In [1]:

```
import pickle
import warnings
from math import sqrt

import lightgbm as lgb
import matplotlib as mpl
import numpy as np
import pandas as pd  # Basic library for all of our dataset operations
#import pmdarima as pm
import tensorflow as tf
import xgboost as xgb
from utils.metrics import evaluate
from bayes_opt import BayesianOptimization
from fbprophet import Prophet
from matplotlib import pyplot as plt
from sklearn import linear_model, svm
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import make_scorer, mean_squared_error
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from statsmodels.tsa.ar_model import AR
from statsmodels.tsa.arima_model import ARIMA, ARMA
from statsmodels.tsa.holtwinters import ExponentialSmoothing, SimpleExpSmoothing
from statsmodels.tsa.statespace.sarimax import SARIMAX
from tqdm import tqdm




# We will use deprecated models of statmodels which throw a lot of warnings to use more
warnings.filterwarnings("ignore")


# Extra settings
seed = 42
tf.random.set_seed(seed)
np.random.seed(seed)
plt.style.use('bmh')
mpl.rcParams['axes.labelsize'] = 14
mpl.rcParams['xtick.labelsize'] = 12
mpl.rcParams['ytick.labelsize'] = 12
mpl.rcParams['text.color'] = 'k'
mpl.rcParams['figure.figsize'] = 18, 8

print(tf.__version__)

air_pollution = pd.read_csv('datasets/air_pollution.csv', parse_dates=['date'])
air_pollution.set_index('date', inplace=True)
```

```
Importing plotly failed. Interactive plots will not work.
2.3.0
```

Prepare data before modeling

In [2]:

```
# We split our dataset to be able to evaluate our models
```

```
resultsDict = {}
predictionsDict = {}

air_pollution = pd.read_csv('C:/Users/hp/Downloads/time-series-forecasting-with-python-
air_pollution.set_index('date', inplace=True)

split_date = '2014-01-01'
df_training = air_pollution.loc[air_pollution.index <= split_date]
df_test = air_pollution.loc[air_pollution.index > split_date]
print(f"{len(df_training)} days of training data \n {len(df_test)} days of testing data

df_training.to_csv('datasets/training.csv')
df_test.to_csv('datasets/test.csv')
```

```
1461 days of training data
 364 days of testing data
```

It is also very important to include some naive forecast as the series mean or previous value to make sure our models perform better than the simplest of the simplest. We dont want to introduce any complexity if it does not provides any performance gain.

In [3]:

```
# Also add the naive mean average value
mean = df_training.pollution_today.mean()
mean = np.array([mean for u in range(len(df_test))])
resultsDict['Naive mean'] = evaluate(df_test.pollution_today, mean)
predictionsDict['Naive mean'] = mean
resultsDict['Yesterdays value'] = evaluate(
    df_test.pollution_today, df_test.pollution_yesterday)
predictionsDict['Yesterdays value'] = df_test.pollution_yesterday.values
```

Simple Exponential Smoothing (SES)

The Simple Exponential Smoothing (SES) method models the next time step as an exponentially weighted linear function of observations at prior time steps. This method expects our time series to be non stationary in order to perform adecuately (no trend or seasonality)

In [4]:

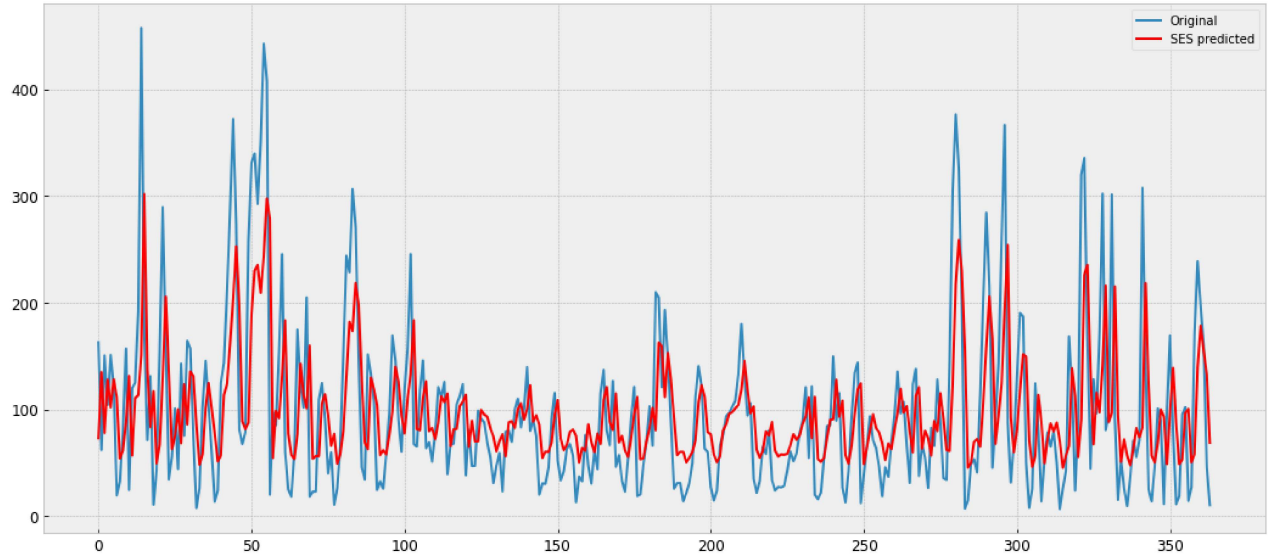
```
# Walk throught the test data, training and predicting 1 day ahead for all the test dat
index = len(df_training)
yhat = list()
for t in tqdm(range(len(df_test.pollution_today))):
    temp_train = air_pollution[:len(df_training)+t]
    model = SimpleExpSmoothing(temp_train.pollution_today)
    model_fit = model.fit()
    predictions = model_fit.predict(start=len(temp_train), end=len(temp_train))
    yhat = yhat + [predictions]

yhat = pd.concat(yhat)
resultsDict['SES'] = evaluate(df_test.pollution_today, yhat.values)
predictionsDict['SES'] = yhat.values
```

```
100%|██████████| 364/364 [00:06<00:00, 53.29it/s]
```

