The **mathematical backbone** of AI/ML

1. Linear Algebra (MOST IMPORTANT)
This is the language of machine learning.
You must prepare **all** of these:

Basics
- Scalars, vectors, matrices, tensors
- Vector operations
- Matrix addition, subtraction
- Matrix multiplication
- Transpose

Core Concepts
- Dot product
- Cross product (basic intuition)
- Norms (L1, L2, L∞)
- Unit vectors
- Distance measures (Euclidean, cosine)

Matrix Properties
- Determinant
- Rank
- Inverse
- Identity matrix
- Orthogonal and orthonormal matrices

Eigen Concepts (VERY IMPORTANT)
- Eigenvalues
- Eigenvectors
- Characteristic equation
- Diagonalization
- Geometric interpretation

Advanced Topics
- Vector spaces
- Linear independence
- Basis and dimension
- Projections
- Orthogonality
- Singular Value Decomposition (SVD)
- Pseudo-inverse

Used in: PCA, regression, neural networks, transformers.

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2. Calculus (OPTIMIZATION ENGINE)
ML is nothing without optimization.

A. Differential Calculus
- Limits
- Continuity
- Differentiation rules
- Chain rule (CRITICAL)
- Higher-order derivatives

B. Multivariable Calculus (VERY IMPORTANT)
- Partial derivatives
- Gradient
- Directional derivatives
- Jacobian matrix
- Hessian matrix

C. Optimization
- Minima and maxima
- Convex and non-convex functions
- Local vs global minima
- Gradient descent
- Learning rate intuition

D. Taylor Expansion
- Taylor series
- First-order and second-order approximation

Used in: Backpropagation, loss minimization, deep learning training.

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3. Probability Theory (CORE FOR ML)
This is where uncertainty lives.

Fundamentals
- Probability axioms
- Conditional probability
- Independence
- Bayes' theorem (NON-NEGOTIABLE)

Random Variables
- Discrete random variables
- Continuous random variables
- Probability mass function (PMF)
- Probability density function (PDF)
- Cumulative distribution function (CDF)

Distributions (YOU MUST KNOW)
- Bernoulli
- Binomial
- Uniform
- Poisson
- Normal (Gaussian)
- Exponential

Expectation & Moments
- Expectation
- Variance
- Standard deviation
- Covariance
- Correlation

Used in: Naive Bayes, probabilistic models, uncertainty estimation.

4. Statistics (DECISION MAKING TOOL)
Statistics tells you whether your model is actually good.

Descriptive Statistics

- Mean, median, mode
- Variance
- Standard deviation
- Skewness
- Kurtosis

Inferential Statistics

- Sampling
- Population vs sample
- Central Limit Theorem (IMPORTANT)

Parameter Estimation

- Maximum Likelihood Estimation (MLE)
- Maximum A Posteriori (MAP)

Hypothesis Testing

- Null and alternative hypothesis
- Z-test
- T-test
- Chi-square test
- P-value

Confidence Measures

- Confidence intervals
- Type I and Type II errors

Used in: Model validation, A/B testing, evaluation metrics.

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5. Information Theory (MODERN ML)
Often ignored, but crucial for deep learning.

- Entropy
- Cross-entropy
- KL divergence
- Mutual information

Used in: Loss functions, classification, transformers, LLMs.

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6. Discrete Mathematics (ENGINEERING SUPPORT)
Important for ML systems and algorithms.

- Sets
- Relations
- Functions
- Logic (AND, OR, NOT, implications)
- Graph theory basics
- Trees and graphs
- Combinatorics
- Permutations and combinations
- Recurrence relations

Used in: Algorithms, optimization, ML system design.

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7. Numerical Methods (PRACTICAL ML)
For real-world computation.

- Numerical differentiation
- Numerical integration
- Floating-point errors
- Convergence
- Stability
- Iterative methods

Used in: Large-scale training, performance optimization.

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8. Optimization Theory (ADVANCED)
For serious ML and research.

- Convex optimization
- Constraints
- Lagrange multipliers
- KKT conditions
- Regularization (L1, L2)

Used in: Advanced ML, research papers, large models.

What to Focus On First (Priority Order)

1. Linear Algebra
2. Calculus (especially gradients + chain rule)
3. Probability
4. Statistics
5. Information Theory
6. Optimization
7. Discrete Math

This order is deliberate. Follow it.
