```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import cufflinks as cf
%matplotlib inline

from scipy import stats
from sklearn.model_selection import train_test_split, GridSearchCV, cross_validate, StratifiedKFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.preprocessing import PowerTransformer, OneHotEncoder, LabelEncoder
from sklearn.pipeline import Pipeline


from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

from sklearn.metrics import make_scorer, precision_score, recall_score, f1_score, accuracy_score
from sklearn.metrics import PrecisionRecallDisplay, roc_curve, average_precision_score, precision_recall_curve
from sklearn.metrics import RocCurveDisplay, roc_auc_score, auc
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay


from yellowbrick.regressor import ResidualsPlot, PredictionError

import warnings
warnings.filterwarnings("ignore")


df = pd.read_csv("/content/adult.csv")

df.shape
```

```
(32561, 15)
```

```
df.head().T
```

	0	1	2	3	4
age	90	82	66	54	41
workclass	?	Private	?	Private	Private
fnlwgt	77053	132870	186061	140359	264663
education	HS-grad	HS-grad	Some-college	7th-8th	Some-college
education.num	9	9	10	4	10
marital.status	Widowed	Widowed	Widowed	Divorced	Separated
occupation	?	Exec-managerial	?	Machine-op-inspct	Prof-specialty
relationship	Not-in-family	Not-in-family	Unmarried	Unmarried	Own-child
race	White	White	Black	White	White
sex	Female	Female	Female	Female	Female
capital.gain	0	0	0	0	0
capital.loss	4356	4356	4356	3900	3900
hours.per.week	40	18	40	40	40
native.country	United-States	United-States	United-States	United-States	United-States
income	<=50K	<=50K	<=50K	<=50K	<=50K

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
```

```
 4   education.num   32561 non-null  int64
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64
 11  capital.loss    32561 non-null  int64
 12  hours.per.week  32561 non-null  int64
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
df.describe()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

```
df.describe(include= 'object').T
```

	count	unique	top	freq
workclass	32561	9	Private	22696
education	32561	16	HS-grad	10501
marital.status	32561	7	Married-civ-spouse	14976
occupation	32561	15	Prof-specialty	4140
relationship	32561	6	Husband	13193
race	32561	5	White	27816
sex	32561	2	Male	21790
native.country	32561	42	United-States	29170
income	32561	2	<=50K	24720

```
def summary(df, pred=None):
    obs = df.shape[0]
    Types = df.dtypes
    Counts = df.apply(lambda x: x.count())
    Min = df.min()
    Max = df.max()
    Uniques = df.apply(lambda x: x.unique().shape[0])
    Nulls = df.apply(lambda x: x.isnull().sum())
    print('Data shape:', df.shape)

    if pred is None:
        cols = ['Types', 'Counts', 'Uniques', 'Nulls', 'Min', 'Max']
        str = pd.concat([Types, Counts, Uniques, Nulls, Min, Max], axis = 1, sort=True)

    str.columns = cols
    print('_______________________________\nData Types:')
    print(str.Types.value_counts())
    print('_______________________________')
    return str

summary(df)
```

```
Data shape: (32561, 15)
_____________________________
Data Types:
Types
object    9
int64     6
Name: count, dtype: int64
_____________________________
```

	Types	Counts	Uniques	Nulls	Min	Max
age	int64	32561	73	0	17	90
capital.gain	int64	32561	119	0	0	99999
capital.loss	int64	32561	92	0	0	4356
education	object	32561	16	0	10th	Some-college
education.num	int64	32561	16	0	1	16
fnlwgt	int64	32561	21648	0	12285	1484705
hours.per.week	int64	32561	94	0	1	99
income	object	32561	2	0	<=50K	>50K
marital.status	object	32561	7	0	Divorced	Widowed
native.country	object	32561	42	0	?	Yugoslavia
occupation	object	32561	15	0	?	Transport-moving
race	object	32561	5	0	Amer-Indian-Eskimo	White
relationship	object	32561	6	0	Husband	Wife
sex	object	32561	2	0	Female	Male
workclass	object	32561	9	0	?	Without-pay

```
df.duplicated().sum()
```

```
24
```

```
def duplicate_values(df):
    print("Duplicate check...")
    num_duplicates = df.duplicated(subset=None, keep='first').sum()
    if num_duplicates > 0:
        print("There are", num_duplicates, "duplicated observations in the dataset.")
        df.drop_duplicates(keep='first', inplace=True)
        print(num_duplicates, "duplicates were dropped!")
        print("No more duplicate rows!")
    else:
        print("There are no duplicated observations in the dataset.")

duplicate_values(df)
```

```
Duplicate check...
There are 24 duplicated observations in the dataset.
24 duplicates were dropped!
No more duplicate rows!
```

```
def get_unique_values(df):
    output_data = []
    for col in df.columns:
        # Check if the column has more than 10 unique values
        if df.loc[:, col].nunique() <= 10:
            # Get the unique values in the column
            unique_values = df.loc[:, col].unique()
            # Append the column name, number of unique values, unique values, and data type to the output data
            output_data.append([col, df.loc[:, col].nunique(), unique_values, df.loc[:, col].dtype])
        else:
            # Otherwise, append only the column name, number of unique values, and data type to the output data
            output_data.append([col, df.loc[:, col].nunique(),"-", df.loc[:, col].dtype])

    output_df = pd.DataFrame(output_data, columns=['Column Name', 'Number of Unique Values', ' Unique Values ', 'Data Type'])

    return output_df


get_unique_values(df)
```

	Column Name	Number of Unique Values	Unique Values	Data Type
0	age	73	-	int64
1	workclass	9	[?, Private, State-gov, Federal-gov, Self-emp-...	object
2	fnlwgt	21648	-	int64
3	education	16	-	object
4	education.num	16	-	int64
5	marital.status	7	[Widowed, Divorced, Separated, Never-married, ...	object
6	occupation	15	-	object
7	relationship	6	[Not-in-family, Unmarried, Own-child, Other-re...	object
8	race	5	[White, Black, Asian-Pac-Islander, Other, Amer...	object
9	sex	2	[Female, Male]	object
10	capital.gain	119	-	int64
11	capital.loss	92	-	int64
12	hours.per.week	94	-	int64
13	native.country	42	-	object
14	income	2	[<=50K, >50K]	object

```
get_unique_values(df)
```

	Column Name	Number of Unique Values	Unique Values	Data Type
0	age	73	-	int64
1	workclass	9	[?, Private, State-gov, Federal-gov, Self-emp-...	object
2	fnlwgt	21648	-	int64
3	education	16	-	object
4	education.num	16	-	int64
5	marital.status	7	[Widowed, Divorced, Separated, Never-married, ...	object
6	occupation	15	-	object
7	relationship	6	[Not-in-family, Unmarried, Own-child, Other-re...	object
8	race	5	[White, Black, Asian-Pac-Islander, Other, Amer...	object
9	sex	2	[Female, Male]	object
10	capital.gain	119	-	int64
11	capital.loss	92	-	int64
12	hours.per.week	94	-	int64
13	native.country	42	-	object
14	income	2	[<=50K, >50K]	object

```
def missing_values(df):

    missing_count = df.isnull().sum()
    value_count = df.isnull().count()
    missing_percentage = round(missing_count / value_count * 100, 2)
    missing_df = pd.DataFrame({"count": missing_count, "percentage": missing_percentage})
    return missing_df

missing_values(df)
```

	count	percentage
age	0	0.0
workclass	0	0.0
fnlwgt	0	0.0
education	0	0.0
education.num	0	0.0
marital.status	0	0.0
occupation	0	0.0
relationship	0	0.0
race	0	0.0
sex	0	0.0
capital.gain	0	0.0
capital.loss	0	0.0
hours.per.week	0	0.0
native.country	0	0.0
income	0	0.0

```
df[df == '?'] = np.nan

missing_values(df)
```

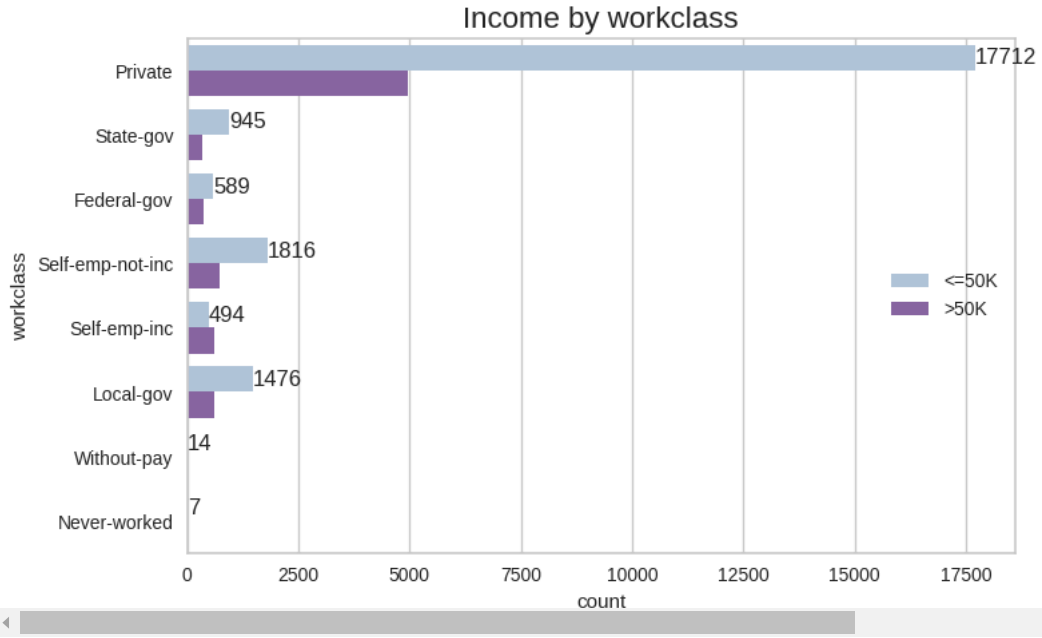
	count	percentage
age	0	0.00
workclass	1836	5.64
fnlwgt	0	0.00
education	0	0.00
education.num	0	0.00
marital.status	0	0.00
occupation	1843	5.66
relationship	0	0.00
race	0	0.00
sex	0	0.00
capital.gain	0	0.00
capital.loss	0	0.00
hours.per.week	0	0.00
native.country	582	1.79
income	0	0.00

```
df['workclass'].value_counts(normalize=True)
```

workclass	proportion
Private	0.738510
Self-emp-not-inc	0.082733
Local-gov	0.068174
State-gov	0.042279
Self-emp-inc	0.036351
Federal-gov	0.031269
Without-pay	0.000456
Never-worked	0.000228

```
plt.figure(figsize = (8,5))
ax = sns.countplot(y = df['workclass'], hue = df['income'] , palette='BuPu')
plt.title("Income by workclass", fontsize = 16)
ax.bar_label(ax.containers[0]);
ax.legend(loc='center right')
```

```
<matplotlib.legend.Legend at 0x7c45e64296c0>
```




```
df['workclass'] = df['workclass'].fillna('Private')
```

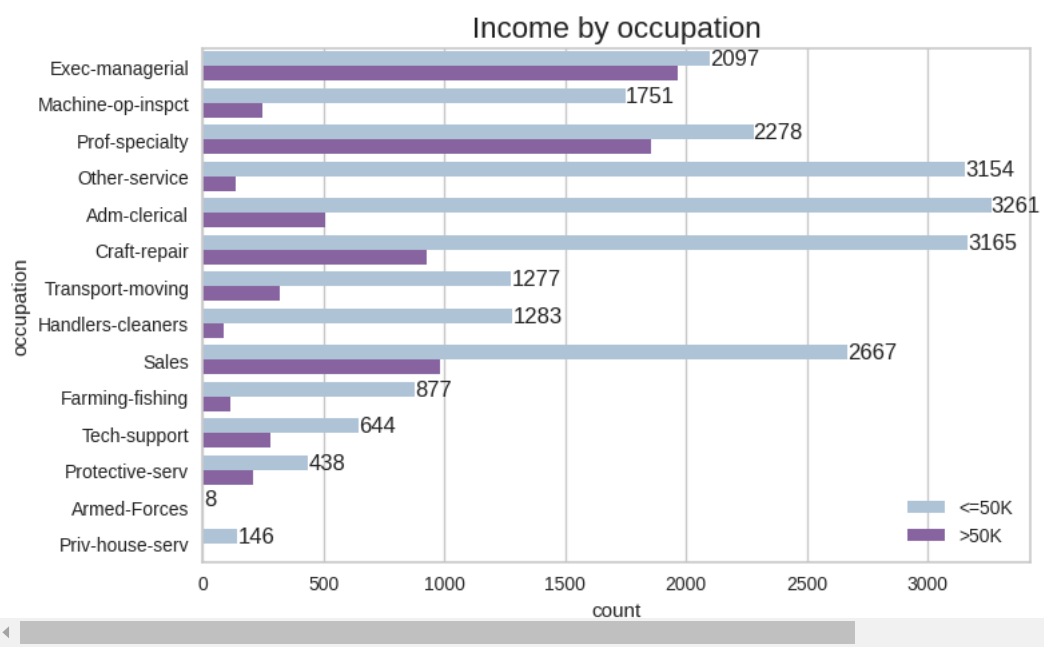
```
missing_values(df)
```

	count	percentage
age	0	0.00
workclass	0	0.00
fnlwgt	0	0.00
education	0	0.00
education.num	0	0.00
marital.status	0	0.00
occupation	1843	5.66
relationship	0	0.00
race	0	0.00
sex	0	0.00
capital.gain	0	0.00
capital.loss	0	0.00
hours.per.week	0	0.00
native.country	582	1.79
income	0	0.00

```
df['occupation'].value_counts(normalize=True)
```

occupation	proportion
Prof-specialty	0.134749
Craft-repair	0.133381
Exec-managerial	0.132436
Adm-clerical	0.122760
Sales	0.118916
Other-service	0.107220
Machine-op-inspct	0.065159
Transport-moving	0.052030
Handlers-cleaners	0.044602
Farming-fishing	0.032319
Tech-support	0.030201
Protective-serv	0.021144
Priv-house-serv	0.004789
Armed-Forces	0.000293

```
plt.figure(figsize = (8,5))
ax = sns.countplot(y = df['occupation'], hue = df['income'], palette='BuPu')
plt.title("Income by occupation", fontsize = 16)
ax.bar_label(ax.containers[0])
ax.legend(loc='lower right')
plt.show()
```




```
df['occupation'] = df['occupation'].fillna(df['occupation'].mode()[0])
```

```
missing_values(df)
```

	count	percentage
age	0	0.00
workclass	0	0.00
fnlwgt	0	0.00
education	0	0.00
education.num	0	0.00
marital.status	0	0.00
occupation	0	0.00
relationship	0	0.00
race	0	0.00
sex	0	0.00
capital.gain	0	0.00
capital.loss	0	0.00
hours.per.week	0	0.00
native.country	582	1.79
income	0	0.00

```
df['native.country'].value_counts(normalize=True)
```

native.country	proportion
United-States	0.912314
Mexico	0.019997
Philippines	0.006196
Germany	0.004287
Canada	0.003787
Puerto-Rico	0.003568
El-Salvador	0.003317
India	0.003129
Cuba	0.002973
England	0.002816
Jamaica	0.002535
South	0.002504
China	0.002347
Italy	0.002284
Dominican-Republic	0.002191
Vietnam	0.002097
Guatemala	0.001940
Japan	0.001940
Poland	0.001878
Columbia	0.001846
Taiwan	0.001596
Haiti	0.001377
Iran	0.001346
Portugal	0.001158
Nicaragua	0.001064
Peru	0.000970
Greece	0.000908
France	0.000908
Ecuador	0.000876
Ireland	0.000751
Hong	0.000626
Trinadad&Tobago	0.000595
Cambodia	0.000595
Thailand	0.000563
Laos	0.000563
Yugoslavia	0.000501
Outlying-US(Guam-USVI-etc)	0.000438
Hungary	0.000407
Honduras	0.000407
Scotland	0.000376
Holand-Netherlands	0.000031

dtype: float64

```
df['native.country'].mode()[0]
```

```
'United-States'
```

```
df['native.country'] = df['native.country'].fillna('United-States')
```

```
missing_values(df)
```

	count	percentage
age	0	0.0
workclass	0	0.0
fnlwgt	0	0.0
education	0	0.0
education.num	0	0.0
marital.status	0	0.0
occupation	0	0.0
relationship	0	0.0
race	0	0.0
sex	0	0.0
capital.gain	0	0.0
capital.loss	0	0.0
hours.per.week	0	0.0
native.country	0	0.0
income	0	0.0

```
def value_cnt_fonc(df, column_name):
    vc = df[column_name].value_counts()
    vc_norm = df[column_name].value_counts(normalize=True)

    vc = vc.rename_axis(column_name).reset_index(name='counts')
    vc_norm = vc_norm.rename_axis(column_name).reset_index(name='norm_counts')

    df_result = pd.concat([vc[column_name], vc['counts'], vc_norm['norm_counts']], axis=1)

    return df_result


cat_features = df.select_dtypes(include='object').columns
num_features = df.select_dtypes(include=['int64','float64']).columns

print('Categoricals:', list(cat_features))
print('---------------------------')
print('Numericals:',list(num_features))
```

```
Categoricals: ['workclass', 'education', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'native.country', 'income']
---------------------------
Numericals: ['age', 'fnlwgt', 'education.num', 'capital.gain', 'capital.loss', 'hours.per.week']
```

```
value_cnt_fonc(df, 'income')
```

	income	counts	norm_counts
0	<=50K	24698	0.759074
1	>50K	7839	0.240926

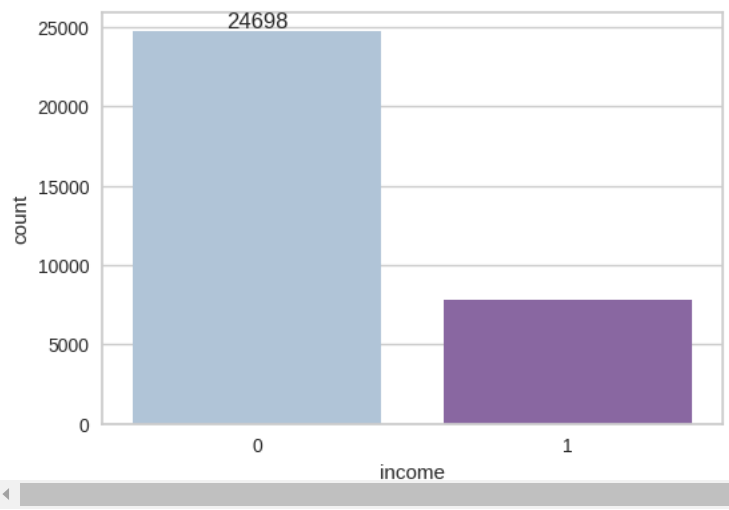
```
df['income'] = df['income'].map({'<=50K': 0, '>50K': 1})


df.sample(3)
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	cap
5183	68	Private	140282	7th-8th	4	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	
3529	36	Private	115360	10th	6	Married-civ-spouse	Machine-op-inspct	Own-child	White	Female	3464	
27914	30	Private	154568	Bachelors	13	Married-civ-spouse	Craft-repair	Husband	Asian-Pac-Islander	Male	0	

```
income_less_50K = df[df['income'] == 0].shape[0]
income_over_50K = df[df['income'] == 1].shape[0]

print(f"Income <= 50K (0) count: {income_less_50K}")
print(f"Income >  50K (1) count: {income_over_50K}")
```

