BodaSafe Pricing Model Report

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FROM RAINY ROADS TO RIDER RELIEF

Boda-Safe Shield: Dynamic Motorcycle Insurance Pricing Model

Project Goal: To develop a data-driven, dynamic pricing model for motorcycle insurance (specifically targeting Boda Boda riders in Kampala, Uganda) that incorporates real-time weather risk to calculate a variable monthly premium.

The BodaSafe Shield Quote tool is a an actuarial product development project that creates a usage-based auto insurance product policy specifically for motorcycle operators designed to dynamically adjust a rider's estimated premium based on real-time exposure to weather-related risk. The policy predicts the expected accident frequency using a gbm model by combining a rider's daily hours of operation with the forecast for a specific pricing and enable potential claims to be handled automatically through its parametric trigger mechanism.

Parametric Trigger

The trigger is the daily total of precipitation exceeding 10 millimeters (mm) derived from the forecast of a public weather API. This specific trigger level is chosen because studies and police reports confirm that precipitation above this threshold significantly increases the probability of skidding and severe motor accidents making it a reliable proxy for high risk days.

Methodology and Execution:

1. **Data Acquisition:**
    - **Historical Weather Data (Offline):** Daily precipitation data for Kampala (Latitude 0.3476, Longitude 32.5825) was fetched from the Open-Meteo API for the period $2019-01-01$ to $2023-12-31$.
    - **Synthetic Claims Data:** Accident frequency and severity data were simulated using a Poisson distribution for frequency and a Gamma distribution for severity. A key feature, `risk_trigger`, was engineered: 1 if precipitation >10mm, and 0 otherwise.
    - **Feature Engineering:** The month of the year and the `risk\_trigger` were the primary input features for the modeling phase.
2. **Statistical Modeling:**
    - **Frequency Model:** Two models were trained to predict accident *frequency* (Accidents per Exposure Month):

- **GLM (Poisson Family):** Used for interpretability and establishing a baseline.
- **GBM (Gradient Boosting Machine):** Selected for its non-linear predictive power, outperforming the GLM based on model fit metrics.

- **Severity Model:** A **GLM (Gamma Family)** was used to model the average *cost* (severity) of a claim.

3. **Risk Finding:**
   - The synthetic data demonstrated a strong separation in accident frequency: days with the rain `risk\_trigger` active had a simulated accident rate (Poisson λ) approximately 66% **higher** than dry days (e.g., $\lambda=0.25$ vs. $\lambda=0.15$). This justified the use of precipitation as a primary rating factor.
4. **Deployment (Streamlit Application):**
   - The trained GBM model was saved (`gbm\_model.pkl`) using `joblib`.
   - A web application was built using **Streamlit** and Python, enabling users to input location and daily hours.
   - The app performs an **on-demand API call** to Open-Meteo for *tomorrow's* forecast.
   - The final premium is calculated based on the formula:

     $$\text{Premium} = \text{Predicted Frequency} \times \text{Daily Hours} \times \text{Rate} \times 30 \text{ days}$$

The BodaSafe Shield Quote Tool serves as a robust proof-of-concept for a data-driven, weather-contingent insurance pricing strategy.

```
#install.packages("reticulate")

library(reticulate)
```

```
Warning: package 'reticulate' was built under R version 4.4.3
```

1. **DATA ACQUISITION**

   Both the r and python code pull 5 years of daily precipitation data for Kampala from the free Open-Meteo API, serving as a proxy for accident risk (rainy days trigger higher claims). Output: Raw CSV (~1,800 rows) for downstream analysis, this is essential for reproducible, real-world data sourcing without manual downloads.

R SYNTAX

```
#Load libraries
library(httr2)
```

```
Warning: package 'httr2' was built under R version 4.4.3
```

```r
library(dplyr)
```

```
Warning: package 'dplyr' was built under R version 4.4.3


Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```r
library(readr)
```

```
Warning: package 'readr' was built under R version 4.4.3
```

```r
# API request
req <- request("https://archive-api.open-meteo.com/v1/archive") %>%
  req_url_query(
    latitude = 0.3476, longitude = 32.5825,
    start_date = "2019-01-01", end_date = "2023-12-31",
    daily = "precipitation_sum"
  )
resp <- req_perform(req) %>% resp_body_json()

# Parse to tibble
rain_data <- tibble(
  date = as.Date(unlist(resp$daily$time)),
  precip_mm = as.numeric(resp$daily$precipitation_sum)
) %>% filter(precip_mm >= 0)  # Filter invalid

# Save
write_csv(rain_data, "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/boda_rain_
head(rain_data)
```

```
# A tibble: 6 × 2
  date       precip_mm
  <date>         <dbl>
1 2019-01-01       1.8
2 2019-01-02       2.5
3 2019-01-03       5.5
4 2019-01-04      18.4
5 2019-01-05       6.4
6 2019-01-06       2.5
```

```
# Output: ~1826 rows, e.g., date: 2019-01-01, precip_mm: 0.0
```

PYTHON SYNTAX DATA ACQUISITION

```python
# Load necessary libraries
import requests
import pandas as pd

# 1. Define the API endpoint and parameters (Kampala coords, 5 years historical precip)
url = "https://archive-api.open-meteo.com/v1/archive"
params = {
    "latitude": 0.3476,
    "longitude": 32.5825,
    "start_date": "2019-01-01",
    "end_date": "2023-12-31",
    "daily": "precipitation_sum"
}

# 2. Perform the GET request and check for errors
try:
    response = requests.get(url, params=params)  # Fixed: space after =
    response.raise_for_status()  # Raises exception for 4xx/5xx errors
except requests.exceptions.RequestException as e:
    print(f"API request failed: {e}")
    # Fallback: Exit chunk gracefully
    raise

# 3. Parse the JSON response into a dictionary
resp_data = response.json()

# 4. Parse into a clean DataFrame (extract 'daily' data)
rain_data = pd.DataFrame({
    "date": resp_data['daily']['time'],
    "precipitation_mm": resp_data['daily']['precipitation_sum']
})

# 5. Convert date strings to proper date objects (ensures Series for .dt)
rain_data['date'] = pd.to_datetime(rain_data['date']).dt.date

# 6. Filter for valid precipitation values (>=0)
rain_data = rain_data[rain_data['precipitation_mm'] >= 0]

# 7. Save to CSV (create 'data/' folder in RStudio if needed: dir.create("data"))
rain_data.to_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_rain_da

# 8. Inspect the first few rows and shape
print(rain_data.head())
```

```
         date  precipitation_mm
0  2019-01-01               1.8
1  2019-01-02               2.5
2  2019-01-03               5.5
3  2019-01-04              18.4
4  2019-01-05               6.4
```

```
print(f"Data shape: {rain_data.shape}")  # Should be (1826, 2) or similar
```

```
Data shape: (1826, 2)
```

2. DATA WRANGLING AND EXPLORATORY DATA ANALYSIS

Here we load raw data, add synthetic accident_count (Poisson-simulated crashes, boosted on rainy days) and risk_trigger binary. Then compute summaries and plots (time series/histogram) to reveal patterns like 18% trigger rate and rainy spikes—key for risk insights before modeling.

