

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 \(Course overview NYU.ipynb\)](#)
- [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 KNN using an Assistant as a private tutor
\(https://www.perplexity.ai/search/using-python-and-sklearn-please-407oe3uzTXu1i9xEHVR2MQ\)](https://www.perplexity.ai/search/using-python-and-sklearn-please-407oe3uzTXu1i9xEHVR2MQ)

Week 2

Recap of last week

- [Summary of Intro to Supervised Machine Learning \(Intro to Supervised Learning Summary.ipynb\)](#)

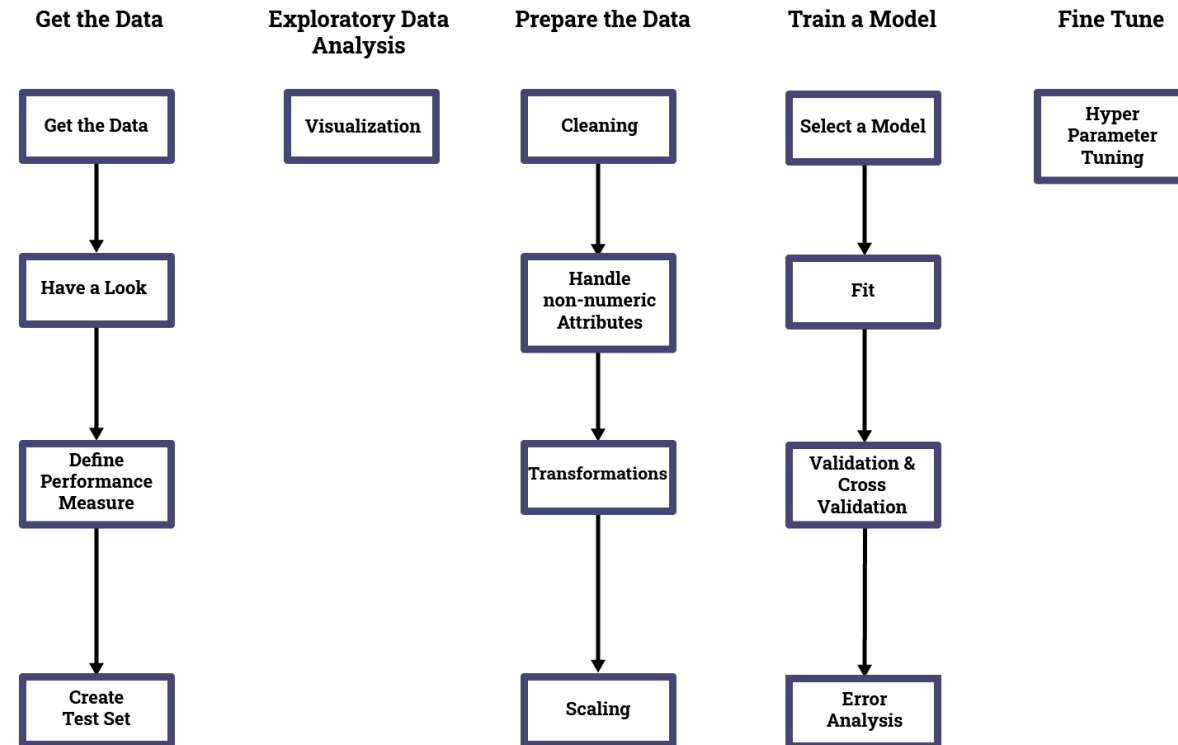
Plan

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, 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

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 \(https://www.perplexity.ai/search/using-python-sklearn-and-matplotlibTYv7oGdRO6upR5L5OSirg\)](#)

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 \(Recipe via Linear Regression.ipynb#Validation-and-Cross-Validation\)](#)
- [Avoiding 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 \(Imbalanced Data.ipynb\)](#)

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 \(Prepare data Overview.ipynb\)](#) (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 \(Becoming a successful Data Scientist.ipynb\)](#)
- [Transformations: overview \(Transformations Overview.ipynb\)](#)
 - 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 \(Recommender Systems.ipynb\)](#)
- [Preview: Some cool Loss functions \(Loss functions.ipynb#Loss-functions-for-Deep-Learning:-Preview\)](#)

Deeper Dive

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](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 \(https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Colab_practical.ipynb\)](https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Colab_practical.ipynb)

Practical advice

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

Here is a quick review of Neural Networks

- [Neural Network summary_\(Neural_Network_summary.ipynb\)](#)

Practical advice (continued)

- Karpathy: [Recipe for training Neural Nets](#)
([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 \(Universal Function Approximator.ipynb\)](#)

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 \(https://colab.research.google.com/github/kenperry-public/ML_Spring_2024/blob/master/Raw_TensorFlow.ipynb\) \(Colab\)](#)

Plan

We introduce a new layer type.

