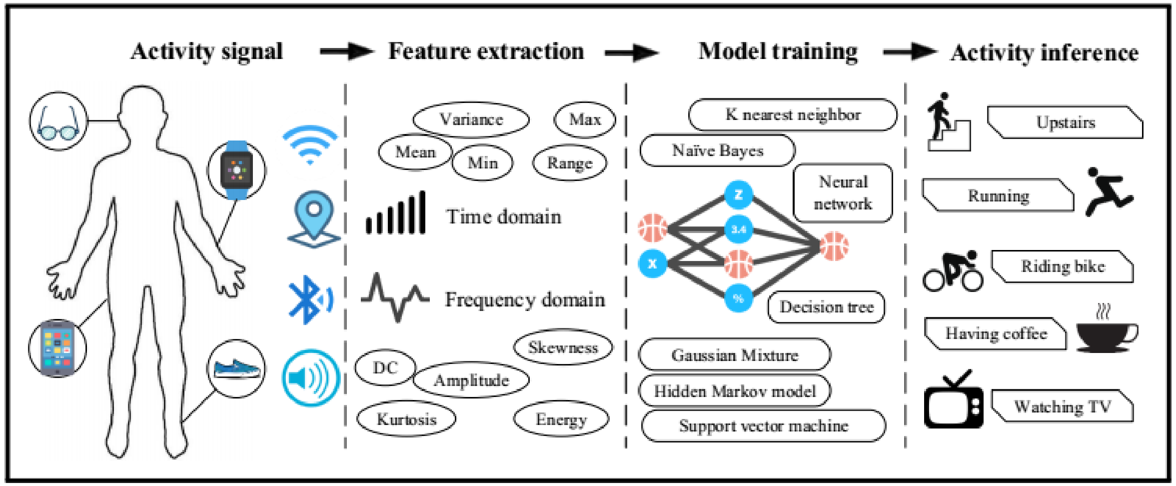
HUMAN ACTIVITY RECOGNITION

In [1]:
```
# Human Activity Image
from IPython.display import Image
Image(filename='Human Activities.png',width=900)
```

Out[1]:



Deep learning model - LSTM's

The model will be carried out on raw-time series data. We have 9 time series files:

1. 3 **body_accelerometer_data** files,
2. 3 **body_gyro_data** files,
3. 3 **total_accelerometer_data** files

We will feed the raw time series data itself into the model.

In [2]:
```
import pandas as pd
```

```
import numpy as np
```

In [3]:
```
# Activities are the class labels and we have a multi-class classificat
ion problem.
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
    3: 'SITTING',
    4: 'STANDING',
    5: 'LAYING',
}

# Utility function to print the confusion matrix
def confusion_matrix(Y_true, Y_pred):
    Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1
)])
    Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1
)])

    return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pr
ed'])
```

In [4]:
```
# Data directory
DATADIR = 'UCI_HAR_Dataset'
```

In [5]:
```
# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
```

```
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]
```

In [6]:
```
# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}
_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps,
 9 signals)
    return np.transpose(signals_data, (1, 2, 0))
```

In [7]:
```
def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to
 6,
    that represents a human activity. We return a binary representation
 of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_
dummies.html)
    """
    filename = f'UCI_HAR_Dataset/y_{subset}.txt'
```

```
    y = _read_csv(filename)[0]

    return pd.get_dummies(y).as_matrix()
```

In [8]:

```
def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_test = load_y('train'), load_y('test')

    return X_train, X_test, y_train, y_test
```

In [9]:

```
# Importing keras libraries

import warnings
warnings.simplefilter("ignore")
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from keras.layers.normalization import BatchNormalization
```

```
Using TensorFlow backend.
```

In [18]:

```
# Initializing parameters
epochs = 30
batch_size = 16
```

In [19]:

```
# Utility function to count the number of classes
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

In [20]:

```
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

In [21]:

```
timesteps = len(X_train[0])
```

```
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)

print(timesteps)
print(input_dim)
print(len(X_train))
```

```
128
9
7352
```

In [22]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(16,return_sequences=True, input_shape=(timesteps, input_dim)))
# Another layer
model.add(LSTM(16))
# Add BN
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.8))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_5 (LSTM)                (None, 128, 16)           1664      
_________________________________________________________________
lstm_6 (LSTM)                (None, 16)                2112      
_________________________________________________________________
batch_normalization_3 (Batch (None, 16)                64        
_________________________________________________________________
dropout_3 (Dropout)          (None, 16)                0         
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 102       
=================================================================
Total params: 3,942
```

```
Trainable params: 3,910
Non-trainable params: 32
_________________________________________________________________
```

In [23]:
```
# Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [24]:
```
# Training the model
model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 98s 13ms/step - loss: 1.67
37 - acc: 0.3572 - val_loss: 0.9923 - val_acc: 0.6081
Epoch 2/30
7352/7352 [==============================] - 90s 12ms/step - loss: 1.10
88 - acc: 0.5169 - val_loss: 0.7525 - val_acc: 0.6440
Epoch 3/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.93
23 - acc: 0.5978 - val_loss: 0.8233 - val_acc: 0.6407
Epoch 4/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.80
80 - acc: 0.6574 - val_loss: 0.5021 - val_acc: 0.8066
Epoch 5/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.72
76 - acc: 0.6836 - val_loss: 0.4306 - val_acc: 0.8225
Epoch 6/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.66
94 - acc: 0.7047 - val_loss: 0.6727 - val_acc: 0.7319
Epoch 7/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.63
61 - acc: 0.7184 - val_loss: 0.3570 - val_acc: 0.8663
Epoch 8/30
```

```
7352/7352 [==============================] - 91s 12ms/step - loss: 0.60
90 - acc: 0.7258 - val_loss: 0.3165 - val_acc: 0.8768
Epoch 9/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.58
69 - acc: 0.7357 - val_loss: 0.3082 - val_acc: 0.8846
Epoch 10/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.57
50 - acc: 0.7352 - val_loss: 0.3227 - val_acc: 0.8819
Epoch 11/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.57
97 - acc: 0.7413 - val_loss: 0.2935 - val_acc: 0.8921
Epoch 12/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.56
09 - acc: 0.7478 - val_loss: 0.4757 - val_acc: 0.8568
Epoch 13/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.54
87 - acc: 0.7481 - val_loss: 0.3061 - val_acc: 0.8863
Epoch 14/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.54
69 - acc: 0.7505 - val_loss: 0.2903 - val_acc: 0.8958
Epoch 15/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.53
16 - acc: 0.7569 - val_loss: 0.3221 - val_acc: 0.8989
Epoch 16/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.53
33 - acc: 0.7558 - val_loss: 0.3454 - val_acc: 0.8918
Epoch 17/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.52
95 - acc: 0.7485 - val_loss: 0.3177 - val_acc: 0.8877
Epoch 18/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.51
86 - acc: 0.7629 - val_loss: 0.3769 - val_acc: 0.8856
Epoch 19/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.52
12 - acc: 0.7651 - val_loss: 0.3883 - val_acc: 0.8901
Epoch 20/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.51
35 - acc: 0.7674 - val_loss: 0.3447 - val_acc: 0.9057
Epoch 21/30
```

```
7352/7352 [==============================] - 92s 12ms/step - loss: 0.52
16 - acc: 0.7640 - val_loss: 0.3144 - val_acc: 0.9070
Epoch 22/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.49
41 - acc: 0.7666 - val_loss: 0.4372 - val_acc: 0.8921
Epoch 23/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.50
99 - acc: 0.7624 - val_loss: 0.3794 - val_acc: 0.8931
Epoch 24/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.49
88 - acc: 0.7662 - val_loss: 0.3214 - val_acc: 0.9040
Epoch 25/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.50
21 - acc: 0.7697 - val_loss: 0.3537 - val_acc: 0.9040
Epoch 26/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.49
12 - acc: 0.7715 - val_loss: 0.3293 - val_acc: 0.9104
Epoch 27/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.50
35 - acc: 0.7567 - val_loss: 0.3350 - val_acc: 0.9036
Epoch 28/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.48
73 - acc: 0.7777 - val_loss: 0.3003 - val_acc: 0.9189
Epoch 29/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.49
95 - acc: 0.7724 - val_loss: 0.4140 - val_acc: 0.9050
Epoch 30/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.49
65 - acc: 0.7686 - val_loss: 0.3089 - val_acc: 0.9145
```

Out[24]:
```
<keras.callbacks.History at 0xec1d2fd470>
```

In [25]:
```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

```
Pred                    LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True

LAYING                     536        0         0        0
```

```
  0
SITTING                  7      411         70         2
  0
STANDING                 0      105        423         3
  0
WALKING                  0        0          0       481
  4
WALKING_DOWNSTAIRS       0        0          0         5
410
WALKING_UPSTAIRS         0        0          0        33
  4

Pred                WALKING_UPSTAIRS
True
LAYING                             1
SITTING                            1
STANDING                           1
WALKING                           11
WALKING_DOWNSTAIRS                 5
WALKING_UPSTAIRS                 434
```

In [26]:

```
# Evaluating test data
score = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 6s 2ms/step
```

In [27]:

```
# Log loss and accuracy on test data
score
```

Out[27]:

```
[0.3088785500611205, 0.9144893111638955]
```

7. Insights & Conclusion

In line with our objective we have predicted human activities from sensors using various machine learning models and have also tried out with one simple deep learning model.

While observing the outputs from t-sne plot and confusion matrix of various machine learning models one pattern is evident that is, there is a confusion while classifying standing and sitting class,that's why we have a high precision and recall rates on non-diagonal cells(read as standing and sitting). Apart from this our model fairly classifies other classes with good accuracy.

Also when we observe the results of the models, our linear models are doing good then our non-linear models like decision tree,random forest. So it's good to stick with our linear models.

One way to avoid this confusion of classification between standing & sitting classes is we could get a feedback from **DOMAIN EXPERT**. Probably he/she could give us feedback on this issue. We could come up with new features that could solve the problem.

I tried out deep learning model because, they can automatically engineer new features for us. But when we observe the output of deep learning model, even they struggle to classify these two classes.

Final conclusion would be use linear models like logistic regression, linear svm. Also with the help of domain expert we can further featurize the data.