

Human Activity Recognition from Accelerometer Data

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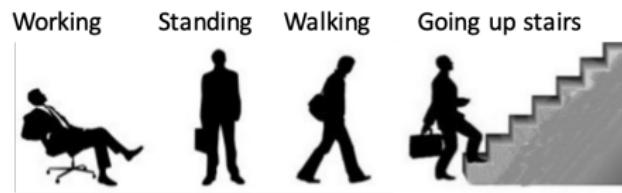
Introduction



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**



Class 1 Class 3

Class 4

Class 5

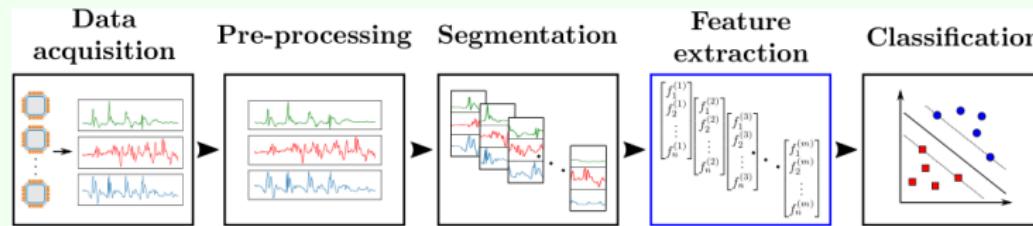


Introduction to the problem and dataset

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

- Input data:
Sequential number, x acceleration, y acceleration, z acceleration
- Output:
Class label (1, 2, ⋯, 7) for each activity.

Procedure

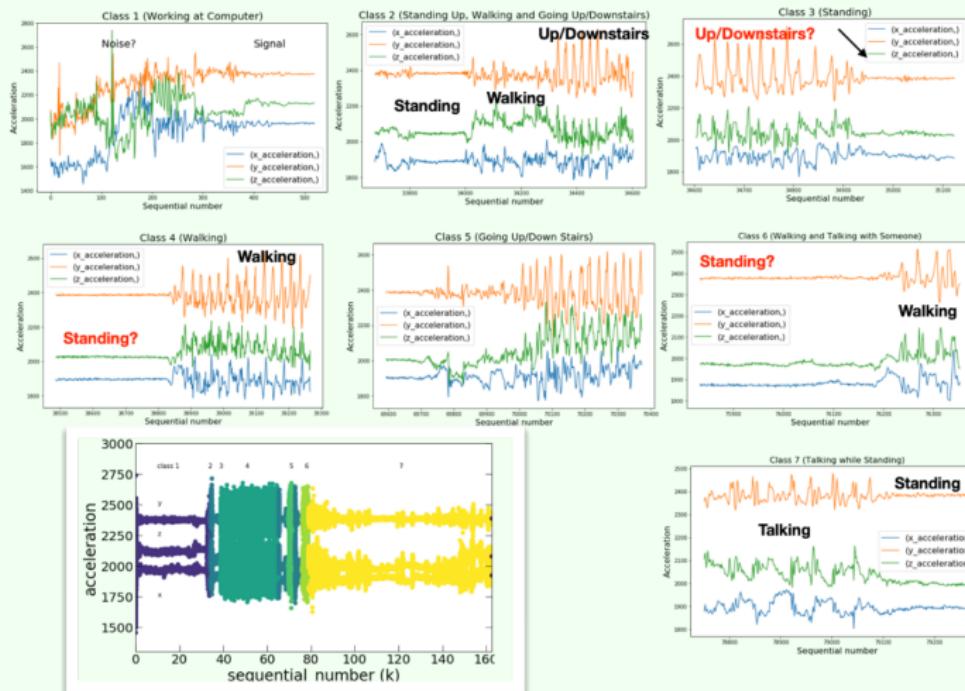


Exploratory data analysis



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 $\text{Corr}(i,j)$, magnitude $\sqrt{\mu_x^2 + \mu_y^2 + \mu_z^2}$

