Lecture1 Introduction to Machine Learning

1. Introduction

Why Now?

- Hardware (GPUs developed for gaming industry)
- Datasets and benchmarks (internet took off)
- Algorithmic advances (making possible to train “deep” models)

Why Deep Learning?

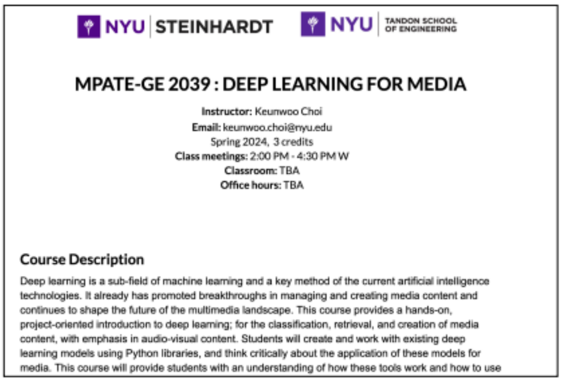
- **Simplicity**: no feature engineering.
- **Scalable**: can be parallelized in multiple GPUs, faster.
- **Versatile and reusable**: viable for continuous online learning and possible to reuse work from one project to another.

What has Deep Learning Achieved?

- Near-human-level:
    - Image classification
    - Speech transcription
    - Handwriting transcription
    - Music transcription for some tasks (e.g. rhythm)
- Dramatically improved machine translation
- Dramatically improved text-to-speech conversion
- Digital assistants such as Google Assistant and Amazon Alexa
- Level=3..(ish) autonomous driving
- Improved ad targeting, as used for Google, Baidu or Bing
- Improved search results on the web
- Ability to answer natural language questions
- Superhuman Go playing
- Text-to-Image prototyping

Course Structure

- Lectures
- Live coding
- Homework assignments
- Paper role-reading
- Final project



NYU STEINHARDT NYU TANDON SCHOOL OF ENGINEERING

MPATE-GE 2039 : DEEP LEARNING FOR MEDIA

Instructor: Keunwoo Choi
Email: keunwoo.choi@nyu.edu
Spring 2024, 3 credits
Class meetings: 2:00 PM - 4:30 PM W
Classroom: TBA
Office hours: TBA

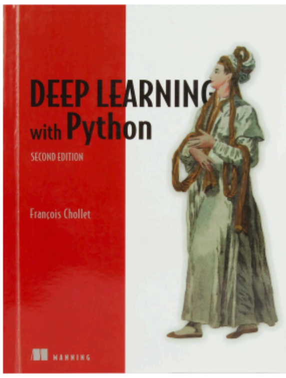
Course Description

Deep learning is a sub-field of machine learning and a key method of the current artificial intelligence technologies. It already has promoted breakthroughs in managing and creating media content and continues to shape the future of the multimedia landscape. This course provides a hands-on, project-oriented introduction to deep learning; for the classification, retrieval, and creation of media content, with emphasis in audio-visual content. Students will create and work with existing deep learning models using Python libraries, and think critically about the application of these models for media. This course will provide students with an understanding of how these tools work and how to use

Prerequisites

- Programming experience, preferably with Python
- Basic knowledge of linear algebra

Textbook



- Chollet, F. (2021). Deep learning with python. Second Edition. Manning Publications.

Lectures

- Week 1: Introduction to Machine Learning
- Week 2: The building blocks of neural networks
- Week 3: The engine of neural networks
- Week 4: Setting up a deep learning project
- Week 5: Classification
- Week 6: Convolutional NNs
- Week 7: Transformers and language models
- Week 8: Audio Understanding
- *Week 9: (Spring Breakes)*
- Week 10: Audio classification
- Week 11: Cross-modal retrieval
- Week 12: Neural style transfer
- Week 13: Image generation

- Week 14: Audio generation
- Week 15: Final project presentations

Grades

- 40% homework assignments (individual)
- 30% final project (groups)
- 30% class participation (individual and groups)

Homework

- There will be 3 homework assignments (two weeks to complete each)
- Instructions & submission will appear on Brightspace (it is your responsibility to check!)
- The lowest grade (out of 3 homework) will be dropped

