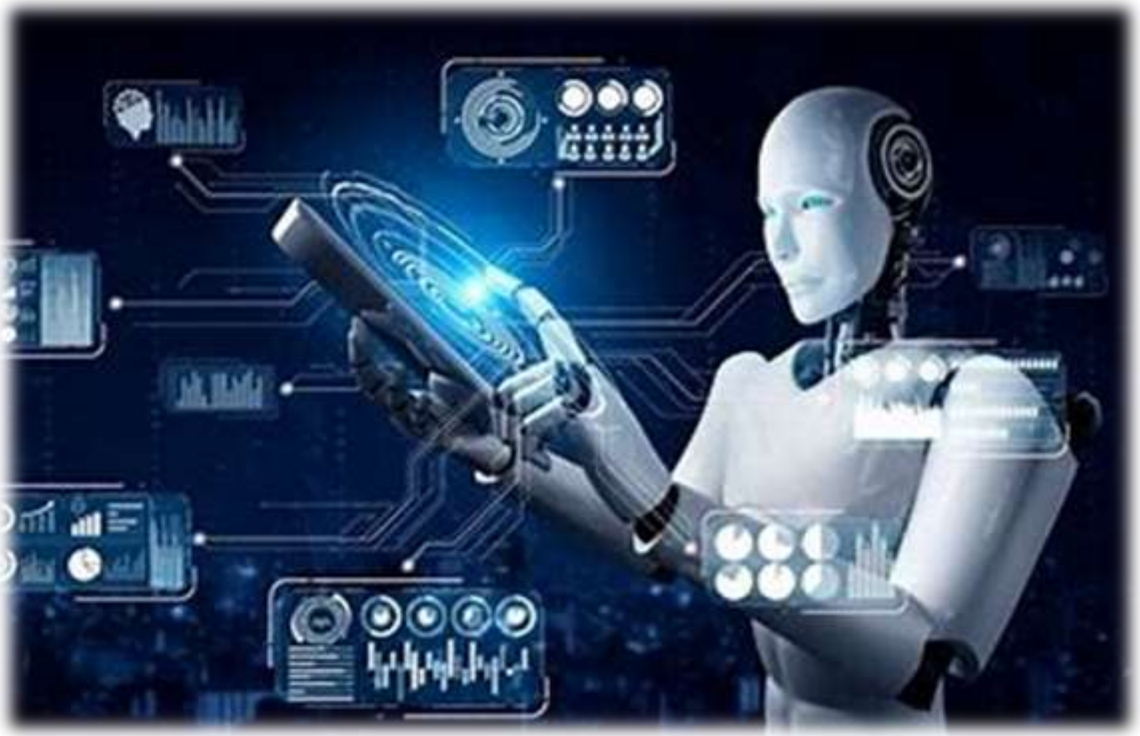
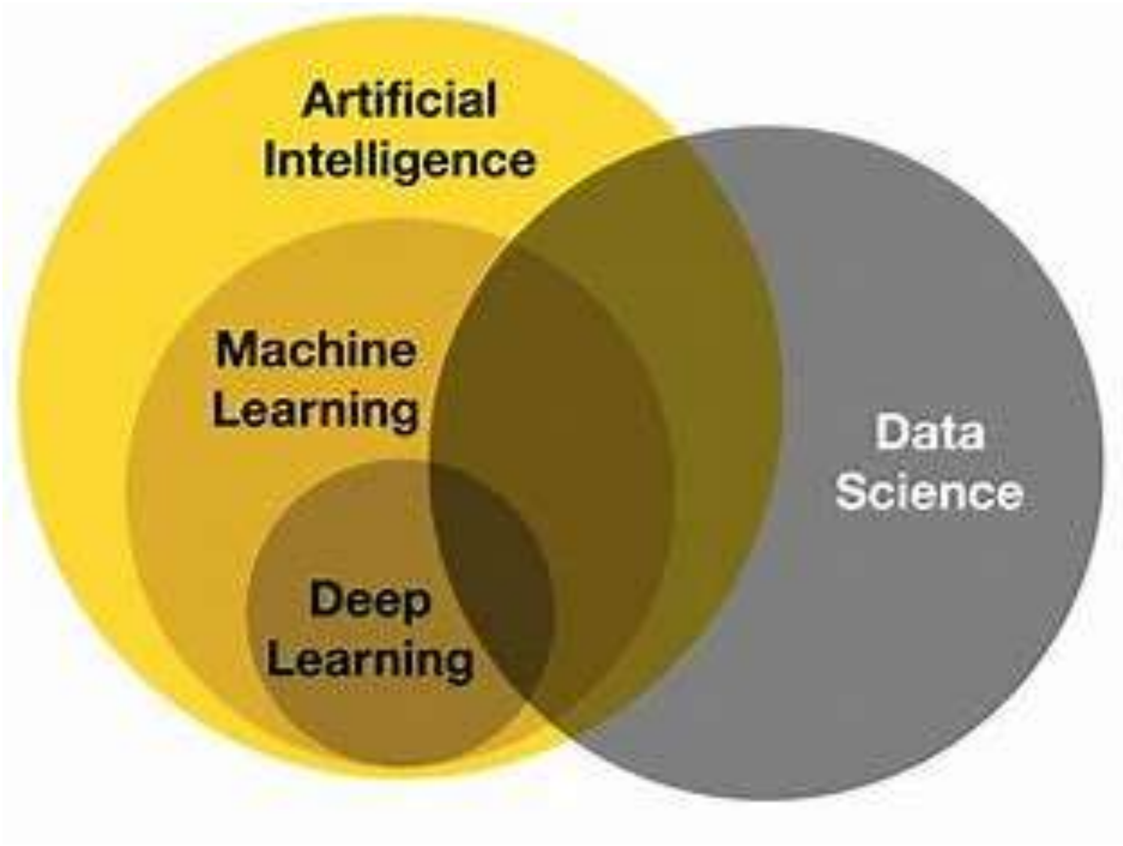
AI/ML Detail Roadmap

