Lungs Auscultation Audios

The auscultation is a technique to explore internal organs of the human body through the stetoscope in order to identify sounds whose are involved in some desease, like crackles and wheezes. These sounds can be identified in a time-frequency analysis, in which several statistic indices can be calculated (Variance, Range, Moving Average, Spectrum average) to build models that help to automatize the diagnosis of Crackles and Wheezes, or even some desease.

This project develops models of **regression and classification** with some of the indices described above using the data set I created in one of my university projects, in which a database of auscultation audios is analyzed, extracting each respiratory cycle from several auscultations performed on 126 patients.

The complete project can be found clicking [here (https://github.com/santiagortiiz/Lungs-Auscultation-Signals.git)](https://github.com/santiagortiiz/Lungs-Auscultation-Signals.git).

And The original audios Database can be found clicking [here (https://www.kaggle.com/vbookshelf/respiratory-sound-database)](https://www.kaggle.com/vbookshelf/respiratory-sound-database)

Let's start by importing principle libraries

In [1]:
```
import random
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Load the dataset as a DataFrame

The dataset describes each of the 126 patients in two ways, the first of which details their basic information such as age, sex, weight, BMI, and their identification. And the second describes each respiratory cycle including start time, end time, `pathologies detected` , status and `statistical indices` .

Note: The status describes the patient as follows:
State
0 -> Healthy (Respiratory cycle without Crackles or Wheezes)
1 -> Respiratory cycle with Crackles
2 -> Respiratory cycle with Wheezes
3 -> Respiratory cycle with Both (Crackles and Wheezes)

In [2]:
```
df = pd.read_excel('auscultation_features.xlsx')
df
```

Out[2]:

	patient_ID	Diagnosis	age	sex	IMC	weight	height	adq_format	start	end	crackl
0	101	URTI	3.0	F	NaN	19.0	99.0	1b1_Al_sc_Meditron	0.036	0.579	
1	101	URTI	3.0	F	NaN	19.0	99.0	1b1_Al_sc_Meditron	0.579	2.450	
2	101	URTI	3.0	F	NaN	19.0	99.0	1b1_Al_sc_Meditron	2.450	3.893	
3	101	URTI	3.0	F	NaN	19.0	99.0	1b1_Al_sc_Meditron	3.893	5.793	
4	101	URTI	3.0	F	NaN	19.0	99.0	1b1_Al_sc_Meditron	5.793	7.521	
...	...	...	...	...	...	...	...	...	...	...	
6893	226	Pneumonia	4.0	M	NaN	16.7	103.0	1b1_Pl_sc_LittC2SE	11.721	13.693	
6894	226	Pneumonia	4.0	M	NaN	16.7	103.0	1b1_Pl_sc_LittC2SE	13.693	15.536	
6895	226	Pneumonia	4.0	M	NaN	16.7	103.0	1b1_Pl_sc_LittC2SE	15.536	17.493	
6896	226	Pneumonia	4.0	M	NaN	16.7	103.0	1b1_Pl_sc_LittC2SE	17.493	19.436	
6897	226	Pneumonia	4.0	M	NaN	16.7	103.0	1b1_Pl_sc_LittC2SE	19.436	19.979	

6898 rows × 18 columns

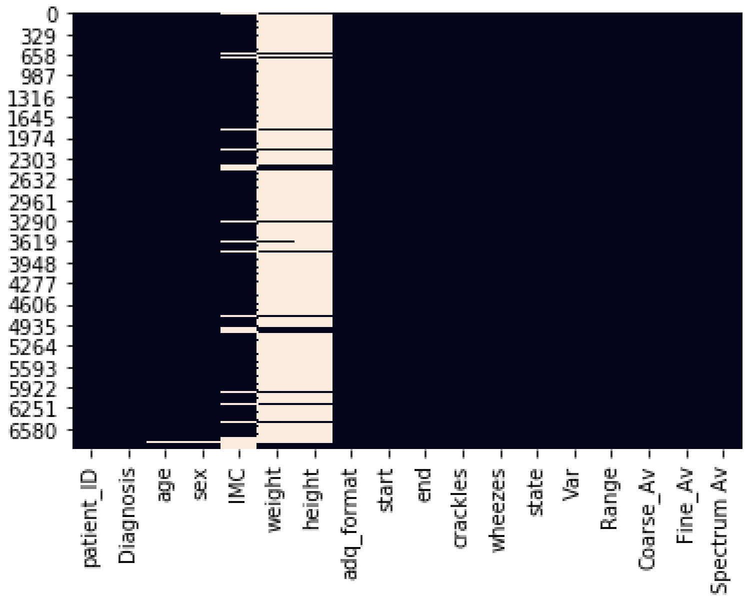
In [3]:
```
len(df)
```

Out[3]: 6898

Preparation required based on missing data

Lets see what proportion of our dataset is `missing` and if it requires some cleaning:

In [4]:
```
sns.heatmap(df.isnull(), cbar=False)
plt.show()
```



In [5]:
```
print(np.sum(df.isnull()==True))
```

