WEEK 11 DELIVERABLES

Team Member’s Details

Group Name: Data Bank

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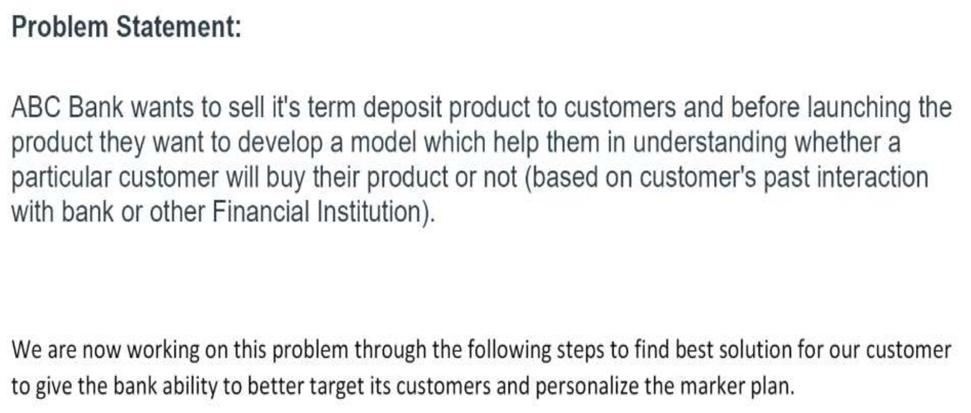


Problem Statement:

ABC Bank wants to sell it's term deposit product to customers and before launching the product they want to develop a model which help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

We are now working on this problem through the following steps to find best solution for our customer to give the bank ability to better target its customers and personalize the marker plan.

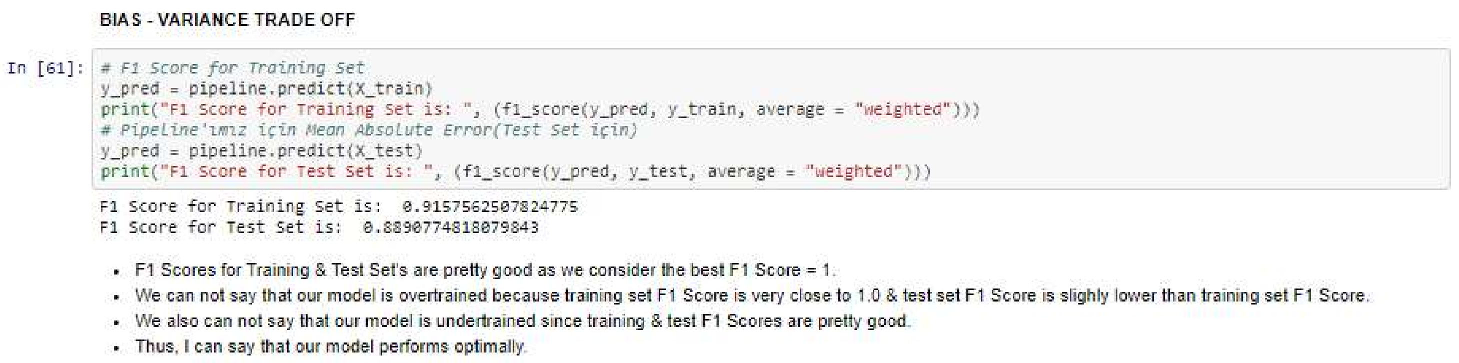
Github Repo Link

Github Repo link: https://github.com/talfik2/Data-Glacier-Data-Bank-Bank-Marketing-Group-Project
Link for Step 5: https://github.com/talfik2/Data-Glacier-Data-Bank Bank-Marketing-Group-Project/tree/Step-5-Model-evaluation

EDA Presentation and proposed modeling technique

This step is completed by Tevfik SASTIM. In this step, Model’s measure metric is set as F1 Score as our data is highly imbalanced.