By: ANANDA RIMAL

Introduction




Artificial Intelligence
Machine Learning
Deep Learning
Data Science

1. Git and Github

Link

2.Linkdein

3 Python

Step1:

•✅ Variables, Data Types (int, float, str, bool)

•✅ Operators (arithmetic, logical, comparison)

•✅ Conditional Statements (if, elif, else)

•✅ Loops (for, while, break, continue)

•✅ Functions (def, return, *args, **kwargs)

•✅ String manipulation

•✅ Input/Output operations

•✅ Exception Handling (try, except, finally)

🛠 Practice: Build small CLI tools (calculator, quiz app)

Step 2: Data Structures & Built-ins

📌 **Goal: Efficient data handling**

✅ **Lists** – Ordered, mutable, indexable, supports slicing

✅ **Dictionaries** – Key-value pairs, fast lookup, dynamic

✅ **Sorting** – sorted(), .sort(), custom key support

✅ **Slicing** – list[start:end], list[-n:], flexible access

✅ **Searching** – in for lists, .get() for dictionaries

🛠 **Practice**: Use user input to create a list and dictionary, then apply sorting, slicing, and search operations

🔴 **Step 3: Object-Oriented Programming (OOP)**

📌 Goal: Organize and structure code like a pro.

- ✅ Classes and Objects
- ✅ Constructors (__init__)
- ✅ Instance vs Class Variables
- ✅ Inheritance, Polymorphism
- ✅ Encapsulation, Abstraction
- ✅ Magic Methods (__str__, __repr__, etc.)

Step 4: Functional Tools & File Handling

📌 **Goal: Write clean, efficient, and reusable code**

✅ **lambda** – Anonymous, one-line functions

- 📌 Used with map(), filter(), sorted()

✅ **generators** – Memory-efficient iterators using yield

- 📌 Useful for large data processing

✅ **iterators** – Objects with __iter__() and __next__()

- 📌 Used in loops and generator expressions

✅ **file handling** – Read/write using open(), with

- 📌 Modes: 'r', 'w', 'a', 'rb', 'wb'

Step5:

Link for python and flask

Estimated :2 months

4 MATHEMATICS FOR ML

Linear Algebra

Vectors – What to Study for AI/ML

- What is a vector
- Vector representation
- Vector addition
- Scalar multiplication
- Vector notation
- Dot product
- Cosine similarity
- Cross product
- Euclidean distance
- How a feature set represents a vector
- Concept of hyperplane

Matrix – What to Study for AI/ML

- represent a matrix
- Types of matrices (square, diagonal, identity, symmetric, orthogonal, sparse)
- Transpose of a matrix
- Determinant of a matrix
- Inverse of a matrix
- Rank of a matrix
- Linear independence of rows and columns
- Null space and column space
- System of linear equations using matrix form (Ax = b)

Link1: for linear algebra

Link2:for linear algebra

- Gaussian elimination method
- Row echelon form and reduced row echelon form
- Matrix multiplication
- Scalar multiplication
- Matrix addition and subtraction
- Matrix factorization methods (LU, QR)

- Eigenvalues and eigenvectors
- Diagonalization of a matrix
- Singular Value Decomposition (SVD)
- Matrix as a linear transformation
- Matrix representation of dataset (features and samples)
- Matrix operations using NumPy

Calculus

Calculus – What to Study for AI/ML

- Limit
- Derivative
- Slope
- Gradient
- Gradient descent
- Chain rule
- Partial derivatives
- Optimization
- Local minima and maxima
- Convex and non-convex functions
- Learning rate
- Cost/loss function
- Jacobian matrix
- Hessian matrix
- Multivariable calculus
- Function approximation
- Taylor series expansion
- Backpropagation

Probability and statistics for ml

◆ 1. Basics of Statistics

 Understand what statistics is and why it's used in ML

- **Definition of Statistics**
- **Types of Statistics**
  - **Descriptive Statistics**
  - **Inferential Statistics**
- **Types of Data**
  - Qualitative (Categorical) vs. Quantitative (Numerical)
  - Discrete vs. Continuous
  - Scales of Measurement: Nominal, Ordinal, Interval, Ratio

2. Descriptive Statistics

📊 To summarize and visualize data

- **Measures of Central Tendency**
    - Mean, Median, Mode
- **Measures of Dispersion**
    - Range, Variance, Standard Deviation, Interquartile Range (IQR)
- **Shape of Distributions**
    - Skewness (left/right)
    - Kurtosis (peaked/flat)
- **Data Visualization**
    - Histograms
    - Box plots
    - Scatter plots
    - Bar charts
    - Pie charts
- **Z-score & Standardization**

Estimated 2 months for mathematics

3. Probability

🎲 Foundation of probabilistic models and inference

- **Basic Concepts**
    - Sample space, Events
    - Independent & Dependent Events
    - Conditional Probability
    - Bayes' Theorem
- **Rules of Probability**
    - Addition Rule
    - Multiplication Rule
- **Combinatorics (briefly)**
    - Permutations
    - Combinations

◆ **4. Random Variables**
📌 **Key for understanding distributions and expectations**
•**Definition**
•**Types**

- Discrete Random Variable
- Continuous Random Variable

•**Probability Mass Function (PMF)** – for discrete
•**Probability Density Function (PDF)** – for continuous
•**Cumulative Distribution Function (CDF)**

◆ **5. Mathematical Expectation**
📈 **Core of understanding expected behavior**
•**Expected Value (Mean)**
•**Variance and Standard Deviation**
•**Linearity of Expectation**
•**Moments (optional unless needed)**

6. Probability Distributions

? Most-used distributions in ML

◆ ***Discrete Distributions:***

- Bernoulli Distribution
- Binomial Distribution
- Poisson Distribution
- Geometric Distribution

◆ ***Continuous Distributions:***

- Uniform Distribution
- Normal (Gaussian) Distribution – VERY IMPORTANT
- Exponential Distribution
- Log-normal Distribution
- Beta & Gamma (optional, but helpful in Bayesian ML)

7. Inferential Statistics

📌 **Drawing conclusions from data**

- **Population vs. Sample**
- **Sampling Techniques**
  - Random, Stratified, Systematic, etc.
- **Central Limit Theorem (CLT)**
- **Estimation**
  - Point Estimation
  - Confidence Intervals
- **Hypothesis Testing**
  - Null vs. Alternative Hypotheses
  - p-value
  - Significance Level (α)
  - Type I and Type II Errors
  - t-tests (1-sample, 2-sample), z-tests
  - Chi-Square Test
  - ANOVA (Analysis of Variance)

8. Correlation and Regression

📉 Understanding relationships between variables

- Covariance vs. Correlation
- Pearson and Spearman Correlation Coefficients
- Simple Linear Regression
- Multiple Linear Regression
- Assumptions of Linear Regression
- Multicollinearity (Variance Inflation Factor)

For statistsics tutorial watch campus x

Stats notes repository on github

5.Data Analysis

Link: click on this

Pandas

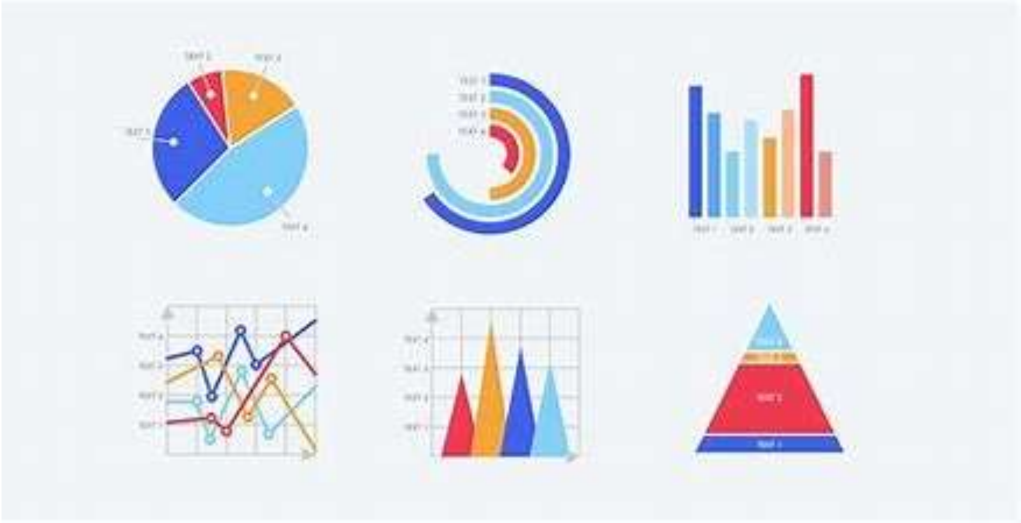
Link for pandas

Used for data analysis

Matplotlib
Seaborn
Plotly

Used for data visualization

Again check for campus x dsmp free course available on youtube



Data Gathering

Web Scrapping

Eda

Link:follows campus x dsmp course for eda,data gathering and web scrapping

Sql

Link1:click on this

Link2:click on this

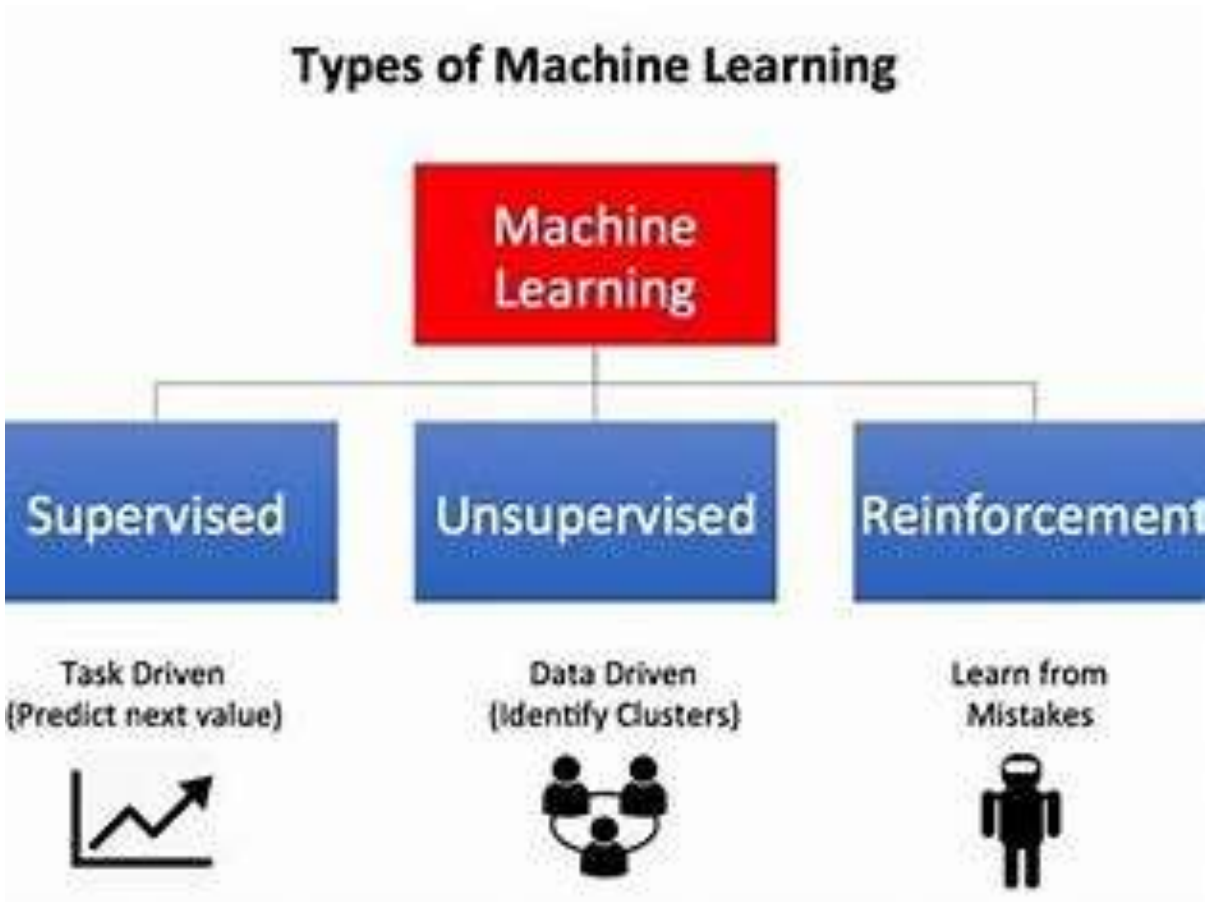
Now Python and Data Analysis part is complete

