Term Project - Milestone 3 (Team 13)

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Georgia Institute of Technology

CS 6795: Introduction to Cognitive Science

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Term Project - Milestone 3 (Team 13)

Literature Review Results

Q1. What were the important findings?

To better understand the relationship between AI and creativity our team is researching how AI systems create analogies - one of many creative activities that humans naturally perform. To the best of our knowledge, embeddings - semantics preserving translations from high dimensional vectors into low dimensional spaces - underpin artificial analogy systems, and thus we would like to understand if the human mind uses a similar mechanism. Below we've outlined our current findings broken down into the following categories:

1. Embeddings Foundations: Our research into how embeddings are created, and used to generate analogies.
2. Neuroscience: Our research into how the mind creates analogies.
3. Translation of Text Generation: How researchers generate text corpora and translate them into vectors and parallelograms.

Embeddings Foundations

Embeddings are lower dimension vector representations of higher dimensional data. An example of a **human generate** embedding is the 3 dimensional RGB representation of a color - where any color can be represented as a vector of three 1 byte integers (0-255). An important property of embeddings is that they preserve the semantics of the object they represent. This is visualized for our RGB example in Figure 1, where the color (255,0,0) is more similar to the color (170,0,0) than it is to the color (0,0,255).

Embeddings don't need to be human generated (like RGB). They can also be learned via Machine Learning approaches, like the word2vec algorithm, by finding tasks that require semantic processing of training data. In word2vec the authors proposed a prediction task where a word in text is used to predict it's n-neighbors and the n-neighbors were used to predict the centered word. After creating this embedding the authors demonstrated how one can translate the task of generating an anology to simple algebra by rewriting the sentence *"Big" is to "Biggest" as "Small" is to "?"* into an equation **? = Vector("Big") - Vector("Biggest") + Vector("Small")**. Thus word2vec offers a possible insight into the process of generating analogies. Mikolov, Chen, et al., 2013 Mikolov, Sutskever, et al., 2013

Neuroscience

Our review of neuroscience literature has uncovered strong evidence supporting the existing of a mechanism that works similar to embeddings as described above. Specifically, it has been shown that semantically similar objects are closer to one another in the brain (Huth et al., 2012) and that indirect relationships between objects share similar abstract geometric patters (Morton et al., 2020). Further more these relationships emerge both when reasoning over abstract ideas and in reasoning over physical human activities (like infering the direction of motion from a photo) (Ziaeefard and Bergevin, 2015).

Translation and Text Generation

P. Finley et al., 2017 states that the Google set and analogy test sets from Microsoft are commonly used text corpora for computing analogies. P. Finley et al., 2017 also finds the Google set problematic because of its "syntactic/semantic division is quite coarse and even questionable in some cases." Rogers et al., 2017 used the BATS dataset instead of the Google set because BATS contains 40 types of linguistic relations compared to the Google set's 15. Both P. Finley et al., 2017 and Rogers et al., 2017 conducted their translation using Word2Vec and GloVe. Rogers et al., 2017 used both 3CosAdd and LRCos for evaluation while P. Finley et al., 2017 used 3CosAdd, 3CosMul, and PairDirection. From a multi-lingual standpoint Moreno et al., 2002 and Kroll, 2008 indicate that switching between two words or languages or juggling multiple languages seems to tax higher congitive load that a single language which may parallel the increase computational and data requirements for creating high performing text embedding tasks, especially those that are machine translation related Zou et al., 2013.

Q2. What is your research plan? How did you conduct the literature review?

As a team, We first aligned on the sub-themes for this literature review identifying broader cognitive analogies and embeddings concepts as well as more specialized ones. We then crowdsourced publications that we would use to inform our review and assigned owners for each one who'd be responsible for reading, initial analysis and eventually full analysis of those publications.

