Excercises Ch1

April 19, 2025

1 Hands-On Data Preprocessing in Python

Learn how to effectively prepare data for successful data analytics

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1.0.1 Chapter 1: Review of the core modules NumPy, Pandas, and Matplotlib

Excercise 1 Use the adult.csv dataset and run the codes shown in the following Screenshots. Then answer the questions.

[1]:
```
import pandas as pd
import numpy as np
adult_df = pd.read_csv('adult.csv')
adult_df.set_index(np.arange(10000,42561),inplace=True)

print(adult_df.iloc[5:7,0:2])

print(adult_df.loc['10005':'10007','age':'fnlwgt'])
```

```
       age workclass
10005   37   Private
10006   49   Private
       age         workclass  fnlwgt
10005   37           Private  284582
10006   49           Private  160187
10007   52  Self-emp-not-inc  209642
```

```
a) Use the output to answer what is the difference in the behavior of .loc and .iloc when it co
b)  Without running but by only looking at the data, what will be the output of adult_df.loc['1
c)  Without running but by only looking at the data, what will be the output of adult_df.iloc[0
```

a) iloc's lower bound is exclusive, loc's lower bound is inclusive

b) `relationship race sex`

   10000 Not-in-family White Male 10001 Husband White Male 10002 Not-in-family White Male 10003 Husband Black Male

c) `relationship race`

   10000 Not-in-family White 10001 Husband White 10002 Not-in-family White

Excercise 2 For adult_df use the .groupby() function to run the following code and create the multi-index Series mlt_sr.

[2]:
```
import pandas as pd

adult_df = pd.read_csv('adult.csv')
mlt_seris =adult_df.groupby(['race','sex','income']).fnlwgt.mean()
mlt_seris
```

[2]:
```
race                sex     income
Amer-Indian-Eskimo  Female  <=50K     109018.626168
                            >50K      148012.000000
                    Male    <=50K     126428.767857
                            >50K      120721.541667
Asian-Pac-Islander  Female  <=50K     148165.333333
                            >50K      142426.093023
                    Male    <=50K     163885.130435
                            >50K      170698.347639
Black               Female  <=50K     213411.580205
                            >50K      205806.033333
                    Male    <=50K     242343.990566
                            >50K      245390.356902
Other               Female  <=50K     173235.932039
                            >50K      160223.333333
                    Male    <=50K     214891.832168
                            >50K      204551.736842
White               Female  <=50K     183485.120961
                            >50K      184030.255837
                    Male    <=50K     189950.465418
                            >50K      186917.770077
Name: fnlwgt, dtype: float64
```

Now that you have created a multi-index Series, run the following codes, study the outputs, and answer the questions.

```
a)  Run the code below first and then answer the following. When we use .iloc[] for a multi-inc
```

[3]:
```
print(mlt_seris.iloc[0])
print(mlt_seris.iloc[1])
print(mlt_seris.iloc[2])
```

```
109018.6261682243
148012.0
126428.76785714286
```

Answer:

.iloc[] selects rows and columns by their integer positions

```
b)  Run the code below first and then answer the following. When we use .loc[] to access the da
```

[5]:
```
mlt_seris.loc['Other']
```

[5]:
```
sex     income
Female  <=50K     173235.932039
        >50K      160223.333333
Male    <=50K     214891.832168
        >50K      204551.736842
Name: fnlwgt, dtype: float64
```

Answer:

.loc[] selects data based on index labels, not positions.

```
c)   Run the codes below first and then answer the following. When we use .loc[] to access the

When you run either line of code below, you will get an error and that is the point of this que
```

[6]:
```
mlt_seris.loc['Female']
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/
↪data_preprocessing/lib/python3.11/site-packages/pandas/core/indexes/base.py:
↪3805, in Index.get_loc(self, key)
   3804 try:
-> 3805     return self._engine.get_loc(casted_key)
   3806 except KeyError as err:

File index.pyx:167, in pandas._libs.index.IndexEngine.get_loc()

File index.pyx:196, in pandas._libs.index.IndexEngine.get_loc()

File pandas/_libs/hashtable_class_helper.pxi:7081, in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()

File pandas/_libs/hashtable_class_helper.pxi:7089, in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()

KeyError: 'Female'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
Cell In[6], line 1
----> 1 mlt_seris.loc[        ]

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/
↪data_preprocessing/lib/python3.11/site-packages/pandas/core/indexing.py:1191,
↪in _LocationIndexer.__getitem__(self, key)
```

```
   1189 maybe_callable = com.apply_if_callable(key, self.obj)
   1190 maybe_callable = self._check_deprecated_callable_usage(key, maybe_callable)
-> 1191 return self._getitem_axis(maybe_callable, axis=axis)

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/data_preprocessing/lib/python3.11/site-packages/pandas/core/indexing.py:1431, in _LocIndexer._getitem_axis(self, key, axis)
   1429 # fall thru to straight lookup
   1430 self._validate_key(key, axis)
-> 1431 return self._get_label(key, axis=axis)

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/data_preprocessing/lib/python3.11/site-packages/pandas/core/indexing.py:1381, in _LocIndexer._get_label(self, label, axis)
   1379 def _get_label(self, label, axis: AxisInt):
   1380     # GH#5567 this will fail if the label is not present in the axis.
-> 1381     return self.obj.xs(label, axis=axis)

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/data_preprocessing/lib/python3.11/site-packages/pandas/core/generic.py:4293, in NDFrame.xs(self, key, axis, level, drop_level)
   4290     index = self.index
   4292 if isinstance(index, MultiIndex):
-> 4293     loc, new_index = index._get_loc_level(key, level=0)
   4294     if not drop_level:
   4295         if lib.is_integer(loc):
   4296             # Slice index must be an integer or None

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/data_preprocessing/lib/python3.11/site-packages/pandas/core/indexes/multi.py:3290, in MultiIndex._get_loc_level(self, key, level)
   3288         return indexer, maybe_mi_droplevels(indexer, ilevels)
   3289 else:
-> 3290     indexer = self._get_level_indexer(key, level=level)
   3291     if (
   3292         isinstance(key, str)
   3293         and self.levels[level]._supports_partial_string_indexing
   3294     ):
   3295         # check to see if we did an exact lookup vs sliced
   3296         check = self.levels[level].get_loc(key)

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/data_preprocessing/lib/python3.11/site-packages/pandas/core/indexes/multi.py:3391, in MultiIndex._get_level_indexer(self, key, level, indexer)
   3388         return slice(i, j, step)
   3390 else:
-> 3391     idx = self._get_loc_single_level_index(level_index, key)
   3393     if level > 0 or self._lexsort_depth == 0:
```

```
   3394         # Desired level is not sorted
   3395         if isinstance(idx, slice):
   3396             # test_get_loc_partial_timestamp_multiindex

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/
 ↪data_preprocessing/lib/python3.11/site-packages/pandas/core/indexes/multi.py:
 ↪2980, in MultiIndex._get_loc_single_level_index(self, level_index, key)
   2978     return -1
   2979 else:
-> 2980     return level_index.get_loc(key)

File /run/media/weida/SSD1/Study Stuff/Hands-On Data Preprocessing in Python/
 ↪data_preprocessing/lib/python3.11/site-packages/pandas/core/indexes/base.py:
 ↪3812, in Index.get_loc(self, key)
   3807     if isinstance(casted_key, slice) or (
   3808         isinstance(casted_key, abc.Iterable)
   3809         and any(isinstance(x, slice) for x in casted_key)
   3810     ):
   3811         raise InvalidIndexError(key)
-> 3812     raise KeyError(key) from err
   3813 except TypeError:
   3814     # If we have a listlike key, _check_indexing_error will raise
   3815     #  InvalidIndexError. Otherwise we fall through and re-raise
   3816     #  the TypeError.
   3817     self._check_indexing_error(key)

KeyError: 'Female'
```

[7]:
```
mlt_seris.loc['<=50K']
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
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 ↪PyObjectHashTable.get_item()
```

```
File pandas/_libs/hashtable_class_helper.pxi:7089, in pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: '<=50K'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
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```

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   3809         and any(isinstance(x, slice) for x in casted_key)
   3810     ):
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-> 3812     raise KeyError(key) from err
   3813 except TypeError:
   3814     # If we have a listlike key, _check_indexing_error will raise
   3815     #  InvalidIndexError. Otherwise we fall through and re-raise
   3816     #  the TypeError.
   3817     self._check_indexing_error(key)

KeyError: '<=50K'
```

Answer:

error

d) Run the codes below first and then answer the following. How is using .loc[] or .iloc[] di

[9]:
```python
print(mlt_seris.loc['Other']['Female']['<=50K'])
print(mlt_seris.iloc[12])
```

```
173235.93203883496
173235.93203883496
```

Answer:

Using .loc[] is label-based (selects by index names at any level), while .iloc[] is position-based (ignores index labels and selects by integer position).

Excercise 3 For this exercise you need to use a new dataset: billboard.csv. Visit https://www.billboard.com/charts/hot-100 and see the latest song rankings of the day. This dataset presents information and ranking of 317 song tracks in 80 columns. The first four columns are artist, track, time, and date_e. The first columns are intuitive descriptions of song tracks. The column date_e shows the date that the songs entered the hot-100 list. The rest of 76 columns are songs ranking at the end of each weeks from 'w1' to 'w76'. Download and read this dataset using pandas and answer the following questions.

[12]:
```python
import pandas as pd

billboard_df = pd.read_csv("billboard.csv")
billboard_df.head()
```

[12]:
```
                artist                                    track  time  \
0      Destiny's Child                  Independent Women Part I  3:38
1              Santana                              Maria, Maria  4:18
2        Savage Garden                        I Knew I Loved You  4:07
3              Madonna                                     Music  3:45
4   Aguilera, Christina  Come On Over Baby (All I Want Is You)  3:38

       date_e  w1    w2    w3    w4    w5    w6  …  w67  w68  w69  w70  w71  \
0  2000-09-23  78  63.0  49.0  33.0  23.0  15.0  …  NaN  NaN  NaN  NaN  NaN
1  2000-02-12  15   8.0   6.0   5.0   2.0   3.0  …  NaN  NaN  NaN  NaN  NaN
2  1999-10-23  71  48.0  43.0  31.0  20.0  13.0  …  NaN  NaN  NaN  NaN  NaN
3  2000-08-12  41  23.0  18.0  14.0   2.0   1.0  …  NaN  NaN  NaN  NaN  NaN
4  2000-08-05  57  47.0  45.0  29.0  23.0  18.0  …  NaN  NaN  NaN  NaN  NaN

   w72  w73  w74  w75  w76
0  NaN  NaN  NaN  NaN  NaN
1  NaN  NaN  NaN  NaN  NaN
2  NaN  NaN  NaN  NaN  NaN
3  NaN  NaN  NaN  NaN  NaN
4  NaN  NaN  NaN  NaN  NaN

[5 rows x 80 columns]
```

```
a)  Write one line of code that gives you a great idea of how many null values each column has
```

[17]:
```python
print(billboard_df.isnull().sum())
billboard_df = billboard_df.dropna(axis=1, how='all')
```

```
artist      0
track       0
time        0
date_e      0
w1          0
         ...
w72       317
w73       317
w74       317
w75       317
w76       317
Length: 80, dtype: int64
```

[19]:
```python
print(billboard_df.isnull().sum())
billboard_df
```

```
artist      0
track       0
time        0
date_e      0
w1          0
         ...
w61       315
w62       315
w63       315
w64       315
w65       316
Length: 69, dtype: int64
```

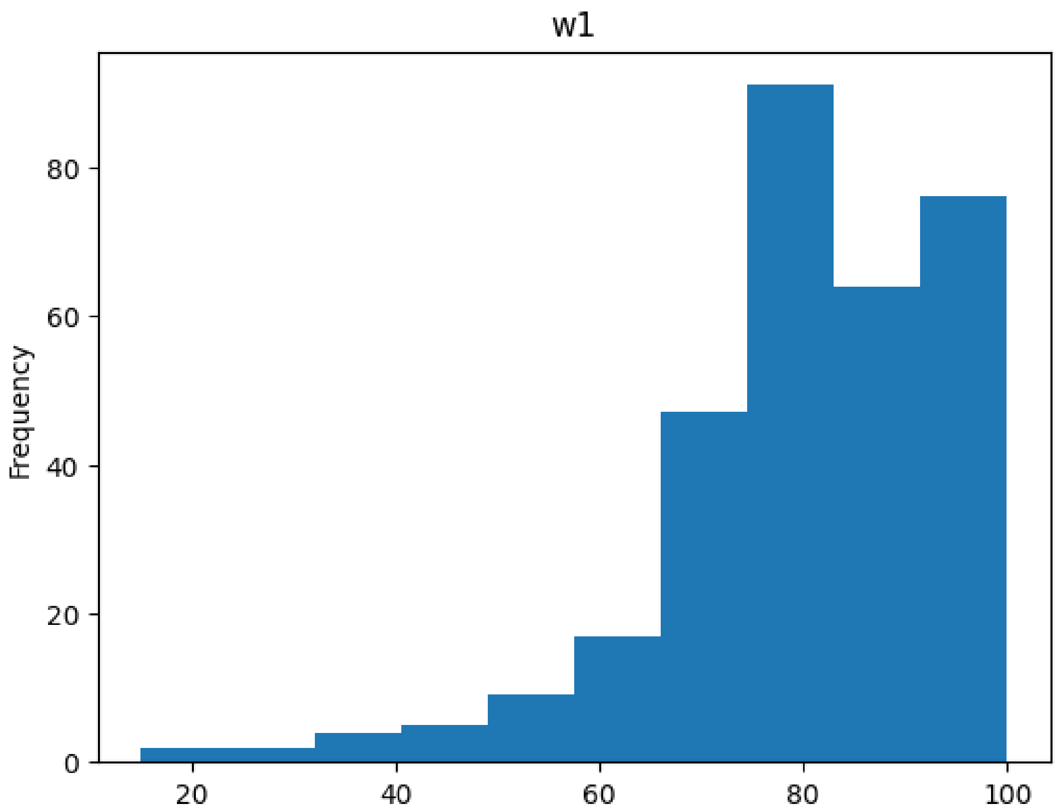
[19]:
```
                  artist                                  track  time  \
0         Destiny's Child               Independent Women Part I  3:38
1                 Santana                           Maria, Maria  4:18
2           Savage Garden                     I Knew I Loved You  4:07
3                 Madonna                                  Music  3:45
4     Aguilera, Christina  Come On Over Baby (All I Want Is You)  3:38
..                   …                                    …   …
312       Ghostface Killah                      Cherchez LaGhost  3:04
313            Smith, Will                           Freakin' It  3:58
314          Zombie Nation                         Kernkraft 400  3:30
315        Eastsidaz, The                              Got Beef  3:58
316                 Fragma                        Toca's Miracle  3:22

         date_e  w1    w2    w3    w4    w5    w6  …  w56  w57  w58  w59  \
0    2000-09-23  78  63.0  49.0  33.0  23.0  15.0  …  NaN  NaN  NaN  NaN
1    2000-02-12  15   8.0   6.0   5.0   2.0   3.0  …  NaN  NaN  NaN  NaN
```

```
2     1999-10-23  71  48.0  43.0  31.0  20.0  13.0  …  NaN  NaN  NaN  NaN
3     2000-08-12  41  23.0  18.0  14.0   2.0   1.0  …  NaN  NaN  NaN  NaN
4     2000-08-05  57  47.0  45.0  29.0  23.0  18.0  …  NaN  NaN  NaN  NaN
..           …  ..    …     …     …     …     …    …    …    …    …
312   2000-08-05  98   NaN   NaN   NaN   NaN   NaN  …  NaN  NaN  NaN  NaN
313   2000-02-12  99  99.0  99.0  99.0   NaN   NaN  …  NaN  NaN  NaN  NaN
314   2000-09-02  99  99.0   NaN   NaN   NaN   NaN  …  NaN  NaN  NaN  NaN
315   2000-07-01  99  99.0   NaN   NaN   NaN   NaN  …  NaN  NaN  NaN  NaN
316   2000-10-28  99   NaN   NaN   NaN   NaN   NaN  …  NaN  NaN  NaN  NaN

     w60  w61  w62  w63  w64  w65
0    NaN  NaN  NaN  NaN  NaN  NaN
1    NaN  NaN  NaN  NaN  NaN  NaN
2    NaN  NaN  NaN  NaN  NaN  NaN
3    NaN  NaN  NaN  NaN  NaN  NaN
4    NaN  NaN  NaN  NaN  NaN  NaN
..     …    …    …    …    …    …
312  NaN  NaN  NaN  NaN  NaN  NaN
313  NaN  NaN  NaN  NaN  NaN  NaN
314  NaN  NaN  NaN  NaN  NaN  NaN
315  NaN  NaN  NaN  NaN  NaN  NaN
316  NaN  NaN  NaN  NaN  NaN  NaN

[317 rows x 69 columns]
```

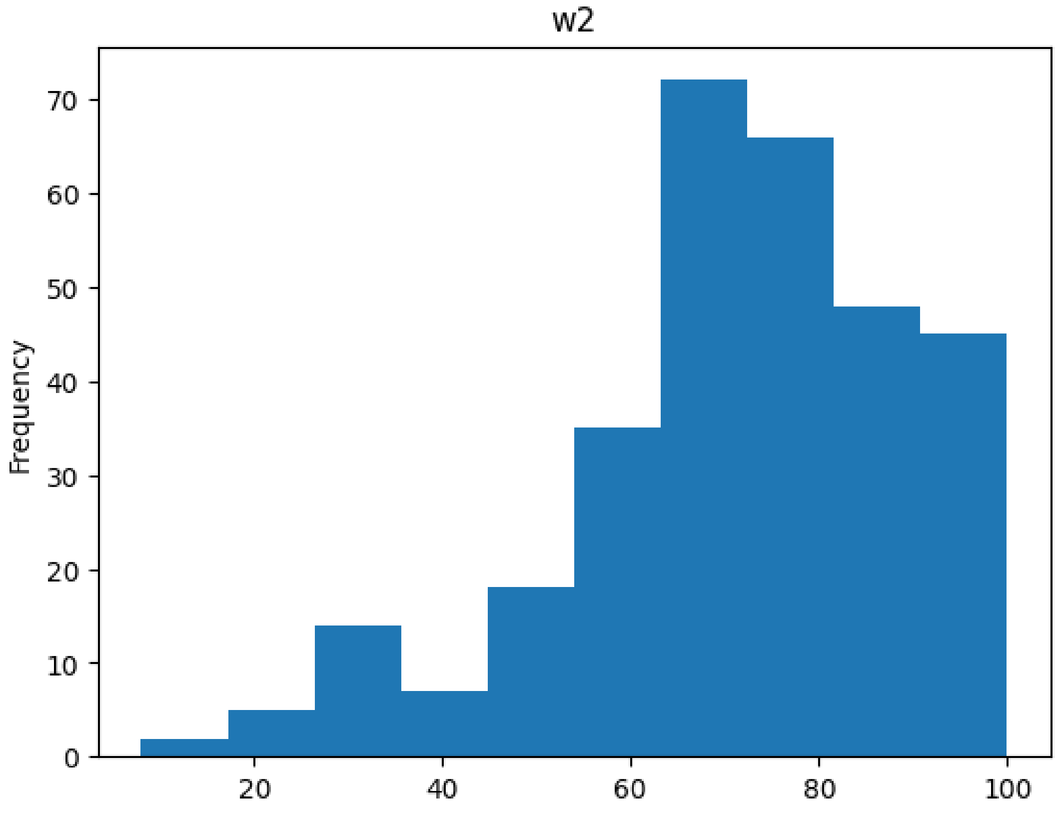
b) With a for loop, draw and study the values in each of the remaining W columns.

[22]:
```
import matplotlib.pyplot as plt

for col in billboard_df.columns[billboard_df.columns.str.startswith('w')]:
    print(f"\n--- Column: {col} ---")
    print(billboard_df[col].describe())
    billboard_df[col].plot.hist(title=col)
    plt.show()
```

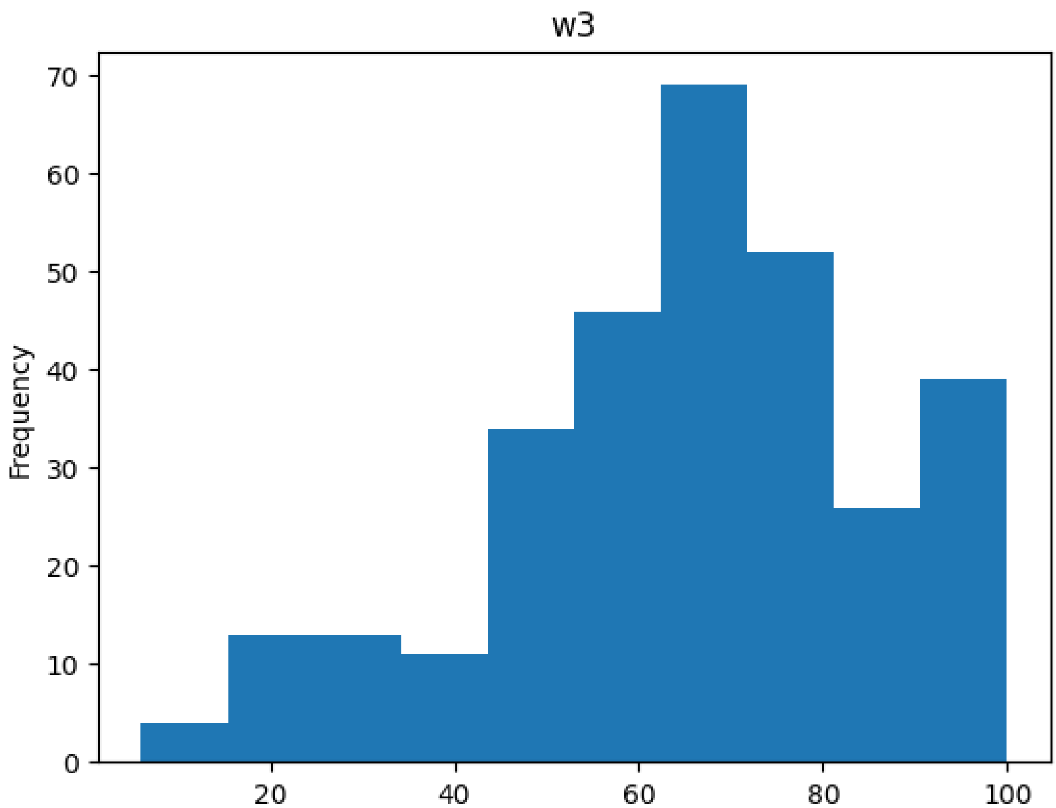
```
--- Column: w1 ---
count    317.000000
mean      79.958991
std       14.686865
min       15.000000
25%       74.000000
50%       81.000000
75%       91.000000
max      100.000000
Name: w1, dtype: float64
```



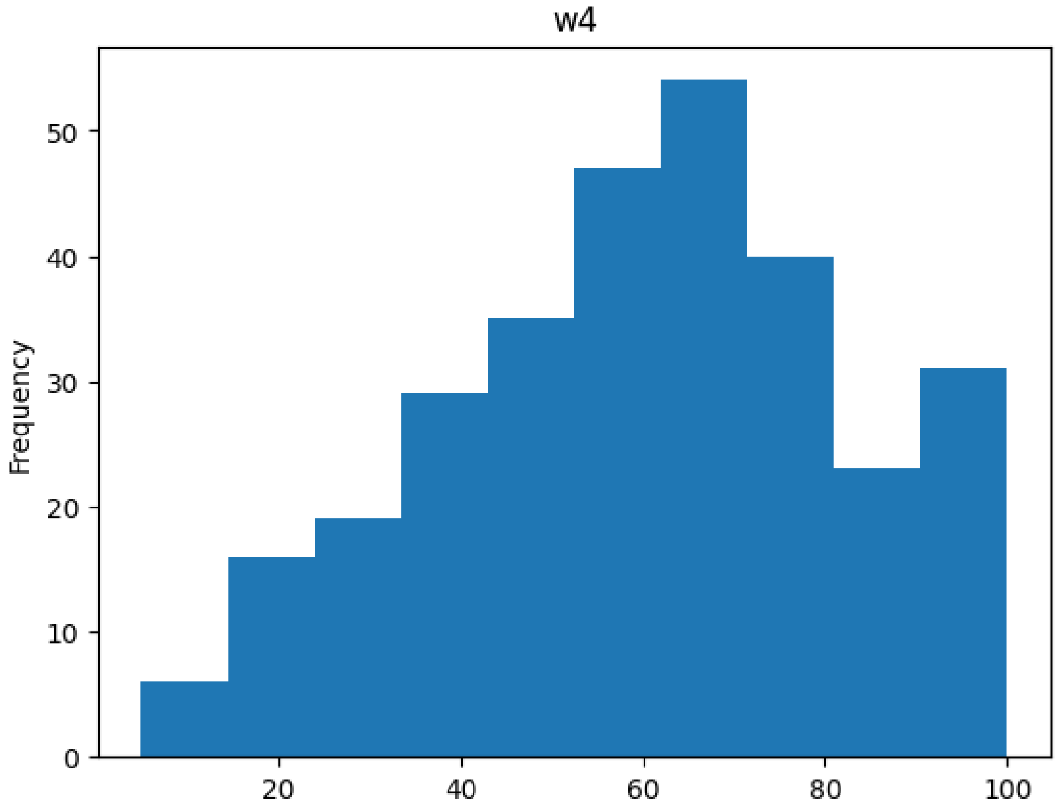

```
--- Column: w2 ---
count    312.000000
mean      71.173077
std       18.200443
min        8.000000
25%       63.000000
50%       73.000000
75%       84.000000
max      100.000000
Name: w2, dtype: float64
```



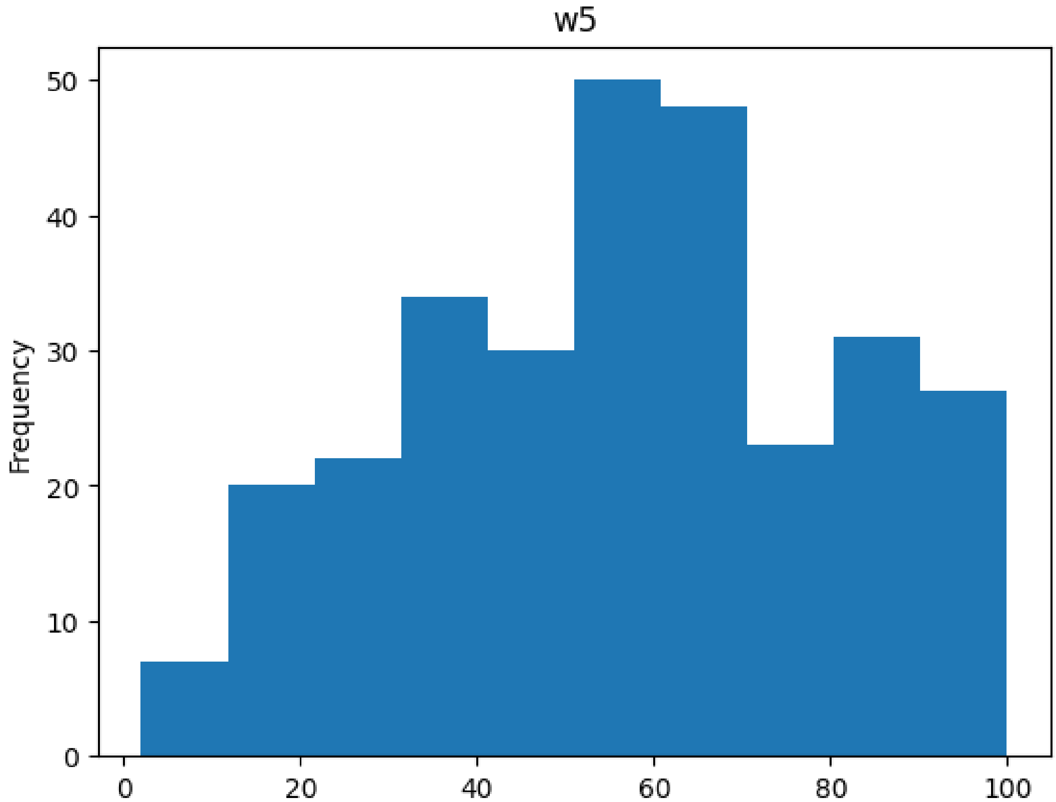

```
--- Column: w3 ---
count    307.000000
mean      65.045603
std       20.752302
min        6.000000
25%       53.000000
50%       66.000000
75%       79.000000
max      100.000000
Name: w3, dtype: float64
```



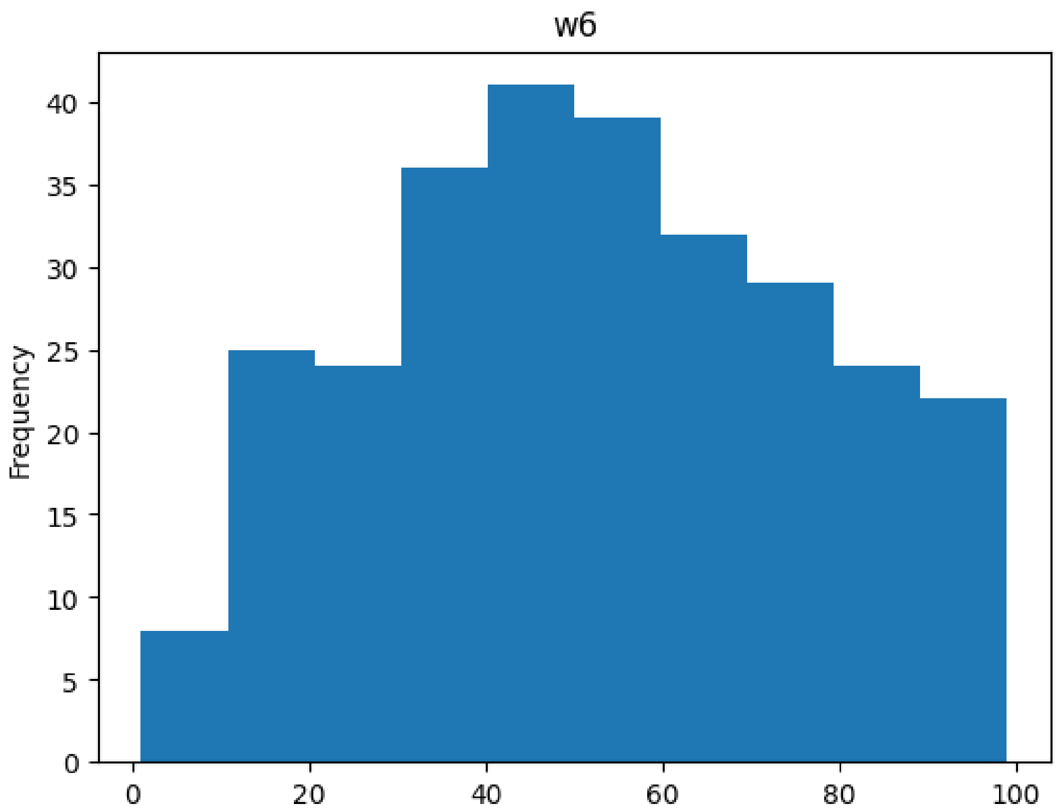

```
--- Column: w4 ---
count    300.000000
mean      59.763333
std       22.324619
min        5.000000
25%       44.750000
50%       61.000000
75%       76.000000
max      100.000000
Name: w4, dtype: float64
```