Paper Presentation

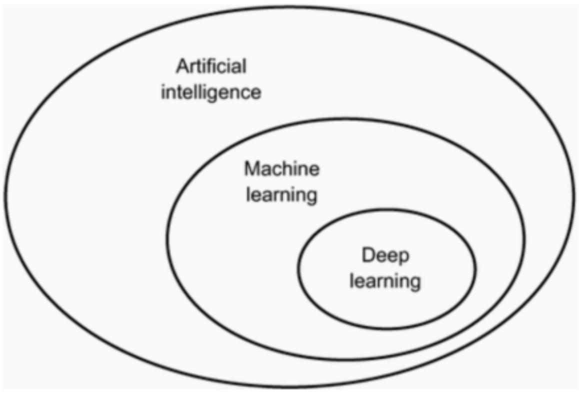
- Role-playing paper reading (see syllabus)
- Roles
    - Academic researcher
    - Industry practitioner
    - Social impact assessor
- Each student playing a role:
    - Short presentation (5min)
    - Embrace your role! Other students
    - Ask questions! Participate!
- Each student will participate with one role during the semester
- Three roles per paper reading; you can choose which role based on your interests
- Papers will be sent the week before presenting
- Which week are you presenting? Randomly assigned

Final Project

- In groups of 2-3 students
- There will be 3 final assignments (see syllabus)
    - Topic, group definition and data report
    - Documented code (almost final)
    - Final presentation
- Instructions & submission will appear on Brightspace (it is your responsibility to check!)
- The lowest grade (out of the 3 assignments) will be dropped
- Final presentations
    - All students should participate
    - Slides required, 5-10 minutes presentation followed by Q&A

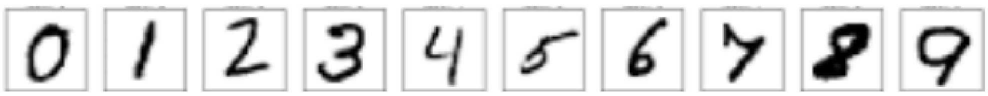
2. Introduction to Machine Learning

AI, machine learning, deep learning



Artificial Intelligence:
Effort to automate intellectual tasks normally performed by humans.

Task: Handwritten Digit Recognition

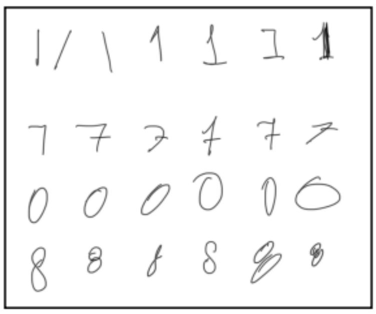


Classical Programming

- The rules are set by humans

```python
def count_vertical_lines(image):
    ...
def count_horizontal_lines(image):
    ...
def count_circles(image):
    ...

def classify(image):

    nvl = count_vertical_lines(image)
    nhl = count_horizontal_lines(image)
    nc = count_circles(image)

    if (nvl == 1) and (nhl == 0):
        return '1'

    if (nvl == 1) and (nhl == 1):
        return '7'

    if (nvl == 0) and (nhl == 0) and (nc=1):
        return '0'

    if (nvl == 0) and (nhl == 0) and (nc=2):
        return '8'
    ...
```

