Classical Machine Learning

Week 0

Plan

- Setting up your learning and programming environment

Getting started

- Setting up your ML environment (Setup_NYU.ipynb)
    - Choosing an ML environment (Choosing_an_ML_Environment_NYU.ipynb)
- Quick intro to the tools (Getting_Started.ipynb)

Week 1

Plan

- Motivate Machine Learning
- Introduce notation used throughout course
- Plan for initial lectures
    - *What*: Introduce, motivate a model
    - *How*: How to use a model: function signature, code (API)
    - *Why*: Mathematical basis -- enhance understanding and ability to improve results

- [Course Overview (Course_overview_NYU.ipynb)](Course_overview_NYU.ipynb)
- [Machine Learning: Overview (ML_Overview.ipynb)](ML_Overview.ipynb)
- [Intro to Classical ML (Intro_Classical_ML.ipynb)](Intro_Classical_ML.ipynb)

Using an AI Assistant

AI Assistants are often very good at coding.

But using one to just "get the answer" deprives you of a valuable tool

- you can ask the Assistant *why* it chose to do something
- keep on asking
- treat it as a private tutor !

[Learning about KNN using an Assistant as a private tutor (https://www.perplexity.ai/search/using-python-and-sklearn-pleas-407oe3uzTXu1i9xEHVR2MQ)](https://www.perplexity.ai/search/using-python-and-sklearn-pleas-407oe3uzTXu1i9xEHVR2MQ)

Week 2

Recap of last week

- Summary of Intro to Supervised Machine Learning (Intro_to_Supervised_Learning_Summary.ipynb)

Plan

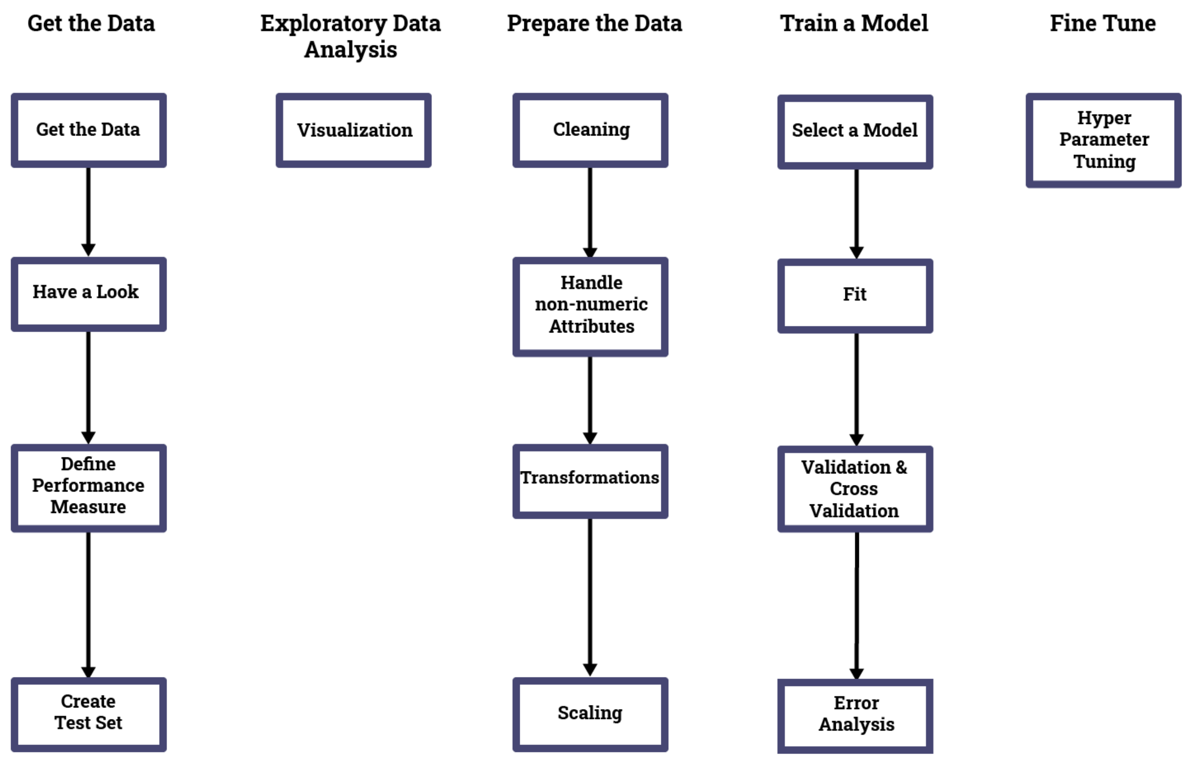
We will learn the Recipe for Machine Learning, a disciplined approach to solving problems in Machine Learning.

We will illustrate the Recipe while, at the same time, introducing a model for the Regression task: Linear Regression.

Our coverage of the Recipe will be rapid and shallow (we use an extremely simple example for illustration).

I highly recommend reviewing and understanding this Geron notebook (external/handson-ml2/02_end_to_end_machine_learning_project.ipynb) in order to acquire a more in-depth appreciation of the Recipe.

Recipe for Machine Learning



Recipe, as illustrated by Linear Regression

[The Recipe for Machine Learning: Solving a Regression task (Recipe_via_Linear_Regression.ipynb)](Recipe_via_Linear_Regression.ipynb)

- A *process* for Machine Learning
    - Go through the methodical, multi-step process
        - Quick first pass, followed by Deeper Dives

Fitting a model: details

Recall: fitting a model (finding optimal value for the parameters) is found by minimizing a Loss function.

Let's examine a typical Loss function for Regression

- Regression: Loss Function (Linear_Regression_Loss_Function.ipynb)

Iterative training: when to stop

Increasing the number of parameters of a model improves in-sample fit (reduces Loss) but may compromise out-of-sample prediction (generalization).

We examine the issues of having too many/too few parameters.

- When to stop iterating: Bias and Variance (Bias_and_Variance.ipynb)

Get the data: Fundamental Assumption of Machine Learning

- Getting *good* training examples (Recipe_Training_data.ipynb)

Regression: final thoughts (for now)

- Regression: coda (Regression_coda.ipynb)

Deeper dives

- Fine tuning techniques (Fine_tuning.ipynb)

Using an AI Assistant

Learning about Linear Regression using an Assistant as private tutor (https://www.perplexity.ai/search/using-python-sklearn-and-matpl-vTYv7oGdRQ6upR5L5OSirg)

Week 3

Recipe "Prepare the Data" step: Transformations

We covered this at end of Week 2

We recap the importance of adding *synthetic* features to our Linear Regression example

- and *preview* the *mechanical* process of creating these features via *Transformations*

Transformations

- [Prepare Data: Intro to Transformations (Prepare_data_Overview.ipynb)]

Validation

We skipped over this topic in Week 2; we cover it now

Our test dataset can be used only once, yet

- we have an iterative process for developing models
- each iteration requires a proxy for out of sample data to use in the Performance Metric

The solution: create a proxy for out of sample that is a *subset* of the training data.

- [Validation and Cross-Validation (Recipe_via_Linear_Regression.ipynb#Validation-and-Cross-Validation)](Recipe_via_Linear_Regression.ipynb#Validation-and-Cross-Validation)
- [Avoiding cheating in Cross-Validation (Prepare_data_Overview.ipynb#Using-pipelines-to-avoid-cheating-in-cross-validation)](Prepare_data_Overview.ipynb#Using-pipelines-to-avoid-cheating-in-cross-validation)

Classification Task

Plan

- We introduce a model for the Classification task: Logistic Regression
- How to deal with Categorical (non-numeric) variables
    - classification target
    - features

Classification intro

- Classification: Overview (Classification_Overview.ipynb)
- Classification and Categorical Variables (Classification_Notebook_Overview.ipynb)
    - linked notebook (Classification_and_Non_Numerical_Data.ipynb)

Categorical variables (contained as subsections of Classification and Categorical Variables)

We examine the proper treatment of categorical variables (target or feature).

Along the way, we run into a subtle difficulty: the Dummy Variable Trap.

- Classification and Categorical Variables: Categorical Variables (Classification_Notebook_Overview.ipynb#Categorical-variables)

Week 4

Multinomial Classification

We generalize Binary Classification into classification into more than two classes.

- Multinomial Classification (Multinomial_Classification.ipynb)

Classification and Categorical variables wrapup

- Classification Loss Function (Classification_Loss_Function.ipynb)
- Baseline model for Classification (Classification_Baseline_Model.ipynb)
- OHE issue: Dummy variable trap (Dummy_Variable_Trap.ipynb)

Classification: final thoughts (for now)

- Classification: coda (Classification_coda.ipynb)

Plan

Good news

- You now know two main tasks in Supervised Learning
    - Regression, Classification
- You now know how to use virtually every model in `sklearn`
    - Consistent API
        - `fit`, `transform`, `predict`
- You survived the "sprint" to get you up and running with ML
- You know the *mechanical process* to implement transformations: Pipelines

Time to re-visit, in more depth, several important topics

Error Analysis

- We explain Error Analysis for the Classification Task, with a detailed example

- How Training Loss can be improved

- Error Analysis (Error_Analysis_Overview.ipynb)

    - linked notebook (Error_Analysis.ipynb)
        - Summary statistics
        - Conditional statistics
    - Worked example (Error_Analysis_MNIST.ipynb)

- Loss Analysis: Using training loss to improve models (Training_Loss.ipynb)

Imbalanced data

- [Imbalanced data (Imbalanced_Data.ipynb)](Imbalanced_Data.ipynb)

Transformations: the "why"

Part of becoming a better Data Scientist is transforming raw features into more useful synthetic features.

In an earlier week, we presented the [mechanics (Prepare_data_Overview.ipynb)](Prepare_data_Overview.ipynb) (how to use `sklearn` to implement transformation Pipelines) of Transformations. This week, we focus on the necessity (the "why"): transforming raw data into something that tells a story

- [Becoming a successful Data Scientist (Becoming_a_successful_Data_Scientist.ipynb)](Becoming_a_successful_Data_Scientist.ipynb)
- [Transformations: overview (Transformations_Overview.ipynb)](Transformations_Overview.ipynb)
    - linked notebooks:

Week 5

Transformations: the "why" (continued)

- [Becoming a successful Data Scientist (Becoming_a_successful_Data_Scientist.ipynb)]
- [Transformations: overview (Transformations_Overview.ipynb#Scaling)]
    - linked notebooks:
        - [Transformations: scaling (Transformations_Scaling.ipynb)]
        - [Transformations: normalization (Transformations_Normalization.ipynb)]
        - [Other Transformations (Transformations_Other.ipynb)]

Loss functions: mathematical basis

Where do the Loss functions of Classical Machine Learning come from ? We take a brief mathematical detour into Loss functions.

- [Entropy, Cross Entropy, and KL Divergence (Entropy_Cross_Entropy_KL_Divergence.ipynb)]
- [Loss functions: the math (Loss_functions.ipynb)]
    - Maximum likelihood
    - Preview: custom loss functions and Deep Learning

More models for classification

Plan

- More models: Decision Trees, Naive Bayes
    - Different flavor: more procedural, less mathematical
    - Decision Trees: a model with *non-linear* boundaries
- Ensembles
    - Bagging and Boosting
    - Random Forests

Decision Trees, Ensembles

- Decision Trees: Overview (Decision_Trees_Overview.ipynb)
- Decision Trees (Decision_Trees_Notebook_Overview.ipynb)
    - linked notebook (Decision_Trees.ipynb)
- Trees, Forests, Ensembles (Ensembles.ipynb)

Naive Bayes

- Naive Bayes (Naive_Bayes.ipynb)

Week 6

More models for classification

Plan

Continue with more models for classification.

We continue with the *ensemble* technique that *combines* the prediction of multiple models.

Combining multiple models: Ensembles (continued)

- Trees, Forests, Ensembles (Ensembles.ipynb#Boosting)

Support Vector Classifiers

- Support Vector Machines: Overview (SVM_Overview.ipynb)
- SVC Loss function (SVM_Hinge_Loss.ipynb)
- SVC: Large Margin Classification (SVM_Large_Margin.ipynb)
- SVM: Kernel Transformations (SVM_Kernel_Functions.ipynb)
- SVM Wrapup (SVM_Coda.ipynb)

Classification: final thoughts

- Classification: coda (Classification_coda.ipynb)

Loss functions: mathematical basis (deferred from previous week)

Where do the Loss functions of Classical Machine Learning come from ? We take a brief mathematical detour into Loss functions.

- Entropy, Cross Entropy, and KL Divergence (Entropy_Cross_Entropy_KL_Divergence.ipynb)
- Loss functions: the math (Loss_functions.ipynb)
    - Maximum likelihood
    - Preview: custom loss functions and Deep Learning

Unsupervised Learning

Unsupervised Learning: PCA

- Unsupervised Learning: Overview (Unsupervised_Overview.ipynb)
- PCA Notebook Overview (Unsupervised_Notebook_Overview.ipynb)
    - linked notebook (Unsupervised.ipynb)
- PCA in Finance (PCA_Yield_Curve_Intro.ipynb)

Week 7

We continue with the Unsupervised Learning topic.

Unsupervised Learning

Unsupervised Learning: PCA (continued)

- [Importance of number of components: visualization (Unsupervised.ipynb#Visualizing-the-fidelity-of-the-reduced-dimension-representation)]
- [Interpreting the components (Unsupervised.ipynb#Can-we-interpret-the-components-?)]

Classical ML: deeper dives

Loss functions: mathematical basis (deferred)

Where do the Loss functions of Classical Machine Learning come from ? We take a brief mathematical detour into Loss functions.

- Entropy, Cross Entropy, and KL Divergence (Entropy_Cross_Entropy_KL_Divergence.ipynb)
- Loss functions: the math (Loss_functions.ipynb)
    - Maximum likelihood
    - Preview: custom loss functions and Deep Learning

Deeper Dives

- Linear Regression in more depth (Linear_Regression_fitting.ipynb)
- Interpretation: Linear Models (Linear_Model_Interpretation.ipynb)
- Missing data: clever ways to impute values (Missing_Data.ipynb)
- Feature importance (Feature_Importance.ipynb)
- SVC Loss function derivation (SVM_Derivation.ipynb)

Bridge between Classical ML and Deep Learning

Gradient Descent

Machine Learning is based on minimization of a Loss Function. Gradient Descent is one algorithm to achieve that.

- Gradient Descent (Gradient_Descent.ipynb)

Recommender Systems (Pseudo SVD)

How does Amazon/Netflix/etc. recommend products/films to us ? We describe a method similar to SVD but that is solved using Gradient Descent.

This theme of creating a custom Loss Functions and minimizing it via Gradient Descent is a recurring theme in the upcoming Deep Learning second half of the course.

- [Recommender Systems (Recommender_Systems.ipynb)](Recommender_Systems.ipynb)
- [Preview: Some cool Loss functions (Loss_functions.ipynb#Loss-functions-for-Deep-Learning:-Preview)](Loss_functions.ipynb#Loss-functions-for-Deep-Learning:-Preview)

Deeper Dives

Deep Learning

DL Week 1 Introduction to Neural Networks and Deep Learning

Plan

Deep Learning/Neural networks

- Set up your Tensorflow environment (Tensorflow_setup.ipynb)
- Neural Networks Overview (Neural_Networks_Overview.ipynb)

Neural network: practical

- Coding Neural Networks: Tensorflow, Keras
  - Intro to Keras (Tensorflow_Keras.ipynb)
  - **Note**
    - If you have problems using the `plot_model` function in Keras on local machine: see here (Setup_ML_Environment_NYU.ipynb#Too visualization-of-graphs-(optional)) for a fix.
  - Linked notebooks
    - DNN Tensorflow example Notebook local (DNN_TensorFlow_example.ipynb) **(local machine)**
    - DNN Tensorflow example Notebook from github (https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/DNN_TensorFlow_example (**Google Colab**)
- Practical Colab
  - **Colab**: Practical Colab Notebook from github (https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Colab_practical.ipynb)

Practical advice

- Karpathy: Recipe for training Neural Nets

DL Week 2 Intro to NN (continued); Convolutional Neural Networks

Practical advice (continued)

- Karpathy: [Recipe for training Neural Nets (Karpathy_Recipe_for_training_NN.ipynb)](Karpathy_Recipe_for_training_NN.ipynb)

Plan

The topics introduced in the Neural Networks Overview are now covered more in-depth.

- Where do Neural Networks get their power from ?
- How exactly do we compute the gradients ?
- How does a special language/library facilitate automatic computation of the gradients ?

Neural network theory

- [A neural network is a Universal Function Approximator (Universal_Function_Approximator.ipynb)](Universal_Function_Approximator.ipynb)

Training Neural Networks (introduction)

- Intro to Training (Neural_Networks_Intro_to_Training.ipynb)
- Training Neural Networks - Back propagation (Training_Neural_Network_Backprop.ipynb)

How to compute gradients automatically

- Why TensorFlow ?: Gradients made easy (Training_Neural_Network_Operation_Forward_and_Backward_Pass.ipynb)

Deeper Dives

- Keras, from past to present (Tensorflow_Keras_Archaeology.ipynb)
- History/Computation Graphs: Tensorflow version 1 (DNN_TensorFlow_Using_TF_version_1.ipynb)
- Raw_TensorFlow example Notebook from github (https://colab.research.google.com/github/kenperry-public/ML_Spring_2024/blob/master/Raw_TensorFlow.ipynb) (**Colab**)
- Computation Graphs (Computation_Graphs.ipynb)

DL Week 3 Training Neural Networks: details

Plan

- Why training a Neural Network can be difficult: fine-details of training
- Introduce a new layer type: Recurrent layers
    - Part of our "sprint": final layer type
    - Will revisit more theoretical issues in subsequent lectures

Training Neural Networks: the fine details

- The dynamics of training (Training_Neural_Networks_Overview.ipynb)
    - Effects of changing: activation functions; weight initialization
    - initialization and scaling
    - dropout
    - learning rate schedules
    - vanishing/exploding gradients

Recurrent Neural Networks (RNN)

- Introduction to Recurrent Neural Network (RNN) (Intro_to_RNN.ipynb)

Additional Deep Learning resources

Here are some resources that I have found very useful.

Some of them are very nitty-gritty, deep-in-the-weeds (even the "introductory" courses)

- For example: let's make believe PyTorch (or Keras/TensorFlow) didn't exists; let's invent Deep Learning without it !
    - You will gain a deeper appreciation and understanding by re-inventing that which you take for granted

[Andrej Karpathy course: Neural Networks, Zero to Hero (https://karpathy.ai/zero-to-hero.html)](https://karpathy.ai/zero-to-hero.html)

- PyTorch
- Introductory, but at a very deep level of understanding
    - you will get very deep into the weeds (hand-coding gradients !) but develop a deeper appreciation

fast.ai

`fast.ai` is a web-site with free courses from Jeremy Howard.

- PyTorch
- Introductory and courses "for coders"
- Same courses offered every few years, but sufficiently different so as to make it worthwhile to repeat the course !
    - Practical Deep Learning (https://course.fast.ai/)
    - Stable diffusion (https://course.fast.ai/Lessons/part2.html)
        - Very detailed, nitty-gritty details (like Karpathy) that will give you a deeper appreciation

Stefan Jansen: Machine Learning for Trading (https://github.com/stefan-jansen/machine-learning-for-trading)

An excellent github repo with notebooks

- using Deep Learning for trading
- Keras
- many notebooks are cleaner implementations of published models

Assignments

Your assignments should follow the Assignment Guidelines (assignments/Assignment_Guidelines.ipynb)

Regression

- Assignment notebook: [Using Machine Learning for Hedging (assignments/Regression%20task/Using_Machine_Learning_for_Hedging.ipynb)](assignments/Regression%20task/Using_Machine_Learning_for_Hedging.ipynb)
- Data
    - There is an archive file containing the data
    - You can find it
        - Under the course page: Content --> Data --> Assignments --> Regression task
        - You won't be able to view the file in the browser, but you **will** be able to Download it
    - You should unzip this archive into the *the same directory* as the assignment notebook
    - The end result is that the directory should contain
        - The assignment notebook and a helper file
        - A directory named `Data`

Classification

- Assignment notebook: [Ships in satellite images (assignments/Classification%20task/Ships_in_satellite_images.ipynb#)](assignments/Classification%20task/Ships_in_satellite_images.ipynb#)
- Data
    - There is an archive file containing the data
    - You can find it
        - Under the course page: Content --> Data --> Assignments --> Classification task
        - You won't be able to view the file in the browser, but you **will** be able to Download it
    - You should unzip this archive into the *the same directory* as the assignment notebook
    - The end result is that the directory should contain
        - The assignment notebook and a helper file

Midterm Project: Bankruptcy One Year Ahead

- Assignment notebook [Bankruptcy One Year Ahead (assignments/bankruptcy_one_yr/Bankruptcy_oya.ipynb)](assignments/bankruptcy_one_yr/Bankruptcy_oya.ipynb)
- Data
    - There is an archive file containing the data
    - You can find it
        - Under the course page: Content --> Data --> Assignments --> Bankruptcy One Year Ahead
        - You won't be able to view the file in the browser, but you **will** be able to Download it
    - You should unzip this archive into the *the same directory* as the assignment notebook
    - The end result is that the directory should contain
        - The assignment notebook and a helper file
        - A directory named `Data`

Keras practice

- Assignment notebook Ships in satellite images: Neural Network (assignments/keras_intro/Ships_in_satellite_images_P1.ipynb)
- Data (same as for the Classification assignment)

In [1]:

```
print("Done")
```

```
Done
```