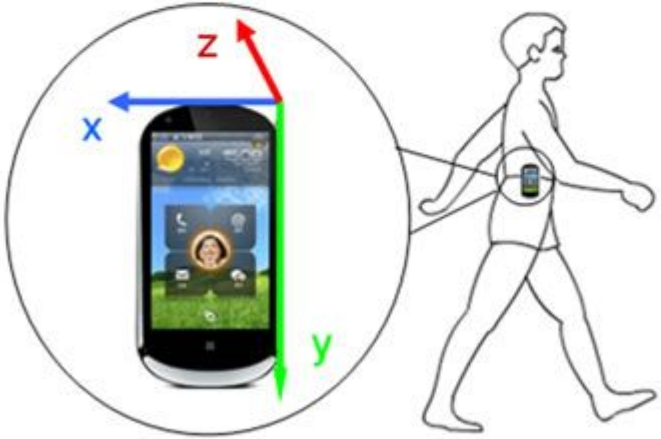
Human Activity Detection with Smartphone Data

by Benjamin Stano

Activity Detection Using Smartphones

- Predicts users action based on sensors
- Smartphones have accelerometer, gyroscope standard
- Smartphones ideal for HAD
  - Endless data
  - Countless uses



Practical Applications

- HAD has many practical uses:
  - Biometric Security
  - Elderly and youth care
  - Industrial Manufacturing and Assisting
  - Daily Life and Fitness monitoring

Research Questions

- Questions to answer:
  1. Predict subject activity while using their smartphone
  2. Many sensor inputs, which are important?
  3. Many modeling types, which one is ideal?

Introducing the Data

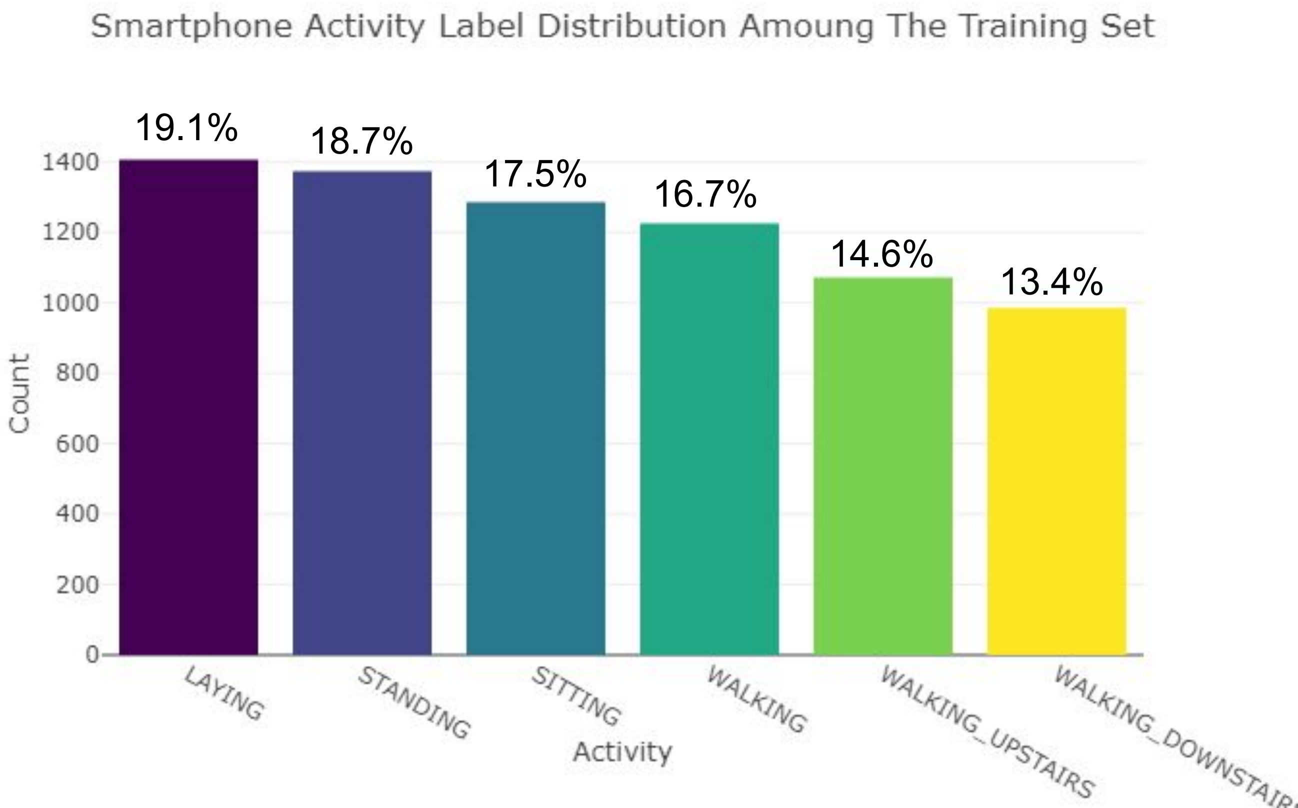
Human Activity Recognition Using Smartphones

