Institute of
Cognitive Science
CARLETON UNIVERSITY
Matthew A. Kelly
Kam Kwok
Robert L. West

Holographic Declarative Memory and the Fan Effect:

A Test Case for a New Memory Module for ACT-R

Presented by Terrence C. Stewart, U. Of Waterloo.

- Holographic Declarative Memory (**HDM**) is a new module for ACT-R, implemented for Python ACT-R (Stewart & West, 2006).

- HDM is an alternative to ACT-R's Declarative Memory (**DM**).

- HDM replaces DM's symbols with *holographic vectors* (Plate, 1995) and implements a holographic theory of memory based on **DSHM** (Rutledge-Taylor, Kelly, West, & Pyke, 2014) and **BEAGLE** (Jones & Mewhort, 2007).

Holographic Declarative Memory

- Holographic vectors retain the expressive power of symbols
  - Compactly store complicated, recursive relations between ideas

- Holographic vectors have a similarity metric, allowing for…
  - Shades of meaning and fuzzy matching
  - Loss compression for modeling forgetting
  - Fault tolerance

- HDM can enhance ACT-R’s ability to:
  - Learn over the long term
  - Store large quantities of data/world knowledge
  - Learn associations

Why use holographic vectors?

- Holographic models of memory in the literature

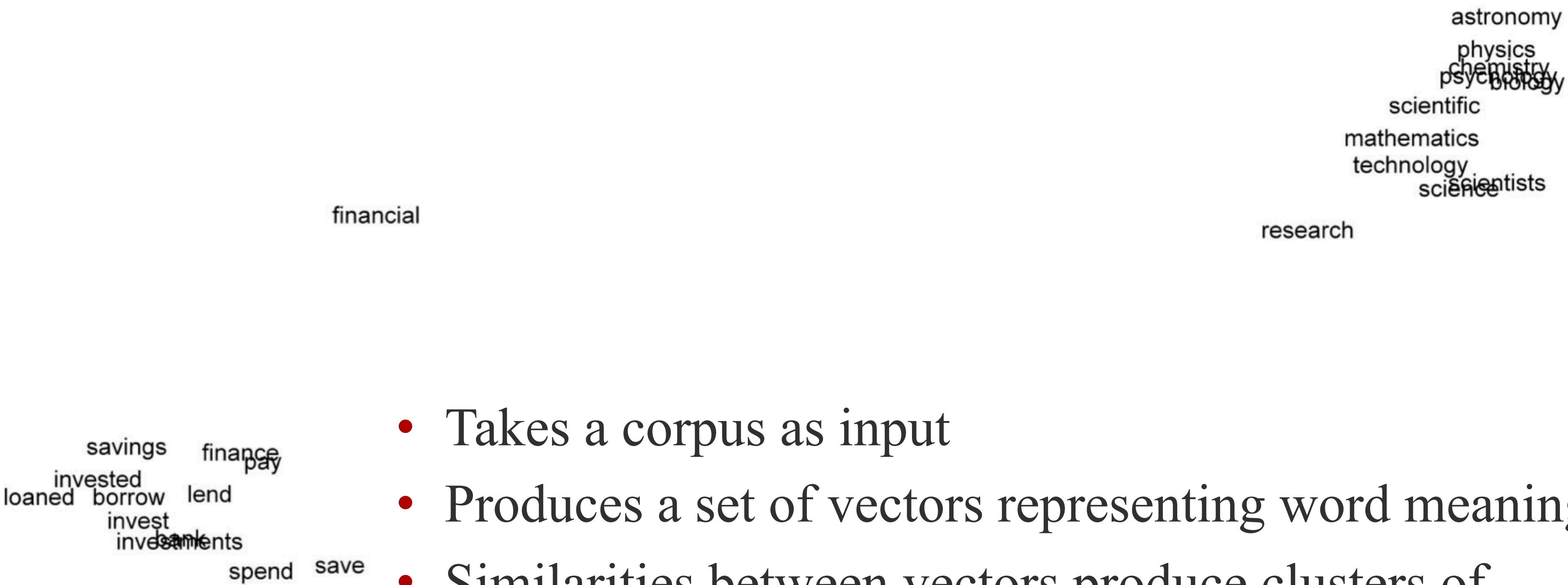
- Case Study: The Fan Effect
  - What is the fan effect?
  - The ACT-R DM model of the fan effect
  - The HDM model of the fan effect

