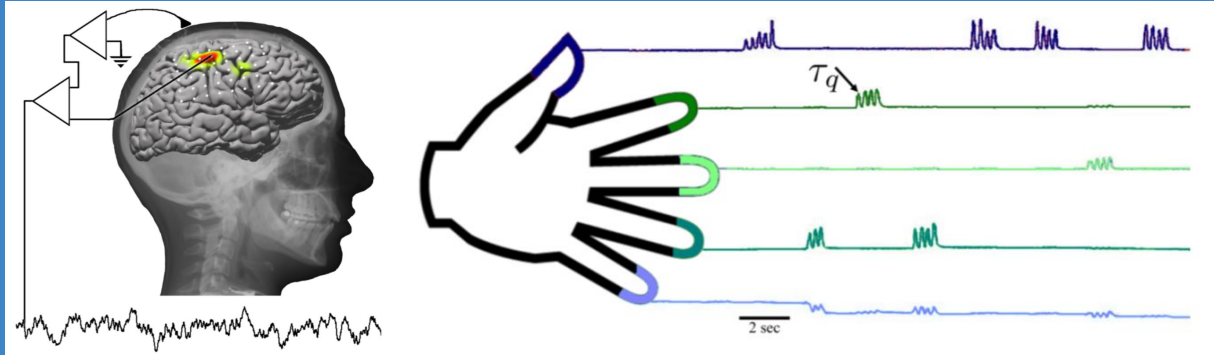


Decoding Finger Movements from Brain Waves

Irving Campbell

Project purpose:

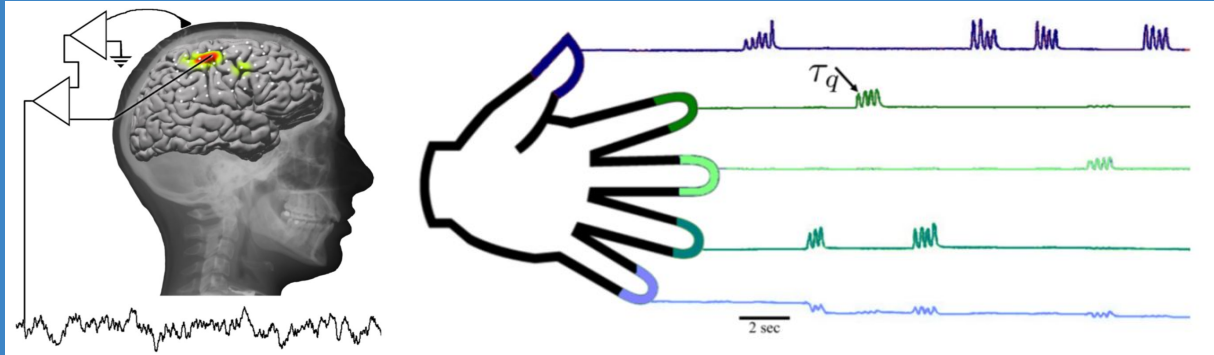
Can you determine which
finger a person is moving
based ONLY on their brain
waves?

