Breast Cancer Classification

Human Ensemble

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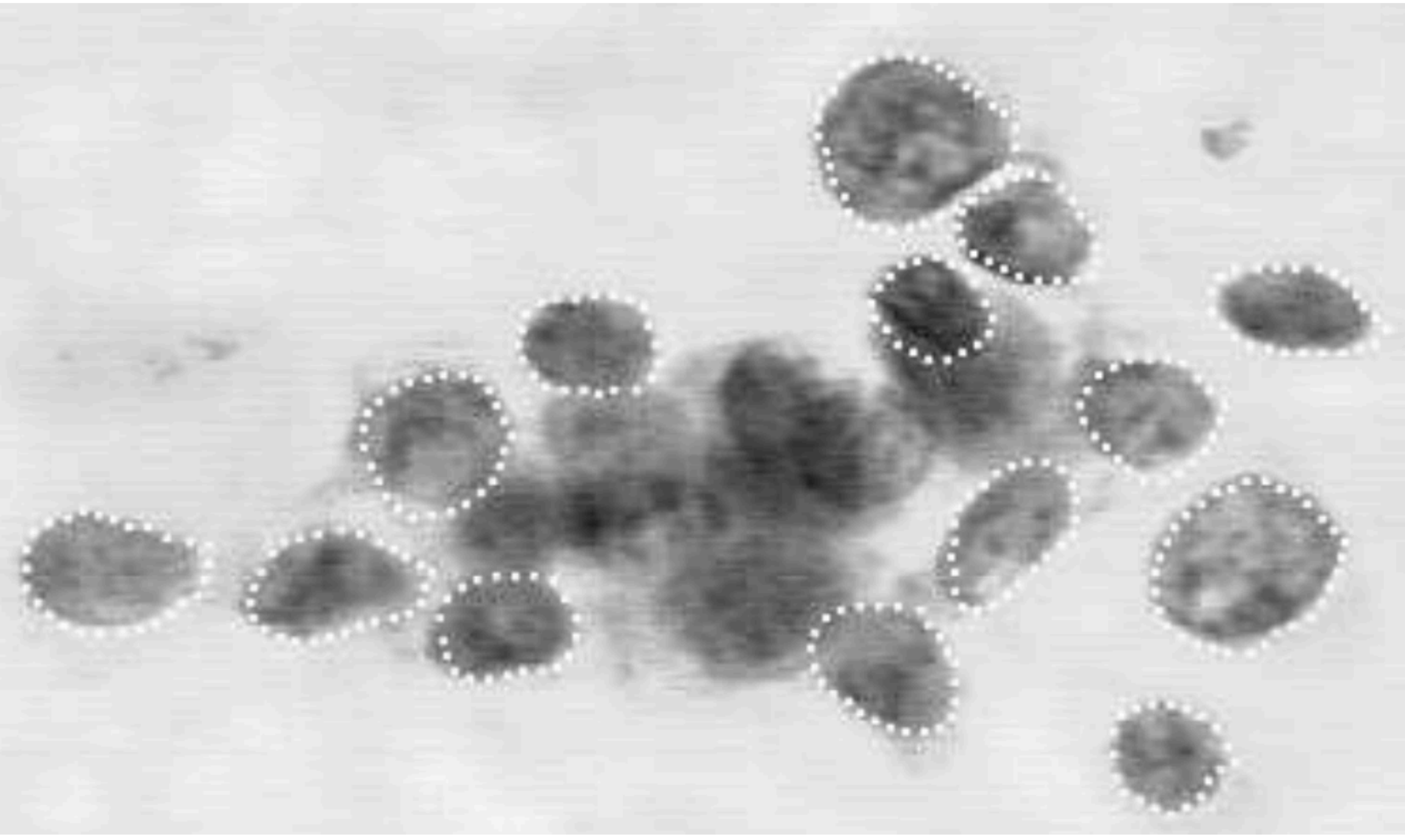
Search Prominent Kernels

이미 모범 답안 처럼

Features **Accuracy**

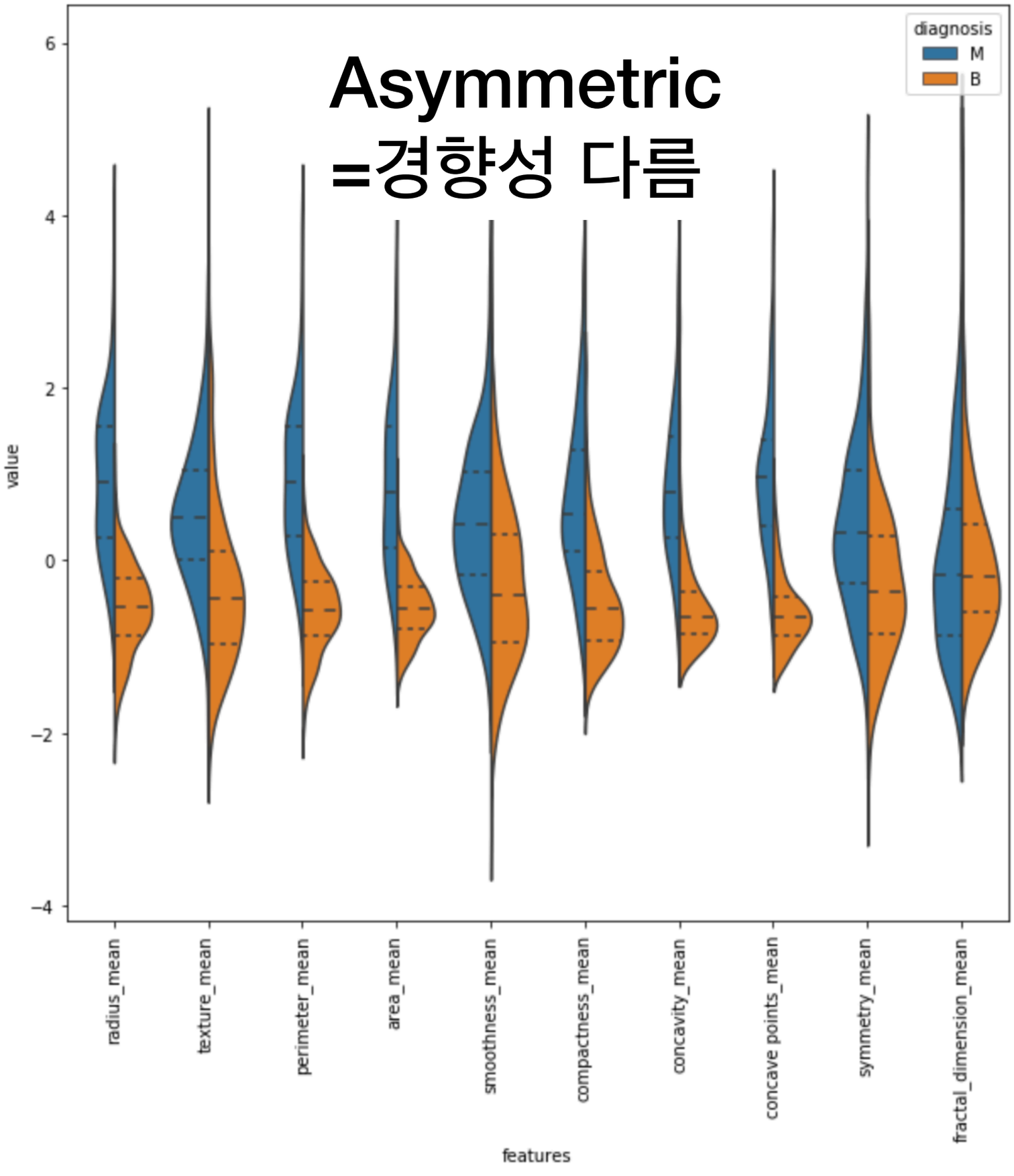
최적화 돼있음

Search Paper

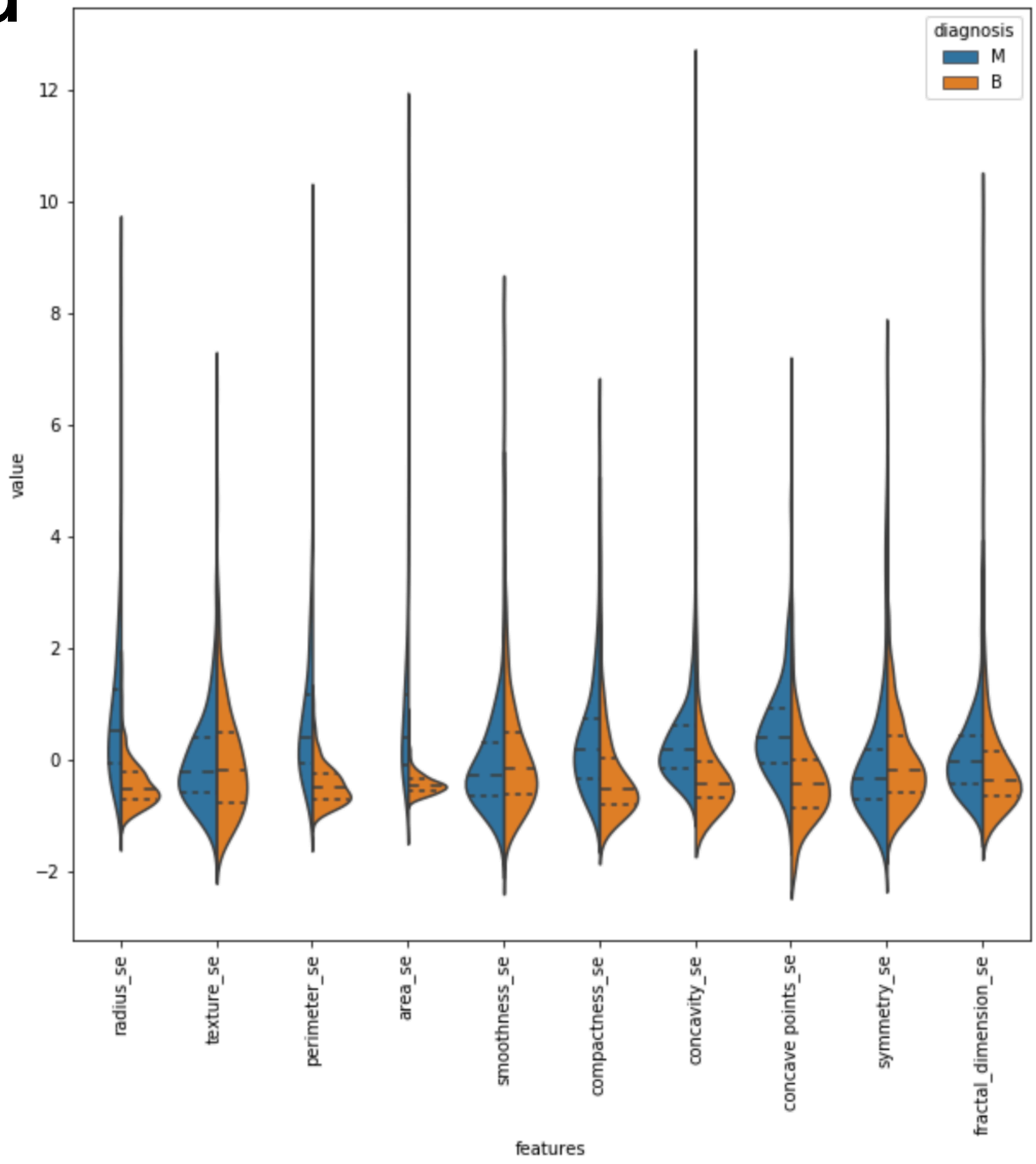


Reference : http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.56.707&rep=rep1&type=pdf