- Results: How does DM and HDM compare?
- Analysis: Why does HDM work?
- Conclusions / future work

In what follows …

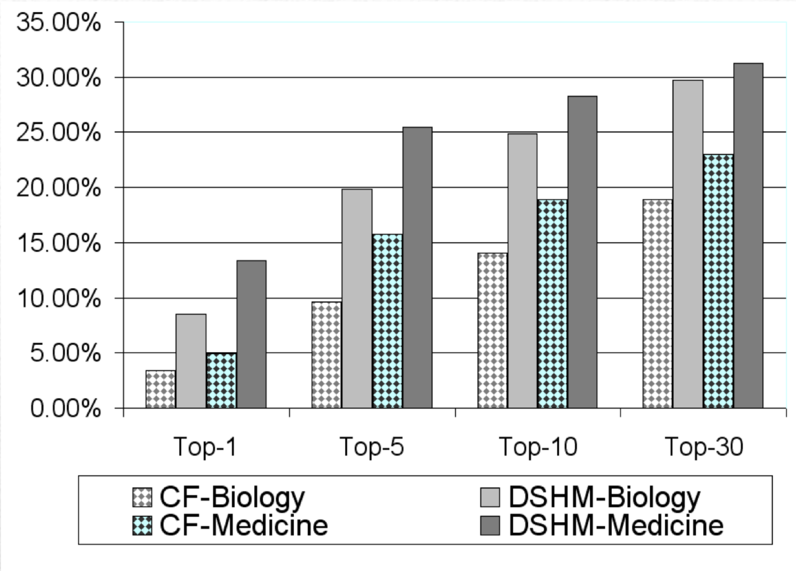
- Explain and predict a variety of human **memory** phenomena
  - **Fan** effect (Rutledge-Taylor et al., 2014)
  - **Serial recall** and **free recall** of lists (Franklin & Mewhort, 2015)
  - **Implicit** learning (Jamieson & Mewhort, 2011)
- **Analogical reasoning**
  - (Plate, 2000; Eliasmith & Thagard, 2001)
- Simple **problem-solving** tasks
  - (Eliasmith, 2013; Rutledge-Taylor et al., 2014)
- **SPAUN**, the world's largest functional **brain model**
  - (Eliasmith, 2013)
- **BEAGLE**, a model of learning **word meaning** from a corpus
  - (Jones & Mewhort, 2007)

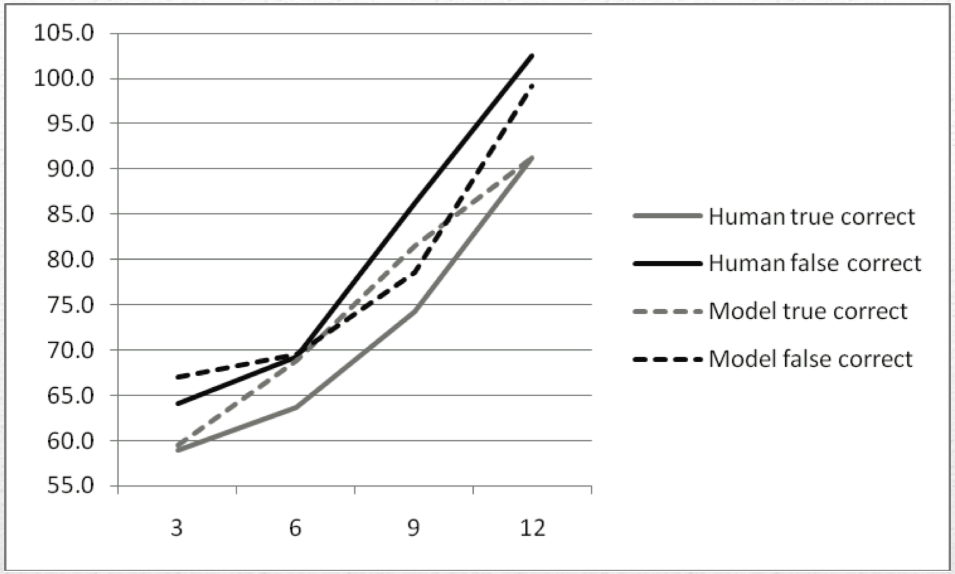
Holographic memory in the literature



- Takes a corpus as input
- Produces a set of vectors representing word meaning
- Similarities between vectors produce clusters of topic and part of speech
- Vector similarities predict semantic priming data