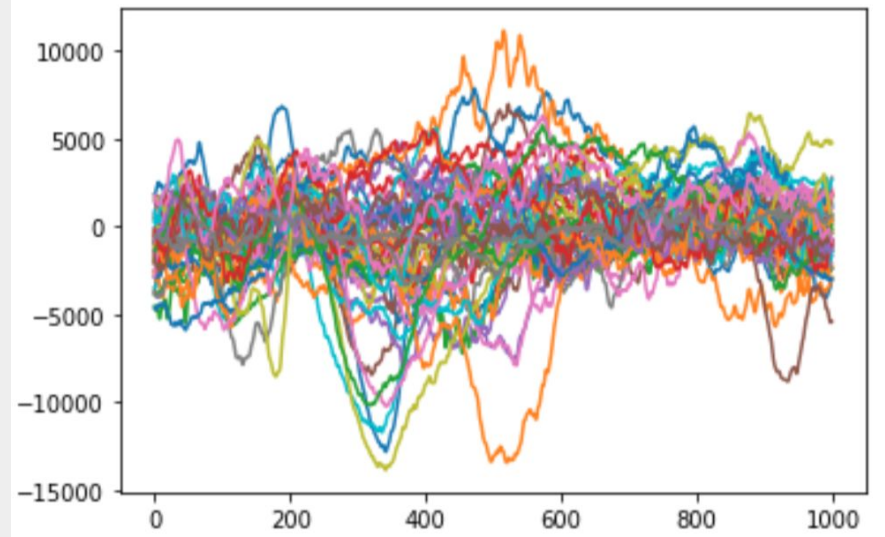


Project purpose:

Can you determine which finger a person is moving based **ONLY** on their brain waves?

Note: This is NOT an easy problem to solve.

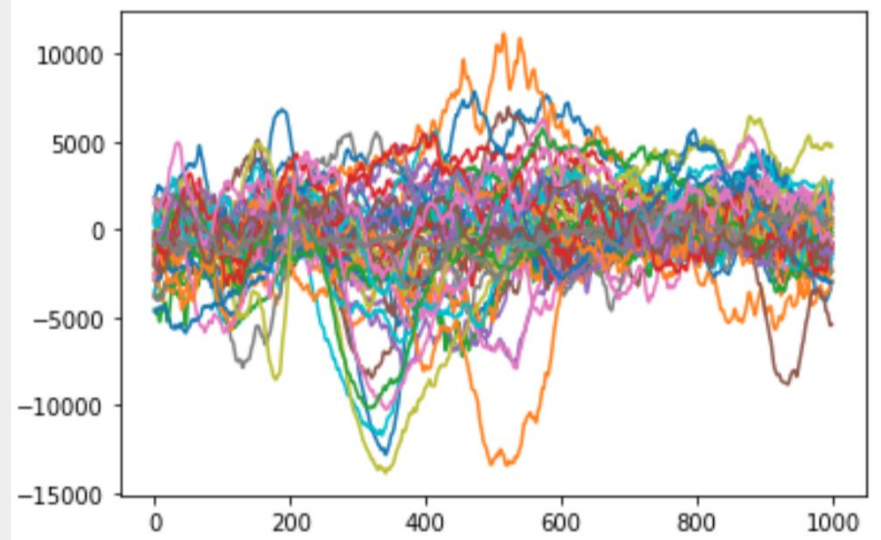




Only ONE SECOND of brainwave activity!

List of noise artifacts

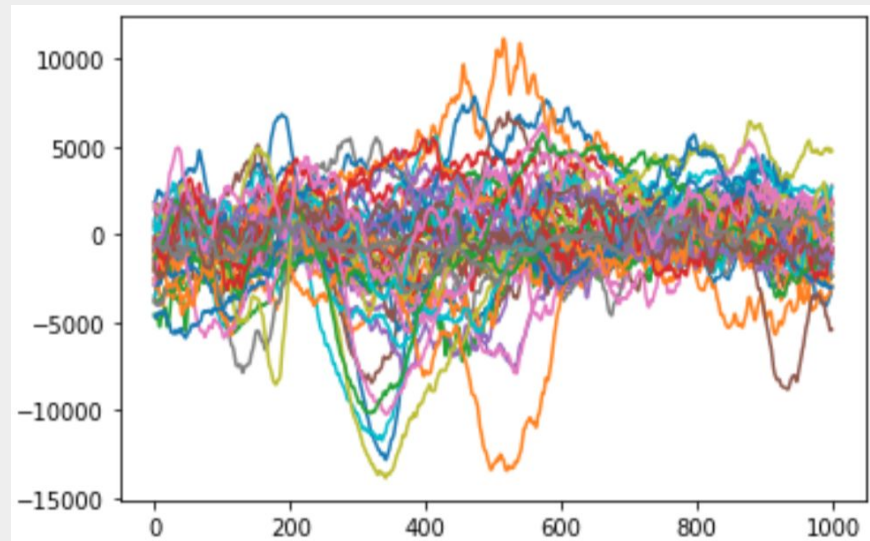
- Cable movement
- Interference from electronics



Only ONE SECOND of brainwave activity!

