**RNN Intro**

Recurrent neural networks address this issue. They are networks with loops in them, allowing information to persist.

In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.

LSTMs also have this chain like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.

**AFTER LSTM INTRO**

**SLIDE 11**

**The whole brain could be decoded at individual timepoint. But fMRI data inherently has a time dependency on previous time points. Therefore they used many methodologies with time windows.**

However, time windows with a properly defined width are required in order to reliably estimate the functional connectivity patterns. Deep belief neural network (DBN) has been adopted to learn a low-dimension representation of 3D fMRI volume for the brain decoding (Jang et al., 2017), where 3D images are flatten into 1D vectors as features for learning the DBN, losing spatial information of the 3D images. More recently, 3D convolutional neural networks (CNNs) are adopted to learn a latent representation for decoding functional brain task states (Wang et al., 2018). Although the CNNs could learn discriminative representations effectively, it is nontrivial to interpret biological meanings of the learned features.

**SLIDE 13 – GOALS**

Particularly, we learn mappings between functional signatures and brain states by using LSTM RNNs which could capture the temporal dependency adaptively by learning from data. Instead of selecting functional signatures using feature selection techniques or a priori knowledge of problems under study, we compute functional profiles of task functional imaging data based on subject-specific intrinsic functional networks (FNs). and the functional profiles are used as features to build brain decoding models using LSTM RNNs.

**SLIDE 14 – Framework**

**SLIDE 16- DATASET SPLIT**

RESTING STATE fMRI

* Patient not stimulated in this fMRI
* Study the functional connectivity of the brain

TASK BASED fMRI

* Patient is stimulated

What is the 0 backed and 2 backed that is written in the Task event section of the graph?

* A common paradigm to assess Working Memory is the called *n*-back task.
* In the *n*-back task subjects are given some stimuli.  
  For each stimulus, they should tell if it matches the stimulus *n* trials before.
* For example, in a 2-back task, in which the trials consist of letters, participants have to decide whether the current letter is the same as the letter in trial *n* – 2.
* It is a cognitive process for the working memory because you need to create a temporary storage of *n* of the stimulus in WM and add one word and remove the last nth word. It’s kind of like a mental queue.
* Eg. B C D A D B

**SLIDE 17 -** functional signature based on intrinsic functional networks

Using the FNs, 3D fMRI data could be represented by a low-dimension feature vector, which could

* ease the curse of dimensionality
* be generally applicable to different brain decoding tasks
* Provide better interpretability. Instead of identifying ROIs at a group level.
* The researchers apply a particular technique called collaborative sparse brain decomposition model to the resting-state fMRI data of all the subjects used for the brain decoding to identify subject-specific FNs.

**SLIDE 19 – LSTM**

**For** Pattern recognition for decoding brain states we use LSTM. In particular they have used the basic LSTM network we discussed above. That’s pretty much why I thought a detailed recap of LSTM would be useful.

Given the functional signatures Fi for I = 1 to n subjects, LSTM is built to predict the brain state of each time point based on its

* functional profile
* temporal dependency on its preceding time points.

The architecture of the LSTM RNNs is given above. including two hidden LSTM layers and one fully connected layer. Multiple hidden LSTM layers could be used to encode the functional information with temporal dependency for each time point, and the fully connected layer is used to learn a mapping between the learned feature representation and the brain states. The functional representation encoded in each LSTM layer is calculated as.

**SLIDE 20 – Equation what goes in and comes out…**

**SLIDE 23 – PREPROC STEPS**

The collaborative sparse brain decomposition model is applied to the resting-state fMRI data of 493 subjects for identifying 90 subject-specific FNs.

The number of FNs was determined automatically based on resting-state fMRI data using MELODIC’s LAP criteria.

The decomposition was performed using cortical surface data, which did not include white matter, ventricle, etc.

Therefore, we did not exclude any components in current study.

It is worth noting that the subject-specific FNs were identified based on resting-state fMRI data.

The subject-specific FNs were then used to extract functional signatures of task fMRI data for each subject, which were matrices of 405 by 90, 284 by 90, and 274 by 90 for characterizing working memory, motor, and social cognition tasks, respectively. The magnitude of functional signatures was normalized using z-score and then used as the input to the LSTM RNNs decoding model to predict theircorresponding brain states for each task separately.

**SLIDE 29 –**

To investigate the capability of LSTM based model for learning informative representations for decoding, we measured the association between the hidden cell states (from the second LSTM layer) of the trained LSTM model and different brain states on the WM dataset. As the states of the hidden LSTM cells contribute to the decoding together, we put the output of the hidden cells from the testing subjects into a 2D plane using t-SNE (Maaten and Hinton, 2008), and compared the embedding result with embeddings obtained based on functional profiles of single time points and time-windows.

SLIDE 35 – PCA drawing

Geometrically speaking, principal components represent the directions of the data that explain a **maximal amount of variance**,

It is pretty much the lines that capture most information of the data.

If the variance is larger the data is dispersed more widely.

Hence it has more information.

One way to put it is, think of PC as a new axis, that gives the best angle to see the data so that the difference between each observation is more visible.

**SLIDE 45 – Conclusion**

* we demonstrated that brain decoding models built on functional signatures of individualized FNs using LSTM RNNs better distinguished subtly distinct brain states based on task fMRI data than those built using Random Forest.
* To build interpretable brain decoding models
  + we extracted functional signatures of different brain states from task fMRI data for each subjects based on their FNs, and built a LSTM based brain decoding model on these data to extract their temporal dependencies and learn the mapping between functional signatures and their corresponding brain states.
* The decoding performance on the working memory, motor, and social cognition task fMRI data from the HCP demonstrated that the proposed brain decoding framework was capable of decoding brain states across different categories of tasks with improved performance.
* The computation of functional connectivity patterns requires to specify a time window with a certain length to reliably estimate the functional connectivity. However, it is nontrivial to determine a time window length that is optimal for different brain decoding tasks due to varying temporal durations and dependency among different cognitive processes.
* Although the proposed brain decoding method has achieved better performance than RF, further efforts are needed in following aspects. First, the brain decoding models were evaluated using block designed tasks, and can be evolved for event designed task fMRI to investigate how the temporal duration of brain states impact the decoding performance. Second, FNs at a single spatial scale were used to compute functional signatures for the brain decoding.