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

Gary King
Harvard University

January 2, 2008

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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  - High classification accuracy $\not\Rightarrow$ unbiased category proportions

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- (Public opinion $\not\Rightarrow$ surveys)

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  - Little common internal structure (no inverted pyramid)

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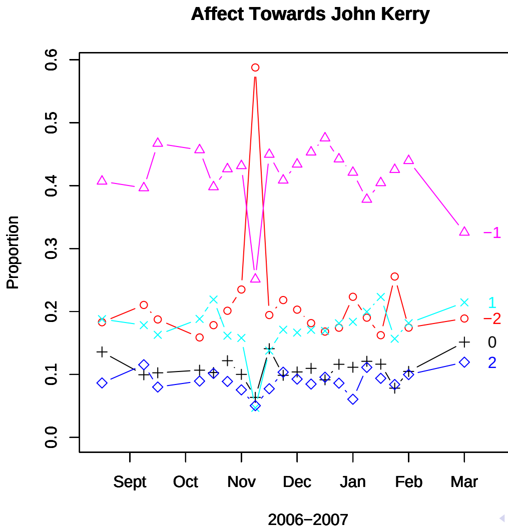

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  - Groups infinite possible posts into "only" $2^{3,672}$ distinct types

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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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- Social Science: proportions in each category

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

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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:

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

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The matrix expression again:

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Document category proportions (quantity of interest)

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Alternative symbols (to emphasize the linear equation)

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Solve for quantity of interest (with no error term)

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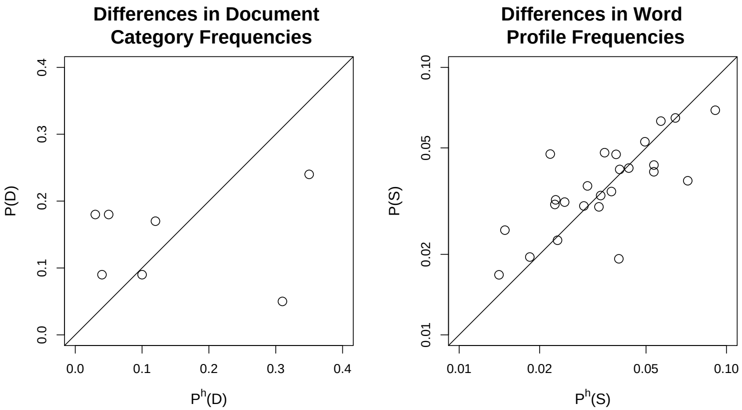
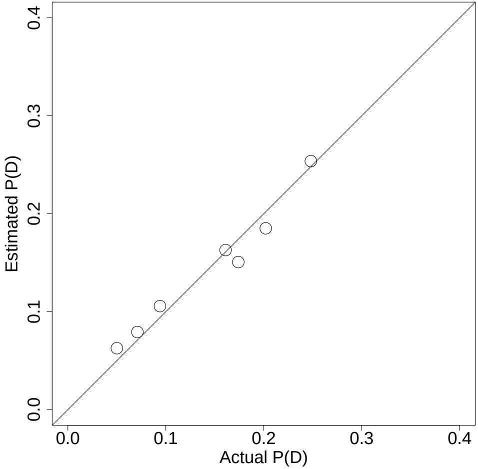
- Uncertainty estimates by bootstrapping

A Nonrandom Hand-coded Sample

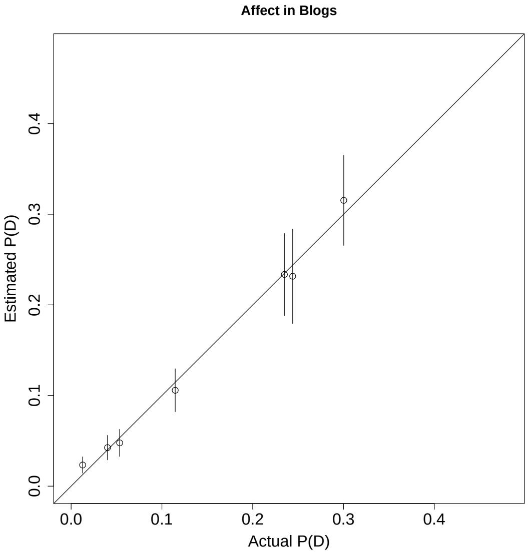


All existing methods would fail with these data.

