Adult Dataset

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

In [2]:
```
url = "http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data"
columns = ["age", "workclass", "fnlwgt", "education", "education_num", "marital_status",
           "occupation", "relationship", "race", "sex", "capital_gain", "capital_loss",
           "hours_per_week", "native_country", "income"]
adult_data = pd.read_csv(url, header=None, names=columns, na_values=' ?')
```

In [3]:
```
print(adult_data.head())
```

```
   age          workclass  fnlwgt   education  education_num  \
0   39          State-gov   77516   Bachelors             13
1   50   Self-emp-not-inc   83311   Bachelors             13
2   38            Private  215646     HS-grad              9
3   53            Private  234721        11th              7
4   28            Private  338409   Bachelors             13

        marital_status          occupation    relationship    race      sex  \
0        Never-married        Adm-clerical   Not-in-family   White     Male
1   Married-civ-spouse     Exec-managerial         Husband   White     Male
2             Divorced   Handlers-cleaners   Not-in-family   White     Male
3   Married-civ-spouse   Handlers-cleaners         Husband   Black     Male
4   Married-civ-spouse      Prof-specialty            Wife   Black   Female

   capital_gain  capital_loss  hours_per_week  native_country  income
0          2174             0              40   United-States   <=50K
1             0             0              13   United-States   <=50K
2             0             0              40   United-States   <=50K
3             0             0              40   United-States   <=50K
4             0             0              40            Cuba   <=50K
```

In [4]:
```
print(adult_data['income'].unique())
```

```
[' <=50K' ' >50K']
```

In [5]:
```
# Handle missing values
adult_data = adult_data.dropna()

adult_data['income'] = adult_data['income'].apply(lambda x: x.strip()).map({'>50K': 1, '<=50K': 0})
adult_data = pd.get_dummies(adult_data, drop_first=True)
```

In [6]:
```
scaler = StandardScaler()
numerical_cols = ['age', 'fnlwgt', 'education_num', 'capital_gain', 'capital_loss', 'hours_per_week']
adult_data[numerical_cols] = scaler.fit_transform(adult_data[numerical_cols])
```

In [7]:
```
X_ad = adult_data.drop('income', axis=1)
y_ad = adult_data['income']
```

In [8]:
```
ad_train_2080, X_ad_test_2080, y_ad_train_2080, y_ad_test_2080 = train_test_split(X_ad, y_ad, test_size=0.80, random_
ad_train_5050, X_ad_test_5050, y_ad_train_5050, y_ad_test_5050 = train_test_split(X_ad, y_ad, test_size=0.50, random_
ad_train_8020, X_ad_test_8020, y_ad_train_8020, y_ad_test_8020 = train_test_split(X_ad, y_ad, test_size=0.20, random_
```

In [9]:
```
# Define the parameter range for 'C'
param_range = [0.001, 0.01, 0.1, 1, 10, 100]
```

In [10]:
```
# Initialize classifiers and parameter grid
log_reg = LogisticRegression(solver='liblinear', class_weight='balanced')
svm = SVC()
rf = RandomForestClassifier(n_estimators=100)  # Example parameter
param_grid = {'C': param_range}
```

In [11]:
```
# Dictionary to store results
results = {}
```

For 20/80 Partition

In [12]:
```
# Logistic Regression with GridSearchCV
grid_lr_2080 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_2080.fit(X_ad_train_2080, y_ad_train_2080)
best_lr_score_2080 = grid_lr_2080.best_score_
```

In [13]:
```
# SVM with GridSearchCV
grid_svm_2080 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_2080.fit(X_ad_train_2080, y_ad_train_2080)
best_svm_score_2080 = grid_svm_2080.best_score_
```

In [14]:
```
# RandomForestClassifier
rf.fit(X_ad_train_2080, y_ad_train_2080)
rf_accuracy_2080 = accuracy_score(y_ad_test_2080, rf.predict(X_ad_test_2080))
```

In [15]:
```
# Store results for 20/80 partition
results_2080 = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}
```

In [16]:
```
print ("For 20/80")
print ("logistic regression accuracy: ",best_lr_score_2080)
print ("SVM accuracy: ",best_svm_score_2080)
print ("Random Forest accuracy: ",rf_accuracy_2080)
```

```
For 20/80
logistic regression accuracy:  0.8028843846406951
SVM accuracy:  0.8456562702812804
Random Forest accuracy:  0.8495234148363033
```

