Code_projet

April 12, 2019

0.1 Jupyter Notebook pour le sujet Kaggle "Bike Sharing Demand"

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0.2.1 Importation des bibliothèques

```
In [1]: import pandas as pd
        import sklearn as skl
        import sklearn.model_selection as skl_model_selection
        import sklearn.linear_model as skl_linear_mdl
        import sklearn.ensemble as skl_ensemble_mdl
        import sklearn.discriminant_analysis as skl_discriminant_analysis
        import sklearn.metrics as skl_metrics
        from sklearn.model_selection import cross_val_score
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.svm import SVR
        import xgboost as xgb
        import seaborn as sns
        from statistics import mean
        import numpy as np
        from sklearn import preprocessing
        import matplotlib.pyplot as plt
        from scipy import stats
        from scipy.special import boxcox, inv_boxcox
        from pandas import Series
        from matplotlib import pyplot
```

0.3 Importation et description du dataset

```
In [4]: ##Importation des fichiers
        df_bike_train = pd.read_csv(r"train.csv")
        df_bike_test = pd.read_csv(r"test.csv")
        df_bike_test["registered"]=0
        df_bike_test["casual"]=0
        df_bike_test["count"]=0
```

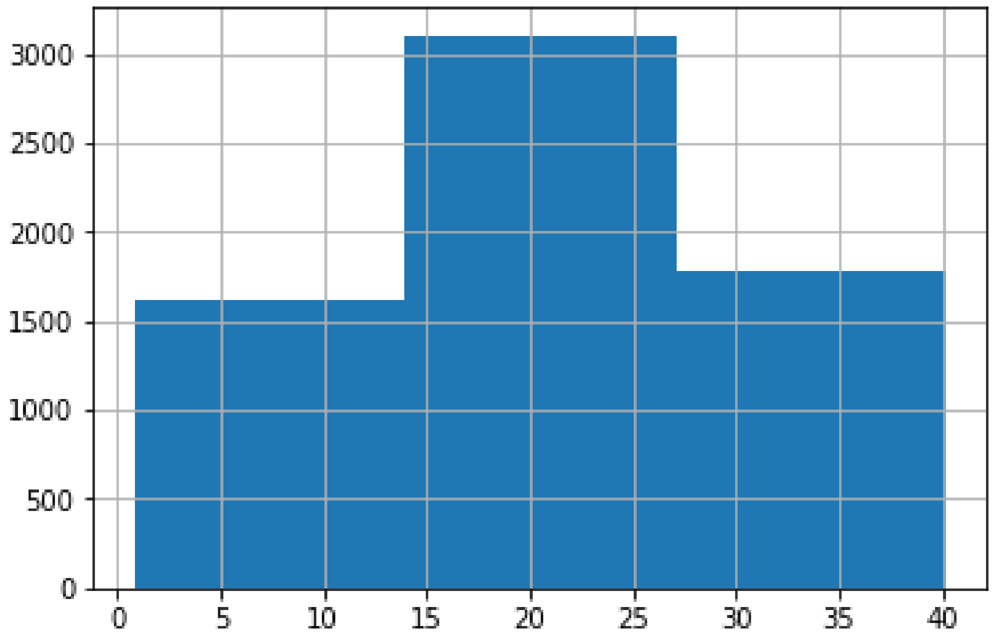
```
In [5]: df_bike_train.head()
```

Out[5]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
3        75        0.0       3          10     13
4        75        0.0       0           1      1
```

0.4 Analyse préalable des données

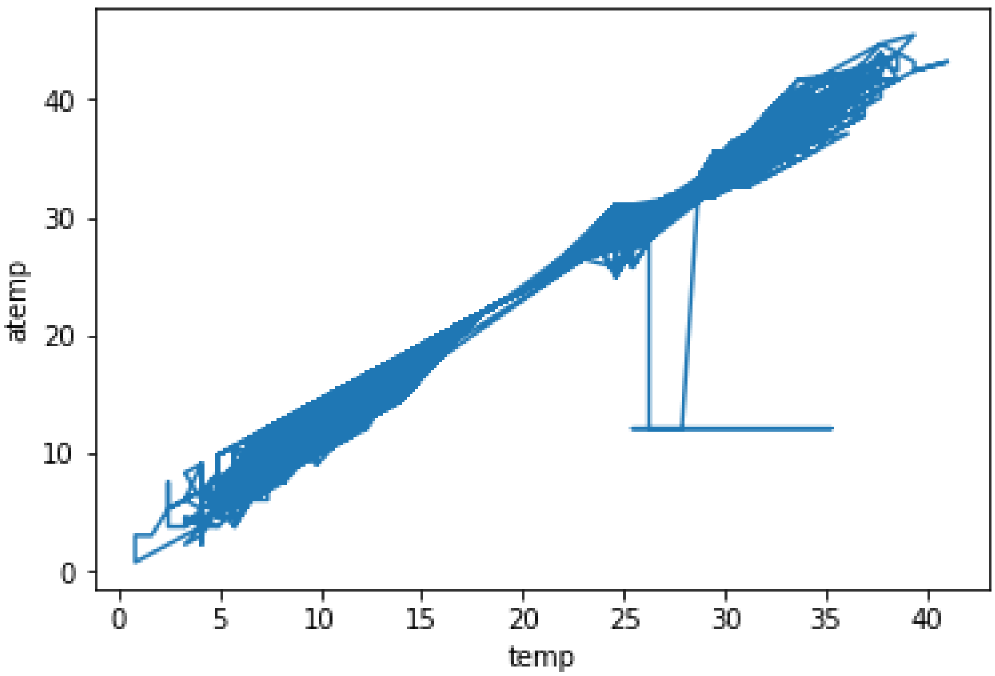
In [6]:
```
df_bike_test["temp"].hist(bins=3)
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x205acd5acc0>



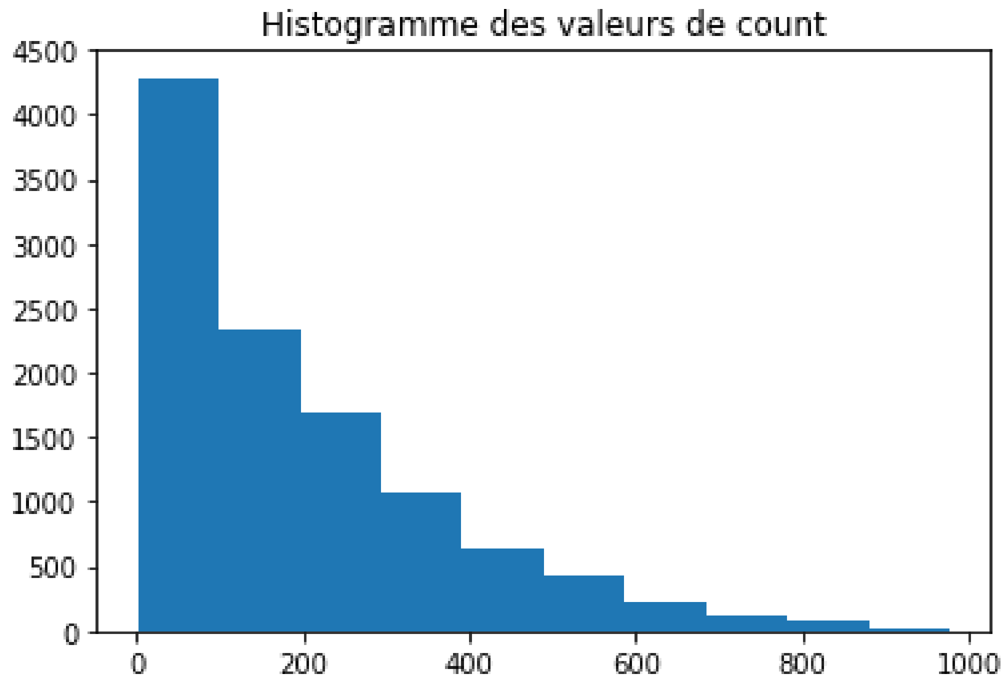
In [8]:
```
plt.plot(df_bike_train["temp"],df_bike_train["atemp"])
plt.xlabel("temp")
plt.ylabel("atemp")
print("Corrélations entre temp et atemp:" + str(round(df_bike_train["temp"].corr(df_bi
```

