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

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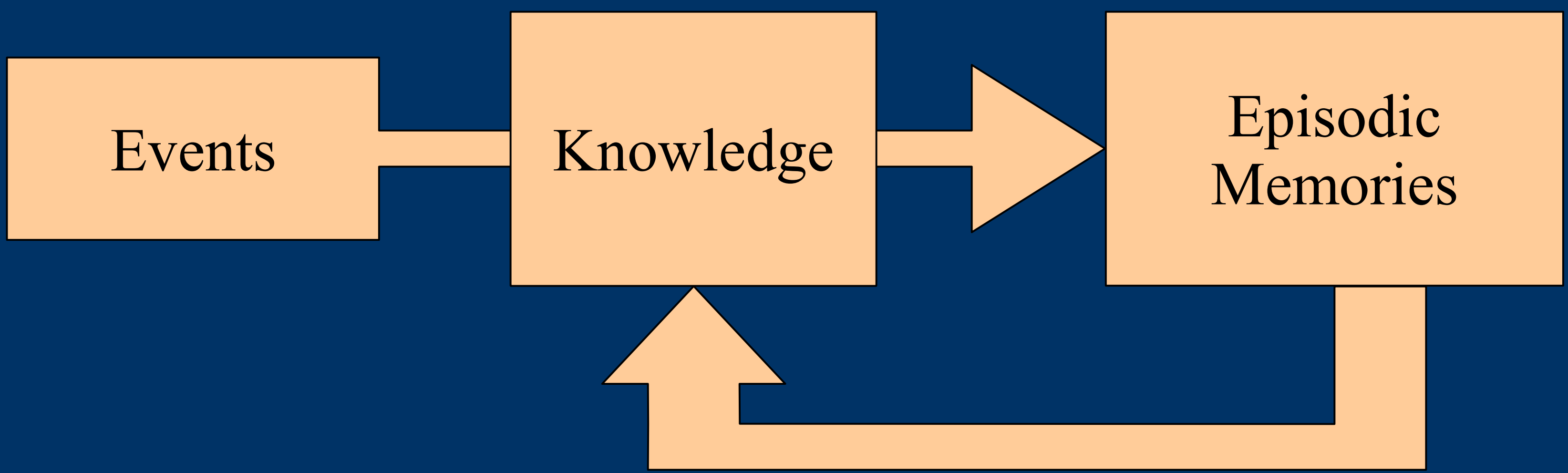
Overview

- 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)

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

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~~

(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.
- Knowledge Matrix:
  - Set of multiple conditional representations

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

<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

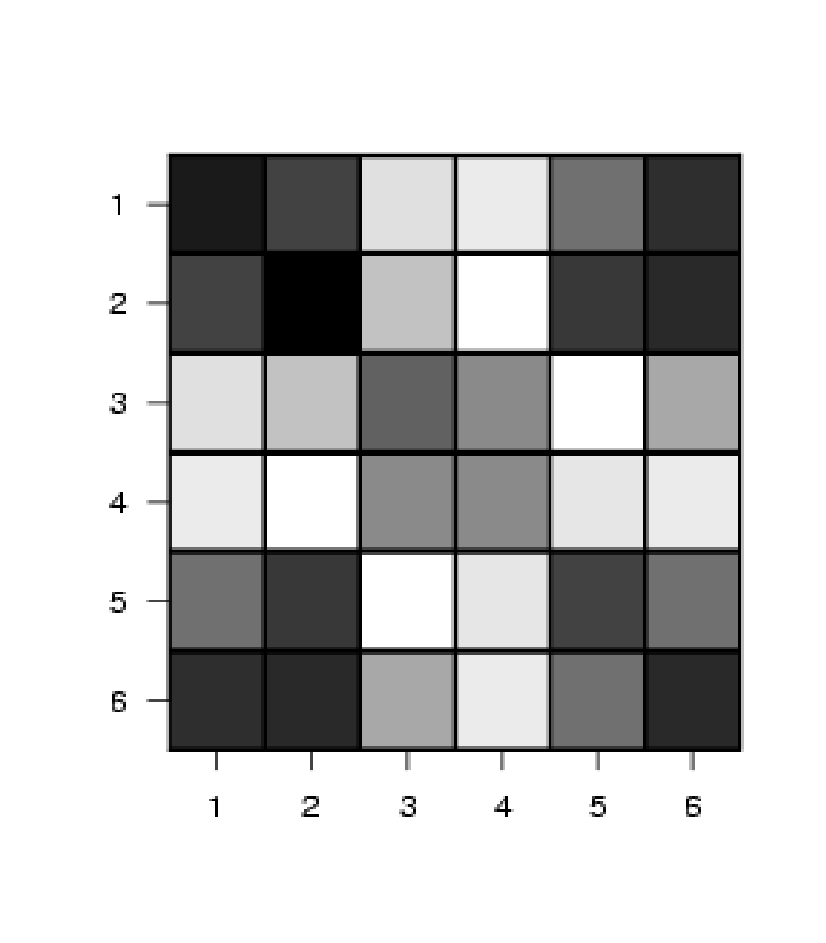
- Any episodic trace can produce a co-occurrence matrix.
- 110011 and 001100 form co-occurrence matrix at right
- Knowledge accrues by incorporating co-occurrence matrix from individual episodes into current knowledge structure.

