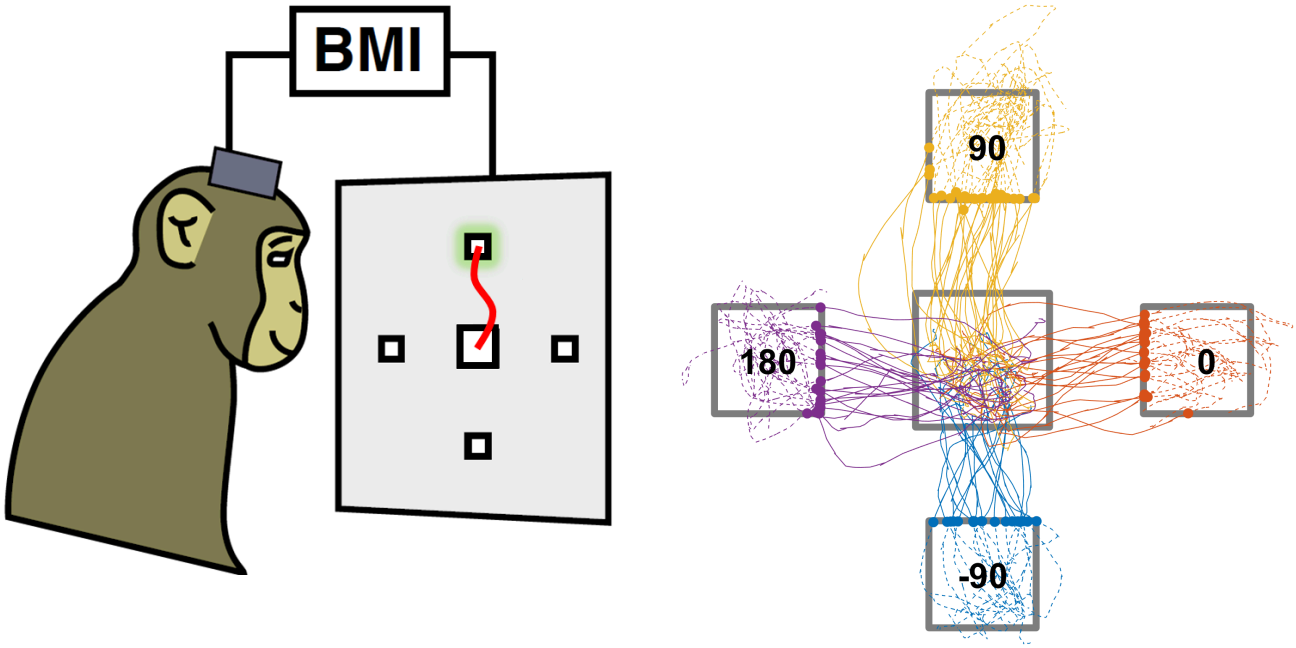
Neuroscience Demo

Description and Interpretation



Source: T. G. Kolda, Monkey BMI Tensor Dataset, GitLab, 2021.

In this experiment, the test subject (Monkey) is connected to a Brain-Machine Interface that measures neural activity during its assigned task of moving the cursor to one of four possible targets. Each target is identified with its position in degrees on the envisioned circle: 0, 90, 180, and -90. The electrodes within the BMI capture the neural impulses and electrical signals sent through the acquisition of a target until the monkey picks a target and holds the signal for 500ms (dashed lines). These two halves of the experiment correspond to the first and second 100 time steps in the data. The overall goal of this research is to gain insight into which regions within the motor cortex are more predominantly engaged in order to further understand the functionality of association areas. Ultimately, this could lead to developing BMIs and devices to aid those with motor impairments.

With this dataset, we are analyzing a 43x200x88 high-dimensional tensor that contains the numbered neuron, time steps, and the numbered trial respectively. Our goal is to be able to represent this data in lower dimensions and break it down in order to reveal patterns that we

otherwise would not have recognized. We will do this through data visualization: first of the whole high-ordered tensor, then implementing GCP decomposition to finish it out.

Load and Download data

```
download (generic function with 1 method)
```

```
file =
  Dict("angle_list" ⇒ 4×1 Matrix{Int64}:, "X" ⇒ 43×200×88 Array{Float64, 3}:
                       -90                      [:, :, 1] =
```

```
1 file = download()
```

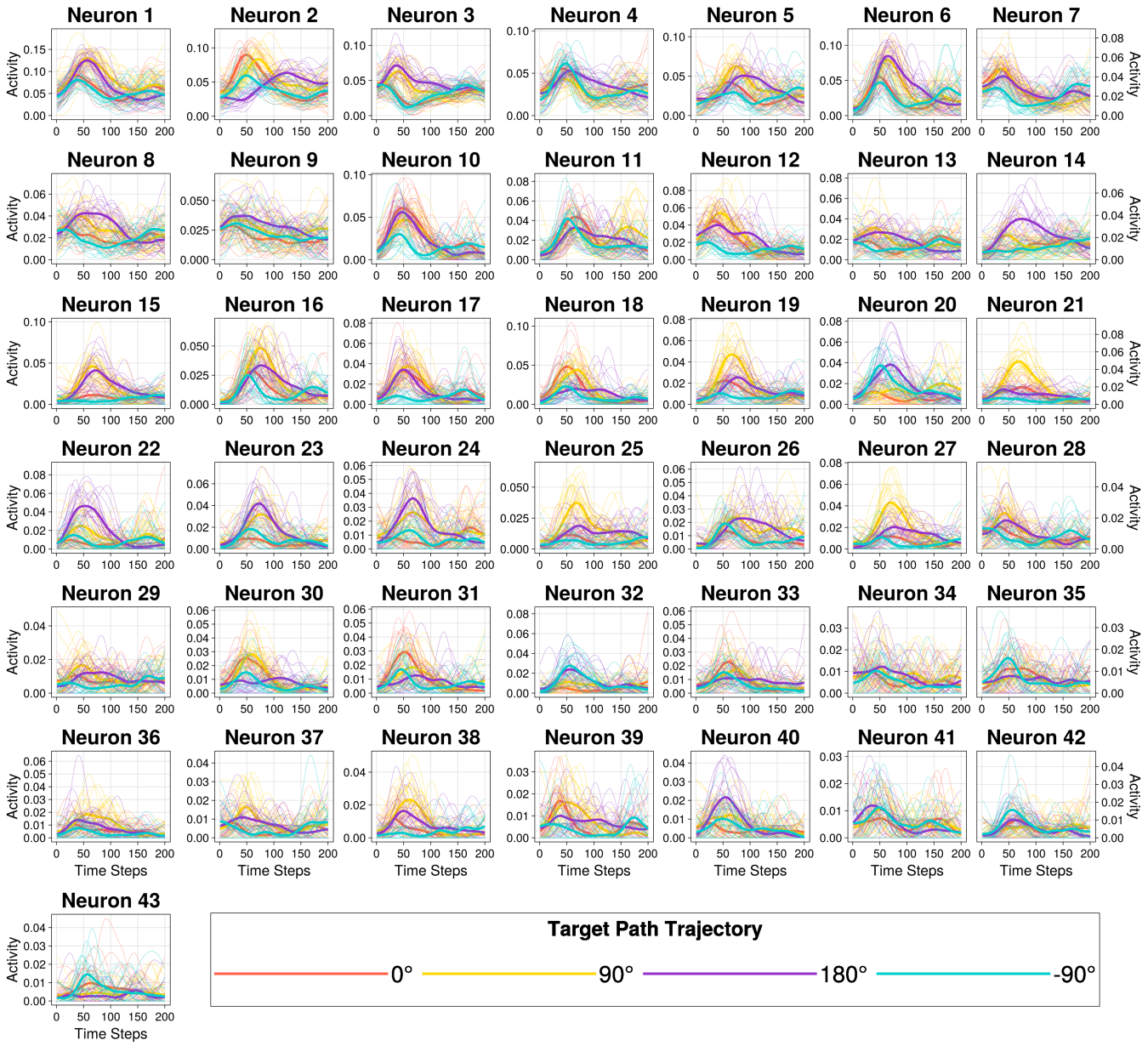
```
1 X = file["X"];
```

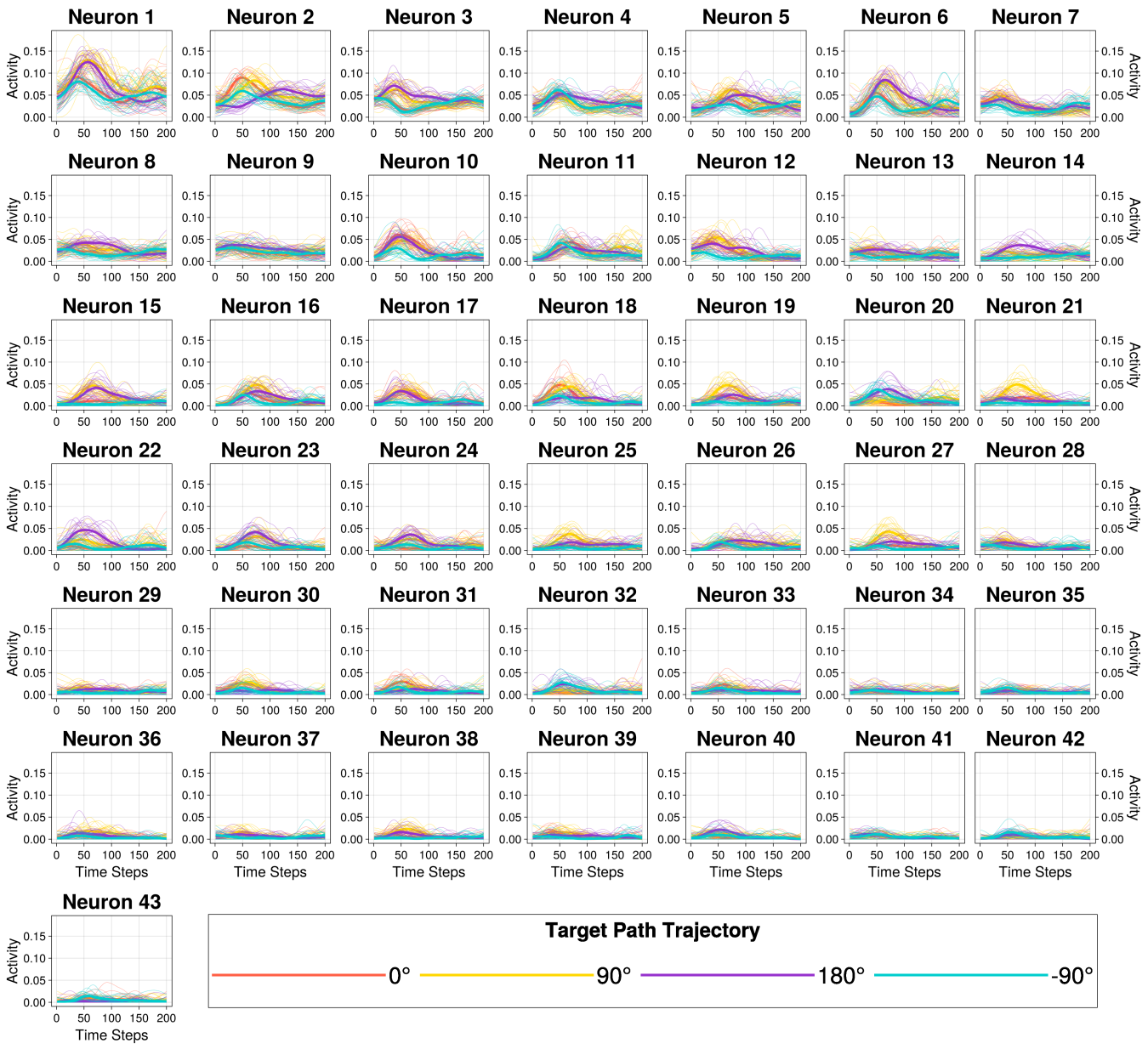
```
1 angle = vec(file["angle"]);
```

Data Visualization

relative versus same scaling

Neural Activity

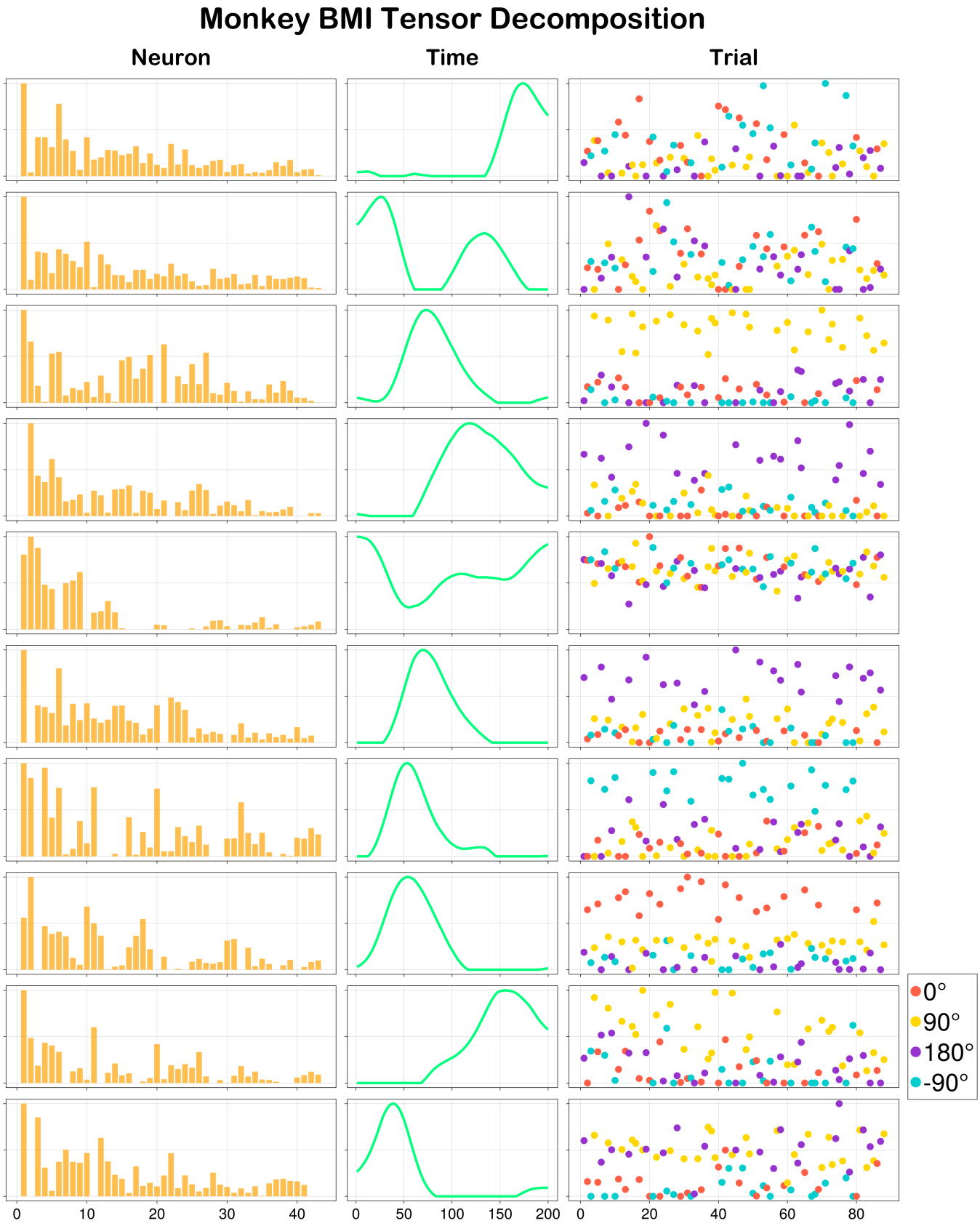




We notice that neural activity dwindles as the numbered neuron increases as well as the acquisition of the target (first 100 steps) takes more neural activity than holding the cursor on the target. We also start to see a more discrete pattern where the choice of either 90 or 180 degrees elicits more neural activity.

GCP Decomposition

```
1 M = gcp(X, 10; loss = GCPLosses.NonnegativeLeastSquares());
```



From this breakdown we confirm our perceived trend that neurons in the lower index range show higher activity more frequently than those in the higher range, meaning they are more commonly involved in the assigned motor task. We do notice that generally after a neural activity peak the signal is not sustained or prolonged, as it tends to significantly diminish. Most intriguingly, we see

the development of certain clusters sorted by angle in our trial plot, which could allude to condition-specific responses with associated high probabilities.

Uncovering these patterns paves the way for targeted neural investigations, showcasing tensor decomposition as a promising tool in neuroscience

References

1. S. Vyas, N. Even-Chen, S. D. Stavisky, S. I. Ryu, P. Nuyujukian, and K. V. Shenoy, Neural Population Dynamics Underlying Motor Learning Transfer, Elsevier BV, Vol. 97, No. 5, pp. 1177-1186.e3, March 2018, DOI: 10.1016/j.neuron.2018.01.040.
2. S. Vyas, D. J. O'Shea, S. I. Ryu, and K. V. Shenoy, Causal Role of Motor Preparation during Error-Driven Learning, Neuron, Elsevier BV, Vol. 106, No. 2, pp. 329-339.e4, April 2020, DOI: 10.1016/j.neuron.2020.01.019.