Location Location Location

Why electrode density matters

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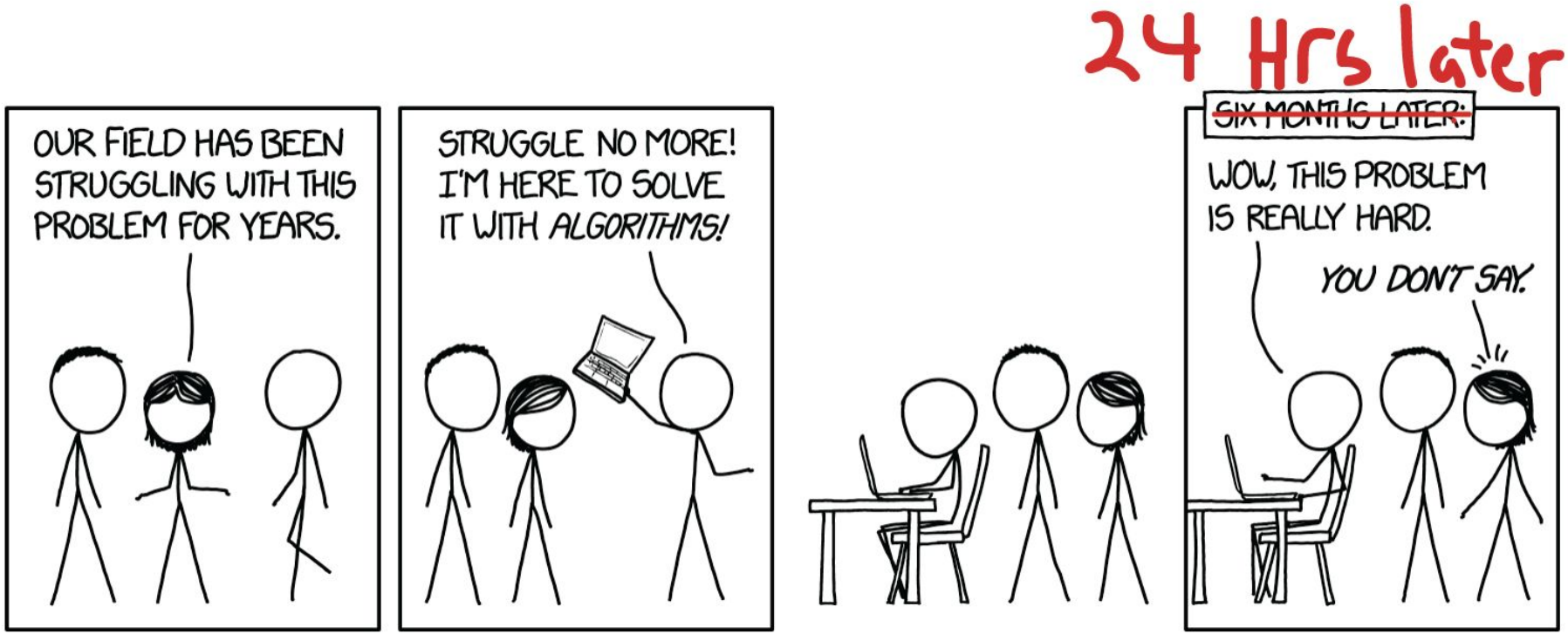
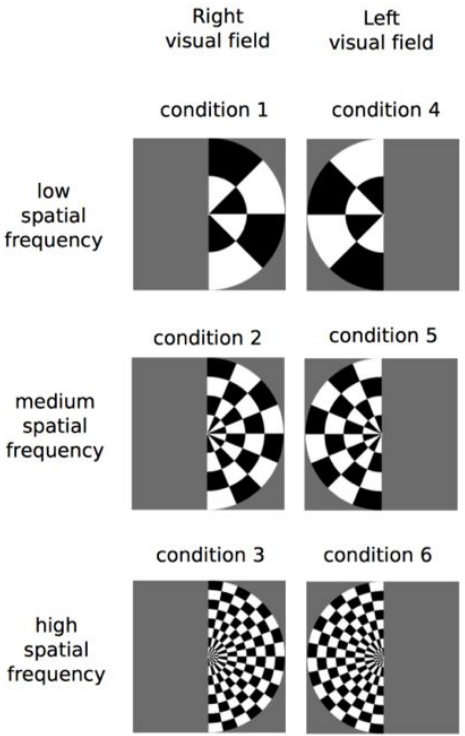
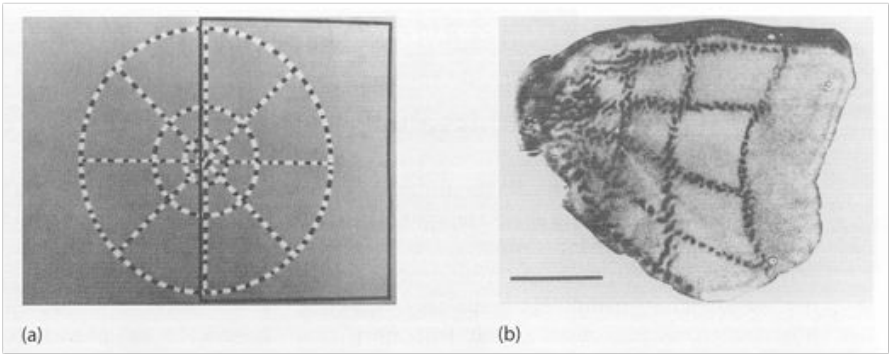

