

# Getting the Right Stuff Wrong: Modeling the Acquisition of Inflectional Morphology

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# Introduction: Morphological Acquisition

- Children **learn inflectional morphology**

- From highly *sparse, skewed* input
- On <1000 word types
- Despite *exceptions*
- With complex systems of *allomorphy*



**Challenging  
problem!**

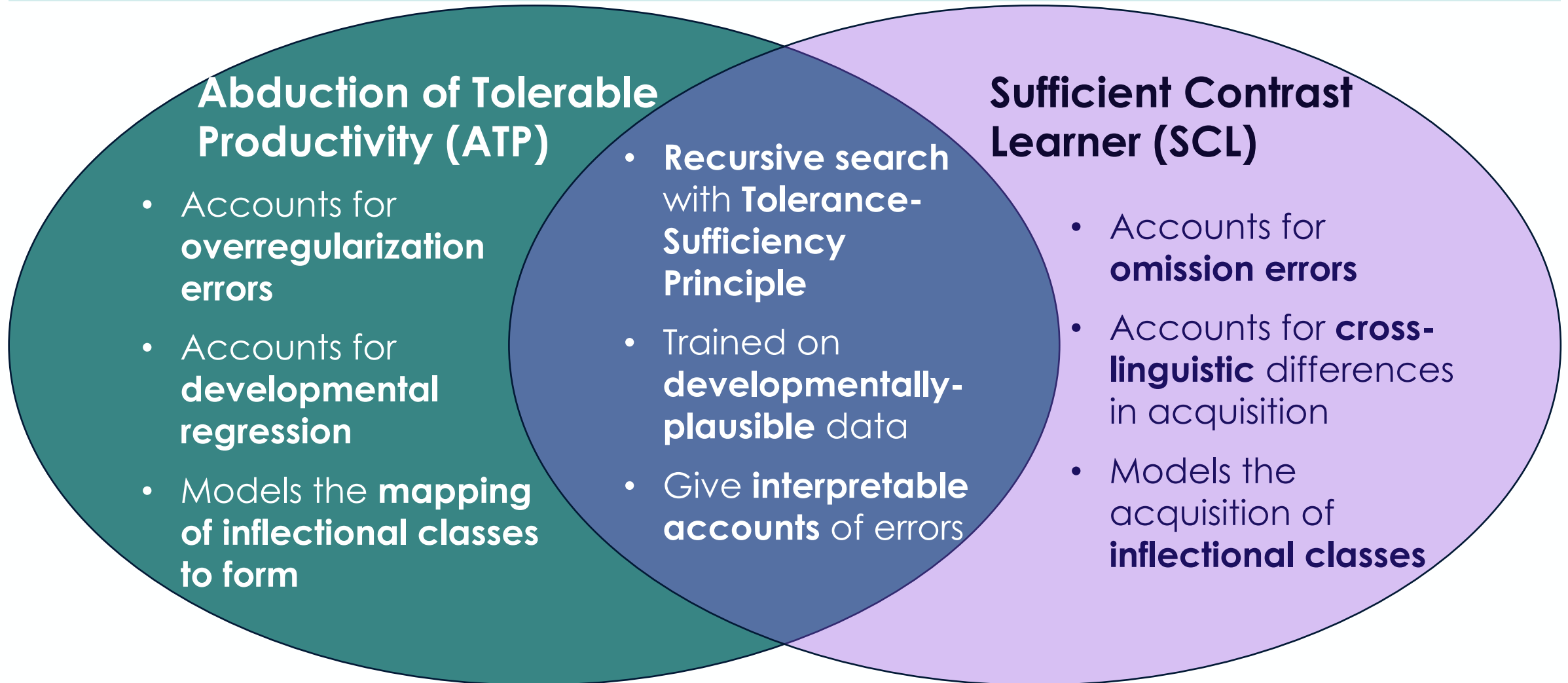
# Introduction: Morphological Acquisition

- Children make **systematic errors** cross-linguistically
    - **Overregularization:** e.g. “feel-feeled”
    - **Omissions of Marking:** e.g. “Papa have it”
  - Why **these** errors and not others?
  - What do the errors tell us about:
    - Acquisition?
    - The resulting grammar?
- Almost all errors**
- Models of morphological acquisition should address these questions**

# Introduction: Mechanistic Accounts

- To provide **mechanistic accounts of error patterns**, models should:
  - Make the **same errors as children**
  - On **developmentally-plausible training data**
  - Be **interpretable**
- **Neural models** struggle with this
  - **Unnatural error patterns:** over-irregularizations common
  - **Data-hungry:** large and/or saturated data
  - **Not interpretable**

# Introduction: Proposal



# Outline

- **What makes a plausible model?**
  - Nature of the input
  - Developmental Findings
- **Previous work**
  - The Past Tense Debate
  - The Past Tense Debate: Reprise
- **Proposal**
  - **ATP**: mapping features to form
  - **SCL**: learning inflectional classes
- **Future work**

**What makes a plausible  
model?**

The Nature of the Input

# Input Sparsity: Zipf's Law

- **Zipf's law:** word *rank* inversely proportional to *frequency*

$$f(r) \propto \frac{1}{r}$$

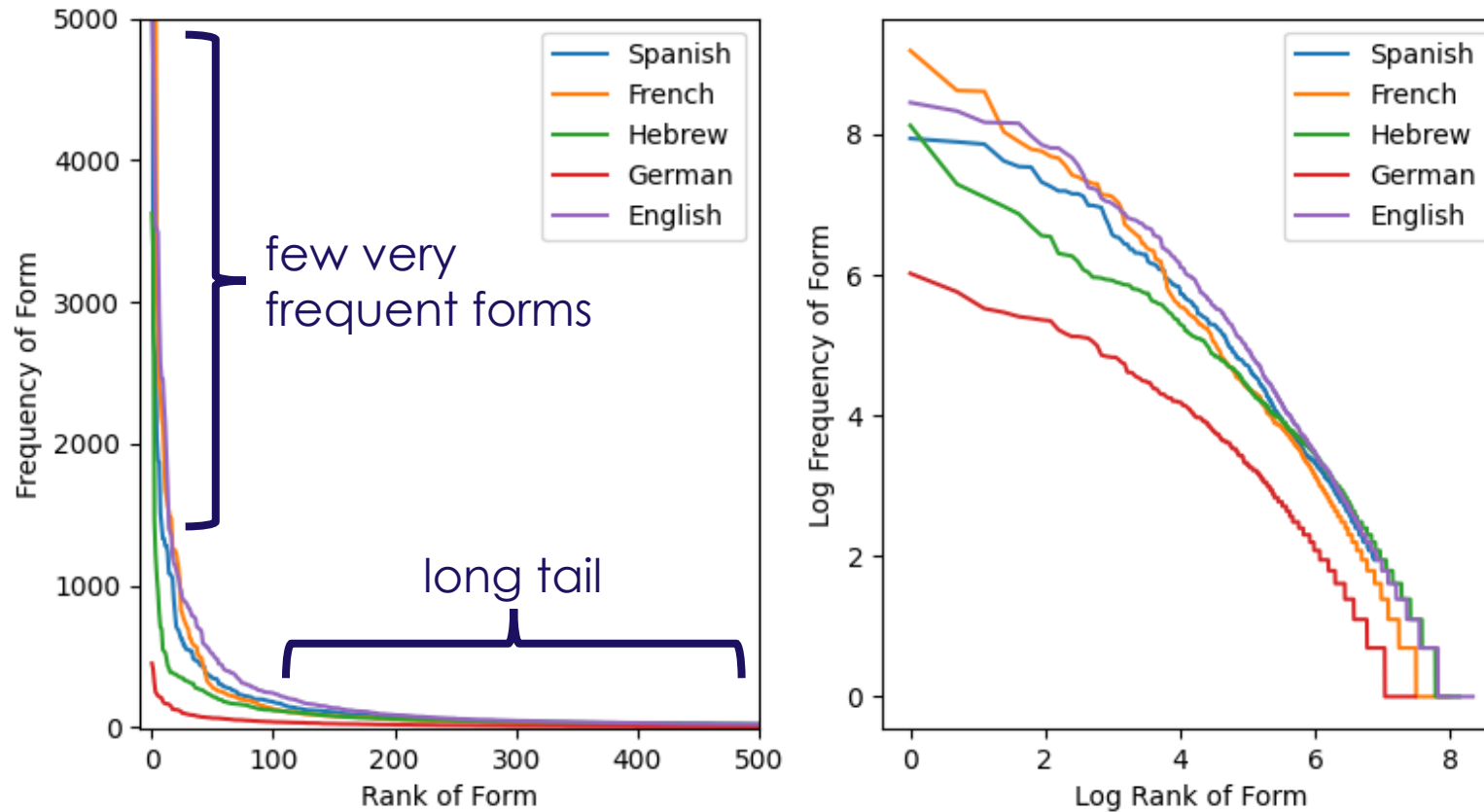
- **Consequences:**

- A few forms occur very frequently
- Most occur very rarely (long tail)



# Input Sparsity: Zipf's Law

Zipfian Distribution of Training Data



(data from Payne et al 2021, Belth et al 2021, Payne 2022, and Payne 2023)

# Input Sparsity: Paradigm Saturation

- Long-tailed distributions in morphology: **Paradigm Saturation**
  - How many possible inflected forms does a lemma actually occur in?

$$\textit{saturation} = \frac{\# \textit{seen}}{\# \textit{possible}}$$

	Present	Preterite	Imperfect	Conditional	Future
1SG	<i>amo</i>	<i>amé</i>	<i>amaba</i>	<i>amaría</i>	<i>amaré</i>
2SG	<i>amas</i>	<i>amaste</i>	<i>amabas</i>	<i>amarías</i>	<i>amarás</i>
3SG	<i>ama</i>	<i>amó</i>	<i>amaba</i>	<i>amaría</i>	<i>amará</i>
1PL	<i>amamos</i>	<i>amamos</i>	<i>amábamos</i>	<i>amaríamos</i>	<i>amaremos</i>
2PL	<i>amáis</i>	<i>amasteis</i>	<i>amabais</i>	<i>amaríais</i>	<i>amaréis</i>
3PL	<i>aman</i>	<i>amaron</i>	<i>amaban</i>	<i>amarían</i>	<i>amarán</i>

(Chan 2008, Lignos & Yang 2016)

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1SG	<i>amo</i>		<i>amaba</i>		<i>amaré</i>
2SG		<i>amaste</i>			
3SG	<i>ama</i>		<i>amaba</i>		
1PL	<i>amamos</i>				
2PL					
3PL					

$$= \frac{7}{\# \textit{possible}}$$

(Chan 2008, Lignos & Yang 2016)

# Input Sparsity: Paradigm Saturation

- Long-tailed distributions in morphology: **Paradigm Saturation**
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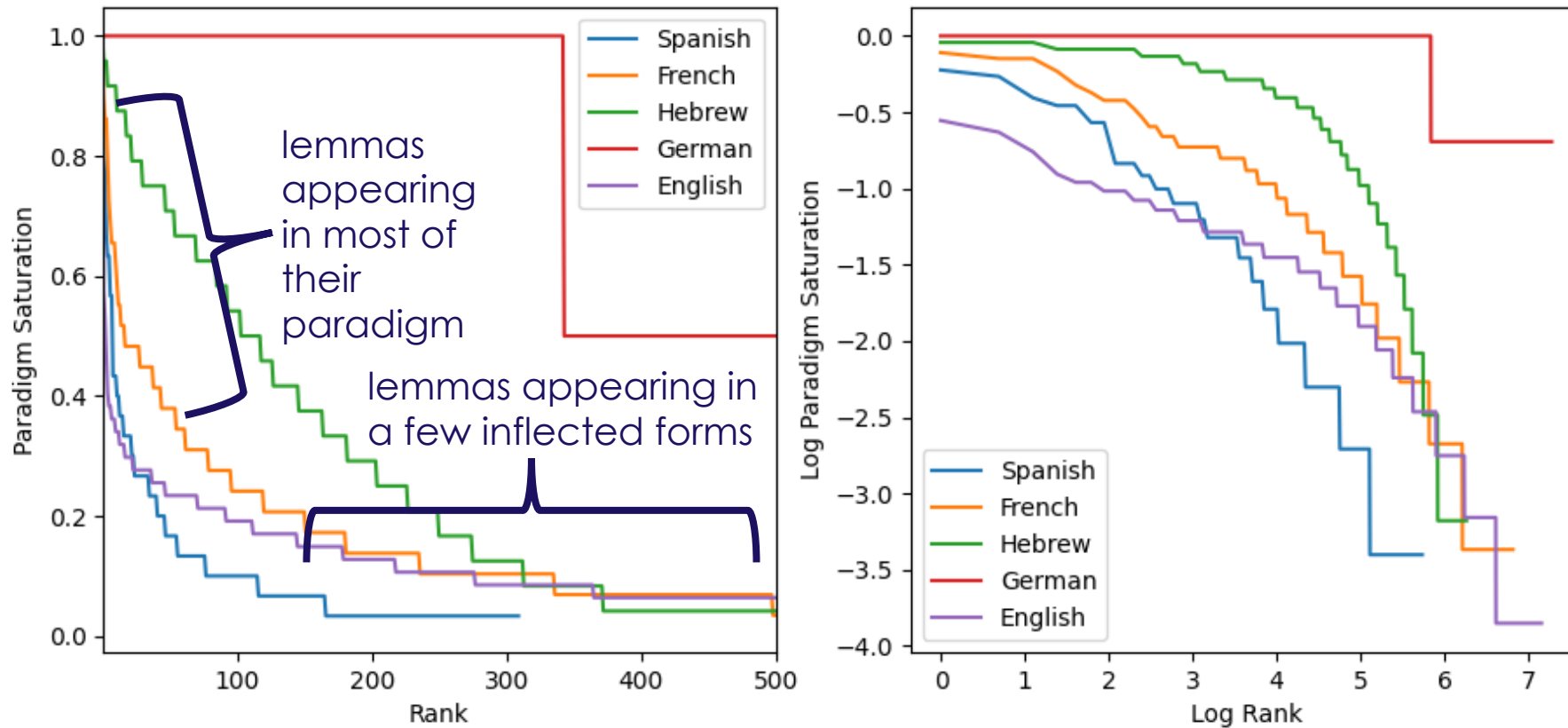
$$= \frac{7}{26} \approx 27\%$$

