📚 Summary Tables

📚 Classical Machine Learning Algorithms (Regression)

Algorithm Name	How it Works	How to Optimize it	Use Cases	Example Use Cases	Pros	Cons	Better Algorithm	Sensitivity	Solution
Linear Regression	Fits a linear equation to model relationships	Feature scaling, feature engineering	Predicting continuous values	Predicting housing prices based on square footage and number of bedrooms	Simplicity, interpretable, fast	Assumes linear relationships, sensitive to outliers	-	Outliers, multicollinearity	Outlier removal, robust regression techniques, feature engineering, transformation of skewed features
Ridge Regression	Linear regression with L2 regularization	Cross-validation for alpha tuning	Multicollinearity, feature selection	Predicting stock prices with correlated features	Reduces overfitting, handles multicollinearity	May not eliminate irrelevant features	Lasso Regression (for feature selection) or Elastic Net Regression (balance of L1 and L2)	Outliers, multicollinearity	Outlier handling, feature engineering, multicollinearity detection and correction

Algorithm Name	How it Works	How to Optimize it	Use Cases	Example Use Cases	Pros	Cons	Better Algorithm	Sensitivity	Solution
Lasso Regression	Linear regression with L1 regularization	Cross-validation for alpha tuning	Feature selection, sparsity	Identifying significant features in gene expression data	Feature selection, handles multicollinearity	May produce unstable solutions with correlated features	Ridge Regression (for multicollinearity) or Elastic Net Regression (balance of L1 and L2)	Outliers, multicollinearity	Outlier handling, feature engineering, multicollinearity detection and correction
Polynomial Regression	Fits polynomial functions to data	Choose appropriate degree, regularization	Modeling non-linear relationships	Modeling the relationship between temperature and ice cream sales	Flexibility in modeling non-linear patterns	Prone to overfitting with high-degree polynomials	Spline Regression or Gaussian Process Regression	Overfitting, high degree	Degree selection, regularization, feature engineering
Elastic Net Regression	Linear regression with combined L2 and L1 regularization	Cross-validation for alpha and l1_ratio tuning	Feature selection, multicollinearity	Predicting customer churn in a telecom company	Balances Ridge and Lasso, robust	Complex tuning process, may not perform well with few features	Lasso Regression (for feature selection) or Ridge Regression (for multicollinearity)	Outliers, multicollinearity	Outlier handling, feature engineering, multicollinearity detection and correction
Exponential Regression	Models exponential growth or decay	Curve fitting, parameter estimation	Modeling exponential relationships	Predicting the spread of a contagious disease	Suitable for growth or decay modeling	Limited to exponential relationships	-	-	-
Logistic Regression	Models probability of binary outcomes	Regularization, feature selection	Binary classification	Predicting whether an email is spam or not	Interpretable, well-suited for binary classification	Assumes linear decision boundary	-	-	-

Algorithm Name	How it Works	How to Optimize it	Use Cases	Example Use Cases	Pros	Cons	Better Algorithm	Sensitivity	Solution
Power Regression	Fits a power-law relationship between variables	Curve fitting, parameter estimation	Modeling power-law relationships	Modeling the relationship between population size and the number of COVID-19 cases	Suitable for power-law distributed data	Limited to power-law relationships	-	-	-
Spline Regression	Uses piecewise-defined polynomials (splines)	Knot selection, regularization	Non-linear, complex patterns	Modeling the response of a patient to a drug treatment	Flexibility in modeling complex data	Sensitive to the choice of knots	Gaussian Process Regression or Random Forest Regression	Knot selection, outliers	Knot selection methods, outlier detection and handling
Gaussian Process Regression	Models relationships as distributions over functions	Kernel selection, hyperparameter tuning	Non-linear, uncertainty estimation	Predicting the trajectory of a robotic arm	Captures complex non-linear patterns, uncertainty	Computationally expensive, data-intensive	-	-	-
Poisson Regression	Models count data with Poisson distribution	Maximum likelihood estimation	Count data, rare events	Analyzing website traffic and predicting page views	Handles count data, appropriate for event modeling	Assumes Poisson distribution	-	-	-
Generalized Additive Models (GAM)	Combines multiple smoothing functions	Spline selection, regularization	Non-linear relationships, structured data	Analyzing the impact of temperature and	Flexible in capturing complex patterns, interpretable	Complexity in specifying smoothing functions	-	-	-

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				humidity on crop yields					
Support Vector Regression (SVR)	Finds a hyperplane with maximum margin	Kernel selection, regularization, parameter tuning	Regression with complex decision boundaries	Predicting stock prices with non-linear patterns	Effective in high-dimensional spaces, robust	Sensitive to choice of kernel and parameters	Random Forest Regression or Gradient Boosting Regression	Choice of kernel, parameter tuning	Kernel selection techniques, hyperparameter tuning, outlier handling
Random Forest Regression	Ensemble of decision trees for regression	Tree depth, number of trees, feature selection	Predicting continuous values	Predicting the price of a used car	Handles non-linearity, robust to outliers	Less interpretable than linear models	Gradient Boosting Regression or SVR	-	-

📚 Neural Network Algorithms (Regression)

Algorithm Name	How it Works	How to Optimize it	Use Cases	Example Use Cases	Pros	Cons	Better Algorithm	Sensitivity	Solution
Neural Network Regression	Uses deep learning networks for regression	Architecture design, hyperparameter tuning	Complex, large-scale regression tasks	Predicting customer lifetime value in e-commerce	Can capture very complex patterns, versatile	Computationally intensive, requires large data	Random Forest Regression or Gradient Boosting Regression	Choice of architecture, data size	Architectural adjustments, regularization, more data
Recurrent Neural Network (RNN) Regression	Processes sequences by looping output back as input	Adjusting learning rate, adding layers, dropout	Sequence modeling, language modeling	Text generation based on a given word sequence	Good for modeling short-term dependencies	Struggles with long-term dependencies, vanishing gradient problem	LSTM	Vanishing gradients, overfitting	Gradient clipping, regularization, LSTM for longer sequences
Long Short-Term Memory (LSTM) Regression	Advanced RNN with gates to regulate information flow	Tuning learning rate, number of layers, dropout	Sequence prediction, time series forecasting	Predicting stock market trends based on historical data	Better at capturing long-term dependencies	More complex and computationally intensive than simple RNNs	GRU (Gated Recurrent Unit)	Vanishing gradients, overfitting	Gradient clipping, regularization, careful architecture design

📚 Boosting Algorithms (Regression)

Algorithm Name	How it Works	How to Optimize it	Use Cases	Example Use Cases	Pros	Cons	Better Algorithm	Sensitivity	Solution
XGBoost (eXtreme Gradient Boosting)	An optimized version of gradient boosting with speed and performance enhancements	Tuning learning rate, number of trees, tree depth	Large datasets, classification and regression tasks	Predicting house prices from various features	High performance, efficient with large datasets	Can overfit if not properly tuned	LightGBM or CatBoost	Overfitting	Cross-validation, regularization
LightGBM (Light Gradient Boosting Machine)	Uses histogram-based algorithms for efficient learning, especially on large datasets	Tuning number of leaves, learning rate, and max depth	Large-scale and high-dimensional data, classification and regression tasks	Predicting customer behavior from transaction data	Fast training, efficient with large datasets and high dimensionality	May struggle with overfitting on smaller datasets	XGBoost or CatBoost	Overfitting, small datasets	Regularization, handling overfitting
CatBoost (Categorical Boosting)	Specializes in handling categorical data with minimal preprocessing	Tuning depth, learning rate, and l2_leaf_reg	Datasets with numerous categorical features	Predicting insurance claim amounts	Handles categorical features well, less prone to overfitting	Requires careful tuning of parameters	XGBoost or LightGBM	Overfitting	Parameter tuning, data preprocessing
Gradient Boosting Machine (GBM)	Traditional gradient boosting method without advanced optimizations	Tuning number of trees, learning rate, and tree depth	General regression and classification tasks	Predicting energy usage from weather data	Good baseline, interpretable models	Slower training, less sophisticated than advanced methods	XGBoost or LightGBM	Overfitting, slow training	Regularization, subsampling
AdaBoost (Adaptive Boosting)	Adjusts weights of	Tuning number of	Classification problems,	Improving accuracy in	Simple to implement,	Sensitive to noisy data	Gradient Boosting	Noisy data, outliers	Outlier removal, data

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	underperforming instances to improve model predictions	estimators and learning rate	can be adapted for regression	predicting loan defaults	less prone to overfitting	and outliers	or XGBoost		preprocessing
H2O's Gradient Boosting Machine	A distributed and scalable version of GBM for big data environments	Tuning tree depth, learning rate, and column sampling	Large datasets, big data platforms	Predicting real estate values from market data	Scalable, integrates with big data platforms	Requires more computational resources	XGBoost or LightGBM	Large datasets	Distributed computing, subsampling
SKLearn's GradientBoostingRegressor	Scikit-learn's implementation of gradient boosting for regression	Tuning number of estimators, learning rate, and max depth	Small to medium datasets, wide range of regression tasks	Estimating medical expenses based on patient data	Easy integration with Python ecosystem, user-friendly	Less efficient with very large datasets	XGBoost or LightGBM	Overfitting, large datasets	Regularization, hyperparameter tuning