- 30 volunteers performing same 6 actions
  - Laying, Standing, Sitting, Walking, Walking Upstairs, and Walking Downstairs
- Manually labeled as six actions
- 50 Hz intervals, or every 0.02 seconds
- Data split: 70% training, 30% testing
  - 7352 training instances, 2947 testing instances
- 561 features in total
  - Triaxial acceleration and estimated body acceleration
  - Triaxial angular momentum

source:
https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones

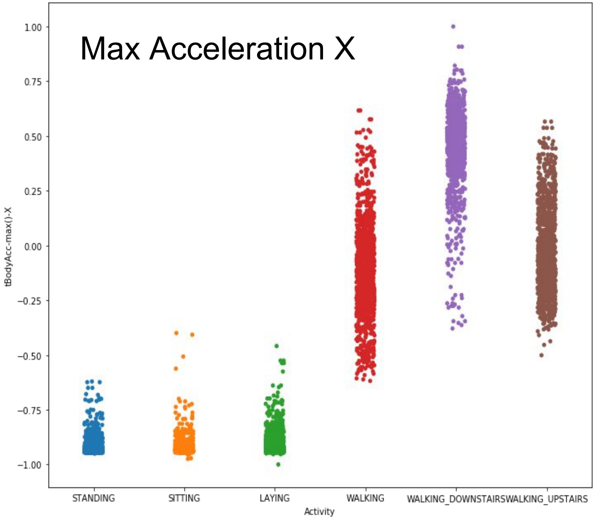
Is the Training Data Balanced?

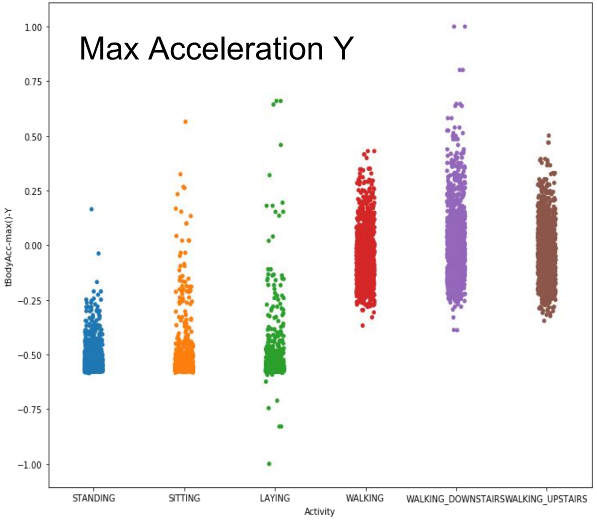
- Unbalanced training set leads to model error
- Percentages relative to total counts
- Outcome is balanced in the training set

