kwd_project_code

February 3, 2020

0.1 Przygotowanie środowiska

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import category_encoders as ce
import sklearn as skl
```

[2]:
```
np.__version__
```

[2]:
```
'1.17.2'
```

0.2 Załadowanie danych z pliku

[3]:
```
data = pd.read_csv('./online_video_dataset/transcoding_mesurment.tsv',␣
 ↪delimiter='\t')
data.head(2)
```

[3]:
```
            id   duration  codec  width  height  bitrate  framerate   i     p  \
0  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
1  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537

   b  …  p_size  b_size    size  o_codec  o_bitrate o_framerate  o_width  \
0  0  …  825054       0  889537    mpeg4      56000        12.0      176
1  0  …  825054       0  889537    mpeg4      56000        12.0      320

   o_height   umem  utime
0       144  22508  0.612
1       240  25164  0.980

[2 rows x 22 columns]
```

0.3 Wstępna analiza danych

[4]:
```
print(data.shape)
print(data.columns)
```

```
(68784, 22)
Index(['id', 'duration', 'codec', 'width', 'height', 'bitrate', 'framerate',
       'i', 'p', 'b', 'frames', 'i_size', 'p_size', 'b_size', 'size',
       'o_codec', 'o_bitrate', 'o_framerate', 'o_width', 'o_height', 'umem',
       'utime'],
      dtype='object')
```

Opis danych: - id = Youtube videp id - duration = duration of video - bitrate bitrate(video) = video bitrate - height = height of video in pixles - width = width of video in pixles - frame rate = actual video frame rate - frame rate(est.) = estimated video frame rate - codec = coding standard used for the video - category = YouTube video category - url = direct link to video (has expiration date) - i = number of i frames in the video (complete image) - p = number of p frames in the video (predicted picture) - b = number of b frames in the video (bidirectional predicted picture) - frames = number of frames in video - i_size = total size in byte of i videos - p_size = total size in byte of p videos - b_size = total size in byte of b videos - size = total size of video - o_codec = output codec used for transcoding - o_bitrate = output bitrate used for transcoding - o_framerate = output framerate used for transcoding - o_width = output width in pixel used for transcoding - o_height = output height used in pixel for transcoding - umem = total codec allocated memory for transcoding - utime = total transcoding time for transcoding

0.4 Analiza eksploracyjna

[5]:
```
# typy danych w kolumnach
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68784 entries, 0 to 68783
Data columns (total 22 columns):
id             68784 non-null object
duration       68784 non-null float64
codec          68784 non-null object
width          68784 non-null int64
height         68784 non-null int64
bitrate        68784 non-null int64
framerate      68784 non-null float64
i              68784 non-null int64
p              68784 non-null int64
b              68784 non-null int64
frames         68784 non-null int64
i_size         68784 non-null int64
p_size         68784 non-null int64
b_size         68784 non-null int64
size           68784 non-null int64
o_codec        68784 non-null object
o_bitrate      68784 non-null int64
o_framerate    68784 non-null float64
o_width        68784 non-null int64
o_height       68784 non-null int64
```

```
umem           68784 non-null int64
utime          68784 non-null float64
dtypes: float64(4), int64(15), object(3)
memory usage: 11.5+ MB
```

[6]:
```python
# Jakie są podstawowe metryki statystyczne poszczególnych kolumn?
data.describe()
```

[6]:

	duration	width	height	bitrate	framerate
count	68784.000000	68784.000000	68784.000000	6.878400e+04	68784.000000
mean	286.413921	624.934171	412.572226	6.937015e+05	23.241321
std	287.257650	463.169069	240.615472	1.095628e+06	7.224848
min	31.080000	176.000000	144.000000	8.384000e+03	5.705752
25%	106.765000	320.000000	240.000000	1.343340e+05	15.000000
50%	239.141660	480.000000	360.000000	2.911500e+05	25.021740
75%	379.320000	640.000000	480.000000	6.529670e+05	29.000000
max	25844.086000	1920.000000	1080.000000	7.628466e+06	48.000000

	i	p	b	frames	i_size
count	68784.000000	68784.000000	68784.000000	68784.000000	6.878400e+04
mean	100.868312	6531.692210	9.147854	6641.708377	2.838987e+06
std	84.764791	6075.871744	92.516177	6153.342453	4.325137e+06
min	7.000000	175.000000	0.000000	192.000000	1.164800e+04
25%	39.000000	2374.000000	0.000000	2417.000000	3.933950e+05
50%	80.000000	5515.000000	0.000000	5628.000000	9.458650e+05
75%	138.000000	9155.000000	0.000000	9232.000000	3.392479e+06
max	5170.000000	304959.000000	9407.000000	310129.000000	9.082855e+07

	p_size	b_size	size	o_bitrate	o_framerate
count	6.878400e+04	68784.0	6.878400e+04	6.878400e+04	68784.000000
mean	2.218057e+07	0.0	2.502294e+07	1.395036e+06	21.190862
std	5.097306e+07	0.0	5.414402e+07	1.749352e+06	6.668703
min	3.384500e+04	0.0	1.918790e+05	5.600000e+04	12.000000
25%	1.851539e+06	0.0	2.258222e+06	1.090000e+05	15.000000
50%	6.166260e+06	0.0	7.881069e+06	5.390000e+05	24.000000
75%	1.515506e+07	0.0	1.977335e+07	3.000000e+06	25.000000
max	7.689970e+08	0.0	8.067111e+08	5.000000e+06	29.970000

	o_width	o_height	umem	utime
count	68784.000000	68784.000000	68784.000000	68784.000000
mean	802.336357	503.825541	228224.717900	9.996355
std	609.959797	315.970438	97430.878373	16.107429
min	176.000000	144.000000	22508.000000	0.184000
25%	320.000000	240.000000	216820.000000	2.096000
50%	480.000000	360.000000	219480.000000	4.408000
75%	1280.000000	720.000000	219656.000000	10.433000
max	1920.000000	1080.000000	711824.000000	224.574000

[7]:
```python
# czy są zduplikowane wartości?
len(data[data.duplicated()])
```

[7]: 0

0.4.1 Korelacja

Na co zwrócić uwagę? * zostawić zmienne, skorelowane z targetem; * usunąć zmienne skorelowane ze sobą.

Informacja przydaje się na etapie **Feature Selection** - co chcemy włączyć w dataset treningowy.

[8]:
```python
# sns.set()

# corr = data.sample(1000).corr()

# fig, ax = plt.subplots(figsize=(50,30)) # Sample figsize in inches
# sns.heatmap(corr, annot=True, linewidths=.5, ax=ax)
# plt.show()
```

Widoczna jest silna korelacja pomiędzy wymiarami docelowego pliku a czasem transkodowania.

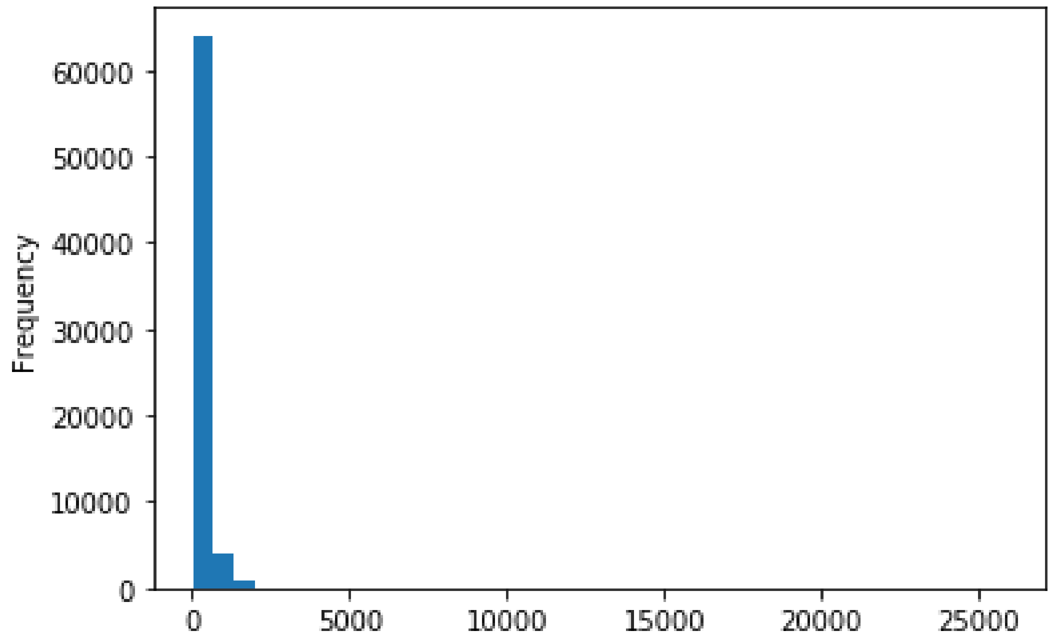
0.4.2 Analiza pól numerycznych

[9]:
```python
numeric_columns = data.select_dtypes(include=np.number).columns
numeric_columns
```

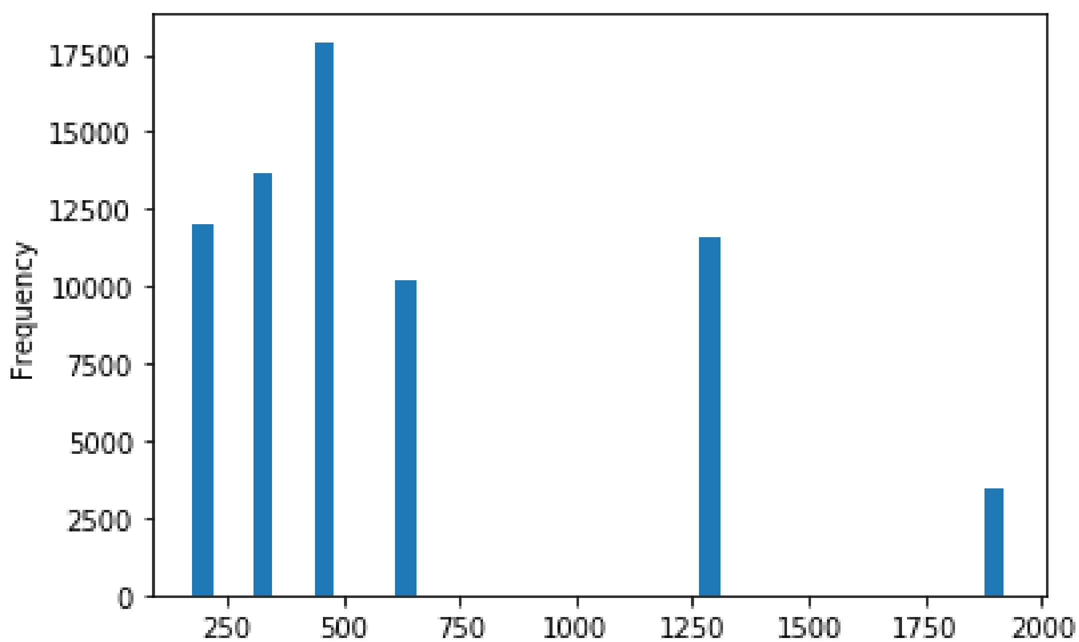
[9]:
```
Index(['duration', 'width', 'height', 'bitrate', 'framerate', 'i', 'p', 'b',
       'frames', 'i_size', 'p_size', 'b_size', 'size', 'o_bitrate',
       'o_framerate', 'o_width', 'o_height', 'umem', 'utime'],
      dtype='object')
```

[10]:
```python
for col in numeric_columns:
  print(f'kolumna: {col}')
  print(f'unikalnych wartości: {len(data[col].unique())}')
  data[col].plot.hist(bins=40)
  plt.show()
```

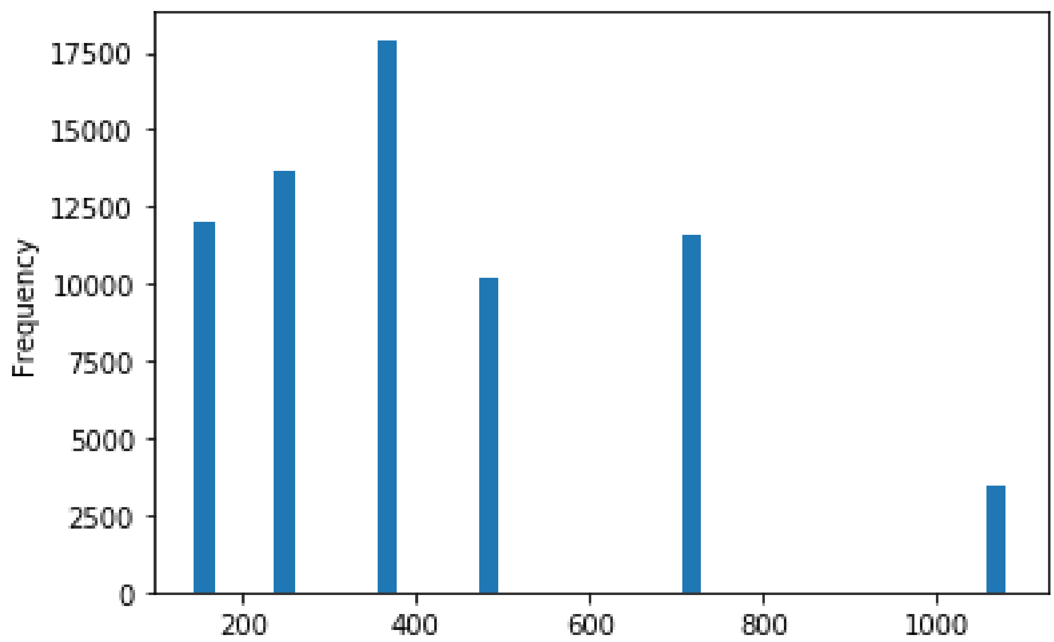
```
kolumna: duration
unikalnych wartości: 1086
```



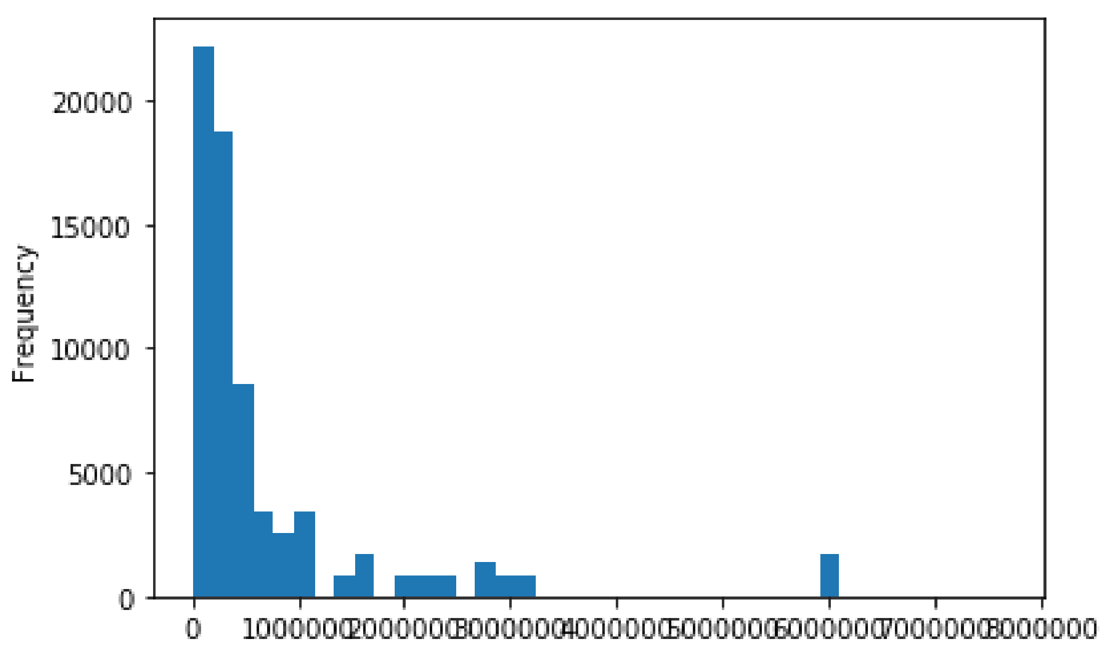
kolumna: width
unikalnych wartości: 6



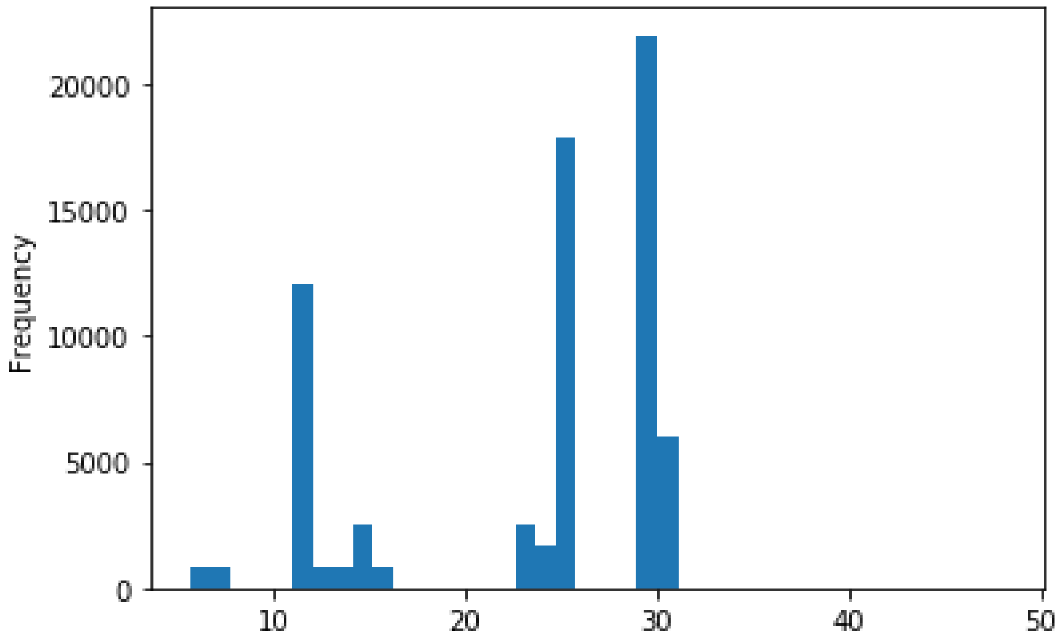
kolumna: height
unikalnych wartości: 6



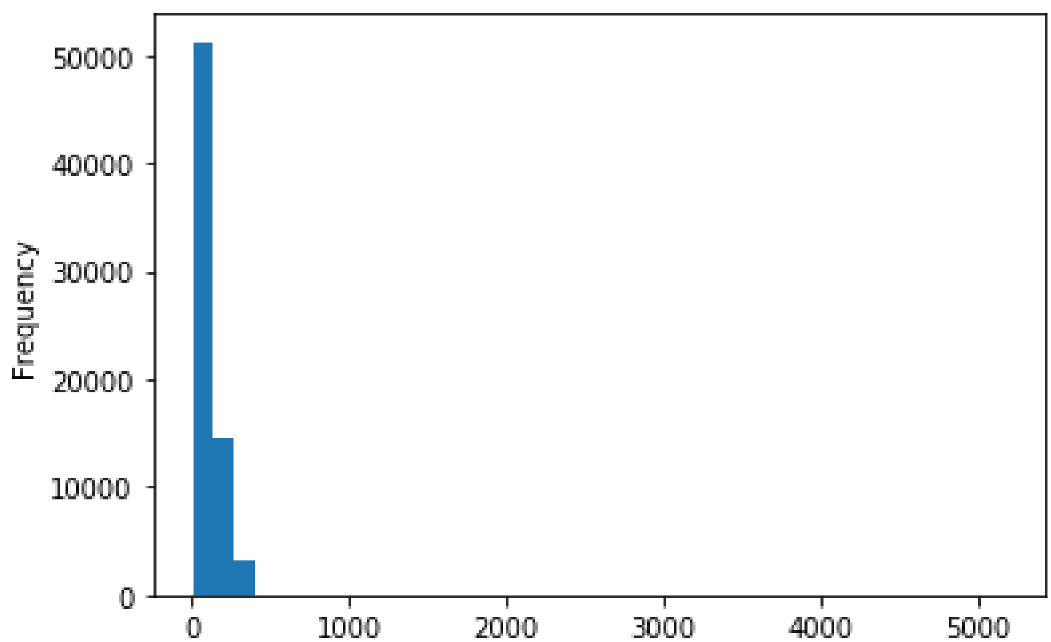

