Vietnam General Confederation of Labor
TON DUC THANG UNIVERSITY
FACULTY OF INFORMATION TECHNOLOGY

FINAL REPORT

MACHINE LEARNING

Instructor: **Mr. LÊ ANH CƯỜNG**

Student: **NGUYỄN MẠNH CƯỜNG – 521H0496**

Class :**21H50301**

Year **: 2023-2024**

HO CHI MINH CITY, 2023

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Ho Chi Minh city, 22th December, 2023

Author

(Sign and write full name)

Nguyễn Mạnh Cường

CONFIRMATION AND ASSESSMENT SECTION

Instructor confirmation section

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Ho Chi Minh 22 December, 2023

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Evaluation section for grading instructor

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SUMMARY

Improving model training requires understanding machine learning optimizers. Several well-known algorithms such as Adam, Stochastic Gradient Descent and Gradient Descent reduce errors by modifying model parameters

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CHAPTER 1 – OPTIMIZER

1.1 Introduction

Optimizer in the context of machine learning model training is an important part of the optimization process. The optimizer's task is to minimize (or maximize) the loss function by updating the model's weights. The ultimate goal is to bring the model to an optimal state, where the loss function reaches its minimum or maximum value depending on the type of problem.

Optimizer in machine learning model training plays an important role by helping to optimize the loss function, while also updating the model's weights based on the gradient. It not only prevents overfitting and underfitting through methods such as regularization and learning rate adjustment, but also accelerates the learning process through learning rate adaptation. The Optimizer also helps overcome the problem of slow learning and is able to adapt the magnitude of the gradient depending on the data. This helps the model learn efficiently and flexibly. The optimizer's strength lies in its easy implementation in popular machine learning libraries, which simplifies the model development process and saves developers time.

In the process of training models, the selection of optimization method plays an important role to update the weight of the model based on the loss jaw. The three common methods are Stochastic Gradient Descent (SGD), Mini-Batch Gradient Descent, Adam (Adaptive Moment Estimation) ....

1.2 Optimizer's optimization algorithms

1.2.1 Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is an optimization algorithm commonly used in machine learning and deep learning for training models. It is a variant of the more traditional Gradient Descent algorithm. The key difference lies in the way it updates the model parameters or weights.

In standard Gradient Descent, the model parameters are updated based on the average gradient of the entire training dataset. However, in SGD, the parameters are updated after computing the gradient of the loss function with respect to the parameters for each individual training example. This means that instead of using the full dataset, SGD randomly selects one training example at a time to compute the gradient and update the parameters.

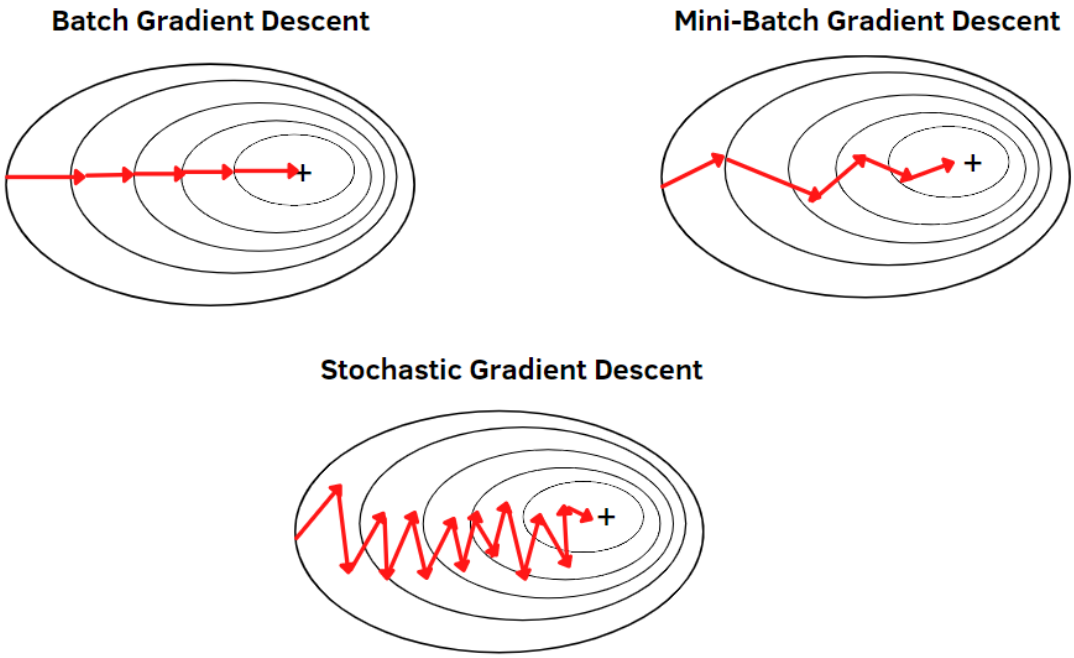
The stochastic nature of SGD introduces randomness and noise into the optimization process. While this can make the optimization path less predictable, it often helps the algorithm escape local minima and reach a solution more quickly. Additionally, the use of a single training example at a time makes SGD computationally less expensive, especially for large datasets.

The update rule for SGD can be represented as follows, where η (eta) is the learning rate: $\mathbf{Parameters \leftarrow Parameters - \eta \times \nabla(Loss)}$

Here, ∇(Loss) represents the gradient of the loss function with respect to the model parameters. The learning rate (η) controls the size of the step taken during each update.

Despite its effectiveness, SGD has some limitations, such as its sensitivity to the choice of the learning rate and the possibility of oscillating around the minimum.

Variants of SGD, such as Mini-batch Gradient Descent and adaptive learning rate methods like Adam, have been developed to address some of these challenges.



Here is a description of Stochastic Gradient Descent (SGD) step by step:

- **Starting parameters:** Starting by randomly creating the parameters of the model, such as Weights (Weights) and the Division (Bias).
- **Repeat via data:** Repeat each data point in training randomly (stochastically).
- **Randomly select a sample:** Randomly select a data point from training.
- **Forecast:** Use the current model to predict the output for the selected data score.
- **Slope calculation:** Calculate the slope of the loss jaw at the selected data point. This slope is usually calculated using Backpropagation.
- **Parametic update:** Update the parameters of the model in the opposite direction to the slope. This helps reduce the value of the loss function.

- **Repeat:** Repeat the process from step 3 until you have repeated the amount of Epoch or achieve the desired convergence.

