Predicting income category from socioeconomic characteristics

by Luke Ni, Michael Oyatsi, Nishanth Kumarasamy & Shruti Sasi

In [1]:
```
#imports
import numpy as np
import pandas as pd
import altair as alt
import altair_ally as aly
import shap
import matplotlib.pyplot as plt
from scipy import stats
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.preprocessing import FunctionTransformer
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report
from sklearn.metrics import make_scorer, precision_score, recall_score, f1_score, a
from sklearn.model_selection import cross_validate

# Simplify working with large dataset in altair_ally
aly.alt.data_transformers.enable('vegafusion')
```

```
C:\Users\Shruti\miniforge3\envs\dsci_522_project_env\Lib\site-packages\tqdm\auto.py:
21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See http
s://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Out[1]:
```
DataTransformerRegistry.enable('vegafusion')
```

Executive Summary

We built a classification model to predict an individual's income group, split by whether they are high earners (> USD 50,000) or low earners (<= USD 50,000). Using a Logistic Regression classifier, our model accuracy was 78% on unseen test data with an associated F1 score of 0.602. To address the class imbalance in the data, we used a balanced weight approach while buidling our model. We also sought to understand what socioeconomic characterstics play a the biggest role in determining an individuals income group. Using SHAP analysis, our findings show that of the features in our model, Marital Status, Age & Education are the biggest drivers of a High Income output.

While the Logistic Regression classifier was chose to easier identify the socioeconomic features that are drivers of high income, we see an opportunity to use an ensemble model such as Random Forest Classification to improve the model's prediction metrics.

Introduction

How is an individual's income affected by other socioeconomic factors? This is the question our team set out to investigate. Socioeconomic status here is defined as a way of describing people based on their education, income and type of job (National Cancer Institute, n.d.). With the diversity of backgrounds that can exist in society, we set out to understand what factors contribute most to an individuals income.

In this analysis, we use machine learning to predict whether an individuals income is above or below $50,000. As the government sets out massive investment in Canadian societies to improve the lives of citizens(Housing, Infrastructure and Communities Canada, 2025), we envision our analysis as a means of providing insights to the government as to what investments can drive the best chances of improving an individuals life. The persistent income and wealth inequeality increase presents a strong case for prudent investing to improve lives across all Canadians. (Yassin, Petit, & Abraham, 2024)

Methods

Data

For our dataset, we use the Adult dataset sourced from the UC Irvine Machine Learning Repository (Becker & Kohavi, 1996). The dataset contains 14 features obtained from census data to describe an individuals attributes. The target is a categorical column comprised of a binary outcome of whether an individual earns more than USD 50,000(>50K) or USD 50,000 or less (<=50K). The data and the descriptions fo the corresponding attributes can be explored using this link

Exploratory Data Analysis

Prior to model fitting and feature selection, we first perform EDA to understand the distribution of our features as it relates to our target.

The code chunk below imports our dataset.

In [2]:
```
# Import the data from the UCI Repostitory.

from ucimlrepo import fetch_ucirepo

DATA_PATH = '../data/raw/adult_census_data.csv'
```

```python
# fetch dataset
adult = fetch_ucirepo(id=2)

# data (as a pandas dataframe)
adult_df = pd.concat([adult.data.features, adult.data.targets], axis=1)

# Store raw data in the project directory
adult_df.to_csv(DATA_PATH)

# Rename target values
adult_df.income = adult_df.income.replace(to_replace=['<=50K.', '>50K.'], value=['<

# Combine all married groups in marital status to one group.
# adult_df['marital-status'] = adult_df['marital-status'].replace(to_replace=r'^Mar

# Remove duplicate rows
adult_df = adult_df.drop_duplicates()

# Remove outliers in capital-gain and capital-loss
numeric_cols = ['capital-gain','capital-loss']
for col in numeric_cols:
    if adult_df[col].nunique() <= 2:
            continue   # skip zero-inflated / categorical numeric columns
    q1 = adult_df[col].quantile(0.25)
    q3 = adult_df[col].quantile(0.75)
    iqr = q3 - q1
    lower = q1 - 1.5 * iqr
    upper = q3 + 1.5 * iqr

    adult_df = adult_df[(adult_df[col] >= lower) & (adult_df[col] <= upper)]

# Remove anomalies in categorical columns (presence of '?')
adult_df = adult_df.replace('?', np.nan)

# Drop null values from the data
adult_df = adult_df.dropna()

# Display First observations of the dataset
adult_df.head(5)
```

Out[2]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
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
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	Whit

Data Validation Check

To ensure the trustworthiness and reproducibility of our analysis, we perform a strict data validation check on the loaded raw data. This validation uses the custom DataValidator class from our **src/validation.py** module to verify critical aspects of the dataset:

- **File integrity** – confirming the file exists and is in the correct format.
- **Structure validation** – ensuring all expected column names and data types are present.
- **Data quality checks** – verifying that missing values are within acceptable limits and that no rows are completely empty.
- **Duplicate detection** – confirming the dataset contains no duplicated observations.
- **Outlier assessment** – checking that extreme values in numerical columns do not distort the analysis.
- **Categorical level verification** – confirming that all categorical features follow the allowed levels defined in the data description.
- **Target distribution check** – ensuring the target/response variable follows an expected distribution.
- **Correlation anomaly detection** – identifying unusually high correlations between the target and numeric features, as well as across features.

If the data fails any of these checks, the DataValidationError will be raised, and the **notebook execution will be halted**. This prevents us from proceeding with downstream steps like modeling and visualization using corrupted or unexpected data.

In [3]:
```
# --- Setup Block for Validation ---
import sys
from pathlib import Path
```

```python
# Add the project root path to the system path
project_root = Path.cwd().parent

if str(project_root) not in sys.path:
    sys.path.append(str(project_root))
    print(f"Added project root ({project_root.name}) to sys.path.")

from src.validation import DataValidator, DataValidationError

expected_income_dist = {
    "<=50K": 0.80,
    ">50K": 0.20
}

# --- Validation ---

try:
    # 1. Check file existence/format
    DataValidator.check_file_format_and_existence(DATA_PATH)

    # 2. Run other stucture & data quality checks
    validator = DataValidator(adult_df)
    validator.validate_all(expected_income_dist)

    print("\n\nSUCCESS: Data passed all validation checks and is ready for analysis

except DataValidationError as e:
    print(f"\n=================================================================
    print(f"VALIDATION FAILED! Analysis Halted to Prevent Data Leakage/Errors.")
    print(f"Error Details: {e}")
    print(f"==================================================================
    adult_df = None

except Exception as e:
    # Catch any other unexpected loading errors
    print(f"An unexpected error occurred during data loading: {e}")
    adult_df = None

if adult_df is not None:
    print(f"\nProceeding with a validated DataFrame of shape: {adult_df.shape}")
```

```
Added project root (522-group33-income-indicators) to sys.path.
Data file format (CSV) is confirmed and the file exists.
--- Starting Data Validation Checks ---
Column names and critical data types are correct.
No entirely empty observations found (i.e., no completely missing rows).
Missingness in all columns is within the 5% threshold.
No duplicate observations found.
No outliers found in numeric columns.
No anomalies found in categorical columns.
Target distribution matches expected proportions.
No anomalous correlations found between target and numeric features.
No anomalous correlations found between numeric features.
--- All core data validation checks passed successfully! ---


SUCCESS: Data passed all validation checks and is ready for analysis!

Proceeding with a validated DataFrame of shape: (39245, 16)
```

Train-Test-Split: Obey the Golden Rule

Before proceeding with further EDA and visualization of the data, we split and stash a test set from our data in order to evaluate our model performance on unseen data in accordance with the pricinples of the Golden rule of machine learning.

In [4]:
```
# Combine all married groups in marital status to one group.
adult_df['marital-status'] = adult_df['marital-status'].replace(to_replace=r'^Marri

# Create a Test train split of the data
adult_train, adult_test = train_test_split(adult_df, test_size=0.3, random_state=52
```

Discern Features & Strategize Missing Data

With the split, complete we review on the `adult_train` data to understand the statistics of the numerical features and to investigate on the presence of null values.

In [5]:
```
# Investigate quality of the data
adult_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 27471 entries, 22466 to 4241
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             27471 non-null  int64 
 1   workclass       27471 non-null  object
 2   fnlwgt          27471 non-null  int64 
 3   education       27471 non-null  object
 4   education-num   27471 non-null  int64 
 5   marital-status  27471 non-null  object
 6   occupation      27471 non-null  object
 7   relationship    27471 non-null  object
 8   race            27471 non-null  object
 9   sex             27471 non-null  object
 10  capital-gain    27471 non-null  int64 
 11  capital-loss    27471 non-null  int64 
 12  hours-per-week  27471 non-null  int64 
 13  native-country  27471 non-null  object
 14  income          27471 non-null  object
 15  income_encoded  27471 non-null  int64 
dtypes: int64(7), object(9)
memory usage: 3.6+ MB
```

In [6]:
```python
# Summarize null values
adult_train.isna().sum()
```

Out[6]:
```
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
income_encoded    0
dtype: int64
```

All null values have been handled during Data Validation.

In [7]:
```python
# Visualize distribution of features containing incomplete information values
# obj_df = adult_train.select_dtypes(include='object')
# for col in obj_df.columns:
#     if obj_df[col].str.contains('?', regex=False).any():
#         print (col)
```

In [8]:
```python
# Visualize distributions of categorical variables in the features with missing dat
# for col in obj_df.columns:
```

```
#     if obj_df[col].str.contains('?', regex=False).any():
#         print (obj_df[col].value_counts())
```

In [9]:
```
# # Reinforce conversion of columns to str object.
# for col in adult_train.select_dtypes(include='object'):
#     adult_train[col] = adult_train[col].astype(str)

# Replace missing data with NA
# adult_train = adult_train.apply(lambda col: col.str.strip() if col.dtype=='object
# adult_train = adult_train.replace('?', np.nan)

# Perform Simple Imputation
simple_imp = SimpleImputer(missing_values = np.nan, strategy='most_frequent')
adult_train_imp = pd.DataFrame(simple_imp.fit_transform(adult_train),
                               index=adult_train.index,
                               columns=adult_train.columns)


# Recast numerical featuers to int data types after Impute
adult_train_imp = adult_train_imp.astype({'age':'int64',
                       'fnlwgt': 'int64',
                       'capital-gain': 'int64',
                       'capital-loss': 'int64',
                       'hours-per-week': 'int64'})

# Confirm all missing values have been imputed
adult_train_imp.info()

# Store Cleaned Data in processed data directory
adult_train.to_csv('../data/processed/adult_census_training_data.csv')
adult_test.to_csv('../data/processed/adult_census_test_data.csv')
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 27471 entries, 22466 to 4241
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             27471 non-null  int64
 1   workclass       27471 non-null  object
 2   fnlwgt          27471 non-null  int64
 3   education       27471 non-null  object
 4   education-num   27471 non-null  object
 5   marital-status  27471 non-null  object
 6   occupation      27471 non-null  object
 7   relationship    27471 non-null  object
 8   race            27471 non-null  object
 9   sex             27471 non-null  object
 10  capital-gain    27471 non-null  int64
 11  capital-loss    27471 non-null  int64
 12  hours-per-week  27471 non-null  int64
 13  native-country  27471 non-null  object
 14  income          27471 non-null  object
 15  income_encoded  27471 non-null  object
dtypes: int64(5), object(11)
memory usage: 3.6+ MB
```

Univariate Distribution of The Quantitative Variables

Note - Visualization of the distributions below using the `altair-ally` package is performed with code adapted from UBC's DSCI-573: Feature and Model Selection Course. Reference on the Altair Ally package can be found in using [this external link]

We first investigate the distribution of the dataset's quantitative variables age against their income bracket. From the plots below, we pay special focus on the age distribution of the respondents. Both distributions are right-skewed. Income earners at or below USD 50,000 skew younger than fellow respondents earning above USD 50,000.

Of note also is the age distribution of hours worked per week, with most respondents in both income brackets reporting about 40 hours per week. The `fnlweight` feature is a final numerical value representing the final weight of the record. This value can be viewed as the number of people represented by the row. Without further breakdown on the methods or derivation of this value, we chose to ignore it in our analysis.

Similarly, no in depth data is provided on the `capital-loss` and `capital-gain` features, but these fields may have strong predictive value for identifying higher-income earners, so we consider creating a binary indicator (like has_capital_gain) to capture the signals.

In [10]:
```
aly.dist(adult_train_imp, color='income')
```

Out[10]:

Univariate Distribution of the Categorical Variables

We also review the distribution of select categorical variables below.

From the first histogram of `income` distribution, we can see that the dataset contains more records of low income earners compared to high income earners, a ration of about 3:1.

Reviewing the marital status of distribution, we can see that the distribution of high income earners is concentrated primarily on married respondents with scant representation the other marital status groups. Note that the orignal dataset contains 3 distinc married groups: `Married-AF-spouse` for respondents whose partners are in the Army, `Married-civ-spouse` for individuals married to civilian spouses & `Married-spouse-absent`. For simiplification, all values have been combined into one variable `Married`.

When analysing the `workclass` feature, a feature to classify the respondents' employer, we notice that high income earners are represented primarily in the private sector and less so in other employer categories.

While the distribution of the `occupation` feature is less conclusive, we see that high income earners in `exec-managerial` and `prof-specialty`, executive management and professional specialties respectively. Likewise when reviewing the `education` feature, we can see that high income earners tend to have at least some college education and are barely present in respondents who did not finish high school (For clarity, 12th grade is the last year of high school)

In order to prevent propagating inherent societal biases in our model, the following categories are not considered for feature or model selection: `race`.

Moreover, the `relationship` feature, which represents the relationship the observation has relative to others is not considered as the useful information is encoded within the respondent's marital status.

We also exclude the `native-country` from our visualization and feature. The overwhelming majority of the respondents are American-born and with little information on other information regarding the foreign-born respondents (e.g. how long they have been in the USA), we exclude this feature from our model.

In [11]:
```
# Look at the univariate distrbutions (counts) for the categorical variables

# Changing churn to an object dtype just for the data passed to the chart
aly.dist(adult_train_imp.select_dtypes(include='object').drop(columns=['relationshi
                                                                        'education-n
                                                                        'native-coun

         dtype='object', color='income')
```

Out[11]:

Features & Model Selection

Pre-processing pipeline

The adult dataset has various types of features: numeric, categorical, binary.

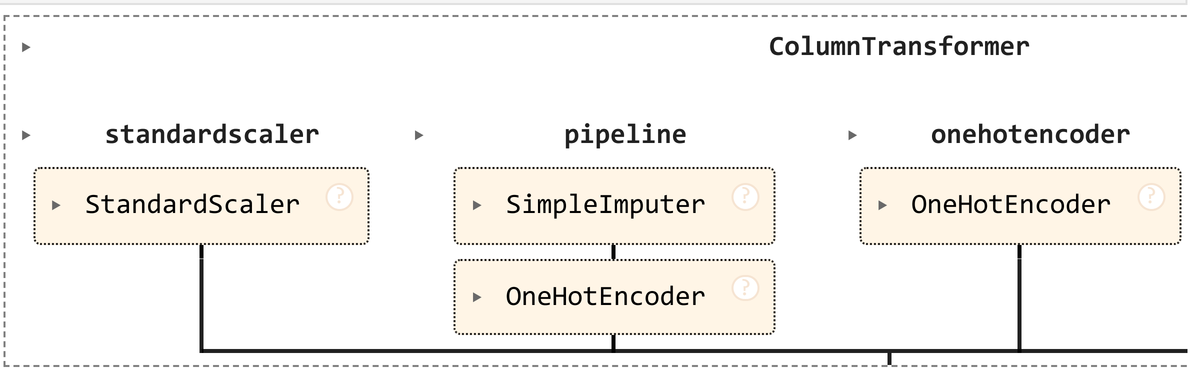
Feature	Type	Transformation
age	Integer	Scaling with StandardScaler
workclass	Categorical	imputation, one-hot encoding
fnlwgt	Integer	drop
education	Categorical	drop
education-num	Integer	no transformation needed
marital-status	Categorical	one-hot encoding
occupation	Categorical	imputation, one-hot encoding
relationship	Categorical	drop

Feature	Type	Transformation
race	Categorical	drop
sex	Binary	one-hot encoding with drop=if_binary
capital-gain	Integer	FunctionTransfor - binary flag
capital-loss	Integer	FunctionTransfor - binary flag
hours-per-week	Integer	Scaling with StandardScaler
native-country	Categorical	imputation, one-hot encoding

In [12]:

```
def binary_flag(x):
    # Binary conversion for captital features
    return (x > 0).astype(int)

# Features
numeric_features = ["age","hours-per-week", "education-num"]
categorical_features = ["workclass", "marital-status", "occupation", "native-countr
binary_features = ["sex"]
drop_features = ["fnlwgt","education", "relationship", "race", "capital-gain", "cap
capital_features = ["capital-gain", "capital-loss"]
target = "income"

# Transformers
numeric_transformer = StandardScaler()
capital_transformer = FunctionTransformer(binary_flag, feature_names_out="one-to-on
binary_transformer = OneHotEncoder(drop="if_binary", dtype=int)
categorical_transformer = make_pipeline(
            SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='U
            # SimpleImputer(missing_values = np.nan, strategy='most_frequent'),
            OneHotEncoder(handle_unknown="ignore", sparse_output=False)
        )

# Preprocessor
preprocessor = make_column_transformer(
    (numeric_transformer, numeric_features),
    (categorical_transformer, categorical_features),
    (binary_transformer, binary_features),
    (capital_transformer, capital_features),
    ("drop", drop_features)
)
preprocessor
```

Out[12]:



In [13]:

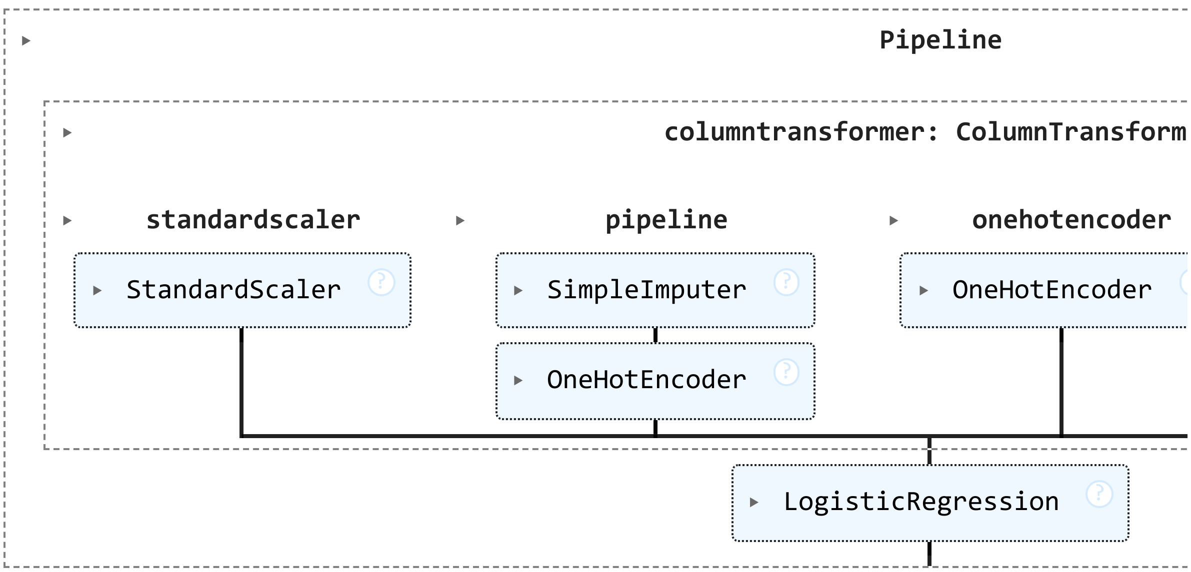
```python
# Replacing ? with NULL values in test dataset
#adult_test = adult_test.replace('?', np.nan)

# splitting features and target
X_train = adult_train.drop(columns=target)
X_test = adult_test.drop(columns=target)
y_train = adult_train[target]
y_test = adult_test[target]
```

Fit a model

In [14]:

```python
# creating a pipeline with preprocessing + LogisticRegression
model = make_pipeline(
    preprocessor,
    LogisticRegression(class_weight='balanced', max_iter=1000, random_state=522, C=
)

# fit model on the entire training set
model.fit(X_train, y_train)
```

Out[14]:



Model Evaluation

Accuracy, Precision, Recall, F1-Score

Our Logistic Regression model demonstrates robust generalization with a test accuracy of **78.08%**, mirroring the cross-validation mean of **78.2%** and indicating no overfitting. By employing balanced class weights to address dataset imbalance, the model strategically prioritizes Recall (83.6%) over Precision (47.0%) for the high-income class (>50K). This configuration results in an F1-score of 0.60, confirming that while the model successfully identifies the vast majority of high earners, it accepts a higher rate of false positives to ensure potential high-income individuals are rarely missed.

In [15]:
```python
# Logistic regression
classification_metrics = {
    "accuracy": "accuracy",
    "precision": make_scorer(precision_score, pos_label=">50K"),
    "recall": make_scorer(recall_score, pos_label=">50K"),
    "f1": make_scorer(f1_score, pos_label=">50K")
}

cross_val_results = {}
cross_val_results['model'] = pd.DataFrame(cross_validate(
    model,
    X_train,
    y_train,
    return_train_score=True,
    scoring=classification_metrics
)).agg(['mean', 'std']).round(3).T

# Show the train and validation scores
print("Test Score: ", model.score(X_test, y_test))
cross_val_results['model']
```

```
Test Score:  0.7808731102429081
```

Out[15]:

	mean	std
fit_time	0.283	0.021
score_time	0.118	0.010
test_accuracy	0.782	0.007
train_accuracy	0.783	0.003
test_precision	0.470	0.010
train_precision	0.473	0.004
test_recall	0.836	0.016
train_recall	0.839	0.002
test_f1	0.602	0.012
train_f1	0.605	0.004

Confusion matrix & Classification report

The matrix confirms our high-recall strategy: the model successfully identifies the vast majority of high-income earners (minimizing False Negatives), though this aggressiveness results in more lower-income individuals being incorrectly flagged (higher False Positives).

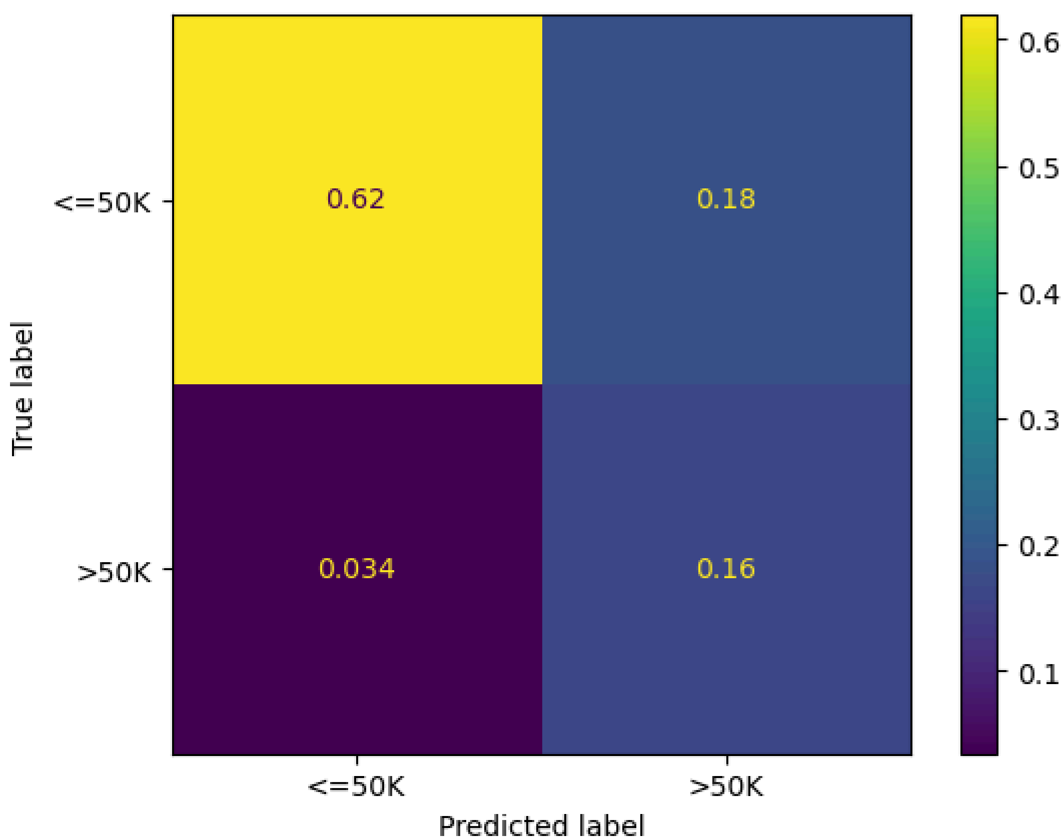
In [16]:
```python
# Confusion matrix for the logistic regression
confmat_logreg = ConfusionMatrixDisplay.from_estimator(
    model,
    X_test,
    y_test,
```

```python
    normalize='all'
)

# Show the matrix
print(confmat_logreg)

# Classification Report

print("Classification Report: ")
pd.DataFrame(classification_report(
    y_test,
    model.predict(X_test),
    target_names=['<=50K', '>50K'],
    output_dict=True
)).transpose()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0x0000020E8
3B1AC60>
Classification Report:
```

Out[16]:

	precision	recall	f1-score	support
<=50K	0.947389	0.770279	0.849703	9468.000000
>50K	0.466389	0.824371	0.595738	2306.000000
accuracy	0.780873	0.780873	0.780873	0.780873
macro avg	0.706889	0.797325	0.722720	11774.000000
weighted avg	0.853182	0.780873	0.799963	11774.000000

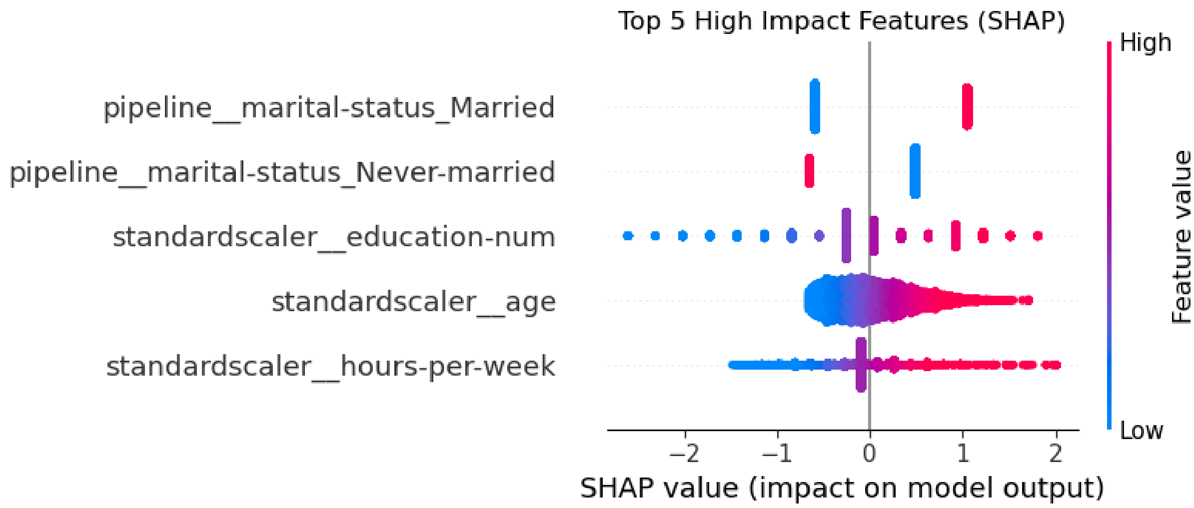


Model Explainability (using SHAP)

SHAP values interpret the model's decisions by assigning an 'importance score' to every feature for every prediction. This allows us to see exactly which factors pushed a specific individual's prediction towards the high-income or low-income category.

In [17]:

```
# A. Extract steps from the pipeline
log_reg_model = model.named_steps['logisticregression']
preprocessor_step = model.named_steps['columntransformer']

# B. Transform Data for SHAP
X_train_transformed = preprocessor_step.transform(X_train)
X_test_transformed = preprocessor_step.transform(X_test)

# C. Get Feature Names
feature_names = preprocessor_step.get_feature_names_out()

# D. Create Explainer
X_train_summary = shap.sample(X_train_transformed, 100)
explainer = shap.LinearExplainer(log_reg_model, X_train_summary)

# E. Calculate SHAP Values
shap_values = explainer.shap_values(X_test_transformed)

# F. Handle Binary Classification Output - Class 1 (>50K)
if isinstance(shap_values, list):
    vals_to_plot = shap_values[1]
else:
    vals_to_plot = shap_values

# G. Plot Summary with only Top 5 Features
plt.figure(figsize=(10, 6))
plt.title("Top 5 High Impact Features (SHAP)")

shap.summary_plot(
    vals_to_plot,
    X_test_transformed,
    feature_names=feature_names,
    max_display=5 # Top 5 important features
)
```



Results:

1. Model Performance:

- **Accuracy:** The model achieved an accuracy of 78% on the test set.
- **Class Imbalance Handling:** By using class_weight='balanced', we prioritized identifying high-income earners (>50K). This likely resulted in higher Recall for the >50K class (catching more high earners) potentially at the cost of some Precision (more false positives).
- **Confusion Matrix Analysis:** As seen in the matrix, the model correctly identified high-income individuals, while missing some False positives.

2. Feature Importance (Explainability)

Using SHAP analysis, we identified the key drivers of income:

- **Marital Status:** Being Married-civ-spouse is often the strongest positive predictor of high income (indicated by the long red bar pushing to the right in the SHAP plots).
- **Age:** The dependence plot shows a positive correlation between age and income up to a certain point (likely 50-60 years old), after which it may plateau or decrease.
- **Education:** Higher education-num consistently pushes predictions toward the >50K category.
- **Hours per week:** Individuals investing more hours per week are overwhelmingly classified as high income.

Conclusion

This analysis successfully established a robust predictive model for income classification, leveraging logistic regression to identify the key drivers of economic disparities. By intentionally designing a pipeline that addresses class imbalance, our model demonstrates a high sensitivity to detecting high-income earners, ensuring that significant predictors of wealth are not overlooked. While we prioritized ethical fairness by excluding explicit racial and relationship identifiers, the model's performance confirms that other structural factors—specifically education, marital status, and career stability—remain powerful proxies for economic success in the current landscape.

From a socioeconomic perspective, our results align closely with established economic theory. **Education** emerged as a dominant differentiator, validating the concept of human capital where higher investment in skills directly correlates with earning potential. Similarly, **Marital Status** proved to be a substantial predictor, likely reflecting the economic stability often associated with dual-income households or the "marriage premium" phenomenon observed in labor economics. **Age** also displayed a strong positive trend, illustrating the natural accumulation of experience and seniority over a career trajectory, though this effect naturally plateaus as individuals near retirement.

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