Advanced Quantitative Research Methodology, Lecture Notes: Text Analysis: Supervised Learning

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References

- Daniel Hopkins and Gary King. "Extracting Systematic Social Science Meaning from Text" *American Journal of Political Science*,

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  crimson hexagon

- Gary King and Ying Lu. "Verbal Autopsy Methods with Multiple Causes of Death," *Statistical Science*
- Copies at `http://gking.harvard.edu`

Inputs and Target Quantities of Interest

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  - $\Rightarrow$ Different methods optimize estimation of the different quantities

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  - Little common internal structure (no inverted pyramid)

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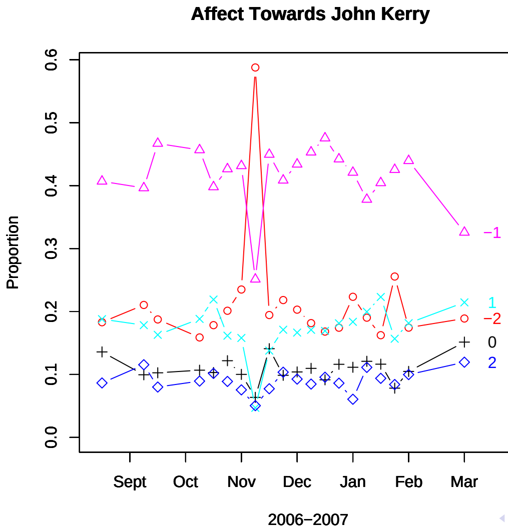

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  - Groups infinite possible posts into "only" $2^{3{,}672}$ distinct types
- More sophisticated summaries: we've used, but they're not necessary

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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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- Computer Science: individual document classifications

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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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(Levy and Kass, 1970)

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- Use this equation to correct $P(\hat{D}=1)$

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

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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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  - Equivalent to kernel density smoothing of sparse categorical data
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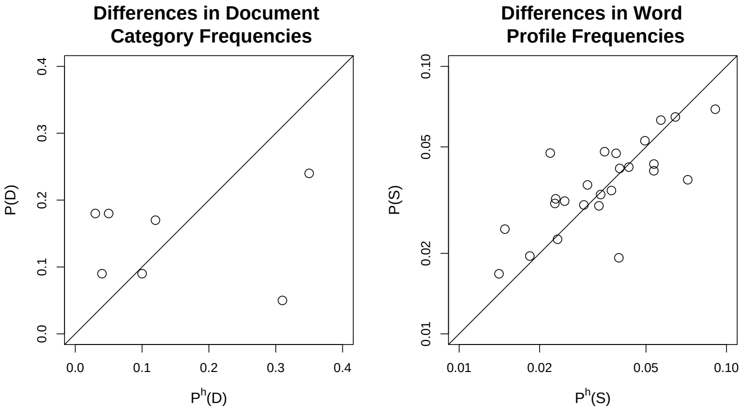
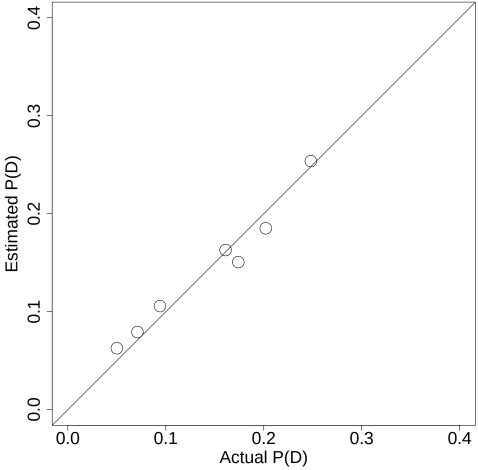
- Result: fast, accurate, with very little (human) tuning required

A Nonrandom Hand-coded Sample

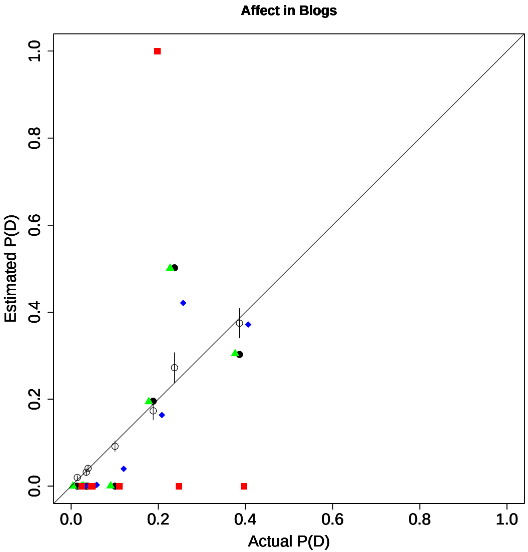


All existing methods would fail with these data.

