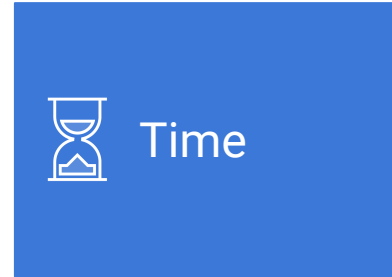
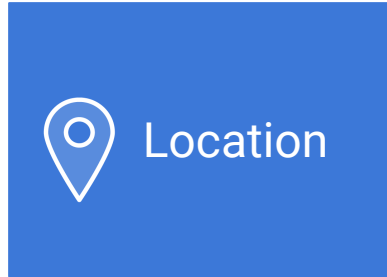

Context Recognition Using Smartphone Sensor Data

Team ContextualHealing : Abhishek, Anant, Brandon, Hank

Introduction

Context Recognition deals with automatic recognition of a user's context using data



Market Potential

Context Aware Apps

\$77 B

Mobile apps market

Healthcare

2 M

Deaths due to physical
inactivity

Smart Mobile Ads

\$ 6 B

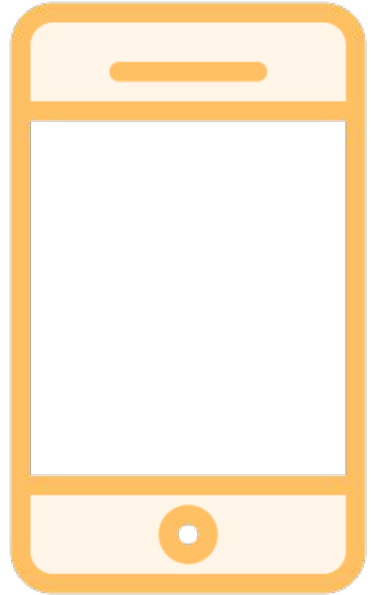
Mobile ads market

Source : <http://www.gartner.com/newsroom/id/2654115>

Source : <https://blog.gyminsight.com/859-most-current-fitness-industry-statistics/>

Why Smartphone for Context Recognition ?

79% Of people ages 18-44 have their
Smartphones with them 22 hours a day

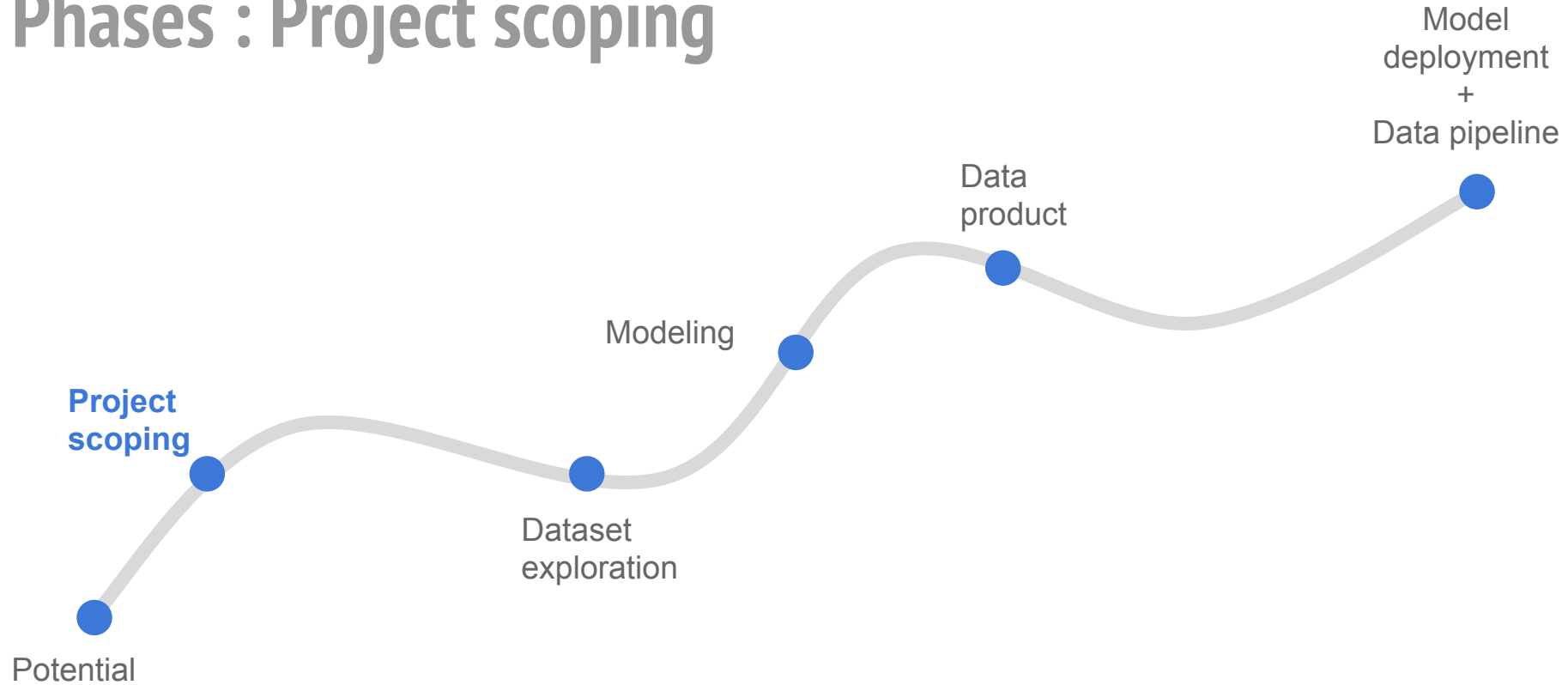


Goal

Build a context recognition service running on a predictive modeling framework developed using publicly available datasets.

Create an android application utilizing the modeling backend for tracking user activity.

Phases : Project scoping



Project Scope

Physical
Activity

Location

Weather

Headphones

Context

Accelerometer

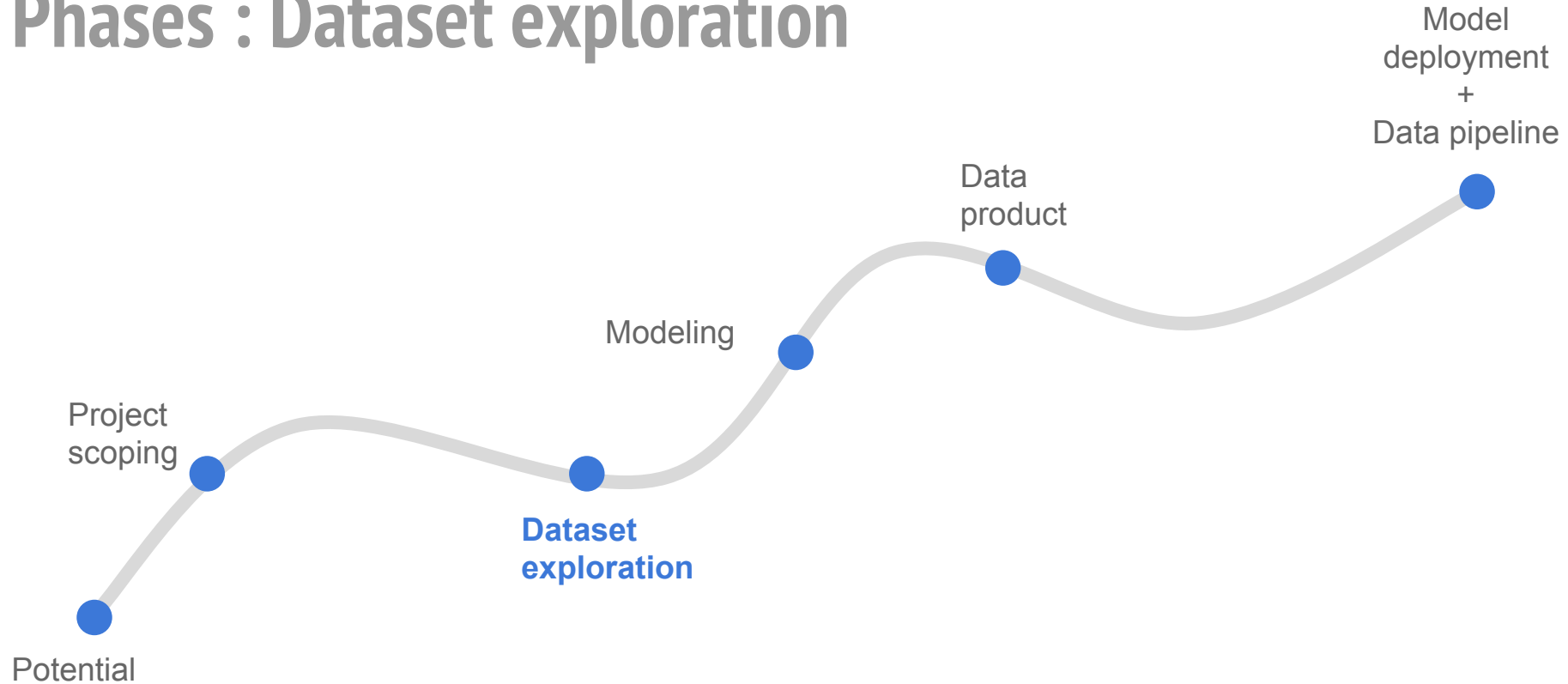
Gyroscope

Magnetometer

GPS

Sensors

Phases : Dataset exploration



Datasets



Actitracker

1.1 M

Rows of raw accelerometer data at 50ms

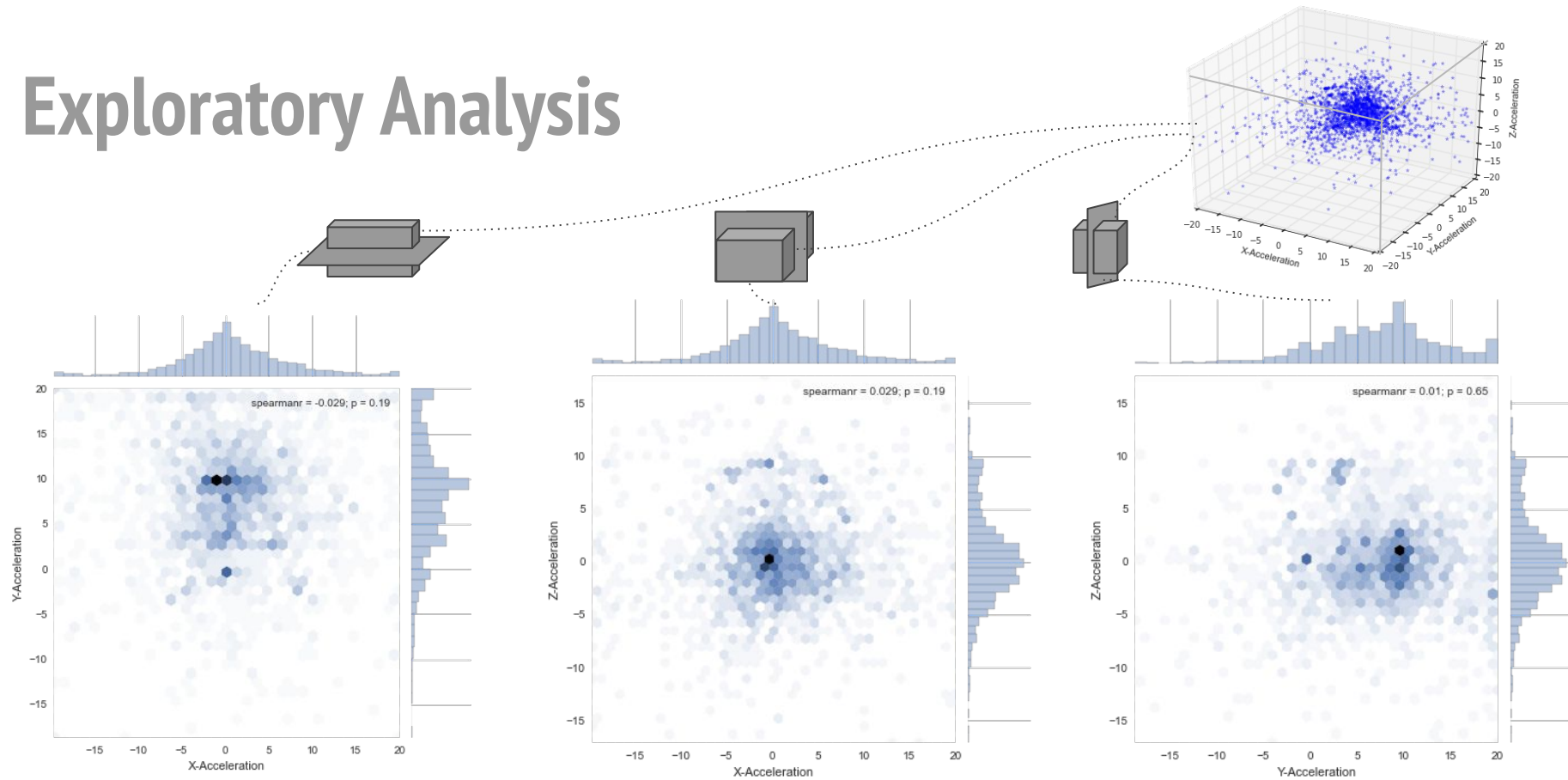


UCI

7 K

Rows of aggregated accelerometer & gyroscope data

Exploratory Analysis

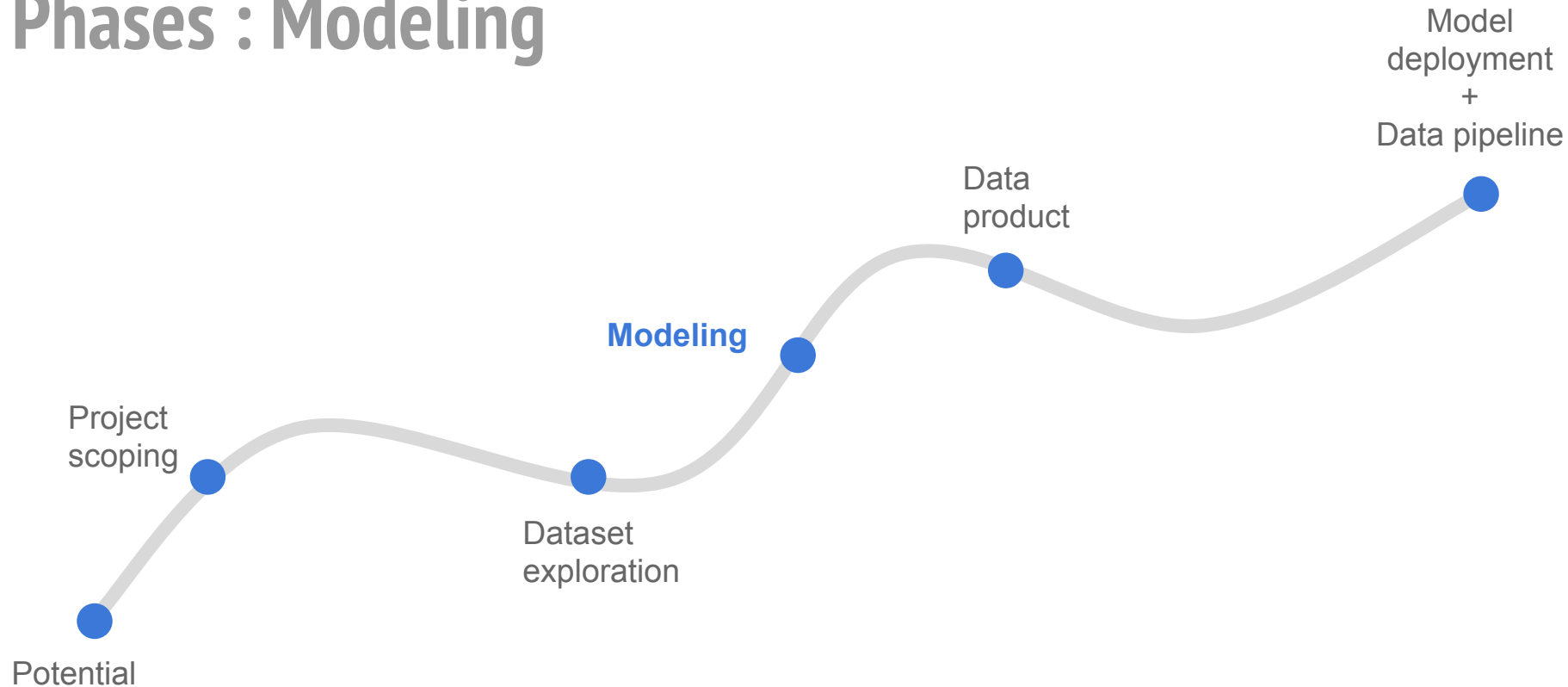


Note: For charts, data is sampled with $N=2000$

Feature Engineering

- Raw data grouped into 5-second 'sessions' (100 raw sensor readings per session)
- For each session, 58 total features:
 - Descriptive statistical features [24]:
 - Mean, median, standard deviation
 - IQR, min, max
 - Kurtosis, skewness
 - Deciles [27]
 - 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th percentiles for each axis & session
 - Average Absolute Difference [3]:
 - Average absolute difference between the value of each of the 100 readings within the session and the mean value over those 100 readings
 - Average Resultant Acceleration [1]:
 - Average of the square roots of the sum of the readings of each axis squared $\sqrt{x^2 + y^2 + z^2}$
 - Time Between Peaks [3]
 - Time between maximum and minimum sensor readings in each session