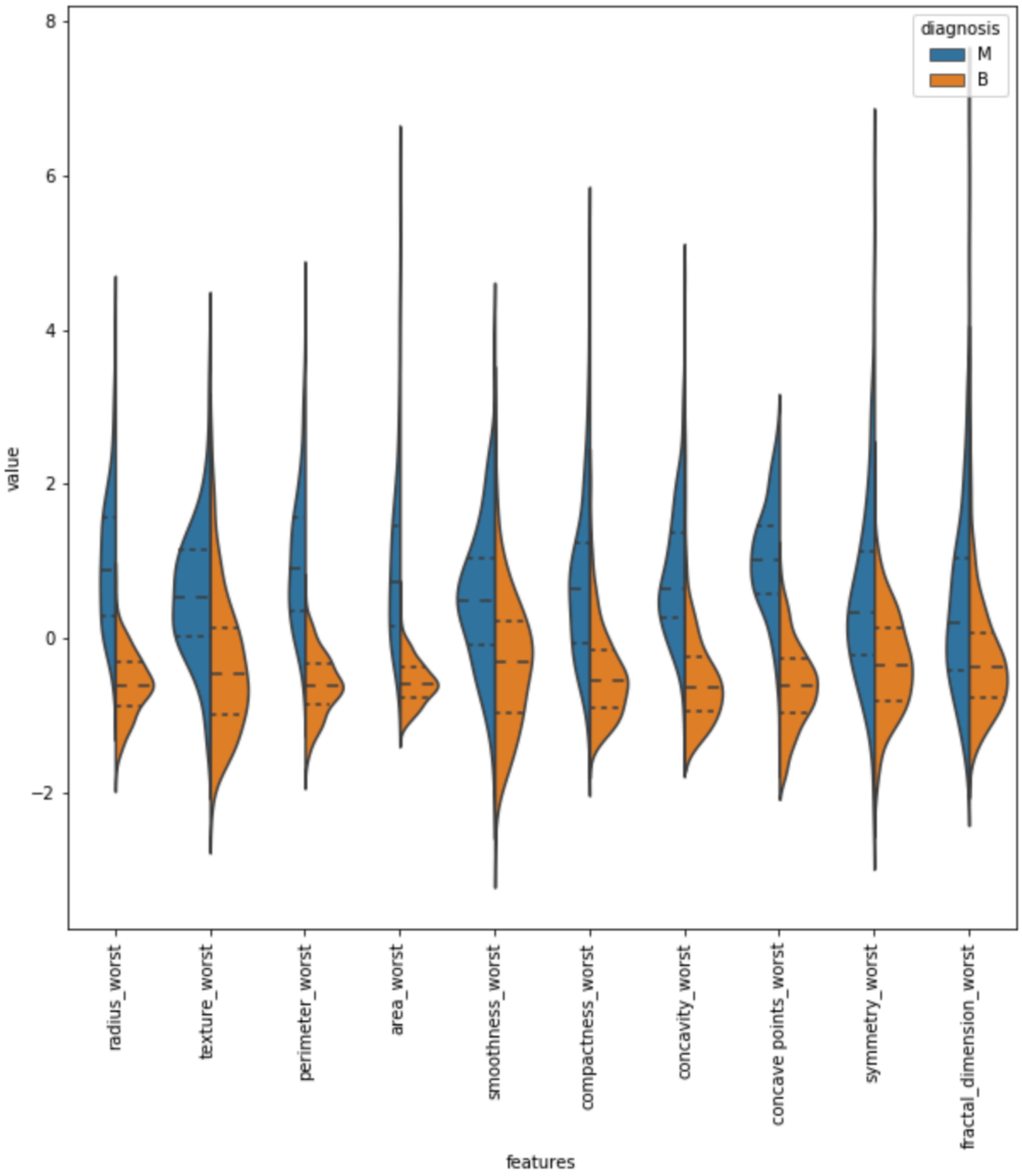
Mean


Asymmetric
=경향성 다름
diagnosis
M
B
value
6
4
2
0
−2
−4
radius_mean
texture_mean
perimeter_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
concave points_mean
symmetry_mean
fractal_dimension_mean
features

Standard Error



Worst


diagnosis
M
B
8
6
4
2
0
−2
value
radius_worst
texture_worst
perimeter_worst
area_worst
smoothness_worst
compactness_worst
concavity_worst
concave points_worst
symmetry_worst
fractal_dimension_worst
features

What to Do

Feature Dimension Reduction

VS

Perfomance Improvement

First Trial

Performance Improvement

1. Data Augment for Original models

    By using Standard error

    Perturb Mean & Worst Data

Statically Stable ?

Not much different from noise!

ㅠ_ㅠ

Performance Improvement

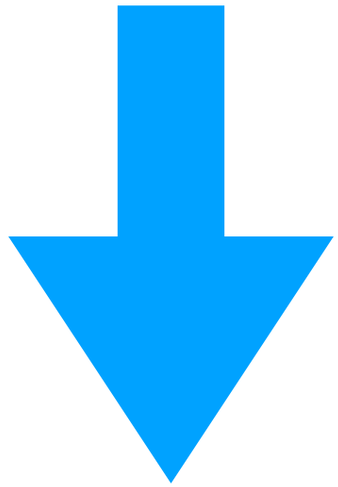
2. Build Robust Model (Accuracy 100%)

Difficult to Adopt to New Features

Hypothesis

If, 독립적인 Feature 찾으면

Then, Optimized Feature찾을 수 있을 것이다



최소 Feature로 최대 정보 표현

Goal

Optimized Feature

Feature Selection Method

Dominant Feature

Dimension reduction

1. PCA, NMF 결과 확인

15~17 개의 Feature들로도 Accuracy 높음

NEW METHOD!

Feature Normalize

Feature data를 각각
Normalize

WHY?

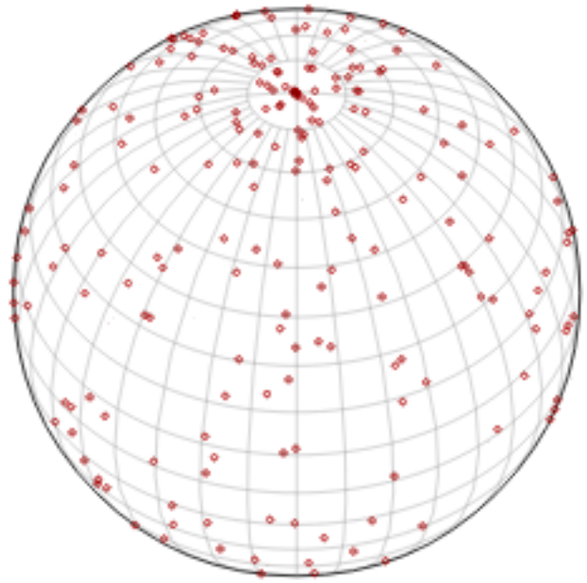
Feature data scale
큰 의미가 없기 때문에
각도만 재면 된다
=> 각도가 **Arclength**와 같은 값을 가진다.

Max Min Selector

f : feature vector

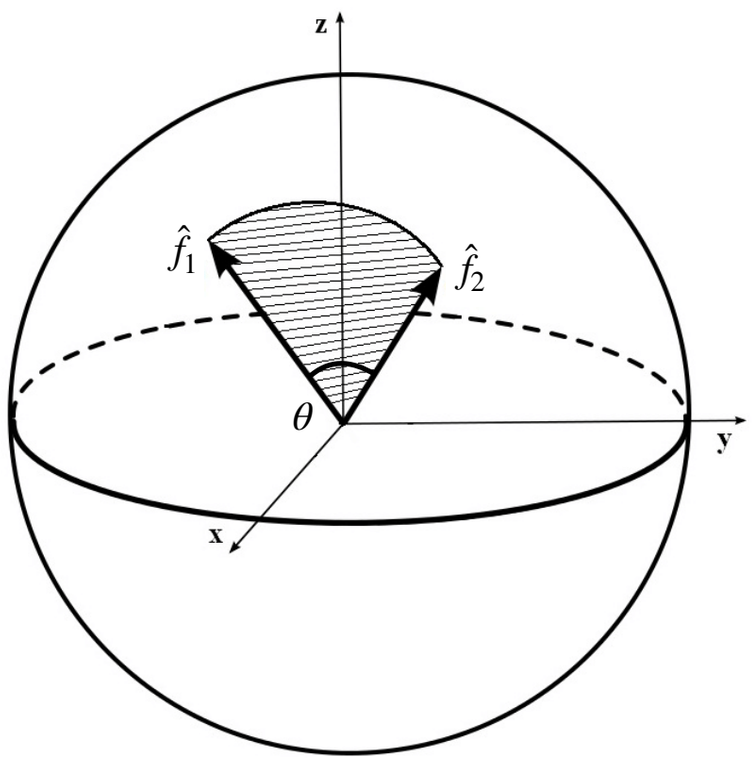
Normalize

$$\hat{f} = \frac{f - \mu_f}{\sigma_f}$$

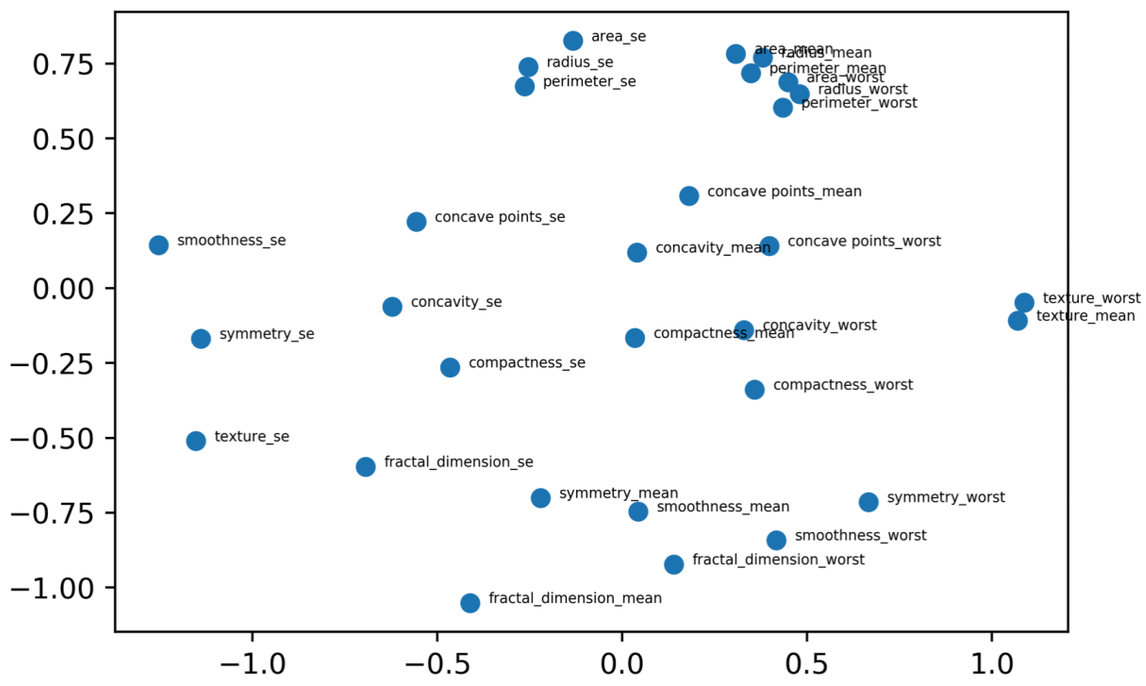


$$corr(f_1, f_2) = \langle \hat{f}_1, \hat{f}_2 \rangle$$

$$d(f_1, f_2) = \theta = \arccos(\langle f_1, f_2 \rangle) = \arccos(corr(f_1, f_2))$$



