A Large-scale Logistic Regression Analysis of Kiezdeutsch Syntax

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January 15, 2020

Outline

1. Overview
2. Methodology
3. Data
4. Experiments & Results
5. Conclusion
6. Discussion

What is Kiezdeutsch?

Definition

German-language variety spoken primarily by teenagers from multi-ethnic urban neighborhoods in casual conversations with their peers.

What is Kiezdeutsch?

- A way of self-identification.

Figure: German rappers Eko Fresh and Ali Bumaye sing

"Lan lass ma' ya!" (Dude, let's go!). Source: YouTube.com

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- **A dialect in its own standing** - Heike Wiese

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Standard German: Können wir eine Party machen?

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(2) Lass mal morgen saufen gehen SPK19.
let once tomorrow drinking go SPK19.
‘Let’s go drinking tomorrow SPK19.’

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Standard German: Ich mache das so.

Other Phenomena in Kiezdeutsch

- Many other phenomena both syntactic (e.g., verb-first declaratives) and non-syntactic (pronouncing ‘ich’ as ‘ish’).

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Goal $\rightarrow$ Fill the gap!

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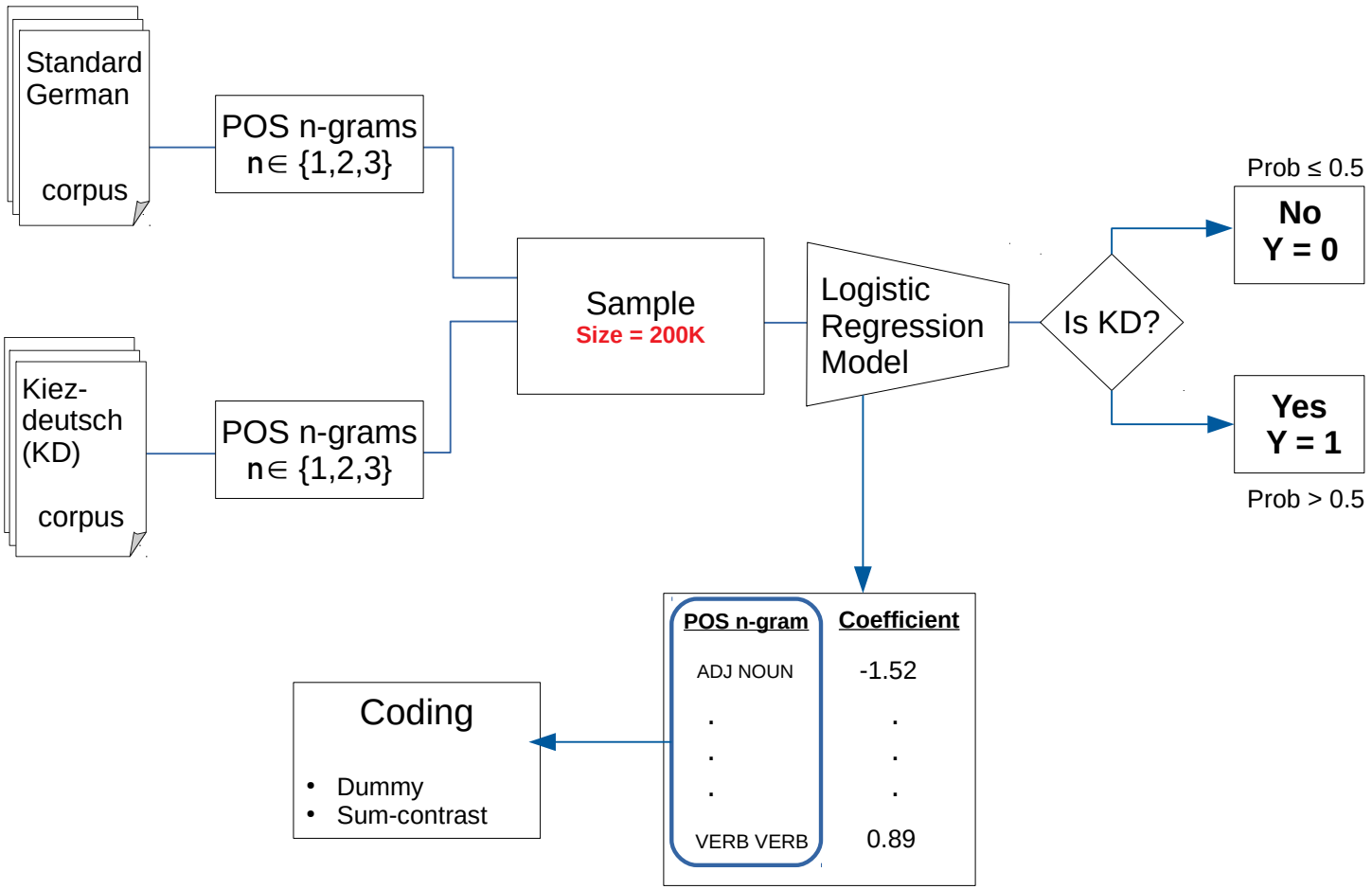
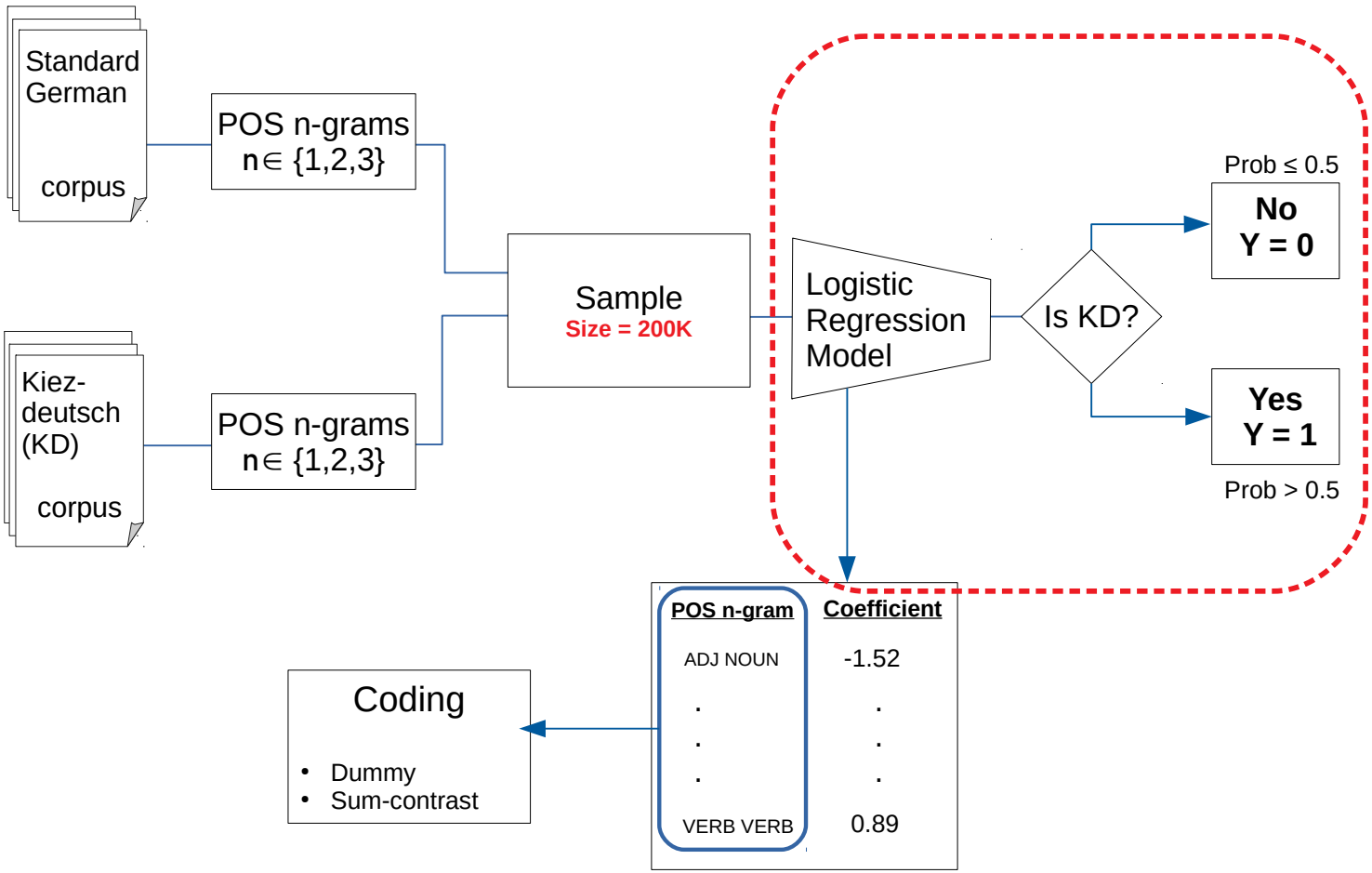


