Data distributions

FEATURE ENGINEERING FOR MACHINE LEARNING IN PYTHON

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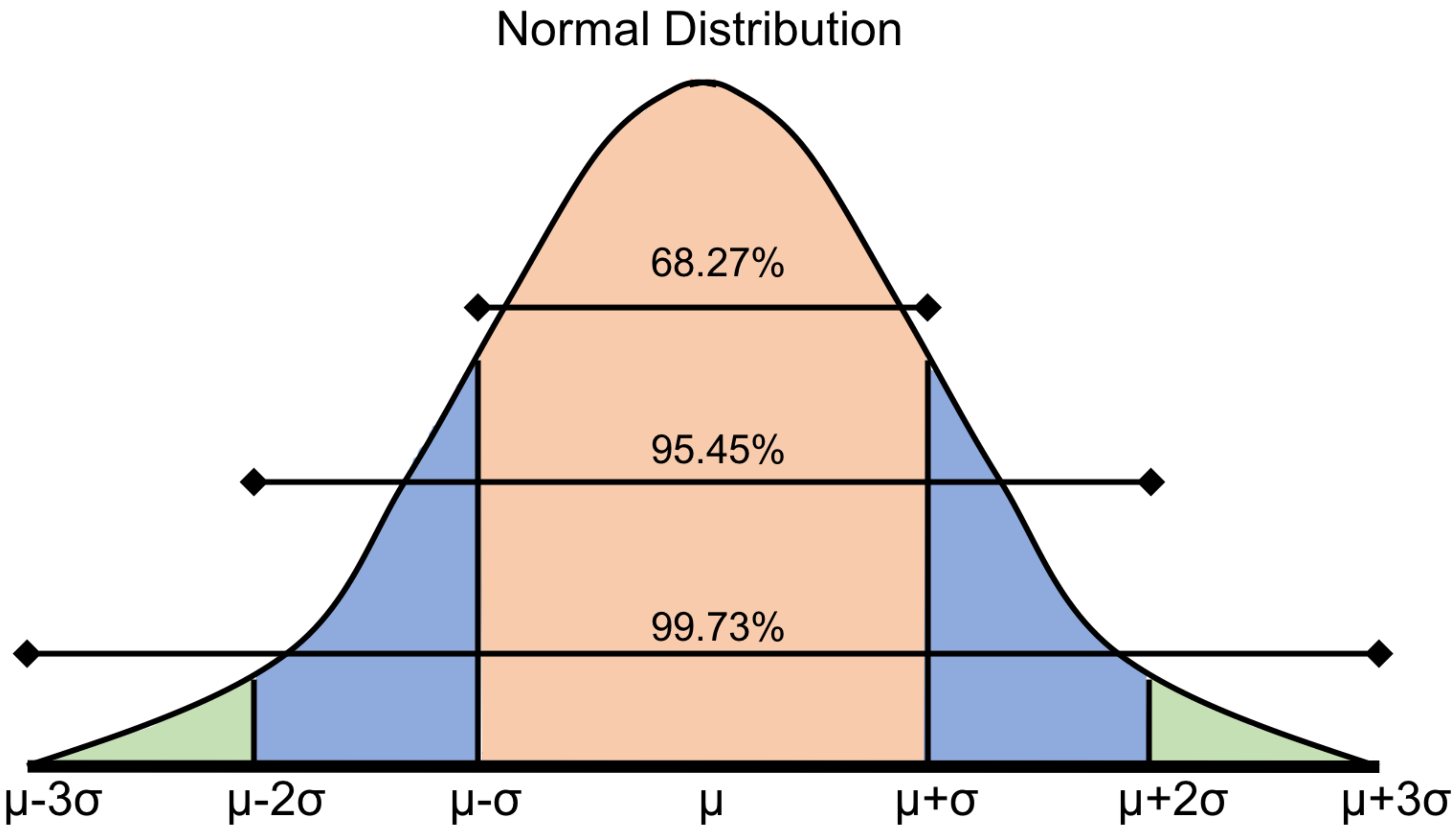
Ordergroove

