# Data distributions

FEATURE ENGINEERING FOR MACHINE LEARNING IN PYTHON

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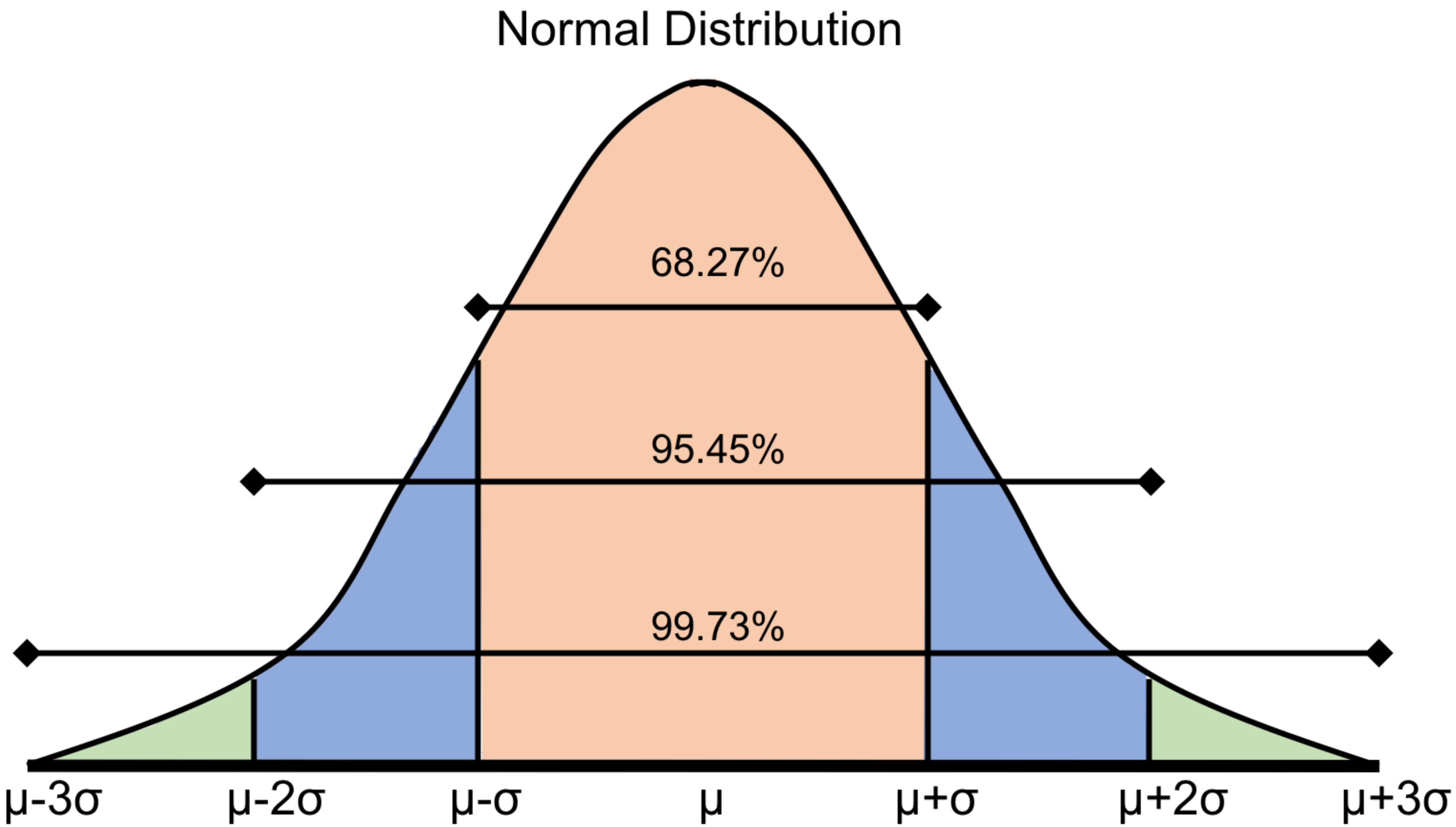
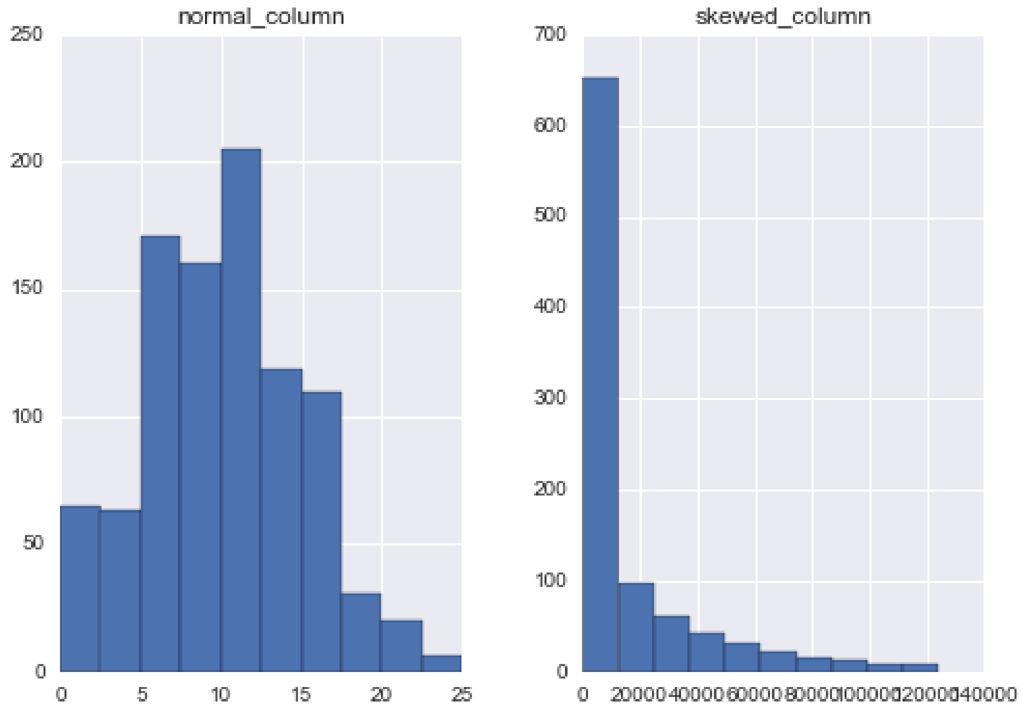
# Distribution assumptions