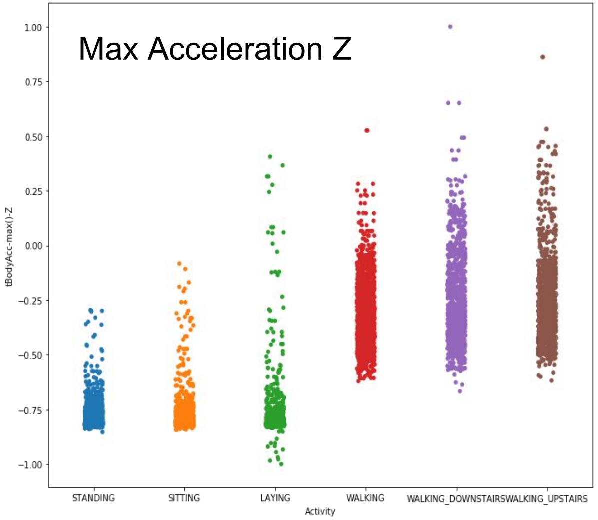


Passive vs. Active Activities

- Plot shows max acceleration readings for each activity type
- Passive: standing, sitting, laying
  - Very clustered
- Active: walking, walking upstairs, walking downstairs
  - Much more variable







Exploring Feature Sets

Exploring Different Feature Sizes

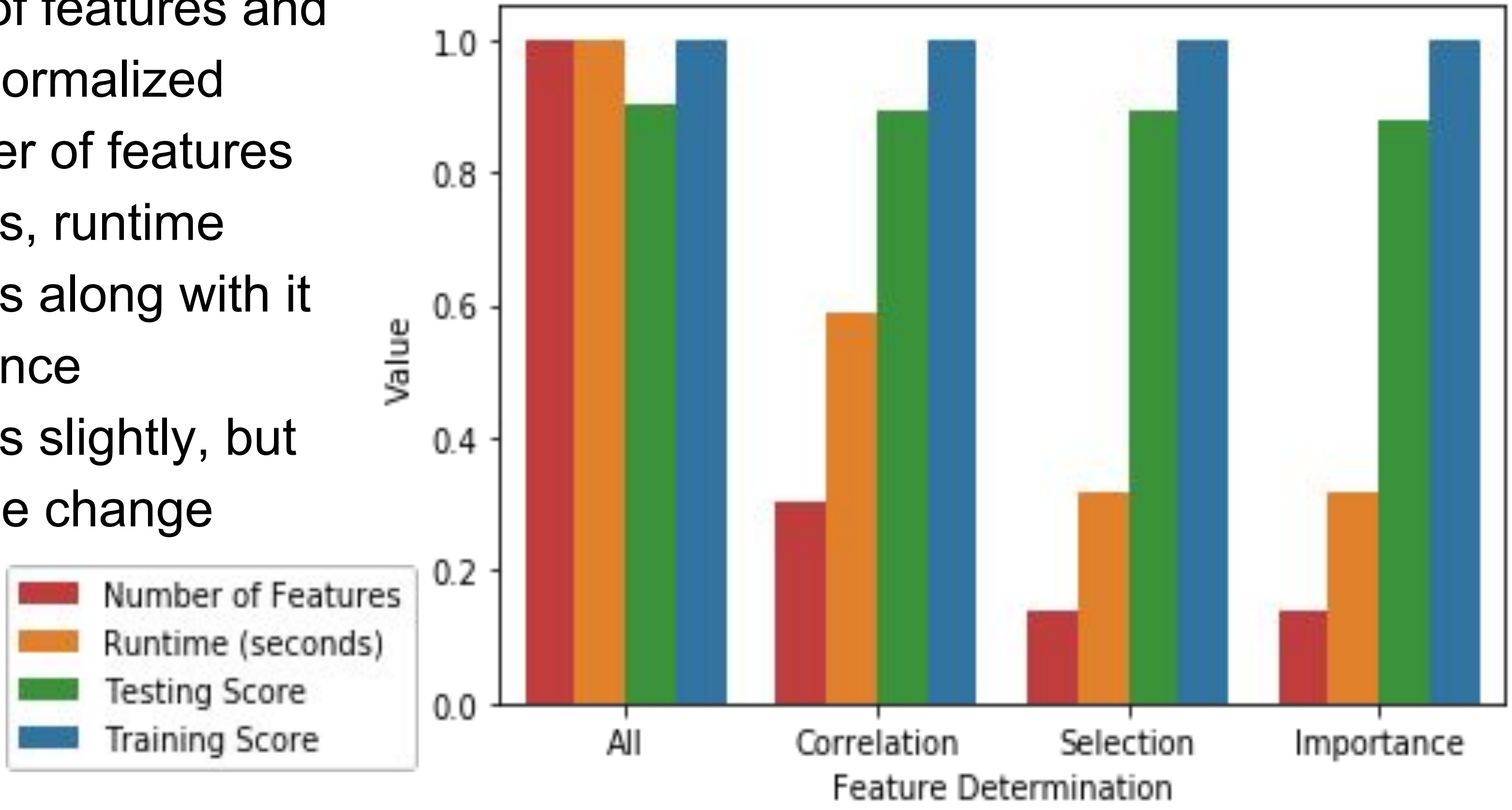
- Find most efficient feature set
- Many models easily overburdened
- Outcome could go unexplained
- HAD data rife with variance
- Use Random Forest Classifier to test different feature sets
    - Easy to train and adaptable
    - Gives feature importance

