Human activity recognition using time-series data

GA DSI0720 Remote Capstone

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Agenda

- Background
- Problem statement
- Preprocess
- Classification Models
- Model validation
- Implementation
- Conclusions
- Future work
- Q & A

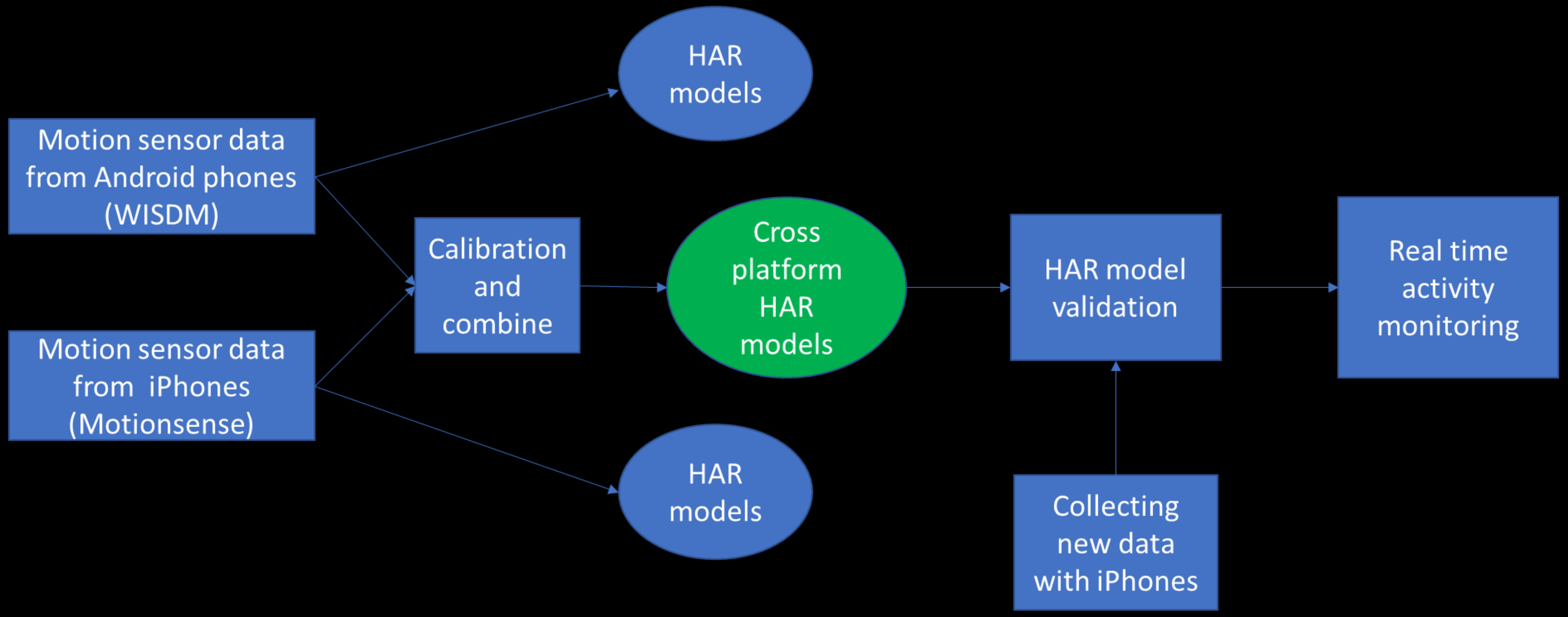
Background

- Wearable devices
  - More and more common
  - Growing market
- Huge amount of data generated by wearable devices
- Challenges: Seamless data driven approach that brings the maximum benefit
- Opportunities: Big data meets machine learning

Problem statement

Goal	Recognize human activities
Metrics	Accuracy
Implementation	Real time human activities monitoring

Project scope

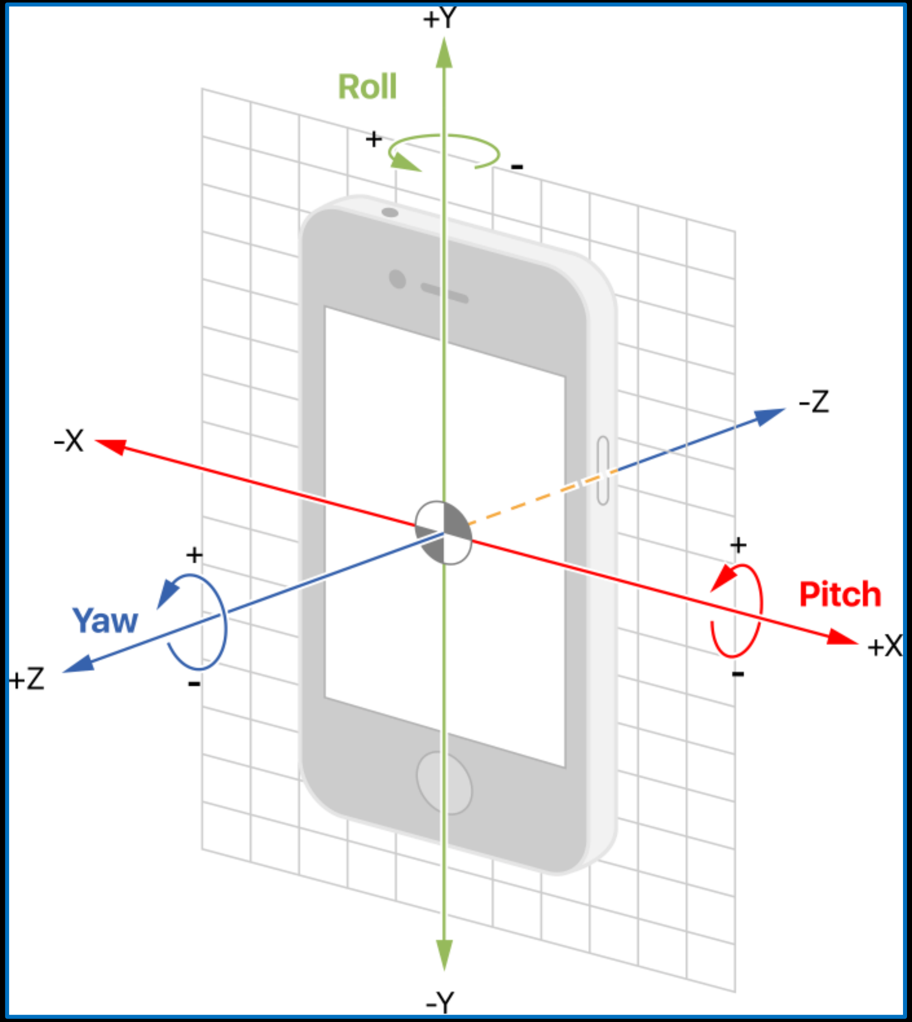


Data source:

- iPhone: http://cis.eecs.qmul.ac.uk/datasets.html
- Android phone: https://www.cis.fordham.edu/wisdm/dataset.php

Preprocessing – Data from smart phone sensors

- Measures
  - Attitude – (pitch, roll, yaw)
  - Gravity – (x, y, z)
  - Rotation rate – (x, y, z)
  - User acceleration – (x, y, z)
- Android phone data
  - Total acceleration (gravity + user acceleration) – 3 features
  - 6 activities from 36 subjects, ~1.1M samples
- iPhone data
  - Attitude, gravity, rotation rate, and user acceleration – 12 features
  - 6 activities from 24 Subjects, ~1.4M samples

