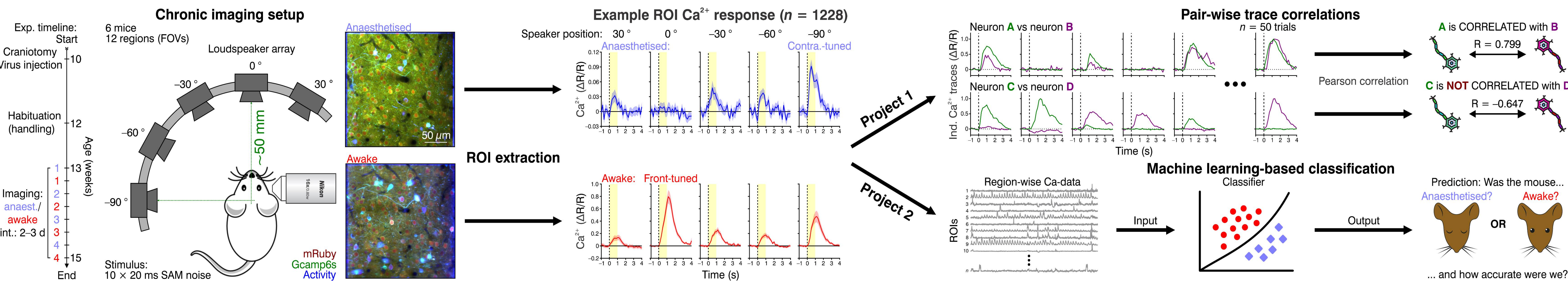


Decoding the representation of space in the auditory cortex

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Introduction



Brain encoding of auditory space is an enigma.

Existing data have been insufficient to prove neuronal tuning toward the front since most of it is collected from mice under anesthesia.

Then, the data in the awake state is collected.

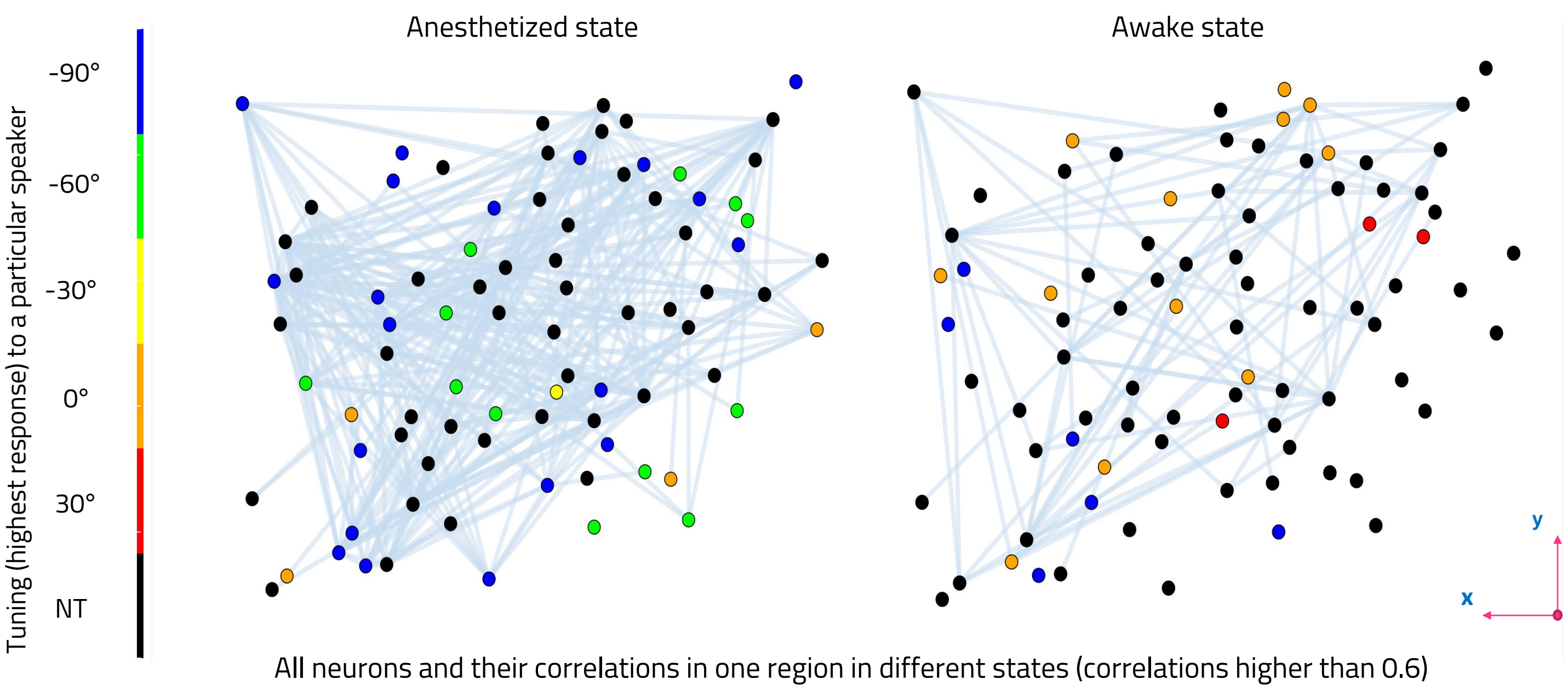
The main aim of this project is to:

- observe correlations between the single neuronal pairs,
- find the difference between anesthetized and awake states.

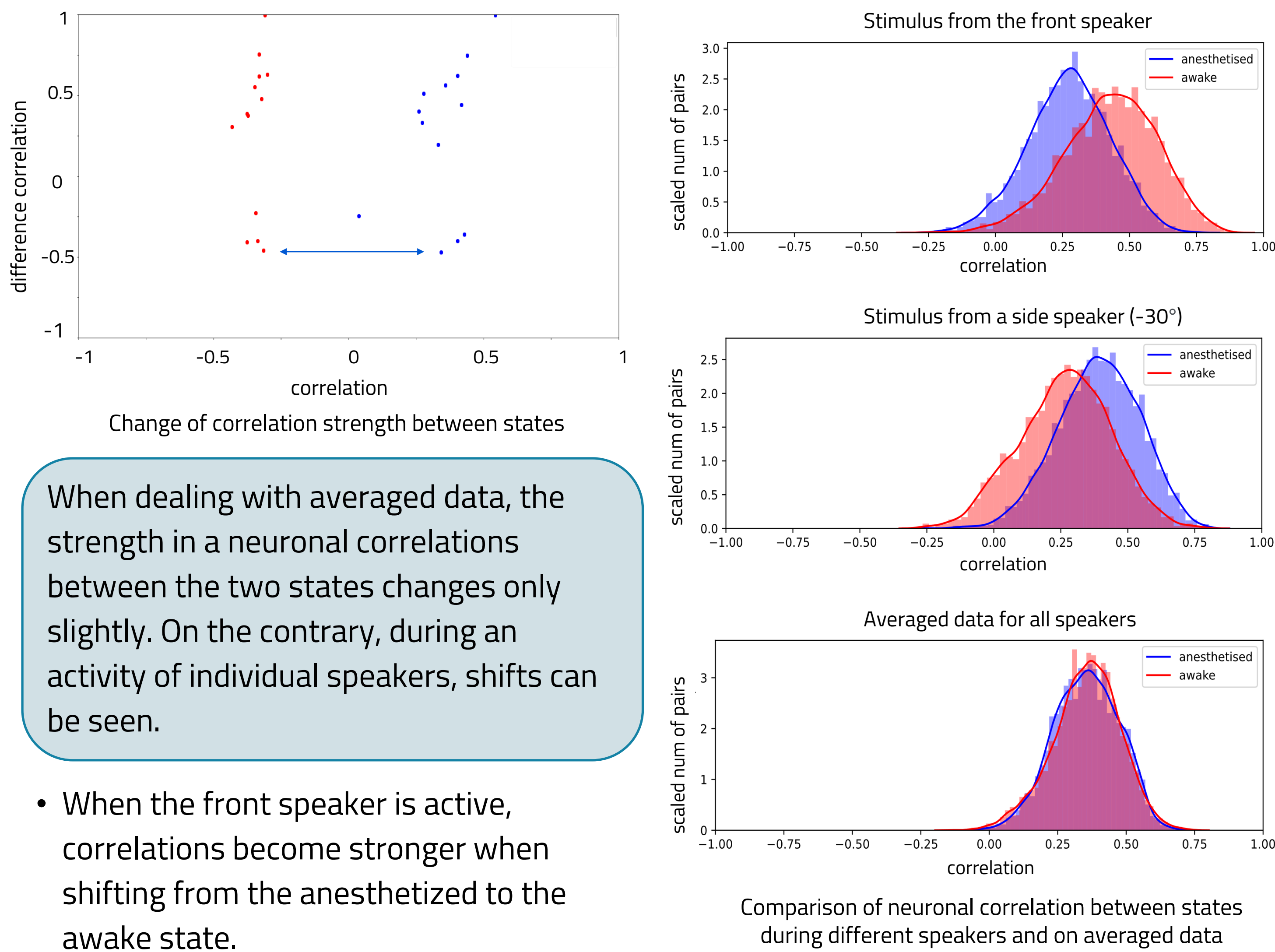
Correlation

A big group of neurons that are tuned to different speakers in anesthetized, shift their tuning to the front speaker in the awake state.

- A large number of high correlations (>0.6) are concentrated in the anesthetic state.
- There are fewer high correlations in the awake state.



Some neurons that were highly correlated in the anesthetized state, change their property to anti-correlated in the awake state.



When dealing with averaged data, the strength in a neuronal correlations between the two states changes only slightly. On the contrary, during an activity of individual speakers, shifts can be seen.

- When the front speaker is active, correlations become stronger when shifting from the anesthetized to the awake state.

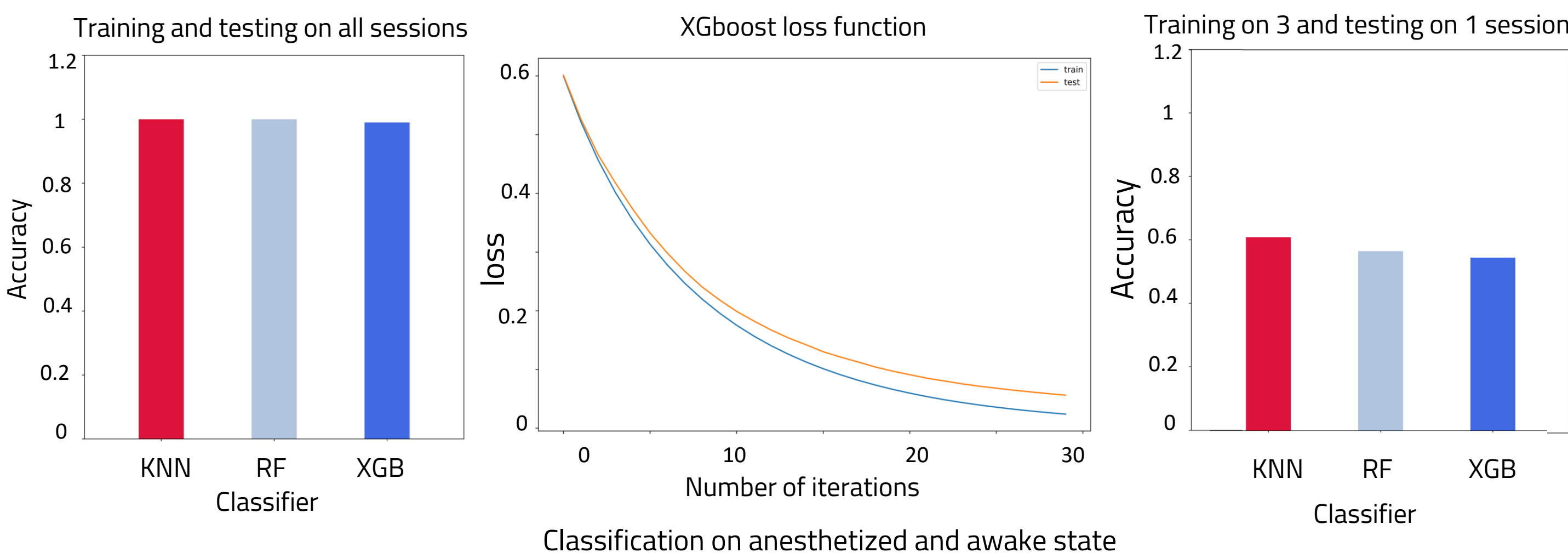
Classification

With a simple analysis of data by looking at individual correlations between neurons, it is practically impossible to observe any significant patterns. In order to understand the data, it is necessary to analyze it in a more complex way. In pursuit of this, the following machine learning models have been applied: K-Nearest Neighbors (KNN), Random Forest (RF), and Extreme Gradient Boosting (XGB).

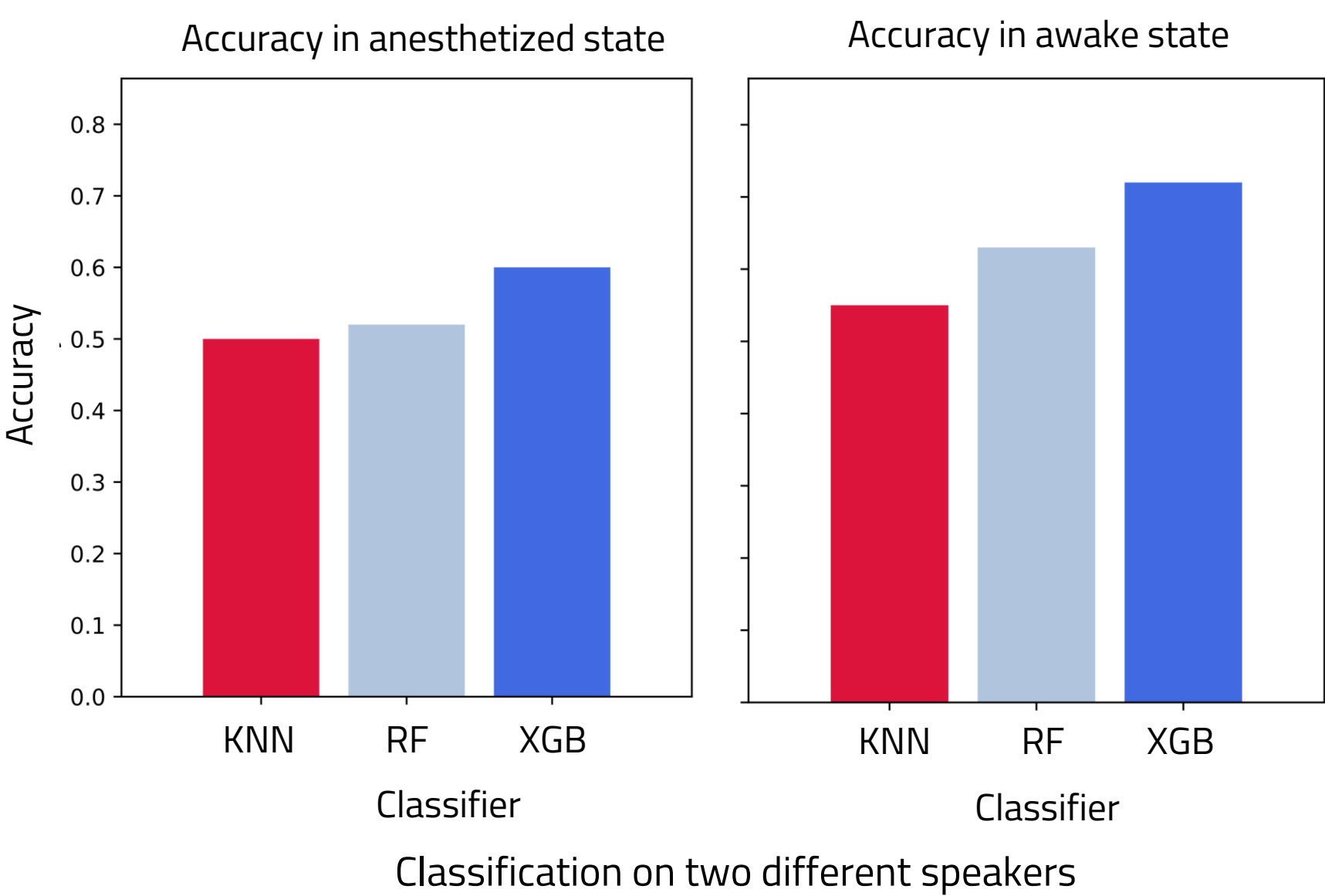
- Before classification, all data were normalized for better algorithm performance, and divided into a train (70%), validation (15%), and test (15%) set.

Training and evaluation of models on all the data were performed with the accuracy of slightly more than 99% for all of the classifiers.

- Differences between anesthetized and awake states are clearly encoded in the data that can be extracted as model features.



- On the contrary, training models on 3 different sessions and evaluating them on the 4th shows much worse results, where KNN gives the best accuracy of 60% on average. Keeping in mind how noisy a brain can be, different sessions are very hard to be separated.
- Due to the very sensitive data, the classification of neuronal activity on different speakers has also proved to be challenging. The accuracy of all classifiers was at chance level.



For each pair of two speakers, the possibility of their classification is observed.

- All the models gave similar accuracy from 60 to 65%.
- The highest accuracy have classes of data obtained when the farthest speakers are active (30° and -90°).

Conclusion

- The awake dataset shows neuronal tuning to the front speaker.
- Single speakers show significant shifts in correlation strength compared to averaged data.

- Even though some of the classifications proved to be challenging, it is clear that the dataset is informative enough to extract the features useful for separating different states, sessions, and speakers.