AIML CSET-301

-Neeraj Baghel

Generalized AIML Life cycle

1. Problem Identification
2. Gathering Data
3. Data Pre-processing
4. Exploratory Data Analysis
5. Model Selection
6. Train Model
7. Hyperparameter Tunning
8. Test Model
9. Deployment

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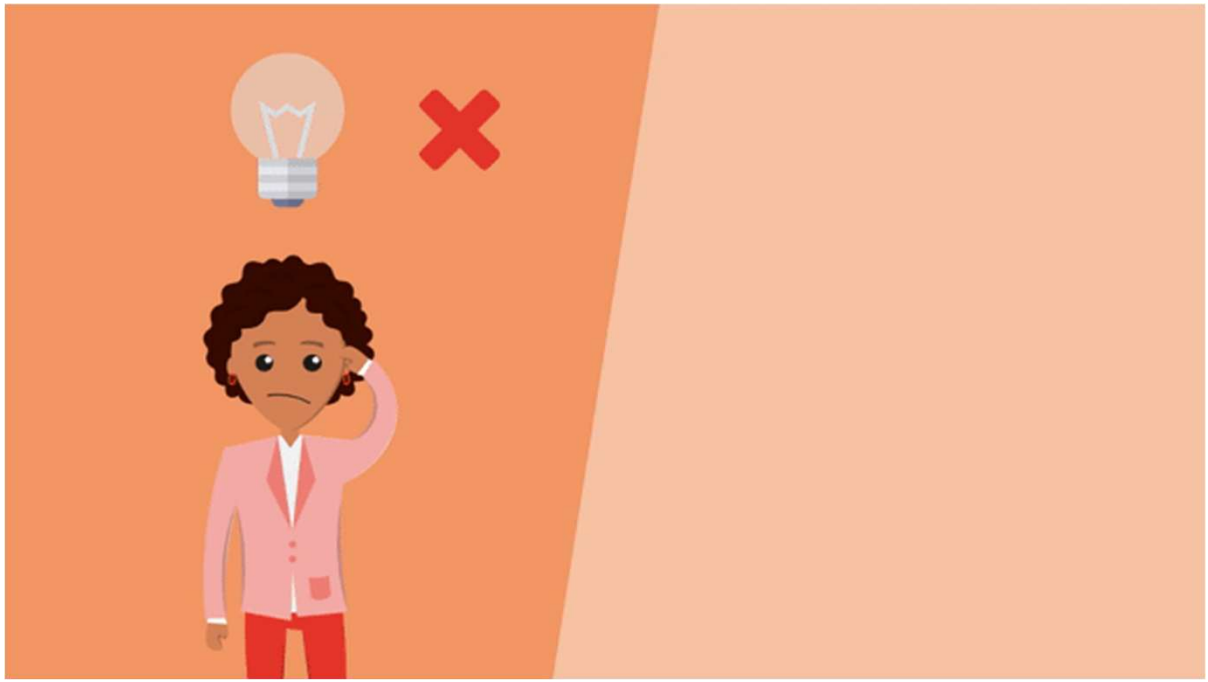
1. Problem Identification

Machine learning project typically begins with the problem definition.



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2. Gathering Data:

This step includes the below tasks:

- Identify various data sources
- Collect data
- Integrate the data obtained from different sources

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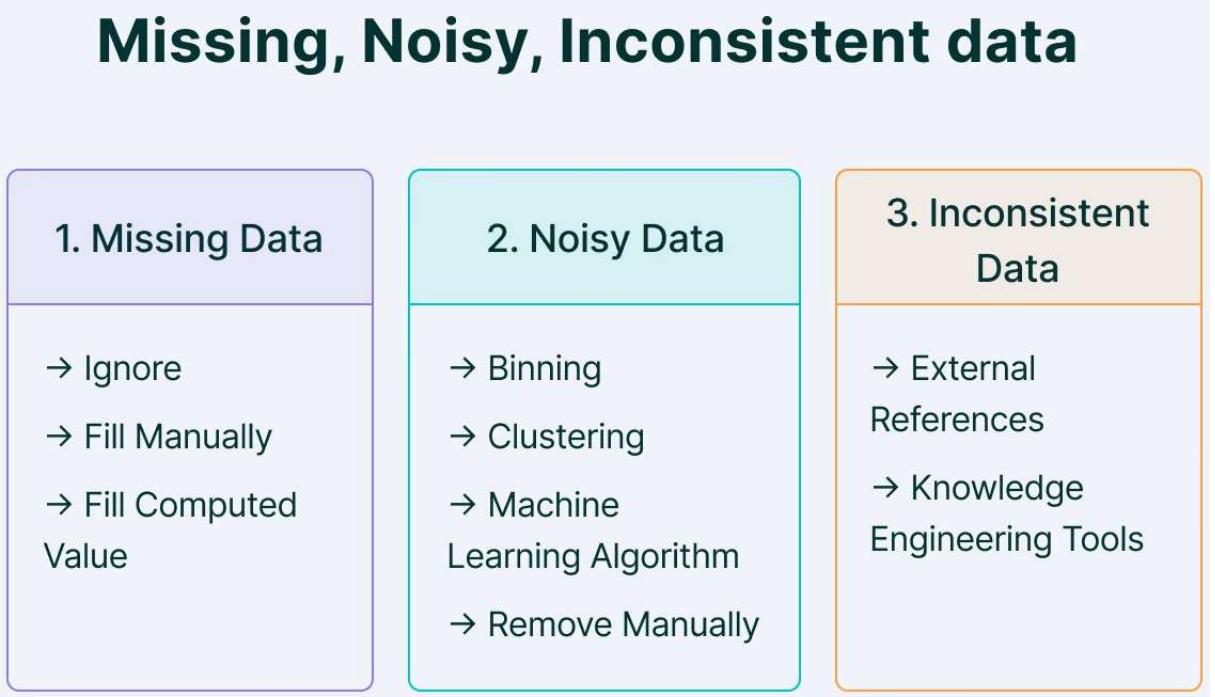
3. Data Pre-processing

Data Pre-processing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.

In real-world applications, collected data may have various issues, including:

- **Missing Values**
- **Duplicate data**
- **Invalid data**
- **Noise**



Focuses on cleaning and transforming data so that it can be used by machine learning algorithms. It is more about **data quality**.

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4. Exploratory Data Analysis:

- **Summary Statistics**:
Calculating and interpreting basic statistics (e.g., mean, median, mode, standard deviation) to get an overview of the data distribution.
- **Visualizations**:
Using plots (e.g., histograms, box plots, scatter plots, heatmaps) to visualize data distributions and relationships between variables.
- **Correlation Analysis**:
Identifying relationships between numerical variables (e.g., using correlation matrices).
- **Identifying Patterns & Anomalies**:
Finding interesting trends, clusters, or outliers in the data.
- **Forming Hypotheses**:
Based on visualizations and patterns, creating hypotheses for further testing and modeling.

Focuses on understanding and interpreting the data. It is more about **data understanding and insight generation**.

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5. Model Selection

Here we select the machine learning techniques such as **Classification**, **Regression and Cluster analysis**, etc. then build the model using prepared data, and evaluate the model.

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6. Train Model:

In this step we train our model to improve its performance for better outcome of the problem.

We use datasets to train the model using various machine learning algorithms.

Training a model is required so that it can understand the various patterns, rules, and, features.

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7. Hyperparameter Tunning

It is the process of finding the best set of hyperparameters for a machine learning model to maximize its performance on a specific task. Hyperparameters can include values such as:

- **Learning Rate:** Determines how quickly the model adapts to the problem.
- **Number of Layers/Neurons:** Defines the architecture of neural networks.
- **Regularization Parameters:** Controls overfitting (e.g., L1/L2 regularization).
- **Batch Size:** Number of samples used in each training iteration.
- **Number of Trees** (for ensemble methods like Random Forests).
- **Kernel Type** (in Support Vector Machines).

How to Implement Hyperparameter Tuning

1.Define a Search Space: Choose the range of possible values for each hyperparameter.

2.Choose a Tuning Technique: Select a method like grid search or random search.

3.Evaluate Model Performance:

1. Use cross-validation to assess the model for each combination.
2. Choose metrics like accuracy, precision, or F1-score.

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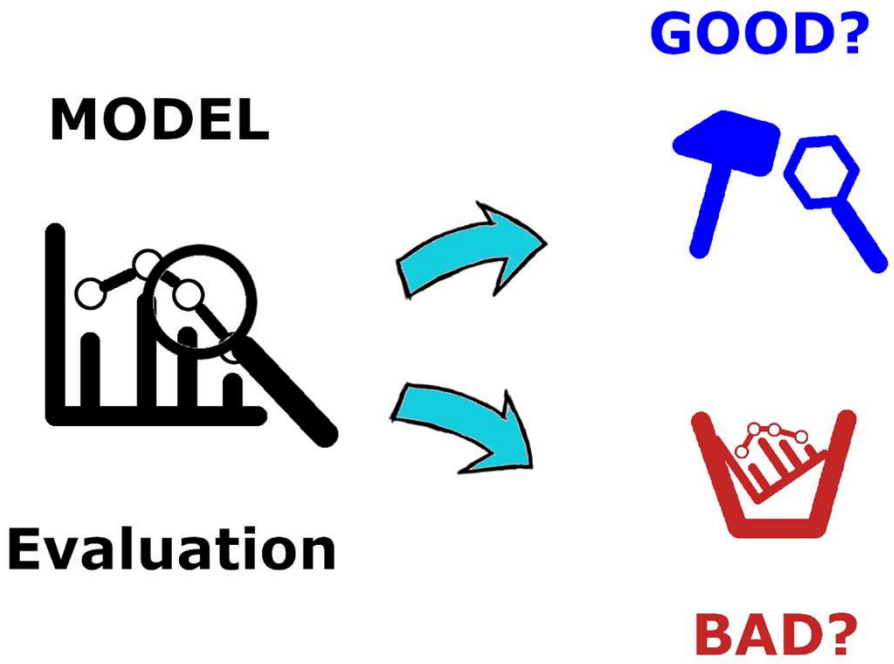
8. Test Model:

Once our machine learning model has been trained on a given dataset, then we test the model.

In this step, we check for the accuracy of our model by providing a test dataset to it.

Testing the model determines the percentage accuracy of the model as per the requirement of project or problem.



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9. Deployment:

The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system.

Key Steps in Deployment

1.Prepare the Model for Deployment:

1. Optimize the model for performance (reduce size, remove unnecessary components).
2. Convert the model to a format compatible with the deployment environment (e.g., TensorFlow Lite, ONNX, or PMML).

2.Select Deployment Environment:

1. **Cloud**: AWS, Azure, Google Cloud, etc.
2. **Edge Devices**: Smartphones, IoT devices, etc.
3. **On-Premise**: For systems requiring higher control or security.

3.Model Integration:

1. Embed the model into an application, API, or microservice for easy access.
2. Example: Using REST APIs to expose the model for use by external systems.

4.Set Up Monitoring and Feedback:

1. Implement monitoring systems to track model performance in real-time.
2. Capture user feedback and data for future improvements.

5.Scalability and Reliability:

1. Ensure the deployed system can handle varying loads efficiently.
2. Use load balancers, distributed systems, or containerization tools like Docker and Kubernetes.