

Monitoring and visualization

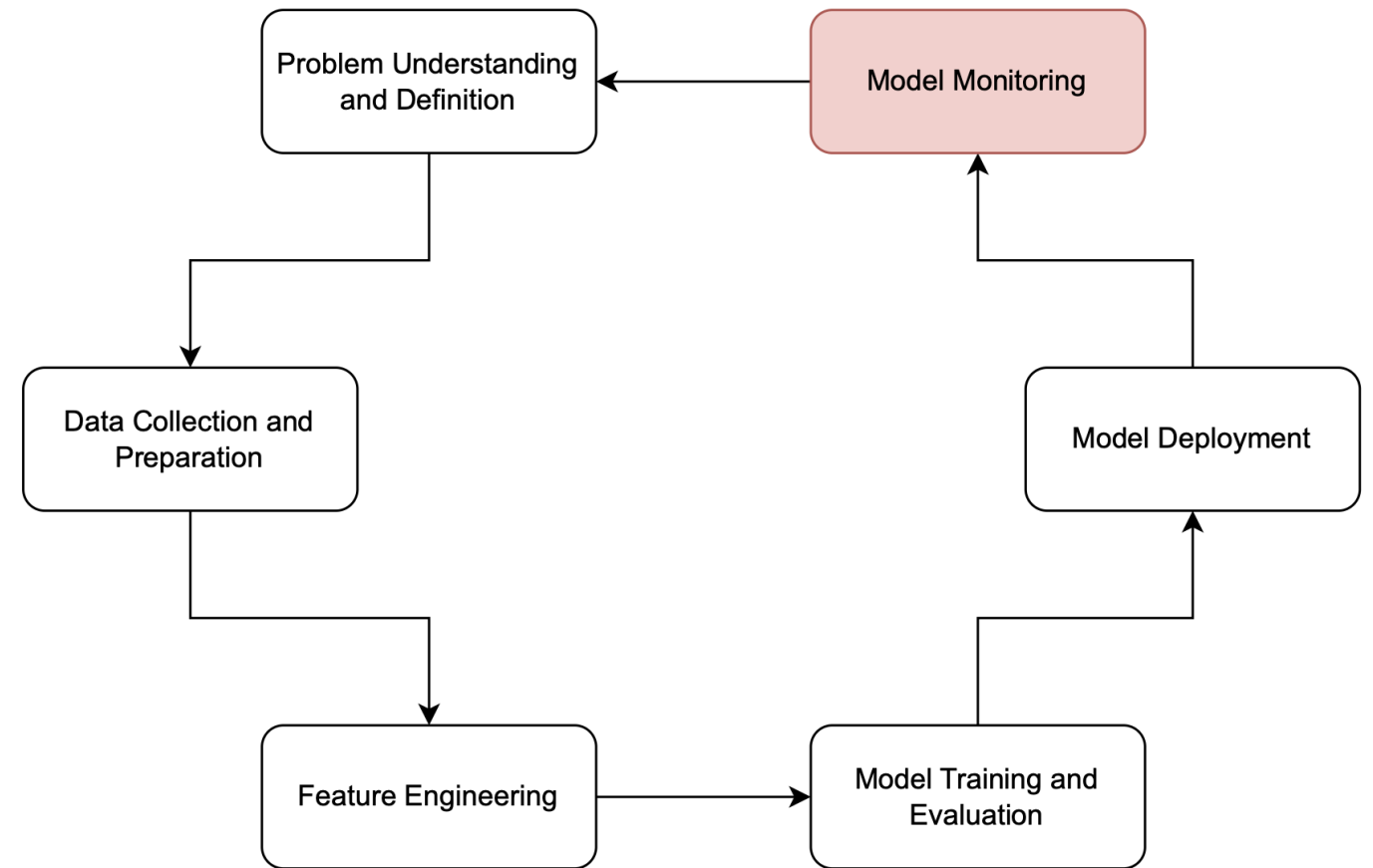
END-TO-END MACHINE LEARNING



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Machine Learning Engineer

What's next?

- Trained, optimized, deployed, predicted... what next?
- Monitoring
 - Logging results
 - Visualizing performance



Logging with python

```
import logging
import matplotlib.pyplot as plt

# Setting up basic logging configuration
logging.basicConfig(filename='predictions.log', level=logging.INFO)

# Make predictions on the test set and log the results
for i in range(X_test.shape[0]):
    instance = X_test[i,:].reshape(1, -1)
    prediction = model.predict(instance)
    logging.info(f'Inst. {i} - PredClass: {prediction[0]}, RealClass: {y_test[i]}')
```

Logging with python (cont.)

```
# Function to visualize the predictions from log
with open(logfile, 'r') as f:
    lines = f.readlines()
    predicted_classes = [int(line.split("Predicted Class: ")[1].split(",")[0]) \
        for line in lines]

# Perform data analysis, visualization, etc.
...
```