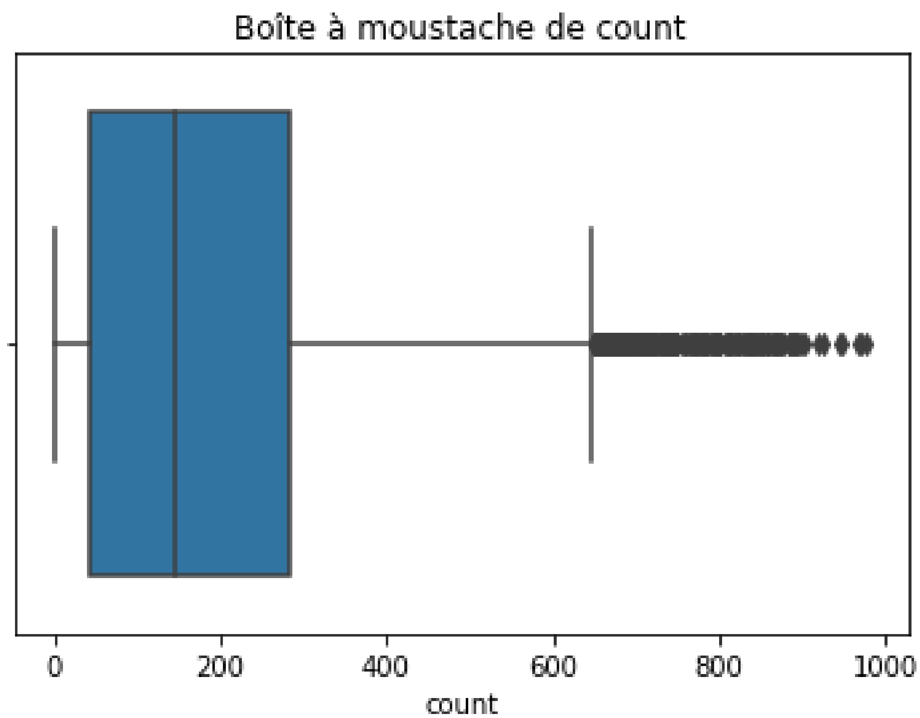
```
Corrélations entre temp et atemp:0.98
```




```
In [9]: df_combine = [df_bike_train, df_bike_test]
```

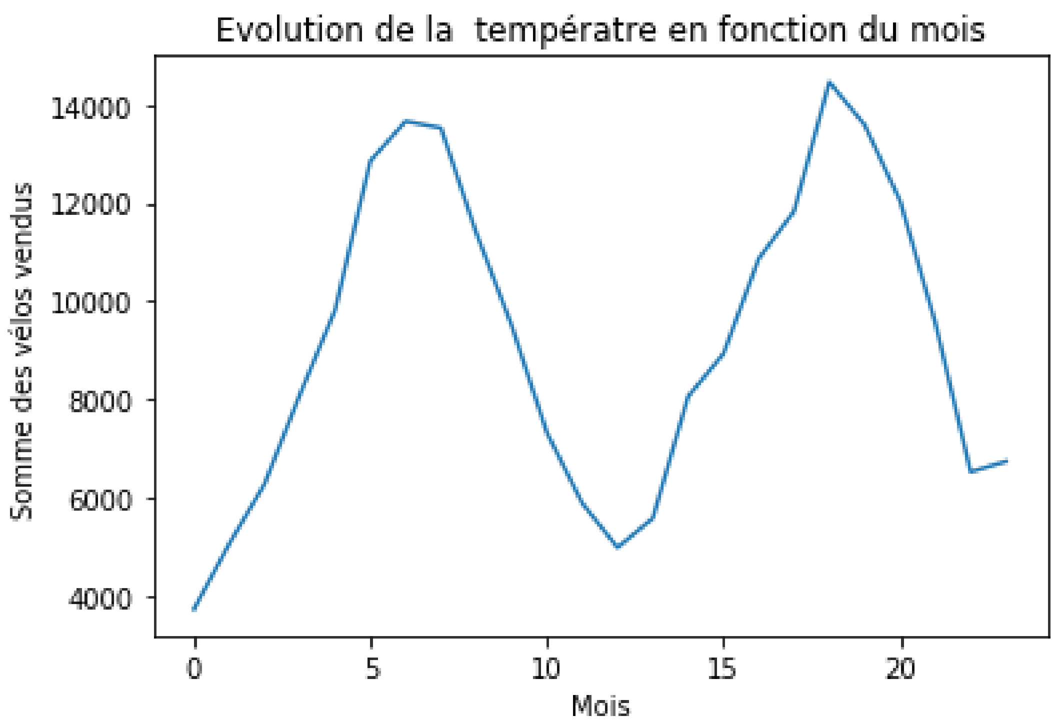
```
In [10]: ##Analyse de la varaible de sortie
         plt.hist(df_bike_train["count"])
         plt.title("Histogramme des valeurs de count")
         plt.show()


         sns.boxplot(df_combine[0]['count'])
         plt.title("Boîte à moustache de count")
         plt.show()
```


Histogramme des valeurs de count
4500
4000
3500
3000
2500
2000
1500
1000
500
0
0
200
400
600
800
1000


Boîte à moustache de count
0
200
400
600
800
1000
count

```
In [11]: df_bike_train["nbr_day"]=1
         df_bike_train['Year'] = pd.DatetimeIndex(df_bike_train["datetime"]).year
         df_bike_train['Month'] = pd.DatetimeIndex(df_bike_train["datetime"]).month
         x=df_bike_train.groupby(['Year','Month']).sum()
         lst=[]
         for i in x["temp"]:
             lst.append(i)
         plt.plot(lst)
         plt.title("Evolution de la  températre en fonction du mois")
         plt.xlabel("Mois")
         plt.ylabel("Somme des vélos vendus")
```

```
Out[11]: Text(0,0.5,'Somme des vélos vendus')
```

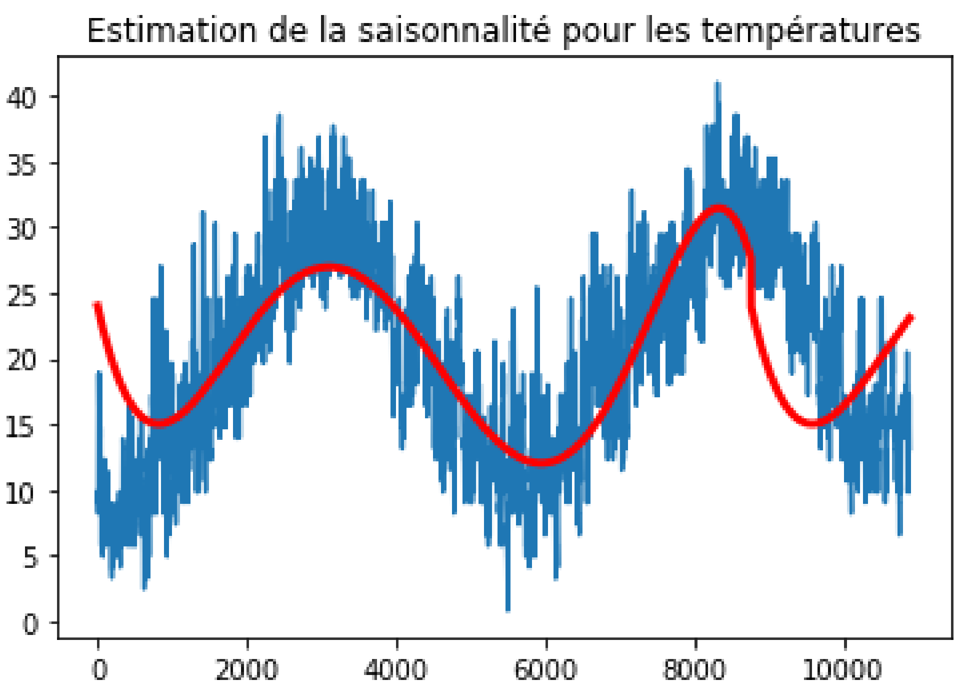


0.4.1 Suppression de la saisonnalité

```
In [13]: series = Series(df_bike_train["temp"])
         # fit polynomial: x^2*b1 + x*b2 + ... + bn
         X = [i%(365*24) for i in range(0, len(series))]
         y = series.values
         degree = 6
         coef = np.polyfit(X, y, degree)
         print('Coefficients: %s' % coef)
         # create curve
```

```
curve = list()
for i in range(len(X)):
    value = coef[-1]
    for d in range(degree):
        value += X[i]**(degree-d) * coef[d]
    curve.append(value)

# plot curve over original data
pyplot.plot(series.values)
pyplot.plot(curve, color='red', linewidth=3)
pyplot.title("Estimation de la saisonnalité pour les températures")
pyplot.show()
```

