

# Feature selection of molecular descriptors

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```
# PATH TO CUSTOM MODULES
import sys

sys.path.append("../src")

# IMPORT LIBRARIES
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```

from sklearn.tree import DecisionTreeClassifier
from genetic_selection import GeneticSelectionCV
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA

# IMPORT CUSTOM MODULES
import utils.statisticsUtils as st

# DIRECTORIES
input_path = "../data/raw/"
input_train_path = "../data/raw/train_data/"
input_test_path = "../data/raw/test_data/"

output_train_path = "../data/processed/train_data/"
output_test_path = "../data/processed/test_data/"

# FILES
molecular_descriptors_training_file = "molecular_descriptors_training.csv"
molecular_descriptors_test_file = "molecular_descriptors_test.csv"

dataset_name = "molecular_descriptors"

# LOAD DATA
molecular_descriptors = pd.read_csv(
    input_train_path + molecular_descriptors_training_file
)
X = molecular_descriptors.drop(columns=["activity"])
Y = molecular_descriptors["activity"]

```

## 1 FILTER METHODS

### 1.1 LOW VARIANCE FILTER

```

# REMOVE VARIABLES WITH LOW VARIANCE
molecules_low_var_filter = st.low_variance_filter(X, 0.1)
X_filter = X[molecules_low_var_filter]

```

## 1.2 CORRELATION FILTER

First of all, we are going to remove the variables that are highly correlated with each other. We will use the Spearman correlation coefficient to measure the correlation between the variables. When two variables are highly correlated, we will remove the one that has the lowest correlation with the target variable.

### 1.2.1 LINEAR CORRELATED VARIABLES

```
# REMOVE VARIABLES WITH HIGH PEARSON CORRELATION
molecules_corr_filter_pearson = st.pearson_corr_filter(X_filter, 0.8, Y)

X_filter = X_filter.drop(columns=molecules_corr_filter_pearson)
```

### 1.2.2 NON-LINEAR CORRELATED VARIABLES

```
# REMOVE VARIABLES WITH HIGH SPEARMAN CORRELATION
molecules_corr_filter_spearman = st.spearman_corr_filter(X_filter, 0.8, Y)

X_filter = X_filter.drop(columns=molecules_corr_filter_spearman)
```

## 2 PCA SELECTION

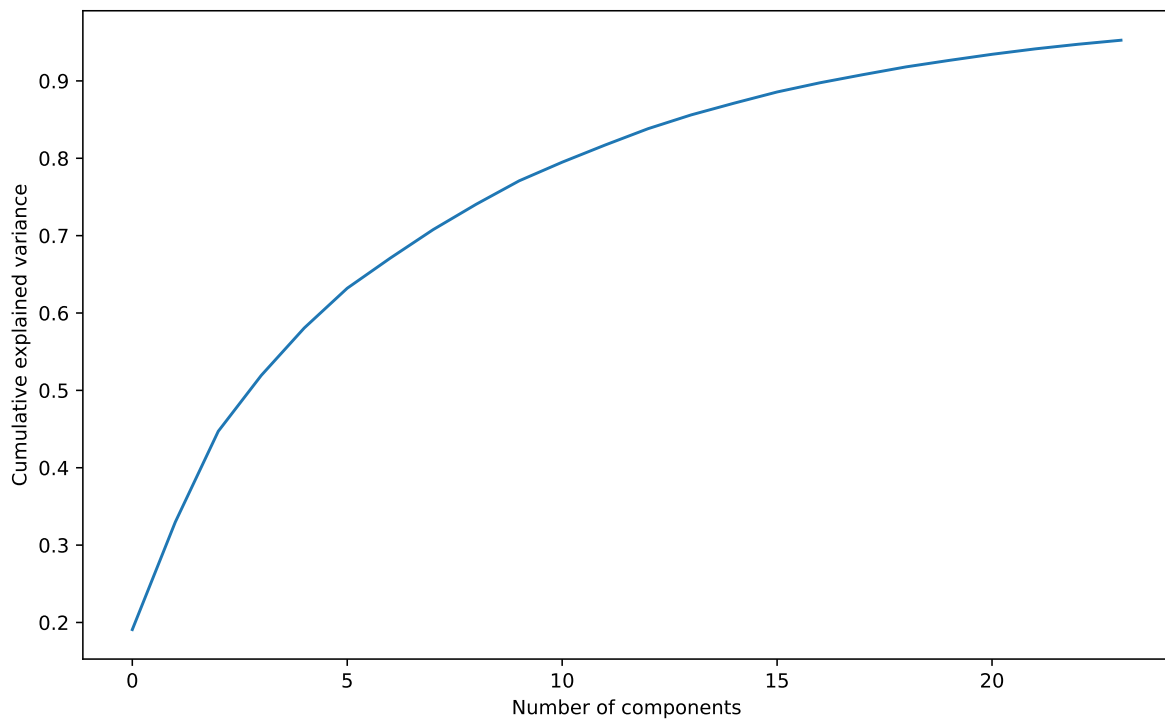
### 2.1 GET NUMBER OF COMPONENTS TO EXPLAIN 95% OF VARIANCE

