Automated Fall Detection

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SFU

PROBLEM

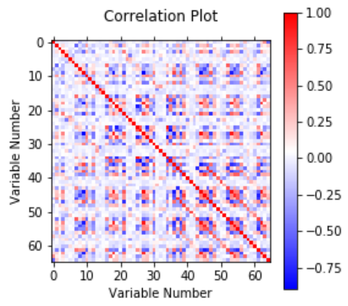
- Falls are leading cause of injury among elderly people[1]
- When elderly people fall, they are often unable to get up and call for help[2]
- Population of elderly people is increasing fast
- Automatically detecting falls[3]:
  - improves response time to falls
  - mitigates severity of injuries
  - reduces healthcare costs

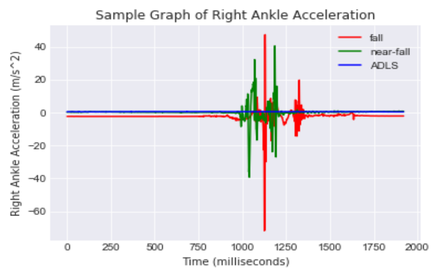
Our project seeks to answer the following questions:

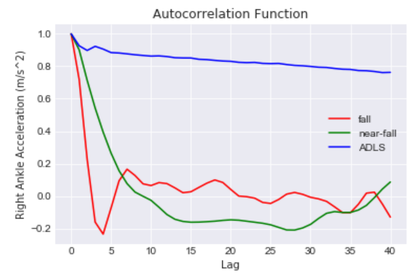
1) Can we detect falls with high accuracy and precision?
2) What models are best for detecting falls?
3) Can a single sensor detect falls with high accuracy and precision?
4) Which single sensor works best at detecting falls?

EXPLORATORY DATA ANALYSIS

- Readings behave differently around a fall
- There is a very short lead-up to a fall
- Certain features are highly correlated
- Features exhibit high autocorrelation at short lags







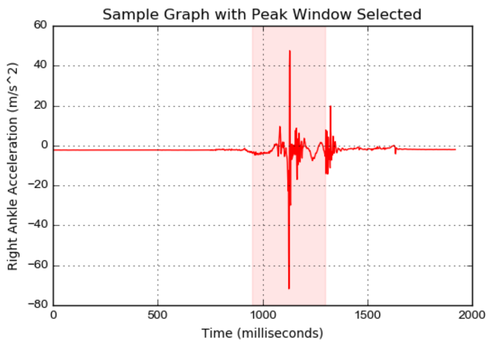
MACHINE LEARNING

1 Data Engineering

1.1 Calculate resultant vector $(X^2 + Y^2 + Z^2)^{0.5}$
1.2 Create windows and summary statistics
1.3 Determine fall period and remove windows outside this period
1.4 Feature selection

2 Machine Learning Models

2.1 Naïve Bayes
2.2 Logistic Regression
2.3 Random Forest Classifier
2.4 Gradient Boosted Trees
2.5 Decision Trees
2.6 Support Vector Machine



Data Pipeline

Raw Data
- 10 subjects, 60 trials of simulated falls, non-falls, and active daily living (ADL)
- Collected using body mounted tri-axial accelerometers
- Each sensor collects acceleration, magnetic field, and velocity data

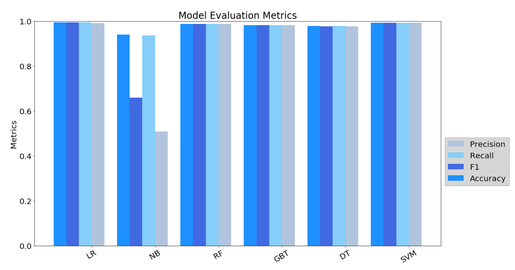
Data Processing
- Convert Excel files to CSV/TXT files
- Reformat data
- Aggregate data into windows
- Extract "Peak" fall measurements

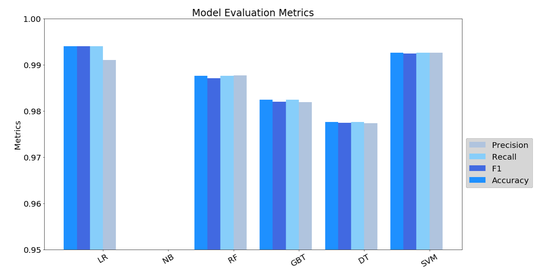
EDA
- Examine difference between trial types
- Examine differences between sensors
- Examine relationships between features

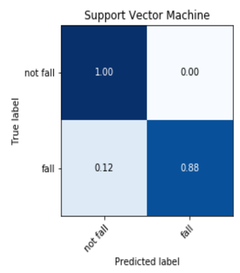
Machine Learning
- Feature selection and engineering
- Test different classification models
- Goal: 0% False positive rate, 90% True positive rate

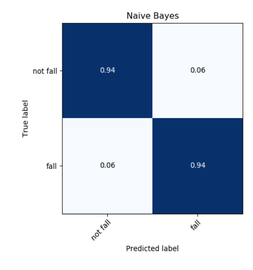
Fall Detection
- Use models to classify trials
- Summarize results

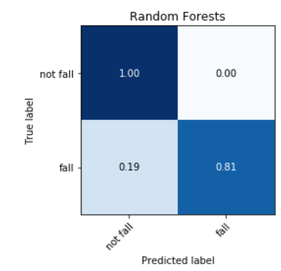
RESULTS

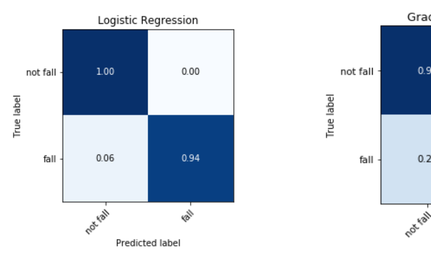


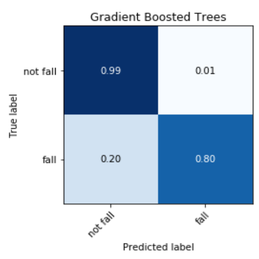


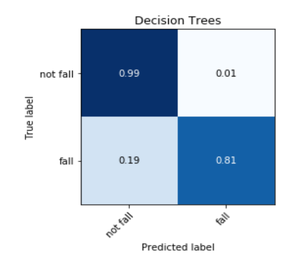


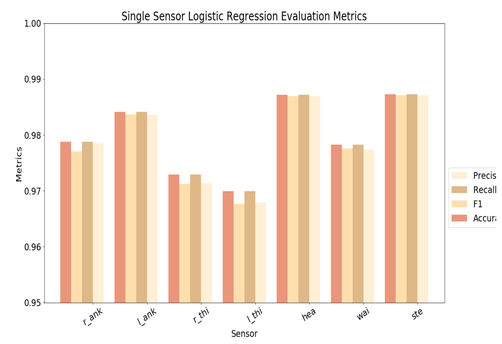


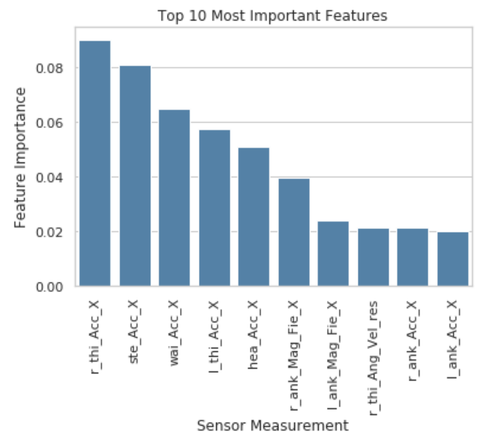






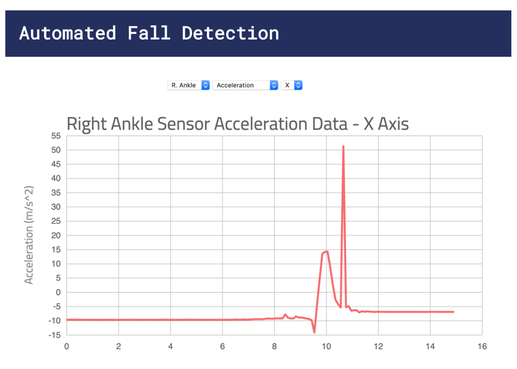






DASHBOARD

- Data exploration tool to visualize sensor data for different trials
- Can explore and compare different measurements for different sensors
- Allows non-technical audience to explore data



FUTURE WORK

- Explore more complex neural network architectures, particularly once that include an LSTM layer and bidirectional layer
- Performed a live demo with participant wearing sensors, and streams sensor data to model
- Gather additional data, or perform analysis on new data set.

REFERENCES

(1) Aziz, O., Klenk, J., Schwickert, L., Chiari, L., Becker, C., Park, E. J., … Robinovitch, S. N. (2017). Validation of accuracy of SVM-based fall detection system using real-world fall and non-fall datasets. *PloS one*, *12*(7), e0180318. doi:10.1371/journal.pone.0180318

(2) Hu, X., & Qu, X. (2016). Pre-impact fall detection. Biomedical engineering online, 15(1), 61. doi:10.1186/s12938-016-0194-x

(3) Vallabh, P., & Malekian, R. (2017). Fall detection monitoring systems: a comprehensive review. Journal of Ambient Intelligence and Humanized Computing, 9(6), 1809–1833. doi:10.1007/s12652-017-0592-3