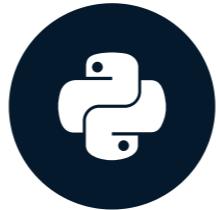


feature

feature

Feature extraction

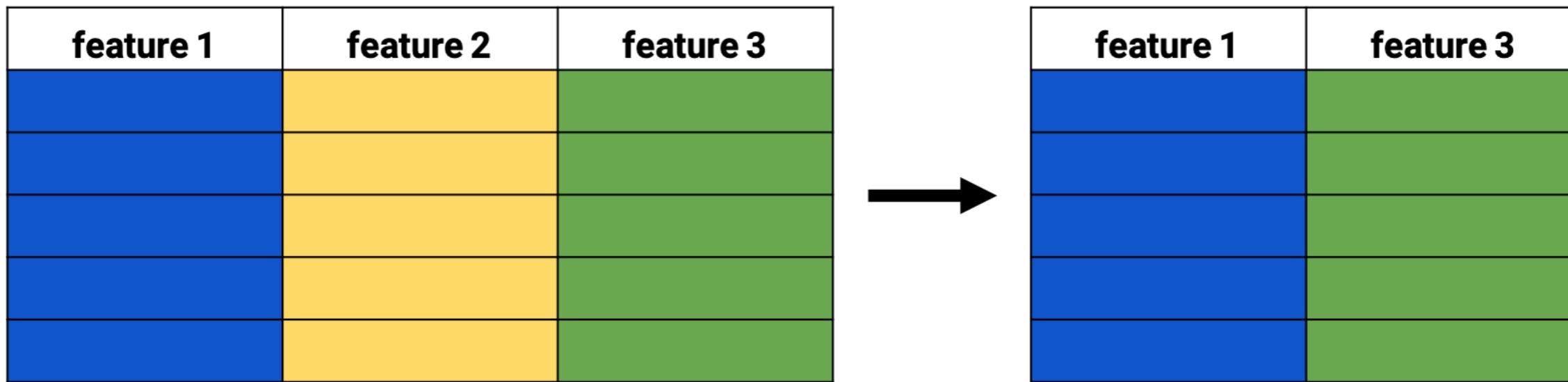
DIMENSIONALITY REDUCTION IN PYTHON



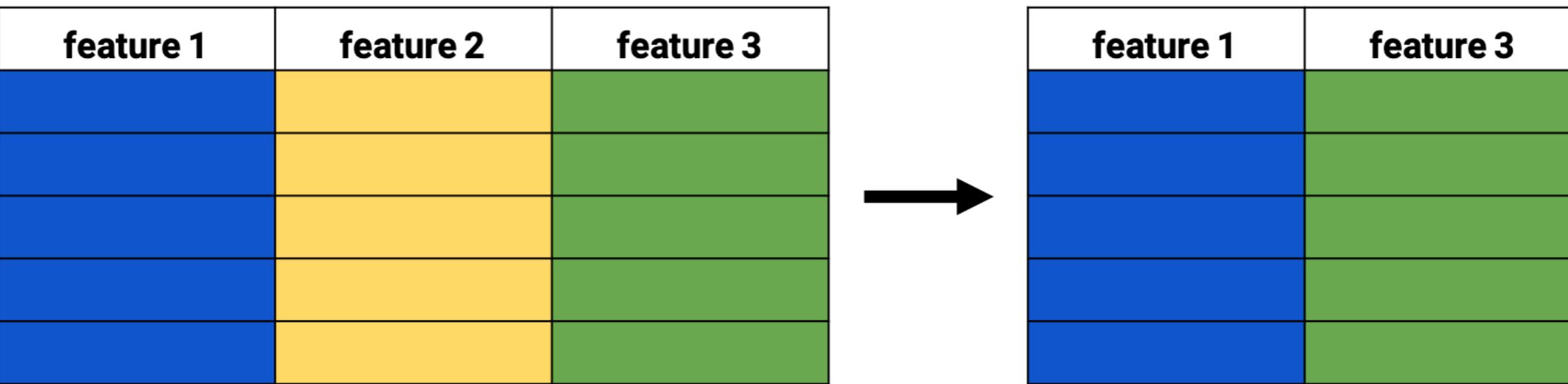
Jeroen Boeye

Machine Learning Engineer, Faktion

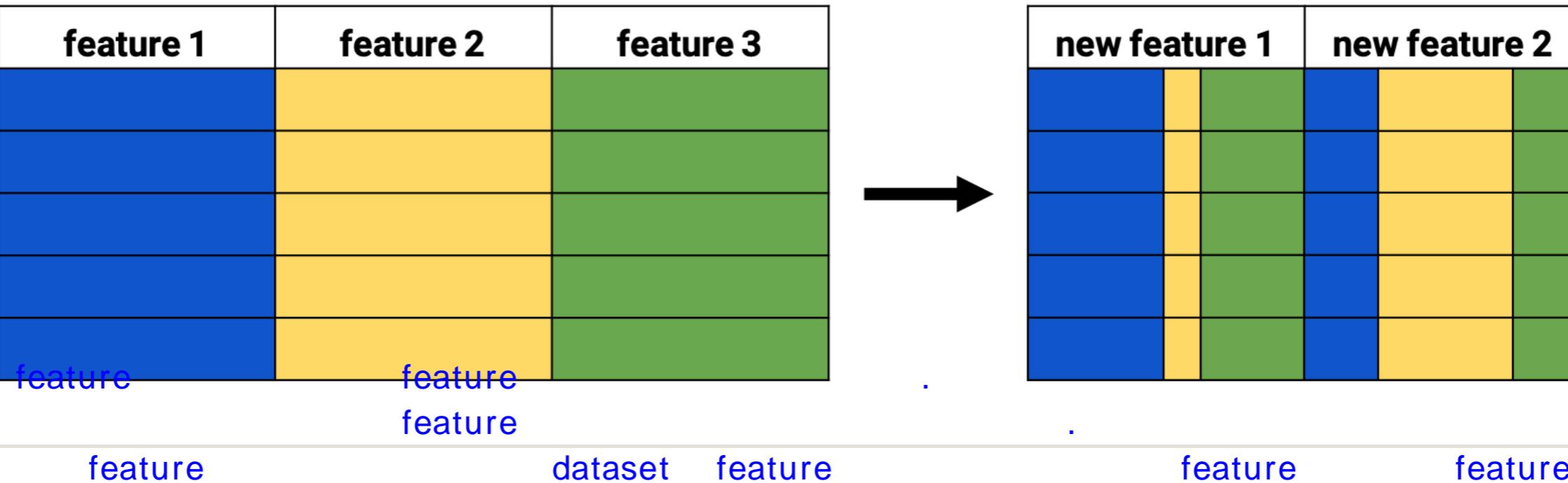
Feature selection



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

model

feature BMI

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

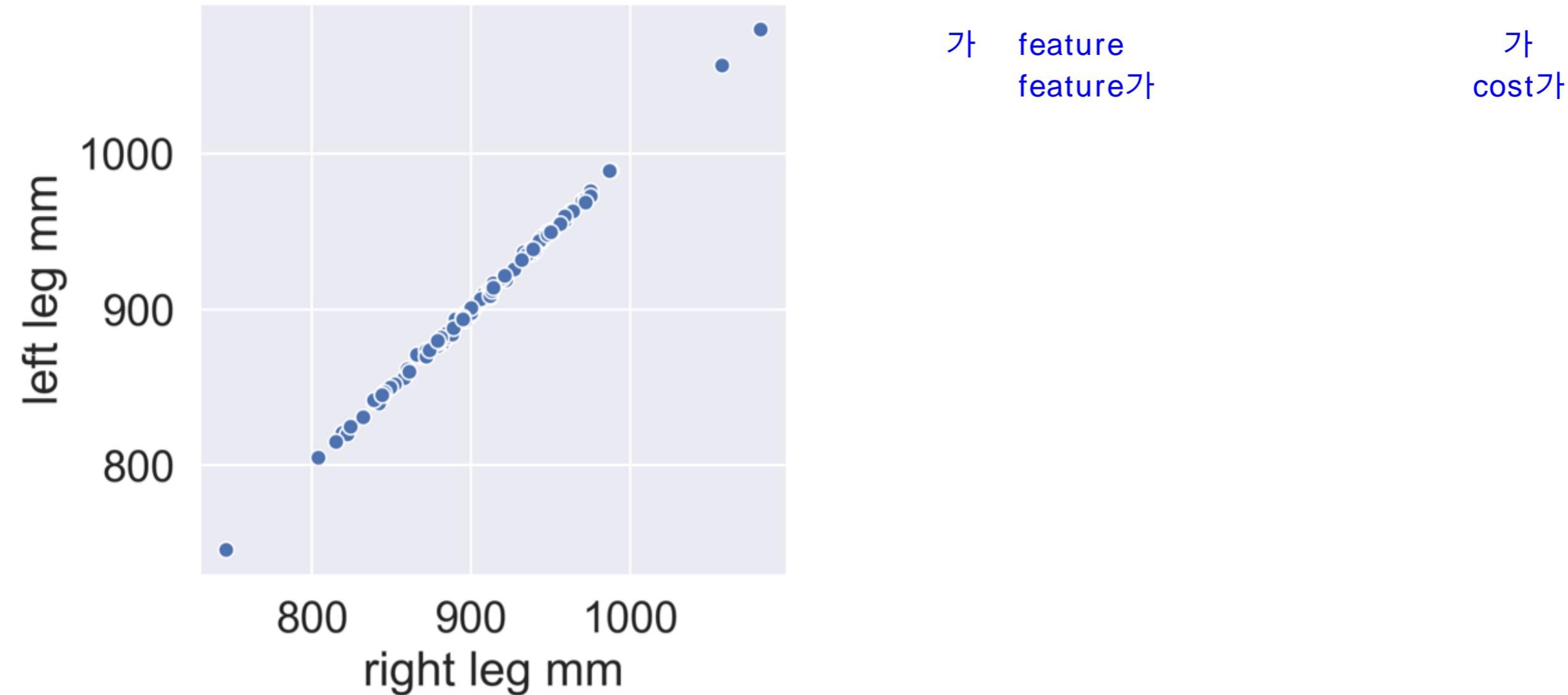
```
leg_df['leg mm'] = leg_df[['right leg mm', 'left leg mm']].mean(axis=1)
```

