Human Activity Recognition from Accelerometer Data

J. M. Yao

FRIB/NSCL, Michigan State University, East Lansing, Michigan 48824, USA

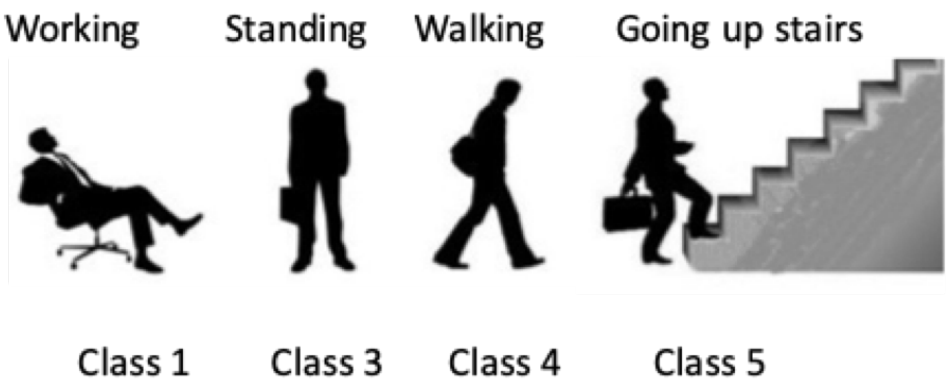
April 11, 2019

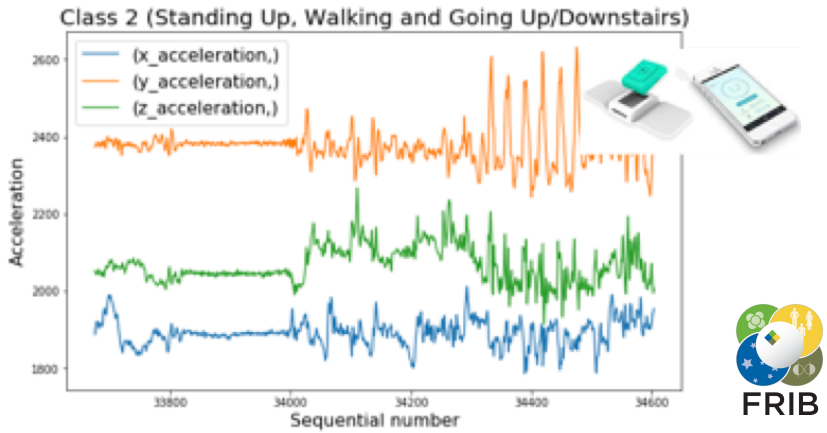
Introduction

Introduction to the problem and dataset

Seven activities (Challenge as not mutually exclusive)

1. Working at Computer
2. Standing Up, **Walking** and Going Up/Downstairs
3. Standing
4. **Walking**
5. Going Up/Down Stairs
6. **Walking** and Talking with Someone
7. Talking while Standing





Introduction to the problem and dataset

Task/Object: **multi-class classification**

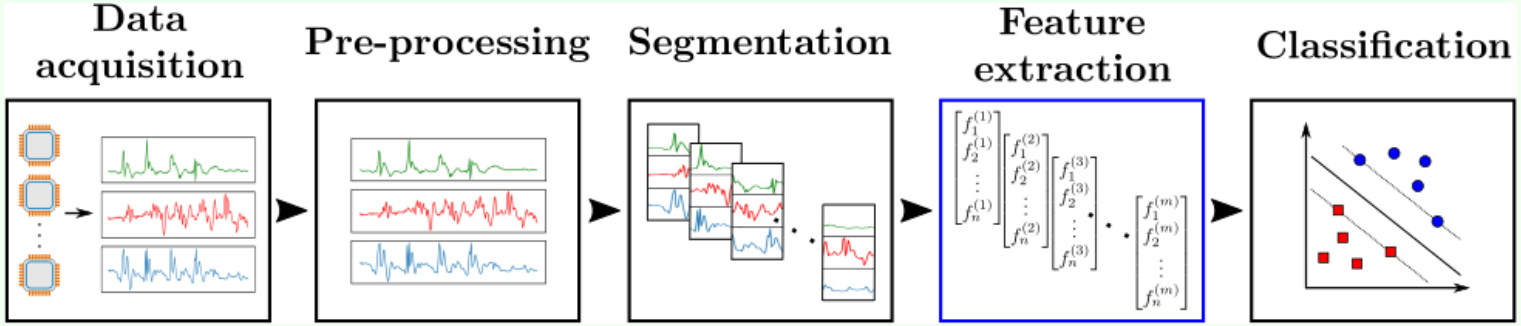
- Input data:

  Sequential number, x acceleration, y acceleration, z acceleration

- Output:

  Class label $(1, 2, \cdots, 7)$ for each activity.

Procedure

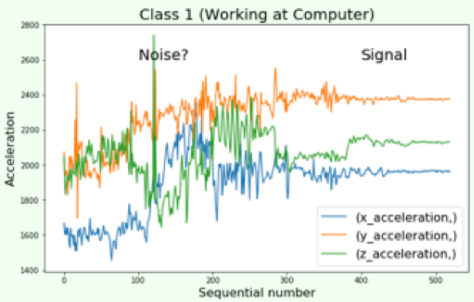


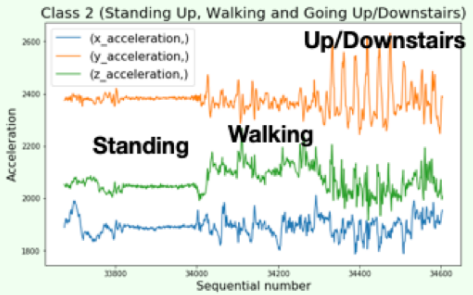
FRIB

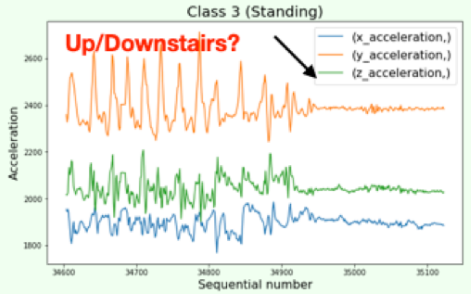
Exploratory data analysis

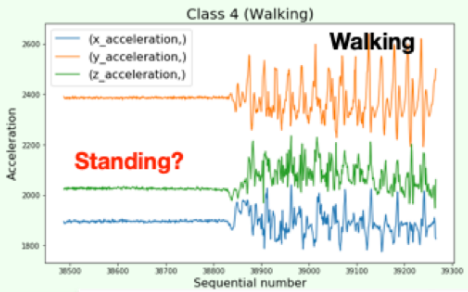
Exploratory data analysis: raw data

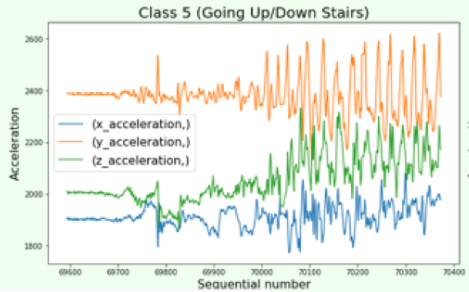
An example data: participant 1

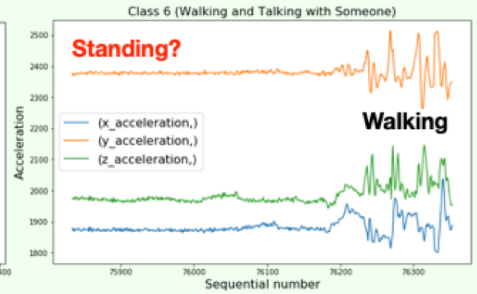


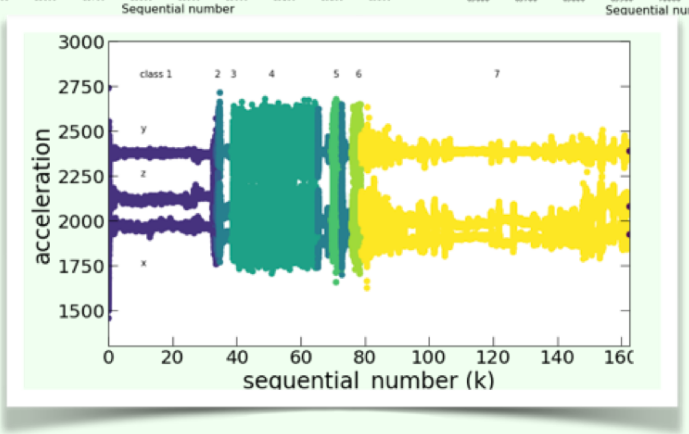


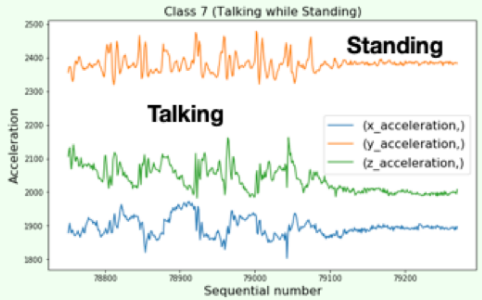












Exploratory data analysis: raw data

Feature extraction

- Generate samples/features using sliding temporal windows which split the raw data into segments.
- The data (x, y, z-accelerations) in each window form one sample.
- Hand-crafted features are extracted from each sample:

– **Time domain features**: related to the distribution of the data

> mean $\mu_{i=x,y,z}$, variance σ_i^2, min, max, mean absolute deviation, skewness, kurtosis, correlation $Corr(i,j)$, magnitude $\sqrt{\mu_x^2+\mu_y^2+\mu_z^2}$

– **Frequency domain features**: energy-weighted moments:

$$M^{(k)} = \int d\omega \cdot \omega^k \cdot F(\omega), \quad k = 1,2,3 \tag{1}$$

where $F(\omega)$ is computed with Fast Fourier Transform (FFT)

$$F(\omega) = \int dt \cdot f(t) \cdot e^{-i(2\pi\omega)t}. \tag{2}$$

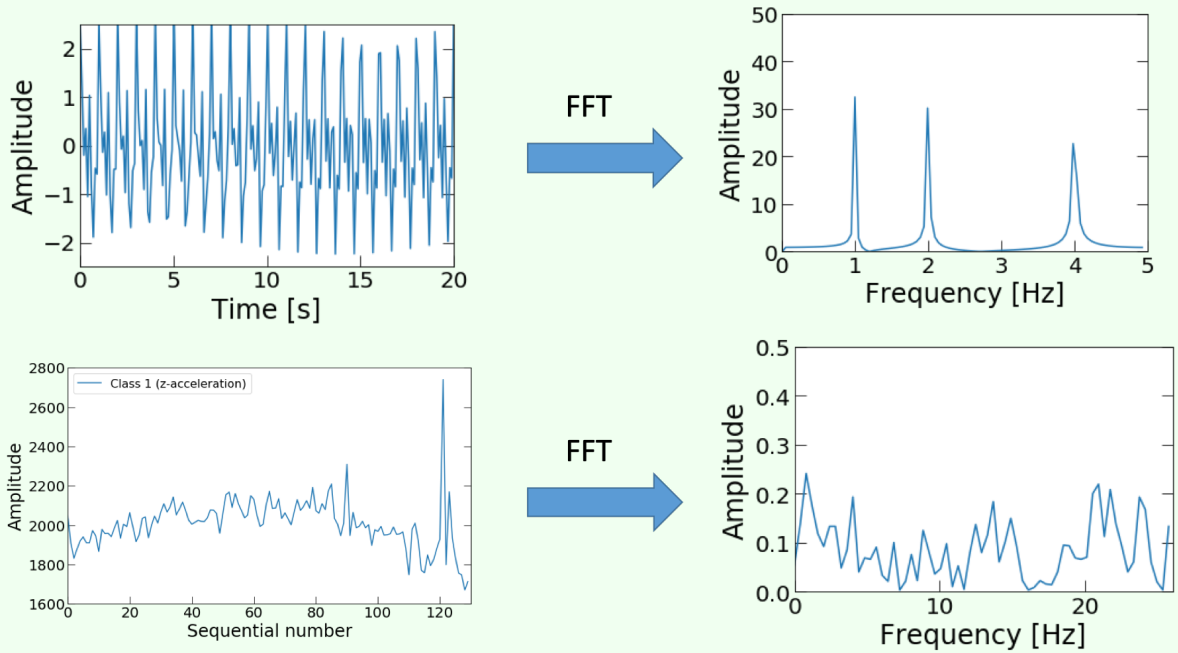
FRIB

Exploratory data analysis: raw data

Fast Fourier Transformation (FFT)

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \qquad k = 0, \ldots, N-1 \tag{3}$$

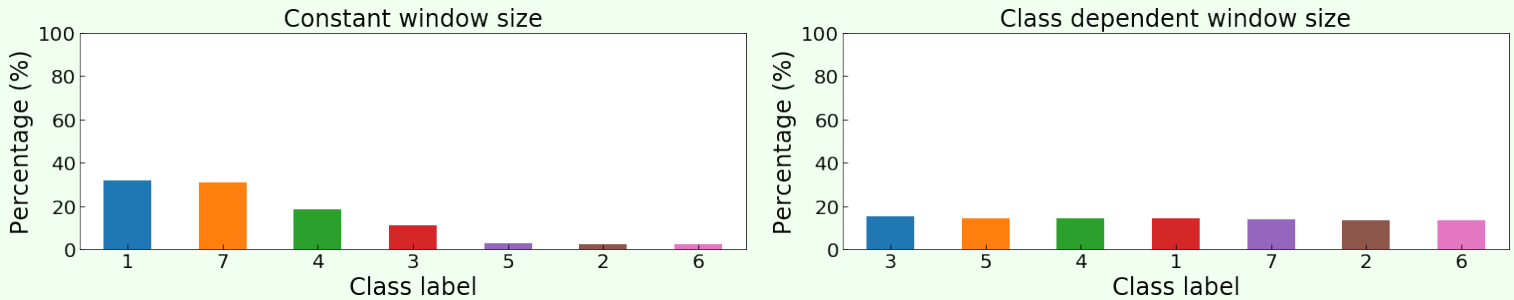
- Compute the discrete Fourier transform of a sequence
- Computation complexity $O(n \log(n))$ (divide and conquer algorithm)



Exploratory data analysis: sample data

Imbalanced data

- Multi-class classification with imbalanced data is challenge.
- Use a class dependent temporal window size.
- Risk of using window size information into training models

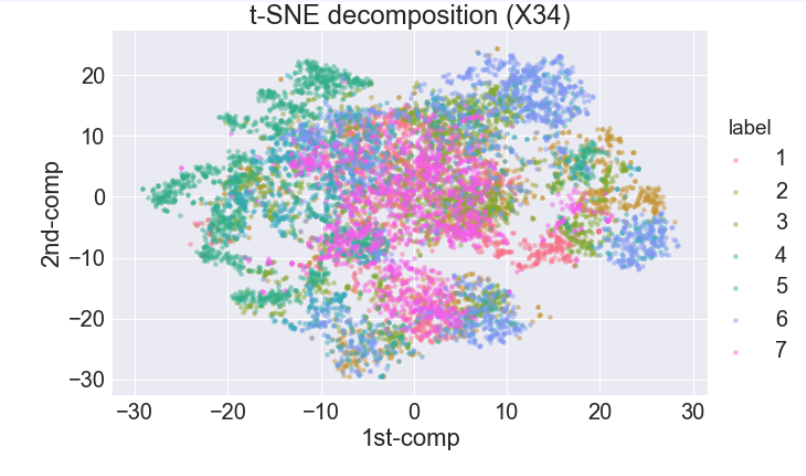


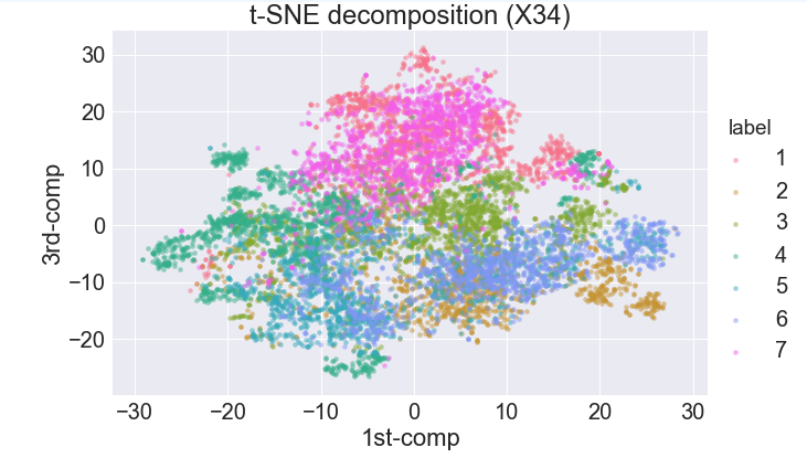
Exploratory data analysis: sample data

t-distributed Stochastic Neighbor Embedding (t-SNE)

- reduces dimensionality, trying to keep similar (dissimilar) instances close (apart)
- tool for visualizing clusters of instances

Data with 34 features





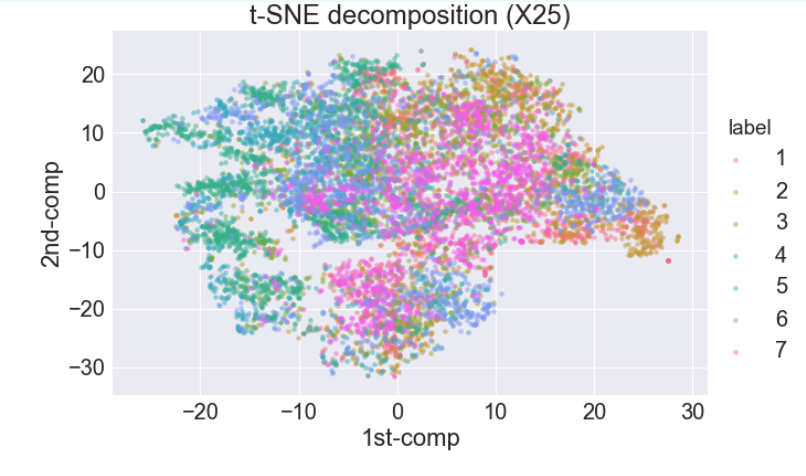
FRIB

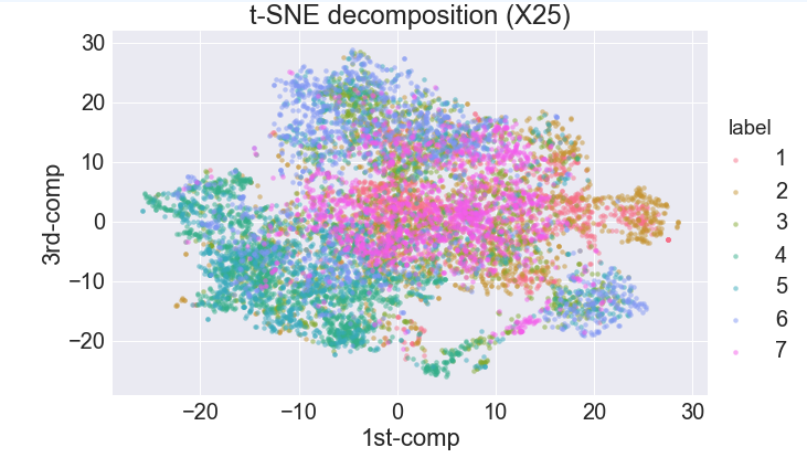
Exploratory data analysis: sample data

t-distributed Stochastic Neighbor Embedding (t-SNE)

- reduces dimensionality, trying to keep similar (dissimilar) instances close (apart)
- tool for visualizing clusters of instances

Data with **25** features (without **frequency domain features)**





FRIB

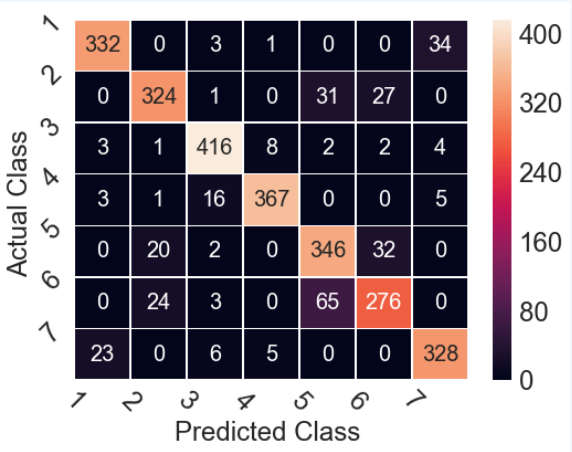
Models

Models

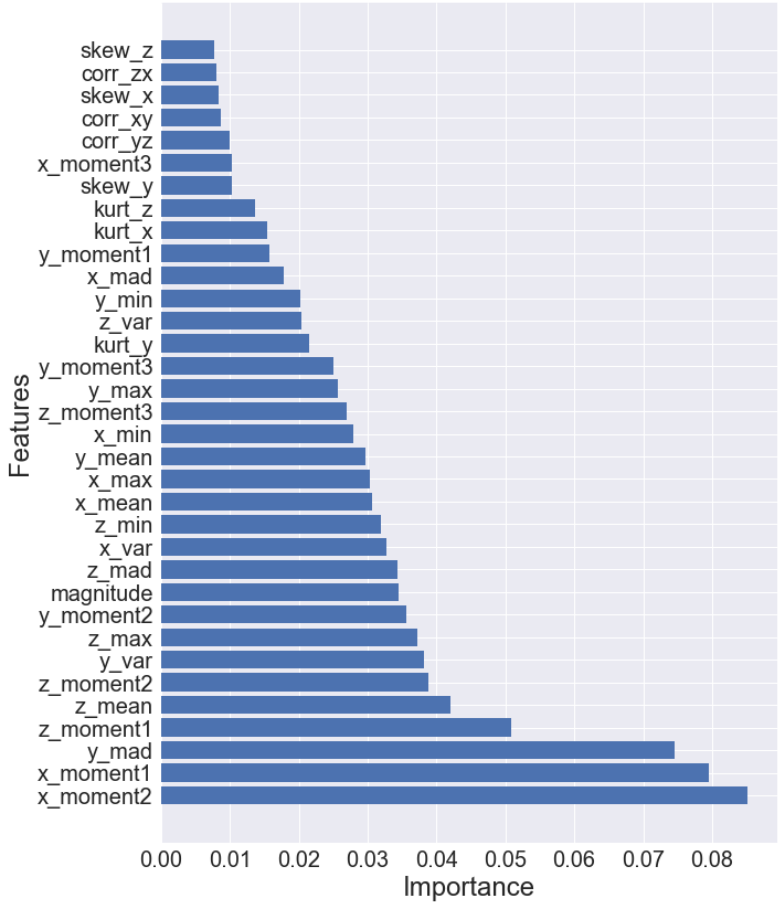
Random Forest

- non-parametric model
- **provide importance of features**
- prone to overfitting
- regularization and monitoring train/test scores

Confusion matrix (Test Data)



Training the model with default parameters



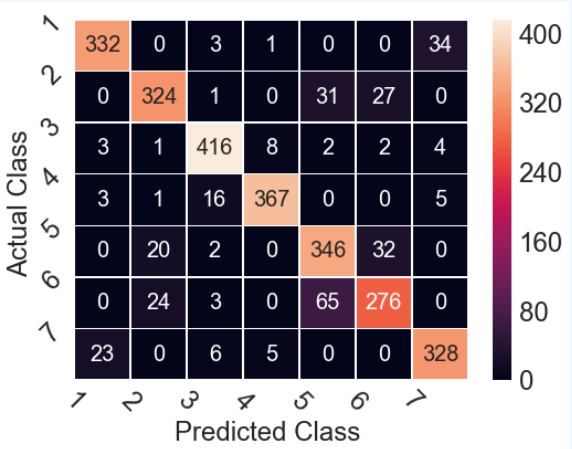
FRIB

Models

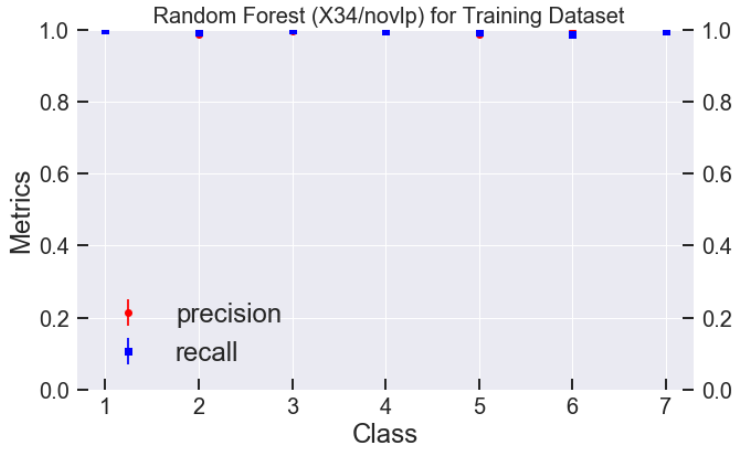
Random Forest

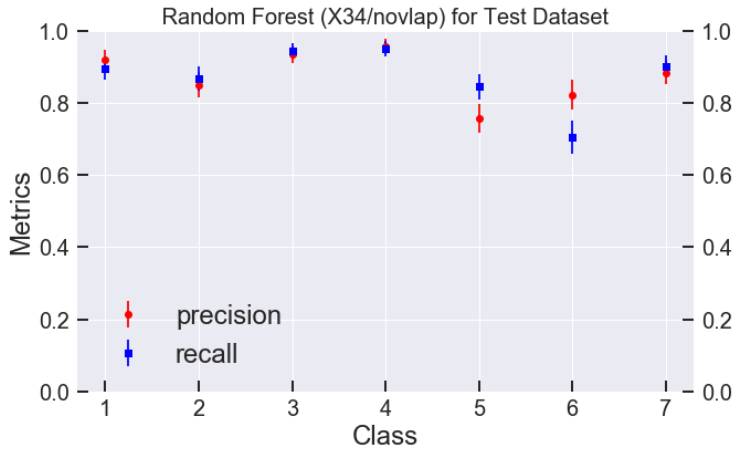
- non-parametric model
- provide importance of features
- **prone to overfitting**
- regularization and monitoring train/test scores

Confusion matrix (Test Data)



Training the model with default parameters





FRIB

Models

Random Forest

- non-parametric model
- provide importance of features
- prone to overfitting
- **regularization and monitoring train/test scores**