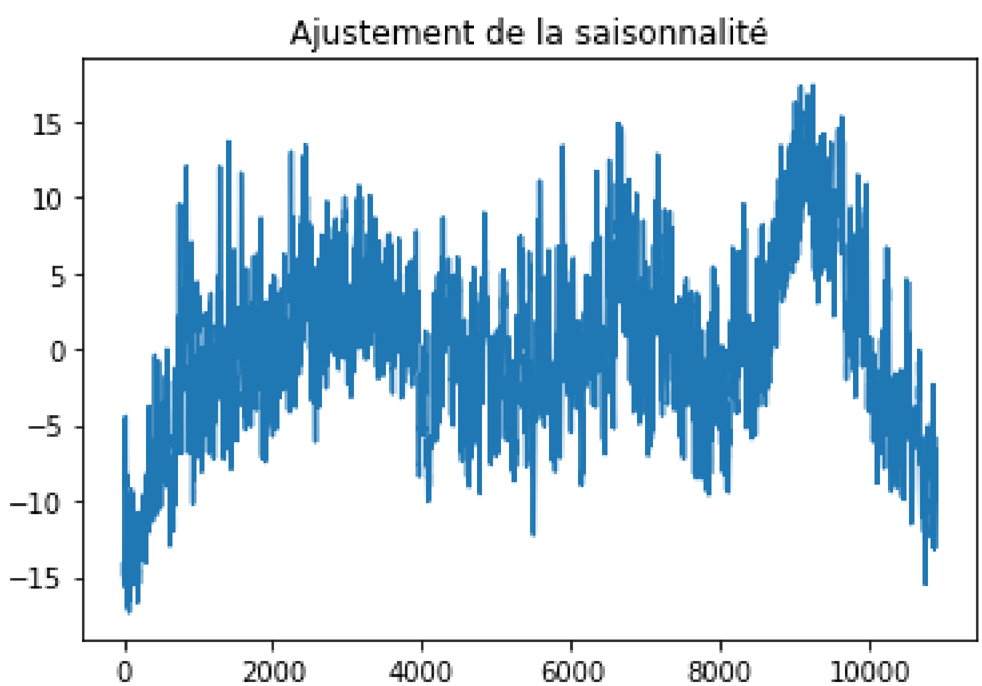
```
Coefficients: [-3.06378331e-21  2.67114400e-17  4.17815112e-13 -5.82847541e-09
  2.20189717e-05 -2.53237491e-02  2.39987762e+01]
```




```
In [14]: series = Series(df_bike_train["temp"])
         # fit polynomial: x^2*b1 + x*b2 + ... + bn
         X = [i%(365*24) for i in range(0, len(series))]
         y = series.values
         degree = 6
         coef = np.polyfit(X, y, degree)
         print('Coefficients: %s' % coef)
         # create curve
```

```
curve = list()
for i in range(len(X)):
        value = coef[-1]
        for d in range(degree):
                value += X[i]**(degree-d) * coef[d]
        curve.append(value)
# create seasonally adjusted
values = series.values
diff = list()
for i in range(len(values)):
        value = values[i] - curve[i]
        diff.append(value)
pyplot.plot(diff)
pyplot.title("Ajustement de la saisonnalité")
pyplot.show()
```

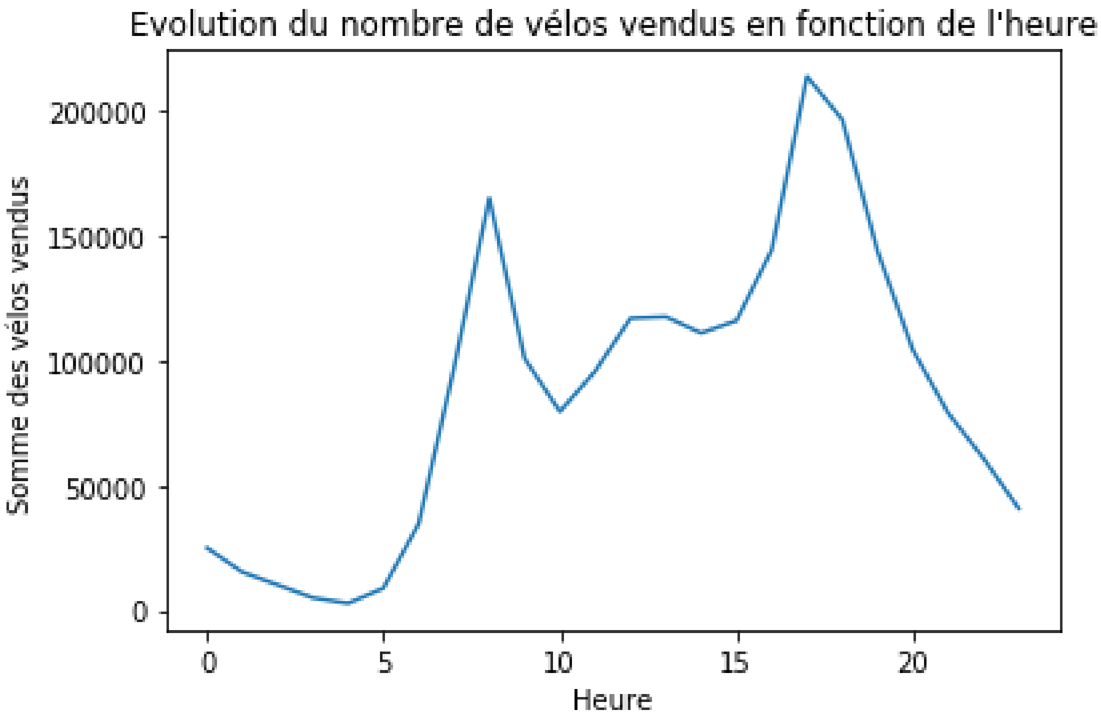
```
Coefficients: [-3.06378331e-21  2.67114400e-17  4.17815112e-13 -5.82847541e-09
  2.20189717e-05 -2.53237491e-02  2.39987762e+01]
```




```
In [15]: df_bike_train["nbr_day"]=1
         df_bike_train['Hour'] = pd.DatetimeIndex(df_bike_train["datetime"]).hour
         x=df_bike_train.groupby(['Hour']).sum()
         lst=[]
         for i in x["count"]:
```

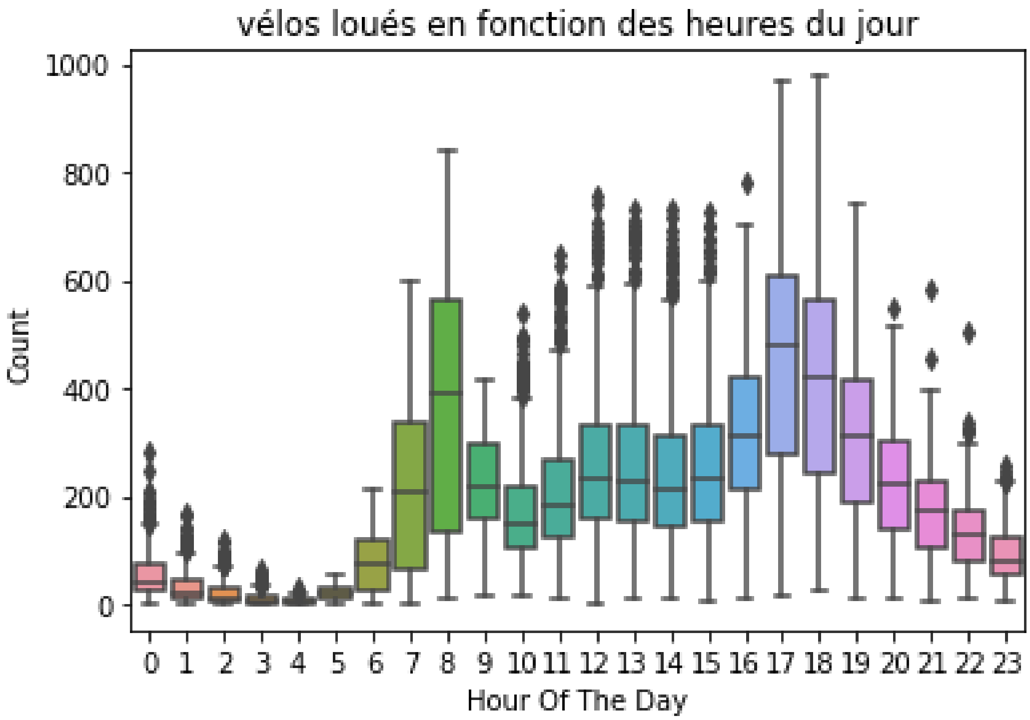
```
        lst.append(i)

    plt.plot(lst)
    plt.title("Evolution du nombre de vélos vendus en fonction de l'heure")
    plt.xlabel("Heure")
    plt.ylabel("Somme des vélos vendus")
```