	Present	Preterite	Imperfect	Conditional	Future
1SG	<b>amo</b>	trabajé	<b>amaba</b>	trabajía	<b>amaré</b>
2SG	tomas	<b>amaste</b>	mirabas	mirarías	esperás
3SG	<b>ama</b>	esperó	<b>amaba</b>	espería	tomará
1PL	<b>amamos</b>	miramos	mirabamos	tomaríamos	miraremos
2PL	tratáis				
3PL	esperan	miraron	entraban	tratarían	entrarán

(Chan 2008, Lignos & Yang 2016)

# Input Sparsity: Paradigm Saturation

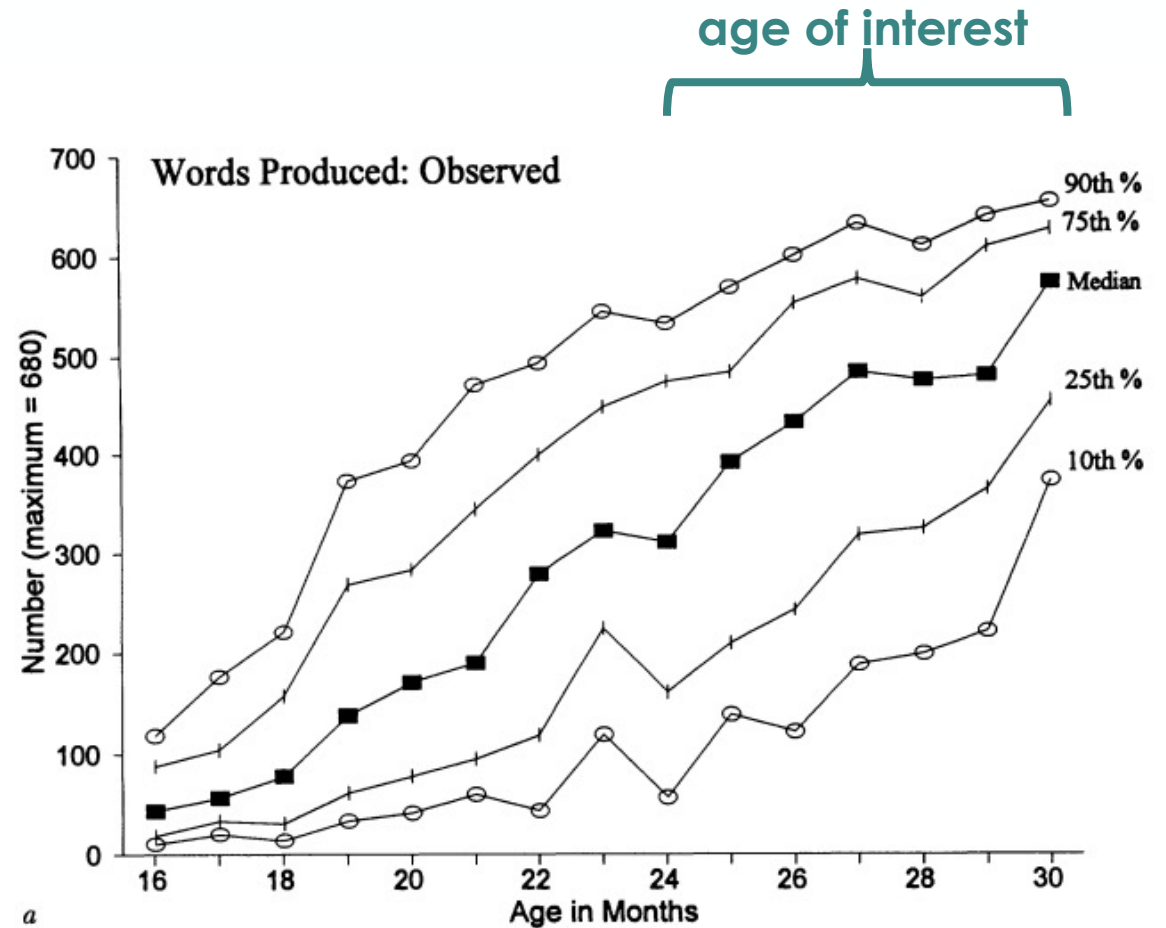
Paradigm Saturation of Training Data



(data from Payne et al 2021, Belth et al 2021, Payne 2022, and Payne 2023)

# Input Sparsity: Early Vocabulary

- At 2;0: 200-500 words cross-linguistically
- At 3;0: <1000 words cross-linguistically
- Early vocabulary makeup:
  - ~50% nouns
  - ~25% verbs



(from Fenson et al 1994)

# What makes a plausible model? Developmental Findings

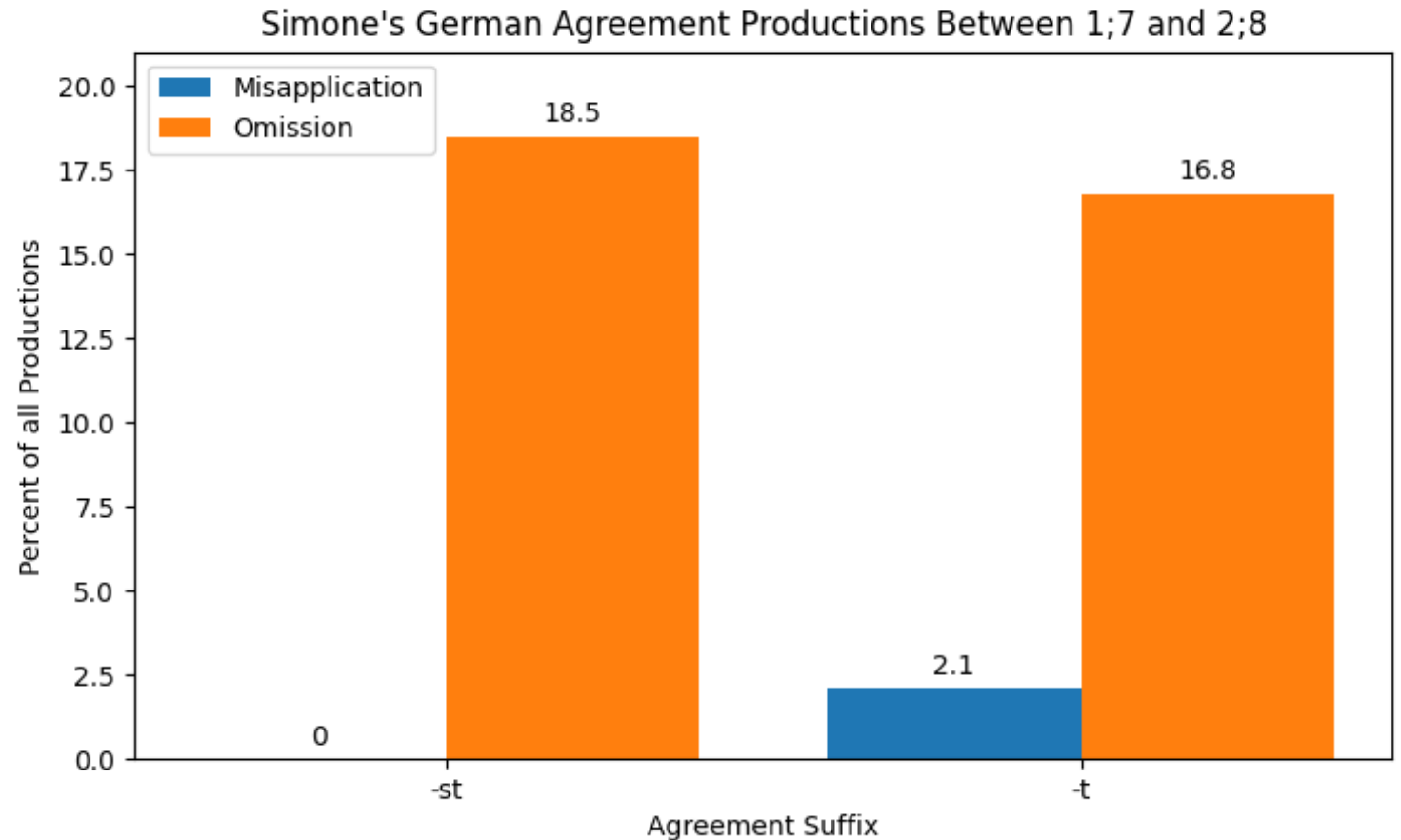
# Background: Production Errors

- **Omissions: *Root Infinitives***

- e.g. “Papa have it”

- **Substitutions: incorrect overt affix**

- e.g. “I has it”

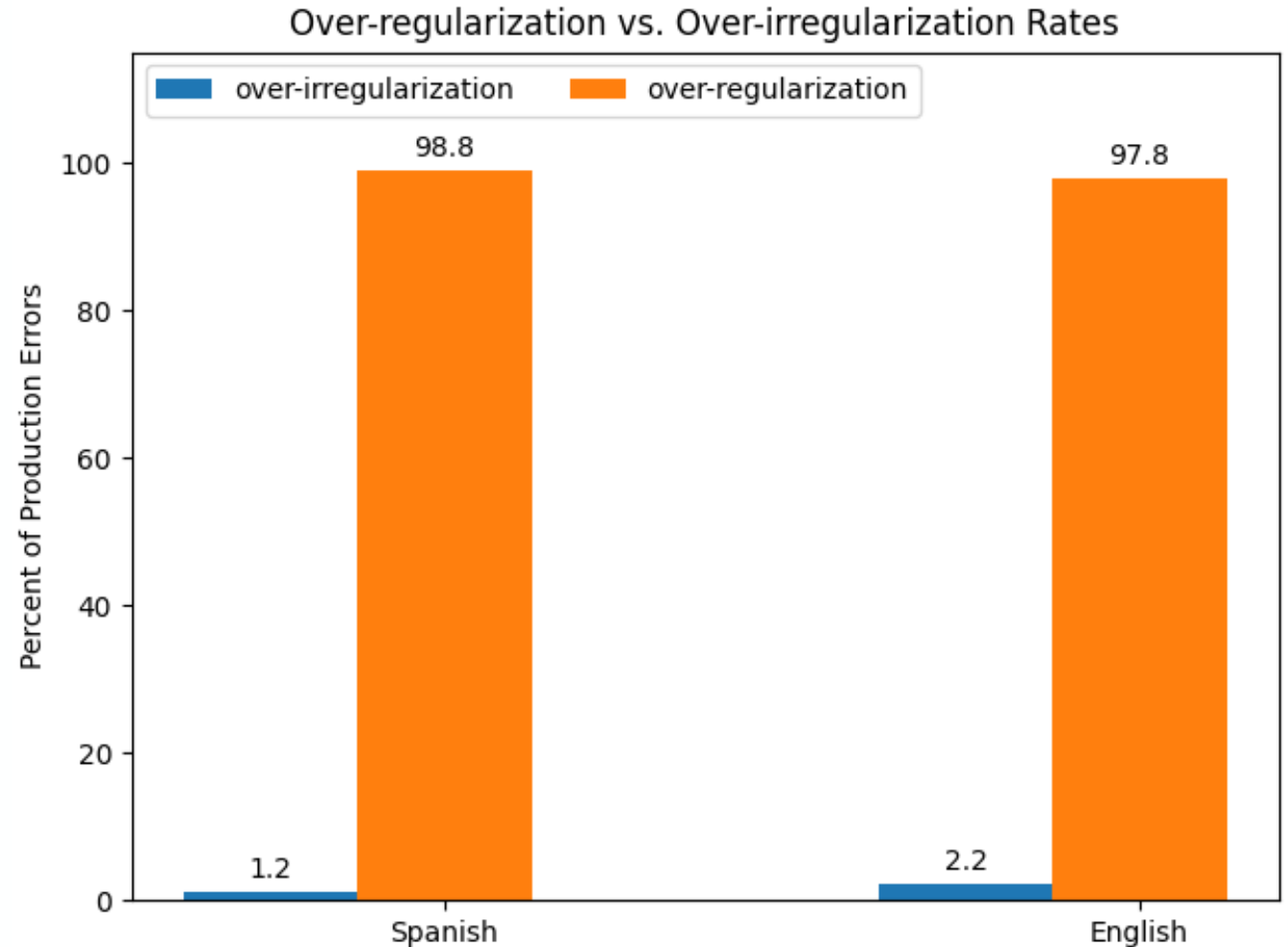


(Clahsen & Penke 1992, Philips 1995, Legate & Yang 2007)