Methodology - Model



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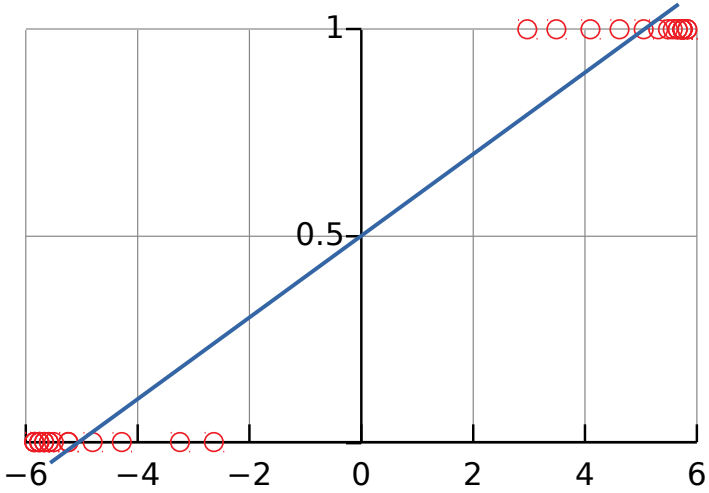

Figure: Linear Regression Model

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α = intercept, β = slope, ϵ = random error

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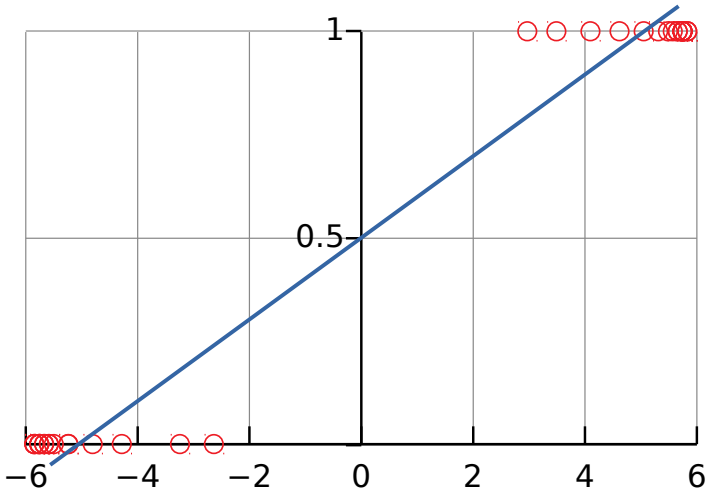

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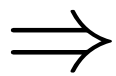