50/50 partition

In [17]:
```
# Logistic Regression with GridSearchCV
grid_lr_5050 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_5050.fit(X_ad_train_5050, y_ad_train_5050)
best_lr_score_5050 = grid_lr_5050.best_score_
```

In [18]:
```
# SVM with GridSearchCV
grid_svm_5050 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_5050.fit(X_ad_train_5050, y_ad_train_5050)
best_svm_score_5050 = grid_svm_5050.best_score_
```

In [19]:
```
# RandomForestClassifier
rf.fit(X_ad_train_5050, y_ad_train_5050)
rf_accuracy_5050 = accuracy_score(y_ad_test_5050, rf.predict(X_ad_test_5050))
```

In [20]:
```
# Store results for 20/80 partition
results_5050 = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}
```

In [21]:
```
print ("For 50/50")
print ("logistic regression accuracy: ",best_lr_score_5050)
print ("SVM accuracy: ",best_svm_score_5050)
print ("Random Forest accuracy: ",rf_accuracy_5050)
```

```
For 50/50
logistic regression accuracy:  0.8047874809362775
SVM accuracy:  0.8488827000862011
Random Forest accuracy:  0.8496120946886812
```

for 80/20 partition

In [22]:
```
# Logistic Regression with GridSearchCV
grid_lr_8020 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_8020.fit(X_ad_train_8020, y_ad_train_8020)
best_lr_score_8020 = grid_lr_8020.best_score_
```

In [23]:
```
# SVM with GridSearchCV
grid_svm_8020 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_8020.fit(X_ad_train_8020, y_ad_train_8020)
best_svm_score_8020 = grid_svm_8020.best_score_
```

In [24]:
```
# RandomForestClassifier
rf.fit(X_ad_train_8020, y_ad_train_8020)
rf_accuracy_8020 = accuracy_score(y_ad_test_8020, rf.predict(X_ad_test_8020))
```

In [25]:
```
# Store results for 80/20 partition
results_8020 = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}
```

In [26]:
```
print ("For 80/20")
print ("logistic regression accuracy: ",best_lr_score_8020)
print ("SVM accuracy: ",best_svm_score_8020)
print ("Random Forest accuracy: ",rf_accuracy_8020)
```

```
For 80/20
logistic regression accuracy:  0.8082804923535994
SVM accuracy:  0.8496000663102491
Random Forest accuracy:  0.8511519973479198
```

In [27]:
```
# Define results for the adult dataset
results_8020_adult = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}

results_5050_adult = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}

results_2080_adult = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}
```

German Credit Dataset

In [28]:
```
# Load the dataset
url = "http://archive.ics.uci.edu/ml/machine-learning-databases/statlog/german/german.data"
columns = ["existing_account", "duration_month", "credit_history", "purpose", "credit_amount", "savings_account",
           "present_employment", "installment_rate", "personal_status_sex", "other_debtors", "present_residence",
           "property", "age", "other_installment_plans", "housing", "number_credits", "job", "people_liable", "telep
           "foreign_worker", "credit_risk"]

german_data = pd.read_csv(url, sep=" ", header=None, names=columns)
```

In [29]:
```
german_data.head()
```

Out[29]:

	existing_account	duration_month	credit_history	purpose	credit_amount	savings_account	present_employment	installment_rate	personal_status_sex	othe
0	A11	6	A34	A43	1169	A65	A75	4	A93	
1	A12	48	A32	A43	5951	A61	A73	2	A92	
2	A14	12	A34	A46	2096	A61	A74	2	A93	
3	A11	42	A32	A42	7882	A61	A74	2	A93	
4	A11	24	A33	A40	4870	A61	A73	3	A93	

5 rows × 21 columns

In [30]:
```
german_data['credit_risk'] = german_data['credit_risk'].replace(2, 0)
```

In [31]:
```
german_data.head()
```

Out[31]:

	existing_account	duration_month	credit_history	purpose	credit_amount	savings_account	present_employment	installment_rate	personal_status_sex	othe
0	A11	6	A34	A43	1169	A65	A75	4	A93	
1	A12	48	A32	A43	5951	A61	A73	2	A92	
2	A14	12	A34	A46	2096	A61	A74	2	A93	
3	A11	42	A32	A42	7882	A61	A74	2	A93	
4	A11	24	A33	A40	4870	A61	A73	3	A93	

