Prediction- and Recall-Defined Online Complexity-Metrics

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Motivation

Observation isn't explanation

Current metrics of processing complexity (eg. surprisal variants [Hale, 2001, Levy, 2008, Roark et al., 2009] and UID [Levy and Jaeger, 2007]) are based on observation of complexity without providing an explanation for why it arises.

Goal: An Explanation

If a model based on current theories of the structure of domain-general working memory can predict processing complexity above the predictions of surprisal, it may provide a rationale for *why* humans have the language processing difficulties they do.

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- Processing difficulty may stem from incorrect predictions
- A model of prediction may predict processing difficulty

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Assumption: Parallel processing (competing hypotheses)

Cueing Predictions

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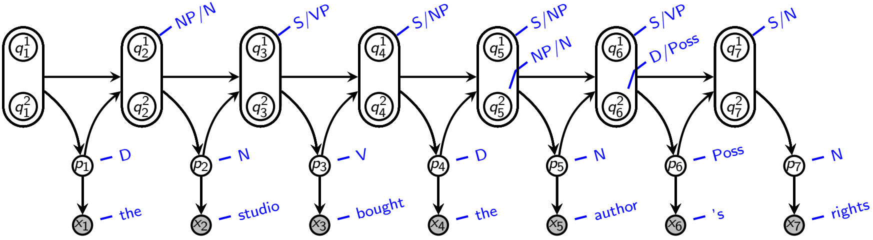
- Memory research indicates that humans have different types of difficulty with different kinds of recall (short-term vs long-term)
- Sequential vs temporal cueing [Sederberg et al., 2008]
- Naturally lends itself to center-embeddeding

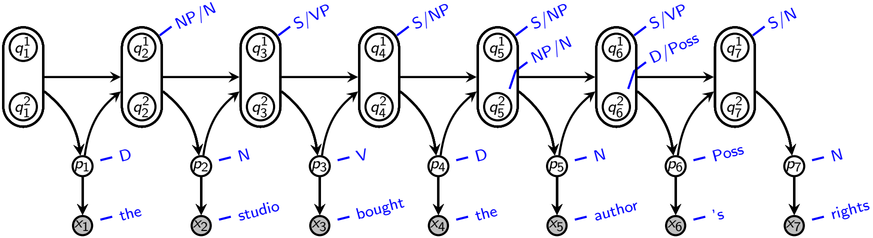
Cueing in Parsing

- Sequential cueing is captured via *active* and *awaited* components
- Temporal cueing is captured via tiers of embeddedness
- Grammar formalism is sensitive to embedding depth



Parser Predictions

- F(irst): Predict the first element of a new tier
- L(ast): Predict that the last element of a tier was just seen
- F and L binary predictions made at each timestep metrics



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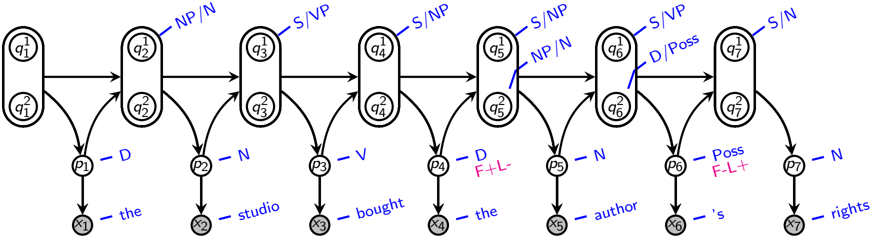

Proposed Complexity Metrics

Loosely correspond to Storage and Integration costs [Gibson, 2000]

- F+: Predict a new tier (incur a *storage* cost)
- DF+: F+ weighted by the tier number
- L+: Predict integration of a tier (incur an *integration* cost)
- DL+: L+ weighted by the tier number
- DistL+: L+ weighted by the length of the tier

Human Complexity

- Reading times provide a window into complexity
- Many different metrics (fixation duration, regression, etc)

People fixate longer on difficult words
People regress more after ambiguous words and difficult constructions

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Choice: First-Pass Fixation (Gaze Duration).

