

Enriched Ensembles for variable selection
----A study on tumor type prediction using a small subset of genes

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Summary

In this project, we identified 2 out of the total 2308 genes in order to yield a no less than 0.8 test accuracy for tumor type prediction. The prediction performance was improved and stabilized at 0.95 when increasing the number of selected variables to 19. The subset of genes that we finally selected that are optimal performance in testing set are:

1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319,
1003,1084.

I. Introduction

The objective of this project is to predict the tumor type using a few selected gene expression as the predictors. Initially, the given dataset is a list of 2308 genes expressions with 4 different tumor types, separated by training and testing. By analyzing the dataset, we intended to chose few informative variables based on their importance level to fit a model to predict the tumor type and test the predict accuracy. To reach the end, we first combined glmnet models of categorical response with LDA to predict the classifications of the testing set. Then we reconstructed the prediction model using the selected top 2 to 50 genes based on the variable importance analysis and recalculated the corresponding prediction accuracy. Finally we visualized the prediction accuracy changes along with an increase of the number of selected variables on a plot and determined the smallest size of our gene type selection for an optimal performance score.

II. Analysis and Results

A. Training and testing data selection

We separated the overall data set into 2 groups by observation labels: training and testing. There are **63 training samples** and **25 testing samples** in total. Then we performed a descriptive analysis based on the tumor types by group. We observed 4 types of tumor types, which represent 83 observations in total and **5 'NA' observations** from testing data. Considering the fact that such 'NA' observations will cause a noise on final tumor type prediction, we chose to eliminate 5 samples with 'NA' at first, and predict their class at last.

B. GLMnet model

Four logistic models with the response of tumor types were constructed respectively on training data and testing data. In this procedure, we applied random sampling, cross validation to our model construction. The selection process is to randomly select 100 out of 2308 variables as the input of logistic model of training data based on the weight of each variable. Then we trained the regularization parameter lambda through a 10-fold cross validation method and fit the glmnet logistic model on training data using the randomly selected samples and the selected regularization parameter. By performing the logistic regression analysis using glmnet, we were able to get 2 important information:

- 1) The predicted probabilities on all tumor types that each one of the 100 selected variables carries.

2) The number of times that each gene got selected through random sampling and the number of times that each gene was selected by glmnet model.

Finally we iterated the entire procedure by 2000 times to ensure the selection coverage of all the 2308 genes many times. The predicted probability results for the sampled training data on the 4 types of tumors are presented as Output 1 (Appendix, Output1).

C. Classification

A linear discriminant analysis (LDA) was conducted based on the predicted probability results we got from part B. This method is used as a way of classification. We implemented LDA model on the training data and then applied the obtained projections to the testing set. Below are the results of the predicted classification versus the true classification on both training set and the valid 20 testing observations.

Training set

Predicted class: 2 1 1 1 1 1 1 1 3 3 3 3 3 3 3 3 3 3
4 1

True class: 2 1 1 1 1 1 1 1 3 3 3 3 3 3 3 3 3 4 4 4
4 1

This result allowed us to compute the model performance-- the training accuracy, which is the percentage of the number of the cases that match the true observations out of the total training observations. The **training accuracy is 1**.

Testing set

Predicted class: 3 2 4 2 1 3 4 2 3 1 3 4 2 2 2 2 4 3 4 3

True class: 3 2 4 2 1 3 4 2 3 1 3 4 1 2 2 2 4 3 4 3

This result allowed us to compute the model performance-- the testing accuracy, which is the percentage of the number of the cases that match the true observations out of the total testing observations. The **testing accuracy is 0.95**.