5 rows × 21 columns

In [32]:
```
# Handle categorical variables using one-hot encoding
german_data = pd.get_dummies(german_data, columns=["existing_account", "credit_history", "purpose", "savings_account"
                                                   "present_employment", "personal_status_sex", "other_debtors",
                                                   "property", "other_installment_plans", "housing", "job",
                                                   "telephone", "foreign_worker"],
                             drop_first=True)
```

In [33]:
```
# Standardize numerical features
scaler = StandardScaler()
numerical_cols = ["duration_month", "credit_amount", "installment_rate", "present_residence", "age", "number_credits"
                  "people_liable"]
german_data[numerical_cols] = scaler.fit_transform(german_data[numerical_cols])
```

In [34]:
```
# Split the dataset into X (features) and y (target)
X_credit = german_data.drop("credit_risk", axis=1)
y_credit = german_data["credit_risk"]
y_credit.head()
```

Out[34]:
```
0    1
1    0
2    1
3    1
4    0
Name: credit_risk, dtype: int64
```

In [35]:
```
# Split the dataset into 80/20, 50/50, and 20/80 partitions
X_credit_train_8020, X_credit_test_8020, y_credit_train_8020, y_credit_test_8020 = train_test_split(X_credit, y_cred
X_credit_train_5050, X_credit_test_5050, y_credit_train_5050, y_credit_test_5050 = train_test_split(X_credit, y_cred
X_credit_train_2080, X_credit_test_2080, y_credit_train_2080, y_credit_test_2080 = train_test_split(X_credit, y_cred
```

In [36]:
```
# Define the parameter range for 'C'
param_range = [0.001, 0.01, 0.1, 1, 10, 100]
```

In [37]:
```
log_reg = LogisticRegression(solver='liblinear', class_weight='balanced')
svm = SVC()
rf = RandomForestClassifier(n_estimators=100)  # Example parameter
param_grid = {'C': param_range}
print(y_credit_train_8020.isnull().sum())
```

```
0
```

In [38]:
```
print(y_credit_train_8020.isnull().sum())
```

```
0
```

In [39]:
```
# Dictionary to store results
results = {}
```

In [40]:
```
# For 80/20 Partition
# Logistic Regression with GridSearchCV
grid_lr_8020 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_8020.fit(X_credit_train_8020, y_credit_train_8020)
best_lr_score_8020 = grid_lr_8020.best_score_

# SVM with GridSearchCV
grid_svm_8020 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_8020.fit(X_credit_train_8020, y_credit_train_8020)
best_svm_score_8020 = grid_svm_8020.best_score_

# RandomForestClassifier
rf.fit(X_credit_train_8020, y_credit_train_8020)
rf_accuracy_8020 = accuracy_score(y_credit_test_8020, rf.predict(X_credit_test_8020))

# Store results for 80/20 partition
results_8020 = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}
```

In [41]:
```
# Print results
print("For 80/20")
print("Logistic Regression accuracy:", best_lr_score_8020)
print("SVM accuracy:", best_svm_score_8020)
print("Random Forest accuracy:", rf_accuracy_8020)
```

```
For 80/20
Logistic Regression accuracy: 0.7037396862943877
SVM accuracy: 0.7362648193517503
Random Forest accuracy: 0.74
```

In [42]:
```
# For 50/50 Partition
# Logistic Regression with GridSearchCV
grid_lr_5050 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_5050.fit(X_credit_train_5050, y_credit_train_5050)
best_lr_score_5050 = grid_lr_5050.best_score_

# SVM with GridSearchCV
grid_svm_5050 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_5050.fit(X_credit_train_5050, y_credit_train_5050)
best_svm_score_5050 = grid_svm_5050.best_score_

# RandomForestClassifier
rf.fit(X_credit_train_5050, y_credit_train_5050)
rf_accuracy_5050 = accuracy_score(y_credit_test_5050, rf.predict(X_credit_test_5050))

# Store results for 50/50 partition
results_5050 = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}
```

