

# How to Read 100 Million Blogs (& Classify Deaths Without Physicians)

Gary King  
Harvard University

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- 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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  - High classification accuracy  $\Rightarrow$  unbiased category proportions

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- (Public opinion  $\nRightarrow$  surveys)

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|--------------|----------------------|
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| -1           | negative             |
| 0            | neutral              |
| 1            | positive             |
| 2            | extremely positive   |
| NA           | no opinion expressed |
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  - Informal language: “**my crunchy gf thinks dubya hid the wmd's, :)**!”
  - Little common internal structure (no inverted pyramid)

# The Conversation about John Kerry's Botched Joke

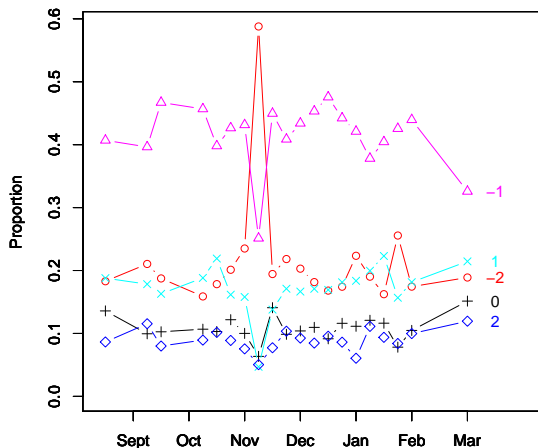
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**Affect Towards John Kerry**



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

# Notation

- Document Category

$$D_i = \left\{ \begin{array}{ll} -2 & \text{extremely negative} \\ -1 & \text{negative} \\ 0 & \text{neutral} \\ 1 & \text{positive} \\ 2 & \text{extremely positive} \\ \text{NA} & \text{no opinion expressed} \\ \text{NB} & \text{not a blog} \end{array} \right.$$

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- Word Stem Profile:

$$S_i = \begin{cases} S_{i1} = 1 & \text{if "awful" is used, 0 if not} \\ S_{i2} = 1 & \text{if "good" is used, 0 if not} \\ \vdots & \vdots \\ S_{iK} = 1 & \text{if "except" is used, 0 if not} \end{cases}$$

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- Social Science: **proportions** in each category

$$P(D) = \begin{pmatrix} P(D = -2) \\ P(D = -1) \\ P(D = 0) \\ P(D = 1) \\ P(D = 2) \\ P(D = \text{NA}) \\ P(D = \text{NB}) \end{pmatrix}$$

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- Bias even with optimal classification and high % correctly classified

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- (still requires random samples, individual classification, etc)

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

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- Simplify to an equivalent matrix expression:

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

# Estimation

The matrix expression again:

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Document category proportions (quantity of interest)

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$$\begin{matrix} P(\mathbf{S}) \\ 2^K \times 1 \end{matrix} = \begin{matrix} P(\mathbf{S}|D) & P(D) \\ 2^K \times J & J \times 1 \end{matrix}$$

Word stem profile proportions (estimate in unlabeled set by tabulation)

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

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$$\begin{matrix} 2^K \times 1 & 2^K \times J & J \times 1 \end{matrix}$$
$$\implies \mathbf{Y} = \mathbf{X}\beta$$

Alternative symbols (to emphasize the linear equation)

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Solve for quantity of interest (with no error term)

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  - Use constrained LS to constrain  $P(D)$  to simplex

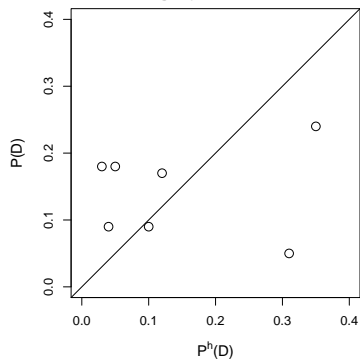
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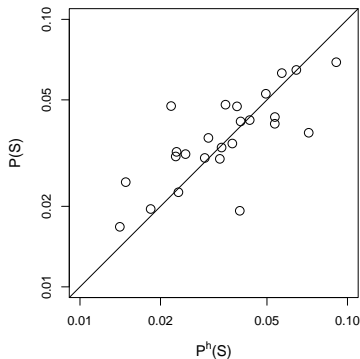
- Technical estimation issues:
  - $2^K$  is enormous, far larger than any existing computer
  - $P(\mathbf{S})$  and  $P(\mathbf{S}|D)$  will be too sparse
  - Elements of  $P(D)$  must be between 0 and 1 and sum to 1
- Solutions
  - Use subsets of  $\mathbf{S}$ ; average results
  - Equivalent to kernel density smoothing of sparse categorical data
  - Use constrained LS to constrain  $P(D)$  to simplex
- Uncertainty estimates by bootstrapping

# A Nonrandom Hand-coded Sample

**Differences in Document  
Category Frequencies**

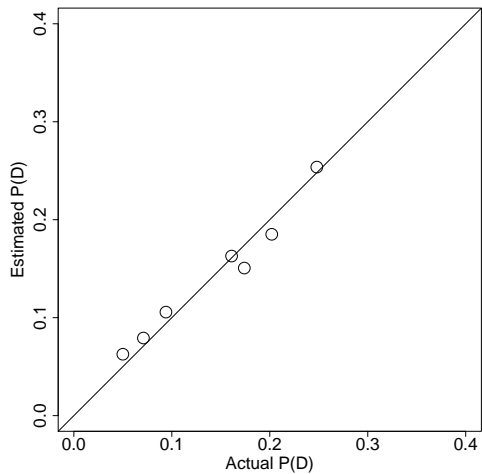


**Differences in Word  
Profile Frequencies**

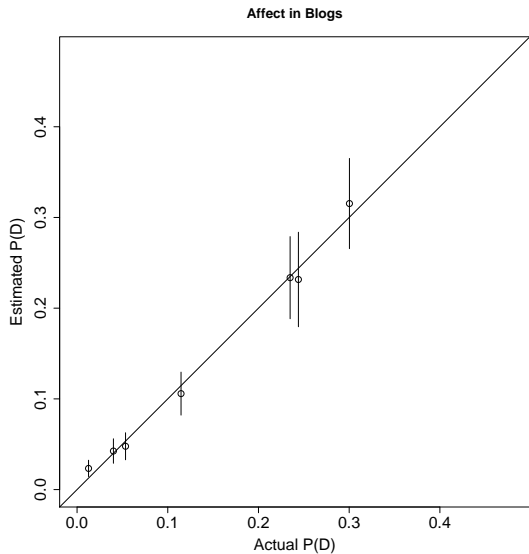


All existing methods would fail with these data.

# Accurate Estimates

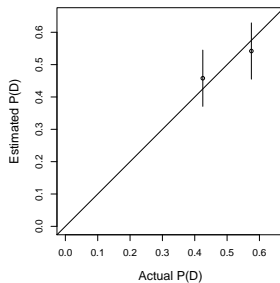


# Out of Sample Validation: Blogs

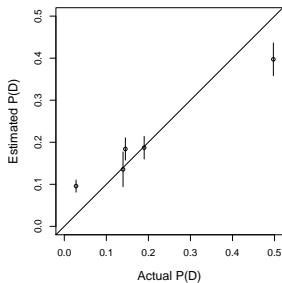


# Out of Sample Validation: Other Examples

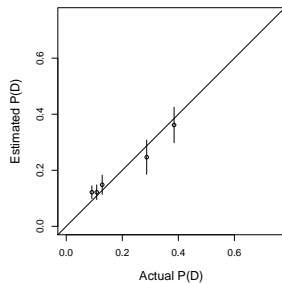
### Congressional Speeches



### Immigration Editorials



### Enron Emails



# Verbal Autopsy Methods

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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, low accuracy)

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- Document-Category, Cause of Death,

$$D_i = \begin{cases} 1 & \text{if bladder cancer} \\ 2 & \text{if cardiovascular disease} \\ 3 & \text{if transportation accident} \\ \vdots & \vdots \\ J & \text{if infectious respiratory} \end{cases}$$

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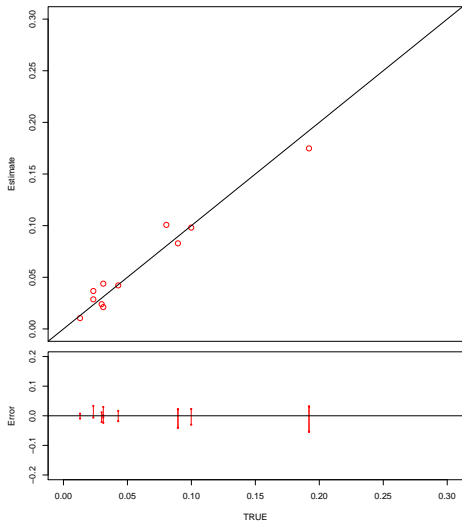
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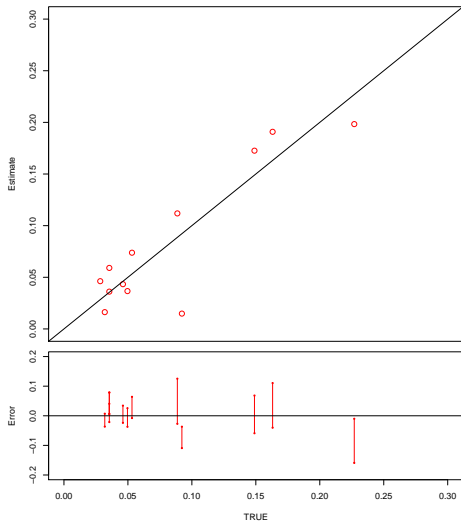
- Apply the ~~same~~ methods