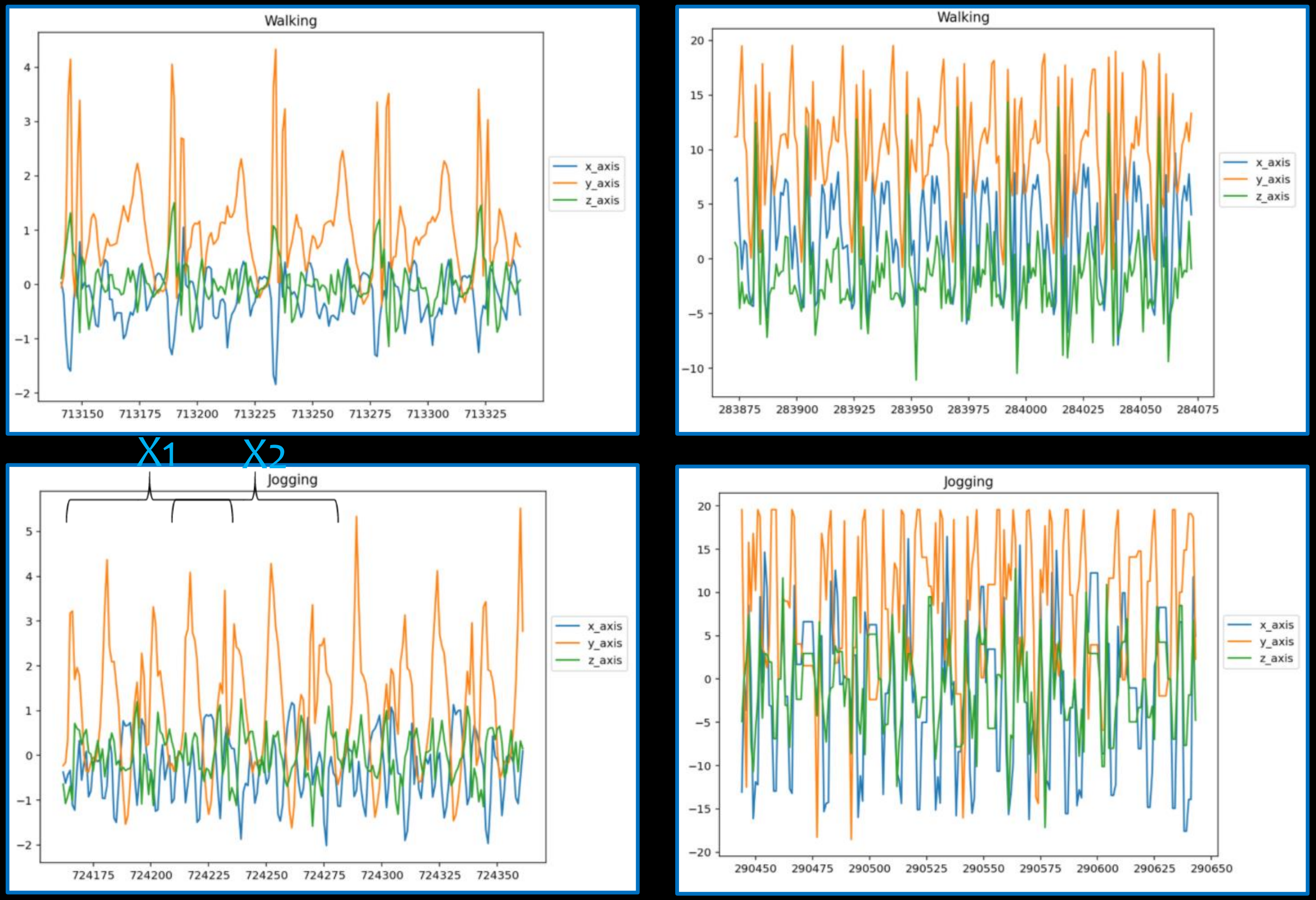


Preprocessing – Create model building datasets

- Select time series data in a window
  - Window length
  - Moving step
- Match iPhone data and Android data
  - Time
  - Amplitude

iPhone

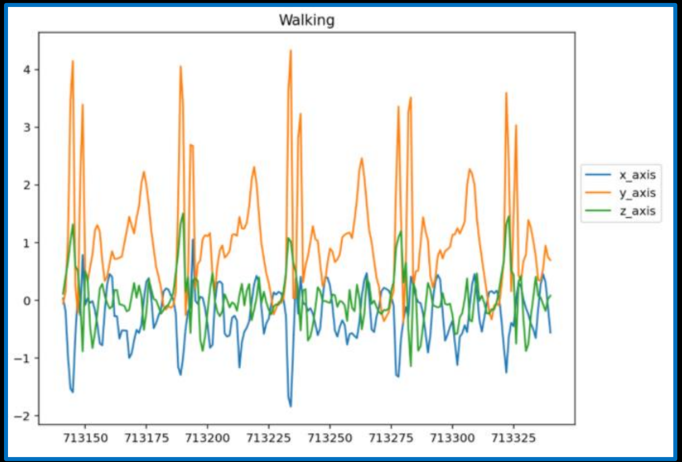
Android Phone

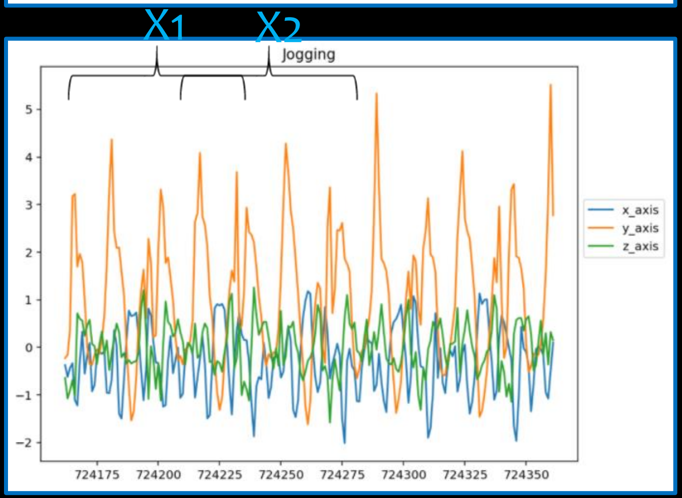


Preprocessing – Create model building datasets

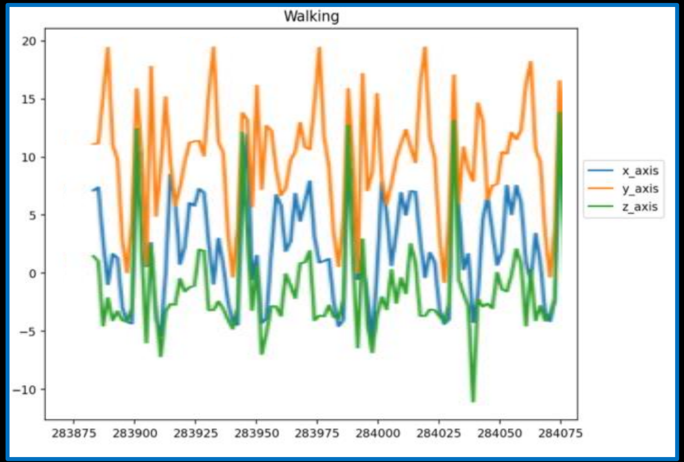
- Select time series data in a window
  - Window length
  - Moving step
- Match iPhone data and Android data
  - Time
  - Amplitude
- Training and testing splitting by subjects
  - Train: 2/3 of the subjects
  - Testing: 1/3 of the subjects

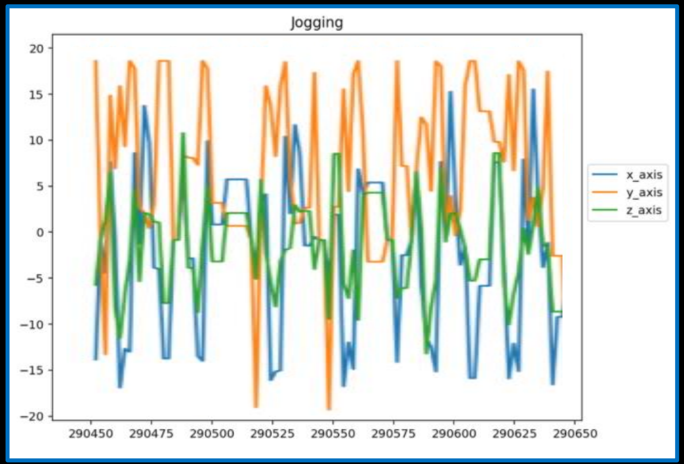
iPhone





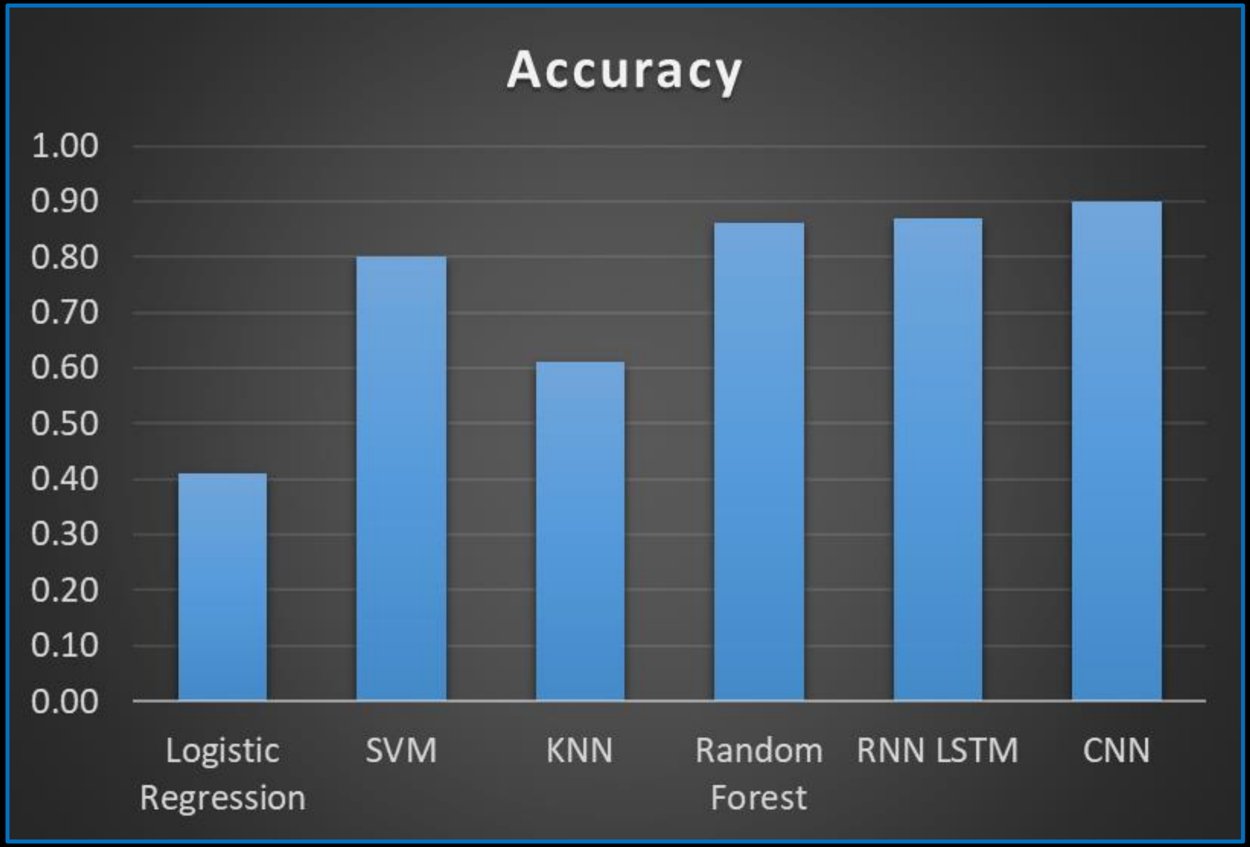
Android Phone





Modeling – Classifiers comparison

- Logistic regression and KNN models - Not good
- SVM, random forest, and RNN LSTM models – Not bad
- CNN model - Selected
  - High accuracy
  - Flexibility for transfer learning



Modeling – CNN models

- CNN model for combined datasets

Datasets	Android phones	iPhones	Combined
Accuracy	0.94	0.90	0.92

Cross platform HAR model

- Further improving CNN models (iPhone datasets)
  - 3 features vs. 12 features
  - Training datasets: part of the subjects vs. all subjects

Models	3 features	12 features	12 features / all subjects
Accuracy	0.90	0.95	0.99

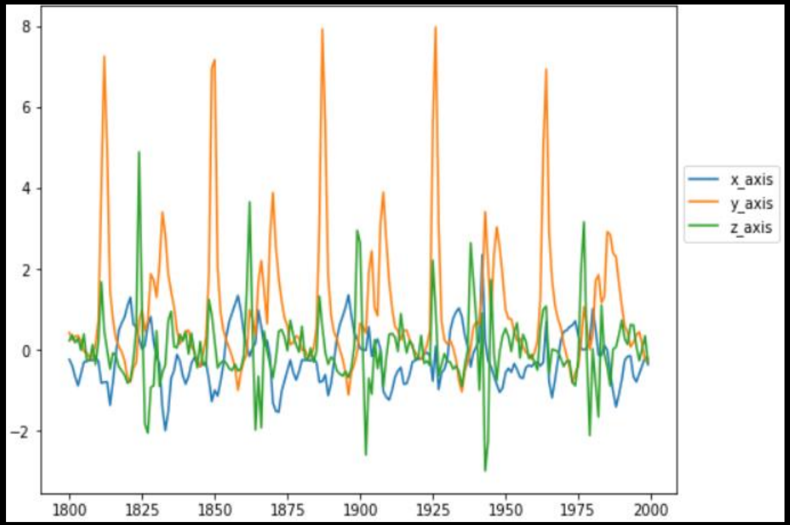
Model validation

- Acquired datasets from 4 subjects by the iPhone App "CrowdSense"

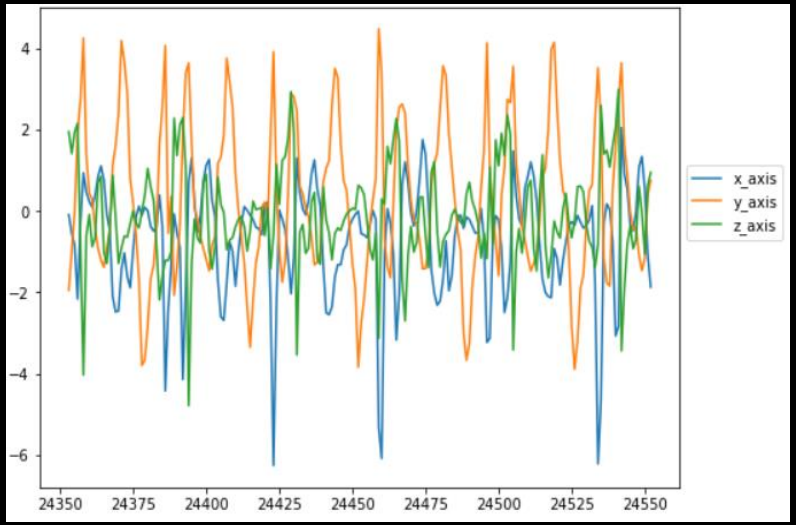
Subject	B	D	L	Z
Activities	Walk	Walk Jog	Walk	Walk Jog

Cross platform HAR model

D Jog



Jog in training data



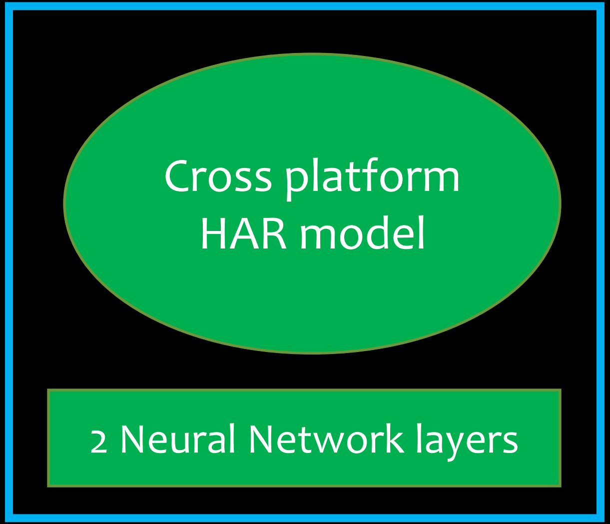
Activity	CNN model
B Walk 1	0.92
D Walk 1	0.66
D Walk 2	0.38
L Walk 1	0.27
Z Walk 2	0.73
D Jog 1	0.01
Z Jog 1	0.03

Model validation – Transfer learning

- Acquired datasets from 4 subjects by the iPhone App "CrowdSense"

Subject	B	D	L	Z
Activities	Walk	Walk Jog	Walk	Walk Jog

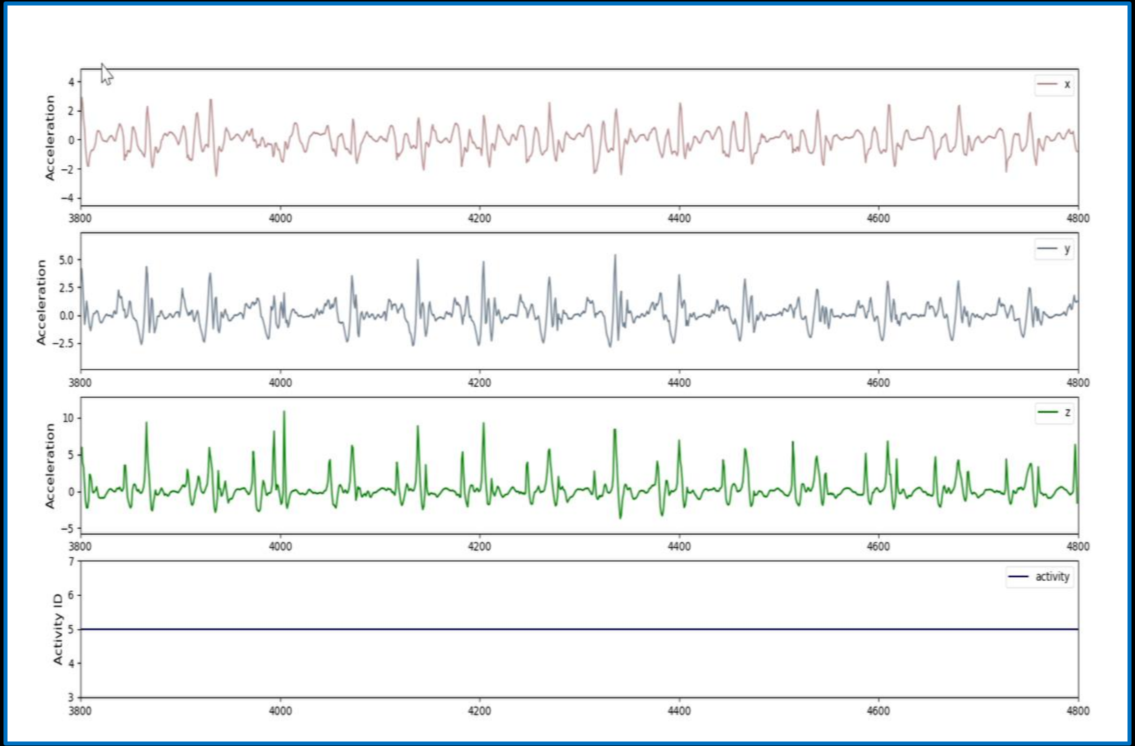
- Build a new model on top of the cross-platform CNN model with acquired data
  - Freeze the CNN model
  - Add 2 Neural Network layers
  - Using the acquired data to train a model



Activity	CNN model	New model
B Walk 1	0.92	0.98
D Walk 1	0.66	0.93
D Walk 2	0.38	0.97
L Walk 1	0.27	0.96
Z Walk 2	0.73	0.95
D Jog 1	0.01	0.99
Z Jog 1	0.03	0.98

Implementation – real time monitoring

- Read in the time series data from sensor
- Convert the data in the format can be used by the model
- Classify the activities
- Map the classification to the time series data
- Display the time series data and classified activities



	0.0-10.0 second	10.0-20.0 second	20.0-30.0 second	30.0-40.0 second	40.0-50.0 second	50.0-60.0 second	60.0-70.0 second	...	270.0-280.0 second	280.0-290.0 second	290.0-300.0 second
Activity	Walking	Walking	Walking	Walking	Walking	Walking	Walking	...	Walking	Walking	Walking

Conclusions and future work

- HAR models were successfully built
  - Cross-platform
  - Transfer learning.
- A prototype of real-time human activities monitoring system were demonstrated.
- All the work could be extended to any time series data
- Future work
  - Multiple sensors
  - Detecting anomalies.

References

1. Jennifer R. Kwapisz, Gary M. Weiss and Samuel A. Moore (2010). Activity Recognition using Cell Phone Accelerometers, Proceedings of the Fourth International Workshop on Knowledge Discovery from Sensor Data (at KDD-10), Washington DC.

2. Mohammad Malekzadeh, Richard G Clegg, Andrea Cavallaro, and Hamed Haddadi. 2018. Protecting sensory data against sensitive inferences. In *Proceedings of the 1st Workshop on Privacy by Design in Distributed Systems.* ACM, 2.

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