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: Introduction

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)
- Machine Learning: Overview (ML_Overview.ipynb)
- Intro to Classical ML (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 the Landscape of ML (https://www.perplexity.ai/search/i-am-interested-in-the-landsca-_yO63NWfSGS8iHR5nyQYVA)

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

Week 2 (early start in Week 1)

We began covering the **Recipe, as illustrated by Linear Regression**

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

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

Week 2: Regression task

Plan

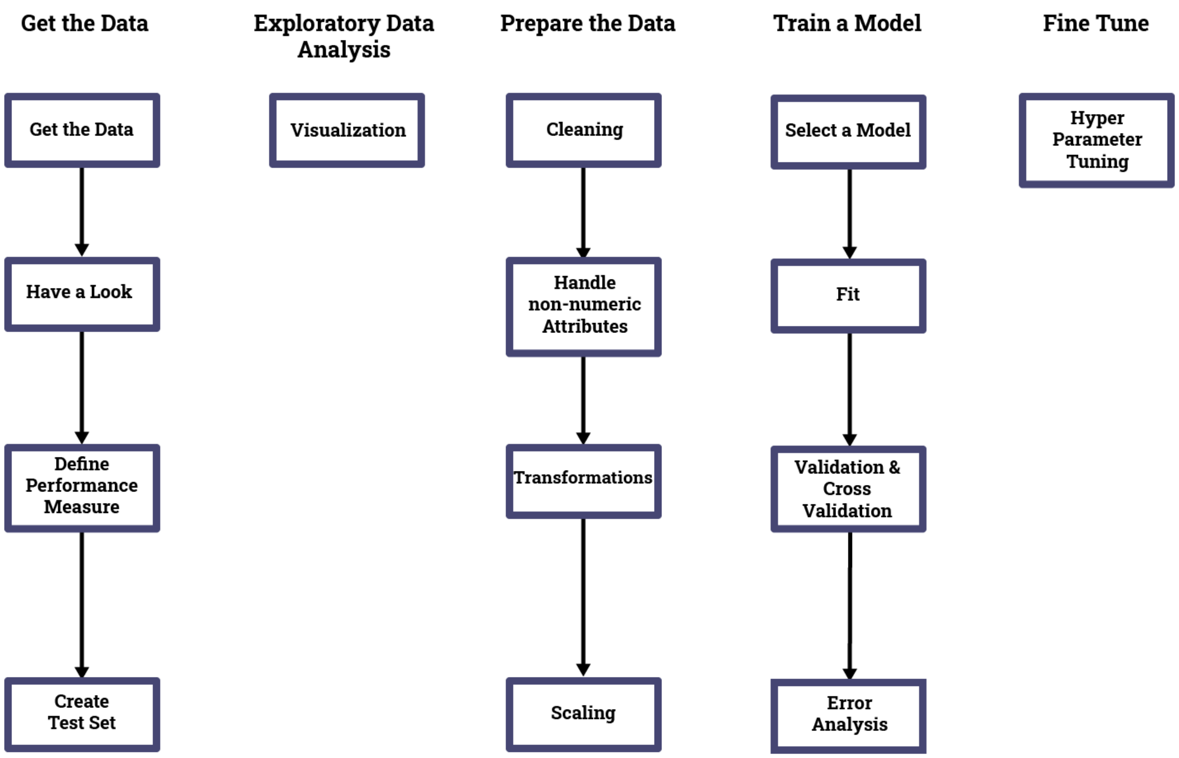
We will learn the Recipe for Machine Learning, a disciplined approach to solving problems in Machine Learning.

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 (continued) (Recipe_via_Linear_Regression.ipynb#Create-a-test-set)](Recipe_via_Linear_Regression.ipynb#Create-a-test-set)

- 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)

Recipe "Prepare the Data" step: Transformations

We discuss 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

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

Week 3 (early start in Week 1)

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)
    - Categorical variables, One Hot Encoding (OHE) (Categorical_Variables.ipynb)

Week 3: Classification task

Non-feature dimensions

In response to questions about Assignment 1,

- we will clarify the limitations in our ability to handle *timeseries* data with our current tools.

[Non-feature dimensions: preview (Non-feature_dimensions_preview.ipynb)](Non-feature_dimensions_preview.ipynb)

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) **Covered last week**
- Classification and Categorical Variables (continued) (Classification_and_Non_Numerical_Data.ipynb#Recipe-Step-B:-Exploratory-Data-Analysis-(EDA))
    - 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)
    - Categorical variables, One Hot Encoding (OHE) (Categorical_Variables.ipynb)

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 Deeper dives

Week 4: Transformations

Plan

Still one major missing piece in our in-depth coverage of the Recipe for Machine Learning

- Transformations

We explain

- why it is often necessary to create *synthetic* features to augment or replace *raw* feature
- the mechanical process in `sklearn` that makes the application of transformations easy and consistent

Transformations: the "why"

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

We focus on the necessity (the "why"): transforming raw data into something that tells a story.

We will then discuss the mechanics (Prepare_data_Overview.ipynb) (how to use `sklearn` to implement transformation Pipelines) of Transformations.

- Becoming a successful Data Scientist (Becoming_a_successful_Data_Scientist.ipynb)
- Transformations: overview (Transformations_Overview.ipynb)
    - linked notebooks:
        - Transformations: adding a missing feature (Transformations_Missing_Features.ipynb)

Transformations: the "how"

Having hopefully motivated the use of transformations in theory

- we turn to the *mechanical* process of creating these features via *Transformations in* `sklearn`

Transformations

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

Transformations: Avoiding cheating when using Cross-Validation

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) (**Covered in week 1**)

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

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

Error Analysis

We can only improve our model's out of sample Performance Metric

- by diagnosing the in-sample errors
- that is the goal of the Error Analysis step of the Recipe
- We explain Error Analysis for the Classification Task, with a detailed example
- How Training Loss can be improved

The conversion of a probability (e.g., model output) to a Class (categorical variable) for Classification

- often involves the comparison of a probability to a threshold
- we show how varying the threshold changes the conditional Performance Metric for Classification
    - the threshold is a hyper-parameter, thus this is a kind of Fine-Tuning
- 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

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`

In [1]:

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

```
Done
```