**Course Outline: Introduction to Machine Learning (BSCS)**

**1. Introduction to Machine Learning (ML)**

* Definition and significance of ML in real-world applications.
* Types of Machine Learning:
  + Supervised Learning
  + Unsupervised Learning
  + Reinforcement Learning

**2. Python Libraries for Data Science**

* **Numpy**: Array operations, broadcasting, and matrix manipulations.
* **Pandas**: DataFrame operations, filtering, grouping, and handling missing data.
* **Matplotlib & Seaborn**: Data visualization basics, creating line plots, scatter plots, bar plots, and heatmaps.

**3. Working with Data**

* File Formats:
  + Reading and writing CSV, JSON files.
* Fetching Data:
  + API integration: Making requests and parsing responses.
  + Web Scraping: Using libraries like BeautifulSoup and Scrapy.
* Exploratory Data Analysis (EDA):
  + Univariate, bivariate, and multivariate analysis.

**4. Feature Engineering and Preprocessing**

* Feature Scaling:
  + Standardization, Min-Max Scaling, Normalization.
* Encoding Techniques:
  + One-Hot Encoding, Binary Encoding, and Mixed-Value Handling.
* Function Transformation:
  + Power Transformations (Box-Cox), Log Transformation.
* Feature Construction and Binning:
  + Date and time features, binning numerical data.
* Handling Missing Data:
  + Techniques for univariate, bivariate, and multivariate imputation.
* Outlier Detection:
  + Identifying and handling outliers using statistical methods and visualization.
* Curse of Dimensionality:
  + Dimensionality reduction techniques (e.g., PCA).

**5. Regression Models**

* Linear Regression:
  + Mean Squared Error (MSE), Mean Absolute Error (MAE).
  + Gradient Descent (Batch, Stochastic, and Mini-Batch).
* Logistic Regression:
  + Sigmoid function, its derivative, and applications.
  + Softmax function for multi-class classification.

**6. Classification Models**

* Naive Bayes Classifier:
  + Working with categorical and continuous data.
* Decision Tree Classifier:
  + Understanding splits, Gini index, and entropy.

**7. Ensemble Learning**

* Voting Ensembles:
  + Hard and Soft Voting.
* Bagging:
  + Random Forest: Working with decision trees in ensemble settings.
* Boosting:
  + AdaBoost, Gradient Boosting.

**8. Clustering**

* K-Means Clustering:
  + Initialization, optimization, and evaluation of clusters.

**9. Neural Networks**

* Introduction to Neural Networks:
  + Architecture (Input, Hidden, and Output layers).
  + Activation Functions (ReLU, Sigmoid, Tanh).
  + Backpropagation.

**10. Recommender Systems**

* Content-Based Filtering:
  + Using item features to recommend similar items.
* Collaborative Filtering:
  + User-user and item-item similarity.
* Matrix Factorization Techniques (e.g., SVD).

**11. Model Evaluation and Optimization**

* Metrics:
  + Accuracy, Precision, Recall, F1 Score.
* Bias-Variance Tradeoff:
  + Underfitting and Overfitting.

**12. Capstone Project**

* End-to-end implementation of an ML project:
  + Data collection, cleaning, preprocessing, model selection, evaluation, and deployment.