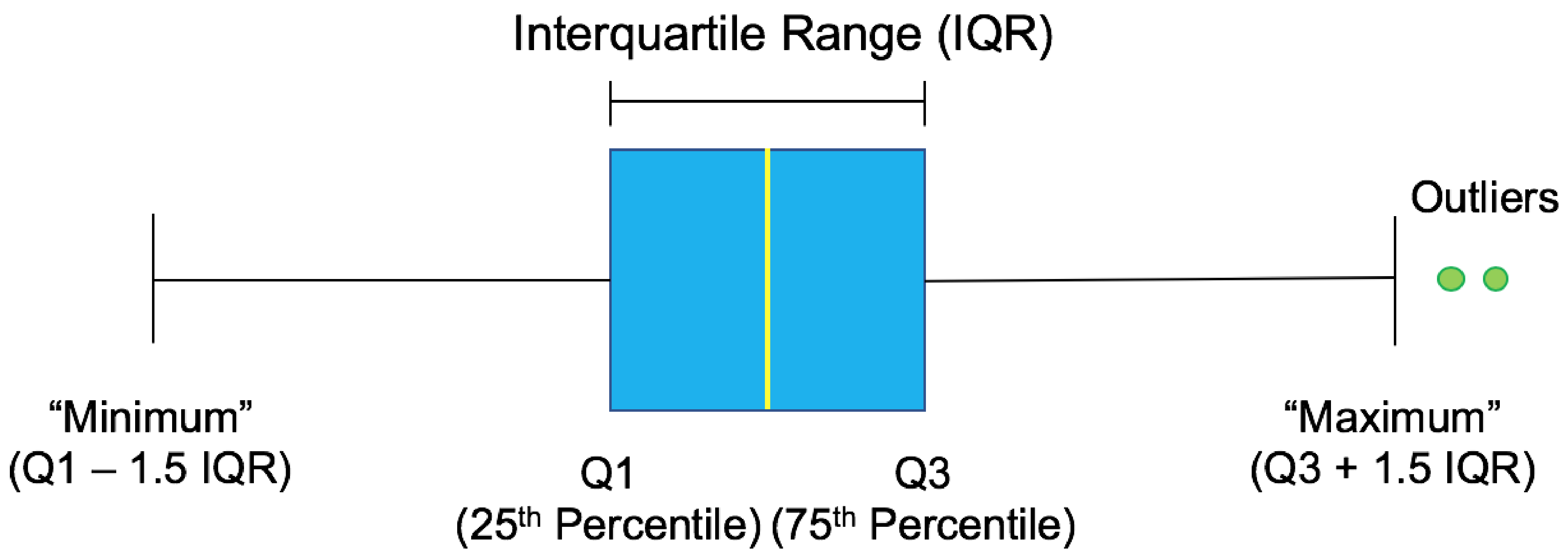
# Observing your data

```python
import matplotlib as plt

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

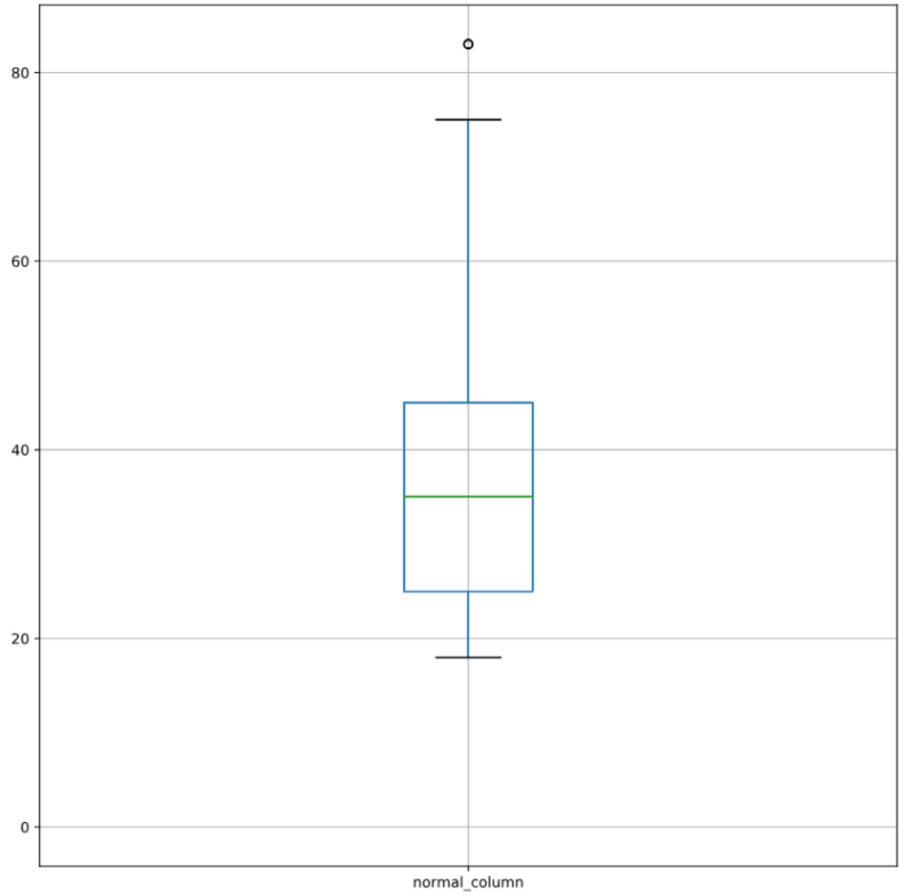


# Delving deeper with box plots



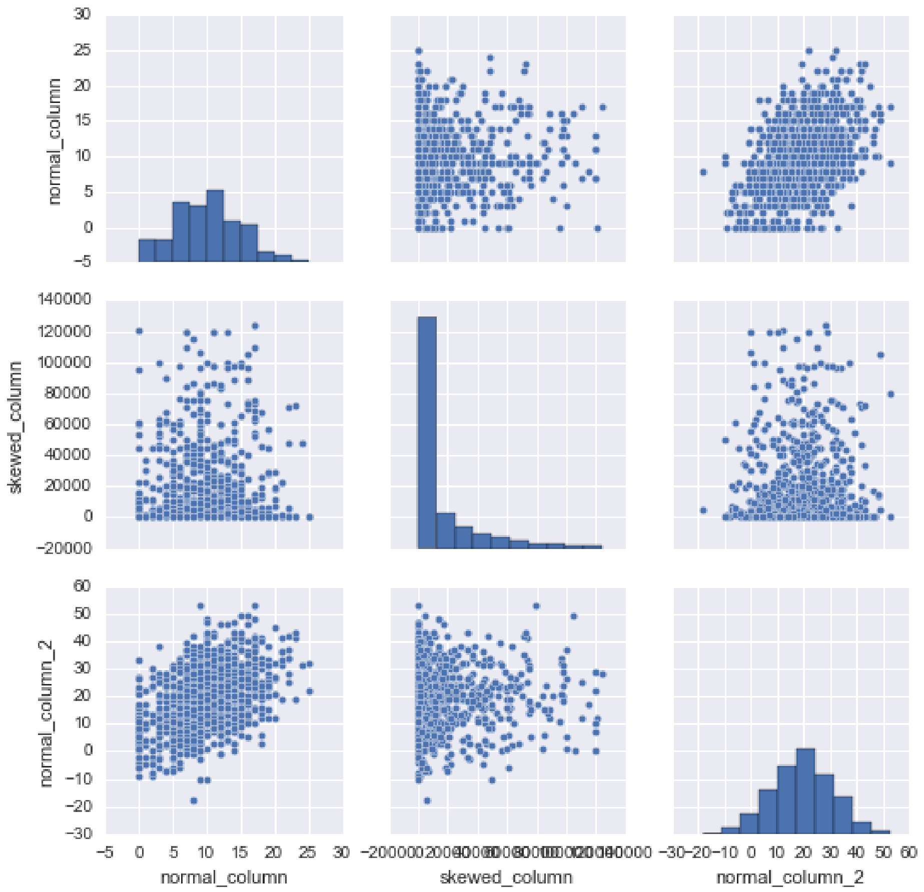
# Box plots in pandas

```
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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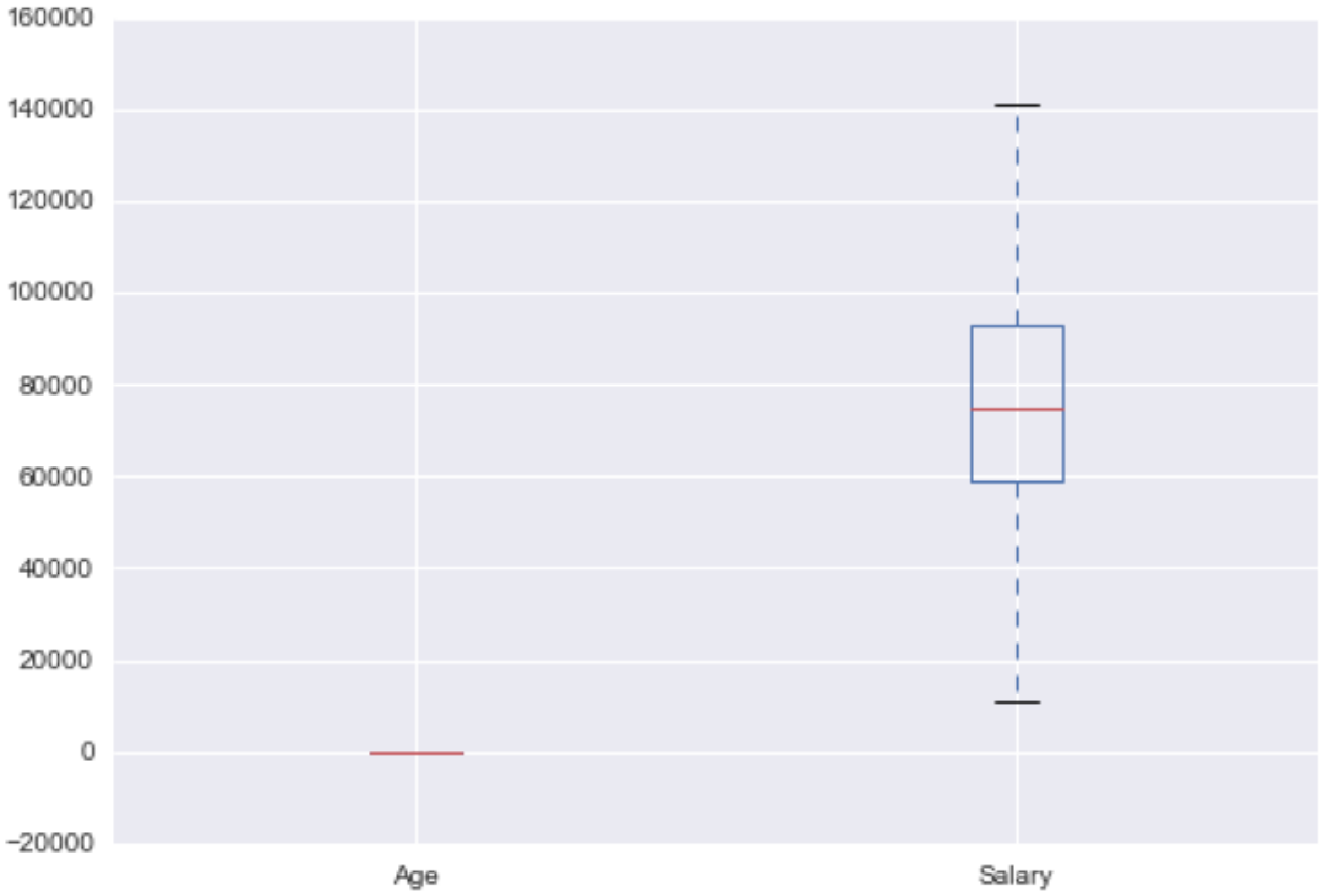
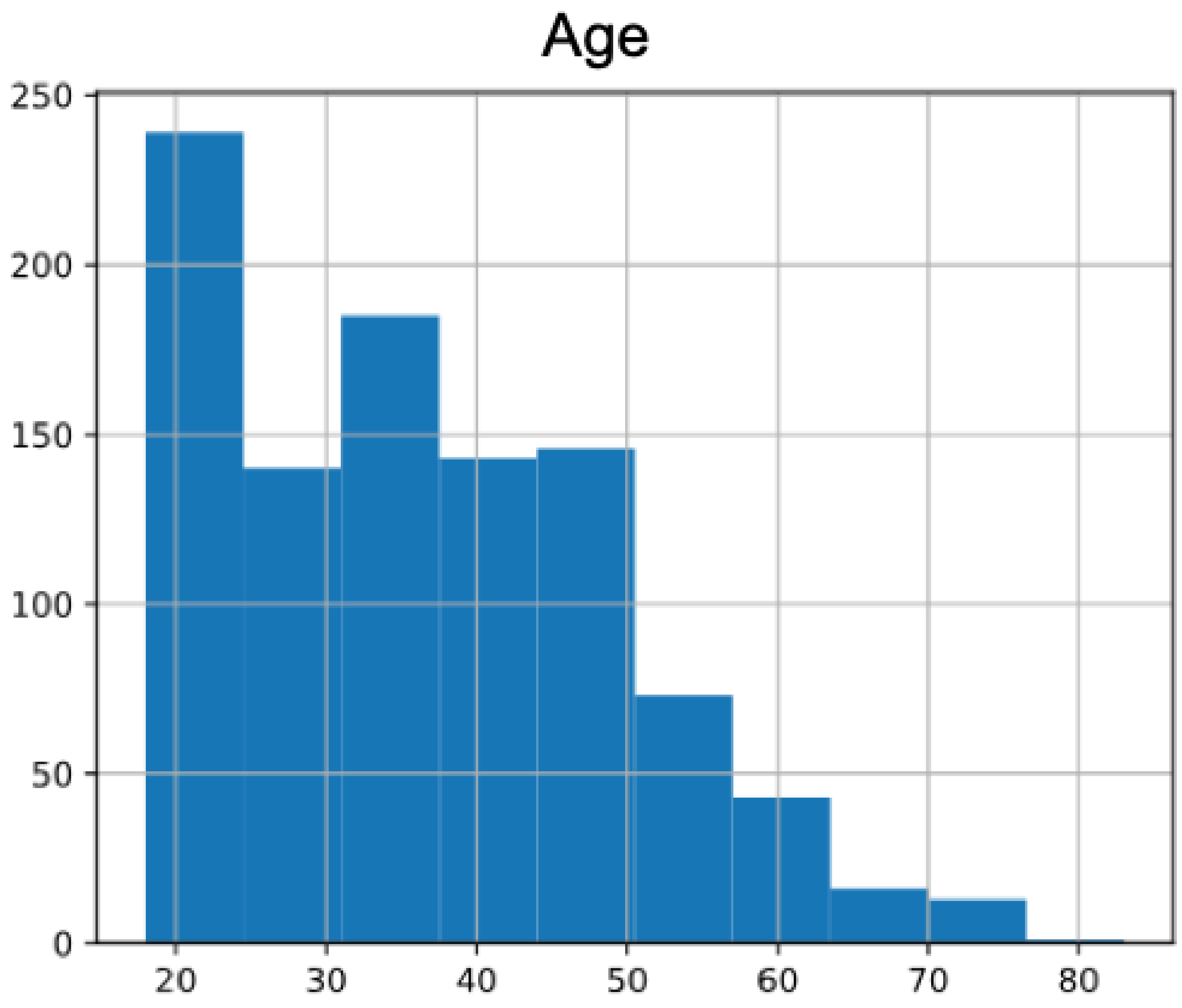
Data Scientist