Out[15]: Text(0,0.5,'Somme des vélos vendus')



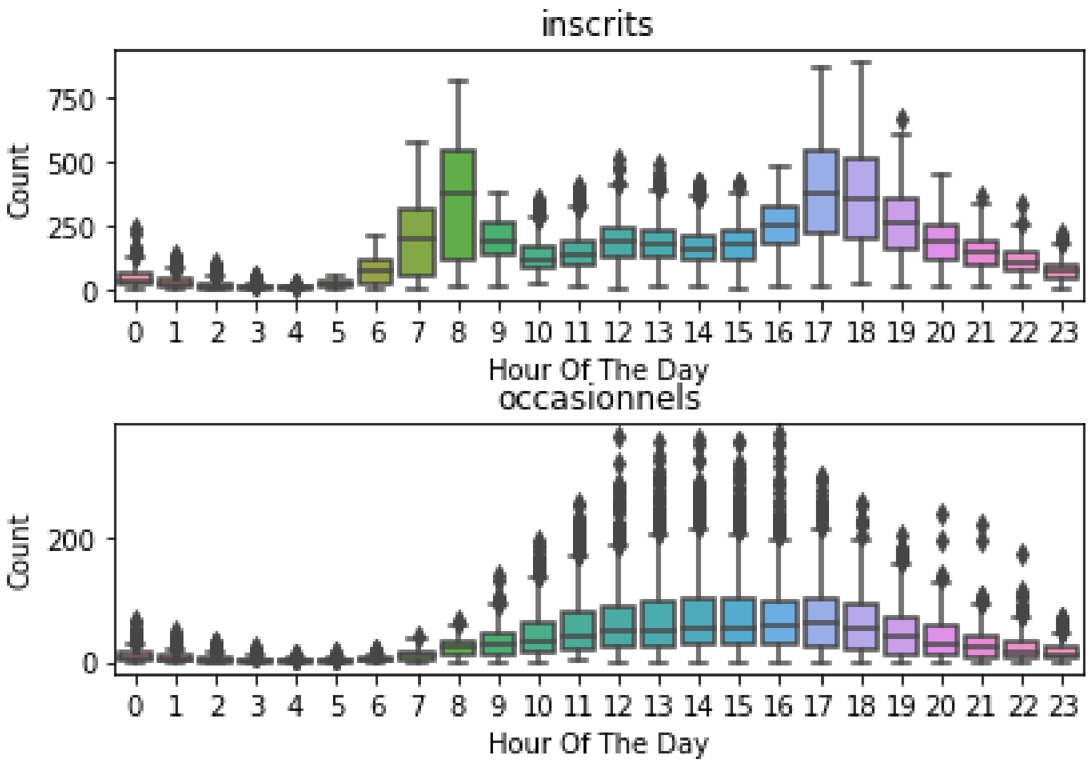
In [16]:
```
#Boite à moustache des vélos loués en fonction des heures du jours:
import seaborn as sn
sn.boxplot(x=df_bike_train['Hour'],y="count",data=df_bike_train,orient="v").set(xlabel
#sns.swarmplot(x=df_bike_train['Hour'], y="count", data=df_bike_train, color=".25")
```

Out[16]: [Text(0,0.5,'Count'),
 Text(0.5,0,'Hour Of The Day'),
 Text(0.5,1,'vélos loués en fonction des heures du jour')]




```
In [17]: # boite à moustache en distinguant les individus inscrits des individus non inscrits
         #fig = plt.subplots(nrows=1,ncols=2)
         #fig.set_size_inches(12, 10)
         plt.subplot(2,1,1)
         plt.tight_layout()
         sn.boxplot(x=df_bike_train['Hour'],y="registered",data=df_bike_train,orient="v").set(x
         plt.subplot(2,1,2)
         plt.tight_layout()
         sn.boxplot(x=df_bike_train['Hour'],y="casual",data=df_bike_train,orient="v").set(xlabe
```

```
Out[17]: [Text(13.175,0.5,'Count'),
          Text(0.5,-10.2,'Hour Of The Day'),
          Text(0.5,1,'occasionnels')]
```



0.5 Features Engineering

```
In [18]: #features engineering
         from sklearn import preprocessing
         df_bike_train = pd.read_csv(r"train.csv")
         df_bike_test = pd.read_csv(r"test.csv")
         df_bike_test["registered"]=0
         df_bike_test["casual"]=0
         df_bike_test["count"]=0
         df_combine = [df_bike_train, df_bike_test]

         i=0
         for df_bike_sharing in df_combine:
             #df_bike_sharing.drop(columns="atemp")
             if i==0:
                 df_bike_sharing['count']=df_bike_sharing['count'].apply(lambda x:np.log(x))
                 df_bike_sharing['registered']=df_bike_sharing['registered'].apply(lambda x:np
                 df_bike_sharing['casual']=df_bike_sharing['casual'].apply(lambda x:np.log(x+1)
                 #train_df['count']=boxcox(train_df['count'])[0]
             #df_bike_sharing["Year"]=0
             #print(df_bike_sharing.head())
             df_bike_sharing['Year'] = pd.DatetimeIndex(df_bike_sharing["datetime"]).year
```

```
df_bike_sharing['Month'] = pd.DatetimeIndex(df_bike_sharing["datetime"]).month
df_bike_sharing['Wday'] = pd.DatetimeIndex(df_bike_sharing["datetime"]).weekday
df_bike_sharing['Week'] = pd.DatetimeIndex(df_bike_sharing["datetime"]).week
df_bike_sharing['Day'] = pd.DatetimeIndex(df_bike_sharing["datetime"]).day
df_bike_sharing["Hour"]= pd.DatetimeIndex(df_bike_sharing["datetime"]).hour

"""
df_bike_sharing['15h'] = np.where((df_bike_sharing['Hour']==15), 1, 0)*(np.where(
df_bike_sharing['16h']= np.where((df_bike_sharing['Hour']==16), 1, 0)*(np.where(d
df_bike_sharing['14h']= np.where((df_bike_sharing['Hour']==14), 1, 0)*(np.where(d
df_bike_sharing['Rush_Hour']=df_bike_sharing['15h']+df_bike_sharing['16h']+df_bik
df_bike_sharing.drop(['16h','15h','14h'], axis=1)
#print(df_bike_sharing['Rush_Hour'].head(50))
"""
df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['weather'])
df_bike_sharing = df_bike_sharing.drop(labels='weather_4', axis=1)


df_bike_sharing['temp_weath_1'] = df_bike_sharing['temp'] * df_bike_sharing['weat
df_bike_sharing['temp_weath_2'] = df_bike_sharing['temp'] * df_bike_sharing['weat
df_bike_sharing['temp_weath_3'] = df_bike_sharing['temp'] * df_bike_sharing['weat


df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['holiday'])
#df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['workingday'])
df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['season'])


###Code pour normaliser des colonnes mais on obtient un moins bon score Kaggle po
#column_names_to_normalize = ['humidity', 'atemp', 'temp']
""""
column_names_to_normalize = ['temp','humidity']
x = df_bike_sharing[column_names_to_normalize].values
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
df_temp = pd.DataFrame(x_scaled, columns=column_names_to_normalize, index = df_bi
df_bike_sharing[column_names_to_normalize] = df_temp
"""
###Création de dummies pour les colonnes de float
"""
cpt_row=0
for row_bike_sharing in df_bike_sharing["humidity"]:
    if row_bike_sharing==0 :
            df_bike_sharing.loc[[cpt_row], ['humidity']]=0
    if row_bike_sharing<45 and row_bike_sharing!=0 :
            df_bike_sharing.loc[[cpt_row], ['humidity']]=1
    if row_bike_sharing<60 and row_bike_sharing>=45 :
            df_bike_sharing.loc[[cpt_row], ['humidity']]=2
```

```
    if row_bike_sharing>=60 :
            df_bike_sharing.loc[[cpt_row], ['humidity']]=3
    cpt_row=cpt_row+1

cpt_row=0
for row_bike_sharing in df_bike_sharing["atemp"]:
    if row_bike_sharing<19 :
            df_bike_sharing.loc[[cpt_row], ['atemp']]=0
    if row_bike_sharing<32 and row_bike_sharing>=19 :
            df_bike_sharing.loc[[cpt_row], ['atemp']]=1
    if row_bike_sharing>=32 :
            df_bike_sharing.loc[[cpt_row], ['atemp']]=2
    cpt_row=cpt_row+1

cpt_row=0
for row_bike_sharing in df_bike_sharing["temp"]:
    if row_bike_sharing<15 :
            df_bike_sharing.loc[[cpt_row], ['temp']]=0
    if row_bike_sharing<26 and row_bike_sharing>=15 :
            df_bike_sharing.loc[[cpt_row], ['temp']]=1
    if row_bike_sharing>=26 :
            df_bike_sharing.loc[[cpt_row], ['temp']]=2
    cpt_row=cpt_row+1

df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['humidity'])
df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['atemp'])
df_bike_sharing = pd.get_dummies(df_bike_sharing, columns=['temp'])

"""
##########################################

#partie engineering à utiliser si on fait le calcul en estimant les registered et
df_bike_sharing['daypart_registered']=Series(np.ones(len(df_bike_sharing)), index=
df_bike_sharing['daypart_casual']=Series(np.ones(len(df_bike_sharing)), index=df_

#Pour les individus enregistrés
df_bike_sharing.loc[(df_bike_sharing['Hour']>=22)  | (df_bike_sharing['Hour']==0)
df_bike_sharing.loc[(df_bike_sharing['Hour']>= 1)  & (df_bike_sharing['Hour']<=5)
df_bike_sharing.loc[(df_bike_sharing['Hour']==6)
                    | ((df_bike_sharing['Hour']>=10) & (df_bike_sharing['Hour']<=
                    | (df_bike_sharing['Hour']==20)
                    | (df_bike_sharing['Hour']==21)
                   ,'daypart_registered']=2
df_bike_sharing.loc[(df_bike_sharing['Hour']==7),'daypart_registered']=3
df_bike_sharing.loc[(df_bike_sharing['Hour']==8),'daypart_registered']=4
df_bike_sharing.loc[(df_bike_sharing['Hour']==17)  | (df_bike_sharing['Hour']==18
df_bike_sharing.loc[(df_bike_sharing['Hour']==9)
                    |(df_bike_sharing['Hour']==16)
```

```
                         | (df_bike_sharing['Hour']==19)
                         ,'daypart_registered']=6

# Pour les occasionnels
df_bike_sharing.loc[(df_bike_sharing['Hour']>=23)  | (df_bike_sharing['Hour']<=7)
df_bike_sharing.loc[(df_bike_sharing['Hour']== 8)
                         | (df_bike_sharing['Hour']==9)
                         | (df_bike_sharing['Hour']==21)
                         | (df_bike_sharing['Hour']==22)
                    ,'daypart_casual']=1
df_bike_sharing.loc[(df_bike_sharing['Hour']>=10) & (df_bike_sharing['Hour']<=20)
#pd.Series(df_bike_sharing.daypart_registered, dtype='int32')
#pd.Series(df_bike_sharing.daypart_casual, dtype='int32')
##########################################

series = Series(df_bike_sharing["temp"])
# fit polynomial: x^2*b1 + x*b2 + ... + bn
X = [i%(365*24) for i in range(0, len(series))]
y = series.values
degree = 8
coef = np.polyfit(X, y, degree)
# create curve
curve = list()
for j in range(len(X)):
    value = coef[-1]
    for d in range(degree):
        value += X[j]**(degree-d) * coef[d]
    curve.append(value)
# create seasonally adjusted
values = series.values
diff = list()
for j in range(len(values)):
    value = values[j] - curve[j]
    diff.append(value)
df_bike_sharing["temp"]=diff

df_combine[i]=df_bike_sharing
i=1
```

1 Neural Networks

In [19]:
```
X=df_combine[0]
Y =df_combine[0]["count"]
#on  définie les features qui vont être intéressants pour la prédiction
features=X.columns.values
features=list(features)
```

```
features.remove("datetime")
features.remove("daypart_casual")
features.remove("daypart_registered")
features.remove("casual")
features.remove("registered")
features.remove("count")

X_train = df_combine[0]
Y_train = df_combine[0]["count"]
X_test = df_combine[1]
X=X_train[features]
Y=X_train['count']
X_testNN=X_test[features]
```

In [20]:
```
#split des données
from sklearn.model_selection import train_test_split

X_trainNN, X_validNN, Y_trainNN, Y_validNN = train_test_split(X, Y, test_size=0.10, ra
```

In [21]:
```
print(features)
```

```
['workingday', 'temp', 'atemp', 'humidity', 'windspeed', 'Year', 'Month', 'Wday', 'Week', 'Day
```

In [22]:
```
#normalisation:

from sklearn.preprocessing import StandardScaler

# Methode choisie pour normaliser: MinMax
scaler = preprocessing.MinMaxScaler()

# Normalise le train set
X_trainNN = scaler.fit_transform(X_trainNN)

# Normalise le validation set
X_validNN = scaler.fit_transform(X_validNN)

# Normalise le test set
X_testNN = scaler.fit_transform(X_testNN)
```

```
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:323: DataConversio
  return self.partial_fit(X, y)
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:323: DataConversio
  return self.partial_fit(X, y)
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:323: DataConversio
  return self.partial_fit(X, y)
```

In [23]:
```
# Model parameters
BATCH_SIZE = 16
```

```
EPOCHS = 100
LEARNING_RATE = 0.001
```

1.0.1 Modèle:

```
In [24]: from keras.models import Sequential

         from keras.layers import Dense,Dropout,Activation

         from keras import regularizers
         from keras.layers.normalization import BatchNormalization
         # Initialisation du modèle

         ##Define neural network
         model = Sequential()
         model.add(Dense(200, activation='relu',input_dim=X_trainNN.shape[1])) #input layer
         model.add(Dropout(0.1))
         model.add(Dense(200, activation='relu')) #hidden layer
         model.add(Dropout(0.1))
         model.add(Dense(1))#outputlayer
         model.compile(loss='mse', optimizer='rmsprop', metrics=['mae'])
```

```
C:\Users\Alexandre\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning: Conversion o
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

1.0.2 Exécution

```
In [25]: model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 200)               4800
_________________________________________________________________
dropout_1 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_2 (Dense)              (None, 200)               40200
_________________________________________________________________
dropout_2 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 201
=================================================================
Total params: 45,201
Trainable params: 45,201
Non-trainable params: 0
_________________________________________________________________
```

In [26]:
```
history = model.fit(x=X_trainNN, y=Y_trainNN, batch_size=BATCH_SIZE, epochs=EPOCHS,
                    verbose=1, validation_data=(X_validNN, Y_validNN),
                    shuffle=True)
```

```
Train on 9797 samples, validate on 1089 samples
Epoch 1/100
9797/9797 [==============================] - 5s 491us/step - loss: 1.4259 - mean_absolute_erro
Epoch 2/100
9797/9797 [==============================] - 1s 143us/step - loss: 1.0754 - mean_absolute_erro
Epoch 3/100
9797/9797 [==============================] - 1s 147us/step - loss: 0.9749 - mean_absolute_erro
Epoch 4/100
9797/9797 [==============================] - 2s 169us/step - loss: 0.8864 - mean_absolute_erro
Epoch 5/100
9797/9797 [==============================] - 2s 160us/step - loss: 0.7734 - mean_absolute_erro
Epoch 6/100
9797/9797 [==============================] - 2s 166us/step - loss: 0.6390 - mean_absolute_erro
Epoch 7/100
9797/9797 [==============================] - 1s 148us/step - loss: 0.5033 - mean_absolute_erro
Epoch 8/100
9797/9797 [==============================] - 1s 139us/step - loss: 0.4096 - mean_absolute_erro
Epoch 9/100
9797/9797 [==============================] - 1s 148us/step - loss: 0.3685 - mean_absolute_erro
Epoch 10/100
9797/9797 [==============================] - 2s 158us/step - loss: 0.3516 - mean_absolute_erro
Epoch 11/100
9797/9797 [==============================] - 2s 156us/step - loss: 0.3245 - mean_absolute_erro
Epoch 12/100
9797/9797 [==============================] - 1s 149us/step - loss: 0.3079 - mean_absolute_erro
Epoch 13/100
9797/9797 [==============================] - 1s 140us/step - loss: 0.3018 - mean_absolute_erro
Epoch 14/100
9797/9797 [==============================] - 2s 159us/step - loss: 0.2882 - mean_absolute_erro
Epoch 15/100
9797/9797 [==============================] - 2s 167us/step - loss: 0.2827 - mean_absolute_erro
Epoch 16/100
9797/9797 [==============================] - 2s 160us/step - loss: 0.2730 - mean_absolute_erro
Epoch 17/100
9797/9797 [==============================] - 2s 187us/step - loss: 0.2690 - mean_absolute_erro
Epoch 18/100
9797/9797 [==============================] - 1s 145us/step - loss: 0.2620 - mean_absolute_erro
Epoch 19/100
9797/9797 [==============================] - 1s 153us/step - loss: 0.2511 - mean_absolute_erro
Epoch 20/100
9797/9797 [==============================] - 2s 167us/step - loss: 0.2426 - mean_absolute_erro
Epoch 21/100
9797/9797 [==============================] - 2s 184us/step - loss: 0.2377 - mean_absolute_erro
Epoch 22/100
```