Estimated 1.5 months for data analysis

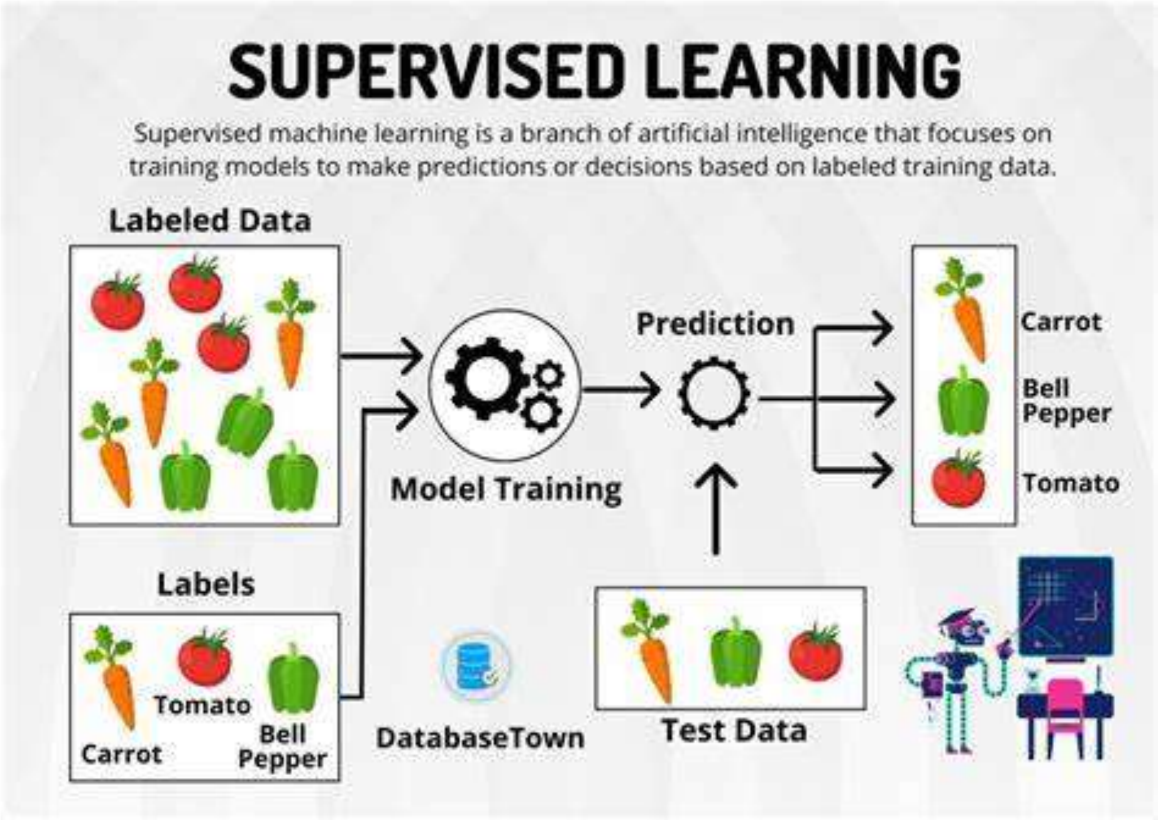
6.Machine Learning

Data Handling

- Data preprocessing
- Handling missing values
- Encoding categorical data
- Feature scaling (normalization, standardization)
- Train-test split
- Pca


Types of Machine Learning
Machine Learning
Supervised
Unsupervised
Reinforcement
Task Driven
(Predict next value)
Data Driven
(Identify Clusters)
Learn from
Mistakes

