Recognition ROCs and exemplar theory

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Introduction

The functional relation between hit and false alarm rates in recognition memory, as reflected in the ROC curve, has played a central role in validating models of recognition memory. The Exemplar-based Random Walk Model (EBRW; Nososky et al., 2011) successfully predicts recognition responses via a single, summed activation process, in contrast to dual-process models of familiarity and recollection. Yet its ability to account for ROC predictions found in typical recognition paradigms is largely unknown. This project examines:

1. EBRW-predicted ROC and zROC graphs for study-test paradigms
2. Impact of model parameters on ROC characteristics

Study-Test Paradigm

Study List Test List

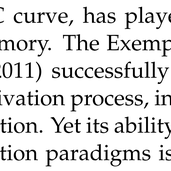
Methods

- Drew inter-item similarities from beta distribution fit to Latent Semantic Analysis (LSA) cos(θ) values (Toronto Word Pool)
- Used EBRW model to predict $p(OLD)$ values for test items in a study-test task
- Varied list length, primacy, recency, and random walk parameters
- Generated ROC via averaging Target $p(OLD)$ values and Lure $p(OLD)$ values at each background noise level (B), across lists.
- Assessed resulting changes in ROC and zROC graphs.

EBRW Main Equations

Similarity (s_{ij}) values are random draws from a Beta distribution; Item strength (m_j) decays with the lag since item presentation:

$$PDF = Beta(\alpha, \beta) \quad (1)$$

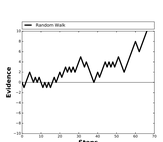


$$m_j = Lag^{-\tau} \quad (2)$$

Summed activation, thresholded by background noise (B), drives a random walk toward either an "OLD" or "NEW" decision threshold:

$$A_i = \sum_{j=1}^{L} m_j s_{ij} \quad (3)$$

$$p_{step} = \frac{A_i}{A_i + B} \quad (4)$$



Results

List Length Effects

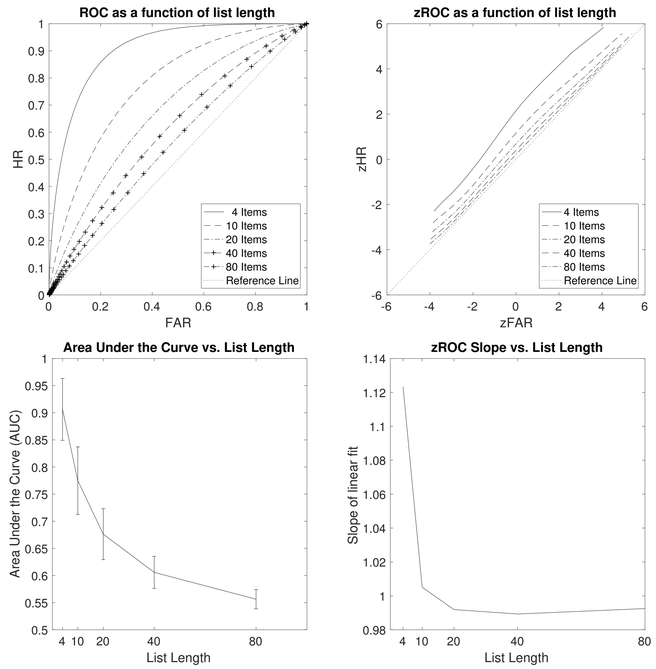


Figure 1: Findings replicate Yotsumoto et al (2008) zROC >1.0 for short lists.

Rate of memory-strength decay

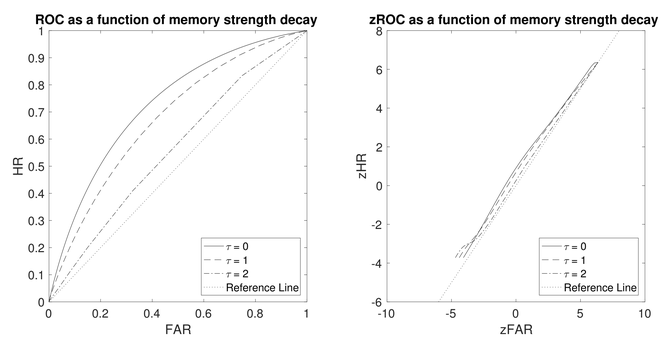


Figure 2: A high rate of memory-strength decay skews the summed activation distributions. List length = 20, $\tau = 0, 1.0, 2.0$.

Results, Continued

Primacy Effects

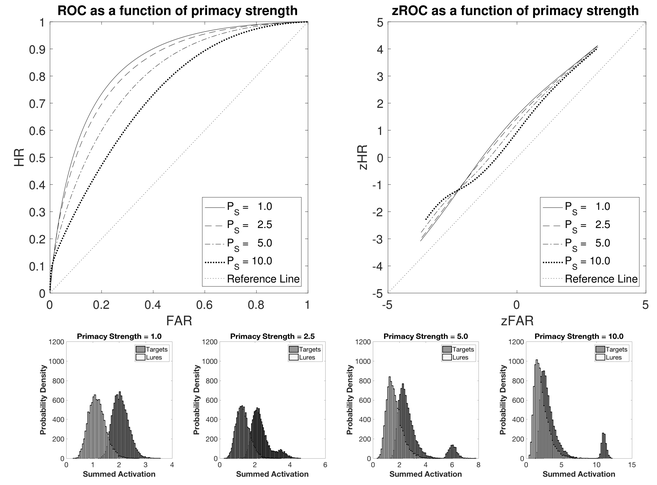


Figure 3: ROC graph becomes asymmetric, and zROC slope decreases, as primacy strength increases ($P_S = 1, 2.5, 5, 10$, List Length = 10). High primacy strength yields bimodal Target and unimodal Lure summed-activation distributions, resembling effects attributed to dual sources of familiarity and recollection (e.g., Yonelinas, 2002). Note that "primacy" is only a single example of a factor that might lead to a large boost in strength for some select items.

Random Walk Thresholds

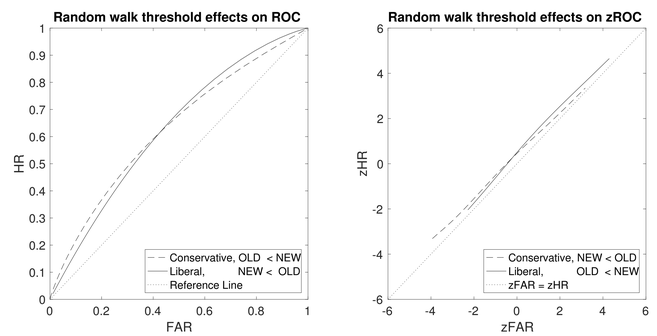


Figure 4: Conservative vs. Liberal responding can be obtained by setting the NEW or OLD threshold, respectively, closer to the beginning of the random walk.

Conclusions

- ROC graphs are bow-shaped, largely symmetrical, and concave-down
- EBRW can account for some effects previously attributed to dual processes