Supervisado

Todo ejercicio debe tener un análisis fundamentado en la teoría vista en la materia, dicho análisis sera parte del informe a entregar en pdf

Se recomienda hacer uso de las herramientas vistas en los demos de la materia.

Objetivos:

- Implementar los modelos random forest y redes neuronales para clasificar las galaxias en tipo Elípticas y Espirales e Irregulares
- Comparar la performance obtenida con los modelos vistos en el anterior práctico y los nuevos modelos de este práctico.

Paquetes necesarios

In [1]:

```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:

```
%matplotlib inline
```

In [3]:

```
plt.rcParams["figure.figsize"] = (10,6)
```

Data set

Se continua con el dataset previamente curado y usado en el anterior práctico. Las variables físicas que caracterizan a las galaxias son:

- **distancia_L**: Es la distancia a la galaxia, su calculo hace uso del brillo de la galaxia
- **Mag_abs**: Es el brillo que tendría la galaxia a una distancia fija (10 Mpc)
- **objID**: Es el id de las galaxias
- **rac y dec** = Posición angular, rac de 0 a 360 y dec de -90 a 90
- **modelMag_u,modelMag_g, modelMag_r,modelMag_i,modelMag_z**= Estas variables representan una fracción de la luz total que observamos de las galaxias según su frecuencia (como por ejemplo, la frecuencia de radio, para más información [wiki (https://es.wikipedia.org/wiki/Espectro_visible)](https://es.wikipedia.org/wiki/Espectro_visible))
- **petroR90_r** = Es una medida del tamaño de la galaxia
- **color**= Como su nombre lo indica es el color más predominante en la galaxia
- **elíptica, espiral, irregular**= Estas columnas identifican el tipo de morfología de las galaxias. Si el valor de una de estas tres columnas es 1, entonces la galaxia tiene esa morfología y las dos restantes tendrán el valor 0.

In [4]:

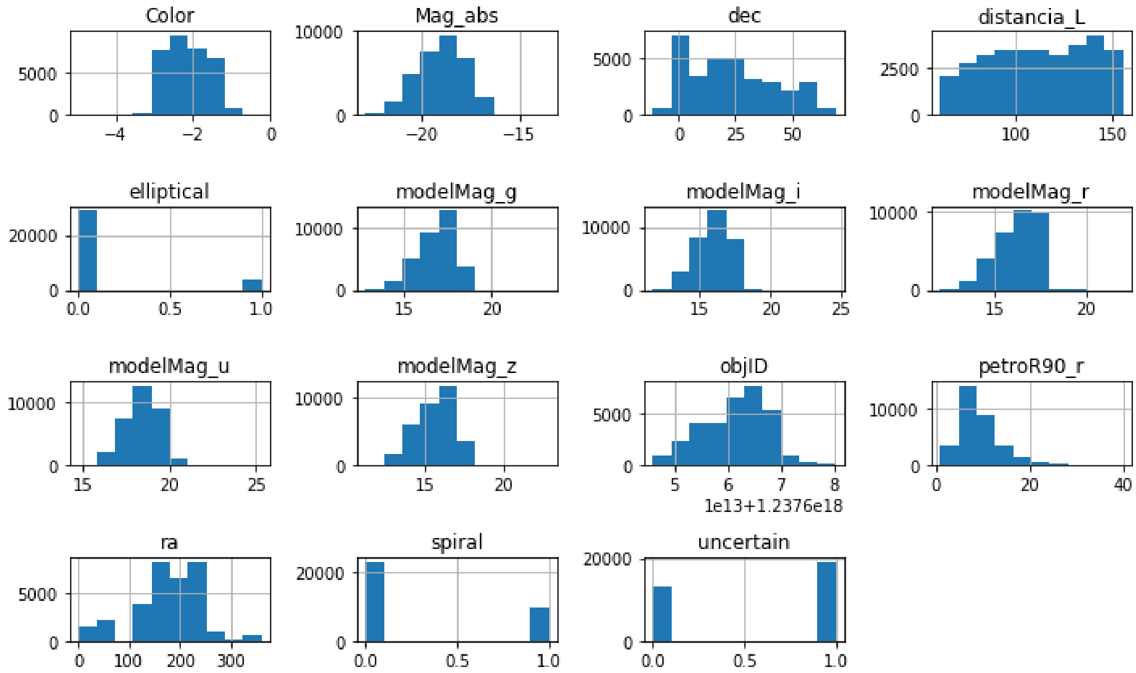
```
dataset=pd.read_csv('galaxias_2.csv')
display(dataset.head(2))
display(dataset.shape)
```

	objID	ra	dec	modelMag_u	modelMag_g	modelMag_r	modelMag_
0	1.237674e+18	119.822479	42.008528	17.36539	15.46586	14.54658	14.0749(
1	1.237674e+18	118.185239	33.699089	19.95136	18.35397	17.54043	17.0502(

```
(32623, 15)
```

In [5]:

```
dataset.hist()
plt.tight_layout()
```



In [6]:

```
data_cl = dataset.loc[~(dataset.index.astype(str).duplicated(keep="first"))]
data_cl.drop("objID",axis=1, inplace=True)
```

Target

Usen como Target la clase de tipo morfológico de las galaxias.

In [9]:

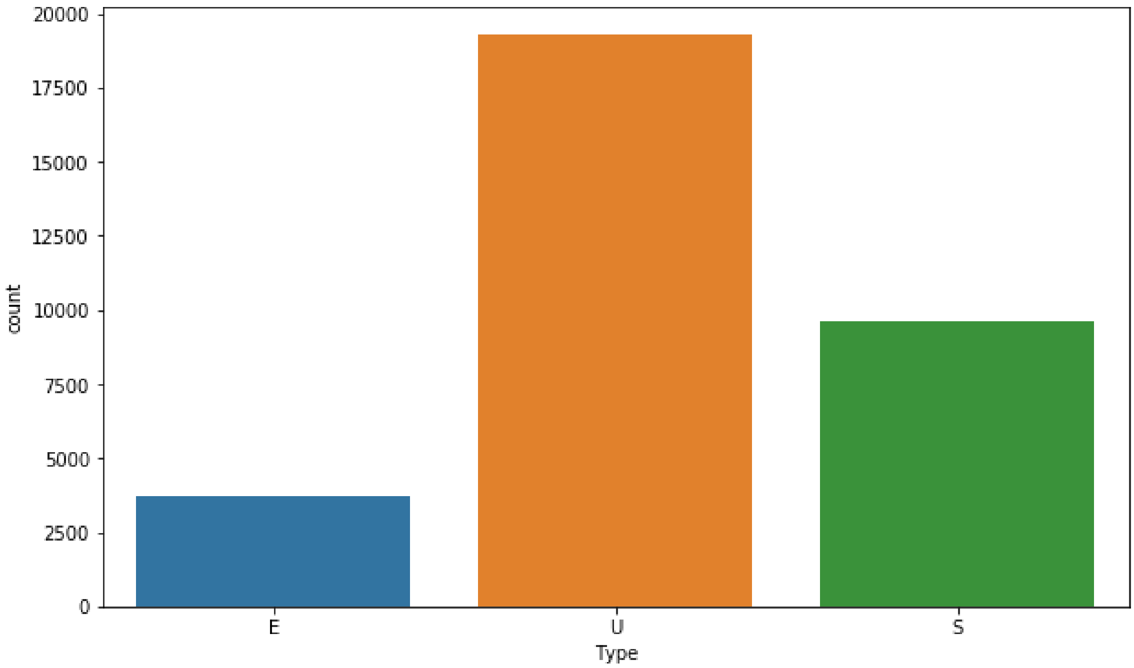
```
data_cl["Type"] = (data_cl["spiral"] * 0 + data_cl["elliptical"] * 1 +\
                   data_cl["uncertain"] * 2).map({0: "S", 1: "E", 2: "U"})
#data_cl["Type"] = data_cl["Type"].map({0: "S", 1: "E", 2: "U"})
```

In [10]:

```
sns.countplot(data_cl["Type"])
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4f8fee6da0>
```



In [11]:

```
def print_classification_report(y_real, y_pred):
    print(f"Accuracy {accuracy_score(y_real, y_pred)}")
    print("-"*100)
    print(classification_report(y_real, y_pred))
    plt.figure()
    sns.heatmap(confusion_matrix(y_real, y_pred),
                #xticklabels=x_ticks, #[0, 1],
                #yticklabels=x_ticks, #[0, 1],
                cmap="jet",
                annot=True,
               )
    plt.xlabel("Predicted Class")
    plt.ylabel("Real Class")
    plt.show()
```

División en entrenamiento y evaluación

- Realizar la respectiva división conjunto de *train* y *test*.

In [12]:

```
from sklearn.model_selection import train_test_split
```

In [13]:

```
data_cl.columns
```

Out[13]:

```
Index(['ra', 'dec', 'modelMag_u', 'modelMag_g', 'modelMag_r', 'model
Mag_i',
       'modelMag_z', 'petroR90_r', 'Color', 'elliptical', 'spiral',
       'uncertain', 'distancia_L', 'Mag_abs', 'Type'],
      dtype='object')
```

In [14]:

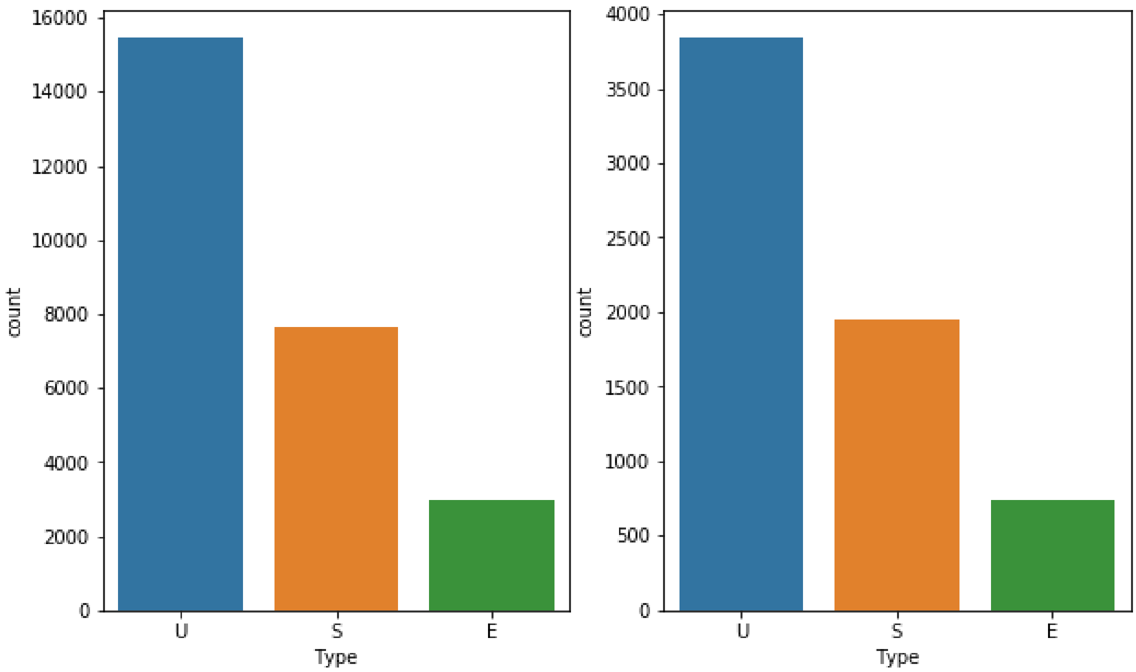
```
X = data_cl.drop(["Type", "uncertain", "spiral", "elliptical"], axis=1)
y = data_cl["Type"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
state=42)

feature3 = ["petroR90_r","Color","Mag_abs"]
X_train_3ft, X_test_3ft, = X_train[feature3] , X_test[feature3]
```

In [15]:

```
f, axs = plt.subplots(1,2)
sns.countplot(y_train, order=["U","S","E"], ax=axs[0])
sns.countplot(y_test, order=["U","S","E"], ax=axs[1])
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4f90383240>
```



Radom Forest

- Entrenar el modelo Random Forest, variando los parámetros del mismo, para cada modelo:
  - Imprimir el *out-of-bag score* cuando se usan todos los features del dataset
  - Imprimir el *out-of-bag score* usando como atributos petroR90_r, Color y Mag_abs
  - Que pueden decir de las puntuaciones obtenidas.
  - Elijan la métrica que crean más propiedad para este problema y compare con los modelos vistos en el anterior práctico.

In [16]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_rep
ort
```

In [17]:

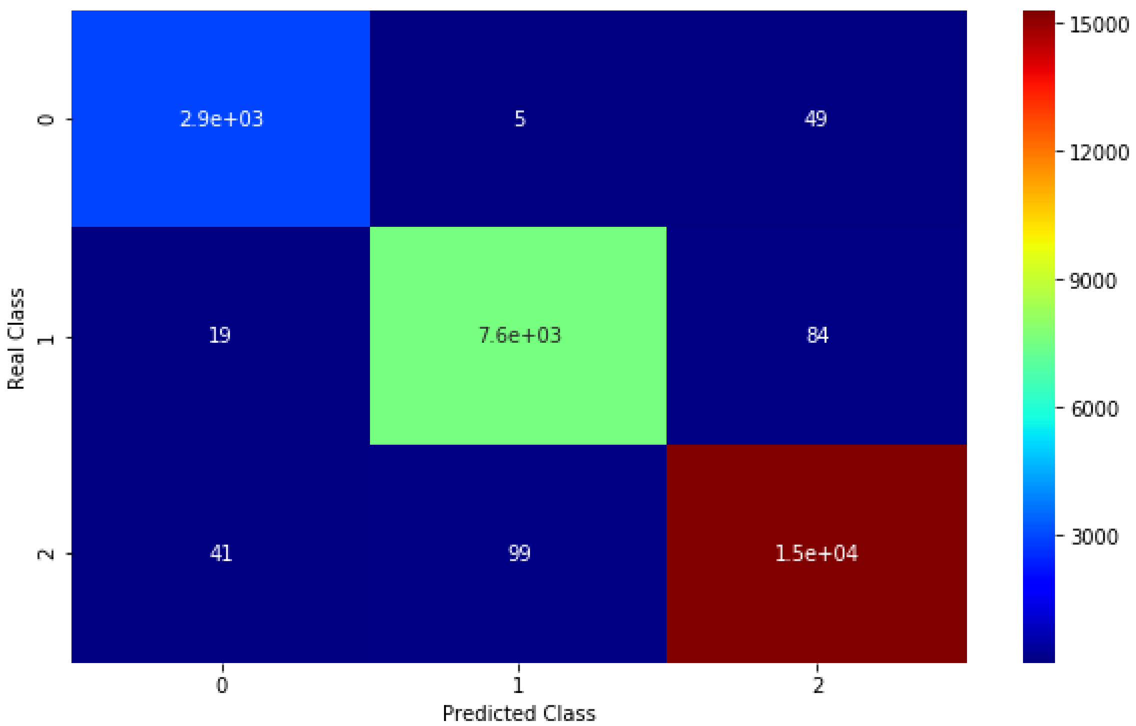
```
rf_clf = RandomForestClassifier(oob_score=True, random_state=421)
```

Parametros por defecto

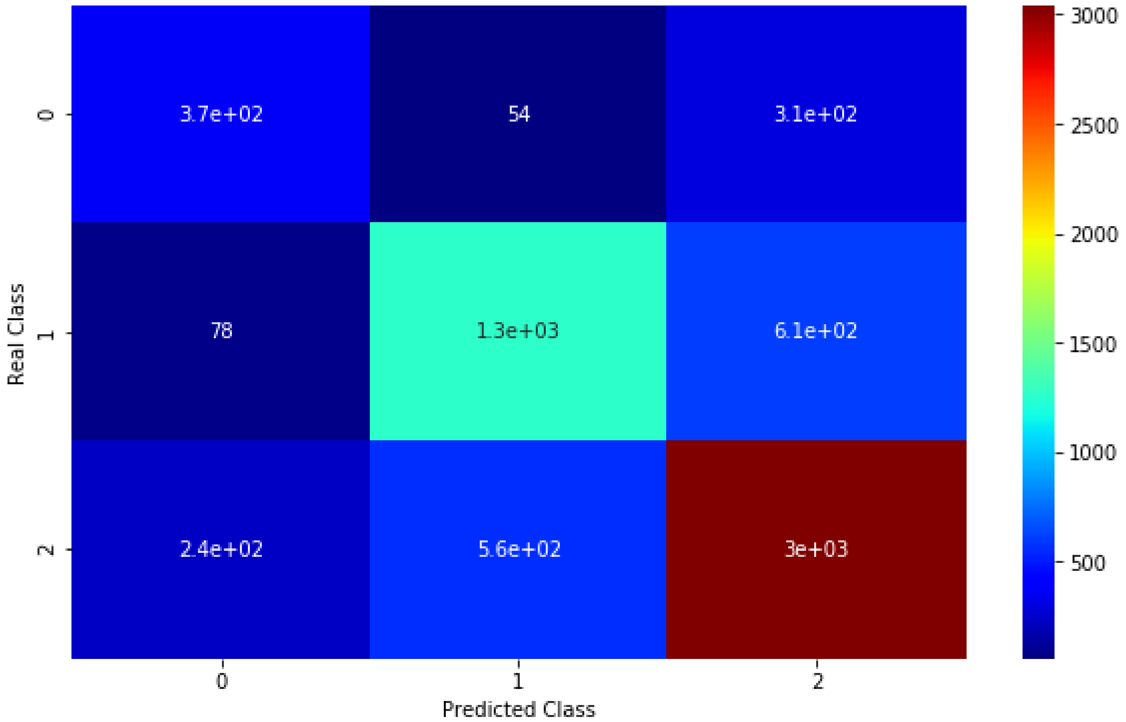
In [18]:

```
rf_clf.fit(X_train, y_train)
y_pred_train = rf_clf.predict(X_train)
y_pred_test  = rf_clf.predict(X_test)
print("Train")
print("-"*80)
print_classification_report(y_train, y_pred_train)
print("-"*80)
print("Test")
print("-"*80)
print_classification_report(y_test, y_pred_test)
```

```
/home/franco/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/
forest.py:245: FutureWarning: The default value of n_estimators will
change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/home/franco/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/
forest.py:460: UserWarning: Some inputs do not have OOB scores. This
probably means too few trees were used to compute any reliable oob e
stimates.
  warn("Some inputs do not have OOB scores. "
/home/franco/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/
forest.py:465: RuntimeWarning: divide by zero encountered in true_di
vide
  predictions[k].sum(axis=1)[:, np.newaxis])
/home/franco/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/
forest.py:465: RuntimeWarning: invalid value encountered in true_div
ide
  predictions[k].sum(axis=1)[:, np.newaxis])

Train
--------------------------------------------------------------------
------------
Accuracy 0.9886198176105448
--------------------------------------------------------------------
--------------------------------
              precision    recall  f1-score   support

           E       0.98      0.98      0.98      2991
           S       0.99      0.99      0.99      7659
           U       0.99      0.99      0.99     15448

    accuracy                           0.99     26098
   macro avg       0.99      0.99      0.99     26098
weighted avg       0.99      0.99      0.99     26098
```



```
---------------------------------------------------------------------
------------
Test
---------------------------------------------------------------------
------------
Accuracy 0.7175478927203065
---------------------------------------------------------------------
--------------------------------
              precision    recall  f1-score   support

           E       0.54      0.51      0.52       738
           S       0.67      0.65      0.66      1949
           U       0.77      0.79      0.78      3838

    accuracy                           0.72      6525
   macro avg       0.66      0.65      0.66      6525
weighted avg       0.71      0.72      0.72      6525
```



De estos resultados es evidente que el modelo esta overfiteando los datos de entrenamiento. Vemos que pasa con el OOB Score

In [19]:

```
rf_clf.oob_score_
```

Out[19]:

```
0.6768334738294122
```

Ajuste de Hiper Parametros

Todos los Features

In [20]:

```
from sklearn.model_selection import GridSearchCV
```

In [21]:

```
param_grid = [
    #{"n_estimators": [10, 50, 80, 100], "max_features": [2, 4, 6, 8, 10, 12],
    #"criterion": ["gini", "entropy"], "min_samples_split": [2,3,4,5]}
    {"n_estimators": [90, 100], "max_features": [4,5,7],
    "min_samples_leaf": [3,4,5]}
]

rf_clf = RandomForestClassifier(oob_score=True, random_state=421,)
grid_search = GridSearchCV(rf_clf, param_grid, cv=3, scoring="accuracy", n_jobs=
6, verbose=3)
```

Los parametros para este modelo (RandomForestClassifier) implican lo siguiente:

- n_estimators: será la cantidad de arboles a ser usados en el bosque debido a que RandomForestClassifier es un metodo de Ensemble Learning.
- max_features: será la cantidad maxima de features aleatorios a ser usada cuando se realiza la particion de un nodo.
- criterion: será el criterio para la particion del nodo de cada arbol de decisión.
- min_samples_split: nos explicita la cantidad minima de elementos requerida para realizar la partición del nodo (interno).
- min_samples_leaf: será la cantidad minima de muestras que debera tener un nodo para ser una hoja (o nodo externo).

Si bien existen mas hiperparametros a ser definidos, en esta oportunidad solo se utilizaron los mencioandos que aparentan ser los mas significativos en el modelo.

In [22]:

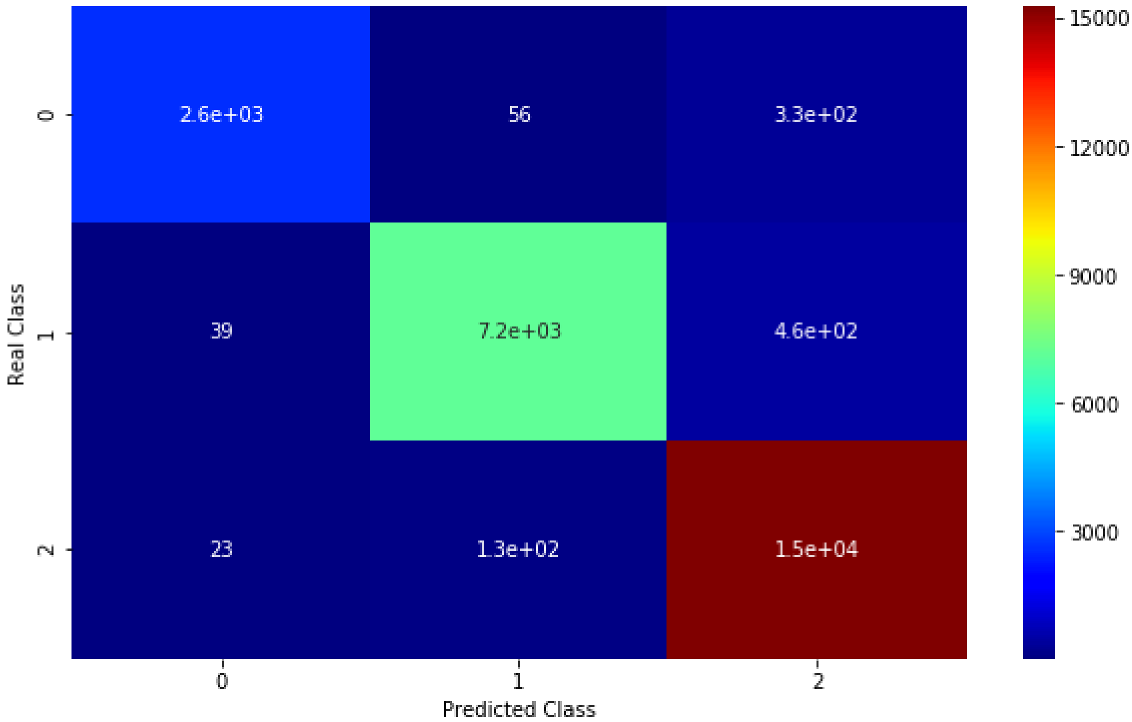
```
grid_search.fit(X_train, y_train)
means = grid_search.cv_results_['mean_test_score']
stds = grid_search.cv_results_['std_test_score']
for mean, std, params in sorted(zip(means, stds, grid_search.cv_results_['param
s']),
                                key=lambda data: data[0], reverse=True):
    print("%0.4f (+/-%0.04f) para %r" % (mean, std * 2, params))
```

```
Fitting 3 folds for each of 18 candidates, totalling 54 fits

[Parallel(n_jobs=6)]: Using backend LokyBackend with 6 concurrent wo
rkers.
[Parallel(n_jobs=6)]: Done  20 tasks      | elapsed:   57.9s
[Parallel(n_jobs=6)]: Done  54 out of  54 | elapsed:  3.1min finishe
d

0.7322 (+/-0.0059) para {'max_features': 5, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7319 (+/-0.0049) para {'max_features': 5, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7317 (+/-0.0082) para {'max_features': 4, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7308 (+/-0.0051) para {'max_features': 4, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7305 (+/-0.0083) para {'max_features': 7, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7298 (+/-0.0084) para {'max_features': 4, 'min_samples_leaf': 5,
'n_estimators': 100}
0.7296 (+/-0.0043) para {'max_features': 5, 'min_samples_leaf': 4,
'n_estimators': 100}
0.7296 (+/-0.0092) para {'max_features': 7, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7292 (+/-0.0082) para {'max_features': 4, 'min_samples_leaf': 4,
'n_estimators': 90}
0.7291 (+/-0.0066) para {'max_features': 4, 'min_samples_leaf': 5,
'n_estimators': 90}
0.7286 (+/-0.0091) para {'max_features': 4, 'min_samples_leaf': 4,
'n_estimators': 100}
0.7281 (+/-0.0084) para {'max_features': 7, 'min_samples_leaf': 4,
'n_estimators': 100}
0.7280 (+/-0.0078) para {'max_features': 5, 'min_samples_leaf': 5,
'n_estimators': 100}
0.7280 (+/-0.0057) para {'max_features': 5, 'min_samples_leaf': 4,
'n_estimators': 90}
0.7278 (+/-0.0073) para {'max_features': 7, 'min_samples_leaf': 5,
'n_estimators': 100}
0.7276 (+/-0.0066) para {'max_features': 7, 'min_samples_leaf': 4,
'n_estimators': 90}
0.7275 (+/-0.0060) para {'max_features': 5, 'min_samples_leaf': 5,
'n_estimators': 90}
0.7273 (+/-0.0062) para {'max_features': 7, 'min_samples_leaf': 5,
'n_estimators': 90}
```

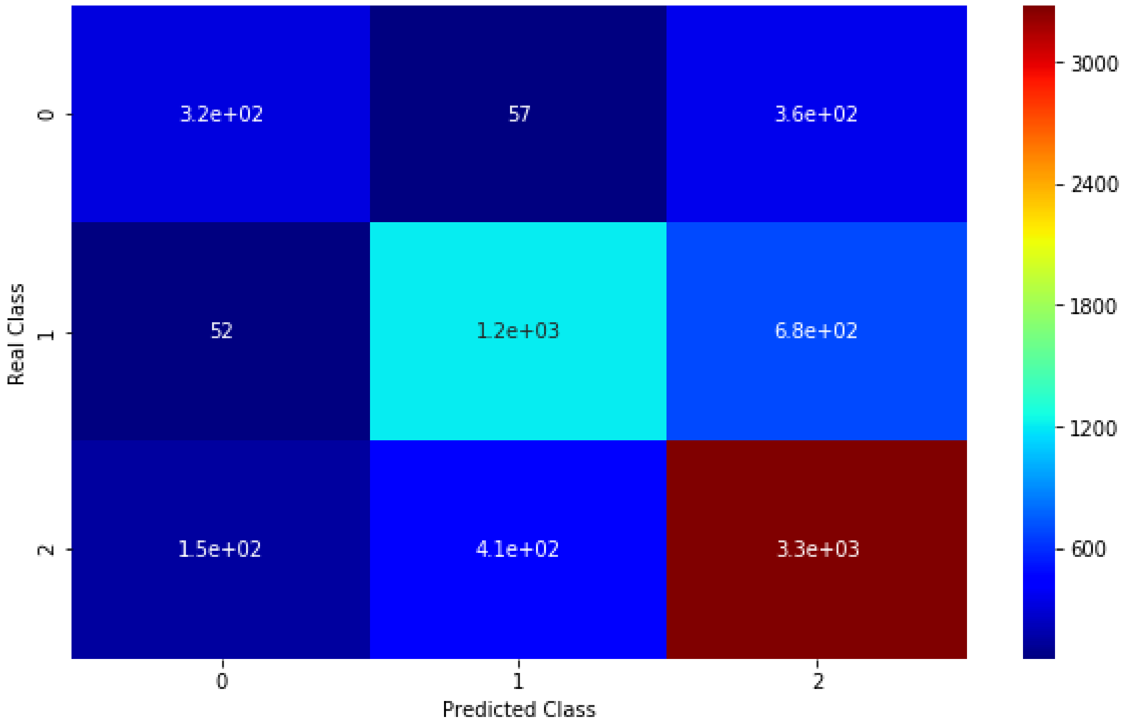
In [35]:

```
best_rf = grid_search.best_estimator_
best_rf.fit(X_train, y_train)

y_pred_train = best_rf.predict(X_train)
y_pred_test  = best_rf.predict(X_test)
print("Train")
print("-"*80)
print_classification_report(y_train, y_pred_train)
print("-"*80)
print("Test")
print("-"*80)
print_classification_report(y_test, y_pred_test)
print("OOB")
print("-"*80)
print(best_rf.oob_score_)
```

```
Train
--------------------------------------------------------------------
------------
Accuracy 0.959881983293739
--------------------------------------------------------------------
--------------------------------
              precision    recall  f1-score   support

           E       0.98      0.87      0.92      2991
           S       0.97      0.93      0.95      7659
           U       0.95      0.99      0.97     15448

    accuracy                           0.96     26098
   macro avg       0.97      0.93      0.95     26098
weighted avg       0.96      0.96      0.96     26098
```




```
--------------------------------------------------------------------
------------
Test
--------------------------------------------------------------------
------------
Accuracy 0.7388505747126437
--------------------------------------------------------------------
--------------------------------
              precision    recall  f1-score   support

           E       0.62      0.44      0.51       738
           S       0.72      0.62      0.67      1949
           U       0.76      0.86      0.80      3838

    accuracy                           0.74      6525
   macro avg       0.70      0.64      0.66      6525
weighted avg       0.73      0.74      0.73      6525
```




```
OOB
------------------------------------------------------------------
------------
0.7407464173499885
```

In [37]:

```
list(sorted(zip(X_train.columns, best_rf.feature_importances_),
            key=lambda x: x[1], reverse=True))
```

Out[37]:

```
[('petroR90_r', 0.22044114230564854),
 ('Color', 0.13237370872471377),
 ('modelMag_z', 0.09444818373159049),
 ('modelMag_g', 0.07542600277026862),
 ('modelMag_i', 0.07259851021225941),
 ('Mag_abs', 0.07213036299760474),
 ('modelMag_r', 0.07194402818142252),
 ('ra', 0.0669366463262414),
 ('distancia_L', 0.06684548038066468),
 ('dec', 0.06510886115400306),
 ('modelMag_u', 0.06174707321558266)]
```

petroR90_r, Color, y Mag_abs

In [29]:

```
param_grid = [
    #{"n_estimators": [10, 50, 80, 100], "max_features": [2, 4, 6, 8, 10, 12],
    #"criterion": ["gini", "entropy"], "min_samples_split": [2,3,4,5]}
    {"n_estimators": [90, 100], "max_features": [1,2,3],
    "min_samples_leaf": [3,4,5]}
]

rf_clf = RandomForestClassifier(oob_score=True, random_state=421,)
grid_search_3f = GridSearchCV(rf_clf, param_grid, cv=3, scoring="accuracy", n_jo
bs=6, verbose=3)
```

In [30]:

```
grid_search_3f.fit(X_train_3ft, y_train)
means = grid_search_3f.cv_results_['mean_test_score']
stds = grid_search_3f.cv_results_['std_test_score']
for mean, std, params in sorted(zip(means, stds, grid_search_3f.cv_results_['par
ams']),
                                key=lambda data: data[0], reverse=True):
    print("%0.4f (+/-%0.04f) para %r" % (mean, std * 2, params))
```

```
Fitting 3 folds for each of 18 candidates, totalling 54 fits

[Parallel(n_jobs=6)]: Using backend LokyBackend with 6 concurrent wo
rkers.
[Parallel(n_jobs=6)]: Done  20 tasks      | elapsed:   24.2s
[Parallel(n_jobs=6)]: Done  54 out of  54 | elapsed:  2.0min finishe
d

0.7063 (+/-0.0092) para {'max_features': 1, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7056 (+/-0.0081) para {'max_features': 1, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7040 (+/-0.0071) para {'max_features': 1, 'min_samples_leaf': 4,
'n_estimators': 90}
0.7035 (+/-0.0060) para {'max_features': 1, 'min_samples_leaf': 4,
'n_estimators': 100}
0.7030 (+/-0.0071) para {'max_features': 2, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7029 (+/-0.0083) para {'max_features': 2, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7024 (+/-0.0029) para {'max_features': 1, 'min_samples_leaf': 5,
'n_estimators': 90}
0.7018 (+/-0.0035) para {'max_features': 1, 'min_samples_leaf': 5,
'n_estimators': 100}
0.7016 (+/-0.0074) para {'max_features': 3, 'min_samples_leaf': 3,
'n_estimators': 100}
0.7015 (+/-0.0073) para {'max_features': 3, 'min_samples_leaf': 3,
'n_estimators': 90}
0.7006 (+/-0.0089) para {'max_features': 2, 'min_samples_leaf': 4,
'n_estimators': 100}
0.7005 (+/-0.0093) para {'max_features': 2, 'min_samples_leaf': 4,
'n_estimators': 90}
0.7001 (+/-0.0064) para {'max_features': 2, 'min_samples_leaf': 5,
'n_estimators': 100}
0.7001 (+/-0.0042) para {'max_features': 3, 'min_samples_leaf': 4,
'n_estimators': 90}
0.6999 (+/-0.0072) para {'max_features': 2, 'min_samples_leaf': 5,
'n_estimators': 90}
0.6994 (+/-0.0053) para {'max_features': 3, 'min_samples_leaf': 4,
'n_estimators': 100}
0.6989 (+/-0.0043) para {'max_features': 3, 'min_samples_leaf': 5,
'n_estimators': 100}
0.6986 (+/-0.0022) para {'max_features': 3, 'min_samples_leaf': 5,
'n_estimators': 90}
```

In [33]:

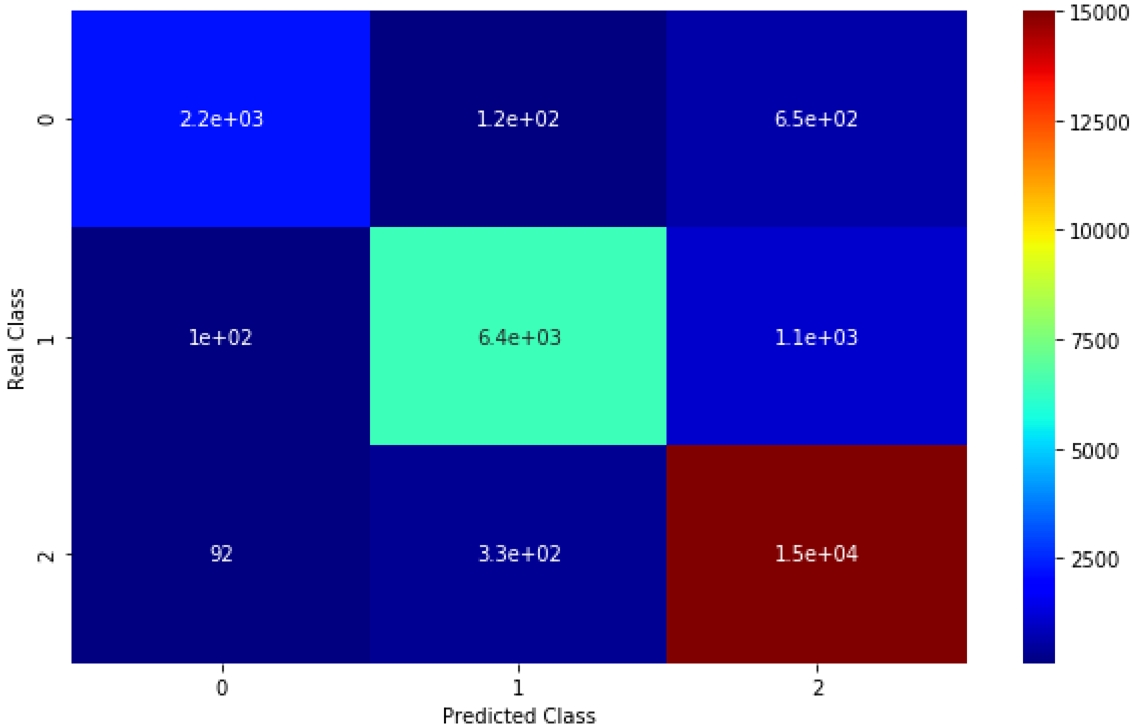
```
best_rf_3f = grid_search_3f.best_estimator_
best_rf_3f.fit(X_train_3ft, y_train)

y_pred_train = best_rf_3f.predict(X_train_3ft)
y_pred_test  = best_rf_3f.predict(X_test_3ft)
print("Train")
print("-"*80)
print_classification_report(y_train, y_pred_train)
print("-"*80)
print("Test")
print("-"*80)
print_classification_report(y_test, y_pred_test)
print("OOB")
print("-"*80)
print(best_rf_3f.oob_score_)
```

Train

Accuracy 0.9076174419495747

----

	precision	recall	f1-score	support
E	0.92	0.74	0.82	2991
S	0.93	0.84	0.89	7659
U	0.89	0.97	0.93	15448
accuracy			0.91	26098
macro avg	0.92	0.85	0.88	26098
weighted avg	0.91	0.91	0.91	26098

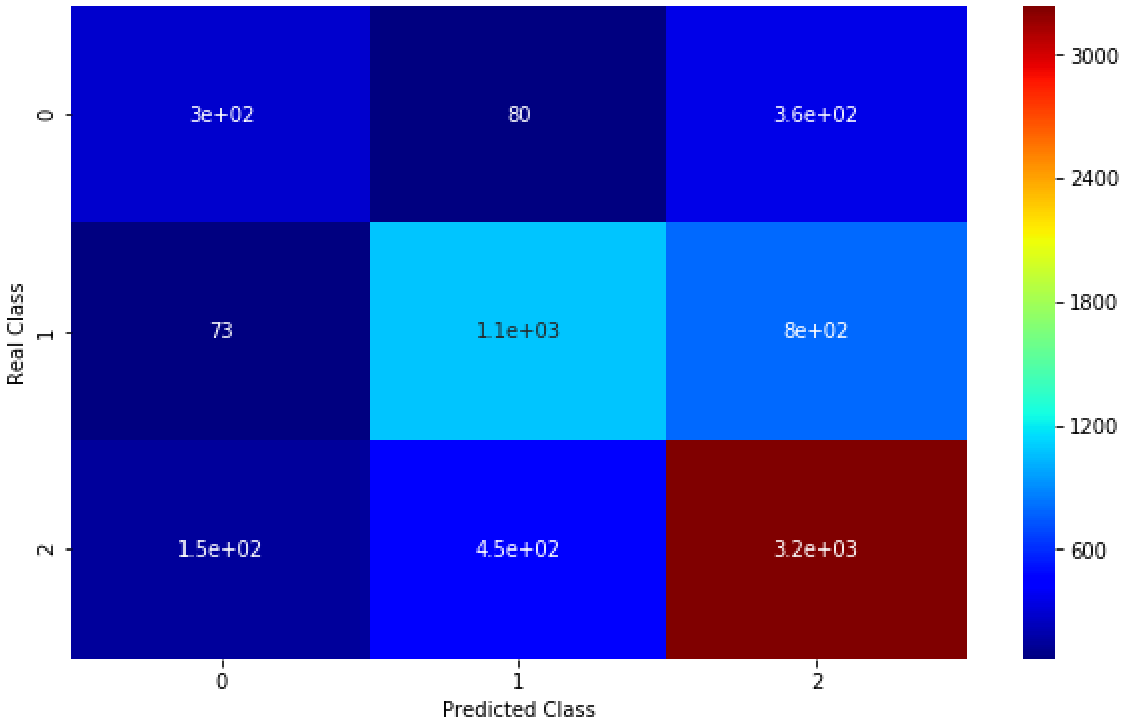


Test

Accuracy 0.7062068965517241

----

	precision	recall	f1-score	support
E	0.57	0.40	0.47	738
S	0.67	0.55	0.61	1949
U	0.74	0.84	0.79	3838
accuracy			0.71	6525
macro avg	0.66	0.60	0.62	6525
weighted avg	0.70	0.71	0.70	6525




```
OOB
--------------------------------------------------------------------
------------
0.710820752548088
```

In [38]:

```
list(sorted(zip(X_train_3ft.columns, best_rf_3f.feature_importances_),
            key=lambda x: x[1], reverse=True))
```

Out[38]:

```
[('petroR90_r', 0.3914490783505787),
 ('Color', 0.30462515936873447),
 ('Mag_abs', 0.3039257622806869)]
```

El accuracy no cambia tanto ya que pertroR90_r, Color y Mag_abs son de las variables más importantes en el modelo

Neural Networks

Implemente el modelo visto en el demo 8 de la materia (*neural_network.MLPClassifier*). Varié algunos de sus parámetros excepto el parámetro *solver* el cual deben fijar en función de la dimensión del dataset.

In [39]:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

In [40]:

```
X = data_cl.drop(["Type", "uncertain", "spiral", "elliptical"], axis=1)
y = data_cl["Type"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
state=42)
```

In [41]:

```
std = StandardScaler()
X_train_std = std.fit_transform(X_train)
X_test_std   = std.transform(X_test)
```

In [42]:

```
from sklearn import neural_network
```

In [43]:

```
param_grid = [
    {"hidden_layer_sizes": [(8,2), (8,3), (8,4), (9,3), (9,2)],
     "alpha": [1e-5,1e-4]
    }
]

mlp_clf = neural_network.MLPClassifier(solver='adam', activation="logistic",
                                       random_state=532, max_iter=1000)
mlp_gs = GridSearchCV(mlp_clf, param_grid, cv=3, scoring="accuracy", n_jobs=6, v
erbose=3)
mlp_gs.fit(X_train_std, y_train)

means = mlp_gs.cv_results_['mean_test_score']
stds = mlp_gs.cv_results_['std_test_score']
for mean, std, params in sorted(zip(means, stds, mlp_gs.cv_results_['params']),
                                key=lambda data: data[0], reverse=True):
    print("%0.4f (+/-%0.04f) para %r" % (mean, std * 2, params))
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=6)]: Using backend LokyBackend with 6 concurrent wo
rkers.
[Parallel(n_jobs=6)]: Done  30 out of  30 | elapsed:  3.4min remaini
ng:    0.0s
[Parallel(n_jobs=6)]: Done  30 out of  30 | elapsed:  3.4min finishe
d

0.7147 (+/-0.0105) para {'alpha': 0.0001, 'hidden_layer_sizes': (9,
2)}
0.7146 (+/-0.0106) para {'alpha': 1e-05, 'hidden_layer_sizes': (9,
2)}
0.7117 (+/-0.0146) para {'alpha': 1e-05, 'hidden_layer_sizes': (9,
3)}
0.7116 (+/-0.0143) para {'alpha': 0.0001, 'hidden_layer_sizes': (9,
3)}
0.7101 (+/-0.0136) para {'alpha': 0.0001, 'hidden_layer_sizes': (8,
3)}
0.7101 (+/-0.0136) para {'alpha': 1e-05, 'hidden_layer_sizes': (8,
3)}
0.7099 (+/-0.0124) para {'alpha': 1e-05, 'hidden_layer_sizes': (8,
4)}
0.7091 (+/-0.0145) para {'alpha': 0.0001, 'hidden_layer_sizes': (8,
4)}
0.7087 (+/-0.0125) para {'alpha': 0.0001, 'hidden_layer_sizes': (8,
2)}
0.7086 (+/-0.0128) para {'alpha': 1e-05, 'hidden_layer_sizes': (8,
2)}
```

Los parametros para este modelo (neural_network.MPLClassifier) implican lo siguiente:

- hidden_layer_sizes: será la cantidad de capas ocultas que tenga el modelo sin contar las capas de entrada y salida. Por ejemplo si tenemos hidden_layer_sizes = (8,2) tendremos 2 capas con 8 neuronas ocultas.
- alpha: será el termino de regulatizacion que se utilice en cada neurona.

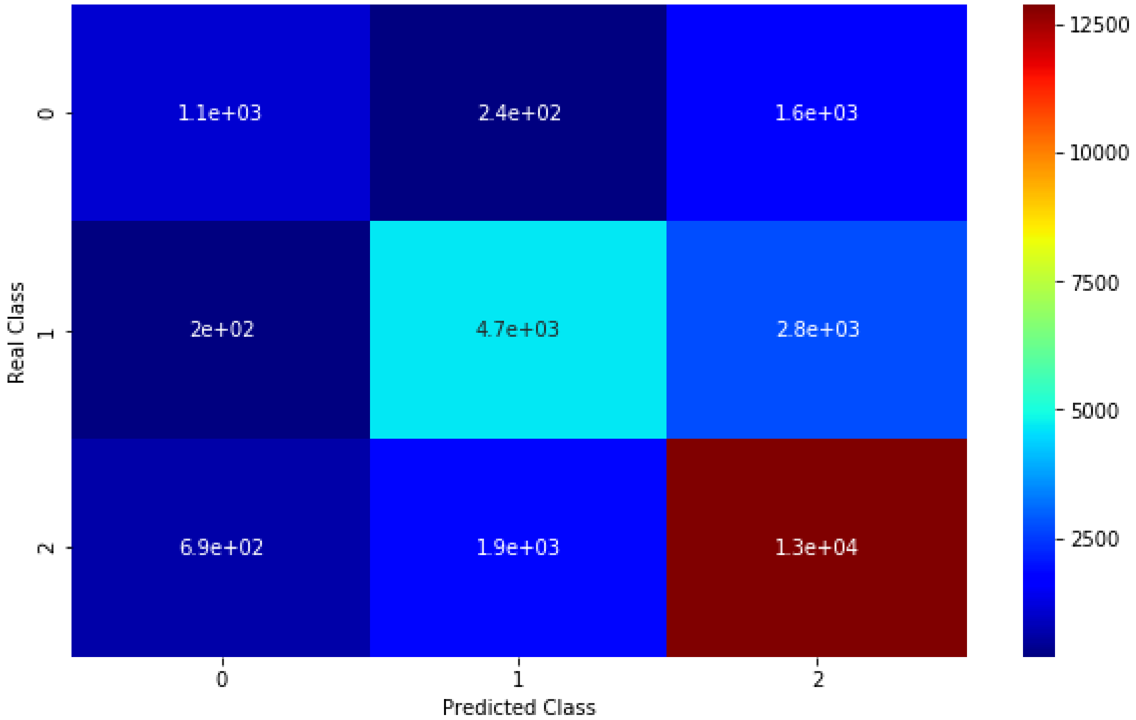
Si bien en este caso solo tomamos estos dos hiperparamentros, otros podrian haber sido tambien:

- activation: el cual especifica la función de activación de cada capa oculta. Puede ser "identity", "logistic", "tanh" o "relu".
- solver: este hiperparametro define el algoritmo de optimización, en este caso podra ser "lbfgs", "sgd" o "adam". En general utilizando "sgd" funciona suficientemente bien, este implica "Descenso por el gradiente estocastico". El solver que esta definido por defecto es "adam", un algoritmo de "Descenso por el gradiente estocastico" con algunas modificaciones.

In [44]:

```
best_mlp = mlp_gs.best_estimator_
best_mlp.fit(X_train_std, y_train)

y_pred_train = best_mlp.predict(X_train_std)
y_pred_test  = best_mlp.predict(X_test_std)
print("Train")
print("-"*80)
print_classification_report(y_train, y_pred_train)
print("-"*80)
print("Test")
print("-"*80)
print_classification_report(y_test, y_pred_test)
```

```
Train
--------------------------------------------------------------------
------------
Accuracy 0.7168748563108284
--------------------------------------------------------------------
--------------------------------
              precision    recall  f1-score   support

           E       0.56      0.38      0.45      2991
           S       0.69      0.61      0.65      7659
           U       0.75      0.83      0.79     15448

    accuracy                           0.72     26098
   macro avg       0.67      0.61      0.63     26098
weighted avg       0.71      0.72      0.71     26098
```



```
------------------------------------------------------------------------------------
Test
------------------------------------------------------------------------------------
Accuracy 0.717088122605364
------------------------------------------------------------------------------------------------------------
              precision    recall  f1-score   support

           E       0.58      0.36      0.45       738
           S       0.69      0.61      0.65      1949
           U       0.74      0.84      0.79      3838

    accuracy                           0.72      6525
   macro avg       0.67      0.60      0.63      6525
weighted avg       0.71      0.72      0.71      6525
```