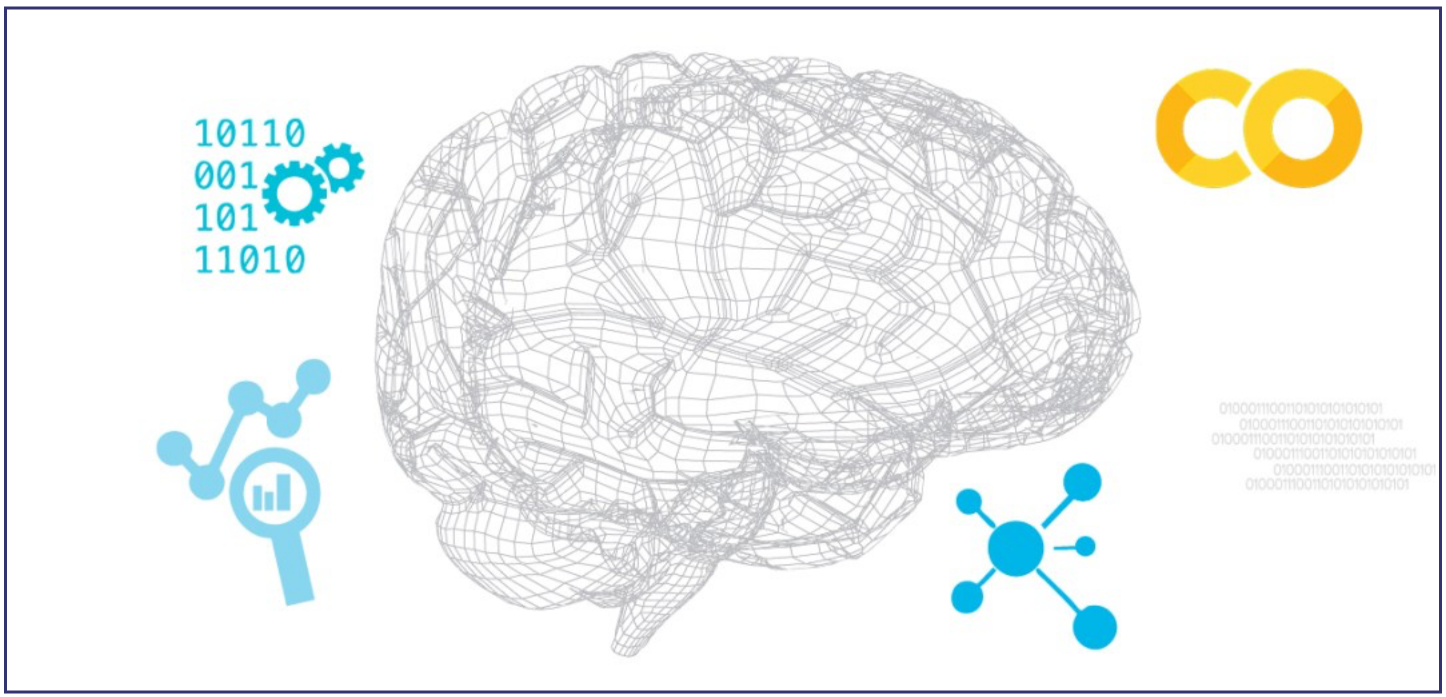
DM/ML tools



Theory => practice

In the two previous lectures, we looked at a variety of algorithms for DM and ML, eg. kNN, clustering, neural networks.

Now we'll examine how these have been/can be implemented - using tools/frameworks or APIs/languages/hardware.

Note that in 'industry' (ie. outside academia and gov't), tools/APIs... are heavily used to build RL products - so you **need** to be aware of, and be knowledgeable in, as many of them as possible.

APIs/frameworks: part 1

These are the most heavily used:

- TensorFlow ('TF')
- Spark MLlib: https://spark.apache.org/mllib/ and https://spark.apache.org/docs/2.2.0/ml-pipeline.html
- Keras: https://keras.io/ [a higher level lib, compared to TF etc]; here are all the types of Keras layers
- Torch, PyTorch: https://pytorch.org, http://torch.ch/
- scikit-learn: https://scikit-learn.org/stable/
- Caffe: https://caffe2.ai/, http://caffe.berkeleyvision.org/ [→ Caffe2 → PyTorch]
- Apache mxnet: https://mxnet.apache.org/ [multi-language APIs, GPU and cloud support...]
- CNTK: https://docs.microsoft.com/en-us/cognitive-toolkit/

TL;DR: simply learn Keras or PyTorch, and if necessary, TF.

APIs/frameworks: part 2

Upcoming/lesser-used/'internal'/specific:

- here is FBLearner Flow - Facebook's version of TensorFlow :)
- Apache Mahout - a collection of ML algorithms, in Java/Scala
- .NET ML: https://dotnet.microsoft.com/apps/machinelearning-ai/ml-dotnet
- fastai [on top of PyTorch]: https://github.com/fastai/fastai
- OpenVINO: https://software.intel.com/en-us/openvino-toolkit and https://www.youtube.com/watch?v=rUwayTZKnmA&t=1s [a tutorial]
- Turi: an alternative to Apple's CreateML: https://github.com/apple/turicreate
- LibSVM: https://www.csie.ntu.edu.tw/~cjlin/libsvm/
- LightGBM: https://github.com/Microsoft/LightGBM
- XGBoost: https://xgboost.ai/ [and, look at Tianqi's slides and talk]
- CatBoost: https://tech.yandex.com/catboost/
- Google - SEED: https://ai.googleblog.com/2020/03/massively-scaling-reinforcement.html
- Uber's 'Fiber', for distributed ML training: https://venturebeat.com/2020/03/26/uber-details-fiber-a-framework-for-distributed-ai-model-training/
- LOTS of smaller efforts: https://github.com/EthicalML/awesome-production-machine-learning

Here is an article about deep learning tools.

Cloud

The virtually unlimited computing power and storage that a cloud offers, make it an ideal platform for data-heavy and computation-heavy applications such as ML.

Amazon: https://aws.amazon.com/machine-learning/ Their latest offerings make it possible to 'plug in' data analysis anywhere.

Google: https://cloud.google.com/products/ai/ [in addition, Colab is an awesome resource!]

Microsoft: https://azure.microsoft.com/en-us/services/machine-learning-studio/ [and AutoML] [aside: alternatives to brute-force 'auto ML' include 'Neural Architecture Search' [incl. this], pruning, and better network design (eg using ODEs - see this).

IBM Cloud, Watson: https://www.ibm.com/cloud/ai [eg. look at https://www.ibm.com/cloud/watson-language-translator]

Others:

- h2o: https://www.h2o.ai/products/h2o/ [supports R, Python, Java, Scala, JSON, native Flow GUI [similar to Jupyter], REST...]
- BigML: https://bigml.com/features#platform
- FloydHub: https://www.floydhub.com/
- Paperspace: https://ml-showcase.paperspace.com/
- Algorithmia, eg. https://info.algorithmia.com/ and https://demos.algorithmia.com/

With so much available out of the box, it's time for citizen data scientists?

Pretrained ML models

A pre-trained model includes an architecture, and weights obtained by training the architecture on specific data (eg. flowers, typical objects in a room, etc) - ready to be deployed.

Eg. this is simple object detection in the browser! You can even run this detector on a command line.

TinyMOT: https://venturebeat.com/2020/04/08/researchers-open-source-state-of-the-art-object-tracking-ai

Apple's CreateML is useful for creating a pre-trained model, which can then be deployed (eg. as an iPad app) using the companion CoreML product. NNEF and ONNX are other formats, for NN interchange.

Pre-trained models in language processing, include Transformer-based BERT and GPT-2. Try this demo (of GPT etc). There is GPT-3 currently available, GPT-4 in the works, Wu Dao 2.0, MT-NLG...

There are also, combined (bimodal) models, based on language+image data.

Tools

Several end-to-end applications exist, for DM/ML. Here popular ones.

Weka is a Java-based collection of machine learning algorithms.

RapidMiner uses a dataflow ("blocks wiring") approach for building ML pipelines.

KNIME is another dataflow-based application.

TIBCO's 'Data Science' software is a similar (to WEKA etc) platform. Statistica [similar to Mathematica] is a flexible, powerful analytics software [with an old-fashioned UI].

bonsai is a newer platform.

To do ML at scale, a job scheduler such as from cnvrg.io can help.

SynapseML is a new ML library from Microsoft.

There are a variety of DATAFLOW ('connect the boxes') tools! This category is likely to become HUGE:

- Perceptilabs: https://www.perceptilabs.com/
- Lobe: https://insights.dice.com/2018/05/07/lobe-deep-learning-platform/
- https://www.producthunt.com/posts/datature
- smartpredict: https://smartpredict.ai/
- StackML: https://stackml.com/ [RIP]
- Baseet: https://baseet.ai/ [RIP]

Languages

These languages are popular, for building ML applications (the APIs we saw earlier, are good examples):

- Python
- R
- Julia [Python 'replacement'?!]
- Wolfram
- JavaScript - this is a good list of JS-based libraries [look at ConvnetJS for nice demos]
- Scala - a functional+OO language - here is a roundup of libraries [these are in addition to Spark's MLlib Scala API]
- Java - another robust language for building ML libs [we already saw WEKA] and apps
- Jupyter [an environment, not a language] (eg. here is a collection of ML notebooks - as an exercise, run them all in Colab!) [also, here are notebooks for 'everything'!]
- ...

Hardware

Because (supervised) ML is computationally intensive, and detection/inference needs to happen in real-time almost always, it makes sense to accelerate the calculations using hardware. Following are examples.

Google TPU: TF is in hardware! Google uses a specialized chip called a 'TPU', and documents TPUs' improved performance compared to GPUs. Here is a pop-sci writeup, and a Google blog post on it.

Amazon Inferentia: a chip, for accelerating inference (detection): https://aws.amazon.com/machine-learning/inferentia/

NVIDIA DGX-1: an 'ML supercomputer': https://www.nvidia.com/en-us/data-center/dgx-1/ [here is another writeup]

Intel's Movidius (VPU): https://www.movidius.com/ - on-device computer vision

In addition to chips and machines, there are also boards and devices:

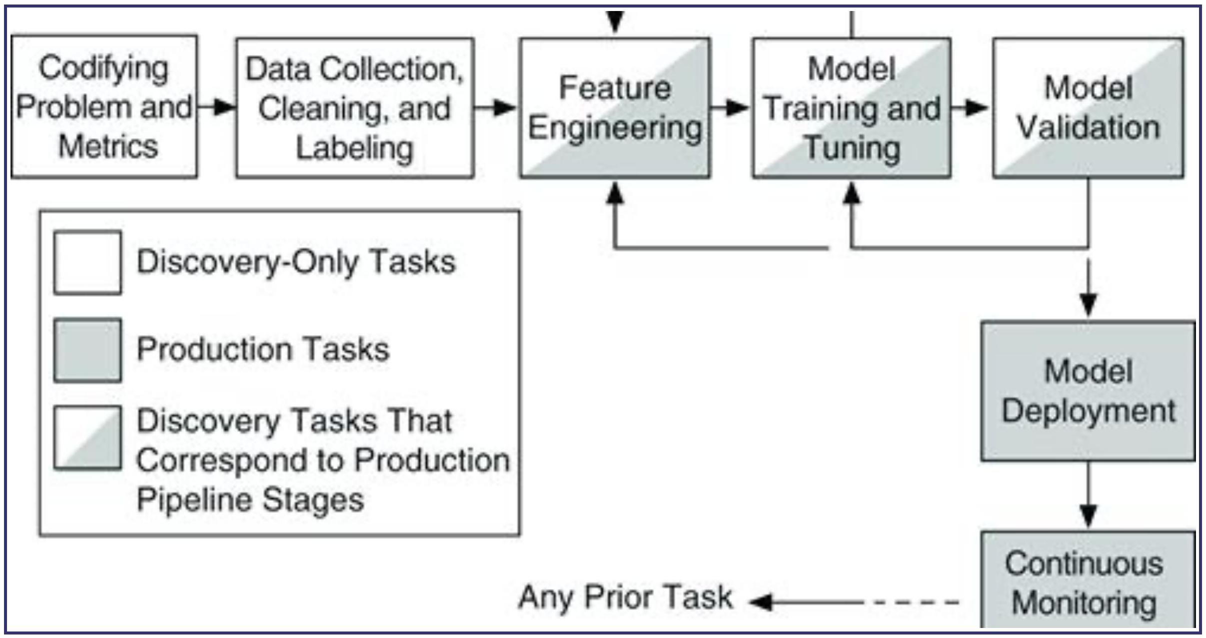
- Pixy2: https://pixycam.com/ - camera + ML in a single board
- Coral: https://coral.withgoogle.com/
- Jetson Nano: https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-nano/
- Movidius NCS: https://software.intel.com/en-us/movidius-ncs
- ...

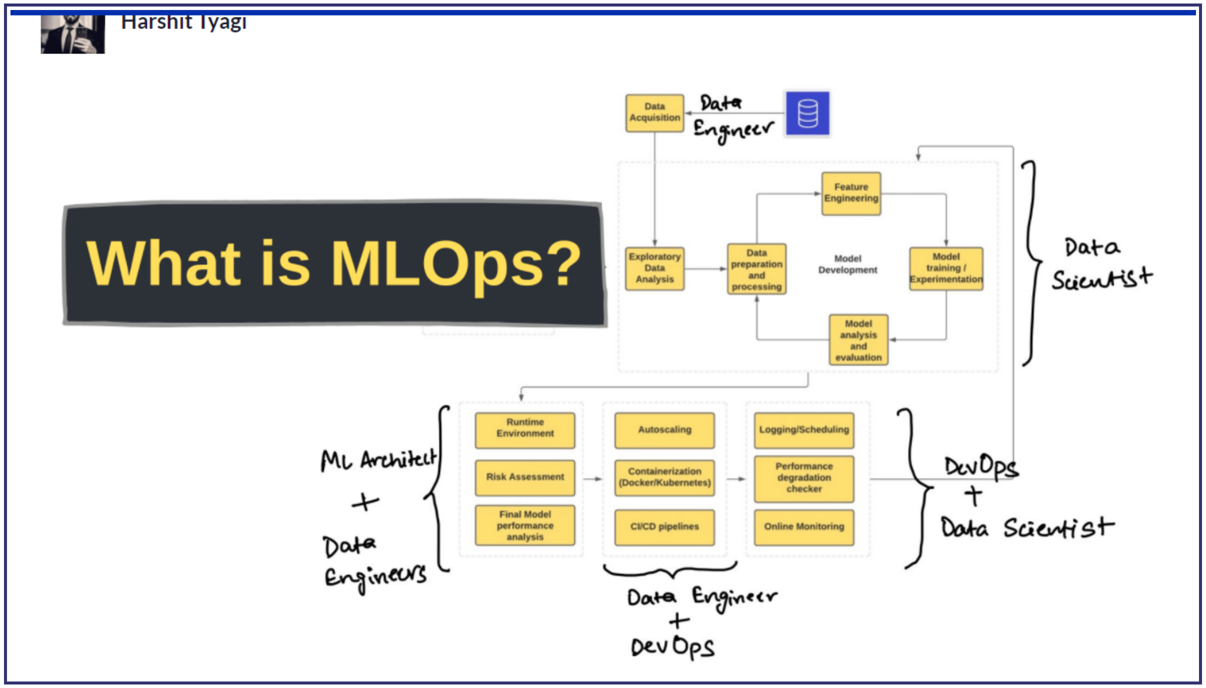
Overall, there's an explosion/resurgence in 'chip design', for accelerating AI training, inference. In April '21, NVIDIA announced its new A30 and A10 GPUs, at the annual [GTC] conference.

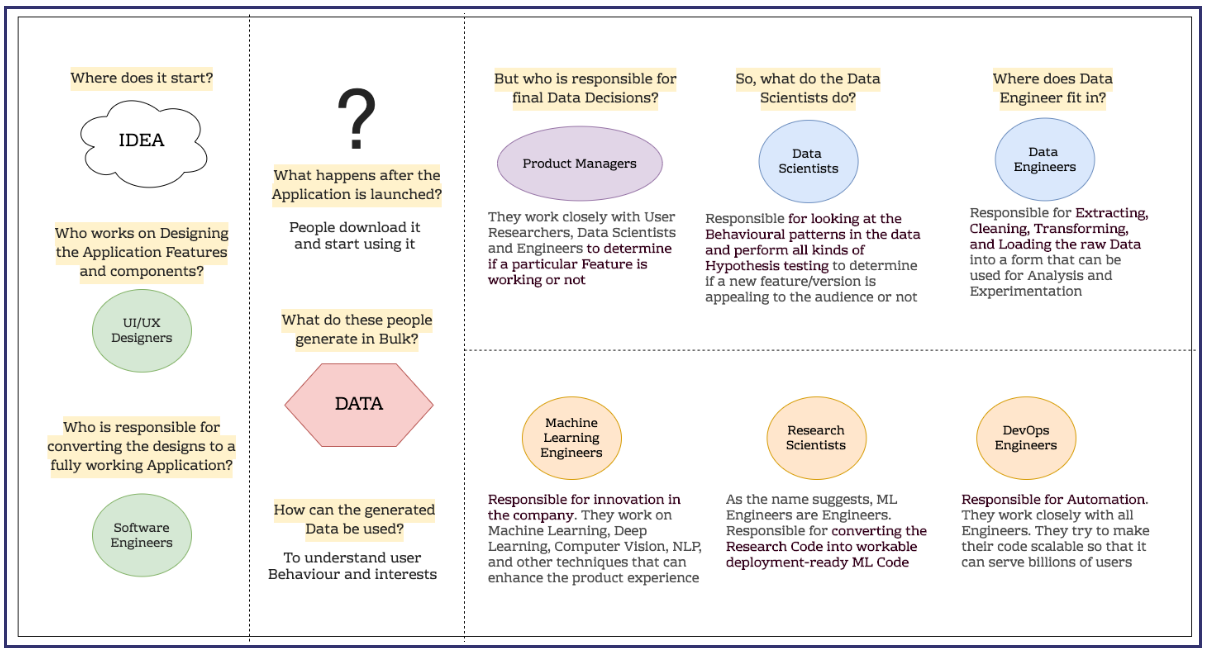
Summary

We looked at a plethora of ways to 'do' ML. Pick a few, and master them - they complement your coursework-based (theoretical) knowledge, and, make you marketable to employers! Aside: LOTS of salaries etc., revealed here :)

Also, FYI - in industry (G-MAFIA/FAANG/MAMMA MIA, BAT, more!), ML is part of a bigger 'production pipeline':




Harshit Tyagi
What is MLOps?
Data Acquisition
Data Engineer
Exploratory Data Analysis
Data preparation and processing
Feature Engineering
Model Development
Model training / Experimentation
Model analysis and evaluation
Data Scientist
Runtime Environment
Risk Assessment
Final Model performance analysis
Autoscaling
Containerization (Docker/Kubernetes)
CI/CD pipelines
Logging/Scheduling
Performance degradation checker
Online Monitoring
ML Architect + Data Engineers
Data Engineer + DevOps
DevOps + Data Scientist


Where does it start?
IDEA
Who works on Designing the Application Features and components?
UI/UX Designers
Who is responsible for converting the designs to a fully working Application?
Software Engineers
?
What happens after the Application is launched?
People download it and start using it
What do these people generate in Bulk?
DATA
How can the generated Data be used?
To understand user Behaviour and interests
But who is responsible for final Data Decisions?
Product Managers
They work closely with User Researchers, Data Scientists and Engineers to determine if a particular Feature is working or not
So, what do the Data Scientists do?
Data Scientists
Responsible for looking at the Behavioural patterns in the data and perform all kinds of Hypothesis testing to determine if a new feature/version is appealing to the audience or not
Where does Data Engineer fit in?
Data Engineers
Responsible for Extracting, Cleaning, Transforming, and Loading the raw Data into a form that can be used for Analysis and Experimentation
Machine Learning Engineers
Responsible for innovation in the company. They work on Machine Learning, Deep Learning, Computer Vision, NLP, and other techniques that can enhance the product experience
Research Scientists
As the name suggests, ML Engineers are Engineers. Responsible for converting the Research Code into workable deployment-ready ML Code
DevOps Engineers
Responsible for Automation. They work closely with all Engineers. They try to make their code scalable so that it can serve billions of users

So, how do you prepare for the Data Roles?

- **SQL ! SQL ! SQL !** Practice a lot of SQL
- Be a savvy **Python** Developer
- **Think like a Product Manager**. Take up your favorite Application, and think of KPI (Key Performance Indicators). Determine the criteria for Decision Making
- **Teamwork and Collaboration** are essential skills needed for any Data Role. Be a good Communicator. Whether it be an interview or a Team Meeting, make sure to speak your mind
- Learn different **Visualization Techniques** and present your findings in the best way possible. Make it impressive
- Study **Datawarehousing concepts** for Data Engineering Roles
- Have a **basic understanding** of Data pipelines, MapReduce Concepts, Graph Models, Data Analytics platforms, Database Concepts, Kubernetes, Containers, and various open-source Apache Products. (Depth Knowledge is not needed – But, basic information will help you understand the bigger picture)