Each repetition is a small step instructing the model to adjust the parameters so that the loss function decreases to the minimum. The random in choosing a sample helps avoid the feeling of facing the minimum point and optimizes the model in an overall direction.

1.2.2 Momentum

Momentum is a technique used in optimization algorithms, particularly in the context of training machine learning models, to accelerate convergence and overcome challenges associated with traditional gradient-based optimization methods. In the context of optimization, momentum is a parameter that enhances the ability of the optimizer to persist in a particular direction, allowing it to navigate through flat or shallow regions and accelerate through steep regions.

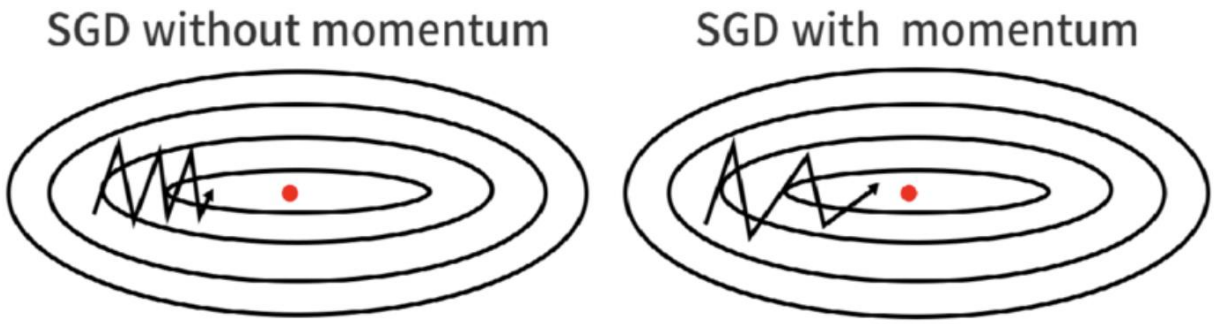
In the context of Stochastic Gradient Descent (SGD) or its variants, momentum is incorporated to address oscillations or slow convergence, especially when the optimization landscape includes flat or elongated valleys. It introduces a moving average of past gradients to the update rule, providing inertia to the optimization process.

The momentum term is usually denoted by β and ranges between 0 and 1. The update rule for the parameters (e.g., weights) with momentum can be expressed as follows:

$$Velocity \leftarrow \beta \times Velocity + (1-\beta) \times \nabla(Loss)$$

$$Parameters \leftarrow Parameters - Learning\ Rate \times Velocity$$

Here, ∇(Loss) represents the gradient of the loss function, and Velocity is a moving average of past gradients. The momentum term β determines the contribution of the previous velocity to the current update.

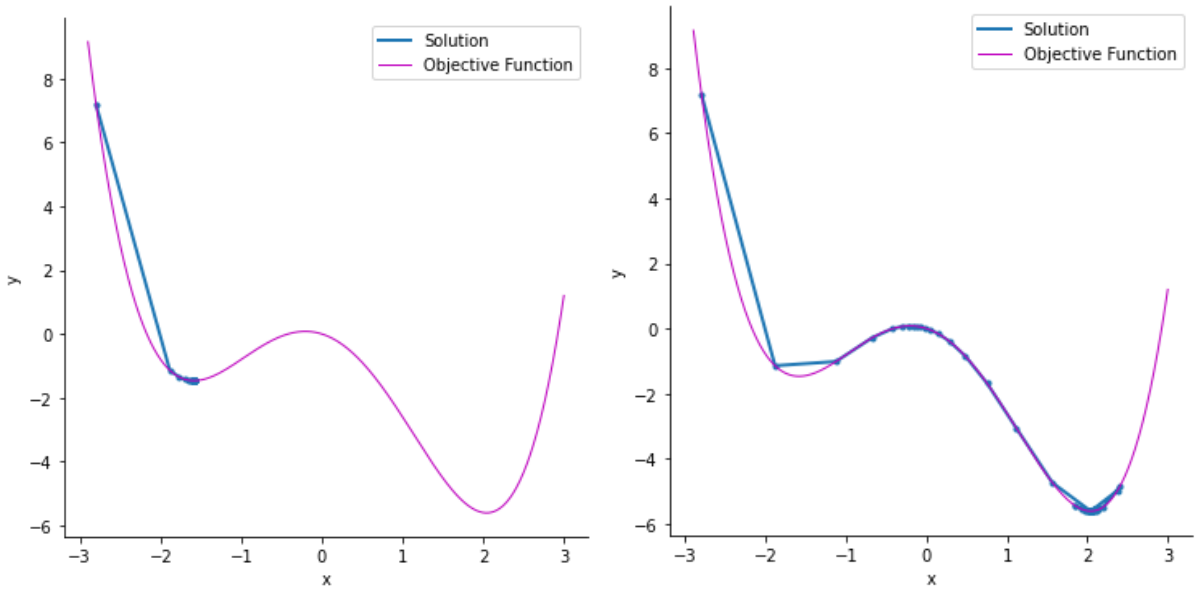


The inclusion of momentum helps the optimizer to build up speed in directions where the gradients consistently point, resulting in faster convergence. It acts as a dampening mechanism in regions with oscillations or irregularities, promoting a smoother and more efficient optimization process. Popular optimization algorithms, such as SGD with Momentum and Adam, leverage momentum to improve their performance.

Below is a description of the steps to perform Momentum in the process of optimizing the machine model, such as in the Stochastic Gradient Descent with Momentum algorithm:

- ***Starting parameters:*** Start by randomly creating the parameters of the model, such as weights (weights) and the degrees (bias).
- ***Initialize velocity:*** Create an initial velocity vector with a small or small random value.
- ***Repeat via data:*** Repeat each data point in training.

- ***Forecast:*** Use the current model to predict the output for the selected data score.
- ***Slope calculation:*** Calculate the slope of the loss jaw at the selected data point.
- ***Update velocity:*** Update velocity based on the current slope and previous velocity according to the formula: $Velocity \leftarrow \beta \times velocity + (1-\beta) \times \nabla(loss)$
- ***Parametic update:*** Update the parameters of the model based on calculated velocity and learning rate (learning rate): *Parameters* ← *Parameters* - *Rearning Rate* × *Velocity*
- **Repeat:** Repeat the process from step 3 until you have repeated the amount of Epoch or achieve the desired convergence.



Stochastic gradient descent without momentum stops at a local minimum. (left picture)

Stochastic gradient descent with momentum stops at the global minimum. (right picture)

Momentum helps to speed up the optimization process by retaining a part of the previous speed when updating the parameter, creating a "momentum" to help overcome flat areas and accelerate through the slopes.

1.2.3 Mini-Batch Gradient Descent

Mini-Batch Gradient Descent is a variation of the traditional Gradient Descent optimization algorithm used in training machine learning models. While standard Gradient Descent computes the gradients and updates the model parameters based on the entire training dataset, Mini-Batch Gradient Descent divides the dataset into smaller batches and performs updates based on each mini-batch.

The key steps in Mini-Batch Gradient Descent are as follows:

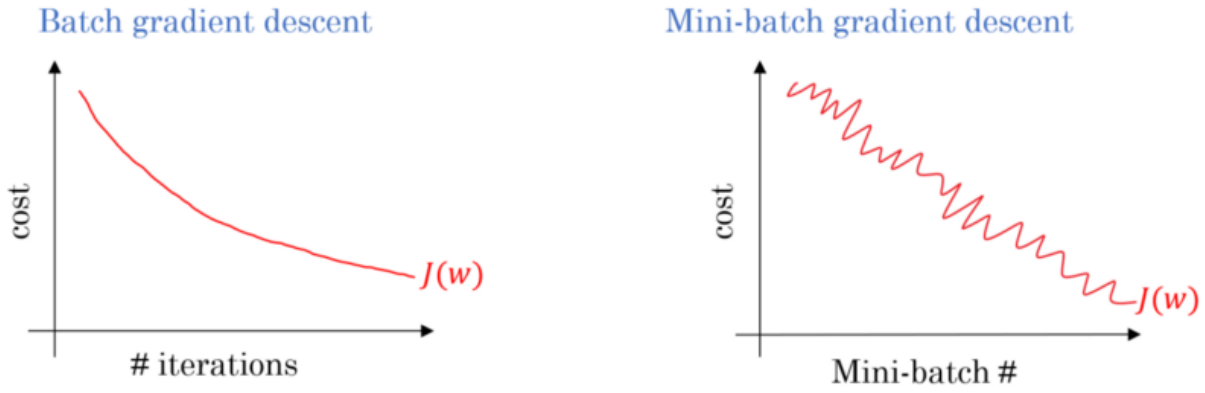
- ***Divide the Dataset into Mini-Batches:*** The training dataset is partitioned into smaller subsets, known as mini-batches. Each mini-batch contains a fixed number of data samples.
- ***Shuffle the Mini-Batches (Optional):*** It's common to shuffle the order of the mini-batches at the beginning of each epoch to introduce randomness and avoid the model learning patterns specific to the order of the training examples.
- ***Iterate Through Mini-Batches:*** The training process involves iterating through the mini-batches, one at a time.
- ***Compute Gradient and Update Parameters:*** For each mini-batch, compute the gradient of the loss function with respect to the model parameters.

  $Parameters \leftarrow Parameters - Learning\ Rate \times \nabla(Loss)$

  The learning rate determines the step size in the parameter space, and ∇(Loss) represents the gradient of the loss function.
- ***Repeat Until Convergence:*** Iterate through the mini-batches for a predefined number of epochs or until convergence is achieved.

The advantage of Mini-Batch Gradient Descent lies in its computational efficiency. By using smaller batches of data, it leverages parallelism and accelerates the optimization process, especially on hardware like GPUs. It also introduces a level of noise, which can help the algorithm escape local minima and converge to a more general solution.

The mini-batch size is a hyperparameter that needs to be tuned based on the characteristics of the dataset and the available computational resources. Common choices for mini-batch sizes include 32, 64, 128, or 256 samples.



1.2.4 RMSprop (Root Mean Square Propagation).

RMSprop, which stands for Root Mean Square Propagation, is an optimization algorithm commonly used in training machine learning models. It is designed to address some of the limitations of basic gradient descent methods, particularly the challenges posed by different scales of gradients in different dimensions.

The key idea behind RMSprop is to adapt the learning rates of individual model parameters by dividing the learning rate for each parameter by a running average of the magnitudes of recent gradients for that parameter. This adaptive learning rate helps to

converge faster in dimensions with steep gradients and slow down in dimensions with shallow gradients.

Here are the main steps involved in the RMSprop algorithm:

- ***Initialize Variables:*** Initialize the model parameters (weights and biases) and a running average variable, denoted by $E[g^2]$, where g is the gradient.
- ***Iterate Through Mini-Batches:*** Divide the training dataset into mini-batches.
- ***Compute Gradients:*** For each mini-batch, compute the gradients of the loss function with respect to the model parameters.
- ***Update Running Average:*** Update the running average of squared gradients using an exponential decay formula:

  $$E[g^2] = \beta \times E[g^2] + (1 - \beta) \times (\nabla(\text{Loss}))^2$$

  where β is a decay factor (typically close to 1, e.g., 0.9).
- ***Update Parameters:*** Update the model parameters using the computed gradients and the adjusted learning rates:

  $$\text{Parameters} \leftarrow \text{Parameters} - \frac{\text{Learning Rate}}{\sqrt{E[g^2]+\epsilon}} \times \nabla(\text{Loss})$$

  Here, ϵ is a small constant added to the denominator for numerical stability.

- ***Repeat Until Convergence***: Repeat the process for a predefined number of iterations or until convergence.

RMSprop's adaptive learning rate helps overcome challenges associated with choosing a global learning rate for all parameters, making it particularly effective for non-stationary or noisy optimization problems. It is often used in combination with

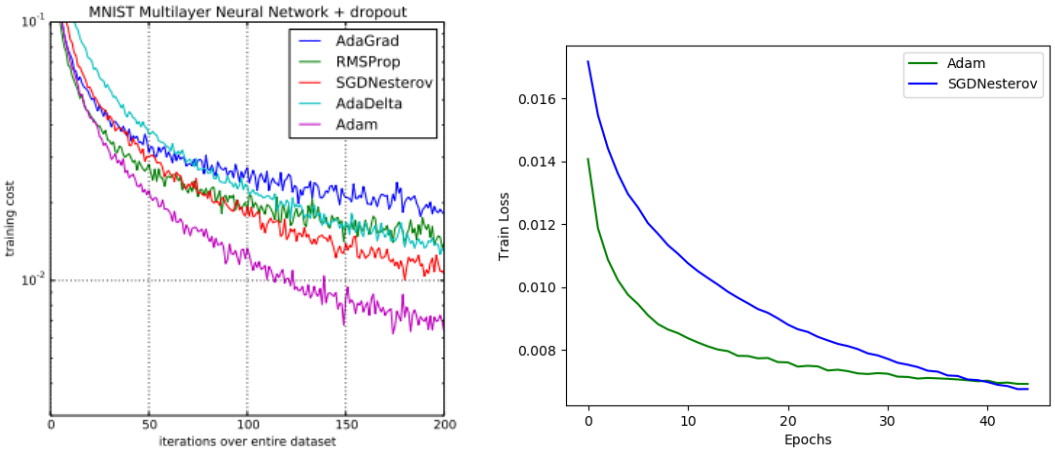
other optimization algorithms and has been influential in the development of more advanced optimizers like Adam.

1.2.5 Adam (Adaptive Moment Estimation).

Adam optimizer, introduced in 2014 and first presented at ICLR 2015, is an advanced optimization algorithm that extends stochastic gradient descent (SGD) and finds applications in various deep learning tasks like computer vision and natural language processing. Named after "adaptive moment estimation," Adam dynamically adjusts the learning rate for each weight in a neural network based on estimations of the first and second moments of the gradient.

Unlike its predecessors, such as AdaGrad and RMSprop, Adam is designed to overcome certain limitations like suboptimal generalization performance in some cases. It has been recognized for its efficiency, requiring minimal memory due to its reliance on first-order gradients. Adam's hyperparameters also have intuitive interpretations, reducing the need for extensive tuning.

While Adam generally performs well, researchers have observed instances where it doesn't converge to the optimal solution as effectively as SGD. In some diverse deep learning tasks, the generalizing performance of Adam may be subpar. Some studies suggest that switching to SGD in specific cases can lead to better generalization compared to Adam alone. The nuanced performance of Adam underscores the ongoing exploration and optimization of optimization algorithms in the field of deep learning.



Here's a more detailed explanation of the key components and steps in the Adam optimization algorithm:

- ***Initialization of Variables:*** Initialize two moving average variables, m (momentum) and v (uncentered variance), both set to zero initially.
- ***Setting Hyperparameters:*** Adam involves the use of hyperparameters, including β_1 and β_2 (decay rates), and ϵ (a small constant for numerical stability). Commonly used values are $\beta_1 = 0.9$, $\beta_2 = 0.999\ 9$, and $\epsilon = 1\times10^{-8}$.
- ***Iterate Through Mini-Batches:*** Divide the training dataset into mini-batches.
- ***Compute Gradients:*** For each mini-batch, compute the gradients of the loss function with respect to the model parameters.
- Update Momentum and Uncentered Variance: Update the moving averages,

$$m = \beta_1 \times m + (1 - \beta_1) \times \nabla(\text{Loss})$$
$$v = \beta_2 \times v + (1 - \beta_2) \times (\nabla(\text{Loss}))^2$$

- ***Bias Correction:*** Correct the bias introduced by initializing m and v with zeros by dividing them by $1-\beta_1^t$ and $1-\beta_2^t$, respectively, where t is the current iteration.
- ***Update Parameters:*** Update the model parameters using the adjusted learning rates:

$$\text{Parameters} \leftarrow \text{Parameters} - \frac{\text{Learning Rate} \times m}{\sqrt{v}+\epsilon}$$

  Here, $\sqrt{v}$ denotes the element-wise square root of v.
- ***Repeat Until Convergence:*** Repeat the process for a predefined number of iterations or until convergence.

1.2.6 AdaGrad

AdaGrad is a class of sub-gradient algorithms designed for stochastic optimization, exhibiting similarities to second-order stochastic gradient descent by approximating the Hessian of the optimized function. The name "AdaGrad" reflects its nature as an Adaptive Gradient algorithm. In essence, AdaGrad dynamically adjusts the learning rate for each feature based on the estimated geometry of the problem. Notably, it assigns higher learning rates to infrequent features, emphasizing relevance over frequency in parameter updates.

Duchi et al. introduced AdaGrad in a widely cited 2011 paper published in the Journal of Machine Learning Research. It has since become one of the most popular algorithms in machine learning, particularly in training deep neural networks, and has influenced the development of subsequent algorithms like Adam.

AdaGrad aims to minimize the expected value of a stochastic objective function concerning a set of parameters, given a sequence of realizations of the function. Employing sub-gradient-based methods, AdaGrad updates parameters in the opposite

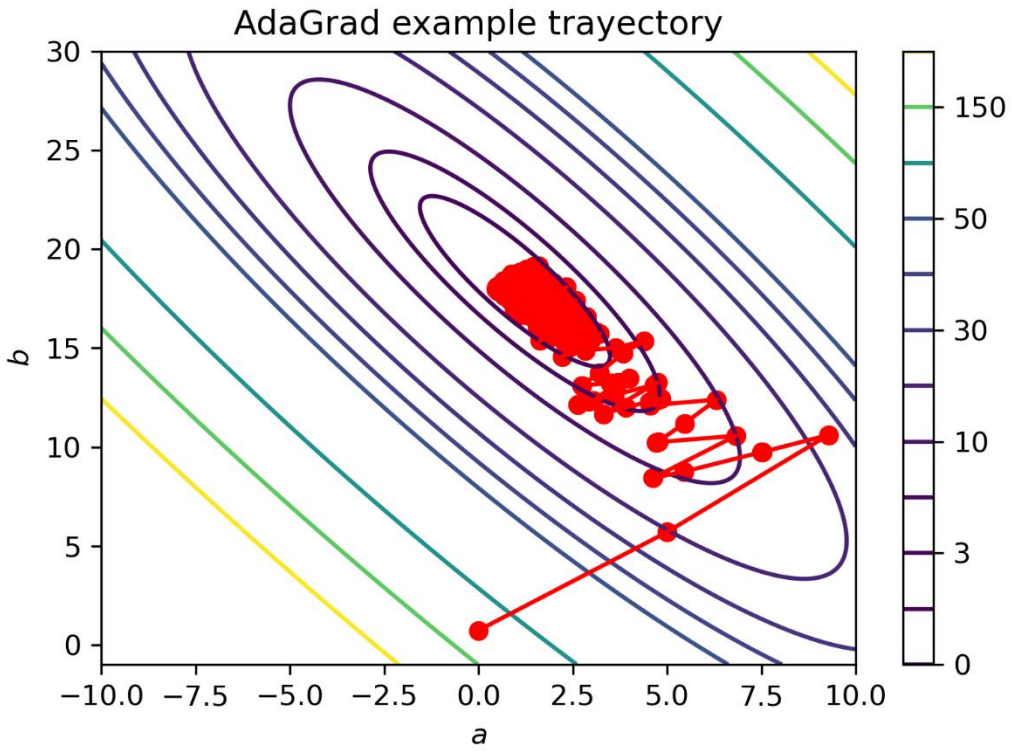
direction of sub-gradients. Unlike standard sub-gradient methods, AdaGrad stands out by adapting the learning rate for each parameter individually, leveraging the sequence of gradient estimates from past observations.

Here is a step-by-step presentation of the AdaGrad optimization algorithm:

- ***Initialization:*** Initialize the model parameters, typically denoted as θ. Initialize a vector G with the same dimensionality as θ to store the sum of squared gradients. Set all elements of G to a small positive constant, e.g., 10^{-8}.
- ***Iterate Through Mini-Batches:*** Divide the training dataset into mini-batches.
- ***Compute Gradients:*** For each mini-batch, compute the gradients of the loss function with respect to the model parameters ∇(Loss).
- ***Accumulate Squared Gradients:*** Accumulate the square of the gradients into the G vector: $G=G+(\nabla(Loss))^2$
- ***Update Parameters:*** Update the model parameters using the accumulated squared gradients and the learning rate η:

  $$\theta = \theta - \frac{\eta}{\sqrt{G}} \odot \nabla(\text{Loss})$$

  Here, ⊙ denotes element-wise multiplication and $\sqrt{G}$ is the element-wise square root of G.
- ***Repeat Until Convergence:*** Repeat the process for a predefined number of iterations or until convergence.



The key idea of AdaGrad is to adapt the learning rates for each parameter based on the historical squared gradients. This adaptation ensures that parameters associated with infrequent features receive larger updates, allowing the algorithm to emphasize the relevance of features over their frequency. While AdaGrad has its strengths, it may suffer from issues like a monotonically decreasing effective learning rate, leading to overly conservative updates over time. Variants like RMSprop and Adam have been introduced to address some of these limitations.

1.3 Advantages and Disadvantages

Algorithm	Advantages	Disadvantages
Stochastic Gradient Descent (SGD)	Easy to implement and understand, Works well on large data sets	May fall into local optimum points, Update directions are not always the best
Momentum	Reduces oscillation momentum, helping to avoid local optimal points, Accelerate the learning process	Need to adjust learning rate to avoid overshooting
Mini-Batch Gradient Descent	Reduce bias compared to SGD, Faster than Batch GD	Requires choosing appropriate batch size
Adam	Effective on many types of models, Automatically adjust learning rate	Requires additional information storage
RMSprop	Adapts to data, requires less memory than Adam	Not suitable for all types of models
Adagrad	Adaptation to individual parameters, Works well on sparse data	Learning rate reduces too much, not suitable for all situations

Comparison and Summary:

- Efficiency: Adam and RMSprop are generally effective on a wide range of models.
- Adaptive: Adam and RMSprop automatically adjust learning rate.

- Special Applications: Adagrad is suitable for sparse data.
- Ease of Deployment: SGD and Mini-Batch GD are easier to deploy than adaptive methods.

The choice between these methods depends on the specific characteristics of the problem, data type, and computational resource requirements. Often testing and tuning on a specific data set is the best way to determine the most suitable optimizer

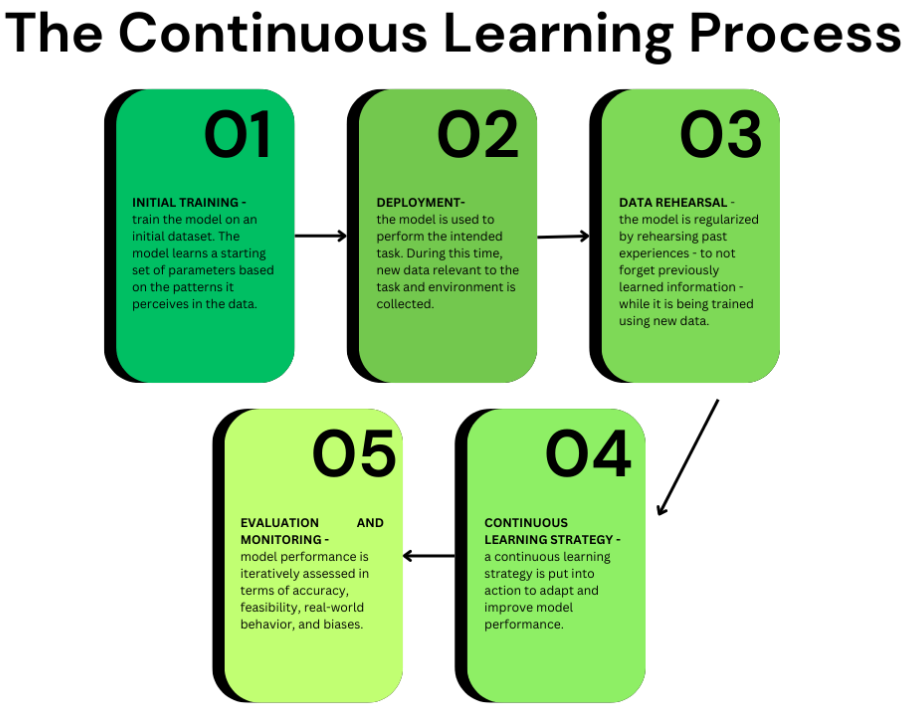
CHAPTER 2 – CONTINUAL LEARNING AND TEST PRODUCTION

2.1. Continual Learning

2.1.1 Understanding about continual learning

Continuous Learning (CL) poses the challenge of learning and adapting to new data while maintaining learned knowledge. In an environment with a constant stream of incoming data, retraining the model from scratch becomes infeasible, and that is why CL becomes important. The main goal is to keep the model flexible and capable of applying learned knowledge to new tasks without forgetting important information from previous tasks.

CL was born to solve the problem of forgetting old information when the model is faced with new data. It helps the model maintain continuous learning and not get too locked into old data.



Catastrophic forgetting is a phenomenon observed in machine learning and artificial intelligence, particularly in the context of neural networks, where a model trained on one task experiences a significant decline in performance when learning a new and different task. In other words, the model forgets or loses knowledge related to the initial task while adapting to the new one.

Key features of catastrophic forgetting include:

- ***Task Interference:*** When a neural network is trained sequentially on multiple tasks, the weights and representations that were effective for the first task may be overwritten or modified during training on subsequent tasks. This interference between tasks leads to a deterioration of performance on the original task.
- ***Overfitting to New Data:*** The model may become overly specialized or overfit to the new task, optimizing its parameters to better suit the characteristics of the most recent task at the expense of performance on previously learned tasks.
- ***Limited Model Capacity:*** Neural networks, especially those with limited capacity or resources, may struggle to maintain knowledge of multiple tasks simultaneously. The finite capacity of the model limits its ability to retain information about earlier tasks when learning new ones.
- ***Non-Stationary Environments:*** Catastrophic forgetting is more pronounced in non-stationary environments, where the statistical properties of the data distribution change over time. In such cases, the model may fail to adapt effectively to the evolving data.

Addressing catastrophic forgetting is a challenging problem, and several approaches have been proposed to mitigate its effects:

- **Rehearsal:** Preserve samples from the original task and include them in the training data for subsequent tasks. This helps the model retain information about the earlier tasks.
- **Regularization Techniques:** Apply regularization methods, such as weight regularization or dropout, to constrain the impact of new task learning on existing parameters.
- **Architectural Modifications:** Modify the architecture of the neural network to include components specifically designed to store and retrieve knowledge from earlier tasks.
- **Ensemble Methods:** Train multiple models on different tasks and combine their outputs. This helps mitigate forgetting by distributing the learning across multiple models.
- **Transfer Learning:** Utilize transfer learning techniques to initialize the model with knowledge gained from pre-training on a diverse set of tasks before fine-tuning on the specific tasks of interest.

Let's consider an example to illustrate the phenomenon of catastrophic forgetting. Suppose we have a neural network initially trained to recognize handwritten digits (Task 1) using the MNIST dataset. The model is proficient at classifying digits from 0 to 9. Now, we want to extend the model's capabilities to recognize spoken words (Task 2) using a dataset of audio samples.

Task 1: Handwritten Digit Recognition (MNIST): The neural network is trained on the MNIST dataset, achieving high accuracy in recognizing handwritten digits.

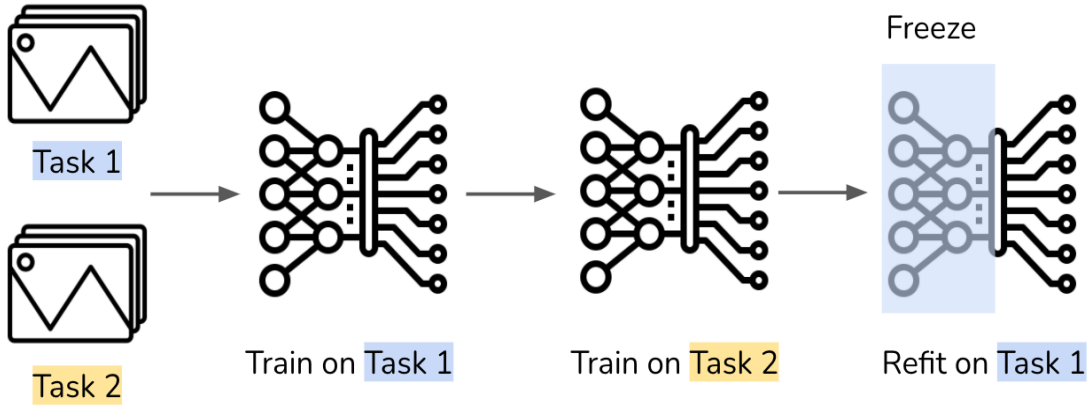
Task 2: Spoken Word Recognition: Without any mechanism to mitigate catastrophic forgetting, we start training the same neural network on a new dataset for spoken word recognition. The network adjusts its weights to optimize for the new task.

Now, the catastrophic forgetting may manifest in the following ways:

Performance Degradation on Task 1: As the neural network adapts to the spoken word recognition task, the weights associated with features important for recognizing handwritten digits may be modified. Consequently, the accuracy of the model on Task 1 (handwritten digit recognition) decreases. The network may start misclassifying digits that it previously handled well.

Overfitting to Task 2: The model may become overly specialized in recognizing spoken words and might overfit to the characteristics of the new dataset. This overfitting comes at the expense of its ability to generalize well to other types of data, such as handwritten digits.

Mitigating catastrophic forgetting is crucial in scenarios where a model needs to continually learn and adapt to new tasks without compromising its performance on previously learned tasks. Strategies such as rehearsal (preserving samples from Task 1 and including them in Task 2 training), regularization techniques, and architectural modifications can be employed to address this issue and allow the model to maintain knowledge across multiple tasks.



2.1.2 Advantages of continual learning

Adaptability: Continual learning fosters adaptability by enabling individuals to acquire new skills and knowledge, allowing them to navigate and thrive in evolving environments. This adaptability is crucial in the face of technological advancements and changes in the workplace.

Professional Development: Individuals engaged in continual learning are more likely to experience professional growth and advancement. The ongoing acquisition of new skills and knowledge enhances their expertise and makes them valuable assets in their respective fields.

Enhanced Problem-Solving: Continual learners develop a broader perspective and diverse skill set, which enhances their problem-solving abilities. They are better equipped to approach challenges creatively and find innovative solutions.

Career Resilience: In dynamic industries and job markets, continual learning enhances career resilience. Individuals who continually update their skills are better positioned to adapt to changes, stay relevant, and navigate career transitions.

Increased Job Satisfaction: Learning new things and expanding one's skill set can contribute to increased job satisfaction. The sense of accomplishment and personal

growth associated with continual learning can positively impact an individual's overall well-being.

Maintained Cognitive Function: Lifelong learning has been associated with improved cognitive function and mental agility. Engaging in intellectually stimulating activities throughout one's life can help maintain cognitive health and reduce the risk of cognitive decline.

Innovation and Creativity: Continual learners are more likely to contribute to innovation and creativity. Exposure to a diverse range of ideas and concepts fosters a creative mindset, allowing individuals to bring fresh perspectives to their work and problem-solving.

Leadership Development: Leaders who prioritize continual learning set an example for their teams. They are more effective in leading and managing change, promoting a culture of learning within their organizations, and inspiring their teams to embrace new challenges.

Economic Value: Continual learning contributes to economic value at both individual and societal levels. Individually, it enhances employability and earning potential. Societally, a workforce committed to continual learning fosters economic growth and competitiveness.

Personal Fulfillment: Beyond professional benefits, continual learning provides a source of personal fulfillment. The pursuit of knowledge and skills for their own sake can bring joy, satisfaction, and a sense of purpose to individuals.

2.1.3 Disadvantages of continual learning

Time and Resource Constraints: Limited time and resources can make continual learning challenging for individuals with busy schedules.

Learning Fatigue: Constant learning may lead to fatigue and burnout, impacting sustained enthusiasm.

Obsolete Information: Rapid advancements in certain fields may render acquired knowledge outdated quickly.

Lack of Recognition: Achievements from continual learning may not always be recognized or rewarded.

Difficulty Applying Knowledge: Challenges may arise in effectively applying newly acquired knowledge in practical scenarios.

Risk of Over-specialization: Overemphasis on specific areas may limit adaptability to diverse challenges.

Financial Costs: Accessing quality learning resources may come with associated financial costs.

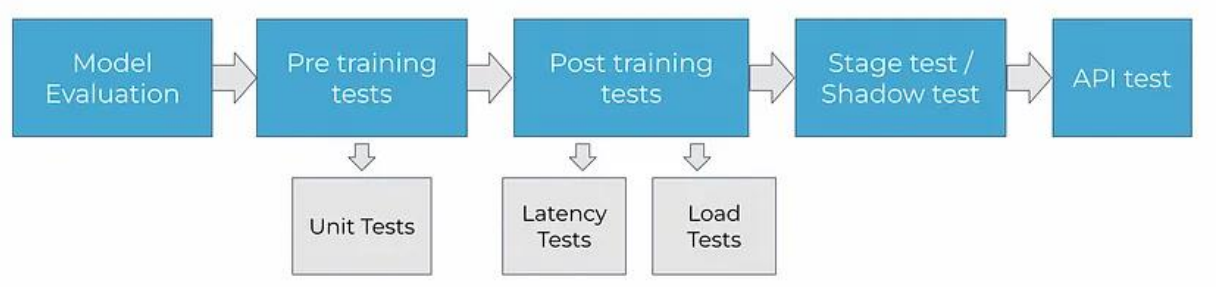
Incompatibility with Learning Style: Not all learning methods may align with everyone's preferred style.

Distraction and Information Overload: Abundant online information can lead to distraction and information overload.

2.2. Test Production

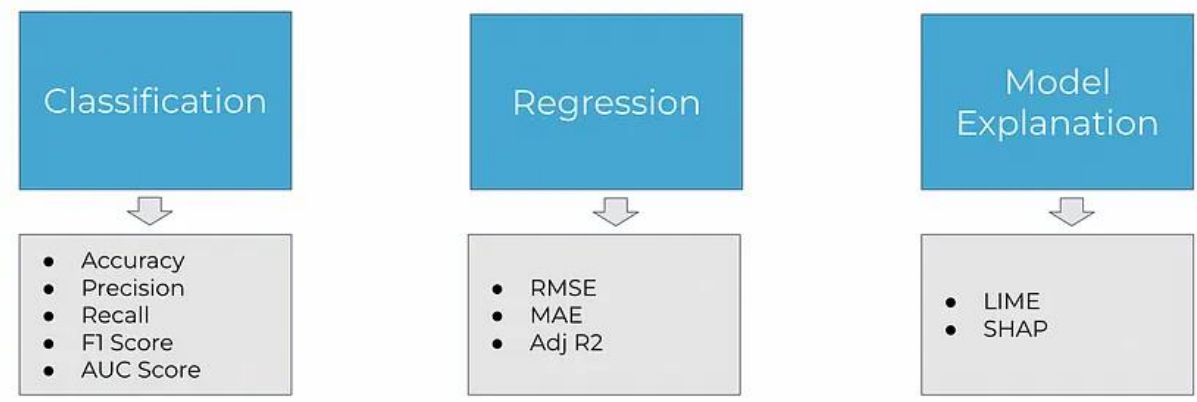
2.2.1 Understanding about test production

Test Production is the final stage in the process of building a machine learning solution, where the model is tested and evaluated to ensure that it responds properly before being deployed into a real environment. This ensures that the model will perform accurately and reliably in real-world applications.



Model evaluation is a critical step in the machine learning pipeline, aiming to assess how well a trained model performs on unseen data. The goal is to measure the model's generalization ability and identify its strengths and weaknesses. Several metrics and techniques are used for model evaluation.

Model evaluation serves as the initial step (Stage 0) in model testing, primarily focusing on assessing the functionality of the model. Specific metrics are employed to evaluate the quality of different types of models. In the context of imbalanced datasets, F1 scores and AUC scores prove effective for classification tasks, while for regression tasks on outlier-heavy data, MAE is a preferable metric. For ensemble-decision tree-based supervised models like XGBoost or Random Forest, SHAP can be utilized to gain insights into the prediction logic due to their inherent black box nature. Additionally, LIME can be employed for scrutinizing specific instances, providing a more detailed inspection of model predictions.



The pre-training test is conducted before the model undergoes the training process. It involves evaluating the initial state or baseline performance of the model using a test dataset. This test helps establish a benchmark for comparison, allowing you to understand how the model performs before any learning or optimization occurs.

The post-training test, on the other hand, is conducted after the model has undergone the training process. Once the model has learned from the training data, it is evaluated again using a separate test dataset. This evaluation assesses how well the model generalizes to new, unseen data after the learning process. It helps determine the effectiveness of the training and whether the model has successfully learned patterns and relationships in the data.

Testing machine learning models involves evaluating their performance, generalization capabilities, and robustness. Here are key steps and considerations for testing machine learning models:

- ***Data Splitting:*** Divide the dataset into training and testing sets. The training set is used to train the model, while the testing set assesses its performance on unseen data. Common splits include 70-30 or 80-20 for training and testing, respectively.
- ***Cross-Validation:*** Implement cross-validation to assess model performance across multiple folds or subsets of the dataset. Common methods include k-fold cross-validation, which helps reduce the impact of dataset variability on performance metrics.
- ***Evaluation Metrics:*** Choose appropriate evaluation metrics based on the nature of the problem:
- ***Classification Metrics:*** Accuracy, Precision, Recall, F1 Score, Area Under the Receiver Operating Characteristic curve (AUC-ROC).
- ***Regression Metrics:*** Mean Absolute Error (MAE), Mean Squared Error (MSE), R-squared.
- ***Baseline Models:*** Establish baseline models to compare against. Simple models or heuristic approaches provide a benchmark for evaluating the effectiveness of your machine learning model.

- ***Model Interpretability:*** For complex models, assess interpretability using techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to understand feature importance and decision rationale.
- ***Outliers and Anomalies:*** Test the model's ability to handle outliers and anomalies, especially if they are critical to the application. Evaluate robustness and performance on instances that deviate significantly from the majority of the data.
- ***Imbalanced Datasets:*** Address imbalanced datasets by considering metrics such as F1 score, precision-recall curves, or AUC-ROC for classification tasks.
- ***Hyperparameter Tuning:*** Optimize model hyperparameters through techniques like grid search or random search. Assess how changes in hyperparameters impact model performance.
- ***Testing on New Data:*** After model deployment, continuously monitor its performance on new, real-world data. This ensures that the model remains effective as the data distribution evolves.
- ***Testing for Bias and Fairness:*** Evaluate models for bias and fairness, especially in applications where ethical considerations are crucial. Assess how the model performs across different demographic groups.
- ***Overfitting and Underfitting:*** Check for signs of overfitting (model memorizing the training data) or underfitting (model too simple). Adjust model complexity and regularization as needed.
- ***Error Analysis:*** Conduct detailed error analysis to understand common types of mistakes the model makes. This helps identify areas for improvement.

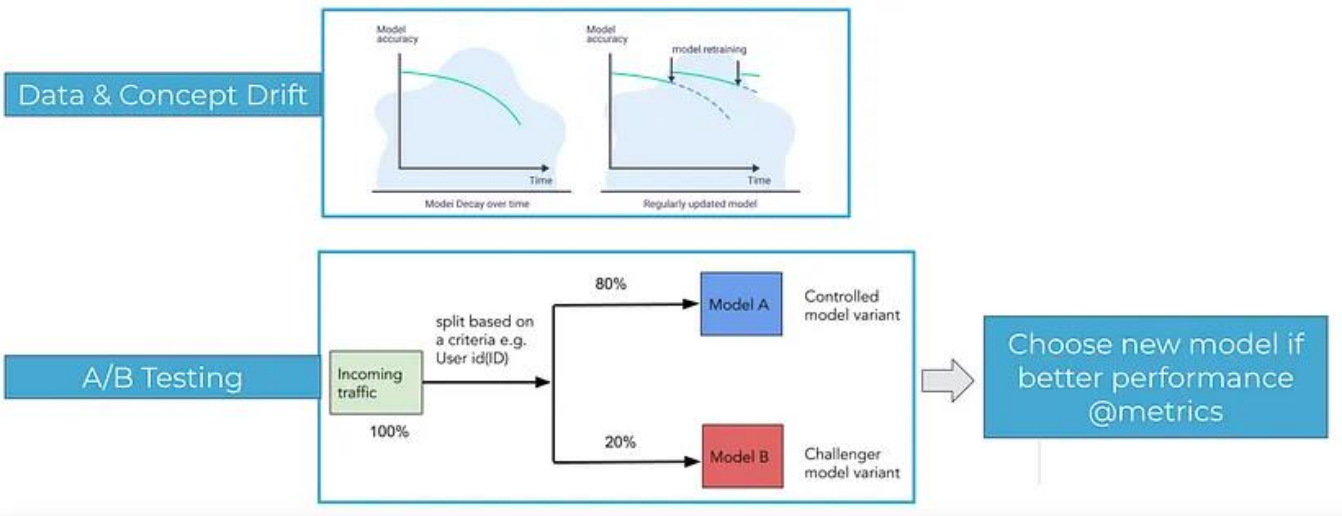
- ***Documentation:*** Document the testing process, including datasets used, evaluation metrics, and any observed challenges. This documentation is valuable for model transparency and reproducibility.

Remember that testing is an iterative process, and refining the model based on testing insights is a common practice in machine learning development. Regularly revisit and update the testing strategy as the model evolves or as new data becomes available.

2.2.2 Methods of implementation.

A/B Testing:

- Description: A/B testing, or split testing, involves comparing the performance of two versions of a model by randomly assigning users or instances to either the current version (A) or an upgraded version (B). Real-world performance metrics are then compared to determine which version performs better.
- Use Case: A/B testing is commonly used to assess the impact of changes, optimizations, or new features in a model on user experience or key performance indicators.



Canary Testing:

- Description: Canary testing involves deploying new versions of a model to a small subset of the production environment while keeping the existing version active in the majority. This allows for a gradual evaluation of the new release before full deployment.
- Use Case: Canary testing is beneficial for identifying potential issues or performance degradation in new releases without affecting the entire user base.

Green Deployment:

- Description: In green deployment, the current version of the model is maintained in the "green" or active environment, while new versions are installed in a separate environment. The new version is fully activated in the "green" environment only after thorough verification.
- Use Case: Green deployment minimizes the risk of introducing errors into the live environment by verifying the new version's stability before full deployment.

Chaos Testing:

- Description: Chaos testing involves intentionally introducing failures, errors, or unusual conditions into a production environment to assess the system's resiliency and ability to handle unexpected events.
- Use Case: Chaos testing helps identify vulnerabilities, weaknesses, or points of failure in the system under stress or unpredictable conditions.

2.3 Code Demo

To build a machine learning solution using Continuous Learning and Test Production, we can choose the problem of object recognition in images (Object Recognition) and use a model based on Convolutional Neural Network (CNN) architecture. This problem requires the ability to continuously learn to recognize and

classify objects in images, and requires a rigorous testing process before deploying into real environments.

Step 1: Prepare Data

Dataset: Choose a suitable dataset like CIFAR-100, where there are many different object classes. Each class represents a specific subject (e.g., animal, object, vehicle).

Step 2: Machine Learning Model

Initial Model: Use a simple CNN to train on the entire CIFAR-100 dataset. This will create a basic model capable of recognizing common objects.

Step 3: Continuous Learning

- Incremental Learning: Adds new data from new layers of CIFAR-100 that the model has never seen before. Use Incremental Learning techniques to learn models from new data without affecting performance on old layers.
- Elastic Weight Consolidation (EWC): Apply EWC to keep the important weights of the model learned from the old class intact, helping to avoid forgetting important information.

Step 4: Performance Testing (Test Production)

- Prepare Test Data: Create an independent test data set containing images from both old and new layers to evaluate the overall performance of the model.
- Performance Evaluation: Perform experiments to evaluate the accuracy, sensitivity, and specificity of the model on the test set. Make sure the model is effective not only on old data but also on new data.

- Debug and Optimize: If the model is not achieving the desired performance, perform a debug and optimize the model process.
- Accept or Reject: Based on the test results, decide whether the model meets the requirements to be deployed into a real environment or not.

Code demo in the attached file