D. Variable Importance and Selection

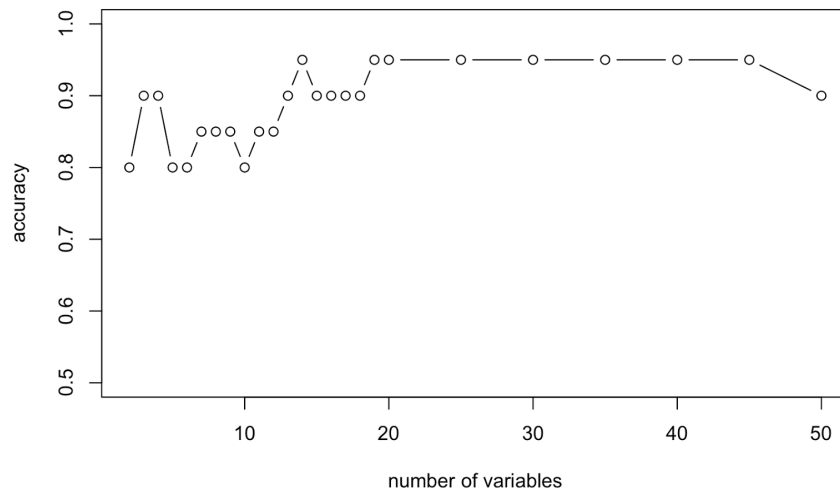
The model glmnet from part B has indicated variable importance information. Here, the importance of each variable is determined by its score, which is the ratio of the number of times when it got selected by glmnet model and the sum of the number of times it got selected during random sampling plus one. Since we applied 4 glmnet models with response of RM, EW, BL and NB, 4 sets of scores are obtained accordingly. Then we ranked the scores by tumor and selected the top 30 variables for each group (Appendix, Table1). Since we are interested in getting a list of variables that are informative in terms of predicting all tumor types, we removed the duplicative genes across the 4 different groups and reranked the variables as a whole by scores.

E. Performance evaluation using selected variables

The variable importance score ranking results allowed us to refit the models using a different number of impactful variables ranging from 2 to 50. The test accuracy was calculated accordingly (Appendix, Table2). With a goal of getting a high prediction accuracy using the an as small as possible subsets of genes, we displayed the test accuracy trend along with an increase of the number of variables selected on a plot so that we can visualize a cutting point.

The graph below shows that there are some fluctuations of test accuracy when the numbers of selected variables are around 3, 4, 10, 14, and 50. But generally, when the number of variables is smaller than 7, the accuracy stays at around 0.8, when the number of variables included are increase from 7 to 12, the test accuracy was improved to 0.85, when there are 13 to 18 variables included in the model, we get a test accuracy at 0.9, when the number of variables being included in the model is greater than 18, the accuracy was improved to 0.95. From part C we got a 100% classification accuracy with training data, similar information can be drawn from output1(Appendix, Output1). We can see that the testing performance is quite closed to the training performance.

Since the accuracy stabilized at 0.95 with an increase of variable selection, we therefore chose **19** variables to maximize the testing performance.



F. Predict the classification of samples with 'NA' (BONUS part)

We used 19 variables model and ran the training data to get the training model, then we used this model to test the "NA" class. According to this model, we predicted that all of the "NA" samples are in class "BL", when the accuracy of other 20 testing samples is 0.95.

III. Problems & Solutions

1) the convergence problem for class— 'BL'

Problem: the length of class 'BL' observation is too short to converge

Solution: use the average probability-8/63 to replace those situations that do not converge

2) Some unstable situations in the whole tendency

Problem: In the tendency of accuracy increases when the number of variables increases, there are some situations that are against the tendency.

Solution: We chose the variables when the tendency becomes stable.

Appendix:

Output1: Probabilities of glmnet model from training set

```
> fit1
  TRAIN1.EW  TRAIN2.EW  TRAIN3.EW  TRAIN4.EW  TRAIN5.EW  TRAIN6.EW  TRAIN7.EW
0.0035502357 0.0018297835 0.0041204987 0.0210348568 0.0126299340 0.0022149029 0.0148488102
  TRAIN8.EW  TRAIN9.EW  TRAIN10.EW  TRAIN11.EW  TRAIN12.EW  TRAIN13.EW  TRAIN14.EW
0.0037461397 0.0014028309 0.0283571191 0.0025234781 0.0037732176 0.0169869424 0.0026387316
  TRAIN15.EW  TRAIN16.EW  TRAIN17.EW  TRAIN18.EW  TRAIN19.EW  TRAIN20.EW  TRAIN21.EW
0.0010806200 0.0007062549 0.0075524590 0.0016990340 0.0013523799 0.0063007155 0.0002949101
  TRAIN22.EW  TRAIN23.EW  TRAIN24.BL  TRAIN25.BL  TRAIN26.BL  TRAIN27.BL  TRAIN28.BL
0.0006143139 0.0013940439 0.0180832192 0.0033603434 0.0050815733 0.0038138980 0.0018494889
  TRAIN29.BL  TRAIN30.BL  TRAIN31.BL  TRAIN32.NB  TRAIN33.NB  TRAIN34.NB  TRAIN35.NB
0.0054074396 0.0047949475 0.0053131446 0.0054986733 0.0070724451 0.0039295700 0.0044545006
  TRAIN36.NB  TRAIN37.NB  TRAIN38.NB  TRAIN39.NB  TRAIN40.NB  TRAIN41.NB  TRAIN42.NB
0.0081719318 0.0084076329 0.0020524935 0.0023872281 0.0056928425 0.0289242387 0.0037441928
  TRAIN43.NB  TRAIN44.RM  TRAIN45.RM  TRAIN46.RM  TRAIN47.RM  TRAIN48.RM  TRAIN49.RM
0.0027651806 0.9992122883 0.9986153927 0.9897174861 0.9991562228 0.9950745643 0.9946326421
  TRAIN50.RM  TRAIN51.RM  TRAIN52.RM  TRAIN53.RM  TRAIN54.RM  TRAIN55.RM  TRAIN56.RM
0.9470360301 0.9520616000 0.9827387953 0.9776011413 0.9999961915 0.9997352396 0.9999497503
  TRAIN57.RM  TRAIN58.RM  TRAIN59.RM  TRAIN60.RM  TRAIN61.RM  TRAIN62.RM  TRAIN63.RM
0.9817742432 0.9436197871 0.9888631256 0.9966753670 0.9928629601 0.9999972027 0.9892230246

> fit2
  TRAIN1.EW  TRAIN2.EW  TRAIN3.EW  TRAIN4.EW  TRAIN5.EW  TRAIN6.EW  TRAIN7.EW
9.999999e-01 9.999818e-01 9.993372e-01 1.000000e+00 1.000000e+00 1.000000e+00 1.000000e+00
  TRAIN8.EW  TRAIN9.EW  TRAIN10.EW  TRAIN11.EW  TRAIN12.EW  TRAIN13.EW  TRAIN14.EW
9.999999e-01 1.000000e+00 1.000000e+00 9.999843e-01 1.000000e+00 1.000000e+00 1.000000e+00
  TRAIN15.EW  TRAIN16.EW  TRAIN17.EW  TRAIN18.EW  TRAIN19.EW  TRAIN20.EW  TRAIN21.EW
9.982904e-01 9.850207e-01 9.981031e-01 9.999998e-01 1.000000e+00 1.000000e+00 9.999933e-01
  TRAIN22.EW  TRAIN23.EW  TRAIN24.BL  TRAIN25.BL  TRAIN26.BL  TRAIN27.BL  TRAIN28.BL
1.000000e+00 9.999739e-01 9.430661e-06 1.038406e-04 3.984102e-06 6.904727e-06 6.305234e-06
  TRAIN29.BL  TRAIN30.BL  TRAIN31.BL  TRAIN32.NB  TRAIN33.NB  TRAIN34.NB  TRAIN35.NB
1.636061e-05 2.748878e-05 3.687257e-05 5.818288e-05 1.503267e-04 6.186691e-04 1.099987e-04
  TRAIN36.NB  TRAIN37.NB  TRAIN38.NB  TRAIN39.NB  TRAIN40.NB  TRAIN41.NB  TRAIN42.NB
7.164463e-05 3.863260e-03 1.156613e-04 2.331503e-05 1.996229e-05 3.994326e-04 7.632738e-04
  TRAIN43.NB  TRAIN44.RM  TRAIN45.RM  TRAIN46.RM  TRAIN47.RM  TRAIN48.RM  TRAIN49.RM
6.623667e-06 3.903666e-06 3.950252e-07 8.040924e-06 4.736912e-03 2.537618e-07 2.967073e-07
  TRAIN50.RM  TRAIN51.RM  TRAIN52.RM  TRAIN53.RM  TRAIN54.RM  TRAIN55.RM  TRAIN56.RM
1.858457e-06 1.778038e-05 9.741928e-06 2.068503e-05 1.361443e-06 5.930535e-05 1.272143e-05
  TRAIN57.RM  TRAIN58.RM  TRAIN59.RM  TRAIN60.RM  TRAIN61.RM  TRAIN62.RM  TRAIN63.RM
5.048506e-05 1.638833e-03 2.536092e-04 6.075911e-07 1.424933e-05 5.970348e-03 1.029930e-04

> fit3
  TRAIN1.EW  TRAIN2.EW  TRAIN3.EW  TRAIN4.EW  TRAIN5.EW  TRAIN6.EW  TRAIN7.EW
8.311848e-04 1.793047e-03 2.606869e-03 6.834694e-05 6.729642e-04 5.995639e-04 5.317840e-04
  TRAIN8.EW  TRAIN9.EW  TRAIN10.EW  TRAIN11.EW  TRAIN12.EW  TRAIN13.EW  TRAIN14.EW
2.782981e-03 6.930181e-05 2.145523e-03 5.397191e-03 1.116812e-04 4.413670e-04 1.819286e-06
  TRAIN15.EW  TRAIN16.EW  TRAIN17.EW  TRAIN18.EW  TRAIN19.EW  TRAIN20.EW  TRAIN21.EW
7.265845e-02 7.139006e-03 2.080574e-02 4.199496e-04 6.165006e-05 3.757383e-06 3.451465e-04
  TRAIN22.EW  TRAIN23.EW  TRAIN24.BL  TRAIN25.BL  TRAIN26.BL  TRAIN27.BL  TRAIN28.BL
2.093643e-05 8.762684e-04 8.521305e-01 4.752302e-01 7.828307e-01 8.795580e-01 8.694472e-01
  TRAIN29.BL  TRAIN30.BL  TRAIN31.BL  TRAIN32.NB  TRAIN33.NB  TRAIN34.NB  TRAIN35.NB
8.225323e-01 6.650992e-01 8.026771e-01 2.761393e-03 8.769921e-03 1.779355e-03 8.061602e-02
  TRAIN36.NB  TRAIN37.NB  TRAIN38.NB  TRAIN39.NB  TRAIN40.NB  TRAIN41.NB  TRAIN42.NB
6.292445e-05 4.478223e-02 8.112615e-03 8.771702e-03 2.020566e-02 4.905874e-02 1.837650e-03
  TRAIN43.NB  TRAIN44.RM  TRAIN45.RM  TRAIN46.RM  TRAIN47.RM  TRAIN48.RM  TRAIN49.RM
3.688383e-02 7.462568e-04 1.605977e-02 3.674138e-03 1.778326e-02 3.863302e-03 2.149116e-03
  TRAIN50.RM  TRAIN51.RM  TRAIN52.RM  TRAIN53.RM  TRAIN54.RM  TRAIN55.RM  TRAIN56.RM
1.186888e-02 3.346004e-02 3.752745e-02 1.893313e-02 4.976096e-03 9.633637e-04 2.716403e-02
  TRAIN57.RM  TRAIN58.RM  TRAIN59.RM  TRAIN60.RM  TRAIN61.RM  TRAIN62.RM  TRAIN63.RM
1.490731e-02 4.371141e-01 1.419187e-01 1.364702e-04 3.173528e-02 6.246292e-03 6.552413e-01

> fit4
  TRAIN1.EW  TRAIN2.EW  TRAIN3.EW  TRAIN4.EW  TRAIN5.EW  TRAIN6.EW  TRAIN7.EW
1.187184e-06 6.797673e-04 5.641099e-05 5.949237e-05 2.836330e-08 6.608525e-08 3.619642e-06
  TRAIN8.EW  TRAIN9.EW  TRAIN10.EW  TRAIN11.EW  TRAIN12.EW  TRAIN13.EW  TRAIN14.EW
2.523342e-06 4.212790e-10 9.062290e-09 1.771909e-05 2.401573e-07 4.837086e-09 1.138747e-05
  TRAIN15.EW  TRAIN16.EW  TRAIN17.EW  TRAIN18.EW  TRAIN19.EW  TRAIN20.EW  TRAIN21.EW
2.949896e-05 3.402065e-02 1.392959e-05 1.643664e-05 1.054874e-06 8.553185e-08 2.115223e-03
  TRAIN22.EW  TRAIN23.EW  TRAIN24.BL  TRAIN25.BL  TRAIN26.BL  TRAIN27.BL  TRAIN28.BL
1.074560e-02 9.473372e-05 1.458065e-03 4.335946e-02 2.547631e-03 4.652858e-03 1.684617e-03
  TRAIN29.BL  TRAIN30.BL  TRAIN31.BL  TRAIN32.NB  TRAIN33.NB  TRAIN34.NB  TRAIN35.NB
3.484219e-03 2.394952e-03 2.774088e-03 9.999995e-01 9.998755e-01 9.999984e-01 9.811961e-01
  TRAIN36.NB  TRAIN37.NB  TRAIN38.NB  TRAIN39.NB  TRAIN40.NB  TRAIN41.NB  TRAIN42.NB
1.000000e+00 7.540517e-01 9.999848e-01 9.999930e-01 9.998584e-01 9.905358e-01 9.999977e-01
  TRAIN43.NB  TRAIN44.RM  TRAIN45.RM  TRAIN46.RM  TRAIN47.RM  TRAIN48.RM  TRAIN49.RM
9.997367e-01 3.343842e-06 4.739905e-06 8.098495e-07 1.429947e-01 9.525919e-05 1.325419e-02
  TRAIN50.RM  TRAIN51.RM  TRAIN52.RM  TRAIN53.RM  TRAIN54.RM  TRAIN55.RM  TRAIN56.RM
1.073345e-04 1.849184e-04 9.924692e-04 8.794788e-05 1.948228e-05 4.877279e-07 1.148781e-05
  TRAIN57.RM  TRAIN58.RM  TRAIN59.RM  TRAIN60.RM  TRAIN61.RM  TRAIN62.RM  TRAIN63.RM
1.906120e-06 2.096492e-04 1.885521e-04 1.039701e-08 2.382201e-03 3.314433e-04 3.675844e-03
```

Table 1: The ranked 30 variables for each group

| Numbers of obs | RM | Score | EW | Score | BL | Score | NB | Score |
|----------------|------|-----------|------|-----------|------|-----------|------|-----------|
| 1 | 1955 | 0.9981413 | 1389 | 0.9986945 | 846 | 0.9175573 | 742 | 0.9985694 |
| 2 | 509 | 0.9971671 | 545 | 0.9981785 | 123 | 0.8956640 | 255 | 0.9981618 |
| 3 | 1911 | 0.9969970 | 246 | 0.9981785 | 758 | 0.8699324 | 823 | 0.9976798 |
| 4 | 1207 | 0.9923274 | 1954 | 0.9980080 | 1606 | 0.8216667 | 2157 | 0.9942529 |
| 5 | 1003 | 0.9845133 | 2050 | 0.9969605 | 1386 | 0.8204633 | 1601 | 0.9939394 |
| 6 | 1723 | 0.9835526 | 1319 | 0.9879808 | 1453 | 0.7708333 | 153 | 0.9922179 |
| 7 | 1030 | 0.9820144 | 1021 | 0.9741935 | 1279 | 0.7657143 | 1776 | 0.9896194 |
| 8 | 1055 | 0.9813953 | 2117 | 0.9708029 | 836 | 0.7612524 | 1084 | 0.9841772 |
| 9 | 603 | 0.9793814 | 731 | 0.9559748 | 1158 | 0.7562893 | 1804 | 0.9821429 |
| 10 | 174 | 0.9724311 | 1023 | 0.9473684 | 589 | 0.7543478 | 1764 | 0.9600000 |
| 11 | 2046 | 0.9677419 | 971 | 0.9356436 | 998 | 0.7526882 | 1662 | 0.9544304 |
| 12 | 1301 | 0.9629630 | 29 | 0.9341085 | 1116 | 0.7506631 | 976 | 0.9520833 |
| 13 | 2083 | 0.9583333 | 1074 | 0.9258242 | 1295 | 0.7463768 | 1434 | 0.9503546 |
| 14 | 2 | 0.9510490 | 626 | 0.9157895 | 1375 | 0.7301205 | 1862 | 0.9457143 |
| 15 | 1105 | 0.9483568 | 1518 | 0.8910256 | 1099 | 0.6559140 | 2144 | 0.9398664 |
| 16 | 910 | 0.9436275 | 1867 | 0.8901099 | 165 | 0.6294737 | 2199 | 0.9213115 |
| 17 | 2146 | 0.9264069 | 865 | 0.8695652 | 74 | 0.6021978 | 879 | 0.9071146 |
| 18 | 483 | 0.9182879 | 1799 | 0.8531746 | 1884 | 0.5649606 | 901 | 0.8927039 |
| 19 | 229 | 0.9161290 | 36 | 0.8513514 | 1387 | 0.5407725 | 422 | 0.8796562 |
| 20 | 828 | 0.9117647 | 1110 | 0.8498024 | 1036 | 0.5353535 | 1198 | 0.8624161 |
| 21 | 187 | 0.9019608 | 229 | 0.8483871 | 1916 | 0.5346535 | 842 | 0.8388626 |
| 22 | 971 | 0.8910891 | 365 | 0.8465347 | 783 | 0.5155963 | 1579 | 0.8255034 |
| 23 | 655 | 0.8898305 | 1012 | 0.8348624 | 85 | 0.5135135 | 575 | 0.7869822 |
| 24 | 67 | 0.8833333 | 1003 | 0.8274336 | 585 | 0.5079365 | 956 | 0.7867299 |
| 25 | 169 | 0.8758170 | 1888 | 0.8244681 | 1735 | 0.4944649 | 1829 | 0.7860082 |
| 26 | 1895 | 0.8641975 | 1831 | 0.8235294 | 1974 | 0.4736842 | 602 | 0.7808989 |
| 27 | 1738 | 0.8632075 | 415 | 0.8208955 | 335 | 0.4688027 | 1066 | 0.7648352 |
| 28 | 554 | 0.8495146 | 1327 | 0.8172324 | 536 | 0.4065041 | 695 | 0.7627119 |
| 29 | 1110 | 0.8418972 | 1194 | 0.8064516 | 667 | 0.3973214 | 1347 | 0.7410072 |
| 30 | 129 | 0.8294574 | 867 | 0.8047945 | 1587 | 0.3948498 | 2163 | 0.7342657 |

Table2: Test Accuracy for models after using different numbers of variables

| Nu mbe rs of Vari able Sele cted | Names of variables | Test Acc urac y |
|--|--|--------------------------|
| 2 | 1389, 742 | 0.8 |
| 3 | 1389,742,545 | 0.9 |
| 4 | 1389,742,545,246 | 0.9 |
| 5 | 1389,742,545,246,255 | 0.8 |
| 6 | 1389,742,545,246,255,1955 | 0.8 |
| 7 | 1389,742,545,246,255,1955,1954 | 0.85 |
| 8 | 1389,742,545,246,255,1955,1954,823 | 0.85 |
| 9 | 1389,742,545,246,255,1955,1954,823,509 | 0.85 |
| 10 | 1389,742,545,246,255,1955,1954,823,509,1911 | 0.8 |
| 11 | 1389,742,545,246,255,1955,1954,823,509,1911,2050 | 0.85 |
| 12 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157 | 0.85 |
| 13 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601 | 0.9 |
| 14 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207 | 0.95 |
| 15 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153 | 0.9 |
| 16 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776 | 0.9 |
| 17 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319 | 0.9 |
| 18 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003 | 0.9 |
| 19 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084 | 0.95 |
| 20 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723 | 0.95 |
| 25 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723,1804,1030,1055,603,1021 | 0.95 |
| 30 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723,1804,1030,1055,603,1021,174,2117,2046,1301,1764 | 0.95 |
| 35 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723,1804,1030,1055,603,1021,174,2117,2046,1301,1764,2083,731,1662,976,2 | 0.95 |
| 40 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723,1804,1030,1055,603,1021,174,2117,2046,1301,1764,2083,731,1662,976,2,1434,1105,1023,1862,910 | 0.95 |
| 45 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319, 1003,1084,1723,1804,1030,1055,603,1021,174,2117,2046,1301,1764,2083,731,1662,976,2,1434,1105,1023,1862,910,2144,971,29,2146,1074 | 0.95 |
| 50 | 1389,742,545,246,255,1955,1954,823,509,1911,2050,2157,1601,1207,153,1776,1319,1003,1084,1723,1804,1030,1055,603,1021, 174,2117,2046,1301,1764,2083,731,1662,976,2,1434,1105,1023,1862,910,2144,971,29,2146,1074,2199,483,846,229,626 | 0.9 |