Association of Neural Assemblies

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Contents

1 Introduction

One of the fundamental, unique problems in neuroscience and cognitive sciences is understanding how the brain forms the mind. Specifically, how can the physical structure and architectural components of the brain give rise to the abstract, mental concepts of the brain, such as memory, experience, and consciousness itself. One proposed framework is the theory of Neural Assemblies. Neural Assemblies, as described in the paper, Brain Computation by Assemblies of Neurons [3], are large clusters of excitatory neurons which lie in specific, strictly-separated brain areas with strong synaptic connections with each other. These Assemblies can be operated upon to produce new Assemblies and other outcomes through a theoretical framework called Assembly Calculus. This framework helps to provide a potential solution to how assemblies can produce cognitive phenomena such as memories, experiences, and language. One particular operation of Assembly Calculus is Association. Association is related to the experimentally proven principle that human brains tend to associate concurrent events with each other. For example, neurons that fire when a visual stimuli of a particular familiar place is present, start to also fire once presented with an image of a familiar person, once a combined stimuli has been shown of this person in that place. Association explains this; it enables neurons that imprint different entities to augment their overlap, whenever the concurrence of these entities is observed. This process occurs with the migration of neurons from one assembly to another. Association seeks to explain the overlap between different assemblies and the connections contained between them. This paper discusses our team's research and simulations of the Association operation on Neural Assembly Calculus.

2 Neural Assemblies and Association

Association and the framework of operations that can act upon assemblies - Assembly Calculus - is written about in the paper, Brain Computation by Assemblies of Neurons. In this paper, Papadimitriou et al. [3] formalize Assembly Calculus as a 'logic' of the brain. This 'logic' is described as an abstract framework or 'language' which arises from the biological architecture of the brain.

The fundamental framework of Assembly Calculus is formalized as the following. Firstly, Assembly Calculus starts off with Neural Assemblies. Assemblies are generally described as clusters of excitatory neurons in certain areas of the brain. In the paper [1], they suggest that each brain area (and subsequently brain) contains a fixed number of excitatory neurons, which is used to potentially form an assembly in that area. Secondly, Assembly Calculus uses plasticity to form and strengthen synaptic connections between pairs of excitatory neurons. Specifically, when a presynaptic neuron fires at a time-step t and the postsynaptic neuron fires at a later timestep $t+1$, their synapse gets strengthened. In the paper [3], they model plasticity using Hebbian plasticity to strengthen the synaptic connection each time a neuron fires. To specify, when a presynaptic neuron fires at a timestep t and the postsynaptic neuron fires at a later timestep $t + 1$, their synapse acts as a weight and gets strengthened by a factor of $(1 + \beta)$, where β is the plasticity coefficient. This process occurs repeatedly and over time. Lastly, Assembly Calculus models inhibition and excitatory-inhibitory balance by suggesting that at any timestep, a fixed number k of the n excitatory neurons, the excitatory neurons that have received the k highest excitatory inputs, would fire. This serves as the fundamental basis for Assembly

Calculus, which uses a variety of operations on these Neural Assemblies and connections to combine and produce a multitude of assemblies and outputs.

However, important questions remain as to the purpose or reasons behind how strengthening connections between Assemblies firing could result in certain outcomes and reasons. Specifically, why in particular would neurons and neural assemblies strengthen the connections between each other? What particular methods of computation does the brain have to create different outputs from strengthening the synaptic connections.

These particular questions lead to Assembly Calculus and how it plays a role in using Neural Assemblies: to manipulate a form of memory and remembrance caused by sensory stimuli. Neural Assemblies have the capacity to hold memory of individuals or objects obtained from sensory input, and allow connections or associations to be drawn with the memory of these individuals and objects. To explain further, one particular case was the experimental discovery of the 'Jennifer Aniston' Neuron. In Quiroga's et al. experiment in 2014, [4], researchers initially showed a picture of Jennifer Aniston to a subject, and after repeatedly showing a picture of Jennifer Aniston to that same subject, they noticed how a specific neuron or neuron cluster would fire. When Jennifer Aniston was not shown to the user, this specific neuron or neuron cluster would not be active. Even when Jennifer Aniston was combined or a part of a picture with many different images and objects, the specific neuron or neuron cluster would fire after the subject receives sensory input of the image of Jennifer Aniston. The outcome of this experimental results were astronomical. It showed that a specific neuron or neuron clusters can have a memory of individuals and objects after obtaining sensory stimuli of that individual or object. Once presented with sensory information of that specific individual or object, the neuron or neuron cluster will fire, potentially strengthening any connections between neuron and neuron clusters. In a way, the neuron remembers an individual or object given the sensory information of that individual and object. The Neuron will break down the object and individual into discrete, basic parts, remembering the general characteristics and attributes of the object and individual, such as color, structural figure, and the identification of that object [1]. The Neuron even remembers the individual or object when that individual or object is in a picture containing other individuals and objects. This allows the brain to form associations between that individual or object with the other individuals and objects.

