In [1]:

```
import csv
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from sklearn import linear_model
import pandas as pd

from sklearn.linear_model import Ridge
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
```

In [39]:

```
def save_to_csv(file_path, X, Y):
    with open(file_path, 'w', newline='') as csv_file:
        csv_writer = csv.writer(csv_file, delimiter=',', quotechar='"', quoting=csv.QUOTE_M
        for i in range(0, len(X)):
                csv_writer.writerow([X.item(i), Y.item(i)])
```

In [297]:

```
poly_reg_path = "C:\\Users\\Ihor\\GSN\\PUM\\Laboratorium 3\\FlapPyBird\\data\\polynomial_mo
lin_reg_path = "C:\\Users\\Ihor\\GSN\\PUM\\Laboratorium 3\\FlapPyBird\\data\\linear_regresi
lin_reg_impl_path = "C:\\Users\\Ihor\\GSN\\PUM\\Laboratorium 3\\FlapPyBird\\data\\linear_re
```

In [2]:

```
train_df = pd.read_csv('C://Users//Ihor//GSN//PUM//Laboratorium 3//FlapPyBird//outfile.csv'
```

In [3]:

```
train_df.head()
```

Out[3]:

	x	y
0	52	68.518519
1	56	68.518519
2	60	68.518519
3	64	68.518519
4	68	68.518519

In [4]:

```
train_df['x'].head()
```

Out[4]:

```
0    52
1    56
2    60
3    64
4    68
Name: x, dtype: int64
```

In [5]:

```
train_df['y'].head()
```

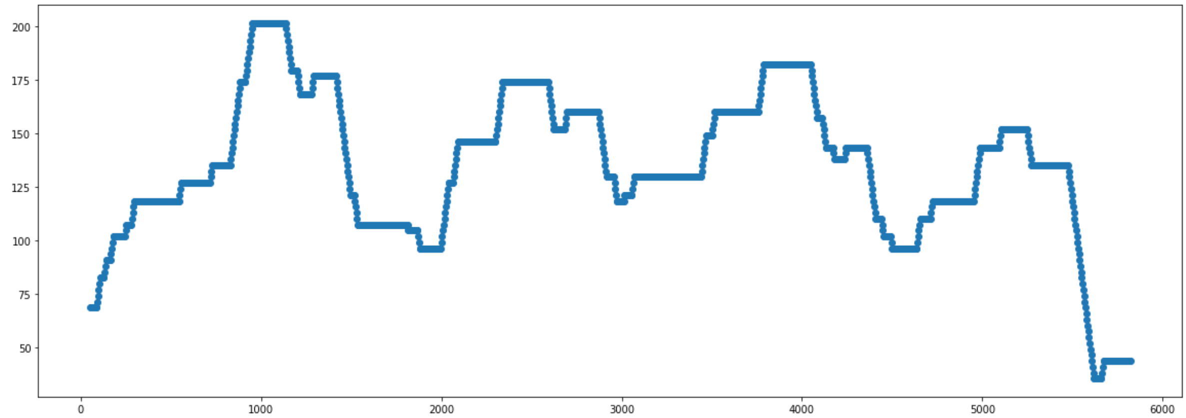
Out[5]:

```
0    68.518519
1    68.518519
2    68.518519
3    68.518519
4    68.518519
Name: y, dtype: float64
```

In [6]:

```
plt.figure(figsize=(20, 7))
plt.scatter(train_df['x'], train_df['y'])

plt.show()
```



Użycie Linear Regression sk-learn

In [7]:

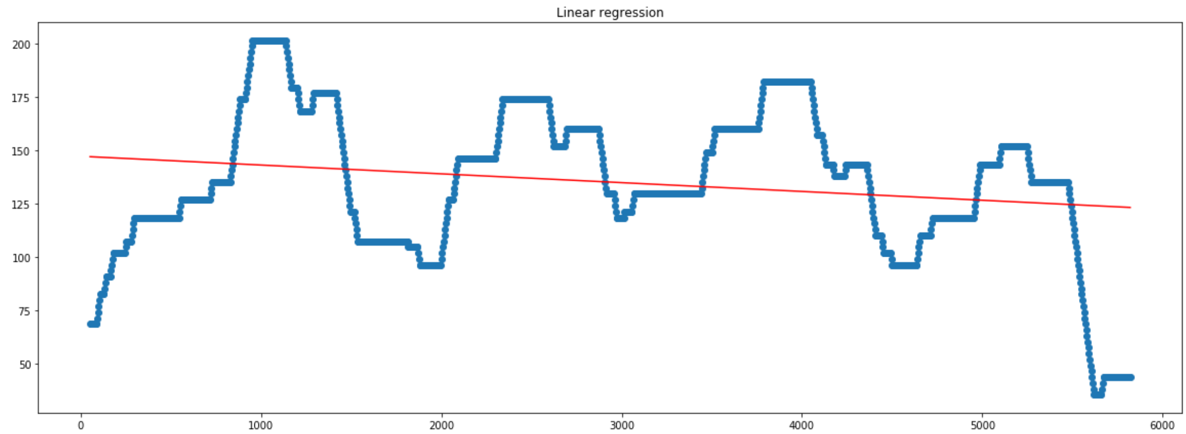
```
X_train = train_df.iloc[:, 0].values.reshape(-1, 1)
Y_train = train_df.iloc[:, 1].values.reshape(-1, 1)
```

In [8]:

```
%%time

sk_linreg = linear_model.LinearRegression()
sk_linreg = linear_model.LinearRegression(fit_intercept=True, normalize=False, copy_X=True,
Y_Pred = sk_linreg.predict(np.array(X_train).reshape(-1, 1))
plt.figure()
plt.figure(figsize=(20, 7))
plt.scatter(X_train, Y_train)
plt.plot(X_train, Y_Pred, color='red')
plt.title('Linear regression')
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



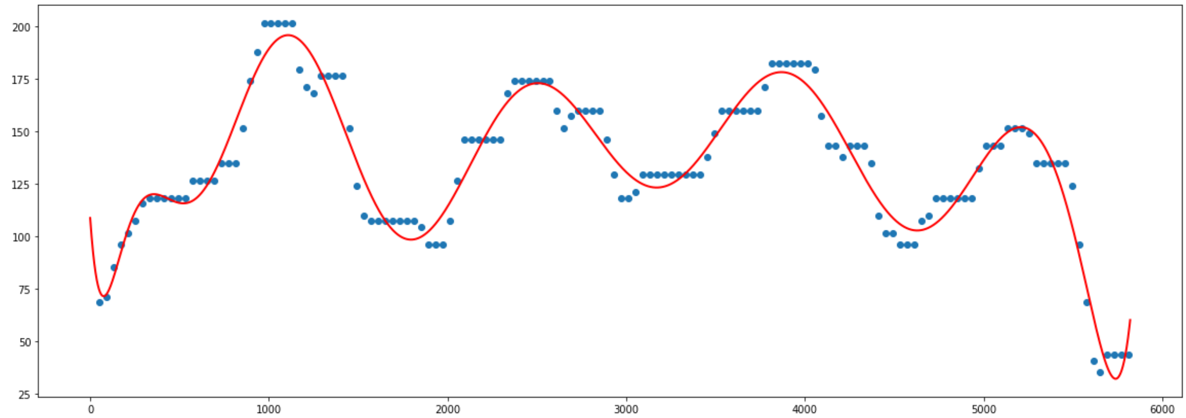

```
Wall time: 368 ms
```

Użycie PolinomialFeatures + PipeLine + LinearRegression sk-learn

In [62]:

```
lastIntInX = int(X_train[-1])
X_poly_predict = np.arange(lastIntInX)
polynomial_model = make_pipeline(PolynomialFeatures(degree=15), linear_model.LinearRegressi
polynomial_model.fit(X_train, Y_train)
Y_poly_predict = polynomial_model.predict(X_poly_predict.reshape(-1, 1))
plt.figure()
plt.figure(figsize=(20, 7))
plt.scatter(X_train[::10], Y_train[::10])
plt.plot(X_poly_predict, Y_poly_predict, color=('red'), linewidth=2,
                      label="degree 3")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

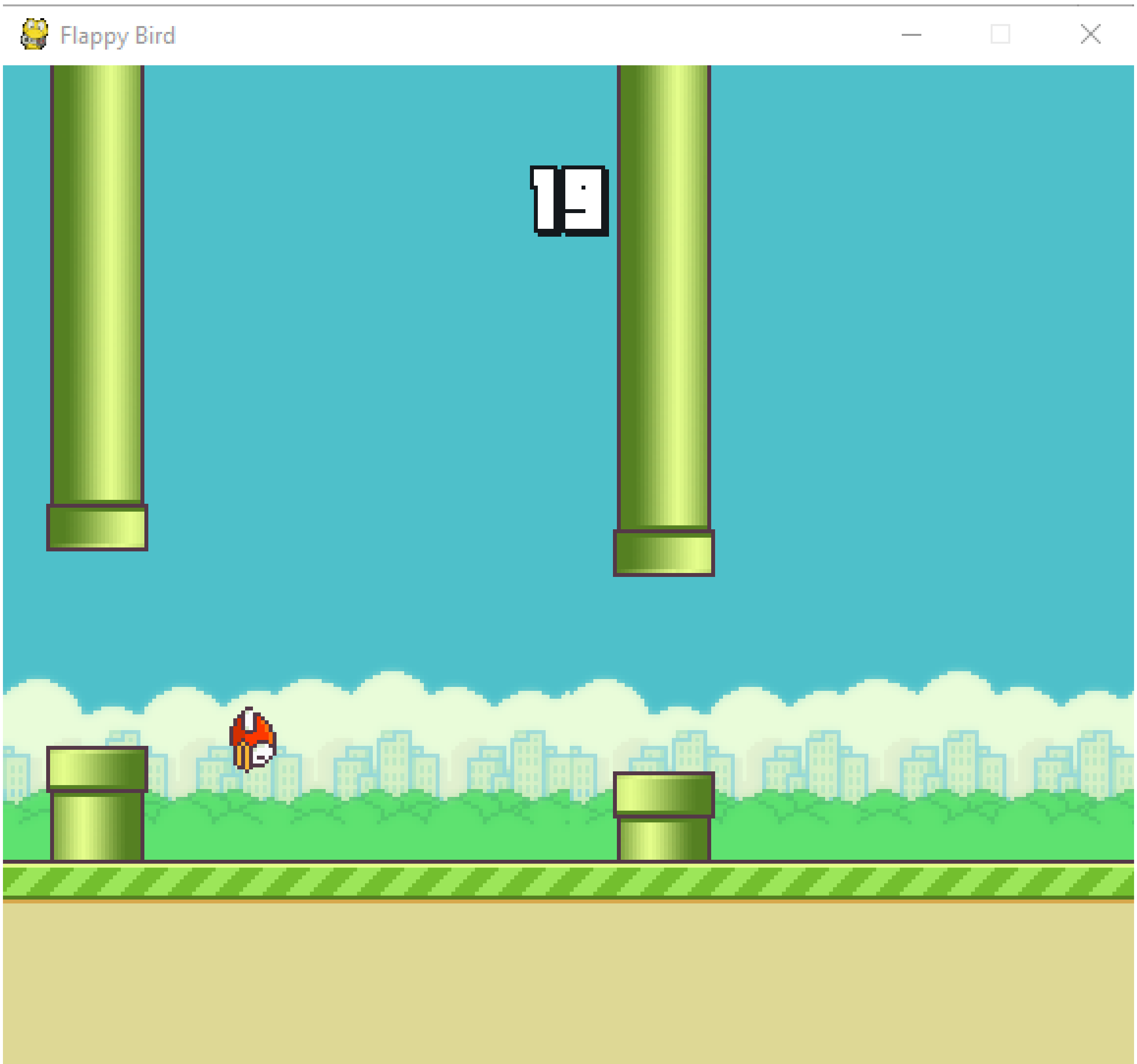


In [64]:

```
save_to_csv(lin_reg_path, X_poly_predict, Y_poly_predict)
```

bez normalizacji flappy móg przelecieć tylko 3 rury, co oznacza że normalizacja dannych ma wielki wplyw na dopasowanie polymonialnej regresji linjowej

z normalizają dopasowanie jest o wielie lepszę i flappy sprawnie kończy trasę



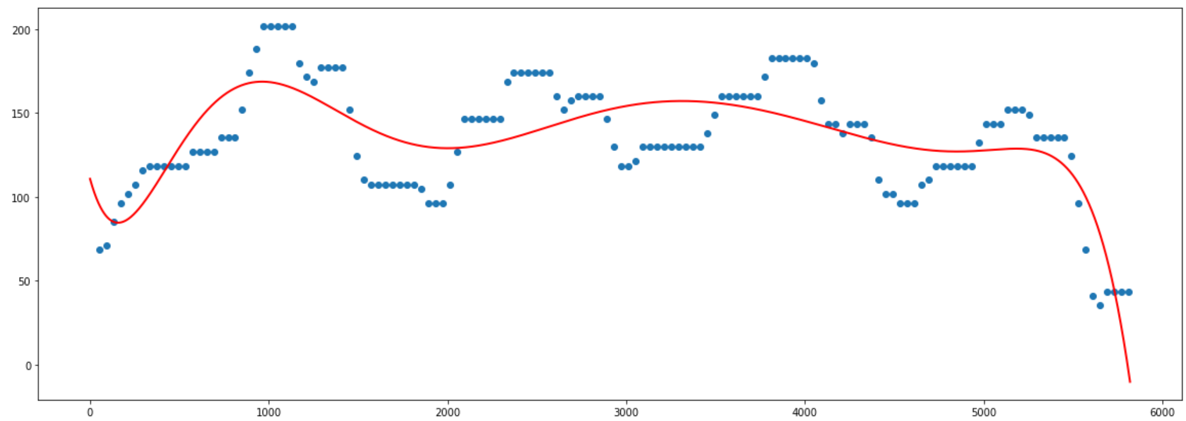
Użycie PolinomialFeaturesPipeLine sk-learn + Ridge

In [63]:

```
lastIntInX = int(X_train[-1])
X_poly_predict = np.arange(lastIntInX)
polynomial_model = make_pipeline(PolynomialFeatures(degree=9), Ridge())
polynomial_model.fit(X_train, Y_train)
Y_poly_predict = polynomial_model.predict(X_poly_predict.reshape(-1, 1))
plt.figure()
plt.figure(figsize=(20, 7))
plt.scatter(X_train[::10], Y_train[::10])
plt.plot(X_poly_predict, Y_poly_predict, color=('red'), linewidth=2,
                      label="degree 9")
plt.show()
```

```
C:\Users\Ihor\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.py:14
8: LinAlgWarning: Ill-conditioned matrix (rcond=2.73379e-70): result may not
be accurate.
  overwrite_a=True).T
```

```
<Figure size 432x288 with 0 Axes>
```

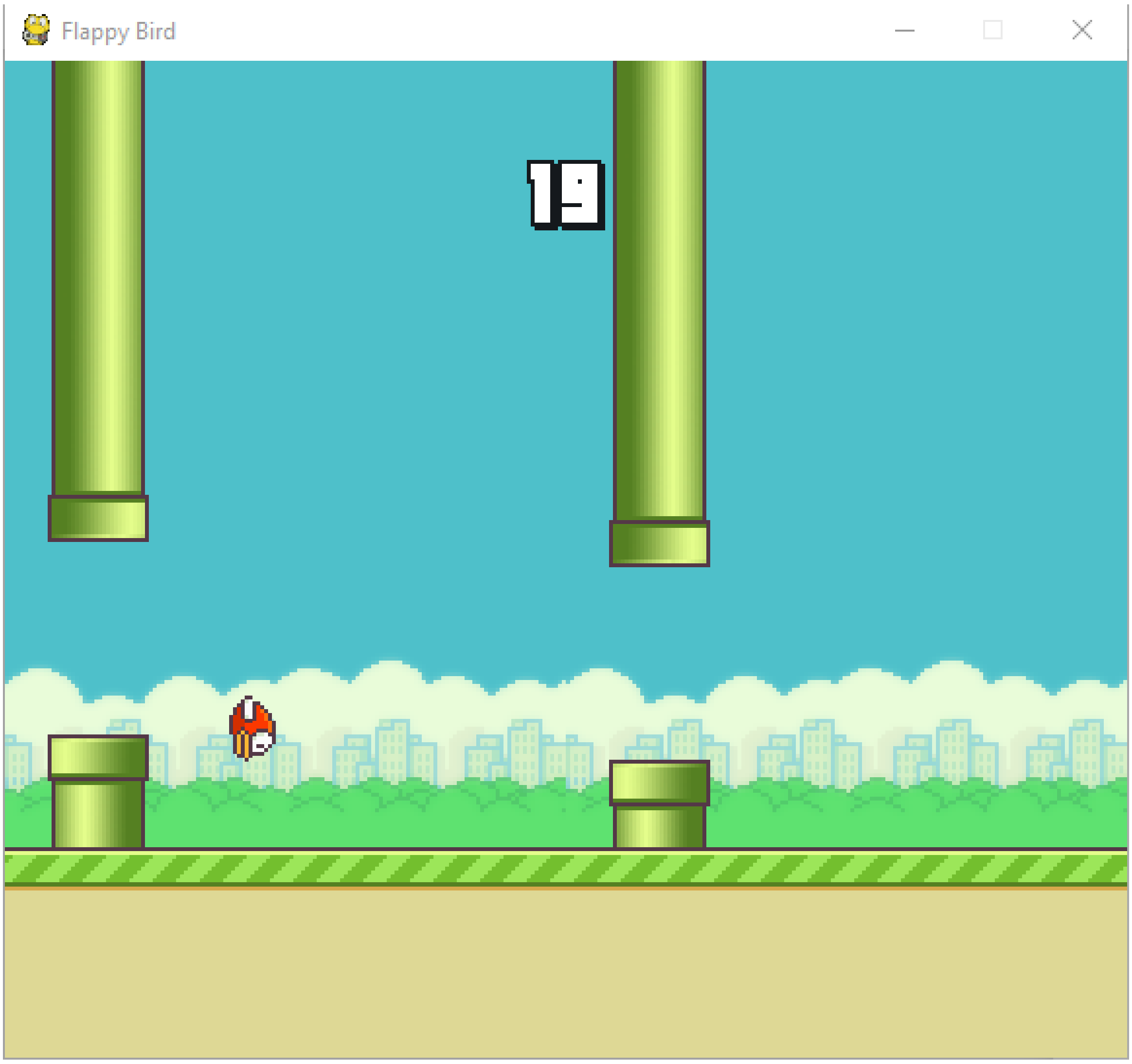


In [41]:

```
save_to_csv(poly_reg_path, X_poly_predict, Y_poly_predict)
```

test funkcji Ridge

Flappy pokonal trasę bez normalizacji



Implementacja Linear Regression

In [278]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [466]:

```
class LinearRegresionImpl:
    def __init__(self, X, y, degree=4):
        self.X = X
        self.y = y
        self.X_ = np.column_stack((np.ones((X.size, 1)), X))
        self.a = a_opt(self.X_, y)
        self.degree = [i for i in range(1, degree+1)]

    def a_opt(X,y) : # linear regression solution a = (X'X)^-1 X'y = pinv(X)y
        a_opt = np.dot( np.linalg.pinv(X), y)
        return a_opt

    def predict_linear(self, X_predict): #funkcja linearna
        return self.a[0] + self.a[1]*X_predict

    def predict_polymonial(self, xt, degree = 5): # funkcja polymonialna
        polyfit = np.polyfit(self.X, Y_lin_reg, degree)
        polycurve1d = np.poly1d(polyfit)
        return polycurve1d(xt)
```

In [304]:

```
X_lin_reg = train_df.iloc[:, 0].values
Y_lin_reg = train_df.iloc[:, 1].values
```

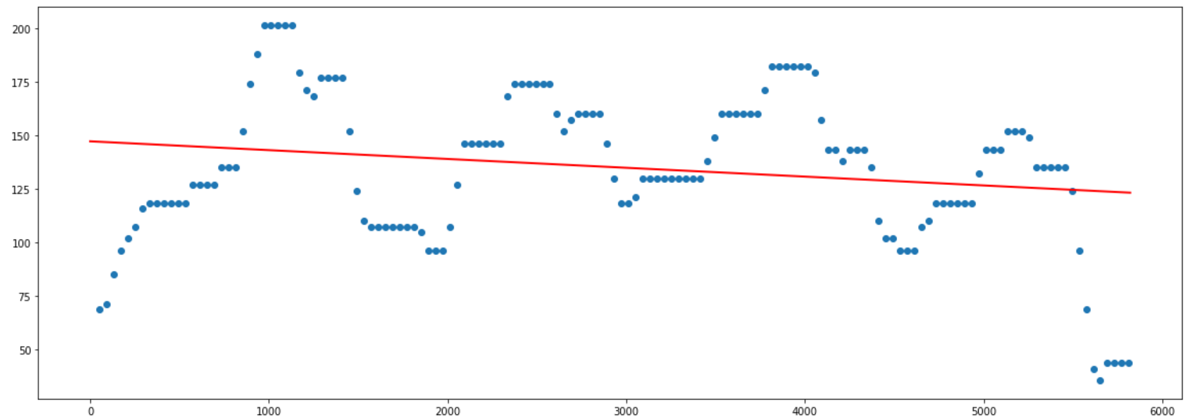
In [305]:

```
linreg = LinearRegresionImpl(X_linear_reg, Y_linear_reg)
Y_pred = linreg.predict_linear(X_poly_predict)
```

In [306]:

```
plt.figure()
plt.figure(figsize=(20, 7))
plt.scatter(X_train[::10], Y_train[::10])
plt.plot(X_poly_predict, Y_pred, color=('red'), linewidth=2,
                      label="degree 9")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



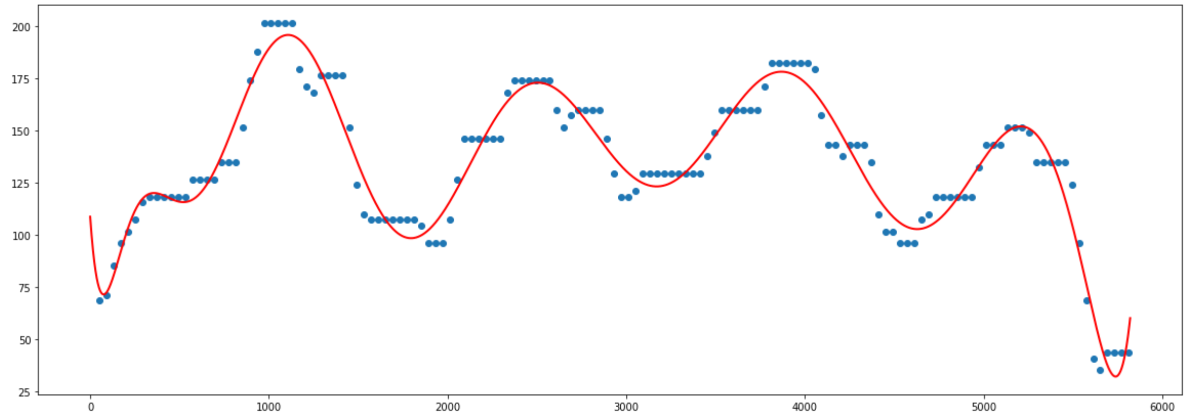
In [307]:

```
linregpoly = LinearRegresionImpl(X_linear_reg, Y_linear_reg)
Y_pred_poly = linregpoly.predict_polymonial(X_poly_predict, degree=15)
```

In [308]:

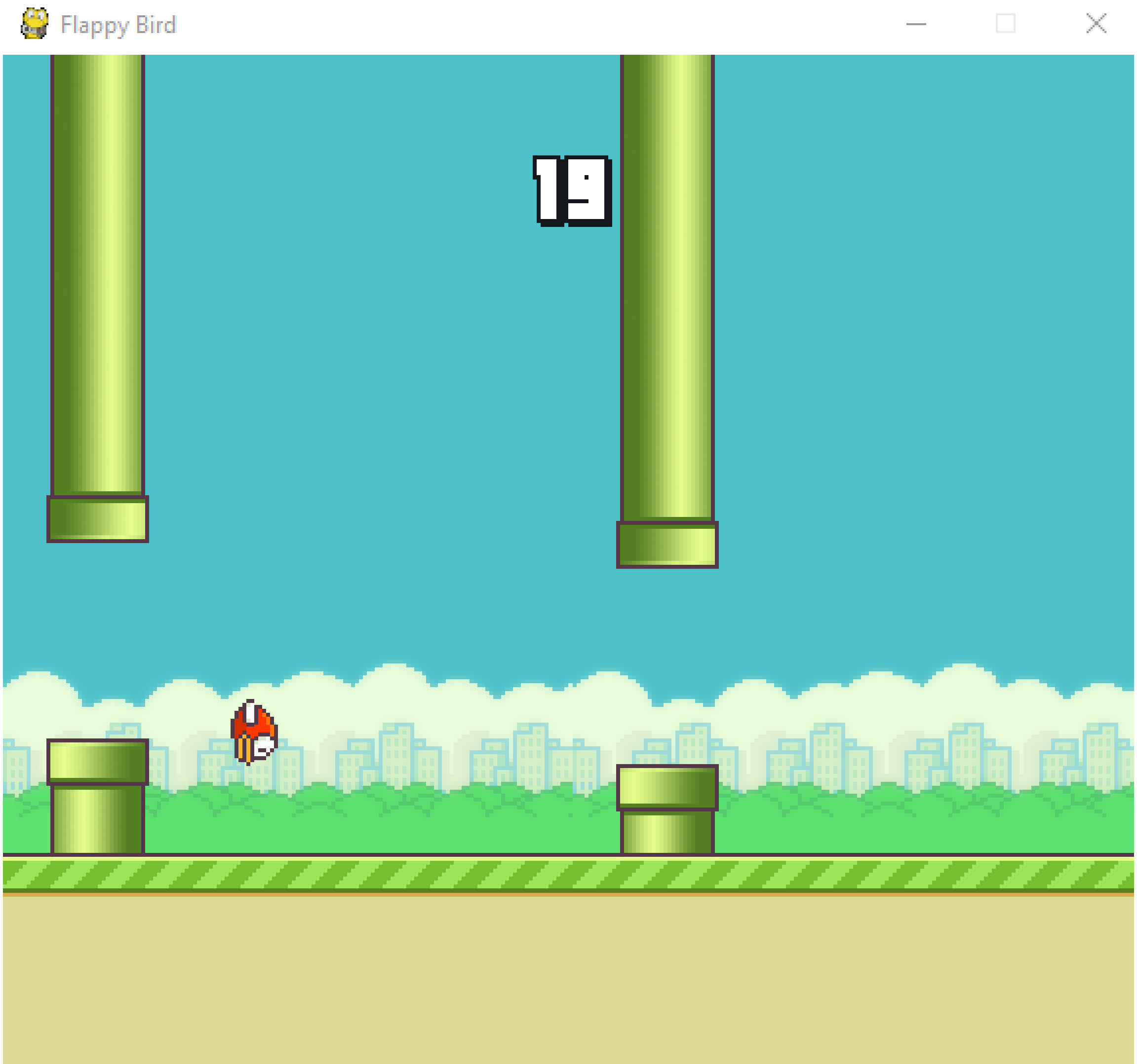
```
plt.figure()
plt.figure(figsize=(20, 7))
plt.scatter(X_train[::10], Y_train[::10])
plt.plot(X_poly_predict, Y_pred_poly, color=('red'), linewidth=2,
                      label="degree 9")
plt.show()
```

<Figure size 432x288 with 0 Axes>



In [310]:

```
save_to_csv(lin_reg_impl_path, X_poly_predict, Y_poly_predict)
```



Zaimplementowana Regresja liniowa działa w miarę szybko i pozwala na przejście Flappy przez wszystkie rury, ale nie zawiera normalizaji dannych

Była też próba zaiplementowania regresji polimonialnej za dopomogą:

```
class LinearRegresionImpl:
    def __init__(self, X, y, degree=4):
        self.X = X
        self.y = y
        self.X_ = np.column_stack((np.ones((X.size, 1)), X))
        self.a = a_opt(self.X_, y)
        self.degree = [i for i in range(1, degree+1)]

    def a_opt(X,y) : # linear regression solution a = (X'X)^-1 X'y = pinv(X)y
        a_opt = np.dot( np.linalg.pinv(X), y)
        return a_opt

    def predict_linear(self, X_predict): #funkcja linearna
        return self.a[0] + self.a[1]*X_predict

    def predict_polymonial(self, xt): # funkcja polymonialna
        X = np.column_stack( (np.ones((self.X.size,1)) , self.X, self.X**2, self.X**3 )) #
construct the augmented matrix X
        polyfit = np.polyfit(self.X, Y_lin_reg, degree)
        polycurve1d = np.poly1d(polyfit)
```

```
        return self.a[0] + self.a[1]*X_predict + self.a[2]*X_predict**2 +
self.a[3]*X_predict**3 + self.a[4]*X_predict**4
```

Ale niestety funkcja predict_polymonial nie mogla się dopasować do skomplikowanej ścieżki Flappy przy takiej implementacji

Partje

In [442]:

```
election_df = pd.read_csv('C://Users//Ihor//GSN//PUM//Laboratorium 3//GoesGold//ElectionDat
```

In [443]:

```
election_df = election_df.sort_values(by='time')
```

In [450]:

```
election_df['time_delta'] = (election_df['time'] - election_df['time'].min())  / np.timedel
```

In [451]:

```
election_df
```

Out[451]:

sPercentage	nullVotes	...	pre.subscribedVoters	pre.totalVoters	Party	Mandates	Percentage	va
2.50	8874	...	813743	428546	PS	0	38.29	
1.86	139	...	13766	8489	A	0	0.37	
1.86	139	...	13766	8489	R.I.R.	0	0.41	
1.86	139	...	13766	8489	L	0	0.51	
1.86	139	...	13766	8489	PAN	0	1.25	
...	...	...	...	...	...	...	...	
2.40	2232	...	181378	104223	MPT	0	0.24	
2.40	2232	...	181378	104223	PNR	0	0.26	
2.40	2232	...	181378	104223	PURP	0	0.29	
3.38	3814	...	390947	220211	CDS-PP	0	3.48	
2.81	3700	...	371931	190712	JPP	0	0.07	

In [610]:

```
parties = list(set(election_df['Party']))
print(parties)
```

```
['PURP', 'PS', 'PPM', 'B.E.', 'CDS-PP', 'JPP', 'CH', 'PCP-PEV', 'PAN', 'A',
'MPT', 'R.I.R.', 'L', 'IL', 'PPD/PSD', 'PDR', 'PTP', 'PCTP/MRPP', 'MAS', 'N
C', 'PNR']
```

In [611]:

```
election_df.loc[election_df['Party'] == 'PS']['Mandates'].sum()
```

Out[611]:

```
6068
```

In [612]:

```
time_ = {party:(election_df.loc[election_df['Party'] == party].groupby(['time_delta']).sum(
                election_df.loc[election_df['Party'] == party].groupby(['time_delta']).sum(
                 for party in parties }
```

Plot with sk_learn linear regression

In [467]:

```
parties = list(set(election_df['territoryName']))
print(parties)
```

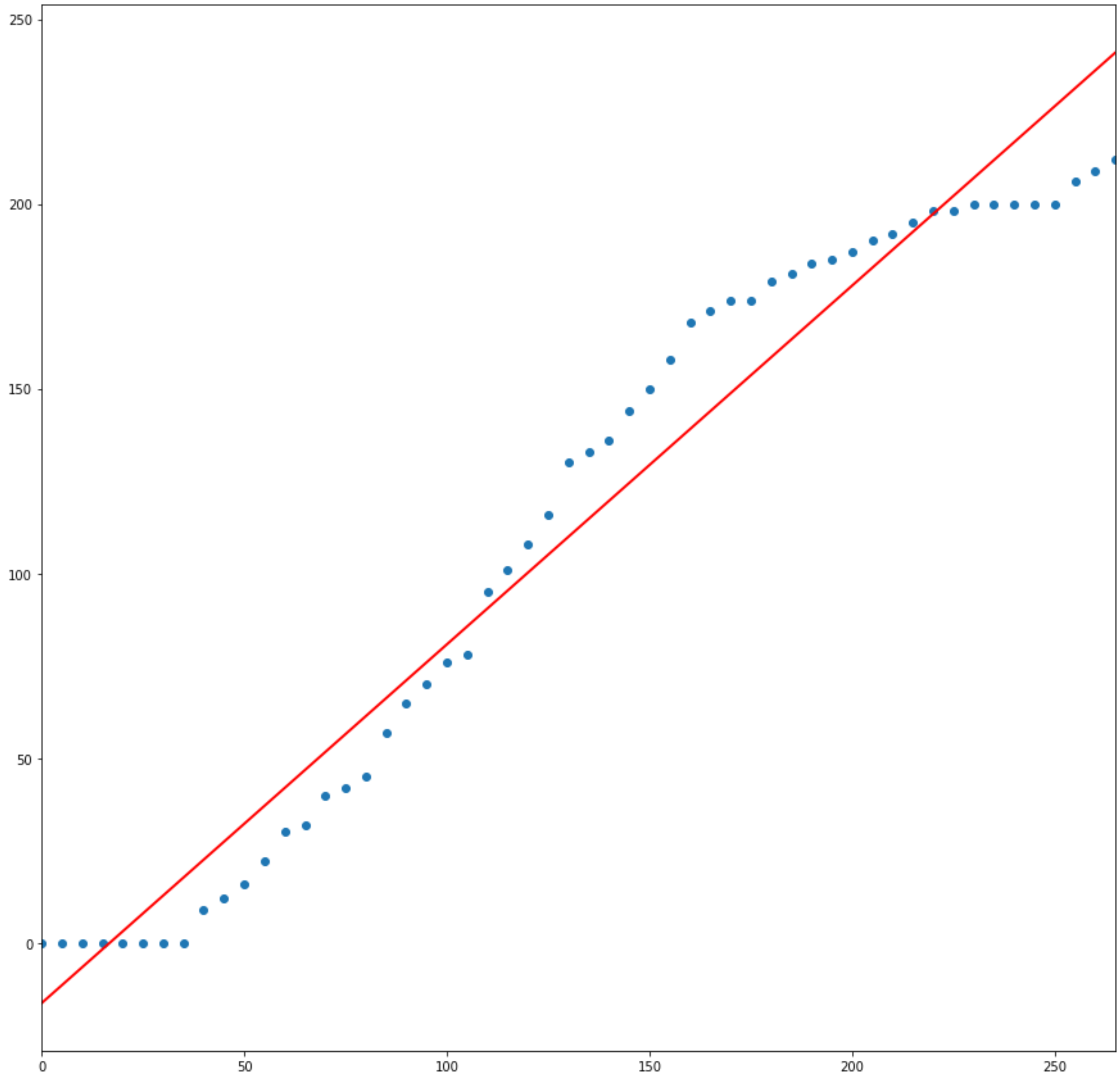
```
['Território Nacional', 'Viana do Castelo', 'Porto', 'Évora', 'Leiria', 'Bej
a', 'Coimbra', 'Madeira', 'Portalegre', 'Castelo Branco', 'Vila Real', 'Vise
u', 'Guarda', 'Setúbal', 'Bragança', 'Lisboa', 'Açores', 'Braga', 'Aveiro',
'Santarém', 'Faro']
```

In [613]:

```
sk_linreg = linear_model.LinearRegression()
sk_linreg.fit(time_['PS'][0].reshape(-1, 1),time_['PS'][1].reshape(-1, 1))
prediction = sk_linreg.predict(time_['PS'][0].reshape(-1, 1))


plt.figure()
plt.figure(figsize=(15, 15))
plt.scatter(time_['PS'][0], time_['PS'][1])
plt.plot(time_['PS'][0], prediction, color=('red'), linewidth=2,
                      label="degree 9")
# prediction = polynomial_model.predict(time_['PS'][0].reshape(-1, 1))
plt.xlim(election_df['time_delta'].min(), election_df['time_delta'].max())
plt.show()
```

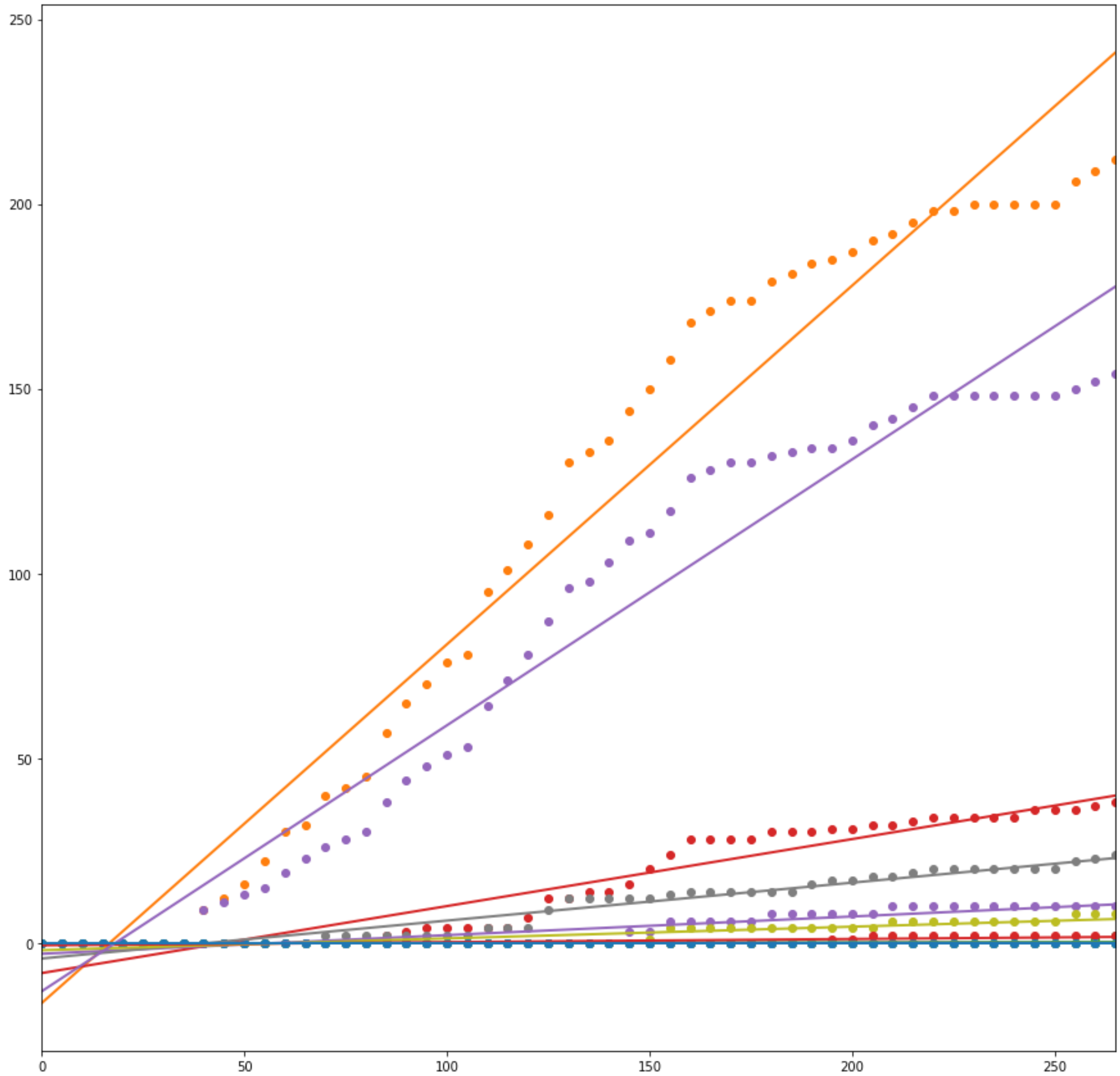
<Figure size 432x288 with 0 Axes>



In [614]:

```
plt.figure()
plt.figure(figsize=(15, 15))
[plt.scatter(time_[party][0], time_[party][1]) for party in parties]
for party in parties:
    sk_linreg.fit(time_[party][0].reshape(-1, 1),time_[party][1].reshape(-1, 1))
    prediction = sk_linreg.predict(time_[party][0].reshape(-1, 1))
    plt.plot(time_[party][0], prediction, linewidth=2)
plt.xlim(election_df['time_delta'].min(), election_df['time_delta'].max())
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

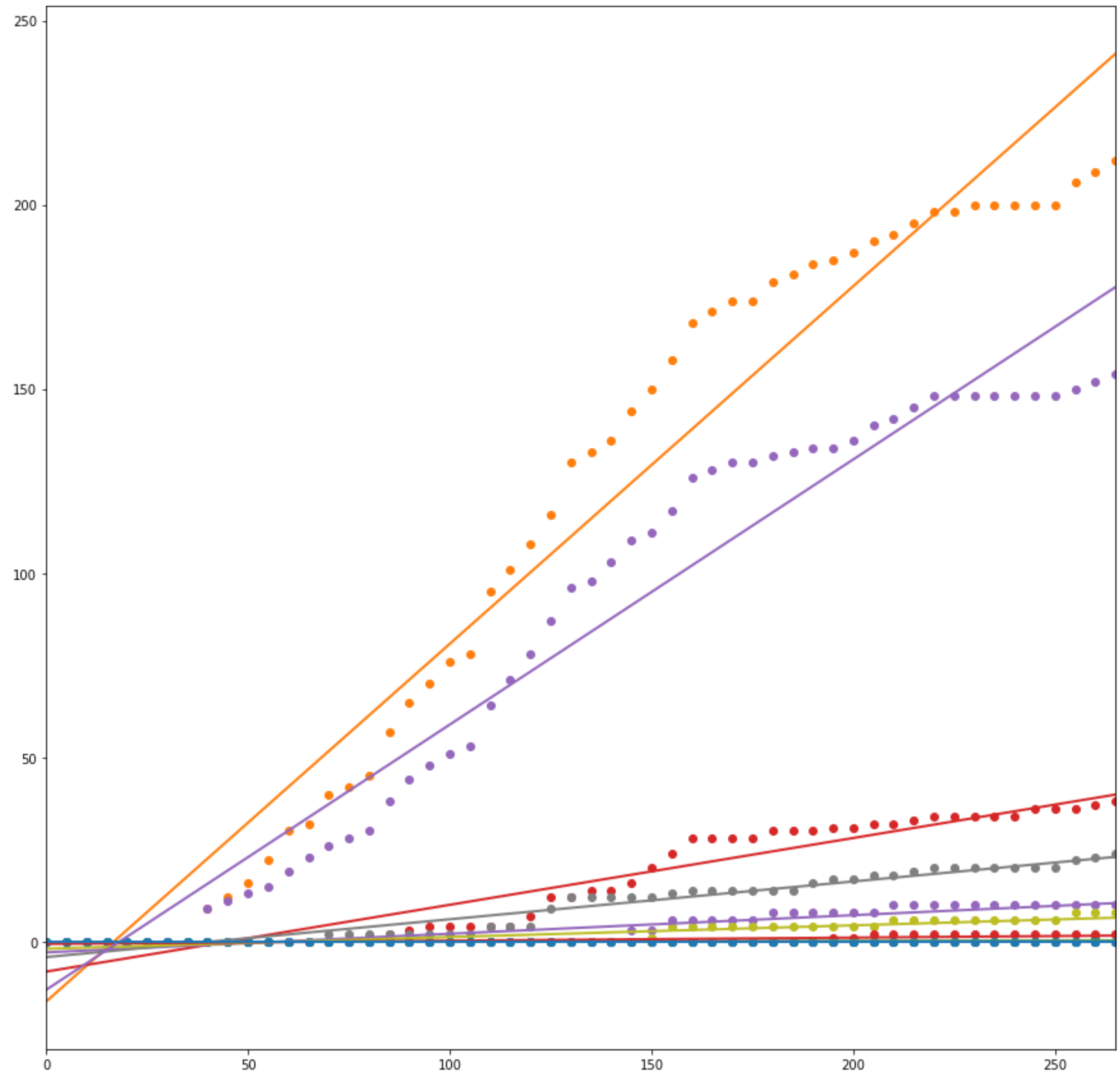


Plot with Wlasna implementacja

In [615]:

```
plt.figure()
plt.figure(figsize=(15, 15))
[plt.scatter(time_[party][0], time_[party][1]) for party in parties]
for party in parties:
    linreg = LinearRegresionImpl(time_[party][0], time_[party][1])
    prediction = linreg.predict_linear(time_[party][0])
#     sk_linreg.fit(time_[party][0].reshape(-1, 1),time_[party][1].reshape(-1, 1))
#     prediction = sk_linreg.predict(time_[party][0].reshape(-1, 1))
    plt.plot(time_[party][0], prediction, linewidth=2)
plt.xlim(election_df['time_delta'].min(), election_df['time_delta'].max())
plt.show()
```

<Figure size 432x288 with 0 Axes>



In [ ]:

Wyszukiwanie najlepszego czasu dla otrzymania najlepszego wynniku partii sk_learn + bsearch

In [651]:

```
bigest_parties = ['PS', 'PPD/PSD', 'B.E.']
```

In [654]:

```
def binary_search(sequence, item):
    begin_index = 0
    end_index = len(sequence) - 1
    while begin_index <= end_index:
        midpoint = begin_index + (end_index - begin_index)//2
        midpoint_value = sequence[midpoint]
        if midpoint_value in list(range(item-4, item+4)):
            return midpoint
        elif item < midpoint_value:
            end_index = midpoint - 1
        else:
            begin_index = midpoint + 1
    return midpoint_value//2
```

In [655]:

```
for party in bigest_parties:
    sk_linreg.fit(time_[party][1].reshape(-1, 1),time_[party][0].reshape(-1, 1))
    prediction = sk_linreg.predict(time_[party][1].reshape(-1, 1))
    timestamp = time_[party][0][binary_search(list(prediction.flatten(order='C').astype(int
    print(party + "party needs minimum " + str(timestamp) + " time to get " + \
          str(time_[party][1].max()) + " mandates in election")
```

```
PSparty needs minimum 215.0 time to get 212 mandates in election
PPD/PSDparty needs minimum 130.0 time to get 154 mandates in election
B.E.party needs minimum 130.0 time to get 38 mandates in election
```

In [660]:

```
for party in bigest_parties:
    sk_linreg.fit(time_[party][1].reshape(-1, 1),time_[party][0].reshape(-1, 1))
    prediction = sk_linreg.predict(time_[party][1].reshape(-1, 1))
    for i, predict in enumerate(prediction.flatten(order='C').astype(int)):
        if predict in list(range(time_[party][1].max()-15, time_[party][1].max()+15)):
            print(party + "party needs minimum " + str(predict) + " time to get " + \
                  str(time_[party][1].max()) + " mandates in election")
            break
```

```
PSparty needs minimum 198 time to get 212 mandates in election
PPD/PSDparty needs minimum 150 time to get 154 mandates in election
B.E.party needs minimum 52 time to get 38 mandates in election
```

Wyszukiwanie najlepszego czasu dla otrzymania najlepszego wynniku partii wlasna implementacja + bsearch

In [661]:

```
for party in bigest_parties:
    linreg = LinearRegresionImpl(time_[party][1], time_[party][0])
    prediction = linreg.predict_linear(time_[party][1])
    timestamp = time_[party][0][binary_search(list(prediction.flatten(order='C').astype(int
    print(party + "party needs minimum " + str(timestamp) + " time to get " + \
          str(time_[party][1].max()) + " mandates in election")
```

```
PSparty needs minimum 215.0 time to get 212 mandates in election
PPD/PSDparty needs minimum 130.0 time to get 154 mandates in election
B.E.party needs minimum 130.0 time to get 38 mandates in election
```

In [662]:

```
for party in bigest_parties:
    linreg = LinearRegresionImpl(time_[party][1], time_[party][0])
    prediction = linreg.predict_linear(time_[party][1])
    for i, predict in enumerate(prediction.flatten(order='C').astype(int)):
        if predict in list(range(time_[party][1].max()-15, time_[party][1].max()+15)):
            print(party + "party needs minimum " + str(predict) + " time to get " + \
                  str(time_[party][1].max()) + " mandates in election")
            break
```

```
PSparty needs minimum 198 time to get 212 mandates in election
PPD/PSDparty needs minimum 150 time to get 154 mandates in election
B.E.party needs minimum 52 time to get 38 mandates in election
```

Przez osobliwości algorytmu B-Search brak możliwości wyznaczyć minimalny czas dla partii B.E

Porwnanie Linear Regression sk-learn i wlasnej implementacji

In [666]:

```
party = 'PS'
```

In [667]:

```
from sklearn import metrics
```

In [668]:

```
import tracemalloc
```

In [680]:

```
%%time

tracemalloc.start()

##########################################################
for i in range(10000):
    sk_linreg.fit(time_[party][1].reshape(-1, 1),time_[party][0].reshape(-1, 1))
    prediction = sk_linreg.predict(time_[party][1].reshape(-1, 1))
##########################################################

current, sk_learn_peak = tracemalloc.get_traced_memory()
print(f"Current:{current / 10**6}MB; Peak was {sk_learn_peak / 10**6}MB")
tracemalloc.stop()
```

```
Current:0.151747MB; Peak was 0.159136MB
Wall time: 6.87 s
```

In [681]:

```
abs_er_sk = metrics.mean_absolute_error(time_[party][1], prediction)
sq_er_sk = metrics.mean_squared_error(time_[party][1], prediction)
mean_sq = np.sqrt(metrics.mean_squared_error(time_[party][1], prediction))
print(abs_er_sk)
print(sq_er_sk)
print(mean_sq)
```

```
20.121296296296308
405.8975358987365
20.14689891518634
```

In [682]:

```
%%time

tracemalloc.start()

##########################################################
for i in range(10000):
    linreg = LinearRegresionImpl(time_[party][1], time_[party][0])
    prediction = linreg.predict_linear(time_[party][1])
##########################################################

current, my_lin_peak = tracemalloc.get_traced_memory()
print(f"Current:{current / 10**6}MB; Peak was {my_lin_peak / 10**6}MB")
tracemalloc.stop()
```

```
Current:0.150058MB; Peak was 0.152554MB
Wall time: 2.14 s
```

In [684]:

```
abs_er = metrics.mean_absolute_error(time_[party][1], prediction)
sq_er = metrics.mean_squared_error(time_[party][1], prediction)
mean = np.sqrt(metrics.mean_squared_error(time_[party][1], prediction))
print(abs_er)
print(sq_er)
print(mean)
```

```
20.12129629629633
405.89753589873726
20.14689891518636
```

Algorytmy czasowo dzialają bardzo szybko i pochlaniają podobną ilość pamięci, ale algorytm wlasnej implementacji ma brak wszytej normalizacji, a także nie może dzialać z dopasowaniem do skąplikowanych krzywych które się znajdują w przestrzeniach większych niż 2D

Zaimplementowana przez mnie regressja linjowa ma nieco większy bląd przy większej dokladności co może być problemem dla zadan które potrzebują wielkiej dokladności predykcji

In [ ]:

```
```

Index of comments

8.1 predict powinien być oparty na A = linalg.inv(X.T @ X) @ (X.T @ y)