

Examining representations formed by the co-evolution of episodic and semantic memory



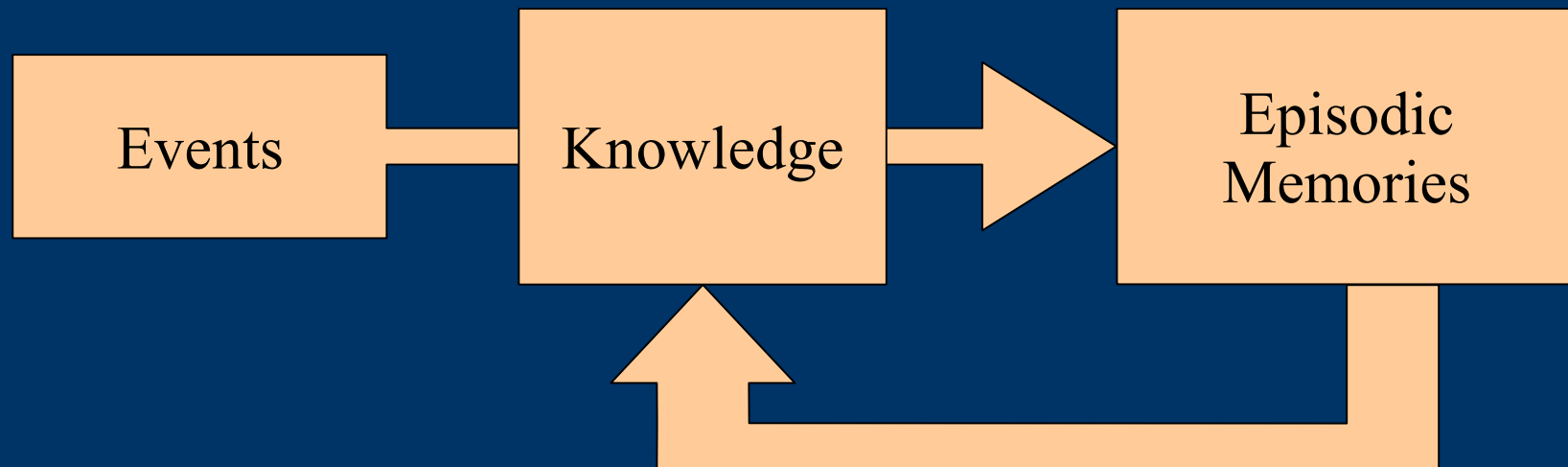
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Overview


- Prior knowledge helps us interpret world, storing meaningful episodic information
- Sparse but durable information accrues to form knowledge.




Past Approaches: Episodic Memory and Semantic Knowledge

- Episodic Memory
 - SAM, Minerva, TODAM
 - REM, BCDMEM
 - Semantic Memory/Knowledge Structure
 - Collins & Quillian / Collins & Loftus, Rosch
 - HAM, ACT-R
 - Rumelhart & McClelland
 - Attractor Network Models, ART
 - Produce Representations of real words
 - Webster, Roget, CYC, WordNet, Word Association Norms
 - LSA, HAL, Topics Model (corpus analysis)
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Goals of REM-II

- Begin with a reasonably sophisticated model of Episodic Memory
 - Specify how episodes accrue to form knowledge
 - Specify how knowledge is marshalled to encode episodes
 - Model the iterative process of knowledge formation and use of this knowledge
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Overview of REM-II Model

- 1) Feature-based representational system
 - 2) Knowledge accumulation as feature co-occurrences
 - 3) Episodic encoding from knowledge
 - 4) Semantic differentiation through sharing features with co-occurrent concepts
 - ~~5) Bayesian probabilistic calculations for matching~~
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(1) Episodic Memory Representation

- Features are any sufficiently unitized memory structure.

< Color | Size | Shape >
<ROYGBIV | SML | round square ...>

- Value-Strength Traces

< 0 1 0 0 0 | 0 0 1 | 0 1 | 1 | | | 1 >
< 1 2 | 0 2 | | 3 4 | 3 0 1 2 | 3 >

- Enables coding of strength and value

- Represents impoverished episodic traces



(2) Feature Representations in Semantic Knowledge

- Accumulate co-occurrence of features corresponding to a concept.

[<5 3 | 3 4 | 1 0 0>
<3 6 | 0 1 | 1 3 0>

- Knowledge Matrix:
 - Set of multiple conditional representations

<3 0 | 4 3 | 0 0 3>
<4 1 | 3 5 | 4 2 1>

<1 1 | 0 4 | 6 0 1>
<0 3 | 0 2 | 0 4 1>
<0 0 | 3 1 | 1 1 4>]



(2) Forming LTM Co-occurrence matrix from Episodes

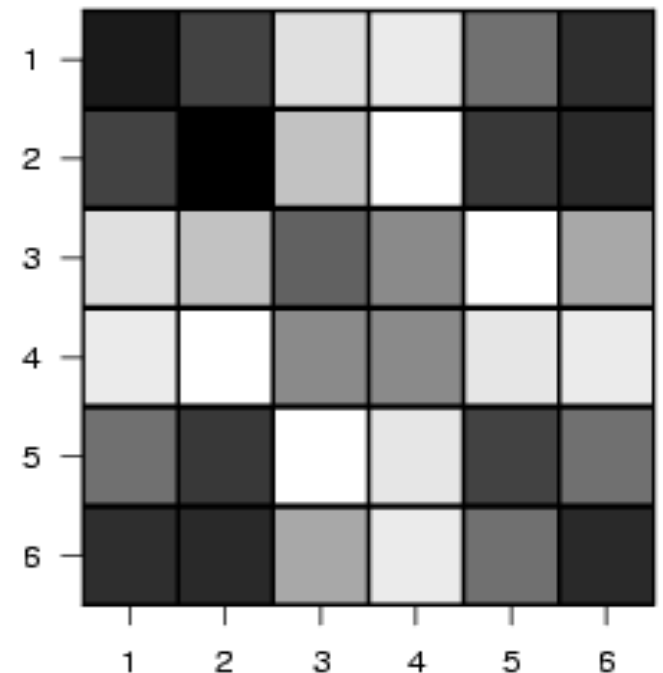
- Any episodic trace can produce a co-occurrence matrix.
- 110011 and 001100 form co-occurrence matrix at right
- Knowledge accrues by incorporating co-occurrence matrix from individual episodes into current knowledge structure.

•	1	1	0	0	1	1
•	1	1	0	0	1	1
•	0	0	0	0	0	0
•	0	0	0	0	0	0
•	1	1	0	0	1	1
•	1	1	0	0	1	1
•	0	0	0	0	0	0
•	0	0	0	0	0	0
•	0	0	1	1	0	0
•	0	0	1	1	0	0
•	0	0	0	0	0	0
•	0	0	0	0	0	0



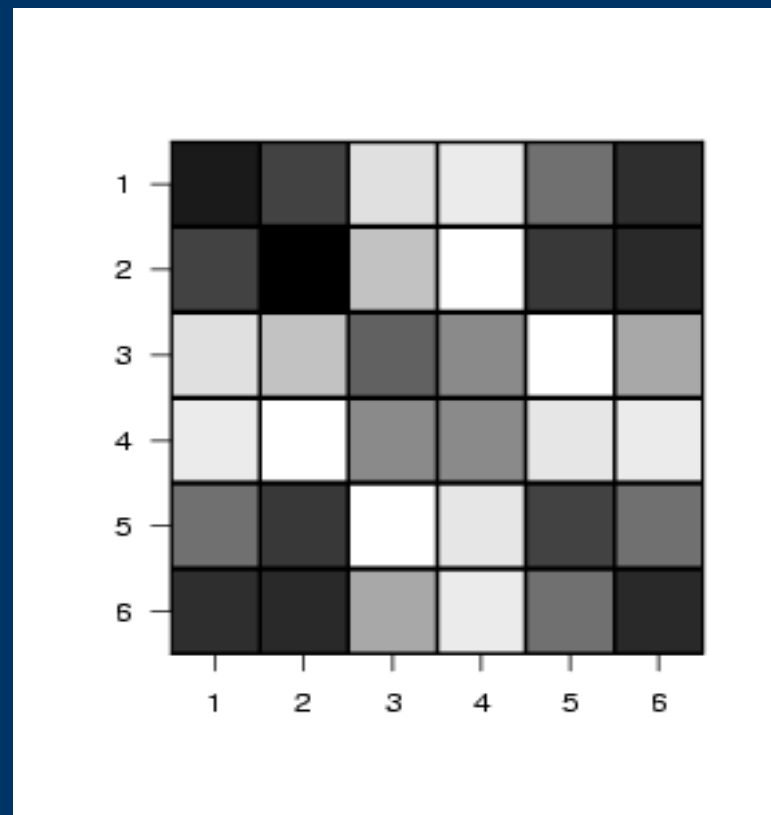
(2) LTM Co-occurrence matrix

- Over time, complex matrix representation will form.
- Word has two primary concepts: 1-2-5-6 and 3-4.
- 1256 is stronger than 34
- Primary meanings could be extracted using factor analysis)




(3) Encoding Episodes from Knowledge Matrix

- Generic Encoding: pick row, pick feature, pick new row based on what has been sampled, repeat.
- Biased Encoding: pick row from another trace, pick feature from that row of current matrix, repeat.



(4) Formation of Model Mental Lexicon

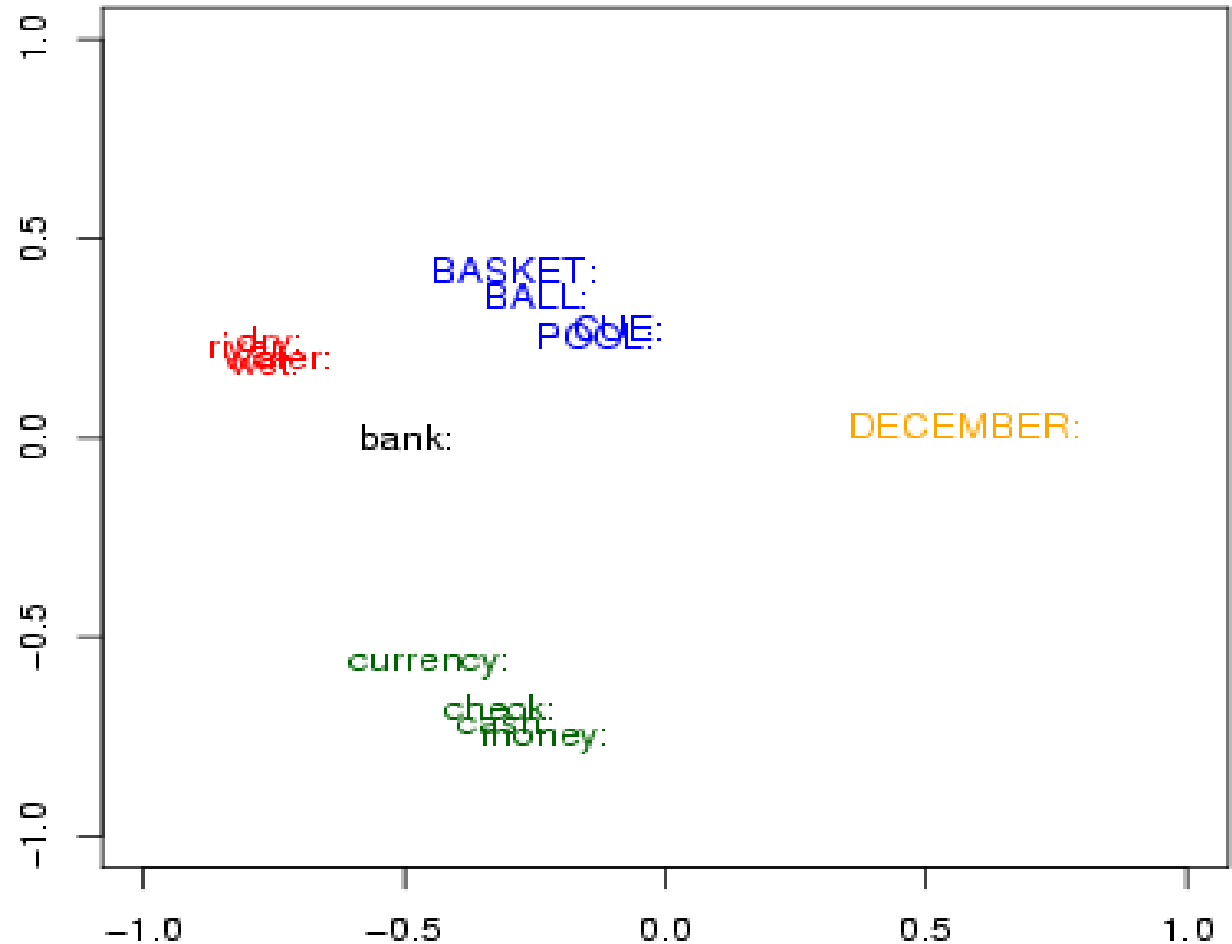
- How do representations with multiple aspects form?
 - Principle: concepts that appear together grow more similar (Hebbian-like principle).
 - Start off each word with a 'unique' representation
 - During encoding, keep track of local feature context
 - Words encoded in a way biased by context.
 - Knowledge re-stored along with some features from local context.
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Semantic Spaces Demonstration: Bank

- Create lexicon for model by “reading” text.
 - In text, BANK appears with MONEY words, RIVER words, or BALL words.
 - I deposit check in bank
 - money is withdrawn from bank
 - the river bank was dry
 - there was water on river bank
 - In demo:
 - Form matrix representation for each word
 - Compute similarity between each obtained matrix
 - Perform 2-D MDS to visualize space.
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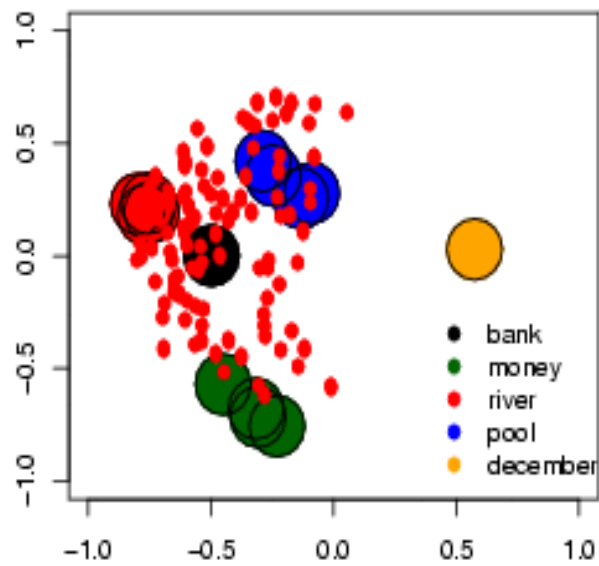
Results: Bank Demonstration

- After lexicon formed from text, perform MDS on feature representations

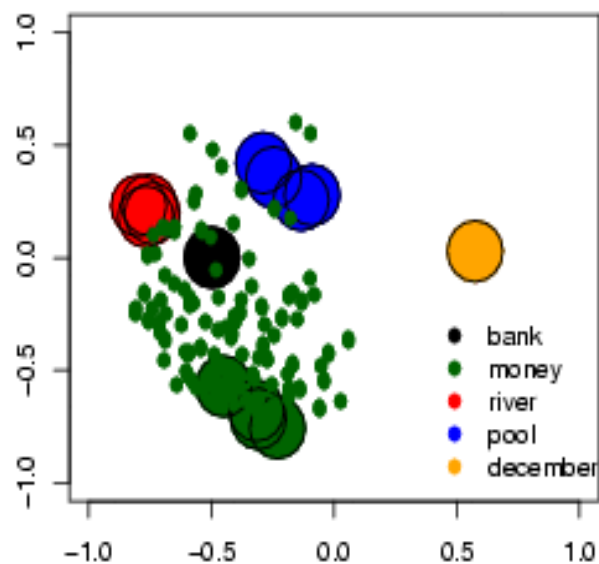


Biased Encodings of “Bank”

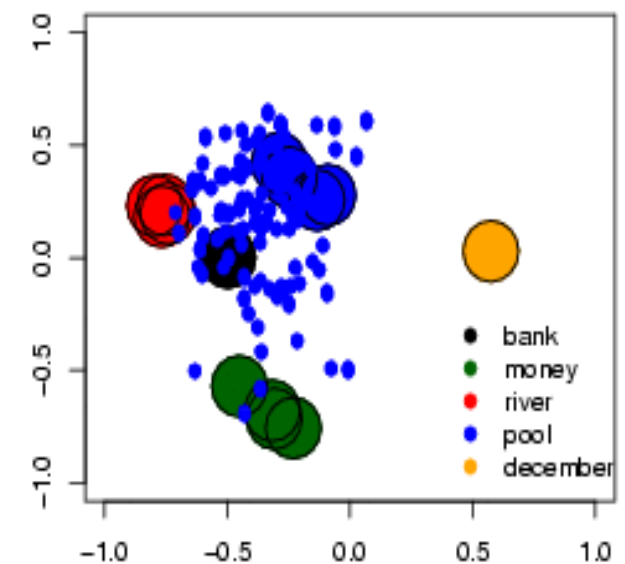
100 'Bank' biased toward 'River'



100 'Bank' biased toward 'Money'

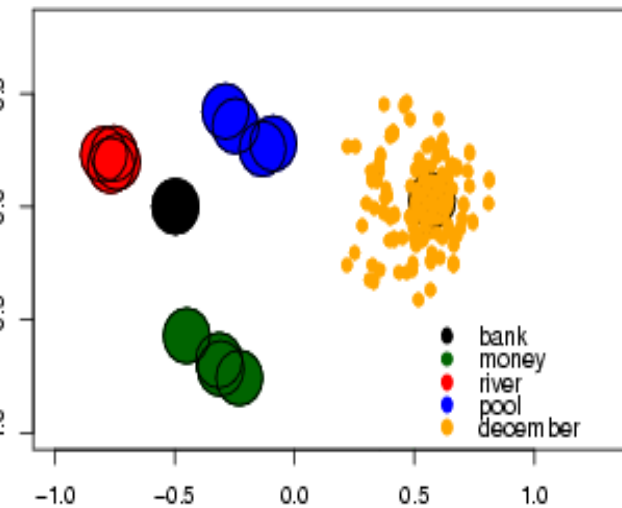


100 'Bank' biased toward 'pool'

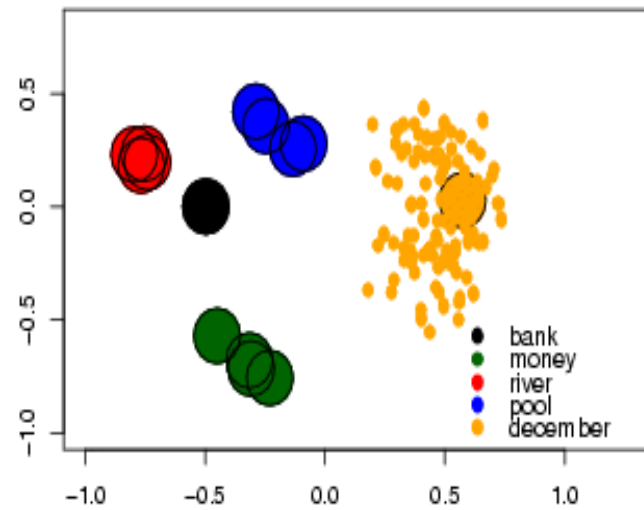


Biased Encodings of “December”

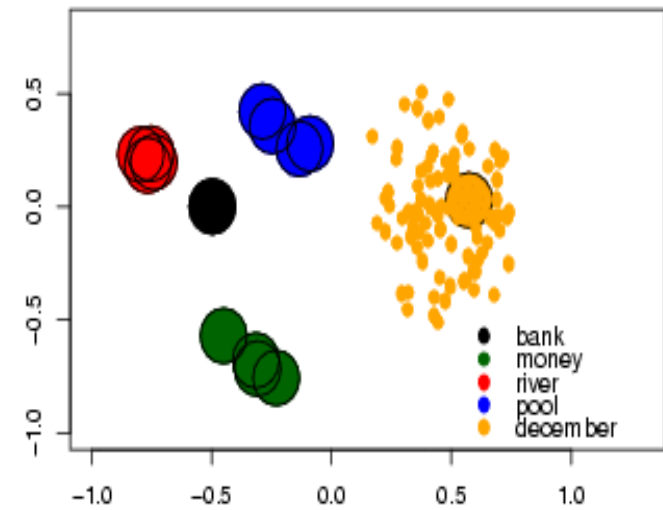
100 'DECEMBER-december'



100 'DECEMBER-money'



100 'DECEMBER-river'



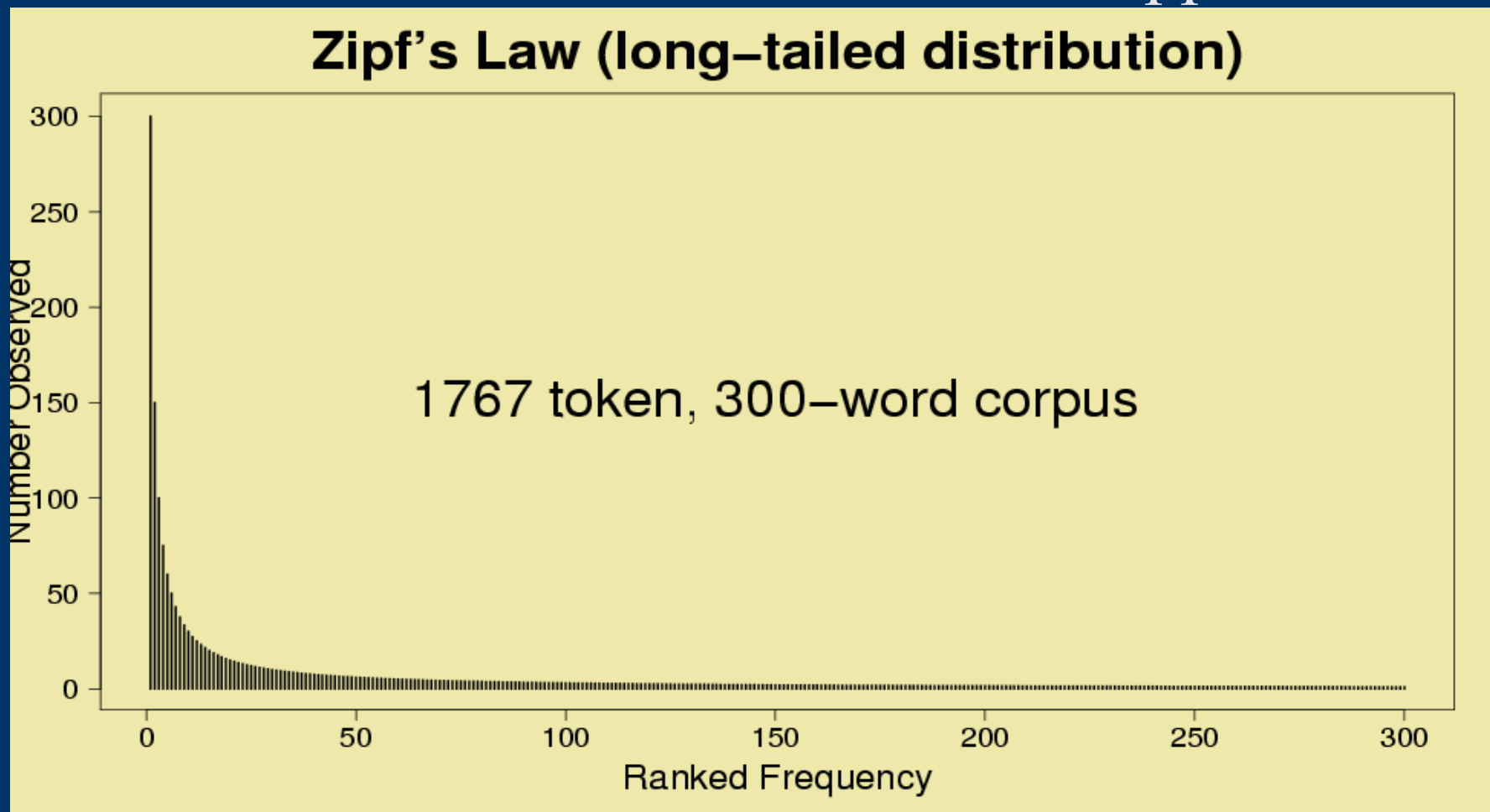
Model for Episodic Memory Tasks

- Previous simulation shows that semantic spaces can emerge within the matrix representation
- System must be extended to form model of episodic memory tasks (primarily list memory)
- Three main steps:
 - Form Model Lexicon
 - Encode Episodes
 - Compute Likelihood



Step 1: Form Model Mental Lexicon

- Real words occur in different frequencies.
- Typically, the few most common words happen a lot, and there are a lot of rare words that happen a little.



Step 1: Form Model Lexicon

- Each word initialized with a unique representation.
 - Half of the features are “Physical” describing physical properties of word
 - Half are relational, forming local semantic context.
 - During lexicon formation:
 - observed tokens are encoded by consulting knowledge
 - features from local semantic context are added to relational features of trace.
 - New augmented trace is added to current semantic matrix for word.
 - In this process, things that co-occur will gradually begin to share relational features.
 - High-frequency words will grow more similar to one another; low frequency words remain unique.
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Step 2: Encode Episodic Traces

Episodic traces encoded from knowledge network

- Traces stored for all words on list
- At test, a probe is encoded as another episodic trace.
- Response depends on likelihood calculation (Step 3): probability trace being produced by that probe.




Step 3: Calculate Likelihood and Make Response

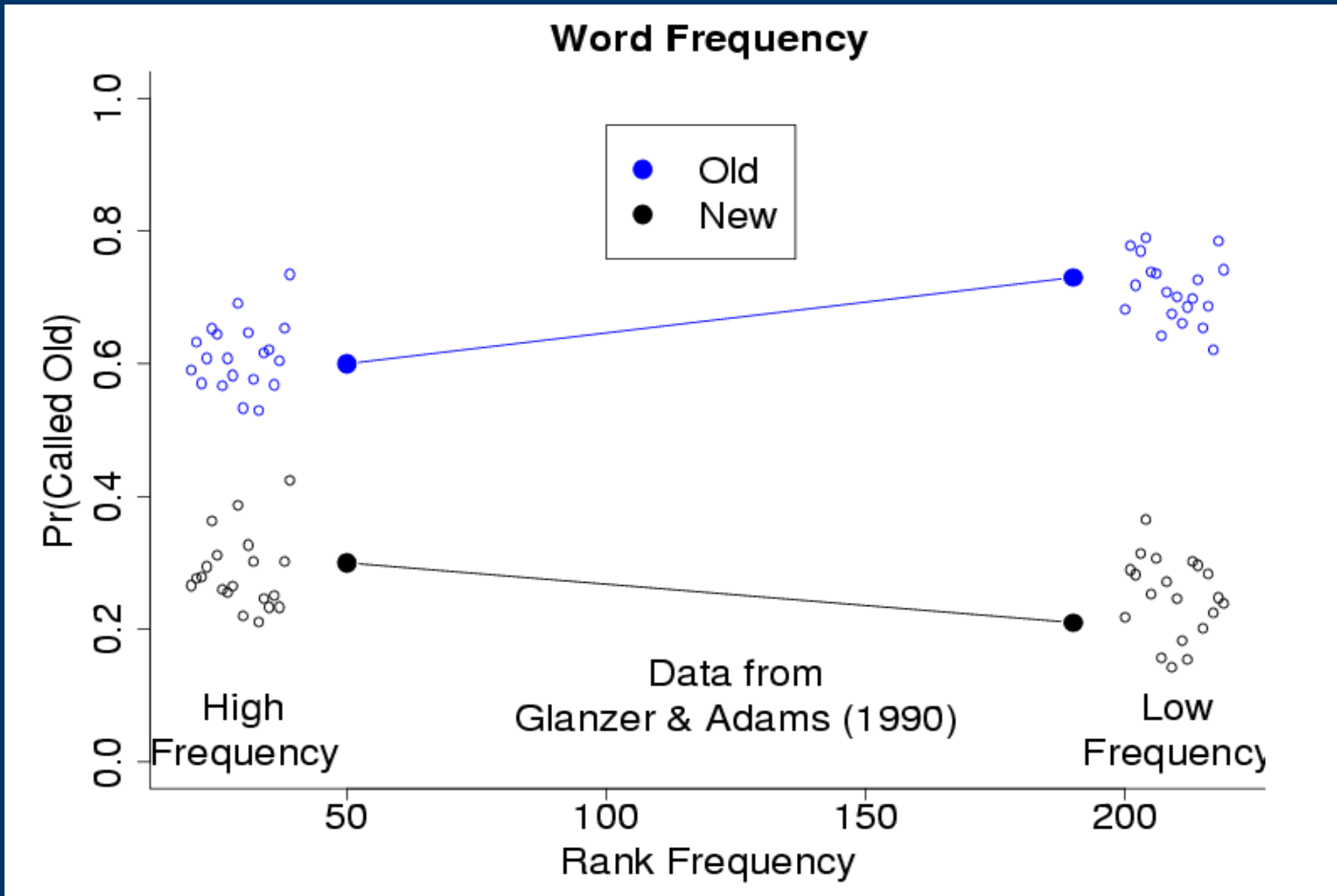
- Essence: Compute probability that target came from probe (as opposed to from somewhere else).
- Compare values on features.
 - Matches $(c)(p(\text{cat}, \text{feat})) + (1-c)(\text{br}.p(\text{cat}, \text{feat})) / (\text{br}.p(\text{cat}, \text{feat}))$
 - Mismatches: $(c)(0) + (1-c)(\text{br}.p(\text{cat}, \text{feat})) / \text{br}.p(\text{cat}, \text{feat}) = 1-c$
- If likelihood is high enough, make positive response



Recognition Memory Demonstration

- Task: present 40-item list for study comprised of high and low-frequency words. Later, present 20 old words and 20 new words; participant says “Old” or “New” for each.
 - Typical finding: LF words remembered better; higher hits and lower false alarms.
 - In the model, lexicon formation makes HF words more similar to one another.
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Mirror Frequency Effect



Model Summary

- Knowledge representation as a feature-based co-occurrence matrix.
- Concepts that co-occur grow more similar by sharing features.
- Together:
 - Form semantic spaces
 - Captures multiple senses and meanings of a concept
 - Accounts for frequency effect in recognition memory
 - Allow encoding biases to be explored.
- Unites previously independent approaches toward memory and knowledge, bringing new insights to both.



Applications

- **Semantic Spaces**
 - **Frequency Effects in Episodic Memory**
 - **Biases in encoding**

 - Priming
 - Implicit Association Test
 - Consistent correlations in environment embed multiple connotations in concepts.
 - Text comprehension/disambiguation
 - Whorfian Hypothesis
 - Corpus Analysis
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