BEAGLE (Jones & Mewhort, 2007)





- Applies BEAGLE to non-lingusitic stimuli
- Models two-term and three-term fan effect
- Models rock-paper-scissors play
- Effective recommender system for movies or research papers

DSHM

Fan Effect

- "the **hippy** is in the **park**"
- "the **hippy** is in the **bank**"
- "the **hippy** is in the **store**"
- "the **officer** is in the **store**"

fan(**hippy**) = 3

fan(**store**) = 2

fan(**officer**) = 1

Fan Effect

- participants are **slower** to recognize or reject sentences that contain concepts that have a **higher** *fan*.
- **availability** of information in memory with respect to a cue is related to the **probability** of that piece of information conditional on the cue.

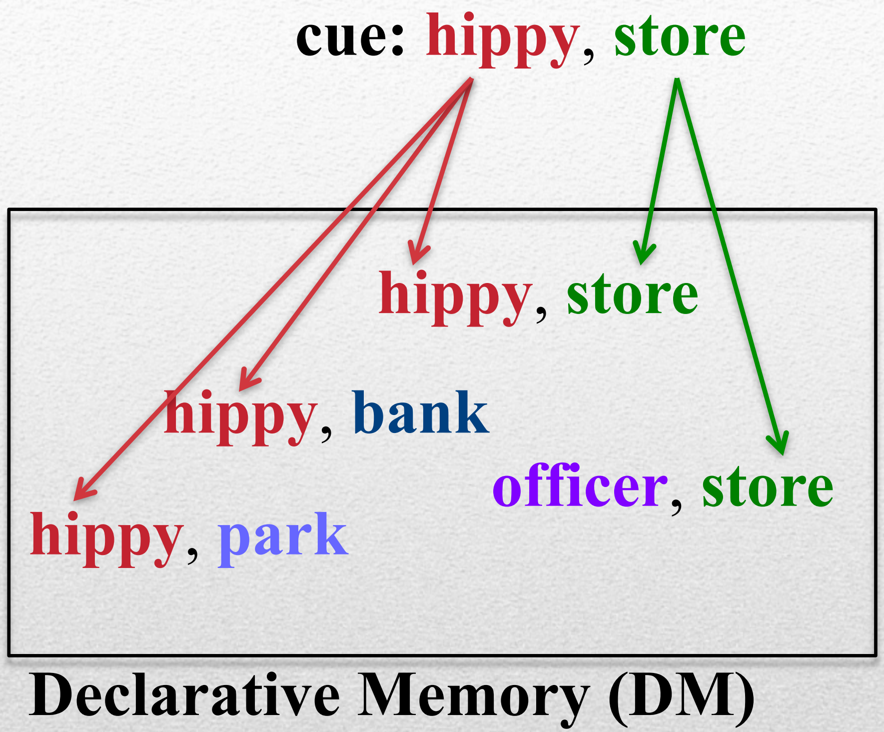
fan(**hippy**) = 3

fan(**store**) = 2

fan(**officer**) = 1

ACT-R DM model

- sentences are represented as *person*, *location* **chunks** in **DM**
- when the model is cued, **activation** spreads to chunks that share concepts with the **cue**
- DM retrieves most active chunk



- Reaction time T is calculated as:

$$T = I + Fe^{-A_i}$$

- Activation A_i of chunk i is calculated as:

$$A_i = B_i + \sum_{j=1}^{n} W_j S_{ji}$$

- Association strength S_{ji} with concept j is:

$$S_{ji} = S + \ln(\, P(i|j) \,)$$

- Where $P(i|j) = 1 / \text{fan of } j$

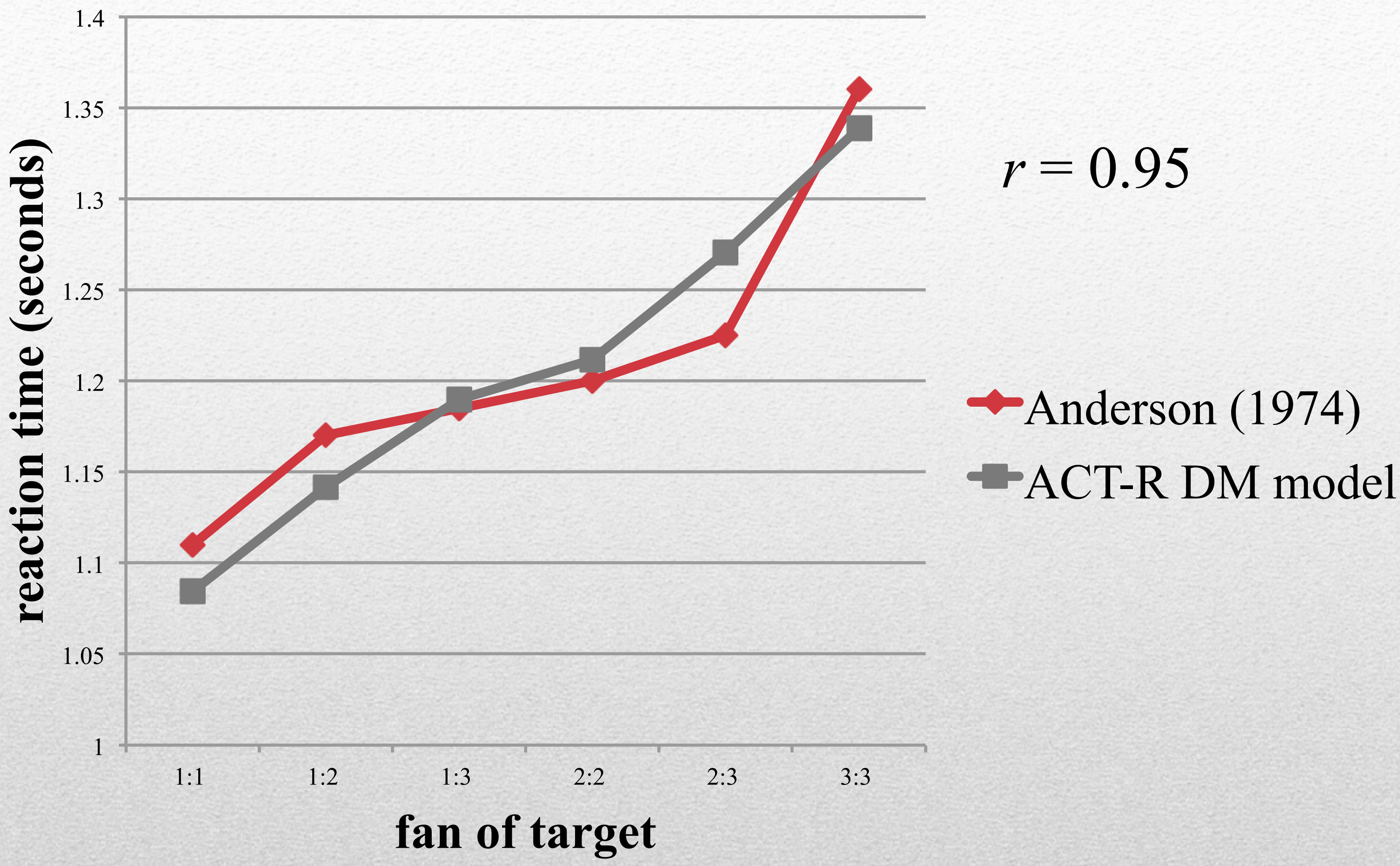
ACT-R DM model

ACT-R DM model

- Anderson and Reder's (1999) model is, in milliseconds:

$$T = 239\, f_{\text{person}}{}^{1/3}\, f_{\text{place}}{}^{1/3} + 845$$

- where f_{person} is the person's fan and f_{place} is the place's fan



ACT-R DM vs. Human

For each task symbol (or concept) there are two vectors:

environmental vector

- a random vector that stands for what the symbol looks like

memory vector

- a continuously updated vector of the symbol's associations

Additionally, there is one special vector used in all associations:

placeholder vector Φ

- can be read as ***?***, i.e., the value that we want to retrieve.
- acts as a stand-in for the purposes of storage and retrieval.

HDM model

* circular convolution is used to create associations between symbols in a sequence.

\+ addition is used to add new associations to a memory vector

$\mathbf{P}_{before}$ is a permutation indicating that the permuted vector comes earlier in a sequence.

Holographic Reduced Representations (Plate, 1995)

"the **hippy** is in the **park**"

$\mathbf{m}_{\text{hippy (updated)}} = \mathbf{m}_{\text{hippy}} + (\mathbf{P}_{\text{before}}\ \mathbf{\Phi})*\mathbf{e}_{\text{park}}$ "what came before park?"

