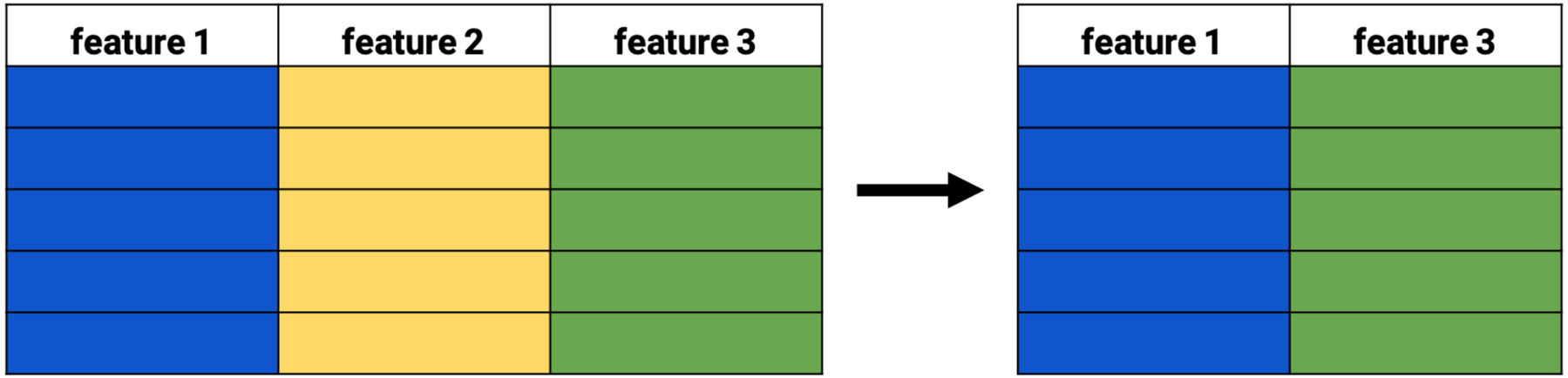
Feature extraction

DIMENSIONALITY REDUCTION IN PYTHON

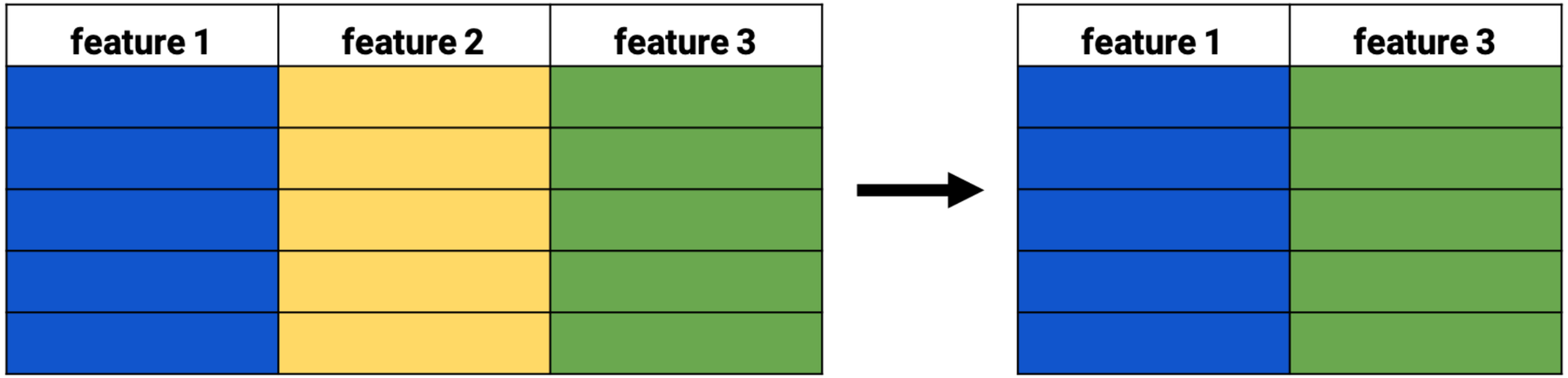
Jeroen Boeye

Machine Learning Engineer, Faktion

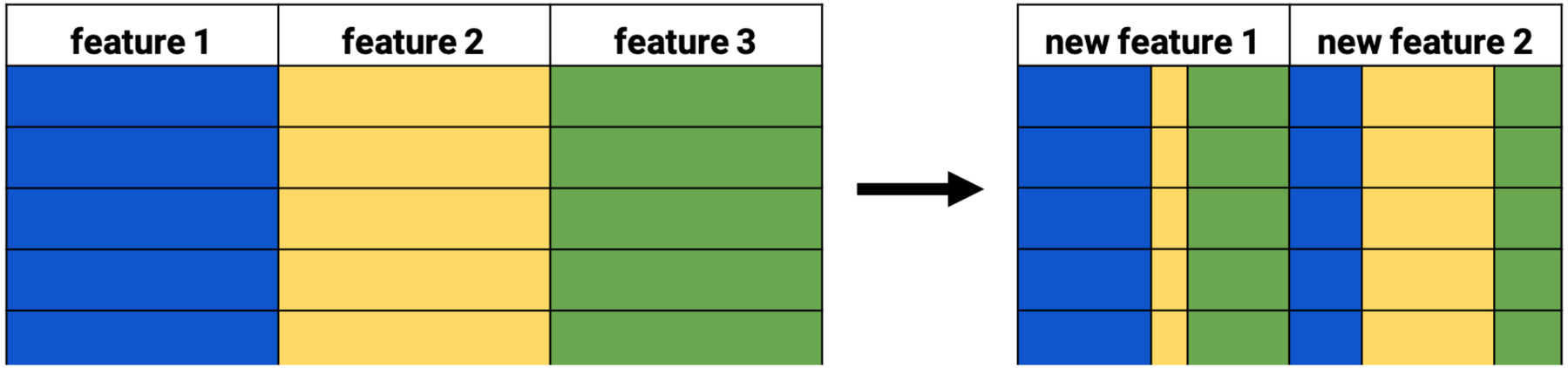
Feature selection



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

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

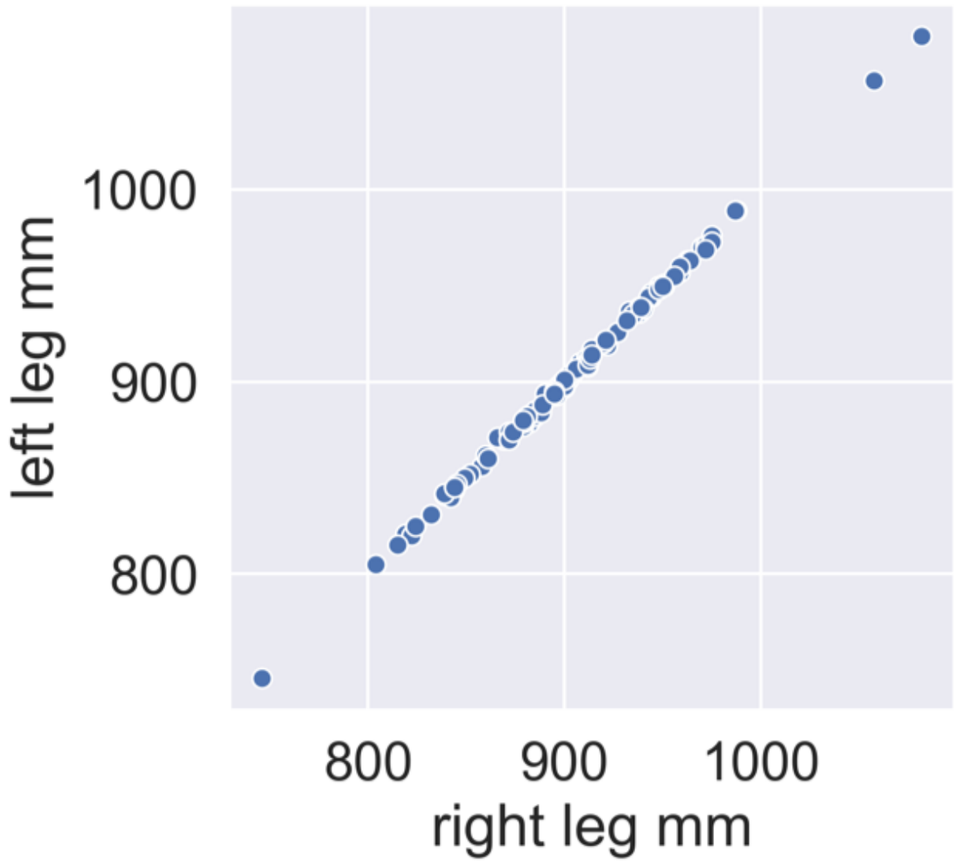
```
leg_df['leg mm'] = leg_df[['right leg mm', 'left leg mm']].mean(axis=1)
```

