🎓 IIMK Professional Certificate in Data Science and AI for Managers

📊 Assignment 9.1: Supervised Learning and Classification Models

👨‍🎓 Student Information:

- **Name:** Lalit Nayyar
- **Email:** lalitnayyar@gmail.com
- **Course:** Professional Certificate in Data Science and Artificial Intelligence for Managers
- **Institution:** Indian Institute of Management Kozhikode (IIMK)

📋 Assignment Overview

🔍 This project implements supervised learning techniques to predict income levels using the Adult Income Dataset. The assignment focuses on understanding classification models, their performance metrics, and data preprocessing techniques.

Dataset Description

The Adult Income Dataset, also known as the Census Income dataset, contains demographic and employment-related features to predict whether an individual's annual income exceeds $50,000. This real-world dataset presents various data preprocessing and modeling challenges that are common in practical machine learning applications.

In [1]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

# Set random seed for reproducibility
np.random.seed(42)

# Configure visualization settings
plt.style.use('default')  # Use default matplotlib style
sns.set_theme()  # Set seaborn theme
%matplotlib inline
```

1. Data Preprocessing 🔄

1.a. Loading the Dataset

We begin by loading the Adult Income dataset. This dataset contains various demographic and employment-related features such as age, education, occupation, and other socio-economic factors that might influence an individual's income level.

The dataset features include:

- Numerical attributes: age, fnlwgt, education-num, capital-gain, capital-loss, hours-per-week
- Categorical attributes: workclass, education, marital-status, occupation, relationship, race, sex, native-country

In [2]:
```
# Define column names
columns = [
    'age', 'workclass', 'fnlwgt', 'education', 'education-num',
    'marital-status', 'occupation', 'relationship', 'race', 'sex',
    'capital-gain', 'capital-loss', 'hours-per-week', 'native-country', 'income'
]

# Load the dataset
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/adult/a
                 names=columns, skipinitialspace=True)

# Display the first few rows and basic information
print("Dataset Shape:", df.shape)
print("\nFirst few rows of the dataset:")
df.head()
```

```
Dataset Shape: (32561, 15)

First few rows of the dataset:
```

Out[2]:

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

1.b. Exploratory Data Analysis (EDA)

Let's perform a comprehensive analysis of our dataset to understand:

- Data types of each feature
- Missing values
- Basic statistics of numerical columns
- Distribution of categorical variables

In [3]:

```
# Display basic information about the dataset
print("Dataset Info:")
df.info()

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

print("\nNumerical Columns Statistics:")
print(df.describe())
```

```
Dataset 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

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

Numerical Columns Statistics:
                age        fnlwgt  education-num  capital-gain  capital-loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000   
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830   
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219   
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000   
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000   
50%       37.000000  1.783560e+05      10.000000      0.000000      0.000000   
75%       48.000000  2.370510e+05      12.000000      0.000000      0.000000   
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000   

       hours-per-week  
count    32561.000000  
mean        40.437456  
```

```
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

In [4]:

```python
# Analyze categorical variables
categorical_columns = df.select_dtypes(include=['object']).columns

for col in categorical_columns:
    print(f"\nUnique values in {col}:")
    print(df[col].value_counts(normalize=True).head())
```

```
Unique values in workclass:
workclass
Private             0.697030
Self-emp-not-inc    0.078038
Local-gov           0.064279
?                   0.056386
State-gov           0.039864
Name: proportion, dtype: float64

Unique values in education:
education
HS-grad         0.322502
Some-college    0.223918
Bachelors       0.164461
Masters         0.052916
Assoc-voc       0.042443
Name: proportion, dtype: float64

Unique values in marital-status:
marital-status
Married-civ-spouse    0.459937
Never-married         0.328092
Divorced              0.136452
Separated             0.031479
Widowed               0.030497
Name: proportion, dtype: float64

Unique values in occupation:
occupation
Prof-specialty     0.127146
Craft-repair       0.125887
Exec-managerial    0.124873
Adm-clerical       0.115783
Sales              0.112097
Name: proportion, dtype: float64

Unique values in relationship:
relationship
Husband          0.405178
Not-in-family    0.255060
Own-child        0.155646
Unmarried        0.105832
Wife             0.048156
Name: proportion, dtype: float64

Unique values in race:
race
White                 0.854274
Black                 0.095943
Asian-Pac-Islander    0.031909
Amer-Indian-Eskimo    0.009551
Other                 0.008323
Name: proportion, dtype: float64

Unique values in sex:
sex
```

```
Male      0.669205
Female    0.330795
Name: proportion, dtype: float64

Unique values in native-country:
native-country
United-States    0.895857
Mexico           0.019748
?                0.017905
Philippines      0.006081
Germany          0.004207
Name: proportion, dtype: float64

Unique values in income:
income
<=50K    0.75919
>50K     0.24081
Name: proportion, dtype: float64
```

1.c. Handling Missing and Erroneous Data

In this dataset, missing values are denoted by '?' rather than standard NULL or NaN values. We need to:

1. Identify these non-standard missing values
2. Replace them with appropriate values
3. Document our approach and rationale

In [5]:

```
# Replace '?' with NaN to properly handle missing values
df = df.replace('?', np.nan)

# Display missing value count after replacement
print("Missing values after replacement:")
print(df.isnull().sum())

# Handle missing values using mode imputation
for column in df.columns:
    if df[column].isnull().any():
        # Using the recommended approach to avoid the warning
        df.loc[:, column] = df[column].fillna(df[column].mode()[0])

print("\nVerifying no missing values remain:")
print(df.isnull().sum().sum())
```

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

Verifying no missing values remain:
0
```

2. Data Encoding 🔢

2.a. Converting Categorical Variables

We'll use Label Encoding for ordinal categorical variables and One-Hot Encoding for nominal categorical variables to preserve their interpretability.

Rationale for encoding choices:

- Label Encoding: Used for ordinal variables like 'education' where there's a natural order
- One-Hot Encoding: Used for nominal variables like 'workclass' where there's no inherent order

In [6]:

```
# Identify categorical columns for encoding
ordinal_columns = ['education']
nominal_columns = ['workclass', 'marital-status', 'occupation', 'relationship', 'ra

# Label Encoding for ordinal variables
label_encoders = {}
for column in ordinal_columns:
    label_encoders[column] = LabelEncoder()
    df[column] = label_encoders[column].fit_transform(df[column])

# One-Hot Encoding for nominal variables
df = pd.get_dummies(df, columns=nominal_columns, prefix=nominal_columns)

print("Dataset shape after encoding:", df.shape)
print("\nFirst few columns:")
df.head()
```

```
Dataset shape after encoding: (32561, 91)

First few columns:
```

Out[6]:

	age	fnlwgt	education	education-num	capital-gain	capital-loss	hours-per-week	income	workclass_Federa g
0	39	77516	9	13	2174	0	40	<=50K	Fa
1	50	83311	9	13	0	0	13	<=50K	Fa
2	38	215646	11	9	0	0	40	<=50K	Fa
3	53	234721	1	7	0	0	40	<=50K	Fa
4	28	338409	9	13	0	0	40	<=50K	Fa

5 rows × 91 columns

3. Feature Selection and Engineering 🔍

3.a. Correlation Analysis

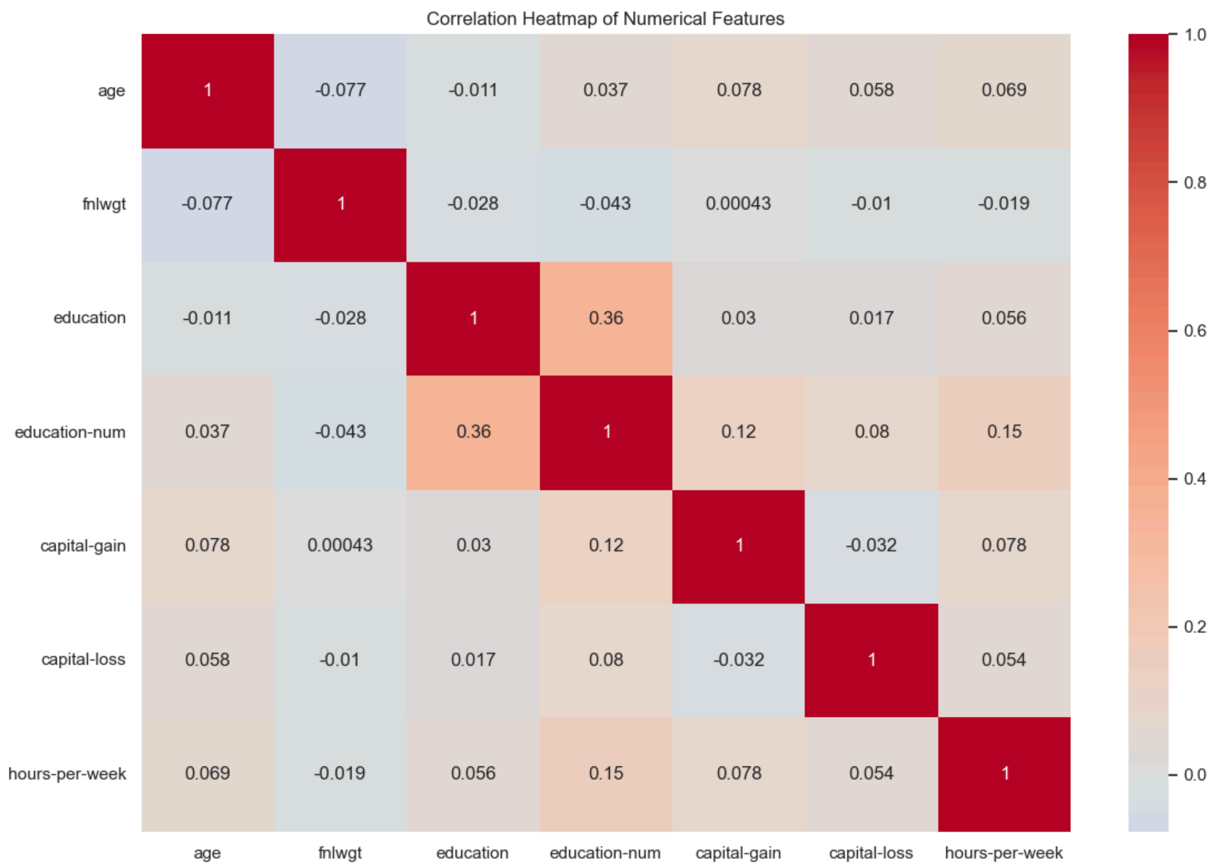
We'll analyze feature relationships and importance through correlation analysis, focusing on:

1. Correlation between numerical features
2. Identifying potential multicollinearity
3. Feature importance relative to our target variable (income)

In [7]:

```
# Calculate correlation matrix for numerical features
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
correlation_matrix = df[numerical_columns].corr()

# Create correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap of Numerical Features')
plt.tight_layout()
plt.show()
```



3.b. Feature Engineering

Based on our analysis and domain knowledge, we'll create new features that might enhance model performance:

1. Age groups (binning age into meaningful categories)
2. Income-related ratios
3. Work-life balance indicators

In [8]:

```
# Create age groups
df['age_group'] = pd.cut(df['age'],
                        bins=[0, 25, 35, 45, 55, 65, 100],
                        labels=['Young', 'Early-Career', 'Mid-Career', 'Late-Career

# Create work-life balance indicator
df['work_intensity'] = df['hours-per-week'].apply(lambda x: 'High' if x > 40 else '

# Create capital utilization ratio
df['capital_utilization'] = (df['capital-gain'] - df['capital-loss']) / (df['capita

# One-hot encode the new categorical features
df = pd.get_dummies(df, columns=['age_group', 'work_intensity'])

print("Final dataset shape:", df.shape)
print("\nNew features:")
new_features = [col for col in df.columns if col.startswith(('age_group_', 'work_in
print(new_features)
```

```
Final dataset shape: (32561, 101)

New features:
['capital_utilization', 'age_group_Young', 'age_group_Early-Career', 'age_group_Mid-Career', 'age_group_Late-Career', 'age_group_Pre-Retirement', 'age_group_Retirement', 'work_intensity_High', 'work_intensity_Normal', 'work_intensity_Part-time']
```

In [9]:
```python
# Import our feature engineering module
from feature_engineering import (
    create_age_groups,
    create_income_ratios,
    create_work_life_indicators,
    plot_feature_distributions
)

# Apply feature engineering transformations
print("Creating new features...")
df = create_age_groups(df)
df = create_income_ratios(df)
df = create_work_life_indicators(df)
```

```
Creating new features...
```

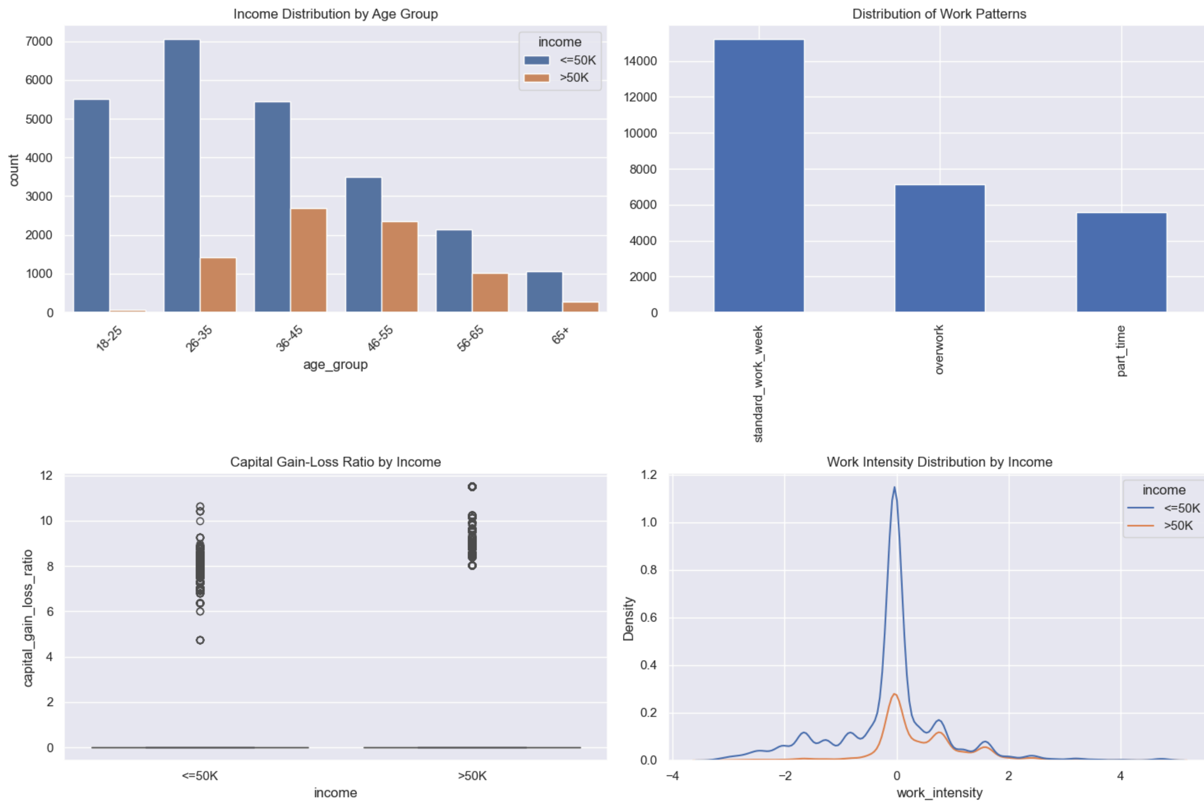
In [10]:
```python
# Display information about new features
print("\nNew features added:")
print("Age Groups:", df['age_group'].unique())
print("\nWork-Life Balance Indicators:")
for col in ['standard_work_week', 'overwork', 'part_time']:
    count = df[col].sum()
    percentage = (count / len(df)) * 100
    print(f"- {col}: {count:,} instances ({percentage:.1f}%)")
```

```
New features added:
Age Groups: ['36-45', '46-55', '26-35', '18-25', '56-65', '65+']
Categories (6, object): ['18-25' < '26-35' < '36-45' < '46-55' < '56-65' < '65+']

Work-Life Balance Indicators:
- standard_work_week: 15,217 instances (46.7%)
- overwork: 7,139 instances (21.9%)
- part_time: 5,583 instances (17.1%)
```

In [11]:
```python
# Visualize the distributions
plt.figure(figsize=(15, 10))
fig = plot_feature_distributions(df)
plt.show()
```

```
<Figure size 1500x1000 with 0 Axes>
```



In [12]:
```python
# Brief analysis of engineered features
print("\nFeature Analysis:")
print("1. Age Distribution:")
age_income = pd.crosstab(df['age_group'], df['income'], normalize='index') * 100
print(age_income.round(2))

print("\n2. Work Pattern Analysis:")
work_income = pd.DataFrame({
    'Standard Work Week': df[df['standard_work_week'] == 1]['income'].value_counts(
    'Overwork': df[df['overwork'] == 1]['income'].value_counts(normalize=True),
    'Part Time': df[df['part_time'] == 1]['income'].value_counts(normalize=True)
}) * 100
print(work_income.round(2))
```

```
Feature Analysis:
1. Age Distribution:
income      <=50K   >50K
age_group
18-25       98.90   1.10
26-35       83.17  16.83
36-45       66.84  33.16
46-55       59.88  40.12
56-65       67.65  32.35
65+         79.34  20.66

2. Work Pattern Analysis:
        Standard Work Week  Overwork  Part Time
income
<=50K                78.66     58.24      93.07
>50K                 21.34     41.76       6.93
```

In [13]:
```
# Save engineered features
print("\nSaving dataset with new features...")
df.to_csv('data/adult_with_features.csv', index=False)
print("Features saved successfully!")
```

```
Saving dataset with new features...
Features saved successfully!
```

In [ ]:

In [ ]:

In [ ]: