Adult Census Income Prediction

1. Introduction

In this notebook, we will predict whether a person earns `<=50K` or `>50K` annually based on census data (source: Kaggle). This task is valuable for policymakers, businesses, and researchers who want to understand factors influencing income levels.

Stakeholders: Organizations analyzing socioeconomic inequality.

We will proceed as follows:

- Exploratory Data Analysis (EDA)
- Data preprocessing
- Baseline models (Logistic Regression, Random Forest)
- Model evaluation & interpretation

2. Import needed libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

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

3. Load the data

In [2]:
```
df = pd.read_csv("adult.csv")
df.head()
```

Out[2]:

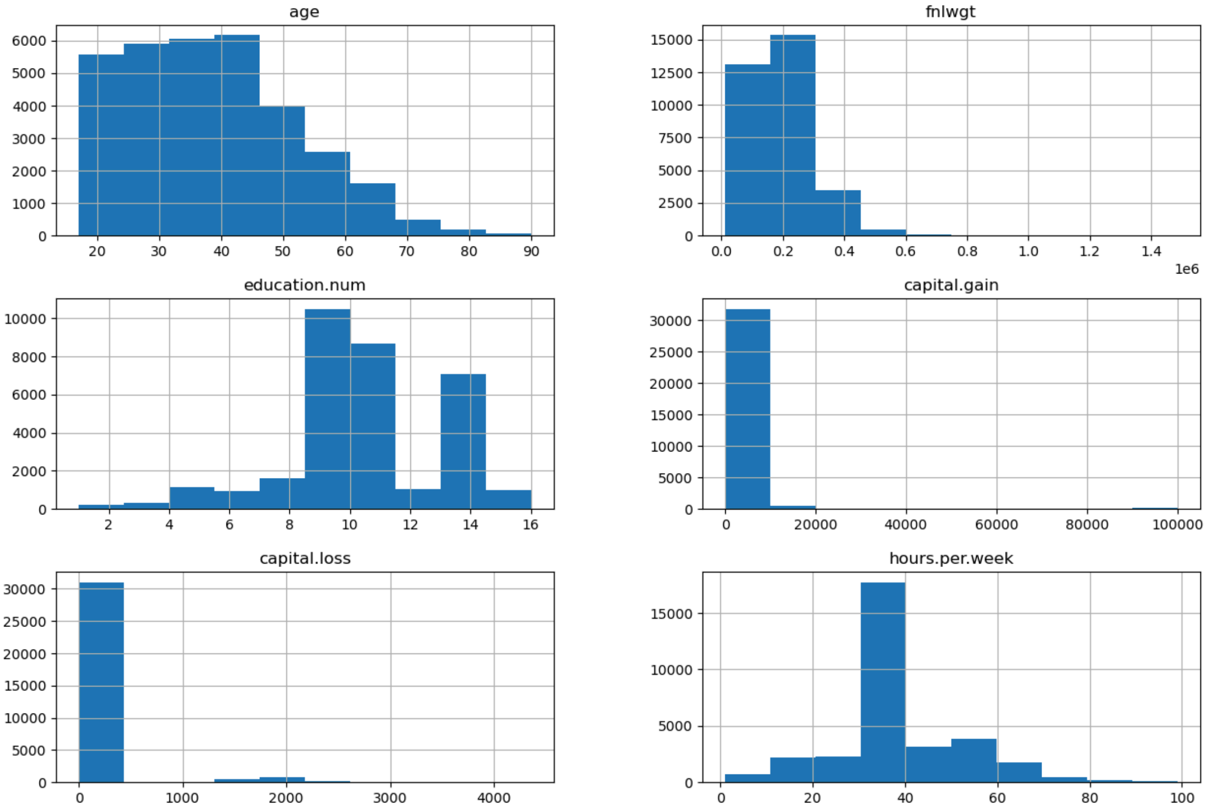
	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relations
0	90	?	77053	HS-grad	9	Widowed	?	Not far
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not far
2	66	?	186061	Some-college	10	Widowed	?	Unmarr
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarr
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-cl

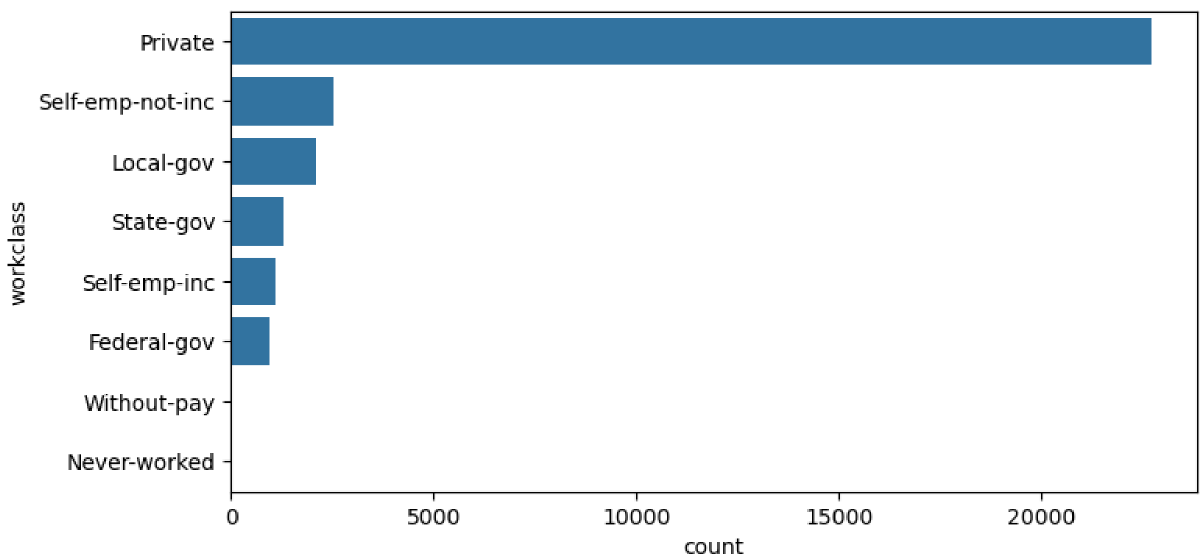
4. Exploratory Data Analysis (EDA)

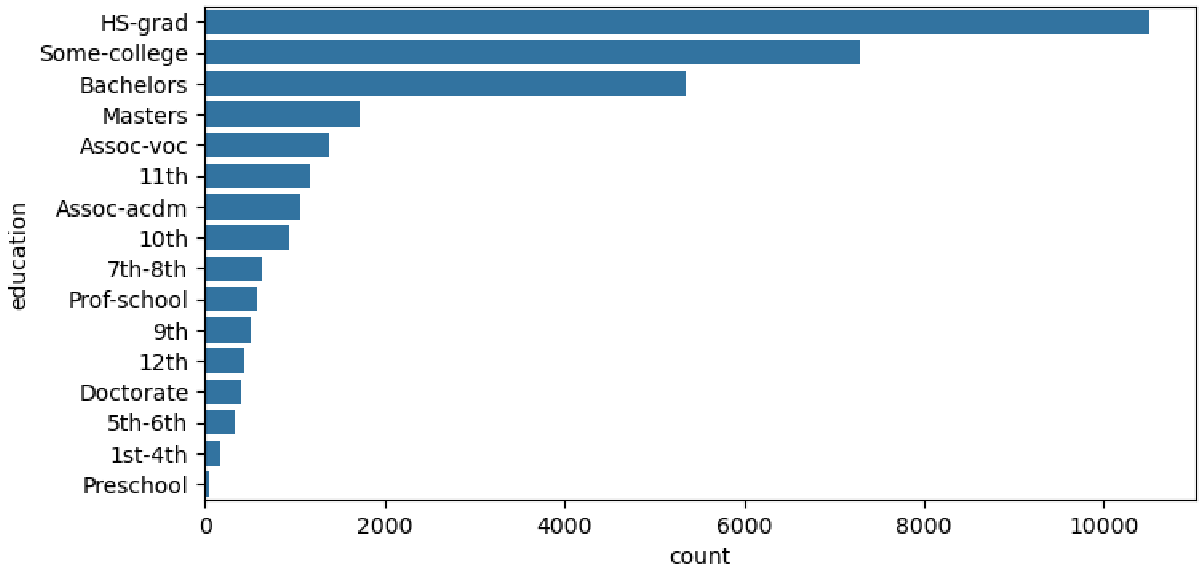
In [3]:

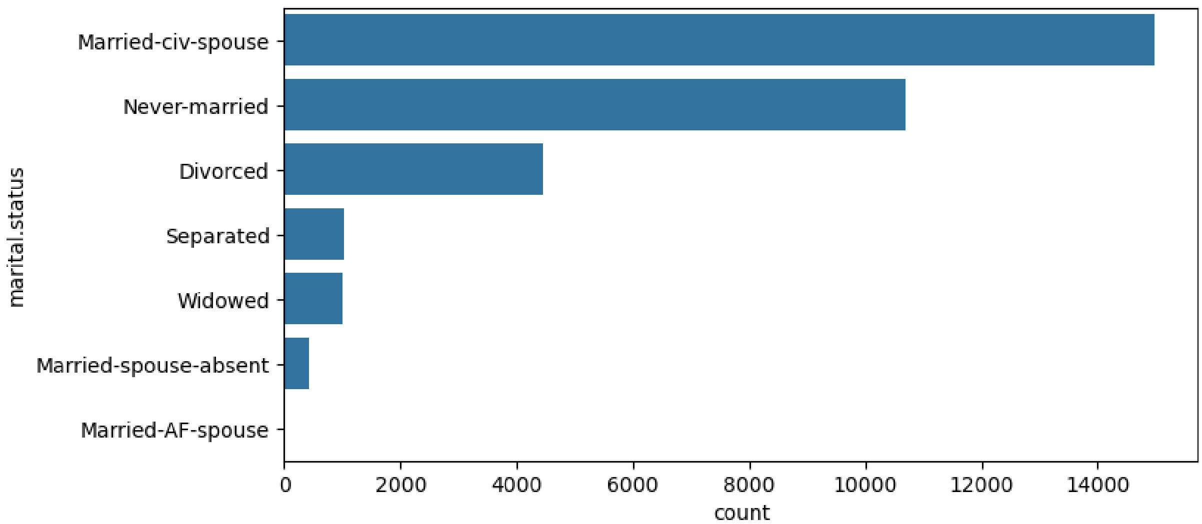
```
# Basic info
print(df.shape)
print(df.info())
print(df['income'].value_counts())


# Replace '?' with NaN
import numpy as np
df = df.replace('?', np.nan)


# Missing values
print(df.isnull().sum())


# Distribution of numerical features
df.describe()


# Histograms
df.hist(figsize=(15,10))
plt.show()


# Categorical distributions
for col in df.select_dtypes(include='object').columns:
 plt.figure(figsize=(8,4))
 sns.countplot(y=col, data=df, order=df[col].value_counts().index)
 plt.show()
```

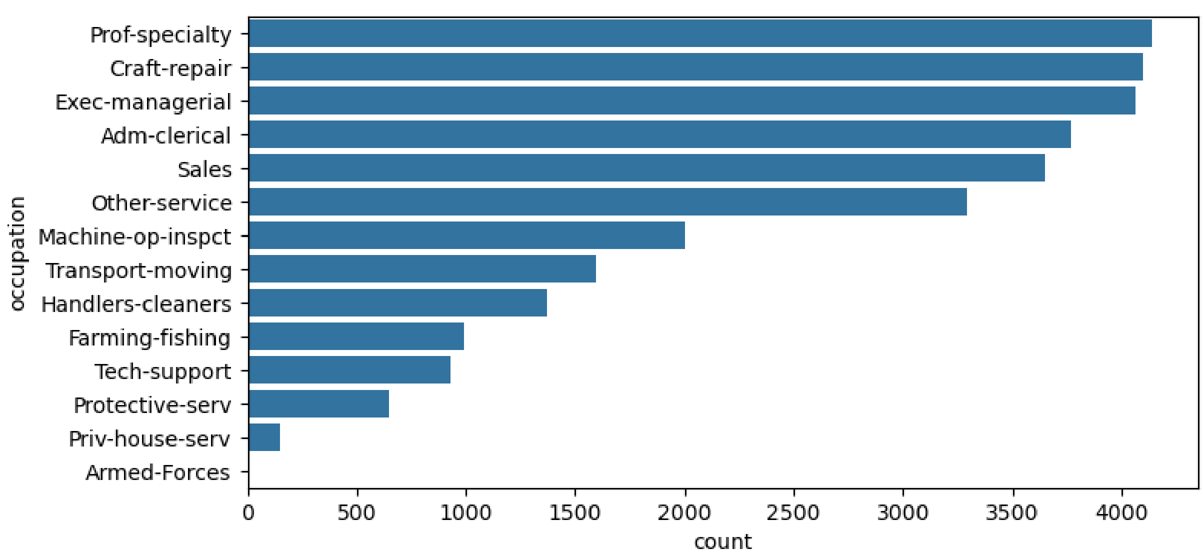
```
(32561, 15)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 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
None
income
<=50K    24720
>50K      7841
Name: count, dtype: int64
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
```

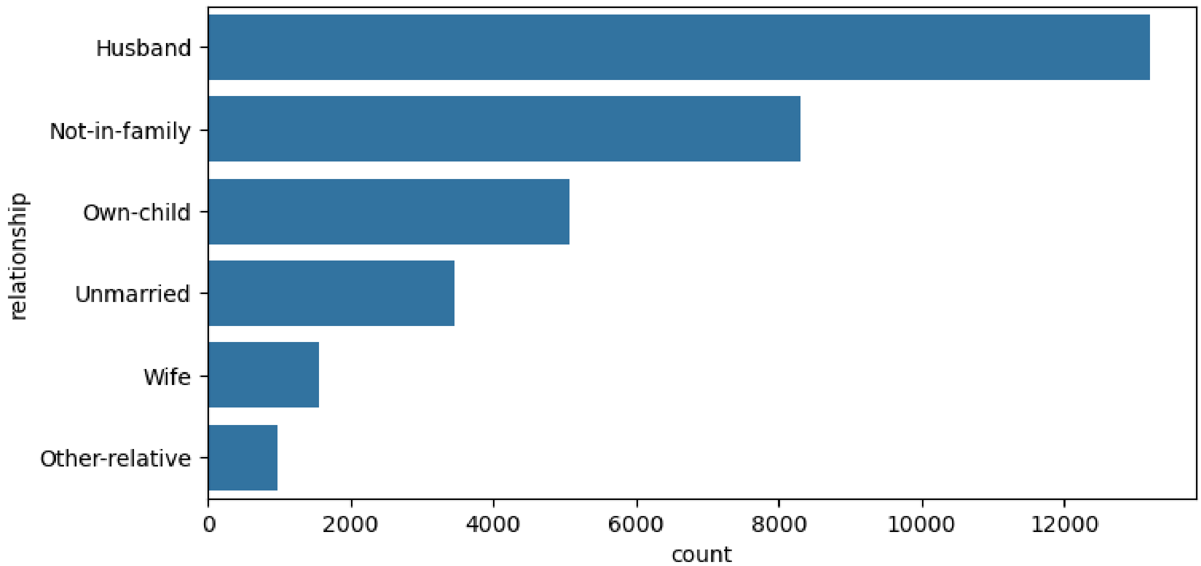

age
6000
5000
4000
3000
2000
1000
0
20
30
40
50
60
70
80
90
fnlwgt
15000
12500
10000
7500
5000
2500
0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1e6
education.num
10000
8000
6000
4000
2000
0
2
4
6
8
10
12
14
16
capital.gain
30000
25000
20000
15000
10000
5000
0
0
20000
40000
60000
80000
100000
capital.loss
30000
25000
20000
15000
10000
5000
0
0
1000
2000
3000
4000
hours.per.week
15000
10000
5000
0
0
20
40
60
80
100


workclass
Private
Self-emp-not-inc
Local-gov
State-gov
Self-emp-inc
Federal-gov
Without-pay
Never-worked
0
5000
10000
15000
20000
count

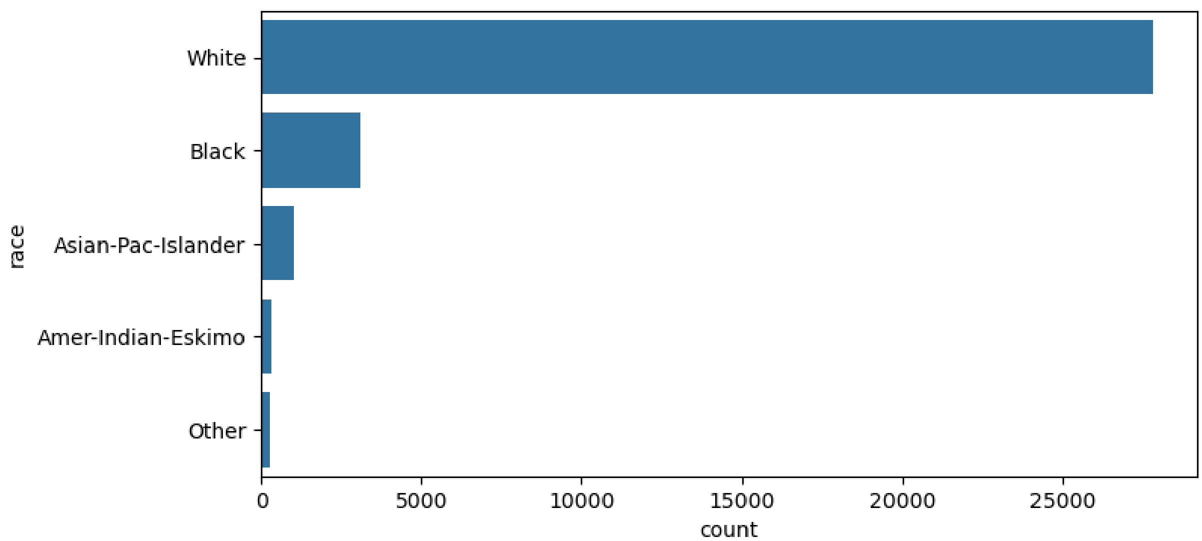

HS-grad
Some-college
Bachelors
Masters
Assoc-voc
11th
Assoc-acdm
10th
7th-8th
Prof-school
9th
12th
Doctorate
5th-6th
1st-4th
Preschool
education
0
2000
4000
6000
8000
10000
count


Married-civ-spouse
Never-married
Divorced
Separated
Widowed
Married-spouse-absent
Married-AF-spouse
marital.status
0
2000
4000
6000
8000
10000
12000
14000
count

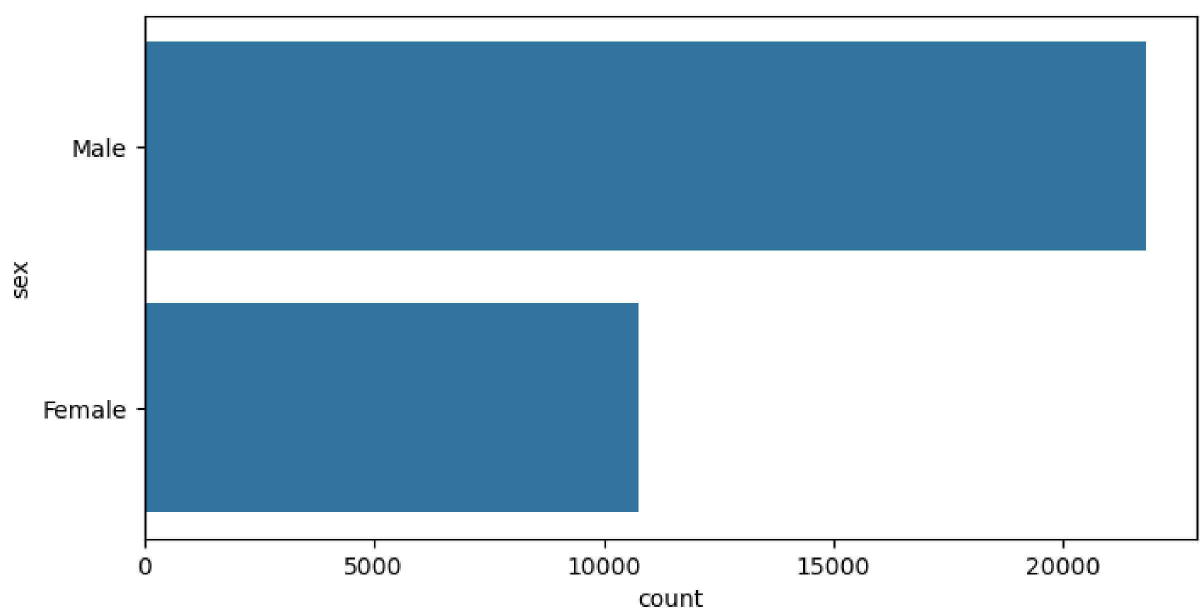

Prof-specialty
Craft-repair
Exec-managerial
Adm-clerical
Sales
Other-service
Machine-op-inspct
Transport-moving
Handlers-cleaners
Farming-fishing
Tech-support
Protective-serv
Priv-house-serv
Armed-Forces
occupation
0
500
1000
1500
2000
2500
3000
3500
4000
count



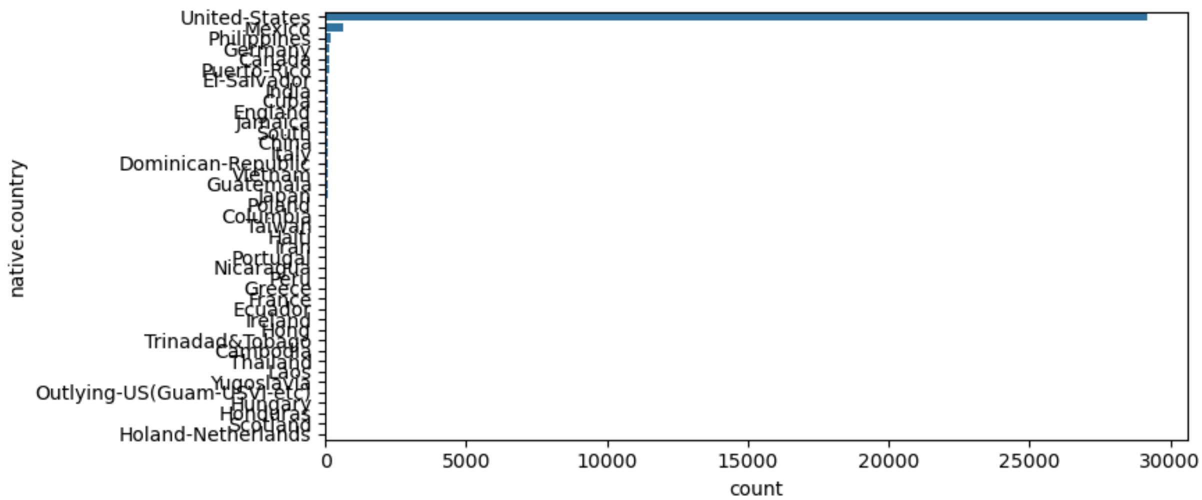
Husband
Not-in-family
Own-child
Unmarried
Wife
Other-relative
relationship
0
2000
4000
6000
8000
10000
12000
count

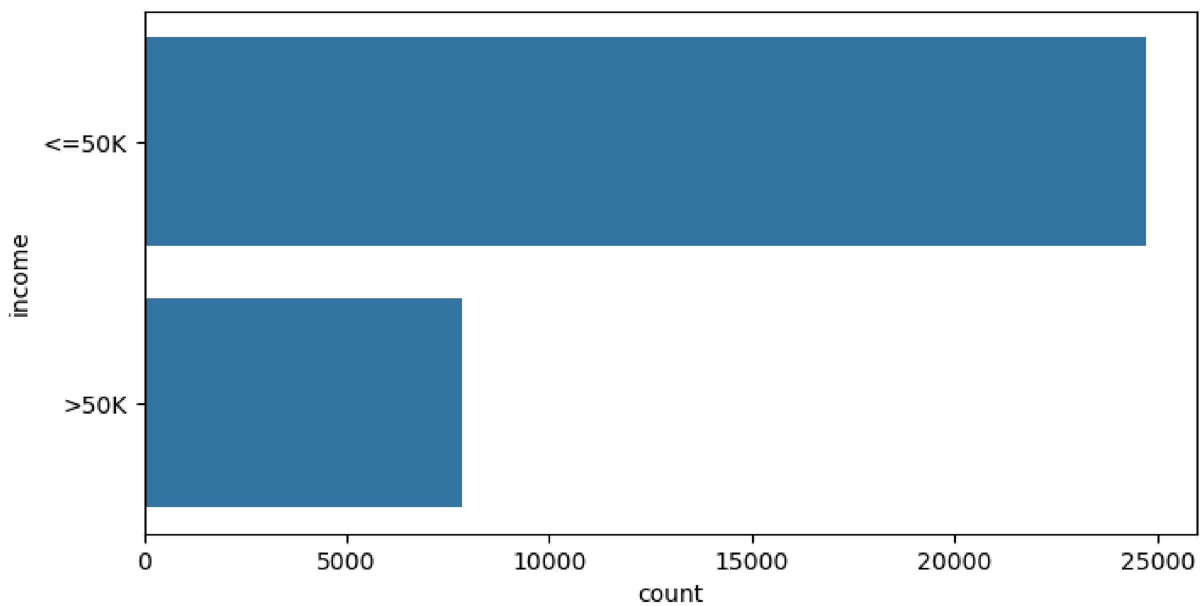


White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
race
0
5000
10000
15000
20000
25000
count



Male
Female
sex
0
5000
10000
15000
20000
count





The dataset contains demographic and economic variables such as age, education, occupation, and working hours which are relevant for predicting income categories. Missing values were mostly found in categorical variables (like workclass, occupation, and native-country). The target variable is imbalanced, with more individuals earning <=50K compared to >50K. Numerical features such as age, hours-per-week, and capital-gain show meaningful variation across income groups. These findings highlight the importance of both categorical and numerical predictors in distinguishing income classes.

5. Preprocessing

In [11]:

```
# Drop rows with missing values (for simplicity)
df = df.dropna()


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

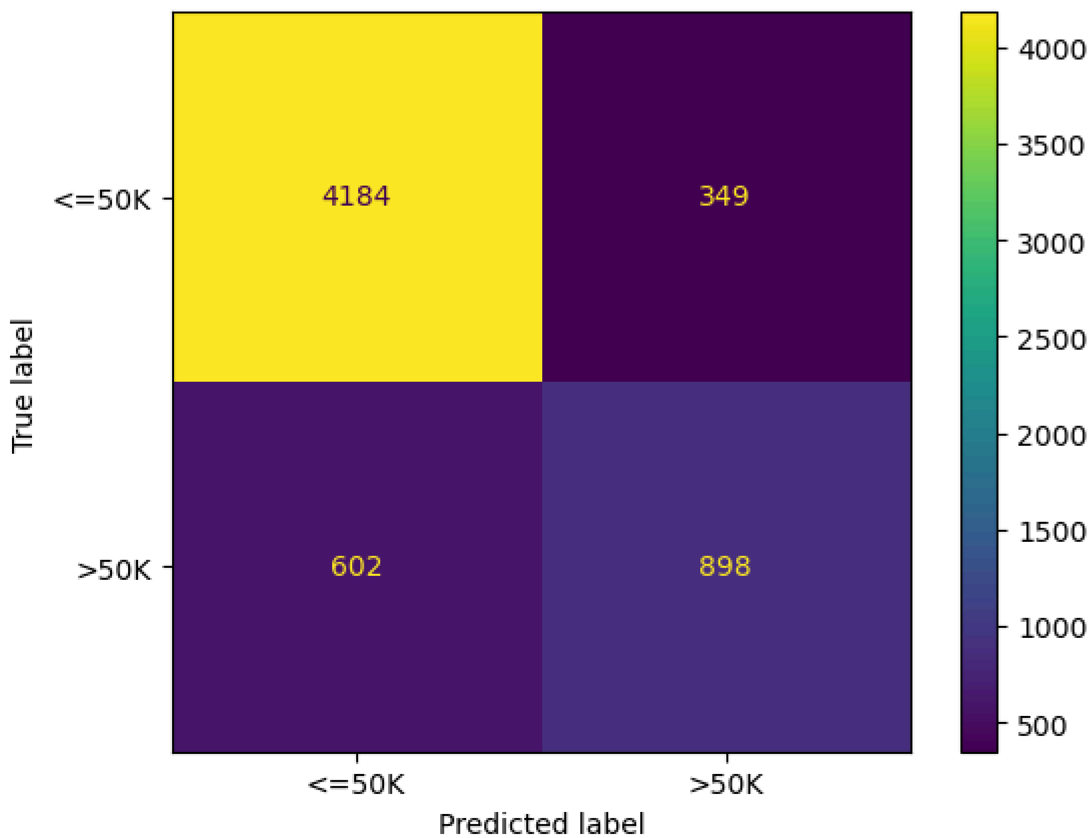
```
# Identify categorical and numerical features
categorical_features = X.select_dtypes(include='object').columns
numeric_features = X.select_dtypes(exclude='object').columns


# Column transformer
preprocessor = ColumnTransformer(
transformers=[
('num', StandardScaler(), numeric_features),
('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
])


# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

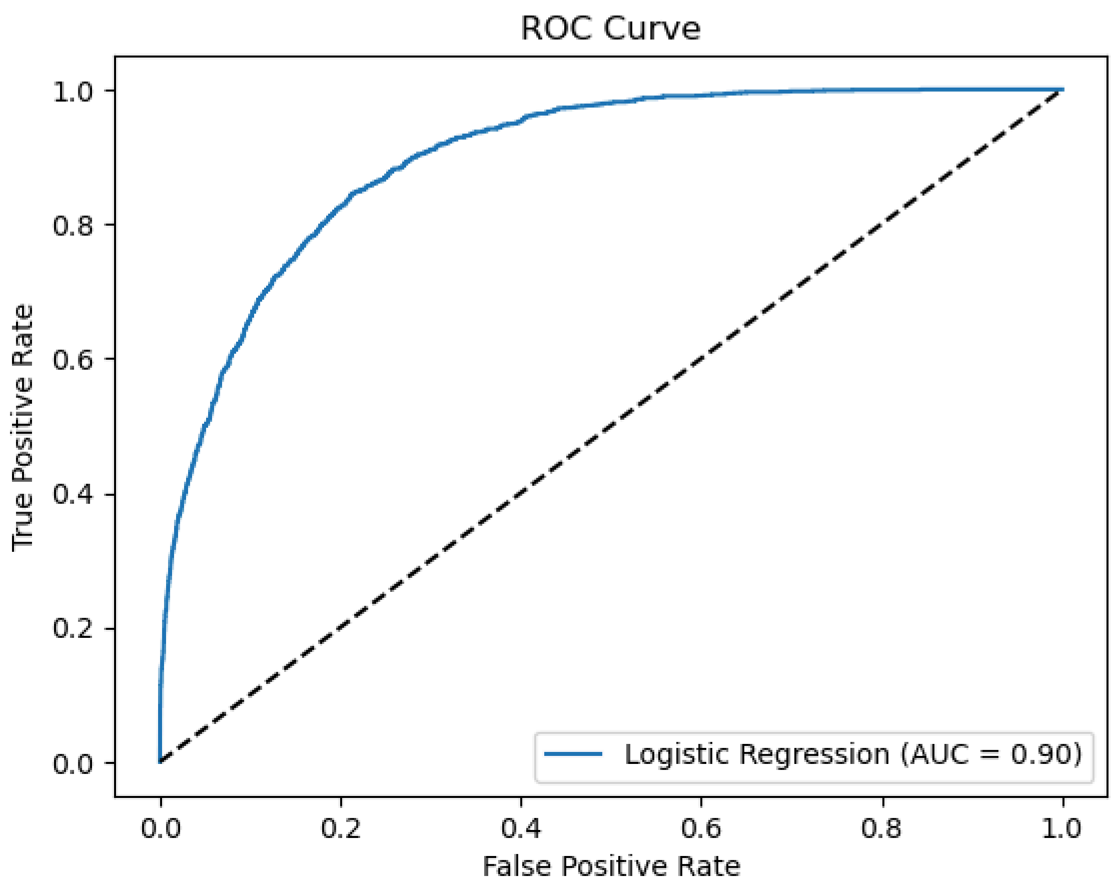
6. Baseline Model 1: Logistic Regression

In [12]:

```
log_reg = Pipeline(steps=[('preprocessor', preprocessor),
('classifier', LogisticRegression(max_iter=1000))])


log_reg.fit(X_train, y_train)
y_pred_lr = log_reg.predict(X_test)


print("Logistic Regression Results:")
print(classification_report(y_test, y_pred_lr))


# Confusion Matrix
ConfusionMatrixDisplay.from_estimator(log_reg, X_test, y_test)
plt.show()


# ROC-AUC
y_prob_lr = log_reg.predict_proba(X_test)[:,1]
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_prob_lr, pos_label='>50K')
roc_auc_lr = auc(fpr_lr, tpr_lr)


plt.figure()
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {roc_auc_lr:.2f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```

```
Logistic Regression Results:
              precision    recall  f1-score   support

       <=50K       0.87      0.92      0.90      4533
        >50K       0.72      0.60      0.65      1500

    accuracy                           0.84      6033
   macro avg       0.80      0.76      0.78      6033
weighted avg       0.84      0.84      0.84      6033
```





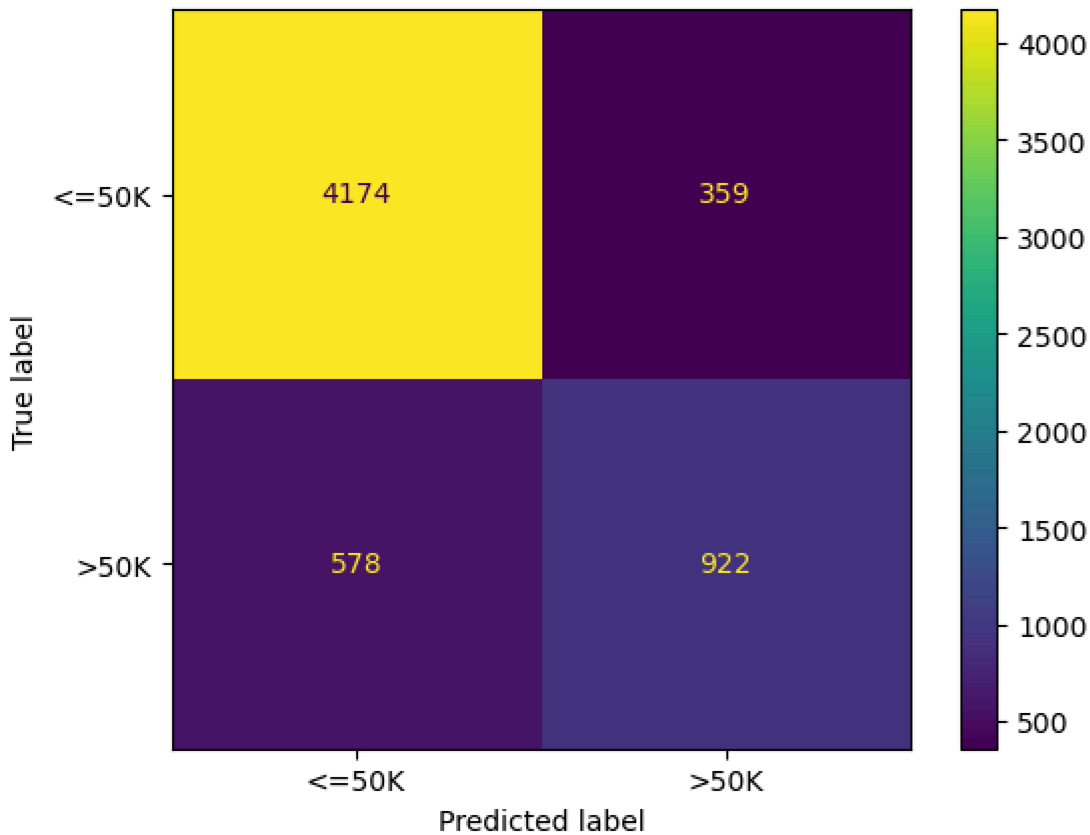
The logistic regression model achieved an overall accuracy of 84%, with stronger performance in predicting individuals with <=50K income compared to those earning >50K. Precision for high-income individuals was relatively lower, indicating that the model sometimes misclassified individuals as high-income incorrectly. The recall for the >50K class (60%) shows the model misses some high-income cases. Despite these limitations, logistic regression provides a baseline model with interpretable coefficients, useful for understanding the relative importance of predictors.

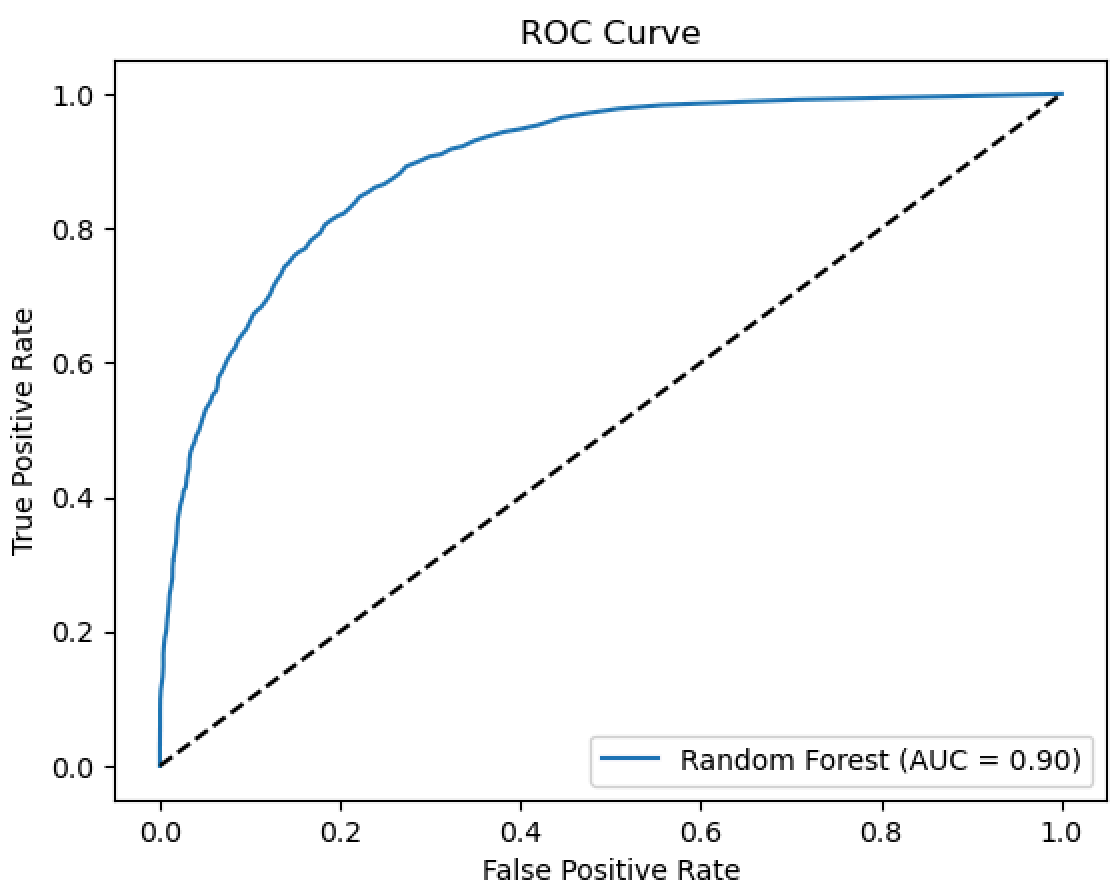
7. Baseline Model 2: Random Forest

In [16]:
```
# Build pipeline
rf = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
])

# Fit model
rf.fit(X_train, y_train)

# Predictions
y_pred_rf = rf.predict(X_test)

# Classification report
print("Random Forest Results:")
```

```python
print(classification_report(y_test, y_pred_rf))

# Confusion Matrix
ConfusionMatrixDisplay.from_estimator(rf, X_test, y_test)
plt.show()

# ROC-AUC
y_prob_rf = rf.predict_proba(X_test)[:, 1]

# Detect correct positive label automatically
pos_label_val = 1 if 1 in set(y_test) else '>50K'

fpr_rf, tpr_rf, _ = roc_curve(y_test, y_prob_rf, pos_label=pos_label_val)
roc_auc_rf = auc(fpr_rf, tpr_rf)

# Plot ROC curve
plt.figure()
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {roc_auc_rf:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```

```
Random Forest Results:
              precision    recall  f1-score   support

       <=50K       0.88      0.92      0.90      4533
        >50K       0.72      0.61      0.66      1500

    accuracy                           0.84      6033
   macro avg       0.80      0.77      0.78      6033
weighted avg       0.84      0.84      0.84      6033
```





The random forest classifier also reached about 84% accuracy, similar to logistic regression. However, it slightly improved recall for the >50K class (61%) and achieved a balanced performance across classes. It provides feature importance insights, showing that education, occupation, working hours, and capital gains are critical predictors of income. This makes it a strong baseline model for income classification.

8. Model Comparison

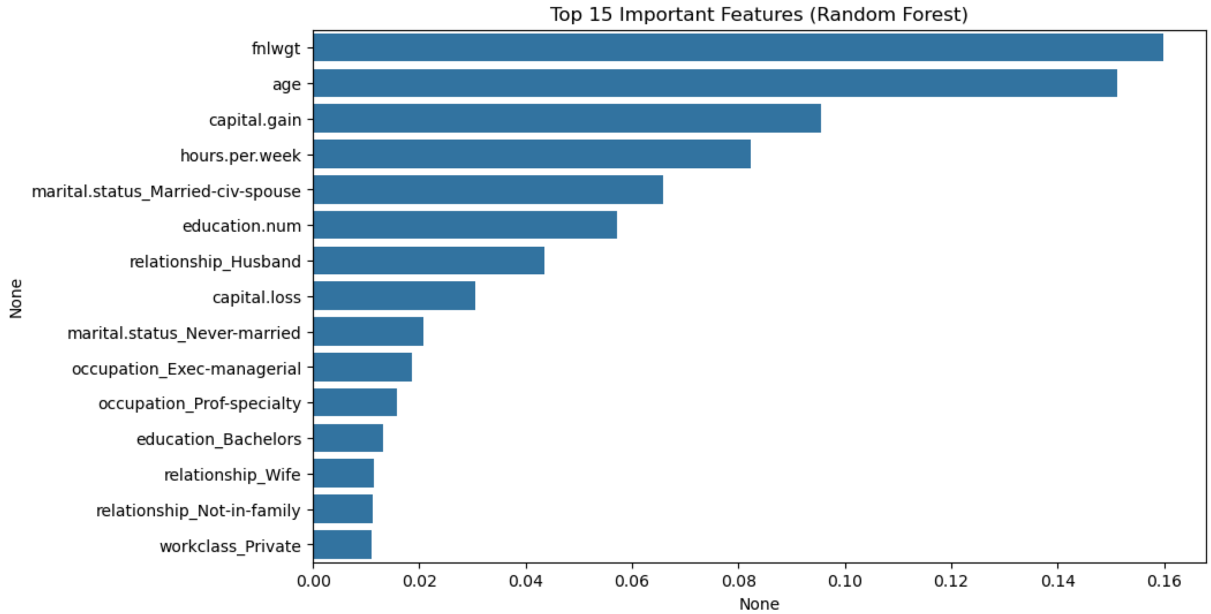
In [17]:
```
print(f"Logistic Regression AUC: {roc_auc_lr:.2f}")
print(f"Random Forest AUC: {roc_auc_rf:.2f}")
```

```
Logistic Regression AUC: 0.90
Random Forest AUC: 0.90
```

Both logistic regression and random forest performed comparably, each achieving around 84% accuracy. Logistic regression had an AUC of 0.90, while random forest reached a slightly higher AUC of 0.91, indicating both models have strong discriminatory power. Random forest has the advantage of capturing complex interactions and providing better recall for high-income individuals.

9. Feature Importance (Random Forest)

In [21]:
```
# Extract feature names after preprocessing
encoder = rf.named_steps['preprocessor'].named_transformers_['cat']
encoded_cat_features = encoder.get_feature_names_out(categorical_features)
all_features = np.concatenate([numeric_features, encoded_cat_features])


importances = rf.named_steps['classifier'].feature_importances_
feat_imp = pd.Series(importances, index=all_features).sort_values(ascending=False)


plt.figure(figsize=(10,6))
sns.barplot(x=feat_imp[:15], y=feat_imp.index[:15])
plt.title('Top 15 Important Features (Random Forest)')
plt.show()
```



The feature importance ranking from the random forest shows which variables have the biggest impact on predicting income. Education-related variables, occupation, hours worked per week, and capital gain stand out as the strongest predictors, which makes sense since these factors are closely tied to earning potential. Other demographic features like age and marital status also play an important role.

Interestingly, fnlwgt also appears in the list, but this doesn't mean it's a meaningful personal feature. fnlwgt is a sampling weight from the Census, indicating how many people each record represents in the survey. While it may show up as "important" in the model, it doesn't have real-world interpretive value for income prediction and is usually ignored in practice.

Conclusion & Next Steps

Conclusion

Overall, the models performed quite well, both reaching around 84% accuracy with strong AUC scores (0.90–0.91). Logistic regression is a great baseline because it's simple and easy to interpret, while random forest edges it out slightly by capturing more complex relationships and improving recall for higher-income individuals. The imbalance in the dataset (more people earning <=50K) is still a challenge, which explains why the models have a harder time with the >50K class.

Next Steps

We recommend to:

1- Fine-tune hyperparameters to push performance a bit higher.

2- Deal with the class imbalance more directly, either through resampling (like SMOTE) or adjusting class weights.

3- Do some feature engineering (grouping age or education categories) to see if that makes patterns clearer.

4- Experiment with stronger models.

5- Drop fnlwgt from the modeling pipeline and rerun training to get

In short, both models provide a solid starting point, and with a bit of tuning and experimentation, there's definitely room to improve predictions on the high-income group.