Exploring Different Feature Sizes contd.

- 4 feature sets in total trained and tested with RFC
- Use set containing all original features (561)
- Make 3 multiple new feature sets:
  1. Highly correlated feature pairs (171)
  2. Features chosen by SelectFromModel (77)
  3. Using 77 most important features (77)
- Compare/contrast Selection and Importance sets

RFC Feature Set Performance Comparison

- Number of features and runtime normalized
- As number of features decreases, runtime decreases along with it
- Performance decreases slightly, but not a large change



Feature Set Performance Comparison

Feature Set	All	Correlation	Selection	Importance
Number of Features	561 (100%)	171 (30.5%)	77 (13.7%)	77 (13.7%)
Runtime (in seconds)	7.0122 (100%)	4.1100 (58.6%)	2.2421 (32.0%)	2.2181 (31.6%)
Testing Accuracy	90.0%	89.3%	89.1%	87.7%
Training Accuracy	100%	99.9%	100%	99.9%

Feature Set Findings

- All had most accuracy, longest runtime
- Correlation much faster, similar accuracy
- Selection performed best, efficient and accurate
  - Use this one to model
- Importance set performed very poorly
- Important to select intelligently while reducing dimensions

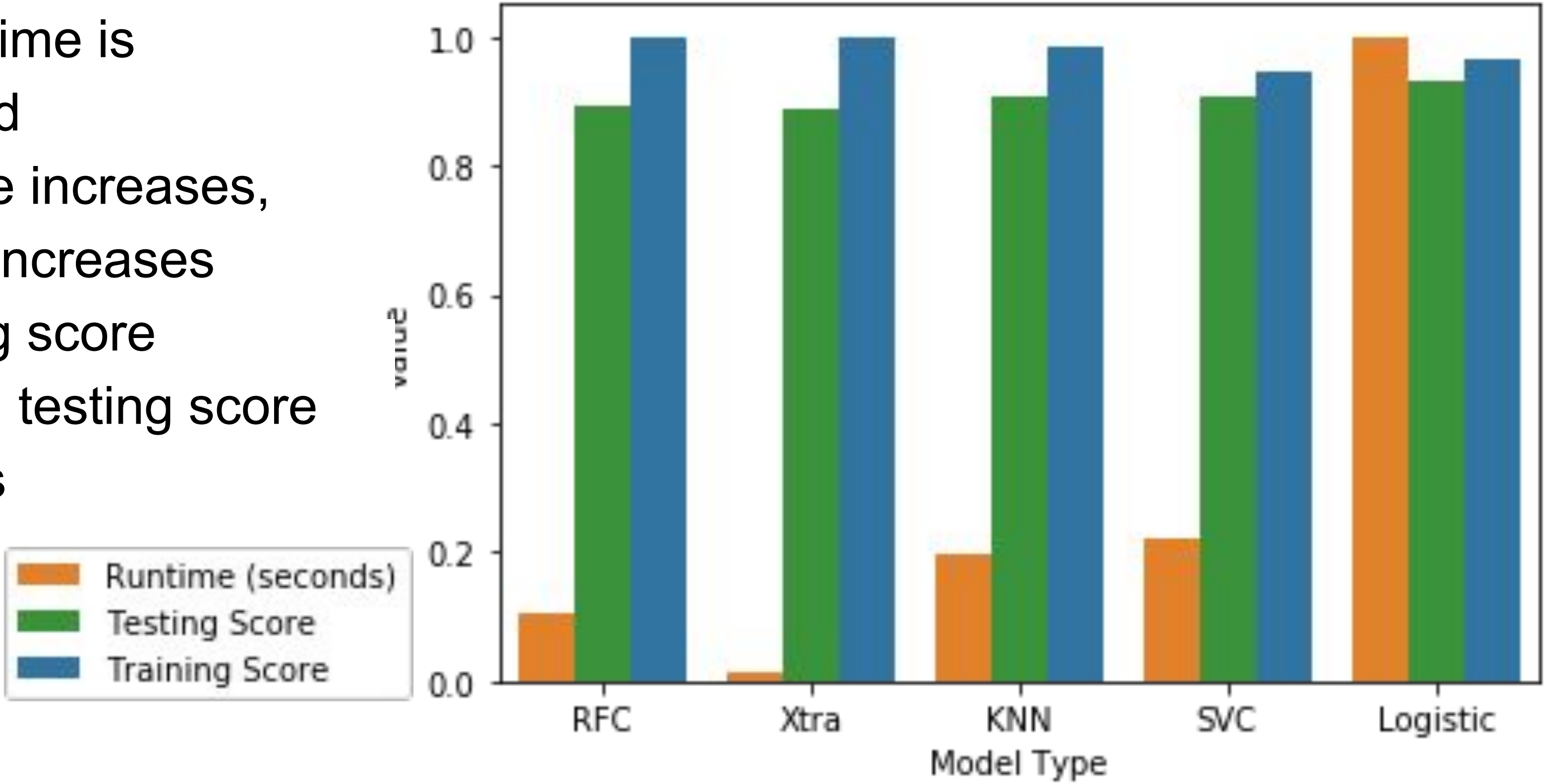
Exploring Different Models

Models Used

- Determine most efficient model
- Model using the Selection feature set
- Use 5 different model types:
  - Random Forest Classifier
  - Extra Trees Classifier
  - K Nearest Neighbors Classifier
  - Support Vector Classifier
  - Lasso Logistic Regression

Normalized Performance Comparison

- Only Runtime is normalized
- As runtime increases, accuracy increases
- As training score increases, testing score decreases



Model Performance Comparison

Model Type	Random Forest	Extra Trees	K Nearest Neighbors	Support Vector	Logistic
Runtime (in seconds)	2.2869	0.5156	7.3311	8.8154	39.9392
Testing Accuracy	89.1%	88.9%	90.6%	**90.8%**	**92.9%**
Training Accuracy	99.9%	100%	98.3%	94.6%	96.5%
CV score (5 folds)	88.2%	86.7%	88.7%	**90.8%**	89.8%

Model Type Findings

- RFC performed well overall
  - Best if runtime is most important
- XTC performed worst, overfit
- KNNC not as good as other choices
- SVMC performed best overfall
  - Best blend of accuracy and efficiency
- Logistic most accurate, may have underlying problems
  - May be best if accuracy is most important

Conclusions

Overview

- Data: *Human Activity Recognition Using Smartphones*
- Feature Sets:
  - All, 561
  - Correlation, 170
  - Selection, 77
  - Importance, 77
- Models Used: RFC, Xtra, KNN, SVC, Logistic

Findings

- Removing features improves efficiency, low effect on accuracy
- Best feature set for modeling is SelectFromModel
- Best model: Support Vector Classifier
  - Best blend of efficiency and performance
  - Best CV score
- RFC if efficiency is important

References

- Dataset:
  - https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones
- Citations:

  - Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine. International Workshop of Ambient Assisted Living (IWAAL 2012). Vitoria-Gasteiz, Spain. Dec 2012
  - Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition Using Smartphones. *21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN* 2013. Bruges, Belgium 24-26 April 2013.
  - Jorge Luis Reyes-Ortiz, Alessandro Ghio, Xavier Parra-Llanas, Davide Anguita, Joan Cabestany, Andreu Català. Human Activity and Motion Disorder Recognition: Towards Smarter Interactive Cognitive Environments. *21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN* 2013. Bruges, Belgium 24-26 April 2013.
  - http://www.ijirst.org/articles/IJIRSTV2I4024.pdf
  - https://www.profactor.at/en/research/industrial-assistive-systems/visual-computing/projects/instructme/
  - https://ieeexplore.ieee.org/document/7737171/
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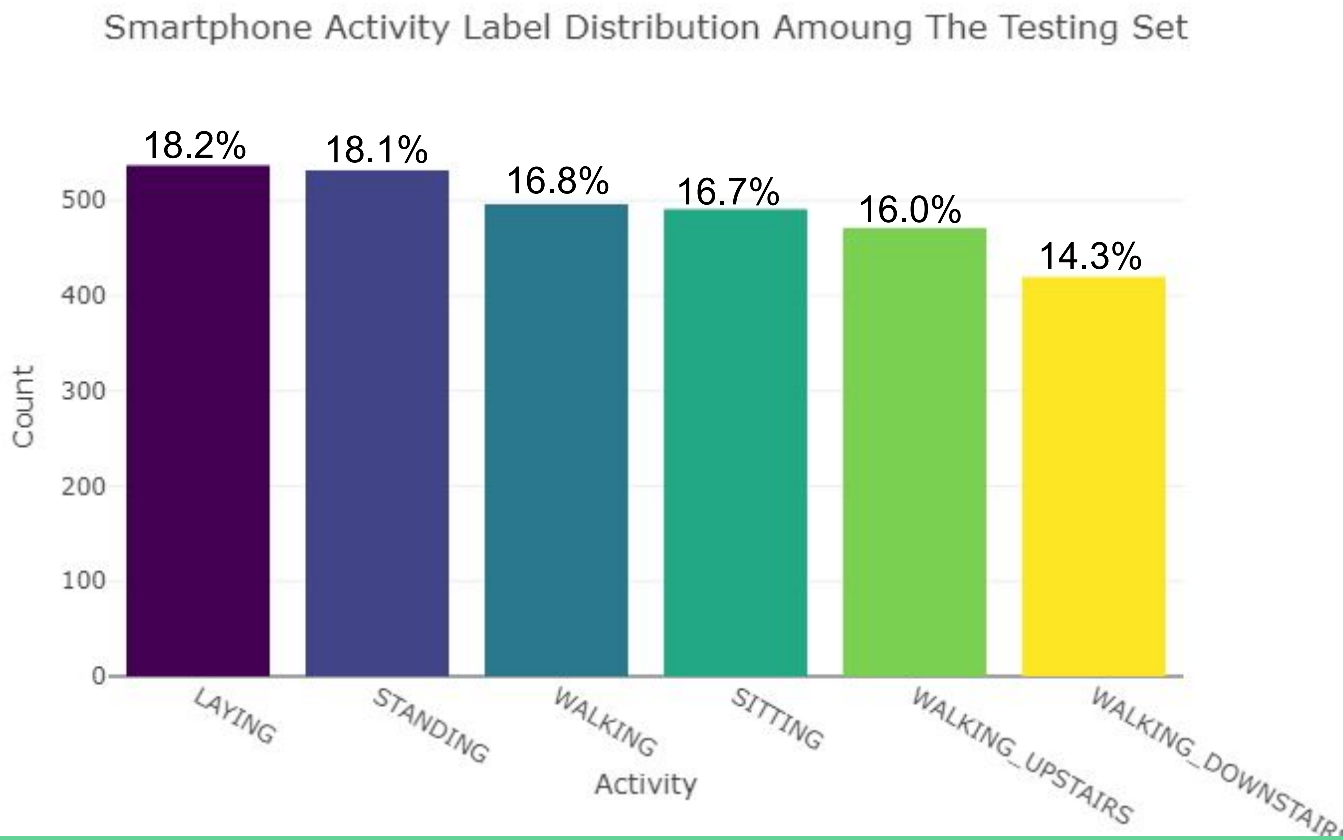
Appendix

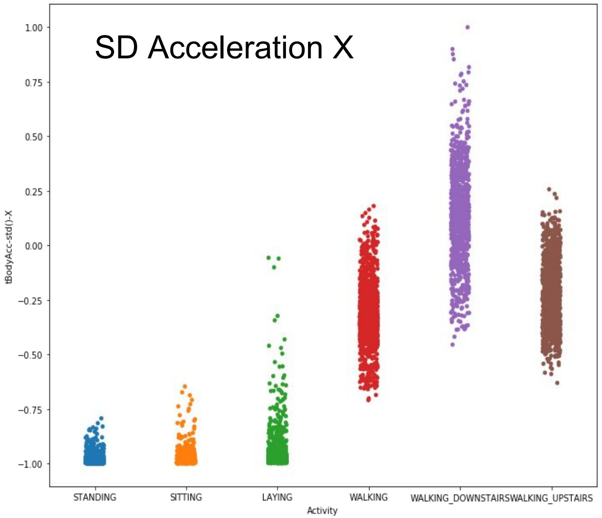
Outcome Class Balance of Test Set

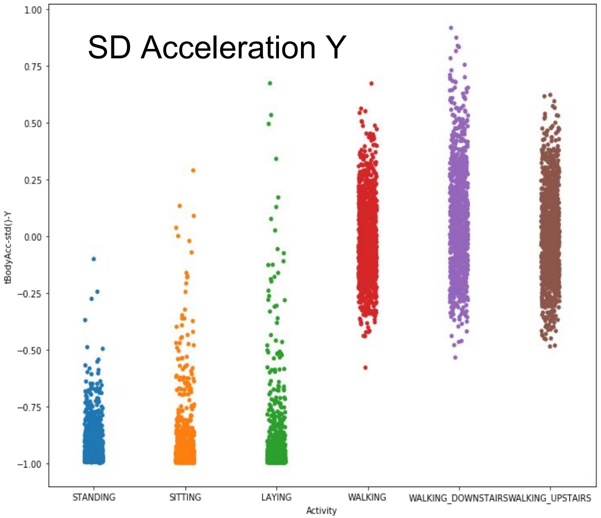
- Testing Set is more balanced than training set
- Not as important for modeling

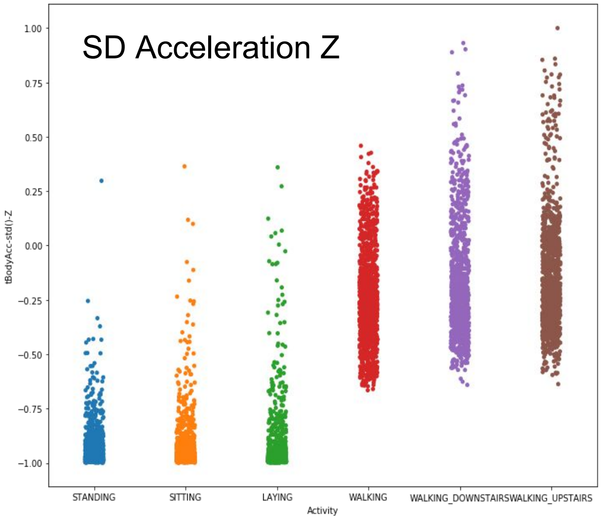


Passive vs. Active contd. 2

- Plot shows standard deviation t-sensor acceleration for all activities
- Passive activities tend to have more lower standard deviation
- Passive less variable, Active more variable

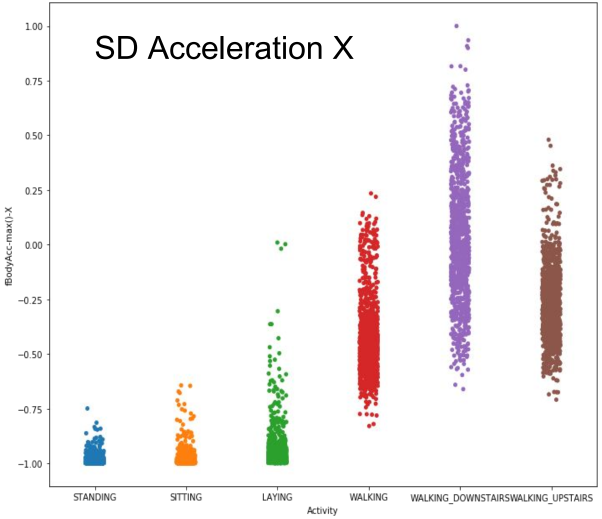


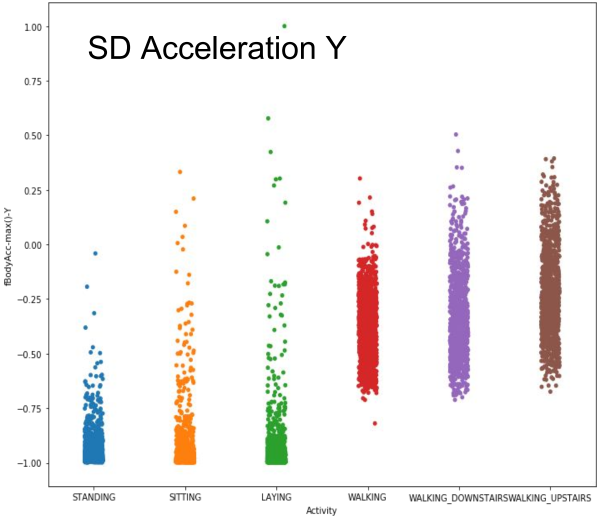


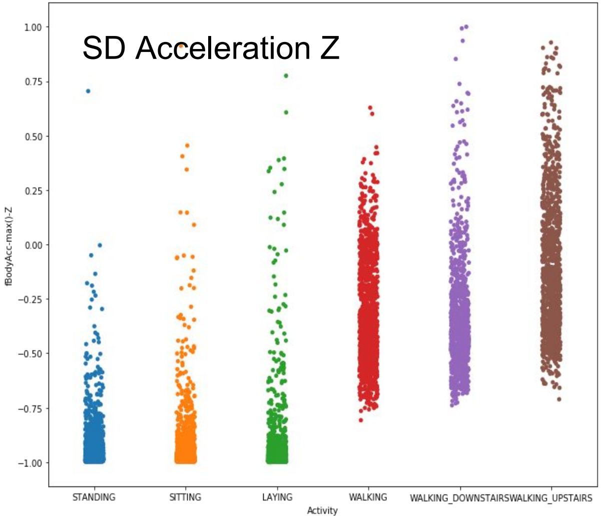


Passive vs. Active contd. 3

- Plot shows max f-sensor acceleration for all activities
- Passive activities tend to have more lower standard deviation
- Passive less variable, Active more variable







Passive vs. Active contd. 4

- Plot shows standard deviation f-sensor acceleration for all activities
- Passive activities tend to have more lower standard deviation
- Passive less variable, Active more variable