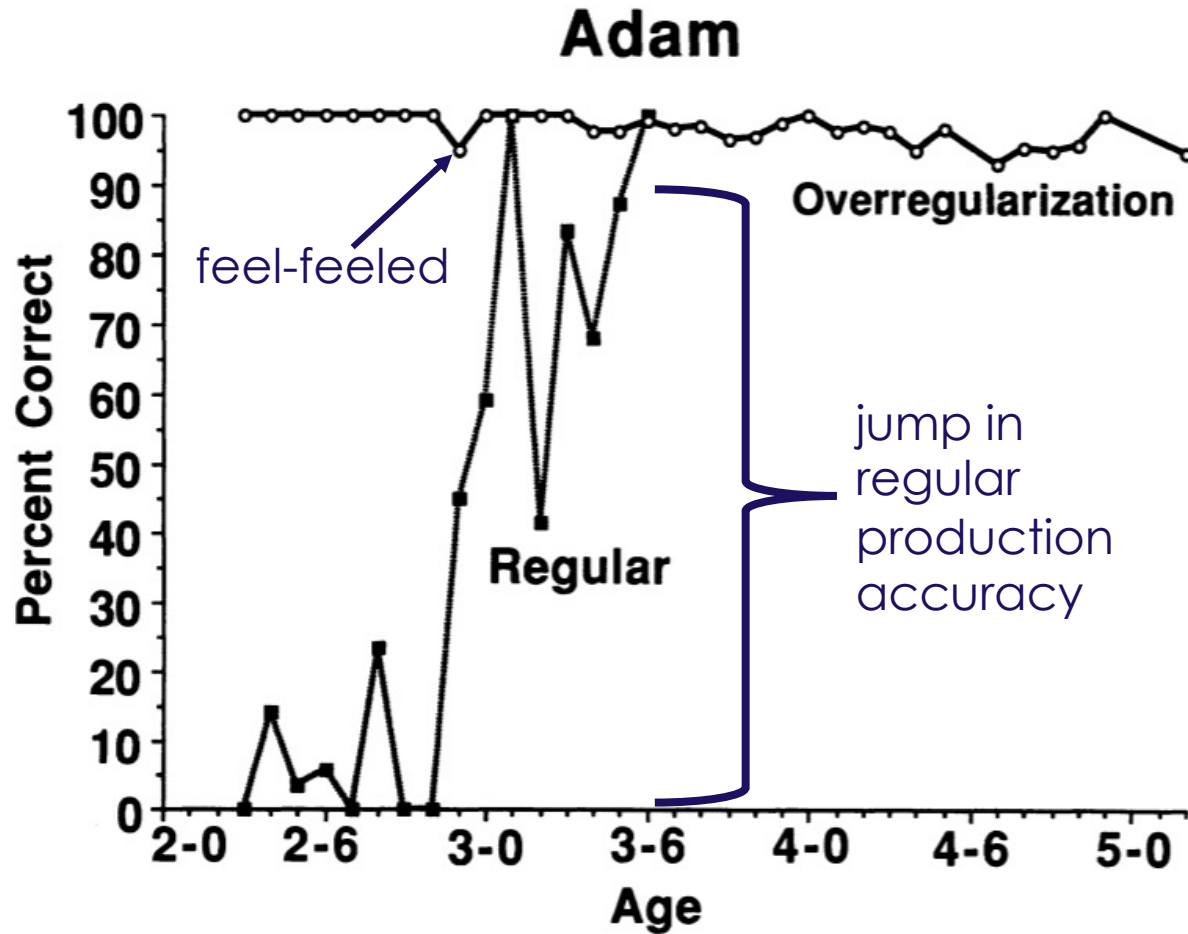
# Background: Production Errors

- **Over-regularization**
  - e.g. *feel-feeled*
- **Over-irregularization**
  - e.g. *bite-bote*



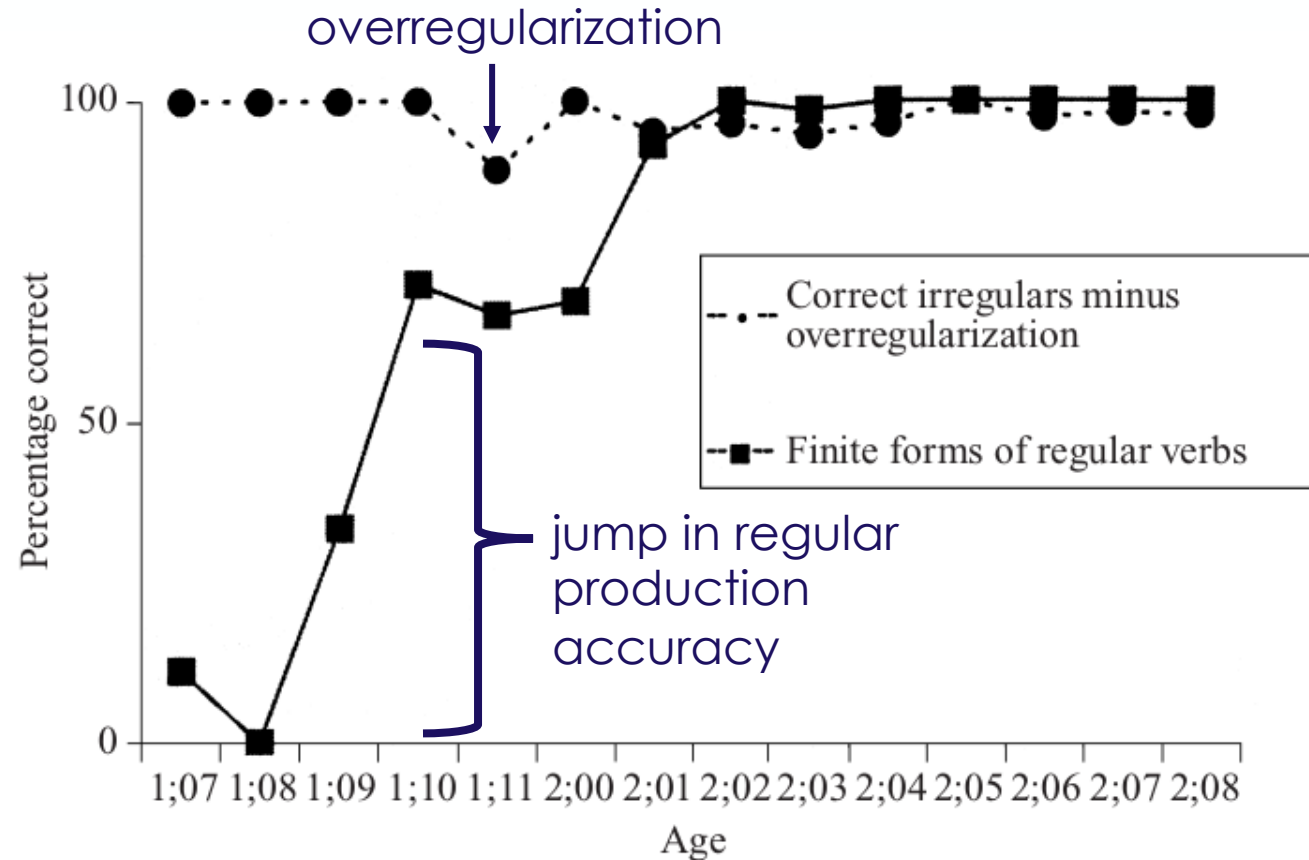
(Maslen et al 2004, Xu & Pinker 1995, Clahsen et al 2002)

# Background: Developmental Regression



(from Marcus et al 1992)

# Background: Developmental Regression



(from Clahsen, Aveledo, and Roca 2002)

# Summary: What Makes a Plausible Model?

- **Learn from:**

- *Small* vocabulary
- *Sparse* paradigms

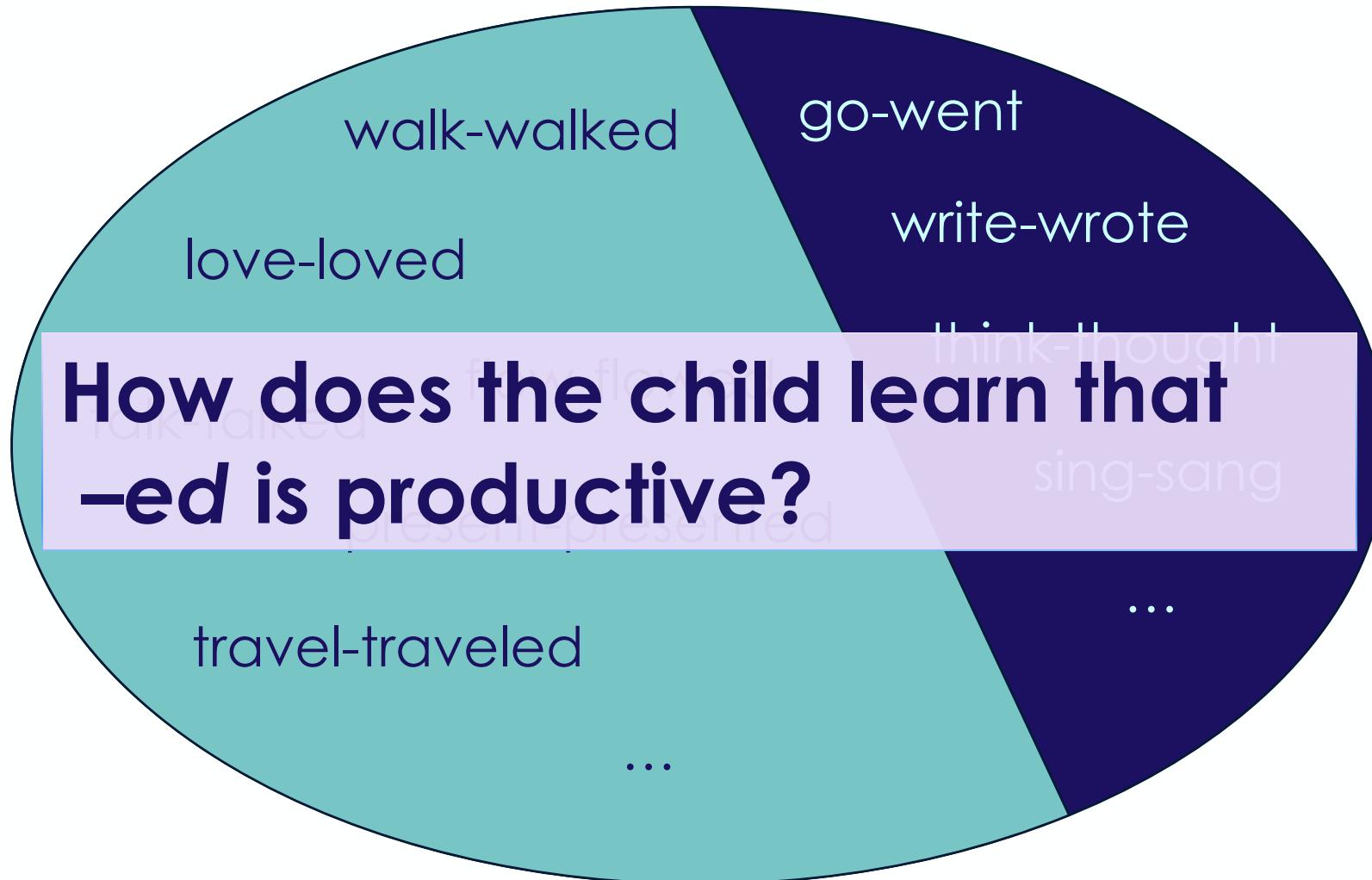
- **Errors:**

- *Omissions*, not substitutions
- *Over-regularizations*, not over-irregularizations
- Developmental *regression*

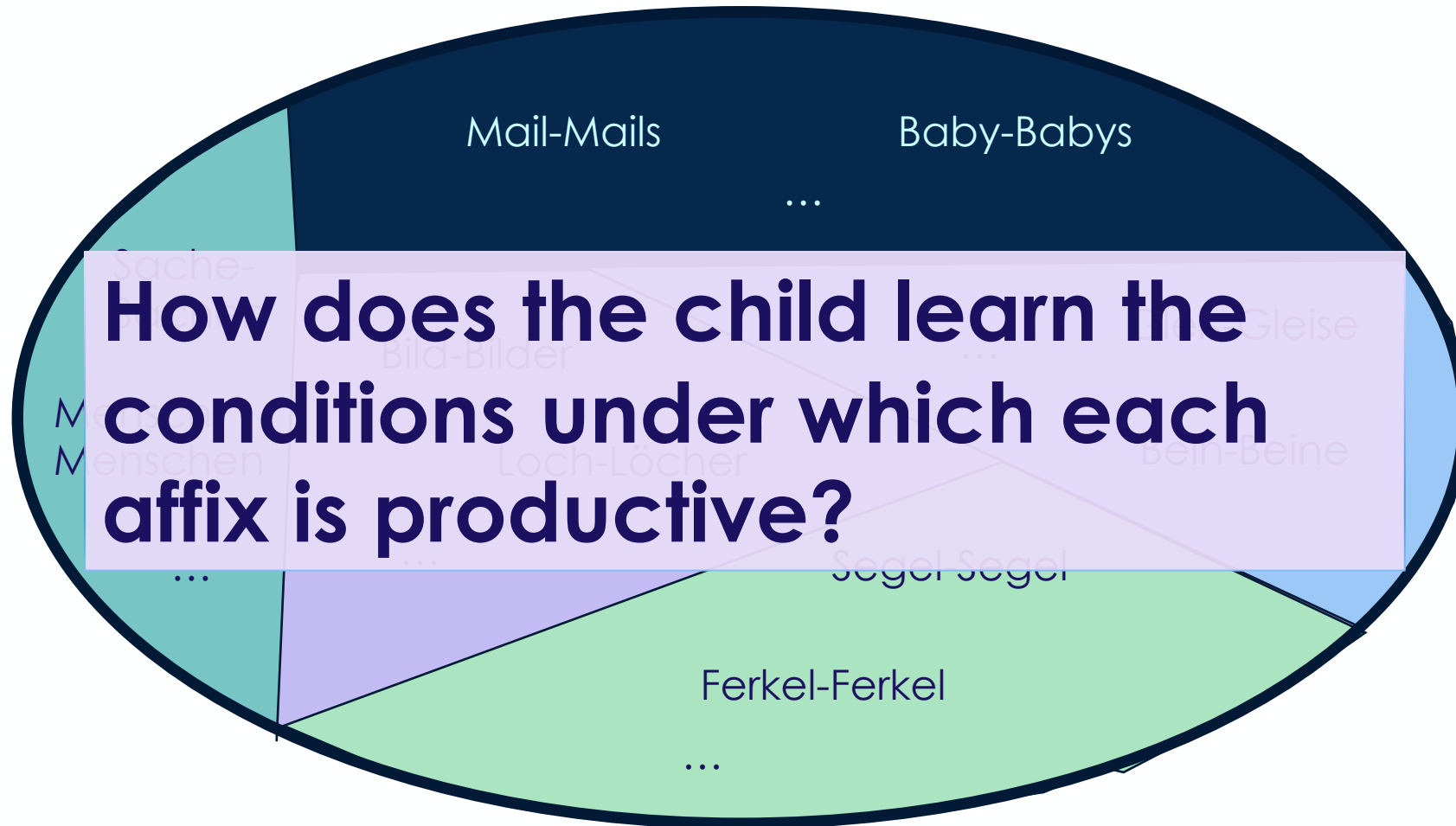
# Previous Work:

## The Past Tense Debate, Rounds 1 and 2

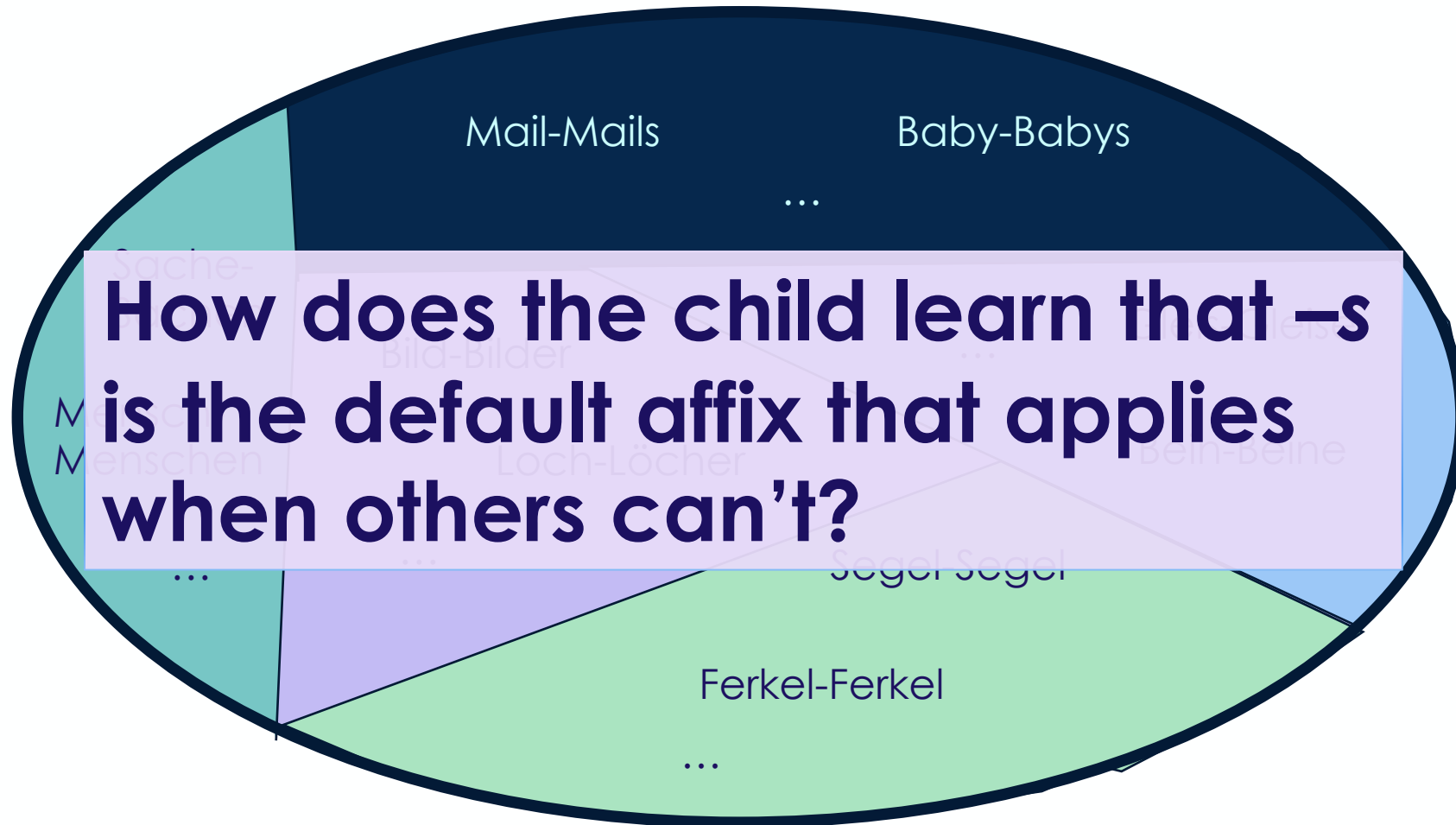
# Handling Exceptionality



# Handling Allomorphic Productivity



# Handling Allomorphic Productivity







# Background: The Past Tense Debate

- Rumelhart & McClelland (1986): *single-route, connectionist* model can:
  - Exhibit *developmental regression*
  - Exhibit *overregularization*

∴ **Rule-like behavior**

- Pinker & Prince (1988): actually...
  -  *Developmental regression* = artifact of training data
    - First trained on *80% irregulars*
    - Then trained on *80% regulars*
  -  Exhibits *over-irregularization*
    - *sip-sept, type-typed, mail-membled*

∴ **No rule-like behavior**

# Background: The Past Tense Debate Revisited

## Recurrent Neural Networks in Linguistic Theory: Revisiting Pinker and Prince (1988) and the Past Tense Debate

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# Background: The Past Tense Debate Revisited

- Kirov & Cotterell (2018): encoder-decoder RNNs can overcome empirical limitations
  - Near **100% test accuracy**
  - Learn **several classes at once**
  - Trained on **developmentally-representative** data
  - Main errors = **overregularizations**
- Corkery et al (2019): ED model **still fails empirically!**
  -  Predictions **don't match well with humans** on nonce English past tense forms
    - **Still over-irregularizes!**
  -  Massive **variability in model rankings** between seeds
    - **Correlation with human ratings** also varies massively

# Background: The Past Tense Debate Revisited

- **Kirov & Cotterell (2018):** encoder-decoder RNNs can overcome empirical limitations
  - Near **100% test accuracy**
  - Learn **several classes at once**
  - Trained on **developmentally-representative** data
  - Main errors = **overregularizations**

 No **developmental regression!**

 Trained on **>3500 verbs in their full paradigm**

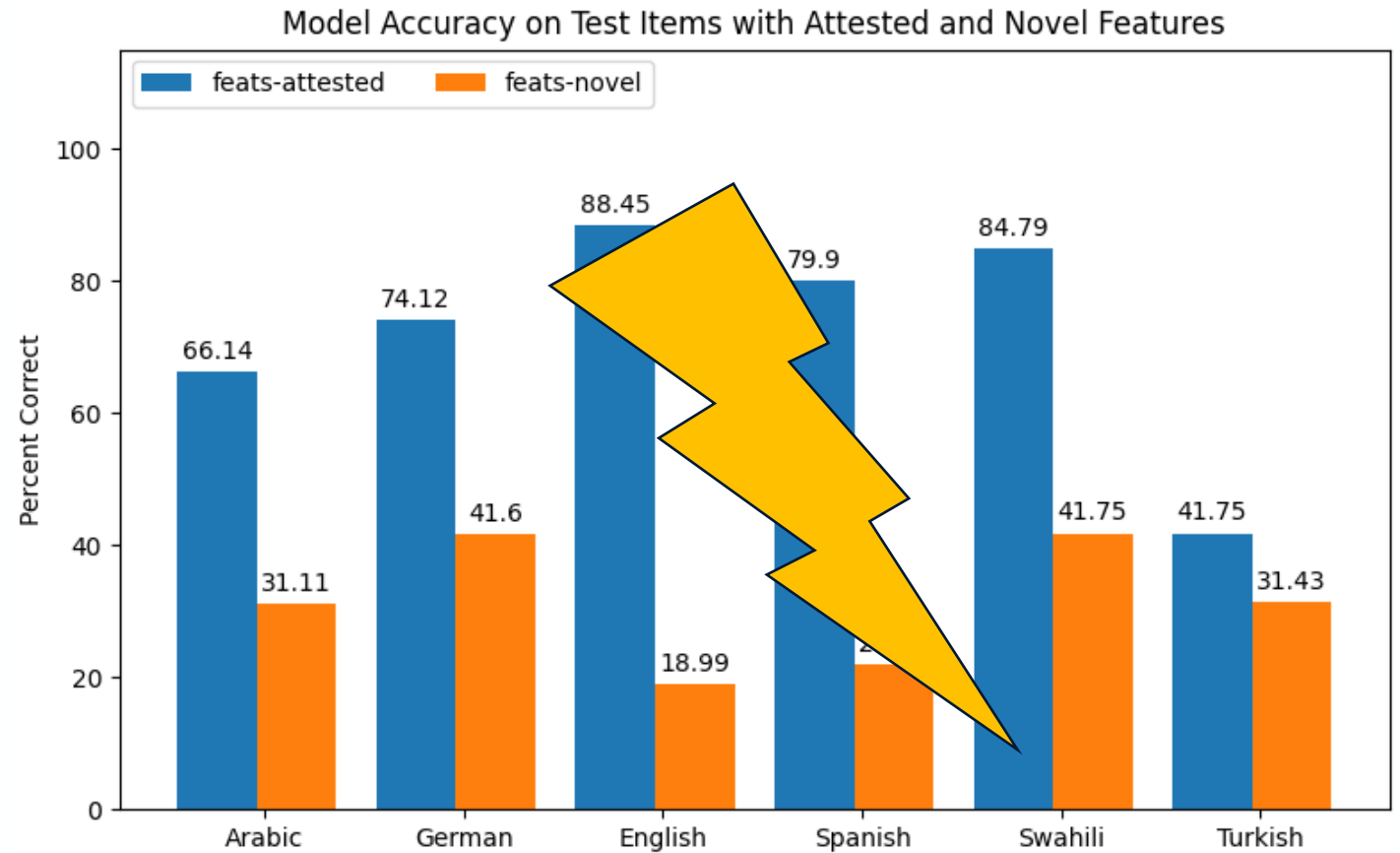
- Children know **< 350 verbs** at 3;0
- Would need to see **> 15k lemmas** to see 3,500 in complete paradigm

# German Noun Plurals: We really aren't there

- **Marcus et al (1995):** NNs overapply the *most common process* rather than the *default*
  - **German:** most common  $\neq$  default
- **McCurdy et al (2020a):** Train on German noun plurals & test on nonce words
  - ⚡ Model predictions *don't match well with human predictions*
  - ⚡ *Overproduction of frequent* affixes rather than default
- ⚡ **McCurdy et al (2020b):** Model **uses gender** as main cue, humans **use phonology**

# Generalization(?) by Neural Models

- Children **generalize** to novel feature combinations
  - e.g. Spanish:
    - See *amarian, ama, aman, amaba*
    - Generalize: *amaban*
- Can NNs do the same?
  - Evaluate 3 models on feature sets **attested vs. unattested** in train



(ongoing work with Salam Khalifa, Jordan Kodner, and Zoey Liu)

# Summary: The Past Tense Debate(s)

- What have we gotten from ~30 years of NN research?
  - Better accuracy
  - More developed architecture

} Good for NLP(?)
- What haven't we gotten?
  - Still **overproduce irregulars**
  - Still **no developmental regression**
  - Still **data-hungry**:
    - Too much, too saturated

} Persistence of issues ⇒  
**fundamental difference  
between connectionist  
models & language faculty**

# Proposal: Recursive, Rule-based Learning



# Models: Making Sense of Errors

- Children **over-regularize** & don't **over-irregularize**
  - Account for this with **rule-based mappings**:
    - Learn rule like **PAST** → **-ed**
    - Apply rule when no exception known
      - **Over-regularization** when exception not yet learned
      - **Developmental regression** when rule first learned
  - **Abduction of Tolerable Productivity (ATP)**: recursively learn productive rules & their exceptions

# Models: Making Sense of Errors

- Children **omit** inflectional affixes, but don't **substitute** them
  - Account for this with **initially-underspecified** inflectional categories:
    - Must learn e.g. that English contrasts **+3SG vs. -3SG**
    - Underspecified category can't be productively mapped to form, so **omit inflection**
  - **Sufficient Contrast Learner (SCL)**: recursively learn inflectional categories

# Preliminaries: The TSP

**Intuitions:** given a set of  $N$  items:

- If **most** do  $X$ , then all do  $X$  (**generalization**)
- If **few** do  $X$ , memorize those that do (**lexicalization**)

## Tolerance of exceptions

Generalize a rule applying to  $N$  items with  $e$  exceptions iff:

$$e \leq \theta_N = \frac{N}{\ln N}$$

(Yang 2016)

## Sufficient positive evidence

Generalize a rule applying to  $N$  items and seen applying to  $M$  iff:

$$\underbrace{N - M}_{\text{worst-case } e} \leq \theta_N = \frac{N}{\ln N}$$

worst-case  $e$

# Preliminaries: Training Data

- Children learn **frequent forms earlier** (Goodman et al 2008)
  - Use *most frequent forms from CHILDES*
- Children use of **distributional cues** to learn meaning
  - Intersect CHILDES with *UniMorph features as a proxy for these cues*
- Input: **(lemma, inflected, features)**

Language	Lemma	Inflected	Features
English	walk	walked	{V, PAST, 3, SG}
Spanish	amar	amaban	{V, 3, PL, PAST, IMPFV}
German	Sache	Sachen	{N, FEM, PL}