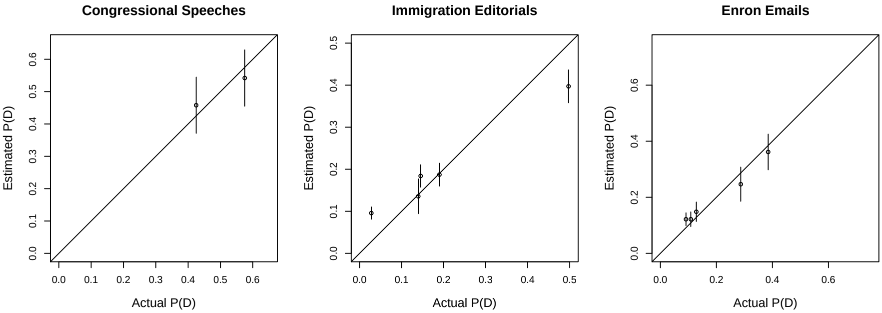
Accurate Estimates



Out of Sample Validation: Blogs



Out of Sample Validation: Other Examples



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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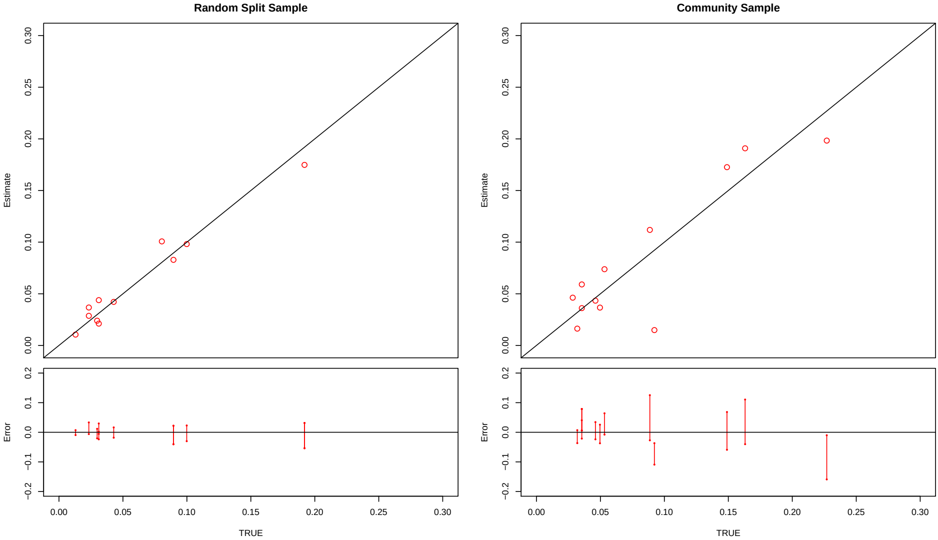
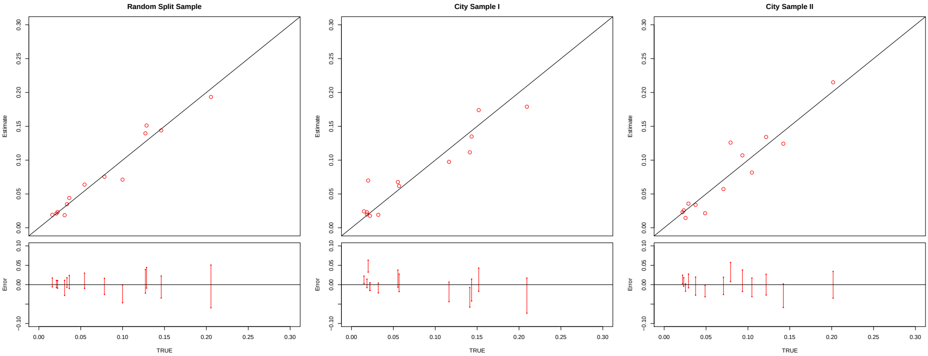
- Apply the same methods

Validation in Tanzania



Validation in China



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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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Nonparametric estimate from unlabeled (community) set

Classification with Less Restrictive Assumptions

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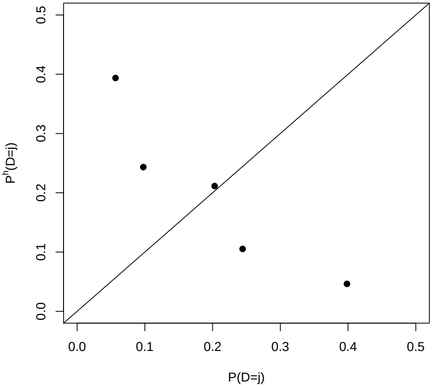

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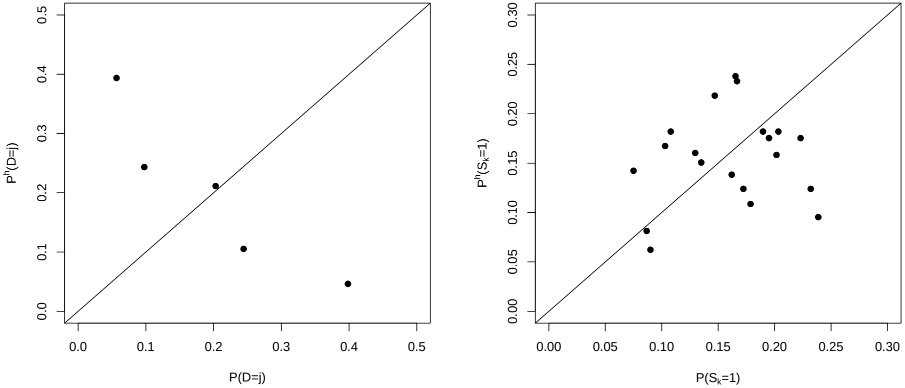

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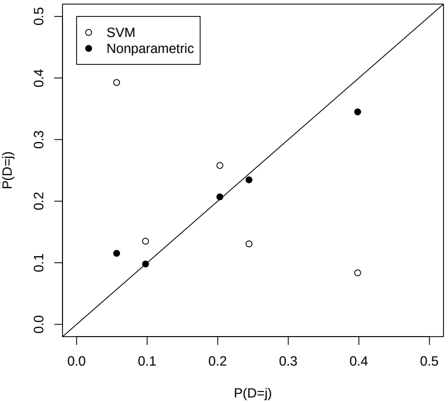

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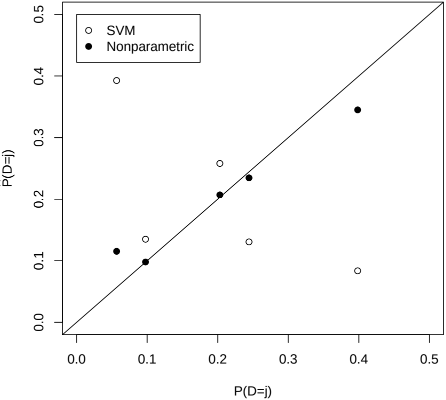
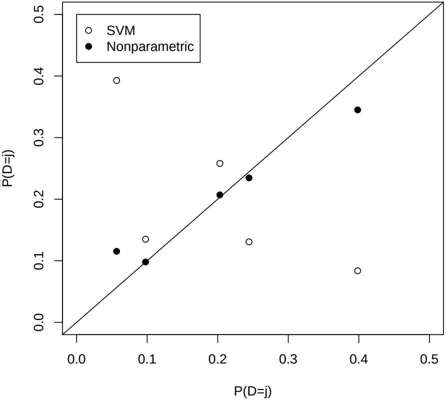


Percent correctly classified:

Classification with Less Restrictive Assumptions



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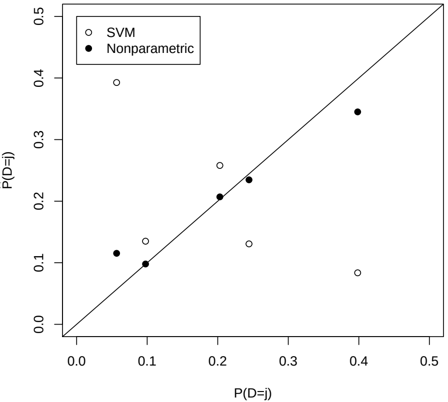

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- Our nonparametric approach: 59.8%

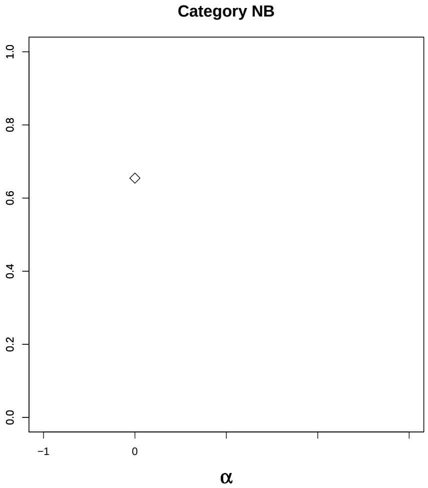
For more information

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



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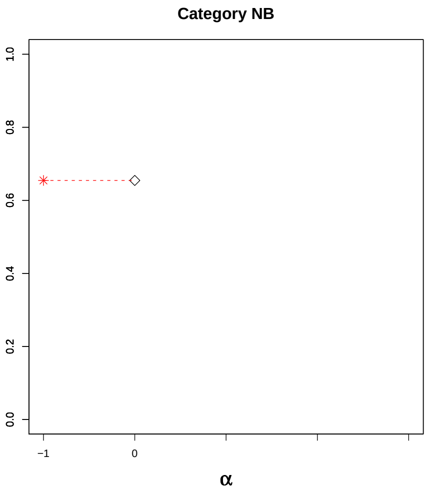

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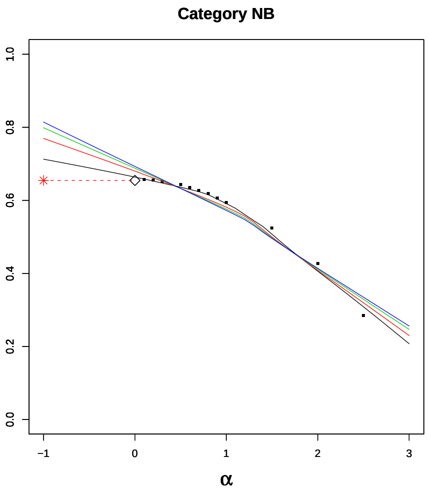
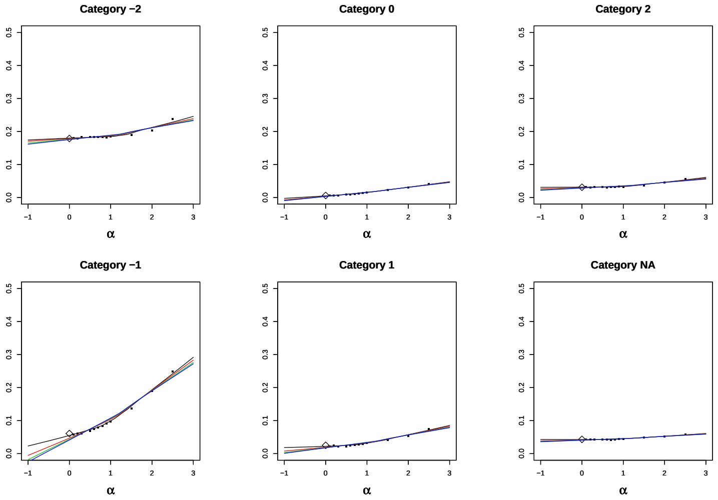


SIMEX Analysis of Other Categories



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- Use additional hand coding to verify assumptions