1: Data preparation
- 1∘1: Perform feature engineering
- 1∘2: Handle missing values
- 1∘3: Encode categorical variables
- 1∘4: Normalize numerical features or not
- 1∘5: Explore data structure
- 1∘6: Outlier detection and removal (z-score thresholding, interquartile range, local outlier factor, isolation forest ...)
- 1∘7: Drop highly correlated features (pairplot)
- 1∘8: Split data into training, validation, and test sets
- 1∘9: Weight imbalanced classes
- 1∘10: Augment data with symmetry and noise
- 1∘11: Collect and clean data

2: Model selection
- 2∘1: Choose a baseline model as benchmark
- 2∘2: Design model architecture
- 2∘3: Decide hyperparameter values
- 2∘4: Techniques: hold-out validation, (stratified) k-fold cross-validation, leave-one-out cross-validation, nested cross-validation, grid search, random search, Bayesian optimization, Bayesian Model Averaging, genetic algorithm, adaptive resampling ...

3: Model training
- 3∘1: Techniques: stochastic gradient descent, Adam, Adagrad, RMSProp, L-BFGS, Conjugate Gradient, Newton's Method, Quasi-Newton Methods, Lookahead ...

4: Model Evaluation
- 4∘1: Identify the strengths and weaknesses of the model
- 4∘2: Analyze the types of errors for refining the model further
- 4∘3: Metrics: accuracy, precision, recall, F1-score, log-loss, ROC-AUC, utility function, Brier score ...

5: Model Calibration
- 5∘1: Adjust predicted probabilities to better reflect the true probabilities of the target variable
- 5∘2: Techniques: Platt scaling, isotonic regression, temperature scaling ...

6: Model Interpretation
- 6∘1: Feature importance scores
- 6∘2: Permutation feature importance
- 6∘3: Global
  - 6∘3∘1: KLLR
  - 6∘3∘2: PDP
  - 6∘3∘3: ALE
  - 6∘3∘4: Decision trees
- 6∘4: Local
  - 6∘4∘1: LIME
  - 6∘4∘2: SHAP

7: Model Deployment
- 7∘1: Robustness test
- 7∘2: Continuous learning
- 7∘3: Ethical and legal considerations