

```
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, cross_val_score, StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
```

```
In [2]: # We read the CSV file into a DataFrame so we can work with it in Python
df = pd.read_csv(r"C:\Users\Top Prix\Downloads\archive (2)\clicks_dataset.csv", encoding='ISO-8859-1')

# 3 BASIC EXPLORATION (EDA = Exploratory Data Analysis)
# Look at first rows, data types, and summary stats
print(df.head()) # quick preview of first 5 rows
print(df.info()) # data types and missing values
print(df.describe()) # basic statistics for numeric columns
```

	Names	emails \
0	Martina Avila	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu
1	Harlan Barnes	eu.dolor@diam.co.uk
2	Naomi Rodriguez	vulputate.mauris.sagittis@ametconsectetueradip...
3	Jade Cunningham	malesuada@dignissim.com
4	Cedric Leach	felis.ullamcorper.viverra@egetmollislectus.net

	Country	Time Spent on Site	Salary	Clicked
0	Bulgaria	25.649648	55330.06006	0
1	Belize	32.456107	79049.07674	1
2	Algeria	20.945978	41098.60826	0
3	Cook Islands	54.039325	37143.35536	1
4	Brazil	34.249729	37355.11276	0

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 499 entries, 0 to 498

Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	Names	499 non-null	object
1	emails	499 non-null	object
2	Country	499 non-null	object
3	Time Spent on Site	499 non-null	float64
4	Salary	499 non-null	float64
5	Clicked	499 non-null	int64

dtypes: float64(2), int64(1), object(3)

memory usage: 23.5+ KB

None

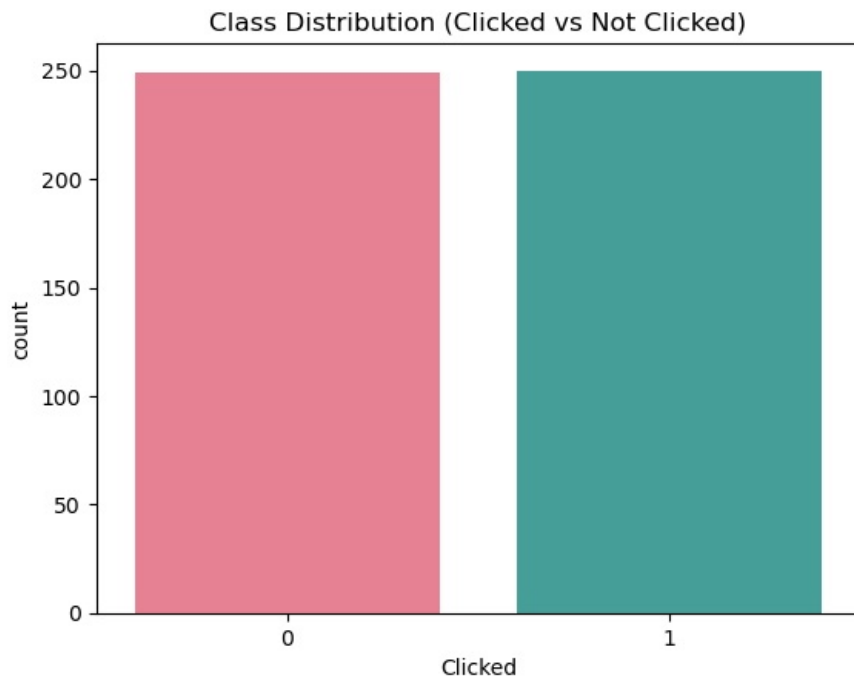
	Time Spent on Site	Salary	Clicked
count	499.000000	499.000000	499.000000
mean	32.920178	52896.992469	0.501002
std	9.103455	18989.183150	0.500501
min	5.000000	20.000000	0.000000
25%	26.425044	38888.117260	0.000000
50%	33.196067	52840.913110	1.000000
75%	39.114995	65837.288190	1.000000
max	60.000000	100000.000000	1.000000

```
In [3]: # --- Class balance plot ---
sns.countplot(x='Clicked', data=df, palette='husl')
plt.title("Class Distribution (Clicked vs Not Clicked)")
plt.show()
```

C:\Users\Top Prix\AppData\Local\Temp\ipykernel_9732\1994828306.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

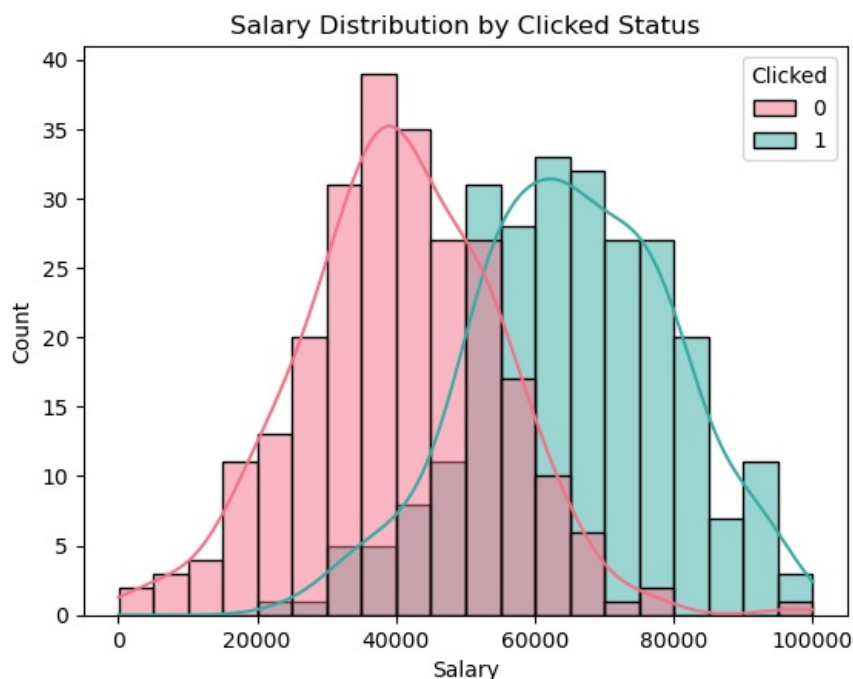
```
sns.countplot(x='Clicked', data=df, palette='husl')
```



```
In [4]: # --- Scatter plot to see if time & salary relate to clicking ---
sns.scatterplot(x='Time Spent on Site', y='Salary', hue='Clicked', data=df, palette='husl')
plt.title("Time Spent on Site vs Salary")
plt.show()
```



```
In [5]: # --- Salary distribution by click status ---
sns.histplot(df, x='Salary', hue='Clicked', bins=20, palette='husl', kde=True)
plt.title("Salary Distribution by Clicked Status")
plt.show()
```



```
In [6]: # 4 FEATURE ENGINEERING
# Here we create new columns that may help the model
df['Time_x_Salary'] = df['Time Spent on Site'] * df['Salary'] # interaction term
df['Log_Salary'] = np.log1p(df['Salary']) # log transform to reduce skew
df['Salary_Level'] = pd.cut(df['Salary'], # bucket salary into categories
                             bins=[0, 30000, 60000, 100000],
                             labels=['Low', 'Medium', 'High'])

# Convert categorical columns to 0/1 (dummy variables)
df = pd.get_dummies(df, columns=['Country', 'Salary_Level'], drop_first=True)

# Remove irrelevant columns
df = df.drop(columns=['emails', 'Names'])
```

