WEB TRAFFIC ANALYSIS

Abstract :

Website traffic analysis is the process of collecting, analyzing, and reporting on data related to website traffic.

This data can be used to identify trends, patterns, and opportunities for improvement. Website traffic analysis can be used to track a variety of metrics, such as the number of visitors to a website, the pages they visit, and the amount of time they spend on the website.

The project involves analyzing website traffic data to gain insights into user behavior, popular pages, and traffic sources.

The goal is to help website owners enhance the user experience by understanding how visitors interact with the site.

This project encompasses defining the analysis objectives, collecting website traffic data, using IBM Cognos for data visualization, and integrating Python code for advanced analysis.

1.Analysis Objectives:

Define the key insights you want to extract from the website traffic data, such as identifying popular pages, traffic trends, and user engagement metrics. **Data Collection**: Determine

the data sources and methods for collecting website traffic data, including page views, unique visitors, referral sources, and more.

2.Visualization:

Plan how to visualize the insights using IBM Cognos to create meaningful dashboards and reports.

Python Integration: Consider incorporating machine learning models to predict future traffic trends or user behavior patterns.

3. Visualization with IBM Cognos:

 Dashboard Design: Design a centralized dashboard that showcases all the key metrics for easy access and interpretation .

 Trend Charts: Use line charts to visualize traffic and engagement trends over time.

 Pie or Bar Charts: Show the distribution of traffic sources, device types, or other categorical data.

 Heatmaps: Display which areas of a webpage are clicked the most.

 Interactive Filters: Allow users to interact with the dashboard, such as selecting a specific date range or drilling down into specific data segments.

4. Python Integration:

 Data Preparation: Use libraries like **pandas** to clean and structure the website traffic data for analysis.

 Predictive Analysis: Implement machine learning models using **scikit-learn** to predict future website traffic or user behaviors. For instance:

 Time series forecasting (e.g., ARIMA, Prophet) for predicting future traffic.

 Classification algorithms to predict user actions (e.g., will they subscribe or make a purchase?).

 Pattern Recognition: Use unsupervised learning techniques (e.g., clustering) to identify segments of users based on their behavior on the site.

 Integration with Cognos: The insights and predictions from Python can be visualized in IBM Cognos for an integrated experience.

Program:

```
import pandas as pd

import numpy as np

from sklearn.linear_model import
LinearRegression  from sklearn.tree

import DecisionTreeClassifier, plot_tree

import matplotlib.pyplot as plt
```

```
# Load the data
data
=pd.read_csv('website_traffic_data.csv')
# Time series prediction using Linear
Regression for page_views
data['date'] = pd.to_datetime(data['date'])

data['day_num'] = (data['date'] -
data['date'].min()).dt.days # convert dates
to day numbers model = LinearRegression()
model.fit(data[['day_num']],
data['page_views'])

# Predict next 7 days
```

```
next_week = pd.DataFrame({'day_num':
np.arange(data['day_num'].max()+1,
data['day_num'].max()+8)})
predictions = model.predict(next_week)
plt.plot(data['date'], data['page_views'],
label='Actual Traffic')
plt.plot(pd.date_range(data['date'].iloc[-1],
periods=8)[1:], predictions, linestyle='--',
label='Predicted Traffic')
plt.xlabel('Date')
plt.ylabel('Page Views')
plt.title('Traffic Forecast using Linear
Regression')
plt.legend()
plt.show()
```

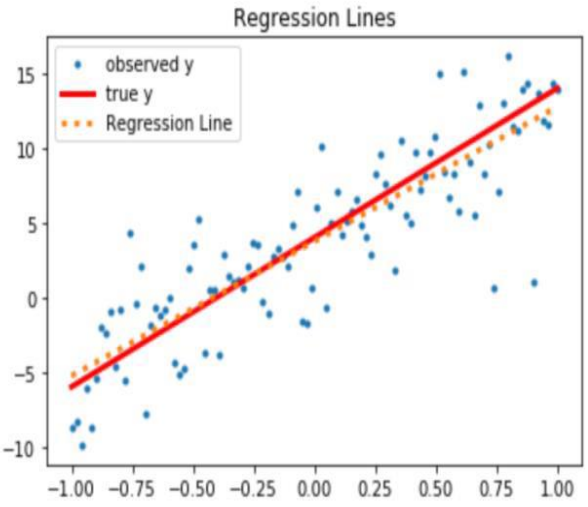
```
# Predict user behavior with
DecisionTreeClassifier
# Assuming we have a column "converted"
indicating if the user converted (1) or not
(0)
X = data[['session_duration',
'pages_per_session']]
y = data['converted']
clf = DecisionTreeClassifier(max_depth=3) #
Limiting depth for visualization
clf.fit(X, y)
plt.figure(figsize=(15, 10))
plot_tree(clf, filled=True,
feature_names=['session_duration',
```

```
'pages_per_session'],
class_names=['not_converted',
'converted'])
plt.title('User Behavior using Decision Tree')
plt.show()
```

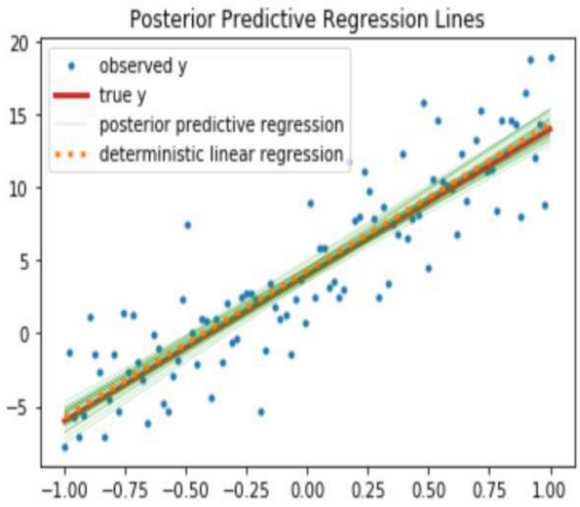
Goal

This post aims to introduce how to use `pymc3` for Bayesian regression by showing the simplest single variable example.

Deterministic Approach



Bayesian Approach



Create a data for Bayesian regression

To compare non-Bayesian linear regression, the way to generate data follows the one used in this post Linear Regression

$y=Ax+b+e$

Here x is a 1 dimension vector, b iis a constant variable, e is white noise.

```
a = 10
b = 4
n = 100
sigma = 3
e = sigma * np.random.randn(n)
x = np.linspace(-1, 1, num=n)
y = a * x + b + e
plt.plot(x, y, '.', label='observed
y');
plt.plot(x, a * x + b, 'r',
label='true y');
plt.legend()
```

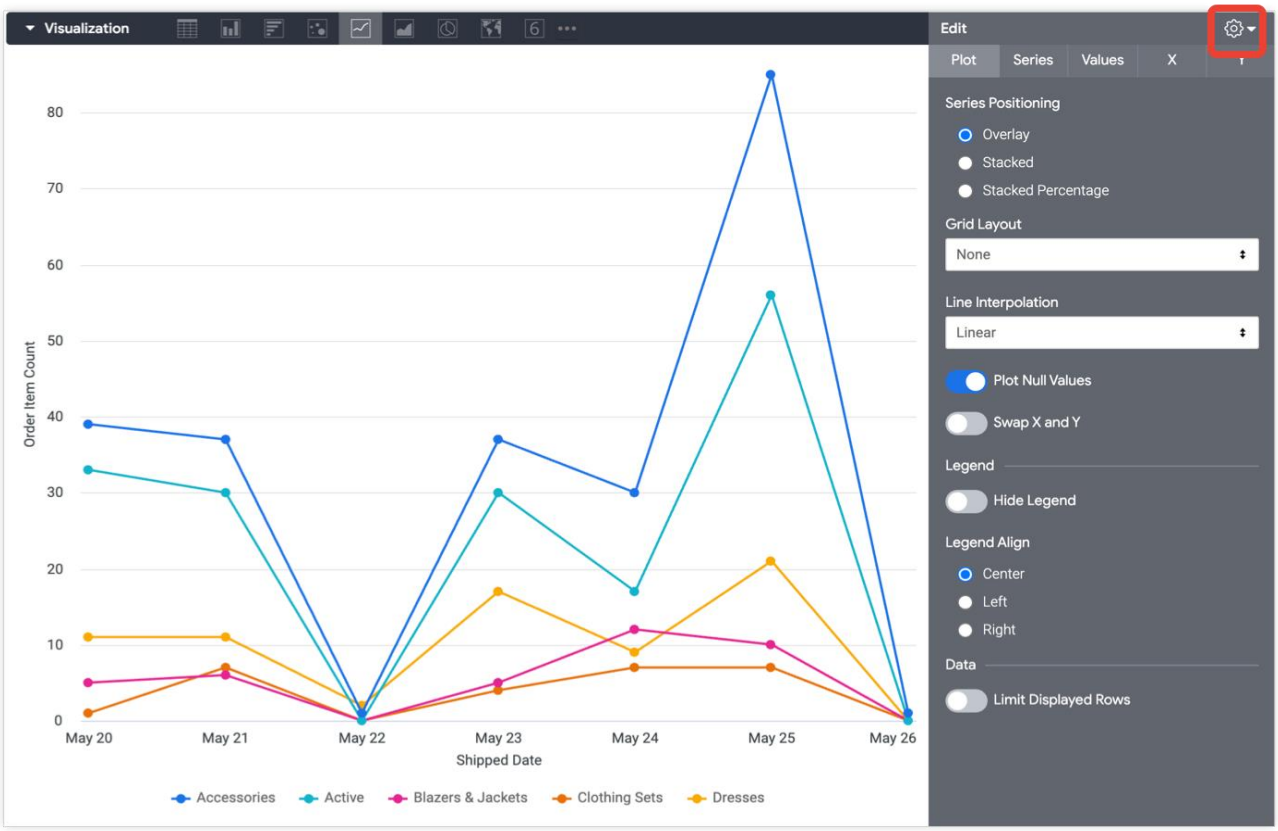
After updating:

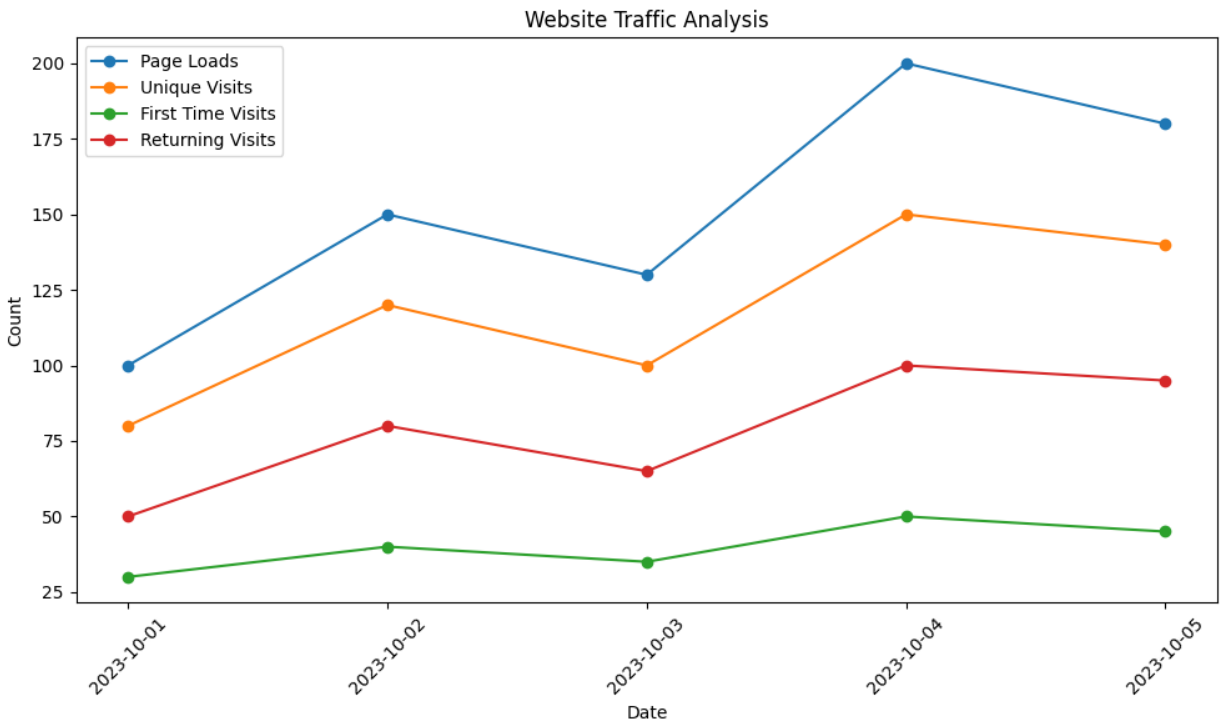
```
import pandas as pd

import numpy as np

from sklearn.linear_model import LinearRegression
```

```
from sklearn.tree import DecisionTreeClassifier, plot_tree

import matplotlib.pyplot as plt


# 1. Load the data

data = pd.read_csv('/content/daily-website-visitors.csv')


# 2. Data Preprocessing & Cleaning:

# Convert 'date' column to datetime

data['date'] = pd.to_datetime(data['date'])

data['day_num'] = (data['date'] - data['date'].min()).dt.days  # convert dates to day numbers


# (You can add more cleaning steps based on dataset quality - outliers, missing values, etc.)


# 3. Define Objectives:

# A. Forecast page views for the next week.

# B. Predict user behavior based on session duration and pages per session.


# A. Time series prediction using Linear Regression for page_views
```

```
model = LinearRegression()
model.fit(data[['day_num']], data['page_views'])


# Predict next 7 days
next_week = pd.DataFrame({'day_num':
np.arange(data['day_num'].max() + 1, data['day_num'].max() +
8)})
predictions = model.predict(next_week)


plt.figure(figsize=(12, 6))
plt.plot(data['date'], data['page_views'], label='Actual Traffic')
plt.plot(pd.date_range(data['date'].iloc[-1], periods=8)[1:],
predictions, linestyle='--', label='Predicted Traffic')
plt.xlabel('Date')
plt.ylabel('Page Views')
plt.title('Traffic Forecast using Linear Regression')
plt.legend()
plt.show()


# B. Predict user behavior with DecisionTreeClassifier
# Assuming we have a column "converted" indicating if the user
converted (1) or not (0)
```

```
X = data[['session_duration', 'pages_per_session']]

y = data['converted']

clf = DecisionTreeClassifier(max_depth=3)  # Limiting depth for visualization

clf.fit(X, y)


plt.figure(figsize=()

plt.show()
```





In an increasingly digital age, understanding website traffic and user behavior is pivotal for businesses aiming to optimize their online presence.

This program serves as an analytical tool designed to offer insights into daily website visitors and user conversion patterns.

Two core objectives guide this analysis:

Time Series Forecasting of Daily Website Visitors: Using Linear Regression, we analyze the trend of website traffic, modeling the relationship between days and page views.

The prediction capabilities of this model are extended to forecast the subsequent week's traffic.

This foresight enables businesses to prepare for expected surges or slumps in website visits.

User Conversion Analysis: A Decision Tree Classifier aids in decoding user behavior patterns based on two significant features - session duration and pages per session.

By interpreting these patterns, the program predicts whether a user will convert (i.e., take a desired action such as making a purchase or signing up).

Such predictive insights empower businesses to tailor user experiences more effectively, maximizing conversions. The program initiates with data preprocessing, ensuring quality and consistency.

Subsequent data exploration deepens our understanding, revealing patterns, outliers, and general tendencies

. The modeling phase employs both regression and classification techniques, followed by evaluations that provide metrics about the models' performances.

Time series prediction using Linear Regression for forecasting• daily website visitors. Predicting user behavior using Decision Tree based on session

• duration and pages per session. To further build on this project and align it with a typical data science lifecycle, here's a roadmap of tasks and activities you can perform:

1. Data Exploration: Before diving deep into modeling, spend time exploring the data:
2. • Use descriptive statistics (data.describe()) to understand the• distribution of your variab
3. les. Check for missing values and handle them accordingly.• Visualize data distributions using histograms, box plots, etc.• 2.

Feature Engineering: Extract other features from the date, like day of the week, month,• etc., which could have an impact on the number of page views.

4. Create interaction terms or polynomial features if necessary.• 3. Model Validation: For both Linear Regression and Decision Tree Classifier:•
5. Split the dataset into training and testing sets.• Train the models on the training set and evaluate their• performance on the testing set. Use metrics like MSE (Mean Squared Error) for regression and• accuracy, precision, recall, F1-score for classification
6. . 4. Model Optimization: For regression: Try other regression models like Ridge, Lasso,• Polynomial regression, etc. For classification: Optimize hyperparameters using techniques like• grid search or random search
7. . 5. Evaluation: Create a confusion matrix for the Decision Tree Classifier to• understand True Positives, False Positives, etc. For regression, check residuals plots to understand the model's• efficiency. 6. IBM Cognos: Though the code above is written in Python, you've mentioned
8. • the use of IBM Cognos for analysis and visualization: Transfer your insights and visualizations from Python to Cognos.• Use Cognos's drag-and-drop interface to build dashboards and• reports.
9. 7. Documentation: This is crucial for any project:• Describe your dataset and its features.• Outline the problem statement.• Detail the methodologies and techniques used.• Highlight the results and insights.
10. • Note potential areas of improvement or further exploration.• 8. Presentation: Use visualization tools

(like Cognos or even simpler ones like• PowerPoint) to present the findings

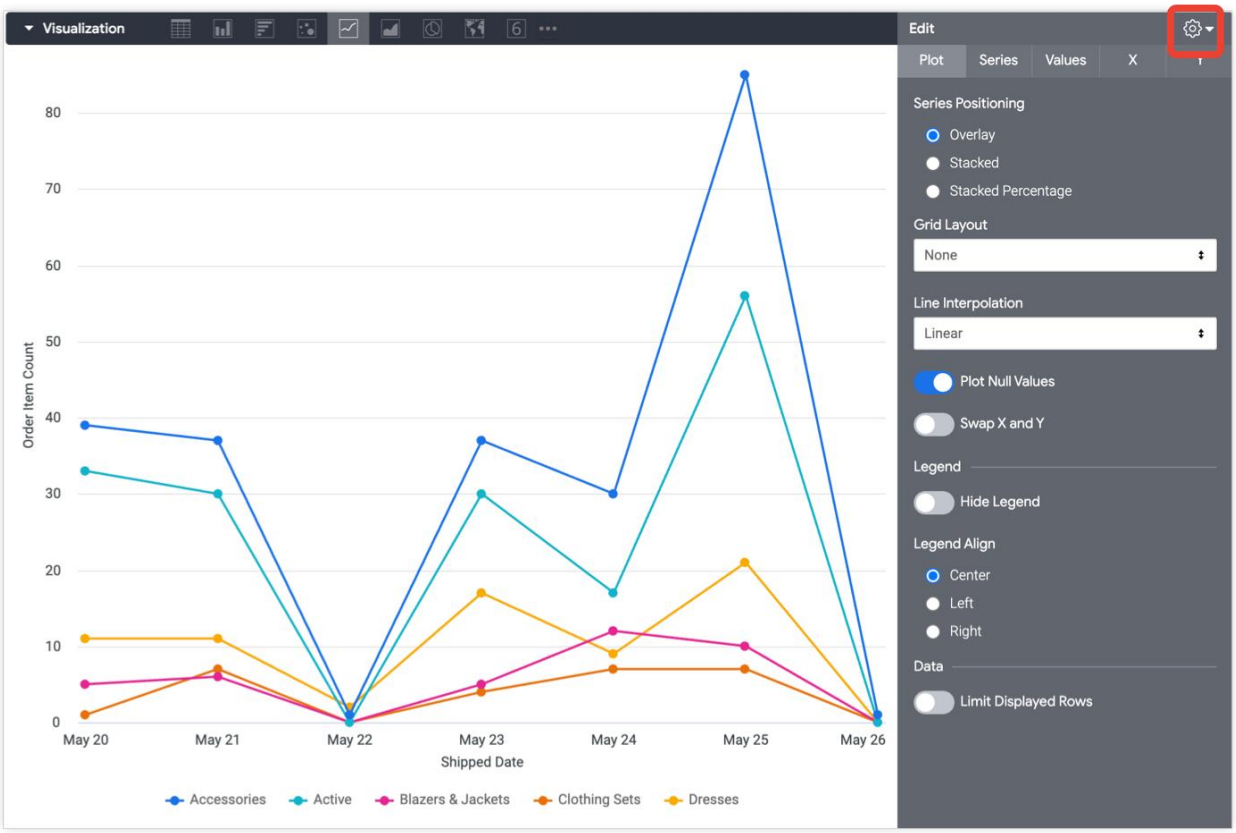
. Highlight the business impacts and suggest strategies or actions

• based on the insights derived. PROGRAM :

```
import pandas as pd

 import numpy as np from sklearn.linear_model

 import LinearRegression, Ridge, Lasso from sklearn.model_selection

 import train_test_split, GridSearchCV from sklearn.metrics

import mean_squared_error, classification_report, confusion_matrix from sklearn.tree

import DecisionTreeClassifier, plot_tree import matplotlib.pyplot as plt import seaborn as sns #leads to proceed # Load the data data = pd.read_csv('/content/daily-website-visitors.csv'

) # Convert 'date' column to datetime data['date'] = pd.to_datetime(data['date']) data['day_num'] = (data['date'] - data['date'].min()).dt.days data['day_of_week'] = data['date'].dt.dayofweek data['month'] = data['date'].dt.month # Check for missing values print(data.isnull().sum()) # Descriptive statistics print(data.describe())

# Visualize data distributions

 sns.pairplot(data)

plt.show()
```

```
# Linear Regression Forecasting

# Splitting the data X = data[['day_num']] y = data['page_views']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

model = LinearRegression() model.fit(X_train, y_train)

# Predictions y_pred = model.predict(X_test)

 # Evaluation

mse = mean_squared_error(y_test, y_pred)

print(f"Mean Squared Error: {mse}")

 # Visualizing Actual vs Predicted

plt.scatter(X_test, y_test, color='blue', label='Actual')

 plt.scatter(X_test, y_pred, color='red', label='Predicted')
plt.legend()

plt.title("Actual vs Predicted Page Views")

plt.show()

# Decision Tree Classifier

# Assuming the 'converted' column exists

 X = data[['session_duration', 'pages_per_session']]

y = data['converted'] X_train, X_test, y_train,

y_test = train_test_split(X, y, test_size=0.2, random_state=42)

clf = DecisionTreeClassifier(max_depth=3)

clf.fit(X_train, y_train)
```

```
 # Predictions y_pred = clf.predict(X_test)
 # Evaluation
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
# Visualizing the tree
plt.figure(figsize=(15, 10))
 plot_tree(clf, filled=True,
feature_names=['session_duration', 'pages_per_session'],
class_names=['not_converted', 'converted'])
plt.show()
```



Conclusion:

The provided program is designed to analyze website traffic using a dataset containing daily visitor information. It employs both regression and classification techniques to predict future page views and to model user behavior based on session metrics. Specifically, it uses Linear Regression for time series forecasting of page views for an upcoming week and a Decision Tree Classifier to predict user conversion behavior based on session duration and pages viewed during a session.