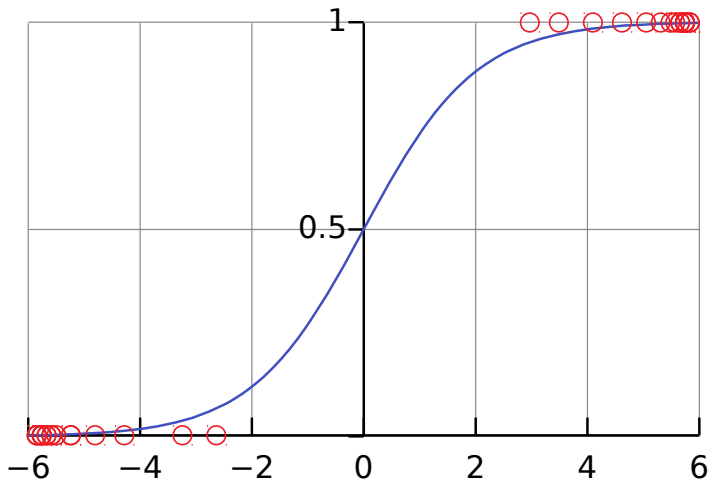

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$$f(Y) = \alpha + \beta X$$

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- **This thesis $\rightarrow$ GLM and GLMM.**

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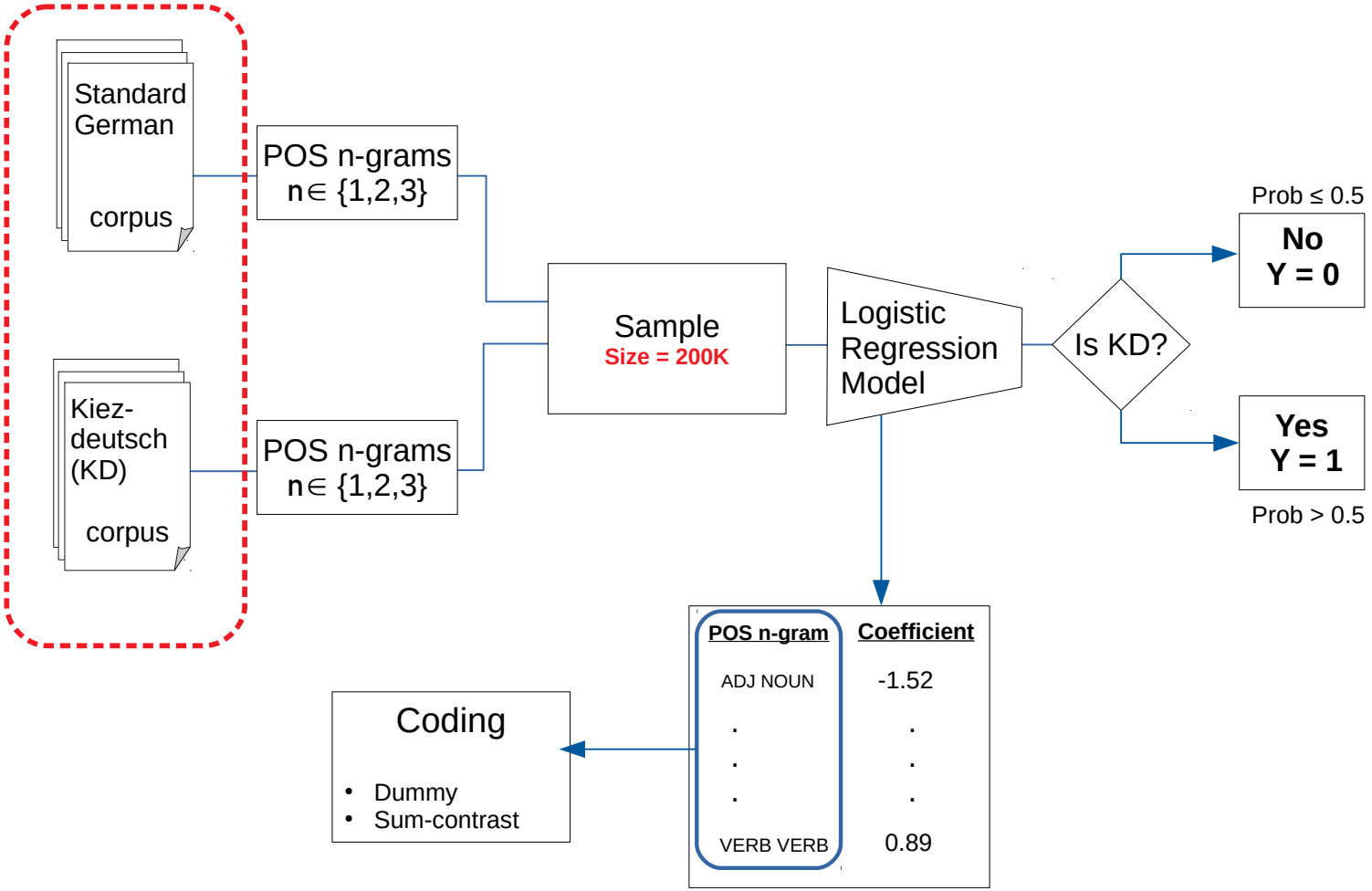

