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                                                                                                          Not Trusted Python 3 O
                                               v = 0 A
A + | % < 4 | A + | ▶ Run | ■ C | ▶ | Code</p>
      In [1]: | 1 import pandas as pd
                  2 import numpy as np
                  3 import matplotlib.pyplot as plt
                  4 import seaborn as sns
                  5 import missingno as msno
             Load the dirty churn data
                                                                                                                        [...]
             Load the clean churn rate data
                                                                                                                        [...]
             Data Preprocessing
      ▼ One Hot Encoder (before tts)
      2 df
         Out[6]: churn age trivia_played trivia_shared_results trivia_view_unlocked trivia_view_results cards_share cards_viewed cards_helpful cards_not_helpful
                 0 1 22.0
                       1 25.0
                                                      0
                                                                                           0
                   2 1 32.0
                                                      0
                                                                     0
                                                                                           0
                                                                                                     49
                                                                                                                0
                    3
                        1 26.0
                                                      0
                                                                    169
                                                                                  0
                                                                                                     184
                                                                                                                0
                                                      0
                                                                    11
                                                                                           0
                 4 1 28.0
                                                                                  Ω
                                                                                                     65
                                                                                                                0
                 48074 0 42.0
                                                                                           0
                                                                                                      6
                 48075
                       0 38.0
                                       0
                                                      0
                                                                     0
                                                                                  0
                                                                                           0
                                                                                                    207
                                                                                                                0
                 48076
                        0 20.0
                                                      0
                                                                    51
                                                                                           0
                                                                                                    132
                                                                                                                0
                 48077 0 27.0
                                       0
                                                      0
                                                                    77
                                                                                  0
                                                                                           0
                                                                                                     143
                                                                                                                0
                 48078 0 33.0
                48079 rows × 42 columns
                4
      In [7]: ▶ 1 # Don't know how to work OneHotEncoder
                  3 # from sklearn.compose import ColumnTransformer
                  4 # from sklearn.preprocessing import OneHotEncoder
                  6 # encoder = OneHotEncoder(handle_unknown="ignore",)
                 7 # df2 = encoder.fit transform(df)
      In [8]: | 1 | X = df.drop(labels="churn", axis=1).to_numpy()
         Out[8]: array([[22., 0., 0., ..., 1., 0., 0.],
                      [25., 0., 0., ..., 0., 0., 0.],
[32., 0., 0., ..., 0., 1., 0.],
                       [20., 5., 0., ..., 0., 0., 0.],
                      [27., 0., 0., ..., 0., 1., 0.],
[33., 3., 2., ..., 0., 0., 0.]])
      In [9]: \mathbf{y} = df["churn"].values
         Out[9]: array([1, 1, 1, ..., 0, 0, 0], dtype=int64)
          3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
          ▼ Feature Scaling
     In [11]: 🔰 1 from sklearn.preprocessing import StandardScaler, MinMaxScaler
                  3 sc = StandardScaler()
                  4 X_train = sc.fit_transform(X_train)
                 5 X_test = sc.transform(X_test)
```

```
In [12]: ▶ 1 from sklearn.linear_model import LogisticRegression
              3 clf = LogisticRegression(random_state=0)
             4 clf.fit(X_train, y_train)
   Out[12]: LogisticRegression(random_state=0)
In [13]: 👂 1 from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
             3 predictions = clf.predict(X_test)
              4 print(classification_report(y_test, predictions))
              5 print(accuracy_score(y_test, predictions))
             6 print(confusion_matrix(y_test, predictions))
                         precision
                                    recall f1-score support
                             0.67
                                      0.77
                                                0.72
                      0
                                                         5620
                                    0.48
                             0.60
                                                0.53
                                                         3996
                                                0.65
                                                         9616
                accuracy
               macro avg
                             0.64
                                      0.62
                                                0.62
                                                         9616
                                             0.64
            weighted avg
                             0.64
                                    0.65
                                                        9616
            0.6491264559068219
            [[4343 1277]
             [2097 1899]]
      ▼ cv
3 accuracies = cross_val_score(estimator=clf, X=X_train, y=y_train, cv=10, verbose=1) # k = 10
                print(accuracies)
              5 print(f"Mean: {accuracies.mean() * 100} %")
             6 print(f"Std: {accuracies.std() * 100} %")
            [Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
            [0.64803743 0.64231869 0.65115675 0.63520541 0.6474259 0.6450858
             0.65444618 0.66016641 0.65106604 0.63806552]
            Mean: 64.72974125619561 %
            Std: 0.7123905317268312 %
            [Parallel(n_jobs=1)]: Done 10 out of 10 | elapsed: 1.2s finished
      ▼ GridSearchCV
parameters = {"C": [0.001, 0.01, 0.1, 1, 10, 100, 1000], "penalty": ['l1', 'l2']}
              grid_search = GridSearchCV(estimator=clf, param_grid=parameters,
                                         scoring="accuracy",
                                         cv=10, # cv = k = 10
                                         n_jobs=-1, # all cpu
                                         verbose=1 # print
             10
             grid_search.fit(X_train, y_train)
             12 print(grid_search.best_estimator_)
             13 print(grid_search.best_params_)
             14 print(grid_search.best_score_) # precision
            15 print(grid_search.best_index_)
            Fitting 10 folds for each of 14 candidates, totalling 140 fits
            C:\Users\Perry\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:922: UserWarning: One or more of the test scor
                                  nan 0.6434494
                                       an 0.6434494 nan 0.64690737
nan 0.64721942 nan 0.64727143
            es are non-finite: [
                                                                             nan 0.64706342
                   nan 0.64729741
                   nan 0.64721942]
              warnings.warn(
            LogisticRegression(C=1, random_state=0)
            {'C': 1, 'penalty': '12'}
0.647297412561956
In [16]: M 1 grid_predictions = grid_search.predict(X_test)
                from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
             5 print(classification_report(y_test, grid_predictions))
             6 print(accuracy_score(y_test, grid_predictions))
              7 print(confusion_matrix(y_test, grid_predictions))
                                   recall f1-score support
                         precision
                              0.67
                                     0.77
                                                0.72
                      1
                             0.60
                                       0.48
                                                0.53
                                                         3996
                                                0.65
                                                         9616
                accuracy
                             0.64
                                       0.62
                                                0.62
                                                          9616
               macro avg
            weighted avg
                             0.64
                                       0.65
                                             0.64
                                                          9616
            0.6491264559068219
            [[4343 1277]
             [2097 1899]]
```



▼ Feature Selection 递归特征消除(Recursive feature elimination) and Re-do Model Training

```
In [18]: 🔰 1 from sklearn.feature_selection import RFE # 递归特征消除 (Recursive feature elimination)
                               3 clf = LogisticRegression()
                               4 rfe = RFE(estimator=clf, n_features_to_select=10) # find 10 columns that are most valuable rfe.fit(X_train, y_train)
       Out[18]: RFE(estimator=LogisticRegression(), n_features_to_select=10)
In [19]: ▶ 1 rfe.support_
       Out[19]: array([ True, True, False, True, True, False, False, False, False, False, True, False, True, False, True, False, True, False, 
                                           False, False, False, False])
In [20]: | 1 rfe.ranking_
       2 # using rfe.support_ as selected features
3 X = X[X.columns[rfe.support_]]
                                4 y = df["churn"]
                               6 from sklearn.model_selection import train_test_split
                               8 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
                              10 from sklearn.preprocessing import StandardScaler, MinMaxScaler
                             12 sc = StandardScaler()
                             13  X_train = sc.fit_transform(X_train)
14  X_test = sc.transform(X_test)
                             16 from sklearn.linear_model import LogisticRegression
                             18 clf = LogisticRegression(random_state=0)
                             19 clf.fit(X_train, y_train)
                             20
                              21 predictions = clf.predict(X_test)
                             23 from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
                             24
                             25 predictions = clf.predict(X_test)
                             26 print(classification_report(y_test, predictions))
                              27 print(accuracy_score(y_test, predictions))
                             28 print(confusion_matrix(y_test, predictions))
                                                                                  recall f1-score support
                                                         precision
                                                   0
                                                                    0.67
                                                                                    0.77
                                                                                                              0.72
                                                                                                                                    5620
                                                                    0.59
                                                                                      0.46
                                                                                                          0.52
                                                                                                                                   3996
                                    accuracy
                                                                                                              0.64
                                                                                                                                    9616
                                  macro avg
                                                                    0.63
                                                                                        0.62
                                                                                                              0.62
                                                                                                                                    9616
                            weighted avg
                                                                    0.64
                                                                                         0.64
                                                                                                            0.63
                                                                                                                                    9616
                            0.6424708818635607
                            [[4344 1276]
                              [2162 1834]]
In [22]: ▶ 1 clf.coef_
```

```
Out[22]: array([[-0.15039154, 0.27296565, -0.71876625, -0.32931913, 0.15731766, 0.1145698, 0.10112571, 0.11232106, -0.13146983, 0.08687853]])
```