

2º Capstone Project

Human Activity Recognition Using Smartphones

Dataset



Train & Test

Features



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Nei Rosa da Costa
April - 2018

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Data set

Abstract:

Human Activity Recognition database built from the recordings of 30 subjects performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors.

Source:

(<http://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones>)

How the data were collected?

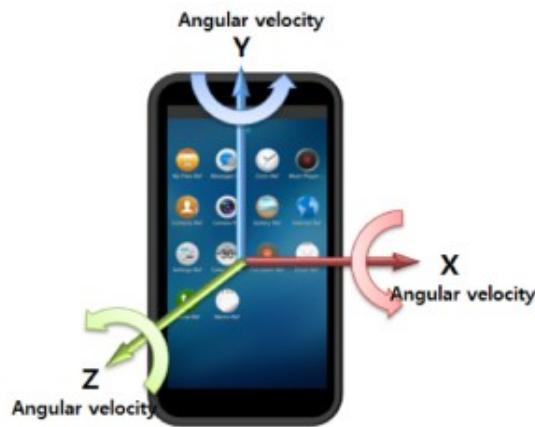
The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities (WALKING, WALKING UPSTAIRS, WALKING DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz.



Accelerometer



Gyroscope



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)

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Who was responsible for collecting the data?



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Train	Test	Total
21 	9 	30 
7,352  71.39%	2,947  28.61%	10,299 

Activity	Train	Test	Total
0 - WALKING	1,226 	496 	1,722  16.72%
1 - WALKING UPSTAIRS	1,073 	471 	1,544  14.99%
2 - WALKING DOWNSTAIRS	986 	420 	1,406  13.65%
3 - SITTING	1,286 	491 	1,777  17.25%
4 - STANDING	1,374 	532 	1,906  18.51%
5 - LAYING	1,407 	537 	1,944  18.88%

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The features selected for this database come from the accelerometer and gyroscope 3-axial raw signals tAcc-XYZ and tGyro-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.



561 features			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Nº	Group	Measurement List	mean(): Mean value	std(): Standard deviation	mad(): Median absolute deviation	max(): Largest value in array	min(): Smallest value in array	sma(): Signal magnitude area	energy(): Energy measure. Sum of the squares divided by the number of values.	iqr(): Interquartile range	entropy(): Signal entropy	arCoeff(): Autoregression coefficients with Burg order 1	arCoeff(): Autoregression coefficients with Burg order 2	arCoeff(): Autoregression coefficients with Burg order 3	arCoeff(): Autoregression coefficients with Burg order 4	correlation(): correlation coefficient between two signals	maxInds(): index of the frequency components with largest magnitude	meanFreq(): Weighted average of the frequency components to obtain a mean frequency	skewness(): skewness of the frequency domain signal	kurtosis(): kurtosis of the frequency domain signal	bandsEnergy(): Energy of a frequency interval within the 64 bins of the FFT of each window.
1	Accelerometer	tBodyAcc-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	
2		tGravityAcc-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	
3		tBodyAccJerk-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	
4	Gyroscope	tBodyGyro-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	
5		tBodyGyroJerk-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	
6	magnitude Euclidean norm	tBodyAccMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
7		tGravityAccMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
8		tBodyAccJerkMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
9		tBodyGyroMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
10		tBodyGyroJerkMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
11	FFT FOURIER	fBodyAcc-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	42	
12		fBodyAccJerk-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	42	
13		fBodyGyro-XYZ	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	42	
14		fBodyAccMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
15		fBodyAccJerkMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
16		fBodyGyroMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
17		fBodyGyroJerkMag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
18	Angle	angle(tBodyAccMean,gravity)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
19		angle(tBodyAccJerkMean,gravityMean)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
20		angle(tBodyGyroMean,gravityMean)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
21		angle(tBodyGyroJerkMean,gravityMean)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
22		angle[X,gravityMean]	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
23		angle[Y,gravityMean]	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
24		angle[Z,gravityMean]	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	

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).



