Brain electroencephalogram (EEG) activity analysis on big data platform

The final project of Data 603

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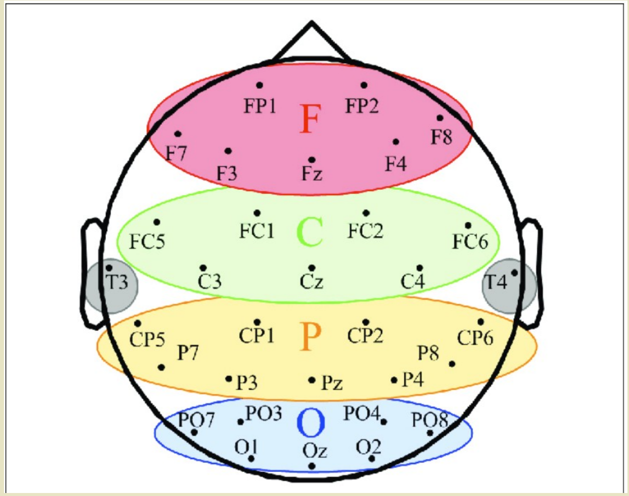
Introduction

- The development of cutting-edge recording technology in neuroscience research increase the data size and complexity.
- For example, the new electroencephalogram (EEG) experiment can simultaneously record several neural activities from multiple brain regions, which induce huge data size yield from one single experiment participants. (~500MB for 30min recording in one participants in compressed format)

