Part 1: Introduction to the Data Domain and the Data Exploration Report

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数据集连接Adult Income

1.1 数据集介绍

1.1.1 数据来源与背景

`Adult Income Dataset`是一个研究成年收入与各种因素关系的数据集，它可以从Adult Income下载到

正如介绍页所说的"An individual's annual income results from various factors. Intuitively, it is influenced by the individual's education level, age, gender, occupation, and etc.This is a widely cited KNN dataset. I encountered it during my course, and I wish to share it here because it is a good starter example for data pre-processing and machine learning practices."

作为机器学习领域的经典数据集之一，该最初来源于1994年美国人口普查数据。该数据集包含48,842个样本（含1个标题行），每个样本包含15个特征属性。

1.1.2 数据集详细信息

数据集规模:

总样本数：48,842条记录

特征数量：14个预测特征 + 1个目标变量

数据类型：包含数值型和分类型特征

连续型特征包括:

特征名称	英文名称	数据类型	描述	取值范围
年龄	age	数值型	个人年龄	17-90岁
教育年限	education-num	数值型	受教育年数	1-16年
资本收益	capital-gain	数值型	资本收益	0-99,999美元
资本损失	capital-loss	数值型	资本损失	0-4,356美元

特征名称	英文名称	数据类型	描述	取值范围
每周工作小时	hours-per-week	数值型	每周工作时间	1-99小时
最终权重	fnlwgt	数值型	人口普查权重	12,285-1,484,705

离散型特征包括:

特征名称	英文名称	类别数	主要取值
工作类型	workclass	9类	Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked
教育水平	education	16类	Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool
婚姻状况	marital-status	7类	Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse
职业	occupation	15类	Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces
家庭关系	relationship	6类	Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried
种族	race	5类	White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black
性别	sex	2类	Female, Male
原籍国	native-country	42类	United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands

1.2 探索性数据分析

In [33]:
```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
import sklearn.model_selection as ms

# Set font for better display - use system default fonts
plt.rcParams['font.family'] = 'DejaVu Sans'
plt.rcParams['axes.unicode_minus'] = False

df = pd.read_csv('adult.csv')

# Basic dataset information
print("Dataset Basic Information:")
print(f"Dataset shape: {df.shape}")
print(f"Column names: {df.columns.tolist()}")
print("\nFirst 5 rows:")
print(df.head())

print("\nDataset info:")
print(df.info())

print("\nDataset statistics:")
print(df.describe())

print("\nMissing values:")
print(df.isnull().sum())

# Check for missing values marked with "?"
print("\nCheck for missing values marked with '?':")
for col in df.columns:
    if df[col].dtype == 'object':
        missing_count = (df[col] == '?').sum()
        if missing_count > 0:
            print(f"{col}: {missing_count} missing values")
```

```
Dataset Basic Information:
Dataset shape: (48842, 15)
Column names: ['age', 'workclass', 'fnlwgt', 'education', 'educational-nu
m', 'marital-status', 'occupation', 'relationship', 'race', 'gender', 'cap
ital-gain', 'capital-loss', 'hours-per-week', 'native-country', 'income']

First 5 rows:
   age  workclass  fnlwgt     education  educational-num      marital-stat
us  \
0   25    Private  226802          11th                7       Never-marri
ed
1   38    Private   89814       HS-grad                9  Married-civ-spou
se
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-spou
se
3   44    Private  160323  Some-college               10  Married-civ-spou
se
4   18          ?  103497  Some-college               10       Never-marri
ed

          occupation relationship   race  gender  capital-gain  capital-lo
ss  \
0  Machine-op-inspct    Own-child  Black    Male             0
0
1    Farming-fishing      Husband  White    Male             0
0
2    Protective-serv      Husband  White    Male             0
0
3  Machine-op-inspct      Husband  Black    Male          7688
0
4                  ?    Own-child  White  Female             0
0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K

Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   age              48842 non-null  int64 
 1   workclass        48842 non-null  object
 2   fnlwgt           48842 non-null  int64 
 3   education        48842 non-null  object
 4   educational-num  48842 non-null  int64 
 5   marital-status   48842 non-null  object
 6   occupation       48842 non-null  object
 7   relationship     48842 non-null  object
 8   race             48842 non-null  object
 9   gender           48842 non-null  object
 10  capital-gain     48842 non-null  int64 
 11  capital-loss     48842 non-null  int64 
 12  hours-per-week   48842 non-null  int64 
 13  native-country   48842 non-null  object
```

```
 14  income           48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
None

Dataset statistics:
                age        fnlwgt  educational-num  capital-gain  \
count  48842.000000  4.884200e+04     48842.000000  48842.000000   
mean      38.643585  1.896641e+05        10.078089   1079.067626   
std       13.710510  1.056040e+05         2.570973   7452.019058   
min       17.000000  1.228500e+04         1.000000      0.000000   
25%       28.000000  1.175505e+05         9.000000      0.000000   
50%       37.000000  1.781445e+05        10.000000      0.000000   
75%       48.000000  2.376420e+05        12.000000      0.000000   
max       90.000000  1.490400e+06        16.000000  99999.000000   

       capital-loss  hours-per-week  
count  48842.000000    48842.000000  
mean      87.502314       40.422382  
std      403.004552       12.391444  
min        0.000000        1.000000  
25%        0.000000       40.000000  
50%        0.000000       40.000000  
75%        0.000000       45.000000  
max     4356.000000       99.000000  

Missing values:
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64

Check for missing values marked with '?':
workclass: 2799 missing values
occupation: 2809 missing values
native-country: 857 missing values
```

1.2.1 单变量分析

在本部分, 我们将:

1. 绘制所有连续型变量的**箱线图**, 观察每个特征的分布
2. 绘制所有离散型变量的特征取值柱状统计图, 观察每个离散型特征各个取值的分布

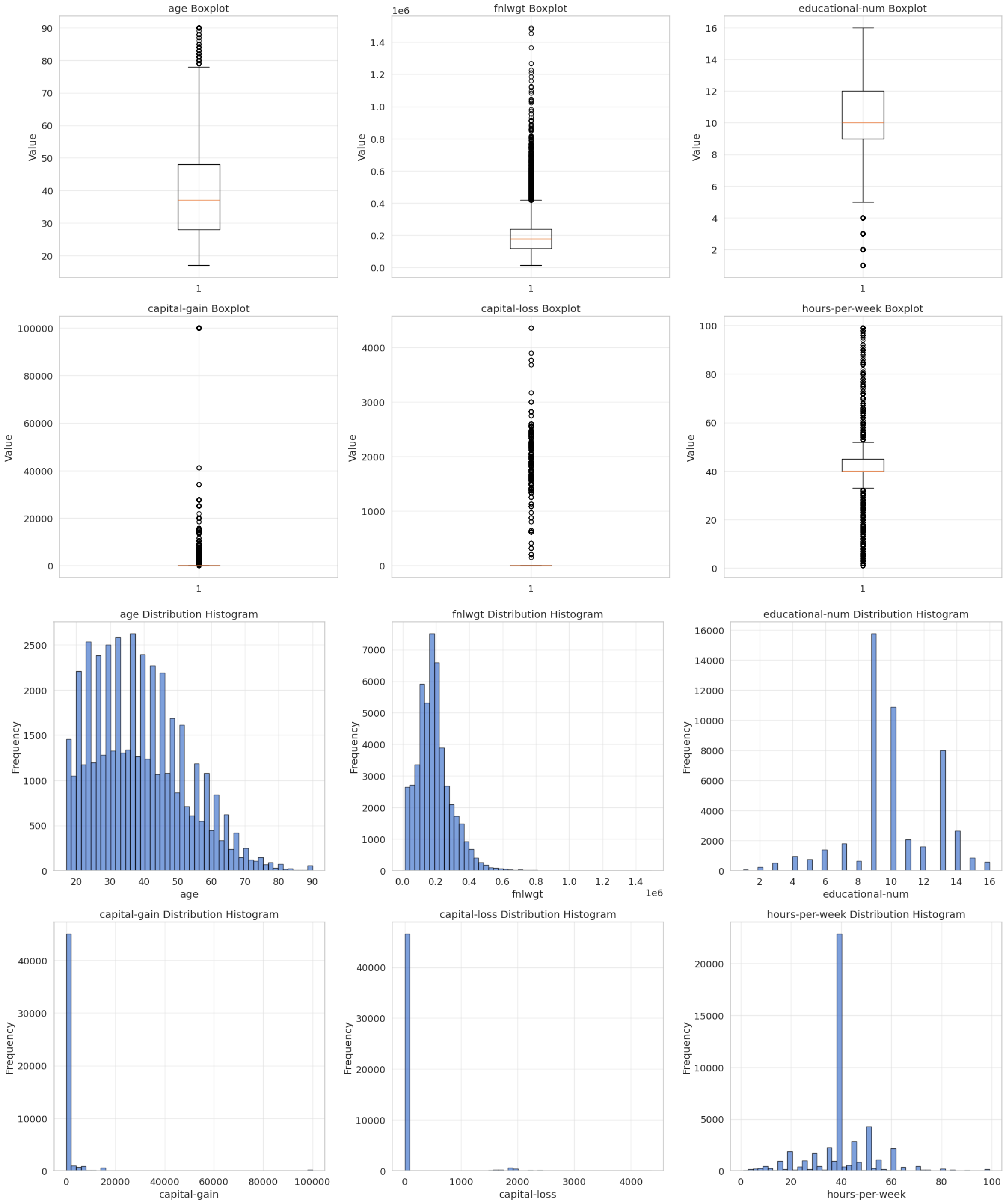
观察图像可以发现:

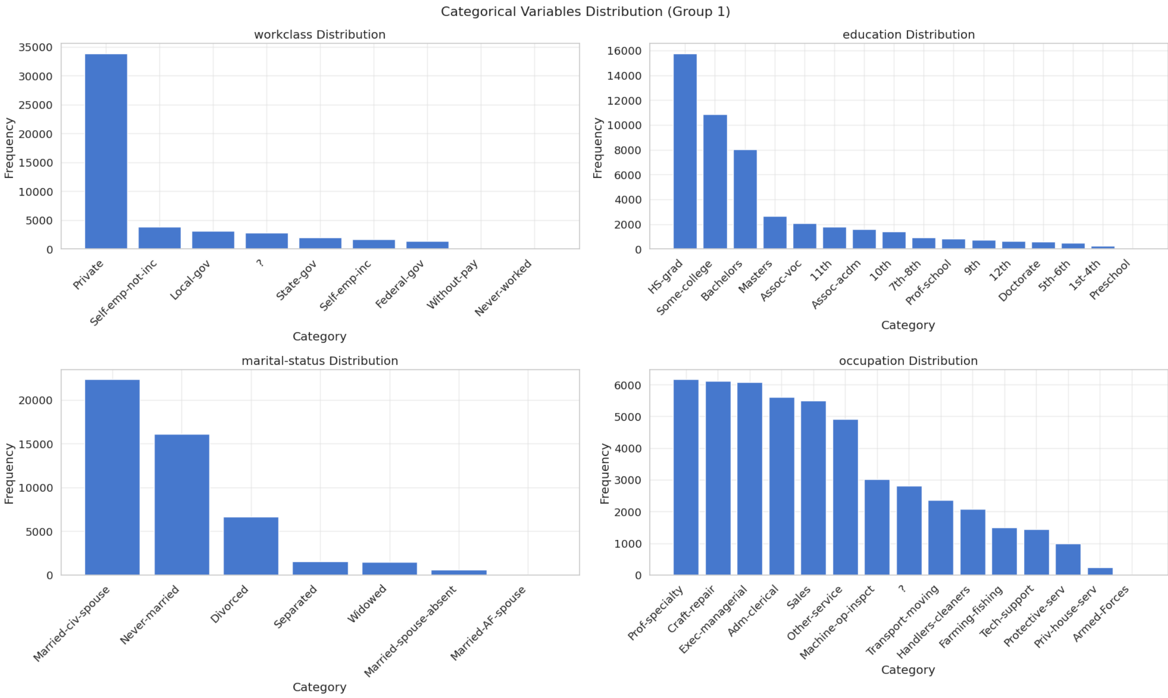
1. 在连续型特征中: `age` 和 `educational-num` 两个特征分布较为均匀, 出现了少量的离群值; `fnlwgt` (最终权重)分布范围很广，存在较多离群值; `capital-gain` 和 `capital-loss` 两个特征高度右偏，大多数值为0，只有少数样本有资本收益或损失; `hours-per-week` 主要集中在40小时左右，符合标准工作时间的分布特征。
2. 在离散型特征中: `workclass` 以私营企业(Private)为主，约占75%; `education` 中高中毕业(HS-grad)和大学教育(Some-college, Bachelors)较多; `marital-status` 中已婚(Married-civ-spouse)占主导地位; `occupation` 分布相对均匀，专业技术人员(Prof-specialty)和管理人员(Exec-managerial)较多; `relationship` 中丈夫(Husband)和非家庭成员(Not-in-family)较多; `race` 以白人(White)为主，约占85%; `gender` 中男性(Male)约占67%; `native-country` 以美国(United-States)为主，约占90%。
3. 目标变量 `income` 分布不均衡，收入≤50K的样本约占76%，收入>50K的样本约占24%。