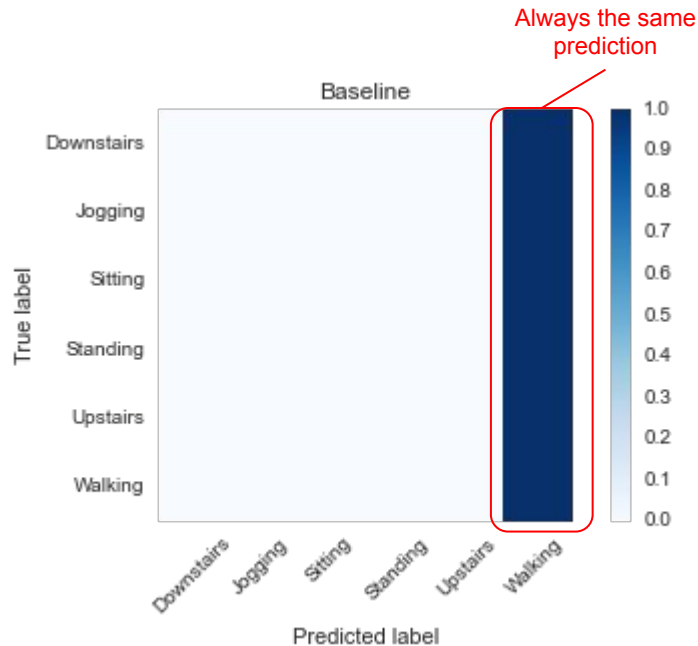
Phases : Modeling



Models : Baseline Model

Baseline

Accuracy : 39.4%
Log-Loss : 1.478

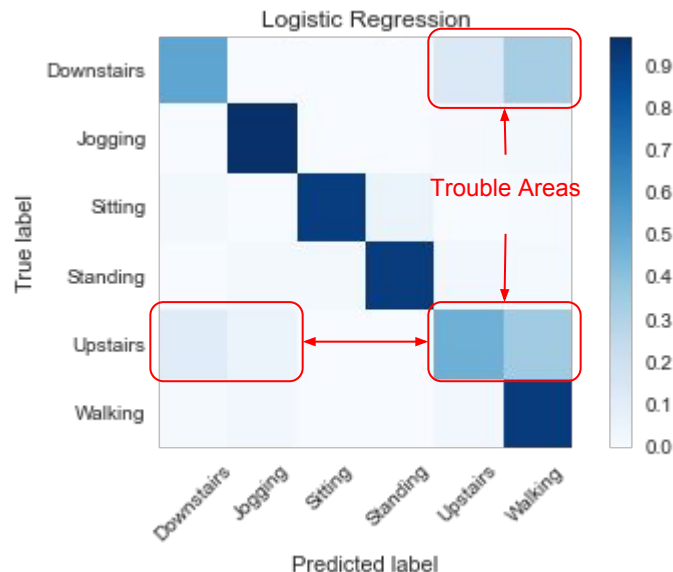


Models : Logistic Regression

Logistic Regression

Accuracy : 85.3 %

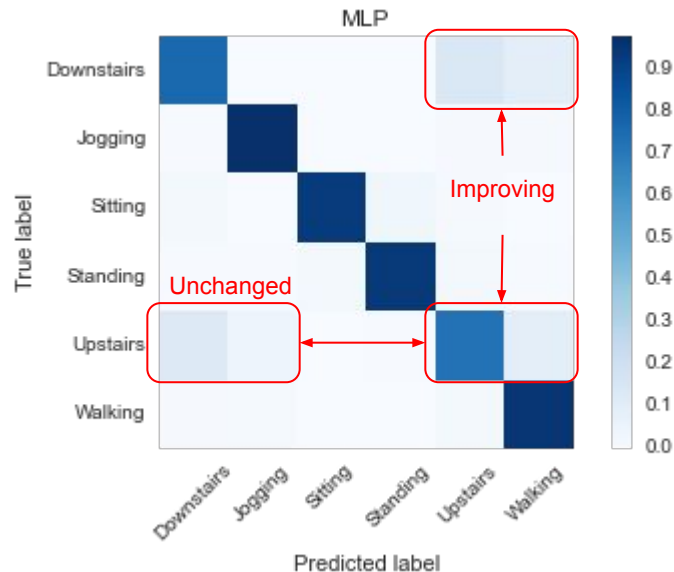
Log-Loss : 0.509



Models : Multilayer Perceptron

Multilayer Perceptron

Accuracy : 91.7 %
Log-Loss : 0.293

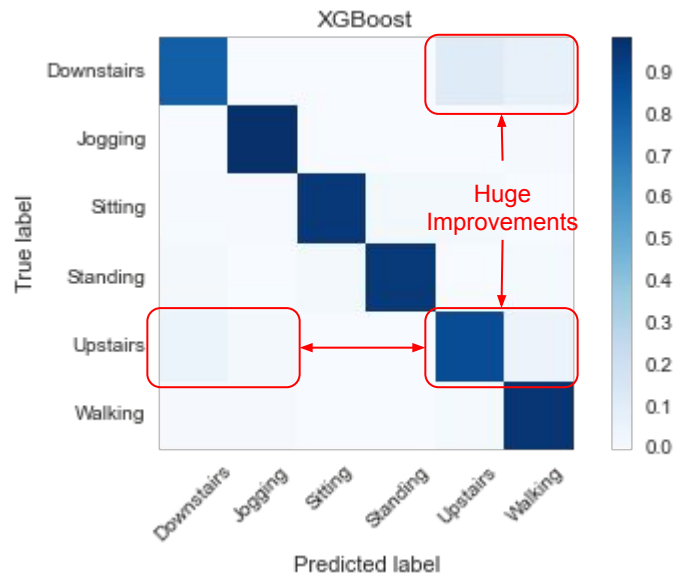


Models : XGBoost

Boosted Trees

Accuracy : 94.7 %

Log-Loss : 0.181



Model Comparisons

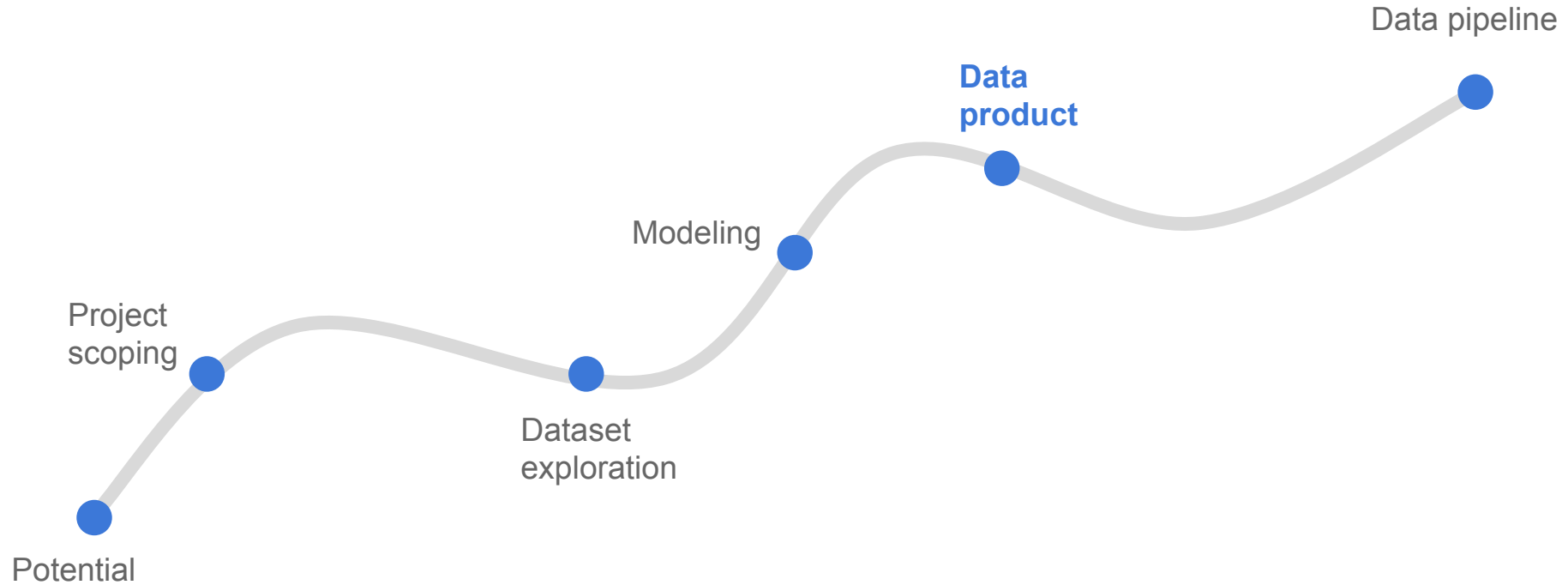


Overall Model Performances

Error Rate Comparisons

	LR	MLP	XGBoost	Δ
Upstairs	52.5%	27.2%	12.2%	-77%
Downstairs	48.0%	23.6%	19.3%	-60%
Walking	7.1%	4.7%	3.6%	-49%
Jogging	2.2%	2.5%	1.2%	-45%
Sitting	8.3%	6.7%	4.7%	-43%
Standing	7.8%	5.8%	5.2%	-33%

Phases : Data Product



Data Product -1 : Android App



GoalTick

The smart personal assistant to tick all your goals

Why Another Fitness/Activity Tracking App ?

Costly wearables



Require internet connection



Moves



Nike +



Google Fit **

** Just have started supporting offline tracking for limited activities but sends out data to the server



GoalTick

- Set your activity goals
- App will track the activity
- Prompt user in between
- Provide summary results
- UI developed using Android Material Design
- Supports both local and server mode for predictions

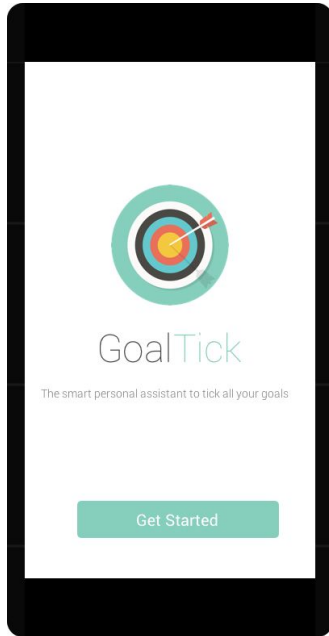


Machine Learning On Device

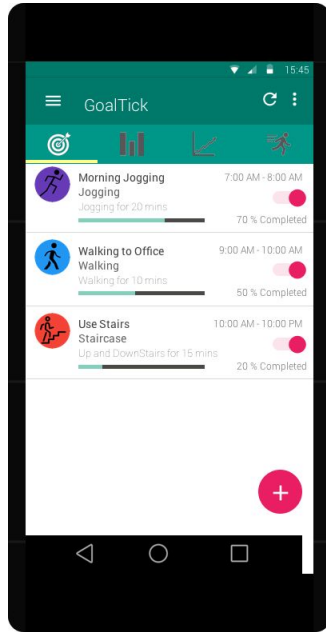
- Tensorflow C++ libraries
- Prediction call written in C++
- Uses JNI (Java Native Interface) to bridge the gap
- Model saved as Protobuf file

UI Prototype

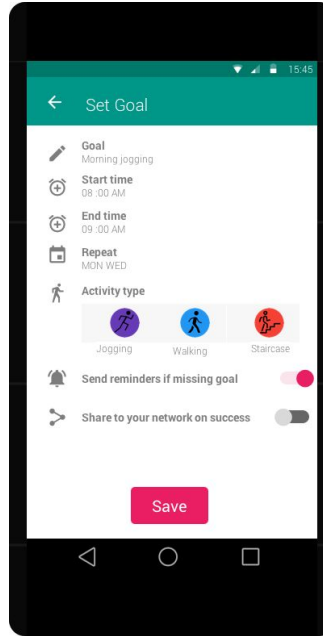
[Link to interactive prototype](#)



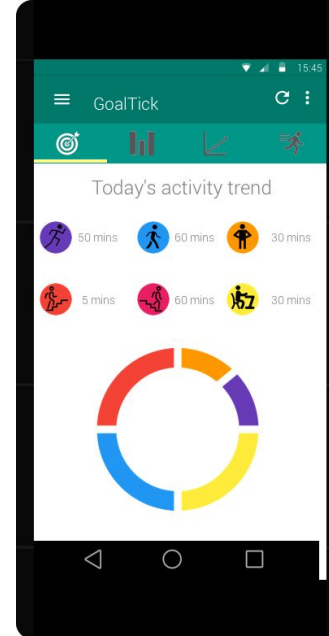
Splash
screen



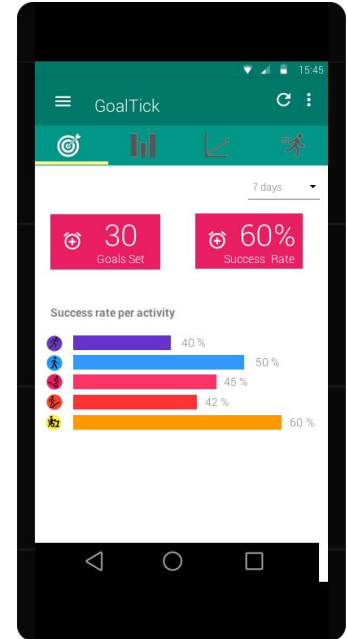
Active
goals



Create
goal



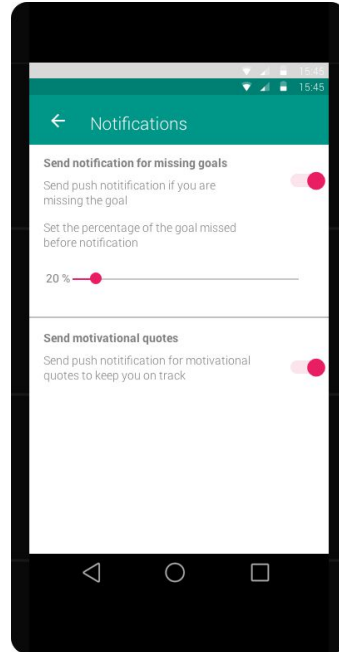
Activity
trend



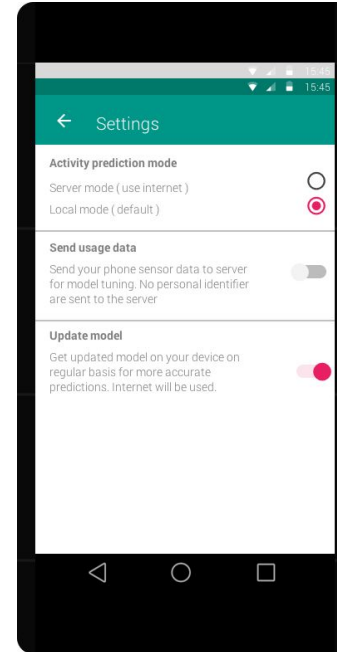
Report

UI Prototype

[Link to interactive prototype](#)



