General question of the project:

**Plan A Question:** How does the network's ability to retrieve a word change with different levels of disorder in the input?

High level items to model:

* Inputs
  + The way words are scrambled
* Mechanism
  + A type of network that can lower/recognize

**Is a hierarchical organization more effective at remembering words? When scrambled?**

* 1. <https://arxiv.org/abs/2107.06446>
  2. <https://pubmed.ncbi.nlm.nih.gov/9572585/>
  3. Data that will need to be modeled:

Model that will learn the words and a hierarchical aspect that is added

Hypothesis:

* Which kind of network hierarchies is better at remembering words
* Threshold for remembering: convergence
* Better: speed/steps it took to convergence + accuracy

Something interesting to explore / discuss

* Efficiency per model complexity

**Proposal**:

The goal is to compare hierarchical and non-hierarchical Hopfield network models. The models will use an input of a selected amount of words with the same or varying lengths. Our hypothesis is that a hierarchical model would encourage the learning of more abstract representations which would improve memory capacity and model robustness due to modular re-use of low-level features in the construction of higher-level features. The limitations of the model are that increasing model complexity comes at the costs of speed and storage. The model should be able to act as an attractor, correctly recognizing words and their scrambled counterparts by converging to fixed point interpretations. The model’s performance will be evaluated by comparing the accuracy of convergence between a single-hidden layer and several multi-hidden layer Hopfield networks over varying depth over a set of dictionaries of varying lengths. Once the network has learned this information, we will test its accuracy in recognizing dictionary words scrambled with varying levels of entropy.

**Abstract**

**Point A**

A. What is the phenomena? Here summarize the part of the phenomena which your modeling addresses.

* Modeling auto associative memory in the hippocampus
* Creating a model to recognize scrambled words
* Describe the word recognition and why words don’t need to be in order to be recognized. Maybe dyslexia.

Adriana: Most word recognition models incorporate the sequential order of words for efficient recognition and mostly relies on the visual perception of words. Here we address word’s identity as redundant patterns from letter-level which can be stored in an auto associative memory model.

Ivonne: Our brains are efficient at recognizing patterns from visual, auditory, and linguistic. We are able to read a word whose letters are rearranged and still recognize the true word without blinking an eye such as ‘university’ and ‘unvierstiy’. Previous research papers suggest that words that are used frequently are better at being recalled than words that are used rarely (Bousfield & Cohen, 1955; Hall, 1955; Sumby, 1963). “This effect is hypothesized to be largely due to the higher mean association value of the frequent words” (Deese, 1960).

Andrew: Skilled human readers could achieve visual word recognition despite the letter sequence of the words being scrambled (e.g. in pseudowords). Previous [literature](https://www.cell.com/trends/cognitive-sciences/fulltext/S1364-6613(13)00269-6) suggested an interactive framework where the brain combines lower-level orthographic processing of words with higher-order linguistic representations to achieve visual word recognition.

Gunnar: Human verbal memory is autoassociative, as evidenced by our ability to succeed at pattern completion tasks, learn new words in one- or few-shots, and converge even after rearrangement of letters to a fixed-point interpretation, or memory, of a word.

Cooper: Associative memory is a kind of memory that has been studied in Psychology for a long time. Word recognition is implemented in the brain based on associative memory.

Our brains are efficient at recognizing patterns from visual, auditory, and linguistic stimuli. We address word’s identity as patterns from letter-level which can be stored in an auto associative memory model. We are able to read a word whose letters are rearranged and still recognize the true word without blinking an eye such as ‘university’ and ‘unvierstiy’. Readers could achieve word recognition despite the letter sequence of the words being scrambled (e.g. in pseudowords).

**Point B**

B. What is the key scientific question?: Clearly articulate the question which your modeling tries to answer.

*How noisy vestibular estimates of motion lead to illusory percepts of self motion is currently unknown.*

* Describe how the recognition happens.
* Describe how this is related to word recognition to the Hopfield network.

Gunnar: A natural modeling choice is a classical Hopfield network (HN), although such flat architectures with a single dense synapse have limited memory capacity and for which increasing memory storage causes loss of accuracy.