Training

- Parser and Lexicon: WSJ02-21 [Marcus et al., 1993]
  - 39,832 sentences
  - 950,028 words
- Ngrams: Brown [Francis and Kucera, 1979], WSJ02-21, BNC, Dundee[Kennedy et al., 2003]
  - 5,052,904 sentences
  - 87,302,312 words

Ngrams calculated using SRILM [Stolcke, 2002] with modified Kneser-Ney smoothing [Chen and Goodman, 1998]

Evaluation

- Dundee corpus [Kennedy et al., 2003]
  - 10 subjects
  - 2,388 sentences
  - 58,439 words
  - 260,124 subject/word pairs (first-pass fixations)
- Filtered Dundee corpus
  - 148,717 words
- Filtered Dundee corpus sans outliers (by subject)
  - 146,671 words

Exclusions: UNK-threshold 5, first and last of a line, first and last of a sentence, multiple capitals, words that contain a non-letter

Baseline Metrics

Fitting a linear mixed effects model

Derived from [Fossum and Levy, 2012] and [Frank and Bod, 2011]

- Number of characters
- Was previous word fixated?
- Unigram and Bigram probs
- Sentence position
- Will next word be fixated?
- Joint interactions

Plus

- Number of intervening words (non-significant)
- Cumulative Total Surprisal [Hale, 2001]

Simplest baseline is determined on development data before fitting test data with factors of interest (see Appendix)

Fixation durations are log-transformed prior to fitting to yield normal distributions (see Appendix)

Results

Metrics residualized from baseline on test set

Model	Improvement (p-value)	Model	p-value
F+	.047	F-	.00029
DF+	–	DF-	.0049
L+	.0014	L-	.020
DL+	–	DL-	–
DistL+	.0021	–	–

Metric improvement over baseline

Conclusion

An explanation

Some of the hypothesized metrics can predict reading times even over those predictions made by a strong baseline including a state-of-the-art complexity metric (cumulative total surprisal). This indicates that domain-general memory processes provide at least a partial account of *why* humans encounter difficulty during language processing.

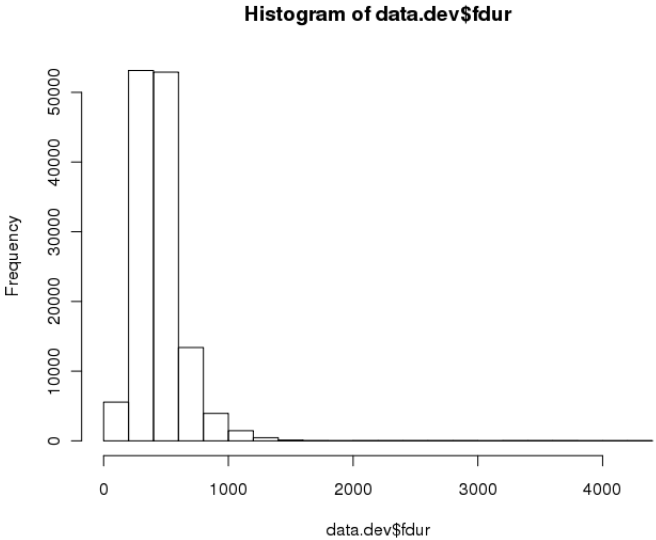
Fin

Thanks!

Especially to Kodi Weatherholtz and Rory Turnbull for their assistance with R-wrangling and working with linear mixed effect models!
Additional thanks due to William Schuler for advising on this project.
Any errors are my own

Questions?