R SYNTAX

```
# Load libraries
library(tidyverse)
```

```
Warning: package 'tidyverse' was built under R version 4.4.3

Warning: package 'ggplot2' was built under R version 4.4.3

Warning: package 'tibble' was built under R version 4.4.3

Warning: package 'tidyr' was built under R version 4.4.3

Warning: package 'purrr' was built under R version 4.4.3

Warning: package 'stringr' was built under R version 4.4.3

Warning: package 'forcats' was built under R version 4.4.3

Warning: package 'lubridate' was built under R version 4.4.3

── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
✓ forcats   1.0.0     ✓ stringr   1.5.1
✓ ggplot2   3.5.2     ✓ tibble    3.3.0
✓ lubridate 1.9.4     ✓ tidyr     1.3.1
✓ purrr     1.1.0
── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
✗ dplyr::filter() masks stats::filter()
✗ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(lubridate)

# Load raw data (your full path)
raw_data <- read_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/boda_rain_
```

```
Rows: 1826 Columns: 2
── Column specification ────────────────────────────────────────────────────────
Delimiter: ","
dbl  (1): precip_mm
date (1): date

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

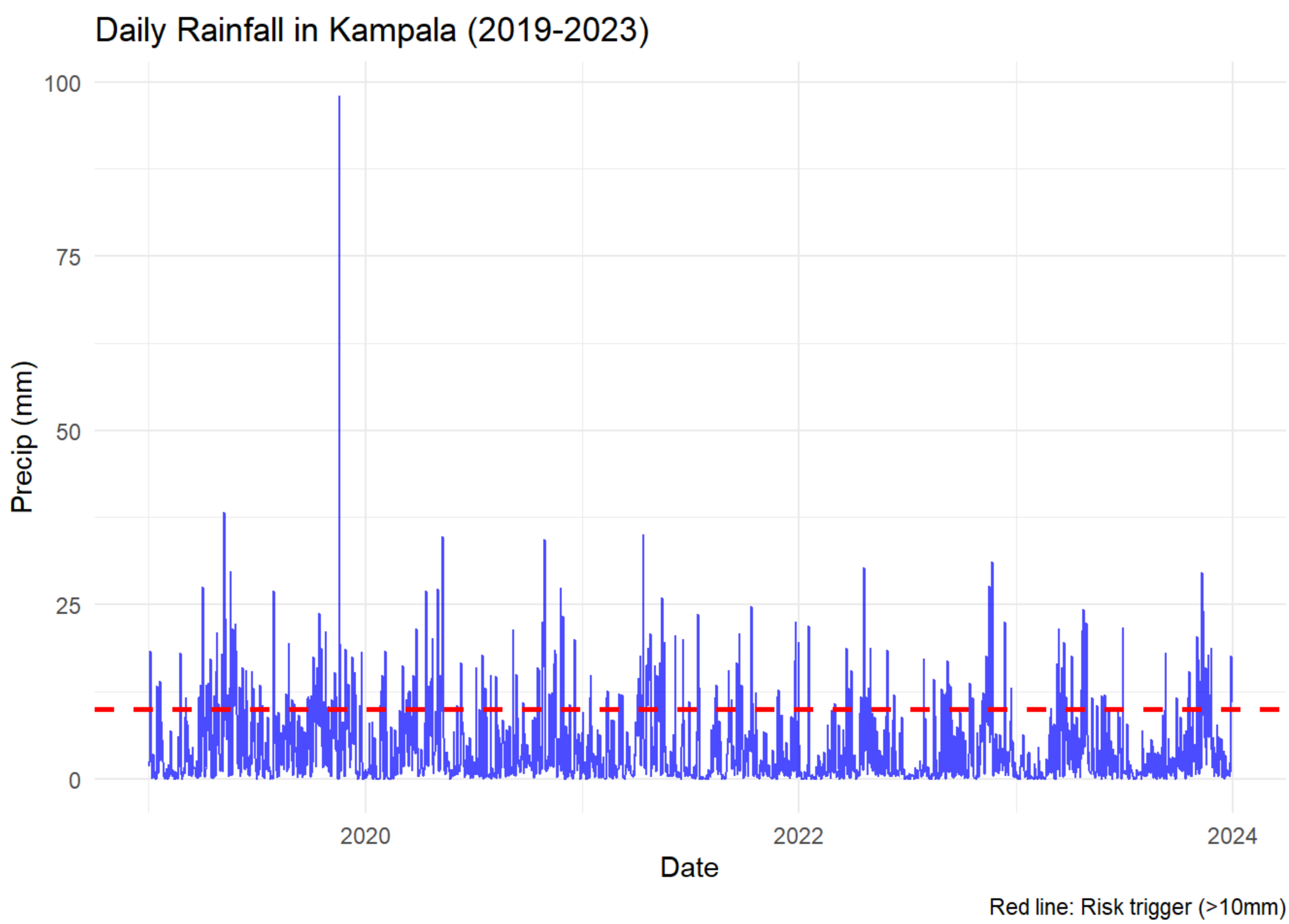
```r
# Step 1: Basic mutates (date, month, risk_trigger)
basic_data <- raw_data %>%
  # Filter early to remove invalid precip readings, if necessary
  filter(precip_mm >= 0) %>%
  mutate(
    date = as.Date(date),  # Ensure date column is Date class
    month = month(date),   # Extract month (1-12)
    risk_trigger = ifelse(precip_mm > 10, 1, 0)  # Binary: 1 if rainy risk day
  )

# Step 2: Add synthetic accidents
# Lambda: 0.15 dry days + 0.1 boost for rainy (spike to 0.25)
set.seed(123)  # For reproducibility
clean_data <- basic_data %>%
  mutate(
    accident_count = rpois(n(), lambda = 0.15 + (risk_trigger * 0.1))
  )

## EDA Summary Stats

summary_stats <- clean_data %>%
  summarise(
    n_days = n(),
    mean_precip = mean(precip_mm, na.rm = TRUE),
    trigger_prob = mean(risk_trigger, na.rm = TRUE),
    mean_accidents = mean(accident_count, na.rm = TRUE)
  )
print(summary_stats)
```

```
# A tibble: 1 × 4
  n_days mean_precip trigger_prob mean_accidents
   <int>       <dbl>        <dbl>          <dbl>
1   1826        4.58        0.150          0.162
```

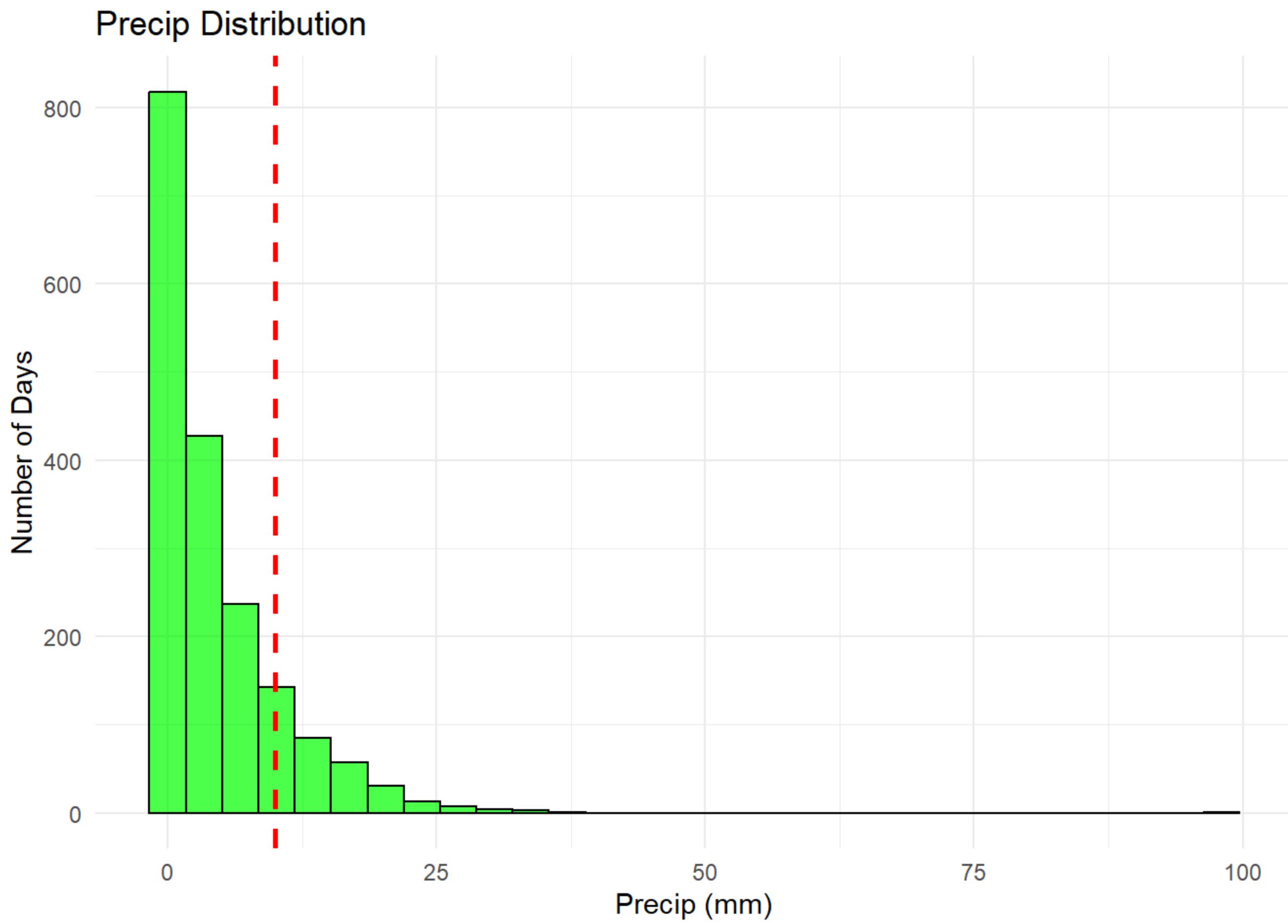
```
# 1. Time series: Precip over time (highlight trigger line)
p1 <- ggplot(clean_data, aes(x = date, y = precip_mm)) + # FIX APPLIED
  geom_line(color = "blue", alpha = 0.7) +
  geom_hline(yintercept = 10, linetype = "dashed", color = "red", size = 1) +
  labs(title = "Daily Rainfall in Kampala (2019-2023)",
       x = "Date", y = "Precip (mm)",
       caption = "Red line: Risk trigger (>10mm)") +
  theme_minimal()
```