Cited from: https://pressrelease.brainproducts.com/actichamp-plus_r-net/

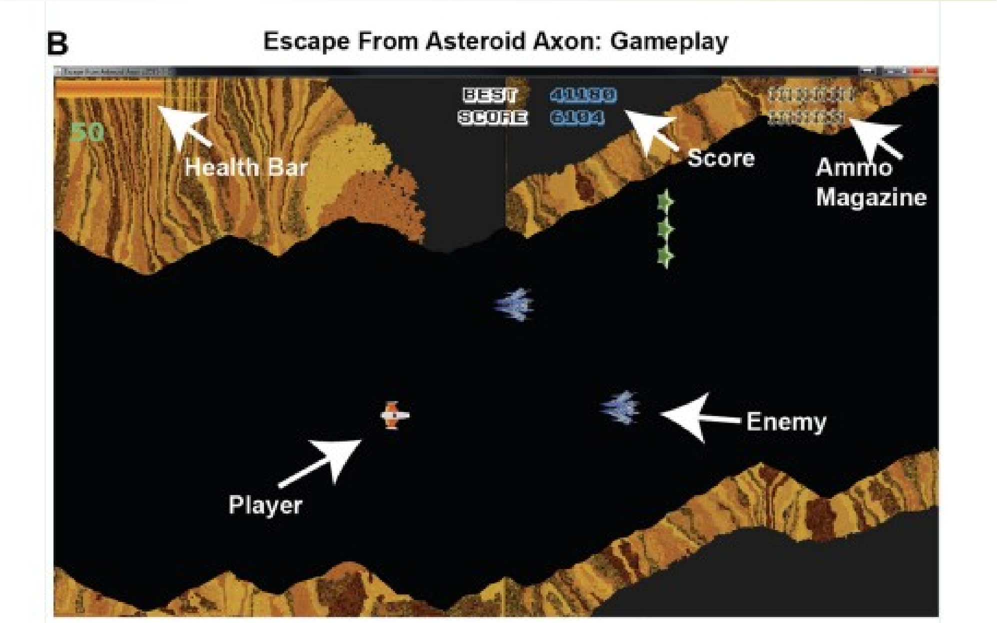


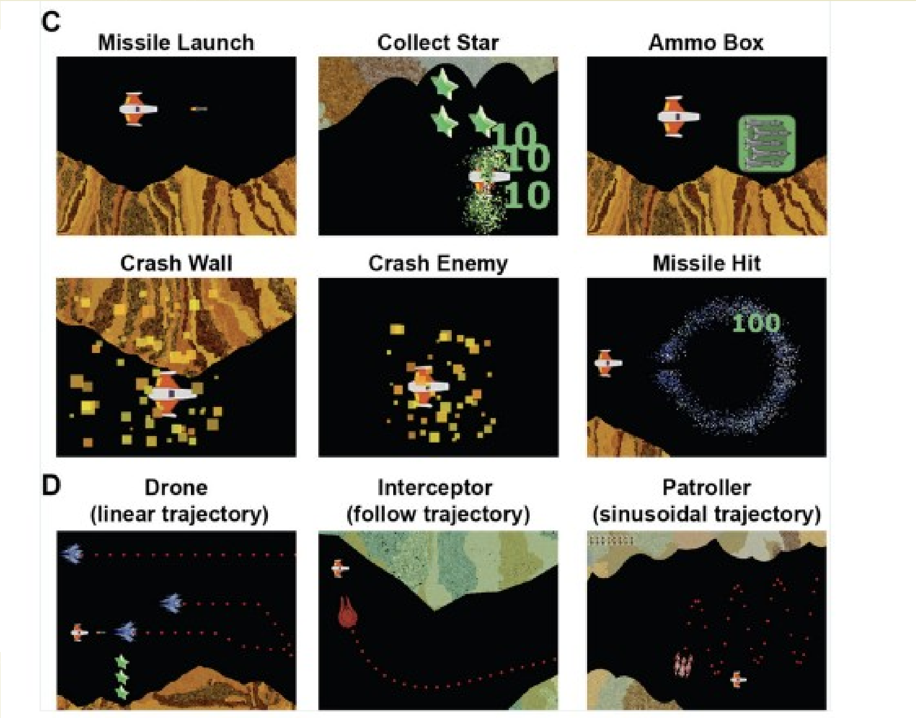
Cited from: Long-Range Temporal Correlations of Patients in Minimally Conscious State Modulated by Spinal Cord Stimulation

Dataset:

Link: https://openneuro.org/datasets/ds003517/versions/1.1.0

- Original data: EEG recording during continuous gameplay of an 8-bit style video game. Total participants number is 17. Several event in the game also recorded.





- Data used in this project: Since size of whole original dataset is about 2GB in compressed format, here, in this project I only use data from 1 participant’s 1 session for demo purpose.

The question that try to answer:

- Whether the EEG data from different channel can predict what event the participant is ongoing?

Technical hurdles to load raw EEG dataset

- The dataset structure is presented by using multiple files, such as files to record channel info, files to record EEG voltage data, and files to record co-order system.
- Files formats are different between different EEG machine. It could be a challenge if any vender using a closed system.

sub-001_task-ContinuousVideoGamePlay_run-02_channels.tsv
sub-001_task-ContinuousVideoGamePlay_run-02_coordsystem.json
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.fdt
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.json
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.set
sub-001_task-ContinuousVideoGamePlay_run-02_electrodes.tsv
sub-001_task-ContinuousVideoGamePlay_run-02_events.json
sub-001_task-ContinuousVideoGamePlay_run-02_events.tsv

Solution: I found Open-source Python package for loading, analysis human neurophysiological data, such as EEG dataset.

Workflow:
1. Pre-processing of raw data

- The package I used to load the raw EEG data is MNE.

sub-001_task-ContinuousVideoGamePlay_run-02_channels.tsv
sub-001_task-ContinuousVideoGamePlay_run-02_coordsystem.json
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.fdt
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.json
sub-001_task-ContinuousVideoGamePlay_run-02_eeg.set
sub-001_task-ContinuousVideoGamePlay_run-02_electrodes.tsv
sub-001_task-ContinuousVideoGamePlay_run-02_events.json
sub-001_task-ContinuousVideoGamePlay_run-02_events.tsv

```
import mne
```

```
df=mne.io.read_raw_eeglab("sub-001_task-ContinuousVideoGamePlay_run-02_eeg.set")
raw=df.to_data_frame()
raw.head()
```

	time	Fp1	Fz	F3	F7	FT9	FC5	FC1
0	0	-21805.175781	8995.654297	-21166.406250	-24166.259766	-8705.029297	-17463.330078	-21718.554688
1	2	-21804.736328	8995.166016	-21168.115234	-24155.468750	-8712.548828	-17456.933594	-21721.826172
2	4	-21800.292969	8995.166016	-21167.529297	-24149.609375	-8687.158203	-17477.783203	-21724.316406
3	6	-21804.248047	8994.384766	-21164.404297	-24148.046875	-8684.326172	-17458.593750	-21721.826172
4	8	-21808.740234	8994.287109	-21161.816406	-24163.476562	-8707.568359	-17481.005859	-21715.576172