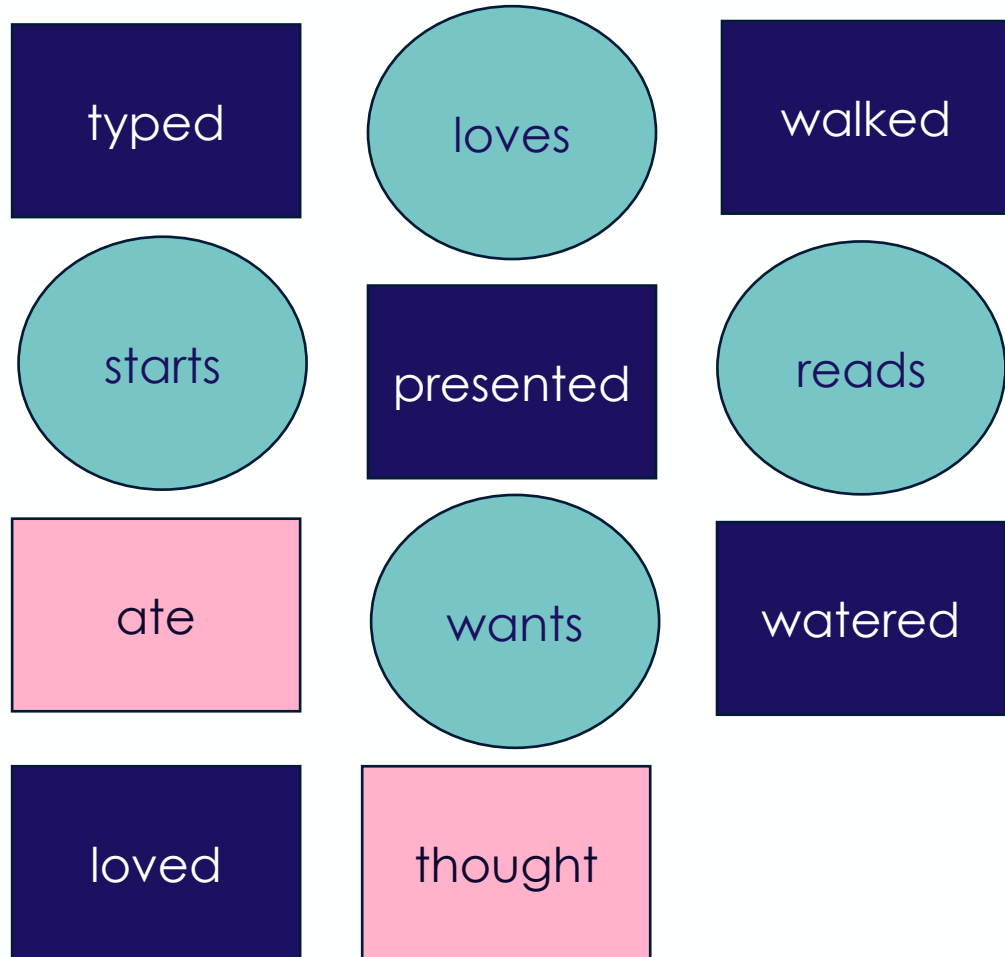
# Mapping Features to Form: Abduction of Tolerable Productivity


(Belth et al 2021)

# ATP Model: Recursive Subdivision

- Apply TSP **recursively**
  - Given ***N*** items, do **enough** of them take **-x affix**?
    - If yes, **productive rule learnt!**
    - If not, **subdivide** into disjoint subsets & **recurse**
- **Terminate** when:
  - Productive rule found (**generalization**)
  - No more subdivisions possible (**lexicalization**)
- Apply to **English past tense** and **German noun plurals**

# ATP Model: Toy Example



- 11 items: 4 **-s**, 5 **-ed**, 2 **other**
- **Generalize** most frequent?  
  $N - M = 11 - 5 = 6 > \theta_{11} = 4.5$
- **Subdivide!** Hypothesize a rule:

# ATP Model: Toy Example

typed

walked



presented

ate

watered

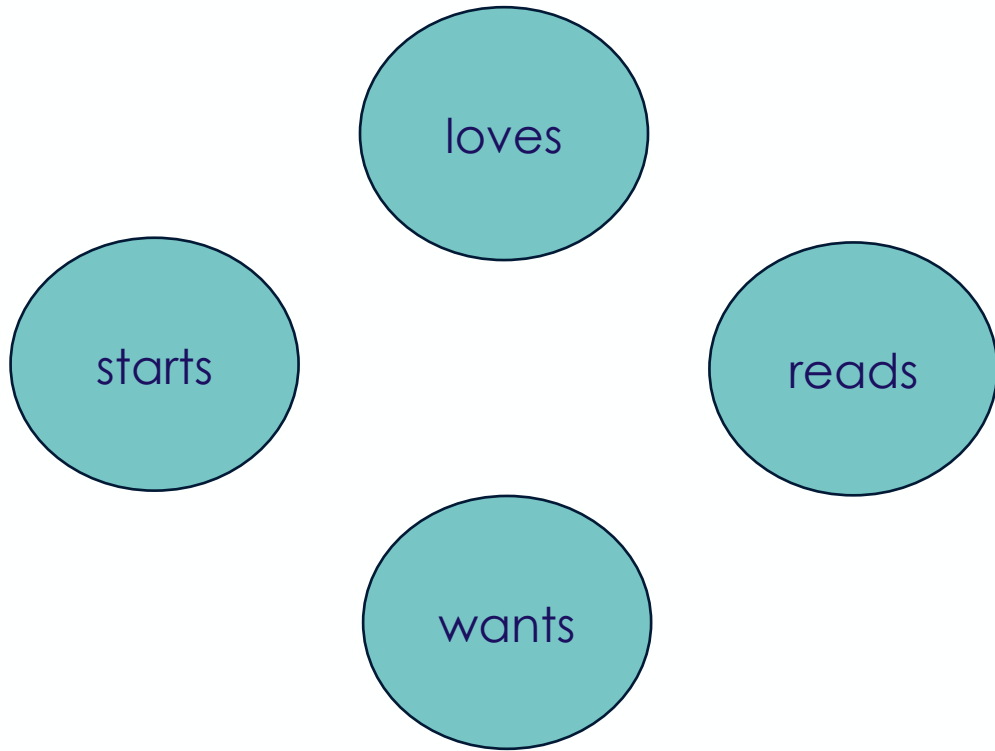
loved

thought

- 11 items: 4 **-s**, 5 **-ed**, 2 **other**
- **Generalize** most frequent?  
  $N - M = 11 - 5 = 6 > \theta_{11} = 4.5$
- **Subdivide!** Hypothesize a rule:
  - PAST  $\rightarrow$  **-ed**
- **Test** the rule:
  - $N - M = 2 < \theta_7 = 3.5$  
- R1 productive! PAST  $\rightarrow$  **-ed**
  - Memorize **ate** and **thought**



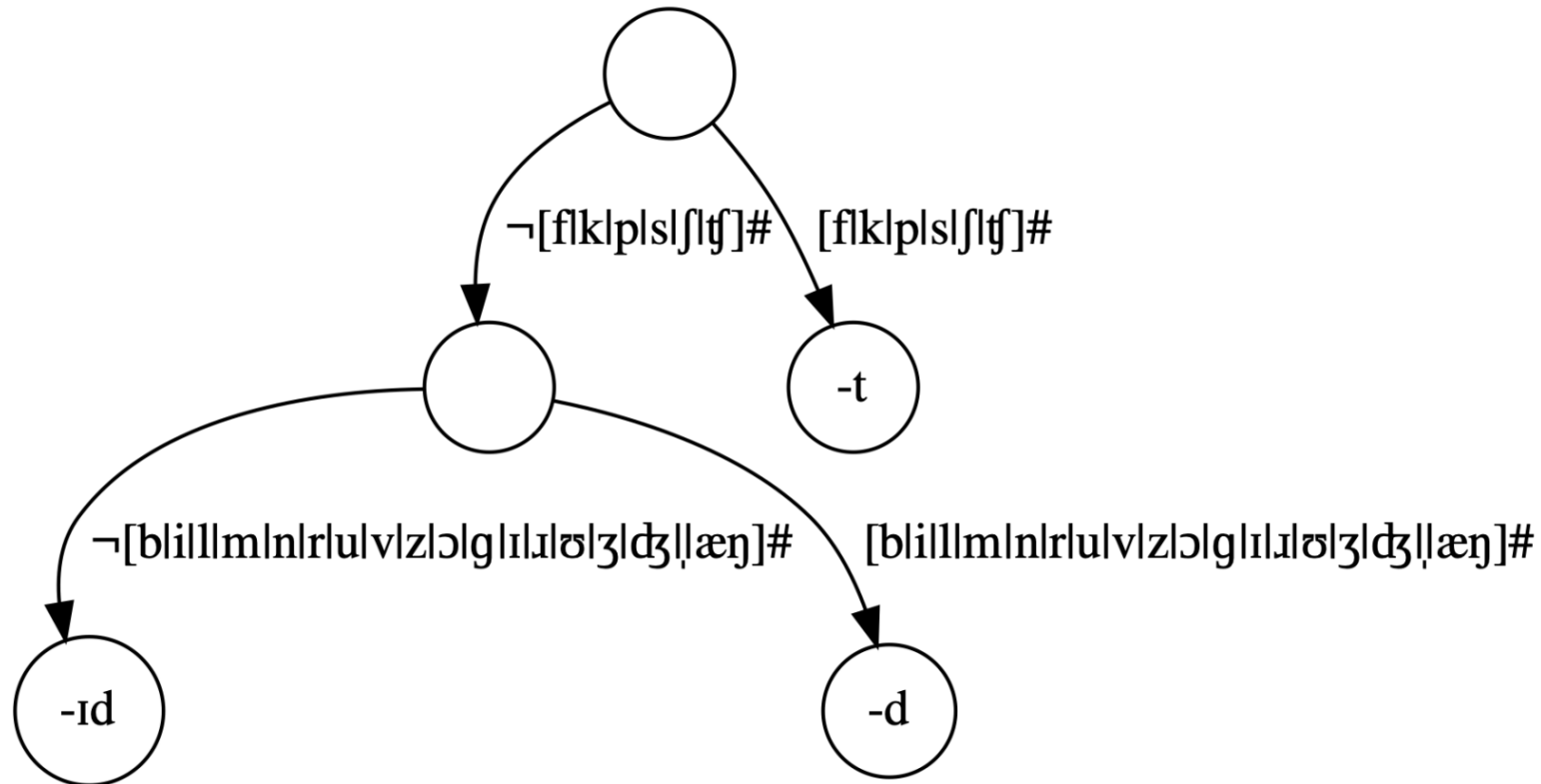
# ATP Model: Toy Example



- 11 items: 4 **-s**, 5 **-ed**, 2 **other**
- **Generalize** most frequent?  
⚡  $N - M = 11 - 5 = 6 > \theta_{11} = 4.5$
- **Subdivide!** Hypothesize a rule:
  - PAST → **-ed**
- **Test** the rule:
  - $N - M = 2 < \theta_7 = 3.5$  ✓
- R1 productive! PAST → **-ed**
  - Memorize **ate** and **thought**
- **Recurse:** PRES,3,SG → **-s**