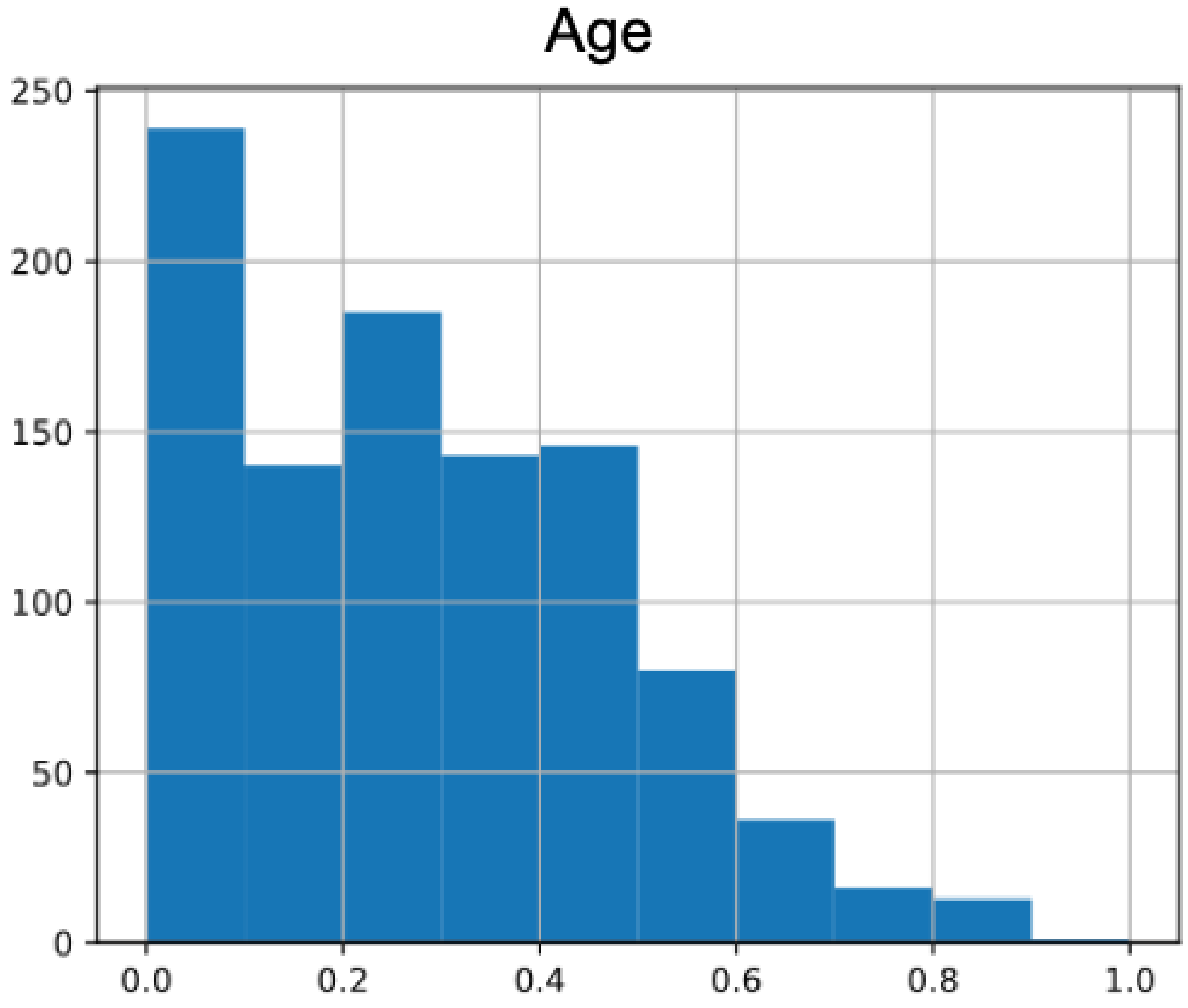
# Scaling data



# Min-Max scaling



# Min-Max scaling



# Min-Max scaling in Python

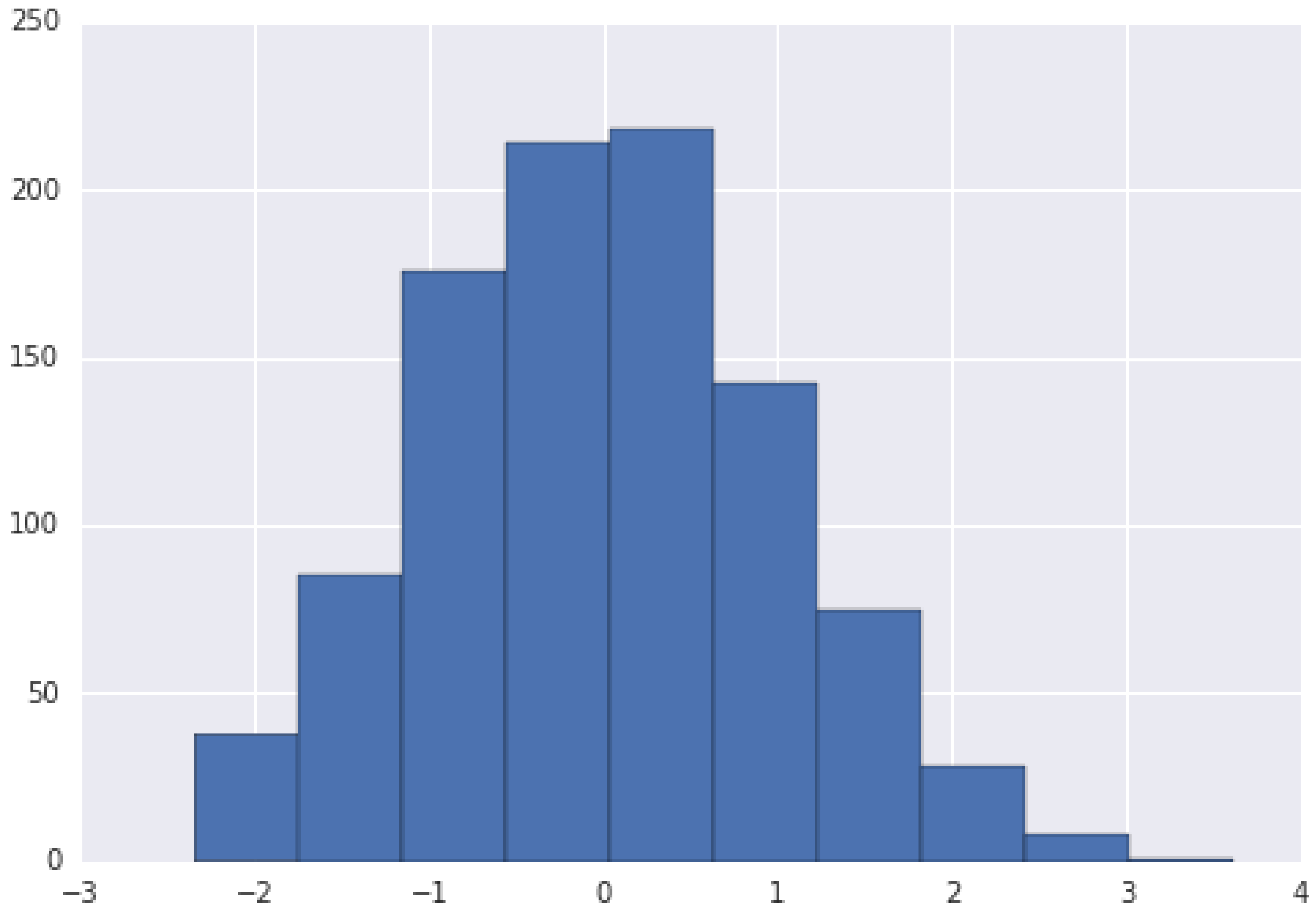
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

