Observed object classification based on fMRI

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Outline:

- Introduction

    - fMRI and BigData:
    - fMRI and Classification:

- Description of Available Data:

    - fMRI Data (ROI, time steps)
    - Image Data as stimulus

- Description of Applied Problem:

- Main deep learning based approach

- Experiments and results

Conclusion and discussion

Introduction:

fMRI and Classification:

- Classification methods have achieved great success in extracting representations from fMRI pattern data

fMRI and BigData:

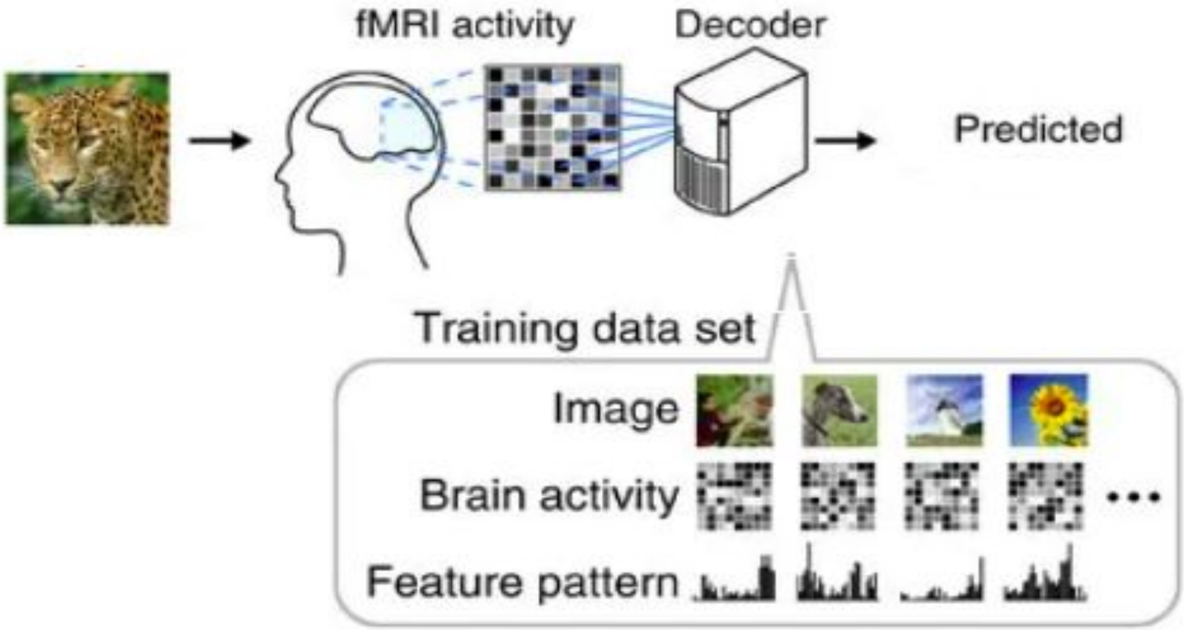
- The amount of neuroimaging data alone, discounting header information, **was increased average of 20GB per published research study.**

John Darrell Van Horn and Arthur W Toga. Human neuroimaging as a “big data” science. Brain imaging and behavior , 8(2):323–331, 2014

Description of Applied Problem:

- **A question**

How does the brain solve visual object recognition?



Description of Available Data (Images):

BOLD5000:

Images were drawn from three standard computer vision data sets:

1.Scenes

- 1,000 images
- outdoor (e.g., mountain scenes) and indoor (e.g., restaurant) scenes

2. COCO

- 2,000 images
- multiple objects,

3. ImageNet.

- 1,916 images
- The object is often centered and clearly distinguishable from the image background

Description of Available Data (fMRI):

Each participant performed a valence **judgment task**, responding with how much they liked the image using the metric:

- "like"
- "Neutral"
- "Dislike"

RoI: In Bold 5000 data set, 10 regions of interest (ROIs) are defined from the localizer:

- LH Early Vis, LH LOC, LH PPA, LH RSC, LH OPA, RH Early Vis, RH LOC, RH PPA, RH RSC and RH OPA .