In [43]:
```
print("For 50/50")
print("Logistic Regression accuracy:", best_lr_score_5050)
print("SVM accuracy:", best_svm_score_5050)
print("Random Forest accuracy:", rf_accuracy_5050)
```

```
For 50/50
Logistic Regression accuracy: 0.735973835461607
SVM accuracy: 0.7420099559916311
Random Forest accuracy: 0.736
```

In [44]:
```
# For 20/80 Partition
# Logistic Regression with GridSearchCV
grid_lr_2080 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_2080.fit(X_credit_train_2080, y_credit_train_2080)
best_lr_score_2080 = grid_lr_2080.best_score_

# SVM with GridSearchCV
grid_svm_2080 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_2080.fit(X_credit_train_2080, y_credit_train_2080)
best_svm_score_2080 = grid_svm_2080.best_score_

# RandomForestClassifier
rf.fit(X_credit_train_2080, y_credit_train_2080)
rf_accuracy_2080 = accuracy_score(y_credit_test_2080, rf.predict(X_credit_test_2080))

# Store results for 20/80 partition
results_2080 = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}
```

In [45]:
```
print("For 20/80")
print("Logistic Regression accuracy:", best_lr_score_2080)
print("SVM accuracy:", best_svm_score_2080)
print("Random Forest accuracy:", rf_accuracy_2080)
```

```
For 20/80
Logistic Regression accuracy: 0.7202623247399367
SVM accuracy: 0.7400120609075834
Random Forest accuracy: 0.7275
```

In [47]:
```
# Define results for the credit dataset
results_8020_credit = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}

results_5050_bank = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}

results_2080_bank = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}
```

Breast Cancer

In [48]:
```
.mport pandas as pd

: URL of the dataset
ırl = "http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/breast-cancer-wisconsin.data"

: Column names as per the dataset description
:olumn_names = ["Sample_code_number", "Clump_thickness", "Uniformity_of_cell_size",
               "Uniformity_of_cell_shape", "Marginal_adhesion", "Single_epithelial_cell_size",
               "Bare_nuclei", "Bland_chromatin", "Normal_nucleoli", "Mitoses", "Class"]

: Import the dataset, handling missing values
lata_cancer = pd.read_csv(url, names=column_names, na_values="?")

: Drop rows with missing values
lata_cancer.dropna(inplace=True)

: Display the first few rows of the dataframe
lata_cancer.head()
```

Out[48]:

	Sample_code_number	Clump_thickness	Uniformity_of_cell_size	Uniformity_of_cell_shape	Marginal_adhesion	Single_epithelial_cell_size	Bare_nuclei	Bland_cl
0	1000025	5	1	1	1	2	1.0	
1	1002945	5	4	4	5	7	10.0	
2	1015425	3	1	1	1	2	2.0	
3	1016277	6	8	8	1	3	4.0	
4	1017023	4	1	1	3	2	1.0	

In [49]:
```
data_cancer.head()
```

Out[49]:

	Sample_code_number	Clump_thickness	Uniformity_of_cell_size	Uniformity_of_cell_shape	Marginal_adhesion	Single_epithelial_cell_size	Bare_nuclei	Bland_cl
0	1000025	5	1	1	1	2	1.0	
1	1002945	5	4	4	5	7	10.0	
2	1015425	3	1	1	1	2	2.0	
3	1016277	6	8	8	1	3	4.0	
4	1017023	4	1	1	3	2	1.0	

In [50]:
```
data_cancer['Class'].unique()
```

Out[50]: array([2, 4])

In [51]:
```
data_cancer['Class'] = data_cancer['Class'].replace(2, 0)
```

In [52]:
```
data_cancer['Class'] = data_cancer['Class'].replace(4, 1)
```

In [53]:
```
data_cancer.head()
```

Out[53]:

	Sample_code_number	Clump_thickness	Uniformity_of_cell_size	Uniformity_of_cell_shape	Marginal_adhesion	Single_epithelial_cell_size	Bare_nuclei	Bland_cl
0	1000025	5	1	1	1	2	1.0	
1	1002945	5	4	4	5	7	10.0	
2	1015425	3	1	1	1	2	2.0	
3	1016277	6	8	8	1	3	4.0	
4	1017023	4	1	1	3	2	1.0	

In [54]:
```
# Split the dataset into X (features) and y (target)
X_cancer = data_cancer.drop("Class", axis=1)
y_cancer = data_cancer["Class"]
```

In [55]:
```
# Standardize numerical features
scaler = StandardScaler()
numerical_cols = ["Clump_thickness", "Uniformity_of_cell_size", "Uniformity_of_cell_shape", "Marginal_adhesion",
                  "Single_epithelial_cell_size", "Bare_nuclei", "Bland_chromatin", "Normal_nucleoli", "Mitoses"]
X_cancer[numerical_cols] = scaler.fit_transform(X_cancer[numerical_cols])
```

In [56]:
```
dataset into 80/20, 50/50, and 20/80 partitions
ain_8020, X_cancer_test_8020, y_cancer_train_8020, y_cancer_test_8020 = train_test_split(X_cancer, y_cancer, test_siz
ain_5050, X_cancer_test_5050, y_cancer_train_5050, y_cancer_test_5050 = train_test_split(X_cancer, y_cancer, test_siz
ain_2080, X_cancer_test_2080, y_cancer_train_2080, y_cancer_test_2080 = train_test_split(X_cancer, y_cancer, test_siz
```

In [57]:
```
# Dictionary to store results for Breast Cancer dataset
results_cancer = {}
```

In [58]:
```
param_range = [0.001, 0.01, 0.1, 1, 10, 100]
```

In [59]:
```
log_reg = LogisticRegression(solver='liblinear', class_weight='balanced')
svm = SVC()
rf = RandomForestClassifier(n_estimators=100)  # Example parameter
param_grid = {'C': param_range}
```

In [60]:
```
# For 80/20 Partition
# Logistic Regression with GridSearchCV
grid_lr_8020 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_8020.fit(X_cancer_train_8020, y_cancer_train_8020)
best_lr_score_8020 = grid_lr_8020.best_score_

# SVM with GridSearchCV
grid_svm_8020 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_8020.fit(X_cancer_train_8020, y_cancer_train_8020)
best_svm_score_8020 = grid_svm_8020.best_score_

# RandomForestClassifier
rf.fit(X_cancer_train_8020, y_cancer_train_8020)
rf_accuracy_8020 = accuracy_score(y_cancer_test_8020, rf.predict(X_cancer_test_8020))

# Store results for 80/20 partition
results_cancer['80/20'] = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}
```

In [61]:
```
# Print results for 50/50 partition
print("For 50/50 Partition")
print("Logistic Regression accuracy:", best_lr_score_8020)
print("SVM accuracy:", best_svm_score_8020)
print("Random Forest accuracy:", rf_accuracy_8020)
```

```
For 50/50 Partition
Logistic Regression accuracy: 0.86996336996337
SVM accuracy: 0.6739926739926739
Random Forest accuracy: 0.9708029197080292
```

In [62]:
```
## For 50/50 Partition
# Logistic Regression with GridSearchCV
grid_lr_5050 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_5050.fit(X_cancer_train_5050, y_cancer_train_5050)
best_lr_score_5050 = grid_lr_5050.best_score_

# SVM with GridSearchCV
grid_svm_5050 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_5050.fit(X_cancer_train_5050, y_cancer_train_5050)
best_svm_score_5050 = grid_svm_5050.best_score_

# RandomForestClassifier
rf.fit(X_cancer_train_5050, y_cancer_train_5050)
rf_accuracy_5050 = accuracy_score(y_cancer_test_5050, rf.predict(X_cancer_test_5050))

# Store results for 50/50 partition
results_cancer['50/50'] = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}
```

In [63]:
```
# Print results for 50/50 partition
print("For 50/50 Partition")
print("Logistic Regression accuracy:", best_lr_score_5050)
print("SVM accuracy:", best_svm_score_5050)
print("Random Forest accuracy:", rf_accuracy_5050)
```

```
For 50/50 Partition
Logistic Regression accuracy: 0.9706308544221912
SVM accuracy: 0.6715313357139161
Random Forest accuracy: 0.9590643274853801
```