OUR FIELD HAS BEEN STRUGGLING WITH THIS PROBLEM FOR YEARS.
STRUGGLE NO MORE! I'M HERE TO SOLVE IT WITH ALGORITHMS!
24 Hrs later
SIX MONTHS LATER:
WOW, THIS PROBLEM IS REALLY HARD.
YOU DON'T SAY.

Reminder of background



How does brain respond to visual stimuli?

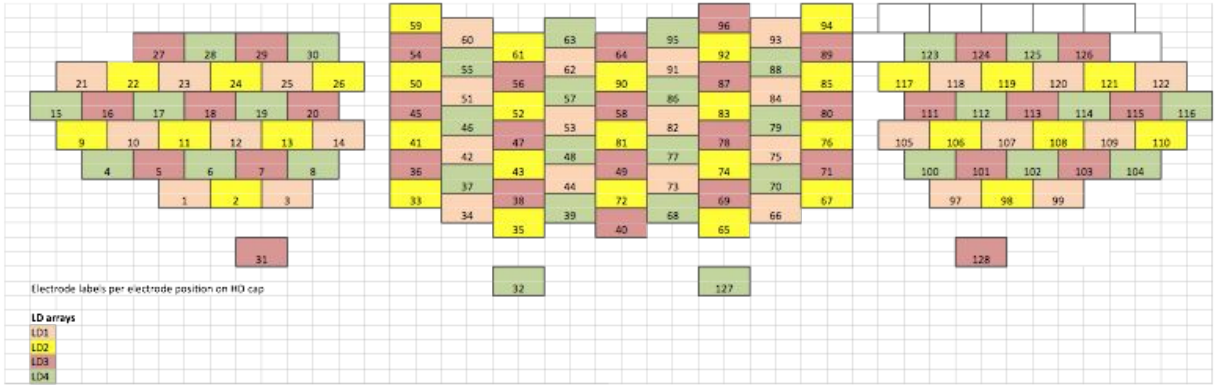


Stimulus

Generated pattern in primary visual cortex

[Tootell et al, 1982]

Description of Data



HD grid contains all 128 electrodes
LD grids contain 32 electrodes each

Data fundamentals:

Matrix size 128 x 307 x 480 (for each of 16 subjects)

- 128 electrodes, 307 time instants per trial, and 480 trials in all
- Data sampled at 256 Hz. 307 time instants = 1200 msec.
- First 200 msec *before* stimulus presentation, 1000 msec after
- 480 trials are separated into six classes (80 trials/class)