In [8]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat.values, color='red', label='SES predicted')
plt.legend()
```

Out[8]: <matplotlib.legend.Legend at 0x1fe4bc37340>



Holt Winter's Exponential Smoothing (HWES)

In [5]:

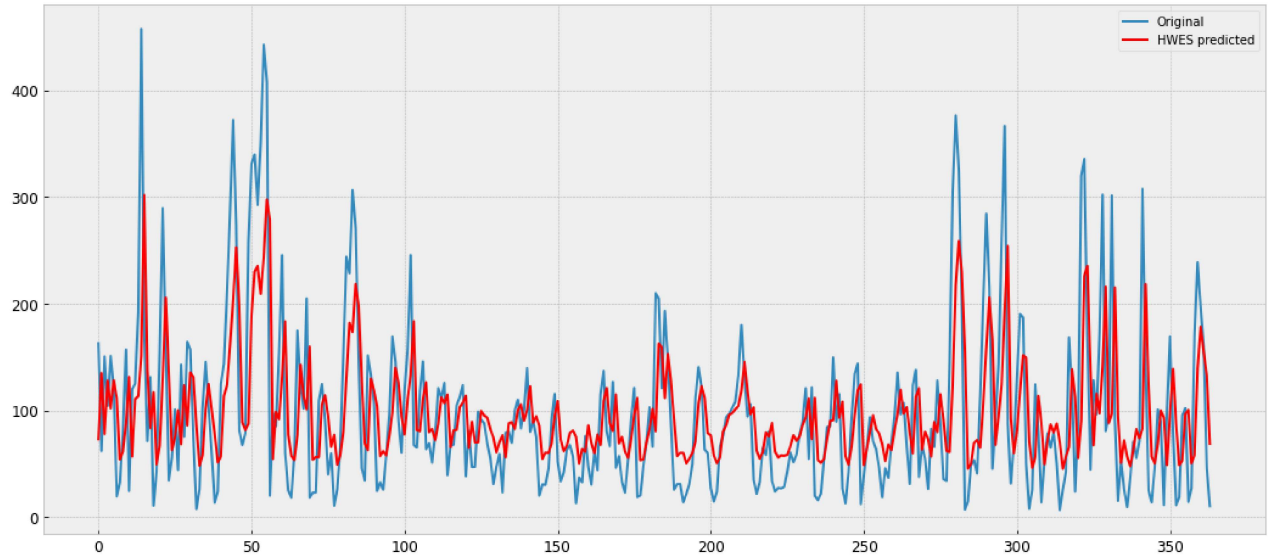
```
# Walk throught the test data, training and predicting 1 day ahead for all the test dat
index = len(df_training)
yhat = list()
for t in tqdm(range(len(df_test.pollution_today))):
    temp_train = air_pollution[:len(df_training)+t]
    model = ExponentialSmoothing(temp_train.pollution_today)
    model_fit = model.fit()
    predictions = model_fit.predict(start=len(temp_train), end=len(temp_train))
    yhat = yhat + [predictions]

yhat = pd.concat(yhat)
resultsDict['HWES'] = evaluate(df_test.pollution_today, yhat.values)
predictionsDict['HWES'] = yhat.values
```

```
100%|██████████| 364/364 [00:06<00:00, 53.03it/s]
```

In [9]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat.values, color='red', label='HWES predicted')
plt.legend()
```

Out[9]: <matplotlib.legend.Legend at 0x1fe4be42340>



Autoregressive integrated moving average (ARIMA)

In [6]:

```
# ARIMA example

# Walk throught the test data, training and predicting 1 day ahead for all the test dat
index = len(df_training)
yhat = list()
for t in tqdm(range(len(df_test.pollution_today))):
    temp_train = air_pollution[:len(df_training)+t]
    model = ARIMA(temp_train.pollution_today, order=(1, 0, 0))
    model_fit = model.fit(disp=False)
    predictions = model_fit.predict(
        start=len(temp_train), end=len(temp_train), dynamic=False)
    yhat = yhat + [predictions]

yhat = pd.concat(yhat)
resultsDict['ARIMA'] = evaluate(df_test.pollution_today, yhat.values)
predictionsDict['ARIMA'] = yhat.values
```

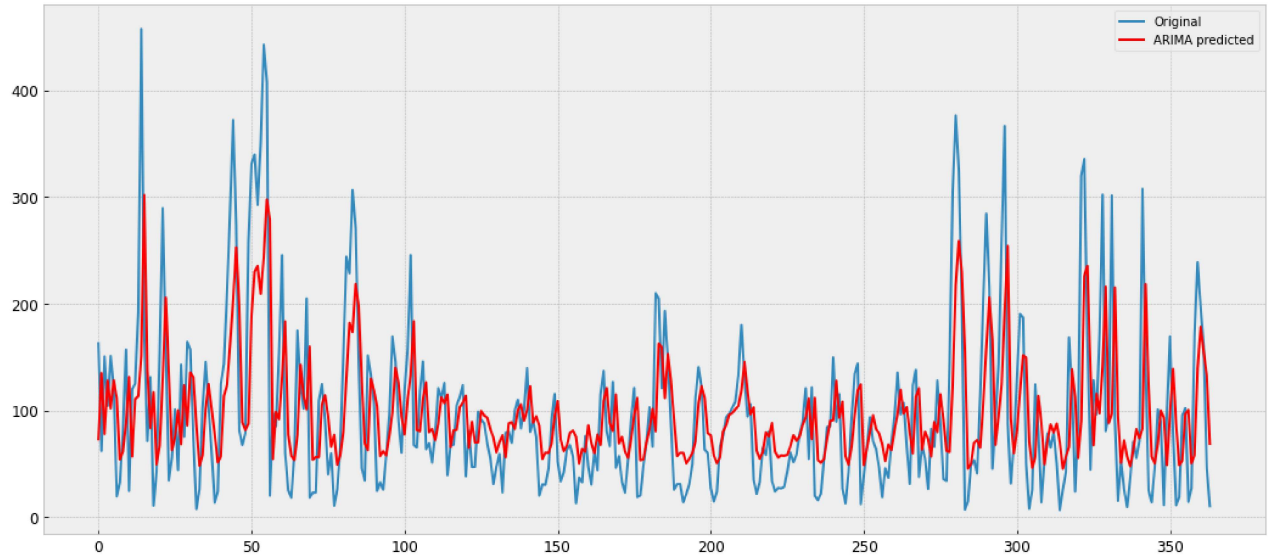
```
100%|██████████| 364/364 [00:25<00:00, 14.51it/s]
```

In [7]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat.values, color='red', label='ARIMA predicted')
plt.legend()
```

Out[7]:

```
<matplotlib.legend.Legend at 0x1fe4bbfdc40>
```



Multivariate time series forecasting

In [10]:

```
# ADD time features to our model
def create_time_features(df, target=None):
    """
    Creates time series features from datetime index
    """
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['sin_day'] = np.sin(df['dayofyear'])
    df['cos_day'] = np.cos(df['dayofyear'])
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.weekofyear
    X = df.drop(['date'], axis=1)
    if target:
        y = df[target]
        X = X.drop([target], axis=1)
        return X, y

    return X
```

In [12]:

```
X_train_df, y_train = create_time_features(df_training, target='pollution_today')
X_test_df, y_test = create_time_features(df_test, target='pollution_today')
scaler = StandardScaler()
scaler.fit(X_train_df)
X_train = scaler.transform(X_train_df)
X_test = scaler.transform(X_test_df)

X_train_df = pd.DataFrame(X_train, columns=X_train_df.columns)
X_test_df = pd.DataFrame(X_test, columns=X_test_df.columns)
```

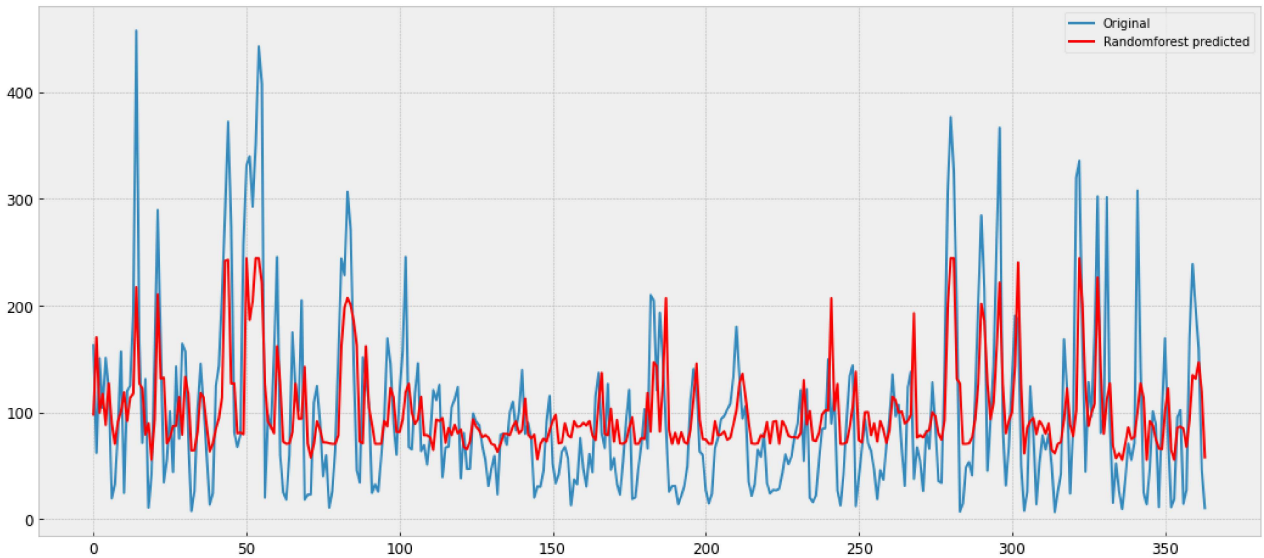
Tree models

Randomforest

In [15]:
```
reg = RandomForestRegressor(max_depth=2, random_state=0)
reg.fit(X_train, y_train)
yhat = reg.predict(X_test)
resultsDict['Randomforest'] = evaluate(df_test.pollution_today, yhat)
predictionsDict['Randomforest'] = yhat
```

In [17]:
```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='Randomforest predicted')
plt.legend()
```

Out[17]: <matplotlib.legend.Legend at 0x1fe4c8f2700>