In [64]:
```
# For 20/80 Partition
# Logistic Regression with GridSearchCV
grid_lr_2080 = GridSearchCV(log_reg, {'C': param_range}, cv=3, scoring='accuracy')
grid_lr_2080.fit(X_cancer_train_2080, y_cancer_train_2080)
best_lr_score_2080 = grid_lr_2080.best_score_

# SVM with GridSearchCV
grid_svm_2080 = GridSearchCV(svm, param_grid, cv=3, scoring='accuracy')
grid_svm_2080.fit(X_cancer_train_2080, y_cancer_train_2080)
best_svm_score_2080 = grid_svm_2080.best_score_

# RandomForestClassifier
rf.fit(X_cancer_train_2080, y_cancer_train_2080)
rf_accuracy_2080 = accuracy_score(y_cancer_test_2080, rf.predict(X_cancer_test_2080))

# Store results for 20/80 partition
results_cancer['20/80'] = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}

# Print results for 20/80 partition
print("For 20/80 Partition")
print("Logistic Regression accuracy:", best_lr_score_2080)
print("SVM accuracy:", best_svm_score_2080)
print("Random Forest accuracy:", rf_accuracy_2080)
```

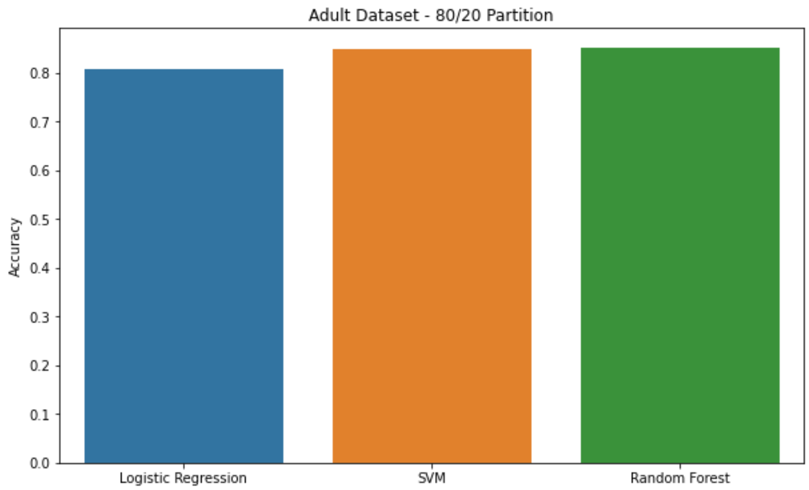
```
For 20/80 Partition
Logistic Regression accuracy: 0.9629629629629629
SVM accuracy: 0.6249597423510468
Random Forest accuracy: 0.9725776965265083
```

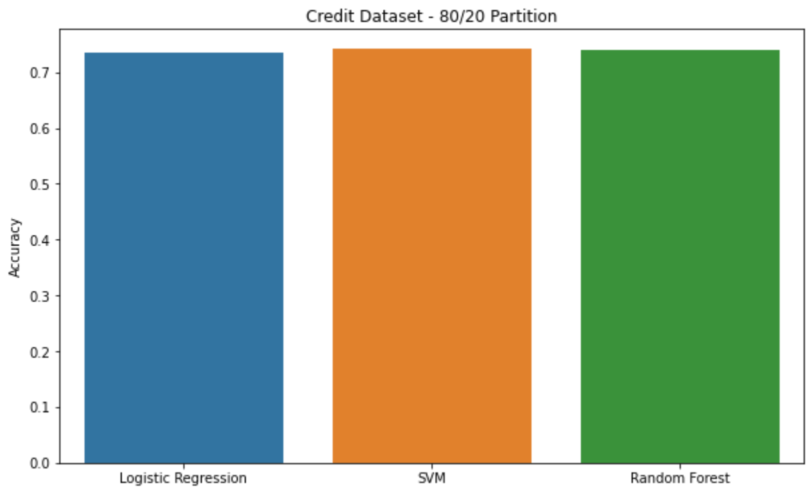
In [65]:
```
# Define results for the breast cancer dataset
results_8020_german = {
    'Logistic Regression': best_lr_score_8020,
    'SVM': best_svm_score_8020,
    'Random Forest': rf_accuracy_8020
}

results_5050_german = {
    'Logistic Regression': best_lr_score_5050,
    'SVM': best_svm_score_5050,
    'Random Forest': rf_accuracy_5050
}

results_2080_german = {
    'Logistic Regression': best_lr_score_2080,
    'SVM': best_svm_score_2080,
    'Random Forest': rf_accuracy_2080
}
```

