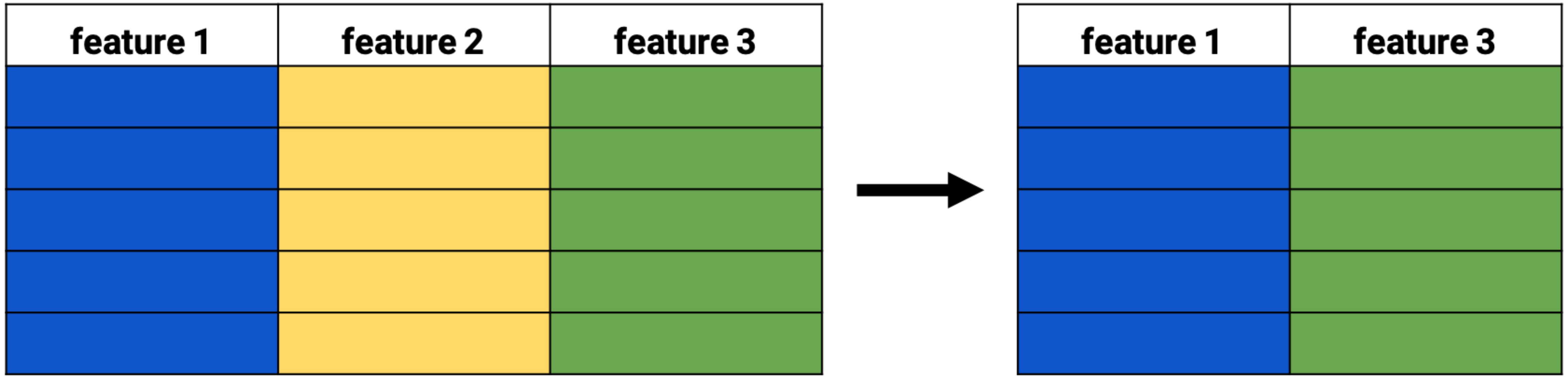
Feature extraction

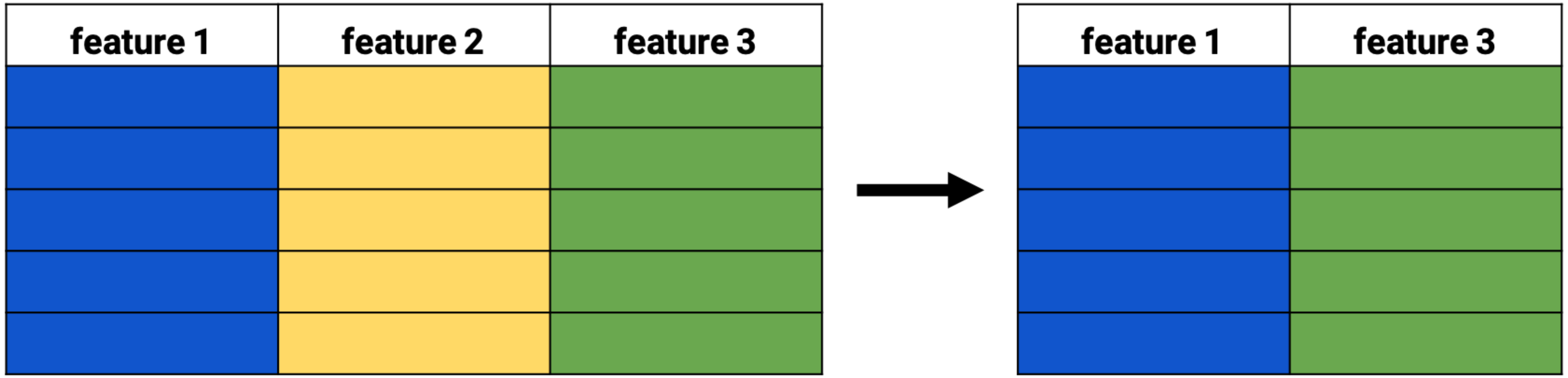
DIMENSIONALITY REDUCTION IN PYTHON

Jeroen Boeye
Head of Machine Learning, Faktion

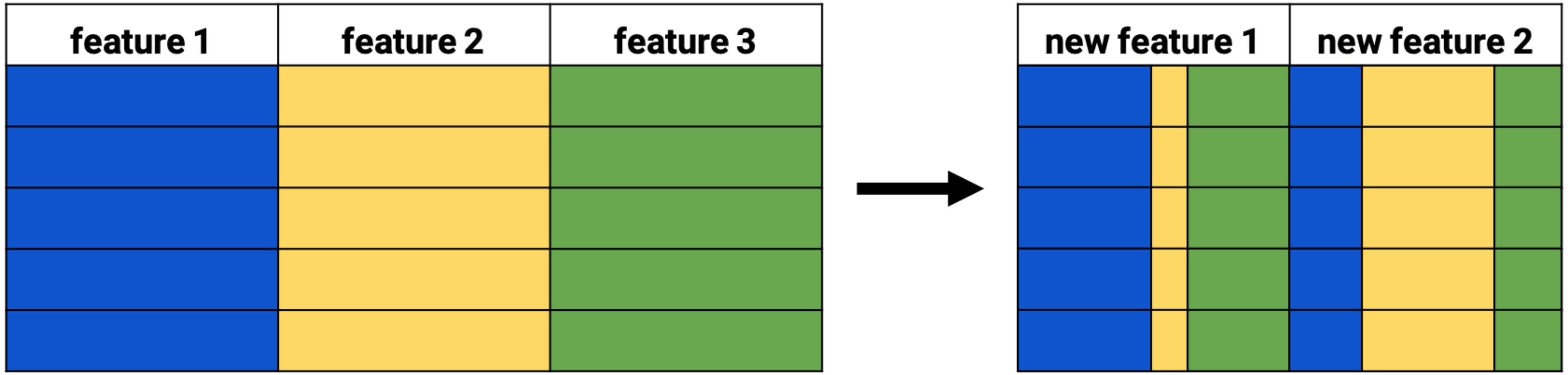
Feature selection



Feature selection



Feature extraction



Feature generation - BMI

```
df_body['BMI'] = df_body['Weight kg'] /  df_body['Height m'] ** 2
```

Feature generation - BMI

```
df_body['BMI'] = df_body['Weight kg'] /  df_body['Height m'] ** 2
```

Weight kg	Height m	BMI
81.5	1.776	25.84
72.6	1.702	25.06
92.9	1.735	30.86

Feature generation - BMI

```
df_body.drop(['Weight kg', 'Height m'], axis=1)
```

BMI
25.84
25.06
30.86

Feature generation - averages

left leg mm	right leg mm
882	885
870	869
901	900

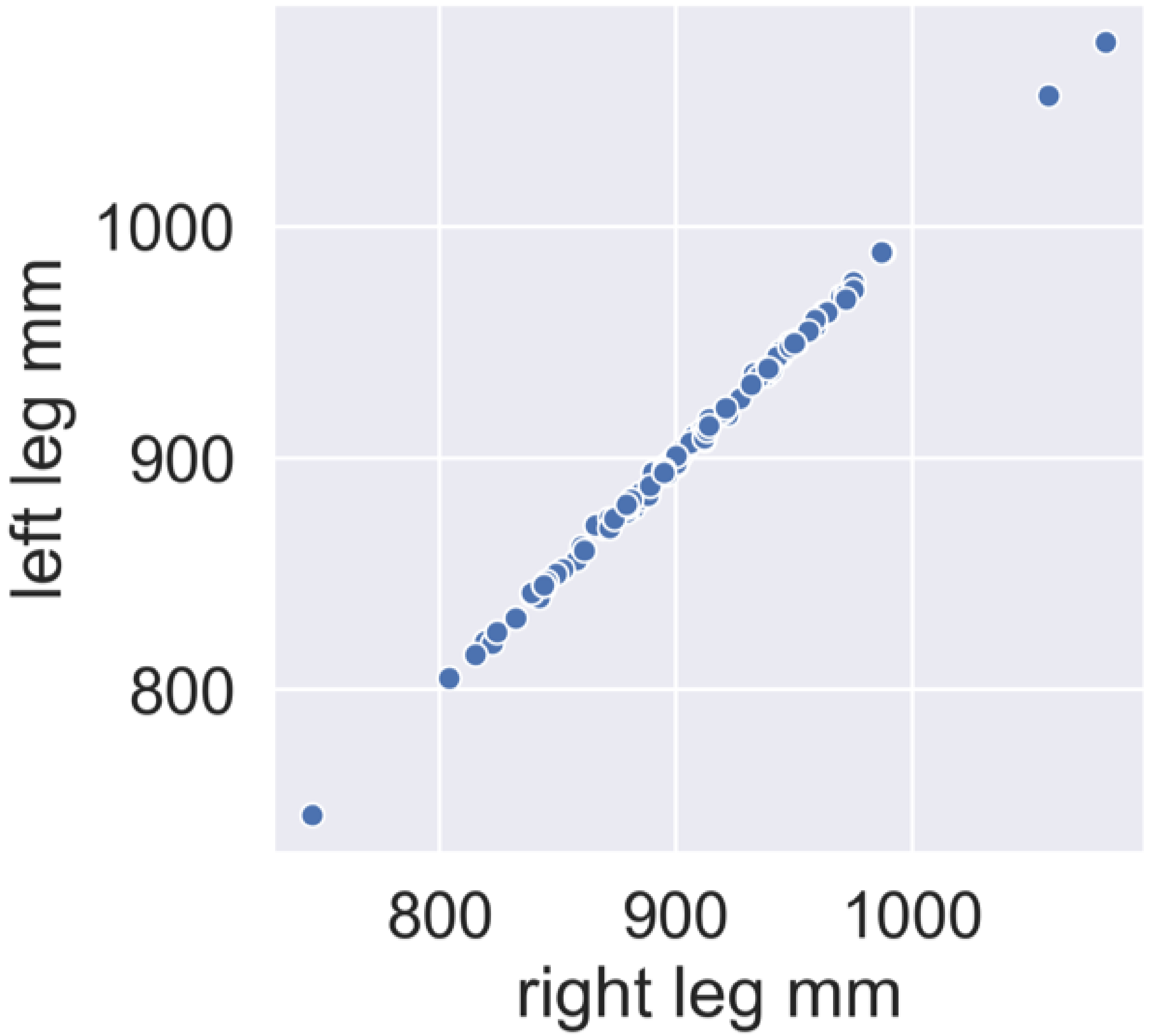
```
leg_df['leg mm'] = leg_df[['right leg mm', 'left leg mm']].mean(axis=1)
```

Feature generation - averages

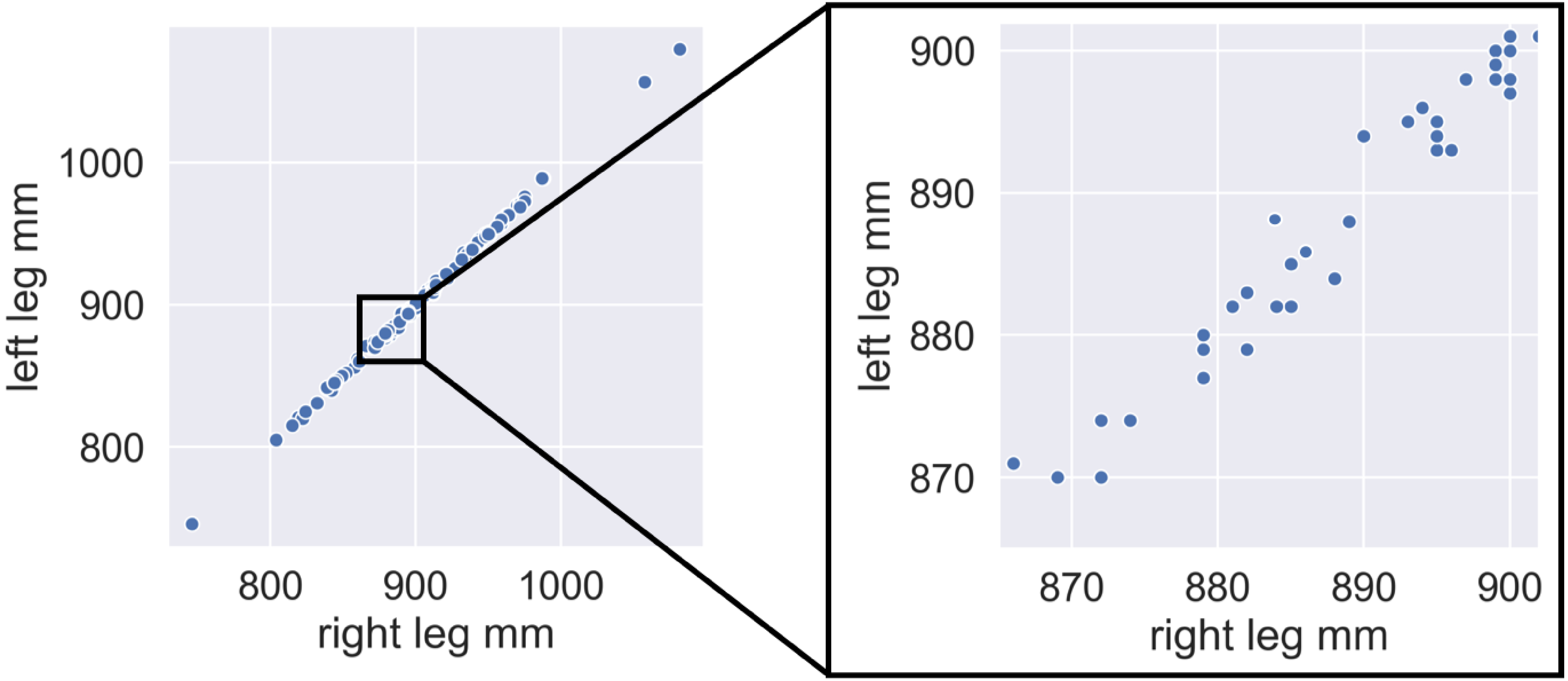
```
leg_df.drop(['right leg mm', 'left leg mm'], axis=1)
```

