

Mathematics for Machine Learning

1. Linear Algebra

- Vectors, Matrices, Tensors
- Matrix operations (addition, multiplication, transpose, inverse, determinant)
- Eigenvalues & Eigenvectors (PCA, dimensionality reduction)
- Orthogonality & projections
- Singular Value Decomposition (SVD)

2. Calculus

- Functions, Limits, Derivatives
- Partial Derivatives (used in gradient descent)
- Multivariable Calculus (optimization in high dimensions)
- Gradient, Jacobian, Hessian
- Chain Rule (for backpropagation in neural networks)

3. Probability & Statistics

- Probability theory (conditional probability, Bayes theorem)
- Random variables & probability distributions (Normal, Bernoulli, Binomial, Poisson, etc.)
- Expectation, Variance, Covariance
- Law of Large Numbers, Central Limit Theorem
- Hypothesis testing, p-values, confidence intervals
- Bayesian statistics

4. Linear & Non-linear Optimization

- Convex vs Non-convex functions
- Gradient Descent & Variants (SGD, Adam, RMSProp)
- Lagrange Multipliers
- Constrained & Unconstrained optimization

5. Discrete Mathematics & Logic

- Sets, Relations, Functions
- Graph theory (useful in Graph Neural Networks)
- Boolean algebra & logic

6. Information Theory

- Entropy, Cross-Entropy
- KL Divergence
- Mutual Information

7. Numerical Methods

- Numerical approximation
- Root finding (Newton-Raphson method)
- Numerical stability

■ Summary

If you're starting, focus on Linear Algebra + Probability & Statistics + Calculus, then move into Optimization & Information Theory as you dive deeper into ML.