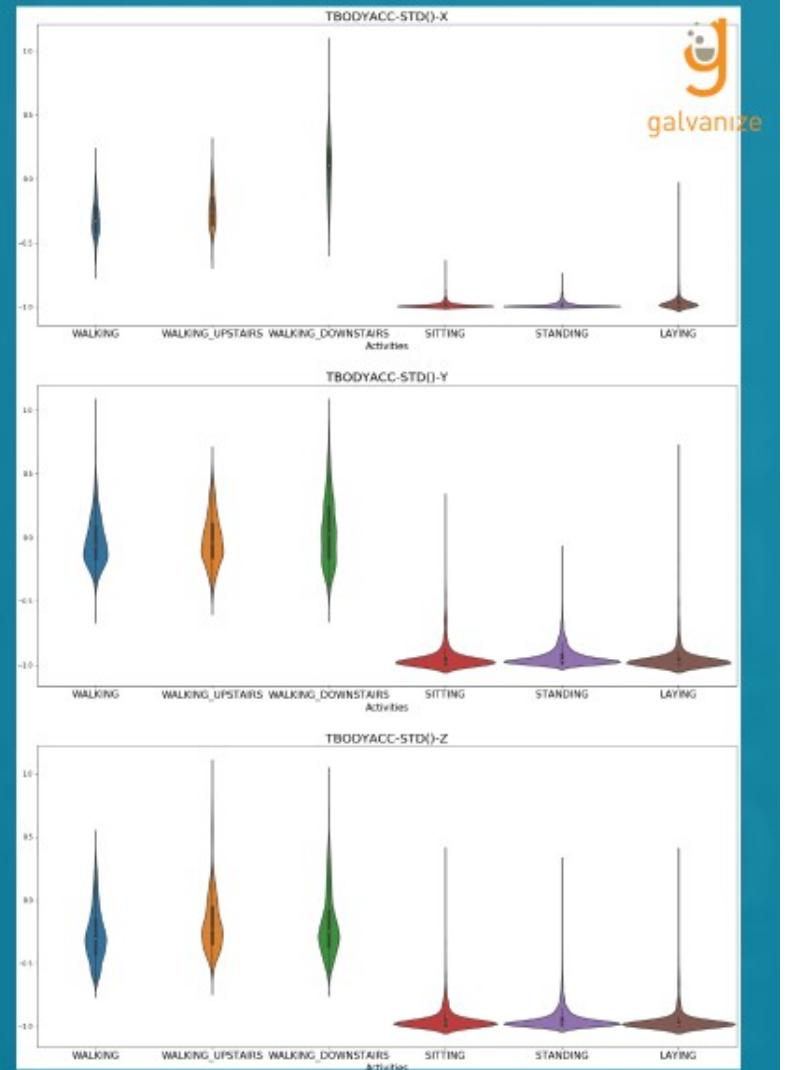
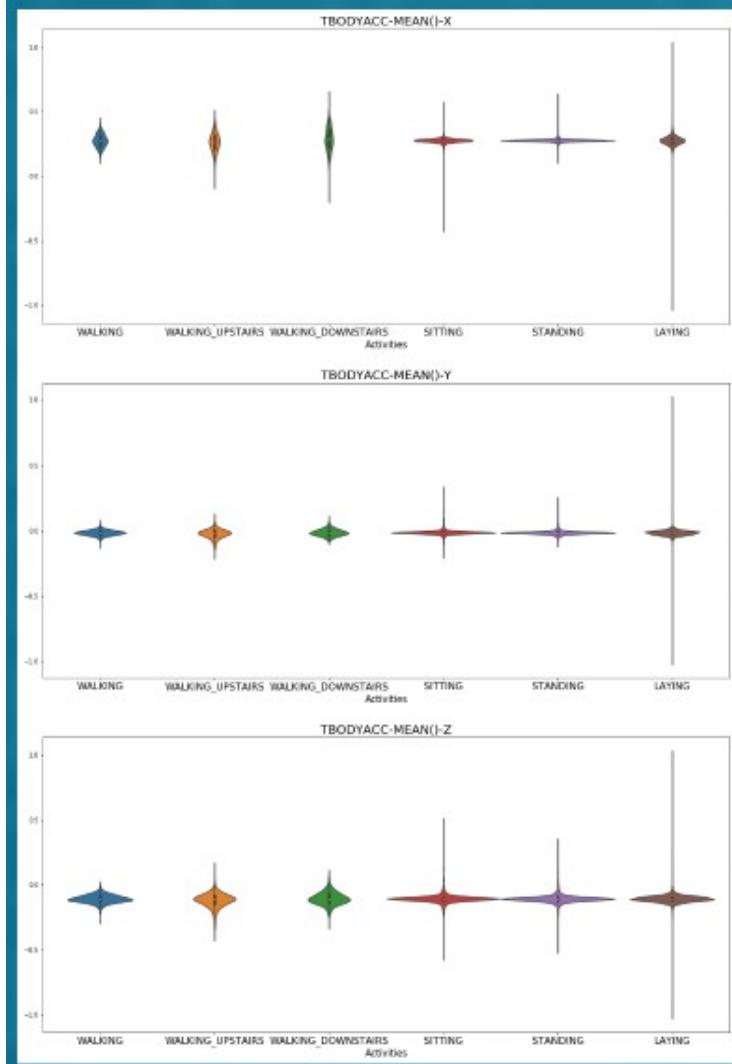
561 features			1	2	3	4	5
Nº	Group	Measurement List	mean(): Mean value	std(): Standard deviation	mad(): Median absolute deviation	max(): Largest value in array	min(): Smallest value in array
1	Accelerometer	tBodyAcc-XYZ	3	3	3	3	3
2		tGravityAcc-XYZ	3	3	3	3	3
3		tBodyAccJerk-XYZ	3	3	3	3	3
4	Gyroscope	tBodyGyro-XYZ	3	3	3	3	3
5		tBodyGyroJerk-XYZ	3	3	3	3	3
6		tBodyAccMag	1	1	1	1	1
7		tGravityAccMag	1	1	1	1	1

Accelerometer Body



\Leftarrow Mean (X,Y,Z)

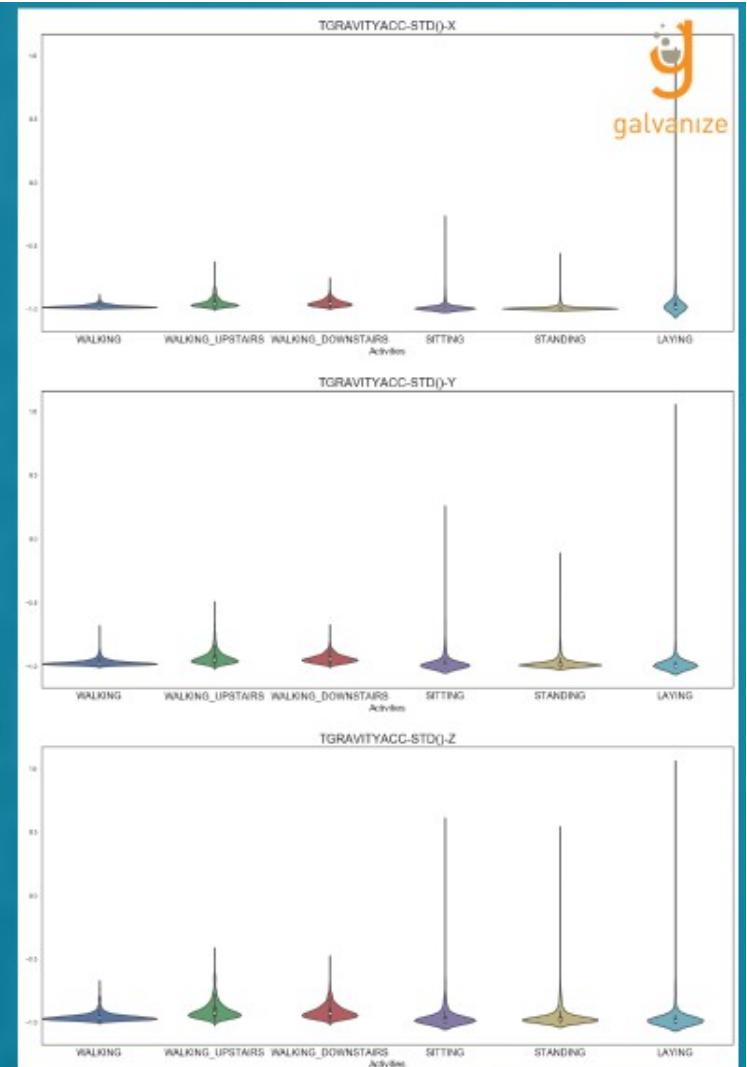
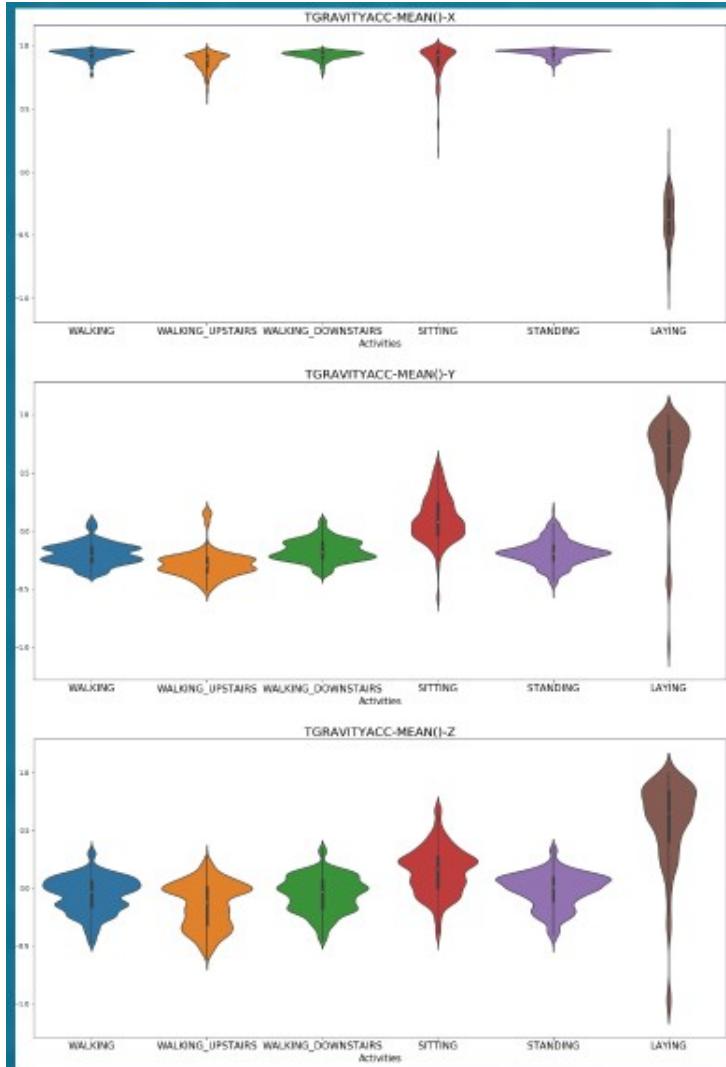
STD (X,Y,Z) \Rightarrow



Accelerometer Gravity

$\Leftarrow \text{Mean } (X,Y,Z)$

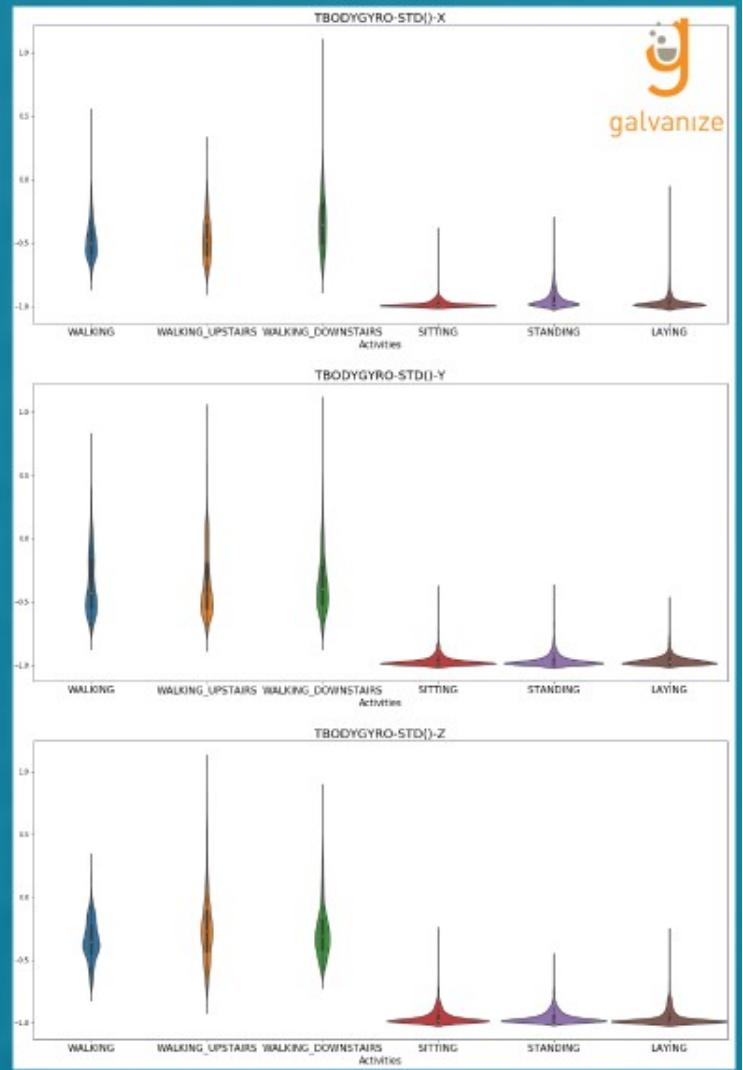
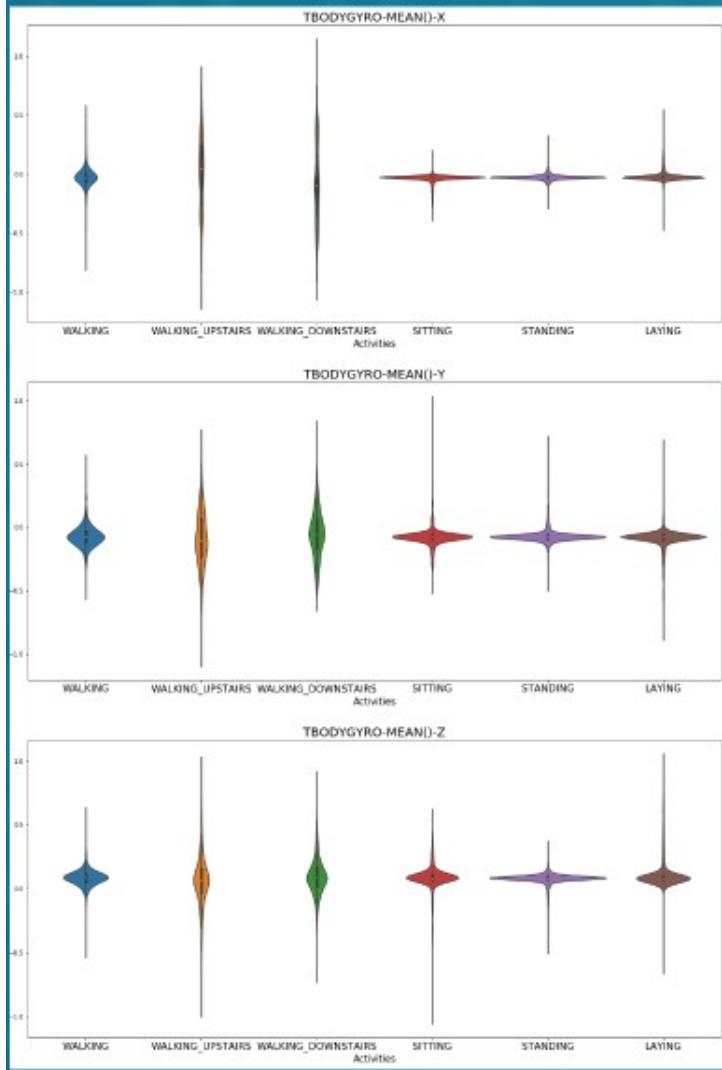
$\Rightarrow \text{STD } (X,Y,Z)$



Gyroscope Body

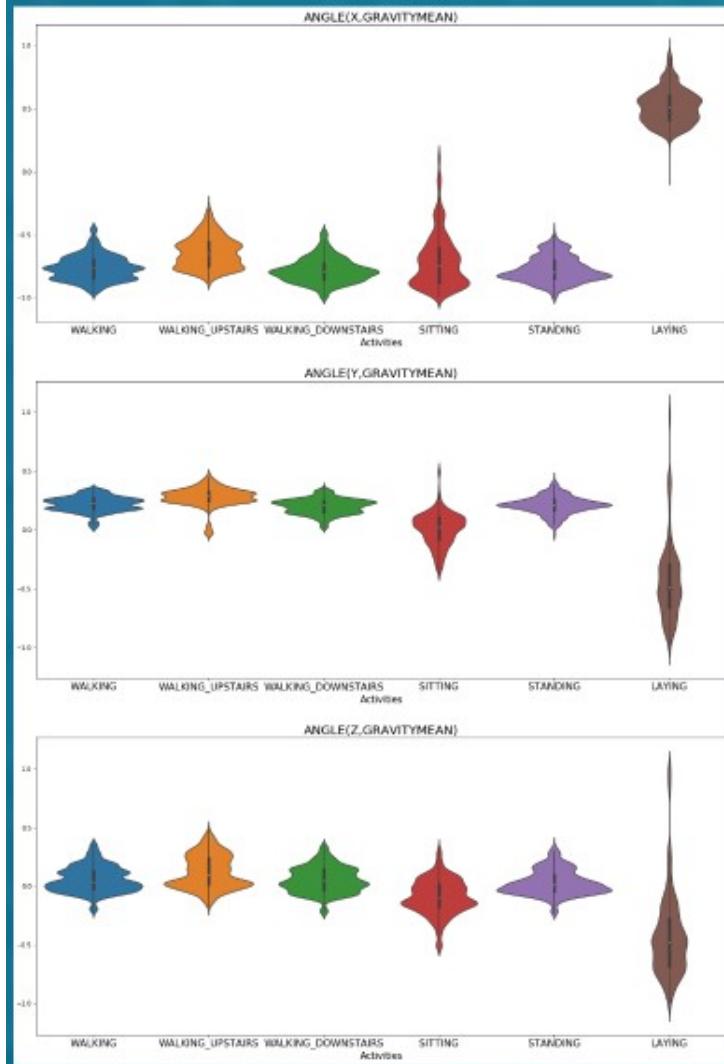
<= Mean (X,Y,Z)

STD (X,Y,Z) =>



Angle Gravity

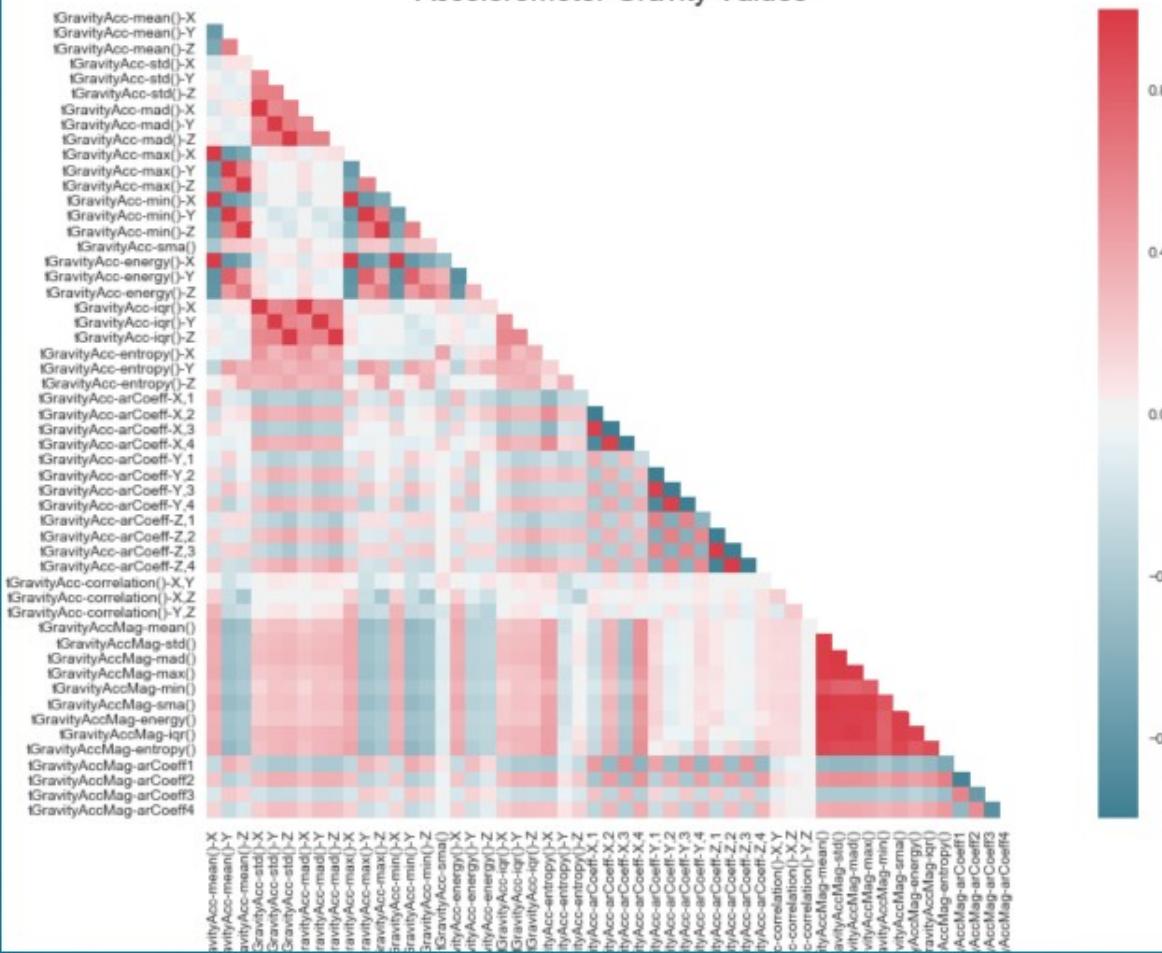
<= Mean (X,Y,Z)



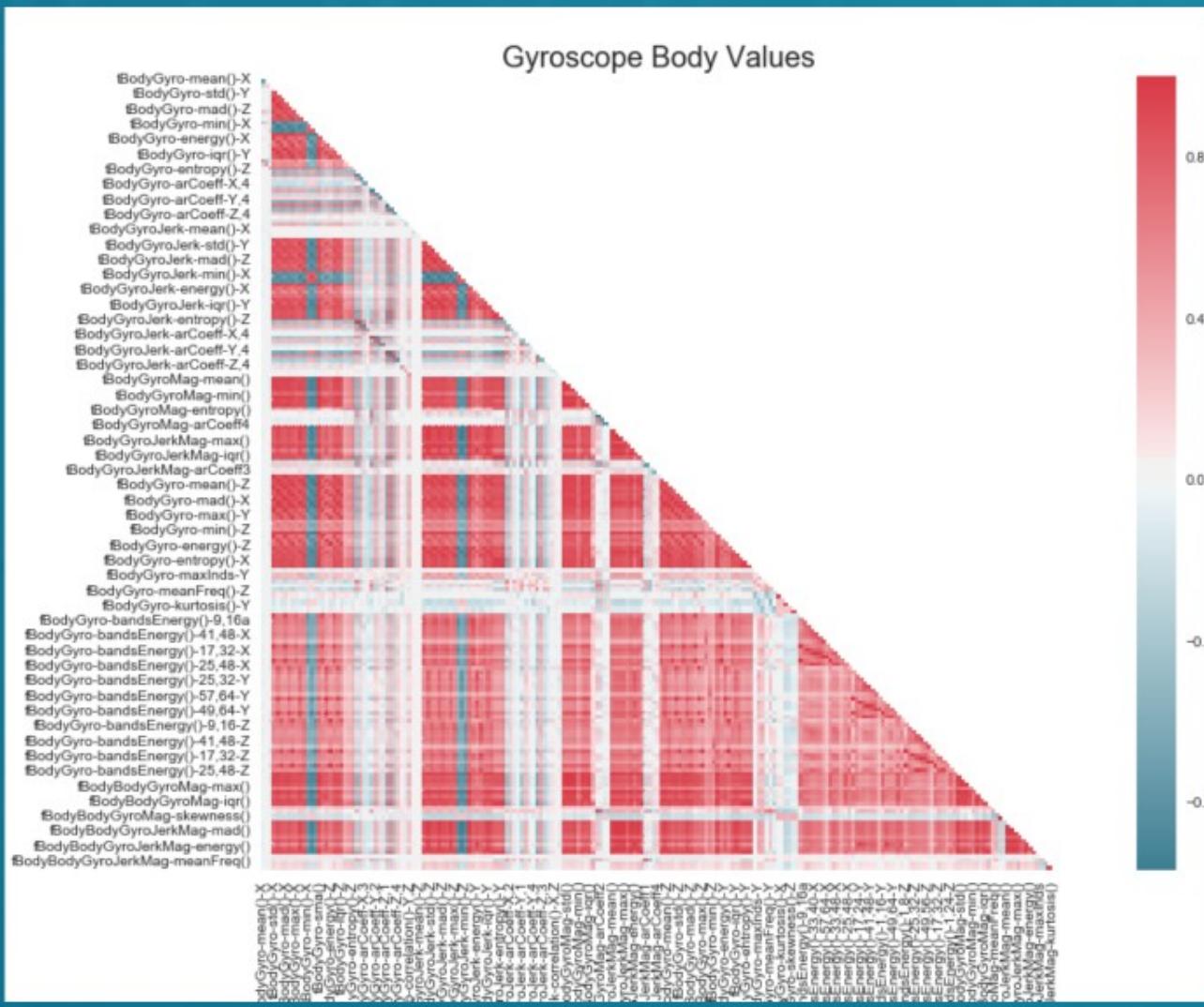
Accelerometer Body Values



Accelerometer Gravity Values



Gyroscope Body Values



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Dataset



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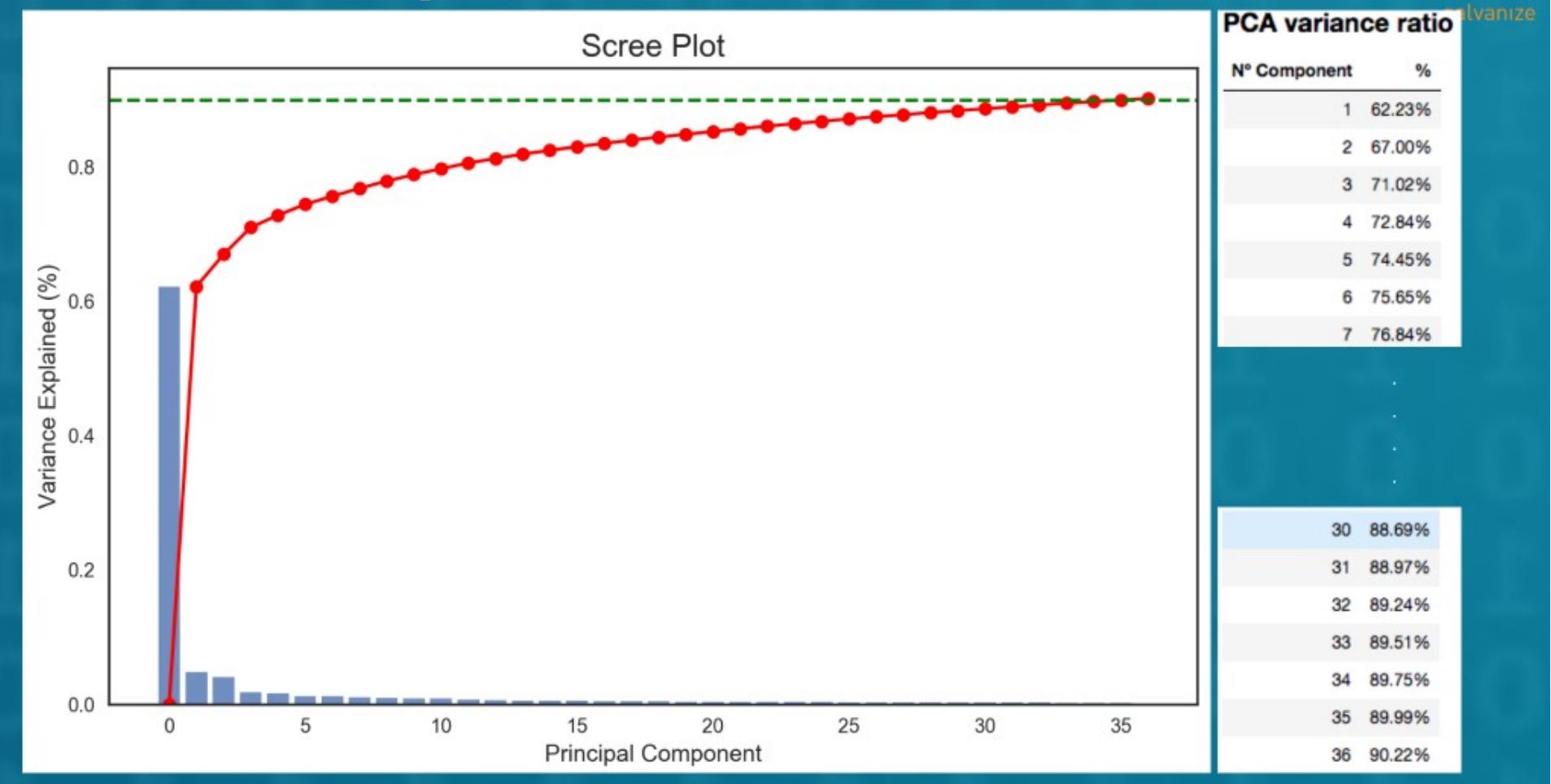
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PCA (36 components)



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AdaBoost

Accuracy
69.7%

**Decision
Tree**

Accuracy
78.4%

**Randon
Forest**

Accuracy
84.9%

Bagging
g
Galvanize

Accuracy
85.8%

Kneighbors

Accuracy
87.6%

**Gradient
Boosting**

Accuracy
89.9%

SVC

Accuracy
92.0%

**Neural
Network**

Accuracy
94.3%

AdaBoost

Accuracy
69.7%

**Decision
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Accuracy
92.0%

**Neural
Network**

Accuracy
94.3%

AdaBoost (Worst Accuracy)

REAL	PREDICT						PRECISION
	WALKING	WALKING UPSTAIRS	WALKING DOWNSTAIRS	SITTING	STANDING	LAYING	
WALKING	434	8	54				87,50%
WALKING UPSTAIRS	15	414	42				87,90%
WALKING DOWNSTAIRS	108	77	235				55,95%
SITTING		2		458	26	5	93,28%
STANDING				494	38		7,14%
LAYING		1		59	2	475	88,45%

AdaBoost

Accuracy
69.7%

**Decision
Tree**

Accuracy
78.4%

**Randon
Forest**

Accuracy
84.9%

Bagging
g
Galvanize

Accuracy
85.8%

Kneighbors

Accuracy
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**Gradient
Boosting**

Accuracy
89.9%

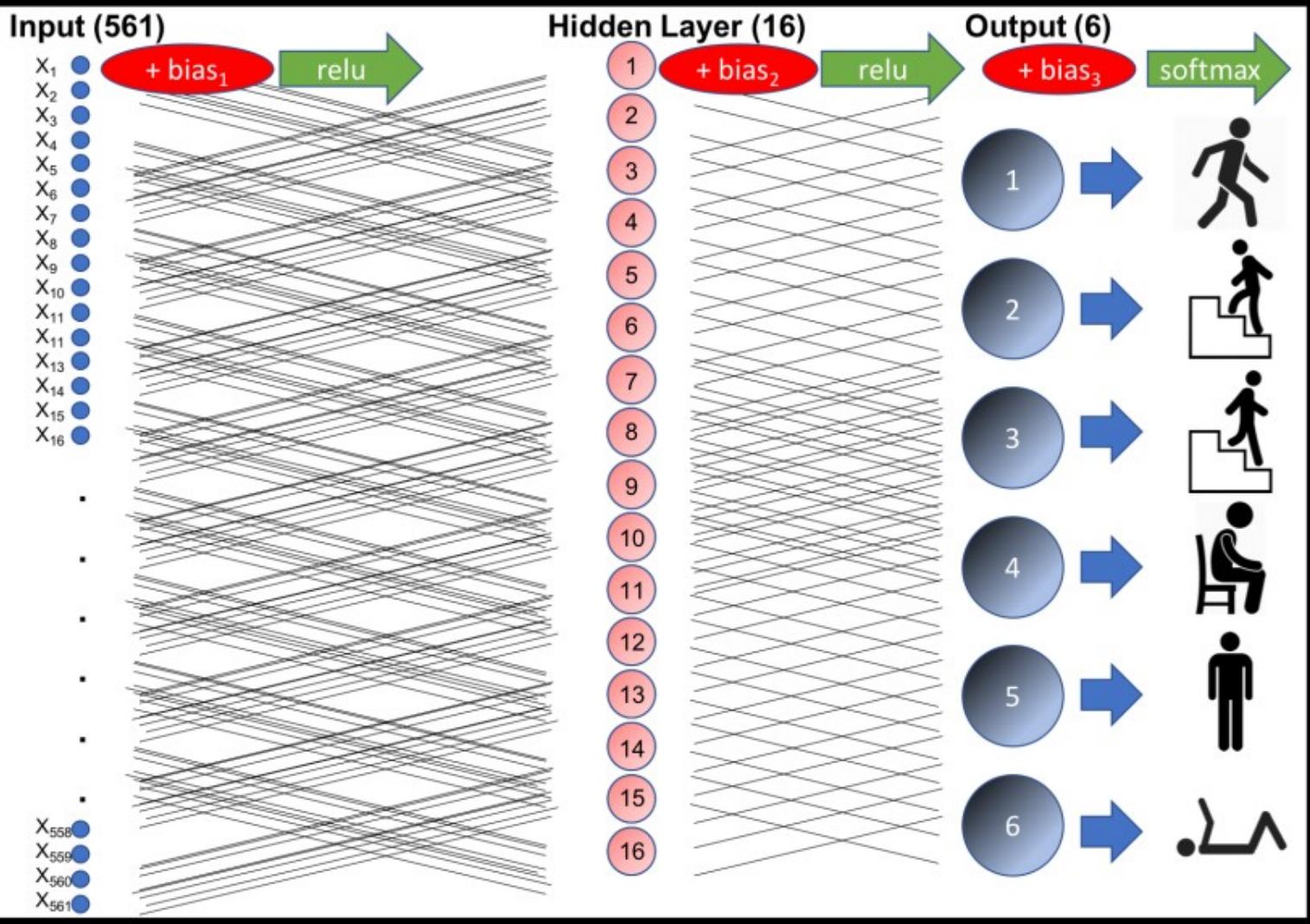
SVC

Accuracy
92.0%

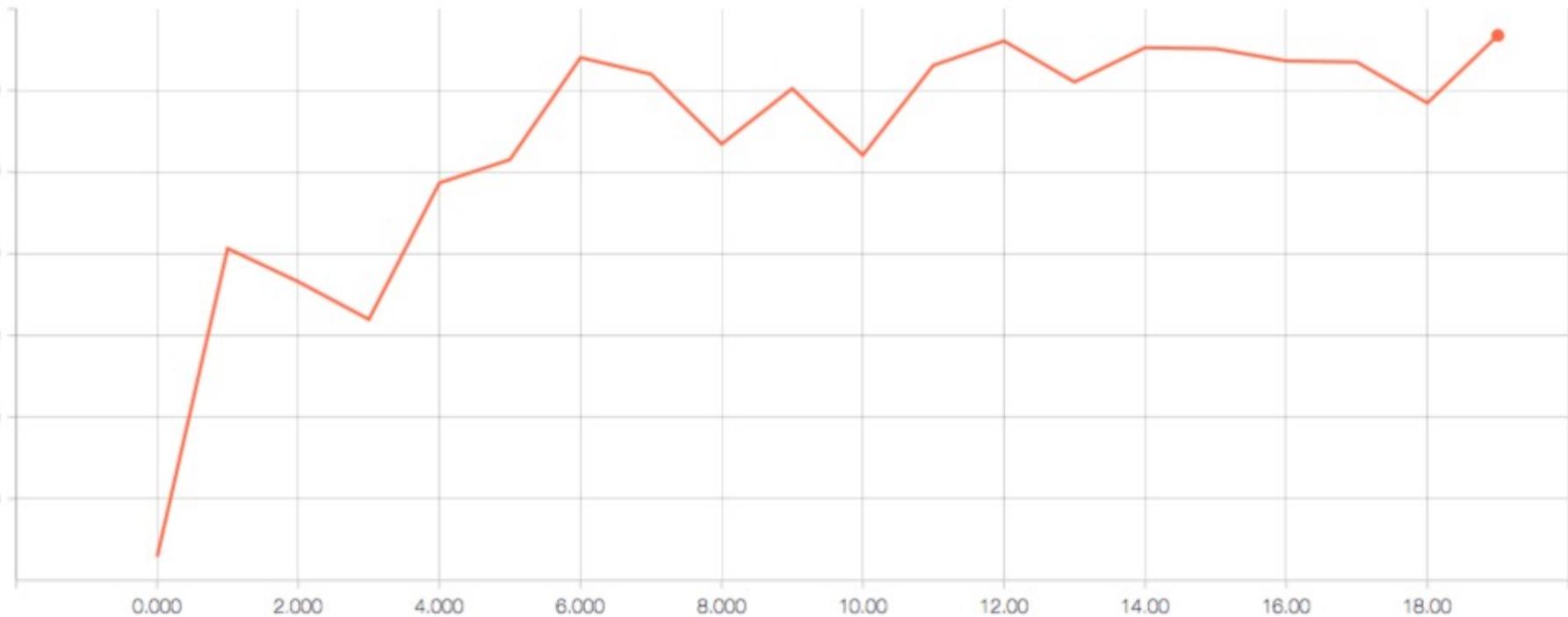
**Neural
Network**

Accuracy
94.3%

Neural Network Architecture



val_acc



val_loss



Neural Network (Best Accuracy)

REAL	PREDICT						PRECISION
	WALKING	WALKING UPSTAIRS	WALKING DOWNSTAIRS	SITTING	STANDING	LAYING	
WALKING	486	5	5				97,98%
WALKING UPSTAIRS	21	435	10		5		92,36%
WALKING DOWNSTAIRS	4	13	403				95,95%
SITTING				477	13	1	97,15%
STANDING	1			75	456		85,71%
LAYING				16		521	97,02%

AdaBoost

Accuracy
69.7%

**Decision
Tree**

Accuracy
78.4%

**Randon
Forest**

Accuracy
84.9%

Bagging
g
Galvanize

Accuracy
85.8%

Kneighbors

Accuracy
87.6%

**Gradient
Boosting**

Accuracy
89.9%

SVC

Accuracy
92.0%

**Neural
Network**

Accuracy
94.3%

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Train & Test

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Conclusion:

- The identification of activities through the analysis of the measurements generated by the cell phone is possible with a good precision;
- The neural network presented better results than other classification models;
- The use of this methodology can allow the creation of applications that identify the type of activity developed by the user while carrying his cell phone next to the body.

Thanks!



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Conclusion:

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