

Infant artificial language learning and language acquisition

Gómez and Gerken (2000)

Presented by Sophia Wiedmann



Why use artificial languages for testing language acquisition?

1. Natural languages are hard to control
 - Simplicity of artificial languages allow experiments to isolate factors of interest

Why use artificial languages for testing language acquisition?

1. Natural languages are hard to control
 - Simplicity of artificial languages allow experiments to isolate factors of interest
2. Prior learning in utero
 - Newborns are already ‘biased’ towards their mother’s language
 - Perceive rhythm, melody, and intonation in utero

Experiment 1: Word Segmentation

Saffran, Aslin, and Newport (1996): Statistical Learning by eight-month-old-infants

Within-word syllables have higher *transitional probabilities* than between-word syllables:

“Pretty **ba**by”, “Pretty **ba**by”

→ **ba** | **ba** has higher transitional probability than **ba** | **ty**

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“Pretty **ba**by”, “Pretty **ba**by”

→ **ba** | **ba** has higher transitional probability than **ba** | **ty**

Research question: Can infants use transitional probabilities to segment words in continuous speech?

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Train: Familiarized for 2 minutes with nonsense tri-syllabic words

 bidakupadotigolabutupiro

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Test: Can they discriminate new words composed of different syllables pairings?

tupiro vs tilado

bidaku vs dapiku

“Nonwords” have transition probability of 0

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“Nonwords” have transition probability of 0

Infants showed differential attention to familiar vs. unfamiliar words

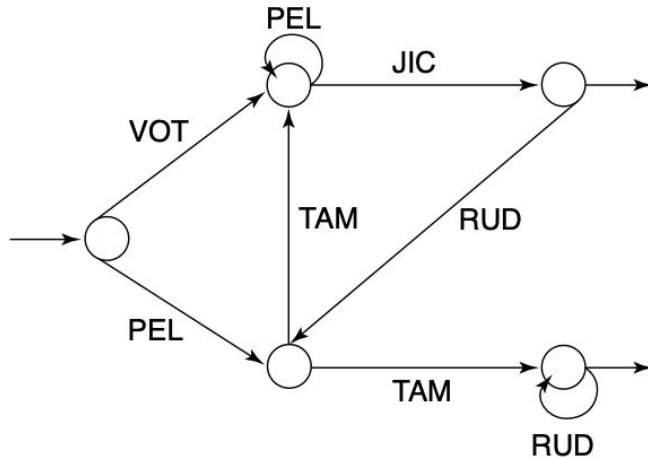
→ **demonstrate sensitivity to transitional probabilities**

Experiment 2: Words in Sequence

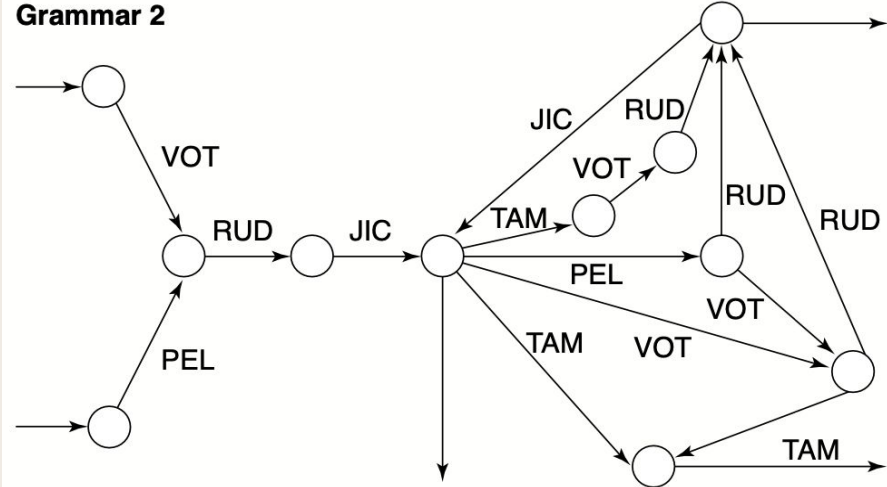
Gómez and Gerken (1999): Artificial grammar learning by one-year-olds leads to specific and abstract knowledge