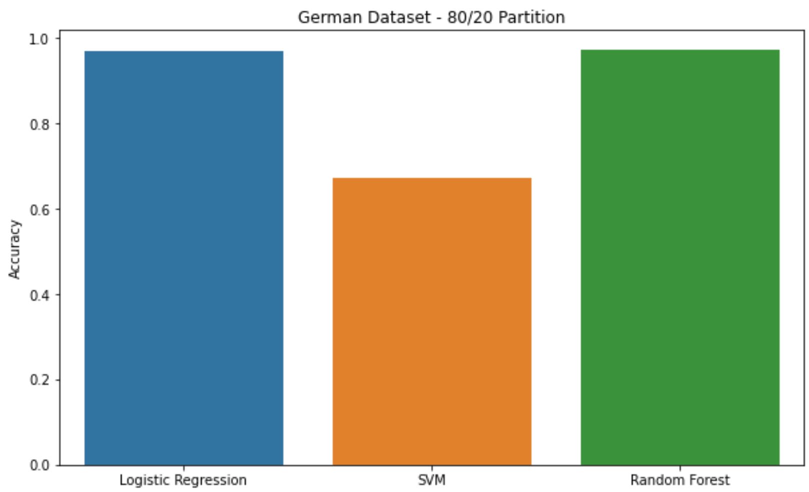
Visualizations

In [71]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Results for different datasets and partitions
results_adult = {
    '20/80': {'Logistic Regression': 0.8028843846406951, 'SVM': 0.8456562702812804, 'Random Forest': 0.8495234148363
    '50/50': {'Logistic Regression': 0.8048, 'SVM': 0.8489, 'Random Forest': 0.8496},
    '80/20': {'Logistic Regression': 0.8083, 'SVM': 0.8496, 'Random Forest': 0.8512}
}

results_credit = {
    '20/80': {'Logistic Regression': 0.7203, 'SVM': 0.7400, 'Random Forest': 0.7275},
    '50/50': {'Logistic Regression': 0.7360, 'SVM': 0.7420, 'Random Forest': 0.7360},
    '80/20': {'Logistic Regression': 0.7037, 'SVM': 0.7363, 'Random Forest': 0.7400}
}

results_german = {
    '20/80': {'Logistic Regression': 0.9630, 'SVM': 0.6250, 'Random Forest': 0.9726},
    '50/50': {'Logistic Regression': 0.9706, 'SVM': 0.6715, 'Random Forest': 0.9591},
    '80/20': {'Logistic Regression': 0.8700, 'SVM': 0.6740, 'Random Forest': 0.9708}
}
```

In [72]:
```
# Plotting results for each dataset
datasets = {'Adult Dataset': results_adult, 'Credit Dataset': results_credit, 'German Dataset': results_german}
for dataset_name, dataset_results in datasets.items():
    plt.figure(figsize=(10, 6))
    for partition, scores in dataset_results.items():
        sns.barplot(x=list(scores.keys()), y=list(scores.values()))
        plt.title(f'{dataset_name} - {partition} Partition')
        plt.ylabel('Accuracy')
    plt.show()
```

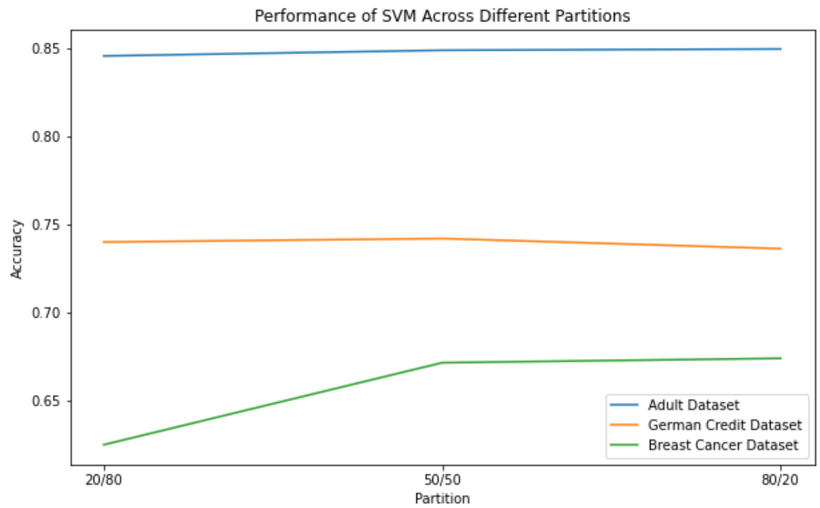


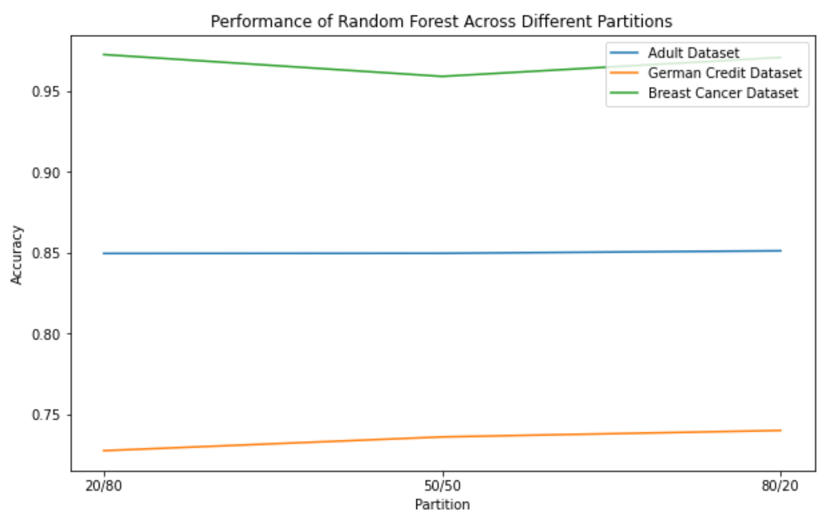




In [73]:
```
import matplotlib.pyplot as plt