MDS



Dimension reduction

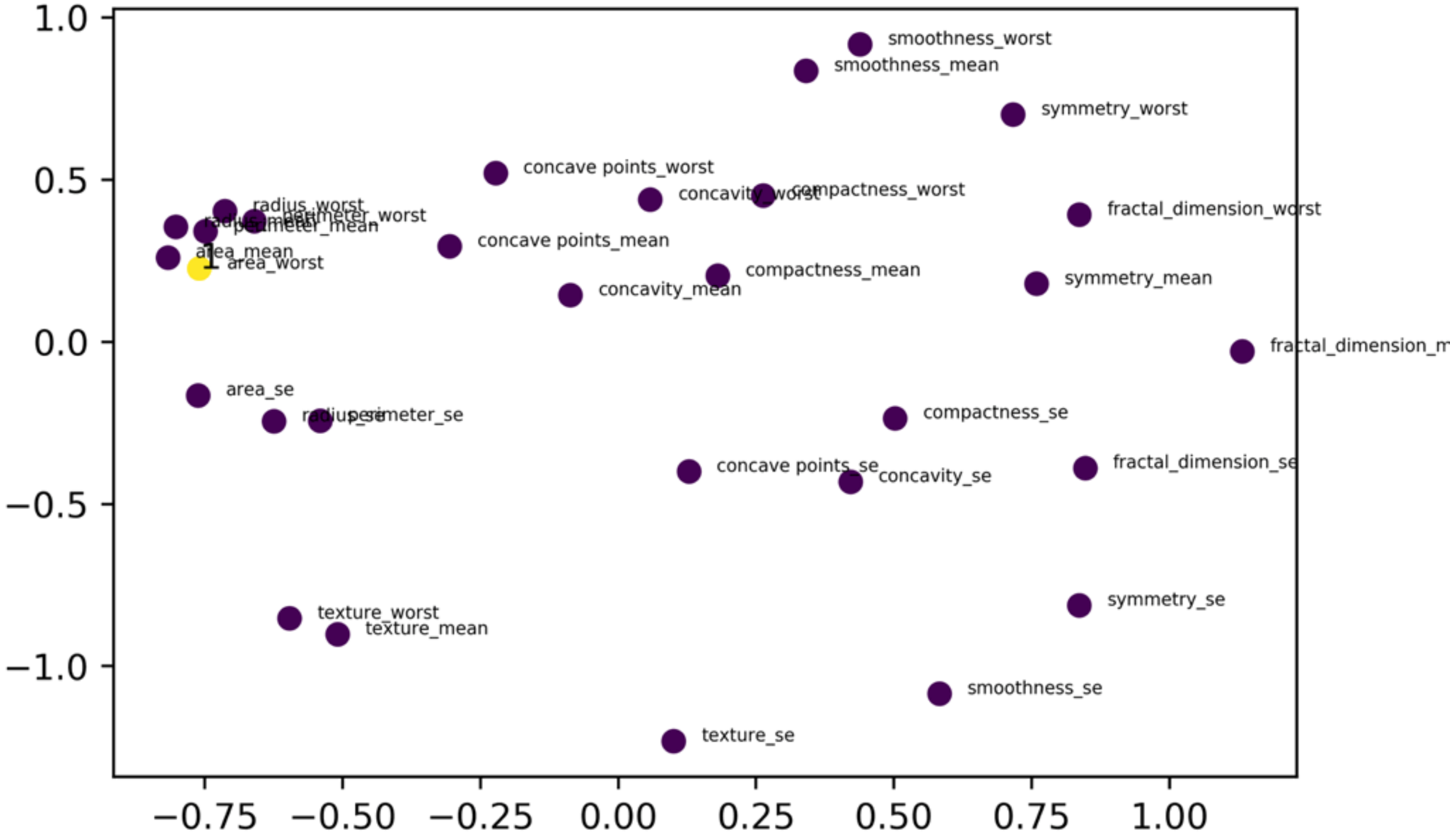
Max Min Selector

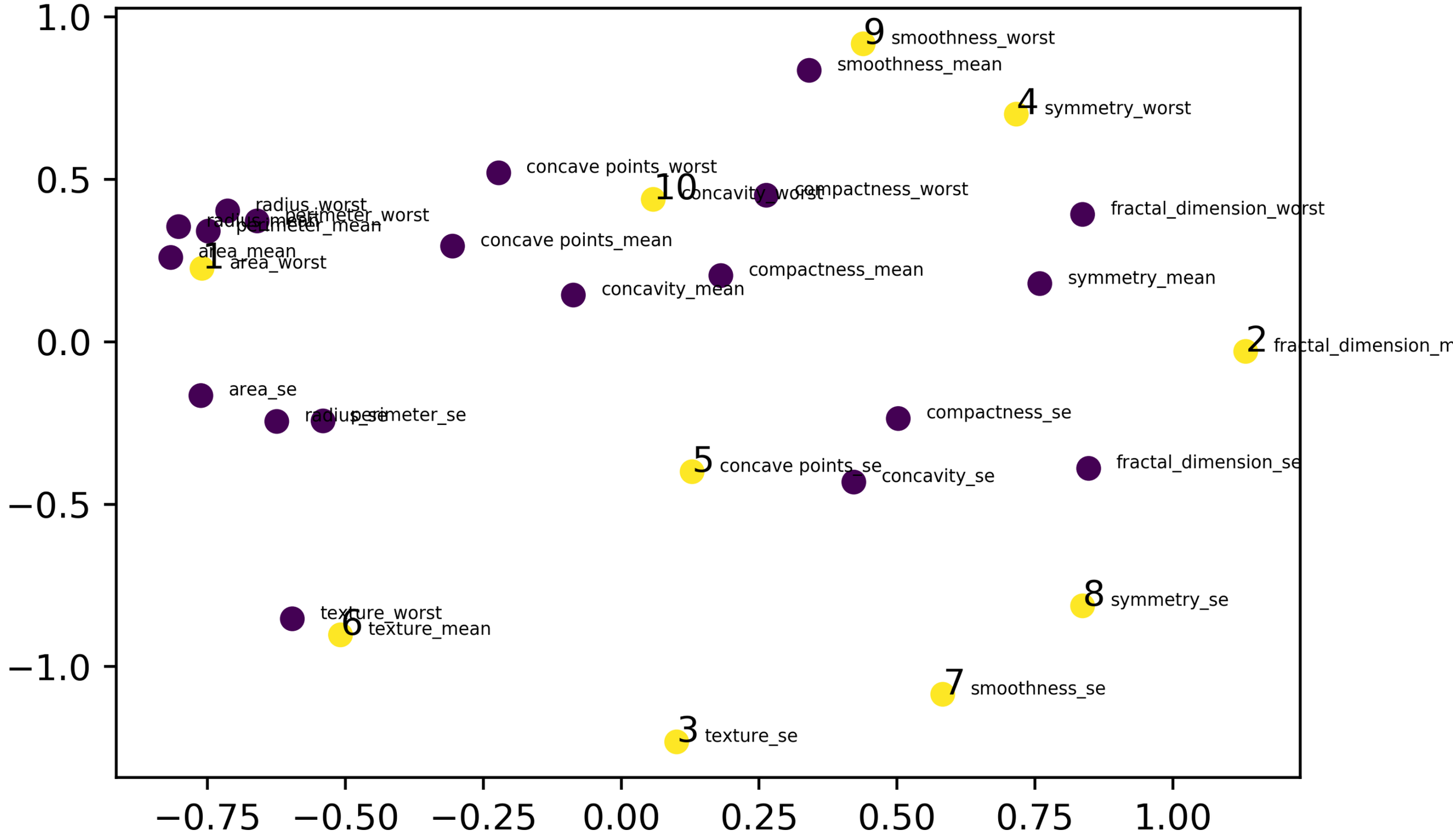
Selector Part

```
def maxminSelector(data, n, initial):
    data = (data-data.mean())/data.std()
    dissmat = pd.DataFrame(np.arccos(np.corrcoef(data.values.T)),index=features,columns=features)
    result = [initial]
    n-=1
    while(n!=0):
        n -= 1
        result += [dissmat[result].min(axis=1).idxmax()]
    return result
```

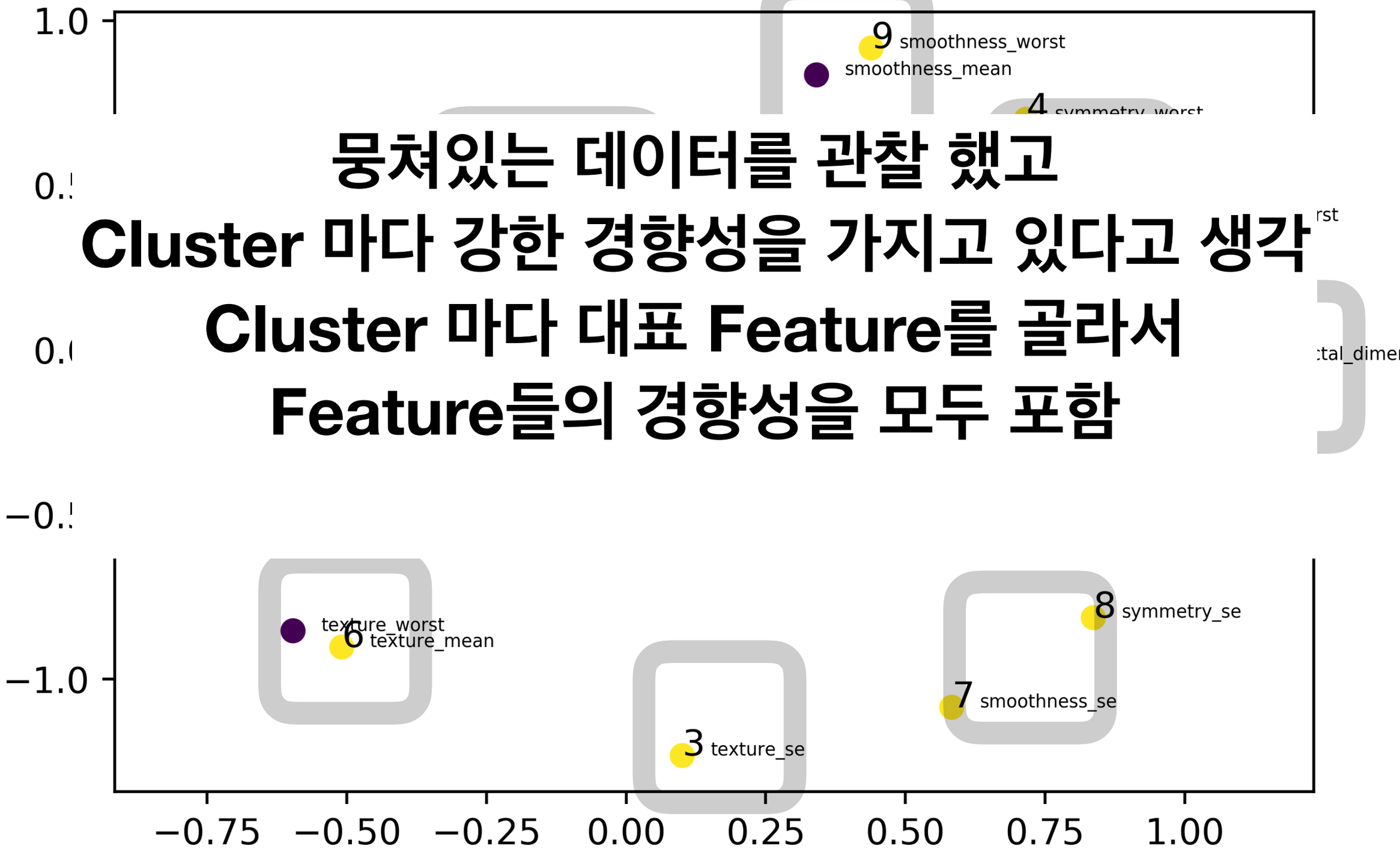
```
def divide_date(data, n, initial):
    choosed_data = maxinSelector(data, n, initial)
    reseted_data = data.drop([[choosed_data]], axis =1)
    return choosed_data, reseted_data
```

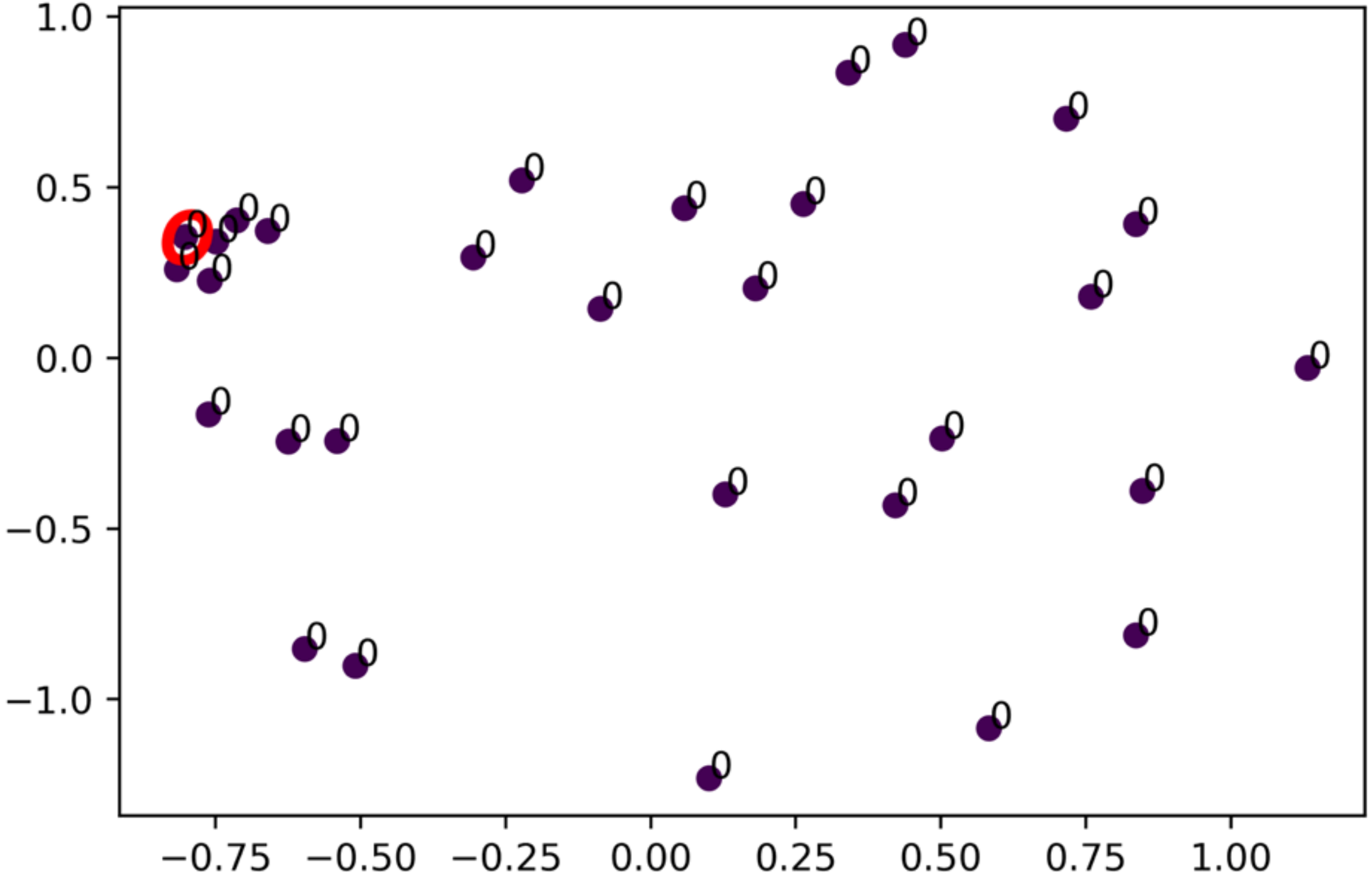
Slicing Part


1.0
0.5
0.0
−0.5
−1.0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
smoothness_worst
smoothness_mean
symmetry_worst
concave points_worst
concavity_worst
compactness_worst
fractal_dimension_worst
radius_worst
perimeter_worst
perimeter_mean
concave points_mean
area_mean
area_worst
compactness_mean
concavity_mean
symmetry_mean
fractal_dimension_m
area_se
compactness_se
concave points_se
concavity_se
fractal_dimension_se
symmetry_se
texture_worst
texture_mean
smoothness_se
texture_se