Adriana: Through the store of redundancies stronger links between the different levels of representation of a word are created, that's why we propose the use of a hierarchical Hopfield network model with a larger memory capacity.

A natural modeling choice is a classical Hopfield network (HN), although such flat architectures have limited memory capacity and for which increasing memory storage causes loss of accuracy.

**Point C**

C. What was our hypothesis?: Explain the key relationships which we relied on to simulate the phenomena.

*We hypothesized that noisy vestibular signals are integrated leading the brain to decide whether self-motion is occurring or not, and that larger noise is linearly associated with more frequent errors in self-motion judgment.*

* We hypothesize that hierarchical hopfield networks will be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden hopfield layers by the highest hidden hopfield layers.

Andrew: However, the hierarchical interactivity of the process are not well understood. We hypothesized that the deeper hierarchies would improve memory capacity and benefit word recognition due to modular re-use of low-level features in the construction of higher-level features.

Gunnar: We hypothesized that hierarchical HNs would be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden HN levels by the highest hidden HN levels. To evaluate what effect hierarchical height has on autoassociative memory capacity, we train our HNs [using the Backpropagation Through Time algorithm] and evaluate their accuracy at remembering dictionaries of progressively greater size using a sparse binary vectorization of the most frequent English words.

Cooper: We hypothesize that there is a linear relationship between the number of configurations a network can store and the number of neurons.

**Point D**

D. How did your modeling work? Give an overview of the model, it’s main components, and how the modeling works. ‘’Here we … ‘’

* Comparing different sized dictionaries and comparing their accuracy with a single layer model and a hierarchical model.
* To evaluate what effect hierarchical depth has on autoassociative memory capacity, we train our hopfield networks and evaluate their accuracy at remembering dictionaries of progressively greater size.
* # The smallest dictionary contains the X most frequent words in English and we add Y more words for each next longest dictionary.
* We constructed two dictionaries of words (normal and scrambled) that are used to train and test the models, respectively.

Andrew: To examine the hypothesis, we modeled the visual word recognition process with a hierarchical Hopfield Network of multiple layers, and tested its word recognition abilities with pseudowords.

Ivonne: To evaluate what effect hierarchical depth has on autoassociative memory capacity, we train our hopfield networks and evaluate their accuracy at remembering dictionaries of progressively greater size.

Gunnar: We observed that the higher hierarchical networks maintained higher accuracy - of pseudowords converging to their attractor point memories - at longer dictionary lengths and in a manner which was more resistant to noise, i.e. letter rearrangement.

Cooper: Calculate the number of configurations(memories) a single-layer or hierarchical Hopfield network can store based on the number of neurons of the system

**Point E**

E. What did you find? Did the modeling work? Explain the key outcomes of your modeling evaluation.

*We observed that higher noise did indeed lead to more frequent errors in self-motion perception but this relationship was not linear.*

* We observed that the deeper hierarchical networks maintained higher accuracy at longer dictionary lengths.

Ivonne: We observed that the deeper hierarchical networks maintained higher accuracy at longer dictionary lengths.

Gunnar: Despite the improved accuracy, we cannot confirm whether the statistical morphological regularities which this network approximates capture human-relevant representations without a means to investigate a lower-dimensional latent space of the model, suggesting that a vertical compression-decompression autoencoding architecture might be a future direction to recreate the generative capacity of humans for word synthesis from morphemes or other meaningful units.

**Point F**

F. What can you conclude? Conclude as much as you can *with reference to the hypothesis*, within the limits of the modeling.

*We conclude that accumulated noisy vestibular information can explain the occurrence of the train illusion, and the higher the noise (or the lower the signal-to-noise ratio), the more frequently such illusions will occur.*

Ivonne: We conclude that a deeper hierarchical network using a dictionary of frequently used words performs higher by *20%* than the network that is trained without the frequently used words.

**Point G**

G. What are the limitations and future directions? What is left to be learned? Briefly argue the plausibility of the approach and/or what you think is essential that may have been left out.

*Future research should investigate whether trial-by-trial variations of noisy vestibular signals actually correlate with self-motion judgments.*

Ivonne: Future research should investigate the type of words used and if there is a correlation between the amount of frequently-used words and the model accuracy percentage.