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

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

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

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

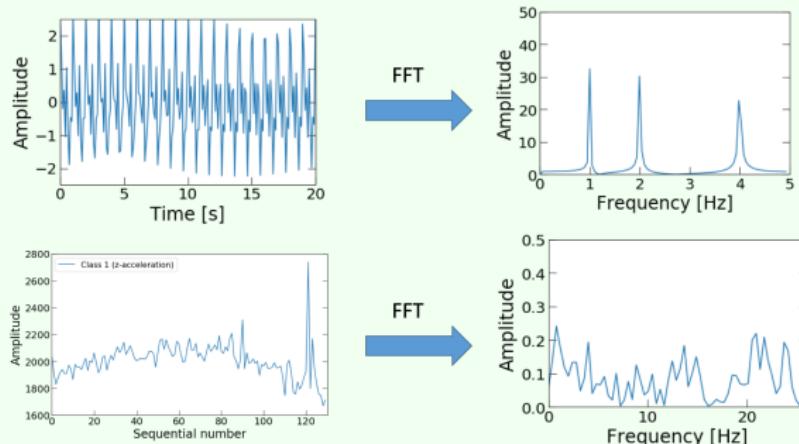


Exploratory data analysis: raw data

Fast Fourier Transformation (FFT)

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \quad k = 0, \dots, N-1 \quad (3)$$

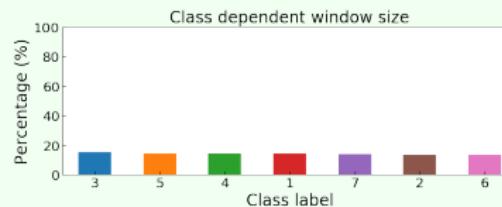
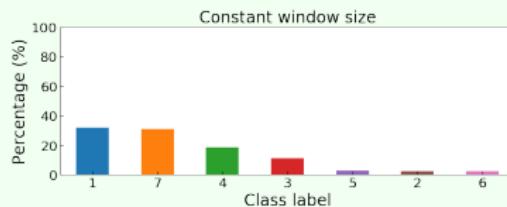
- Compute the discrete Fourier transform of a sequence
- Computation complexity $O(n \log(n))$ (divide and conquer algorithm)



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

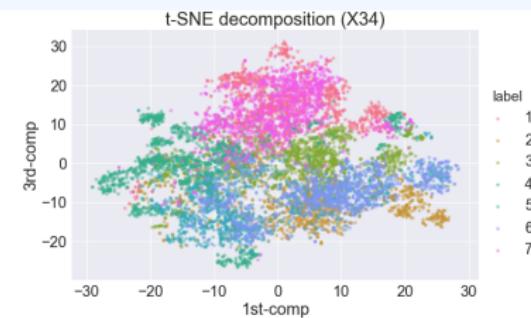
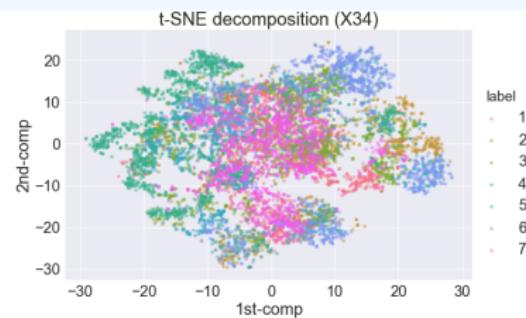


Exploratory data analysis: sample data

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

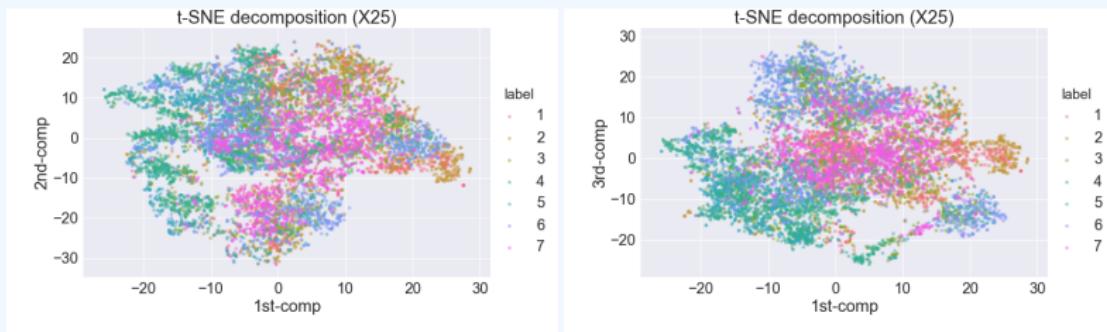


Exploratory data analysis: sample data

t-distributed Stochastic Neighbor Embedding (t-SNE)