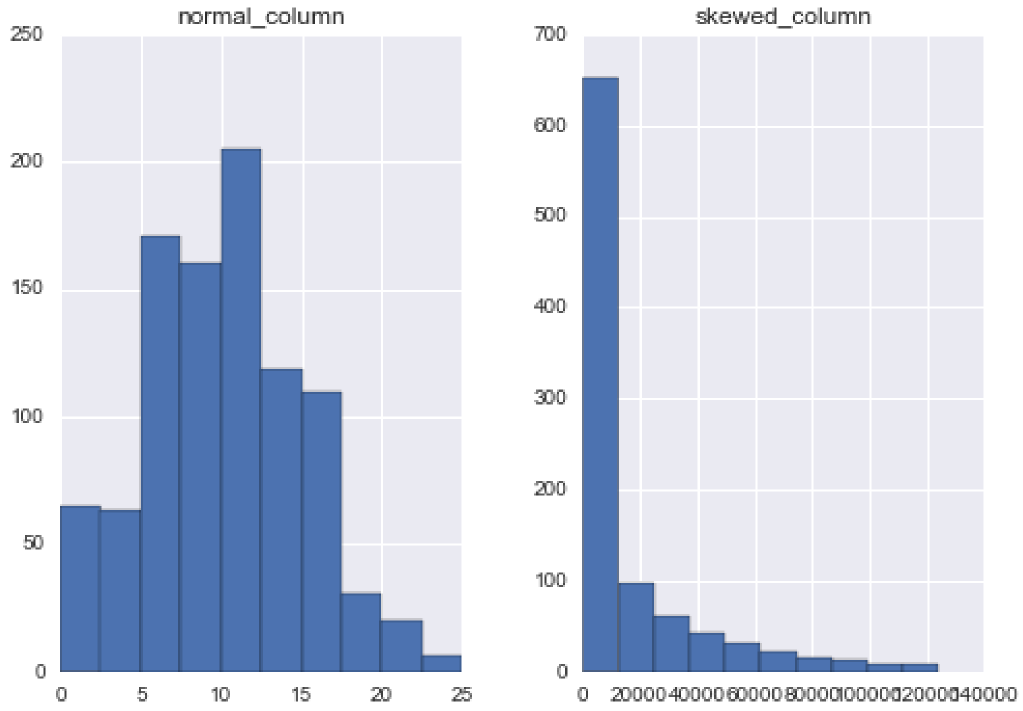
Distribution assumptions



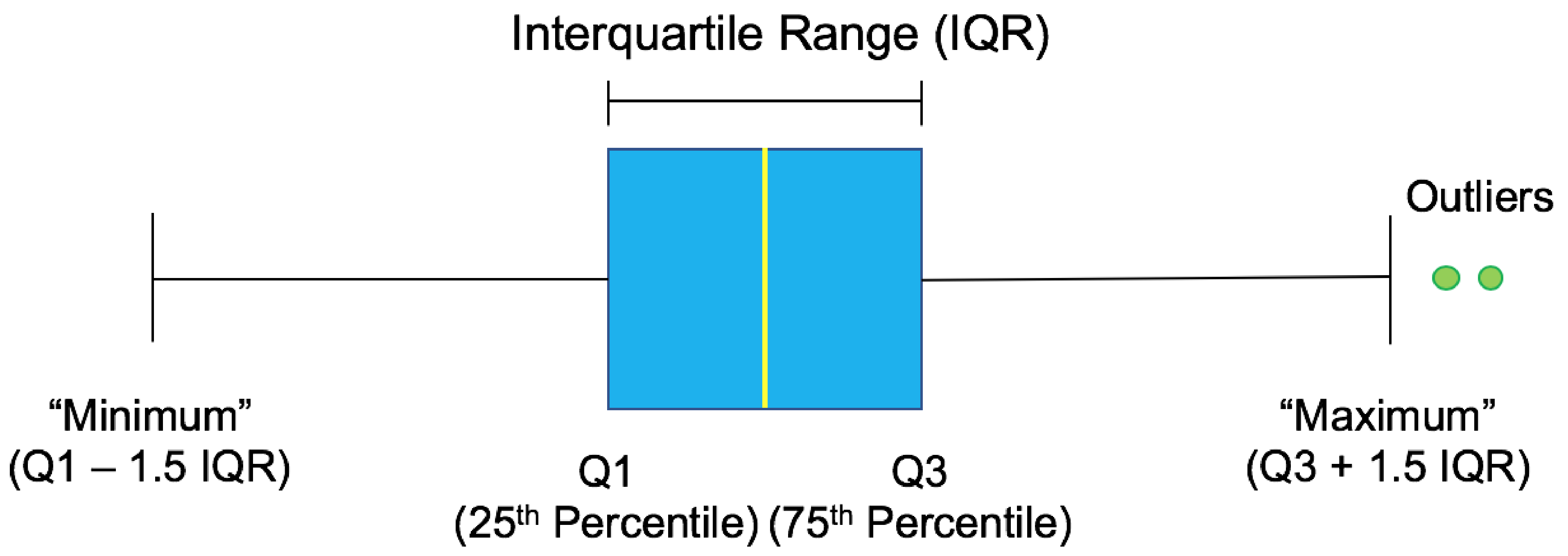
Observing your data

```python
import matplotlib as plt

df.hist()
plt.show()
```

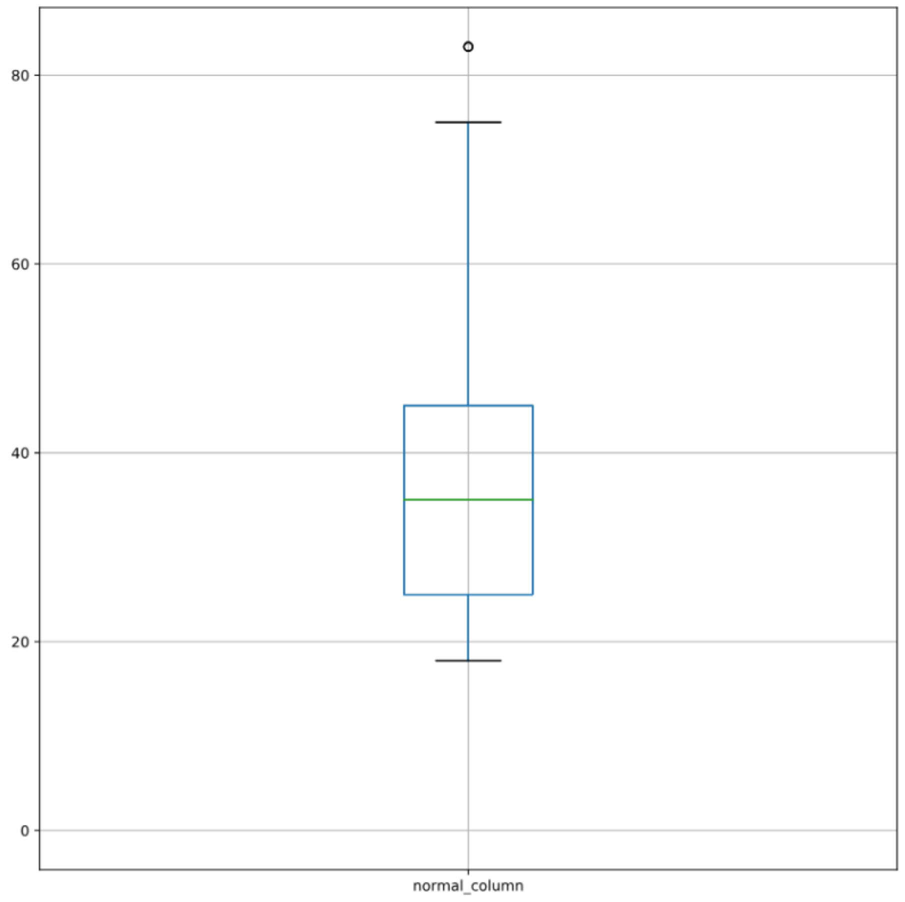


Delving deeper with box plots



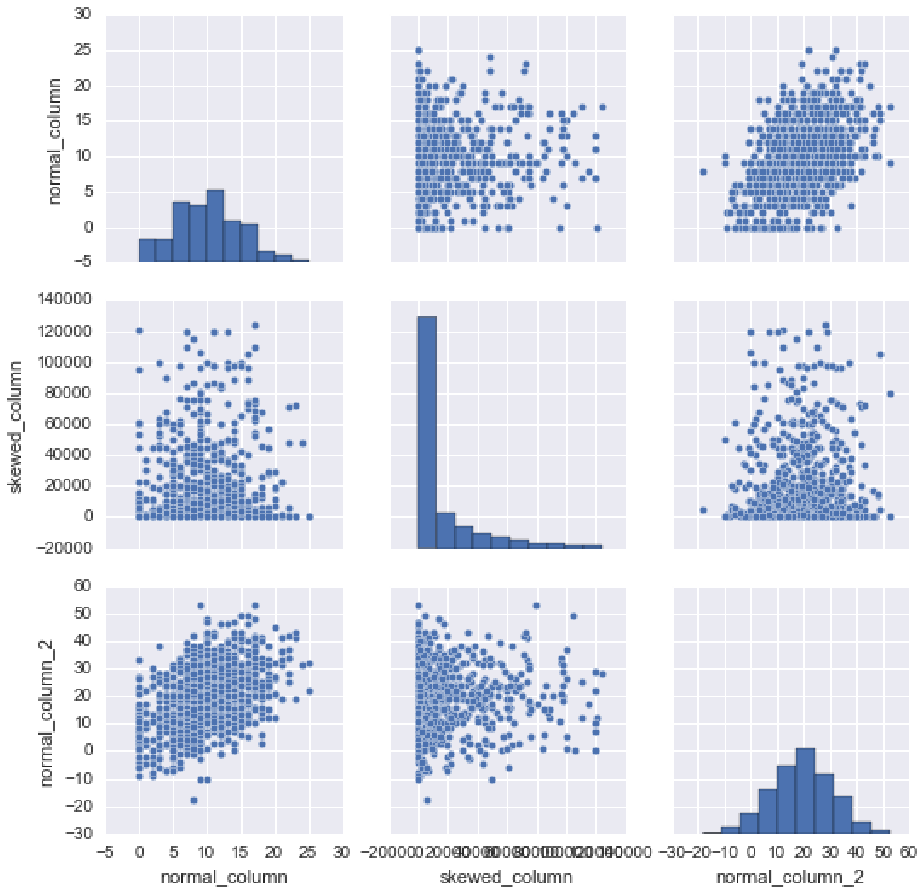
Box plots in pandas

```
df[['column_1']].boxplot()
plt.show()
```



Paring distributions

```python
import seaborn as sns
sns.pairplot(df)
```



Further details on your distributions

```
df.describe()
```

	Col1	Col2	Col3	Col4
count	100.000000	100.000000	100.000000	100.000000
mean	-0.163779	-0.014801	-0.087965	-0.045790
std	1.046370	0.920881	0.936678	0.916474
min	-2.781872	-2.156124	-2.647595	-1.957858
25%	-0.849232	-0.655239	-0.602699	-0.736089
50%	-0.179495	0.032115	-0.051863	0.066803
75%	0.663515	0.615688	0.417917	0.689591
max	2.466219	2.353921	2.059511	1.838561

Let's practice!

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Scaling and transformations

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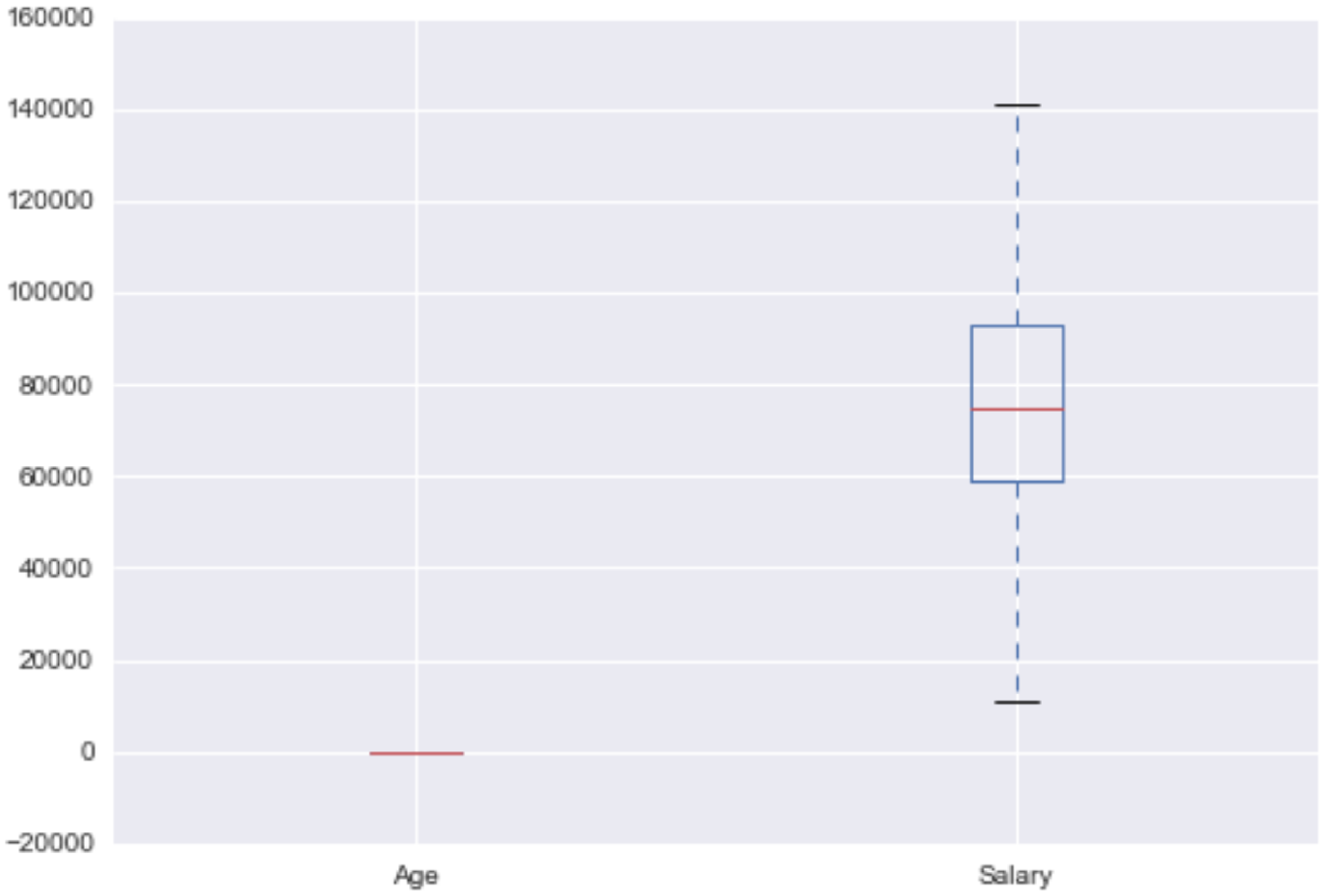
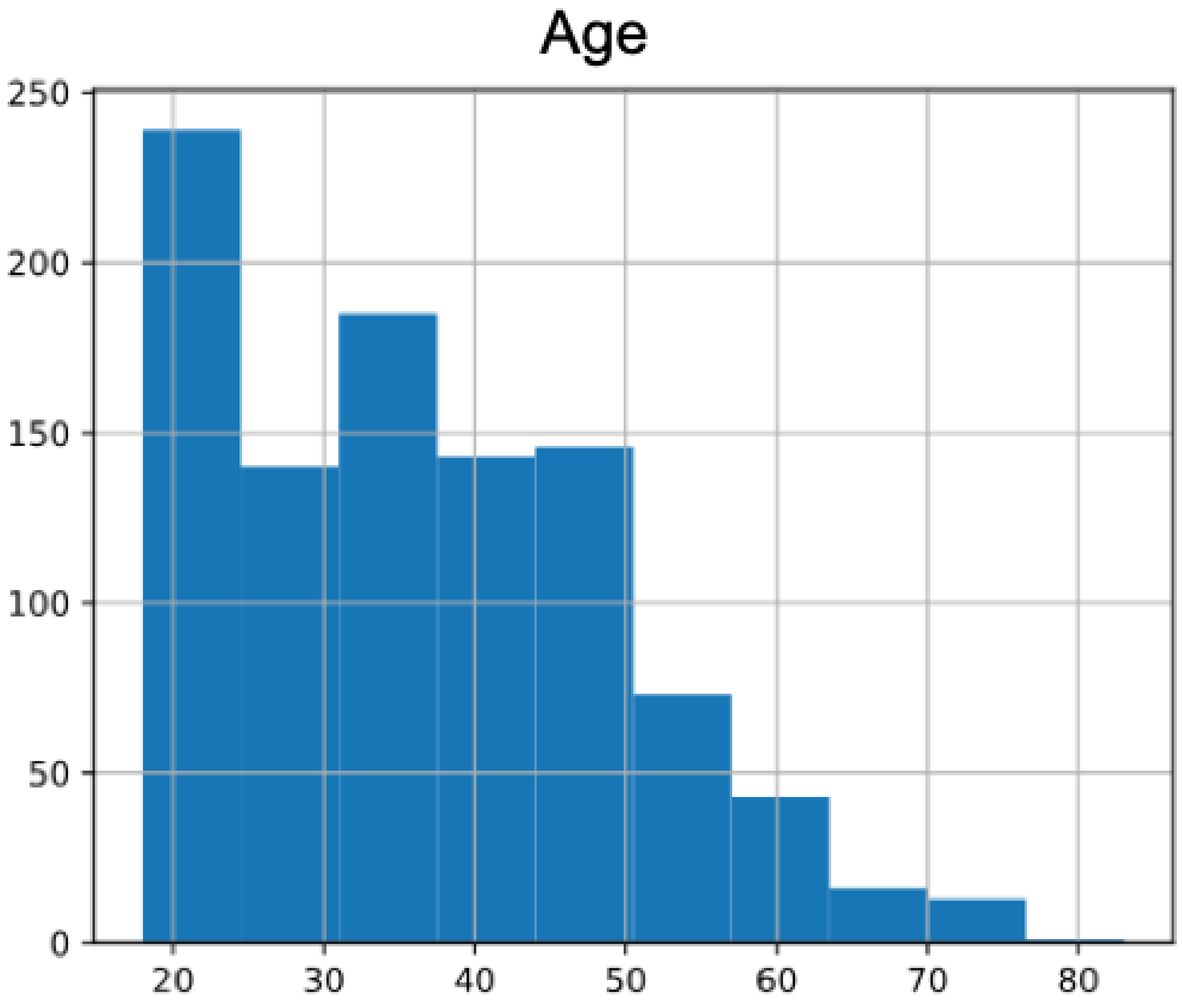
Data Scientist