GridSearch for the parameters

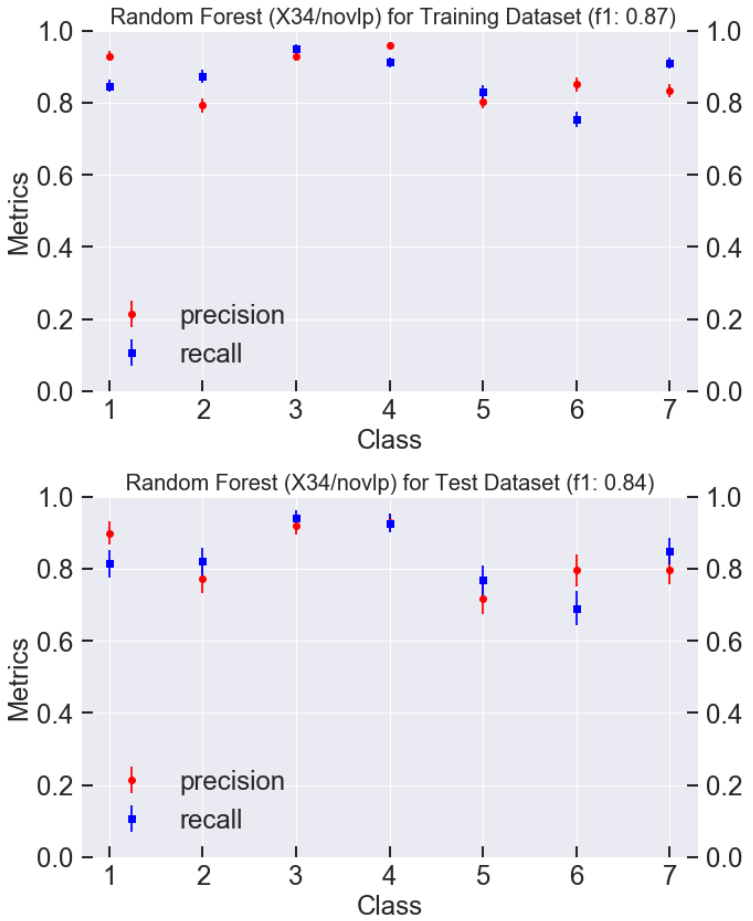
Introduce a new metric to take care of overfitting:

$$F_1 \equiv f_1(\text{test}) - \mathbf{1.5}|f_1(\text{train}) - f_1(\text{test})|$$

where the f_1 measure is defined as

$$f_1 = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \qquad (4)$$

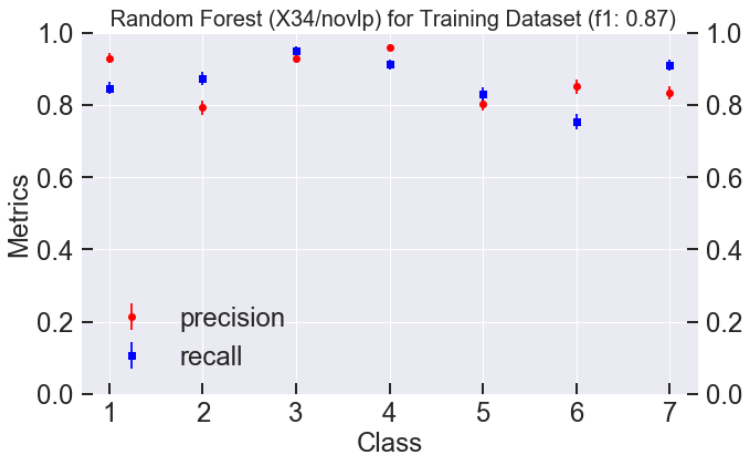
Training the model with GridSearch

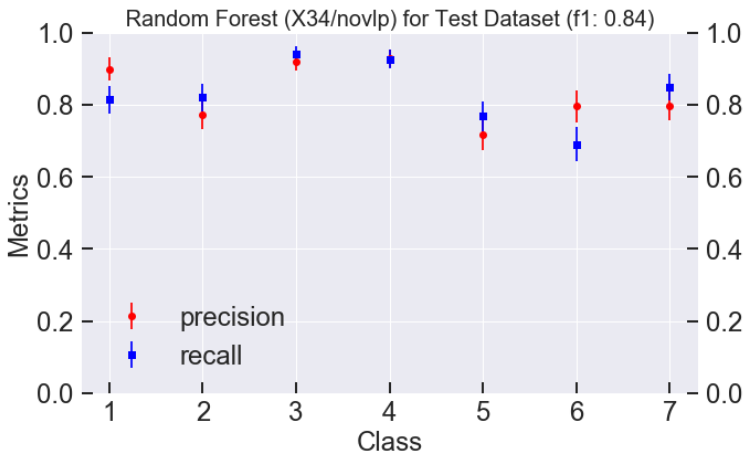


FRIB

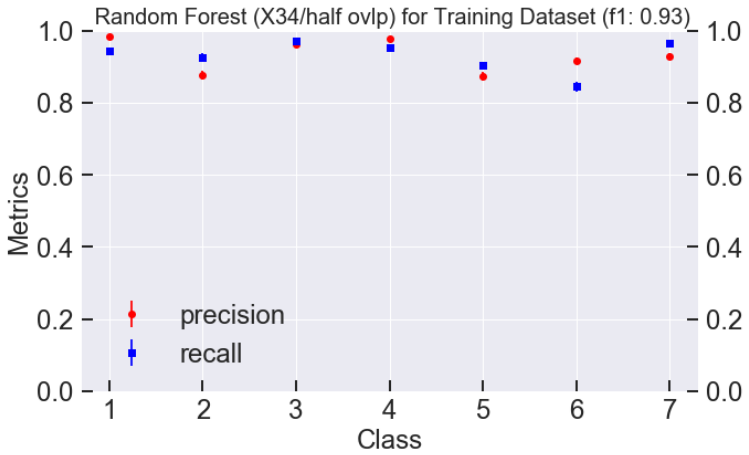
Models: overlapping windows or not

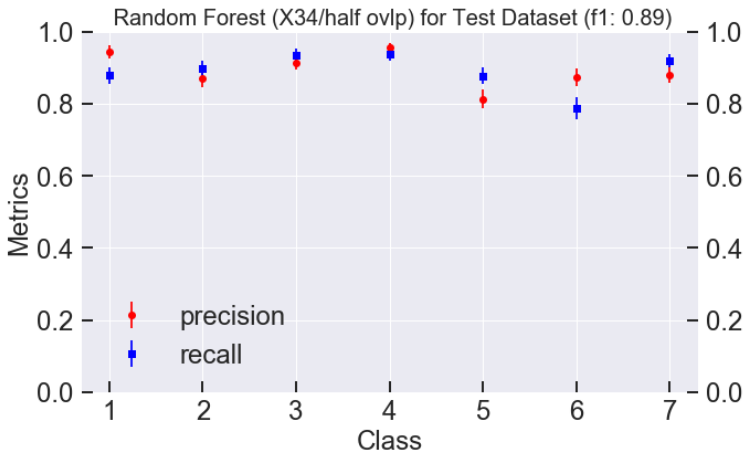
Non-overlapping windows





Half-overlapping windows

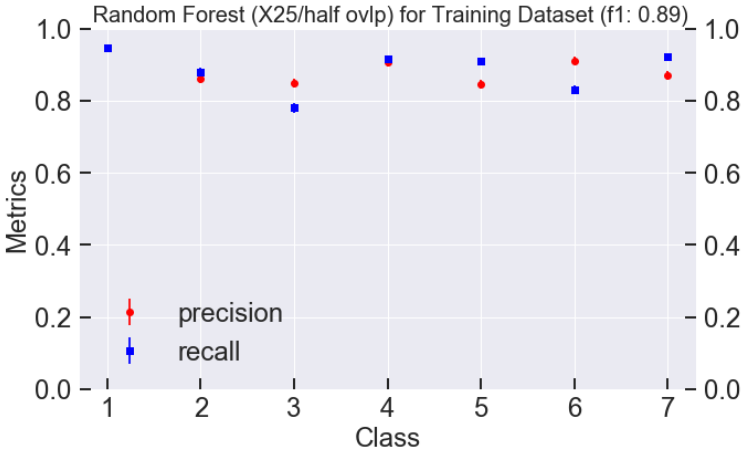


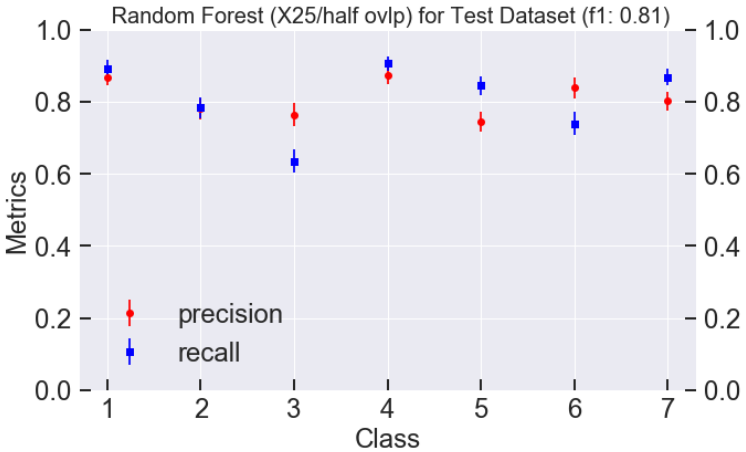


FRIB

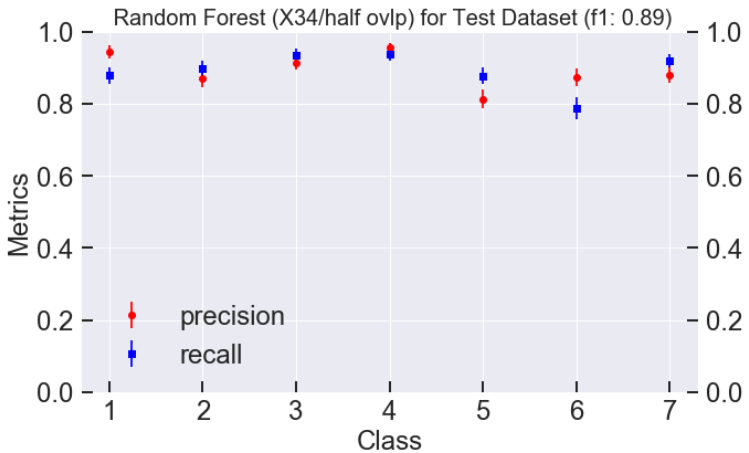
Models: with frequency domain features or not