Assemblies and Assembly Calculus provide a framework, rooted from biological discovery, that could potentially provide an answer to the question of how the brain can obtain memory of individuals and objects, and how the brain draws connections between these individuals and objects. As Neurons and Neural Assemblies can remember the general characteristics and attributes of an individual or object, the synaptic connections and the strengthening of these connections allow the brain to draw connections between different 'vessels' of memory. In a sense, when the brain sees an individual or object with other individuals or objects, or when the brain sees an individual or object perform a specific function, it draws a connection or association between the individual and object. The brain can do this with Neural Assemblies. When a neuron or assembly fires to another neuron or neural assembly, the synaptic connection strengthens until convergence. This means that anytime the previous neuron fires, the other neuron or neural assembly will also fire, forming an association of the memories between each other. In essence, the brain creates a representation of the correlating connection between an individual or object with other individuals and objects with neural assemblies. How can the brain produce different connections? Through Assembly Calculus. The use of operations under Assembly Calculus allows for the manipulation and transformation of memory and assemblies such that it can form different connections between assemblies to produce a certain output assembly. One of these primary operations of Assembly Calculus is Association.

Association is an operation related to the experimentally proven principle that human brains tend to associate concurrent events. Specifically, the brain tries to draw connections between the occurrence of certain objects or individuals with other objects and individuals, helping to create correlations that could provide meaning in the essence of learning. For example, neuron clusters that fire when a visual stimuli of a particular familiar place is present, start to also fire once presented with an image of that person or an image containing a person, once a combined stimuli has been shown of this person in that place. This allows the brain to 'learn' from memory and visual stimuli, helping to draw further connections when the neuron clusters fire if one of the visual stimuli is present in another event.

Association, at least the operation modeled for the Assembly Calculus, is described as the following [3]. Firstly, brain areas with a certain amount of excitatory neurons (which in the paper is denoted by n) are shown to be the basis for possible assemblies located in that area. Essentially, these areas must have the possibility of producing assemblies, and a constant of the amount of excitatory neurons is kept to provide a generalization of the model for the brain. Secondly, two parent assemblies exist, each in their own brain area containing a certain amount of excitatory neurons. Thirdly, each parent assembly fires their neuron, or projects, to a different area in the brain to form a new assembly. When a parent assembly projects, then the creation of the new assembly forms as a "copy" of the parent in another area in the sense that it responds to the same stimuli as the parent assembly. The memory contained in the parent assembly, such as the general characteristics and attributes of an individual or object, is now copied over to the new assembly y. Projection is important; anytime the parent assembly fires, then the projected assembly i.e. y will also fire. Lastly, is the primary process of association. Suppose there exists two parents in two different areas. Each parent assembly projects into two different areas to form two new assemblies, which are essentially copies of the parent assembly. Suppose these two assemblies independently project to a common area to form two different assemblies, which we denote as x and y, and the parent assemblies fire simultaneously. For clarification, the common area will contain two assemblies, which were created from the projection of the copies of the parent assemblies. As the parent assemblies now fire simultaneously, the assemblies in this common area, i.e. x and y, will have each of their neurons migrate to the other assembly in the common area, creating an overlap between these assemblies. With simultaneous sustained firing of the two parent assemblies, the overlap between these assemblies x and y will converge. Thus, a common correlation between these two assemblies forms. Whenever one of x or y fires, then the other one will have its neurons fire in the boundary shape similar to where the overlap occurred. Similarly, if the two parent assemblies fire, then the copy of the parent assemblies will fire, and then the overlap of x and y. This completes Association.

3 Project

We examined two different test cases which translated into two different set of experiments. The first scenario can be translated as follows. In separate brain areas, information about a particular individual or object are stored in the form of assemblies of neurons. This information can include characteristics and qualities of the individual or object - which we call the attributes - and one identifier - such as the name of the individual or object. The different attributes can be thought of as the descriptive characteristics of the individual or object, and therefore, are expected to be associated with the identifier. For clarification on our simulation experiment, the attributes are characteristics that do not need to be remembered, since they come from sensory inputs. This means that attributes can be recognized through vision, hearing, smell, and other sensory inputs. The identifier, on the hand, refers to an attribute that for the purposes of our experiments cannot stimulate the senses, such as a name. This means that when one sees a specific individual or object, the attributes except the identifier can be recognized through the senses, but the identifier must be remembered. We proceeded in examining whether the stimulation of the remaining assemblies which contain the attributes information could lead to the remembrance of the identifier.

To test this scenario, our team devised the following experiment. Firstly, our team created neural assemblies in different areas for each individual attribute and identifier. In the original implementation of association, the creation of two assemblies signifies the existence of one attribute and one identifier. In our implementation [2], the number of these assemblies (attributes and identifier) is set parametrically and referred to as **number_of_assemblies**. In our implementation, we set **number_of_assemblies** to 2, 3, 4, 5, 6, 7 and 8 assemblies, with each **number_of_assemblies** containing **number_of_assemblies** - 1 attributes and one identifier.

