# Small Language Models as a tool to investigate the acquisition of the Null-Subject constraint

Thomas Morton

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I want to investigate **how humans learn syntactic generalizations** from linguistic evidence.

I seek to use **large language models as candidate models** of a language learner that we can **intervene on and investigate** the representations of.

I chose to use the **acquisition and representation of null subjects** as a case study in this investigation.

# The Null-Subject Constraint in Language Acquisition

## Cross-Linguistic Variation

Languages differ in whether they allow phonologically null subjects

**English (Non-pro-drop):**

- *She/*∅ runs*
- *It/*∅ rains*
- Overt subjects required

**Italian (Pro-drop):**

- *(Lei) corre* '(She) runs'
- *∅/*Ci piove* '(It) rains'
- Rich verbal agreement

**Acquisition Challenge (Hyams, 1986; Rizzi, 1994) :**

- Children show early null subjects across languages
- Must learn when overt subjects are required vs. optional

# The Poverty of Stimulus Problem

## Learnability Challenge

How do children learn from positive evidence alone? (Hyams & Wexler, 1993)

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- **Indirect distributional evidence:** Orthogonal grammatical information guides linguistic generalizations (Yang, 2004)
- **Direct evidence:** Overt forms signal constraints (Hyams & Wexler, 1993)

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**This Work:** Train models on developmentally-plausible corpora to test questions of sufficiency of the language input.

# The Contravariance Principle

## Why Do Models and Humans Converge? (Cao & Yamins, 2021)

Hard computational problems constrain possible solutions

**Core Insight:**

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- Null-subject acquisition involves multiple competing constraints
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**Applied to Language:**

- Null-subject acquisition involves multiple competing constraints
- Flexible learners (models and humans) should converge to similar solutions
- Convergence toward the simplest viable explanation

# The Planonic Representation Hypothesis

**Linking Theory: Internal Representations $\leftrightarrow$ Linguistic Competence**

Abstract syntactic knowledge should be observable in model representations

**Key Claims:**

- **Structural priming** reveals abstract grammatical representations (Bock, 1986)

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**Methodological Innovation:**

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- Test representations beyond surface performance
- Bridge psycholinguistics and computational modeling

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**Empirical Tests:**

- **Chapter 1:** Do models learn null-subject constraints like humans?
- **Chapter 2:** Do bilingual models show human-like transfer effects?
- **Chapter 3:** Do models exhibit cross-linguistic structural priming?

# Contents

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- Manipulation of evaluation stimuli to examine contextual processing effects

# The Null-Subject Constraint in English

## What is the null-subject constraint?

English requires overt subjects in finite clauses (unlike Spanish, Italian, etc.)

**Adult English Constraint:**

- * ∅ *Finished the book* (ungrammatical)
- ✓ *She finished the book* (grammatical)

**Child Null-Subject Use Examples:**

- *Shake hands.*
- *Turn light off.*
- *Want go get it.*
- *Show mommy that.*
- *Now making muffins.*

# Performance vs. Competence Accounts

## Why Do Children Drop Subjects?

Two competing explanations for child null-subject patterns

**Performance Account (L. Bloom, 1970; P. Bloom, 1990):**

- Children drop subjects under processing load
- Cognitive resource limitations
- More drops with negation, longer sentences
- Subject/object asymmetry due to planning

**Competence Account (Hyams, 1986; Hyams & Wexler, 1993):**

- Children initially set null-subject parameter
- Must learn overt subject requirement
- Grammatical learning, not performance
- Direct evidence from overt pronouns

**Key Debate:** Processing limitation vs. grammatical parameter setting

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- Nominal domain provides indirect evidence
- Focus shifts from verbal to determiner system

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# Experimental Design Rationale

**Testing Causal Contributions**

Each experiment targets specific theoretical predictions

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- **Exp 3 - Remove Articles:** Further tests determiner system importance
- **Exp 4 - Lemmatize Verbs:** Tests Hyams' verbal morphology prediction
- **Exp 5 - Remove Pronouns:** Tests direct vs. indirect evidence accounts

# Experimental Design: Controlled Rearing

## Controlled Rearing Paradigm

Train models on systematically modified datasets to isolate evidence contributions

**Ablation Experiments:**

0. **Baseline:** Full training corpus
1. **Remove Expletives:** No *it/there* expletive constructions
2. **Impoverish Determiners:** Reduce *a/the* to *DET*
3. **Remove Articles:** No *a/the* entirely
4. **Lemmatize Verbs:** Remove *-s/-ed/-ing* morphology
5. **Remove Subject Pronominals:** No *I/you/he/she/it/we/they*

**Evaluation:** Null vs. overt subject preferences in controlled contexts

# Measures and Analysis: Overview

## Data and Coding

- Binary outcome: `over preference` $= 1$ when *overt* $<$ *null* surprisal
- Factors: `model`, `form_type`, `item_group`, `form`
- Training progress: $\log_{10}(\texttt{checkpoint} + 1)$
- Baseline condition as reference level

## Outcome Definition

- Minimal pairs: *null* vs. *overt* subject realization
- Binary response $Y \in \{0, 1\}$ encodes preference
- End-state: *overt* preference (probability scale)
- Acquisition-time: *null* preference

# Logistic Models: Learning Curves and Splines

## GLMMs

$$\operatorname{logit} \Pr(Y = 1) = \beta_0 + \operatorname{ns}\big(\log_{10}(t+1),\ k\big) + u_i$$

- Natural spline over log-checkpoint, complexity $k$
- Random intercept: $u_{\texttt{item}} \sim \mathcal{N}(0, \sigma^2)$
- Spline selection: AIC over $K \in \{3, \ldots, 7\}$

## Training Progress

- $\text{Log}_{10}$ scale: $\{0, 10, 100, 1\text{K}, 10\text{K}\}$
- Reflects neural network log-learning dynamics
- Uniform checkpointing across conditions

# Age of Acquisition (AoA) Analysis

## $t_{50}$ (Chance-Level Acquisition)

- Last crossing of 0.50 after burn-in ($\geq$ 100 checkpoints)
- Linear interpolation between fitted points
- Right-censored if no crossing
- Bootstrap 95% CIs ($n = 500$)

## $\mathrm{AoA}_{1/2}$ (Halfway-to-Asymptote)

- End-state $p_\infty$ from last 10% of training
- Threshold: $\theta = (p_\infty + 0.5)/2$
- First post-burn-in crossing of $\theta$
- Between-model $\Delta\mathrm{AoA}_{1/2}$ via paired bootstrap

# Materials: BabyLM Dataset

**Training Corpus**

- 90M word corpus designed for human-sized models
- Linguistically diverse with child-directed speech
- Models linguistic input of 10-14 year old child
- 10M word held-out test set
- 10M word ablation replacement set

**Dataset Composition**

- CHILDES (child-directed speech): 29M words
- Project Gutenberg (children's stories): 26M words
- OpenSubtitles (movie subtitles): 20M words
- Simple English Wikipedia: 15M words
- BNC dialogue + Switchboard: 9M words

# Evaluation Stimuli: Null vs. Overt Subjects

### Core Contrasts (English non-pro-drop)

- **Person/Number**: Anna finished. She/*∅ thinks...
- **Control**: Maria convinced her brother ∅/*him to leave
- **Expletives**: *∅/It seems that students passed
- **Topic shift**: Anna called Mark and *∅/he refused

### Minimal Pairs Design

- Sentences differ only in subject realization
- Lexical and contextual content held constant
- Testsfamilies
- Evaluates grammatical vs. processing accounts

# Processing Manipulations

**Context Complexity (Bloom 1990)**

1. **Simple**: The dog barked. He/*∅ scared...
2. **Long NPs**: The large brown dog with red collar barked...
3. **Embedded**: The dog that lived in the house...

**Negation Effects (Bloom 1970)**

1. **Target negation**: She/*∅ doesn't think...
2. **Context negation**: Anna didn't finish. She/*∅ thinks...
3. **Double negation**: Both context and target negated

*Tests processing load effects on subject drop preferences*

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Figure 1: Model preference for null and overt evaluation stimuli over training, training steps transformed to log-scale to reflect model log-learning dynamics for Experiment 0 - Baseline

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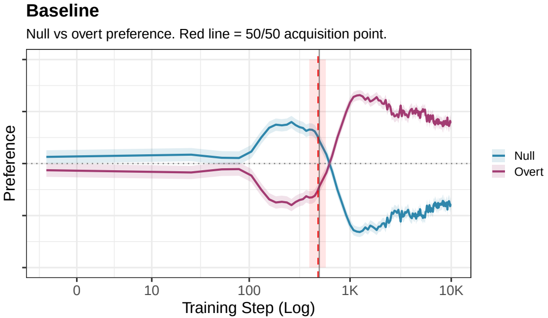


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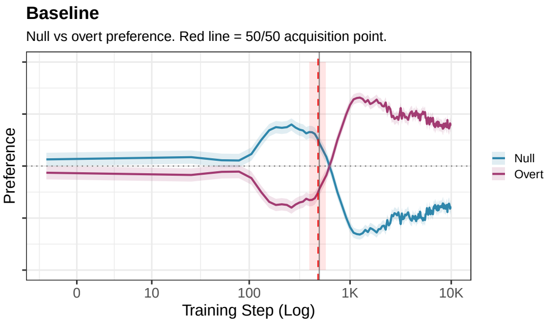


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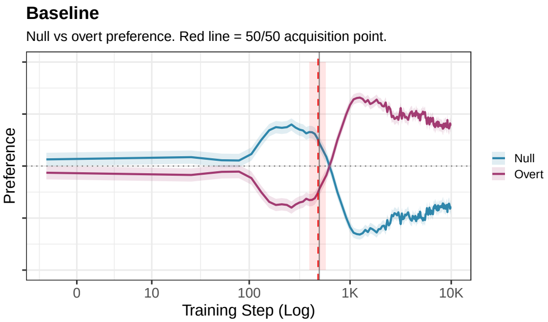


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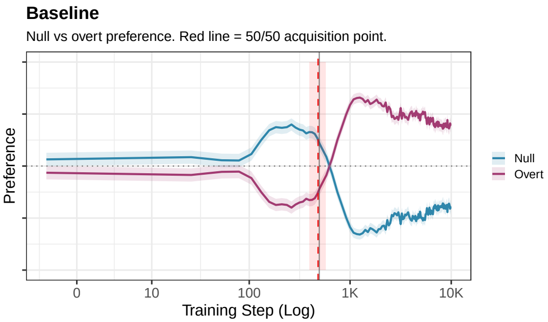


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- A **63.4% preference for null subjects over first epoch** (95% CI [62.7, 64.1], $p<.001$)
- a **69.6% preference for overt subjects in the last two epochs of training** (95% CI [66.5%, 72.5%], $p < .001$)

# Exp 1: 'Remove Expletives' – Training Curves

Figure 2: Model overt preference over training, training steps transformed to log-scale to reflect model log-learning dynamics comparing Experiment 0 and Experiment 1.

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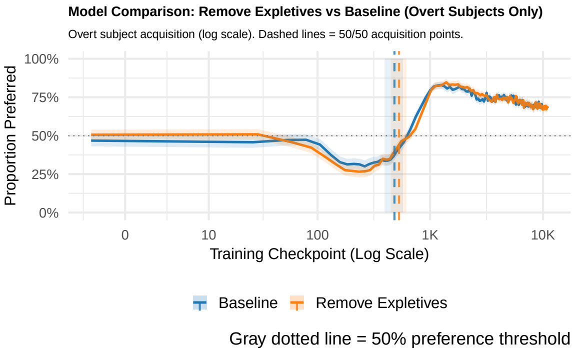


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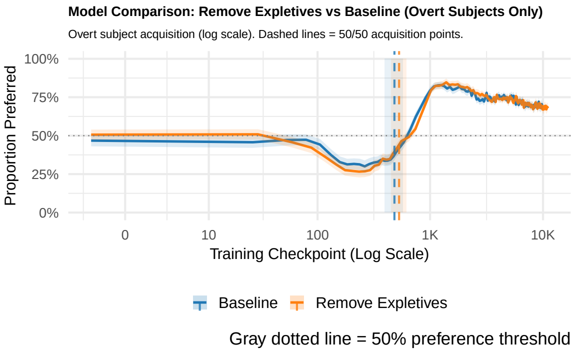


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- Age of Acquisition analysis revealed that baseline achieved **AoA at checkpoint 767** (95% CI [709, 821]).
  - Which is significantly later than the baseline model ($\Delta$AoA = 39 epochs, 95% CI [24, 55], p<.001)

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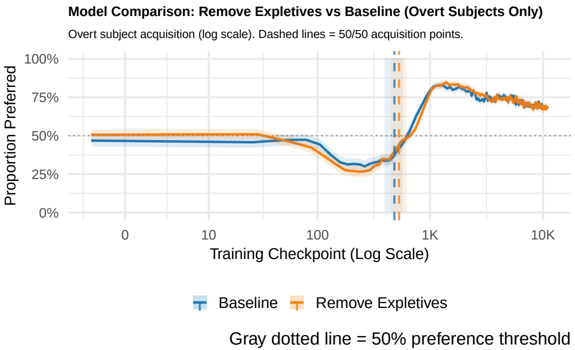


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    - Which is significantly later than the baseline model ($\Delta$AoA $=$ 39 epochs, 95% CI [24, 55], p$<$.001)
- Start-performance and end-performance did not significantly differ from base model.

# Exp 2: 'Impoverish Determiners' – Training Curves

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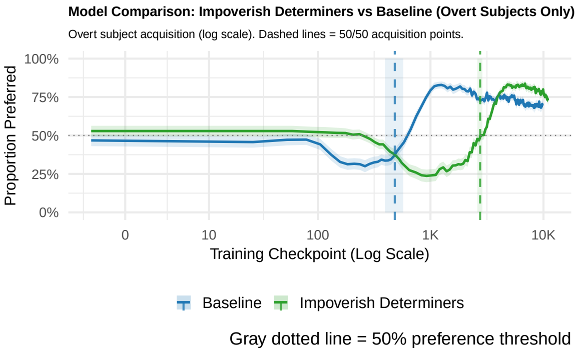


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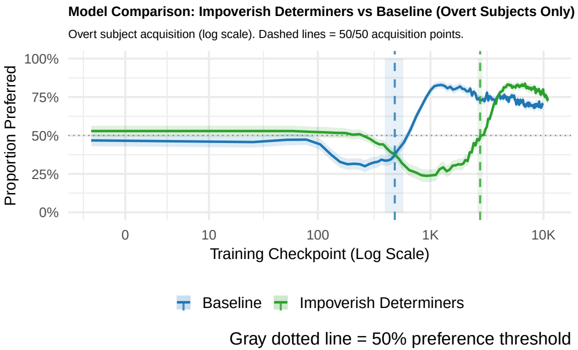


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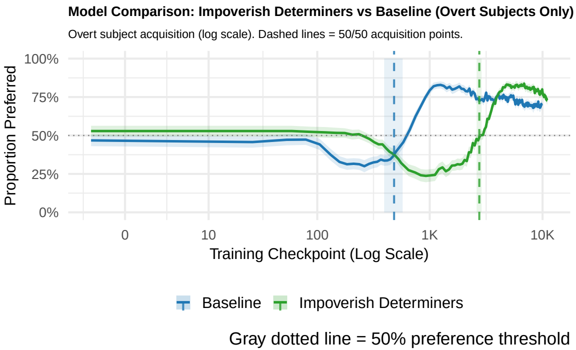


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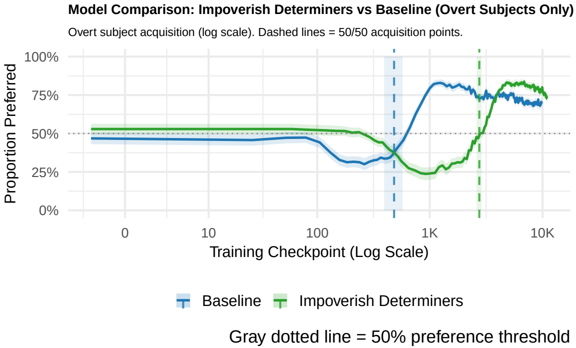


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# Exp 3: 'Remove Articles' – Training Curves

Figure 4: Model overt preference over training, training steps transformed to log-scale to reflect model log-learning dynamics comparing Experiment 0 and Experiment 3.