w/o frequency domain features





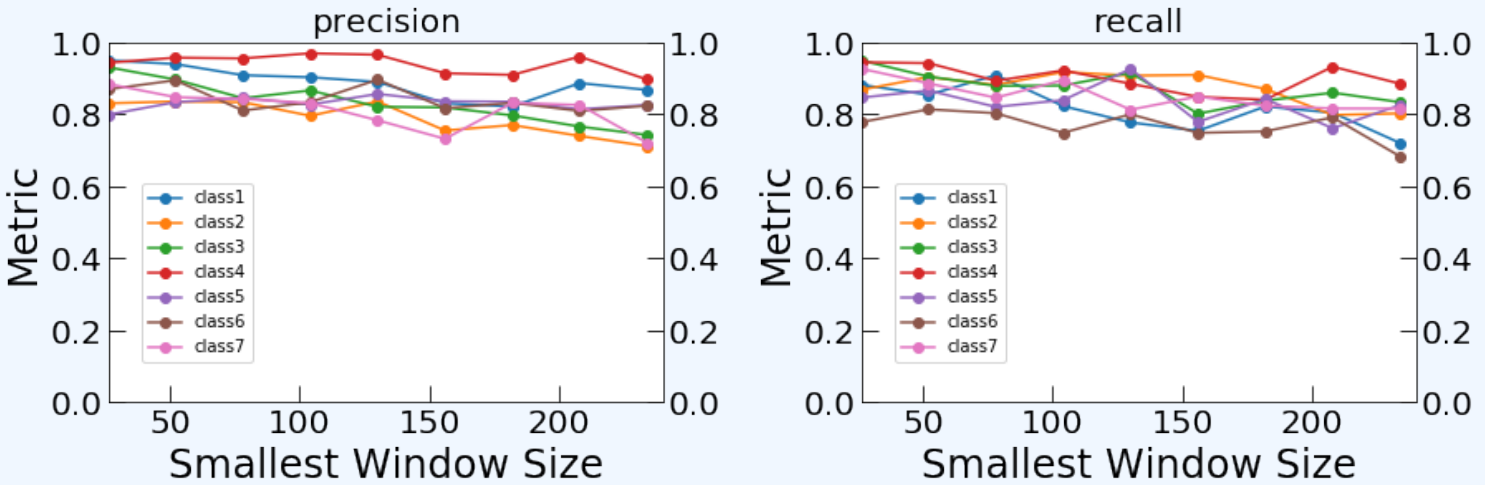
w/ frequency domain features



FRIB

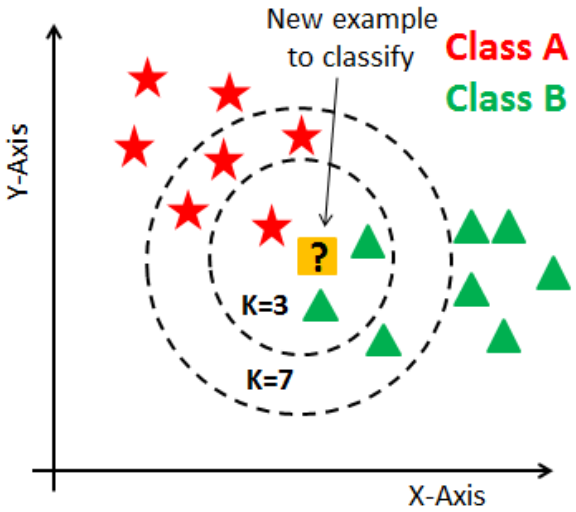
Models: window size effect

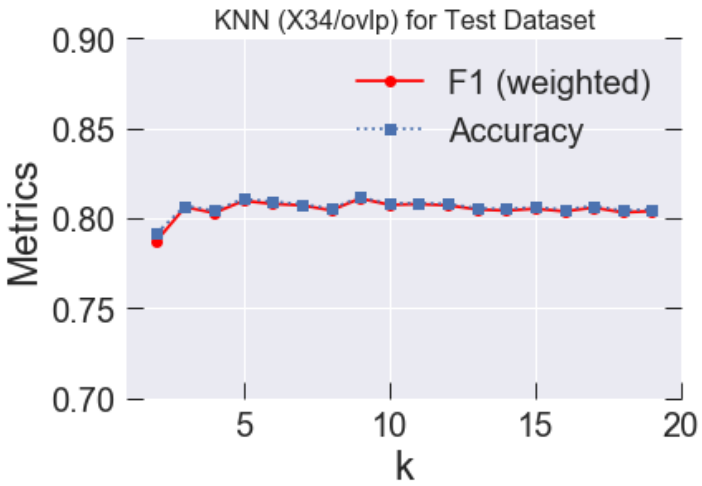
Precision/Recall for test data in the Random Forest

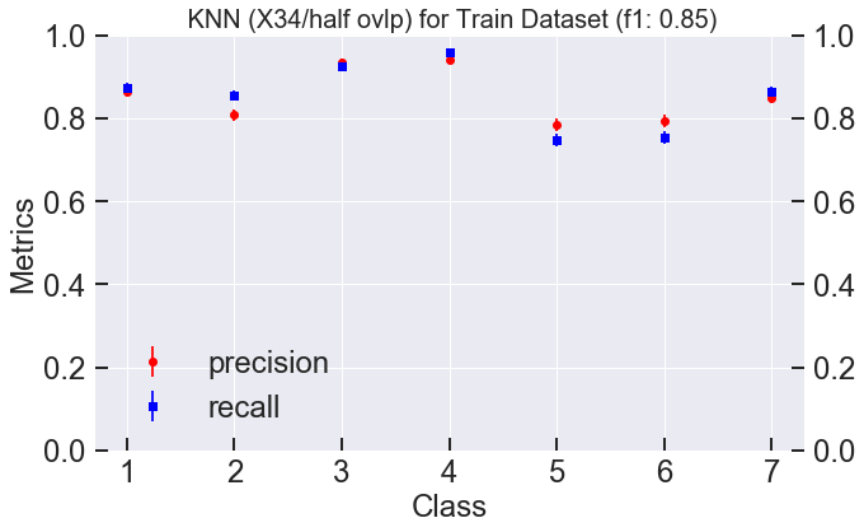


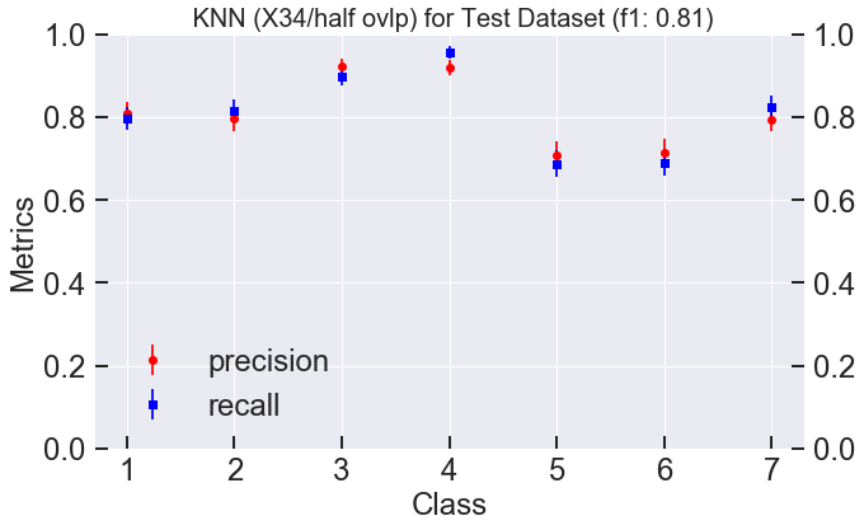
- Globally, the score is slightly decreasing with the window size.

