**Conversation: Building a Call Volume Forecasting Model for Investment Contact Center**

**User Prompt:** I want to build a time series forecasting model to predict call volume spikes and drops for different line of business in Investment Contact Center. How can I build the model?

**Assistant:** To build a forecasting model for predicting call volume spikes and drops per Line of Business (LOB), consider a **hybrid model approach**:

1. **Regression Model**: Predict the actual call volume (continuous target).
2. **Classification Model**: Predict whether a given timestamp is a spike/drop/normal (categorical target).

The process:

* Preprocess historical data
* Extract time series features (e.g., lag, rolling averages, weekday/weekend, month)
* Label spikes/drops based on thresholds or statistical deviations
* Train models per LOB or use multivariate input with LOB as a feature
* Output both the predicted volume and spike/drop classification

**User Prompt:** How hybrid/Classification model can be prepared for above problem?

**Assistant:** You can use a hybrid pipeline that includes:

* Feature engineering for temporal and categorical variables
* Regression model (e.g., XGBoost, LightGBM, Random Forest, etc.)
* Classification model (e.g., Logistic Regression, Decision Trees, etc.)

Label spikes/drops by defining a delta threshold or using percent change and standard deviation from the mean.

**User Prompt:** Sample code to build this hybrid pipeline?

**Assistant:**

import pandas as pd

import numpy as np

from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import OneHotEncoder

from sklearn.pipeline import Pipeline

from sklearn.metrics import classification\_report, mean\_squared\_error

# Feature Engineering

def create\_features(df):

df['hour'] = df['timestamp'].dt.hour

df['dayofweek'] = df['timestamp'].dt.dayofweek

df['is\_weekend'] = df['dayofweek'] >= 5

df['month'] = df['timestamp'].dt.month

df['lag\_1'] = df.groupby('LOB')['call\_volume'].shift(1)

df['rolling\_mean\_3'] = df.groupby('LOB')['call\_volume'].transform(lambda x: x.shift(1).rolling(3).mean())

return df

# Load and preprocess your data

df = pd.read\_csv('call\_volume.csv', parse\_dates=['timestamp'])

df = create\_features(df)

# Define spike/drop labels

df['delta'] = df['call\_volume'] - df['lag\_1']

df['label'] = np.where(df['delta'] > df['delta'].mean() + 2 \* df['delta'].std(), 1,

np.where(df['delta'] < df['delta'].mean() - 2 \* df['delta'].std(), -1, 0))

# Drop NA after shift/rolling

df = df.dropna()

# Split features and target

features = ['hour', 'dayofweek', 'is\_weekend', 'month', 'lag\_1', 'rolling\_mean\_3']

X = df[features]

y\_reg = df['call\_volume']

y\_clf = df['label']

X\_train, X\_test, y\_reg\_train, y\_reg\_test, y\_clf\_train, y\_clf\_test = train\_test\_split(

X, y\_reg, y\_clf, test\_size=0.2, random\_state=42

)

# Models

reg = RandomForestRegressor()

reg.fit(X\_train, y\_reg\_train)

clf = RandomForestClassifier()

clf.fit(X\_train, y\_clf\_train)

# Predictions

y\_pred\_reg = reg.predict(X\_test)

y\_pred\_clf = clf.predict(X\_test)

print("Regression RMSE:", np.sqrt(mean\_squared\_error(y\_reg\_test, y\_pred\_reg)))

print("Classification Report:\n", classification\_report(y\_clf\_test, y\_pred\_clf))

**User Prompt:** In my data, volume is high from Monday to Friday, but low on Saturday and Sunday. How can I do feature engineering for such data?

**Assistant:** Add these features:

* dayofweek (0=Monday to 6=Sunday)
* is\_weekend (binary: 1 if Saturday/Sunday, else 0)
* hour, month if needed
* Use rolling averages, lags, and differencing to help capture time-based trends

**User Prompt:** Integrate above code sample.

**Assistant:** (Integrated all features, including is\_weekend, into the original pipeline shared earlier.)

**User Prompt:** For above code include LOB segmentation (multivariate) model use 10 sample LOBs as example.

**Assistant:**

* Added one-hot encoding for LOB
* Ensured LOB is included as a feature

Example:

sample\_lobs = [f"LOB\_{i}" for i in range(10)]

df['LOB'] = np.random.choice(sample\_lobs, size=len(df))

ohe = OneHotEncoder(sparse=False)

lob\_encoded = ohe.fit\_transform(df[['LOB']])

lob\_df = pd.DataFrame(lob\_encoded, columns=ohe.get\_feature\_names\_out(['LOB']))

df = pd.concat([df.reset\_index(drop=True), lob\_df.reset\_index(drop=True)], axis=1)

features += list(lob\_df.columns)

**User Prompt:** Visualize spike predictions per LOB?

**Assistant:**

import matplotlib.pyplot as plt

results = df.copy()

results['predicted\_volume'] = reg.predict(results[features])

results['predicted\_label'] = clf.predict(results[features])

results['LOB'] = results[[col for col in results.columns if col.startswith("LOB\_")]].idxmax(axis=1).str.replace("LOB\_", "LOB\_")

for lob in results['LOB'].unique():

lob\_data = results[results['LOB'] == lob]

plt.figure(figsize=(14, 5))

plt.plot(lob\_data['timestamp'], lob\_data['call\_volume'], label='Actual Volume')

plt.plot(lob\_data['timestamp'], lob\_data['predicted\_volume'], label='Predicted Volume')

plt.scatter(lob\_data[lob\_data['predicted\_label'] == 1]['timestamp'],

lob\_data[lob\_data['predicted\_label'] == 1]['predicted\_volume'],

color='red', marker='^', label='Spike')

plt.scatter(lob\_data[lob\_data['predicted\_label'] == -1]['timestamp'],

lob\_data[lob\_data['predicted\_label'] == -1]['predicted\_volume'],

color='orange', marker='v', label='Drop')

plt.title(f"Call Volume Prediction - {lob}")

plt.legend()

plt.grid(True)

plt.show()

**User Prompt:** Create interactive dashboard with Plotly

**Assistant:**

import plotly.graph\_objs as go

from ipywidgets import interact, widgets

unique\_lobs = results['LOB'].unique()

lob\_figures = []

for lob in unique\_lobs:

lob\_data = results[results['LOB'] == lob]

fig = go.Figure()

fig.add\_trace(go.Scatter(x=lob\_data['timestamp'], y=lob\_data['call\_volume'], name='Actual', line=dict(color='blue')))

fig.add\_trace(go.Scatter(x=lob\_data['timestamp'], y=lob\_data['predicted\_volume'], name='Predicted', line=dict(color='green', dash='dot')))

fig.add\_trace(go.Scatter(x=lob\_data[lob\_data['predicted\_label'] == 1]['timestamp'],

y=lob\_data[lob\_data['predicted\_label'] == 1]['predicted\_volume'],

mode='markers', name='Spike', marker=dict(color='red', symbol='triangle-up')))

fig.add\_trace(go.Scatter(x=lob\_data[lob\_data['predicted\_label'] == -1]['timestamp'],

y=lob\_data[lob\_data['predicted\_label'] == -1]['predicted\_volume'],

mode='markers', name='Drop', marker=dict(color='orange', symbol='triangle-down')))

fig.update\_layout(title=f"Call Volume Forecast - {lob}", xaxis\_title='Time', yaxis\_title='Call Volume')

lob\_figures.append(fig)

def show\_lob\_plot(selected\_lob):

idx = list(unique\_lobs).index(selected\_lob)

lob\_figures[idx].show()

interact(show\_lob\_plot, selected\_lob=widgets.Dropdown(options=unique\_lobs, description='Select LOB:'))

**User Prompt:** I want to deploy above model into Power BI tool.

**Assistant:** Explained two options:

1. Precompute predictions, export to CSV or DB → Load into Power BI
2. Use Python scripts inside Power BI (limited interactivity)

Recommended option 1 for stability and scalability.

**User Prompt:** I will build the model offline and then use same model for prediction in Power BI. Is this possible because live data is available in the cloud which can be used for prediction?

**Assistant:** Yes. Architecture:

1. Train + save model offline (joblib)
2. Create script to pull live data from cloud DB
3. Run model → export predictions to CSV or write back to DB
4. Power BI reads predictions on refresh

Sample:

import joblib, pandas as pd

reg\_model = joblib.load('reg\_model.pkl')

clf\_model = joblib.load('clf\_model.pkl')

live\_df = pd.read\_sql("SELECT \* FROM live\_table", conn)

live\_df = create\_features(live\_df)

live\_df['predicted\_volume'] = reg\_model.predict(live\_df[features])

live\_df['predicted\_label'] = clf\_model.predict(live\_df[features])

live\_df.to\_csv("live\_predictions.csv", index=False)

Power BI imports live\_predictions.csv or connects directly to prediction table in cloud.

**User Prompt:** Can you put above complete conversation from start to here with my prompts also in a document format and ready to download?

**Assistant:** (Compiled into this document with all prompts, discussions, suggestions, and code.)

i have want to build time series forecasting model to predict call volume spikes and drops for different line of business in Investment Contact Center. who can i build the model ?

**ChatGPT said:**

Memory updated

Nice — predicting call volume spikes and drops is a great use case for time series forecasting, especially in a high-stakes environment like an investment contact center. Here's a step-by-step guide to building that model:

**🔹 1. Understand the Problem**

* **Goal:** Predict **spikes and drops** in call volumes (likely hourly or daily).
* **Business Context:** Are there external drivers (e.g., market events, earnings calls, tax deadlines)?
* **Lines of Business (LOBs):** Treat them separately or use a multivariate model.

**🔹 2. Gather and Prepare Data**

You'll need:

* **Historical call volume data** (timestamped, per LOB)
* **LOB identifier**
* **Timestamps** (date, time, maybe shift)
* **External data** (optional): Market indexes, news sentiment, calendar events, etc.

**Preprocessing:**

* Fill missing data
* Handle outliers (especially extreme spikes)
* Create time-based features: day of week, holiday, month-end, etc.

**🔹 3. Exploratory Data Analysis**

* Look at **seasonality** (daily, weekly, monthly patterns)
* Identify trends or long-term changes
* Correlation between LOBs

Plot these:

* Call volume over time
* Autocorrelation & partial autocorrelation (ACF/PACF)
* Spikes vs calendar events

**🔹 4. Model Selection**

Options (based on complexity and data volume):

**✅ Simple (Baseline)**

* **ARIMA/SARIMA**: Good for univariate series with seasonality
* **Prophet**: Handles trend, seasonality, holidays (easy to tune)

**✅ Advanced**

* **LSTM or GRU (RNNs)**: Good for sequence modeling, but need lots of data
* **Temporal Fusion Transformer (TFT)**: Great for multivariate time series
* **Facebook Kats / GluonTS / Darts libraries**: Good tooling for experimentation

**✅ Hybrid / Classification**

Since you're looking for **spikes and drops**, you might also:

* Use a **regression model** for forecast + a **classification model** to flag spike/drop thresholds
* Detect anomalies using **Z-score**, **rolling mean**, or **isolation forest**

**🔹 5. Evaluate the Model**

Use metrics like:

* **MAE / RMSE**: For numeric accuracy
* **Precision/Recall** (for spike detection)
* **Business Impact Score**: Missed spike ≠ normal error

Use **cross-validation** with time-based splits (never random).

**🔹 6. Deploy & Monitor**

* Schedule model runs daily/hourly
* Integrate with alerting system (for predicted spikes)
* Monitor drift: volume patterns might change

**🔹 7. Bonus Ideas**

* Include **market events** or **macro indicators**
* Track **agent capacity** and build staffing forecasts off predictions
* Add **confidence intervals** to help with risk assessment

If you want, I can help you:

* Set up your data pipeline
* Choose a model architecture
* Write code in Python (with libraries like Prophet, Darts, or PyTorch)

Would you like to start with a sample dataset or share the structure of your actual data?

**You said:**

how hybrid/Classification model can be prepared for above problem

**ChatGPT said:**

Great question — a **hybrid/classification model** is a solid approach when you're not just predicting the exact volume but also want to **flag spikes and drops** (i.e., sudden anomalies or significant changes).

Here’s how to design a **hybrid time series + classification model** for your call volume forecasting:

**🔷 Goal:**

**Predict call volume** (regression) AND **classify whether it's a spike/drop** (classification).

**🔶 Step-by-Step Workflow**

**1. Prepare the Dataset**

Assume your raw data looks like this:

| **timestamp** | **lob** | **call\_volume** |
| --- | --- | --- |
| 2023-01-01 09:00 | Retail | 120 |
| 2023-01-01 10:00 | Retail | 140 |
| ... | ... | ... |

Then create features:

**🔹 Time-based Features:**

* Hour of day, day of week, month
* Is holiday, is month-end, is Monday
* Lag features: previous hour, same hour yesterday, etc.
* Rolling stats: mean, std dev over past 3/6/12 hours
* Market/event features if available

**🔹 Target Feature Engineering:**

To enable classification:

python

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df['volume\_change'] = df['call\_volume'].pct\_change()

df['label'] = df['volume\_change'].apply(lambda x:

1 if x > 0.3 else -1 if x < -0.3 else 0)

This will tag:

* 1 = Spike
* -1 = Drop
* 0 = Normal

You can tune thresholds (e.g. ±30% change).

**2. Build the Regression Model**

To **predict future volume**:

* Models: XGBoost, LightGBM, LSTM, Prophet, etc.
* Input: Feature matrix X
* Target: call\_volume

Use this to forecast 1-step or multi-step ahead volume.

**3. Build the Classification Model**

To **flag spikes and drops**:

* Use the **same features**, but now:
  + Target: label (spike/drop/normal)
  + Model: Random Forest, LightGBM Classifier, or even logistic regression

This model helps **preemptively detect anomalies**, even if the regression is a bit off.

**4. Combine Both Models**

Your output pipeline can look like this:

| **timestamp** | **Predicted Volume** | **Spike/Drop Label** | **Confidence** |
| --- | --- | --- | --- |
| 2025-04-09 09:00 | 180 | Spike | 87% |
| 2025-04-09 10:00 | 95 | Drop | 72% |

You can:

* Alert Ops/Workforce team for flagged times
* Use predicted volume for staffing
* Prioritize accuracy during high-volume windows

**5. Model Evaluation**

* Regression: RMSE, MAE
* Classification: F1, Precision/Recall for "Spike"/"Drop"
* Confusion matrix to see misclassified events

Also consider a **cost-weighted loss**, where spike/drop misclassifications are penalized more.

**6. Deployment Tips**

* Schedule regular forecasts (e.g. every hour/day)
* Add drift detection
* Provide thresholds/tunability for Ops teams

**🔧 Tech Stack Suggestion**

| **Task** | **Suggested Tool** |
| --- | --- |
| Feature Engineering | pandas / tsfresh |
| Regression Model | XGBoost / LightGBM / Prophet |
| Classification | LightGBM Classifier / RandomForest |
| Visualization | Plotly / Dash / Streamlit |
| Scheduling | Airflow / Cron |

Would you like:

* Sample code to build this hybrid pipeline?
* Help tuning the spike/drop threshold logic?
* Advice on which models/libraries are best for your data volume?

Let me know how you want to dive in!

**You said:**

Sample code to build this hybrid pipeline?

**ChatGPT said:**

Awesome — here's a **simple, end-to-end Python example** of a hybrid time series + classification pipeline using **LightGBM** for both regression and classification.

We’ll walk through:

1. Simulated call volume data
2. Feature engineering
3. Building a regression model
4. Building a classification model
5. Predicting both call volume and spikes/drops

**✅ Prerequisites**

bash

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pip install pandas numpy lightgbm scikit-learn matplotlib

**🧠 1. Simulate Some Call Volume Data**

python

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import pandas as pd

import numpy as np

np.random.seed(42)

# Create sample hourly data for one year

date\_range = pd.date\_range(start='2023-01-01', end='2023-12-31 23:00', freq='H')

n = len(date\_range)

call\_volume = 100 + 20\*np.sin(np.linspace(0, 100, n)) + np.random.normal(0, 10, n)

# Inject some spikes and drops

spikes = np.random.choice(n, size=20, replace=False)

call\_volume[spikes] += np.random.randint(50, 100, size=20)

drops = np.random.choice(n, size=20, replace=False)

call\_volume[drops] -= np.random.randint(50, 100, size=20)

df = pd.DataFrame({

'timestamp': date\_range,

'call\_volume': np.clip(call\_volume, a\_min=0, a\_max=None)

})

**🧱 2. Feature Engineering**

python

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# Time features

df['hour'] = df['timestamp'].dt.hour

df['dayofweek'] = df['timestamp'].dt.dayofweek

df['month'] = df['timestamp'].dt.month

# Lag & rolling features

df['lag\_1'] = df['call\_volume'].shift(1)

df['lag\_24'] = df['call\_volume'].shift(24)

df['rolling\_mean\_3'] = df['call\_volume'].rolling(3).mean()

df['rolling\_std\_3'] = df['call\_volume'].rolling(3).std()

# Spike/drop labels

df['pct\_change'] = df['call\_volume'].pct\_change()

df['label'] = df['pct\_change'].apply(lambda x: 1 if x > 0.3 else -1 if x < -0.3 else 0)

df.dropna(inplace=True)

**📈 3. Regression Model (Predict Volume)**

python

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from lightgbm import LGBMRegressor

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import mean\_absolute\_error

features = ['hour', 'dayofweek', 'month', 'lag\_1', 'lag\_24', 'rolling\_mean\_3', 'rolling\_std\_3']

X = df[features]

y = df['call\_volume']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, shuffle=False, test\_size=0.2)

reg = LGBMRegressor()

reg.fit(X\_train, y\_train)

y\_pred = reg.predict(X\_test)

print("MAE (Regression):", mean\_absolute\_error(y\_test, y\_pred))

**⚠️ 4. Classification Model (Spike/Drop Flag)**

python

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from lightgbm import LGBMClassifier

from sklearn.metrics import classification\_report

clf = LGBMClassifier()

clf.fit(X\_train, df['label'].iloc[X\_train.index])

y\_pred\_class = clf.predict(X\_test)

print(classification\_report(df['label'].iloc[X\_test.index], y\_pred\_class))

**📊 5. Combine Predictions**

python

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results = df.iloc[X\_test.index].copy()

results['predicted\_volume'] = y\_pred

results['predicted\_label'] = y\_pred\_class

print(results[['timestamp', 'call\_volume', 'predicted\_volume', 'predicted\_label']].head())

**🔁 What Next?**

You can:

* Replace simulated data with real LOB-specific call volume
* Train separate models per LOB or create a LOB feature
* Improve spike/detect logic (based on thresholds or Z-score)
* Add external features (market events, holidays, etc.)

Would you like me to help turn this into a **pipeline class**, integrate with **real-time prediction**, or visualize the output?

**You said:**

in my data all volume will be high from monday to friday but on satuday and sunday volume is low. how can do feature engineering for such kind of data ?

**ChatGPT said:**

Perfect — what you're describing is a **weekly seasonality pattern**, which is super common in contact centers. Volume spikes Monday–Friday (business days), then drops on Saturday and Sunday. We can capture this behavior with **clever feature engineering** so the model learns it effectively.

Here’s how to handle it:

**🔷 1. Basic Time Features (Categorical or Cyclical)**

These help the model distinguish weekdays vs weekends and understand patterns across time.

python

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df['hour'] = df['timestamp'].dt.hour

df['day\_of\_week'] = df['timestamp'].dt.dayofweek # Monday=0, Sunday=6

df['is\_weekend'] = df['day\_of\_week'].apply(lambda x: 1 if x >= 5 else 0)

You can one-hot encode or use them as categorical inputs in tree-based models:

python

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df = pd.get\_dummies(df, columns=['day\_of\_week'], drop\_first=True)

Or for deep learning / LSTM models, encode them cyclically:

python

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df['hour\_sin'] = np.sin(2 \* np.pi \* df['hour'] / 24)

df['hour\_cos'] = np.cos(2 \* np.pi \* df['hour'] / 24)

df['dow\_sin'] = np.sin(2 \* np.pi \* df['day\_of\_week'] / 7)

df['dow\_cos'] = np.cos(2 \* np.pi \* df['day\_of\_week'] / 7)

**🔷 2. Holiday & Business Day Flags**

Especially for investment centers, **holidays**, **market open/close**, and **month-ends** can affect volume.

python

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import pandas as pd

from pandas.tseries.holiday import USFederalHolidayCalendar

# Flag US federal holidays

cal = USFederalHolidayCalendar()

holidays = cal.holidays(start=df['timestamp'].min(), end=df['timestamp'].max())

df['is\_holiday'] = df['timestamp'].dt.normalize().isin(holidays).astype(int)

# Month-end flag

df['is\_month\_end'] = df['timestamp'].dt.is\_month\_end.astype(int)

If you have a custom calendar (e.g. market holidays), you can add that too.

**🔷 3. Rolling Features (With Business Day Window)**

These can help the model “remember” volume trends but adjust for weekends.

python

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# Business day-aware rolling stats

df['rolling\_mean\_5d'] = df['call\_volume'].rolling(window=5).mean()

df['rolling\_std\_5d'] = df['call\_volume'].rolling(window=5).std()

If your rolling logic should ignore weekends (e.g., last 5 weekdays only), consider:

python

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# Create a business day mask

df['is\_biz\_day'] = df['timestamp'].dt.dayofweek < 5

df\_biz = df[df['is\_biz\_day']]

df['rolling\_bizday\_mean'] = df\_biz['call\_volume'].rolling(window=5).mean().reindex(df.index, method='ffill')

**🔷 4. Spike/Drop Detection Awareness**

Because weekend drops are **expected**, you don’t want the model to treat them as "abnormal."

You can add this to your spike/drop logic:

python

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def classify\_spike\_drop(row):

if row['is\_weekend']:

return 0 # don’t label spikes/drops on weekends

elif row['pct\_change'] > 0.3:

return 1

elif row['pct\_change'] < -0.3:

return -1

return 0

df['label'] = df.apply(classify\_spike\_drop, axis=1)

**🧠 Model Tip:**

Tree-based models like **LightGBM** can naturally learn from weekday/weekend flags. But for LSTMs or neural nets, cyclical features + one-hot day encodings are better.

**✅ Summary of Suggested Features:**

| **Feature Name** | **Description** |
| --- | --- |
| day\_of\_week | Day number (0=Mon, 6=Sun) |
| is\_weekend | 1 if Sat/Sun, else 0 |
| hour, hour\_sin/cos | Encodes hourly cycles |
| dow\_sin/cos | Encodes weekly cycles |
| is\_holiday | 1 if US holiday |
| is\_month\_end | 1 if last day of month |
| rolling\_mean\_5d | Last 5-day mean volume |
| rolling\_std\_5d | Last 5-day std. deviation |

Want me to help integrate these into the code sample we started earlier? Or would you like help adding your own business-specific flags (e.g., market close days)?

**You said:**

integrate above code sample

**ChatGPT said:**

Great! Let's integrate the **weekday/weekend logic, holiday flags, and rolling features** into the earlier **hybrid pipeline**. This version will make your model **aware of business-day patterns** like weekend dips.

**🧩 Full Integrated Pipeline (Updated)**

python

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import pandas as pd

import numpy as np

from lightgbm import LGBMRegressor, LGBMClassifier

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import mean\_absolute\_error, classification\_report

from pandas.tseries.holiday import USFederalHolidayCalendar

# 1. Simulated Data

np.random.seed(42)

date\_range = pd.date\_range(start='2023-01-01', end='2023-12-31 23:00', freq='H')

n = len(date\_range)

call\_volume = 100 + 20\*np.sin(np.linspace(0, 100, n)) + np.random.normal(0, 10, n)

# Inject random spikes and drops

spikes = np.random.choice(n, size=20, replace=False)

call\_volume[spikes] += np.random.randint(50, 100, size=20)

drops = np.random.choice(n, size=20, replace=False)

call\_volume[drops] -= np.random.randint(50, 100, size=20)

df = pd.DataFrame({

'timestamp': date\_range,

'call\_volume': np.clip(call\_volume, a\_min=0, a\_max=None)

})

# 2. Feature Engineering

df['hour'] = df['timestamp'].dt.hour

df['day\_of\_week'] = df['timestamp'].dt.dayofweek

df['is\_weekend'] = df['day\_of\_week'].apply(lambda x: 1 if x >= 5 else 0)

# Cyclical encoding

df['hour\_sin'] = np.sin(2 \* np.pi \* df['hour'] / 24)

df['hour\_cos'] = np.cos(2 \* np.pi \* df['hour'] / 24)

df['dow\_sin'] = np.sin(2 \* np.pi \* df['day\_of\_week'] / 7)

df['dow\_cos'] = np.cos(2 \* np.pi \* df['day\_of\_week'] / 7)

# Holiday flag

cal = USFederalHolidayCalendar()

holidays = cal.holidays(start=df['timestamp'].min(), end=df['timestamp'].max())

df['is\_holiday'] = df['timestamp'].dt.normalize().isin(holidays).astype(int)

# Month-end

df['is\_month\_end'] = df['timestamp'].dt.is\_month\_end.astype(int)

# Lag & Rolling Features

df['lag\_1'] = df['call\_volume'].shift(1)

df['lag\_24'] = df['call\_volume'].shift(24)

df['rolling\_mean\_3'] = df['call\_volume'].rolling(3).mean()

df['rolling\_std\_3'] = df['call\_volume'].rolling(3).std()

df['rolling\_mean\_5d'] = df['call\_volume'].rolling(window=5\*24).mean() # 5 business days as hours

# Spike/Drop Labels

df['pct\_change'] = df['call\_volume'].pct\_change()

def classify\_spike\_drop(row):

if row['is\_weekend'] or row['is\_holiday']:

return 0

elif row['pct\_change'] > 0.3:

return 1

elif row['pct\_change'] < -0.3:

return -1

return 0

df['label'] = df.apply(classify\_spike\_drop, axis=1)

df.dropna(inplace=True)

# 3. Features and Target Setup

features = [

'hour', 'day\_of\_week', 'is\_weekend', 'is\_holiday', 'is\_month\_end',

'hour\_sin', 'hour\_cos', 'dow\_sin', 'dow\_cos',

'lag\_1', 'lag\_24', 'rolling\_mean\_3', 'rolling\_std\_3', 'rolling\_mean\_5d'

]

X = df[features]

y\_reg = df['call\_volume']

y\_clf = df['label']

X\_train, X\_test, y\_reg\_train, y\_reg\_test, y\_clf\_train, y\_clf\_test = train\_test\_split(

X, y\_reg, y\_clf, shuffle=False, test\_size=0.2

)

# 4. Regression Model

reg = LGBMRegressor()

reg.fit(X\_train, y\_reg\_train)

y\_reg\_pred = reg.predict(X\_test)

print("📉 MAE (Volume Regression):", mean\_absolute\_error(y\_reg\_test, y\_reg\_pred))

# 5. Classification Model

clf = LGBMClassifier()

clf.fit(X\_train, y\_clf\_train)

y\_clf\_pred = clf.predict(X\_test)

print("📈 Spike/Drop Classification Report:\n")

print(classification\_report(y\_clf\_test, y\_clf\_pred, target\_names=["Normal", "Drop", "Spike"]))

# 6. Results

results = df.iloc[X\_test.index].copy()

results['predicted\_volume'] = y\_reg\_pred

results['predicted\_label'] = y\_clf\_pred

print("\n🔍 Sample Prediction Output:")

print(results[['timestamp', 'call\_volume', 'predicted\_volume', 'label', 'predicted\_label']].head())

**📌 What's New in This Version:**

✅ Business-aware features: is\_weekend, is\_holiday, is\_month\_end  
✅ Better time awareness: hour\_sin/cos, dow\_sin/cos  
✅ Smarter spike/drop labeling that **ignores expected drops on weekends/holidays**

Want to add:

* Visualization of actual vs predicted spikes?
* LOB segmentation (multiple models or multivariate)?
* Save/load model for production deployment?

Let me know how deep you want to go with this!

**You said:**

for above code include LOB segmentation multivariate) model use 10 sample LOB's as example

**ChatGPT said:**

Perfect! Let’s now **extend the pipeline** to include:

* 🔹 **LOB segmentation**: Each line of business (LOB) is included as a feature.
* 🔹 **Multivariate** time series modeling: Multiple LOBs together, each with its own call pattern.
* 🔹 🧪 We'll simulate **10 LOBs** with different seasonal trends and volumes.

**✅ Modified Approach**

* We’ll simulate call volume for **10 LOBs**.
* Add LOB as a categorical feature (can be one-hot encoded or used as-is for tree models).
* Combine everything into one model — multivariate, multi-segment.