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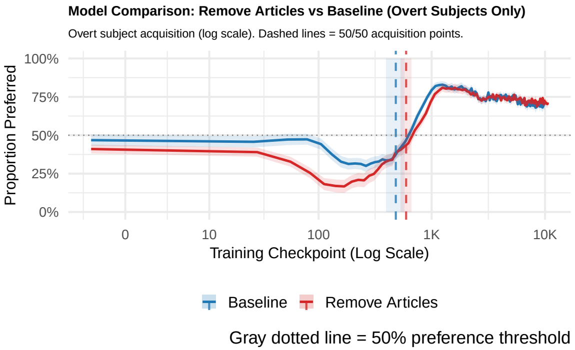


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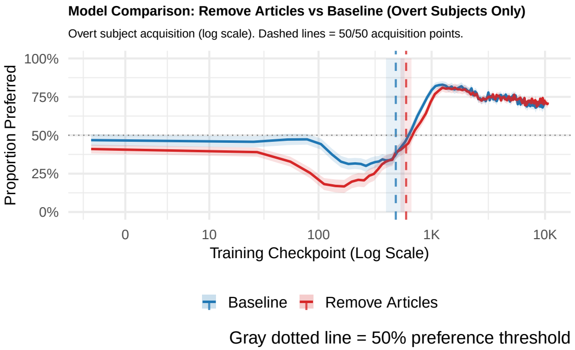


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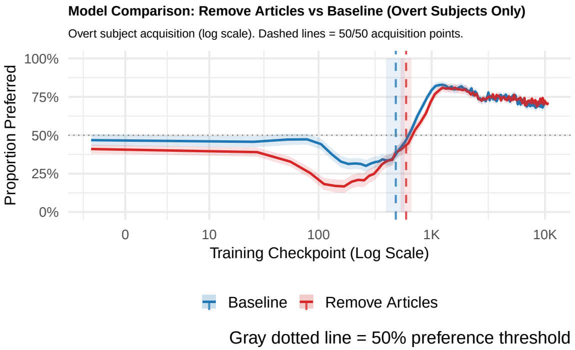


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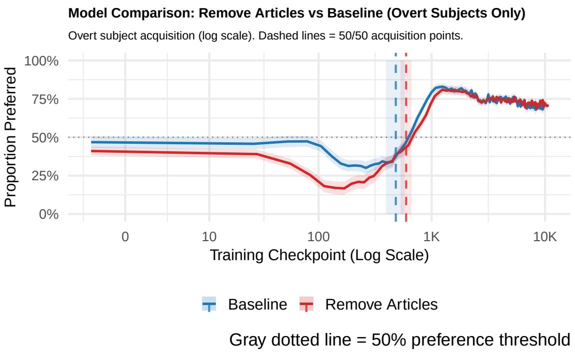


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- Shows significantly stronger null preference in first epoch (71.7%) compared to baseline.
- End-state overt preference (68.2%) is significantly lower than baseline model.

# Exp 4: ‘Lemmatize Verbs’ – Training Curves

Figure 5: Model overt preference over training, training steps transformed to log-scale to reflect model log-learning dynamics comparing Experiment 0 and Experiment 4.

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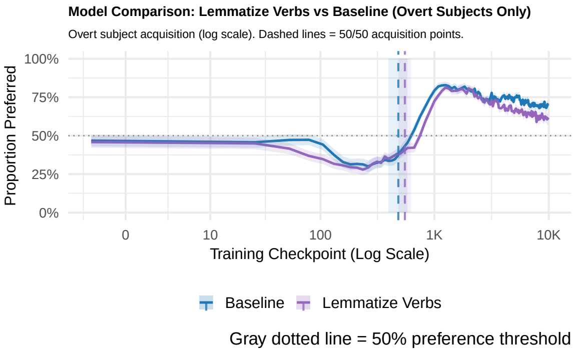


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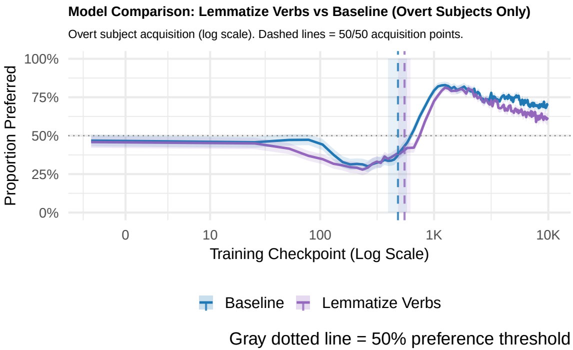


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- Age of Acquisition analysis revealed that this model achieved **AoA at checkpoint 705** (95% CI [660, 748]).
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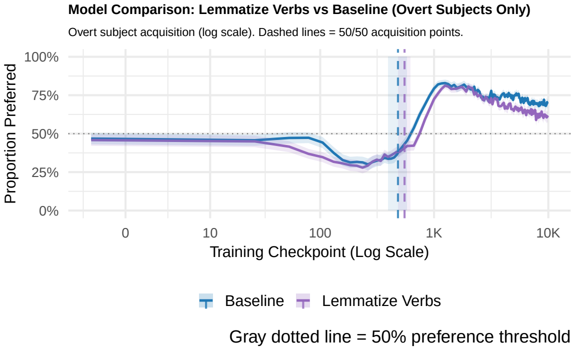


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    - Which is significantly **earlier** than baseline ($\Delta$AoA = -22 epochs, 95% CI [-43, -1.65], p = .034)
- Fastest acquisition among all interventions.

# Exp 5: ‘Remove Subject Pronominals’ – Training Curves

Figure 6: Model overt preference over training, training steps transformed to log-scale to reflect model log-learning dynamics comparing Experiment 0 and Experiment 5.

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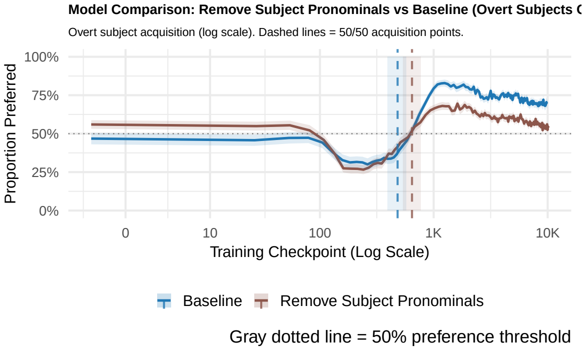


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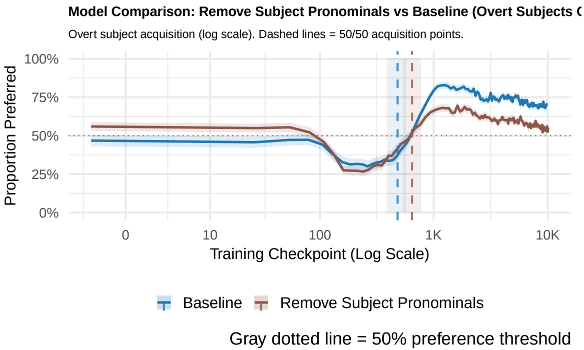


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- Age of Acquisition analysis revealed that this model achieved **AoA at checkpoint 774** (95% CI [706, >5000]).
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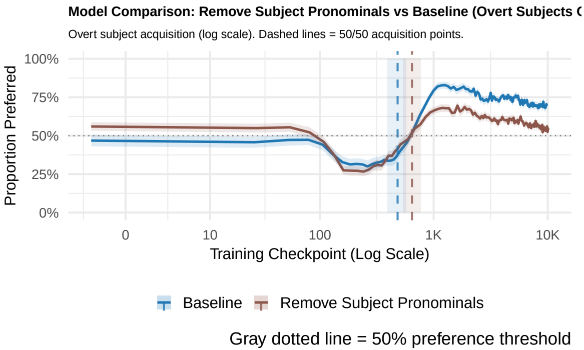


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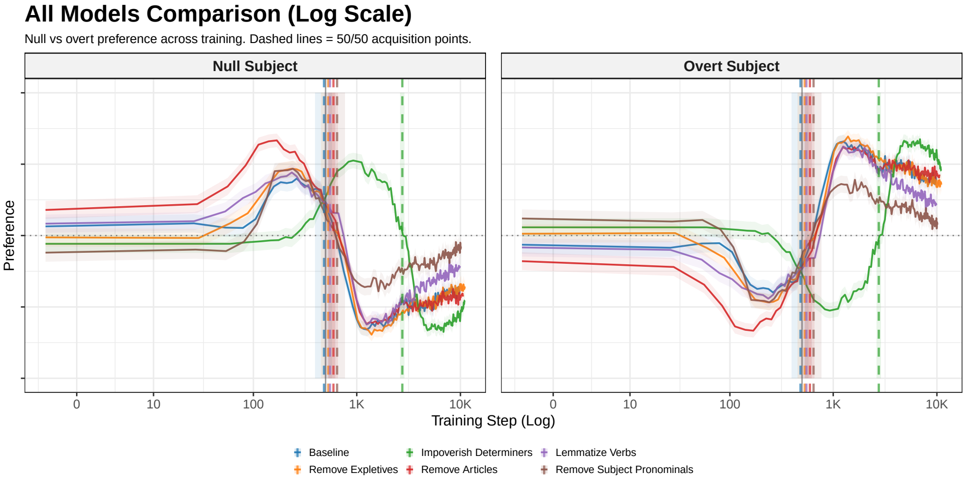
- Age of Acquisition analysis revealed that this model achieved **AoA at checkpoint 774** (95% CI [706, >5000]).
  - Slightly later than baseline ($\Delta$AoA = 47 epochs, p<.05)
- Weakest overall overt preference (54.4%) among all models.

# Cross-Model Comparison

Figure 7: Cross-model comparison of null subject acquisition trajectories (log scale)



# Processing Account: Predicted vs. Observed

**Bloom's Processing Account Prediction**

Under increased processing load, children should drop subjects MORE frequently

**Processing Manipulations:**

- Long noun phrases
- Embedded relative clauses
- Negation contexts
- Target vs. context negation

**Implication:** Do LLMs omit more subjects in contexts with heavy processing load?

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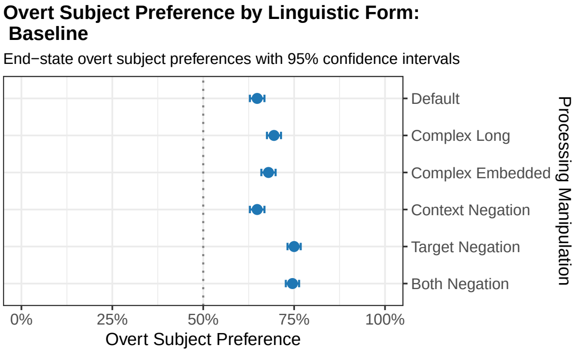


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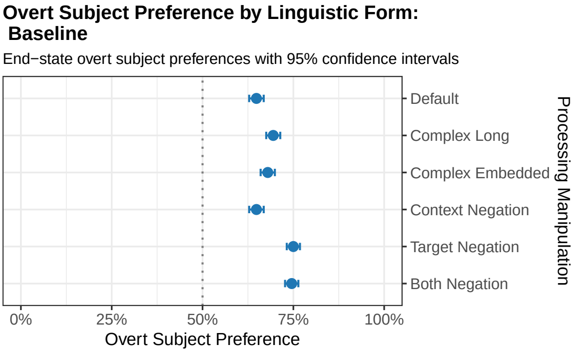


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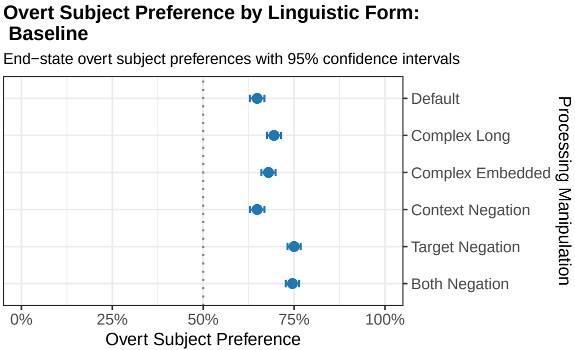


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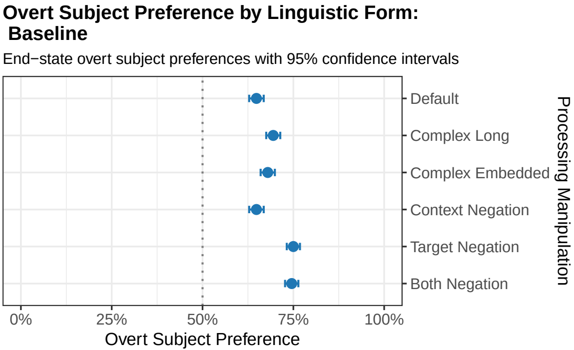


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- Negation shows the strongest influence on models' choice for overt subjects.
- The model under these contexts show increased overt preference
- This is counter to the reported human pattern of higher null subject use in negation contexts.