Workflow:
2. Load event data from EEG raw data

parse event label

```
event=df.annotations.to_data_frame()
event["onset"]=event["onset"].astype('datetime64[ns]').astype(np.int64) / int(1e6)
event=event.rename(columns={'onset':'time', 'description':'event'})
event
```

	time	duration	event
0	0.0	0.000	boundary
1	90440.0	0.002	S100
2	91758.0	0.002	S 90
3	92110.0	0.002	S 97
4	94466.0	0.002	S 90
...	...	...	...
4065	2794426.0	0.002	S 90
4066	2795344.0	0.002	S 97
4067	2795390.0	0.002	S 90
4068	2795580.0	0.002	S 97
4069	2796230.0	0.002	S 98

4070 rows × 3 columns

Workflow:

3. Pre-processing data and loading the raw into pyspark session

combine EEG voltage with event

```
total_raw=pd.merge(raw, event, on='time', how='outer')
```

add event label to raw data

```
#df=total_raw.copy()
for i in range(1, len(total_raw)):
    if pd.notna(total_raw.at[i, "event"]):
        total_raw.loc[i-1, "add_event"] =total_raw.at[i, 'event']
        total_raw.loc[i, "add_event"] =total_raw.at[i, 'event']
        total_raw.loc[i+1, "add_event"] =total_raw.at[i, 'event']
```

```
project_df=total_raw[total_raw["add_event"].notna()]
```

```
project_df.to_csv("project_data.csv", index=False)
```

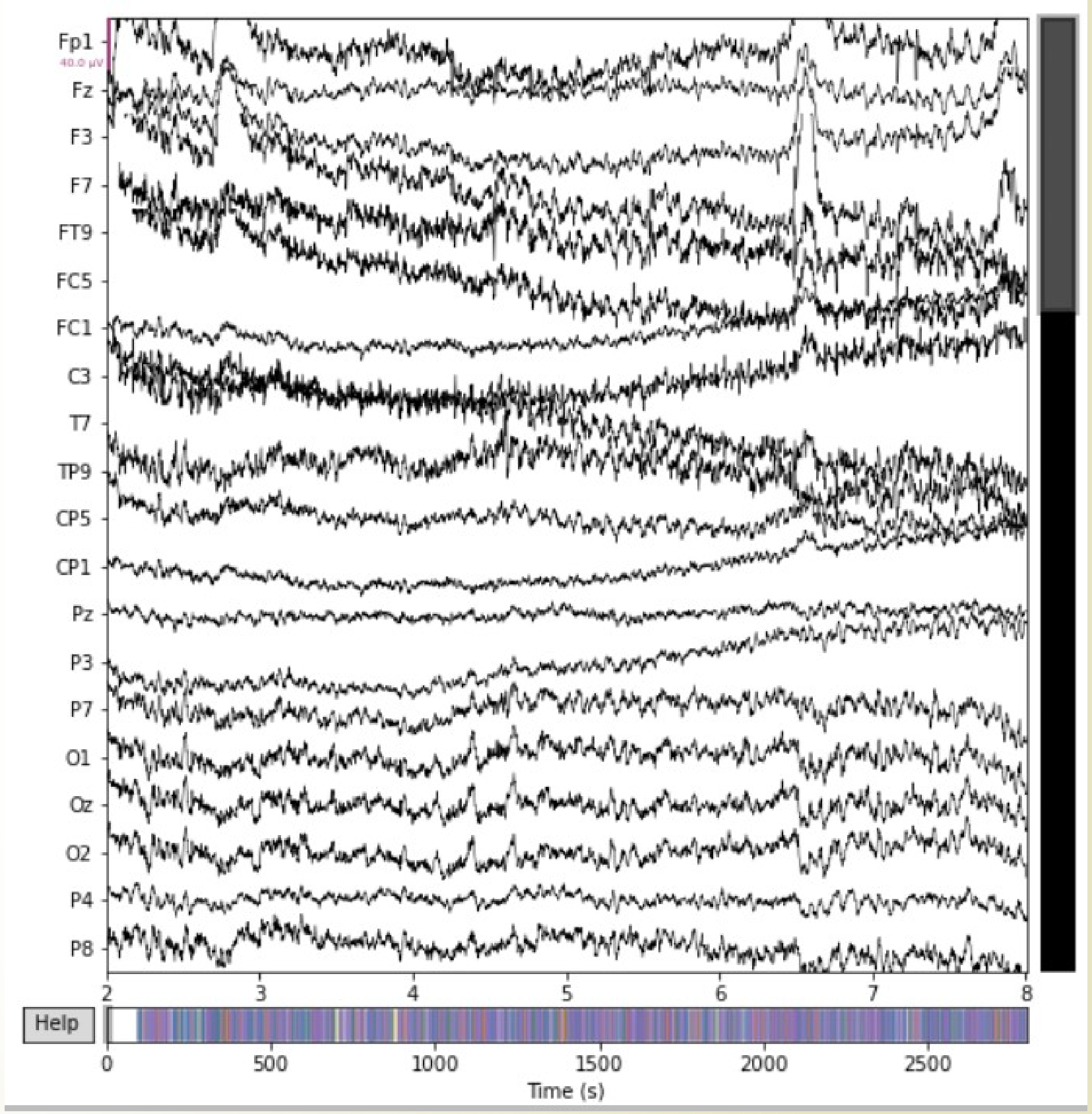
```
project_df.shape
```

```
(12207, 69)
```