- 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

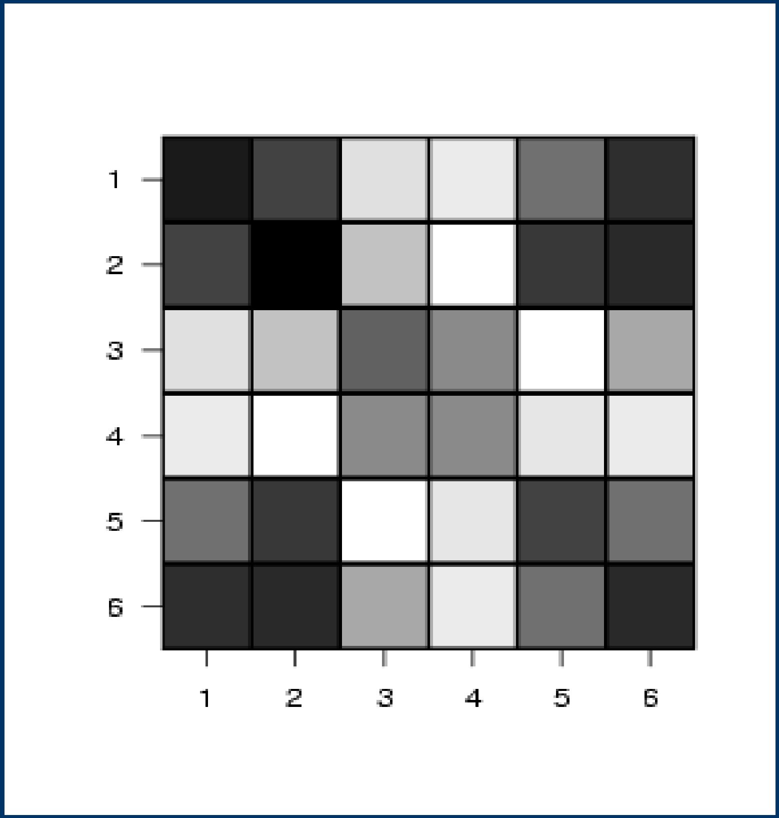
- Over time, complex matrix representation will form.
- Word has two primary concepts: 1-2-5-6 and 3-4.
- 1256 is stronger than 34
- Primary meanings could be extracted using factor analysis)



(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.

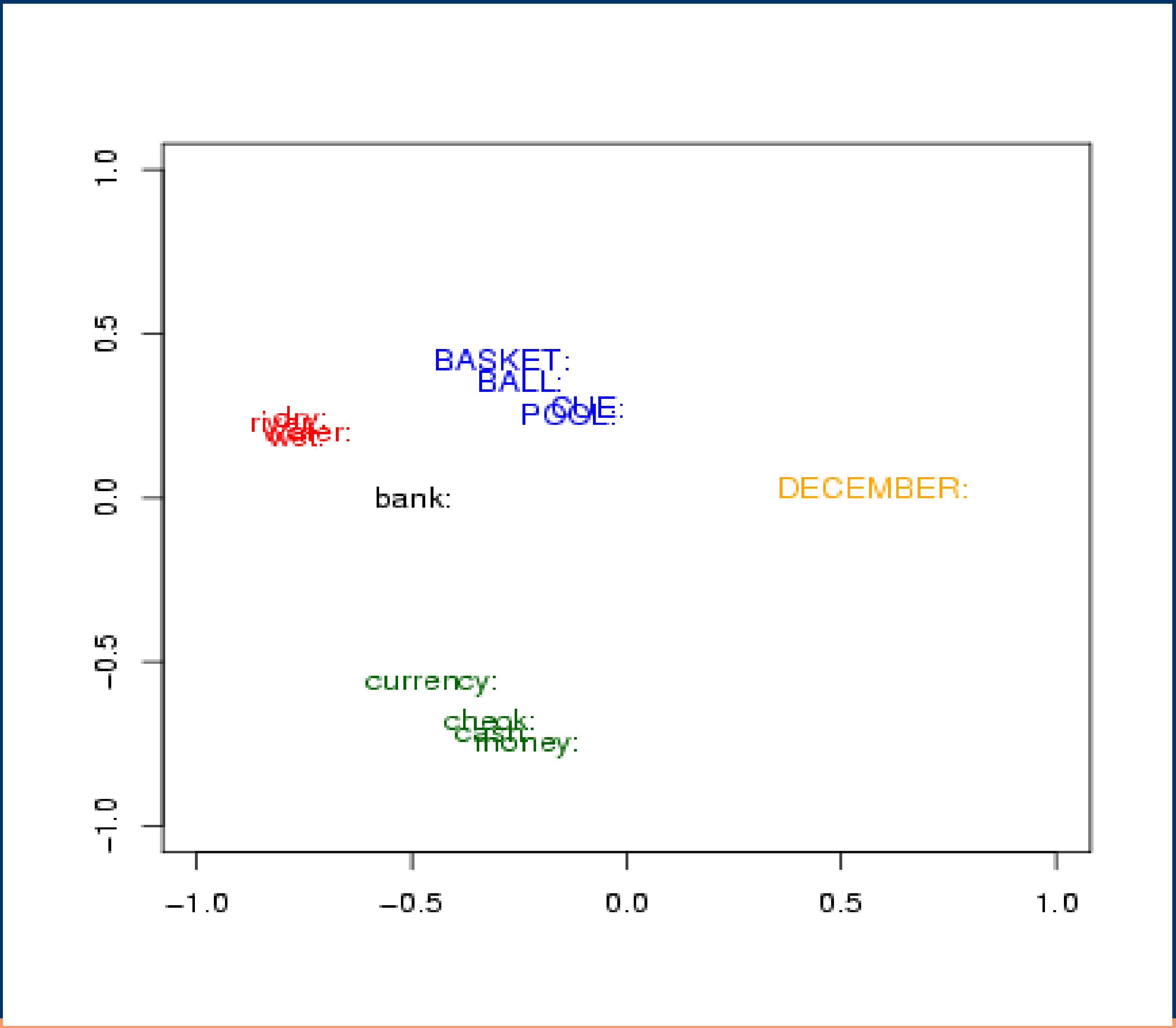
Semantic Spaces Demonstration: Bank

- 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

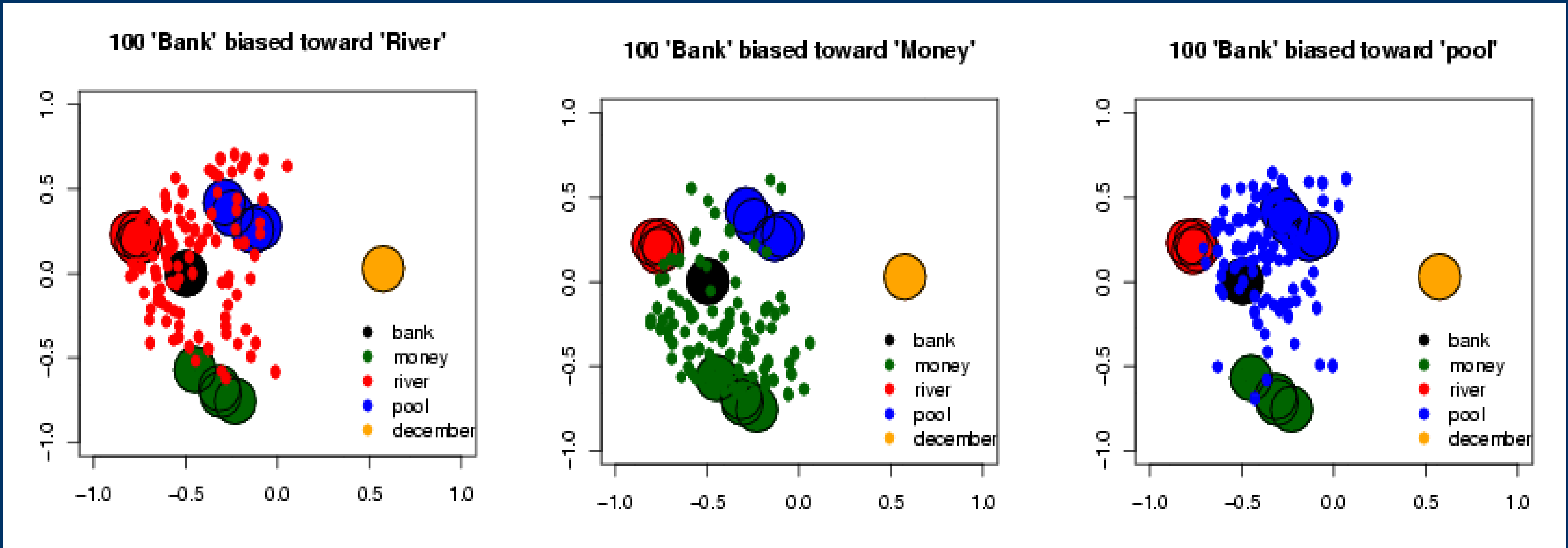
  - the river bank was dry
  - there was water on river bank
- In demo:
  - Form matrix representation for each word
  - Compute similarity between each obtained matrix
  - Perform 2-D MDS to visualize space.

Results: Bank Demonstration

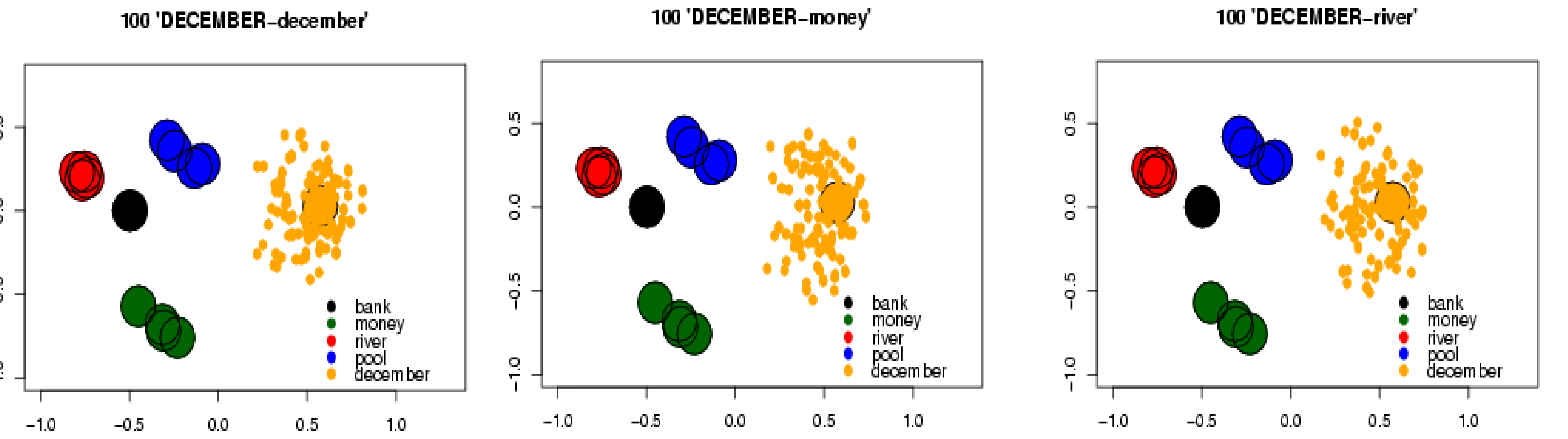
- After lexicon formed from text, perform MDS on feature representations



Biased Encodings of "Bank"



Biased Encodings of "December"



Model for Episodic Memory Tasks

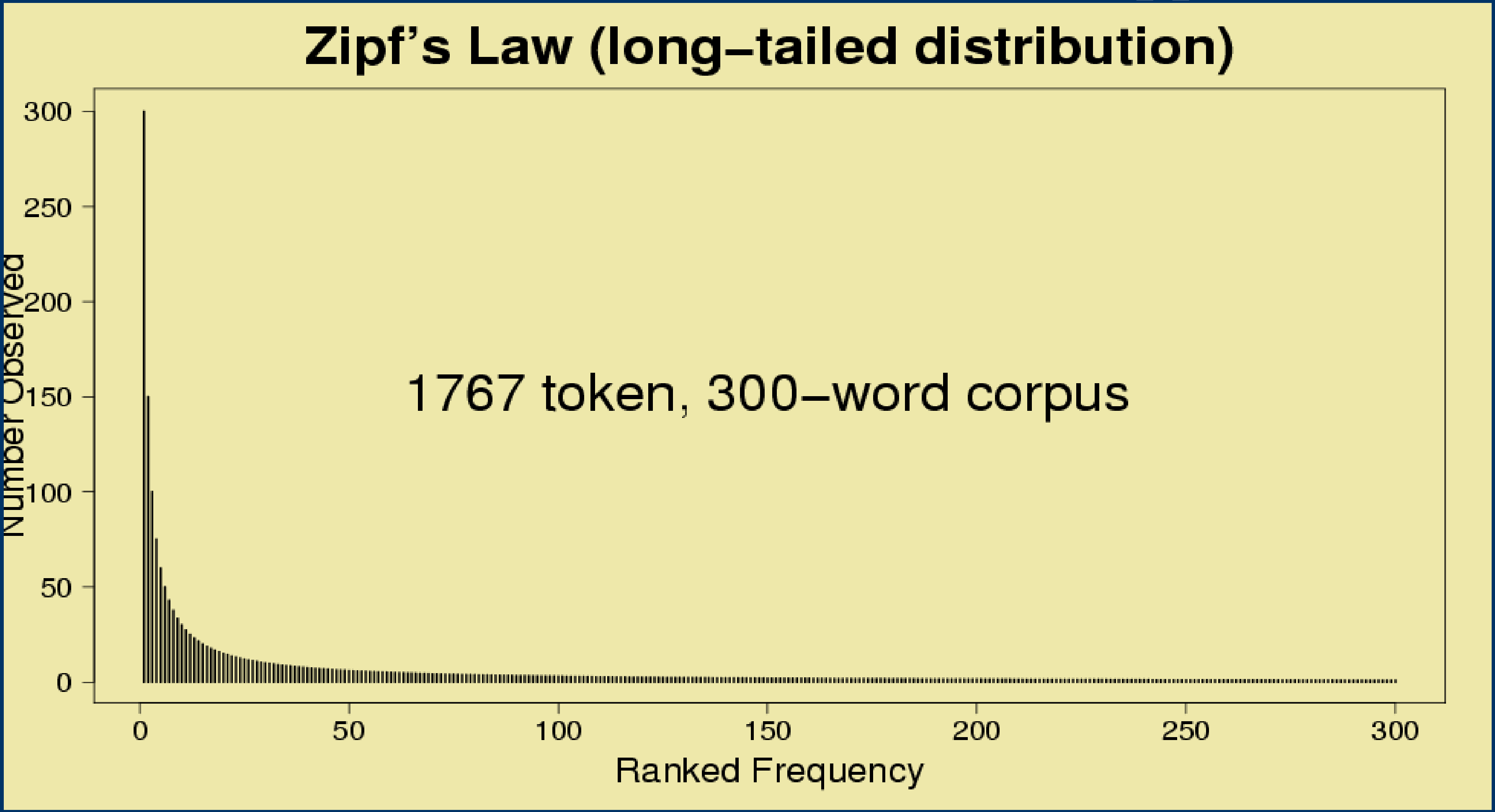
- Previous simulation shows that semantic spaces can emerge within the matrix representation

- 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.