Hard to do in practice

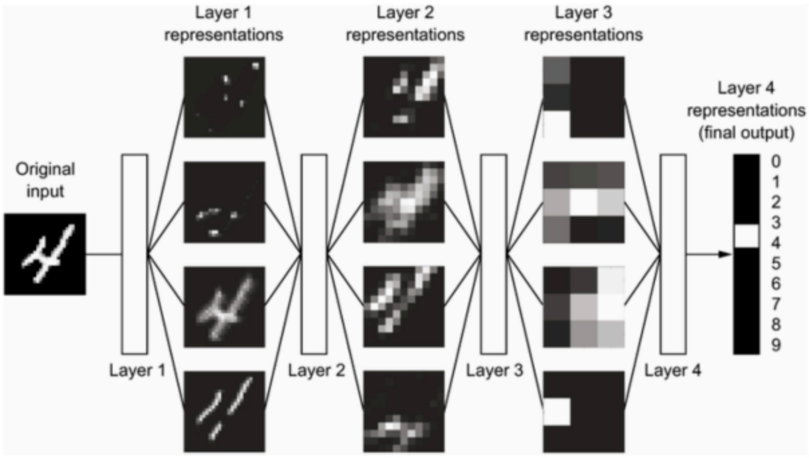


- hard to do in practice

Machine Learning

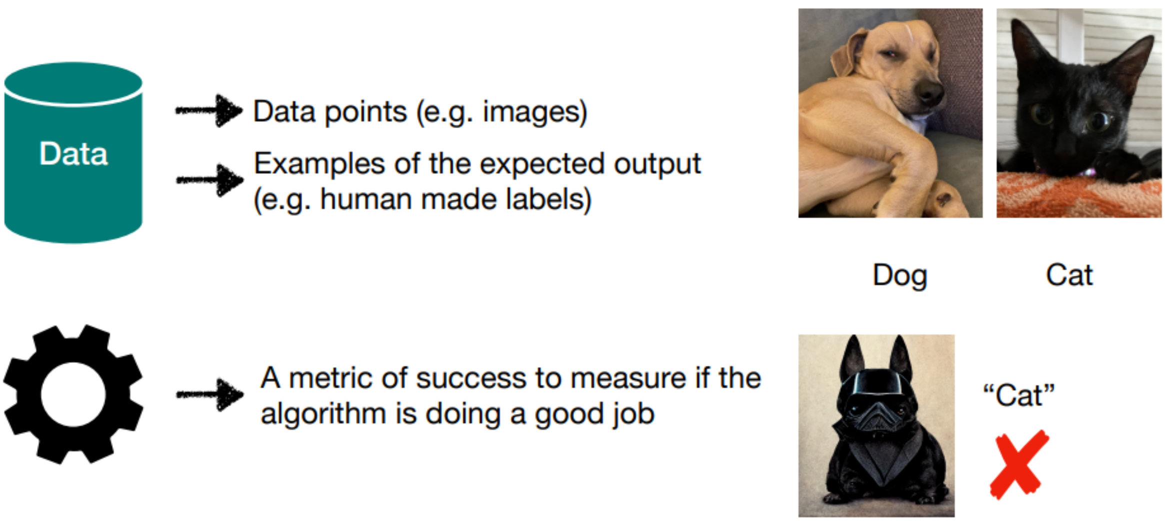
- Machine generates the rules

Deep Learning

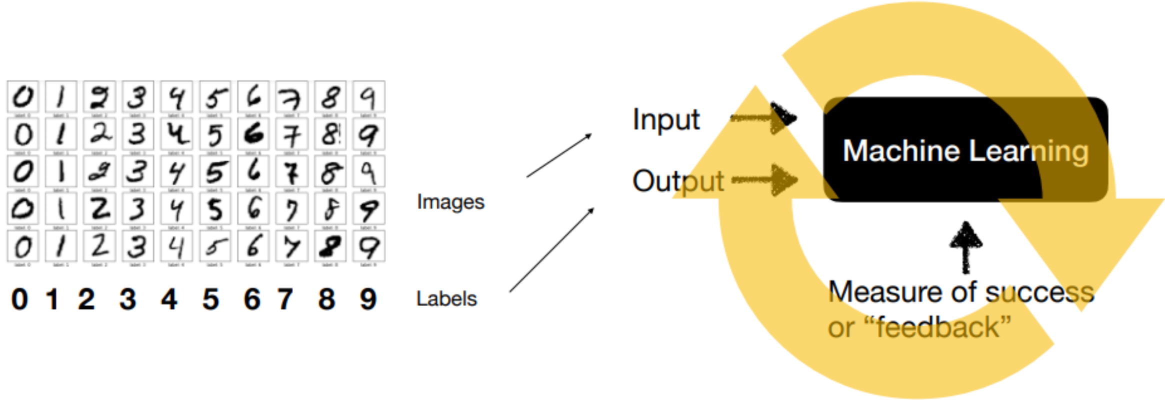


- The DNN is learning **representations** that are increasingly meaningful for the task.
  - representation is also some sort of "learning features"
- Deep learning
  - input -> (extract features/representations | extract rules to classify) -> output
- Machine learning
  - input -> manually create features -> extract rules to classify -> output