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- **This thesis $\rightarrow$ Silver standard set.**

Key Statistics

Corpus	Original Size	Processed Size	Speakers
KiDKo (Mu)	359,000	230,000	201
GRAIN (Silver set)	221,000	220,000	124

Table: Key statistics of the corpora used in this thesis. Numbers are approximates.

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- Lemmatize KiDKo tokens (e.g., habe, hast $\rightarrow$ haben)

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- GRAIN has much more determiners, nouns and adpositions.
- Some speech disfluencies in KiDKo are not tagged as such.
  Example: repeated words tagged according to their POS.

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- **Models:** 22 GLMs & GLMMs for main experiment, 12 models for additional experiments (e.g., test granularity & interaction).
- We discuss the results of the POS n-grams GLMs with sum-contrast coding.

Experiment 1 - POS Unigram Results

- **Most predictive:** Particles (e.g., Ja, nicht), numerals (e.g., zwei, 2008) and pronouns (e.g., ich, du).
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- **Least predictive:** Determiners (die, der), adpositions (in, auf), and nouns (Deutschland, Alter).
  → GLM supports bare NPs phenomenon.

Experiment 1 - POS Bigram Results

- **Most predictive:** "PRT PRT" (e.g., Ja ja), "VERB ADV" (e.g., Lass mal), "PRT NOUN" (e.g., nicht Training), and "PRT NUM" (e.g., nicht 360).
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- **Models:** 6 GLMs were tested on a sample of size 100,000.

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Positional information was added in two ways:

- **Sentence Markers:** introduce 2 POS tags to mark sentence boundaries, SOS (start of sentence) and EOS (end of sentence).

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- **Augmented POS tags:** add affix to each POS tag to indicate its position in the sentence.

Experiment 2 - Positional Information 2

(4) a. <SOS> Was machst du <EOS>
SOS PRON VERB PRON EOS
'What are you doing?'

b. Was machst du
SOS_PRON VERB_MID PRON_EOS
'What are you doing?'

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Sentence markers results:

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  → support for bare NPs, directive particles and particle 'so'.
- POS bigram "SOS VERB" (e.g., <SOS> Sehe), POS trigrams "SOS VERB NOUN" (e.g., <SOS> War Deutscher), "SOS VERB ADV" (e.g., <SOS> Habe doch), "SOS VERB ADP" (e.g., <SOS> Ist bei) are some of the most predictive of Kiezdeutsch in the data.
  → support verb-first declaratives phenomenon.

Experiment 2 - Results 2

Augmented POS tags results:

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Augmented POS tags results:

- Results for POS unigram model in line with experiment 1.
  → support for bare NPs, directive particles and particle 'so'.
- POS bigram and trigram models suffered from data sparsity and separation.
  → data and models are insufficient to produce significant results.

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- Adding positional information improves representation of syntactic phenomena given enough data.

Conclusion

Thank you for listening.
Questions?

Coding Categorical Variables

Flavor	**C1**	**C2**	**C3**
Vanilla	0	0	0
Chocolate	**1**	0	0
Lemon	0	**1**	0
Other	0	0	**1**

Table: Dummy coding for the variable ice cream flavor with 4 groups. Vanilla is the reference level.

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Flavor	C1	C2	C3
Vanilla	**0.75**	-0.25	-0.25
Chocolate	-0.25	**0.75**	-0.25
Lemon	-0.25	-0.25	**0.75**
Other	-0.25	-0.25	-0.25

Table: Sum contrast coding for the variable ice cream flavor with 4 groups. The grand mean is the reference level.

Logistic Regression

- A logistic regression model is a type of Generalized Linear Model (GLM) which uses the logit (log-odds) for the link function f(Y).
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- It uses the logistic/sigmoid function to calculate the probability of the outcome.

$$f(Y) = \alpha + \beta X$$

$$f(Y) = \log\left[\frac{p}{(1-p)}\right]$$

where $p = P(Y = 1)$

$$P(Y = 1) = \frac{1}{1+e^{-\theta}}$$

$\theta = \alpha, \beta$ (model parameters)

Comparing Models

- Analysis of Variance (ANOVA) using likelihood ratio test (LRT) reveals if the more complex model is significantly better at capturing the data than the simpler model.

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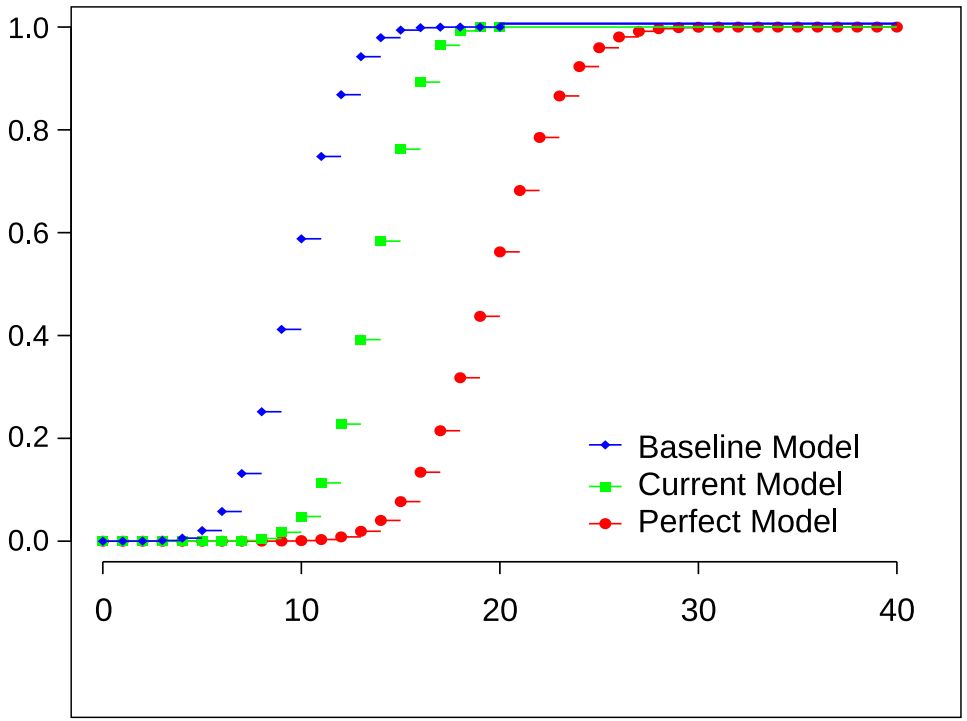

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