cs577projectcode

January 11, 2025

[1]:
```
pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(0.0.7)
Requirement already satisfied: pandas>=1.0.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from ucimlrepo) (2.2.3)
Requirement already satisfied: certifi>=2020.12.5 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from ucimlrepo) (2024.8.30)
Requirement already satisfied: numpy>=1.26.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2024.2)
Requirement already satisfied: six>=1.5 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages
(from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.17.0)
Note: you may need to restart the kernel to use updated packages.
```

[2]:
```
from ucimlrepo import fetch_ucirepo

# fetch dataset
online_shoppers_purchasing_intention_dataset = fetch_ucirepo(id=468)

# data (as pandas dataframes)
X = online_shoppers_purchasing_intention_dataset.data.features
y = online_shoppers_purchasing_intention_dataset.data.targets

# metadata
```

```
print(online_shoppers_purchasing_intention_dataset.metadata)

# variable information
print(online_shoppers_purchasing_intention_dataset.variables)
```

{'uci_id': 468, 'name': 'Online Shoppers Purchasing Intention Dataset', 'repository_url': 'https://archive.ics.uci.edu/dataset/468/online+shoppers+purchasing+intention+dataset', 'data_url': 'https://archive.ics.uci.edu/static/public/468/data.csv', 'abstract': 'Of the 12,330 sessions in the dataset,\n84.5% (10,422) were negative class samples that did not\nend with shopping, and the rest (1908) were positive class\nsamples ending with shopping.', 'area': 'Business', 'tasks': ['Classification', 'Clustering'], 'characteristics': ['Multivariate'], 'num_instances': 12330, 'num_features': 17, 'feature_types': ['Integer', 'Real'], 'demographics': [], 'target_col': ['Revenue'], 'index_col': None, 'has_missing_values': 'no', 'missing_values_symbol': None, 'year_of_dataset_creation': 2018, 'last_updated': 'Thu Jan 11 2024', 'dataset_doi': '10.24432/C5F88Q', 'creators': ['C. Sakar', 'Yomi Kastro'], 'intro_paper': {'ID': 367, 'type': 'NATIVE', 'title': 'Real-time prediction of online shoppers' purchasing intention using multilayer perceptron and LSTM recurrent neural networks', 'authors': 'C. O. Sakar, S. Polat, Mete Katircioglu, Yomi Kastro', 'venue': 'Neural computing & applications (Print)', 'year': 2019, 'journal': None, 'DOI': '10.1007/s00521-018-3523-0', 'URL': 'https://www.semanticscholar.org/paper/747e098f85ca2d20afd6313b11242c0c427e6fb3', 'sha': None, 'corpus': None, 'arxiv': None, 'mag': None, 'acl': None, 'pmid': None, 'pmcid': None}, 'additional_info': {'summary': 'The dataset consists of feature vectors belonging to 12,330 sessions. \r\nThe dataset was formed so that each session\r\nwould belong to a different user in a 1-year period to avoid\r\nany tendency to a specific campaign, special day, user\r\nprofile, or period. ', 'purpose': None, 'funded_by': None, 'instances_represent': None, 'recommended_data_splits': None, 'sensitive_data': None, 'preprocessing_description': None, 'variable_info': 'The dataset consists of 10 numerical and 8 categorical attributes.\r\nThe \'Revenue\' attribute can be used as the class label.\r\n\r\n"Administrative", "Administrative Duration", "Informational", "Informational Duration", "Product Related" and "Product Related Duration" represent the number of different types of pages visited by the visitor in that session and total time spent in each of these page categories. The values of these features are derived from the URL information of the pages visited by the user and updated in real time when a user takes an action, e.g. moving from one page to another. The "Bounce Rate", "Exit Rate" and "Page Value" features represent the metrics measured by "Google Analytics" for each page in the e-commerce site. The value of "Bounce Rate" feature for a web page refers to the percentage of visitors who enter the site from that page and then leave ("bounce") without triggering any other requests to the analytics server during that session. The value of "Exit Rate" feature for a specific web page is calculated as for all pageviews to the page, the percentage that were the last in the session. The "Page Value" feature represents the average value for a web page that a user visited before completing an e-commerce transaction. The "Special Day" feature indicates the closeness of the site visiting time to a

specific special day (e.g. Mother’s Day, Valentine\'s Day) in which the sessions are more likely to be finalized with transaction. The value of this attribute is determined by considering the dynamics of e-commerce such as the duration between the order date and delivery date. For example, for Valentina’s day, this value takes a nonzero value between February 2 and February 12, zero before and after this date unless it is close to another special day, and its maximum value of 1 on February 8. The dataset also includes operating system, browser, region, traffic type, visitor type as returning or new visitor, a Boolean value indicating whether the date of the visit is weekend, and month of the year.', 'citation': None}}

	name	role	type	demographic	description	\
0	Administrative	Feature	Integer	None	None	
1	Administrative_Duration	Feature	Integer	None	None	
2	Informational	Feature	Integer	None	None	
3	Informational_Duration	Feature	Integer	None	None	
4	ProductRelated	Feature	Integer	None	None	
5	ProductRelated_Duration	Feature	Continuous	None	None	
6	BounceRates	Feature	Continuous	None	None	
7	ExitRates	Feature	Continuous	None	None	
8	PageValues	Feature	Integer	None	None	
9	SpecialDay	Feature	Integer	None	None	
10	Month	Feature	Categorical	None	None	
11	OperatingSystems	Feature	Integer	None	None	
12	Browser	Feature	Integer	None	None	
13	Region	Feature	Integer	None	None	
14	TrafficType	Feature	Integer	None	None	
15	VisitorType	Feature	Categorical	None	None	
16	Weekend	Feature	Binary	None	None	
17	Revenue	Target	Binary	None	None	

	units	missing_values
0	None	no
1	None	no
2	None	no
3	None	no
4	None	no
5	None	no
6	None	no
7	None	no
8	None	no
9	None	no
10	None	no
11	None	no
12	None	no
13	None	no
14	None	no
15	None	no
16	None	no

```
17  None             no
```

[3]:
```
import pandas as pd
```

[4]:
```
features = pd.DataFrame(X)
print(features.head())
```

```
   Administrative  Administrative_Duration  Informational  \
0               0                      0.0              0
1               0                      0.0              0
2               0                      0.0              0
3               0                      0.0              0
4               0                      0.0              0

   Informational_Duration  ProductRelated  ProductRelated_Duration  \
0                     0.0               1                 0.000000
1                     0.0               2                64.000000
2                     0.0               1                 0.000000
3                     0.0               2                 2.666667
4                     0.0              10               627.500000

   BounceRates  ExitRates  PageValues  SpecialDay Month  OperatingSystems  \
0         0.20       0.20         0.0         0.0   Feb                 1
1         0.00       0.10         0.0         0.0   Feb                 2
2         0.20       0.20         0.0         0.0   Feb                 4
3         0.05       0.14         0.0         0.0   Feb                 3
4         0.02       0.05         0.0         0.0   Feb                 3

   Browser  Region  TrafficType        VisitorType  Weekend
0        1       1            1  Returning_Visitor    False
1        2       1            2  Returning_Visitor    False
2        1       9            3  Returning_Visitor    False
3        2       2            4  Returning_Visitor    False
4        3       1            4  Returning_Visitor     True
```

[5]:
```
targets = pd.DataFrame(y)
print(targets.head())
```

```
   Revenue
0    False
1    False
2    False
3    False
4    False
```

[6]:
```
dataset = pd.read_csv("online_shoppers_intention.csv")
dataset.head()
```

[6]:

	Administrative	Administrative_Duration	Informational	Informational_Duration	ProductRelated	ProductRelated_Duration	BounceRates	ExitRates	PageValues	SpecialDay	Month	OperatingSystems	Browser	Region	TrafficType	VisitorType	Weekend	Revenue
0	0	0.0	0	0.0	1	0.000000	0.20	0.20	0.0	0.0	Feb	1	1	1	1	Returning_Visitor	False	False
1	0	0.0	0	0.0	2	64.000000	0.00	0.10	0.0	0.0	Feb	2	2	1	2	Returning_Visitor	False	False
2	0	0.0	0	0.0	1	0.000000	0.20	0.20	0.0	0.0	Feb	4	1	9	3	Returning_Visitor	False	False
3	0	0.0	0	0.0	2	2.666667	0.05	0.14	0.0	0.0	Feb	3	2	2	4	Returning_Visitor	False	False
4	0	0.0	0	0.0	10	627.500000	0.02	0.05	0.0	0.0	Feb	3	3	1	4	Returning_Visitor	True	False

[7]:
```
missing_values_summary = dataset.isnull().sum()
print(missing_values_summary)
```

```
Administrative             0
Administrative_Duration    0
Informational              0
Informational_Duration     0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
PageValues                 0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
TrafficType                0
VisitorType                0
Weekend                    0
```

```
Revenue                    0
dtype: int64
```

[8]:
```
all_month_values = dataset['Month'].value_counts().sort_index()

print(all_month_values)
```

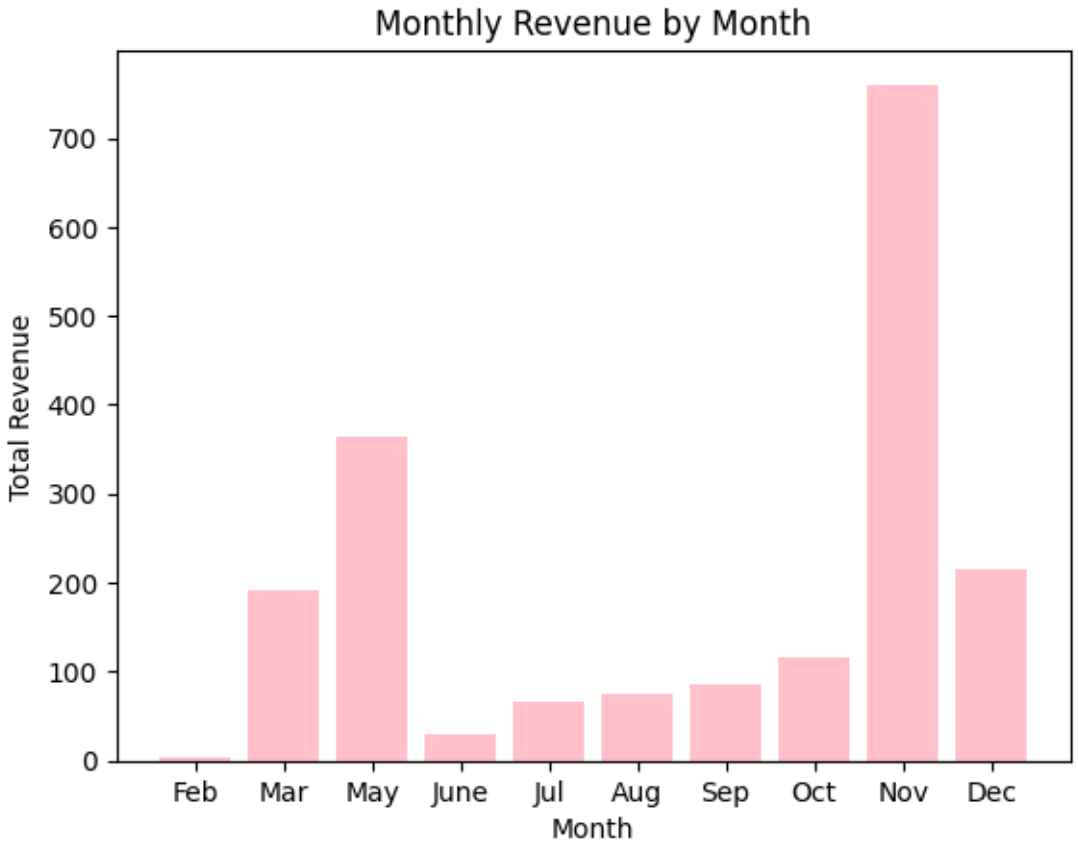
```
Month
Aug      433
Dec     1727
Feb      184
Jul      432
June     288
Mar     1907
May     3364
Nov     2998
Oct      549
Sep      448
Name: count, dtype: int64
```

[9]:
```
all_month_values = dataset['Month'].value_counts().sort_index()

print(all_month_values)
```

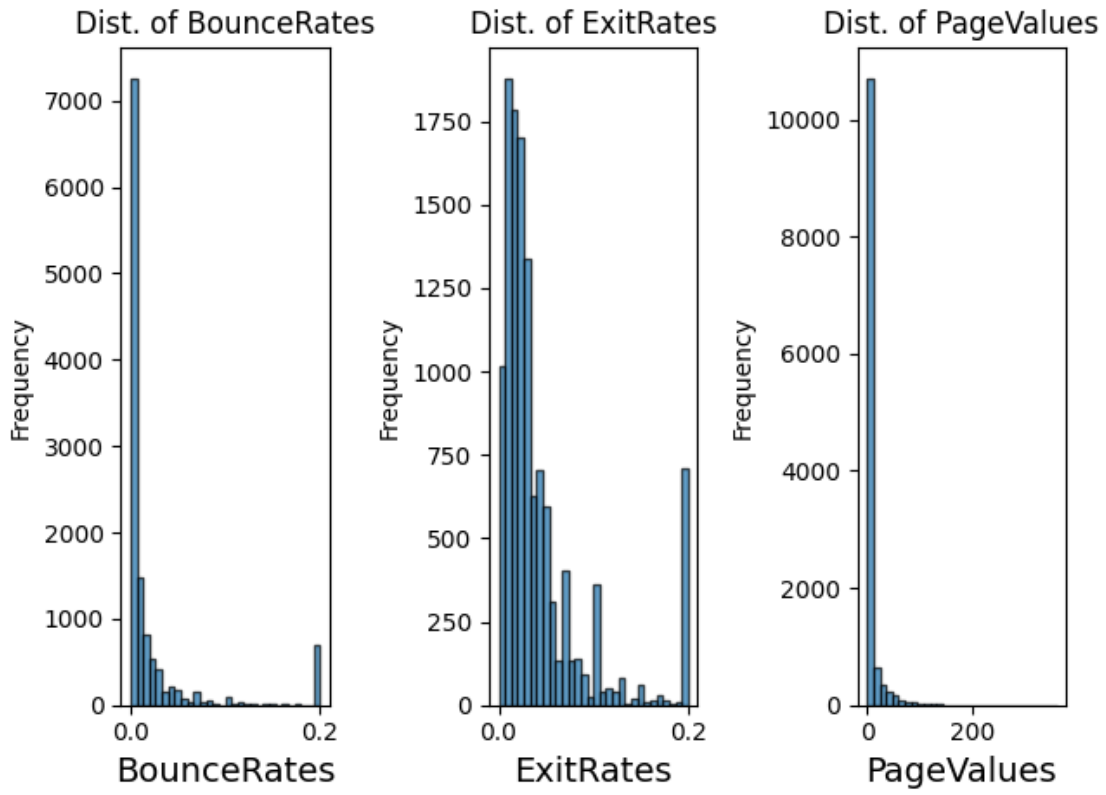
```
Month
Aug      433
Dec     1727
Feb      184
Jul      432
June     288
Mar     1907
May     3364
Nov     2998
Oct      549
Sep      448
Name: count, dtype: int64
```

[10]:
```
import matplotlib.pyplot as plt
monthly_mean = dataset.groupby('Month')['Revenue'].sum()

month_order = ['Feb', 'Mar', 'May', 'June', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov',␣
 ↪'Dec']

monthly_mean = monthly_mean.reindex(month_order, fill_value=0)

plt.bar(month_order, monthly_mean.values, color='pink')
plt.title('Monthly Revenue by Month')
plt.xlabel('Month')
```

```
plt.ylabel('Total Revenue')
plt.show()
```