Consist of same vocabulary: VOT, PEL, JIC, TAM, RUD

Grammar 1



Grammar 2

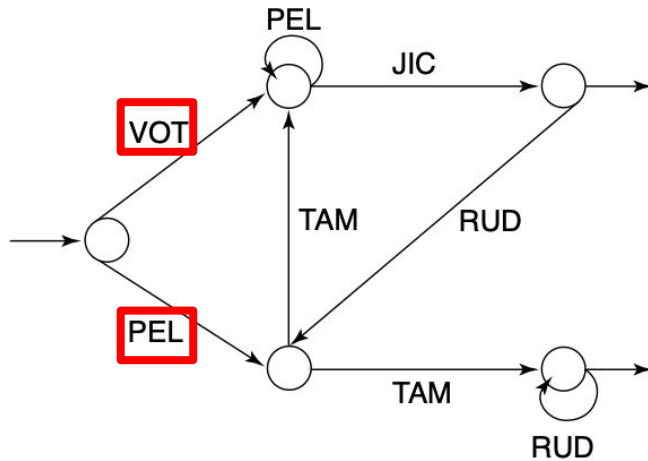


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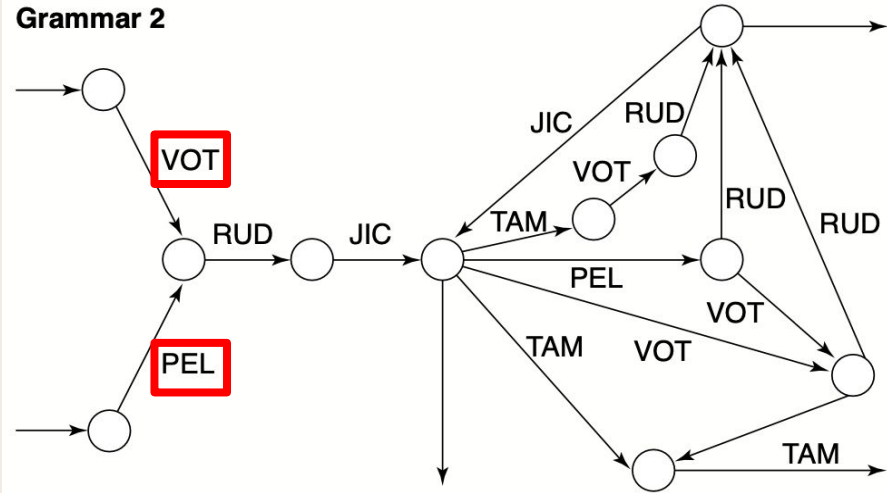
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Start with same words

Grammar 1



Grammar 2

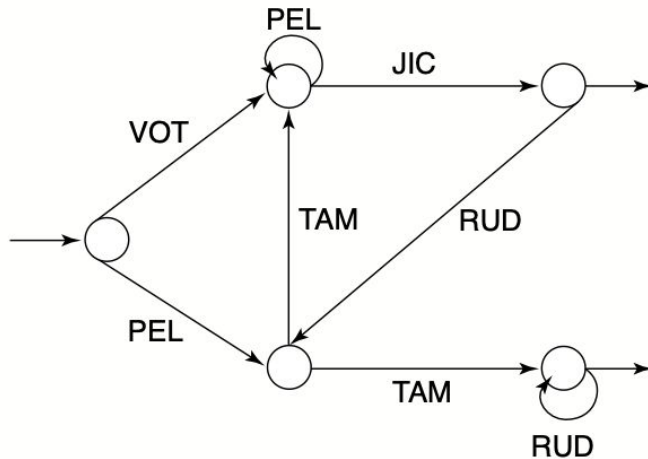


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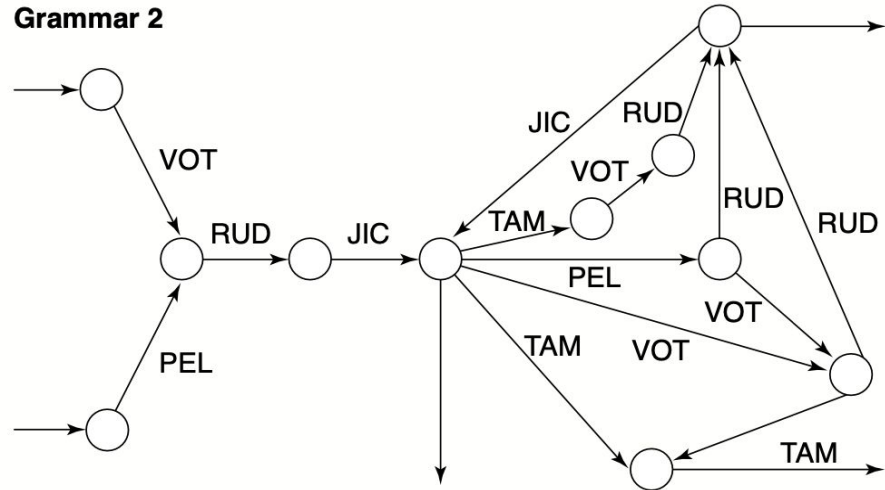
Only differ in word order