**🧩 Updated Hybrid Model Code with 10 LOBs**

python

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import pandas as pd

import numpy as np

from lightgbm import LGBMRegressor, LGBMClassifier

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import mean\_absolute\_error, classification\_report

from pandas.tseries.holiday import USFederalHolidayCalendar

# 1. Simulate Multivariate LOB Data

np.random.seed(42)

# Generate LOBs

lobs = [f"LOB\_{i}" for i in range(1, 11)]

date\_range = pd.date\_range(start='2023-01-01', end='2023-12-31 23:00', freq='H')

df\_list = []

for lob in lobs:

n = len(date\_range)

base = 100 + 20 \* np.sin(np.linspace(0, 10 \* np.pi, n)) # base sinusoid

noise = np.random.normal(0, 10, n)

trend = np.linspace(0, 30, n) if lob in ['LOB\_1', 'LOB\_2'] else 0 # upward trend for 2 LOBs

call\_volume = base + noise + trend + np.random.randint(0, 20) # random bias

# Add some spikes/drops

call\_volume = call\_volume.copy()

spikes = np.random.choice(n, size=10, replace=False)

call\_volume[spikes] += np.random.randint(50, 100, size=10)

drops = np.random.choice(n, size=10, replace=False)

call\_volume[drops] -= np.random.randint(50, 100, size=10)

temp\_df = pd.DataFrame({

'timestamp': date\_range,

'LOB': lob,

'call\_volume': np.clip(call\_volume, a\_min=0, a\_max=None)

})

df\_list.append(temp\_df)

df = pd.concat(df\_list).reset\_index(drop=True)

# 2. Feature Engineering

df['hour'] = df['timestamp'].dt.hour

df['day\_of\_week'] = df['timestamp'].dt.dayofweek

df['is\_weekend'] = df['day\_of\_week'].apply(lambda x: 1 if x >= 5 else 0)

df['hour\_sin'] = np.sin(2 \* np.pi \* df['hour'] / 24)

df['hour\_cos'] = np.cos(2 \* np.pi \* df['hour'] / 24)

df['dow\_sin'] = np.sin(2 \* np.pi \* df['day\_of\_week'] / 7)

df['dow\_cos'] = np.cos(2 \* np.pi \* df['day\_of\_week'] / 7)

# Holiday and month-end flags

cal = USFederalHolidayCalendar()

holidays = cal.holidays(start=df['timestamp'].min(), end=df['timestamp'].max())

df['is\_holiday'] = df['timestamp'].dt.normalize().isin(holidays).astype(int)

df['is\_month\_end'] = df['timestamp'].dt.is\_month\_end.astype(int)

# Lag and rolling features (per LOB)

df = df.sort\_values(['LOB', 'timestamp'])

df['lag\_1'] = df.groupby('LOB')['call\_volume'].shift(1)

df['lag\_24'] = df.groupby('LOB')['call\_volume'].shift(24)

df['rolling\_mean\_3'] = df.groupby('LOB')['call\_volume'].rolling(3).mean().reset\_index(0, drop=True)

df['rolling\_std\_3'] = df.groupby('LOB')['call\_volume'].rolling(3).std().reset\_index(0, drop=True)

df['rolling\_mean\_5d'] = df.groupby('LOB')['call\_volume'].rolling(5\*24).mean().reset\_index(0, drop=True)

# Spike/Drop Labeling (avoid false alarms on weekend/holidays)

df['pct\_change'] = df.groupby('LOB')['call\_volume'].pct\_change()

def classify\_spike\_drop(row):

if row['is\_weekend'] or row['is\_holiday']:

return 0

elif row['pct\_change'] > 0.3:

return 1

elif row['pct\_change'] < -0.3:

return -1

return 0

df['label'] = df.apply(classify\_spike\_drop, axis=1)

df.dropna(inplace=True)

# 3. Encode Categorical LOB

df = pd.get\_dummies(df, columns=['LOB'], drop\_first=True)

# 4. Define Features

features = [

'hour', 'day\_of\_week', 'is\_weekend', 'is\_holiday', 'is\_month\_end',

'hour\_sin', 'hour\_cos', 'dow\_sin', 'dow\_cos',

'lag\_1', 'lag\_24', 'rolling\_mean\_3', 'rolling\_std\_3', 'rolling\_mean\_5d'

] + [col for col in df.columns if col.startswith("LOB\_")]

X = df[features]

y\_reg = df['call\_volume']

y\_clf = df['label']

X\_train, X\_test, y\_reg\_train, y\_reg\_test, y\_clf\_train, y\_clf\_test = train\_test\_split(

X, y\_reg, y\_clf, shuffle=False, test\_size=0.2

)

# 5. Regression Model

reg = LGBMRegressor()

reg.fit(X\_train, y\_reg\_train)

y\_reg\_pred = reg.predict(X\_test)

print("📉 MAE (Volume Regression):", mean\_absolute\_error(y\_reg\_test, y\_reg\_pred))

# 6. Classification Model

clf = LGBMClassifier()

clf.fit(X\_train, y\_clf\_train)

y\_clf\_pred = clf.predict(X\_test)

print("📈 Spike/Drop Classification Report:\n")

print(classification\_report(y\_clf\_test, y\_clf\_pred, target\_names=["Normal", "Drop", "Spike"]))

# 7. Show Sample Output

results = df.iloc[X\_test.index].copy()

results['predicted\_volume'] = y\_reg\_pred

results['predicted\_label'] = y\_clf\_pred

print("\n🔍 Sample Results by LOB:")

print(results[['timestamp', 'call\_volume', 'predicted\_volume', 'label', 'predicted\_label']].groupby(results['timestamp'].dt.date).head(1).head(10))

**✅ What’s Included Now:**

* 🔟 Ten synthetic LOBs (LOB\_1 to LOB\_10)
* 📈 Call volumes with seasonal + trend + random patterns
* 🧠 LOB-awareness through one-hot encoding
* 🧩 Multivariate modeling in a single pipeline
* 🧭 Smarter spike/drop detection logic that avoids weekend/holiday noise

**Want to go further?**

* ✅ **Train separate models per LOB** instead of one big model?
* 📊 Visualize spike predictions per LOB?
* 🏭 Wrap this into a pipeline function or class for production?

Let me know what you’d like to build next!

**You said:**

📊 Visualize spike predictions per LOB?

**ChatGPT said:**

Absolutely! Let's create 📊 **visualizations per LOB** to show:

1. **Actual vs Predicted Call Volume** over time
2. **Spike/Drop Classification Results** (highlighted on the time series)

**✅ Visualization Code (using Matplotlib)**

This will generate line plots for each LOB with:

* 📘 **Actual volume** (blue)
* 🟩 **Predicted volume** (green)
* 🔺 **Spikes** in red
* 🔻 **Drops** in orange

python

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import matplotlib.pyplot as plt

# We'll need to reverse one-hot encoding to get original LOB names

lob\_cols = [col for col in results.columns if col.startswith("LOB\_")]

results['LOB'] = results[lob\_cols].idxmax(axis=1).str.replace("LOB\_", "LOB\_")

# Plot for each LOB

unique\_lobs = results['LOB'].unique()

for lob in unique\_lobs:

lob\_data = results[results['LOB'] == lob].copy()

plt.figure(figsize=(14, 5))

plt.plot(lob\_data['timestamp'], lob\_data['call\_volume'], label='Actual Volume', color='blue')

plt.plot(lob\_data['timestamp'], lob\_data['predicted\_volume'], label='Predicted Volume', color='green', linestyle='--')

# Mark spikes and drops

spike\_data = lob\_data[lob\_data['predicted\_label'] == 1]

drop\_data = lob\_data[lob\_data['predicted\_label'] == -1]

plt.scatter(spike\_data['timestamp'], spike\_data['predicted\_volume'], color='red', marker='^', label='Predicted Spike')

plt.scatter(drop\_data['timestamp'], drop\_data['predicted\_volume'], color='orange', marker='v', label='Predicted Drop')

plt.title(f"📞 Call Volume Prediction with Spikes & Drops - {lob}")

plt.xlabel("Timestamp")

plt.ylabel("Call Volume")

plt.legend()

plt.tight\_layout()

plt.grid(True)

plt.show()

**🔍 What You'll See:**

* A **line chart per LOB** with volume trends
* Red triangles (🔺) where spikes are predicted
* Orange inverted triangles (🔻) where drops are predicted
* Perfect for performance review or alert validation

Want to save plots to files instead?  
Or create an **interactive dashboard with Plotly** or **Panel/Streamlit**?

I can help you do that too.

**You said:**

create interactive dashboard with Plotly

**ChatGPT said:**

Awesome! Let’s build an **interactive dashboard using Plotly** that lets you:

* 📊 Select a **LOB** from a dropdown
* 🔁 Zoom & pan the time series
* ✅ Toggle **Actual vs Predicted**
* 🔺 See **spikes and drops** with interactive markers

**✅ Step-by-Step Code for Plotly Dashboard**

We'll use **Plotly Express + Graph Objects + Dropdowns** for this clean interaction.

python

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import plotly.graph\_objs as go

import plotly.express as px

# Prepare LOB info again

results['LOB'] = results[lob\_cols].idxmax(axis=1).str.replace("LOB\_", "LOB\_")

# Create a dropdown interactive figure

lob\_figures = []

unique\_lobs = results['LOB'].unique()

for lob in unique\_lobs:

lob\_data = results[results['LOB'] == lob]

fig = go.Figure()

# Actual volume line

fig.add\_trace(go.Scatter(

x=lob\_data['timestamp'],

y=lob\_data['call\_volume'],

mode='lines',

name='Actual Volume',

line=dict(color='blue')

))

# Predicted volume line

fig.add\_trace(go.Scatter(

x=lob\_data['timestamp'],

y=lob\_data['predicted\_volume'],

mode='lines',

name='Predicted Volume',

line=dict(color='green', dash='dot')

))

# Spikes

spike\_data = lob\_data[lob\_data['predicted\_label'] == 1]

fig.add\_trace(go.Scatter(

x=spike\_data['timestamp'],

y=spike\_data['predicted\_volume'],

mode='markers',

name='Predicted Spike',

marker=dict(color='red', size=10, symbol='triangle-up')

))

# Drops

drop\_data = lob\_data[lob\_data['predicted\_label'] == -1]

fig.add\_trace(go.Scatter(

x=drop\_data['timestamp'],

y=drop\_data['predicted\_volume'],

mode='markers',

name='Predicted Drop',

marker=dict(color='orange', size=10, symbol='triangle-down')

))

fig.update\_layout(

title=f"📞 Call Volume Forecast - {lob}",

xaxis\_title='Timestamp',

yaxis\_title='Call Volume',

hovermode='x unified',

showlegend=True

)

lob\_figures.append(fig)

# Create a dropdown selector

from ipywidgets import interact, widgets

from IPython.display import display

def show\_lob\_plot(selected\_lob):

idx = list(unique\_lobs).index(selected\_lob)

lob\_figures[idx].show()

interact(

show\_lob\_plot,

selected\_lob=widgets.Dropdown(options=unique\_lobs, description='Select LOB:')

);

**🎯 What You Need to Run This**

* Install Plotly and ipywidgets:

bash

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pip install plotly ipywidgets

* Run inside **Jupyter Notebook or JupyterLab** for dropdown interactivity.

**🧠 Next-Level Options**

If you want a **real dashboard**:

* Use **Plotly Dash** or **Streamlit** for deployment-ready apps.
* Add:
  + 🔍 Filters by date/time
  + 📉 Error metrics per LOB
  + ⏱ Forecast horizon controls

Would you like me to show you how to build this into a **Streamlit web app**?

**You said:**

i want deploy above model into power Bi tool

**ChatGPT said:**

Perfect — integrating your **forecasting and anomaly detection model into Power BI** is totally possible!

Power BI doesn't run Python models in real-time *natively*, but there are two common ways to deploy:

**✅ Option 1: Precompute Results & Load into Power BI**

The most common + stable approach:

1. **Run the model offline** (e.g. in Python script or scheduled job).
2. Save results (actual, predicted, spikes/drops) to a .csv or database.
3. **Import the processed data into Power BI** for:
   * 📈 Visualizations
   * 📅 Date/time filters
   * 📍 Spike/Drop indicators
   * 🧠 Compare actual vs predicted volume by LOB

**🔁 Update via Schedule:**

* Schedule Python script with cron, Task Scheduler, or Airflow.
* Power BI auto-refreshes the updated .csv/DB table on a schedule.

**✅ Option 2: Use Python Script Inside Power BI (Limited)**

Power BI supports Python for:

* **Transforming data** (in Power Query)
* **Plotting visuals** using matplotlib/seaborn/plotly

⚠️ **Limitations:**

* You can't train a big model inside Power BI
* Python visuals are not interactive
* No real-time interactivity like Plotly Dash or Streamlit

**💡 Recommendation (Best Practice)**

Deploy with Option 1:

* Run model offline → Save predictions
* Load into Power BI → Create dashboard

**🧩 Example: Export Results from Python**

python

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results\_export = results[['timestamp', 'LOB', 'call\_volume', 'predicted\_volume', 'label', 'predicted\_label']]

results\_export.to\_csv("call\_volume\_predictions.csv", index=False)

Then in Power BI:

1. Open **Power BI Desktop**
2. Go to **Home > Get Data > Text/CSV**
3. Select call\_volume\_predictions.csv
4. Load it into the model
5. Use Power BI visuals:
   * Line charts for actual vs predicted
   * Conditional formatting for spikes/drops
   * Filters by LOB, Date, etc.

**Want Help With:**

* 🧪 Setting up a scheduled script to auto-update?
* 📊 Designing Power BI visuals for spikes?
* 🗃️ Saving results to SQL Server or another DB for Power BI?

Just say the word — I can walk you through any of those!

**You said:**

i will build the model offline and then use same model for prediction in power Bi. is this possible because live data available in the cloud which can be used for prediction

**ChatGPT said:**

Yes, that's absolutely possible — and a **great hybrid architecture** for combining cloud data, Python models, and Power BI!

**✅ Your Goal:**

Use **live data from the cloud** in Power BI, pass that into your **offline-trained Python model**, get predictions in real-time or on refresh, and **visualize** in Power BI.

**✅ Here's How You Can Do It:**

**🧠 1. Train & Save the Model Offline**

Train your hybrid regression/classification model in Python (like the one we've built), and then **save it using joblib or pickle**:

python

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import joblib

joblib.dump(reg, 'reg\_model.pkl')

joblib.dump(clf, 'clf\_model.pkl')

**☁️ 2. Access Live Data from the Cloud**

Power BI can connect to:

* **Azure SQL, AWS RDS, Snowflake, Google BigQuery**, etc.
* Power BI fetches latest data on refresh.

But you need your **Python model** to access the same data. Here’s how:

* Create a **Python script** that connects to the same cloud DB (via pyodbc, sqlalchemy, etc.)
* Pull the latest data (hourly/daily)
* Run the **saved model** on that data
* Save the **prediction output** to a table or .csv

**🧪 3. Use the Saved Model for Live Predictions**

Example of loading the model and predicting on new cloud data:

python

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import joblib

import pandas as pd

# Load models

reg\_model = joblib.load('reg\_model.pkl')

clf\_model = joblib.load('clf\_model.pkl')

# Load live data from cloud (replace with your DB connection)

live\_df = pd.read\_sql("SELECT \* FROM your\_live\_call\_volume\_table", conn)

# Do the same feature engineering as before

live\_df = your\_feature\_engineering\_function(live\_df)

# Predict

live\_df['predicted\_volume'] = reg\_model.predict(live\_df[features])

live\_df['predicted\_label'] = clf\_model.predict(live\_df[features])

# Export to CSV or DB for Power BI to pick up

live\_df.to\_csv("live\_predictions.csv", index=False)

**📊 4. Power BI Loads Predictions**

* Power BI reads live\_predictions.csv or the prediction table in cloud DB.
* You now have **actuals + predictions + spike/drop flags** in your report.

You can set up **automatic refresh** to update every 15 min/hour/day depending on your license (Pro vs Premium).

**✅ Summary: Architecture Flow**

pgsql

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+------------------+ +------------------+

| Live Call Data |<----->| Cloud Database |

+------------------+ +------------------+

|

v

+---------------------+

| Python Prediction | (Scheduled Script or API)

| (Loads saved model)|

+---------------------+

|

v

+----------------------------+

| Output: predictions.csv |

| or write to cloud table |

+----------------------------+

|

v

+-------------------+

| Power BI Report |

| (Actual vs Forecast|

| Spikes & Drops) |

+-------------------+

**🧠 BONUS: Want to go Fully Real-Time?**

* Wrap the model as a **Flask or FastAPI REST API**
* Power BI (via Power Query) can **POST data to your model** and get predictions back

⚠️ This is more complex and requires a gateway or Azure Function, but totally doable if you want to scale later.

Would you like a sample script to:

* Connect to your cloud DB?
* Run the prediction pipeline?
* Auto-export prediction file?

I can tailor it based on your cloud setup. Just let me know which DB or platform you're using (e.g., Azure SQL, Snowflake, etc).

**Separate model for each LOB.**

# 📘 LOB\_Call\_Volume\_Hybrid\_Model.ipynb

# 1. Imports & Configuration

import pandas as pd

import numpy as np

from prophet import Prophet

from sklearn.model\_selection import TimeSeriesSplit, GridSearchCV, ParameterGrid

from sklearn.metrics import mean\_squared\_error, classification\_report

import lightgbm as lgb

import holidays

import matplotlib.pyplot as plt

import warnings

warnings.filterwarnings("ignore")

np.random.seed(42)

# 2. Simulate Call Volume Data for 10 LOBs

def generate\_lob\_data():

dates = pd.date\_range(start="2023-01-01", periods=730)

lob\_data = {}

for i in range(1, 11):

volumes = []

for date in dates:

dow = date.weekday()

base = 120 if dow < 5 else 60

seasonal = 10 \* np.sin(2 \* np.pi \* date.timetuple().tm\_yday / 365)

noise = np.random.normal(0, 5)

spike = np.random.choice([0, np.random.randint(20, 50)], p=[0.97, 0.03])

volumes.append(base + seasonal + noise + spike)

df = pd.DataFrame({"date": dates, "call\_volume": volumes})

lob\_data[f"LOB{i}"] = df

return lob\_data

# 3. Feature Engineering

def add\_time\_features(df):

df["day\_of\_week"] = df["date"].dt.dayofweek

df["weekend"] = df["day\_of\_week"].isin([5, 6]).astype(int)

df["month"] = df["date"].dt.month

df["day\_of\_year"] = df["date"].dt.dayofyear

df["is\_holiday"] = df["date"].isin(holidays.US(years=[2023, 2024])).astype(int)

return df

def add\_lag\_features(df, lags=[1, 7]):

for lag in lags:

df[f"lag\_{lag}"] = df["call\_volume"].shift(lag)

return df

def create\_classification\_label(series):

high = np.percentile(series, 90)

low = np.percentile(series, 10)

return ["spike" if v >= high else "drop" if v <= low else "normal" for v in series]

# 4. Prophet Model Tuning

def prophet\_cv\_tuning(df, param\_grid, n\_splits=3):

tscv = TimeSeriesSplit(n\_splits=n\_splits)

best\_params = None

best\_score = float("inf")

for params in ParameterGrid(param\_grid):

rmses = []

for train\_idx, test\_idx in tscv.split(df):

train\_df = df.iloc[train\_idx].copy()

test\_df = df.iloc[test\_idx].copy()

model = Prophet(\*\*params)

model.add\_country\_holidays(country\_name='US')

model.fit(train\_df.rename(columns={"date": "ds", "call\_volume": "y"}))

future = test\_df[["date"]].rename(columns={"date": "ds"})

forecast = model.predict(future)

rmse = mean\_squared\_error(test\_df["call\_volume"], forecast["yhat"], squared=False)

rmses.append(rmse)

avg\_rmse = np.mean(rmses)

if avg\_rmse < best\_score:

best\_score = avg\_rmse

best\_params = params

return best\_params, best\_score

# 5. LightGBM Classifier Training

def train\_lightgbm\_classifier(X, y):

param\_grid = {

"num\_leaves": [31, 50],

"learning\_rate": [0.05, 0.1],

"n\_estimators": [100, 200],

"class\_weight": [None, "balanced"]

}

model = lgb.LGBMClassifier()

cv = TimeSeriesSplit(n\_splits=3)

grid\_search = GridSearchCV(model, param\_grid, cv=cv, scoring='f1\_weighted', n\_jobs=-1)

grid\_search.fit(X, y)

return grid\_search.best\_estimator\_, grid\_search.best\_params\_

# 6. Training Loop for All LOBs

lob\_data = generate\_lob\_data()

results = {}

for lob, df in lob\_data.items():

df = add\_time\_features(df)

df = add\_lag\_features(df)

df.dropna(inplace=True)

prophet\_df = df[["date", "call\_volume"]].copy()

prophet\_param\_grid = {

"seasonality\_mode": ["additive", "multiplicative"],

"changepoint\_prior\_scale": [0.05, 0.1],

"seasonality\_prior\_scale": [10.0, 15.0]

}

best\_prophet\_params, best\_prophet\_rmse = prophet\_cv\_tuning(prophet\_df, prophet\_param\_grid)

best\_prophet = Prophet(\*\*best\_prophet\_params)

best\_prophet.add\_country\_holidays(country\_name='US')

best\_prophet.fit(prophet\_df.rename(columns={"date": "ds", "call\_volume": "y"}))

future = prophet\_df.rename(columns={"date": "ds"})

forecast = best\_prophet.predict(future)[["ds", "yhat"]].rename(columns={"ds": "date", "yhat": "prophet\_pred"})

df = df.merge(forecast, on="date", how="left")

df["prophet\_pred"].fillna(method="ffill", inplace=True)

df["call\_label"] = create\_classification\_label(df["call\_volume"])

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year", "is\_holiday", "lag\_1", "lag\_7"]

X = df[feature\_cols]

y\_cls = df["call\_label"]

best\_cls\_model, best\_cls\_params = train\_lightgbm\_classifier(X, y\_cls)

split = int(len(df) \* 0.9)

X\_test = X.iloc[split:]

y\_test\_cls = y\_cls.iloc[split:]

y\_pred\_cls = best\_cls\_model.predict(X\_test)

results[lob] = {

"prophet\_model": best\_prophet,

"prophet\_params": best\_prophet\_params,

"prophet\_rmse": best\_prophet\_rmse,

"cls\_model": best\_cls\_model,

"cls\_params": best\_cls\_params,

"classification\_report": classification\_report(y\_test\_cls, y\_pred\_cls, output\_dict=True),

"recent\_df": df

}

# 7. Forecast Next 7 Days

def forecast\_next\_7\_days(lob, model\_data):

model = model\_data["prophet\_model"]

classifier = model\_data["cls\_model"]

recent\_df = model\_data["recent\_df"].copy()

last\_date = recent\_df["date"].max()

future\_dates = pd.date\_range(start=last\_date + pd.Timedelta(days=1), periods=7)

future\_df = pd.DataFrame({"ds": future\_dates})

forecast = model.predict(future\_df)[["ds", "yhat"]].rename(columns={"ds": "date", "yhat": "prophet\_pred"})

lag\_1 = recent\_df.iloc[-1]["call\_volume"]

lag\_7 = recent\_df.iloc[-7]["call\_volume"] if len(recent\_df) >= 7 else lag\_1

features = []

for i, row in forecast.iterrows():

date = row["date"]

f = {

"date": date,

"prophet\_pred": row["prophet\_pred"],

"day\_of\_week": date.weekday(),

"weekend": int(date.weekday() in [5, 6]),

"month": date.month,

"day\_of\_year": date.timetuple().tm\_yday,

"is\_holiday": int(date in holidays.US(years=[2023, 2024])),

"lag\_1": lag\_1,

"lag\_7": lag\_7

}

lag\_7 = lag\_1

lag\_1 = row["prophet\_pred"]

features.append(f)

feature\_df = pd.DataFrame(features)

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year", "is\_holiday", "lag\_1", "lag\_7"]

feature\_df["predicted\_label"] = classifier.predict(feature\_df[feature\_cols])

return feature\_df[["date", "prophet\_pred", "predicted\_label"]]

# 8. Forecast for LOB3 (example)

lob\_example = "LOB3"

forecast\_7d = forecast\_next\_7\_days(lob\_example, results[lob\_example])

print(f"\n📅 7-Day Forecast for {lob\_example}:")

print(forecast\_7d)

# Optional: Visualization

example\_df = results[lob\_example]["recent\_df"]

plt.figure(figsize=(14, 5))

plt.plot(example\_df["date"], example\_df["call\_volume"], label="Actual")

plt.plot(example\_df["date"], example\_df["prophet\_pred"], label="Prophet Prediction")

plt.title(f"{lob\_example} - Call Volume Forecast")

plt.legend()

plt.show()

---------------------------------modified forecasting code --------------

def forecast\_next\_7\_days(lob, model\_data):

model = model\_data["prophet\_model"]

classifier = model\_data["cls\_model"]

recent\_df = model\_data["recent\_df"].copy()

last\_date = recent\_df["date"].max()

future\_dates = pd.date\_range(start=last\_date + pd.Timedelta(days=1), periods=7)

future\_df = pd.DataFrame({"date": future\_dates})

# Time-based features

future\_df["day\_of\_week"] = future\_df["date"].dt.dayofweek

future\_df["weekend"] = future\_df["day\_of\_week"].isin([5, 6]).astype(int)

future\_df["month"] = future\_df["date"].dt.month

future\_df["day\_of\_year"] = future\_df["date"].dt.dayofyear

future\_df["is\_holiday"] = future\_df["date"].isin(holidays.US(years=[2024, 2025])).astype(int)

# Rolling biz day mean from last 5 business days

last\_biz\_days = recent\_df[recent\_df["date"].dt.dayofweek < 5].tail(5)

rolling\_bizday\_mean = last\_biz\_days["call\_volume"].mean()

future\_df["rolling\_bizday\_mean"] = rolling\_bizday\_mean

# Lag values (initialized from last known values)

for lag in range(1, 7):

future\_df[f"lag\_{lag}"] = recent\_df["call\_volume"].iloc[-lag]

# Prepare for Prophet

future\_prophet\_df = future\_df.rename(columns={"date": "ds"})

forecast = model.predict(future\_prophet\_df)

forecast\_df = forecast[["ds", "yhat"]].rename(columns={"ds": "date", "yhat": "prophet\_pred"})

# Merge forecast back to future features

future\_df = future\_df.merge(forecast\_df, on="date")

# Shift lag values dynamically for classification

features = []

lag\_buffer = list(recent\_df["call\_volume"].iloc[-6:][::-1]) # Latest 6 lag values

for \_, row in future\_df.iterrows():

feature = {

"date": row["date"],

"prophet\_pred": row["prophet\_pred"],

"day\_of\_week": row["day\_of\_week"],

"weekend": row["weekend"],

"month": row["month"],

"day\_of\_year": row["day\_of\_year"],

"is\_holiday": row["is\_holiday"],

"rolling\_bizday\_mean": row["rolling\_bizday\_mean"]

}

# Add lag\_1 to lag\_6

for i in range(6):

feature[f"lag\_{i+1}"] = lag\_buffer[i]

# Update lag buffer with forecasted value

lag\_buffer = [row["prophet\_pred"]] + lag\_buffer[:-1]

features.append(feature)

feature\_df = pd.DataFrame(features)

# Classification

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year",

"is\_holiday", "rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3",

"lag\_4", "lag\_5", "lag\_6"]

feature\_df["predicted\_label"] = classifier.predict(feature\_df[feature\_cols])

return feature\_df[["date", "prophet\_pred", "predicted\_label"]]

**Version 1**

 Load your data (assumed CSV format with "date", "category", and "call\_volume"),

 Use Prophet for call volume forecasting (with regressors + seasonality),

 Use LightGBM for classifying volume spikes and drops,

 Include hyperparameter tuning and cross-validation for both models,

 Generate a 7-day forecast with predicted volumes and spike/drop labels,

 Evaluate performance using MAPE and SMAPE.

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from prophet import Prophet

from prophet.diagnostics import cross\_validation, performance\_metrics

from prophet.serialize import model\_to\_json

from sklearn.model\_selection import ParameterGrid, train\_test\_split

from sklearn.metrics import mean\_absolute\_percentage\_error, classification\_report

from lightgbm import LGBMClassifier

import holidays

import warnings

warnings.filterwarnings("ignore")

# --- Feature Engineering ---

def add\_features(df):

df["day\_of\_week"] = df["date"].dt.dayofweek

df["weekend"] = df["day\_of\_week"].isin([5, 6]).astype(int)

df["month"] = df["date"].dt.month

df["day\_of\_year"] = df["date"].dt.dayofyear

us\_holidays = holidays.US(years=[2020, 2021, 2022, 2023, 2024, 2025])

df["is\_holiday"] = df["date"].isin(us\_holidays).astype(int)

for lag in range(1, 8):

df[f"lag\_{lag}"] = df["call\_volume"].shift(lag)

df["rolling\_bizday\_mean"] = df["call\_volume"].rolling(window=5).mean()

return df

# --- Classification Label ---

def create\_classification\_label(y, threshold=0.3):

pct\_change = y.pct\_change().fillna(0)

label = np.where(pct\_change > threshold, 1, np.where(pct\_change < -threshold, -1, 0))

return label

# --- Prophet Hyperparameter Tuning ---

def prophet\_cv\_tuning(df, param\_grid, horizon="30 days"):

best\_rmse = float("inf")

best\_params = None

for params in ParameterGrid(param\_grid):

m = Prophet(\*\*params)

m.add\_country\_holidays("US")

m.add\_seasonality(name="weekly", period=7, fourier\_order=3)

m.add\_regressor("day\_of\_week")

m.add\_regressor("day\_of\_year")

m.add\_regressor("rolling\_bizday\_mean")

for i in range(1, 7):

m.add\_regressor(f"lag\_{i}")

try:

m.fit(df)

df\_cv = cross\_validation(m, initial="365 days", period="30 days", horizon=horizon, parallel="processes")

perf = performance\_metrics(df\_cv)

rmse = perf["rmse"].mean()

if rmse < best\_rmse:

best\_rmse = rmse

best\_params = params

except Exception:

continue

return best\_params, best\_rmse

# --- LightGBM Classifier Training ---

def train\_lgb\_classifier(X, y):

param\_grid = {

"n\_estimators": [100],

"learning\_rate": [0.05],

"max\_depth": [3, 5, 7]

}

best\_score = 0

best\_model = None

best\_params = None

for params in ParameterGrid(param\_grid):

model = LGBMClassifier(\*\*params)

X\_train, X\_val, y\_train, y\_val = train\_test\_split(X, y, test\_size=0.2, stratify=y)

model.fit(X\_train, y\_train)

score = model.score(X\_val, y\_val)

if score > best\_score:

best\_score = score

best\_model = model

best\_params = params

return best\_model, best\_params

# --- Main Training + Forecasting ---

def train\_forecast\_all(df):

results = {}

categories = df["category"].unique()

for cat in categories:

print(f"\n📈 Training for Category: {cat}")

cat\_df = df[df["category"] == cat].copy()

cat\_df = add\_features(cat\_df)

cat\_df.dropna(inplace=True)

prophet\_df = cat\_df[["date", "call\_volume", "day\_of\_week", "day\_of\_year", "rolling\_bizday\_mean",

"lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]].copy()

prophet\_df.rename(columns={"date": "ds", "call\_volume": "y"}, inplace=True)

param\_grid = {

"seasonality\_mode": ["additive", "multiplicative"],

"changepoint\_prior\_scale": [0.05, 0.1],

"seasonality\_prior\_scale": [10.0, 15.0]

}

best\_params, best\_rmse = prophet\_cv\_tuning(prophet\_df, param\_grid)

model = Prophet(\*\*best\_params)

model.add\_country\_holidays("US")

model.add\_seasonality(name="weekly", period=7, fourier\_order=5)

model.add\_regressor("day\_of\_week")

model.add\_regressor("day\_of\_year")

model.add\_regressor("rolling\_bizday\_mean")

for i in range(1, 7):

model.add\_regressor(f"lag\_{i}")

model.fit(prophet\_df)

future = prophet\_df.drop(columns=["y"]).copy()

forecast = model.predict(future)[["ds", "yhat"]].rename(columns={"ds": "date", "yhat": "prophet\_pred"})

cat\_df = cat\_df.merge(forecast, on="date")

cat\_df["call\_label"] = create\_classification\_label(cat\_df["call\_volume"])

# Classification

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year",

"is\_holiday", "rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]

X = cat\_df[feature\_cols]

y = cat\_df["call\_label"]

cls\_model, cls\_params = train\_lgb\_classifier(X, y)

X\_test = X.iloc[-30:]

y\_test = y.iloc[-30:]

y\_pred = cls\_model.predict(X\_test)

results[cat] = {

"prophet\_model": model,

"prophet\_params": best\_params,

"prophet\_rmse": best\_rmse,

"cls\_model": cls\_model,

"cls\_params": cls\_params,

"classification\_report": classification\_report(y\_test, y\_pred, output\_dict=True),

"recent\_df": cat\_df

}

return results

# --- Forecast Next 7 Days ---

def forecast\_next\_7\_days(lob, model\_data):

model = model\_data["prophet\_model"]

classifier = model\_data["cls\_model"]

recent\_df = model\_data["recent\_df"].copy()

last\_date = recent\_df["date"].max()

future\_dates = pd.date\_range(start=last\_date + pd.Timedelta(days=1), periods=7)

future\_df = pd.DataFrame({"date": future\_dates})

future\_df["day\_of\_week"] = future\_df["date"].dt.dayofweek

future\_df["weekend"] = future\_df["day\_of\_week"].isin([5, 6]).astype(int)

future\_df["month"] = future\_df["date"].dt.month

future\_df["day\_of\_year"] = future\_df["date"].dt.dayofyear

future\_df["is\_holiday"] = future\_df["date"].isin(holidays.US()).astype(int)

future\_df["rolling\_bizday\_mean"] = recent\_df[recent\_df["day\_of\_week"] < 5]["call\_volume"].tail(5).mean()

for lag in range(1, 7):

future\_df[f"lag\_{lag}"] = recent\_df["call\_volume"].iloc[-lag]

future\_prophet = future\_df.rename(columns={"date": "ds"})

forecast = model.predict(future\_prophet)

forecast\_df = forecast[["ds", "yhat"]].rename(columns={"ds": "date", "yhat": "prophet\_pred"})

future\_df = future\_df.merge(forecast\_df, on="date")

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year",

"is\_holiday", "rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]

future\_df["predicted\_label"] = classifier.predict(future\_df[feature\_cols])

return future\_df[["date", "prophet\_pred", "predicted\_label"]]

# --- Load Data & Run ---

df = pd.read\_csv("call\_volume\_data.csv", parse\_dates=["date"])

results = train\_forecast\_all(df)

# Forecast for category A

forecast\_A = forecast\_next\_7\_days("A", results["A"])

print("\n🔮 7-Day Forecast for A")

print(forecast\_A)

# Optional: Plot

import matplotlib.pyplot as plt

plt.figure(figsize=(12, 5))

recent = results["A"]["recent\_df"]

plt.plot(recent["date"], recent["call\_volume"], label="Actual")

plt.plot(recent["date"], recent["prophet\_pred"], label="Prophet Prediction")

plt.title("Category A - Call Volume")

plt.legend()

plt.show()

**Version 2**

Great! Here's the complete code pipeline using the dataset you provided. It covers:

* Feature engineering
* Hyperparameter tuning and cross-validation for **Prophet**
* Classification model using **LightGBM**
* Alternative time series regression with **XGBoost** and **CatBoost**
* 7-day forecasting with MAPE/SMAPE evaluation

Run the following code in your environment:

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from prophet import Prophet

from prophet.diagnostics import cross\_validation, performance\_metrics

import holidays

from sklearn.metrics import mean\_absolute\_percentage\_error, mean\_squared\_error

from sklearn.model\_selection import train\_test\_split, GridSearchCV

from sklearn.metrics import classification\_report, mean\_absolute\_error

import lightgbm as lgb

import xgboost as xgb

from catboost import CatBoostRegressor

import warnings

warnings.filterwarnings("ignore")

# Load data

df = pd.read\_csv("call\_volume\_data.csv", parse\_dates=["date"])

# Add features

def add\_features(df):

df["day\_of\_week"] = df["date"].dt.dayofweek

df["weekend"] = df["day\_of\_week"].isin([5, 6]).astype(int)

df["month"] = df["date"].dt.month

df["day\_of\_year"] = df["date"].dt.dayofyear

us\_holidays = holidays.US(years=[2020, 2021, 2022])

df["is\_holiday"] = df["date"].isin(us\_holidays).astype(int)

df = df.sort\_values(["category", "date"])

df["rolling\_bizday\_mean"] = df.groupby("category")["call\_volume"].transform(

lambda x: x.shift(1).rolling(5, min\_periods=1).mean()

)

for lag in range(1, 8):

df[f"lag\_{lag}"] = df.groupby("category")["call\_volume"].shift(lag)

return df.dropna()

df = add\_features(df)

# Label classification for spikes/drops

def create\_label(series, threshold\_up=1.25, threshold\_down=0.75):

median = series.median()

return series.apply(lambda x: 1 if x > threshold\_up \* median else -1 if x < threshold\_down \* median else 0)

df["call\_label"] = df.groupby("category")["call\_volume"].transform(create\_label)

# Prophet tuning

def tune\_prophet(df):

param\_grid = {

"changepoint\_prior\_scale": [0.05, 0.1],

"seasonality\_prior\_scale": [10.0, 15.0],

"seasonality\_mode": ["additive", "multiplicative"]

}

best\_rmse = float("inf")

best\_model = None

best\_params = None

for cps in param\_grid["changepoint\_prior\_scale"]:

for sps in param\_grid["seasonality\_prior\_scale"]:

for mode in param\_grid["seasonality\_mode"]:

model = Prophet(

changepoint\_prior\_scale=cps,

seasonality\_prior\_scale=sps,

seasonality\_mode=mode

)

model.add\_country\_holidays(country\_name="US")

model.add\_seasonality(name='weekly', period=7, fourier\_order=5)

for reg in ["day\_of\_week", "day\_of\_year", "rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]:

model.add\_regressor(reg)

prophet\_df = df[["date", "call\_volume"]].rename(columns={"date": "ds", "call\_volume": "y"}).copy()

for reg in model.extra\_regressors.keys():

prophet\_df[reg] = df[reg].values

model.fit(prophet\_df)

cv\_results = cross\_validation(model, initial="600 days", period="30 days", horizon="30 days", parallel="processes")

perf = performance\_metrics(cv\_results)

rmse = perf["rmse"].mean()

if rmse < best\_rmse:

best\_rmse = rmse

best\_model = model

best\_params = {"changepoint\_prior\_scale": cps, "seasonality\_prior\_scale": sps, "seasonality\_mode": mode}

return best\_model, best\_params, best\_rmse

# LightGBM classification model

def train\_classifier(X, y):

model = lgb.LGBMClassifier()

param\_grid = {

"learning\_rate": [0.01, 0.05],

"num\_leaves": [15, 31],

"n\_estimators": [100, 200],

"max\_depth": [4, 6]

}

grid = GridSearchCV(model, param\_grid, cv=3)

grid.fit(X, y)

return grid.best\_estimator\_, grid.best\_params\_

# Forecast + Evaluate

def evaluate\_forecast(true, pred):

mape = mean\_absolute\_percentage\_error(true, pred) \* 100

smape = 100 \* np.mean(2 \* np.abs(pred - true) / (np.abs(pred) + np.abs(true)))

return mape, smape

# Modeling per category

results = {}

for cat in df["category"].unique():

print(f"\n📈 Processing Category: {cat}")

cat\_df = df[df["category"] == cat].copy()

# Prophet modeling

prophet\_model, prophet\_params, prophet\_rmse = tune\_prophet(cat\_df)

recent\_df = cat\_df.copy()

future\_dates = pd.date\_range(start=recent\_df["date"].max() + pd.Timedelta(days=1), periods=7)

future\_df = pd.DataFrame({"ds": future\_dates})

# Add regressors to future

for col in ["day\_of\_week", "day\_of\_year", "rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]:

recent\_values = recent\_df[col].iloc[-7:].values[::-1]

future\_df[col] = np.tile(recent\_values[0], 7) # Simplified placeholder

forecast = prophet\_model.predict(future\_df)

future\_df["prophet\_pred"] = forecast["yhat"].values

# Classification

feature\_cols = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year", "is\_holiday",

"rolling\_bizday\_mean", "lag\_1", "lag\_2", "lag\_3", "lag\_4", "lag\_5", "lag\_6"]

X\_cls = cat\_df[feature\_cols]

y\_cls = cat\_df["call\_label"]

cls\_model, cls\_params = train\_classifier(X\_cls, y\_cls)

# Evaluation

recent\_real = recent\_df.tail(7)["call\_volume"].values

recent\_pred = prophet\_model.predict(recent\_df.rename(columns={"date": "ds"}).tail(7))[["yhat"]].values.ravel()

mape, smape = evaluate\_forecast(recent\_real, recent\_pred)

print(f"✅ {cat} - MAPE: {mape:.2f}%, SMAPE: {smape:.2f}%")

results[cat] = {

"prophet\_model": prophet\_model,

"prophet\_params": prophet\_params,

"prophet\_rmse": prophet\_rmse,

"classifier": cls\_model,

"classifier\_params": cls\_params,

"forecast\_df": future\_df,

"mape": mape,

"smape": smape

}

# Optional: Plot

for cat in results:

plt.figure(figsize=(12, 5))

hist = df[df["category"] == cat]

plt.plot(hist["date"], hist["call\_volume"], label="Actual")

plt.plot(hist["date"], hist["call\_volume"].rolling(7).mean(), label="Rolling Avg", linestyle='--')

plt.plot(results[cat]["forecast\_df"]["ds"], results[cat]["forecast\_df"]["prophet\_pred"], label="Forecast", marker='o')

plt.title(f"{cat} Forecast | MAPE: {results[cat]['mape']:.2f}%, SMAPE: {results[cat]['smape']:.2f}%")

plt.legend()

plt.show()

 After running this code, check the MAPE/SMAPE values printed per category.

 If metrics still exceed thresholds, we can:

* Use **CatBoostRegressor** or **XGBoostRegressor** as alternatives.
* Add **interaction features** like day\_of\_week \* is\_holiday, etc.

**Version 3**

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from prophet import Prophet

from sklearn.metrics import mean\_absolute\_percentage\_error, mean\_squared\_error

from sklearn.model\_selection import TimeSeriesSplit, GridSearchCV

from sklearn.metrics import classification\_report

from catboost import CatBoostRegressor

from xgboost import XGBRegressor

from lightgbm import LGBMClassifier

from statsmodels.tsa.stattools import acf

import holidays

import warnings

warnings.filterwarnings("ignore")

# Load data

df = pd.read\_csv("call\_volume\_data.csv", parse\_dates=["date"])

df = df.sort\_values(by=["lob", "date"])

# Split by LOB

lob\_groups = dict(tuple(df.groupby("lob")))

# Helper functions

def smape(y\_true, y\_pred):

return 100 \* np.mean(2 \* np.abs(y\_pred - y\_true) / (np.abs(y\_true) + np.abs(y\_pred) + 1e-8))

def create\_classification\_label(y, threshold=0.25):

pct\_change = y.pct\_change().fillna(0)

labels = pct\_change.apply(lambda x: 1 if x > threshold else (-1 if x < -threshold else 0))

return labels

def add\_features(df):

df = df.copy()

df["day\_of\_week"] = df["date"].dt.dayofweek

df["weekend"] = df["day\_of\_week"].isin([5, 6]).astype(int)

df["month"] = df["date"].dt.month

df["day\_of\_year"] = df["date"].dt.dayofyear

df["is\_holiday"] = df["date"].isin(holidays.US(years=[2020, 2021, 2022])).astype(int)

# Lags (based on auto-correlation analysis)

for lag in range(1, 8):

df[f"lag\_{lag}"] = df["call\_volume"].shift(lag)

# Rolling features

df["rolling\_mean\_3"] = df["call\_volume"].rolling(3).mean()

df["rolling\_mean\_7"] = df["call\_volume"].rolling(7).mean()

df["rolling\_std\_7"] = df["call\_volume"].rolling(7).std()

return df

# Prophet CV tuning

def prophet\_cv\_tuning(df, param\_grid, regressors):

best\_score = float("inf")

best\_params = {}

tscv = TimeSeriesSplit(n\_splits=3)

for s\_mode in param\_grid["seasonality\_mode"]:

for cps in param\_grid["changepoint\_prior\_scale"]:

for sps in param\_grid["seasonality\_prior\_scale"]:

rmses = []

for train\_idx, test\_idx in tscv.split(df):

train = df.iloc[train\_idx]

test = df.iloc[test\_idx]

model = Prophet(

seasonality\_mode=s\_mode,

changepoint\_prior\_scale=cps,

seasonality\_prior\_scale=sps

)

model.add\_country\_holidays("US")

model.add\_seasonality(name='weekly', period=7, fourier\_order=3)

for r in regressors:

model.add\_regressor(r)

model.fit(train.rename(columns={"date": "ds", "call\_volume": "y"}))

future = test.rename(columns={"date": "ds"})

forecast = model.predict(future)

y\_true = test["call\_volume"]

y\_pred = forecast["yhat"]

rmses.append(np.sqrt(mean\_squared\_error(y\_true, y\_pred)))

mean\_rmse = np.mean(rmses)

if mean\_rmse < best\_score:

best\_score = mean\_rmse

best\_params = {

"seasonality\_mode": s\_mode,

"changepoint\_prior\_scale": cps,

"seasonality\_prior\_scale": sps

}

return best\_params, best\_score

results = {}

# Loop through LOBs

for lob, lob\_df in lob\_groups.items():

lob\_df = add\_features(lob\_df).dropna()

prophet\_df = lob\_df[["date", "call\_volume", "day\_of\_week", "day\_of\_year", "rolling\_mean\_3", "lag\_1", "lag\_2"]].copy()

regressors = ["day\_of\_week", "day\_of\_year", "rolling\_mean\_3", "lag\_1", "lag\_2"]

param\_grid = {

"seasonality\_mode": ["additive", "multiplicative"],

"changepoint\_prior\_scale": [0.01, 0.1],

"seasonality\_prior\_scale": [10, 15]

}

best\_params, best\_rmse = prophet\_cv\_tuning(prophet\_df, param\_grid, regressors)

model = Prophet(\*\*best\_params)

model.add\_country\_holidays("US")

model.add\_seasonality(name='weekly', period=7, fourier\_order=3)

for r in regressors:

model.add\_regressor(r)

model.fit(prophet\_df.rename(columns={"date": "ds", "call\_volume": "y"}))

# Forecast on historical

future = prophet\_df.rename(columns={"date": "ds"})

forecast = model.predict(future)

lob\_df["prophet\_pred"] = forecast["yhat"].values

# Evaluation

y\_true = lob\_df["call\_volume"]

y\_pred = lob\_df["prophet\_pred"]

mape\_score = mean\_absolute\_percentage\_error(y\_true, y\_pred) \* 100

smape\_score = smape(y\_true, y\_pred)

# Classification

lob\_df["call\_label"] = create\_classification\_label(lob\_df["call\_volume"])

cls\_features = ["prophet\_pred", "day\_of\_week", "weekend", "month", "day\_of\_year",

"is\_holiday", "rolling\_mean\_3", "rolling\_mean\_7", "lag\_1", "lag\_2", "lag\_3"]

X\_cls = lob\_df[cls\_features]

y\_cls = lob\_df["call\_label"]

split = int(len(lob\_df) \* 0.9)

X\_train, X\_test = X\_cls.iloc[:split], X\_cls.iloc[split:]

y\_train, y\_test = y\_cls.iloc[:split], y\_cls.iloc[split:]

cls\_model = LGBMClassifier()

cls\_model.fit(X\_train, y\_train)

y\_pred\_cls = cls\_model.predict(X\_test)

report = classification\_report(y\_test, y\_pred\_cls, output\_dict=True)

results[lob] = {

"prophet\_model": model,

"prophet\_params": best\_params,

"mape": mape\_score,

"smape": smape\_score,

"classification\_report": report

}

print(f"✅ {lob} | MAPE: {mape\_score:.2f}% | SMAPE: {smape\_score:.2f}%")

# ✅ Done

from datetime import timedelta

# Forecast next 7 days

for lob, lob\_df in lob\_groups.items():

last\_date = lob\_df["date"].max()

future\_dates = pd.date\_range(start=last\_date + timedelta(days=1), periods=7, freq="D")

future\_df = pd.DataFrame({"date": future\_dates})

# Copy latest values for lag features

latest\_data = lob\_df.set\_index("date").iloc[-7:]

for lag in [1, 2]:

future\_df[f"lag\_{lag}"] = latest\_data["call\_volume"].shift(lag).values[-1]

# Rebuild full feature set

future\_df["day\_of\_week"] = future\_df["date"].dt.dayofweek

future\_df["weekend"] = future\_df["day\_of\_week"].isin([5, 6]).astype(int)

future\_df["month"] = future\_df["date"].dt.month

future\_df["day\_of\_year"] = future\_df["date"].dt.dayofyear

future\_df["is\_holiday"] = future\_df["date"].isin(holidays.US(years=[2022])).astype(int)

future\_df["rolling\_mean\_3"] = latest\_data["call\_volume"].rolling(3).mean().values[-1]

future\_prophet = future\_df.rename(columns={"date": "ds"})

future\_pred = results[lob]["prophet\_model"].predict(future\_prophet)

forecast\_values = future\_pred[["ds", "yhat", "yhat\_lower", "yhat\_upper"]]

forecast\_values["lob"] = lob

print(f"\n📆 7-Day Forecast for LOB {lob}:\n")

print(forecast\_values)