Hackathon

Which customers will leave "Kin Safety" product before 2 years?

A HISTORY WITH DATA TO IMPROVE CUSTOMER RETENTION

"Data are just summaries of thousands of stories – tell a few of those stories to help make the data meaningful." Dan Heath

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Introduction

Hello dear reviewer, In this short presentation I will show you an abstract of the process to find a solution to predict which customers will leave “Kin Safety” product within 2 years.

For this purpose, I created 6 sections for each step of my proposed solution:

1) **Desired Population:** Explanation of the adequacy of the data , each filter to obtain only the desired customers to analyze.
2) **New Variables:** Explanation of how I got the age, number of products, account balance, and bureau score at the moment of application of each costumer.
3) **Exploring Data:** Explanation of how I decided the way to select a prediction model.
4) **Prediction model:** Explanation of the creation of different classifier models.
5) **Evaluation:** Explanation of comparison with a base model, cross-validation process, and some predictions for a confusion matrix.
6) **Conclusion:** Some thoughts about the process.

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Desired Population

Objective | Process | Result

I provide two ways:
1) Online. Files uploaded to a folder on google drive.
2) Local files. The path must be changed on different computers.

Check and delete duplicate entries:
```
*clients.drop_duplicates(inplace = True)
*assert len(clients['CustomerId’].unique()) == len(clients)
```

Convert to datetime format and querying:
```
*clients['application_date'] = pd.to_datetime(clients['application_date’])
*clients = clients[(clients['application_date'] >= '2015') & (clients['application_date'] <= max(clients['application_date']) - pd.Timedelta('730d'))]
```

Check if Italy appears in the dataset:
```
*print(clients['Geography'].unique())
```

Check missing values:
```
*print(clients.apply(lambda x: np.sum(x.isna()), axis = 0))
```

Load Data

Only one contract per client.

- Contracts from 2015 onwards.
- Clients with at least two years of information within the company.

Operations in Italy.

Costumers missing more than 75% of their info.

clients dataset:
1545000 entries

Duplicated entries:
45000 duplicate entries removed
1500000 entries after filter

Querying data:
1490000 entries don’t have the requirements
10000 entries after filtering.

Italy and missing data:
Italy doesn’t appear in the new dataset; no filter needed.
Missing data only in one column. No client has more than 75% missing info; no filter needed
10000 entries, No filter was applied.

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New Variables

Age

- It was calculated using the difference between the application date and birth date.

```
•clients['Age']=(clients['application_date']-clients['birth_date']).astype('timedelta64[Y]')
```

Number of products

- It was calculated with 'groupby' with the customer ID and 'agg' with the 'len' function. Then, the result was merged with the clients' dataset.

```
•products=clientProducts.groupby('CustomerId').agg({'Products':len})
•clients=pd.merge(clients,products,how='left',on='CustomerId')
```

Account balance

- It was calculated with 'groupby' with the customer ID and 'agg' with the 'np.sum' function. Then, the result was merged with the clients' dataset and converted the small numbers to 0.

```
•balance=transactions.groupby('CustomerId').agg({'Value':np.sum})
•clients=pd.merge(clients,balance,how='left',on='CustomerId')
```

Bureau Score

- It was calculated by searching the bureau's score dataset using the customer ID and month of the application. This was done by the 'get_score' function through apply function.

```
•clients['Score']=clients.apply(get_score,axis=1)
```

Statistics of new variables.

	Age	Products	Balance	Score
Mean	38.92	1.53	76485.88	650.52
Std	10.48	0.581	62397.40	96.65
Max	92	4	250898.09	850.00
Min	18	1	0.00	350.00

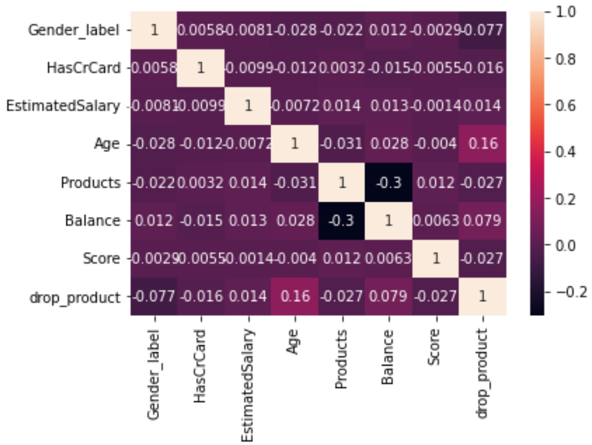
This table was made with:

