

Stay Tuned with your Model

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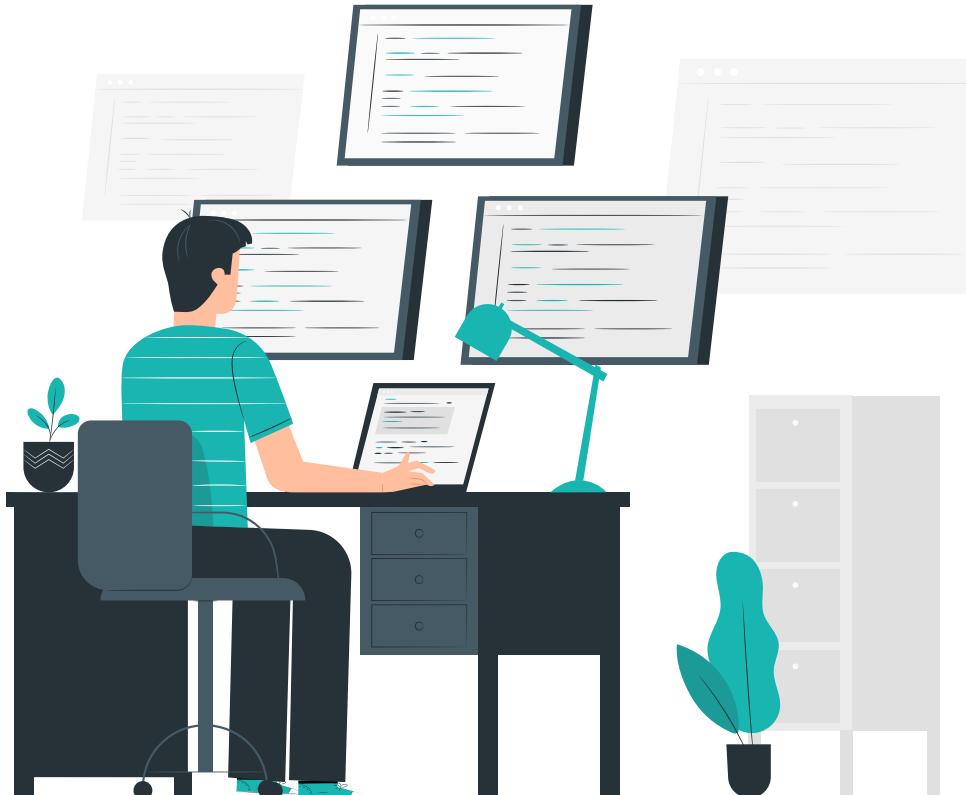


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Motivation

What happens to a Model after deployment?
How does Model performance monitoring help?



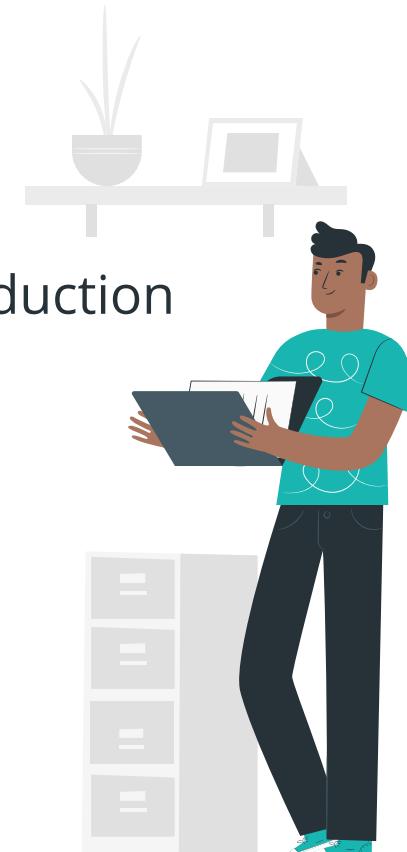
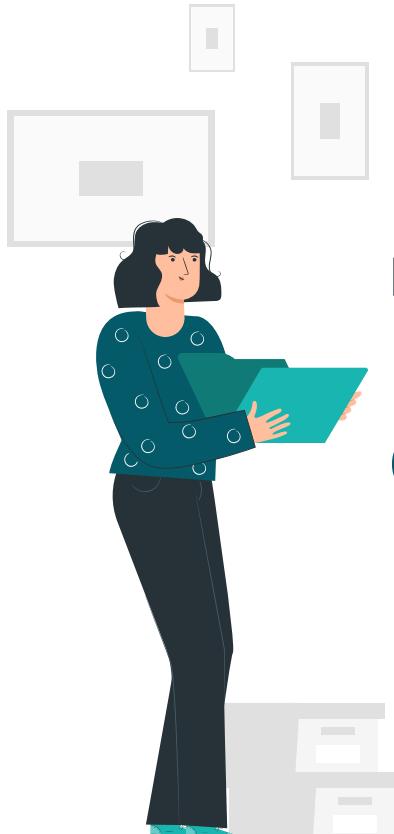
Motivation

Fact

Models start to degrade once in production

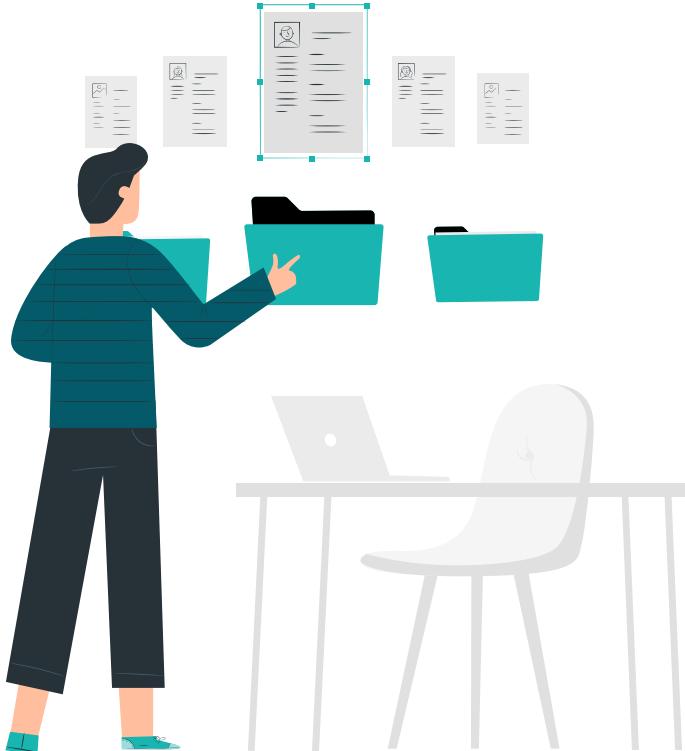
Goal

- How to detect
- Which features to look for
- What strategies to take



Concept Drift

Description & Types



Types of Drift

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Sudden Drift

An abrupt change where one concept replaces another.

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Gradual Drift

As time passes the probability of sampling from one concept increases while another decreases

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Incremental Drift

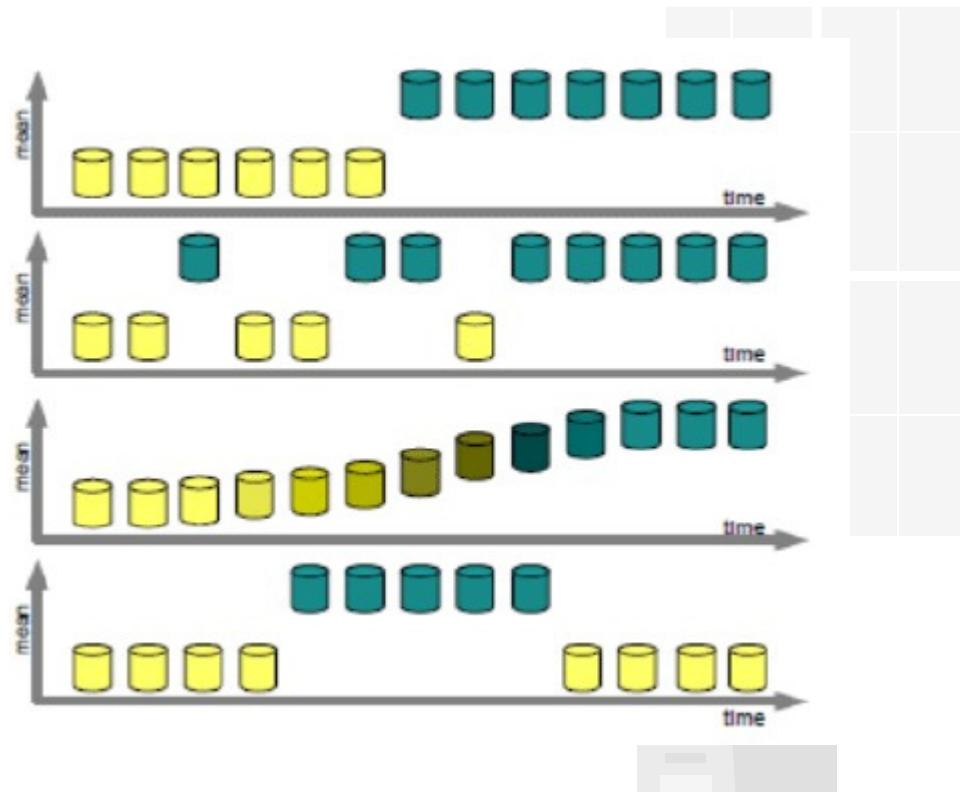
A type of gradual drift. A stepwise transition from one concept to another.

04

Recurring Concepts

Previously active concepts reappear after some time

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Metrics to capture Drift



PSI

Population Stability Index



Somers' D

Measures predictive ability



Population Stability Index (PSI)

Population stability index (PSI) is a metric to measure how much a variable has shifted in distribution between two samples or over time. It is widely used for monitoring changes in the characteristics of a population and for diagnosing possible problems in model performance.

Formula:

$$PSI = \sum \left((\%Actual - \%Expected) \times \ln \frac{\%Actual}{\%Expected} \right)$$

Rule of thumb:

PSI Value	Inference	Action
Less than 0.1	Insignificant	No action required
0.1 -0.25	change Some	Check other metrics (Somers' D)
Greater than 0.25	Major Shift in population	Need to delve deeper

Data and Demonstration

Brief intro to data set and Visualizations



Demonstration

In order to demonstrate that PSI captures the change in Data distribution,
We manually manipulated a feature each day

Day 1 -Increased % of Cars with Number of Doors = 2

Day 2 -Decreased % of Cars with Low Safety

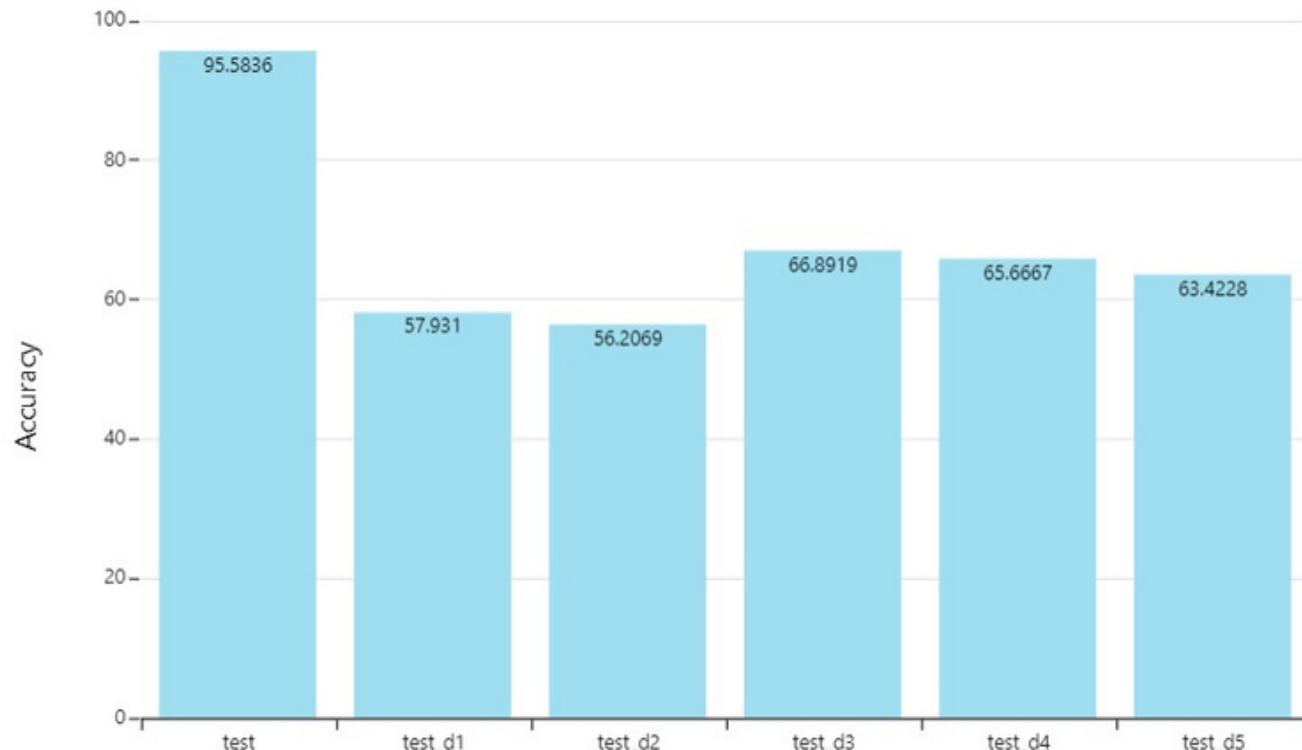
Day 3 -Increased % of Cars with Very high buying price

Day 4 -Decreased % of Cars with Number of People = 4

Day 5 -Increased % of Cars with Very high Maintenance

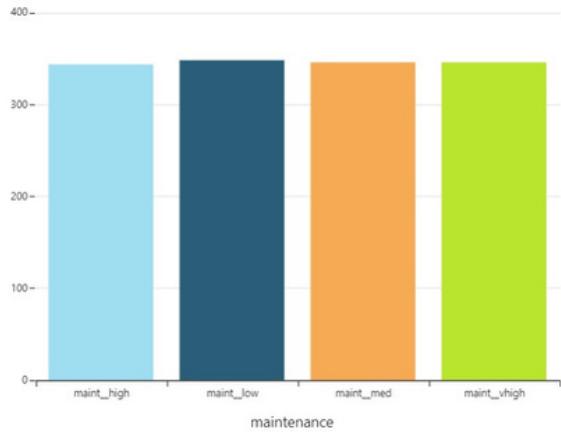
Accuracy decreased with change in data distribution

Accuracy By Data Set

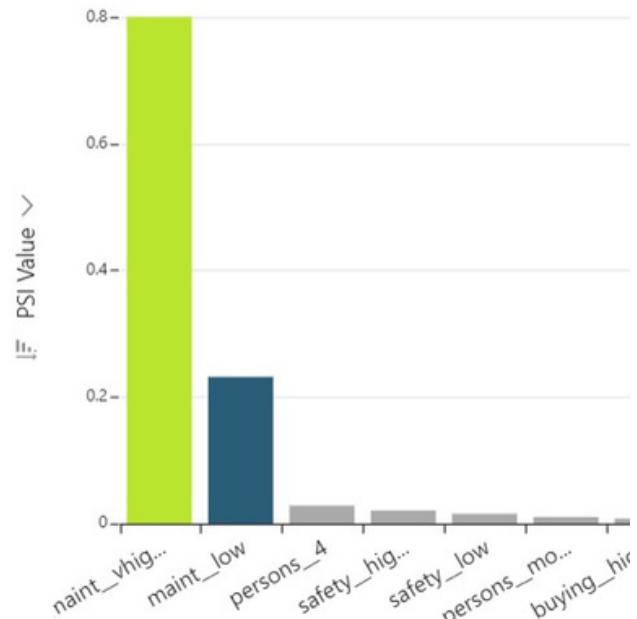
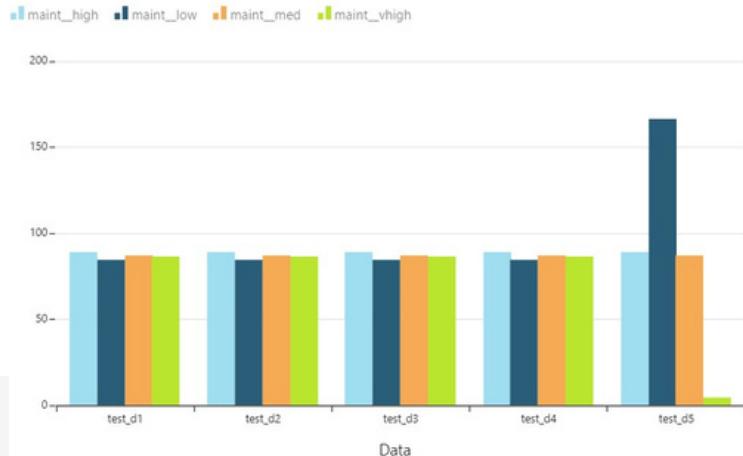


Quicksight dashboard to identify changed columns

Distribution of Maintenance Categories in Training Data



Distribution of Maintenance Categories by Data Set

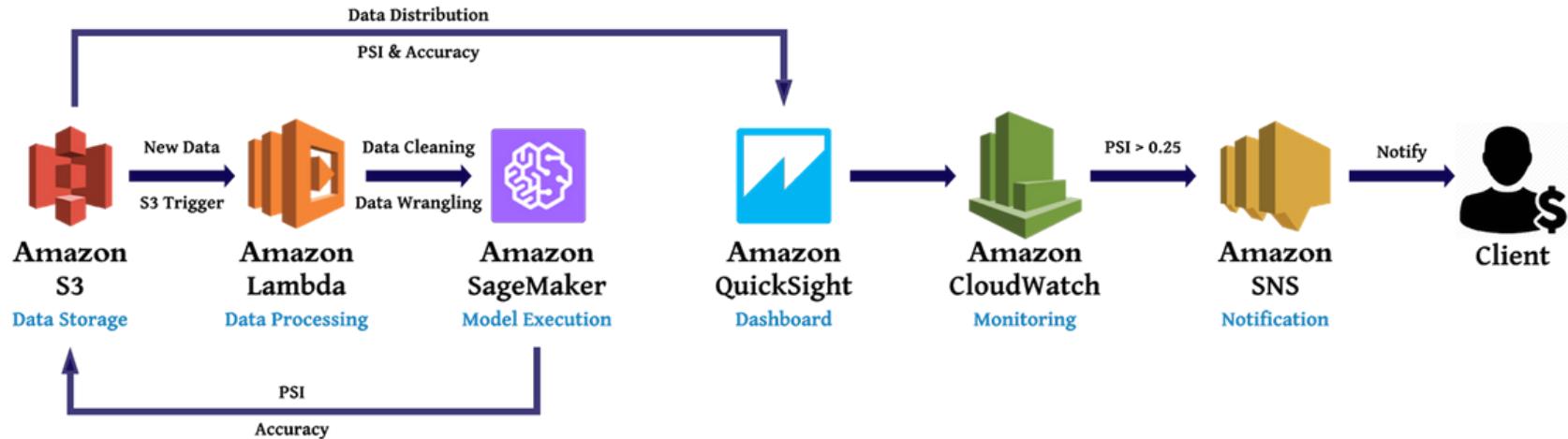


AWS Architecture

What modules are needed?
Upgrade scope?



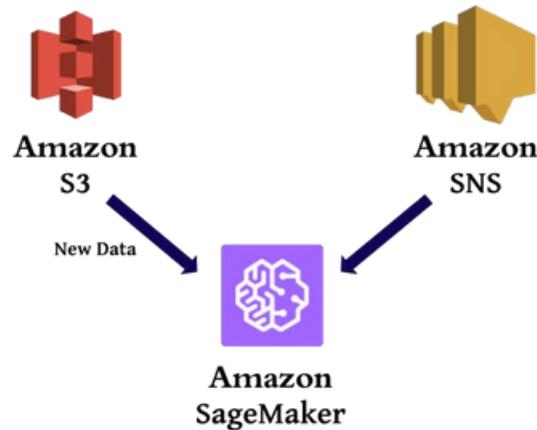
Architecture



Future

Current architecture supports to the stage of notifying the stakeholders about the change in Data distributions. This can be extended to model retuning as per business requirements and policies.

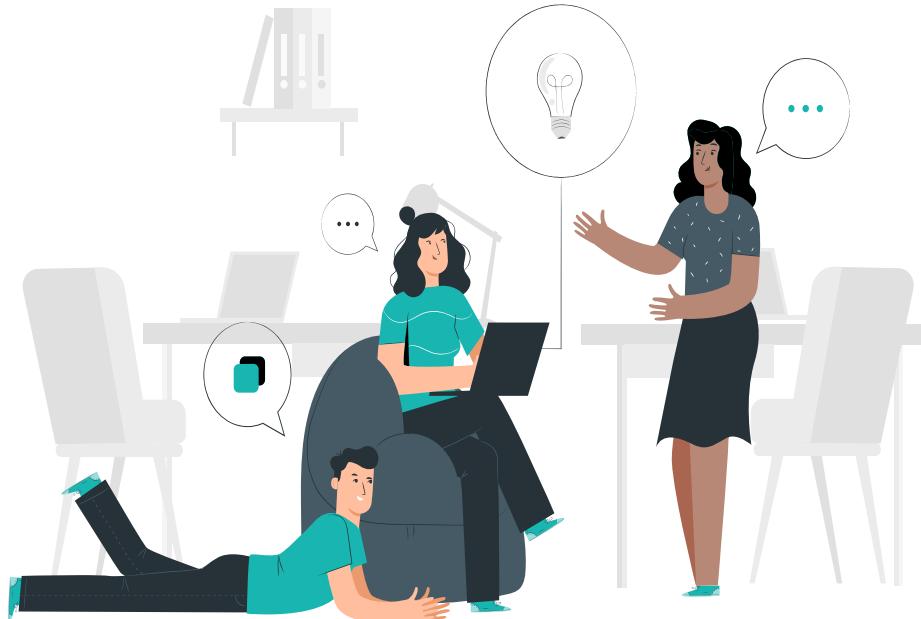
Below is the Extended Architecture to trigger model retuning



Next Steps & Use Cases

Part 1 -Once we detect the significant change in data distributions, what should we do next?

Part 2 -Real business cases that can apply our method.





Next Steps



Modify Feature

Considering Feature
Importance



Retune Model

1. Fixed Training Window
2. Variable Training Window

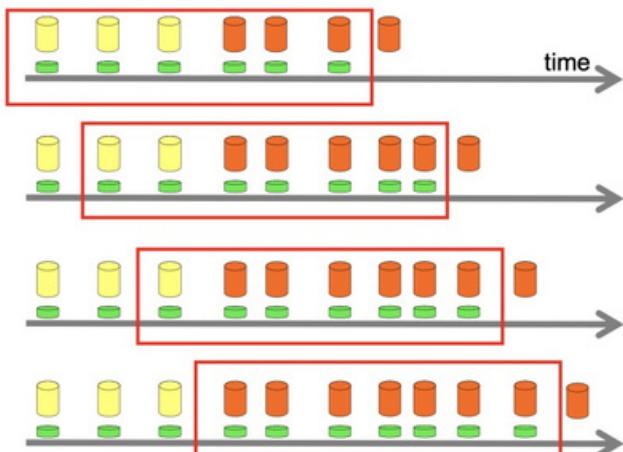
Next Steps

1. Feature Modification

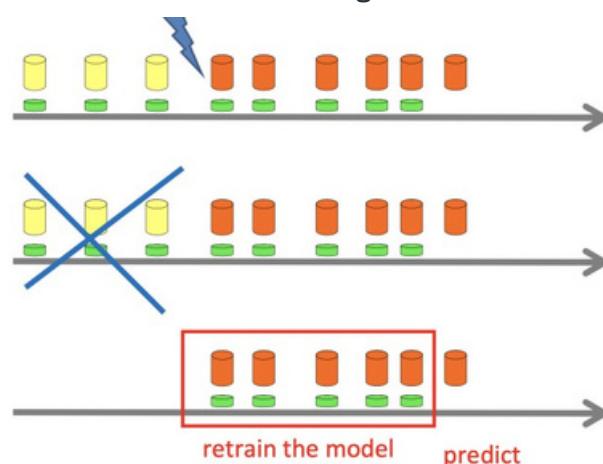
Creating new features to capture the new variation in data.

2. Model Retuning

- Fixed Training Window



- Variable Training Window



Use Cases