# Validation in Tanzania

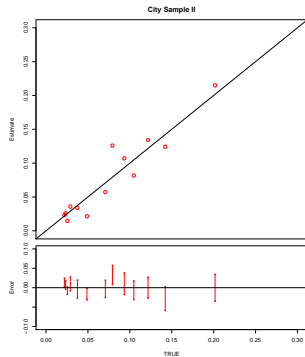
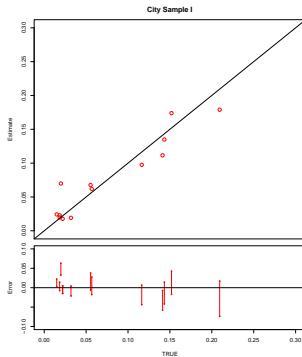
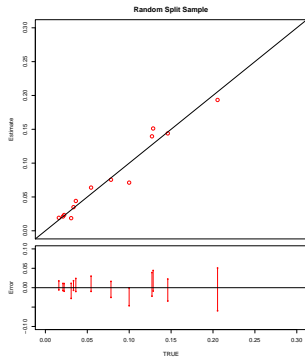
Random Split Sample



Community Sample



# Validation in China



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The goal: individual classification

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Output from our estimator (described above)

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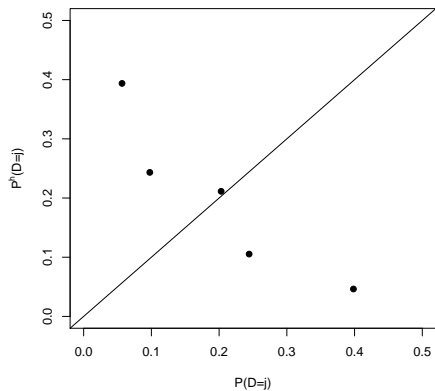
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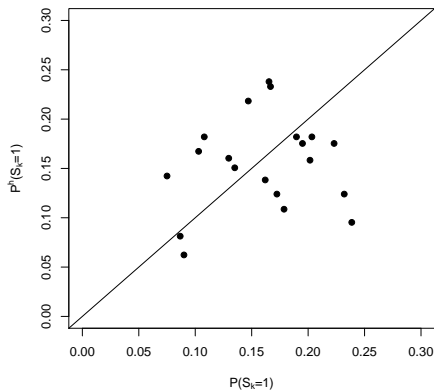
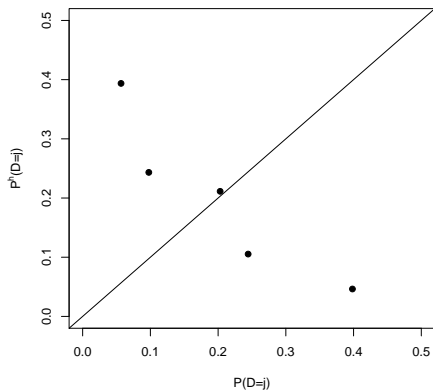
Nonparametric estimate from unlabeled (community) set

# Classification with Less Restrictive Assumptions

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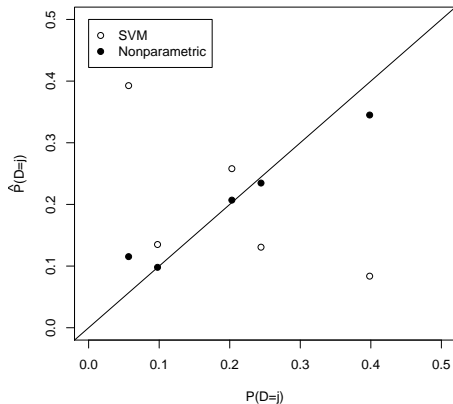


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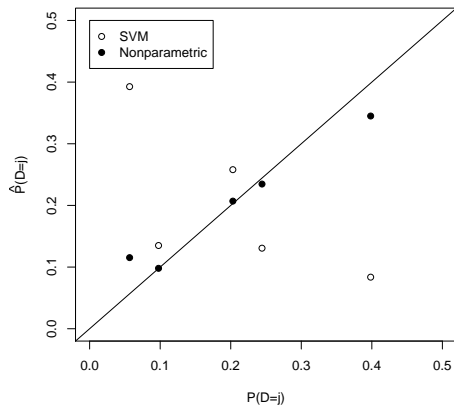


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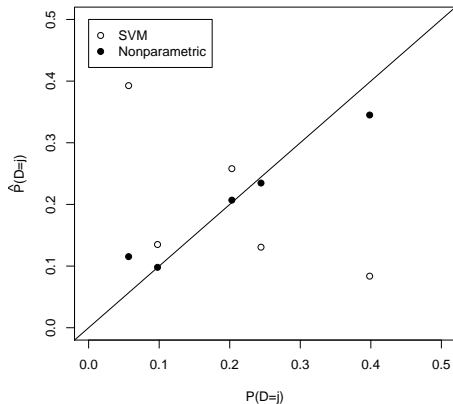


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Percent correctly classified:

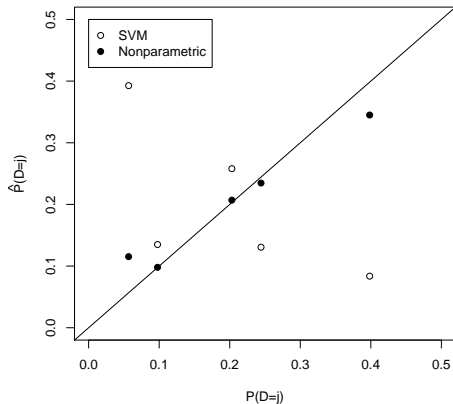
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Percent correctly classified:

- SVM (best existing classifier): 40.5%
- Our nonparametric approach: 59.8%

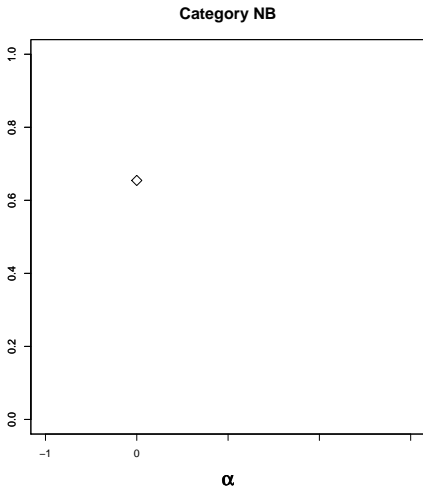
For more information

<http://GKing.Harvard.edu>

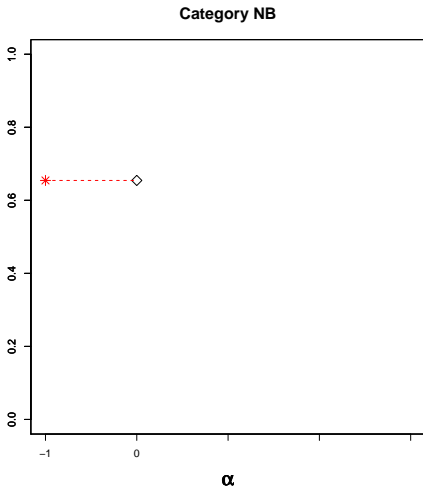
# Misclassification Matrix for Blog Posts

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

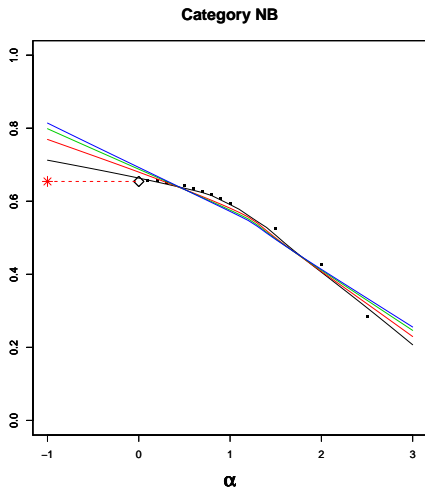
# SIMEX Analysis of “Not a Blog” Category



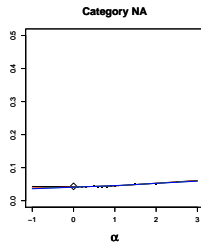
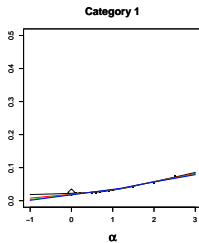
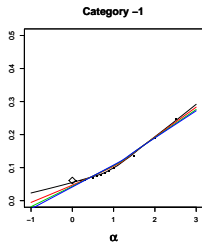
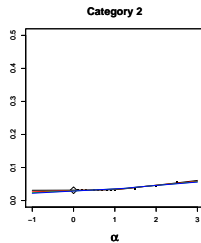
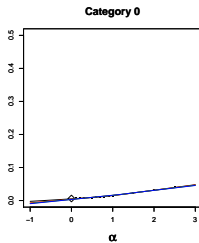
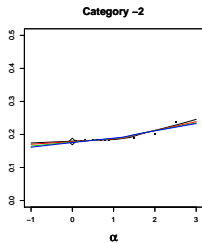
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# SIMEX Analysis of Other Categories



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- Use additional hand coding to verify assumptions