```
9797/9797 [==============================] - 2s 197us/step - loss: 0.2345 - mean_absolute_erro
Epoch 23/100
9797/9797 [==============================] - 2s 186us/step - loss: 0.2323 - mean_absolute_erro
Epoch 24/100
9797/9797 [==============================] - 2s 200us/step - loss: 0.2248 - mean_absolute_erro
Epoch 25/100
9797/9797 [==============================] - 2s 212us/step - loss: 0.2269 - mean_absolute_erro
Epoch 26/100
9797/9797 [==============================] - 2s 182us/step - loss: 0.2210 - mean_absolute_erro
Epoch 27/100
9797/9797 [==============================] - 2s 191us/step - loss: 0.2201 - mean_absolute_erro
Epoch 28/100
9797/9797 [==============================] - 2s 215us/step - loss: 0.2079 - mean_absolute_erro
Epoch 29/100
9797/9797 [==============================] - 2s 196us/step - loss: 0.2089 - mean_absolute_erro
Epoch 30/100
9797/9797 [==============================] - 2s 218us/step - loss: 0.2057 - mean_absolute_erro
Epoch 31/100
9797/9797 [==============================] - 2s 199us/step - loss: 0.2058 - mean_absolute_erro
Epoch 32/100
9797/9797 [==============================] - 2s 185us/step - loss: 0.2027 - mean_absolute_erro
Epoch 33/100
9797/9797 [==============================] - 2s 176us/step - loss: 0.2020 - mean_absolute_erro
Epoch 34/100
9797/9797 [==============================] - 2s 167us/step - loss: 0.1993 - mean_absolute_erro
Epoch 35/100
9797/9797 [==============================] - 2s 164us/step - loss: 0.1970 - mean_absolute_erro
Epoch 36/100
9797/9797 [==============================] - 1s 145us/step - loss: 0.1910 - mean_absolute_erro
Epoch 37/100
9797/9797 [==============================] - 1s 145us/step - loss: 0.1937 - mean_absolute_erro
Epoch 38/100
9797/9797 [==============================] - 1s 145us/step - loss: 0.1911 - mean_absolute_erro
Epoch 39/100
9797/9797 [==============================] - 1s 141us/step - loss: 0.1871 - mean_absolute_erro
Epoch 40/100
9797/9797 [==============================] - 1s 143us/step - loss: 0.1839 - mean_absolute_erro
Epoch 41/100
9797/9797 [==============================] - 1s 142us/step - loss: 0.1852 - mean_absolute_erro
Epoch 42/100
9797/9797 [==============================] - 2s 160us/step - loss: 0.1821 - mean_absolute_erro
Epoch 43/100
9797/9797 [==============================] - 2s 180us/step - loss: 0.1810 - mean_absolute_erro
Epoch 44/100
9797/9797 [==============================] - 2s 163us/step - loss: 0.1814 - mean_absolute_erro
Epoch 45/100
9797/9797 [==============================] - 2s 167us/step - loss: 0.1792 - mean_absolute_erro
Epoch 46/100
```

```
9797/9797 [==============================] - 2s 173us/step - loss: 0.1778 - mean_absolute_erro
Epoch 47/100
9797/9797 [==============================] - 1s 149us/step - loss: 0.1768 - mean_absolute_erro
Epoch 48/100
9797/9797 [==============================] - 1s 144us/step - loss: 0.1763 - mean_absolute_erro
Epoch 49/100
9797/9797 [==============================] - 1s 134us/step - loss: 0.1744 - mean_absolute_erro
Epoch 50/100
9797/9797 [==============================] - 1s 134us/step - loss: 0.1748 - mean_absolute_erro
Epoch 51/100
9797/9797 [==============================] - 1s 136us/step - loss: 0.1707 - mean_absolute_erro
Epoch 52/100
9797/9797 [==============================] - 1s 136us/step - loss: 0.1714 - mean_absolute_erro
Epoch 53/100
9797/9797 [==============================] - 2s 162us/step - loss: 0.1723 - mean_absolute_erro
Epoch 54/100
9797/9797 [==============================] - 2s 163us/step - loss: 0.1682 - mean_absolute_erro
Epoch 55/100
9797/9797 [==============================] - 1s 151us/step - loss: 0.1663 - mean_absolute_erro
Epoch 56/100
9797/9797 [==============================] - 1s 150us/step - loss: 0.1693 - mean_absolute_erro
Epoch 57/100
9797/9797 [==============================] - 1s 148us/step - loss: 0.1662 - mean_absolute_erro
Epoch 58/100
9797/9797 [==============================] - 1s 148us/step - loss: 0.1657 - mean_absolute_erro
Epoch 59/100
9797/9797 [==============================] - 1s 139us/step - loss: 0.1644 - mean_absolute_erro
Epoch 60/100
9797/9797 [==============================] - 1s 143us/step - loss: 0.1660 - mean_absolute_erro
Epoch 61/100
9797/9797 [==============================] - 1s 138us/step - loss: 0.1654 - mean_absolute_erro
Epoch 62/100
9797/9797 [==============================] - 1s 138us/step - loss: 0.1614 - mean_absolute_erro
Epoch 63/100
9797/9797 [==============================] - 2s 155us/step - loss: 0.1615 - mean_absolute_erro
Epoch 64/100
9797/9797 [==============================] - 2s 194us/step - loss: 0.1625 - mean_absolute_erro
Epoch 65/100
9797/9797 [==============================] - 2s 187us/step - loss: 0.1583 - mean_absolute_erro
Epoch 66/100
9797/9797 [==============================] - 2s 194us/step - loss: 0.1541 - mean_absolute_erro
Epoch 67/100
9797/9797 [==============================] - 2s 195us/step - loss: 0.1587 - mean_absolute_erro
Epoch 68/100
9797/9797 [==============================] - 2s 162us/step - loss: 0.1560 - mean_absolute_erro
Epoch 69/100
9797/9797 [==============================] - 1s 149us/step - loss: 0.1578 - mean_absolute_erro
Epoch 70/100
```

```
9797/9797 [==============================] - 2s 159us/step - loss: 0.1575 - mean_absolute_erro
Epoch 71/100
9797/9797 [==============================] - 1s 149us/step - loss: 0.1578 - mean_absolute_erro
Epoch 72/100
9797/9797 [==============================] - 1s 143us/step - loss: 0.1567 - mean_absolute_erro
Epoch 73/100
9797/9797 [==============================] - 2s 155us/step - loss: 0.1538 - mean_absolute_erro
Epoch 74/100
9797/9797 [==============================] - 2s 188us/step - loss: 0.1543 - mean_absolute_erro
Epoch 75/100
9797/9797 [==============================] - 2s 177us/step - loss: 0.1507 - mean_absolute_erro
Epoch 76/100
9797/9797 [==============================] - 2s 166us/step - loss: 0.1504 - mean_absolute_erro
Epoch 77/100
9797/9797 [==============================] - 2s 159us/step - loss: 0.1536 - mean_absolute_erro
Epoch 78/100
9797/9797 [==============================] - 2s 162us/step - loss: 0.1472 - mean_absolute_erro
Epoch 79/100
9797/9797 [==============================] - 2s 158us/step - loss: 0.1475 - mean_absolute_erro
Epoch 80/100
9797/9797 [==============================] - 1s 149us/step - loss: 0.1522 - mean_absolute_erro
Epoch 81/100
9797/9797 [==============================] - 2s 159us/step - loss: 0.1497 - mean_absolute_erro
Epoch 82/100
9797/9797 [==============================] - 2s 167us/step - loss: 0.1493 - mean_absolute_erro
Epoch 83/100
9797/9797 [==============================] - 2s 179us/step - loss: 0.1512 - mean_absolute_erro
Epoch 84/100
9797/9797 [==============================] - 2s 193us/step - loss: 0.1497 - mean_absolute_erro
Epoch 85/100
9797/9797 [==============================] - 2s 193us/step - loss: 0.1467 - mean_absolute_erro
Epoch 86/100
9797/9797 [==============================] - 2s 176us/step - loss: 0.1504 - mean_absolute_erro
Epoch 87/100
9797/9797 [==============================] - 2s 183us/step - loss: 0.1471 - mean_absolute_erro
Epoch 88/100
9797/9797 [==============================] - 2s 184us/step - loss: 0.1473 - mean_absolute_erro
Epoch 89/100
9797/9797 [==============================] - 2s 196us/step - loss: 0.1490 - mean_absolute_erro
Epoch 90/100
9797/9797 [==============================] - 2s 196us/step - loss: 0.1483 - mean_absolute_erro
Epoch 91/100
9797/9797 [==============================] - 2s 192us/step - loss: 0.1496 - mean_absolute_erro
Epoch 92/100
9797/9797 [==============================] - 2s 197us/step - loss: 0.1451 - mean_absolute_erro
Epoch 93/100
9797/9797 [==============================] - 2s 197us/step - loss: 0.1469 - mean_absolute_erro
Epoch 94/100
```

```
9797/9797 [==============================] - 2s 184us/step - loss: 0.1488 - mean_absolute_erro
Epoch 95/100
9797/9797 [==============================] - 2s 182us/step - loss: 0.1430 - mean_absolute_erro
Epoch 96/100
9797/9797 [==============================] - 2s 181us/step - loss: 0.1446 - mean_absolute_erro
Epoch 97/100
9797/9797 [==============================] - 1s 144us/step - loss: 0.1406 - mean_absolute_erro
Epoch 98/100
9797/9797 [==============================] - 1s 137us/step - loss: 0.1398 - mean_absolute_erro
Epoch 99/100
9797/9797 [==============================] - 1s 138us/step - loss: 0.1423 - mean_absolute_erro
Epoch 100/100
9797/9797 [==============================] - 1s 137us/step - loss: 0.1434 - mean_absolute_erro
```

```
In [27]: training_loss = history.history['loss']
         test_loss = history.history['val_loss']
```

```
In [28]: training_accuracy = history.history['mean_absolute_error']
         test_accuracy = history.history['val_mean_absolute_error']
```

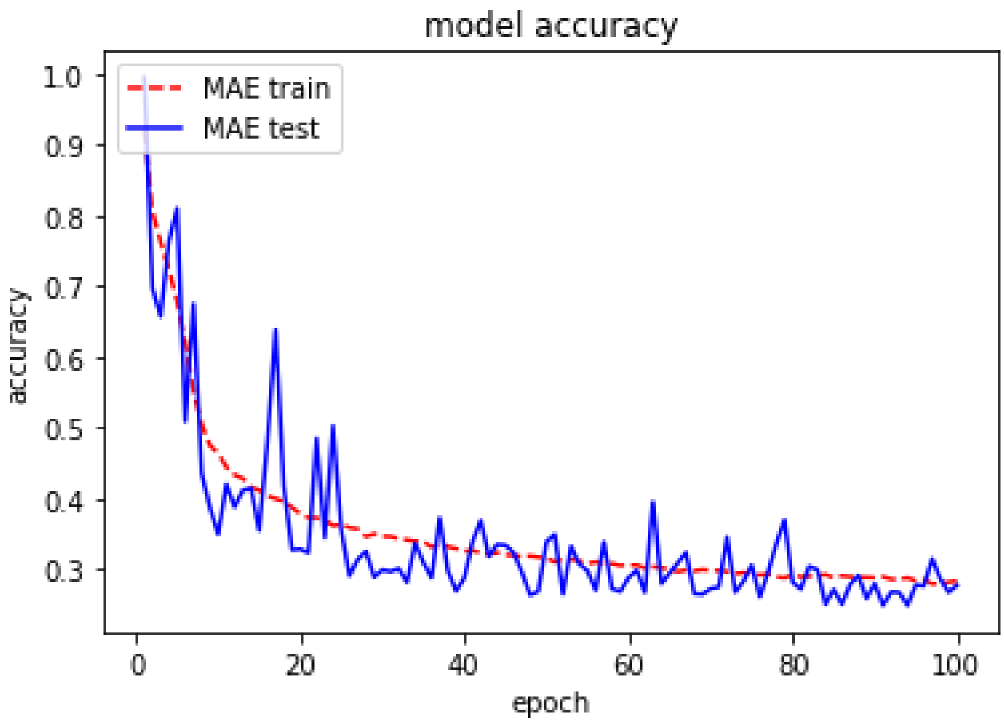
```
In [29]: from sklearn import metrics
         predic= model.predict(X_validNN, batch_size=BATCH_SIZE, verbose=1)
         mseNN = metrics.mean_squared_error(Y_validNN, predic)
         maeNN = metrics.mean_absolute_error(Y_validNN, predic)
         rmsleNN = np.sqrt(metrics.mean_squared_log_error(Y_validNN, predic))
         #mape = metrics.mean_absolute_percentage_error(Y_validNN, predic)
         print('mse=%f, mae=%f, rmsle=%f' % (mseNN,maeNN,rmsleNN))
```

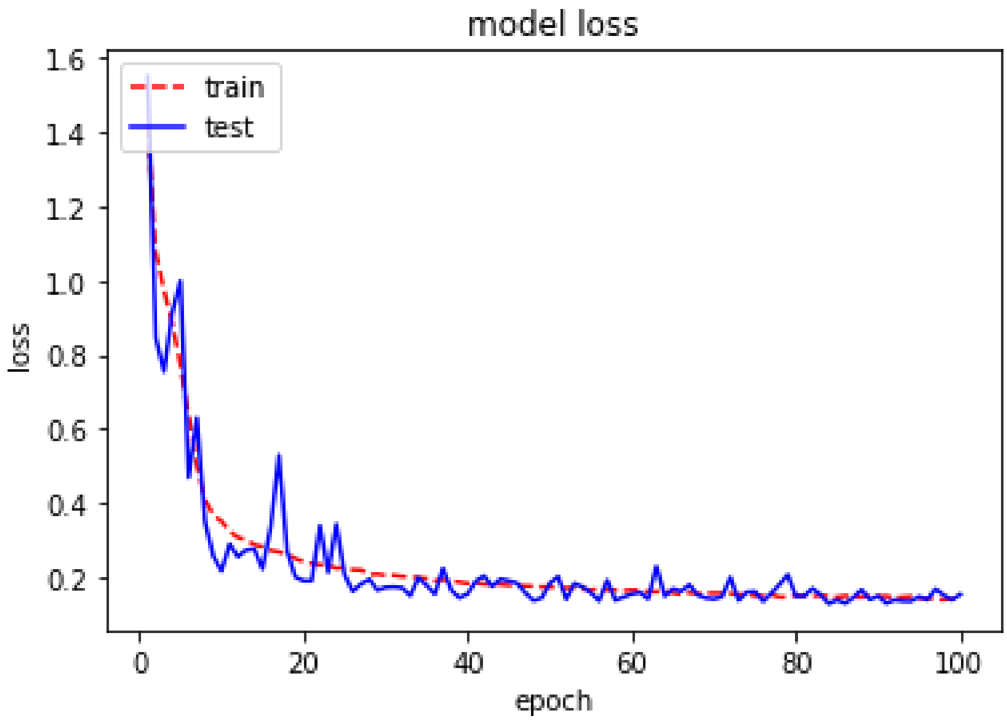
```
1089/1089 [==============================] - 0s 212us/step
mse=0.154205, mae=0.277753, rmsle=0.123777
```

```
In [30]: # list all data in history
         print(history.history.keys())

         # Create count of the number of epochs
         nbepocs = range(1, len(training_loss) + 1)

         # summarize history for accuracy
         plt.plot(nbepocs,training_accuracy,'r--')
         plt.plot(nbepocs,test_accuracy, 'b-')
         plt.title('model accuracy')
         plt.ylabel('accuracy')
         plt.xlabel('epoch')
         plt.legend(['MAE train', 'MAE test'], loc='upper left')
         plt.show()

         # summarize history for loss
```

```
plt.plot(nbepocs,training_loss,'r--')
plt.plot(nbepocs,test_loss, 'b-')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

```
dict_keys(['val_loss', 'val_mean_absolute_error', 'loss', 'mean_absolute_error'])
```






```
In [31]: # genere une prediction
         prediction = model.predict(X_testNN, batch_size=BATCH_SIZE, verbose=1)
```

```
6493/6493 [==============================] - 0s 33us/step
```

