Santander Customer Transaction Prediction

Introduction

Challenge description by the holder:

At Santander our mission is to help people and businesses prosper. We are always looking for ways to help our customers understand their financial health and identify which products and services might help them achieve their monetary goals.

Our data science team is continually challenging our machine learning algorithms, working with the global data science community to make sure we can more accurately identify new ways to solve our most common challenge, binary classification problems such as: is a customer satisfied? Will a customer buy this product? Can a customer pay this loan?

In this challenge, we invite Kagglers to help us identify which customers will make a specific transaction in the future, irrespective of the amount of money transacted. The data provided for this competition has the same structure as the real data we have available to solve this problem.

More information can be found in the [Santander Customer Transaction Prediction (https://www.kaggle.com/c/santander-customer-transaction-prediction/)](https://www.kaggle.com/c/santander-customer-transaction-prediction/) on Kaggle.

Implementation

In [8]:
```
# data analysis
import pandas as pd
import numpy as np

# visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# machine learning
from sklearn import preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
# from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
# from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, auc, roc_cur
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.metrics import roc_auc_score
from tqdm import tqdm
# from skopt import BayesSearchCV
# import sweetviz as sv
# import warnings
# warnings.filterwarnings('ignore')
```

Fetch the data:

In [2]:
```
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
```

Preview the data

In [4]:
```
train_data.shape, test_data.shape
```

Out[4]:
```
((200000, 202), (200000, 201))
```

In [4]:
```
train_data.head()
```

Out[4]:

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	...	var_
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266	...	4.4
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	...	7.6
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155	...	2.9
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250	...	4.4
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	...	-1.4

5 rows × 202 columns

In [4]:
```
test_data.head()
```

Out[4]:

	ID_code	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	...	var_1
0	test_0	11.0656	7.7798	12.9536	9.4292	11.4327	-2.3805	5.8493	18.2675	2.1337	...	-2.15
1	test_1	8.5304	1.2543	11.3047	5.1858	9.1974	-4.0117	6.0196	18.6316	-4.4131	...	10.61
2	test_2	5.4827	-10.3581	10.1407	7.0479	10.2628	9.8052	4.8950	20.2537	1.5233	...	-0.74
3	test_3	8.5374	-1.3222	12.0220	6.5749	8.8458	3.1744	4.9397	20.5660	3.3755	...	9.57
4	test_4	11.7058	-0.1327	14.1295	7.7506	9.1035	-8.5848	6.8595	10.6048	2.9890	...	4.22

5 rows × 201 columns

In [5]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Columns: 202 entries, ID_code to var_199
dtypes: float64(200), int64(1), object(1)
memory usage: 308.2+ MB
```

In [6]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Columns: 201 entries, ID_code to var_199
dtypes: float64(200), object(1)
memory usage: 306.7+ MB
```

In [94]:
```
train_data.describe()
```

Out[94]:

	target	var_0	var_1	var_2	var_3	var_4	var_5
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	0.097500	10.706520	-1.618377	10.627213	6.843388	11.054107	-5.114619
std	0.296712	3.005849	4.137456	2.597002	2.034015	1.641553	8.015311
min	0.000000	2.825300	-13.202600	3.678500	1.154100	6.394000	-29.013300
25%	0.000000	8.523225	-4.770550	8.613675	5.286475	9.806875	-11.388125
50%	0.000000	10.550900	-1.556500	10.518700	6.865350	11.064100	-5.115700
75%	0.000000	12.720400	1.315100	12.424250	8.379400	12.262225	1.127850
max	1.000000	19.289300	8.416000	18.347700	12.674000	15.110800	17.251600

8 rows × 201 columns

In [95]:
```
test_data.describe()
```

Out[95]:

	var_0	var_1	var_2	var_3	var_4	var_5	var_6
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	10.660195	-1.678150	10.657813	6.790664	11.081248	-5.008449	5.387836
std	3.044544	4.135478	2.596784	2.068614	1.608655	7.891081	0.857044
min	2.194500	-11.556900	2.516400	1.241400	6.579700	-25.537100	2.873300
25%	8.398725	-4.860800	8.731575	5.207275	9.890075	-11.113325	4.755900
50%	10.489750	-1.550500	10.504650	6.840000	11.059950	-4.927750	5.348000
75%	12.744550	1.271025	12.419125	8.379900	12.237100	0.884000	5.953450
max	20.064900	8.487900	17.923800	12.700400	15.432900	14.761300	7.955700

8 rows × 200 columns

There are 200 features named with var_0 to var_199 and 20000 rows of data. All the features are numerical and all the types are float64.

