Machine Learning: Adult Census Case Study

http://archive.ics.uci.edu/ml/datasets/Adult (http://archive.ics.uci.edu/ml/datasets/Adult)

In [26]:

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

In [27]:

```
url = 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/'

cnames = [
    'age', 'workclass', 'fnlwgt',
    'education', 'education-num',
    'marital-status', 'occupation',
    'relationship', 'race', 'sex',
    'capital-gain', 'capital-loss',
    'hours-per-week', 'native-country',
    'income'
]

df = pd.read_csv(url + 'adult.data', names=cnames)

df.head()
```

Out[27]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

In [28]:

```
X = df.drop('income', axis=1)
y = df['income']

X.shape, y.shape
```

Out[28]:

```
((32561, 14), (32561,))
```

Data Exploration

In [29]:

```
pd.Series(df['occupation'].unique())
```

Out[29]:

```
0          Adm-clerical
1       Exec-managerial
2     Handlers-cleaners
3        Prof-specialty
4         Other-service
5                 Sales
6          Craft-repair
7     Transport-moving
8       Farming-fishing
9     Machine-op-inspct
10         Tech-support
11                    ?
12      Protective-serv
13         Armed-Forces
14      Priv-house-serv
dtype: object
```

Data Preparation: Sketching

In [30]:

```
X = X.replace({' ?': np.nan})
X.isna().sum()
```

Out[30]:

```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     583
dtype: int64
```

In [31]:

```
{c: X[c].dtype for c in X.columns}
```

Out[31]:

```
{'age': dtype('int64'),
 'workclass': dtype('O'),
 'fnlwgt': dtype('int64'),
 'education': dtype('O'),
 'education-num': dtype('int64'),
 'marital-status': dtype('O'),
 'occupation': dtype('O'),
 'relationship': dtype('O'),
 'race': dtype('O'),
 'sex': dtype('O'),
 'capital-gain': dtype('int64'),
 'capital-loss': dtype('int64'),
 'hours-per-week': dtype('int64'),
 'native-country': dtype('O')}
```

In [32]:

```
df.select_dtypes(include=['O']).columns
```

Out[32]:

```
Index(['workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country', 'income'],
      dtype='object')
```

In [33]:

```
from sklearn.preprocessing import LabelEncoder

unlabelled = df.select_dtypes(include=['O']).columns
encoders = { c: LabelEncoder().fit(df[c]) for c in unlabelled }


encoders
```

Out[33]:

```
{'workclass': LabelEncoder(),
 'education': LabelEncoder(),
 'marital-status': LabelEncoder(),
 'occupation': LabelEncoder(),
 'relationship': LabelEncoder(),
 'race': LabelEncoder(),
 'sex': LabelEncoder(),
 'native-country': LabelEncoder(),
 'income': LabelEncoder()}
```

Data Preparation

Sketching: Encoders, NaNs, Splitting

In [34]:

```
from sklearn.model_selection import train_test_split

train_X, test_X, train_y, test_y = train_test_split(
    X,
    y,
    test_size = 0.3,
    random_state = 3
)
```

In [35]:

```
train_df = train_X.join(train_y).replace({' ?': np.nan}).dropna()
test_df = test_X.join(test_y).replace({' ?': np.nan}).dropna()
```

In [36]:

```
for c in encoders:
    train_df[c] = encoders[c].transform(train_df[c])
    test_df[c] = encoders[c].transform(test_df[c])

train_df.head()
```

Out[36]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
21591	43	4	281138	11	9	5	7	1	
23500	31	4	241885	11	9	2	8	0	
20830	33	4	188352	12	14	4	10	1	
6345	42	5	369781	5	4	0	3	4	
32177	43	4	133584	15	10	2	7	0	

In [37]:

```
from scipy.stats import ttest_ind


pd.Series({ c: ttest_ind(train_df[c], test_df[c]).pvalue for c in train_df.colum
ns })
```