# ATP Model: Sample learning trace

English past tense: morphophonological conditioning

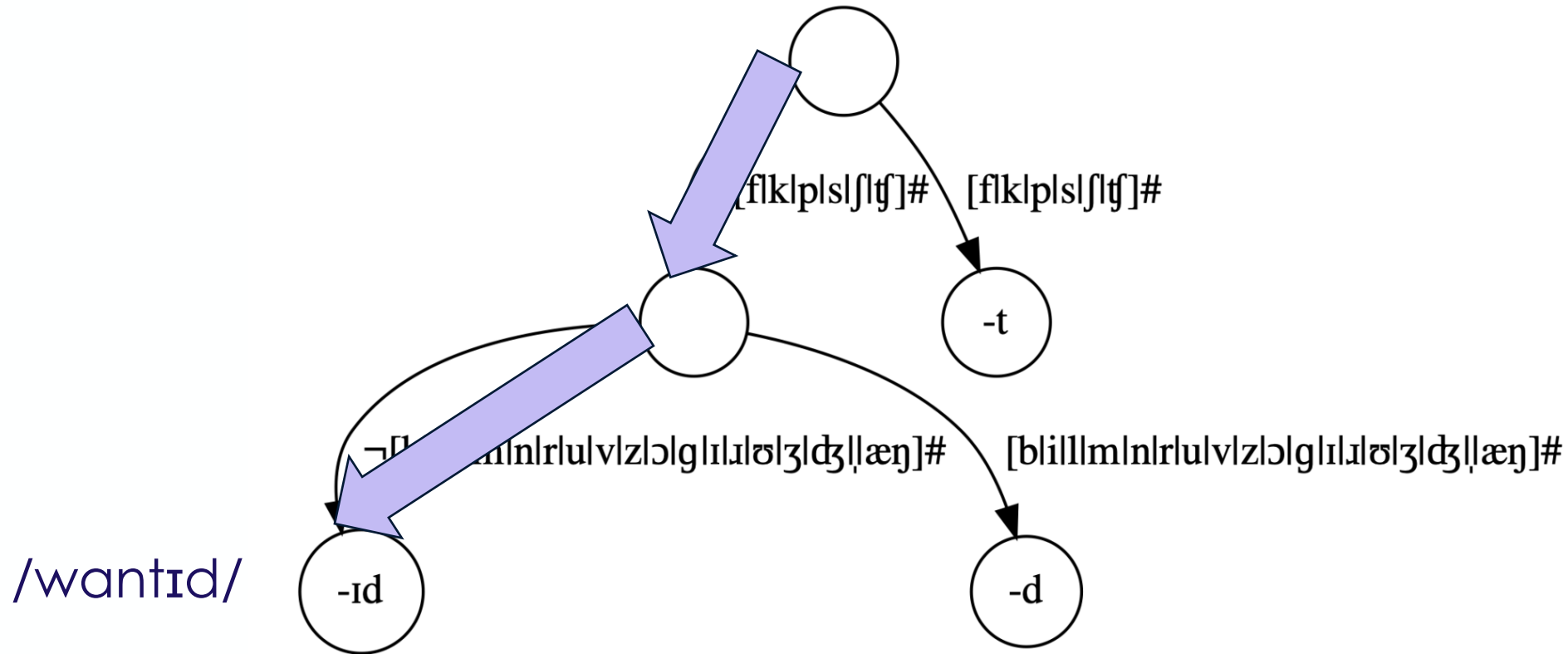


# ATP Model: Inflection and Generation

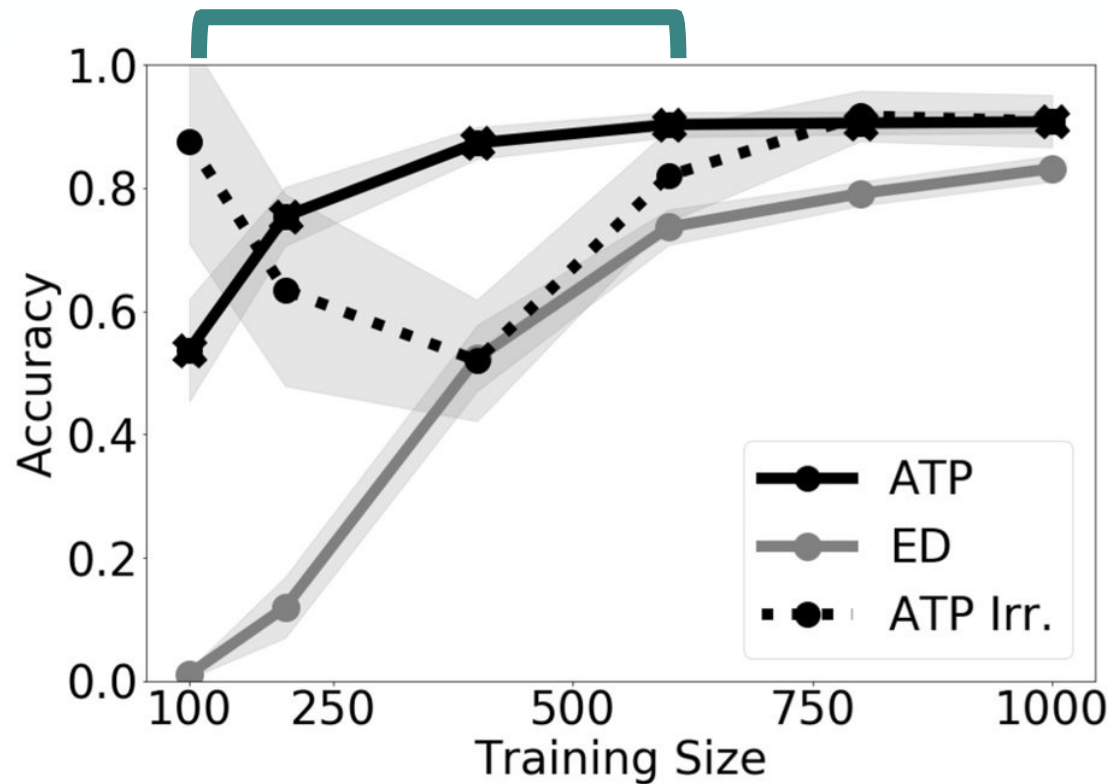
- During test, given **novel forms & features** to inflect
- Traverse decision tree to correct node
  - If node has **productive rule**, apply the rule
  - If no **productive rule**, either:
    - Produce unmarked form
    - **Analogize** to a known form at this node

# ATP Model: Sample learning trace

English past tense: inflect /want/



# ATP: English Results

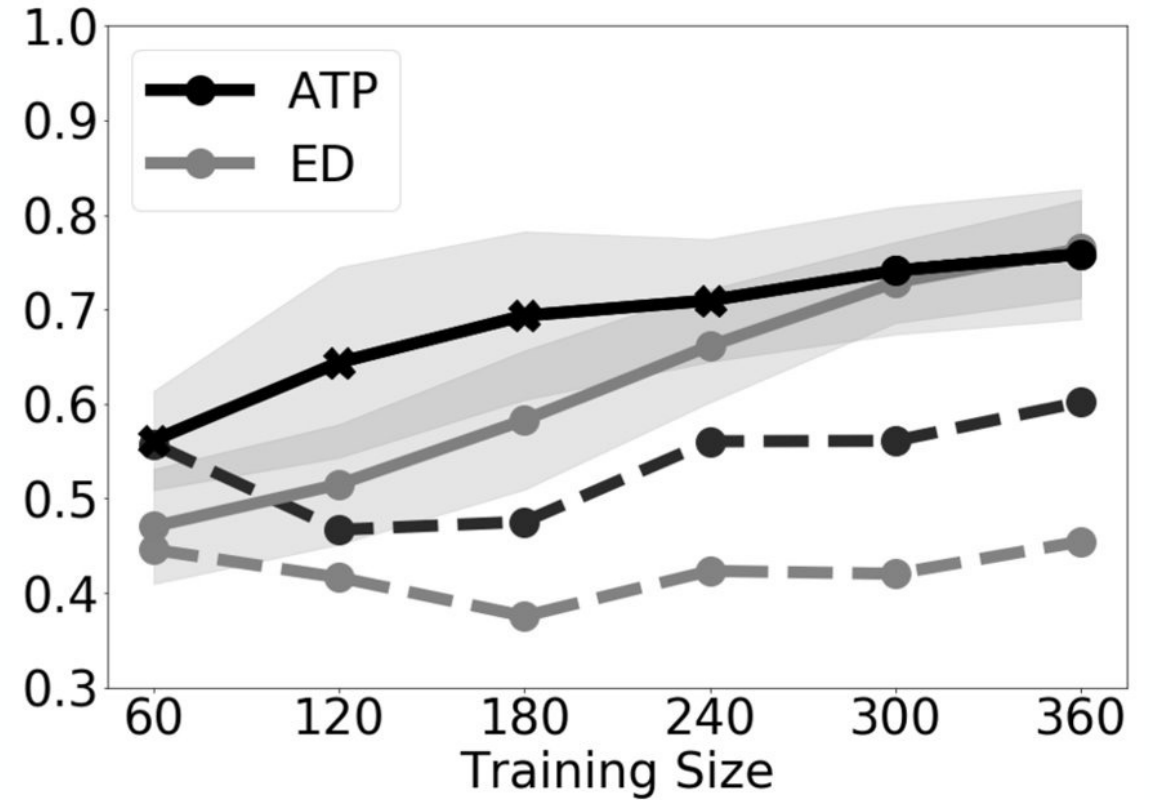


(a) English

- **Developmental regression** and **overregularization**
- Trained on **plausible vocabulary**
  - **1000** inflected forms
- Mechanistic account of developmental regression

# ATP: German Results

- Relies less on gender than K&C
  - **Solid lines** = gender info given at test
  - **Dashed lines** = gender info not given at test
- Trained on **plausible vocabulary**
  - **400** inflected forms



(b) German

# ATP: Summary

- Children **overregularize**
  - *So does ATP!*
- Children show **developmental regression** when learning some paradigms
  - *So does ATP!*
- Children learn from **extremely sparse, skewed input**
  - *So does ATP!*

**ATP gives mechanistic account of *why* these errors occur and what the resulting grammar looks like**

# Learning which Features are Marked: Sufficient Contrast Learner

(Payne 2022, 2023)



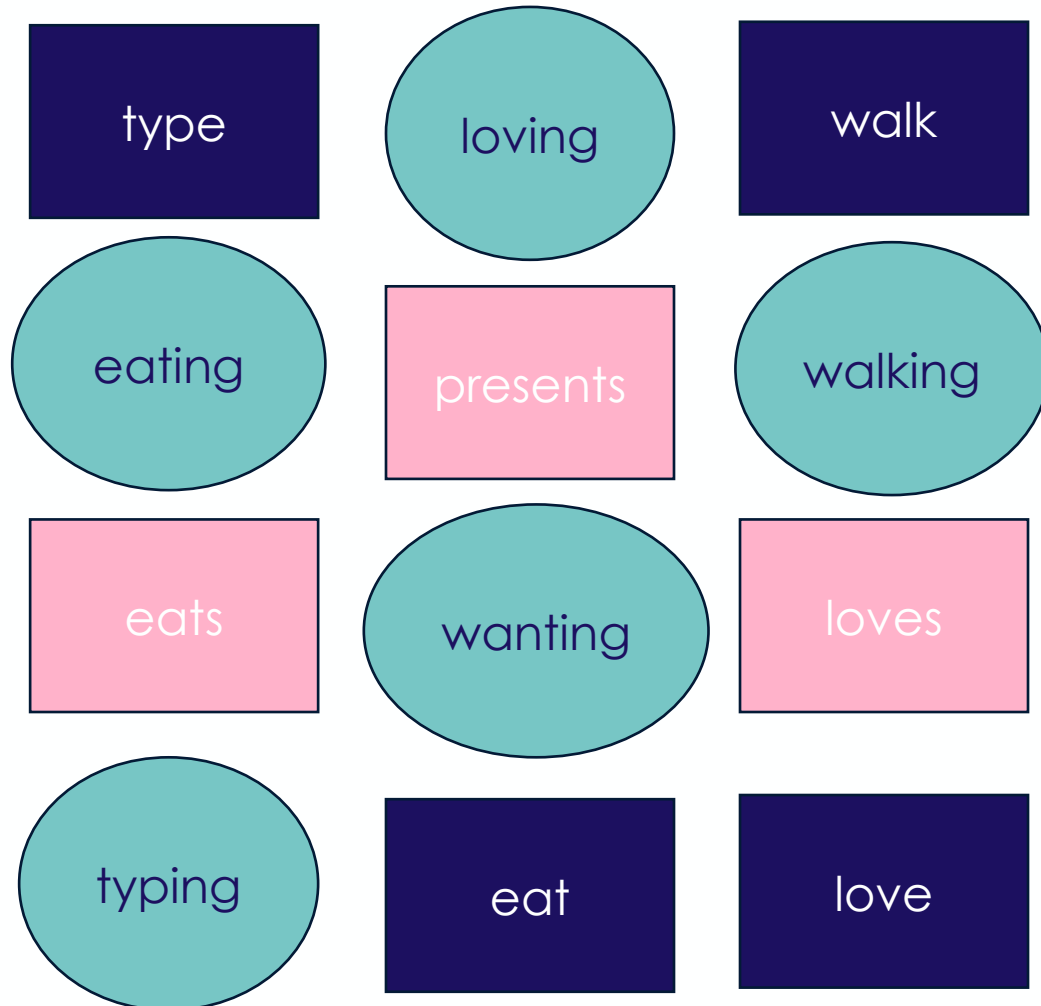
# SCL Model: Preliminaries

- **Principle of Contrast: distinct forms  $\Rightarrow$  distinct meanings**
  - e.g. *walk* and *walked* must mean something different
- **Collisions: one lemma in multiple inflected forms**
  - e.g. *walk-walked* tells us that **+/-PAST** is marked
- **TSP: when are there enough collisions to learn marking?**
  - e.g. don't learn from *am-are* that **1 vs. 2** marked in English
  - Learn from *walk-walked, sing-sang*, etc. that **+/-PAST** marked

# SCL Model: Collisions

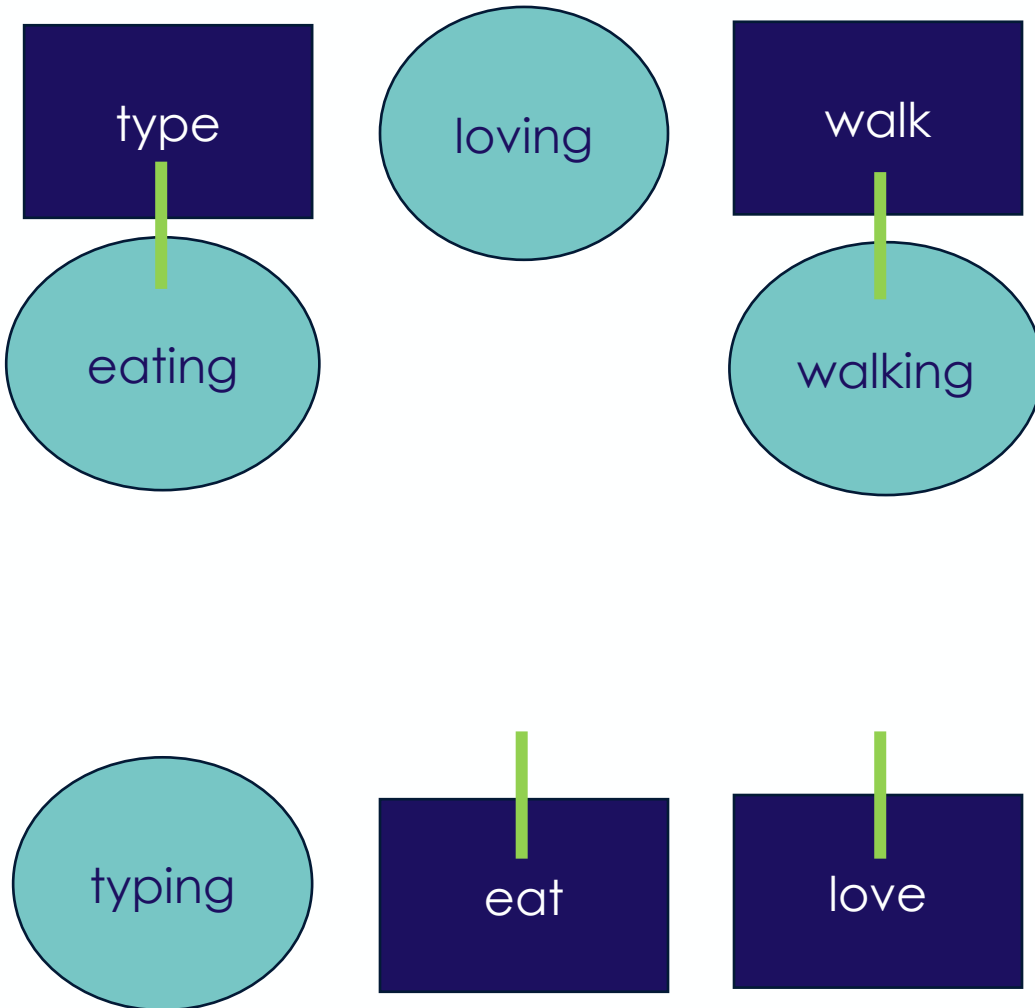
- Apply TSP **recursively** again!
  - Input taken in **incrementally**
  - When  **$j^{\text{th}}$  input** encountered, is there a collision?
  - If so, do enough forms appearing in **inflection A** also appear in **inflection B** in a different form?
    - If yes, **productive contrast learnt!** Subdivide and recurse
    - If no, **continue** to take in input
- Apply to **English verbs, German noun plurals, Spanish verbs, and Hebrew verbs**