```
patient_ID         0
Diagnosis          0
age               61
sex               61
IMC              894
weight          6149
height          6172
adq_format         0
start              0
end                0
crackles           0
wheezes            0
state              0
Var                0
Range              0
Coarse_Av          0
Fine_Av            0
Spectrum Av        0
dtype: int64
```

Cleaning dataset

The models in which I am interested, just need the statistical features and the diagnosis, so let's drop IMC, weight, height and the adquisition format columns:

In [6]:
```
df.drop(['IMC','weight','height','adq_format'], axis=1, inplace=True)
features = df.columns
df
```

Out[6]:

	patient_ID	Diagnosis	age	sex	start	end	crackles	wheezes	state	Var	Range
0	101	URTI	3.0	F	0.036	0.579	0	0	0	0.000048	0.113594
1	101	URTI	3.0	F	0.579	2.450	0	0	0	0.000066	0.159031
2	101	URTI	3.0	F	2.450	3.893	0	0	0	0.000044	0.115345
3	101	URTI	3.0	F	3.893	5.793	0	0	0	0.000074	0.187316
4	101	URTI	3.0	F	5.793	7.521	0	0	0	0.000036	0.117565
...	...	...	...	...	...	...	...	...	...	...	...
6893	226	Pneumonia	4.0	M	11.721	13.693	1	0	1	0.000015	0.056514
6894	226	Pneumonia	4.0	M	13.693	15.536	0	0	0	0.000026	0.107412
6895	226	Pneumonia	4.0	M	15.536	17.493	0	0	0	0.000017	0.089678
6896	226	Pneumonia	4.0	M	17.493	19.436	1	0	1	0.000018	0.059962
6897	226	Pneumonia	4.0	M	19.436	19.979	0	0	0	0.000042	0.046713

6898 rows × 14 columns

Then, notice that only 61 values of the age and sex columns are missing, so there are two options:

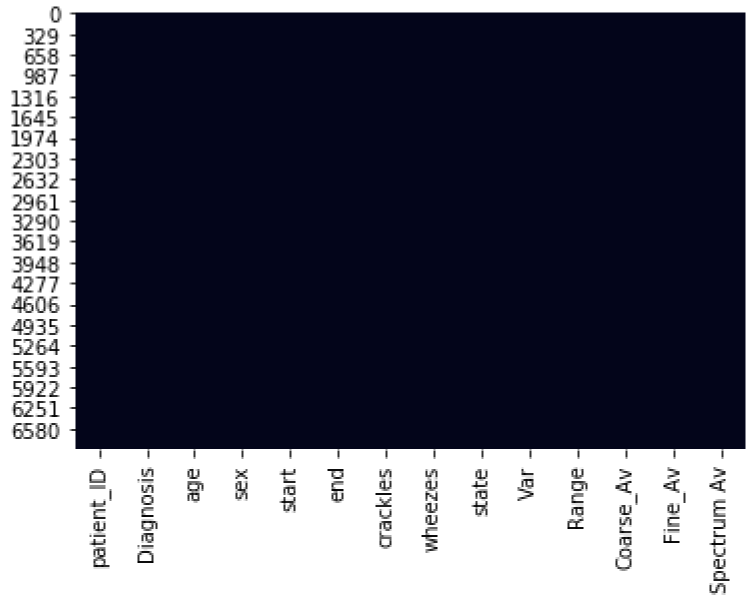
1) Discard the missing data: df = df.dropna()
2) Impute the missing data

Lets go ahead imputing these data with the scikit learn library using the SimpleImputer class

In [7]:
```
from sklearn.impute import SimpleImputer
```

In [8]:
```
imp = SimpleImputer(strategy="most_frequent")
df = pd.DataFrame(imp.fit_transform(df), columns = features)
```

In [9]:
```
sns.heatmap(df.isnull(), cbar=False)
plt.show()
print(np.sum(df.isnull()==True))
```