Feature generation - averages

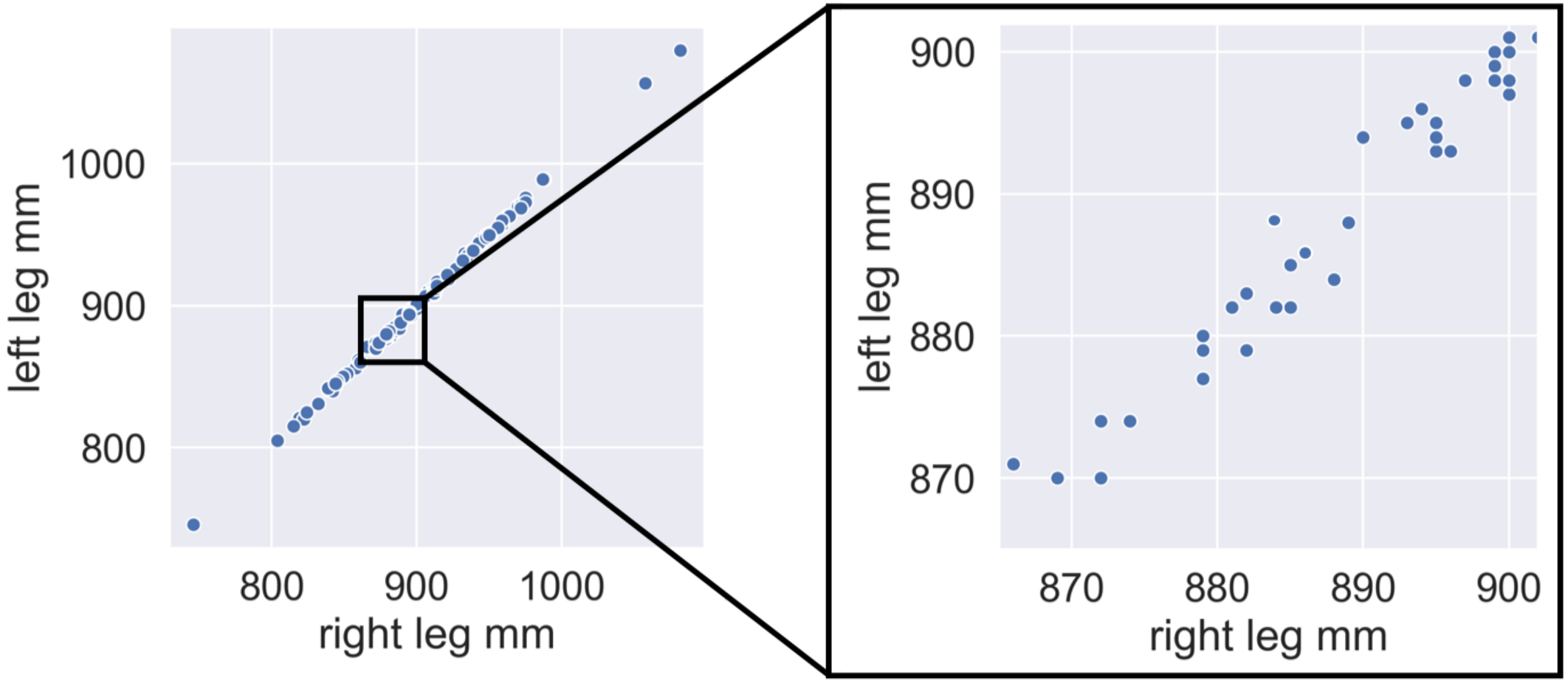
```
leg_df.drop(['right leg mm', 'left leg mm'], axis=1)
```

leg mm
883.5
869.5
900.5

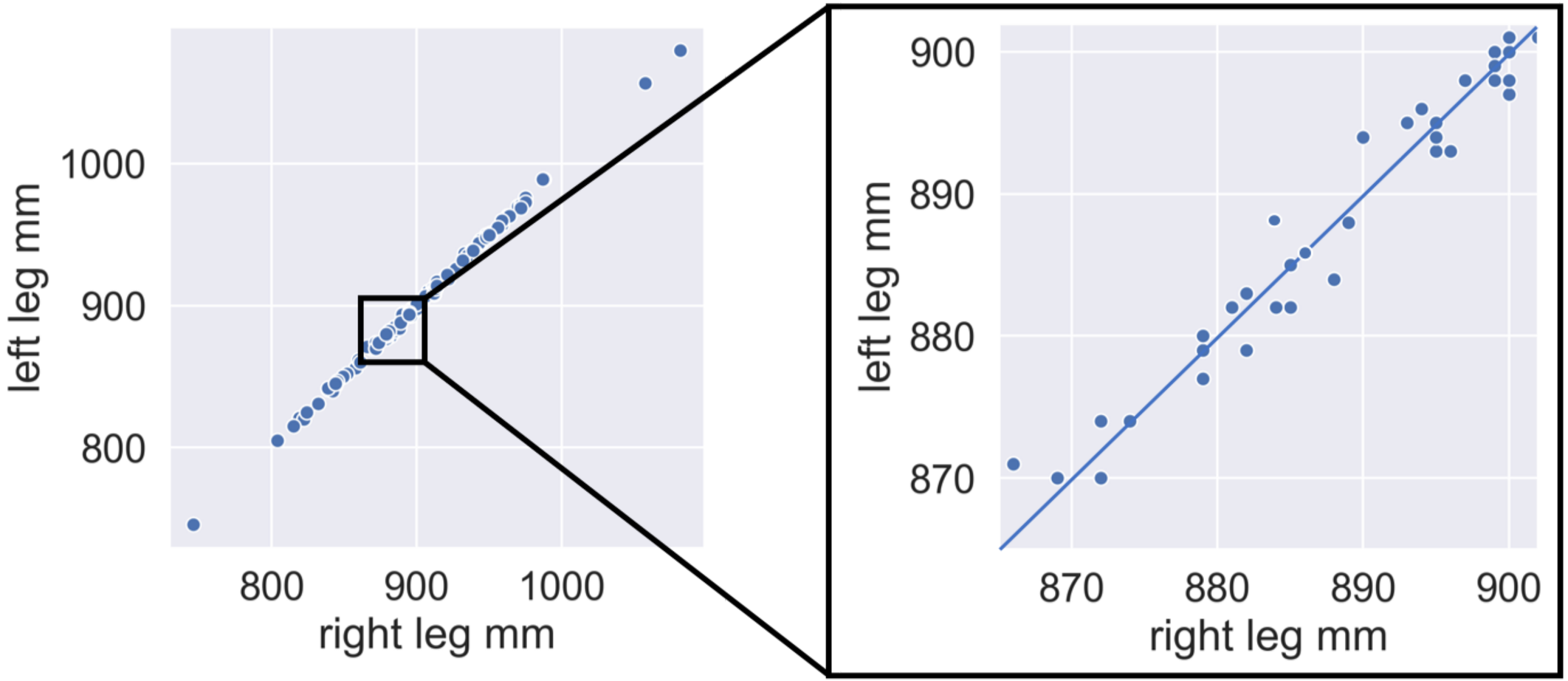
Cost of taking the average



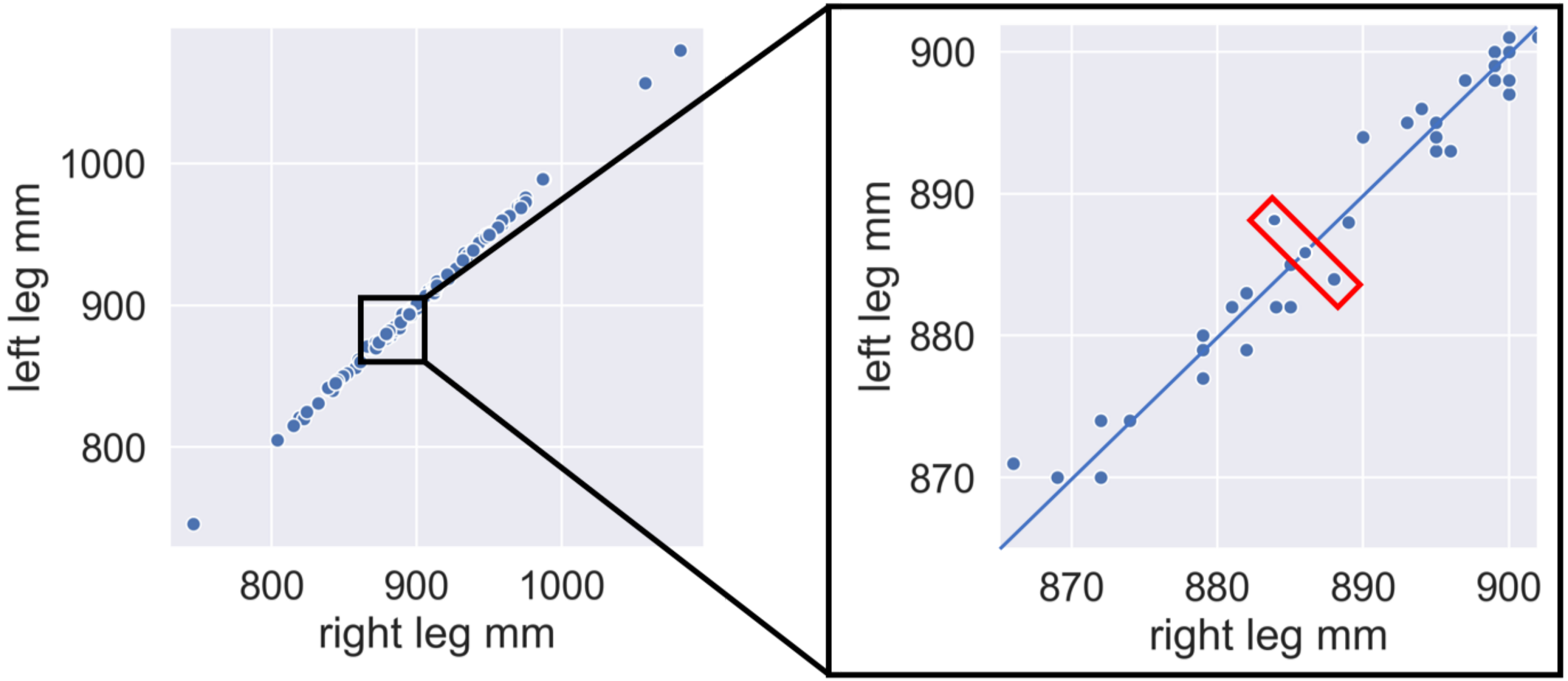
Cost of taking the average



Cost of taking the average

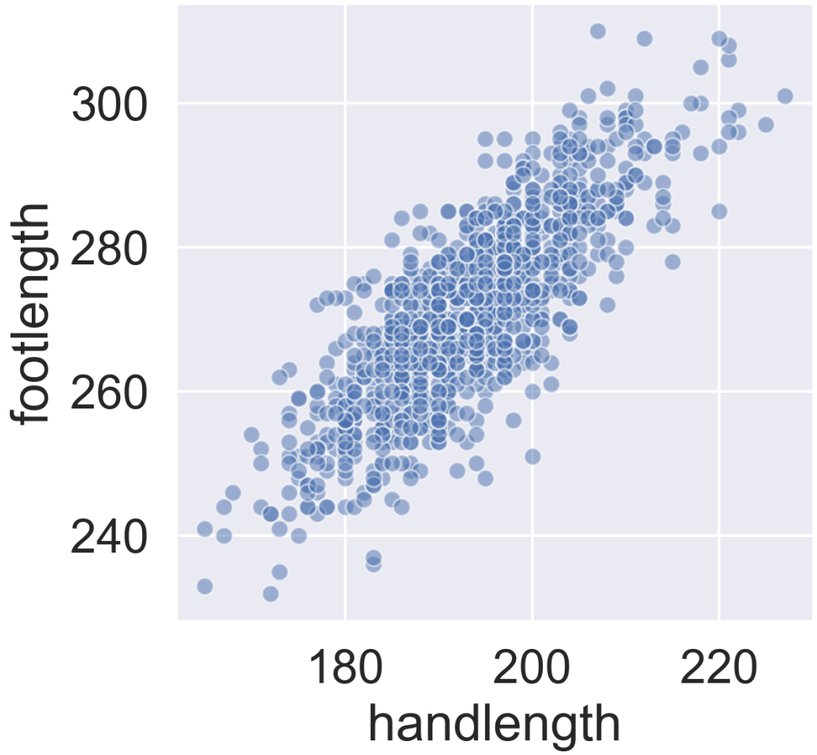


Cost of taking the average



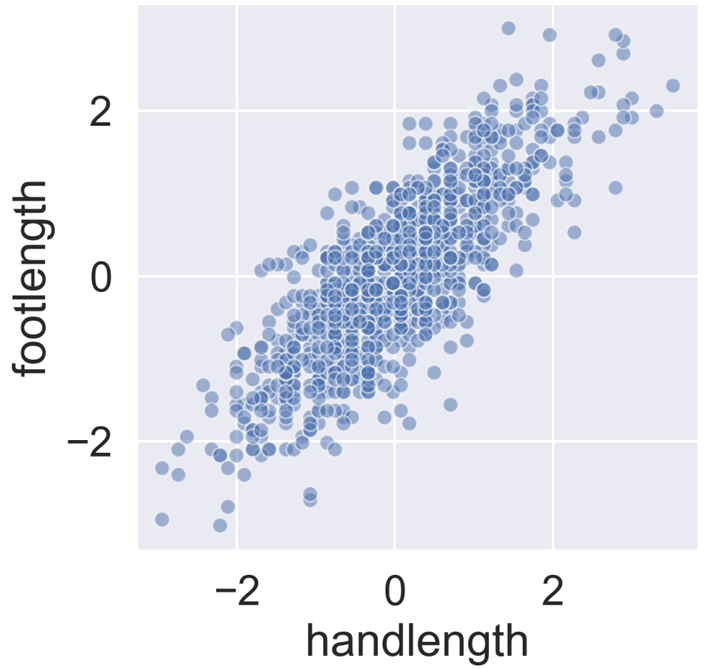
Intro to PCA

```
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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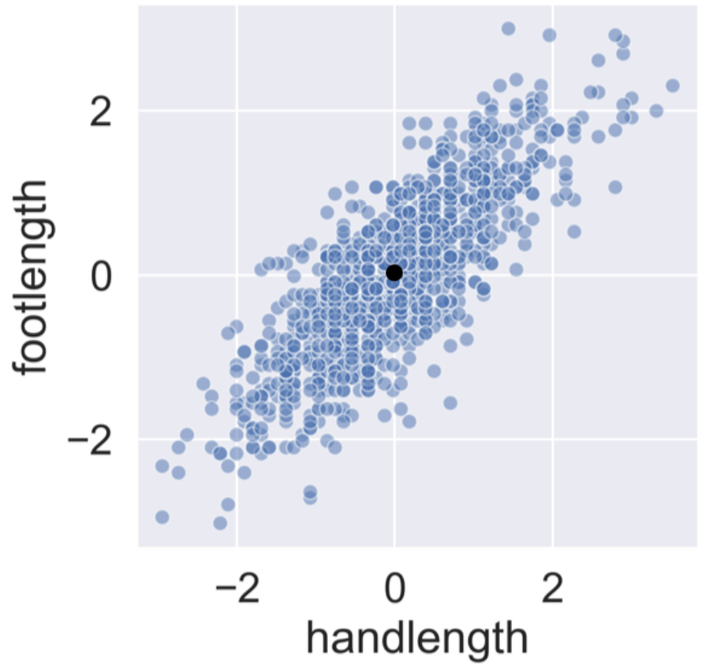

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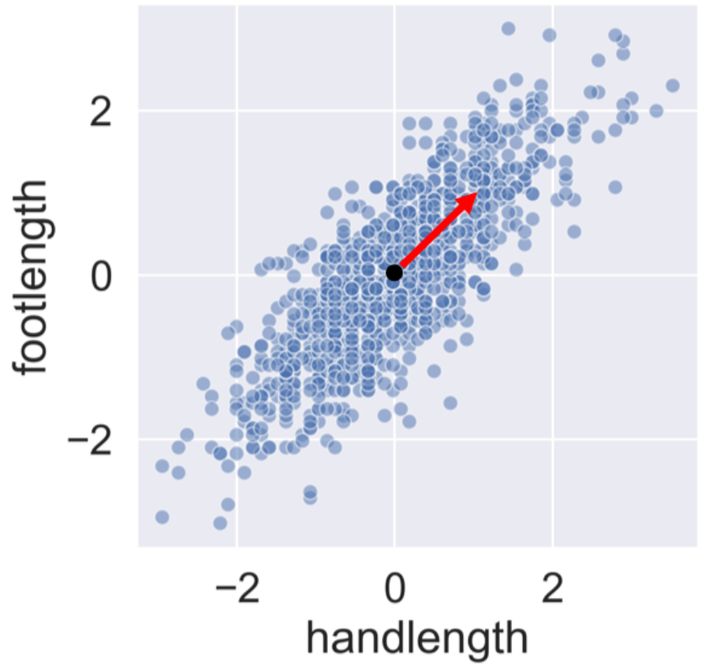

Intro to PCA

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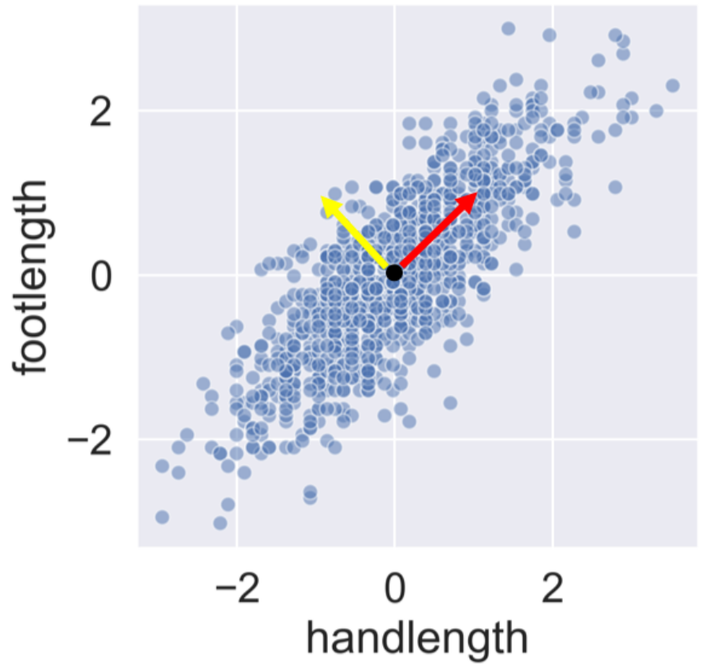
```



Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

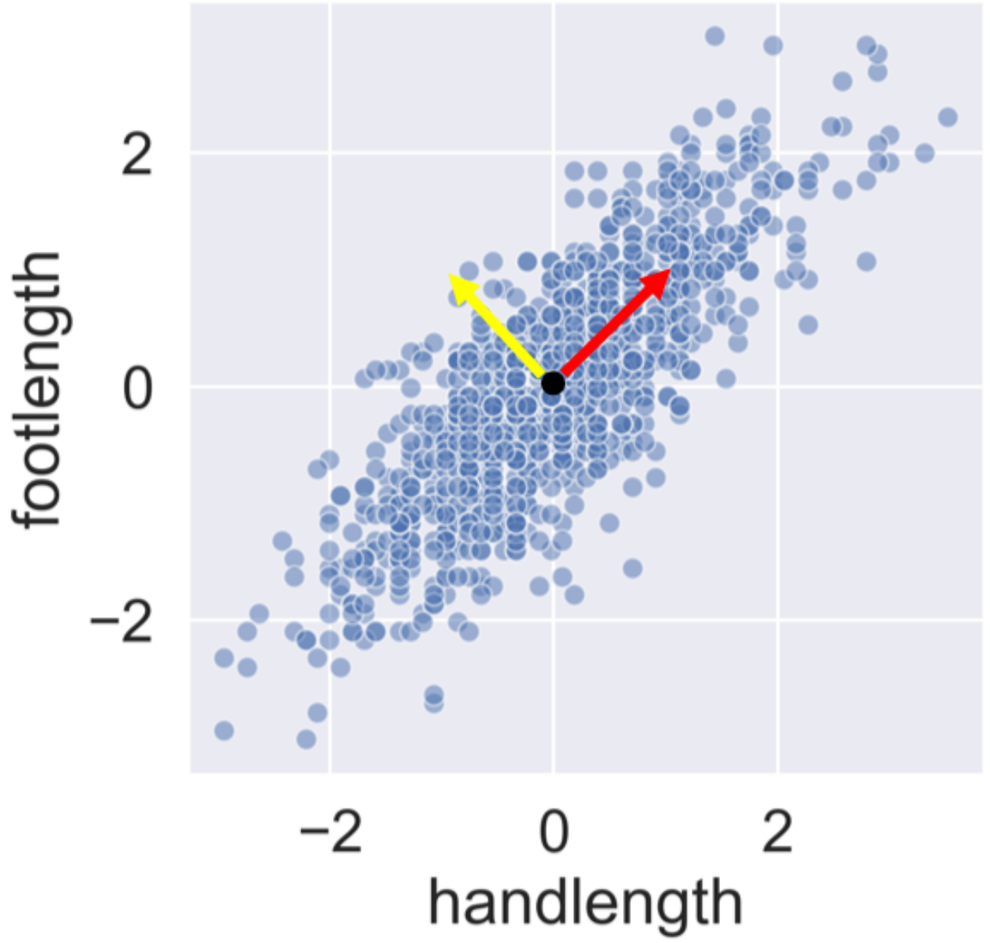
Principal component analysis

DIMENSIONALITY REDUCTION IN PYTHON

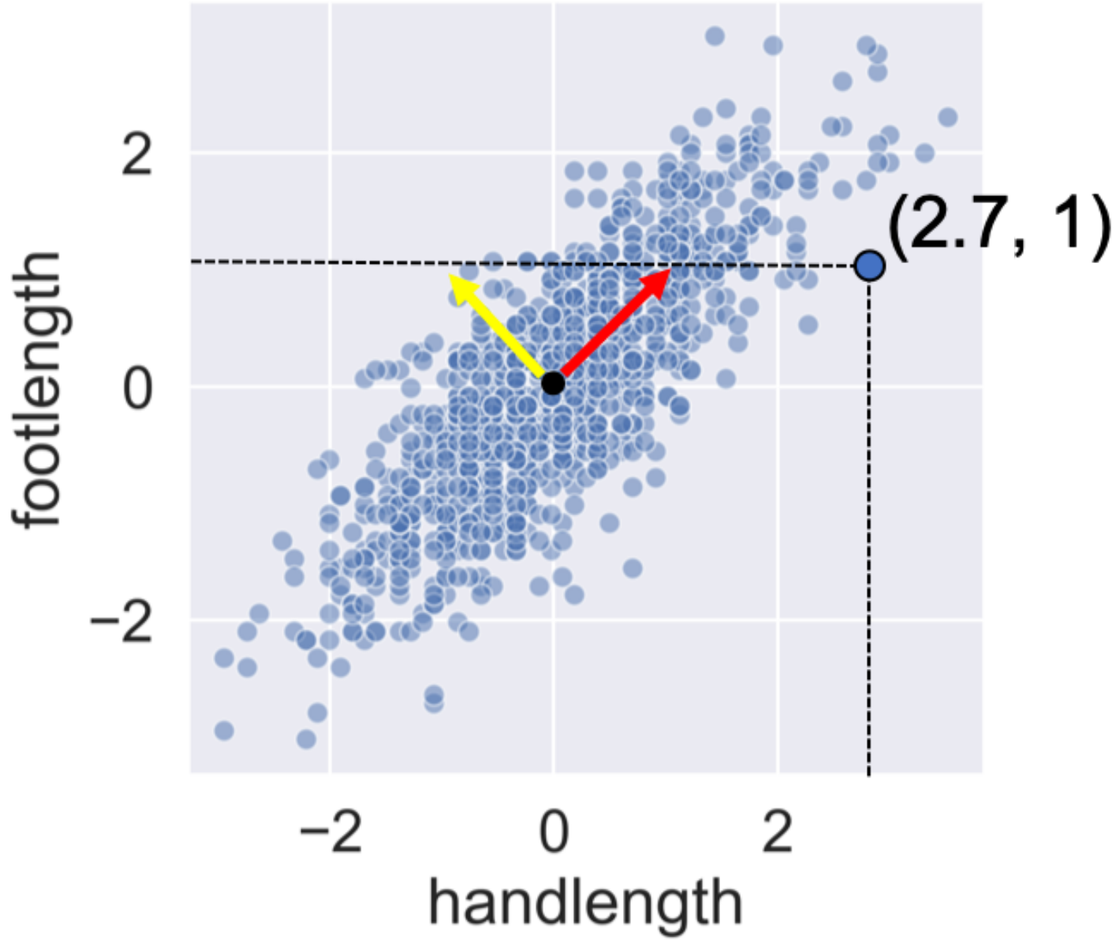
Jeroen Boeye

Machine Learning Engineer, Faktion

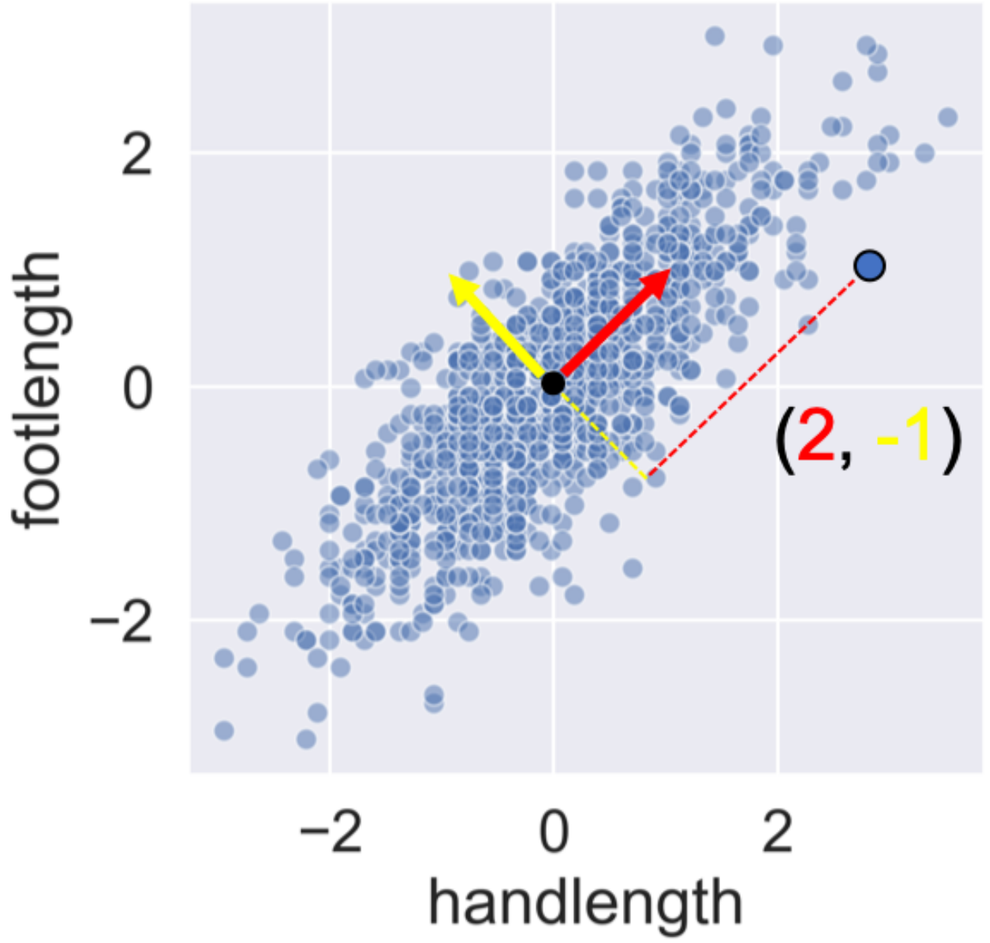
PCA concept



PCA concept



PCA concept



Calculating the principal components

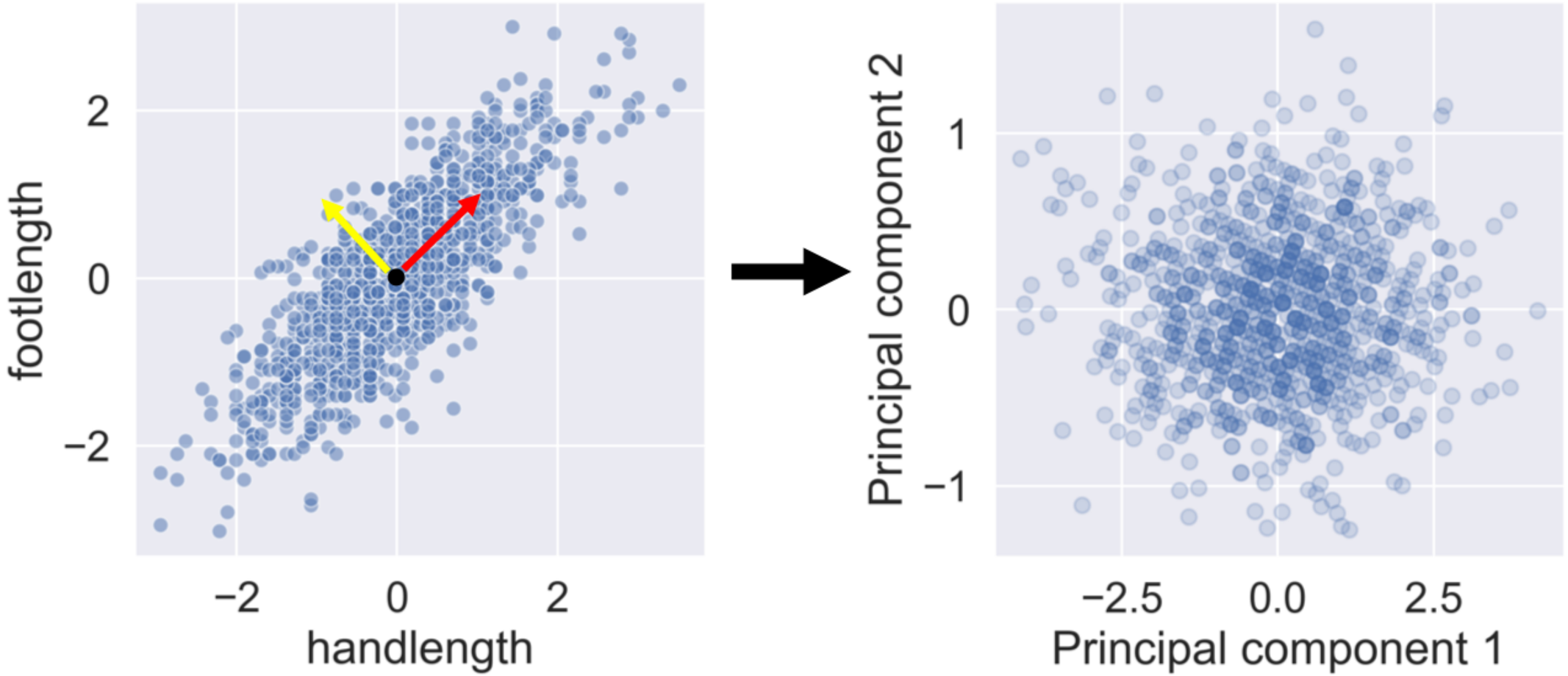
```
from sklearn.preprocessing import StandardScaler

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

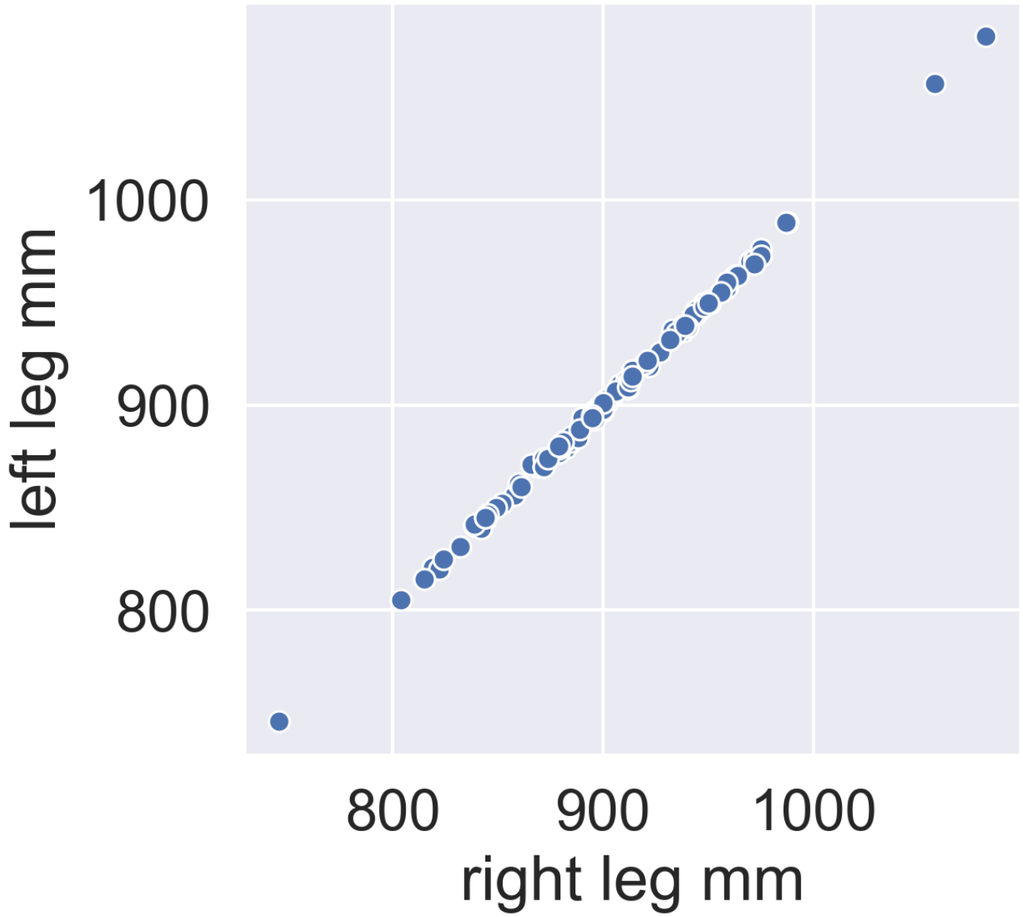
pca = PCA()

pca.fit(std_df)

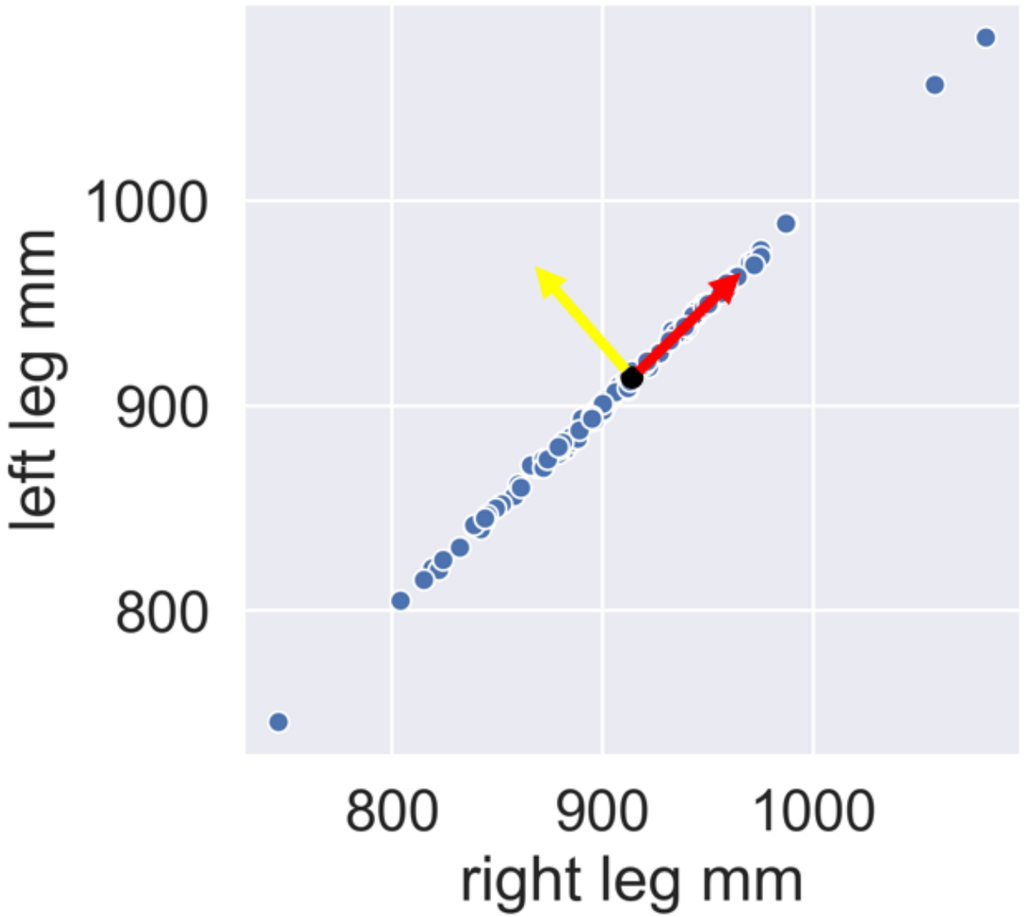
print(pca.explained_variance_ratio_)
```

