Contents

1 Introduction and Recap

1.1 Talk by Dr. Kenneth Kay

1.2 Hopfield networks

Type of network that can store associative memories.

Most important: the special case of Restricted Boltzmann Machines [Hinton 2005] that can be stacked to create deep neural networks

1.3 Feedforward + Recurrent networks

Based off of the interplay of random synapses and the excitation-inhibition balance created; near Gaussian due to the Law of Large Numbers.

2 Guest Lecture by Melina Tsitsiklis, PhD candidate in Neurobiology at Columbia

How does the brain encode spatial memories?

2.1 The medial temporal lobe is essential for episodic memory

How do we know?

Patient H.M.: had his medial temporal lobe part on both sides removed (1950s), lost many memories including all of his "creepiest" memories, and lost the ability to form new memories

2.2 The hippocampus contains place cells

By tracking the cells firing in the rodent's hippocampus you can decode where the rodent is in the environment. This is an indication of **place cells**.

2.3 How can we look at these signals in humans?

People who have intractable epilepsy will sometimes get a piece of their brain removed. In order for this to happen, they first need to map out where their seizures are starting. To do this, doctors can put an electro grid on the surface of the brain to read the activity from many many cells, but with this method you can't pick out individual cells and can't read deeper than the surface. To look deeper, they put a depth wire in the brain. These microwires / microelectrodes can pick up the activity of a single cell. Doctors do imaging (MRI, CT) before and after the surgery to see where the electrodes ended up. Patients generally spend 1-3 weeks in the hospital for this procedure, called an **intracranial EEG**.

2.4 Combine intracranial EEG with virtual reality task

Hook the intracranial EEG patients up to a computer that tracks cell activity from the microwires and ask them to play a computer game ("virtual reality task") while they're spending time waiting in the hospital.

2.5 Humans have spatially modulated cells too

Use this procedure to look for human place cells i.e. which neuron "prefers" which spatial section of the environment.

Evidence of human grid cells was also found in 2013

2.6 Research-Guiding Question

- Does the human medial temporal lobe (MTL) represent broader aspects of behavior beyond current location?

2.7 What are individual neurons doing during navigation in this task?

Sections of the treasure hunting game: navigation, encoding, recall (object cued), recall (location cued)

Tsitsiklis looks specifically at the navigation phase.

2.8 Place-like cells

Create cell activity maps based on the subject position to see which cells increase in activity depending on the location of the subject

2.9 Goal-position cells

Then, look for goal-position cells i.e. place cells that are focused on the goal position, not the subject's current position.

Finding: Making the same maps as before, we are able to see that some cells are indeed modulated by the goal and not the subject position.

2.10 Memory-related cells

Some cells have higher firing rate if they are told they have to remember the object. The opposite was also shown in some cases.

2.11 Pre-Conclusion

Finding: MTL cells are modulated by the goal location and subsequent memory more than the subject location.

Follow-up Question: Is there a low percentage of place-like cells because subjects are attending to goal while navigating?

2.12 Moving forward: multivariate approaches

See: another ("less-biased") study that looked at cells modulated by position, head direction, speed, and theta (local field potential)

Finding: Some cells are modulated by multiple variables, or even all of the variables.

2.13 Moving forward: past spatial dimensions

Repeated the original experiment, but this time with the rodents navigating sound frequency space. (Rat would let go of lever when it got into a specific sound frequency space.) Looked at cells in the hippocampus and the (didn't catch it) and track how the cells modulate with different sound frequencies.

Finding: Not only did they find cells that modulate to certain frequencies, but they also found that some of those frequency cells were place cells as well.

Question from the class: Did they find grid cells for the sound i.e. relating octaves and whatnot?

→ Tsitsiklis didn't remember

2.14 Conclusion

- MTL codes for behaviorally relevant aspects of an experience
- We need improved, unbaised statistical approaches to better understand neuronal activity in relation to behavior both at the single cell level and at the population level

Question from the class: How are you thinking about the edges of your map? What if your place cell cares about a spot I don't go in the map?
→ I can't prove that

Continuation: Is it then fair to say that the max activity we see is really indicative of the preferred location of any given place cell?
→ This is a natural limitation of any place cell experiment. However, places cells also do something we call remapping, which means they "pick" a new location for many different environments. A place cell attuned the corner of this room may be attuned to the "center" of another environment, or maybe even nowhere in a another environment.

Question from the class: Have we tried picking two place cells and mapping them to the same location?
→ [?]

Question from the class: How long does it take for a place cell to be assigned? Does that affect the findings?
→ Rodents are overtrained...

Remark 2.1. "I want to understand what place cells are doing in this task, how they are altered by, say, rewards" is a line of thinking that leads to researchers finding place cells to then do research on. Therefore, there is little data on "if I put an electrode in the brain here what are the odds of finding a place cell."

Question from the class: If you could characterize what each cell was doing, what is the next step of this research?
→ There are many other cell types, and right now this study is only looking at firing. Even if we could characterize every cell, there's still a lot we don't know

3 Dynamical System for E-I Balance

3.1 E-I Balance: Solving the ODE numerically

Recall lowpass filter ODE:

$$\tau * \frac{dv}{dt} = -v + F(W * u + R * v)$$

$$\tau_E E = -E + GT(T_E, np(E-I), np(1-p)(E+I))$$
$$\tau_I I = -I + GT(T_I, npI, np(1-p)I)$$

Recall notation GT(T,m,var)

If τ_E is sufficiently larger than τ_I, an E-I balance will be reached after a few up and down oscillations

Remark 3.1. Assume that every time this (the straight line) happens, a constant K number of neurons are firing

"If I notice something creates a straight line, I want to use it in my model."

3.2 More E-I Balance: How fruit flies remember smells

- An odor is inputted, the mean is centered, there is a random projection, and then the winner takes all
- There was a surprise: the fly was able to memorize better than a complex hashing algorithm
- Fly outperformed algorithm at a series of benchmarks
- Flies have a random graph in their brain, nature has made use of randomness. This brings up the question: is DNA random or do we have a random number generator in our DNA?

4 Random projection and Cap (RP and C)

Gaussian map, where the x-axis is the magnitude of impact and the y-axis is how many cells are firing

Finding: They recorded everything and did a bunch of randomness tests and found that the random bipartite graph was indeed mostly random. Some of these auto (projection) cells have more outgoing (i.e. are more powerful), but other than that the graph is random is random. *Note*: Random does not mean uniform.

The real defense of this field (fly algorithm) is that hashing means going down in dimension, but this goes up in dimension. It goes through a few well-known benchmarks and the fly performs.

Remark 4.1. If flies have a random graph in their brain, this is very interesting because flies have 80,000 neurons and every neuron has to do something. To have randomness is very unusual cause everything has to go somewhere.

Remark 4.2. Natural selection has found it useful for this to be random.

Question: Do we have a random number generator in your DNA or is your DNA random? Is there such thing as genetically-endoded randomness? Or is it random in the sense that there is no organizational principle, even though they are still genetically encoded?

Question from the class: No two brains are exactly the same? Connectome exists at no point?
→ Pretty much

4.1 What happens when you smell something?

Olfactory receptors receive scent, and this is projected to the olfactory bulb. An odorant may cause a small subset of neurons to fire and inhibition triggered by this activity will prevent further firing. This small fraction of cells would generate sufficient recurrent excitation to recruit a larger population of neurons. In the extreme, some cells could receive enough recurrent input to fire without receiving initial input.

4.2 What is the underlying mathematical reason?

(a) Random $n \times n$ bipartite graph

(b) A set A of k out of n nodes of the lefthand side fire, and a new set cap(A) is formed by RPC

(c) Repeat for B, cap(B)

If A and B overlap in αK nodes, what is the overlap of cap(A) and cap(B)?

By the way, why am taking the two sides to be symmetric?
→ Will be helpful in what follows, so that anything on the left creates a "Bernoulli shower" on the right

4.2.1 Calculemus (Let Us Calculate)

What is the distribution of the input?

Theorem: The intersection of cap(A) and cap(B) will be, with high probability, at least

$$\frac{k}{n}$$

Compare with simulations

4.3 Does something homologous happen in mammals?

An odorant may cause a small subset of PC neurons to fire. Inhibition triggered by this activity will prevent further firing. This small fraction of cells would then generate sufficient recurrent excitation to recruit a larger population of neurons This is new! This did not exist in the fly! In the extreme, some cells could receive enough recurrent input to fire even without receiving initial input.

Does this process converge?

Does it preserve similarity?

4.4 Upgrade the model: the GNP model

- fruit fly, plus
- recurrent synapses
- all random connections with probability p
- discrete time
- Hebbian plasticity
- fixed number of brain areas, each with n excitatory neurons and recurrent connectivity

Update parameters and intended values

4.5 Linearized System

Remarkable because you can solve it!

4.6 Linearized system: solution

Theorem: The linearized dynamics converges geometrically and with high probability to

$$x_j = s_j + \Sigma_{i \to j} x_i^2 / \Sigma_{i \to j} x_i$$

"To be successful, you either have to be born rich, or have many successful supporters, or both."

Question from the class: Doesn't this depend on how you define n?
→ [?]

4.7 OK, how about the real, nonlinear system?

That was warmup. We are interested in the nonlinear system.

When one is off, there is always k of them. You are assuming that the E-I [missed it].
Theorem: The process converges exponentially fast, with high probability, and the total number of cells involved is at most

- If $\beta \geq \beta^*$: $k + o(k)$
- If $0 < \beta < \beta^*$: $k \cdot \exp(0.17 \cdot \ln(n/k)/\beta)$

- NB: $\beta^* = (\sqrt{2} - 1)/(1 + \sqrt{pk/\ln n})$

If you have beta very large, you converge immediately. If you have beta very small, it takes awhile.

CHANGE: Suppose this kind of set of neurons created this way are very important and all over the brain. Let's call them an Assembly.

4.8 The result of such projection: an Assembly

Assembly: Set of k neurons in a brain area whose firing (in a pattern) is tantamount of our thinking of a particular memory, concept, name, word, episode, etc.

(a) conjectured 70 years ago by Hebb

(b) simulations of a far more biologically accurate STDP model

(c) presumably highly connected - important reasons:
1. plasticity: fired together so wired together
2. origin: support each other - how can they if not connected?
3. synaptic biases

Also called: grandmother neurons, Jennifer Aniston neurons

Question from the class: How are you thinking of time in these assemblies? Are these traveling waves or actual synchrony?
→ If you Google assemblies, you are likely to see something like "this" : neurons, random stuff, and then markers i.e. the projection of the assembly on their electr[missed it]. This starts somehow: because the same stimulus fires together? Maybe because a random neuron fires and the whole assembly was "ignited"?

Question from the class: Or do you think that what we are seeing is just a bunch of assemblies in sequence?
→ These converge eventually.

4.9 The Big Picture - Computation in the brain: What is the right level?

Take a thousand steps back. Compuation can happen in molecules, in a beautiful molecular dance. It can also happen in dendrites, spiking neurons and synapses... and then we know it can happen with the whole brain.

KEY: There is a big gap!

"We do not have a logic for the transformation of neural activity into thought and action. I view dissecting this logic as the most important future direction of neuroscience."

5 Neuron assemblies and their operations

5.1 The assembly hypothesis

There may be an intermediate level of brain computation implicated in carrying out higher cognitive functions such as reasoning, planning, lanugage, story-telling, math, music, etc. Assemblies are its basic representation, its main "data structure".

Remark 5.1. This is a wide hypothesis.

"Don't waste time pursuing this if you are younger than me."

What are its fundamental operations? An operation must be **useful** and **plausible**.

5.2 Useful and plausible?

Useful: Helps us understand an experiment or two - ultimately the brain.
Plausible: No magic involved, must be compiled down to neurons and synapses.

5.3 The model

Finite number of "brain areas"
E-I Balance: assemblies have k neurons each
Assemblies barely intersect
Each has n (excitatory) neurons

5.4 The assembly hypothesis: operations

Project(x,A,y)
A = area(y), x = parent(y)

Plus, this is how an assembly is created

Projection superficially looks like assignment

Question from the class: Are there other operations?
→ Two assemblies may be associated by sharing cells. Association encodes "affinity", similarity, and co-occurence.

Example 5.2. Show people the Eiffel tower, then show people the Eiffel tower with Obama photoshopped in front of it.
→ There was an Obama assembly. Then, upon seeing a picture of Obama in front of the Eiffel Tower, some of the cells in the Eiffel Tower assembly decided to become also Obama cells. About 7-8 percent of the Eiffel Tower cells did this migration. (Researchers were very lucky to find ones that did.) The cells come together, come closer, and acquire some overlap. There are also new cells created that respond only to the combination of Obama and the Eiffel Tower!

5.5 So association is useful, but is it plausible?

Yes, through simulations under submission.

5.6 But is association preserved under projection?

Yes, very well preserved. (Recall the fly.)

Assembly association also means associative memory through pattern completion.

Association graph: which assemblies/concepts are similar?

"How do you remember things? You say, OK, Swedish, starts with a D, met him in Paris.... this is association."

Note: Because you know your brother so well, his assembly is robust an refreshed all the time.

Question from the class: What about abstraction? Obama and Trump have overlapping cells?
→ [?]

Question from the class: Are assemblies failsafe?
→ [?]

6 The Coming Weeks

- Locomotion and dynamical systems
- Reinforcement Learning
- Language
- December 6: Project Presentations, with projects due a few days later
- *Anything else?*