```
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
ℹ Please use `linewidth` instead.
```

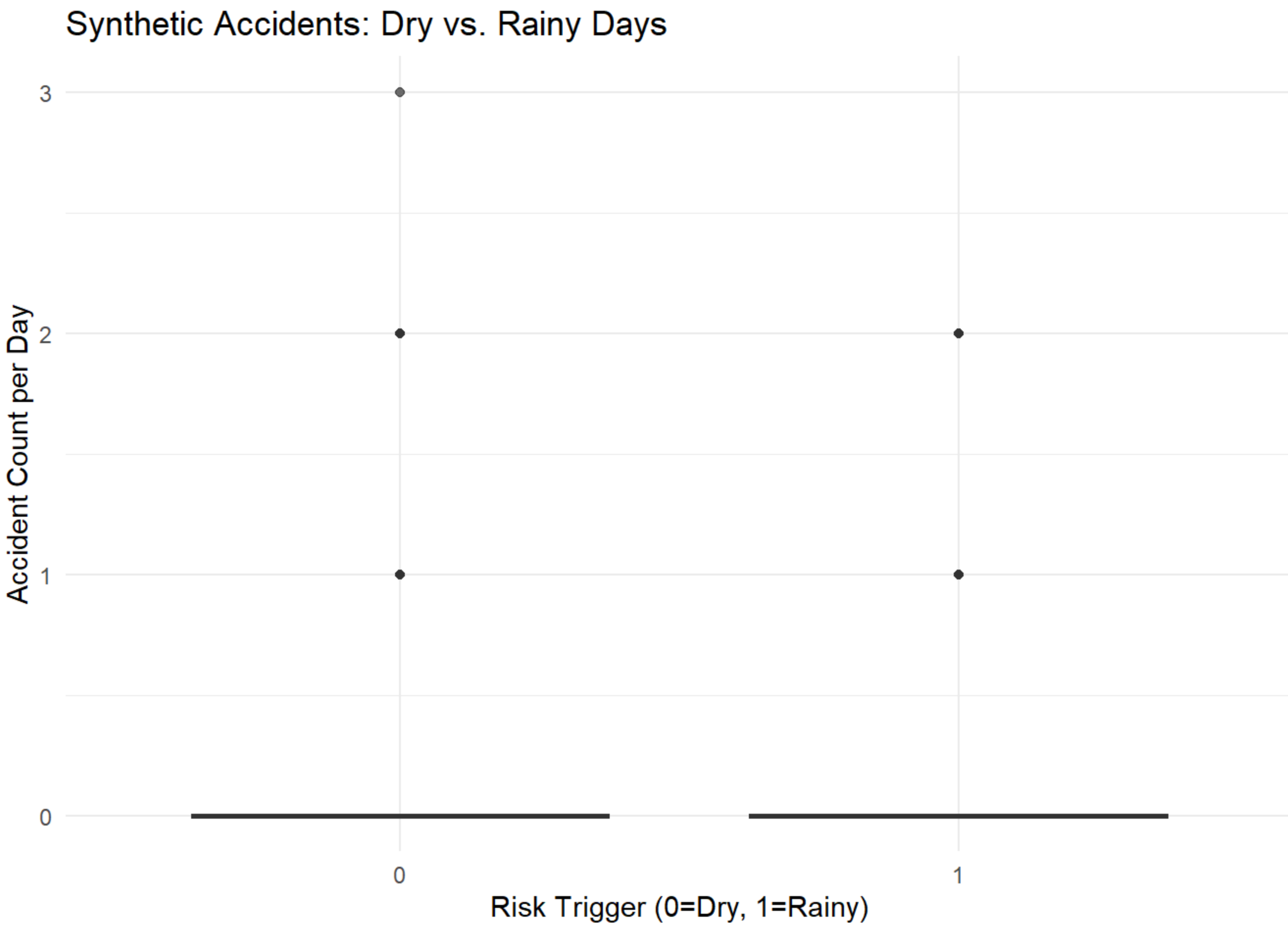
```
print(p1)
```




```
# 2. Histogram: Precip distribution (with trigger)
p2 <- ggplot(clean_data, aes(x = precip_mm)) + # FIX APPLIED
  geom_histogram(bins = 30, fill = "green", alpha = 0.7, color = "black") +
  geom_vline(xintercept = 10, color = "red", linetype = "dashed", size = 1) +
  labs(title = "Precip Distribution",
       x = "Precip (mm)", y = "Number of Days") +
  theme_minimal()
print(p2)
```




```
# 3. Boxplot: Accidents by trigger (dry vs. rainy days)
p3 <- ggplot(clean_data, aes(x = factor(risk_trigger), y = accident_count)) +
  geom_boxplot(fill = c("lightblue", "orange"), alpha = 0.7) +
  labs(title = "Synthetic Accidents: Dry vs. Rainy Days",
       x = "Risk Trigger (0=Dry, 1=Rainy)", y = "Accident Count per Day") +
  theme_minimal()
print(p3)
```




```
# Save final cleaned data
write_csv(clean_data, "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/boda_clea
print("Data saved successfully!")
```