```
patient_ID     0
Diagnosis      0
age            0
sex            0
start          0
end            0
crackles       0
wheezes        0
state          0
Var            0
Range          0
Coarse_Av      0
Fine_Av        0
Spectrum Av    0
dtype: int64
```

Shuffle the dataset because:

1) Shuffled samples will help us avoid areas of the model that under/overfil the data

2) If we evaluate a movel based on data it has seen before, we may overestimate its performance

In [10]:
```
df = df.sample(frac=1)
df['ones'] = 1 # Intercept parameter
df
```

Out[10]:

	patient_ID	Diagnosis	age	sex	start	end	crackles	wheezes	state	Var	Rang
1473	130	COPD	85	F	17.065	19.911	1	1	3	0.000246658	0.22835
2090	140	Pneumonia	79	F	0.207	3.479	0	0	0	3.80814e-05	0.20934
2818	154	COPD	65	M	12.266	16.764	0	0	0	8.6154e-05	0.16846
810	120	COPD	78	M	29.852	32.015	0	0	0	1.62333e-05	0.050244
5193	193	COPD	77	M	9.507	11.162	0	1	2	0.00735029	1.1980
...	...	...	...	...	...	...	...	...	...	...	
4942	186	COPD	71	M	1.185	5.268	1	0	1	0.00198866	0.9629
1707	134	COPD	61	M	1.879	6.55	0	0	0	6.85978e-06	0.045351
817	120	COPD	78	M	46.495	48.213	1	0	1	6.49744e-05	0.23612
4123	172	COPD	73	M	15.801	18.322	0	0	0	0.0131668	2.4016
127	107	COPD	75	F	10.53	13.196	1	0	1	0.00192446	0.64727

6898 rows × 15 columns

1) Regression

1.a) Linear Regression with Numpy

Model Generated with Numpy.linalg.lstsq (Least Square of Linear Algebra's Library)

Labels to predict:

In [11]:
```
y = df['state'].values.reshape(-1,1)  # -1 means that calculate the dimension of row
y = y.tolist()
```

Features used to predict

In [12]:
```
X = pd.concat([df['ones'], df.loc[:, 'Var':'Spectrum Av']], axis=1)
X
```

Out[12]:

	ones	Var	Range	Coarse_Av	Fine_Av	Spectrum Av
1473	1	0.000246658	0.228359	-0.0130017	-0.0118159	1.20827e-07
2090	1	3.80814e-05	0.209343	0.00178729	0.00442789	1.78598e-08
2818	1	8.6154e-05	0.168467	0.00440061	0.0087567	4.19739e-08
810	1	1.62333e-05	0.0502448	-0.000388107	-0.000315144	8.12325e-09
5193	1	0.00735029	1.19805	0.0619296	-0.0735627	3.80217e-06
...	...	...	...	...	...	...
4942	1	0.00198866	0.96295	0.00977568	0.0043438	1.03598e-06
1707	1	6.85978e-06	0.0453517	-0.00932395	-0.000557135	3.31628e-09
817	1	6.49744e-05	0.236125	0.00530234	0.00080912	3.1536e-08
4123	1	0.0131668	2.40166	-0.468886	-0.0668553	6.24007e-06
127	1	0.00192446	0.647278	-0.281156	-0.219324	9.73581e-07

6898 rows × 6 columns

In [13]:
```
X = np.matrix(X, dtype = float)
X = X.tolist()
```

In [14]:
```
print(np.shape(X), type(X))
print(np.shape(y), type(y))
```

```
(6898, 6) <class 'list'>
(6898, 1) <class 'list'>
```

In [15]:
```
theta, residuals, rank, s = np.linalg.lstsq(X, y, rcond = None)
```

In [16]:
```
theta
```

Out[16]:
```
array([[ 6.25792526e-01],
       [-1.82641935e+02],
       [ 2.18285781e-01],
       [ 2.46472680e-02],
       [-8.22214973e-02],
       [ 3.86809005e+05]])
```

Model Generated:
State = theta_0 + theta_1xVariance + theta_2xRange + theta_3xCoarse_Av + theta_4xFine_Av + theta_5xSpectrum_Av

1.b) Linear Regression with Sickit Learn

In [17]:
```
from sklearn.linear_model import LinearRegression
```

Take the one half of the data for training, and the other one for testing

In [18]:
```
N = len(X)
X_train = X[:N//2] # First half to train
X_test = X[N//2:] # Last half to test
y_train = y[:N//2]
y_test = y[N//2:]
```

Create the instance of the class LinearRegression() and fit it with the training parameters.
This will be the model

In [19]:
```
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X_train, y_train)  # perform linear regression
```

Out[19]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

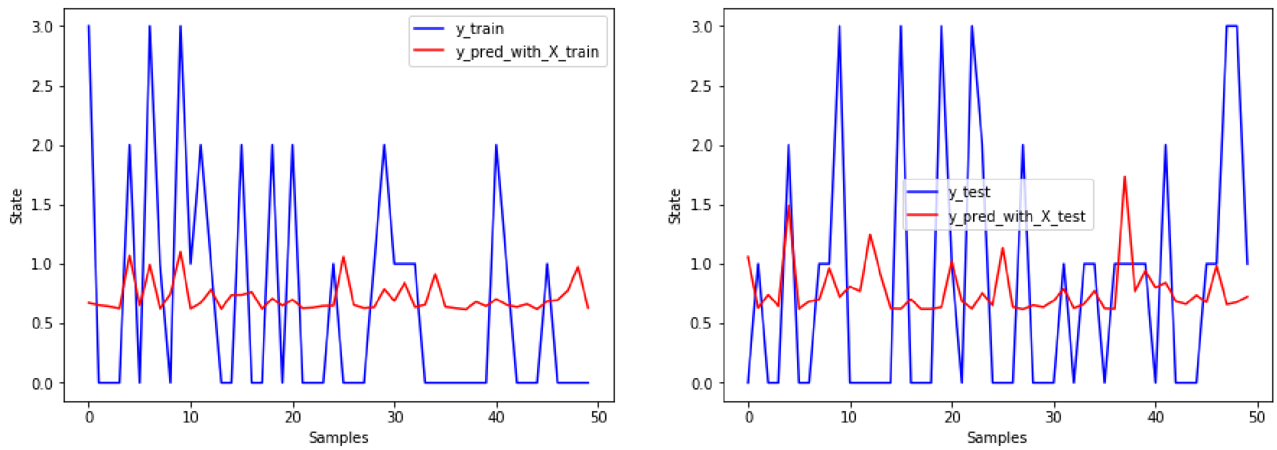
Generate the predictions of the model with the training and testing data

In [20]:
```
y_pred_with_X_train = linear_regressor.predict(X_train)  # make predictions
y_pred_with_X_test = linear_regressor.predict(X_test)
```

Plotting a portion of the predictions and compare with the originals

In [21]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
plt.plot(y_train[:50], color='blue')
plt.plot(y_pred_with_X_train[:50], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_train','y_pred_with_X_train'])

plt.subplot(1,2,2)
plt.plot(y_test[:50], color='blue')
plt.plot(y_pred_with_X_test[:50], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_test','y_pred_with_X_test'])
plt.show()
```



