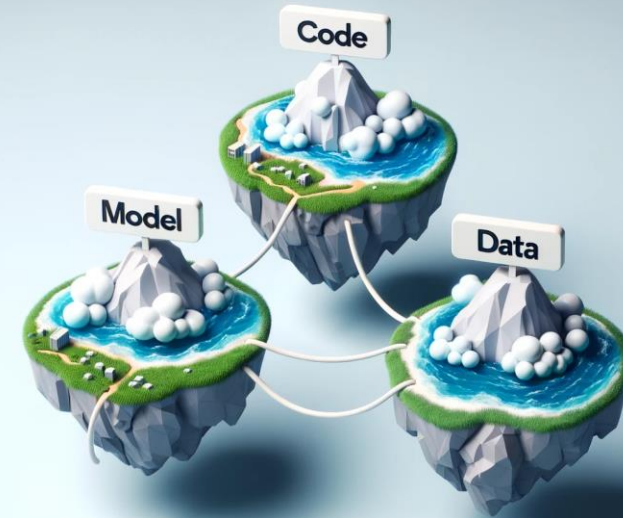




# Model Drift

Dr. Harald Stein  
Feb 2024

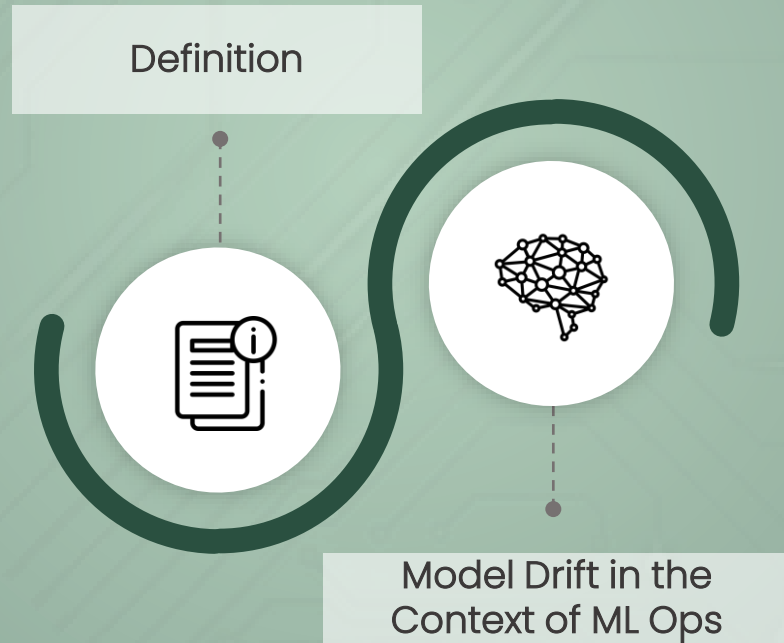


# Agenda

- **What is Model Drift?**
- **Types and Triggers**
- **Drift Detection techniques**
- **Infrastructure for monitoring, alerting, retraining**
- **Examples with classification and segmentation**



# What is Model Drift?



# What is Model Drift?

... occurs when the statistical properties of input features or target variable, which predictive model is trying to estimate, change over time.

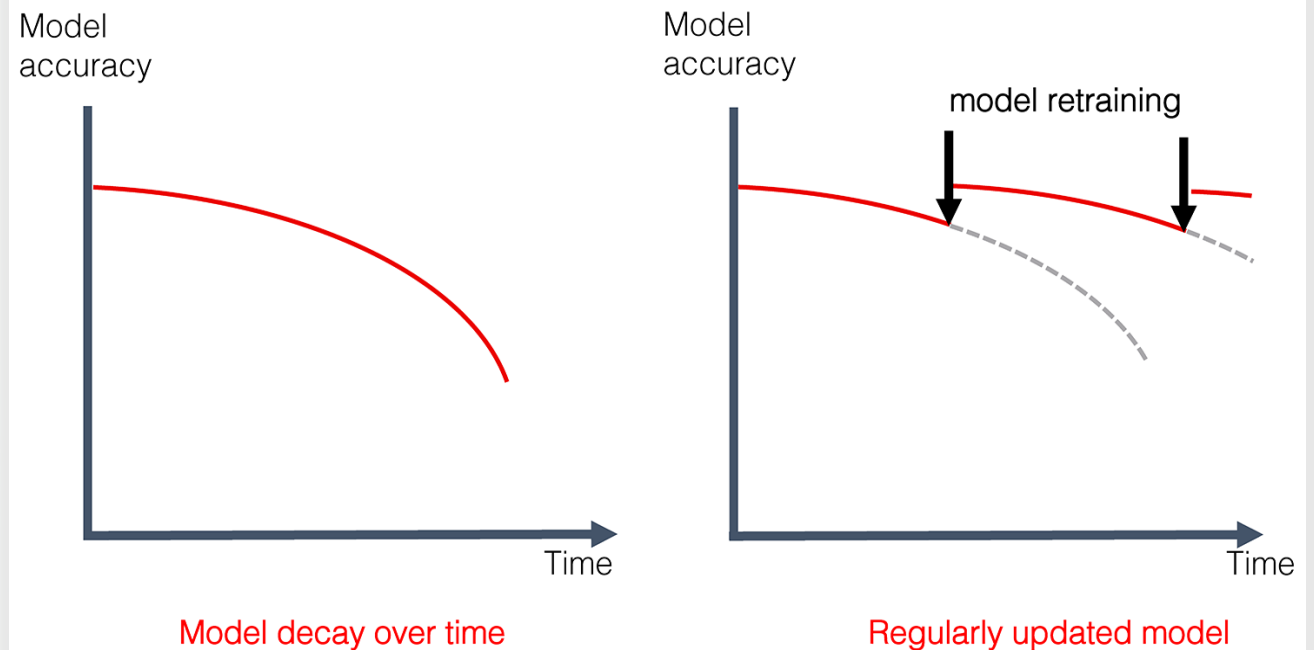
This leads to decrease in model accuracy and effectiveness, as learned patterns no longer represent current situation.

## Causes

- Changes in underlying data patterns
- due to various factors like
  - evolving trends
  - user behavior
  - or environmental shifts

## Recognizing and addressing model drift

- by regularly updating the model
- is crucial for maintaining reliability, accuracy of machine learning models in real-world applications



# Model Drift in the Context of MLOps

Model drift is a critical factor in MLOps, emphasizing the need for continuous monitoring and updating of ML models in production.

## Lifecycle Management

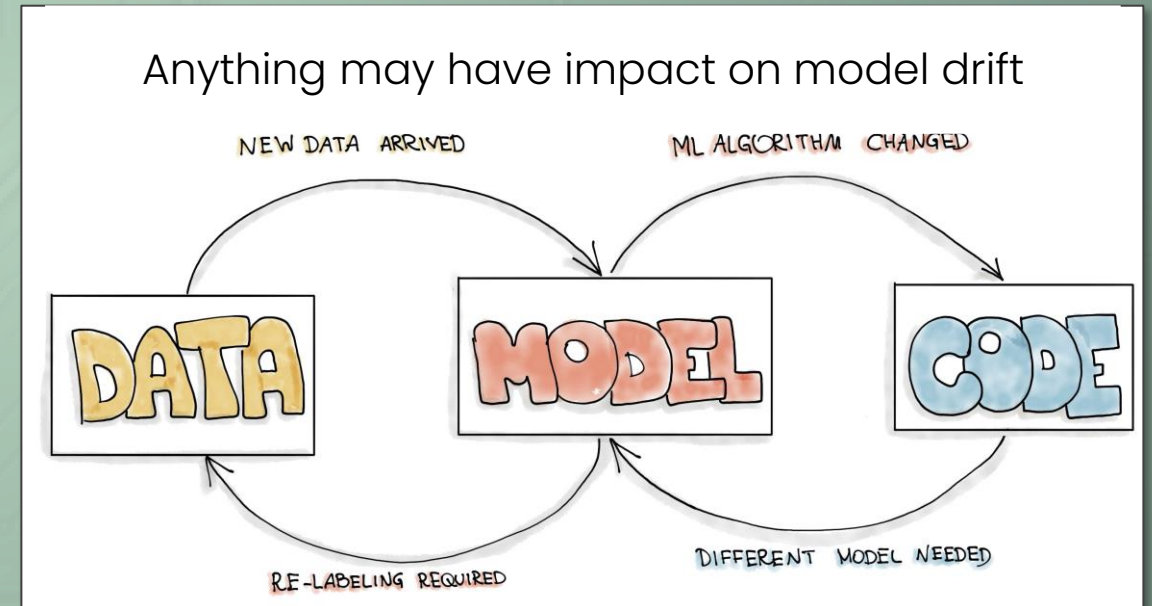
MLOps involves

- ... entire lifecycle of a model
- from development to deployment and maintenance
- where identifying, addressing model drift is a key maintenance activity.

## Automated Responses

MLOps frameworks often include

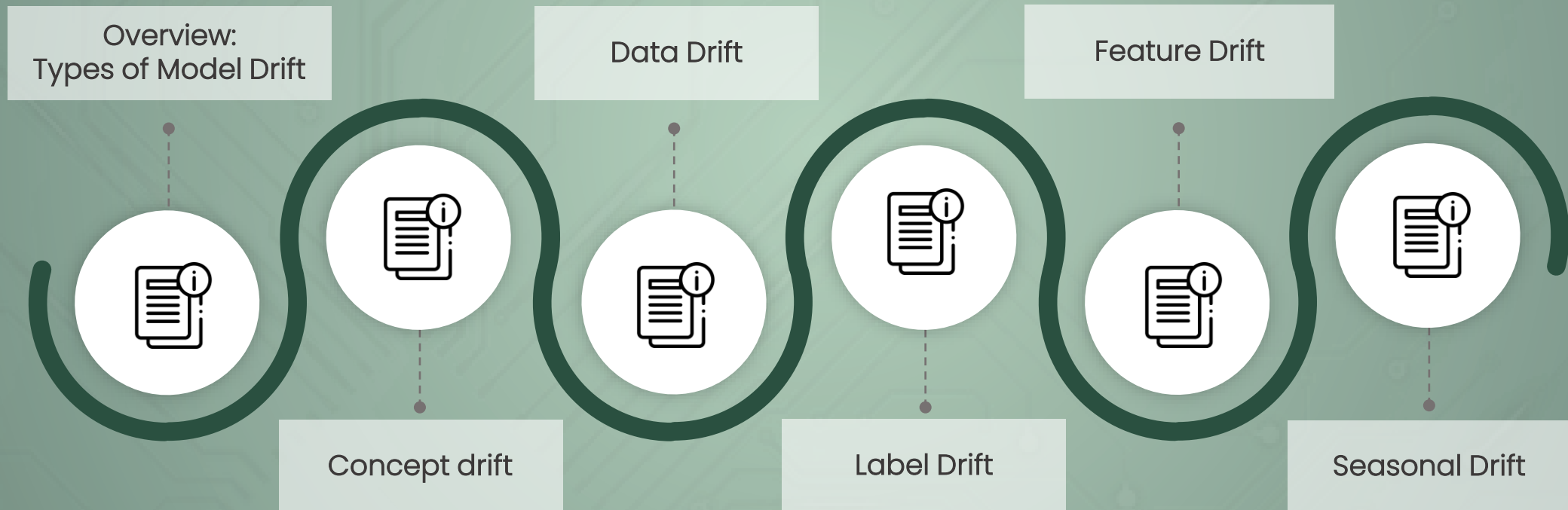
- ... automated systems to detect and respond to model drift
- ensuring models remain accurate and relevant.





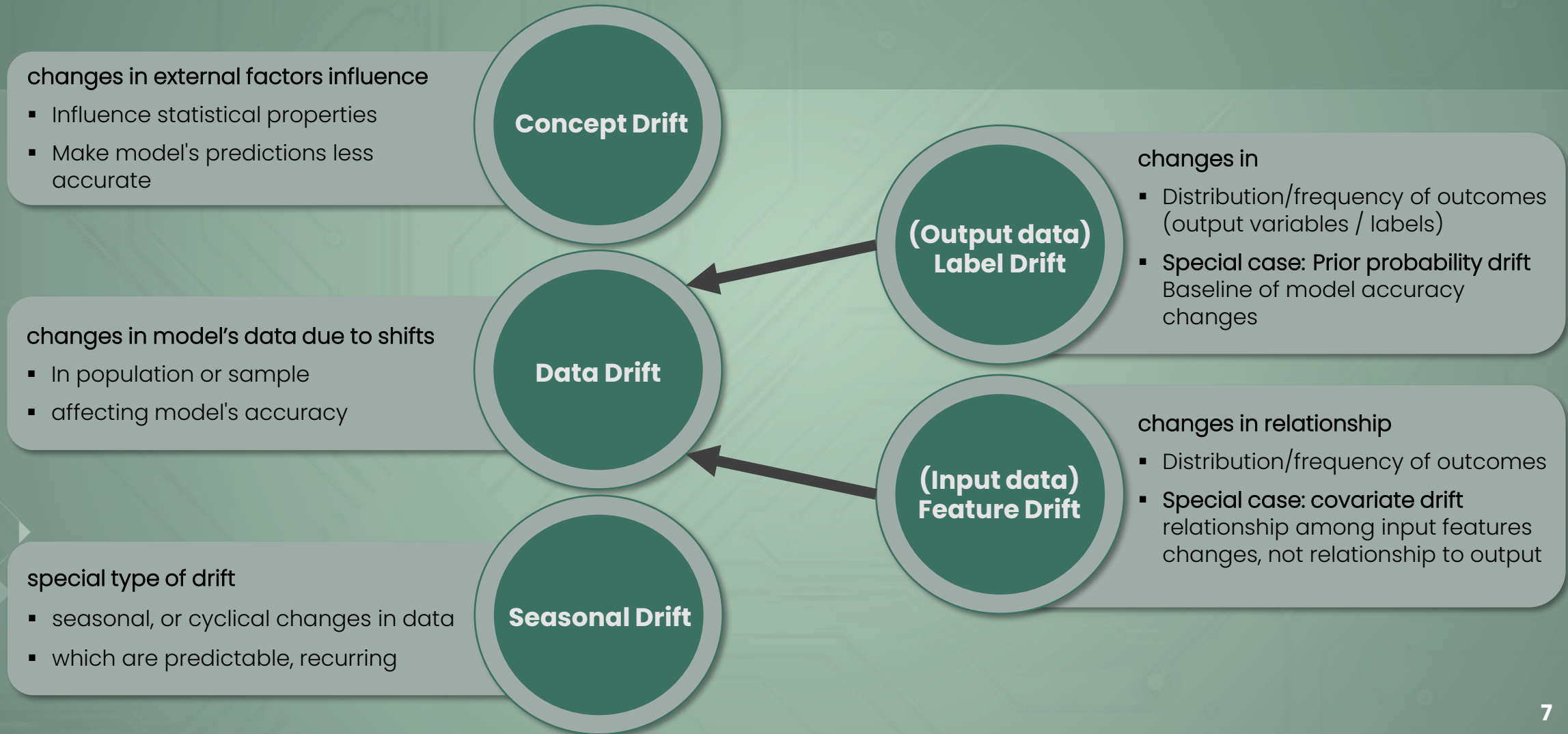
# Types and Triggers

... include concept, data, label and feature drift, and are often triggered by changes in external factors, evolving user behaviors, or alterations in the underlying data distribution



# Overview: Types of Model Drift

... all of them may lead to decrease in model performance



# Concept drift

... occurs due to external factors that influence statistical properties

## Causes

- Evolving consumer behaviors, social trends
- Changes in economic conditions, technology

## Impact

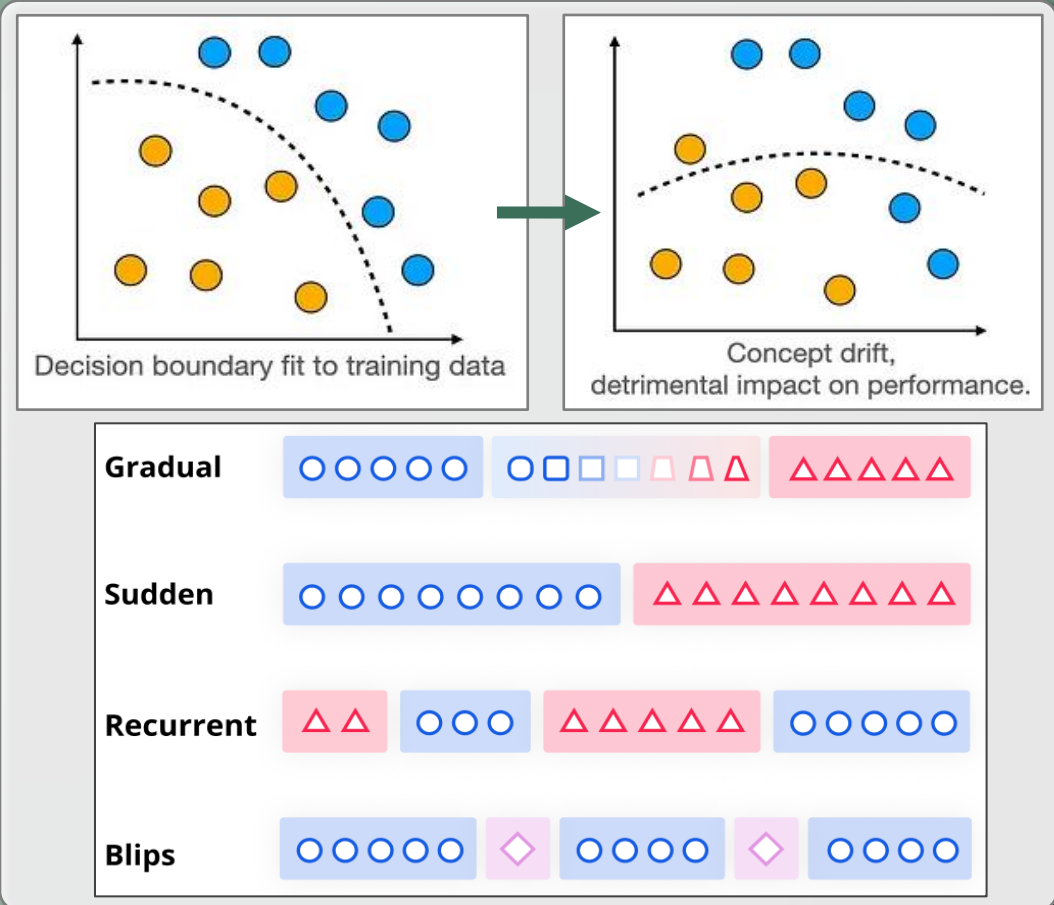
- Decreased model accuracy and predictive reliability.
- Misalignment between learned patterns and current data.

## Detection

- Monitoring performance metrics.
- Analyzing prediction errors over time.

## Response

- Regular model retraining with updated data.
- Implementing adaptive learning algorithms.





# Gradual Concept Drift

Gradual or incremental drift is expected phenomenon that explains how world's changes lead to models' aging and decline in quality

## Examples of Gradual Drift

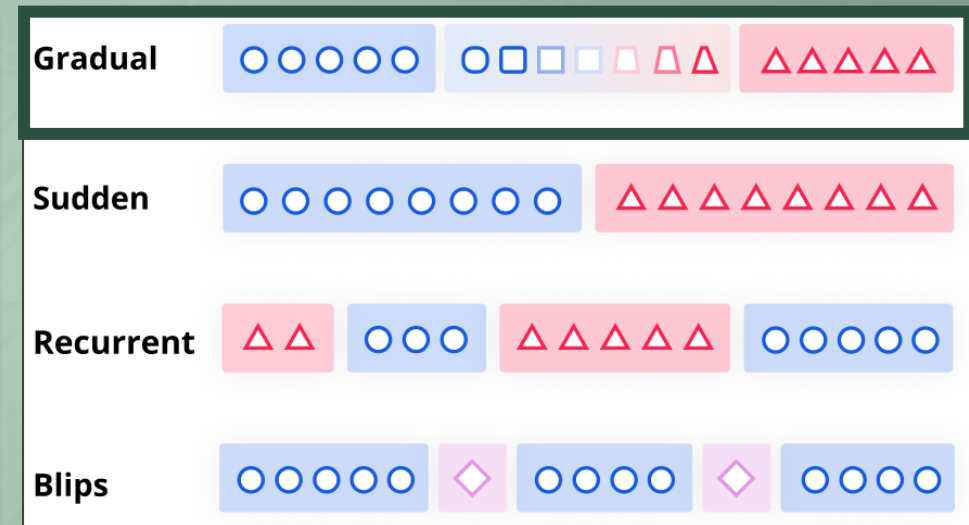
- New competitors alter consumer choices, impacting sales forecasts.
- Macroeconomic shifts redefine credit risk, affecting scoring models.

## Observing Shifts

- Shifts detected at individual feature level in tasks like churn prediction.
- Stable feature distribution, but increasing target class proportion in certain ranges signals new patterns.

## Model Lifespan and Updates

- Model aging varies
- testing with historical data can guide update frequency.
- Retraining intervals ensure models accuracy.



# Sudden concept drift

Sudden or drastic external changes are easily noticeable disruptions

## Pandemics

COVID-19 pandemic exemplified such changes, significantly altering mobility and shopping patterns.

## Financial Models

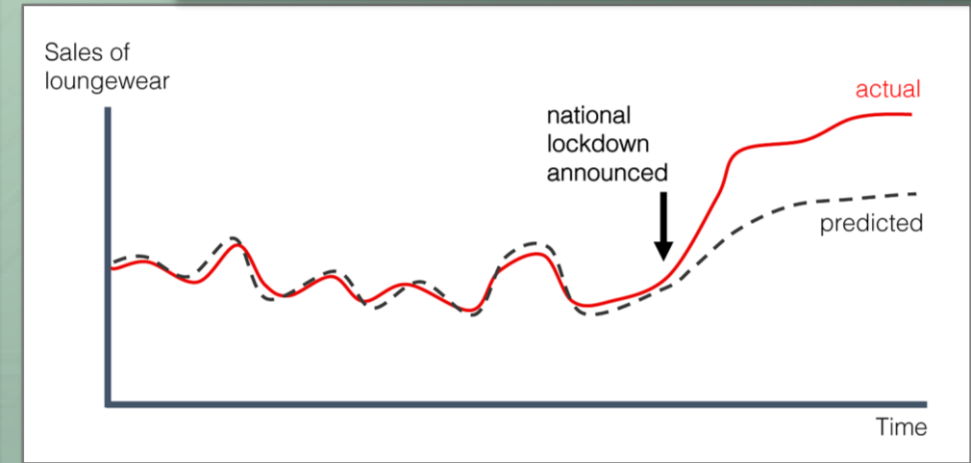
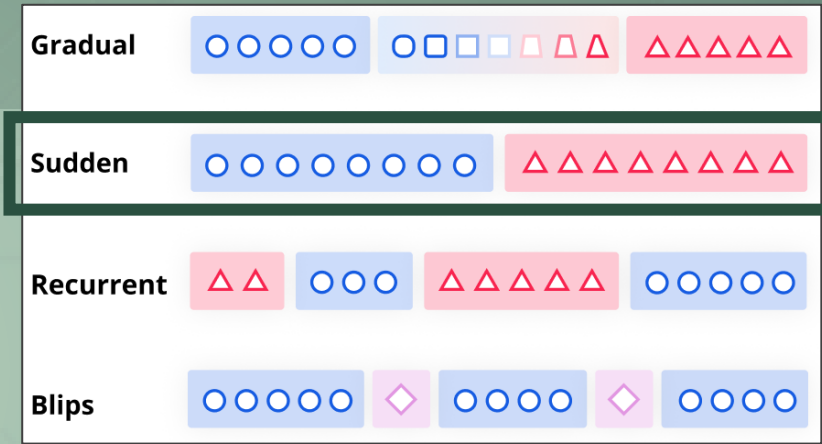
Interest rate adjustments by central banks can immediately render existing financial models outdated.

## Manufacturing Processes

Updates in production lines necessitate new predictive maintenance strategies due to changes in equipment failure modes.

## Digital Platforms

Major app interface overhauls make historical user interaction data obsolete, requiring a reevaluation of user journey models.



# Data Drift

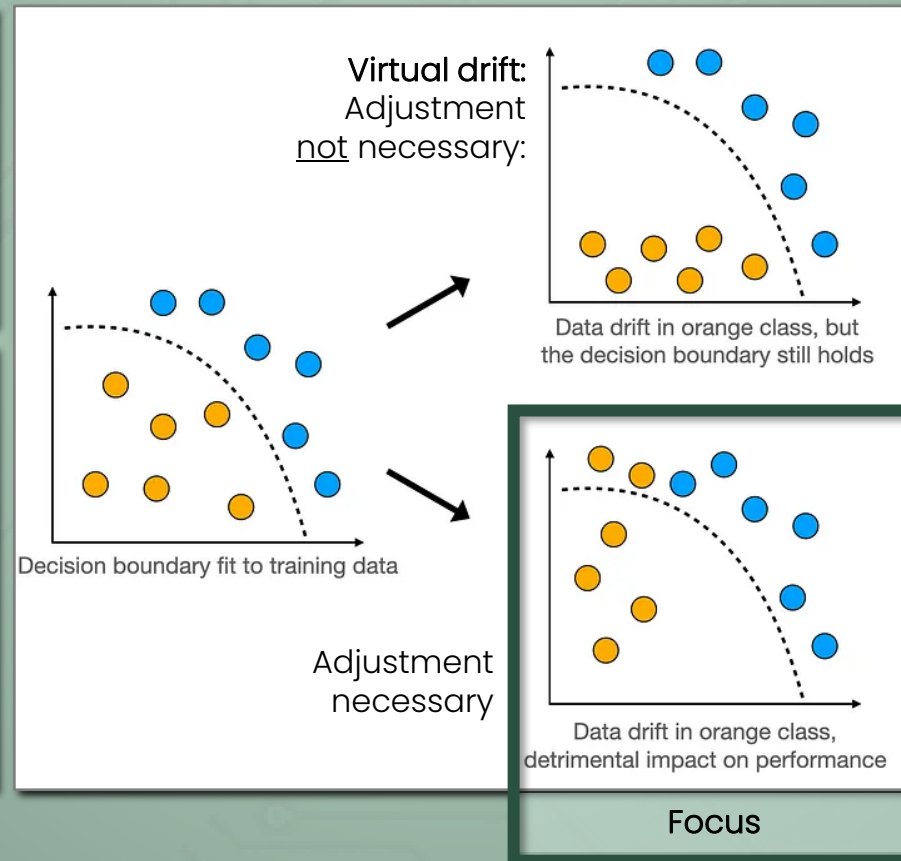
... change in input data's distribution or characteristics over time, affecting model performance.

## Causes: Shift or changes in

- ... user behavior or preferences.
- ... data collection methods.
- ... population demographics.

## Impact

- Decreased model prediction accuracy



## Detection by regular monitoring of

- ... changes in data statistics, distributions.
- ... model inputs compared with training data.

## Response

- Retraining model with current data.
- Using different input features

# Label Drift as kind of data drift

... changes in the distribution or definition of labels in the dataset over time

## Causes: Changing data due to

- ... changing societal norms or definitions.
- ... evolving user behavior or preferences.
- ... modifications in labeling criteria or errors.

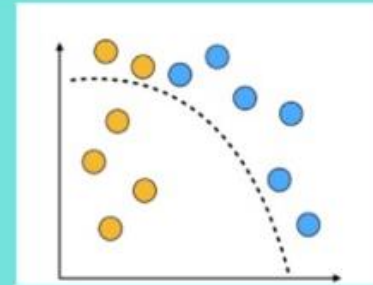
## Label Drift, example: Fashion Trend Forecasting

- Trend prediction model may suffer from label drift
- as certain styles gain or lose popularity.

## Prior Probability Drift

- **Email Spam Filters:**  
Outbreak of spam emails due to new spamming technique, prior probability of any email being spam increases
- **Loan Default Prediction:**  
During economic downturn, base rate of loan defaults may rise, representing shift in prior probability of default.

## Data Drift\*



- Data changes
- Fundamental relationships do not change

Special case  
Prior probability drift  
Base rate changes

## Label Drift

- Output data shifts
- $P(Y)$  Changes

## Feature Drift

- Input data shifts
- $P(X)$  Changes

# Feature Drift as kind of data drift

... changes in relationship between input features and target variable over time.

## Causes

- Evolution in underlying data patterns.
- Technological advancements impacting data collection.
- Shifts in environmental or socio-economic factors.

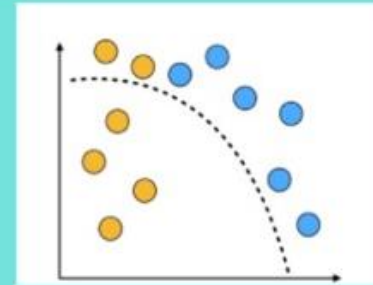
## Feature Drift, example: Consumer Behavior Tracking

- Online retailer's customer segmentation model may face feature drift
- as consumer spending patterns shift due to changing economic conditions.

## Covariate Drift, example: Ad Click Prediction

- Advertising model sees shift in type of users
- e.g., younger demographics
- clicking on ads without change in click-through rate

## Data Drift\*



- Data changes
- Fundamental relationships do not change

## Label Drift

- Output data shifts
- $P(Y)$  Changes

## Feature Drift

- Input data shifts
- $P(X)$  Changes

## Special case

### Covariate drift

Features change without impact on output



# Seasonal Drift

... predictable and recurring changes in data patterns due to seasonal factors

## Causes

- Regular events: holidays, weather changes, economic cycles, etc.
- Season-specific consumer behaviors or activities

## Impact

- Temporary shifts in model performance aligned with seasons.
- Potential misinterpretation as long-term trends

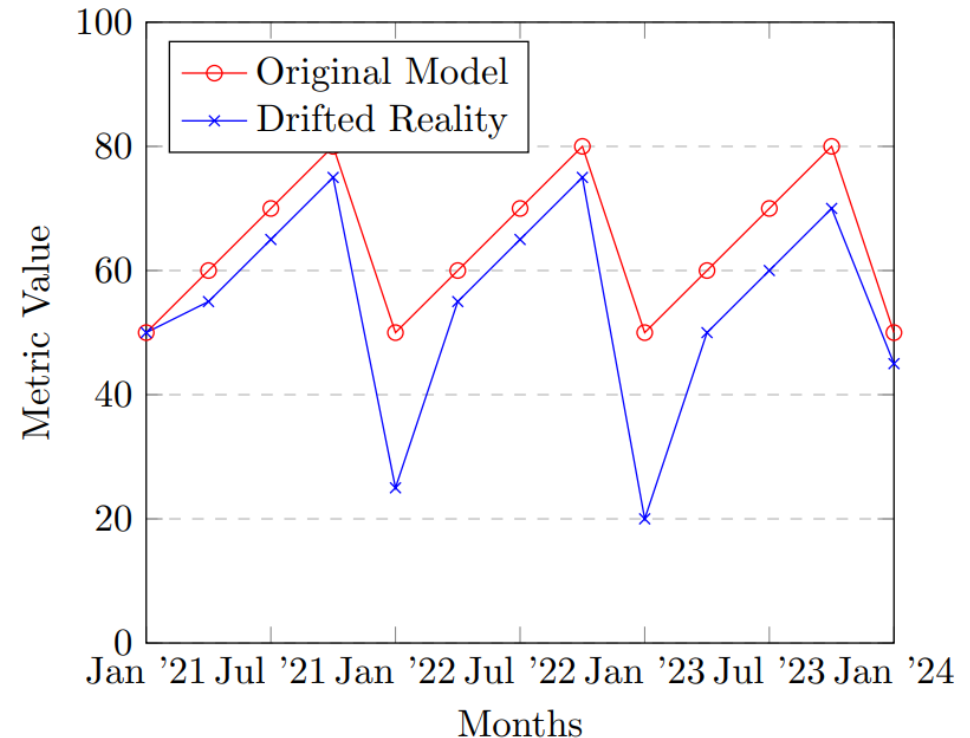
## Detection

- Analyzing data trends over multiple seasonal cycles.
- Comparing model performance across different times of year.

## Response

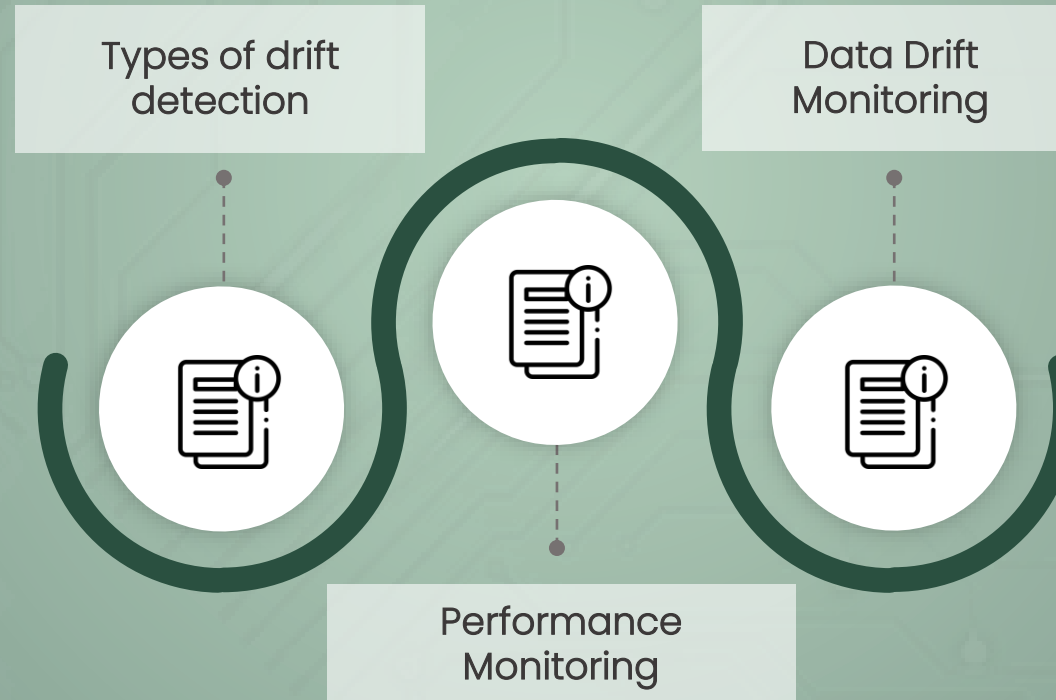
- Incorporating seasonal factors into model design.
- Using time series analysis techniques for better prediction.

Comparison of Original Model vs. Drifted Reality Over Three Years



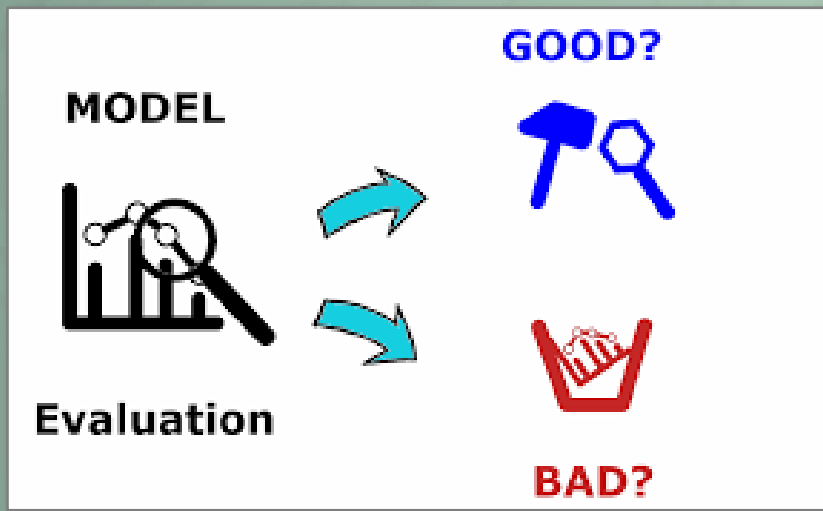
# Drift Detection techniques

... for supervised and unsupervised learning



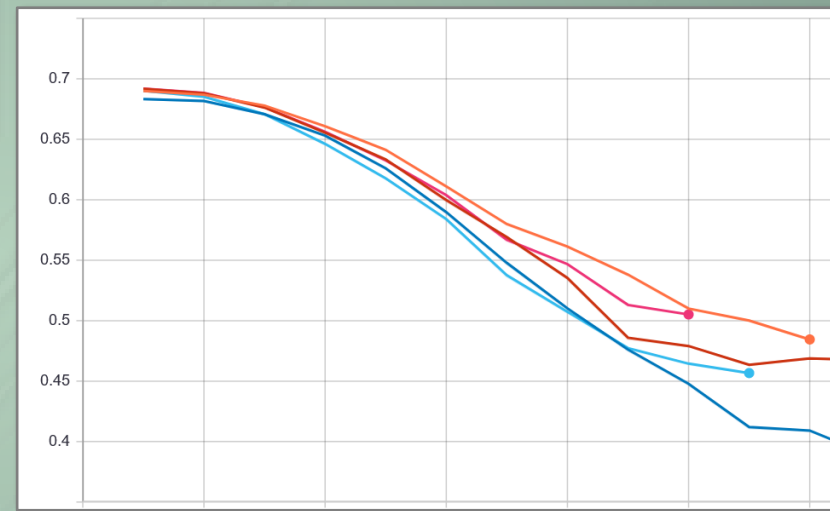
# Types of drift detection

... groups of techniques used to identify and manage different types of data drift in machine learning models



Supervised learning evaluation:

- accuracy decrease & false positives increase



Comparison with baseline data distribution:

- Population Stability Index
- Kolmogorov-Smirnov test
- Kullback-Leibler divergence

# Detecting Label Drift in Classification Models

... occurs when distribution of classes/labels in dataset changes over time

## Example spam detection model

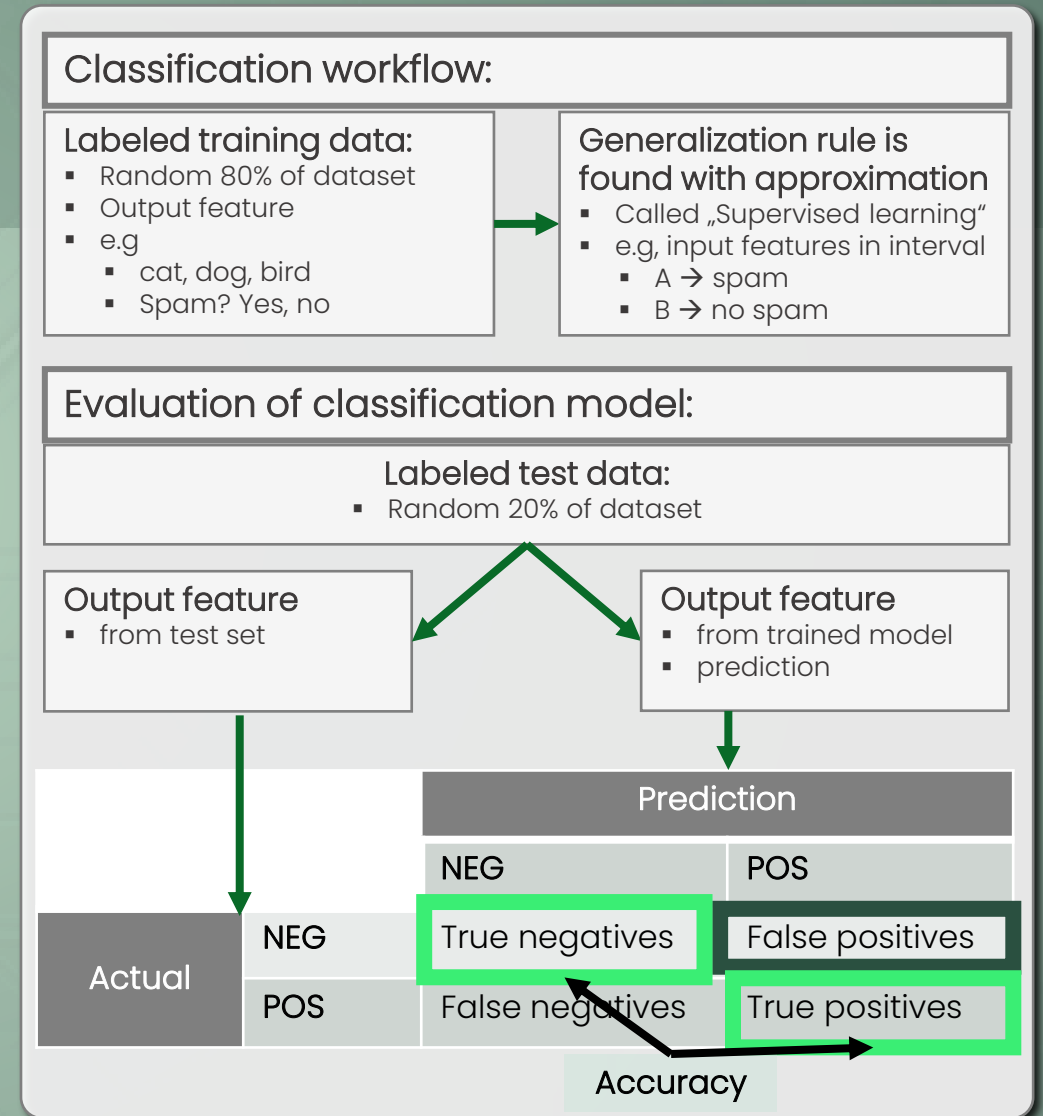
- sudden increase in legitimate emails classified as spam (false positives)
- coupled with decrease in overall accuracy could signal label drift

## Tracking Accuracy and False Positives

- **Accuracy:** Drop in overall accuracy can indicate label drift, especially if model was previously well-calibrated.
- **False Positives:** Increase in false positive rates can be strong indicator of label drift in specific classes.

## Actionable Responses

- **Data Analysis:**  
Examine distribution of classes in recent data vs. training set.
- **Model Update:**  
Retraining model with updated data reflecting new class distribution.



# Detecting Label Drift in Classification Models

Example spam detection model. sudden increase in legitimate emails being classified as spam (false positives) coupled with decrease in overall accuracy could signal label drift

Example numbers: Ex ante		Prediction	
		NEG	POS
Actual	NEG	True negatives: 30%	False positives: 10%
	POS	False negatives: 20%	True positives: 40%

Example numbers: Ex post		Prediction	
		NEG	POS
Actual	NEG	True negatives: 25%	False positives: 15%
	POS	False negatives: 30%	True positives: 30%

False positives:	10% → 15%
Accuracy:	70% → 55%



# Population Stability Index (PSI)

... is statistical measure for determining stability of model's population over time. It quantifies how much input variables' distribution has shifted: training dataset ⇔ new dataset.

- PSI is calculated by dividing population into buckets
- based on variable distribution and
- comparing distribution in each bucket between training and new datasets

$$PSI = \sum (\%_{actual} - \%_{expected}) \times \ln \frac{\%_{actual}}{\%_{expected}}$$

## Interpreting PSI

- Low PSI value (typically < 0.1) indicates little to no shift in population, suggesting stable model performance.
- Higher PSI values suggest significant shifts, indicating potential model drift, need for model recalibration

Input Feature, e.g.:  
income, size, speed

Score Range	Decile	Scoring% (A)	Training% (B)	A - B	ln(A/B)	PSI
>720	1	12%	11%	1%	0.09	0.001
671-720	2	11%	11%	0%	0.00	0.000
641-670	3	14%	12%	2%	0.15	0.003
611-640	4	12%	13%	-1%	-0.08	0.001
581-610	5	12%	11%	1%	0.09	0.001
551-580	6	10%	11%	-1%	-0.10	0.001
521-550	7	12%	13%	-1%	-0.08	0.001
491-520	8	6%	5%	1%	0.18	0.002
451-490	9	6%	7%	-1%	-0.15	0.002
< 451	10	5%	6%	-1%	-0.18	0.002
						0.013

Population Stability Index

# Kolmogorov-Smirnov (KS) test with Bonferroni correction

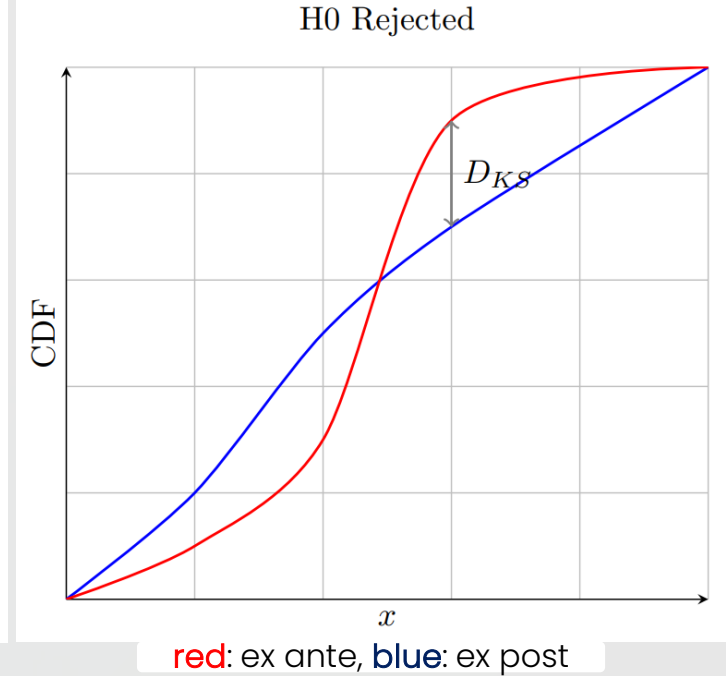
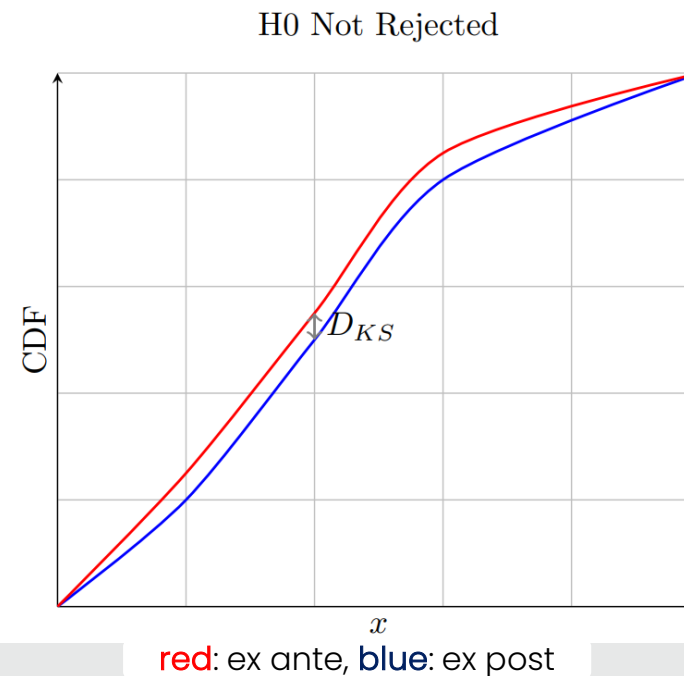
is non-parametric test used to compare distributions of two datasets which measures largest distance between cumulative distribution functions of two datasets.

## Null hypothesis ( $H_0$ )

- Distributions  $x, y$  come from same population
- If KS statistic has p-value  $< \alpha$ , reject  $H_0$

## Bonferroni correction

- Adjusts  $\alpha$  level to reduce false positives
- $\alpha_{\text{new}} = \alpha_{\text{original}} / n$ , where  $n$  = total number of feature comparisons



# Kullback-Leibler divergence

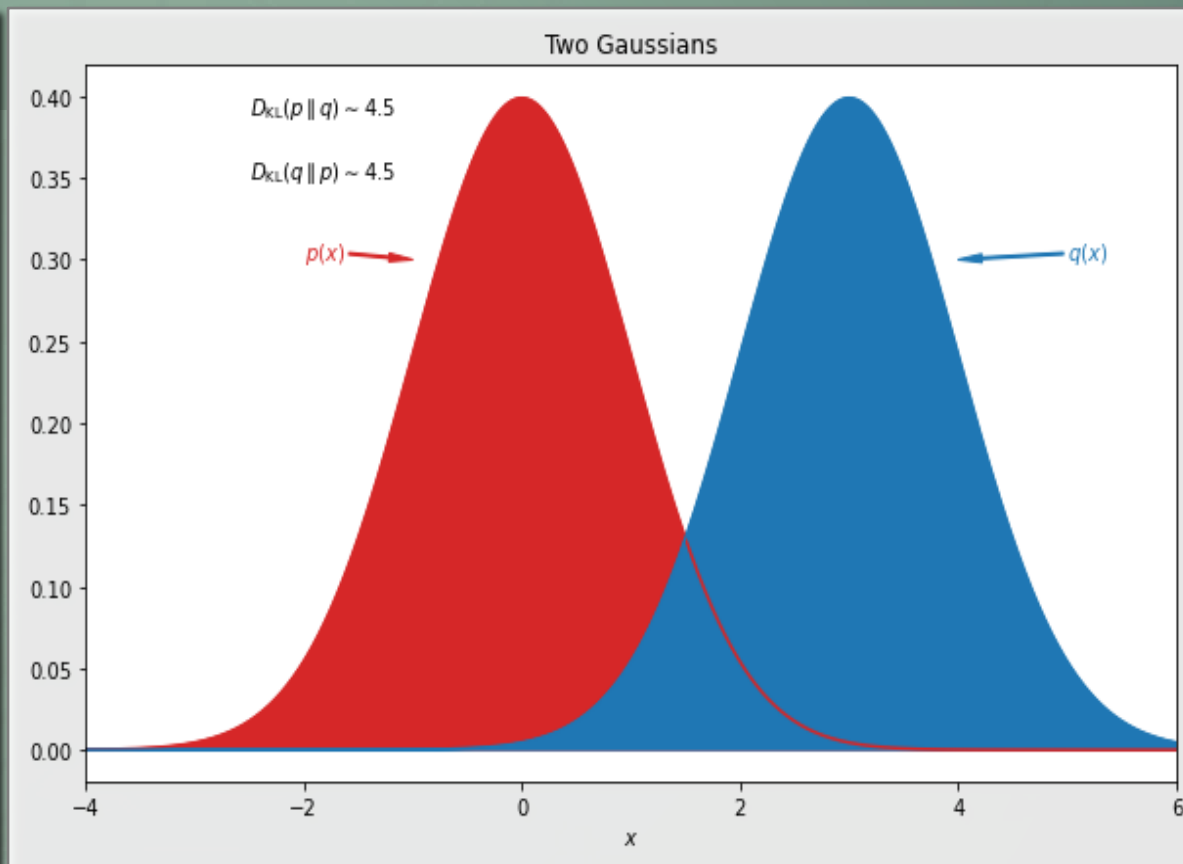
... measures the difference between two probability distributions over the same variable

## Formula

$$D_{KL}(P||Q) = \sum_{x \in X} P(x) \log \left( \frac{P(x)}{Q(x)} \right)$$

## Process Overview

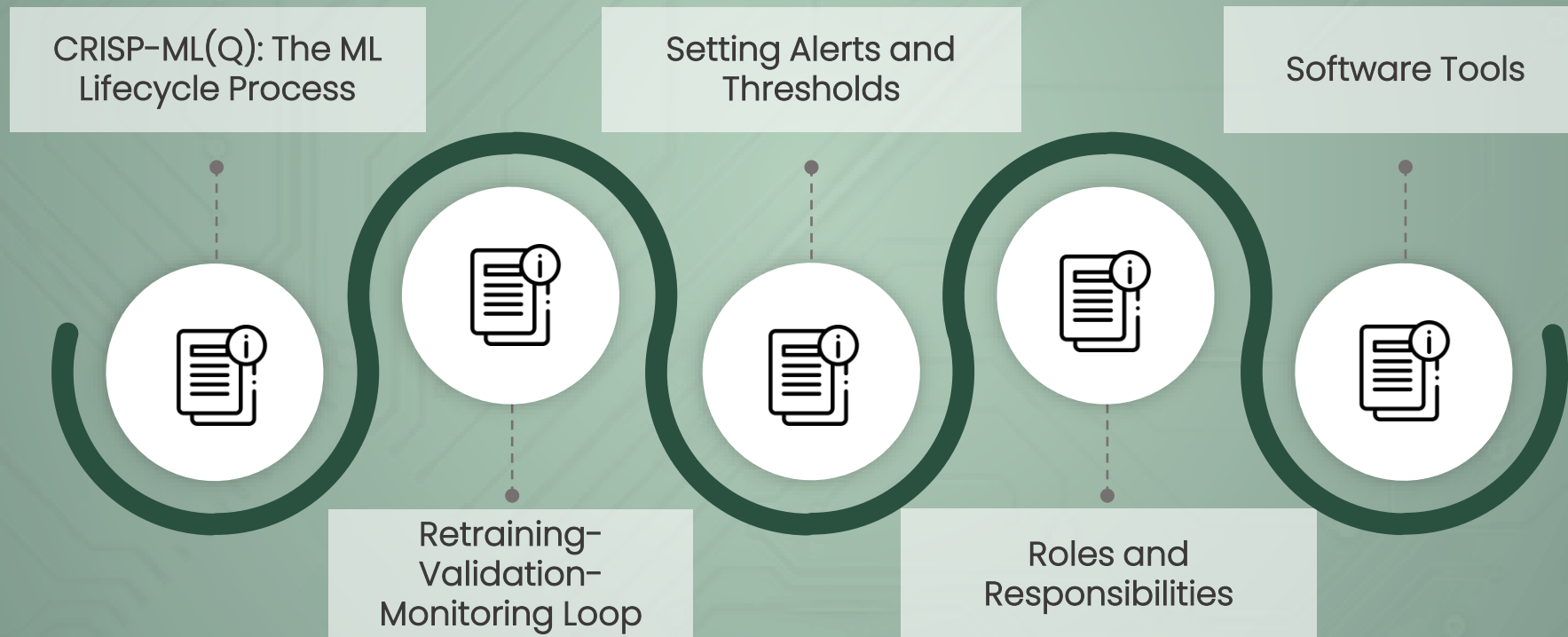
- **Baseline Distribution:**  
Establish baseline distribution  $P(x)$  from the data used to train model.
- **Current Distribution:**  
Calculate current distribution  $Q(x)$  from newly incoming data.
- **Calculate KL Divergence:**  
Use the KL Divergence formula to quantify the difference between both
- **Threshold Setting:**  
Define threshold for KL Divergence  
above data drift is considered significant  
→ further investigation or model retraining.



→ KL divergence is also used for Large Language Model alignment, because model drift due to finetuning should remain small.

# Infrastructure for monitoring, alerting, retraining

... involves automated systems for performance tracking and processes for periodic model updates

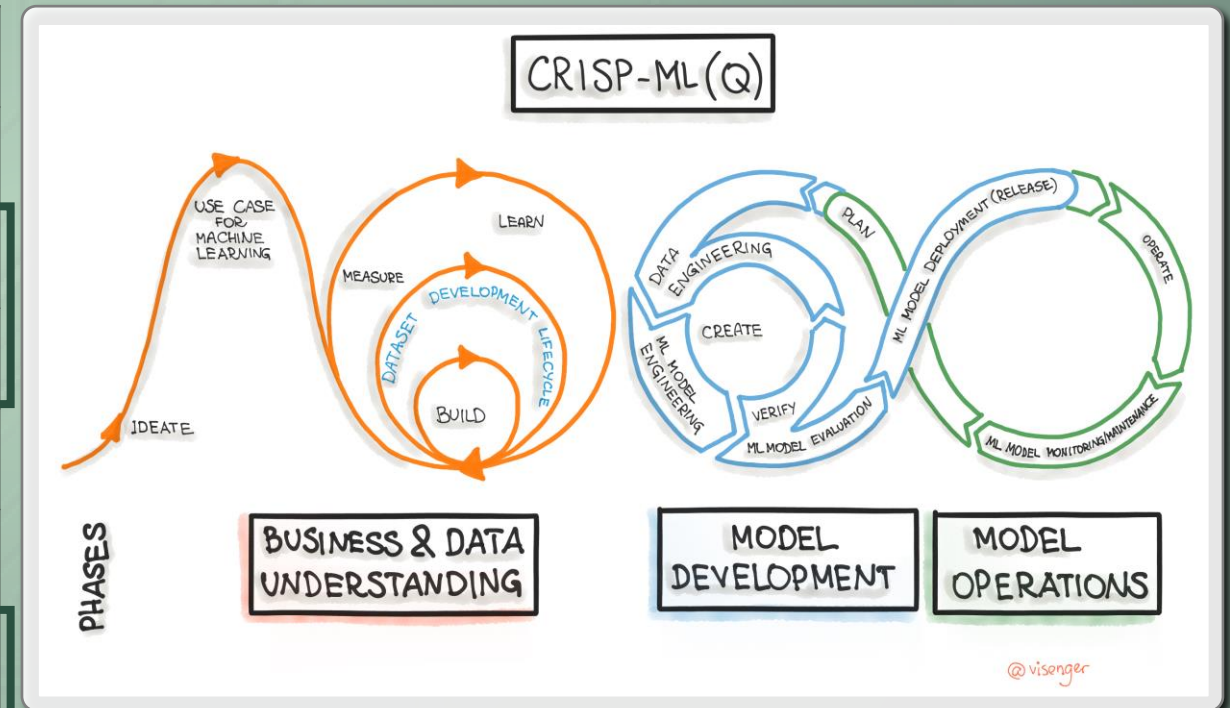


# CRISP-ML(Q): The ML Lifecycle Process

... proposed standard to structure, enhance the organization of ML and data science projects.

Phase No.	Phase Name	Description
1	Business and Data Understanding	Setting context, understanding data sources.
2	Data Engineering (Data Preparation)	Processing and transforming raw data.
3	Machine Learning Model Engineering	Algorithm selection, training, and tuning.
4	Quality Assurance for ML Applications	Ensuring model robustness, performance, etc.
5	Deployment	Launching the model into a production or operational environment.
6	Monitoring and Maintenance	Continuous monitoring / drift detection and updating the model as needed.

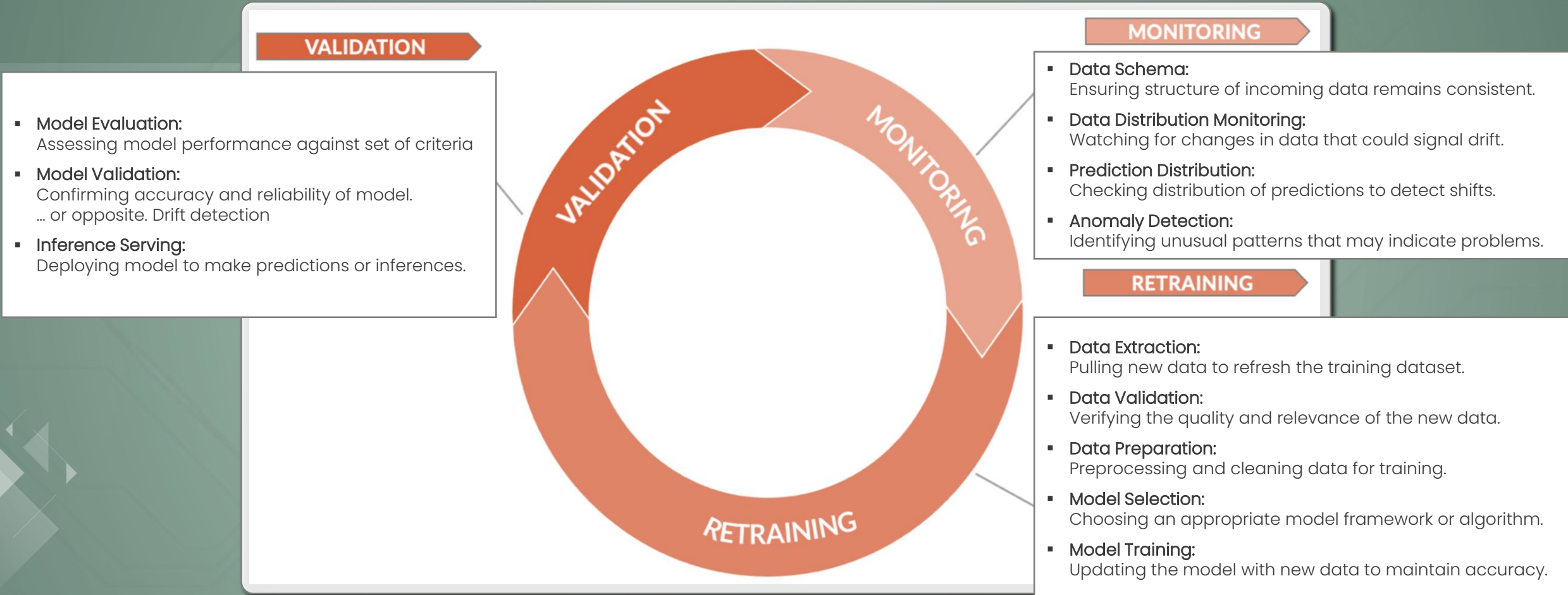
Monitoring





# Retraining-Validation-Monitoring Loop

... is loop of monitoring, retraining, validation or drift detection



# Setting Alerts and Thresholds

Strategy for alerts should be according to potential business impact of model performance issues. Efficient alerting, threshold settings are balancing act

## Alert Mechanisms

- Utilizing email alerts as primary communication channel for stakeholders.
- Selecting relevant measures like model accuracy, KS-test, etc. for alerting.

## Threshold Definition

- Align thresholds with business impact to avoid overburdening the system.
- Ensures thresholds are neither too sensitive (causing false alarms) nor too insensitive (missing important alerts).
  - Sensitive thresholds for high-stakes decisions, e.g., medical diagnoses.
  - More relaxed thresholds for less critical misclassifications, e.g., marketing campaigns.



# Roles and Responsibilities

Strategy for alerts should be according to potential business impact of model performance issues. Efficient alerting, threshold settings are balancing act

## Alert Recipients

- Determine who within organization needs to be notified
- Typically includes data engineers and data scientists involved in model development and data management.

## Technical Involvement

- Ensure technical teams are poised to analyze and address root drift causes
- Automation in ML pipeline may handle some issues, but human oversight remains crucial for unanticipated problems.

## Documentation of changes

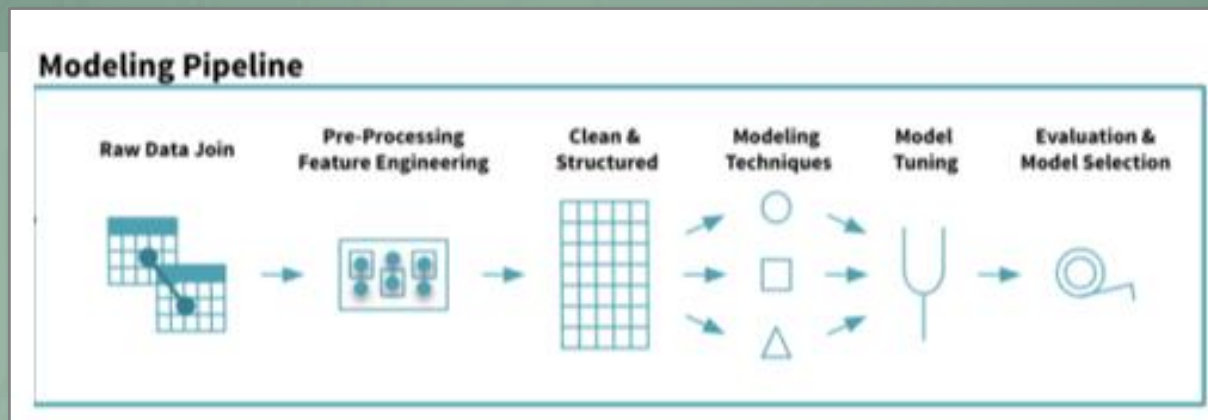
- Record all modifications made in response to drift to maintain a history of actions and their outcomes.
- Inform affected stakeholders of changes in ML models, data, pipelines, etc.





# Software Tools: MLflow

Open-source platform designed to manage end-to-end machine learning lifecycle, encompassing creation, deployment and maintenance stages.



## Benefits

- **Unified Interface:**  
Streamlines workflow for different ML tasks.
- **Cross-platform:**  
Compatible with various ML frameworks and languages.
- **Community-Driven:**  
Contributions from a wide range of users and companies.

## Use Cases

- Ideal for teams seeking to streamline experimentation, reproducibility, and deployment of ML models.

**mlflow**

### Tracking

Record and query experiments: code, data, config, results

### Projects

Packaging format for reproducible runs on any platform

### Models

General format for sending models to diverse deploy tools

# Software Tools: Python

... is used for handling model drift because it offers extensive libraries and tools for data analysis, machine learning, and statistical testing

## Editors

- IDE: Spyder
- Notebook: Jupyter

## Basic Python packages

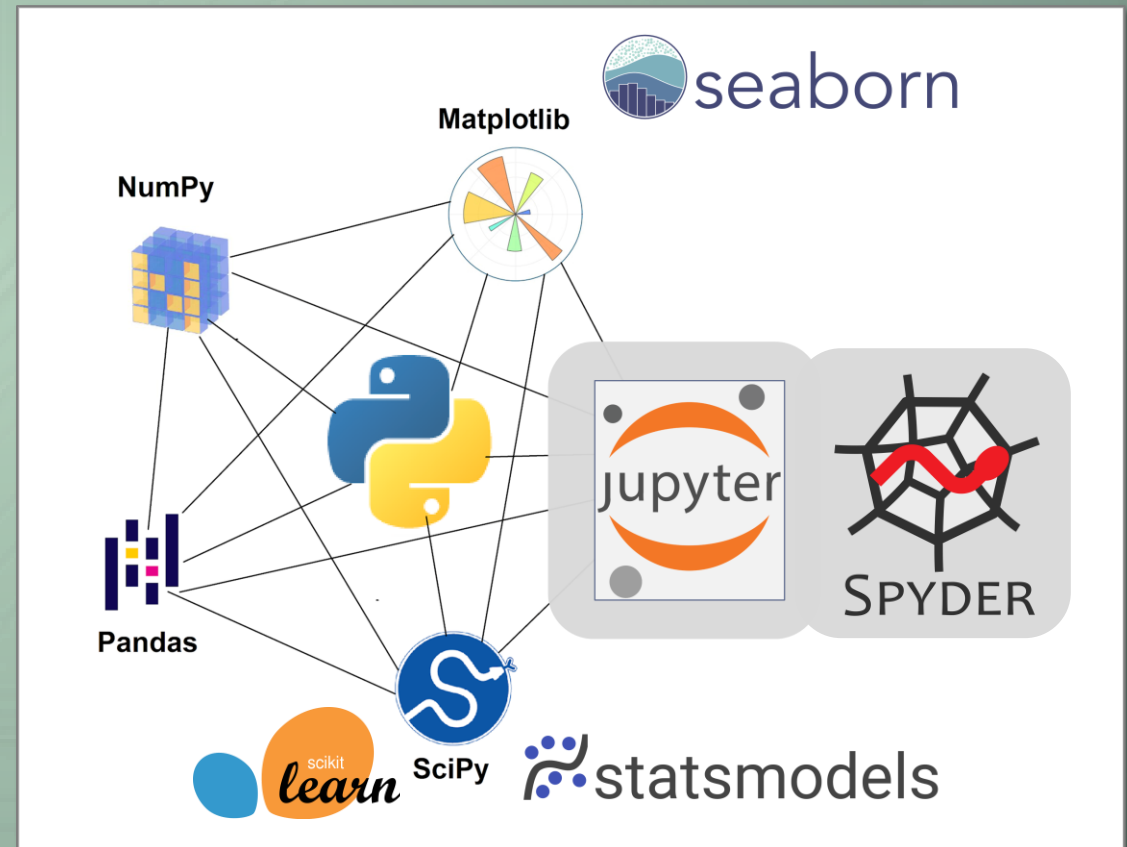
- Linear Algebra, general math: Numpy
- Dataframes: Pandas

## Statistics

- Hypothesis tests: Scipy
- Machine learning: SKLearn, Scipy

## Visualization

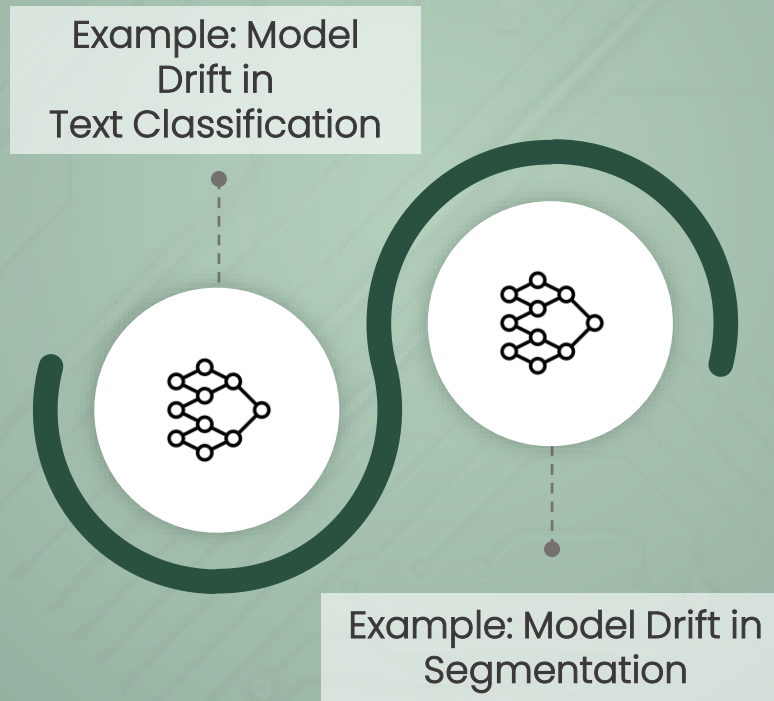
- Matplotlib
- Seaborn





# Examples with classification and segmentation

... i.e. with supervised learning (classification) and unsupervised learning (segmentation)



# Example: Model Drift in Text Classification

Sentiments of cinema reviews are classified. Later in production model performance will deteriorate

## Model Overview

- Model is trained on cinema review comments
- In production (e.g. as tool running on website):
  - trained model gets new, unplanned comments as input
  - makes classification based on training

## Performance Evaluation

- Focus on accuracy (true positives + false negatives, assumption: balanced classed)
- It is expected that accuracy will deteriorate

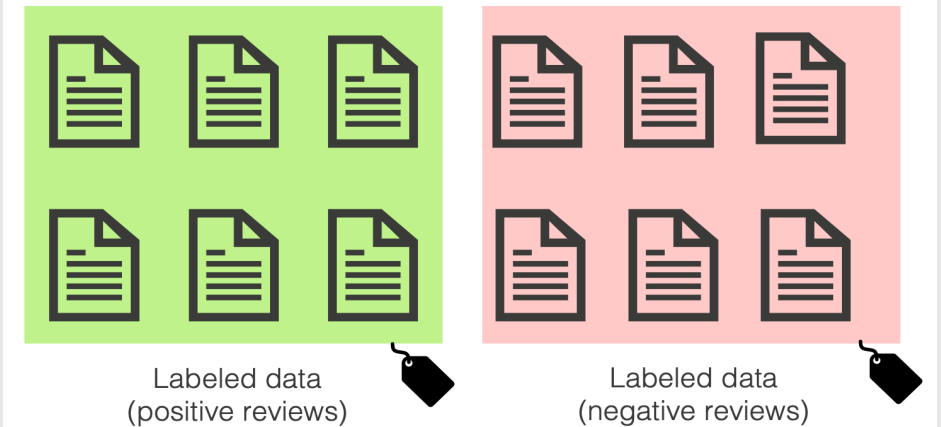
## Model Drift Consideration

- Potential for drift as new, unseen data is introduced.
- Need for continuous monitoring of these performance metrics to detect and address any degradation over time.

### Use case:



### Labeled training data:



### Evaluation of model performance:

Classification Model Performance. Target: 'is_positive'					
Current: Model Quality Metrics					
0.836	0.858	0.94	0.897	0.728	5.243
Accuracy	Precision	Recall	F1	ROC AUC	LogLoss

Focus

# Example: Model Drift in Text Classification

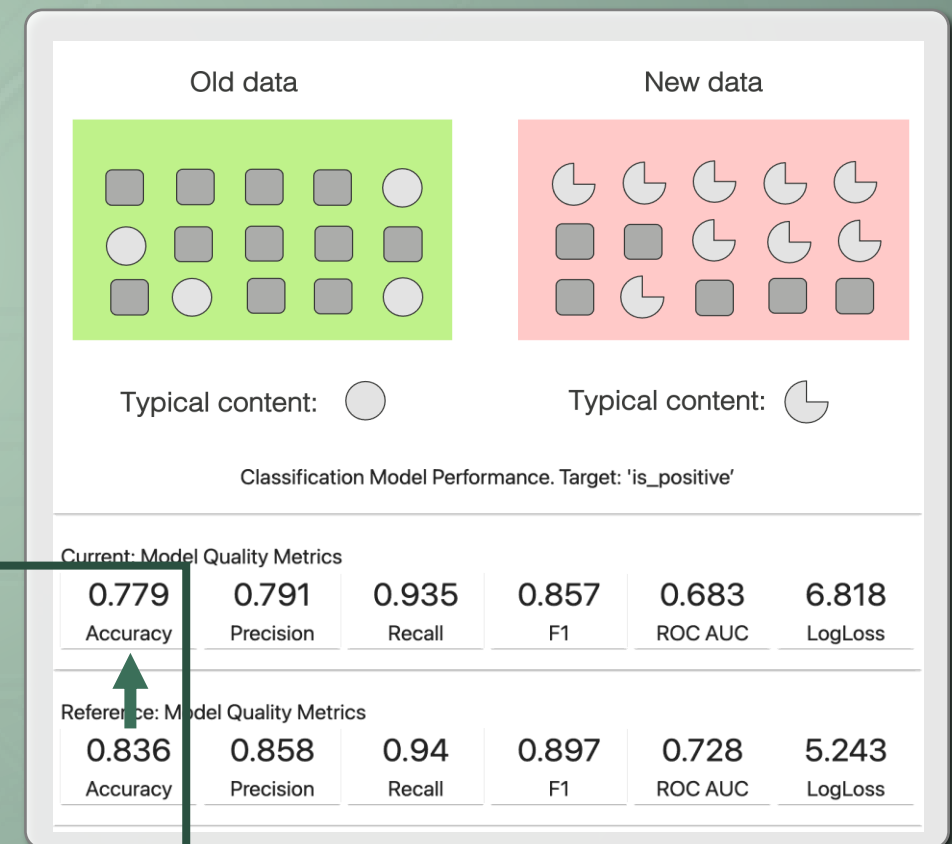
Changes in kind of text content can lead to model drift, affecting model performance

## Types of Drift

- **Concept drift:**
  - Changing word meanings
  - evolution of movie genres.
  - Shifted vocabulary: E.g. Multiple reviews contain over 30% of out-of-vocabulary words
  - Changing text lengths
- **Data Drift:** New data differing from training data, disrupting learned patterns, maybe due to used data sources.

## Consequences

- Checking if drift is permanent, systematic
- If yes, retraining based on thresholds or schedules



Accuracy  
deterioration

# Drift Management in E-commerce Recommendation Systems

Ensuring recommendation systems adapt to changing customer preferences, product trends, and seasonal influences.

## KS Test for Drift Detection:

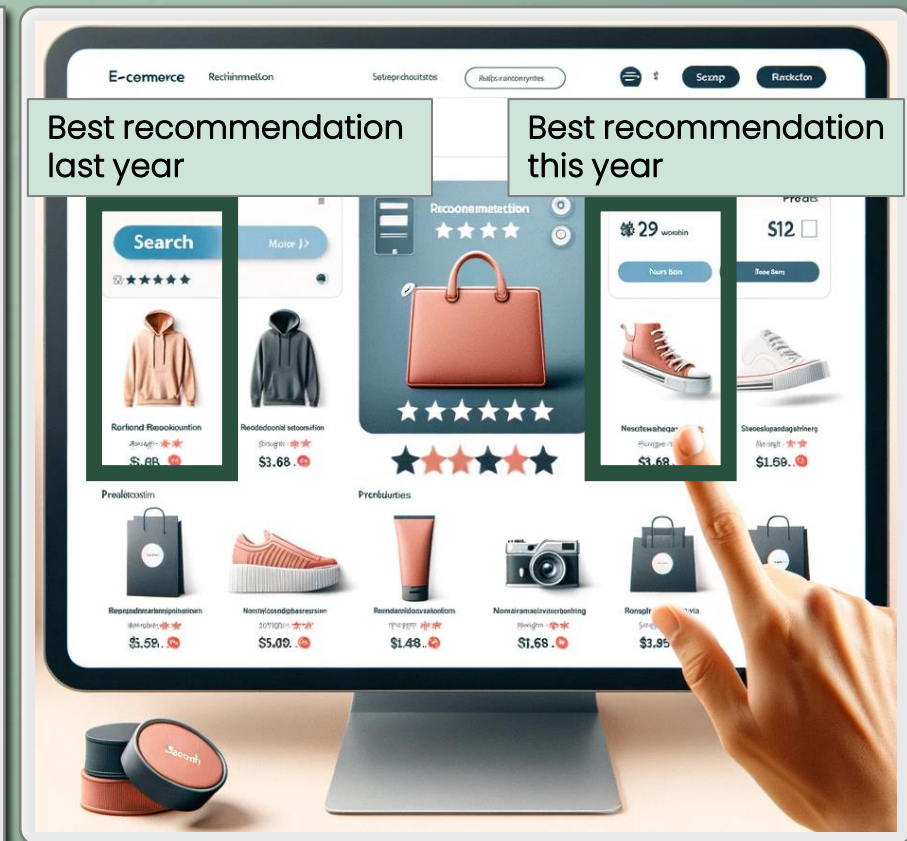
- Monthly KS tests compare current user interaction data with reference dataset to monitor recommendation relevancy.
- Multiple comparisons across product categories necessitate Bonferroni correction to maintain statistical rigor.

## Drift Identification and Response

- Sales numbers of highest recommended sales items decrease
- Analysis follows to understand market trends influencing detected drift
- KS test detects significant shift in preferences

## Adaptive Model Update Strategy

- Update and retrain models with recent data reflecting current trends.
- Validate improvements through A/B testing against original model.
- Continual adaptation cycle initiated by regular application of KS test.



# Links

i.e. sources for self-learning

	Title	Link
Model Drift: Overview	ML Drift: Identifying Issues Before You Have a Problem	<a href="https://www.youtube.com/watch?v=uOG685WFO00">https://www.youtube.com/watch?v=uOG685WFO00</a>
	A unifying view on dataset shift in classification	<a href="https://www.sciencedirect.com/science/article/abs/pii/S0031320311002901">https://www.sciencedirect.com/science/article/abs/pii/S0031320311002901</a>
	Concept Drift Detection in Data Stream Mining : A literature review	<a href="https://www.sciencedirect.com/science/article/pii/S1319157821003062">https://www.sciencedirect.com/science/article/pii/S1319157821003062</a>
	Understanding Dataset Shift	<a href="https://towardsdatascience.com/understanding-dataset-shift-f2a5a262a766">https://towardsdatascience.com/understanding-dataset-shift-f2a5a262a766</a>
	Model Drift in Machine Learning: How to Detect and Avoid It	<a href="https://blog.nimblebox.ai/machine-learning-model-drift">https://blog.nimblebox.ai/machine-learning-model-drift</a>
	Machine Learning Monitoring, Part 5: Why You Should Care About Data and Concept Drift	<a href="https://www.evidentlyai.com/blog/machine-learning-monitoring-data-and-concept-drift">https://www.evidentlyai.com/blog/machine-learning-monitoring-data-and-concept-drift</a>
	End To End ML Life cycle	<a href="https://www.linkedin.com/pulse/end-ml-life-cycle-satya-pati/">https://www.linkedin.com/pulse/end-ml-life-cycle-satya-pati/</a>
	The Value Proposition for ML Ops	<a href="https://www.credera.com/insights/the-value-proposition-for-mlops">https://www.credera.com/insights/the-value-proposition-for-mlops</a>
	A Survey on Concept Drift Adaptation	<a href="https://www.win.tue.nl/~mpechen/publications/pubs/Gama_ACMCS_AdaptationCD_accepted.pdf">https://www.win.tue.nl/~mpechen/publications/pubs/Gama_ACMCS_AdaptationCD_accepted.pdf</a>



# Links

i.e. sources for self-learning

	Title	Link
Types and triggers	Don't let your model's quality drift away	<a href="https://towardsdatascience.com/dont-let-your-model-s-quality-drift-away-53d2f7899c09">https://towardsdatascience.com/dont-let-your-model-s-quality-drift-away-53d2f7899c09</a>
	What Are Drifts and How to Detect Them?	<a href="https://www.youtube.com/watch?v=5KjpZCj853k">https://www.youtube.com/watch?v=5KjpZCj853k</a>
	Model Drift in Machine Learning – Data Science	<a href="https://priyanka-dalmia.medium.com/model-drift-in-machine-learning-395313b655c2">https://priyanka-dalmia.medium.com/model-drift-in-machine-learning-395313b655c2</a>
	An introduction to Model drift in machine learning	<a href="https://ubiops.com/an-introduction-to-model-drift-in-machine-learning/">https://ubiops.com/an-introduction-to-model-drift-in-machine-learning/</a>
	Drift in Machine Learning: How to Identify Issues Before You Have a Problem	<a href="https://www.fiddler.ai/blog/drift-in-machine-learning-how-to-identify-issues-before-you-have-a-problem">https://www.fiddler.ai/blog/drift-in-machine-learning-how-to-identify-issues-before-you-have-a-problem</a>
	Machine Learning Monitoring, Part 5: Why You Should Care About Data and Concept Drift	<a href="https://www.evidentlyai.com/blog/machine-learning-monitoring-data-and-concept-drift">https://www.evidentlyai.com/blog/machine-learning-monitoring-data-and-concept-drift</a>
	Machine Learning Concept Drift – What is it and Five Steps to Deal With it	<a href="https://www.seldon.io/machine-learning-concept-drift">https://www.seldon.io/machine-learning-concept-drift</a>
	A Survey on Concept Drift Adaptation	<a href="https://www.researchgate.net/publication/261961254_A_Survey_on_Concept_Drift_Adaptation">https://www.researchgate.net/publication/261961254_A_Survey_on_Concept_Drift_Adaptation</a>
	Everything you need to know about drift in machine learning	<a href="https://superwise.ai/blog/everything-you-need-to-know-about-drift-in-machine-learning/">https://superwise.ai/blog/everything-you-need-to-know-about-drift-in-machine-learning/</a>
	Data Drift	<a href="https://medium.com/@evertongomede/data-drift-dee73dcb8b6b">https://medium.com/@evertongomede/data-drift-dee73dcb8b6b</a>

# Links

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	Title	Link
Drift Detection techniques	From concept drift to model degradation: An overview on performance-aware drift detectors	<a href="https://www.sciencedirect.com/science/article/pii/S0950705122002854">https://www.sciencedirect.com/science/article/pii/S0950705122002854</a>
	Shift happens: we compared 5 methods to detect drift in ML embeddings	<a href="https://www.evidentlyai.com/blog/embedding-drift-detection">https://www.evidentlyai.com/blog/embedding-drift-detection</a>
	Q&A: ML drift that matters. "How to interpret data and prediction drift together?"	<a href="https://www.evidentlyai.com/blog/data-and-prediction-drift">https://www.evidentlyai.com/blog/data-and-prediction-drift</a>
	Take My Drift Away	<a href="https://arize.com/blog/take-my-drift-away/">https://arize.com/blog/take-my-drift-away/</a>
	Inferring Concept Drift Without Labeled Data	<a href="https://concept-drift.fastforwardlabs.com/">https://concept-drift.fastforwardlabs.com/</a>
	Production Machine Learning Monitoring: Outliers, Drift, Explainers & Statistical Performance	<a href="https://towardsdatascience.com/production-machine-learning-monitoring-outliers-drift-explainers-statistical-performance-d9b1d02ac158">https://towardsdatascience.com/production-machine-learning-monitoring-outliers-drift-explainers-statistical-performance-d9b1d02ac158</a>
	Detecting Data Drift with KS Test Using Attention Map	<a href="https://link.springer.com/chapter/10.1007/978-3-031-47634-1_6">https://link.springer.com/chapter/10.1007/978-3-031-47634-1_6</a>
	Understanding Kolmogorov-Smirnov (KS) Tests for Data Drift on Profiled Data	<a href="https://towardsdatascience.com/understanding-kolmogorov-smirnov-ks-tests-for-data-drift-on-profiled-data-5c8317796f78">https://towardsdatascience.com/understanding-kolmogorov-smirnov-ks-tests-for-data-drift-on-profiled-data-5c8317796f78</a>
	Monitoring NLP models in production: a tutorial on detecting drift in text data	<a href="https://www.evidentlyai.com/blog/tutorial-detecting-drift-in-text-data">https://www.evidentlyai.com/blog/tutorial-detecting-drift-in-text-data</a>
	Survey of distancemeasures for quantifying concept drift and shift in numeric data	<a href="https://www.researchgate.net/publication/327539525_Survey_of_distance_measures_for_quantifying_concept_drift_and_shift_in_numeric_data">https://www.researchgate.net/publication/327539525_Survey_of_distance_measures_for_quantifying_concept_drift_and_shift_in_numeric_data</a>
	Population Stability Index (PSI)	<a href="https://medium.com/model-monitoring-psi/population-stability-index-psi-ab133b0a5d42">https://medium.com/model-monitoring-psi/population-stability-index-psi-ab133b0a5d42</a>
	Calculating Data Drift in Machine Learning using Python	<a href="https://towardsdatascience.com/calculating-data-drift-in-machine-learning-53676ff5646b">https://towardsdatascience.com/calculating-data-drift-in-machine-learning-53676ff5646b</a>
	Difference between KL Divergence and PSI	<a href="https://medium.com/@mumbaiyachori/difference-between-kl-divergence-and-psi-e7d9aa0ade12">https://medium.com/@mumbaiyachori/difference-between-kl-divergence-and-psi-e7d9aa0ade12</a>

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	Title	Link
Infrastructure: Monitoring, Alerts, Mitigation	Staying on Track: The Impact of Data Drift on Machine Learning and How to Overcome It	<a href="https://www.linkedin.com/pulse/staying-track-impact-data-drift-machine-learning-how-iaian-brown-ph-d-/">https://www.linkedin.com/pulse/staying-track-impact-data-drift-machine-learning-how-iaian-brown-ph-d-/</a>
	Chapter 7. Monitoring and Feedback Loop	<a href="https://www.oreilly.com/library/view/introducing-mlops/9781492083283/ch07.html#:~:text=Monitoring%20and%20feedback%20loop%20highlighted,correctly%20in%20the%20production%20environment.">https://www.oreilly.com/library/view/introducing-mlops/9781492083283/ch07.html#:~:text=Monitoring%20and%20feedback%20loop%20highlighted,correctly%20in%20the%20production%20environment.</a>
	The Value Proposition for ML Ops	<a href="https://www.credera.com/insights/the-value-proposition-for-mlops">https://www.credera.com/insights/the-value-proposition-for-mlops</a>
	MLOps Principles	<a href="https://ml-ops.org/content/mlops-principles">https://ml-ops.org/content/mlops-principles</a>
	Title	Link
Tools and Technologies	Getting a Grip on Data and Model Drift with Azure Machine Learning	<a href="https://towardsdatascience.com/getting-a-grip-on-data-and-model-drift-with-azure-machine-learning-ebd240176b8b">https://towardsdatascience.com/getting-a-grip-on-data-and-model-drift-with-azure-machine-learning-ebd240176b8b</a>
	Deploy Your Own MLflow Workspace On-Premise with Docker	<a href="https://towardsdatascience.com/deploy-your-own-mlflow-workspace-on-premise-with-docker-b54294676f0b">https://towardsdatascience.com/deploy-your-own-mlflow-workspace-on-premise-with-docker-b54294676f0b</a>
	Mary Grace Moesta - MLOps Deployment Patterns with Delta Lake and MLflow   PyData Seattle 2023	<a href="https://www.youtube.com/watch?v=BkUuH51zSYo">https://www.youtube.com/watch?v=BkUuH51zSYo</a>
	I built an awesome ML model with Spark, Delta and MLFlow. How do I get the right people to use it?	<a href="https://fukumaruuu.medium.com/i-built-an-awesome-ml-model-with-spark-delta-and-mlflow-how-do-i-get-the-right-people-to-use-it-db0c34e46605">https://fukumaruuu.medium.com/i-built-an-awesome-ml-model-with-spark-delta-and-mlflow-how-do-i-get-the-right-people-to-use-it-db0c34e46605</a>
	MLflow: A Primer Why/how to transform on-premise ML frameworks into a unified one	<a href="https://towardsdatascience.com/mlflow-a-primer-6dfe6be48353">https://towardsdatascience.com/mlflow-a-primer-6dfe6be48353</a>
	Drifting Away: Testing ML Models in Production	<a href="https://www.youtube.com/watch?v=tGckE83S-4s">https://www.youtube.com/watch?v=tGckE83S-4s</a>

# ChatGPT/Dall-E3 Prompts

Photo of three floating islands, each labeled 'Code', 'Model', and 'Data'. The 'Model' island is slightly shifted from its original position, indicating drift. Connecting bridges show the interdependence. The title 'Model Drift: When Code, Model, or Data Shifts' is displayed above.

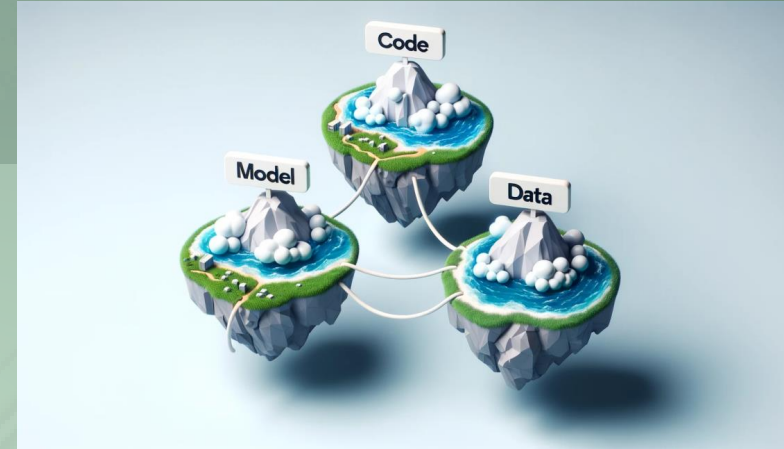


Photo of a frustrated data scientist sitting at a desk, staring at a computer screen displaying a prediction model's performance metrics. The graph on the screen shows a noticeable downward trend in model accuracy and other key performance indicators. Papers with printed charts and graphs are scattered across the desk, and a crumpled paper can be seen in the corner, symbolizing disappointment and concern over the deteriorating model performance. The room is dimly lit to emphasize the challenging situation.





# About me

Dr. Harald Stein

- Data Scientist ~ 8 years experience
  - Algotrader ~ 4 years experience
  - Ph.D. in Economics, Game Theory
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- LinkedIn: <https://www.linkedin.com/in/harald-stein-phd-1648b51a>
  - ResearchGate: <https://www.researchgate.net/profile/Harald-Stein>