- Use Python logging to trace model performance

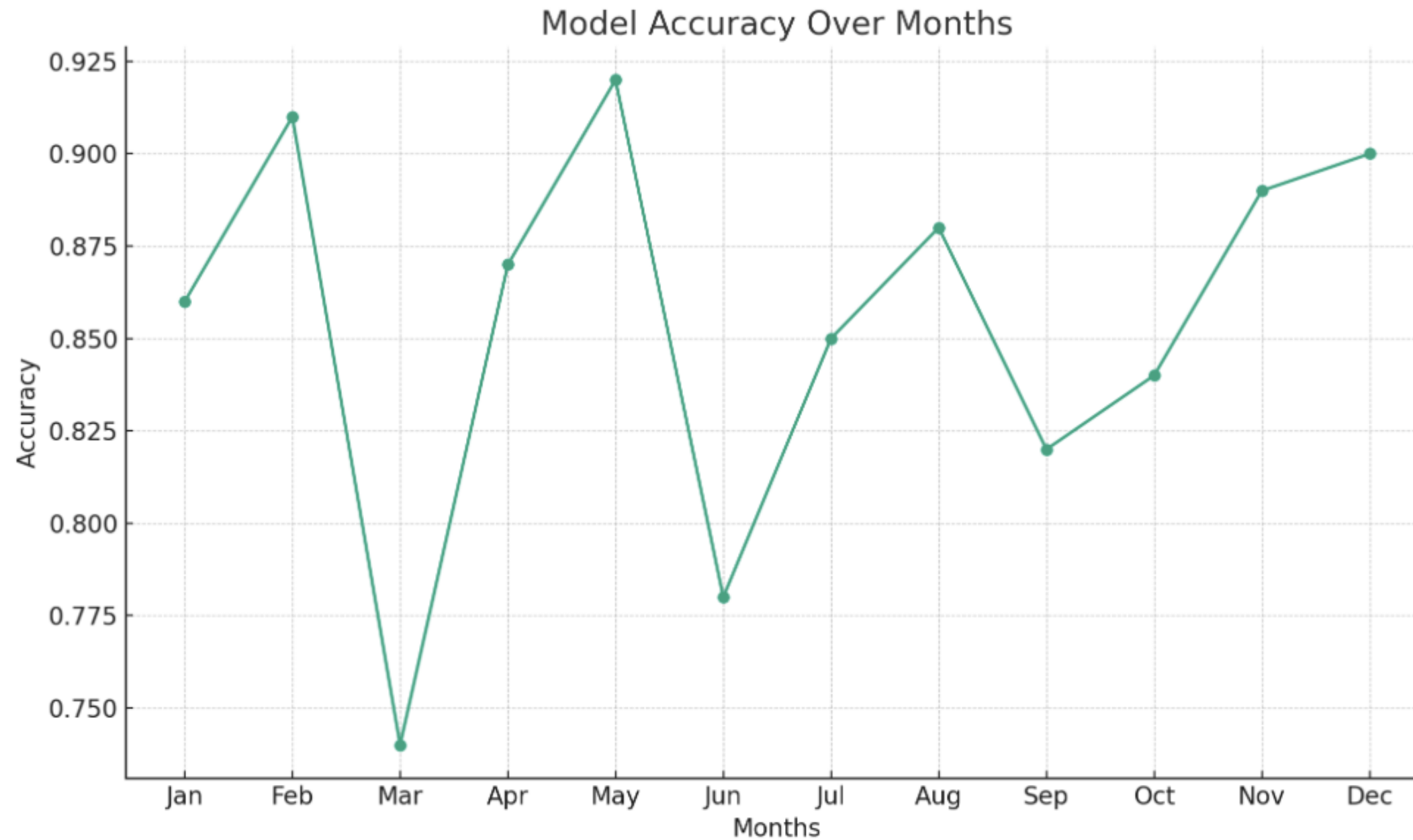
Visualization

- Inspect performance over time
- Transform raw data of inputs / predictions into insights

```
import matplotlib.pyplot as plt

# Sample data: Random accuracy values for 12 months
months = ["Jan", "Feb", "Mar", ...]
accuracies = [0.86, 0.91, 0.74, ...]
plt.plot(months, accuracies, '-o')
plt.title("Model Accuracy Over Months")
plt.xlabel("Months")
plt.ylabel("Accuracy")
plt.show()
```

Visualization example



Logging

- Recording of events
 - Tracking variable values, Function calls
 - Information that informs execution + performance
- Monitoring helps track:
 - Usage, Performance, Errors/anomalies

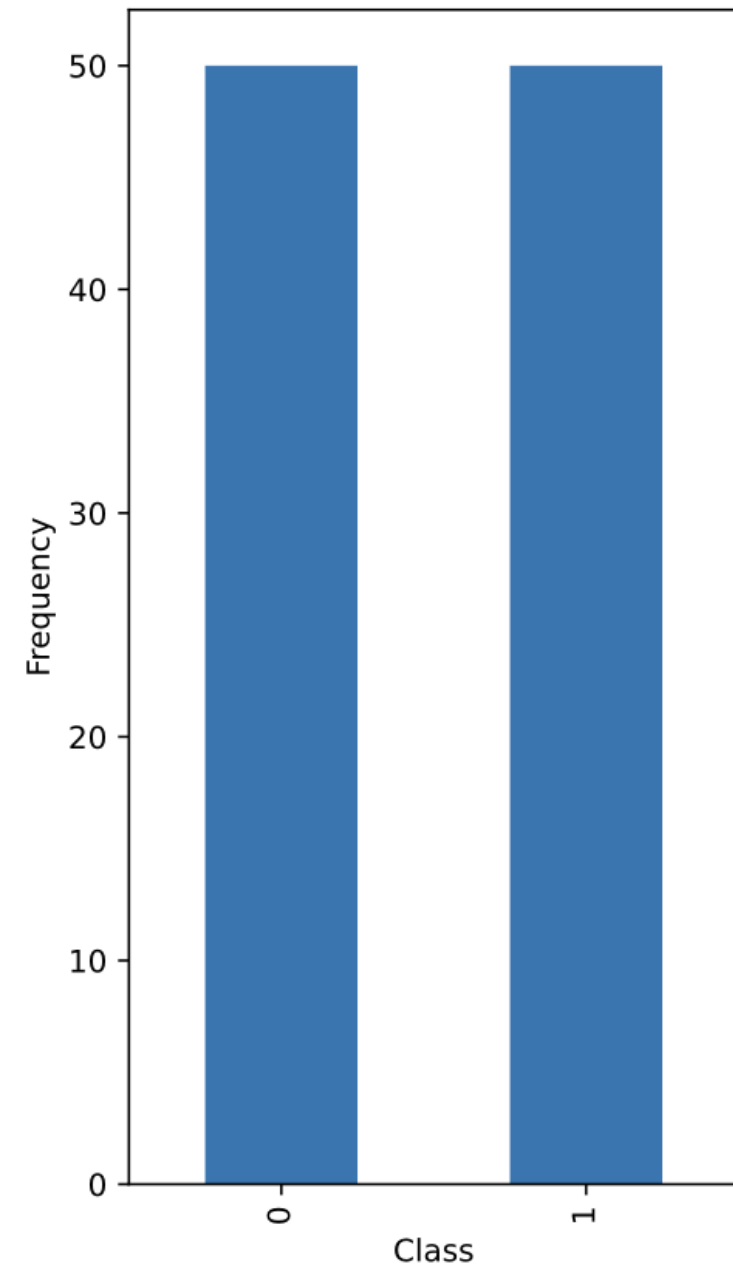
```
2023-08-04 09:15:20 [INFO] Model version 1.2.7 started
2023-08-04 09:15:45 [INFO] Preprocessing input data for prediction
2023-08-04 09:15:47 [DEBUG] Input data shape: (1, 12)
2023-08-04 09:15:48 [INFO] Making prediction
2023-08-04 09:15:50 [DEBUG] Output prediction: [0.78]
...
```

Visualization examples

- Helpful metric for our model: balanced accuracy over time
- Spot trends, see if performance degrades
- See if retraining is necessary
- Choose helpful metrics for our use-case

Example:

- Balanced accuracy changes relative to expected, real-world rate
- Potentially indicative of problem
- Choose and evaluate



Let's practice!

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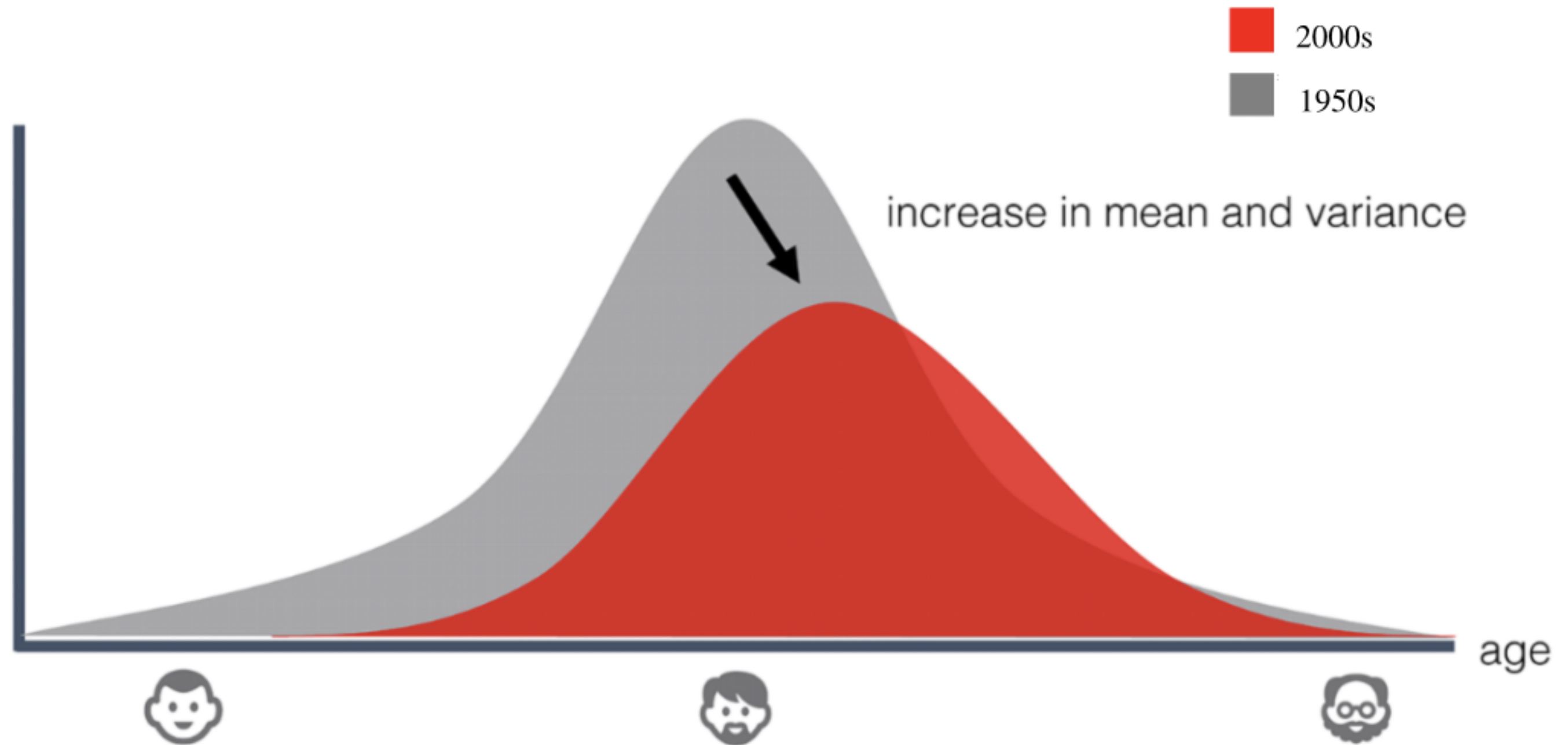
Data drift

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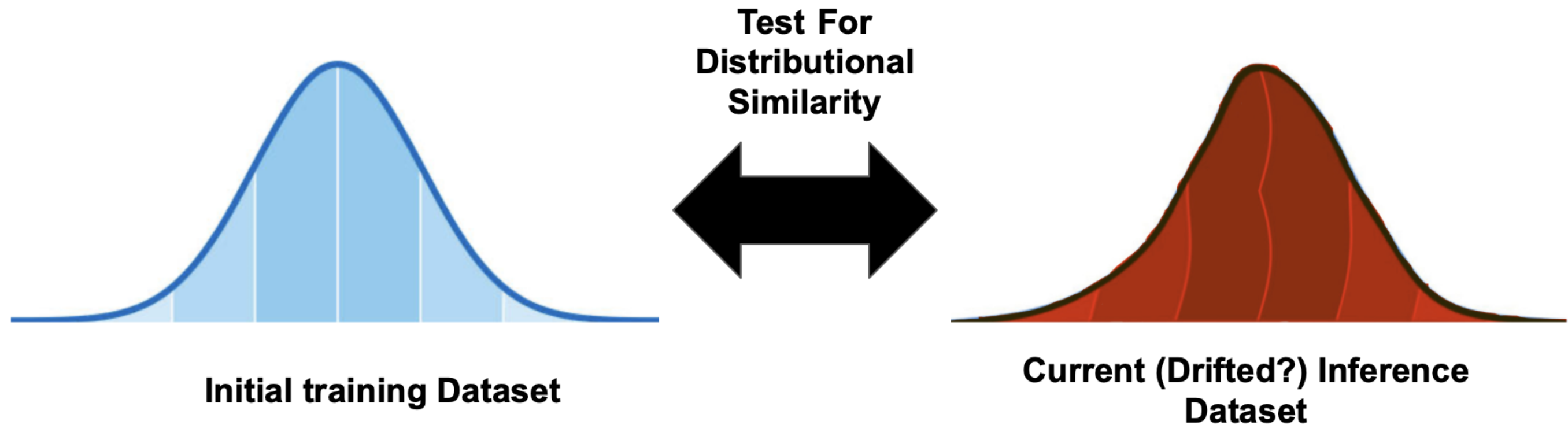
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The need for data drift detection



The Kolmogorov-Smirnov test

- Commonly used for detecting data drift
- Compares differences between dataset samples to determine distributional similarity



Using the `ks_2samp()` function

- `ks_2samp()` function returns two values: test statistic, p-value.
- Use p-value to accept/reject the null hypothesis of distributional similarity.

```
from scipy.stats import ks_2samp
```

```
# load the 1D data distribution samples for comparison
sample_1, sample_2 = training_dataset_sample, current_inference_sample
```

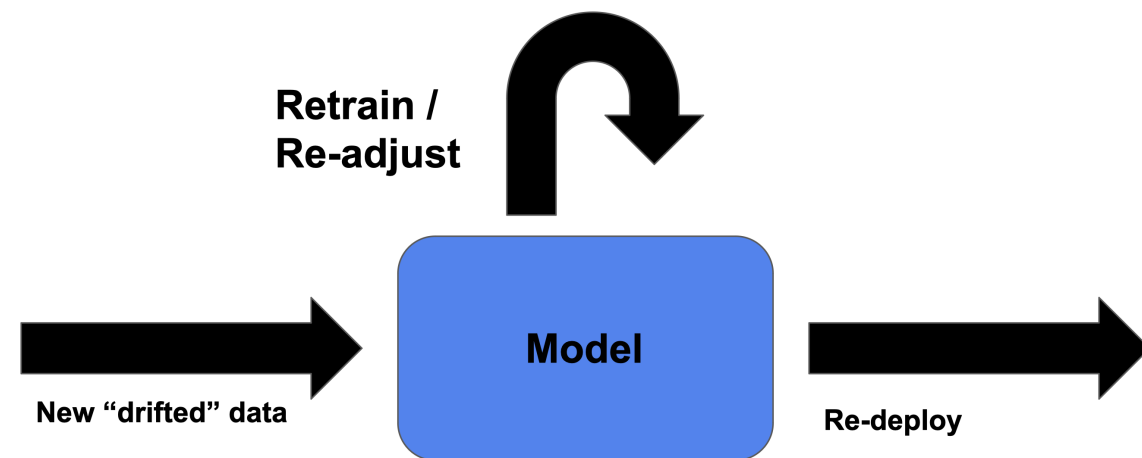
```
# perform the KS-test - ensure input samples are numpy arrays
test_statistic, p_value = ks_2samp(sample_1, sample_2)
```

```
if p_value < 0.05:
    print("Reject null hypothesis - data drift might be occurring")
else:
    print("Samples are likely to be from the same dataset")
```

Correcting data drift

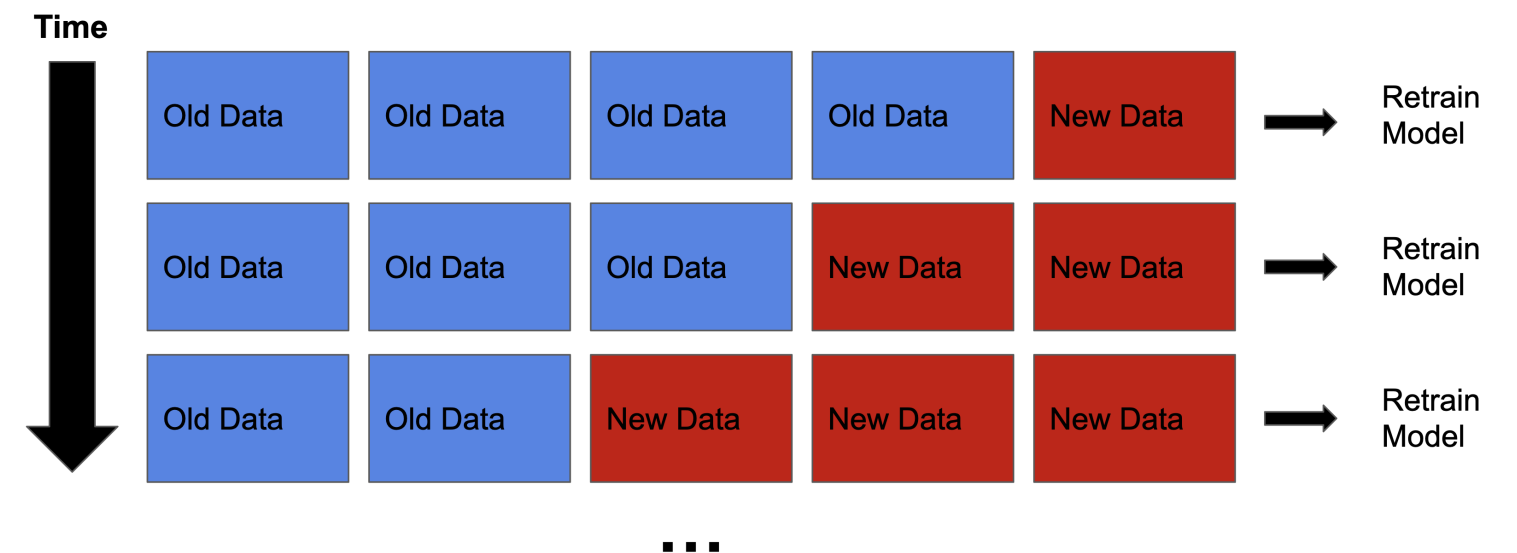
Update model to account for new data

- Retrain model
- Re-adjust / update model parameters



Not enough new/inference data?

- Re-train model on mixed dataset
- Increase amounts of new data



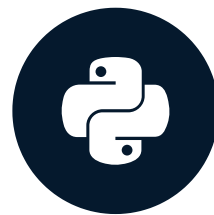
Further resources for detecting and rectifying data drift

- **Population Stability Index (PSI)**
 - Compares single categorical variables / columns
- **Evidently**
 - Open-source Python library
 - Robustly test and correct for data drift
- **NannyML**
 - Monitor deployed model performance

Let's practice!
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Feedback loop, re-training, and labeling

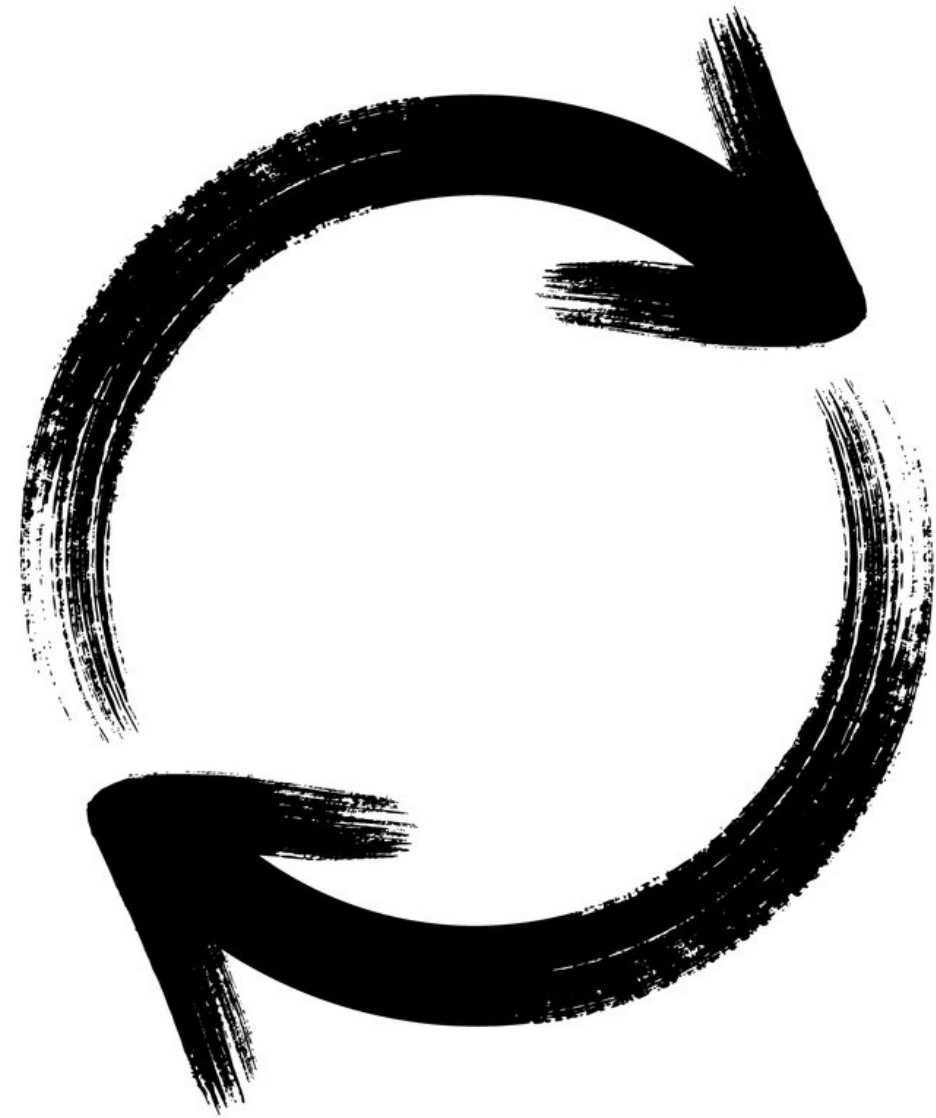
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Feedback loop

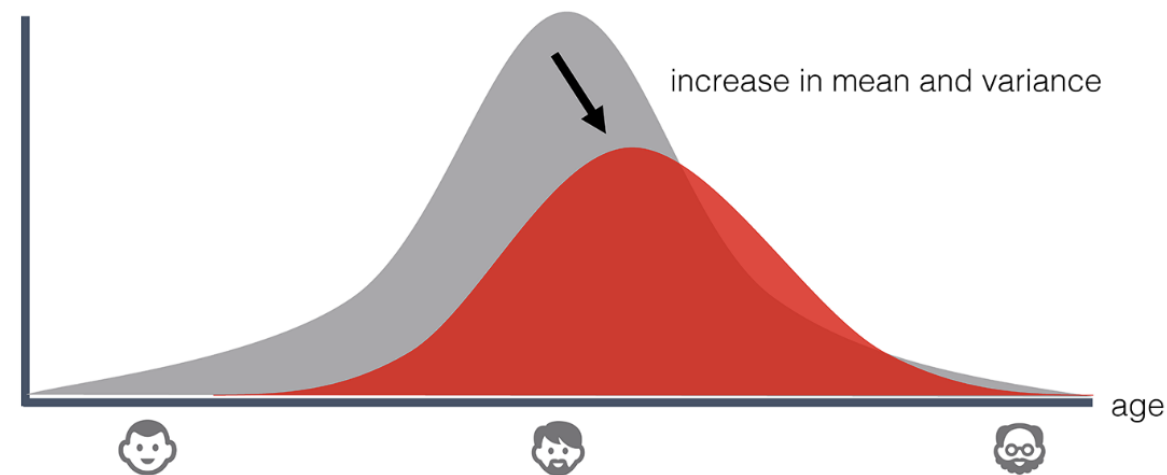
- Model output considered as system input:
 - Using metrics/predictions to inform system evolution
 - Can use model monitoring
- Integral part of ML:
 - Allows for rapid learning and adjustment
 - Better adapt to change



Feedback loop implementation

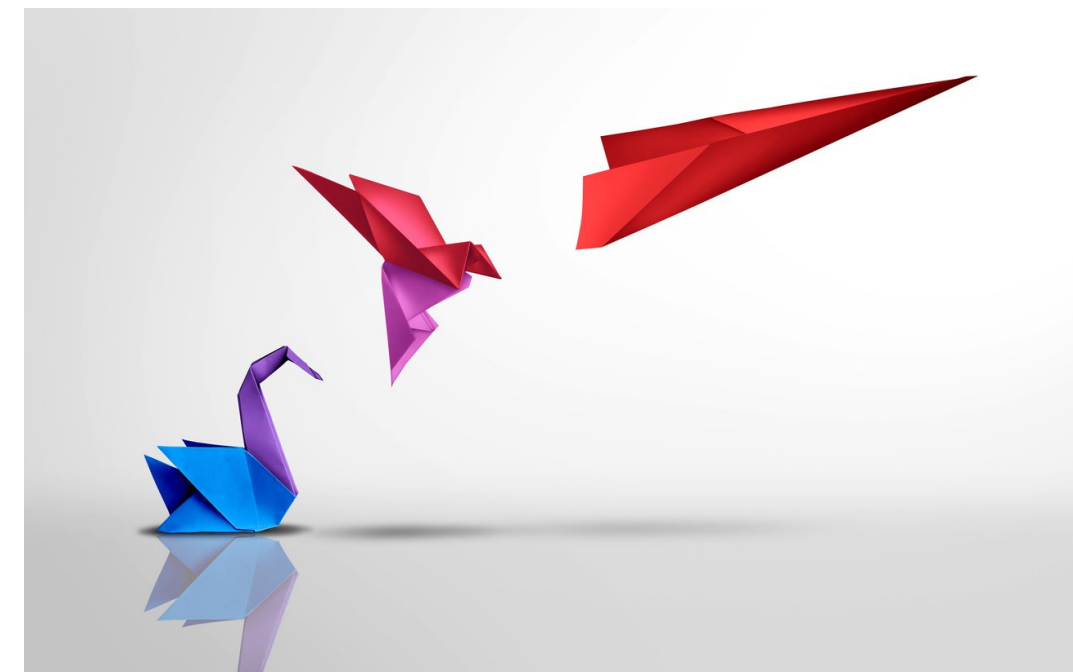
Data drift detection

- Input data distribution changes over time
- Feedback loop: retrain on newer data



Online learning

- Periodically retrain based on changing data
- Beyond data drift: adapts to changes in data structure



Dangers of feedback loops

Dangers...

- Model's outputs affect inputs
- Eg: social media recommendation:
 - Maximize user engagement
 - Learns to serve certain type of content
 - Causes user to view more of this content
 - etc.
- Develops undesired behavioral patterns
- More dangerous when automated



Better usage of feedback loop

- Reactive:
 - Human in the loop
 - Model's predictions don't change input data
- Caution and oversight are key!



Let's practice!
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Serving the model

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Model-as-a-service

- Stakeholders / users access model over internet
- Surface model through portal
 - Users post queries / data
 - Receive diagnosis / predictions
- Concerns:
 - Rural clinic / no internet access
 - Highly secure environment / sensitive data



On-device serving

Integrated serving architectures

- Edge-computing
- Helpful for unreliable internet cases



Pros and cons of on-device serving

Pros:

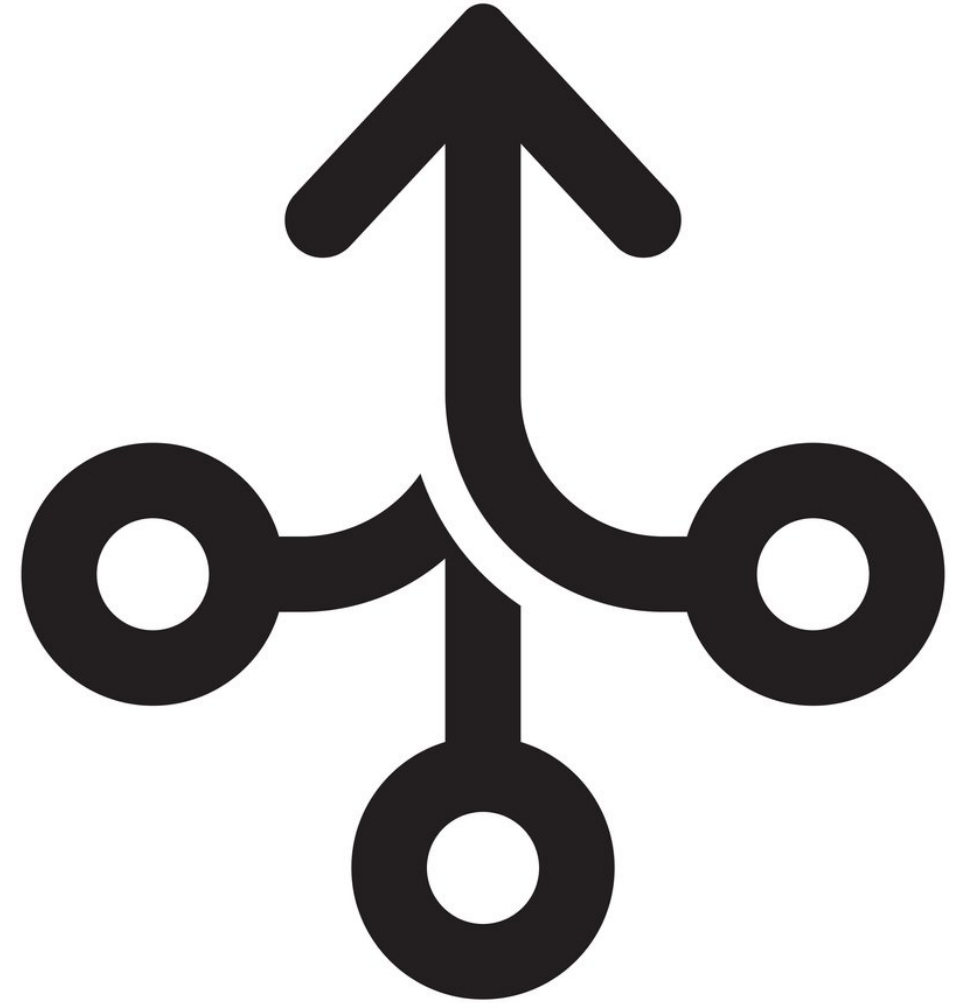
- Lower latency
- Security
- Applications for remote / disconnected areas

Cons:

- Resource constraints
- Model updates
- Monitoring

Implementation strategies

- Pruning
- Transfer Learning
- Use Dedicated Frameworks



Let's practice!

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Wrap-up

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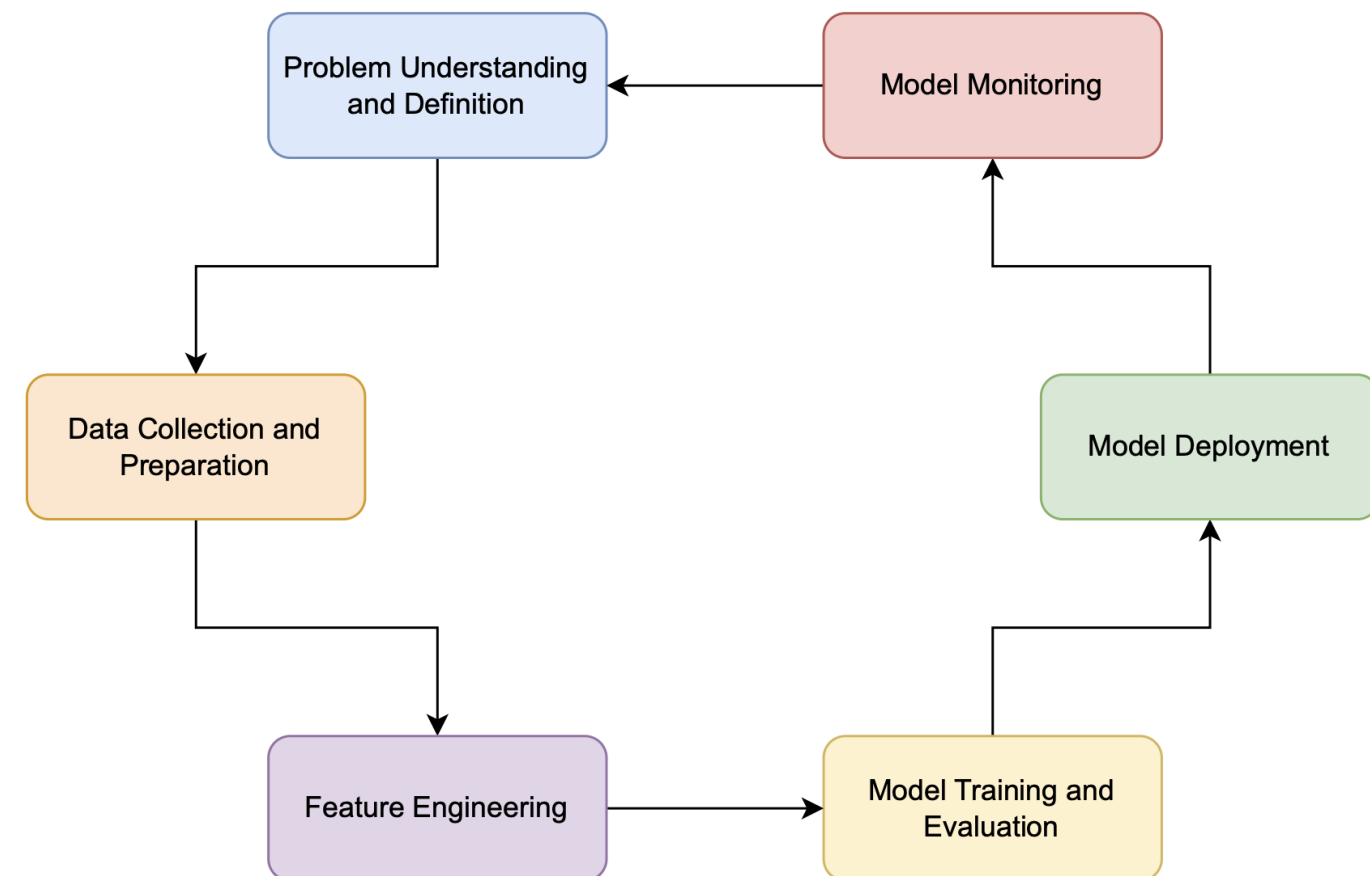


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How far we've come

Built a full ML pipeline:

- Problem Definition
- Data Cleaning
- Feature engineering and selection
- Model Training and evaluation
- Model deployment using TDD and CI/CD
- Model monitoring
- Feedback loop



What's next?



So much more to do!

- ML lifecycle isn't a once-off solution.
 - It's iterative, organic.
 - Continue to improve!

Let's practice!
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