Feature generation - averages

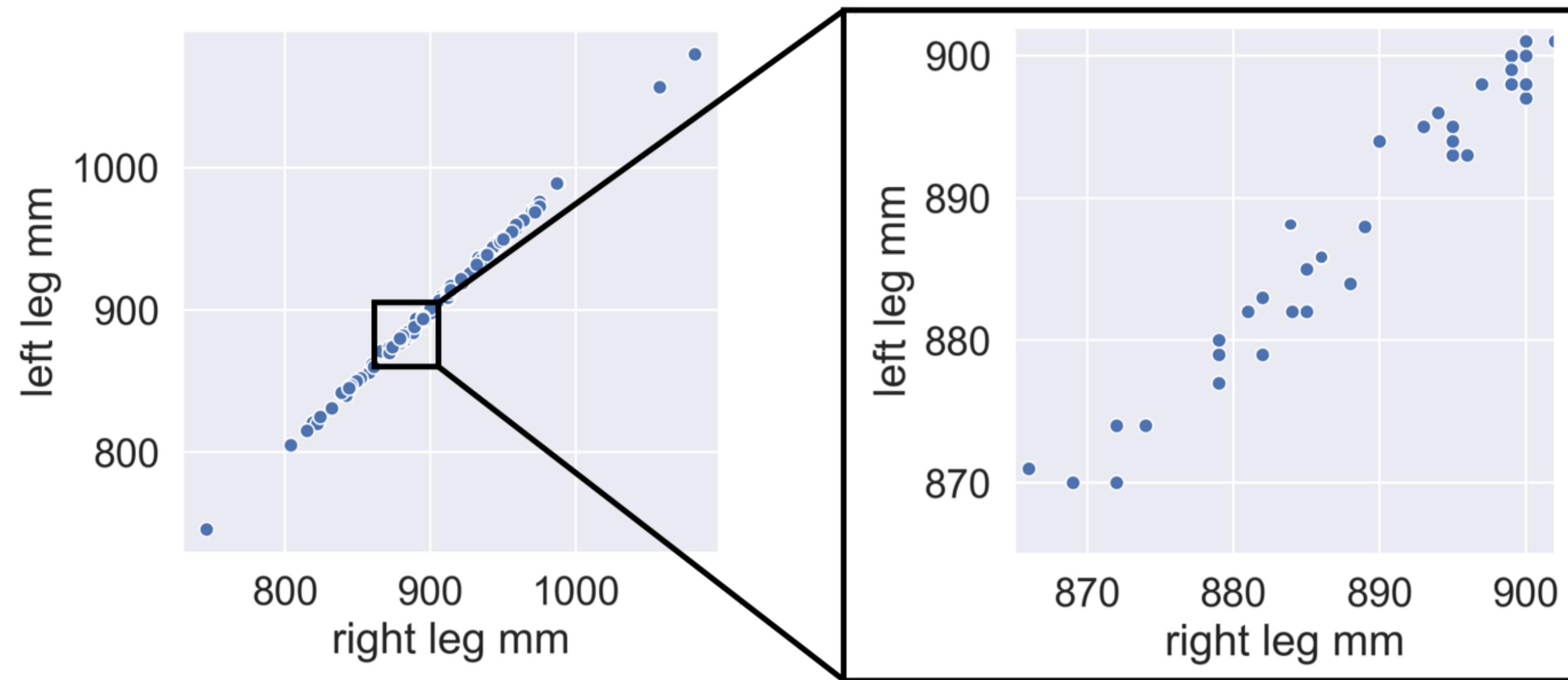
```
leg_df.drop(['right leg mm', 'left leg mm'], axis=1)
```