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- tool for visualizing clusters of instances

Data with 25 features (without frequency domain features)



Models

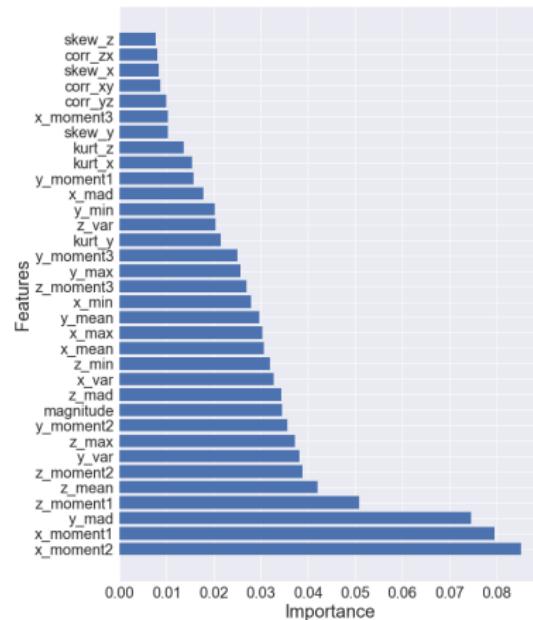


Models

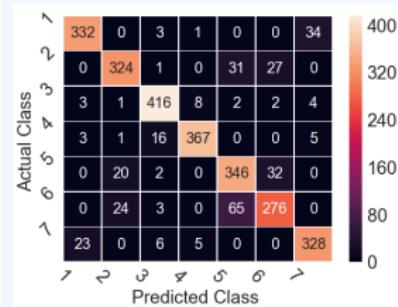
Random Forest

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

Training the model with default parameters



Confusion matrix (Test Data)

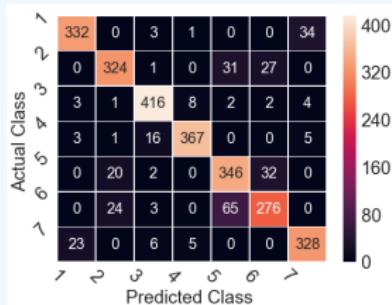


Models

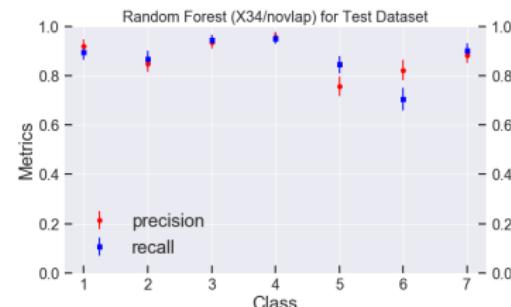
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Confusion matrix (Test Data)



Training the model with default parameters



Models

Random Forest

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

GridSearch for the parameters

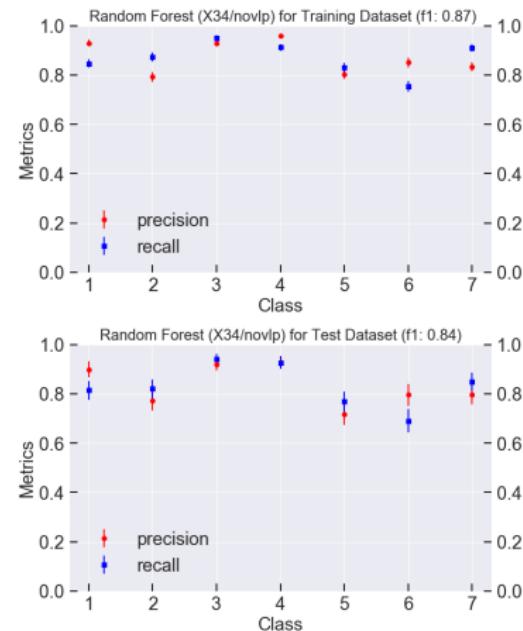
Introduce a new metric to take care of overfitting:

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

where the f_1 measure is defined as

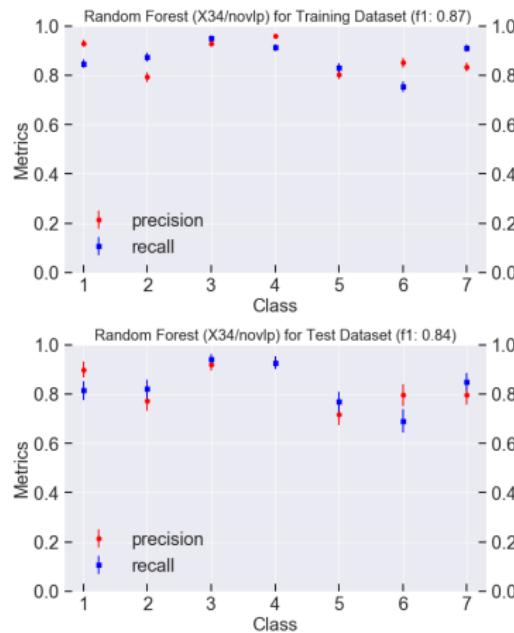
$$f_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} \quad (4)$$

Training the model with GridSearch

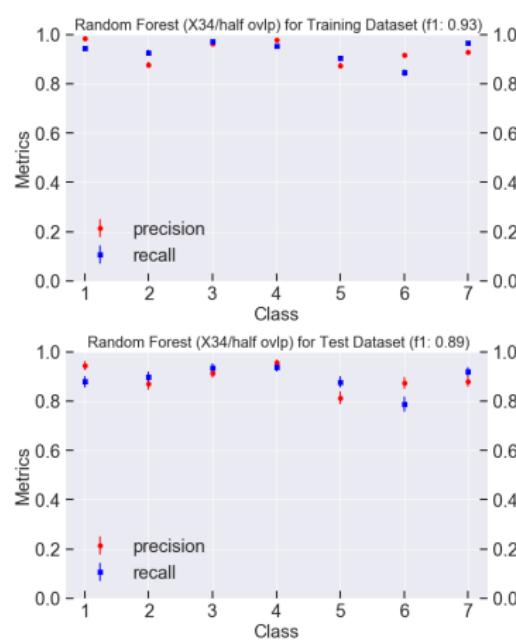


Models: overlapping windows or not

Non-overlapping windows

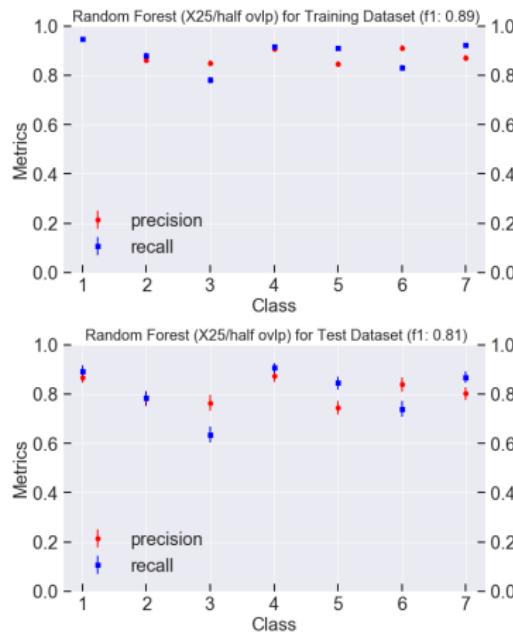


Half-overlapping windows

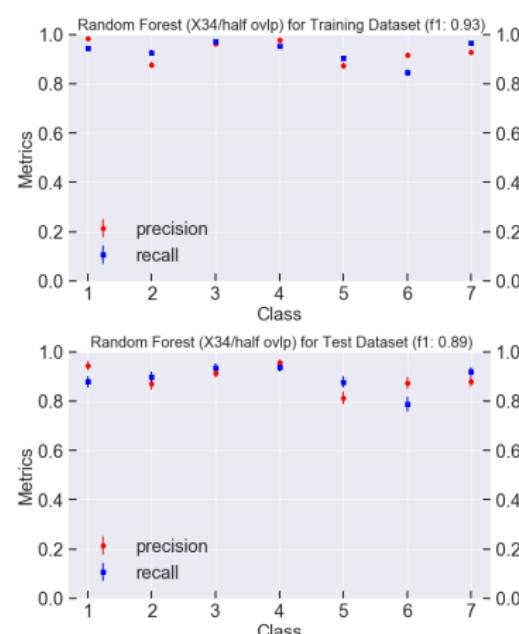


Models: with frequency domain features or not