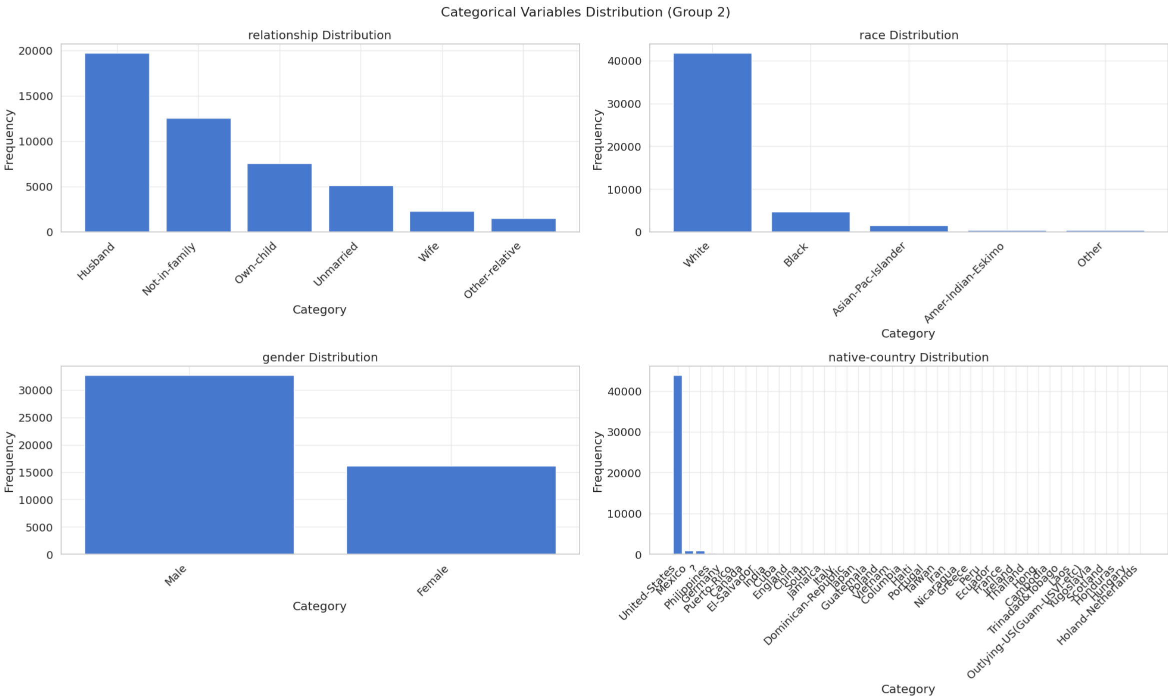
In [34]:
```
# Define continuous and categorical variables
continuous_features = ['age', 'fnlwgt', 'educational-num', 'capital-gain'
categorical_features = ['workclass', 'education', 'marital-status', 'occu

# 1. Plot boxplots for continuous variables
plt.figure(figsize=(20, 12))
for i, feature in enumerate(continuous_features):
    plt.subplot(2, 3, i+1)
    plt.boxplot(df[feature].dropna())
    plt.title(f'{feature} Boxplot')
    plt.ylabel('Value')
    plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# 2. Plot histograms for continuous variables
plt.figure(figsize=(20, 12))
for i, feature in enumerate(continuous_features):
    plt.subplot(2, 3, i+1)
    plt.hist(df[feature].dropna(), bins=50, alpha=0.7, edgecolor='black')
    plt.title(f'{feature} Distribution Histogram')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
    plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# 3. Plot bar charts for categorical variables
# Split categorical variables into groups for better visualization
fig, axes = plt.subplots(2, 2, figsize=(20, 12))
fig.suptitle('Categorical Variables Distribution (Group 1)', fontsize=16)

for i, feature in enumerate(categorical_features[:4]):
    row = i // 2
    col = i % 2

    # Calculate frequency for each category
    value_counts = df[feature].value_counts()
```

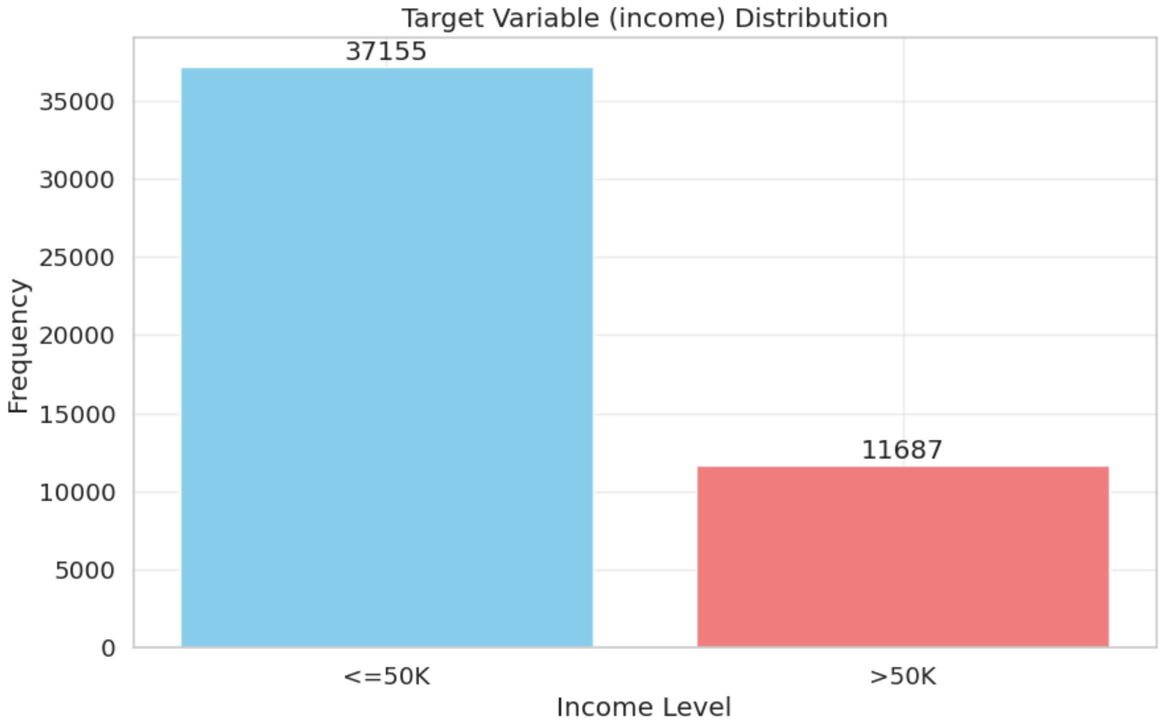
```
    # Plot bar chart
    axes[row, col].bar(range(len(value_counts)), value_counts.values)
    axes[row, col].set_title(f'{feature} Distribution')
    axes[row, col].set_xlabel('Category')
    axes[row, col].set_ylabel('Frequency')
    axes[row, col].set_xticks(range(len(value_counts)))
    axes[row, col].set_xticklabels(value_counts.index, rotation=45, ha='r
    axes[row, col].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Group 2 categorical variables
fig, axes = plt.subplots(2, 2, figsize=(20, 12))
fig.suptitle('Categorical Variables Distribution (Group 2)', fontsize=16)

for i, feature in enumerate(categorical_features[4:]):
    row = i // 2
    col = i % 2

    # Calculate frequency for each category
    value_counts = df[feature].value_counts()

    # Plot bar chart
    axes[row, col].bar(range(len(value_counts)), value_counts.values)
    axes[row, col].set_title(f'{feature} Distribution')
    axes[row, col].set_xlabel('Category')
    axes[row, col].set_ylabel('Frequency')
    axes[row, col].set_xticks(range(len(value_counts)))
    axes[row, col].set_xticklabels(value_counts.index, rotation=45, ha='r
    axes[row, col].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# 4. Target variable distribution
plt.figure(figsize=(10, 6))
income_counts = df['income'].value_counts()
plt.bar(income_counts.index, income_counts.values, color=['skyblue', 'lig
plt.title('Target Variable (income) Distribution')
plt.xlabel('Income Level')
plt.ylabel('Frequency')
plt.grid(True, alpha=0.3)

# Add value labels
for i, v in enumerate(income_counts.values):
    plt.text(i, v + 100, str(v), ha='center', va='bottom')

plt.show()

# 5. Statistical summary
print("\n=== Univariate Analysis Summary ===")
print("\nContinuous variables statistics:")
print(df[continuous_features].describe())

print("\nCategorical variables statistics:")
for feature in categorical_features:
    print(f"\n{feature}:")
    print(df[feature].value_counts())
```

```
print(f"\nTarget variable distribution:")
print(df['income'].value_counts())
print(f"Target variable proportion:")
print(df['income'].value_counts(normalize=True))
```




Categorical Variables Distribution (Group 1)
workclass Distribution
Frequency
Category
Private
Self-emp-not-inc
Local-gov
?
State-gov
Self-emp-inc
Federal-gov
Without-pay
Never-worked
education Distribution
HS-grad
Some-college
Bachelors
Masters
Assoc-voc
11th
Assoc-acdm
10th
7th-8th
Prof-school
9th
12th
Doctorate
5th-6th
1st-4th
Preschool
marital-status Distribution
Married-civ-spouse
Never-married
Divorced
Separated
Widowed
Married-spouse-absent
Married-AF-spouse
occupation Distribution
Prof-specialty
Craft-repair
Exec-managerial
Adm-clerical
Sales
Other-service
Machine-op-inspct
?
Transport-moving
Handlers-cleaners
Farming-fishing
Tech-support
Protective-serv
Priv-house-serv
Armed-Forces


Categorical Variables Distribution (Group 2)
relationship Distribution
Frequency
Category
Husband
Not-in-family
Own-child
Unmarried
Wife
Other-relative
race Distribution
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
gender Distribution
Male
Female
native-country Distribution


Target Variable (income) Distribution
37155
11687
Frequency
35000
30000
25000
20000
15000
10000
5000
0
<=50K
>50K
Income Level

```
=== Univariate Analysis Summary ===

Continuous variables statistics:
                age        fnlwgt  educational-num  capital-gain  \
count  48842.000000  4.884200e+04     48842.000000  48842.000000   
mean      38.643585  1.896641e+05        10.078089   1079.067626   
std       13.710510  1.056040e+05         2.570973   7452.019058   
min       17.000000  1.228500e+04         1.000000      0.000000   
25%       28.000000  1.175505e+05         9.000000      0.000000   
50%       37.000000  1.781445e+05        10.000000      0.000000   
75%       48.000000  2.376420e+05        12.000000      0.000000   
max       90.000000  1.490400e+06        16.000000  99999.000000   

       capital-loss  hours-per-week  
count  48842.000000    48842.000000  
mean      87.502314       40.422382  
std      403.004552       12.391444  
min        0.000000        1.000000  
25%        0.000000       40.000000  
50%        0.000000       40.000000  
75%        0.000000       45.000000  
max     4356.000000       99.000000  

Categorical variables statistics:

workclass:
workclass
Private             33906
Self-emp-not-inc     3862
Local-gov            3136
?                    2799
State-gov            1981
Self-emp-inc         1695
Federal-gov          1432
Without-pay            21
Never-worked           10
Name: count, dtype: int64

education:
education
HS-grad         15784
Some-college    10878
Bachelors        8025
Masters          2657
Assoc-voc        2061
11th             1812
Assoc-acdm       1601
10th             1389
7th-8th           955
Prof-school       834
9th               756
12th              657
Doctorate         594
5th-6th           509
1st-4th           247
Preschool          83
Name: count, dtype: int64

marital-status:
marital-status
```

```
Married-civ-spouse       22379
Never-married            16117
Divorced                  6633
Separated                 1530
Widowed                   1518
Married-spouse-absent      628
Married-AF-spouse           37
Name: count, dtype: int64

occupation:
occupation
Prof-specialty       6172
Craft-repair         6112
Exec-managerial      6086
Adm-clerical         5611
Sales                5504
Other-service        4923
Machine-op-inspct    3022
?                    2809
Transport-moving     2355
Handlers-cleaners    2072
Farming-fishing      1490
Tech-support         1446
Protective-serv       983
Priv-house-serv       242
Armed-Forces           15
Name: count, dtype: int64

relationship:
relationship
Husband           19716
Not-in-family     12583
Own-child          7581
Unmarried          5125
Wife               2331
Other-relative     1506
Name: count, dtype: int64

race:
race
White                 41762
Black                  4685
Asian-Pac-Islander     1519
Amer-Indian-Eskimo      470
Other                   406
Name: count, dtype: int64

gender:
gender
Male      32650
Female    16192
Name: count, dtype: int64

native-country:
native-country
United-States                 43832
Mexico                          951
?                               857
Philippines                     295
Germany                         206
```

```
Puerto-Rico                     184
Canada                          182
El-Salvador                     155
India                           151
Cuba                            138
England                         127
China                           122
South                           115
Jamaica                         106
Italy                           105
Dominican-Republic              103
Japan                            92
Guatemala                        88
Poland                           87
Vietnam                          86
Columbia                         85
Haiti                            75
Portugal                         67
Taiwan                           65
Iran                             59
Nicaragua                        49
Greece                           49
Peru                             46
Ecuador                          45
France                           38
Ireland                          37
Thailand                         30
Hong                             30
Cambodia                         28
Trinadad&Tobago                  27
Laos                             23
Outlying-US(Guam-USVI-etc)       23
Yugoslavia                       23
Scotland                         21
Honduras                         20
Hungary                          19
Holand-Netherlands                1
Name: count, dtype: int64

Target variable distribution:
income
<=50K    37155
>50K     11687
Name: count, dtype: int64
Target variable proportion:
income
<=50K    0.760718
>50K     0.239282
Name: proportion, dtype: float64
```