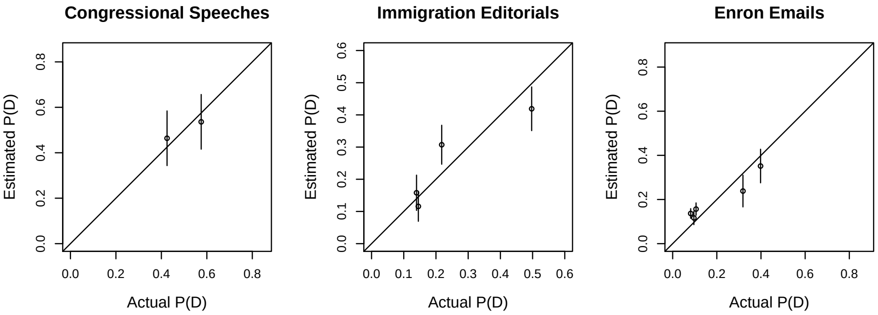
Accurate Estimates



Out-of-sample Comparison: 60 Seconds vs. 8.7 Days



Out of Sample Validation: Other Examples



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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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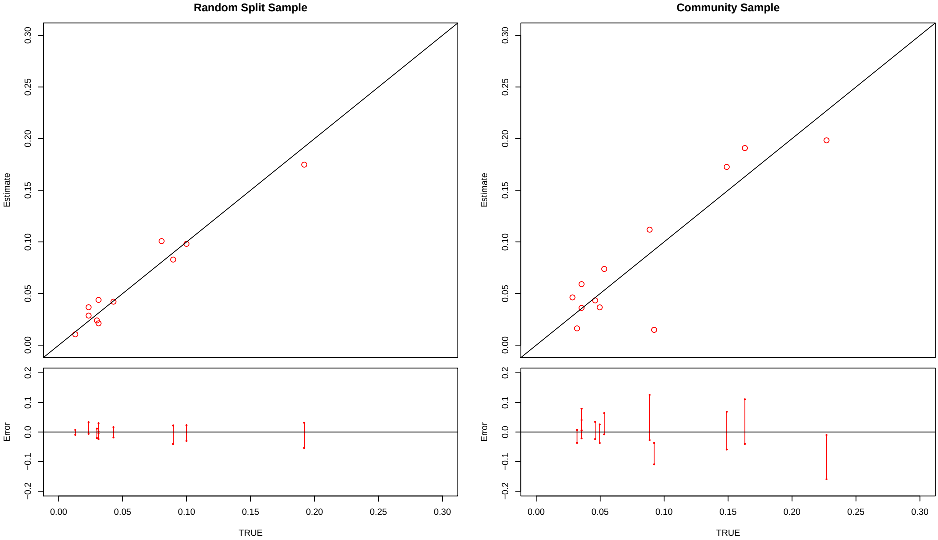
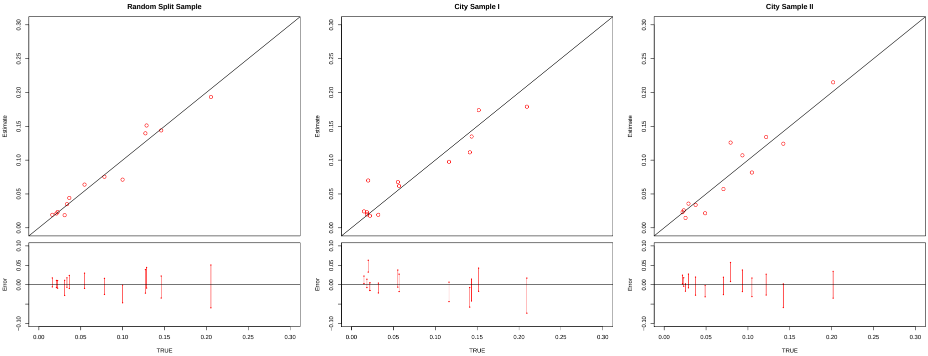
- Apply the same methods

Validation in Tanzania



Validation in China



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The goal: individual classification

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Output from our estimator (described above)

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Nonparametric estimate from unlabeled set (no assumption)

Classification with Less Restrictive Assumptions

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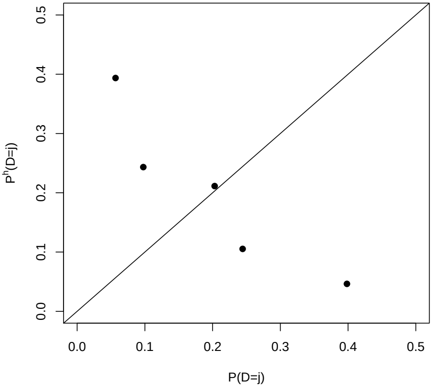

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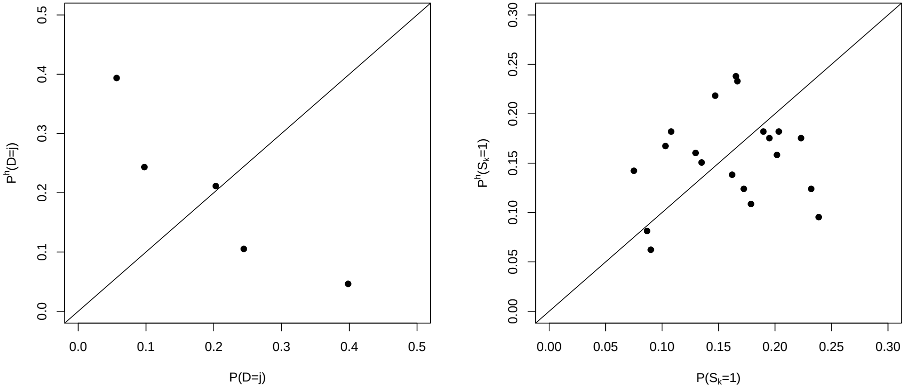

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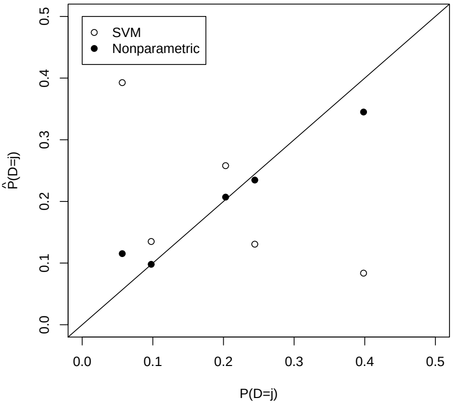

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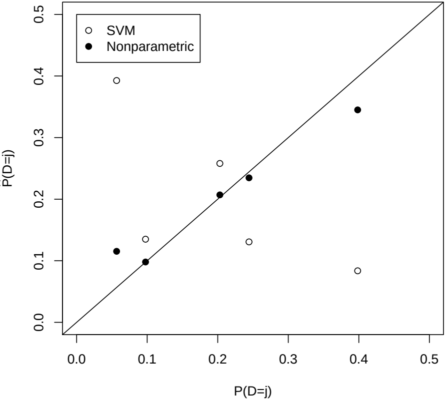
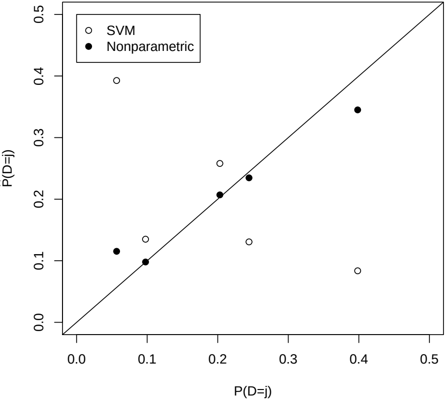


Percent correctly classified:



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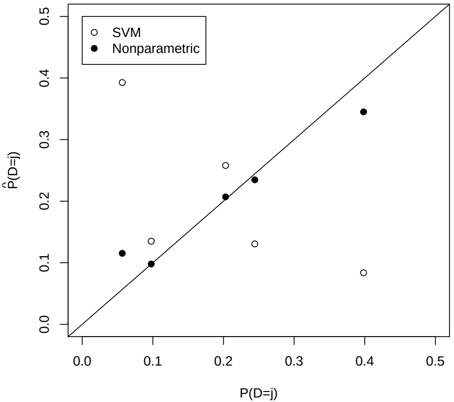


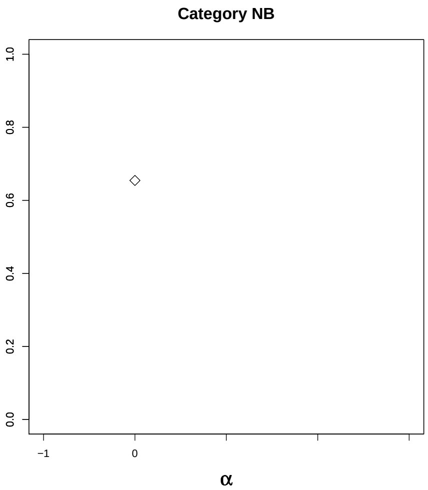
Percent correctly classified:

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

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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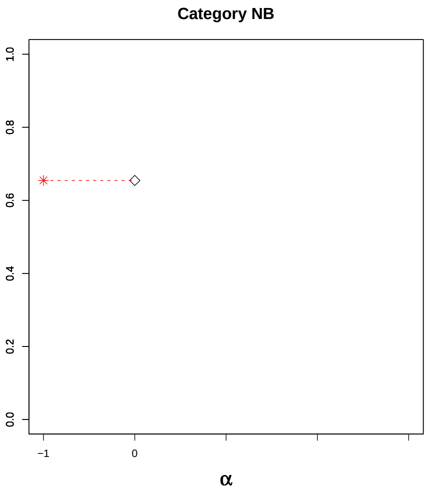

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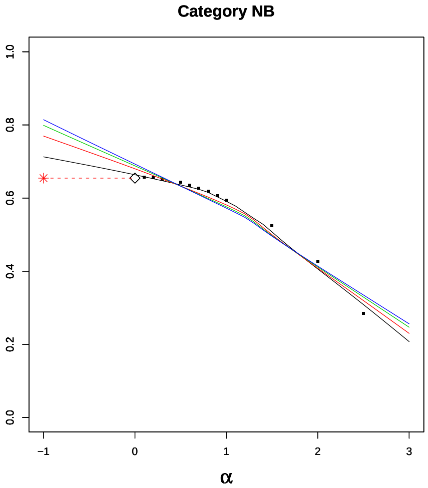
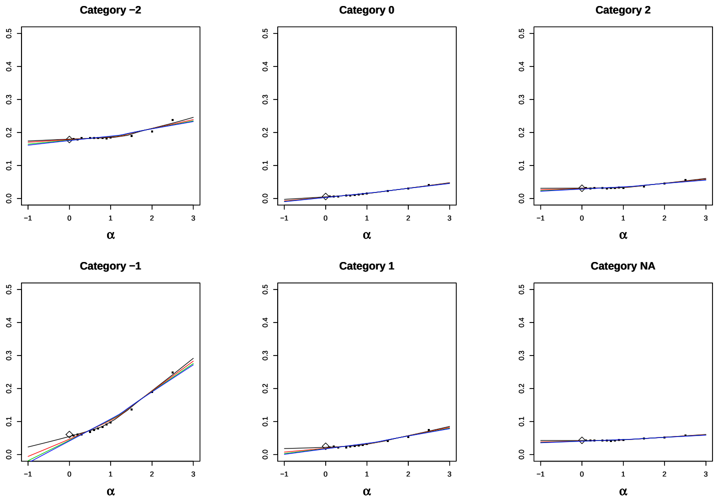


SIMEX Analysis of Other Categories



For more information

http://GKing.Harvard.edu