Out[37]:

```
age               0.991788
workclass         0.096669
fnlwgt            0.920012
education         0.190251
education-num     0.713303
marital-status    0.017984
occupation        0.327789
relationship      0.634100
race              0.582117
sex               0.742670
capital-gain      0.335890
capital-loss      0.719606
hours-per-week    0.160184
native-country    0.363897
income            0.208701
dtype: float64
```

Sketching: Scaler Features

In [38]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

pd.DataFrame(
    scaler.fit_transform(train_df.astype(float)),
    columns = train_df.columns
).sample(6)
```

Out[38]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relatior
15921	0.725210	-0.081043	-0.385033	0.170470	-0.439582	1.612497	-0.984115	1.61
9911	0.042594	-0.081043	-0.236049	0.170470	-0.439582	-0.397637	-0.984115	-0.88
14079	-1.626022	-0.081043	-1.105565	-2.462375	-1.226102	0.942452	1.244258	0.98
5266	-0.564175	-0.081043	0.721292	-0.356099	1.133456	0.942452	1.244258	-0.26
3095	-0.943406	-0.081043	0.156173	0.170470	-0.439582	0.942452	-1.479309	0.98
4965	1.028595	0.795959	-1.028661	0.960324	1.919975	-0.397637	1.244258	-0.88

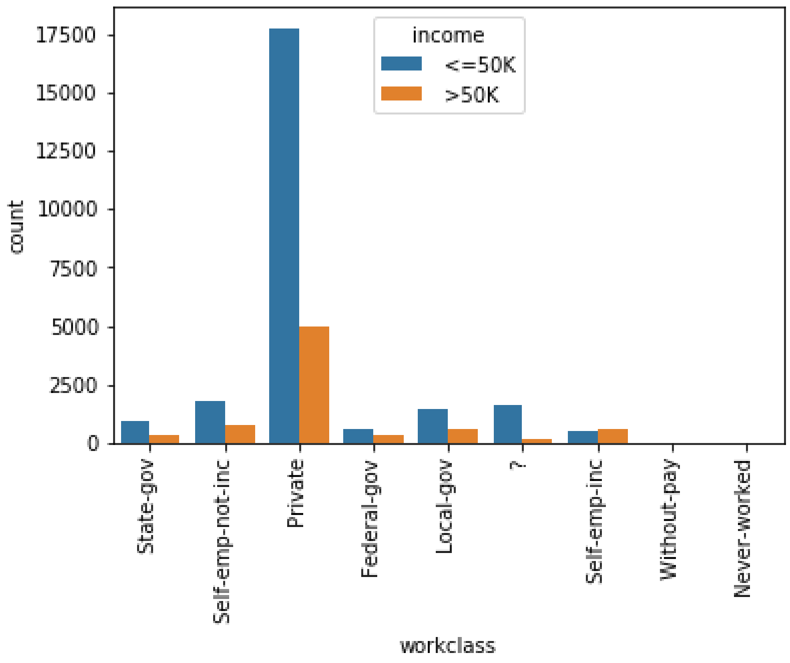
Feature Selection

In [39]:

```
plt.xticks(rotation=90)
sns.countplot(
    data = df,
    x = 'workclass',
    hue = 'income'
)
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b4c25f4be0>
```

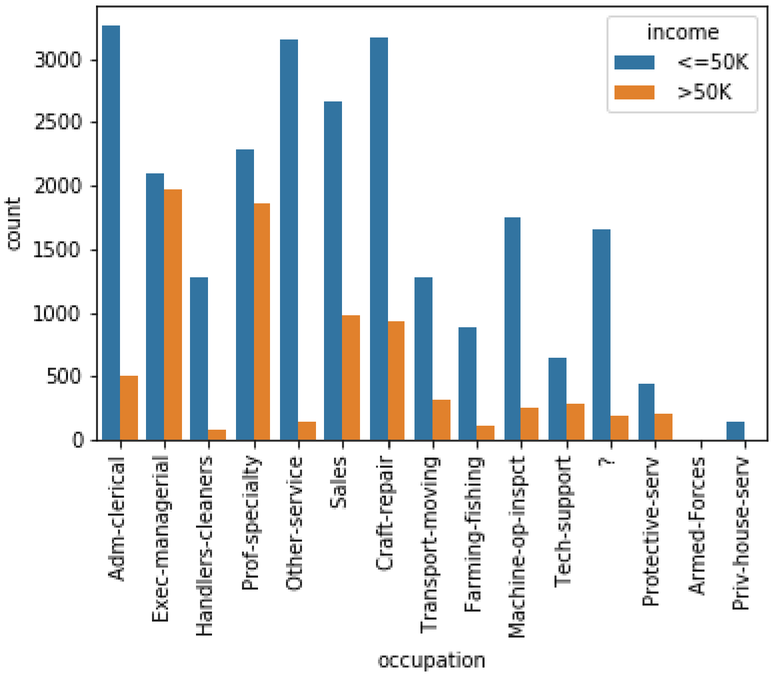


In [40]:

```
plt.xticks(rotation=90)
sns.countplot(
    data = df,
    x = 'occupation',
    hue = 'income'
)
```

Out[40]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b4c2660860>
```

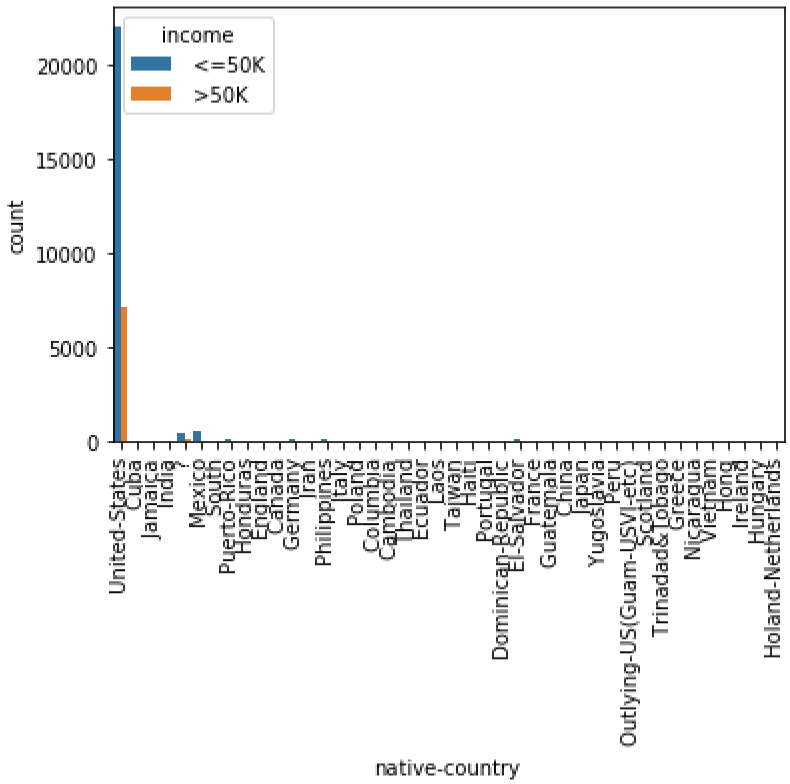


In [41]:

```
plt.xticks(rotation=90)
sns.countplot(
    data = df,
    x = 'native-country',
    hue = 'income'
)
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b4c306b940>
```



In [42]:

```
X = X.drop(['workclass', 'occupation', 'native-country', 'capital-gain'], axis=1
)
```

Defining the Pipeline

In [43]:

```
from sklearn.base import TransformerMixin

class ToNaN(TransformerMixin):
    def fit(self, X): return self

    def transform(self, X):
        return X.replace({' ?': np.nan})
```

In [44]:

```
class ToCleaned(TransformerMixin):
    def fit(self, X): return self

    def transform(self, X):
        return X.dropna(axis=0)
```

In [45]:

```
class ToEncoded(TransformerMixin):
    def fit(self, X):
        labels = X.select_dtypes(include=['O']).columns
        self.encoders = { c: LabelEncoder().fit(X[c]) for c in labels }
        return self

    def transform(self, X):
        for c in self.encoders:
            X[c] = self.encoders[c].transform(X[c])

        return X
```

In [46]:

```
class ToScaled(TransformerMixin):
    def fit(self, X):
        self.scaler = StandardScaler()
        self.scaler.fit(X.astype(float))

        return self

    def transform(self, X):
        df = pd.DataFrame(
            self.scaler.transform(X),
            columns = X.columns
        )

        df['income'] = X['income']
        return df
```

In [47]:

```
class ToSelected(TransformerMixin):
    def fit(self, X): return self

    def transform(self, X):
        return X.drop(['workclass', 'occupation', 'native-country', 'capital-gai
n'], axis=1)
```

In [48]:

```
from sklearn.pipeline import Pipeline

adult_pipeline = Pipeline([
    ('SelectFeatures', ToSelected()),
    ('ReplaceNaN', ToNaN()),
    ('RemoveNaN', ToCleaned()),
    ('EncodeNumeric', ToEncoded()),
    ('ScaleNumeric', ToScaled())
])
```

Data Preparation

In [49]:

```
adult_df = adult_pipeline.fit_transform(df)
adult_df.sample(6)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:10:
DataConversionWarning: Data with input dtype int32, int64 were all c
onverted to float64 by StandardScaler.
  # Remove the CWD from sys.path while we load stuff.
```

Out[49]:

	age	fnlwgt	education	education-num	marital-status	relationship	race	se
16769	-1.142331	0.243155	1.214869	-0.031360	0.921634	-0.277805	0.393668	0.70307
30977	0.397233	0.559911	-0.335437	1.134739	-1.734058	-0.277805	0.393668	0.70307
7084	0.397233	0.609840	0.439716	1.523438	-0.406212	-0.900181	0.393668	0.70307
25626	-1.215643	0.193150	1.214869	-0.031360	0.921634	-0.277805	0.393668	0.70307
4282	-0.555830	1.098204	1.214869	-0.031360	-0.406212	2.211698	-1.962621	-1.42233
2900	0.617171	3.636292	0.181332	-0.420060	-0.406212	-0.900181	0.393668	0.70307

In [50]:

```
X = adult_df.drop('income', axis=1)
y = adult_df['income']

train_X, test_X, train_y, test_y = train_test_split(
    X,
    y,
    test_size = 0.3,
    random_state = 2
)
```

Modelling

In [51]:

```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(
    max_depth = 9
)

model.fit(train_X, train_y)
```

Out[51]:

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_dept
h=9,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='best')
```

Prediction

In [198]:

```
predicted_y = model.predict(test_X)
predicted_y[:5]
```

Out[198]:

```
array([0, 0, 1, 0, 0])
```

Evaluation

In [23]:

```
from sklearn.metrics import confusion_matrix, classification_report
```

In [199]:

```
confusion_matrix(test_y, predicted_y)
```

Out[199]:

```
array([[6763,  597],
       [1089, 1320]])
```

In [68]:

```
l = adult_pipeline.steps[3][1].encoders['income'].classes_

print(classification_report(test_y, model.predict(test_X)))
```

```
              precision    recall  f1-score   support

           0       0.86      0.92      0.89      7360
           1       0.69      0.54      0.61      2409

   micro avg       0.83      0.83      0.83      9769
   macro avg       0.77      0.73      0.75      9769
weighted avg       0.82      0.83      0.82      9769
```

In [64]:

```
help(classification_report)
```

```
Help on function classification_report in module sklearn.metrics.cla
ssification:

classification_report(y_true, y_pred, labels=None, target_names=Non
e, sample_weight=None, digits=2, output_dict=False)
    Build a text report showing the main classification metrics

    Read more in the :ref:`User Guide <classification_report>`.

    Parameters
    ----------
    y_true : 1d array-like, or label indicator array / sparse matrix
        Ground truth (correct) target values.

    y_pred : 1d array-like, or label indicator array / sparse matrix
        Estimated targets as returned by a classifier.

    labels : array, shape = [n_labels]
        Optional list of label indices to include in the report.

    target_names : list of strings
        Optional display names matching the labels (same order).

    sample_weight : array-like of shape = [n_samples], optional
        Sample weights.

    digits : int
        Number of digits for formatting output floating point value
s.
        When ``output_dict`` is ``True``, this will be ignored and t
he
        returned values will not be rounded.

    output_dict : bool (default = False)
        If True, return output as dict

    Returns
    -------
    report : string / dict
        Text summary of the precision, recall, F1 score for each cla
ss.
        Dictionary returned if output_dict is True. Dictionary has t
he
        following structure::

            {'label 1': {'precision':0.5,
                         'recall':1.0,
                         'f1-score':0.67,
                         'support':1},
             'label 2': { ... },
              ...
            }

        The reported averages include micro average (averaging the
        total true positives, false negatives and false positives),
macro
        average (averaging the unweighted mean per label), weighted
average
        (averaging the support-weighted mean per label) and sample a
verage
        (only for multilabel classification). See also
```

```
        :func:`precision_recall_fscore_support` for more details on
averages.

        Note that in binary classification, recall of the positive c
lass
        is also known as "sensitivity"; recall of the negative class
is
        "specificity".

    Examples
    --------
    >>> from sklearn.metrics import classification_report
    >>> y_true = [0, 1, 2, 2, 2]
    >>> y_pred = [0, 0, 2, 2, 1]
    >>> target_names = ['class 0', 'class 1', 'class 2']
    >>> print(classification_report(y_true, y_pred, target_names=tar
get_names))
                  precision    recall  f1-score   support
    <BLANKLINE>
         class 0       0.50      1.00      0.67         1
         class 1       0.00      0.00      0.00         1
         class 2       1.00      0.67      0.80         3
    <BLANKLINE>
       micro avg       0.60      0.60      0.60         5
       macro avg       0.50      0.56      0.49         5
    weighted avg       0.70      0.60      0.61         5
    <BLANKLINE>
```

Improvements

In [204]:

```python
from sklearn.ensemble import RandomForestClassifier


model = RandomForestClassifier(
     max_depth = 7,
     n_estimators = 20,
     class_weight = {0:1, 1:1}
)

model.fit(train_X, train_y)
```

Out[204]:

```
RandomForestClassifier(bootstrap=True, class_weight={0: 1, 1: 1},
            criterion='gini', max_depth=7, max_features='auto',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=20, n_jobs=None, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

In [205]:

```
print(classification_report(test_y, model.predict(test_X)))
```

```
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7360
           1       0.73      0.46      0.57      2409

   micro avg       0.83      0.83      0.83      9769
   macro avg       0.79      0.70      0.73      9769
weighted avg       0.82      0.83      0.81      9769
```

In [211]:

```
from sklearn.model_selection import GridSearchCV

params = {'max_depth': [5,9,15],
          'n_estimators': [10, 50, 100, 150]}

model = GridSearchCV(
    RandomForestClassifier(class_weight = {0:1, 1:1}),
    params,
    scoring = 'f1_macro'
)

model.fit(X, y)
model.best_estimator_
```

```
/Users/mjburgess/anaconda3/lib/python3.7/site-packages/sklearn/model
_selection/_split.py:2053: FutureWarning: You should specify a value
for 'cv' instead of relying on the default value. The default value
will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

Out[211]:

```
RandomForestClassifier(bootstrap=True, class_weight={0: 1, 1: 1},
            criterion='gini', max_depth=15, max_features='auto',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=150, n_jobs=None, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

In [212]:

```
print(classification_report(test_y, model.best_estimator_.predict(test_X)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.95      0.93      7360
           1       0.82      0.69      0.75      2409

   micro avg       0.89      0.89      0.89      9769
   macro avg       0.86      0.82      0.84      9769
weighted avg       0.88      0.89      0.88      9769
```