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BLiSS 1.0: Evaluating Bilingual Learner Competence in Second Language Small Language Models

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The Challenge in Evaluating Acquisition-oriented Language Models

- Current benchmarks evaluate models on native-like grammaticality.
- Human L2 learners, however, produce systematic, predictable "errors" (interlanguage).
- **The Gap:** No benchmarks test for cognitively plausible, human-like error patterns.

	Standard LMs Focus: Grammaticality	L2 Learners Process: Interlanguage
We play sports.	🟢	🟢
*We play **the** sports.*	🔴	🟢
*We **the** play sports.*	🔴	🔴

How can we test if a model prefers a plausible human error over a contrived one?

Our Paradigm: Selective Tolerance

- To solve the evaluation gap, we need a method that can measure two things at once: a model's grammatical knowledge AND its sensitivity to human-like error patterns. A simple "right vs. wrong" test can't do this.

Principle 1: Isolate Sensitivity to Plausibility.
We must test if the model can distinguish a systematic, human-like error from a contrived one

Principle 2: Ground the Test in Grammaticality
This sensitivity must not come at the cost of grammatical competence.

The BLiSS Benchmark

- Over 2.8 million raw learner sentences from large corpora (EFCAMDAT, W&I, FCE).
- Yields 136,867 high-quality triplets after a rigorous validation pipeline.
- Includes rich metadata: Learner L1, CEFR proficiency, and error type.
- **Key Unit: The Plausibility Triplet**

🟢 **Corrected**
There are a lot of benefits when we play sports.

🟡 **Naturalistic Learner Error**
There are a lot of benefits when we play **the** sports.

🔴 **Contrived Artificial Error**
There are a lot of benefits when **the** we play sports.


```
{
  "learnerID": "8421",
  "L1": "Vietnamese",
  "cefr": "C1",
  "topic": "play  sports ",
  "corrected": "There are a lot of
     benefits when we play  sports .",
  "learner error": "There are a lot of
      benefits when we play  the
     sports .",
  "artificial error": "There are a lot
      of benefits when the we play
     sports .",

  "errant_edits": [{
    "type": "U:DET",
    "o_str": "the",
    "c_str": ""
  }],
  "all_error_types": [
    "U:DET"
  ]
}
```


Quantifying Selective Tolerance

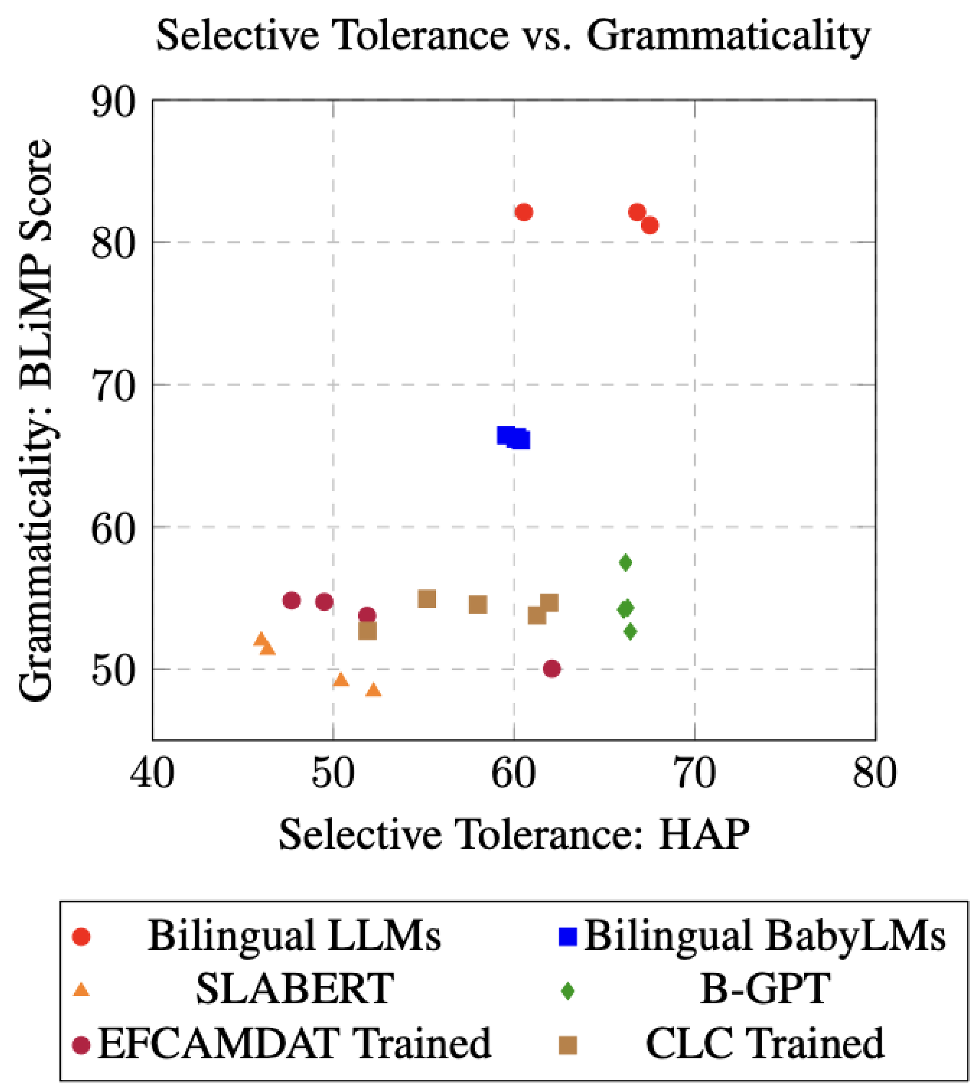
Scoring: Token-normalized Surprisal (BPT) measures plausibility.