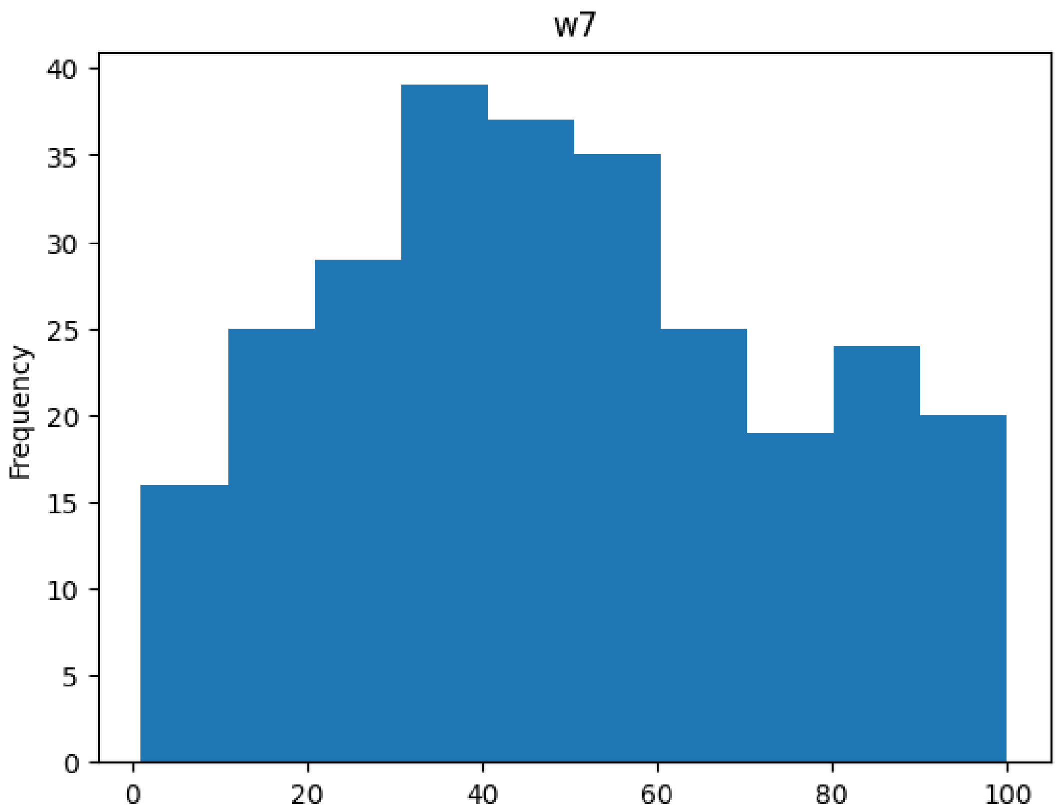

```
--- Column: w5 ---
count    292.000000
mean      56.339041
std       23.780022
min        2.000000
25%       38.750000
50%       57.000000
75%       73.250000
max      100.000000
Name: w5, dtype: float64
```



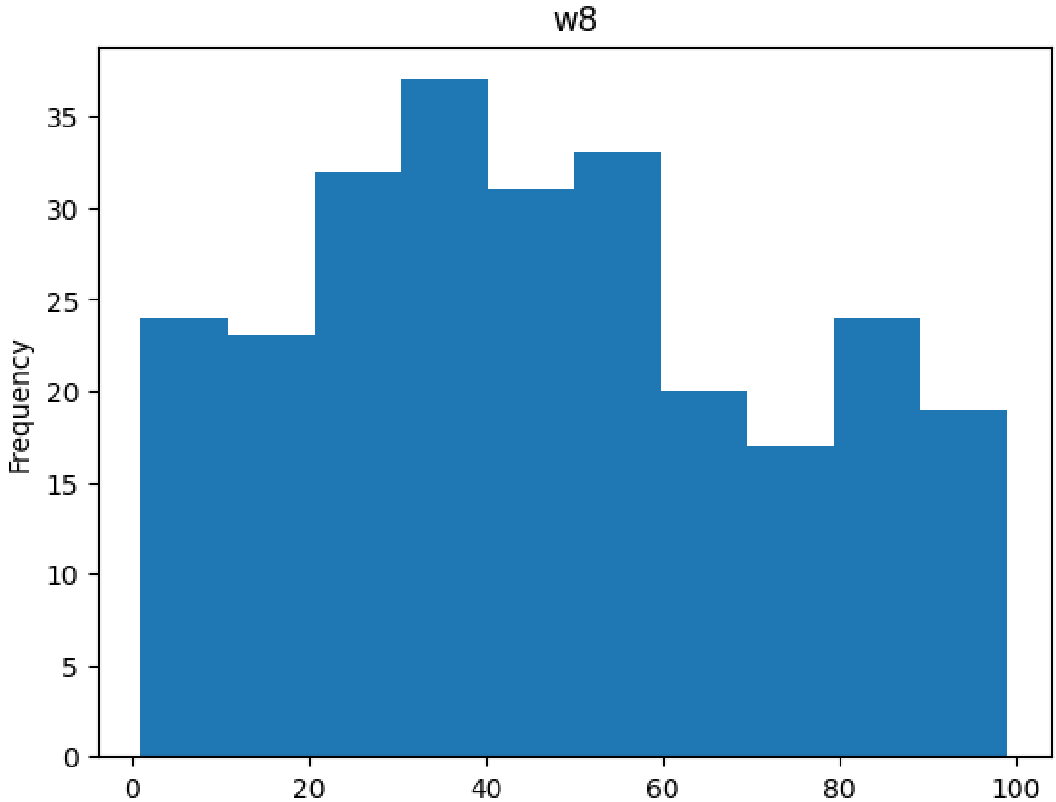

```
--- Column: w6 ---
count    280.000000
mean      52.360714
std       24.473273
min        1.000000
25%       33.750000
50%       51.500000
75%       72.250000
max       99.000000
Name: w6, dtype: float64
```



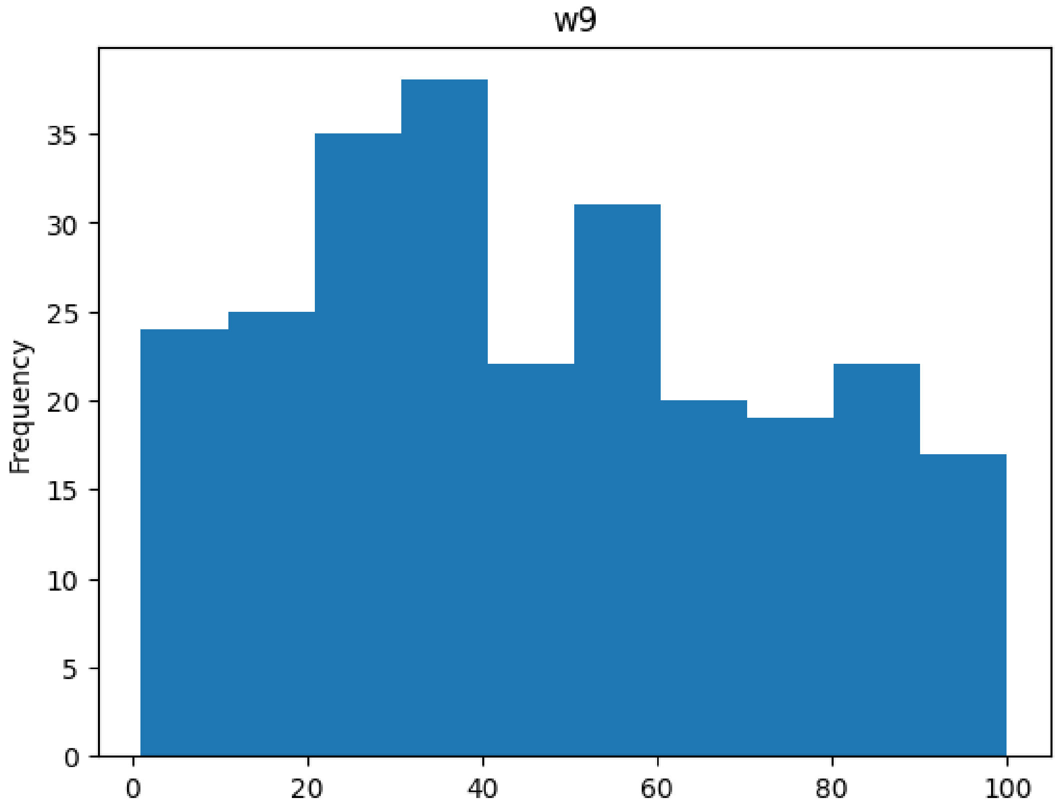

```
--- Column: w7 ---
count    269.000000
mean      49.219331
std       25.654279
min        1.000000
25%       30.000000
50%       47.000000
75%       67.000000
max      100.000000
Name: w7, dtype: float64
```



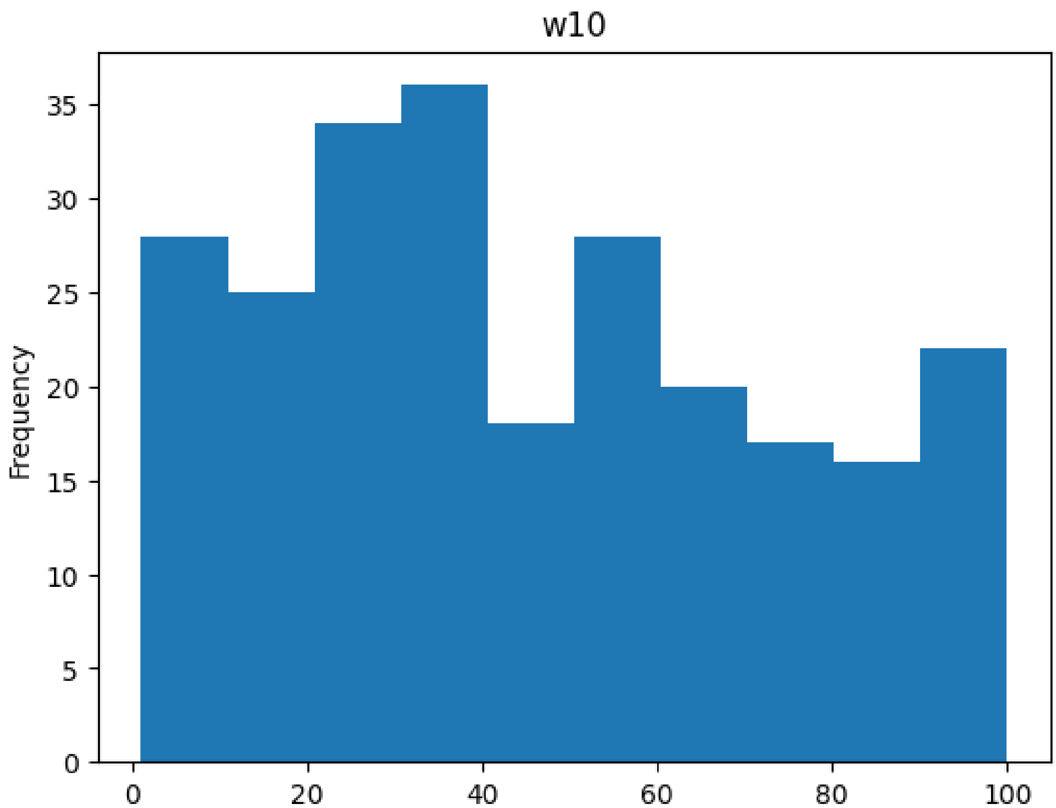

```
--- Column: w8 ---
count    260.000000
mean      47.119231
std       26.370782
min        1.000000
25%       27.000000
50%       45.500000
75%       67.000000
max       99.000000
Name: w8, dtype: float64
```



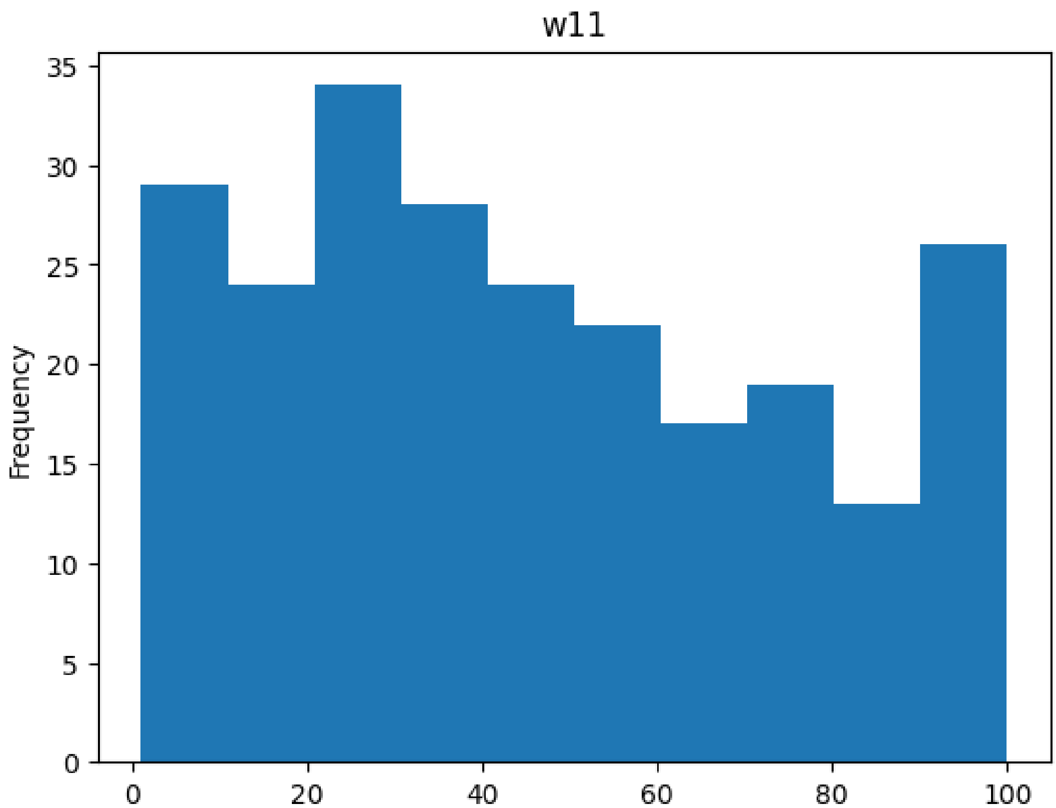

```
--- Column: w9 ---
count    253.000000
mean      46.343874
std       27.136419
min        1.000000
25%       26.000000
50%       42.000000
75%       67.000000
max      100.000000
Name: w9, dtype: float64
```



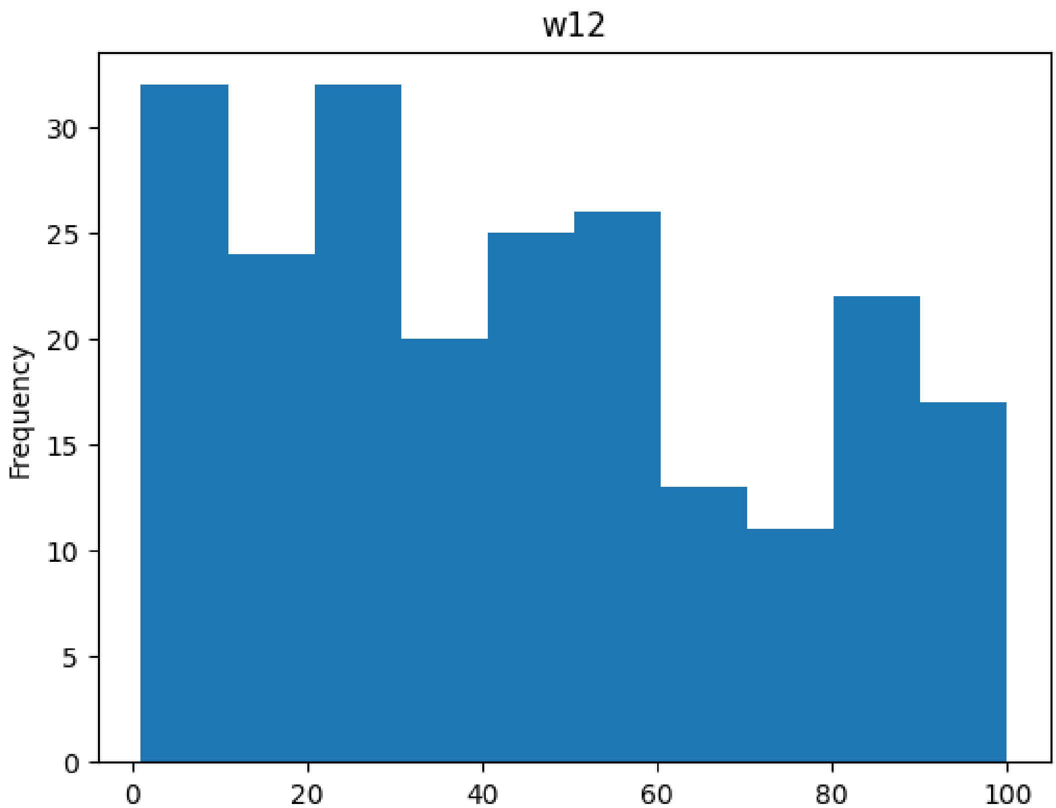

```
--- Column: w10 ---
count    244.000000
mean      45.786885
std       28.152357
min        1.000000
25%       24.750000
50%       40.000000
75%       69.000000
max      100.000000
Name: w10, dtype: float64
```



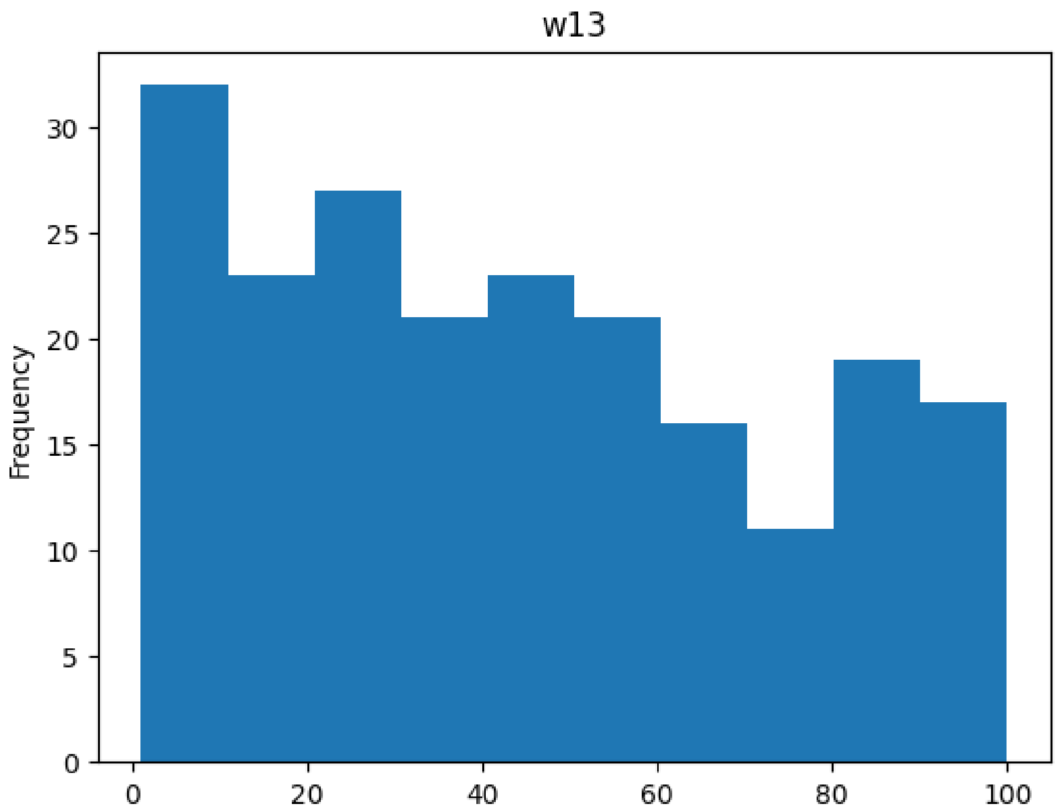

```
--- Column: w11 ---
count    236.000000
mean      45.474576
std       29.060527
min        1.000000
25%       22.000000
50%       42.500000
75%       69.250000
max      100.000000
Name: w11, dtype: float64
```



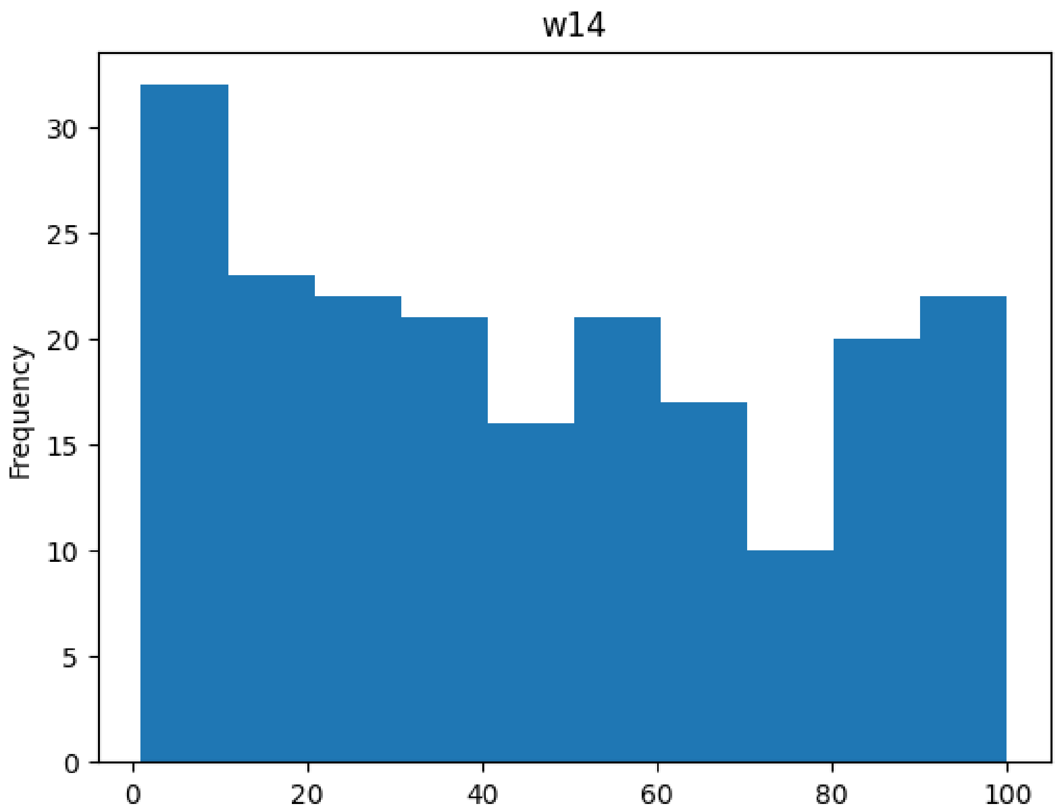

```
--- Column: w12 ---
count    222.000000
mean      44.198198
std       28.893100
min        1.000000
25%       20.250000
50%       42.000000
75%       67.750000
max      100.000000
Name: w12, dtype: float64
```



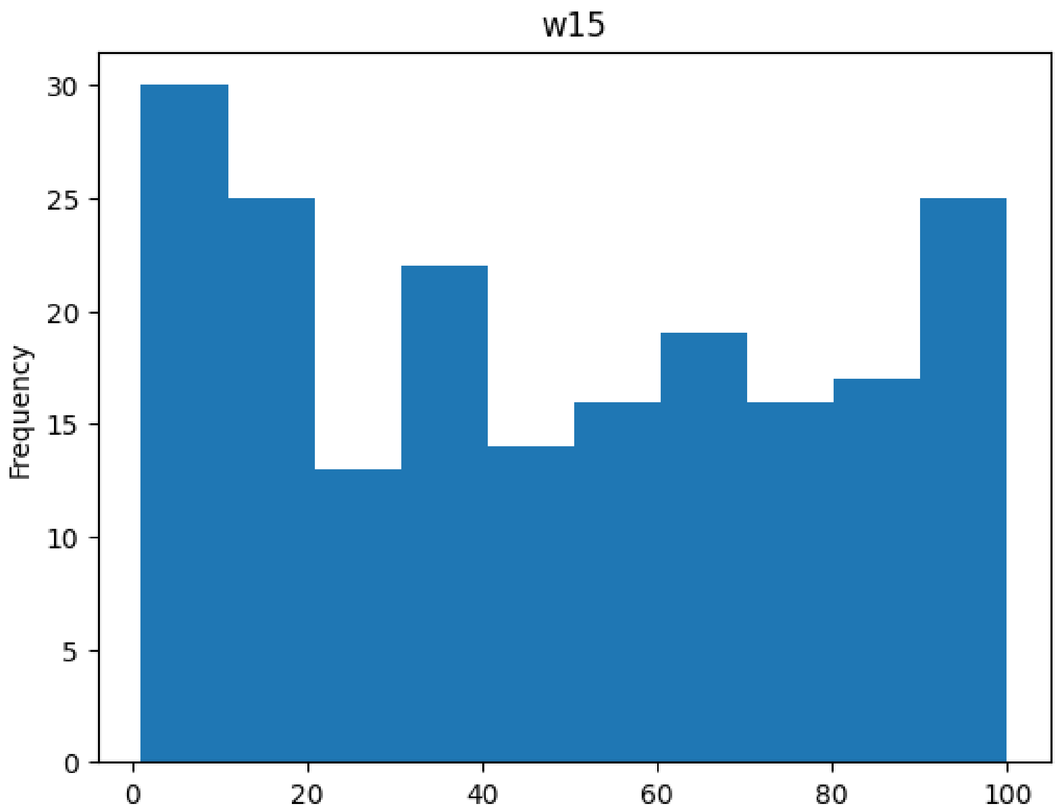

```
--- Column: w13 ---
count    210.000000
mean      44.352381
std       29.481315
min        1.000000
25%       19.000000
50%       42.500000
75%       68.750000
max      100.000000
Name: w13, dtype: float64
```



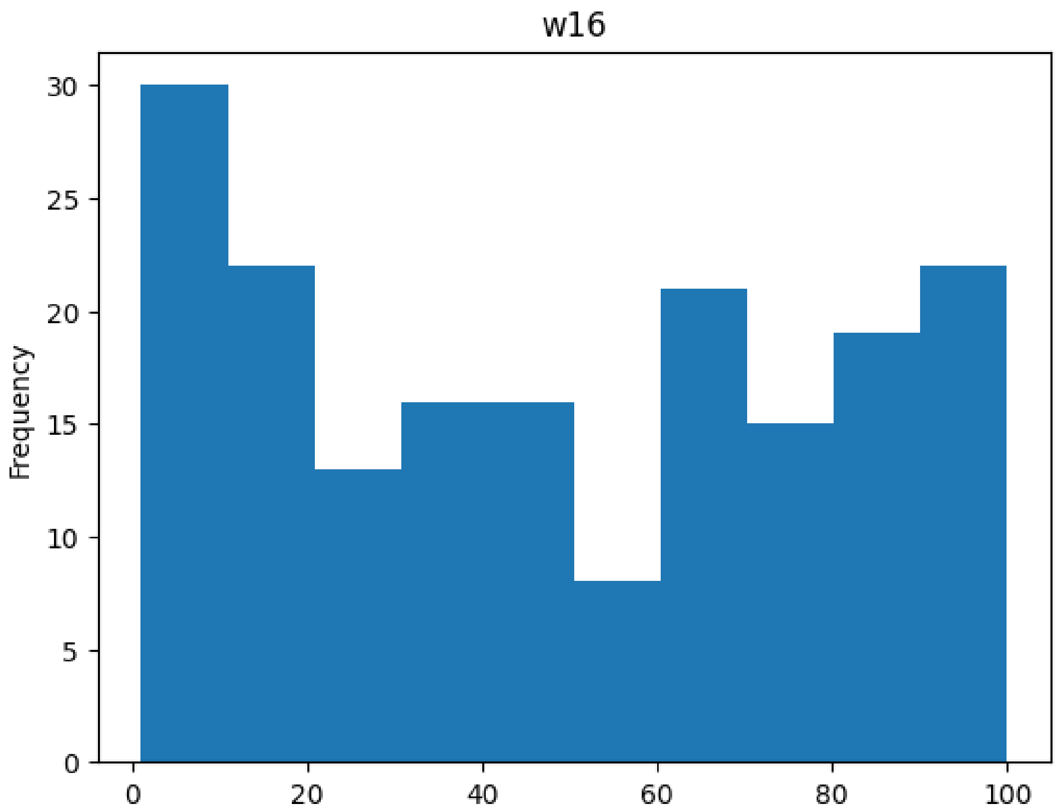

```
--- Column: w14 ---
count    204.000000
mean      45.892157
std       30.529936
min        1.000000
25%       20.000000
50%       44.000000
75%       72.500000
max      100.000000
Name: w14, dtype: float64
```



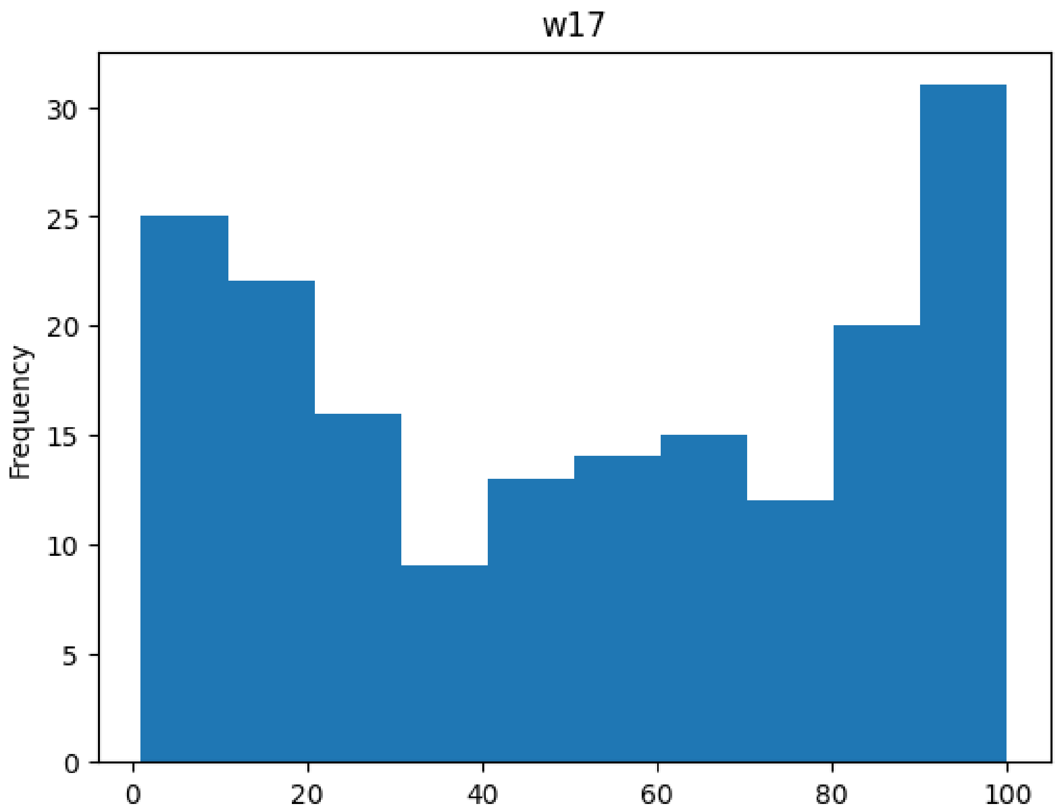

```
--- Column: w15 ---
count    197.000000
mean      47.898477
std       31.542486
min        1.000000
25%       18.000000
50%       46.000000
75%       76.000000
max      100.000000
Name: w15, dtype: float64
```