Research question

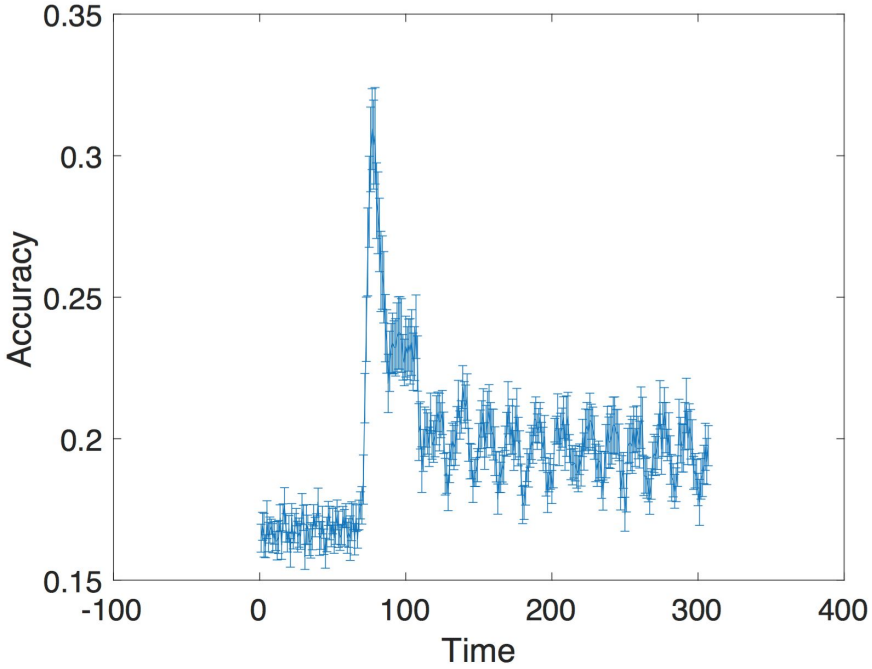
Is there more information in higher density electrodes?

if so, where and how is it spatially localized?

Approach

1. First replicate existing results with linear classification, then apply feature selection.
2. Try to do better with SVM
3. Examine spatial information (adopting techniques from fMRI and using selective feature selection)
4. Implement CNN (taking into account spatial information)

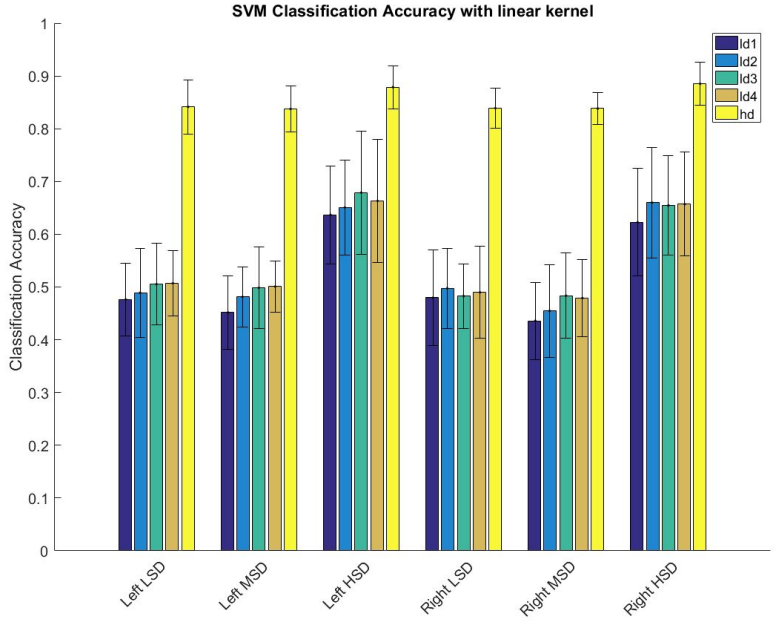
First approach: Linear Classifier (10 fold cross validation)



High Density array only for sanity checking

Relationship between accuracy and time consistent with expectation.