```
Income <= 50K (0) count: 24698
Income >  50K (1) count: 7839
```

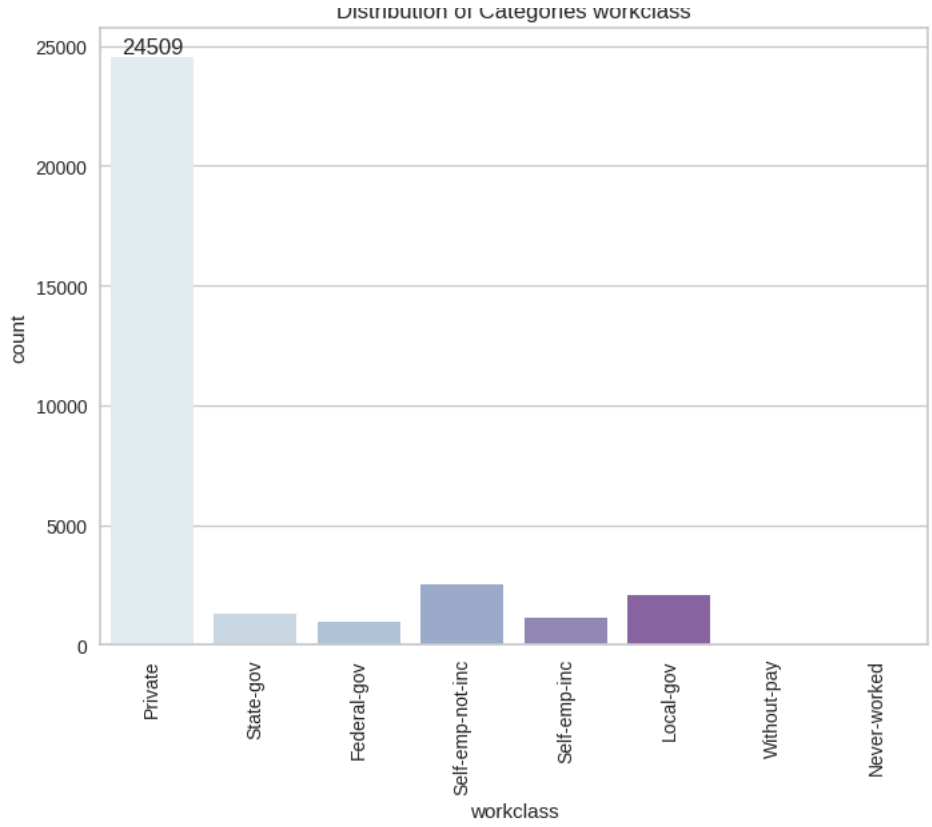
```
plt.figure(figsize=(6,4))
ax = sns.countplot( data=df, x="income", palette='BuPu')

ax.bar_label(ax.containers[0])
plt.show()
```

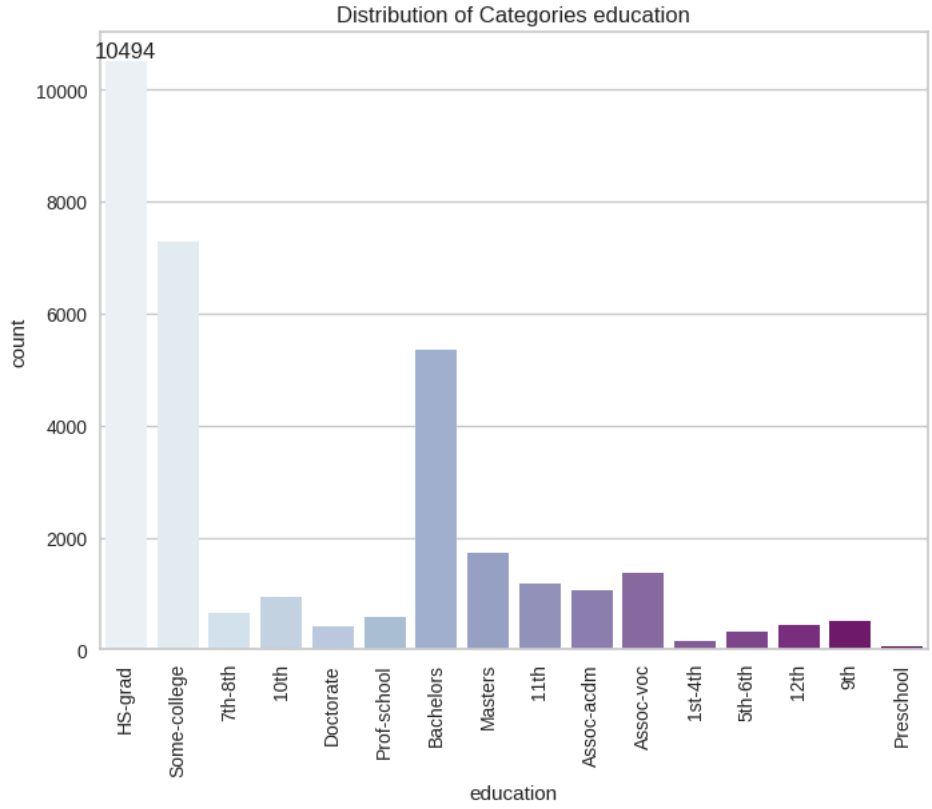


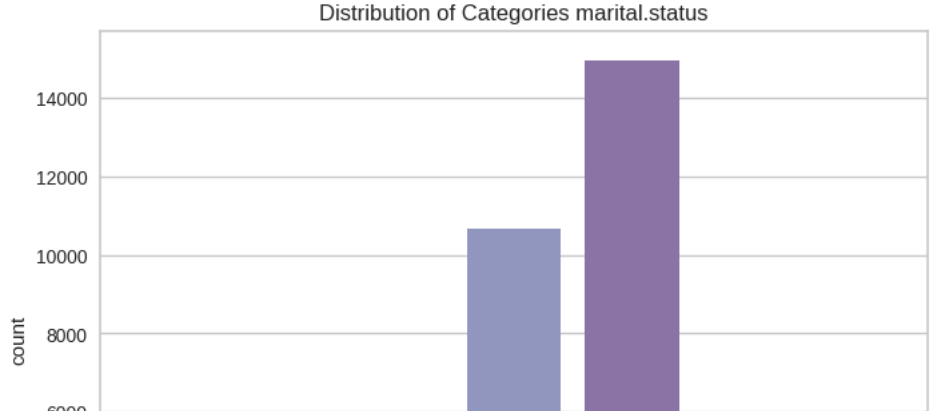

```
list(cat_features)
```

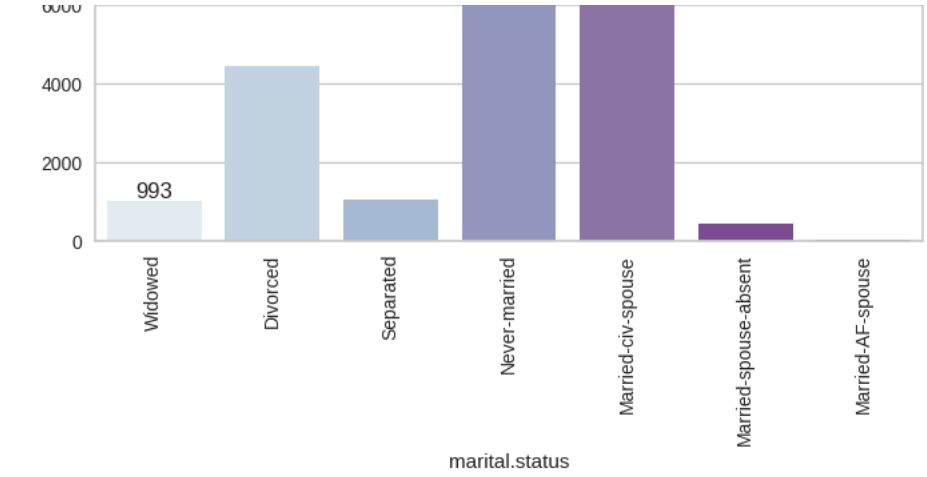
```
['workclass',
 'education',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native.country',
 'income']
```

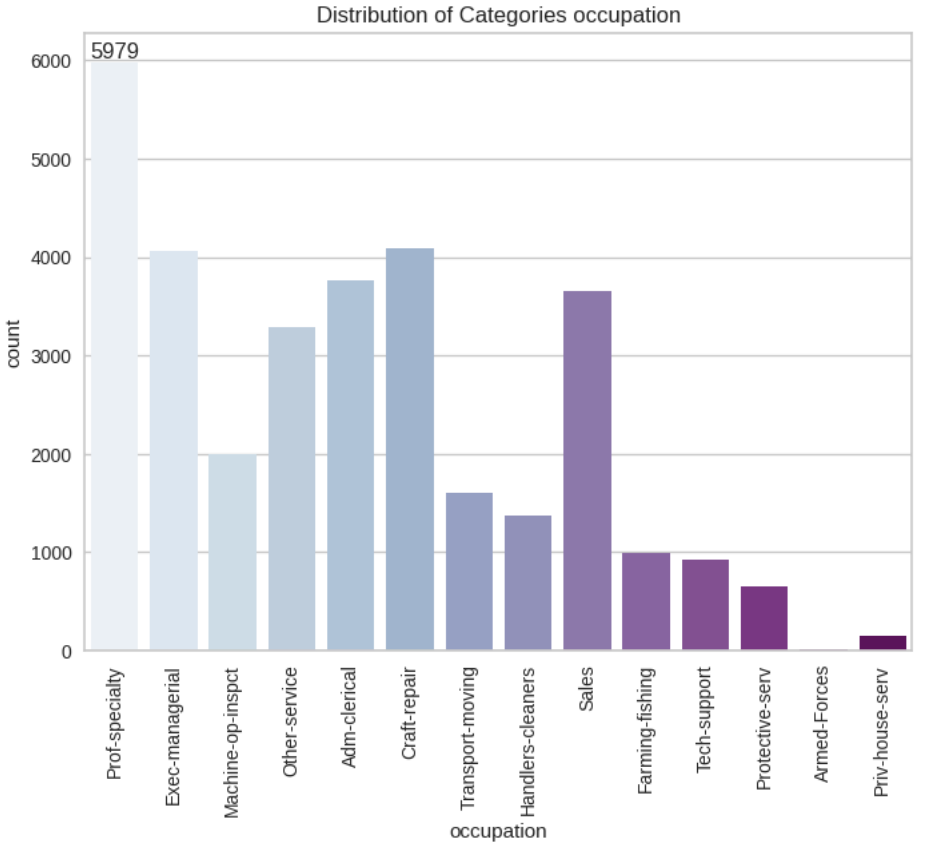
```
for column in cat_features:
    plt.figure(figsize=(8, 6))
    ax = sns.countplot(x=column, data=df, palette='BuPu')
    plt.title(f'Distribution of Categories {column}')

    ax.bar_label(ax.containers[0])

    plt.xticks(rotation=90)
    plt.show()
```

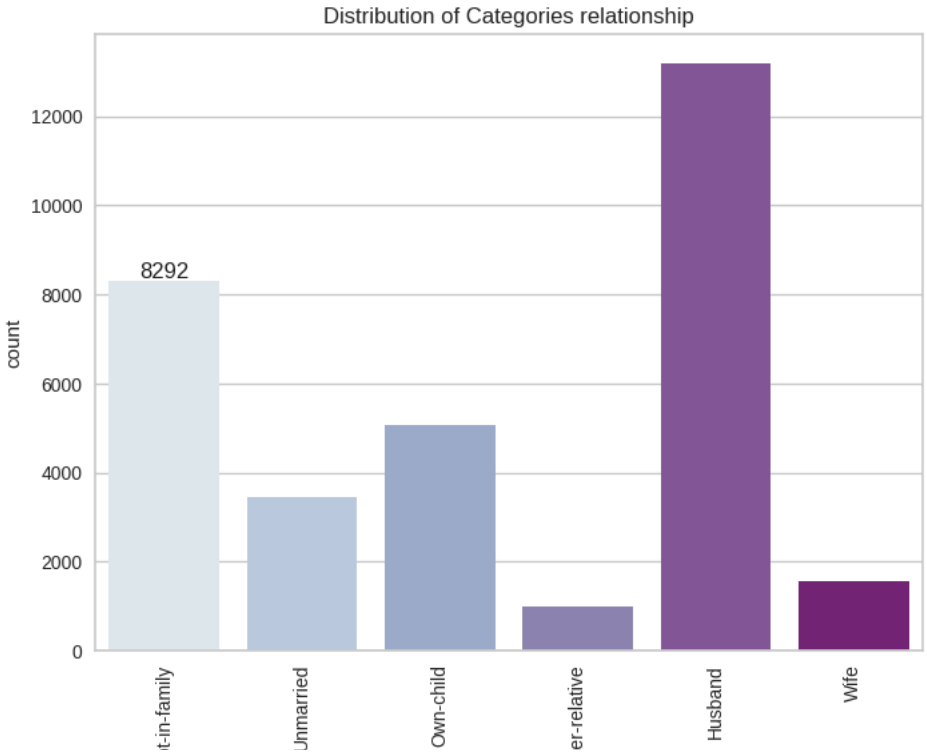

Distribution of Categories workclass
24509
count
workclass
Private
State-gov
Federal-gov
Self-emp-not-inc
Self-emp-inc
Local-gov
Without-pay
Never-worked

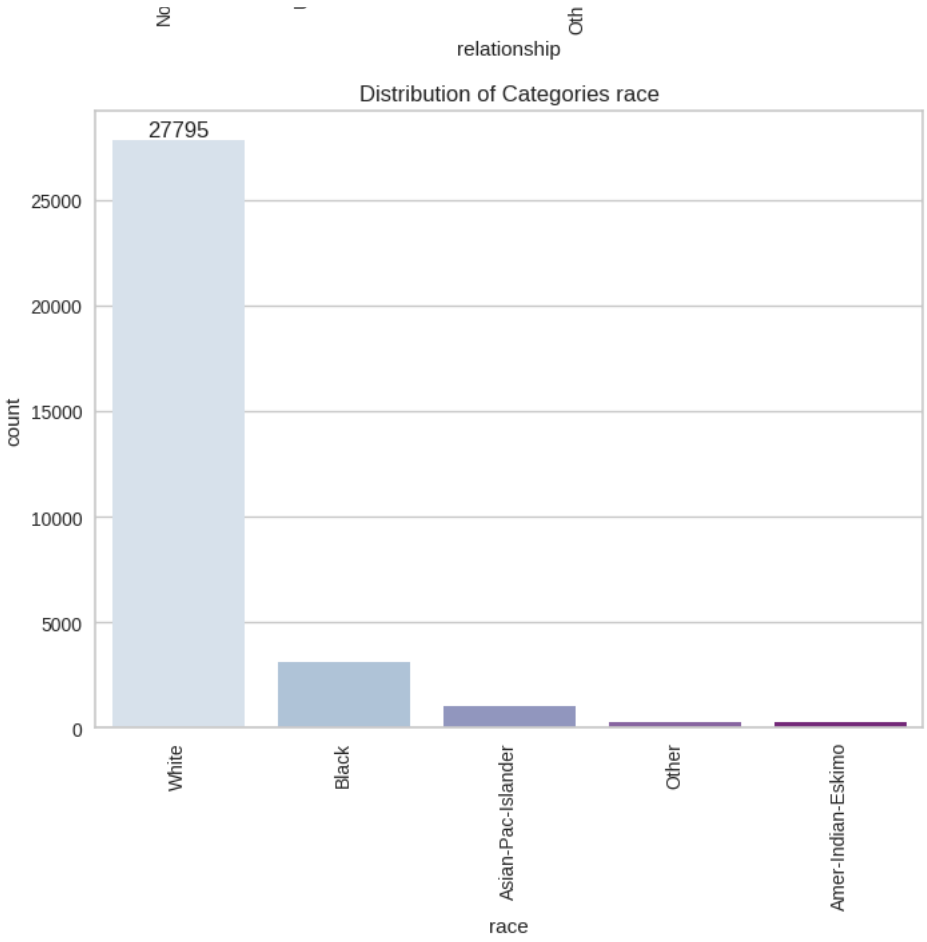

Distribution of Categories education
10494
count
education
HS-grad
Some-college
7th-8th
10th
Doctorate
Prof-school
Bachelors
Masters
11th
Assoc-acdm
Assoc-voc
1st-4th
5th-6th
12th
9th
Preschool

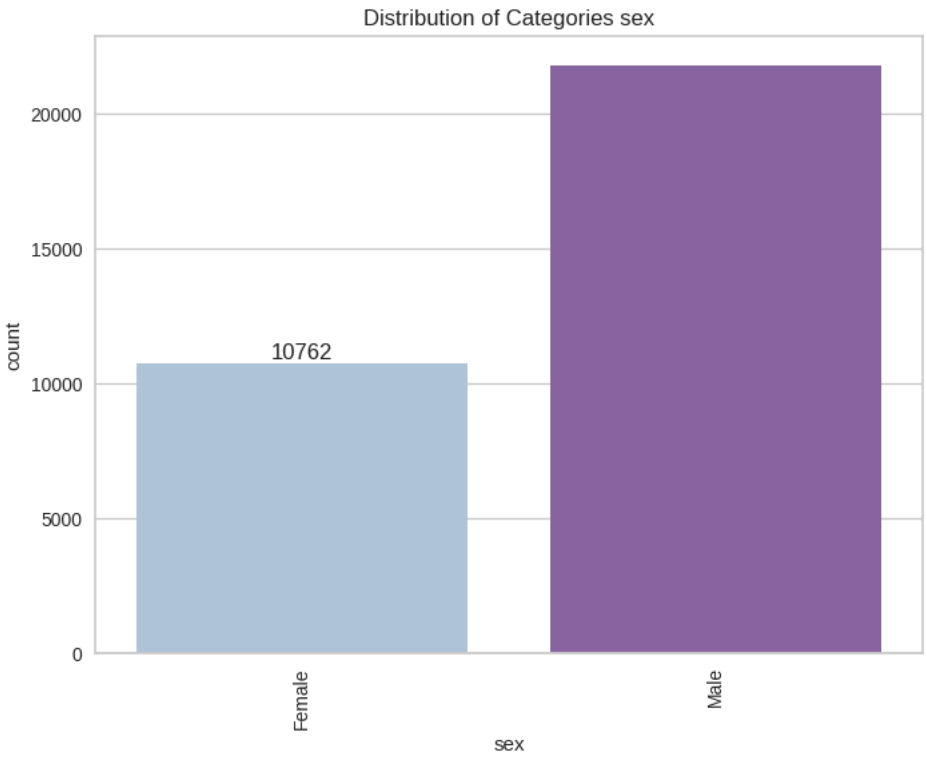

Distribution of Categories marital.status
count

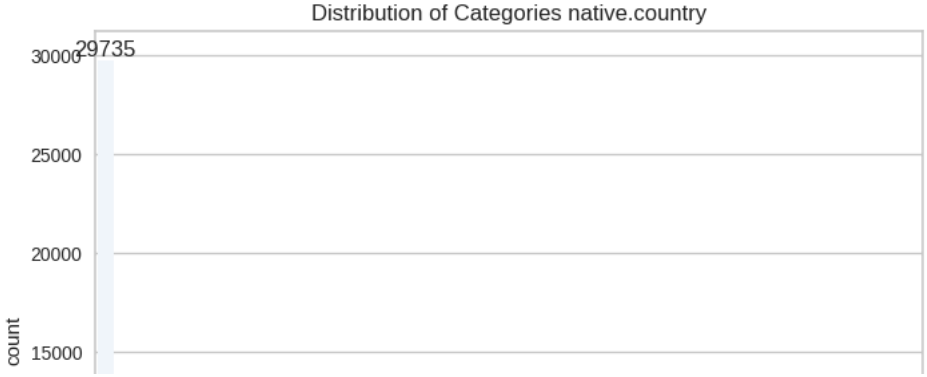

6000
4000
2000
0
993
Widowed
Divorced
Separated
Never-married
Married-civ-spouse
Married-spouse-absent
Married-AF-spouse
marital.status

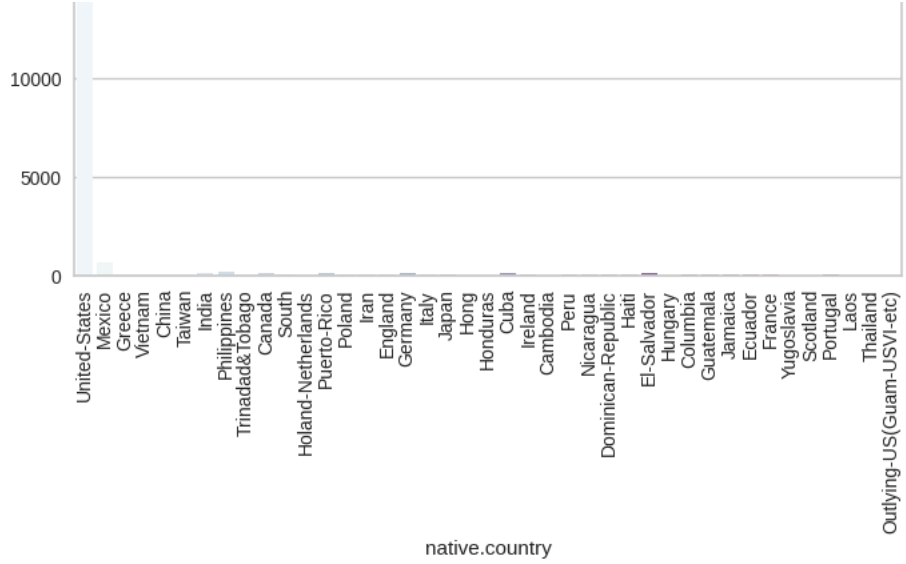

Distribution of Categories occupation
5979
6000
5000
4000
3000
2000
1000
0
count
Prof-specialty
Exec-managerial
Machine-op-inspct
Other-service
Adm-clerical
Craft-repair
Transport-moving
Handlers-cleaners
Sales
Farming-fishing
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
occupation

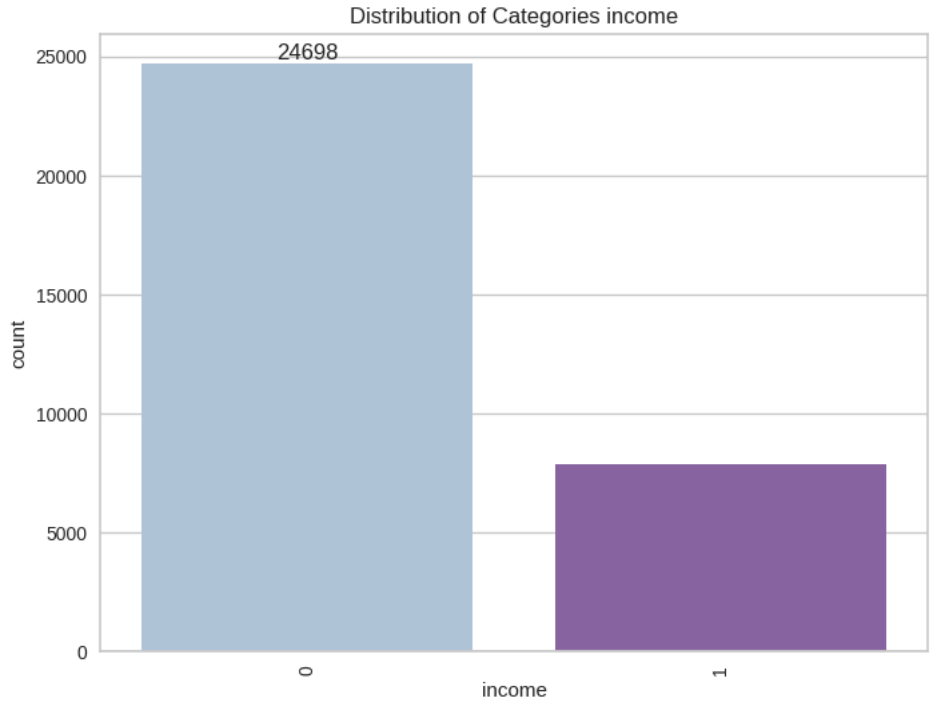

Distribution of Categories relationship
12000
10000
8000
6000
4000
2000
0
8292
count
Own-child
Husband
Wife


No
Oth
relationship
Distribution of Categories race
27795
25000
20000
15000
10000
5000
0
count
White
Black
Asian-Pac-Islander
Other
Amer-Indian-Eskimo
race


Distribution of Categories sex
20000
15000
10000
5000
0
count
10762
Female
Male
sex


Distribution of Categories native.country
29735
30000
25000
20000
15000
count






```
value_cnt_fonc(df, 'education')
```

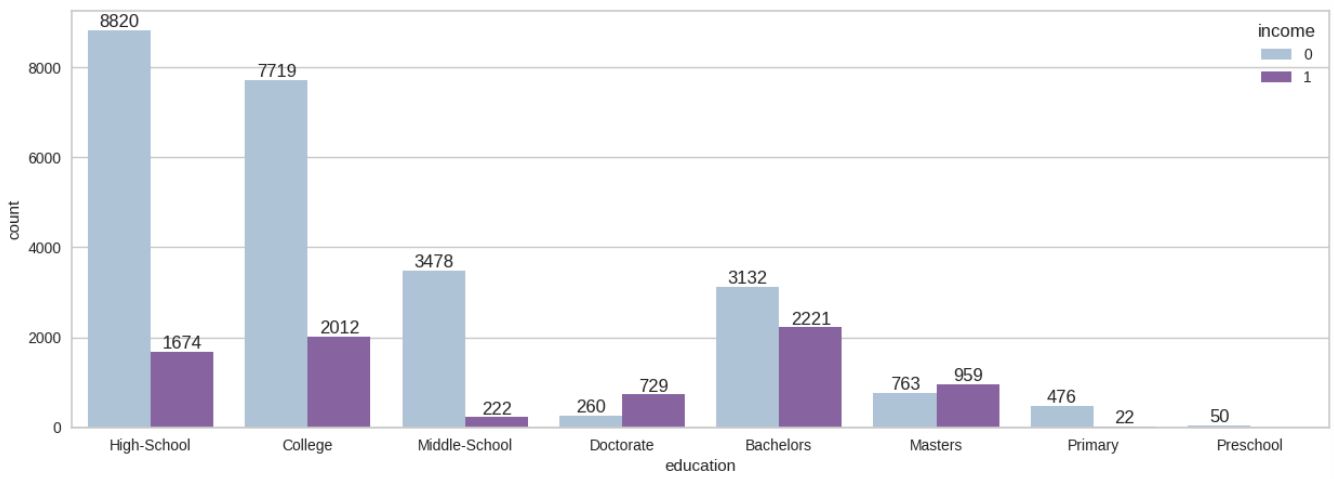
	education	counts	norm_counts
0	HS-grad	10494	0.322525
1	Some-college	7282	0.223807
2	Bachelors	5353	0.164520
3	Masters	1722	0.052924
4	Assoc-voc	1382	0.042475
5	11th	1175	0.036113
6	Assoc-acdm	1067	0.032793
7	10th	933	0.028675
8	7th-8th	645	0.019824
9	Prof-school	576	0.017703
10	9th	514	0.015797
11	12th	433	0.013308
12	Doctorate	413	0.012693
13	5th-6th	332	0.010204
14	1st-4th	166	0.005102
15	Preschool	50	0.001537

```
df['education'].replace(['1st-4th', '5th-6th'], 'Primary', inplace=True)
df['education'].replace(['7th-8th', '9th', '10th', '11th', '12th'], 'Middle-School', inplace=True)
df['education'].replace(['HS-grad'], 'High-School', inplace=True)
df['education'].replace(['Some-college', 'Assoc-voc', 'Assoc-acdm'], 'College', inplace=True)
df['education'].replace(['Bachelors'], 'Bachelors', inplace=True)
df['education'].replace(['Prof-school', 'Doctorate'], 'Doctorate', inplace=True)
```

```
value_cnt_fonc(df, 'education')
```

	education	counts	norm_counts
0	High-School	10494	0.322525
1	College	9731	0.299075
2	Bachelors	5353	0.164520
3	Middle-School	3700	0.113717
4	Masters	1722	0.052924
5	Doctorate	989	0.030396
6	Primary	498	0.015306
7	Preschool	50	0.001537

```
plt.figure(figsize=(15,5))
ax = sns.countplot( data=df, x="education",hue="income", palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```




```
value_cnt_fonc(df, 'race')
```

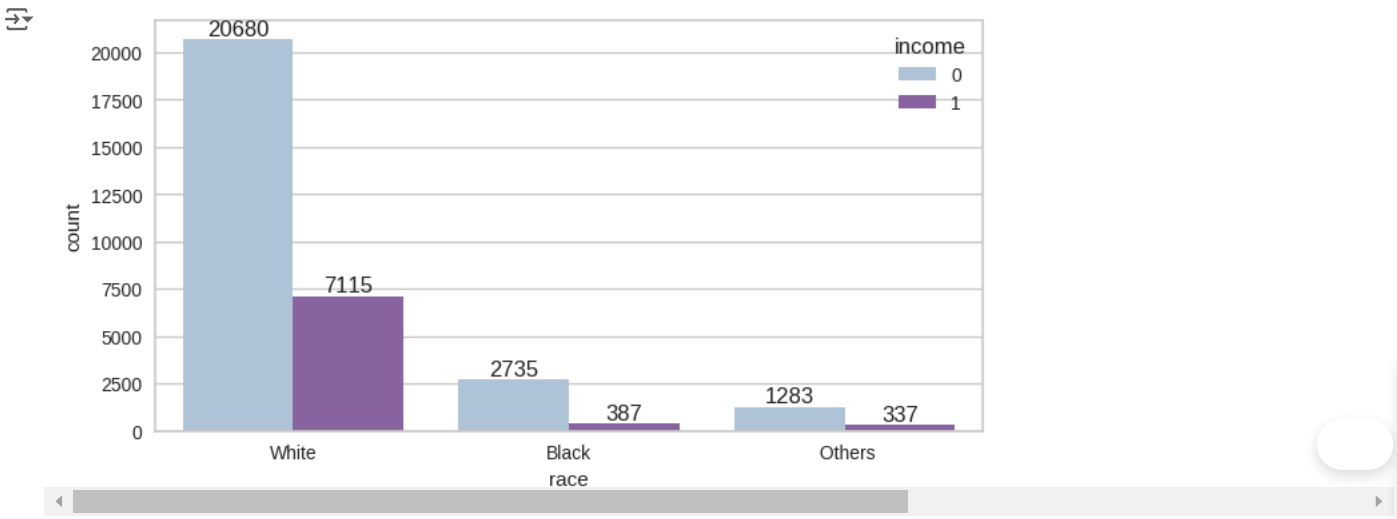
	race	counts	norm_counts
0	White	27795	0.854258
1	Black	3122	0.095952
2	Asian-Pac-Islander	1038	0.031902
3	Amer-Indian-Eskimo	311	0.009558
4	Other	271	0.008329

```
df['race'].replace(['Asian-Pac-Islander', 'Amer-Indian-Eskimo', 'Other'],' Others', inplace = True)
```

```
value_cnt_fonc(df, 'race')
```

	race	counts	norm_counts
0	White	27795	0.854258
1	Black	3122	0.095952
2	Others	1620	0.049789

```
plt.figure(figsize=(8,4))
ax = sns.countplot( data=df, x="race",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```




```
value_cnt_fonc(df, 'native.country')
```

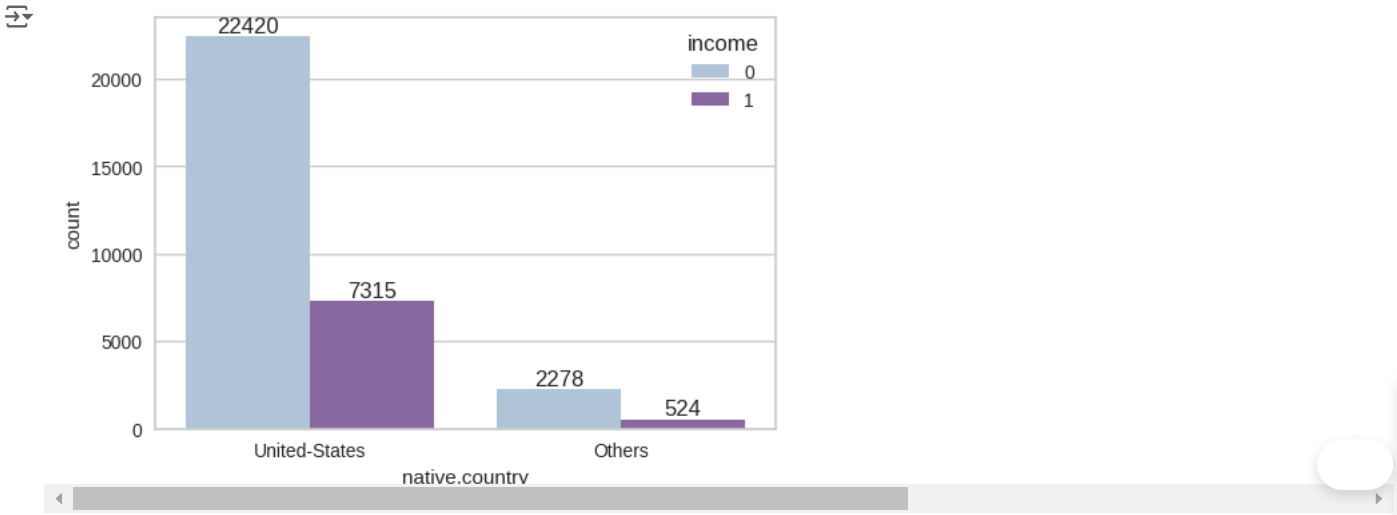
	native.country	counts	norm_counts
0	United-States	29735	0.913883
1	Mexico	639	0.019639
2	Philippines	198	0.006085
3	Germany	137	0.004211
4	Canada	121	0.003719
5	Puerto-Rico	114	0.003504
6	El-Salvador	106	0.003258
7	India	100	0.003073
8	Cuba	95	0.002920
9	England	90	0.002766
10	Jamaica	81	0.002489
11	South	80	0.002459
12	China	75	0.002305
13	Italy	73	0.002244
14	Dominican-Republic	70	0.002151
15	Vietnam	67	0.002059
16	Guatemala	62	0.001906
17	Japan	62	0.001906
18	Poland	60	0.001844
19	Columbia	59	0.001813
20	Taiwan	51	0.001567
21	Haiti	44	0.001352
22	Iran	43	0.001322
23	Portugal	37	0.001137
24	Nicaragua	34	0.001045
25	Peru	31	0.000953
26	Greece	29	0.000891
27	France	29	0.000891
28	Ecuador	28	0.000861
29	Ireland	24	0.000738
30	Hong	20	0.000615
31	Trinadad&Tobago	19	0.000584
32	Cambodia	19	0.000584
33	Thailand	18	0.000553
34	Laos	18	0.000553
35	Yugoslavia	16	0.000492
36	Outlying-US(Guam-USVI-etc)	14	0.000430
37	Hungary	13	0.000400
38	Honduras	13	0.000400
39	Scotland	12	0.000369
40	Holand-Netherlands	1	0.000031

```
df['native.country'].loc[df['native.country'] != 'United-States'] = 'Others'
```

```
value_cnt_fonc(df, 'native.country')
```

	native.country	counts	norm_counts
0	United-States	29735	0.913883
1	Others	2802	0.086117

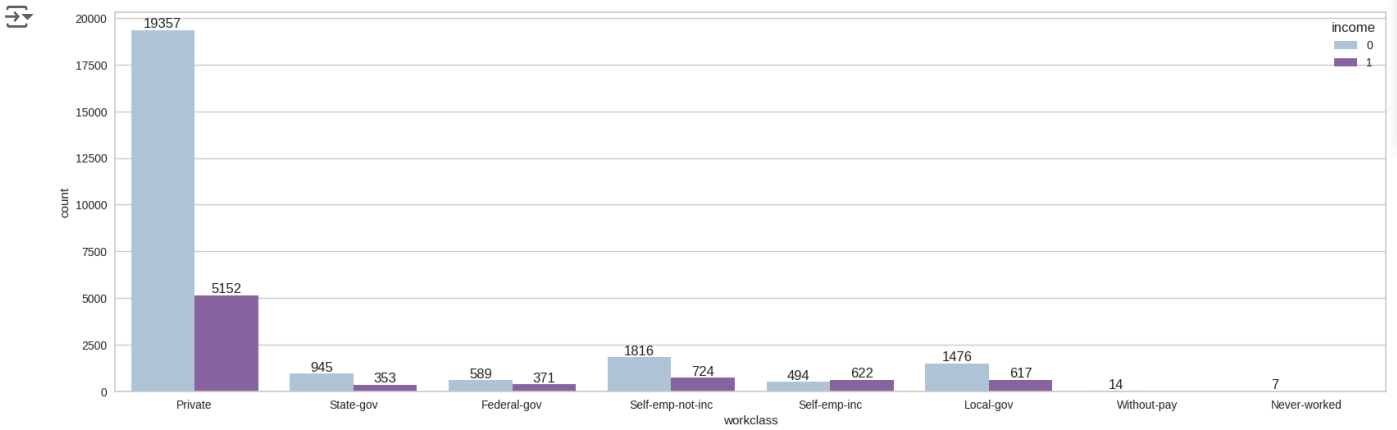
```
plt.figure(figsize=(6,4))
ax = sns.countplot( data=df, x="native.country",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```




```
value_cnt_fonc(df, 'workclass')
```

	workclass	counts	norm_counts
0	Private	24509	0.753266
1	Self-emp-not-inc	2540	0.078065
2	Local-gov	2093	0.064327
3	State-gov	1298	0.039893
4	Self-emp-inc	1116	0.034299
5	Federal-gov	960	0.029505
6	Without-pay	14	0.000430
7	Never-worked	7	0.000215

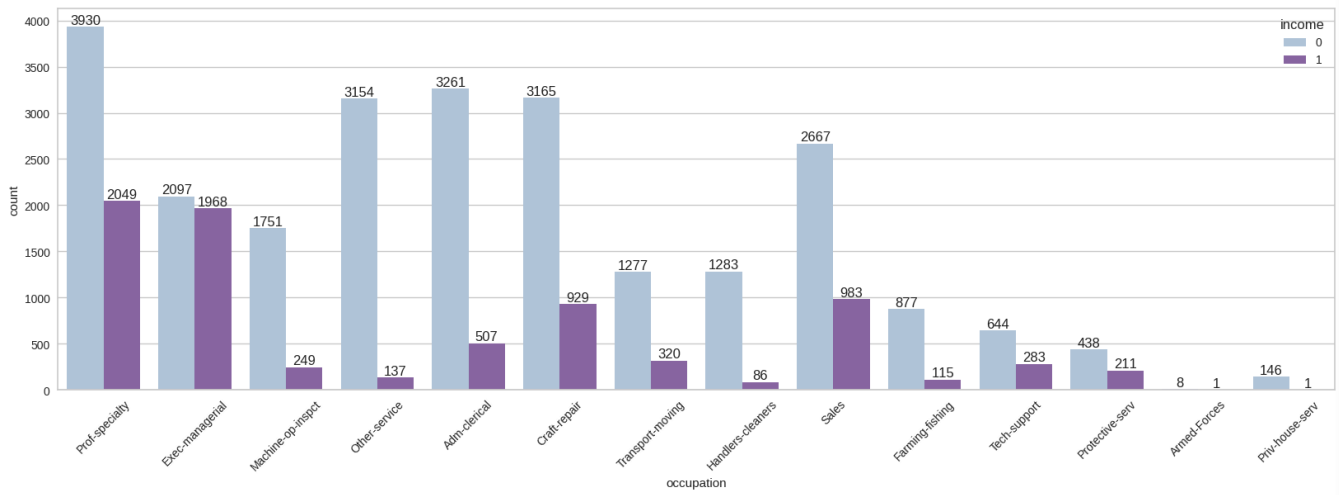
```
plt.figure(figsize=(20,6))
ax = sns.countplot( data=df, x="workclass",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```




```
value_cnt_fonc(df, 'occupation')
```

	occupation	counts	norm_counts
0	Prof-specialty	5979	0.183760
1	Craft-repair	4094	0.125826
2	Exec-managerial	4065	0.124935
3	Adm-clerical	3768	0.115807
4	Sales	3650	0.112180
5	Other-service	3291	0.101146
6	Machine-op-inspct	2000	0.061468
7	Transport-moving	1597	0.049083
8	Handlers-cleaners	1369	0.042075
9	Farming-fishing	992	0.030488
10	Tech-support	927	0.028491
11	Protective-serv	649	0.019947
12	Priv-house-serv	147	0.004518
13	Armed-Forces	9	0.000277

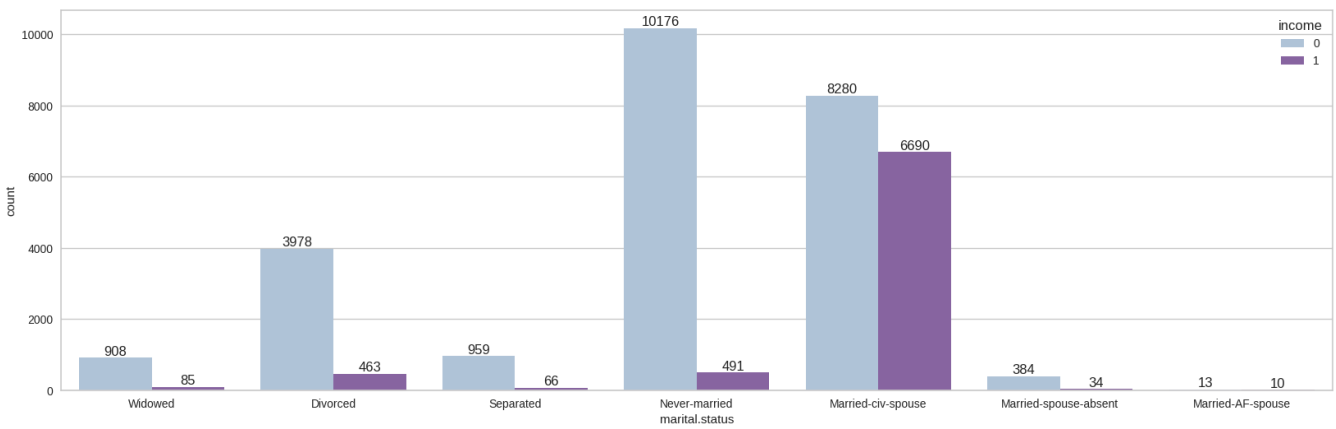
```
plt.figure(figsize=(20,6))
ax = sns.countplot( data=df, x="occupation",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.xticks(rotation=45)
plt.show()
```




```
value_cnt_fonc(df, 'marital.status')
```

	marital.status	counts	norm_counts
0	Married-civ-spouse	14970	0.460092
1	Never-married	10667	0.327842
2	Divorced	4441	0.136491
3	Separated	1025	0.031503
4	Widowed	993	0.030519
5	Married-spouse-absent	418	0.012847
6	Married-AF-spouse	23	0.000707

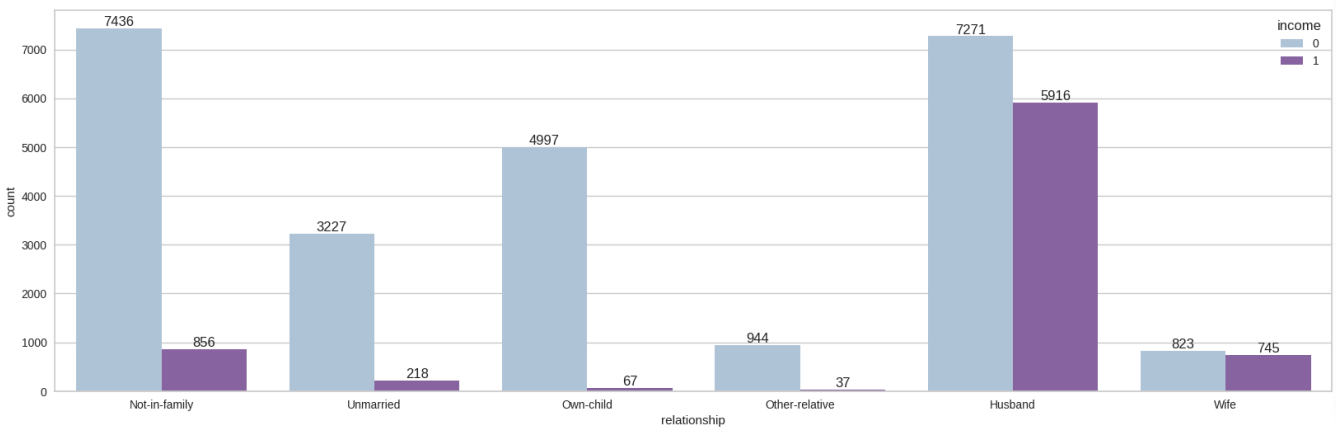
```
plt.figure(figsize=(20,6))
ax = sns.countplot( data=df, x="marital.status",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```




```
value_cnt_fonc(df, 'relationship')
```

	relationship	counts	norm_counts
0	Husband	13187	0.405292
1	Not-in-family	8292	0.254848
2	Own-child	5064	0.155638
3	Unmarried	3445	0.105879
4	Wife	1568	0.048191
5	Other-relative	981	0.030150

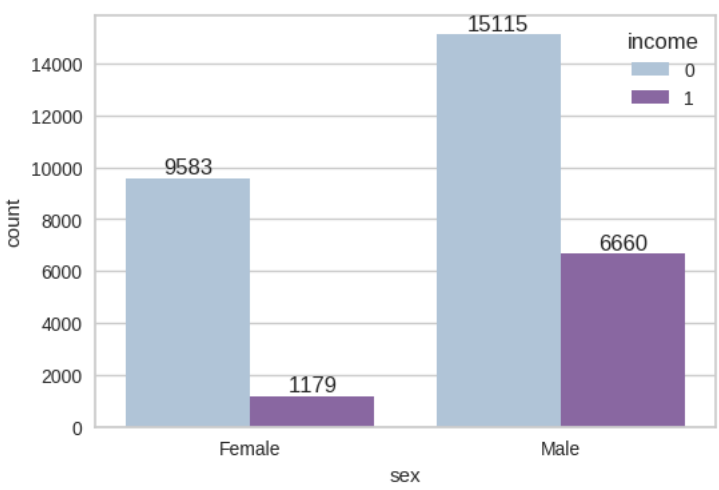
```
plt.figure(figsize=(20,6))
ax = sns.countplot( data=df, x="relationship",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```



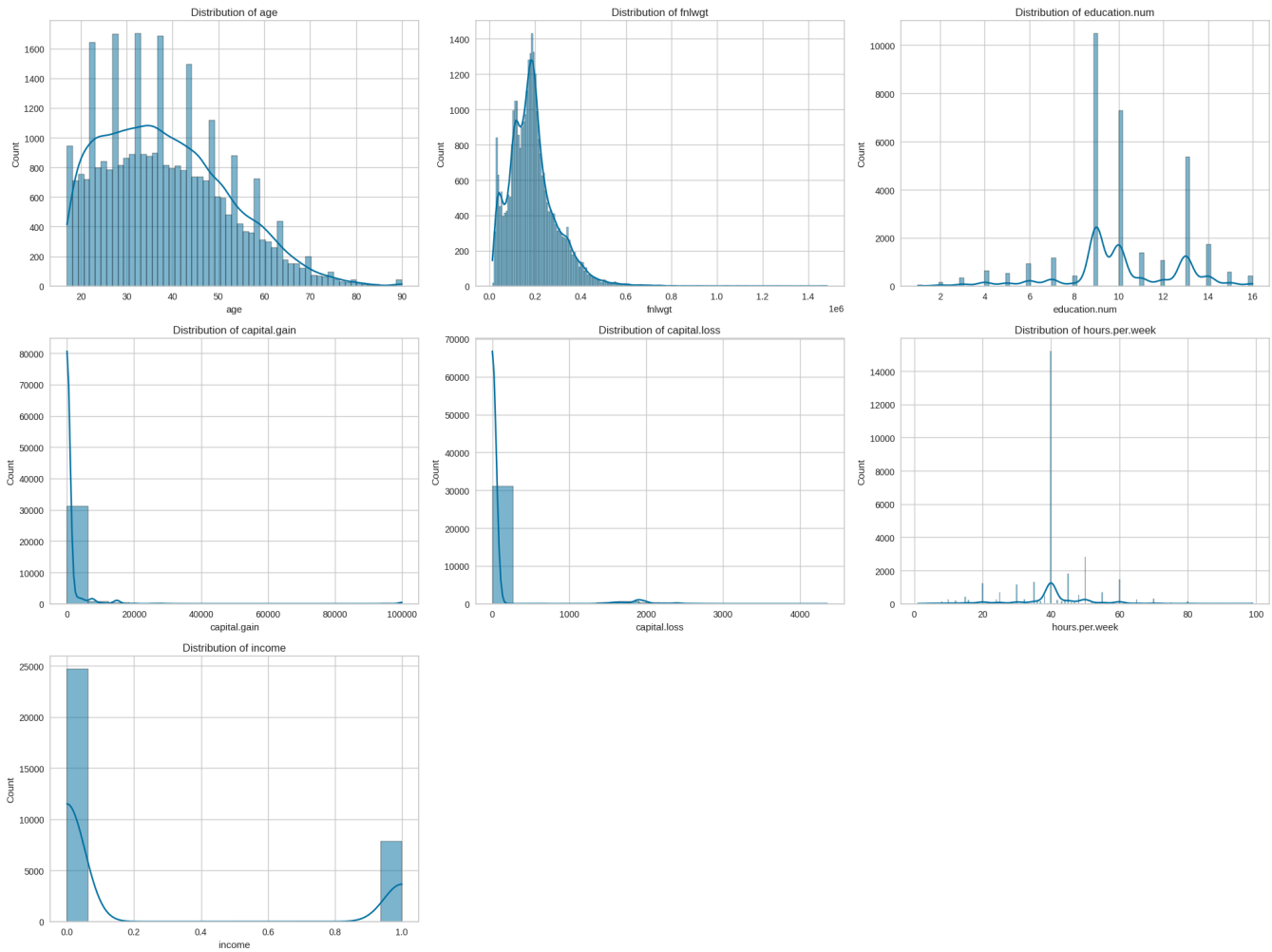

```
value_cnt_fonc(df, 'sex')
```

	sex	counts	norm_counts
0	Male	21775	0.669238
1	Female	10762	0.330762

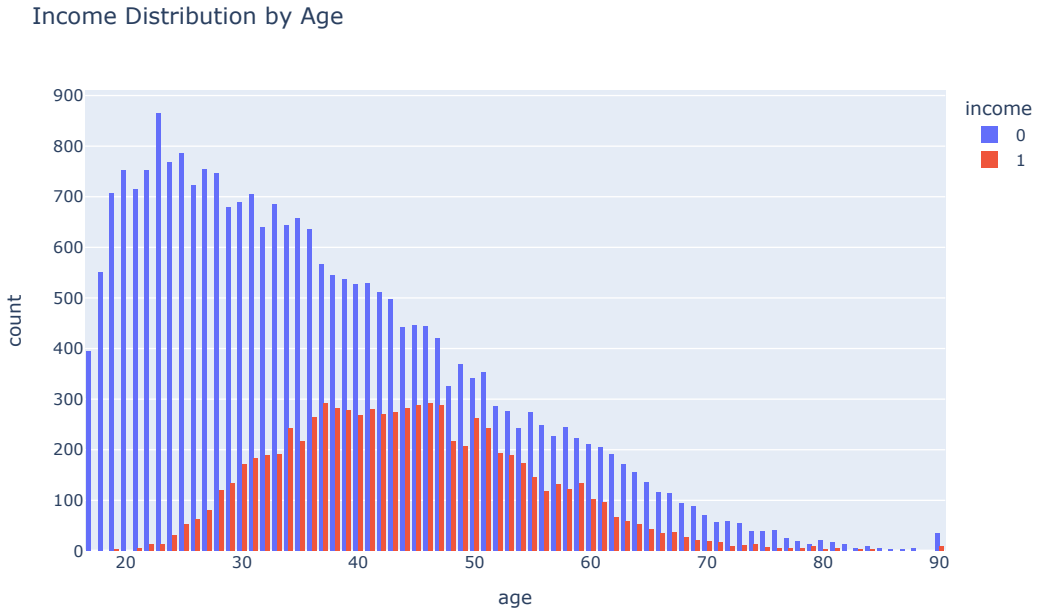
```
plt.figure(figsize=(6,4))
ax = sns.countplot( data=df, x="sex",hue='income', palette='BuPu')

ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```



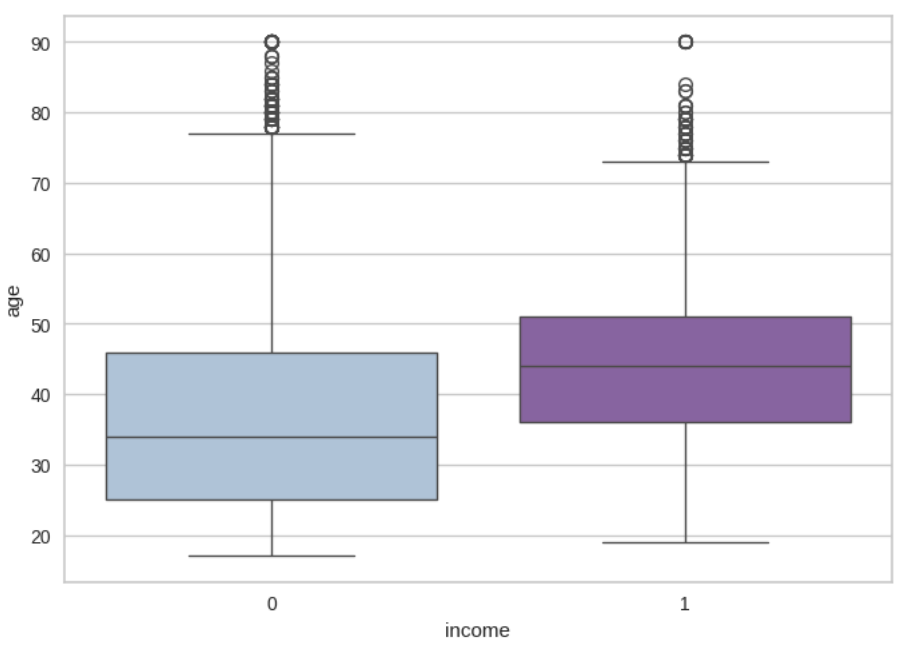

```
numerical_df = df.select_dtypes(include=['number'])

plt.figure(figsize=(20,15))

num_vars = len(numerical_df.columns)

for i, var in enumerate(numerical_df.columns, 1):
    plt.subplot((num_vars // 3) + 1, 3, i)
    sns.histplot(data=df, x=var, kde=True)
    plt.title(f'Distribution of {var}')

plt.tight_layout()
plt.show()
```




```
px.histogram(df, x='age', color="income", barmode='group', title='Income Distribution by Age')
```



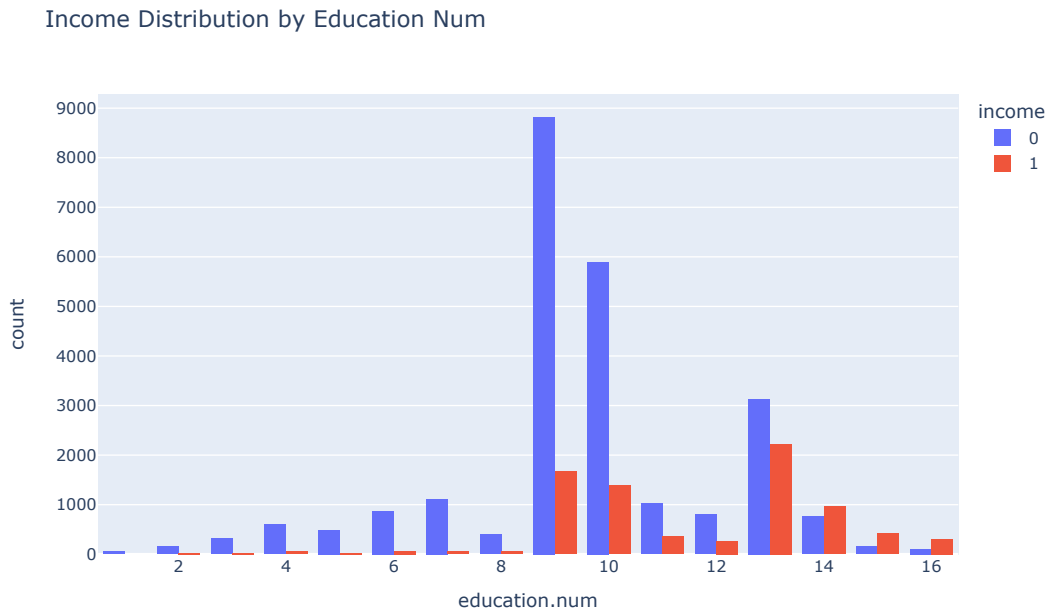

```
sns.boxplot(data=df,y="age",x='income',palette='BuPu');
```



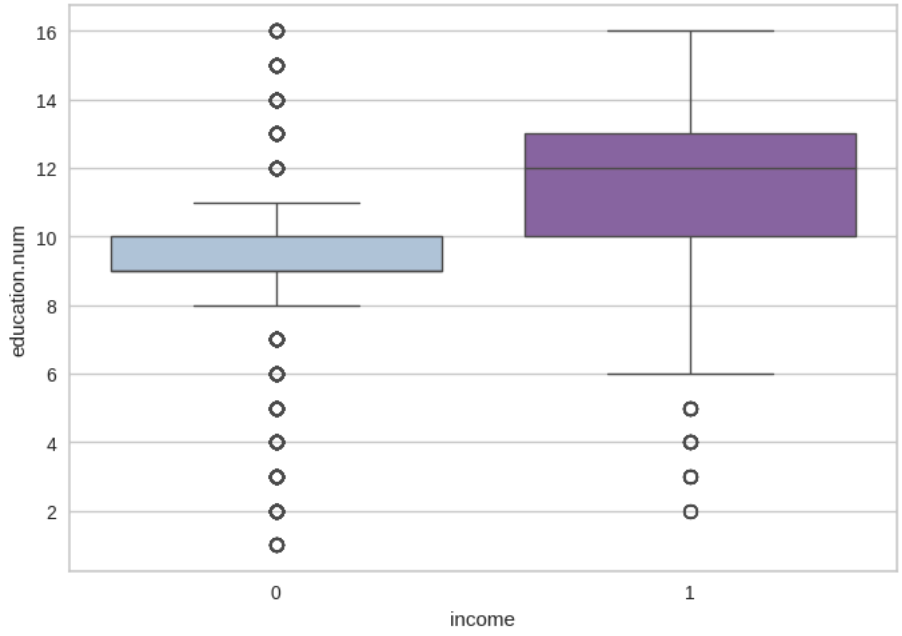

```
value_cnt_fonc(df, 'education.num')
```

	education.num	counts	norm_counts
0	9	10494	0.322525
1	10	7282	0.223807
2	13	5353	0.164520
3	14	1722	0.052924
4	11	1382	0.042475
5	7	1175	0.036113
6	12	1067	0.032793
7	6	933	0.028675
8	4	645	0.019824
9	15	576	0.017703
10	5	514	0.015797
11	8	433	0.013308
12	16	413	0.012693
13	3	332	0.010204
14	2	166	0.005102
15	1	50	0.001537

```
px.histogram(df, x='education.num', color="income", barmode='group', title='Income Distribution by Education Num')
```




```
sns.boxplot(data=df,y="education.num",x='income', palette='BuPu');
```




```
value_cnt_fonc(df, 'capital.gain')
```

	capital.gain	counts	norm_counts
0	0	29825	0.916649
1	15024	347	0.010665
2	7688	284	0.008729
3	7298	246	0.007561
4	99999	159	0.004887
...	...	...	...
114	1111	1	0.000031
115	4931	1	0.000031
116	7978	1	0.000031
117	5060	1	0.000031
118	2538	1	0.000031

119 rows × 3 columns

```
value_cnt_fonc(df, 'capital.loss')
```

	capital.loss	counts	norm_counts
0	0	31018	0.953315
1	1902	202	0.006208
2	1977	168	0.005163
3	1887	159	0.004887
4	1485	51	0.001567
...	...	...	...
87	2201	1	0.000031
88	2163	1	0.000031
89	1944	1	0.000031
90	1539	1	0.000031
91	2472	1	0.000031

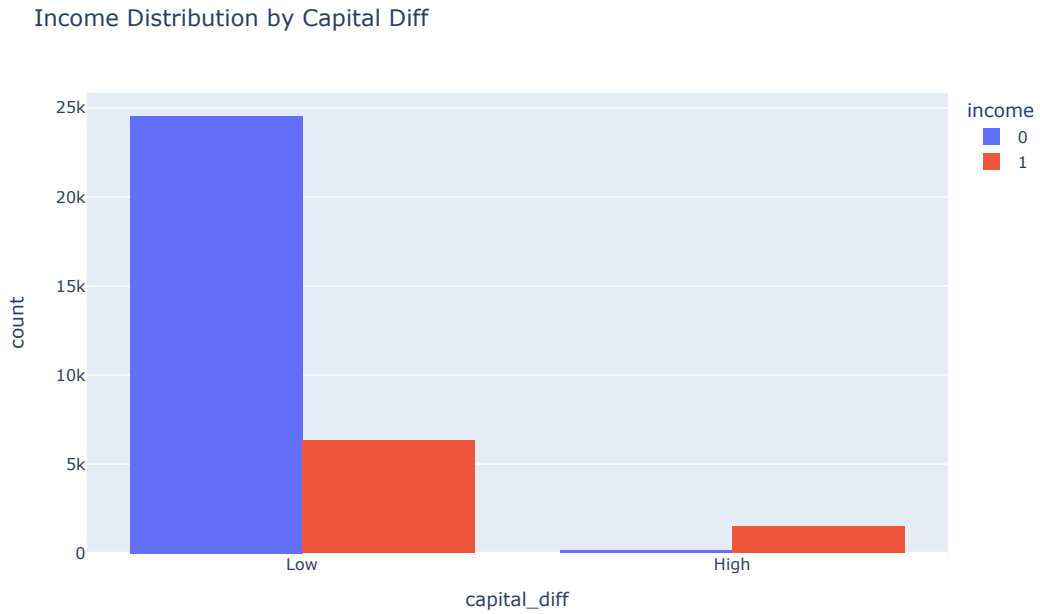
92 rows × 3 columns

```
df['capital_diff'] = df['capital.gain'] - df['capital.loss']
df['capital_diff'] = pd.cut(df['capital_diff'], bins = [-5000, 5000, 100000], labels = ['Low', 'High'])
df['capital_diff'] = df['capital_diff'].astype('object')
df.drop(['capital.gain'], axis = 1, inplace = True)
df.drop(['capital.loss'], axis = 1, inplace = True)
```

```
value_cnt_fonc(df, 'capital_diff')
```

	capital_diff	counts	norm_counts
0	Low	30889	0.94935
1	High	1648	0.05065

```
px.histogram(df, x='capital_diff', color="income", barmode='group', title='Income Distribution by Capital Diff')
```

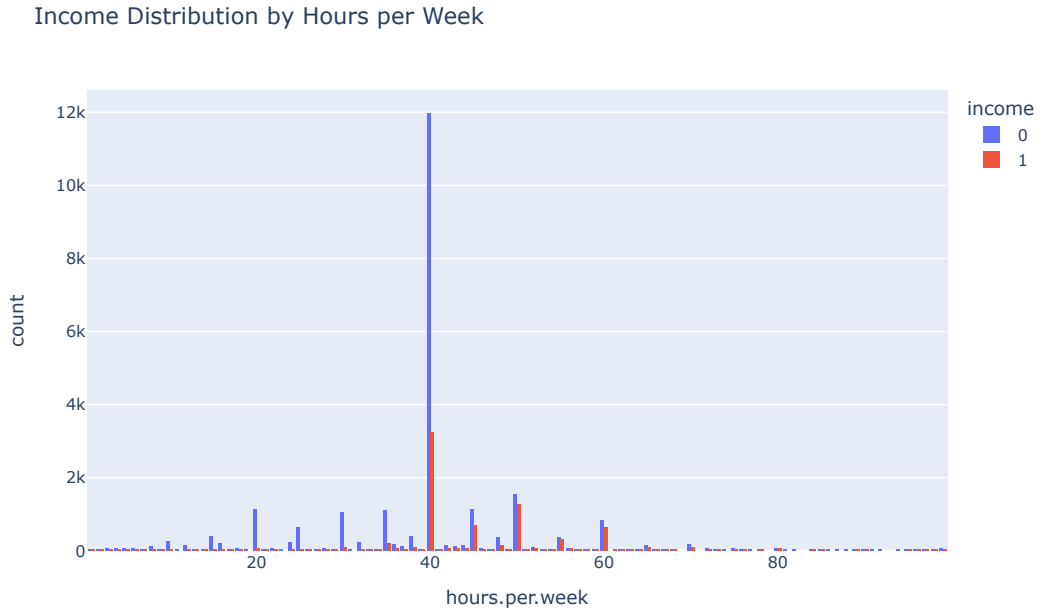



```
value_cnt_fonc(df, 'hours.per.week')
```

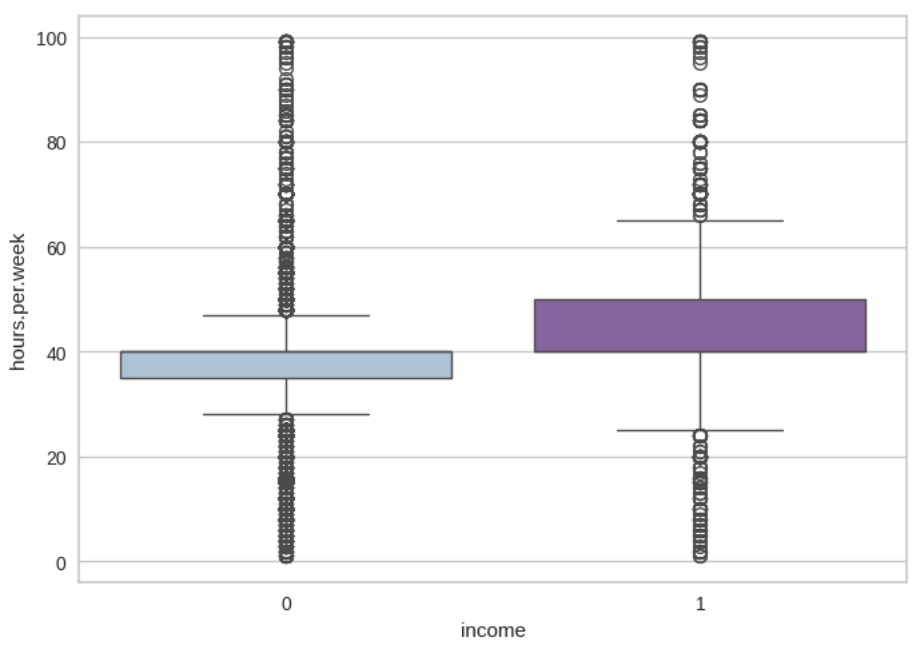
	hours.per.week	counts	norm_counts
0	40	15204	0.467283
1	50	2817	0.086578
2	45	1823	0.056029
3	60	1475	0.045333
4	35	1296	0.039832
...	...	...	...
89	94	1	0.000031
90	82	1	0.000031
91	92	1	0.000031
92	87	1	0.000031
93	74	1	0.000031

94 rows × 3 columns

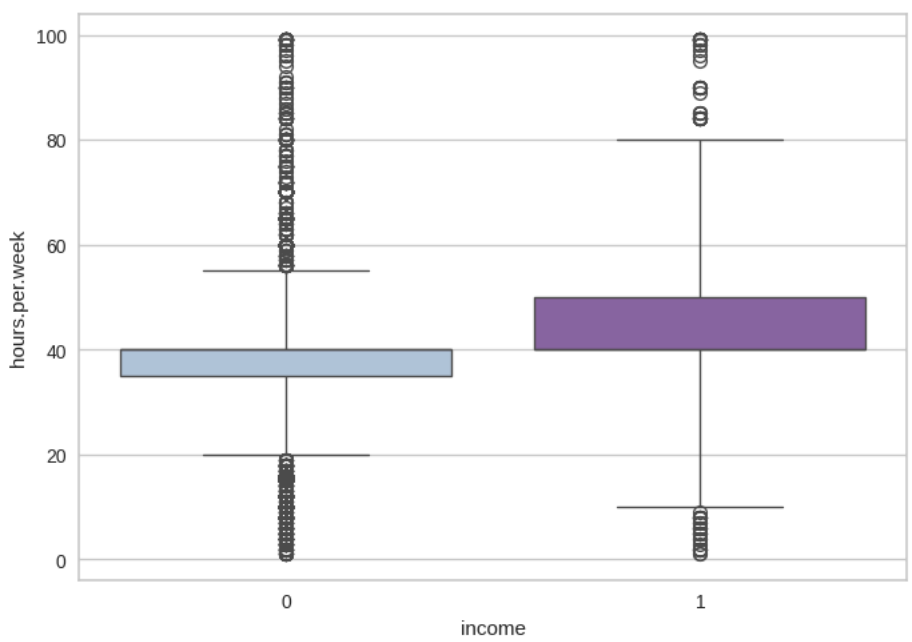
```
px.histogram(df, x='hours.per.week', color="income", barmode='group', title='Income Distribution by Hours per Week')
```




```
sns.boxplot(data=df,y="hours.per.week",x='income', palette='BuPu');
```




```
sns.boxplot(data=df,y="hours.per.week",x='income', palette='BuPu', whis=3);
```




```
len(df[df["hours.per.week"]>72])
```

```
427
```

```
len(df[df["hours.per.week"] < 20])
```

```
1700
```

```
len(df[(df["hours.per.week"] > 72) | (df["hours.per.week"] < 20)])
```

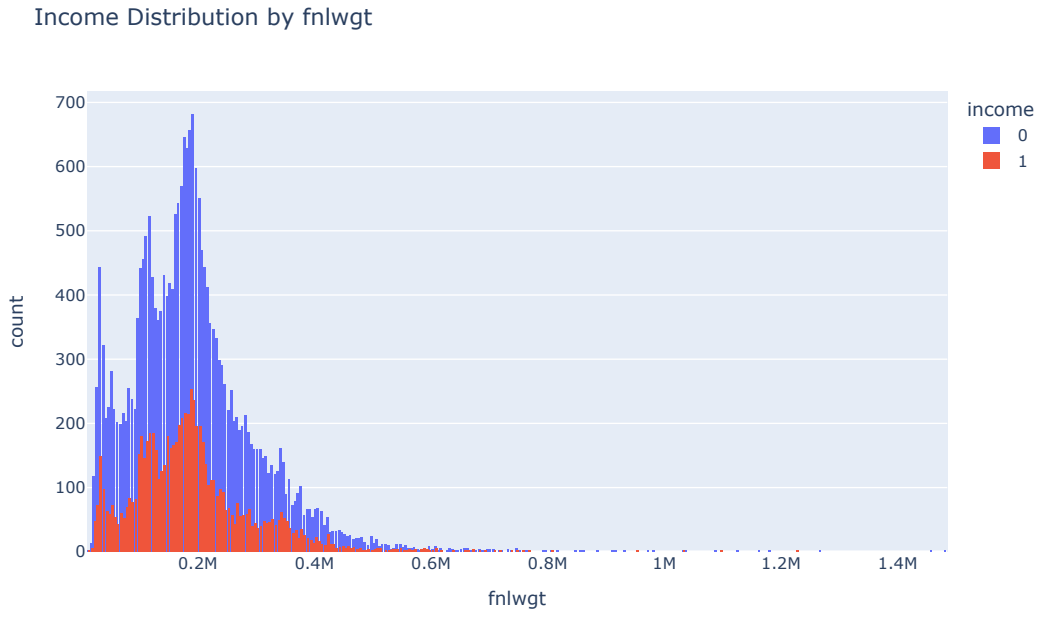
```
2127
```

```
df = df[~((df["hours.per.week"] > 72) | (df["hours.per.week"] < 20))]
```

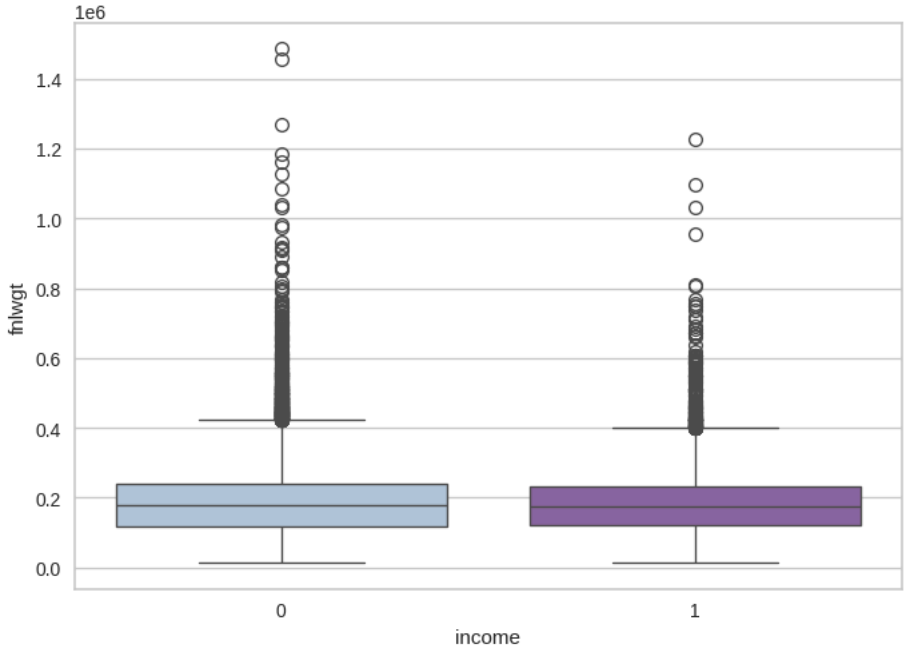
```
df.shape
```

```
(30410, 14)
```

```
px.histogram(df, x='fnlwgt', color="income", barmode='group', title='Income Distribution by fnlwgt')
```




```
sns.boxplot(data=df,y="fnlwgt",x='income', palette='BuPu');
```




```
df.drop(['fnlwgt'], axis = 1, inplace = True)
```

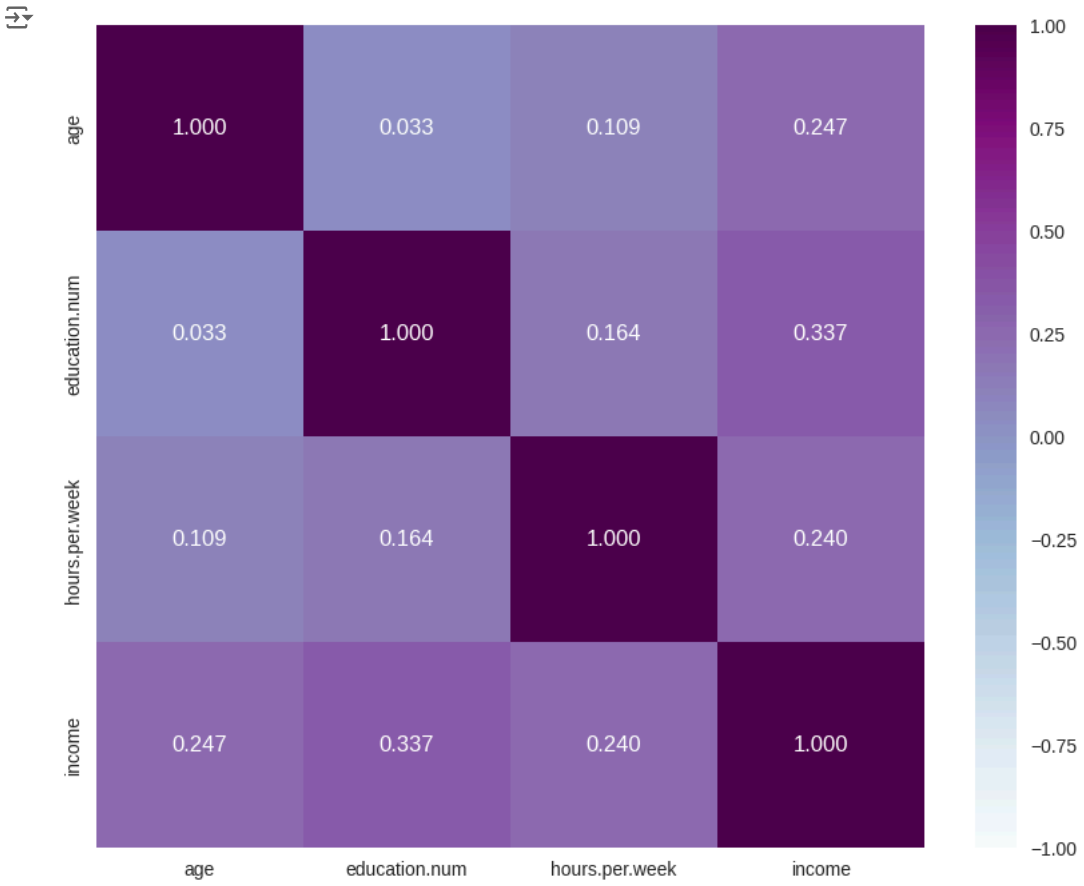
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 30410 entries, 0 to 32560
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             30410 non-null  int64 
 1   workclass       30410 non-null  object
 2   education       30410 non-null  object
 3   education.num   30410 non-null  int64 
 4   marital.status  30410 non-null  object
 5   occupation      30410 non-null  object
 6   relationship    30410 non-null  object
 7   race            30410 non-null  object
 8   sex             30410 non-null  object
 9   hours.per.week  30410 non-null  int64 
 10  native.country  30410 non-null  object
 11  income          30410 non-null  int64 
 12  capital_diff    30410 non-null  object
dtypes: int64(4), object(9)
memory usage: 3.2+ MB
```

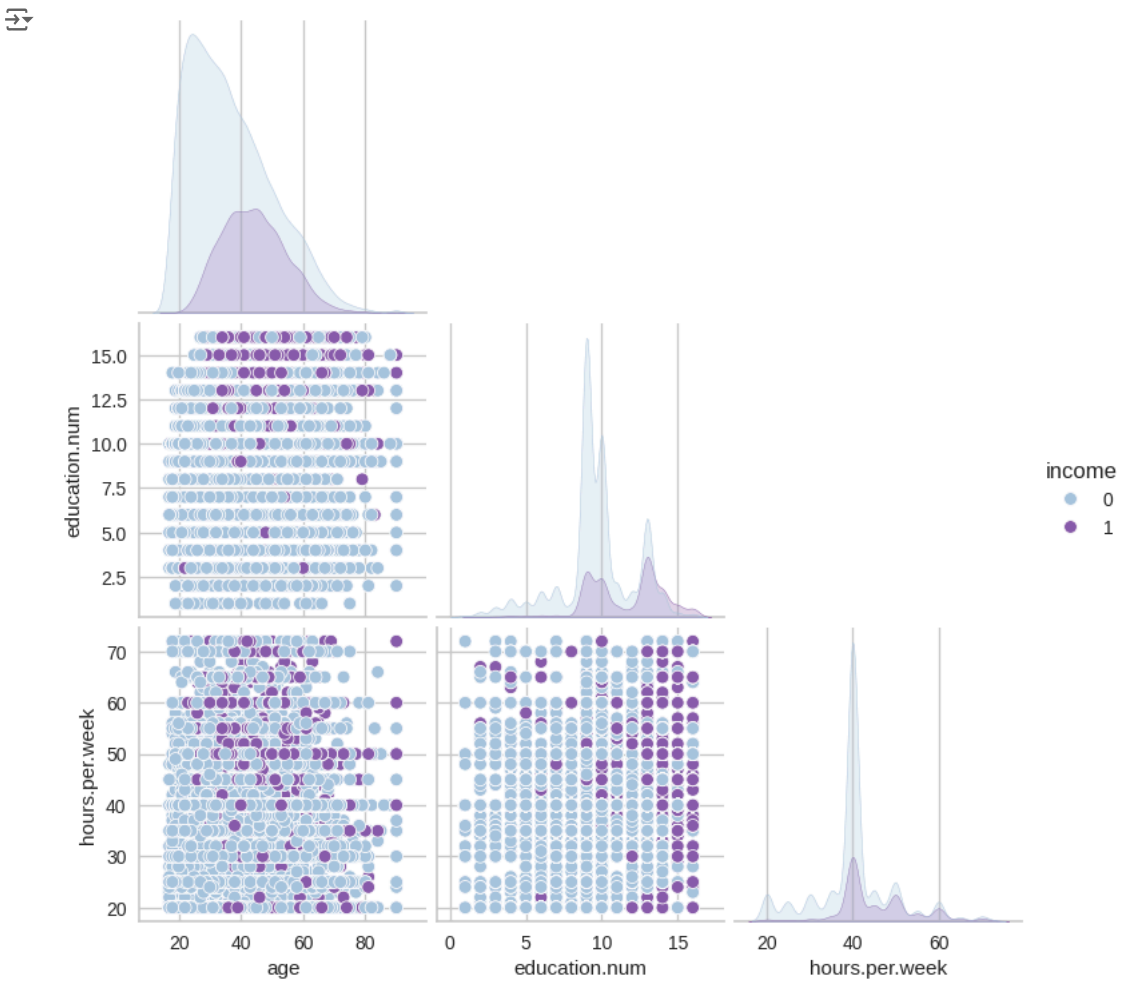
```
df.sample(3)
```

	age	workclass	education	education.num	marital.status	occupation	relationship	race	sex	hours.per.week	native.cou
27340	51	Local-gov	Masters	14	Married-civ-spouse	Prof-specialty	Wife	White	Female	70	United-S
14879	36	Local-gov	Masters	14	Never-married	Prof-specialty	Not-in-family	Black	Female	40	United-S
21399	38	Local-gov	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	45	United-S

```
plt.figure(figsize=(10,8))
sns.heatmap(df.select_dtypes("number").corr(), vmin = -1, vmax = 1, annot = True, fmt = '.3f', cmap='BuPu');
```




```
sns.pairplot(data=df, corner=True, hue='income',palette='BuPu');
```



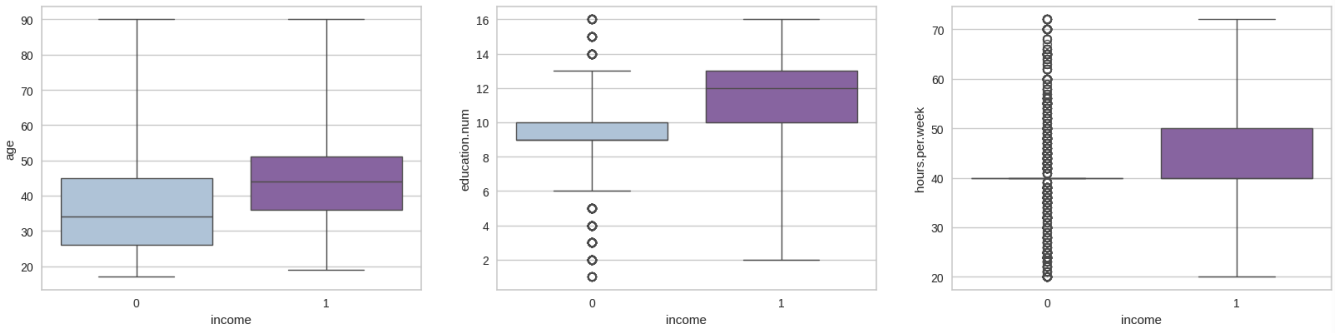
```
def color_custom(val):
    if val > 0.90 and val < 0.99:
        color = 'red'
    elif val >= 1:
        color = 'blue'
    else:
        color = 'black'
    return f'color: {color}'

df.select_dtypes("number").corr().style.map(color_custom)
```

	age	education.num	hours.per.week	income
age	1.000000	0.032813	0.109031	0.246707
education.num	0.032813	1.000000	0.164250	0.337060
hours.per.week	0.109031	0.164250	1.000000	0.239573
income	0.246707	0.337060	0.239573	1.000000

```
print(f"Income <= 50K (0) count: {income_less_50K}")
print(f"Income >  50K (1) count: {income_over_50K}")
```

```
Income <= 50K (0) count: 24698
Income >  50K (1) count: 7839
```

```
index = 0
plt.figure(figsize=(20,15))
for feature in df.select_dtypes(include=['number']).columns:
    if feature != "income":
        index += 1
        plt.subplot(3,3,index)
        sns.boxplot(x='income',y=feature,data=df, whis=3, palette='BuPu')
plt.show()
```




```
cat_features = df.select_dtypes(include='object').columns
num_features = df.select_dtypes(include=['int64','float64']).columns

print('Categoricals:', list(cat_features))
print('---------------------------')
print('Numericals:',list(num_features))
```

```
Categoricals: ['workclass', 'education', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'native.country', 'capital_
---------------------------
Numericals: ['age', 'education.num', 'hours.per.week', 'income']
```

```
df.sample(3)
```

	age	workclass	education	education.num	marital.status	occupation	relationship	race	sex	hours.per.week	native.cou
6002	19	Private	High-School	9	Never-married	Handlers-cleaners	Own-child	White	Male	30	United-S
16115	42	Private	High-School	9	Married-civ-spouse	Transport-moving	Husband	White	Male	50	United-S
7362	71	Self-emp-not-inc	High-School	9	Widowed	Adm-clerical	Not-in-family	White	Female	35	United-S

```
X= df.drop(columns="income")
y= df.income
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=101)
```

```
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
```

```
onehot_categorics = ["workclass", "marital.status", "occupation", "relationship", "race", "sex", "native.country"]
ordinal_categorics = ["education", "capital_diff"]
```

```
column_transformed = make_column_transformer((OneHotEncoder(handle_unknown="ignore", sparse_output=False), onehot_categorics),
                                             (OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value=-1), ordinal_categorics),
                                             remainder='passthrough')
```

```
X_train_trans = column_transformed.fit_transform(X_train)
X_test_trans = column_transformed.transform(X_test)
```

```
X_train_trans.shape, X_test_trans.shape
```

```
((24328, 47), (6082, 47))
```

```
features = column_transformed.get_feature_names_out()
features
```

```
array(['onehotencoder__workclass_Federal-gov',
       'onehotencoder__workclass_Local-gov',
       'onehotencoder__workclass_Never-worked',
       'onehotencoder__workclass_Private',
       'onehotencoder__workclass_Self-emp-inc',
       'onehotencoder__workclass_Self-emp-not-inc',
       'onehotencoder__workclass_State-gov',
       'onehotencoder__workclass_Without-pay',
       'onehotencoder__marital.status_Divorced',
       'onehotencoder__marital.status_Married-AF-spouse',
       'onehotencoder__marital.status_Married-civ-spouse',
       'onehotencoder__marital.status_Married-spouse-absent',
       'onehotencoder__marital.status_Never-married',
       'onehotencoder__marital.status_Separated',
       'onehotencoder__marital.status_Widowed',
       'onehotencoder__occupation_Adm-clerical',
       'onehotencoder__occupation_Armed-Forces',
       'onehotencoder__occupation_Craft-repair',
       'onehotencoder__occupation_Exec-managerial',
       'onehotencoder__occupation_Farming-fishing',
       'onehotencoder__occupation_Handlers-cleaners',
       'onehotencoder__occupation_Machine-op-inspct',
       'onehotencoder__occupation_Other-service',
       'onehotencoder__occupation_Priv-house-serv',
       'onehotencoder__occupation_Prof-specialty',
       'onehotencoder__occupation_Protective-serv',
       'onehotencoder__occupation_Sales',
       'onehotencoder__occupation_Tech-support',
       'onehotencoder__occupation_Transport-moving',
       'onehotencoder__relationship_Husband',
       'onehotencoder__relationship_Not-in-family',
       'onehotencoder__relationship_Other-relative',
       'onehotencoder__relationship_Own-child',
       'onehotencoder__relationship_Unmarried',
       'onehotencoder__relationship_Wife', 'onehotencoder__race_ Others',
       'onehotencoder__race_Black', 'onehotencoder__race_White',
       'onehotencoder__sex_Female', 'onehotencoder__sex_Male',
       'onehotencoder__native.country_Others',
       'onehotencoder__native.country_United-States',
       'ordinalencoder__education', 'ordinalencoder__capital_diff',
       'remainder__age', 'remainder__education.num',
       'remainder__hours.per.week'], dtype=object)
```

```
X_train= pd.DataFrame(X_train_trans, columns=features, index=X_train.index)
X_train.head()
```

	onehotencoder__workclass_Federal-gov	onehotencoder__workclass_Local-gov	onehotencoder__workclass_Never-worked	onehotencoder__workclas
7378	0.0	0.0	0.0	
1937	0.0	0.0	0.0	
10749	0.0	0.0	0.0	
23929	0.0	0.0	0.0	
22481	0.0	0.0	0.0	

5 rows × 47 columns

```
X_test= pd.DataFrame(X_test_trans, columns=features, index=X_test.index)
X_test.head()
```

	onehotencoder__workclass_Federal-gov	onehotencoder__workclass_Local-gov	onehotencoder__workclass_Never-worked	onehotencoder__workclas
15234	0.0	0.0	0.0	
30963	0.0	1.0	0.0	
18499	0.0	0.0	0.0	
7790	0.0	0.0	0.0	
26879	0.0	0.0	0.0	

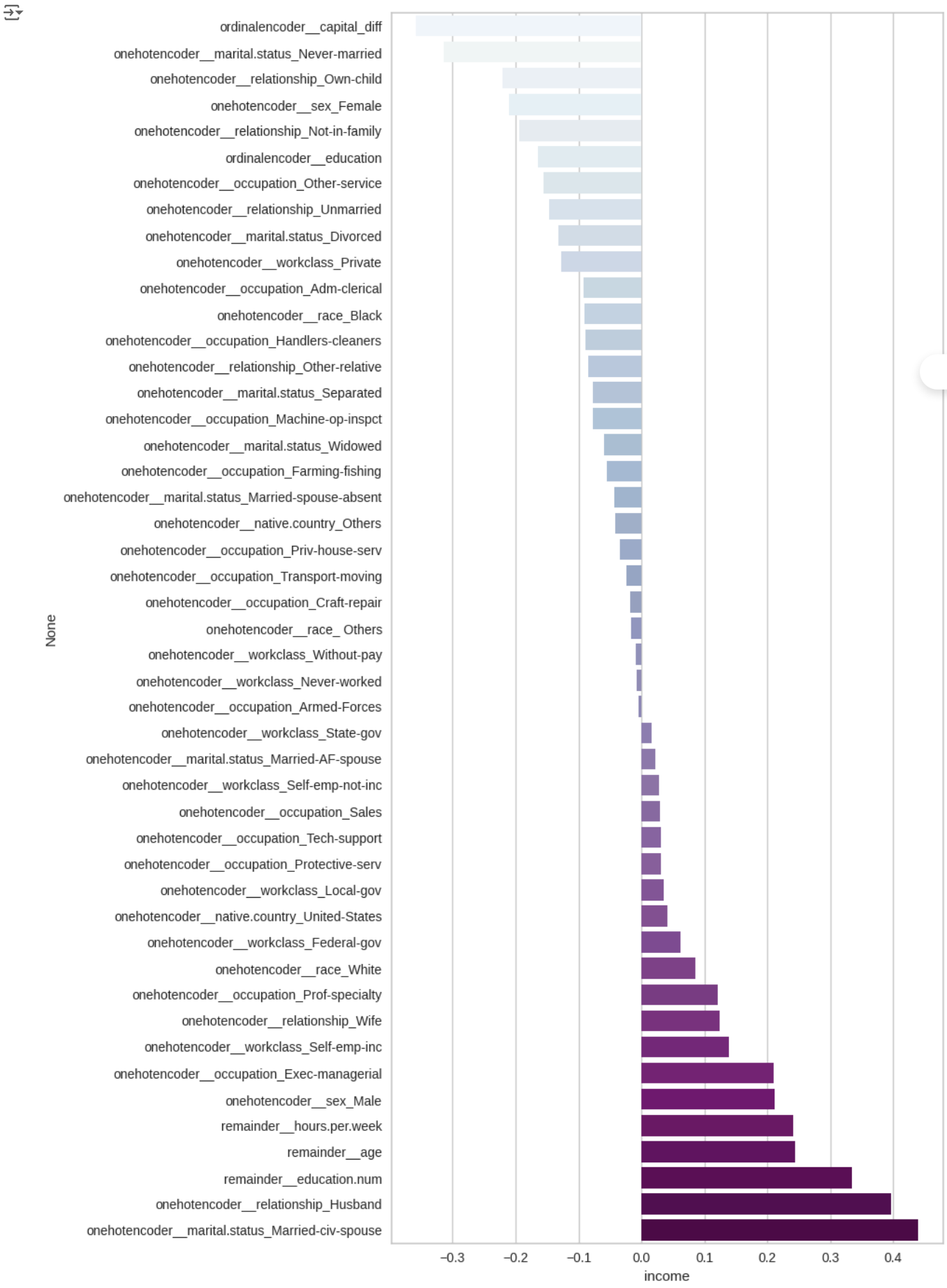
5 rows × 47 columns

```
corr_by_income = X_train.join(y_train).corr()["income"].sort_values()[:-1]
corr_by_income
```

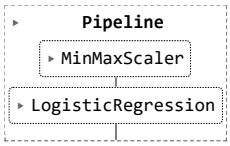
	income
ordinalencoder__capital_diff	-0.357570
onehotencoder__marital.status_Never-married	-0.314213
onehotencoder__relationship_Own-child	-0.221005
onehotencoder__sex_Female	-0.210939
onehotencoder__relationship_Not-in-family	-0.193319
ordinalencoder__education	-0.164939
onehotencoder__occupation_Other-service	-0.154886
onehotencoder__relationship_Unmarried	-0.147372
onehotencoder__marital.status_Divorced	-0.132096
onehotencoder__workclass_Private	-0.127657
onehotencoder__occupation_Adm-clerical	-0.092074
onehotencoder__race_Black	-0.090854
onehotencoder__occupation_Handlers-cleaners	-0.089431
onehotencoder__relationship_Other-relative	-0.083928
onehotencoder__marital.status_Separated	-0.076641
onehotencoder__occupation_Machine-op-inspct	-0.076483
onehotencoder__marital.status_Widowed	-0.060090
onehotencoder__occupation_Farming-fishing	-0.055590
onehotencoder__marital.status_Married-spouse-absent	-0.043274
onehotencoder__native.country_Others	-0.041719
onehotencoder__occupation_Priv-house-serv	-0.033910
onehotencoder__occupation_Transport-moving	-0.024402
onehotencoder__occupation_Craft-repair	-0.017401
onehotencoder__race_ Others	-0.016491
onehotencoder__workclass_Without-pay	-0.009773
onehotencoder__workclass_Never-worked	-0.007388
onehotencoder__occupation_Armed-Forces	-0.004170
onehotencoder__workclass_State-gov	0.015388
onehotencoder__marital.status_Married-AF-spouse	0.022290
onehotencoder__workclass_Self-emp-not-inc	0.028635
onehotencoder__occupation_Sales	0.028951
onehotencoder__occupation_Tech-support	0.030713
onehotencoder__occupation_Protective-serv	0.031129
onehotencoder__workclass_Local-gov	0.034995
onehotencoder__native.country_United-States	0.041719
onehotencoder__workclass_Federal-gov	0.061921
onehotencoder__race_White	0.086126
onehotencoder__occupation_Prof-specialty	0.120956
onehotencoder__relationship_Wife	0.123757
onehotencoder__workclass_Self-emp-inc	0.139121
onehotencoder__occupation_Exec-managerial	0.210296
onehotencoder__sex_Male	0.210939
remainder__hours.per.week	0.240863
remainder__age	0.243469
remainder__education.num	0.334915
onehotencoder__relationship_Husband	0.395761
onehotencoder__marital.status_Married-civ-spouse	0.439405

dtype: float64

```
plt.figure(figsize = (10,14))
sns.barplot(y = corr_by_income.index, x = corr_by_income,palette='BuPu')
plt.tight_layout();
```




```
logistic_model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression())])

logistic_model.fit(X_train, y_train)
```




```
y_pred=logistic_model.predict(X_test)
y_pred_proba = logistic_model.predict_proba(X_test)

log_f1 = f1_score(y_test, y_pred)
log_recall = recall_score(y_test, y_pred)
log_auc = roc_auc_score(y_test, y_pred)


coefficients = logistic_model["logistic"].coef_[0]

feature_importances = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': coefficients
})

# Sort by importance
logistic_fi = feature_importances.sort_values(by='Importance', ascending=False)
logistic_fi.head(10)
```

	Feature	Importance
45	remainder__education.num	4.661115
44	remainder__age	1.918749
46	remainder__hours.per.week	1.828463
9	onehotencoder__marital.status_Married-AF-spouse	1.578302
34	onehotencoder__relationship_Wife	1.218004
10	onehotencoder__marital.status_Married-civ-spouse	1.066136
18	onehotencoder__occupation_Exec-managerial	0.853528
27	onehotencoder__occupation_Tech-support	0.769093
25	onehotencoder__occupation_Protective-serv	0.661074
0	onehotencoder__workclass_Federal-gov	0.620479

Next steps: Generate code with `logistic_fi` View recommended plots New interactive sheet

```
print(f"Income <= 50K (0) count: {income_less_50K}")
print(f"Income >  50K (1) count: {income_over_50K}")
```

```
Income <= 50K (0) count: 24698
Income >  50K (1) count: 7839
```

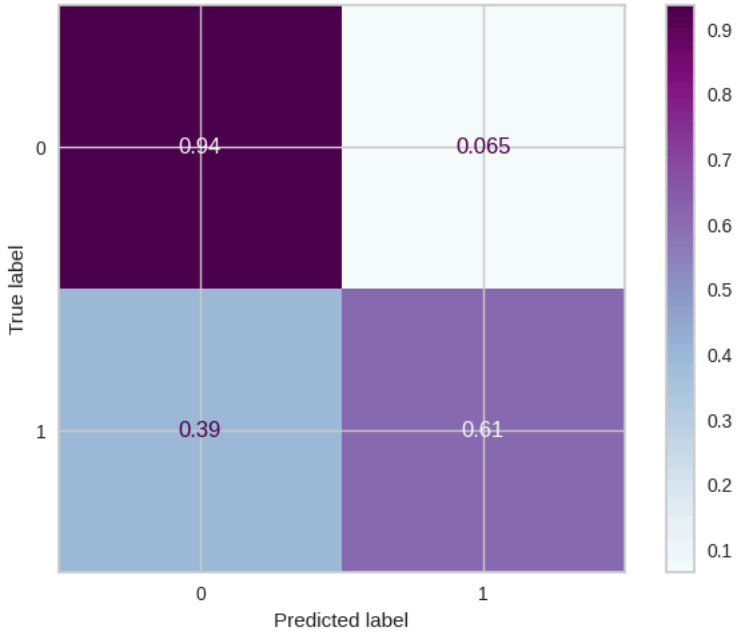
```
def eval_metric(model, X_train, y_train, X_test, y_test, i):

    """ to get the metrics for the model """

    y_train_pred = model.predict(X_train)
    y_pred = model.predict(X_test)

    print(f"{i} Test_Set")
    print(confusion_matrix(y_test, y_pred))
    print(classification_report(y_test, y_pred))
    print()
    print(f"{i} Train_Set")
    print(confusion_matrix(y_train, y_train_pred))
    print(classification_report(y_train, y_train_pred))


eval_metric(logistic_model, X_train, y_train, X_test, y_test, 'logistic_model')
```

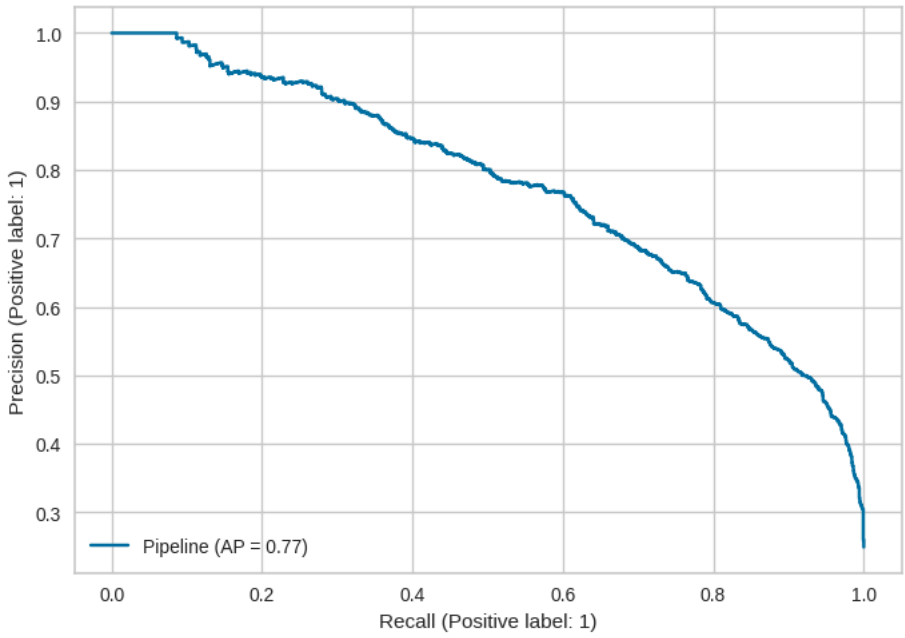
```
logistic_model Test_Set
[[4272  295]
 [ 588  927]]
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      4567
           1       0.76      0.61      0.68      1515

    accuracy                           0.85      6082
   macro avg       0.82      0.77      0.79      6082
```

```
weighted avg       0.85      0.85      0.85      6082


logistic_model Train_Set
[[16986  1280]
 [ 2477  3585]]
              precision    recall  f1-score   support

           0       0.87      0.93      0.90     18266
           1       0.74      0.59      0.66      6062

    accuracy                           0.85     24328
   macro avg       0.80      0.76      0.78     24328
weighted avg       0.84      0.85      0.84     24328
```

```
print('logistic_model ROC_AUC Score:', roc_auc_score(y_test, y_pred_proba[:,1]))
print('-----------------------------------------------------')

# Confusion Matrix
log_matrix = ConfusionMatrixDisplay.from_estimator(logistic_model, X_test, y_test, normalize='true', cmap='BuPu')

# Precision-Recall Curve
log_prCurve = PrecisionRecallDisplay.from_estimator(logistic_model, X_test, y_test)
```

```
logistic_model ROC_AUC Score: 0.9045484863791832
-----------------------------------------------------
```





```
model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression())])

cv = StratifiedKFold(n_splits=10) # for unbalanced data validation

scores = cross_validate(model,
                        X_train,
                        y_train,
                        scoring=['accuracy', 'precision', 'recall', 'f1'],
                        cv=cv,
                        return_train_score=True)

df_scores = pd.DataFrame(scores, index=range(1, 11))
df_scores.mean()[2:]
```

	0
test_accuracy	0.845034
train_accuracy	0.845299
test_precision	0.735819
train_precision	0.736636
test_recall	0.590233
train_recall	0.590143
test_f1	0.654811
train_f1	0.655300

dtype: float64

```
logistic_model.get_params()
```

```
{'memory': None,
 'steps': [('scaler', MinMaxScaler()), ('logistic', LogisticRegression())],
 'verbose': False,
 'scaler': MinMaxScaler(),
 'logistic': LogisticRegression(),
 'scaler__clip': False,
 'scaler__copy': True,
 'scaler__feature_range': (0, 1),
 'logistic__C': 1.0,
 'logistic__class_weight': None,
 'logistic__dual': False,
 'logistic__fit_intercept': True,
 'logistic__intercept_scaling': 1,
 'logistic__l1_ratio': None,
 'logistic__max_iter': 100,
 'logistic__multi_class': 'auto',
 'logistic__n_jobs': None,
 'logistic__penalty': 'l2',
 'logistic__random_state': None,
 'logistic__solver': 'lbfgs',
 'logistic__tol': 0.0001,
 'logistic__verbose': 0,
 'logistic__warm_start': False}
```

```
model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression(max_iter = 1000))])

# Define hyperparameters for tuning
penalty = ["l1", "l2"]       # Regularization terms: l1 (Lasso) and l2 (Ridge)
C  = [0.01, 0.1, 1]    # Regularization strength; inverse of regularization parameter
class_weight= ["balanced", None] # for unbalanced data


param_grid = [
    {
        "logistic__penalty" : ['l2', 'none'],
        "logistic__C" : C,
        "logistic__class_weight": class_weight,
        "logistic__solver": ['sag', 'lbfgs']
    },
    {
        "logistic__penalty" : ['l1', 'l2'],
        "logistic__C" : C,
        "logistic__class_weight": class_weight,
        "logistic__solver": ['liblinear', 'saga']
    }
]

cv = StratifiedKFold(n_splits = 5) # for unbalanced data
grid_model = GridSearchCV(model,
                          param_grid=param_grid,
                          cv=cv,
                          scoring = "recall",
                          n_jobs = -1, # Uses all available cores
                          verbose=1,
                          return_train_score=True).fit(X_train, y_train) # Returns training scores
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
```

```
print('Best Params:', grid_model.best_params_)
print('Best Recall Score(test):', grid_model.best_score_)
print('Best Score Index:', grid_model.best_index_)
```

```
Best Params: {'logistic__C': 0.01, 'logistic__class_weight': 'balanced', 'logistic__penalty': 'l1', 'logistic__solver': 'saga'}
Best Recall Score(test): 0.8670377837453985
Best Score Index: 25
```

```
pd.DataFrame(grid_model.cv_results_).loc[25 , ["mean_test_score", "mean_train_score"]]
```

	25
mean_test_score	0.867038
mean_train_score	0.868071

dtype: object

```
y_pred=grid_model.predict(X_test)
y_pred_proba = grid_model.predict_proba(X_test)


log_grid_f1 = f1_score(y_test, y_pred)
log_grid_recall = recall_score(y_test, y_pred)
log_grid_auc = roc_auc_score(y_test, y_pred)


test_data = pd.concat([X_test, y_test], axis=1)

# Create new column for 'predicted' classes to compore with actual target classes
test_data["pred"] = y_pred

# Filtering the wrong predicted obs
wrong_pred = test_data[((test_data["income"] == 0) & (test_data["pred"] == 1)) |
             ((test_data["income"] == 1) & (test_data["pred"] == 0))]

print('log_grid_model Total Incorrect Predictions:', wrong_pred.shape)


print('------------------------------------------------')
# Actual-Predicted-Probalility of Pozitive Class(1)

my_dict = {"Actual": y_test, "Pred":y_pred, "Proba_1":y_pred_proba[:,1]}
pd.DataFrame.from_dict(my_dict).sample(10)
```

```
log_grid_model Total Incorrect Predictions: (1315, 49)
------------------------------------------------
```

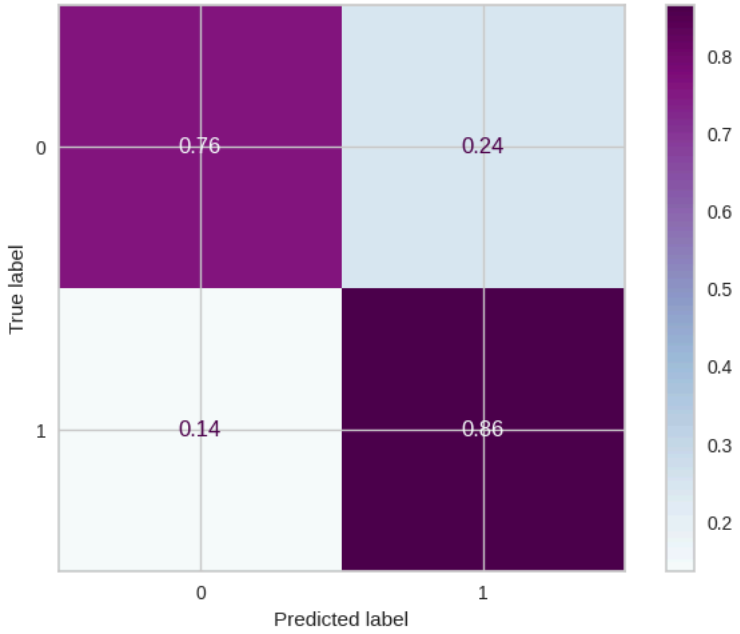
	Actual	Pred	Proba_1
28004	0	1	0.564602
30992	0	0	0.071531
17976	0	0	0.313835
20520	1	1	0.557961
3640	0	0	0.211374
26586	0	1	0.696288
23492	0	0	0.284704
21563	0	0	0.209902
15642	0	0	0.032334
32430	1	1	0.632255

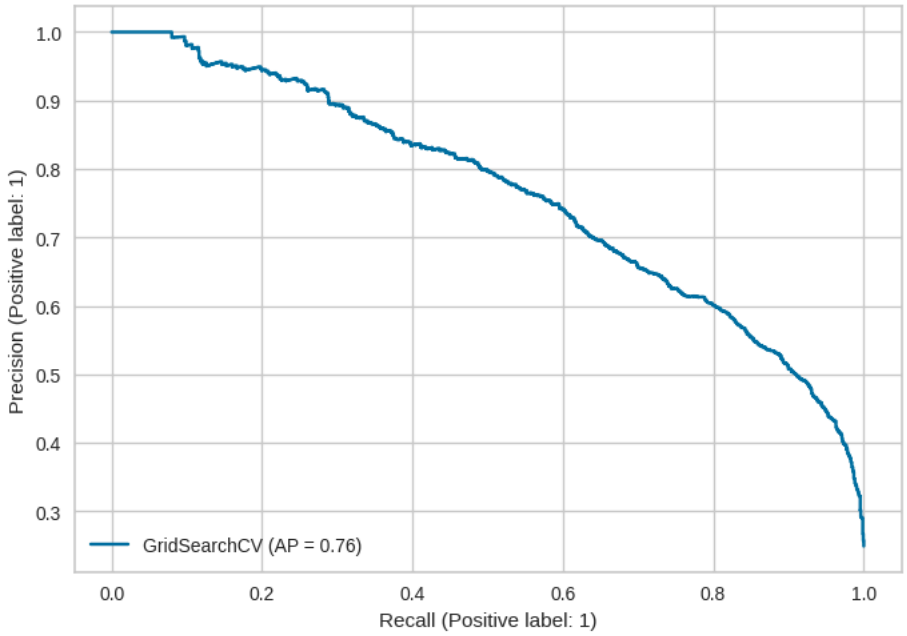
```
eval_metric(grid_model, X_train, y_train, X_test, y_test, 'log_grid_model')
```

```
log_grid_model Test_Set
[[3458 1109]
 [ 206 1309]]
              precision    recall  f1-score   support

           0       0.94      0.76      0.84      4567
           1       0.54      0.86      0.67      1515

    accuracy                           0.78      6082
   macro avg       0.74      0.81      0.75      6082
weighted avg       0.84      0.78      0.80      6082


log_grid_model Train_Set
[[13750  4516]
 [  823  5239]]
              precision    recall  f1-score   support

           0       0.94      0.75      0.84     18266
           1       0.54      0.86      0.66      6062

    accuracy                           0.78     24328
   macro avg       0.74      0.81      0.75     24328
weighted avg       0.84      0.78      0.79     24328
```

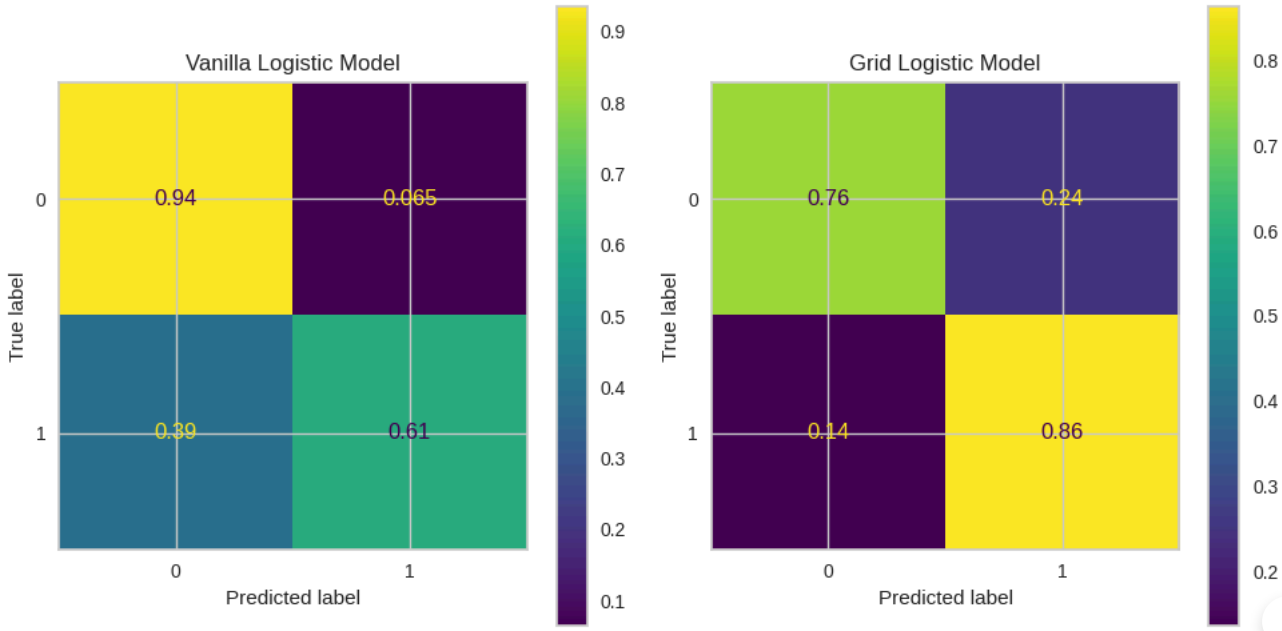
```
print('log_grid_model ROC_AUC Score:', roc_auc_score(y_test, y_pred_proba[:,1]))
print('------------------------------------------------')


# Confusion Matrix
grid_log_matrix = ConfusionMatrixDisplay.from_estimator(grid_model, X_test, y_test, normalize='true', cmap='BuPu')

# Precision-Recall Curve
grid_log_prCurve = PrecisionRecallDisplay.from_estimator(grid_model, X_test, y_test)
```

```
log_grid_model ROC_AUC Score: 0.8983590126036909
--------------------------------------------------
```



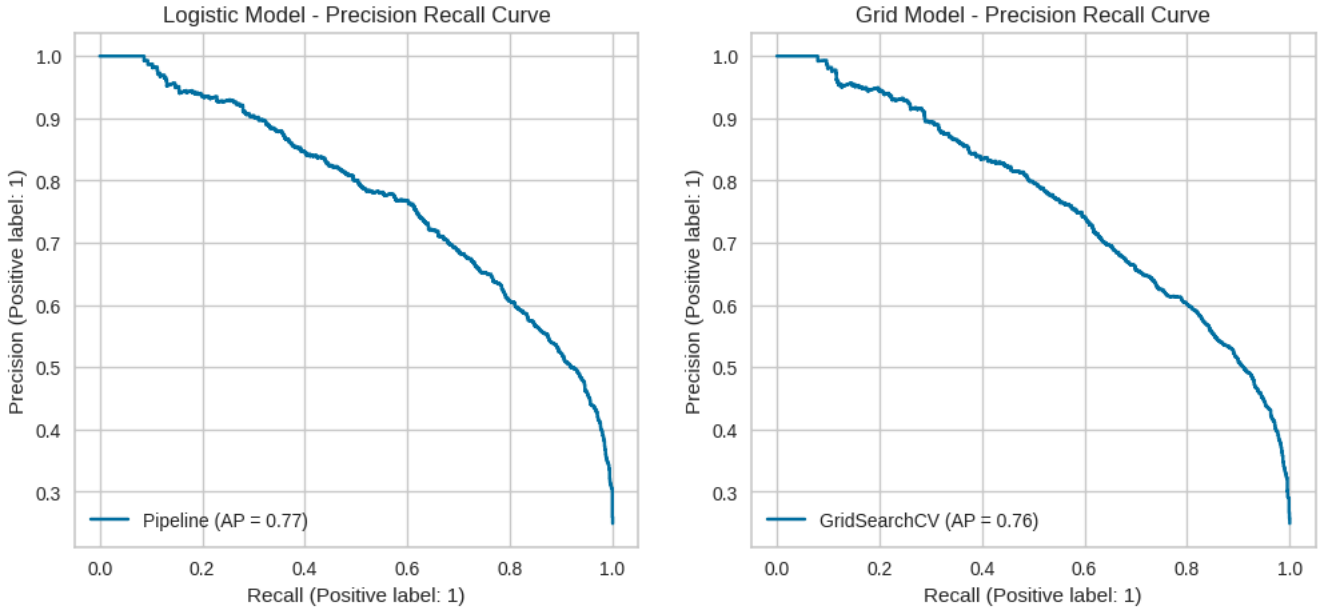



```
fig, ax = plt.subplots(1, 2, figsize=(10,5))

log_matrix.plot(ax=ax[0])
ax[0].set_title("Vanilla Logistic Model")
grid_log_matrix.plot(ax=ax[1])
ax[1].set_title("Grid Logistic Model")

plt.tight_layout()
plt.show()
```




```
fig, ax = plt.subplots(1, 2, figsize=(12, 5))

log_prCurve.plot(ax=ax[0])
ax[0].set_title("Logistic Model - Precision Recall Curve")
grid_log_prCurve.plot(ax=ax[1])
ax[1].set_title("Grid Model - Precision Recall Curve")
```

```
Text(0.5, 1.0, 'Grid Model - Precision Recall Curve')
```



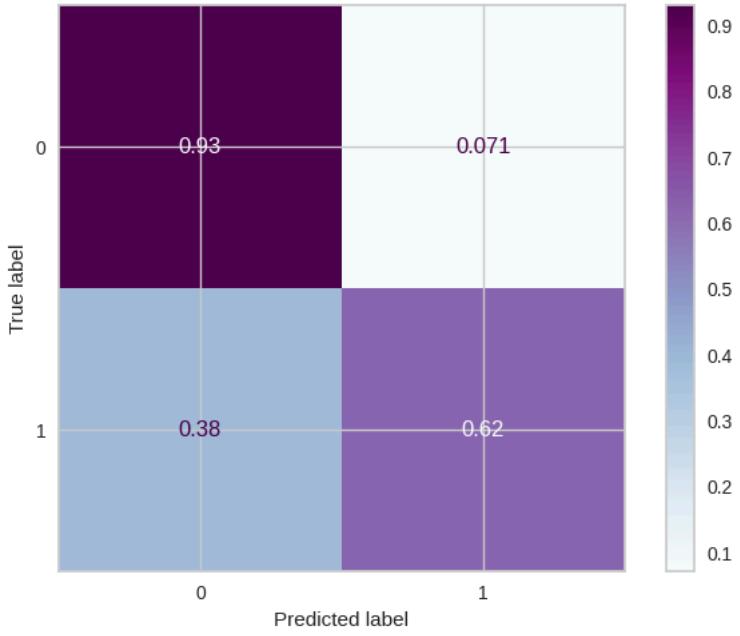

```
svm_model = Pipeline([("scaler", MinMaxScaler()), ("SVC", SVC(probability=True))])

#Fit the model
svm_model.fit(X_train, y_train)

# Prediction
y_pred=svm_model.predict(X_test)


eval_metric(svm_model, X_train, y_train, X_test, y_test, 'svm_model')
```

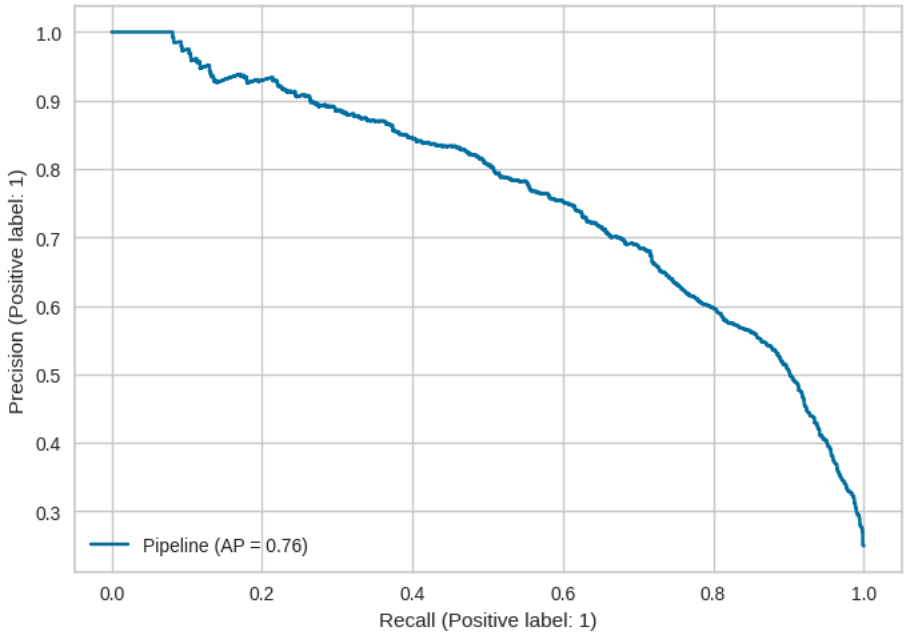
```
svm_model Test_Set
[[4243  324]
 [ 582  933]]
              precision    recall  f1-score   support

           0       0.88      0.93      0.90      4567
           1       0.74      0.62      0.67      1515

    accuracy                           0.85      6082
   macro avg       0.81      0.77      0.79      6082
weighted avg       0.85      0.85      0.85      6082
```

```
svm_model Train_Set
[[16977  1289]
 [ 2472  3590]]
              precision    recall  f1-score   support

           0       0.87      0.93      0.90     18266
           1       0.74      0.59      0.66      6062

    accuracy                           0.85     24328
   macro avg       0.80      0.76      0.78     24328
weighted avg       0.84      0.85      0.84     24328
```

```
print('svm_model ROC_AUC Score:', roc_auc_score(y_test, y_pred_proba[:,1]))
print('-------------------------------------------------')

# Confusion Matrix
svm_matrix = ConfusionMatrixDisplay.from_estimator(svm_model, X_test,y_test, normalize='true', cmap='BuPu' )

# Precision-Recall Curve
svm_prCurve = PrecisionRecallDisplay.from_estimator(svm_model, X_test, y_test)
```

```
svm_model ROC_AUC Score: 0.8983590126036909
-------------------------------------------------
```





```
model = Pipeline([("scaler", MinMaxScaler()), ("SVC", SVC())])

cv = StratifiedKFold(n_splits=5) # for unbalanced data validation

scores = cross_validate(model,
                        X_train,
                        y_train,
                        scoring=['accuracy', 'precision', 'recall', 'f1'],
                        cv=cv,
                        return_train_score=True)

df_scores = pd.DataFrame(scores, index=range(1, 6))
df_scores.mean()[2:]
```

	0
test_accuracy	0.842815
train_accuracy	0.845641
test_precision	0.729220
train_precision	0.736658
test_recall	0.587264
train_recall	0.592338
test_f1	0.650547
train_f1	0.656617

dtype: float64

```
svm_model.get_params()


model = Pipeline([("scaler", MinMaxScaler()), ("SVC", SVC(class_weight="balanced"))])


param_grid = {"SVC__C":[0.5,1],
              "SVC__gamma":["scale","auto", 0.1,0.3],
              "SVC__kernel":["rbf", "linear"]}

cv = StratifiedKFold(n_splits = 5) # for unbalanced data

svm_grid_model = GridSearchCV(model,
                          param_grid=param_grid,
                          cv=cv,
                          scoring = "recall_macro",
                          n_jobs = -1, # Uses all available cores
                          verbose=1,
                          return_train_score=True).fit(X_train, y_train) # fit the model
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
```

```
print('Best Params:', svm_grid_model.best_params_)
print('Best Recall Score(test):', svm_grid_model.best_score_)
print('Best Score Index:', svm_grid_model.best_index_)
```

```
Best Params: {'SVC__C': 1, 'SVC__gamma': 'scale', 'SVC__kernel': 'rbf'}
Best Recall Score(test): 0.8119453688234672
Best Score Index: 8
```

```
pd.DataFrame(svm_grid_model.cv_results_).loc[14, ["mean_test_score", "mean_train_score"]]
```

	14
mean_test_score	0.811642
mean_train_score	0.832004

dtype: object

```
y_pred=svm_grid_model.predict(X_test)
decision_fonc = svm_grid_model.decision_function(X_test)
# In an SVM model with probability=True, predict_proba uses the decision function's output, applying Platt scaling to provide probabili

svm_grid_f1 = f1_score(y_test, y_pred)
svm_grid_recall = recall_score(y_test, y_pred)
svm_grid_auc = roc_auc_score(y_test, y_pred)
```

```
# Checking the Incorrect Predictions

# Test Data df
test_data = pd.concat([X_test, y_test], axis=1)

# Create new column for 'predicted' classes to compore with actual target classes
test_data["pred"] = y_pred

# Filtering the wrong predicted obs
wrong_pred = test_data[((test_data["income"] == 0) & (test_data["pred"] == 1)) |
            ((test_data["income"] == 1) & (test_data["pred"] == 0))]

print('svm_grid_model Total Incorrect Predictions:', wrong_pred.shape)


print('-------------------------------------------------')
# Actual-Predicted-Probalility of Pozitive Class(1)

my_dict = {"Actual": y_test, "Pred":y_pred, "Proba_1":y_pred_proba[:,1]}
pd.DataFrame.from_dict(my_dict).sample(10)
```

```
svm_grid_model Total Incorrect Predictions: (1241, 49)
-------------------------------------------------
```

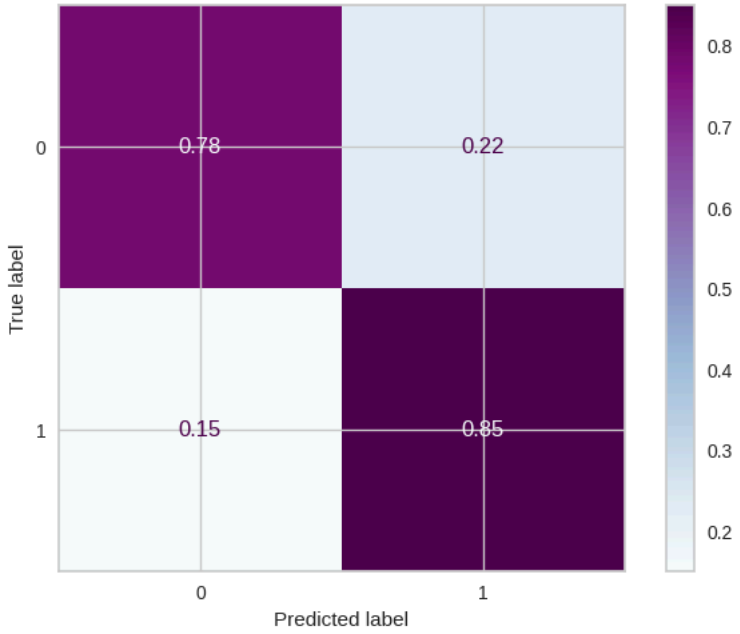
	Actual	Pred	Proba_1
26982	0	0	0.321105
17536	0	0	0.090360
21951	0	0	0.046785
23021	0	0	0.149390
8661	0	0	0.071340
6992	0	1	0.627051
12342	0	1	0.520753
28755	0	1	0.762226
31538	0	1	0.780580
17348	0	1	0.703307

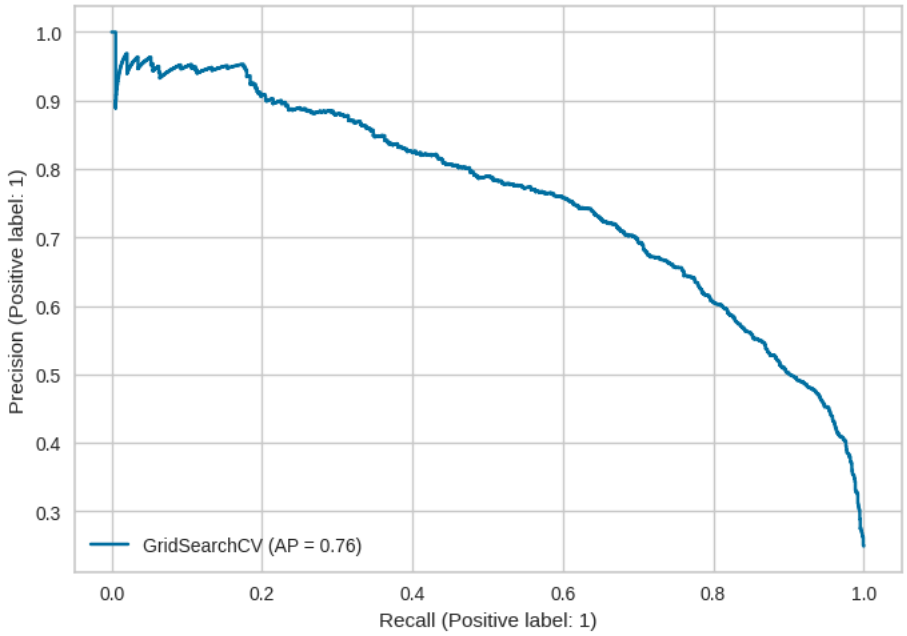
```
eval_metric(svm_grid_model, X_train, y_train, X_test, y_test, 'svm_grid_model')
```

```
svm_grid_model Test_Set
[[3554 1013]
 [ 228 1287]]
              precision    recall  f1-score   support

           0       0.94      0.78      0.85      4567
           1       0.56      0.85      0.67      1515

    accuracy                           0.80      6082
   macro avg       0.75      0.81      0.76      6082
weighted avg       0.85      0.80      0.81      6082


svm_grid_model Train_Set
[[14179  4087]
 [  815  5247]]
              precision    recall  f1-score   support

           0       0.95      0.78      0.85     18266
           1       0.56      0.87      0.68      6062

    accuracy                           0.80     24328
   macro avg       0.75      0.82      0.77     24328
weighted avg       0.85      0.80      0.81     24328
```

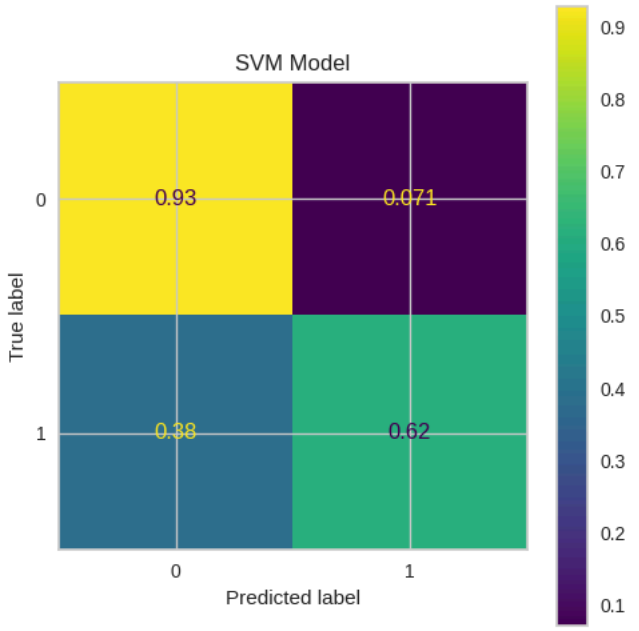
```
# Roc_AUC_score
print('svm_grid_model ROC_AUC Score:', roc_auc_score(y_test, decision_fonc))
print('-------------------------------------------------')

# Confusion Matrix
svm_grid_matrix = ConfusionMatrixDisplay.from_estimator(svm_grid_model, X_test, y_test, normalize='true', cmap='BuPu')

# Precision-Recall Curve
svm_grid_prCurve = PrecisionRecallDisplay.from_estimator(svm_grid_model, X_test, y_test)
```

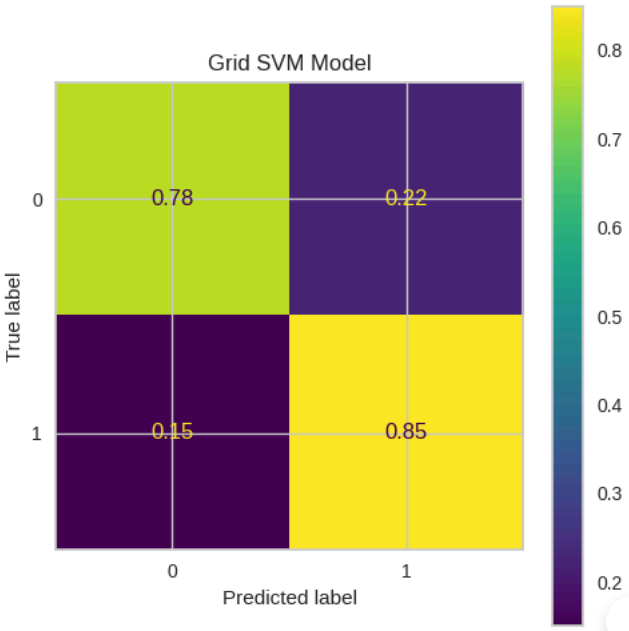
```
svm_grid_model ROC_AUC Score: 0.8997057380360326
--------------------------------------------------
```





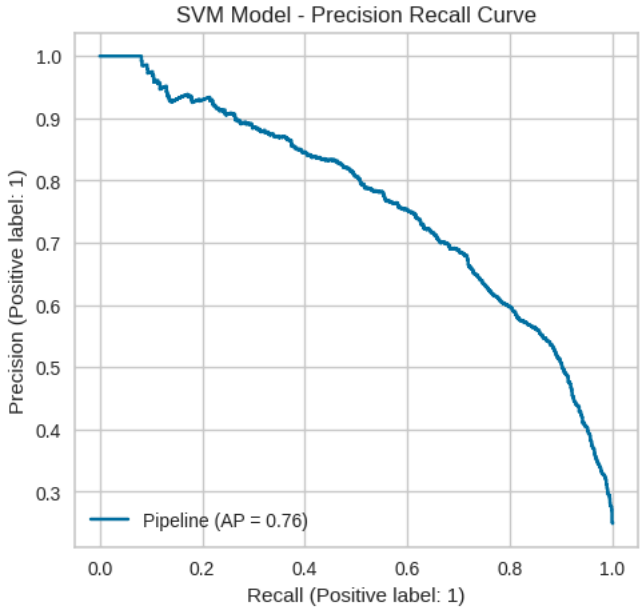

```
fig, ax = plt.subplots(1, 2, figsize=(10,5))

svm_matrix.plot(ax=ax[0])
ax[0].set_title("SVM Model")
svm_grid_matrix.plot(ax=ax[1])
ax[1].set_title("Grid SVM Model")

plt.tight_layout()
plt.show()
```

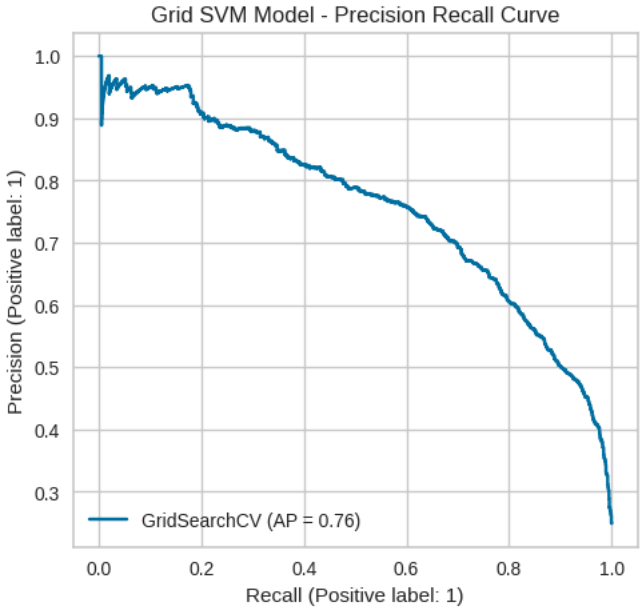




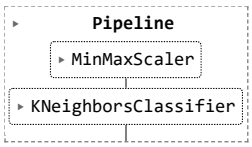

```
fig, ax = plt.subplots(1, 2, figsize=(12, 5))

svm_prCurve.plot(ax=ax[0])
ax[0].set_title("SVM Model - Precision Recall Curve")
svm_grid_prCurve.plot(ax=ax[1])
ax[1].set_title("Grid SVM Model - Precision Recall Curve")
```

```
Text(0.5, 1.0, 'Grid SVM Model - Precision Recall Curve')
```






```
knn_model = Pipeline([("scaler", MinMaxScaler()),("knn", KNeighborsClassifier())])

knn_model.fit(X_train, y_train)
```




```
# Prediction
y_pred = knn_model.predict(X_test)
y_pred_proba = knn_model.predict_proba(X_test)

# Scores to compare the models at the end.
knn_f1 = f1_score(y_test, y_pred)
knn_recall = recall_score(y_test, y_pred)
knn_auc = roc_auc_score(y_test, y_pred)
```