Check the missing values

In [5]:
```
train_data.isnull().sum().any(), test_data.isnull().sum().any()
```

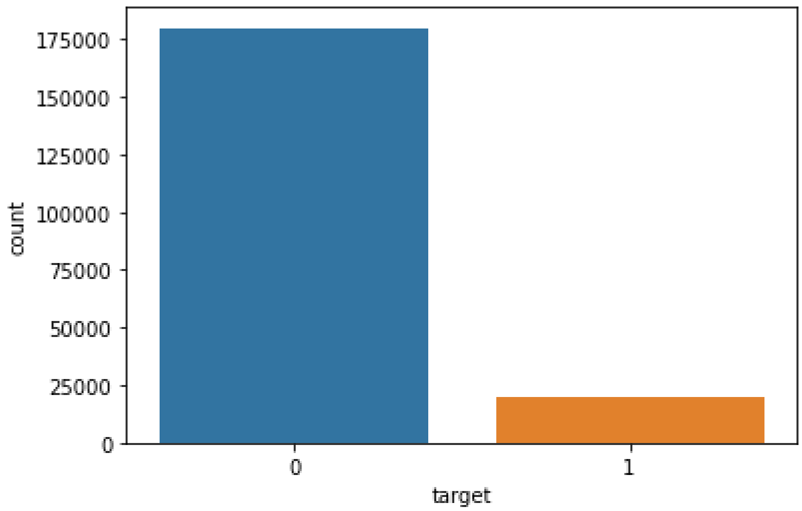
Out[5]:
```
(False, False)
```

There are no missiing values (blank, null or empty). So we don't need to drop NA values.

Plot the target value in training set

In [9]:
```
sns.countplot(x = train_data['target'])
```

Out[9]: <AxesSubplot:xlabel='target', ylabel='count'>



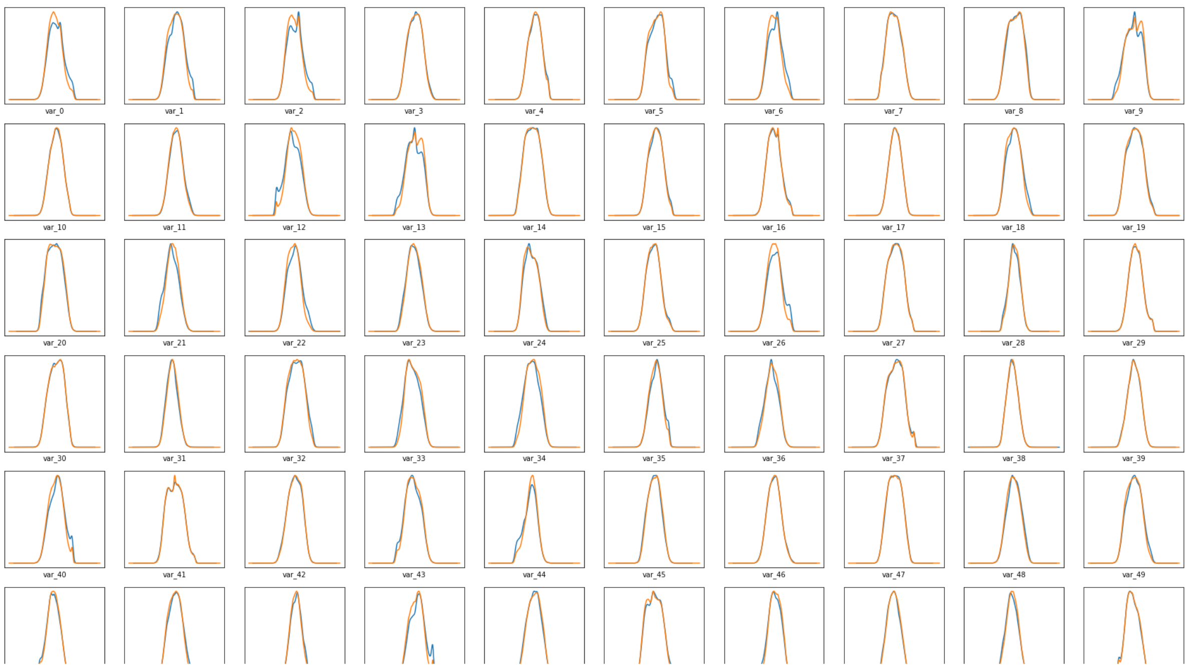
In [ ]:
```
sum(train_data['target'])
```

We can see that the outcome is imbalance. Most target values are 0.

Draw density plot for all features

In [5]:
```
train0 = train_data[train_data['target']==0]
train1 = train_data[train_data['target']==1]
```

In [111]:
```
fig,axs = plt.subplots(20,10,figsize=(30,60))
counter = 0
for i in range(20):
    for j in range(10):
        axs[i,j].tick_params(left = False, labelleft = False, labelbottom=False, bottom
        var = 'var_'+str(counter)
        train1.plot(kind='density',y=var,ax=axs[i,j],legend=False)
        train0.plot(kind='density',y=var,ax=axs[i,j],legend=False)
        axs[i,j].set_ylabel('')
        axs[i,j].set_xlabel(var)
        counter += 1
```



Find X_train, Y_train, X_test

In [130]:
```
X_train = train_data.drop(['ID_code','target'],axis = 1)
Y_train = train_data['target']
X_test = test_data.drop(['ID_code'],axis = 1)
```