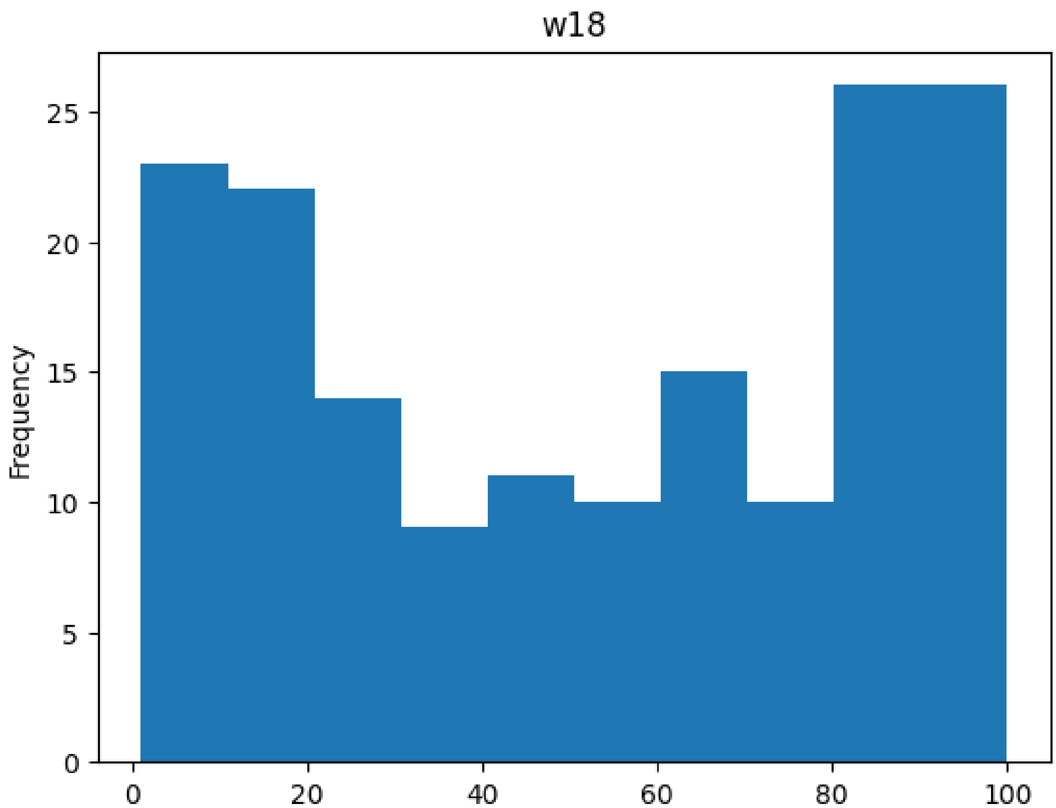

```
--- Column: w16 ---
count    182.000000
mean      48.241758
std       31.899476
min        1.000000
25%       17.000000
50%       47.000000
75%       76.000000
max      100.000000
Name: w16, dtype: float64
```



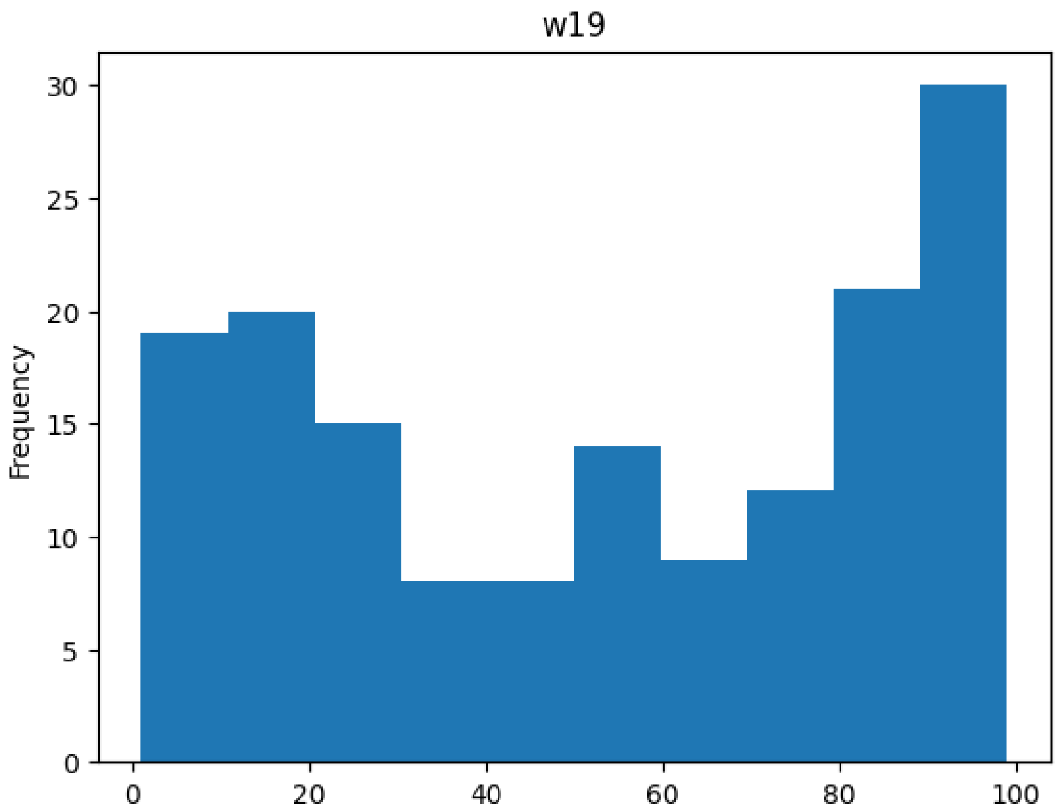

```
--- Column: w17 ---
count    177.000000
mean      51.265537
std       33.093233
min        1.000000
25%       19.000000
50%       52.000000
75%       85.000000
max      100.000000
Name: w17, dtype: float64
```



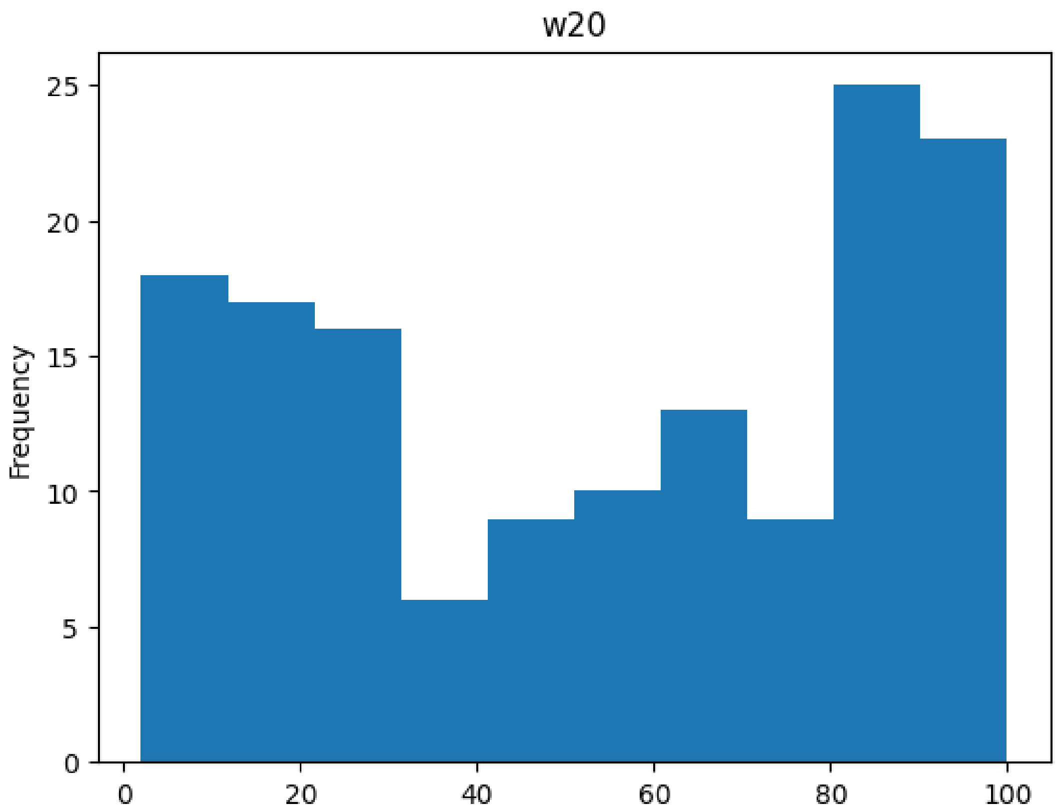

```
--- Column: w18 ---
count    166.000000
mean      52.108434
std       33.194199
min        1.000000
25%       19.000000
50%       56.500000
75%       84.000000
max      100.000000
Name: w18, dtype: float64
```



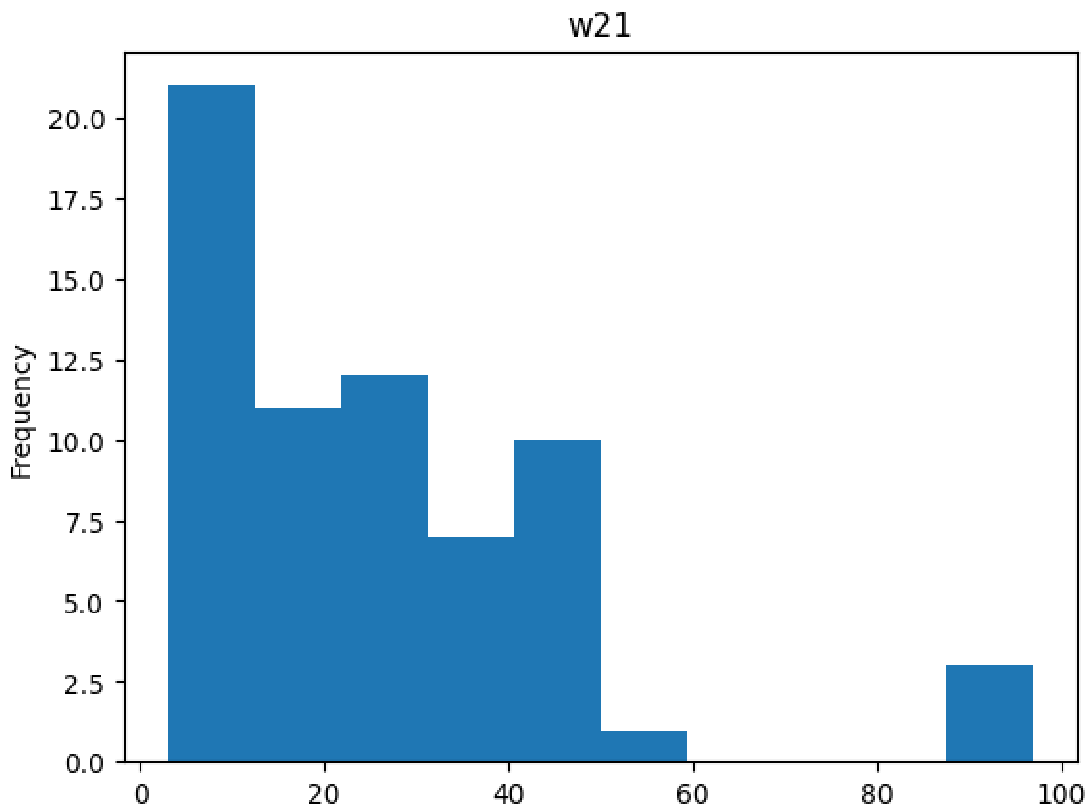

```
--- Column: w19 ---
count    156.000000
mean      53.166667
std       33.022540
min        1.000000
25%       20.750000
50%       55.500000
75%       85.000000
max       99.000000
Name: w19, dtype: float64
```



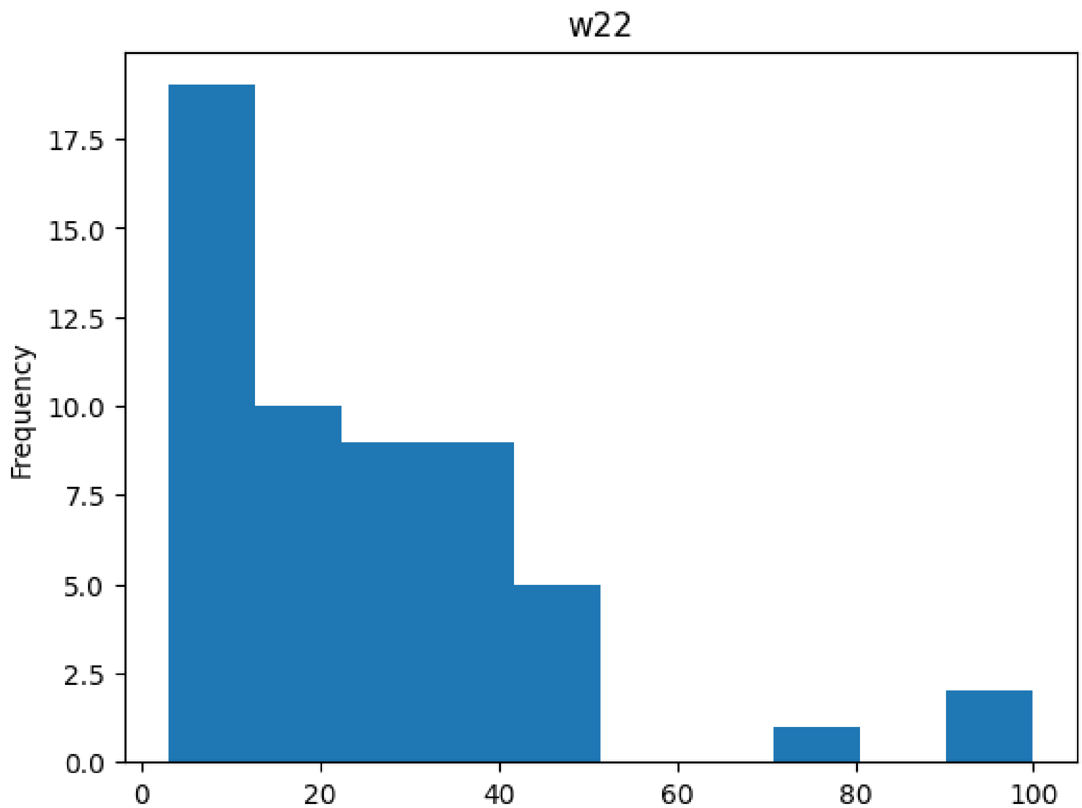

```
--- Column: w20 ---
count    146.000000
mean      54.267123
std       32.890475
min        2.000000
25%       22.250000
50%       58.500000
75%       87.000000
max      100.000000
Name: w20, dtype: float64
```



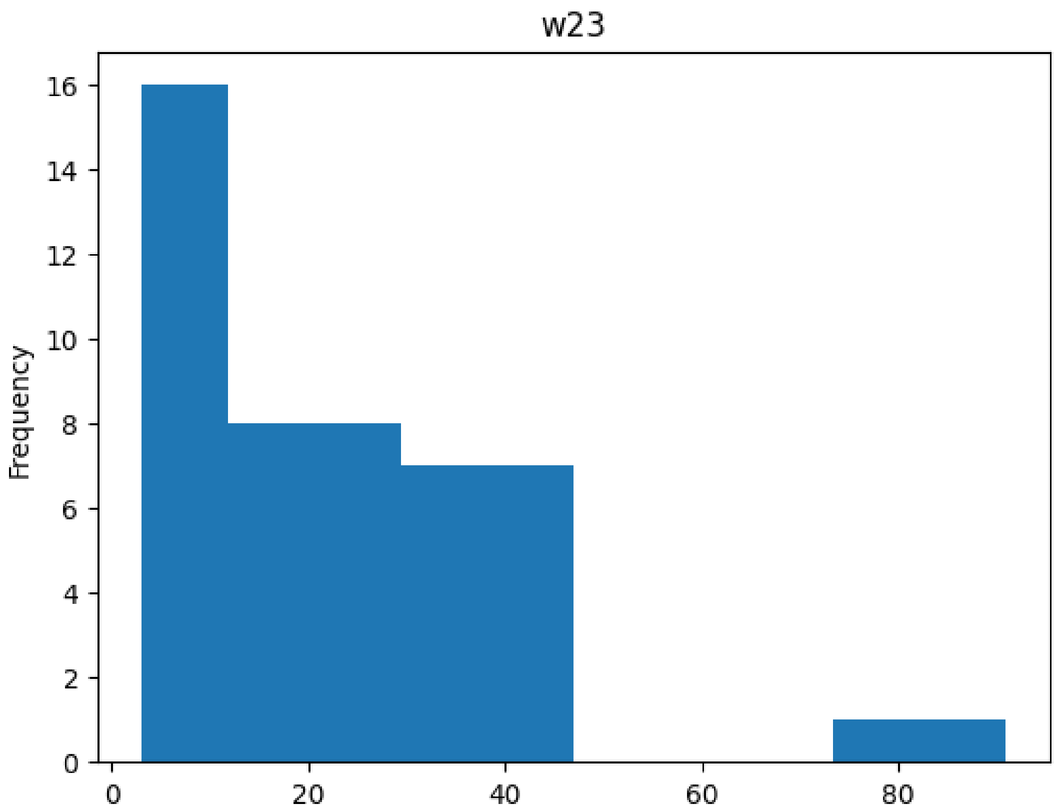

```
--- Column: w21 ---
count    65.000000
mean     26.184615
std      20.232162
min       3.000000
25%      10.000000
50%      24.000000
75%      35.000000
max      97.000000
Name: w21, dtype: float64
```



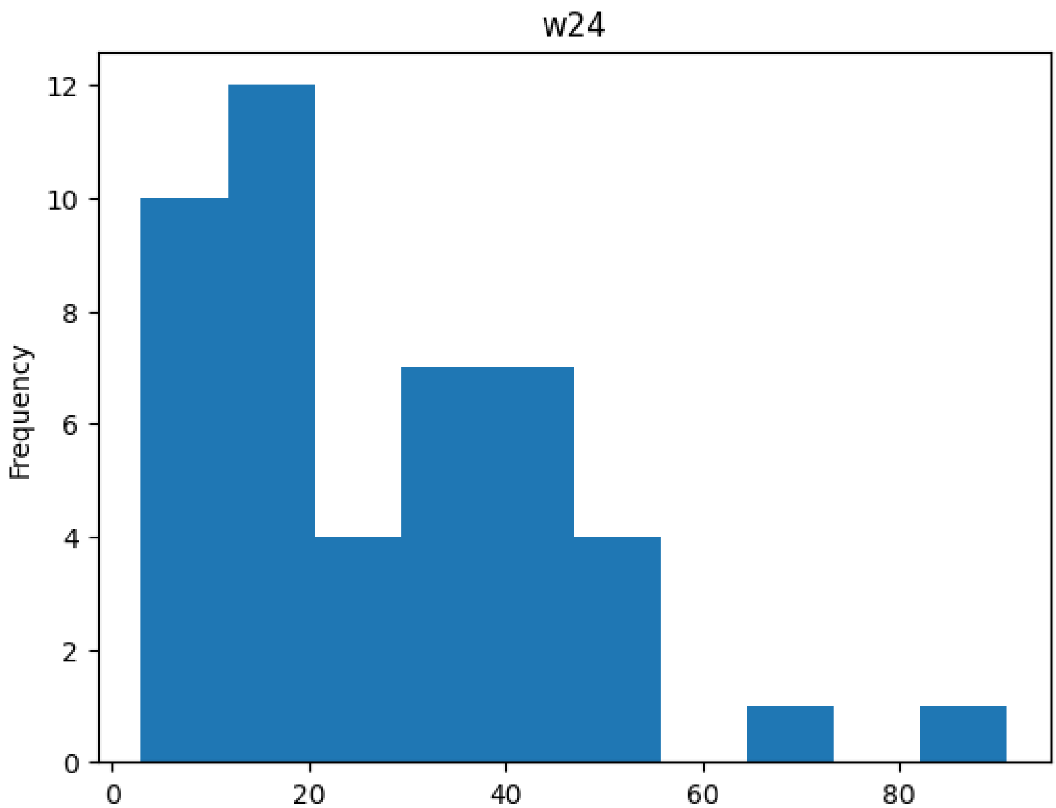

```
--- Column: w22 ---
count     55.000000
mean      25.636364
std       21.127798
min        3.000000
25%        9.000000
50%       21.000000
75%       36.500000
max      100.000000
Name: w22, dtype: float64
```



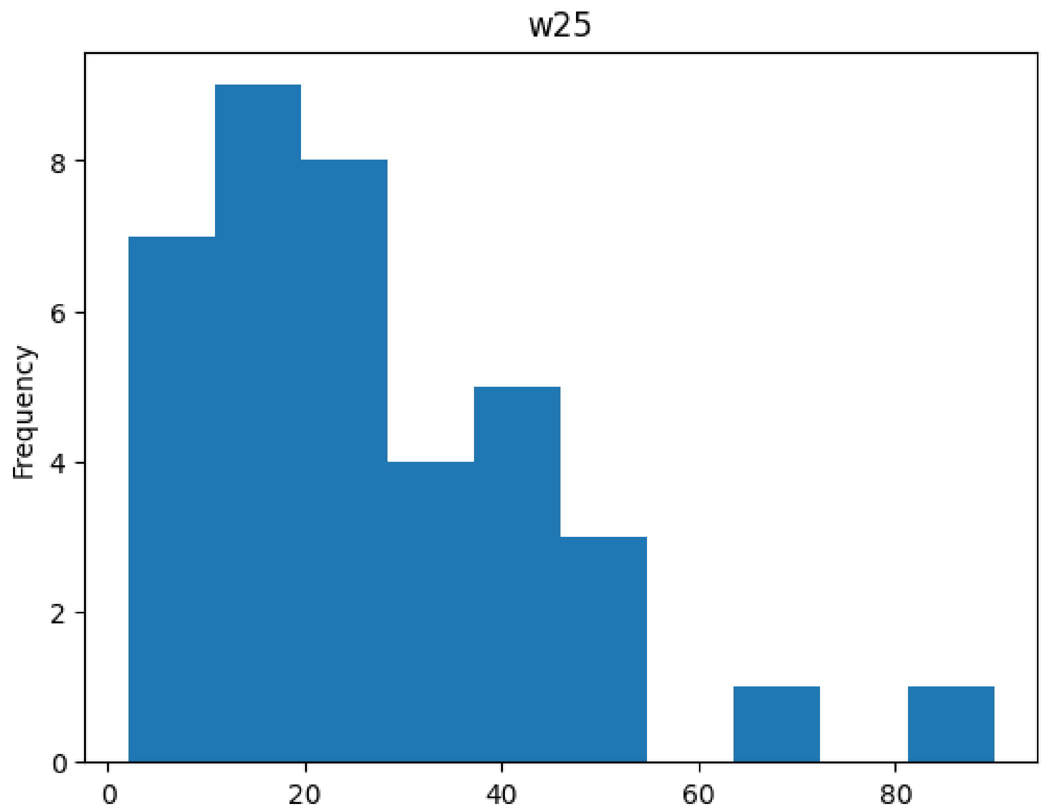

```
--- Column: w23 ---
count    48.00000
mean     23.81250
std      18.23564
min       3.00000
25%      10.00000
50%      20.50000
75%      36.00000
max      91.00000
Name: w23, dtype: float64
```



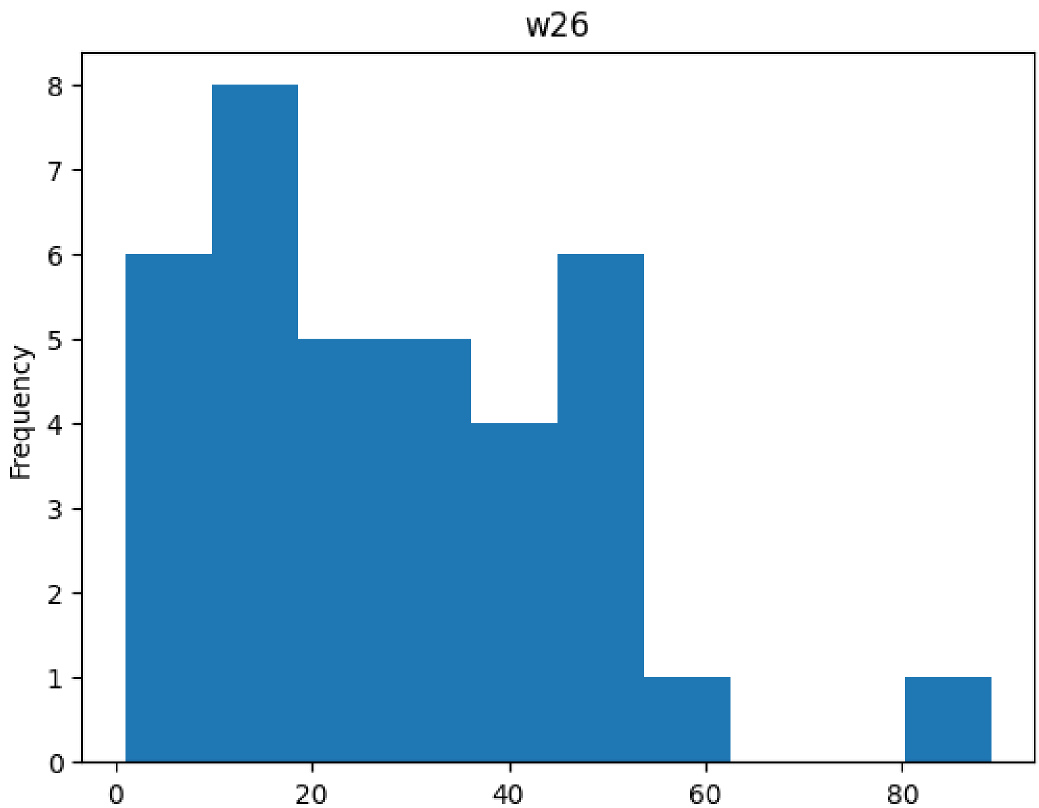

```
--- Column: w24 ---
count    46.000000
mean     26.782609
std      18.556716
min       3.000000
25%      12.000000
50%      21.500000
75%      40.500000
max      91.000000
Name: w24, dtype: float64
```



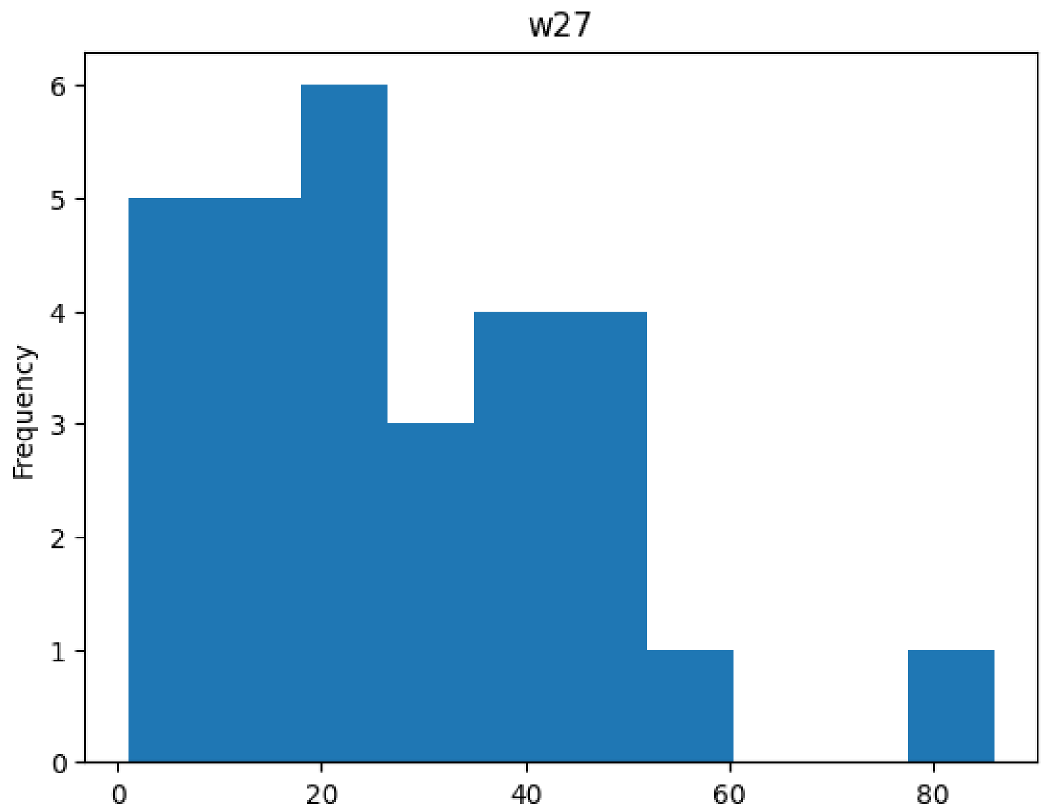

```
--- Column: w25 ---
count    38.000000
mean     26.131579
std      18.737404
min       2.000000
25%      12.250000
50%      22.500000
75%      38.250000
max      90.000000
Name: w25, dtype: float64
```



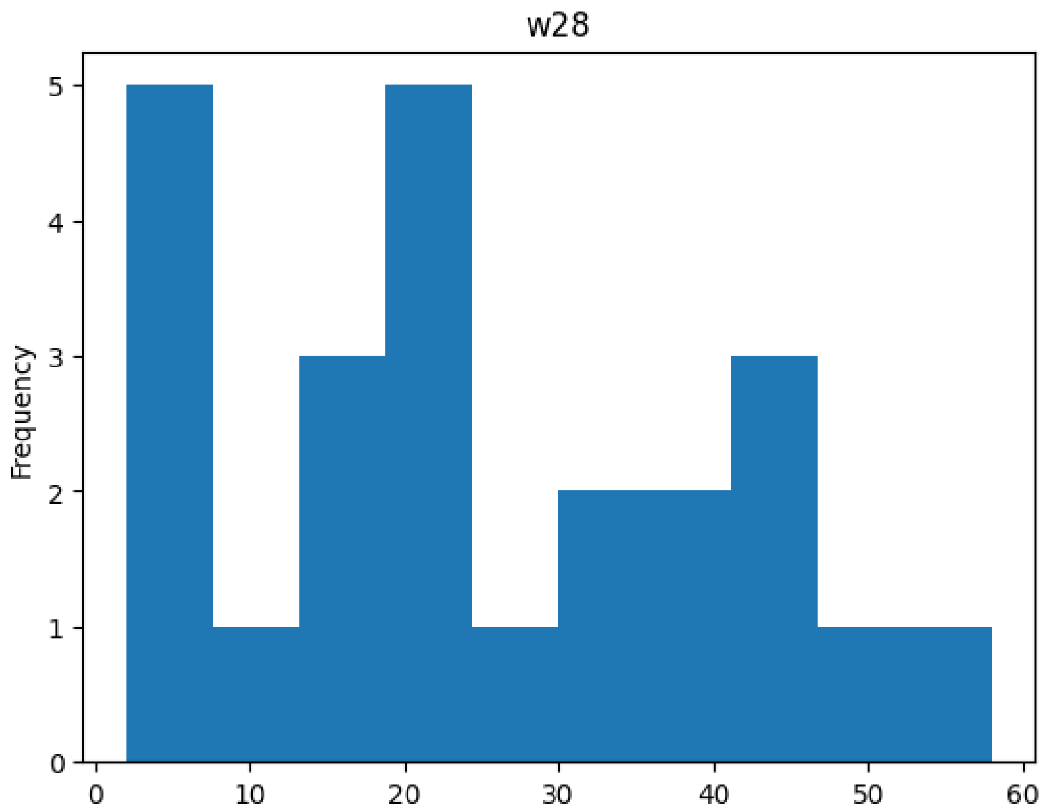

```
--- Column: w26 ---
count    36.00000
mean     28.00000
std      19.14904
min       1.00000
25%      13.75000
50%      26.00000
75%      40.25000
max      89.00000
Name: w26, dtype: float64
```



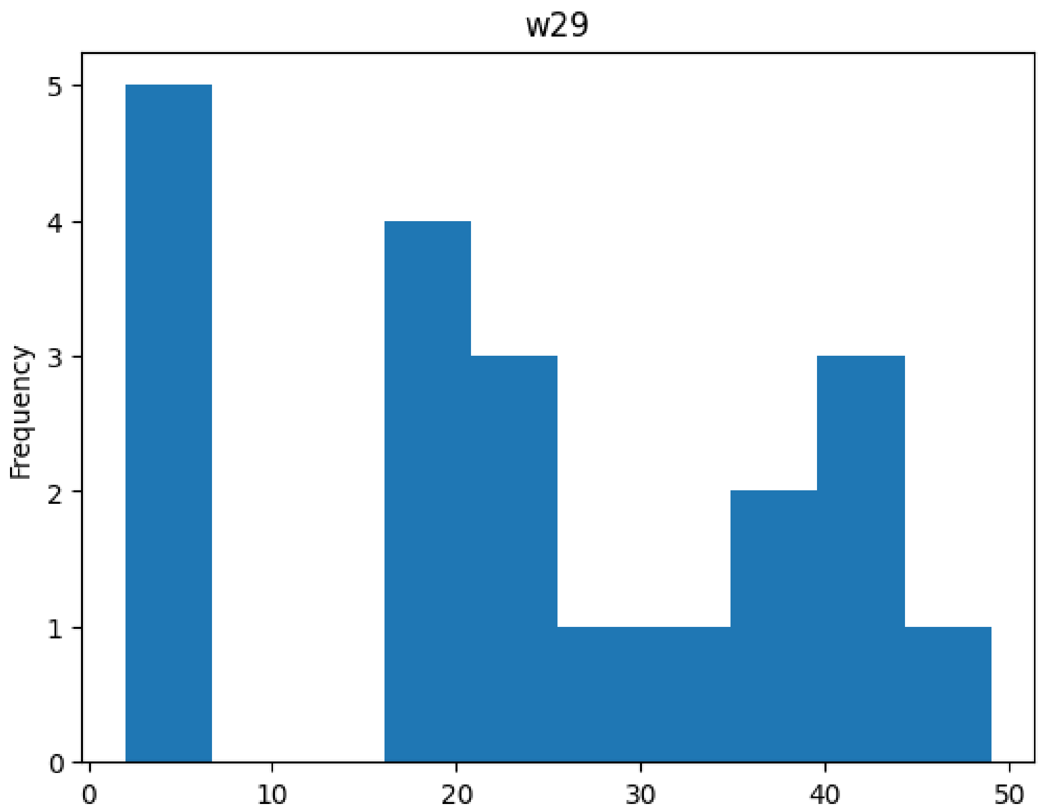

```
--- Column: w27 ---
count    29.000000
mean     27.344828
std      19.736254
min       1.000000
25%      12.000000
50%      26.000000
75%      38.000000
max      86.000000
Name: w27, dtype: float64
```



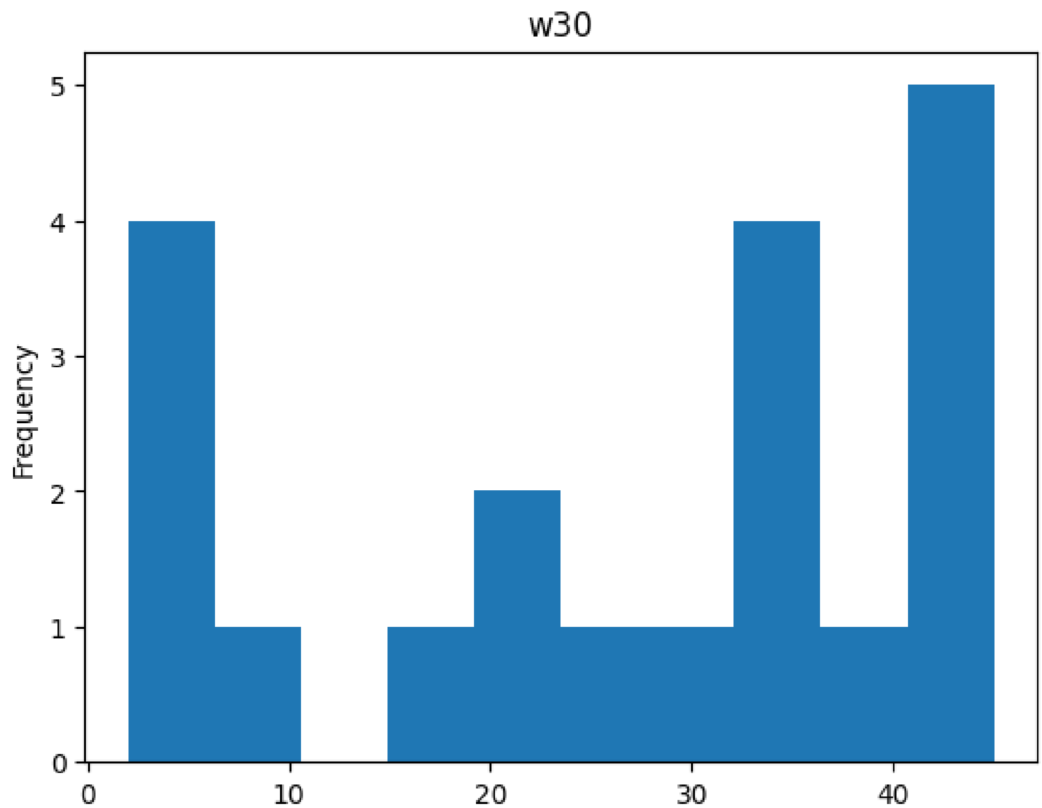

```
--- Column: w28 ---
count    24.000000
mean     25.000000
std      16.229335
min       2.000000
25%      14.500000
50%      23.500000
75%      37.500000
max      58.000000
Name: w28, dtype: float64
```



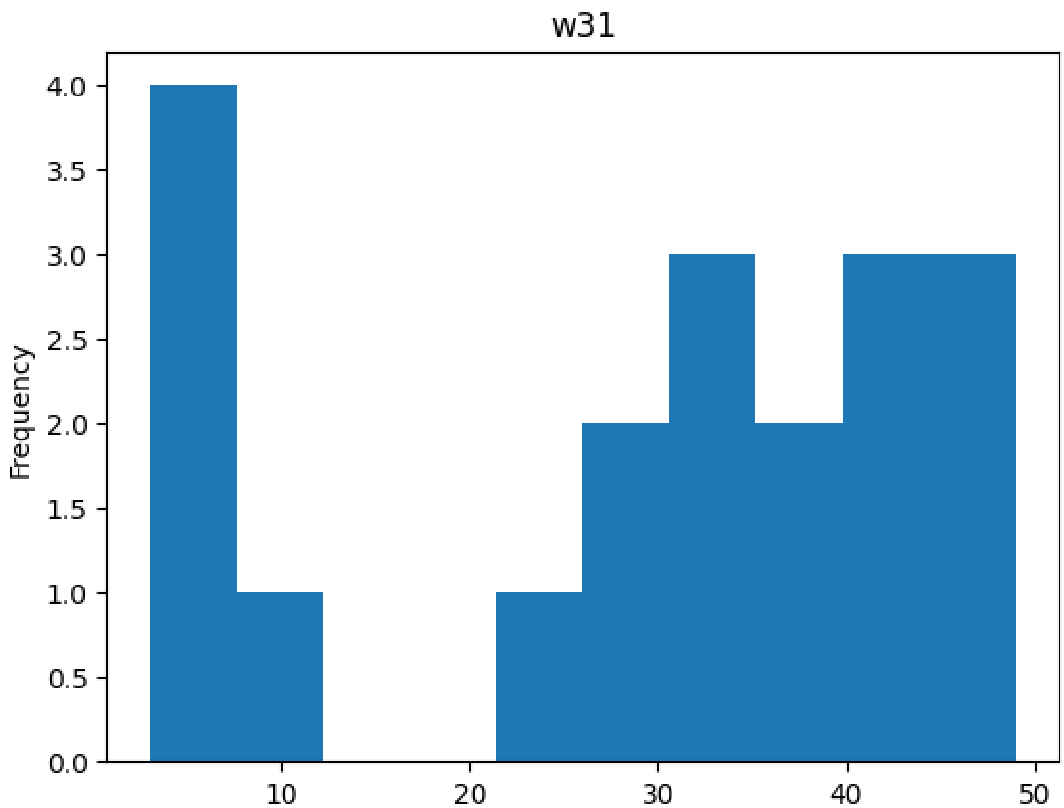

```
--- Column: w29 ---
count    20.000000
mean     23.650000
std      15.239405
min       2.000000
25%      13.750000
50%      22.500000
75%      36.000000
max      49.000000
Name: w29, dtype: float64
```



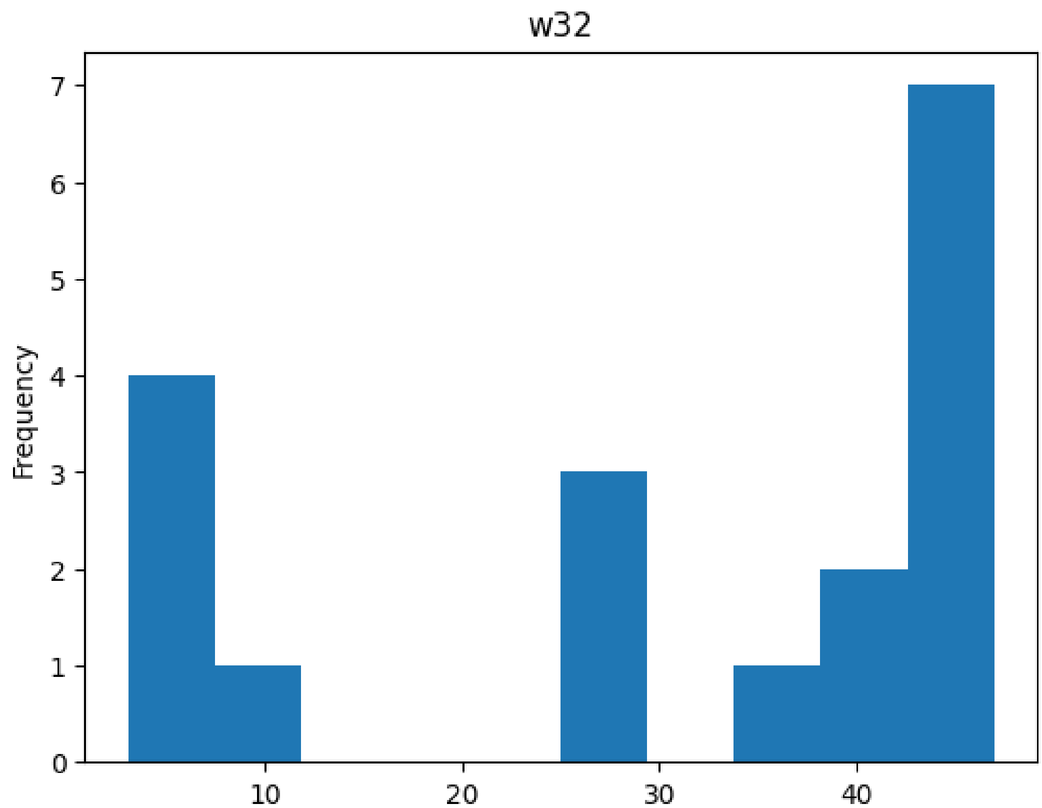

```
--- Column: w30 ---
count    20.000000
mean     26.400000
std      15.104548
min       2.000000
25%      16.000000
50%      31.500000
75%      38.000000
max      45.000000
Name: w30, dtype: float64
```



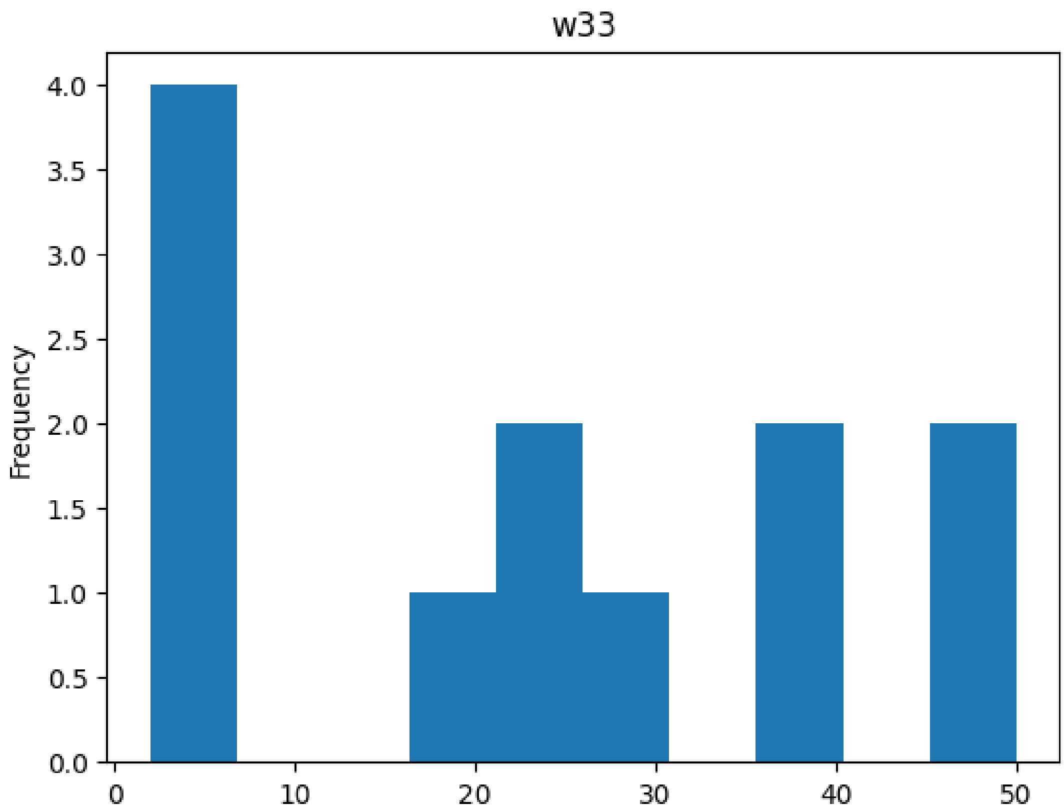

```
--- Column: w31 ---
count    19.000000
mean     28.736842
std      16.002924
min       3.000000
25%      16.000000
50%      34.000000
75%      41.000000
max      49.000000
Name: w31, dtype: float64
```



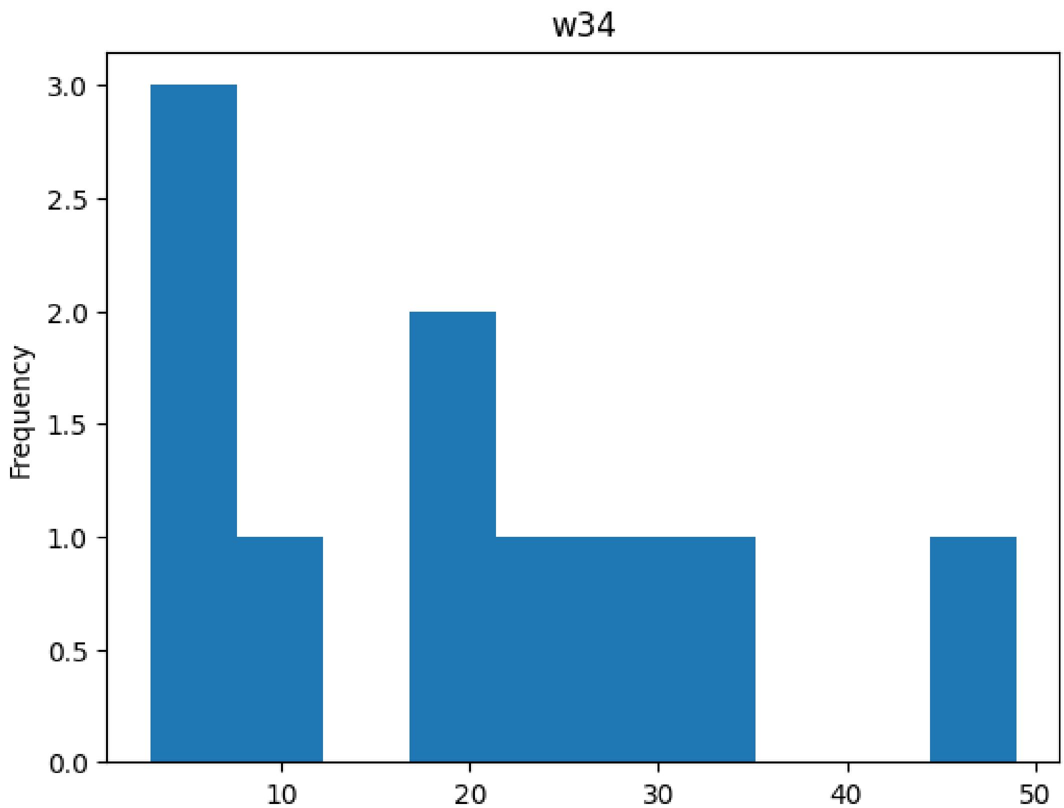

```
--- Column: w32 ---
count    18.000000
mean     30.277778
std      17.032169
min       3.000000
25%      14.500000
50%      38.000000
75%      44.000000
max      47.000000
Name: w32, dtype: float64
```



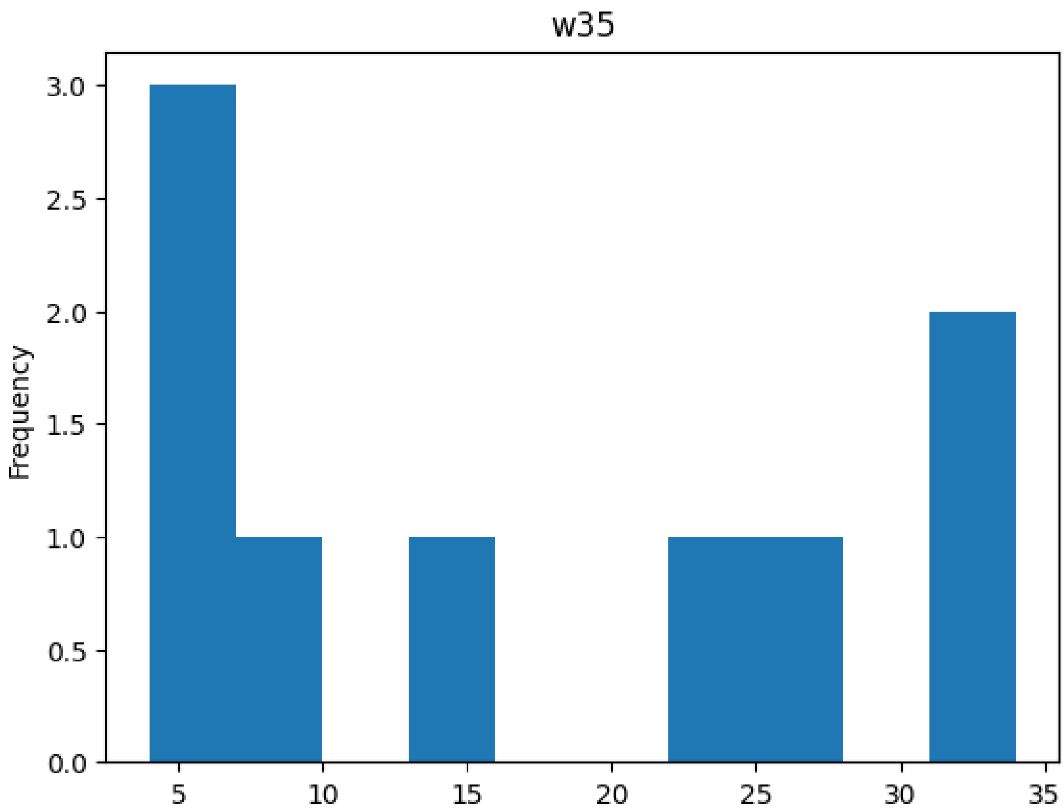

```
--- Column: w33 ---
count    12.000000
mean     23.166667
std      17.071152
min       2.000000
25%       5.500000
50%      24.000000
75%      36.250000
max      50.000000
Name: w33, dtype: float64
```



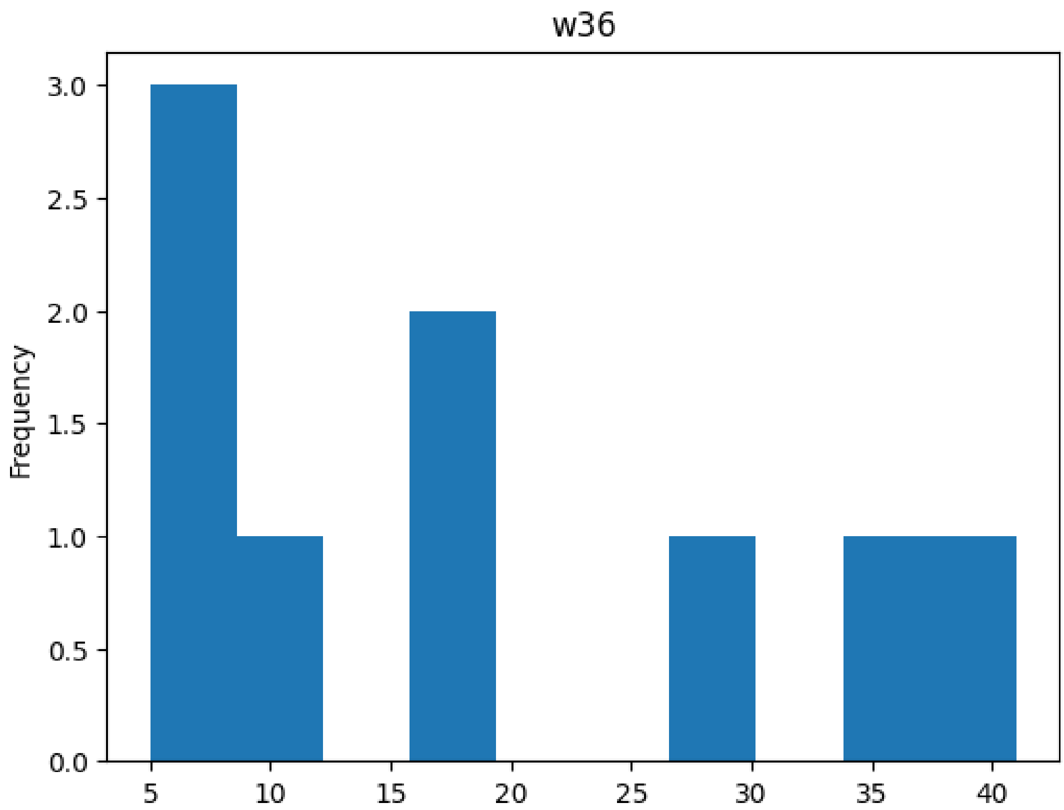

```
--- Column: w34 ---
count    10.000000
mean     19.300000
std      14.929836
min       3.000000
25%       5.750000
50%      18.500000
75%      28.250000
max      49.000000
Name: w34, dtype: float64
```



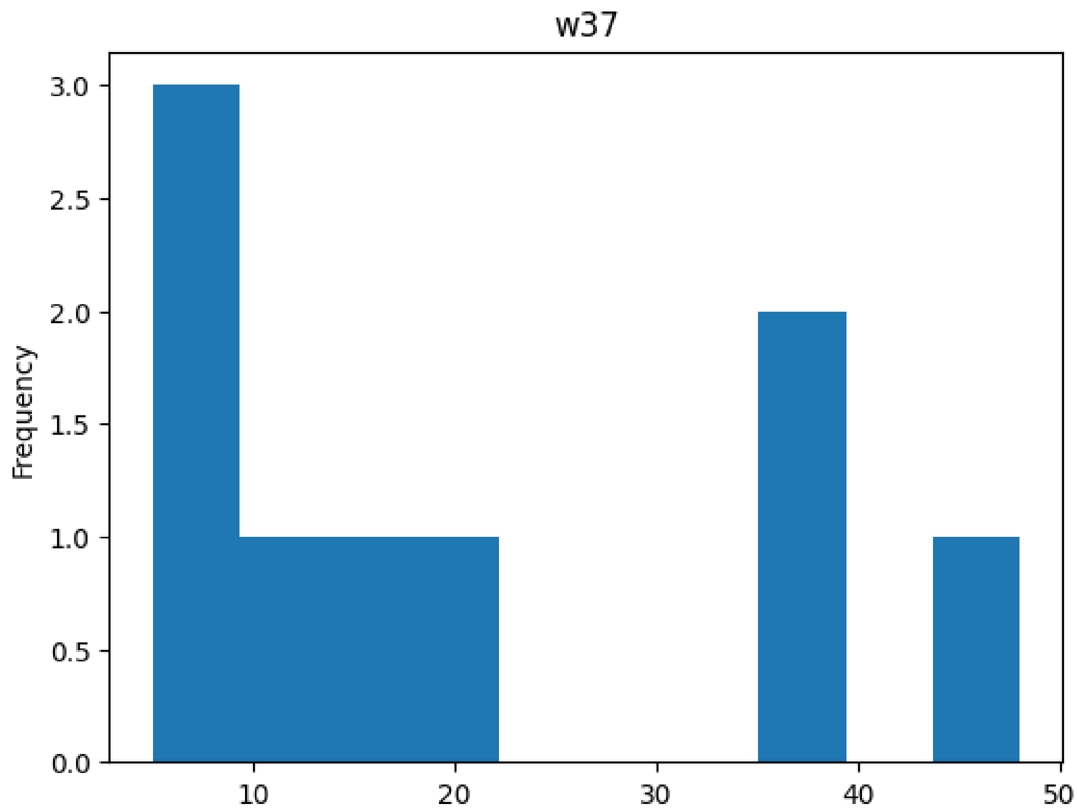

```
--- Column: w35 ---
count     9.000000
mean     16.888889
std      12.333333
min       4.000000
25%       5.000000
50%      14.000000
75%      27.000000
max      34.000000
Name: w35, dtype: float64
```



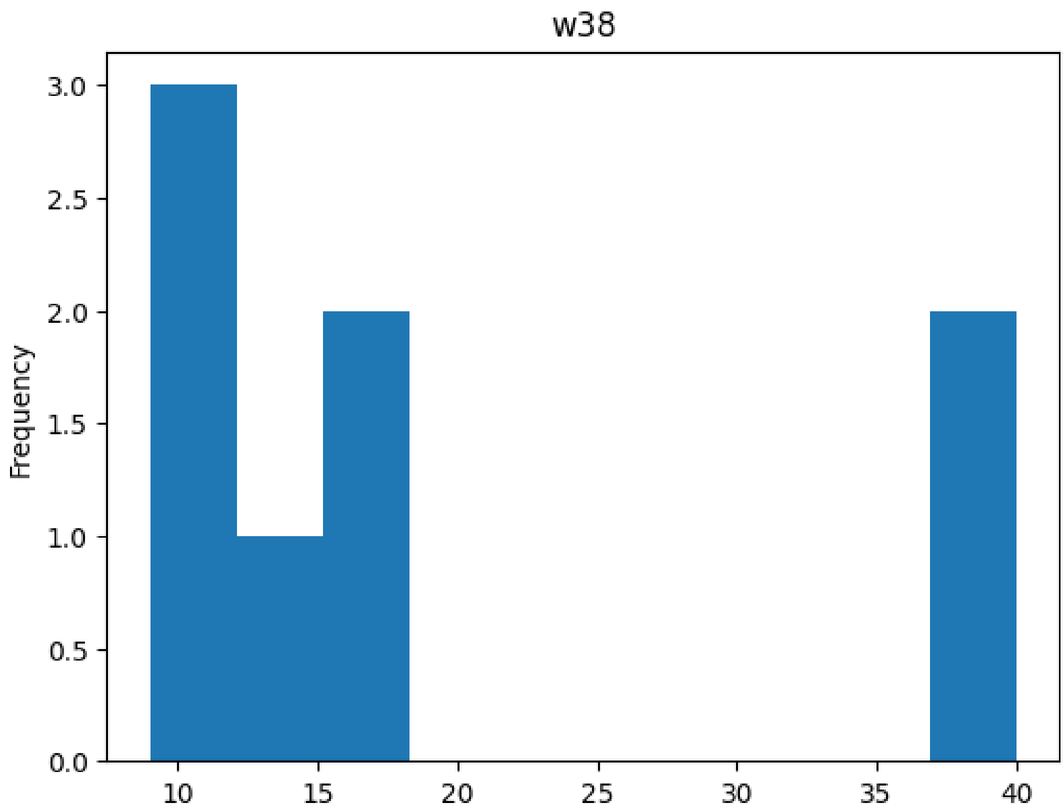

```
--- Column: w36 ---
count     9.000000
mean     18.555556
std      13.893444
min       5.000000
25%       6.000000
50%      16.000000
75%      29.000000
max      41.000000
Name: w36, dtype: float64
```



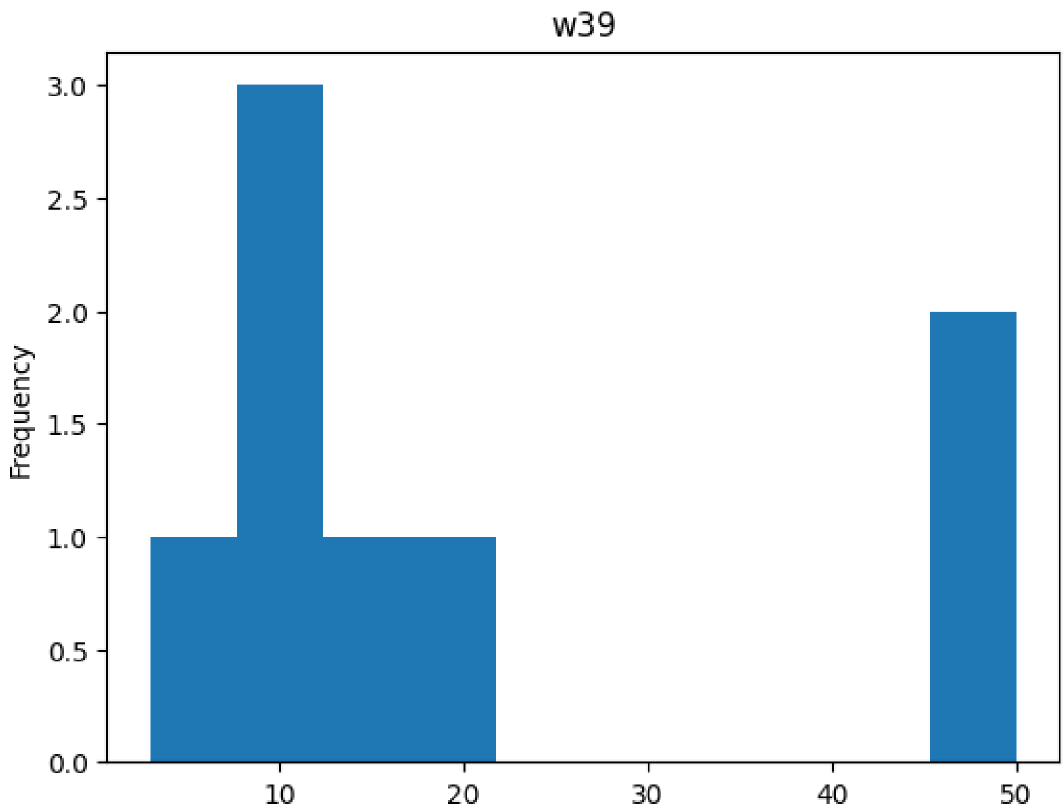

```
--- Column: w37 ---
count     9.000000
mean     20.888889
std      15.799086
min       5.000000
25%       9.000000
50%      16.000000
75%      36.000000
max      48.000000
Name: w37, dtype: float64
```



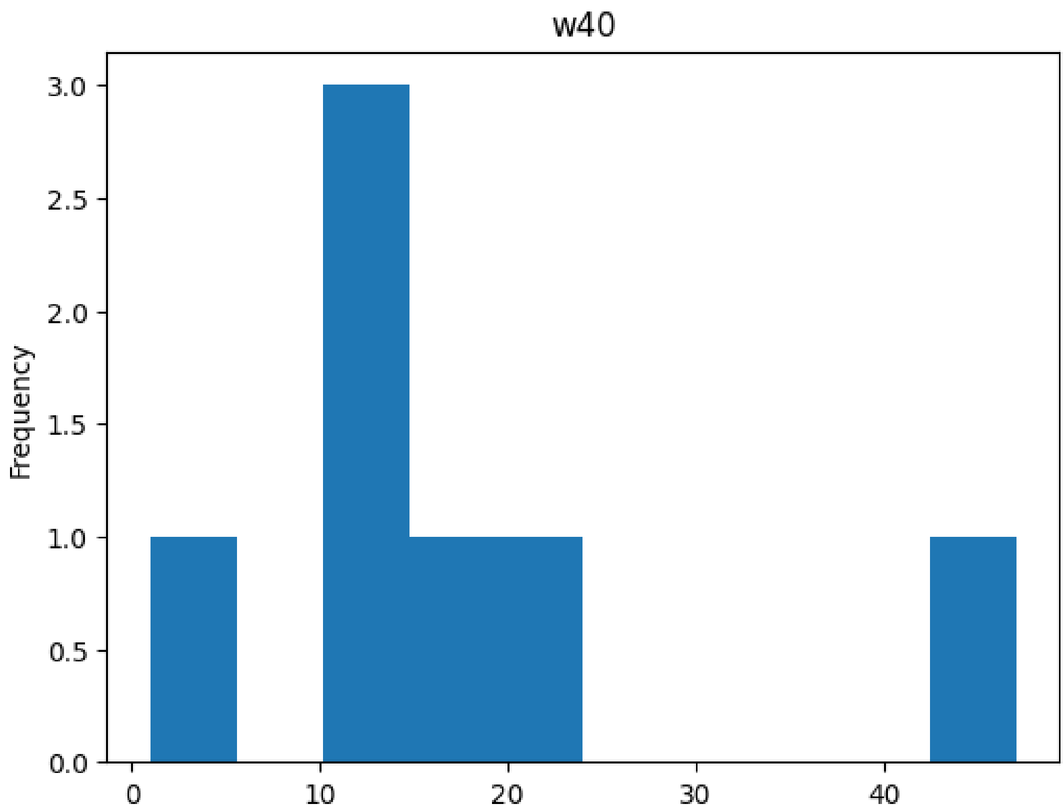

```
--- Column: w38 ---
count     8.000000
mean     19.375000
std      12.693502
min       9.000000
25%       9.000000
50%      16.000000
75%      23.000000
max      40.000000
Name: w38, dtype: float64
```



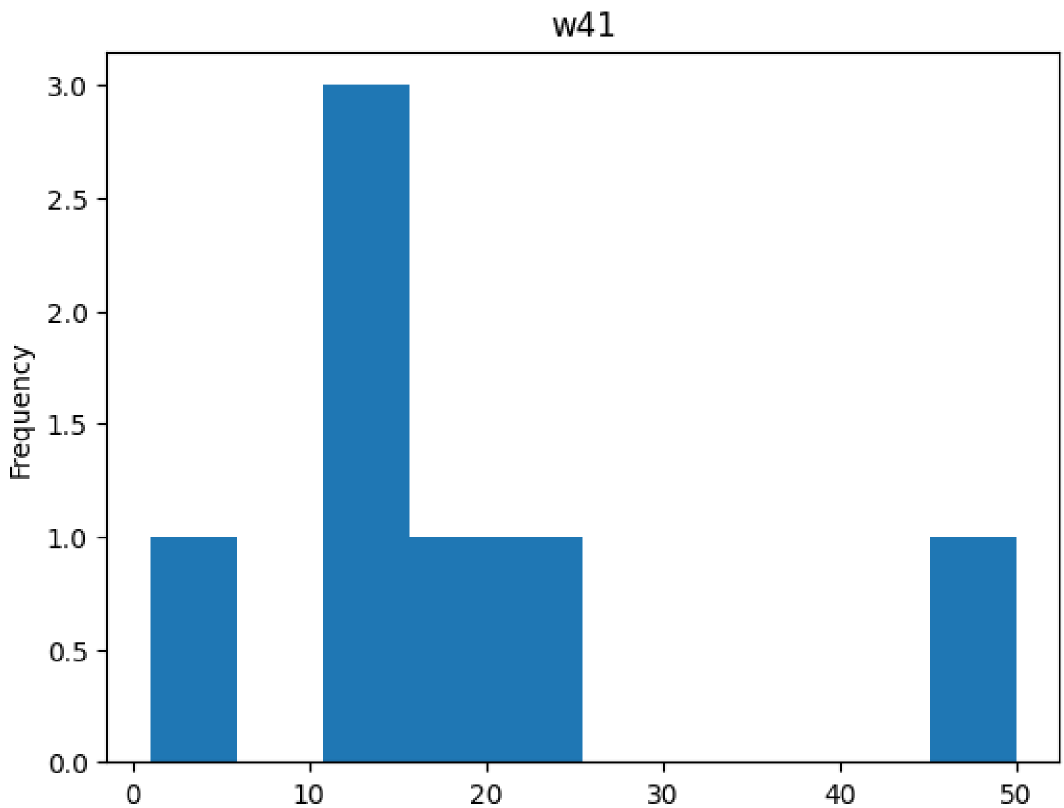

```
--- Column: w39 ---
count     8.000000
mean     20.250000
std      18.289341
min       3.000000
25%       8.750000
50%      13.000000
75%      25.500000
max      50.000000
Name: w39, dtype: float64
```



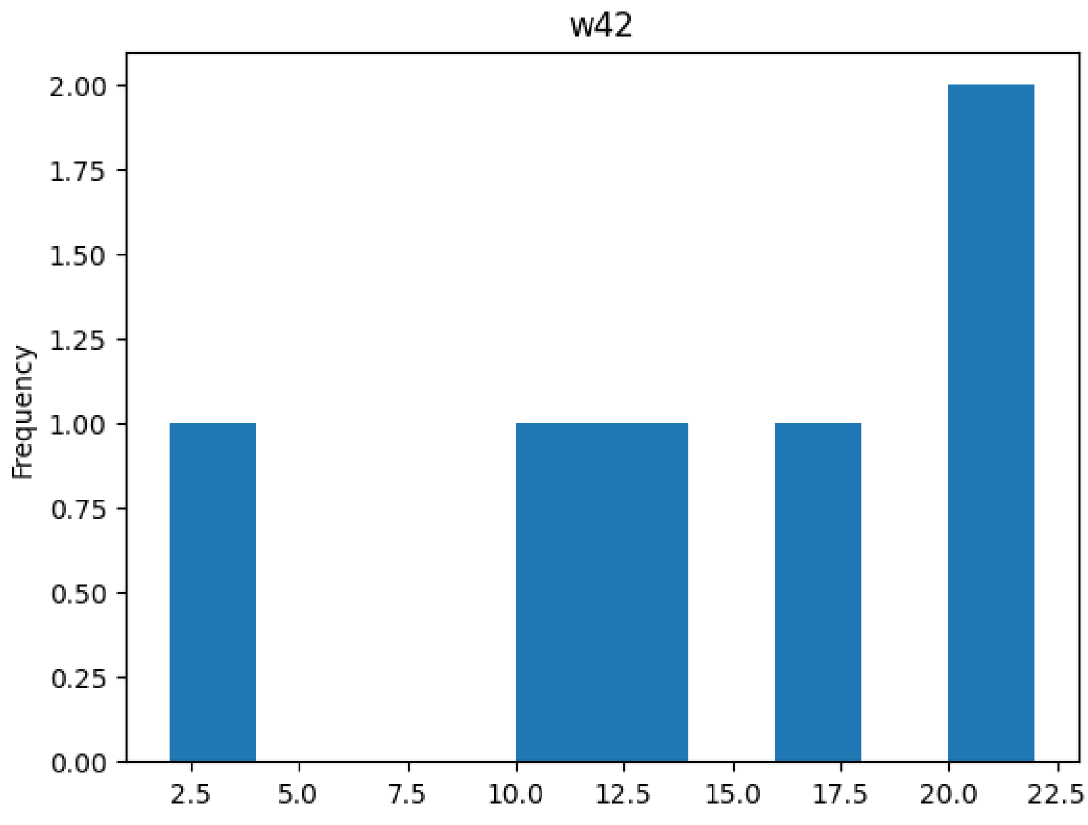

```
--- Column: w40 ---
count     7.000000
mean     17.857143
std      14.264508
min       1.000000
25%      13.000000
50%      14.000000
75%      18.500000
max      47.000000
Name: w40, dtype: float64
```



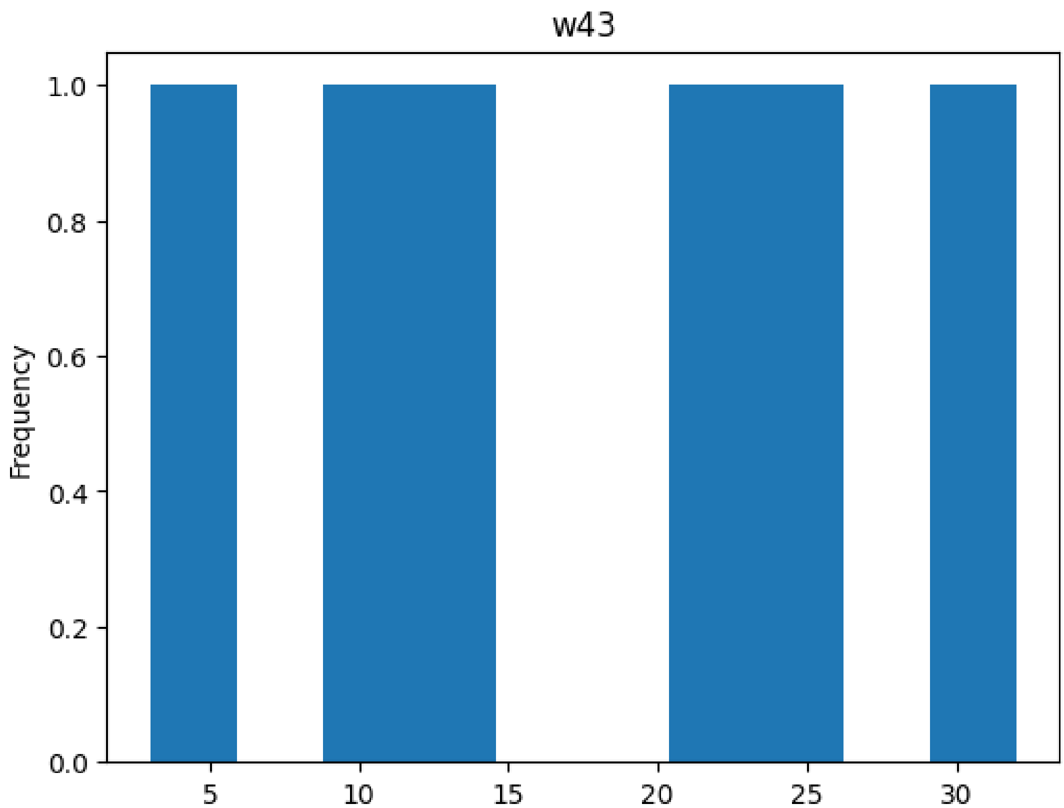

```
--- Column: w41 ---
count     7.000000
mean     18.571429
std      15.306395
min       1.000000
25%      13.000000
50%      14.000000
75%      19.500000
max      50.000000
Name: w41, dtype: float64
```



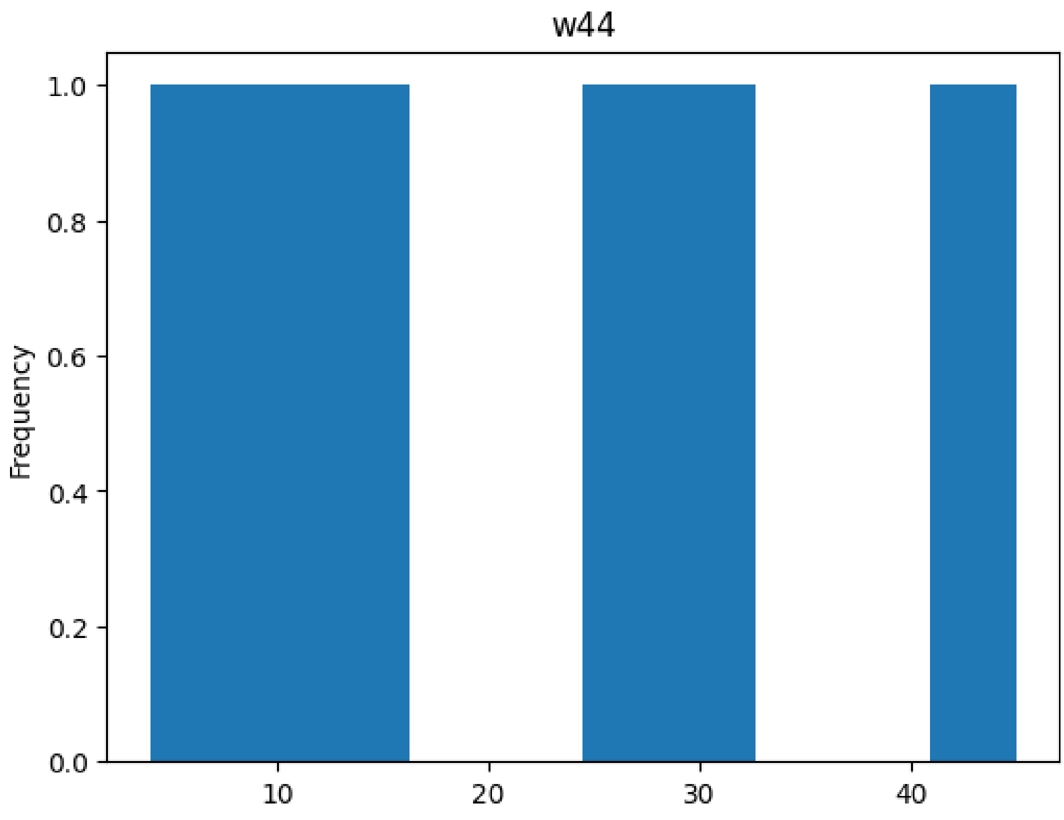

```
--- Column: w42 ---
count     6.000000
mean     14.166667
std       7.250287
min       2.000000
25%      11.500000
50%      15.000000
75%      19.250000
max      22.000000
Name: w42, dtype: float64
```



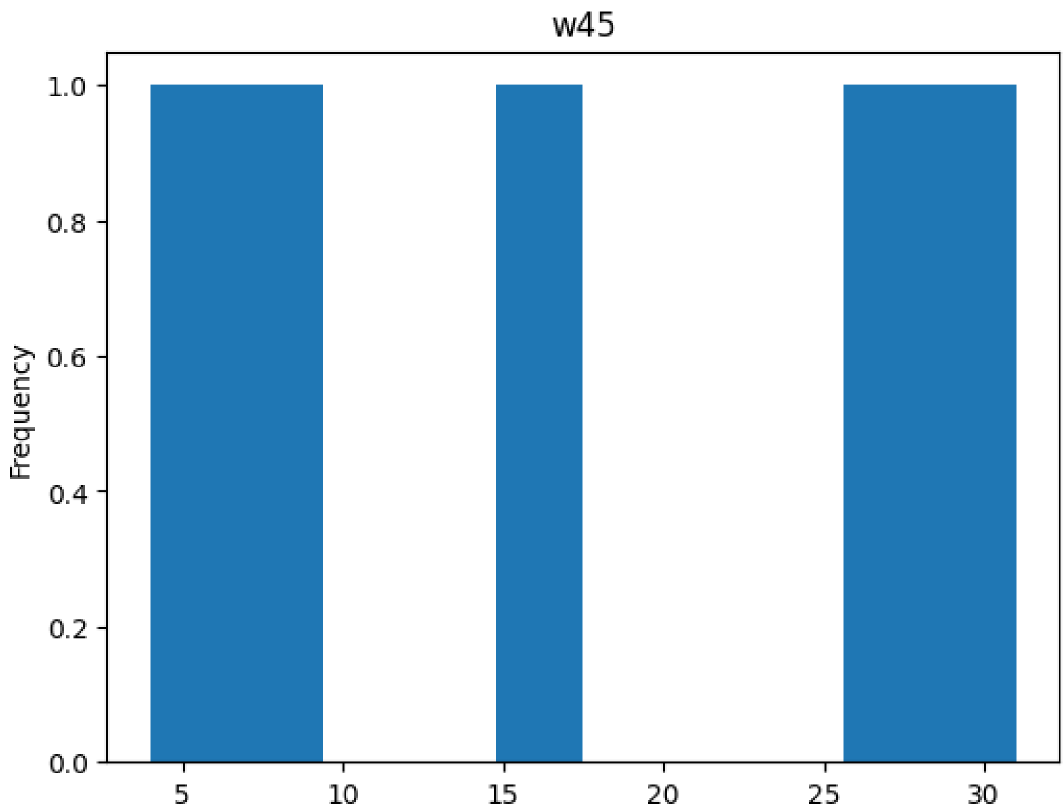

```
--- Column: w43 ---
count     6.000000
mean     17.666667
std      10.366613
min       3.000000
25%      11.750000
50%      18.000000
75%      23.500000
max      32.000000
Name: w43, dtype: float64
```



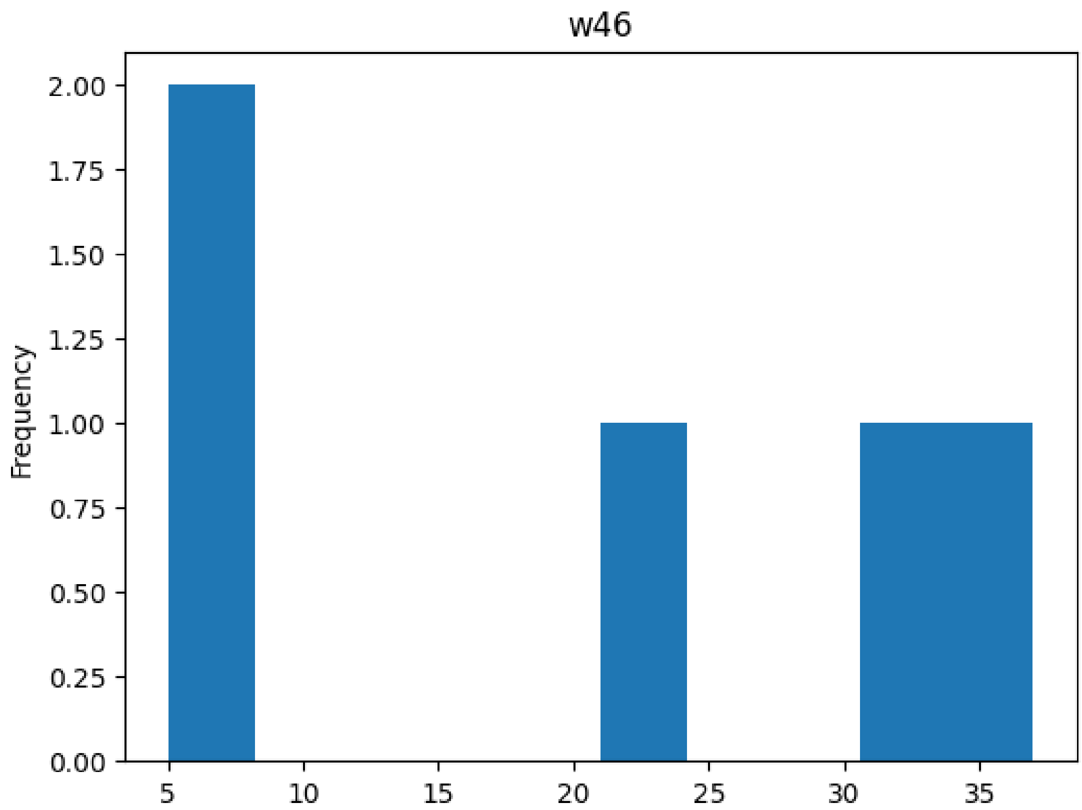

```
--- Column: w44 ---
count     6.000000
mean     21.666667
std      15.081998
min       4.000000
25%      10.750000
50%      21.000000
75%      29.000000
max      45.000000
Name: w44, dtype: float64
```



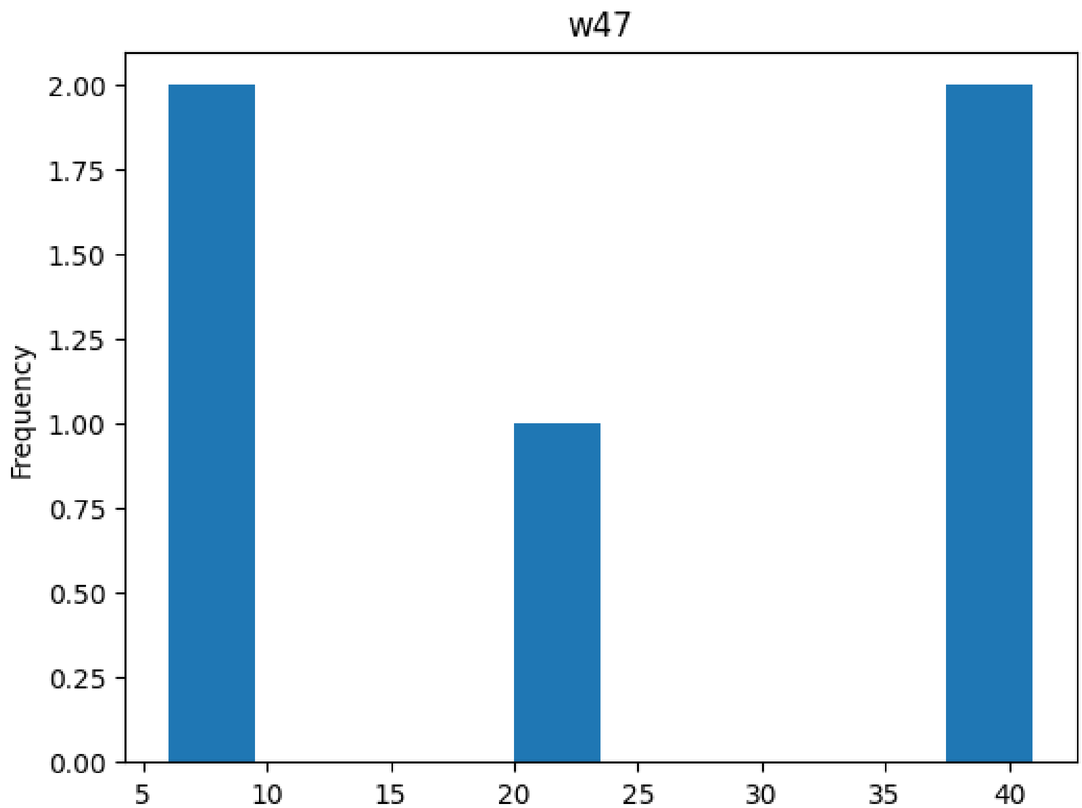

```
--- Column: w45 ---
count     5.000000
mean     17.800000
std      11.691878
min       4.000000
25%       9.000000
50%      17.000000
75%      28.000000
max      31.000000
Name: w45, dtype: float64
```



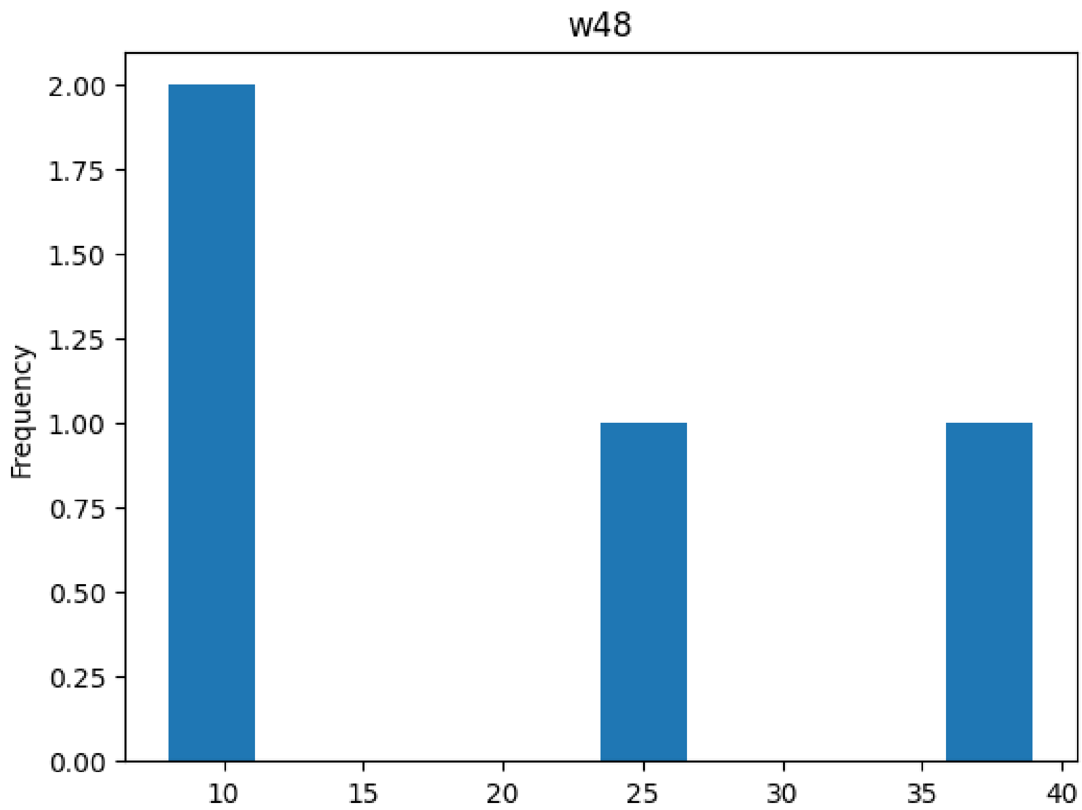

```
--- Column: w46 ---
count     5.000000
mean     20.200000
std      14.184499
min       5.000000
25%       7.000000
50%      21.000000
75%      31.000000
max      37.000000
Name: w46, dtype: float64
```



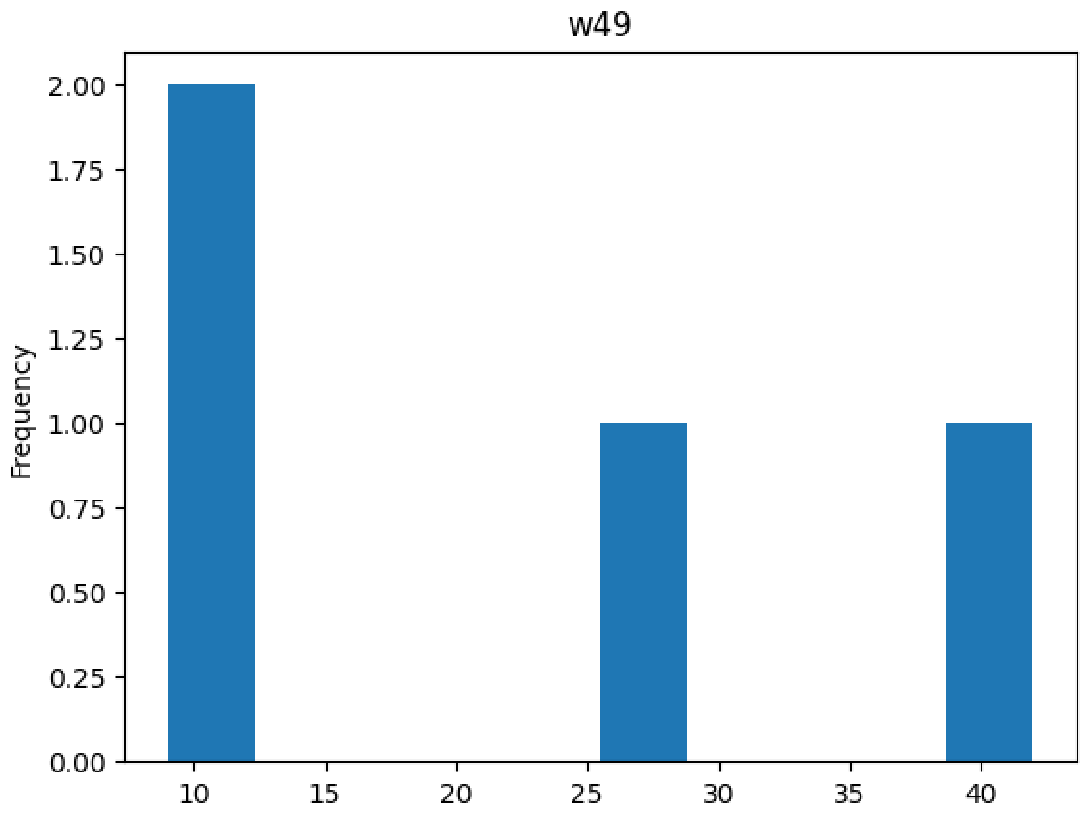

```
--- Column: w47 ---
count     5.000000
mean     22.800000
std      16.543881
min       6.000000
25%       7.000000
50%      22.000000
75%      38.000000
max      41.000000
Name: w47, dtype: float64
```



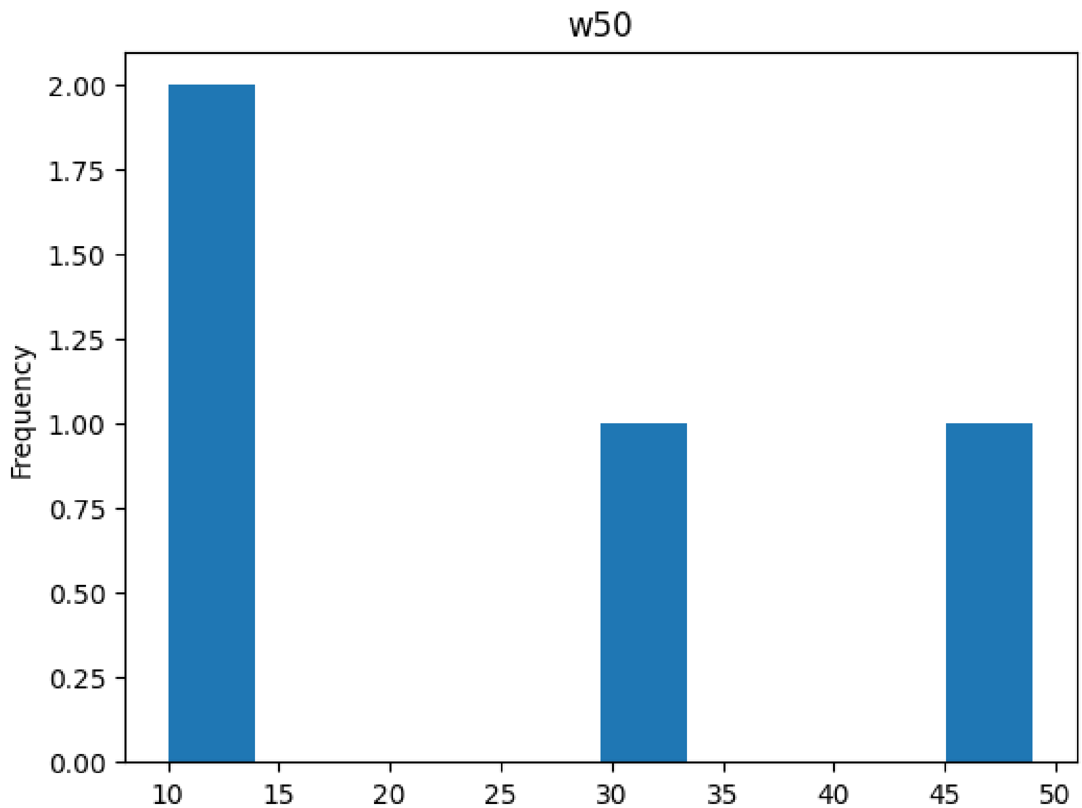

```
--- Column: w48 ---
count     4.000000
mean     20.000000
std      14.628739
min       8.000000
25%       8.750000
50%      16.500000
75%      27.750000
max      39.000000
Name: w48, dtype: float64
```



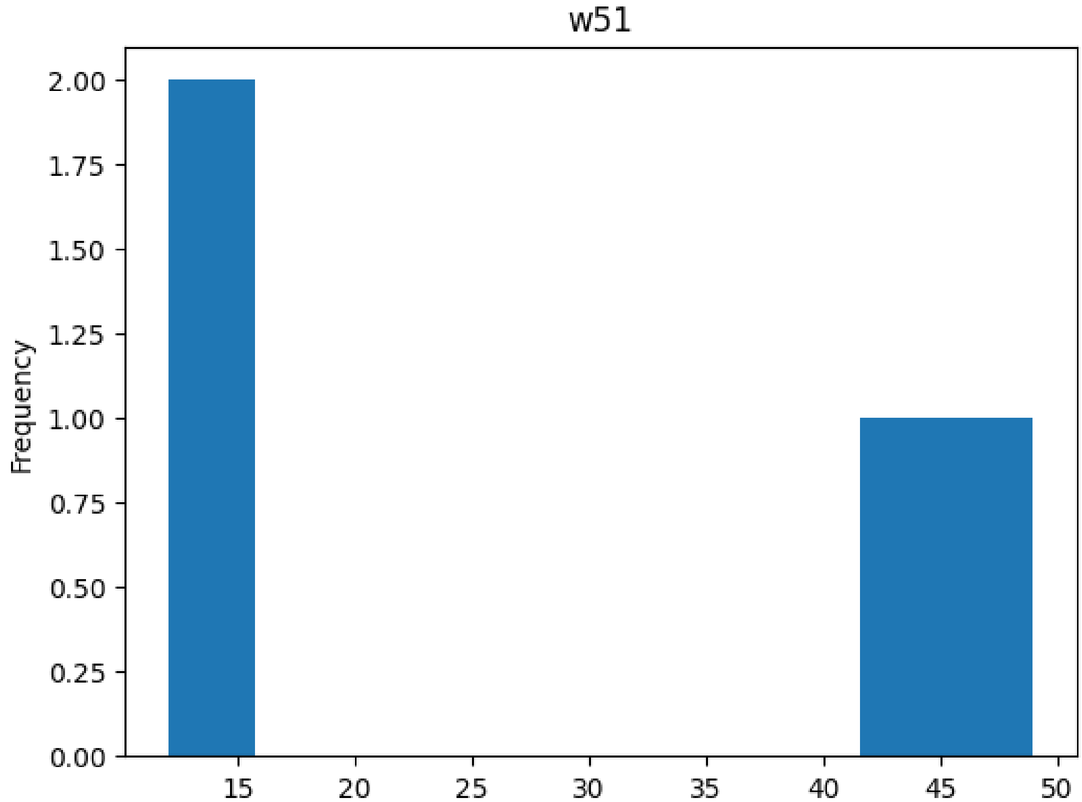

```
--- Column: w49 ---
count     4.000000
mean     22.000000
std      16.062378
min       9.000000
25%       9.000000
50%      18.500000
75%      31.500000
max      42.000000
Name: w49, dtype: float64
```



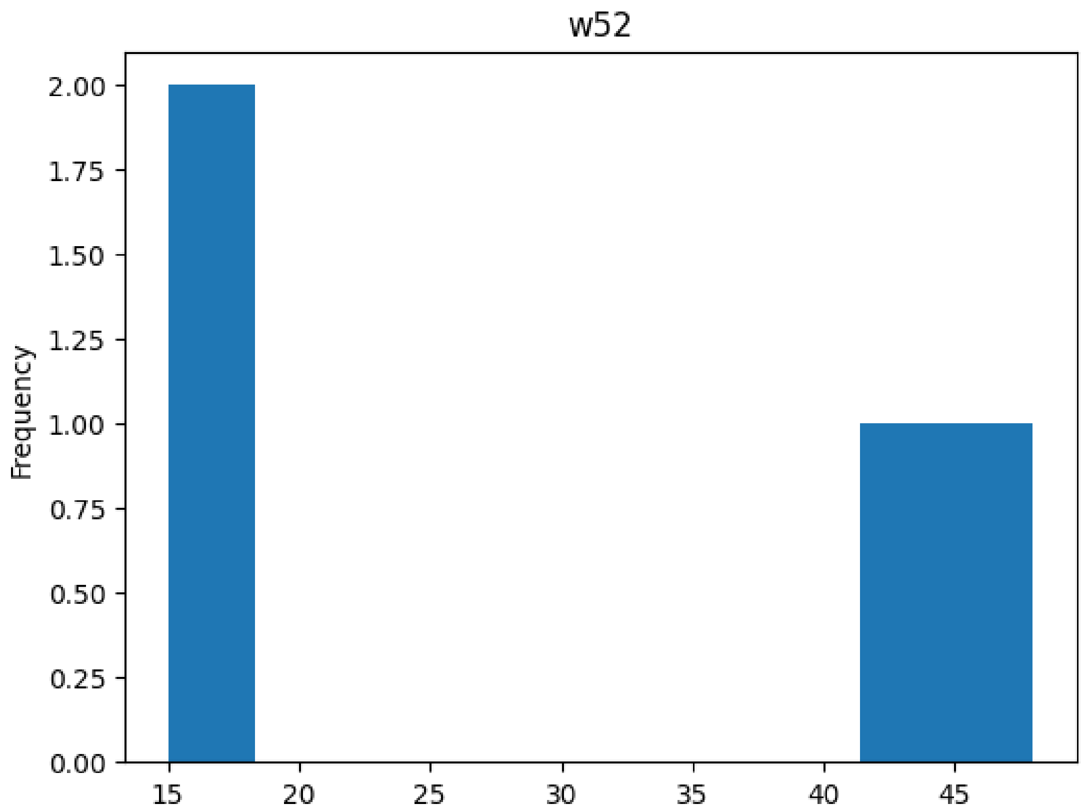

```
--- Column: w50 ---
count     4.000000
mean     26.000000
std      18.529256
min      10.000000
25%      11.500000
50%      22.500000
75%      37.000000
max      49.000000
Name: w50, dtype: float64
```



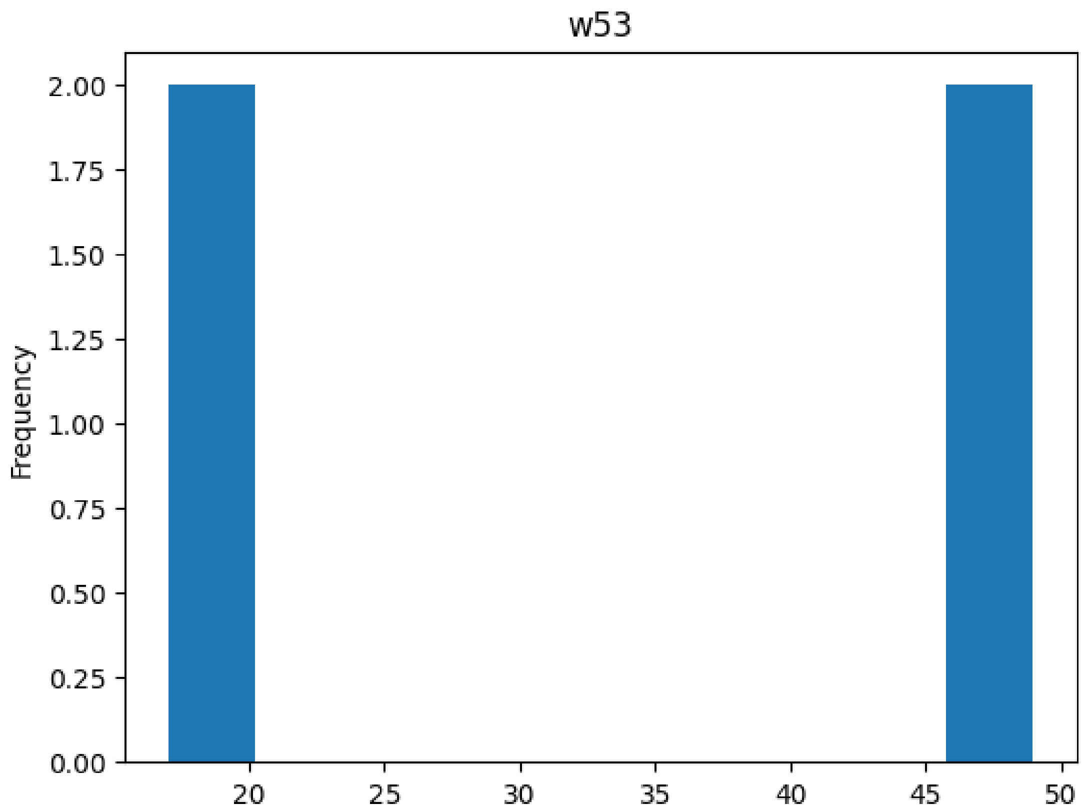

```
--- Column: w51 ---
count     4.000000
mean     29.250000
std      18.997807
min      12.000000
25%      13.500000
50%      28.000000
75%      43.750000
max      49.000000
Name: w51, dtype: float64
```



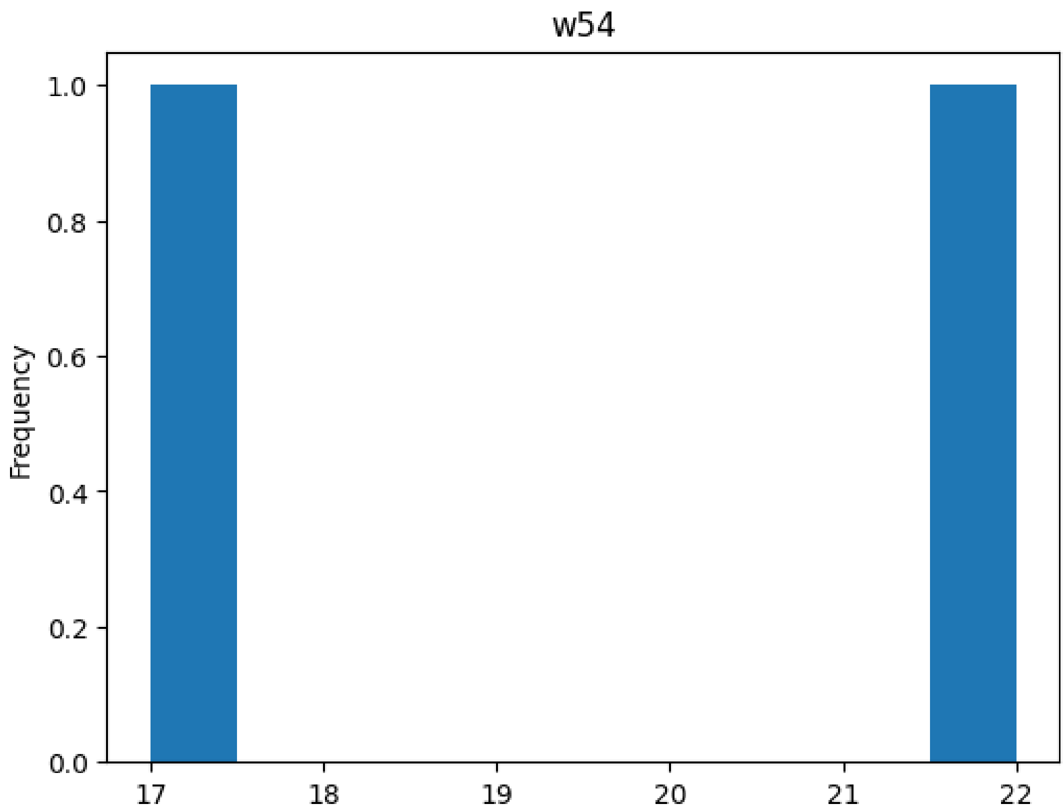

```
--- Column: w52 ---
count     4.000000
mean     30.250000
std      17.211914
min      15.000000
25%      15.750000
50%      29.000000
75%      43.500000
max      48.000000
Name: w52, dtype: float64
```



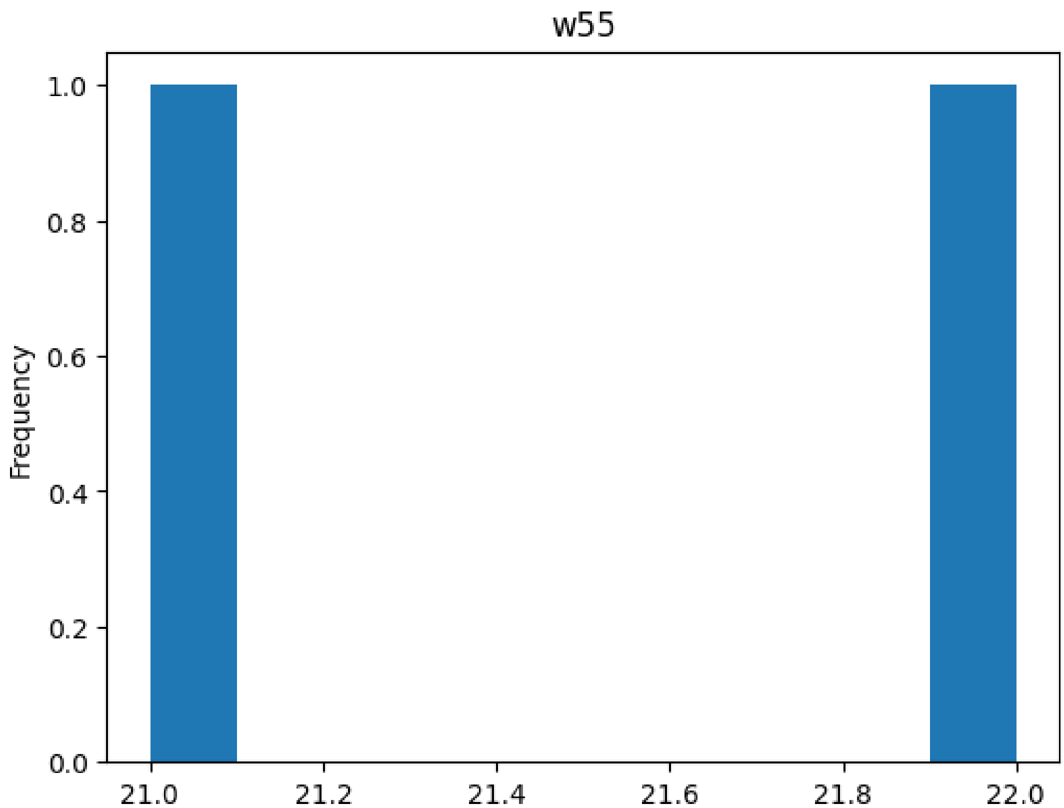

```
--- Column: w53 ---
count     4.000000
mean     33.250000
std      17.095321
min      17.000000
25%      19.250000
50%      33.500000
75%      47.500000
max      49.000000
Name: w53, dtype: float64
```



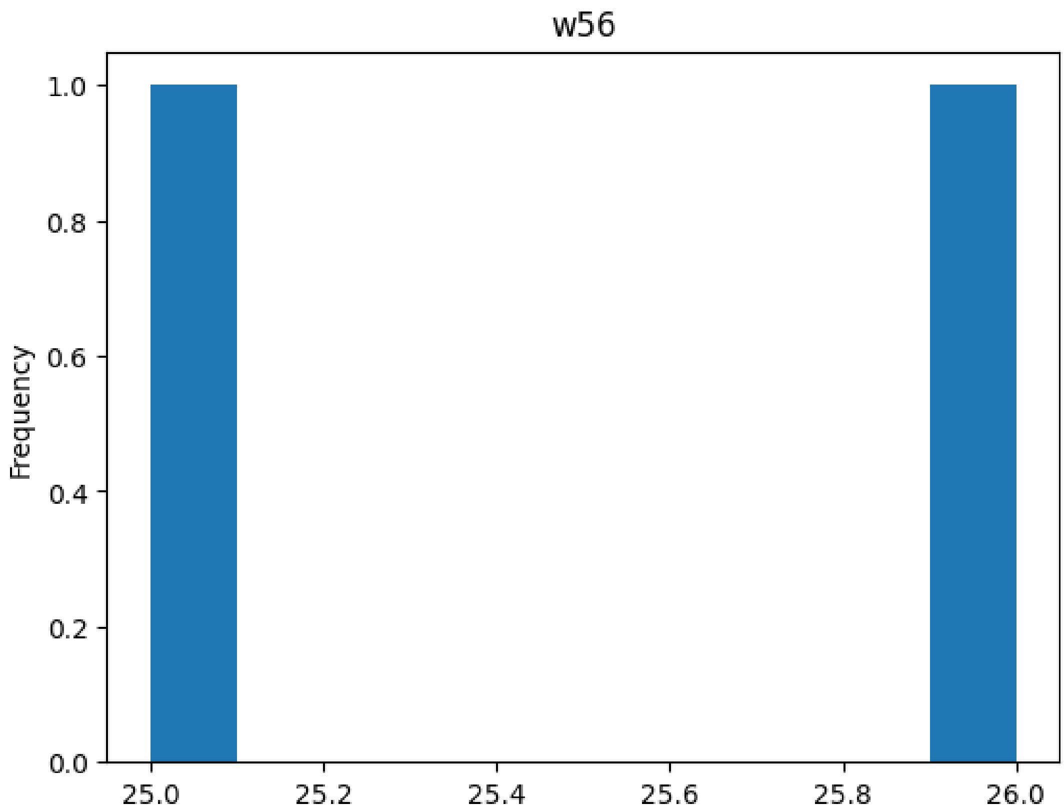

```
--- Column: w54 ---
count     2.000000
mean     19.500000
std       3.535534
min      17.000000
25%      18.250000
50%      19.500000
75%      20.750000
max      22.000000
Name: w54, dtype: float64
```



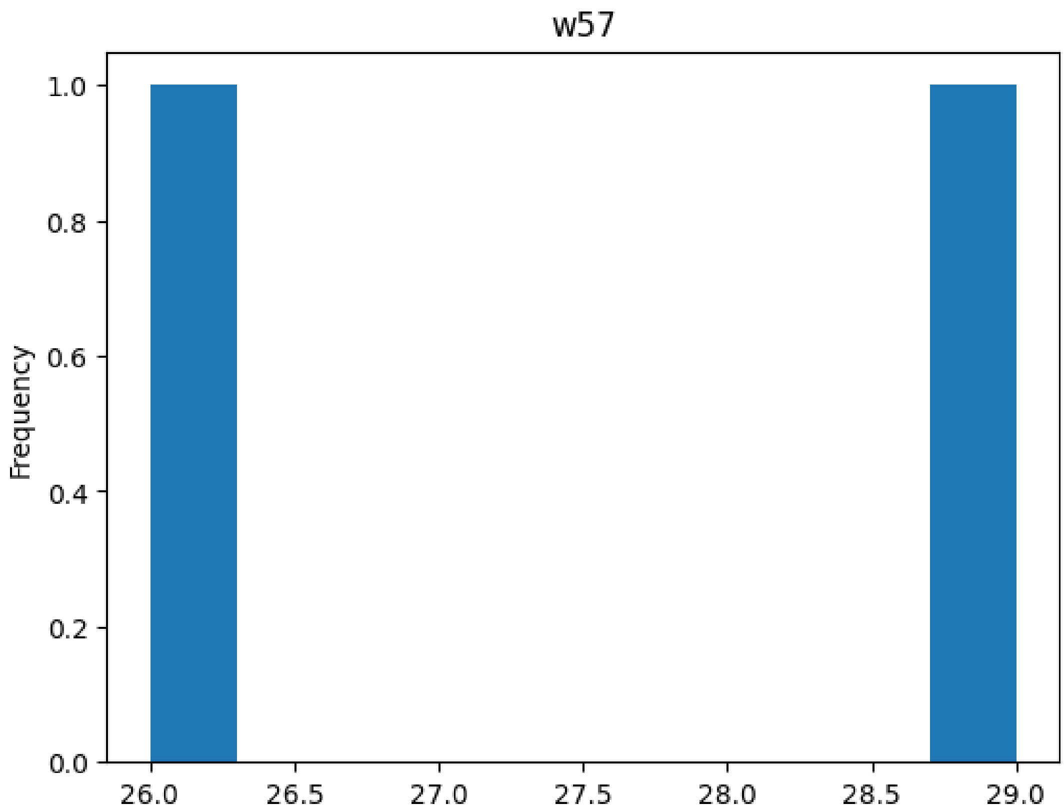

```
--- Column: w55 ---
count     2.000000
mean     21.500000
std       0.707107
min      21.000000
25%      21.250000
50%      21.500000
75%      21.750000
max      22.000000
Name: w55, dtype: float64
```



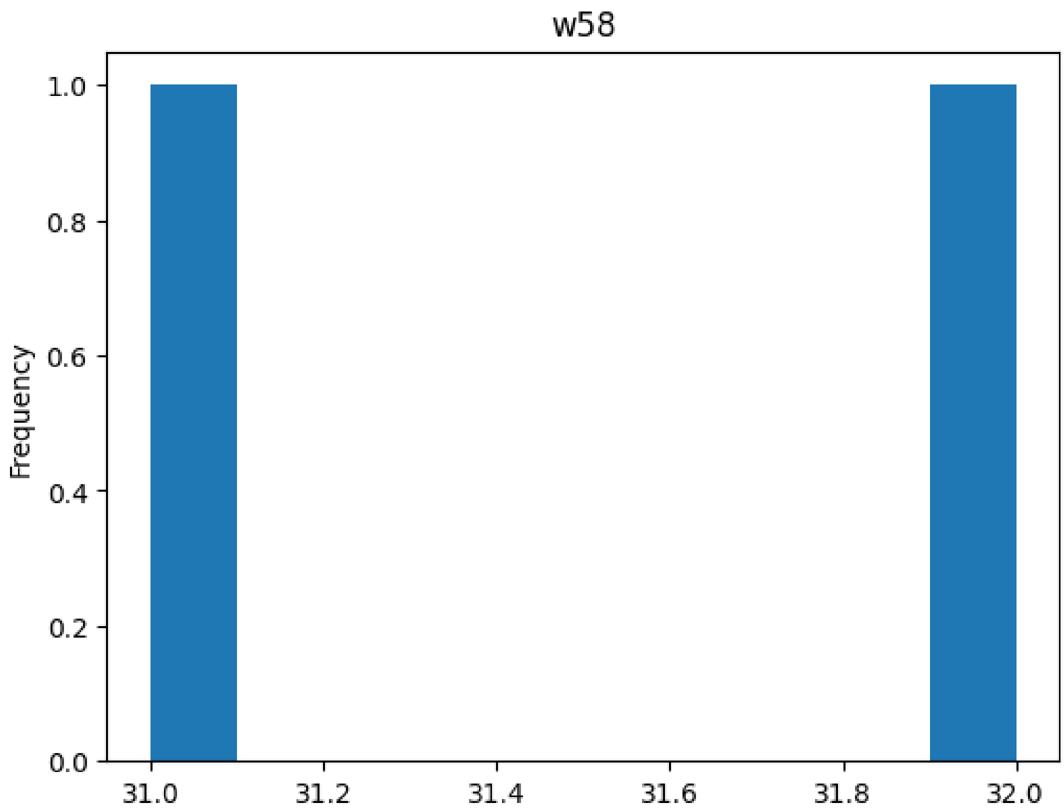

```
--- Column: w56 ---
count     2.000000
mean     25.500000
std       0.707107
min      25.000000
25%      25.250000
50%      25.500000
75%      25.750000
max      26.000000
Name: w56, dtype: float64
```



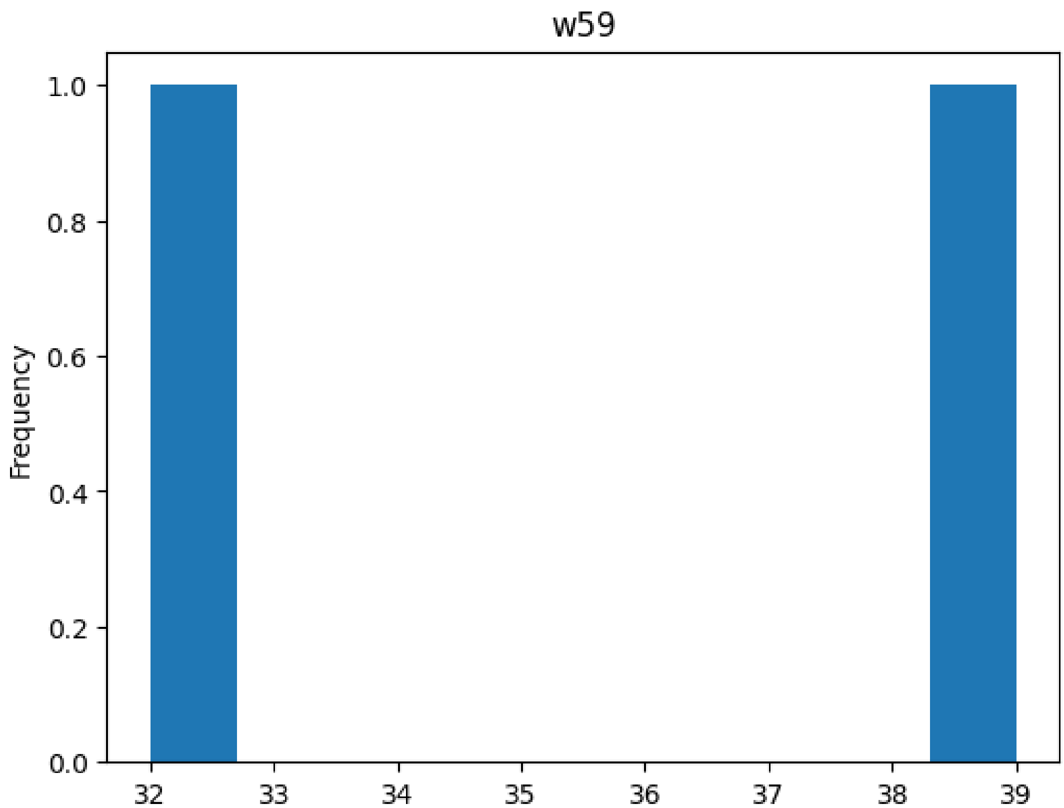

```
--- Column: w57 ---
count     2.00000
mean     27.50000
std       2.12132
min      26.00000
25%      26.75000
50%      27.50000
75%      28.25000
max      29.00000
Name: w57, dtype: float64
```



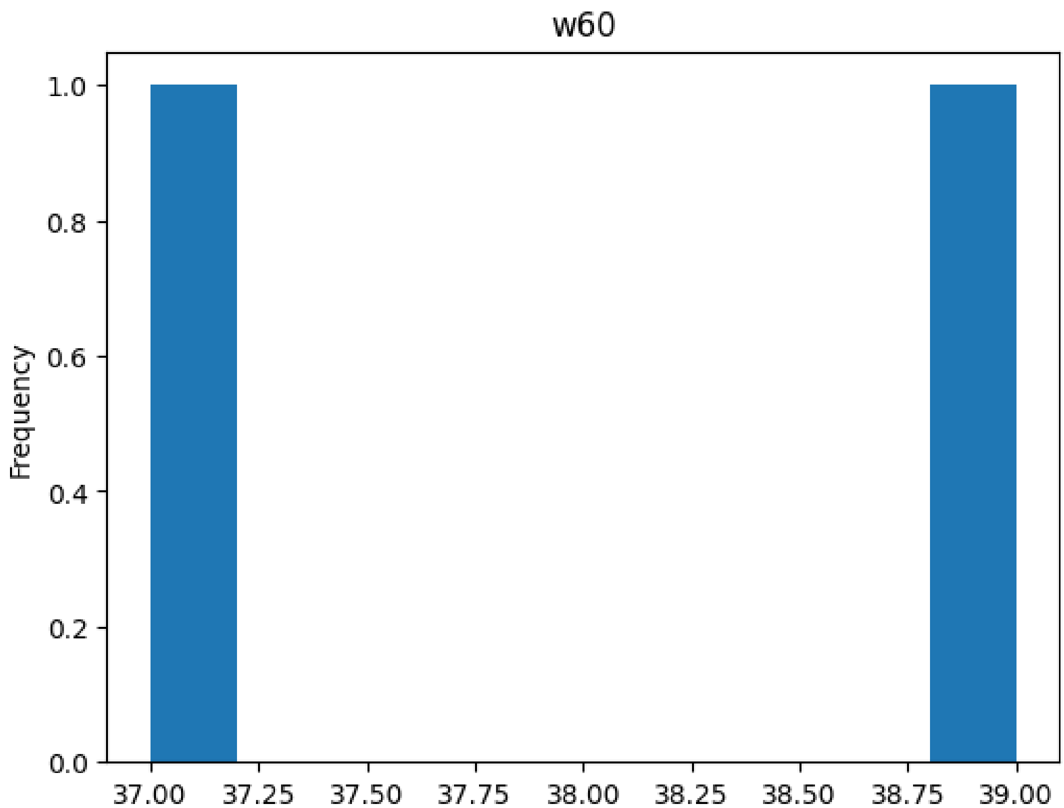

```
--- Column: w58 ---
count     2.000000
mean     31.500000
std       0.707107
min      31.000000
25%      31.250000
50%      31.500000
75%      31.750000
max      32.000000
Name: w58, dtype: float64
```



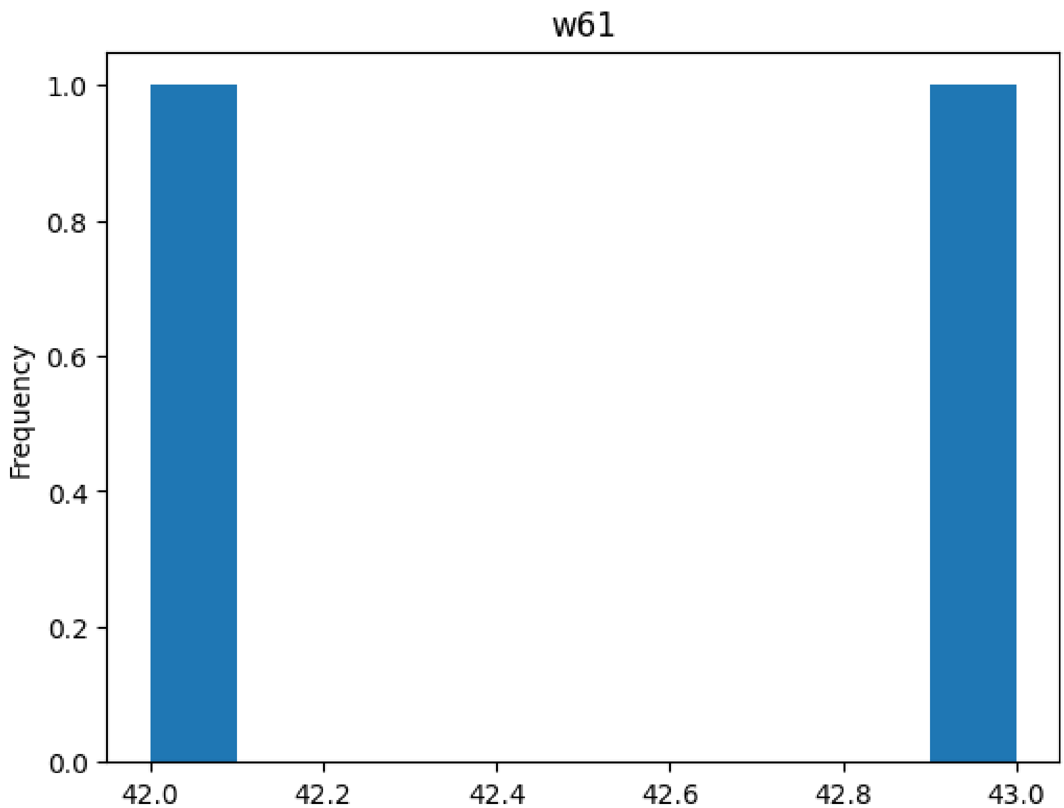

```
--- Column: w59 ---
count     2.000000
mean     35.500000
std       4.949747
min      32.000000
25%      33.750000
50%      35.500000
75%      37.250000
max      39.000000
Name: w59, dtype: float64
```



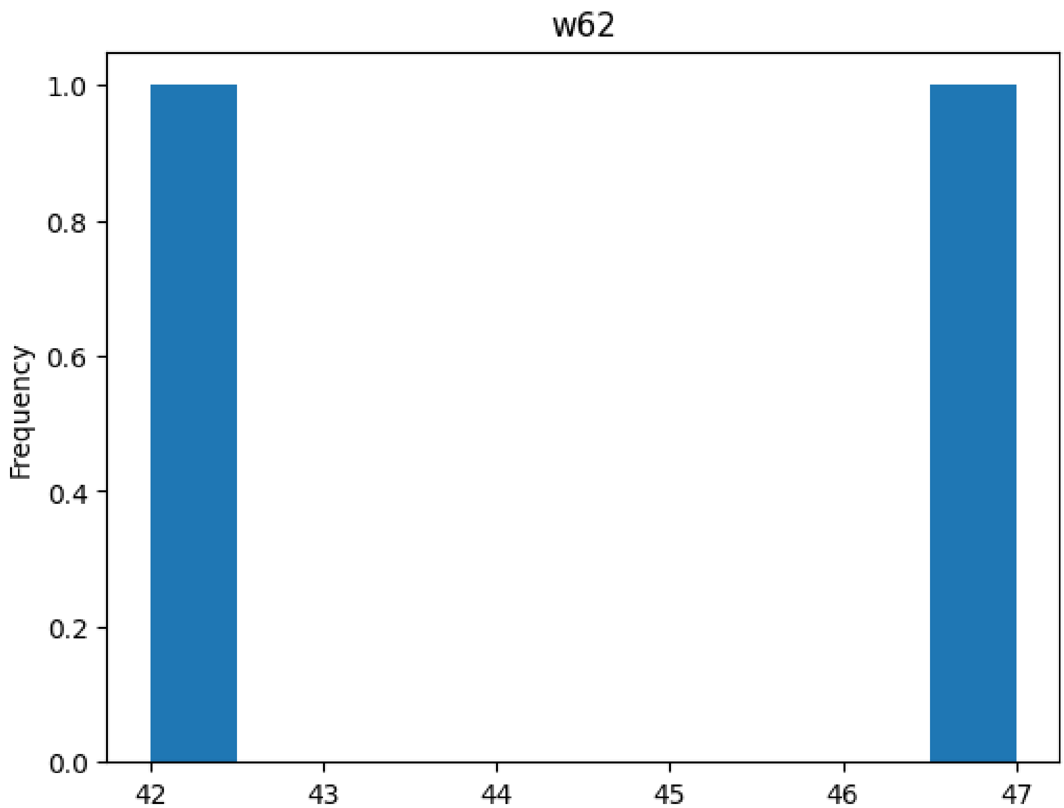

```
--- Column: w60 ---
count     2.000000
mean     38.000000
std       1.414214
min      37.000000
25%      37.500000
50%      38.000000
75%      38.500000
max      39.000000
Name: w60, dtype: float64
```



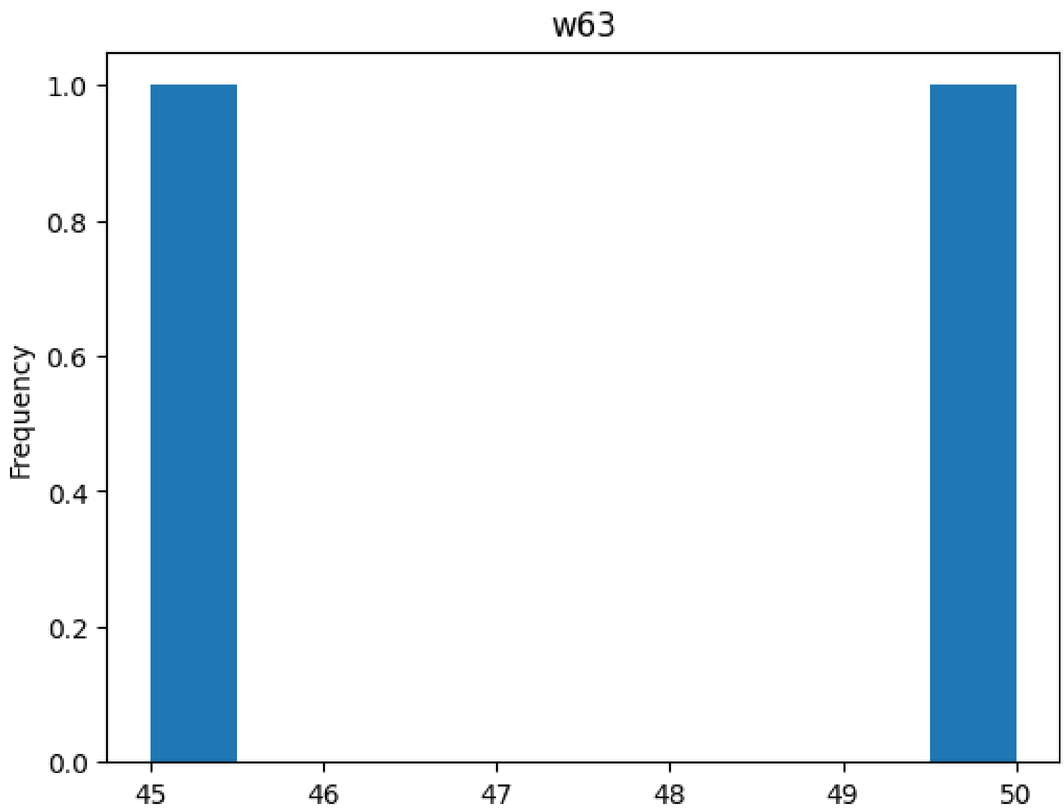

```
--- Column: w61 ---
count     2.000000
mean     42.500000
std       0.707107
min      42.000000
25%      42.250000
50%      42.500000
75%      42.750000
max      43.000000
Name: w61, dtype: float64
```



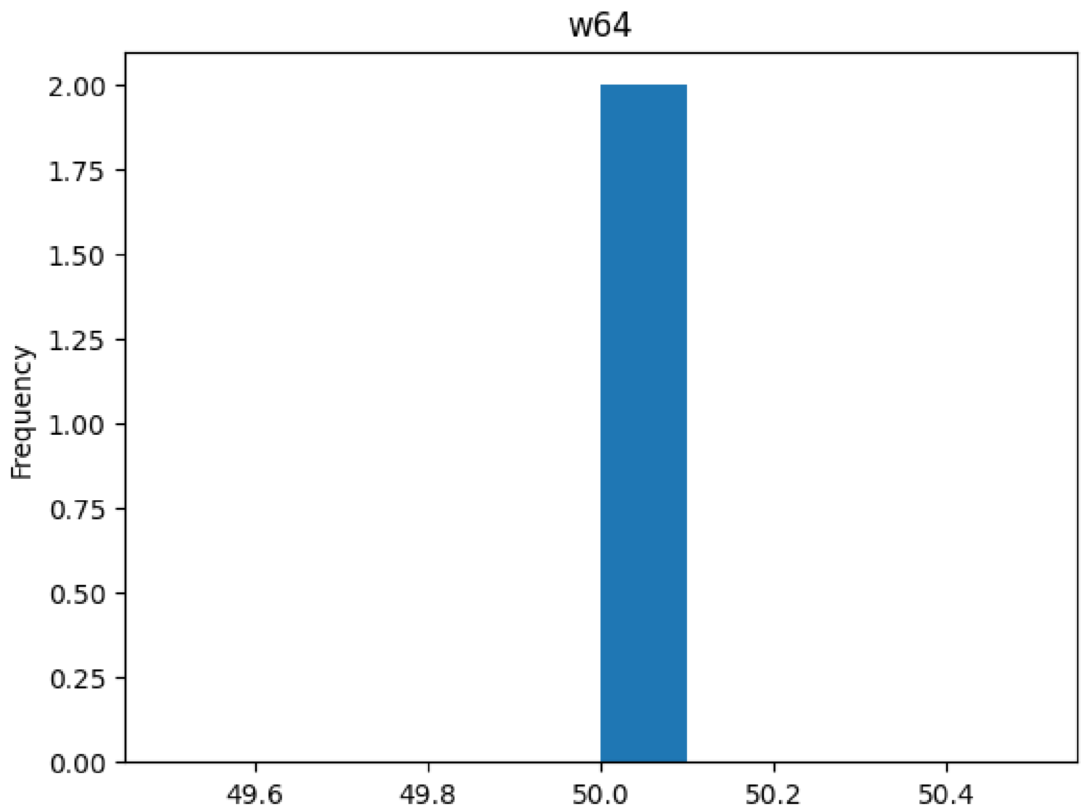

```
--- Column: w62 ---
count     2.000000
mean     44.500000
std       3.535534
min      42.000000
25%      43.250000
50%      44.500000
75%      45.750000
max      47.000000
Name: w62, dtype: float64
```



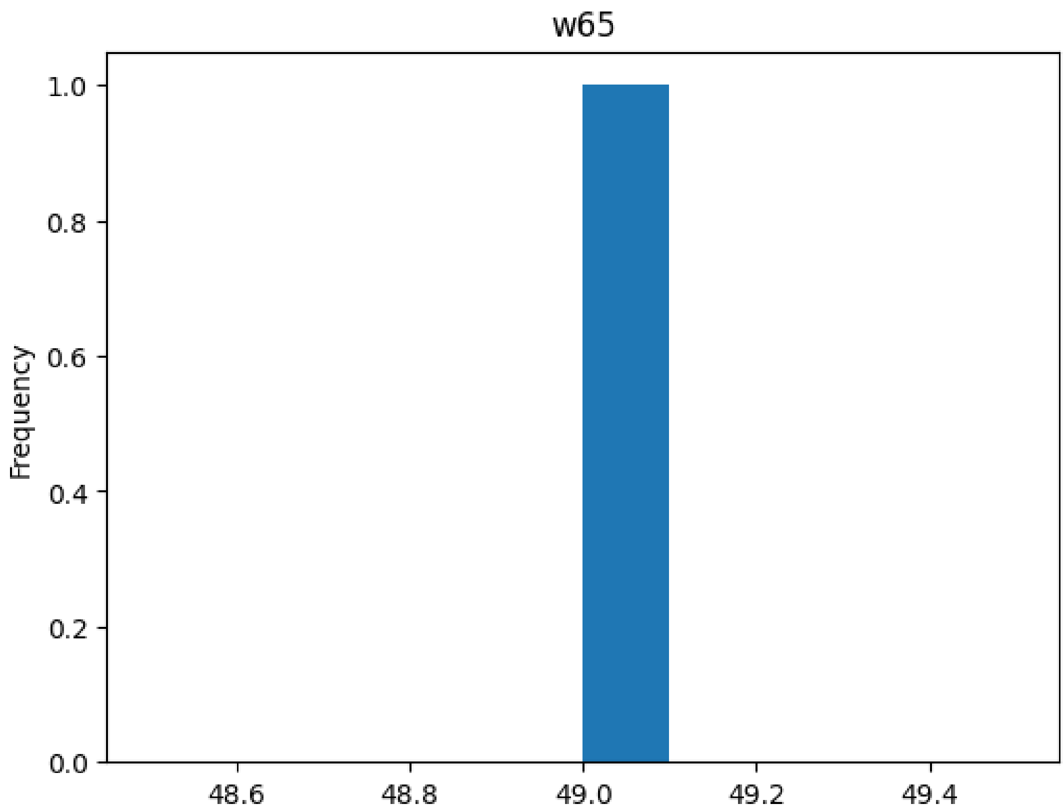

```
--- Column: w63 ---
count     2.000000
mean     47.500000
std       3.535534
min      45.000000
25%      46.250000
50%      47.500000
75%      48.750000
max      50.000000
Name: w63, dtype: float64
```




```
--- Column: w64 ---
count     2.0
mean     50.0
std       0.0
min      50.0
25%      50.0
50%      50.0
75%      50.0
max      50.0
Name: w64, dtype: float64
```




```
--- Column: w65 ---
count     1.0
mean     49.0
std       NaN
min      49.0
25%      49.0
50%      49.0
75%      49.0
max      49.0
Name: w65, dtype: float64
```



c) The dataset is in wide format, use an appropriate function to switch to a long fromat, and

[26]:
```
mlt_df = billboard_df.melt(
    id_vars=["artist", "track", "time",        "date_e"],
    value_vars=billboard_df.columns[billboard_df.columns.str.startswith('w')],
    var_name='W',
    value_name='Value'
)
mlt_df
```

[26]:
```
                     artist                                    track  time  \
0          Destiny's Child                 Independent Women Part I  3:38
1                  Santana                             Maria, Maria  4:18
2            Savage Garden                       I Knew I Loved You  4:07
3                  Madonna                                    Music  3:45
4       Aguilera, Christina  Come On Over Baby (All I Want Is You)  3:38
…                       …                                      …    …
20600      Ghostface Killah                       Cherchez LaGhost  3:04
20601           Smith, Will                            Freakin' It  3:58
20602         Zombie Nation                          Kernkraft 400  3:30
20603        Eastsidaz, The                               Got Beef  3:58
```

```
20604              Fragma                       Toca's Miracle  3:22

          date_e    W  Value
0       2000-09-23   w1   78.0
1       2000-02-12   w1   15.0
2       1999-10-23   w1   71.0
3       2000-08-12   w1   41.0
4       2000-08-05   w1   57.0
…              …   …     …
20600   2000-08-05  w65    NaN
20601   2000-02-12  w65    NaN
20602   2000-09-02  w65    NaN
20603   2000-07-01  w65    NaN
20604   2000-10-28  w65    NaN

[20605 rows x 6 columns]
```

d) Write a code that shows mlt_df's every 1200 rows.

[27]:
```
mlt_df[0:20605:1200]
```

[27]:
```
                 artist                               track  time      date_e  \
0        Destiny's Child             Independent Women Part I  3:38  2000-09-23
1200         Limp Bizkit                       N 2 Gether Now  3:55  1999-12-04
2400        Urban, Keith                      Your Everything  4:10  2000-07-15
3600           Mary Mary                Shackles (Praise You)  3:12  2000-03-25
4800                Pink                         There U Go  3:23  2000-03-04
6000      Levert, Gerald                         Baby U Are  4:10  2000-08-19
7200               Jay-Z         Do It Again (Put Ya Hands Up)  3:47  2000-01-15
8400       Tippin, Aaron                           Kiss This  2:53  2000-08-26
9600        Rimes, LeAnn                            Big Deal  3:03  1999-10-16
10800               98¡  Give Me Just One Night (Una Noche)  3:24  2000-08-19
12000     Estefan, Gloria                 No Me Dejes De Querer  3:25  2000-06-10
13200         Diffie, Joe                 It's Always Somethin'  2:55  2000-08-12
14400             Aaliyah                       I Don't Wanna  4:15  2000-01-29
15600    Barenaked Ladies                            Pinch Me  3:46  2000-09-09
16800              Fragma                      Toca's Miracle  3:22  2000-10-28
18000               Drama                   Left, Right, Left  3:37  2000-02-12
19200     Lopez, Jennifer                         Feelin' Good  4:28  2000-02-19
20400      Counting Crows                        Hanginaround  4:07  1999-11-06

         W  Value
0       w1   78.0
1200    w4   78.0
2400    w8   59.0
3600   w12   39.0
4800   w16   14.0
6000   w19    NaN
```

```
7200   w23    NaN
8400   w27    NaN
9600   w31    NaN
10800  w35    NaN
12000  w38    NaN
13200  w42    NaN
14400  w46    NaN
15600  w50    NaN
16800  w53    NaN
18000  w57    NaN
19200  w61    NaN
20400  w65    NaN
```

```
e)  Run the following code first and answer the question. Could you have done this by using Boo
```

[28]:
```
mlt_df.query('artist == "Spears, Britney"')
```

[28]:
```
                artist                               track  time      date_e  \
51     Spears, Britney              Oops!.. I Did It Again  3:30  2000-04-22
63     Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
93     Spears, Britney                               Lucky  3:23  2000-08-12
368    Spears, Britney              Oops!.. I Did It Again  3:30  2000-04-22
380    Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
…                  …                                 …   …         …
20034  Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
20064  Spears, Britney                               Lucky  3:23  2000-08-12
20339  Spears, Britney              Oops!.. I Did It Again  3:30  2000-04-22
20351  Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
20381  Spears, Britney                               Lucky  3:23  2000-08-12

         W  Value
51      w1   67.0
63      w1   76.0
93      w1   61.0
368     w2   38.0
380     w2   59.0
…      …     …
20034  w64    NaN
20064  w64    NaN
20339  w65    NaN
20351  w65    NaN
20381  w65    NaN

[195 rows x 6 columns]
```

Could have done this by using Boolean masking too?

Answer:

[30]:
```python
BM = mlt_df.artist == "Spears, Britney"
mlt_df[BM]
```

[30]:
```
                artist                              track  time      date_e  \
51     Spears, Britney            Oops!.. I Did It Again  3:30  2000-04-22
63     Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
93     Spears, Britney                              Lucky  3:23  2000-08-12
368    Spears, Britney            Oops!.. I Did It Again  3:30  2000-04-22
380    Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
…                  …                                  …   …         …
20034  Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
20064  Spears, Britney                              Lucky  3:23  2000-08-12
20339  Spears, Britney            Oops!.. I Did It Again  3:30  2000-04-22
20351  Spears, Britney  From The Bottom Of My Broken Heart  4:30  2000-01-29
20381  Spears, Britney                              Lucky  3:23  2000-08-12

         W  Value
51      w1   67.0
63      w1   76.0
93      w1   61.0
368     w2   38.0
380     w2   59.0
…     …    …
20034  w64    NaN
20064  w64    NaN
20339  w65    NaN
20351  w65    NaN
20381  w65    NaN

[195 rows x 6 columns]
```

f) Use either the approach in e or the Boolean mask, to extract all the unique songs that Br

[33]:
```python
mlt_df[BM].track.unique()
```

[33]:
```
array(['Oops!.. I Did It Again', 'From The Bottom Of My Broken Heart',
       'Lucky'], dtype=object)
```

g) In mlt_df show all of the weeks that the song "Oops!.. I Did It Again" was on the top-100

[44]:
```python
BM2 = mlt_df.track == "Oops!.. I Did It Again"
BM3 = mlt_df.Value <= 100
print(mlt_df[BM & BM2 & BM3])
mlt_df[BM & BM2 & BM3].W.unique()
```

```
              artist                   track  time      date_e   W  Value
51    Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w1   67.0
368   Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w2   38.0
685   Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w3   26.0
```

```
1002  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w4   19.0
1319  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w5   15.0
1636  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w6   13.0
1953  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w7   12.0
2270  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w8    9.0
2587  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22   w9    9.0
2904  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w10   10.0
3221  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w11   14.0
3538  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w12   15.0
3855  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w13   17.0
4172  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w14   24.0
4489  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w15   35.0
4806  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w16   49.0
5123  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w17   77.0
5440  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w18   85.0
5757  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w19   90.0
6074  Spears, Britney  Oops!.. I Did It Again  3:30  2000-04-22  w20   96.0
```

[44]:
```
array(['w1', 'w2', 'w3', 'w4', 'w5', 'w6', 'w7', 'w8', 'w9', 'w10', 'w11',
       'w12', 'w13', 'w14', 'w15', 'w16', 'w17', 'w18', 'w19', 'w20'],
      dtype=object)
```

Excercise 4 We will use LaqnData.csv for this exercise. Each row of this dataset shows an hourly measurement recording of one of the five following air pollutants: NO, NO2, NOX, PM10, and PM2.5. The data was collected in a location in Londan for the entirety of year 2017. Read the data using Pandas and perform the following tasks.

[48]:
```python
import pandas as pd
import matplotlib.pyplot as plt

air_df = pd.read_csv('LaqnData.csv')
air_df
```

[48]:
```
      Site Species   ReadingDateTime  Value   Units Provisional or Ratified
0      CT3      NO  01/01/2017 00:00    3.5  ug m-3                       R
1      CT3      NO  01/01/2017 01:00    3.6  ug m-3                       R
2      CT3      NO  01/01/2017 02:00    2.2  ug m-3                       R
3      CT3      NO  01/01/2017 03:00    2.1  ug m-3                       R
4      CT3      NO  01/01/2017 04:00    3.3  ug m-3                       R
…      …      …                …      …      …                     …
43795  CT3   PM2.5  31/12/2017 19:00   -2.0  ug m-3                       R
43796  CT3   PM2.5  31/12/2017 20:00    6.0  ug m-3                       R
43797  CT3   PM2.5  31/12/2017 21:00    5.0  ug m-3                       R
43798  CT3   PM2.5  31/12/2017 22:00    5.0  ug m-3                       R
43799  CT3   PM2.5  31/12/2017 23:00    6.0  ug m-3                       R

[43800 rows x 6 columns]
```

a) The dataset has 6 columns. Three of them, naming 'Site','Units','Provisional or Ratified' a

[49]:
```python
air_df.drop(columns=['Site','Units','Provisional or Ratified'], inplace=True)
air_df
```

[49]:
```
      Species   ReadingDateTime  Value
0          NO  01/01/2017 00:00    3.5
1          NO  01/01/2017 01:00    3.6
2          NO  01/01/2017 02:00    2.2
3          NO  01/01/2017 03:00    2.1
4          NO  01/01/2017 04:00    3.3
…         …               …      …
43795   PM2.5  31/12/2017 19:00   -2.0
43796   PM2.5  31/12/2017 20:00    6.0
43797   PM2.5  31/12/2017 21:00    5.0
43798   PM2.5  31/12/2017 22:00    5.0
43799   PM2.5  31/12/2017 23:00    6.0

[43800 rows x 3 columns]
```

b) The dataset is in a long format. Apply the appropriate function to switch it to the wide fo

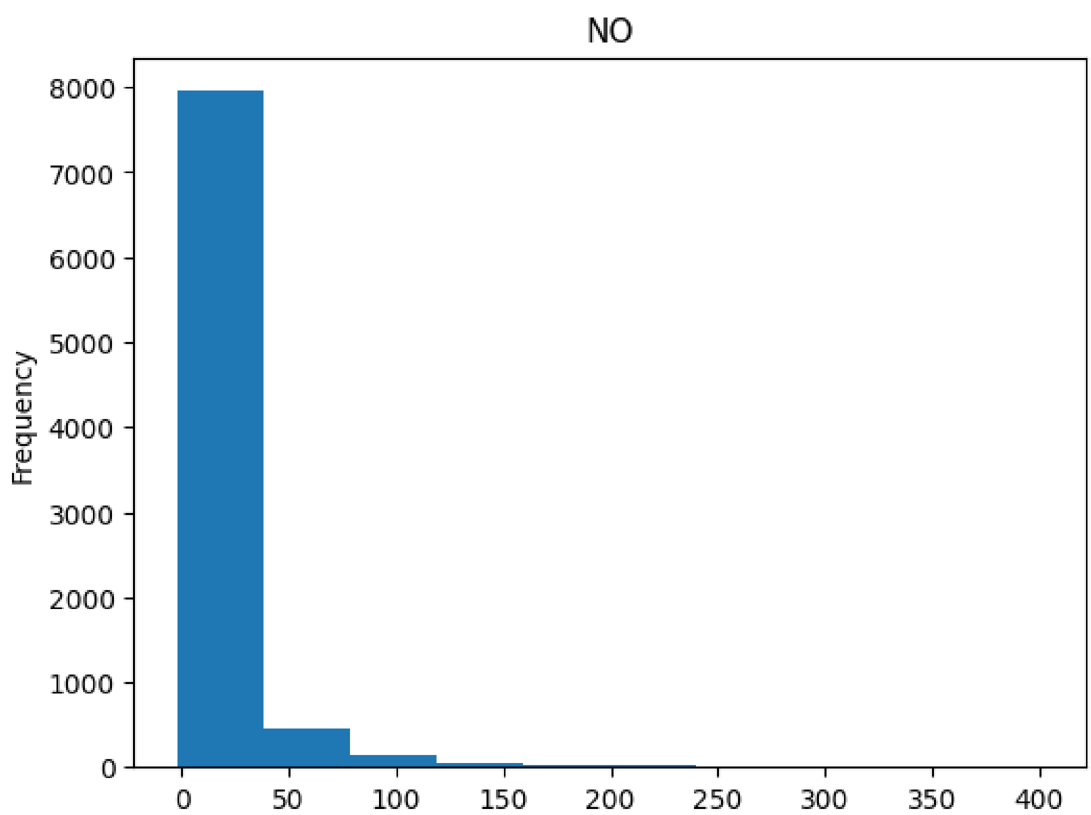
[51]:
```python
pvt_df = air_df.pivot(
    index="ReadingDateTime",
    columns="Species",
    values="Value"
)
pvt_df
```

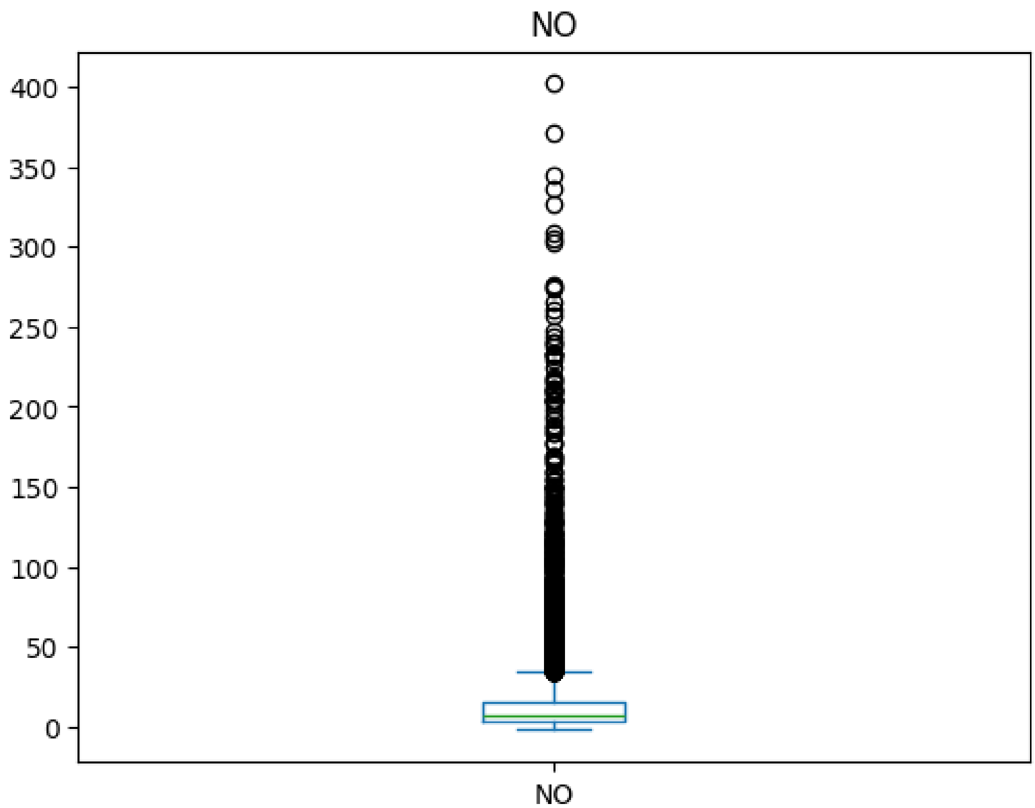
[51]:
```
Species            NO   NO2   NOX  PM10  PM2.5
ReadingDateTime
01/01/2017 00:00  3.5  30.8  36.2  35.7    NaN
01/01/2017 01:00  3.6  31.5  37.0  28.5    NaN
01/01/2017 02:00  2.2  27.3  30.7  22.7    NaN
01/01/2017 03:00  2.1  23.5  26.8  20.5    NaN
01/01/2017 04:00  3.3  28.0  33.0  22.1    NaN
…                 …    …     …     …      …
31/12/2017 19:00  0.7  17.5  18.5  16.3   -2.0
31/12/2017 20:00  0.7  17.5  18.6  14.5    6.0
31/12/2017 21:00  0.7  14.1  15.1   8.6    5.0
31/12/2017 22:00  1.1  22.0  23.6  12.5    5.0
31/12/2017 23:00  0.9  19.4  20.7  10.4    6.0

[8760 rows x 5 columns]
```

c) Draw and study the histogram and boxplots for columns of pvt_df.

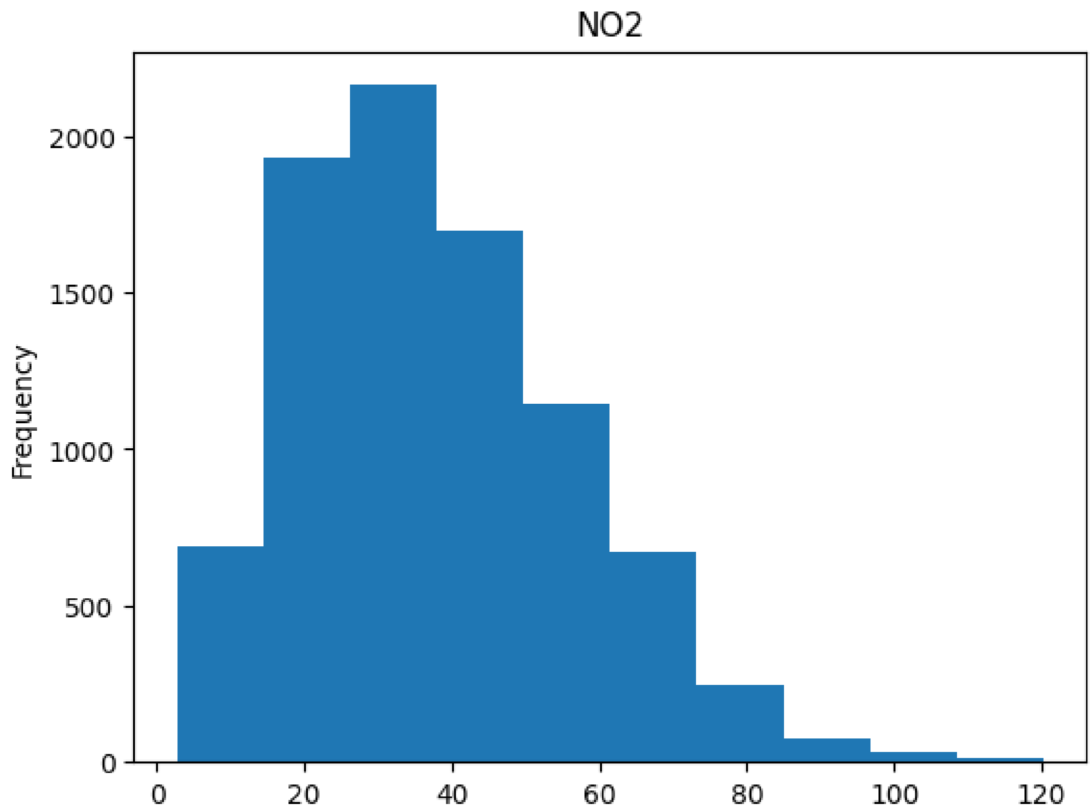
[55]:
```python
import matplotlib.pyplot as plt

for col in pvt_df:
    print(f"\n--- Column: {col} ---")
    print(pvt_df[col].describe())
    pvt_df[col].plot.hist(title=col)
    plt.show()
    pvt_df[col].plot.box(title=col)
    plt.show()
```

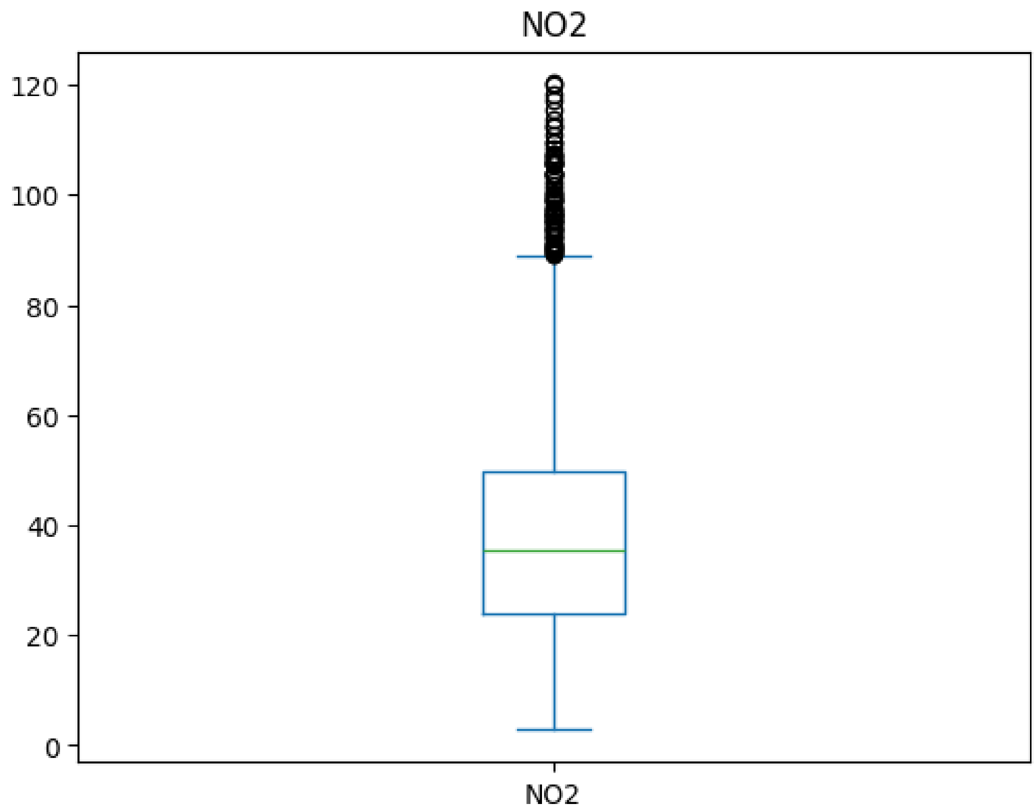
```
--- Column: NO ---
count    8660.000000
mean       15.045115
std        26.678565
min        -2.000000
25%         3.100000
50%         7.100000
75%        15.500000
max       401.799990
Name: NO, dtype: float64
```



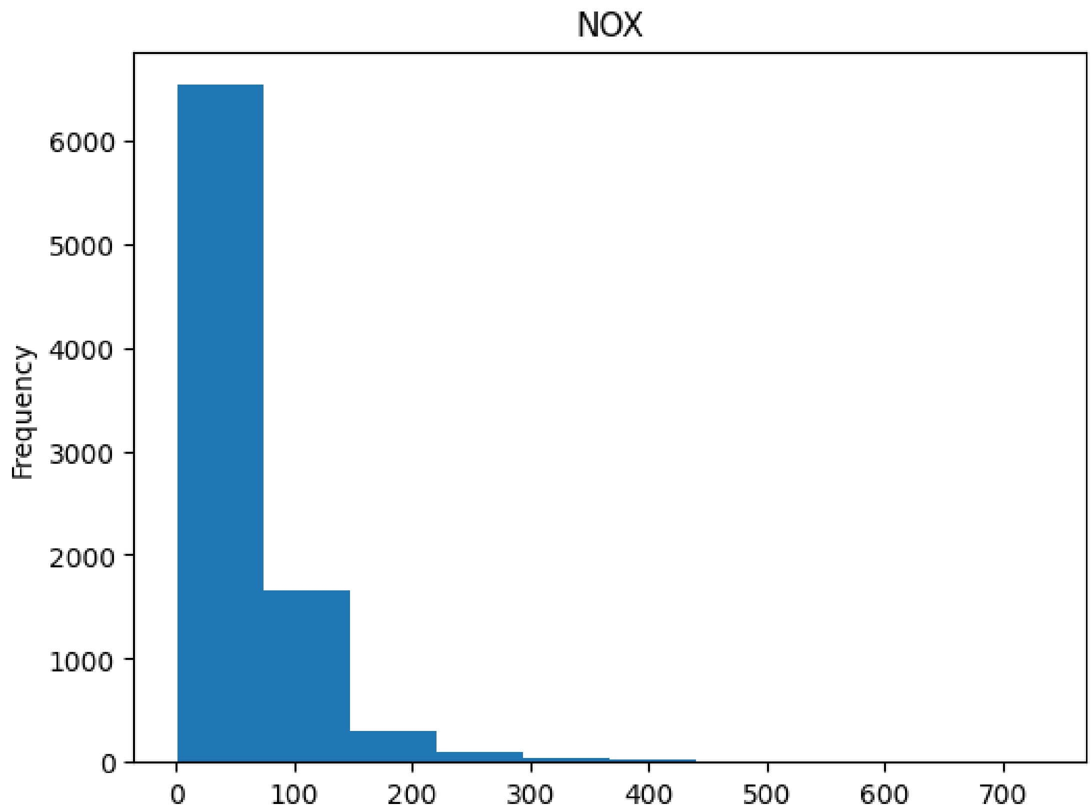


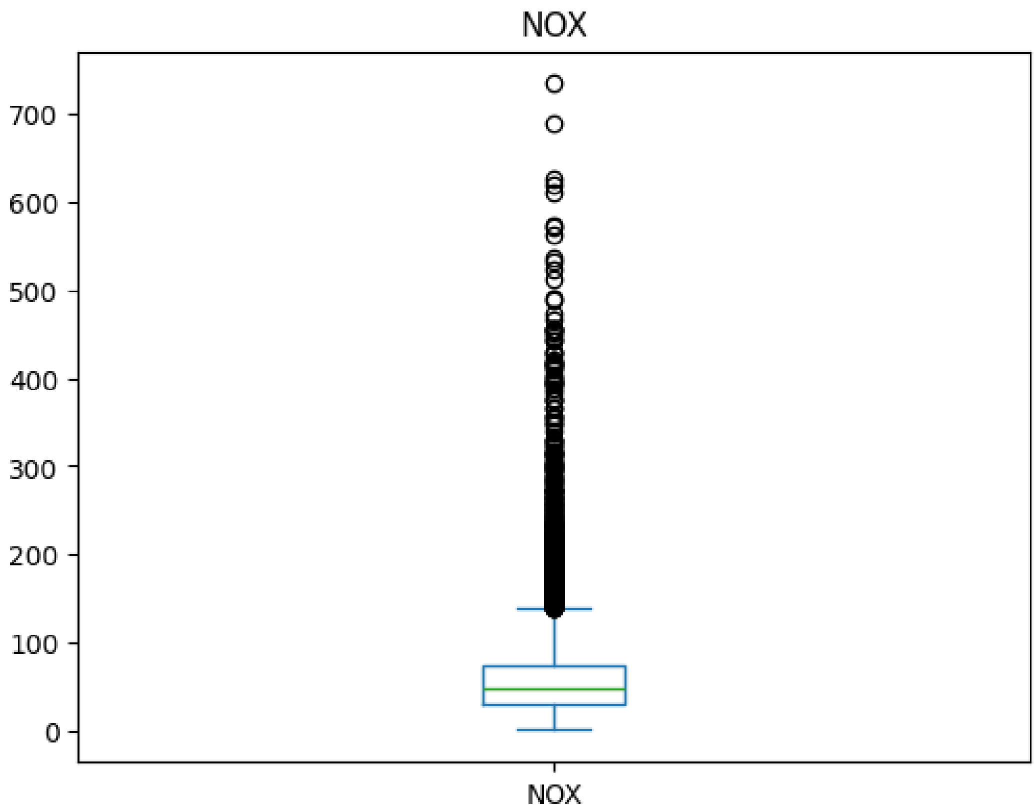

```
--- Column: NO2 ---
count    8660.000000
mean       38.010185
std        18.580841
min         2.800000
25%        23.800000
50%        35.300000
75%        49.900000
max       120.200000
Name: NO2, dtype: float64
```


NO2
Frequency
2000
1500
1000
500
0
0
20
40
60
80
100
120

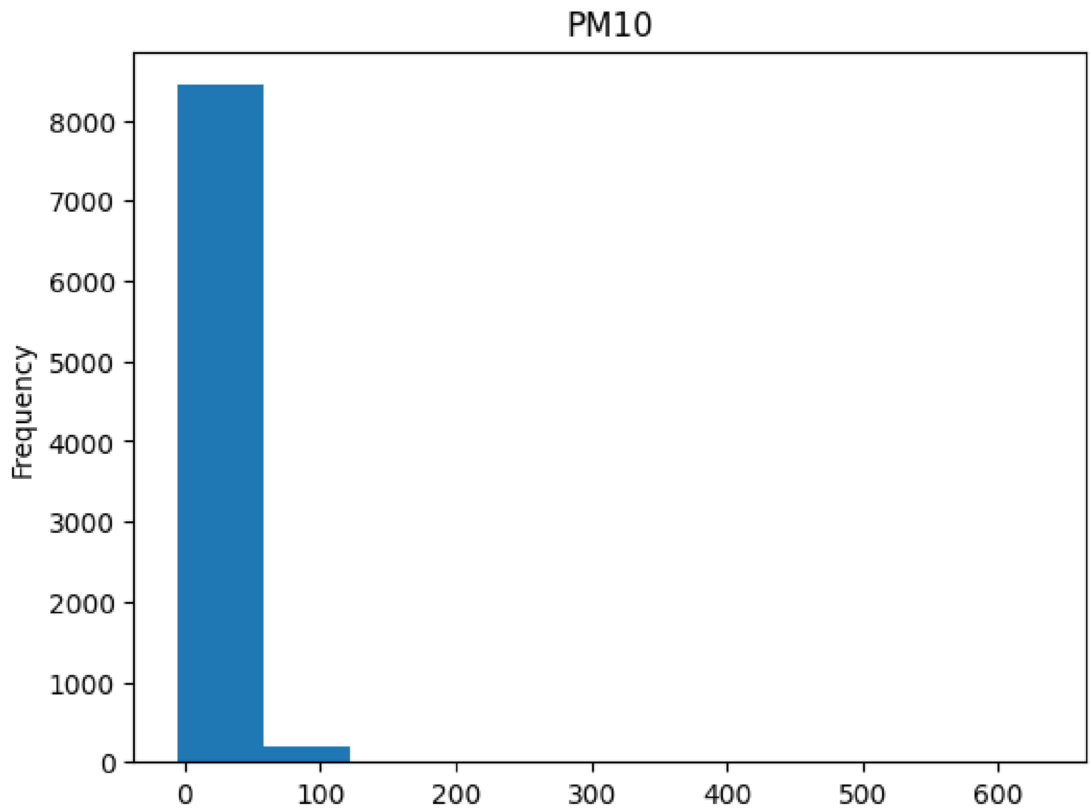


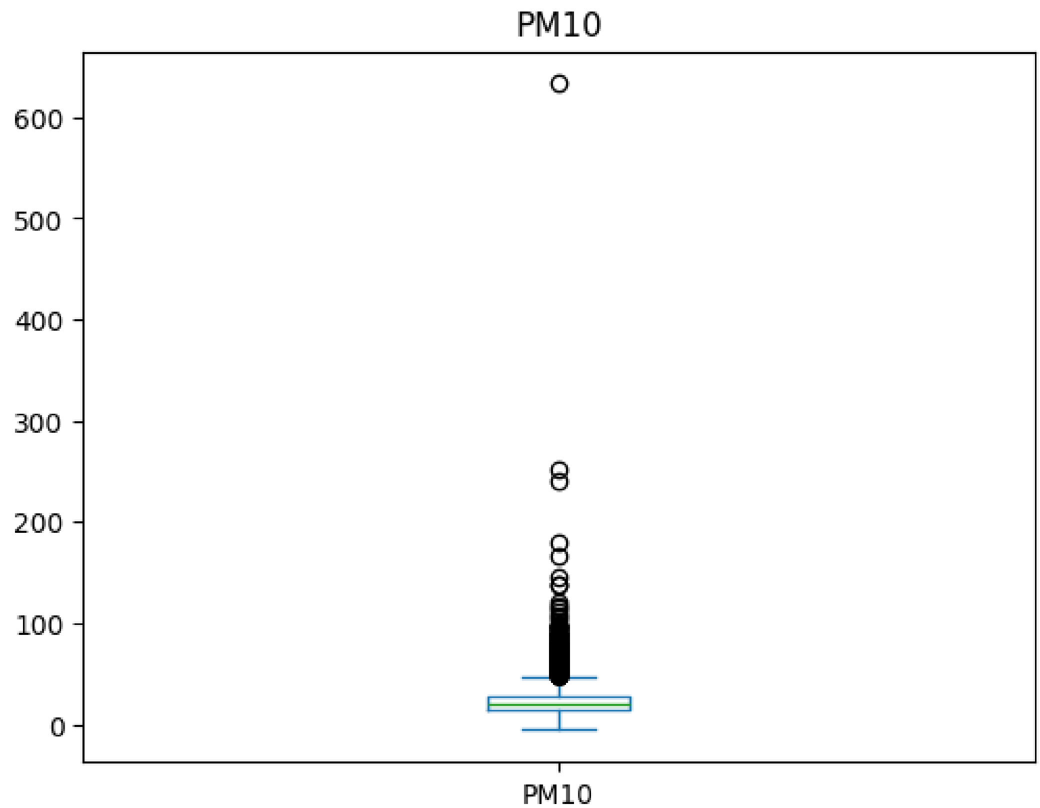

```
--- Column: NOX ---
count    8660.000000
mean       61.078661
std        54.584805
min         1.000000
25%        30.300000
50%        46.900000
75%        73.800000
max       734.299990
Name: NOX, dtype: float64
```


NOX
Frequency
6000
5000
4000
3000
2000
1000
0
0
100
200
300
400
500
600
700

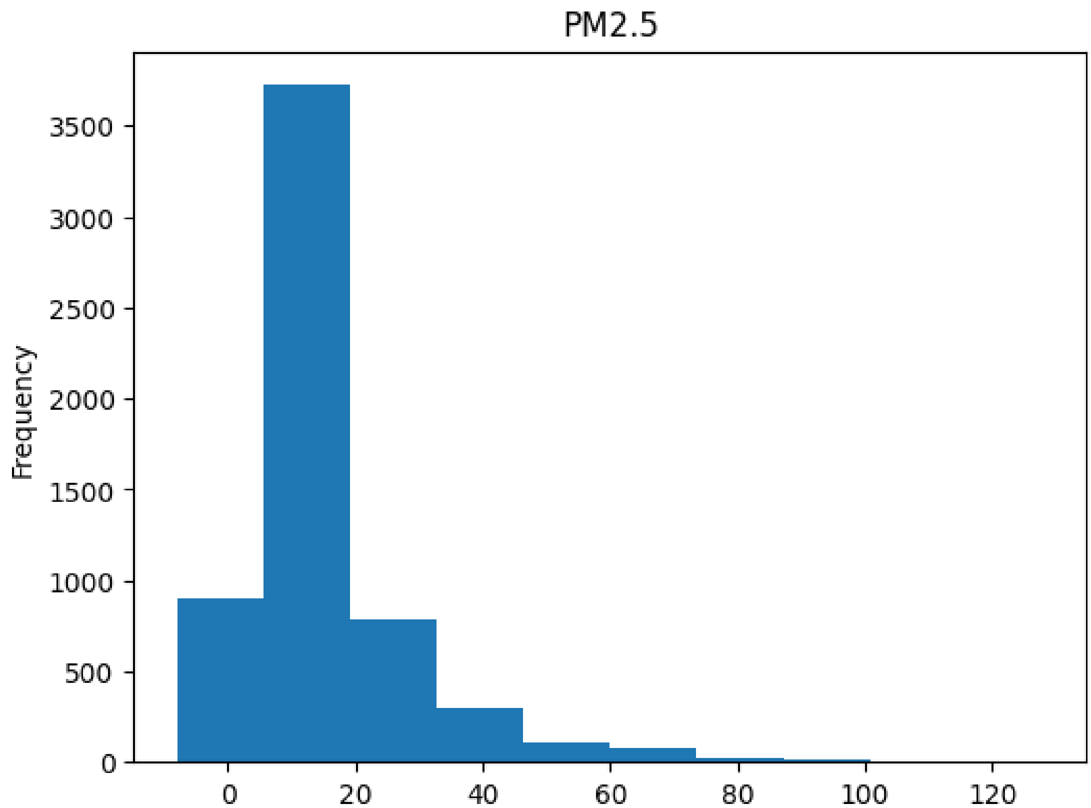


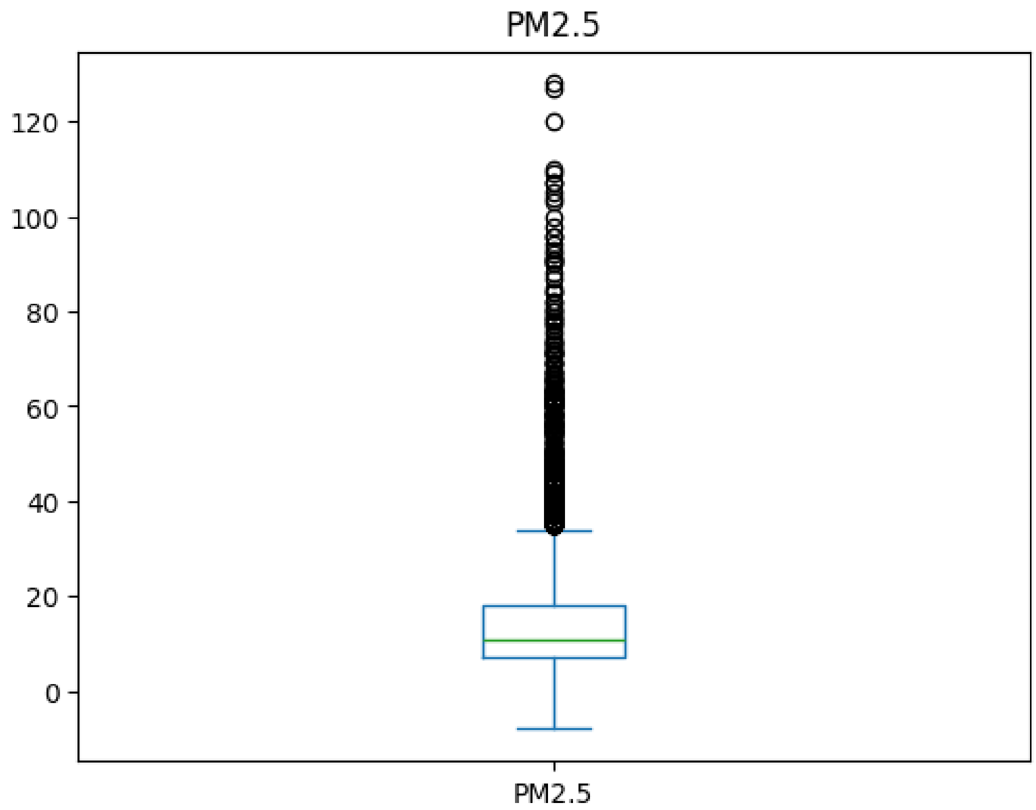

```
--- Column: PM10 ---
count    8657.000000
mean       22.551704
std        15.344755
min        -5.600000
25%        13.900000
50%        19.500000
75%        27.300000
max       633.099980
Name: PM10, dtype: float64
```


PM10
Frequency
0
1000
2000
3000
4000
5000
6000
7000
8000
0
100
200
300
400
500
600




```
--- Column: PM2.5 ---
count    5933.000000
mean       14.999831
std        13.558588
min        -8.000000
25%         7.000000
50%        11.000000
75%        18.000000
max       128.000000
Name: PM2.5, dtype: float64
```


PM2.5
Frequency
3500
3000
2500
2000
1500
1000
500
0
0
20
40
60
80
100
120



Excercise 5 We will continue working with LaqnData.csv.

a) Run the following code, see its output, and then study the code to answer what each line o

[56]:
```
import pandas as pd
air_df = pd.read_csv('LaqnData.csv')
air_df.drop(columns=['Site','Units','Provisional or Ratified'], inplace=True)
datetime_df = air_df.ReadingDateTime.str.split(' ',expand=True)
datetime_df.columns = ['Date','Time']
date_df = datetime_df.Date.str.split('/',expand=True)
date_df.columns = ['Day','Month','Year']
air_df = air_df.join(date_df).join(datetime_df.Time).
 ↪drop(columns=['ReadingDateTime','Year'])
air_df
```

[56]:

	Species	Value	Day	Month	Time
0	NO	3.5	01	01	00:00
1	NO	3.6	01	01	01:00
2	NO	2.2	01	01	02:00
3	NO	2.1	01	01	03:00
4	NO	3.3	01	01	04:00

```
…        …     …   ..    …     …
43795    PM2.5   -2.0   31     12   19:00
43796    PM2.5    6.0   31     12   20:00
43797    PM2.5    5.0   31     12   21:00
43798    PM2.5    5.0   31     12   22:00
43799    PM2.5    6.0   31     12   23:00

[43800 rows x 5 columns]
```

Answer:

- Imports the Pandas library and assigns it the alias pd for easier use.
- Reads the CSV file LaqnData.csv into a Pandas DataFrame called air_df.
- Drops unnecessary columns ('Site', 'Units', 'Provisional or Ratified') from air_df permanently (inplace=True).
- Takes the ReadingDateTime column (e.g., "01/01/2020 00:00") and splits it into two columns using space (' ') as the delimiter, expand=True ensures the split parts are returned as separate columns in a new DataFrame (datetime_df).
- Renames the columns of datetime_df to 'Date' and 'Time'.
- Takes the Date column (e.g., "01/01/2020") and splits it into three columns using / as the delimiter. The result is stored in a new DataFrame (date_df).
- Renames the columns of date_df to 'Day', 'Month', and 'Year'.
- Joins the new columns (Day, Month, Time) back to the original air_df. Drops the original ReadingDateTime and Year columns (since they are redundant after splitting).

b) Run the following code, see its output, and then study the code to answer what does this li

[57]:
```python
air_df = air_df.set_index(['Month','Day','Time','Species'])
air_df
```

[57]:
```
                          Value
Month Day Time  Species
01    01  00:00 NO          3.5
          01:00 NO          3.6
          02:00 NO          2.2
          03:00 NO          2.1
          04:00 NO          3.3
…                         …
12    31  19:00 PM2.5      -2.0
          20:00 PM2.5       6.0
          21:00 PM2.5       5.0
          22:00 PM2.5       5.0
          23:00 PM2.5       6.0

[43800 rows x 1 columns]
```

Answer:

Converts air_df into a MultiIndex DataFrame by setting the columns ['Month','Day','Time','Species'] as the new index levels.

c) Run the following code, see its output, and then study the code to answer what does this li

[58]:
```
air_df.unstack()
```

[58]:
```
                  Value
Species              NO   NO2   NOX  PM10 PM2.5
Month Day Time
01    01  00:00     3.5  30.8  36.2  35.7   NaN
          01:00     3.6  31.5  37.0  28.5   NaN
          02:00     2.2  27.3  30.7  22.7   NaN
          03:00     2.1  23.5  26.8  20.5   NaN
          04:00     3.3  28.0  33.0  22.1   NaN
…                 …   …    …    …    …
12    31  19:00     0.7  17.5  18.5  16.3  -2.0
          20:00     0.7  17.5  18.6  14.5   6.0
          21:00     0.7  14.1  15.1   8.6   5.0
          22:00     1.1  22.0  23.6  12.5   5.0
          23:00     0.9  19.4  20.7  10.4   6.0

[8760 rows x 5 columns]
```

Answer:

Reshapes a MultiIndex DataFrame by "pivoting" one or more levels of the row index into columns, creating a wide-format table.

d) Compare the output of the code above with pvt_df from Exercise 4. Are they basically the sa
e) Explain what are the differences and similarities between the pair .melt()/.pivot() and the
f) If you were to choose one counterpart for .melt() between .stack()/.unstack() which one wou

Answer:

d) Yes
e) .melt()/.pivot() is to reshape between wide and long formats. .stack()/.unstack() is to reshape between hierarchical indexes and columns. .melt()/.pivot() input dataframes with regular columns. .stack()/.unstack() input dataframes with multiindex rows/columns.
f) Choose .stack() as the counterpart to .melt().