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

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

# Standardization



# Standardization in Python

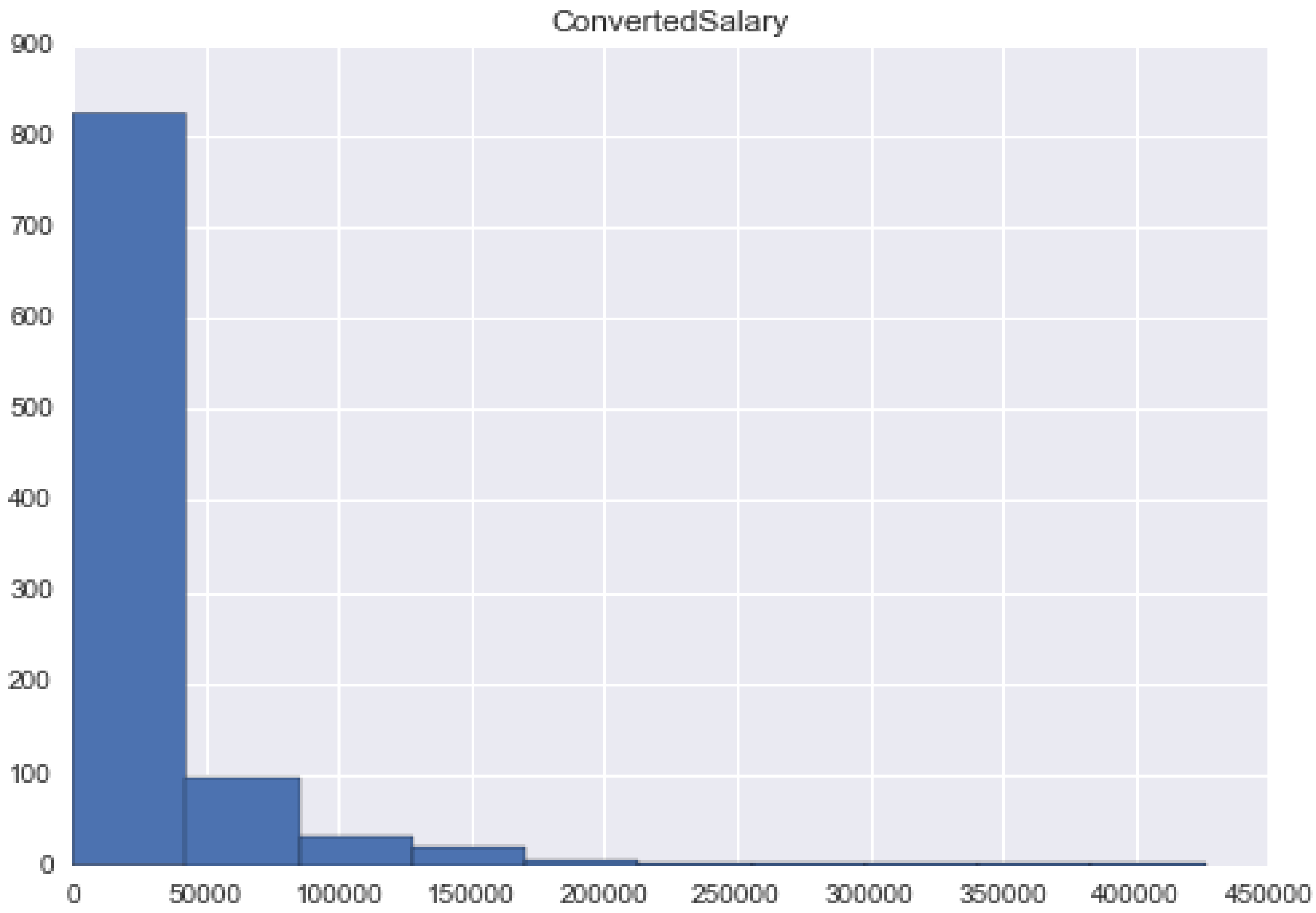
```