Notifications



Settings

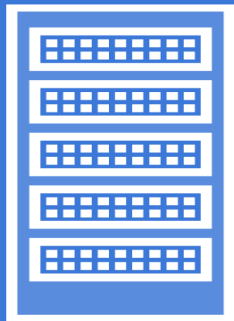
Data Product : GoalTick

[Link to interactive prototype](#)



GoalTick



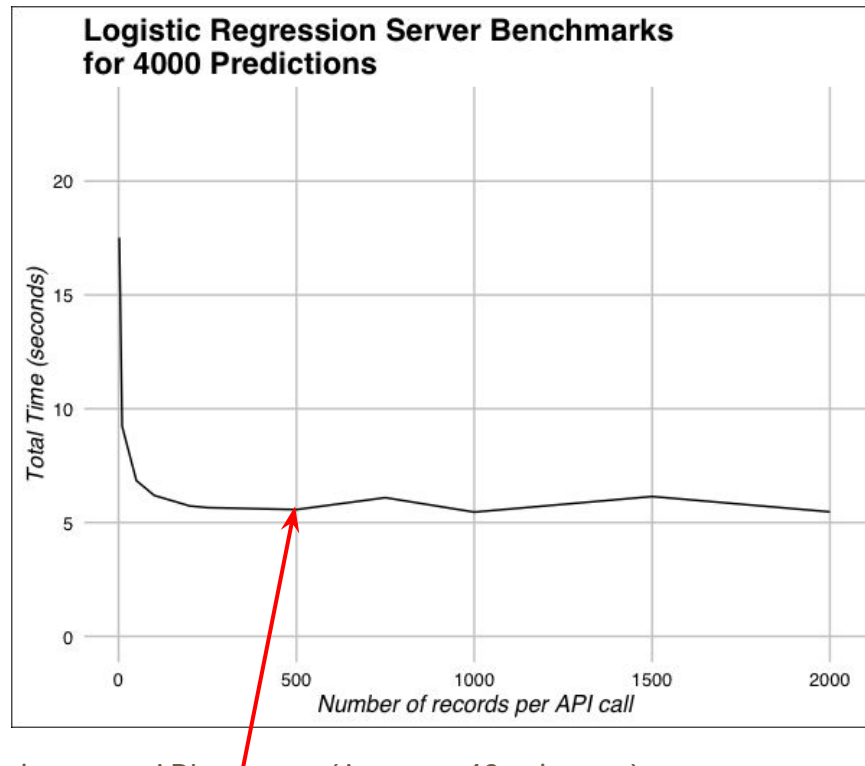
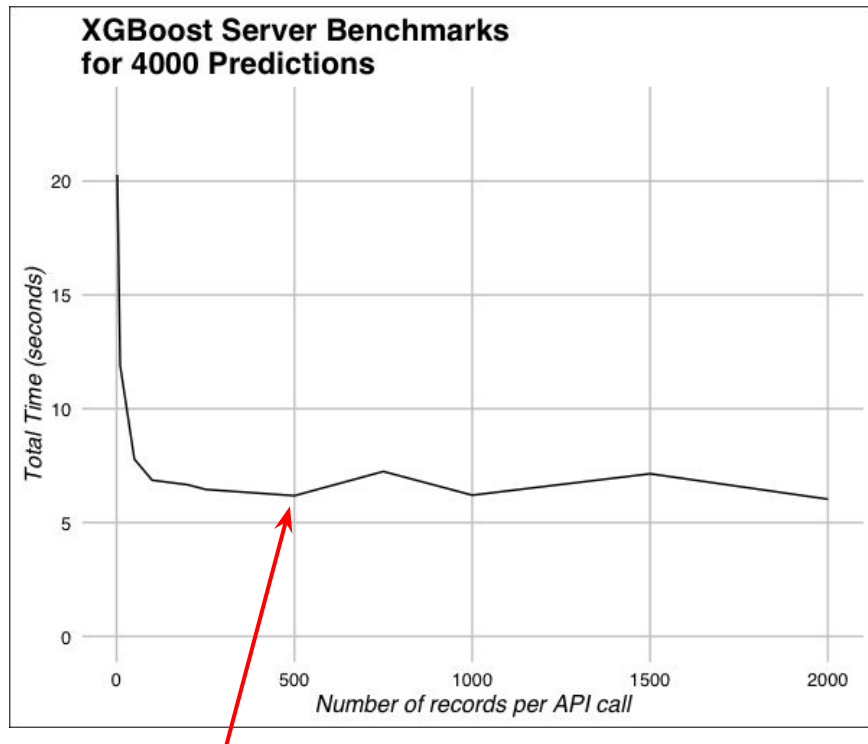


Model Deployment :
REST API

Data Product -2 : Activity Prediction Service

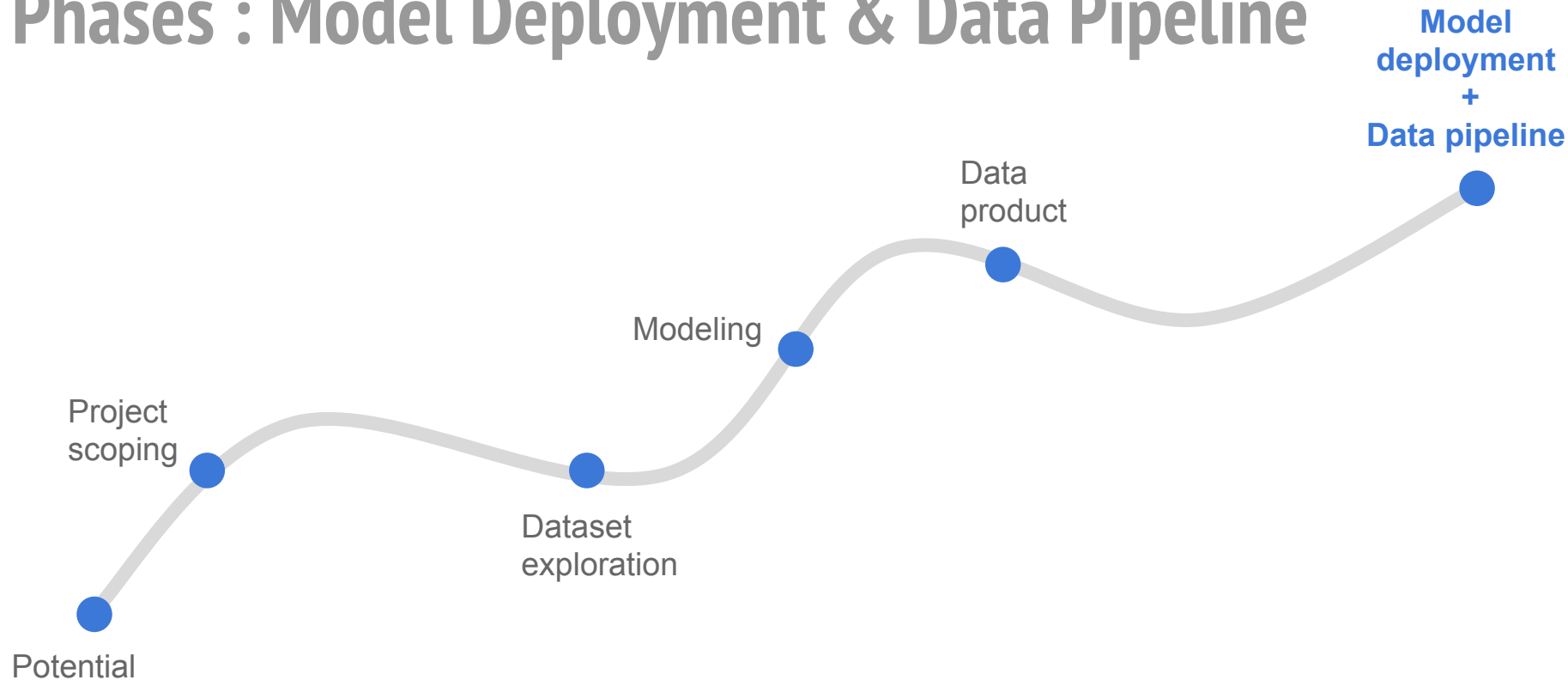
- Flask-based REST API using python
- Endpoint exposed for single or multiple predictions
- For enterprise customers (for bulk predictions)

REST API Performance for 5.5 Hours of Data



Total prediction time stops improving at around 500 predictions per API request (Approx. 40 minutes)

Phases : Model Deployment & Data Pipeline



Model Deployment: Modes



REST API

For enterprise consumers



On-Device

For consumer app with high
frequency prediction

Deployment Architecture: REST API



Enterprise User / App



POST request with motion data

Predictions

Server loads trained models
at regular intervals

Raw data stored
in scalable
backend



Updated Model Weights saved to S3

Daily algorithm training



Machine Learning Cluster

Deployment Architecture: Model On-Device



Daily Log of Motion Data with labels via Kinesis for training



Installed Mobile App

Raw data stored in
scalable backend



App downloads trained model on regular basis

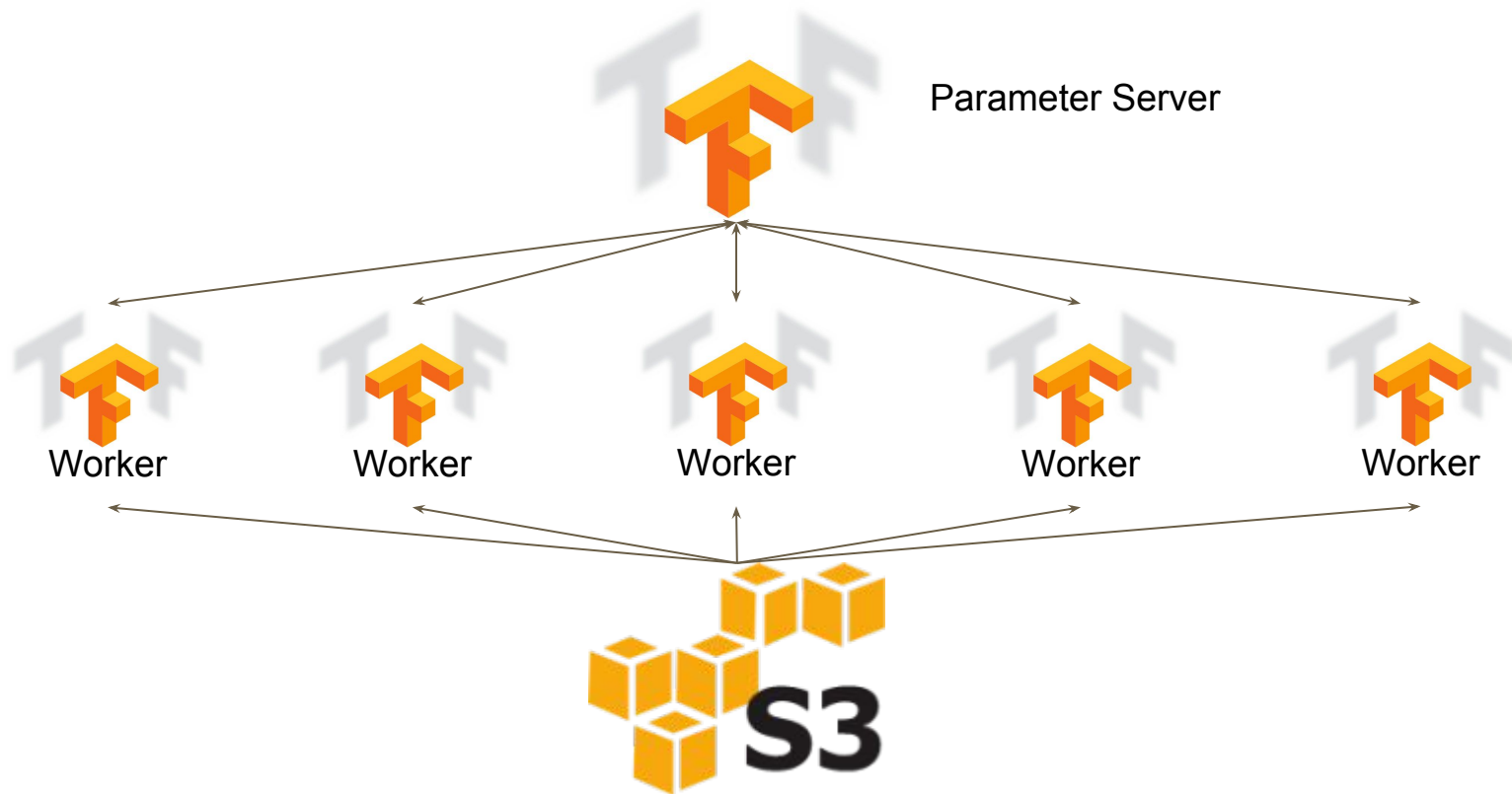
Updated Model Weights saved to S3

Daily algorithm training



Machine Learning Cluster

Deployment Architecture: Distributed TF Training





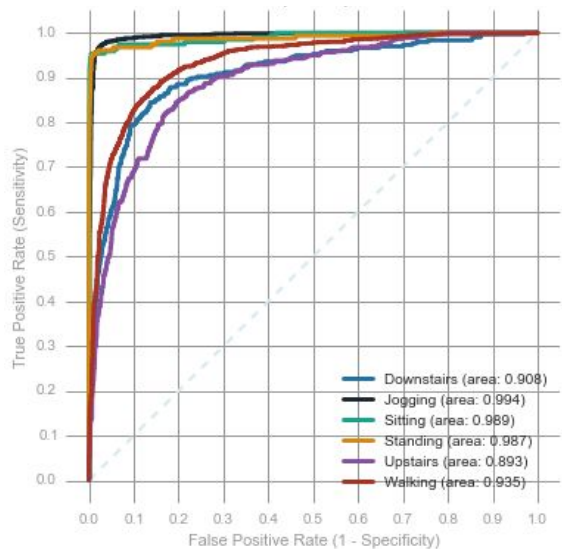
Future Works

- More contextual features such location, time
- More sensors such as rotational vectors, environmental sensors, GPS
- Working with unlabelled dataset and unsupervised learning

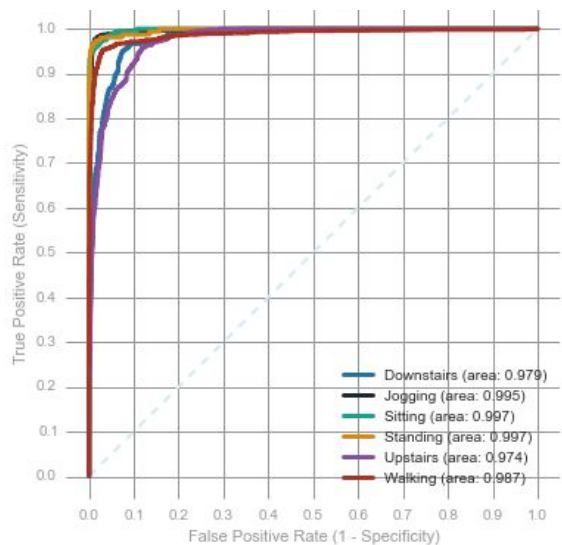
Thank You

Appendix: Model Comparison (ROC Curves)

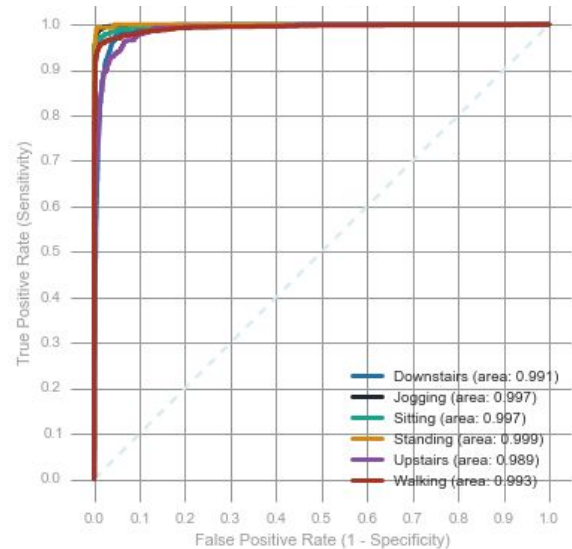
Logistic Regression



Multilayer Perception

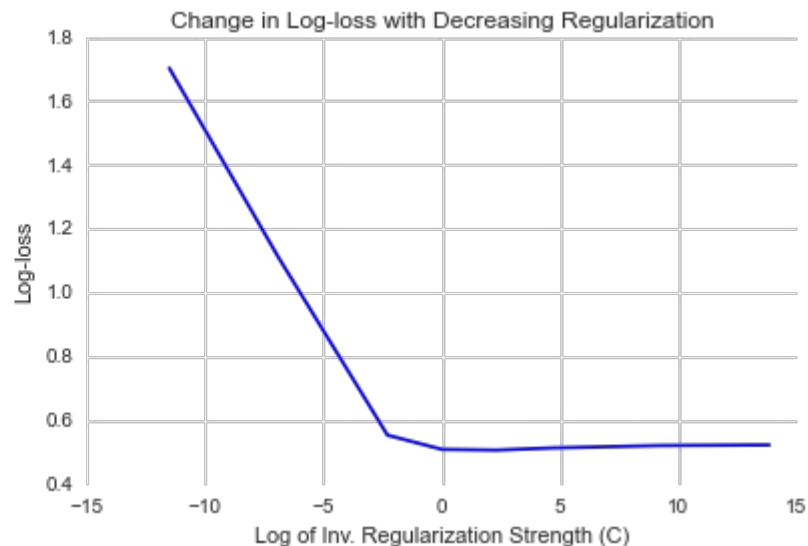
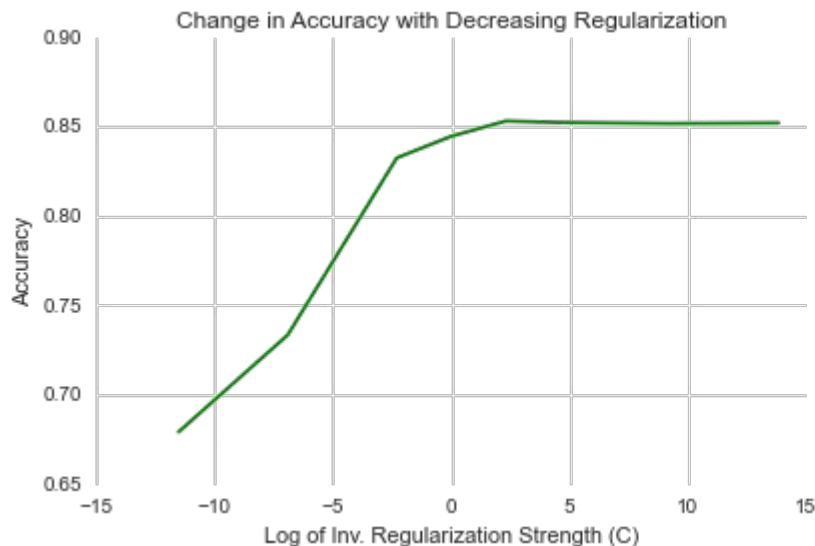


Boosted Trees



Appendix: Parameter Tuning

Logistic Regression



Appendix: Parameter Tuning

XGBoost