Conclusion: The Linear Regression Model can't fit the state of the patients

2) Classification

2.a) Nearest Neighbors with Scikit learn

In [22]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [23]:
```
X = pd.concat([df['ones'], df.loc[:, 'Var':'Spectrum Av']], axis=1)
y = df['state']
```

In [24]:
```
N = len(X)
X_train = X[:N//2] # First half to train
X_test = X[N//2:] # Last half to test
y_train = y[:N//2]
y_test = y[N//2:]
```

Create the instance of the class KNeighborsClassifier with the selected **k**, and train this model

In [25]:
```
k = 5
nearest_neighbors = KNeighborsClassifier(n_neighbors = k)
nearest_neighbors.fit(X_train.values.tolist(), y_train.values.tolist())
```

Out[25]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

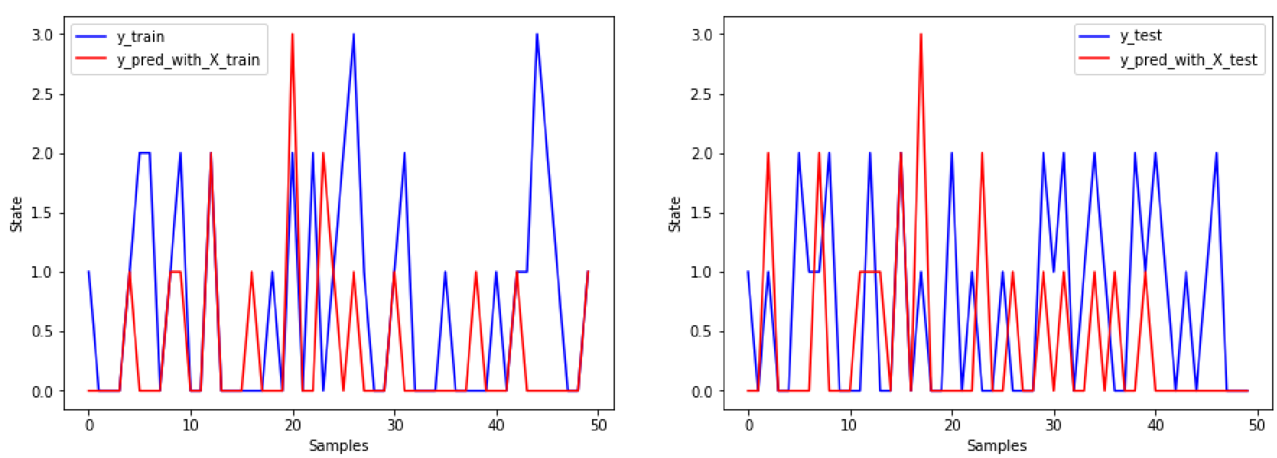
Make Predictions with the model created, using the training/testing dataset

In [26]:
```
y_pred_with_X_train = nearest_neighbors.predict(X_train)
y_pred_with_X_test = nearest_neighbors.predict(X_test)
```