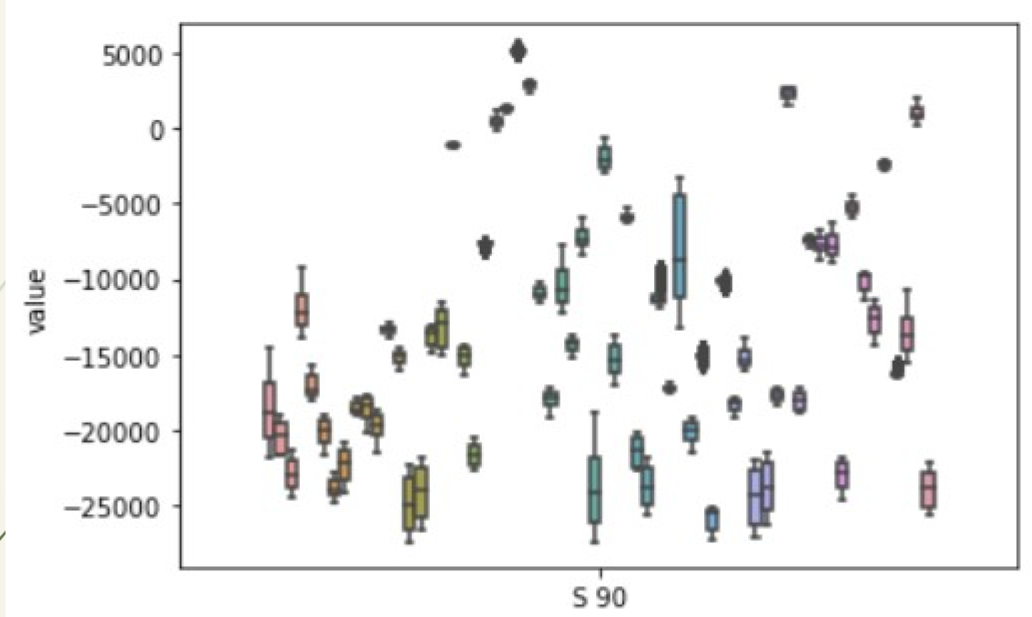
```
root
 |-- time: integer (nullable = true)
 |-- Fp1: double (nullable = true)
 |-- Fz: double (nullable = true)
 |-- F3: double (nullable = true)
 |-- F7: double (nullable = true)
 |-- FT9: double (nullable = true)
 |-- FC5: double (nullable = true)
 |-- FC1: double (nullable = true)
 |-- C3: double (nullable = true)
 |-- T7: double (nullable = true)
 |-- TP9: double (nullable = true)
 |-- CP5: double (nullable = true)
 |-- CP1: double (nullable = true)
 |-- Pz: double (nullable = true)
 |-- P3: double (nullable = true)
 |-- P7: double (nullable = true)
 |-- O1: double (nullable = true)
 |-- Oz: double (nullable = true)
 |-- O2: double (nullable = true)
 |-- P4: double (nullable = true)
 |-- P8: double (nullable = true)
```

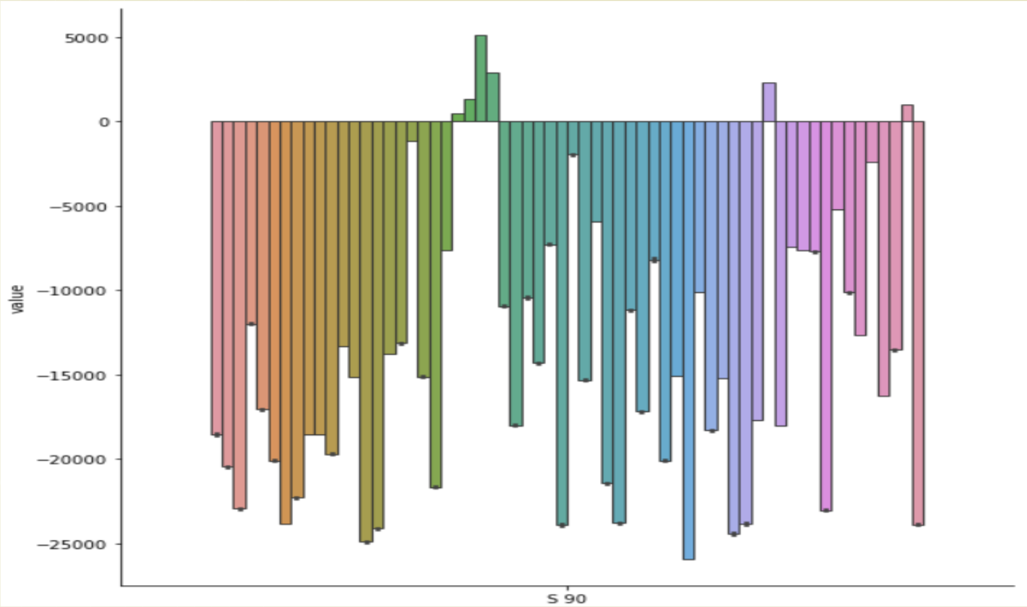
……

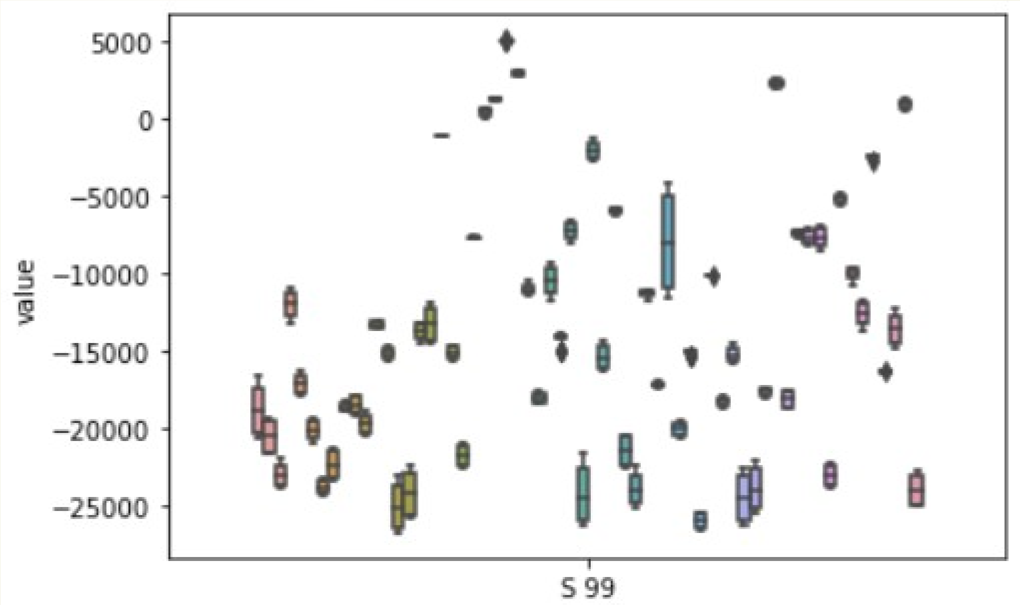
Workflow:
4. Data visualization: EEG voltage in different channel