Models: KNeighborsClassifier (KNN)

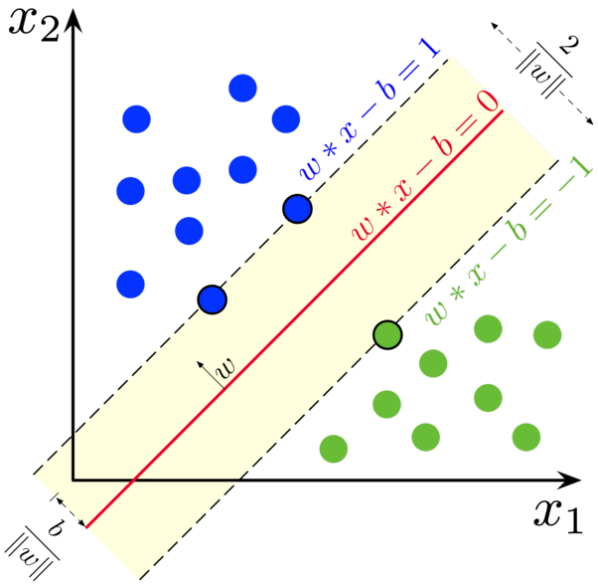








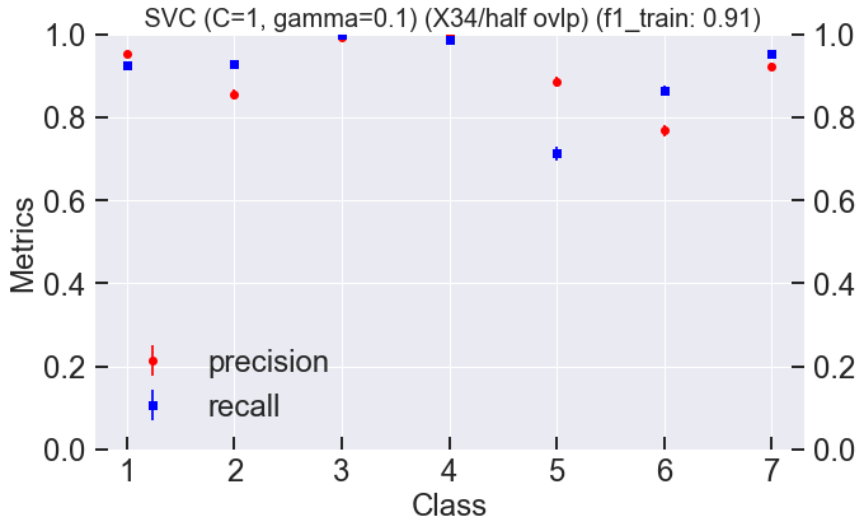
Models: Support Vector Machine Classification (SVC)

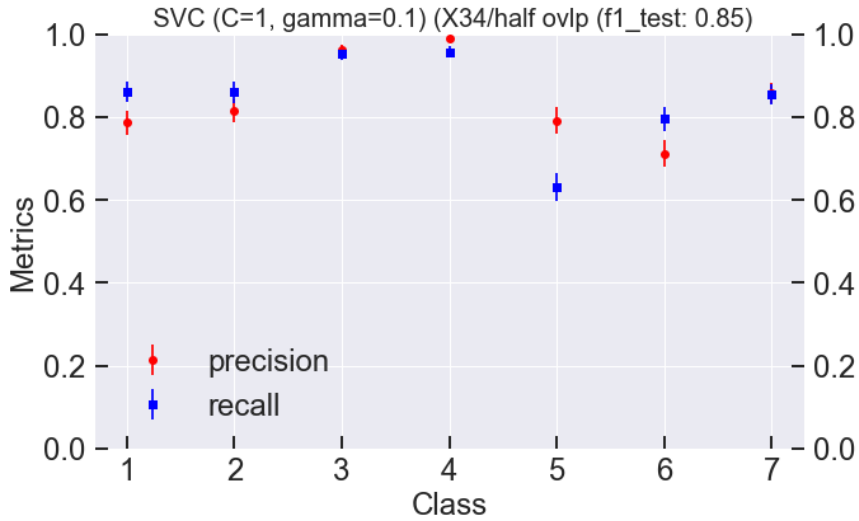


- kernel: radial basis function

$$K(X_i, X_j) = \exp[-\gamma(X_i - X_j)^2] \quad (5)$$

- decrease γ to prevent overfitting
- decrease C to prevent overfitting

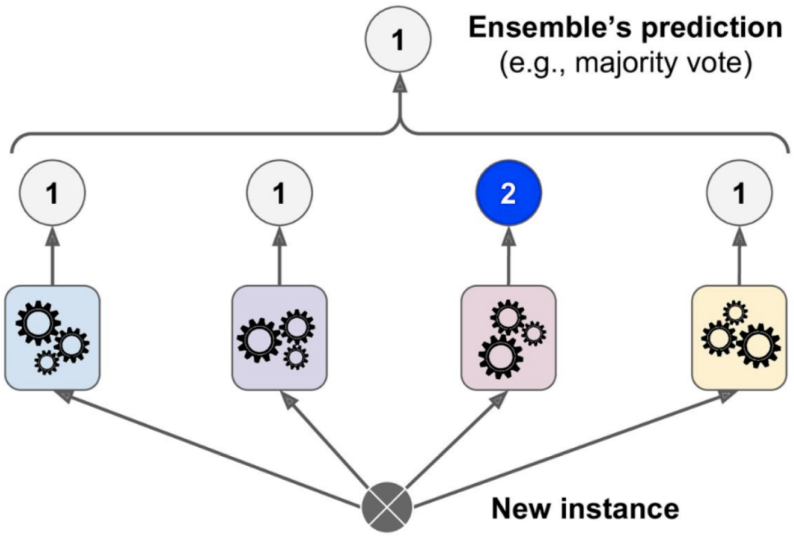


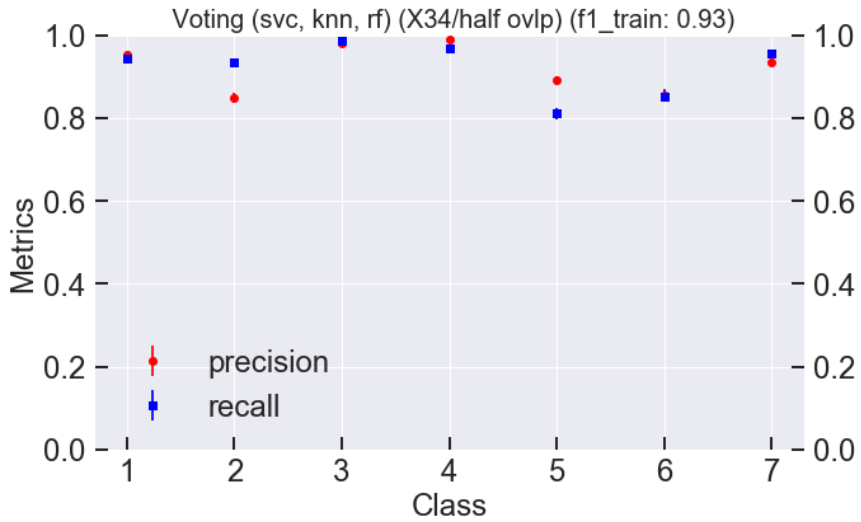


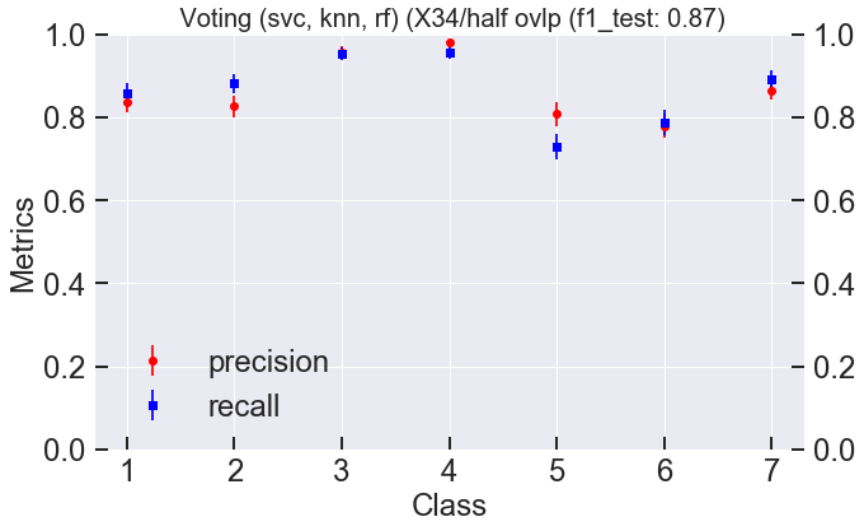
Models: Ensemble methods

Voting

- Use the pre-trained (optimized) SVC, KNN, and Random Forest algorithms
- Aggregate the predictions of each classifier and predict the class that gets the most votes
- Generally, better than each of the three algorithms



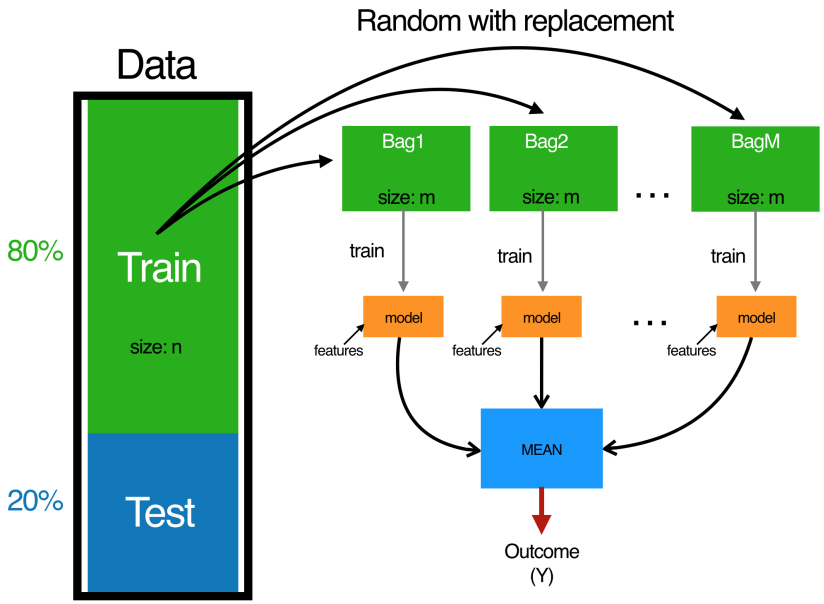


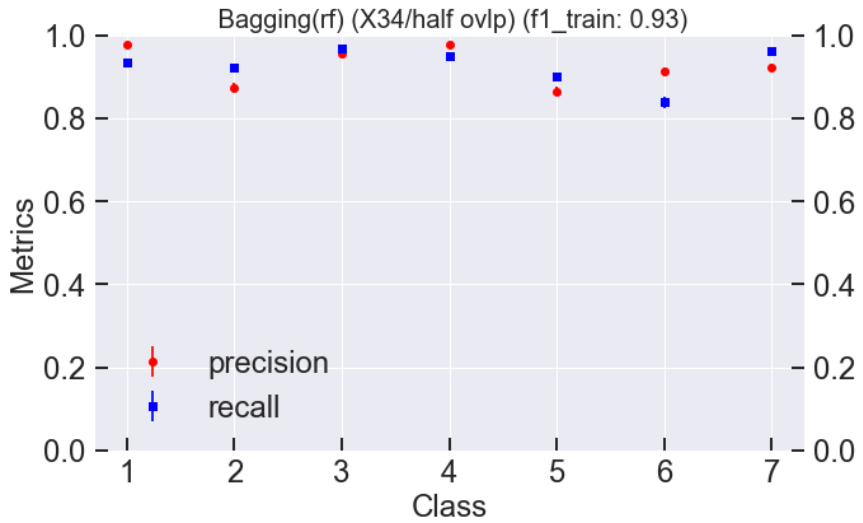


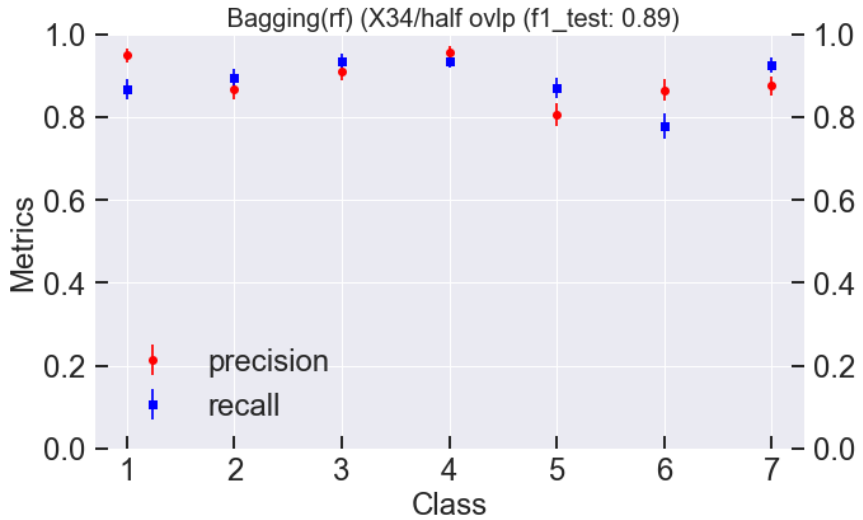
Models: Ensemble methods

Bagging

- Use the pre-trained Random Forest classifier as the base classifier
- Fit the base classifier to random 20 subsets of the original dataset (reduce variance)



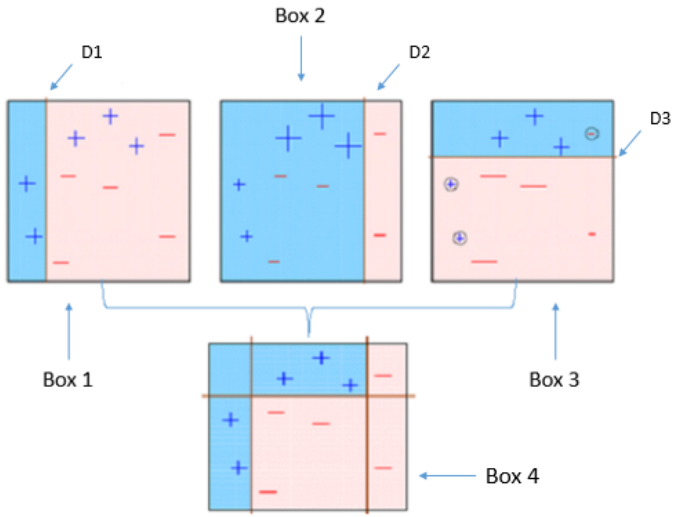


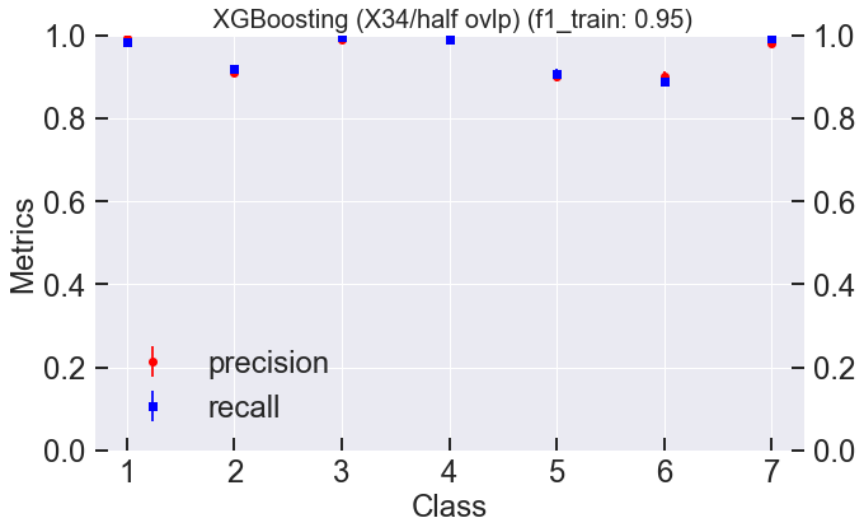


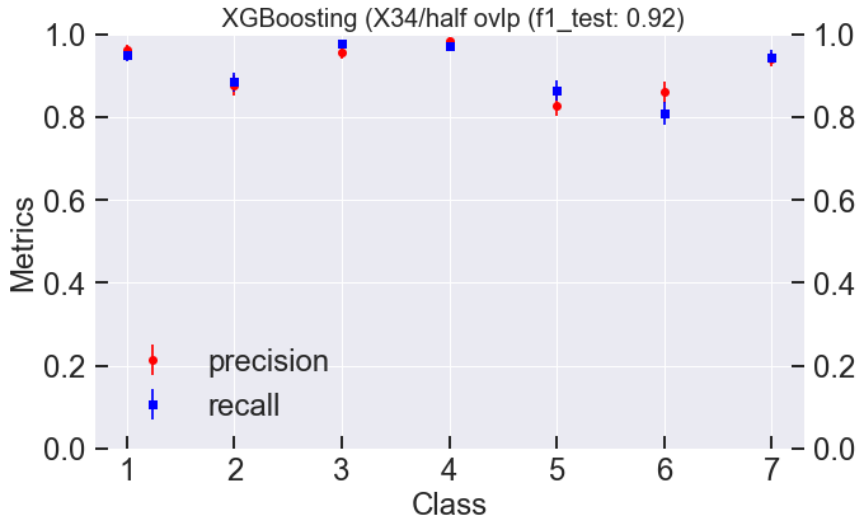
Models: Ensemble methods

XGBoost (eXtreme Gradient Boosting)

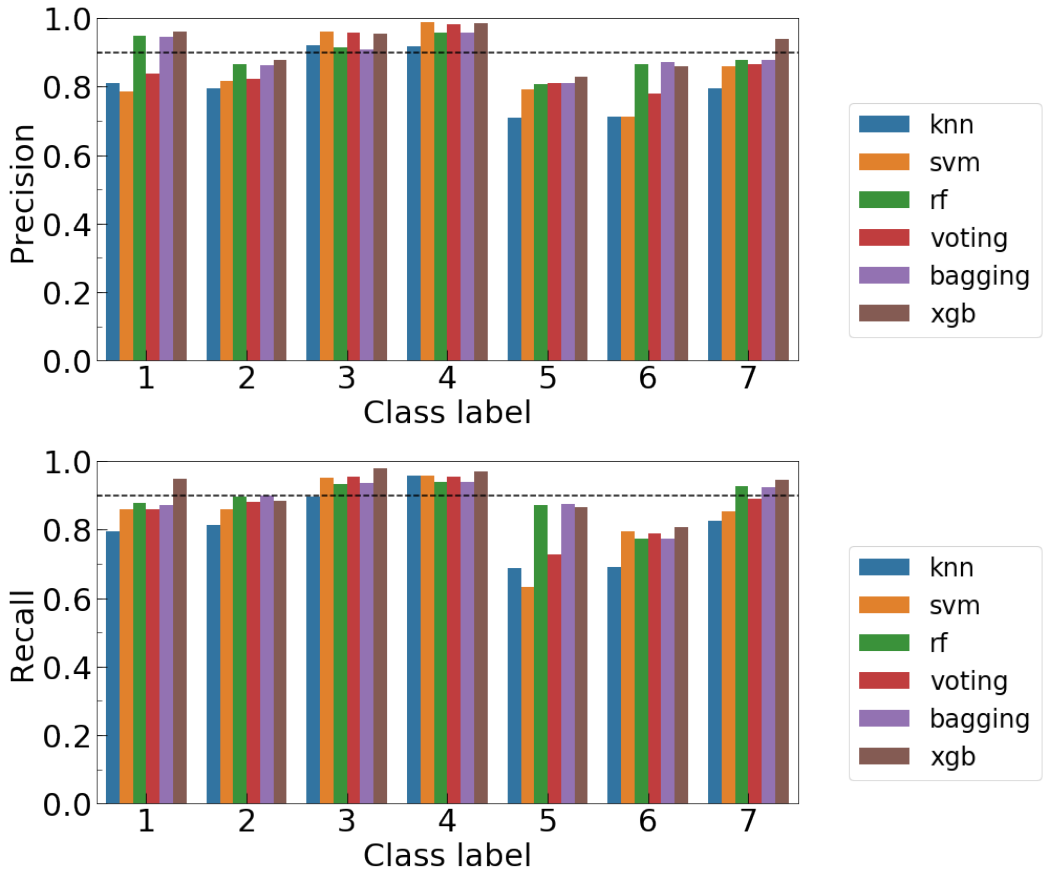
- Gradient boosted decision trees
- "state-of-the-art" machine learning algorithm for structured or tabular datasets on classification and regression (faster, wide variety of tuning parameters, better performance)





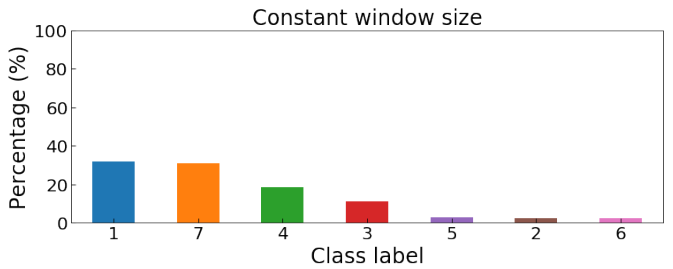


Models: comparison



Activities

1. Working at Computer
2. **Standing Up, Walking and Going Up/Downstairs**
3. Standing
4. Walking
5. **Going Up/Down Stairs**
6. **Walking and Talking with Someone**
7. Talking while Standing



Summary and outlook

Summary and outlook

Summary

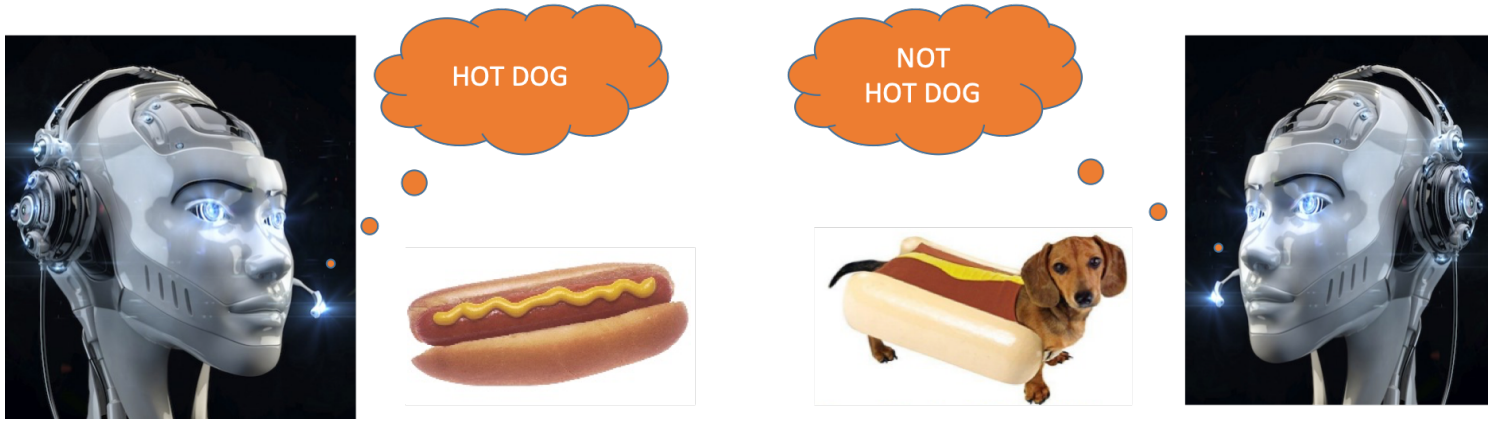
- Frequency domain features are very important
- Using non-overlapping and half-overlapping sliding windows have a significant influence (leaking test data into the training data, larger sample size?)
- Increase in window size globally decreases the performance (sample size effect?)
- Balanced data are important in multi-class classification to have a similar performance on each class.
- XGBoost turns out to have the best performance among machine learning models

Outlook

- Collect more data for the class 2, 5, and 6
- Collect some information other than the acceleration along 3 directions (angles?)
- More detailed fine tunings on the model parameters
- Deep learning models (CNN/RNN) are worth to try when the dataset is large enough

FRIB

Acknowledgement



Special thanks to Alexander Tolpygo from SFL Scientific for providing all the data for the project.

Thank you all for your attention !

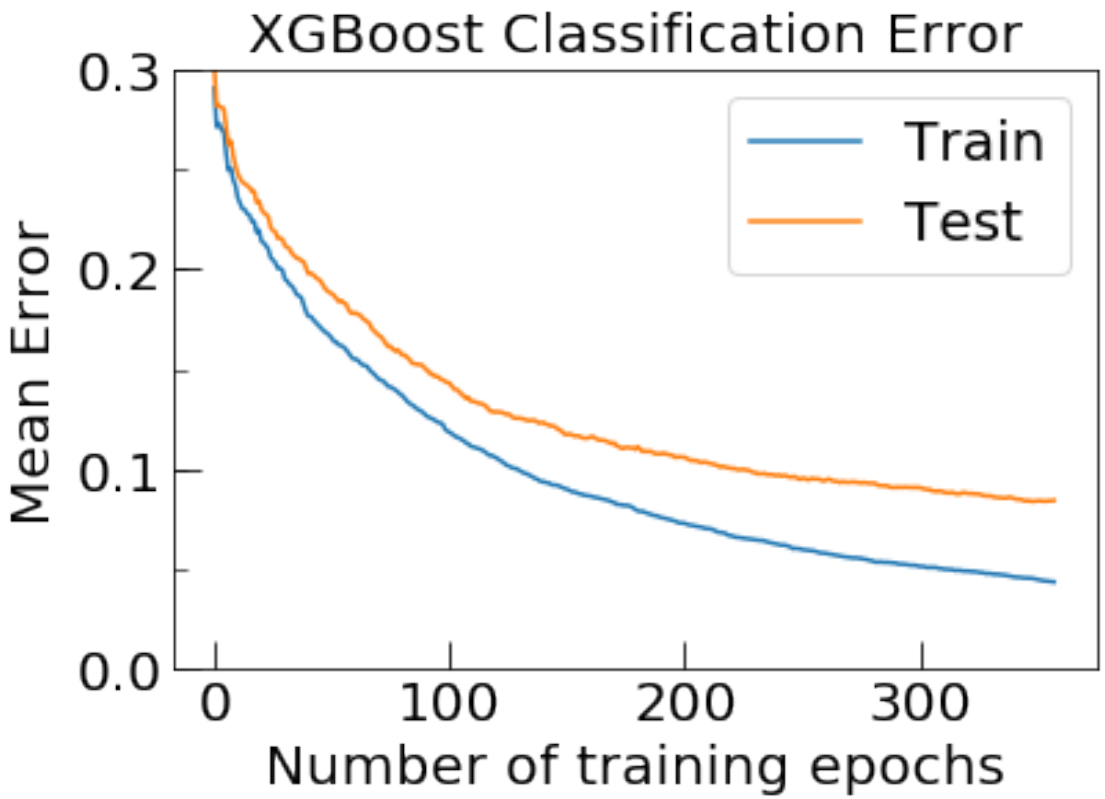
FRIB

Code Example #1

XGBoost

```
1       def xgboost_fit_predict(X_train,y_train,X_test,y_test):
2           xgb_reg = xgboost.XGBClassifier(n_estimators=1000, random_state=42)
3           xgb_reg = xgb_reg.fit(X_train, y_train, eval_metric=["merror"],
4                                 eval_set=[[X_train, y_train],[X_test, y_test]],
5                                 verbose=100,
6                                 early_stopping_rounds=10)
7
8           y_pred = xgb_reg.predict(X_test)
9           val_error = mean_squared_error(y_test, y_pred)
10          print("Validation MSE:", val_error)
11
12
13          y_pred4test        = xgb_reg.predict(X_test)
14          y_pred4train       = xgb_reg.predict(X_train)
15
16          xgb_clf_best_cm4test = metrics.confusion_matrix(y_test, y_pred4test)
17          xgb_clf_best_cm4train = metrics.confusion_matrix(y_train, y_pred4train)
18
19          print("F1 score for Test: {}".format(f1_score(y_test,y_pred4test, average
        ='weighted')))
20          print("F1 score for Train: {}".format(f1_score(y_train,y_pred4train,
        average='weighted')))
21
22
```

XGBoost: merror in train and test



FRIB