Second approach: SVM



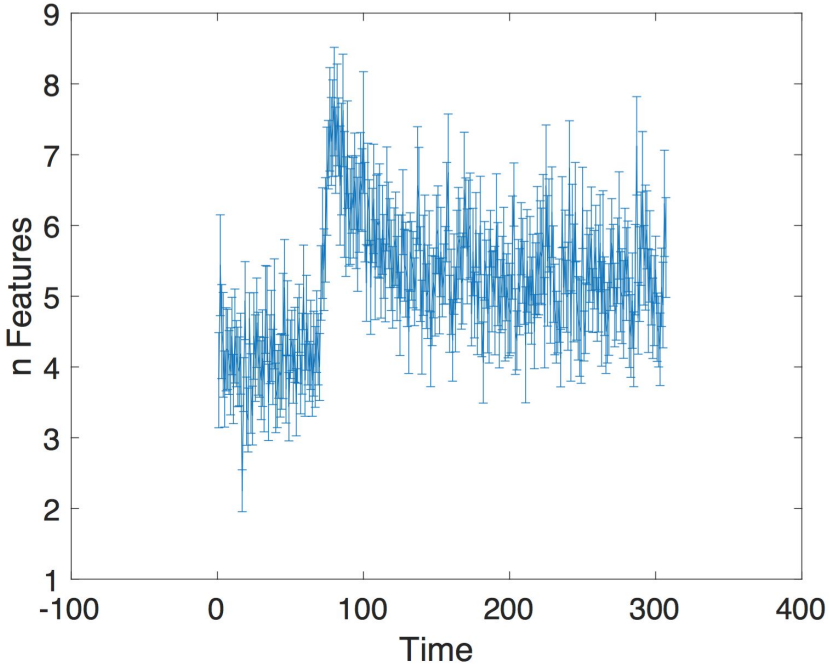
It is better

-> Accuracies significantly better than LDA particular for HD

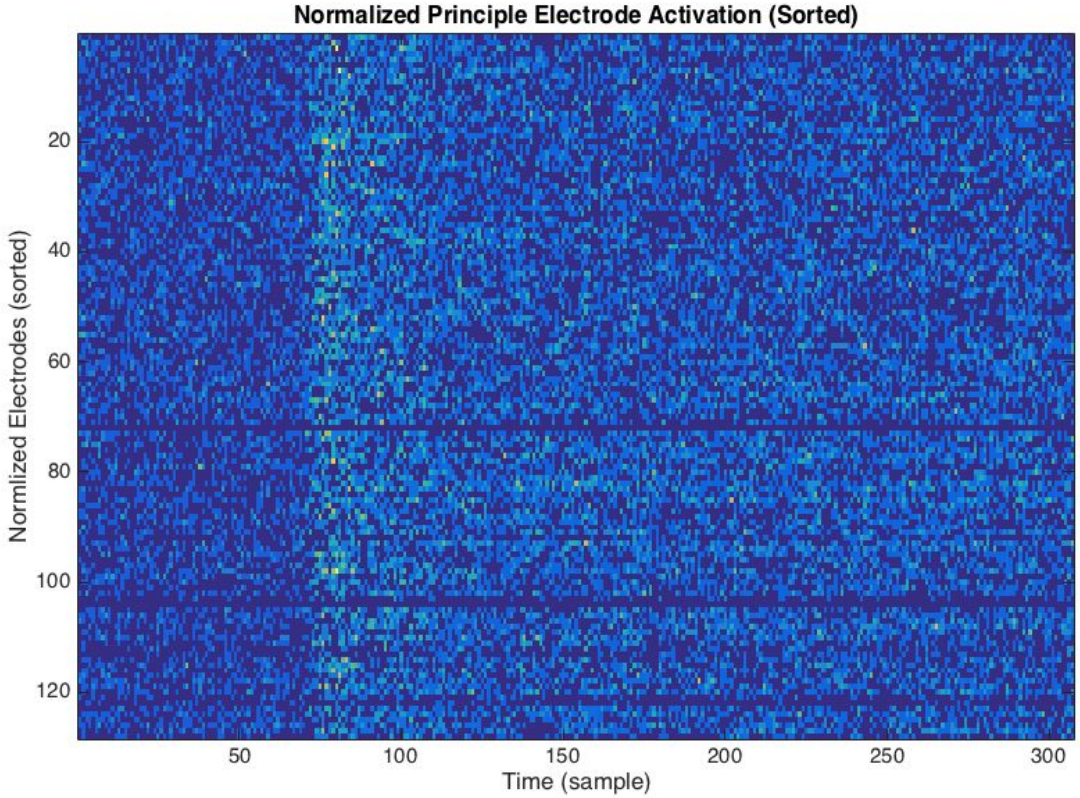
-> Consistent with increase in information of High density array compared to Low density

-> But appears to be heavily consistent

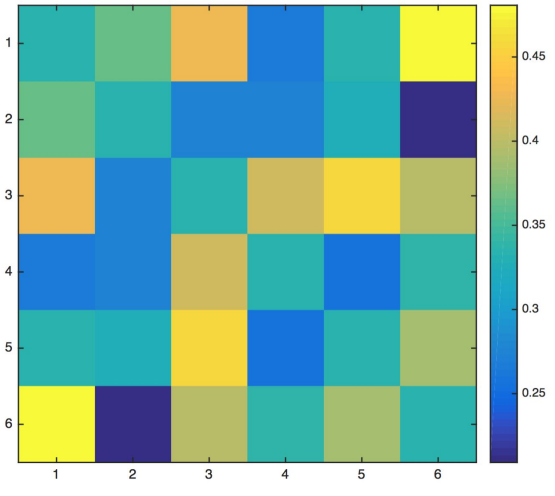
Accuracy depends on only a few features (for linear)

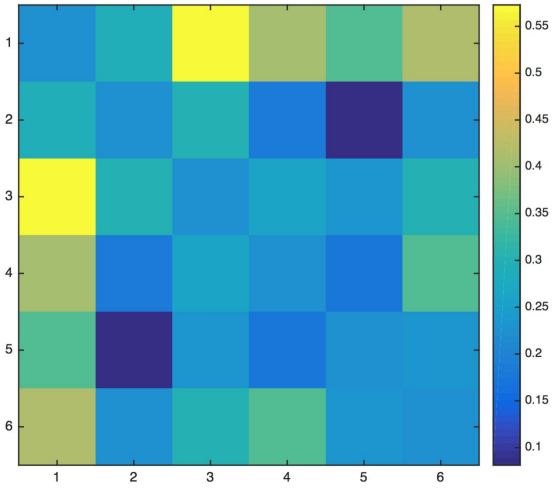


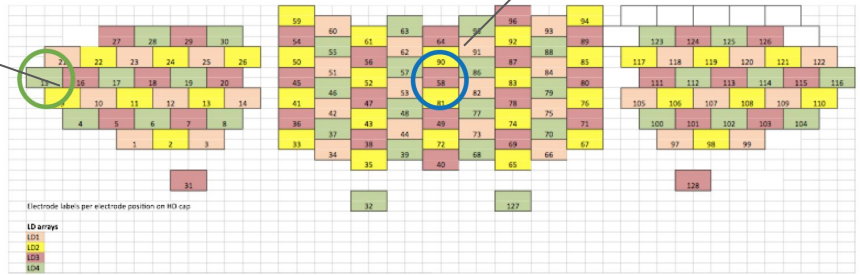
Feature selection shows some spatial information



Representational Similarity analysis

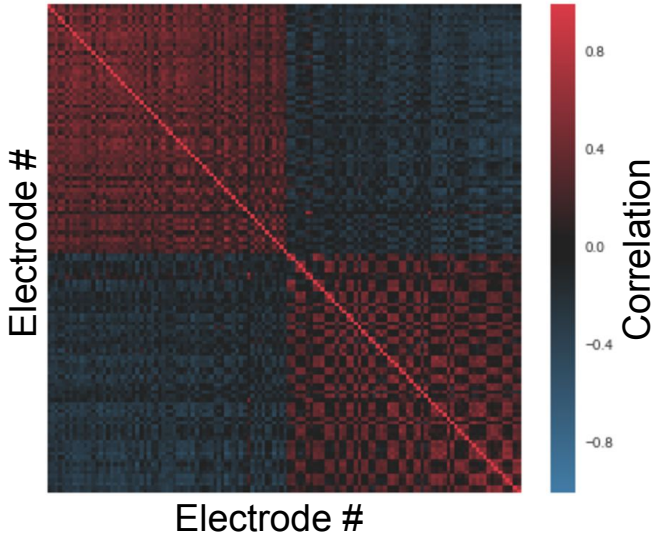


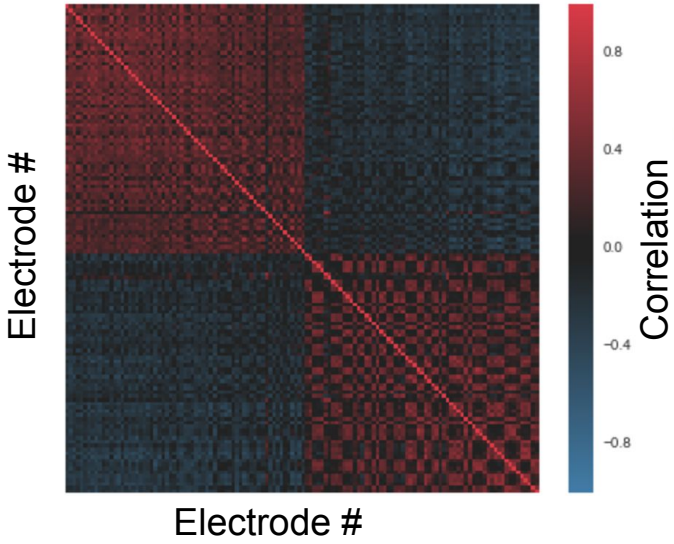


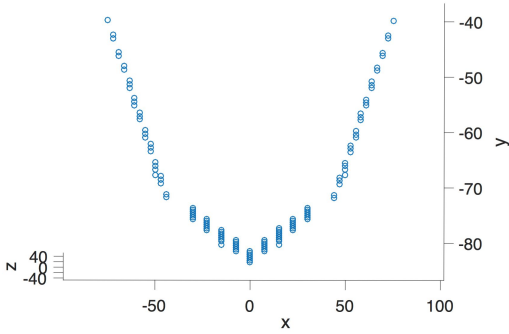


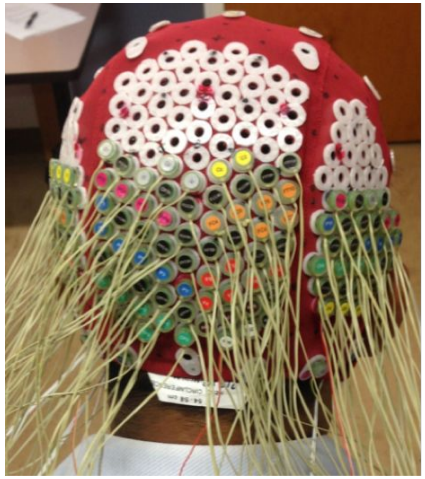
shows structures are consistent both directly at fovea and more anterior

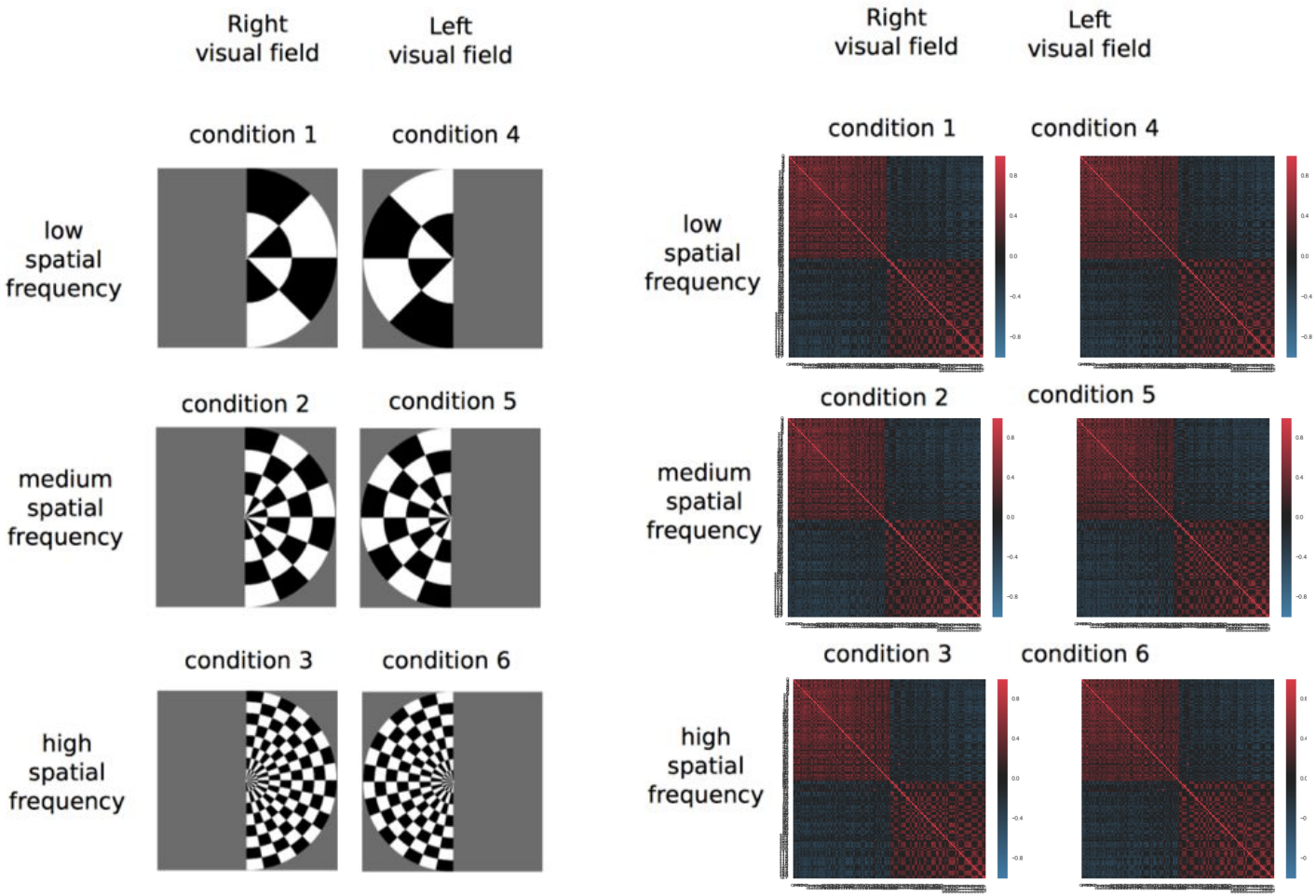
Correlation Matrices also show spatial featuring