leg mm
883.5
869.5
900.5

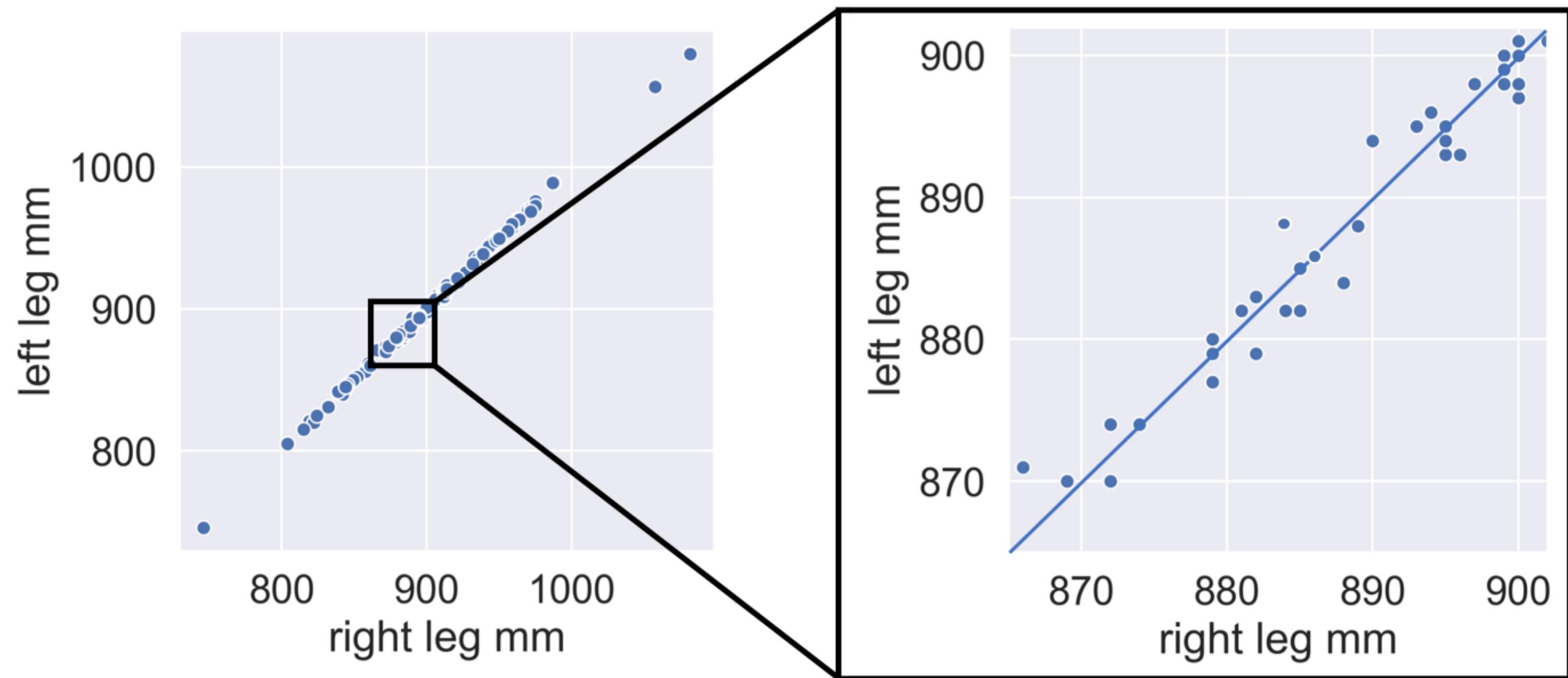
Cost of taking the average



Cost of taking the average



Cost of taking the average



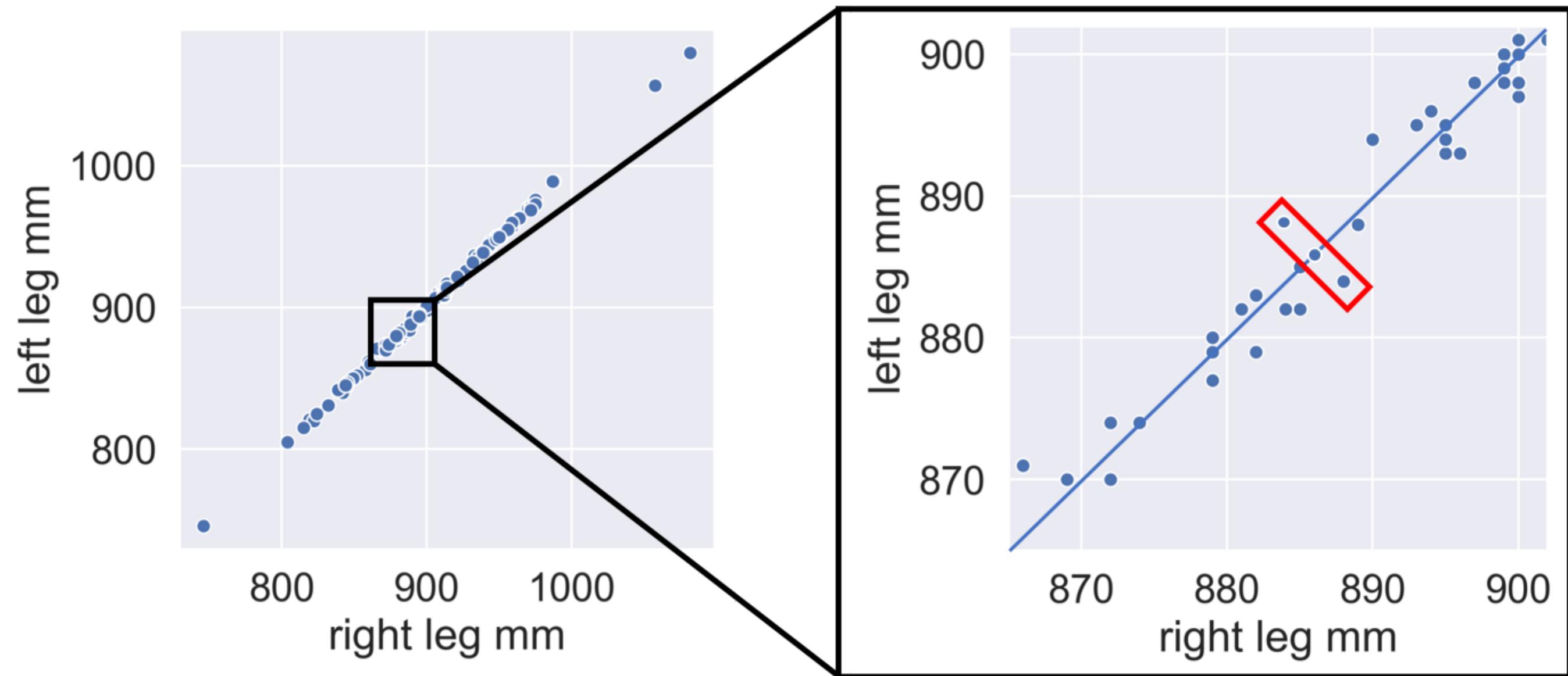
feature가

가

가

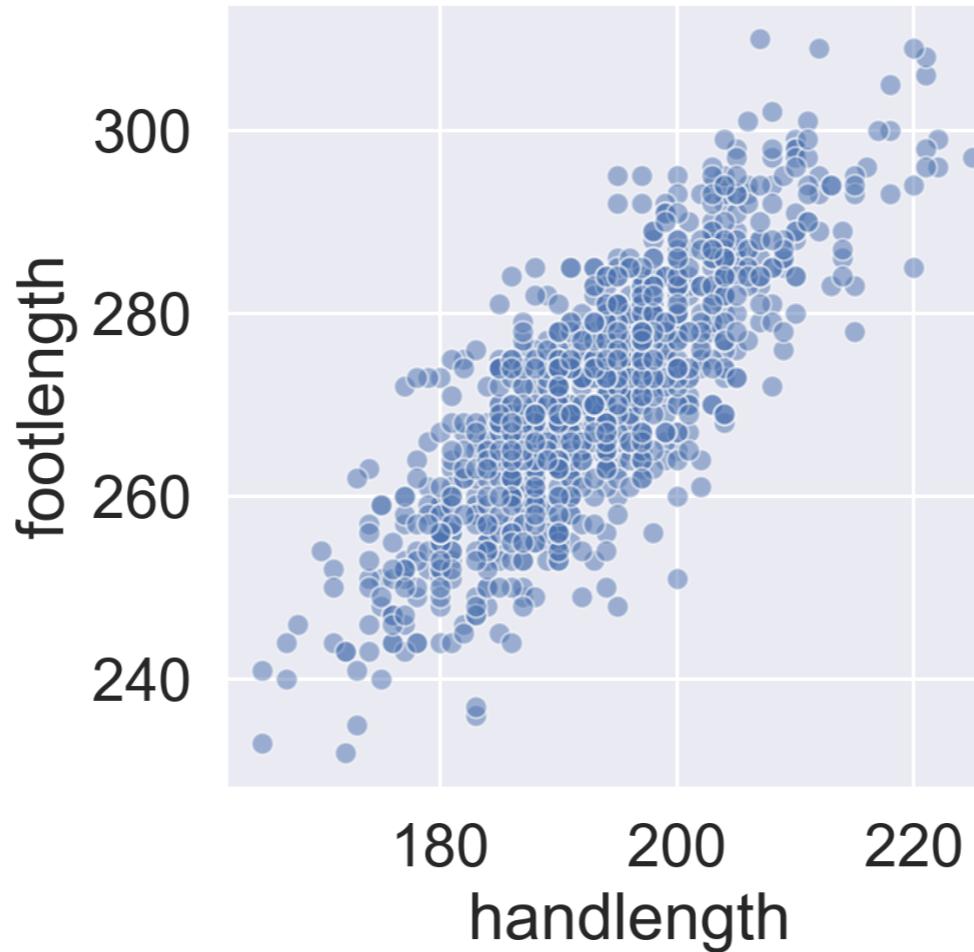
Cost of taking the average

가



Intro to PCA

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

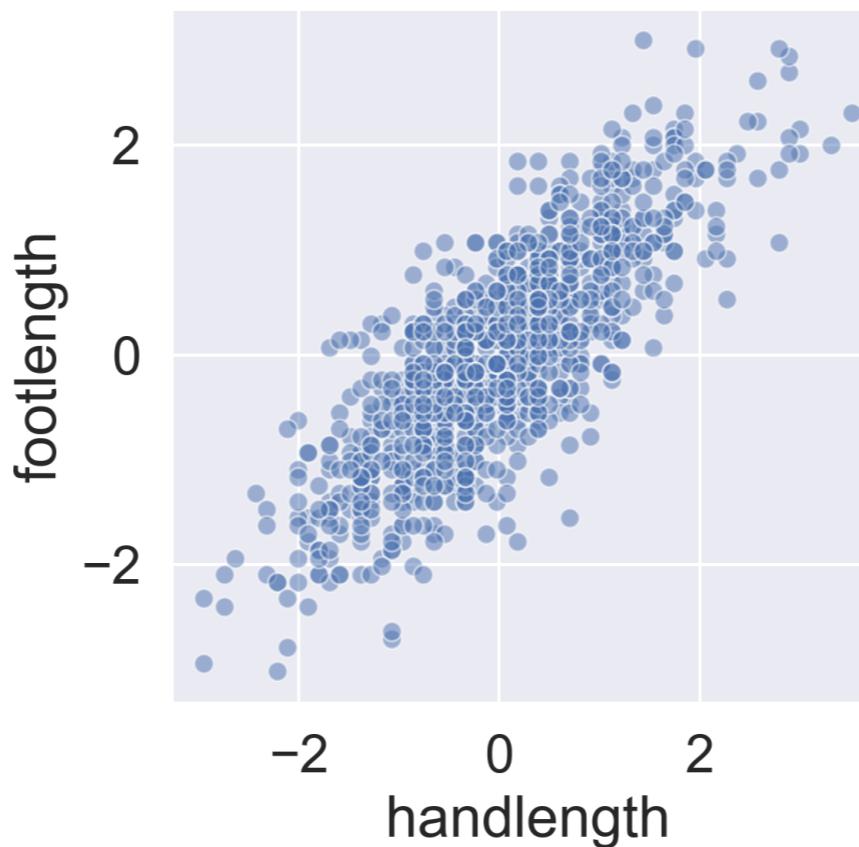


Intro to PCA

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

PCA
feature
dataset

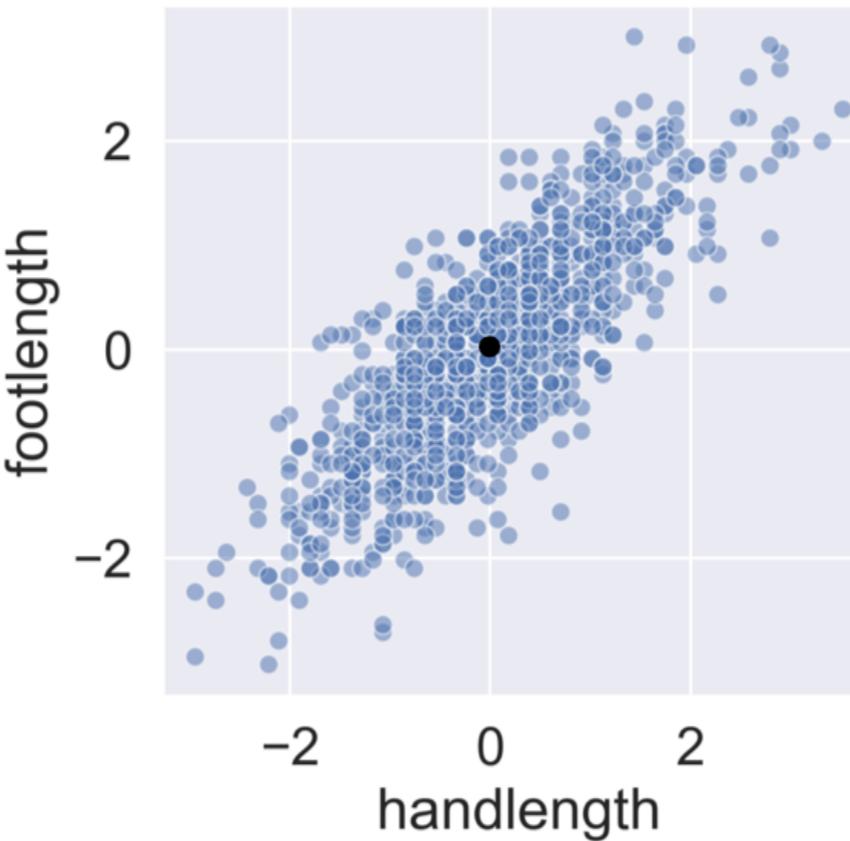
feature



Intro to PCA

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

가

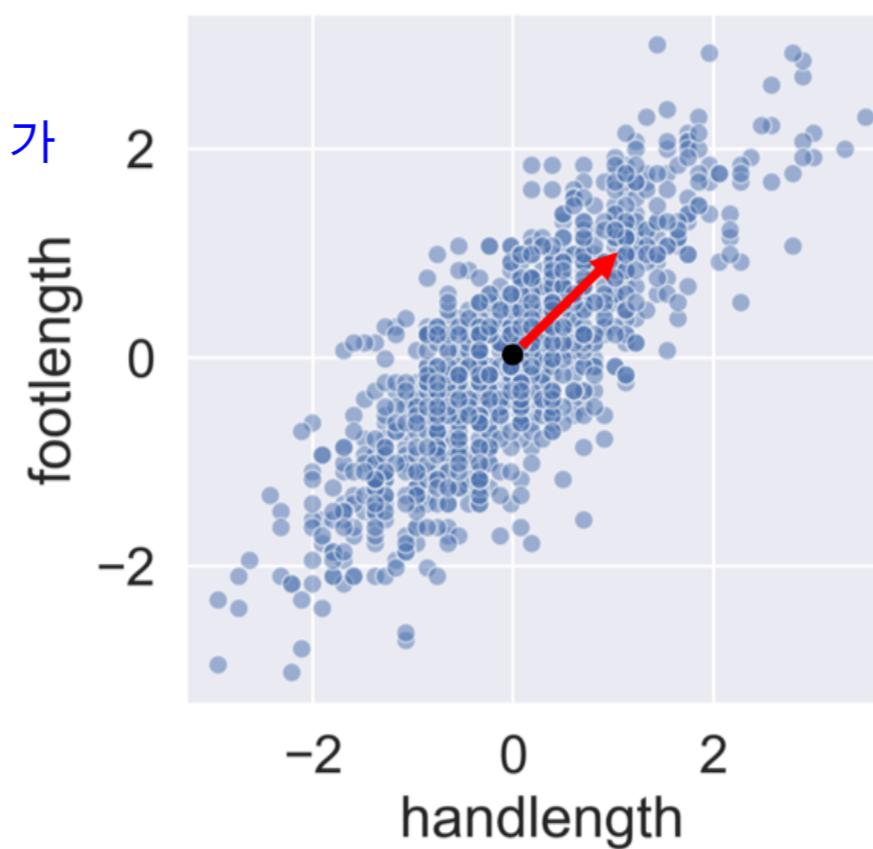


Intro to PCA

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

가

가
가
가

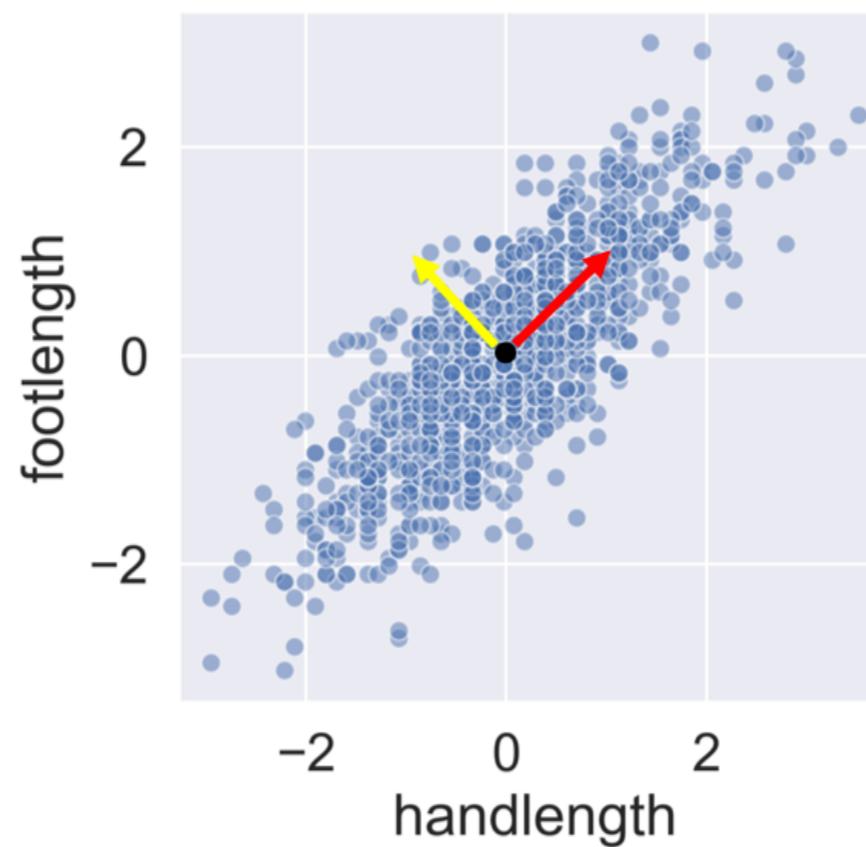


Intro to PCA

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

dataset
dataset

가
가
가

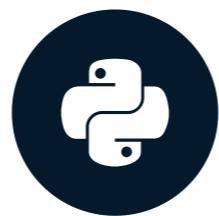


Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Principal component analysis

