A4 Afternoon Session 4: (25 min) Jørgen Jensen Farner, Ola Huse Ramstad, Stefano Nichele and Kristine Heiney Beyond weight plasticity: Local learning with propagation delays in spiking neural networks

Supporting link - https://arxiv.org/pdf/2211.08397.pdf

Quick summary and Notes with example for abstract and introdution:

Pre-synaptic Spikes (Sending Signals): Think of pre-synaptic spikes as electrical signals that travel down a neuron's "sending wire" when it gets excited. When a neuron gets stimulated enough, it sends out these spikes. At the end of this wire, there's a special zone called the "sending station." Here, the spikes trigger the release of tiny messenger molecules called neurotransmitters. These neurotransmitters are like messengers carrying a note to the next neuron.
Post-synaptic Spikes (Receiving Signals): On the other side, there's a "receiving wire" belonging to another neuron. This neuron has a different job – it waits to get a message. When the neurotransmitters from the first neuron arrive, they're like keys fitting into locks on the receiving neuron. If enough keys (neurotransmitters) fit into enough locks (receptors) and turn them, they open a gate. When this gate opens, it can cause the receiving neuron to send its own electrical signal – this is the post-synaptic spike. It's like getting a green light to send a message of its own. This signal then travels down the receiving neuron's wire to continue the message relay.

- **Presynaptic Spike Time:** This refers to the specific moment in time when a pre-synaptic neuron generates and emits an action potential or spike. It's when the "sending" neuron fires an electrical signal down its axon.
- **Spike Arrival Time:** This is the time at which the spike generated by the pre-synaptic neuron arrives at the synapse, where it can influence the post-synaptic neuron. Spike arrival time is crucial because it determines when the signal from the sending neuron reaches the receiving neuron's synaptic region.
- **Average Arrival Time:** This term represents the statistical or typical timing at which pre-synaptic spikes from a given neuron arrive at the synapse over a period of time. It's a measure of the average timing of spikes reaching the synapse and can provide insights into the regularity or predictability of spike arrivals. It's calculated by considering multiple instances of spike arrival times.
- **Post-synaptic Spike Time:** This is the moment when the post-synaptic neuron generates its own action potential or spike in response to the influence of pre-synaptic spikes. The timing of the post-synaptic spike depends on when and how the neurotransmitters released by the pre-synaptic spike affect the post-synaptic neuron's membrane potential.

Interdependency:
The interdependency among these terms lies in the communication process between neurons at a synapse. The presynaptic spike time determines when the signal is sent, and this timing ultimately affects the spike arrival time at the synapse. The average arrival time provides insight into the regularity of this timing over multiple instances. The post-synaptic spike time depends on when the neurotransmitters released due to the pre-synaptic spike reach a critical threshold, leading to an action potential in the post-synaptic neuron. In essence, the timing of pre-synaptic spikes, their arrival at the synapse, and the post-synaptic spike time are interconnected elements of the neural communication process, where the timing of events plays a critical role in information processing within the neural network. The order and timing of these events determine the strength and timing of the signal passed from one neuron to another.

Presynaptic Spike Time (Sending Signals): Imagine you have a sender neuron that generates electrical signals, like sending messages through a wire. The moment this sender neuron gets excited enough to send out these signals, we call it "presynaptic spike time." It's when this neuron fires an electrical signal down its wire, like sending a text message.
Spike Arrival Time (Receiving Signals): Now, on the other side, you have a receiver neuron with a different role. It's like a person waiting to receive a message. When the electrical signals (spikes) from the sender neuron arrive at the synapse, it's like the messages being delivered to the receiver. This moment in time is what we call "spike arrival time." It's important because it tells us when the sender's message reaches the receiver's location.
Average Arrival Time (Timing Patterns): Imagine if you're sending messages to your friend every day. The "average arrival time" is like figuring out, on average, when your messages tend to reach your friend. It helps you understand if your messages are usually fast or slow. It's calculated by looking at many instances of message delivery.
Post-synaptic Spike Time (Responding to Messages): When your friend receives your messages, they might decide to send a response. In our example, the receiver neuron decides to send its own message when it receives enough signals from the sender. This is what we call "post-synaptic spike time." It's like your friend deciding to reply to your messages after getting them.
Interdependency (Message Exchange): So, think of it like a conversation. The presynaptic spike time is when you send a message, and spike arrival time is when your friend gets it. The average arrival time tells you if your messages tend to be early or late. Post-synaptic spike time is when your friend replies to your messages. These terms are interconnected because they describe the timing of events in this neural conversation, just like how messages between friends depend on when they send and receive them, and whether they reply quickly or slowly. In the brain, these timings affect how neurons communicate and process information.

Example 1:
Novel STDP Analogue for Local Delay Learning: Imagine you and your friend want to improve your messaging system. You come up with a new rule: instead of just sending and receiving messages, you'll also focus on how long it takes for the messages to travel between you. This is like inventing a new way to learn how your messages can be delivered faster. In the world of neurons, this is called a "STDP analogue for local delay learning."
Influencing the Delay of the Connection: Now, in your messaging system, you discover that the timing of when you send and when your friend receives the message affects how fast the messages travel between you. It's not about changing the content of the messages (weight), but about making sure they reach each other more quickly. So, the new rule focuses on "influencing the delay of the connection" – making sure messages arrive faster.
Aligning Messages for a Faster Response: The main idea here is to make sure that all your messages are timed in such a way that they help your friend respond more quickly. In our messaging analogy, you want your friend to reply faster, so you find a way to "align" your messages in a way that they make your friend respond "causally," meaning in direct response to your messages. This way, you can have a "faster and stronger response," just like how neurons want to respond quickly and effectively to signals.
Application to Handwritten Digit Classification: Now, think of using this improved messaging system to classify handwritten digits. You and your friend decide to use this new system to sort out handwritten numbers. It turns out that training your messaging system in this way helps you not only understand the numbers better but also allows you to apply this knowledge to new numbers you've never seen before. This is like using your enhanced messaging to recognize and classify different handwritten digits.
Consistent Improvement and Generalization: Your messaging system consistently performs better than the old one, and it's not limited to recognizing the numbers you practiced with. It can apply what it learned to understand and classify new, unseen numbers. Similarly, in the world of neural networks, these enhancements are showing consistent improvement and the ability to generalize their training to new situations.

Example 2:
Novel STDP Analogue for Local Delay Learning: Imagine you're a chef trying to improve your cooking techniques. You come up with a new rule for your kitchen: instead of just following recipes and cooking at a fixed pace, you'll also focus on the timing of each ingredient you add to the dish. This is like inventing a new way to learn how to cook dishes more efficiently. In the world of neurons, this could be compared to a "STDP analogue for local delay learning."
Influencing the Delay of the Connection: Now, in your kitchen, you discover that the timing of when you add ingredients to a recipe affects how fast the dish cooks. It's not about changing the ingredients themselves (weight), but about making sure they are added at the right times to speed up the cooking

process. So, the new rule focuses on "influencing the delay of the connection" – making sure ingredients are added at the right moments to expedite cooking.
Aligning Ingredients for a Faster Cooking Time: The main idea here is to make sure that all the ingredients in your recipe are timed in such a way that they help the dish cook faster. You want to align your ingredients in a way that they make the cooking process happen "causally," meaning they directly impact how fast the dish is prepared. This way, you can achieve a "faster and stronger cooking result," just like how neurons aim for a quicker and more robust response to signals.
Application to Recipe Creation: Now, think of using this improved cooking technique to create new recipes. You apply this new rule to your culinary experiments and find that it not only speeds up the cooking time but also allows you to create new, delicious dishes more efficiently. This is like using your enhanced cooking skills to invent and cook new recipes that you've never tried before.
Consistent Improvement and Creativity: Your new cooking technique consistently produces better dishes, and you're not limited to just recreating existing recipes. You can apply what you've learned to create innovative and tasty dishes that were previously unexplored. In the world of neural networks, these enhancements represent consistent improvement and the ability to apply knowledge to novel situations, just as you've improved your cooking skills and creativity in the kitchen.

Main Explanation
The text describes the introduction of a novel learning mechanism, referred to as a "STDP analogue for local delay learning." This mechanism is designed to enhance the communication between neurons in a neural network. Instead of focusing solely on the strength of connections between neurons, as is common in traditional synaptic plasticity rules, this new approach emphasizes the timing of signals or spikes. the timing is dependent on activity. **(acitivity dependent delay plasticity)**
Here's a breakdown of the key elements:

- **Timing Influence:** The novel learning rule considers the precise timing of both pre-synaptic spikes (signals from sending neurons) and post-synaptic spikes (signals from receiving neurons). The relative timing of these spikes influences the delay of signal transmission between neurons.
- **Delay Adjustment:** Unlike traditional synaptic weight adjustments, this approach is concerned with modifying the delay of signal transmission between neurons. By adjusting the timing of spike transmission, the goal is to align pre-synaptic spikes in a way that causally relates to post-synaptic spikes, leading to faster and stronger responses in the receiving neurons.
- **Application:** The text mentions the application of this delay learning method to the classification of handwritten digits. This means it's being tested in a practical scenario where the neural network needs to recognize and classify different digits based on their input patterns.
- **Performance and Generalization:** The results indicate that using this novel learning mechanism consistently improves the neural network's

performance. Furthermore, the network demonstrates the ability to generalize its training to handle input patterns it hasn't encountered during training, suggesting its potential for expanding the network's capabilities.

The text discusses a novel approach to learning in neural networks known as "activity-dependent delay plasticity." This method is designed to optimize the timing of signals (spikes) between neurons, allowing the network to produce consistent patterns of activity in response to similar inputs. It mentions two specific encoding and decoding approaches used in this learning framework: "latency coding" (LC) and "polychronous group pattern" (PGP) clustering.

Let's break down the key elements of this text using both the chef and friend messaging examples:

Chef Example (Encoding and Decoding): Think of a chef who is trying to improve the timing of adding ingredients to a recipe. The chef wants to ensure that when certain ingredients come together, they create a consistent taste in the dish. This is similar to the neural network's goal of producing consistent patterns of activity in response to specific inputs. The chef's approach involves adjusting the timing of when ingredients are added to achieve this goal.

Friend Messaging Example (Alignment Process): Consider two friends who want to have more synchronized conversations. They decide to adjust the timing of their messages to ensure they respond to each other more quickly and consistently. In the neural network context, this is akin to better aligning the timing of pre-synaptic spikes (messages from sending neurons) to achieve faster and stronger responses in the receiving neurons.

Now, let's delve into the equation provided:

- **Δdi,j = -3 tanh(ti + di,j - t¯pre 3 , 0 ≤ Δtlag < 10 ms:** This equation describes how the delay (Δdi,j) between a pre-synaptic neuron i and a post-synaptic neuron j is adjusted. Here's a breakdown:

   - **Δdi,j:** This represents the change in delay between the pre-synaptic and post-synaptic neurons.

   - **tanh:** This is the hyperbolic tangent function, which scales values between -1 and 1.

   - **ti:** Spike time of pre-synaptic neuron i.

   - **di,j:** Initial delay between neuron i and neuron j.

   - **t¯pre:** Average pre-synaptic arrival time across all neurons with spikes arriving within 10 ms before the post-synaptic spike.

   - **Δtlag:** This is the time lag between when the pre-synaptic spike arrives at the post-synaptic neuron and when the post-synaptic neuron fires. It's calculated as tj - ti + di,j.

The equation essentially computes the change in delay (Δdi,j) based on the spike times of the neurons involved, their initial delay, and the time lag. This change in delay aims to better align pre-synaptic spikes in a way that enhances the post-synaptic response, as illustrated in the figure provided in the text. The 10 ms time window is chosen because it's within the window where a pre-synaptic spike can elicit a response in the post-synaptic neuron.

In summary, this approach optimizes the timing of spike transmission between neurons in a neural network to achieve more consistent and effective responses to specific inputs, similar to how a chef adjusts ingredient timing to create a consistent taste in a dish or how friends synchronize their messages for quicker and more consistent conversations. The equation is a mathematical representation of how these timing adjustments are made.

NOTES: