# Coisas estranhas que podemos fazer com dados coletados em dispositivos móveis: bye-bye privacidade!

Human Activity Recognition

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# Exemplos de dispositivos e dados que podem ser coletados

# Celulares

Coleta informações sobre:

- Localização (latitude e longitude);
- Movimentação (acelerômetro, giroscópio);
- Ambiente (audio, proximidade, luminosidade);
- Social (histórico de ligações, contatos).

# Relógios

Coleta informações sobre:

- Frequência cardíaca;
- Pressão arterial.

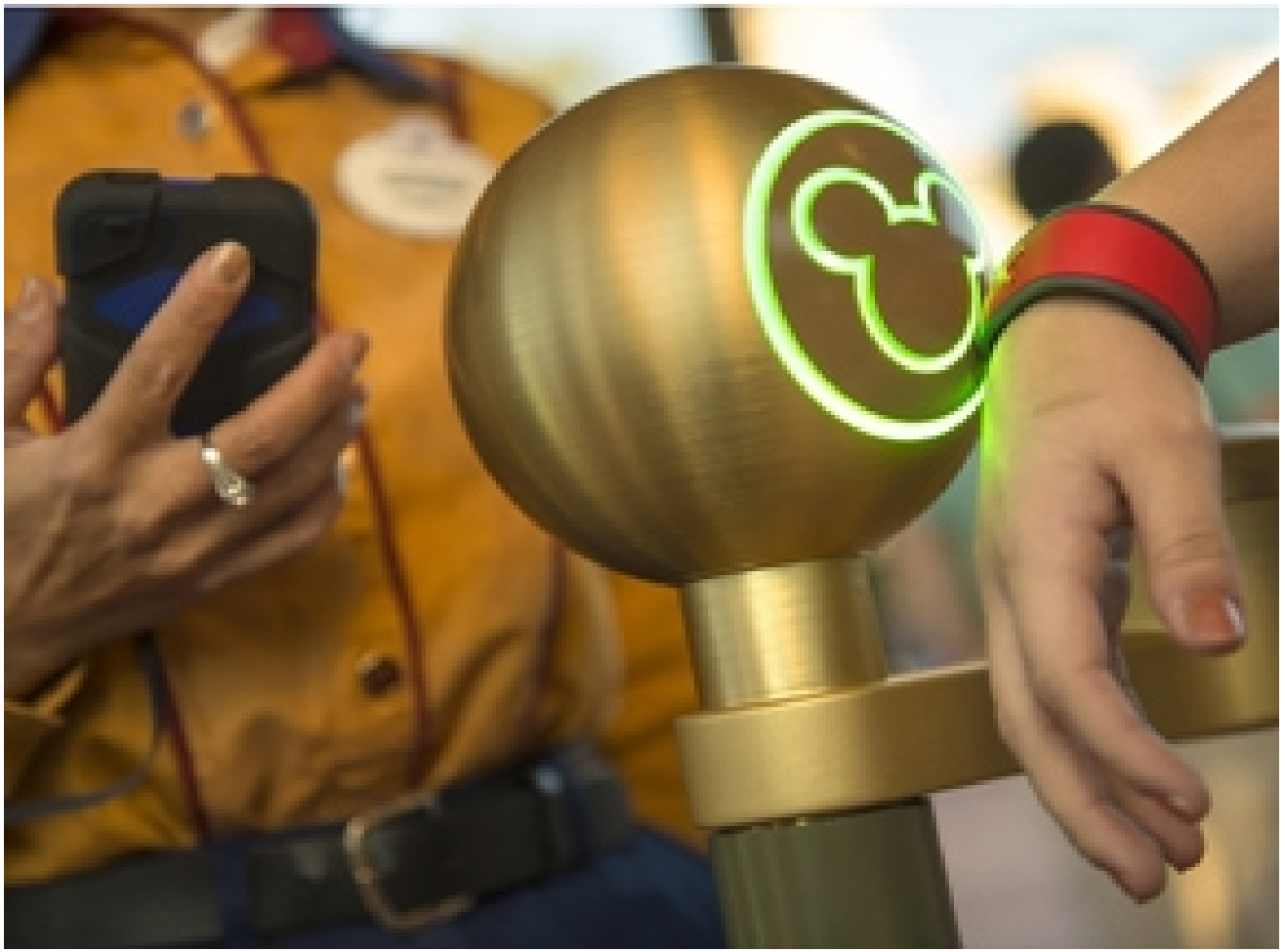
# Outras aplicações (talvez menos úteis)

# Monitora atividades físicas

Monitora:

- Que atividade está sendo realizada;
- Qual a duração;
- Qual a frequência.

# Disney



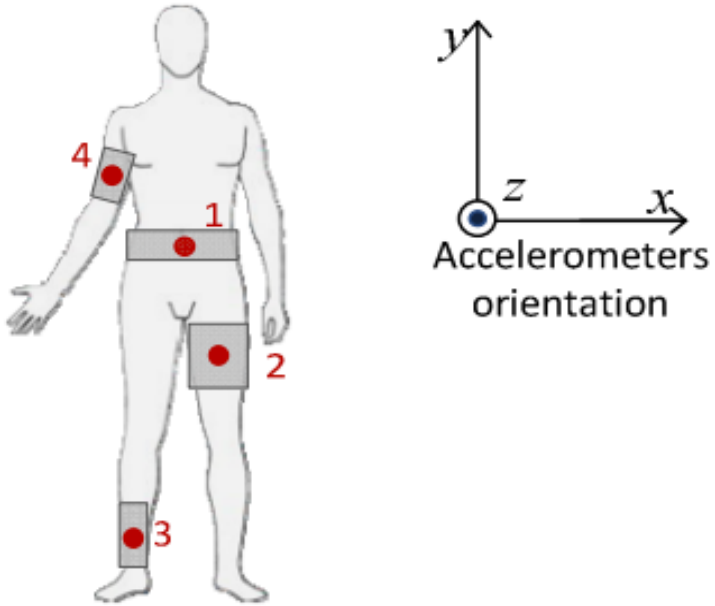
Monitora:

- Quando entrou e saiu do parque;
- Por onde andou;
- O que e quando comprou;
- Em quais parques foi e quando foi.

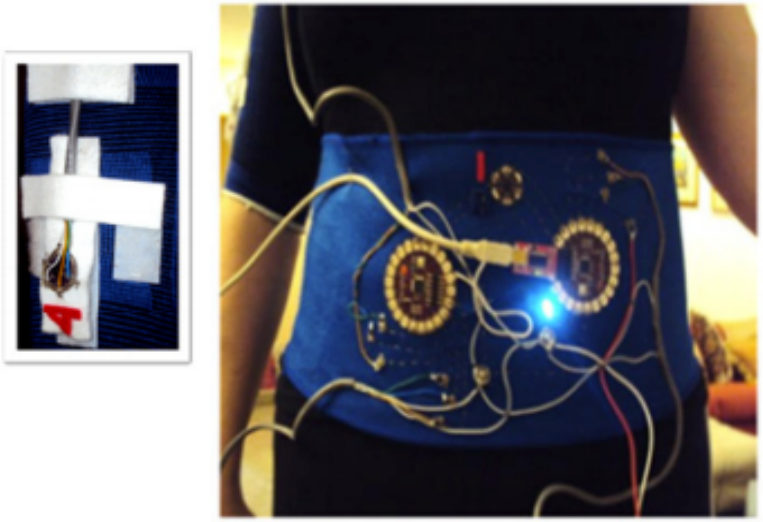
# O que podemos fazer com os dados coletados?

# Primeiro exemplo de aplicação [2]

Scheme of positioning and orientation




User wearing the device



O objetivo deste exemplo é construir um classificador capaz de dizer que atividade (**sitting, sitting down, standing, standing up, walking**) uma pessoa está realizando a partir de dados coletados de acelerômetros presentes no corpo desta pessoa.

# Pipeline do processo para reconhecimento de atividades [1]

# Dados coletados e filtrados

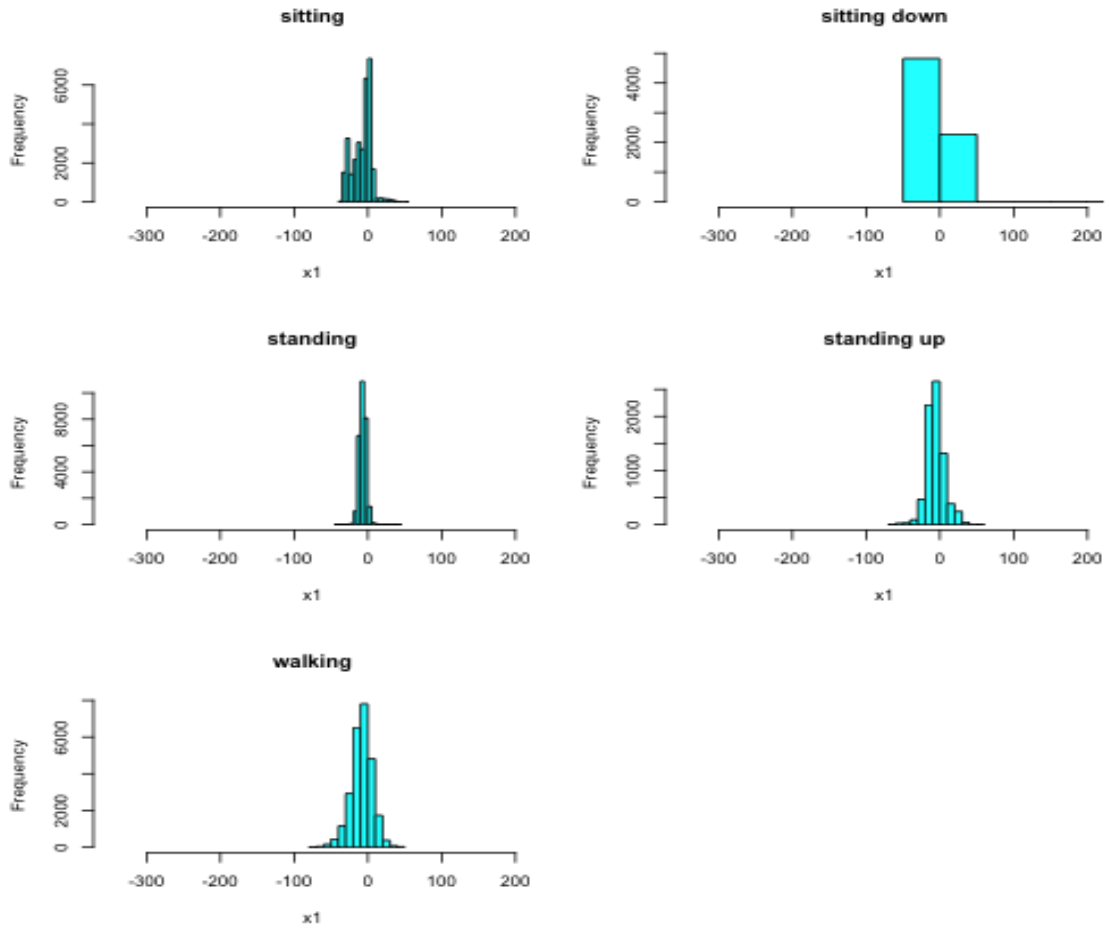
- Dados coletados a partir de 4 tri-axial acelerômetros.
- Foram consideradas janelas de tempo de 1 segundo, com overlapping de 150ms.
- Medidas de roll, pitch e módulo de aceleração foram adquiridas.
- A amostra dentro da janela de tempo foi agrupada e atributos foram gerados (i.e., variância, média).
- Foram filtrados 12 atributos finais - três para cada acelerômetro.

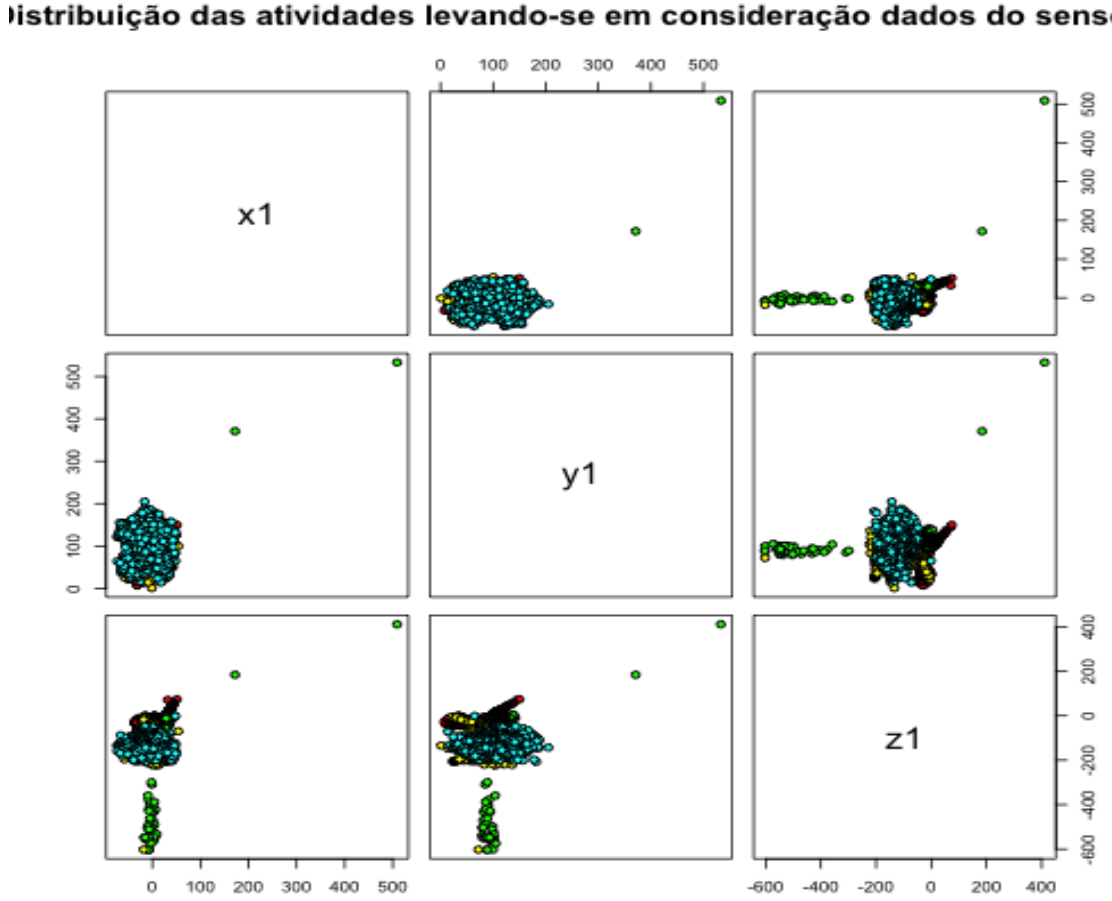
# Construção do classificador

- O dataset possui 165.633 exemplos e 19 atributos:
  - ⋆ user, gender, age, how_tall_in_meters, weight, body_mass_index, $x_1$, $y_1$, $z_1$, $\cdots$, $x_4$, $y_4$, $z_4$, **class**
- O dataset foi dividido em conjunto de treinamento e teste, respeitando a proporção dos valores do atributo **class**.

Referência: http://rpubs.com/fbarth/har01

# Alguns resultados da análise descritiva




Distribuição das atividades levando-se em consideração dados do sensor
x1
y1
z1
0
100
200
300
400
500
-600
-400
-200

# Algoritmo utilizado para criação do modelo: **Random Forest**

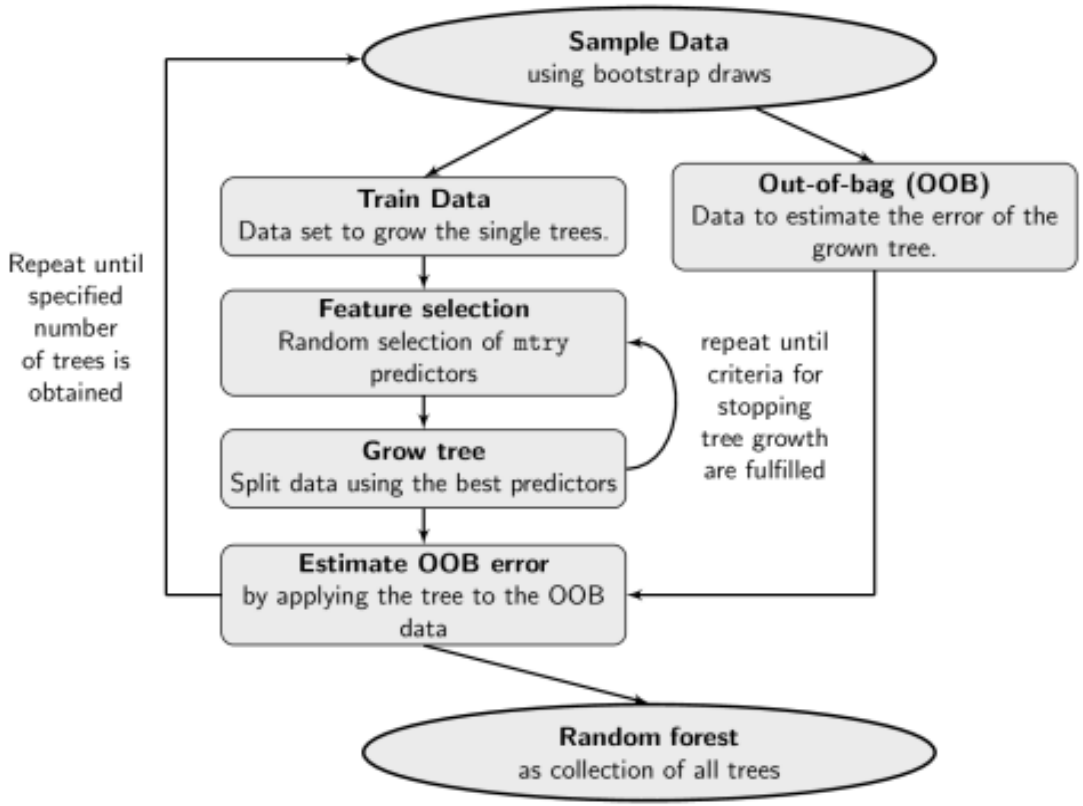



Figure 1: Random Forest Algorithm

# Criando o modelo...

```
library(randomForest)
```

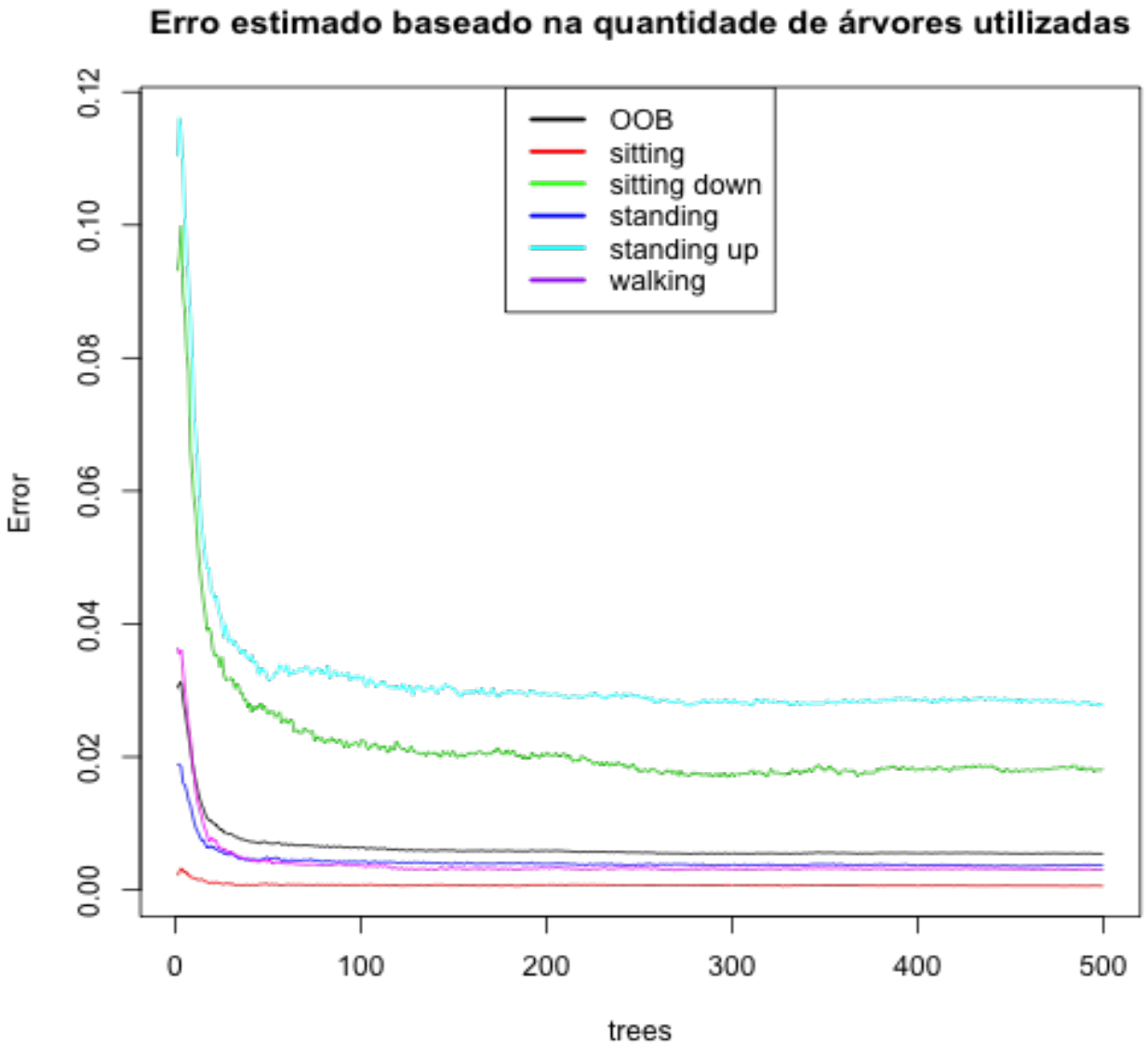
```
## randomForest 4.6-7
## Type rfNews() to see new features/changes/bug fixes.
```

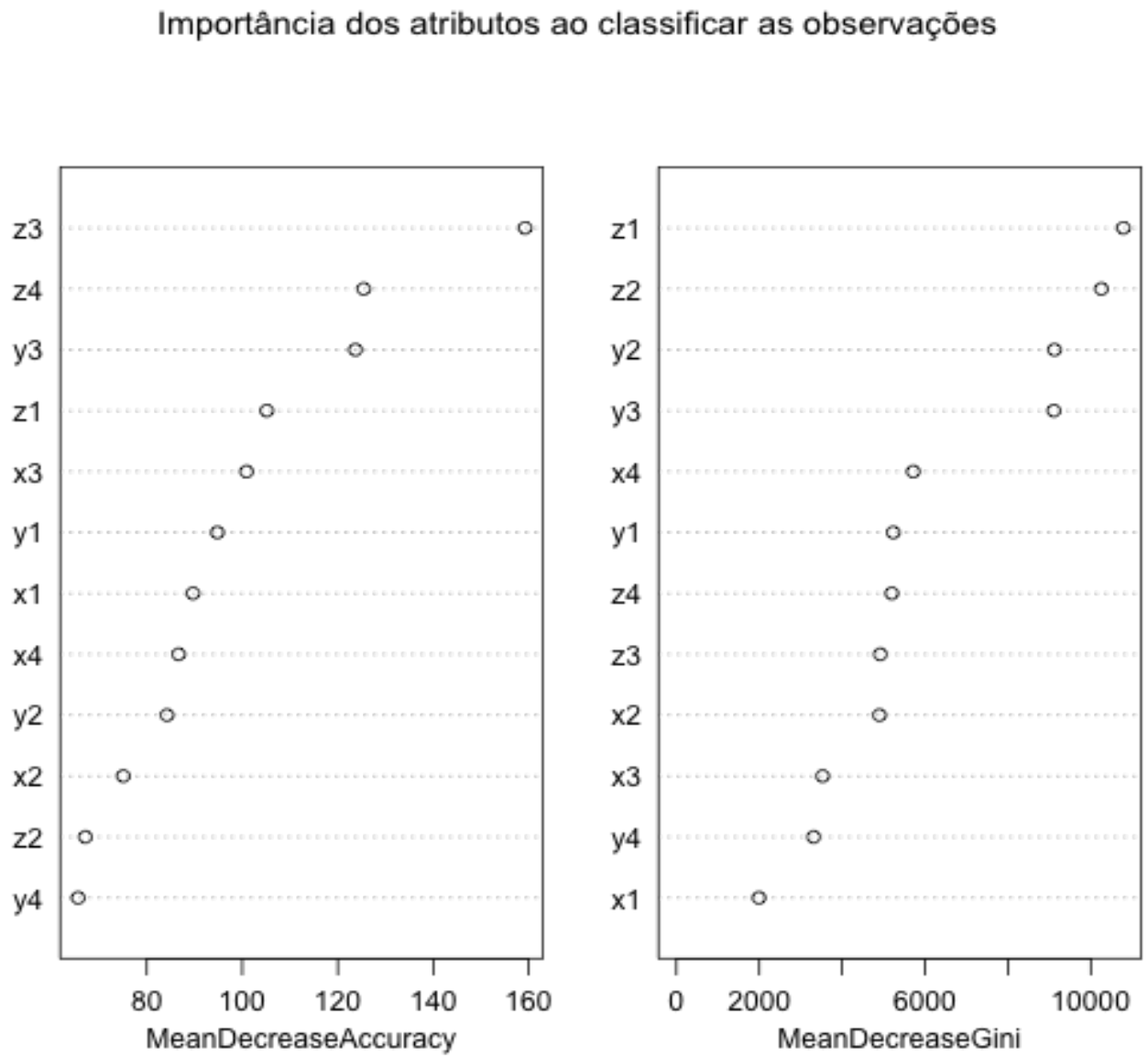
```
formula <- class ~ x1 + y1 + z1 + x2 + y2 + z2 + x3 + y3 + z3 + x4 + y4 + z4
model <- randomForest(formula, data = treinamento, do.trace = 100, importance = TRUE)
```

```
## ntree      OOB      1      2      3      4      5
##   100:   0.64%  0.07%  2.25%  0.43%  3.20%  0.37%
##   200:   0.59%  0.07%  2.07%  0.39%  2.94%  0.34%
##   300:   0.54%  0.07%  1.76%  0.37%  2.81%  0.30%
##   400:   0.55%  0.06%  1.82%  0.37%  2.85%  0.32%
##   500:   0.54%  0.06%  1.82%  0.37%  2.77%  0.30%
```

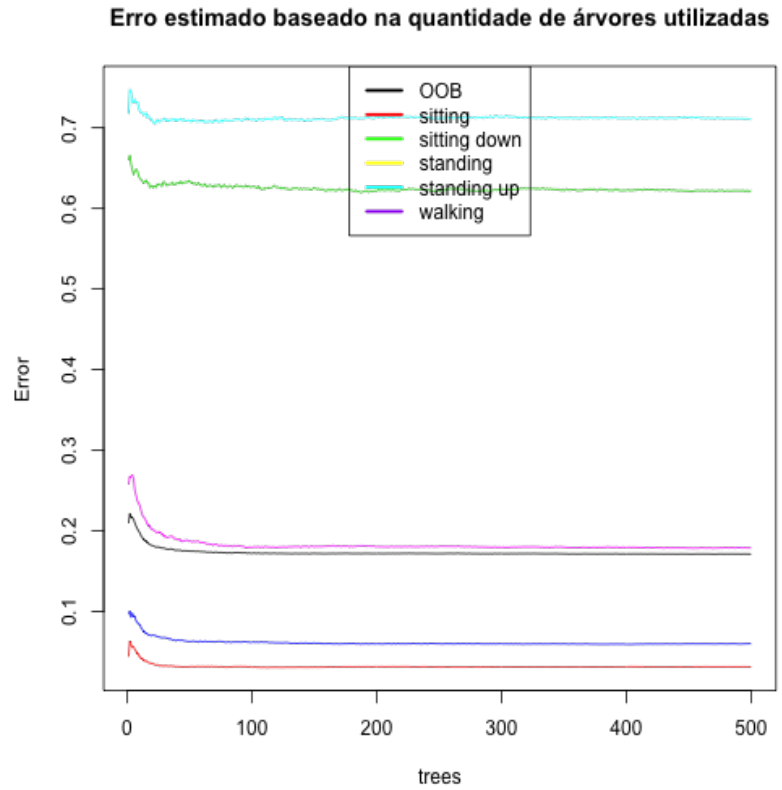
```
model
```

```
##
## Call:
##  randomForest(formula = formula, data = treinamento, do.trace = 100,      importance =
TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 3
##
##         OOB estimate of  error rate: 0.54%
## Confusion matrix:
##              sitting sittingdown standing standingup walking class.error
## sitting        30361           4        0         14       0   0.0005925
## sittingdown        3        6968       23         60      43   0.0181767
## standing           0           0    28316          8      98   0.0037295
## standingup         8          77       53       7243      68   0.0276547
## walking            0          14       47         18   25955   0.0030345
```


Erro estimado baseado na quantidade de árvores utilizadas
OOB
sitting
sitting down
standing
standing up
walking
Error
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0
100
200
300
400
500
trees


Importância dos atributos ao classificar as observações
z3
z4
y3
z1
x3
y1
x1
x4
y2
x2
z2
y4
80
100
120
140
160
MeanDecreaseAccuracy
z1
z2
y2
y3
x4
y1
z4
z3
x2
x3
y4
x1
0
2000
6000
10000
MeanDecreaseGini

# Outro modelo




Modelo que utiliza apenas dados do acelerômetro localizado na cintura (Erro estimado: 17.12%)

# Validando o modelo completo com o conjunto de testes

```
testPred <- predict(model, newdata = teste)
t <- table(testPred, teste$class)
confusionMatrix(t)
```

```
## Confusion Matrix and Statistics
##
##
## testPred      sitting sittingdown standing standingup walking
##   sitting       20236           2        0         3       0
##   sittingdown       0        4651        0        54      20
##   standing          0          14    18879        39      43
##   standingup       16          39        6      4819       9
##   walking           0          24       63        51   17284
##
## Overall Statistics
##
##                Accuracy : 0.994
##                  95% CI : (0.994, 0.995)
##     No Information Rate : 0.306
##     P-Value [Acc > NIR] : <2e-16
```

# Resultados do trabalho original [2]

We used AdaBoost with 10 iterations and configured the C4.5 tree for a confidence factor of 0.25. The overall recognition performance was of 99.4% (weighted average) using a 10-fold cross validation testing mode, with the following accuracies per class: "sitting" 100%, "sitting down" 96.9%, "standing" 99.8%, "standing up" 96.9%, and "walking" 99.8%. The confusion matrix is presented in Table 3.

**Table 3.** Confusion Matrix

| Predicted class | | | | | | |
|---|---|---|---|---|---|---|
| Sitting | Sitting down | Standing | Standing Up | Walking | | Actual class |
| 50,601 | 9 | 0 | 20 | 1 | Sitting | |
| 10 | 11,484 | 29 | 297 | 7 | Sitting down | |
| 0 | 4 | 47,342 | 11 | 13 | Standing | |
| 14 | 351 | 24 | 11,940 | 85 | Standing up | |
| 0 | 8 | 27 | 60 | 43,295 | Walking | |

The results obtained in this research are very close to the top results of the literature (99.4% in [14], and 99.6% in [15]), even though, it is hard to compare them. Each research used a different dataset, a different set of classes, and different test modes.

# Dado o mesmo dataset, será que é possível determinar quem está realizando a atividade?

http://fbarth.net.br/humanActivityRecognition/scripts/har_case01_user.html

# Segundo exemplo de aplicação [1]

Os experimentos foram realizados com um grupo de 30 voluntários entre 19-48 anos. Cada pessoa executou seis atividades:

- WALKING: andando
- WALKING_UPSTAIRS: andando escada acima
- WALKING_DOWNSTAIRS: andando escada abaixo
- SITTING: sentado
- STANDING: em pé
- LAYING: deitado

usando um smartphone (Samsung Galaxy II) na cintura.

Com base nos sensores do smartphone, acelerom̂etro e giroscópio, foram capturados a aceleração linear nos três eixos e a velocidade angular nos três eixos.

# Adquirindo os dados

```
load("../data/samsungData.rda")
names(samsungData) <- gsub("\\)", "_", gsub("\\(", "_", gsub(",", "_", gsub("-",
    "_", names(samsungData)))))
samsungData$activity <- as.factor(samsungData$activity)
```

http://rpubs.com/fbarth/har02

# Separando os dados

```
train <- subset(samsungData, samsungData$subject < 20)
test <- subset(samsungData, samsungData$subject > 20)
train$subject <- NULL
test$subject <- NULL
```

# Construindo o modelo

```
library(randomForest)
```

```
## randomForest 4.6-7
## Type rfNews() to see new features/changes/bug fixes.
```

```
model <- randomForest(activity ~ ., data = train, importance = TRUE, do.trace = 100)
```

```
## ntree      OOB      1      2      3      4      5      6
##   100:   2.17%  0.00%  3.31%  4.84%  1.41%  2.39%  1.01%
##   200:   1.79%  0.00%  3.31%  4.15%  1.41%  1.10%  0.50%
##   300:   1.72%  0.00%  3.01%  4.01%  1.13%  1.10%  0.84%
##   400:   1.59%  0.00%  2.26%  3.87%  1.41%  1.10%  0.67%
##   500:   1.51%  0.00%  2.26%  3.73%  1.41%  0.92%  0.50%
```

# Construindo o modelo

```
model
```

```
##
## Call:
##  randomForest(formula = activity ~ ., data = train, importance = TRUE,      do.trace =
100)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 23
##
##         OOB estimate of  error rate: 1.51%
## Confusion matrix:
##          laying sitting standing walk walkdown walkup class.error
## laying      731       0        0    0        0      0    0.000000
## sitting       0     649       15    0        0      0    0.022590
## standing      0      27      696    0        0      0    0.037344
## walk          0       0        0  697        7      3    0.014144
## walkdown      0       0        0    5      538      0    0.009208
## walkup        0       0        0    1        2    594    0.005025
```

# Validando o modelo

```
testPred <- predict(model, newdata = test)
t <- table(testPred, test$activity)
confusionMatrix(t)
```

```
## Confusion Matrix and Statistics
##
##
## testPred   laying sitting standing walk walkdown walkup
##   laying      676       0        0    0        0      0
##   sitting       0     578       70    0        0      0
##   standing      0      44      581    0        0     23
##   walk          0       0        0  471       14      9
##   walkdown      0       0        0    4      335      6
##   walkup        0       0        0   44       94    438
##
## Overall Statistics
##
##                Accuracy : 0.909
##                  95% CI : (0.899, 0.919)
##     No Information Rate : 0.2
##     P-Value [Acc > NIR] : <2e-16
```

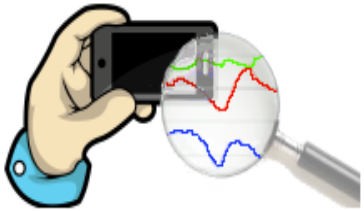
# Comparando com o artigo original [1]

| Method | MC-SVM | | | | | | | MC-HF-SVM $k = 8$ bits | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Activity | Walking | Upstairs | Downstairs | Standing | Sitting | Laying | *Recall %* | Walking | Upstairs | Downstairs | Standing | Sitting | Laying | *Recall %* |
| Walking | **109** | 0 | 5 | 0 | 0 | 0 | *95.6* | **109** | 2 | 3 | 0 | 0 | 0 | *95.6* |
| Upstairs | 1 | **95** | 40 | 0 | 0 | 0 | *69.8* | 1 | **98** | 37 | 0 | 0 | 0 | *72.1* |
| Downstairs | 15 | 9 | **119** | 0 | 0 | 0 | *83.2* | 15 | 14 | **114** | 0 | 0 | 0 | *79.7* |
| Standing | 0 | 5 | 0 | **132** | 5 | 0 | *93.0* | 0 | 5 | 0 | **131** | 6 | 0 | *92.2* |
| Sitting | 0 | 0 | 0 | 4 | **108** | 0 | *96.4* | 0 | 1 | 0 | 3 | **108** | 0 | *96.4* |
| Laying | 0 | 0 | 0 | 0 | 0 | **142** | *100* | 0 | 0 | 0 | 0 | 0 | **142** | *100* |
| *Precision %* | *87.2* | *87.2* | *72.6* | *97.1* | *95.6* | *100* | ***89.3*** | *87.2* | *81.7* | *74.0* | *97.8* | *94.7* | *100* | ***89.0*** |

**Table 1.** Confusion Matrix of the classification results on the test data using the traditional floating-point MC-SVM (Left) and the MC-HF-SVM with $k = 8$ bits (Right). Rows represent the actual class and columns the predicted class. The diagonal entries (in bold) show the number of test samples correctly classified.

# Kaggle: Accelerometer Biometric Competition

kaggle | Customer Solutions | Competitions | Community ▾ | Fabrício J. Barth | Logout



Completed • $5,000 • 633 teams

# Accelerometer Biometric Competition

Tue 23 Jul 2013 – Fri 22 Nov 2013 (12 months ago)

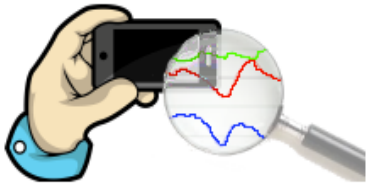
Dashboard

- Home
  - Data
  - Make a submission
- Information
  - Description
  - Evaluation
  - Rules
  - Prizes
  - About the Sponsor
  - More on Accelerometer D...

Competition Details » Get the Data » Make a submission

## Recognize users of mobile devices from accelerometer data

Since everyone moves differently and accelerometers are fast becoming ubiquitous, this competition is designed to investigate the feasibility of using accelerometer data as a biometric for identifying users of mobile devices.



Completed • $5,000 • 633 teams

# Accelerometer Biometric Competition

Tue 23 Jul 2013 – Fri 22 Nov 2013 (12 months ago)

Dashboard

## Public Leaderboard - Accelerometer Biometric Competition

This leaderboard is calculated on approximately 30% of the test data.
The final results will be based on the other 70%, so the final standings may be different.

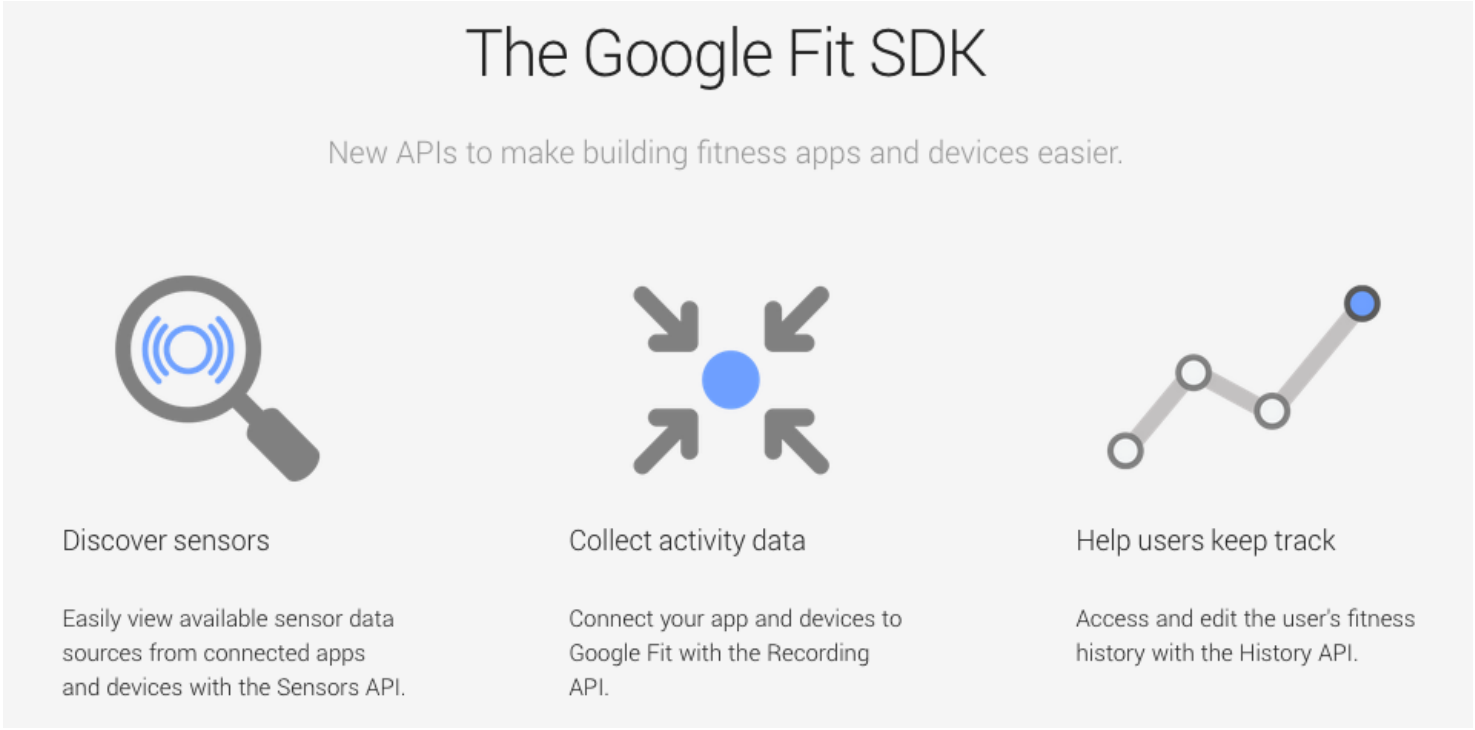
See someone using multiple accounts?
Let us know.

| # | Δ1w | Team Name * in the money | Score | Entries | Last Submission UTC (Best – Last Submission) |
|---|---|---|---|---|---|
| 1 | – | gaddawin * | 0.99905 | 108 | Fri, 22 Nov 2013 19:34:13 (-1.6h) |
| 2 | ↑1 | Solórzano * | 0.99898 | 62 | Fri, 22 Nov 2013 23:26:39 |
| 3 | ↓1 | Target Leak Model * | 0.99782 | 63 | Fri, 22 Nov 2013 07:17:54 (-23.8h) |
| 4 | ↑1 | Dan Stahlke * | 0.99659 | 48 | Thu, 21 Nov 2013 00:55:00 (-22.4h) |
| 5 | ↓1 | Dieselboy | 0.99555 | 338 | Fri, 22 Nov 2013 22:56:48 (-3.7h) |
| 6 | ↑1 | Victor | 0.99456 | 43 | Fri, 22 Nov 2013 23:01:34 |
| 7 | ↑10 | YS-L | 0.99289 | 36 | Thu, 21 Nov 2013 15:10:37 (-0.1h) |
| 8 | ↑44 | Guillaume BS | 0.98853 | 36 | Fri, 22 Nov 2013 22:37:44 (-0.4h) |

# Google Fit, Google Fit SDK, funf

# Google Fit: lançado em 28/10/2014

# Google Fit SDK



# funf: Open Sensing Framework

# Perguntas?

# Obrigado!

- Todo o material (slides e código) aqui apresentado é *Copyleft*
- O código fonte é encontrado em http://github.com/fbarth
- Demais materias são encontrado em http://fbarth.net.br
- fabricio dot barth at gmail dot com

# References

[1] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, and JorgeL. Reyes-Ortiz. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In José Bravo, Ramón Hervás, and Marcela Rodríguez, editors, *Ambient Assisted Living and Home Care*, volume 7657 of *Lecture Notes in Computer Science*, pages 216–223. Springer Berlin Heidelberg, 2012.

[2] Wallace Ugulino, Débora Cardador, Katia Vega, Eduardo Velloso, Ruy Milidiú, and Hugo Fuks. Wearable computing: Accelerometers' data classification of body postures and movements. In LelianeN. Barros, Marcelo Finger, AuroraT. Pozo, GustavoA. Gimenénez-Lugo, and Marcos Castilho, editors, *Advances in Artificial Intelligence - SBIA 2012*, Lecture Notes in Computer Science, pages 52–61. Springer Berlin Heidelberg, 2012.