w/o frequency domain features

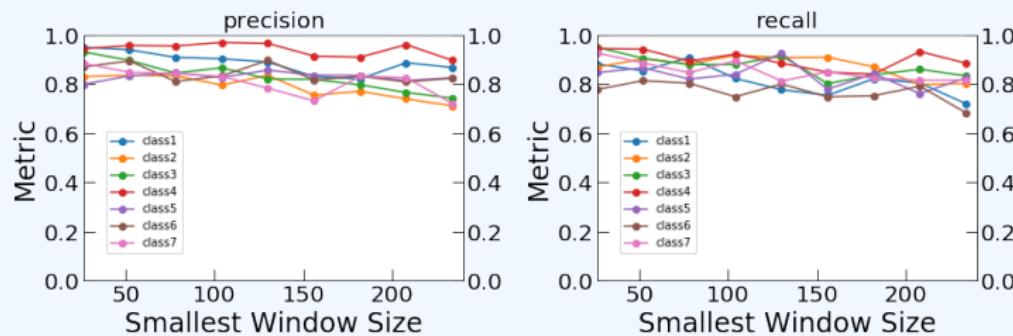


w/ frequency domain features



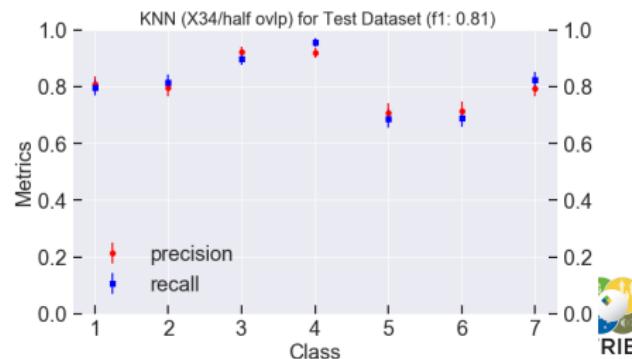
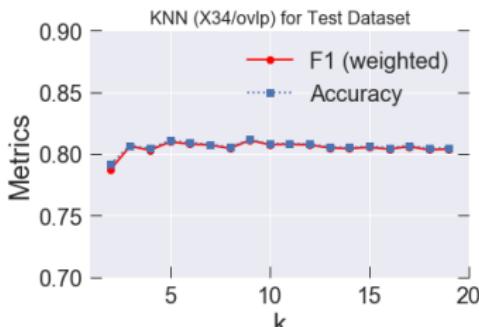
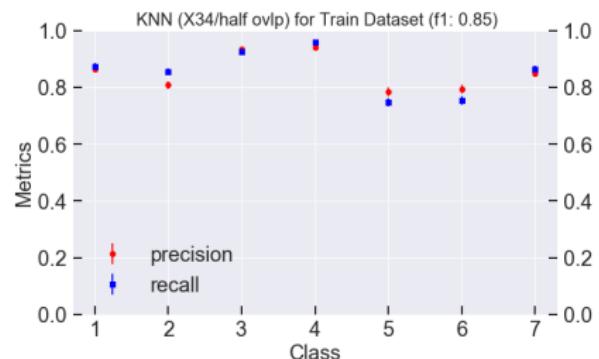
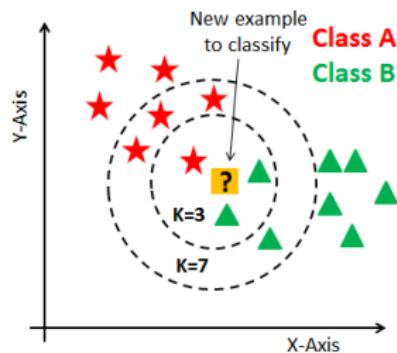
Models: window size effect

Precision/Recall for test data in the Random Forest

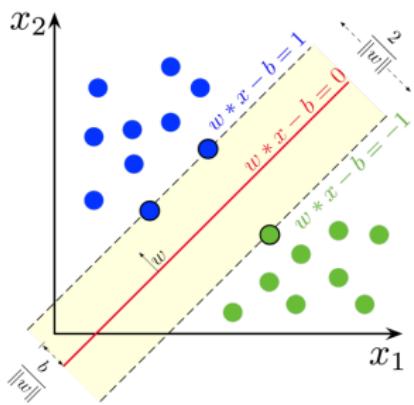


- Globally, the score is slightly decreasing with the window size.