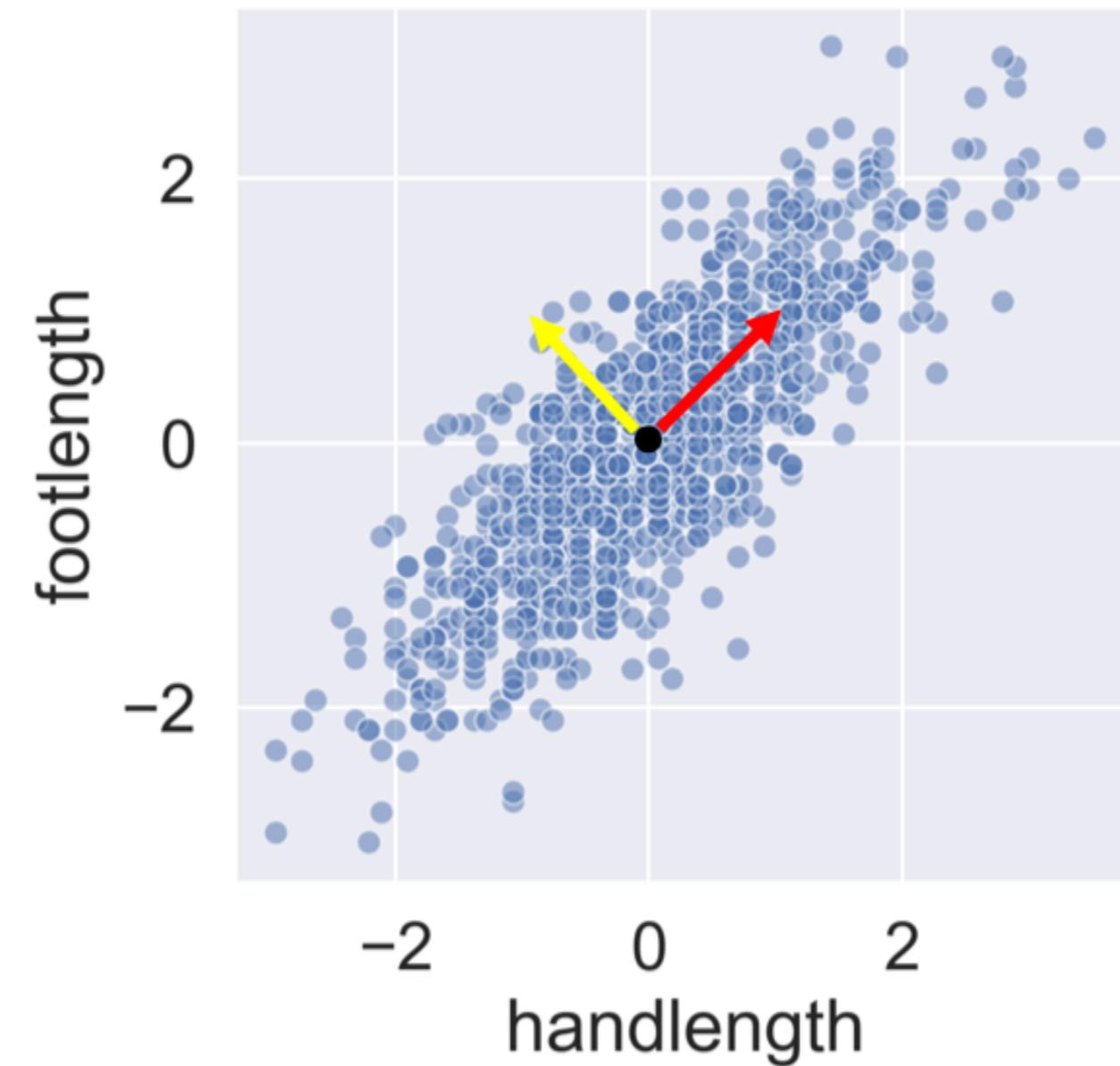
DIMENSIONALITY REDUCTION IN PYTHON



Jeroen Boeye

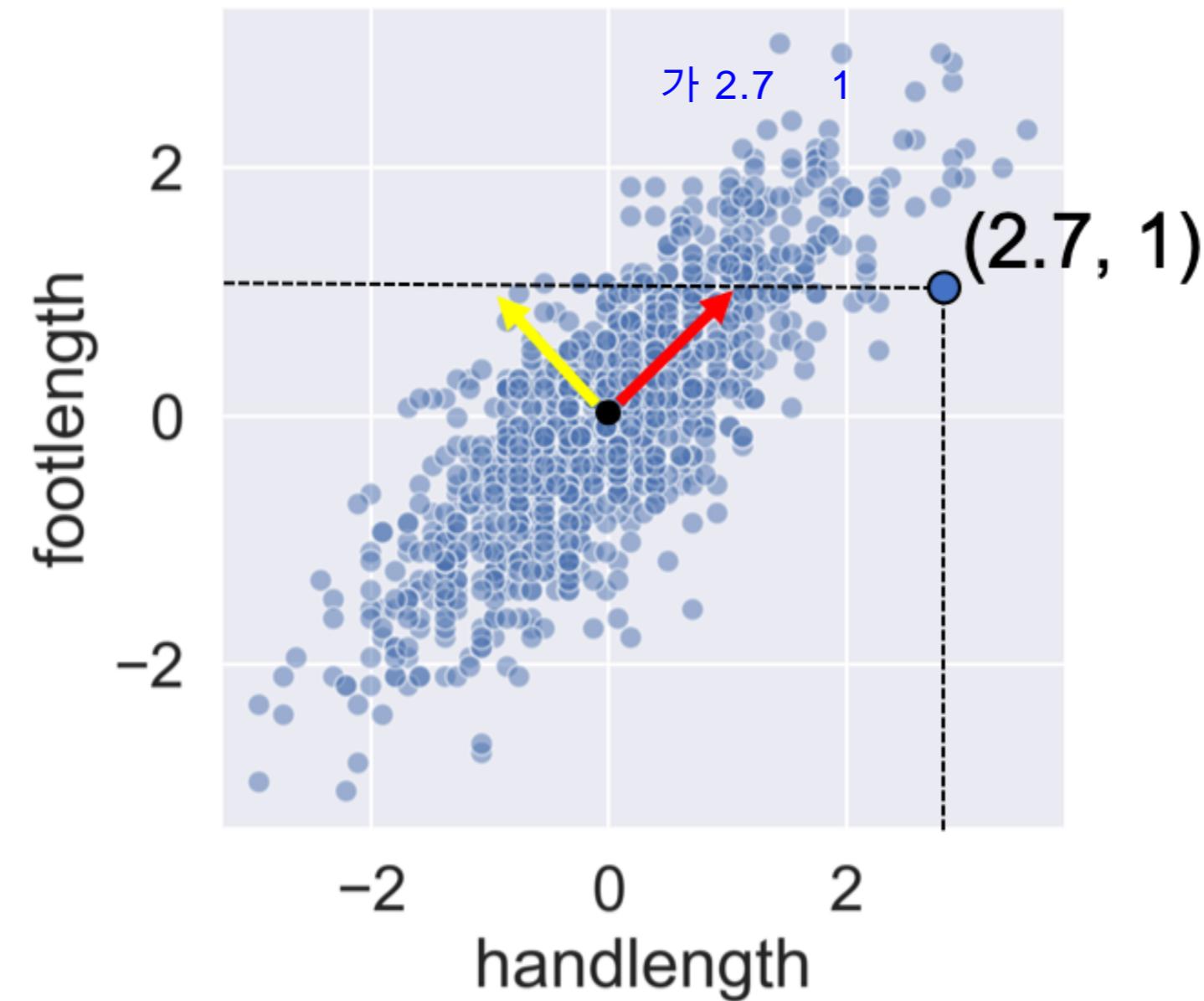
Machine Learning Engineer, Faktion

PCA concept



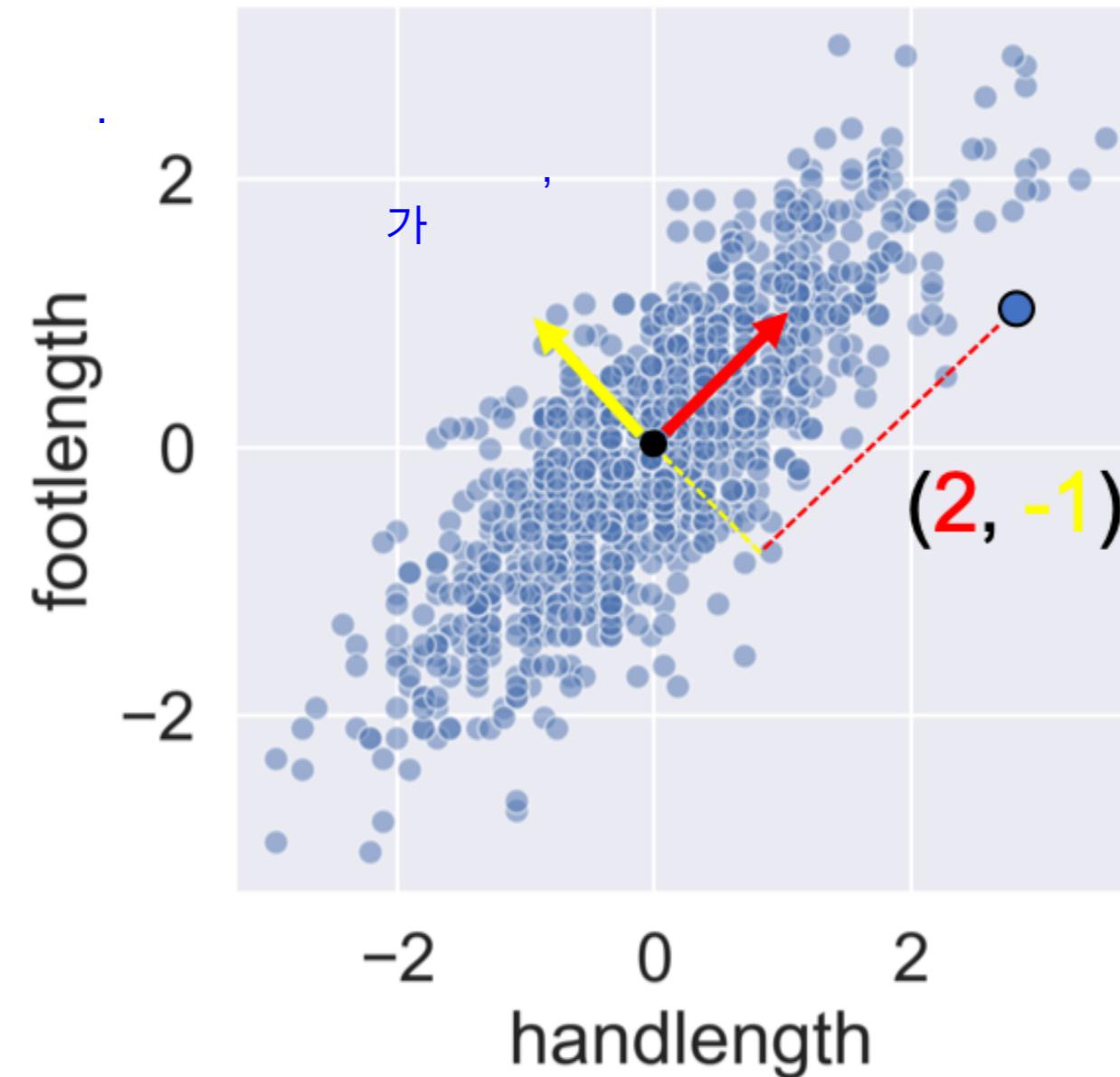
PCA concept

ex)



PCA concept

2 ,
- 1
data 가

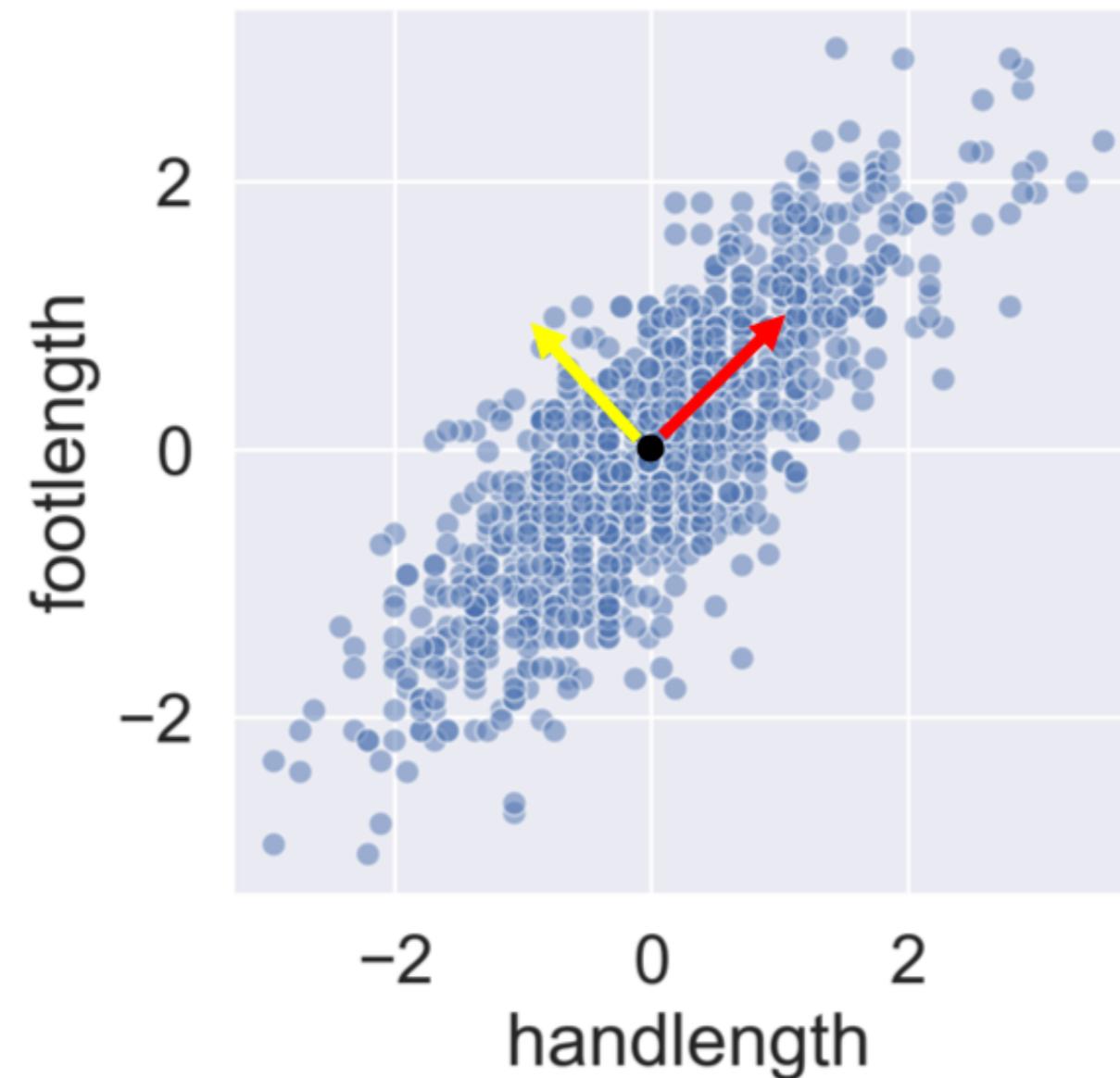


Calculating the principal components

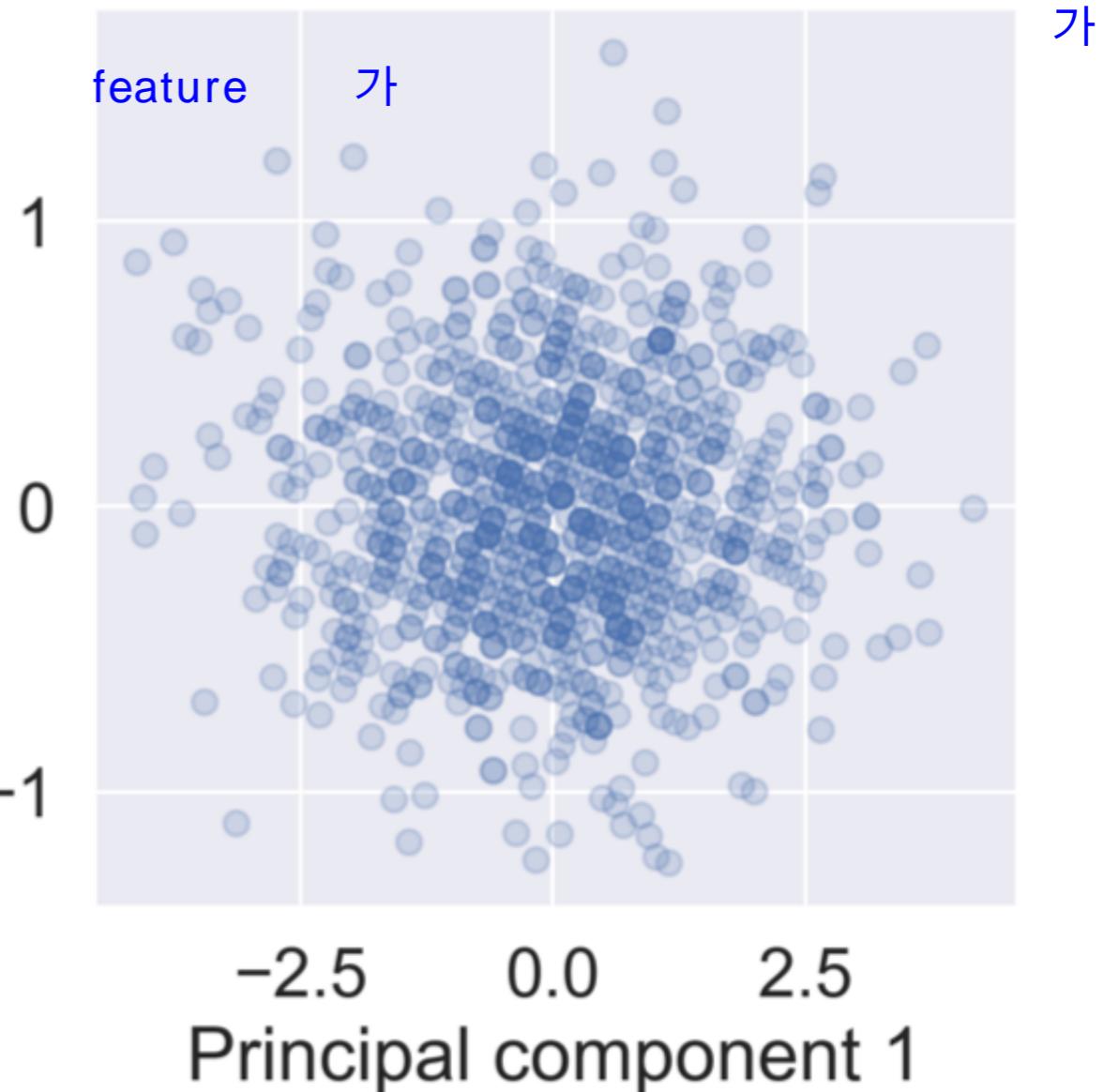
```
from sklearn.preprocessing import StandardScaler  
  
scaler = StandardScaler() StandardScaler() PCA  
std_df = scaler.fit_transform(df)  
from sklearn.decomposition import PCA  
  
pca = PCA()  
print(pca.fit_transform(std_df))
```

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

PCA removes correlation



Principal component 2



Principal component explained variance ratio

```
from sklearn.decomposition import PCA
```

```
pca = PCA()
```

