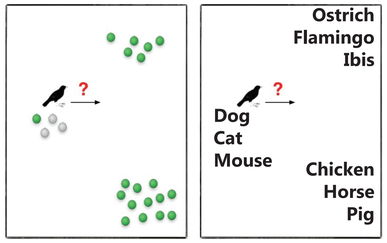
Representation and Retrieval in Semantic Memory

Johnathan E. Avery, Indiana University
Michael N. Jones, Indiana University

Background

The semantic fluency task (SFT) is a free recall task that allows for the study of **organization** and **retrieval** from semantic memory both experimentally[1] and clinically[2]. In SFT, the participant is asked to produce as many exemplars of the category as possible within a fixed amount of time.

Statistical signatures of responses suggest evolutionary exaptation of animal food search patterns switching between global exploration and local exploitation[3]:
- Decrease in semantic similarity in patch transition
- Patch switches occur when a patch is sufficiently depleted
- Patch switches can be predicted by marginal value theorem[4]



The Counter Argument

A retrieval mechanism is highly **responsive** to the assumptions of a **representational structure**[5]. A Random Walk model could produce the same behavior given a network representation of memory. This was demonstrated using free association norms[6] and child directed speech[7].

However, model comparisons are ridden with **confounds**:

	HJT	AAG	NMS
Learning Environment	Wikipedia	USF FA	CHILDES
Learning Model	BEAGLE	Human	Word Learner
Representation	Space	Network	Network
Search Model	Foraging	RW	RW

Abridged References:

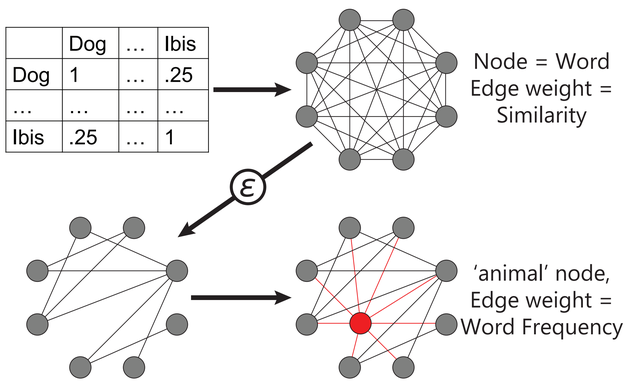
[1]Raajmakers et al (1981); [2]Troyer et al (1998); [3]Hills et al (2012); [4]Charnov (1976); [5]Anderson (1978); [6]Abbott et al (2015); [7]Nematzedah et al (2016); [8]Jones et al (2007); [9]Luce (1959); [10]Farrell et al (2018); [11]Zemla et al (2017)

Bridging Representational Assumptions

- BEAGLE[8] treats words as points in multidimensional space
- Network treats words as nodes connected by edges
- Need to bridge the divide between a structured network and unstructured space

Distance matrix between 765 animal words

	Dog	…	Ibis
Dog	1	…	.25
…	…	…	…
Ibis	.25	…	1



Weighted Networks:

$$W_{ij} = \begin{cases} 0 & Wij < \varepsilon \\ W_{ij} & Wij \geq \varepsilon \end{cases}$$

Unweighted Networks:

$$W_{ij} = \begin{cases} 0 & Wij = 0 \\ 1 & Wij > 0 \end{cases}$$

Cue Switching Model

Cue Switching model[3] incorporates multiple cues dynamically within a Luce choice rule[9]:
- Strategic tradeoff between exploitation and exploration
- Tradeoff operationalized as similarity and frequency cues

$$P(X_{n+1}|Q_1, Q_2, X_n) =$$

$$\frac{W(X_{n+1}, X_n)^{\beta/} \times W(X_{n+1}, "animal")^{\beta g}}{\sum_{k=1}^{N} W(X_k, X_n)^{\beta/} \times W(X_k, "animal")^{\beta g}}$$

Random Walk Model

Random Walk model[6] performs a local traversal of the network by randomly visiting nodes based on the edge weights of directed connections:
- Two cues, but no strategic switch

$$P(X_{n+1}|Q_1, Q_2, X_n) =$$

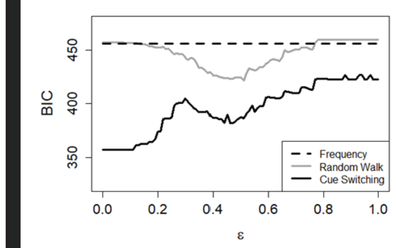
$$\rho P(X_{n+1}|Q_2) + (1-\rho) P(X_{n+1}|Q_1(X_{n+1}, X_n))$$

Qualitative Comparisons

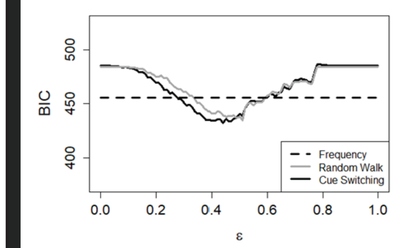
Evaluated the ability of the random walk model to produce the core qualitative phenomena indicative of optimal foraging. Statistical signatures may be achieved via different avenues.

Quantitative Comparisons

Used BIC[10] to evaluate the model's ability to capture data



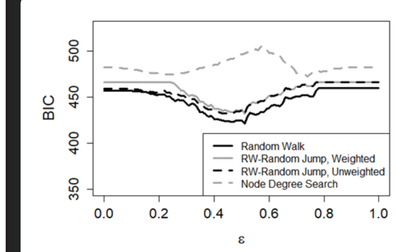
Weighted Networks
- CS performs best on a complete network, RW on a connected network
- There is no interaction between model fit at any epsilon



Unweighted Networks
- Both models perform worse on an unweighted network.

Extended Random Walk models

Tested other random walk models[11]



- None of the new RW models performed better than the original
- The RWRJ model performs best of alternative approaches.

Assumptions of the Cue Switching model:
unstructured representation + structured retrieval mechanism
Assumptions of the Random Walk model:
structured representation + unstructured retrieval mechanism

Our quantitative comparison supports the assumptions of the **Cue Switching model**.