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).

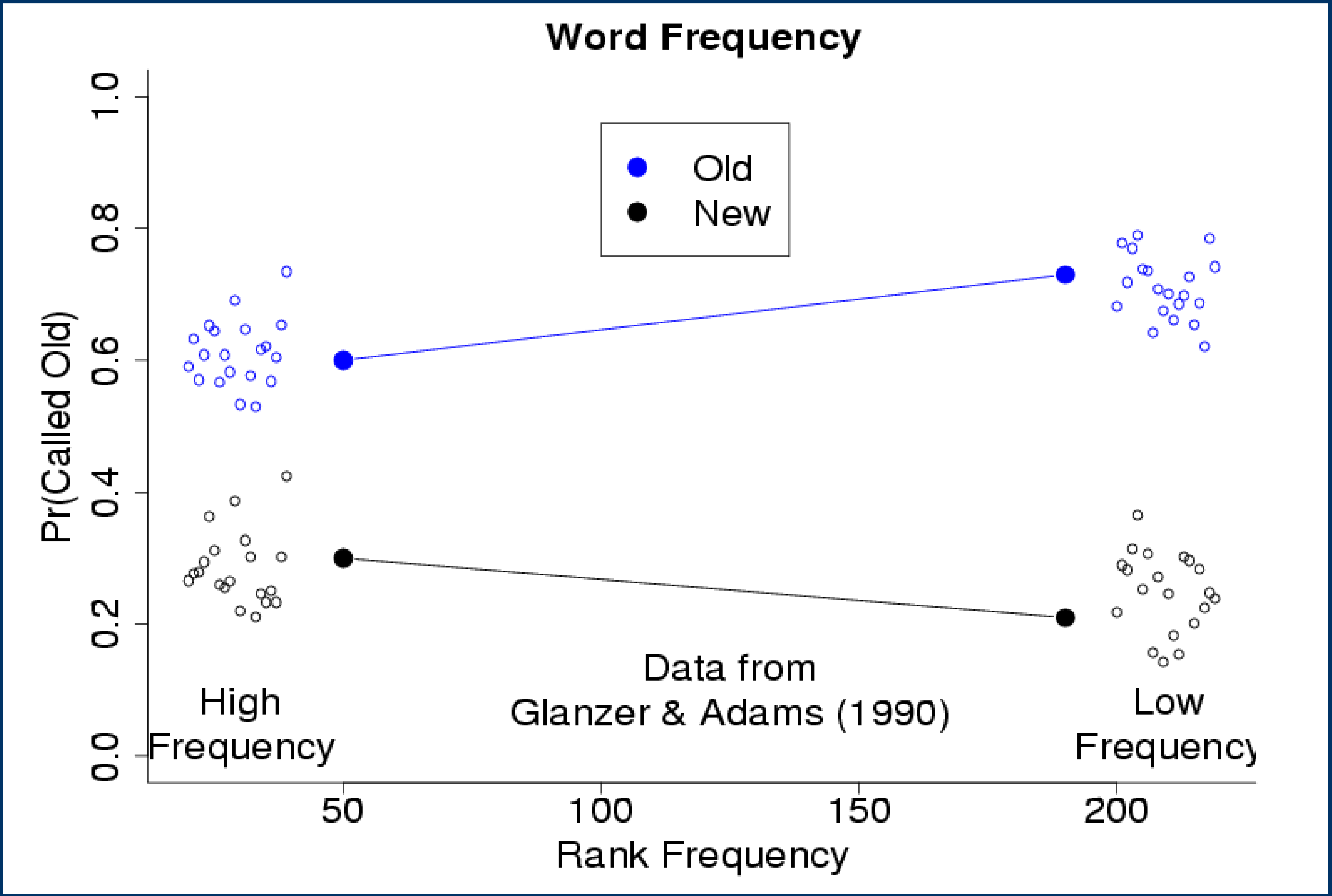
- Compare values on features.
  - Matches (c)(p(cat,feat)) + (1-c)(br.p(cat,feat))/(br.p(cat,feat))
  - Mismatches: (c)(0)+(1-c)(br.p(cat,feat))/br.p(cat,feat) = 1-c

- 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.

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