This is motivated by inputs with dimensions in addition to the feature dimension.

The Convolutional Neural Network layer type

- [Introduction to CNN \(Intro to CNN.ipynb\)](#)
 - [CNN pictorial \(CNN pictorial.ipynb\)](#)
- [Notational standards, definitions \(CNN Notation.ipynb\)](#)
- [CNN: Space and Time \(CNN Space and Time.ipynb\)](#)
 - [CNN example from github](#)
(https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/CNN_demo.ipynb) (**Colab**)
 - [CNN example from github \(CNN demo.ipynb\)](#) (**local machine**)

The following notebooks are an older attempt at a *visual* explanation of the CNN.

Hopefully, the "Introduction" notebook is more intuitive and may supercede these visual notebooks.

- [CNN: explained in pictures \(CNN Overview.ipynb\)](#)

Deeper dives

- Convolution as Matrix Multiplication
(CNN Convolution as Matrix Multiplication.ipynb)

DL Week 3 Training Neural Networks: details

Convolutional Neural Networks (CNN) wrap-up

- [Remaining details \(CNN Space and Time.ipynb#Kernel-size-1\)](#)

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 \(RNN\) \(Intro to RNN.ipynb\)](#)

DL Week 4 Recurrent Neural Networks

Recurrent Neural Networks (RNN) Continued

- [Recurrent Neural Network Overview \(RNN Overview.ipynb\)](#)
 - [linked notebook: RNN in code -- Imdb sentiment classification \(Keras examples imdb_cnn.ipynb#Try-an-LSTM-as-a-means-of-obtaining-a-finite-length-representation-of-the-sequence\)](#)

RNN: Issues

- [Gradients of an RNN \(RNN Gradients.ipynb\)](#)
- [RNN: Gradients that Vanish/Explode \(RNN Vanishing and exploding gradients.ipynb\)](#)
- [RNN: Visualization \(RNN Visualization.ipynb\)](#)

Sprint is over ! We have covered the basic layer types; time for you to learn by experimenting.

Review of layer types

- [What layer type to choose \(Neural Network Layer Review.ipynb\)](#)

Deeper dives

- [RNN: How to deal with long sequences \(RNN_Long_Sequences.ipynb\)](#)
- [Using an RNN for Generative AI \(RNN_generative.ipynb\)](#)
 - [LSTM text generation from github](#)
(https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Keras_examples_LSTM_text_generat
(Colab)
 - [LSTM text generation from github \(Keras_examples_LSTM_text_generatio](#)
(local machine)

DL Week 5 Transfer Learning; Natural Language Processing

Advanced Recurrent Architectures: LSTM

Plan

The "vanilla" Recurrent Neural Network (RNN) layer we learned is very much exposed to the problem of vanishing/exploding gradients.

We will review the issue and demonstrate a related layer type (the LSTM) designed to mitigate the problem.

We present an extremely useful trick (Transfer Learning) for leveraging the hard work that others have done.

Concepts

There are a number of pieces of the LSTM which can appear overwhelming when seen together for the first time. We will explore these concepts separately before seeing how they are integrated into the LSTM.

- [Residual connections \(RNN Residual Networks.ipynb\)](#)
- [Neural Programming \(Neural Programming.ipynb\)](#)

LSTM: An improved RNN

- [Introduction to the LSTM \(Intro to LSTM.ipynb\)](#)
- [LSTM Overview \(LSTM Overview.ipynb\)](#)

Transfer Learning

Transfer learning allows us to adapt a model trained for one task to be able to solve a new task with a small amount of work. As models get bigger and bigger, the future of Deep Learning may be one where you use Transfer Learning more than developing your own models from scratch.

