Chapter six from the *Theoretical Neuroscience* book continued the discussion on conductance-based models to capture a wider range of dynamic interplay of the neurons’ conductance. The idea behind the model is the basic action potential mechanism where the concentration of Na+ and K+ inside and outside the membrane changes in response to different stimuli. The model uses a series of differential equations to accurately quantify the process including the membrane potential equation, the gating equations with opening and closing rates that characterized the membrane currents. Then the conductance-based model is generalized to capture the behavior of currents depending on other ions like Ca2+. The derivation and integration of all the equations became harder, but the book did communicate an idea that we used throughout the modeling project in the lab that choosing the appropriate level of modeling is crucial. Oversimplified model can give misleading results but overly excessively detailed model could just as well disguise the interesting findings with unnecessary complexity. The memory model I am working with currently has only one parameter, the memory decay rate. To capture the tmr effect, spatial-task accuracy and timing of different events, we have to make a number of assumptions and intentionally ignore other measurement for memory such as fidelity or robustness. We need to somehow come up with a special accuracy in pixels to memory strength conversion formula. All the assumptions could be questionable and we do not have a solid approach to check the validity of the assumptions. However, with more variable, the model could become intractable easily and we would end up making more assumption about the different parameters and the connections with the behavior data. To assure the modeling work is practical and the model is understandable to a new audience, we always start with a simple model, look for data that would break the model, update the model to make a fit and keep adding the parameter as the last option. Similarly, this idea is seen in the models in traduced in the book. The single-compartment model is able to describe the membrane potential changes over a neuron with a single variable. The cable theory is able to express the signal propagation within neurons with two variables: the spatial coordinate x and time t.

Chapter six from the MATLAB book introduced ways to collect reaction time and analyze the data by using the function tic and toc. The function is fairly straightforward and easy to use. The code for collecting the reaction time is cleaner than doing it in Python or in Java, but the experiment design packages in python is used more often in different labs than MATLAB.

I continued the work of reconstructing the exact timeline for all the events happened in the experiment. We need to use the knowledge about the experiment protocol, information from EEG data indicating when each cue is played and the file creation time created during the actual experiment to reconstruct the timeline. However, the file creation time is susceptible to change when we copy or move the file. I wrote a script the get the creation time, but had to go back and check manually if they match with the screenshots of the timing information from the original data in Dr. Paller’s lab. I did find a few unmatched ones, but it is unclear which time should I use because the EEG recording starting time might match one of them or might be a random new time. We are waiting on the .bdf file of the original EEG data from the group working in SRI. After process the timing, we would need a new way to graph the results for the whole group because each subject and each picture now would have a different timing set with practice sessions, pre-nap test time, tmr cueing time and post-nap test time. The number of cues played during sleep is different across subjects depending on the nap quality as well. So direct averaging across all subjects clearly does not fit the situation anymore.

Chapter seven from the *Theoretical Neuroscience* book started the discussion on Network Models and this model would bring together the individual models introduced before including the firing-rate model for the sequence of spikes, the conductance models for each neurons and the multi-compartment models for action potentials propagation along the axons. The discussion is then divided into feed-forward network and recurrent network. It is fascinating to see how a dynamic model could be generated and how complicated it could be to try to model a simple cell in primary visual cortex. The content is very arresting, but the mathematical structure behind is very hard to follow now. This chapter has a short discussion on working memory and associative memory which relates to the paired tmr tasks we are working with in the lab. One of the post doc in the lab is studying working memory and memory chunk especially how we process the memory of music and analyzing the EEG data to see when first couple notes of the music piece is cued during sleep, would it evoke reply and memory consolidation of the remaining piece. The recurrent network model could be applied to build an associative memory network and simulate recall of memory patterns. The application would not be directly applicable to the studies we had in the lab, but would definitely be an interesting project for me to do. There might also be data available that could be used to check the validity of the model’s simulation and prediction results

Chapter seven from the MATLAB book made a more in depth discussion about collecting reaction time in MATLAB. It introduced the Posner Paradigm and showed how to create an experiment like Posner Paradigm in MATLAB, collect data and use the reaction time data to infer the mental process of spatial attention. The MATLAB tool seems very useful in spatial attention related tasks. For example, the energy drink study seems to be in the category of a Posner Paradigm and the MATLAB code is a fancier way to analyze the reaction time than in Excel.

I got the .bdf file from SRI, but had to use biosemi’s labVIEW runtime engine to go through each file and copy down the creation time. Luckily we have only about twenty subjects in each experiment and two experiments to go through. With the EEG timing, I could run a sanity check on the previous timestamps I processed. For example, the recording should start after pretest, but before the post nap test. If the recording did not start until two hours after pretest, that was not a good sign either. With more and more complete and accurate information in the model, now we would like to insert more constraints to the model to improve the accuracy. The linear regression we used to predict a pre nap test score reduces the variance of the test scores among the whole data set, but some predictions are above one. However, in our definition, memory strength is the probability of successful retrieval and the range should be between 0 and 1. Another assumption in the model is that the weaker your current memory is the better the boost from additional study would be. Combing all these characteristics, we would like to use a log linear regression to predict the pre nap test accuracy. Dr. Reber guided me through finding the correct variable to log, transforming the pixel-to-strength formula to the right format and adjusting everything else in the exponential decay model to work under the log linear approach but remain in the exponential decay instead of power log decay framework. This is a big change in the model and I would be working on recoding the model this week and next week.