

LingPredict

Developmental Norms and Second Language Acquisition

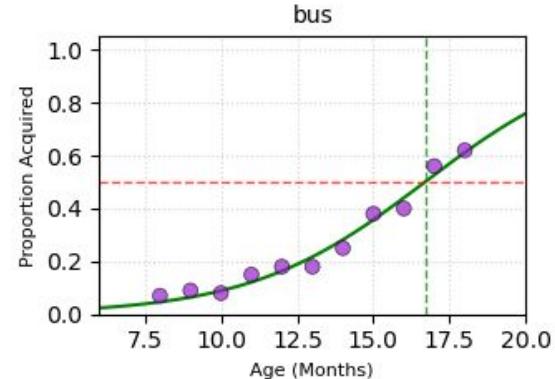
Q: Does L1 Age of Acquisition (AoA) influence L2 vocabulary learning?



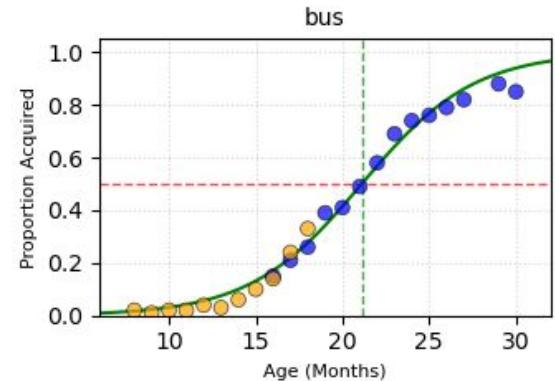
Data sources

- Wordbank (L1)

- Open data repository on language acquisition in children
- Data compiled from MacArthur-Bates Communicative Development Inventory (CDI) surveys completed by parents of young children.
- Large-scale repository (105,290 surveys across 42 languages).
- CDI Forms:**
 - Words & Gestures (**WG**): comprehension/early vocabulary (8-18 months).
 - Words & Sentences (**WS**): production/grammar (16-30 months).
- Measures:**
 - Understands
 - Produces



Produces (WG + WS)





Data sources

- **Duolingo SLAM (Second Language Acquisition Modeling) 2018 (L2)**

- Data from Duolingo learners over their first 30 days of study.
- Over 6,000 students learning English, Spanish, and French.
- Over 2 million tokens from three exercise formats (reverse_translate, reverse_tap, listen).
- Data features:
 - Student History: Anonymized **user** ID, **days** since starting
 - L2 word **token**, Part of Speech, and Morphological Features
 - **time** taken to complete the exercise
 - **token**-level correctness: 0 = correct; 1 = incorrect

```
# prompt:Yo tengo una habitación.
```

```
# user:G86T0ut3 countries:MX days:19.692 client:ios session:practice format:reverse_translate time:13
ut0q00+s0301 I PRON Case=Nom|Number=Sing|Person=1|PronType=Prs|fPOS=PRON++PRP
ut0q00+s0302 have VERB Mood=Ind|Tense=Pres|VerbForm=Fin|fPOS=VERB++VBP
ut0q00+s0303 a DET Definite=Ind|PronType=Art|fPOS=DET++DT
ut0q00+s0304 room NOUN Number=Sing|fPOS=NOUN++NN
```

Our contribution:
Age of acquisition (produce and understand) for native Spanish speakers

nsubj	0	28.5	16.9
ROOT	1	30.8	19.5
det	0	28.5	19.8
dobj	1	25.8	14.7

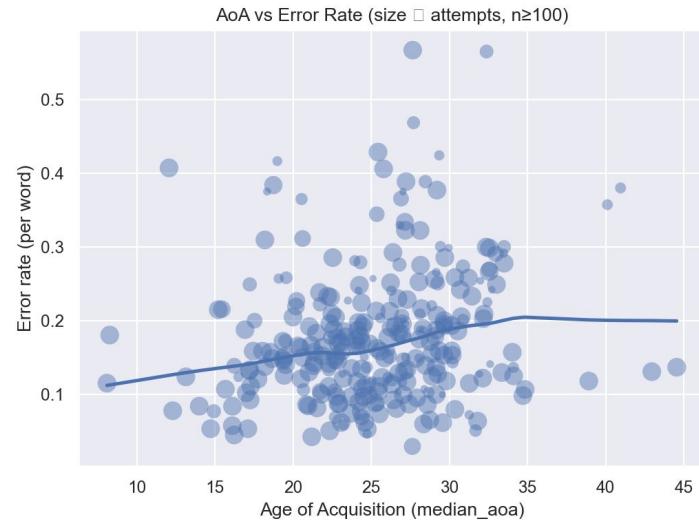
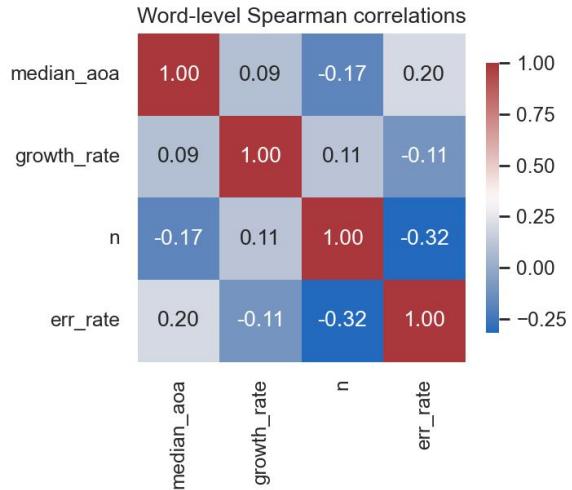


Feature Engineering

- ❑ **Age of acquisition:** fit a 2-parameter logistic curve to each word's acquisition trajectory: Age (in months) vs. Proportion of Children Knowing Word. Parameters describe `median_aoa` and `growth_rate`
- ❑ **Category (from Wordbank):** 'sounds', 'animals', 'toys', 'food_drink',..., 'pronouns', 'question_words', 'quantifiers', 'helping_verbs'
- ❑ **Word frequency:** how frequently a given word occurs in everyday language use. It is obtained from large-scale language corpora (e.g., Common Crawl, Wikipedia, news sources) using the `wordfreq` library serving as a proxy for general exposure.
- ❑ **Token frequency:** raw count of how often the exact word token appeared within the specific Duolingo SLAM dataset



Inferential Results



- Later-acquired words tend to elicit more errors ($r = 0.20$).
- Error rate decreases with exposure, which is consistent with practice/frequency effects ($n = 0.32$).
- AoA and growth rate show limited collinearity ($p = 0.11$).

- Positive association between AoA and error rate, with a plateau beyond ~33–35 months.
- These findings motivate including AoA in subsequent models.



Logistic Regression Results

- Logistic regression with SAGA solver and L2 regularization.
- Cross-validation conducted on TRAIN only to select regularization strengths.
- After training, we selected a threshold on DEV that maximizes recall subject to a minimum precision target (0.30).
- Hyper-parameters (penalty, C) were tuned by CV on TRAIN only (best C=0.2, L2 for both).

Metric	LG-Baseline	LG-Enhanced
AUC (%)	0.59	0.62
AP (%)	0.22	0.23
Accuracy (%)	83.1	82.8
Precision (%)	32.0	31.3
Recall (%)	5.6	7.1
F1-Score (%)	9.5	11.5
Overall Rank	2	1

Enhanced feature set produced modest but consistent improvements:

On TEST, Enhanced model outperformed the Baseline on ranking metrics (AUC, AP) and increased recall at the selected precision target.



Histogram-Based Gradient Boosting

- Class imbalance in token error was handled via class weight = “balanced”.
- Parameters: Learning rate 0.08, up to 31 leaf nodes per tree, min samples per leaf=50, 300 boosting iterations.
- In contrast to LR model, this setup models non-linear effects and cross-feature interactions implicitly.
- As in the LR model, thresholds were chosen on DEV to satisfy a precision floor of ~0.30.

Metric	HGB-Base	HGB-Enhanced
AUC (%)	0.63	0.68
AP (%)	0.27	0.32
Accuracy (%)	80.4	76.3
Precision (%)	31.1	30.8
Recall (%)	19.4	39.6
F1-Score (%)	23.9	34.6
Overall Rank	2	1

Enhanced model improves ranking quality (AUC, AP) and increases recall:

- On TEST: AUC increased from 0.63 to 0.68 and AP from 0.27 to 0.32. Recall nearly doubled from 0.19 to 0.40.
- Accuracy decreased as expected under class imbalance when retrieving more positives.



Conclusion/Next Steps

- Model comparison (LR vs. HGB):
 - Adding AoA, conceptual category and frequency features **improved ranking and retrieval**.
 - LR: AUC/AP rose modestly (AUC 0.59 to 0.62, AP 0.22 to 0.23) and recall increased from 5.6% to 7.1%
 - **Larger gains in HGB:** AUC/AP increased (0.64 to 0.68, AP: 0.27 to 0.32) and recalled doubled from 19.4% to 39.6%.
 - HGB provides **strongest retrieval**, whereas LR provides smaller but consistent improvements. LR model is still valuable for **interpretability** and as a transparent baseline.
- Integrating Wordbank developmental norms with Duolingo SLAM data shows that early-acquired L1 words are generally easier to learn in L2.
- Our gradient-boosting model, using features like AoA, word frequency, and Levenshtein distance, modestly improved predictive accuracy over the SLAM baseline.
- Future work should refine word matching, add longitudinal learner data, and expand developmental datasets to strengthen cross-linguistic insights.