Compare Predicted values with the train and test datas

In [27]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
plt.plot(y_train[2000:2050].values, color='blue')
plt.plot(y_pred_with_X_train[2000:2050], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_train','y_pred_with_X_train'])

plt.subplot(1,2,2)
plt.plot(y_test[2000:2050].values, color='blue')
plt.plot(y_pred_with_X_test[2000:2050], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_test','y_pred_with_X_test'])
plt.show()
```



In [28]:
```
percentage_good_predictions_with_X_train = y_pred_with_X_train == y_train.values
percentage_good_predictions_with_X_train = sum(percentage_good_predictions_with_X_tr
print('% Good Predictions with known data: ' + str(percentage_good_predictions_with_

percentage_good_predictions_with_X_test = y_pred_with_X_test == y_test.values
percentage_good_predictions_with_X_test = sum(percentage_good_predictions_with_X_tes
print('% Good Predictions with unknown data: ' + str(percentage_good_predictions_wit
```

```
% Good Predictions with known data: 0.6213395187010727
% Good Predictions with unknown data: 0.47781965787184694
```

If you wish, you can modify "k" or the range of plot and run the lines here to verify its effect

Conclusion: Nearest Neighbors Model doesn't have a high hit rate with any k-value, but with `k=1` it get's a percentage of prediction of `100% with knowns data`, but very poor percentage with unknown data. On the other hand, the `better percentage` of prediction for `unknow data`, is about `50%` with some values of k.

2.b) Support Vector Machines

In [29]:
```
from sklearn.svm import SVR, SVC
from sklearn.metrics import accuracy_score
```

Another form to get the train/test dataset from sickit learn's library

In [30]:
```
from sklearn.model_selection import train_test_split
X_train , X_test , y_train, y_test = train_test_split(X, y, random_state=0)
```

Create and train the instance of the class **SVR** or SVC from SVMs

In [31]:
```
clf = SVR()
clf.fit(X_train.values.tolist(), y_train.values.tolist())
```

Out[31]:
```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma='scale',
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

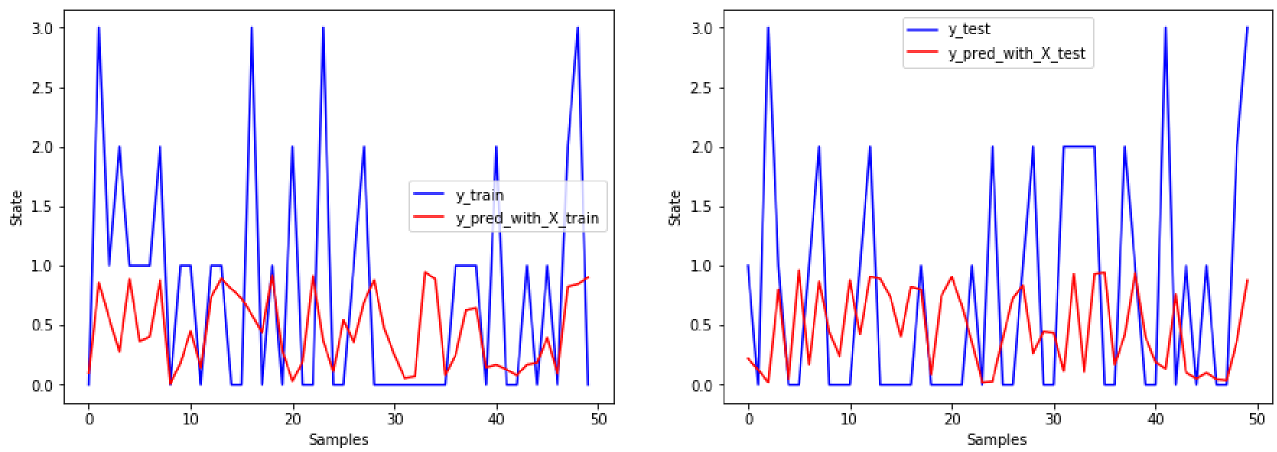
Generate predictions using the training/testing dataset with the model created