Metrics:

- **HAP (Human vs. Artificial):**
  Does the model prefer 🟡 over 🔴?
  (Tests for basic selective tolerance)
- **SO (Strict Order):**
  Does the model rank 🟢 < 🟡 < 🔴?
  (The strictest test of grammar and tolerance)
- **LP (Learner Preference):**
  Does the model prefer 🟡 over 🟢?
  (A diagnostic for over-imitating errors)

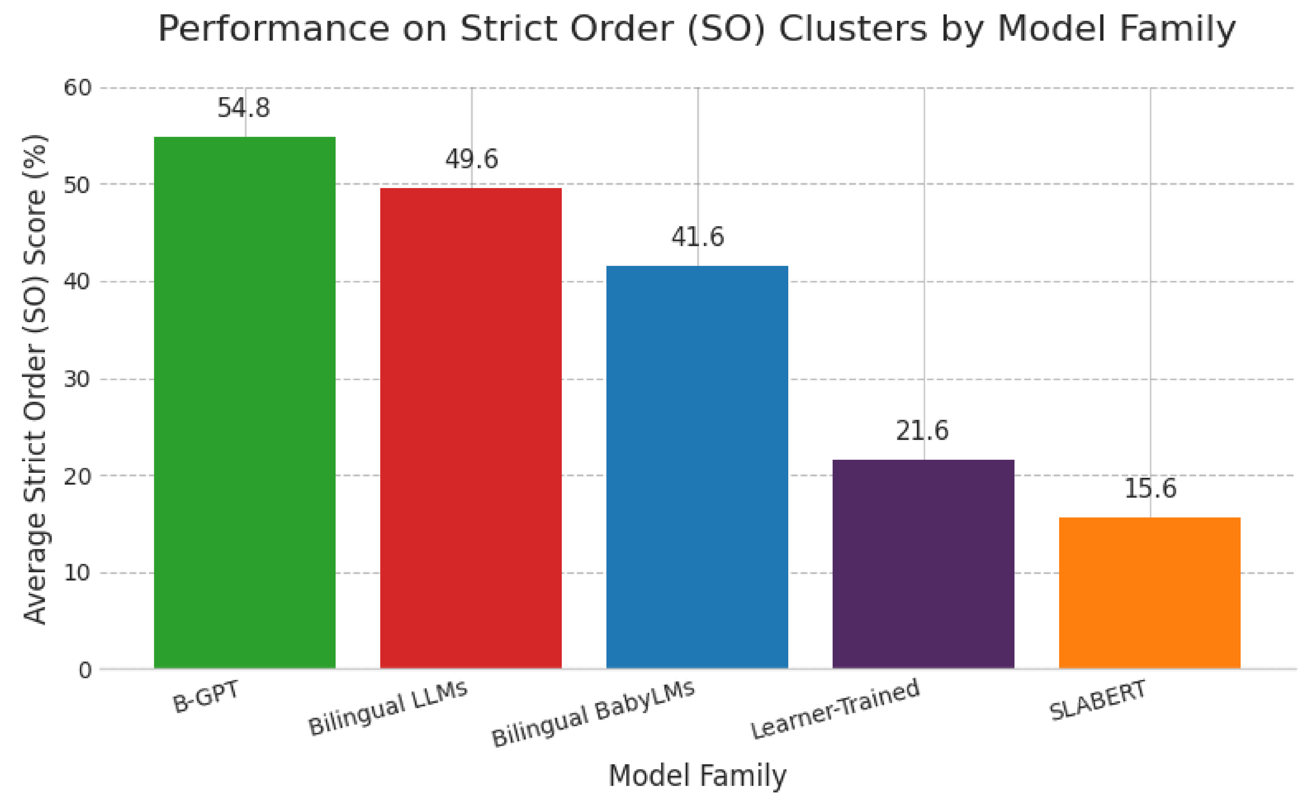
Key Findings

Finding 1: Selective Tolerance is Distinct from Grammaticality. High Grammaticality Does Not Guarantee High Selective Tolerance.



Takeaway: BLiSS measures a complementary skill. A model can master formal grammar but still fail to understand the nuanced patterns of human learner errors.

Finding 2: Training Paradigm is the Key Predictor of Performance.



Takeaway: A model's training paradigm is the strongest predictor of its performance.