Draw feature correlation heatmap

In [126]:

```
X_train_corr = X_train.corr()
print(X_train_corr)
fig2,axs2 = plt.subplots(1,1,figsize=(50,40))
sns.heatmap(X_train_corr,cmap="Blues",ax=axs2)
```

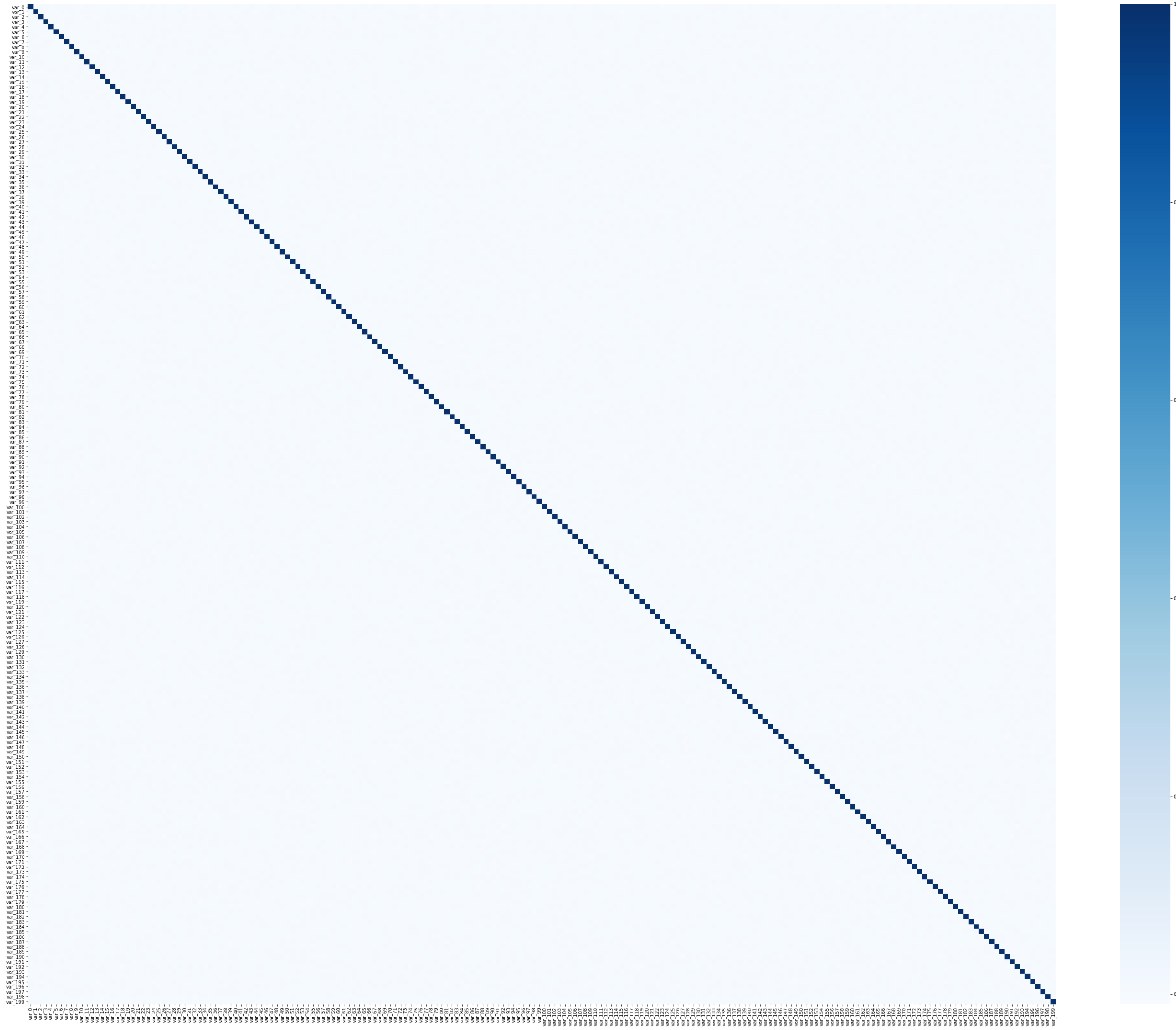
```
            var_0     var_1     var_2     var_3     var_4     var_5     var_6  \
var_0    1.000000 -0.000544  0.006573  0.003801  0.001326  0.003046  0.006983
var_1   -0.000544  1.000000  0.003980  0.000010  0.000303 -0.000902  0.003258
var_2    0.006573  0.003980  1.000000  0.001001  0.000723  0.001569  0.000883
var_3    0.003801  0.000010  0.001001  1.000000 -0.000322  0.003253 -0.000774
var_4    0.001326  0.000303  0.000723 -0.000322  1.000000 -0.001368  0.000049
...           ...       ...       ...       ...       ...       ...       ...
var_195  0.002073 -0.000785 -0.001070  0.001206  0.003706 -0.001274  0.001244
var_196  0.004386 -0.000377  0.003952 -0.002800  0.000513  0.002880  0.005378
var_197 -0.000753 -0.004157  0.001078  0.001164 -0.000046 -0.000535 -0.003565
var_198 -0.005776 -0.004861 -0.000877 -0.001651 -0.001821 -0.000953 -0.003025
var_199  0.003850  0.002287  0.003855  0.000506 -0.000786  0.002767  0.006096

            var_7     var_8     var_9  ...   var_190   var_191   var_192  \
var_0    0.002429  0.004962 -0.002613  ...  0.002752  0.000206 -0.005373
var_1    0.001511  0.004098 -0.000832  ...  0.006627  0.003621 -0.002604
var_2   -0.000991  0.002648 -0.001932  ...  0.000197  0.001285 -0.003400
var_3    0.002500  0.003553 -0.000826  ...  0.000151  0.002445 -0.001530
var_4    0.004549  0.001194 -0.000918  ...  0.001514  0.004357  0.003347
...           ...       ...       ...  ...       ...       ...       ...
var_195  0.001854  0.001396 -0.000868  ...  0.004571  0.000870 -0.004745
var_196  0.001045 -0.003242  0.000052  ... -0.000847  0.002466 -0.001386
var_197  0.003466 -0.004583  0.003701  ... -0.004974  0.000906 -0.000527
var_198  0.000650  0.002950  0.002343  ... -0.000153 -0.000067  0.003451
var_199 -0.001457  0.000854  0.001070  ... -0.000404  0.003595 -0.001239

          var_193   var_194   var_195   var_196   var_197   var_198   var_199
var_0    0.001616 -0.001514  0.002073  0.004386 -0.000753 -0.005776  0.003850
var_1    0.001153 -0.002557 -0.000785 -0.000377 -0.004157 -0.004861  0.002287
var_2    0.000549  0.002104 -0.001070  0.003952  0.001078 -0.000877  0.003855
var_3   -0.001699 -0.001054  0.001206 -0.002800  0.001164 -0.001651  0.000506
var_4    0.000813 -0.000068  0.003706  0.000513 -0.000046 -0.001821 -0.000786
...           ...       ...       ...       ...       ...       ...       ...
var_195 -0.003143 -0.001201  1.000000  0.002517 -0.004170 -0.000536  0.002042
var_196 -0.005308 -0.005040  0.002517  1.000000 -0.000454  0.000253  0.000607
var_197  0.005068  0.000884 -0.004170 -0.000454  1.000000  0.001183  0.004991
var_198  0.001646  0.003194 -0.000536  0.000253  0.001183  1.000000 -0.004731
var_199 -0.000552 -0.005615  0.002042  0.000607  0.004991 -0.004731  1.000000

[200 rows x 200 columns]
```

Out[126]: <AxesSubplot:>



Add new features

[...]

Modelling

The model list we decide to choose:

- Decision Tree
- Logistic Regression
- Support Vector Machines

- Stochastic Gradient Descent
- Random Forest
- Naive Bayes classifier

Define a function for evaluation or hyperparameter tuning using K Fold Cross Validation:

In [213]:
```
def tuning(clf, param_name, param_list, X_train, Y_train, k):
    kf = KFold(n_splits=k)

    if not param_name: # evaluation
        # how many decimal places to round up
        dec_num = 3
        score, accs, precs, recs, f1s = [],[],[],[],[] # record metrics of K folds

        for train,test in tqdm(kf.split(X_train, Y_train)):
            clf.fit(X_train.iloc[train], Y_train.iloc[train])
            Y_predict = clf.decision_function(X_train.iloc[test]) # used for SGD, LinearSV
            score.append(roc_auc_score(Y_train.iloc[test], Y_predict))
#             Y_predict_proba = clf.predict_proba(X_train.iloc[test]) # used for others
#             score.append(roc_auc_score(Y_train.iloc[test], Y_predict_proba[:,1]))
            print(score)

            Y_predict = clf.predict(X_train.iloc[test])
            accs.append(accuracy_score(Y_train.iloc[test],Y_predict))
            prec, rec, f1, _ = precision_recall_fscore_support(Y_train.iloc[test], Y_predi
            precs.append(prec)
            recs.append(rec)
            f1s.append(f1)
        return {'roc_auc_score':sum(score)/k, 'accuracy':sum(accs)/k, 'precision':sum(pre

    else: # hyperparameter tuning
        scores = []
        for param in param_list:
            score = [] # record scores of K folds
            clf.__dict__[param_name] = param
            for train,test in tqdm(kf.split(X_train, Y_train)):
                clf.fit(X_train.iloc[train], Y_train.iloc[train])
                Y_predict_proba = clf.predict_proba(X_train.iloc[test])
                score.append(roc_auc_score(Y_train.iloc[test], Y_predict_proba[:,1]))
            scores.append(score)
            print(score)
        return scores
```

Define a function for drawing the output table of K Fold Cross Validation:

In [27]:
```
def table_score(param_name, param_list, score_list, k):
    '''
        use example:
        result = table_score('C', [0.005, 0.01, 0.05, 0.1, 0.5], res, 5)
        here res is the return score list from tuning function
        return a DataFrame
    '''
    plot_c = {}
    i = 0
    for param in param_list:
        plot_c[f'{param_name}={param}']=score_list[i]
        i += 1
    result = pd.DataFrame(plot_c)
    result = result.append(result.describe().loc['mean'])
    result = result.append(result.describe().loc['std'])
    for j in range(k):
        result = result.rename(index={j: f"score_{j}"})
    return result
```

In [211]:
```
X_train = train_data.drop(['ID_code','target'],axis = 1)
Y_train = train_data['target']
lim = 100000
X_train = X_train[0:lim]
Y_train = Y_train[0:lim]
```

Decision Tree

In [29]:
```
DT_model = DecisionTreeClassifier(random_state=0)
tuning(DT_model, None, None, X_train, Y_train, 5)
```

```
5it [24:07, 289.50s/it]
```

Out[29]:
```
0.557388566677161
```

Logistic Regression

In [125]:
```
logistic_model = LogisticRegression(penalty='l2',C=0.01,class_weight='balanced', solver='l
tuning(logistic_model,None, None, X_train, Y_train, 5)
```

```
5it [05:30, 66.10s/it]
```

Out[125]:
```
{'roc_auc_score': 0.8543984877026499,
 'accuracy': 0.77746,
 'precision': 0.77746,
 'recall': 0.77746,
 'f1': 0.77746}
```

In [124]:
```
# tuning
logistic_model = LogisticRegression(penalty='l2',class_weight='balanced', solver='lbfgs',
scores = tuning(logistic_model,'C',[0.0001,0.001,0.01,0.1,1,10,100,1000], X_train, Y_train
```

```
5it [00:59, 11.94s/it]
0it [00:00, ?it/s]

[0.8403895276960202, 0.841247786483253, 0.8408431799015871, 0.8404002028245192, 0.84081
76891146383]

5it [02:40, 32.03s/it]
0it [00:00, ?it/s]

[0.8503631022265747, 0.8514806772777141, 0.8521868446687396, 0.8497725199605083, 0.8515
182015749385]

5it [05:26, 65.30s/it]
0it [00:00, ?it/s]

[0.8538149038114715, 0.8543725775306179, 0.8567204419673644, 0.851879426725618, 0.85520
50884781781]

5it [04:47, 57.59s/it]
0it [00:00, ?it/s]

[0.8533161010957936, 0.854040305763127, 0.856770486941993, 0.8517235523265796, 0.854679
0672665209]

5it [03:13, 38.60s/it]
0it [00:00, ?it/s]

[0.8536947188737637, 0.8541776230175209, 0.8572916515763509, 0.8511593728537088, 0.8552
402599768878]

5it [03:50, 46.12s/it]
0it [00:00, ?it/s]

[0.8537275759985861, 0.8541072493304307, 0.8573419983572956, 0.851134529532967, 0.85521
7921703449]

5it [04:03, 48.78s/it]
0it [00:00, ?it/s]

[0.8537064696636872, 0.8541190579395309, 0.8573540157360716, 0.851090342762706, 0.85524
09933040461]

5it [03:38, 43.62s/it]

[0.8536973113741785, 0.8540446637021997, 0.8573400503347087, 0.8511070301768544, 0.8552
433343099747]
```

In [126]:
```
res = table_score('C', [0.0001,0.001,0.01,0.1,1,10,100,1000], scores, 5)
res
```

Out[126]:

	C=0.0001	C=0.001	C=0.01	C=0.1	C=1	C=10	C=100	C=1000
score_0	0.840390	0.850363	0.853815	0.853316	0.853695	0.853728	0.853706	0.853697
score_1	0.841248	0.851481	0.854373	0.854040	0.854178	0.854107	0.854119	0.854045
score_2	0.840843	0.852187	0.856720	0.856770	0.857292	0.857342	0.857354	0.857340
score_3	0.840400	0.849773	0.851879	0.851724	0.851159	0.851135	0.851090	0.851107
score_4	0.840818	0.851518	0.855205	0.854679	0.855240	0.855218	0.855241	0.855243
mean	0.840740	0.851064	0.854398	0.854106	0.854313	0.854306	0.854302	0.854286
std	0.000320	0.000872	0.001596	0.001657	0.002004	0.002024	0.002044	0.002037

SVM

In [6]:
```
SVM_model = SVC(gamma='scale',probability=True)
tuning(SVM_model, None, None, X_train, Y_train, 2)
```

```
2it [17:07, 513.81s/it]
```

Out[6]: 0.8194039512542012

In [57]:
```
LinearSVM_model = LinearSVC()
tuning(LinearSVM_model, None, None, X_train, Y_train, 5)
```

```
0it [00:00, ?it/s]E:\ANACONDA\lib\site-packages\sklearn\svm\_base.py:985: ConvergenceWa
rning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
1it [00:32, 32.38s/it]E:\ANACONDA\lib\site-packages\sklearn\svm\_base.py:985: Convergen
ceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
2it [01:04, 32.33s/it]E:\ANACONDA\lib\site-packages\sklearn\svm\_base.py:985: Convergen
ceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
3it [01:36, 32.14s/it]E:\ANACONDA\lib\site-packages\sklearn\svm\_base.py:985: Convergen
ceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
4it [02:09, 32.36s/it]E:\ANACONDA\lib\site-packages\sklearn\svm\_base.py:985: Convergen
ceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
5it [02:40, 32.17s/it]
```

Out[57]: (0.7919891642926179,)

SGD

In [214]:
```
SGD_model = SGDClassifier(class_weight='balanced',learning_rate='adaptive',eta0=0.01,alpha
tuning(SGD_model, None, None, X_train, Y_train, 5)
```

```
1it [00:03,  3.30s/it]

[0.8498284553747266]

2it [00:06,  3.28s/it]

[0.8498284553747266, 0.8516869062009285]

3it [00:09,  3.11s/it]

[0.8498284553747266, 0.8516869062009285, 0.8526993941046142]

4it [00:12,  3.27s/it]

[0.8498284553747266, 0.8516869062009285, 0.8526993941046142, 0.8505365996308378]

5it [00:15,  3.16s/it]

[0.8498284553747266, 0.8516869062009285, 0.8526993941046142, 0.8505365996308378, 0.8512
956649872723]
```

Out[214]:
```
{'roc_auc_score': 0.8512094040596759,
 'accuracy': 0.76371,
 'precision': 0.76371,
 'recall': 0.76371,
 'f1': 0.76371}
```

Random Forest

In [101]:
```
random_forest_model = RandomForestClassifier(n_estimators=10000,random_state=0,max_depth=2
tuning(random_forest_model, None, None, X_train, Y_train, 5)
```

```
5it [1:39:42, 1196.41s/it]
```

Out[101]:
```
{'roc_auc_score': 0.8929845380450153,
 'accuracy': 0.89985,
 'precision': 0.89985,
 'recall': 0.89985,
 'f1': 0.89985}
```

In [98]:

```
# tuning max_depth
random_forest_model = RandomForestClassifier(n_estimators=10000,random_state=0,min_samples
scores = tuning(random_forest_model, 'max_depth', [5,10,15,20,30,50,100,None], X_train, Y_
```

```
5it [00:50, 10.12s/it]
0it [00:00, ?it/s]

[0.8713074634404274, 0.882845597421994, 0.8713908904761405, 0.8611061657438259, 0.87
46448054663716]

5it [01:14, 14.92s/it]
0it [00:00, ?it/s]

[0.8755612377773042, 0.8888496507808383, 0.879961156622729, 0.8686610190405479, 0.88
1482097391845]

5it [01:21, 16.28s/it]
0it [00:00, ?it/s]

[0.8777836178390195, 0.8889767075116686, 0.8824216832193871, 0.8685091053635435, 0.8
807207841001434]

5it [01:24, 16.97s/it]
0it [00:00, ?it/s]
```

In [99]:

```
res = table_score('max_depth', [5,10,15,20,30,50,100,None], scores, 5)
res
```

Out[99]:

	max_depth=5	max_depth=10	max_depth=15	max_depth=20	max_depth=30	max_depth=50
score_0	0.871307	0.875561	0.877784	0.877696	0.877919	0.877919
score_1	0.882846	0.888850	0.888977	0.889141	0.888587	0.888587
score_2	0.871391	0.879961	0.882422	0.884174	0.883673	0.883673
score_3	0.861106	0.868661	0.868509	0.867142	0.867039	0.867039
score_4	0.874645	0.881482	0.880721	0.881683	0.882000	0.882000
mean	0.872259	0.878903	0.879682	0.879967	0.879844	0.879844
std	0.006983	0.006675	0.006685	0.007409	0.007258	0.007258

In [82]:
```
# tuning min_sample_leaf
random_forest_model = RandomForestClassifier(n_estimators=10000,random_state=0,max_feature
tuning(random_forest_model, 'min_samples_leaf', [20,50,100,200,300,500,1000], X_train, Y_t
```

```
5it [1:23:37, 1003.51s/it]
5it [1:00:45, 729.04s/it]
5it [4:57:11, 3566.29s/it]
5it [27:38, 331.65s/it]
5it [24:57, 299.40s/it]
5it [21:40, 260.12s/it]
5it [16:57, 203.53s/it]
```

Out[82]:
```
[[0.889586463931267,
  0.8961174676305866,
  0.8883795075340337,
  0.8945193562168998,
  0.880591997710961],
 [0.8905079376994814,
  0.8955884233137126,
  0.8897741555103655,
  0.8966834216962818,
  0.883000020469124],
 [0.8897788239541625,
  0.8961815080413371,
  0.8885760005366321,
  0.897268251560569,
  0.8819453680178805],
 [0.8894662668437897,
  0.8956282352919764,
  0.8873949463014743,
  0.8964538022830043,
  0.881834484475264],
 [0.8886234350361552,
  0.8944477532621934,
  0.8875153134355759,
  0.895639811785486,
  0.8810678227452684],
 [0.8878099822564076,
  0.8943646031018765,
  0.8872191948398577,
  0.8956963564262181,
  0.8801502149093814],
 [0.8831399456029984,
  0.8919823680710665,
  0.8837578950248545,
  0.8910763266628627,
  0.877045475716121]]
```

In [97]:
```
scores = [[0.889586463931267,
  0.8961174676305866,
  0.8883795075340337,
  0.8945193562168998,
  0.880591997710961],
 [0.8905079376994814,
  0.8955884233137126,
  0.8897741555103655,
  0.8966834216962818,
  0.883000020469124],
 [0.8897788239541625,
  0.8961815080413371,
  0.8885760005366321,
  0.897268251560569,
  0.8819453680178805],
 [0.8894662668437897,
  0.8956282352919764,
  0.8873949463014743,
  0.8964538022830043,
  0.881834484475264],
 [0.8886234350361552,
  0.8944477532621934,
  0.8875153134355759,
  0.895639811785486,
  0.8810678227452684],
 [0.8878099822564076,
  0.8943646031018765,
  0.8872191948398577,
  0.8956963564262181,
  0.8801502149093814],
 [0.8831399456029984,
  0.8919823680710665,
  0.8837578950248545,
  0.8910763266628627,
  0.877045475716121]]
```

In [86]:
```
res = table_score('min_samples_leaf', [20,50,100,200,300,500,1000], scores, 5)
res
```

Out[86]:

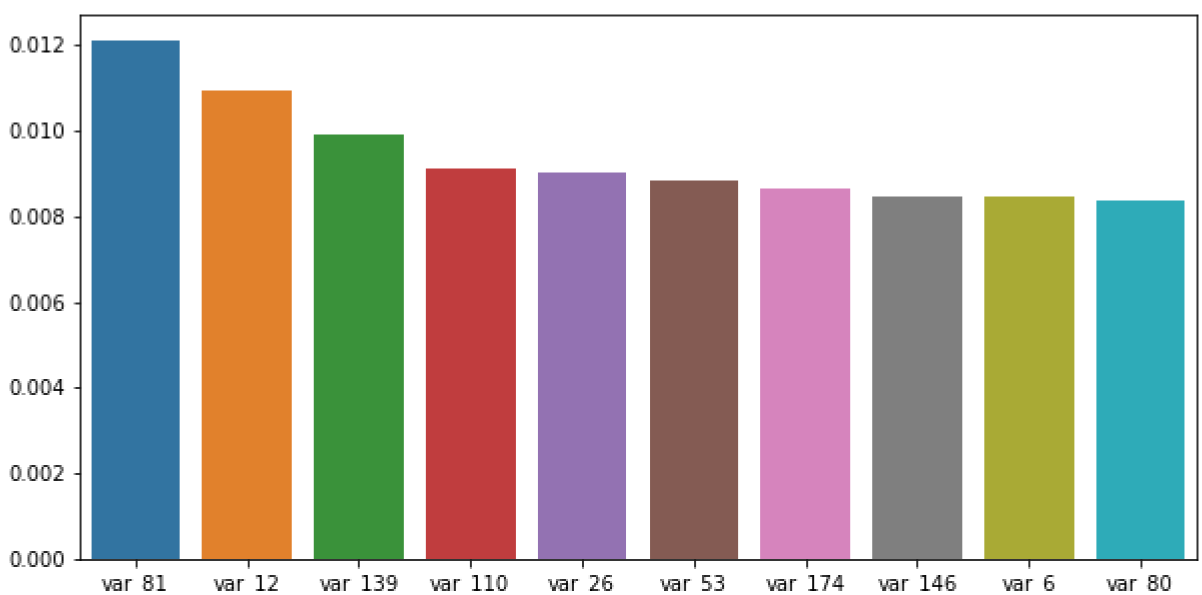
	min_samples_leaf=20	min_samples_leaf=50	min_samples_leaf=100	min_samples_leaf=200
score_0	0.889586	0.890508	0.889779	0.889466
score_1	0.896117	0.895588	0.896182	0.895628
score_2	0.888380	0.889774	0.888576	0.887395
score_3	0.894519	0.896683	0.897268	0.896454
score_4	0.880592	0.883000	0.881945	0.881834
mean	0.889839	0.891111	0.890750	0.890156
std	0.005459	0.004879	0.005571	0.005421

In [187]:
```
feature_importance = random_forest_model.feature_importances_
dic = {}
i = 0
for i in range(0,200):
    dic[f'var_{i}']=feature_importance[i]
dic_sorted = sorted(dic.values(), reverse=True)[:10]
var_sorted = sorted(dic, key=dic.get, reverse=True)[:10]
```

Out[187]:
```
{'var_0': 0.006633803905408577,
 'var_1': 0.00677599400795011З,
 'var_2': 0.007078896665510021,
 'var_3': 0.003871501904485278,
 'var_4': 0.0038628144068256717,
 'var_5': 0.0051919382526953535,
 'var_6': 0.008451053621786454,
 'var_7': 0.003491538109159815,
 'var_8': 0.004059686825546001,
 'var_9': 0.006000638966862994,
 'var_10': 0.003484393027198032,
 'var_11': 0.004297851934838769,
 'var_12': 0.010919109857035116,
 'var_13': 0.006563099214113199,
 'var_14': 0.0035667014843903232,
 'var_15': 0.0039994700861687325,
 'var_16': 0.003584151699176138З,
 'var_17': 0.003445916619241449,
 'var_18': 0.0061596884246055165,
```

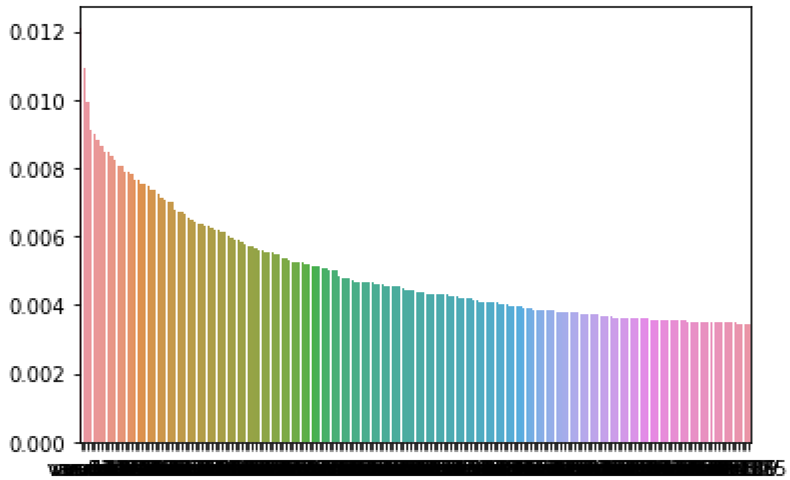
In [203]:
```
dic_sorted = sorted(dic.values(), reverse=True)[:10]
var_sorted = sorted(dic, key=dic.get, reverse=True)[:10]
plt.figure(figsize = (10,5))
sns.barplot(x=var_sorted,y=dic_sorted)
```

Out[203]: <AxesSubplot:>



In [209]:
```
dic_sorted = sorted(dic.values(), reverse=True)
var_sorted = sorted(dic, key=dic.get, reverse=True)
sns.barplot(x=var_sorted,y=dic_sorted)
```

Out[209]: <AxesSubplot:>



Naive Bayes

In [46]:
```
# tuning
naive_bayes_model = GaussianNB()
scores = tuning(naive_bayes_model, 'var_smoothing', [1e-10,1e-9,1e-8,1e-7,1e-6,1e-5], X_tr
```

```
5it [00:05,  1.16s/it]
5it [00:05,  1.15s/it]
5it [00:05,  1.14s/it]
5it [00:05,  1.16s/it]
5it [00:05,  1.17s/it]
5it [00:05,  1.17s/it]
```

In [66]:
```
res = table_score('var_smoothing', [1e-10,1e-9,1e-8,1e-7,1e-6,1e-5], scores, 5)
res
```

Out[66]:

	var_smoothing=1e-10	var_smoothing=1e-09	var_smoothing=1e-08	var_smoothing=1e-07	var_smootl
score_0	0.886705	0.886703	0.886693	0.886625	(
score_1	0.884776	0.884774	0.884754	0.884638	(
score_2	0.888192	0.888194	0.888210	0.888255	(
score_3	0.889562	0.889562	0.889567	0.889556	(
score_4	0.892805	0.892805	0.892798	0.892751	(
mean	0.888408	0.888408	0.888404	0.888365	(
std	0.002713	0.002714	0.002718	0.002742	(

In [65]:
```
# final result
naive_bayes_model = GaussianNB()
tuning(naive_bayes_model, None, None, X_train, Y_train, 5)
```

```
5it [00:07,  1.43s/it]
```

Out[65]:
```
{'roc_auc_score': 0.8884075007201743,
 'accuracy': 0.921515,
 'precision': 0.921515,
 'recall': 0.921515,
 'f1': 0.921515}
```

Final Prediction

In [140]:
```
Y_pred1 = random_forest_model.predict_proba(X_test)
Y_pred2 = naive_bayes_model.predict_proba(X_test)
```

Make submission

In [145]:
```
submission1 = pd.DataFrame({"ID_code": test_data["ID_code"],"target": Y_pred1[:,1]})
submission1.to_csv('submission1.csv', index=False)

submission2 = pd.DataFrame({"ID_code": test_data["ID_code"],"target": Y_pred2[:,1]})
submission2.to_csv('submission2.csv', index=False)
```