Grammar 1



VOT-PEL-JIC-RUD-TAM-RUD

Grammar 2



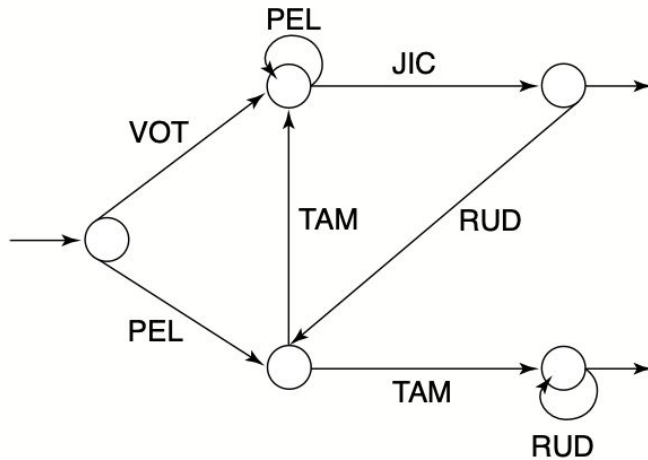
VOT-RUD-JIC-TAM-VOT-RUD

Experiment 2: Words in Sequence

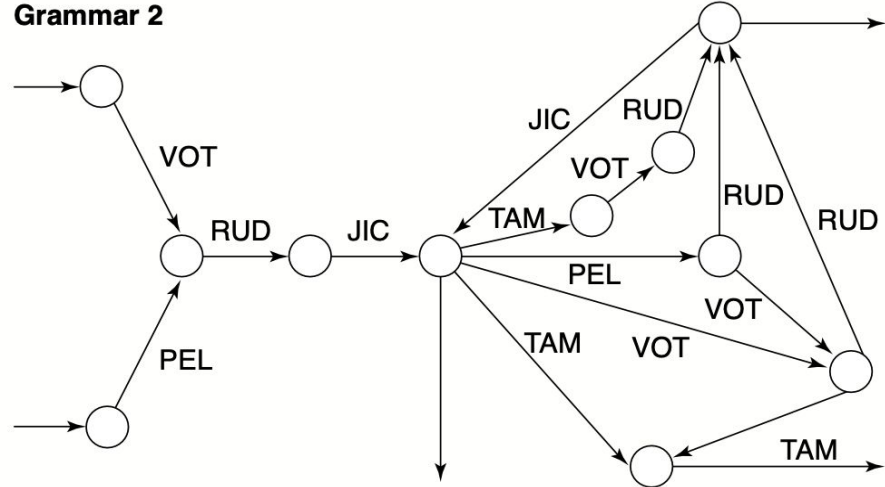
Gómez and Gerken (1999): Artificial grammar learning by one-year-olds leads to specific and abstract knowledge

Train: Listen to strings in either grammar for 50-127 seconds

Grammar 1



Grammar 2

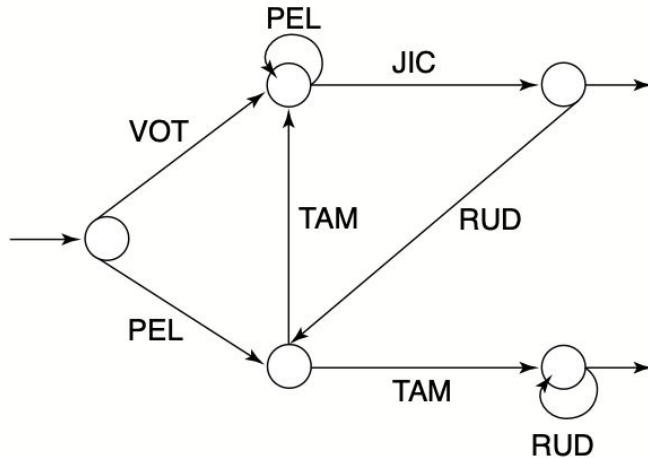


Experiment 2: Words in Sequence

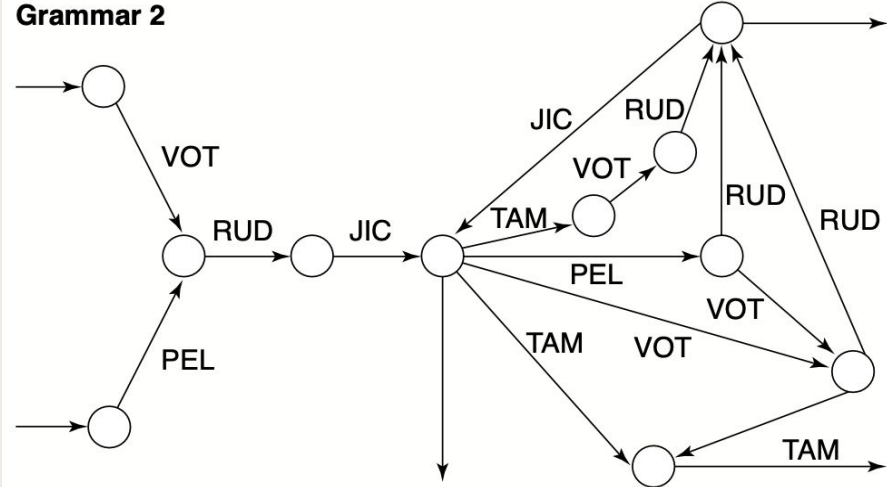
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Test: Listen to strings in both grammars and see if they can differentiate