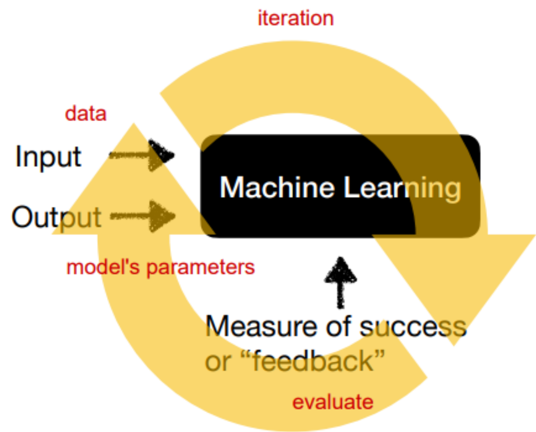
3. What do you need to do machine learning?



Training




```python
def load_data(path_to_data):
    ...

def get_model(hyperparameters):
    ...

def train_model(model, input_data, output_data):
    ...


def main():
    ...

    input_data, output_data = load_data(path_to_data)

    hyperparam_1 = 150
    hyperparam_2 = 0.3

    model = get_model({'hparam_1': hyperparam_1,
                       'hparam_2': hyperparam_2})

    trained_model = train_model(model, input_data, output_data)
```

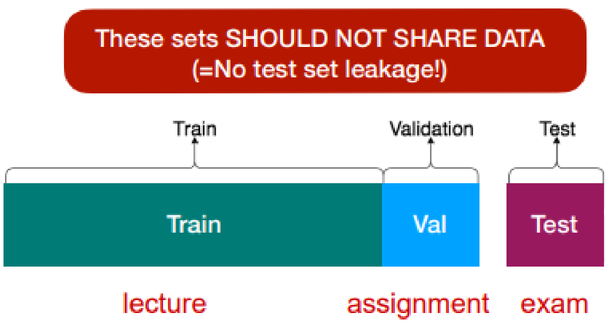


Inference = Prediction


```python

model.predict(test_data)
```

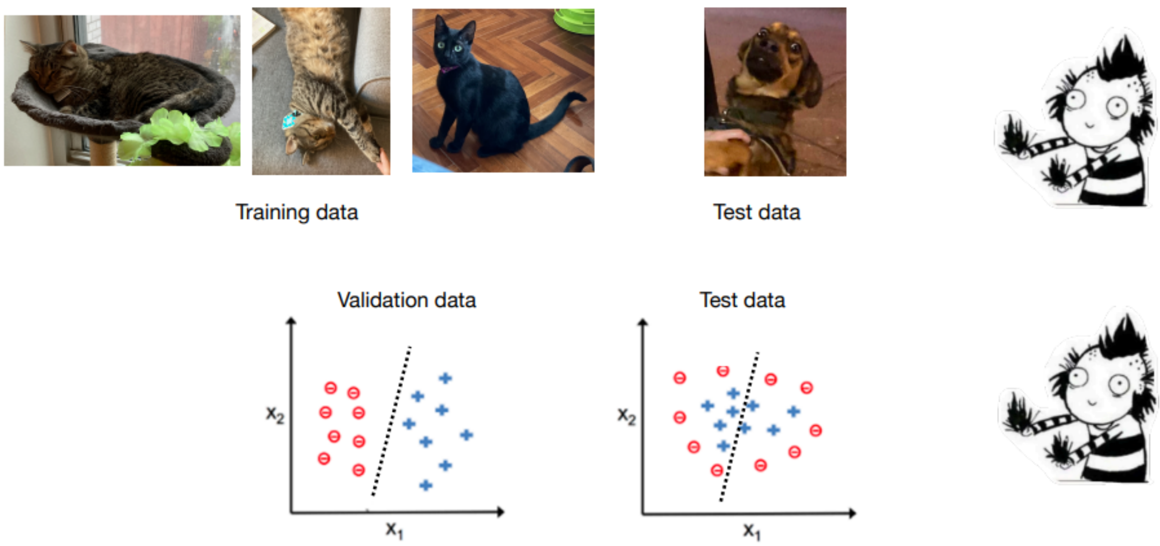
The final outcome, the trained model, can be used

