

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

Gary King
Harvard University

January 2, 2008

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

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- Gary King and Ying Lu. “Verbal Autopsy Methods with Multiple Causes of Death,” forthcoming, *Statistical Science*

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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 |
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 - Little common internal structure (no inverted pyramid)

The Conversation about John Kerry's Botched Joke

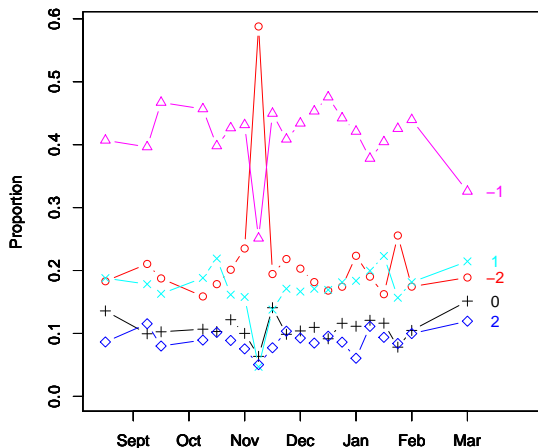
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Affect Towards John Kerry



2006-2007

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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:

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

Quantities of Interest

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$$D_1, D_2, \dots, D_L$$

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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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$$\implies \mathbf{Y} = \mathbf{X}\beta$$

Alternative symbols (to emphasize the linear equation)

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Solve for quantity of interest (with no error term)

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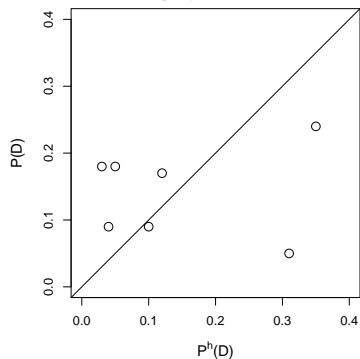
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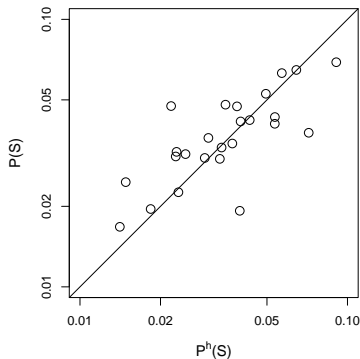
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- Uncertainty estimates by bootstrapping

A Nonrandom Hand-coded Sample

**Differences in Document
Category Frequencies**

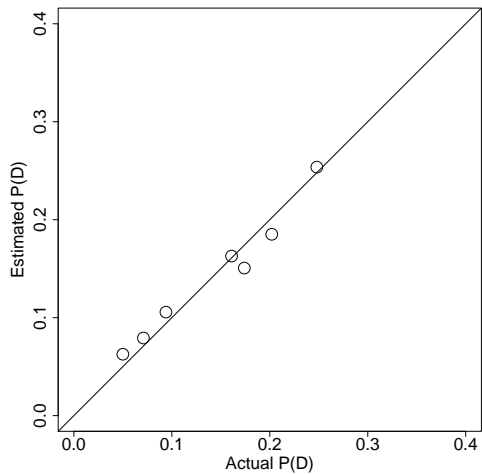


**Differences in Word
Profile Frequencies**

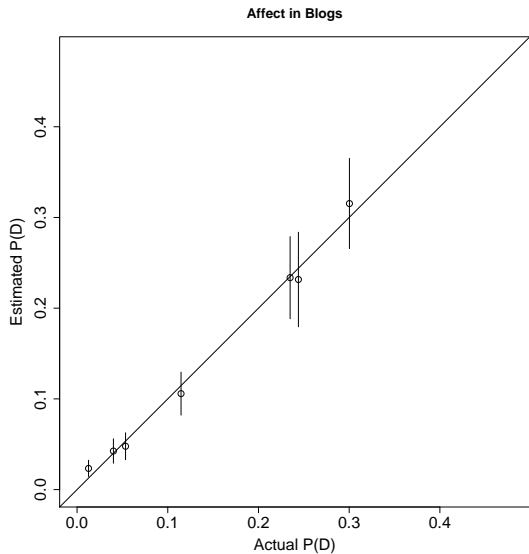


All existing methods would fail with these data.

Accurate Estimates

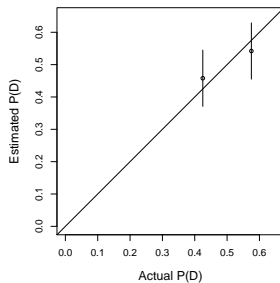


Out of Sample Validation: Blogs

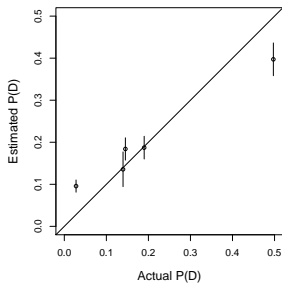


Out of Sample Validation: Other Examples

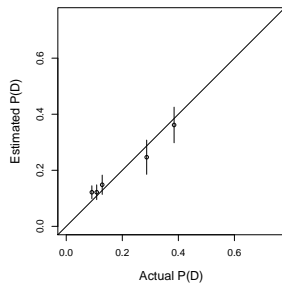
Congressional Speeches



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)

An Alternative Approach

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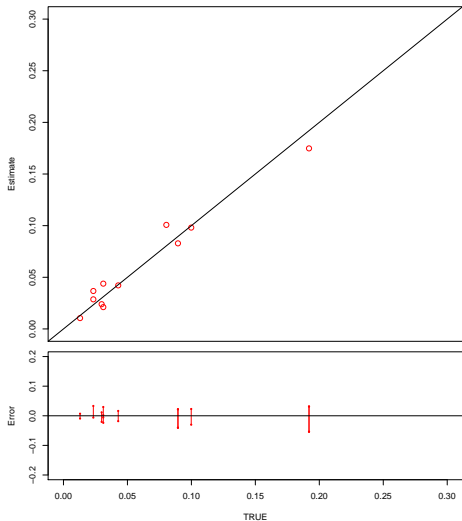
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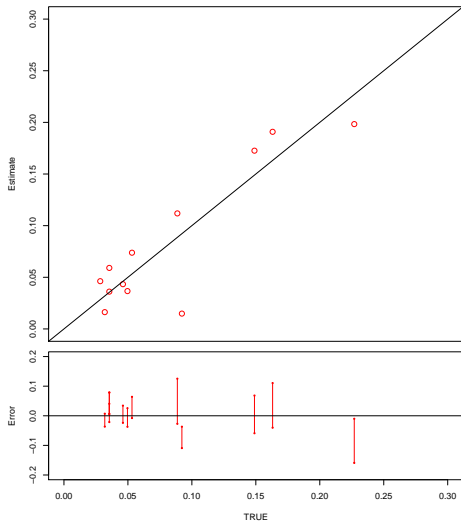
- Apply the **same** methods

Validation in Tanzania

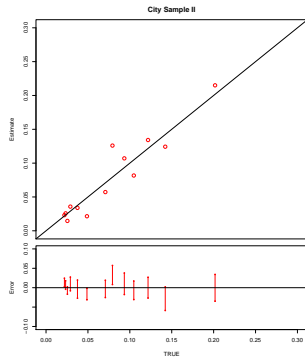
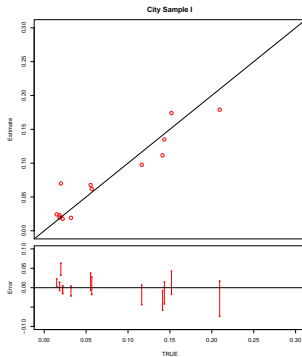
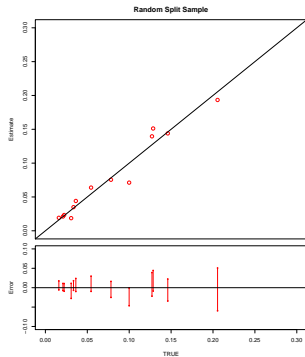
Random Split Sample



Community Sample



Validation in China



Implications for an Individual Classifier

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Output from our estimator (described above)

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Nonparametric estimate from labeled (hand coded) set

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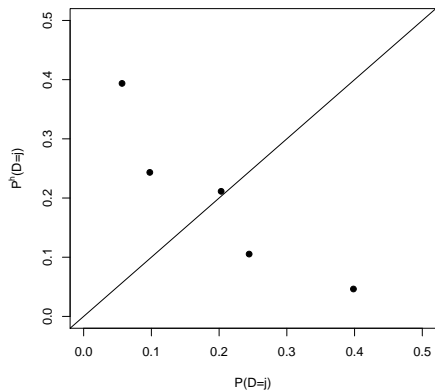
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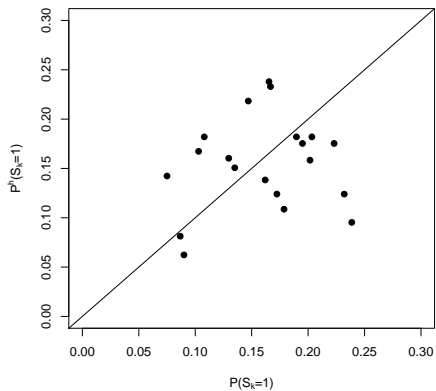
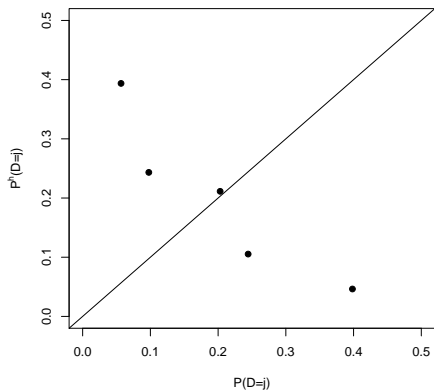
Nonparametric estimate from unlabeled (community) set

Classification with Less Restrictive Assumptions

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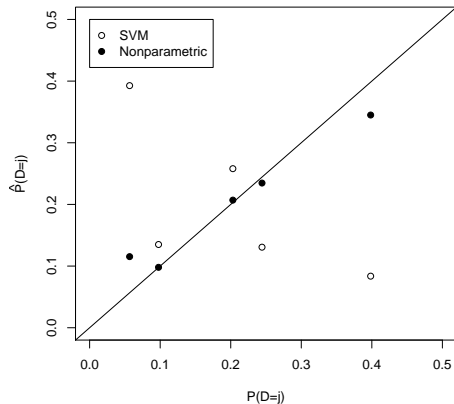


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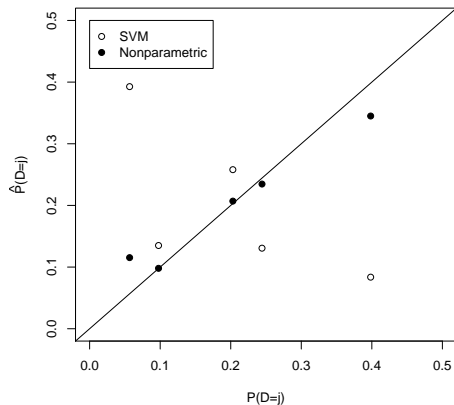


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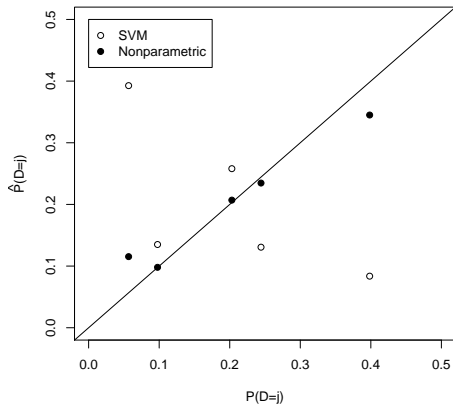


Classification with Less Restrictive Assumptions



Percent correctly classified:

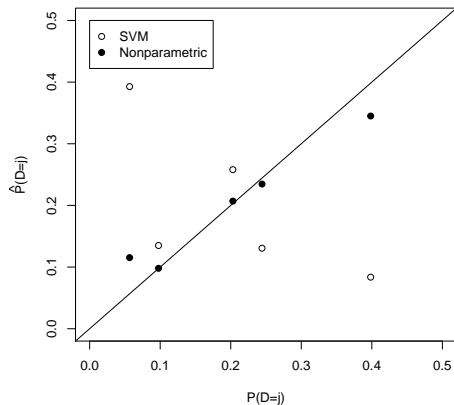
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Classification with Less Restrictive Assumptions



Percent correctly classified:

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- Our nonparametric approach: 59.8%

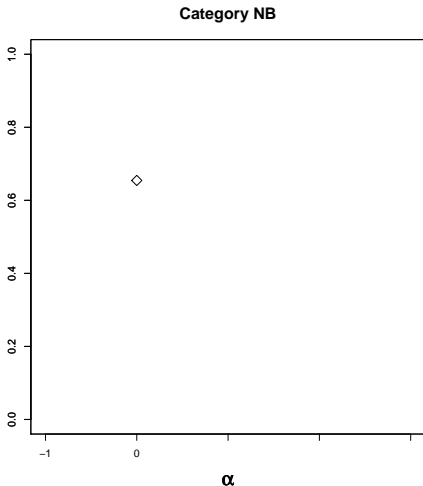
For more information

<http://GKing.Harvard.edu>

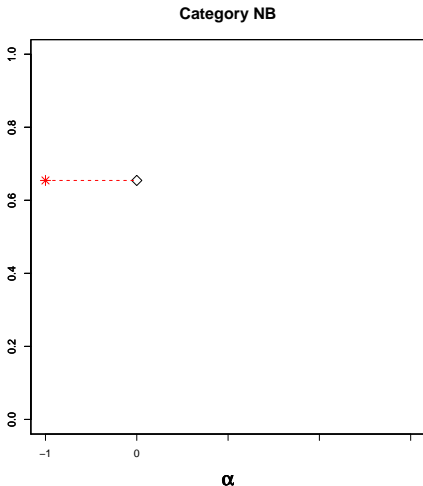
Misclassification Matrix for Blog Posts

	-2	-1	0	1	2	NA	NB	$P(D_1)$
-2	.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

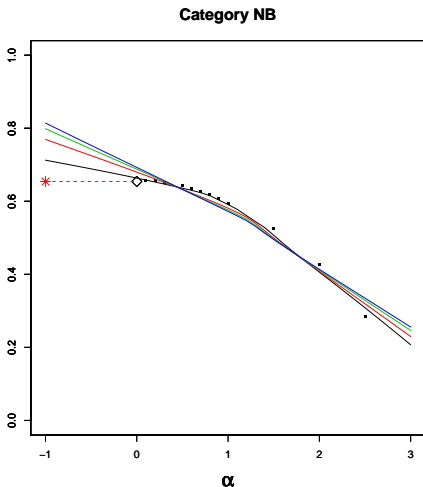
SIMEX Analysis of “Not a Blog” Category



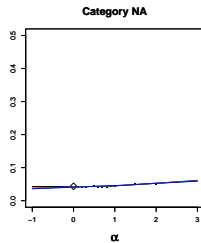
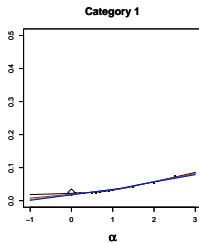
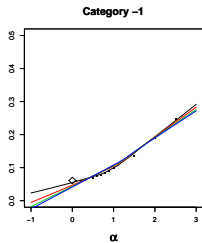
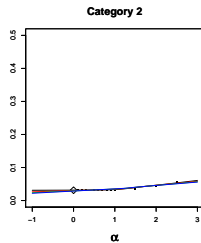
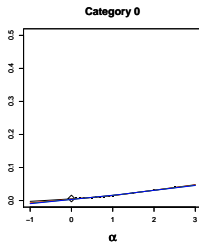
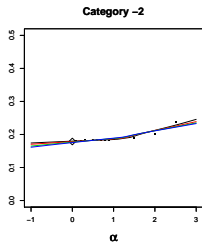
SIMEX Analysis of “Not a Blog” Category



SIMEX Analysis of “Not a Blog” Category



SIMEX Analysis of Other Categories



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- Use additional hand coding to verify assumptions