Major spatial separation between regions (Big red versus Big blue squares)

CNNs for classification

- Used CNNs to preserve the spatial information (placement of electrodes on head)
- Converted the EEG recordings from the electrodes into images (7*9 array resized to 35*45 array)
- Experimented with two different settings:
  - Full time series data
  - Data from 80ms to 140ms
- Splitted the 480 trials into 330 (training data) and 150 (testing data) trials
- Compared the classification accuracies for High Density (HD) and Low Density (LD) grid

Why didn’t it work?

- Limited data
  - High accuracy during very short period of time
  - Low number of trials
  - Bad electrodes

- Not enough variability in the inter and intra classes EEG recording images
  - Not enough resolution to differentiate between inter class images
  - Intra class images also similar (recorded from the same stimulus image)

Convolutional Neural Network Approach

S.No	Architecture	Accuracy (HD and LD)
1	Convolution(16,(2,2)) ->Activation(sigmoid) -> Flatten -> Dense(6 class) -> Activation(Softmax); Objective function - SGD	~16%
2	Convolution(16,(2,2)) -> Activation(sigmoid) -> Convolution(16,(2,2)) -> Activation(sigmoid) -> Flatten -> Dense(6 class) -> Activation(Softmax); Objective function - SGD	~16%
3	Convolution(16,(2,2)) -> Activation(sigmoid) - > Max pooling (2,2) -> Convolution(16,(2,2)) -> Activation(sigmoid) -> Flatten -> Dense(6 class) -> Activation(Softmax); Objective function - SGD	~16%

S.No	Architecture	Accuracy (HD and LD)
4	Convolution(16,(2,2)) -> Activation(sigmoid) - > Max pooling (2,2) -> Convolution(16,(2,2)) -> Activation(sigmoid) - > Max pooling (2,2) -> Flatten -> Dense(6 class) -> Activation(Softmax); Objective function - SGD	~17%
5	Convolution(16,(2,2)) -> Activation(relu) - > Max pooling (2,2) -> Convolution(16,(2,2)) -> Activation(relu) - > Max pooling (2,2) -> Flatten -> Dense(6 class) -> Activation(Softmax); Objective function - Adam	~16%
6	Convolution(16,(2,2)) -> Activation(relu) - > Max pooling (2,2) -> Convolution(16,(2,2)) -> Activation(relu) - > Max pooling (2,2) -> Flatten -> Dense(20)->Dense(6 class) -> Activation(Softmax) Objective function - Adam	~18%

Conclusion

-> Hyperparameter tuning adding spatial information may increase accuracies further

-> Data is consistent with HD carrying increased information, and less consistent with LD carrying equal information.

-> It appears that neural data is unfortunately (still) complicated

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