Training, Validation and Test



- **Training data**
  - Fit/train the model (the “examples”)
  - Most of the computational cost is here
- **Validation data**
  - Select the best model parameters by maximizing your success metric
- **Test data**
  - Measure the model's performance

Same Distribution



Important: the three datasets should be drawn from the **same distribution**.

- If the test data is different from the training data, the model might fit the training data but fail to **generalize** to the test data
  - generalize: model can handle different cases
- If the validation data is different from the testing data, we will select bad parameters

Features

- Instead of using the **raw inputs** x_i as directly, it’s often useful (or necessary) to compute **features** from the raw input
  - **hand-crafted features**: information which is believed to be useful for the task, selected by the model designer
  - **learned features**: information extracted by a model (using the training set)
    - Neural networks are very good at this
- The choice of features matters a lot!

Example: Spam Detection

How do you represent an entire email as an input vector?

- compute features instead

	"money"	"pills"	"Mr."	bad spelling	known-sender	spam?	
	Y	N	Y	Y	N	Y	
	N	N	N	Y	Y	N	
	N	Y	N	N	N	Y	
example	Y	N	N	N	Y	N	label
	N	N	Y	N	Y	N	
	Y	N	N	Y	N	Y	
	N	N	Y	N	N	N	

What features?

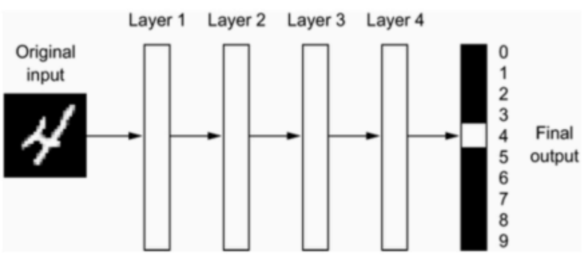
> We want to train a classifier to determine what is your favorite music genre between
>
> [classical, pop, rock]
>
> We need to decide what data we will give the classifier as input, i.e. what features?

- Options
  - How old are you?
  - Do you play an instrument?
  - How do you listen to music (headphones/speakers/car/concert?)
- These all could be features, some are more important? some are less important?

More Examples

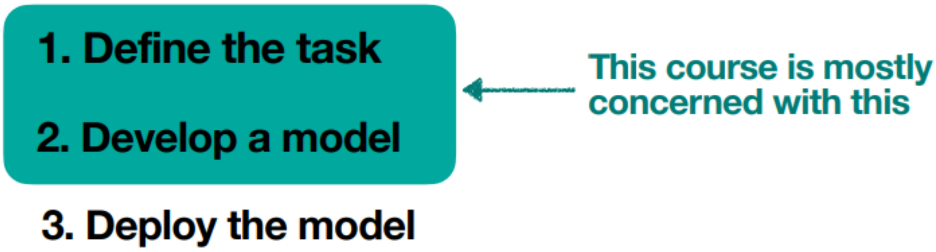
	Inputs	Outputs	Possible Features
Internet Search Engines	Text query	List of websites	bag of words, n-gram
Weather Forecasting	Day & Location	probability of rain, humidity, temperature…	current weather, weather nearby
Music Recommendation	The user	A list of songs	recent listening, user demographics
Stock Price Prediction	The time	The stock price	time of year, time of day, company news, world events
Speech Recognition	Audio of someone speaking	Text transcript	Mel spectrogram
Language Translation	text in input language	text in target language	position in sentence, part of speech

Features learned by deep learning



- A deep neural network (DNN) is a stack of layers, where each layer transforms the data into something useful for the task for which the network was trained

4. Machine Learning Workflow

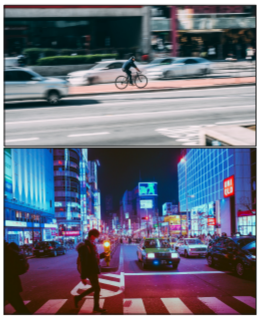


Define the Task

Frame the problem

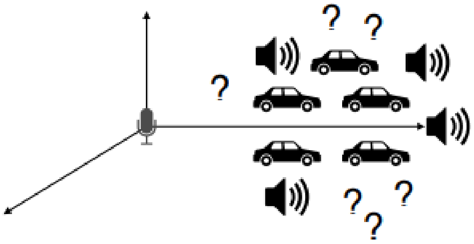
- What are you trying to achieve?
- What is the input?
- What is the output?
- What is a good metric of success?

Real Example:



- “We want to have a machine be able to help people navigate in urban environments.”
- “The machine could use vision and audition as humans do, e.g. using cameras and microphones.”
- “The machine would have to recognize objects by the way they look and/or sound.”
- **Input**: audio and video.
- **Success**: object + event detection

Collect the dataset



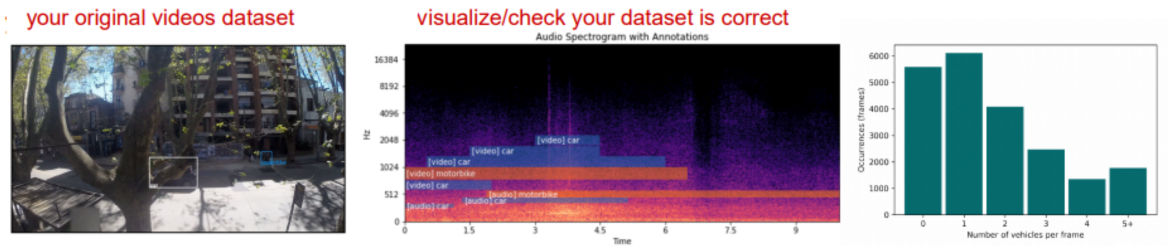
- What data is available and ready? Otherwise, what data sources there are available?
- The number of your data points, the reliability of your labels, will impact the performance of your model greatly

Real Example:

- Looks for months for any ready-to-use dataset…
- Nothing is exactly what they need…
- Decides to create their own by compiling and annotating existing resources. Needs to define a protocol and make many decisions about what to annotate.

Understand your data

Treating a dataset as a black box is pretty bad practice. Before training models, you should explore, visualize and inspect your data to gain insights about its patterns



Real Example:

- Novel problem, decides to start by "normal size" models.
- Once those show that they work and they have learned more about the problem, starts discussing further constrains for the model.

Choose a measure of success

It should be aligned with your high-level goal.

Develop a Model

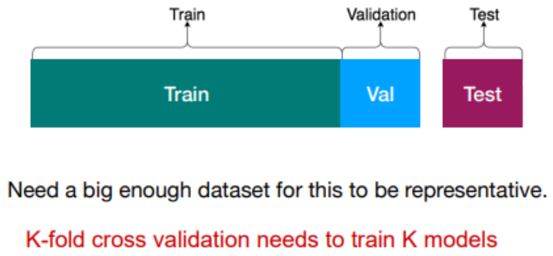
Prepare the data

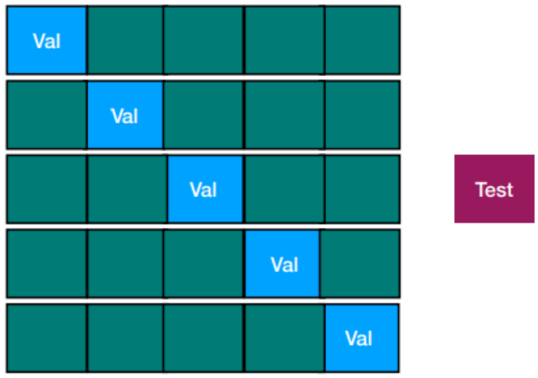
Models don't typically ingest "raw" data.

Prepare the data for the model by vectorizing, normalizing, handling missing values, etc.

Choose an evaluation protocol

Keep a holdout validation set, or do K-fold cross validation





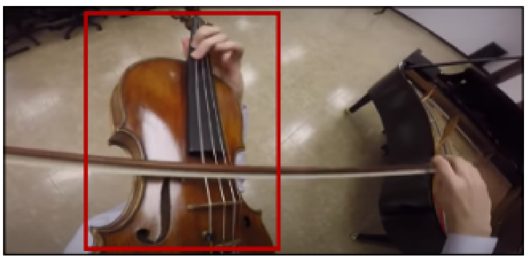
Beat a baseline

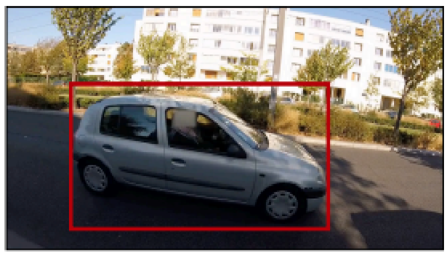
Use feature engineering, or design a simple but effective DNN.

- the one you want you beat it by your model

Real Example

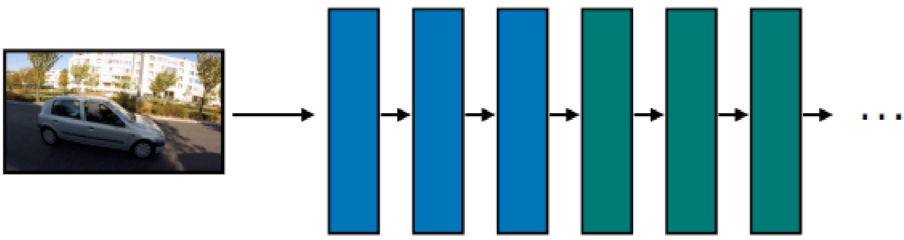
- Naive baseline - place boxes of objects in “expected positions”, try to use your knowledge of the problem to understand if your model is doing what you expect





Scale up: develop a model that overfits

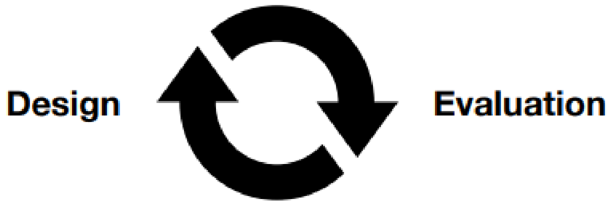
Add layers, make layers bigger, train for more epochs.



Regularize and tune your model

Start trying small model modifications until you get the model as good as it can get

- Warning: the most you repeat this process, the more leakage you add from your validation set.
- Repeating this a few times it’s innocuous, but done many times makes the evaluation process less reliable



Deploy the Model

Set Expectations

Models don't "understand" the task and aren't capable of using human-like common sense.

Making this clear helps setting expectations. Consider showing some failure cases.

https://resource.revealdata.com/en/blog/testing-the-efficacy-of-image-labeling

Shift an inference model

You rarely put in production the same exact model you developed in Python. There are different deployment options, some of them:

- **REST API**: When you can get the predictions over internet over to the model that sits on a server (e.g. music recommendation, image search engine).
  - Easy to deploy models this way.
  - Not good if data involved is sensitive
- **Model on a device**: Good if data is sensitive and should stay in the device.
  - Your model should be sufficiently small to fit there.
  - The highest accuracy is not needed, but a tradeoff between accuracy and latency is accepted.
  - Low connectivity.
- **Model in the browser**: Inference computed by the end-user device, offloads server.
  - Good for sensitive data.
  - Need the model to work after downloaded.
  - Need a model that's small enough it doesn't overload the users' device.

Monitor your model in the wild and maintain your model

5. Remember these terms

> Representation Learning (RL) is a subset of Feature Extraction (FE)
> given that RL also extracts features, but RL emphasizes the extraction of features automatically.

- Artificial intelligence
- Machine Learning
- Deep Learning
- Features
- Representations
- Neural Networks
- Data
- Dataset
- Labels
- Training
- Validation
- Test
- Model
- Measure of success
- Evaluation protocol
- Problem framing
- Model development
- Model deployment