



Human Activity Recognition Using Smartphone Data

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Agenda



INTRODUCTION



PROBLEM
STATEMENT



DATASETS



TYPE OF
PROBLEM



PROPOSE
MODELS



REVIEW



Problem Statement

Human Activity Recognition using Data collected from Smartphone's sensors.

What are we doing?

Here, we are trying to **predict the Activity of a user.**

The goal is to build a model that can predict whether a person is **Laying, Standing, Sitting, Walking, Walking_upstairs,** or **Walking_downstairs, etc.**

Applications: Real World Impact

The demands for understanding human activities have grown in health-care domain, especially in elder care support, rehabilitation assistance, diabetes, and cognitive disorders.

A huge amount of resources can be saved if sensors can help caretakers record and monitor the patients all the time and report automatically when any abnormal behavior is detected. Other applications such as human survey system and location indicator are all benefited from the study.

What Data is being collected?

The information which is collected is the measurements from the accelerometer and gyroscope of the smartphone.

Using its embedded accelerometer and gyroscope, It has captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz.

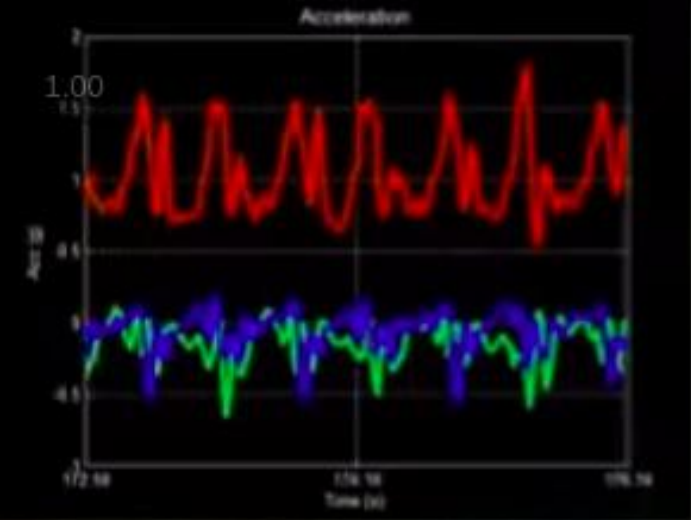


Data Set Characteristics:	Multivariate, Time-Series	Number of Instances:	10929
Labeled:	Yes		

How do we get the data?

<https://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions>

We also plan to generate our own data and test our Neural Network Classifier on it.



Different Activities (Classes)

LAYING

•1407

STANDING

•1374

SITTING

•1286

WALKING

•1226

WALKING_UP

•1073

WALKING_DOWN

•986

More about dataset...

So, we had the data for 3-axial linear acceleration and 3-axial angular velocity.

The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window).

From each window, a **vector of 561 features** was obtained by calculating variables from the time and frequency domain



Datasets Features(#561):

tBodyAcc-
mean()-X

tBodyAcc-
mean()-Y

tBodyAcc-
mean()-Z

tBodyAcc-
std()-X

tBodyAcc-
std()-Y

tBodyAcc-
std()-Z

tBodyAcc-
max()-X

tBodyAcc-
max()-Y

tBodyAcc-
max()-Z

And more ...

Overview of dataset:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672

angle(X,gravityMean)	angle(Y,gravityMean)	angle(Z,gravityMean)	subject	Activity
-0.841247	0.179941	-0.058627	1	STANDING
-0.844788	0.180289	-0.054317	1	STANDING
-0.848933	0.180637	-0.049118	1	STANDING
-0.848649	0.181935	-0.047663	1	STANDING
-0.847865	0.185151	-0.043892	1	STANDING

Feature extraction:

The features selected for this database come from the **accelerometer** and **gyroscope** 3-axial raw signals **tAcc-XYZ** . These time domain signals (prefix '**t**' to denote time) were captured at a constant rate of 50 Hz. Then they were filtered using a median filter and a 3rd order low pass Butterworth filter with a corner frequency of 20 Hz to remove noise.

Similarly, the acceleration signal was then separated into body and gravity acceleration signals (**tBodyAcc-XYZ** and **tGravityAcc-XYZ**) using another low pass Butterworth filter with a corner frequency of 0.3 Hz.

Subsequently, the body linear acceleration and angular velocity were derived in time to obtain **Jerk signals** (**tBodyAccJerk-XYZ** and **tBodyGyroJerk-XYZ**) . Also, the magnitude of these three-dimensional signals were calculated using the Euclidean norm (tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag, tBodyGyroJerkMag)

Data Pre-processing

- Features are normalized and bounded within $[-1,1]$.
- Each feature vector is a row on the 'X' and 'y' files.
- Removing All Null Values.
- Balancing the Dataset.

**What kind
of problem?**



Few interesting Points

Discrete vs **Continuous**

Supervised vs Unsupervised

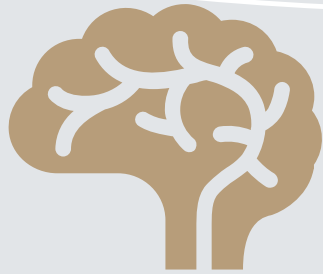
Labelled vs Unlabelled

Classification vs Clustering

**It is Multi-class
classification
problem!**



We plan to implement the following algorithms:



Artificial Neural Network



Recurrent Neural Network

Because...

We plan to implement the following

ANN, because it is a multi-class classification problem, and ANN have shown to be best for solving multi-class classification problem.

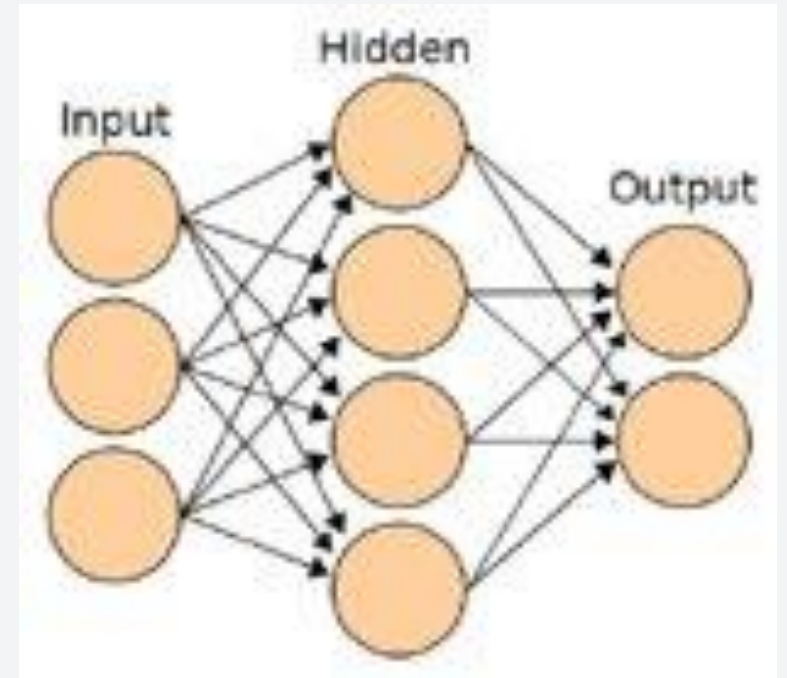
Recently, deep learning methods such as recurrent neural networks and one-dimensional convolutional neural networks, or CNNs, have been shown to provide state-of-the-art results on challenging activity recognition tasks with little or no data feature engineering.

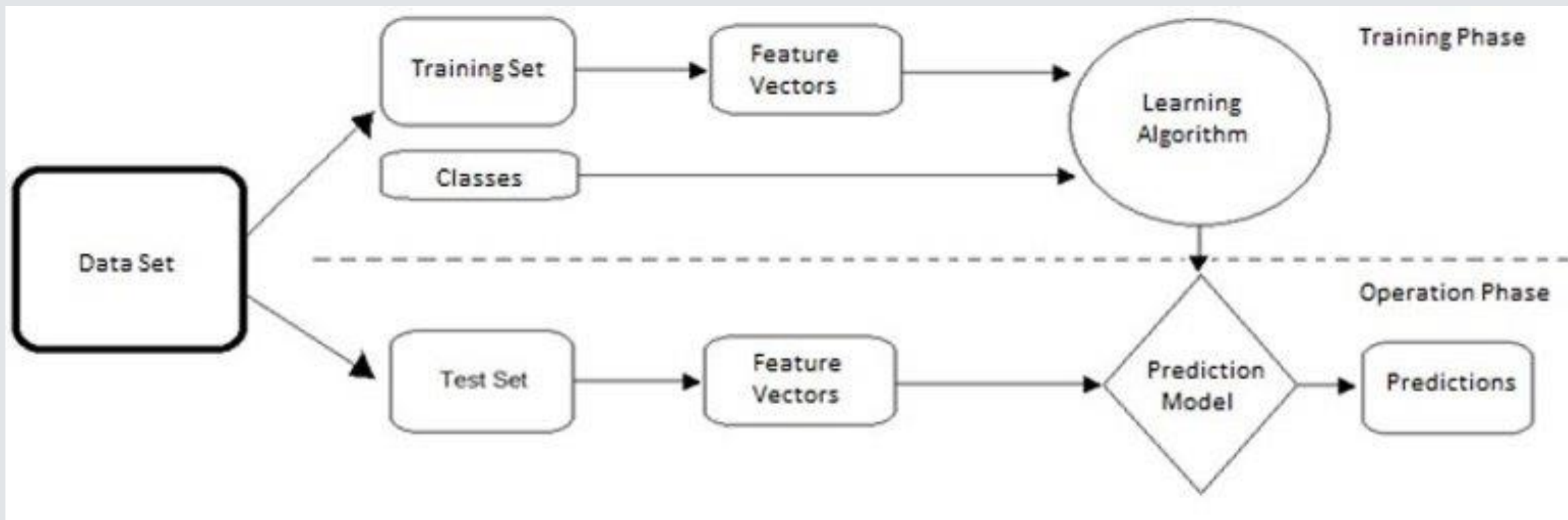


Artificial Neural Network

Number of input neurons = 561 (Because there are 561 features in our pre-processed data-set)

Number of output neurons = 6 (Because we have 6 activities)





References

- E. Bulbul, A. Cetin and I. A. Dogru, "Human Activity Recognition Using Smartphones," 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 2018, pp. 1-6, doi: 10.1109/ISMSIT.2018.8567275.
- Akram Bayat, Marc Pomplun, Duc A. Tran, A Study on Human Activity Recognition Using Accelerometer Data from Smartphones, Procedia Computer Science, Volume 34, 2014, Pages 450-457, ISSN 1877-0509, <https://doi.org/10.1016/j.procs.2014.07.009> (<https://www.sciencedirect.com/science/article/pii/S1877050914008643>)

References

- Rasekh, Amin & Chen, Chien-An & Lu, Yan. (2014). Human Activity Recognition using Smartphone.
- Jorge-L. Reyes-Ortiz, Luca Oneto, Albert Samà , Xavier Parra, Davide Anguita. Transition-Aware Human Activity Recognition Using Smartphones. Neurocomputing. Springer 2015.

The background of the slide features two large, red and yellow striped popcorn buckets filled to the brim with white, fluffy popcorn. The buckets have a repeating pattern of white popcorn kernels on a yellow background, with red vertical stripes. The word "POPCORN" is printed in red on the yellow sections. A semi-transparent white circle with a thin red outline is positioned in the lower-left foreground, containing the text "Suggestions Please".

**Suggestions
Please**



Thank you