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# Final Abstract

Our brains are efficient at recognizing patterns from visual, auditory, and linguistic stimuli. We are able to read a word whose letters are rearranged and still recognize the true word without blinking an eye such as ‘university’ and ‘unvierstiy’. Readers could achieve word recognition despite the letter sequence of the words being scrambled (e.g. in pseudowords). Here we address word’s identity as patterns from letter-level which can be stored in an auto associative memory model.We constructed two dictionaries of words (normal and scrambled) that are used to train and test the models, respectively.

A natural modeling choice would be the classical Hopfield network, however its flat architecture causes it to have a limited memory capacity and loss of accuracy.

We hypothesize that hierarchical hopfield networks will be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden hopfield layers by the highest hidden hopfield layers.

To examine the hypothesis, we modeled a hierarchical hopfield network and evaluated their accuracy at remembering dictionaries of progressively greater size using a sparse binary vectorization of the most frequent English words. We observed that the deeper hierarchical networks maintained higher accuracy at longer dictionary lengths and maintained higher accuracy - of pseudowords converging to their attractor point memories.

Despite the improved accuracy, we cannot confirm whether the statistical morphological regularities which this network approximates capture human-relevant representations without a means to investigate a lower-dimensional latent space of the model, suggesting that a vertical compression-decompression autoencoding architecture might be a future direction to recreate the generative capacity of humans for word synthesis from morphemes or other meaningful units. Further investigations could also include the correlation between vocabulary diversity, word frequency, and model accuracy.

**Abstract**

(andrew)

Skilled human readers could achieve visual word recognition despite the letter sequence of the words being scrambled (e.g. in pseudowords). Previous [literature](https://www.cell.com/trends/cognitive-sciences/fulltext/S1364-6613(13)00269-6) suggested an interactive framework where the brain combines lower-level orthographic processing of words with higher-order linguistic representations to achieve visual word recognition. However, the hierarchical interactivity of the process are not well understood. We hypothesized that the deeper hierarchies would improve memory capacity and benefit word recognition due to modular re-use of low-level features in the construction of higher-level features. To examine the hypothesis, we modeled the visual word recognition process with a hierarchical Hopfield Network of multiple layers, and tested its word recognition abilities with pseudowords.

**Ivonne Abstract**

Our brains are efficient at recognizing patterns from visual, auditory, and linguistic. We are able to read a word whose letters are rearranged and still recognize the true word without blinking an eye such as ‘university’ and ‘unvierstiy’. Previous research papers suggest that words that are used frequently are better at being recalled than words that are used rarely (Bousfield & Cohen, 1955; Hall, 1955; Sumby, 1963). “This effect is hypothesized to be largely due to the higher mean association value of the frequent words” (Deese, 1960).

We hypothesize that hierarchical hopfield networks will be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden hopfield layers by the highest hidden hopfield layers.

To evaluate what effect hierarchical depth has on autoassociative memory capacity, we train our hopfield networks and evaluate their accuracy at remembering dictionaries of progressively greater size.

We observed that the deeper hierarchical networks maintained higher accuracy at longer dictionary lengths. We conclude that a deeper hierarchical network using a dictionary of frequently used words performs higher by *20%* than the network that is trained without the frequently used words.

Future research should investigate the type of words used and if there is a correlation between the amount of frequently-used words and the model accuracy percentage.

***Gunnar abstract***

A: Human verbal memory is autoassociative, as evidenced by our ability to succeed at pattern completion tasks, learn new words in one- or few-shots, and converge even after rearrangement of letters to a fixed-point interpretation, or memory, of a word.

B: A natural modeling choice is a classical Hopfield network (HN), although such flat architectures with a single dense synapse have limited memory capacity and for which increasing memory storage causes loss of accuracy.

C: We hypothesized that hierarchical HNs would be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden HN levels by the highest hidden HN levels. To evaluate what effect hierarchical height has on autoassociative memory capacity, we train our HNs [using the Backpropagation Through Time algorithm] and evaluate their accuracy at remembering dictionaries of progressively greater size using a sparse binary vectorization of the most frequent English words.

D:We observed that the higher hierarchical networks maintained higher accuracy - of pseudowords converging to their attractor point memories - at longer dictionary lengths and in a manner which was more resistant to noise, i.e. letter rearrangement.

E-F-G: Despite the improved accuracy, we cannot confirm whether the statistical morphological regularities which this network approximates capture human-relevant representations without a means to investigate a lower-dimensional latent space of the model, suggesting that a vertical compression-decompression autoencoding architecture might be a future direction to recreate the generative capacity of humans for word synthesis from morphemes or other meaningful units.

G: This model relies on the unbiological assumption that vertical connections are bi-directional (top-down and bottom-up processing share the same weight parameters), which however ensures dynamical convergence to a single fixed point attractor and the existence of a global energy function. This model is also trained at the word level only, which…

**Bofang Wang**

1. Associative memory is a kind of memory that has been studied in Psychology for a long time. Recognizing scrambled words is implemented in the brain based on associative memory. b) If and how does the classic and hierarchical Hopfield network implement word recognition based on associative memory? c) We hypothesize that hierarchical Hopfield networks will be better able to reflect the hierarchical structure of language by making use of modular reorganization of English morpheme representations in the lowest hidden Hopfield layers by the highest hidden Hopfield layers. We also hypothesize that there is a linear relationship between the number of configurations a network can store and the number of neurons. d) Calculate the number of configurations(memories) a single-layer or hierarchical Hopfield network can store based on the number of neurons of the system and compare different-sized dictionaries and comparing their accuracy with a single-layer model and a hierarchical model. e) We observed that the deeper hierarchical networks maintained higher accuracy at longer dictionary lengths, and there is an linear relationship between the number of configurations a network can store and the number of neurons. f)

**Abstract Ankey**

Abstract:

A. The phenomena of interest in our modeling effort is the cognitive capability to recognize and interpret scrambled words. This highlights the exceptional efficiency of the human brain in pattern recognition and language processing. We build on this foundation by introducing a novel idea of applying hierarchical modular organization to Hopfield Network Models, thereby simulating the brain's ability to decipher scrambled words.

B. Our primary scientific inquiry revolves around how the hierarchical structuring of Hopfield Network Models influences their proficiency in word recognition. We also aim to probe whether this hierarchical model design can be extrapolated to handle larger vocabularies and more complex linguistic structures.

C. Hypothesizing that hierarchical Hopfield Network Models would be superior in learning abstract representations, we propose that these models will exhibit increased memory capacity and robustness. This stems from the potential for modular re-use of low-level features in higher-level constructs, mirroring the organization of neural networks in the human brain.

F. In conclusion, we establish that the introduction of hierarchical structure to Hopfield Network Models significantly enhances word recognition capabilities. This suggests a promising avenue for improving memory capacity and model robustness by emulating the hierarchical organization of neural networks in human cognition.

G. Recognizing the computational challenge of increased model complexity, future research should strive for an optimized trade-off between computational resources and model sophistication. Further investigations could also include the correlation between vocabulary diversity, word frequency, and model accuracy. The integration of such complex and diverse linguistic elements is plausible in enhancing the practicality and applicability of machine learning algorithms in language processing tasks.

List of biological related questions:

1. When reading a pseudoword does your brain/model use the same pathways? Does it overlap with similar words?
   1. Data that will need to be modeled:
      1. Model needs to be tractable
2. Could this model be similar to how children acquire word recognition since fluid intelligence relies on working memory at early stages of life?
   1. Is there a parallel between the brain's process of synaptic pruning and the way artificial neural networks are trained?
   2. From which complexity/amount of neurons can we affirm that the model is starting to store memories?
3. **Is a hierarchical organization more effective at remembering words? When scrambled?**
   1. <https://arxiv.org/abs/2107.06446>
   2. Data that will need to be modeled:
      1. Model that will learn the words and a hierarchical aspect that is added
4. Can the model include both inhibitory and excitatory neurons to increase the memory capacity of the model?

**Plan B Question**: Does/Can the brain/network start off fully-connected, then undergoing synaptic pruning? Is that an effective initialization method for training a Hopfield network?

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