```
kolumna: bitrate
unikalnych wartości: 1095
```



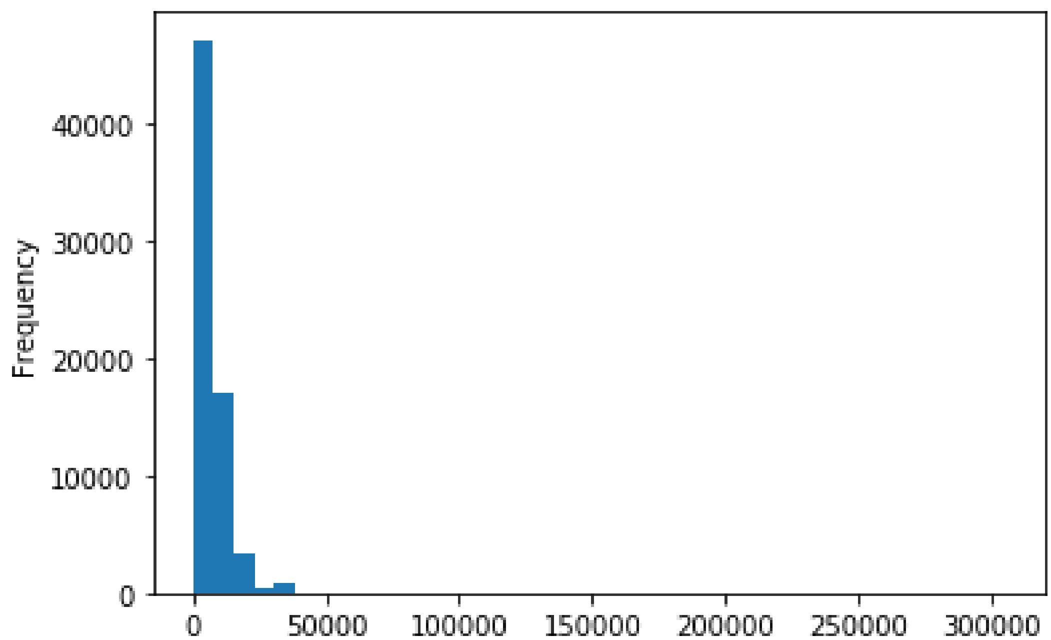

```
kolumna: framerate
unikalnych wartości: 261
```



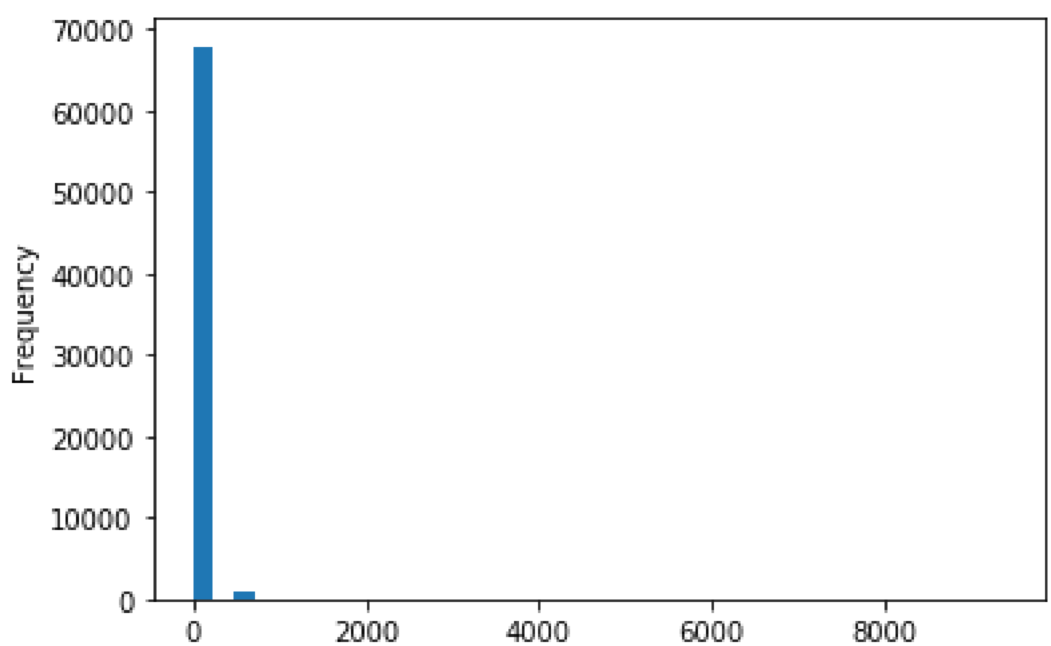

```
kolumna: i
unikalnych wartości: 306
```



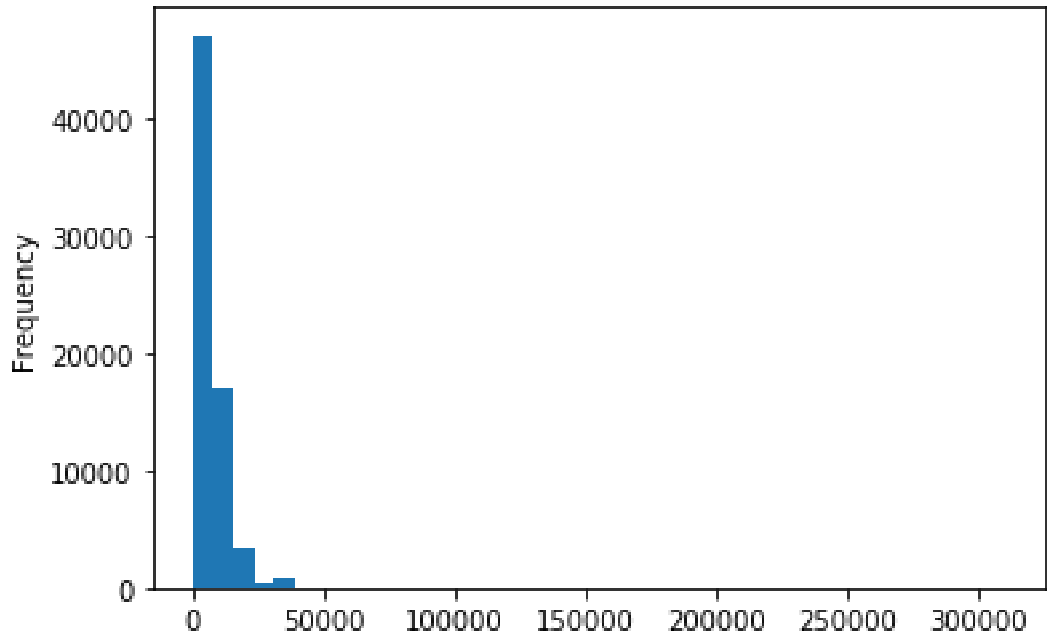

```
kolumna: p
unikalnych wartości: 1042
```



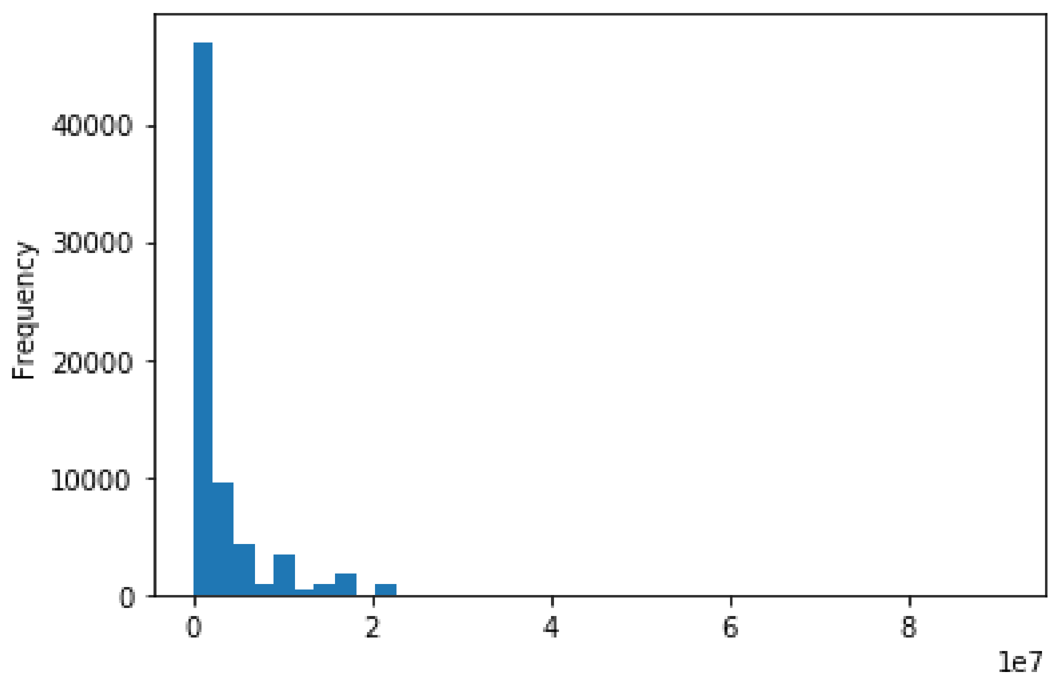

```
kolumna: b
unikalnych wartości: 20
```




```
kolumna: frames
unikalnych wartości: 1044
```

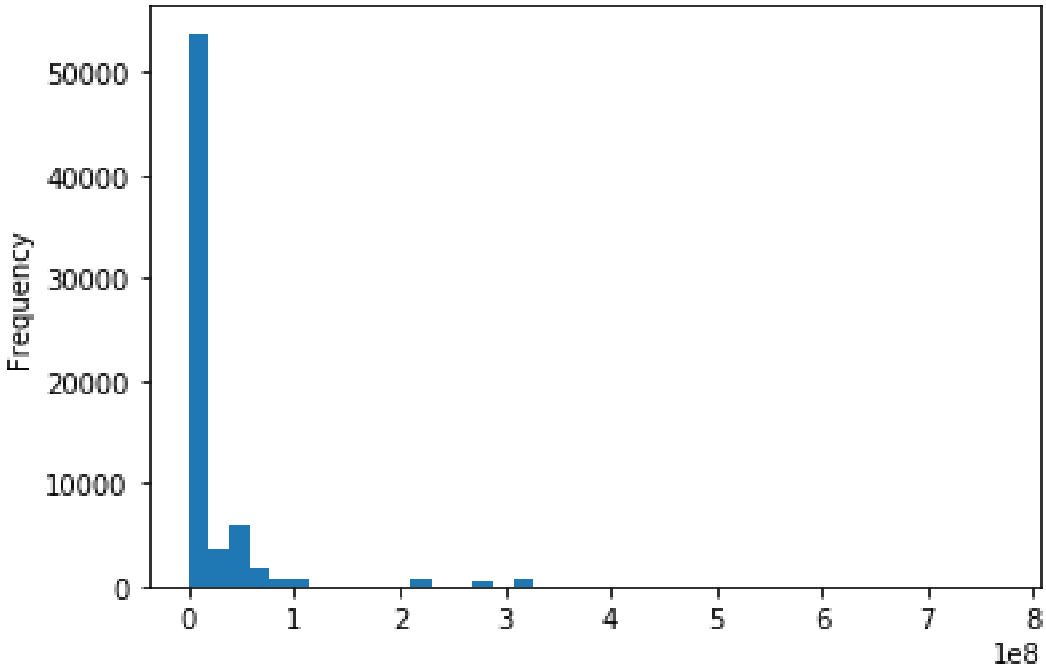


`kolumna: i_size`
`unikalnych wartości: 1099`

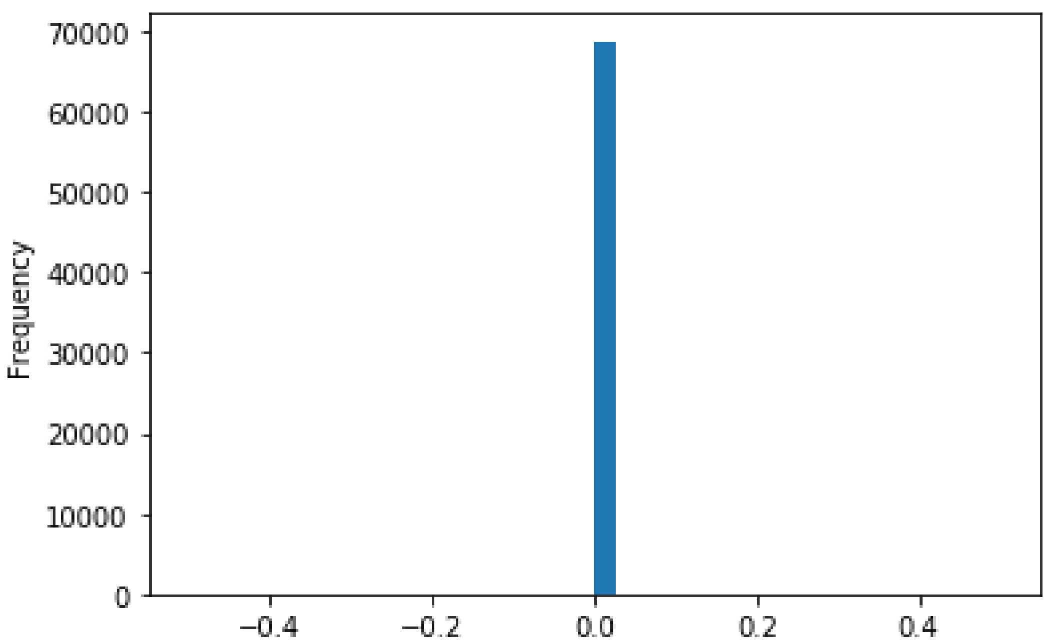


`kolumna: p_size`

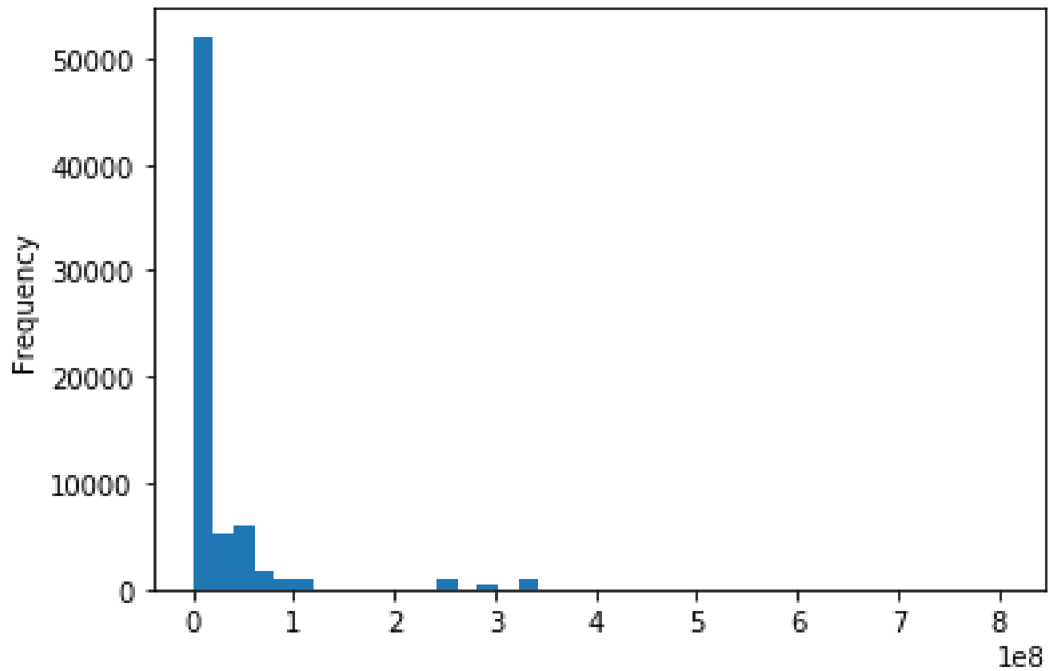
```
unikalnych wartości: 1099
```



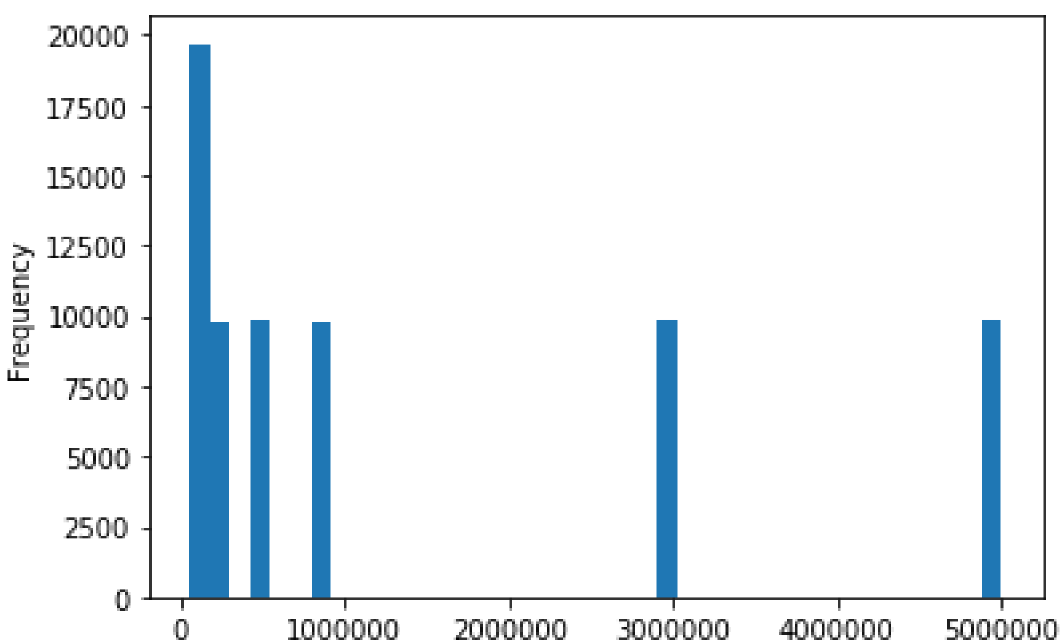