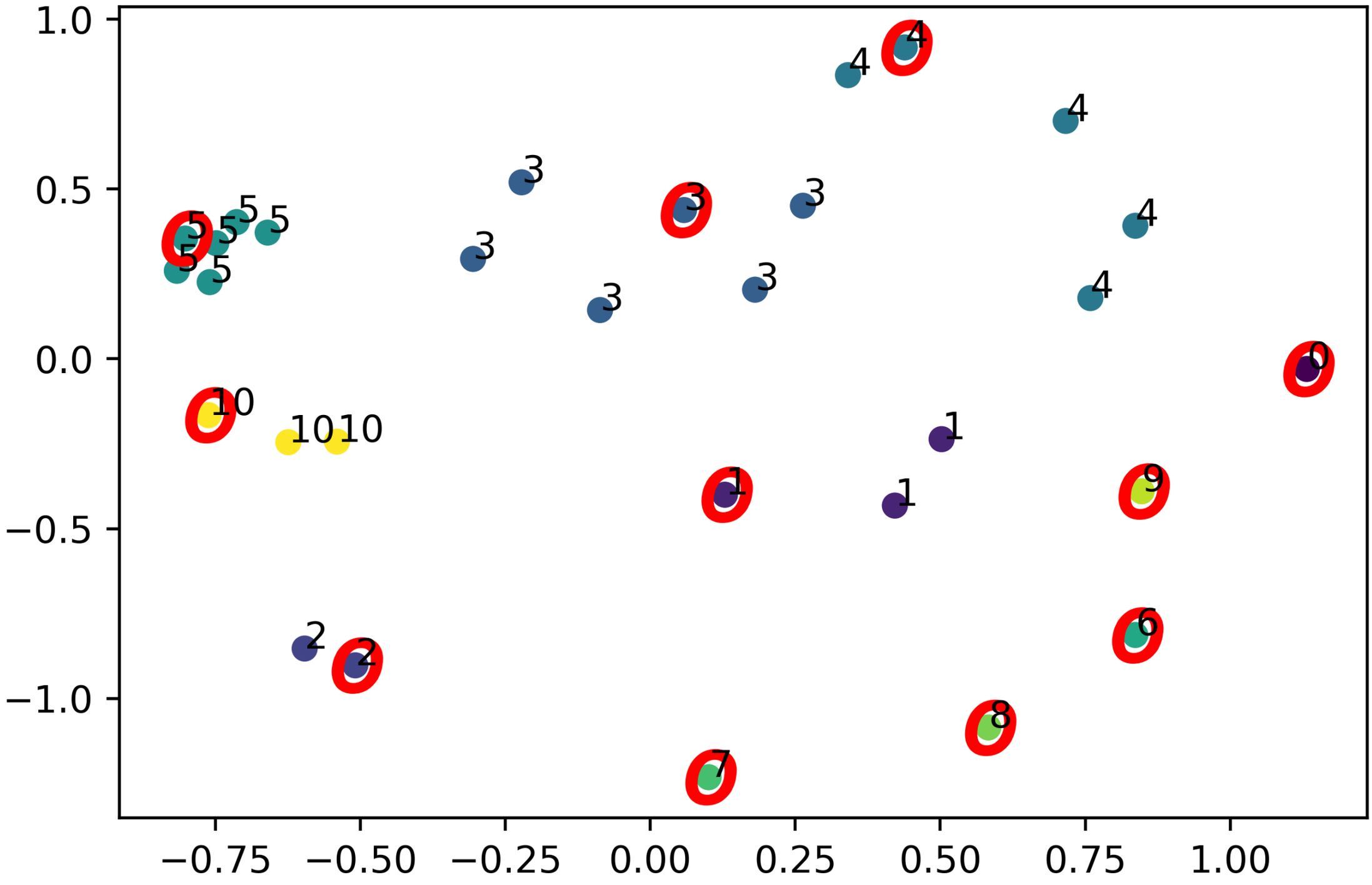

1.0
0.5
0.0
−0.5
−1.0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
9 smoothness_worst
smoothness_mean
4 symmetry_worst
concave points_worst
10
concavity_worst
compactness_worst
fractal_dimension_worst
radius_worst
perimeter_worst
radius_mean
perimeter_mean
concave points_mean
area_mean
1 area_worst
compactness_mean
concavity_mean
symmetry_mean
2 fractal_dimension_m
area_se
radius_se
perimeter_se
compactness_se
5 concave points_se
concavity_se
fractal_dimension_se
8 symmetry_se
texture_worst
6 texture_mean
7 smoothness_se
3 texture_se

뭉쳐있는 데이터를 관찰 했고
Cluster 마다 강한 경향성을 가지고 있다고 생각
Cluster 마다 대표 Feature를 골라서
Feature들의 경향성을 모두 포함




1.0
0.5
0.0
−0.5
−1.0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00

Clustering Selector



INITIAL FEATURE!

The Very First Feature

Orthodox
Method

NO
JAM

Independency

Chi square

Specs	Score
concave points_mean	52.405743
concave points_worst	46.341648
concavity_mean	46.186395
area_worst	35.043882
perimeter_worst	34.438091
radius_worst	34.124937
concavity_worst	31.563031
area_mean	29.328594
perimeter_mean	26.528902
radius_mean	24.897293
compactness_worst	20.992541
compactness_mean	20.353176
area_se	19.676975
radius_se	17.324128
perimeter_se	16.044344
texture_worst	8.741628
texture_mean	6.394071
concave points_se	5.781996
smoothness_worst	5.675733
symmetry_worst	5.560093

Laplacian

Feature	Score
symmetry_se	0.389442
smoothness_se	0.352192
texture_se	0.294414
symmetry_worst	0.280945
fractal_dimension_se	0.275966
symmetry_mean	0.261482
concavity_se	0.230877
concave points_se	0.227426
radius_se	0.209268
perimeter_se	0.204753
smoothness_mean	0.200331
texture_mean	0.200033
compactness_se	0.198070
ctal_dimension_worst	0.188476
actal_dimension_mean	0.183858
smoothness_worst	0.181468
area_se	0.170987
texture_worst	0.168997
compactness_worst	0.111559
concavity_worst	0.108950
compactness_mean	0.093500
concavity_mean	0.067730
radius_mean	0.064922
concave points_worst	0.063395

~Related ~

Fisher

Feature	Score
concave points_worst	1.700856
perimeter_worst	1.583676
concave points_mean	1.519711
radius_worst	1.518134
perimeter_mean	1.229692
area_worst	1.166843
radius_mean	1.141060
area_mean	1.010689
concavity_mean	0.941434
concavity_worst	0.770180
compactness_mean	0.552439
compactness_worst	0.536757
radius_se	0.474145
perimeter_se	0.447791
area_se	0.429721
texture_worst	0.263839
smoothness_worst	0.216002
symmetry_worst	0.209630
texture_mean	0.208282
concave points_se	0.199758
smoothness_mean	0.147533
symmetry_mean	0.122623
ractal_dimension_worst	0.117185
compactness_se	0.093911
concavity_se	0.068809
fractal_dimension_se	0.006117
smoothness_se	0.004511

Ranking System

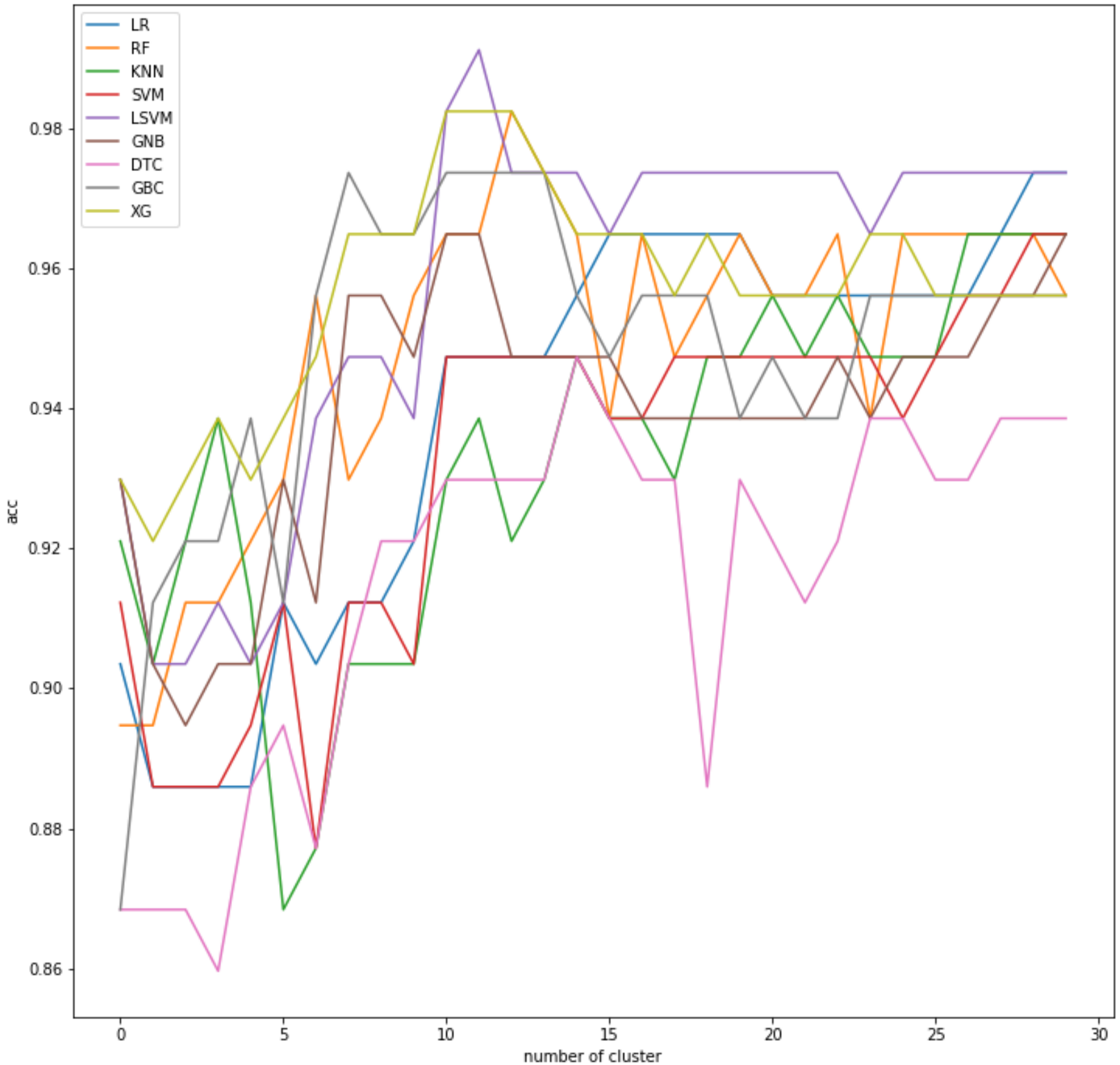
$$\frac{\mathrm{X}^2 + \frac{1}{2}(Laplacian + Fisher)}{2}$$