List of noise artifacts

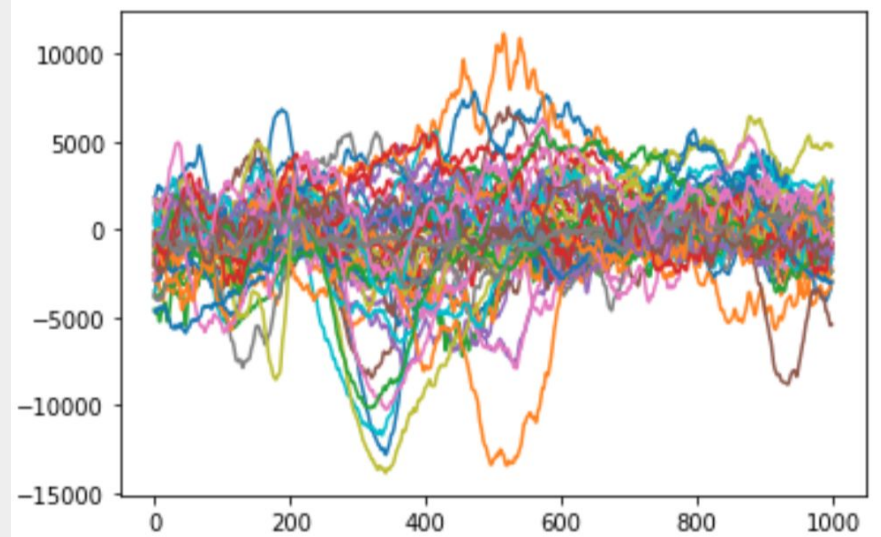
- Cable movement
- Interference from electronics
- Heartbeat
- Blinking
- Sneezing
- Coughing
- Grinding teeth
- Laughing
- Talking



Only ONE SECOND of brainwave activity!