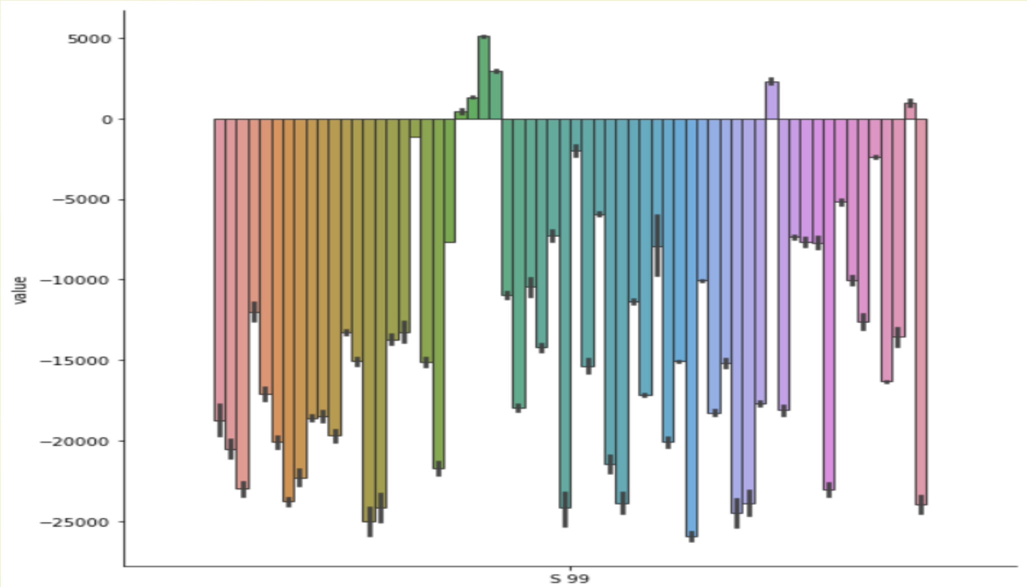


Workflow:
4. Data visualization: channel shape between different event









5.1 First, I try to predict three different event: ***game start, game over and in game***. In this way, I label all event in the game (such as SHOOT_BUTTON, PLAYER_CRASH_WALL, PLAYER_CRASH_ENEMY et al.) into same category.

```
formula = RFormula(
    formula="add_event ~ .",
    featuresCol="features",
    labelCol="label")

output = formula.fit(df1).transform(df1)
output.select("features", "label").show()
```

```
+--------------------+-----+
|            features|label|
+--------------------+-----+
|[-21769.482421875...|  1.0|
|[-21771.093749999...|  1.0|
|[-21771.484375,92...|  1.0|
|[-21738.427734375...|  0.0|
|[-21739.697265625...|  0.0|
|[-21739.306640624...|  0.0|
|[-21748.4375,9236...|  0.0|
|[-21748.53515625,...|  0.0|
|[-21747.998046874...|  0.0|
|[-21709.423828124...|  0.0|
|[-21708.349609375...|  0.0|
|[-21720.8984375,9...|  0.0|
|[-21717.3828125,9...|  0.0|
|[-21724.70703125,...|  0.0|
|[-21724.21875,925...|  0.0|
|[-21702.636718749...|  0.0|
|[-21701.708984375...|  0.0|
|[-21702.636718749...|  0.0|
|[-21717.724609375...|  0.0|
|[-21719.384765625...|  0.0|
+--------------------+-----+
only showing top 20 rows
```

```
from pyspark.ml import Pipeline
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.feature import StringIndexer, VectorIndexer
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
```

```
labelIndexer = StringIndexer(inputCol="label", outputCol="indexedLabel").fit(output)

# Automatically identify categorical features, and index them.
# We specify maxCategories so features with > 4 distinct values are treated as continuous.
featureIndexer = (VectorIndexer(inputCol="features", outputCol="indexedFeatures", maxCategories=3).fit(output))

(trainingData, testData) = output.randomSplit([0.7, 0.3], seed=12345)

dt = DecisionTreeClassifier(labelCol="indexedLabel", featuresCol="indexedFeatures")

pipeline = Pipeline(stages=[labelIndexer, featureIndexer, dt])

# Train model.  This also runs the indexers.
model = pipeline.fit(trainingData)

# Make predictions.
predictions = model.transform(testData)

# Select example rows to display.
predictions.select("prediction", "indexedLabel", "features").show(5)

# Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Test Error = %g " % (1.0 - accuracy))

treeModel = model.stages[2]
# summary only
print(treeModel)
```

```
+----------+------------+--------------------+
|prediction|indexedLabel|            features|
+----------+------------+--------------------+
|       0.0|         0.0|[-21739.697265625...|
|       0.0|         0.0|[-21724.70703125,...|
|       0.0|         0.0|[-21717.724609375...|
|       0.0|         0.0|[-21690.087890624...|
|       0.0|         0.0|[-21690.087890624...|
+----------+------------+--------------------+
only showing top 5 rows

Test Error = 0.00218221
DecisionTreeClassificationModel: uid=DecisionTreeClassifier_f529ff142492, depth=5, numNodes=25, numClasses=3, numFeatures=63
```

