How Not to Let Your Model and Data Drift Away Silently

Chengyin Eng

About

Chengyin Eng

Data Scientist @ Databricks

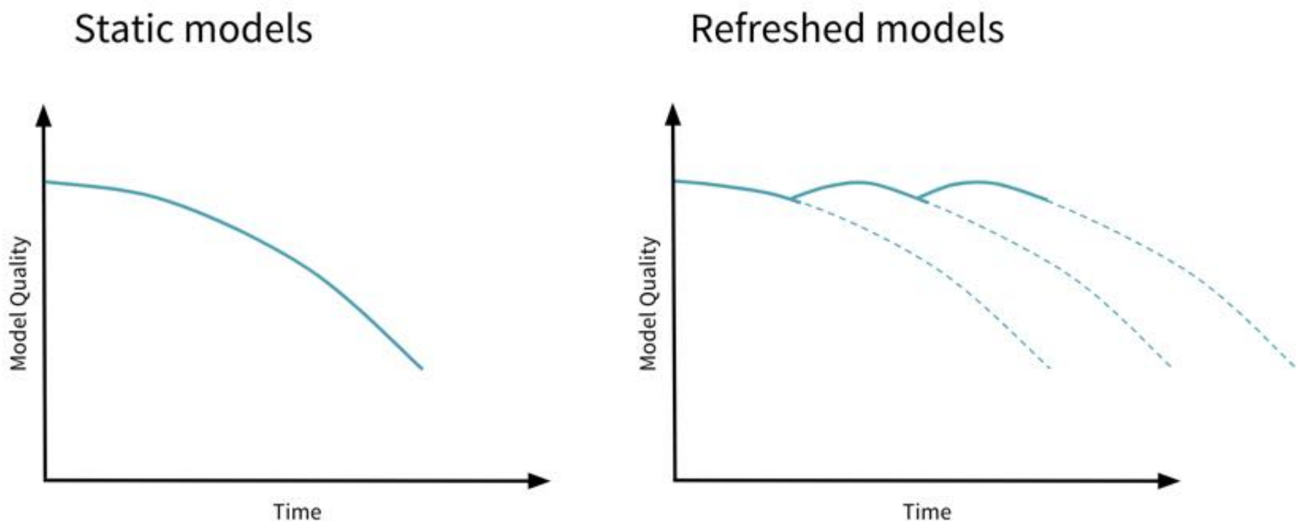
- Machine Learning Practice Team
- Experience
  - Life Insurance
  - Teaching ML in Production, Deep Learning, NLP, etc.
- MS in Computer Science at University of Massachusetts, Amherst
- BA in Statistics & Environmental Studies at Mount Holyoke College, Massachusetts

Outline

- Motivation
- Machine Learning System Life Cycle
- Why Monitor?
  - Types of drift
- What to Monitor?
- How to Monitor?
- Demo

Why do 96% of ML projects fail in production?

Neglect maintenance: Lack of re-training and testing



Sources:

https://databricks.com/blog/2019/09/18/productionizing-machine-learning-from-deployment-to-drift-detection.html

https://www.datanami.com/2020/10/01/most-data-science-projects-fail-but-yours-doesnt-have-to/

This talk focuses on two questions:

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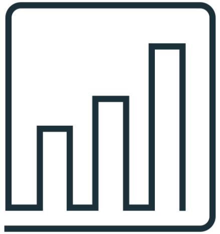


What are the statistical tests to use when monitoring models in production?

This talk focuses on two questions:

What are the statistical tests to use when monitoring models in production?

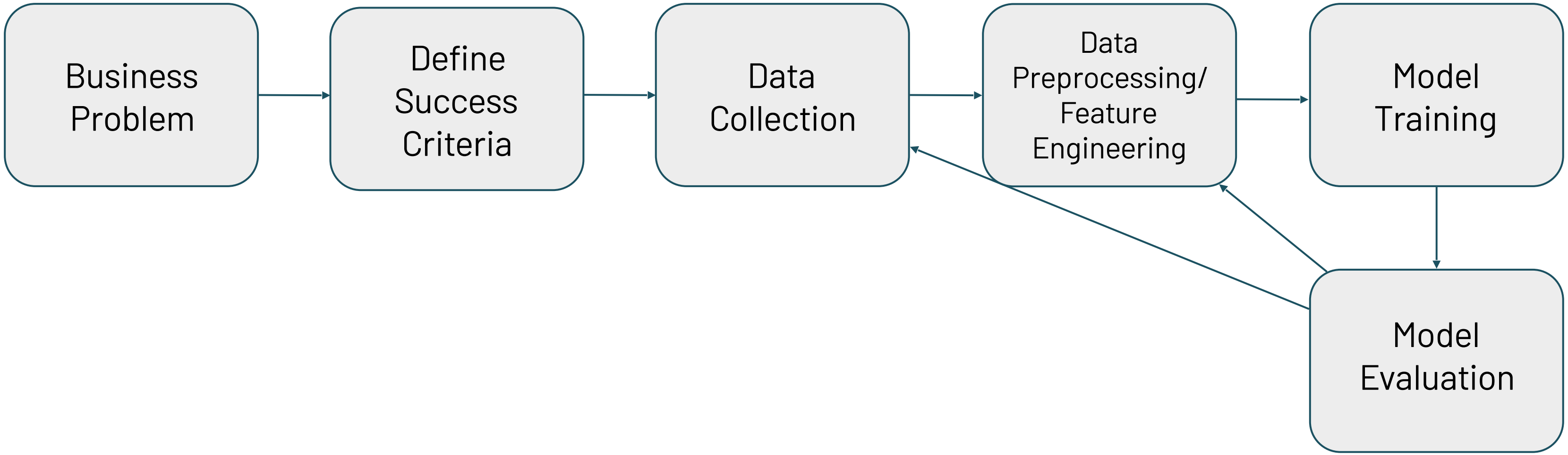
What tools can I use to coordinate the monitoring of data and models?

What this talk is *not*

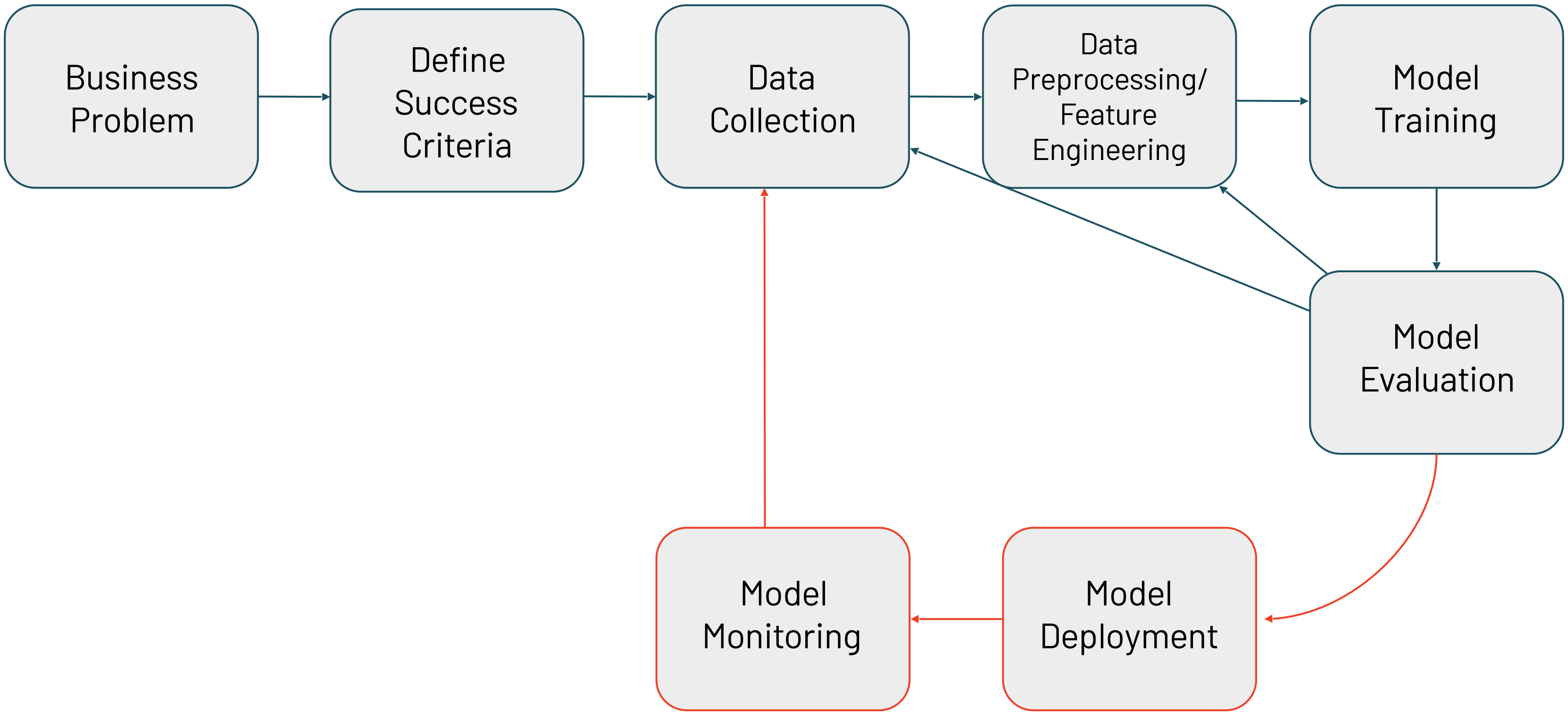
- A tutorial on model deployment strategies
- An exhaustive walk through of how to robustly test your production ML code
- A prescriptive list of *when* to update a model in production

Machine Learning System Life Cycle

ML system life cycle



ML system life cycle



Why Monitor?

Model deployment is not the end

It is the beginning of model measurement and monitoring

- Data distributions and feature types can change over time due to:

Potential model performance degradation

Models *will* degrade over time

Challenge: catching this when it happens

Types of drift

Data Drift

One of more distributions deviate:

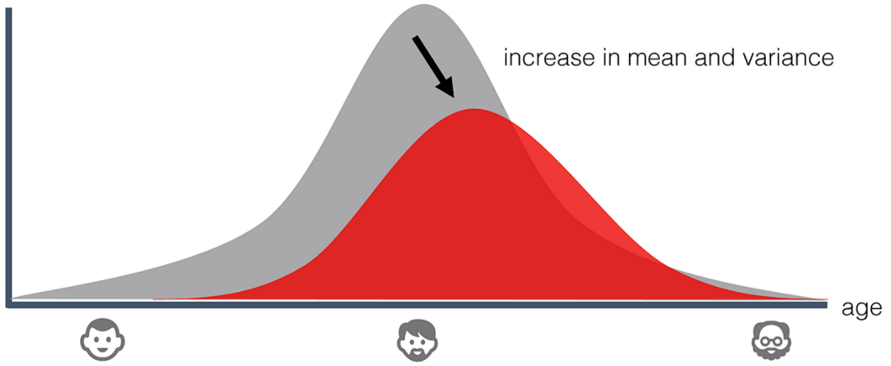
- Input features
- Label
- Model prediction

Concept Drift

External factors cause the label to evolve

Data Drift

Categories	Expected	Observed	Total
A	25	35	60
B	25	20	56
C	25	25	50
D	25	20	45
Total	100	100	100

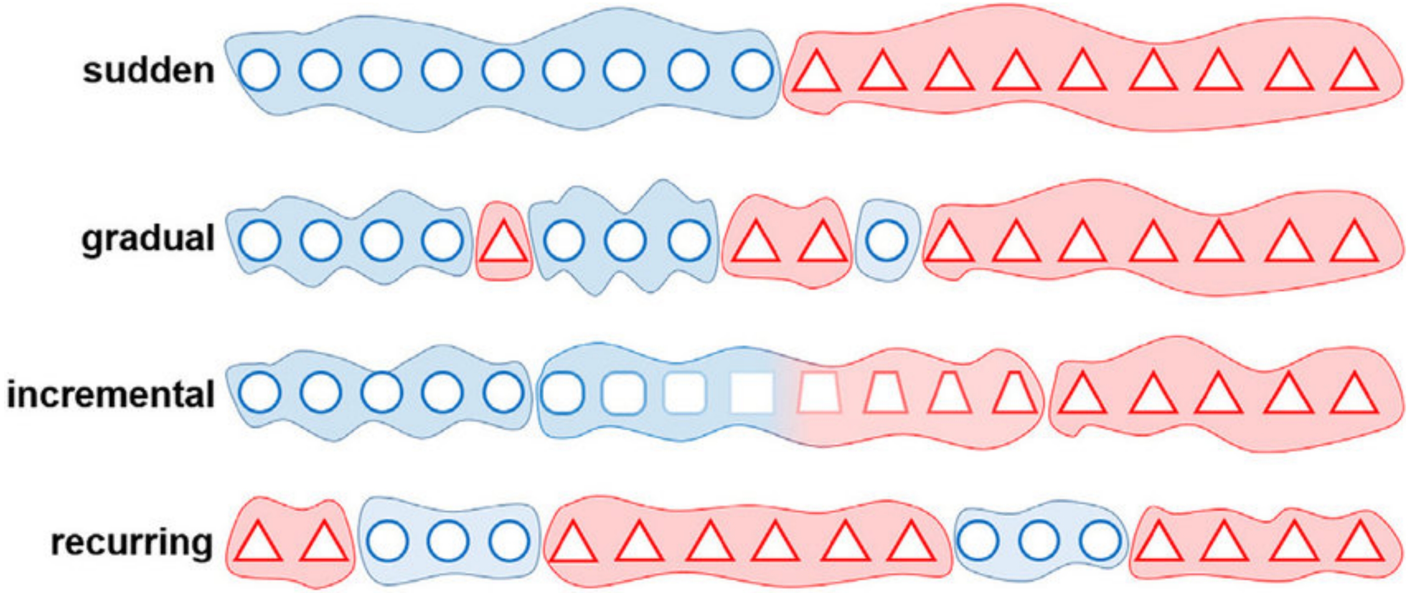


Sources:

https://dataz4s.com/statistics/chi-square-test/

https://towardsdatascience.com/machine-learning-in-production-why-you-should-care-about-data-and-concept-drift-d96d0bc907fb

Concept drift



Source: [Krawczyk and Cano 2018. Online Ensemble Learning for Drifting and Noisy Data Streams]

Drift types and actions to take

Drift Type	Retrain using new data	Investigate process	Assess business impact	Consider alternative solutions
Feature Drift	Y	Y		
Label Drift	Y	Y		
Prediction Drift		Y (Model training)	Y	
Concept Drift	Y (Or tune)			Y (Additional feature engineering)

What to Monitor?

What should I monitor?

- Basic summary statistics of features and target
- Distributions of features and target
- Model performance metrics
- Business metrics

Monitoring tests on data

Numeric Features

- Summary statistics:
  - Median / mean
  - Minimum
  - Maximum
  - Percentage of missing values
- Statistical tests:
  - Mean:
    - Two-sample Kolmogorov-Smirnov (KS) test with Bonferroni correction
    - Mann-Whitney (MW) test
  - Variance:
    - Levene test

Kolmogorov-Smirnov (KS) test with Bonferroni correction

Comparison of two continuous distributions

- Null hypothesis (H_0):

  Distributions x and y come from the same population

- If the KS statistic has a *p*-value lower than α, reject H_0

- Bonferroni correction:
  - Adjusts the α level to reduce false positives
  - $\alpha_{new} = \alpha_{original} / n$, where n = total number of feature comparisons

Levene test

Comparison of variances between two continuous distributions

- Null hypothesis (H_0):

$$\sigma^2_1 = \sigma^2_2 = \ldots = \sigma^2_n$$

- If the Levene statistic has a *p*-value lower than α, reject H_0

Monitoring tests on data

Numeric Features

- Summary statistics:
  - Median / mean
  - Minimum
  - Maximum
  - Percentage of missing values
- Statistical tests:
  - Mean:
    - Two-sample Kolmogorov-Smirnov (KS) test with Bonferroni correction
    - Mann-Whitney (MW) test
  - Variance:
    - Levene test

Categorical Features

- Summary statistics:
  - Mode
  - Number of unique levels
  - Percentage of missing values
- Statistical test:
  - One-way chi-squared test

One-way chi-squared test

Comparison of two categorical distributions

- Null hypothesis (H_0):

  Expected distribution = observed distribution

- If the Chi-squared statistic has a *p*-value lower than α, reject H_0

Monitoring tests on models

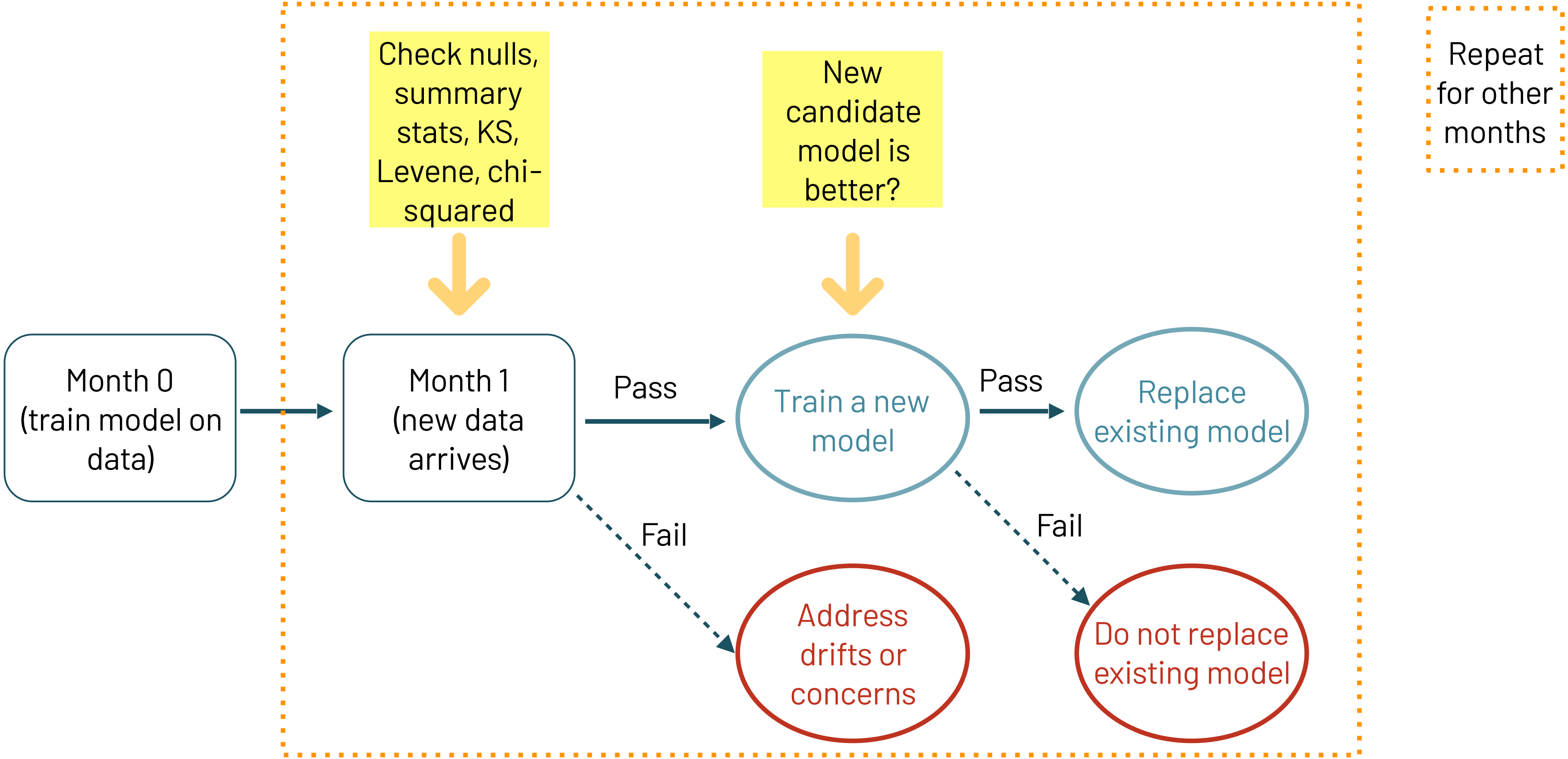
- Relationship between target and features
  - Numeric Target: Pearson Coefficient
  - Categorical Target: Contingency tables

- Model Performance
  - Regression models: MSE, error distribution plots etc
  - Classification models: ROC, confusion matrix, F1-score etc
  - Performance on data slices

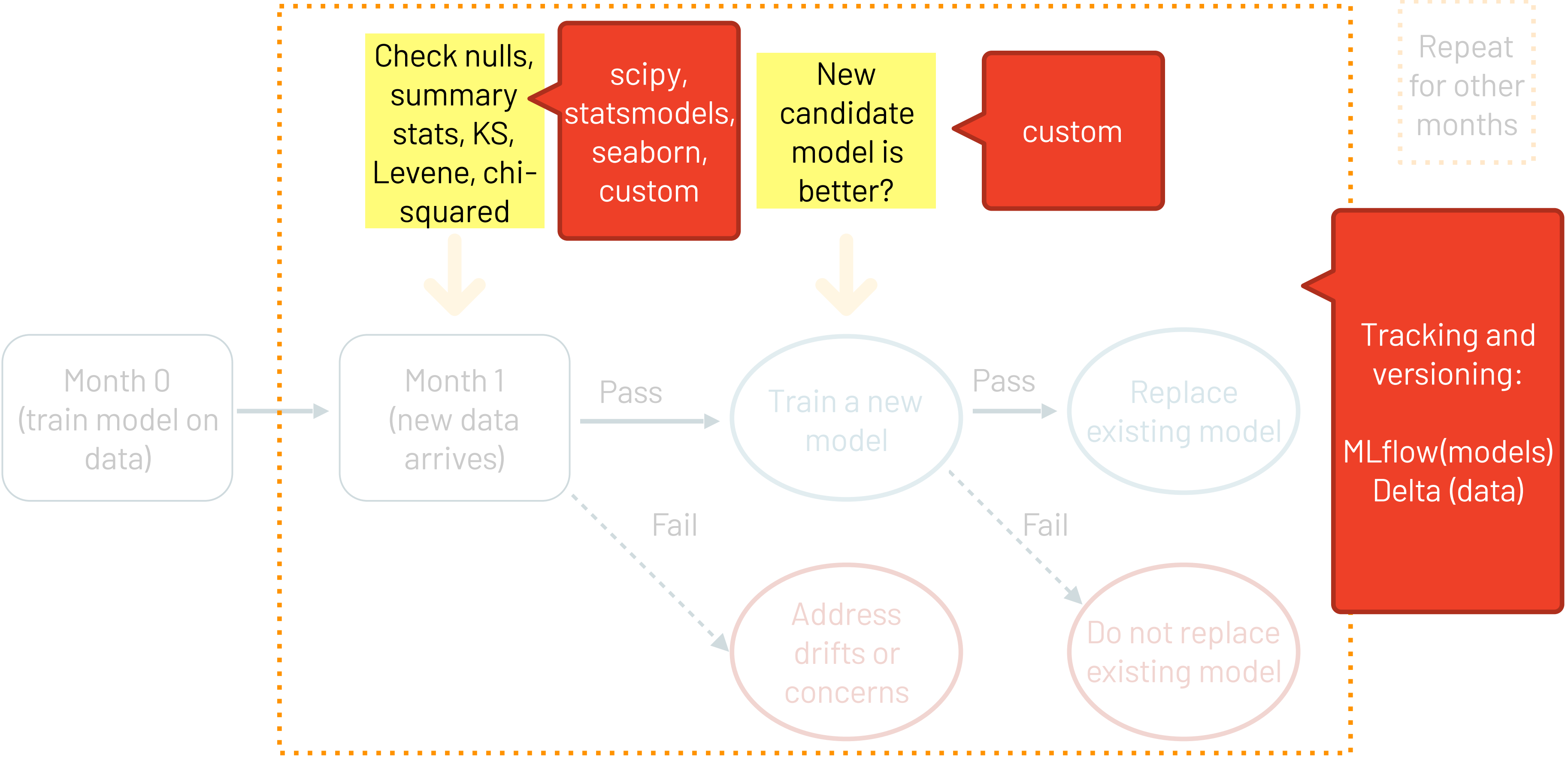
- Time taken to train

How to Monitor?

Workflow


Check nulls, summary stats, KS, Levene, chi-squared
New candidate model is better?
Repeat for other months
Month 0 (train model on data)
Month 1 (new data arrives)
Pass
Train a new model
Pass
Replace existing model
Fail
Fail
Address drifts or concerns
Do not replace existing model

Workflow


Check nulls, summary stats, KS, Levene, chi-squared
scipy, statsmodels, seaborn, custom
New candidate model is better?
custom
Repeat for other months
Tracking and versioning:
MLflow(models)
Delta (data)
Month 0 (train model on data)
Month 1 (new data arrives)
Pass
Train a new model
Pass
Replace existing model
Fail
Fail
Address drifts or concerns
Do not replace existing model

An open-source platform for ML lifecycle that helps with operationalizing ML

Tracking

Record and query experiments: code, metrics, parameters, artifacts, models

Projects

Packaging format for reproducible runs on any compute platform

Models

General model format that standardizes deployment options

Model Registry

Centralized and collaborative model lifecycle management

MLflow documentation linked here: https://www.mlflow.org/docs/latest/index.html

MLflow Experiment UI

Experiments > /Users/chengyin.eng@databricks.com/mlops2021/airbnb_hawaii

Track machine learning training runs in an experiment. Learn more

Experiment ID : 2808846569707146

Artifact Location : dbfs:/databricks/mlflow-tracking/2808846569707146

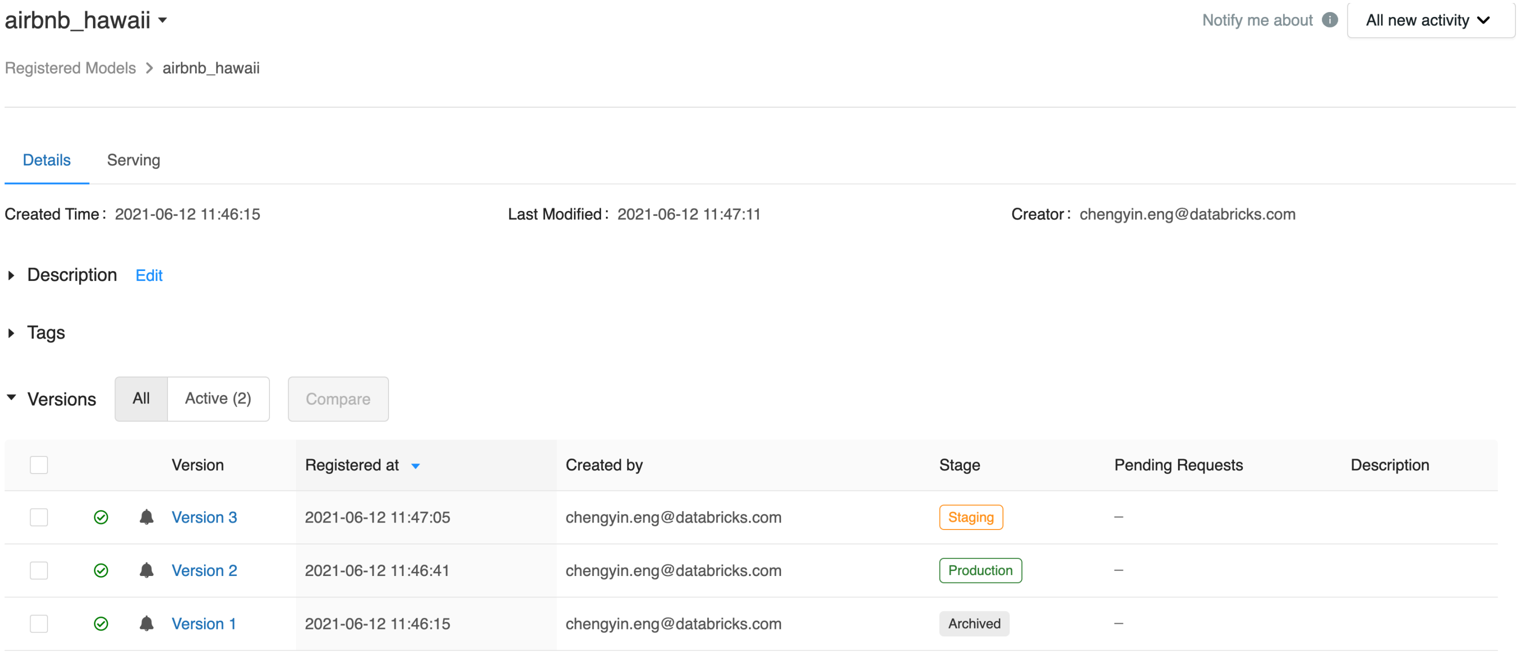
Notes

Showing 3 matching runs

Refresh | Compare | Delete | Download CSV | Columns | metrics.rmse < 1 and params.model = "tree" | Search | Filter | Clear

						Parameters			Metrics			Tags		
Start Time	Run Name	User	Source	Version	Models	delta_path	delta_versic	memory	test_mse	test_r2	training_ma	estimator_c	estimator_n	sparkDatas
2021-06-12 11:46:5	month_2	chengyi...	mlops2C	-	airbnb_haw.../3	/Users/...	2	None	48573...	0.043	394.7	sklearn....	Pipeline	path=d...
2021-06-12 11:46:3	month_1	chengyi...	mlops2C	-	airbnb_haw.../2	/Users/...	1	None	16962...	0.113	276	sklearn....	Pipeline	path=d...
2021-06-12 11:46:0	month_0	chengyi...	mlops2C	-	airbnb_haw.../1	/Users/...	0	None	24371...	0.08	230.8	sklearn....	Pipeline	path=d...

MLflow Model Registry



DELTA LAKE

An open-source data storage format that allows ACID transaction and metadata handling

Parquet files combined with transaction logs

```
/mytable/_delta_log/00000000000000000000.json
/mytable/_delta_log/00000000000000000001.json
/mytable/_delta_log/00000000000000000003.json
/mytable/_delta_log/00000000000000000003.checkpoint.parquet
/mytable/_delta_log/_last_checkpoint
/mytable/part-00000-3935a07c-416b-4344-ad97-2a38342ee2fc.c000.snappy.parquet
```

Read older versions of data using time travel

Python

```python
df1 = spark.read.format("delta").option("timestampAsOf", timestamp_string).load("/delta/events")
df2 = spark.read.format("delta").option("versionAsOf", version).load("/delta/events")
```

Delta documentation linked here: https://docs.delta.io/latest/index.html

Delta Table History

```
gold_delta_path = "/Users/chengyin.eng@databricks.com/mlops2021/data/airbnb_hawaii_delta"
display(DeltaTable.forPath(spark, gold_delta_path).history())
```

(1) Spark Jobs

	version	timestamp	userId	userName	operation	operationParameters
1	2	2021-06-12T16:46:54.000+0000	4470711271069202	chengyin.eng@databricks.com	WRITE	{"mode": "Append",
2	1	2021-06-12T16:46:30.000+0000	4470711271069202	chengyin.eng@databricks.com	WRITE	{"mode": "Append",
3	0	2021-06-12T16:46:03.000+0000	4470711271069202	chengyin.eng@databricks.com	WRITE	{"mode": "ErrorIfExis

Showing all 3 rows

Demo Notebook

http://bit.ly/mlops2021-drifting-away

Conclusion

- Model measurement and monitoring are crucial when operationalizing ML models
- No one-size fits all
  - Domain & problem specific considerations
- Reproducibility
  - Enable rollbacks and maintain record of historic performance

Literature resources

- Paleyes et al 2021. Challenges in Deploying ML
- Klaise et al. 2020 Monitoring and explainability of models in production
- Rabanser et al 2019 Failing Loudly: An Empirical Study of Methods for Detecting Dataset Shift
- Martin Fowler: Continuous Delivery for Machine Learning

Emerging open-source monitoring packages

- EvidentlyAI
- Data Drift Detector
- Alibi Detect