models

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0.0.1 Import the needed libraries

```
In [1]: import warnings
        from itertools import chain
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt

        from sklearn.impute import SimpleImputer
        from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
        from sklearn.model_selection import train_test_split, GridSearchCV
        from sklearn.naive_bayes import GaussianNB
        from sklearn import metrics
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear_model import LogisticRegression
        from sklearn.svm import SVC
        from sklearn.neural_network import MLPClassifier
        from sklearn.ensemble import VotingClassifier

        from sklearn.exceptions import ConvergenceWarning, DataConversionWarning
        warnings.filterwarnings(action='ignore', category=ConvergenceWarning)
        warnings.filterwarnings(action='ignore', category=DataConversionWarning)
```

0.0.2 Semi-Structured Text Processor

```
In [2]: def process_text_feature(data: pd.DataFrame, unique: list):
            """
            :param data: Pandas DataFrame - text feature (semi-structured)
            :param unique: List - unique code
            :return: Pandas DataFrame - processed codes
            """
            df = pd.DataFrame(columns=unique,
                              index=range(len(data)))

            for i in range(len(data)):
                text = data.code[i].split(',')

                for j in text:
```

```
        index_col = unique.index(j)
        df.loc[i][index_col] = 1

    df.fillna(0, inplace=True)

    return df
```

0.0.3 Load data and Preprocessing

```
In [3]: def preprocess_data():
            """
            Load and pre-process data.
            Implemented the following:
                - removed redundant variables
                - removed variables with high missing ratio
                - handle missing values by imputation
                - processed and incorporated the text codes columns
                    - it was extended to multiple variables
                - One-hot encoded the categorical variables (ignored ordering)
                - implemented [0, 1] normalization

            :return: X_data, y_data
            """

            X_data = pd.read_csv("data.csv")
            y_data = X_data.class_label

            # removed redundant variables and the class label
            X_data.drop(["id", "date", "class_label"], axis=1, inplace=True)

            # - calculate % of missing values
            perc_missing = pd.DataFrame(
                {"perc_missing_values": X_data.isnull().mean() * 100}
            ).sort_values("perc_missing_values")

            perc_missing.query("perc_missing_values > 0", inplace=True)
            perc_missing

            perc_missing.iloc[:, 0].plot(
                kind="bar", title="% of missing values per variables", figsize=(15, 10)
            )

            # The following variables will be dropped,
            # because over 50% of them are missing X6 and K6
            X_data.drop(["X6", "K6"], axis=1, inplace=True)

            # Filling missing values by imputation via most_frequent
            imputer = SimpleImputer(missing_values=np.nan, strategy="most_frequent")
```

```
        imputer.fit(X_data)
        X_data = pd.DataFrame(imputer.transform(X_data), columns=X_data.columns)

        # working on coded variable (semi structured in nature)
        code_data = pd.DataFrame(X_data.codes.values, columns=["code"])
        X_data.drop(["codes"], axis=1, inplace=True)
        code_unique = sorted(list(set(chain(*code_data.code.str.split(",").tolist()))))
        processed_codes = process_text_feature(code_data, code_unique)

        # One-hot encoding for the categorical variables
        cat_var = ["C1", "C2", "C3", "C4", "C5", "C6"]
        data_encode = X_data[cat_var]
        encoder = OneHotEncoder(handle_unknown="ignore")
        encoder.fit(data_encode)

        data_onehot = pd.DataFrame(
            encoder.transform(data_encode).toarray(),
            columns=encoder.get_feature_names()
        )

        # drop encoded variables from X_data and add data_onehot
        # and processed codes X_data to it
        X_data.drop(cat_var, axis=1, inplace=True)
        X_data = pd.concat([X_data, data_onehot, processed_codes], axis=1)

        scaler = MinMaxScaler()
        scaler.fit(X_data)
        X_data = scaler.fit_transform(X_data)

        return X_data, y_data
```

Environment Variables

```
In [4]: MERIC_SCORING = 'roc_auc'
        CV = 10
```

1 Model Evaluation Metric:

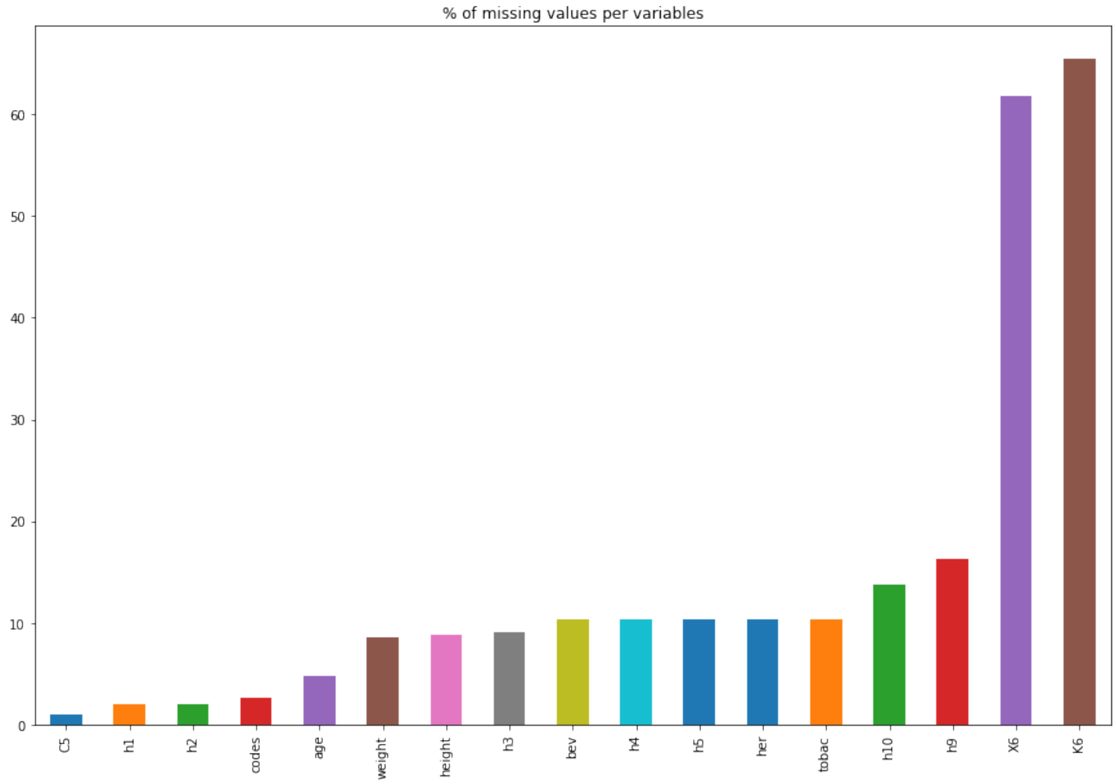
ROC-AUC will be used to evaluate the models in this project. ROC is a curve (False Positive Rate vs Sensitivity) that show the ability of a binary classifier as its discrimination threshold is varied. While AUC is the area under the curve.

2 Working With Dataset

```
In [5]: model_eval_df = pd.DataFrame(
            columns = ['model', 'optimal_param', 'testing_ROC_AUC'],
```

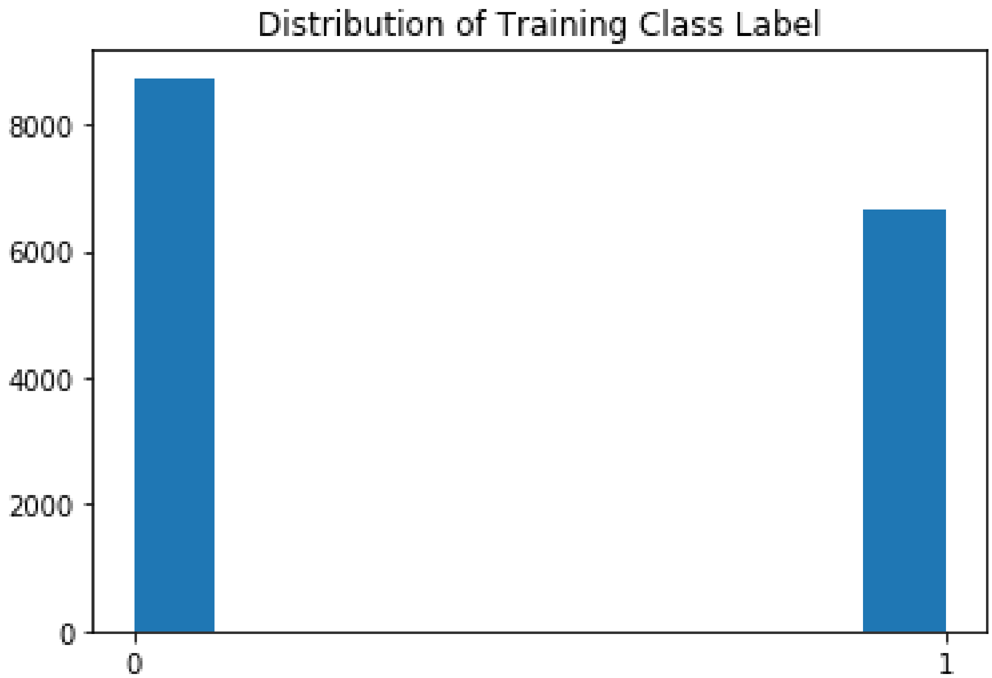
```
            index=range(6)
        )
```

In [6]:
```
X_TRAIN, Y_TRAIN = preprocess_data()
```



2.0.1 Distribution of the Class Label

In [7]:
```
plt.hist(Y_TRAIN)
plt.xticks([0, 1])
plt.title('Distribution of Training Class Label')
plt.show()
```



2.0.2 Divide Train set into Train and Test

```
In [8]: x_train, x_test, y_train, y_test = train_test_split(
            X_TRAIN, Y_TRAIN, test_size=0.2, random_state=42
        )
```

3 1. Model: Naive Bayes

3.0.1 (1a) Fitting the model

```
In [9]: nb_fit = GaussianNB().fit(x_train, y_train)
```

3.0.2 (1b) Testing

```
In [10]: nb_y_pred = nb_fit.predict(x_test)
         nb_score = round(metrics.roc_auc_score(y_test, nb_y_pred), 4)
         model_eval_df.loc[0] = ('Naive Bayes', '-', nb_score)
         print("Testing Score = {}".format(nb_score))
```

```
Testing Score = 0.6189
```

3.0.3 (1c) Confusion Matrix - Actual vs. Predicted

```
In [11]: pd.DataFrame(metrics.confusion_matrix(y_test, nb_y_pred))
```

Out[11]:
```
      0     1
0   470  1315
1    33  1259
```

4 2. Model: KNN

4.0.1 (2a) Fitting the model with optimal Hyperparamters via Grid Search with 5-folds CV

In [12]:
```
k = np.arange(22, 27)
param_tune = {"n_neighbors": k}

knn = GridSearchCV(
    KNeighborsClassifier(), param_tune, cv=CV, scoring=MERIC_SCORING
)

knn.fit(x_train, y_train)
```

Out[12]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
           metric_params=None, n_jobs=None, n_neighbors=5, p=2,
           weights='uniform'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'n_neighbors': array([22, 23, 24, 25, 26])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

4.0.2 (2b) The optimal hyperparameters are:

In [13]:
```
model_eval_df.optimal_param[1] = 'k = {}'.format(*knn.best_params_.values())
print("k = {}".format(*knn.best_params_.values()))
```

```
k = 26
```

4.0.3 (2c) Testing

In [14]:
```
knn_y_pred = knn.predict(x_test)
knn_score = round(metrics.roc_auc_score(y_test, knn_y_pred), 4)
model_eval_df.iloc[1, [0, 2]] = ('KNN', knn_score)
print("Testing Score = {}".format(knn_score))
```

```
Testing Score = 0.6097
```

4.0.4 (2d) Confusion Matrix - Actual vs. Predicted

In [15]:
```
pd.DataFrame(metrics.confusion_matrix(y_test, knn_y_pred))
```

Out[15]:
```
      0    1
0  1132  653
1   536  756
```

5 3. Model: Logistic Regression - Ridge

5.0.1 (3a) Fitting the model with optimal Hyperparamters via Grid Search with 5-folds CV

In [16]:
```
lg_cost = np.logspace(-1, 1, 3)
param_tune = {'C': lg_cost}

lg_regr = GridSearchCV(
    LogisticRegression(solver='lbfgs', max_iter=500),
    param_tune, cv=CV, scoring=MERIC_SCORING
)

lg_regr.fit(x_train, y_train)
```

Out[16]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
          intercept_scaling=1, max_iter=500, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'C': array([ 0.1,  1. , 10. ])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

5.0.2 (3b) The optimal hyperparameters are:

In [17]:
```
model_eval_df.optimal_param[2] = 'C = {}'.format(*lg_regr.best_params_.values())
print("C = {}".format(*lg_regr.best_params_.values()))
```

```
C = 1.0
```

5.0.3 (3c) Testing

In [18]:
```
lg_regr_y_pred = lg_regr.predict(x_test)
lg_regr_score = round(metrics.roc_auc_score(y_test, lg_regr_y_pred), 4)
model_eval_df.iloc[2, [0, 2]] = ('Logistic Regression', lg_regr_score)
print("Testing Score = {}".format(lg_regr_score))
```

```
Testing Score = 0.6594
```

5.0.4 (3d) Confusion Matrix - Actual vs. Predicted

In [19]:
```
pd.DataFrame(metrics.confusion_matrix(y_test, lg_regr_y_pred))
```

Out[19]:

	0	1
0	1246	539
1	490	802

6 4. Model: SVM - RBF Kernel

6.0.1 (4a) Fitting the model with optimal Hyperparamters via Grid Search with 5-folds CV

```
In [20]: svm_cost = np.logspace(-4, -3, 2)

         param_tune = {'C': svm_cost}

         svm = GridSearchCV(
             SVC(gamma='auto'), param_tune, cv=CV, scoring=MERIC_SCORING
         )

         svm.fit(x_train, y_train)
```

```
Out[20]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False),
                fit_params=None, iid='warn', n_jobs=None,
                param_grid={'C': array([0.0001, 0.001 ])}, pre_dispatch='2*n_jobs',
                refit=True, return_train_score='warn', scoring='roc_auc', verbose=0)
```

6.0.2 (4b) The optimal hyperparameters are:

```
In [21]: model_eval_df.optimal_param[3] = 'C = {}'.format(*svm.best_params_.values())
         print("C = {}".format(*svm.best_params_.values()))
```

```
C = 0.001
```

6.0.3 (4c) Testing

```
In [22]: svm_y_pred = svm.predict(x_test)
         svm_score = round(metrics.roc_auc_score(y_test, svm_y_pred), 4)
         model_eval_df.iloc[3, [0, 2]] = ('SVM', svm_score)
         print("Testing Score = {}".format(svm_score))
```

```
Testing Score = 0.5
```

6.0.4 (4d) Confusion Matrix - Actual vs. Predicted

```
In [23]: pd.DataFrame(metrics.confusion_matrix(y_test, svm_y_pred))
```

Out[23]:

	0	1
0	1785	0
1	1292	0

7 5. Model: Multi-layer Perceptron

7.0.1 (5a) Fitting the model with optimal Hyperparamters via Grid Search with 5-folds CV

```
In [24]: mp_alpha = np.logspace(-4, -3, 2) # l2 penalty
         param_tune = {'alpha': mp_alpha}

         mlp = GridSearchCV(
             MLPClassifier(hidden_layer_sizes=(512, 256), max_iter=300),
             param_tune, cv=CV, scoring=MERIC_SCORING
         )

         mlp.fit(x_train, y_train)
```

```
Out[24]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', be
                beta_2=0.999, early_stopping=False, epsilon=1e-08,
                hidden_layer_sizes=(512, 256), learning_rate='constant',
                learning_rate_init=0.001, max_iter=300, momentum=0.9,
                n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
                random_state=None, shuffle=True, solver='adam', tol=0.0001,
                validation_fraction=0.1, verbose=False, warm_start=False),
                fit_params=None, iid='warn', n_jobs=None,
                param_grid={'alpha': array([0.0001, 0.001 ])},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
```

7.0.2 (5b) The optimal hyperparameters are:

```
In [25]: model_eval_df.optimal_param[4] = 'Alpha = {}'.format(*mlp.best_params_.values())
         print("Alpha = {}".format(*mlp.best_params_.values()))
```

```
Alpha = 0.001
```

7.0.3 (5c) Testing

```
In [26]: mlp_y_pred = mlp.predict(x_test)
         mlp_score = round(metrics.roc_auc_score(y_test, mlp_y_pred), 4)
         model_eval_df.iloc[4, [0, 2]] = ('MLP', mlp_score)
         print("Testing Score = {}".format(mlp_score))
```

```
Testing Score = 0.6063
```

7.0.4 (5d) Confusion Matrix - Actual vs. Predicted

```
In [27]: pd.DataFrame(metrics.confusion_matrix(y_test, mlp_y_pred))
```

```
Out[27]:       0    1
         0  1207  578
         1   599  693
```

8 Ensemble (with all the Models) by Voting

```
In [ ]: voting = VotingClassifier(
            estimators=[
                ('nb', nb_fit),
                ('knn', knn),
                ('lgr', lg_regr),
                ('svm', svm),
                ('mlp', mlp)
            ],
            voting='hard'
        )

        voting.fit(x_train, y_train)
```

```
In [ ]: voting_y_pred = voting.predict(x_test)
```

```
In [ ]: voting_score = round(metrics.roc_auc_score(y_test, voting_y_pred), 4)
        model_eval_df.loc[5] = ('Ensemble Voting', '-', voting_score)
        print("Testing Score = {}".format(voting_score))
```

9 Summary

```
In [31]: model_eval_df.sort_values('testing_ROC_AUC', ascending=False)
```

Out[31]:

	model	optimal_param	testing_ROC_AUC
2	Logistic Regression	C = 1.0	0.6594
5	Ensemble Voting	-	0.6425
0	Naive Bayes	-	0.6189
1	KNN	k = 26	0.6097
4	MLP	Alpha = 0.001	0.6063
3	SVM	C = 0.001	0.5