Transforming the response variable



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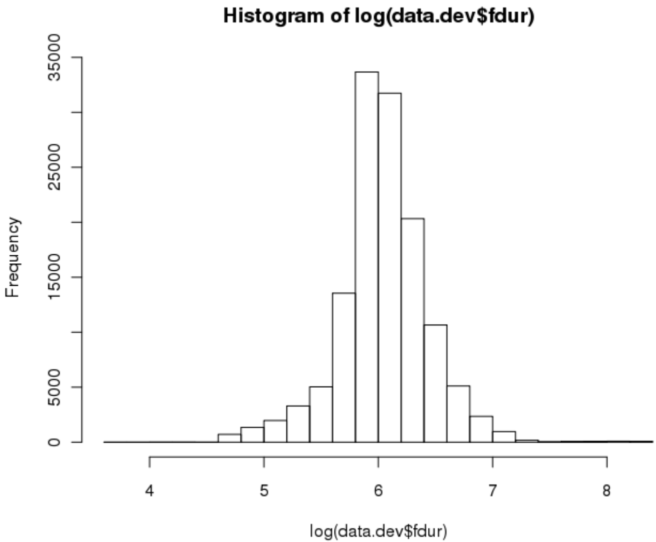
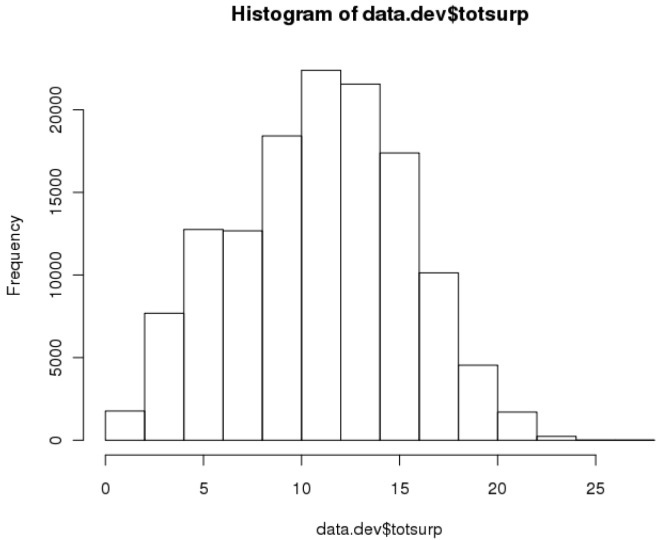


Transforming the response variable

Model	LogLikelihood (dev)
fdur $\sim$ Baseline	-882,585
log(fdur) $\sim$ Baseline	-55,378

Improvement from transforming the response

An underrepresented innovation



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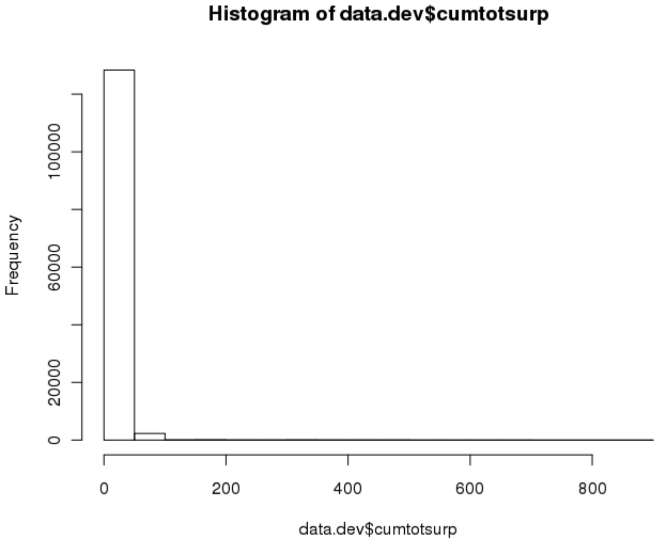

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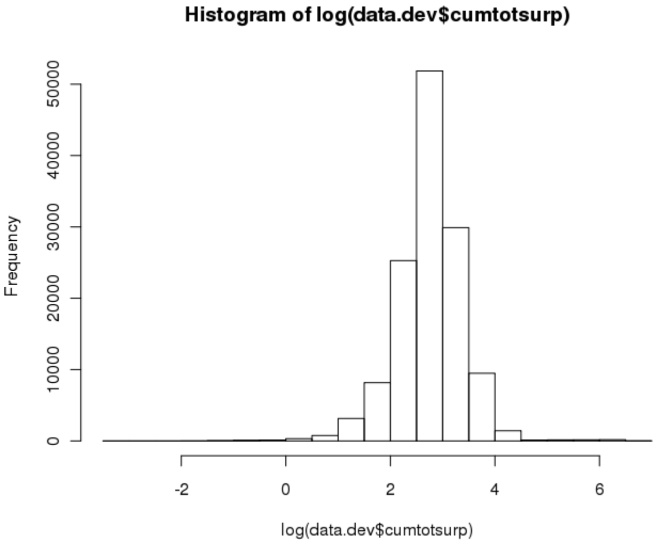


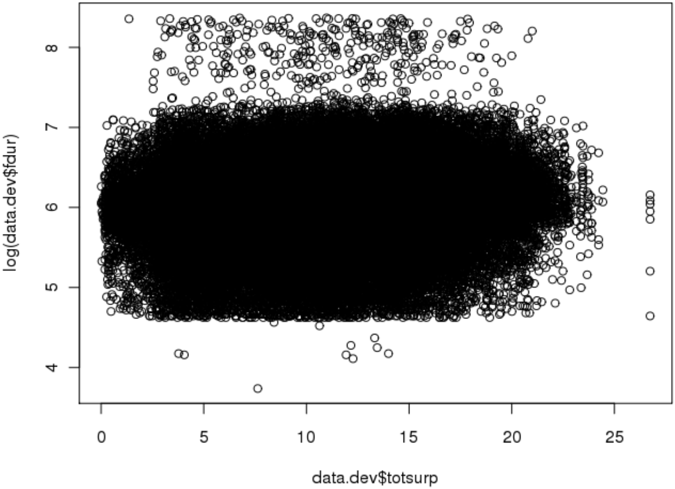
An underrepresented innovation

Model	LogLikelihood (dev)
Baseline + Total Surprisal	-56307
Baseline + log(Cum. Total Surprisal)	-55753
Baseline + Cum. Total Surprisal	-55378

Improvement from accumulating metrics

Cumulative Total Surprisal seems to be the best

An underrepresented innovation



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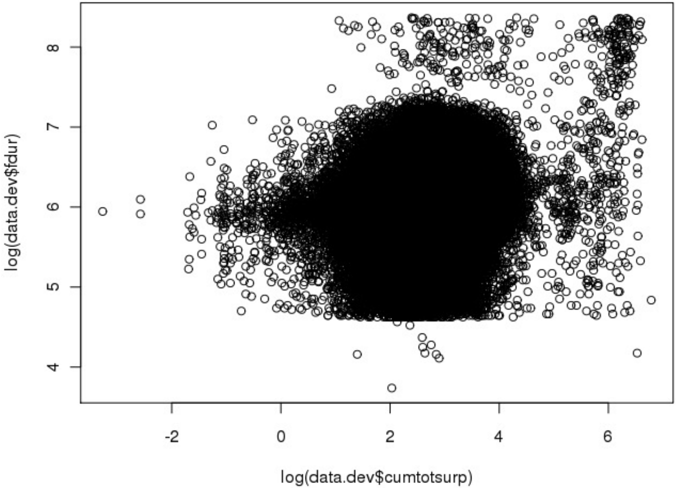

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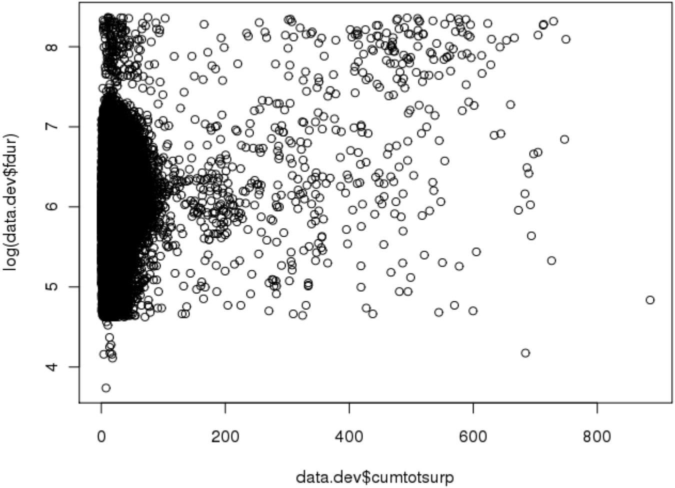


Finding the Simplest Baseline Model

1. Begin with all baseline effects thrown into model along with their joint interactions.
2. Reduce multicollinearity: Using Variance Inflation Factors (VIFs), remove largest contributor to multicollinearity until loglikelihood of model is negatively affected (interactions removed first)
3. Simplify model: Using t-scores, remove least significant factor until an ANOVA reveals a significant effect

Problems with multicollinearity

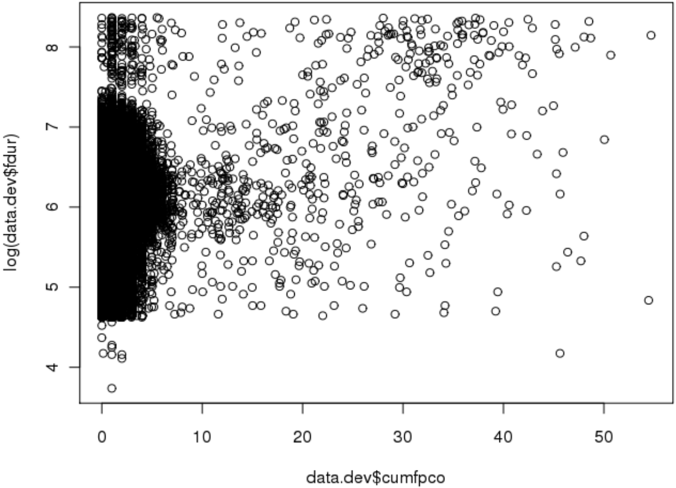
- Algorithms to determine coefficients fail or are inaccurate
- Results won't generalize to new populations
- Significance found will still be significant without collinearity but bias can lead to incorrect predictions on new data

Simplest Baseline Model

log(fdur)∼

- nchar
- sentpos
- previsfix
- nrchar:logwordprob
- sentpos:nextisfix
- sentpos:logfwprob
- nextisfix:cumtotsurp
- subject and item random intercepts
- logprob
- logfwprob
- cumtotsurp
- previsfix:logprob
- previsfix:logfwprob
- previsfix:cumtotsurp
- logprob:cumtotsurp
- logfwprob:cumtotsurp

Graphs



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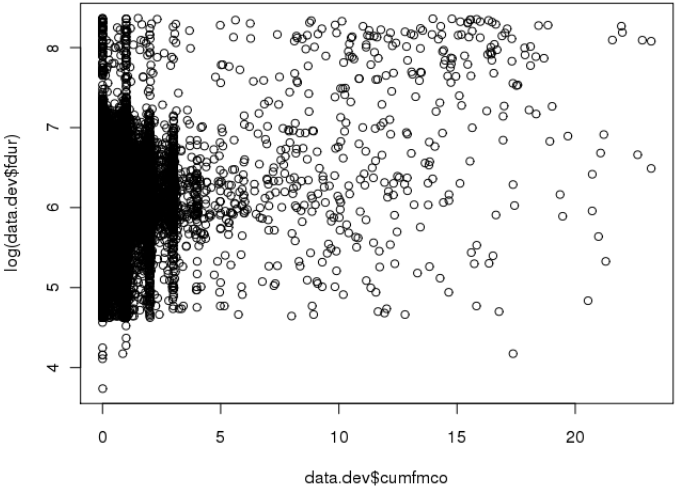

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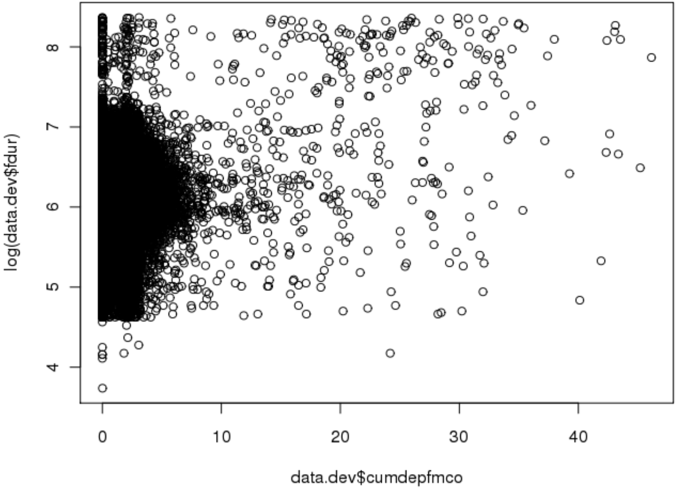

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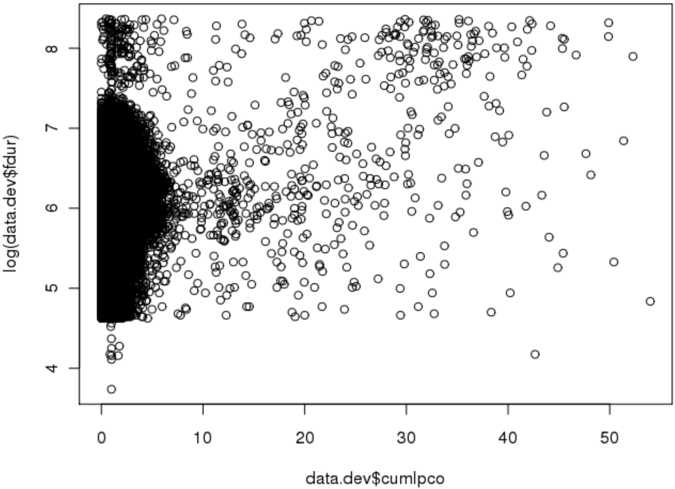

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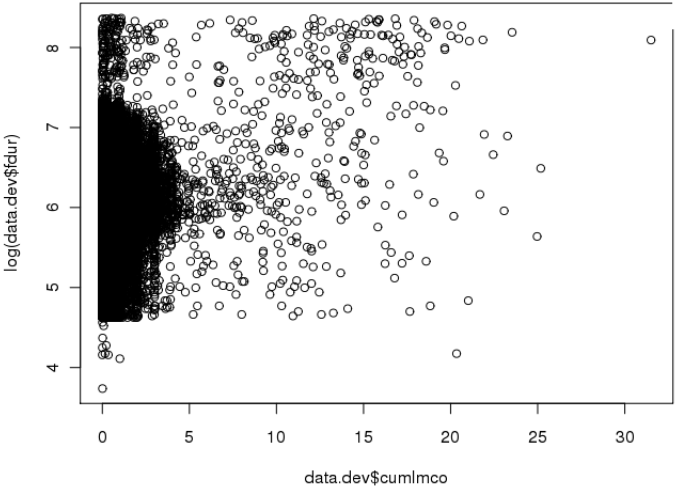

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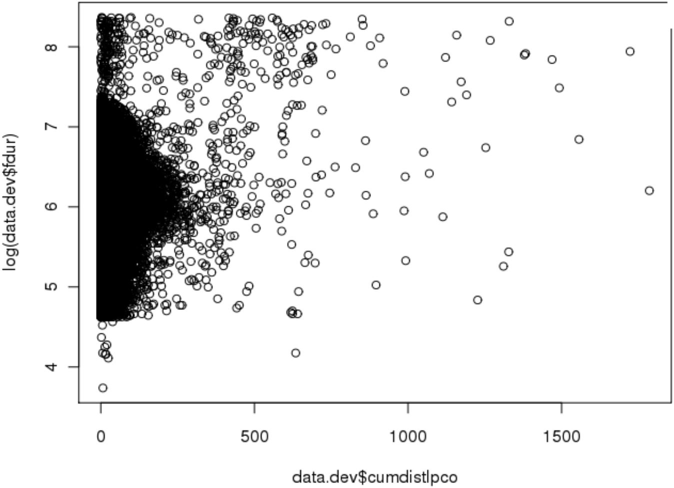

Shhh. Secrets!

Look no farther! (Secrets...)

Shhh. Secrets!

Metrics residualized from baseline on test set

Model	Improvement (p-value)	Model	p-value
B+	–	B-	$2.61 * e^{-06}$
DistB+	.043	–	–

Metric improvement over baseline

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