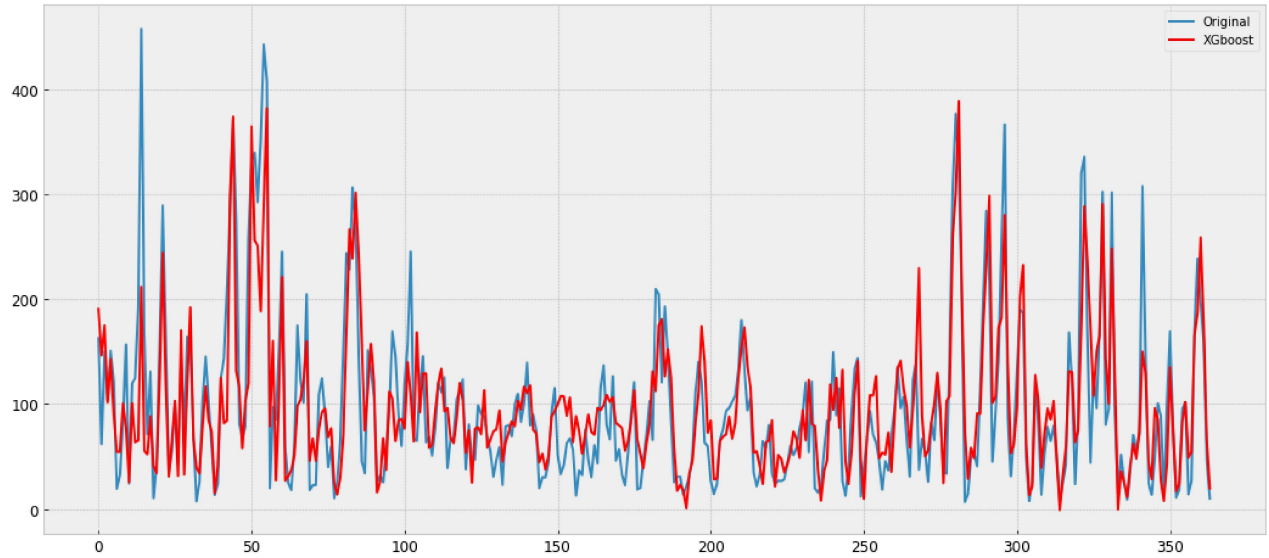


XGBoost

In [18]:
```
reg = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=1000)
reg.fit(X_train, y_train,
        verbose=False)  # Change verbose to True if you want to see it train
yhat = reg.predict(X_test)
resultsDict['XGBoost'] = evaluate(df_test.pollution_today, yhat)
predictionsDict['XGBoost'] = yhat
```

In [19]:
```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='XGboost')
plt.legend()
```

Out[19]: <matplotlib.legend.Legend at 0x1fe4c950670>



Lightgbm

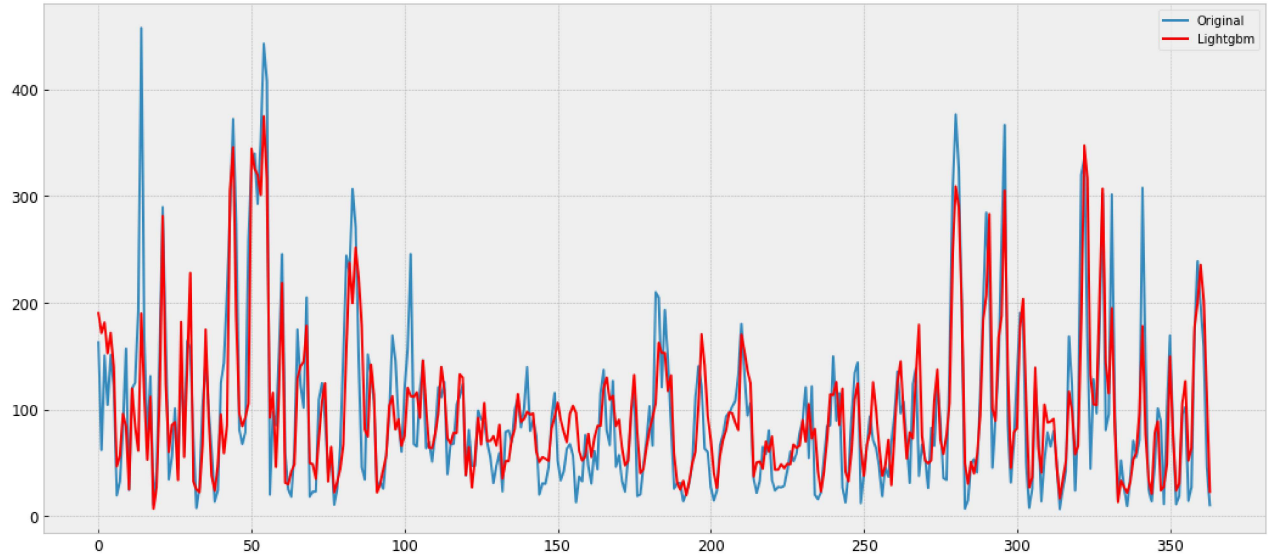
In [20]:

```
lightGBM = lgb.LGBMRegressor()
lightGBM.fit(X_train, y_train)
yhat = lightGBM.predict(X_test)
resultsDict['Lightgbm'] = evaluate(df_test.pollution_today, yhat)
predictionsDict['Lightgbm'] = yhat
```

In [21]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='Lightgbm')
plt.legend()
```

Out[21]: <matplotlib.legend.Legend at 0x1fe4cde2c70>



Nearest neighbors

In [25]:

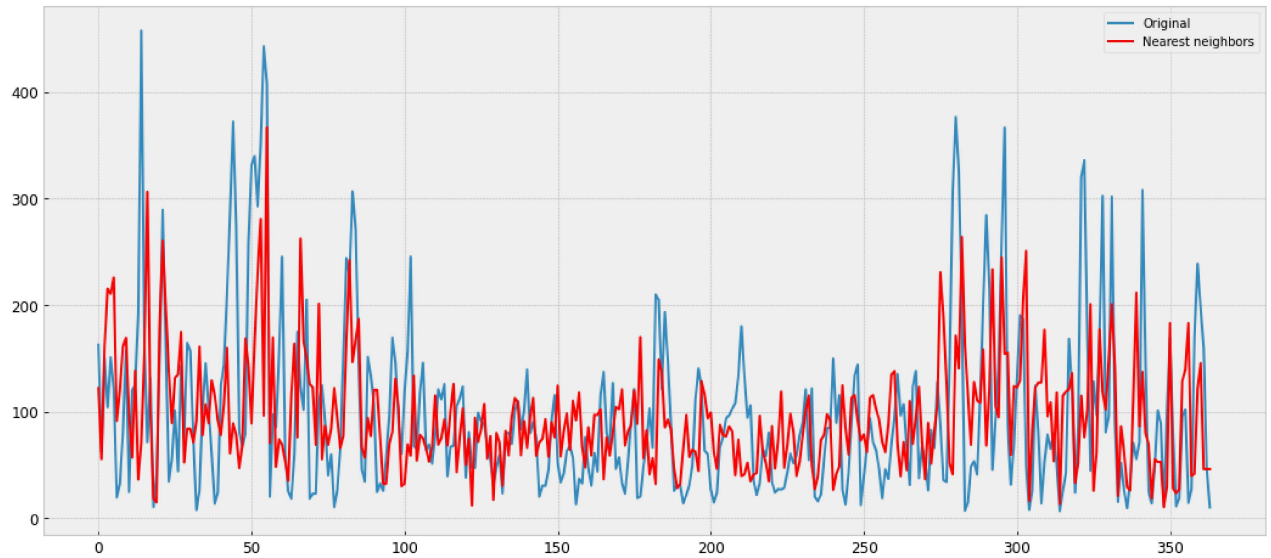
```
reg = KNeighborsRegressor(n_neighbors=2)
reg.fit(X_train, y_train)
yhat = reg.predict(X_test)
```

```
resultsDict['Kneighbors'] = evaluate(df_test.pollution_today, yhat)
predictionsDict['Kneighbors'] = yhat
```

In [26]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='Nearest neighbors')
plt.legend()
```

Out[26]: <matplotlib.legend.Legend at 0x1fe4f293100>



Deep learning

Tensorlfow LSTM

In [27]:

```
# For our dl model we will create windows of data that will be feeded into the datasets
BATCH_SIZE = 64
BUFFER_SIZE = 100
WINDOW_LENGTH = 24


def window_data(X, Y, window=7):
    '''
    The dataset length will be reduced to guarante all samples have the window, so new
    '''
    x = []
    y = []
    for i in range(window-1, len(X)):
        x.append(X[i-window+1:i+1])
        y.append(Y[i])
    return np.array(x), np.array(y)


# Since we are doing sliding, we need to join the datasets again of train and test
X_w = np.concatenate((X_train, X_test))
y_w = np.concatenate((y_train, y_test))

X_w, y_w = window_data(X_w, y_w, window=WINDOW_LENGTH)
X_train_w = X_w[:-len(X_test)]
y_train_w = y_w[:-len(X_test)]
```

```
X_test_w = X_w[-len(X_test):]
y_test_w = y_w[-len(X_test):]

# Check we will have same test set as in the previous models, make sure we didnt screw
print(f"Test set equal: {np.array_equal(y_test_w,y_test)}")

train_data = tf.data.Dataset.from_tensor_slices((X_train_w, y_train_w))
train_data = train_data.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()

val_data = tf.data.Dataset.from_tensor_slices((X_test_w, y_test_w))
val_data = val_data.batch(BATCH_SIZE).repeat()
```

```
Test set equal: True
```

In [28]:

```
dropout = 0.0
simple_lstm_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(
        128, input_shape=X_train_w.shape[-2:], dropout=dropout),
    tf.keras.layers.Dense(128),
    tf.keras.layers.Dense(128),
    tf.keras.layers.Dense(1)
])

simple_lstm_model.compile(optimizer='rmsprop', loss='mae')
```

In [29]:

```
EVALUATION_INTERVAL = 200
EPOCHS = 5

model_history = simple_lstm_model.fit(train_data, epochs=EPOCHS,
                                      steps_per_epoch=EVALUATION_INTERVAL,
                                      validation_data=val_data, validation_steps=50)
```

```
Epoch 1/5
200/200 [==============================] - 17s 85ms/step - loss: 52.4530 - val_loss: 44.
7995
Epoch 2/5
200/200 [==============================] - 6s 31ms/step - loss: 36.0138 - val_loss: 36.1
902
Epoch 3/5
200/200 [==============================] - 6s 31ms/step - loss: 30.2429 - val_loss: 31.1
008
Epoch 4/5
200/200 [==============================] - 6s 31ms/step - loss: 27.4843 - val_loss: 31.9
176
Epoch 5/5
200/200 [==============================] - 6s 29ms/step - loss: 25.1883 - val_loss: 31.4
675
```

In [31]:

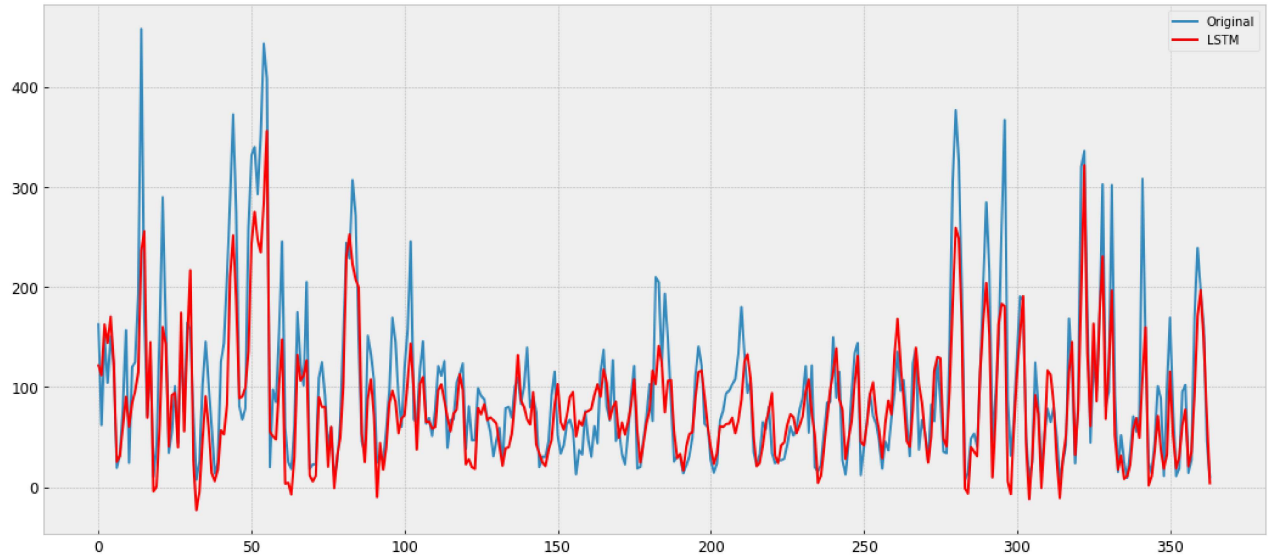
```
yhat = simple_lstm_model.predict(X_test_w).reshape(1, -1)[0]
resultsDict['Tensorflow simple LSTM'] = evaluate(y_test, yhat)
predictionsDict['Tensorflow simple LSTM'] = yhat
```

In [32]:

```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='LSTM')
plt.legend()
```

Out[32]:

```
<matplotlib.legend.Legend at 0x1fe54722af0>
```



Hyperparameter optimization

Hyperparameter optimization is trying to find the best parameters in an automatic way. We present two methods that are used frequently:

- **Grid search** Brute force method to try all different possible combinations of parameters. Will always find the best combination
- **Bayesian processes** "Brute" force method, optimizes parameter search by using gausian processes to model each parameter distribution and don't go over all the possible values.

Bayesian processes - Xgboost

In [33]:

```
def rms(y_actual, y_predicted):
    return sqrt(mean_squared_error(y_actual, y_predicted))


my_scorer = make_scorer(rms, greater_is_better=False)
pbounds = {
    'n_estimators': (100, 10000),
    'max_depth': (3, 15),
    'min_samples_leaf': (1, 4),
    'min_samples_split': (2, 10),
}


def rf_hyper_param(n_estimators,
                   max_depth,
                   min_samples_leaf,
                   min_samples_split):

    max_depth = int(max_depth)
    n_estimators = int(n_estimators)

    clf = RandomForestRegressor(n_estimators=n_estimators,
                                max_depth=int(max_depth),
                                min_samples_leaf=int(min_samples_leaf),
                                min_samples_split=int(min_samples_split),
                                n_jobs=1)
```

```
    return -np.mean(cross_val_score(clf, X_train, y_train, cv=3))


optimizer = BayesianOptimization(
    f=rf_hyper_param,
    pbounds=pbounds,
    random_state=1,
)
```

In [34]:

```
optimizer.maximize(
    init_points=3,
    n_iter=20,
    acq='ei'
)
```

iter	target	max_depth	min_sa...	min_sa...	n_esti...
1	-0.5469	8.004	3.161	2.001	3.093e+0
2	-0.5111	4.761	1.277	3.49	3.521e+0
3	-0.5459	7.761	2.616	5.354	6.884e+0
4	-0.508	4.298	3.175	5.441	3.52e+03
5	-0.5428	7.947	3.133	9.549	3.506e+0
6	-0.5457	7.243	1.491	8.858	3.524e+0
7	-0.4608	3.549	3.036	6.999	3.518e+0
8	-0.4619	3.891	2.847	7.469	3.52e+03
9	-0.5392	6.417	2.061	4.706	3.516e+0
10	-0.5528	14.77	1.811	8.47	4.521e+0
11	-0.5281	5.947	2.751	8.017	3.517e+0
12	-0.5379	6.627	1.359	8.891	3.52e+03
13	-0.4623	3.286	2.762	8.621	3.52e+03
14	-0.4631	3.114	2.651	3.296	4.83e+03
15	-0.5459	7.162	2.005	4.747	4.829e+0
16	-0.4623	3.23	1.671	7.848	3.52e+03
17	-0.4627	3.721	2.176	8.349	3.518e+0
18	-0.5115	4.174	1.104	4.611	4.837e+0
19	-0.4604	3.058	3.419	6.25	4.825e+0
20	-0.4611	3.479	3.8	8.409	4.822e+0
21	-0.5089	4.461	2.674	7.546	4.822e+0
22	-0.5091	4.708	2.258	6.952	4.792e+0
23	-0.5539	12.82	1.491	2.12	1.694e+0

In [35]:

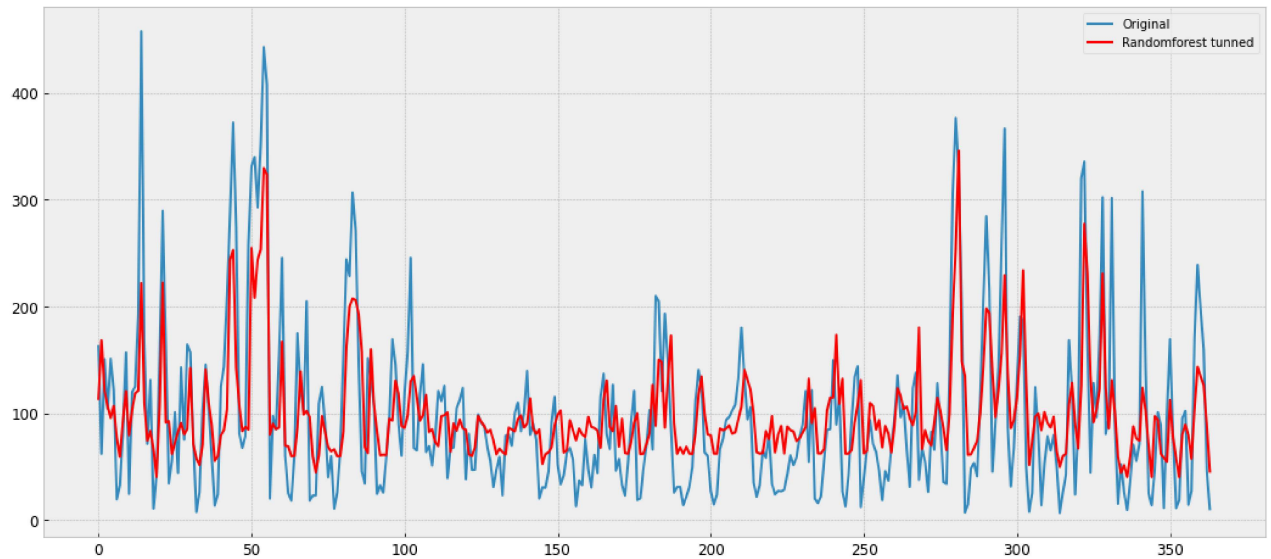
```
params = optimizer.max['params']

# Converting the max_depth and n_estimator values from float to int
params['max_depth'] = int(params['max_depth'])
params['n_estimators'] = int(params['n_estimators'])
params['min_samples_leaf'] = int(params['min_samples_leaf'])
params['min_samples_split'] = int(params['min_samples_split'])

# Initialize an XGBRegressor with the tuned parameters and fit the training data
tunned_rf = RandomForestRegressor(**params)
# Change verbose to True if you want to see it train
tunned_rf.fit(X_train, y_train)

yhat = tunned_rf.predict(X_test)
resultsDict['Randomforest tunned'] = evaluate(y_test, yhat)
```

In [36]:
```
increase = 1 - (resultsDict['Randomforest tunned']
                ['rmse']/resultsDict['Randomforest']['rmse'])
print(
    f"Bayesian optimized Randomforest is {increase*100}% better than the Randomforest w
```

```
Bayesian optimized Randomforest is 10.560836174067278% better than the Randomforest with
default parameters
```

In [37]:
```
plt.plot(df_test.pollution_today.values, label='Original')
plt.plot(yhat, color='red', label='Randomforest tunned')
plt.legend()
```

Out[37]:
```
<matplotlib.legend.Legend at 0x1fe547e0bb0>
```



In [40]:
```
with open('C:/Users/hp/Downloads/time-series-forecasting-with-python-master/results/sco
    pickle.dump(resultsDict, handle, protocol=pickle.HIGHEST_PROTOCOL)

with open('C:/Users/hp/Downloads/time-series-forecasting-with-python-master/results/pre
    pickle.dump(predictionsDict, handle, protocol=pickle.HIGHEST_PROTOCOL)
```