MACHINE LEARNING QUICK REFERENCE: BEST PRACTICES

Topic	Common Challenges	Suggested Best Practice
Data Preparation		
Data collection	Biased dataIncomplete dataThe curse of dimensionalitySparsity	Take time to understand the business problem and its context Enrich the data Dimension-reduction techniques Change representation of data (e.g., COO)
"Untidy" data	 Value ranges as columns Multiple variables in the same column Variables in both rows and columns	Restructure the data to be "tidy" by using the melt and cast process
Outliers	 Out-of-range numeric values and unknown categorical values in score data Undue influence on squared loss functions (e.g., regression, GBM, k-means) 	 Robust methods (e.g., Huber loss function) Discretization (binning) Winsorizing
Sparse target variables	Low primary event occurrence rate Overw helming preponderance of zero or missing values in target	Proportional oversamplingInverse prior probabilitiesMixture models
Variables of disparate magnitudes	Misleading variable importanceDistance measure imbalanceGradient dominance	Standardization
High-cardinality variables	Overfitting Unknow n categorical values in holdout data	Discretization (binning)Weight of evidenceLeave-one-out event rate
Missing data	Information lossBias	Discretization (binning)ImputationTree-based modeling techniques
Strong multicollinearity	Unstable parameter estimates	Regularization Dimension reduction
Training		
Overfitting	High-variance and low-bias models that fail to generalize well	RegularizationNoise injectionPartitioning or cross validation
Hyperparameter tuning	Combinatorial explosion of hyperparameters in conventional algorithms (e.g., deep neural networks, super learners)	Local search optimization, including genetic algorithmsGrid search, random search
Ensemble models	 Single models that fail to provide adequate accuracy High-variance and low-bias models that fail to generalize well 	Established ensemble methods (e.g., bagging, boosting, stacking) Custom or manual combinations of predictions
Model Interpretation	Large number of parameters, rules, or other complexity obscures model interpretation	 Variable selection by regularization (e.g., L1) Surrogate models Partial dependency plots, variable importance measures
Computational resource exploitation	 Single-threaded algorithm implementations Heavy reliance on interpreted languages 	 Train many single-threaded models in parallel Hardware acceleration (e.g. SSD, GPU) Low-level, native libraries Distributed computing, when appropriate
Deployment		
Model deployment	Trained model logic must be transferred from a development environment to an operational computing system to assist in organizational decision-making processes	Portable scoring code or scoring executables In-database scoring Web service scoring
Model decay	 Business problem or market conditions have changed since the model was created New observations fall outside domain of training data 	 Monitor models for decreasing accuracy Update/retrain models regularly Champion-challenger tests Online updates