1.0.3 Pour confronter le modèle sur Kaggle

```
In [33]: prediction=[float(i) for i in prediction]
         submission = pd.DataFrame({'datetime':df_bike_test['datetime'],'count':prediction})
         #submission["count"] = submission["count"].astype(int)
         #print(submission)
         submission["count"]=np.exp(submission["count"])
         cpt_row=0
         for row_submisson in submission["count"]:
                 #print(submission.loc[[cpt_row], ['count']])
             #submission.loc[[cpt_row], ['count']]=submission.loc[[cpt_row], ['count']]
             if row_submisson<0 :
                     submission.loc[[cpt_row], ['count']]=0
             cpt_row=cpt_row+1

         filename = 'Bike Sharing_NN.csv'
         submission.to_csv(filename,index=False)
         print('Saved file: ' + filename)
```

```
Saved file: Bike Sharing_NN.csv
```

1.1 Fonctions utiles

```
In [34]: lst_mae_score=[]
         lst_mae_score.append('MAE')
         lst_mse_score=[]
         lst_mse_score.append('MSE')
         lst_rmsle_score=[]
         lst_rmsle_score.append('RMSLE')

In [35]: def rmsle_score(preds, true):
             rmsle_score = (np.sum((np.log1p(preds)-np.log1p(true))**2)/len(true))**0.5
             return rmsle_score

In [36]: from sklearn.metrics.scorer import make_scorer

         RMSLE2 = make_scorer(rmsle_score)

In [37]: df_train, df_test = skl_model_selection.train_test_split(df_combine[0])
         #print(df_combine[0].head(2))
         X=df_combine[0].iloc[:, 2:27]
         Y =df_combine[0]["count"]
         df_train = df_train.reset_index(drop=True)
         df_test = df_test.reset_index(drop=True)

         # On split le dataset en train-set et test-set
         X_train = df_train.iloc[:, 2:27] #27 car 28 et 29 features spécifiques à casuals et r
         #Y_train = df_train["Target"]
         Y_train = df_train["count"]
         #print(df_train.head())
         X_test = df_test.iloc[:, 2:27] #27 car 28 et 29 features spécifiques à casuals et reg
         #Y_test = df_test["Target"]
         Y_test = df_test["count"]

In [38]: def format_e(n):
             n=abs(n)
             a = '%E' % n
             return str(round(float(a.split('E')[0].rstrip('0').rstrip('.')),2)) + 'E' + a.spli
```

1.2 Comparaison des différents modèles

```
In [39]: from sklearn.ensemble import RandomForestRegressor
         from sklearn import metrics
         RFR= RandomForestRegressor()
         model=RFR
         #score=cross_val_score(RFR, X, Y, cv=5, scoring='mean_squared_error')
         lst_mse_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_squ
```

```
        lst_mae_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_median_a
        lst_rmsle_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_s
```

```
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:248: FutureWarning: T
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
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C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:248: FutureWarning: T
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  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:248: FutureWarning: T
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
In [40]: from sklearn.svm import SVR
         model=SVR()
         #lR = LogisticRegression()

         lst_mse_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_squ
         lst_mae_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_median_a
         lst_rmsle_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_s
```

```
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```

```
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  "avoid this warning.", FutureWarning)
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\svm\base.py:196: FutureWarning: The defa
  "avoid this warning.", FutureWarning)
```

```
In [41]: from sklearn import mixture
         from sklearn.mixture import GaussianMixture
         #lm=LinearRegression()
         model = GaussianMixture()
         lst_mse_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_squ
         lst_mae_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_median_a
         lst_rmsle_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_s
```

```
In [42]: from sklearn.ensemble import AdaBoostRegressor
         model = AdaBoostRegressor()
         #score=cross_val_score(RFR, X, Y, cv=5, scoring='mean_squared_error')
         lst_mse_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_squ
         lst_mae_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_median_a
         lst_rmsle_score.append(format_e(cross_val_score(model, X, Y, cv=5, scoring='neg_mean_s
```

```
In [43]: ##NN score:
         lst_mse_score.append(round(mseNN,2))
         lst_mae_score.append(round(maeNN,2))
         lst_rmsle_score.append(round(rmsleNN,2))
```

```
In [44]: from prettytable import PrettyTable
         t = PrettyTable(['    ','RandomForestRegressor','SVM Regressor','GaussianMixture','Ada
```

```
t.add_row(lst_mse_score)
t.add_row(lst_mae_score)
t.add_row(lst_rmsle_score)
print(t)
```

```
+-------+----------------------+--------------+-----------------+-------------------+--------
|       | RandomForestRegressor | SVM Regressor | GaussianMixture | AdaBoostRegressor | NeuralN
+-------+----------------------+--------------+-----------------+-------------------+--------
|  MSE  |        6.4E-06       |   1.96E+00   |     2.29E+01    |      2.4E-02      |       0
|  MAE  |       8.44E-16       |   8.46E-01   |     5.0E+00     |      1.09E-01     |       0
| RMSLE |       9.31E-08       |   1.21E-01   |     2.89E+00    |      2.25E-03     |       0
+-------+----------------------+--------------+-----------------+-------------------+--------
```

1.3 Pour Kaggle:

In [45]:
```
X=df_combine[0]
Y =df_combine[0]["count"]
#on  définie les features qui vont être intéressants pour la prédiction
features=X.columns.values
features=list(features)
features.remove("datetime")
features.remove("daypart_casual")
features.remove("daypart_registered")
features.remove("casual")
features.remove("registered")
features.remove("count")

X_train = df_combine[0]
Y_train = df_combine[0]["count"]
X_test = df_combine[1]
```

In [47]:
```
RFR= RandomForestRegressor()
RFR.fit(X_train[features],Y_train)
pred = RFR.predict(X_test[features])
submission = pd.DataFrame({'datetime':df_bike_test['datetime'],'count':pred})
#submission["count"] = submission["count"].astype(int)
#print(submission)
submission["count"]=np.exp(submission["count"])
cpt_row=0
for row_submisson in submission["count"]:
        #print(submission.loc[[cpt_row], ['count']])
    #submission.loc[[cpt_row], ['count']]=submission.loc[[cpt_row], ['count']]
    if row_submisson<0 :
            submission.loc[[cpt_row], ['count']]=0
    cpt_row=cpt_row+1

filename = 'Bike Sharing.csv'
```

```
        submission.to_csv(filename,index=False)
        print('Saved file: ' + filename)
```

```
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:248: FutureWarning: T
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


Saved file: Bike Sharing.csv
```

1.4 Si on distingue registered et casuals comme vu dans le train set

```
In [48]: df_train, df_test = skl_model_selection.train_test_split(df_combine[0])
         #print(df_combine[0].head(2))
         X=df_combine[0]
         Y =df_combine[0]["count"]
         df_train = df_train.reset_index(drop=True)
         df_test = df_test.reset_index(drop=True)
```

```
In [49]: features_casual=X.columns.values
         features_registered=X.columns.values
         features_casual=list(features_casual)
         features_registered=list(features_registered)
         features_casual.remove("datetime")
         features_registered.remove("datetime")
         features_casual.remove("registered")
         features_registered.remove("registered")
         features_casual.remove("casual")
         features_registered.remove("casual")
         features_casual.remove("count")
         features_registered.remove("count")
         features_casual.remove("daypart_registered")
         features_registered.remove("daypart_casual")
```

```
In [50]: X_cas=X_train[features_casual]
         Y_cas=X_train['casual']
         X_testcas=X_test[features_casual]
         X_reg=X_train[features_registered]
         Y_reg=X_train['registered']
         X_testreg=X_test[features_registered]
```

```
In [51]: from sklearn.model_selection import train_test_split

         X_trainreg, X_validreg, Y_trainreg, Y_validreg = train_test_split(X_reg, Y_reg, test_s
         X_traincas, X_validcas, Y_traincas, Y_validcas = train_test_split(X_cas, Y_cas, test_s
```

```
In [52]: #normalisation:
         from sklearn.preprocessing import StandardScaler
```

Utilisation de Randomforest en séparant casual et registered et soumission sur Kaggle

```
In [54]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.svm import SVR

         #avec randomforest
         model= RandomForestRegressor()
         model.fit(X_trainreg,Y_trainreg)
         predreg = model.predict(X_testreg)

         model.fit(X_traincas,Y_traincas)
         predcas = model.predict(X_testcas)

         pred=np.exp(predreg)+np.exp(predcas)
         submission = pd.DataFrame({'datetime':df_bike_test['datetime'],'count':pred})

         submission["count"]=submission["count"]
         cpt_row=0
         for row_submisson in submission["count"]:
             if row_submisson<0 :
                     submission.loc[[cpt_row], ['count']]=0
             cpt_row=cpt_row+1

         filename = 'Bike Sharingregcas.csv'
         submission.to_csv(filename,index=False)
         print('Saved file: ' + filename)
```

```
C:\Users\Alexandre\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:248: FutureWarning: T
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


Saved file: Bike Sharingregcas.csv
```