from sklearn.preprocessing import StandardScaler

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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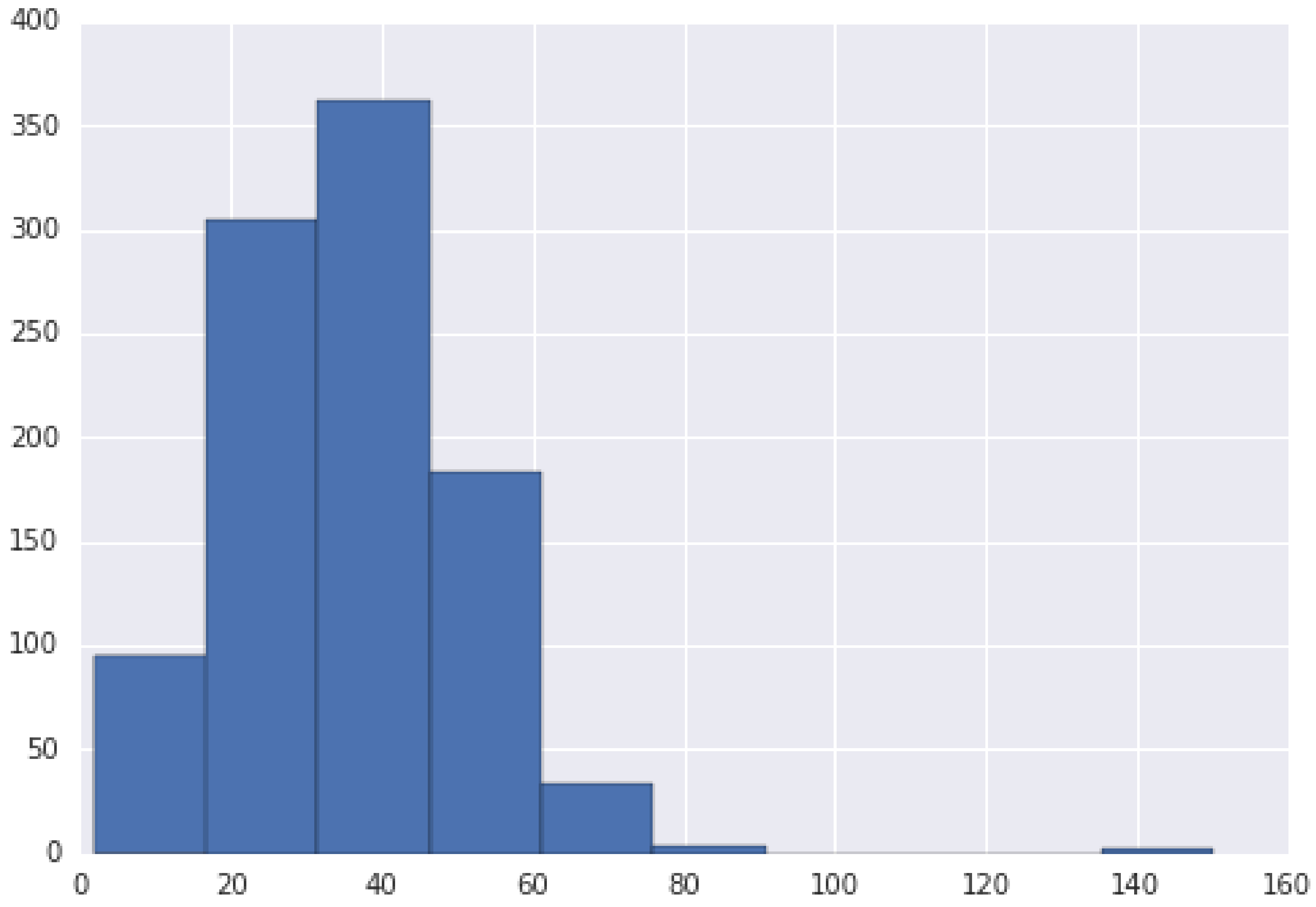
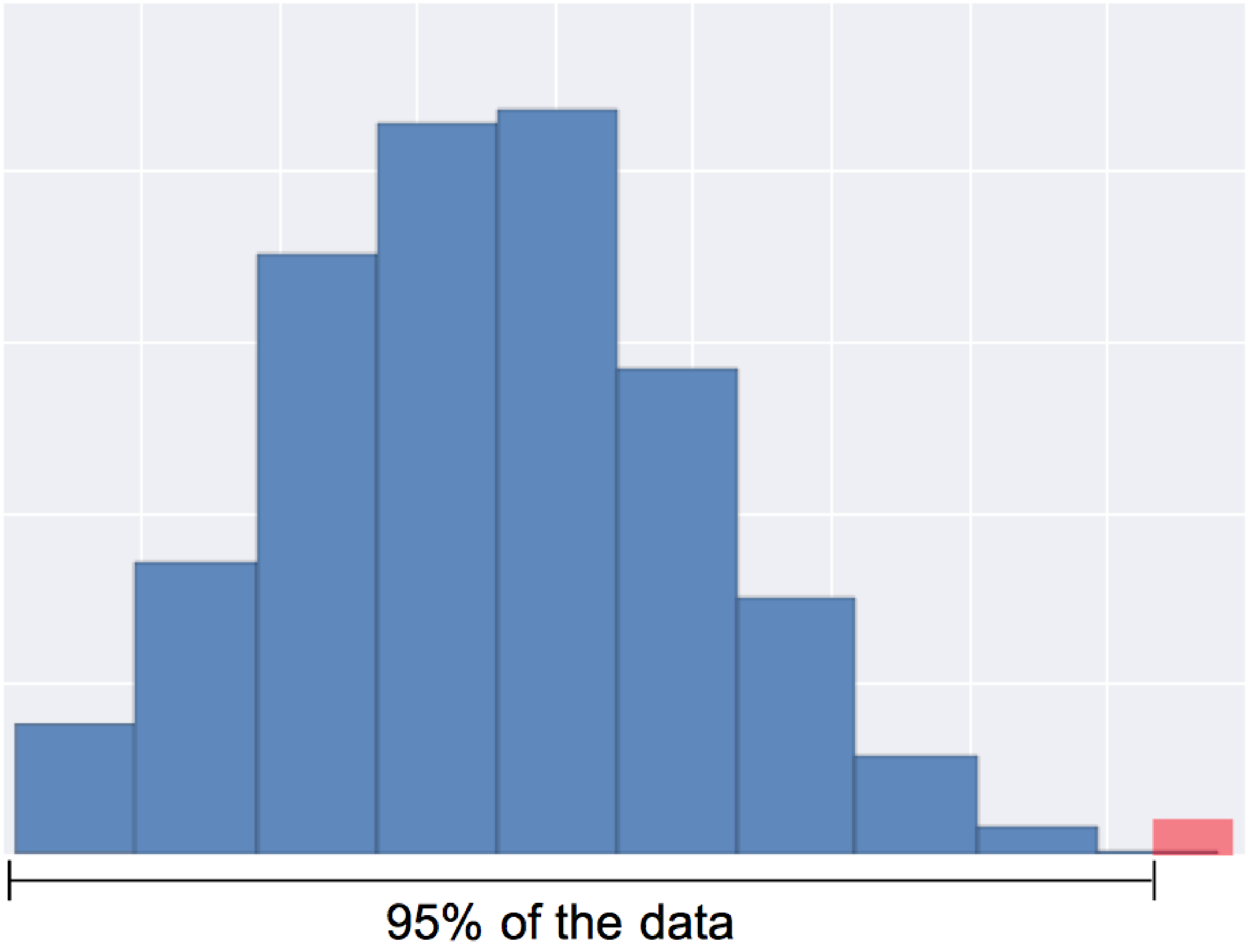
# What are outliers?



# Quantile based detection



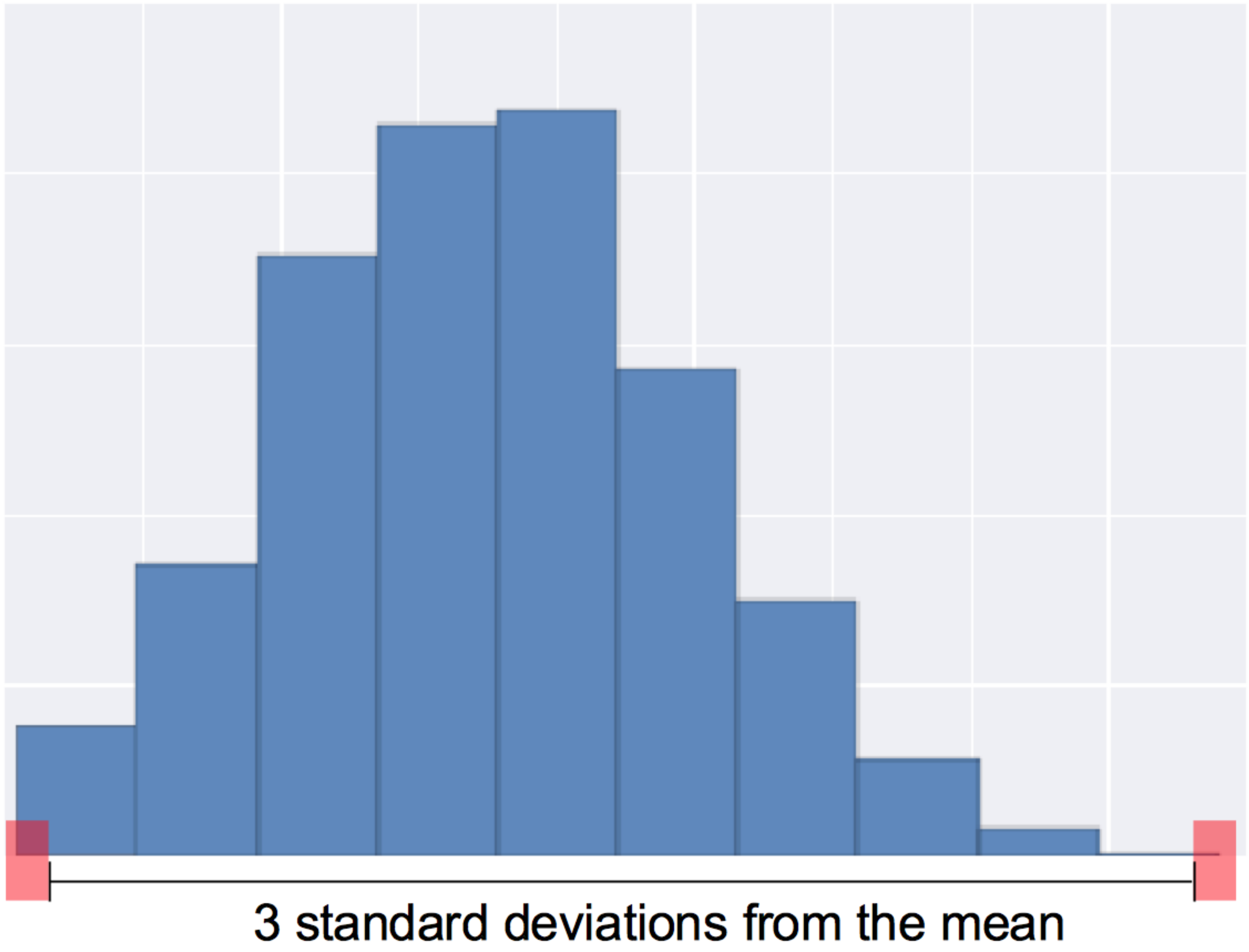
# Quantiles in Python

```
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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