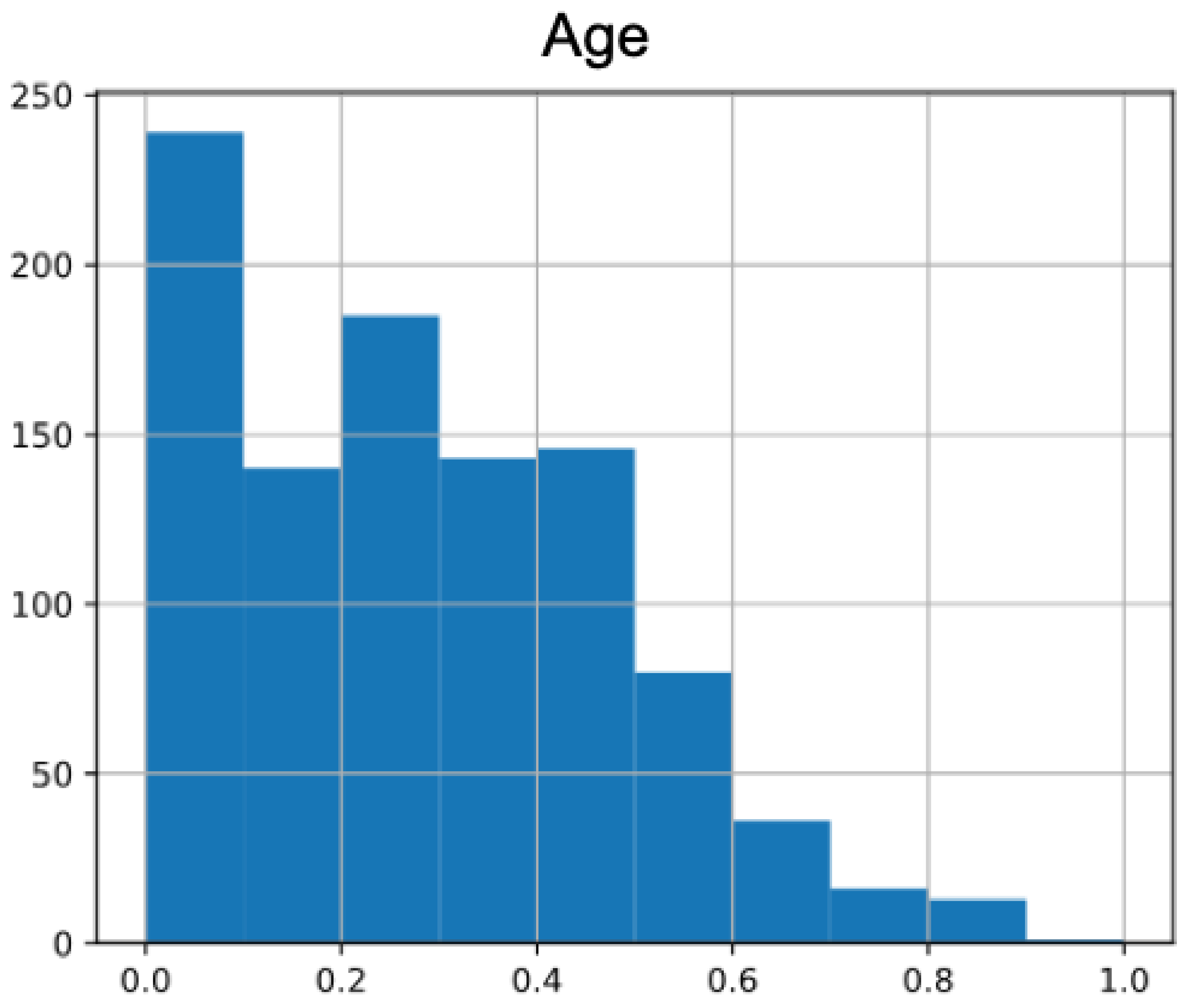
Scaling data



Min-Max scaling



Min-Max scaling



Min-Max scaling in Python

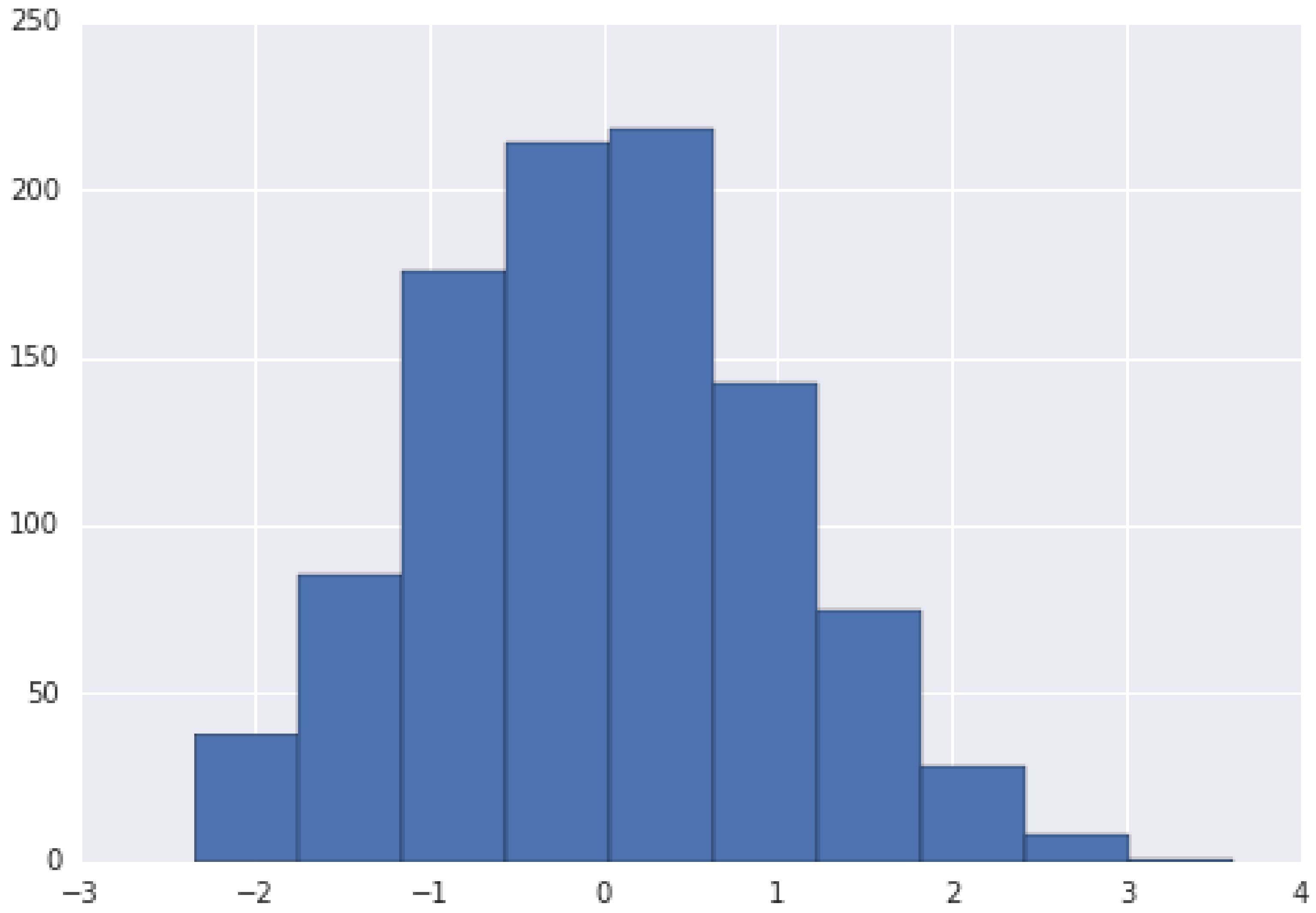
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

scaler.fit(df[['Age']])

df['normalized_age'] = scaler.transform(df[['Age']])
```

Standardization



Standardization in Python

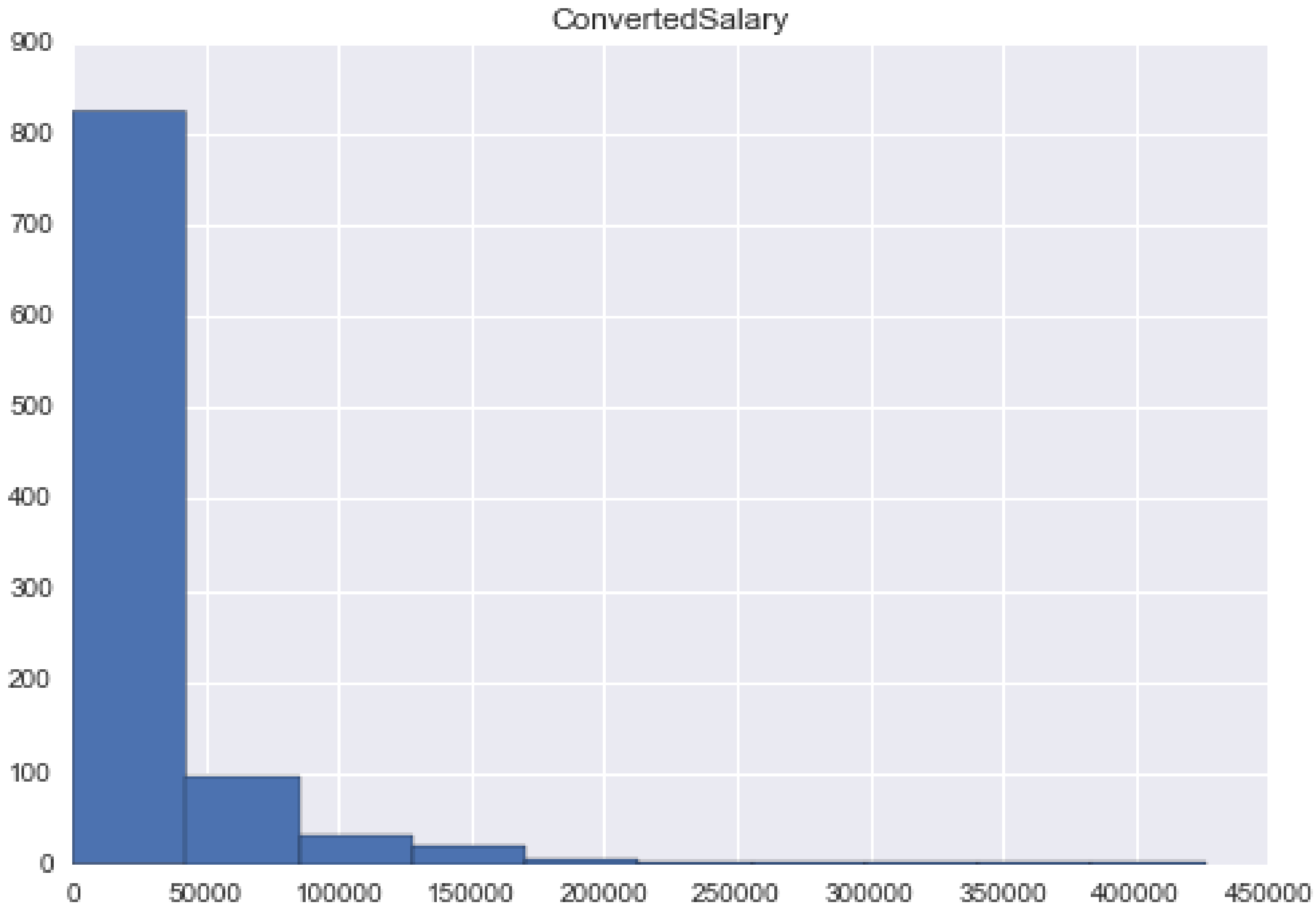
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

scaler.fit(df[['Age']])

df['standardized_col'] = scaler\
                        .transform(df[['Age']])
```

Log Transformation



Log transformation in Python

```
from sklearn.preprocessing import PowerTransformer

log = PowerTransformer()

log.fit(df[['ConvertedSalary']])

df['log_ConvertedSalary'] =
     log.transform(df[['ConvertedSalary']])
```

Final Slide

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Removing outliers

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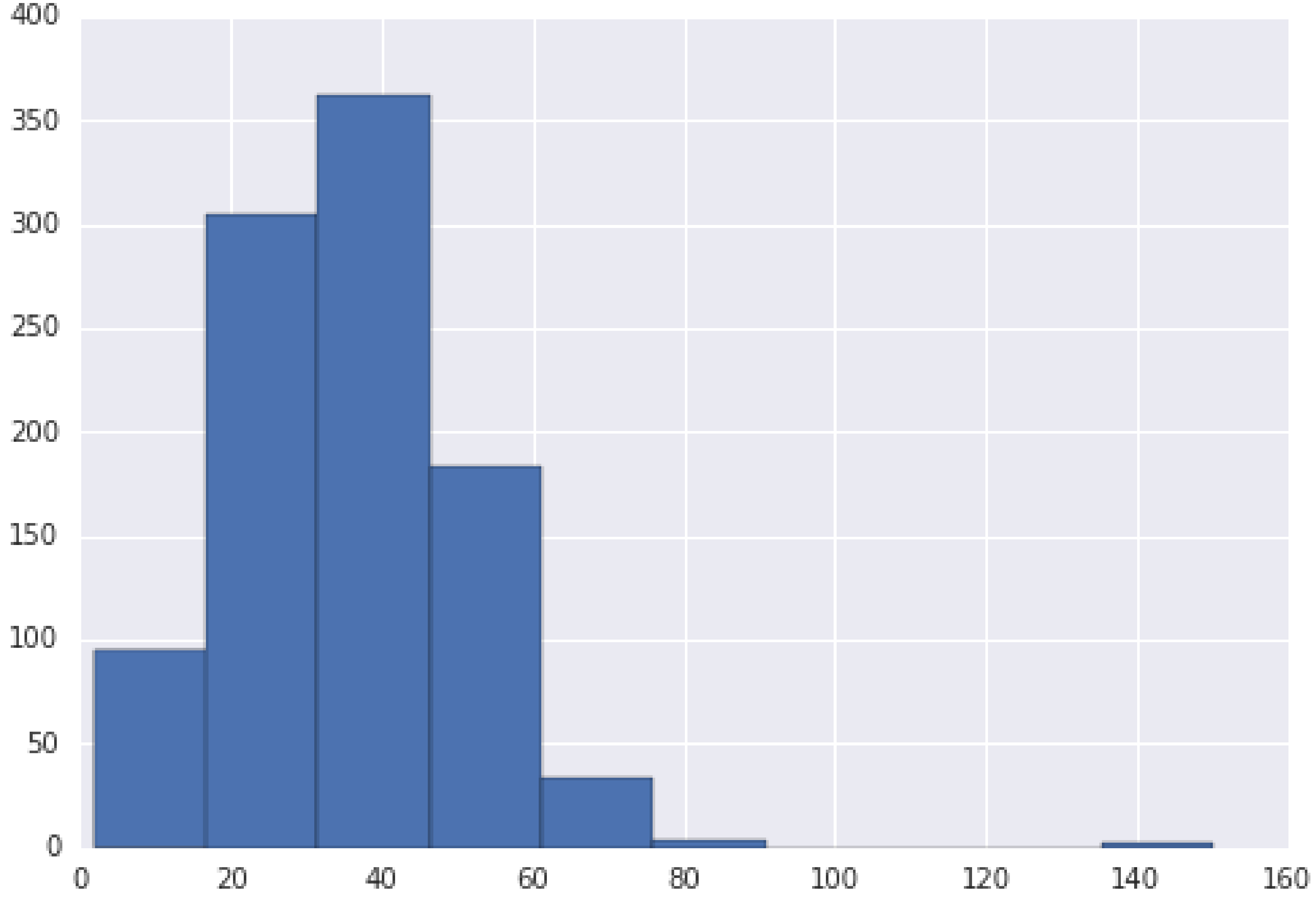
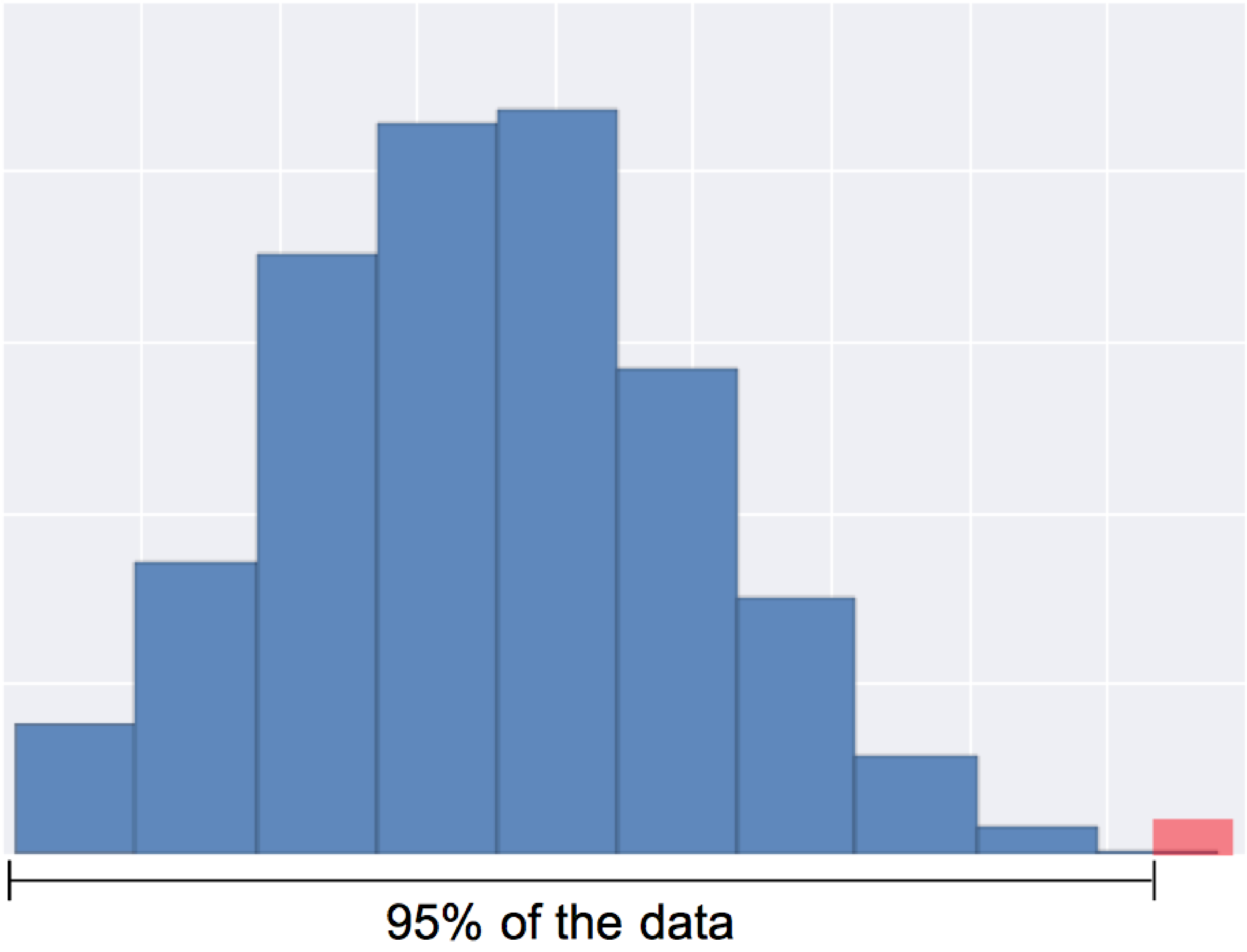
What are outliers?



Quantile based detection



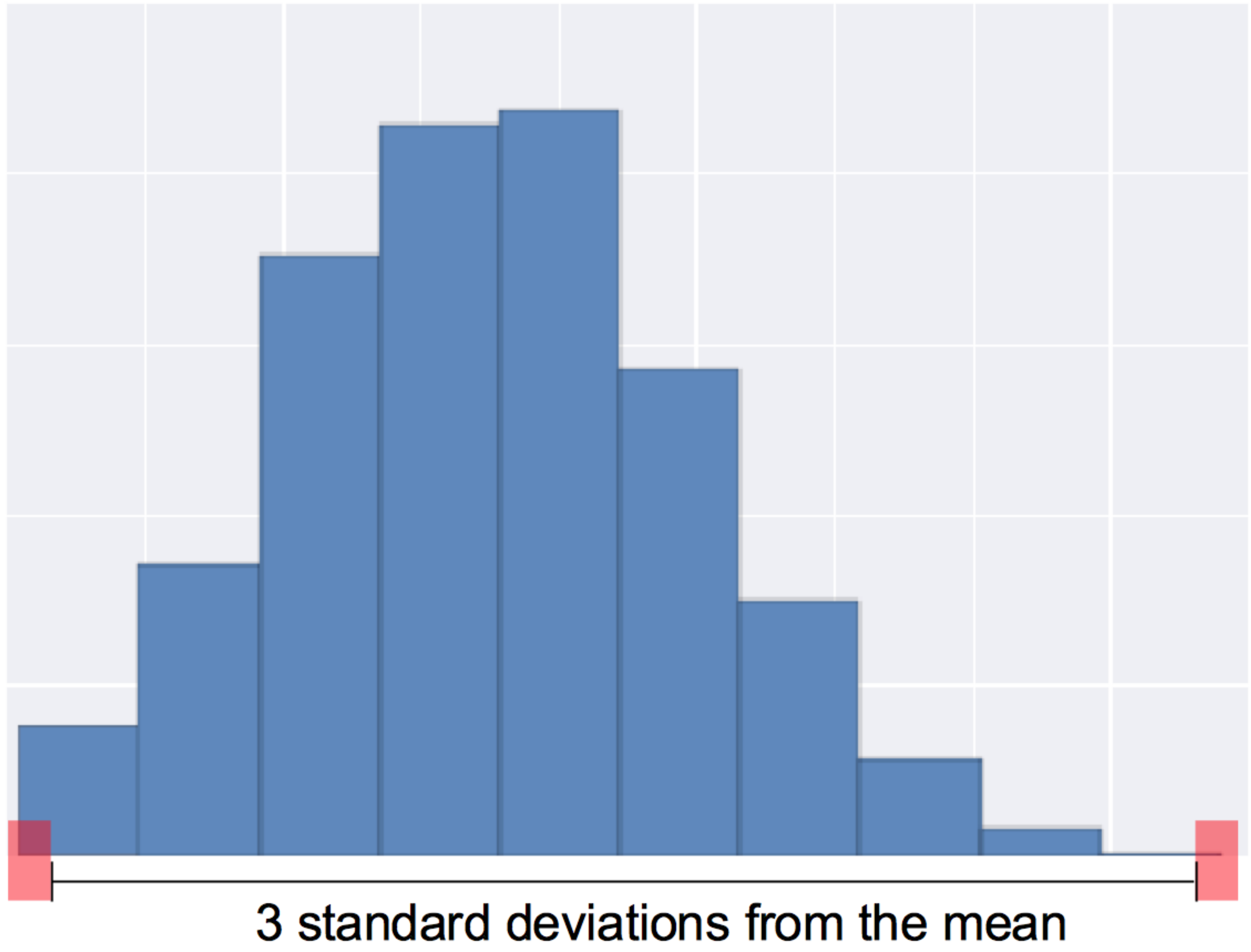
Quantiles in Python

```
q_cutoff = df['col_name'].quantile(0.95)

mask = df['col_name'] < q_cutoff

trimmed_df = df[mask]
```

Standard deviation based detection



Standard deviation detection in Python

```
mean = df['col_name'].mean()
std = df['col_name'].std()
cut_off = std * 3


lower, upper = mean - cut_off, mean + cut_off
new_df = df[(df['col_name'] < upper) &
                 (df['col_name'] > lower)]
```

Let's practice!

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Scaling and transforming new data

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Reuse training scalers

```
scaler = StandardScaler()

scaler.fit(train[['col']])

train['scaled_col'] = scaler.transform(train[['col']])

# FIT SOME MODEL
# ....

test = pd.read_csv('test_csv')

test['scaled_col'] = scaler.transform(test[['col']])
```

Training transformations for reuse

```
train_mean = train[['col']].mean()
train_std = train[['col']].std()

cut_off = train_std * 3
train_lower = train_mean - cut_off
train_upper = train_mean + cut_off

# Subset train data

test = pd.read_csv('test_csv')

# Subset test data
test = test[(test[['col']] < train_upper) &
              (test[['col']] > train_lower)]
```

Why only use training data?

Data leakage: Using data that you won't have access to when assessing the performance of your model

Avoid data leakage!

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