Moreover, model is evaluated by Bias – Variance Tradeoff,

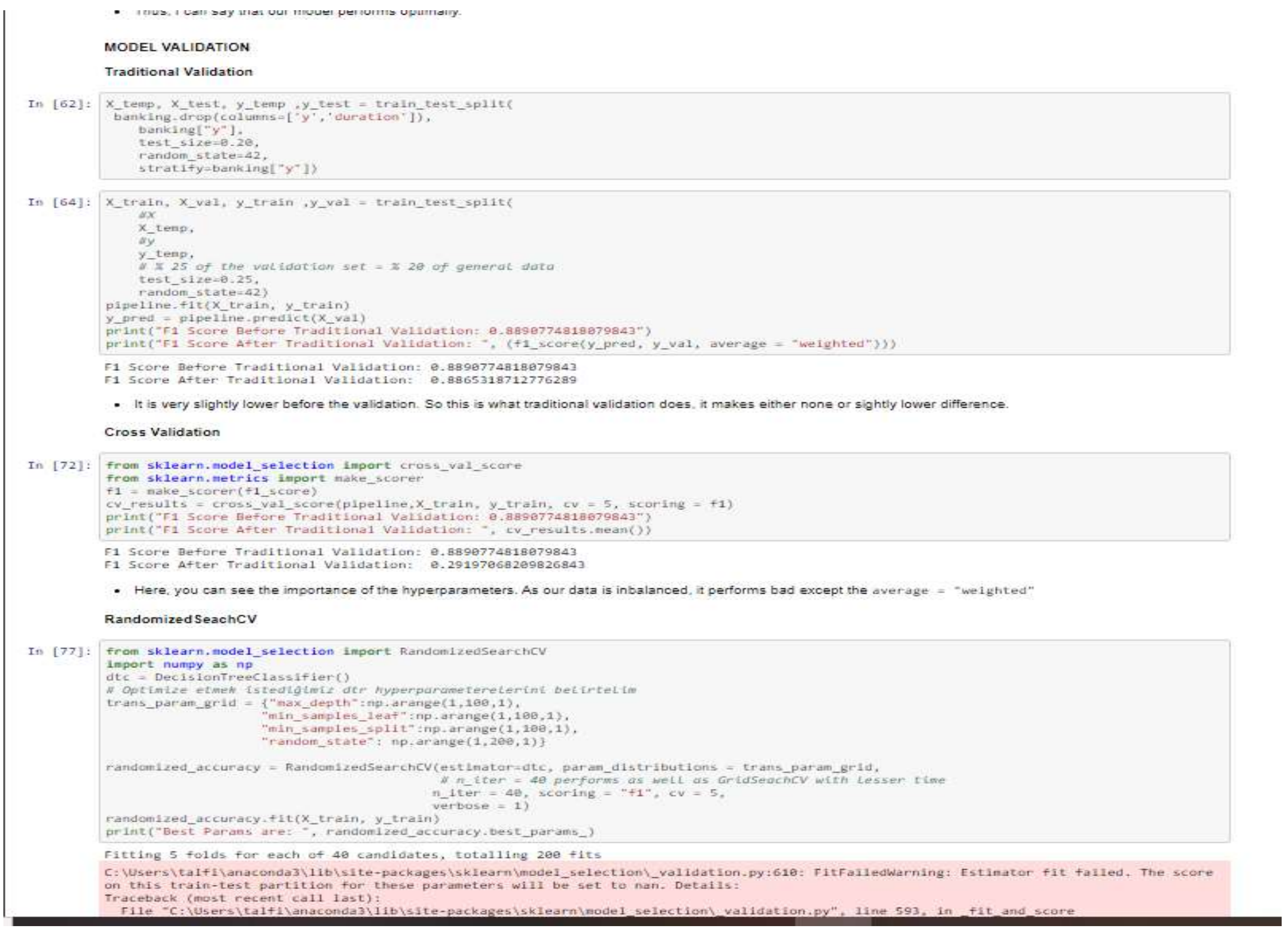


BIAS - VARIANCE TRADE OFF

```
In [61]: # F1 Score for Training Set
         y_pred = pipeline.predict(X_train)
         print("F1 Score for Training Set is: ", (f1_score(y_pred, y_train, average = "weighted")))
         # Pipeline'ımız için Mean Absolute Error(Test Set için)
         y_pred = pipeline.predict(X_test)
         print("F1 Score for Test Set is: ", (f1_score(y_pred, y_test, average = "weighted")))

         F1 Score for Training Set is:  0.9157562507824775
         F1 Score for Test Set is:  0.8890774818079843
```

- F1 Scores for Training & Test Set's are pretty good as we consider the best F1 Score = 1.
- We can not say that our model is overtrained because training set F1 Score is very close to 1.0 & test set F1 Score is slighly lower than training set F1 Score.
- We also can not say that our model is undertrained since training & test F1 Scores are pretty good.
- Thus, I can say that our model performs optimally.

And it is validated by Traditional Validation, K – fold Cross Validation & Randomized Search CV.



- Thus, I can say that our model performs optimally.

MODEL VALIDATION

Traditional Validation

```
In [62]: X_temp, X_test, y_temp ,y_test = train_test_split(
          banking.drop(columns=['y','duration']),
             banking["y"],
             test_size=0.20,
             random_state=42,
             stratify=banking["y"])

In [64]: X_train, X_val, y_train ,y_val = train_test_split(
             #X
             X_temp,
             #y
             y_temp,
             # % 25 of the validation set = % 20 of general data
             test_size=0.25,
             random_state=42)
         pipeline.fit(X_train, y_train)
         y_pred = pipeline.predict(X_val)
         print("F1 Score Before Traditional Validation: 0.8890774818079843")
         print("F1 Score After Traditional Validation: ", (f1_score(y_pred, y_val, average = "weighted")))

         F1 Score Before Traditional Validation: 0.8890774818079843
         F1 Score After Traditional Validation:  0.8865318712776289
```

- It is very slightly lower before the validation. So this is what traditional validation does, it makes either none or sightly lower difference.

Cross Validation

```
In [72]: from sklearn.model_selection import cross_val_score
         from sklearn.metrics import make_scorer
         f1 = make_scorer(f1_score)
         cv_results = cross_val_score(pipeline,X_train, y_train, cv = 5, scoring = f1)
         print("F1 Score Before Traditional Validation: 0.8890774818079843")
         print("F1 Score After Traditional Validation: ", cv_results.mean())

         F1 Score Before Traditional Validation: 0.8890774818079843
         F1 Score After Traditional Validation:  0.29197068209826843
```

- Here, you can see the importance of the hyperparameters. As our data is inbalanced, it performs bad except the `average = "weighted"`

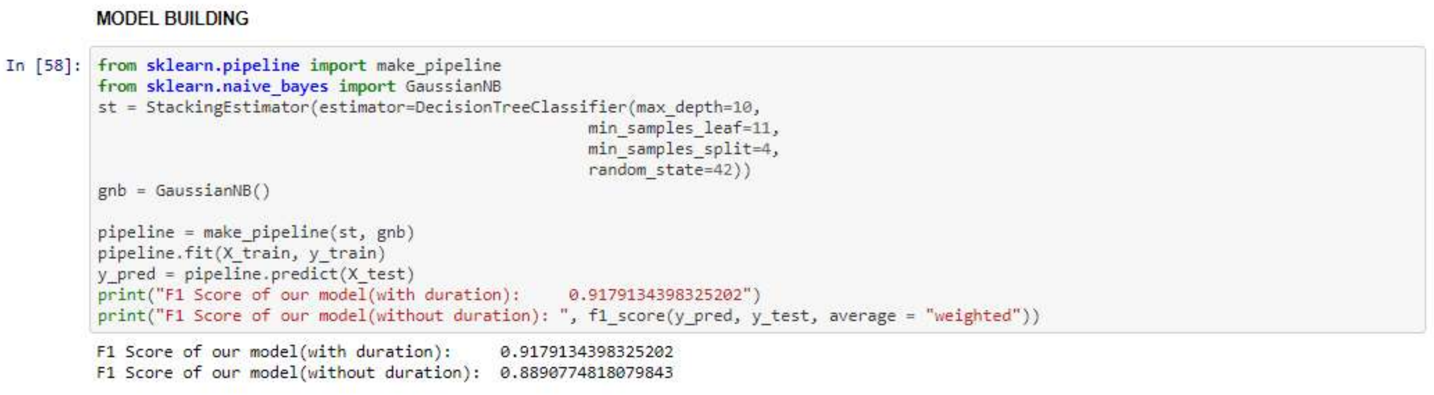
RandomizedSeachCV

```
In [77]: from sklearn.model_selection import RandomizedSearchCV
         import numpy as np
         dtc = DecisionTreeClassifier()
         # Optimize etmek istediğimiz dtr hyperparameterelerini belirtelim
         trans_param_grid = {"max_depth":np.arange(1,100,1),
                             "min_samples_leaf":np.arange(1,100,1),
                             "min_samples_split":np.arange(1,100,1),
                             "random_state": np.arange(1,200,1)}

         randomized_accuracy = RandomizedSearchCV(estimator=dtc, param_distributions = trans_param_grid,
                                                   # n_iter = 40 performs as well as GridSeachCV with lesser time
                                                  n_iter = 40, scoring = "f1", cv = 5,
                                                  verbose = 1)
         randomized_accuracy.fit(X_train, y_train)
         print("Best Params are: ", randomized_accuracy.best_params_)

         Fitting 5 folds for each of 40 candidates, totalling 200 fits
         C:\Users\talfi\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py:610: FitFailedWarning: Estimator fit failed. The score
         on this train-test partition for these parameters will be set to nan. Details:
         Traceback (most recent call last):
           File "C:\Users\talfi\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py", line 593, in _fit_and_score
```

Final Recommendation

Recommended models for this dataset are:

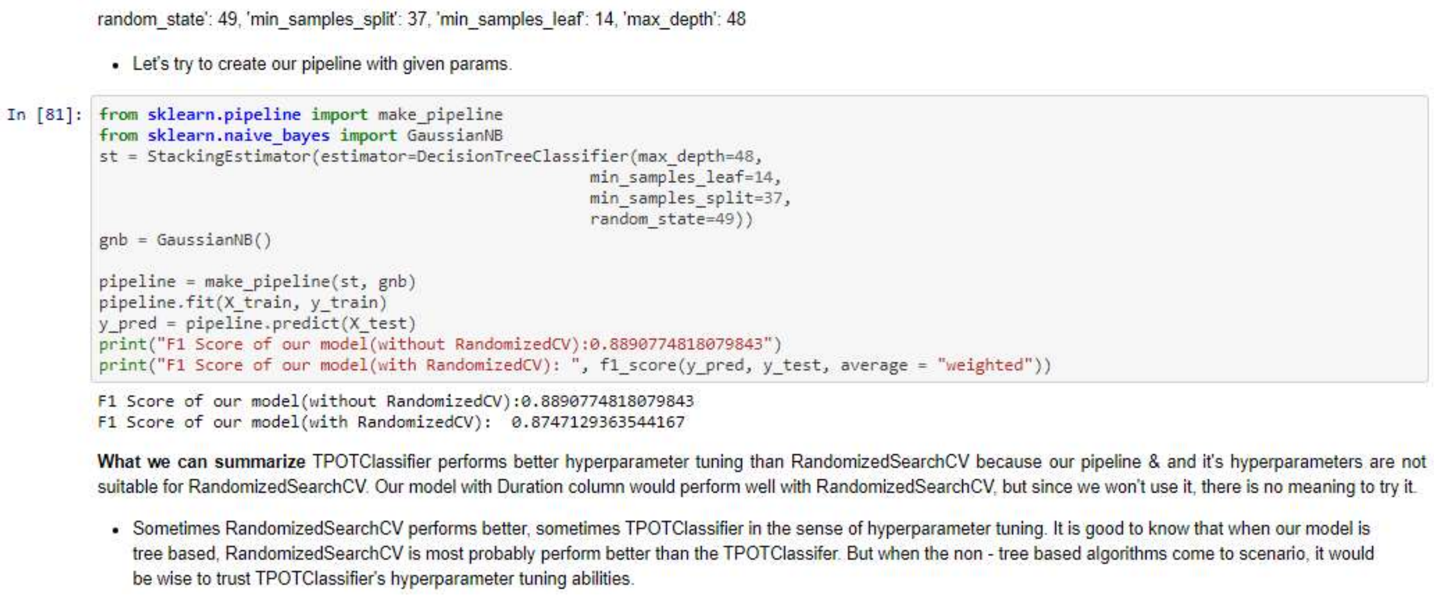
- Recommended Model without Randomized CV:



MODEL BUILDING

```
In [58]: from sklearn.pipeline import make_pipeline
         from sklearn.naive_bayes import GaussianNB
         st = StackingEstimator(estimator=DecisionTreeClassifier(max_depth=10,
                                                                  min_samples_leaf=11,
                                                                  min_samples_split=4,
                                                                  random_state=42))
         gnb = GaussianNB()

         pipeline = make_pipeline(st, gnb)
         pipeline.fit(X_train, y_train)
         y_pred = pipeline.predict(X_test)
         print("F1 Score of our model(with duration):     0.9179134398325202")
         print("F1 Score of our model(without duration): ", f1_score(y_pred, y_test, average = "weighted"))

         F1 Score of our model(with duration):     0.9179134398325202
         F1 Score of our model(without duration):  0.8890774818079843
```

- Recommended Model with Randomized CV:



random_state': 49, 'min_samples_split': 37, 'min_samples_leaf': 14, 'max_depth': 48

- Let's try to create our pipeline with given params.

```
In [81]: from sklearn.pipeline import make_pipeline
         from sklearn.naive_bayes import GaussianNB
         st = StackingEstimator(estimator=DecisionTreeClassifier(max_depth=48,
                                                                  min_samples_leaf=14,
                                                                  min_samples_split=37,
                                                                  random_state=49))
         gnb = GaussianNB()

         pipeline = make_pipeline(st, gnb)
         pipeline.fit(X_train, y_train)
         y_pred = pipeline.predict(X_test)
         print("F1 Score of our model(without RandomizedCV):0.8890774818079843")
         print("F1 Score of our model(with RandomizedCV): ", f1_score(y_pred, y_test, average = "weighted"))

         F1 Score of our model(without RandomizedCV):0.8890774818079843
         F1 Score of our model(with RandomizedCV):  0.8747129363544167
```

What we can summarize TPOTClassifier performs better hyperparameter tuning than RandomizedSearchCV because our pipeline & and it's hyperparameters are not suitable for RandomizedSearchCV. Our model with Duration column would perform well with RandomizedSearchCV, but since we won't use it, there is no meaning to try it.

- Sometimes RandomizedSearchCV performs better, sometimes TPOTClassifier in the sense of hyperparameter tuning. It is good to know that when our model is tree based, RandomizedSearchCV is most probably perform better than the TPOTClassifer. But when the non - tree based algorithms come to scenario, it would be wise to trust TPOTClassifier's hyperparameter tuning abilities.

As I stated above, because F1 Score without Randomized CV performed better, my final recommendation is the pipeline without Randomized CV.

MODEL BUILDING

```
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         st = StackingEstimator(estimator=DecisionTreeClassifier(max_depth=10,
                                                       min_samples_leaf=11,
                                                       min_samples_split=4,
                                                       random_state=42))
         gnb = GaussianNB()

         pipeline = make_pipeline(st, gnb)
         pipeline.fit(X_train, y_train)
         y_pred = pipeline.predict(X_test)
         print("F1 Score of our model(with duration):     0.9179134398325202")
         print("F1 Score of our model(without duration): ", f1_score(y_pred, y_test, average = "weighted"))
```

```
F1 Score of our model(with duration):     0.9179134398325202
F1 Score of our model(without duration):  0.8890774818079843
```