# Extracted results from the PDF document
results = {
    'Logistic Regression': {
        'Adult Dataset': {
            '20/80': 0.8028843846406951,
            '50/50': 0.8047874809362775,
            '80/20': 0.8082804923535994
        },
        'German Credit Dataset': {
            '20/80': 0.7202623247399367,
            '50/50': 0.735973835461607,
            '80/20': 0.7037396862943877
        },
        'Breast Cancer Dataset': {
            '20/80': 0.9629629629629629,
            '50/50': 0.9706308544221912,
            '80/20': 0.86996336996337
        }
    },
    'SVM': {
        'Adult Dataset': {
            '20/80': 0.8456562702812804,
            '50/50': 0.8488827000862011,
            '80/20': 0.8496000663102491
        },
        'German Credit Dataset': {
            '20/80': 0.7400120609075834,
            '50/50': 0.7420099559916311,
            '80/20': 0.7362648193517503
        },
        'Breast Cancer Dataset': {
            '20/80': 0.6249597423510468,
            '50/50': 0.6715313357139161,
            '80/20': 0.6739926739926739
        }
    },
    'Random Forest': {
        'Adult Dataset': {
            '20/80': 0.8495234148363033,
            '50/50': 0.8496120946886812,
            '80/20': 0.8511519973479198
        },
        'German Credit Dataset': {
            '20/80': 0.7275,
            '50/50': 0.736,
            '80/20': 0.74
        },
        'Breast Cancer Dataset': {
            '20/80': 0.9725776965265083,
            '50/50': 0.9590643274853801,
            '80/20': 0.9708029197080292
        }
    }
}

# Plotting
for classifier, datasets in results.items():
    plt.figure(figsize=(10, 6))
    for dataset, partitions in datasets.items():
        plt.plot(partitions.keys(), partitions.values(), label=dataset)
    plt.title(f'Performance of {classifier} Across Different Partitions')
    plt.xlabel('Partition')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```


Performance of Logistic Regression Across Different Partitions
Adult Dataset
German Credit Dataset
Breast Cancer Dataset
0.95
0.90
0.85
0.80
0.75
0.70
Accuracy
20/80
50/50
80/20
Partition


Performance of SVM Across Different Partitions
0.85
0.80
0.75
0.70
0.65
Accuracy
Adult Dataset
German Credit Dataset
Breast Cancer Dataset
20/80
50/50
80/20
Partition


Performance of Random Forest Across Different Partitions
Adult Dataset
German Credit Dataset
Breast Cancer Dataset
0.95
0.90
0.85
0.80
0.75
Accuracy
20/80
50/50
80/20
Partition

In [ ]: