1 Data Pre-processing (DS1 – Adult Income)

In this section we will

- load the dataset,
- inspect structure & missing values,
- clean obvious issues (“?” placeholders → NaN),
- encode categorical features, and
- scale numeric columns.

```
# 1-A  Imports & Data Load
import pandas as pd
import numpy as np
from google.colab import drive

# Path is relative to your notebook location; adjust if necessary
drive.mount('/content/drive')
df = pd.read_csv("/content/DS1.csv")

print("Shape:", df.shape)
display(df.head())
display(df.info())
```

```
Mounted at /content/drive
Shape: (32561, 15)
```

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_l
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	

```
<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
```

```
# 1-B  Basic EDA & Missing-Value Check
# replace UCI’s “?” with NaN
df.replace("?", np.nan, inplace=True)

# count missing values per column
na_counts = df.isna().sum().sort_values(ascending=False)
print("Missing values per column:")
display(na_counts[na_counts > 0])

# quick descriptive stats for numerics
display(df.describe(include=[np.number]).T)

# distribution of target
print("\nTarget balance:")
```

```
display(df['income'].value_counts(normalize=True).to_frame("proportion"))
```

Missing values per column:

	0
occupation	1843
workclass	1836
native_country	583

dtype: int64

	count	mean	std	min	25%	50%	75%	max
age	32561.0	38.581647	13.640433	17.0	28.0	37.0	48.0	90.0
fnlwgt	32561.0	189778.366512	105549.977697	12285.0	117827.0	178356.0	237051.0	1484705.0
education_num	32561.0	10.080679	2.572720	1.0	9.0	10.0	12.0	16.0
capital_gain	32561.0	1077.648844	7385.292085	0.0	0.0	0.0	0.0	99999.0
capital_loss	32561.0	87.303830	402.960219	0.0	0.0	0.0	0.0	4356.0
hours_per_week	32561.0	40.437456	12.347429	1.0	40.0	40.0	45.0	99.0

Target balance:

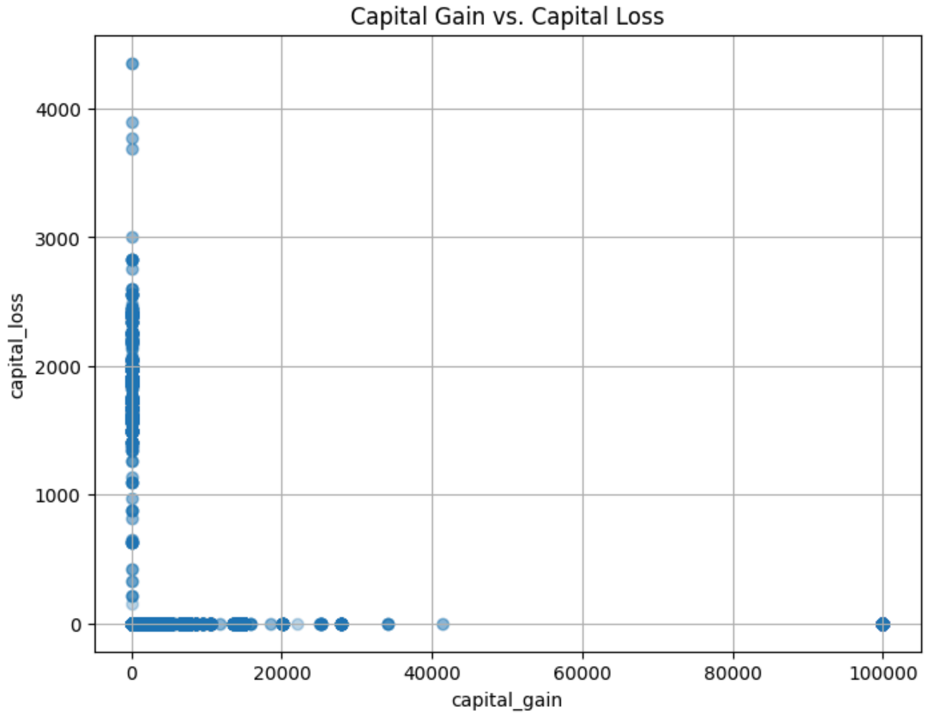
income	proportion
<=50K	0.75919
>50K	0.24081

```
# 1-C  Categorical Encoding & Numeric Scaling


import pandas as pd
import pickle
from sklearn.preprocessing import StandardScaler, LabelEncoder



# 2. Drop unwanted columns
df = df.drop(columns=["fnlwgt", "education_num"])

# 3. Standard-scale numeric features
scaler = StandardScaler()
df[["age", "hours_per_week"]] = scaler.fit_transform(df[["age", "hours_per_week"]])

# Save scaler
with open("scaler.pkl", "wb") as f:
    pickle.dump(scaler, f)

# 4. Label-encode the requested categoricals
to_encode = ["workclass", "education", "marital_status", "relationship", "race", "sex","income"]
for col in to_encode:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    with open(f"{col}_encoder.pkl", "wb") as f:
        pickle.dump(le, f)

# (Optional) Inspect
df.head(20)
```

