Exercise 01

July 15, 2019

1 Exercise 01

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[45]:
```
import warnings
warnings.filterwarnings('ignore')

from nltk.classify import accuracy
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score,␣
 ↪roc_curve, classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import shap

import pandas as pd
import pickle

import matplotlib.pyplot as plt
from matplotlib import rcParams
import seaborn as sns

RANDOM_STATE = 90617
```

2 0.0 Loading the Data

[2]:
```
# set default figure size for plots
rcParams['figure.figsize'] = 15,8

data = pd.read_csv('../data/exercise01.csv')
data.head(10)
```

[2]:

```
   id  age  workclass_id    workclass_name  education_level_id  \
0   1   39             8         State-gov                  10   
1   2   50             7  Self-emp-not-inc                  10   
2   3   38             5           Private                  12   
3   4   53             5           Private                   2   
4   5   28             5           Private                  10   
5   6   37             5           Private                  13   
6   7   49             5           Private                   7   
7   8   52             7  Self-emp-not-inc                  12   
8   9   31             5           Private                  13   
9  10   42             5           Private                  10   

  education_level_name  education_num  marital_status_id  \
0            Bachelors             13                  5   
1            Bachelors             13                  3   
2              HS-grad              9                  1   
3                 11th              7                  3   
4            Bachelors             13                  3   
5              Masters             14                  3   
6                  9th              5                  4   
7              HS-grad              9                  3   
8              Masters             14                  5   
9            Bachelors             13                  3   

      marital_status_name  occupation_id  ... race_id  race_name sex_id  \
0           Never-married              2  ...       5      White      2   
1      Married-civ-spouse              5  ...       5      White      2   
2                Divorced              7  ...       5      White      2   
3      Married-civ-spouse              7  ...       3      Black      2   
4      Married-civ-spouse             11  ...       3      Black      1   
5      Married-civ-spouse              5  ...       5      White      1   
6   Married-spouse-absent              9  ...       3      Black      1   
7      Married-civ-spouse              5  ...       5      White      2   
8           Never-married             11  ...       5      White      1   
9      Married-civ-spouse              5  ...       5      White      2   

  sex_name capital_gain  capital_loss hours_week  country_id   country_name  \
0     Male         2174             0         40          40  United-States   
1     Male            0             0         13          40  United-States   
2     Male            0             0         40          40  United-States   
3     Male            0             0         40          40  United-States   
4   Female            0             0         40           6           Cuba   
5   Female            0             0         40          40  United-States   
6   Female            0             0         16          24        Jamaica   
7     Male            0             0         45          40  United-States   
8   Female        14084             0         50          40  United-States   
9     Male         5178             0         40          40  United-States   
```

```
   over_50k
0         0
1         0
2         0
3         0
4         0
5         0
6         0
7         1
8         1
9         1

[10 rows x 23 columns]
```

[3]:
```
data.columns
```

[3]:
```
Index(['id', 'age', 'workclass_id', 'workclass_name', 'education_level_id',
       'education_level_name', 'education_num', 'marital_status_id',
       'marital_status_name', 'occupation_id', 'occupation_name',
       'relationship_id', 'relationship_name', 'race_id', 'race_name',
       'sex_id', 'sex_name', 'capital_gain', 'capital_loss', 'hours_week',
       'country_id', 'country_name', 'over_50k'],
      dtype='object')
```

[4]:
```
# converting all '?' to NaN
data = data.mask(data=='?', float('NaN'))

# counting null rows for deciding on impute vs. remove
null_counts = data.isnull().sum(axis=1)
print(f'{sum(null_counts.mask(null_counts > 0, 1))} rows with 1 or more null␣
↪values, or {sum(null_counts.mask(null_counts > 0, 1))/len(data)*100}% of␣
↪dataset.')
```

```
3620 rows with 1 or more null values, or 7.411653904426519% of dataset.
```

3 Exploratory Data Analysis

[5]:
```
# for use in easier subsetting later
num_vars = ['age', 'education_num', 'capital_gain', 'capital_loss',␣
↪'hours_week', 'over_50k']
cat_vars = ['workclass_name', 'education_level_name', 'marital_status_name',␣
↪'occupation_name',
            'relationship_name', 'race_name', 'sex_name', 'country_name']
cat_vars_id = ['workclass_id', 'education_level_id', 'marital_status_id',␣
↪'occupation_id',
            'relationship_id', 'race_id', 'sex_id', 'country_id']
```

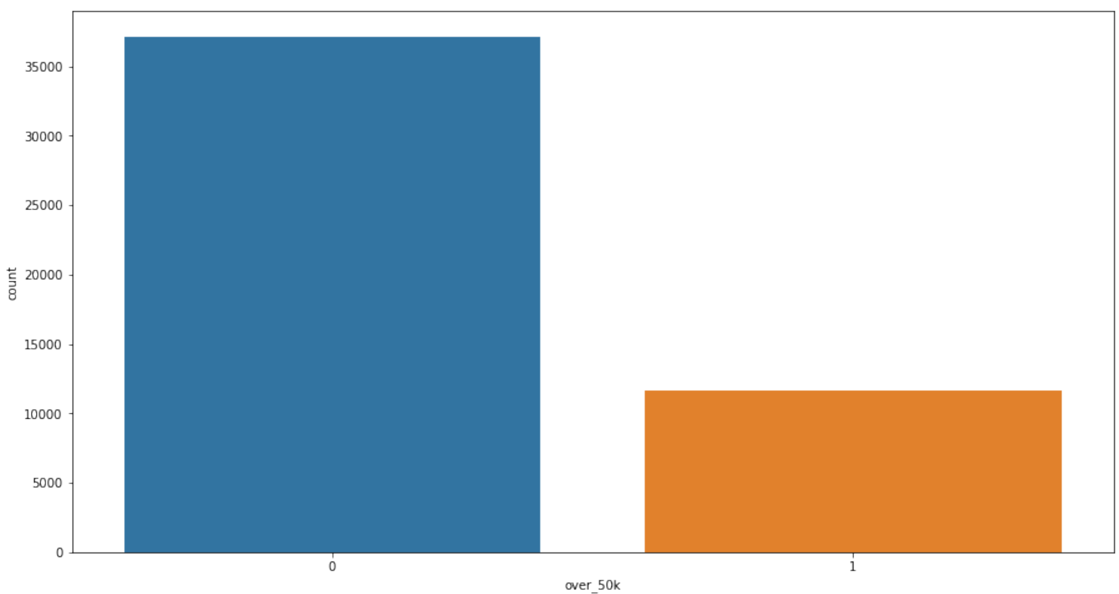
```
target = ['over_50k']

data[num_vars].describe()
```

[5]:

```
                age  education_num  capital_gain  capital_loss    hours_week  \
count  48842.000000   48842.000000  48842.000000  48842.000000  48842.000000
mean      38.643585      10.078089   1079.067626     87.502314     40.422382
std       13.710510       2.570973   7452.019058    403.004552     12.391444
min       17.000000       1.000000      0.000000      0.000000      1.000000
25%       28.000000       9.000000      0.000000      0.000000     40.000000
50%       37.000000      10.000000      0.000000      0.000000     40.000000
75%       48.000000      12.000000      0.000000      0.000000     45.000000
max       90.000000      16.000000  99999.000000   4356.000000     99.000000

           over_50k
count  48842.000000
mean       0.239282
std        0.426649
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
```

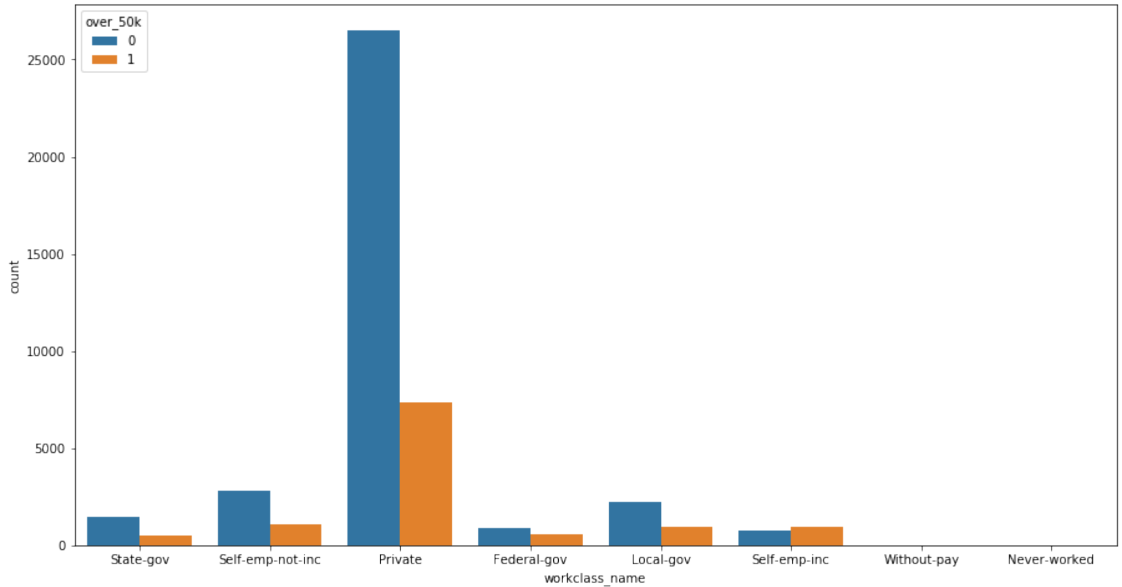
[6]:

```
sns.countplot('over_50k', data=data)
plt.show()
```