```
# SCALE DATA FOR PCA
scaler = MinMaxScaler()
X_filter_scaled = pd.DataFrame(scaler.fit_transform(X_filter), columns=X_filter.columns)

# PCA 95% VARIANCE
pca = PCA(n_components=0.95)
# DATAFRAME
X_pca = pd.DataFrame(pca.fit_transform(X_filter_scaled))
```

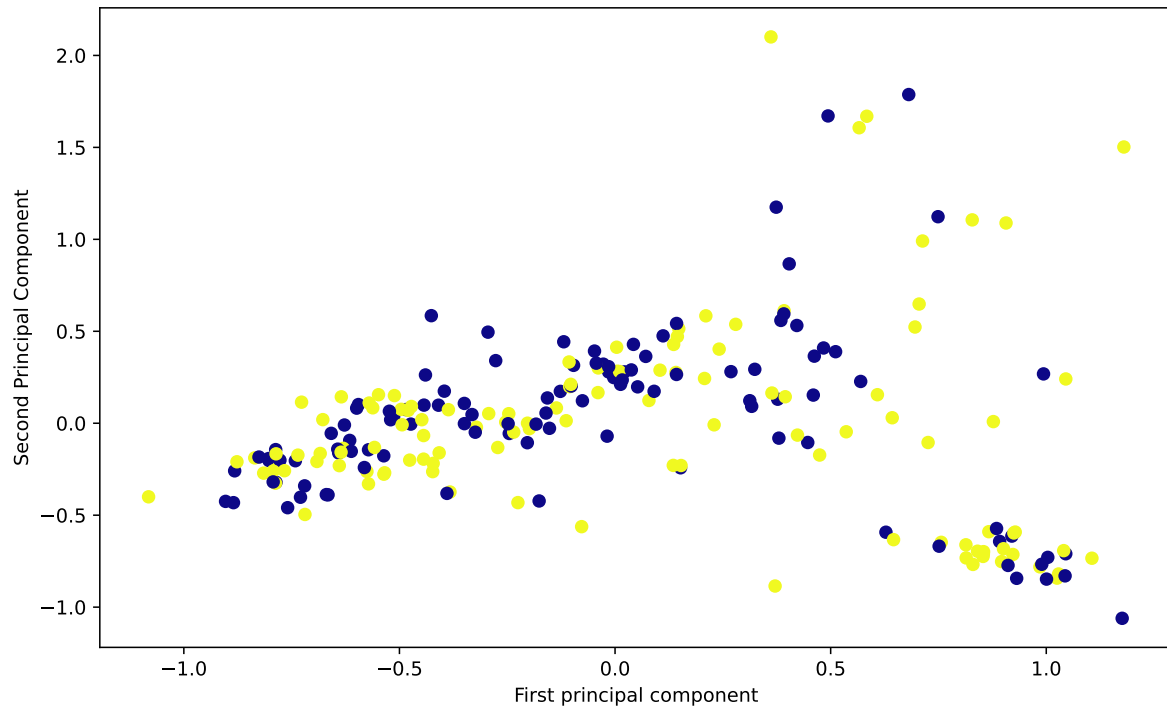
```
# PLOT PCA
pca.fit(X_filter_scaled)
plt.figure(figsize=(10, 6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel("Number of components")
plt.ylabel("Cumulative explained variance")
```

```
Text(0, 0.5, 'Cumulative explained variance')
```



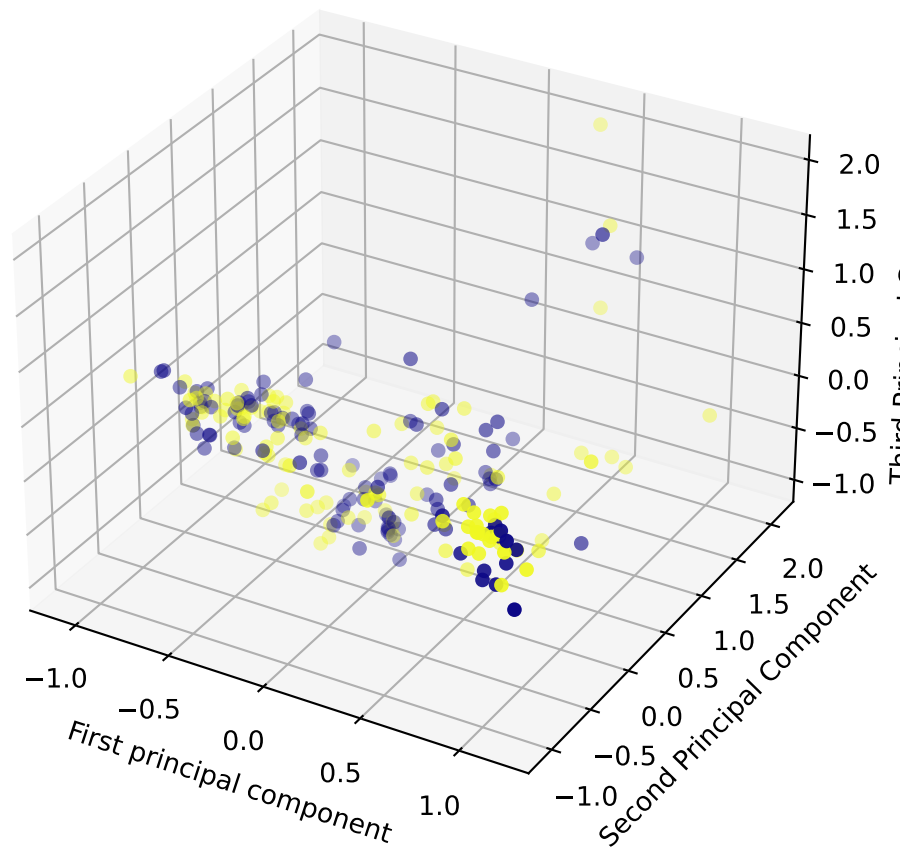
```
# PLOT TWO FIRST COMPONENTS
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[0], X_pca[1], c=Y, cmap="plasma")
plt.xlabel("First principal component")
plt.ylabel("Second Principal Component")
```

```
Text(0, 0.5, 'Second Principal Component')
```



```
# PLOT THREE FIRST COMPONENTS 3D
fig = plt.figure(figsize=(10, 6))
ax = fig.add_subplot(111, projection="3d")
ax.scatter(X_pca[0], X_pca[1], X_pca[2], c=Y, cmap="plasma")
ax.set_xlabel("First principal component")
ax.set_ylabel("Second Principal Component")
ax.set_zlabel("Third Principal Component")
```

```
Text(0.5, 0, 'Third Principal Component')
```



### 3 GENETIC ALGORITHM FEATURE SELECTION

```
# GENETIC ALGORITHM FEATURE SELECTION
from genetic_selection import GeneticSelectionCV
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestClassifier
```

```
# TRAIN MODEL
model = RandomForestClassifier(random_state=100)
```

```
# SCALED VARIABLES
scaler = MinMaxScaler()
```

```
X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

```
model.fit(X_scaled, Y)
```

```
RandomForestClassifier(random_state=100)
```

```
# SELECT FEATURES
selector = GeneticSelectionCV(
    model,
    cv=5,
    verbose=1,
    scoring="roc_auc",
    crossover_proba=0.5,
    mutation_proba=0.2,
    n_generations=50,
    crossover_independent_proba=0.5,
    mutation_independent_proba=0.05,
    tournament_size=3,
    n_gen_no_change=20,
    caching=True,
    n_jobs=-1,
)
selector = selector.fit(X_scaled, Y)
```

Selecting features with genetic algorithm.

	gen	nevals	avg			std			min
	0	300	[ 0.573265	128.873333	0.092016]	[ 0.018993	74.47839	0.014836]	[ 0.4
	1	184	[ 0.58419	136.536667	0.09442 ]	[ 0.015855	60.05205	0.013189]	[ 0.5
	2	176	[ 0.590926	124.78	0.097293]	[ 0.014292	48.874925	0.011463]	[ 0.6
	3	183	[ 0.597088	110.743333	0.099676]	[ 0.014172	41.634891	0.011473]	[ 0.7
	4	172	[ 0.603395	97.483333	0.100622]	[ 0.013932	30.713999	0.012123]	[ 0.8

5	187	[	0.606323	88.243333	0.101197]	[	0.015546	22.267408	0.013112]	[	0
6	172	[	0.611837	87.543333	0.101945]	[	0.015105	16.729857	0.012711]	[	0
7	176	[	0.617656	84.91	0.104028]	[	0.013429	14.790602	0.014061]	[	0
8	187	[	0.621171	83.346667	0.103753]	[	0.014518	11.941517	0.013333]	[	0
9	159	[	0.626471	80.88	0.102773]	[	0.014646	11.206201	0.012394]	[	0
10	159	[	0.631809	79.68	0.102946]	[	0.013999	9.479677	0.011901]	[	0
11	185	[	0.634524	77.71	0.103872]	[	0.014935	9.277171	0.011813]	[	0
12	183	[	0.638116	77.036667	0.104608]	[	0.014048	8.570219	0.010897]	[	0
13	185	[	0.642037	75.453333	0.1033 ]	[	0.014724	7.866881	0.011702]	[	0
14	178	[	0.646757	75.	0.10212 ]	[	0.013558	7.038939	0.012101]	[	0
15	188	[	0.649964	74.516667	0.102001]	[	0.013822	7.040103	0.012729]	[	0
16	148	[	0.654273	74.333333	0.101356]	[	0.013325	7.077821	0.012061]	[	0
17	175	[	0.656859	73.33	0.100979]	[	0.014006	7.219956	0.011449]	[	0
18	175	[	0.65874	71.78	0.100204]	[	0.013677	6.800853	0.010531]	[	0
19	180	[	0.660418	72.04	0.100266]	[	0.013935	6.984631	0.011668]	[	0
20	179	[	0.661462	70.766667	0.09877 ]	[	0.014368	6.81363	0.011846]	[	0
21	184	[	0.662965	70.27	0.098818]	[	0.014483	6.076493	0.01104 ]	[	0
22	181	[	0.664708	70.56	0.099474]	[	0.014438	5.702023	0.010117]	[	0
23	193	[	0.66597	71.573333	0.098559]	[	0.015313	6.025332	0.010889]	[	0



24	177	[	0.667745	71.35	0.097099]	[	0.014582	5.921219	0.009789]	[	0
25	189	[	0.670357	70.51	0.09775 ]	[	0.014746	5.986365	0.01097 ]	[	0
26	177	[	0.673995	69.283333	0.097842]	[	0.014345	6.23028	0.010393]	[	0
27	164	[	0.676947	68.253333	0.097579]	[	0.014798	5.509007	0.010795]	[	0
28	196	[	0.678373	67.846667	0.097864]	[	0.014701	4.91289	0.010842]	[	0
29	183	[	0.680024	68.216667	0.095833]	[	0.014718	4.92237	0.010833]	[	0
30	192	[	0.679777	68.403333	0.09632 ]	[	0.01532	4.79451	0.010881]	[	0
31	183	[	0.681877	68.123333	0.095653]	[	0.013854	4.726675	0.010424]	[	0
32	163	[	0.682006	67.663333	0.09544 ]	[	0.015592	4.843895	0.010679]	[	0
33	188	[	0.68259	67.616667	0.095714]	[	0.017148	5.084262	0.01078 ]	[	0
34	194	[	0.683459	67.26	0.094917]	[	0.017192	4.740506	0.01007 ]	[	0
35	190	[	0.685088	67.003333	0.093564]	[	0.016554	5.17848	0.010562]	[	0
36	178	[	0.688469	65.69	0.094038]	[	0.01628	5.286514	0.01074 ]	[	0
37	185	[	0.687644	65.54	0.094165]	[	0.016646	5.167372	0.010711]	[	0
38	170	[	0.689826	64.486667	0.093035]	[	0.017134	5.004314	0.01163 ]	[	0
39	198	[	0.688494	64.54	0.092361]	[	0.017534	5.084788	0.011161]	[	0
40	176	[	0.68911	64.206667	0.093254]	[	0.01855	5.059376	0.010896]	[	0
41	187	[	0.692418	62.876667	0.093929]	[	0.018293	5.403837	0.009809]	[	0
42	178	[	0.695126	61.903333	0.094527]	[	0.018711	4.964607	0.01013 ]	[	0

43	161	[	0.699744	60.753333	0.095559]	[	0.019064	4.569371	0.010088]	[	0
44	171	[	0.702384	59.586667	0.097205]	[	0.019461	3.899892	0.009401]	[	0
45	188	[	0.703221	59.126667	0.09687 ]	[	0.020518	3.816275	0.009162]	[	0
46	190	[	0.707132	58.54	0.09736 ]	[	0.018435	3.396331	0.008577]	[	0
47	182	[	0.704882	59.056667	0.097366]	[	0.020474	3.740783	0.009494]	[	0
48	190	[	0.706111	58.703333	0.096083]	[	0.019928	3.390475	0.010232]	[	0
49	166	[	0.706648	58.813333	0.094813]	[	0.020248	3.640305	0.010795]	[	0
50	181	[	0.703603	58.86	0.092685]	[	0.020489	3.425454	0.011632]	[	0

```
# SELECT GENETIC SELECTION VARIABLES
X_genetic_selection = X[X.columns[selector.support_]]
```

## 4 SCALE DATA

```
# MIN-MAX SCALER
scaler = MinMaxScaler()
# SCALE FILTER SELECTION DATA
X_filter = pd.DataFrame(scaler.fit_transform(X_filter), columns=X_filter.columns)
# SCALE PCA SELECTION DATA
X_pca = pd.DataFrame(scaler.fit_transform(X_pca), columns=X_pca.columns)
# SCALE GENETIC SELECTION DATA
X_genetic_selection = pd.DataFrame(
    scaler.fit_transform(X_genetic_selection), columns=X_genetic_selection.columns
)
```

## 5 CONCATENATE X AND Y

```

# CONCATENATE X AND Y
## FILTER SELECTION
molecular_descriptors_filter = pd.concat([X_filter, Y], axis=1)
## PCA SELECTION
molecular_descriptors_pca = pd.concat([X_pca, Y], axis=1)
## GENETIC SELECTION
molecular_descriptors_genetic_selection = pd.concat([X_genetic_selection, Y], axis=1)

```

## 6 PREPARE TEST DATA

```

# WE DO THE SAME WITH THE TEST DATA
molecular_descriptors_test = pd.read_csv(
    input_test_path + molecular_descriptors_test_file
)
## X TEST
X_test = molecular_descriptors_test.drop(columns=["activity"])
## Y TEST
Y_test = molecular_descriptors_test["activity"]

# TEST DATA FOR FILTER SELECTION
X_filter_test = X_test[X_filter.columns]

## MIN-MAX SCALER FOR X TEST
X_filter_test = pd.DataFrame(
    scaler.fit_transform(X_filter_test), columns=X_filter_test.columns
)

## CONCATENATE X AND Y
molecular_descriptors_filter_test = pd.concat([X_filter_test, Y_test], axis=1)

# TEST DATA FOR PCA SELECTION
## PCA TRANSFORMATION DATAFRAME
X_pca_test = pd.DataFrame(pca.transform(X_filter_test))

## MIN-MAX SCALER FOR X TEST
X_pca_test = pd.DataFrame(scaler.fit_transform(X_pca_test), columns=X_pca_test.columns)

## CONCATENATE X AND Y
molecular_descriptors_pca_test = pd.concat([X_pca_test, Y_test], axis=1)

```

```

# TEST DATA FOR GENETIC SELECTION
X_genetic_selection_test = X_test[X_genetic_selection.columns]

## MIN-MAX SCALER FOR X TEST
X_genetic_selection_test = pd.DataFrame(
    scaler.fit_transform(X_genetic_selection_test),
    columns=X_genetic_selection_test.columns,
)

## CONCATENATE X AND Y
molecular_descriptors_genetic_selection_test = pd.concat(
    [X_genetic_selection_test, Y_test], axis=1
)

```

## 7 SAVE DATA

```

# SAVE DATA FILTER SELECTION
## SAVE TRAIN DATA
molecular_descriptors_filter.to_csv(
    output_train_path + dataset_name + "_filter_training.csv", index=False
)
## SAVE TEST DATA
molecular_descriptors_filter_test.to_csv(
    output_test_path + dataset_name + "_filter_test.csv", index=False
)

# SAVE DATA PCA SELECTION
## SAVE TRAIN DATA
molecular_descriptors_pca.to_csv(
    output_train_path + dataset_name + "_pca_training.csv", index=False
)
## SAVE TEST DATA
molecular_descriptors_pca_test.to_csv(
    output_test_path + dataset_name + "_pca_test.csv", index=False
)

# SAVE DATA GENETIC SELECTION
## SAVE TRAIN DATA
molecular_descriptors_genetic_selection.to_csv(

```

```
        output_train_path + dataset_name + "_genetic_selection_training.csv", index=False
    )
    ## SAVE TEST DATA
    molecular_descriptors_genetic_selection_test.to_csv(
        output_test_path + dataset_name + "_genetic_selection_test.csv", index=False
    )
```