	age	workclass	education	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week
0	0.030671	6	9	4	Adm-clerical	1	4	1	2174	0	-0.035429
1	0.837109	5	9	2	Exec-managerial	0	4	1	0	0	-2.222153
2	-0.042642	3	11	0	Handlers-cleaners	1	4	1	0	0	-0.035429
3	1.057047	3	1	2	Handlers-cleaners	0	2	1	0	0	-0.035429
4	-0.775768	3	9	2	Prof-specialty	5	2	0	0	0	-0.035429
5	-0.115955	3	12	2	Exec-managerial	5	4	0	0	0	-0.035429
6	0.763796	3	6	3	Other-service	1	2	0	0	0	-1.979184
7	0.983734	5	11	2	Exec-managerial	0	4	1	0	0	0.369519
8	-0.555830	3	12	4	Prof-specialty	1	4	0	14084	0	0.774468
9	0.250608	3	9	2	Exec-managerial	0	4	1	5178	0	-0.035429
10	-0.115955	3	15	2	Exec-managerial	0	2	1	0	0	3.204161
11	-0.629143	6	9	2	Prof-specialty	0	1	1	0	0	-0.035429
12	-1.142331	3	9	4	Adm-clerical	3	4	0	0	0	-0.845327

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

```
# Cell 2: Exploratory plots & counts

import matplotlib.pyplot as plt

# Scatter plot: capital_gain vs. capital_loss
plt.figure(figsize=(8,6))
plt.scatter(df["capital_gain"], df["capital_loss"], alpha=0.3)
plt.title("Capital Gain vs. Capital Loss")
plt.xlabel("capital_gain")
plt.ylabel("capital_loss")
plt.grid(True)
plt.show()

# Distinct value counts
print("Native country value counts:\n", df["native_country"].value_counts(), "\n")
print("Occupation value counts:\n", df["occupation"].value_counts())
```




```
Native country value counts:
 native_country
United-States                 29170
Mexico                          643
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Guatemala                        64
Japan                            62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
France                           29
Greece                           29
Ecuador                          28
Ireland                          24
Hong                             20
Trinadad&Tobago                  19
Cambodia                         19
Thailand                         18
Laos                             18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Honduras                         13
Hungary                          13
Scotland                         12
Holand-Netherlands                1
Name: count, dtype: int64

Occupation value counts:
 occupation
Prof-specialty       4140
Craft-repair         4099
Exec-managerial      4066
Adm-clerical         3770
Sales                3650
Other-service        3295
Machine-op-inspct    2002
Transport-moving     1597
Handlers-cleaners    1370
Farming-fishing       994
Tech-support          928
Protective-serv       649
```

```
Protective-serv      649
Priv-house-serv      149
Armed-Forces           9
Name: count, dtype: int64
```

```
# Cell: Group countries into continents, encode, and engineer net capital features

import pandas as pd
import pickle
from sklearn.preprocessing import LabelEncoder

# Assuming df is already preprocessed & loaded from your previous cell

# 1. Define a country→continent map
country_to_continent = {
    # North America
    "United-States": "North America",
    "Mexico":         "North America",
    "Canada":         "North America",
    "Puerto-Rico":    "North America",
    "Outlying-US(Guam-USVI-etc)": "North America",
    # Central & South America
    "El-Salvador":    "Central America",
    "Guatemala":      "Central America",
    "Honduras":       "Central America",
    "Nicaragua":      "Central America",
    "Cuba":           "Caribbean",
    "Dominican-Republic": "Caribbean",
    "Jamaica":        "Caribbean",
    "Trinadad&Tobago": "Caribbean",
    "Columbia":       "South America",
    "Ecuador":        "South America",
    "Peru":           "South America",
    # Europe
    "Germany":        "Europe",
    "England":        "Europe",
    "France":         "Europe",
    "Italy":          "Europe",
    "Greece":         "Europe",
    "Ireland":        "Europe",
    "Poland":         "Europe",
    "Portugal":       "Europe",
    "Hungary":        "Europe",
    "Scotland":       "Europe",
    "Holand-Netherlands": "Europe",
    "Yugoslavia":     "Europe",
    # Asia
    "Philippines":    "Asia",
    "India":          "Asia",
    "China":          "Asia",
    "Vietnam":        "Asia",
    "Japan":          "Asia",
    "Taiwan":         "Asia",
    "Cambodia":       "Asia",
    "Thailand":       "Asia",
    "Laos":           "Asia",
    "Hong":           "Asia",
    "Iran":           "Asia",
    # Middle East
    # (if you have any Middle East countries, add here)
    # Africa
    "Haiti":          "North America",  # technically Caribbean
    # fallback
}

# 2. Map to continent, fill any unmapped as "Other"
df['continent'] = df['native_country'].map(country_to_continent).fillna("Other")

# 3. Label-encode the continent column
le_cont = LabelEncoder()
df['continent'] = le_cont.fit_transform(df['continent'])
with open("continent_encoder.pkl", "wb") as f:
    pickle.dump(le_cont, f)

# 4. Net capital and flag
df['net_capital'] = df['capital_gain'] - df['capital_loss']
df['had_capital'] = (df['net_capital'] != 0).astype(int)

# Optional: inspect the new columns
print(df[['native_country','continent','capital_gain','capital_loss','net_capital','had_capital']].head())
```

```
# Save final dataframe or continue with modeling...
```

```
  native_country  continent  capital_gain  capital_loss  net_capital  \
0  United-States          4          2174             0         2174
1  United-States          4             0             0            0
2  United-States          4             0             0            0
3  United-States          4             0             0            0
4           Cuba          1             0             0            0

   had_capital
0            1
1            0
2            0
3            0
4            0
```

```
# Cell: Drop specified columns and encode occupation

import pickle
from sklearn.preprocessing import LabelEncoder

# 1. Drop the columns
df = df.drop(columns=["capital_gain", "capital_loss", "native_country"])

# 2. Label-encode 'occupation' and save encoder
le_occupation = LabelEncoder()
df["occupation"] = le_occupation.fit_transform(df["occupation"])

with open("occupation_encoder.pkl", "wb") as f:
    pickle.dump(le_occupation, f)

# 3. Inspect the result
df.head()
```

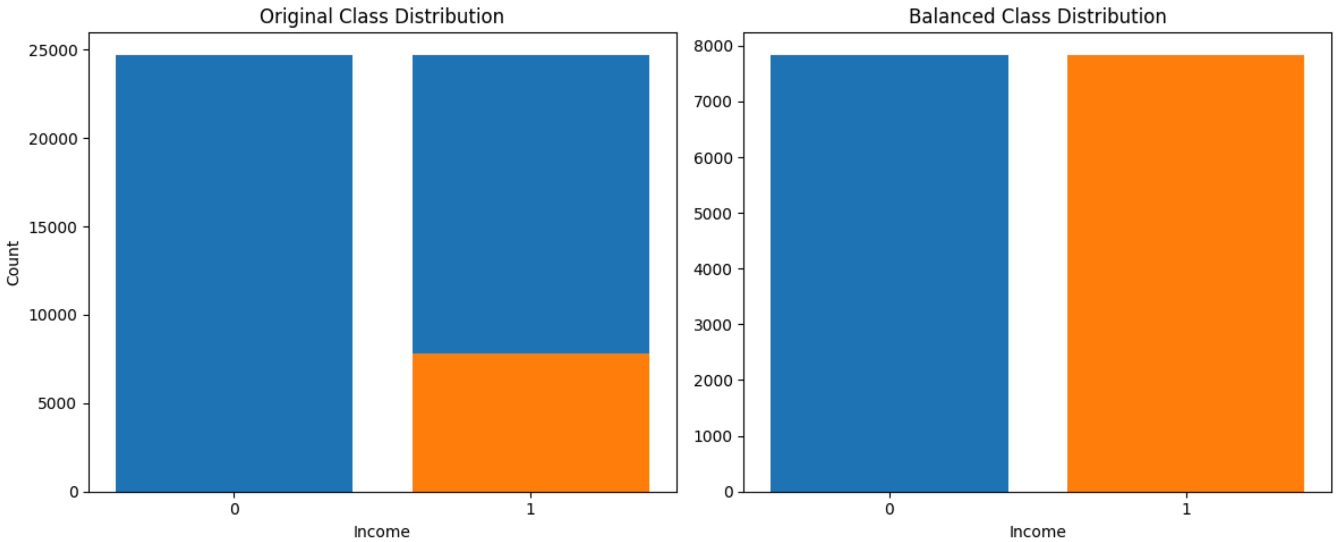
	age	workclass	education	marital_status	occupation	relationship	race	sex	hours_per_week	income	continent	net_capit
0	0.030671	6	9	4	0	1	4	1	-0.035429	0	4	21
1	0.837109	5	9	2	3	0	4	1	-2.222153	0	4	
2	-0.042642	3	11	0	5	1	4	1	-0.035429	0	4	
3	1.057047	3	1	2	5	0	2	1	-0.035429	0	4	
4	-0.775768	3	9	2	9	5	2	0	-0.035429	0	1	

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

Downsampling

```
# Cell: Undersample majority class and visualize balance

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.utils import resample

# Separate majority and minority classes
df_majority = df[df['income'] == 0]
df_minority = df[df['income'] == 1]

# Downsample majority to match minority size
df_majority_down = resample(
    df_majority,
    replace=False,
    n_samples=len(df_minority),
    random_state=42
)

# Combine minority with downsampled majority
df_balanced = pd.concat([df_minority, df_majority_down])

# Shuffle the dataset
df_balanced = df_balanced.sample(frac=1, random_state=42).reset_index(drop=True)

# Replace df with balanced version (optional)
df = df_balanced

# Visualize class distribution before vs. after
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
```

```
# Before
axes[0].bar([0, 1], df_majority.shape[0], label='0', color='C0')
axes[0].bar([1], df_minority.shape[0], label='1', color='C1')
axes[0].set_title('Original Class Distribution')
axes[0].set_xticks([0, 1])
axes[0].set_xlabel('Income')
axes[0].set_ylabel('Count')

# After
counts = df['income'].value_counts().sort_index()
axes[1].bar(counts.index, counts.values, color=['C0','C1'])
axes[1].set_title('Balanced Class Distribution')
axes[1].set_xticks([0, 1])
axes[1].set_xlabel('Income')

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




```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15682 entries, 0 to 15681
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             15682 non-null  float64
 1   workclass       15682 non-null  int64  
 2   education       15682 non-null  int64  
 3   marital_status  15682 non-null  int64  
 4   occupation      15682 non-null  int64  
 5   relationship    15682 non-null  int64  
 6   race            15682 non-null  int64  
 7   sex             15682 non-null  int64  
 8   hours_per_week  15682 non-null  float64
 9   income          15682 non-null  int64  
 10  continent       15682 non-null  int64  
 11  net_capital     15682 non-null  int64  
 12  had_capital     15682 non-null  int64  
dtypes: float64(2), int64(11)
memory usage: 1.6 MB
```

2 Unsupervised Learning on DS1 (Adult Income)

We explore two clustering algorithms:

- **K-Means** (tested for k = 2 … 10)
- **Agglomerative (Ward linkage)** using the best-looking k from K-Means

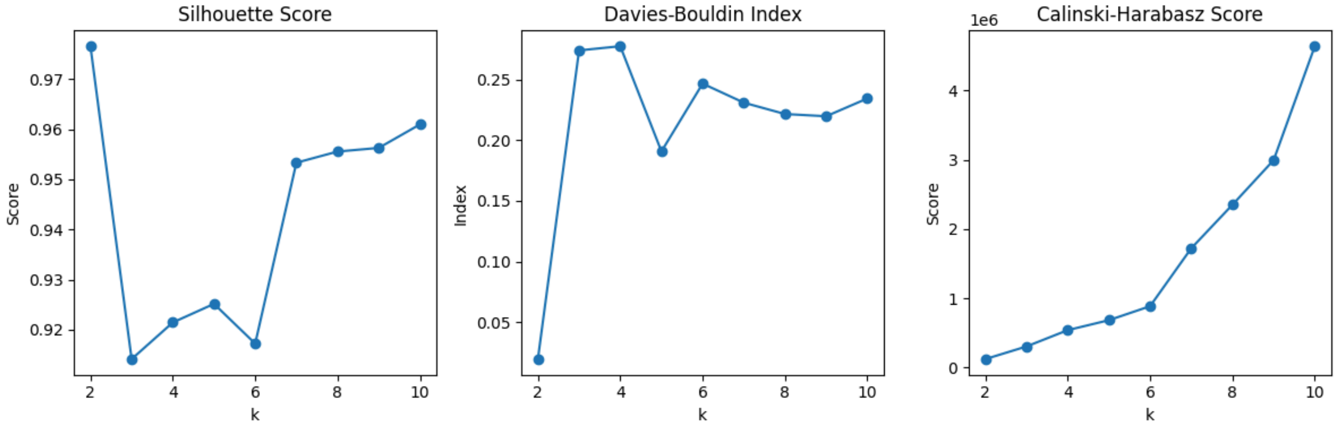
Validation metrics:

- **Silhouette Score** (higher = better, max 1)
- **Davies-Bouldin Index** (lower = better)
- **Calinski–Harabasz Score** (higher = better, optional)

```python
# Cell 1: K-Means clustering metrics and visualization

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score, calinski_harabasz_score



