1. Problem Definition

- Clearly define the problem statement and the prediction target (dependent variable).
- Identify the type of task: regression, classification, clustering, etc.
- Understand the business context and goals, including success criteria and performance metrics.

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2. Data Collection

- Gather data from relevant sources (databases, APIs, or raw files).
- Ensure data quality and relevance to the problem.
- Understand the data format, volume, and any potential privacy or compliance constraints.

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3. Data Understanding and Exploration

- Study the structure and summary statistics of the data.
- Perform exploratory data analysis (EDA) to identify patterns, distributions, and relationships.
- Use visualization techniques to understand trends and detect anomalies or correlations.

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4. Data Cleaning

- Handle missing values through imputation or removal.
- Remove duplicate entries and irrelevant features.
- Detect and address outliers that may distort model performance.
- Standardize or normalize numerical data for consistency.

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5. Feature Engineering

- Create meaningful features from raw data, such as aggregations or domain-specific transformations.
- Encode categorical variables into numerical representations.
- Reduce dimensionality if the feature set is too large or sparse.
- Assess feature importance and select the most relevant ones.

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6. Data Splitting

- Split the data into training, validation, and testing sets (e.g., 70-20-10 split).
- Ensure the splits are representative of the overall data distribution.
- Use stratified sampling for imbalanced datasets.

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7. Model Selection

- Choose algorithms suitable for the problem type and dataset size (e.g., linear models, tree-based models, or neural networks).
- Start with simple baseline models to understand performance benchmarks.

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8. Model Training

- Train models on the training dataset using appropriate algorithms.
- Experiment with different model architectures and configurations.
- Document all parameters and settings for reproducibility.

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9. Model Evaluation

- Evaluate the model on the validation set using appropriate metrics:
    - Regression: RMSE, MAE, R^2.
    - Classification: Accuracy, Precision, Recall, F1 Score, ROC-AUC.
- Compare results against baseline and check for underfitting or overfitting.

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10. Hyperparameter Tuning

- Optimize model performance by fine-tuning hyperparameters (e.g., learning rates, depth, regularization).
- Use systematic approaches like grid search, random search, or Bayesian optimization.

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11. Final Testing

- Test the final model on the unseen test dataset to ensure generalization.
- Compare predictions with actual values and analyze discrepancies.

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12. Model Deployment

- Save the trained model for deployment using appropriate tools.
- Integrate the model into a production environment (web app, API, or embedded system).
- Ensure the system handles real-time or batch predictions effectively.

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13. Monitoring and Maintenance

- Monitor model performance post-deployment (e.g., accuracy drift, data drift).
- Retrain or update the model periodically with new data.
- Collect user feedback and adjust the model or features as necessary.