Applied Machine Learning Course Schedule

DATE	MODULE	CHAPTER	TOPIC
2019-09-02	Module 1: Fundamentals of Programming	Python for Data Science: Python For Datascience	Keywords and identifiers, comments, indentation and statements, Variables and data types in Python, Standard Input and Output, Operators
2019-09-03	Module 1: Fundamentals of Programming	Python for Data Science: Python For Datascience	Control flow: if else, Control flow: while loop, Control flow: for loop, Control flow: break and continue,Revision Python for Data Science: Python For Datascience
2019-09-04	Module 1: Fundamentals of Programming	Python for Data Science: Data Structures	Lists, Tuples part 1, Tuples part-2, Sets
2019-09-05	Module 1: Fundamentals of Programming	Python for Data Science: Data Structures	Dictionary, Strings,Revision Python for Data Science: Data Structures
2019-09-06	Module 1: Fundamentals of Programming	Python for Data Science: Python For Datascience	Introduction, Types of functions, Function arguments, Recursive functions

2019-09-07	Module 1: Fundamentals of Programming	Python for Data Science: Python For Datascience	Lambda functions, Modules, Packages, File Handling, Exception Handling, Debugging Python, Assignment-1,Revision Python for Data Science: Python For Datascience
2019-09-08	Module 1: Fundamentals of Programming	Python for Data Science: Numpy	Numpy Introduction, Numerical operations on Numpy,Revision Python for Data Science: Numpy
2019-09-09	Module 1: Fundamentals of Programming	Python for Data Science: Matplotlib	Getting started with Matplotlib,Revision Python for Data Science: Matplotlib
2019-09-10	Module 1: Fundamentals of Programming	Python for Data Science:Pandas	Getting started with pandas, Data Frame Basics, Key Operations on Data Frames,Revision Python for Data Science:Pandas
2019-09-11	Module 1: Fundamentals of Programming	Python for Data Science:Computational Complexity	Space and Time Complexity: Find largest number in a list , Binary search, Find elements common in two lists, Find elements common in two lists using a Hashtable/ Dict,Revision Python for Data Science:Computational Complexity
2019-09-12	Module 1: Fundamentals of Programming	SQL	Introduction to Databases, Why SQL?, Execution of an SQL statement., IMDB dataset

2019-09-13	Module 1: Fundamentals of Programming	SQL	Installing MySQL, Load IMDB data., USE, DESCRIBE, SHOW TABLES, SELECT , LIMIT, OFFSET, ORDER BY, DISTINCT , WHERE, Comparison operators, NULL, Logical Operators, Aggregate Functions: COUNT, MIN, MAX, AVG, SUM
2019-09-14	Module 1: Fundamentals of Programming	SQL	GROUP BY, HAVING, Order of keywords., Join and Natural Join, Inner, Left, Right and Outer joins., Sub Queries/Nested Queries/Inner Queries, DML:INSERT, DML:UPDATE , DELETE, DDL:CREATE TABLE, DDL:ALTER: ADD, MODIFY, DROP, DDL:DROP TABLE, TRUNCATE, DELETE, Data Control Language: GRANT, REVOKE, Learning resources, Assignment-22: SQL Assignment on IMDB data,Revision SQL

2019-09-15	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Plotting for exploratory data analysis (EDA)	Introduction to IRIS dataset and 2D scatter plot, 3D scatter plot, Pair plots, Limitations of Pair Plots, Histogram and Introduction to PDF(Probability Density Function), Univariate Analysis using PDF, CDF(Cumulative Distribution Function), Mean, Variance and Standard Deviation, Median, Percentiles and Quantiles
2019-09-16	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Plotting for exploratory data analysis (EDA)	IQR(Inter Quartile Range) and MAD(Median Absolute Deviation), Box-plot with Whiskers, Violin Plots, Summarizing Plots, Univariate, Bivariate and Multivariate analysis, Multivariate Probability Density, Contour Plot, Exercise: Perform EDA on Haberman dataset
2019-09-17	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Plotting for exploratory data analysis (EDA)	Revision Plotting for exploratory data analysis (EDA)

2019-09-18	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Linear Algebra	Why learn it ?, Introduction to Vectors(2-D, 3-D, n-D) , Row Vector and Column Vector, Dot Product and Angle between 2 Vectors, Projection and Unit Vector, Equation of a line (2-D), Plane(3-D) and Hyperplane (n-D), Plane Passing through origin, Normal to a Plane, Distance of a point from a Plane/ Hyperplane, Half-Spaces, Equation of a Circle (2-D), Sphere (3-D) and Hypersphere (n-D), Equation of an Ellipse (2-D), Ellipsoid (3-D) and Hyperellipsoid (n-D), Square ,Rectangle, Hyper Cube,Hyper Cuboid, Revision Questions
2019-09-19	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Linear Algebra	Revision Linear Algebra
2019-09-20	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Probability And Statistics	Introduction to Probability and Statistics, Population and Sample, Gaussian/ Normal Distribution and its PDF(Probability Density Function), CDF(Cumulative Distribution function) of Gaussian/Normal distribution

2019-09-21	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Probability And Statistics	Symmetric distribution, Skewness and Kurtosis, Standard normal variate (Z) and standardization, Kernel density estimation, Sampling distribution & Central Limit theorem, Q-Q plot:How to test if a random variable is normally distributed or not?, How distributions are used?, Chebyshev’s inequality, Discrete and Continuous Uniform distributions, How to randomly sample data points (Uniform Distribution), Bernoulli and Binomial Distribution

2019-09-22	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Probability And Statistics	Log Normal Distribution, Power law distribution, Box cox transform, Applications of non-gaussian distributions?, Co-variance, Pearson Correlation Coefficient, Spearman Rank Correlation Coefficient, Correlation vs Causation, How to use correlations? , Confidence interval (C.I) Introduction, Computing confidence interval given the underlying distribution, C.I for mean of a normal random variable, Confidence interval using bootstrapping, Hypothesis testing methodology, Null-hypothesis, p-value, Hypothesis Testing Intution with coin toss example, Resampling and permutation test, K-S Test for similarity of two distributions, Code Snippet K-S Test
2019-09-23	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Probability And Statistics	Hypothesis testing: another example, Resampling and Permutation test: another example, How to use hypothesis testing?, Propotional sampling, Revision Questions,Revision Probability And Statistics

2019-09-24	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Dimensionality Reduction And Visualization	What is Dimensionality reduction?, Row Vector and Column Vector, How to represent a data set?, How to represent a dataset as a Matrix., Data Preprocessing: Feature Normalisation, Mean of a data matrix, Data Preprocessing: Column Standardization
2019-09-25	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Dimensionality Reduction And Visualization	Co-variance of a Data Matrix, MNIST dataset (784 dimensional), Code to Load MNIST Data Set,Revision Dimensionality Reduction And Visualization
2019-09-26	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Principal Component Analysis	Why learn PCA?, Geometric intuition of PCA, Mathematical objective function of PCA, Alternative formulation of PCA: Distance minimization, Eigen values and Eigen vectors (PCA): Dimensionality reduction
2019-09-27	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	Principal Component Analysis	PCA for Dimensionality Reduction and Visualization, Visualize MNIST dataset, Limitations of PCA, PCA Code example, PCA for dimensionality reduction (not-visualization),Revision Principal Component Analysis

2019-09-28	Module 2: Datascience: Exploratory Data Analysis and Data Visualization	T-Sne	What is t-SNE?, Neighborhood of a point, Embedding, Geometric intuition of t-SNE, Crowding Problem, How to apply t-SNE and interpret its output, t-SNE on MNIST, Code example of t-SNE, Revision Questions,Revision T-Sne
2019-09-29	Module 3: Foundations of Natural Language Processing and Machine Learning	Predict rating given product reviews on amazon	Dataset overview: Amazon Fine Food reviews(EDA), Data Cleaning: Deduplication, Why convert text to a vector?, Bag of Words (BoW), Text Preprocessing: Stemming, Stop-word removal, Tokenization, Lemmatization., uni-gram, bi-gram, n-grams., tf-idf (term frequency- inverse document frequency), Why use log in IDF?
2019-09-30	Module 3: Foundations of Natural Language Processing and Machine Learning	Predict rating given product reviews on amazon	Word2Vec., Avg-Word2Vec, tf-idf weighted Word2Vec, Bag of Words(Code Sample), Text Preprocessing(Code Sample), Bi-Grams and n-grams (Code Sample), TF-IDF (Code Sample), Word2Vec (Code Sample), Avg-Word2Vec and TFIDF-Word2Vec (Code Sample), Assignment-2 : Apply t-SNE

2019-10-01	Module 3: Foundations of Natural Language Processing and Machine Learning	Predict rating given product reviews on amazon	Revision Predict rating given product reviews on amazon
2019-10-02	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification And Regression Models: K-Nearest Neighbors	How “Classification” works?, Data matrix notation, Classification vs Regression (examples), K-Nearest Neighbours Geometric intuition with a toy example, Failure cases of KNN, Distance measures: Euclidean(L2) , Manhattan(L1), Minkowski, Hamming
2019-10-03	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification And Regression Models: K-Nearest Neighbors	Cosine Distance & Cosine Similarity, How to measure the effectiveness of k-NN?, Test/Evaluation time and space complexity, KNN Limitations, Decision surface for K-NN as K changes
2019-10-04	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification And Regression Models: K-Nearest Neighbors	Overfitting and Underfitting, Need for Cross validation, K-fold cross validation, Visualizing train, validation and test datasets

2019-10-05	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification And Regression Models: K-Nearest Neighbors	How to determine overfitting and underfitting?, Time based splitting, k-NN for regression, Weighted k-NN, Voronoi diagram, Binary search tree, How to build a kd-tree, Find nearest neighbours using kd-tree, Limitations of Kd tree, Extensions, Hashing vs LSH
2019-10-06	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification And Regression Models: K-Nearest Neighbors	LSH for cosine similarity, LSH for euclidean distance, Probabilistic class label, Code Sample:Decision boundary ., Code Sample:Cross Validation, Question and Answers,Revision Classification And Regression Models: K-Nearest Neighbors
2019-10-07	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification Algorithms in Various Situations	Introduction, Imbalanced vs balanced dataset, Multi-class classification, k-NN, given a distance or similarity matrix, Train and test set differences
2019-10-08	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification Algorithms in Various Situations	Impact of outliers, Local outlier Factor (Simple solution :Mean distance to Knn), K-Distance(A),N(A), Reachability-Distance(A,B), Local reachability-density(A), Local outlier Factor(A)

2019-10-09	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification Algorithms in Various Situations	Impact of Scale & Column standardization, Interpretability, Feature Importance and Forward Feature selection, Handling categorical and numerical features
2019-10-10	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification Algorithms in Various Situations	Handling missing values by imputation, Curse of dimensionality, Bias-Variance tradeoff
2019-10-11	Module 3: Foundations of Natural Language Processing and Machine Learning	Classification Algorithms in Various Situations	Intuitive understanding of bias-variance., Best and worst cases for an algorithm, Question and Answers,Revision Classification Algorithms in Various Situations
2019-10-12	Module 3: Foundations of Natural Language Processing and Machine Learning	Performance Measurement of Models	Accuracy, Confusion matrix, TPR, FPR, FNR, TNR, Precision and recall, F1-score, Receiver Operating Characteristic Curve (ROC) curve and AUC, Log-loss, R-Squared/ Coefficient of determination, Median absolute deviation (MAD), Distribution of errors, Assignment-3: Apply k-nearest neighbour
2019-10-13	Module 3: Foundations of Natural Language Processing and Machine Learning	Performance Measurement of Models	Revision Performance Measurement of Models

2019-10-14	Module 3: Foundations of Natural Language Processing and Machine Learning	Naive Bayes	Conditional probability, Independent vs Mutually exclusive events, Bayes Theorem with examples, Exercise problems on Bayes Theorem
2019-10-15	Module 3: Foundations of Natural Language Processing and Machine Learning	Naive Bayes	Naive Bayes algorithm, Toy example: Train and test stages, Naive Bayes on Text data
2019-10-16	Module 3: Foundations of Natural Language Processing and Machine Learning	Naive Bayes	Laplace/Additive Smoothing, Log-probabilities for numerical stability, Bias and Variance tradeoff, Feature importance and interpretability, Imbalanced data
2019-10-17	Module 3: Foundations of Natural Language Processing and Machine Learning	Naive Bayes	Outliers, Missing values, Handling Numerical features (Gaussian NB), Multiclass classification, Similarity or Distance matrix, Large dimensionality, Best and worst cases, Code example, Assignment-4: Apply Naive Bayes
2019-10-18	Module 3: Foundations of Natural Language Processing and Machine Learning	Naive Bayes	Revision Naive Bayes

2019-10-19	Module 3: Foundations of Natural Language Processing and Machine Learning	Logistic Regression	Geometric intuition of Logistic Regression, Sigmoid function: Squashing, Mathematical formulation of Objective function, Weight vector, L2 Regularization: Overfitting and Underfitting
2019-10-20	Module 3: Foundations of Natural Language Processing and Machine Learning	Logistic Regression	L1 regularization and sparsity, Probabilistic Interpretation: Gaussian Naive Bayes, Loss minimization interpretation, Hyperparameter search: Grid Search and Random Search, Column Standardization, Feature importance and Model interpretability, Collinearity of features, Test/Run time space and time complexity, Real world cases
2019-10-21	Module 3: Foundations of Natural Language Processing and Machine Learning	Logistic Regression	Non-linearly separable data & feature engineering, Code sample: Logistic regression, GridSearchCV, RandomSearchCV, Assignment-5: Apply Logistic Regression
2019-10-22	Module 3: Foundations of Natural Language Processing and Machine Learning	Logistic Regression	Extensions to Logistic Regression: Generalized linear models,Revision Logistic Regression

2019-10-23	Module 3: Foundations of Natural Language Processing and Machine Learning	Linear Regression	Geometric intuition of Linear Regression, Mathematical formulation, Real world Cases, Code sample for Linear Regression, Question and Answers
2019-10-24	Module 3: Foundations of Natural Language Processing and Machine Learning	Linear Regression	Revision Linear Regression
2019-10-25	Module 3: Foundations of Natural Language Processing and Machine Learning	Solving Optimization Problems	Differentiation, Online differentiation tools, Maxima and Minima, Vector calculus: Grad, Gradient descent: geometric intuition
2019-10-26	Module 3: Foundations of Natural Language Processing and Machine Learning	Solving Optimization Problems	Learning rate, Gradient descent for linear regression, SGD algorithm, Constrained Optimization & PCA, Logistic regression formulation revisited, Why L1 regularization creates sparsity?, Assignment 6: Implement SGD for linear regression
2019-10-27	Module 3: Foundations of Natural Language Processing and Machine Learning	Solving Optimization Problems	Revision Solving Optimization Problems

2019-10-28	Module 4: Machine Learning-II (Supervised Learning Models)	Support Vector Machines	Geometric Intuition, Why we take values +1 and and -1 for Support vector planes, Mathematical derivation
2019-10-29	Module 4: Machine Learning-II (Supervised Learning Models)	Support Vector Machines	Loss function (Hinge Loss) based interpretation, Dual form of SVM formulation, Kernel trick, Polynomial kernel, RBF-Kernel
2019-10-30	Module 4: Machine Learning-II (Supervised Learning Models)	Support Vector Machines	Domain specific Kernels, Train and run time complexities, nu-SVM: control errors and support vectors, SVM Regression, Cases, Code Sample, Assignment 7: Apply SVM
2019-10-31	Module 4: Machine Learning-II (Supervised Learning Models)	Support Vector Machines	Revision Support Vector Machines
2019-11-01	Module 4: Machine Learning-II (Supervised Learning Models)	Decision Trees	Geometric Intuition of decision tree: Axis parallel hyperplanes, Sample Decision tree, Building a decision Tree:Entropy, Building a decision Tree:Information Gain, Building a decision Tree: Gini Impurity

2019-11-02	Module 4: Machine Learning-II (Supervised Learning Models)	Decision Trees	Building a decision Tree: Constructing a DT, Building a decision Tree: Splitting numerical features, Feature standardization, Building a decision Tree:Categorical features with many possible values, Overfitting and Underfitting, Train and Run time complexity, Regression using Decision Trees, Cases, Code Samples, Assignment 8: Apply Decision Trees
2019-11-03	Module 4: Machine Learning-II (Supervised Learning Models)	Decision Trees	Revision Decision Trees
2019-11-04	Module 4: Machine Learning-II (Supervised Learning Models)	Ensemble Models	What are ensembles?, Bootstrapped Aggregation (Bagging) Intuition, Random Forest and their construction, Bias-Variance tradeoff, Bagging :Train and Run-time Complexity., Bagging:Code Sample, Extremely randomized trees

2019-11-05	Module 4: Machine Learning-II (Supervised Learning Models)	Ensemble Models	Random Tree :Cases, Boosting Intuition, Residuals, Loss functions and gradients, Gradient Boosting, Regularization by Shrinkage, Train and Run time complexity, XGBoost: Boosting + Randomization, AdaBoost: geometric intuition, Stacking models, Cascading classifiers, Kaggle competitions vs Real world
2019-11-06	Module 4: Machine Learning-II (Supervised Learning Models)	Ensemble Models	Assignment-9: Apply Random Forests & GBDT,Revision Ensemble Models
2019-11-07	Module 5: Feature Engineering, Productionization and Deployment of ML Models	Featurization And Feature Importance	Introduction, Moving window for Time Series Data, Fourier decomposition
2019-11-08	Module 5: Feature Engineering, Productionization and Deployment of ML Models	Featurization And Feature Importance	Deep learning features: LSTM, Image histogram, Keypoints: SIFT., Deep learning features: CNN, Relational data, Graph data

2019-11-09	Module 5: Feature Engineering, Productionization and Deployment of ML Models	Featurization And Feature Importance	Indicator variables, Feature binning, Interaction variables, Mathematical transforms, Model specific featurizations, Feature orthogonality, Domain specific featurizations, Feature slicing, Kaggle Winners solutions,Revision Featurization And Feature Importance
2019-11-10	Module 5: Feature Engineering, Productionization and Deployment of ML Models	Miscellaneous Topics	Calibration of Models:Need for calibration, Calibration Plots., Platt’s Calibration/Scaling., Isotonic Regression, Code Samples, Modeling in the presence of outliers: RANSAC, Productionizing models, Retraining models periodically., A/B testing., Data Science Life cycle
2019-11-11	Module 5: Feature Engineering, Productionization and Deployment of ML Models	Miscellaneous Topics	VC dimension,Revision Miscellaneous Topics

2019-11-12	Module 6: Machine Learning Real World Case studies	Quora Question Pair Similarity	Business/Real world problem : Problem definition , Business objectives and constraints., Mapping to an ML problem : Data overview , Mapping to an ML problem : ML problem and performance metric., Mapping to an ML problem : Train-test split, EDA: Basic Statistics., EDA: Basic Feature Extraction, EDA: Text Preprocessing, EDA: Advanced Feature Extraction
2019-11-13	Module 6: Machine Learning Real World Case studies	Quora Question Pair Similarity	EDA: Feature analysis., EDA: Data Visualization: T-SNE., EDA: TF-IDF weighted Word2Vec featurization., ML Models :Loading Data, ML Models: Random Model, ML Models : Logistic Regression and Linear SVM, ML Models : XGBoost, Assignments
2019-11-14	Module 6: Machine Learning Real World Case studies	Quora Question Pair Similarity	Revision Quora Question Pair Similarity

2019-11-15	Module 6: Machine Learning Real World Case studies	Personalized Cancer Diagnosis	Business/Real world problem : Overview, Business objectives and constraints., ML problem formulation :Data, ML problem formulation: Mapping real world to ML problem., ML problem formulation :Train, CV and Test data construction, Exploratory Data Analysis:Reading data & preprocessing, Exploratory Data Analysis:Distribution of Class-labels
2019-11-16	Module 6: Machine Learning Real World Case studies	Personalized Cancer Diagnosis	Exploratory Data Analysis: “Random” Model, Univariate Analysis:Gene feature, Univariate Analysis:Variation Feature, Univariate Analysis:Text feature, Machine Learning Models:Data preparation, Baseline Model: Naive Bayes, K-Nearest Neighbors Classification

2019-11-17	Module 6: Machine Learning Real World Case studies	Personalized Cancer Diagnosis	Logistic Regression with class balancing, Logistic Regression without class balancing, Linear-SVM., Random-Forest with one-hot encoded features, Random-Forest with response-coded features, Stacking Classifier, Majority Voting classifier, Assignment,Revision Personalized Cancer Diagnosis
2019-11-18	Module 6: Machine Learning Real World Case studies	Facebook Friend Recommendation Using Graph Mining	Problem definition. , Overview of Graphs: node/vertex, edge/link, directed-edge, path. , Data format & Limitations. , Mapping to a supervised classification problem. , Business constraints & Metrics. , EDA:Basic Stats
2019-11-19	Module 6: Machine Learning Real World Case studies	Facebook Friend Recommendation Using Graph Mining	EDA:Follower and following stats., EDA:Binary Classification Task, EDA:Train and test split.
2019-11-20	Module 6: Machine Learning Real World Case studies	Facebook Friend Recommendation Using Graph Mining	Feature engineering on Graphs:Jaccard & Cosine Similarities, PageRank, Shortest Path, Connected-components, Adar Index, Kartz Centrality
2019-11-21	Module 6: Machine Learning Real World Case studies	Facebook Friend Recommendation Using Graph Mining	HITS Score, SVD, Weight features, Modeling, Assignment

2019-11-22	Module 6: Machine Learning Real World Case studies	Facebook Friend Recommendation Using Graph Mining	Revision Facebook Friend Recommendation Using Graph Mining
2019-11-23	Module 6: Machine Learning Real World Case studies	Taxi Demand Prediction in New York City	Business/Real world problem Overview, Objectives and Constraints, Mapping to ML problem :Data, Mapping to ML problem :dask dataframes, Mapping to ML problem :Fields/ Features., Mapping to ML problem :Time series forecasting/ Regression, Mapping to ML problem :Performance metrics, Data Cleaning :Latitude and Longitude data, Data Cleaning :Trip Duration., Data Cleaning :Speed., Data Cleaning :Distance., Data Cleaning :Fare, Data Cleaning :Remove all outliers/ erroneous points, Data Preparation:Clustering/ Segmentation, Data Preparation:Time binning, Data Preparation:Smoothing time-series data., Data Preparation:Smoothing time-series data cont.., Data Preparation: Time series and Fourier transforms.

2019-11-24	Module 6: Machine Learning Real World Case studies	Taxi Demand Prediction in New York City	Ratios and previous-time-bin values, Simple moving average, Weighted Moving average., Exponential weighted moving average, Results., Regression models :Train-Test split & Features, Linear regression., Random Forest regression, Xgboost Regression, Model comparison, Assignment.,Revision Taxi Demand Prediction in New York City
2019-11-25	Module 6: Machine Learning Real World Case studies	Stack Overflow Tag Predictor	Business/Real world problem, Business objectives and constraints, Mapping to an ML problem: Data overview, Mapping to an ML problem:ML problem formulation., Mapping to an ML problem:Performance metrics., Hamming loss, EDA:Data Loading
2019-11-26	Module 6: Machine Learning Real World Case studies	Stack Overflow Tag Predictor	EDA:Analysis of tags, EDA:Data Preprocessing, Data Modeling : Multi label Classification, Data preparation., Train-Test Split, Featurization, Logistic regression: One VS Rest

2019-11-27	Module 6: Machine Learning Real World Case studies	Stack Overflow Tag Predictor	Sampling data and tags+Weighted models., Logistic regression revisited, Why not use advanced techniques, Assignments.
2019-11-28	Module 6: Machine Learning Real World Case studies	Stack Overflow Tag Predictor	Revision Stack Overflow Tag Predictor
2019-11-29	Module 6: Machine Learning Real World Case studies	Microsoft Malware Detection	Problem Definition, Objectives and Constraints, Data Overview, ML Problem, Train and Test Splitting, Exploratory Data Analysis:Class Distribution, Exploratory Data Analysis:Feature Extraction from Byte Files, Exploratory Data Analysis:Multivariate analysis of features from byte files, Train-Test class Distribution, ML models – using byte files only :Random Model

2019-11-30	Module 6: Machine Learning Real World Case studies	Microsoft Malware Detection	K-NN, Logistic regression, Random Forest and XGBoost, Feature Extraction and Multi Threading, File Size Feature, Univariate Analysis, T-SNE Analysis, ML Models on ASM File features, Models on all features: t-SNE, Models on all features: RandomForest and XGBoost, Assignment,Revision Microsoft Malware Detection
2019-12-01	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Clustering	What is Clustering?, Unsupervised learning, Applications, Metrics for Clustering, K-Means: Geometric intuition, Centroids, K-Means: Mathematical formulation: Objective function, K-Means Algorithm., How to initialize: K-Means++, Failure cases/ Limitations, K-Medoids
2019-12-02	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Clustering	Determining the right K, Code Samples, Time and space complexity,Revision Clustering

2019-12-03	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Hierarchical Clustering	Agglomerative & Divisive, Dendrograms, Agglomerative Clustering, Proximity methods: Advantages and Limitations., Time and Space Complexity, Limitations of Hierarchical Clustering, Code sample, Assignment 10: Apply k-means, agglomerative, DBSCAN Clustering algorithms
2019-12-04	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Hierarchical Clustering	Revision Hierarchical Clustering
2019-12-05	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	DBSCAN Technique	Density based clustering, MinPts and Eps: Density, Core, Border and Noise points, Density edge and Density connected points., DBSCAN Algorithm, Hyper Parameters: MinPts and Eps, Advantages and Limitations of DBSCAN, Time and Space Complexity, Code samples.
2019-12-06	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	DBSCAN Technique	Question and Answers,Revision DBSCAN Technique

2019-12-07	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Recommender Systems and Matrix Factorization	Problem formulation: IMDB Movie reviews, Content based vs Collaborative Filtering, Similarity based Algorithms, Matrix Factorization: PCA, SVD, Matrix Factorization: NMF, Matrix Factorization for Collaborative filtering, Matrix Factorization for feature engineering, Clustering as MF
2019-12-08	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Recommender Systems and Matrix Factorization	Hyperparameter tuning, Matrix Factorization for recommender systems: Netflix Prize Solution, Cold Start problem, Word vectors as MF, Eigen-Faces, Code example., Assignment-11: Apply Truncated SVD
2019-12-09	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Recommender Systems and Matrix Factorization	Revision Recommender Systems and Matrix Factorization

2019-12-10	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Amazon Fashion Discovery Engine	Problem Statement: Recommend similar apparel products in e-commerce using product descriptions and Images, Plan of action, Amazon product advertising API, Data folders and paths, Overview of the data and Terminology, Data cleaning and understanding:Missing data in various features
2019-12-11	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Amazon Fashion Discovery Engine	Understand duplicate rows, Remove duplicates : Part 1 , Remove duplicates: Part 2, Text Pre-Processing: Tokenization and Stop-word removal, Stemming, Text based product similarity :Converting text to an n-D vector: bag of words
2019-12-12	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Amazon Fashion Discovery Engine	Code for bag of words based product similarity, TF-IDF: featurizing text based on word-importance, Code for TF-IDF based product similarity, Code for IDF based product similarity

2019-12-13	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Amazon Fashion Discovery Engine	Text Semantics based product similarity: Word2Vec(featurizing text based on semantic similarity), Code for Average Word2Vec product similarity, TF-IDF weighted Word2Vec, Code for IDF weighted Word2Vec product similarity, Weighted similarity using brand and color, Code for weighted similarity
2019-12-14	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Amazon Fashion Discovery Engine	Building a real world solution, Deep learning based visual product similarity:ConvNets: How to featurize an image: edges, shapes, parts, Using Keras + Tensorflow to extract features, Visual similarity based product similarity, Measuring goodness of our solution :A/B testing, Exercise :Build a weighted Nearest neighbor model using Visual, Text, Brand and Color,Revision Amazon Fashion Discovery Engine

2019-12-15	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Netflix Movie Recommendation system	Business/Real World Problem:Problem Definition, Objectives and Constraints, Mapping to ML problem : Data Overview, Mapping to ML problem : ML problem formulation, Exploratory Data Analysis: Data preprocessing, Exploratory Data Analysis: Temporal Train-Test split, Exploratory Data Analysis: Preliminary Data Analysis, Exploratory Data Analysis: Sparse matrix representation, Exploratory Data Analysis:Average ratings for various slices , Exploratory Data Analysis:Cold start problem, Computing Similarity matrices:User-User similarity matrix , Computing Similarity matrices:Movie-Movie similarity , Computing Similarity matrices:Does movie-movie similarity work?, ML Models:Surprise library , Overview of the modelling strategy. , Data Sampling.

2019-12-16	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Netflix Movie Recommendation system	Google drive with intermediate files , Featurizations for regression. , Data transformation for Surprise. , Xgboost with 13 features , Surprise Baseline model. , Xgboost + 13 features +Surprise baseline model , Surprise KNN predictors , Matrix Factorization models using Surprise , SVD ++ with implicit feedback
2019-12-17	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Netflix Movie Recommendation system	Final models with all features and predictors., Comparison between various models., Assignments
2019-12-18	Module 7: Data Mining (Unsupervised Learning) and Recommender systems+Real World Case studies	Netflix Movie Recommendation system	Revision Netflix Movie Recommendation system
2019-12-19	Module 8: Neural Networks, Computer Vision and Deep Learning	Neural Networks	History of Neural networks and Deep Learning., How Biological Neurons work?, Growth of biological neural networks, Diagrammatic representation: Logistic Regression and Perceptron

2019-12-20	Module 8: Neural Networks, Computer Vision and Deep Learning	Neural Networks	Multi-Layered Perceptron (MLP)., Notation, Training a single-neuron model.
2019-12-21	Module 8: Neural Networks, Computer Vision and Deep Learning	Neural Networks	Training an MLP: Chain Rule, Training an MLP:Memoization, Backpropagation., Activation functions, Vanishing Gradient problem., Bias-Variance tradeoff., Decision surfaces: Playground,Revision Neural Networks
2019-12-22	Module 8: Neural Networks, Computer Vision and Deep Learning	Deep Multi Layer Perceptrons	Deep Multi-layer perceptrons:1980s to 2010s, Dropout layers & Regularization., Rectified Linear Units (ReLU)., Weight initialization., Batch Normalization., Optimizers:Hill-descent analogy in 2D
2019-12-23	Module 8: Neural Networks, Computer Vision and Deep Learning	Deep Multi Layer Perceptrons	Optimizers:Hill descent in 3D and contours., SGD Recap, Batch SGD with momentum., Nesterov Accelerated Gradient (NAG)
2019-12-24	Module 8: Neural Networks, Computer Vision and Deep Learning	Deep Multi Layer Perceptrons	Optimizers:AdaGrad, Optimizers : Adadelta andRMSProp, Adam, Which algorithm to choose when?, Gradient Checking and clipping, Softmax and Cross-entropy for multi-class classification.

2019-12-25	Module 8: Neural Networks, Computer Vision and Deep Learning	Deep Multi Layer Perceptrons	How to train a Deep MLP?, Auto Encoders., Word2Vec :CBOW, Word2Vec: Skip-gram
2019-12-26	Module 8: Neural Networks, Computer Vision and Deep Learning	Deep Multi Layer Perceptrons	Word2Vec :Algorithmic Optimizations.,Revision Deep Multi Layer Perceptrons
2019-12-27	Module 8: Neural Networks, Computer Vision and Deep Learning	Tensorflow And Keras	Tensorflow and Keras overview, GPU vs CPU for Deep Learning., Google Colaboratory., Install TensorFlow, Online documentation and tutorials
2019-12-28	Module 8: Neural Networks, Computer Vision and Deep Learning	Tensorflow And Keras	Softmax Classifier on MNIST dataset., MLP: Initialization, Model 1: Sigmoid activation., Model 2: ReLU activation., Model 3: Batch Normalization., Model 4 : Dropout., MNIST classification in Keras., Hyperparameter tuning in Keras., Exercise: Try different MLP architectures on MNIST dataset.,Revision Tensorflow And Keras
2019-12-29	Module 8: Neural Networks, Computer Vision and Deep Learning	Convolutional Neural Nets	Biological inspiration: Visual Cortex, Convolution:Edge Detection on images., Convolution:Padding and strides, Convolution over RGB images., Convolutional layer., Max-pooling., CNN Training: Optimization, Example CNN: LeNet [1998]

2019-12-30	Module 8: Neural Networks, Computer Vision and Deep Learning	Convolutional Neural Nets	ImageNet dataset., Data Augmentation., Convolution Layers in Keras, AlexNet, VGGNet, Residual Network.
2019-12-31	Module 8: Neural Networks, Computer Vision and Deep Learning	Convolutional Neural Nets	Inception Network., What is Transfer learning., Code example: Cats vs Dogs., Code Example: MNIST dataset.
2020-01-01	Module 8: Neural Networks, Computer Vision and Deep Learning	Convolutional Neural Nets	Assignment: Try various CNN networks on MNIST dataset.,Revision Convolutional Neural Nets
2020-01-02	Module 8: Neural Networks, Computer Vision and Deep Learning	Long Short-Term Memory(LSTMS)	Why RNNs? , Recurrent Neural Network., Training RNNs: Backprop.
2020-01-03	Module 8: Neural Networks, Computer Vision and Deep Learning	Long Short-Term Memory(LSTMS)	Types of RNNs., Need for LSTM/GRU., LSTM., GRUs.
2020-01-04	Module 8: Neural Networks, Computer Vision and Deep Learning	Long Short-Term Memory(LSTMS)	Deep RNN., Bidirectional RNN., Code example : IMDB Sentiment classification, Exercise: Amazon Fine Food reviews LSTM model.,Revision Long Short-Term Memory(LSTMS)

2020-01-05	Module 9: Deep Learning Real World Case Studies	Human Activity Recognition	Human Activity Recognition Problem definition, Dataset understanding, Data cleaning & preprocessing, EDA:Univariate analysis., EDA:Data visualization using t-SNE, Classical ML models., Deep-learning Model., Exercise: Build deeper LSTM models and hyper-param tune them
2020-01-06	Module 9: Deep Learning Real World Case Studies	Human Activity Recognition	Revision Human Activity Recognition
2020-01-07	Module 9: Deep Learning Real World Case Studies	Self Driving Car	Problem Definition, Datasets., Data understanding & Analysis :Files and folders., Dash-cam images and steering angles., Split the dataset: Train vs Test, EDA: Steering angles, Mean Baseline model: simple, Deep-learning model:Deep Learning for regression: CNN, CNN+RNN, Batch load the dataset.
2020-01-08	Module 9: Deep Learning Real World Case Studies	Self Driving Car	NVIDIA's end to end CNN model., Train the model., Test and visualize the output., Extensions., Assignment.
2020-01-09	Module 9: Deep Learning Real World Case Studies	Self Driving Car	Revision Self Driving Car

2020-01-10	Module 9: Deep Learning Real World Case Studies	Music Generation Using Deep Learning	Real-world problem, Music representation, Char-RNN with abc-notation :Char-RNN model, Char-RNN with abc-notation :Data preparation.
2020-01-11	Module 9: Deep Learning Real World Case Studies	Music Generation Using Deep Learning	Char-RNN with abc-notation:Many to Many RNN ,TimeDistributed-Dense layer, Char-RNN with abc-notation : State full RNN, Char-RNN with abc-notation :Model architecture,Model training., Char-RNN with abc-notation :Music generation., Char-RNN with abc-notation :Generate tabla music, MIDI music generation., Survey blog, Assignment
2020-01-12	Module 9: Deep Learning Real World Case Studies	Music Generation Using Deep Learning	Revision Music Generation Using Deep Learning

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Please mail us to team@appliedaicourse.com if you have any queries