

Kafka Crash Prediction Model

Model Processes

1. Data Preprocessing

System and Kafka metrics are collected in real time via Prometheus every 5 seconds. Each data point includes metrics such as ``messages_in``, ``bytes_in``, ``cpu_usage``, ``memory_usage``, and ``disk_usage``. Raw values are filtered for ``None`` entries and converted to appropriate types. Timestamps are standardized to ensure consistent time-series alignment.

2. Feature Engineering

To capture short-term trends, I maintain a rolling history of the last hour (360 data points). From this history, statistical features such as moving averages, deltas, and standard deviations are calculated. In addition to current values, these derived features provide temporal context to the model.

Prophet is used to forecast three critical metrics: ``messages_in``, ``cpu_usage``, and ``memory_usage``. The forecasts are processed to extract trend components (e.g., increasing or decreasing), and these trend deltas are included as additional features for the classifier.

3. Model Training

I use a LightGBM classifier to learn patterns that precede Kafka crashes. The classifier is trained on labeled data under both normal and stressed conditions. The model learns a binary classification task (crash vs. no crash) based on a combination of real-time and historical metrics.

Training is scheduled periodically (e.g., every 5 minutes) using APScheduler to allow the model to adapt as new data becomes available.

4. Prophet Forecasting

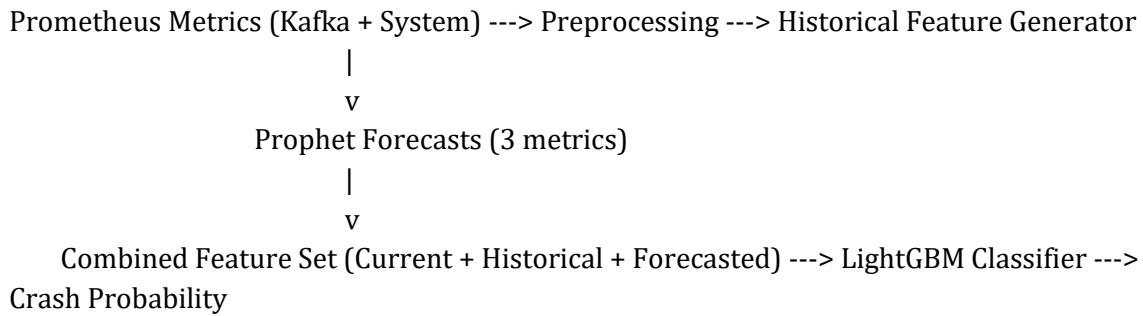
Prophet is trained independently for each target metric using the latest time series data. The forecast horizon matches the monitoring frequency, and the first-step forecast along with the trend slope are used as features for crash prediction.

5. Prediction

At each 5-second interval, the model computes the crash probability using both current metrics and the short-term forecast trends. These predictions are smoothed using a moving average to avoid alert spikes due to noise. Depending on the probability and its recent growth trend, severity levels (``info``, ``low``, ``medium``, ``high``, ``critical``) are determined, and alerts are triggered with contextual information.

Model Details

Flow Diagram:



Classifier:

- Model: LightGBMClassifier
- Inputs: 30+ features from historical window and forecast trends
- Target: Binary label (0 = no crash, 1 = crash)
- Training Frequency: Periodic (e.g., 5 minutes)
- Evaluation: Trained on labeled historical data under different system loads

Prophet:

- Separate models for: `messages_in`, `cpu_usage`, `memory_usage`
- Extracts: 1-step ahead forecast, trend slope
- Update frequency: matches the 5-second monitoring interval

Model Evolution









Initially, I began with a Linear Regression model to predict CPU usage and Kafka traffic. However, this model lacked the capacity to handle non-linear interactions and failed to generalize across variable loads.

Next, I switched to a LightGBM Regressor, which improved prediction accuracy significantly. However, I had to manually define thresholds (e.g., CPU > 85%) to detect crash conditions, which wasn't scalable.

Finally, I redesigned the model as a LightGBM Classifier, trained with actual crash labels. This classifier was further enhanced by incorporating Prophet-based trend forecasts as inputs. The result is a more robust system that not only captures current system behavior but also anticipates near-future conditions to provide early warnings. This version has shown the best precision in identifying crash risk with minimal false positives.

Model Result

```
=== Training Results ===
Average metrics (excluding invalid folds):
auc: 0.750 (from 2 folds)
balanced_accuracy: No valid folds for evaluation
precision: 0.500 (from 2 folds)
recall: 0.500 (from 2 folds)
f1: No valid folds for evaluation
ap: 0.683 (from 2 folds)

 Status: NORMAL | Crash risk: 0.0% | CPU: 2.0% | Memory: 88.1%
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 Status: NORMAL | Crash risk: 0.0% | CPU: 2.1% | Memory: 88.2%
 Status: NORMAL | Crash risk: 0.0% | CPU: 1.8% | Memory: 88.2%
```

```
=== Model Training Phase ===

Fold 1:
Train range: 0-7147
Test range: 7147-14294
Train class distribution: crash
0    7147
Name: count, dtype: int64
Test class distribution: crash
0    4535
1     2612
Name: count, dtype: int64
Added missing class to training set
Error generating classification report: 'f1'
Fold 1 completed

Fold 2:
Train range: 0-14294
Test range: 14294-21441
Train class distribution: crash
0    11682
1     2612
Name: count, dtype: int64
Test class distribution: crash
1     5030
0     2117
Name: count, dtype: int64
Error generating classification report: 'f1'
Fold 2 completed

Fold 3:
Train range: 0-21441
Test range: 21441-21441
Train class distribution: crash
0    13799
1     7642
Name: count, dtype: int64
Test class distribution: Series([], Name: count, dtype: int64)
Test set has only one class - skipping evaluation callbacks
Skipping evaluation - test set has only one class
Fold 3 completed
```