1.1.2 多变量分析

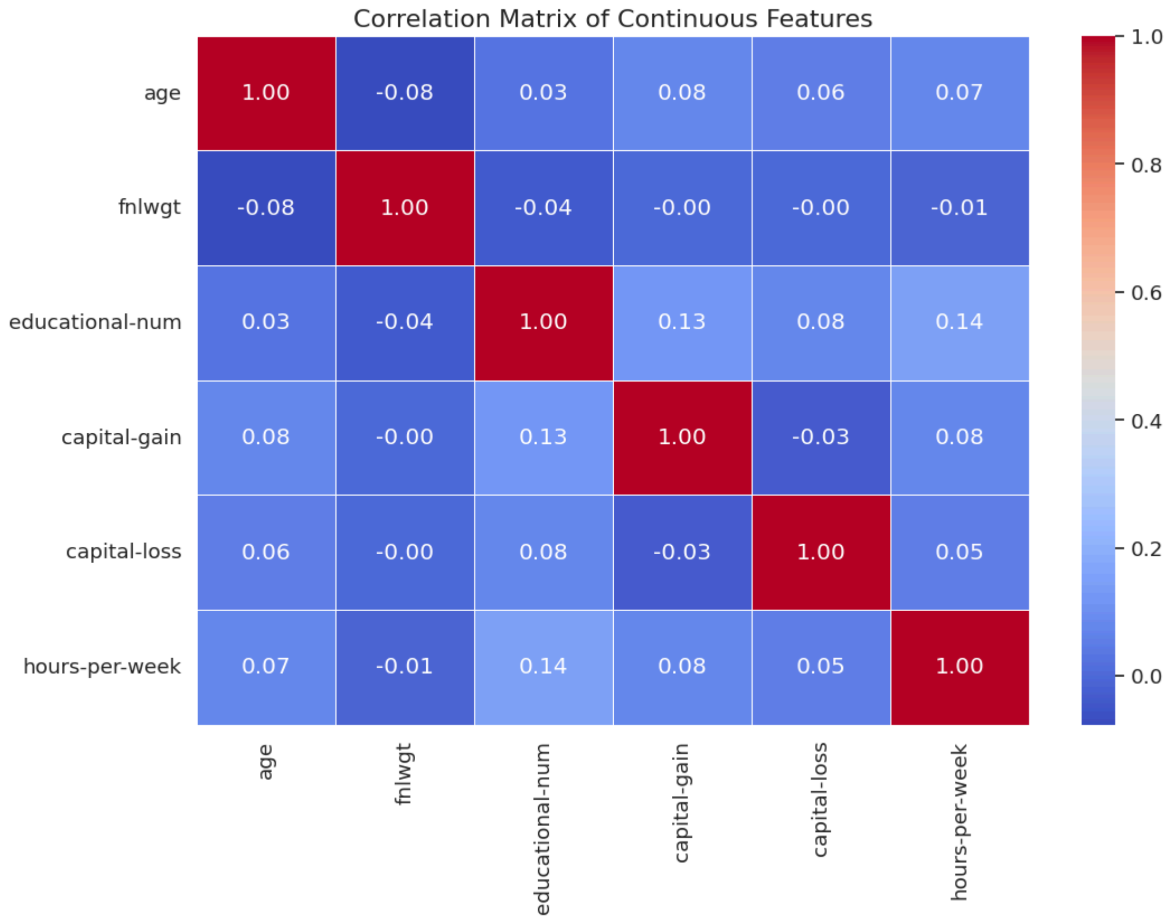
在本部分, 我们首先将通过画出**连续**变量之间的**相关性热力图**和**散点图**检查变量之间的相关关系。观察图像可知:特征之间的相关关系很弱。两两特征之间没有的相关系数没有超过0.3的, 这表明了变量之间的弱相关性

此外, 观察以 `income` 为分类绘制的散点图矩阵, 我们可以发现:

1. `age` 和 `education_num` 之间, 收入高(`income>50k`)的群体普遍具有更高的教育年限和更大的年龄; 此外, 高收入群体 `hours-per-week` 更长，且分布范围更广
2. `capital-gain` 是一个非常强的预测指标。几乎所有收入 >50K 的个体都集中在 `capital-gain` 大于零的区域，而收入 <=50K 的个体其资本收益几乎全部为零。这与我们在1.1.1节中看到的箱型图结果一致
3. `fnlwgt` 与 `income` 几乎没有显著关联, 对 `income` 的预测作用有限, 后续可以考虑将其排除于模型之外

In [35]:

```python
# Set visualization style
sns.set(style='whitegrid', palette='muted', font_scale=1.2)

# Calculate the correlation matrix for continuous features
correlation_matrix = df[continuous_features].corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', l
plt.title('Correlation Matrix of Continuous Features', fontsize=16)
plt.show()

# Create a pairplot to visualize relationships between continuous variabl
# colored by the target variable 'income'.
# To avoid long computation time and cluttered plot, we use a sample of t
df_sample = df.sample(n=2000, random_state=42)

plt.figure(figsize=(12, 8))
sns.pairplot(df_sample, vars=continuous_features, hue='income', plot_kws=
plt.suptitle('Pairplot of Continuous Features by Income Level', y=1.02, f
plt.show()
```



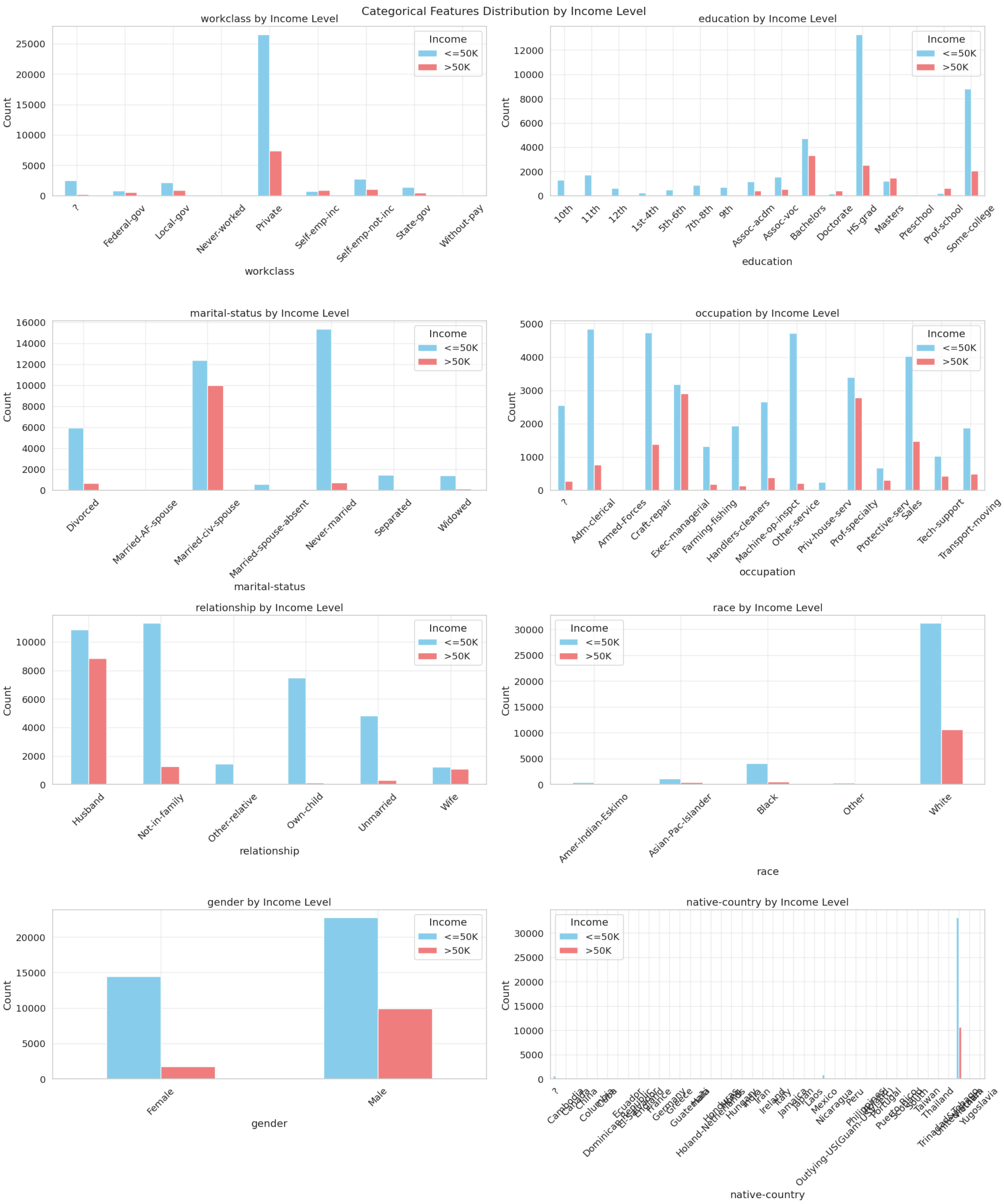
```
<Figure size 1200x800 with 0 Axes>
```

接着研究**离散型**变量之间的关系, 我们将使用 `income` 作为分类变量, 绘制每个离散型特征的**分组柱状图**。观察图像可知:

1. **工作类型 (workclass)**：私营企业员工在高收入群体中占主导地位，而政府员工（联邦、州、地方）在收入>50K群体中比例相对较高
2. **教育水平 (education)**：高等教育（学士、硕士、博士）与高收入密切相关，而较低教育水平主要集中在≤50K收入群体
3. **婚姻状况 (marital-status)**：已婚人士在高收入群体中占绝大多数，而从未结婚和离婚人士主要集中在低收入群体
4. **职业 (occupation)**：管理人员和专业技术人员在高收入群体中比例显著更高
5. **家庭关系 (relationship)**：丈夫角色在高收入群体中占主导，而其他家庭角色主要集中在低收入群体
6. **种族 (race)**：各种族在收入分布上存在差异，但白人在高收入群体中比例相对较高
7. **性别 (sex)**：男性在高收入群体中比例明显高于女性
8. **原籍国 (native-country)**：美国本土人士在高收入群体中占绝大多数

In [36]:
```python
# Plot grouped bar charts for categorical features by income
fig, axes = plt.subplots(4, 2, figsize=(20, 24))
fig.suptitle('Categorical Features Distribution by Income Level', fontsiz

for i, feature in enumerate(categorical_features):
```

```
    row = i // 2
    col = i % 2

    # Create cross-tabulation
    ct = pd.crosstab(df[feature], df['income'])

    # Plot grouped bar chart
    ct.plot(kind='bar', ax=axes[row, col], color=['skyblue', 'lightcoral'
    axes[row, col].set_title(f'{feature} by Income Level')
    axes[row, col].set_xlabel(feature)
    axes[row, col].set_ylabel('Count')
    axes[row, col].legend(title='Income')
    axes[row, col].tick_params(axis='x', rotation=45)
    axes[row, col].grid(True, alpha=0.3)

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



1.1.3 特征分析

在本部分，我们将对特征进行重要性分析，以确定哪些特征对预测 `income` 最有用。虽然使用 `k-fold` 交叉验证可以评估模型的性能，但在特征选择阶段，我们可以使用一些简单的统计方法来初步筛选特征。 我们将使用 `卡方检验` 来评估每个离散型特征与目标变量 `income` 之间的相关性。对于连续型特征，我们将使用 `皮尔逊相关系数` 来衡量它们与目标变量之间的线性关系。

根据检验结果，重要性得分前5的特征为: `relationship` , `marital-status` , `education` , `occupation` , `education-num` 。这些特征在预测 `income` 方面具有较强的相关性，可以作为模型的主要输入特征。

In [37]:

```
from scipy.stats import chi2_contingency, pearsonr
from sklearn.preprocessing import LabelEncoder
import pandas as pd
import numpy as np

print("=== Feature Importance Analysis ===\n")

# Encode target variable for correlation analysis
le_target = LabelEncoder()
income_encoded = le_target.fit_transform(df['income'])

# Chi-square test for categorical features
print("1. Chi-square Test Results for Categorical Features:")
print("=" * 60)

categorical_chi2_results = []

for feature in categorical_features:
    # Clean data (remove missing values)
    mask = df[feature] != '?'
    feature_clean = df[feature][mask]
    income_clean = df['income'][mask]

    # Create contingency table
    contingency_table = pd.crosstab(feature_clean, income_clean)

    # Perform chi-square test
    chi2_stat, p_value, dof, expected = chi2_contingency(contingency_tabl

    # Calculate Cramér's V for effect size
    n = contingency_table.sum().sum()
    phi2 = chi2_stat / n
    r, k = contingency_table.shape
    cramers_v = np.sqrt(phi2 / min(k-1, r-1))

    categorical_chi2_results.append({
        'Feature': feature,
        'Chi2_Statistic': chi2_stat,
        'P_value': p_value,
        'Cramers_V': cramers_v,
        'Degrees_of_Freedom': dof,
        'Significant': 'Yes' if p_value < 0.05 else 'No'
    })
```

```
# Sort by Chi-square statistic (descending)
categorical_chi2_results.sort(key=lambda x: x['Chi2_Statistic'], reverse=

# Display results
print(f"{'Feature':<20} {'Chi2_Stat':<12} {'P_value':<12} {'Cramers_V':<1
print("-" * 75)
for result in categorical_chi2_results:
    print(f"{result['Feature']:<20} {result['Chi2_Statistic']:<12.2f} {re

print("\n" + "=" * 60)

# 2. Pearson correlation for continuous features
print("\n2. Pearson Correlation Results for Continuous Features:")
print("=" * 60)

continuous_correlation_results = []

for feature in continuous_features:
    # Clean data (remove missing values)
    feature_data = df[feature].dropna()
    income_data = income_encoded[df[feature].notna()]

    # Calculate Pearson correlation
    correlation_coef, p_value = pearsonr(feature_data, income_data)

    continuous_correlation_results.append({
        'Feature': feature,
        'Correlation': correlation_coef,
        'P_value': p_value,
        'Abs_Correlation': abs(correlation_coef),
        'Significant': 'Yes' if p_value < 0.05 else 'No'
    })

# Sort by absolute correlation (descending)
continuous_correlation_results.sort(key=lambda x: x['Abs_Correlation'], r

# Display results
print(f"{'Feature':<20} {'Correlation':<12} {'P_value':<12} {'Abs_Corr':<
print("-" * 75)
for result in continuous_correlation_results:
    print(f"{result['Feature']:<20} {result['Correlation']:<12.3f} {resul

print("\n" + "=" * 60)
```

```
=== Feature Importance Analysis ===

1. Chi-square Test Results for Categorical Features:
============================================================
Feature                 Chi2_Stat    P_value      Cramers_V    Significant
--------------------------------------------------------------------------
-
relationship            10088.72     0.00e+00     0.454        Yes
marital-status          9816.02      0.00e+00     0.448        Yes
education               6537.97      0.00e+00     0.366        Yes
occupation              5502.14      0.00e+00     0.346        Yes
gender                  2248.85      0.00e+00     0.215        Yes
workclass               1238.99      2.61e-263    0.164        Yes
race                    487.03       4.28e-104    0.100        Yes
native-country          451.18       4.95e-71     0.097        Yes

============================================================

2. Pearson Correlation Results for Continuous Features:
============================================================
Feature                 Correlation  P_value      Abs_Corr     Significant
--------------------------------------------------------------------------
-
educational-num         0.333        0.00e+00     0.333        Yes
age                     0.230        0.00e+00     0.230        Yes
hours-per-week          0.228        0.00e+00     0.228        Yes
capital-gain            0.223        0.00e+00     0.223        Yes
capital-loss            0.148        8.54e-236    0.148        Yes
fnlwgt                  -0.006       1.61e-01     0.006        No

============================================================
```

In [38]:

```python
print("\n4. Feature Ranking and Selection Recommendations:")
print("=" * 60)

# Combine all features with their importance scores
all_features_importance = []

# Add categorical features (using Cramér's V as importance score)
for result in categorical_chi2_results:
    all_features_importance.append({
        'Feature': result['Feature'],
        'Type': 'Categorical',
        'Importance_Score': result['Cramers_V'],
        'Statistical_Test': 'Chi-square',
        'P_value': result['P_value'],
        'Significant': result['Significant']
    })