Next, our team projected all the assemblies into one area, which we refer to as the memory area. All assemblies that are projected into the memory area have been stabilized prior to making any further changes in the brain by causing neurons to fire. Once this is completed, we associate each assembly with an identifier in that 'brain' area. Essentially, a connection is drawn between each attribute assembly and the identifier assembly, which is located in the memory area upon projection. Then our team observed how the assemblies in the memory area are shaped at t timesteps after the association of each attribute-identifier pair is completed. Waiting for t timesteps before causing any further firings - and hence changes in the synaptic weights - allows us to observe how the system will evolve till convergence. We call this time parameter **timesteps_after_association** and its values can be 0, 1, 3 or 5. At t **timesteps_after_association** each attribute assembly and the identifier assembly share some neurons. We call the percentage of neurons of the identifier assembly which are shared with another assembly after the association as **pairwise_association_overlap**. We keep track of **pairwise_association_overlap** as it averages over all assemblies. We also keep track of the **total_association_overlap** which denotes the percentage of the identifier's assembly neurons that is shared between all the assemblies. Lastly, our team tested the system's ability to retrieve the information for the identifier without stimulating the particular assembly in the following way. We stimulate simultaneously at t=timesteps_after_association some of the attributes assemblies in their initial brain areas. This number is kept as parameter, ranging from 1 to number_of_assemblies-1 and is named **assemblies_firing**. We then observe how many of the identifier's neurons are stimulated in memory area and we record their percentage to the total number of neurons of that identifier assembly. It is important to point out that this number changes in consecutive timesteps after the stimulation of the attributes assemblies. Therefore, we log the discussed neuron overlap three times. Firstly, right after the stimulation of the assemblies_firing and store it as **overlap_after_1_firing**. Secondly, after the system has stabilized/converged and store it as **overlap_upon_convergence**. The condition that is set to define convergence is that the neurons firing in time t should be the same as the neurons firing at time $t-1$. In the case that it does not happen within 10 timesteps, we keep the overlap of the 10th timestep. Finally, we also keep track of the maximum overlap achieved between the times of stimulation and convergence and we name it **max_overlap**. We also keep the number of timesteps if takes for the system to converge in **timesteps_until_convergence**.

Parameter	Values	Outputs
number_of_assemblies	2,3,4,5,6,7,8	pairwise_association_overlap
beta (plasticity)	0.4,0.3,0.25,0.2,0.15,0.1,0.075,0.05,0.03	total_association_overlap
assemblies_firing	[1,...,number_of_assemblies-1]	overlap_after_1_firing
timesteps_after_association	0,1,3,5	max_overlap
		overlap_upon_convergence
		timesteps_until_convergence

Table 1: Parameters and Metrics for 1st set of experiments

In the second scenario, we followed a slightly different approach [2]. In this case, we assume that the attributes are all intrinsic characteristics of the individual that are not identifiable through senses. For example, those may include a name, a profession, an address etc. What changes in this case is that all the attributes including the identifier are associated together simultaneously instead of performing pairwise associations between the identifier and every other characteristic. We believe this is feasible for a small number of characteristics, however, it would not be feasible for a large number.

As far as the parameters are concerned, we discarded the timesteps_after_association parameter. Since all the assemblies are associated simultaneously, the system was found to be stable right after the association finished, that is at 0 timesteps_after_association. At the same time, we introduced another parameter, **association_overlap_threshold**, that ensures that the percentage of the identifier's assembly neurons that is shared between all the assemblies (total_association_overlap) upon the association will be above the respective threshold. This is necessary to ensure that all the assemblies with be sufficiently associated and allows us to attribute the results to the association of the assemblies. The values of the association_overlap_threshold are 0.10, 0.15, and 0.20. We use this values as i) very large threshold values would cause almost perfect overlap which we do not consider feasible from a physical perspective, and ii) if we get a high final overlap with lower **association_overlap_threshold** then we will not get a worse final overlap with higher **total_association_overlap** for the same parameter configuration (over large number of experiments).

We track the number of timesteps it takes for total_association_overlap to surpass the given threshold in **timesteps_until_assoc_threshold**.

Parameter	Values	Outputs
number_of_assemblies	2,3,4,5,6,7,8	timesteps_until_assoc_threshold
beta (plasticity)	0.4,0.3,0.25,0.2,0.15,0.1,0.075,0.05,0.03	total_association_overlap
assemblies_firing	[1,...,number_of_assemblies-1]	overlap_after_1_firing
association_overlap_threshold	[0.10,0.15,0.20]	max_overlap
		overlap_upon_convergence
		timesteps_until_convergence

Table 2: Parameters and Metrics for 2nd set of experiments

4 Complications

The biggest issue that we faced during the execution of the previous scenarios was the running time of each experiment. Since modeling the brain involves taking into account its innate randomness, the results of our experiments are not deterministic. Therefore, in order to validate our results, we had to repeat the experiments multiple times. Particular when the plasticity of the neurons was set to a small value, the running time of the experiments was enormously large. This was the result of having multiple neurons with similar synaptic weights competing for stimulation whenever a stimulus (e.g., firing of an assembly) was present.

To speed up computations, we slightly modified our experiments. One thing to note is that no matter what the value of assemblies_firing is, the computations performed before the final firing of the attributes are exactly the same. Thus, instead of performing one experiment from scratch per number_of_assemblies, betas, assemblies_firing, and timesteps_after_association, we decided to run the code once for every number_of_assemblies, betas, and timesteps_after_association combination, keep copies of the brain's structure after the performance of the association (either pairwise or simultaneous), and then for each possible value of assemblies_firing, fire the respective number of assemblies in a different copy of the brain each time, and record the results for the respective value of assemblies_firing. For that reason, in all the records for the different number of assemblies firing in each experiment (assemblies_firing records), we have the same pairwise and total association overlap. In theory, the two versions of running the experiments should lead to the same aggregate results, if a sufficient number of experiments are run. We test the validity of this assumption in the Results section.

5 Results

5.1 Pairwise Association

In this section, we will discuss the results of the first set of experiments, where we associated pairwise each attribute-assembly with the identifier-assembly in the memory area.

5.1.1 number_of_assemblies = 4

We will first discuss the experiments that concern the case where 3 attributes are present along with one identifier (number_of_assemblies=4).

Overlap with assembly of interest upon convergence - general case

In Figures 1 and 2, we can see the final overlap - upon convergence - of the neurons of the memory area that are stimulated after the attributes fire, with the neurons of the memory area that belong to the identifier assembly. The attributes fire 3 timesteps after the association has been completed (timesteps_after_association=3). The three different lines correspond to different numbers of attributes firing. Moreover, the vertical lines show the average pairwise overlap, after the association of all pairs of assemblies has taken place, of the identifier assembly with each attribute assembly in the memory area. We performed this experiment using both versions of the code described in section 4 to verify the similarity of the results and then proceeded to using only the speed up version of our implementation.

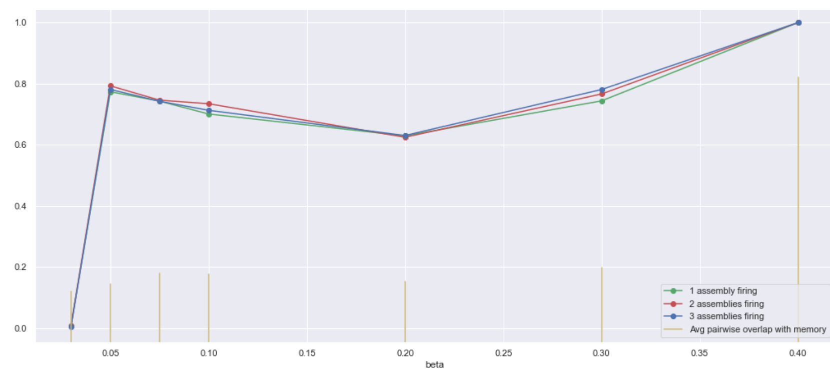

Figure 1: Final overlap with assembly of interest. Attribute assemblies fire at time step t=3 after association.

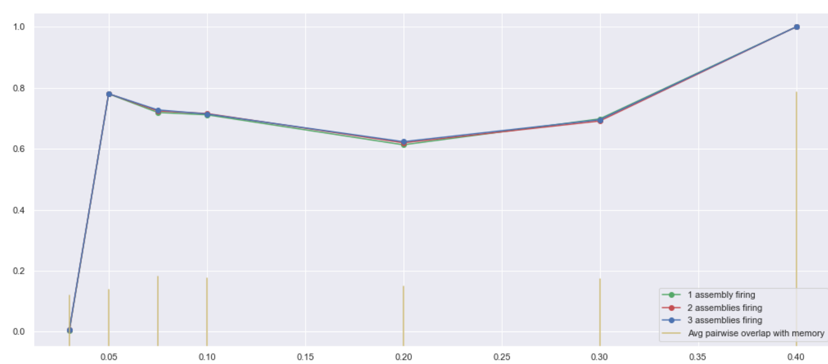

Figure 2: Final overlap with assembly of interest. Attribute assemblies fire at time step t=3 after association. Using brain copies.

We observe that the two experiments yield similar results as we initially expected. For the "quicker" experiments (Figure 2), the overlaps for different numbers of firing areas are almost identical. For the non-accelerated experiments, we observe a very small variation of the overlaps for different numbers of firing areas at some betas, which do not constitute a sufficient evidence to believe that the experiments are not equivalent. The final overlap is very low for betas near 0.03 and steeply increases when beta is increased to 0.05. Surprisingly, the final overlap is not monotonic on beta, but slightly decreases after beta=0.05 before increasing again for beta greater than 0.2. We cannot explain this fluctuation intuitively, although it might be a result of a not sufficient number of experiments. In almost all our experiments when the plasticity was near 0.4 the final total overlap converged to 1.

Maximum overlap with assembly of interest vs overlap upon convergence

In Figure 3, we can see the overlap of the neurons of the memory area that are stimulated after just one attribute fires, with the neurons of the memory area that belong to the identifier, in the following timesteps: 1) right after the attribute fires, and 2) upon convergence of the system. We can also see the maximum achieved overlap. The attribute fires immediately after the association has been completed (timesteps_after_association=0).

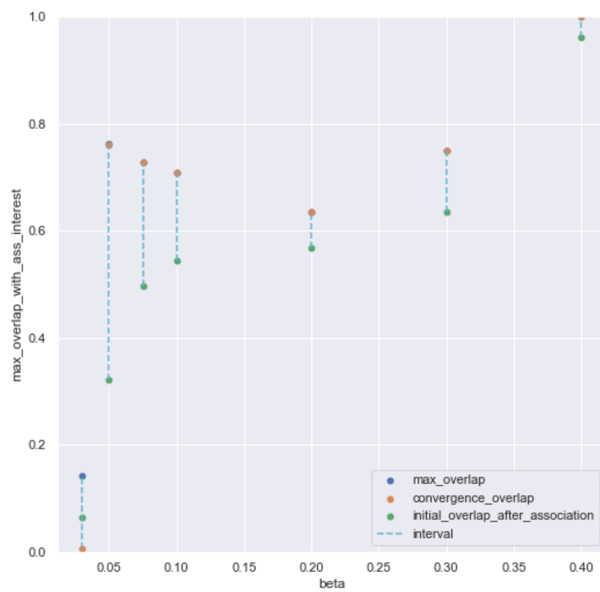

Figure 3: Overlaps achieved between the firing of attributes and convergence. 1 assembly is firing right after the association takes place (timesteps_after_association=0).

For betas greater or equal to 0.05, we observed that the overlap of memory area's most excited neurons with the identifier assembly grew from the moment the attributes start to fire and until convergence. For very small plasticity, the neurons of the memory area that get stimulated after the attribute assemblies fire and, until the system converges seem to be chosen more at random. We can see that the discussed overlap starts from an initial value, increases throughout the timesteps of this time interval, and decreases to zero upon convergence. Another interesting observation is that for the rest of betas and excluding beta=0.2, the range of the values that the overlap takes until it finally converges seems to decrease with the increase of beta and also with the increase of the initial overlap after 1 firing.

