Study Guide: Mathematics for Machine Learning

1. Linear Algebra (Handout Section 1)

Corresponding Book Sections: Chapter 2: Linear Algebra
Pages: 13–72

Key Topics:

- **Vectors and Vector Spaces**
  - **Page 14**: Definition and properties of vectors.
  - **Page 18**: Vector addition and scalar multiplication.
  - **Page 25**: Basis and dimension of vector spaces.
- **Matrices and Matrix Operations**
  - **Page 29**: Matrix multiplication, transpose, and inverse.
  - **Page 37**: Properties of special matrices (identity, diagonal).
- **Systems of Linear Equations**
  - **Page 45**: Solving $Ax = b$ using Gaussian elimination.
  - **Page 52**: LU decomposition.
- **Eigenvalues and Eigenvectors**
  - **Page 61**: Finding eigenvalues through the characteristic polynomial.
  - **Page 65**: Applications in PCA.

Suggested Practice:

- Solve the exercises on **Page 70** to reinforce Gaussian elimination and eigenvector concepts.

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2. Analytic Geometry (Handout Section 2)

Corresponding Book Sections: Chapter 3: Analytic Geometry
Pages: 73–104

Key Topics:

- **Inner Products and Norms**
  - **Page 75**: Definition of inner product, angle between vectors.
  - **Page 81**: Vector norms and their properties.
- **Projections and Orthogonality**
  - **Page 89**: Orthogonal projection onto a subspace.
  - **Page 92**: Gram-Schmidt orthogonalization.

Suggested Practice:

- Derive the projection formula from the inner product definition on **Page 94**.

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3. Matrix Decompositions (Handout Section 3)

Corresponding Book Sections: Chapter 4: Matrix Decompositions
Pages: 105–135

Key Topics:

- **LU Decomposition**
  - **Page 108**: Expressing a matrix as the product of a lower and upper triangular matrix.
  - **Page 112**: Applications in solving linear systems.
- **Singular Value Decomposition (SVD)**
  - **Page 121**: Theory of SVD and computing $A = U\Sigma V^T$.

  - **Page 128**: Applications in dimensionality reduction.
- **Eigenvalue Decomposition**
  - **Page 130**: Relating eigenvalues to matrix decompositions.

Suggested Practice:

- Work through the decomposition example on **Page 132** using the provided dataset.

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4. Vector Calculus (Handout Section 4)

Corresponding Book Sections: Chapter 5: Vector Calculus
Pages: 136–172

Key Topics:

- **Gradients and Jacobians**
  - **Page 140**: Gradient as a vector of partial derivatives.
  - **Page 150**: Jacobians for multivariable functions.
- **Optimization with Gradients**
  - **Page 155**: Gradient descent algorithm.
  - **Page 165**: Backpropagation in neural networks.

Suggested Practice:

- Implement gradient descent using the numerical example on **Page 170**.

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5. Probability and Distributions (Handout Section 5)

Corresponding Book Sections: Chapter 6: Probability and Distributions
Pages: 173–220

Key Topics:

- **Basic Probability Concepts**
  - **Page 176**: Conditional probability and Bayes' theorem.
  - **Page 183**: Independence and random variables.
- **Gaussian Distributions**
  - **Page 190**: Properties of normal distributions.
  - **Page 200**: Multivariate Gaussians in machine learning.

Suggested Practice:

- Derive the likelihood function for a Gaussian model on **Page 210**.

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6. Optimization Techniques (Handout Section 6)

Corresponding Book Sections: Chapter 7: Optimization
Pages: 221–258

Key Topics:

- **Convex Functions**
  - **Page 223**: Properties of convex and concave functions.
  - **Page 230**: Role of convexity in optimization.
- **Gradient Descent Variants**
  - **Page 235**: Stochastic Gradient Descent (SGD).
  - **Page 245**: Mini-batch gradient descent.
- **Regularization Techniques**

- **Page 250**: L1 (lasso) and L2 (ridge) regularization.

Suggested Practice:

- Implement lasso regression on the dataset example on **Page 255**.

Mapping Topics from Handouts to the Book

Handout Topic	Book Chapter	Page Numbers
Vectors and Vector Spaces	Linear Algebra	13–72
Solving Linear Systems	Linear Algebra	45–52
Eigenvalues and Eigenvectors	Linear Algebra	61–72
Matrix Decompositions (LU, SVD)	Matrix Decompositions	105–135
Projections and Orthogonality	Analytic Geometry	89–94
Gradient and Jacobian Calculations	Vector Calculus	136–172
Probability and Distributions	Probability and Distributions	173–220
Optimization Techniques	Optimization	221–258

How to Use this Guide for Lecture Preparation

1. **Before the Lecture**:
    - Read the specified sections from the book and focus on examples provided on the indicated pages.

- Solve the recommended practice problems to solidify concepts.

2. **During the Lecture**:
   - Map the lecture content to the sections you've pre-studied for better understanding.
   - Note any new examples or derivations provided.
3. **After the Lecture**:
   - Revisit unclear sections using the book for a deeper understanding.
   - Complete additional practice problems for mastery.

This comprehensive guide ensures that the handouts and book content are well-aligned for effective study.