Grammar 1



Grammar 2



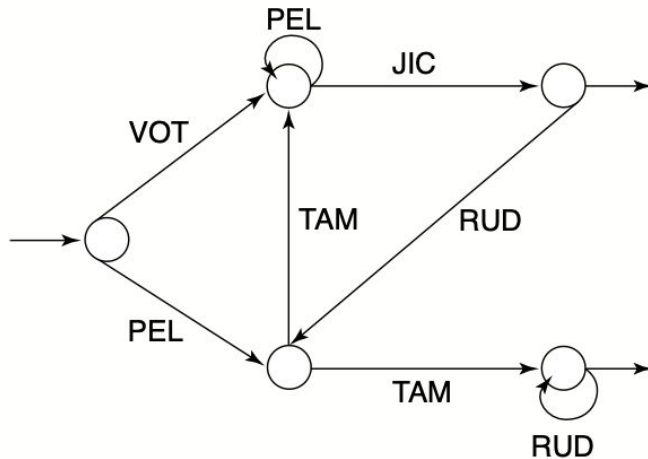
Important: Train strings were never encountered in test strings

Experiment 2: Words in Sequence

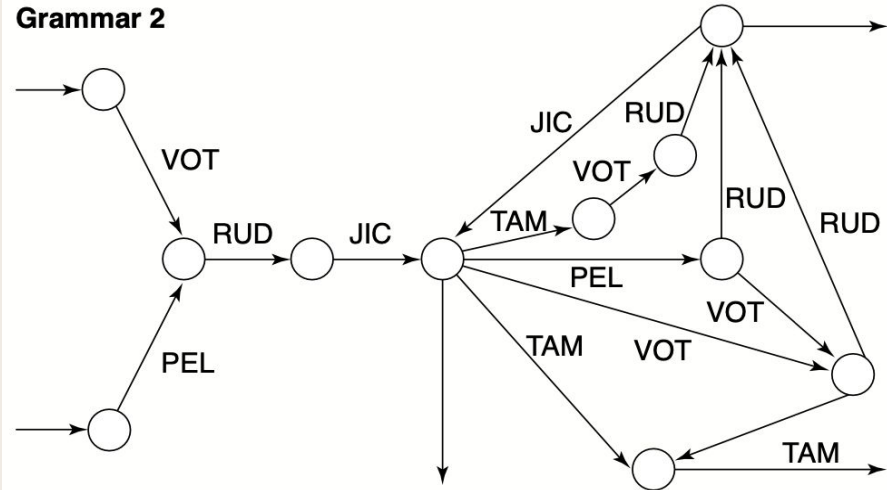
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Results: Babies listened longer to strings from their trained grammar

Grammar 1



Grammar 2

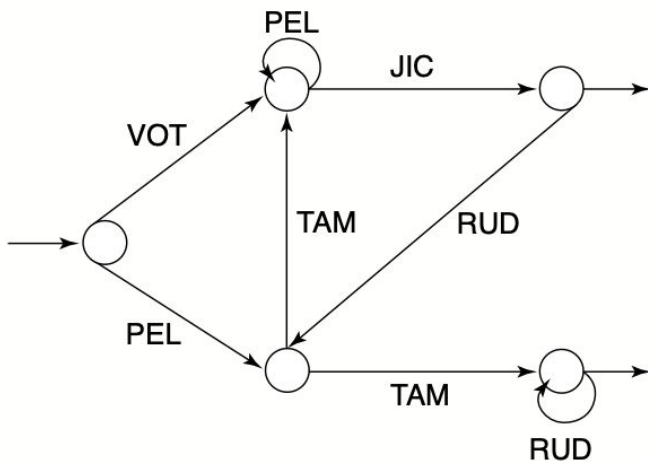


Experiment 2.2: Words in Abstract Patterns

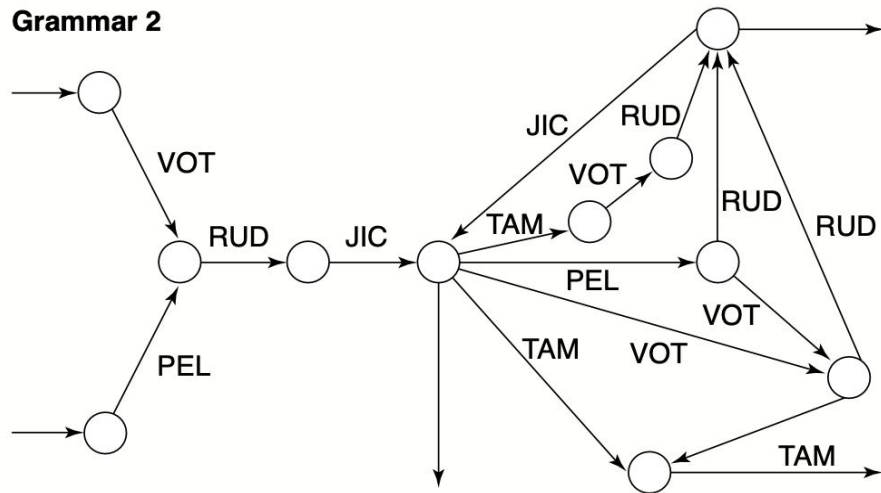
Gómez and Gerken (1999): Artificial grammar learning by one-year-olds leads to specific and abstract knowledge

Same idea, but: train set vocabulary differs from test set vocabulary

Grammar 1



Grammar 2



Train: PEL-TAM-PEL-PEL-JIC

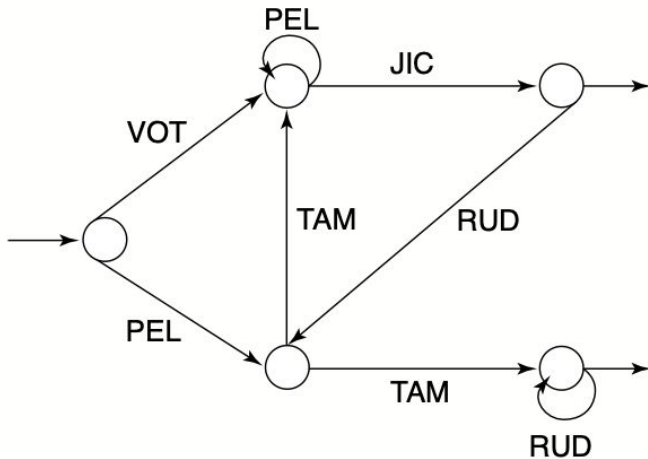
Test: FIM-SOG-FIM-FIM-TUP

Experiment 2.2: Words in Abstract Patterns

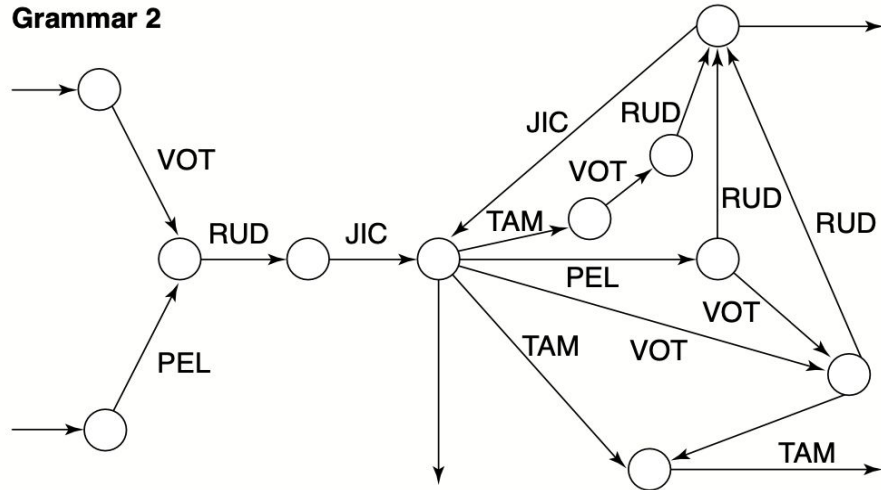
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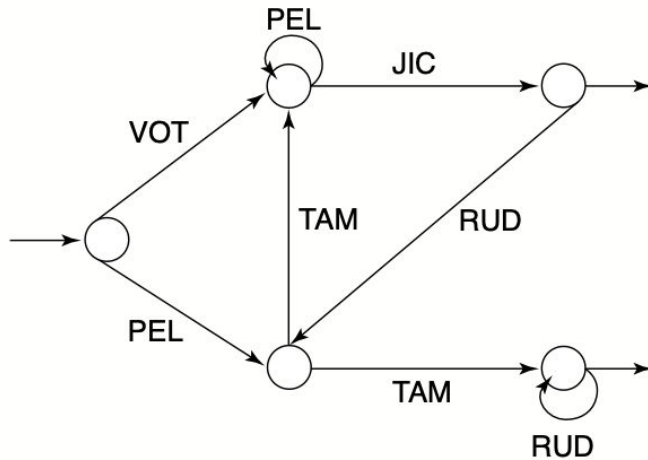
Learners could not simply memorize word pairs: vocabulary was different and again, train strings were never presented in test strings