Number of timesteps till convergence

Figure 4 shows the distribution of the timesteps needed for the system to converge after the firing of assemblies. This graphs includes data from all the experiments we ran for number_of_assemblies=4, that is assemblies_firing=[1,2,3] and timesteps_after_association=[0,1,3,5].

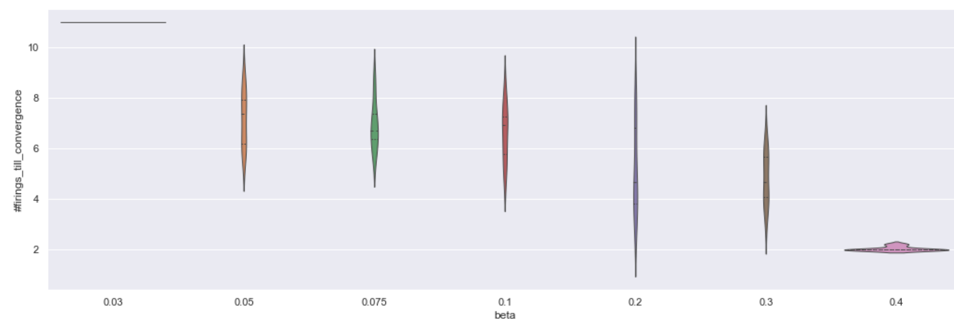

Figure 4: Distribution of timesteps needed until the system converges, for different beta.

For beta equal to 0.03, we do not achieve convergence before the maximum iterations of the relevant loop (10) are exceeded and therefore, we always fire for the maximum number of timesteps. As beta increases, the average value of iterations needed decreases. For beta=0.04 we only need two firings to converge and the relevant variance in all our experiments is very low. We observe that particularly for beta=0.2 the range of values that the number of firings until convergence has, is the largest amongst all. This observation is related to beta=0.2 achieving a relatively small final overlap value in 2.

Randomly stimulate memory area right after association

In the experiments ran so far, the firing of the attributes happened 0, 1, 3, or 5 timesteps after the association had been completed. During those timesteps, the memory area continued to project to itself, allowing the system to keep evolving towards convergence. With the way the experiments were implemented, the neurons that stimulated this projection were the neurons of the memory area that were the most excited after the association. Another idea would be to use random neurons to stimulate the projection of the memory area to itself, as this behavior simulates the random firings that can happen in the memory area after the association and between the firing of the attributes. A potential question pertaining to this would be how the final overlap of the neurons of the memory area that are stimulated after some attributes fire with the neurons of the memory area that belong to the identifier would change.

Figure 5, is similar to Figure 2. We observe that there is no significant change to the final overlap compared to Figure 2, where the neurons that stimulated the projection weren't random. However, we fired the random assembly just once. Firing it more times could have a larger impact on the final overlap. That needs to be explored by running more experiments with multiple numbers of firing the random assembly.

Keep projecting the assembly of interest to the memory area after the association

After the pairwise association of each attribute-assembly with the identifier-assembly has taken place

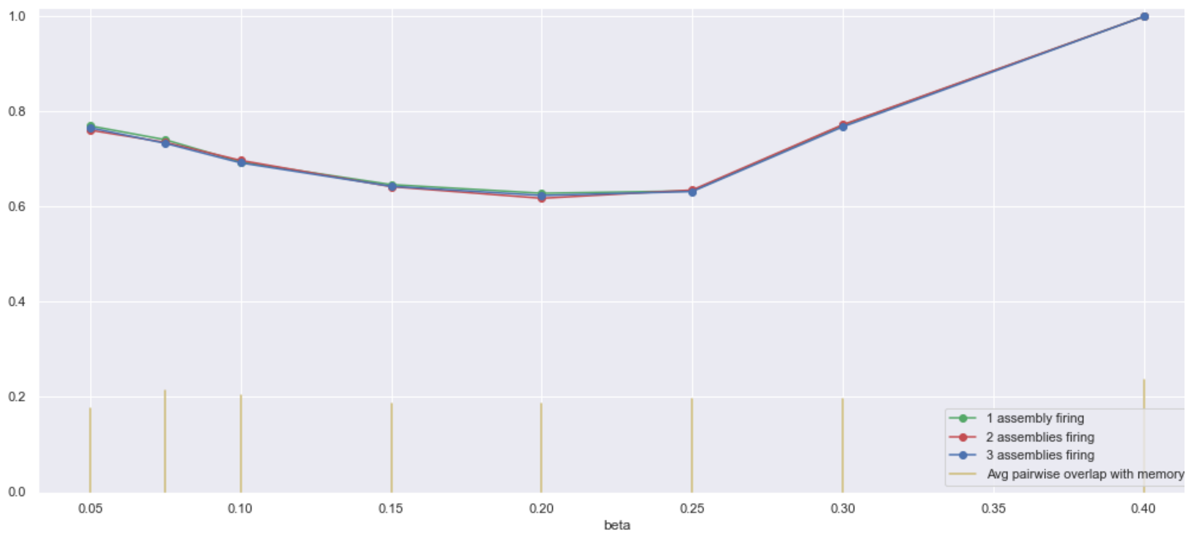

Figure 5: Final overlap after random set of neurons of the memory area are excited.

and the system has converged, there is significant overlap between the most excited neurons of the memory area and the neurons of the identifier-assembly. For this reason, if we keep projecting the identifier-assembly to the memory area, we expect that the synaptic weights of the identifier-assembly will get strengthened even more. A question here would be how the continuous firing of the identifier-assembly to the memory area affects the final overlap of the neurons of the memory area that are stimulated after some attributes fire, with the neurons of the memory area that belong to the identifier. Will the final overlap increase?

In Figure 6, we can see the final overlap - upon convergence - of the neurons of the memory area that are stimulated after the attributes fire, with the neurons of the memory area that belong to the identifier assembly. The three different lines correspond to different numbers of attributes (1,2,3) firing. Moreover, the vertical lines show the average pairwise overlap, after the association of all pairs of assemblies has taken place, of the identifier assembly with each attribute assembly in memory area.

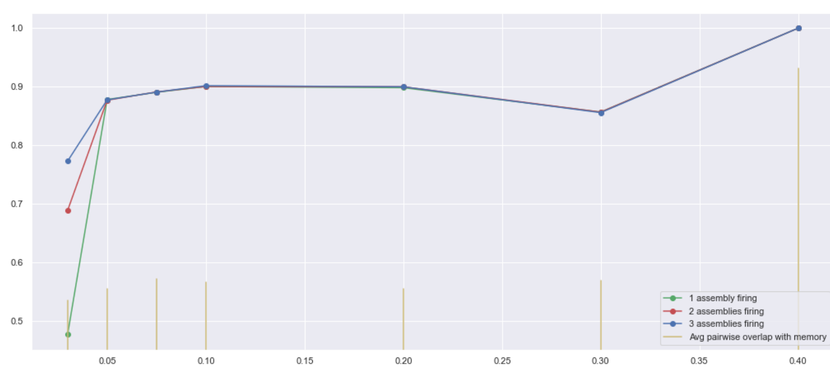

Figure 6: Overlap with assembly of interest when the identifier assembly keeps projecting in memory area after pair-wised associations have converged.

We observe that there is a significant increase in the final overlap for all the values of the plasticity coefficient beta. That means that the continuous firing of the identifier-assembly to the memory area after the association increases the final overlap, and hence facilitates the recall of the identifier. We can also see that for small betas (beta=0.03) not only does the final overlap increase dramatically, but also the number of attributes that fire affects the final overlap, in contrast with our previous observations. Further experimentation is needed for this behavior to be understood.

5.1.2 number_of_assemblies = 2

We will now discuss an experiment that concerns the case where just one attribute is present along with one identifier (number_of_assemblies=2). In this experiment, the attribute fired 0, 1, 3, or 5 timesteps after the association was completed (s=[0,1,3,5]).

In Figure 7, the dashed lines represent final overlap (overlap_upon_convergence) when the attribute fires 0 or 5 timesteps upon the association, while the solid line represents the mean final overlap over all the possible values of timesteps_after_association.

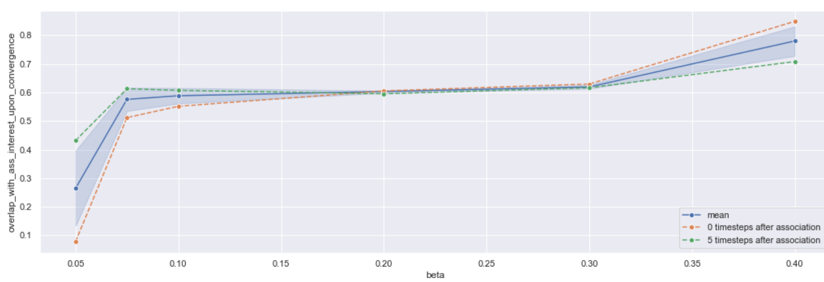

Figure 7: Mean 0verlap upon convergence for 1 attribute, 1 identifier, and all timesteps. Overlaps for timesteps 0, 5 are represented by the dashed lines.

The final overlap achieved in experiments with 1 attribute and 1 identifier, is in general smaller than the one achieved when more attributes are present. We further observed that in this case the overlap is monotonic on beta. The dashed lines show the convergence overlap for attribute firings that take place in different timesteps after the association. We see that if some time passes between the association and the final firings of the attributes, during which the winner neurons of the memory area keep firing, our final overlap is in general equal or higher to the one achieved in no time passes. Only for beta=0.4 is when this relationship is reversed, which is an observation that we could not find an explanatioin for. Finally, we would like to note that the difference in the final overlap as a result of different timesteps_after_association were more apparent in the case of 2 assemblies and became insignificant for larger number of assemblies.

5.1.3 beta=0.1, number_of_assemblies=[5,6,7,8]

In this section, we will discuss an experiment we designed to observe the effect the number of assemblies and the plasticity coefficient have on the final overlap upon convergence.

Figure 8 shows the final overlap upon convergence as well as its variance. The four different lines correspond to different number of assemblies (number_of_assemblies=[5,6,7,8]).

We observe that the more attribute-assemblies are used, the larger the final overlap will be upon

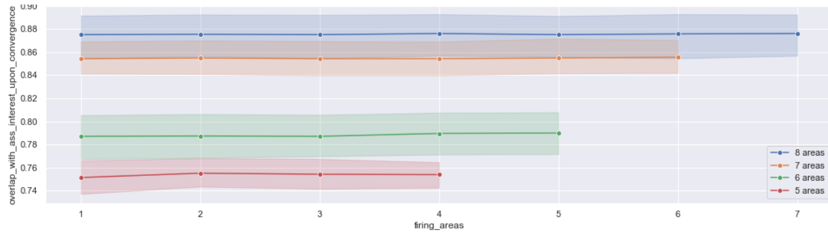

Figure 8: Overlap upon convergence for different number_of_assemblies and different number of assemblies_firing.

convergence. This can be translated as follows: the more the attribute-assemblies the identifier-assembly gets associated with, the higher its final overlap - upon convergence - with the neurons of the memory area that are stimulated after the attributes fire will be. This could be attributed to the fact that the more times the identifier participates in associations the more its synaptic weights will get strengthened, and hence the probability that the neurons of the memory area that belong to the identifier-assembly will be among the k most excited neurons increases. We can also observe that the number of attributes that fire has almost zero effect to the final overlap. That means that the probability of remembering the identifier is the same regardless of the number of the attributes that fire, which is surprising.

5.2 Simultaneous Association

In this section, we will discuss the results of the second set of experiments, where we associated all the attribute-assemblies including the identifier-assembly together simultaneously.

5.2.1 number_of_assemblies = 4

We will first discuss an experiment that concerns the case where 3 attributes are present along with one identifier (number_of_assemblies=4).

Figure 9 is similar to Figure 1 that showed the results for 4 assemblies in the case of Pairwise Association. The association overlap threshold used for this experiment is 0.10. However, the Figure also shows the mean overlap upon convergence over all possible numbers of firing assemblies for association_overlap_threshold=0.2

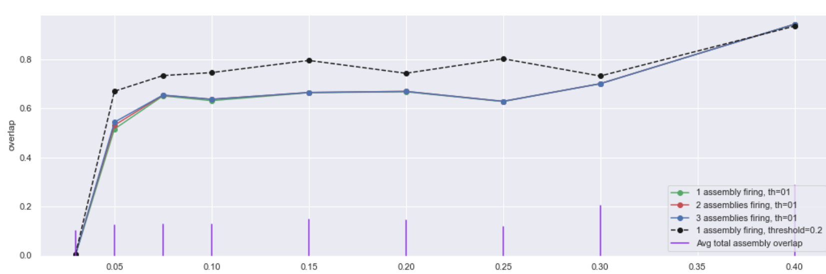

Figure 9: Overlap upon convergence for number_of_assemblies=4 and assemblies_firing=[1,2,3].

Once again, the final overlap is not monotonic to the different betas neither the total assembly overlap after the association (before the firing of attributes). It seems however that the final overlap is more strictly related to the total assembly overlap after the association, as the former increases when the later is increased and decreases in the opposite case.

5.2.2 number_of_assemblies = 2

We will now present experiments that concern the case where just one attribute is present along with one identifier (number_of_assemblies=2).

Overlap with assembly of interest upon convergence per association_overlap_threshold
In Figure 10, we can see the final overlap - upon convergence - of the neurons of the memory area that are stimulated after the attributes fire, with the neurons of the memory area that belong to the identifier assembly. The dashed lines correspond to the experiments in which we set the association_overlap_threshold to 0.1 and 0.2 respectively. The solid line represents the mean final overlap over all the possible values of association overlap thresholds.

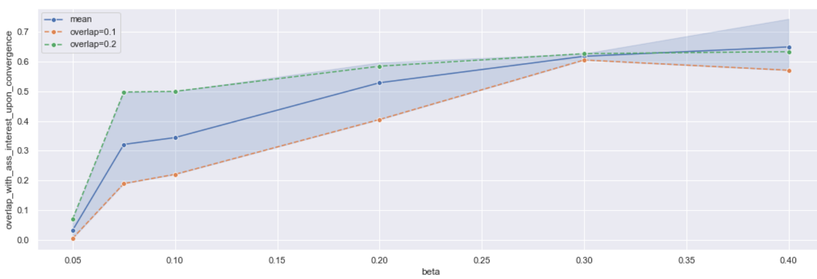

Figure 10: Overlap upon convergence for 2 assemblies. The average overlap for all association thresholds can be seen as well as overlaps for 0.1 and 0.2 thresholds.

This figure shows that the higher the threshold for the association overlap, the higher the final overlap is. This is to be expected, as the higher the threshold the higher the association overlap, and as discussed in Section 5.2.1, the final overlap seems to depend on the total overlap after association. The final overlap achieved in experiments with 1 attribute and 1 identifier, is in general smaller than the one achieved when more attributes are present, also in the case of Simultaneous Association.

Timesteps till association is completed per association_overlap_threshold
Figure 11 shows the distribution of the timesteps needed for the total association overlap to surpass the required threshold.

We observe that the higher the threshold for the association overlap, the larger the number of timesteps that are needed for the association overlap to surpass the respective threshold. This is expected. It should be mentioned that the experiments indicated that during the majority of the timesteps the overlap was very close to 0 and then steeply increased. That means -and was experimentally verified- that after just a few more timesteps, the total association overlap would be close to the maximum possible for total association overlap.

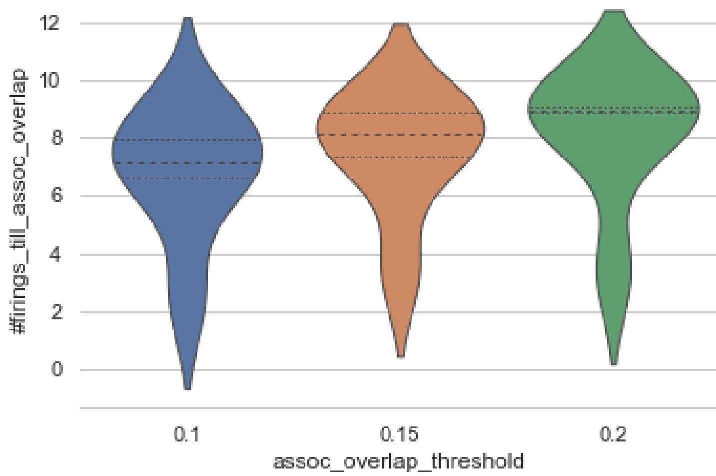

Figure 11: Distribution of time steps needed for the association overlap to reach the overlap threshold.

5.2.3 beta=0.1, number_of_assemblies=[5,6,7,8]

In this section, we will discuss an experiment we designed to observe the effect the number of assemblies and the plasticity coefficient have on the final overlap upon convergence. Figure 12 is similar to Figure 8, which showed the results of Pairwise Association.

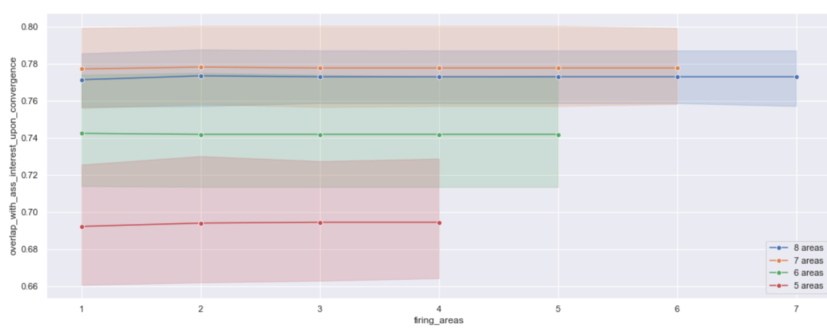

Figure 12: Overlap upon convergence for different number_of_assemblies and different number of assemblies_firing.

As in the case of Figure 8, we once again observe that the number of attributes that fire have almost zero effect to the final overlap. However, we see that the final overlap is larger for 6 attributes (7 areas) than it is for 7 (8 areas). This seems counter-intuitive and needs to be verified by more experiments, especially since the difference between the final overlaps is small. However, some possible explanations could be that 1) since all the attribute-assemblies get associated with the identifier-assembly simultaneously, the synaptic weights of the identifier don't get strengthened at the same degree as in the case of the Pairwise Association, and 2) that the Simultaneous Association is not suitable when there are more than a few attributes, as we initially speculated.

6 Conclusion

The results of our tests and experiments on the nature of the Association operation in Assembly Calculus showed promising leads. The framework was proven capable of examining the patterns of neural activity during associative memory formation and also during associative memory retrieval. We believe that our findings can be biologically explainable and can be observed in human behaviour in our every day lives. The main conclusion of our work is that the particular framework of assembly calculus can provide an explanation of how associative memories are formed in the medial temporal lobe, and how we can access such information and leverage it so as to remember other associated information stored in the brain.

6.1 Possibilities and Future Work

Although the conducted experiments showed promising results, future work is required to further validate our findings and answer the new questions that arose from our experimentations. The next steps include the following:

1. Run each experiment again multiple times in order to further validate the results. Although running each experiment 10 times is enough to identify trends, the limited amount of generated data cannot be considered sufficient evidence.

2. Design experiments to explore why the relationship between the final overlap and beta is not monotonic. What happens in the area around specific betas (e.g., 0.2) that causes a significant drop in the overlap?

3. As discussed in Section 5.1.1, we randomly stimulate the memory area right after association just once. We observed that firing it once doesn't affect the final overlap. The question is what would happen if we randomly fired the memory area multiple times?

4. In Section 5.1.1, we discussed an experiment in which we kept projecting the assembly of interest to the memory area after the association. We mentioned how we expected that the synaptic weights of the identifier-assembly would get strengthened. We still need to explore the degree of the synaptic weight strengthening.

5. In section 5.1.1, we observed in Figure 3 that the range of the values that the overlap would take until it finally converged decreased as plasticity (beta) and the initial overlap increased after one firing. We think that it would be worth investigating this relationship formally.

6. Contingent on the validation of our results via the running of each experiment multiple times, the next step is to explain and verify them mathematically.

References

[1] György Buzsáki. "Neural Syntax: Cell Assemblies, Synapsembles, and Readers". In: *Neuron* 68.3 (2010), pp. 362–385. ISSN: 0896-6273. DOI: https://doi.org/10.1016/j.neuron.2010.09.023. URL: https://www.sciencedirect.com/science/article/pii/S0896627310007658.

[2] Silvia Vlachou Dafne Papaefthymiou and Manuel Paez. *Assembly Calculus and Association.* URL: `https://github.com/dafnep/assemblies/tree/dafne`. (accessed: 05.13.2022).

[3] Christos H. Papadimitriou et al. "Brain computation by assemblies of neurons". In: *Proceedings of the National Academy of Sciences* 117.25 (2020), pp. 14464–14472. DOI: `10.1073/pnas.2001893117`. eprint: `https://www.pnas.org/doi/pdf/10.1073/pnas.2001893117`. URL: `https://www.pnas.org/doi/abs/10.1073/pnas.2001893117`.

[4] Rodrigo Quian Quiroga et al. "Single-Cell Responses to Face Adaptation in the Human Medial Temporal Lobe". In: *Neuron* 84.2 (2014), pp. 363–369. ISSN: 0896-6273. DOI: `https://doi.org/10.1016/j.neuron.2014.09.006`. URL: `https://www.sciencedirect.com/science/article/pii/S0896627314007946`.