$$Best = Area\ Worst$$

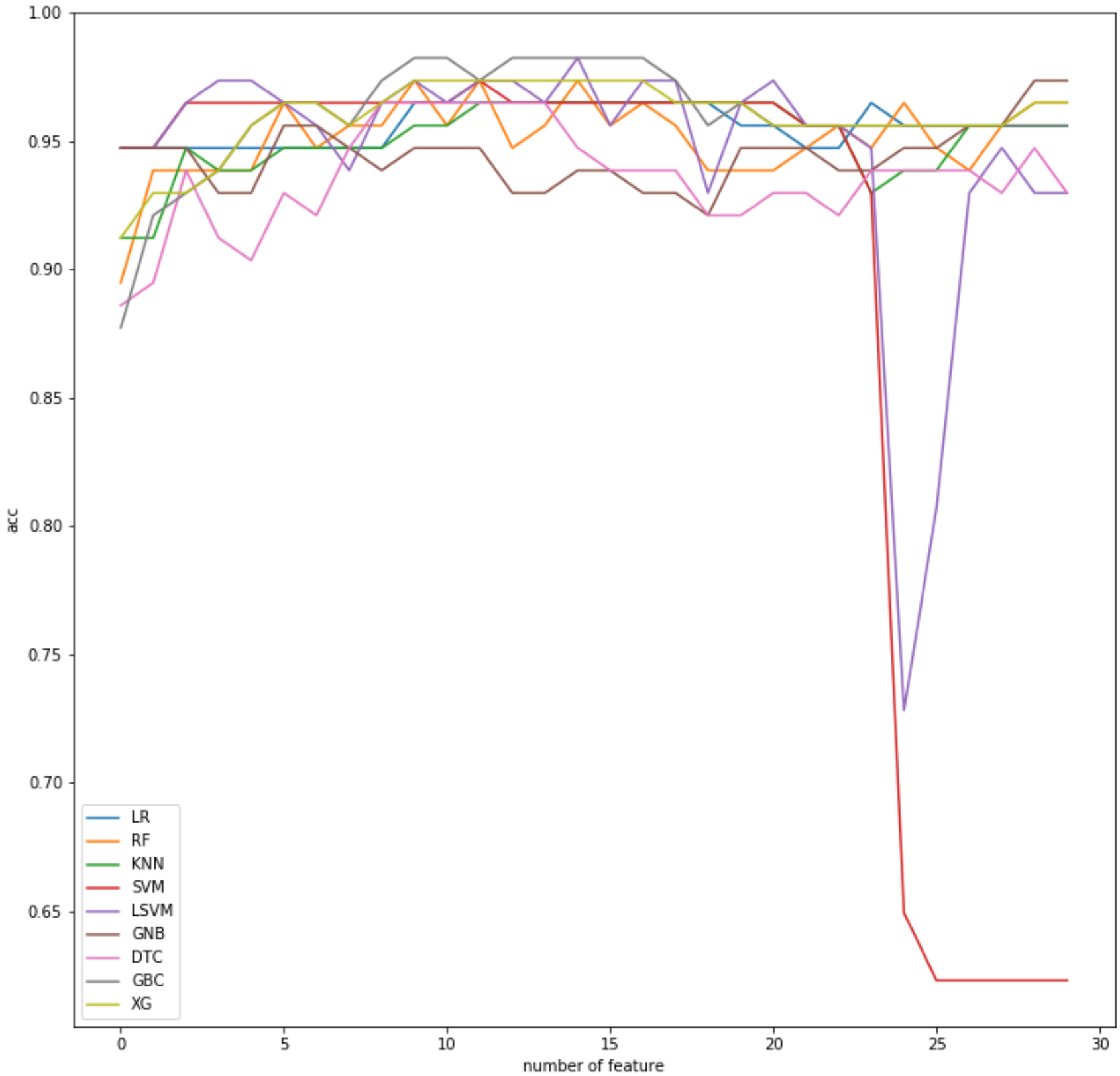
$$Worst = Smoothness\ Standard\ Error$$

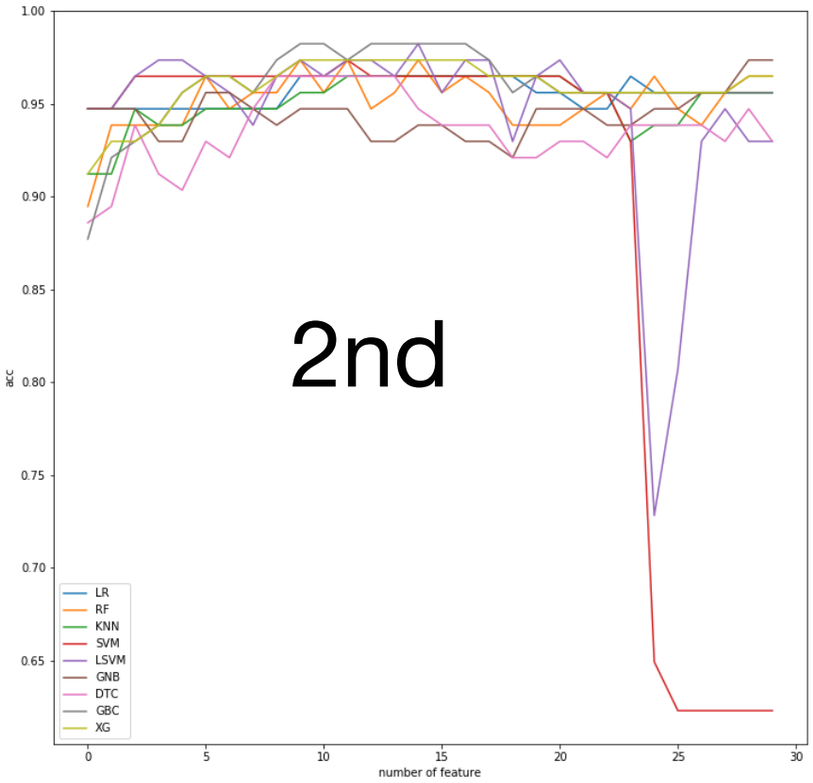
	Feature	ranking
23	area_worst	2.689655
20	radius_worst	2.655172
3	area_mean	2.551724
2	perimeter_mean	2.517241
0	radius_mean	2.310345
7	concave points_mean	2.310345
6	concavity_mean	2.000000
13	area_se	1.965517
26	concavity_worst	1.965517
22	perimeter_worst	1.827586
25	compactness_worst	1.758621
5	compactness_mean	1.758621
21	texture_worst	1.758621
12	perimeter_se	1.586207
10	radius_se	1.448276
1	texture_mean	1.413793
27	concave points_worst	1.275862
24	smoothness_worst	1.241379
15	compactness_se	0.931034
28	symmetry_worst	0.896552
29	fractal_dimension_worst	0.862069
17	concave points_se	0.827586
4	smoothness_mean	0.793103
16	concavity_se	0.724138
8	symmetry_mean	0.655172
9	fractal_dimension_mean	0.551724
19	fractal_dimension_se	0.344828
11	texture_se	0.206897
14	smoothness_se	0.172414

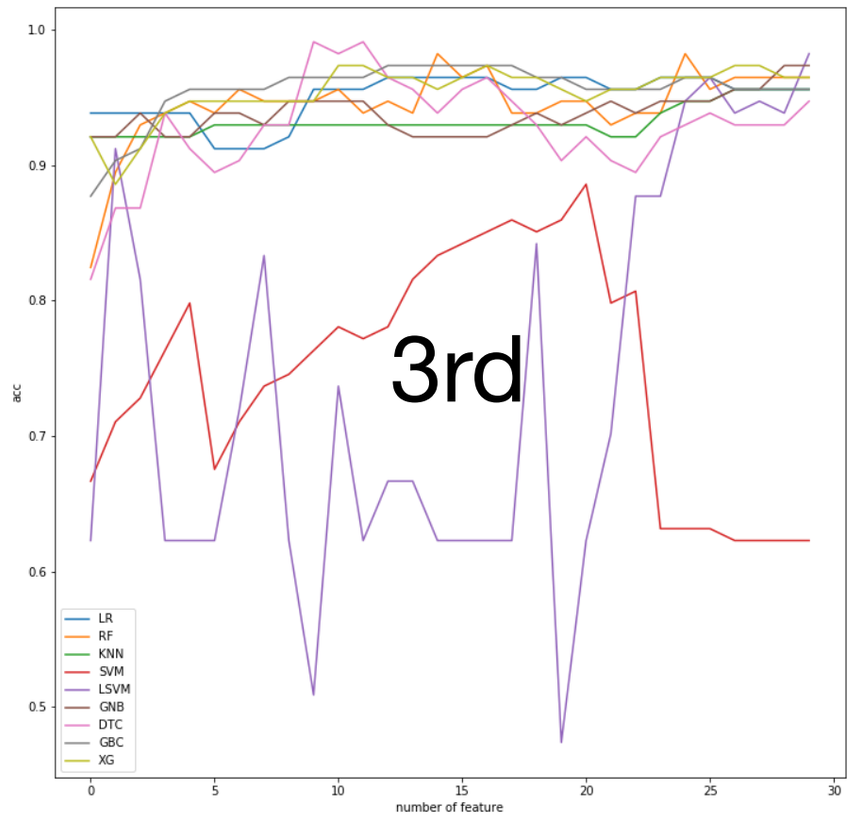
Accuracy by Cluster Method

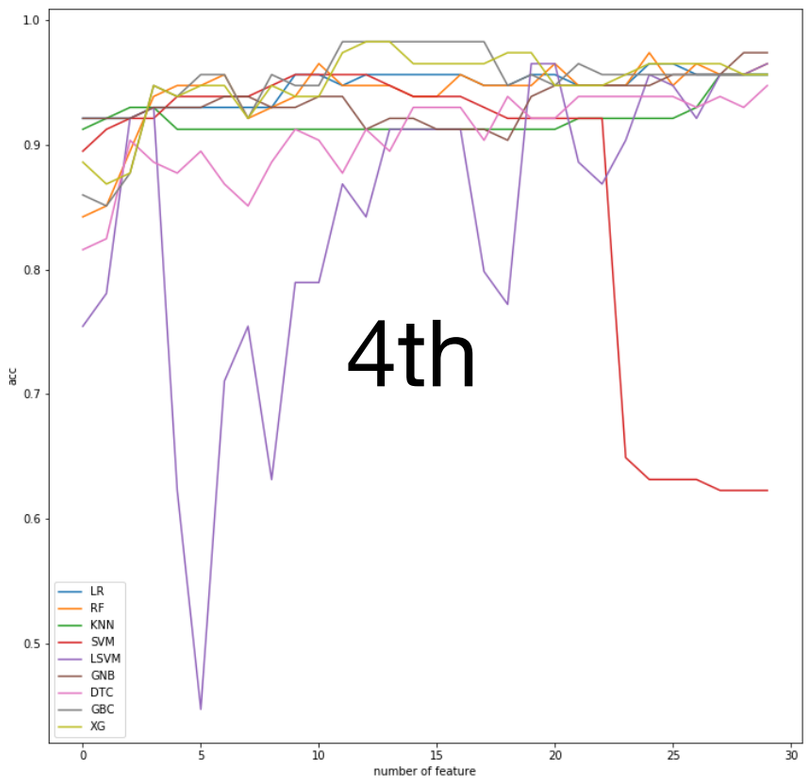


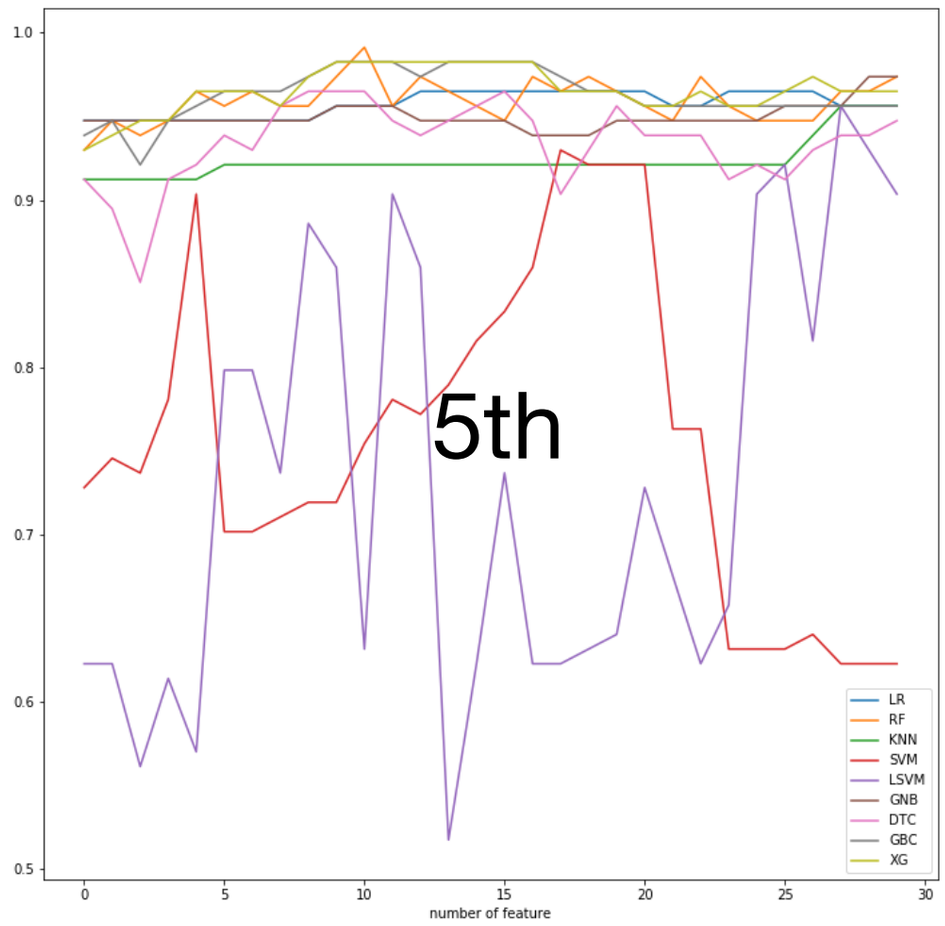
Compare Models with best



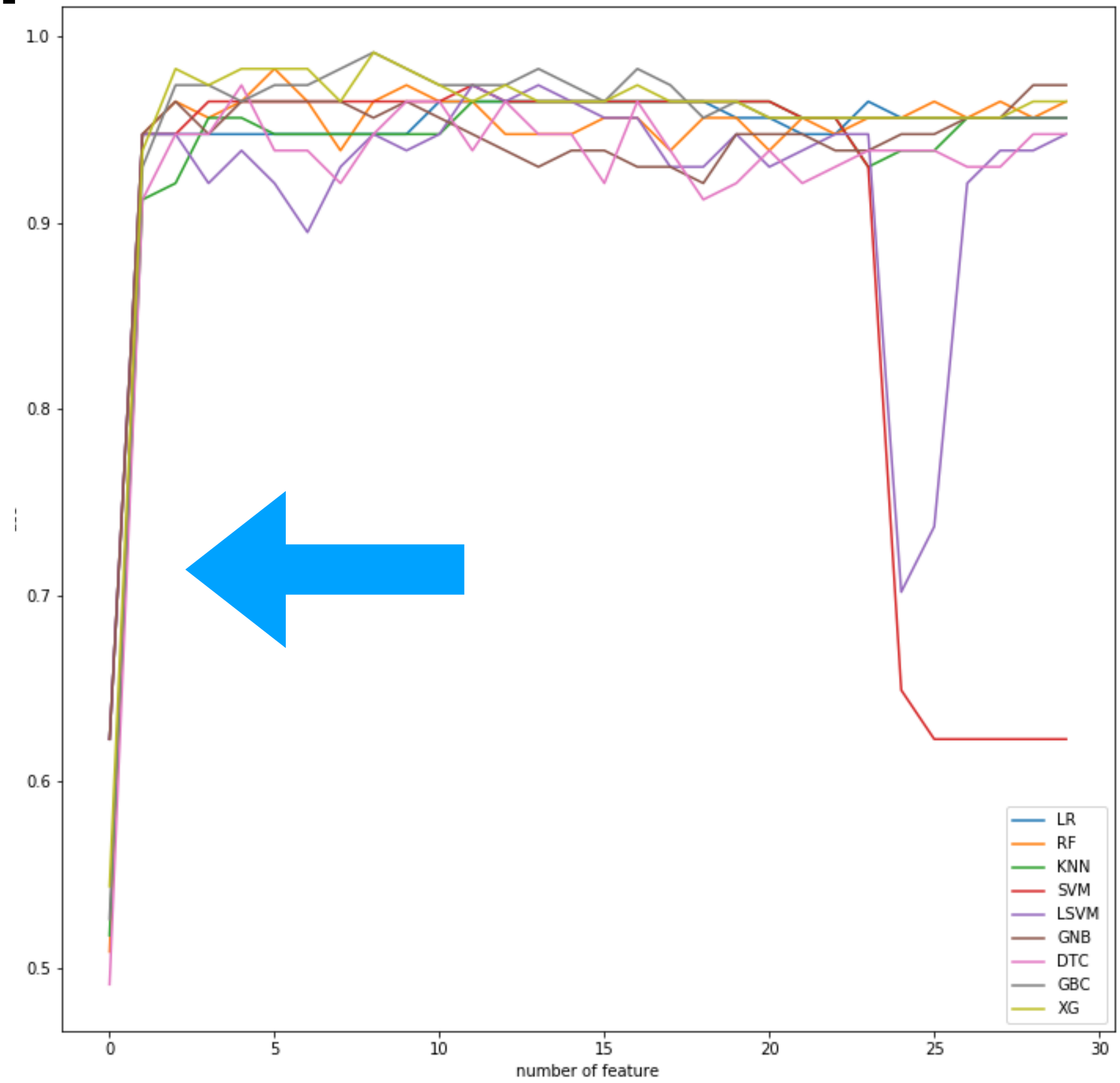

2nd
acc
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG

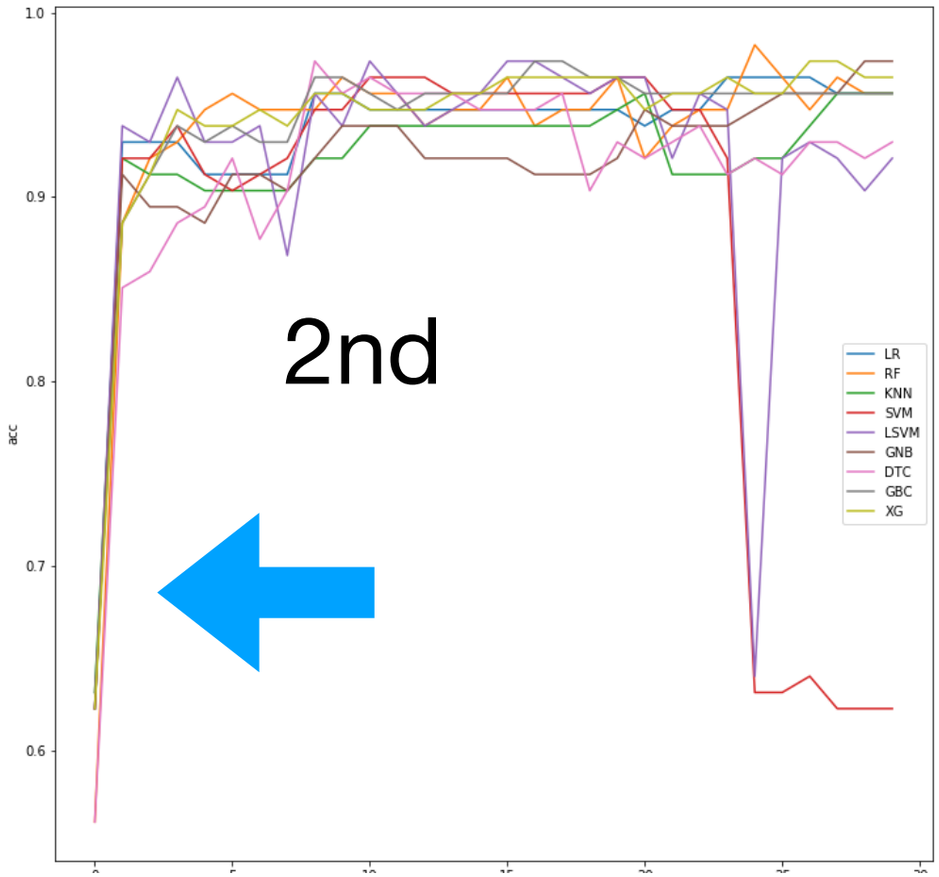

3rd
acc
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG

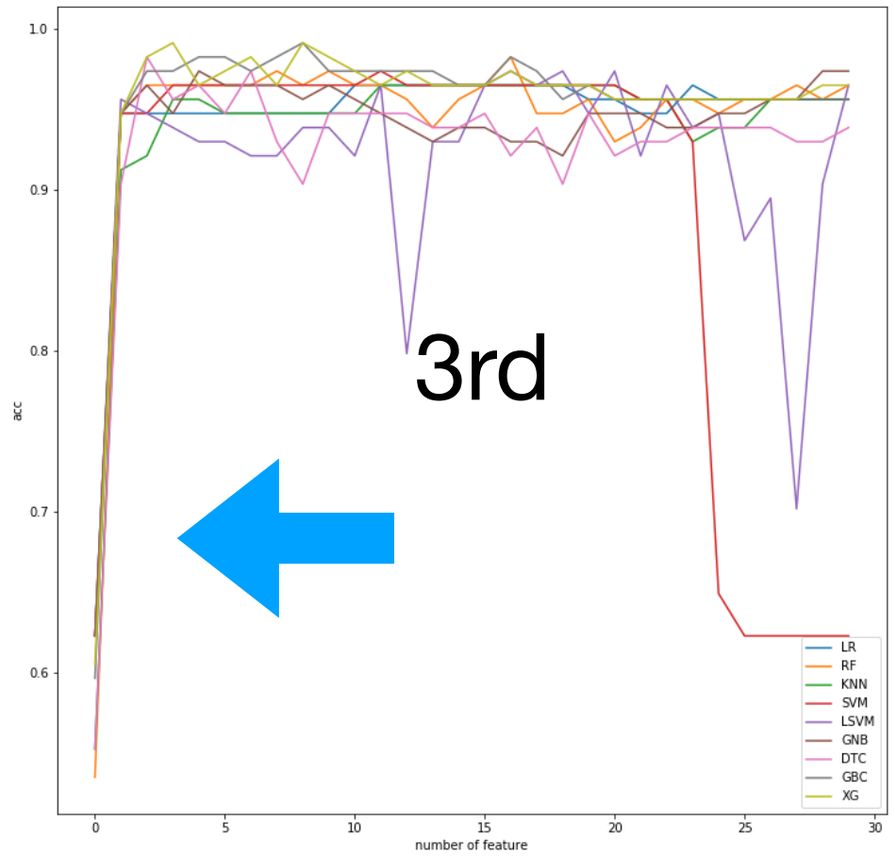

4th
acc
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG


5th
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG

Compare Models with worst




2nd
acc
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG


3rd
acc
number of feature
LR
RF
KNN
SVM
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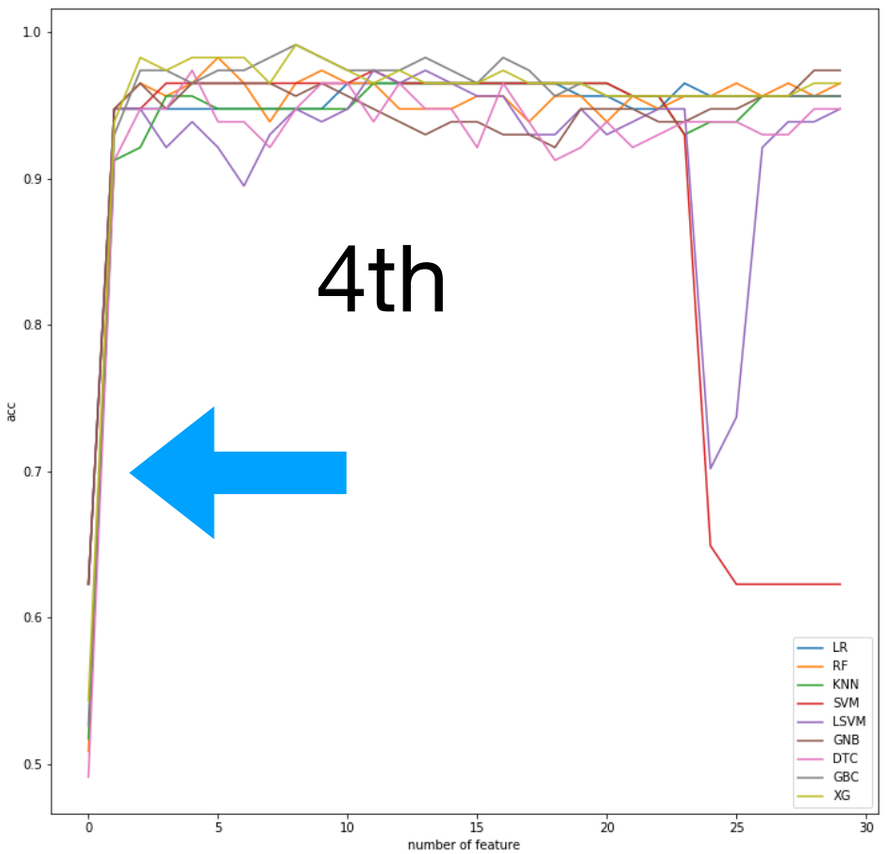
4th
acc
number of feature
LR
RF
KNN
SVM
LSVM
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DTC
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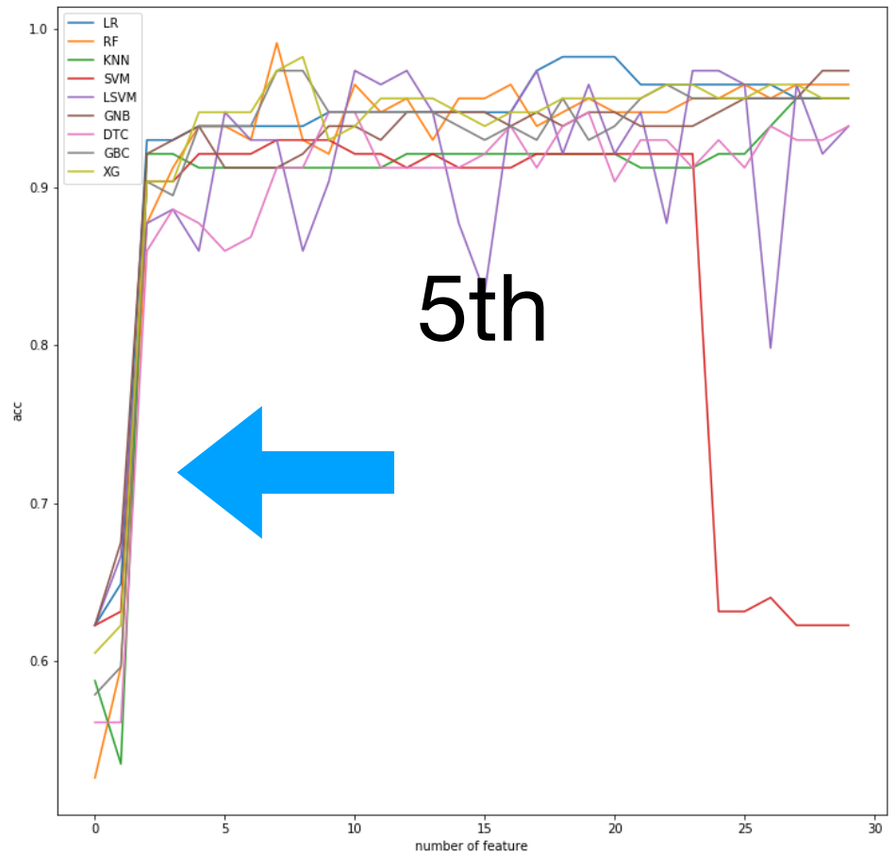
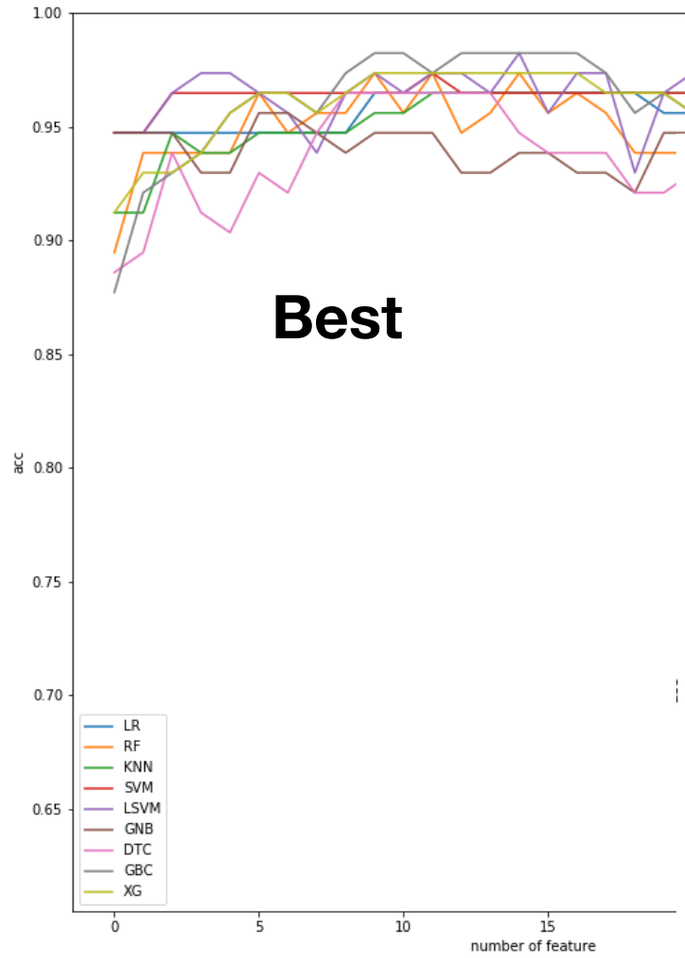
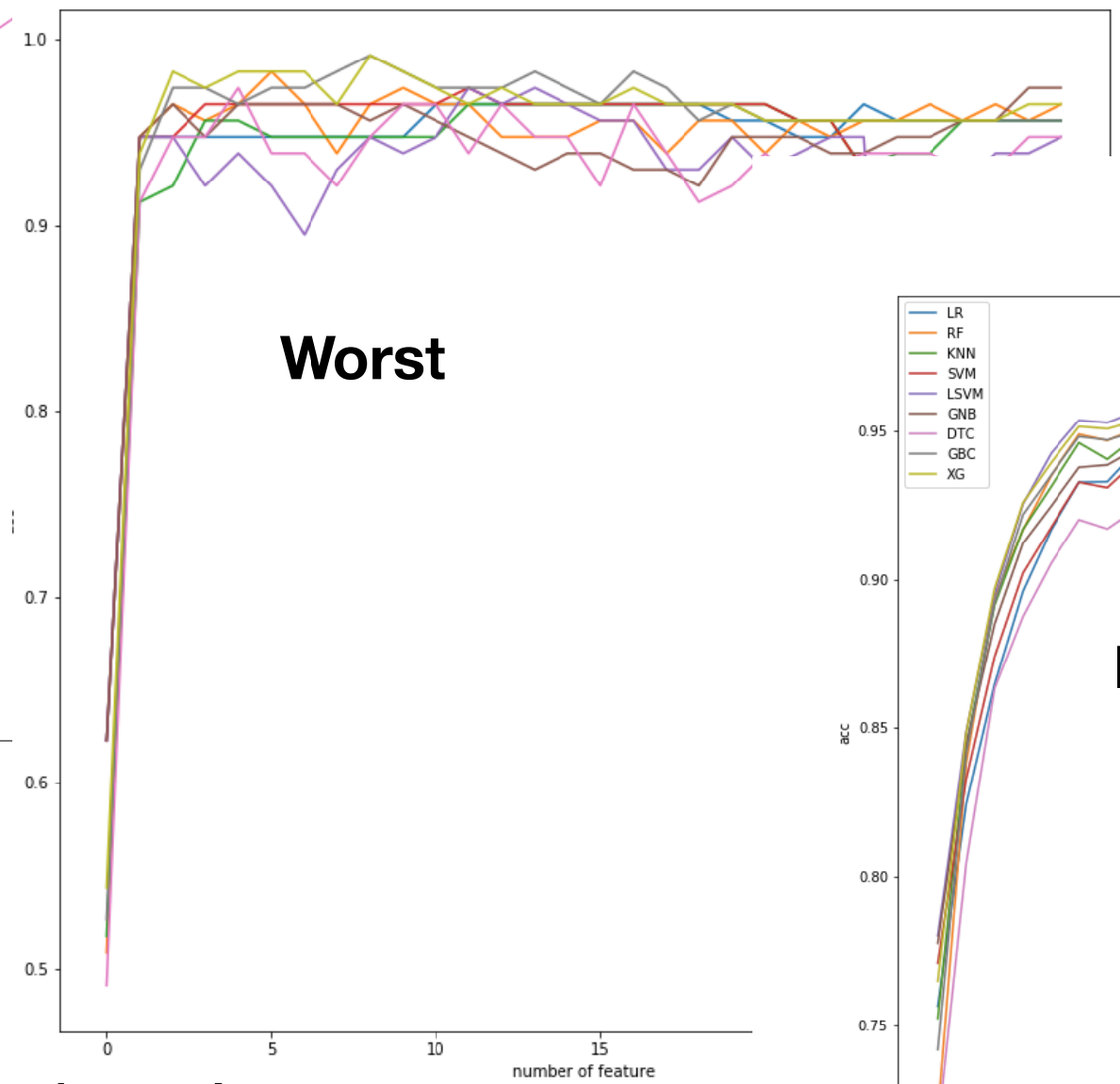
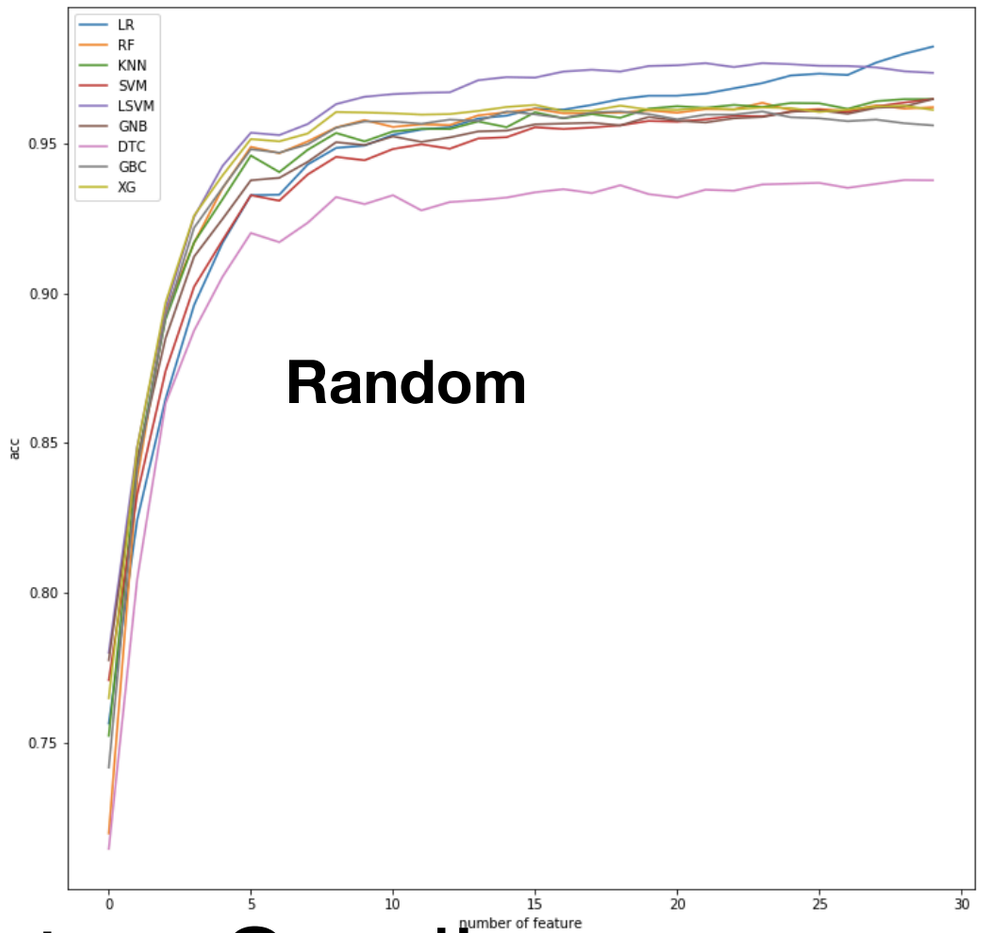
XG


5th
acc
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG

Compare Models (Random selection)







Random 과 비교해보면

Best 는 처음부터 좋고 => Ranking system Good!

Worst는 두번째부터 좋아짐 => Feature selection Good!

Future Work

```python
x_input = x

w1 = tf.Variable(tf.random_normal([20, 64]))
b1 = tf.Variable(tf.random_normal([64]))
y1 = tf.math.sigmoid(tf.linalg.matmul(x, w1)+b1)
#y1 = tf.nn.relu(tf.linalg.matmul(x, w1)+b1)


w2 = tf.Variable(tf.random_normal([64, 128]))
b2 = tf.Variable(tf.random_normal([128]))
y2 = tf.math.sigmoid(tf.linalg.matmul(y1, w2)+b2)
#y2 = tf.nn.relu(tf.linalg.matmul(y1, w2)+b2)


w3 = tf.Variable(tf.random_normal([128, 128]))
b3 = tf.Variable(tf.random_normal([128]))
y3 = tf.math.sigmoid(tf.linalg.matmul(y2, w3)+b3)
#y3 = tf.nn.relu(tf.linalg.matmul(y2, w3)+b3)


w4 = tf.Variable(tf.random_normal([128, 128]))
b4 = tf.Variable(tf.random_normal([128]))
y4 = tf.math.sigmoid(tf.linalg.matmul(y3, w4)+b4)
#y4 = tf.nn.relu(tf.linalg.matmul(y3, w4)+b4)


w5 = tf.Variable(tf.random_normal([128, 64]))
b5 = tf.Variable(tf.random_normal([64]))
y5 = tf.math.sigmoid(tf.linalg.matmul(y4, w5)+b5)
#y5 = tf.nn.relu(tf.linalg.matmul(y3, w4)+b4)


w6 = tf.Variable(tf.random_normal([64, 20]))
b6 = tf.Variable(tf.random_normal([20]))
y6 = tf.math.sigmoid(tf.linalg.matmul(y5, w6)+b6)
#y6 = tf.nn.relu(tf.linalg.matmul(y5, w6)+b6)


w7 = tf.Variable(tf.random_normal([20, 1]))
b7 = tf.Variable(tf.random_normal([1]))
y7 = tf.math.sigmoid(tf.linalg.matmul(y6, w7)+b7)
#y7 = tf.nn.relu(tf.linalg.matmul(y6, w7)+b7)

y_pred = y7
```

Waste Processing

Simple Int with 7 layers

Loss int = MSE

Optimizer = Adam

Train : Validation : Test = 8 : 2 : 2

어제는 3개의 layers 에서 0.625625 정확도

Test Accuracy

=0.690265

Git & Kaggle

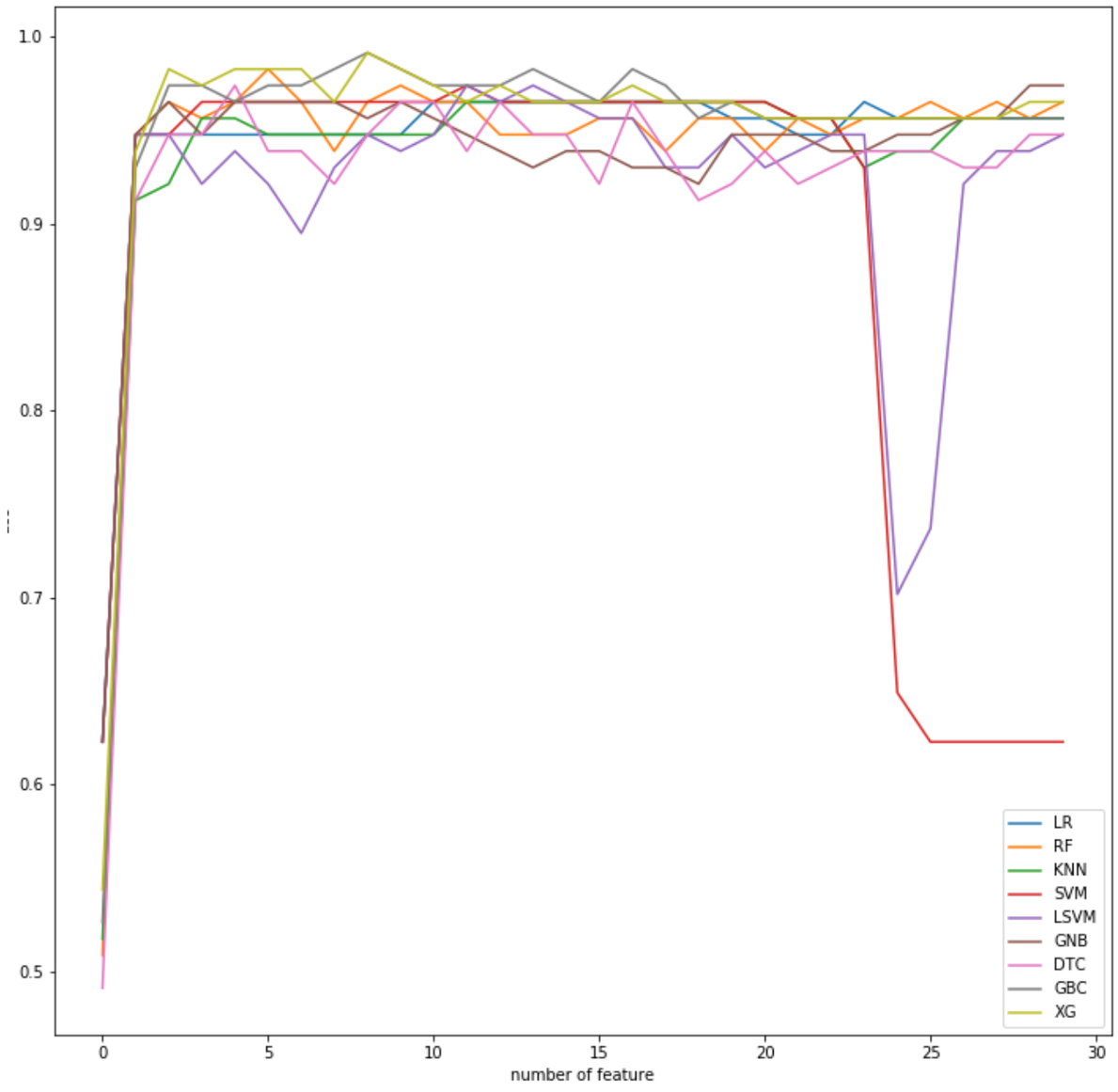
Git : https://github.com/Team-Human-Ensemble/icim_5th_academy

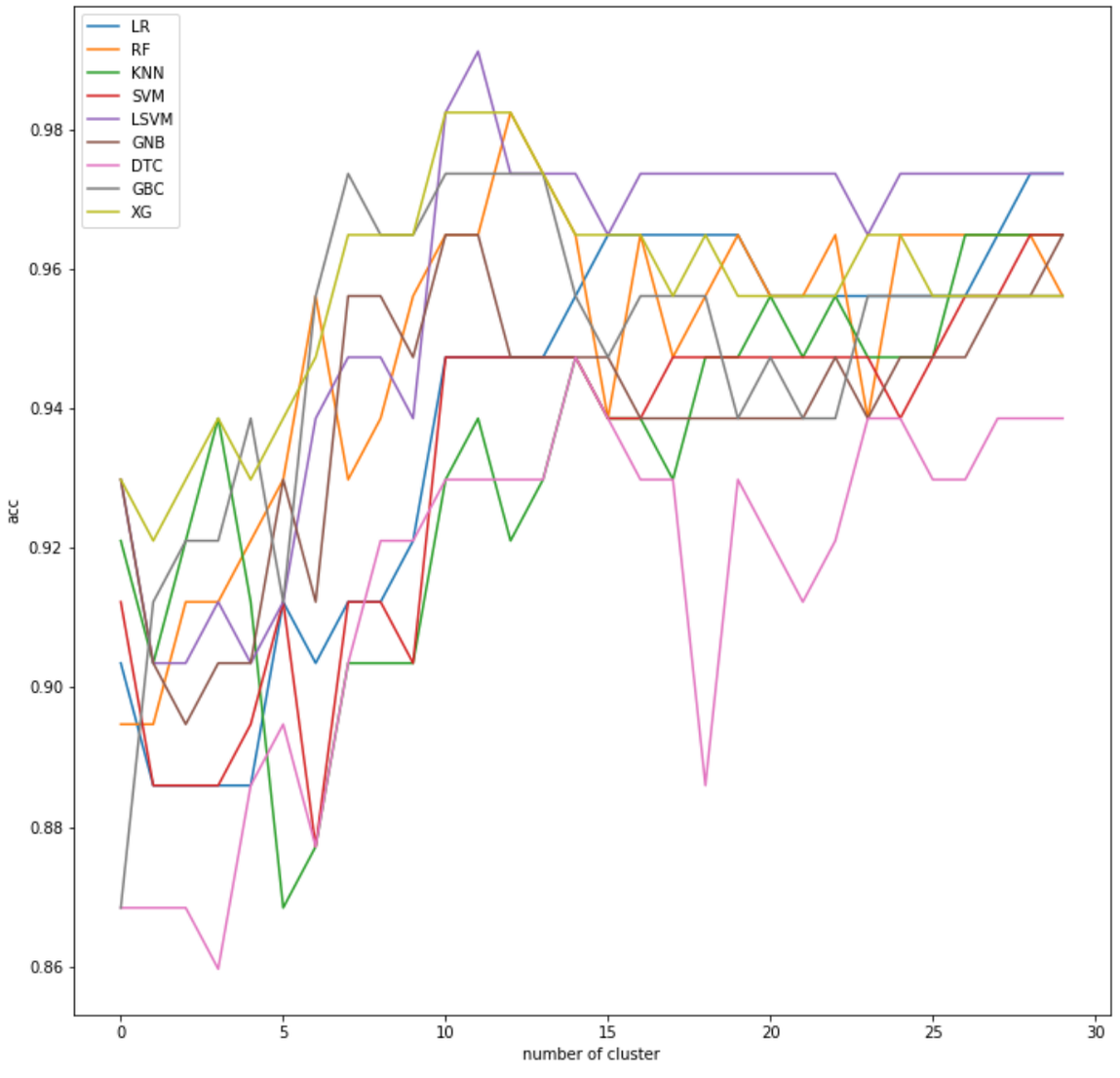
Summary

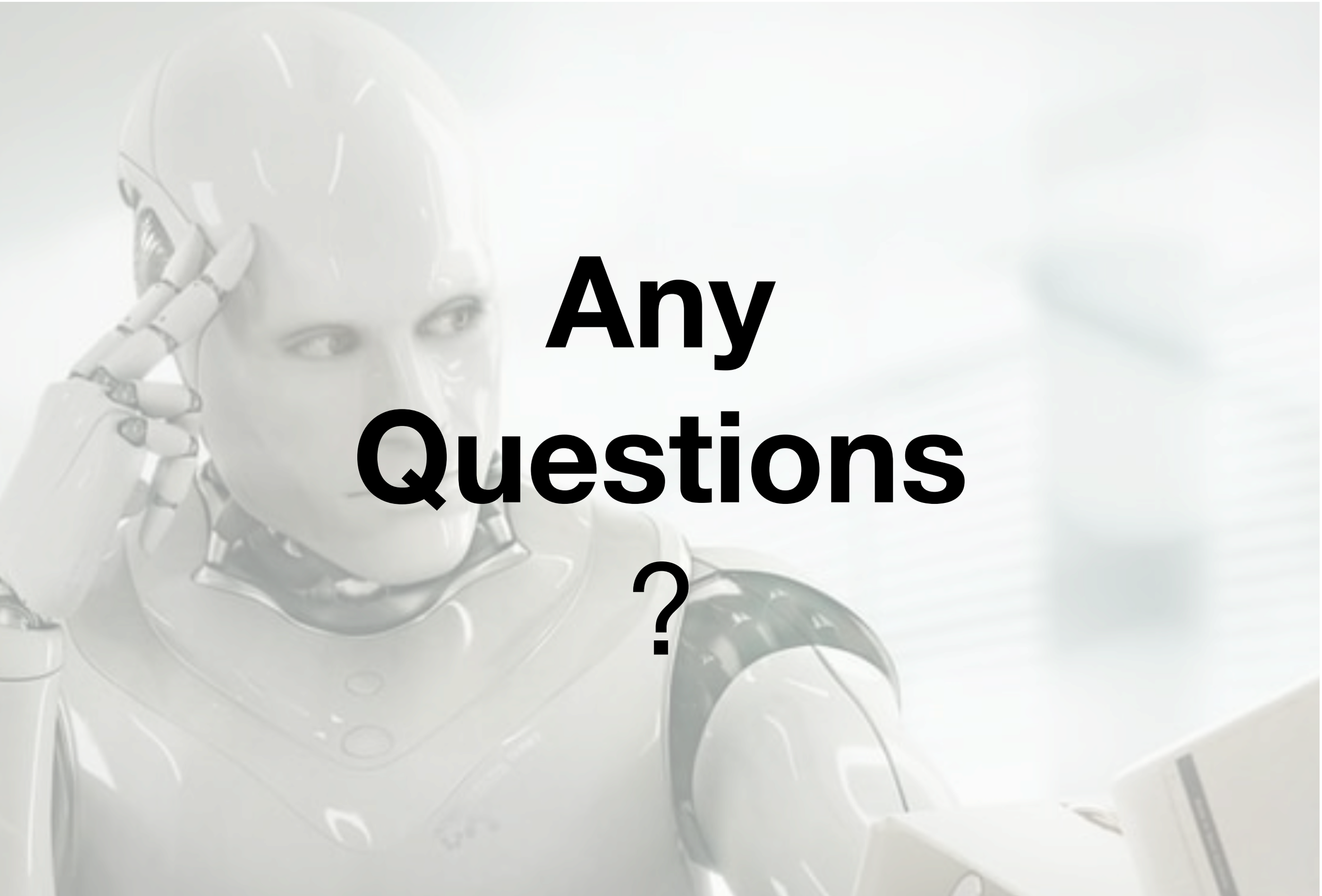
Optimized Feature

Dominant Feature
-Ranking System

Feature Selection Method
-MMS, Cluster


1.0
0.9
0.8
0.7
0.6
0.5
0
5
10
15
20
25
30
number of feature
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG


acc
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0
5
10
15
20
25
30
number of cluster
LR
RF
KNN
SVM
LSVM
GNB
DTC
GBC
XG



Any Questions ?

Thank You !