For predict ongoing event game start, in game and game over, the model had a great performance.

Workflow:
5. Predict ongoing event: decision tree model building

5.2 Here, I try to predict three different in game event: ***crash wall, crash enemy and missile hit enemy***. In this way, I only label there three event in the dataframe. I also applied the paramgridbuilder method with hyperparameter turning.

```
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder

grid = ParamGridBuilder() \
    .addGrid(dt.impurity, ["gini", "entropy"]) \
    .addGrid(dt.maxBins, [5, 10, 15]) \
    .addGrid(dt.minInfoGain, [0.0, 0.2, 0.4]) \
    .addGrid(dt.maxDepth, [3, 5, 7]) \
    .build()
```

```
cv= CrossValidator(estimator=pipeline, evaluator=evaluator, estimatorParamMaps=grid, numFolds=3)

cvModel = cv.fit(trainingData)
```

```
#print out the hyperparameter of best model

best_Model = cvModel.bestModel

predictions=best_Model.transform(testData)
predictions.select("prediction", "indexedLabel", "features").show(5) #select("prediction", "indexedLabel", "features", "accuracy")

test_metric = evaluator.evaluate(best_Model.transform(testData))
print("Test Error = %g " % (1.0 - test_metric))

for x in range(len(best_Model.stages)):
    print(best_Model.stages[x])

java_model = best_Model.stages[-1]._java_obj
{param.name: java_model.getOrDefault(java_model.getParam(param.name))
    for param in grid[0]}
```

```
+----------+------------+--------------------+
|prediction|indexedLabel|            features|
+----------+------------+--------------------+
|       0.0|         0.0|[-21748.4375,9236...|
|       0.0|         0.0|[-21717.3828125,9...|
|       0.0|         0.0|[-21654.736328125...|
|       0.0|         1.0|[-21593.701171875...|
|       2.0|         0.0|[-21581.201171874...|
+----------+------------+--------------------+
only showing top 5 rows

Test Error = 0.27176
StringIndexerModel: uid=StringIndexer_fb606add02bf, handleInvalid=error
VectorIndexerModel: uid=VectorIndexer_6fabd9376fbb, numFeatures=63, handleInvalid=error
DecisionTreeClassificationModel: uid=DecisionTreeClassifier_0ef63c4fe303, depth=7, numNodes=143, numClasses=3, numFeatures=63
{'impurity': 'gini', 'maxBins': 10, 'minInfoGain': 0.0, 'maxDepth': 7}
```

Next step:

1. Further raw data clean, such as clean the artificial signal in EEG, noise filtering, data re-sample, and epoch data transferring.

2. Analyzing all the data from participants.

3. Trying the other training model and ts-flint package.

Thanks!