Import packages and classes

In [1]:

```
import pandas as pd
import numpy as np
from datetime import datetime
import time

import statsmodels.api as sm

from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
# Suppress scientific notation in Pandas
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

Define a function

In [3]:

```
# Convert timestamp to date format
# Useful for making the timestamp humanely friendly

def timestampToDate(timestamp):

    return timestampToDateTime(timestamp).date()
```

In [4]:

```
# Convert timestamp to date and time format
# Useful for making the timestamp humanely friendly

def timestampToDateTime(timestamp):

    return datetime.fromtimestamp(timestamp)
```

Importing the data

In [5]:

```
dfOriginal = pd.read_csv('Datasets/rvnHalvingPrediction.csv')
df = dfOriginal.copy()
df
```

Out[5]:

	Unnamed: 0	height	time
0	0	1778781	1622516234
1	1	1778780	1622516196
2	2	1778779	1622516185
3	3	1778778	1622516158
4	4	1778777	1622515956
...	...	...	...
1774755	1774755	5	1515015840
1774756	1774756	4	1515015833
1774757	1774757	3	1515015816
1774758	1774758	2	1515015759
1774759	1774759	1	1515015723

1774760 rows × 3 columns

In [6]:

```
df.dtypes
```

Out[6]:

```
Unnamed: 0    int64
height        int64
time          int64
dtype: object
```

Data Transformation

In [7]:

```
# Missing values by columns/variables
df.isna().sum()
```

Out[7]:

```
Unnamed: 0    0
height        0
time          0
dtype: int64
```

In [8]:

```
# Removing garbage
df = df.drop('Unnamed: 0', 1)

df.head(10)
```

Out[8]:

	height	time
0	1778781	1622516234
1	1778780	1622516196
2	1778779	1622516185
3	1778778	1622516158
4	1778777	1622515956
5	1778776	1622515953
6	1778775	1622515941
7	1778774	1622515909
8	1778773	1622515865
9	1778772	1622515833

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1774760 entries, 0 to 1774759
Data columns (total 2 columns):
 #   Column  Dtype
---  ------  -----
 0   height  int64
 1   time    int64
dtypes: int64(2)
memory usage: 27.1 MB
```

Data exploration

Check the average time elapsed between blocks being generated monthly

In [10]:

```
dfExploration = df.copy()
dfExploration
```

Out[10]:

	height	time
0	1778781	1622516234
1	1778780	1622516196
2	1778779	1622516185
3	1778778	1622516158
4	1778777	1622515956
...	...	...
1774755	5	1515015840
1774756	4	1515015833
1774757	3	1515015816
1774758	2	1515015759
1774759	1	1515015723

1774760 rows × 2 columns

In [11]:

```
# Handling the dates
dfExploration['dateTime']  = dfExploration['time']
dfExploration['dateTime']  = dfExploration['dateTime'].apply(timestampToDateTime)
dfExploration['monthYear'] = dfExploration['dateTime'].dt.to_period('M')

dfExploration.head(10)
```

Out[11]:

	height	time	dateTime	monthYear
0	1778781	1622516234	2021-05-31 23:57:14	2021-05
1	1778780	1622516196	2021-05-31 23:56:36	2021-05
2	1778779	1622516185	2021-05-31 23:56:25	2021-05
3	1778778	1622516158	2021-05-31 23:55:58	2021-05
4	1778777	1622515956	2021-05-31 23:52:36	2021-05
5	1778776	1622515953	2021-05-31 23:52:33	2021-05
6	1778775	1622515941	2021-05-31 23:52:21	2021-05
7	1778774	1622515909	2021-05-31 23:51:49	2021-05
8	1778773	1622515865	2021-05-31 23:51:05	2021-05
9	1778772	1622515833	2021-05-31 23:50:33	2021-05

In [12]:

```
# Time between blocks

dfExploration['secondsBetweenBlocks'] = dfExploration['dateTime'].diff().astype('timedelta6
dfExploration['secondsBetweenBlocks'] = dfExploration['secondsBetweenBlocks'].fillna(0)
dfExploration.head(10)
```

Out[12]:

	height	time	dateTime	monthYear	secondsBetweenBlocks
0	1778781	1622516234	2021-05-31 23:57:14	2021-05	0.00000
1	1778780	1622516196	2021-05-31 23:56:36	2021-05	38.00000
2	1778779	1622516185	2021-05-31 23:56:25	2021-05	11.00000
3	1778778	1622516158	2021-05-31 23:55:58	2021-05	27.00000
4	1778777	1622515956	2021-05-31 23:52:36	2021-05	202.00000
5	1778776	1622515953	2021-05-31 23:52:33	2021-05	3.00000
6	1778775	1622515941	2021-05-31 23:52:21	2021-05	12.00000
7	1778774	1622515909	2021-05-31 23:51:49	2021-05	32.00000
8	1778773	1622515865	2021-05-31 23:51:05	2021-05	44.00000
9	1778772	1622515833	2021-05-31 23:50:33	2021-05	32.00000

In [13]:

```
# After verifying that the time between blocks is correct, time and dateTime can be deleted
dfExploration = dfExploration.drop('time', 1)
dfExploration = dfExploration.drop('dateTime', 1)
dfExploration = dfExploration.drop('height', 1)
dfExploration.head(10)
```

Out[13]:

	monthYear	secondsBetweenBlocks
0	2021-05	0.00000
1	2021-05	38.00000
2	2021-05	11.00000
3	2021-05	27.00000
4	2021-05	202.00000
5	2021-05	3.00000
6	2021-05	12.00000
7	2021-05	32.00000
8	2021-05	44.00000
9	2021-05	32.00000

In [14]:

```
# seconds between blocks
dfExploration = dfExploration.groupby('monthYear').mean('secondsBetweenBlocks')

dfExploration
```

Out[14]:

	secondsBetweenBlocks
monthYear	
2018-01	45.78702
2018-02	54.31378
2018-03	56.14346
2018-04	61.29363
2018-05	59.86616
2018-06	60.45927
2018-07	63.21432
2018-08	134.28796
2018-09	60.41391
2018-10	60.29142
2018-11	60.40072
2018-12	60.41646
2019-01	60.41121
2019-02	60.38584
2019-03	60.25751
2019-04	60.39157
2019-05	60.41244
2019-06	60.43658
2019-07	60.37024
2019-08	60.33564
2019-09	60.35429
2019-10	60.54681
2019-11	60.43723
2019-12	60.34316
2020-01	60.32122
2020-02	60.35775
2020-03	60.38163
2020-04	60.40399
2020-05	59.70763
2020-06	60.39351
2020-07	60.46485

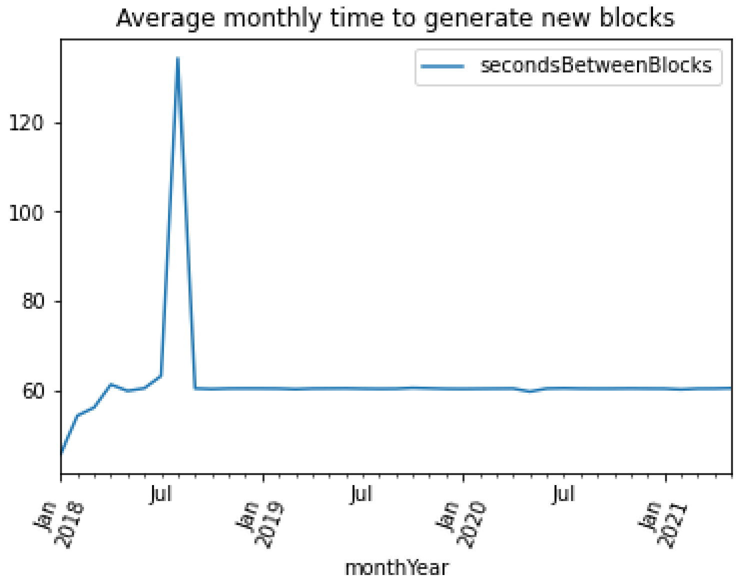
	secondsBetweenBlocks
monthYear	
2020-08	60.39594
2020-09	60.37655
2020-10	60.38597
2020-11	60.41836
2020-12	60.38870
2021-01	60.37425
2021-02	60.19517
2021-03	60.37560
2021-04	60.39257
2021-05	60.47608

In [15]:

```
## The line / model
for i, col in enumerate(dfExploration.columns):
    dfExploration[col].plot()

plt.title('Average monthly time to generate new blocks')

plt.xticks(rotation=70)
plt.legend(dfExploration.columns)
```

Out[15]:

```
<matplotlib.legend.Legend at 0x1f03bbf2fa0>
```



Results of the data exploration

We can see that the average time for creating new blocks has been stable from 09/2018, so that it is possible to predict the date of the next halvings

Data Transformation - last step

In [16]:

```
df
```

Out[16]:

	height	time
0	1778781	1622516234
1	1778780	1622516196
2	1778779	1622516185
3	1778778	1622516158
4	1778777	1622515956
...	...	...
1774755	5	1515015840
1774756	4	1515015833
1774757	3	1515015816
1774758	2	1515015759
1774759	1	1515015723

1774760 rows × 2 columns

In [17]:

```
df.sort_values(by=['height'], inplace=True)
df.reset_index(drop=True, inplace=True)

df.head(10)
```

Out[17]:

	height	time
0	1	1515015723
1	2	1515015759
2	3	1515015816
3	4	1515015833
4	5	1515015840
5	6	1515015847
6	7	1515015905
7	8	1515015936
8	9	1515015970
9	10	1515015971

Cut data prior to 09/01/2018

In [18]:

```
cutoff_date = datetime(2018, 9, 1)
cutoff_date
```

Out[18]:

```
datetime.datetime(2018, 9, 1, 0, 0)
```

In [19]:

```
cutoff_datetime = datetime.combine(cutoff_date, datetime.min.time())
cutoff_datetime
```

Out[19]:

```
datetime.datetime(2018, 9, 1, 0, 0)
```

In [20]:

```
cutoff_timestamp = time.mktime(cutoff_datetime.timetuple())
cutoff_timestamp = int(cutoff_timestamp)
cutoff_timestamp
```

Out[20]:

```
1535770800
```

In [21]:

```
df = df[df["time"] > cutoff_timestamp]
df
```

Out[21]:

	height	time
337717	341701	1535770808
337718	341702	1535770841
337719	341703	1535770887
337720	341704	1535770907
337721	341705	1535770972
...	...	...
1774755	1778777	1622515956
1774756	1778778	1622516158
1774757	1778779	1622516185
1774758	1778780	1622516196
1774759	1778781	1622516234

1437043 rows × 2 columns

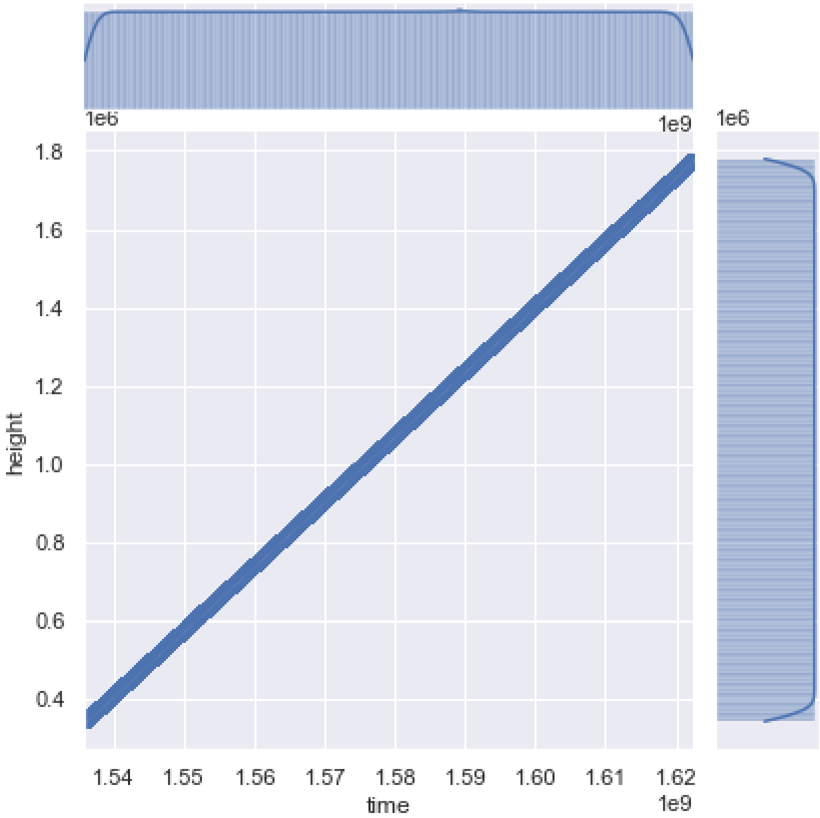
Plotting the data

In [22]:

```
sns.set_theme(color_codes=True)
sns.jointplot(x='time', y='height', data=df, kind="reg")
```

Out[22]:

```
<seaborn.axisgrid.JointGrid at 0x1f03bbf2940>
```



Correlation Analysis

In [23]:

```
correlations = df.corr()
correlations
```

Out[23]:

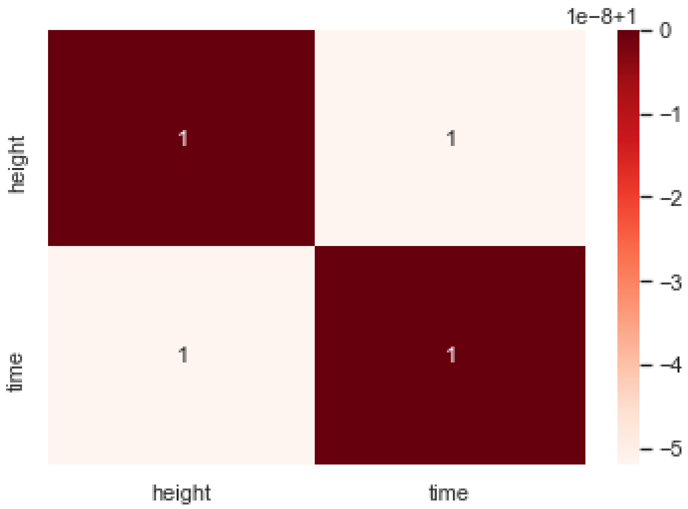
	height	time
height	1.00000	1.00000
time	1.00000	1.00000

In [24]:

```
#heatmap


sns.heatmap(df.corr(),annot=True, cmap='Reds')
```

Out[24]:

```
<AxesSubplot:>
```



Defining training and testing dataframes

In [25]:

```
# x = independent variable -> height
# y = dependent variable -> time

# here we have 1 variable for linear regression
X = df['height']
y = df['time']

X_training, X_test, y_training, y_test = train_test_split( X, y,
                                                           test_size = 0.2, random_state = 2

print(f"Training dataframe: {X_training.shape[0]} lines")
print(f"Test dataframe....: {X_test.shape[0]} lines")
```

```
Training dataframe: 1149634 lines
Test dataframe....: 287409 lines
```

Linear Regression

In [26]:

```
X_training = sm.add_constant(X_training)
X_test = sm.add_constant(X_test)
```

In [27]:

```
# Create a model and fit it
model_SM = sm.OLS(y_training, X_training).fit()
type(model_SM)

# SM = statsmodels
```

Out[27]:

```
statsmodels.regression.linear_model.RegressionResultsWrapper
```

Get results

In [28]:

```
print('Coefficient of Determination (𝑅²):', model_SM.rsquared)
```

```
Coefficient of Determination (𝑅²): 0.9999998959774744
```

In [29]:

```
print('Adjusted Coefficient of Determination (adjusted 𝑅²):', model_SM.rsquared_adj)
```

```
Adjusted Coefficient of Determination (adjusted 𝑅²): 0.9999998959773839
```

In [30]:

```
print('Regression Coefficients(intercept, 𝑏₀, 𝑏₁):\n', model_SM.params)
```

```
Regression Coefficients(intercept, 𝑏₀, 𝑏₁):
 const    1515155592.04584
height           60.35495
dtype: float64
```

In [31]:

```
print('P-values:\n', model_SM.pvalues)
```

```
P-values:
 const    0.00000
height   0.00000
dtype: float64
```

In [32]:

```
model_SM.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	time	**R-squared:**	1.000
Model:	OLS	**Adj. R-squared:**	1.000
Method:	Least Squares	**F-statistic:**	1.105e+13
Date:	Mon, 26 Jul 2021	**Prob (F-statistic):**	0.00
Time:	15:00:33	**Log-Likelihood:**	-1.1974e+07
No. Observations:	1149634	**AIC:**	2.395e+07
Df Residuals:	1149632	**BIC:**	2.395e+07
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.515e+09	20.672	7.33e+07	0.000	1.52e+09	1.52e+09
height	60.3549	1.82e-05	3.32e+06	0.000	60.355	60.355

Omnibus:	101837.268	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	66204.888
Skew:	0.469	**Prob(JB):**	0.00
Kurtosis:	2.290	**Cond. No.**	3.12e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.12e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

Evaluate

In [33]:

```
y_pred_SM = model_SM.predict(X_test)
print('predicted response:', y_pred_SM, sep='\n')
```

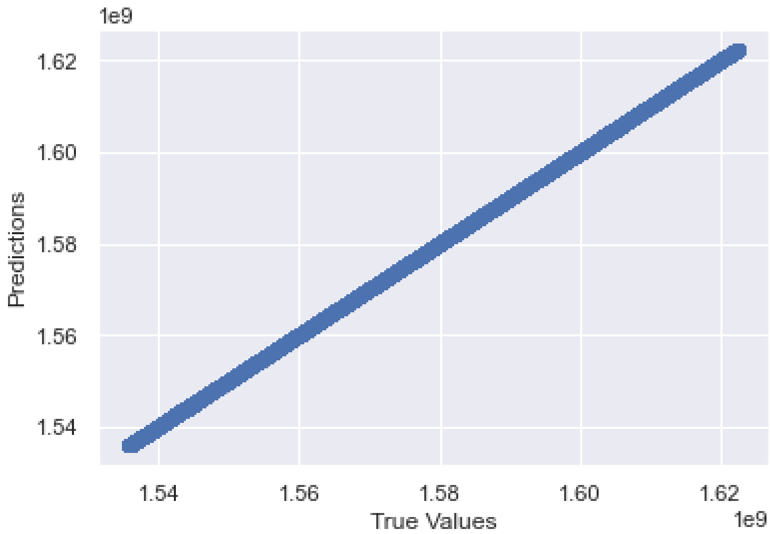
```
predicted response:
555866     1548945551.26831
821299     1564965866.96886
1572819    1610325386.93980
1427873    1601576454.34492
1133921    1583834272.32448
                 ...
606496     1552001443.01035
1312800    1594630927.60509
1542586    1608500494.72317
623655     1553037073.56814
1676371    1616575383.25549
Length: 287409, dtype: float64
```

In [34]:

```
## The line / model
plt.scatter(y_test, y_pred_SM)
plt.xlabel("True Values")
plt.ylabel("Predictions")
```

Out[34]:

```
Text(0, 0.5, 'Predictions')
```



In [35]:

```
print('Mean Absolute Error(MAE): ', metrics.mean_absolute_error(y_test, y_pred_SM))
```

```
Mean Absolute Error(MAE):  6525.262966041408
```

In [36]:

```
print('Mean Square Error(MSE): ', metrics.mean_squared_error(y_test, y_pred_SM))
```

```
Mean Square Error(MSE):  65073053.70010137
```

In [37]:

```
print('Root Mean Square Error(RMSE): ', np.sqrt(metrics.mean_squared_error(y_test, y_pred_S
```

```
Root Mean Square Error(RMSE):  8066.787074176519
```

About the results

R2 and the graph of predictions vs correct values give us good results, while MAE, MSE and RMSE indicate that the model is bad.

Let's examine the data and determine what the forecast error is on a scale of minutes, so we'll know how useful a forecast obtained with this model can be.

In [38]:

```
dfResults = pd.DataFrame()
dfResults= pd.concat([y_test, y_pred_SM], axis=1)
dfResults.rename(columns={0:"prediction"}, inplace=True)
dfResults
```

Out[38]:

	time	prediction
555866	1548943376	1548945551.26831
821299	1564970602	1564965866.96886
1572819	1610326237	1610325386.93980
1427873	1601571728	1601576454.34492
1133921	1583846688	1583834272.32448
...	...	...
606496	1551997975	1552001443.01035
1312800	1594620203	1594630927.60509
1542586	1608500160	1608500494.72317
623655	1553035136	1553037073.56814
1676371	1616570133	1616575383.25549

287409 rows × 2 columns

In [39]:

```
# Handling the dates
dfResults.sort_index(inplace=True)

dfResults['dateTime']  = dfResults['time']
dfResults['dateTime']  = dfResults['dateTime'].apply(timestampToDateTime)

dfResults['dateTime_pred']  = dfResults['prediction']
dfResults['dateTime_pred']  = dfResults['dateTime_pred'].apply(timestampToDateTime)

dfResults
```

Out[39]:

	time	prediction	dateTime	dateTime_pred
337718	1535770841	1535778998.58797	2018-09-01 00:00:41	2018-09-01 02:16:38.587965
337720	1535770907	1535779119.29786	2018-09-01 00:01:47	2018-09-01 02:18:39.297862
337725	1535771192	1535779421.07260	2018-09-01 00:06:32	2018-09-01 02:23:41.072603
337726	1535771219	1535779481.42755	2018-09-01 00:06:59	2018-09-01 02:24:41.427551
337727	1535771479	1535779541.78250	2018-09-01 00:11:19	2018-09-01 02:25:41.782500
...	...	...	...	...
1774728	1622514088	1622511956.32468	2021-05-31 23:21:28	2021-05-31 22:45:56.324683
1774730	1622514365	1622512077.03458	2021-05-31 23:26:05	2021-05-31 22:47:57.034580
1774732	1622514596	1622512197.74448	2021-05-31 23:29:56	2021-05-31 22:49:57.744476
1774736	1622514853	1622512439.16427	2021-05-31 23:34:13	2021-05-31 22:53:59.164269
1774738	1622515092	1622512559.87417	2021-05-31 23:38:12	2021-05-31 22:55:59.874166

287409 rows × 4 columns

In [40]:

```
dfResults['error'] = (dfResults['dateTime'] - dfResults['dateTime_pred']).astype('timedelta
dfResults['error'] = dfResults['error'].fillna(0)
dfResults
```

Out[40]:

	time	prediction	dateTime	dateTime_pred	error
337718	1535770841	1535778998.58797	2018-09-01 00:00:41	2018-09-01 02:16:38.587965	-136.00000
337720	1535770907	1535779119.29786	2018-09-01 00:01:47	2018-09-01 02:18:39.297862	-137.00000
337725	1535771192	1535779421.07260	2018-09-01 00:06:32	2018-09-01 02:23:41.072603	-138.00000
337726	1535771219	1535779481.42755	2018-09-01 00:06:59	2018-09-01 02:24:41.427551	-138.00000
337727	1535771479	1535779541.78250	2018-09-01 00:11:19	2018-09-01 02:25:41.782500	-135.00000
...	...	...	...	...	...
1774728	1622514088	1622511956.32468	2021-05-31 23:21:28	2021-05-31 22:45:56.324683	35.00000
1774730	1622514365	1622512077.03458	2021-05-31 23:26:05	2021-05-31 22:47:57.034580	38.00000
1774732	1622514596	1622512197.74448	2021-05-31 23:29:56	2021-05-31 22:49:57.744476	39.00000
1774736	1622514853	1622512439.16427	2021-05-31 23:34:13	2021-05-31 22:53:59.164269	40.00000
1774738	1622515092	1622512559.87417	2021-05-31 23:38:12	2021-05-31 22:55:59.874166	42.00000

287409 rows × 5 columns

In [41]:

```
dfError = pd.DataFrame()
dfError['error_min'] = dfResults['error'].astype(int)

dfError.sort_index(inplace=True)

dfError.reset_index(inplace=True)
dfError = dfError.drop('index', 1)

dfError
```

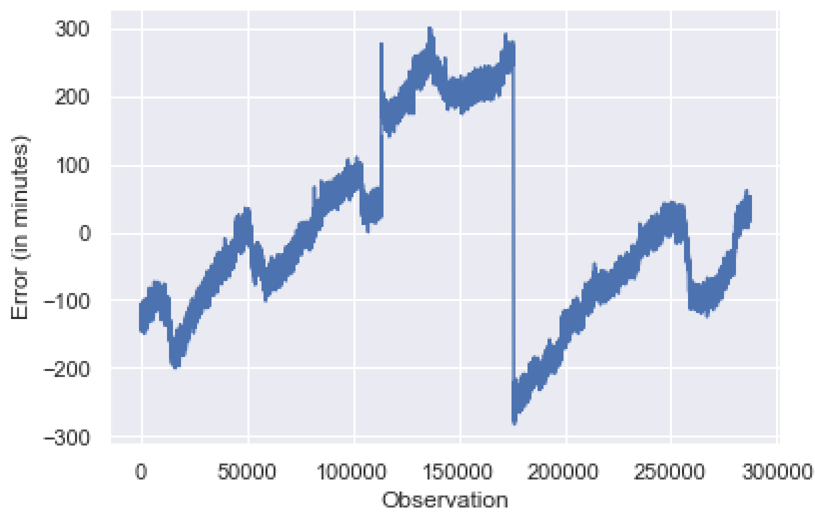
Out[41]:

	error_min
0	-136
1	-137
2	-138
3	-138
4	-135
...	...
287404	35
287405	38
287406	39
287407	40
287408	42

287409 rows × 1 columns

In [42]:

```
plt.plot(dfError)
plt.xlabel("Observation")
plt.ylabel("Error (in minutes)")
plt.show()
```



In [43]:

```
dfError['error_min_module'] = dfError['error_min'].abs()
dfError
```

Out[43]:

	error_min	error_min_module
0	-136	136
1	-137	137
2	-138	138
3	-138	138
4	-135	135
...	...	...
287404	35	35
287405	38	38
287406	39	39
287407	40	40
287408	42	42

287409 rows × 2 columns

In [44]:

```
def toHourMin(minutes):

    minutes = abs(minutes)

    h = 0
    m = 0

    if (minutes % 60 >= 0):
        h = int(minutes/60)
        m = int(minutes % 60)
    else:
        m = minutes

    return str(h)+'h '+str(m)+ 'm'
```

In [45]:

```
print('Highest error value: ', dfError['error_min'].max())
toHourMin(dfError['error_min'].max())
```

```
Highest error value:  301
```

Out[45]:

```
'5h 1m'
```

In [46]:

```
print('Lowest error value: ', dfError['error_min'].min())
toHourMin(dfError['error_min'].min())
```

```
Lowest error value:  -283
```

Out[46]:

```
'4h 43m'
```

In [47]:

```
print('Average error: ', dfError['error_min_module'].mean())
toHourMin(dfError['error_min_module'].mean())
```

```
Average error:  108.8352626396529
```

Out[47]:

```
'1h 48m'
```

Understanding the error

In [48]:

```
dfErrorAnalysis = dfError['error_min'].value_counts(bins = 7, sort=False)

dfErrorAnalysis = dfErrorAnalysis.reset_index()
dfErrorAnalysis.rename(columns={'index':'Class_Interval'}, inplace=True)

dfErrorAnalysis.rename(columns={'error_min':'Frequency'}, inplace=True)

dfErrorAnalysis['Relative_Frequency'] = dfErrorAnalysis['Frequency']/dfErrorAnalysis['Frequ

dfErrorAnalysis
```

Out[48]:

	Class_Interval	Frequency	Relative_Frequency
0	(-283.585, -199.571]	14584	0.05074
1	(-199.571, -116.143]	33783	0.11754
2	(-116.143, -32.714]	93234	0.32439
3	(-32.714, 50.714]	66962	0.23299
4	(50.714, 134.143]	16423	0.05714
5	(134.143, 217.571]	33211	0.11555
6	(217.571, 301.0]	29212	0.10164

In [49]:

```
fig = plt.figure(figsize=(10, 4))
ax = fig.add_axes([0,0,1,1])
ax.bar(dfErrorAnalysis['Class_Interval'].astype(str), dfErrorAnalysis['Frequency'])
plt.xticks(size = 9.5)
plt.grid(True)
plt.title('Understanding the error')
plt.xlabel('Frequency')
plt.ylabel('Class Interval')
plt.show()
```

Conclusion on the evaluation of results

Considering the maximum margin of error of about 5 hours, the application of this technique seems to be didactically adequate for the purpose of trying to predict the moment of occurrence of the next Ravencoin reduction.

Real world application: Predicting the next halvings

In [50]:

```
blocks2HalvingRVN = 2100000
blocks2nextHalvingsRVN = [blocks2HalvingRVN, blocks2HalvingRVN*2, blocks2HalvingRVN*3, bloc
new_x = np.array(blocks2nextHalvingsRVN).reshape((-1, 1))
new_x = sm.add_constant(new_x)
new_x
```

Out[50]:

```
array([[1.0e+00, 2.1e+06],
       [1.0e+00, 4.2e+06],
       [1.0e+00, 6.3e+06],
       [1.0e+00, 8.4e+06]])
```

In [51]:

```
new_y = model_SM.predict(new_x)
print('predicted response:', new_y, sep='\n')
```

```
predicted response:
[1.64190098e+09 1.76864637e+09 1.89539177e+09 2.02213716e+09]
```

In [52]:

```
dfHalvingProjection = pd.DataFrame(new_y)
dfHalvingProjection.columns = ['predicted_timestamp']
dfHalvingProjection
```

Out[52]:

	predicted_timestamp
0	1641900983.46429
1	1768646374.88275
2	1895391766.30120
3	2022137157.71966

In [53]:

```
# Making timestamp humanly friendly
# For each timestamp a new block is generated, and each block corresponds to 5,000 new coin

dfHalvingProjection['predicted_date']  = dfHalvingProjection['predicted_timestamp']
dfHalvingProjection['predicted_date']  = dfHalvingProjection['predicted_timestamp'].apply(t

dfHalvingProjection['predicted_datetime']  = dfHalvingProjection['predicted_timestamp']
dfHalvingProjection['predicted_datetime']  = dfHalvingProjection['predicted_timestamp'].app
dfHalvingProjection
```

Out[53]:

	predicted_timestamp	predicted_date	predicted_datetime
0	1641900983.46429	2022-01-11	2022-01-11 08:36:23.464292
1	1768646374.88275	2026-01-17	2026-01-17 07:39:34.882746
2	1895391766.30120	2030-01-23	2030-01-23 06:42:46.301201
3	2022137157.71966	2034-01-29	2034-01-29 05:45:57.719656

In [54]:

```
dfPlot = pd.DataFrame()
dfPlot['Forecast'] = dfHalvingProjection['predicted_date']
dfPlot
```

Out[54]:

	Forecast
0	2022-01-11
1	2026-01-17
2	2030-01-23
3	2034-01-29

In [55]:

```
# Adding date of first mined block
dfPlot.loc[4] = [datetime.strptime('10/03/2018', '%d/%m/%Y').date()]
dfPlot.sort_values(by=['Forecast'], inplace=True)

dfPlot.reset_index(inplace=True)
dfPlot = dfPlot.drop('index', 1)

dfPlot.reset_index(inplace=True)
dfPlot.rename(columns={'index':'Halving'}, inplace=True)

dfPlot
```

Out[55]:

	Halving	Forecast
0	0	2018-03-10
1	1	2022-01-11
2	2	2026-01-17
3	3	2030-01-23
4	4	2034-01-29

In [56]:

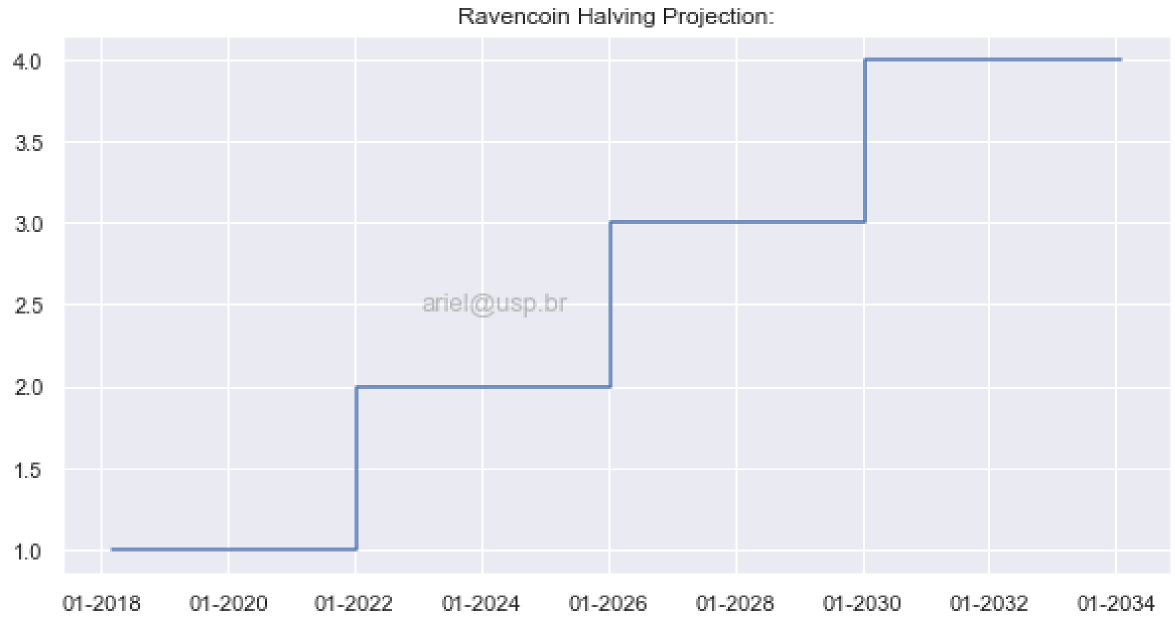
```
#The first halving only happen in 2022
dfPlot.at[0, 'Halving'] = 1
dfPlot
```

Out[56]:

	Halving	Forecast
0	1	2018-03-10
1	1	2022-01-11
2	2	2026-01-17
3	3	2030-01-23
4	4	2034-01-29

In [57]:

```
from matplotlib.dates import DateFormatter

fig, ax = plt.subplots(figsize=(10, 5))

date_form = DateFormatter("%m-%Y")
ax.xaxis.set_major_formatter(date_form)

ax.text(0.39, 0.5, 'ariel@usp.br', fontsize=13, ha='center', va='center',
           transform=ax.transAxes, color='grey', alpha=0.5)

plt.title('Ravencoin Halving Projection:')

plt.step(dfPlot['Forecast'], dfPlot['Halving'])

plt.show()
```



The validity of the projection shown in the graph depends on the allocated mining power and the difficulty setting. Maintaining current conditions, the first halving should take place on January 11, 2022.

An indication that our projection may be correct is that the official Ravencoin website informs that the first halving is expected to take place in January 2022. Source: [https://ravencoin.org/halving/ (https://ravencoin.org/halving/)](https://ravencoin.org/halving/)

It is too early to make an assertive prediction of the subsequent halvings, the prediction attempt was made just to facilitate the understanding of the results.

Type *Markdown* and LaTeX: α^2