# Processing Effects Across All Models

| Form | Baseline | Rmv. Expletives | Impvr. Detrmn. | Rmv. Articles | Lemmatize Verbs | Rmv. Subject Pronominals |
|---|---|---|---|---|---|---|
| Complex Long | ✓ | | ✓ | | | |
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- **Complex syntax:** Largely does not increase overt preference
- **Context negation:** No effect across models

# Implications for Processing Theories

**Traditional View**

- Processing load $\rightarrow$ omit subjects
- "Good enough" processing
- Resource limitation effects

**Model Behavior**

- Processing load $\rightarrow$ *insert* subjects
- More explicit under complexity
- Robust to context effects

**Possible Explanations:**

- Models and children process complexity fundamentally differently
- Processing accounts may not fully explain child null subject errors
- Need empirical validation of processing effects in human production

# Universal Early Null Subject Stage

**Surprising Finding: All Models Show Initial Null Subject Preference**

Despite English being overt-subject, ALL models prefer null subjects early in training

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**Question:** Is this a learning bias or evidence from the input environment?

# Evidence Types: Shortcuts vs. Deep Learning

## Direct Evidence

- **Subject pronouns:** Critical
- Remove pronouns → near-chance performance
- Supports Hyams' direct evidence account

## Indirect Evidence

- **Determiners:** Provide "shortcuts"
- **Verbal morphology:** Affects final strength
- **Expletives:** Minimal effect

## Grokking Hypothesis

Removing shortcuts (determiners) forces slower but potentially more robust generalization

# Broader Theoretical Implications

**What This Study Challenges**

Multiple acquisition theories do not capture model learning behavior

**Challenges:**

- Yang's variational learning
- Simple parameter-setting

**Supports:**

- Hyams' direct evidence account
- Duguine's implication of the article system
- Gradual, evidence-based learning

**Future Work:** Test these patterns with human participants and cross-linguistic data

# Chapter 2: Transfer Effects in Bilingual Acquisition

**Core Research Questions:**

- Are large language models capable of maintaining competence when trained multilingually?

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- Evaluate null-subject competence in both languages

# Chapter 2: Four Bilingual Training Experiments

**Training Protocol: 90M Dataset**

*L1 training (1 or 2 epochs) → L2 training (5 epochs opposite language)*

**English First Models:**

1. **Experiment 0:** English 1 epoch → Italian 5 epochs
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**Key Question:** Is there asymmetric transfer/impairment between languages?

# Italian Stimuli: Pro-Drop Language

**Core Contrasts (Italian pro-drop)**

**Person/Number**: Anna ha finito il libro. ∅/%Lei pensa che il finale sia perfetto.
*Anna has finished the book. ∅/She thinks that the ending is perfect.*

**Control**: Maria ha convinto suo fratello ∅/*lui a partire presto.
*Maria convinced her brother ∅/*him to leave early.*

**Expletives**: ∅/*Sembra che gli studenti abbiano superato l'esame.
*∅/*It seems that the students have passed the exam.*

**Conjunctions**: Giovanni si è svegliato tardi e ∅/lui ha perso il treno.
*Giovanni woke up late and ∅/he missed the train.*

*Italian allows null subjects where English requires overt realization*

# The 'Default' Account and Predictions

**Theoretical Background**

Children initially default to null subjects, then learn overt subject requirements

**Asymmetry Prediction:**

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**Critical Test:** Do we see greater transfer benefits vs. interference costs?

# Training Methodology: Four Bilingual Models

## Training Protocol

Four models trained for 6-7 epochs total with systematic checkpointing

**Checkpoint Strategy:**

- **Log-step checkpoints** within first epoch: 1, 2, 4, 8, 16, 32...

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- Learning curves constructed for L1 and L2 acquisition
- Age of Acquisition (AoA) and end-state performance measured

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**Key Hypothesis:**

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**Specific Predictions:**

**English L1 Models:**

- More English training $\rightarrow$ slower Italian L2
- Delayed AoA for Italian null subjects
- Stronger interference effects

**Italian L1 Models:**

- Amount of Italian training has minimal effect
- Consistent English L2 acquisition
- No systematic interference

# Chapter 3: Cross-Linguistic Priming of Null Subjects

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**Method:**

- Prime with null/overt subjects in Language A

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- Effects independent of lexical overlap or surface similarity

# Structural Priming Methodology

## Surprisal-Based Measurement

Following Sinclair et al. (2022) and Momma et al. (2025)

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- Pure test of abstract syntactic representation

# From Parallel Stimuli to Cross-Linguistic Priming

## Leveraging Bilingual Evaluation Sets

Transform parallel English/Italian stimuli into priming experiments

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- Compare surprisal differences across prime conditions

# Cross-Linguistic Priming Matrix

**Experimental Design:**

| Prime Language | Target Language | Measurement |
|---|---|---|
| Italian null | English | Surprisal on English verb |
| Italian overt | English | Surprisal on English verb |
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**Key Advantages:**

- Syntactic priming should occur with **no lexical overlap** between prime and target
- Simple stimuli construction, as we can use any parallel eval set to assess abstract representations as well as preferences

# Priming as a Window into Abstract Syntax

## What Cross-Linguistic Priming Reveals

Abstract syntactic knowledge that transcends surface linguistic differences

**Theoretical Predictions:**

- If the model's are not showing robust cross-linguistic priming effects, that indicates that they are developing generalizations in a shallow, concrete way.

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- and Vice Versa

# References I


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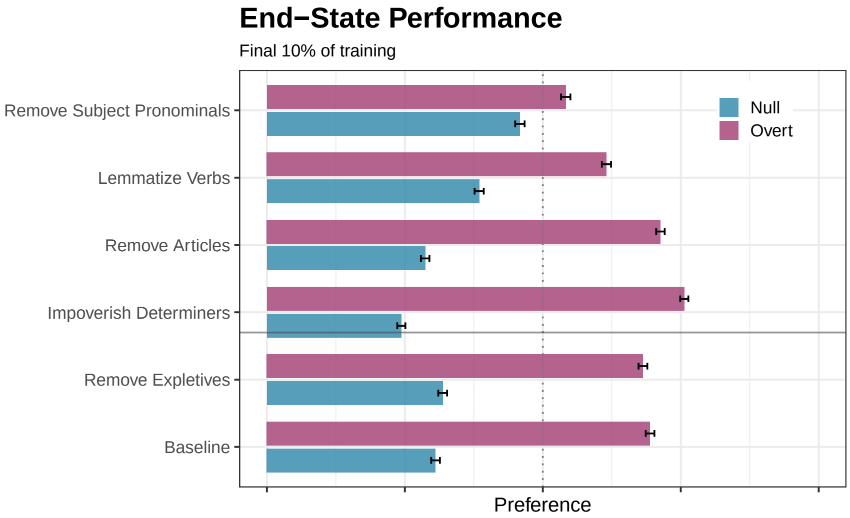
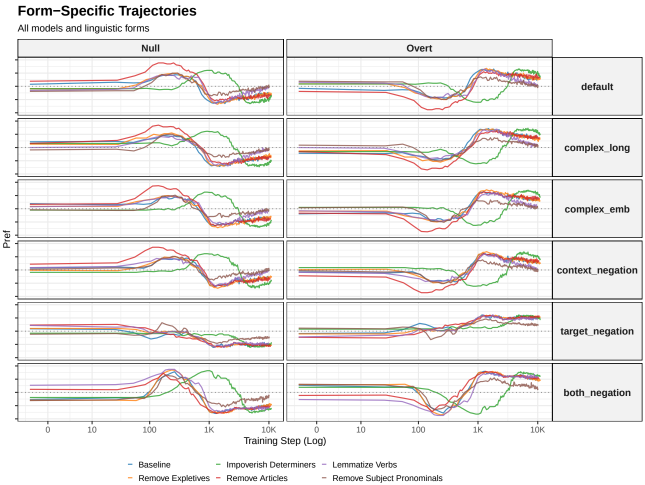
# End-State Performance Comparison



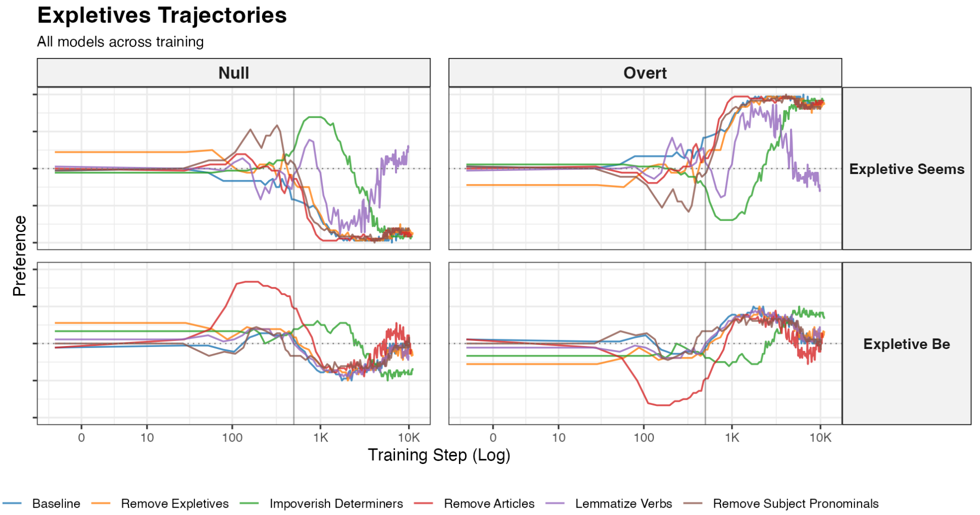
# Processing Forms vs Default Performance

| Form | Baseline | Rmv. Expletives | Impvr. Detrmn. | Rmv. Articles | Lemmatize Verbs | Rmv. Subject Pronominals |
|---|---|---|---|---|---|---|
| Complex Long | ✓ | | ✓ | | | |
| Complex Emb | | | ✓ | | | |
| Context Negation | | | | | | |
| Target Negation | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Both Negation | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

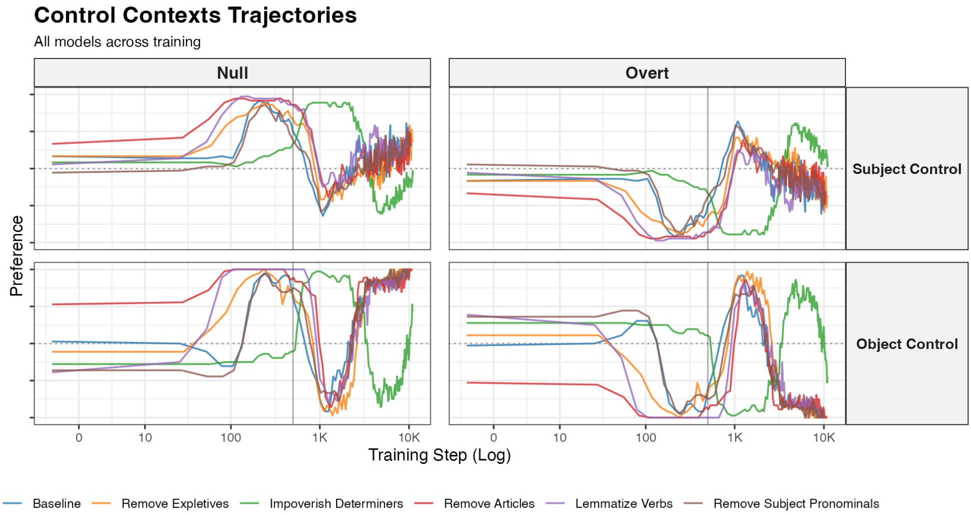
# Developmental Trajectories by Processing Manipulation



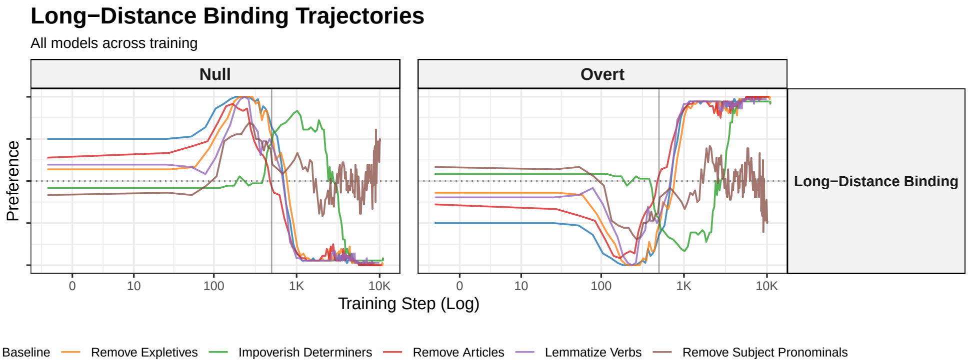
# Learning Trajectories: Expletive Constructions



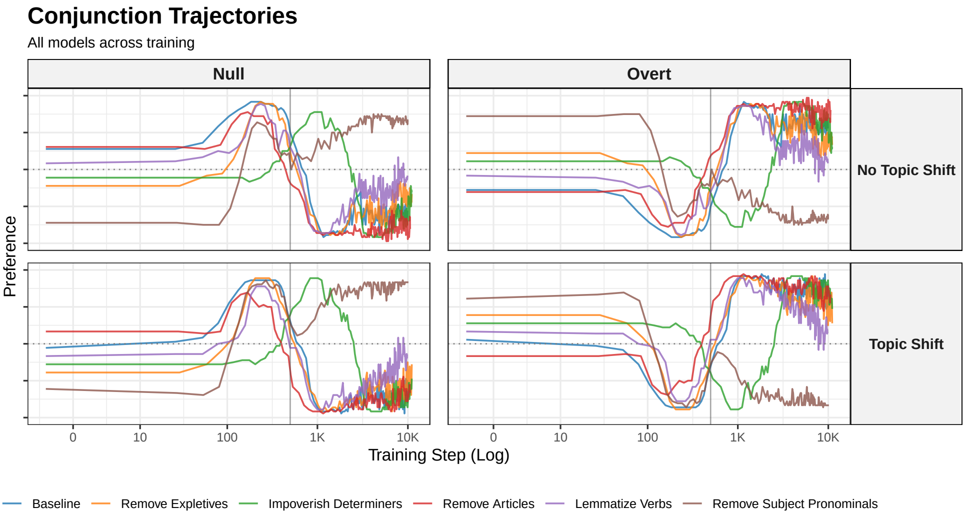
# Learning Trajectories: Control Constructions



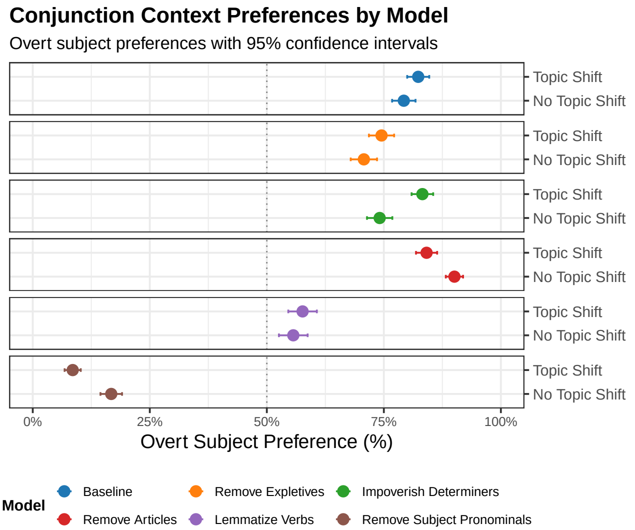
# Learning Trajectories: Long-Distance Binding



# Learning Trajectories: Conjunction Contexts



# Conjunction Context Performance by Model



# Model Preferences: Null vs Overt Subjects

| Model | Null Pref | Overt Pref |
|---|---|---|
| Baseline | 0.326 | 0.674 |
| Remove Expletives | 0.328 | 0.672 |
| Impoverish Determiners | 0.353 | 0.647 |
| Remove Articles | 0.336 | 0.664 |
| Lemmatize Verbs | 0.378 | 0.622 |
| Remove Subject Pronominals | 0.439 | 0.561 |

# Age of Acquisition by Model

| Model | AOA | CI |
|---|---|---|
| Lemmatize Verbs | 705.00 | [661, 749] |
| Baseline | 727.00 | [665, 792] |
| Rmv. Expletives | 767.00 | [709, 821] |
| Rmv. Subject Pronominals | 775.00 | [707, >5000] |
| Rmv. Articles | 808.00 | [759, 861] |
| Impvr. Detrmn. | 3400.00 | [3307, 3499] |