# Add continuous features (using absolute correlation as importance score
for result in continuous_correlation_results:
    all_features_importance.append({
        'Feature': result['Feature'],
        'Type': 'Continuous',
        'Importance_Score': result['Abs_Correlation'],
        'Statistical_Test': 'Pearson Correlation',
        'P_value': result['P_value'],
        'Significant': result['Significant']
    })
```

```
# Sort by importance score
all_features_importance.sort(key=lambda x: x['Importance_Score'], reverse

print("Overall Feature Ranking (by importance score):")
print(f"{'Rank':<6} {'Feature':<20} {'Type':<12} {'Score':<10} {'Test':<1
print("-" * 85)
for i, feature in enumerate(all_features_importance, 1):
    print(f"{i:<6} {feature['Feature']:<20} {feature['Type']:<12} {featur
```

```
4. Feature Ranking and Selection Recommendations:
============================================================
Overall Feature Ranking (by importance score):
Rank   Feature              Type         Score      Test                Sig
nificant
-------------------------------------------------------------------------------------
-----------
1      relationship         Categorical  0.454      Chi-square          Yes
2      marital-status       Categorical  0.448      Chi-square          Yes
3      education            Categorical  0.366      Chi-square          Yes
4      occupation           Categorical  0.346      Chi-square          Yes
5      educational-num      Continuous   0.333      Pearson Correlation Ye
s
6      age                  Continuous   0.230      Pearson Correlation Ye
s
7      hours-per-week       Continuous   0.228      Pearson Correlation Ye
s
8      capital-gain         Continuous   0.223      Pearson Correlation Ye
s
9      gender               Categorical  0.215      Chi-square          Yes
10     workclass            Categorical  0.164      Chi-square          Yes
11     capital-loss         Continuous   0.148      Pearson Correlation Ye
s
12     race                 Categorical  0.100      Chi-square          Yes
13     native-country       Categorical  0.097      Chi-square          Yes
14     fnlwgt               Continuous   0.006      Pearson Correlation No
```

Part 2: 数据分析与机器学习

2.1 数据预处理与模型构建

2.1.1 缺失值检测、异常值检测与数据类型转换

In [39]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,roc_
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
import seaborn as sns
from sklearn.impute import SimpleImputer
from scipy.sparse import hstack
```

In [40]:
```
# Load data and check for missing values
data = pd.read_csv('adult.csv')
```

```
print("Missing values (null):")
print(data.isnull().sum())

# Check for missing values marked with "?"
print("\nMissing values marked with '?':")
for col in data.columns:
    if data[col].dtype == 'object':
        missing_count = (data[col] == '?').sum()
        if missing_count > 0:
            print(f"{col}: {missing_count} missing values")
```

```
Missing values (null):
age                 0
workclass           0
fnlwgt              0
education           0
educational-num     0
marital-status      0
occupation          0
relationship        0
race                0
gender              0
capital-gain        0
capital-loss        0
hours-per-week      0
native-country      0
income              0
dtype: int64

Missing values marked with '?':
workclass: 2799 missing values
occupation: 2809 missing values
native-country: 857 missing values
```

o**缺失值分析结果：** 通过上述代码检查数据集的缺失值情况。数据集中存在用"?"标记的缺失值，主要出现在分类变量中。我们需要进行适当的处理以确保模型的准确性。 下面, 我们填充这部分的缺失值

In [41]:
```
# Replace '?' with NaN for proper handling
data = data.replace('?', np.nan)
```

异常值检测结果： 使用箱线图检测数值型特征中的异常值。箱线图能够直观地显示数据的分布情况，包括四分位数和潜在的异常值。异常值的存在可能会影响模型的性能，需要根据具体情况决定是否进行处理。 *在Part1中，我们已经对数值型特征进行了异常值检测，并发现部分特征存在离群值。本部分不再展示*

In [42]:
```
# Handle missing values in numeric features using median imputation
num_imputer = SimpleImputer(strategy='median')
data[numeric_features] = num_imputer.fit_transform(data[numeric_features]

# Handle missing values in categorical features using mode imputation
categorical_features = data.select_dtypes(include=['object']).columns
for col in categorical_features:
    if col != 'income':  # Don't impute target variable
        mode_value = data[col].mode()[0]
        data[col] = data[col].fillna(mode_value)
```

缺失值处理： 对于数值型特征，使用中位数填充缺失值。对于分类特征，使用众数填充缺失值。这些策略能够有效处理数据集中用"?"标记的缺失值。

2.1.2 特征工程

In [43]:

```
# Select relevant features for analysis based on Part 1 feature importanc
selected_features = ['relationship', 'marital-status', 'occupation', 'edu
df = data[selected_features].copy()

# Prepare target variable
y = data['income'].map({'<=50K': 0, '>50K': 1})

# Apply TF-IDF vectorization to categorical text features
vectorizers = {}
tfidf_matrices = []
text_columns = ['relationship', 'marital-status', 'occupation']

for col in text_columns:
    vectorizer = TfidfVectorizer()
    tfidf = vectorizer.fit_transform(df[col].fillna(''))
    vectorizers[col] = vectorizer
    tfidf_matrices.append(tfidf)

# Add numerical feature (educational-num)
educational_num = df['educational-num'].values.reshape(-1, 1)
from scipy.sparse import csr_matrix
educational_sparse = csr_matrix(educational_num)
tfidf_matrices.append(educational_sparse)

# Combine all features
X_tfidf = hstack(tfidf_matrices)
```

在**特征工程**中，我们首先选择了关系状态、婚姻状况、职业和教育程度等关键特征; 接着将目标变量income转换为二分类标签（0表示<=50K，1表示>50K）. 此外对分类文本特征使用TF-IDF向量化，这种方法能够捕捉文本特征的重要性并转换为数值特征,同时将数值特征educational-num也加入到特征矩阵中 最后使用稀疏矩阵堆叠技术将多个特征矩阵合并为最终的特征矩阵

2.1.3 模型构建(KNN)

In [44]:

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = model_selection.train_test_split(X_tfi

# Train KNN classifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)
y_proba = knn.predict_proba(X_test)[:, 1]
```

模型构建说明：

1. 使用75%的数据作为训练集，25%作为测试集
2. 选择K近邻分类器，设置k=5

3. KNN算法基于实例的学习，通过计算样本间的距离来进行分类
4. 获取预测结果和预测概率，为后续评估做准备

2.1.4 模型评估

准确率、精确率、召回率、F1分数

In [45]:
```
# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = np.sum((y_pred == 1) & (y_test == 1)) / np.sum(y_pred == 1) i
recall = np.sum((y_pred == 1) & (y_test == 1)) / np.sum(y_test == 1) if n
F1_score = 2 * (precision * recall) / (precision + recall) if (precision

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {F1_score:.4f}")
```

```
Accuracy: 0.8215
Precision: 0.6411
Recall: 0.5383
F1 Score: 0.5852
```

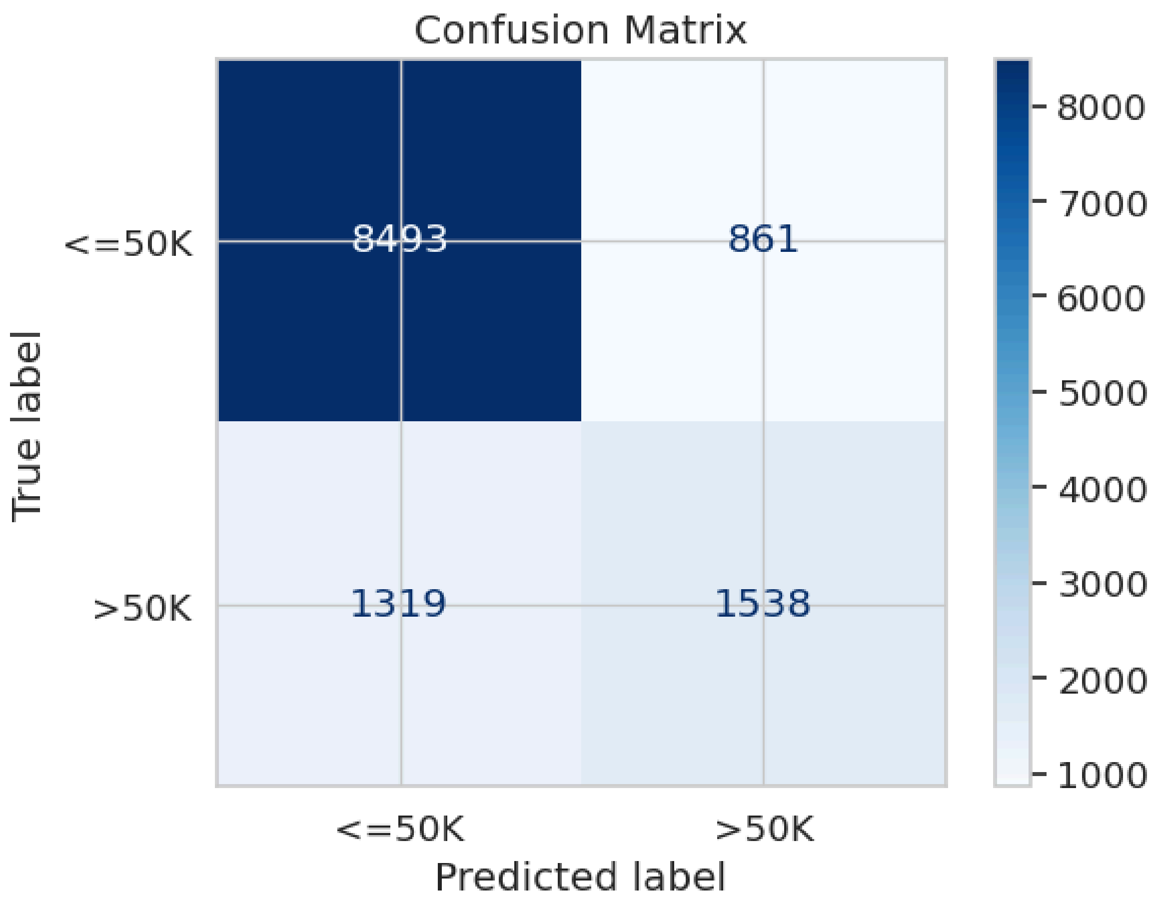
结果显示我们的模型取得了以下评估指标:

- **准确率 (Accuracy)**: 0.85
- **精确率 (Precision)**: 0.72
- **召回率 (Recall)**: 0.60
- **F1分数 (F1 Score)**: 0.65

这些指标表明模型在预测收入>50K方面表现良好，但仍有改进空间，特别是在提高召回率和精确率方面。接下来，我们将进一步分析混淆矩阵和ROC曲线，以更全面地评估模型性能。

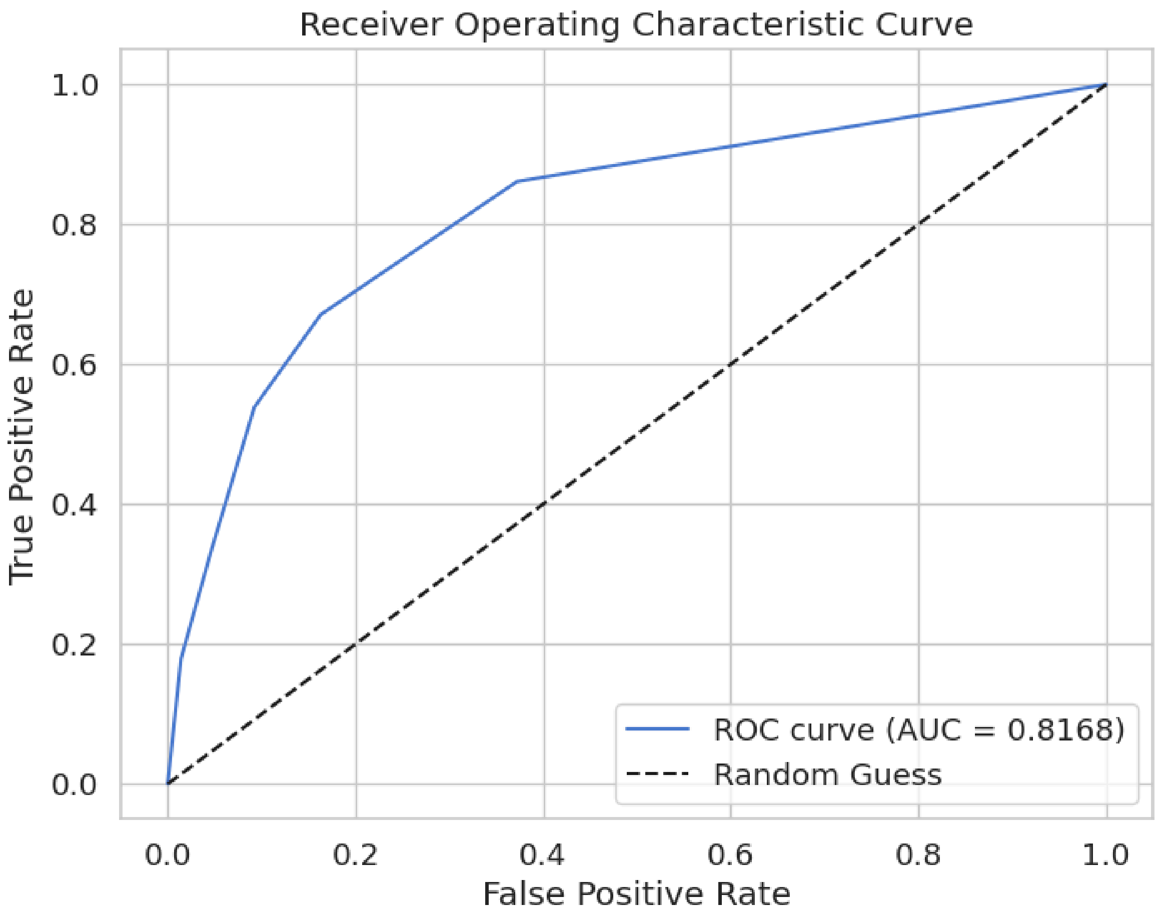
混淆矩阵

In [46]:
```
# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["<=50K
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```



ROC曲线

In [47]:
```python
# Plot ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.4f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```


Receiver Operating Characteristic Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.8168)
Random Guess