# SCL Model: Toy Example



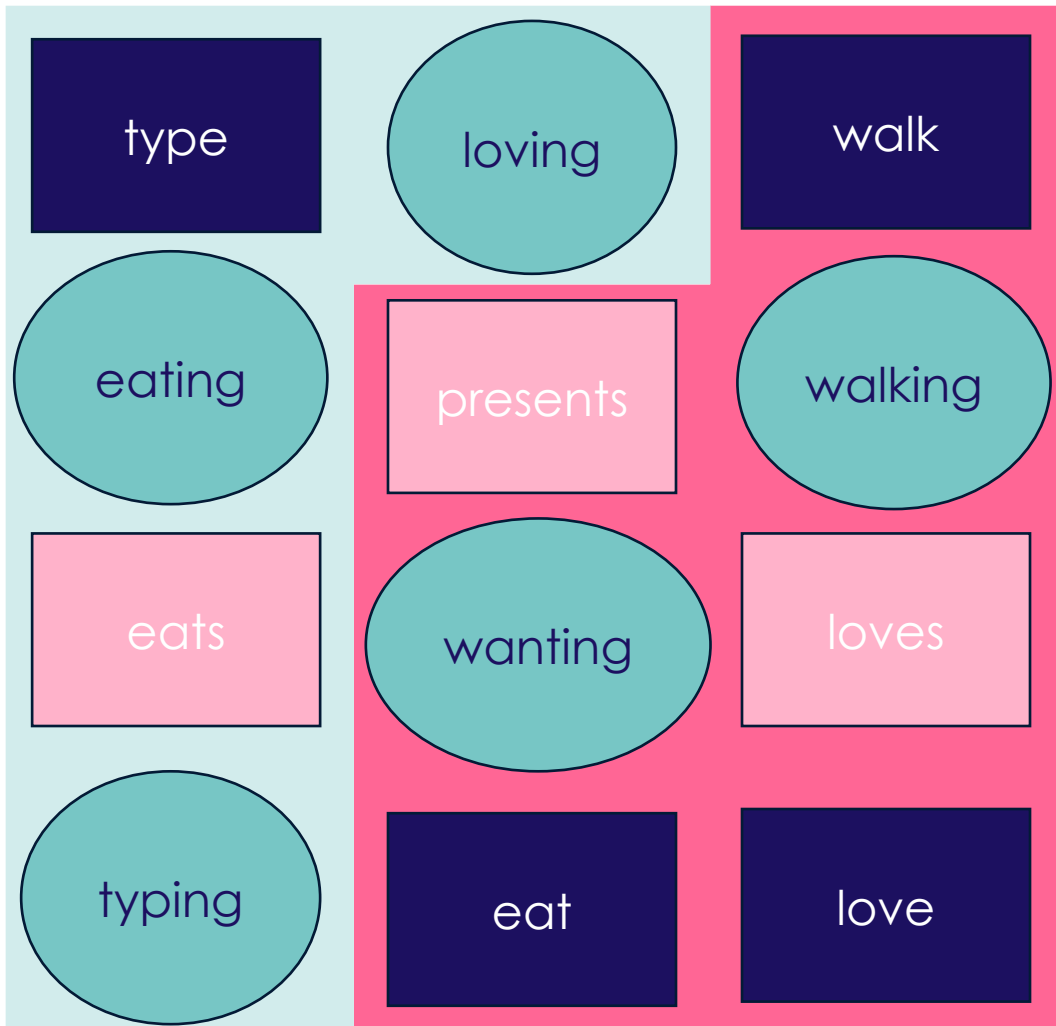
- Collision: **walk-walking**
- **+/-PARTICIPLE** marked?

# SCL Model: Toy Example



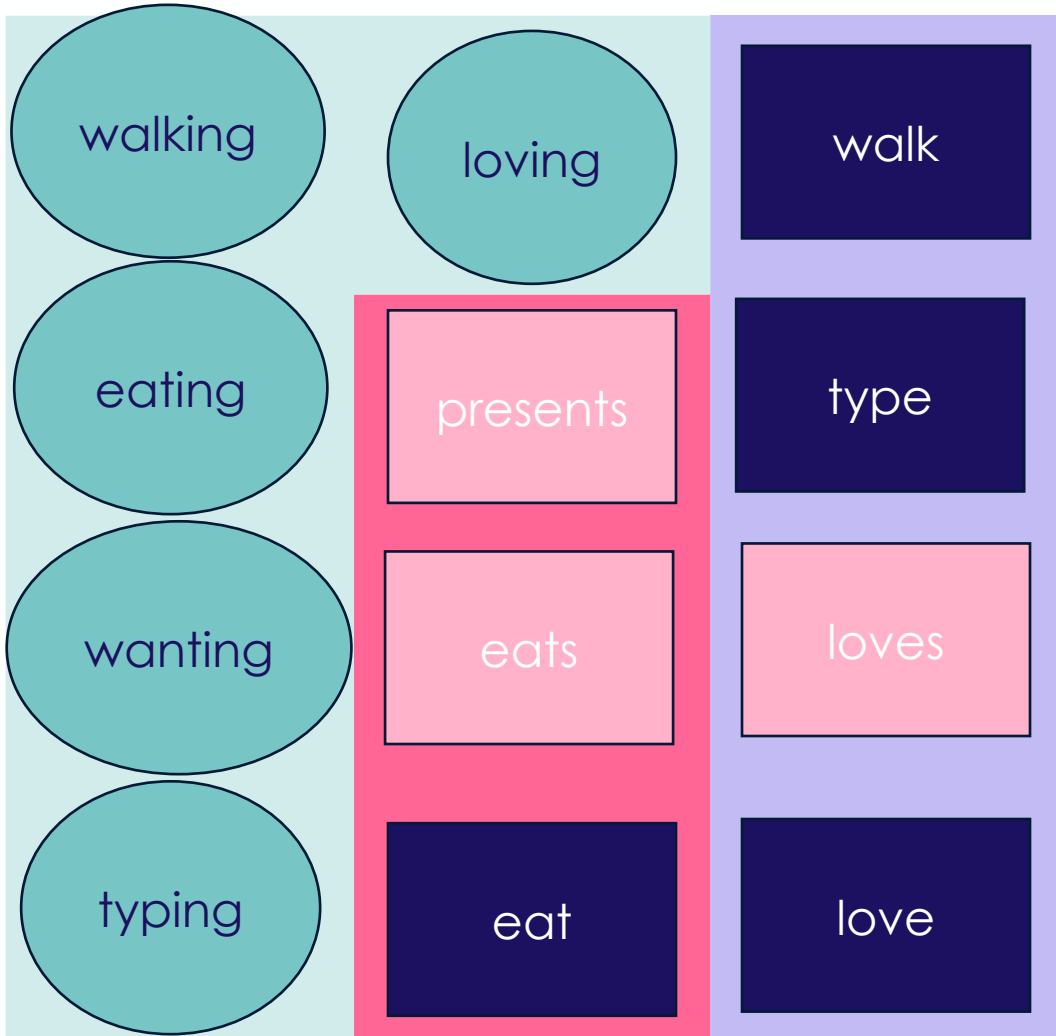
- Collision: **walk-walking**
- **+/-PARTICIPLE** marked?
  - 5 participles, 4 collisions (not **wanting**)
  - $N - M = 1 < \theta_5 = 3$  ✓
- Contrast 1 productive!  
**+/-PARTICIPLE** marked

# SCL Model: Toy Example



- Collision: **walk-walking**
- **+/-PARTICIPLE** marked?
  - 5 participles, 4 collisions (not **wanting**)
  - $N - M = 1 < \theta_5 = 3$  ✓
- Contrast 1 productive!  
**+PARTICIPLE** marked
- **Subdivide** into **+PARTICIPLE** and **-PARTICIPLE** forms

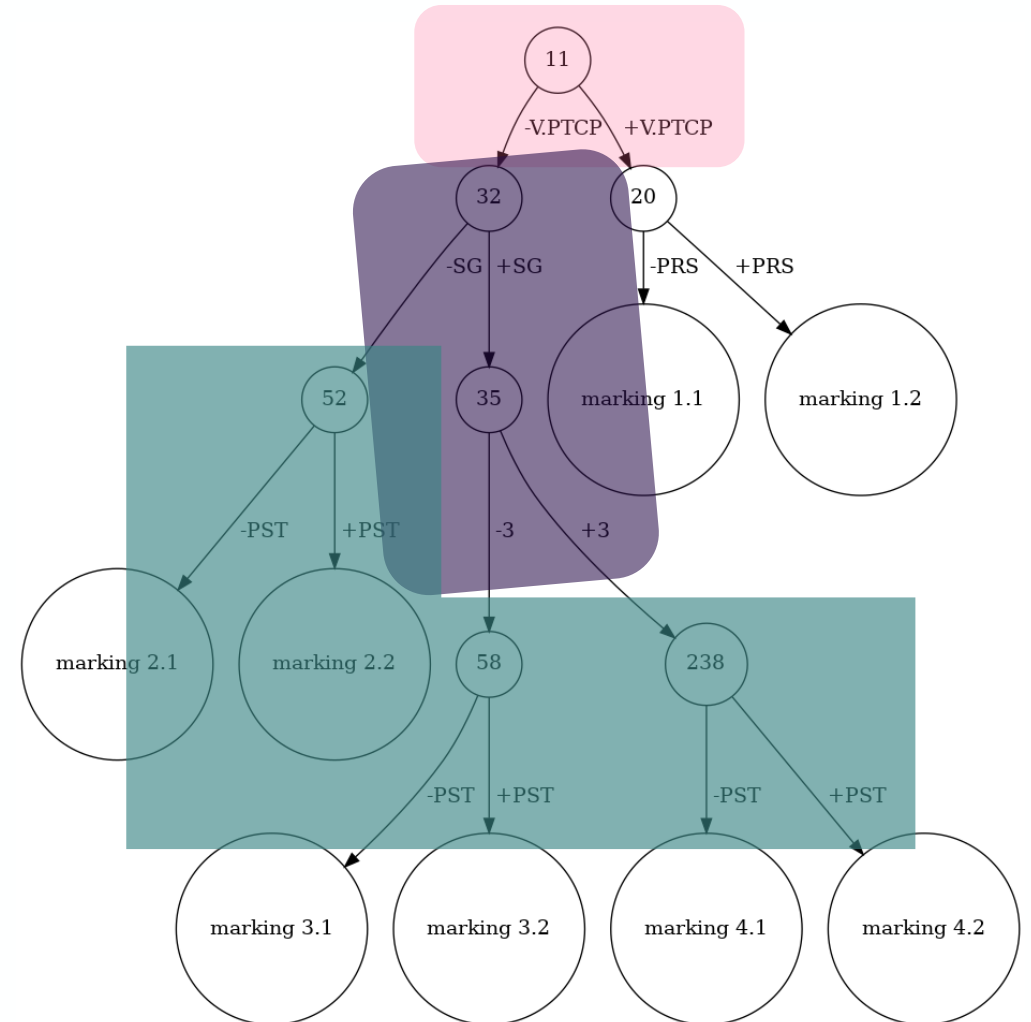
# SCL Model: Toy Example



- Collision: **walk-walking**
- **+/-PARTICIPLE** marked?
  - 5 participles, 4 collisions (not **wanting**)
  - $N - M = 1 < \theta_5 = 3$  ✓
- Contrast 1 productive! **+PARTICIPLE** marked
- **Subdivide** into **+PARTICIPLE** and **-PARTICIPLE** forms
- Recursively learn that **+/-3SG** marked

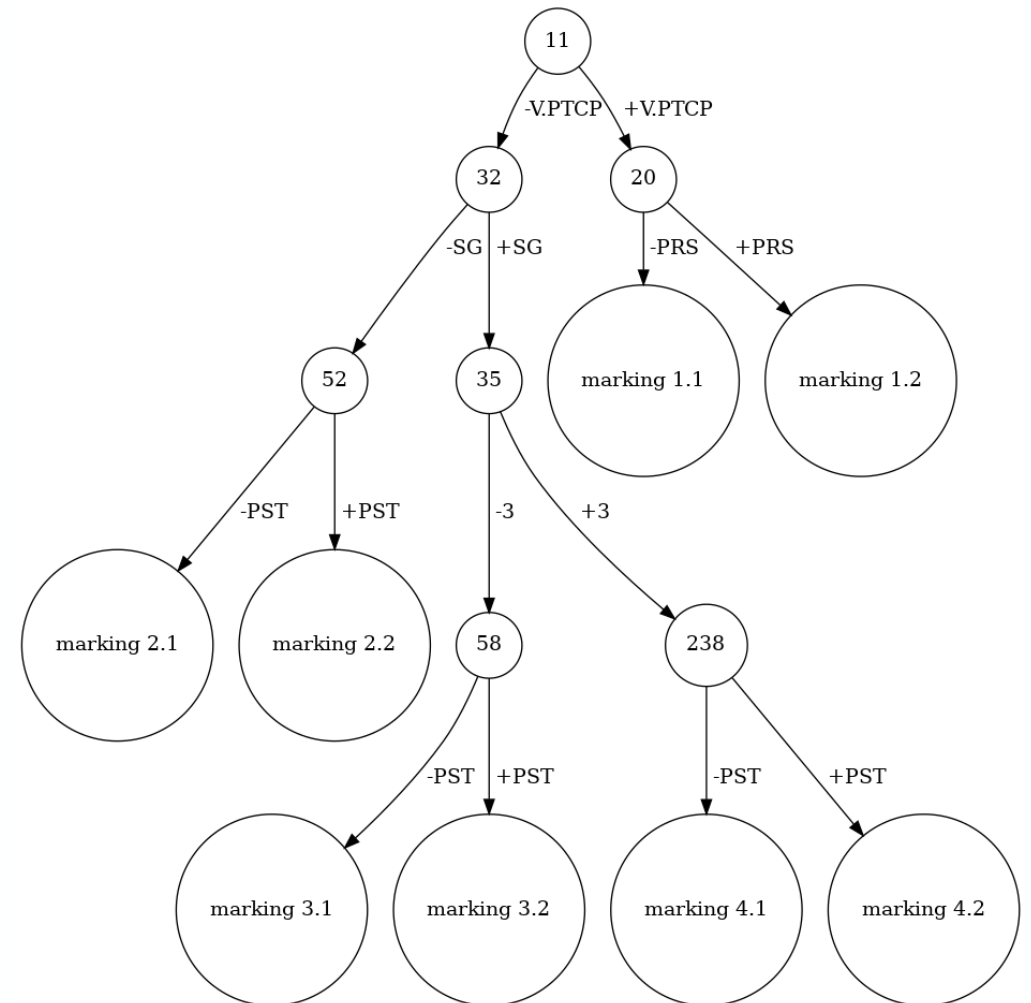
# SCL: English Results

- Plausible **order of acquisition**
  1. **Participle** (-ing)
  2. **3,SG** (-s)
  3. **Past** (-ed)
- Plausible vocabulary size:
  - **112** lemmas
  - **238** inflected forms
- Learning past tense separately for each agreement?



# SCL: English Results

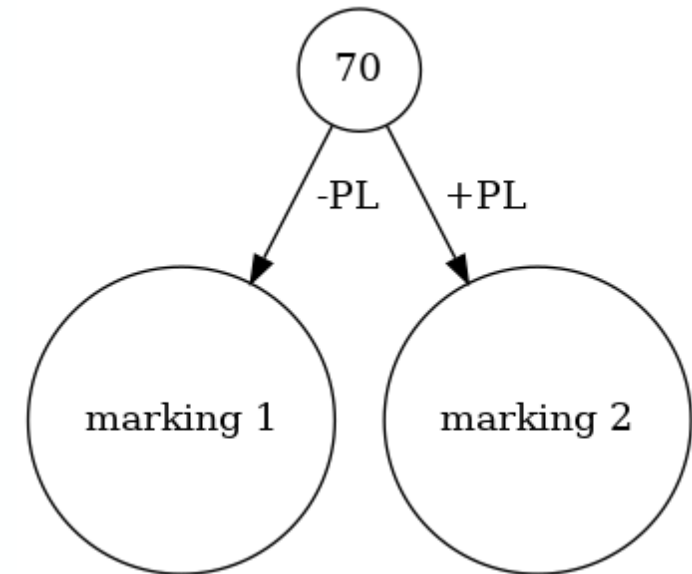
- Learning past tense separately for each agreement?
  - **Yang, Elman, and Legate (2015):** past tense acquired later for learners of AAE
  - **Difference in input** = agreement, not tense
  - TSP tolerates *relatively fewer exceptions* for larger  $N$





# SCL: German results

- Plausible vocabulary size:
  - **66** lemmas
  - **70** inflected forms
- Well under vocab size at which plural affix overapplication begins



# SCL: Spanish Results

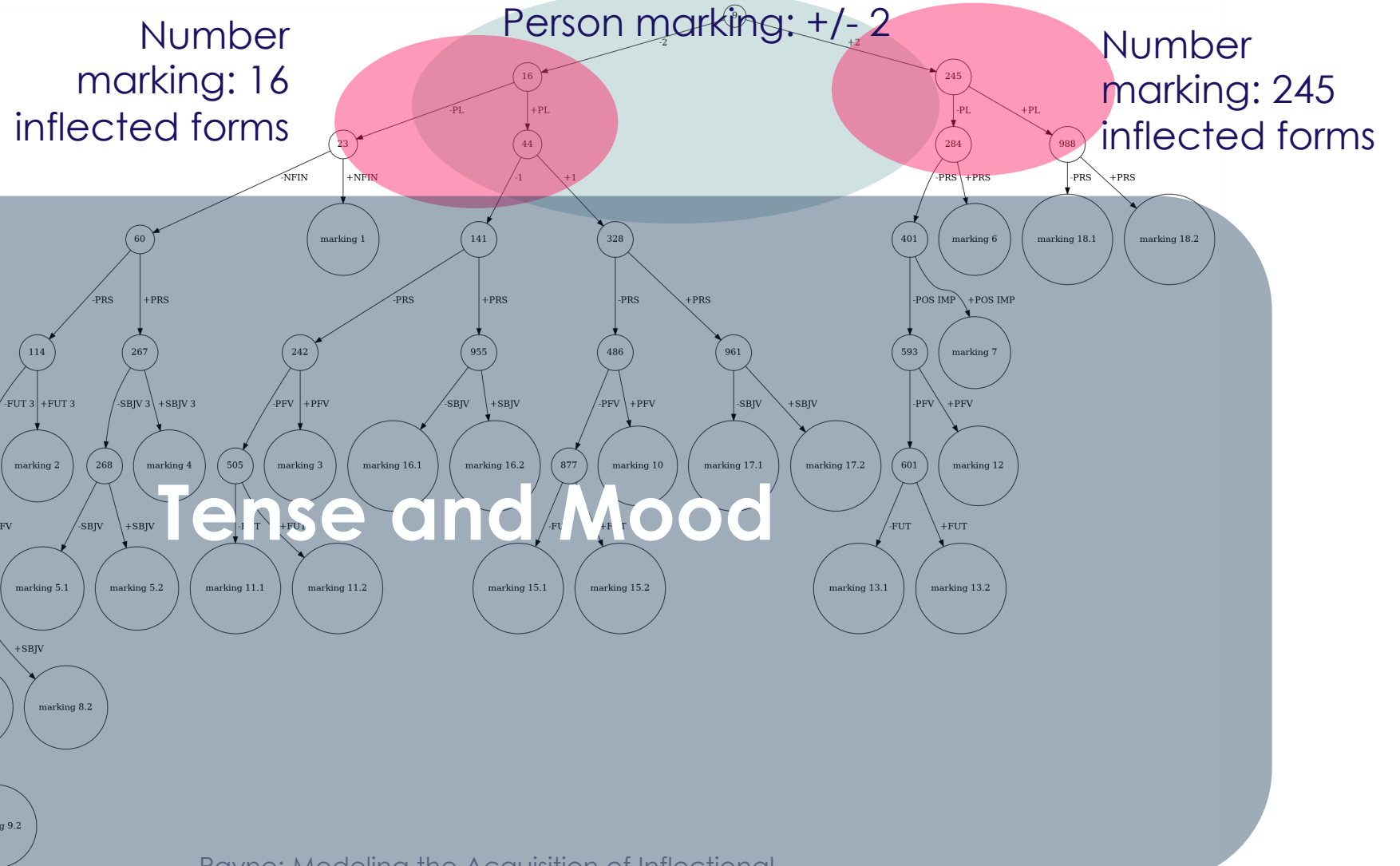
- Spanish order of acquisition:
  - **Finiteness & person marking:** 1;7
  - **Number marking:** 1;7-2;0
    - Second plural emerges later than other agreements in many learners
  - **Tense:** 2;0-2;2
  - **Mood:** 1;7-2;2

(Montrul 2004)

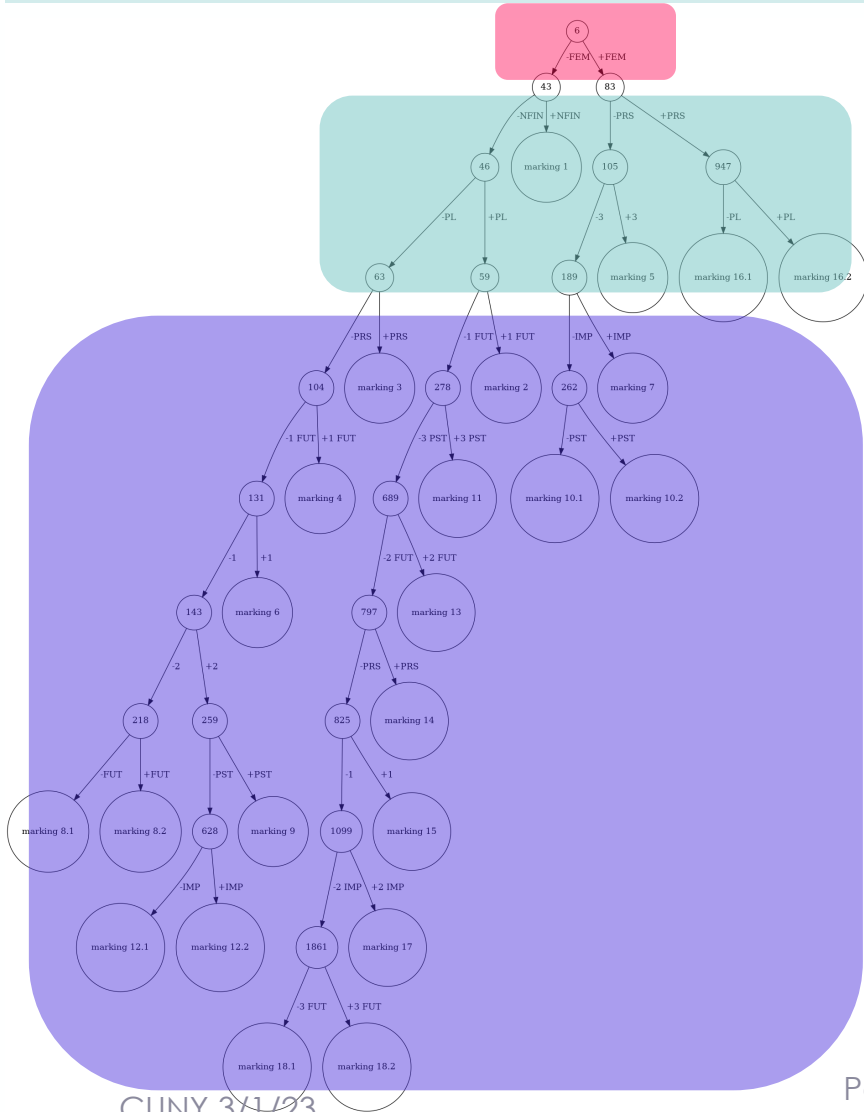
# SCL: Spanish Results

Learning done by:

- **299** lemmas
- **961** inflected forms



# SCL: Hebrew Results



- Hebrew order of acquisition:
  - **Person, number, gender** before tense
  - **Person vs. number** varies
  - **Gender** appears before or at the same time as **number**
- Our model:
  - Order of acquisition:
    - **Gender, person & number, tense**
  - Vocab size:
    - **323** lemmas
    - **1861** inflected forms

# SCL Implications: Root Infinitives

- **Root Infinitive (RI) Stage:** stage of omission errors
- Cross-linguistically, “**richer**” morphology ⇒ **shorter RI stage**
- Richer morphology also means **more subdivision**
  - TSP tolerates more exceptions for **smaller N**
  - More subdivision ⇒ **smaller N**
  - Smaller N ⇒ **quicker learning** of inflectional categories
- SCL gives a **mechanistic account** of cross-linguistic differences

(Philips 1995, Legate & Yang 2007)

Payne: Modeling the Acquisition of Inflectional  
Morphology

# SCL: Summary

- Children **omit affixes**
  - *SCL gives an account for why!*
- Children show clear **order of acquisition effects**
  - *So does SCL!*
- Children learn from **extremely sparse, skewed input**
  - *So does SCL!*

**SCL gives mechanistic account of order of acquisition, omission errors and cross-linguistic differences in acquisition**

# Conclusion & Future Directions

# Conclusion: Getting the Right Stuff Wrong

	NNs	ATP	SCL
Learn from plausible data	✗	✓	✓
Account for over-regularization and developmental regression	✗	✓	---
Account for omission and the RI stage	✗	---	✓
Interpretability	✗	✓	✓



# SCL & ATP

- **SCL** learns the features required by **ATP**
  - **Combination** of these two learning strategies
  - First learn the inflectional classes, then map them to form
- **Expand ATP:**
  - Handle **templatic & agglutinative** morphology
- **Expand SCL:**
  - Explore model **subdivision predictions**
  - Learn features from **distributional information**

# Thank you!!

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