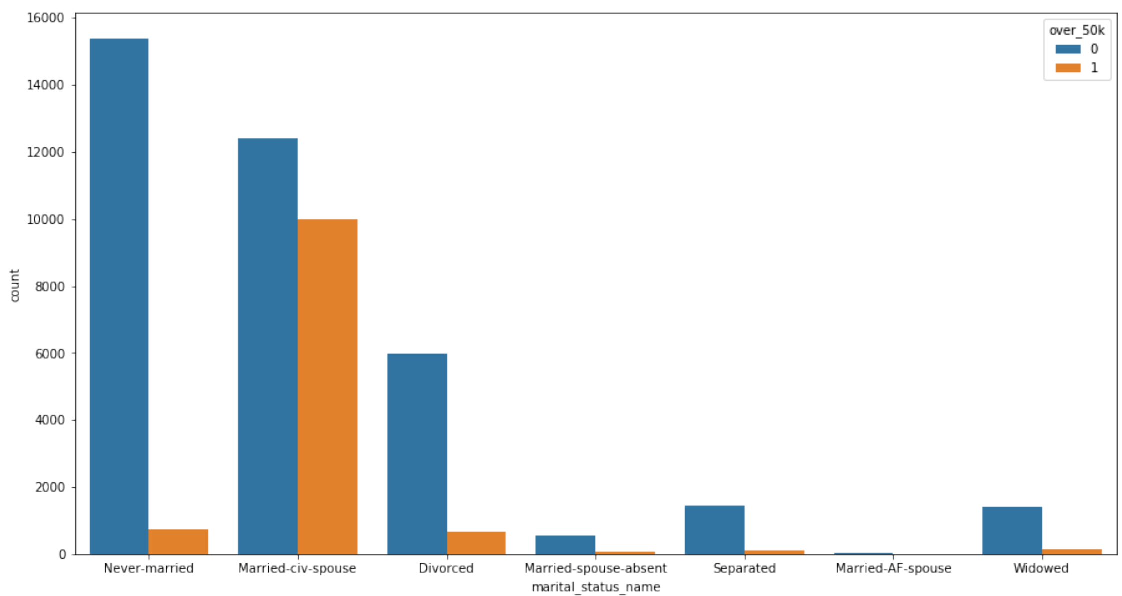


4 Analysis of Categorical Data

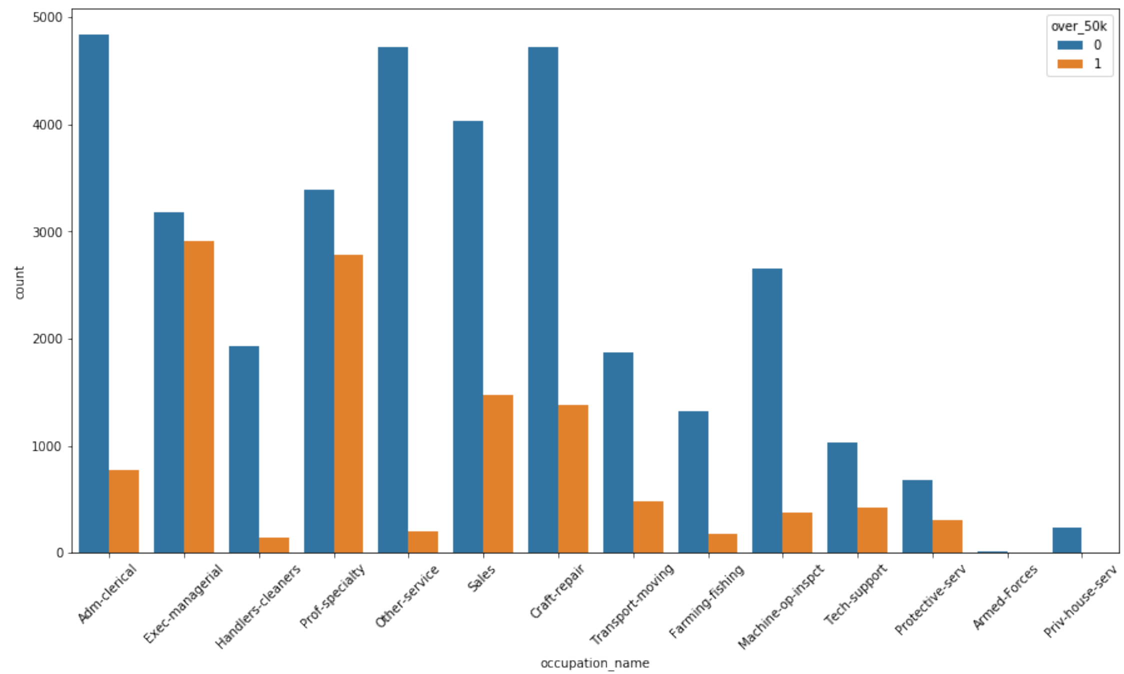
[7]:
```
ax = sns.countplot('workclass_name', hue='over_50k', data=data)
```



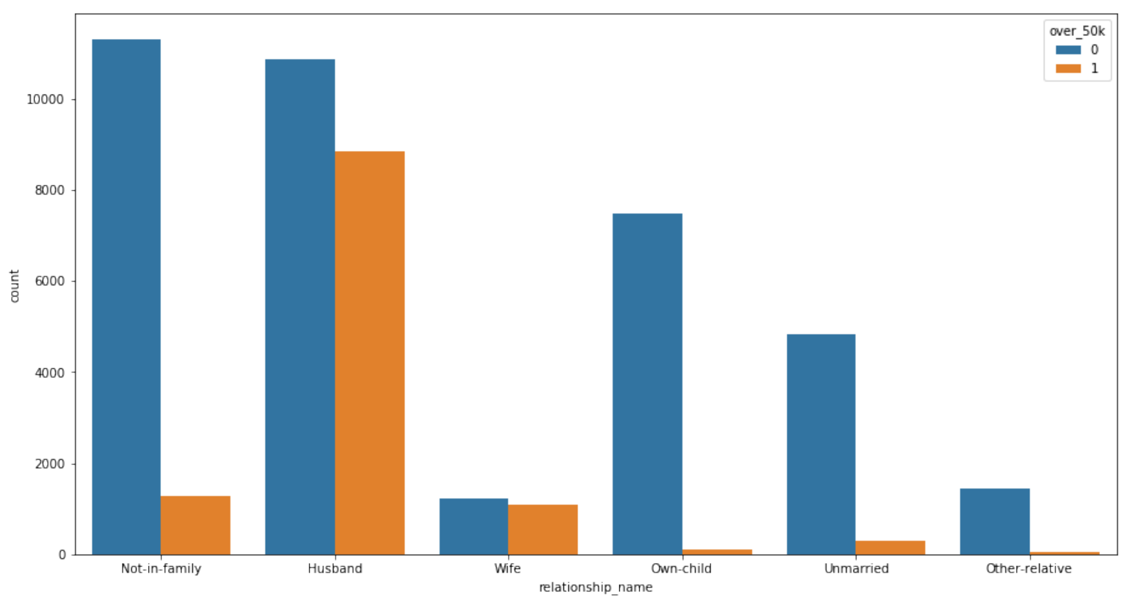
[8]:
```
# Fairly clear that married individuals have a higher chance of making over 50k␣
↪per year.
# However, this may be a result from other factors
ax = sns.countplot('marital_status_name', hue='over_50k', data=data)
```



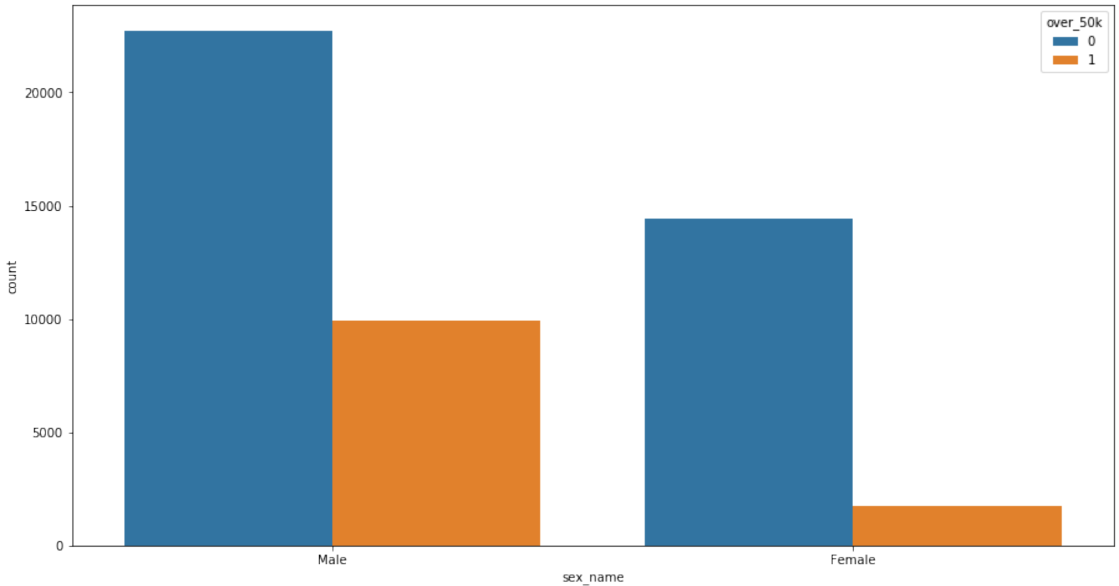
[9]:
```
ax = sns.countplot('occupation_name', hue='over_50k', data=data)
for item in ax.get_xticklabels():
    item.set_rotation(45)
```