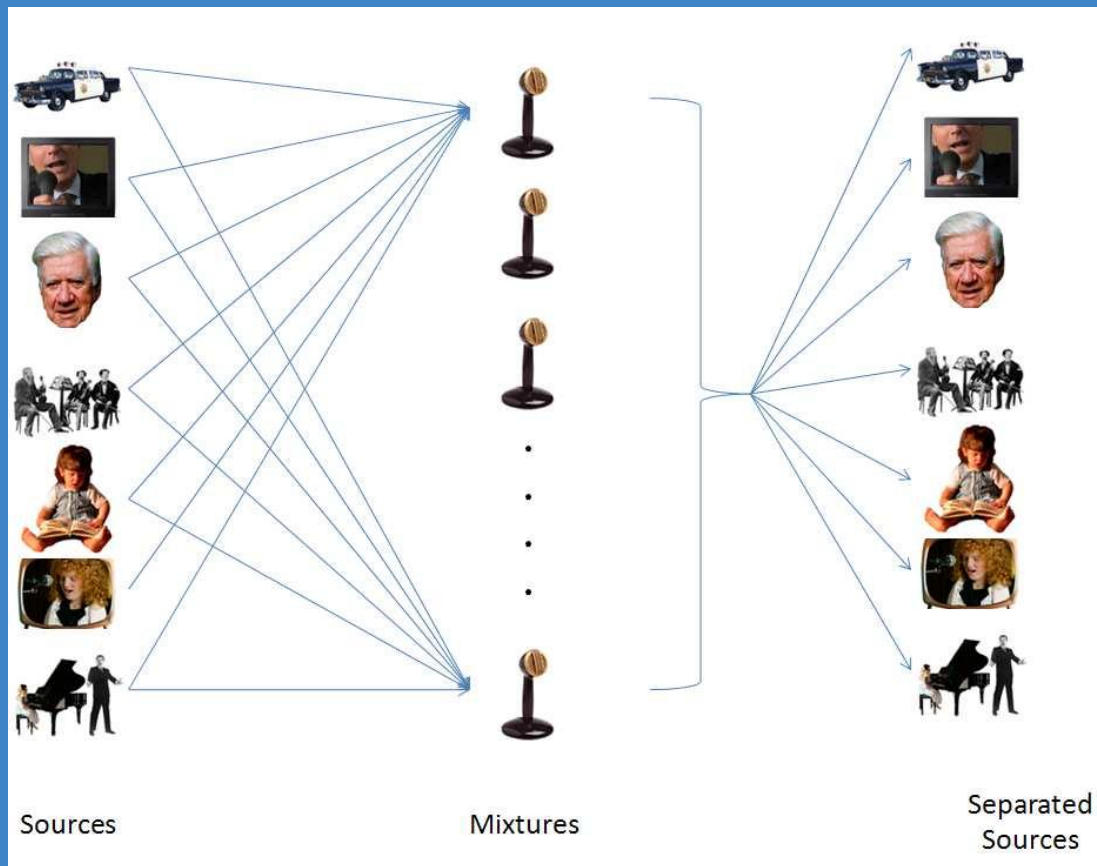
List of noise artifacts

- Cable movement
- Interference from electronics
- Heartbeat
- Blinking
- Sneezing
- Coughing
- Grinding teeth
- Laughing
- Talking
- Moving in your seat
- Doing mental arithmetic
- Exhaustion/sleepiness
- Thinking about lunch
- Remembering you left your lunch at home
- Being upset because the Capitals lost
- Being upset because the Capitals won
- Being upset just because...

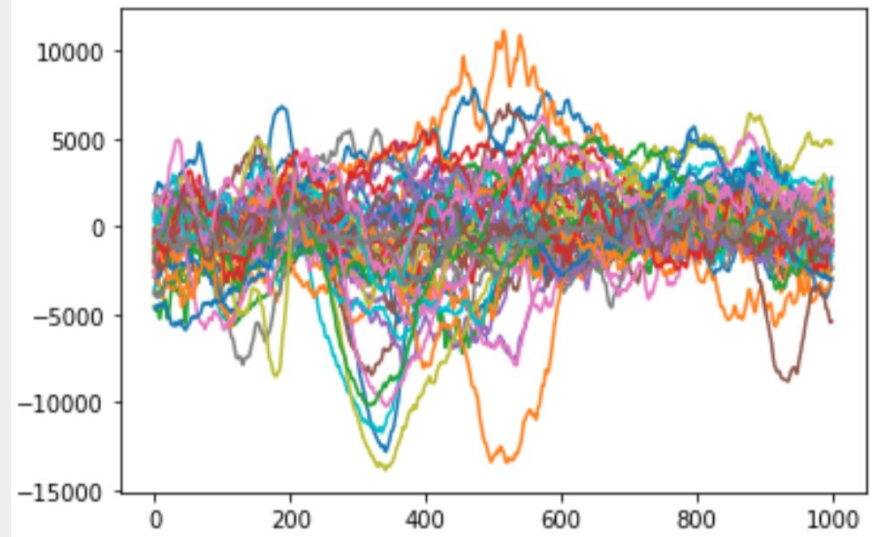


Only ONE SECOND of brainwave activity!

The Cocktail Party Problem



So, how DO we solve it?



Only ONE SECOND of brainwave activity!

So, how DO we solve it?

1. “Amplify” the signal

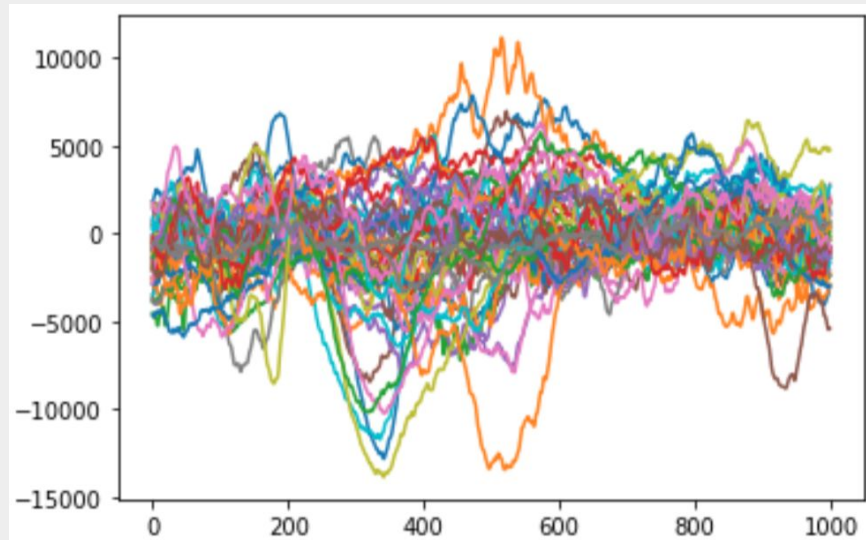
- **More robust measurement methods give “louder” results**

2. “Clean” the signal

- Getting rid of artifacts, i.e. unwanted noise

3. LOTS of calculation

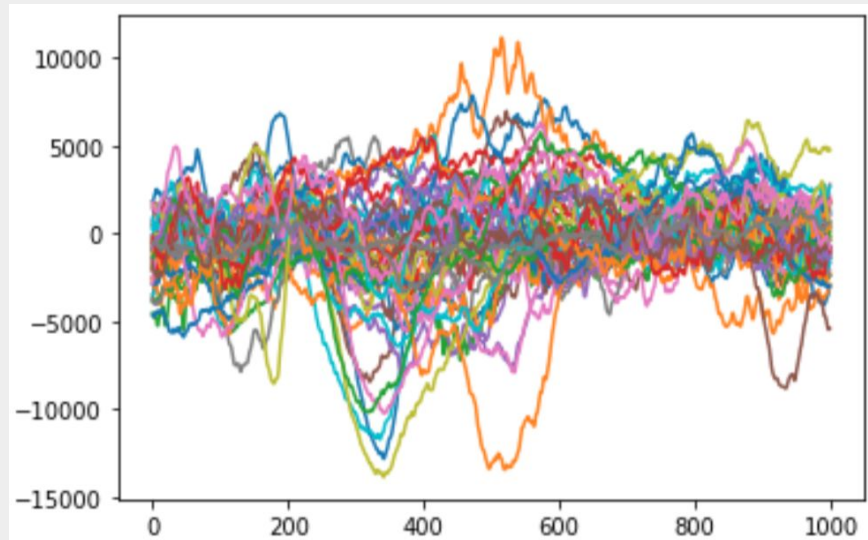
- Training a machine learning algorithm takes a lot of calculation...and so does cleaning



Only ONE SECOND of brainwave activity!

So, how DO we solve it?

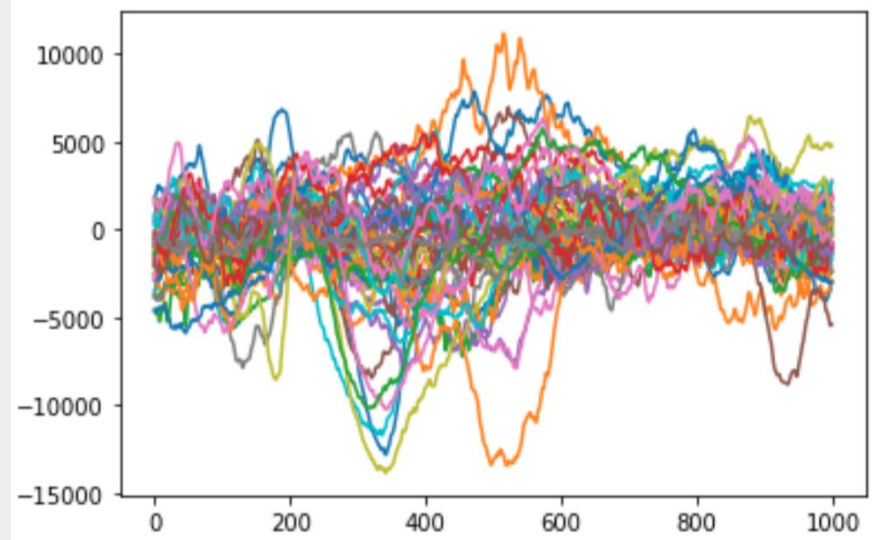
1. “Amplify” the signal
 - More robust measurement methods give “louder” results
2. “Clean” the signal
 - **Getting rid of artifacts, i.e. unwanted noise**
3. LOTS of calculation
 - Training a machine learning algorithm takes a lot of calculation...and so does cleaning



Only ONE SECOND of brainwave activity!