In [7]: df

```
Out[7]:
```

	Time Spent on Site	Salary	Clicked	Time_x_Salary	Log_Salary	Country_Algeria	Country_American Samoa	Country_Andorra	Country_A...
0	25.649648	55330.06006	0	1.419197e+06	10.921090	False	False	False	
1	32.456107	79049.07674	1	2.565625e+06	11.277837	False	False	False	
2	20.945978	41098.60826	0	8.608505e+05	10.623754	True	False	False	
3	54.039325	37143.35536	1	2.007202e+06	10.522567	False	False	False	
4	34.249729	37355.11276	0	1.279402e+06	10.528252	False	False	False	
...
494	19.222746	44969.13495	0	8.644303e+05	10.713754	False	False	False	
495	22.665662	41686.20425	0	9.448454e+05	10.637950	False	False	False	
496	35.320239	23989.80864	0	8.473258e+05	10.085426	False	False	False	
497	26.539170	31708.57054	0	8.415192e+05	10.364374	False	False	False	
498	32.386148	74331.35442	1	2.407306e+06	11.216302	False	False	False	

499 rows × 216 columns

```
In [8]: # SPLIT INTO TRAIN AND TEST SETS

# stratify=y ensures both sets have same click/not click ratio
X = df.drop('Clicked', axis=1)
y = df['Clicked']
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

```
In [9]: # SET UP MODELS FOR CROSS-VALIDATION

log_model = Pipeline([
    ("scaler", StandardScaler()),
```

```
("clf", LogisticRegression(max_iter=500, random_state=42))
])
```

```
In [10]: # Random Forest doesn't need scaling
rf_model = RandomForestClassifier(random_state=42, n_jobs=-1)
```

```
In [11]: # Cross-validation setup: 5 folds, keep class balance
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

```
In [12]: # Run cross-validation on training set
cv_log_acc = cross_val_score(log_model, X_train, y_train, cv=cv, scoring="accuracy").mean()
cv_log_auc = cross_val_score(log_model, X_train, y_train, cv=cv, scoring="roc_auc").mean()

cv_rf_acc = cross_val_score(rf_model, X_train, y_train, cv=cv, scoring="accuracy").mean()
cv_rf_auc = cross_val_score(rf_model, X_train, y_train, cv=cv, scoring="roc_auc").mean()

print(f"Logistic Regression CV  Acc: {cv_log_acc:.3f} | AUC: {cv_log_auc:.3f}")
print(f"Random Forest          CV  Acc: {cv_rf_acc:.3f} | AUC: {cv_rf_auc:.3f}")

Logistic Regression CV  Acc: 0.845 | AUC: 0.920
Random Forest          CV  Acc: 0.882 | AUC: 0.948
```

```
In [13]: # FINAL TRAINING AND TEST EVALUATION
# Fit both models on the full training data
log_model.fit(X_train, y_train)
rf_model.fit(X_train, y_train)

# Predict on test set and evaluate
log_acc = accuracy_score(y_test, log_model.predict(X_test))
rf_acc = accuracy_score(y_test, rf_model.predict(X_test))

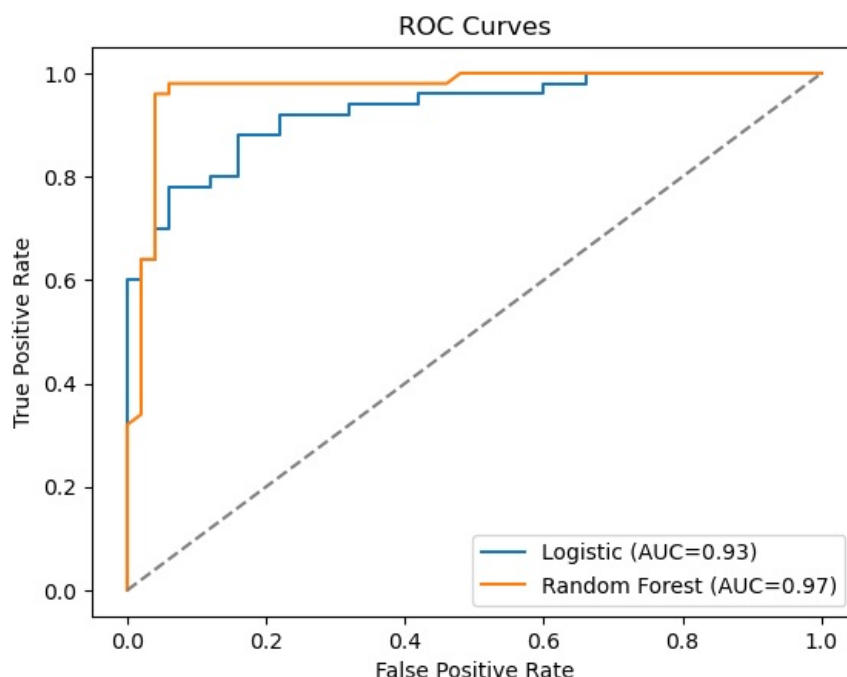
log_auc = roc_auc_score(y_test, log_model.predict_proba(X_test)[:, 1])
rf_auc = roc_auc_score(y_test, rf_model.predict_proba(X_test)[:, 1])

print("\n=== Test Set Performance ===")
print(f"Logistic Regression - Accuracy: {log_acc:.3f}, AUC: {log_auc:.3f}")
print(f"Random Forest          - Accuracy: {rf_acc:.3f}, AUC: {rf_auc:.3f}")

=== Test Set Performance ===
Logistic Regression - Accuracy: 0.840, AUC: 0.928
Random Forest      - Accuracy: 0.950, AUC: 0.970
```

```
In [14]: # VISUALIZE ROC CURVES FOR BOTH MODELS
fpr_log, tpr_log, _ = roc_curve(y_test, log_model.predict_proba(X_test)[:, 1])
fpr_rf, tpr_rf, _ = roc_curve(y_test, rf_model.predict_proba(X_test)[:, 1])

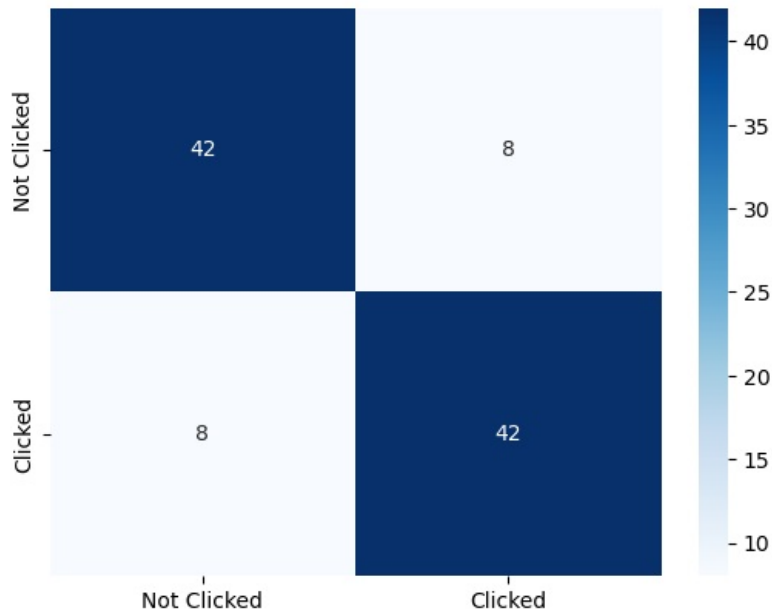
plt.plot(fpr_log, tpr_log, label=f"Logistic (AUC={log_auc:.2f})")
plt.plot(fpr_rf, tpr_rf, label=f"Random Forest (AUC={rf_auc:.2f})")
plt.plot([0, 1], [0, 1], linestyle="--", color="grey")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves")
plt.legend()
plt.show()
```



```
In [15]: from sklearn.metrics import confusion_matrix
```

```
corr_matrix=confusion_matrix(y_test, log_model.predict(X_test))
sns.heatmap(corr_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Not Clicked', 'Clicked'],
            yticklabels=['Not Clicked', 'Clicked'])
```

Out[15]: <Axes: >



```
In [16]: corr_matrix1= confusion_matrix(y_test, rf_model.predict(X_test))
sns.heatmap(corr_matrix1, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Not Clicked', 'Clicked'],
            yticklabels=['Not Clicked', 'Clicked'])
```

Out[16]: <Axes: >