$\mathbf{m}_{\text{park (updated)}} = \mathbf{m}_{\text{park}} + (\mathbf{P}_{\text{before}}\ \mathbf{e}_{\text{hippy}})*\mathbf{\Phi}$ "what came after hippy?"

To **encode** an association in HDM, memory vectors are updated with all **questions** to which the memory vector's **concept** is an appropriate answer given HDM's experiences.

Encoding associations

To test if “the **hippy** is in the **park**” is in memory, two cues are constructed:

$\mathbf{q}_{\text{hippy?}} = (\mathbf{P}_{\text{before}}\ \mathbf{e}_{\text{hippy}})*\mathbf{\Phi}$ “what came after hippy?”

$\mathbf{q}_{\text{?park}} = (\mathbf{P}_{\text{before}}\ \mathbf{\Phi})*\mathbf{e}_{\text{park}}$ “what came before park?”

The memory vectors most **similar** to these cues are retrieved.

Similarity is measured as the **cosine** of the angle between vectors.

Retrieving associations

Activation is calculated as the **mean** of the **cosines** between each cue and the memory vector substituted out to create the cue:

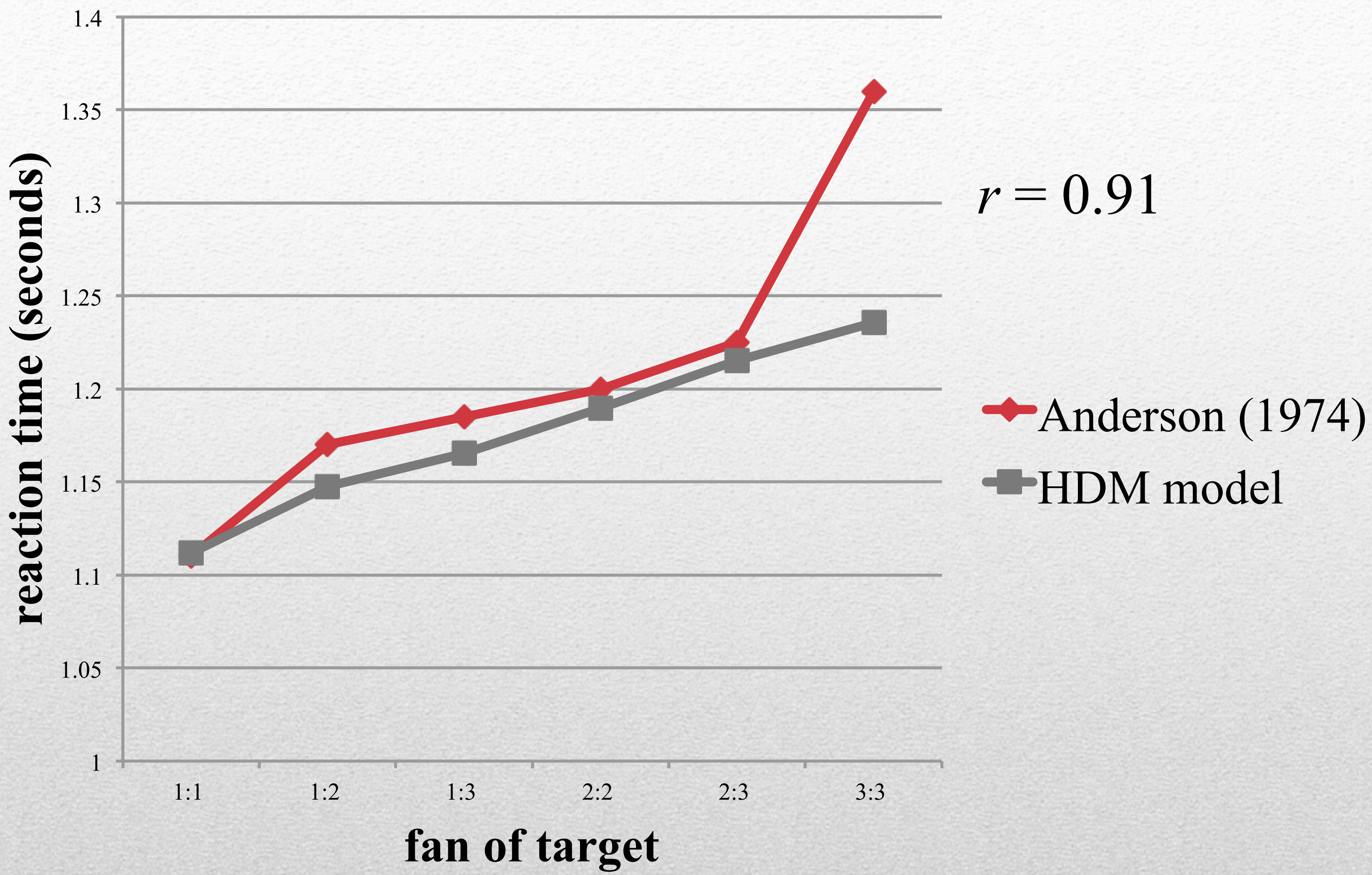
$$A = 0.5\ \mathrm{cosine}(\mathbf{q}_{\mathrm{hippy?}}, \mathbf{m}_{\mathrm{park}}) + 0.5\ \mathrm{cosine}(\mathbf{q}_{\mathrm{?park}}, \mathbf{m}_{\mathrm{hippy}})$$

Reaction **time** computed using **DM**'s reaction time equation:

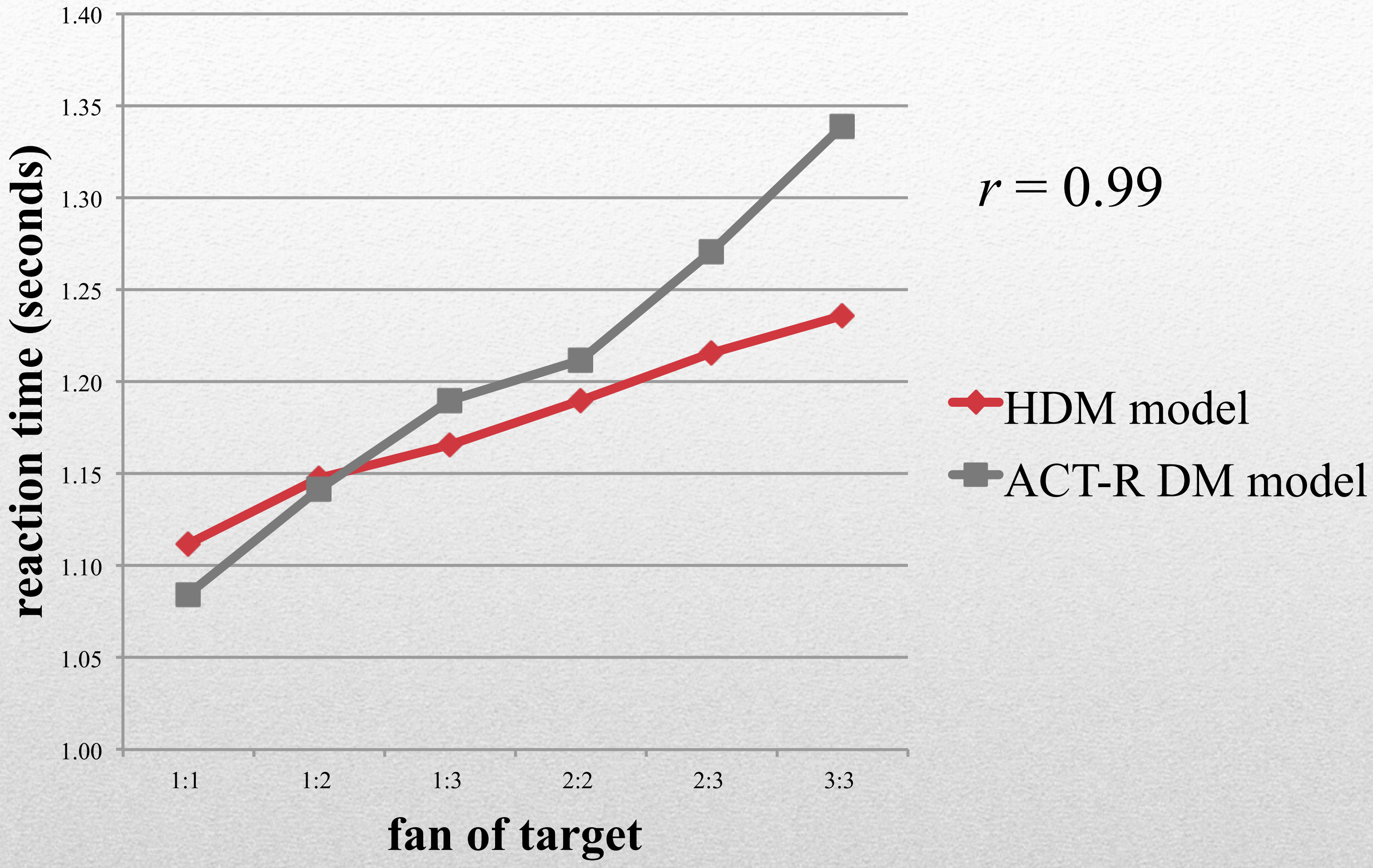
$$T = I + Fe^{-A_i}$$

Parameters *I* and *F* set to the values used by Anderson and Reder's (1999) ACT-R DM model.

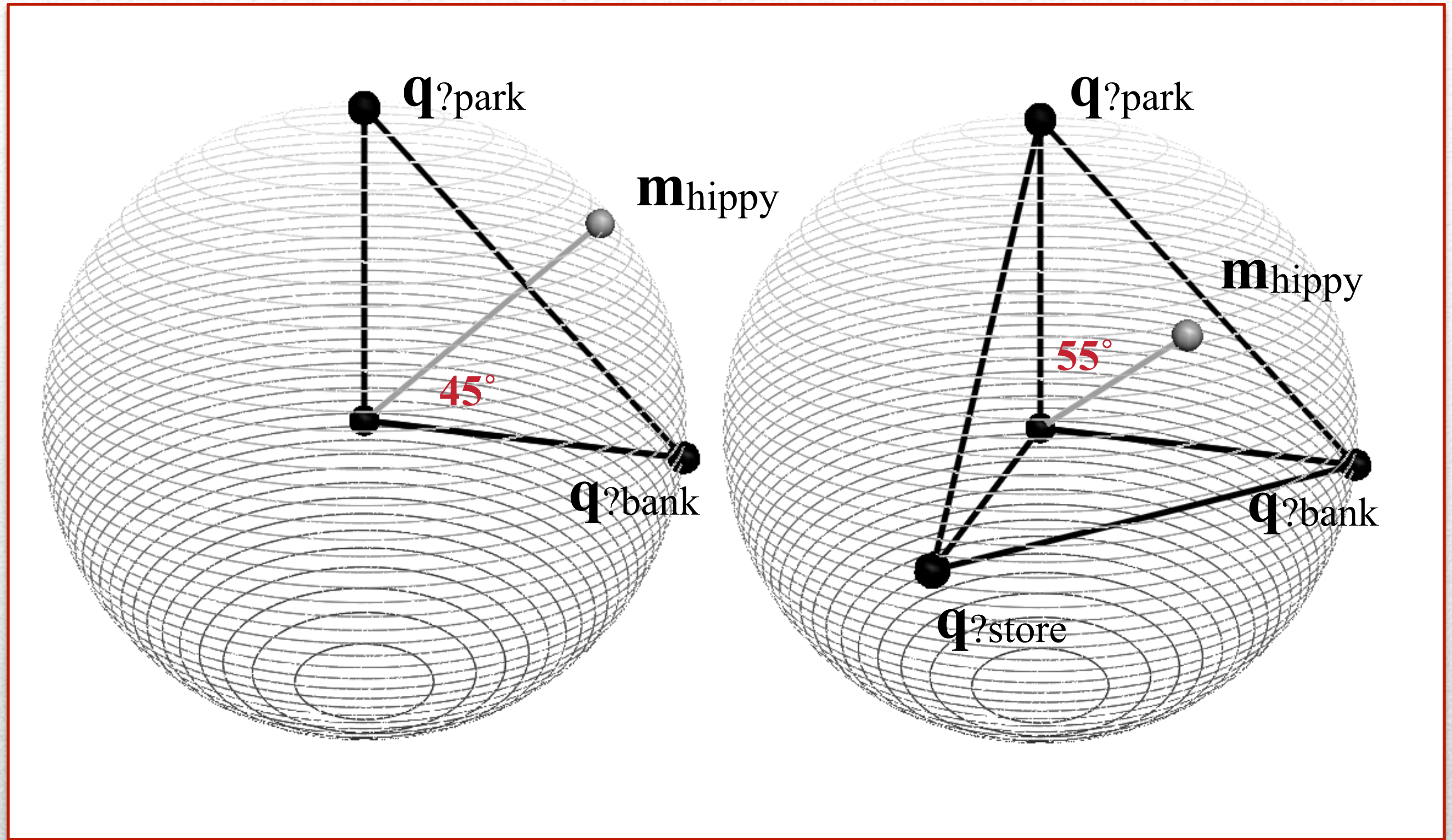
Activation & Reaction Time


1.4
1.35
1.3
1.25
1.2
1.15
1.1
1.05
1
reaction time (seconds)
1:1
1:2
1:3
2:2
2:3
3:3
fan of target
r = 0.91
Anderson (1974)
HDM model

HDM vs. Human



ACT-R DM vs. HDM



Fan in Vector Space

- Where f is the fan, the **cosine** between a **cue** and a **memory** vector is $f^{-1/2}$ if the vectors are perfectly orthogonal, or approximates $f^{-1/2}$ for the random vectors used by HDM.

- The cosine in HDM approximates the square-root of the probability only when the events are **equiprobable**.

- For n events with frequencies v_1 to v_n, cosine of event i is:

$$\text{cosine} = \frac{v_i}{\sqrt{v_1^2 + \ldots + v_i^2 + \ldots v_n^2}}$$

Probability in Vector Space

We substitute **HDM** for **DM** in the ACT-R model of the fan effect and find that *without changing any parameters* HDM provides a good fit to the **fan effect**.

We present an **analysis** that allows us to specify the **mathematical** relationship between the **DM** and **HDM** models of the fan effect, and the relationship between HDM and the **conditional probability**.

Conclusions

HDM, by virtue of being a holographic model, has a number of capabilities for which DM is less suited:

- learning associations between concepts without having association strengths set by the modeler
- analogical or case-based reasoning
- performing tasks that require large amounts of knowledge

Future work

- Anderson, J. R. (1974). Retrieval of propositional information from long-term memory. *Cognitive Psychology, 6,* 451-474.

- Anderson, J. R., & Reder, L. M. (1999). The fan effect: New results and new theories. *Journal of Experimental Psychology: General, 128,* 186-197.

- Eliasmith, C. (2013). *How to build a brain: A neural architecture for biological cognition*. Oxford University Press.

- Eliasmith, C., & Thagard, P. (2001). Integrating structure and meaning: a distributed model of analogical mapping. *Cognitive Science, 25*, 245-286.

- Franklin, D. R. J., & Mewhort, D. J. K. (2015). Memory as a hologram: An analysis of learning and recall. *Canadian Journal of Experimental Psychology, 69*, 115-135.

- Jamieson, R. K., & Mewhort, D. J. K. (2011). Grammaticality is inferred from global similarity: A reply to Kinder (2010). *The Quarterly Journal of Experimental Psychology, 64*, 209-216. doi: 10.1080/17470218.2010.537932

- Jones, M. N., &Mewhort, D. J. K. (2007). Representing word meaning and order information in a composite holographic lexicon. *Psychological Review, 114*, 1-37.

References

- Plate, T. A. (1995). Holographic reduced representations. *IEEE Transactions on Neural Networks, 6*, 623– 641.
- Plate, T. A. (2000). Analogy retrieval and processing with distributed vector representations. *Expert Systems: The International Journal of Knowledge Engineering and Neural Networks, 17*, 29-40. doi: 10.1111/1468-0394.00125
- Rutledge-Taylor, M. F., Pyke, A., West, R. L., & Lang, H. (2010). Modeling a three term fan effect. *Proceedings of the 10th International Conference on Cognitive Modeling*, 211-216.
- Rutledge-Taylor, M. F., Vellino, A., & West, R. L. (2008). A holographic associative memory recommender system, *Proceedings of the Third International Conference on Digital Information Management*, 87-92.
- Rutledge-Taylor, M. F., & West R. L. (2008). Modeling the fan-effect using dynamically structured holographic memory. *Proceedings of the 30th Annual Conference of the Cognitive Science Society*, 385-390.
- Rutledge-Taylor, M. F., Kelly, M. A., West, R. L., & Pyke, A. A. (2014). Dynamically structured holographic memory. *Biologically Inspired Cognitive Architectures, 9*, 9-32.
- Stewart, T. C., & West, R. L. (2006). Deconstructing ACT-R. In *Proceedings of the Seventh International Conference on Cognitive Modeling* (pp. 298-303). Trieste, Italy.

References