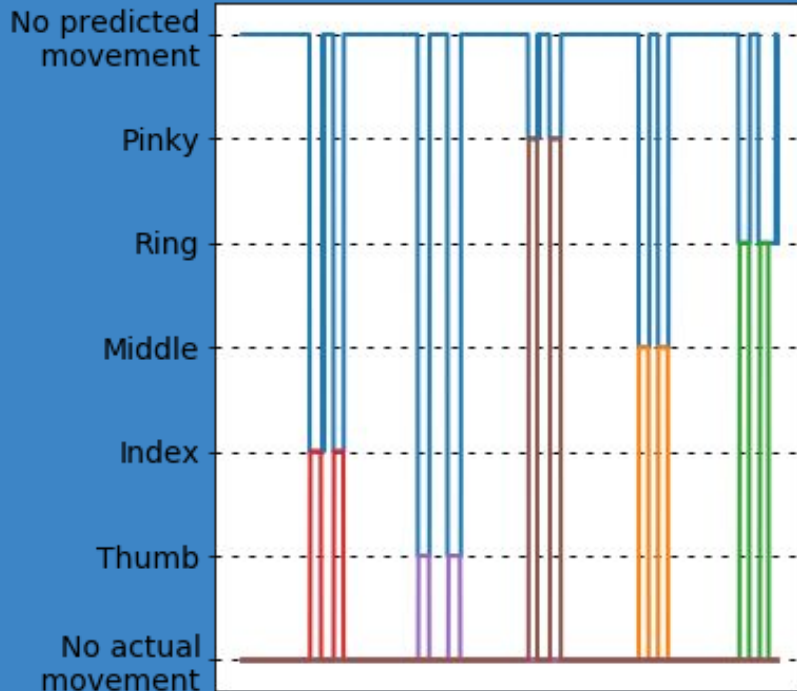
So, how DO we solve it?

1. “Amplify” the signal
 - More robust measurement methods give “louder” results
2. “Clean” the signal
 - Getting rid of artifacts, i.e. unwanted noise
3. **LOTS of calculation**
 - **Training a machine learning algorithm takes a lot of calculation...and so does cleaning**



Only ONE SECOND of brainwave activity!

Training Results:



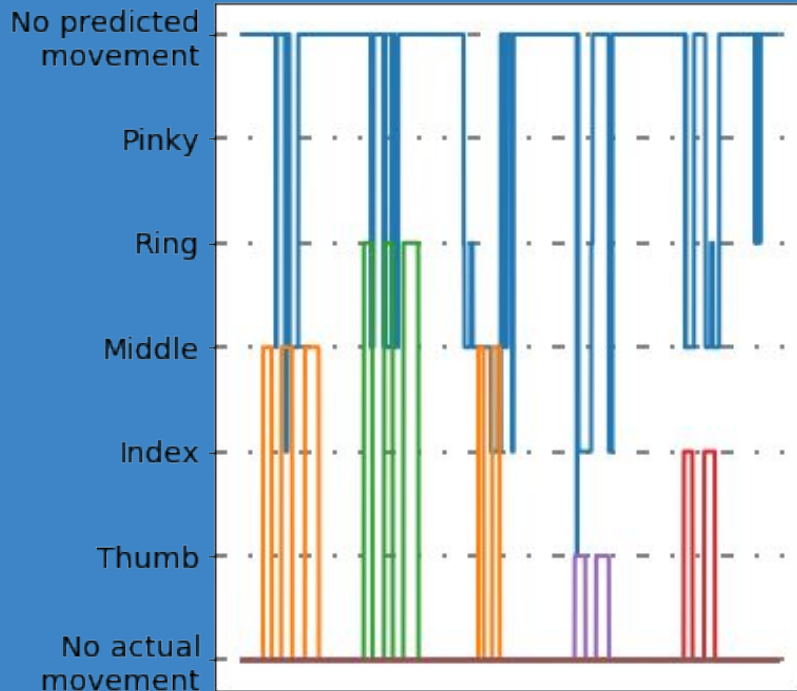
Blue represents the predicted finger while the other colors represent the actual finger.

As you can see, the algorithm correctly predicts almost all the time.

BUT...this is the result of training. We gave the algorithm the correct answers here so it could make good guesses when new data was entered.

The testing results are more informative...

Testing Results:



Again, blue represents the predicted finger while the other colors represent the actual finger.

The results here are nowhere near as accurate as before, but there is clearly a trend.

The algorithm guesses fingers correctly some of the time. It also recognizes non-movement very well.

While not perfect, this is promising.

Main takeaways:

Due to biological, mathematical and measurement issues, there is a lot of noise in this process, and that noise adversely affects the accuracy of the results.

Still, the algorithm itself is well on its way towards predicting correctly and, with further work, could function better as a classifier.

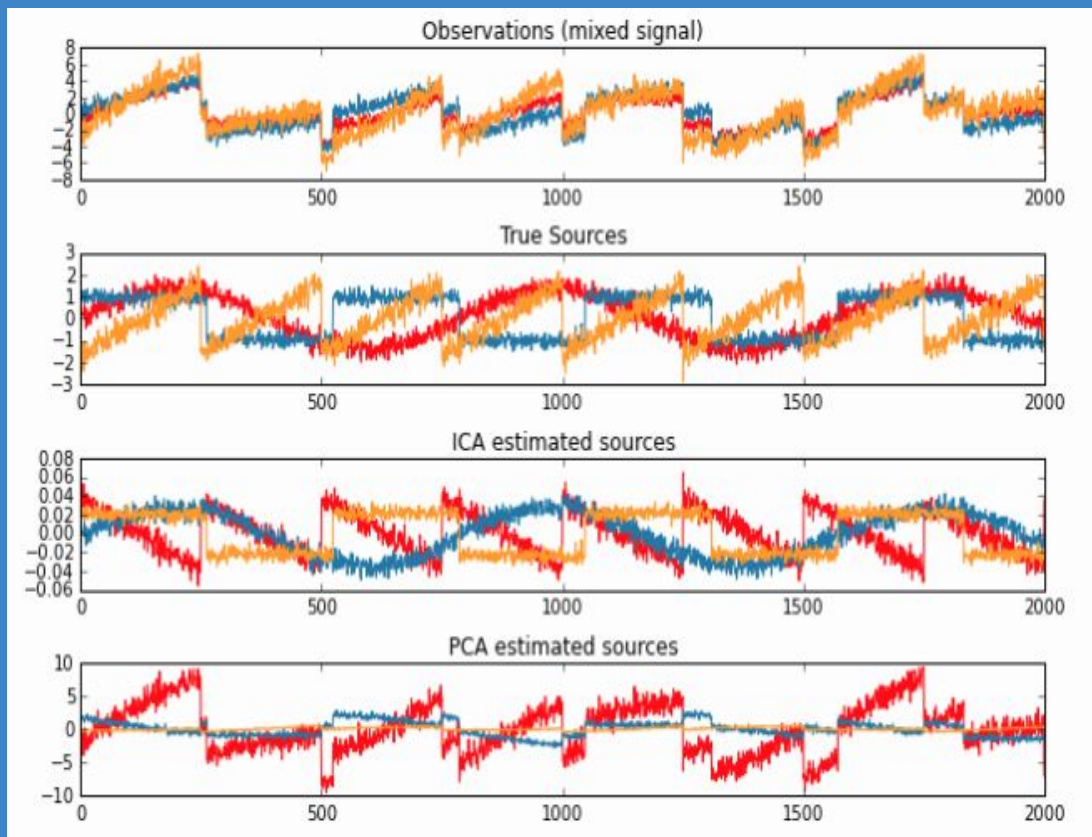
Future work:

- Further processing of the data before inputting it into the machine learning model to increase the accuracy of the results
- Create an ensemble method that, once the correct finger has been identified, can predict where that finger is in space



Thank you!