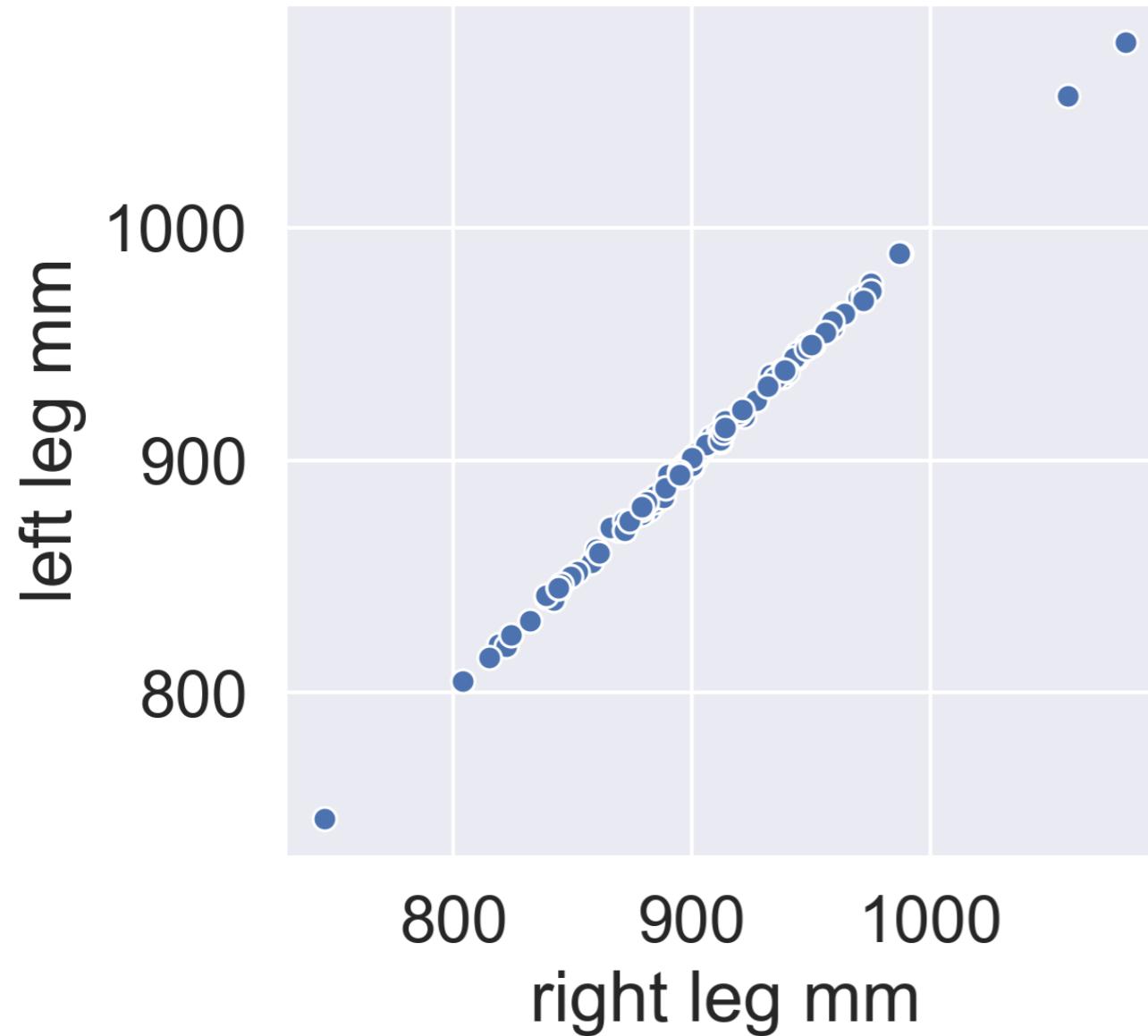
```
pca.fit(std_df)
```

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

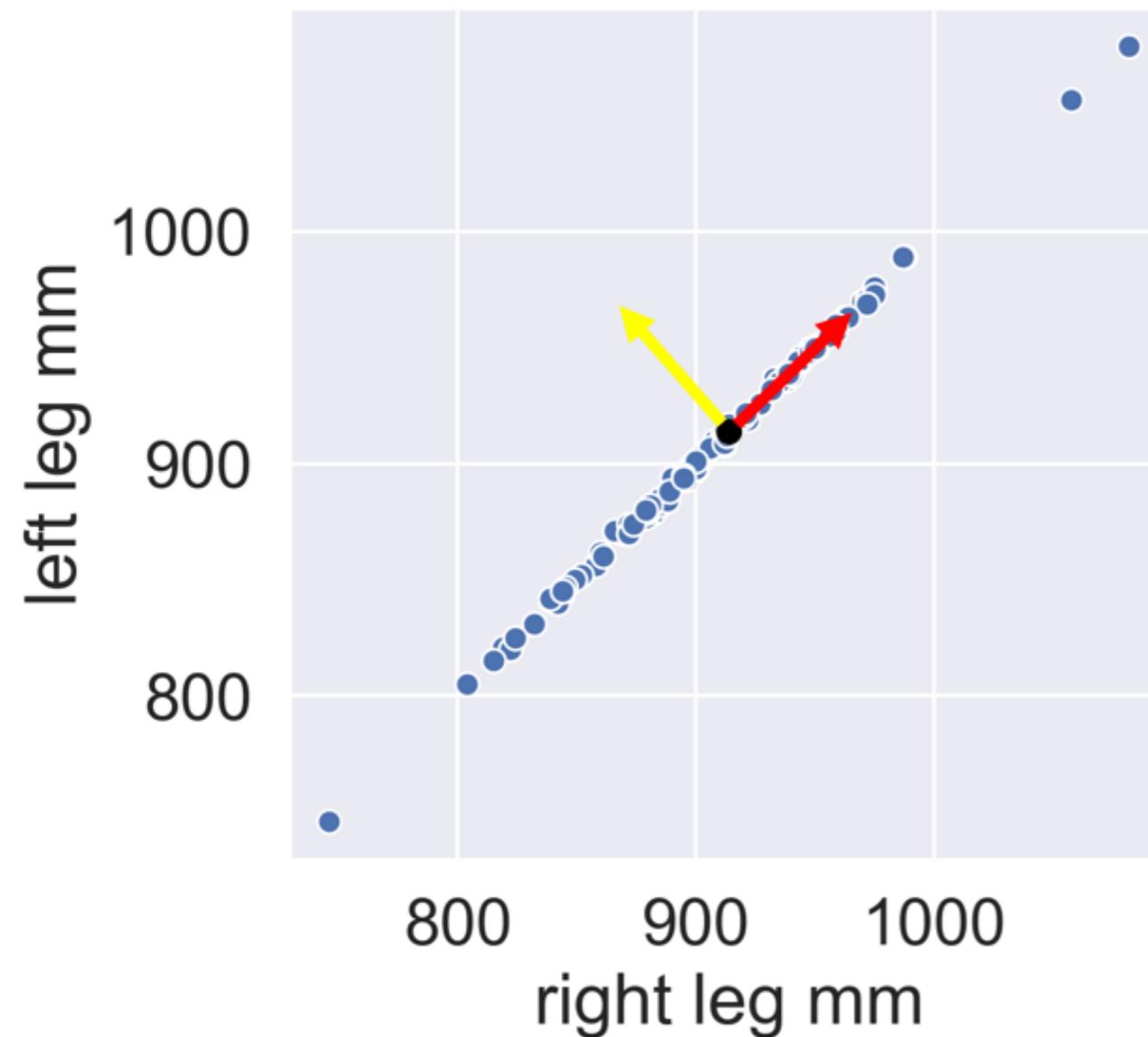
```
array([0.90, 0.10])
```



PCA for dimensionality reduction



PCA for dimensionality reduction



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

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

99.9%

(feature 2

)

PCA for dimensionality reduction

```
pca = PCA()  
  
pca.fit(ansur_std_df)          pca fit  
                                44% 18%  
  
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, 0.01, 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, 0.01, 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, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01])
```

PCA for dimensionality reduction

```
pca = PCA()  
  
pca.fit(ansur_std_df)           .explained_variance_ratio_    NumPy  
  
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. ])
```

62%

80%

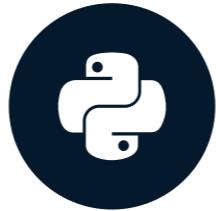
10

Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

PCA applications

DIMENSIONALITY REDUCTION IN PYTHON



Jeroen Boeye

Machine Learning Engineer, Faktion

Understanding the components

```
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

```
=> feature 0.71
```

```
=>
```

가
가
가

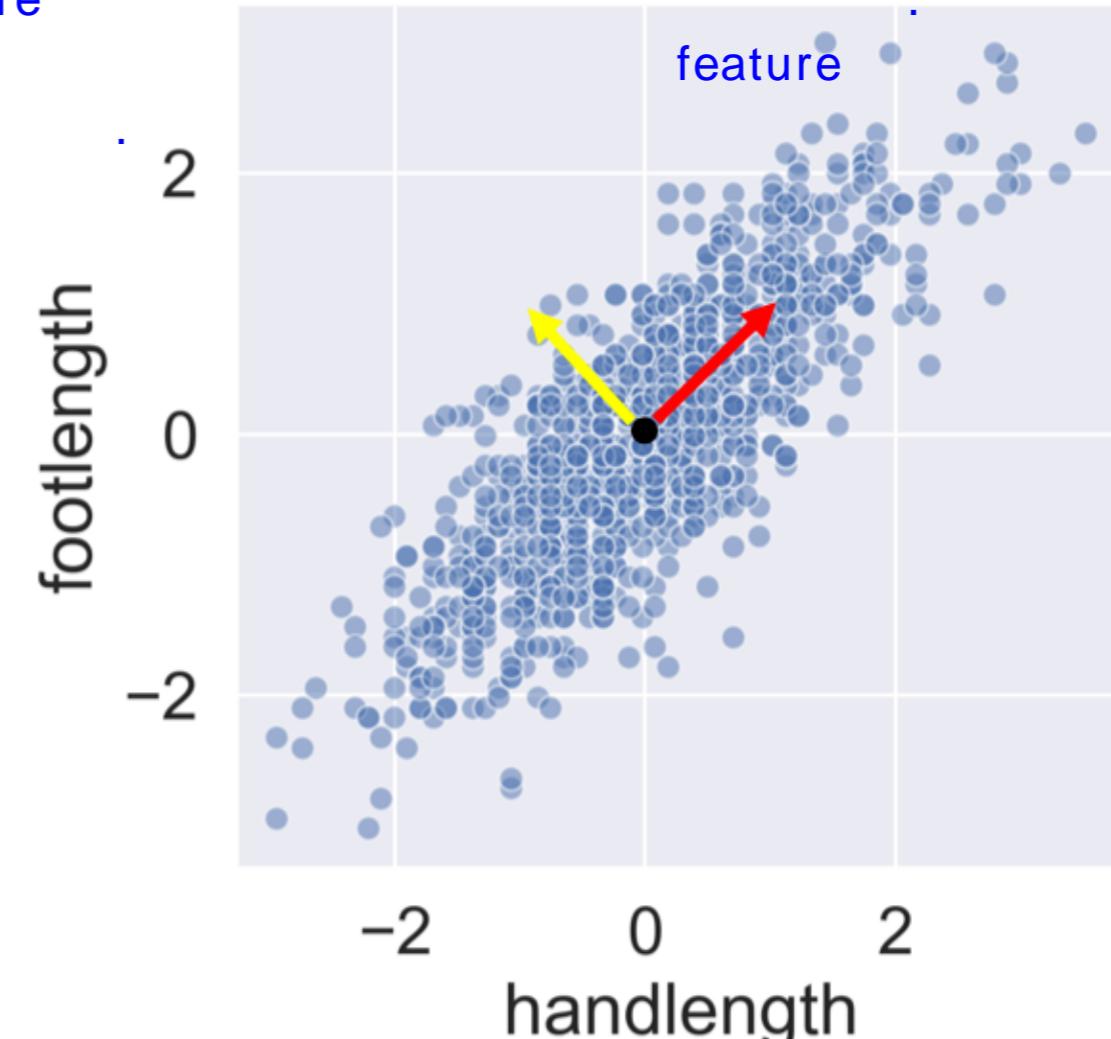
feature

가

footlength

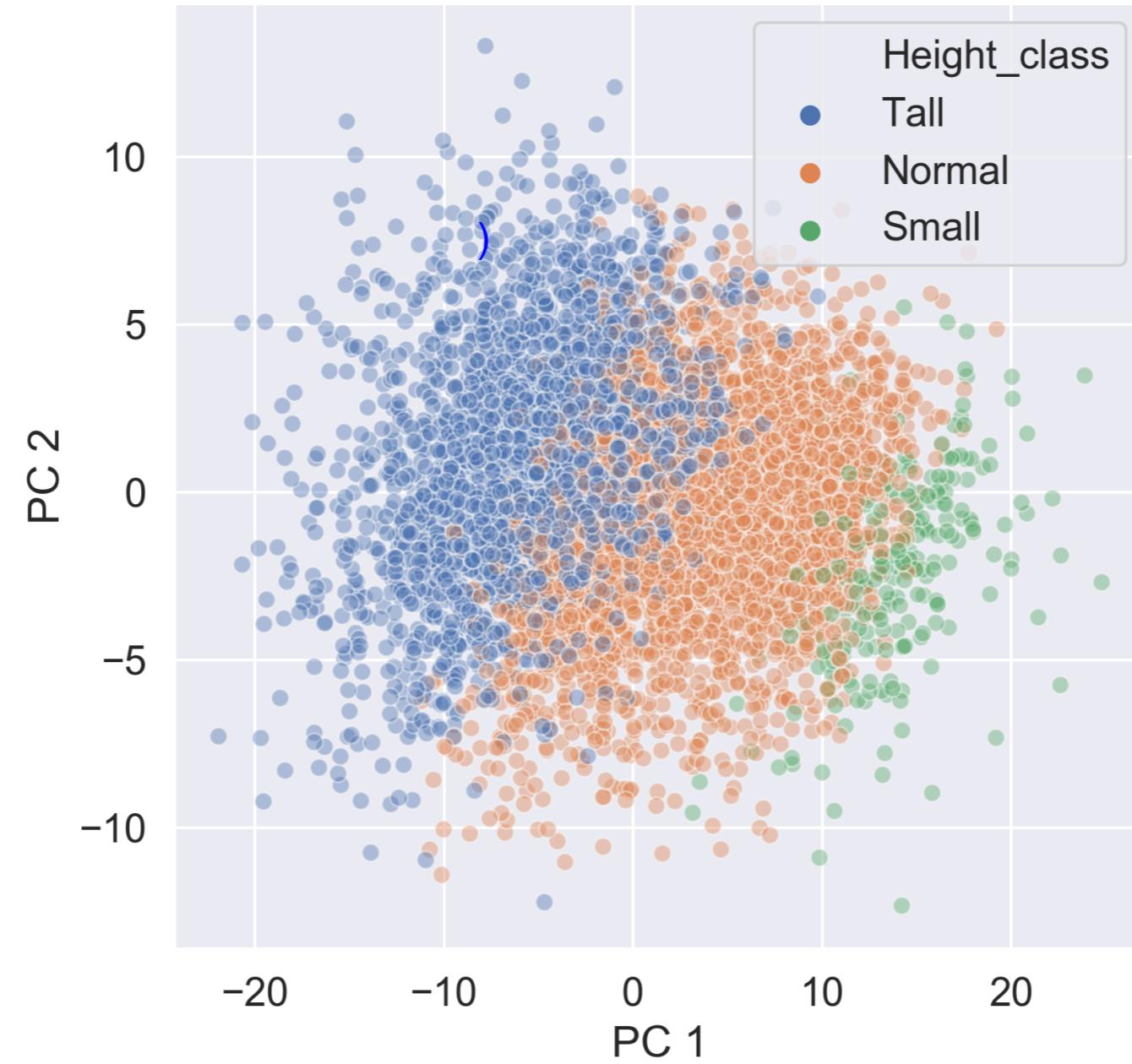
2
0
-2

-2 0 2
handlength



PCA for data exploration

X
(=> dataset 가



PCA in a pipeline

```
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())
```

PCA
data

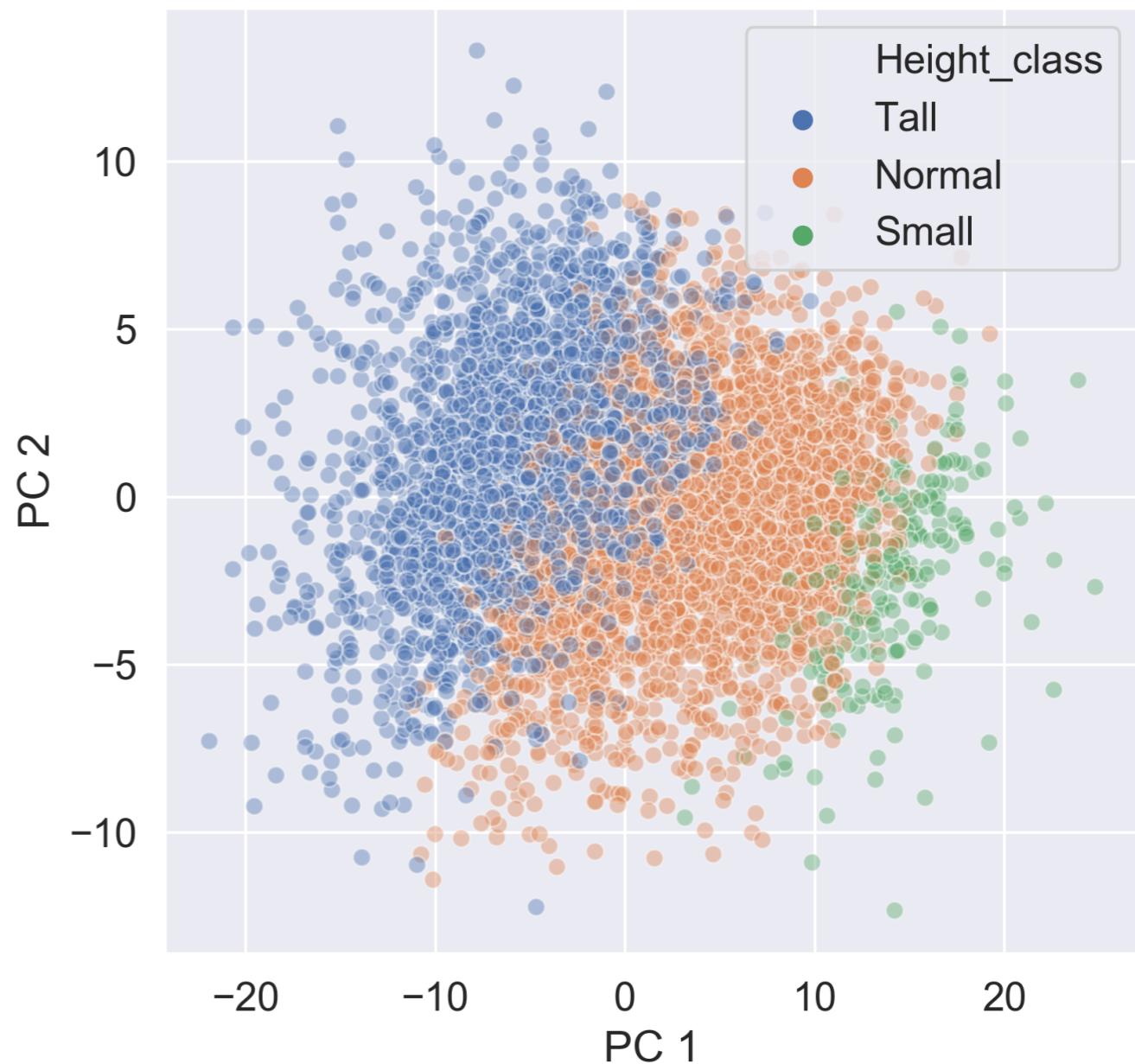
가

Branch	Component	Gender	BMI_class	Height_class
Combat Arms	Regular Army	Male	Overweight	Tall
Combat Support	Regular Army	Male	Overweight	Normal
Combat Support	Regular Army	Male	Overweight	Normal
Combat Service Support	Regular Army	Male	Overweight	Normal
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)
```

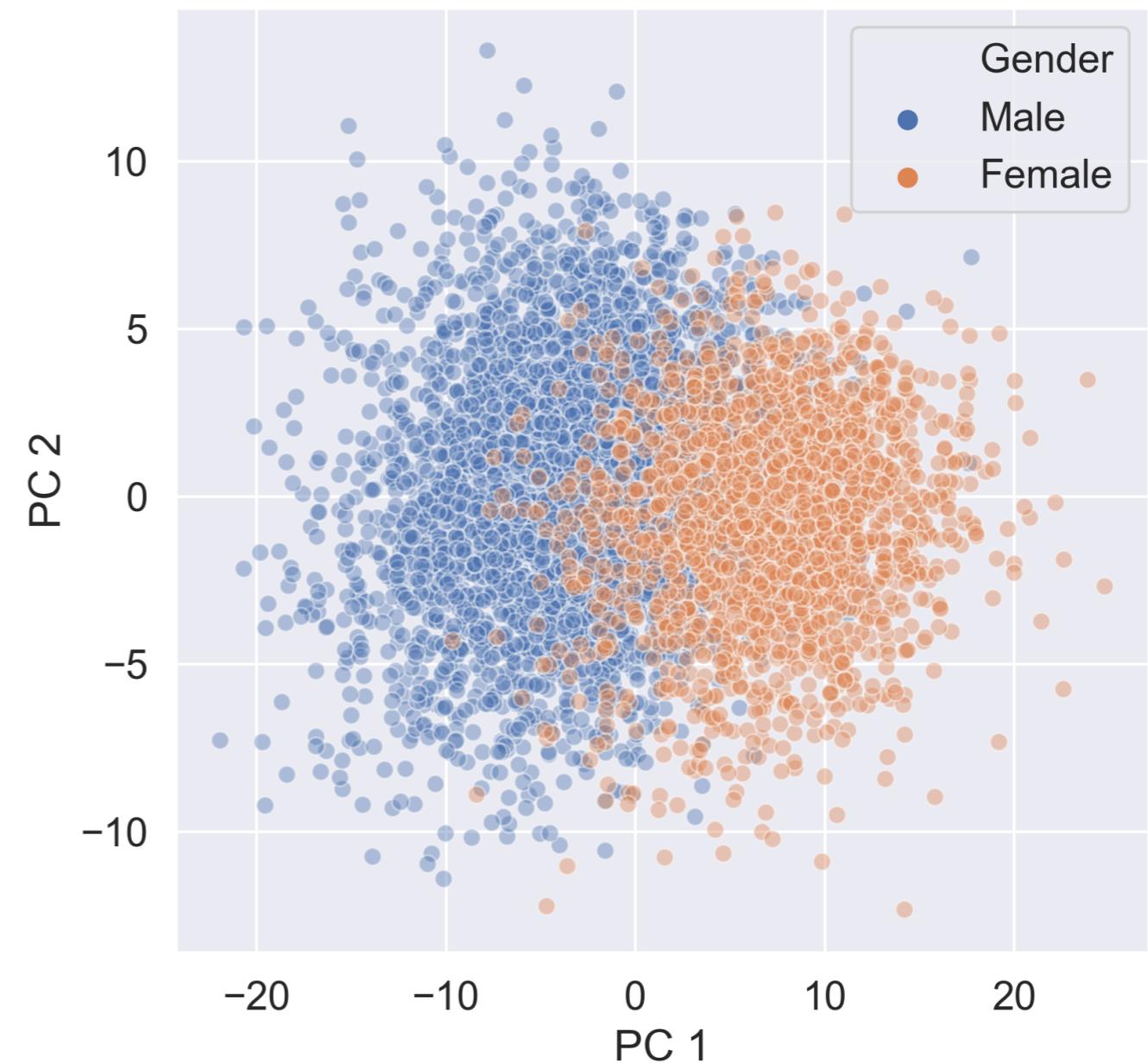
가
'height_class'
, 가



Checking the effect of categorical features

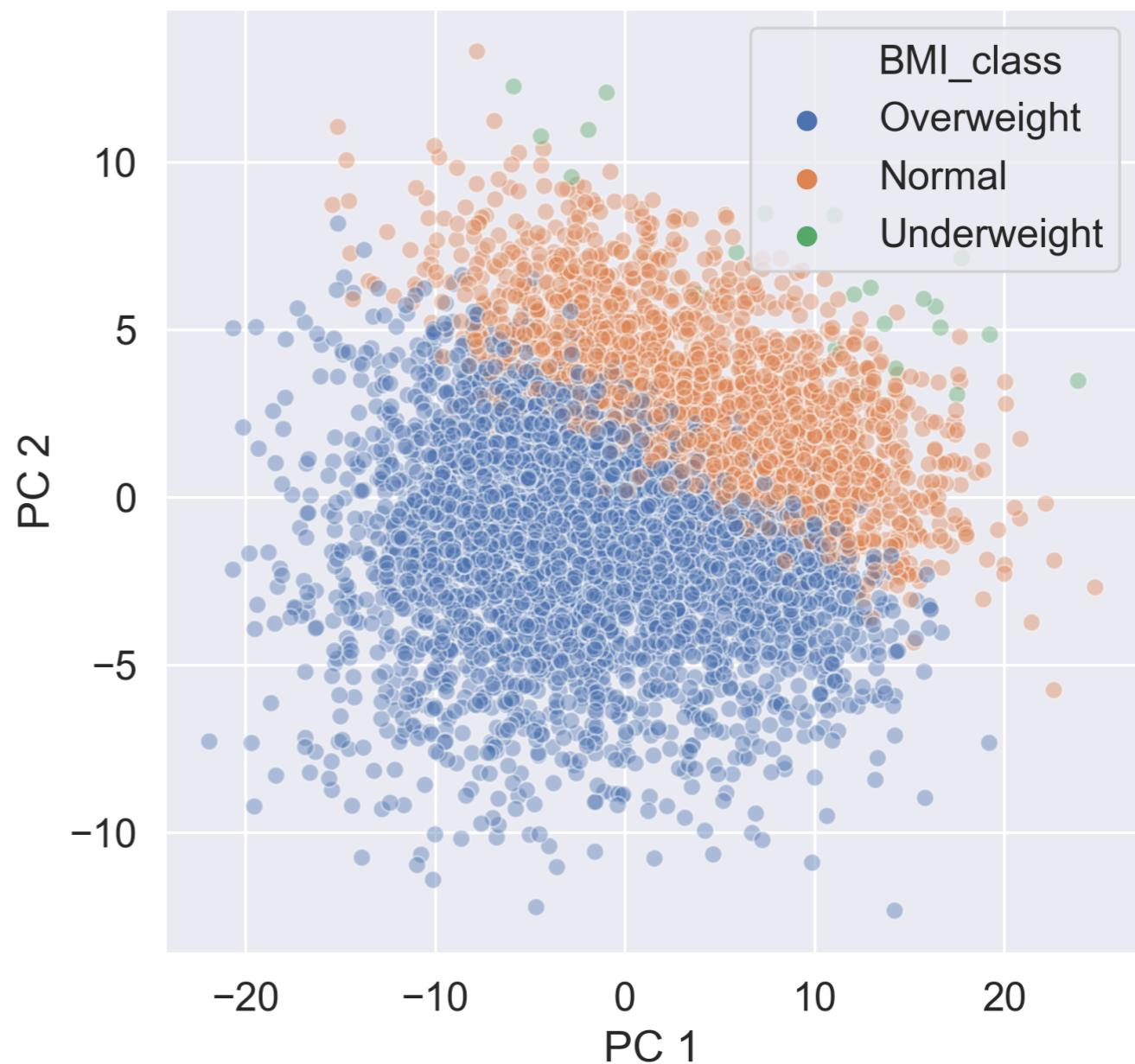
```
sns.scatterplot(data=ansur_categories,  
                  x='PC 1', y='PC 2',  
                  hue='Gender', alpha=0.4)
```

, 가



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())])
pipe.fit(X_train, y_train)
print(pipe.steps[1])
```

```
('reducer',
PCA(copy=True, iterated_power='auto', n_components=3, random_state=None,
svd_solver='auto', tol=0.0, whiten=False))
```

가

PCA in a model pipeline

```
pipe.steps[1][1].explained_variance_ratio_.cumsum()
```

가

74%

```
array([0.56, 0.69, 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

Jeroen Boeye

Machine Learning Engineer, 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.steps[1][1].components_))
```

5

PCA n_components
5가 . 가 가 . 0.9 90%
,"?"

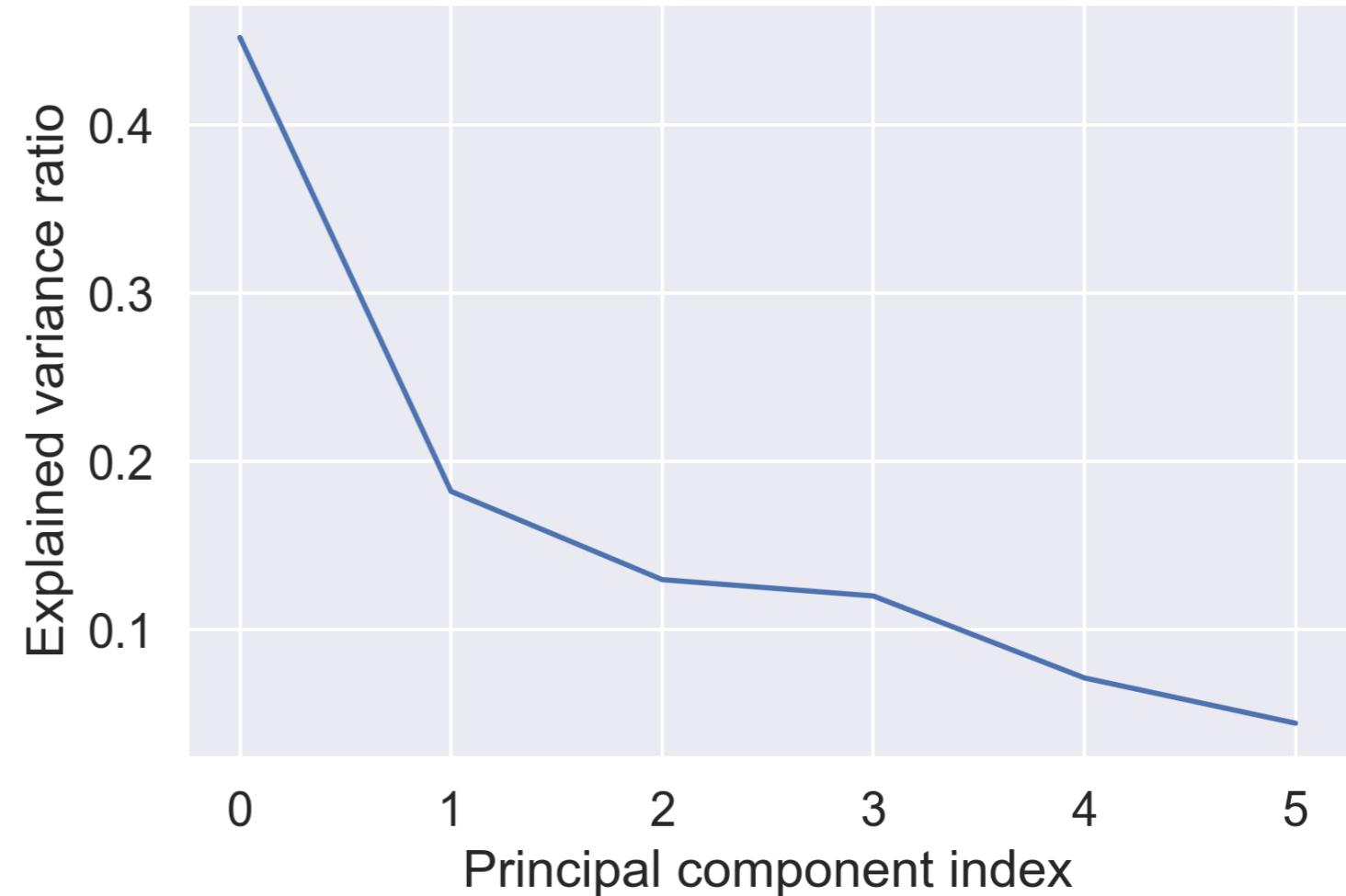
An optimal number of components

```
pipe.fit(poke_df)

var = pipe.steps[1][1].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.steps[1][1].explained_variance_ratio_

plt.plot(var)

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



PCA operations

PCA

pca
X pc NumPy
가

pca.fit(X)

X

pca.transform(X)

pc

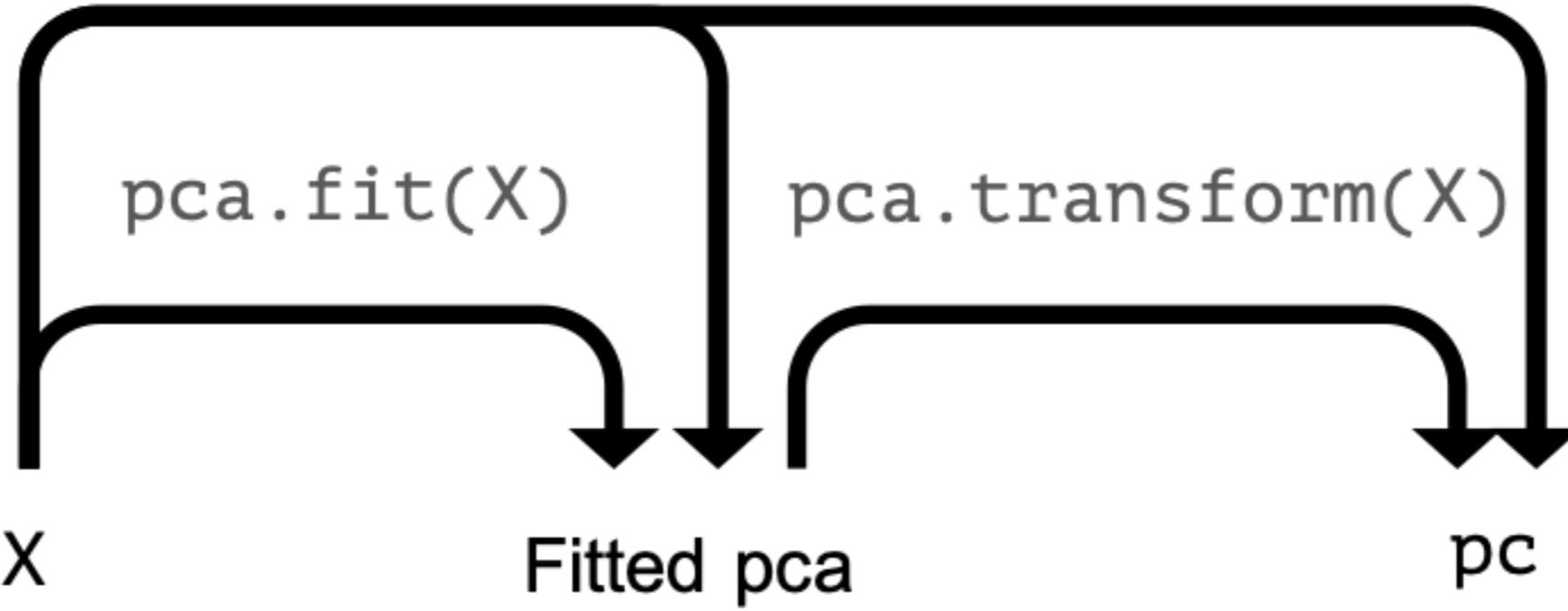
Fitted pca

PCA operations

.fit_transform()

가

pca.fit_transform(X)



PCA operations

.inverse_transform()

가

pca.fit_transform(X)

가

가

pca.fit(X)

pca.transform(X)

X

Fitted pca

pc

pca.inverse_transform(pc)

Compressing images



Compressing images

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

```
(15, 2914)
```

62 x 47 pixels = 2914 grayscale values (grayscale)

```
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



quality loss 가 ,

Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Congratulations!

DIMENSIONALITY REDUCTION IN PYTHON



Jeroen

Machine Learning Engineer, Faktion

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