- [Transfer Learning \(Continued\) \(Transfer_Learning.ipynb\)](#)
 - [Transfer Learning example from github \(https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/TransferLearning_demo.ipynb\)](#) (Colab)
 - [Transfer Learning example from github \(TransferLearning_demo.ipynb\)](#) (local machine)
 - [Utility notebook \(Dogs and Cats reformat.ipynb\)](#)
 - Takes the *very large* raw data (from Kaggle) used in the Transfer Learning example
 - Creates a much smaller subset, using a different directory structure
 - The above notebook uses this reorganized, smaller subset

NLP

Plan

We will make an initial pass on the topic of learning from text: Natural Language Processing.

The first pass will use well-established techniques that are relatively easy to follow.

We then explore some recent advances that have greatly increased the power of NLP.

The Transformer architecture is a key contributor.

Learning from text: Deep Learning for Natural Language Processing (NLP)

- [Natural Language Processing Overview \(NLP Overview.ipynb\)](#)

We revisit some code we had previously studied

- in the RNN module: to illustrate various ways to eliminate the time dimension
- but this time with an emphasis on the NLP aspects
 - [NLP from github \(Colab\)](#)
[\(https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Keras_examples_imdb_cnn.ipynb\)](https://colab.research.google.com/github/kenperry-public/ML_Spring_2025/blob/master/Keras_examples_imdb_cnn.ipynb)
 - [NLP from github \(local machine\) \(Keras_examples_imdb_cnn.ipynb\)](#)

Evolution of Word representations

- [How to represent a word: syntax \(NLP Tokenization.ipynb\)](#)

DL Week 6 Transformers

Plan

We present Attention, a way to enhance the power of RNN's, which is heavily used in a new layer type for sequence processing: the Transformer.

The Transformer layer type is now predominant in the area of Natural Language Processing (NLP). We give a quick introduction but we will revisit it in the module on advanced NLP.

Attention

- [Attention: motivation \(Intro to Attention.ipynb\)](#)

We summarize (with illustrations) the key points regarding attention.

- The evolution of the Encoder/Decoder RNN to
 - a "loop-free" architecture via Self-Attention
 - combined with Cross attention from Encoder to Decoder
- [Transformer motivation: Illustrated \(Attention motivation illustrated.ipynb\)](#)

These ideas are combined into a new architecture called the **Transformer**

Transformers

- [Transformer \(Transformer.ipynb\)](#)

Attention: in depth

- [Implementing Attention \(Attention Lookup.ipynb\)](#)

Deeper dives

- Transformer
 - [Keras example: pre-defined Attention layers \(https://keras.io/examples/nlp/notebook \(https://colab.research.google.com/github/keras-team/keras/blob/master/examples/nlp/ipynb/text_classification_with_transformer.ipynb\)\)](#)
 - [TensorFlow tutorial: implements Attention, positional encoding \(https://www.tensorflow.org/text/tutorials/transformer\)](#)
 - [notebook \(https://colab.research.google.com/github/tensorflow/text/blob/master/docs/tutorials/transformer.ipynb\)](#)

Further reading

- Attention
 - [Neural Machine Translation by Jointly Learning To Align and Translate \(https://arxiv.org/pdf/1409.0473.pdf\)](https://arxiv.org/pdf/1409.0473.pdf)

Language Models

Language Models: the future (present ?) of NLP ?

- [Language Models, the future \(present ?\) of NLP: Review \(Review LLM.ipynb\)](#)

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 exist; 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/) (<https://course.fast.ai/>)
 - [Stable diffusion](https://course.fast.ai/Lessons/part2.html) (<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 \(assignments/Regression%20task/Using_Machine_Learning_for_Hedging.ipynb\)](#)
- 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#](#)).
- 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 \(assignments/bankruptcy_one_yr/Bankruptcy_oya.ipynb\)](#)
- 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)

Convolutional Neural Networks (CNN)

- Assignment notebook [Ships in satellite images: Neural Network \(assignments/CNN intro/Ships in satellite images P2.ipynb\)](#)
- Data (same as for the Classification assignment)
 - please repeat the directions given in that assignment for obtaining the data

```
In [1]: print("Done")
```

Done