Models: KNeighborsClassifier (KNN)



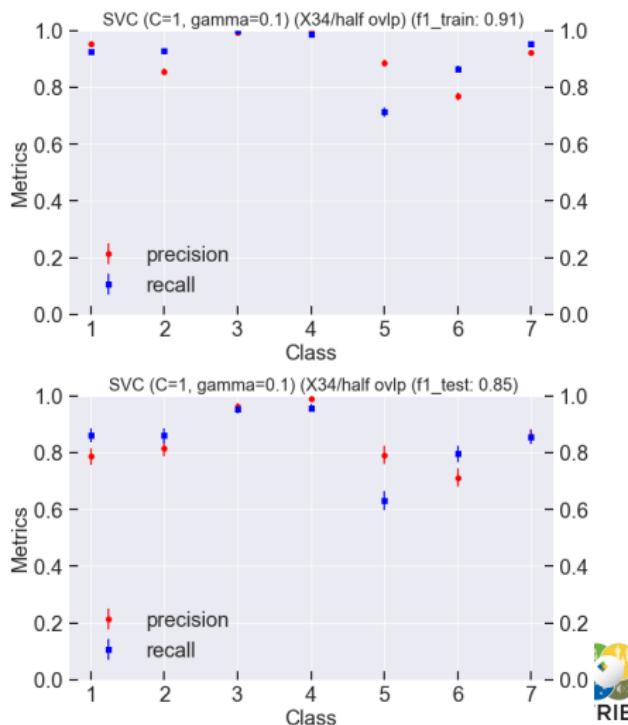
Models: Support Vector Machine Classification (SVC)



- kernel: radial basis function

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

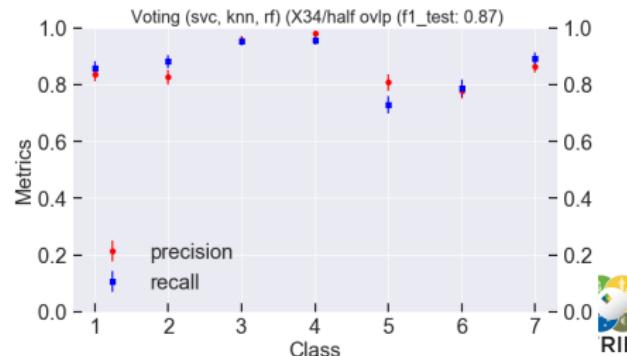
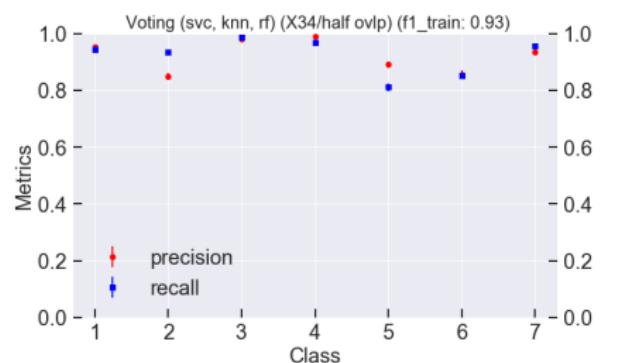
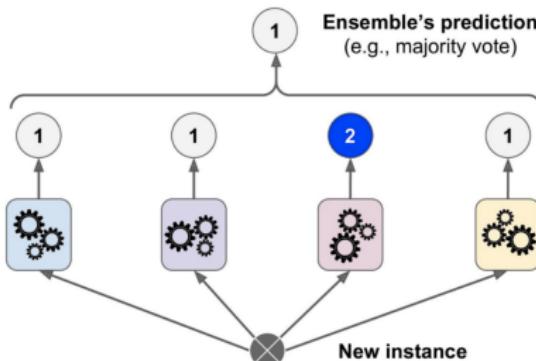
- decrease γ to prevent overfitting
- decrease C to prevent overfitting



Models: Ensemble methods

Voting

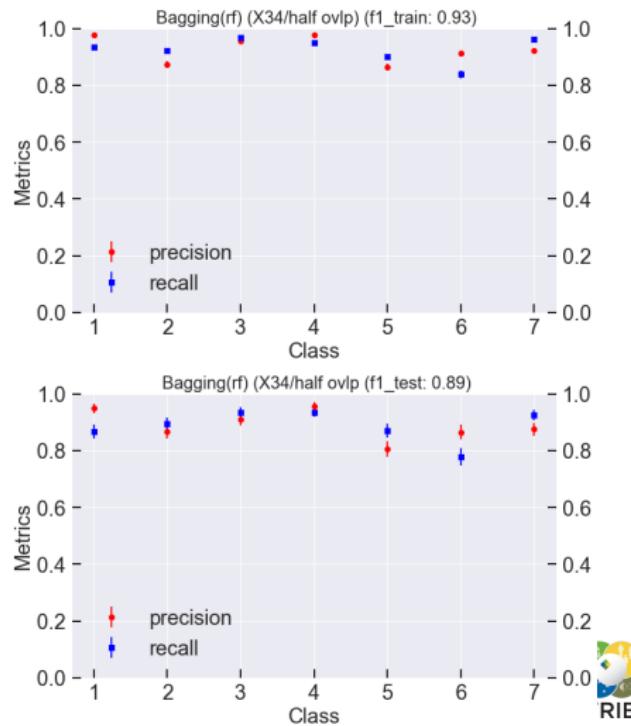
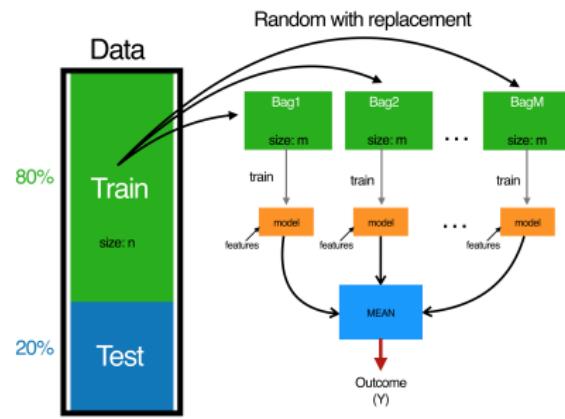
- Use the pre-trained (optimized) SVC, KNN, and Random Forest algorithms
- Aggregate the predictions of each classifier and predict the class that gets the most votes
- Generally, better than each of the three algorithms



Models: Ensemble methods

Bagging

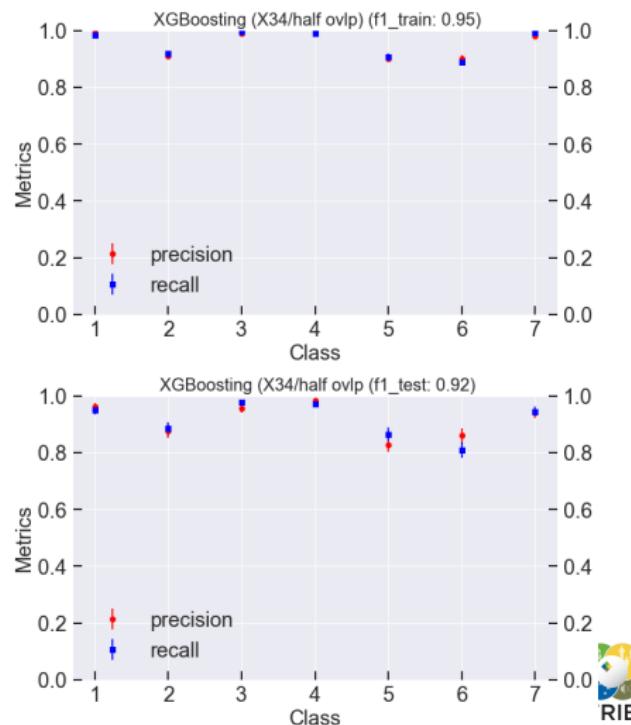
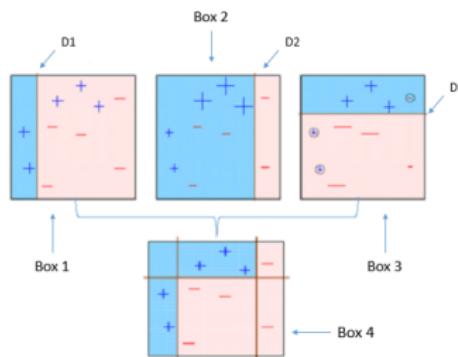
- Use the pre-trained Random Forest classifier as the base classifier
- Fit the base classifier to random 20 subsets of the original dataset (reduce variance)



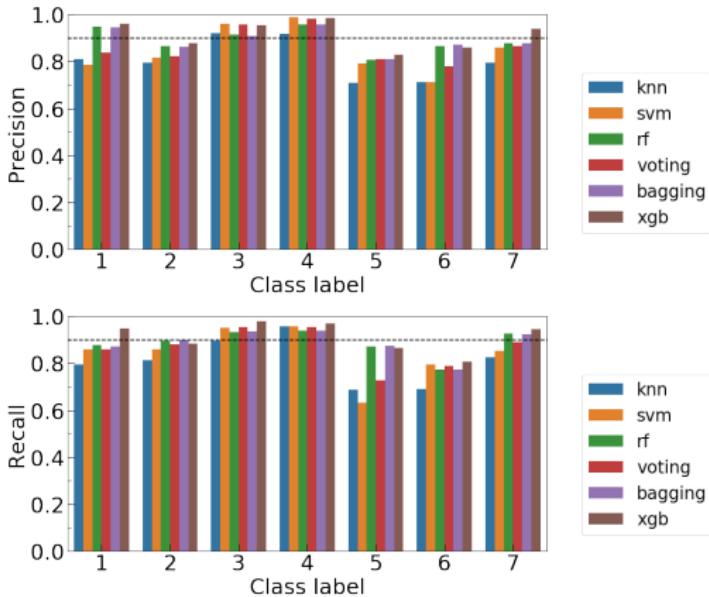
Models: Ensemble methods

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)

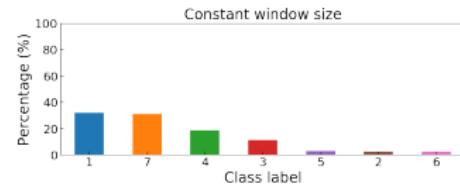


Models: comparison



Activities

- 1 Working at Computer
- 2 Standing Up, Walking and Going Up/Downstairs
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Summary and outlook



Summary and outlook

Summary

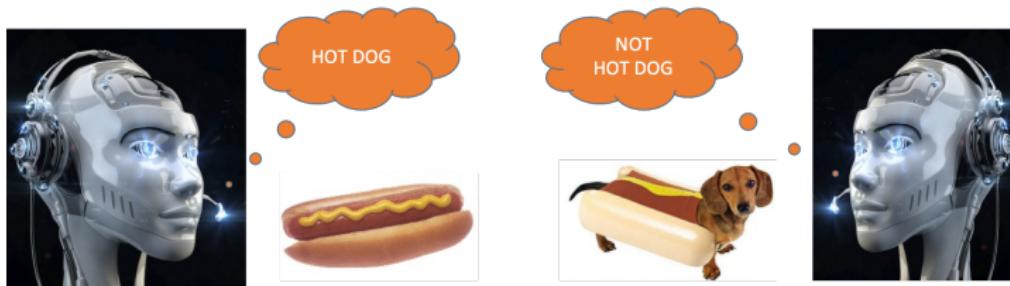
- Frequency domain features are very important
- Using non-overlapping and half-overlapping sliding windows have a significant influence (leaking test data into the training data, larger sample size?)
- Increase in window size globally decreases the performance (sample size effect?)
- Balanced data are 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



Acknowledgement



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

Thank you all for your attention !

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
20 = 'weighted'))))
21         print("F1 score for Train: {}".format(f1_score(y_train,y_pred4train,
average='weighted')))
```



XGBoost: mirror in train and test