```
kolumna: b_size
unikalnych wartości: 1
```



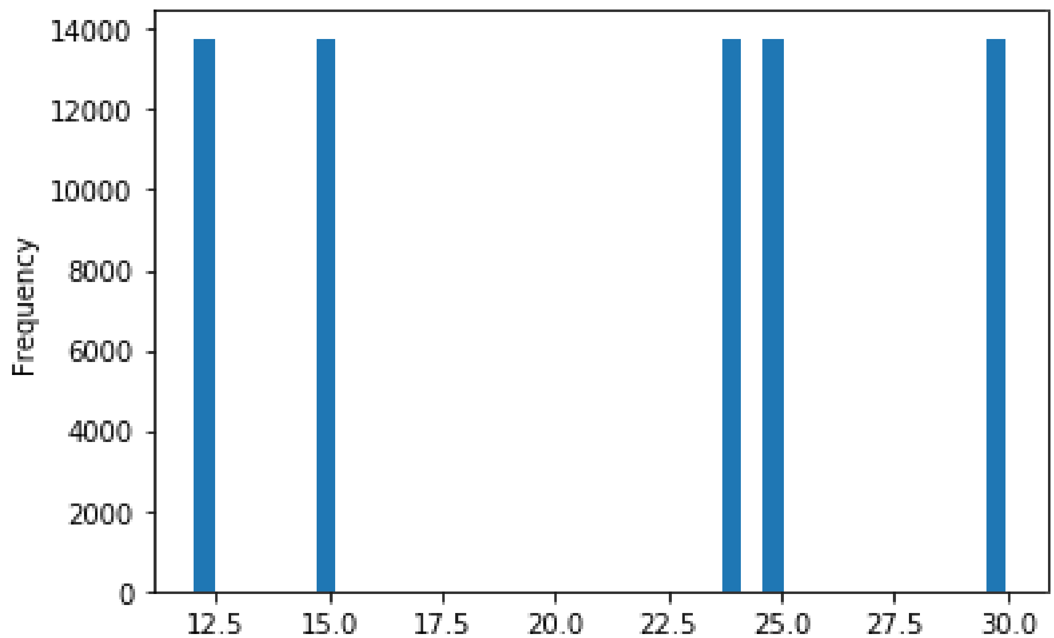
```
kolumna: size
unikalnych wartości: 1099
```



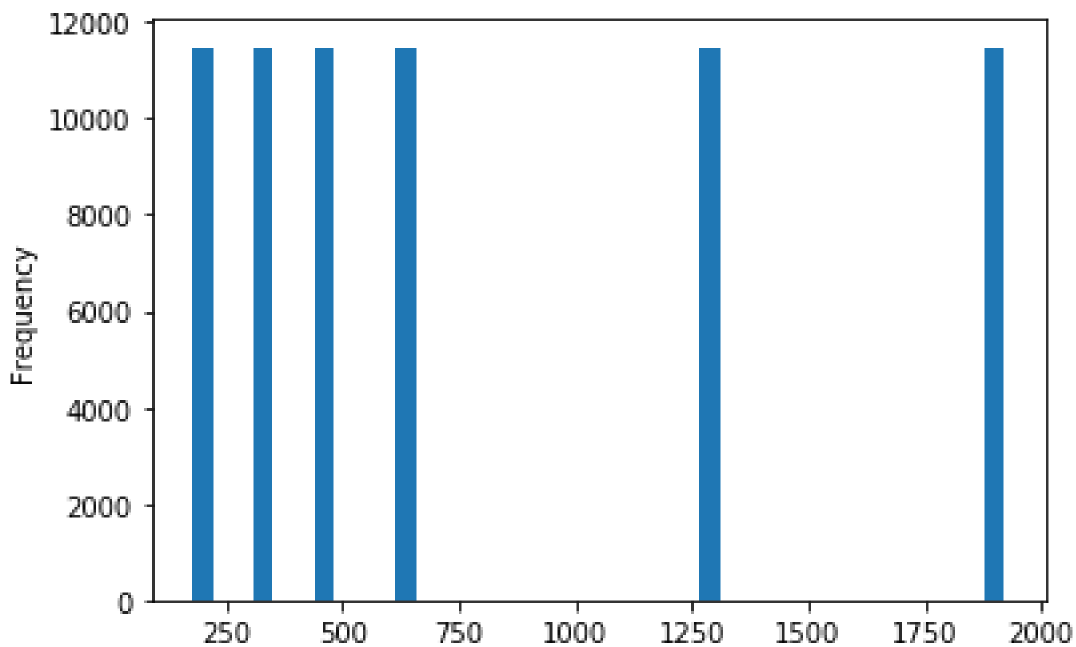

```
kolumna: o_bitrate
unikalnych wartości: 7
```



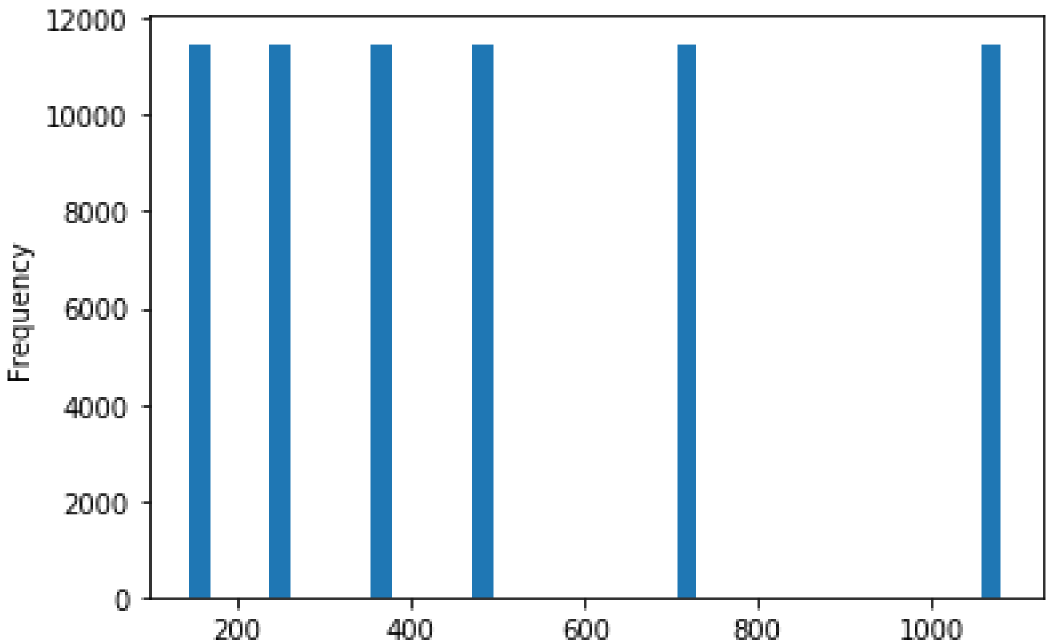
```
kolumna: o_framerate
unikalnych wartości: 5
```



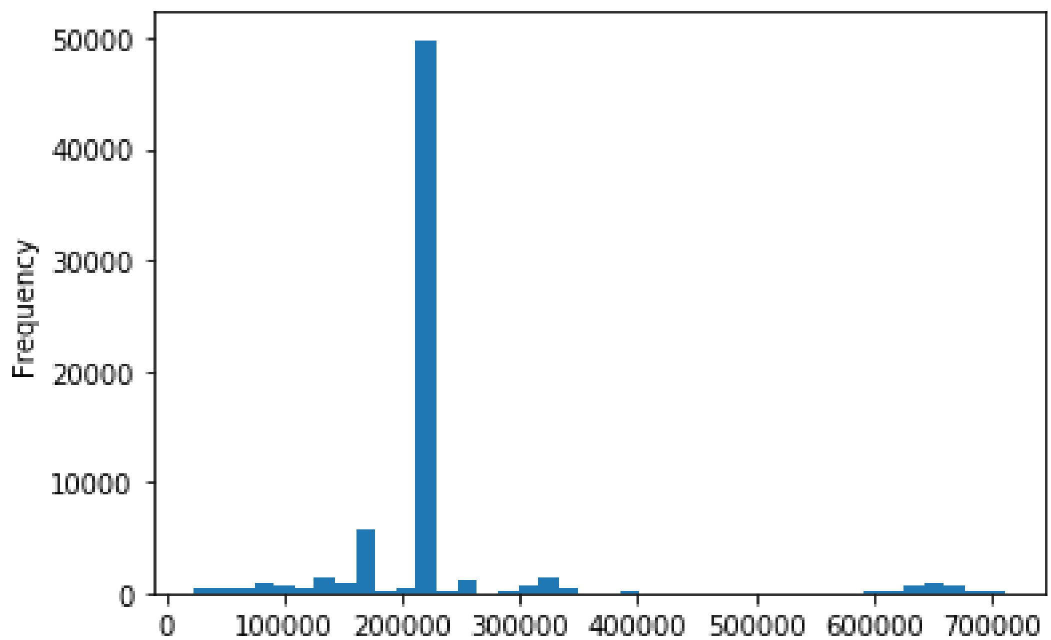

```
kolumna: o_width
unikalnych wartości: 6
```



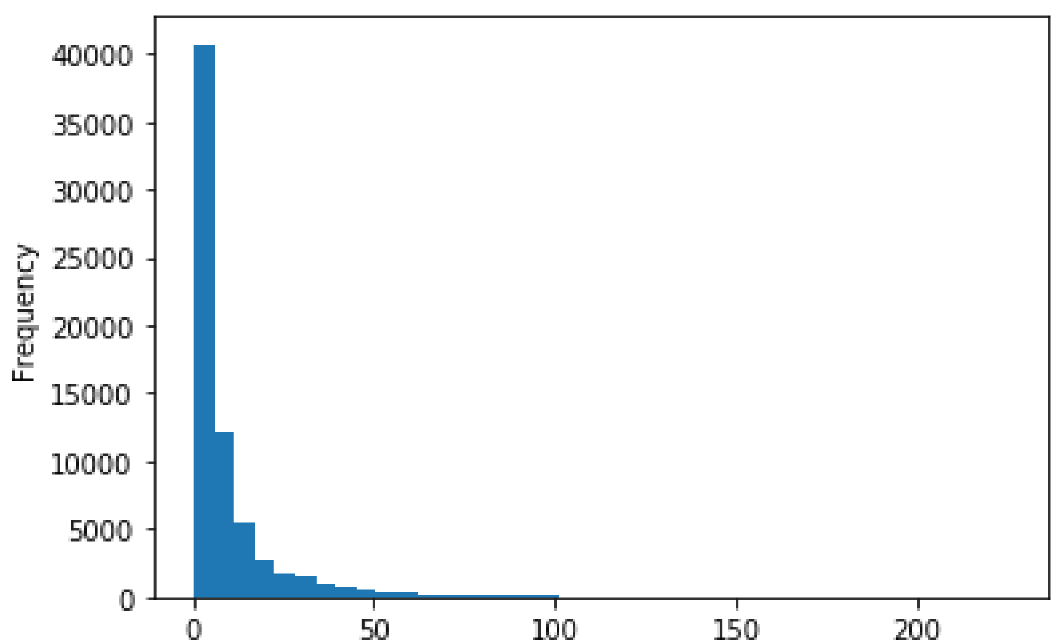
```
kolumna: o_height
unikalnych wartości: 6
```




```
kolumna: umem
unikalnych wartości: 9395
```




```
kolumna: utime
unikalnych wartości: 10960
```



[11]:
```
print(f"unikalnych wartości w 'b_size': {len(data['b_size'].unique())}")
print(f"Wierszy z polem 'b' != 0: {len(data[data['b'] > 0])}")
print(f"Wierszy z polem 'b' != 0: {len(data[data['b'] > 0])/len(data)*100}%")
```

```
unikalnych wartości w 'b_size': 1
Wierszy z polem 'b' != 0: 859
Wierszy z polem 'b' != 0: 1.248836938822982%
```

Wnioski Kolumna 'b_size' nie zawiera niezerowych wartości. Można ją usunąć. Kolumna 'b' jest niezerowa w ~1% przypadków.

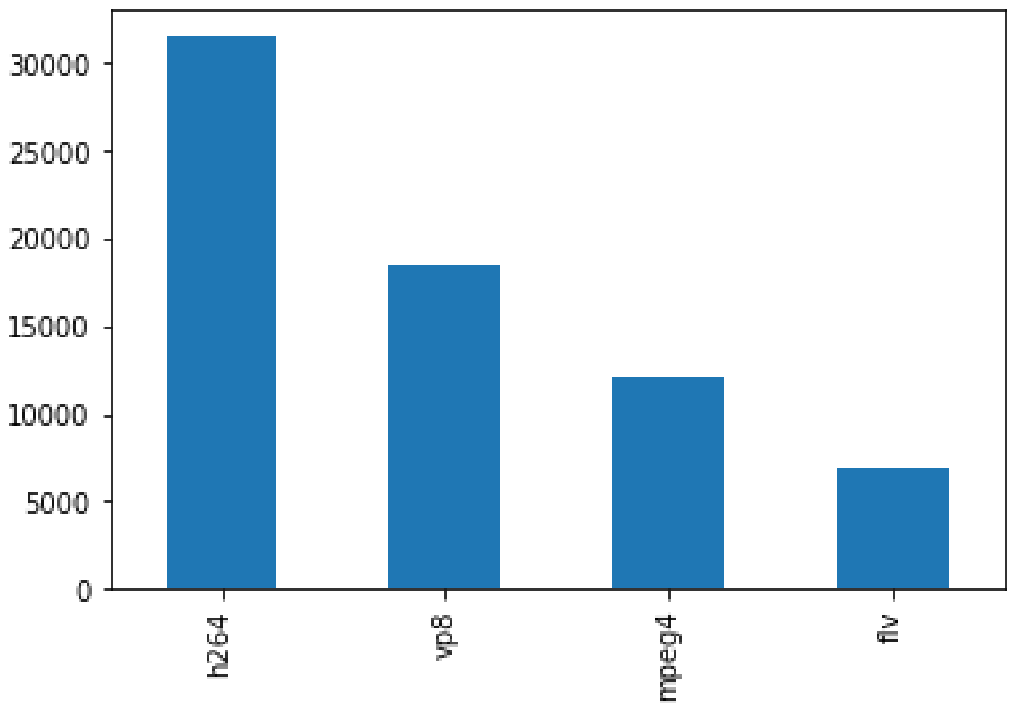
Analiza kolumn kategorycznych

[12]:
```
non_numeric_columns = data.select_dtypes(exclude=np.number).columns
non_numeric_columns
```

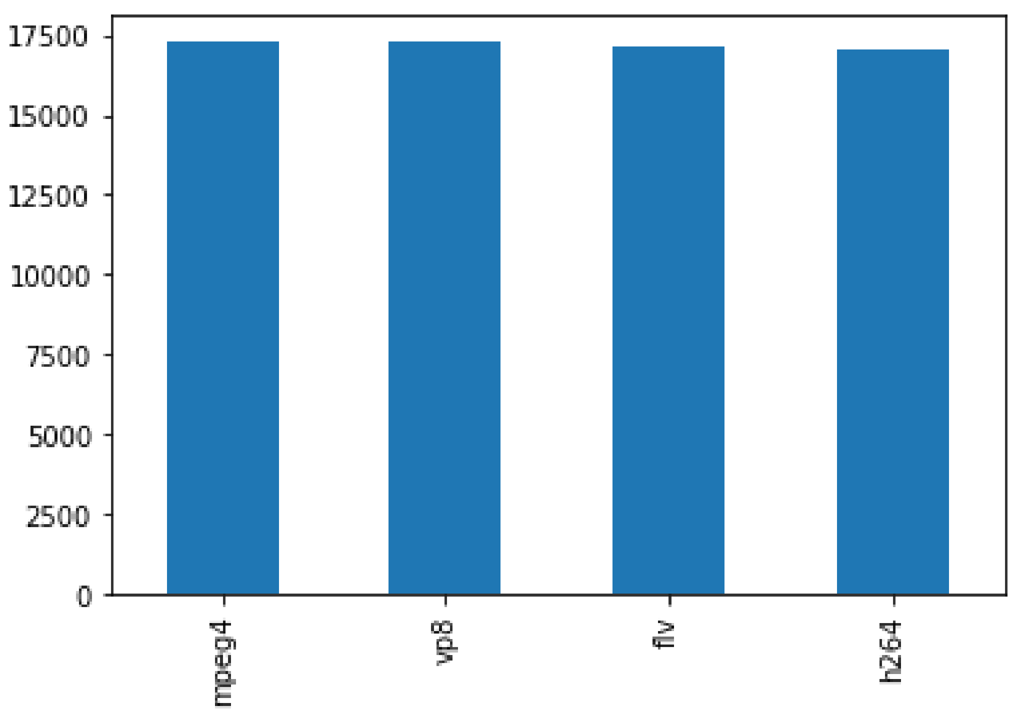
[12]:
```
Index(['id', 'codec', 'o_codec'], dtype='object')
```

[13]:
```
for col in non_numeric_columns:
  print(f'kolumna: {col}')
  print(f'unikalnych wartości: {len(data[col].unique())}')
  if len(data[col].unique()) < 15:
    data[col].value_counts().plot.bar()
    plt.show()
```

```
kolumna: id
unikalnych wartości: 1099
kolumna: codec
unikalnych wartości: 4
```




```
kolumna: o_codec
unikalnych wartości: 4
```



0.4.3 Wartości brakujące

[14]:
```
data.isnull().sum()
```

[14]:
```
id             0
duration       0
codec          0
width          0
height         0
bitrate        0
framerate      0
i              0
p              0
b              0
frames         0
i_size         0
p_size         0
b_size         0
size           0
o_codec        0
o_bitrate      0
o_framerate    0
o_width        0
o_height       0
umem           0
utime          0
dtype: int64
```

0.5 Outliers

[15]:
```
data_2 = data.copy()
```

Do obcięcia outlierów pomocniczo wykorzystujemy poniższe wzory: - IQR (interquartile range) = P(75) - P(25) - Dolna_granica = P(25) - 1,5*IQR - Gorna_granica = P(75) + 1,5*IQR - (P - percentyl)

[16]:
```
def outliners_range(data, column_name):
    rows = data[column_name]
    iqr = np.nanpercentile(rows, 75) - np.nanpercentile(rows, 25)
    lower = (np.nanpercentile(rows, 25) - 1.5*iqr)
    upper = (np.nanpercentile(rows, 75) + 1.5*iqr)
    return lower, upper
```

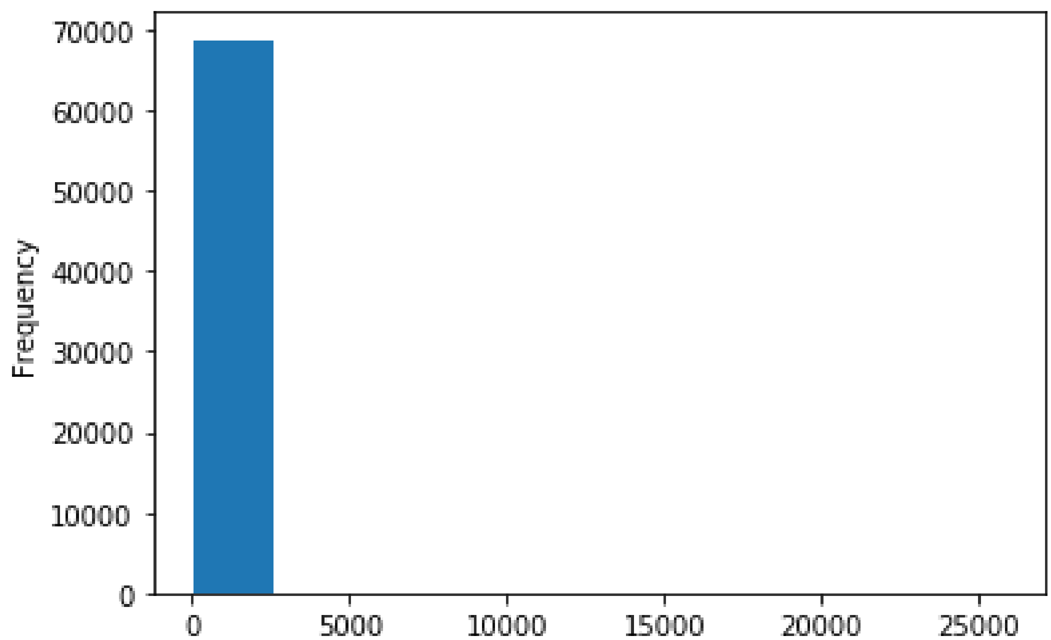
0.5.1 Kolumny numeryczne

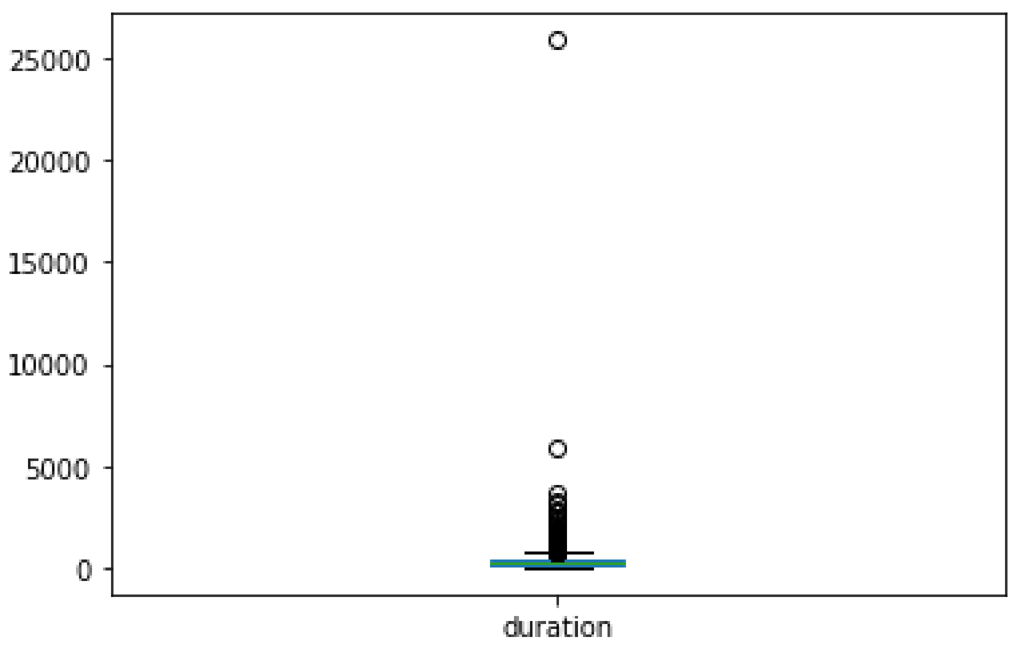
[17]:
```
numeric_columns = data_2.select_dtypes(include=np.number).columns
numeric_data = data_2[numeric_columns]
numeric_data.head()
```

[17]:
```
    duration  width  height  bitrate  framerate   i     p  b  frames  i_size  \
0  130.35667    176     144    54590       12.0  27  1537  0    1564   64483
1  130.35667    176     144    54590       12.0  27  1537  0    1564   64483
2  130.35667    176     144    54590       12.0  27  1537  0    1564   64483
3  130.35667    176     144    54590       12.0  27  1537  0    1564   64483
4  130.35667    176     144    54590       12.0  27  1537  0    1564   64483

   p_size  b_size    size  o_bitrate  o_framerate  o_width  o_height   umem  \
0  825054       0  889537      56000         12.0      176       144  22508
1  825054       0  889537      56000         12.0      320       240  25164
2  825054       0  889537      56000         12.0      480       360  29228
3  825054       0  889537      56000         12.0      640       480  34316
4  825054       0  889537      56000         12.0     1280       720  58528

   utime
0  0.612
1  0.980
2  1.216
3  1.692
4  3.456
```

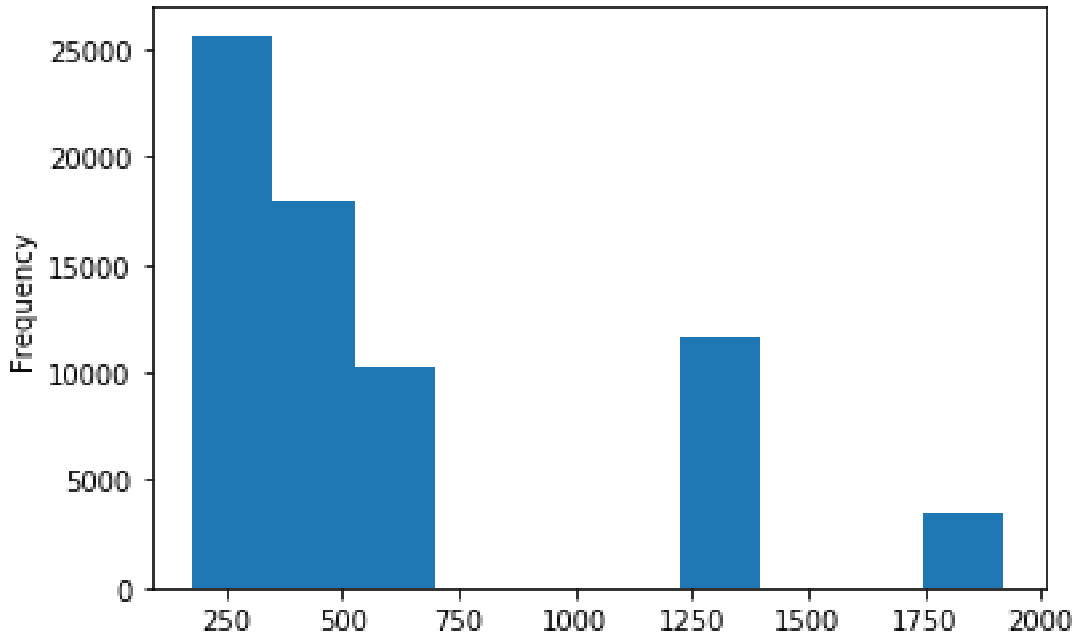
[18]:
```
# wizualizacja rozkładu danych poszczególnych kolumn
for column in numeric_data:
  print(f'Kolumna: {column}')
  numeric_data[column].plot.hist()
  plt.show()
  numeric_data[column].plot.box()
  plt.show()
```

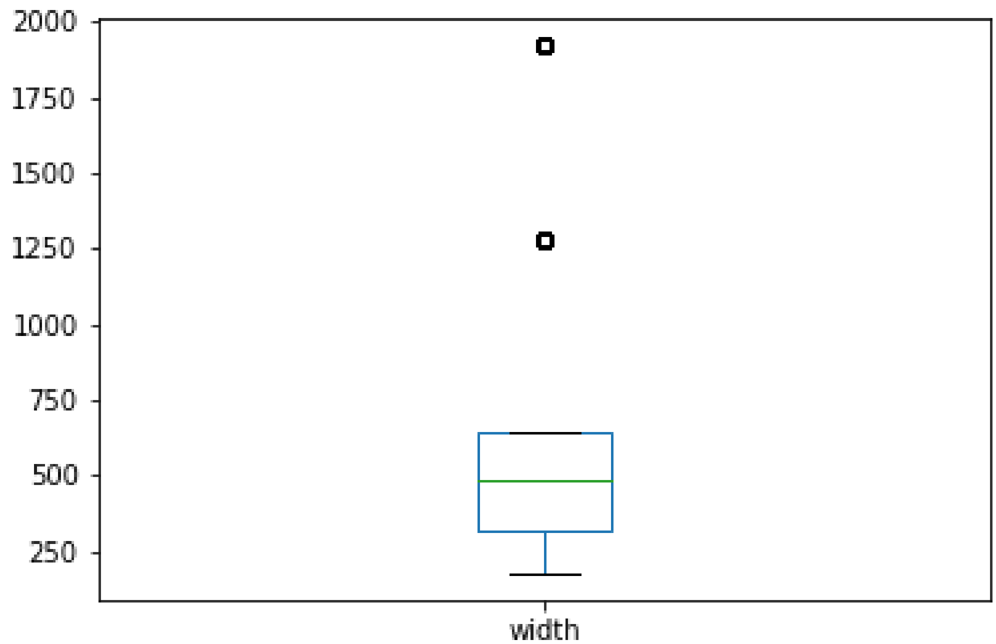
```
Kolumna: duration
```



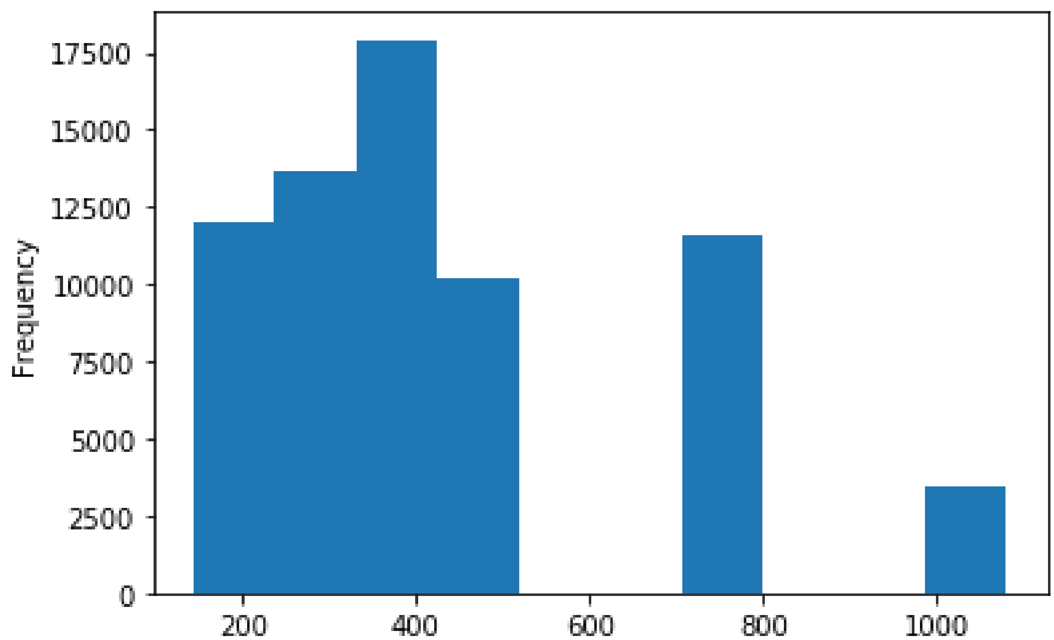


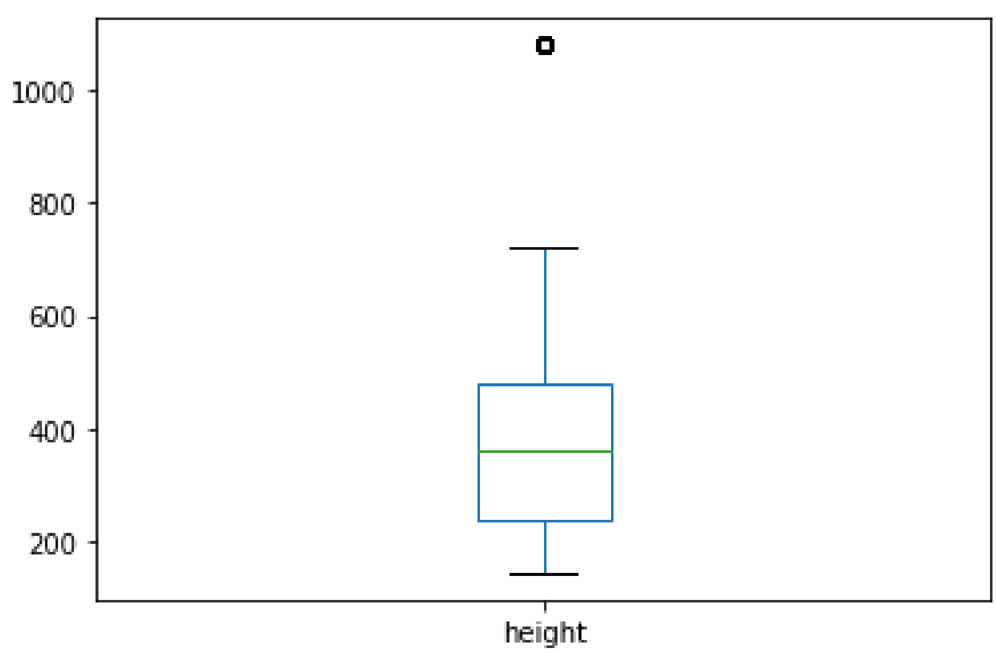
Kolumna: width



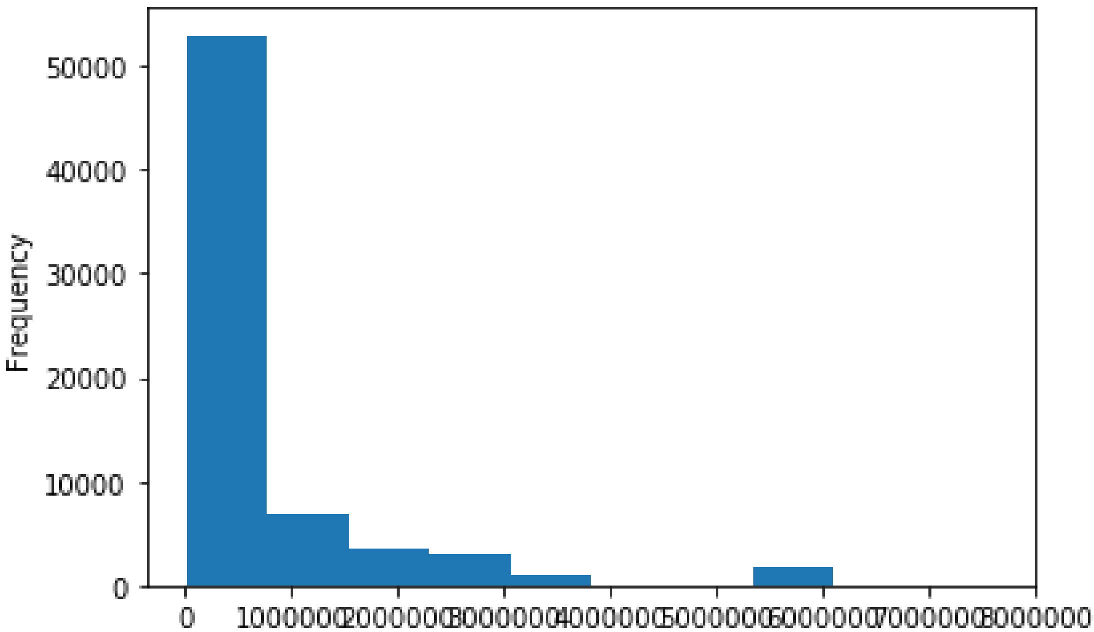


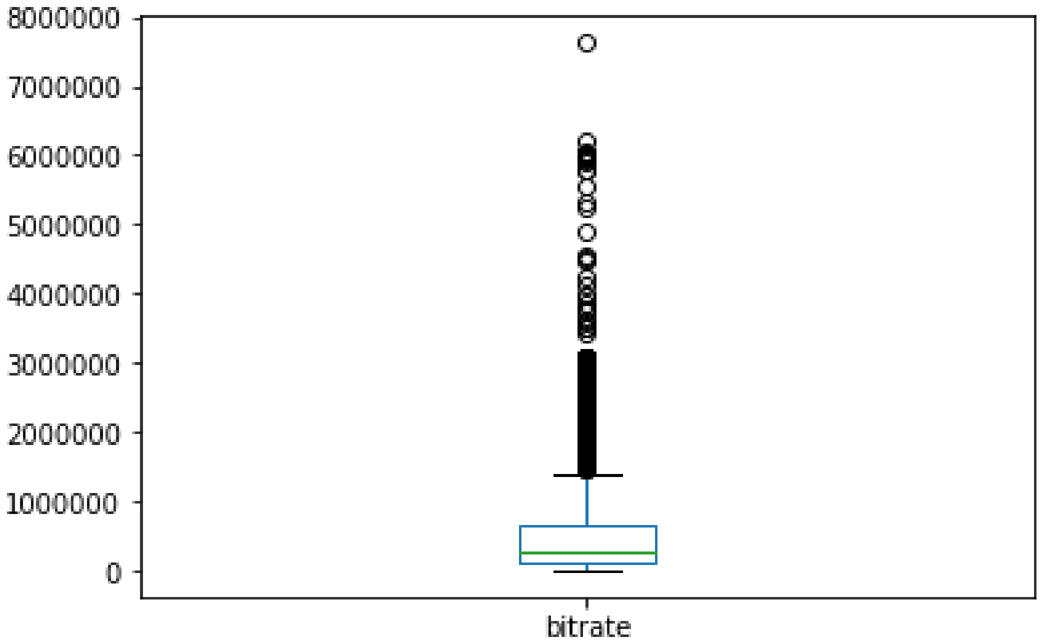

```
Kolumna: height
```



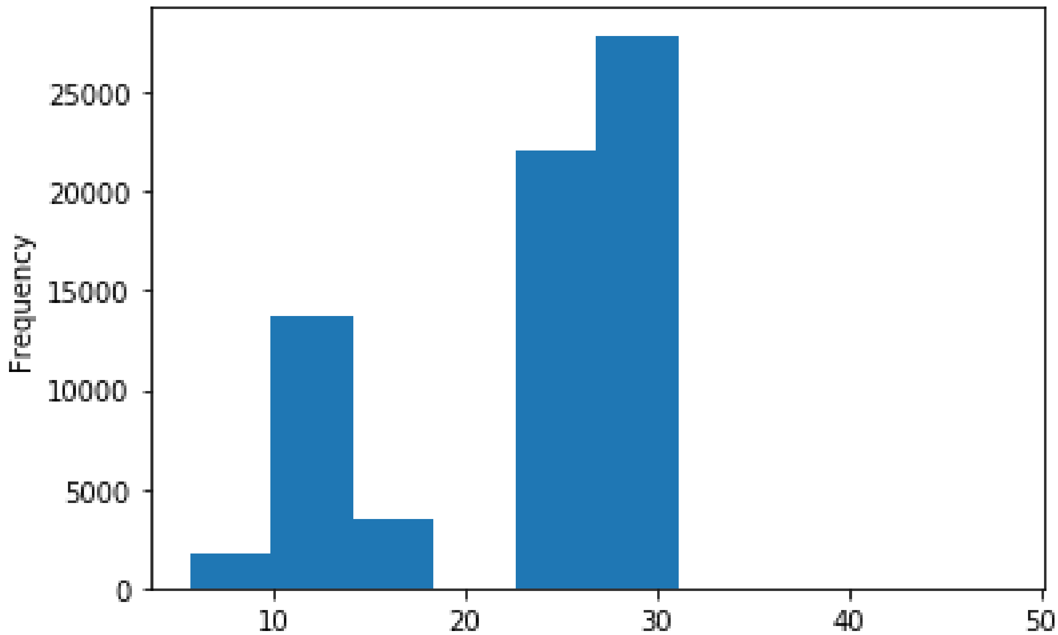


`Kolumna: bitrate`

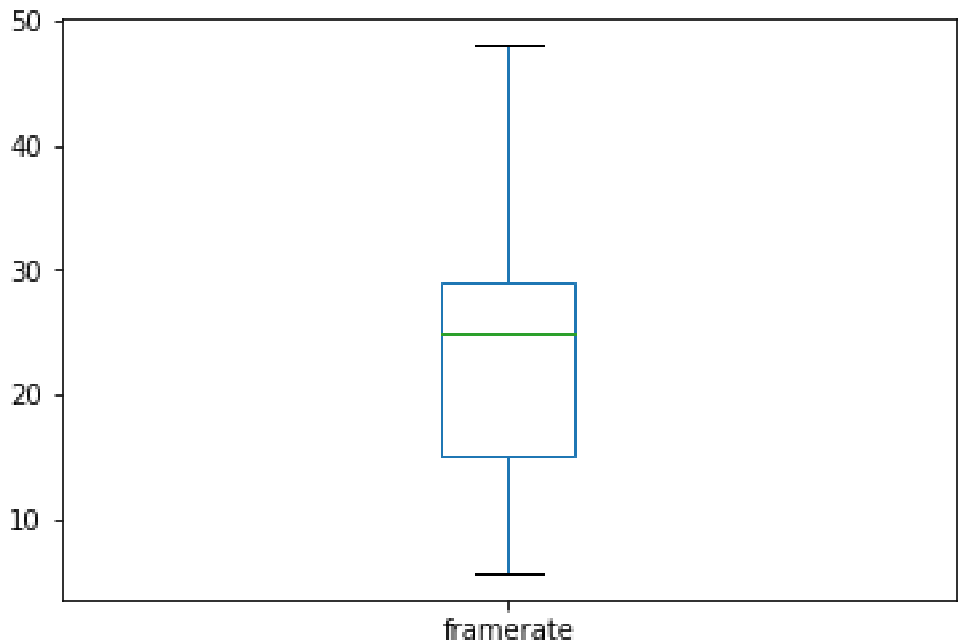




Kolumna: framerate

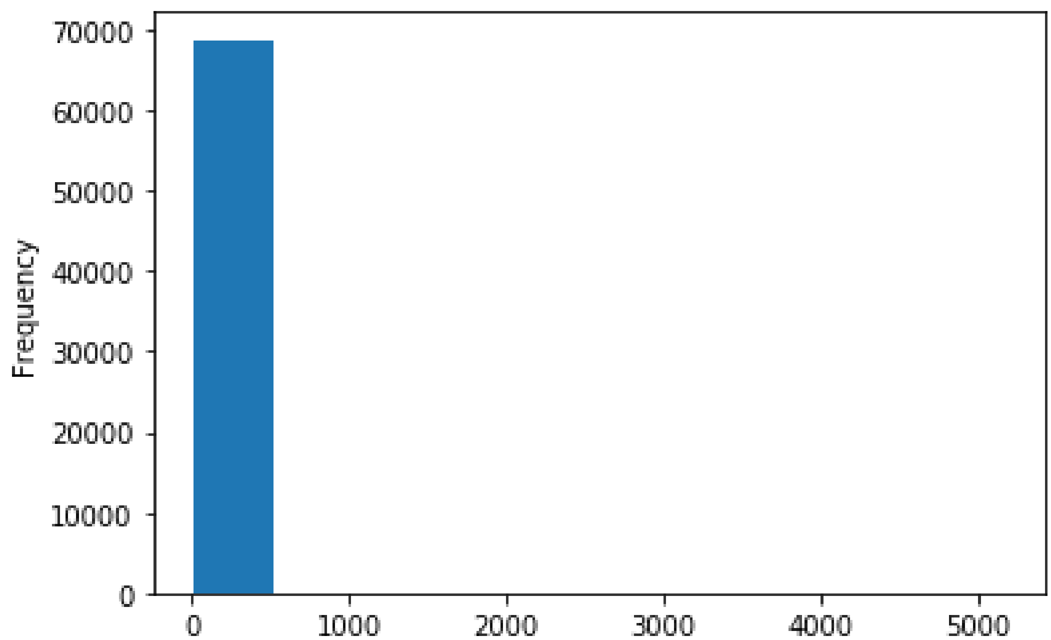


Frequency
25000
20000
15000
10000
5000
0
10
20
30
40
50

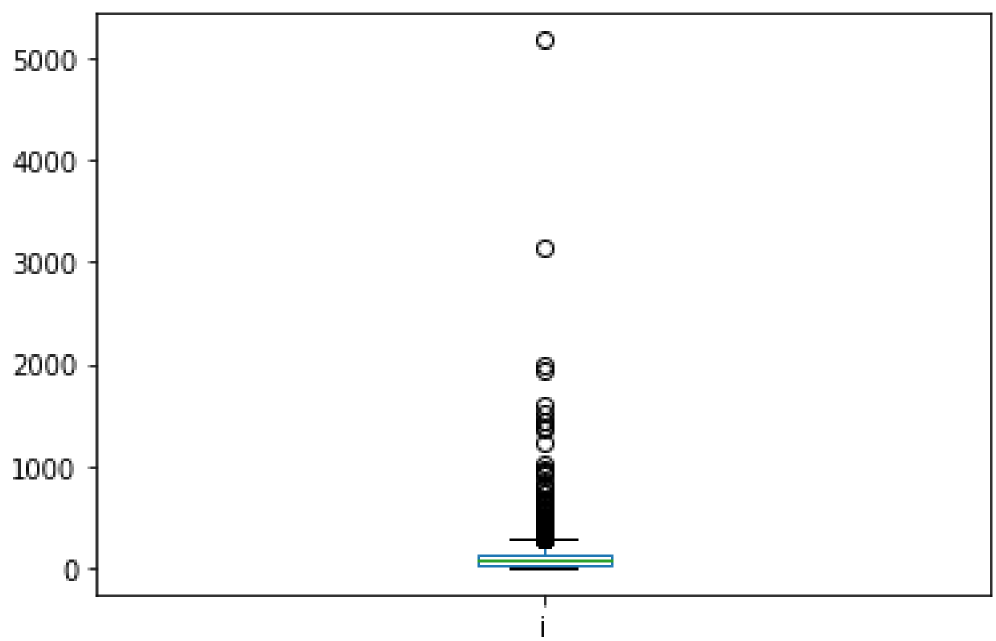


50
40
30
20
10
framerate


```
Kolumna: i
```

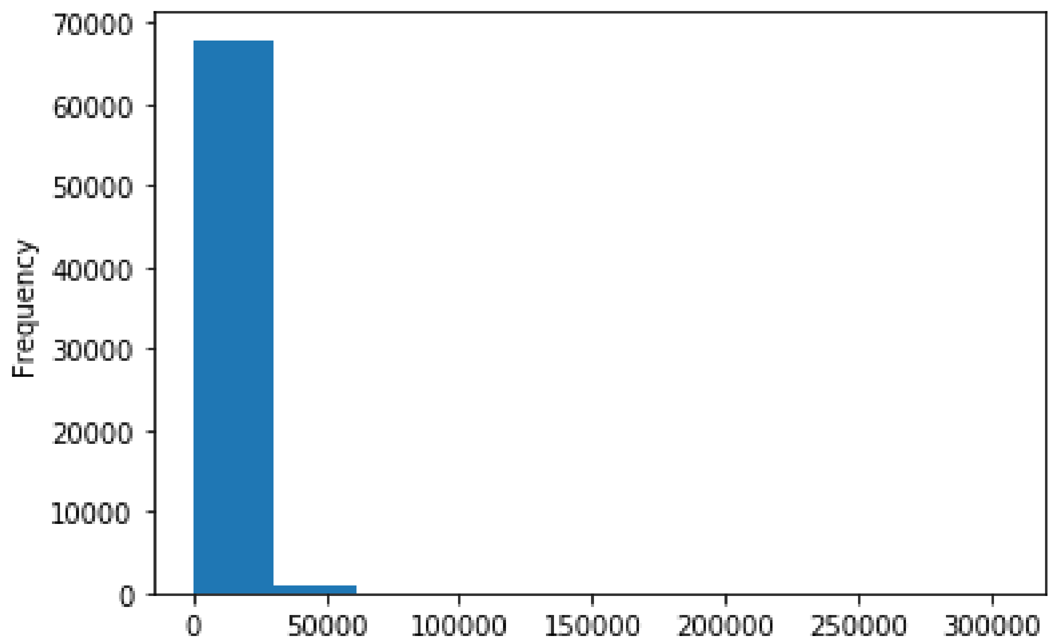


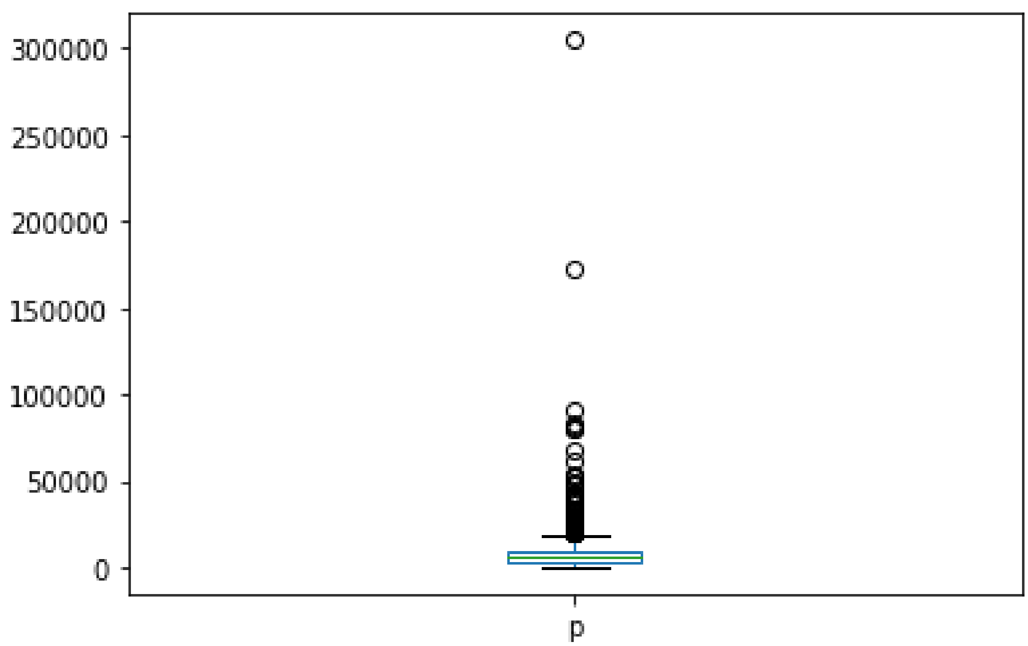
70000
60000
50000
40000
30000
20000
10000
0
Frequency
0
1000
2000
3000
4000
5000



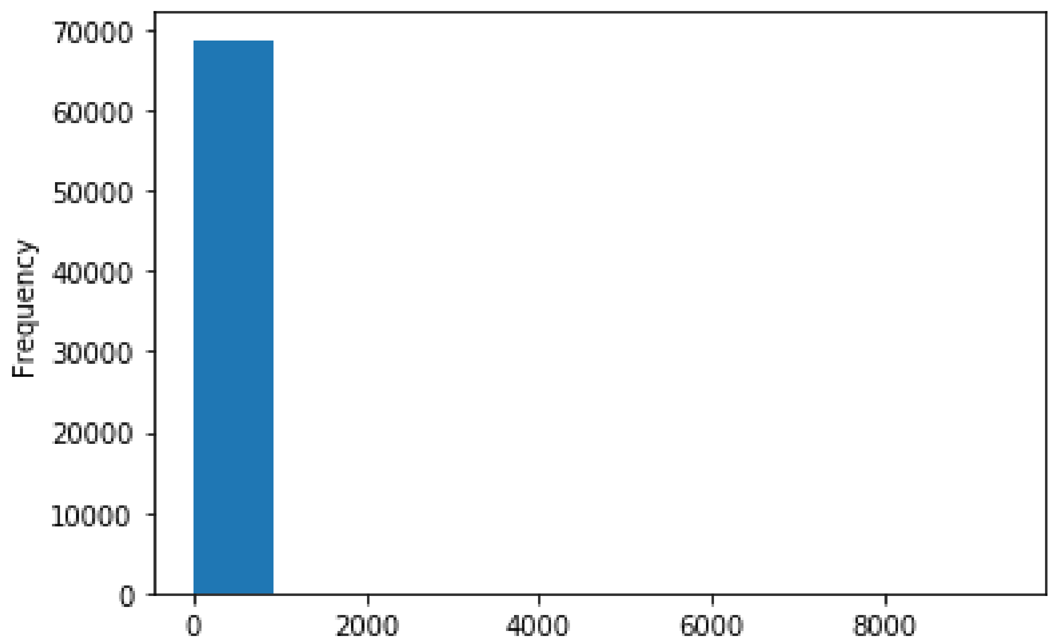
5000
4000
3000
2000
1000
0
i

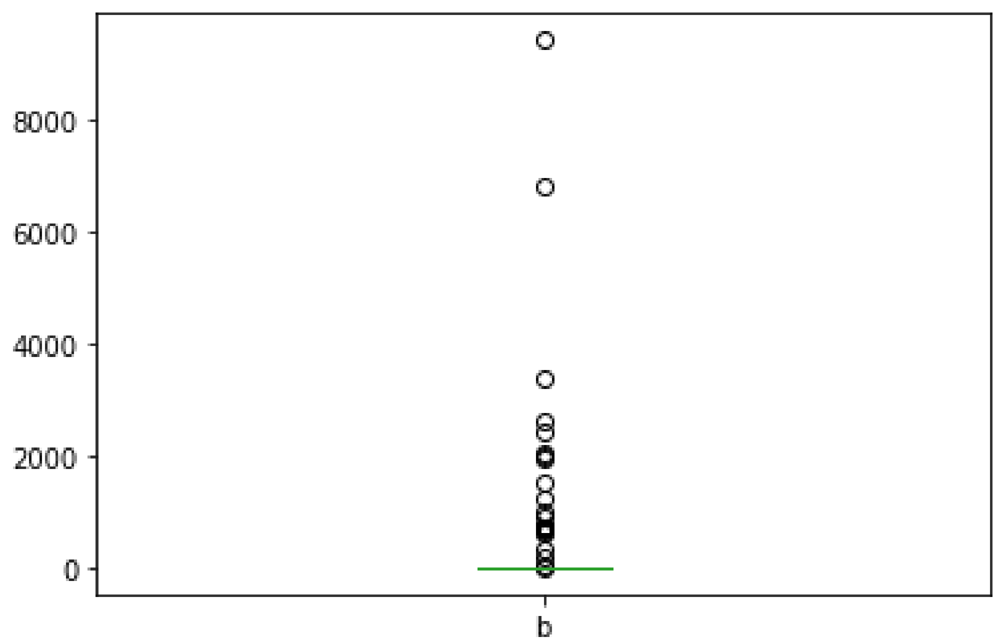
Kolumna: p


Frequency
70000
60000
50000
40000
30000
20000
10000
0
0
50000
100000
150000
200000
250000
300000

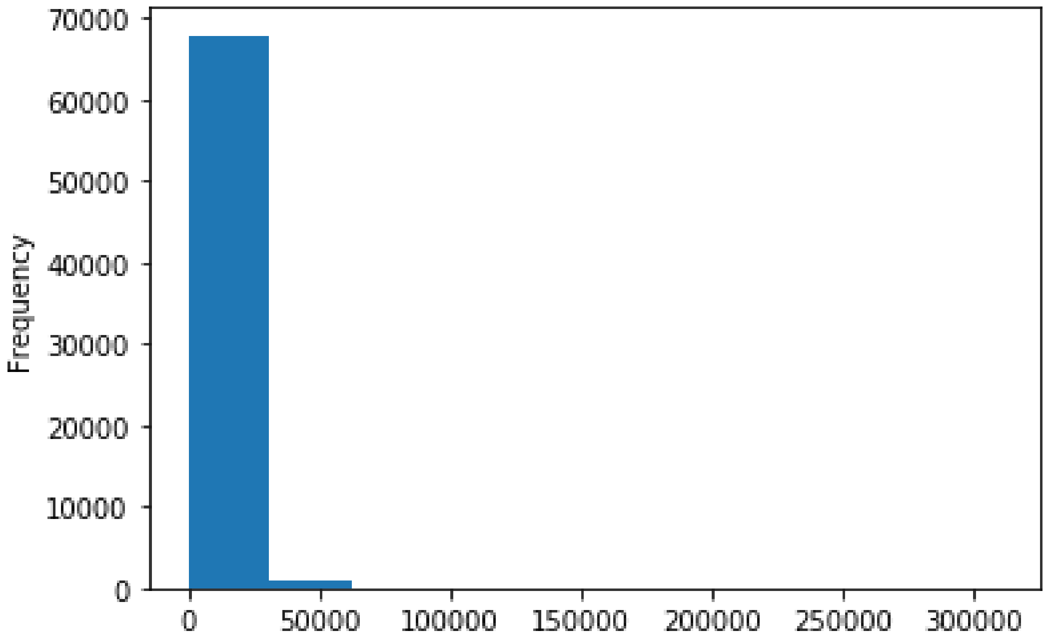

300000
250000
200000
150000
100000
50000
0
p

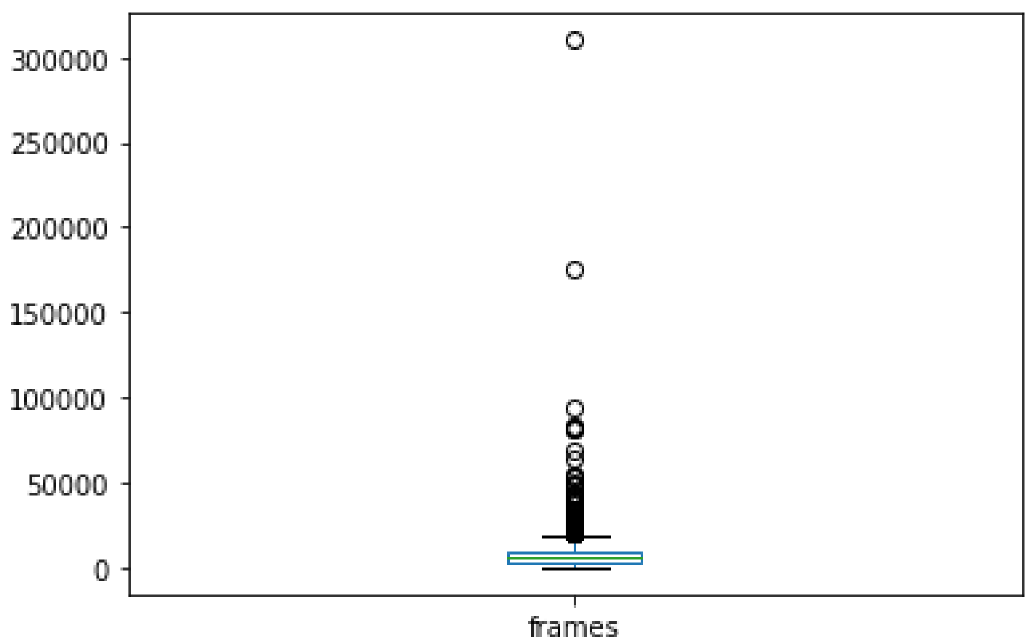
```
Kolumna: b
```



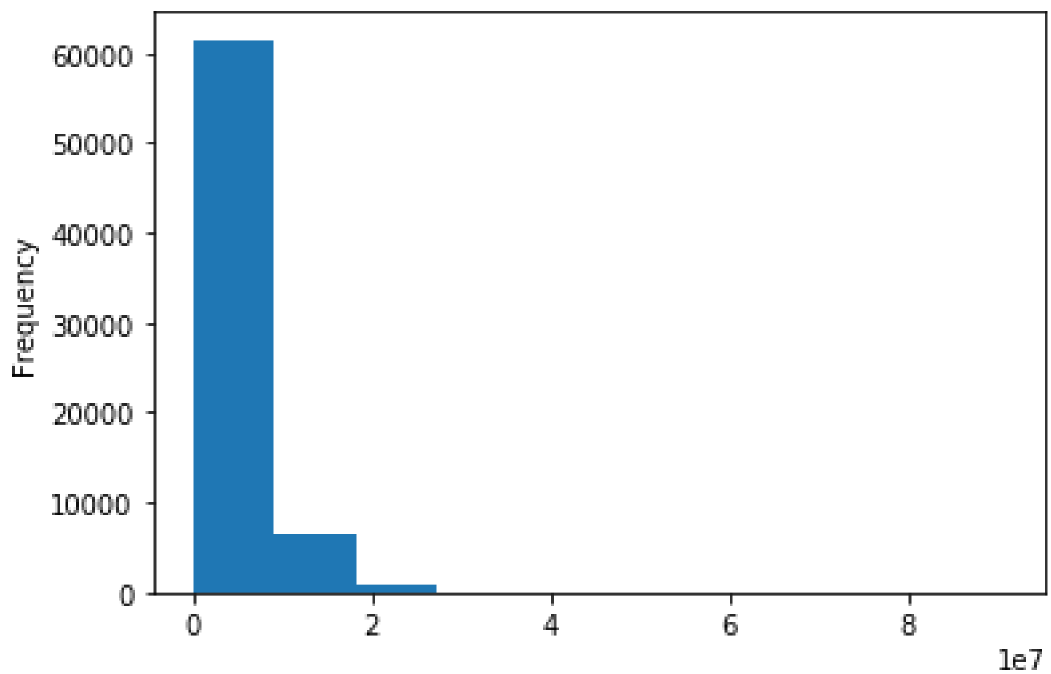


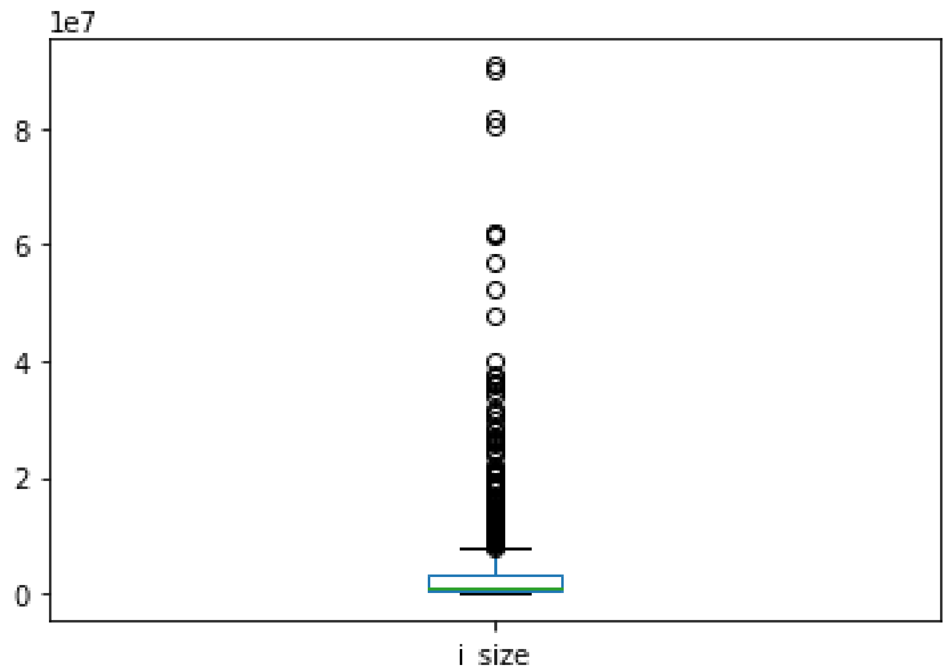
Kolumna: frames



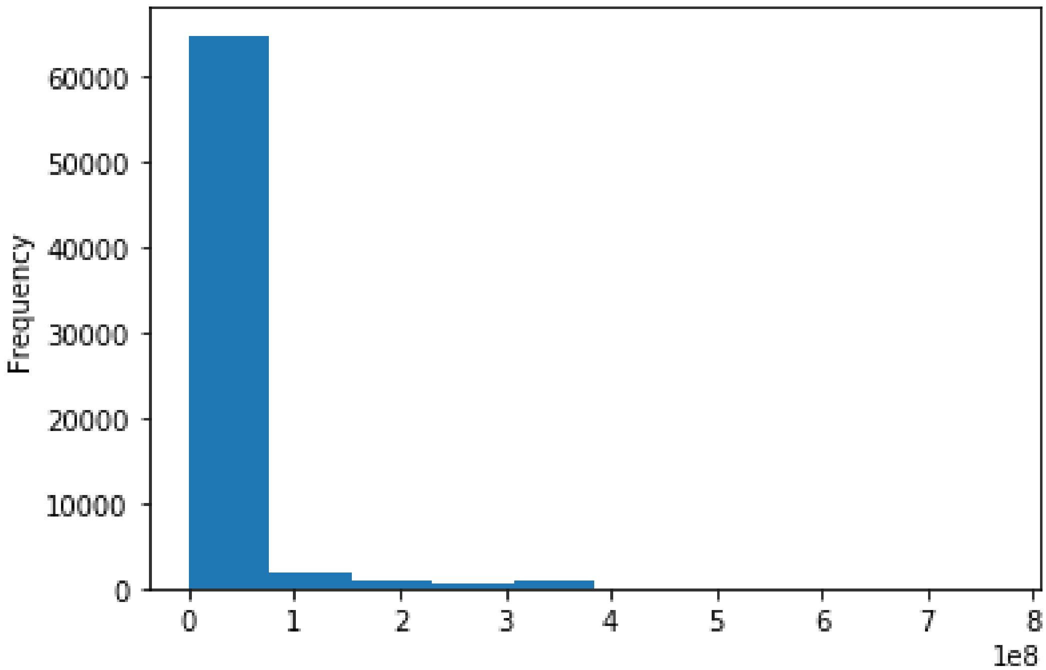


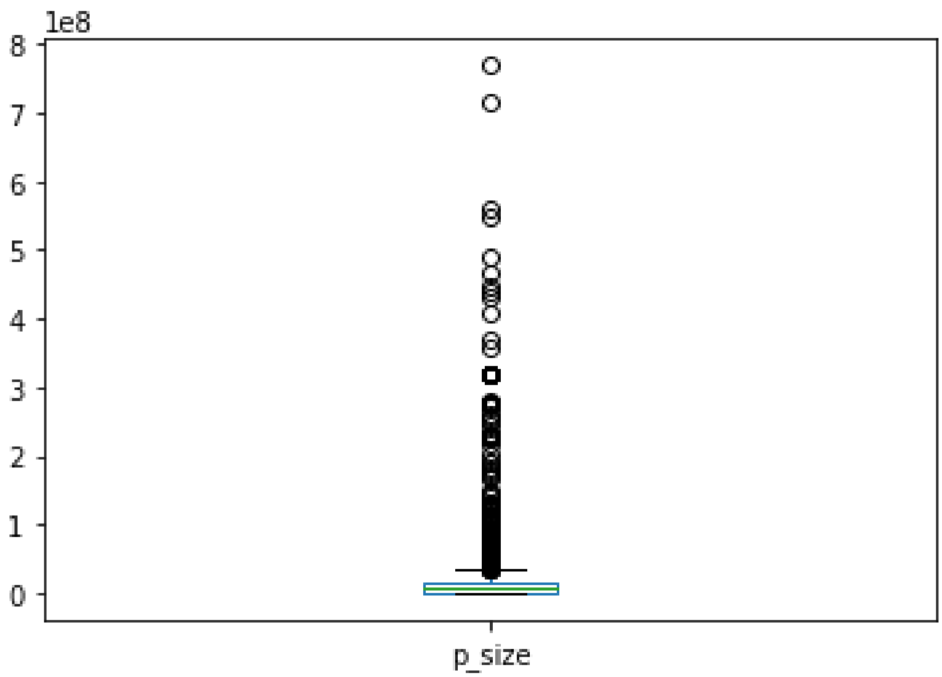
Kolumna: i_size



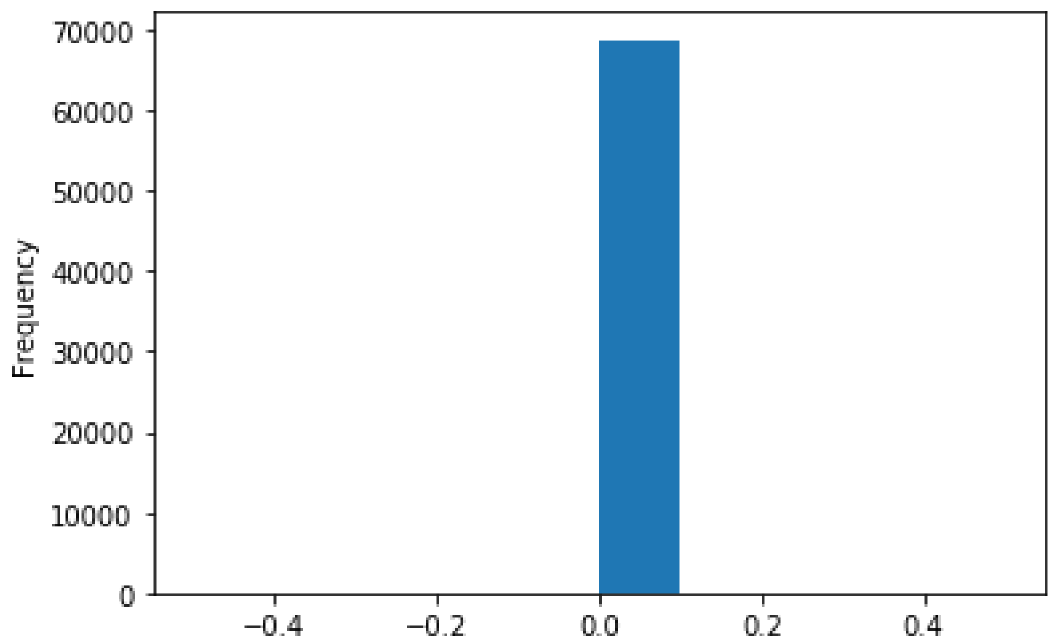


Kolumna: p_size

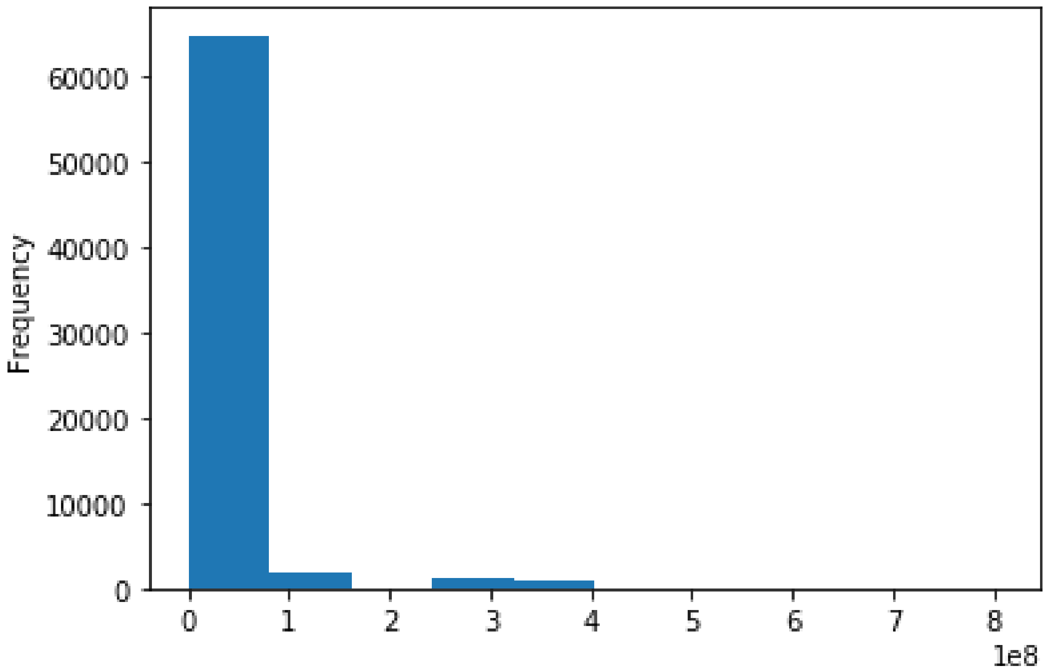


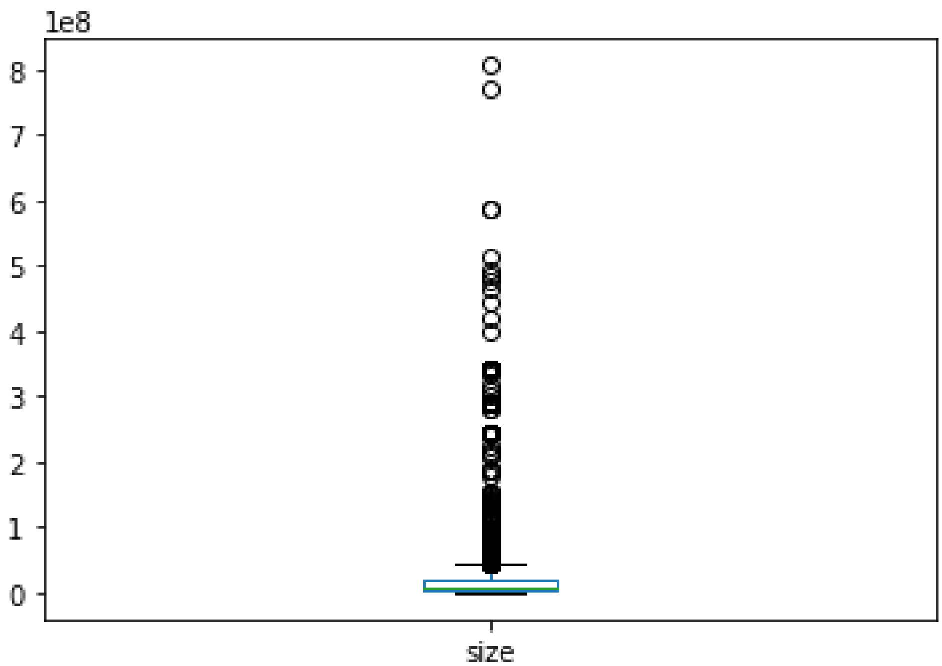


Kolumna: b_size

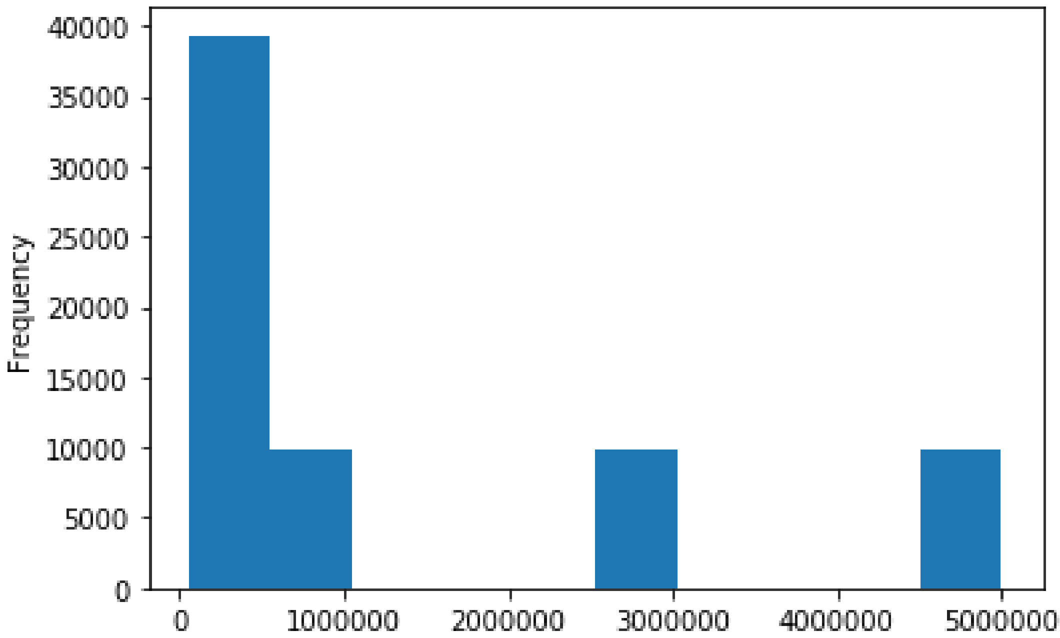


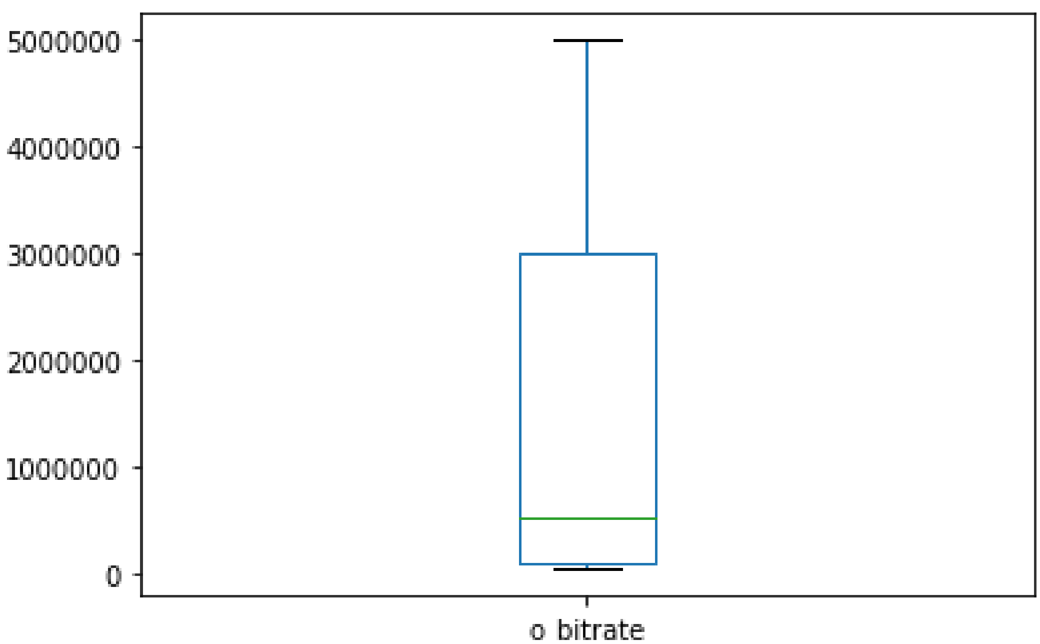
`Kolumna: size`



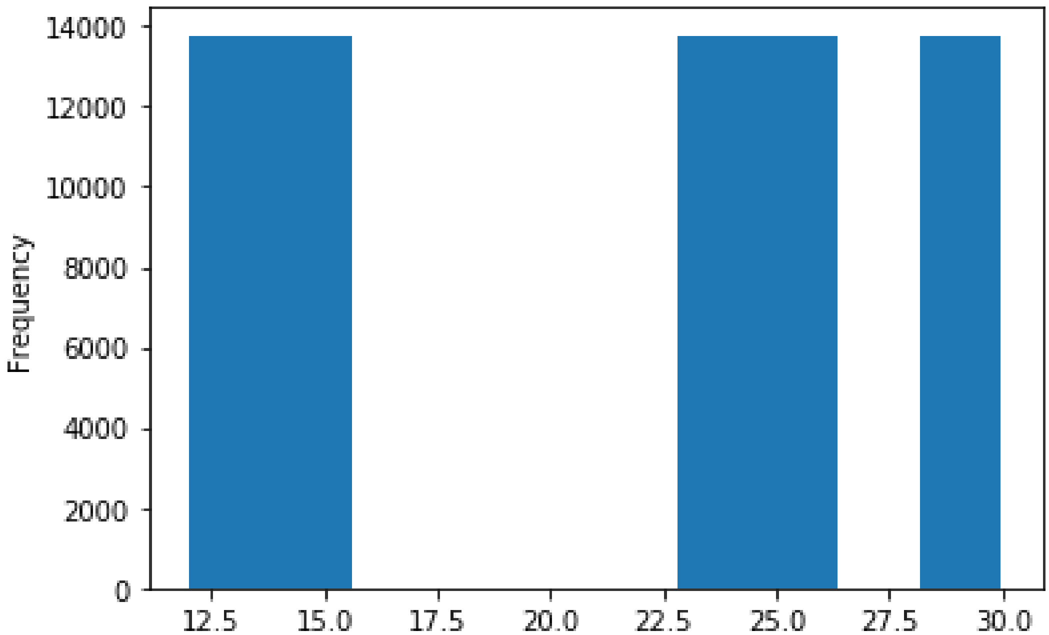


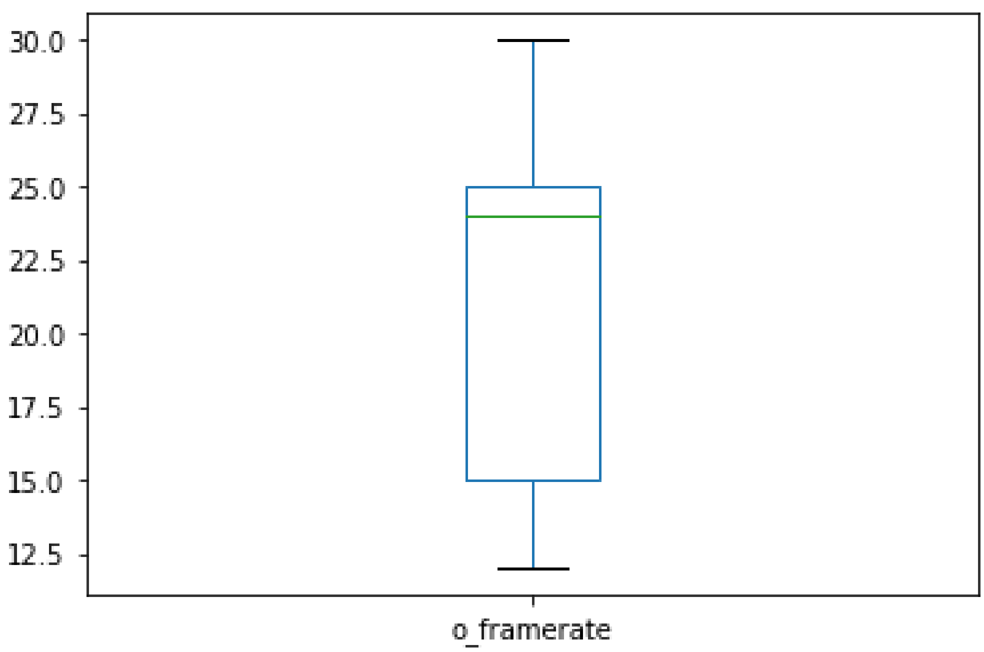
Kolumna: o_bitrate



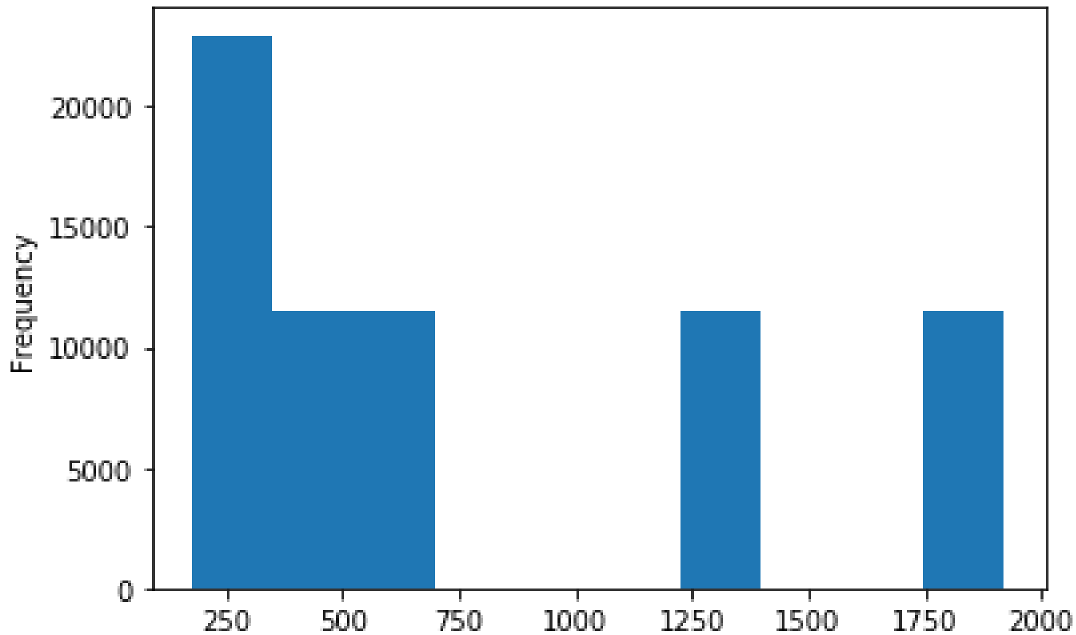


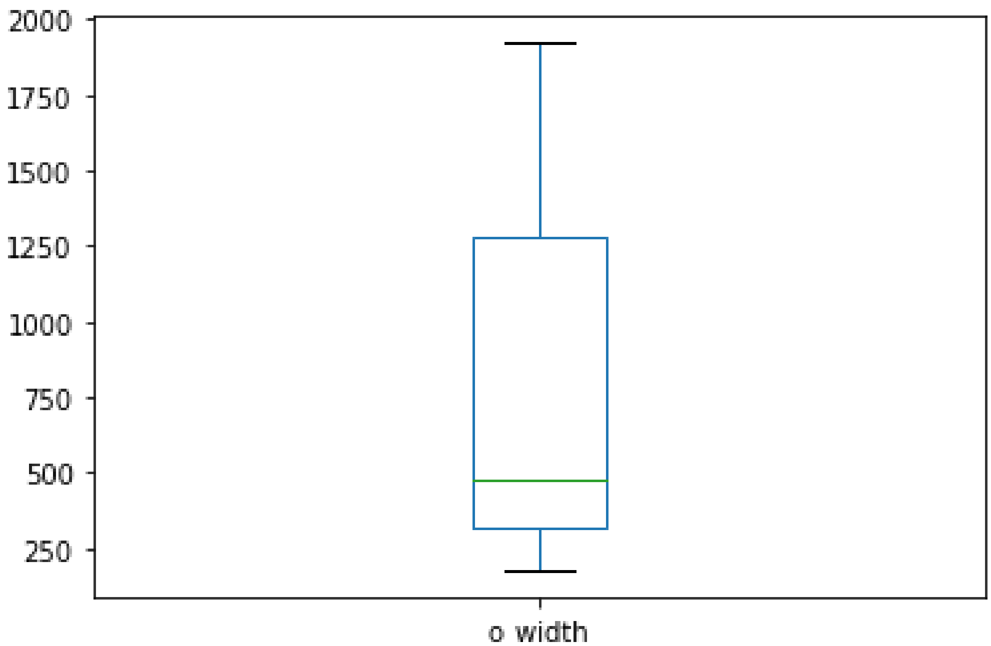
Kolumna: o_framerate



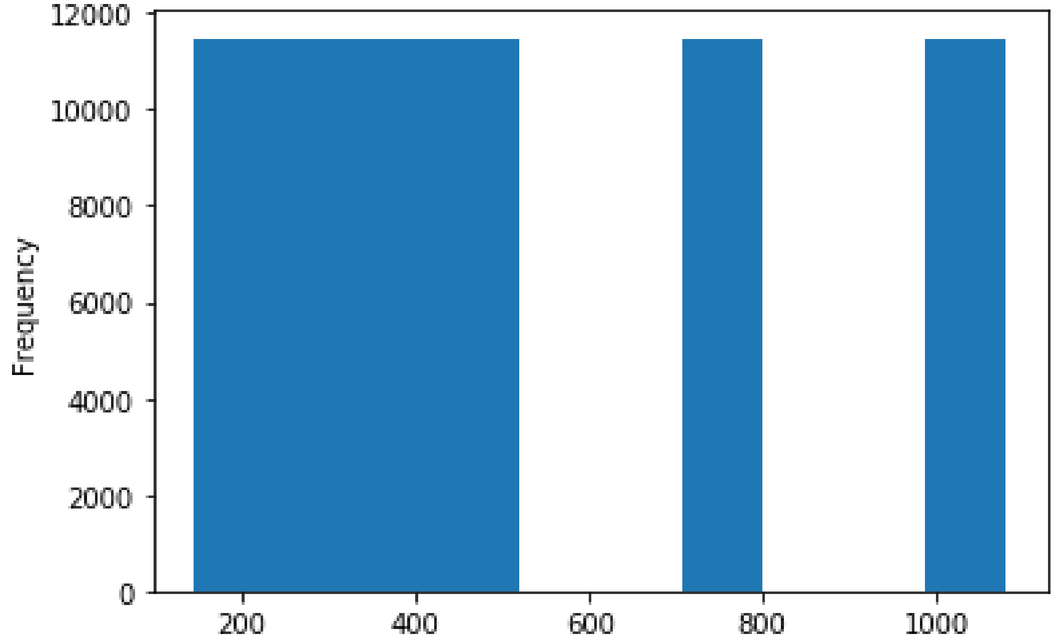


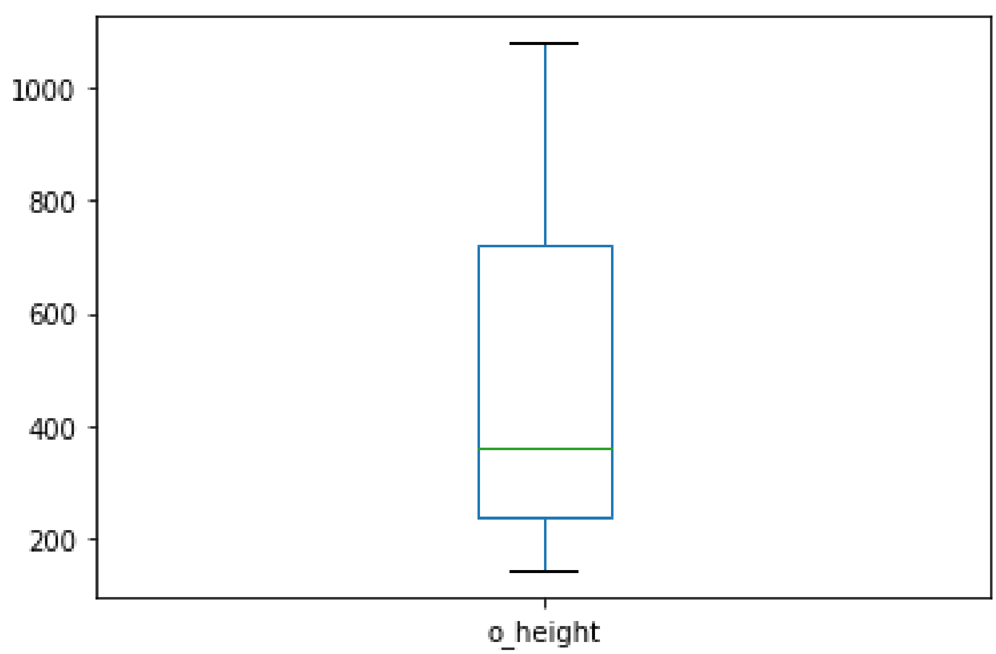
Kolumna: o_width



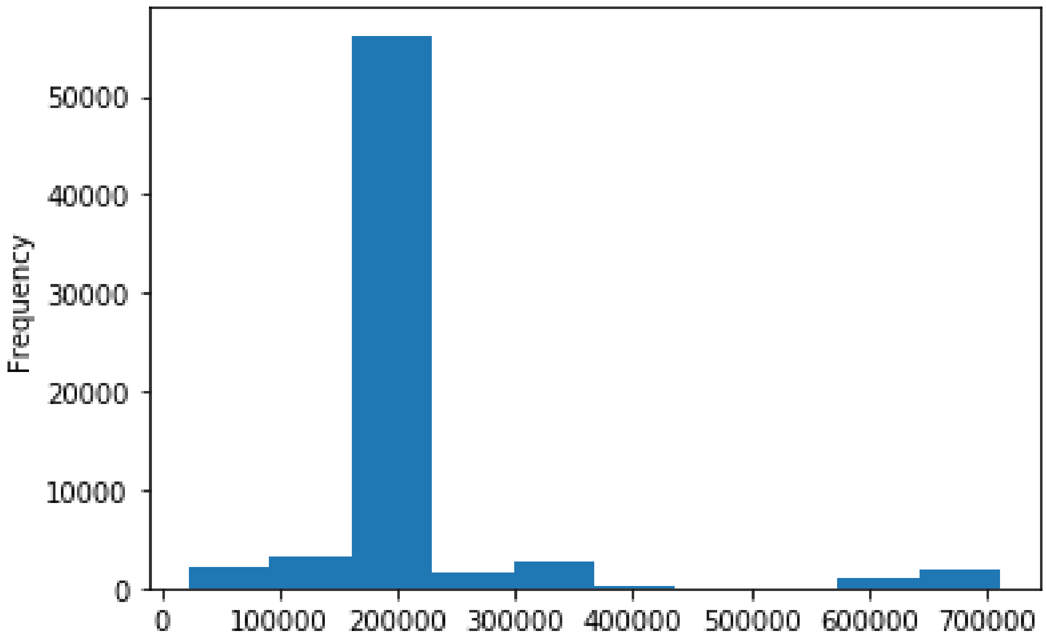


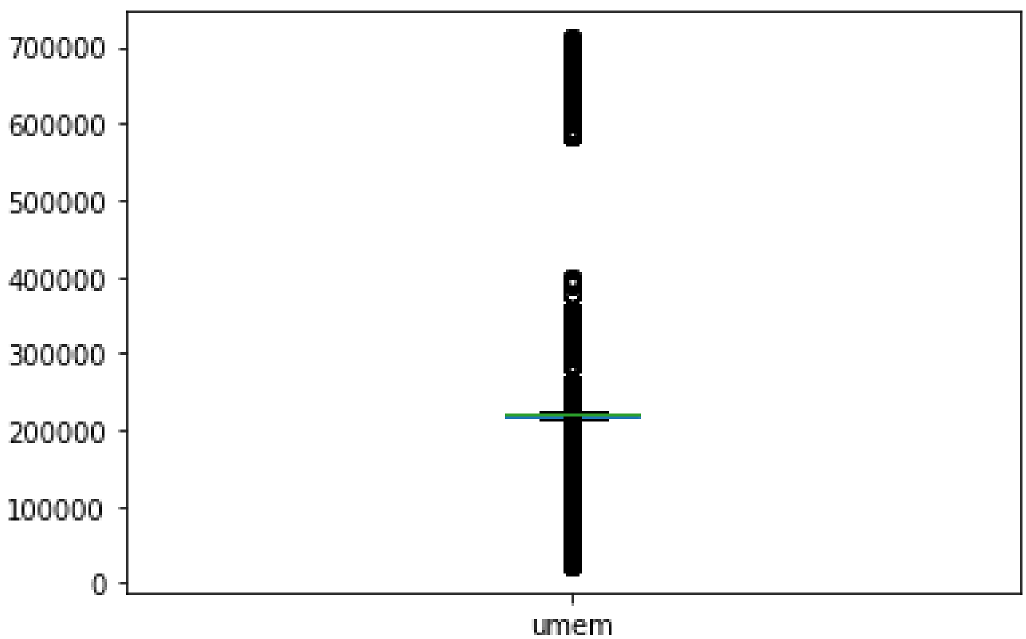

```
Kolumna: o_height
```



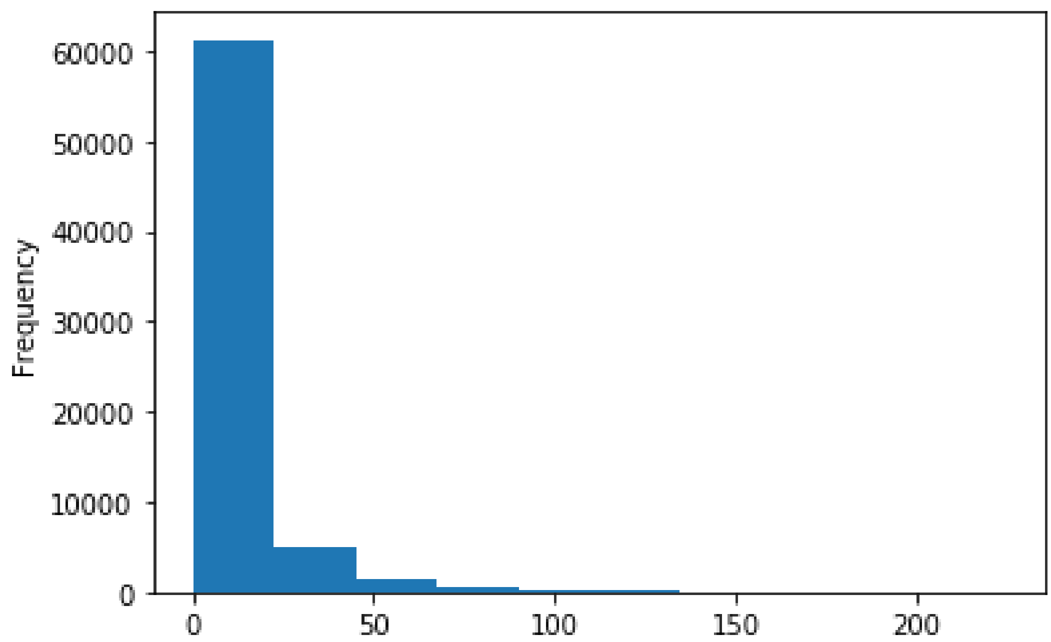


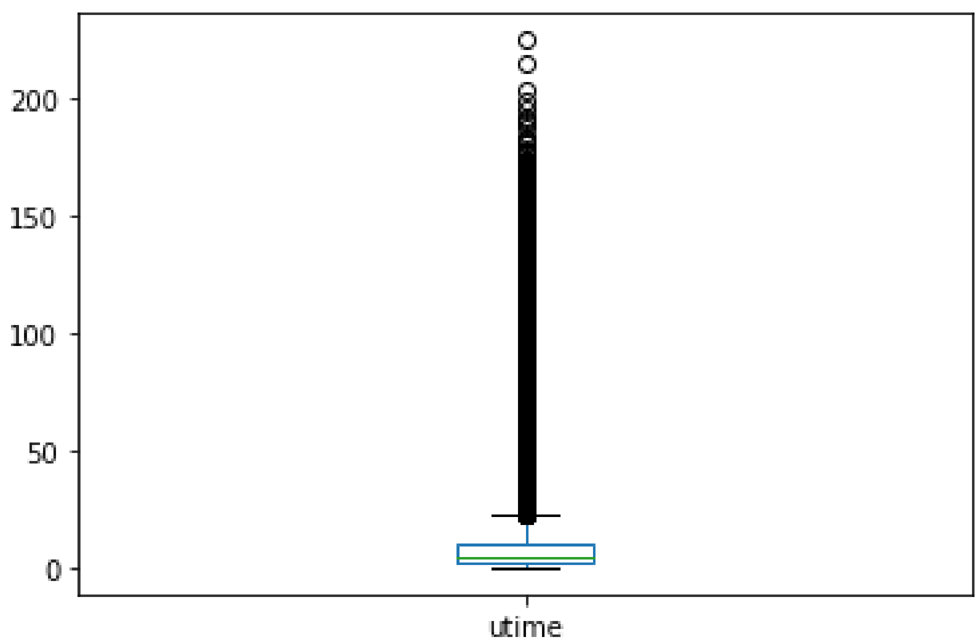
`Kolumna: umem`





`Kolumna: utime`





Kolumna "frames"

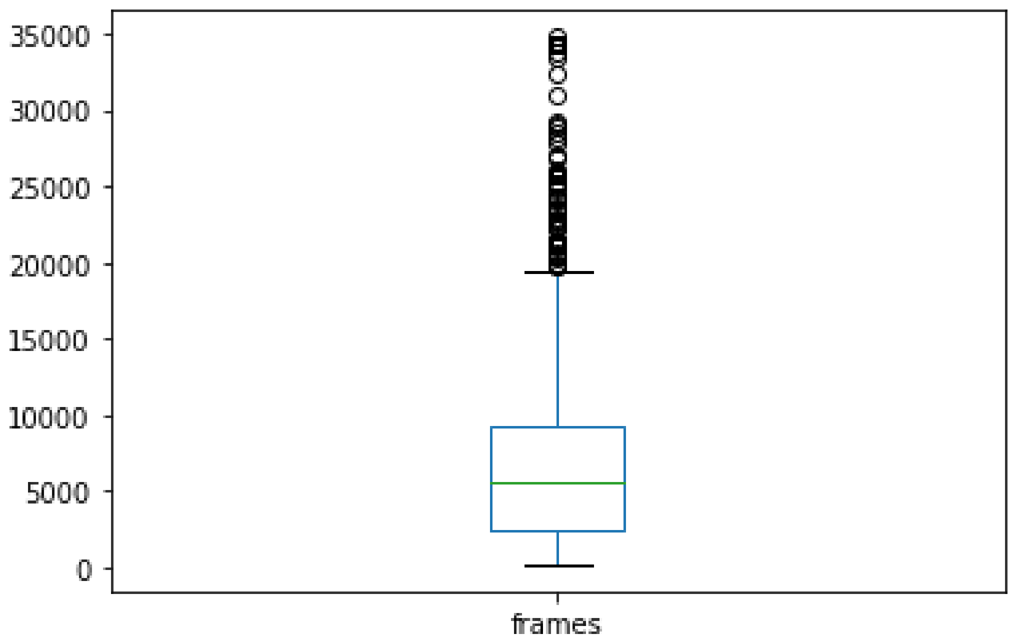
[19]:
```
lower, upper = outliners_range(numeric_data, 'frames')
lower, upper
```

[19]: (-7805.5, 19454.5)

[20]:
```
num = len(numeric_data[numeric_data["frames"]>upper])
print(f'wartości >{upper}: {num} ({round(num/len(data_2)*100, 2)}%)')
num = len(numeric_data[numeric_data["frames"]>30000])
print(f'wartości >30k: {num} ({round(num/len(data_2)*100, 2)}%)')
num = len(numeric_data[numeric_data["frames"]>40000])
print(f'wartości >35k: {num} ({round(num/len(data_2)*100, 2)}%)')
```

```
wartości >19454.5: 3076 (4.47%)
wartości >30k: 869 (1.26%)
wartości >35k: 20 (0.03%)
```

[21]:
```
# Obcięcie outlierów ( usunięcie wierszy z wart. >35k)
data_2 = data_2[data_2['frames'] <= 35000 ]

data_2['frames'].plot.box()
plt.show()
```



Kolumna "duration"

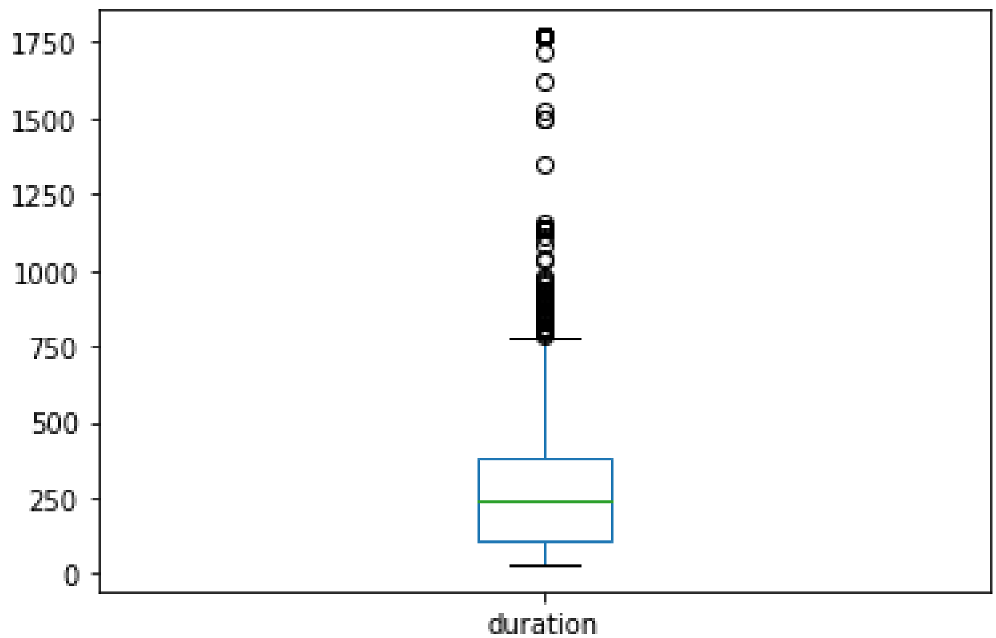
[22]:
```
lower, upper = outliners_range(numeric_data, 'duration')
lower, upper
```

[22]: (-302.0675, 788.1524999999999)

[23]:
```
num = len(numeric_data[numeric_data["duration"]>788])
print(f'wartości >788: {num} ({round(num/len(data_2)*100, 2)}%)')
num = len(numeric_data[numeric_data["duration"]>1000])
print(f'wartości >1000: {num} ({round(num/len(data_2)*100, 2)}%)')
num = len(numeric_data[numeric_data["duration"]>1500])
print(f'wartości >1500: {num} ({round(num/len(data_2)*100, 2)}%)')
num = len(numeric_data[numeric_data["duration"]>2000])
print(f'wartości >2000: {num} ({round(num/len(data_2)*100, 2)}%)')
```

```
wartości >788: 3080 (4.48%)
wartości >1000: 1718 (2.5%)
wartości >1500: 865 (1.26%)
wartości >2000: 13 (0.02%)
```

[24]:
```
# Obcięcie outlierów ( usunięcie wierszy z wart. >2k)
data_2 = data_2[data_2['duration'] <= 2000 ]

data_2['duration'].plot.box()
plt.show()
```



0.6 Feature Engineering

[25]:
```
data_3 = data_2.copy()
```

[26]:
```
codecs_with_b    = data_3[data_3['b']==0]['codec'].unique()
codecs_without_b = data_3[data_3['b']!=0]['codec'].unique()
print(f"codecs_with_b: {codecs_with_b}")
print(f"codecs_without_b: {codecs_without_b}")
```

```
codecs_with_b: ['mpeg4' 'h264' 'vp8' 'flv']
codecs_without_b: ['h264']
```

Wniosek: Parametr 'b' jest niezerowy tylko w przypadku użycia kodeka 'h264'

Dodatkowe pole - pixels (width*height)

[27]:
```
data_3['pixels'] = data_3['width'] * data_3['height']
data_3.head()
```

[27]:
```
            id   duration  codec  width  height  bitrate  framerate   i     p  \
0  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
1  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
2  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
3  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
4  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537

   b  …  b_size    size  o_codec  o_bitrate  o_framerate o_width  o_height  \
0  0  …       0  889537    mpeg4      56000         12.0     176       144
1  0  …       0  889537    mpeg4      56000         12.0     320       240
2  0  …       0  889537    mpeg4      56000         12.0     480       360
3  0  …       0  889537    mpeg4      56000         12.0     640       480
4  0  …       0  889537    mpeg4      56000         12.0    1280       720

    umem  utime  pixels
0  22508  0.612   25344
1  25164  0.980   25344
2  29228  1.216   25344
3  34316  1.692   25344
4  58528  3.456   25344

[5 rows x 23 columns]
```

Dodatkowe pole - o_pixels (o_width*o_height)

[28]:
```
data_3['o_pixels'] = data_3['o_width'] * data_3['o_height']
data_3.head()
```

[28]:
```
            id   duration  codec  width  height  bitrate  framerate   i     p  \
0  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
1  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
2  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
3  04t6-jw9czg  130.35667  mpeg4    176     144    54590       12.0  27  1537
```

```
4  04t6-jw9czg  130.35667  mpeg4    176     144    54590        12.0   27  1537

   b  …    size  o_codec  o_bitrate  o_framerate  o_width o_height   umem  \
0  0  …  889537    mpeg4      56000         12.0      176      144  22508
1  0  …  889537    mpeg4      56000         12.0      320      240  25164
2  0  …  889537    mpeg4      56000         12.0      480      360  29228
3  0  …  889537    mpeg4      56000         12.0      640      480  34316
4  0  …  889537    mpeg4      56000         12.0     1280      720  58528

   utime  pixels  o_pixels
0  0.612   25344     25344
1  0.980   25344     76800
2  1.216   25344    172800
3  1.692   25344    307200
4  3.456   25344    921600

[5 rows x 24 columns]
```

0.7 Feature selection - usunięcie zbędnych kolumn

- pole id
- pole b_size (brak niezerowych wartości)
- pole umem (wartość wynikowa, jednak nie podlegająca analizie)

[29]:
```python
data_4 = data_3.copy()
```

[30]:
```python
data_4 = data_4.drop(['id', 'b_size', 'umem'], axis=1)
data_4.head(3)
```

[30]:
```
    duration  codec  width  height  bitrate  framerate   i     p  b  frames  \
0  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
1  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
2  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564

   …  p_size    size  o_codec o_bitrate  o_framerate  o_width  o_height  \
0  …  825054  889537    mpeg4     56000         12.0      176       144
1  …  825054  889537    mpeg4     56000         12.0      320       240
2  …  825054  889537    mpeg4     56000         12.0      480       360

   utime  pixels  o_pixels
0  0.612   25344     25344
1  0.980   25344     76800
2  1.216   25344    172800

[3 rows x 21 columns]
```

0.8 Data Preparation - przygotowanie danych do uczenia

- kodowanie pól kategorycznych
- skalowanie danych

[31]:
```
data_5 = data_4.copy()
data_5.head()
```

[31]:
```
     duration  codec  width  height  bitrate  framerate   i     p  b  frames  \
0  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
1  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
2  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
3  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564
4  130.35667  mpeg4    176     144    54590       12.0  27  1537  0    1564

   …  p_size    size  o_codec o_bitrate  o_framerate  o_width  o_height  \
0  …  825054  889537    mpeg4     56000         12.0      176       144
1  …  825054  889537    mpeg4     56000         12.0      320       240
2  …  825054  889537    mpeg4     56000         12.0      480       360
3  …  825054  889537    mpeg4     56000         12.0      640       480
4  …  825054  889537    mpeg4     56000         12.0     1280       720

   utime  pixels  o_pixels
0  0.612   25344     25344
1  0.980   25344     76800
2  1.216   25344    172800
3  1.692   25344    307200
4  3.456   25344    921600

[5 rows x 21 columns]
```

[32]:
```
categorical_cols = ['codec', 'o_codec']
for column in categorical_cols:
  print(column)
  print(data_5[column].unique())
```

```
codec
['mpeg4' 'h264' 'vp8' 'flv']
o_codec
['mpeg4' 'vp8' 'flv' 'h264']
```

[33]:
```
ohe = ce.OneHotEncoder(cols=categorical_cols, return_df=True,
        use_cat_names=True, handle_unknown=0)
data_5 = ohe.fit_transform(data_5)
data_5.head()
```

[33]:
```
     duration  codec_mpeg4  codec_h264  codec_vp8  codec_flv  width  height  \
0  130.35667            1           0          0          0    176     144
```

```
1  130.35667          1          0          0          0    176     144
2  130.35667          1          0          0          0    176     144
3  130.35667          1          0          0          0    176     144
4  130.35667          1          0          0          0    176     144

   bitrate  framerate   i  …  o_codec_vp8  o_codec_flv  o_codec_h264  \
0    54590       12.0  27  …            0            0             0
1    54590       12.0  27  …            0            0             0
2    54590       12.0  27  …            0            0             0
3    54590       12.0  27  …            0            0             0
4    54590       12.0  27  …            0            0             0

   o_bitrate  o_framerate  o_width  o_height  utime  pixels  o_pixels
0      56000         12.0      176       144  0.612   25344     25344
1      56000         12.0      320       240  0.980   25344     76800
2      56000         12.0      480       360  1.216   25344    172800
3      56000         12.0      640       480  1.692   25344    307200
4      56000         12.0     1280       720  3.456   25344    921600

[5 rows x 27 columns]
```

[34]:
```python
data_5.info() # teraz wszystkie pola są numeryczne
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 68759 entries, 0 to 68783
Data columns (total 27 columns):
duration        68759 non-null float64
codec_mpeg4     68759 non-null int64
codec_h264      68759 non-null int64
codec_vp8       68759 non-null int64
codec_flv       68759 non-null int64
width           68759 non-null int64
height          68759 non-null int64
bitrate         68759 non-null int64
framerate       68759 non-null float64
i               68759 non-null int64
p               68759 non-null int64
b               68759 non-null int64
frames          68759 non-null int64
i_size          68759 non-null int64
p_size          68759 non-null int64
size            68759 non-null int64
o_codec_mpeg4   68759 non-null int64
o_codec_vp8     68759 non-null int64
o_codec_flv     68759 non-null int64
o_codec_h264    68759 non-null int64
o_bitrate       68759 non-null int64
```

```
o_framerate      68759 non-null float64
o_width          68759 non-null int64
o_height         68759 non-null int64
utime            68759 non-null float64
pixels           68759 non-null int64
o_pixels         68759 non-null int64
dtypes: float64(4), int64(23)
memory usage: 14.7 MB
```

0.8.1 Podział na 'target' i 'features'

[35]:
```
target = data_5['utime']
features = data_5.drop('utime', axis=1)
```

[36]:
```
print(features.shape)
features.head(2)
```

```
(68759, 26)
```

[36]:
```
    duration  codec_mpeg4  codec_h264  codec_vp8  codec_flv  width  height  \
0  130.35667            1           0          0          0    176     144
1  130.35667            1           0          0          0    176     144

   bitrate  framerate   i  …  o_codec_mpeg4  o_codec_vp8  o_codec_flv  \
0    54590       12.0  27  …              1            0            0
1    54590       12.0  27  …              1            0            0

   o_codec_h264  o_bitrate  o_framerate  o_width  o_height  pixels  o_pixels
0             0      56000         12.0      176       144   25344     25344
1             0      56000         12.0      320       240   25344     76800

[2 rows x 26 columns]
```

[37]:
```
print(target.shape)
target.head(2)
```

```
(68759,)
```

[37]:
```
0    0.612
1    0.980
Name: utime, dtype: float64
```

0.8.2 Skalowanie danych

[38]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
```

```
features_scaled = scaler.fit_transform(features)
features_scaled[1]
```

[38]:
```
array([5.71257598e-02, 1.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 6.06371427e-03,
       1.48820418e-01, 1.00959112e-02, 3.96760662e-02, 0.00000000e+00,
       3.96738187e-02, 5.81774952e-04, 1.02892969e-03, 8.65023435e-04,
       1.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 8.25688073e-02, 1.02564103e-01,
       0.00000000e+00, 2.51218598e-02])
```

[39]:
```
features_scaled.shape
```

[39]:
```
(68759, 26)
```

0.9 Trenowanie modeli

[40]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import GridSearchCV
```

0.9.1 Podział na dane trenujące i testujące

[41]:
```
X_train, X_test, y_train, y_test = train_test_split(features_scaled,
                                                    target,
                                                    test_size=0.3,␣
 ↪random_state=0)
```

0.9.2 Podstawowy model regresji liniowej

[42]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)

print("Mean squared error of a linear model: %.2f" %
      mean_squared_error(y_test, lr.predict(X_test)))
score = lr.score(X_test, y_test) #r2_score
print("Linear Regression R2 score: %.2f" % score)
```

```
Mean squared error of a linear model: 124.55
Linear Regression R2 score: 0.53
```

0.9.3 Wyszukiwanie optymalnego modelu z wykorzystaniem Polynominal Features, ElasticNet oraz GridSearch

[43]:
```
parameters=[{
     'alpha':[0.1, 0.2, 0.5, 0.9],
     'l1_ratio':[0.1, 0.2, 0.5, 0.9],
     }
]

for pf_level in range(1,3):
    print(f"polynominal features level {pf_level}:")

    pf = PolynomialFeatures(pf_level)
    train_poly = pf.fit_transform(X_train)
    test_poly  = pf.fit_transform(X_test)

    model = GridSearchCV( ElasticNet(), parameters, cv=5 )
    model.fit(train_poly, y_train)

    print(f"  {model.best_estimator_}")
    print("    Mean squared error: %.2f" %
    mean_squared_error(y_test, model.predict(test_poly)))
    score = model.score(test_poly, y_test) #r2_score
    print("    R2 score: %.2f" % score)
```

```
polynominal features level 1:
  ElasticNet(alpha=0.1, copy_X=True, fit_intercept=True, l1_ratio=0.9,
           max_iter=1000, normalize=False, positive=False, precompute=False,
           random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
    Mean squared error: 127.97
    R2 score: 0.52
polynominal features level 2:
  ElasticNet(alpha=0.1, copy_X=True, fit_intercept=True, l1_ratio=0.9,
           max_iter=1000, normalize=False, positive=False, precompute=False,
           random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
    Mean squared error: 57.47
    R2 score: 0.78
```