[11]:
```
import matplotlib.pyplot as plt

# Focus on BounceRates, ExitRates, and PageValues
focus_columns = ['BounceRates', 'ExitRates', 'PageValues']

for i, col in enumerate(focus_columns, 1):
    plt.subplot(1, 3, i)
    plt.hist(dataset[col], bins=30, alpha=0.7, edgecolor='black')
    plt.title(f'Dist. of {col}')
    plt.xlabel(col, fontsize=14)
    plt.ylabel('Frequency')

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

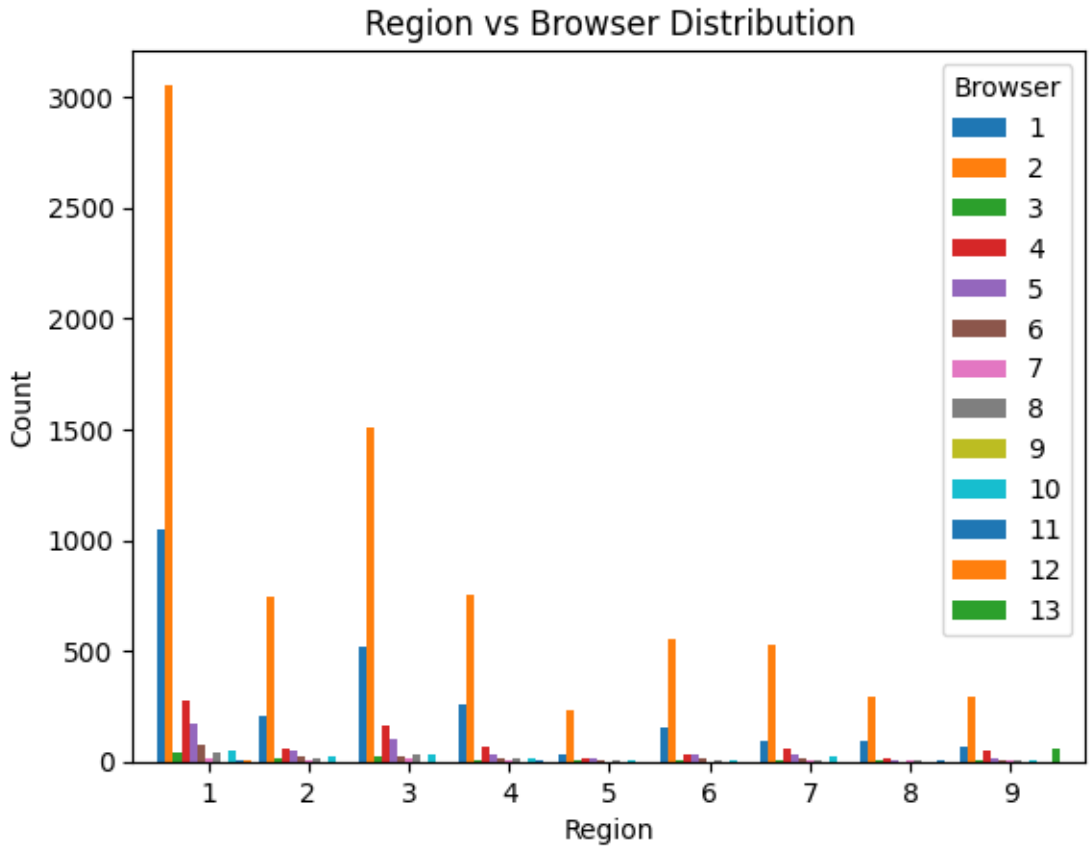


[12]:
```
missing_Values = dataset.isna().sum()
print(missing_Values)
```

```
Administrative             0
Administrative_Duration    0
Informational              0
Informational_Duration     0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
PageValues                 0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
TrafficType                0
VisitorType                0
Weekend                    0
Revenue                    0
dtype: int64
```

[13]:
```
contingency_table = pd.crosstab(dataset['Region'], dataset['Browser'])
```

[14]:
```
import matplotlib.pyplot as plt

contingency_table.plot(kind= 'bar', width = 1.0)
plt.xticks(rotation=0)
plt.xlabel('Region')
plt.ylabel('Count')
plt.title('Region vs Browser Distribution')
plt.legend(title='Browser')
plt.show()
```



[15]:
```
# We need to do more research on the region and browser relationship.
```

[16]:
```
dataset.columns
```

[16]:
```
Index(['Administrative', 'Administrative_Duration', 'Informational',
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay', 'Month',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType', 'VisitorType',
```

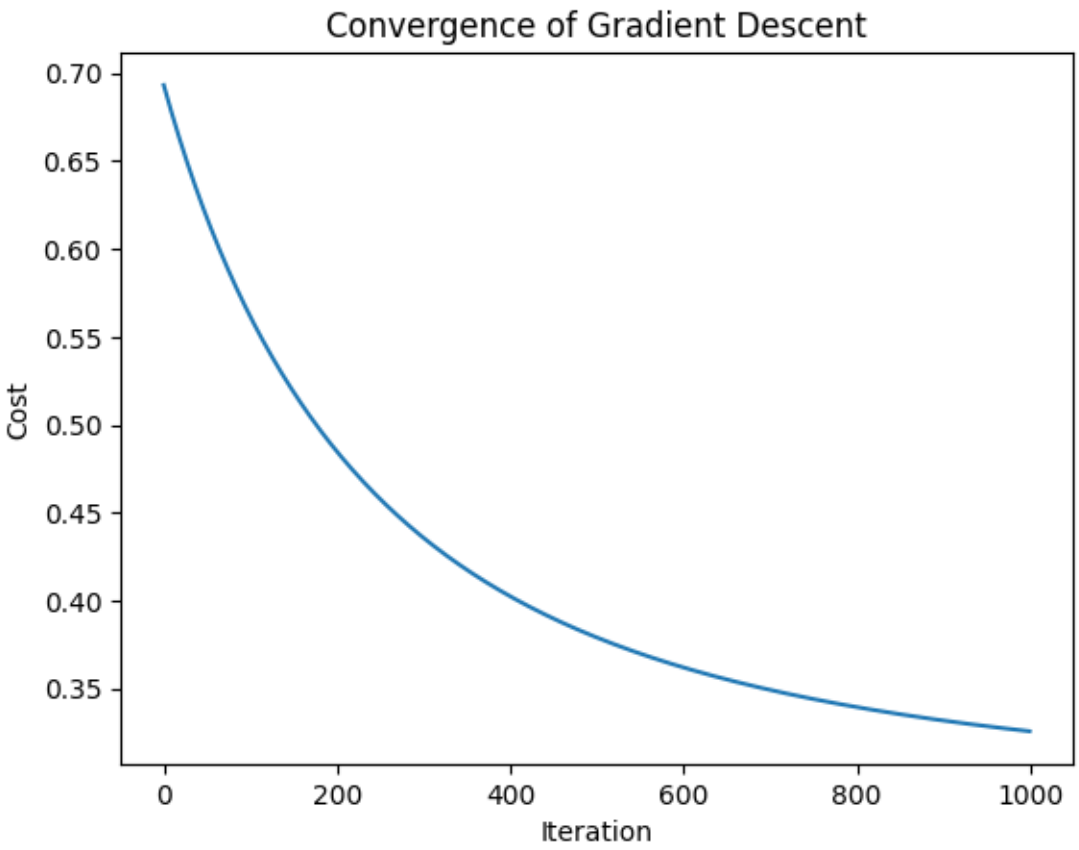
```
       'Weekend', 'Revenue'],
      dtype='object')
```

[17]:
```
non_numeric_columns = dataset.select_dtypes(exclude=['number']).columns

print("Non-numeric columns in the dataset:")
print(non_numeric_columns)
```

```
Non-numeric columns in the dataset:
Index(['Month', 'VisitorType', 'Weekend', 'Revenue'], dtype='object')
```

[18]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score

data_copy = dataset.copy()
data_encoded = pd.get_dummies(data_copy, columns=['Month', 'VisitorType'],␣
 ↪drop_first=False)
data_encoded['Weekend'] = data_encoded['Weekend'].astype(int)
data_encoded['Revenue'] = data_encoded['Revenue'].astype(int)

X = data_encoded.drop('Revenue', axis=1)
y = data_encoded['Revenue']

def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def gradient_descent_with_cost(X, y, initial_guess, alpha, n):
    m, n_features = X.shape
    guesses = [initial_guess]
    costs = []
    guess = initial_guess

    for _ in range(n):
        weights = guess[:-1]
        bias = guess[-1]

        z = np.dot(X, weights) + bias
        y_pred = sigmoid(z)

        cost = -np.mean(y * np.log(y_pred + 1e-9) + (1 - y) * np.log(1 - y_pred␣
 ↪+ 1e-9))
        costs.append(cost)

        dw = np.dot(X.T, (y_pred - y)) / m
```

```
        db = np.sum(y_pred - y) / m

        gradients = np.append(dw, db)
        guess = guess - alpha * gradients

        guesses.append(guess)

    return np.array(guesses), costs


def predict(X, weights, bias):
    z = np.dot(X, weights) + bias
    y_pred = sigmoid(z)
    return (y_pred > 0.5).astype(int)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.4,␣
 ↪random_state=42)

n_features = X_train.shape[1]
initial_guess = np.zeros(n_features + 1)
alpha = 0.01
iterations = 1000

guesses, costs = gradient_descent_with_cost(X_train, y_train.values,␣
 ↪initial_guess, alpha, iterations)
final_params = guesses[-1]

final_weights = final_params[:-1]
final_bias = final_params[-1]

# Make predictions
y_test_pred = predict(X_test, final_weights, final_bias)

accuracy = accuracy_score(y_test, y_test_pred)
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)

import matplotlib.pyplot as plt

plt.plot(range(len(costs)), costs)
plt.xlabel('Iteration')
plt.ylabel('Cost')
plt.title('Convergence of Gradient Descent')
plt.show()
```



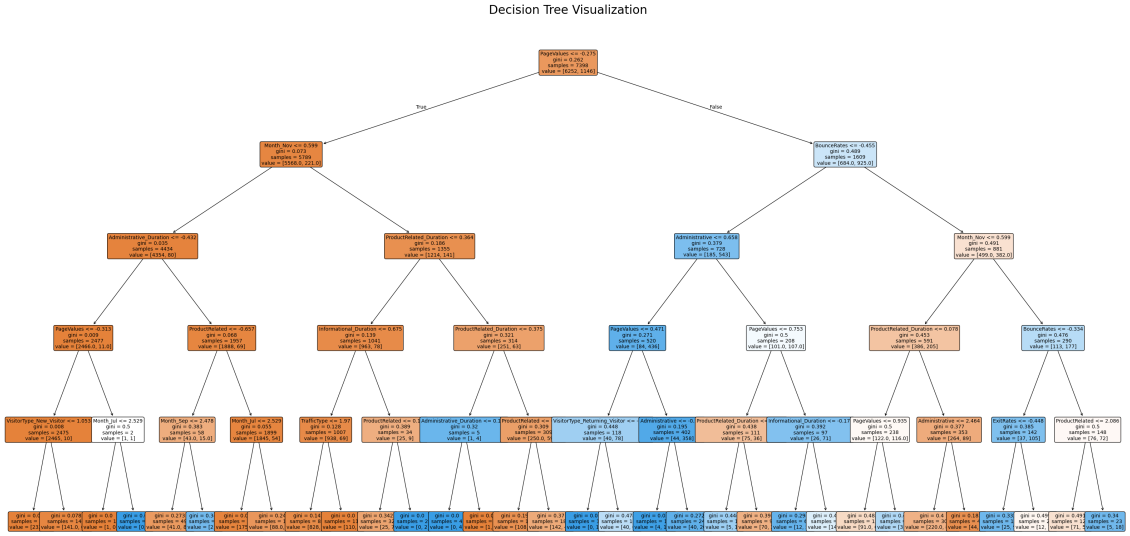
[19]:
```
metrics_table = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall'],
    'Value': [round(accuracy, 3), round(precision, 3), round(recall, 3)]
})
```

[20]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score

dt_classifier = DecisionTreeClassifier(criterion='gini', max_depth=5,␣
 ↪random_state=42)

dt_classifier.fit(X_train, y_train)

y_test_pred = dt_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_test_pred)
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)
```

```
metrics_table = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall'],
    'Value': [round(accuracy, 3), round(precision, 3), round(recall, 3)]
})

print(metrics_table)
```

```
      Metric  Value
0   Accuracy  0.895
1  Precision  0.716
2     Recall  0.531
```

[21]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(40, 20))
plot_tree(
    dt_classifier,
    feature_names=X.columns,
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title("Decision Tree Visualization", fontsize=24)

plt.savefig("decisiontree577.png", dpi=600)
plt.show()
```



[22]:
```
print(data_encoded.columns)
```

```
Index(['Administrative', 'Administrative_Duration', 'Informational',
```

```
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType', 'Weekend',
       'Revenue', 'Month_Aug', 'Month_Dec', 'Month_Feb', 'Month_Jul',
       'Month_June', 'Month_Mar', 'Month_May', 'Month_Nov', 'Month_Oct',
       'Month_Sep', 'VisitorType_New_Visitor', 'VisitorType_Other',
       'VisitorType_Returning_Visitor'],
      dtype='object')
```

[24]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

log_reg = LogisticRegression(random_state=42, max_iter=2000, solver='lbfgs')

dt_classifier = DecisionTreeClassifier(criterion='gini', max_depth=5,␣
 ↪random_state=42)

log_reg.fit(X_train, y_train)
dt_classifier.fit(X_train, y_train)

guesses, costs = gradient_descent_with_cost(X_train, y_train.values,␣
 ↪initial_guess, alpha, iterations)
final_params = guesses[-1]
final_weights = final_params[:-1]
final_bias = final_params[-1]

log_fpr, log_tpr, _ = roc_curve(y_test, log_reg.predict_proba(X_test)[:, 1])
log_display = RocCurveDisplay(fpr=log_fpr, tpr=log_tpr,␣
 ↪roc_auc=roc_auc_score(y_test, log_reg.predict_proba(X_test)[:, 1]),␣
 ↪estimator_name="Logistic Regression")

tree_fpr, tree_tpr, _ = roc_curve(y_test, dt_classifier.predict_proba(X_test)[:
 ↪, 1])
tree_display = RocCurveDisplay(fpr=tree_fpr, tpr=tree_tpr,␣
 ↪roc_auc=roc_auc_score(y_test, dt_classifier.predict_proba(X_test)[:, 1]),␣
 ↪estimator_name="Decision Tree")

grad_probabilities = sigmoid(np.dot(X_test, final_weights) + final_bias)
grad_fpr, grad_tpr, _ = roc_curve(y_test, grad_probabilities)
grad_auc = roc_auc_score(y_test, grad_probabilities)
grad_display = RocCurveDisplay(fpr=grad_fpr, tpr=grad_tpr, roc_auc=grad_auc,␣
 ↪estimator_name="Gradient Descent")

plt.figure(figsize=(10, 8))
log_display.plot(ax=plt.gca(), color="blue")
tree_display.plot(ax=plt.gca(), color="green")
grad_display.plot(ax=plt.gca(), color="red")
```

```
plt.title("ROC Curves for Logistic Regression, Decision Tree, and Gradient␣
  ↪Descent")
plt.show()
```