Supervised Learning

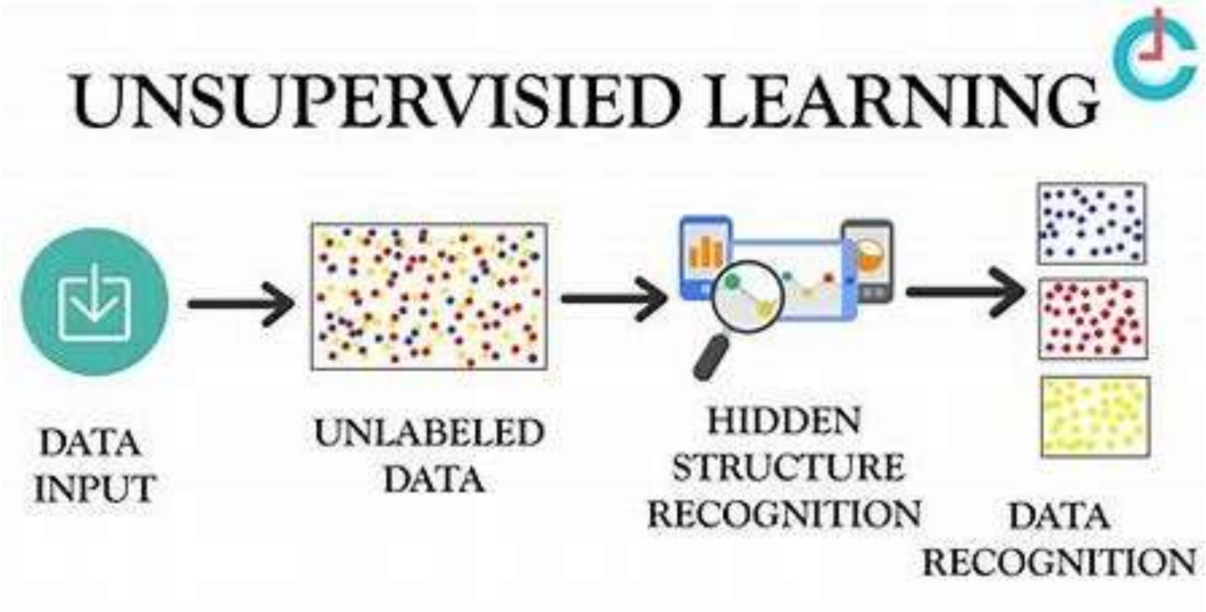


Supervised Learning Algorithm Types

1.Regression
Linear regression
Polynomial regression
Naïve Bayes
Gradient Boosting
Lasso regression
Ridge regression
Elastic regression

2.Classification
Logistic regression
Support vector machine
Decision tree
Random forest
K nearest neighbors

Unsupervised Learning Algorithm



Unsupervised Learning Algorithm

- Basic concept of unsupervised learning
- Types: Clustering, Dimensionality Reduction, Association Rule Learning
- K-Means Clustering
- Hierarchical Clustering: Agglomerative, Divisive
- Density-based Clustering: DBSCAN
- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA

Reinforcement Learning

Reinforcement Learning – What to Study

- Basic concept of reinforcement learning
- Agent, environment, state, action, reward

Estimated time 3 months

Scikit Learn

Link for ml course by campus x

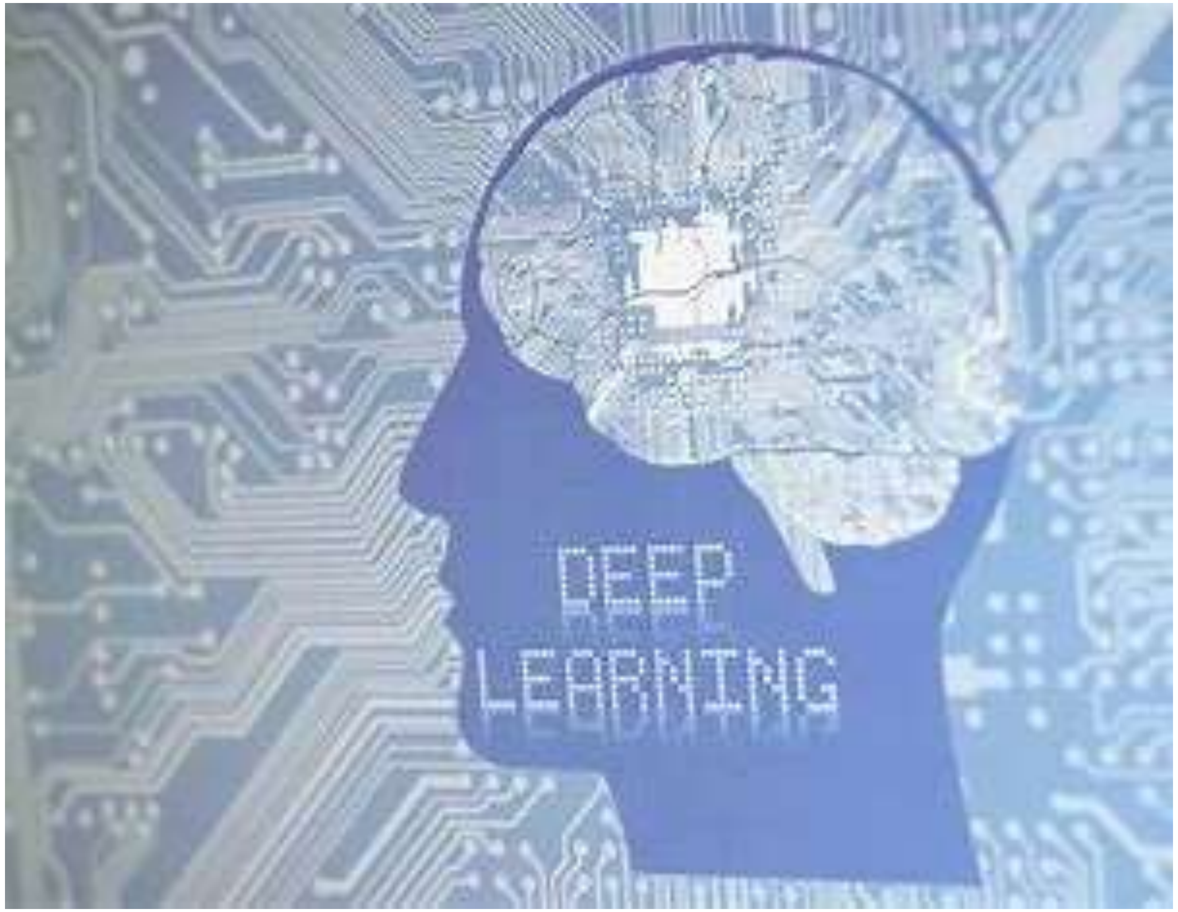
Link 2 :ml by Andrew ng

Scikit-learn

📌 **What is Scikit-learn?**

- A powerful Python library for **Machine Learning**
- Built on top of **NumPy**, **SciPy**, and **matplotlib**
- Provides tools for **data preprocessing**, **model building**, and **evaluation**

7.Deep Learning



Deep Learning – What to Learn (Beginner Level)

- Deep Learning is 95% about Neural Networks
- Learn how Neural Networks work
- Understand Forward Propagation
- Understand Backward Propagation (Backpropagation)
- What is Gradient Descent and how weights are updated
- Activation Functions: ReLU, Sigmoid, Tanh
- Loss Functions: MSE, Cross-Entropy
- Epochs, Batches, Learning Rate

CNN (Convolutional Neural Network)

- How images are classified using CNN
- Convolution, Pooling, Flattening, Fully Connected Layers
- Use cases: image classification, object detection

RNN (Recurrent Neural Network)

- Designed for sequence data like text and time-series
- Concepts of memory and feedback in networks
- Learn LSTM and GRU (advanced types of RNNs)

Other Topics for Beginners

- Overfitting and Regularization (Dropout, L2)
- Optimizers: SGD, Adam
- Model Evaluation: Accuracy, Precision, Recall
- Hands-on with TensorFlow or Keras
- Build your first Neural Network from scratch
- Practice with image and text datasets (e.g. MNIST, IMDB)

Link 1: deep learning by alexander amini

Link2:deep learning by Andrew ng

Estimated time 3 months

8.Natural Language Processing

Coursera course on nlp click here

? NLP for Beginners – Key Topics

1. Text preprocessing
2. Tokenization
3. Stemming and Lemmatization
4. Bag of Words & TF-IDF
5. Word Embeddings (Word2Vec, GloVe)
6. POS Tagging & NER
7. Text Classification & Sentiment Analysis
8. Transformers (BERT, GPT)
9. Libraries: NLTK, spaCy, Hugging Face
10. Practice on datasets (IMDb, Twitter)

9 Computer Vison

Computer Vision for Beginners – Key Topics

1. Image basics (pixels, RGB, grayscale)
2. Image preprocessing (resizing, normalization, augmentation)
3. Image classification
4. Convolutional Neural Networks (CNNs)
5. Object detection (YOLO, SSD, Faster R-CNN)
6. Image segmentation (semantic & instance)
7. Transfer learning (using pre-trained models like VGG, ResNet)
8. Face detection & recognition
9. Libraries: OpenCV, TensorFlow, PyTorch, Keras
10. Practice with datasets (MNIST, CIFAR-10, COCO)

Computer Vision by Murtaza workshop

Computer vison by computer vision engineer

Course on coursera

10 Generative AI – What to Study

1. Introduction to GenAI & use cases
2. Language Models (GPT, LLaMA, Claude, etc.)
3. Text Generation (prompting, fine-tuning)
4. Diffusion Models (for image generation)
5. Generative Adversarial Networks (GANs)
6. Prompt Engineering techniques
7. Retrieval-Augmented Generation (RAG)
8. Evaluation metrics (BLEU, ROUGE, FID)
9. Tools & Libraries: OpenAI API, Hugging Face, LangChain

Gen ai course

Kaggle

link

For different kind of datasets

Thank you