leg mm
883.5
869.5
900.5

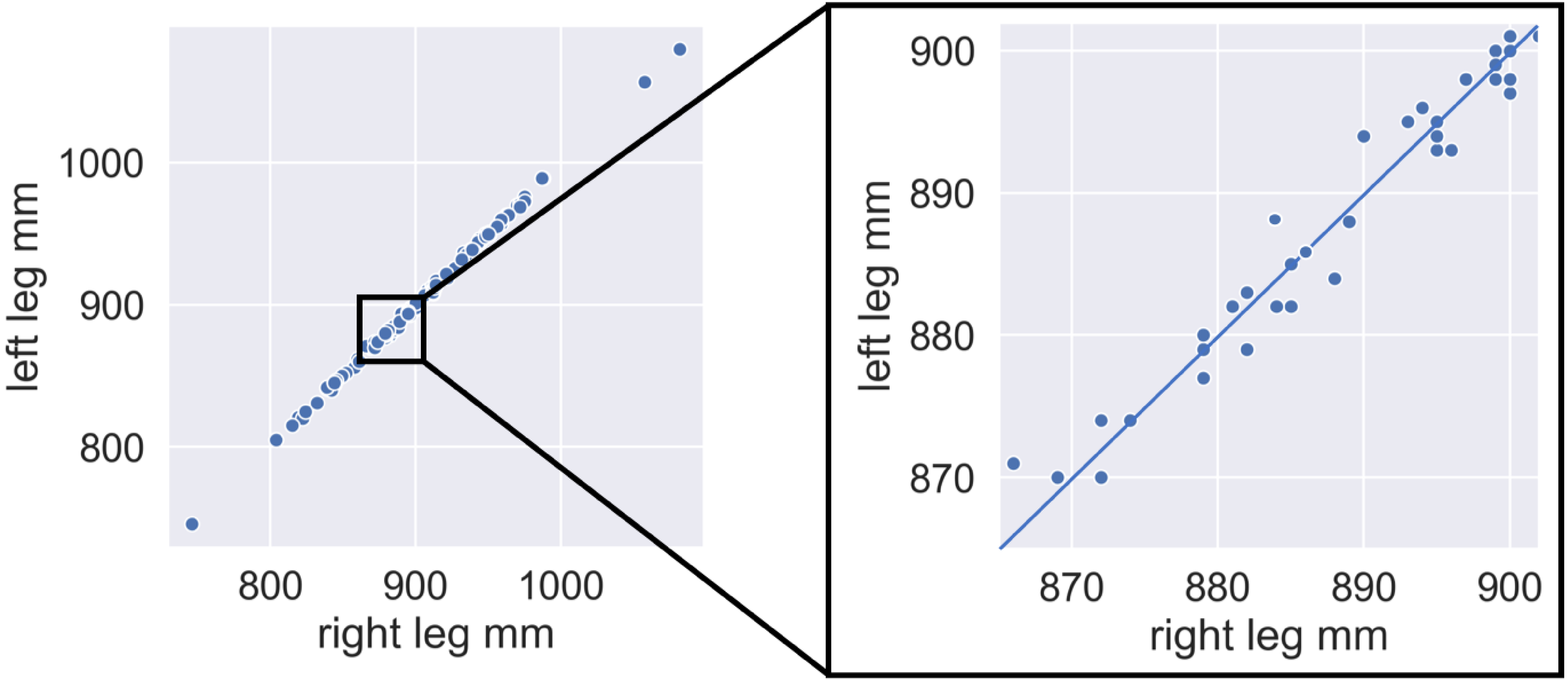
Cost of taking the average



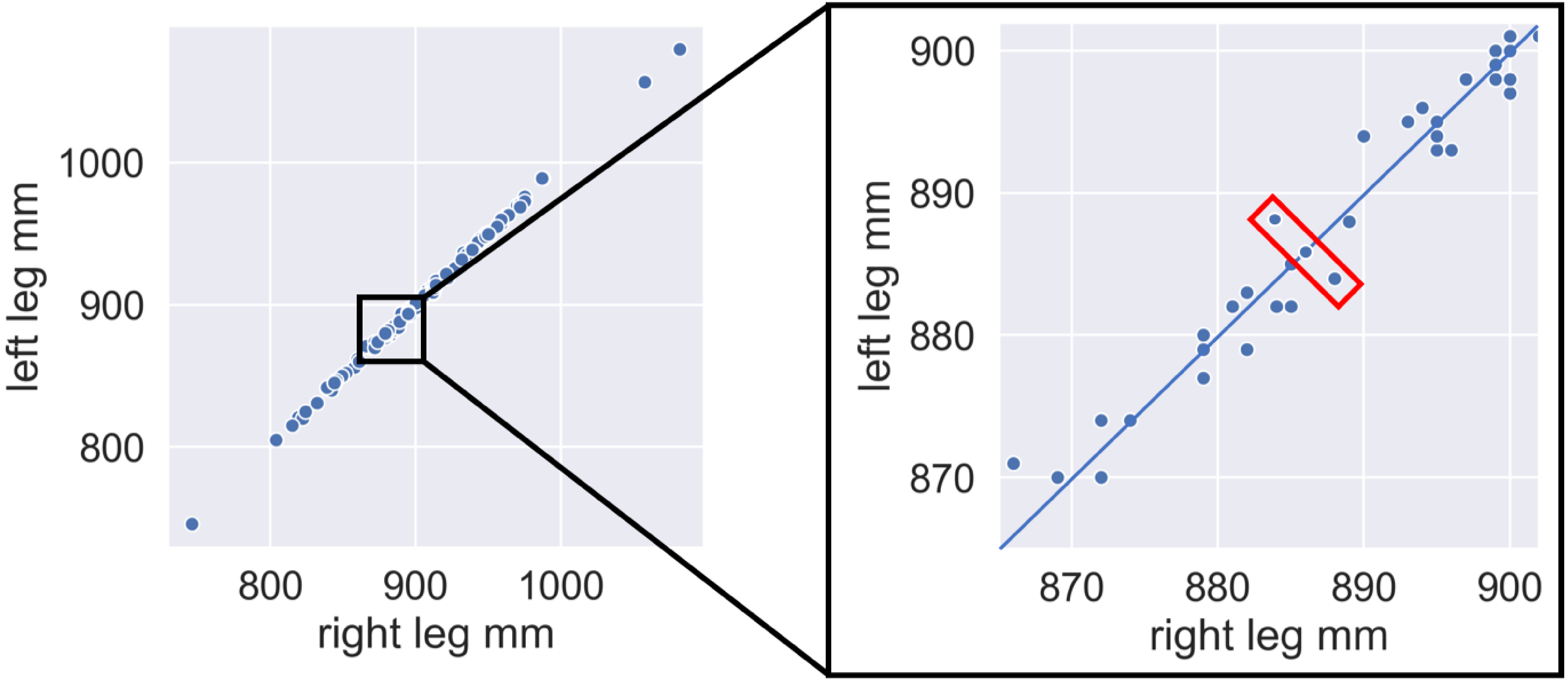
Cost of taking the average



Cost of taking the average

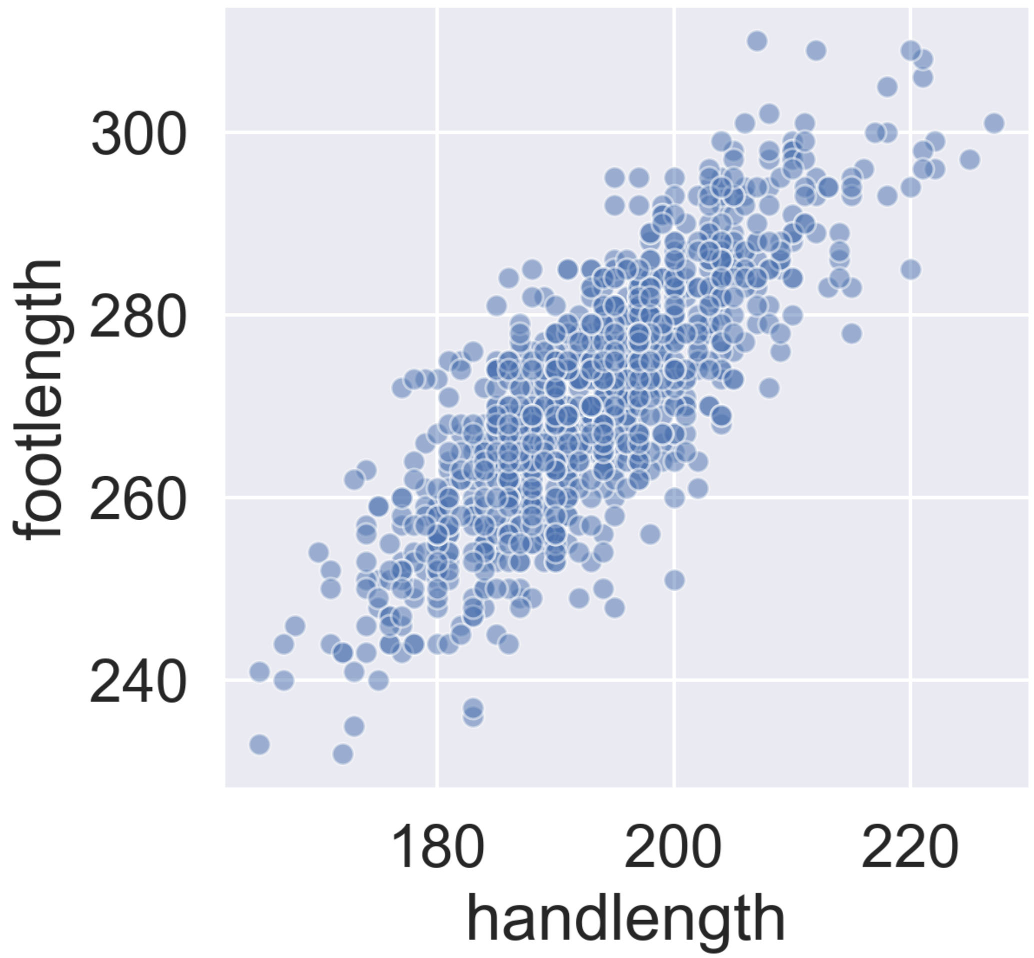


Cost of taking the average



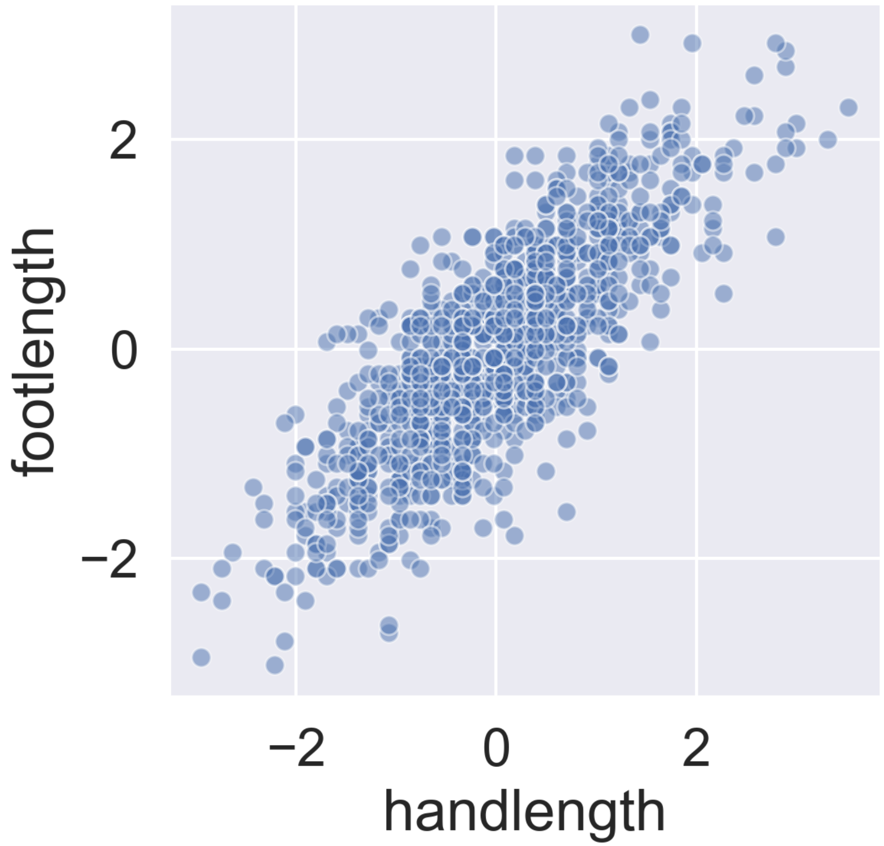
Intro to PCA

```
sns.scatterplot(data=df, x='handlength', y='footlength')
```



Intro to PCA

```
scaler = StandardScaler()
df_std = pd.DataFrame(scaler.fit_transform(df), columns = df.columns)
```



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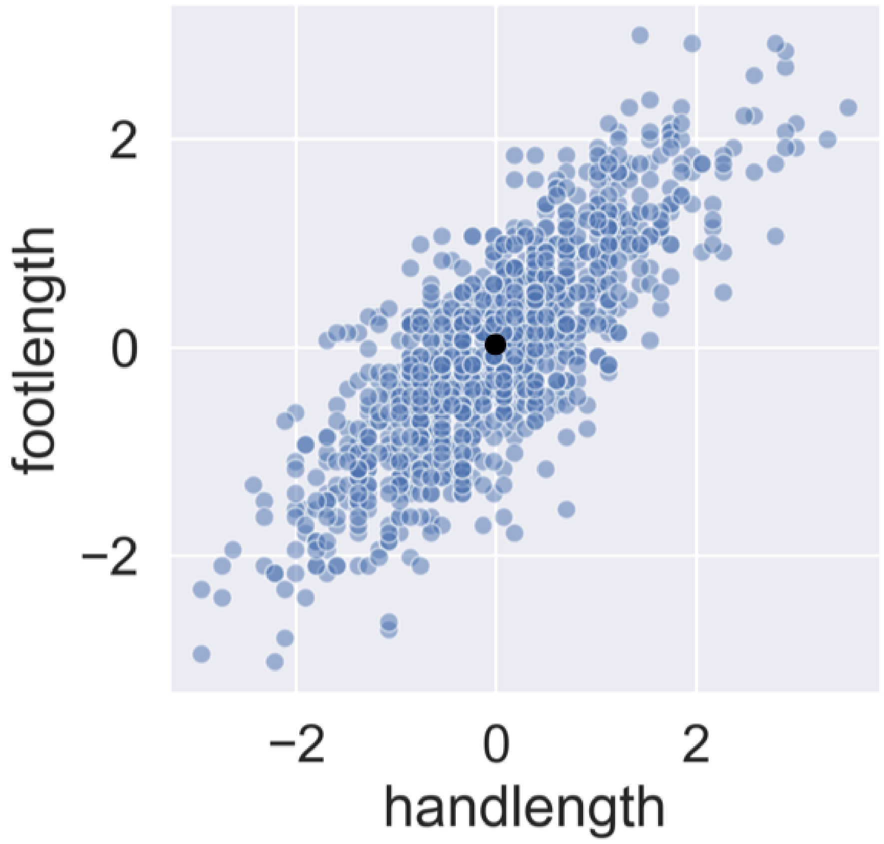

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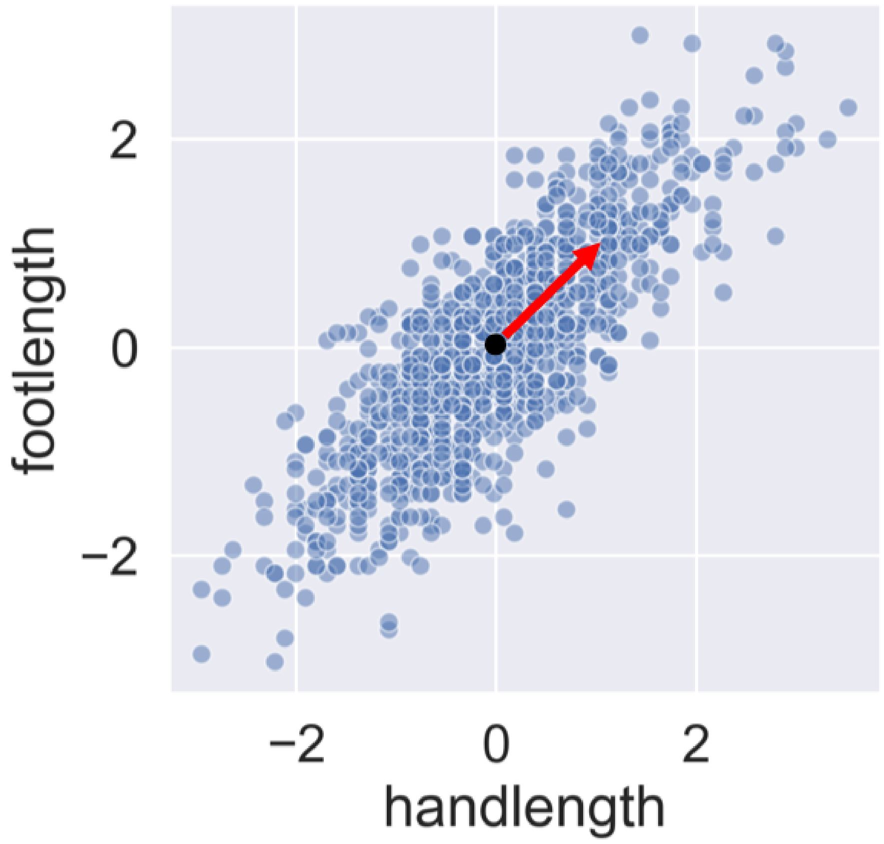

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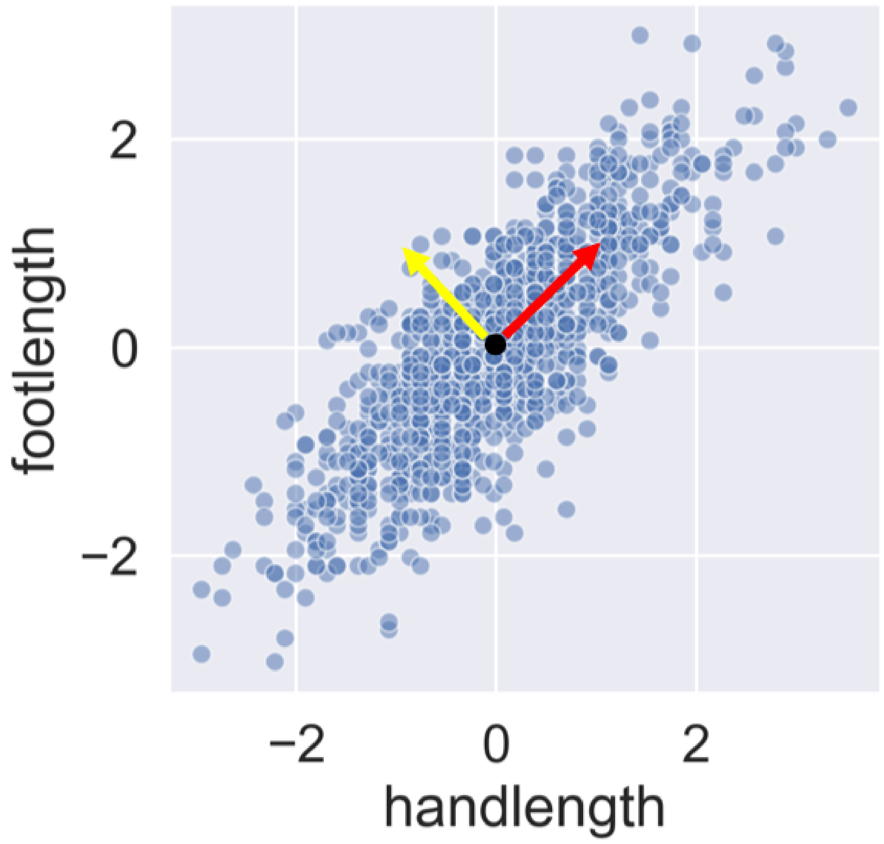

Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Principal component analysis

DIMENSIONALITY REDUCTION IN PYTHON

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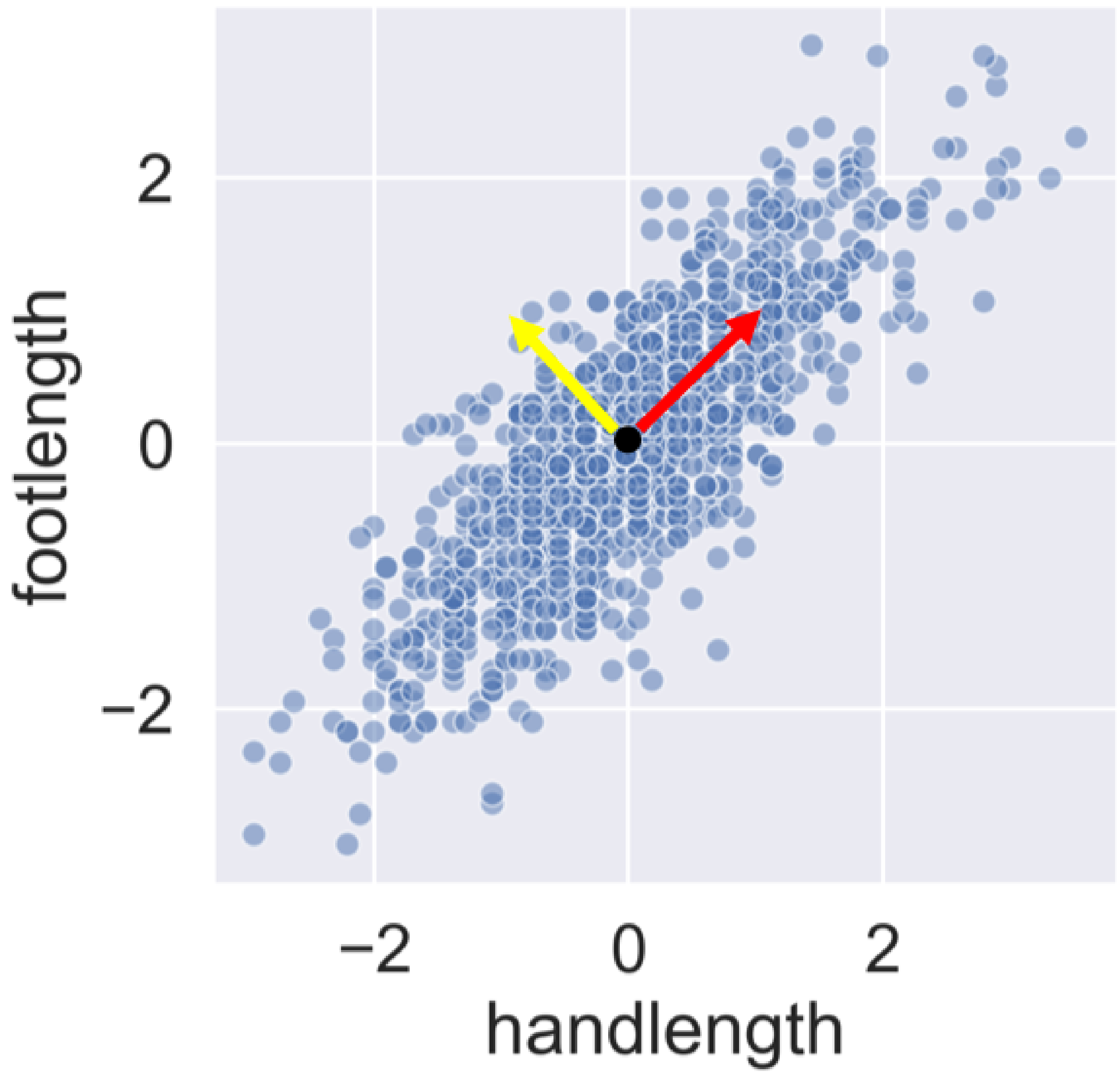
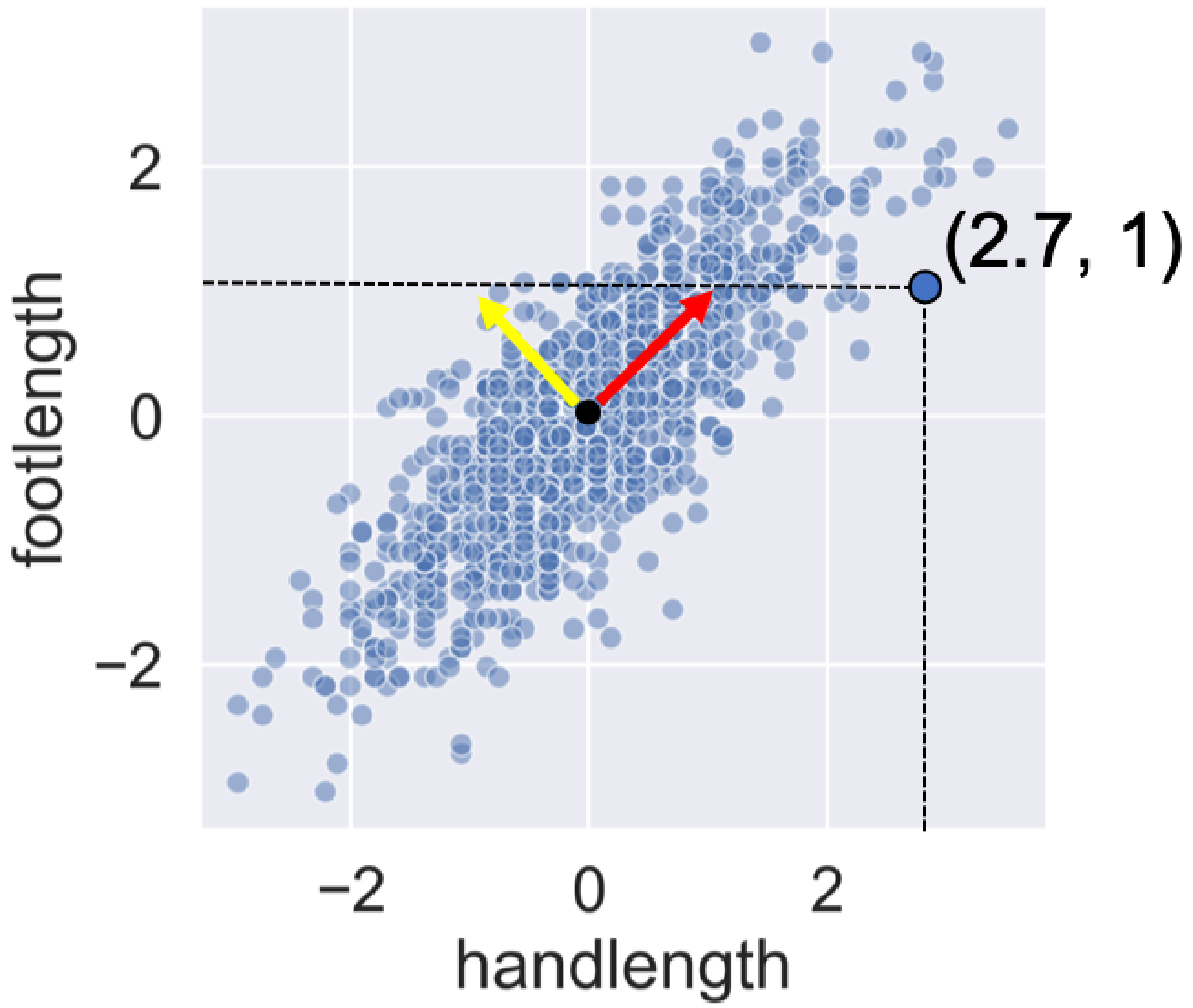
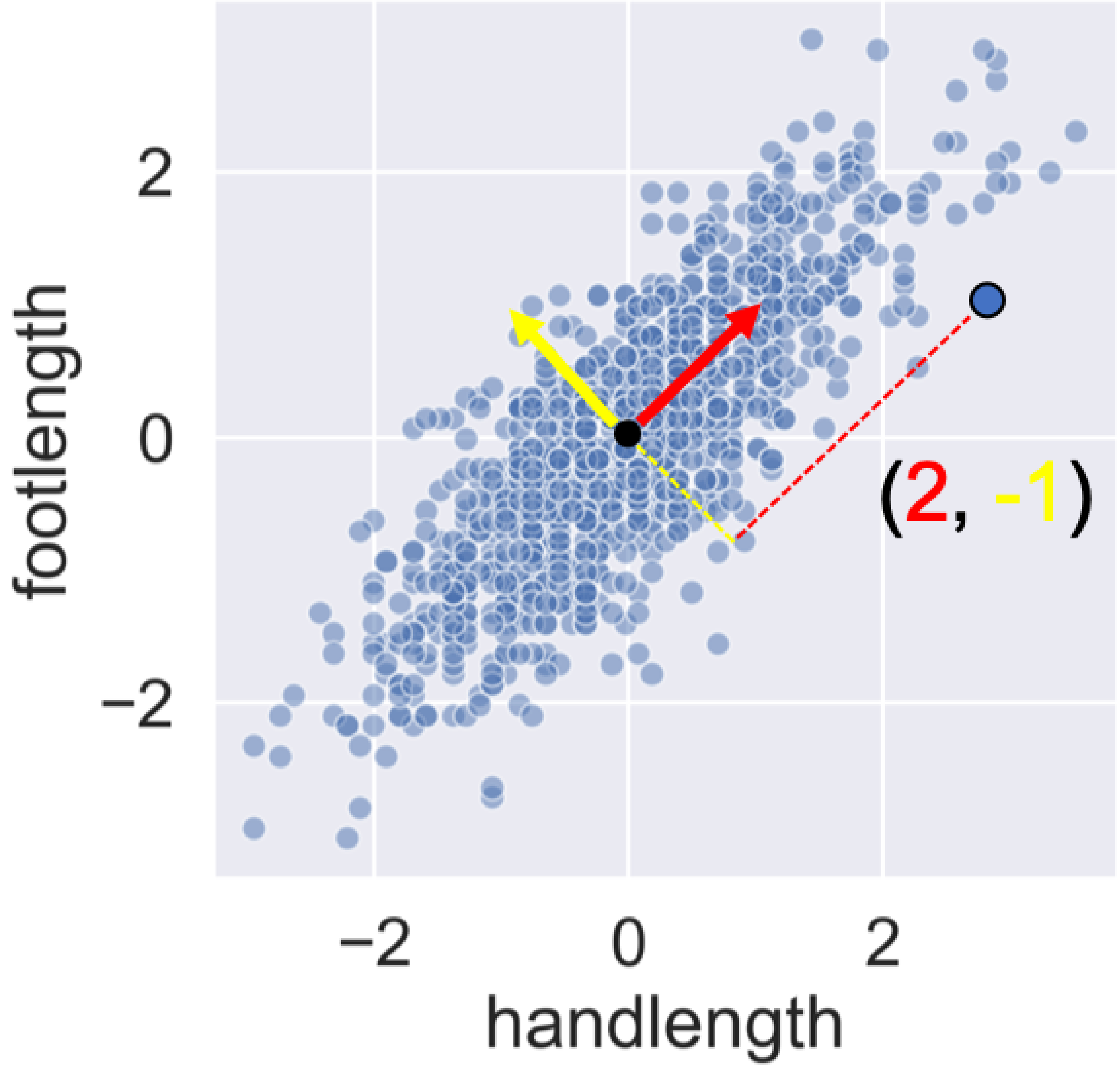
PCA concept



PCA concept



PCA concept

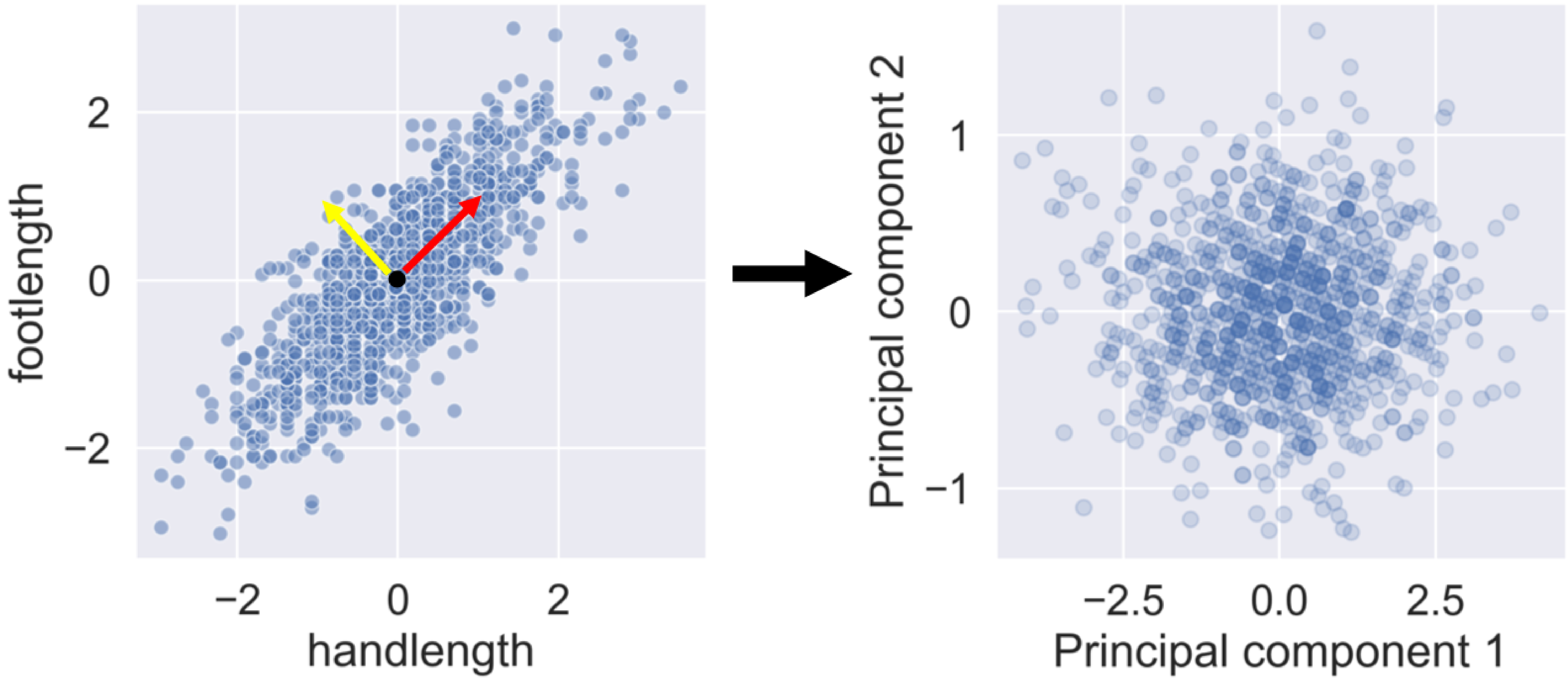


Calculating the principal components

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
std_df = scaler.fit_transform(df)
from sklearn.decomposition import PCA

pca = PCA()
print(pca.fit_transform(std_df))
```

```
[[-0.08320426 -0.12242952]
 [ 0.31478004  0.57048158]
 ...
 [-0.5609523   0.13713944]
 [-0.0448304  -0.37898246]]
```

PCA removes correlation

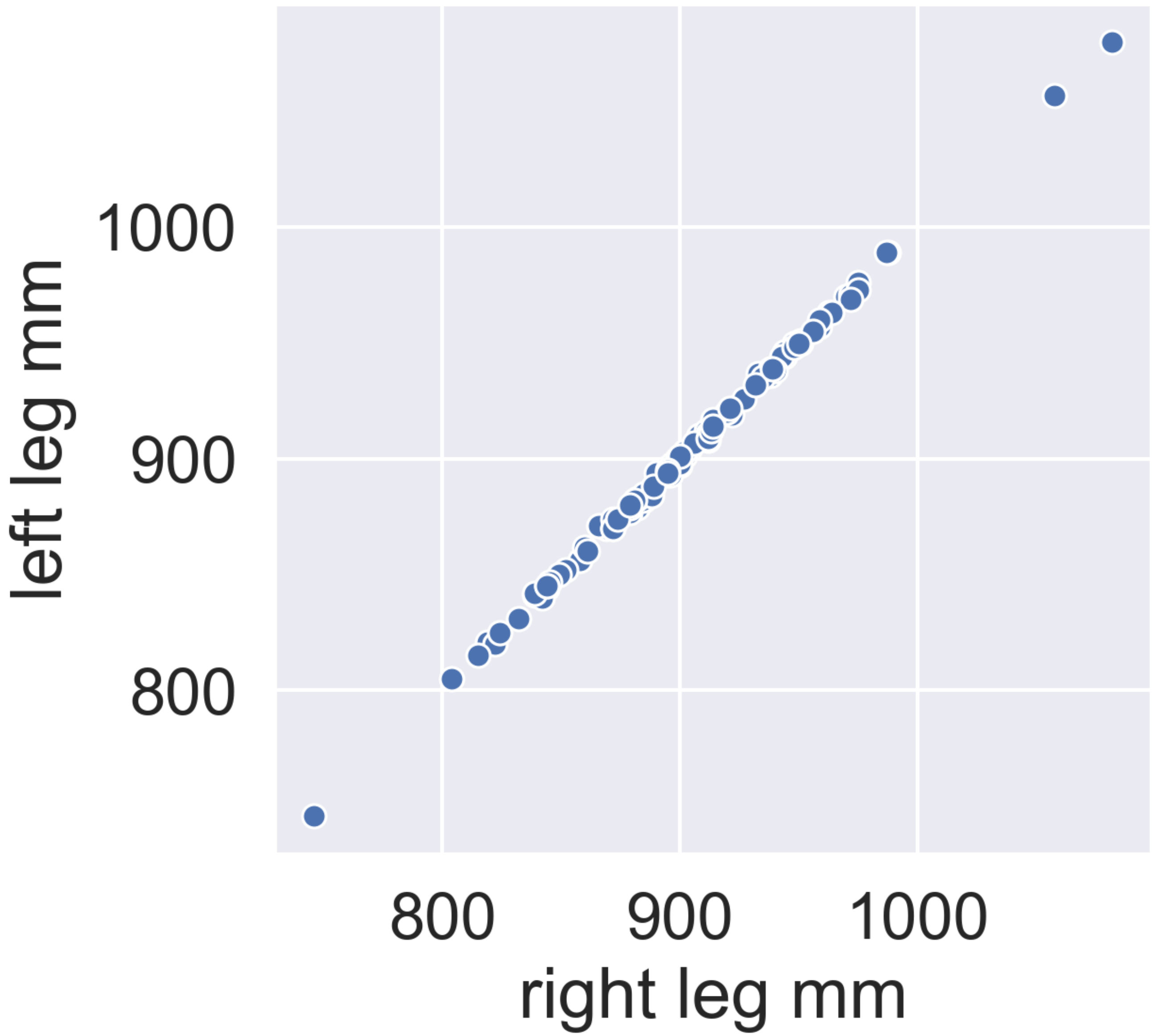


Principal component explained variance ratio

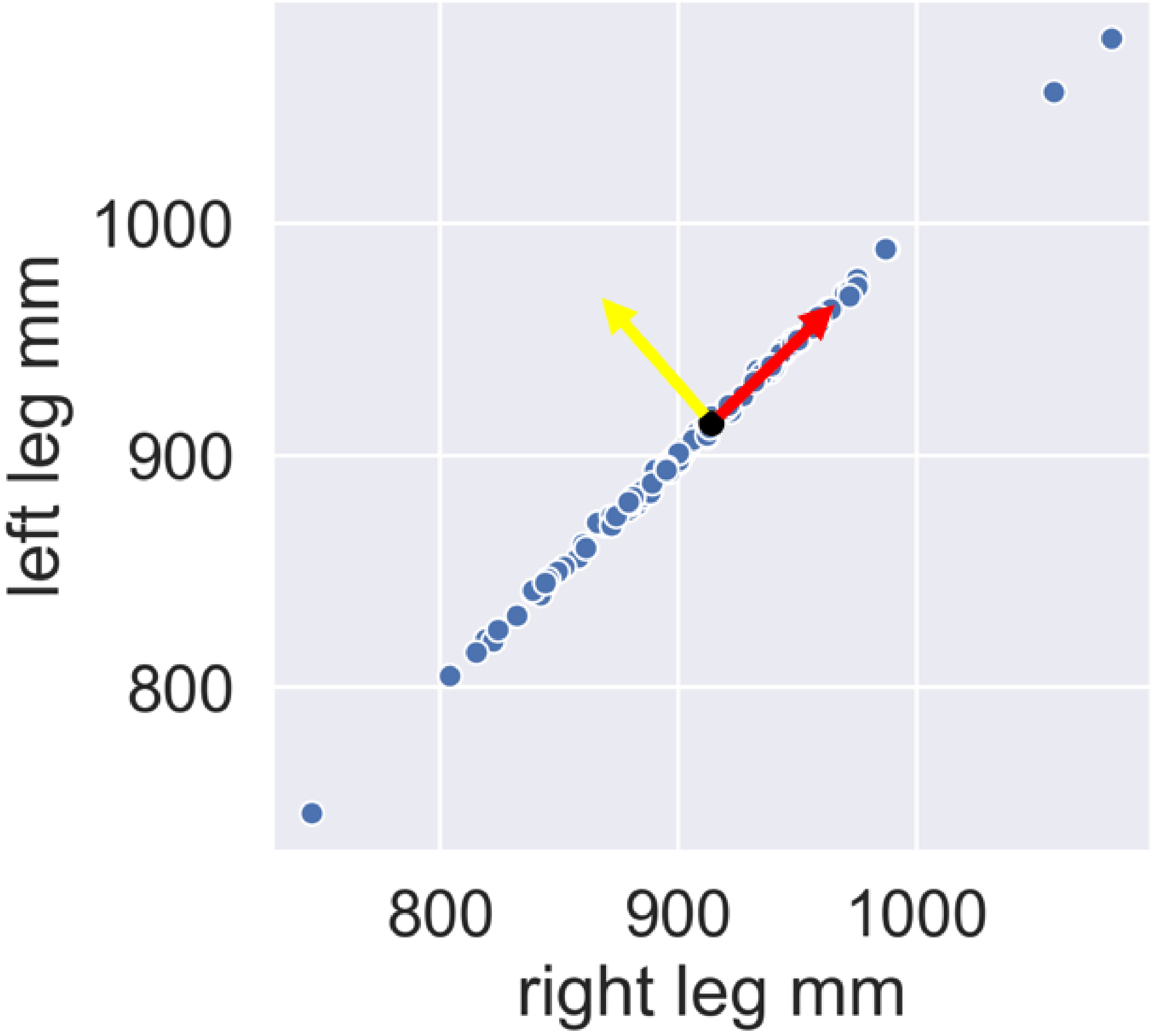
```
from sklearn.decomposition import PCA

pca = PCA()

pca.fit(std_df)

print(pca.explained_variance_ratio_)
```

```
array([0.90, 0.10])
```

PCA for dimensionality reduction



PCA for dimensionality reduction




```python
print(pca.explained_variance_ratio_)
```

```
array([0.9997, 0.0003])
```

PCA for dimensionality reduction

```
pca = PCA()

pca.fit(ansur_std_df)

print(pca.explained_variance_ratio_)
```

```
array([0.44, 0.18, 0.04, 0.03, 0.02, 0.02, 0.02, 0.01, 0.01, 0.01, 0.01,
       0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01,
       0.01, 0.01, 0.01, 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ,
       ...
       0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ,
       0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ,
       0.  , 0.  , 0.  , 0.  , 0.  , 0.  ])
```

PCA for dimensionality reduction

```
pca = PCA()

pca.fit(ansur_std_df)

print(pca.explained_variance_ratio_.cumsum())
```

```
array([0.44, 0.62, 0.66, 0.69, 0.72, 0.74, 0.76, 0.77, 0.79, 0.8 , 0.81,
       0.82, 0.83, 0.84, 0.85, 0.86, 0.87, 0.87, 0.88, 0.89, 0.89, 0.9 ,
       0.9 , 0.91, 0.92, 0.92, 0.92, 0.93, 0.93, 0.94, 0.94, 0.94, 0.95,
       ...
       0.99, 0.99, 0.99, 0.99, 0.99, 1.  , 1.  , 1.  , 1.  , 1.  , 1.  ,
       1.  , 1.  , 1.  , 1.  , 1.  , 1.  , 1.  , 1.  , 1.  , 1.  , 1.  ,
       1.  , 1.  , 1.  , 1.  , 1.  , 1.  ])
```

Let's practice!

PCA applications

DIMENSIONALITY REDUCTION IN PYTHON

Jeroen Boeye
Head of Machine Learning, Faktion

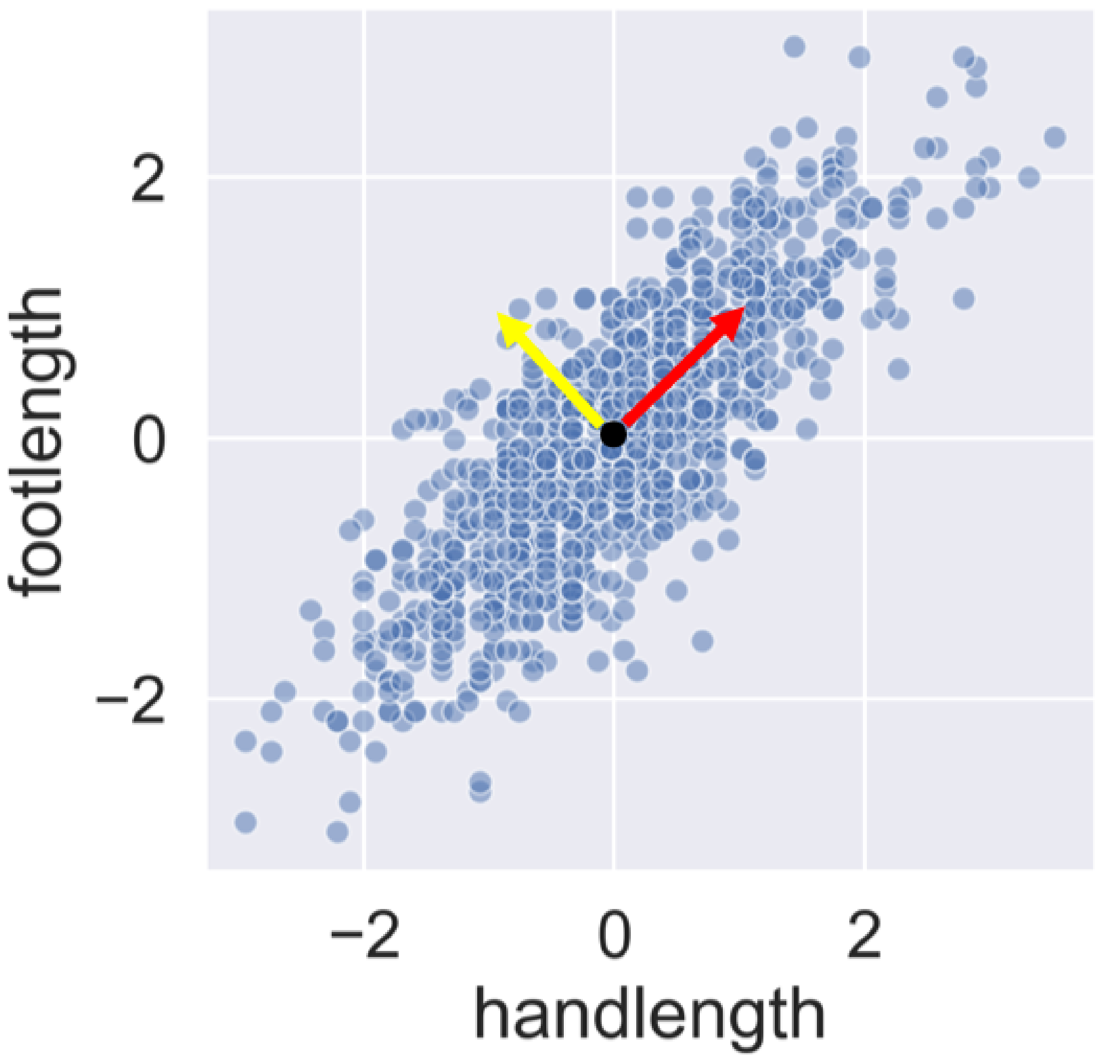
Understanding the components

```python
print(pca.components_)
```

```
array([[  0.71, 0.71],
       [ -0.71, 0.71]])
```

PC 1 = 0.71 x Hand length + 0.71 x Foot length

PC 2 = -0.71 x Hand length + 0.71 x Foot length



PCA for data exploration

PCA in a pipeline

```python
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline

pipe = Pipeline([
        ('scaler', StandardScaler()),
        ('reducer', PCA())])
pc = pipe.fit_transform(ansur_df)

print(pc[:,:2])
```

```
array([[-3.46114925,  1.5785215 ],
       [ 0.90860615,  2.02379935],
       ...,
       [10.7569818 , -1.40222755],
       [ 7.64802025,  1.07406209]])
```

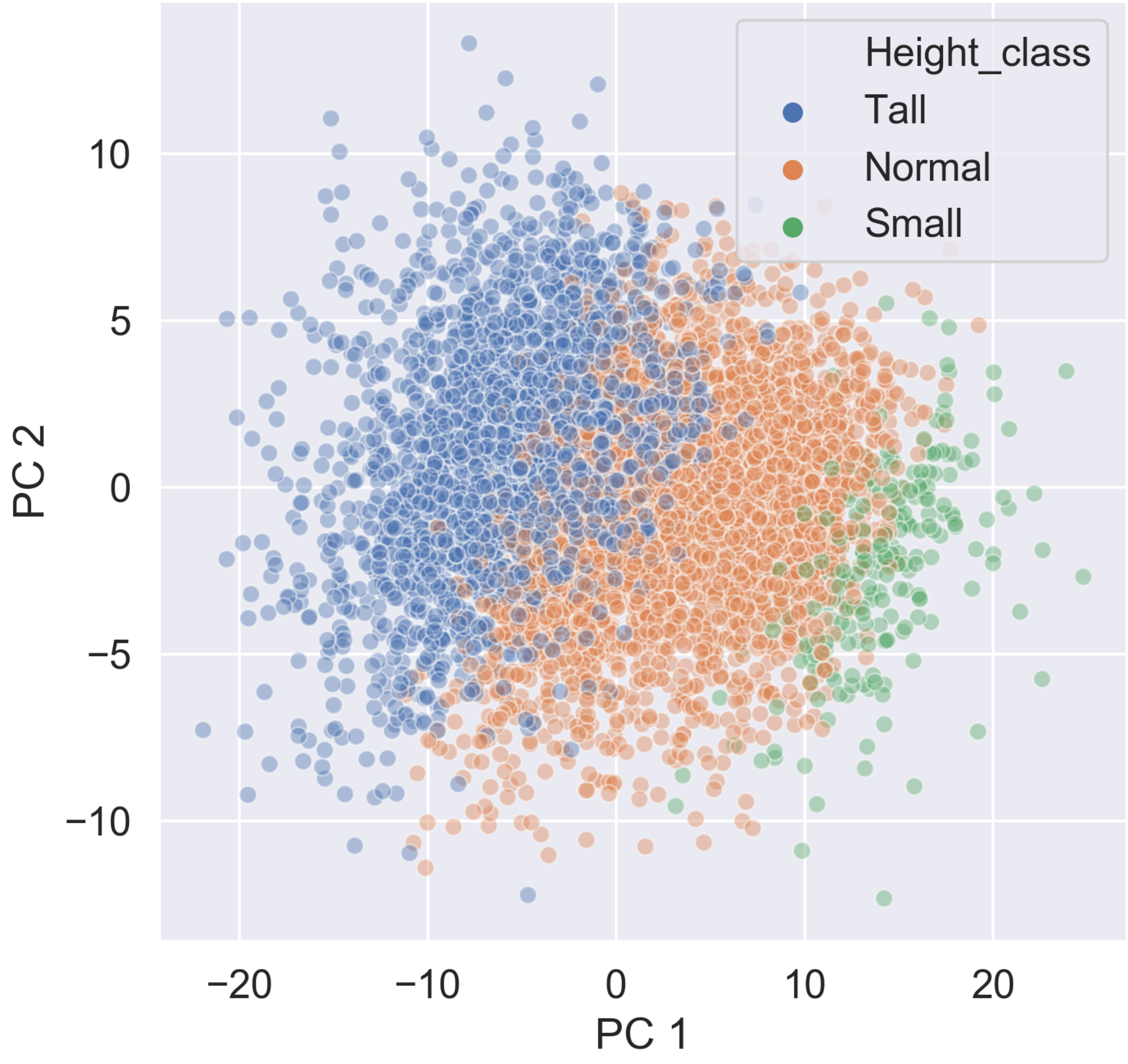
Checking the effect of categorical features

```
print(ansur_categories.head())
```

```
   Branch                   Component     Gender  BMI_class   Height_class
0  Combat Arms              Regular Army  Male    Overweight  Tall
1  Combat Support           Regular Army  Male    Overweight  Normal
2  Combat Support           Regular Army  Male    Overweight  Normal
3  Combat Service Support   Regular Army  Male    Overweight  Normal
4  Combat Service Support   Regular Army  Male    Overweight  Tall
```

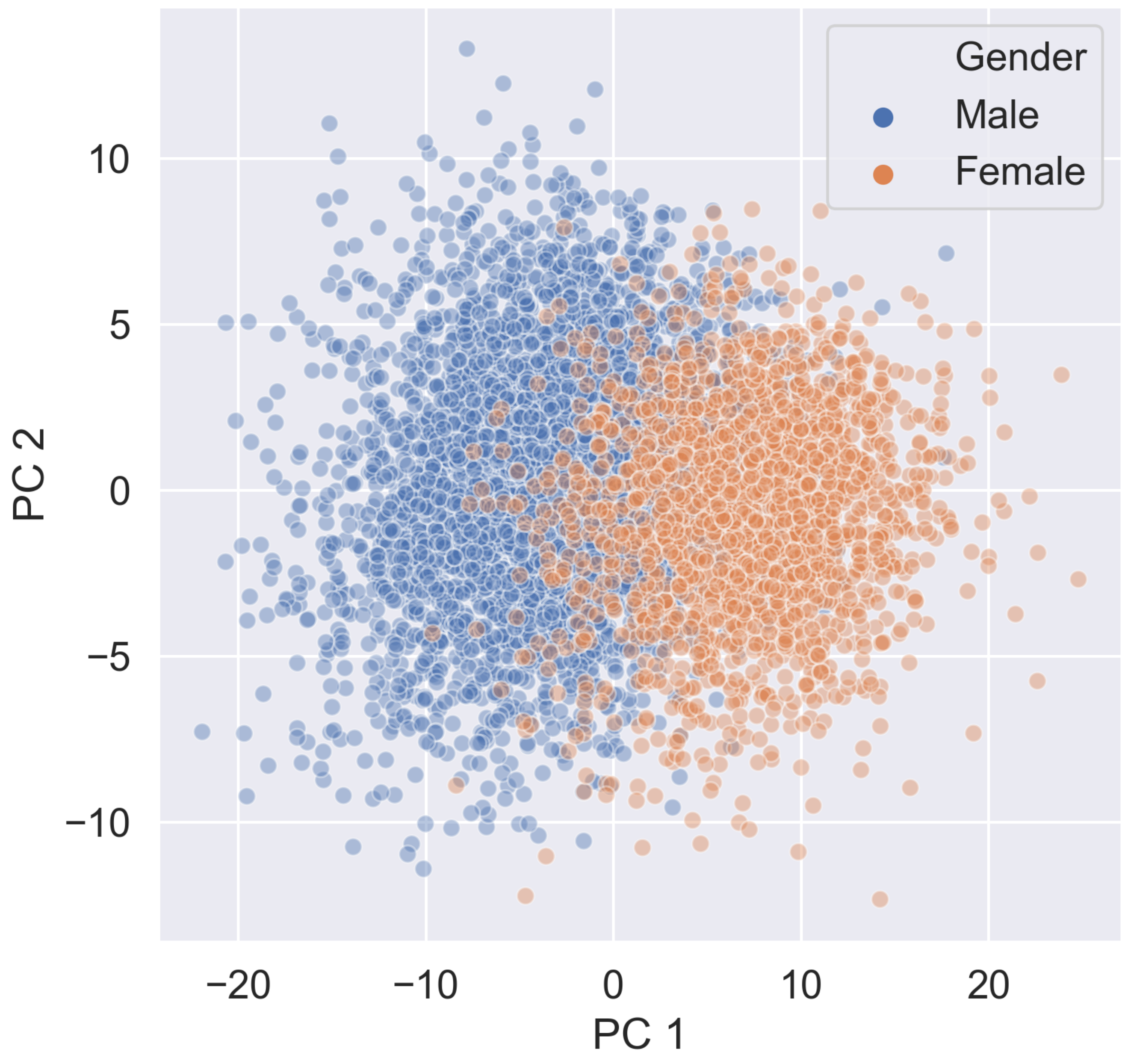
Checking the effect of categorical features

```
ansur_categories['PC 1'] = pc[:,0]
ansur_categories['PC 2'] = pc[:,1]
sns.scatterplot(data=ansur_categories,
                x='PC 1', y='PC 2',
                hue='Height_class', alpha=0.4)
```



Checking the effect of categorical features

```
sns.scatterplot(data=ansur_categories,
                x='PC 1', y='PC 2',
                hue='Gender', alpha=0.4)
```



Checking the effect of categorical features

```
sns.scatterplot(data=ansur_categories,
                x='PC 1', y='PC 2',
                hue='BMI_class', alpha=0.4)
```

PCA in a model pipeline

```
pipe = Pipeline([
        ('scaler', StandardScaler()),
        ('reducer', PCA(n_components=3)),
        ('classifier', RandomForestClassifier())])
print(pipe['reducer'])
```

```
PCA(n_components=3)
```

PCA in a model pipeline

```
pipe.fit(X_train, y_train)
pipe['reducer'].explained_variance_ratio_
```

```
array([0.56, 0.13, 0.05])
```

```
pipe['reducer'].explained_variance_ratio_.sum()
```

```
0.74
```

```
print(pipe.score(X_test, y_test))
```

```
0.986
```

Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Principal Component selection

DIMENSIONALITY REDUCTION IN PYTHON

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Head of Machine Learning, Faktion

Setting an explained variance threshold

```
pipe = Pipeline([
        ('scaler', StandardScaler()),
        ('reducer', PCA(n_components=0.9))])
# Fit the pipe to the data
pipe.fit(poke_df)

print(len(pipe['reducer'].components_))
```

```
5
```

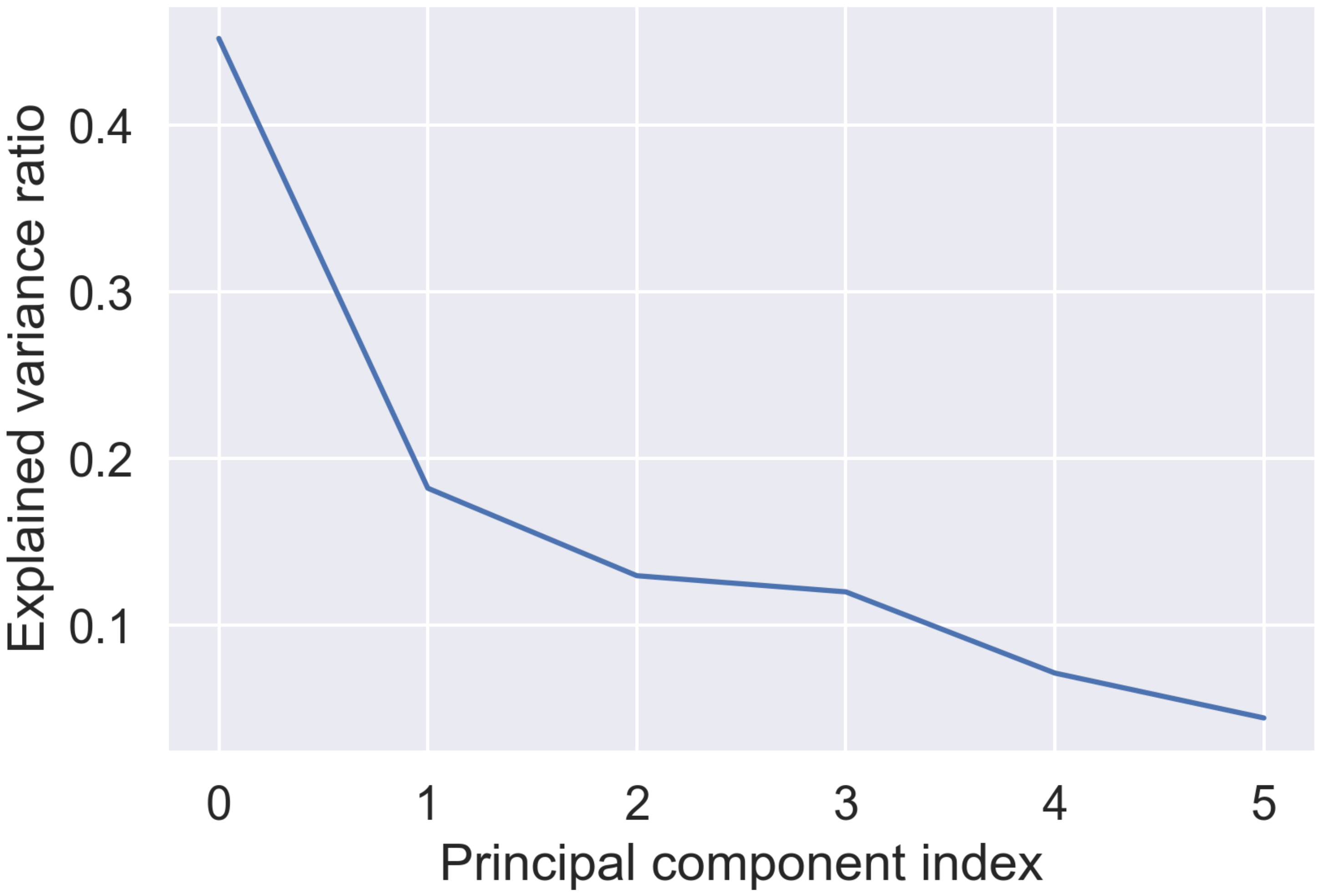
An optimal number of components

```
pipe.fit(poke_df)

var = pipe['reducer'].explained_variance_ratio_

plt.plot(var)

plt.xlabel('Principal component index')
plt.ylabel('Explained variance ratio')
plt.show()
```



An optimal number of components

```
pipe.fit(poke_df)

var = pipe['reducer'].explained_variance_ratio_

plt.plot(var)

plt.xlabel('Principal component index')
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plt.show()
```
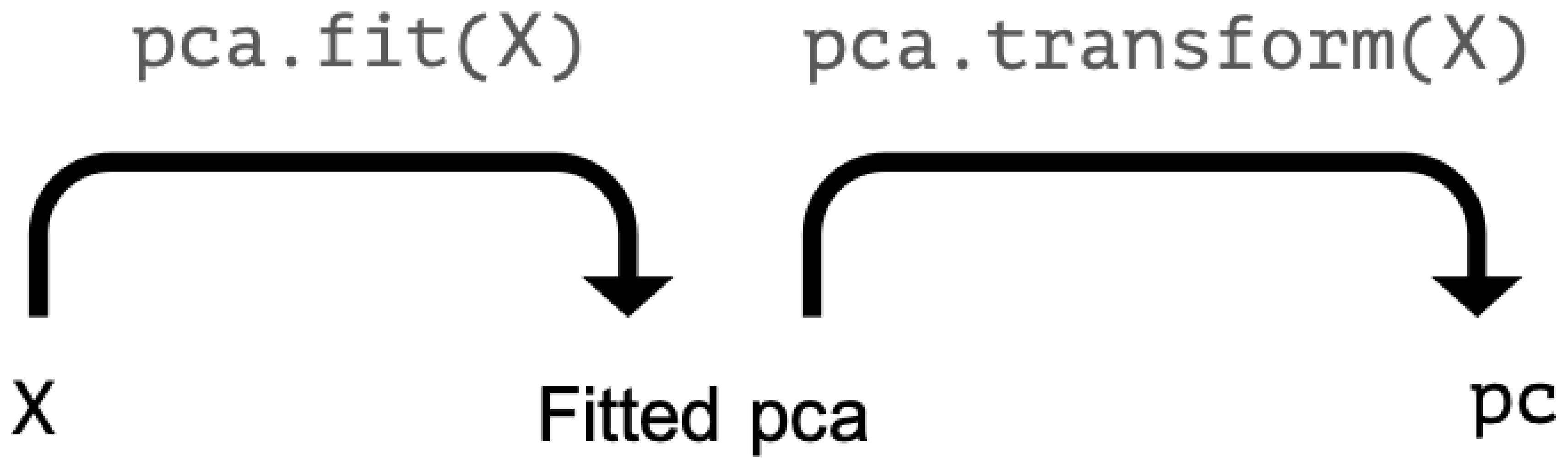
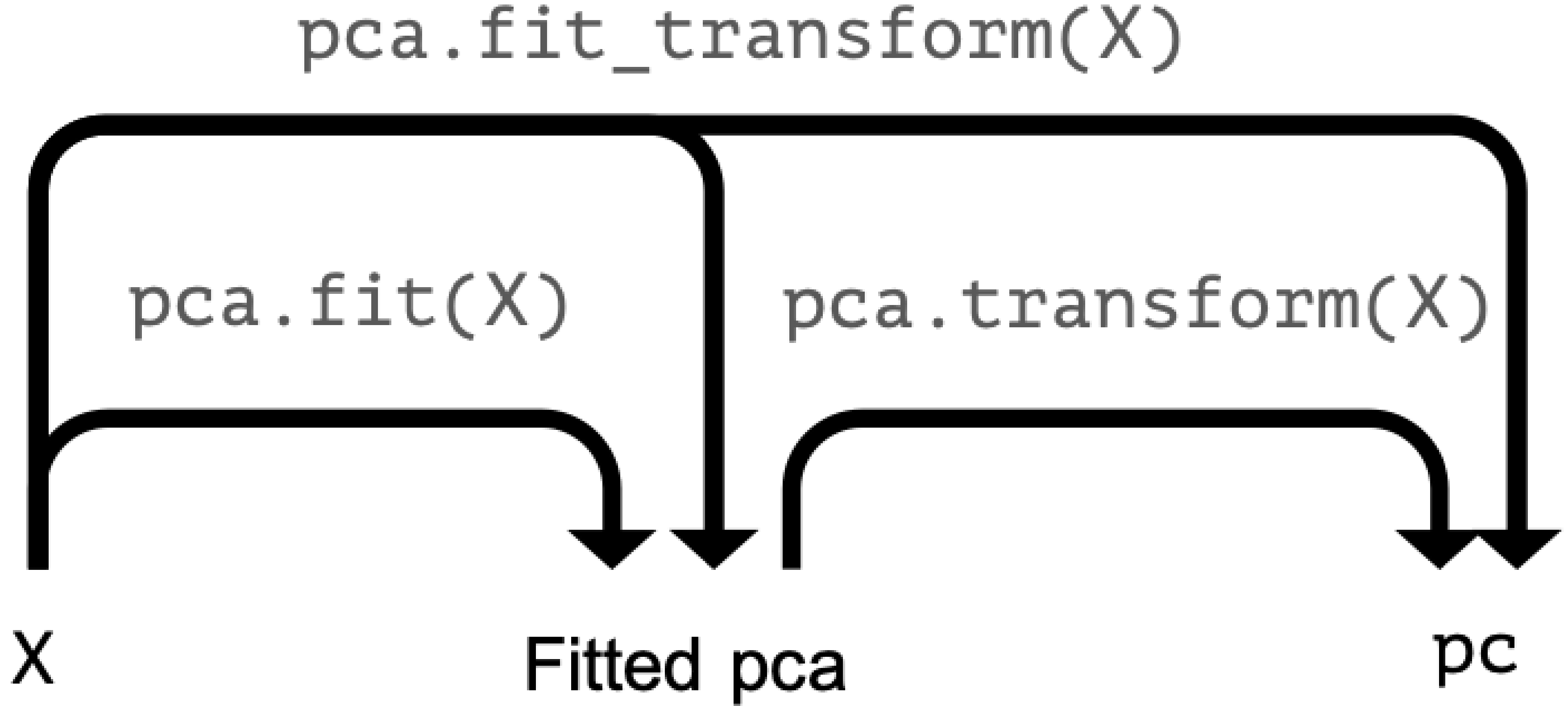
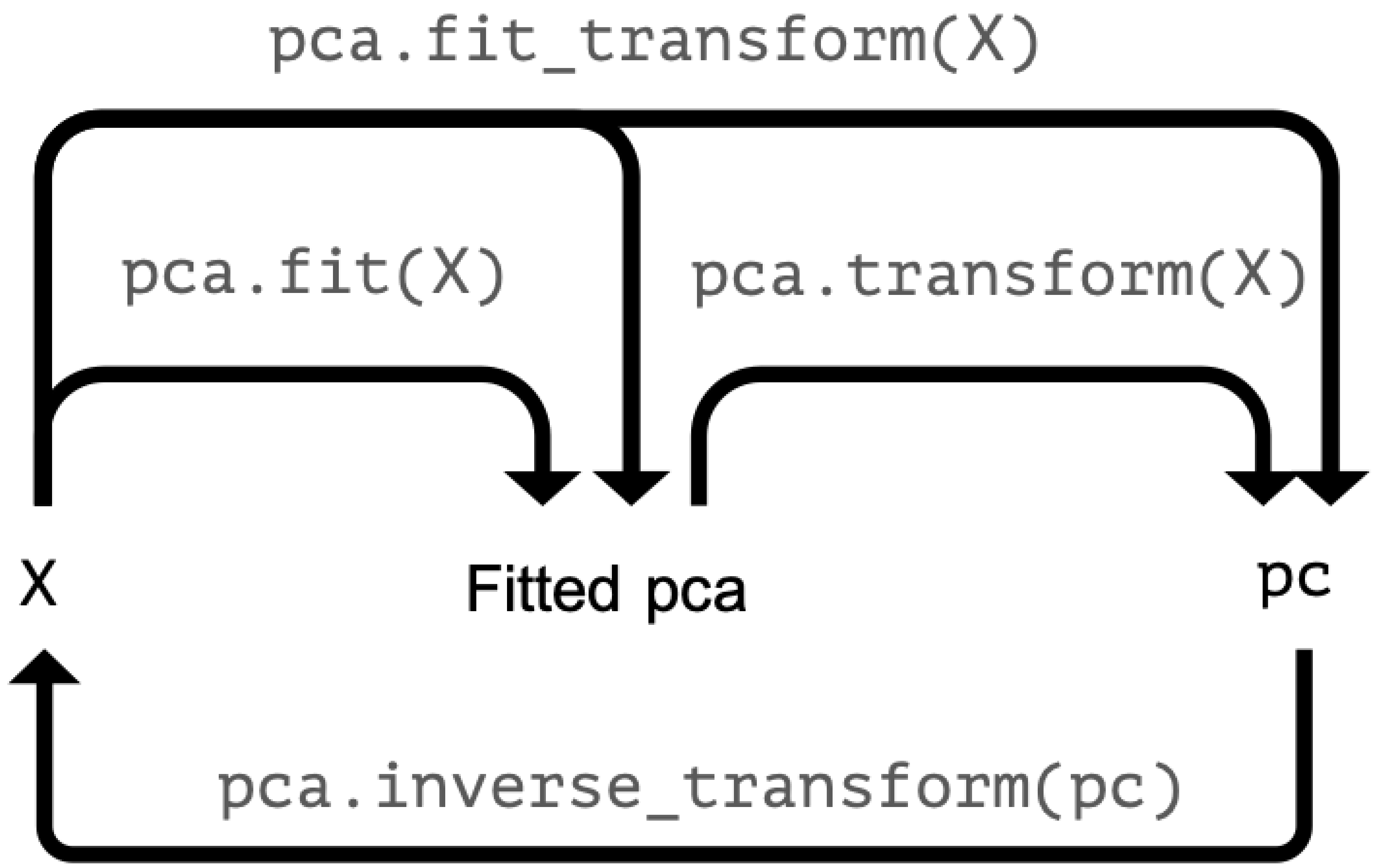

PCA operations



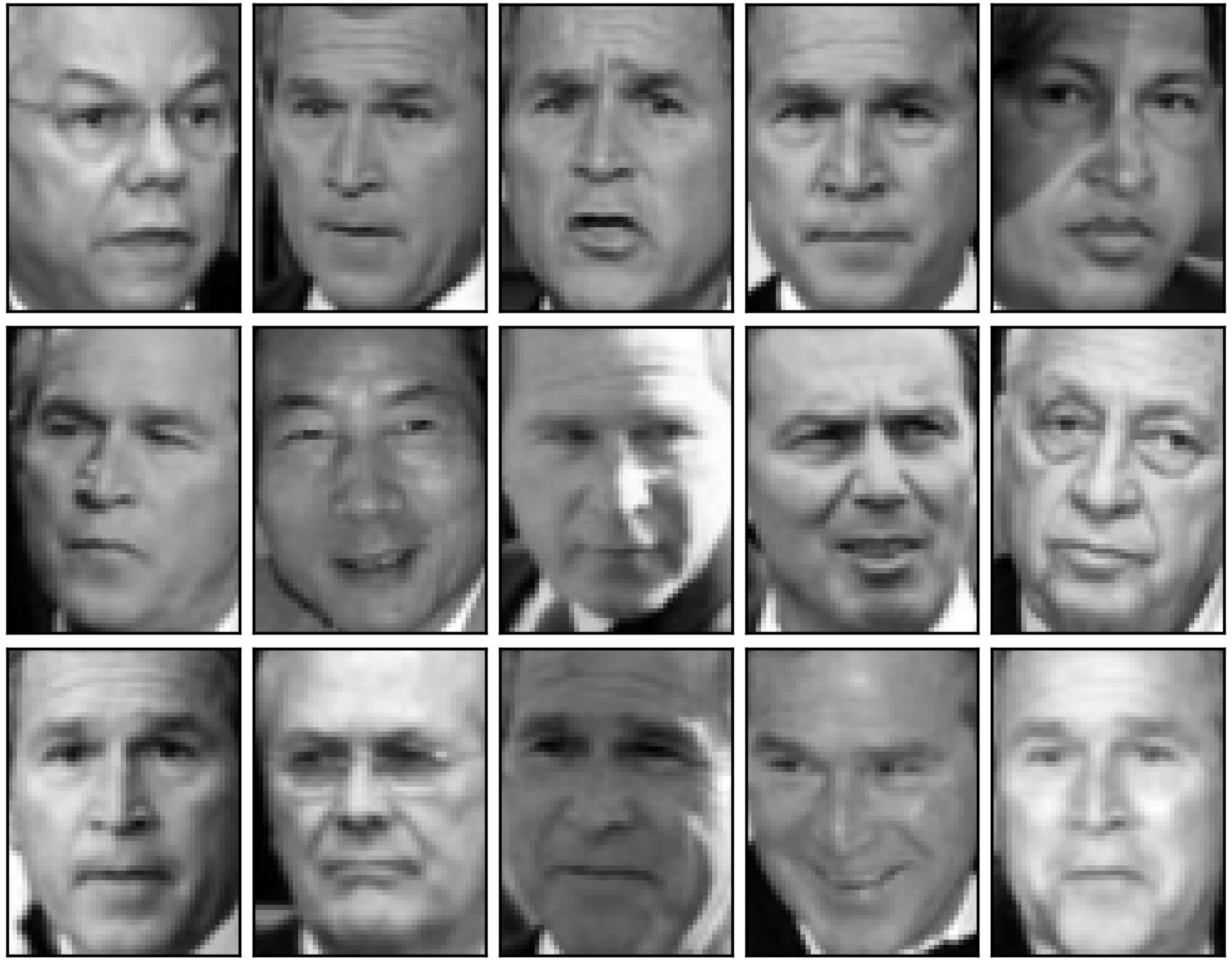
PCA operations



PCA operations



Compressing images



Compressing images

```
print(X_test.shape)
```

```
(15, 2914)
```

62 x 47 pixels = 2914 grayscale values

```
print(X_train.shape)
```

```
(1333, 2914)
```

Compressing images

```
pipe = Pipeline([
        ('scaler', StandardScaler()),
        ('reducer', PCA(n_components=290))])
pipe.fit(X_train)
pc = pipe.fit_transform(X_test)

print(pc.shape)
```

```
(15, 290)
```

Rebuilding images

```
pc = pipe.transform(X_test)

print(pc.shape)
```

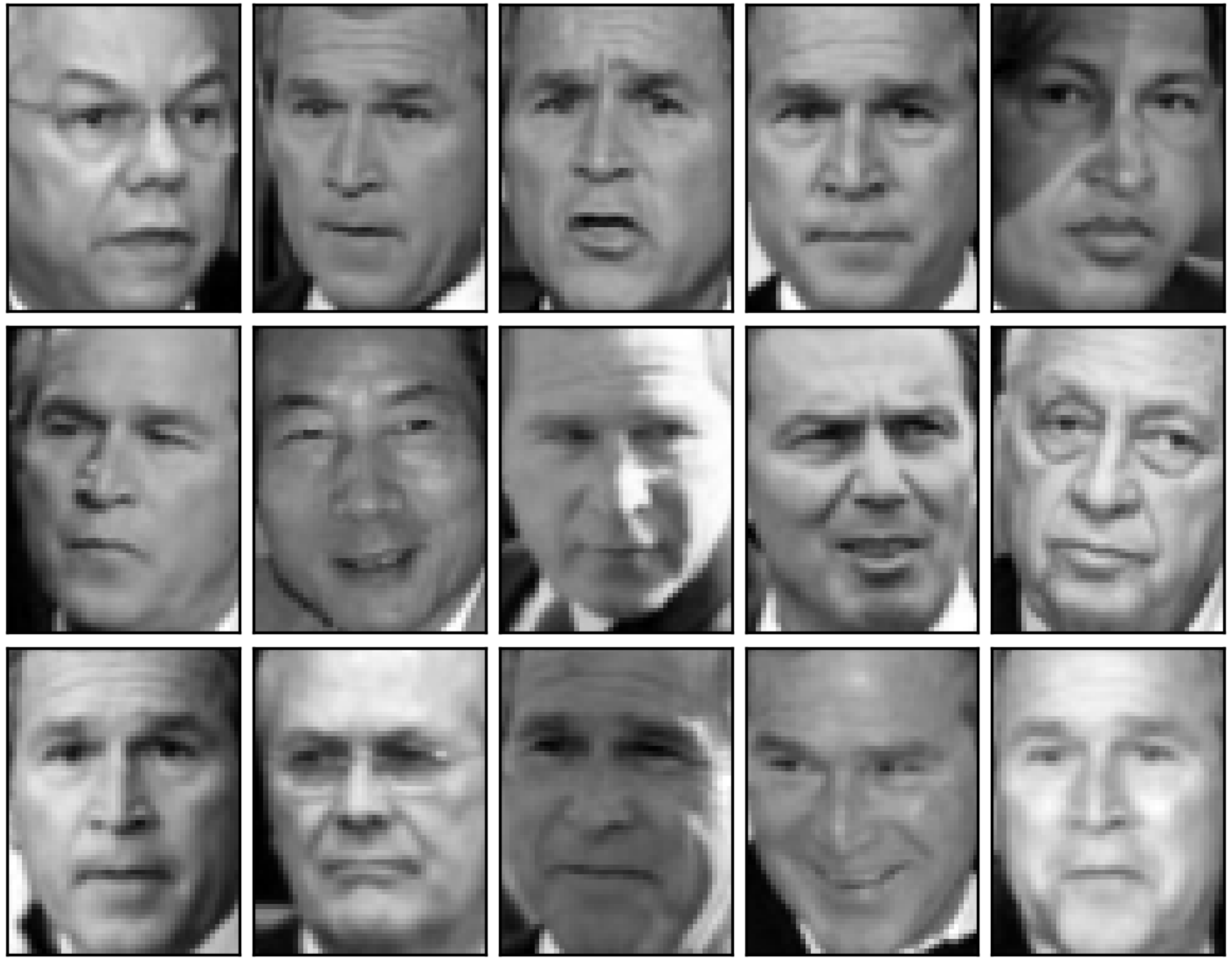
```
(15, 290)
```

```
X_rebuilt = pipe.inverse_transform(pc)

print(X_rebuilt.shape)
```

```
(15, 2914)
```

```
img_plotter(X_rebuilt)
```

Rebuilding images



Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Congratulations!

DIMENSIONALITY REDUCTION IN PYTHON

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What you've learned

- Why dimensionality reduction is important & when to use it
- Feature selection vs. extraction
- High dimensional data exploration with t-SNE & PCA
- Use models to find important features
- Remove unimportant ones

Thank you!

DIMENSIONALITY REDUCTION IN PYTHON