Contents

Bitcoin price prediction with Py the past does not repeat

Joaquín Amat Rodrigo, Javier Escobar Ortiz
March, 2022 (last update September, 2022)

- Skforecast: time series forecasting with Python and Scikit-learn (https://www.cienciadedatos.net/documentos/py2 scikitlearn.html)
- Forecasting electricity demand with Python (https://www.cienciadedatos.net/documentos/py29-forecasting-electri
- Forecasting web traffic with machine learning and Python (https://www.cienciadedatos.net/documentos/py37-fore learning.html)
- Forecasting time series with gradient boosting: Skforecast, XGBoost, LightGBM and CatBoost (https://www.cienc forecasting-time-series-with-skforecast-xgboost-lightgbm-catboost.html)
- Prediction intervals in forecasting models (https://www.cienciadedatos.net/documentos/py42-forecasting-predictio

Introduction

A time series is a succession of chronologically ordered data spaced at equal or u (https://joaquinamatrodrigo.github.io/skforecast/latest/quick-start/introduction-forecasting.html) proce value of a time series, either by modeling the series solely based on its past behavior (autoreg variables.

When creating a forecaster model, historical data are used to get a mathematical representation cap idea is based on a very important assumption: **the future behavior of a phenomenon can be** However, this rarely happens in reality, or at least not in its entirety. For more on this, see the followir

$$Forecast = pattern + unexplained\ variance$$

The first term of the equation refers to everything that has a repetitive character over time (trend, second term represents everything that influences the response variable but is not captured (explain

The greater the importance of the first term relative to the second, the greater the probability of autoregressive forecasting models. As the second term gains weight, it becomes necessary to inc into the model to help explain the observed behavior.

A good study of the modeled phenomenon and the ability to recognize to what extent its behavior ca a lot of unnecessary effort.

This document shows an example of how to identify situations where the autoregressive forecas results. As an example, an attempt to predict the daily closing price of Bitcoin using machine l purpose, **Skforecast** (https://joaquinamatrodrigo.github.io/skforecast/latest/index.html) is used, a among other things, to adapt any **Scikit-learn** regressor to forecasting problems.

Use Case

Bitcoin (https://en.wikipedia.org/wiki/Bitcoin) (₿) is a decentralized cryptocurrency t another through the bitcoin peer-to-peer network without intermediaries. Transactions distributed ledger called Blockchain. Bitcoins are created as a reward fo (https://en.wikipedia.org/wiki/Bitcoin#Mining) and can be exchanged for other currencies, products, a

Although there may be different opinions about Bitcoin, whether as a high-risk speculative asset value, it is undeniable that it has become one of the most valuable financial assets globally (https://8marketcap.com/) shows a list of all financial assets ranked by market capitalization. Bitcoi 10. It is close to world-renowned companies such as Tesla or globally accepted safe-haven assets s Bitcoin, and the world of cryptocurrencies, makes it an interesting phenomenon to model.

The aim is to generate a forecasting model capable of predicting the price of Bitcoin. A time series i closing (Close), maximum (High), and minimum (Low) prices of Bitcoin in US dollars (USD) from 201

Libraries

The libraries used in this document are:

In [34]:
```
# Data manipulation
# ==============================================================================
import pandas as pd
import numpy as np
import datetime
from cryptocmd import CmcScraper

# Plots
# ==============================================================================
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.express as px
import seaborn as sns
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
plt.style.use('ggplot')

# Bitcoin colors
# ==============================================================================
palette_btc = {'orange': '#f7931a',
               'white' : '#ffffff',
               'gray'  : '#4d4d4d',
               'blue'  : '#0d579b',
               'green' : '#329239'
              }

# Modelling and Forecasting
# ==============================================================================
from skforecast.ForecasterAutoreg import ForecasterAutoreg
from skforecast.model_selection import backtesting_forecaster
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_absolute_error
```

Data

The data download is performed using cryptocmd (https://openbase.com/python/cryptocmd). Thi historical cryptocurrency data from the Coinmarketcap (https://coinmarketcap.com/) website. The info

- `Date`: date of the record.
- `Open`: the opening price, the price at which an asset, in this case, Bitcoin, trades at the beginnin
- `High`: the maximum price of the day, the highest price reached by Bitcoin on that day, (USD).
- `Low`: the minimum price of the day, the lowest price reached by the Bitcoin on that day, (USD).
- `Close`: the closing price, the price at which Bitcoin trades at the end of the day, (USD).
- `Volume`: the sum of actual trades made during the day, (USD).
- `Market Cap`: market capitalization, the total value of all shares of a company or, in the case of all coins in circulation, (USD).

Note: the cryptocurrency market is uninterrupted. It operates 24 hours a day, 7 days a week. Howev close price coincides with the open price of the next day because of the fluctuations that the value o undergo during the last second of the day.

In [2]:
```
# Data download
# ==============================================================================

# Scraper is initialized, symbol, start and end of download are included
scraper = CmcScraper('BTC', '28-04-2013', '01-01-2022')

# Transform collected data into a dataframe
data = scraper.get_dataframe()
data.sort_values(by='Date', ascending=True, inplace=True)

pd.set_option('display.max_columns', None)
display(data)
pd.reset_option('display.max_columns')
```

	Date	Open	High	Low	Close	Volume	Market Ca
3170	2013-04-28	135.300003	135.979996	132.100006	134.210007	0.000000e+00	1.488567e+(
3169	2013-04-29	134.444000	147.488007	134.000000	144.539993	0.000000e+00	1.603769e+(
3168	2013-04-30	144.000000	146.929993	134.050003	139.000000	0.000000e+00	1.542813e+(
3167	2013-05-01	139.000000	139.889999	107.720001	116.989998	0.000000e+00	1.298955e+(
3166	2013-05-02	116.379997	125.599998	92.281898	105.209999	0.000000e+00	1.168517e+(
...	...	...	...	...	...	...	
4	2021-12-28	50679.859377	50679.859377	47414.209925	47588.854777	3.343038e+10	9.000762e+
3	2021-12-29	47623.870463	48119.740950	46201.494371	46444.710491	3.004923e+10	8.784788e+
2	2021-12-30	46490.606049	47879.965500	46060.313166	47178.125843	2.668649e+10	8.923863e+
1	2021-12-31	47169.372859	48472.527490	45819.954553	46306.446123	3.697417e+10	8.759394e+
0	2022-01-01	46311.744663	47827.310995	46288.486095	47686.811509	2.458267e+10	9.021042e+

3171 rows × 7 columns

In [3]:
```
# Data preparation
# ==============================================================================
data['date'] = pd.to_datetime(data['Date'], format='%Y-%m-%d %H:%M:%S')
data = data.loc[:, ['date', 'Open', 'Close', 'High', 'Low']]
data = data.rename({'Open': 'open', 'Close': 'close', 'High': 'high', 'Low': 'low
                    axis=1)
data = data.set_index('date')
data = data.asfreq('D')
data = data.sort_index()
```

When setting a frequency with the `asfreq()` method, **Pandas** fills the gaps that may exist in the ti ensure the indicated frequency. Therefore, it should be checked if missing values have appeared afte

In [4]:
```
print(f'Number of rows with missing values: {data.isnull().any(axis=1).mean()}')
```

```
Number of rows with missing values: 0.0
```

Bitcoin halving as an exogenous variable

Halving is a programmed event and is part of the design and operation of some cryptocurrencies. blocks of the network, in this case, Bitcoin, and each time they succeed, they receive an amount varies from time to time.

Every time 210,000 blocks are added, the reward in the Bitcoin blockchain change occurs. approximately every 4 years and reduces the coins miners receive as a reward by half.

In the history of Bitcoin, there have been 3 halvings. When Bitcoin mining started, miners receive block. In 2012, it reduced this reward to 25 BTC; in 2016, it dropped to 12.5 BTC, and in 2020 to 6.2 halving has affected the price, although it has not been in the short term after it.

It is intended to use the days remaining until the next halving and its mining rewards as exogen Bitcoin. The next halving is estimated to occur approximately in 2024, although its exact date is ur 2022-01-14 from the Coinmarketcap (https://coinmarketcap.com/halving/bitcoin/) website, 121,400, network blocks mined per day, 144 (average block time (https://en.wikipedia.org/wiki/Bitcoin) ≈ 10 mi

Note: when incorporating predicted data as an exogenous variable, their error is introduced in th predictions.

In [5]:
```
# Dict with Bitcoin halvings info
# ==============================================================================
btc_halving = {'halving'             : [0, 1 , 2, 3, 4],
               'date'                : ['2009-01-03', '2012-11-28',
                                        '2016-07-09', '2020-05-11', np.nan],
               'reward'              : [50, 25, 12.5, 6.25, 3.125],
               'halving_block_number' : [0, 210000, 420000 ,630000, 840000]
              }
```

In [6]:
```
# Next halving calculation
# The remaining blocks according to the coinmarketcap.com website for
# the next halving as of 2022-01-14 are taken as a starting point
# ==============================================================================
remaining_blocks = 121400
blocks_per_day = 144

days = remaining_blocks / blocks_per_day

next_halving = pd.to_datetime('2022-01-14', format='%Y-%m-%d') + datetime.timedelt
next_halving = next_halving.replace(microsecond=0, second=0, minute=0, hour=0)
next_halving = next_halving.strftime('%Y-%m-%d')

btc_halving['date'][-1] = next_halving

print(f'The next halving will occur on approximately: {next_halving}')
```

```
The next halving will occur on approximately: 2024-05-06
```

In [7]:
```
# Include rewards and countdown to next halving in dataset
# ==============================================================================
data['reward'] = np.nan
data['countdown_halving'] = np.nan

for i in range(len(btc_halving['halving'])-1):

    # Start and end date of each halving
    if btc_halving['date'][i] < data.index.min().strftime('%Y-%m-%d'):
        start_date = data.index.min().strftime('%Y-%m-%d')
    else:
        start_date = btc_halving['date'][i]

    end_date = btc_halving['date'][i+1]
    mask = (data.index >= start_date) & (data.index < end_date)

    # Fill column 'reward' with mining rewards
    data.loc[mask, 'reward'] = btc_halving['reward'][i]

    # Fill column 'countdown_halving' with remaining days
    time_to_next_halving = pd.to_datetime(end_date) - pd.to_datetime(start_date)

    data.loc[mask, 'countdown_halving'] = np.arange(time_to_next_halving.days)[::-
```

In [8]:
```
# Check that the data have been created correctly
# ==============================================================================
print('Second halving:', btc_halving['date'][2])
display(data.loc['2016-07-08':'2016-07-09'])
print('')
print('Third halving:', btc_halving['date'][3])
display(data.loc['2020-05-10':'2020-05-11'])
print('')
print('Next halving:', btc_halving['date'][4])
data.tail(2)
```

```
Second halving: 2016-07-09
```

date	open	close	high	low	reward	countdown_halving
2016-07-08	640.687988	666.523010	666.706970	636.466980	25.0	0.0
2016-07-09	666.383972	650.960022	666.383972	633.398987	12.5	1401.0

```
Third halving: 2020-05-11
```

date	open	close	high	low	reward	countdown_halving
2020-05-10	9591.169231	8756.431142	9595.580629	8395.107451	12.50	0.0
2020-05-11	8755.535639	8601.796202	9033.471176	8374.322975	6.25	1455.0

```
Next halving: 2024-05-06
```

Out[8]:

date	open	close	high	low	reward	countdown_halving
2021-12-31	47169.372859	46306.446123	48472.527490	45819.954553	6.25	856.0
2022-01-01	46311.744663	47686.811509	47827.310995	46288.486095	6.25	855.0

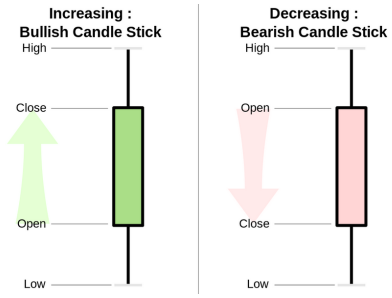
Graphic exploration

When it is necessary to generate a forecasting model, plotting the time series values could be us such as trends and seasonality.

Contents

Candlestick chart

A candlestick chart (https://en.wikipedia.org/wiki/Candlestick_chart) is a style of financial chart use security, derivative, or currency. The thick body shows the variation between the opening and c shadows show the minimum and maximum values reached during that period.



Scheme of the 2 kinds of basic candlestick chart. Source: Wikipedia (https://en.wikipedia.org/wiki/Candlestick_chart#/media/

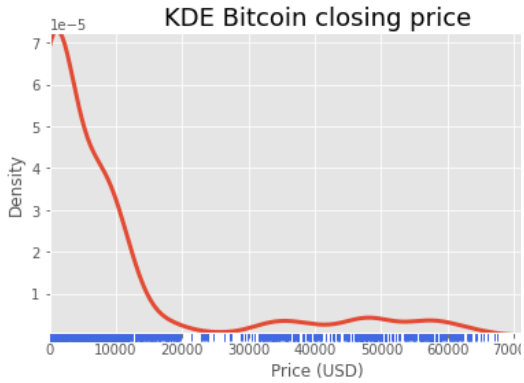
In [9]:
```
# Interactive candlestick chart with Plotly
# ==============================================================================
candlestick = go.Candlestick(
                  x     = data.index,
                  open  = data.open,
                  close = data.close,
                  low   = data.low,
                  high  = data.high,
              )

fig = go.Figure(data=[candlestick])

fig.update_layout(
    width       = 900,
    height      = 450,
    title       = dict(text='<b>Bitcoin/USD Chart</b>', font=dict(size=30)),
    yaxis_title = dict(text='Price (USD)', font=dict(size=15)),
    margin      = dict(l=10, r=20, t=80, b=20),
    shapes      = [dict(x0=btc_halving['date'][2], x1=btc_halving['date'][2],
                        y0=0, y1=1, xref='x', yref='paper', line_width=2),
                   dict(x0=btc_halving['date'][3], x1=btc_halving['date'][3],
                        y0=0, y1=1, xref='x', yref='paper', line_width=2),
                   dict(x0=btc_halving['date'][4], x1=btc_halving['date'][4],
                        y0=0, y1=1, xref='x', yref='paper', line_width=2)
                  ],
    annotations = [dict(x=btc_halving['date'][2], y=1, xref='x', yref='paper',
                       showarrow=False, xanchor='left', text='Second halving'),
                   dict(x=btc_halving['date'][3], y=1, xref='x', yref='paper',
                       showarrow=False, xanchor='left', text='Third halving'),
                   dict(x=btc_halving['date'][4], y=1, xref='x', yref='paper',
                       showarrow=False, xanchor='left', text='Fourth halving')
                  ],
    xaxis_rangeslider_visible = False,
)

fig.show()
```

Data distribution

The distribution of the Bitcoin closing price, variable `close`, is shown:

Contents

In [10]:
```
# KDE distribution of Bitcoin closing price
# ==============================================================================
fig, ax = plt.subplots(figsize=(7, 4))
p = sns.kdeplot(data=data, x='close', linewidth=3, ax=ax)
r = sns.rugplot(data=data, x='close', ax=ax, c='royalblue',
                height=-.03, clip_on=False)
p.set(xlim=(0, None))
p.set_title('KDE Bitcoin closing price', fontsize=18)
p.set_xlabel('Price (USD)');
```



The study data shows a majority distribution of prices below 20,000 (USD). This stage correspon September 2020. Since 2021, the price has been in the range of 35,000 - 67,500 (USD).

Trying to model a time series with a highly asymmetric distribution and distinct orders of magnitude One strategy is model changes (deltas) rather than direct values to minimize these problems. It c only whether the price increases or decreases from the previous day.

Note: when a distribution is asymmetric, modeling deltas instead of price may result in a more symm

In [11]:
```
# Create deltas column (% change)
# ==============================================================================
# data['change_pct'] = 100*(data['close'] - data['open']) / data['open']
# # With Pandas pct_change() method
# data['change_pct'] = data.pct_change(axis='columns').iloc[:, 1]*100
# data.head(2)
```

Price per year

In [12]:
```
# Locate corresponding data for each year
# ==============================================================================
years = list(data.index.year.unique())
df_plot = pd.DataFrame()

for year in years:

    year_open  = data.loc[data.index.year == year, 'open'][0]
    year_close = data.loc[data.index.year == year, 'close'][-1]
    year_low   = data.loc[data.index.year == year, 'low'].min()
    year_high  = data.loc[data.index.year == year, 'high'].max()

    df_plot[year] = pd.Series([year_open, year_close, year_low, year_high])

df_plot = df_plot.T
df_plot = df_plot.set_axis(['open', 'close', 'low', 'high'], axis=1)

# Calculate % change between the open and close price of the year
# ==============================================================================
df_plot['year_change'] = 100*(df_plot['close'] - df_plot['open']) / df_plot['open
df_plot.head(3)
```

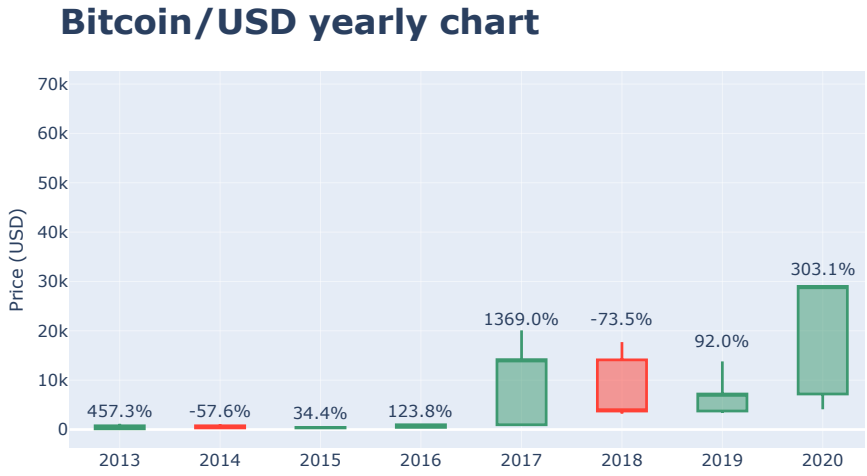
Out[12]:

	open	close	low	high	year_change
2013	135.300003	754.010010	65.526001	1156.140015	457.287504
2014	754.969971	320.192993	289.295990	1017.119995	-57.588645
2015	320.434998	430.566986	171.509995	495.562012	34.369526

Contents

In [13]:

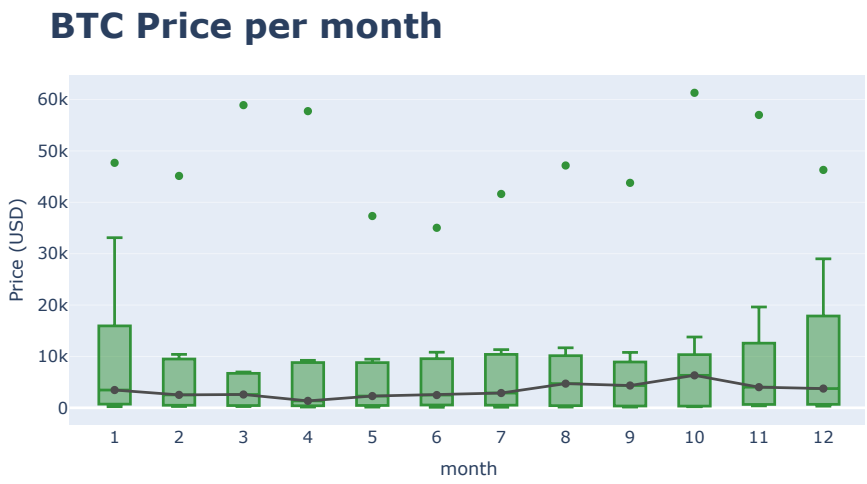
```
# Create a list of dicts with the % change annotations for the plot
# ==============================================================================
annotations_list = []
max_high = df_plot['high'].max()

for year in years:

    df_aux = df_plot.loc[df_plot.index == year,]
    loc_x  = pd.to_datetime(df_aux.index[0], format='%Y')
    loc_y  = df_aux['high'].values[0]/max_high + 0.05
    text   = '{:.1f}%'.format(df_aux['year_change'].values[0])

    annotation = dict(x=loc_x, y=loc_y,
                      xref='x', yref='paper',
                      showarrow=False, xanchor='center',
                      text=text)

    annotations_list.append(annotation)

# Interactive candlestick chart with Plotly
# ==============================================================================
candlestick = go.Candlestick(
                  x     = pd.to_datetime(df_plot.index, format='%Y'),
                  open  = df_plot.open,
                  close = df_plot.close,
                  low   = df_plot.low,
                  high  = df_plot.high
              )

fig = go.Figure(data=[candlestick])

fig.update_layout(
    width       = 800,
    height      = 350,
    title       = dict(text='<b>Bitcoin/USD yearly chart</b>', font=dict(size=25)),
    yaxis_title = dict(text='Price (USD)', font=dict(size=13)),
    margin      = dict(l=0, r=20, t=55, b=20),
    xaxis_rangeslider_visible = False,
    annotations = annotations_list
)

fig.show()
```



Annual, monthly and weekly seasonality

In [14]:
```
# Locate corresponding data for each month
# ==============================================================================
years = list(data.index.year.unique())
df_plot = pd.DataFrame()

for year in years:
    for month in range(12):

        start_date = pd.to_datetime(f'{year}-{month+1}-01', format='%Y-%m-%d')
        end_date = (start_date + pd.offsets.MonthBegin())
        mask = (data.index >= start_date) & (data.index < end_date)

        if not data.loc[mask, :].empty:

            month_open  = data.loc[mask, 'open'][0]
            month_close = data.loc[mask, 'close'][-1]
            month_low   = data.loc[mask, 'low'].min()
            month_high  = data.loc[mask, 'high'].max()

            serie  = pd.Series([month_open, month_close, month_low, month_high])
            df_aux = pd.DataFrame(serie, columns=[f'{str(month+1).zfill(2)}-{year}

            if df_plot.empty:
                df_plot = df_aux.copy()
            else:
                df_plot = pd.concat([df_plot, df_aux], axis=1)

df_plot = df_plot.T
df_plot = df_plot.set_axis(['open', 'close', 'low', 'high'], axis=1)
```

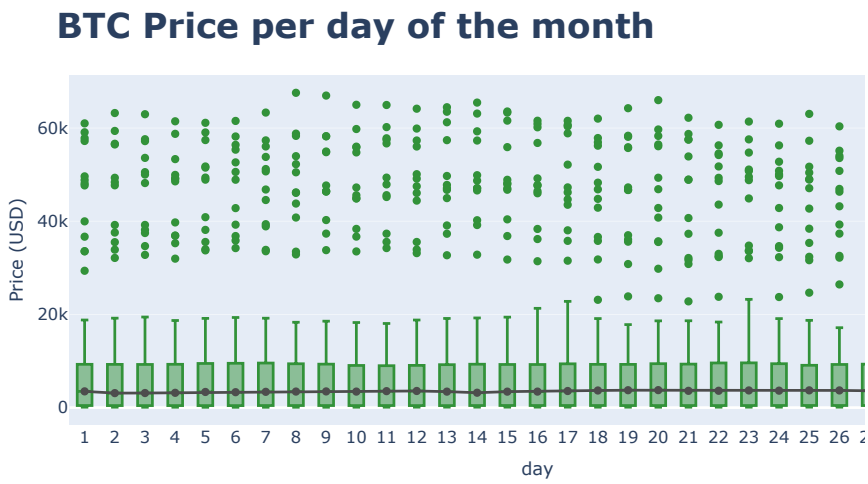
In [15]:
```
# Boxplot chart for annual seasonality
# ==============================================================================
# df_plot['month'] = pd.to_datetime(df_plot.index, format='%m-%Y').month
# fig, ax = plt.subplots(figsize=(7, 3.5))
# df_plot.boxplot(column='close', by='month', ax=ax)
# df_plot.groupby('month')['close'].median().plot(style='o-', linewidth=0.8, ax=ax
# ax.set_ylabel('Price (USD)')
# ax.set_title('BTC Price per month')
# fig.suptitle('');

df_plot['month'] = pd.to_datetime(df_plot.index, format='%m-%Y').month

# fig 1 monthly boxplot
fig1 = px.box(df_plot.sort_values('month'), x='month', y='close',
              color_discrete_sequence=[palette_btc['green']])

# fig 2 line with median data for each month
df_median = pd.DataFrame(df_plot.groupby('month')['close'].median()).reset_index()
fig2 = px.line(df_median, x='month', y='close', markers=True,
               color_discrete_sequence=[palette_btc['gray']])

fig = go.Figure(data=fig1.data + fig2.data)

fig.update_layout(
    width       = 650,
    height      = 350,
    title       = dict(text='<b>BTC Price per month</b>', font=dict(size=25)),
    yaxis_title = dict(text='Price (USD)', font=dict(size=13)),
    xaxis       = dict(tickmode='linear'),
    xaxis_title = dict(text='month', font=dict(size=13)),
    margin      = dict(l=0, r=20, t=55, b=20)
)

fig.show()
```



Contents

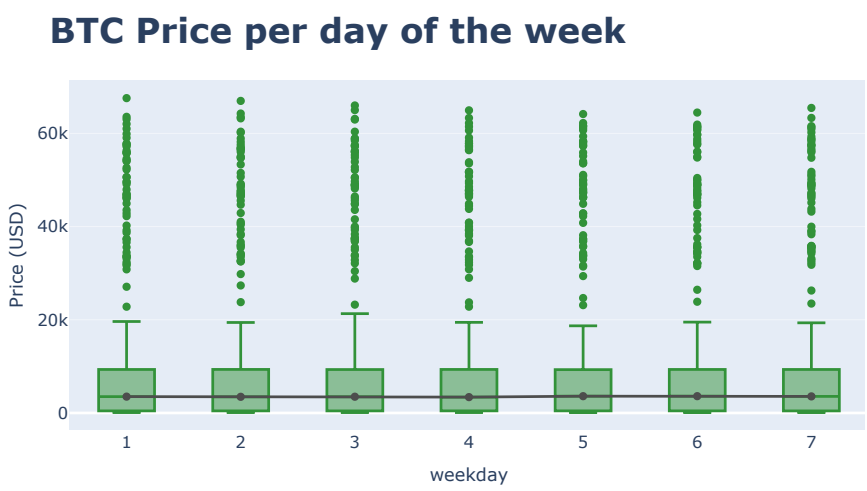
In [16]:

```
# Boxplot chart for monthly seasonality
# ==============================================================================
# fig, ax = plt.subplots(figsize=(9, 3.5))
# data['day'] = pd.Series(data.index).dt.day.values
# data.boxplot(column='close', by='day', ax=ax)
# data.groupby('day')['close'].median().plot(style='o-', linewidth=0.8, ax=ax)
# ax.set_ylabel('Price (USD)')
# ax.set_title('BTC Price per day of the month')
# fig.suptitle('');

data['day'] = pd.Series(data.index).dt.day.values

# fig 1 dayly boxplot
fig1 = px.box(data.sort_values('day'), x='day', y='close',
              color_discrete_sequence=[palette_btc['green']])

# fig 2 line with median data for each day
df_median = pd.DataFrame(data.groupby('day')['close'].median()).reset_index()
fig2 = px.line(df_median, x='day', y='close', markers=True,
               color_discrete_sequence=[palette_btc['gray']])

fig = go.Figure(data=fig1.data + fig2.data)

fig.update_layout(
    width       = 750,
    height      = 350,
    title       = dict(text='<b>BTC Price per day of the month</b>', font=dict(si
    yaxis_title = dict(text='Price (USD)', font=dict(size=13)),
    xaxis       = dict(tickmode='linear', tickangle=0, range=[0.5, 31.5]),
    xaxis_title = dict(text='day', font=dict(size=13)),
    margin      = dict(l=0, r=20, t=55, b=20)
)

fig.show()
```



Contents

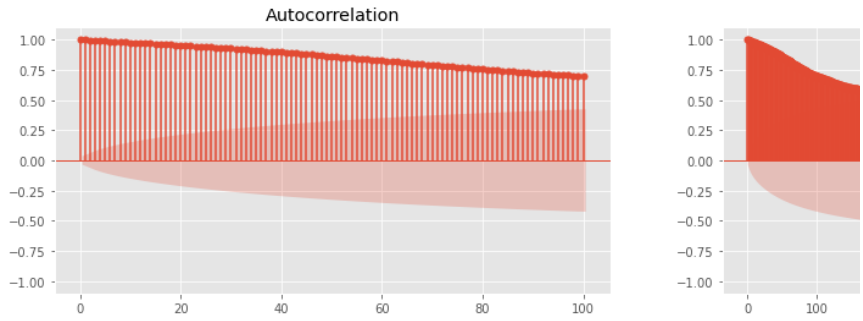
In [17]:
```
# Boxplot chart for weekly seasonality
# ==============================================================================
# fig, ax = plt.subplots(figsize=(7, 3.5))
# data['weekday'] = data.index.day_of_week + 1
# data.boxplot(column='close', by='weekday', ax=ax)
# data.groupby('weekday')['close'].median().plot(style='o-', linewidth=0.8, ax=ax)
# ax.set_ylabel('Price (USD)')
# ax.set_title('BTC Price per day of the week');

data['weekday'] = data.index.day_of_week + 1

# fig 1 weekly boxplot
fig1 = px.box(data.sort_values('weekday'), x='weekday', y='close',
              color_discrete_sequence=[palette_btc['green']])

# fig 2 line with median data for each weekday
df_median = pd.DataFrame(data.groupby('weekday')['close'].median()).reset_index()
fig2 = px.line(df_median, x='weekday', y='close', markers=True,
               color_discrete_sequence=[palette_btc['gray']])

fig = go.Figure(data=fig1.data + fig2.data)

fig.update_layout(
    width       = 650,
    height      = 350,
    title       = dict(text='<b>BTC Price per day of the week</b>', font=dict(size
    yaxis_title = dict(text='Price (USD)', font=dict(size=13)),
    xaxis       = dict(tickmode='linear'),
    xaxis_title = dict(text='weekday', font=dict(size=13)),
    margin      = dict(l=0, r=20, t=55, b=20)
)

fig.show()
```



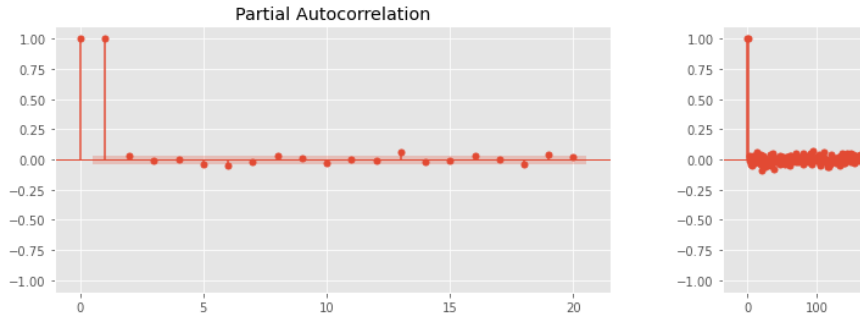
Usually, time series with an autoregressive pattern produce a repetitive shape (trend, seasonality, c
certain annual seasonality appears at the end and beginning of the year, with larger variations in p
monthly and weekly intervals, with very similar distributions.

Autocorrelation plots

In [18]:
```
# Autocorrelation plot
# ==============================================================================
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(18, 4))
axes = axes.flat
plot_acf(data.close, ax=axes[0], linewidth = 1, lags=100)
axes[0].set_ylim(-1.1, 1.1)
plot_acf(data.close, ax=axes[1], linewidth = 1, lags=730)
axes[1].set_ylim(-1.1, 1.1)
plt.show();
```



In [19]:
```
# Partial autocorrelation plot
# ==============================================================================
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(18, 4))
axes = axes.flat
plot_pacf(data.close, ax=axes[0], lags=20, method='ywm',  linewidth = 1)
axes[0].set_ylim(-1.1, 1.1)
plot_pacf(data.close, ax=axes[1], lags=730, method='ywm',  linewidth = 1)
axes[1].set_ylim(-1.1, 1.1)
plt.show();
```



The autocorrelation plots show that lag 1 is the only one correlated with lag 0. The following la threshold.

Baseline - Random walk simulation

When generating a predictive model, it is convenient to identify a base model, or baseline, on whic iterations or models. In the case of finance, according to random walk theory (https://en.wikipedia market prices behave randomly and not as a function of their time series. Thus, the best estimate o an unpredictable change.

Although a broad time series is available, it presents periods with highly differentiated prices, as det Only data from the **last two years** are used.

Contents

In [20]:
```
# Selection of train-test dates
# ======================================================================================
start_train = '2020-01-01 00:00:00'
end_train = '2021-06-30 23:59:59'

print(f"Complete time series : {data.index.min()} --- {data.index.max()}  (n={len(
print(f"Train dates          : {data.loc[start_train:end_train].index.min()} --- {
ndex.max()}  (n={len(data.loc[start_train:end_train])})")
print(f"Test dates           : {data.loc[end_train:].index.min()} --- {data.loc[en
ata.loc[end_train:])})")
```

```
Complete time series : 2013-04-28 00:00:00 --- 2022-01-01 00:00:00  (n=3171)
Train dates          : 2020-01-01 00:00:00 --- 2021-06-30 00:00:00  (n=547)
Test dates           : 2021-07-01 00:00:00 --- 2022-01-01 00:00:00  (n=185)
```

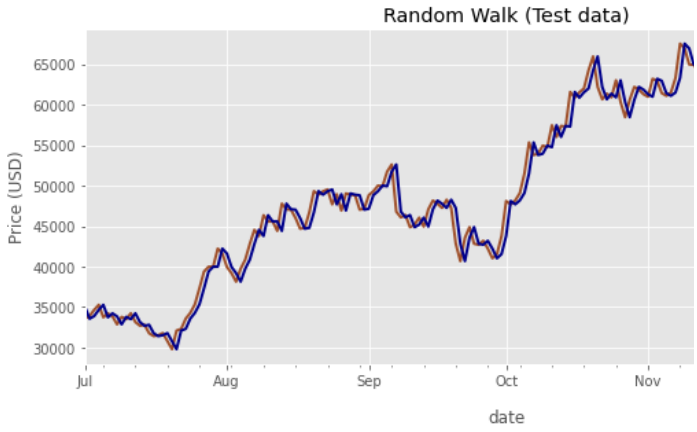
As mentioned above, random walk suggests that the best estimate for the t_{n+1} value is the t_n v
Therefore, the simplest viable model uses the value of t_n as the prediction for the t_{n+1} value. It is se

In [21]:
```
# Random walk simulation
# ======================================================================================
df_rw = data[['close']].copy()
df_rw['pred_close'] = df_rw['close'].shift(1)

# Test error
# ======================================================================================
y_true = df_rw.loc[end_train:, 'close']
y_pred = df_rw.loc[end_train:, 'pred_close']
metric = mean_absolute_error(y_true, y_pred)

print(f'Test error: {metric}')
display(df_rw.loc[end_train:,].head(4))
```

```
Test error: 1267.7978352283603
```

date	close	pred_close
2021-07-01	33572.117653	35040.837249
2021-07-02	33897.048590	33572.117653
2021-07-03	34668.548402	33897.048590
2021-07-04	35287.779766	34668.548402

In [22]:
```
# Plot
# ======================================================================================
fig, ax = plt.subplots(figsize=(11, 4.5))
df_rw.loc[end_train:, 'close'].plot(ax=ax, linewidth=2, label='Test',
                                    c='sienna')
df_rw.loc[end_train:, 'pred_close'].plot(ax=ax, linewidth=2, label='Prediction',
                                    c='darkblue')
ax.set_title('Random Walk (Test data)')
ax.set_ylabel('Price (USD)')
ax.legend();
```



In [23]:
```
# DataFrame models' test error
# ==============================================================================
df_errors = pd.DataFrame({'model': 'Base - Random Walk', 'lags': 1,
                          'test_error': metric, 'exog_variables': False},
                         index=[0])
df_errors
```

Out[23]:

	model	lags	test_error	exog_variables
0	Base - Random Walk	1	1267.797835	False

The model test error is 1,267.8. The following sections intend to generate a model capable of reducir

Recursive autoregressive forecaster

An Autoregressive Forecaster (ForecasterAutoreg (https://joaquinamatrodrigo.github.io/skforeca forecaster.html)) with a LightGBM (https://lightgbm.readthedocs.io/en/latest/) regressor, an implem algorithm developed by Microsoft that usually achieves excellent results, is used to model the Bitcoin

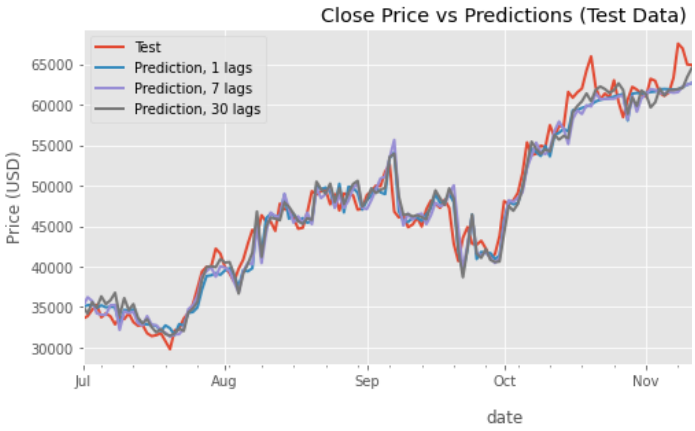
Previous sections show an absence of autocorrelation beyond the first lag. One way to verify thi increasing amount of lags and check if the error doesn't reduce. This approach (https://joaquinamatrodrigo.github.io/skforecast/latest/user_guides/backtesting.html), using `steps` the series, t_{n+1}) it reproduces the random walk model methodology.

Note: It is not rigorously necessary to perform any data preprocessing when working with (`StandardScaler`, `MinMaxScaler`...). *Example of forecasting wit (https://joaquinamatrodrigo.github.io/skforecast/latest/user_guides/sklearn-transformers-and-pipeline*

In [24]:
```
# Forecasters backtest with different lags
# ==============================================================================
lags = [1, 7, 30]
metrics = []
predictions_list = []

for lag in lags:

    # Create forecaster
    forecaster = ForecasterAutoreg(
                     regressor     = LGBMRegressor(random_state=123),
                     lags          = lag,
                     transformer_y = None
                 )

    # Backtest test data, 1 step
    metric, predictions = backtesting_forecaster(
                              forecaster         = forecaster,
                              y                  = data.loc[start_train:, 'close'
                              initial_train_size = len(data.loc[start_train:end_tr
                              fixed_train_size   = True,
                              steps              = 1,
                              refit              = True,
                              metric             = 'mean_absolute_error',
                              verbose            = False
                          )

    metrics.append(metric)
    predictions_list.append(predictions)
```

```
Forecaster will be fit 185 times. This can take substantial amounts of time. If nc

Forecaster will be fit 185 times. This can take substantial amounts of time. If nc

Forecaster will be fit 185 times. This can take substantial amounts of time. If nc
```

In [25]:
```
# Plot
# ==============================================================================
fig, ax = plt.subplots(figsize=(11, 4.5))
data.loc[end_train:, 'close'].plot(ax=ax, linewidth=2, label='Test')

# Plot test predictions for different lags
for predictions, lag in zip(predictions_list, lags):
    predictions = predictions.rename(columns={'pred': f'Prediction, {lag} lags'})
    predictions.plot(ax=ax, linewidth=2)

ax.set_title('Close Price vs Predictions (Test Data)')
ax.set_ylabel('Price (USD)')
ax.legend();
```



In [26]:
```
# DataFrame models' test error
# ==============================================================================
model = 'LGBMRegressor'

df_errors = pd.concat([
                df_errors,
                pd.DataFrame({'model': model, 'lags': lags,
                              'test_error': metrics, 'exog_variables': False})
                ]).reset_index(drop=True)

df_errors.sort_values(by='test_error')
```

Out[26]:

	model	lags	test_error	exog_variables
0	Base - Random Walk	1	1267.797835	False
1	LGBMRegressor	1	1529.633756	False
2	LGBMRegressor	7	1582.363518	False
3	LGBMRegressor	30	1601.381059	False

The **test errors** (which reflect how well each model generalizes) show that none of the moc incorporating more information from the past (number of lags). Because of the results, othe incorporating exogenous variables into the series.

Forecasting with exogenous variables

In the previous example, only lags of the predicted variable itself have been used as predictors. In s information about other variables, **whose future value is known**, and which can serve as additic examples are:

- Holidays (local, national...)
- Month of the year
- Day of the week
- Time of day

For this case, it is used the variables resulting from the section about Bitcoin halving and, after stu year.

Note: The `reward` and `month` variables, although encoded as numbers, are categorical, so it is which they are stored. Since these variables do not have many levels, the One Hot Encoding transfo into the model.

In [27]:
```
# Change of the categorical variables to category type
# ==============================================================================
data['month'] = data.index.month
data['month'] = data['month'].astype('category')
data['reward'] = data['reward'].astype('category')

# One hot encoding
data = pd.get_dummies(data, columns=['reward', 'month'])
data.head(2)
```

Out[27]:

date	open	close	high	low	countdown_halving	day	weekday	reward_6.2
2013-04-28	135.300003	134.210007	135.979996	132.100006	1167.0	28	7	
2013-04-29	134.444000	144.539993	147.488007	134.000000	1166.0	29	1	

2 rows × 22 columns

In [28]:
```
# All exogenous variables are selected, including those obtained
# during one hot encoding.
# ==============================================================================
exog = [column for column in data.columns if column.startswith(('reward', 'month')
exog.extend(['countdown_halving'])
print(exog)
```

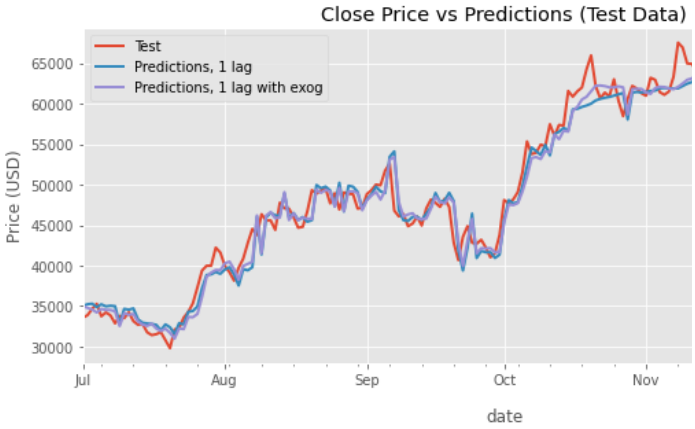
```
['reward_6.25', 'reward_12.5', 'reward_25.0', 'month_1', 'month_2', 'month_3', 'mo
'month_8', 'month_9', 'month_10', 'month_11', 'month_12', 'countdown_halving']
```

Contents

In [29]:
```
# Forecaster backtest with exogenous variables
# ==============================================================================
forecaster = ForecasterAutoreg(
                 regressor        = LGBMRegressor(random_state=123),
                 lags             = 1,
                 transformer_y    = None,
                 transformer_exog = None
             )

# Backtest test data, 1 step
metric, predictions = backtesting_forecaster(
                          forecaster         = forecaster,
                          y                  = data.loc[start_train:, 'close'],
                          exog               = data.loc[start_train:, exog],
                          initial_train_size = len(data.loc[start_train:end_train,
                          fixed_train_size   = True,
                          steps              = 1,
                          refit              = True,
                          metric             = 'mean_absolute_error',
                          verbose            = False
                      )
```

```
Forecaster will be fit 185 times. This can take substantial amounts of time. If nc
```

In [30]:
```
# Plot
# ==============================================================================
fig, ax = plt.subplots(figsize=(11, 4.5))
data.loc[end_train:, 'close'].plot(ax=ax, linewidth=2, label='Test')

# Plot predictions 1 lag without exogenous variables
predictions_no_exog = predictions_list[0].rename(columns={'pred': f'Predictions, 1
predictions_no_exog.plot(ax=ax, linewidth=2)

# Plot predictions 1 lag with exogenous variables
predictions_exog = predictions.rename(columns={'pred': f'Predictions, 1 lag with e
predictions_exog.plot(ax=ax, linewidth=2)

ax.set_title('Close Price vs Predictions (Test Data)')
ax.set_ylabel('Price (USD)')
ax.legend();
```



In [31]:
```
# DataFrame models' test error
# ==============================================================================
model = 'LGBMRegressor'

df_errors = pd.concat([
                df_errors,
                pd.DataFrame({'model': model, 'lags': 1,
                              'test_error': metric, 'exog_variables': True},
                             index=[4])
                ]).reset_index(drop=True)

df_errors.sort_values(by='test_error')
```

Out[31]:

	model	lags	test_error	exog_variables
0	Base - Random Walk	1	1267.797835	False
4	LGBMRegressor	1	1473.148609	True
1	LGBMRegressor	1	1529.633756	False
2	LGBMRegressor	7	1582.363518	False
3	LGBMRegressor	30	1601.381059	False

Incorporating exogenous variables increases the predictive capacity of the model in this case. But, the base model.

Conclusions

- Bitcoin price does not follow an autoregressive pattern. The best estimate for the t_{n+1} value is change. Early identification of the absence of this correlation by descriptive analysis avoids unne
- When a time series with no autocorrelation is available, one should look for exogenous va problem. For example, to predict the price of Bitcoin in the short term (hours), exogenous vari through the analysis of tweets, impact of the so-called key opinion leaders, analysis of the most r
- Using machine learning models in forecasting problems is very simple thanks to the fur (https://joaquinamatrodrigo.github.io/skforecast/latest/index.html).

Session information

In [32]:
```
import session_info
session_info.show(html=False)
```

```
-----
cryptocmd           0.6.1
ipykernel           5.5.6
lightgbm            3.3.2
matplotlib          3.5.0
numpy               1.23.0
pandas              1.4.0
plotly              5.10.0
seaborn             0.11.0
session_info        1.0.0
skforecast          0.5.0
sklearn             1.1.0
statsmodels         0.13.0
-----
IPython             8.5.0
jupyter_client      7.3.5
jupyter_core        4.11.1
notebook            6.4.12
-----
Python 3.9.13 (main, Aug 25 2022, 23:26:10) [GCC 11.2.0]
Linux-5.15.0-48-generic-x86_64-with-glibc2.31
-----
Session information updated at 2022-10-03 21:51
```

How to cite this document?

Bitcoin price prediction with Python, when the past does not repeat itself by Joaquín Amat Rodrigo an
under a Attribution 4.0 International (CC BY 4.0) at https://www.cienciadedatos.net/documentos/py41-
machine-learning-python.html

Did you like the article? Your support is important

Website maintenance has high cost, your contribution will help me to continue generating free educat