In [32]:
```
y_pred_with_X_train = clf.predict(X_train.values.tolist())
y_pred_with_X_test = clf.predict(X_test.values.tolist())
```

Comparison between predicted and original values with each dataset

In [33]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
plt.plot(y_train[0:50].values, color='blue')
plt.plot(y_pred_with_X_train[0:50], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_train','y_pred_with_X_train'])

plt.subplot(1,2,2)
plt.plot(y_test[0:50].values, color='blue')
plt.plot(y_pred_with_X_test[0:50], color='red')
plt.xlabel('Samples')
plt.ylabel('State')
plt.legend(['y_test','y_pred_with_X_test'])
plt.show()
```



Conclusion: As in the linear regression model, the predicted responses do not match the real ones, because this is not a good model for the system

2.c) Gradient Descent with TensorFlow

In [34]:
```python
import tensorflow as tf
```

```
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:516: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:517: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:518: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:519: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:520: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.
py:525: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depre
cated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:541: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:542: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:543: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:544: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:545: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
```

```
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub
\dtypes.py:550: FutureWarning: Passing (type, 1) or '1type' as a synonym of type
is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

In [35]:
```
X = pd.concat([df['ones'], df.loc[:, 'Var':'Spectrum Av']], axis=1)
y = df['state']
```

In [36]:
```
y = tf.constant(y.values.tolist(), dtype = float, shape=[len(y),1])
y
```

Out[36]:
```
<tf.Tensor 'Const:0' shape=(6898, 1) dtype=float32>
```

In [37]:
```
K = len(X.values[0])
K
```

Out[37]:
```
6
```

In [38]:
```
theta = tf.Variable(tf.constant([0.0]*K, shape=[K,1]))
theta
```

Out[38]:
```
<tf.Variable 'Variable:0' shape=(6, 1) dtype=float32_ref>
```

In [39]:
```
optimizer = tf.train.AdamOptimizer(0.01)
```

In [40]:
```
def MSE(X, y, theta):
    return tf.reduce_mean((tf.matmul(X, theta) - y)**2)
```

note: The function tf.matmul(a,b) need that a & b have the **same data type**

In [41]:
```
objective = MSE(X.values.tolist(), y, theta)
```

In [42]:
```
train = optimizer.minimize(objective)
```

```
WARNING:tensorflow:From C:\Users\SANTIAGO\anaconda3\lib\site-packages\tensorflow\py
thon\ops\math_grad.py:1205: add_dispatch_support.<locals>.wrapper (from tensorflow.
python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

In [43]:
```
init = tf.global_variables_initializer()
```

In [44]:
```
sess = tf.Session()
sess.run(init)
```

In [45]:
```
for iteration in range(1000):
    cvalues = sess.run([train, objective])
    print("objective = " + str(cvalues[1]))
```

```
objective = 0.87433934
objective = 0.87406844
objective = 0.87382185
objective = 0.87359655
objective = 0.8733894
objective = 0.8731989
objective = 0.8730219
objective = 0.8728568
objective = 0.87270164
objective = 0.8725556
objective = 0.8724171
objective = 0.87228423
objective = 0.87215644
objective = 0.87203324
objective = 0.8719135
objective = 0.87179667
objective = 0.8716823
objective = 0.87157
objective = 0.8714594
objective = 0.8713502
```

In [46]:
```
with sess.as_default():
    print(MSE(X.values.tolist(), y, theta).eval())
    print(theta.eval())
```

```
0.86489314
[[ 6.1612320e-01]
 [ 3.0784912e+00]
 [ 2.7023834e-01]
 [-7.7528815e-04]
 [ 3.4751575e-02]
 [ 3.0014188e+00]]
```

Conclusion: Gradient Descent with tensor flow is the best option to make predictions of the state of a patient based on the statistic indices of their respiratorie's cycles. And MSE close to 0 indicates good model performance.

In Addition, i hope that the validation of each model, will be teach in next courses!

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In [ ]: