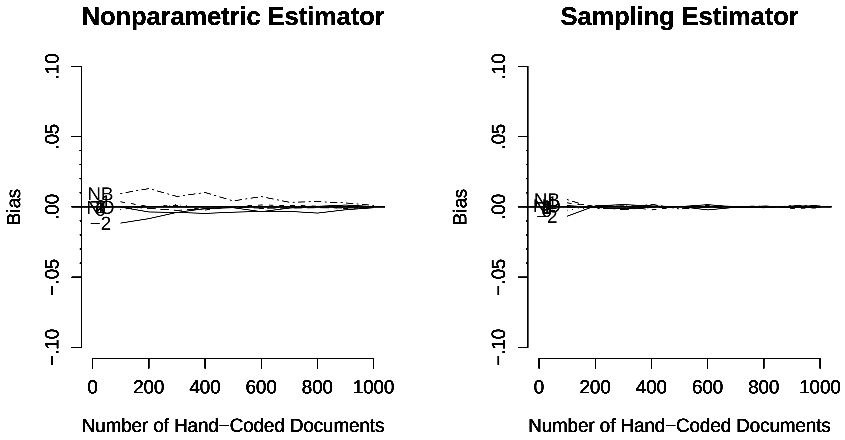


# Out of Sample Validation: Other Examples

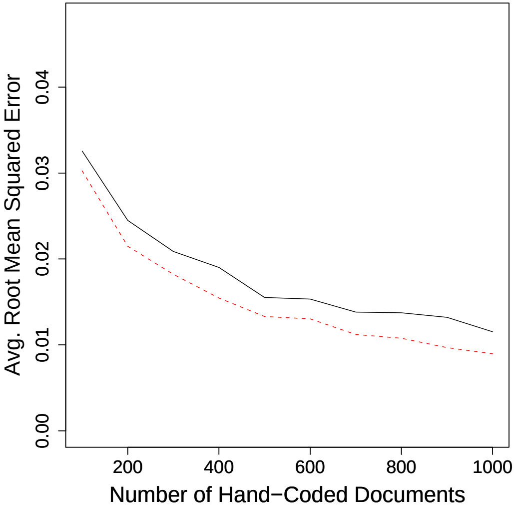


# Bias by Number of Hand Coded Documents



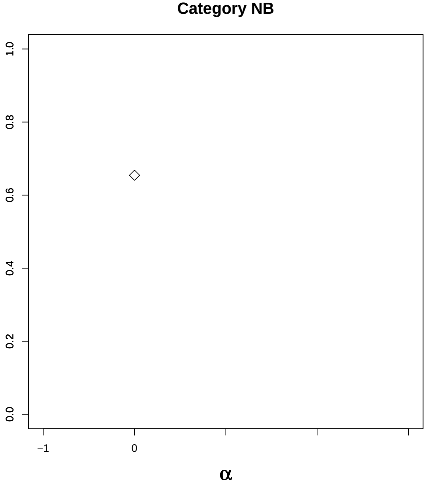
# Average RMSE by Number of Hand Coded Documents



# Misclassification Matrix for Blog Posts

| | -2 | -1 | 0 | 1 | 2 | NA | NB | $P(D_1)$ |
|---|---|---|---|---|---|---|---|---|
| -2 | **.70** | .10 | .01 | .01 | .00 | .02 | .16 | .28 |
| -1 | .33 | **.25** | .04 | .02 | .01 | .01 | .35 | .08 |
| 0 | .13 | .17 | **.13** | .11 | .05 | .02 | .40 | .02 |
| 1 | .07 | .06 | .08 | **.20** | .25 | .01 | .34 | .03 |
| 2 | .03 | .03 | .03 | .22 | **.43** | .01 | .25 | .03 |
| NA | .04 | .01 | .00 | .00 | .00 | **.81** | .14 | .12 |
| NB | .10 | .07 | .02 | .02 | .02 | .04 | **.75** | .45 |

# SIMEX Analysis of Not a Blog Category



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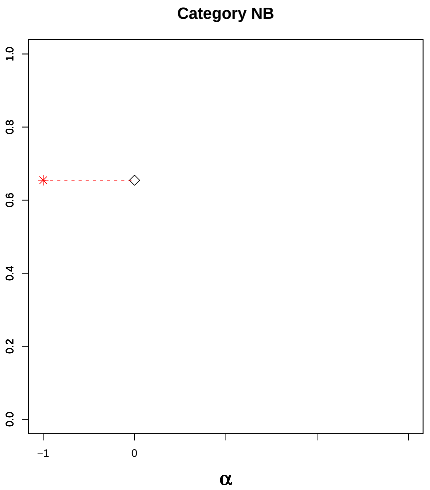

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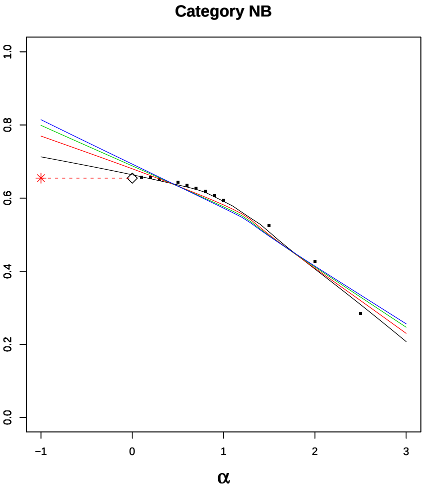
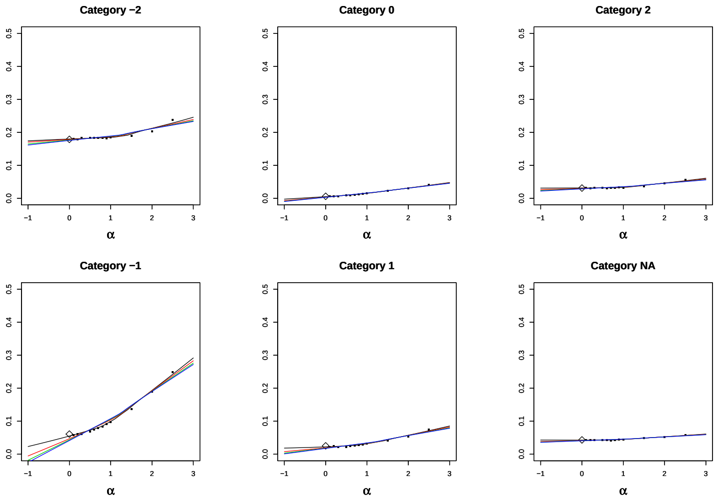


# SIMEX Analysis of Other Categories



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- Use additional hand coding to verify assumptions

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  - Find deaths with medically certified causes from a local hospital, trace caregivers to their homes, ask the same symptom questions, and statistically classify deaths in population (model-dependent)

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- ~~Document Category~~, Cause of Death,

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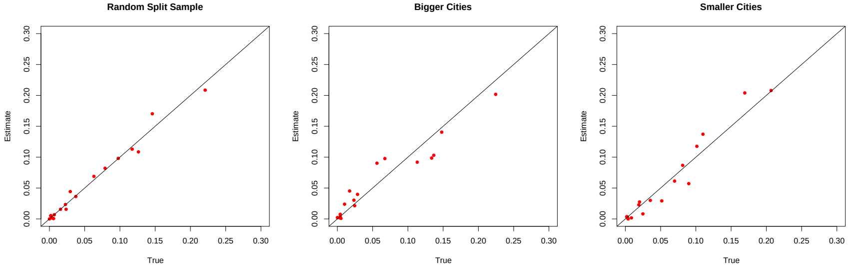
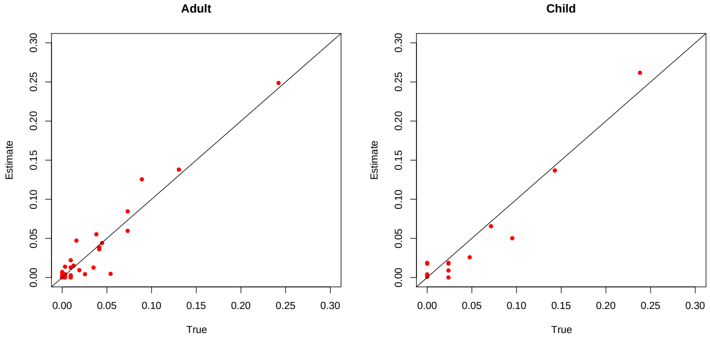
- ~~Word Stem Profile~~, Symptoms:

$$\mathbf{S}_i = \begin{cases} S_{i1} = 1 & \text{if ``breathing difficulties'', 0 if not} \\ S_{i2} = 1 & \text{if ``stomach ache'', 0 if not} \\ \vdots & \vdots \\ S_{iK} = 1 & \text{if ``diarrhea'', 0 if not} \end{cases}$$

# Validation in China



# Validation in Tanzania



# For more information

http://GKing.Harvard.edu