Appendix: Throwing a Cocktail



There are different algorithms to deal with the cocktail party problem. I chose ICA.

Another popular choice is PCA which picks a waveform that “best describes” as much of the data as possible, then finds other waveforms that best describe the remaining error.

ICA finds statistically independent waveforms instead, so it can sometimes better represent the original sources.

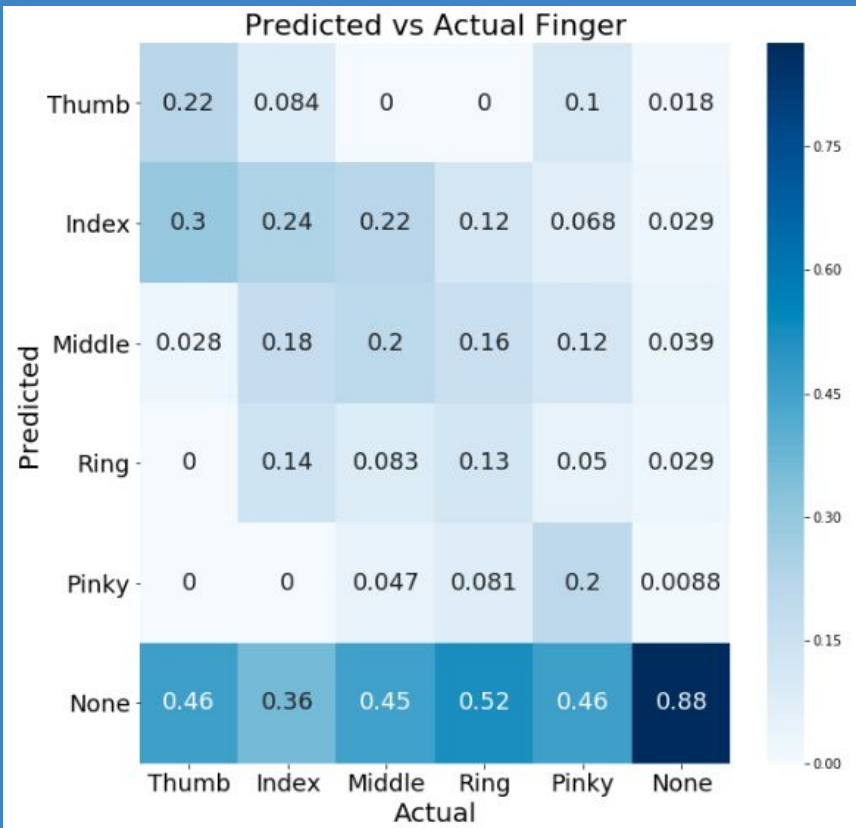
Appendix: More detailed results

	precision	recall	f1-score	support
0	0.29	0.22	0.25	4440
1	0.12	0.24	0.16	3640
2	0.20	0.20	0.20	6880
3	0.13	0.13	0.13	4880
4	0.28	0.20	0.24	3080
5	0.89	0.88	0.88	96930
accuracy			0.75	119850
macro avg	0.32	0.31	0.31	119850
weighted avg	0.76	0.75	0.75	119850

Total accuracy driven by identification of non-movement states. These non-movement states dominate the individual finger movements by 15-30:1.

This explains the difference between the “macro avg” and the “weighted avg” calculations.

Appendix: More detailed results



Each square designates a predicted finger movement versus an actual finger movement.

The darker the square, the more often that pairing occurred.

The squares along the main diagonal - from the upper left to the lower right - represents correct predictions.

Clearly, the model overpredicts no finger movement. But outside of that, you can see that the main diagonal is a bit darker than the surrounding squares. This is a positive trend.