wine-reviews (winemag-data_first150k)

1. Data Visualization and Data Summary

1.1 data summary

In [1]:
```
import pandas as pd  # data processing, csv file I/O
import numpy as np
import matplotlib.pyplot as plt

# load csv file
data = pd.read_csv('../wine-reviews/winemag-data_first150k.csv')
```

Descriptors of the raw datase

In [2]:
```
data.info()
data_shape = data.shape
print(data_shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150925 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        137235 non-null  float64
 6   province     150925 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
(150930, 11)
```

Find indexes of nominal and numerical data

remove the redundent column of row number

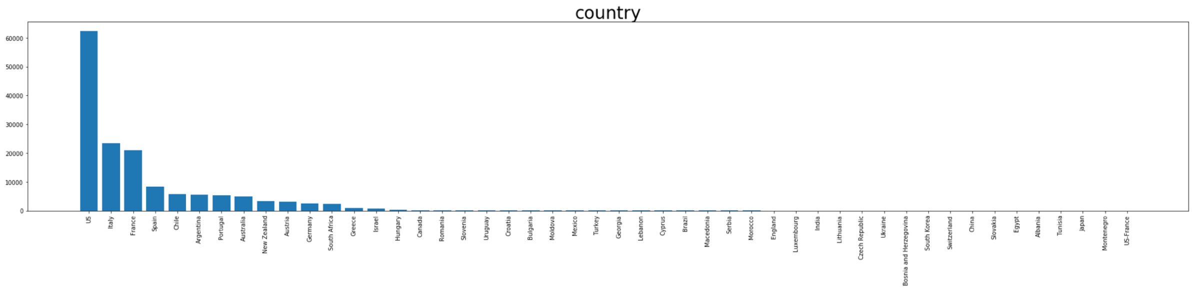
In [2]:
```
# Nominal index
nominal_index = ['country', 'designation', 'province', 'region_1',
'region_2', 'variety', 'winery']
# Numerical index
numerical_index = ['points', 'price']

# Get frequency of each arrtibute
data_frequency = {key: data[key].value_counts() for key in data.col
umns}
```

Nominal data summary

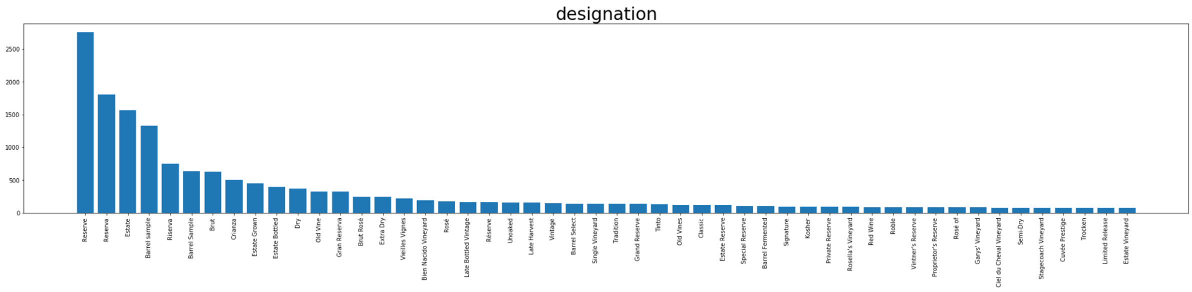
- Show top 5 frequency values
- Bar chart visualization of nominal data frequency (Top 50)

In [4]:
```
def bar_chart(nominal_data):
    x = nominal_data.index
    y = nominal_data.values

    print('Top 5 frequency of %s:'%nominal_data.name)
    top5_x = x[:5]
    top5_y = y[:5]
    top5_sum = np.sum(top5_y)
    s = ''
    for i in range(len(top5_x)):
        s += str(top5_x[i]) + ' ({:.2%})'.format(top5_y[i] / top5_s
um) + ' | '
    print(s)

    plt.figure(figsize=(36,6))
    plt.title(nominal_data.name, fontsize=30)
    plt.bar(x[:50], y[:50])
    plt.xticks(rotation=90)
    plt.show()

# bar chart for each nominal attribute
for i in nominal_index:
    bar_chart(data_frequency[i])
```

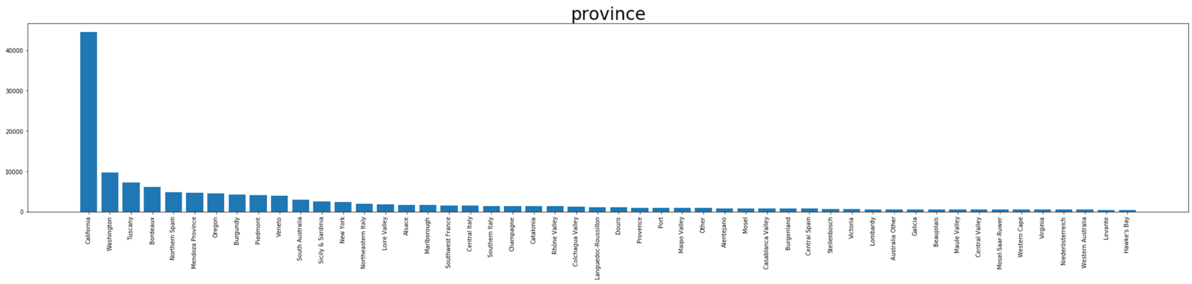
```
Top 5 frequency of country:
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
```



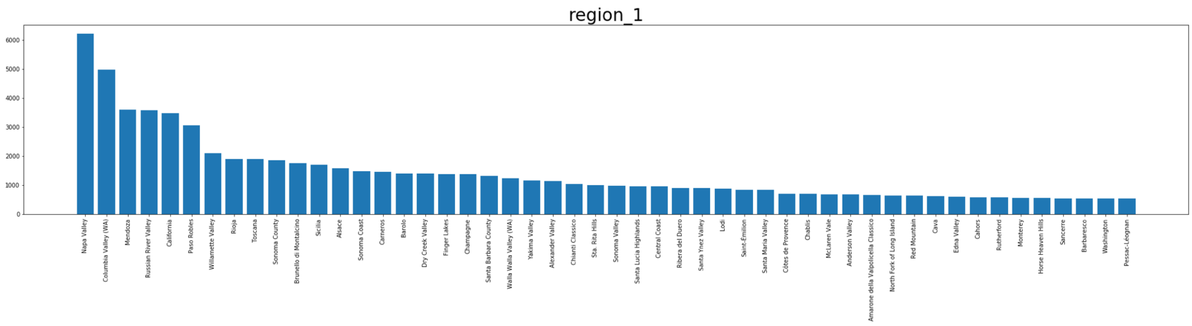

```
Top 5 frequency of designation:
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
```



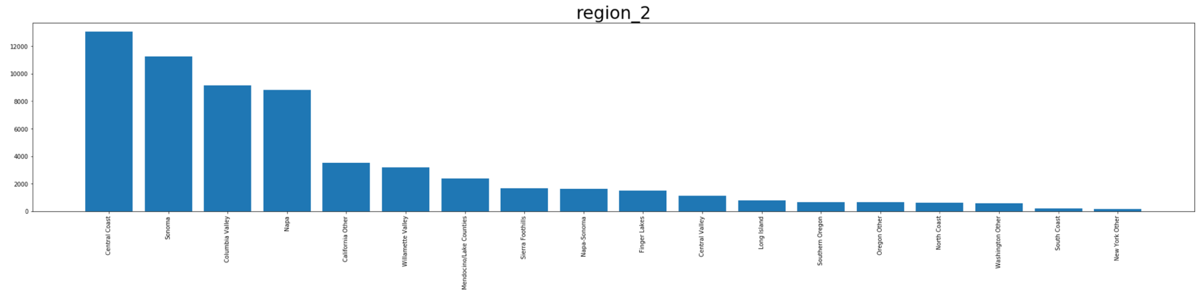

```
Top 5 frequency of province:
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
```



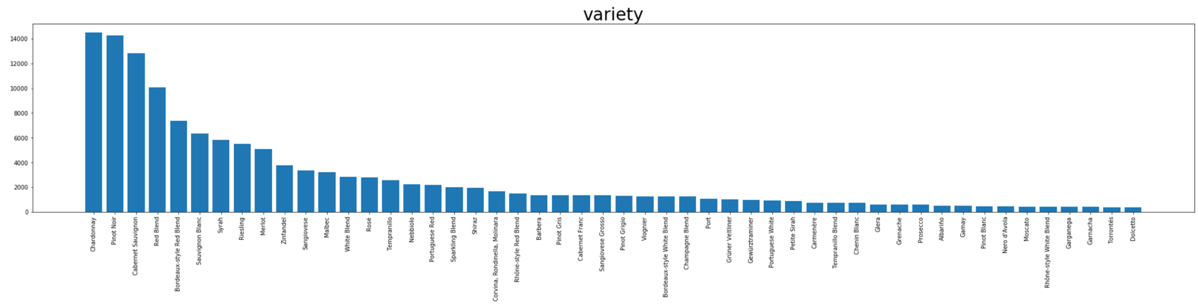

```
Top 5 frequency of region_1:
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
```



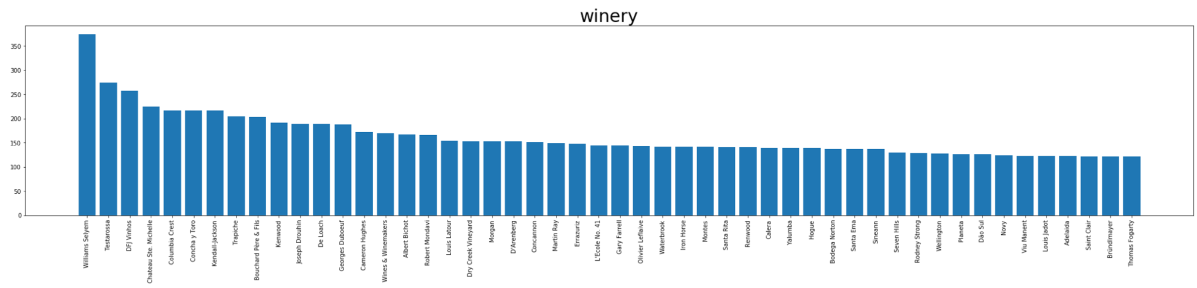

```
Top 5 frequency of region_2:
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
```




```
Top 5 frequency of variety:
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
```




```
Top 5 frequency of winery:
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
```



Numerical data summary

- Five-number summary:
  - Min
  - Q1(25%)
  - Q2(50%)
  - Q3(75%)
  - Max

In [5]:
```
def data_describe(data):
    """
    Generate descriptive statistics.

    Descriptive statistics include those that summarize the central
tendency, dispersion and shape of a dataset’s distribution, excludi
ng NaN values.
    """
    print('descriptive statistics (%s):' % data.name)
    info = data.describe()
    print('Min: ', info['min'], '\tQ1 (25%): ', info['25%'], '\tQ2
(50%): ', info['50%'], '\tQ3 (75%): ', info['75%'], '\tMax:', info[
'max'])
    print('Missing: %d'%(data_shape[0] - info['count']))
    print('-'*100)

# five-number summary for each attribute
for i in numerical_index:
    data_describe(data[i])
```

```
descriptive statistics (points):
Min:  80.0      Q1 (25%):  86.0        Q2 (50%):  88.0          Q3
(75%):  90.0    Max: 100.0
Missing: 0
-------------------------------------------------------------------
----------------------------------
descriptive statistics (price):
Min:  4.0       Q1 (25%):  16.0        Q2 (50%):  24.0          Q3
(75%):  40.0    Max: 2300.0
Missing: 13695
-------------------------------------------------------------------
----------------------------------
```

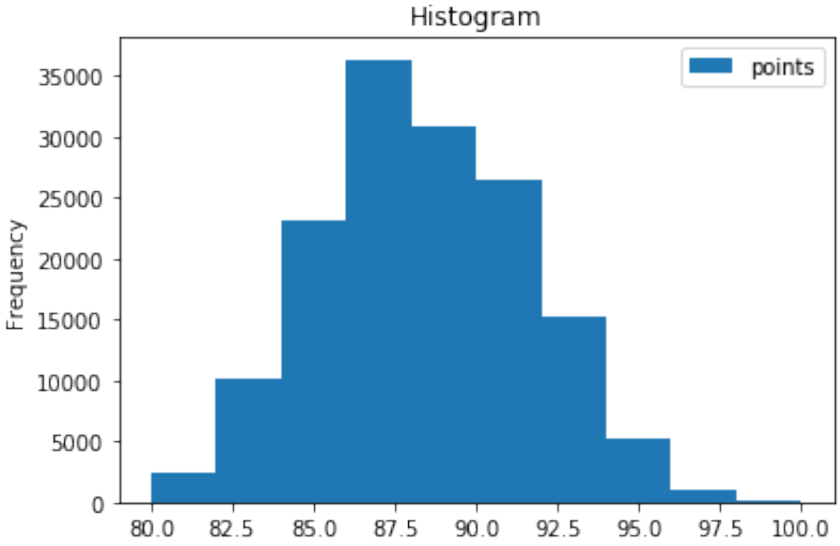
1.2 Data Visualization

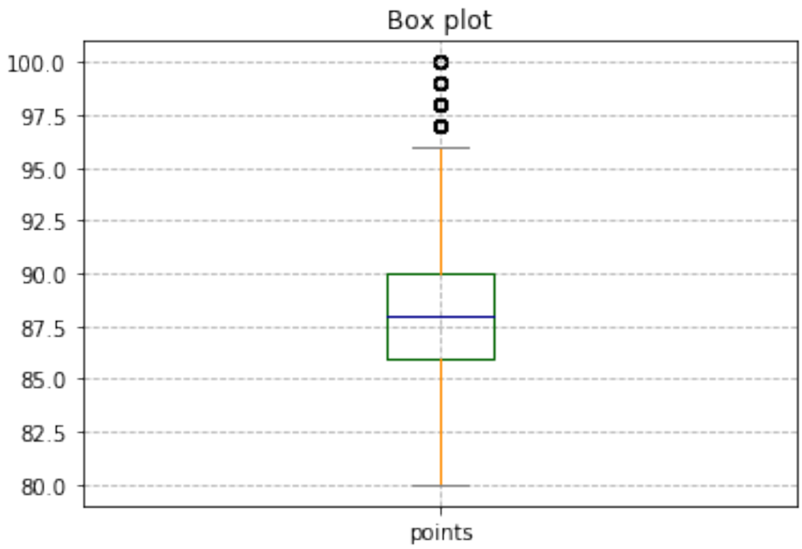
Numerical data visualization

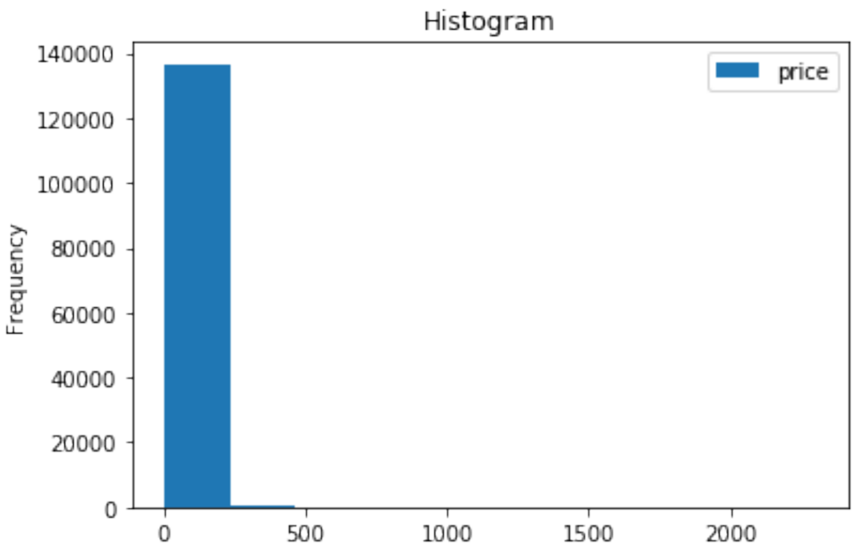
- histogram
- box plot
- scatter matrix

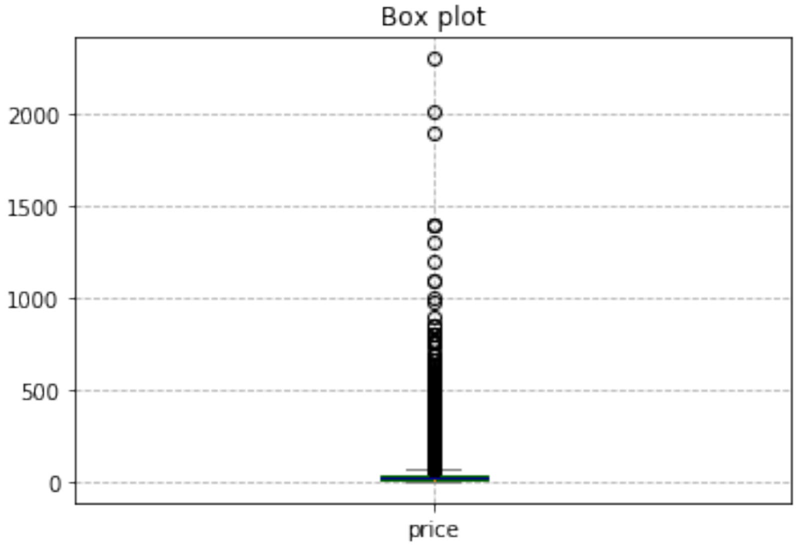
In [6]:
```
# histogram
def histogram(data):
    df = pd.DataFrame(data)
    df.plot.hist()
    plt.title('Histogram')
    plt.show()

# box plot
```

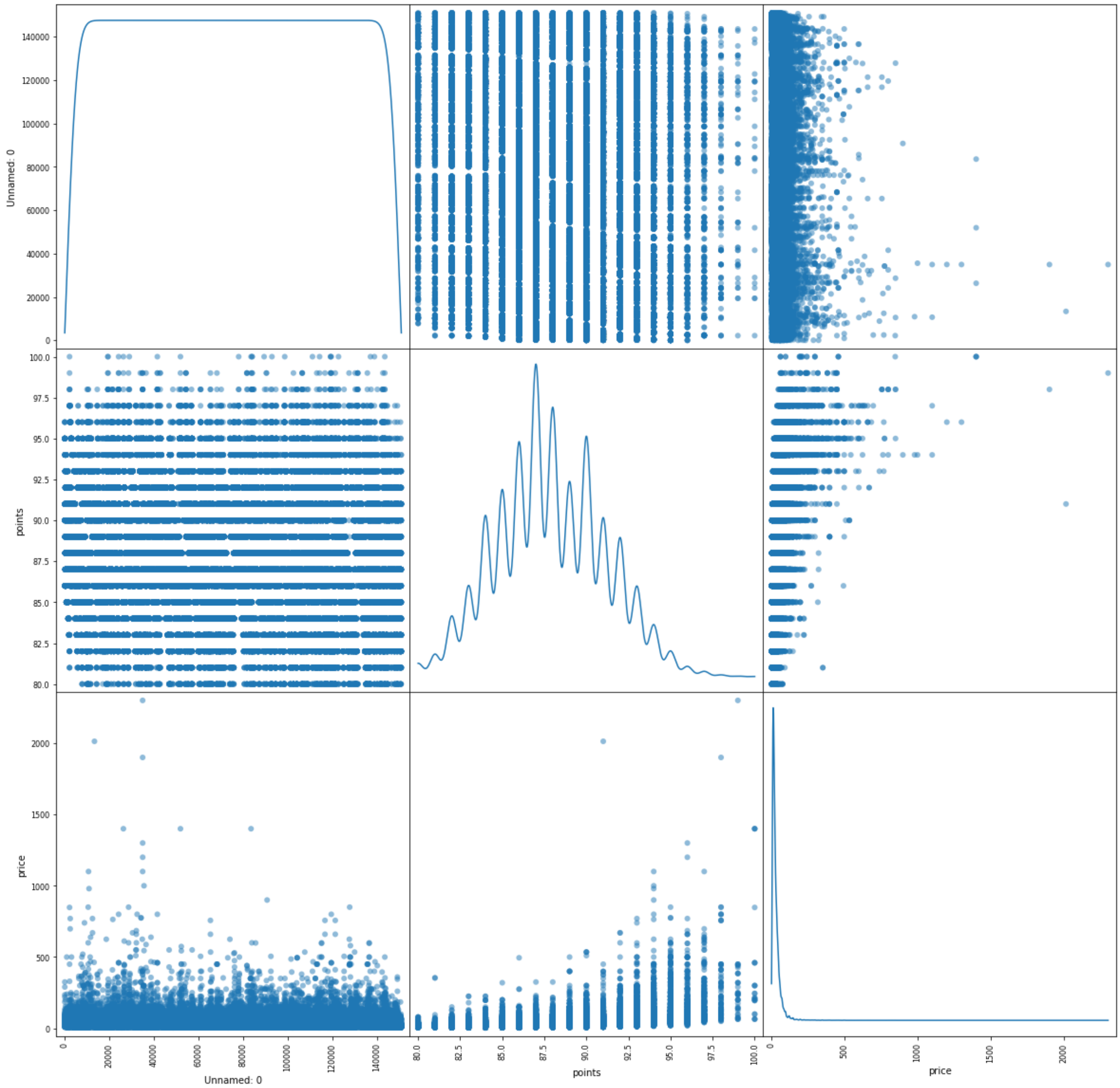
```
def box_plot(data):
    # boxes 箱线
    # whiskers 分为数于error bar横线之间的竖线的颜色
    # medians 中位线的颜色
    # caps error bar 横线的颜色
    color = dict(boxes  = 'DarkGreen',whiskers = 'DarkOrange',media
ns = 'DarkBlue',caps ='Gray')
    data.plot.box(grid=True, color=color)   # color 样式填充
    plt.grid(linestyle='--')
    plt.title('Box plot')
    plt.show()

def box_plot1(data):
    df = pd.DataFrame(data)
    df.boxplot(sym = 'o',    #异常点形状
                   vert = True,           # 是否垂直
                   whis=1.5,              # IQR
                   patch_artist = True,   # 上下四分位框是否填充
                   meanline = False,showmeans = True,   # 是否有均值线
及其形状
                   showbox = True,    # 是否显示箱线
                   showfliers = True,  #是否显示异常值
                   notch = False,     # 中间箱体是否缺口
                   return_type='dict')  # 返回类型为字典
    plt.grid(linestyle='--')
    plt.title('Box plot')
    plt.show()

# scatter plot
def scatter_plot(data1, index1, index2):
    data.plot.scatter(x=index1,
                   y=index2,
                   c='DarkBlue')
    plt.title('Scatter plot')
    plt.show()

for i in numerical_index:
    histogram(data[i])
    box_plot(data[i])

# scatter matrix
# The diagonal of the matrix is the KDE(Kernel Density Estimation)
of each feature, and the color is the variety of wine
pd.plotting.scatter_matrix(data, marker='o', figsize=(20, 20), diag
onal='kde')
plt.show()
```


Histogram
points
Frequency
35000
30000
25000
20000
15000
10000
5000
0
80.0
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0


Box plot
100.0
97.5
95.0
92.5
90.0
87.5
85.0
82.5
80.0
points


Histogram
price
Frequency
140000
120000
100000
80000
60000
40000
20000
0
0
500
1000
1500
2000


Box plot
2000
1500
1000
500
0
price


Unnamed: 0
points
price

2. Processing of missing data

2.1 Remove missing values

In [6]:
```
# Remove missing values
data_remove = data.dropna()
data_remove.info()

# Get frequency of each arrtibute (after remove missing values)
data_remove_frequency = {key: data_remove[key].value_counts() for k
ey in data_remove.columns}
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39241 entries, 0 to 150916
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Unnamed: 0   39241 non-null  int64
 1   country      39241 non-null  object
 2   description  39241 non-null  object
 3   designation  39241 non-null  object
 4   points       39241 non-null  int64
 5   price        39241 non-null  float64
 6   province     39241 non-null  object
 7   region_1     39241 non-null  object
 8   region_2     39241 non-null  object
 9   variety      39241 non-null  object
 10  winery       39241 non-null  object
dtypes: float64(1), int64(2), object(8)
memory usage: 3.6+ MB
```

compare with raw data

- compare top 5 frequency of nominal_data
- Compared Histogram
- Compared box plot
- Compared scatter plot

In [3]:
```
def compare_top5_frequency(nominal_data, nominal_data1):
    x = nominal_data.index
    y = nominal_data.values

    print('Top 5 frequency of %s (raw data):' % nominal_data.name)
    top5_x = x[:5]
    top5_y = y[:5]
    top5_sum = np.sum(top5_y)
    s = ''
    for i in range(len(top5_x)):
        s += str(top5_x[i]) + ' ({:.2%})'.format(top5_y[i] / top5_sum) + ' | '
    print(s)

    x = nominal_data1.index
    y = nominal_data1.values
    print('\033[95mTop 5 frequency of %s (after remove missing values):' % nominal_data1.name + '\033[0m')
    top5_x = x[:5]
    top5_y = y[:5]
    top5_sum = np.sum(top5_y)
    s = ''
    for i in range(len(top5_x)):
        s += str(top5_x[i]) + ' ({:.2%})'.format(top5_y[i] / top5_sum) + ' | '
    print('\033[95m' + s + '\033[0m')
    print('-'*100)
```

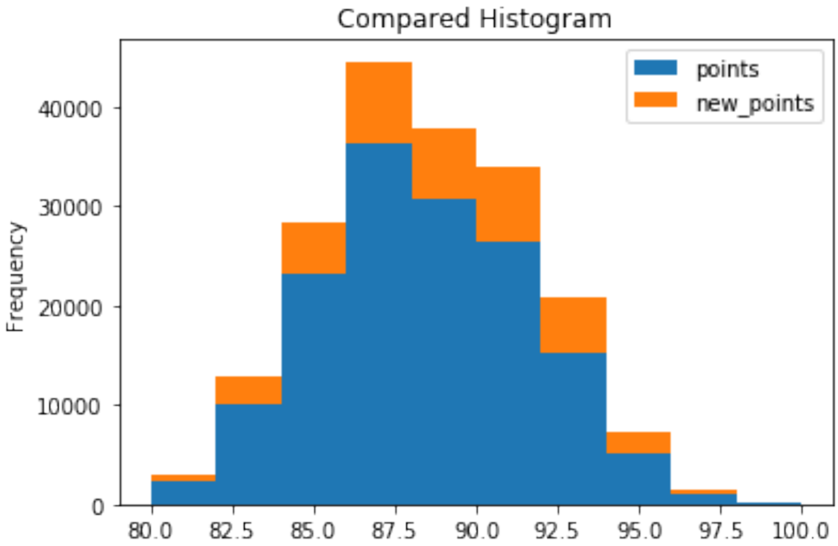
In [4]:
```
# Compared Histogram
def histogram_compare(raw_data, new_data):
    new_name = ['new_' + new_data.name]
    raw_data = pd.DataFrame(raw_data)
    new_data = pd.DataFrame(new_data)
    new_data.columns=new_name
    df = raw_data.append(new_data)
    df.plot.hist(stacked=True)
    plt.title('Compared Histogram')
    plt.show()

# Compared Box plot
def box_plot_compare(raw_data, new_data):
    # boxes 箱线
    # whiskers 分为数于error bar横线之间的竖线的颜色
    # medians 中位线的颜色
    # caps error bar 横线的颜色
    new_name = ['new_' + new_data.name]
    raw_data = pd.DataFrame(raw_data)
    new_data = pd.DataFrame(new_data)
    new_data.columns=new_name
    df = raw_data.append(new_data)
    color = dict(boxes  = 'DarkGreen',whiskers = 'DarkOrange',media
ns = 'DarkBlue',caps ='Gray')
    df.plot.box(grid=True, color=color)   # color 样式填充
    plt.grid(linestyle='--')
    plt.title('Compared Box plot')
    plt.show()

# Compared Scatter plot
def scatter_plot_compare(data1, data2, index1, index2):
    ax = data.plot.scatter(x=index1, y=index2, c='DarkBlue', label=
'Raw data')
    data_remove.plot.scatter(x=index1, y=index2, c='r', label='New
data', ax=ax)
    plt.title('Compared Scatter plot')
    plt.show()
```

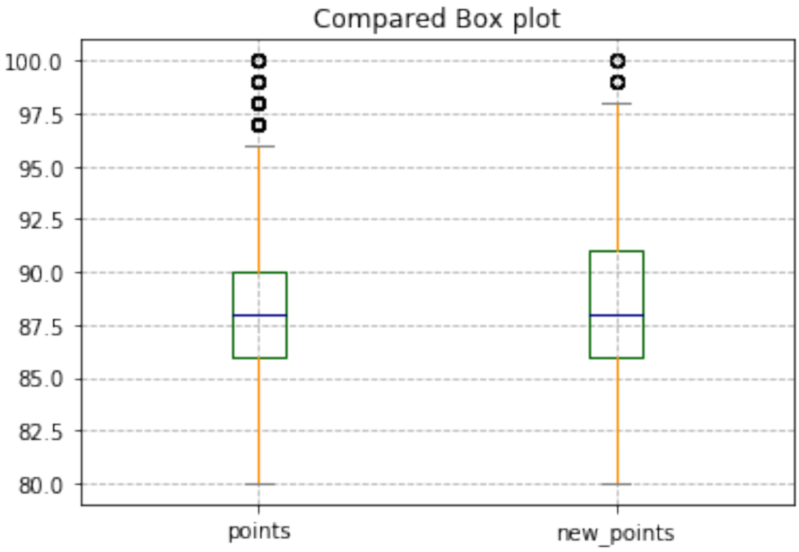
In [7]:
```
# compare top 5 frequency of nominal_data
for i in nominal_index:
    compare_top5_frequency(data_frequency[i], data_remove_frequency
[i])
```

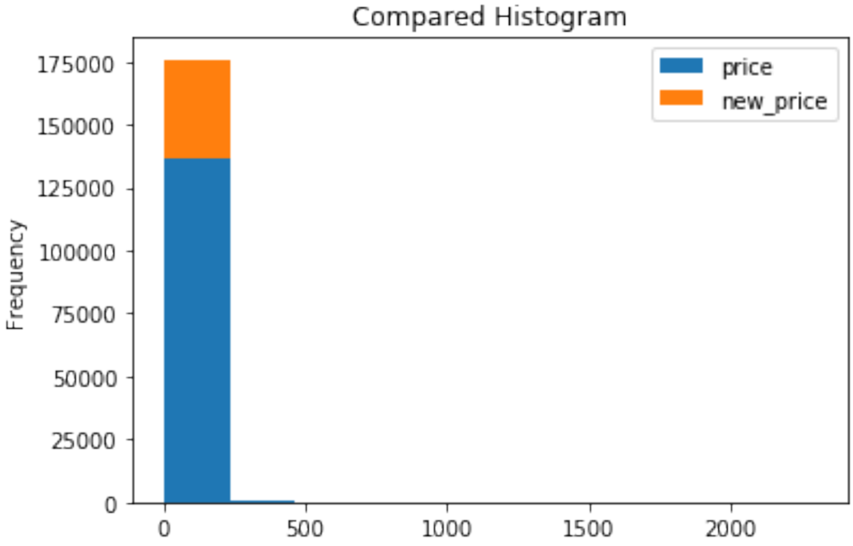
```
Top 5 frequency of country (raw data):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
Top 5 frequency of country (after remove missing values):
US (100.00%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of designation (raw data):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
```

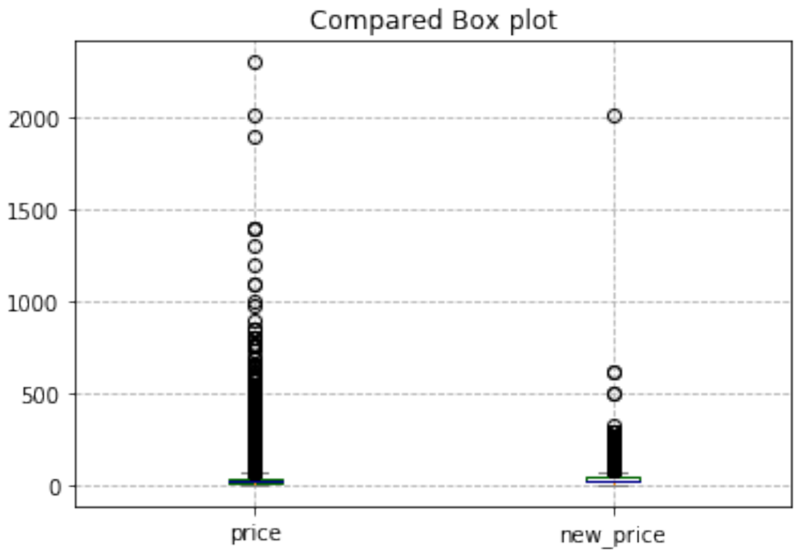
```
ple (16.15%) | Riserva (9.18%) |
Top 5 frequency of designation (after remove missing values):
Reserve (44.77%) | Estate (33.28%) | Estate Grown (9.59%) | Old Vi
ne (6.20%) | Dry (6.15%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of province (raw data):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
Top 5 frequency of province (after remove missing values):
California (72.77%) | Washington (15.60%) | Oregon (7.74%) | New Y
ork (3.89%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_1 (raw data):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
Top 5 frequency of region_1 (after remove missing values):
Napa Valley (27.62%) | Columbia Valley (WA) (22.69%) | Russian Riv
er Valley (20.70%) | Paso Robles (16.49%) | California (12.49%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_2 (raw data):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
Top 5 frequency of region_2 (after remove missing values):
Central Coast (30.28%) | Sonoma (25.77%) | Columbia Valley (19.15%
) | Napa (16.91%) | Willamette Valley (7.89%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of variety (raw data):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
Top 5 frequency of variety (after remove missing values):
Pinot Noir (32.40%) | Chardonnay (21.30%) | Cabernet Sauvignon (21
.28%) | Red Blend (12.77%) | Zinfandel (12.25%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of winery (raw data):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
Top 5 frequency of winery (after remove missing values):
Williams Selyem (26.26%) | Testarossa (22.96%) | Kendall-Jackson (
18.61%) | Columbia Crest (18.43%) | Chateau Ste. Michelle (13.74%)
|
-------------------------------------------------------------------
----------------------------------
```

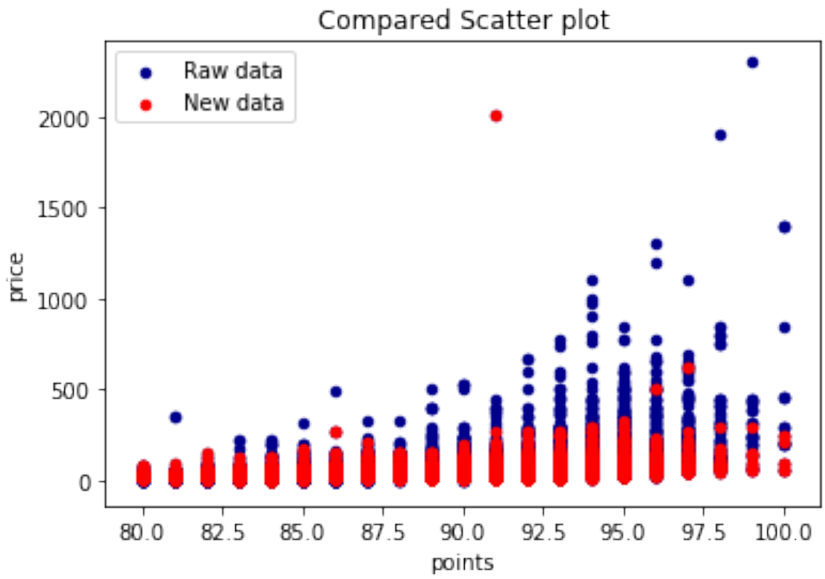
In [8]:
```
for i in numerical_index:
    histogram_compare(data[i], data_remove[i])
    box_plot_compare(data[i], data_remove[i])

# Compare between raw and new data using 'points' & 'price' scatter plot
scatter_plot_compare(data, data_remove, 'points', 'price')
```











2.2 Fill NA/NaN values using the highest frequency value

In [10]:
```
# Fill NA/NaN values using the highest frequency value.
highest_frequency_values = {key: data[key].value_counts().index[0]
for key in data.columns}
data_highest = data.fillna(value=highest_frequency_values)
data_highest.info()

# Get frequency of each arrtibute (after fill NaN vaues using the h
igest frequency value)
data_highest_frequency = {key: data_highest[key].value_counts() for
key in data_highest.columns}
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  150930 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     150930 non-null  object 
 8   region_2     150930 non-null  object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

compare with raw data

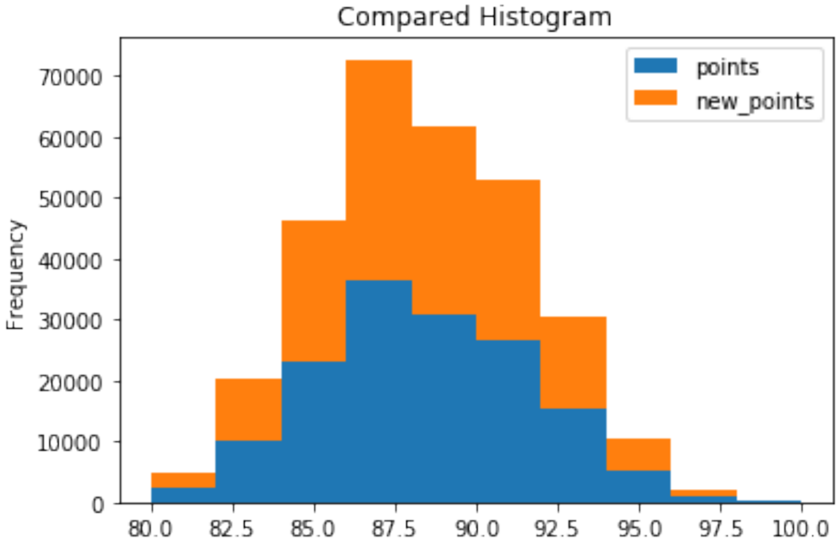
- compare top 5 frequency of nominal_data
- Compared Histogram
- Compared box plot
- Compared scatter plot

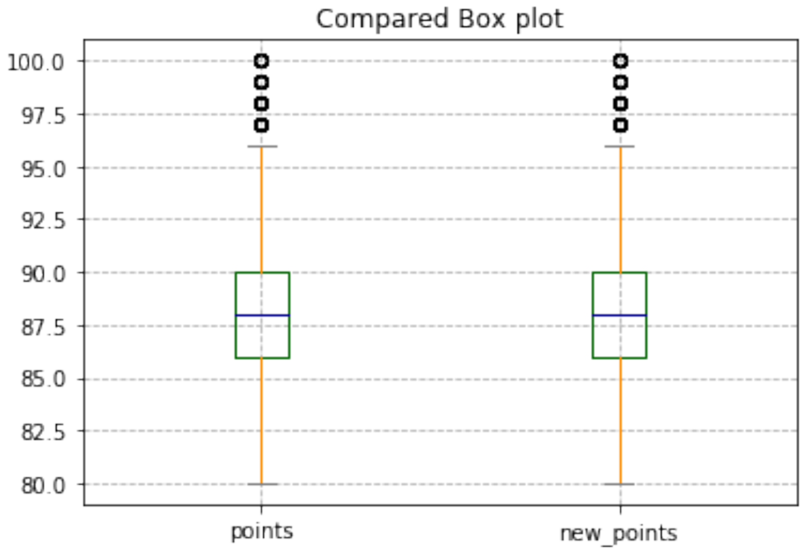
In [11]:
```
# compare top 5 frequency of nominal_data
for i in nominal_index:
    compare_top5_frequency(data_frequency[i], data_highest_frequenc
y[i])
```

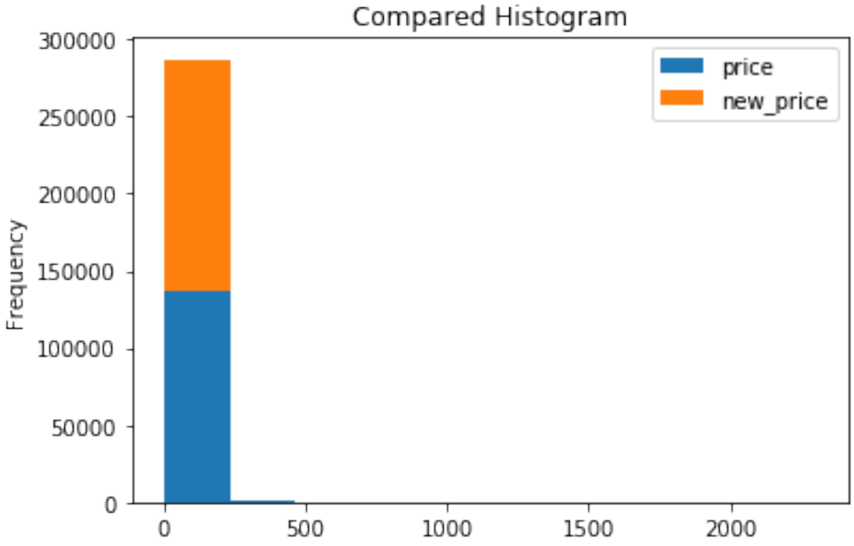
```
Top 5 frequency of country (raw data):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
Top 5 frequency of country (after remove missing values):
US (51.55%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
------------------------------------------------------------------
----------------------------------
```

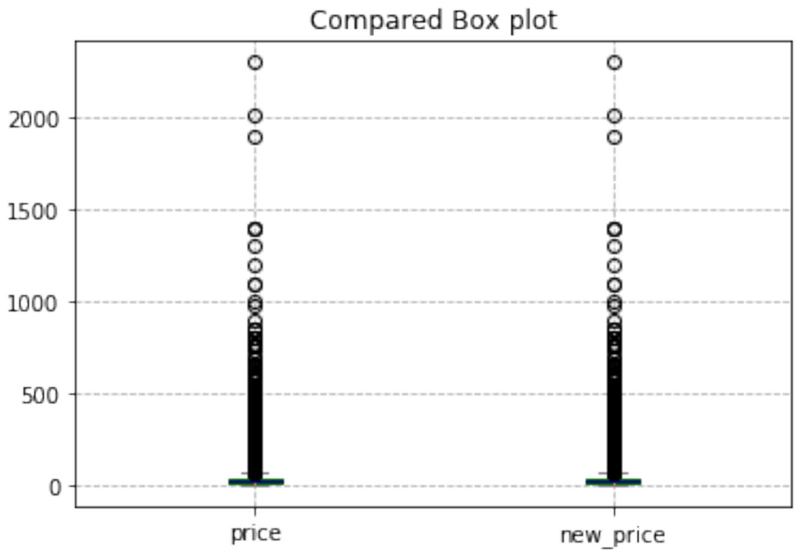
```
Top 5 frequency of designation (raw data):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
Top 5 frequency of designation (after remove missing values):
Reserve (89.88%) | Reserva (3.36%) | Estate (2.91%) | Barrel sampl
e (2.46%) | Riserva (1.40%) |
--------------------------------------------------------------------
-----------------------------------
Top 5 frequency of province (raw data):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
Top 5 frequency of province (after remove missing values):
California (61.36%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
--------------------------------------------------------------------
-----------------------------------
Top 5 frequency of region_1 (raw data):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
Top 5 frequency of region_1 (after remove missing values):
Napa Valley (66.72%) | Columbia Valley (WA) (10.62%) | Mendoza (7.
65%) | Russian River Valley (7.62%) | California (7.39%) |
--------------------------------------------------------------------
-----------------------------------
Top 5 frequency of region_2 (raw data):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
Top 5 frequency of region_2 (after remove missing values):
Central Coast (75.89%) | Sonoma (8.29%) | Columbia Valley (6.74%)
| Napa (6.48%) | California Other (2.59%) |
--------------------------------------------------------------------
-----------------------------------
Top 5 frequency of variety (raw data):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
Top 5 frequency of variety (after remove missing values):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
--------------------------------------------------------------------
-----------------------------------
Top 5 frequency of winery (raw data):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
Top 5 frequency of winery (after remove missing values):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
--------------------------------------------------------------------
-----------------------------------
```

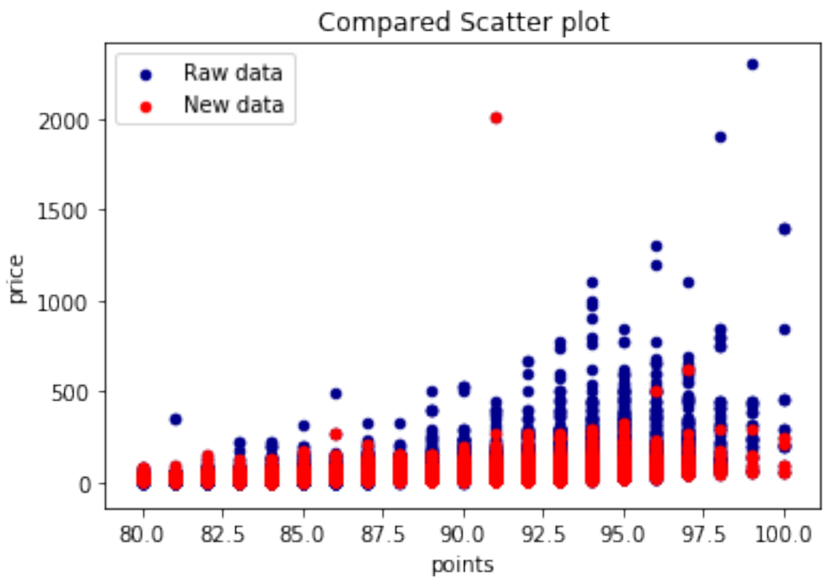
In [12]:
```
for i in numerical_index:
    histogram_compare(data[i], data_highest[i])
    box_plot_compare(data[i], data_highest[i])

# Compare between raw and new data using 'points' & 'price' scatter plot
scatter_plot_compare(data, data_highest, 'points', 'price')
```






Compared Histogram
Frequency
price
new_price
300000
250000
200000
150000
100000
50000
0
0
500
1000
1500
2000


Compared Box plot
2000
1500
1000
500
0
price
new_price


Compared Scatter plot
Raw data
New data
price
points
2000
1500
1000
500
0
80.0
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0

In [13]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150925 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        137235 non-null  float64
 6   province     150925 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

2.3 Fill in missing values by the correlation of the attribute

Random Forest Regressor

Missing attributes: country (5) | province (5) | region_1 (25060) | region_2 (89977) | price(13695) | designation (45735) |

In [9]:
```
from sklearn.preprocessing import OrdinalEncoder
from sklearn.ensemble import RandomForestRegressor
def set_missing_values(df, complete_index):

    enc_label = OrdinalEncoder()
    enc_fea = OrdinalEncoder()
    missing_index = complete_index[0]

    # Take out the existing numerical data (no NaN) and throw them
in Random Forest Regressor
    train_df = df[complete_index]
    # known & unknow values
    known_values = np.array(train_df[train_df[missing_index].notnul
l()])
    unknow_values = np.array(train_df[train_df[missing_index].isnul
l()])

    # y is the know missing_index
    y = known_values[:, 0].reshape(-1, 1)
    enc_label.fit(y)
#     print(enc_label.categories_)
    y = enc_label.transform(y)

    # X are the features
    X = known_values[:, 1:]
    test_X = unknow_values[:, 1:]
    all_X = np.row_stack((X,test_X))
#     print(X.shape, test_X.shape, all_X.shape)
    enc_fea.fit(all_X)
#     print(enc_fea.categories_)
    X = enc_fea.transform(X)

    # fit
    rfr = RandomForestRegressor(random_state=0, n_estimators=2000,
n_jobs=-1)
    rfr.fit(X, y.ravel())
    # predict
    predicted_values = rfr.predict(enc_fea.transform(unknow_values[
:, 1:]))
    predicted_values = enc_label.inverse_transform(predicted_values
.reshape(-1, 1))
    print('fill in values of %s:'%missing_index, predicted_values)
     # fill in with predicted values
    df.loc[ (df[missing_index].isnull()), missing_index] = predicte
d_values
```

First, fill in missing values of '**country**' using complete attribute data ('description' & 'variety' & 'winery')

In [10]:
```
new_data1 = data.copy()
set_missing_values(new_data1, ['country','description', 'variety',
'winery'])
new_data1.info()
```

```
fill in values of country: [['Germany']
 ['Slovenia']
 ['Chile']
 ['Chile']
 ['Chile']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        137235 non-null  float64
 6   province     150925 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Second, fill in missing values of '**province**' using complete attribute data ('country' & 'description' & 'variety' & 'winery')

In [16]:
```python
new_data2 = new_data1.copy()
set_missing_values(new_data2, ['province','country','description',
'variety', 'winery'])
new_data2.info()
```

```
fill in values of province: [['Moutere']
 ['Overberg']
 ['Krania Olympus']
 ['Krania Olympus']
 ['Krania Olympus']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Unnamed: 0   150930 non-null  int64
 1   country      150930 non-null  object
 2   description  150930 non-null  object
 3   designation  105195 non-null  object
 4   points       150930 non-null  int64
 5   price        137235 non-null  float64
 6   province     150930 non-null  object
 7   region_1     125870 non-null  object
 8   region_2     60953 non-null   object
 9   variety      150930 non-null  object
 10  winery       150930 non-null  object
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Third, fill in missing values of '**region_1**' using complete attribute data ('province' & 'country' & 'description' & 'variety' & 'winery')

In [17]:
```
new_data3 = new_data2.copy()
set_missing_values(new_data3, ['region_1', 'province','country','de
scription', 'variety', 'winery'])
new_data3.info()
```

```
fill in values of region_1: [['Rattlesnake Hills']
 ['Old Mission Peninsula']
 ['Monreale']
 ...
 ['Lake County']
 ['Martina']
 ['Offida Rosso']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Unnamed: 0   150930 non-null  int64
 1   country      150930 non-null  object
 2   description  150930 non-null  object
 3   designation  105195 non-null  object
 4   points       150930 non-null  int64
 5   price        137235 non-null  float64
 6   province     150930 non-null  object
 7   region_1     150930 non-null  object
 8   region_2     60953 non-null   object
 9   variety      150930 non-null  object
 10  winery       150930 non-null  object
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Forth, fill in missing values of '**region_2**' using complete attribute data ('region_1' & 'province' & 'country' & 'description' & 'variety' & 'winery')

In [18]:
```
new_data4 = new_data3.copy()
set_missing_values(new_data4, ['region_2', 'region_1', 'province','
country','description', 'variety', 'winery'])
new_data4.info()
```

```
fill in values of region_2: [['Finger Lakes']
 ['Central Coast']
 ['Long Island']
 ...
 ['Washington Other']
 ['Central Coast']
 ['Central Valley']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Unnamed: 0   150930 non-null  int64
 1   country      150930 non-null  object
 2   description  150930 non-null  object
 3   designation  105195 non-null  object
 4   points       150930 non-null  int64
 5   price        137235 non-null  float64
 6   province     150930 non-null  object
 7   region_1     150930 non-null  object
 8   region_2     150930 non-null  object
 9   variety      150930 non-null  object
 10  winery       150930 non-null  object
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Fivth, fill in missing values of '**price**' using complete attribute data ('region_2' & 'region_1' & 'province' & 'country' & 'description' & 'variety' & 'winery')

In [19]:
```
new_data5 = new_data4.copy()
set_missing_values(new_data5, ['price', 'region_2', 'region_1', 'pr
ovince','country','description', 'variety', 'winery'])
new_data5.info()
```

```
fill in values of price: [[65.0]
 [37.0]
 [60.0]
 ...
 [22.0]
 [26.0]
 [23.0]]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Unnamed: 0   150930 non-null  int64
 1   country      150930 non-null  object
 2   description  150930 non-null  object
 3   designation  105195 non-null  object
 4   points       150930 non-null  int64
 5   price        150930 non-null  float64
 6   province     150930 non-null  object
 7   region_1     150930 non-null  object
 8   region_2     150930 non-null  object
 9   variety      150930 non-null  object
 10  winery       150930 non-null  object
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Finally, fill in missing values of '**designation**' using complete attribute data ('price' & region_2' & 'region_1' & 'province' & 'country' & 'description' & 'variety' & 'winery')

In [20]:
```
new_data = new_data5.copy()
set_missing_values(new_data, ['designation', 'price', 'region_2', '
region_1', 'province','country','description', 'variety', 'winery']
)
new_data.info()
# Get frequency of each arrtibute (after fill in missing values by
the correlation of the attribute)
new_data_frequency = {key: new_data[key].value_counts() for key in
new_data.columns}
```

```
fill in values of designation: [['Hooker Old Boys']
 ['Munjebel 7 VA']
 ["Mountainview Ranch Winemaker's Reserve"]
 ...
 ['Grand Muscadelle']
 ['Gran Assemblage']
 ['Jeriko Vineyard']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  150930 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     150930 non-null  object 
 8   region_2     150930 non-null  object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

compare with raw data

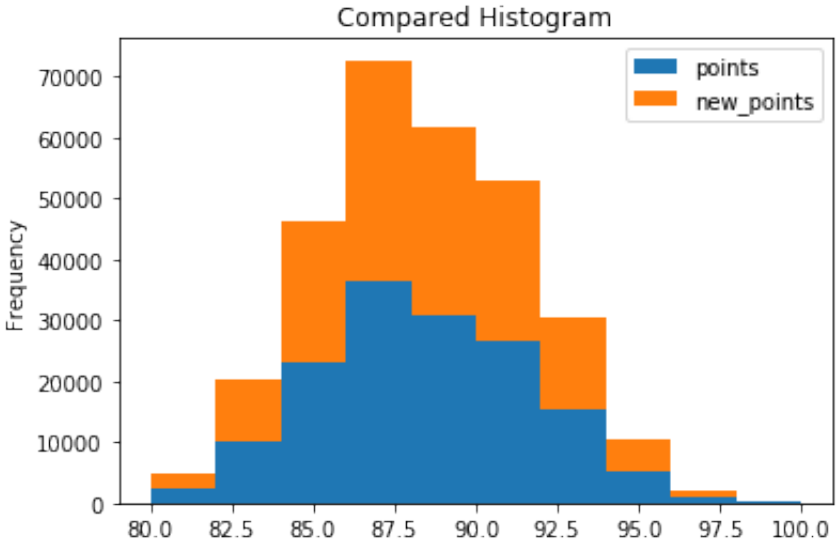
- compare top 5 frequency of nominal_data
- Compared Histogram
- Compared box plot
- Compared scatter plot

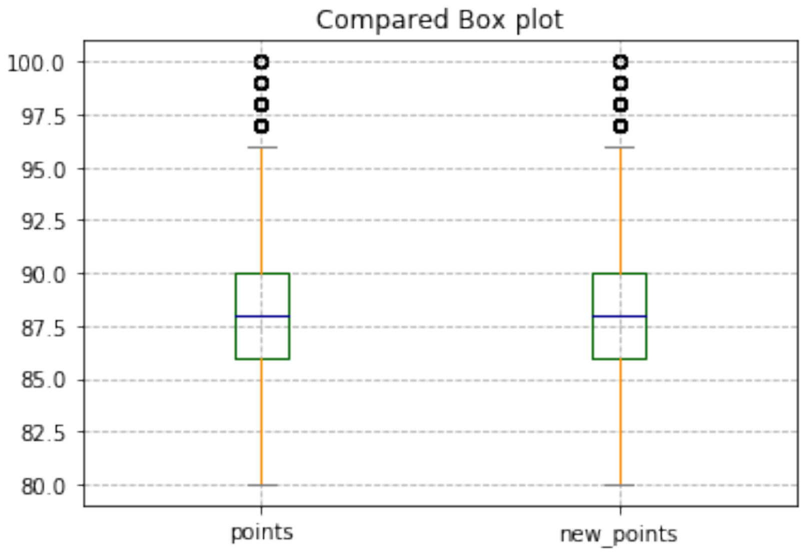
In [21]:
```
# compare top 5 frequency of nominal_data
for i in nominal_index:
    compare_top5_frequency(data_frequency[i], new_data_frequency[i]
)
```

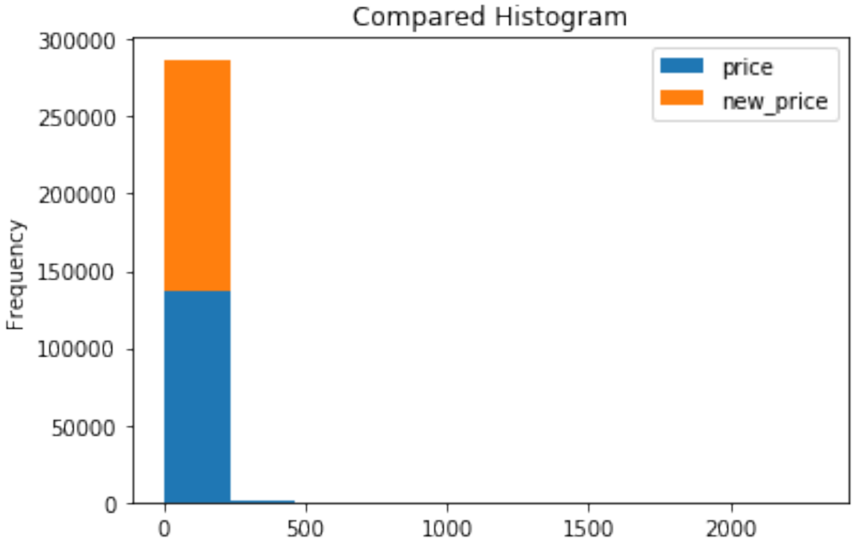
```
Top 5 frequency of country (raw data):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
```

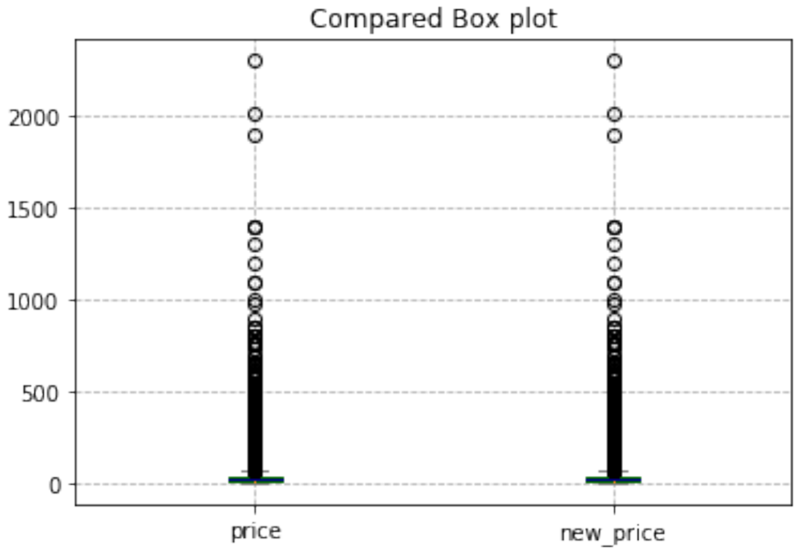
```
hile (4.80%) |
Top 5 frequency of country (after remove missing values):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.81%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of designation (raw data):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
Top 5 frequency of designation (after remove missing values):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of province (raw data):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
Top 5 frequency of province (after remove missing values):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_1 (raw data):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
Top 5 frequency of region_1 (after remove missing values):
Napa Valley (28.50%) | Columbia Valley (WA) (22.73%) | Mendoza (16
.55%) | Russian River Valley (16.41%) | California (15.81%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_2 (raw data):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
Top 5 frequency of region_2 (after remove missing values):
Central Coast (30.06%) | Columbia Valley (23.91%) | Sonoma (21.69%
) | Napa (13.58%) | Willamette Valley (10.75%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of variety (raw data):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
Top 5 frequency of variety (after remove missing values):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of winery (raw data):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
Top 5 frequency of winery (after remove missing values):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
-------------------------------------------------------------------
```

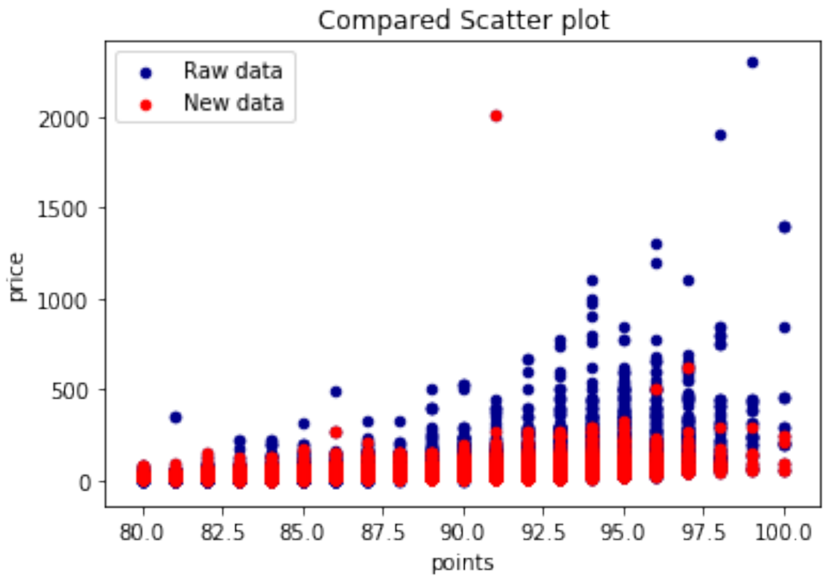
In [22]:
```
for i in numerical_index:
    histogram_compare(data[i], data_highest[i])
    box_plot_compare(data[i], data_highest[i])

# Compare between raw and new data using 'points' & 'price' scatter plot
scatter_plot_compare(data, data_highest, 'points', 'price')
```






Compared Histogram
price
new_price
Frequency
300000
250000
200000
150000
100000
50000
0
0
500
1000
1500
2000


Compared Box plot
2000
1500
1000
500
0
price
new_price


Compared Scatter plot
Raw data
New data
price
2000
1500
1000
500
0
80.0
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0
points

2.4 Fill in missing values by similarity between data objects

Cosine similarity & Euclidean distance

Missing attributes: country (5) | province (5) | region_1 (25,060) | region_2 (89,977) | price(13,695) | designation (45,735) |

Due to insufficient memory, I did fill in missing values of '**country**', '**province**', '**price**'

In [11]:
```
from sklearn.preprocessing import OrdinalEncoder
from sklearn.metrics.pairwise import cosine_similarity
from scipy.spatial.distance import cdist
def set_missing_values_cosine(df, complete_index, metric='cosine'):

    enc_label = OrdinalEncoder()
    enc_fea = OrdinalEncoder()

    missing_index = complete_index[0]

    # Take out the existing numerical data (no NaN) and throw them
in Random Forest Regressor
    train_df = df[complete_index]
    # known & unknow values
    known_values = np.array(train_df[train_df[missing_index].notnul
l()])
    unknow_values = np.array(train_df[train_df[missing_index].isnul
l()])

    # y is the know missing_index
    y = known_values[:, 0].reshape(-1, 1)
    enc_label.fit(y)
    y = enc_label.transform(y)

    # X are the features
    X = known_values[:, 1:]

    test_X = unknow_values[:, 1:]
    all_X = np.row_stack((X,test_X))
    enc_fea.fit(all_X)
    X = enc_fea.transform(X)
    test_X = enc_fea.transform(test_X)


    if metric == 'cosine':
        # fit
        dist = cosine_similarity(test_X, X)
        # predict
        most_similar_index = dist.argmax(axis=1)
    elif metric == 'euclidean':
         # fit
        dist = cdist(test_X,X,metric='euclidean')
        # predict
        most_similar_index = dist.argmin(axis=1)

    predicted_values = y[most_similar_index]
    predicted_values = enc_label.inverse_transform(predicted_values
.reshape(-1, 1))
    print('fill in values of %s:'%missing_index, predicted_values)
     # fill in with predicted values
    df.loc[ (df[missing_index].isnull()), missing_index] = predicte
d_values
```

First, fill in missing values of '**country**' using complete attribute data ('description' & 'variety' & 'winery')

In [22]:
```
# cosine similarity
cos_data1 = data.copy()
set_missing_values_cosine(cos_data1, ['country','description', 'var
iety', 'winery'], 'cosine')
cos_data1.info()

# euclidean distance
euclidean_data1 = data.copy()
set_missing_values_cosine(euclidean_data1, ['country','description'
, 'variety', 'winery'], 'euclidean')
euclidean_data1.info()
```

```
fill in values of country: [['Austria']
 ['Italy']
 ['Portugal']
 ['Portugal']
 ['Portugal']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        137235 non-null  float64
 6   province     150925 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
fill in values of country: [['Austria']
 ['Serbia']
 ['Italy']
 ['Italy']
 ['Italy']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        137235 non-null  float64
 6   province     150925 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Second, fill in missing values of '**province**' using complete attribute data ('country' & 'description' & 'variety' & 'winery')

In [13]:
```
# cosine similarity
cos_data2 = cos_data1.copy()
set_missing_values_cosine(cos_data2, ['province','country','descrip
tion', 'variety', 'winery'], 'cosine')
cos_data2.info()

# euclidean distance
euclidean_data2 = euclidean_data1.copy()
set_missing_values_cosine(euclidean_data2, ['province','country','d
escription', 'variety', 'winery'], 'euclidean')
euclidean_data2.info()
```

```
fill in values of province: [['Vienna']
 ['Sicily & Sardinia']
 ['Port']
 ['Port']
 ['Port']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Unnamed: 0    150930 non-null  int64  
 1   country       150930 non-null  object 
 2   description   150930 non-null  object 
 3   designation   105195 non-null  object 
 4   points        150930 non-null  int64  
 5   price         137235 non-null  float64
 6   province      150930 non-null  object 
 7   region_1      125870 non-null  object 
 8   region_2      60953 non-null   object 
 9   variety       150930 non-null  object 
 10  winery        150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
fill in values of province: [['Eisenberg']
 ['Župa']
 ['Piedmont']
 ['Piedmont']
 ['Piedmont']]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Unnamed: 0    150930 non-null  int64  
 1   country       150930 non-null  object 
 2   description   150930 non-null  object 
 3   designation   105195 non-null  object 
 4   points        150930 non-null  int64  
 5   price         137235 non-null  float64
 6   province      150930 non-null  object 
 7   region_1      125870 non-null  object 
 8   region_2      60953 non-null   object 
 9   variety       150930 non-null  object 
 10  winery        150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Delete, dut to insufficient memory

Third, fill in missing values of '**region_1**' using complete attribute data ('province' & 'country' & 'description' & 'variety' & 'winery')

In [ ]:
```
# cosine similarity
cos_data3 = cos_data2.copy()
set_missing_values_cosine(cos_data3, ['region_1', 'province','count
ry','description', 'variety', 'winery'], 'cosine')
cos_data3.info()

# euclidean distance
euclidean_data3 = euclidean_data2.copy()
set_missing_values_cosine(euclidean_data3, ['region_1', 'province',
'country','description', 'variety', 'winery'], 'euclidean')
euclidean_data3.info()
```

Delete, dut to insufficient memory

Forth, fill in missing values of '**region_2**' using complete attribute data ('region_1' & 'province' & 'country' & 'description' & 'variety' & 'winery')

In [ ]:
```
# cosine similarity
cos_data4 = cos_data3.copy()
set_missing_values_cosine(cos_data4, ['region_2', 'region_1', 'prov
ince','country','description', 'variety', 'winery'], 'cosine')
cos_data4.info()

# euclidean distance
euclidean_data4 = euclidean_data3.copy()
set_missing_values_cosine(euclidean_data4, ['region_2', 'region_1',
'province','country','description', 'variety', 'winery'], 'euclidea
n')
euclidean_data4.info()
```

Fivth, fill in missing values of '**price**' using complete attribute data ('province' & 'country' & 'description' & 'variety' & 'winery')

In [15]:
```
# cosine similarity
cos_data5 = cos_data2.copy()
set_missing_values_cosine(cos_data5, ['price', 'province','country'
,'description', 'variety', 'winery'], 'cosine')
cos_data5.info()

# euclidean distance
euclidean_data5 = euclidean_data2.copy()
set_missing_values_cosine(euclidean_data5, ['price', 'province','co
untry','description', 'variety', 'winery'], 'euclidean')
euclidean_data5.info()
```

```
fill in values of price: [[11.0]
 [26.0]
 [70.0]
 ...
 [21.0]
 [45.0]
 [12.0]]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
fill in values of price: [[105.0]
 [24.0]
 [29.0]
 ...
 [10.0]
 [20.0]
 [30.0]]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

Delete, dut to insufficient memory

Finally, fill in missing values of '**designation**' using complete attribute data ('price' & region_2' & 'region_1' & 'province' & 'country' & 'description' & 'variety' & 'winery')

In [ ]:
```
# cosine similarity
cos_data = cos_data5.copy()
set_missing_values_cosine(cos_data, ['designation', 'price', 'region_2', 'region_1', 'province','country','description', 'variety', 'winery'], 'cosine')
cos_data.info()

# euclidean distance
euclidean_data = euclidean_data5.copy()
set_missing_values_cosine(euclidean_data, ['designation', 'price', 'region_2', 'region_1', 'province','country','description', 'variety', 'winery'], 'euclidean')
euclidean_data.info()

# Get frequency of each arrtibute (after fill in missing values by the cosine similarity of the object)
cos_data_frequency = {key: cos_data[key].value_counts() for key in cos_data.columns}

# Get frequency of each arrtibute (after fill in missing values by the uclidean distance of the object)
euclidean_data_frequency = {key: euclidean_data[key].value_counts() for key in euclidean_data.columns}
```

Final filling data

In [16]:
```
cos_data = cos_data5.copy()
cos_data.info()
# Get frequency of each arrtibute (after fill in missing values by the correlation of the attribute)
cos_data_frequency = {key: cos_data[key].value_counts() for key in cos_data.columns}

euclidean_data = euclidean_data5.copy()
euclidean_data.info()
# Get frequency of each arrtibute (after fill in missing values by the correlation of the attribute)
euclidean_data_frequency = {key: euclidean_data[key].value_counts() for key in euclidean_data.columns}
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150930 entries, 0 to 150929
Data columns (total 11 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Unnamed: 0   150930 non-null  int64  
 1   country      150930 non-null  object 
 2   description  150930 non-null  object 
 3   designation  105195 non-null  object 
 4   points       150930 non-null  int64  
 5   price        150930 non-null  float64
 6   province     150930 non-null  object 
 7   region_1     125870 non-null  object 
 8   region_2     60953 non-null   object 
 9   variety      150930 non-null  object 
 10  winery       150930 non-null  object 
dtypes: float64(1), int64(2), object(8)
memory usage: 12.7+ MB
```

compare with raw data (Cosine similarity)

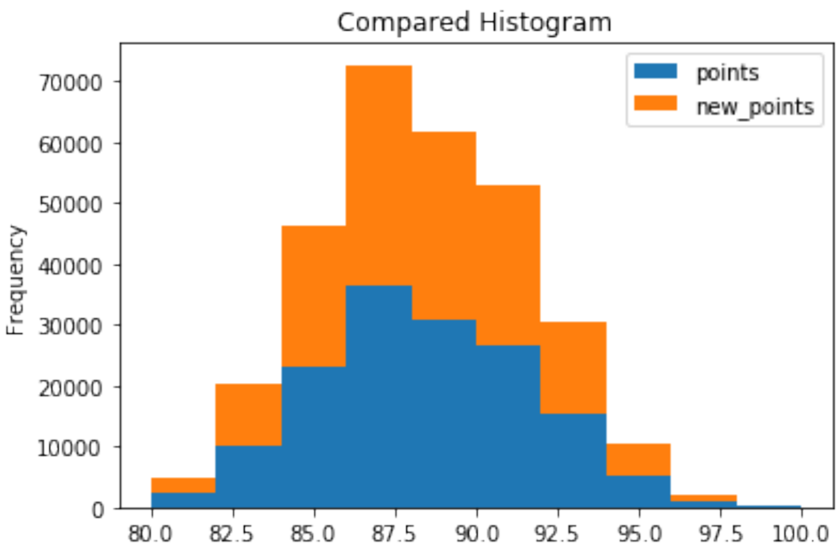
- compare top 5 frequency of nominal_data
- Compared Histogram
- Compared box plot
- Compared scatter plot

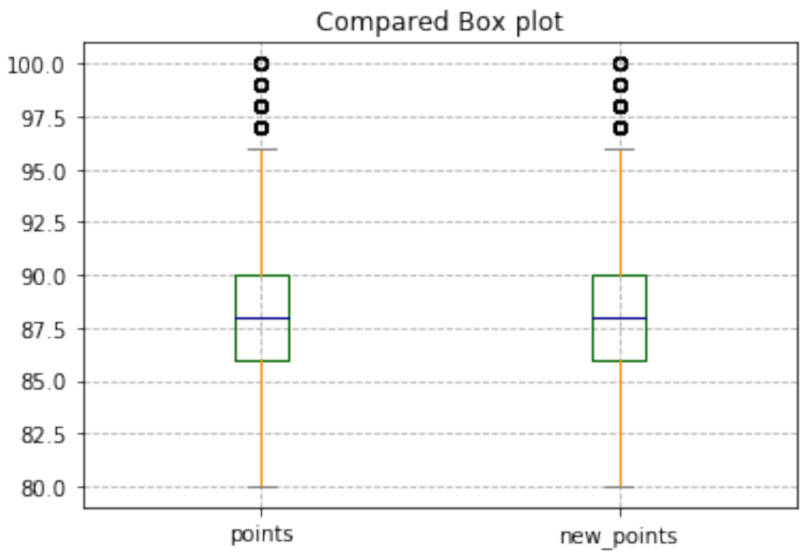
In [17]:
```
# compare top 5 frequency of nominal_data
for i in nominal_index:
    compare_top5_frequency(data_frequency[i], cos_data_frequency[i]
)
```

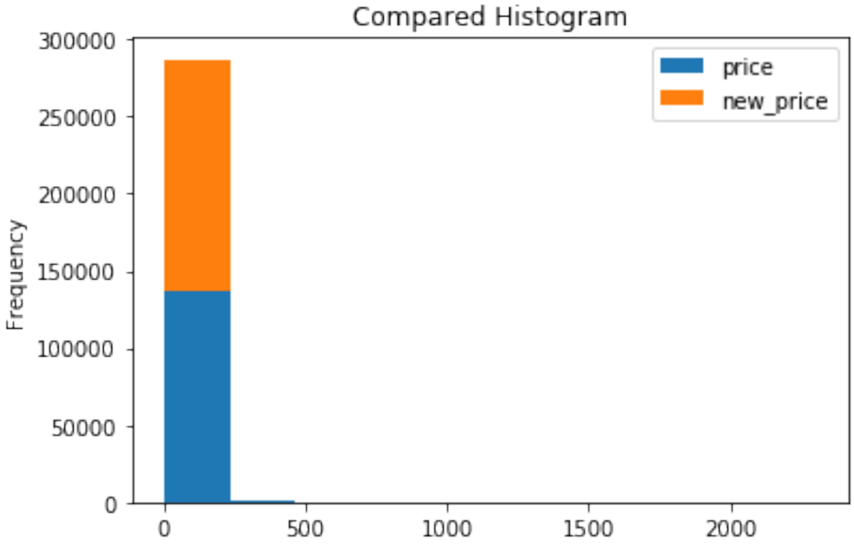
```
Top 5 frequency of country (raw data):
```

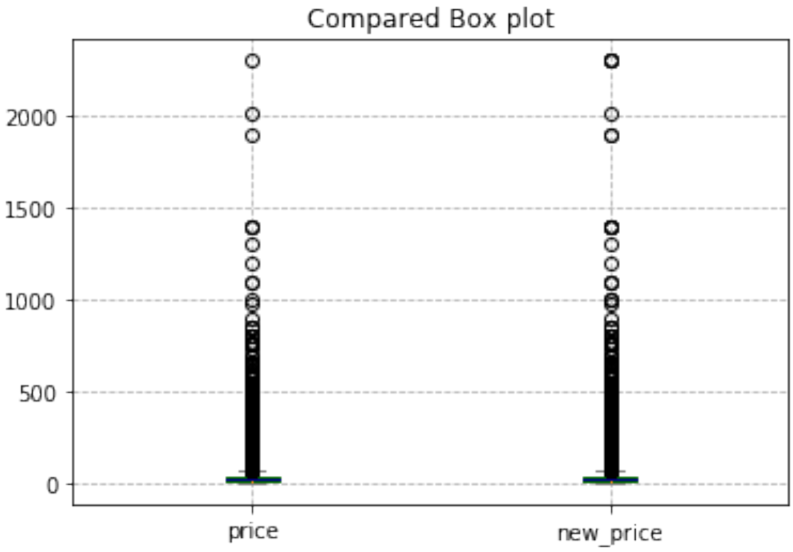
```
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
Top 5 frequency of country (after remove missing values):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of designation (raw data):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
Top 5 frequency of designation (after remove missing values):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of province (raw data):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
Top 5 frequency of province (after remove missing values):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_1 (raw data):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
Top 5 frequency of region_1 (after remove missing values):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_2 (raw data):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
Top 5 frequency of region_2 (after remove missing values):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of variety (raw data):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
Top 5 frequency of variety (after remove missing values):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of winery (raw data):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
Top 5 frequency of winery (after remove missing values):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
```

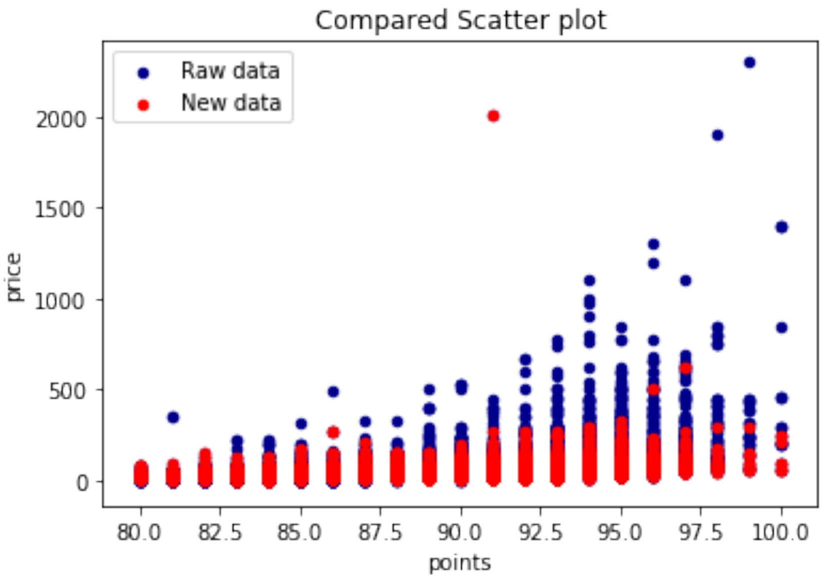

In [18]:
```
for i in numerical_index:
    histogram_compare(data[i], cos_data[i])
    box_plot_compare(data[i], cos_data[i])

# Compare between raw and new data using 'points' & 'price' scatter plot
scatter_plot_compare(data, cos_data, 'points', 'price')
```






Compared Histogram
price
new_price
Frequency
300000
250000
200000
150000
100000
50000
0
0
500
1000
1500
2000


Compared Box plot
2000
1500
1000
500
0
price
new_price


Compared Scatter plot
Raw data
New data
price
2000
1500
1000
500
0
80.0
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0
points

compare with raw data (Euclidean distance)

- compare top 5 frequency of nominal_data
- Compared Histogram
- Compared box plot
- Compared scatter plot

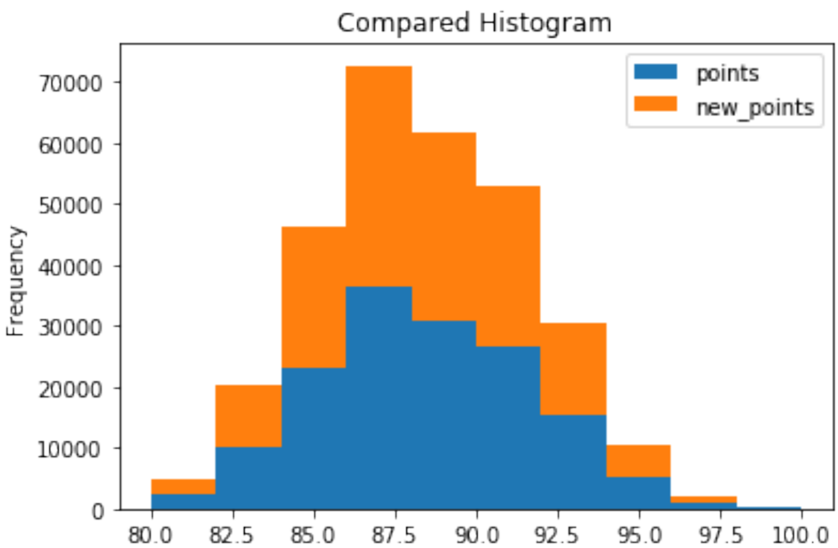
In [19]:
```
# compare top 5 frequency of nominal_data
for i in nominal_index:
    compare_top5_frequency(data_frequency[i], euclidean_data_freque
ncy[i])
```

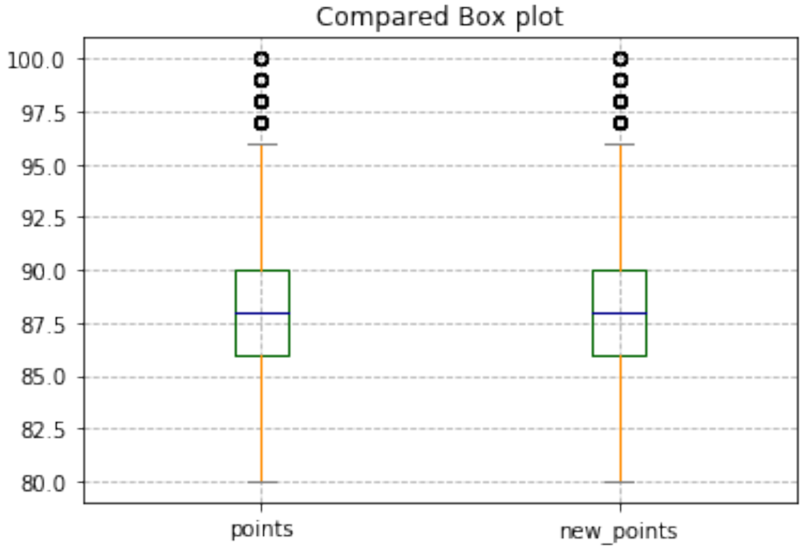
```
Top 5 frequency of country (raw data):
US (51.54%) | Italy (19.39%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
Top 5 frequency of country (after remove missing values):
US (51.54%) | Italy (19.40%) | France (17.43%) | Spain (6.83%) | C
hile (4.80%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of designation (raw data):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
Top 5 frequency of designation (after remove missing values):
Reserve (33.51%) | Reserva (22.04%) | Estate (19.13%) | Barrel sam
ple (16.15%) | Riserva (9.18%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of province (raw data):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
Top 5 frequency of province (after remove missing values):
California (61.35%) | Washington (13.44%) | Tuscany (10.04%) | Bor
deaux (8.42%) | Northern Spain (6.74%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_1 (raw data):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
Top 5 frequency of region_1 (after remove missing values):
Napa Valley (28.48%) | Columbia Valley (WA) (22.82%) | Mendoza (16
.45%) | Russian River Valley (16.38%) | California (15.88%) |
------------------------------------------------------------------
----------------------------------
Top 5 frequency of region_2 (raw data):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
Top 5 frequency of region_2 (after remove missing values):
Central Coast (28.52%) | Sonoma (24.59%) | Columbia Valley (20.00%
) | Napa (19.22%) | California Other (7.68%) |
```

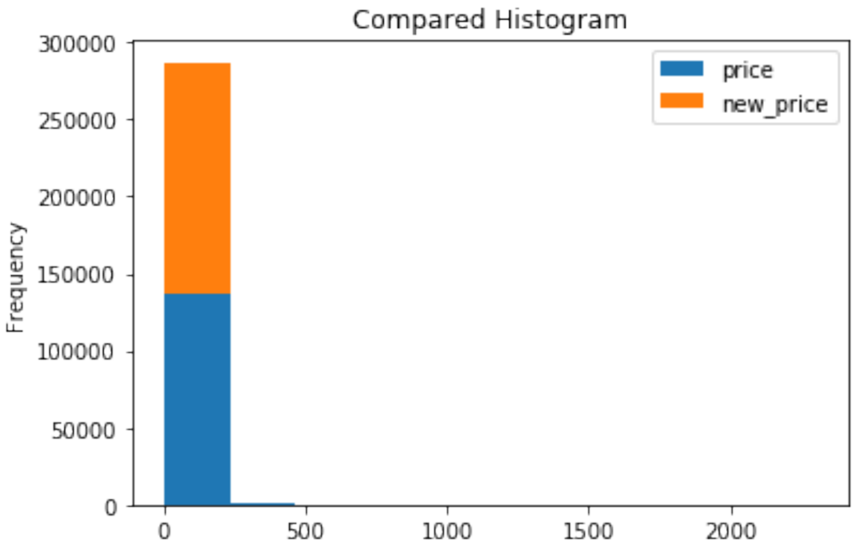
```
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of variety (raw data):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
Top 5 frequency of variety (after remove missing values):
Chardonnay (24.55%) | Pinot Noir (24.23%) | Cabernet Sauvignon (21
.70%) | Red Blend (17.06%) | Bordeaux-style Red Blend (12.46%) |
-------------------------------------------------------------------
----------------------------------
Top 5 frequency of winery (raw data):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
Top 5 frequency of winery (after remove missing values):
Williams Selyem (27.74%) | Testarossa (20.33%) | DFJ Vinhos (19.14
%) | Chateau Ste. Michelle (16.69%) | Columbia Crest (16.10%) |
-------------------------------------------------------------------
----------------------------------
```

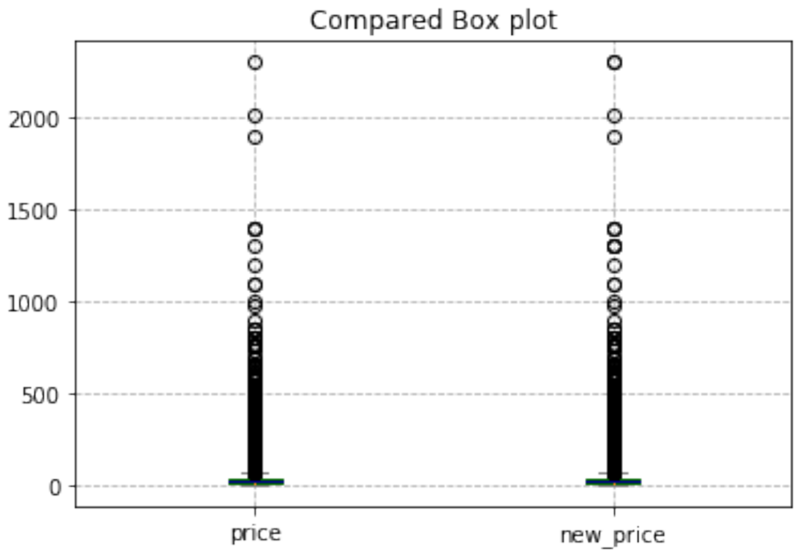
In [20]:

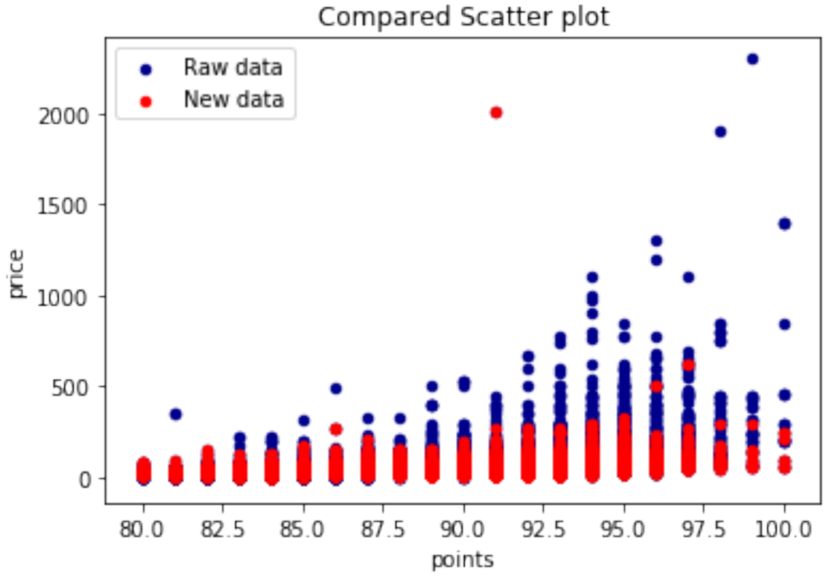
```python
for i in numerical_index:
    histogram_compare(data[i], euclidean_data[i])
    box_plot_compare(data[i], euclidean_data[i])

# Compare between raw and new data using 'points' & 'price' scatter plot
scatter_plot_compare(data, euclidean_data, 'points', 'price')
```




Compared Box plot
100.0
97.5
95.0
92.5
90.0
87.5
85.0
82.5
80.0
points
new_points


Compared Histogram
300000
250000
200000
150000
100000
50000
0
Frequency
0
500
1000
1500
2000
price
new_price


Compared Box plot
2000
1500
1000
500
0
price
new_price


Compared Scatter plot
Raw data
New data
price
points
0
500
1000
1500
2000
80.0
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0