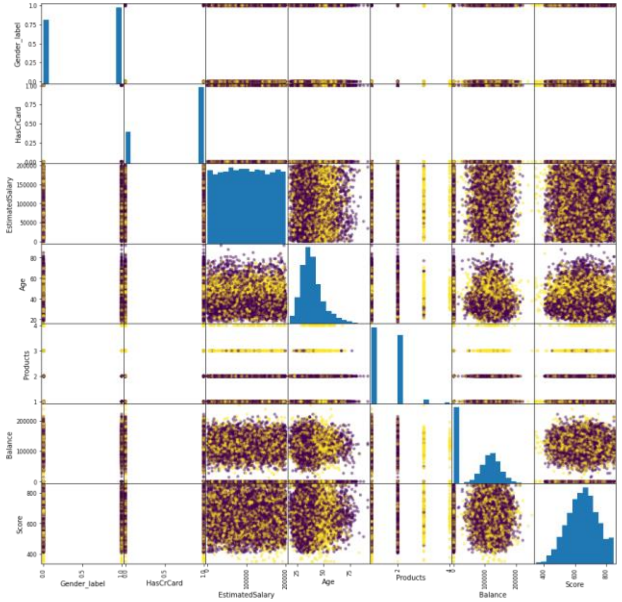
```
*clients[['Age', 'Products', 'Balance', 'Score']]
  .agg({'Age': [np.mean, np.std, np.max, np.min],
   'Products': [np.mean, np.std, np.max, np.min],
    'Balance': [np.mean, np.std, np.max, np.min],
     'Score': [np.mean, np.std, np.max, np.min]})
```

Exploring Data

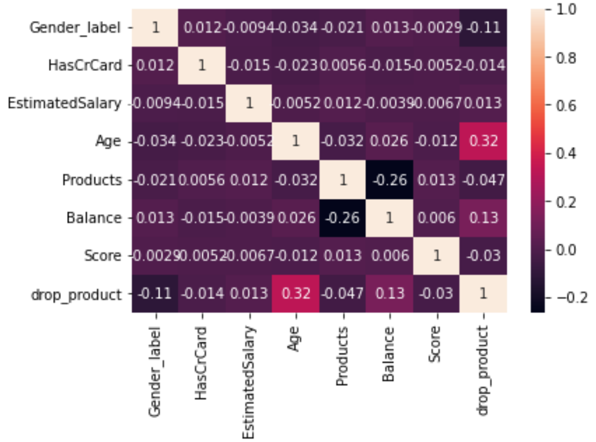
- First, I calculate the number of days of customer stay with the difference between the application date and the exit date, but a problem wasn't solved in the preparation data: The missing values of the exit date.
- By creating a new variable 'drop_product' with 1 if the client cancelled the product before 2 years and 0 otherwise, I had NaT values.
- I tried to fill this with 0 if the client is an active member but the result had too much noise.
- I decided to remove these values and the correlation matrix and scatter chart look better.

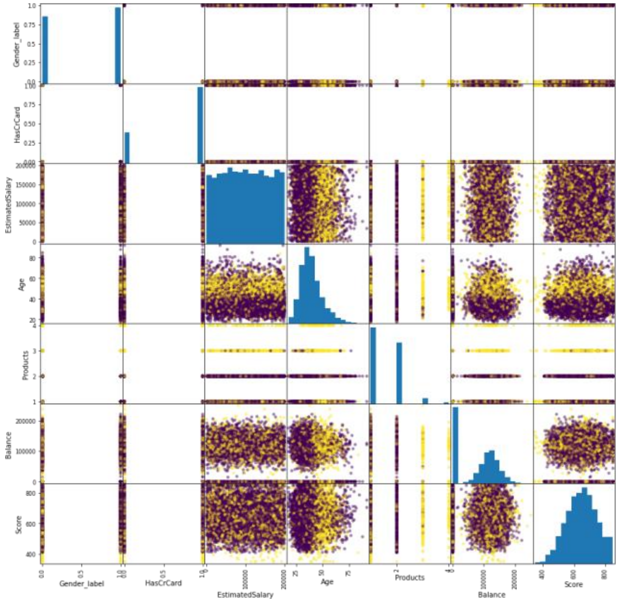
Without dropping missing values





Dropping missing values





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Prediction model

Get train and test data

```
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=0)
```

Normalize data

```
sc=StandardScaler()
x_train=sc.fit_transform(x_train.values)
x_test=sc.transform(x_test.values)
```

Fit models

```
knn=KNeighborsClassifier(n_neighbors=10).fit(x_train,y_train)
dtc=DecisionTreeClassifier(max_depth=3).fit(x_train,y_train)
⋮
gbc=GradientBoostingClassifier(random_state=0,learning_rate=0.2).fit(x_train,y_train)
```

Results of the models

Model	Accuracy
K Neighbors	0.75835
Decision Tree	0.77394
Logistic Regression	0.70545
Support Vector, poly kernel	0.76726
Support Vector, rbf kernel	0.77116
Random Forest	0.78341
Gradient Boosting	0.79065

After this step, I selected the Random Forest Classifier and the Gradient Boosting Classifier to evaluate.

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Evaluation

Compare with a baseline model

The models were compared with a Dummy Classifier from the sklearn package.

```
dc=DummyClassifier(strategy=
'most_frequent').fit(x_train,y_train)
```

Random Forest Classifier is **8.797%** better than the Dummy Classifier.

Gradient Boosting Classifier is **9.521%** better than the Dummy classifier

Cross-validation

Get the scores of cross-validation test.

Get the mean and standard deviation of the test score.

```
cross_val_score(rfc,np.concatenate((x_train,x_test)),np.concatenate((y_train,y_test)))
```

RFC mean is: **0.7938**, and std is: **0.01159**.

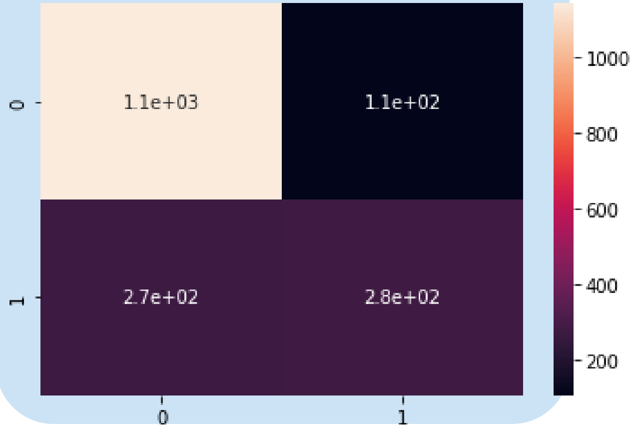
GBC mean is: **0.8013**, and std is: **0.0066**.

Confusion matrix

Get the predictions of the Gradient Boosting Classifier.

Create and graph the confusion matrix.

```
y_pred=gbc.predict(x_test)
cm=confusion_matrix(y_test,y_pred)heatmap=sn.heatmap(cm,annot=True)
```



Conclusion

In this section, I only share some ideas about the process and the result.

- I'm seeking the best binary classifier to do this task. The requirement is: Predict whether or not a customer leaves the "Kin safety" product before 2 years. It's a yes or no question, that is the reason to select a binary classifier.
- I decided not to take geographic location to make a prediction. The reason is that the leaked dataset has only 3 countries, and I am interested in making a model as general as possible.
- The result has a significant difference between the Dummy Classifier and the Gradient Boosting Classifier, I conclude the process was successful.
- The model has more false-positive rates than false-negative rates. In a business context, It isn't very bad. It's better to focus on clients that we believe will leave our product, although this may not happen.
- In order to do better prediction, it is interesting to explore AI techniques, especially a few-point learning.

Acknowledgment

Thanks for reading and for the opportunity to show what I can do. I hope we can work together, good luck with everything, and feel free to visit the GitHub site of this project : https://github.com/DataGonza/cancellationFinancialProducts

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