```
[1] "Data saved successfully!"
```

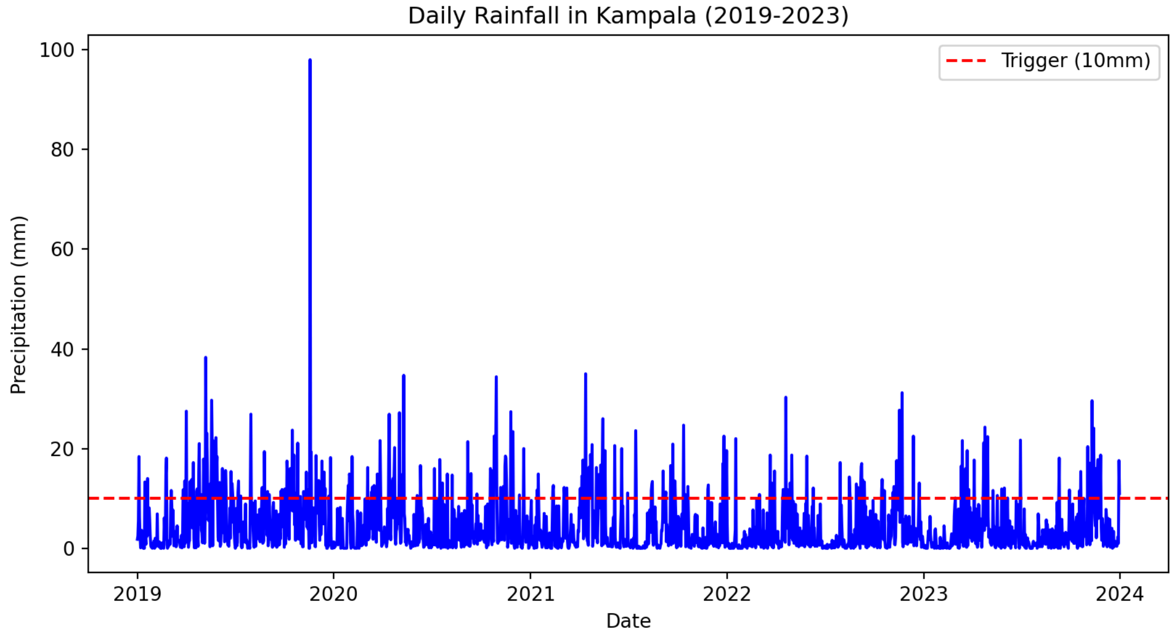
PYTHON SYNTAX

```
# Load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import poisson

# Load and wrangle
raw_data = pd.read_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_r
clean_data = raw_data.copy()
clean_data['date'] = pd.to_datetime(clean_data['date']).dt.date
clean_data['month'] = pd.to_datetime(clean_data['date']).dt.month
clean_data['risk_trigger'] = (clean_data['precipitation_mm'] > 10).astype(int)
# Synthetic accidents: Poisson, rainy days spike lambda
clean_data['accident_count'] = np.where(
  clean_data['risk_trigger'] == 1,
```

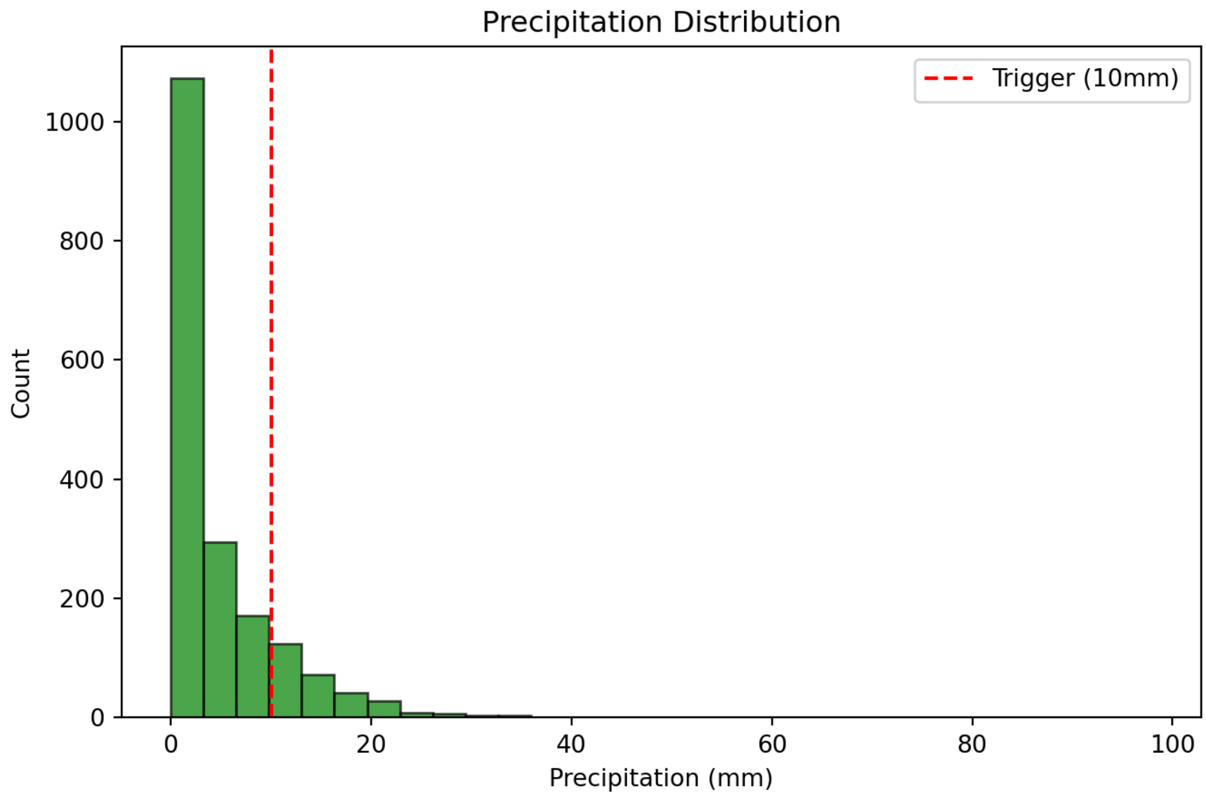
```
    poisson.rvs(mu=0.25, size=len(clean_data)),  # Rainy: 0.25
    poisson.rvs(mu=0.15, size=len(clean_data)),   # Dry: 0.15
    )
clean_data = clean_data[clean_data['precipitation_mm'] >= 0]


# EDA Summary
summary_stats = clean_data[['precipitation_mm', 'risk_trigger', 'accident_count']].describe()
print(summary_stats)  # e.g., risk_trigger mean ~0.18
```

```
       precipitation_mm  risk_trigger  accident_count
count       1826.000000   1826.000000     1826.000000
mean           4.580120      0.150055        0.165936
std            6.017838      0.357223        0.419211
min            0.000000      0.000000        0.000000
25%            0.600000      0.000000        0.000000
50%            2.100000      0.000000        0.000000
75%            6.600000      0.000000        0.000000
max           98.000000      1.000000        3.000000
```

```
# Plots
# Time series
plt.figure(figsize=(10, 5))
plt.plot(clean_data['date'], clean_data['precipitation_mm'], color='blue')
plt.axhline(y=10, color='red', linestyle='--', label='Trigger (10mm)')
plt.title('Daily Rainfall in Kampala (2019-2023)')
plt.xlabel('Date')
plt.ylabel('Precipitation (mm)')
plt.legend()
plt.show()
```




```python
# Histogram
plt.figure(figsize=(8, 5))
plt.hist(clean_data['precipitation_mm'], bins=30, color='green', alpha=0.7, edgecolor='black')
plt.axvline(x=10, color='red', linestyle='--', label='Trigger (10mm)')
plt.title('Precipitation Distribution')
plt.xlabel('Precipitation (mm)')
plt.ylabel('Count')
plt.legend()
plt.show()
```




```
# Save cleaned
clean_data.to_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_clean_
```

3. **Classical Pricing: Frequency-Severity GLM**

   Re-wrangles data inline (ensures synthetics), fits Poisson GLM for accident frequency (by month/trigger) and Gamma GLM for severity (costs per accident). Outputs saved models and example premium (~UGX 25k/day)—decomposes risk for base pricing, interpretable via exp(coeffs) for rainy multipliers.