After researching some historical context about word embeddings and how they are generated, the next step was to review more recent publications about word embeddings. Additionally, re-reading the papers cited in the nueroscience section to develop a deeper understanding of significance of proximity in activation patterns was critical because our understanding was incomplete (as might be expected from a CS student who is long removed from his last biology class).

This section of the literature review was conducted by analyzing the results from five research papers investigating the abilities of vector spaces to represent and solve analogies. Before analyzing the results of the papers, some key questions were posed in order to guide the analysis. The questions relate to: the effectiveness of parallelogram models at modeling analogies, the conditions under which vector representations are effective, the main limitation of using vector representations, and the connection to human relational learning. After reading the papers with these questions in mind, the answers given were noted for further discussion with the group. In some cases reading the papers led to more questions or a more nuanced approach to the original questions. For example, P. Finley et al., 2017 states that vector representation are most effective when there are few co-occurrences between words, this raises new questions about relationship between human attention and the vector model's limitations.

Coming together on a bi-weekly basis, we synchronized over video call or asynchronously through discord or overleaf comments ensuring we were sharing knowledge uncovered and aligning on approach. Once we converged on the overall framing of the review, we co-authored the review through the Overleaf collaboration platform.

Q3. What worked and what did not work during the project?

Evy

I feel incredibly fortunate that I am struggling to think of things that are not working in our project. Dan has taken on the "project manager" responsibility and smoothed out all of the issues that *typically* come up during a group project. It's been a pleasure to work with peers who share similar goals and similar interests.

Will

The segmentation of the project by subjects was important to supporting member engagement. Having different segments that are relevant to each of our specific interest encourages members to dive deeper into their portion. Listing our research questions and hypothesizing possible answers was important for my framing while reading the papers. The papers chosen are long, complex, and address many topics not directly relevant to this paper. Framing our questions before reading helped make the research papers more useful for this project.

Dan

The team set a great foundation by aligning early and ensuring we we're on the same page in terms of the research questions, scope and approach. While we did decide to divide-and-conquer this project, we were not siloed in our collaboration often building upon each others ideas.

Q4. What were the lessons learned and key takeaways from your project?

A key takeaway from this project - thus far - is how interconnected seemingly disparate fields are. When Evy initially suggested this research topic, we expected to discover that the mechanisms that underpin human anolgoical reasoning would be completely different from artificial analogies, but that doesn't seem to be the case.

An additional takeaway was to limit the scope of what we want to address because while conducting the literature review there was an abundance of tangential topics that would have been interesting to address but would have been distracting to the paper's focus. For example, Chen et al., 2017 states that the dataset used in their generation of analogical parallelograms led to some geometric contradictions. While I would like to explore this portion of computational analogies it would distract from the focus of this paper which is about the relation to human cognition.

Although there's great many research related to our research area, it is difficult finding a clear, quantitative measure to our questions within this complex field and constrained within the bounds and time limits of a classroom environment: how similar are analogical reasoning and neural network embeddings.

Execution-wise, communication between group members was especially important during this project because we had to segment the tasks amongst ourselves while making sure each member had interesting work that did not overlap. Creating a shared document helped greatly in this regard but asynchronous communication via Discord was also important because of our disjointed schedules.

Q5. Task List

Please see Team 13 Task List; see preview in Figure 2

References

Chen, D., C. Peterson, J., & L. Griffiths, T. (2017). Evaluating vector-space models of analogy. *ArXiv*. https://arxiv.org/pdf/1705.04416.pdf

Huth, A. G., Nishimoto, S., Vu, A. T., & Gallant, J. L. (2012). A continuous semantic space describes the representation of thousands of object and action categories across the human brain. *Neuron*, *76*(6), 1210 1224. https://doi.org/https://doi.org/10.1016/j.neuron.2012.10.014

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Zou, W. Y., Socher, R., Cer, D., & Manning, C. D. (2013). Bilingual word embeddings for phrase-based machine translation. *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, 1393 1398. https://aclanthology.org/D13-1141

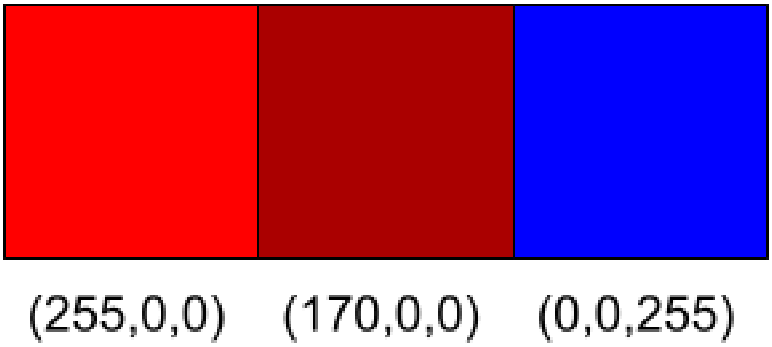

Figure 1

RGB Embedding preserves the visual similarity of colors

[CS 6795] Term Project: Task List

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A1 Term Project: Task List

Deadline	Task	Owner	Status	Notes
Term Project: Task List				
[redacted]				
Milestone 1		[redacted]		
2022-02-05	Setup sync availiabity poll	[redacted]	complete	
2022-02-07	Submit sync availabilty	[redacted]	complete	
2022-02-07	Submit sync availabilty	[redacted]	complete	
2022-02-07	Submit sync availabilty	[redacted]	complete	
2022-02-07	Setup M1 collaboration doc	[redacted]	complete	google doc
2022-02-13	Setup M1 sync meeting	[redacted]	complete	
2022-02-20	Submit M1 (Individual Assignment)	[redacted]	complete	
2022-02-20	Submit M1 (Individual Assignment)	[redacted]	complete	
2022-02-20	Submit M1 (Individual Assignment)	[redacted]	complete	
Milestone 2		[redacted]		
2022-02-28	Setup Overleaf Project Space	[redacted]	complete	overleaf space
2022-02-28	Setup M2.tex	[redacted]	complete	
2022-03-12	Add Proposed Papers for Literature Review	[redacted]	complete	
2022-03-12	Add Proposed Papers for Literature Review	[redacted]	complete	
2022-03-12	Add Proposed Papers for Literature Review	[redacted]	complete	
2022-03-13	M2.tex pre-review	[redacted]	complete	
2022-03-14	M2.tex pre-review	[redacted]	complete	
2022-03-14	Submit M2 (Group Assignment)	[redacted]	complete	
Milestone 3		[redacted]		
2022-03-21	Setup M3.tex	[redacted]	complete	overleaf
2022-03-21	Setup M3 sync meeting	[redacted]	complete	
2022-04-01	Intial Analyis of Publications 1-5	[redacted]	complete	
2022-04-01	Initial Analyis of Publications 6-10	[redacted]	complete	
2022-04-01	Initial Analysis of Publication 11-15	[redacted]	complete	
2022-04-02	Inputs for Q1, Q3, Q4 & Q5	[redacted]	complete	
2022-04-02	Inputs for Q1, Q3, Q4 & Q5	[redacted]	complete	
2022-04-02	Inputs for Q1, Q3, Q4 & Q5	[redacted]	complete	
2022-04-02	Wrap-up Q2 and Q6	[redacted]	complete	self-link
2022-04-03	Submit M3 (Group Assignment)	[redacted]	complete	
Milestone 4		[redacted]		
2022-04-21	Full Analyis of Publications 1-5	[redacted]	proposed	
2022-04-21	Full Analyis of Publications 6-10	[redacted]	proposed	
2022-04-21	Full Analysis of Publication 11-15	[redacted]	proposed	
2022-04-22	Final Sync	[redacted]	proposed	
2022-04-23	Submit M4 (Group Assignment)	[redacted]	proposed	

Figure 2

Team 13 Task List for Term Project