Experiment 2.2: Words in Abstract Patterns

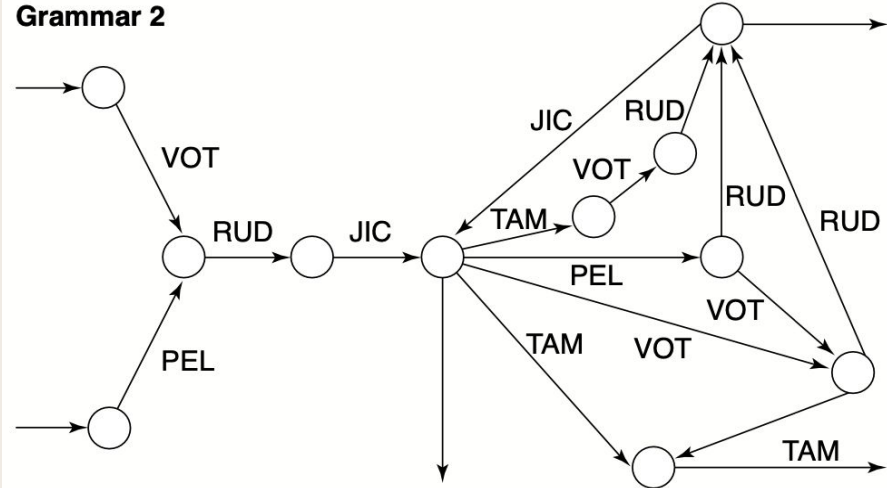
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Results: Babies discriminated between grammars despite change in vocabulary

Grammar 1



Grammar 2

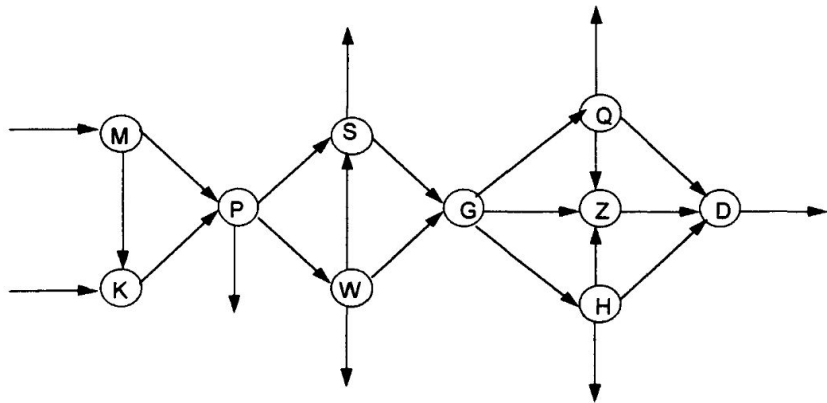


Experiment 3: Limitations of pattern-based representations

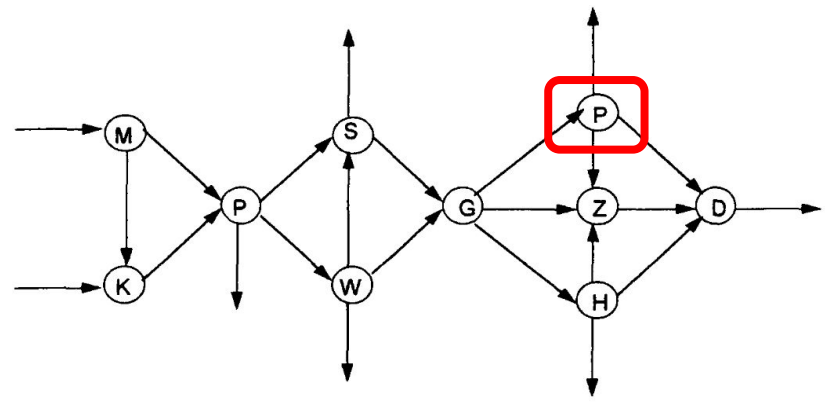
Gómez et al. (2000): The basis of transfer in artificial grammar learning.

Expose adult learners to 1 of 2 grammars and test if they can recognize ungrammatical forms

No repeating/identical elements



One identical element in $\frac{1}{3}$ of sentences



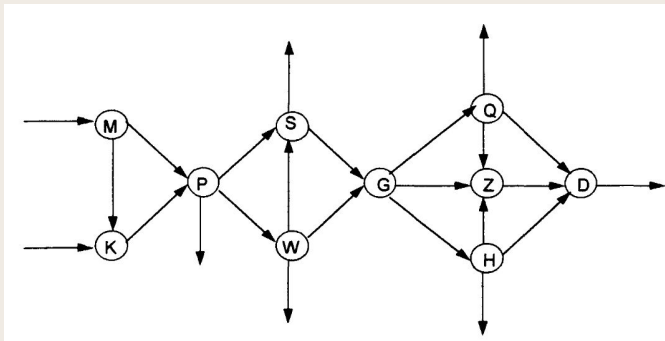
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Train: Listen to strings formed by one grammar

Test: Listen to strings which are grammatical and ungrammatical, according to their trained grammar

Non-repeating condition

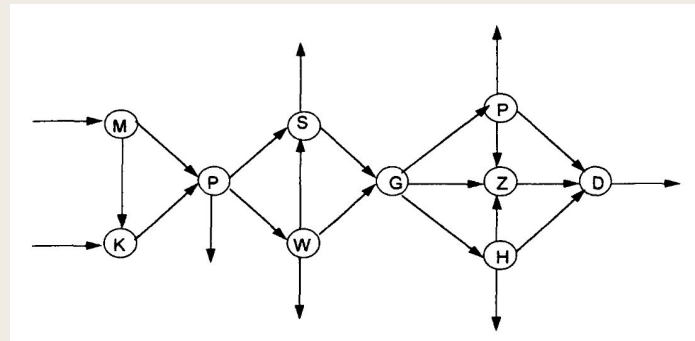


MKPDGQ

MKPWGQ

One illegal transition per item

Repeating condition



MPSWSGH

MPWSGH

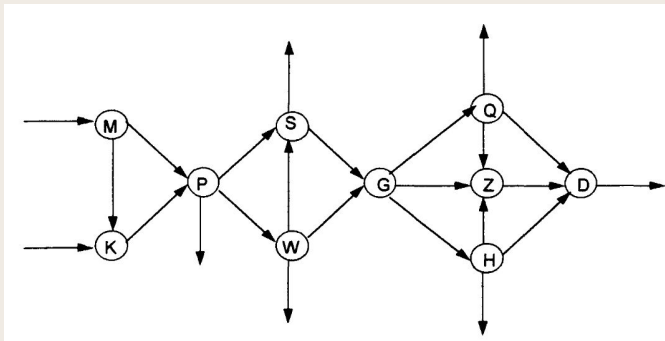
One illegal transition + one illegal repetition per item

Experiment 3: Limitations of pattern-based representations

Gómez et al. (2000): The basis of transfer in artificial grammar learning.

Results: Learners able to discriminate ungrammatical forms, regardless of which grammar they were trained on.

Non-repeating condition

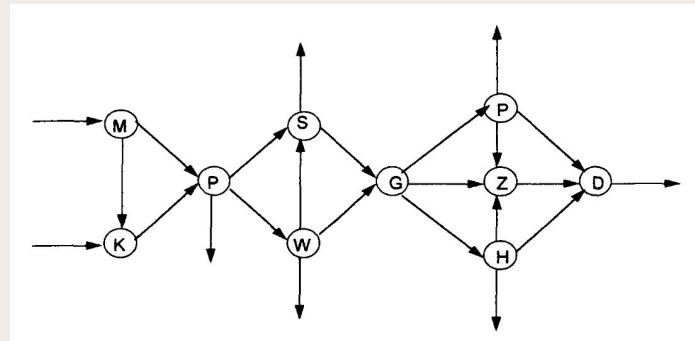


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One illegal transition per item

Repeating condition



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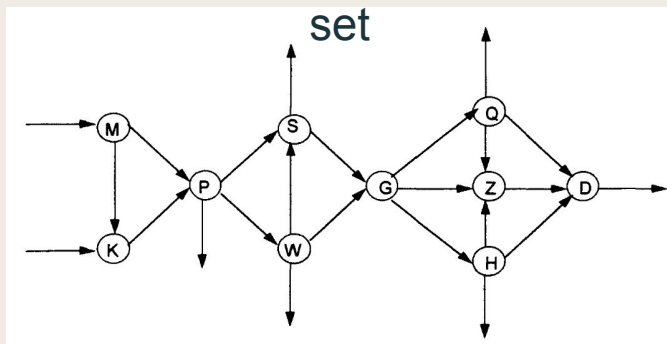
One illegal transition + one illegal repetition per item

Experiment 3: Limitations of pattern-based representations

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Results: However, when using different test than train-vocabulary, learners could *only generalize in the repeating condition*.

Non-repeating condition train set

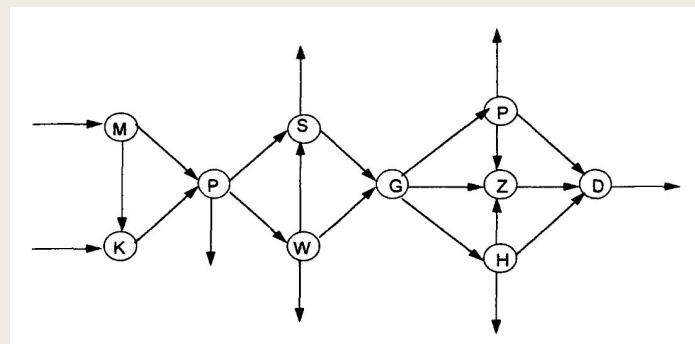


MKPDGZD

MKPWGZD

One illegal transition per item

Repeating condition train set



MPSWSGH

MPWSGH

One illegal transition + one illegal repetition per item

Pattern vs. Category-Based Abstraction

🤔 How do language learners abstract grammatical rules?

Pattern-based: perceptually bound

- ABA word pattern - humans can obviously recognize identical words because they sound the same
- Rising or falling frequency patterns

Category-based: over abstract categories

- humans can further abstract into broader categories:
- can access rules associated with categories

“Here is a wug. Now there are two of them. There are two ____”

“A bear washed himself” vs. “A bear washed him”

“The” precedes a noun but never a verb

Pattern vs. Category-Based Abstraction

Smith (1969): Learning co-occurrence restrictions: rule learning or rote learning?

| | N ₁ | N ₂ | N ₃ |
|----------------|----------------|----------------|----------------|
| M ₁ | x | x | ? |
| M ₂ | ? | x | x |
| M ₃ | x | ? | x |

| | Q ₁ | Q ₂ | Q ₃ |
|----------------|----------------|----------------|----------------|
| P ₁ | x | ? | x |
| P ₂ | x | x | ? |
| P ₃ | ? | x | x |

Train: Learners given some but not all possible $M \rightarrow N$ pairs and $P \rightarrow Q$ pairs

Note: the M,N,P,Q categories consists of 12 letters: h j l n p q r s w x y z

Example: $M = \{h, z, q\}$, $N = \{j, x, l\}$, $P = \{n, w, y\}$, $Q = \{s, r, p\}$

hx ql ws np

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| M ₂ | ? | x | x |
| M ₃ | x | ? | x |

| | Q ₁ | Q ₂ | Q ₃ |
|----------------|----------------|----------------|----------------|
| P ₁ | x | ? | x |
| P ₂ | x | x | ? |
| P ₃ | ? | x | x |

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Test: Can learners generalize to new pairs?

Example: $M = \{h, z, q\}$, $N = \{j, x, l\}$, $P = \{n, w, y\}$, $Q = \{s, r, p\}$

zj? nr? hp? zs?

Pattern vs. Category-Based Abstraction

Smith (1969): Learning co-occurrence restrictions: rule learning or rote learning?

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|----------------|----------------|----------------|----------------|
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| M ₂ | ? | x | x |
| M ₃ | x | ? | x |

| | Q ₁ | Q ₂ | Q ₃ |
|----------------|----------------|----------------|----------------|
| P ₁ | x | ? | x |
| P ₂ | x | x | ? |
| P ₃ | ? | x | x |

Train: Learners given some but not all possible $M \rightarrow N$ pairs and $P \rightarrow Q$ pairs

Test: Can learners generalize to new pairs?

No. Learners may accept $M_1 \rightarrow Q_3$. Not enough information to generalize dependencies between categories.

Pattern vs. Category-Based Abstraction

Smith (1969): Learning co-occurrence restrictions: rule learning or rote learning?

| | N ₁ | N ₂ | N ₃ |
|----------------|----------------|----------------|----------------|
| M ₁ | x | x | ? |
| M ₂ | ? | x | x |
| M ₃ | x | ? | x |

| | Q ₁ | Q ₂ | Q ₃ |
|----------------|----------------|----------------|----------------|
| P ₁ | x | ? | x |
| P ₂ | x | x | ? |
| P ₃ | ? | x | x |



Problem is fixed when category members are marked with salient perceptual cues:

N members: [**kais**]ermil[**rish**]

Q members: [**wan**]ersum[**glot**]

→ Can use category markings to make inferences about new pairs

Pattern vs. Category-Based Abstraction

🤔 How do language learners abstract grammatical rules?

by gaining sufficient evidence from systematically related cues

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Category-based: over abstract categories

- humans can further abstract into broader categories **(by using salient perceptually-bound cues)**
- can access rules associated with categories

“Here is a wug. Now there are two of them. There are two ____” **“s” indicates plurality**

“A bear washed himself” vs. “A bear washed him” **“self” indicates reflexivity**

“The” precedes a noun but never a verb

Pattern vs. Category-Based Abstraction

🤔 How do language learners abstract grammatical rules?

By gaining sufficient evidence from systematically related cues

More examples from English:

- Verbs have inflectional endings (“-ed”, “-ing”)
- Different stress patterns:
 - “The”, “a” exhibit reduced stress
 - “Permit” is a verb vs “**Permit**” is a noun

→ 🤔 How *much* evidence is needed to generalize?



Review

Infants can ..

- parse word constituents based on syllabic relationships
- learn word-order constraints
- abstract familiar patterns to unseen vocabulary by learning ‘abstract-level’ categories

In using *artificial languages* we can demonstrate learning of syntactic form without initial connection to semantic form

Final question...

How representative are artificial grammars/languages of natural languages anyway?

- we should drive feature manipulation based on knowledge of natural language acquisition