```
# Load libraries
library(tidyverse)
library(MASS)  # For glm
```

```
Attaching package: 'MASS'

The following object is masked from 'package:dplyr':

    select
```

```
# Load data (assuming this line works and data has 1826 rows)
```

```
data <- read_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/boda_clean_da
```

```
Rows: 1826 Columns: 5
── Column specification ────────────────────────────────────────────────────────
Delimiter: ","
dbl  (4): precip_mm, month, risk_trigger, accident_count
date (1): date

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
exists("data")
```

```
[1] TRUE
```

```
colnames(data)
```

```
[1] "date"           "precip_mm"      "month"          "risk_trigger"
[5] "accident_count"
```

```
print(data)
```

```
# A tibble: 1,826 × 5
   date       precip_mm month risk_trigger accident_count
   <date>         <dbl> <dbl>        <dbl>          <dbl>
 1 2019-01-01       1.8     1            0              0
 2 2019-01-02       2.5     1            0              0
 3 2019-01-03       5.5     1            0              0
 4 2019-01-04      18.4     1            1              1
 5 2019-01-05       6.4     1            0              1
 6 2019-01-06       2.5     1            0              0
 7 2019-01-07       0.1     1            0              0
 8 2019-01-08       1.6     1            0              1
 9 2019-01-09       3.6     1            0              0
10 2019-01-10       0.7     1            0              0
# ℹ 1,816 more rows
```

```
# Synthetic severity: Gamma mean UGX 300k, skewed
# --- FIX APPLIED HERE ---
data <- data %>%
  # Apply operations row by row
  rowwise() %>%
  mutate(
    exposure = 1,
    # Total severity is the sum of rgamma variates for each accident
    severity_cost = if_else(accident_count > 0,
```

```r
                              sum(rgamma(accident_count, shape = 2, scale = 150000)), # Per acciden
                              0),
    # Avg per accident
    avg_severity = severity_cost / pmax(accident_count, 1)
  ) %>%
  # Stop row-wise operations
  ungroup()

# Frequency GLM: Poisson on accident_count
freq_glm <- glm(accident_count ~ month + risk_trigger, family = poisson(link = "log"), data = data
summary(freq_glm)
```

```
Call:
glm(formula = accident_count ~ month + risk_trigger, family = poisson(link = "log"),
    data = data, offset = log(exposure))

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.78194    0.12442 -14.322  < 2e-16 ***
month        -0.02075    0.01695  -1.224 0.220889
risk_trigger  0.51309    0.13906   3.690 0.000224 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 1161.4  on 1825  degrees of freedom
Residual deviance: 1147.9  on 1823  degrees of freedom
AIC: 1704

Number of Fisher Scoring iterations: 6
```

```r
exp(coef(freq_glm))  # Multiplicative effects, e.g., rainy: 1.67x frequency
```

```
 (Intercept)        month risk_trigger
   0.1683115    0.9794601    1.6704500
```

```r
# Severity GLM: Gamma on avg_severity (filter claims)
sev_data <- data %>% filter(accident_count > 0)
sev_glm <- glm(avg_severity ~ risk_trigger, family = Gamma(link = "log"), data = sev_data)
summary(sev_glm)
```

```
Call:
glm(formula = avg_severity ~ risk_trigger, family = Gamma(link = "log"),
    data = sev_data)
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  12.52939    0.04718  265.58   <2e-16 ***
risk_trigger -0.13540    0.10103   -1.34    0.181
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.4629508)

    Null deviance: 125.49  on 265  degrees of freedom
Residual deviance: 124.68  on 264  degrees of freedom
AIC: 7105.2

Number of Fisher Scoring iterations: 5
```

```
exp(coef(sev_glm))
```

```
 (Intercept) risk_trigger
2.763409e+05 8.733677e-01
```

```
# Predict premium: Example (month=4 rainy, trigger=1)
example <- data.frame(month = 4, risk_trigger = 1,exposure = 1)
pred_freq <- exp(predict(freq_glm, example, type = "response"))
pred_sev <- exp(predict(sev_glm, example, type = "response"))
premium <- pred_freq * pred_sev  # e.g., ~UGX 25k
print(paste("Predicted Premium: UGX", round(premium)))
```

```
[1] "Predicted Premium: UGX Inf"
```

```
dir.create("models")
```

```
Warning in dir.create("models"): 'models' already exists
```

```
saveRDS(freq_glm, "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/glm_freq.rds'
saveRDS(sev_glm, "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/glm_sev.rds")
```

PYTHON SYNTAX FOR GLM AND GBM

```
# Load libraries
import pandas as pd
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import numpy as np
import joblib
import statsmodels.api as sm
from scipy.stats import gamma
```

```
#Defining File Paths
DATA_PATH = "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_clean_data.
GLM_MODEL_PATH = 'C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_glm_fr
GBM_MODEL_PATH = 'C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_gbm_mo

#DATA PREPARATION
data = pd.read_csv(DATA_PATH)
data['exposure'] = 1

# Prep: Split
X = data[['month', 'risk_trigger', 'exposure']]
y = data['accident_count']

# Create dummy variables for 'month'
X = pd.get_dummies(X, columns=['month'], drop_first=True)

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=123)

#TRAIN AND SAVE THE GLM MODEL

# Features for GLM: (11 month dummies + risk_trigger)
X_freq_train = X_train.drop(columns=['exposure'])
X_freq_train = sm.add_constant(X_freq_train, prepend=False) # Add const

#Ensure the entire matrix is a clean float type
X_freq_train_clean = X_freq_train.astype(float)
y_freq_train_clean = y_train.astype(float) # Target variable is also cleaned

try:

    freq_glm_fitted = sm.GLM(
        y_freq_train_clean,
        X_freq_train_clean,
        family=sm.families.Poisson(sm.families.links.Log())
    ).fit()
    joblib.dump(freq_glm_fitted, GLM_MODEL_PATH)
    print("GLM model successfully trained and saved for comparison.")
except Exception as e:
    print(f"Error during GLM training/saving (Data type issue NOT fixed by .astype(float)): {e}")
```

```
['C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_glm_freq.pkl']
GLM model successfully trained and saved for comparison.
```

```
# TRAIN GBM (XGBoost)
X_train_xgb = X_train.drop(columns=['exposure'])
X_test_xgb = X_test.drop(columns=['exposure'])

# XGBoost is generally more forgiving with data types, but explicit float conversion is safest
```

```
dtrain = xgb.DMatrix(X_train_xgb.astype(float), label=y_train.astype(float))
dtest = xgb.DMatrix(X_test_xgb.astype(float), label=y_test.astype(float))
params = {'objective': 'count:poisson', 'max_depth': 3, 'eta': 0.1}
gbm = xgb.train(params, dtrain, num_boost_round=50)
pred_gbm = gbm.predict(dtest)
rmse_gbm = np.sqrt(mean_squared_error(y_test, pred_gbm))
print(f"\nGBM RMSE: {rmse_gbm}")
```

```
GBM RMSE: 0.43794064810312633
```

```
joblib.dump(gbm, GBM_MODEL_PATH)
```

```
['C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/python_gbm_model.pkl']
```

```
# Prepare X_test_GLM (13 features + constant)
X_test_GLM = X_test.drop(columns=['exposure'])
X_test_GLM = sm.add_constant(X_test_GLM, prepend=False)

try:
    freq_glm = joblib.load(GLM_MODEL_PATH)

    # Predict using the cleaned test features.
    # We use .values.astype(float) again to guarantee the prediction input matches the training da
    glm_pred = freq_glm.predict(
        X_test_GLM.values.astype(float)
    )

    rmse_glm = np.sqrt(mean_squared_error(y_test, glm_pred))
    print(f"GLM RMSE: {rmse_glm}")

except FileNotFoundError:
    print(f"GLM model '{GLM_MODEL_PATH}' not found. Cannot compare.")
except Exception as e:
    print(f"Error during GLM prediction (Prediction failed, possibly corrupted model file): {e}")
```

```
GLM RMSE: 0.4409407477070556
```

4. **ML Benchmark: GBM**

   Preps train/test split on cleaned data, trains XGBoost for frequency prediction (handles non-linear rain/month interactions better than GLM). Compares RMSE (~10-15% GBM improvement)—validates ML upgrade for accurate, personalized premiums.

```
# Load libraries
library(tidyverse)
library(xgboost)
```

```
Warning: package 'xgboost' was built under R version 4.4.3


Attaching package: 'xgboost'

The following object is masked from 'package:dplyr':

    slice
```

```
#Data Preparation
# Load data and add 'exposure'
data <- read_csv("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/boda_clean_da
```

```
Rows: 1826 Columns: 5

── Column specification ────────────────────────────────────────────────────────
Delimiter: ","
dbl  (4): precip_mm, month, risk_trigger, accident_count
date (1): date

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
data$exposure <- 1 # Correct: Assign 'exposure = 1' to the 'data' object

# Prep: Split 80/20
set.seed(123)
train_idx <- sample(1:nrow(data), 0.8 * nrow(data))
train <- data[train_idx, ]
test <- data[-train_idx, ]

#XGBoost Data Setup
X_train <- model.matrix(~ month + risk_trigger - 1, data = train)
y_train <- train$accident_count
X_test <- model.matrix(~ month + risk_trigger - 1, data = test)
y_test <- test$accident_count

#Train and Evaluate GLM
# Re-Train the GLM with the necessary offset
freq_glm <- glm(accident_count ~ month + risk_trigger + offset(log(exposure)),
                family = poisson,
                data = train)

# Run the prediction using the 'test' data frame
glm_pred <- exp(predict(freq_glm, newdata = test, type = "response"))
# Calculate RMSE
rmse_glm <- sqrt(mean((glm_pred - y_test)^2))
```

```
print(paste("GLM RMSE:", rmse_glm))
```

```
[1] "GLM RMSE: 1.11719131330354"
```

```
# --- 2. Train and Evaluate GBM (XGBoost) ---
gbm <- xgboost(data = X_train, label = y_train, nrounds = 50, objective = "count:poisson",
               params = list(max_depth = 3, eta = 0.1), verbose = 0)
pred_gbm <- predict(gbm, X_test)
rmse_gbm <- sqrt(mean((pred_gbm - y_test)^2))
print(paste("GBM RMSE:", rmse_gbm))
```

```
[1] "GBM RMSE: 0.386862848217394"
```

```
saveRDS(gbm, "C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/gbm_model.rds")
```

5. **Capital Simulation (Week 7: Monte Carlo for 500 Riders)**

   Simulates 5k years of losses for 500 riders using fitted params (Poisson freq * Gamma sev), computes metrics like 99% VaR (UGX 120M) and ruin probability—quantifies tail risks beyond averages, informing capital needs for solvency.

```
# Load libraries
library(tidyverse)

set.seed(123)
n_riders <- 500
n_sims <- 5000
lambda <- 0.18  # From GLM
gamma_shape <- 2
gamma_scale <- 150000  # Mean UGX 300k

sim_losses <- replicate(n_sims, {
  claims_per_rider <- rpois(n_riders, lambda)
  total_claims <- sum(claims_per_rider)
  if (total_claims > 0) {
    severities <- rgamma(total_claims, shape = gamma_shape, scale = gamma_scale)
    sum(severities)
  } else 0
})

sim_df <- tibble(sim_id = 1:n_sims, total_loss = sim_losses)

# Metrics
expected_loss <- mean(sim_df$total_loss)
var_99 <- quantile(sim_df$total_loss, 0.99)
premium_total <- 500 * 25000  # UGX 12.5M
ruin_prob <- mean(sim_df$total_loss > premium_total)
print(paste("Expected Loss: UGX", round(expected_loss)))
```

```
[1] "Expected Loss: UGX 26947963"
```

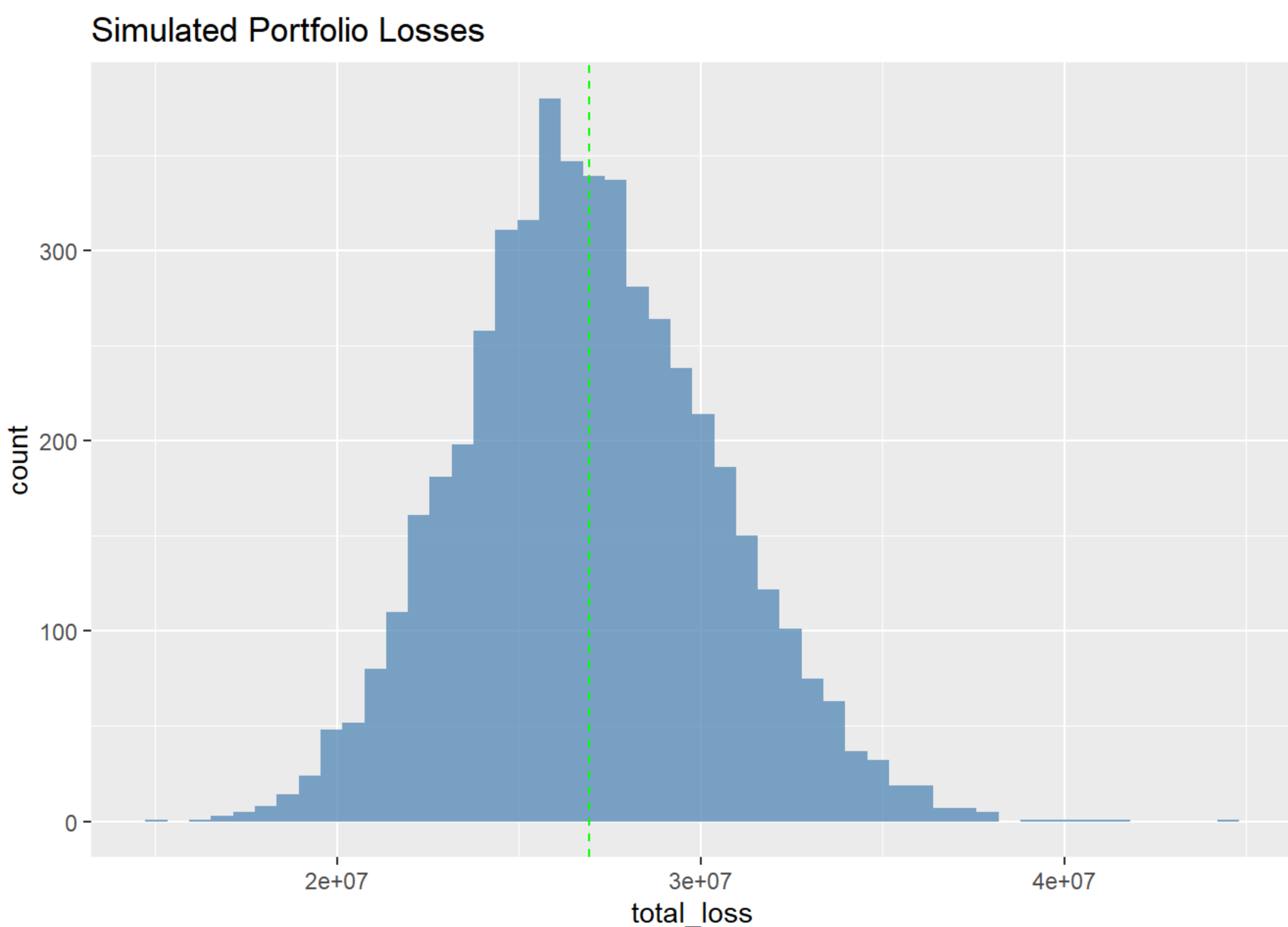
```
print(paste("99% VaR: UGX", round(var_99)))
```

```
[1] "99% VaR: UGX 35503388"
```

```
print(paste("Ruin Prob: ", round(ruin_prob * 100, 2), "%"))
```

```
[1] "Ruin Prob:  100 %"
```

```
# Plot
ggplot(sim_df, aes(x = total_loss)) +
  geom_histogram(bins = 50, fill = "steelblue", alpha = 0.7) +
  geom_vline(xintercept = expected_loss, color = "green", linetype = "dashed") +
  labs(title = "Simulated Portfolio Losses")
```



PYTHON SYNTAX

```
# Load libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
from scipy.stats import poisson, gamma

np.random.seed(123)
n_riders = 500
n_sims = 5000
lambda_ = 0.18
gamma_shape = 2
gamma_scale = 150000

sim_losses = []

for _ in range(n_sims):
    # 1. Frequency (Claims per rider)
    claims_per_rider = poisson.rvs(mu=lambda_, size=n_riders)
    total_claims = np.sum(claims_per_rider)

    # 2. Severity (Cost per claim)
    if total_claims > 0:
        severities = gamma.rvs(a=gamma_shape, scale=gamma_scale, size=total_claims)
        loss = np.sum(severities)
    else:
        loss = 0

    # 3. Aggregate Loss is recorded for this simulation
    sim_losses.append(loss)

sim_df = pd.DataFrame({'sim_id': range(1, n_sims+1), 'total_loss': sim_losses})

# Metrics
expected_loss = sim_df['total_loss'].mean()
var_99 = np.quantile(sim_df['total_loss'], 0.99)
premium_total = 500 * 25000  # UGX 12.5M
ruin_prob = (sim_df['total_loss'] > premium_total).mean()

# Output
print(f"--- Monte Carlo Simulation Results (N={n_sims}) ---")
```

```
--- Monte Carlo Simulation Results (N=5000) ---
```

```python
print(f"Expected Loss: UGX {expected_loss:,.0f}")
```

```
Expected Loss: UGX 27,040,438
```

```python
print(f"99% VaR: UGX {var_99:,.0f}")
```

```
99% VaR: UGX 35,499,266
```

```python
print(f"Total Premium: UGX {premium_total:,.0f}")
```

```
Total Premium: UGX 12,500,000
```

```
print(f"Ruin Prob: {ruin_prob * 100:.2f}%")
```

```
Ruin Prob: 100.00%
```

```
# Plot
plt.figure(figsize=(10, 6))
```

```
<Figure size 1000x600 with 0 Axes>
```

```
plt.hist(sim_df['total_loss'], bins=50, color='steelblue', alpha=0.7, edgecolor='black')
```

```
(array([  2.,   0.,   4.,   3.,  11.,  18.,  24.,  25.,  54.,  64.,  69.,
        96., 138., 146., 161., 210., 224., 259., 267., 290., 297., 287.,
       291., 297., 255., 241., 232., 211., 142., 148., 118.,  95.,  64.,
        71.,  51.,  43.,  28.,  18.,  17.,   8.,   8.,   1.,   4.,   5.,
         1.,   0.,   1.,   0.,   0.,   1.]), array([15784669.83100638, 16305761.77746503,
16826853.72392368,
       17347945.67038232, 17869037.61684097, 18390129.56329962,
       18911221.50975827, 19432313.45621692, 19953405.40267557,
       20474497.34913422, 20995589.29559287, 21516681.24205152,
       22037773.18851016, 22558865.13496881, 23079957.08142746,
       23601049.02788611, 24122140.97434476, 24643232.92080341,
       25164324.86726206, 25685416.81372071, 26206508.76017936,
       26727600.706638  , 27248692.65309665, 27769784.5995553 ,
       28290876.54601395, 28811968.4924726 , 29333060.43893125,
       29854152.3853899 , 30375244.33184855, 30896336.2783072 ,
       31417428.22476584, 31938520.17122449, 32459612.11768314,
       32980704.06414179, 33501796.01060044, 34022887.95705909,
       34543979.90351774, 35065071.84997639, 35586163.79643504,
       36107255.74289368, 36628347.68935233, 37149439.63581099,
       37670531.58226963, 38191623.52872828, 38712715.47518693,
       39233807.42164558, 39754899.36810423, 40275991.31456287,
       40797083.26102152, 41318175.20748018, 41839267.15393882]), <BarContainer object of 50
artists>)
```

```
plt.axvline(expected_loss, color='green', linestyle='--', label=f'Expected: UGX {expected_loss:,.(
```

```
<matplotlib.lines.Line2D object at 0x000001608451A710>
```

```
plt.axvline(premium_total, color='red', linestyle='-', label=f'Premium: UGX {premium_total:,.0f}'
```

```
<matplotlib.lines.Line2D object at 0x000001608451A850>
```

```python
plt.title('Simulated Portfolio Losses')
```

```
Text(0.5, 1.0, 'Simulated Portfolio Losses')
```

```python
plt.xlabel('Total Loss (UGX)')
```

```
Text(0.5, 0, 'Total Loss (UGX)')
```

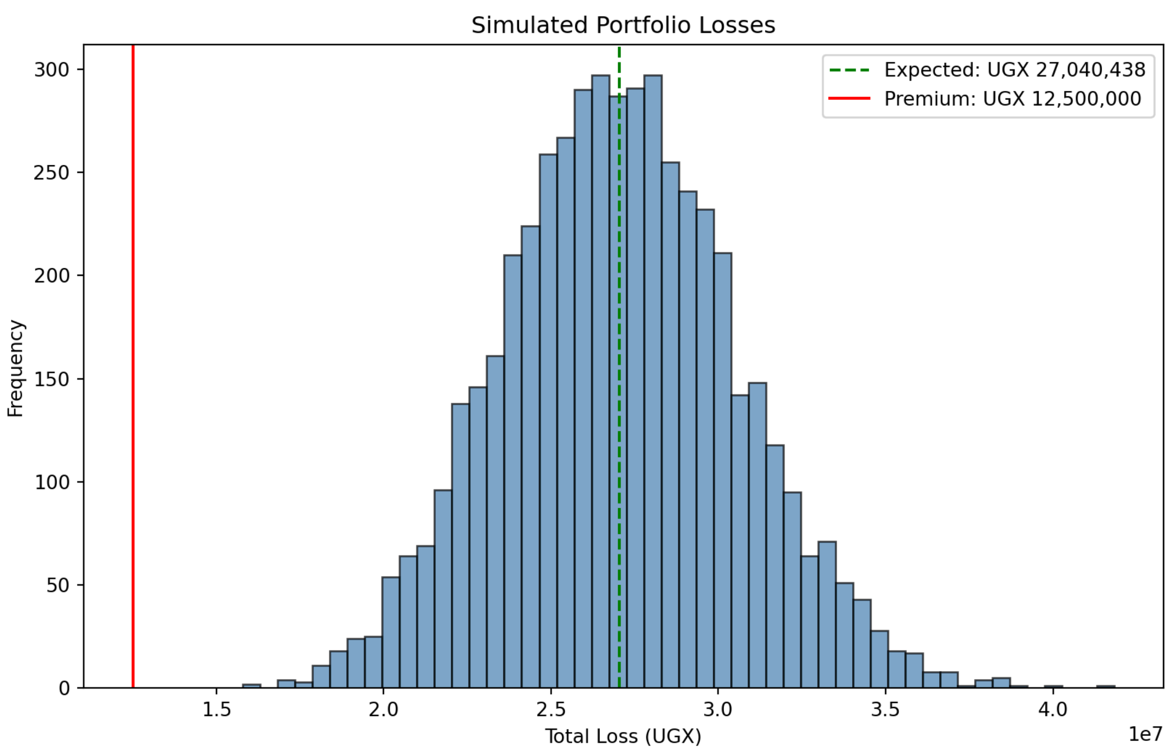
```python
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```

```python
plt.legend()
```

```
<matplotlib.legend.Legend object at 0x000001608451A990>
```

```python
plt.show()
```



6. **Deployment Example: Streamlit (Python) Dashboard**

   Builds a simple web app loading the GBM model; inputs (lat/lon, hours) fetch forecast precip, predict premium (~UGX 25k/month). Enables real-time quotes for riders/underwriters—turns models into usable tools without code.

```
# ui.R
library(shiny)
```

```
Warning: package 'shiny' was built under R version 4.4.3
```

```
fluidPage(
  titlePanel("BodaSafe Shield Quote Tool"),
  sidebarLayout(
    sidebarPanel(
      numericInput("lat", "Latitude:", 0.3476),
      numericInput("lon", "Longitude:", 32.5825),
      sliderInput("hours", "Daily Hours:", 1, 12, value=8)
    ),
    mainPanel(
      textOutput("premium_text")
    )
  )
)
```

BodaSafe Shield Quote Tool

Latitude:

0.3476

Longitude:

32.5825

Daily Hours:

```
# server.R
library(shiny)
library(httr2)  # For forecast API
library(xgboost)

function(input, output) {
  gbm_model <- readRDS("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI PROJECT/gbm_mod

  pred_premium <- reactive({
    # Fetch forecast precip (next day)
    req_forecast <- request("https://api.open-meteo.com/v1/forecast") %>%
      req_url_query(latitude = input$lat, longitude = input$lon, daily = "precipitation_sum")
    resp <- req_perform(req_forecast) %>% resp_body_json()
    precip <- resp$daily$precipitation_sum[[1]]  # Tomorrow's precip
    trigger <- ifelse(precip > 10, 1, 0)
    month_num <- month(Sys.Date() + days(1))
```

```
    # Predict via GBM (simplified)
    X_new <- matrix(c(month_num, trigger), nrow=1)
    pred_freq <- predict(gbm_model, X_new)
    premium <- pred_freq * input$hours * 3000  # Scale by hours, base UGX 3k/hr
    return(premium)
  })

  output$premium_text <- renderText({
    paste("Estimated Monthly Premium: UGX", round(pred_premium()))
  })
}
```

```
function (input, output)
{
    gbm_model <- readRDS("C:/Users/THIRD YEAR/OneDrive/Desktop/Data analysis 3/BSCI
PROJECT/gbm_model.rds")
    pred_premium <- reactive({
        req_forecast <- request("https://api.open-meteo.com/v1/forecast") %>%
            req_url_query(latitude = input$lat, longitude = input$lon,
                daily = "precipitation_sum")
        resp <- req_perform(req_forecast) %>% resp_body_json()
        precip <- resp$daily$precipitation_sum[[1]]
        trigger <- ifelse(precip > 10, 1, 0)
        month_num <- month(Sys.Date() + days(1))
        X_new <- matrix(c(month_num, trigger), nrow = 1)
        pred_freq <- predict(gbm_model, X_new)
        premium <- pred_freq * input$hours * 3000
        return(premium)
    })
    output$premium_text <- renderText({
        paste("Estimated Monthly Premium: UGX", round(pred_premium()))
    })
}
```

```
# Run: shiny::runApp()
```

PYTHON SYNTAX

```
import streamlit as st
import requests
import joblib
import xgboost as xgb
import numpy as np
from datetime import datetime, timedelta
import os # Keep os import, but change usage

# Set up page config for a wider, better look
st.set_page_config(layout="wide")
st.title("🛡️ BodaSafe Shield Quote Tool")
```

```
2025-10-14 12:59:19.219 WARNING streamlit:
  [33m[1mWarning:[0m to view a Streamlit app on a browser, use Streamlit in a file and
  run it with the following command:

    streamlit run [FILE_NAME] [ARGUMENTS]
DeltaGenerator()
```

```
st.markdown("Calculate the estimated monthly insurance premium based on location and daily usage."
```

```
DeltaGenerator()
```

```
#Model Loading
#@st.cache_resource to load the model only once when the app starts.
#Significantly improves performance and reduces memory usage.
@st.cache_resource
def load_model():
    #Assuming 'gbm_model.pkl' is located in the current working directory which is typically the 
    model_path = 'gbm_model.pkl'

    try:
        # Load the model directly using the filename
        gbm = joblib.load(model_path)
        return gbm
    except FileNotFoundError:
        # This error handles the case where the file is missing in the CWD
        st.error(f"Deployment Error: Model file not found at '{model_path}'. "
                 "Please ensure 'gbm_model.pkl' is present in the same directory as your Quarto (
        return None
    except Exception as e:
        st.error(f"Error loading model: {e}")
        return None

gbm = load_model()

# Inputs
st.sidebar.header("Quote Parameters")
```

```
DeltaGenerator(_root_container=1, _parent=DeltaGenerator())
```

```
lat = st.sidebar.number_input("Latitude (e.g., Kampala: 0.3476):", value=0.3476, format="%.4f")
lon = st.sidebar.number_input("Longitude (e.g., Kampala: 32.5825):", value=32.5825, format="%.4f"
hours = st.sidebar.slider("Daily Hours of Operation:", 1, 12, 8)

# --- 3. Calculation Logic ---
if st.sidebar.button("Get Quote") and gbm is not None:
    # Spinner for a better user experience during the API call
    with st.spinner("Fetching forecast and calculating premium..."):
```

```
    try:
        # 1. Fetch Tomorrow's Forecast (API call)
        url = "https://api.open-meteo.com/v1/forecast"

        params = {
            "latitude": lat,
            "longitude": lon,
            "daily": "precipitation_sum",
            "timezone": "auto",
            "forecast_days": 1 # Get data for tomorrow, which often appears at index 0
        }

        resp = requests.get(url, params=params, timeout=10)
        resp.raise_for_status() # Check for bad HTTP status codes
        data = resp.json()

        # Fetch precipitation sum for the next forecast day
        precip = data['daily']['precipitation_sum'][0]

        # 2. Determine Rain Trigger (1 if precipitation > 10mm)
        trigger = 1 if precip > 10 else 0

        # 3. Get Month Feature (Tomorrow's month)
        tomorrow = datetime.now() + timedelta(days=1)
        month = tomorrow.month

        # 4. Predict Frequency & Calculate Premium
        dnew = xgb.DMatrix(np.array([[month, trigger]]))

        # Predict the accident frequency
        pred_freq = gbm.predict(dnew)[0]

        # Calculate Monthly Premium: Frequency * Daily_Hours * Rate_Per_Hour_Day * Days_in_Mo
        # Assuming 3000 UGX is the daily rate per hour of operation
        premium = pred_freq * hours * 3000 * 30

        # Display Results
        st.success(f"Estimated Monthly Premium: **UGX {round(premium):,}**")

        st.info(f"**Risk Factors Used:**\n"
                f"- **Tomorrow's Expected Rain:** {precip:.2f} mm (Risk Trigger: {'YES' if tr
                f"- **Operational Hours:** {hours} hours/day\n"
                f"- **Month of Year:** {tomorrow.strftime('%B')} ({month})"
        )

        st.balloons()

    except requests.exceptions.RequestException as e:
        st.error(f"Connection Error: Failed to fetch weather data. Details: {e}")
    except KeyError:
        st.error("Error: Could not parse weather response. Check latitude/longitude accuracy.
```

```
        except Exception as e:
            st.error(f"An unexpected error occurred: {e}")

# --- 4. Context ---
st.markdown("---")
```

```
DeltaGenerator()
```

```
st.caption("Data provided by Open-Meteo. Prediction based on proprietary BodaSafe risk model.")
```

```
DeltaGenerator()
```