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

PCA for dimensionality reduction



PCA for dimensionality reduction




```
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!

DIMENSIONALITY REDUCTION IN PYTHON

PCA applications

DIMENSIONALITY REDUCTION IN PYTHON

Jeroen Boeye

Machine Learning Engineer, Faktion

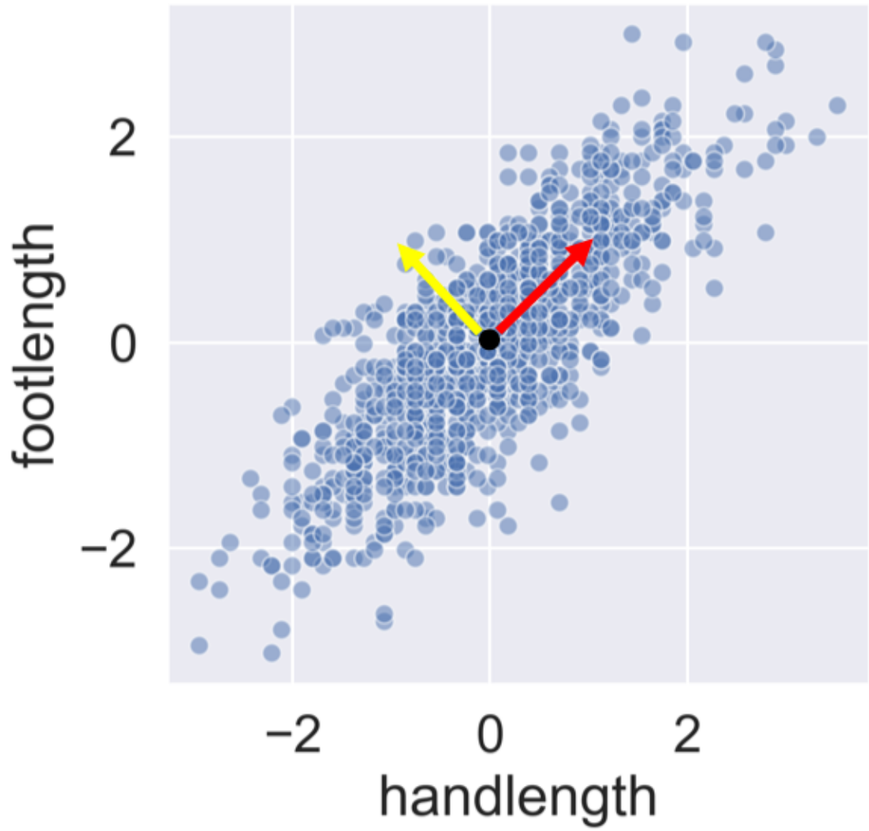
Understanding the components

```
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



PCA for data exploration

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

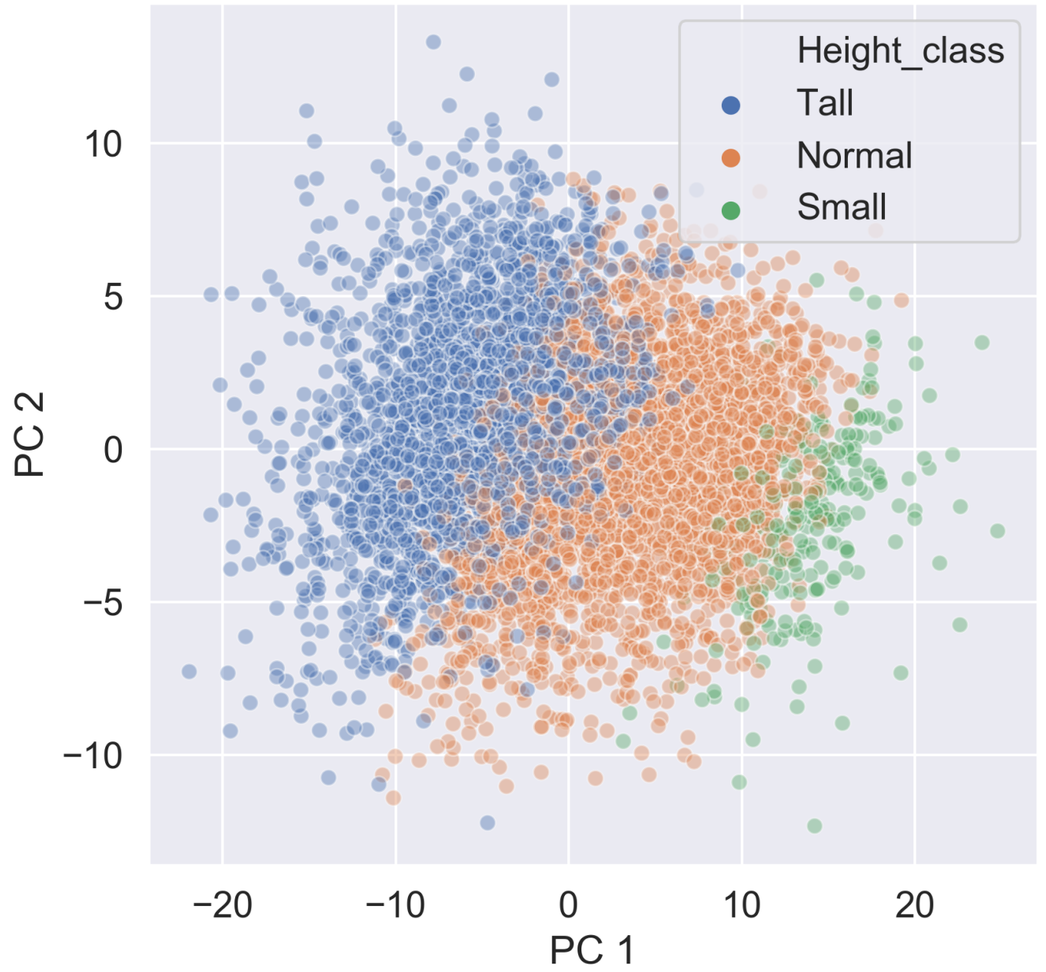
```
print(ansur_categories.head())
```

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)
```

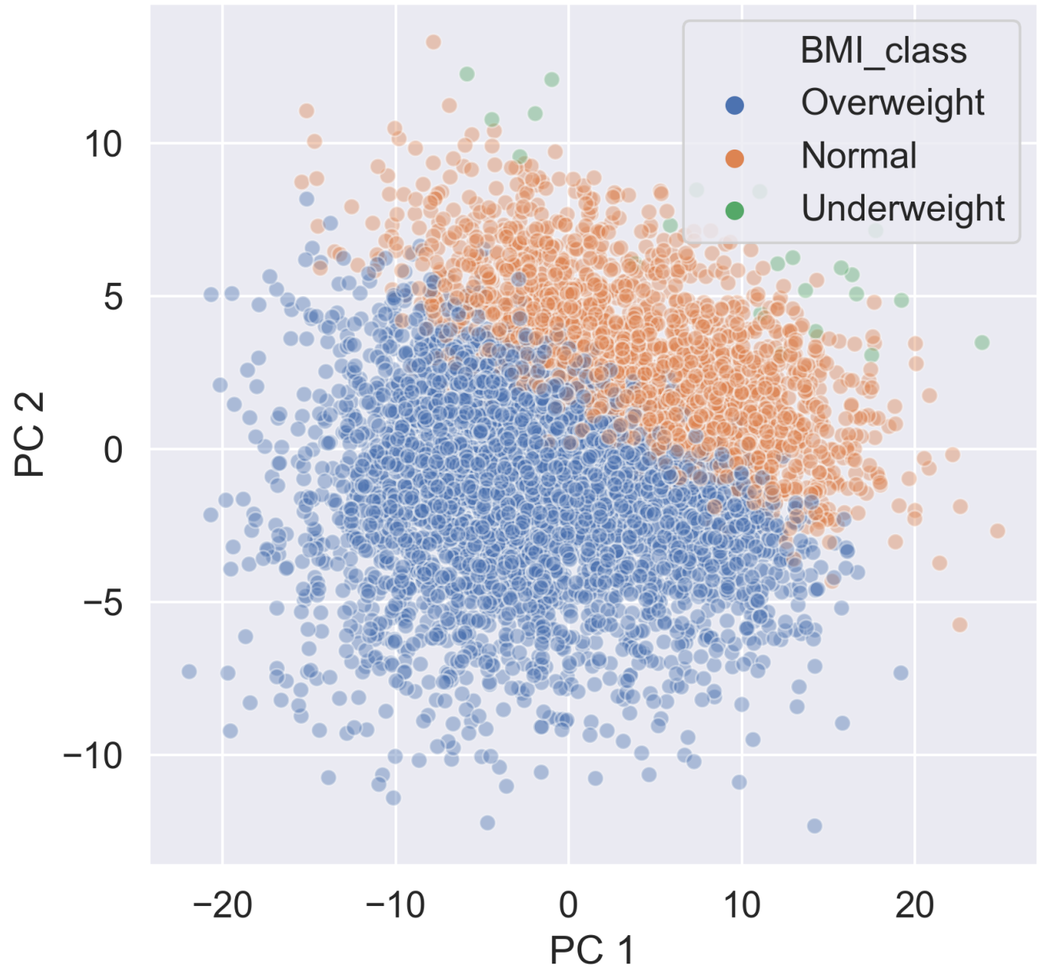


Checking the effect of categorical features

```
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())])

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))
```

PCA in a model pipeline

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

```
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 treshold

```
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
```

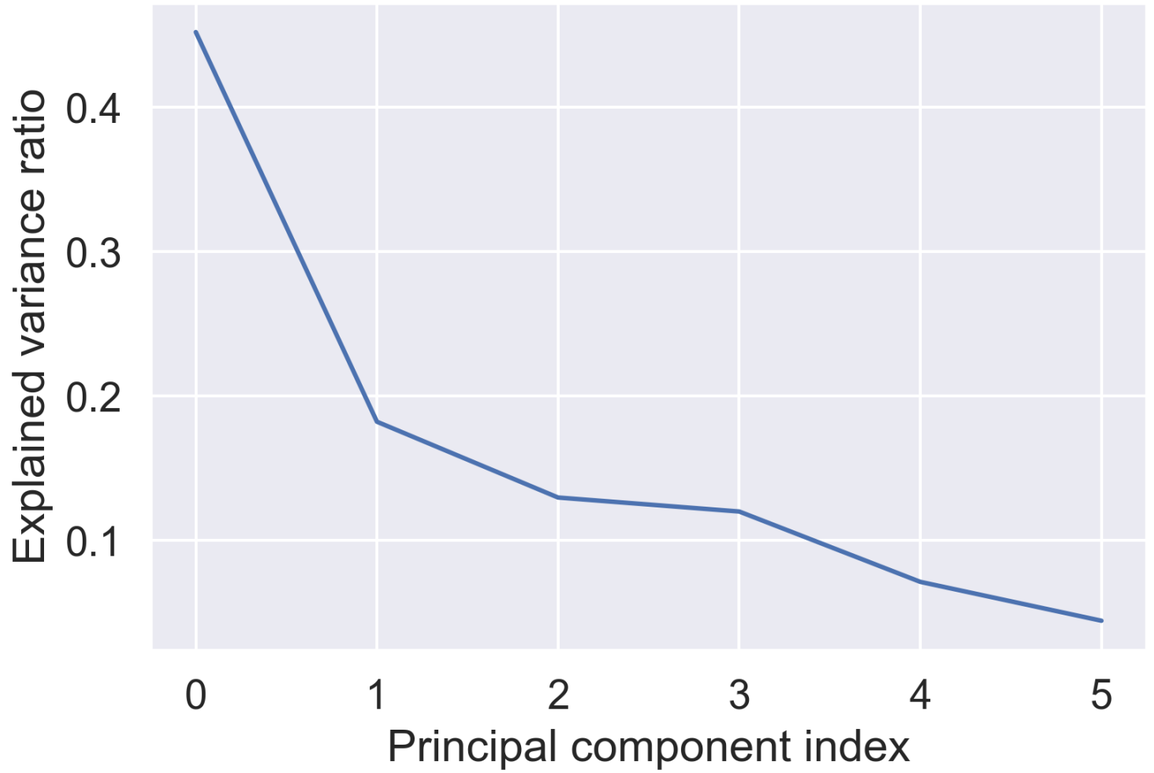
An optimal number of components

```
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_

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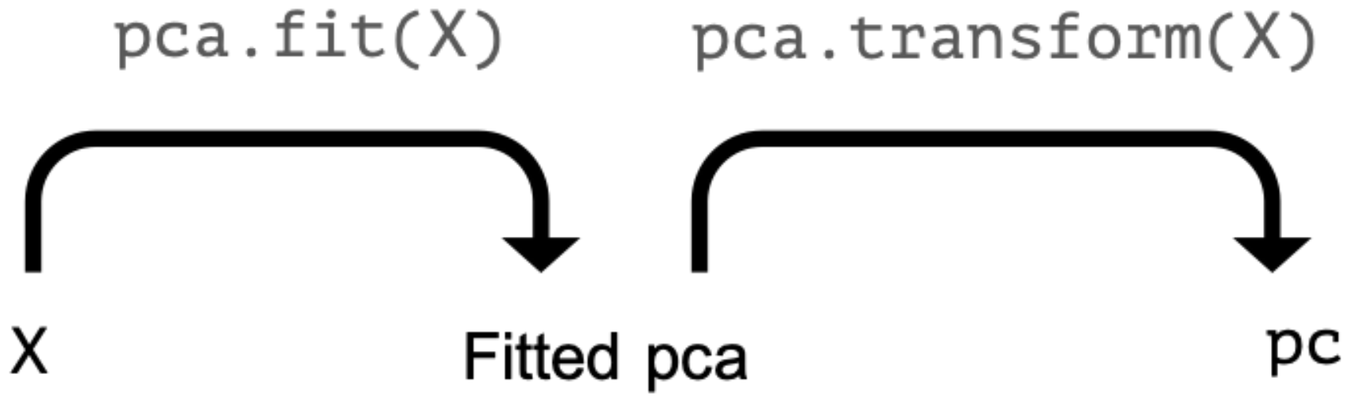
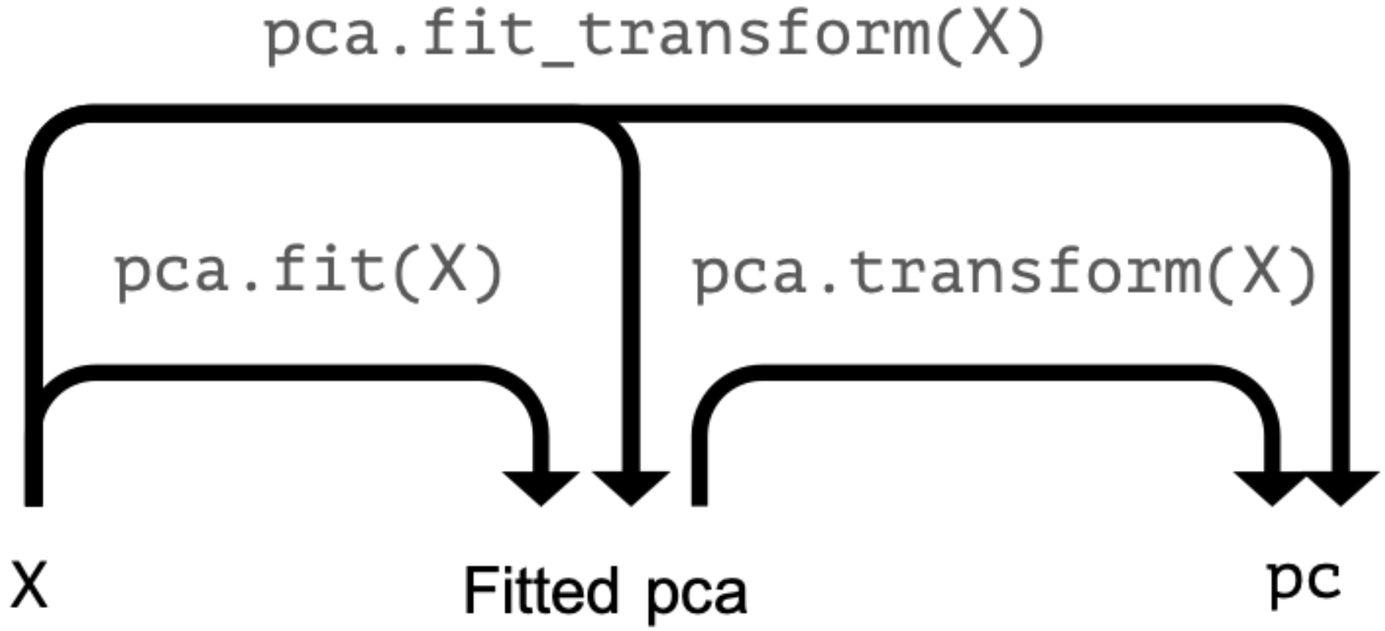
plt.xlabel('Principal component index')
plt.ylabel('Explained variance ratio')
plt.show()
```

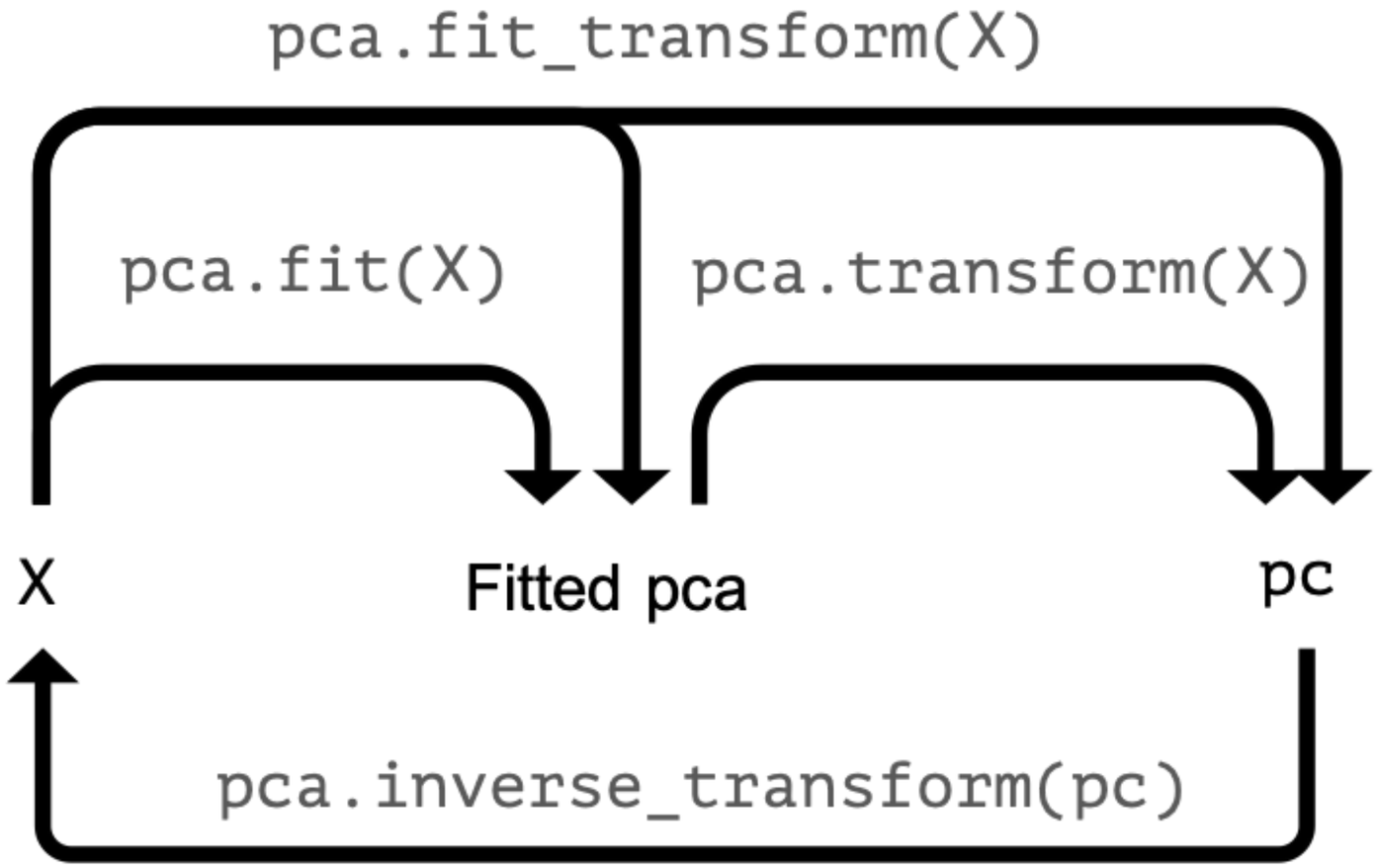
PCA operations



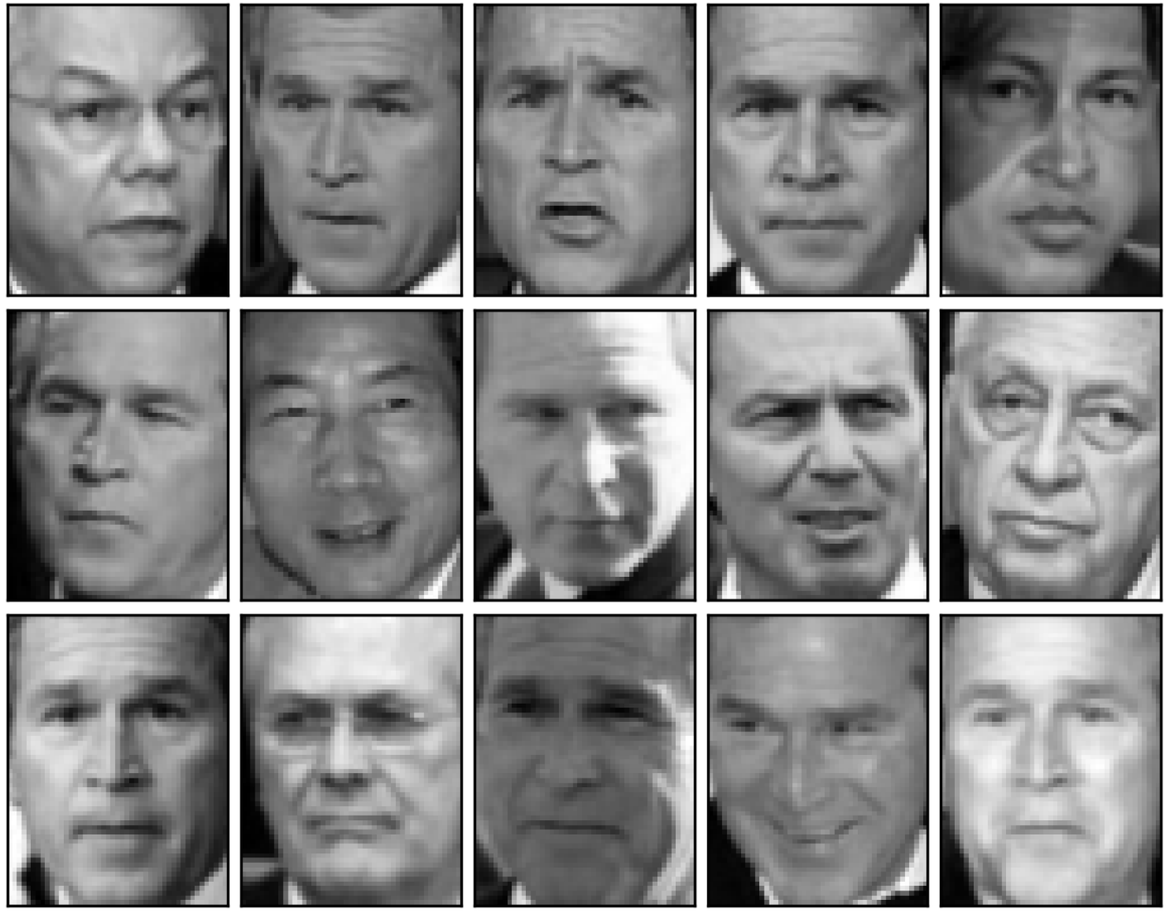
PCA operations



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)
```

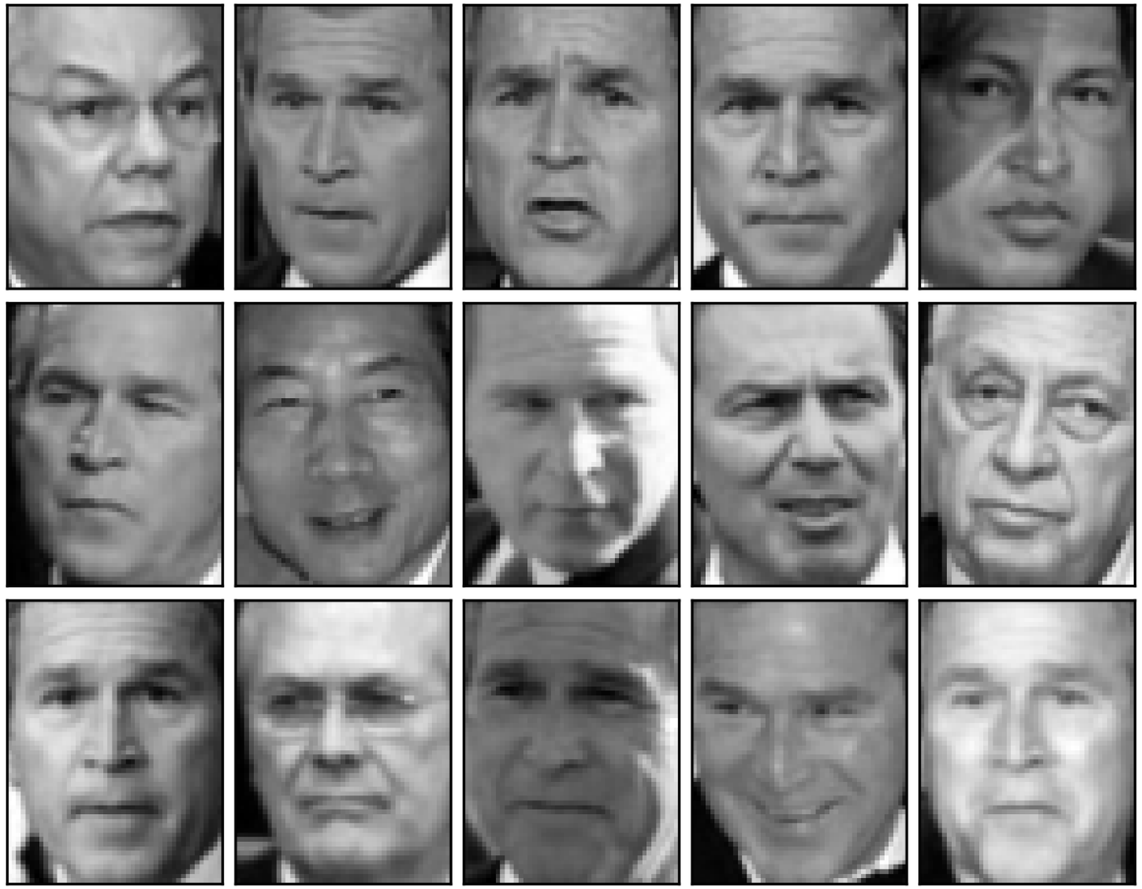
```
X_rebuilt = pipe.inverse_transform(pc)

print(X_rebuilt.shape)
```

```
(15, 2914)
```

```
img_plotter(X_rebuilt)
```

Rebuilding images



Let's practice!

DIMENSIONALITY REDUCTION IN PYTHON

Congratulations!

DIMENSIONALITY REDUCTION IN PYTHON

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