Time Points: The data of the ROIs were extracted across the time course of the trial presentation:

- TR1 = 0-2s, TR2 = 2-4s, TR3 = 4-6s, TR4 = 6-8s and TR5 = 8-10s.

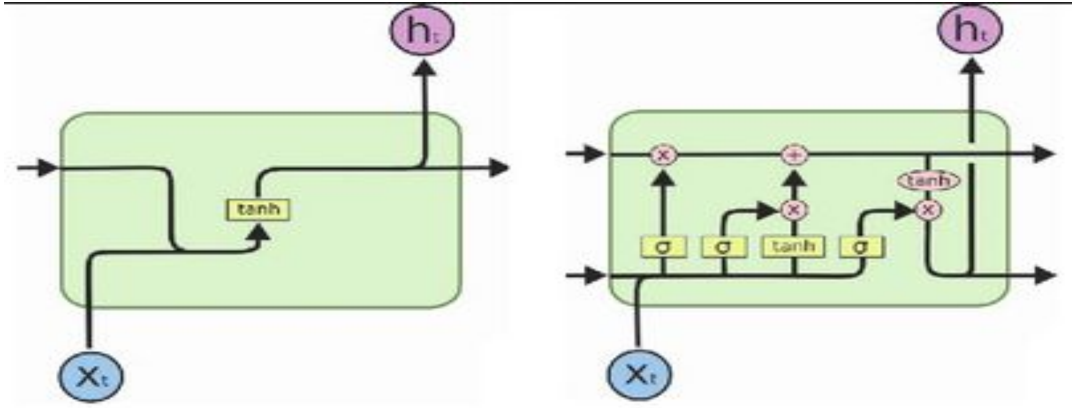
Main deep learning based approach 1:

- Classic methods of Machine learning ignore the temporal dynamics of fMRI data which accounts as the most important feature of fMRI data.

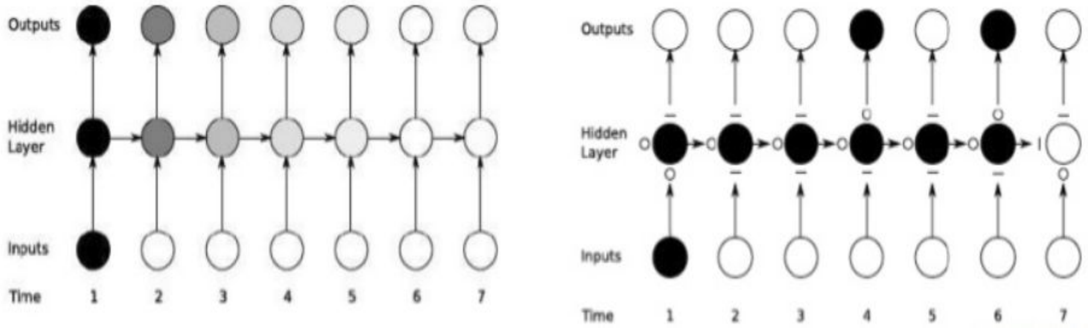
- For this purpose, we applied LSTM recurrent neural networks, which is more commonly used than simple recurrent neural network due to their capability of tracking long-term dynamics of fMRI time series data.

Main deep learning based approach 1:

RNN forgot the previous inputs (Vanish gradient)



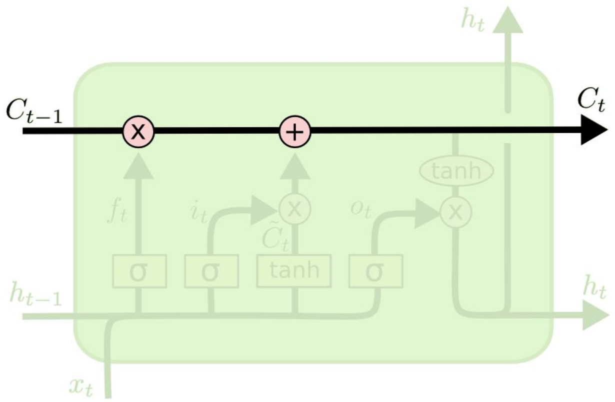
(a) RNN (b) LSTM



Main deep learning based approach 2:

The key to LSTMs is the cell state, the horizontal line running through the top of the diagram.

- The cell state is kind of like a conveyor belt.
- It runs straight down the entire chain, with only some minor linear interactions.
- It’s very easy for information to just flow along it unchanged.



Implementation 1:

The images in ImageNet dataset are labeled with ImageNet super categories. From 61 final WordNet categories, images are labeled as “Living Animate”, “Living Inanimate”, “Objects”, “Food”or “Geography”. An example of label mapping is “Dog” to “Living Animate” and “Vehicle” to “Objects”.

In our work, the proposed network includes:

- *Five LSTM layers*
- *One dense layer*
- *In LSTM layers we used tanh activation function.*
- *In the last dense layer to predict the probability of each class we used softmax activation function*
- *dropout rate is 0. 2 in all LSTM layers*

Stacked LSTM networks has been implemented using keras library (TensorFlow backend)

Environment properties:

- Cloud vm on Compute canada
- CentOS Linux release 7.6.181
- CPUs: GenuineIntel Speed(MHz): 2.6 GHz
- RAM: 15GB
- HDD: 220GB

Resource used and run time table:

subject	Data size	# of the experiments	# of the features	Memory used (MB)	Processing time	Training times
1	425 MB	1916	1685	2034	14.19	210.20
2	573 MB	1916	2270	2315	15.54	305.29
3	783 MB	1916	3104	2785	18.07	253.41
4	416 MB	1122	2787	2129MB	9.25	173.68

Results of the subject 1

Correctness metrics

index	Precisi on	Recall	F1_scor e	Support
0	0.33	0.10	0.15	20
1	0	0	0	5
2	0.74	0.70	0.72	142
3	0	0	0	3
4	0.74	0.84	0.79	214

Confusion matrix

2	0	4	0	14
0	0	0	0	5
1	0	100	1	40
0	0	0	0	3
3	0	31	1	179

Results of the Subject 2

Correctness metrics

index	Precision	Recall	F1_score	Support
0	0	0	0	20
1	0	0	0	8
2	0.75	0.70	0.72	165
3	0	0	0	4
4	0.67	0.80	0.73	187

Confusion matrix

0	0	2	0	18
1	0	1	0	6
1	0	115	0	49
1	0	1	0	2
3	0	35	0	149

Results of the Subject 3

Correctness metrics

index	Precision	Recall	F1_score	Support
0	0.11	0.05	0.07	19
1	0	0	0	2
2	0.66	0.63	0.65	154
3	0	0	0	1
4	0.70	0.76	0.73	208

Confusion matrix

1	0	7	1	10
0	0	0	0	2
0	0	97	1	56
0	0	1	0	0
8	0	41	1	158

Results of the Subject 4

Correctness metrics

index	Precision	Recall	F1_score	Support
0	0.25	0.29	0.27	14
1	0.00	0.00	0.00	2
2	0.75	0.72	0.74	87
3	0.00	0.00	0.00	5
4	0.73	0.77	0.75	117

Confusion matrix

4	1	2	0	7
0	0	0	0	2
3	0	63	0	21
0	0	1	0	4
9	0	18	0	90

Conclusion and future work

Conclusion: Based on these experiments using following feature vectors:

- Using 30 of the best features based on PCA
- Combination of the T3 and T4

We can conclude that :more features does not mean higher accuracy. If we pre-process data efficiently, we can get higher accuracy when using less resources.

Future work: If we want to have more efficient classifier based on LSTM, we need to apply our model on:

- The data set with more time steps
- Apply on video data instead of image

Because temporal dynamics of fMRI data accounts the most important feature of fMRI data.

Thank YOU :)