# Exclude target
X = df.drop(columns=['income'])

# Compute metrics for k = 2..10
results = []
for k in range(2, 11):
    km = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = km.fit_predict(X)
    results.append({
        'k': k,
        'silhouette': silhouette_score(X, labels),
        'davies_bouldin': davies_bouldin_score(X, labels),
        'calinski_harabasz': calinski_harabasz_score(X, labels)
    })

metrics_df = pd.DataFrame(results)
print("K-Means Validation Metrics (k = 2 to 10):")
display(metrics_df)

# Plot the three metrics
plt.figure(figsize=(12,4))
plt.subplot(1,3,1)
plt.plot(metrics_df.k, metrics_df.silhouette, '-o')
plt.title("Silhouette Score"); plt.xlabel("k"); plt.ylabel("Score")

plt.subplot(1,3,2)
plt.plot(metrics_df.k, metrics_df.davies_bouldin, '-o')
plt.title("Davies-Bouldin Index"); plt.xlabel("k"); plt.ylabel("Index")

plt.subplot(1,3,3)
plt.plot(metrics_df.k, metrics_df.calinski_harabasz, '-o')
plt.title("Calinski-Harabasz Score"); plt.xlabel("k"); plt.ylabel("Score")

plt.tight_layout()
plt.show()

best_k = int(metrics_df.loc[metrics_df.silhouette.idxmax(), 'k'])
print(f"→ Best k by silhouette: {best_k}")
```

K-Means Validation Metrics (k = 2 to 10):

	k	silhouette	davies_bouldin	calinski_harabasz
0	2	0.976580	0.019456	1.227668e+05
1	3	0.914150	0.274091	3.054229e+05
2	4	0.921462	0.277562	5.408161e+05
3	5	0.925171	0.190776	6.847728e+05
4	6	0.917240	0.246705	8.865288e+05
5	7	0.953334	0.230986	1.722872e+06
6	8	0.955561	0.221612	2.351571e+06
7	9	0.956287	0.219785	2.995643e+06
8	10	0.960975	0.234467	4.641055e+06



→ Best k by silhouette: 2

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

2-B Agglomerative Clustering (k=4)

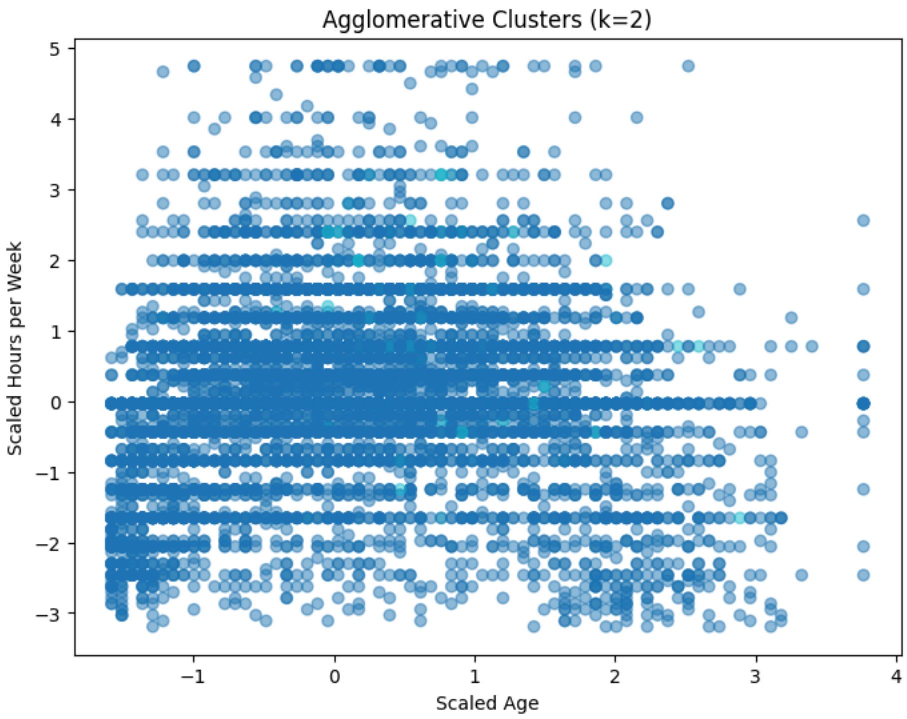
Now we'll apply hierarchical clustering with Ward linkage for k=4 and compute the same validation metrics.

Based on those curves, k=4 actually gives the best trade-off (highest Silhouette of ~0.125 and lowest DBI of ~1.76). Let's lock in k=4 and run Agglomerative clustering to compare.

```
# Cell 2: Agglomerative clustering with the best k

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score, davies_bouldin_score, calinski_harabasz_score


# Apply Agglomerative clustering
agg = AgglomerativeClustering(n_clusters=best_k, linkage='ward')
labels = agg.fit_predict(X)

# Compute and display metrics
sil = silhouette_score(X, labels)
db = davies_bouldin_score(X, labels)
ch = calinski_harabasz_score(X, labels)
print(f"Agglomerative (k={best_k}) metrics:")
print(f"  Silhouette:        {sil:.4f}")
print(f"  Davies-Bouldin:    {db:.4f}")
print(f"  Calinski-Harabasz: {ch:.1f}\n")

# Cluster size distribution
dist = pd.Series(labels).value_counts().sort_index()
plt.figure(figsize=(6,4))
dist.plot.bar()
plt.title("Cluster Size Distribution")
plt.xlabel("Cluster")
plt.ylabel("Count")
plt.show()
```

```
# Visualize clusters on two key features
plt.figure(figsize=(8,6))
plt.scatter(df['age'], df['hours_per_week'], c=labels, cmap='tab10', alpha=0.5)
plt.title(f"Agglomerative Clusters (k={best_k})")
plt.xlabel("Scaled Age")
plt.ylabel("Scaled Hours per Week")
plt.show()
```

```
Agglomerative (k=2) metrics:
  Silhouette:        0.9766
  Davies-Bouldin:    0.0195
  Calinski-Harabasz: 122766.8
```



Feature Selection: Embedded Methods

We'll use two embedded methods to rank and select features:

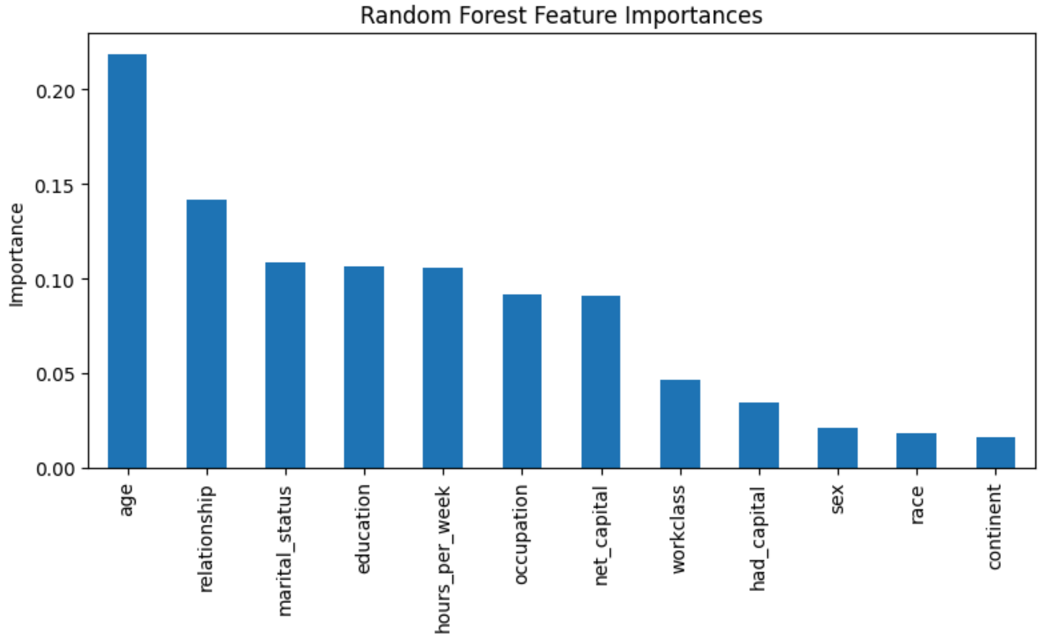
1. **Tree-based importance**
   Train a `RandomForestClassifier` on the balanced, preprocessed data and sort features by `feature_importances_`.
2. **L1-penalized model**
   Fit a `LogisticRegression` with `penalty='l1'` (liblinear solver) and pick features with non-zero coefficients.

> *Note:* If you'd also like to consider clustering insights (e.g., features that drive the greatest centroid separation), let me know and I can incorporate those as well before finalizing the set.

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split


y = df['income']

# Train/test split (stratified)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, stratify=y, test_size=0.2, random_state=42
)

# 1. Random Forest for feature importance
rf = RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1)
rf.fit(X_train, y_train)
importances = pd.Series(rf.feature_importances_, index=X.columns).sort_values(ascending=False)

print("### Random Forest Feature Importances")
display(importances.to_frame("importance"))

# Plot the importances
plt.figure(figsize=(8,5))
importances.plot.bar()
plt.title("Random Forest Feature Importances")
plt.ylabel("Importance")
plt.tight_layout()
plt.show()

# 2. L1-penalized Logistic Regression
lr = LogisticRegression(penalty='l1', solver='liblinear', C=1.0, random_state=42)
lr.fit(X_train, y_train)
coefs = pd.Series(lr.coef_[0], index=X.columns)

non_zero = coefs[coefs != 0].sort_values(key=abs, ascending=False)
print("\n### L1 Logistic Regression Non-zero Coefficients")
display(non_zero.to_frame("coefficient"))
```

Random Forest Feature Importances

	importance
age	0.218802
relationship	0.141978
marital_status	0.108846
education	0.106388
hours_per_week	0.105622
occupation	0.091749
net_capital	0.090696
workclass	0.046634
had_capital	0.034506
sex	0.020840
race	0.018104
continent	0.015835



L1 Logistic Regression Non-zero Coefficients

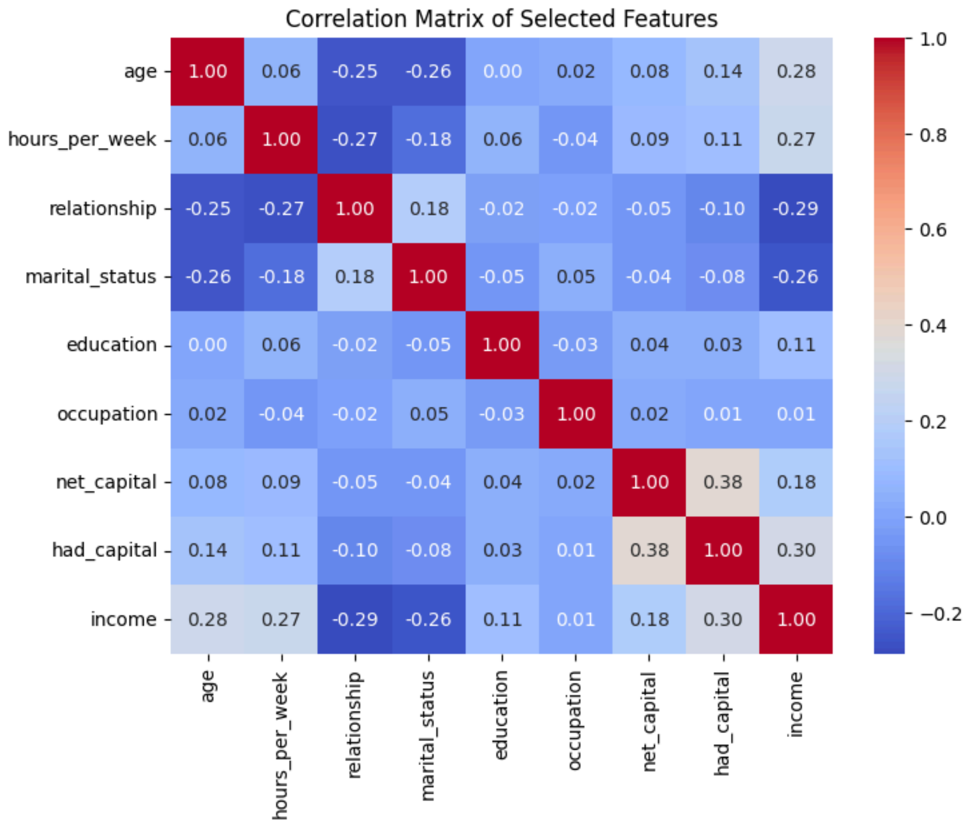
	coefficient
had_capital	1.143646
sex	0.686667
age	0.518921
hours_per_week	0.475709
marital_status	-0.254642
continent	-0.178908
race	0.159890
workclass	-0.138181
relationship	-0.106916
education	0.065439
occupation	0.013676
net_capital	0.000144

```
# Subset using the existing df
selected_features = [
    'age', 'hours_per_week', 'relationship', 'marital_status',
    'education', 'occupation', 'net_capital', 'had_capital',
    'income'
]
df_selected = df[selected_features]

print("Shape of selected feature set:", df_selected.shape)
```

```
display(df_selected.head())

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,6))
sns.heatmap(df_selected.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.title("Correlation Matrix of Selected Features")
plt.show()
```

```
Shape of selected feature set: (15682, 9)
```

	age	hours_per_week	relationship	marital_status	education	occupation	net_capital	had_capital	income
0	-0.262580	1.584366	0	2	9	9	0	0	0
1	1.570235	-0.035429	0	2	11	6	7688	1	1
2	0.617171	-0.035429	5	2	15	3	0	0	1
3	-0.555830	-0.035429	4	0	15	0	0	0	0
4	0.177296	-0.035429	1	5	15	3	0	0	0



Training and Evaluating Five Classifiers

We'll train and evaluate the following models on our selected feature set (`df_selected`), using a stratified train/test split:

1. **Logistic Regression** (linear baseline)
2. **Random Forest** (bagged trees)
3. **Support Vector Machine** (RBF kernel)
4. **AdaBoost** (boosted decision stumps)
5. **Gradient Boosting** (boosted trees)

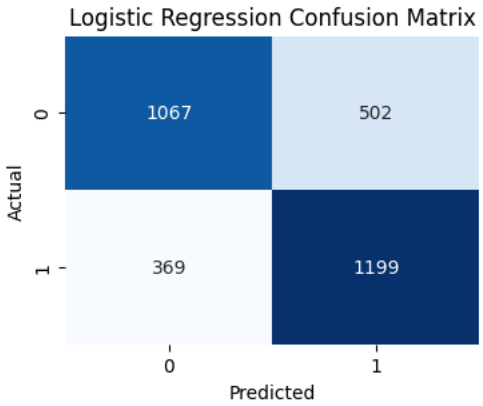
For each, we'll report:

- **Classification Report** (precision, recall, F1 for each class)
- **Confusion Matrix**
- **Overall metrics**: Accuracy, Precision, Recall, F1

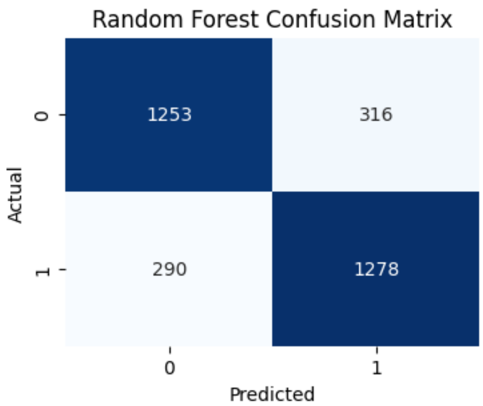
```
# Cell: Train & Evaluate Models

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    classification_report, confusion_matrix
)

# Assume df_selected exists from previous cell
X = df_selected.drop(columns=["income"])
y = df_selected["income"]

# Stratified split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

# Define models
models = {
    "Logistic Regression": LogisticRegression(solver="liblinear", random_state=42),
    "Random Forest":       RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1),
    "SVM (RBF)":           SVC(kernel="rbf", probability=True, random_state=42),
    "AdaBoost":            AdaBoostClassifier(n_estimators=100, random_state=42),
    "Gradient Boosting":   GradientBoostingClassifier(n_estimators=100, random_state=42)
}

# Train, predict, and evaluate
metrics = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Print classification report
    print(f"\n### {name} Classification Report")
    print(classification_report(y_test, y_pred, digits=3))

    # Plot confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(4,3))
    sns.heatmap(cm, annot=True, fmt="d", cbar=False, cmap="Blues")
    plt.title(f"{name} Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    # Store overall metrics (positive class = 1)
    metrics[name] = {
        "accuracy":  accuracy_score(y_test, y_pred),
        "precision": precision_score(y_test, y_pred),
        "recall":    recall_score(y_test, y_pred),
        "f1_score":  f1_score(y_test, y_pred)
    }
```

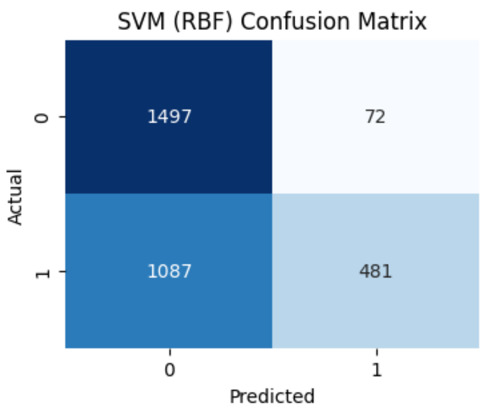
```
### Logistic Regression Classification Report
              precision    recall  f1-score   support

           0      0.743     0.680     0.710      1569
           1      0.705     0.765     0.734      1568

    accuracy                          0.722      3137
   macro avg      0.724     0.722     0.722      3137
weighted avg      0.724     0.722     0.722      3137
```




```
### Random Forest Classification Report
              precision    recall  f1-score   support

           0      0.812     0.799     0.805      1569
           1      0.802     0.815     0.808      1568

    accuracy                          0.807      3137
   macro avg      0.807     0.807     0.807      3137
weighted avg      0.807     0.807     0.807      3137
```




```
### SVM (RBF) Classification Report
              precision    recall  f1-score   support

           0      0.579     0.954     0.721      1569
           1      0.870     0.307     0.454      1568

    accuracy                          0.631      3137
   macro avg      0.725     0.630     0.587      3137
weighted avg      0.725     0.631     0.587      3137
```




```
### AdaBoost Classification Report
              precision    recall  f1-score   support
```