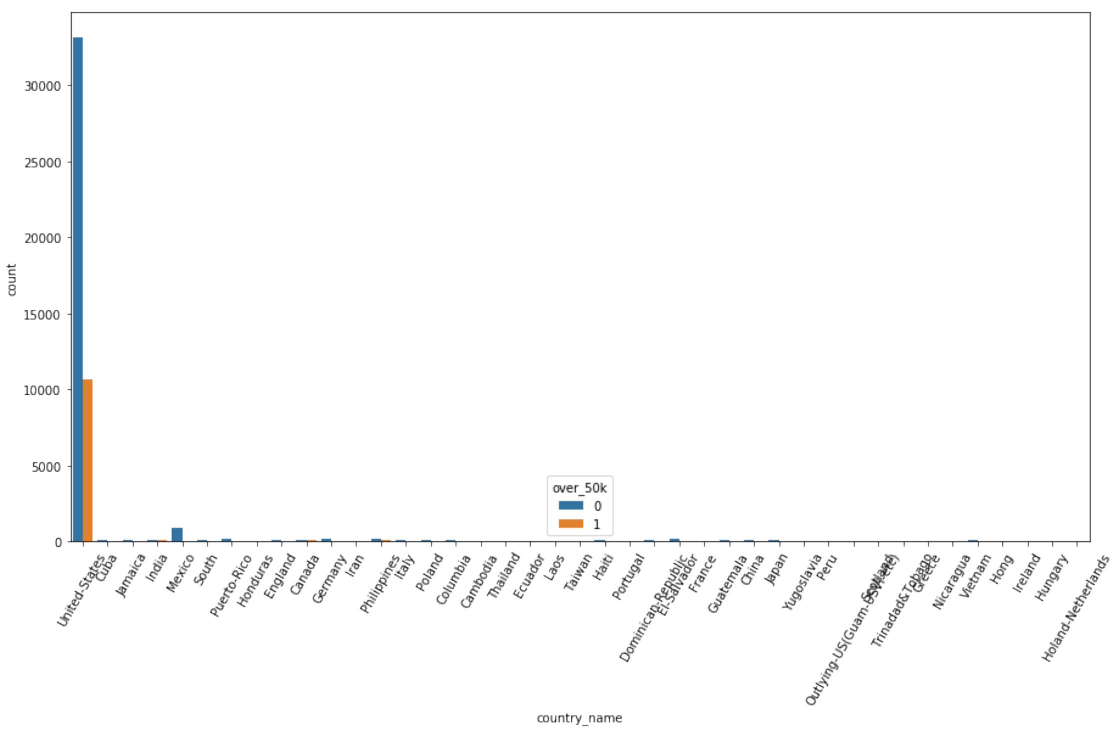
[10]:
```
ax = sns.countplot('relationship_name', hue='over_50k', data=data)
```



[11]:
```
ax = sns.countplot('sex_name', hue='over_50k', data=data) # higher percentage␣
↪of men making over 50k
```

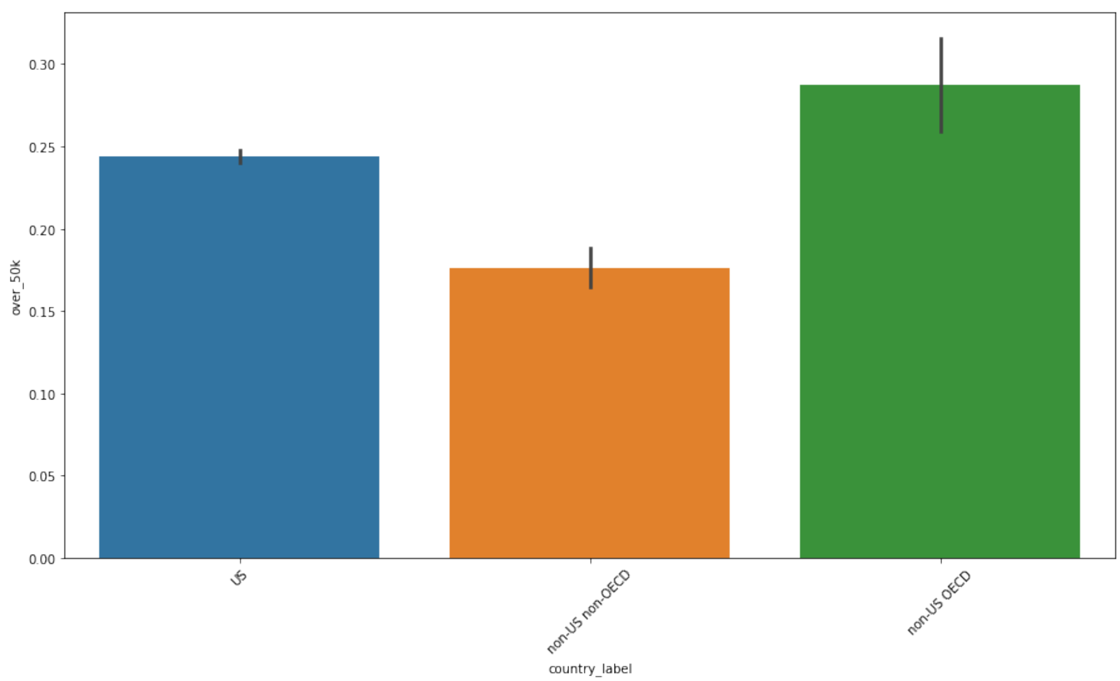


[12]:
```
# data
ax = sns.countplot('country_name', hue='over_50k', data=data)
for item in ax.get_xticklabels():
    item.set_rotation(60)
```



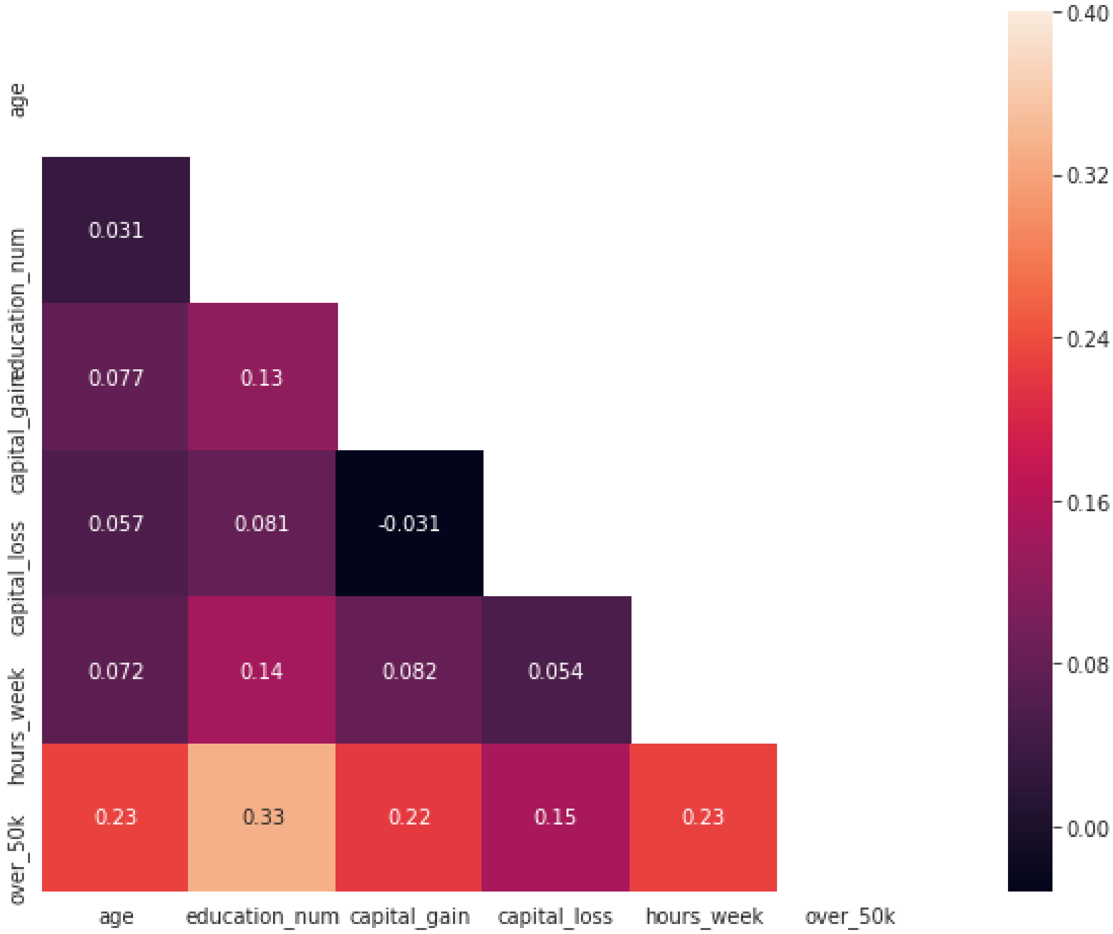
[13]:
```
# making new column for the US, non-US OECD high income, and non-US non-OECD␣
↪high income
def label_country(row):
    # to be used in apply function later
    oecd_high_income = ['Austria', 'Belgium', 'Czech-Republic', 'Denmark',␣
↪'Estonia', 'Finland', 'France',
                        'Germany', 'Greece', 'Hungary', 'Iceland', 'Ireland',␣
↪'Italy', 'Latvia', 'Lithuania',
                        'Luxembourg', 'Holand-Netherlands', 'Norway', 'Poland',␣
↪'Portugal', 'Romania', 'Slovakia', 'Slovenia',
                        'Spain', 'Sweden', 'Switzerland', 'United-Kingdom',␣
↪'Israel', 'Japan', 'South', 'Canada', 'Australia',
                        'New-Zealand', 'Chile']

    if row['country_name'] == 'United-States':
        return 'US'
    if row['country_name'] in oecd_high_income:
        return 'non-US OECD'
    else:
        return 'non-US non-OECD'

data['country_label'] = data.apply(lambda row: label_country(row), axis=1)
```

[14]:
```
ax = sns.barplot(x="country_label", y="over_50k", data=data)
for item in ax.get_xticklabels():
    item.set_rotation(45)
```



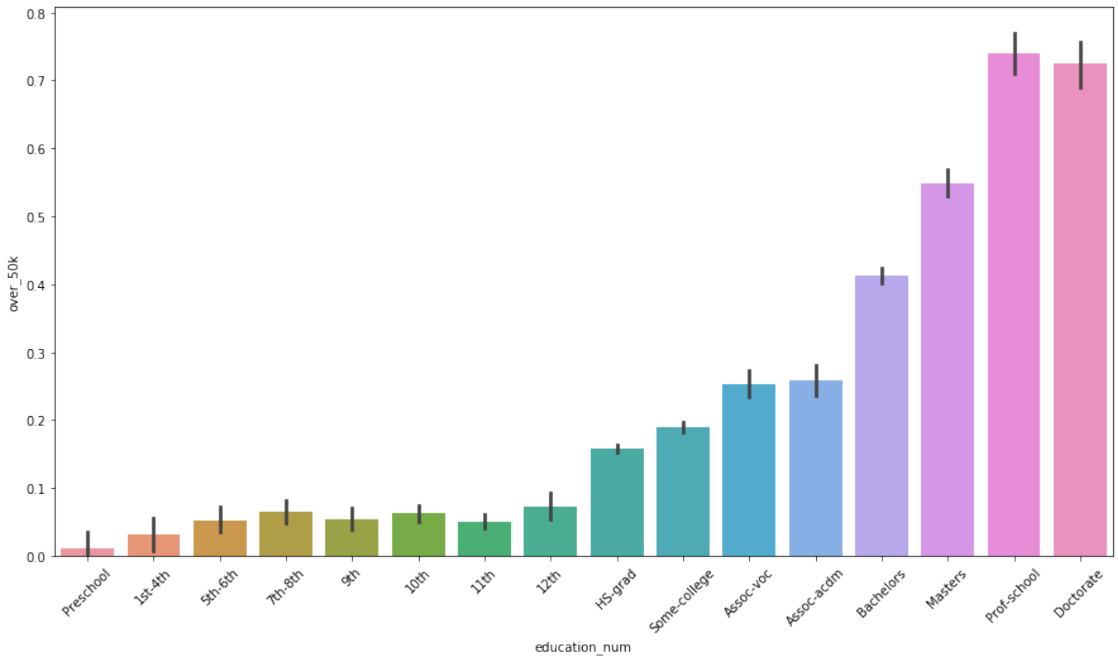
5 Analysis of Numeric Data

[15]:
```
corr = data[num_vars].corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("white"):
    ax = sns.heatmap(corr, mask=mask, vmax=.4, annot=True, square=True)
```

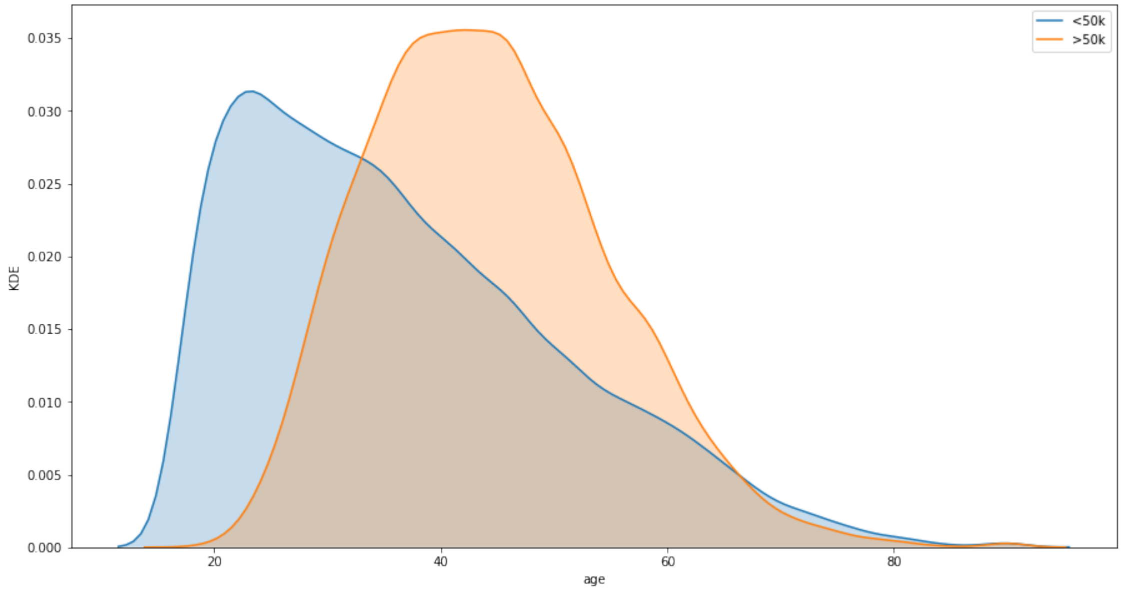


[16]:
```
ax = sns.barplot(x="education_num", y="over_50k", data=data)
for item in ax.get_xticklabels():
    item.set_rotation(45)

# manually setting xticks to correspond with education level name
set_xticks = ax.set_xticklabels(['Preschool', '1st-4th', '5th-6th', '7th-8th',␣
 ↪'9th', '10th', '11th', '12th',
```

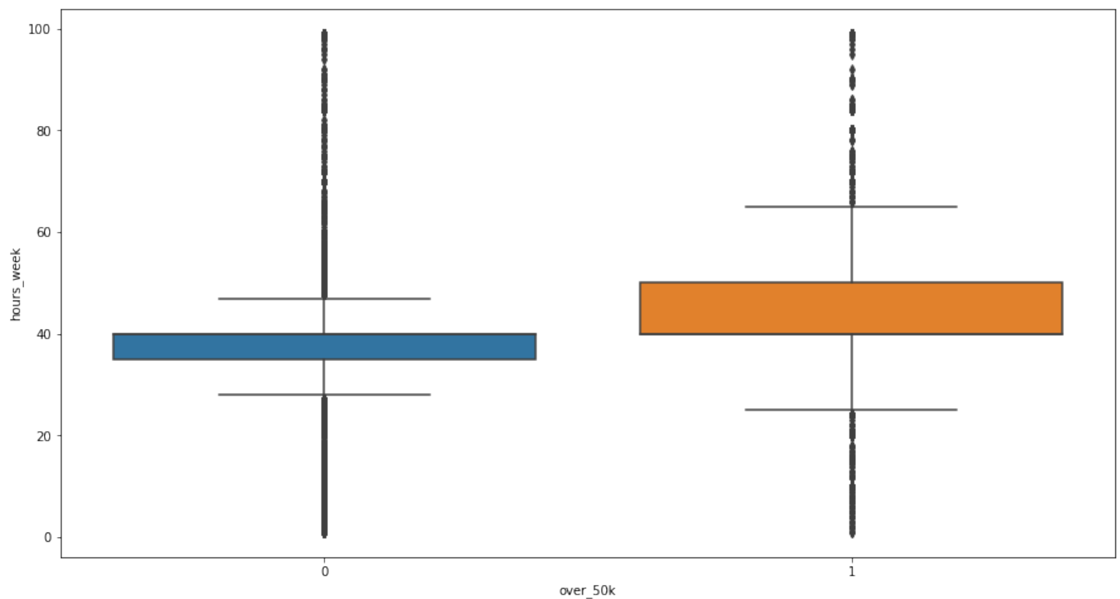
```
                    'HS-grad', 'Some-college', 'Assoc-voc', 'Assoc-acdm',␣
↪'Bachelors', 'Masters', 'Prof-school',
                     'Doctorate'])

# shows strong correlation between years of education and making over 50k
```



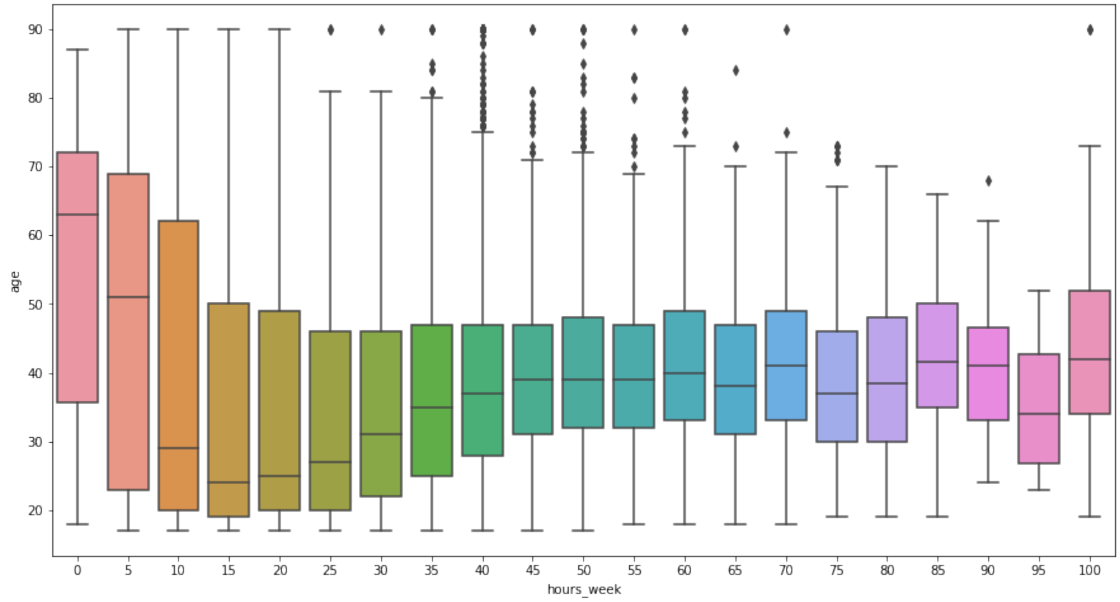
[17]:
```
ax = sns.kdeplot(data['age'].where(data['over_50k']==0), shade=True)
sns.kdeplot(data['age'].where(data['over_50k']==1), shade=True)

ax.set_xlabel('age')
ax.set_ylabel('KDE')
ax.legend( labels=['<50k', '>50k'])
plt.show()
```



[18]:
```
ax = sns.boxplot(x = data['over_50k'], y=data['hours_week'])
plt.show()
```

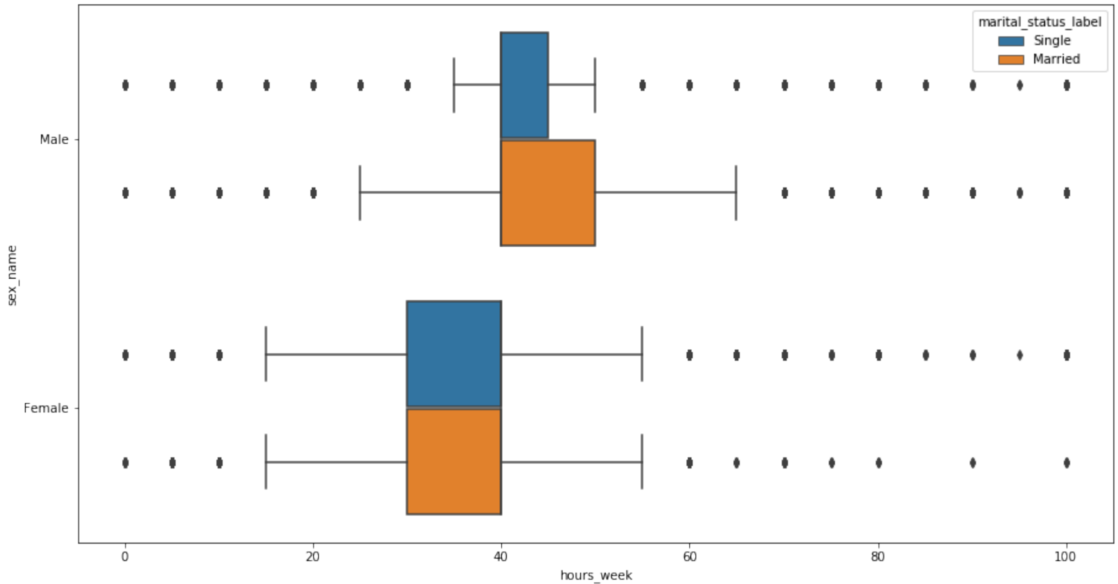


[19]:
```
ax = sns.boxplot(x = data['hours_week'].apply(lambda x: round(x/5) * 5),
    y=data['age'])
plt.show()
```

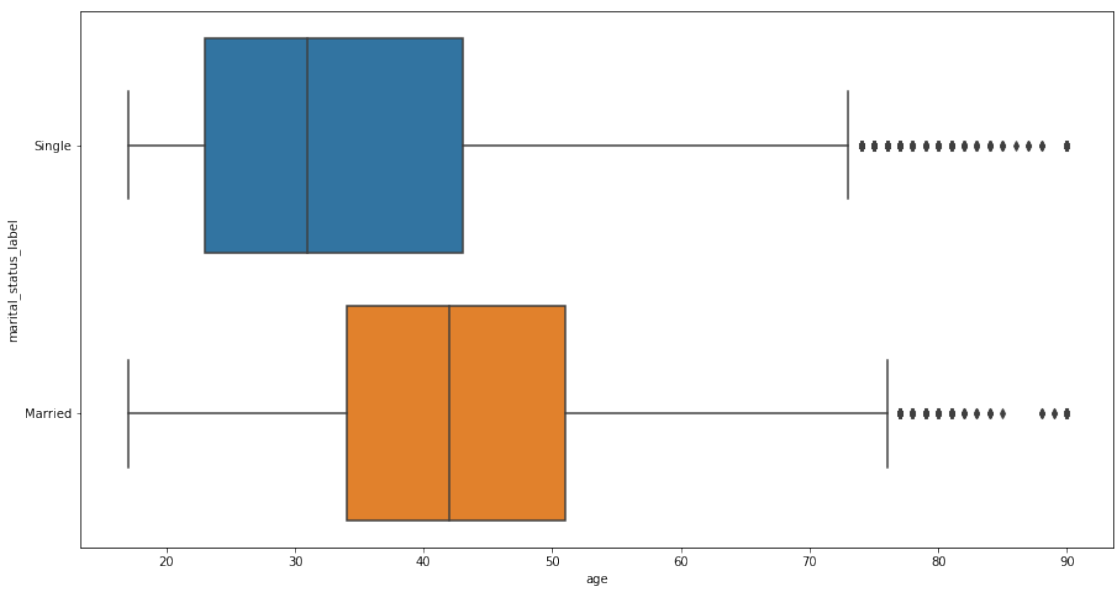


[20]:
```
# making new column for the US, non-US OECD high income, and non-US non-OECD high income
def label_marital_status(row):


    if row['marital_status_name'] in ['Married-civ-spouse', 'Married-AF-spouse']:
        return 'Married'
    else:
        return 'Single'

data['marital_status_label'] = data.apply(lambda row: label_marital_status(row), axis=1)
```

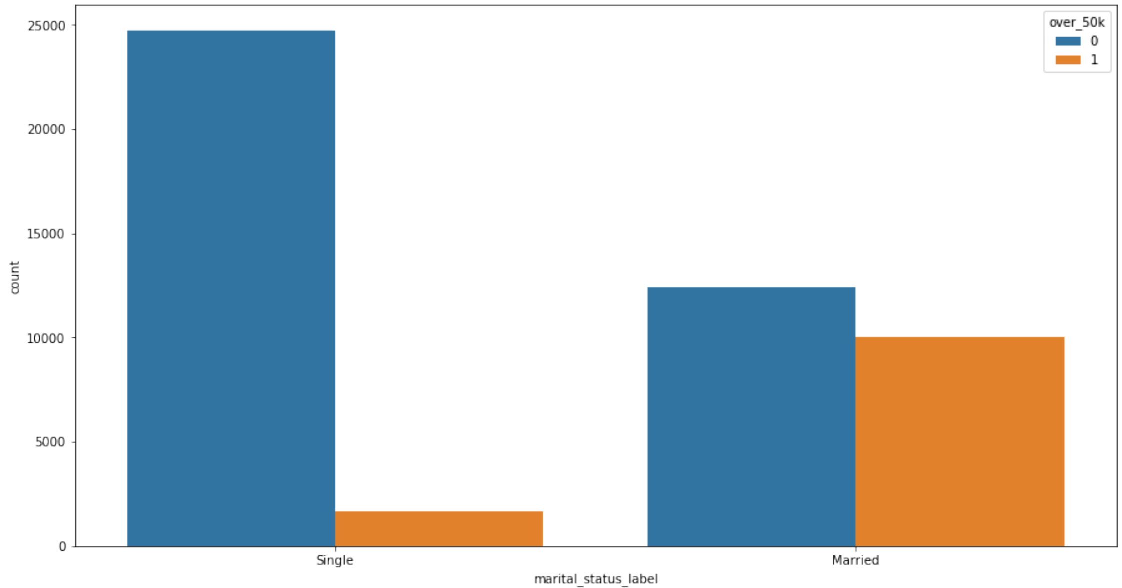
[21]:
```
ax = sns.boxplot(x = data['hours_week'].apply(lambda x: round(x/5) * 5), y=data['sex_name'], hue=data['marital_status_label'])
plt.show()
```



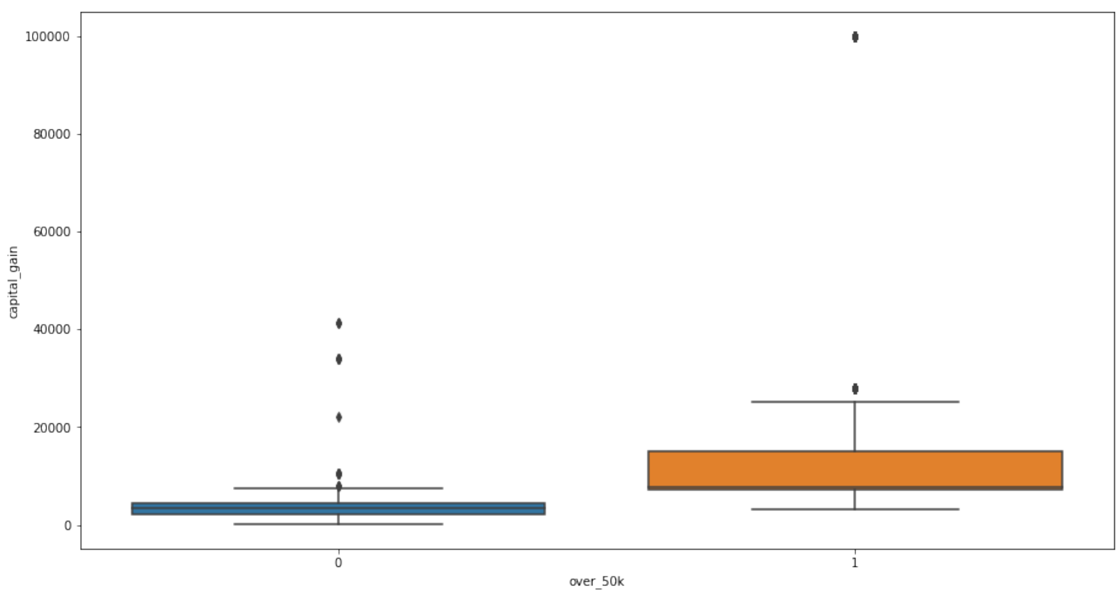
[22]:
```
ax = sns.boxplot(x = data['age'], y=data['marital_status_label'])
plt.show()
```



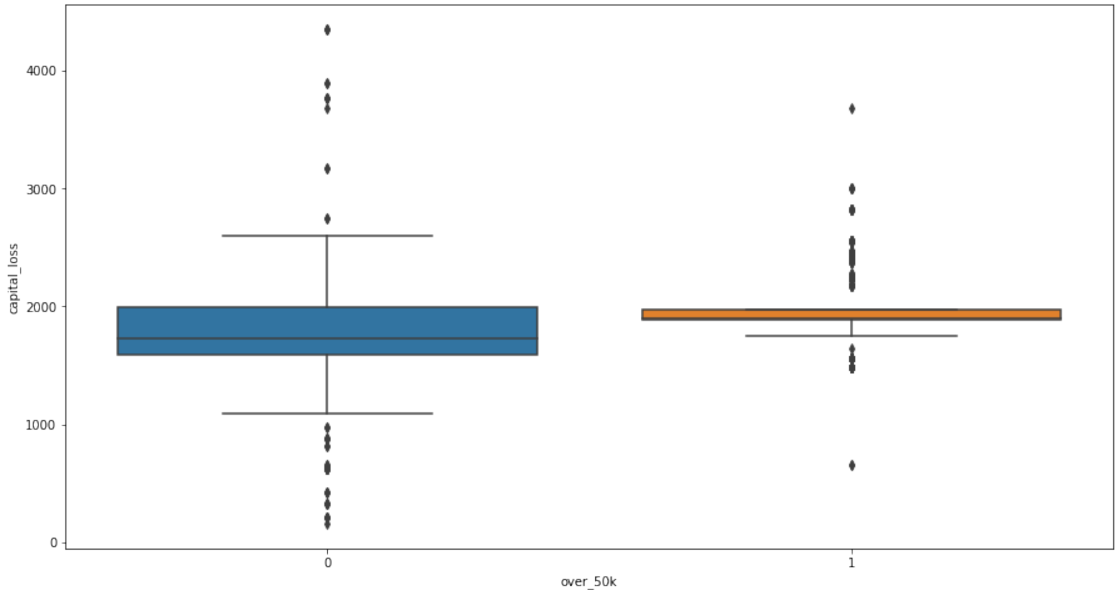
[23]:
```
ax = sns.countplot(data['marital_status_label'], hue=data['over_50k'])
```



[24]:
```
ax = sns.boxplot(x = data['over_50k'], y=data['capital_gain'].
 ↪where(data['capital_gain']>0))
plt.show()
```



[25]:
```
ax = sns.boxplot(x = data['over_50k'], y=data['capital_loss'].
 ↪where(data['capital_loss']>0))
plt.show()
```



6 Building Models

[26]:
```
# reloading data
data = pd.read_csv('../data/exercise01.csv')
data = data.mask(data=='?', float('NaN'))

# imputing the mode for columns with missing data
imp = SimpleImputer(missing_values=float('NaN'), strategy='most_frequent')
data['workclass_name'] = imp.fit_transform(data[['workclass_name']]).ravel()
data['occupation_name'] = imp.fit_transform(data[['occupation_name']]).ravel()
data['country_name'] = imp.fit_transform(data[['country_name']]).ravel()

# checking that nulls have been imputer
null_counts = data.isnull().sum(axis=1)
print(f'{sum(null_counts.mask(null_counts > 0, 1))} rows with 1 or more null␣
↪values, or {sum(null_counts.mask(null_counts > 0, 1))/len(data)*100}% of␣
↪dataset.')

# scaling the larger continuous variables
scaler = StandardScaler()
data['capital_gain'] = scaler.fit_transform(data[['capital_gain']])
data['capital_loss'] = scaler.fit_transform(data[['capital_loss']])

# applying flags and binning
data['marital_status_label'] = data.apply(lambda row:␣
↪label_marital_status(row), axis=1)
```

```
data['country_label'] = data.apply(lambda row: label_country(row), axis=1)
data['ages_binned'] = data['age'].apply(lambda x: round(x/5)*5)
data['hours_week_binned'] = data['hours_week'].apply(lambda x: round(x/10)*10)

# one hot encoding categorical variables
data = pd.concat([data, pd.get_dummies(data['workclass_name'],␣
 ↪prefix='workclass_name')],axis=1).drop(['workclass_name'],axis=1)
data = pd.concat([data, pd.get_dummies(data['occupation_name'],␣
 ↪prefix='occupation_name')],axis=1).drop(['occupation_name'],axis=1)
data = pd.concat([data, pd.get_dummies(data['sex_name'],␣
 ↪prefix='sex_name')],axis=1).drop(['sex_name'],axis=1)
data = pd.concat([data, pd.get_dummies(data['marital_status_label'],␣
 ↪prefix='marital_status_label')],axis=1).drop(['marital_status_label'],axis=1)
data = pd.concat([data, pd.get_dummies(data['country_label'],␣
 ↪prefix='country_label')],axis=1).drop(['country_label'],axis=1)

data.columns
```

```
0 rows with 1 or more null values, or 0.0% of dataset.
```

[26]:
```
Index(['id', 'age', 'workclass_id', 'education_level_id',
       'education_level_name', 'education_num', 'marital_status_id',
       'marital_status_name', 'occupation_id', 'relationship_id',
       'relationship_name', 'race_id', 'race_name', 'sex_id', 'capital_gain',
       'capital_loss', 'hours_week', 'country_id', 'country_name', 'over_50k',
       'ages_binned', 'hours_week_binned', 'workclass_name_Federal-gov',
       'workclass_name_Local-gov', 'workclass_name_Never-worked',
       'workclass_name_Private', 'workclass_name_Self-emp-inc',
       'workclass_name_Self-emp-not-inc', 'workclass_name_State-gov',
       'workclass_name_Without-pay', 'occupation_name_Adm-clerical',
       'occupation_name_Armed-Forces', 'occupation_name_Craft-repair',
       'occupation_name_Exec-managerial', 'occupation_name_Farming-fishing',
       'occupation_name_Handlers-cleaners',
       'occupation_name_Machine-op-inspct', 'occupation_name_Other-service',
       'occupation_name_Priv-house-serv', 'occupation_name_Prof-specialty',
       'occupation_name_Protective-serv', 'occupation_name_Sales',
       'occupation_name_Tech-support', 'occupation_name_Transport-moving',
       'sex_name_Female', 'sex_name_Male', 'marital_status_label_Married',
       'marital_status_label_Single', 'country_label_US',
       'country_label_non-US OECD', 'country_label_non-US non-OECD'],
      dtype='object')
```

[27]:
```
target = ['over_50k']

# list containing only features to be used in the model
features = ['education_num','ages_binned', 'capital_gain', 'capital_loss',
       'hours_week_binned', 'workclass_name_Federal-gov',
```

```
       'workclass_name_Local-gov', 'workclass_name_Never-worked',
       'workclass_name_Private', 'workclass_name_Self-emp-inc',
       'workclass_name_Self-emp-not-inc', 'workclass_name_State-gov',
       'workclass_name_Without-pay', 'occupation_name_Adm-clerical',
       'occupation_name_Armed-Forces', 'occupation_name_Craft-repair',
       'occupation_name_Exec-managerial', 'occupation_name_Farming-fishing',
       'occupation_name_Handlers-cleaners',
       'occupation_name_Machine-op-inspct', 'occupation_name_Other-service',
       'occupation_name_Priv-house-serv', 'occupation_name_Prof-specialty',
       'occupation_name_Protective-serv', 'occupation_name_Sales',
       'occupation_name_Tech-support', 'occupation_name_Transport-moving',
       'sex_name_Female', 'sex_name_Male', 'marital_status_label_Married',
       'marital_status_label_Single', 'country_label_US',
       'country_label_non-US OECD', 'country_label_non-US non-OECD']

# subsetting
X = data[features]
y = data[target]

# creating train, test, holdout datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2,␣
 ↪random_state=RANDOM_STATE)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=.
 ↪2, random_state=RANDOM_STATE)
```

7 2.0 Baseline Model

[28]:
```
# baseline model - guessing 0 for all targets
print(f'{y_train["over_50k"].value_counts()[0]/len(y_train) * 100}% Accuracy␣
 ↪guessing 0 for all rows - train')
print(f'{y_test["over_50k"].value_counts()[0]/len(y_test) * 100}% Accuracy␣
 ↪guessing 0 for all rows - test')
print(f'{y_val["over_50k"].value_counts()[0]/len(y_val) * 100}% Accuracy␣
 ↪guessing 0 for all rows - holdout')
```

```
76.14050802994433% Accuracy guessing 0 for all rows - train
75.92384072064694% Accuracy guessing 0 for all rows - test
75.98208573256558% Accuracy guessing 0 for all rows - holdout
```

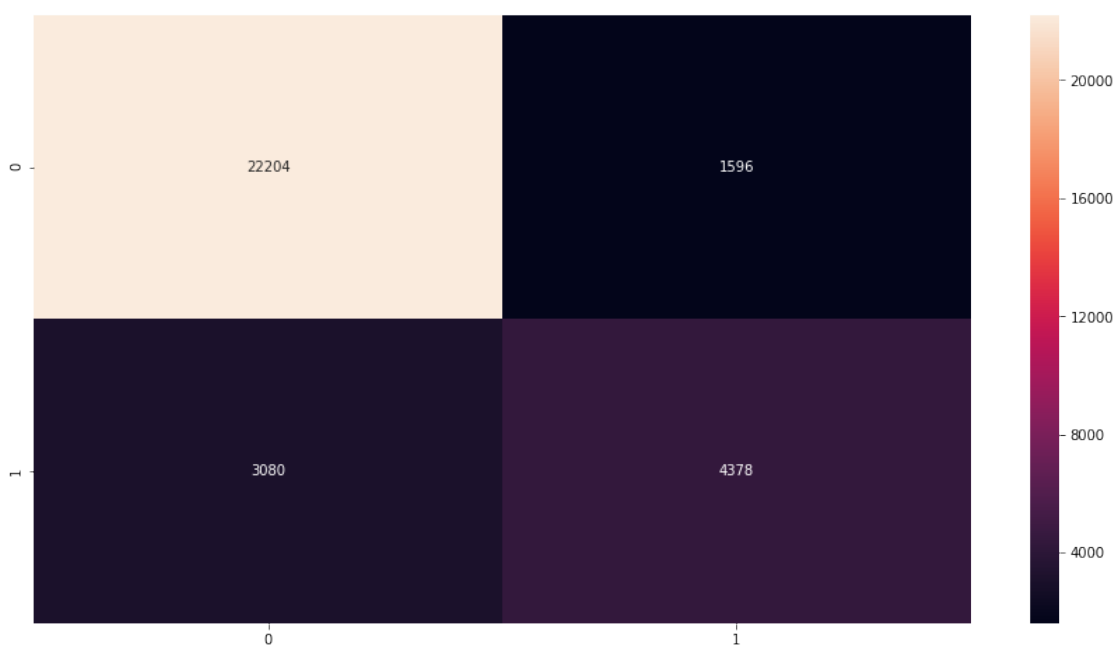
8 2.1 Logistic Regression Model

[49]:
```
clf = LogisticRegression()

# params = {'penalty': ['l1','l2'], 'C': [0.001,0.01,0.1,1,10,100,1000]}
# grid = GridSearchCV(clf, params, cv=12, scoring = 'accuracy', verbose=1)
```

```
# grid.fit(X_train, y_train)
# best params found to be default

clf.fit(X_train, y_train)
pickle.dump(clf, open('../models/LinearRegression_Model.p', 'wb'))
```

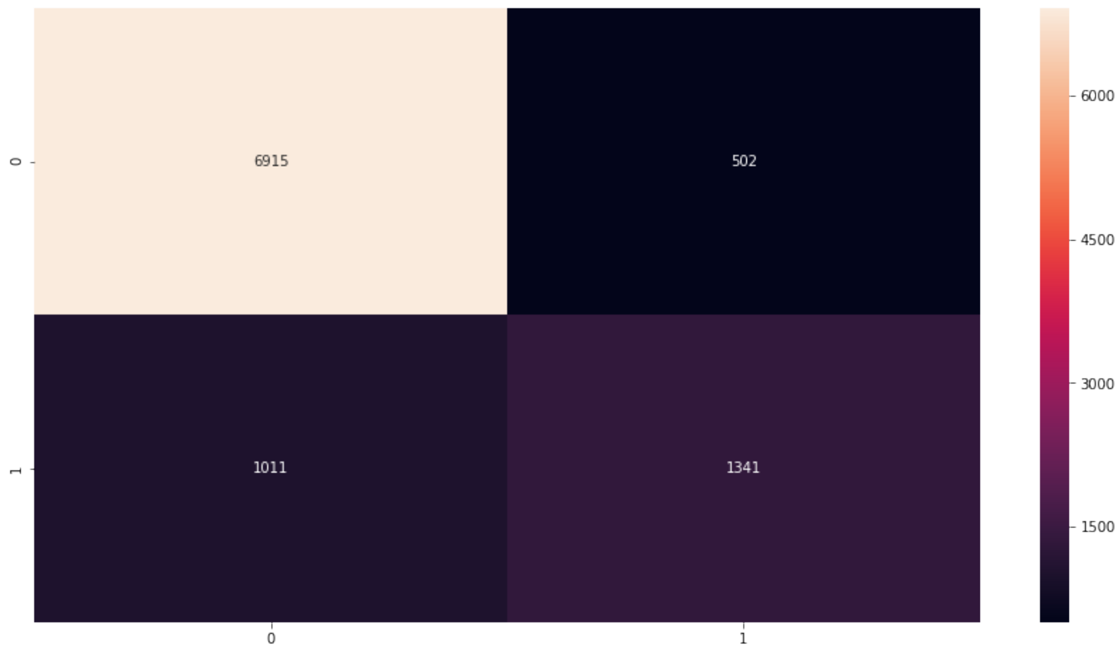
[30]:
```
print(f'{clf.score(X_train, y_train)}% accuracy for train data')
print(classification_report(y_train, clf.predict(X_train)))

preds_test = clf.predict(X_test)

preds_val = clf.predict(X_val)

ax = sns.heatmap(confusion_matrix(y_train,  clf.predict(X_train)), annot=True,␣
 ↪fmt='g')
```

```
0.850406295988227% accuracy for train data
              precision    recall  f1-score   support

           0       0.88      0.93      0.90     23800
           1       0.73      0.59      0.65      7458

    accuracy                           0.85     31258
   macro avg       0.81      0.76      0.78     31258
weighted avg       0.84      0.85      0.84     31258
```



[31]:
```
ax = sns.heatmap(confusion_matrix(y_test, preds_test), annot=True, fmt='g')
print(f'{accuracy_score(y_test, preds_test)}% accuracy for test data')
print(classification_report(y_test, preds_test))
```

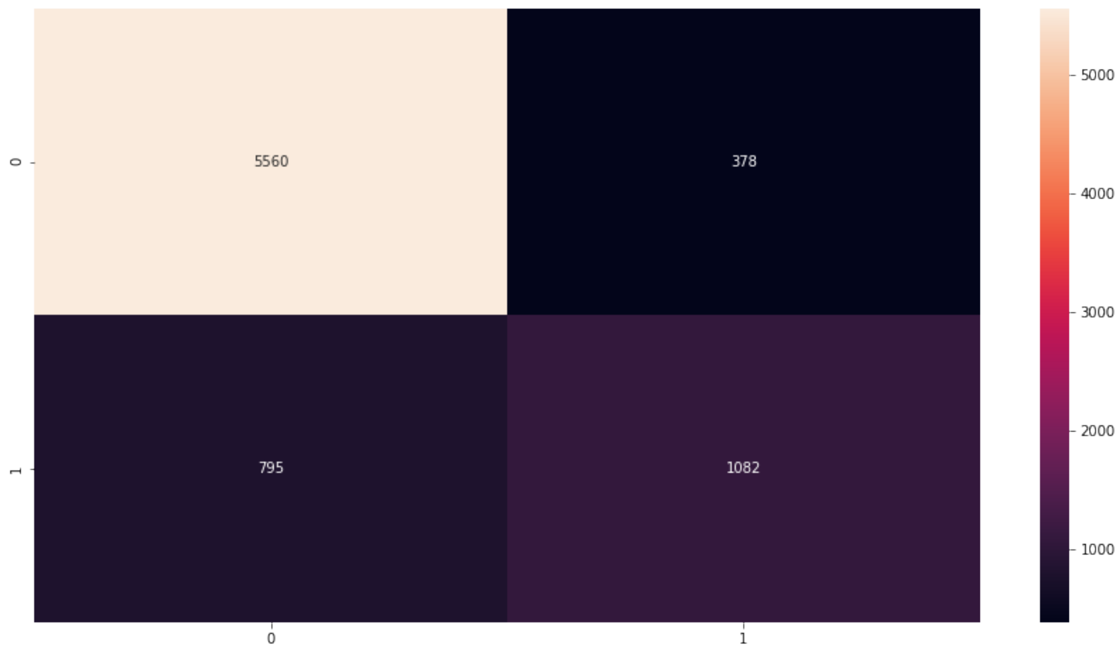
```
0.8451223257242297% accuracy for test data
              precision    recall  f1-score   support

           0       0.87      0.93      0.90      7417
           1       0.73      0.57      0.64      2352

    accuracy                           0.85      9769
   macro avg       0.80      0.75      0.77      9769
weighted avg       0.84      0.85      0.84      9769
```



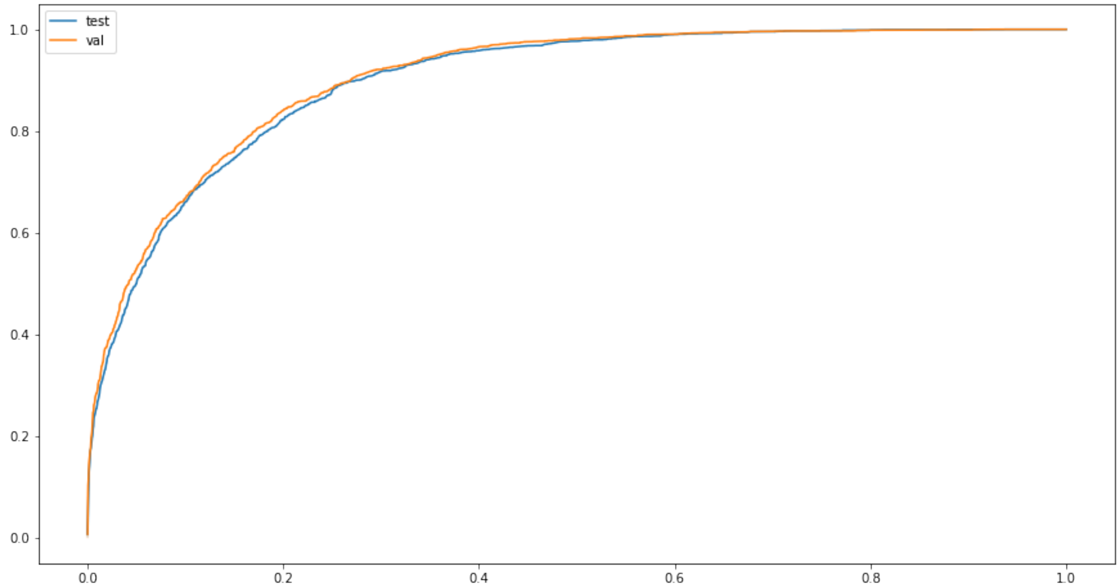
[33]:
```
ax = sns.heatmap(confusion_matrix(y_val, preds_val), annot=True, fmt='g')
print(f'{accuracy_score(y_val, preds_val)}% accuracy for test data')
print(classification_report(y_val, preds_val))
```

```
0.8499040307101727% accuracy for test data
              precision    recall  f1-score   support

           0       0.87      0.94      0.90      5938
           1       0.74      0.58      0.65      1877

    accuracy                           0.85      7815
```

```
   macro avg       0.81      0.76      0.78      7815
weighted avg       0.84      0.85      0.84      7815
```



[34]:
```python
# get confidence scores from samples
conf_scores_test = clf.fit(X_train, y_train).decision_function(X_test)

#calculating fpr, tpr to plot
fpr, tpr, thresholds = roc_curve(y_test, conf_scores_test)
ax = sns.lineplot(fpr, tpr, )

conf_scores_val = clf.fit(X_train, y_train).decision_function(X_val)

fpr,tpr, thresholds = roc_curve(y_val, conf_scores_val)
sns.lineplot(fpr, tpr, )

ax.legend( labels=['test', 'val'])

plt.show()
```



[35]:
```
print(f'{roc_auc_score(y_test, conf_scores_test)} AUC for test')
print((f'{roc_auc_score(y_val, conf_scores_val)} AUC for val'))
```

```
0.8977866392613402 AUC for test
0.9040363905984283 AUC for val
```

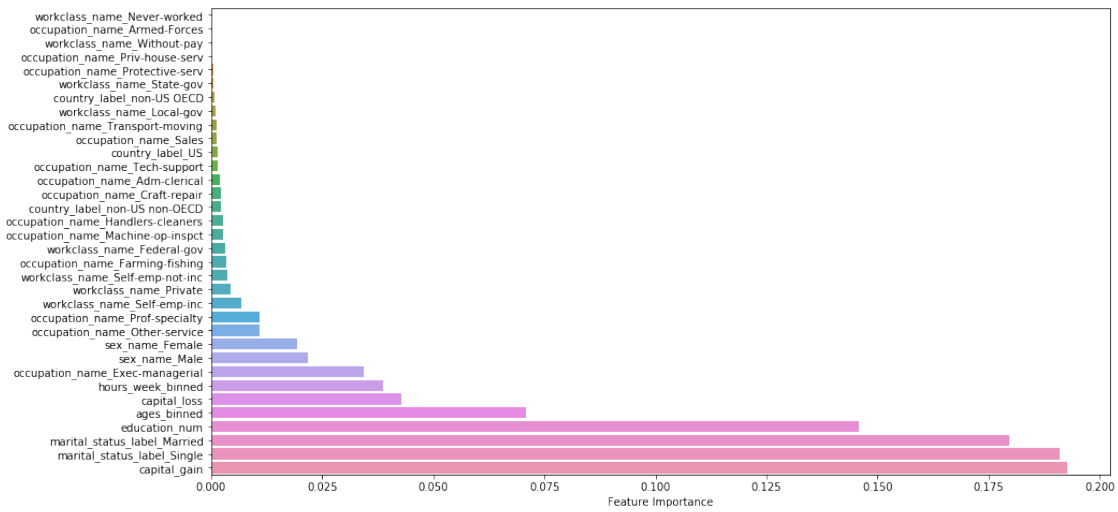
9 2.2 Random Forest Model

[50]:
```
rf = RandomForestClassifier(random_state = RANDOM_STATE, n_estimators=1000,␣
 ↪max_depth=8)

# params = {
#     'n_estimators': [200, 500, 1000],
#     'max_features': ['sqrt', 'log2'],
#     'max_depth' : [2,4,6,8],
#     'criterion' :['gini', 'entropy']
# }

# grid = GridSearchCV(rf, params)
# grid.fit(X_train, y_train)

pickle.dump(clf, open('../models/RandomForest_Model.p', 'wb'))
```

[37]:
```
rf.fit(X_train, y_train)
print(f'{rf.score(X_train, y_train)} mean accuracy for train')
print(f'{rf.score(X_test, y_test)} mean accuracy for test')
print(f'{rf.score(X_val, y_val)} mean accuracy for val')
```

```
0.8634589545076461 mean accuracy for train
0.8582249974408844 mean accuracy for test
0.8632117722328855 mean accuracy for val
```

[38]:
```python
f_importances = rf.feature_importances_
# getting sorted indexes of f_importance
idx = np.argsort(f_importances)

sns.barplot(f_importances[idx], list(range(len(idx))), orient='h')
plt.yticks(range(len(idx)), [features[i] for i in idx])
plt.xlabel('Feature Importance')
plt.show()
```



10 2.2 XGBoost Model

[39]:
```python
import xgboost as xgb
```

[51]:
```python
xgbm = xgb.XGBClassifier(n_estimators=750, min_child_weight=5, max_depth=5,
                         early_stopping=10, gamma=.1, seed=RANDOM_STATE)
pickle.dump(clf, open('../models/XGB_Model.p', 'wb'))
xgbm
```

[51]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, early_stopping=10,
              gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=5,
              min_child_weight=5, missing=None, n_estimators=750, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=90617,
              silent=None, subsample=1, verbosity=1)
```

[41]:
```
xgbm.fit(X_train, y_train)
print(f'{accuracy_score(y_train, xgbm.predict(X_train))}% accuracy for test␣
 ↪data')
print(classification_report(y_train,xgbm.predict(X_train)))
```

```
0.8843176146906392% accuracy for test data
              precision    recall  f1-score   support

           0       0.91      0.95      0.93     23800
           1       0.80      0.69      0.74      7458

    accuracy                           0.88     31258
   macro avg       0.85      0.82      0.83     31258
weighted avg       0.88      0.88      0.88     31258
```

[42]:
```
print(f'{accuracy_score(y_test, xgbm.predict(X_test))}% accuracy for test data')
print(classification_report(y_test,xgbm.predict(X_test)))
```

```
0.8725560446309756% accuracy for test data
              precision    recall  f1-score   support

           0       0.90      0.94      0.92      7417
           1       0.78      0.65      0.71      2352

    accuracy                           0.87      9769
   macro avg       0.84      0.80      0.81      9769
weighted avg       0.87      0.87      0.87      9769
```

[43]:
```
print(f'{accuracy_score(y_val, xgbm.predict(X_val))}% accuracy for test data')
print(classification_report(y_val,xgbm.predict(X_val)))
```

```
0.873576455534229% accuracy for test data
              precision    recall  f1-score   support

           0       0.90      0.94      0.92      5938
           1       0.78      0.66      0.71      1877

    accuracy                           0.87      7815
   macro avg       0.84      0.80      0.82      7815
weighted avg       0.87      0.87      0.87      7815
```

[44]:
```
# graph of shap values - ordered by overall feature importance according to␣
 ↪docs
```

```python
shap_values = shap.TreeExplainer(xgbm).shap_values(X)
shap.summary_plot(shap_values, X)
```