Udacity Nanodegree / Scholarship
(L3 of Mod-2)

–	3	10	17	24
–	4	11	18	25
–	5	12	19	26
–	6	13	20	27
–	7	14	21	28
1	8	15	22	29
2	9	16	23	–

Abolition of Slavery Day (Mauritius), Federal Territory Day (Malaysia)

A) Using AI & ML Business:

Developing AI in a business setting.
↳ Facial Recognition, Retail Inventory, E-commerce, Customer support automation, Data Classification, Agricultural automation, OCR, Autonomous vehicles, Sentiment Analysis, Manufacturing efficiency & quality control.

AI approach: (X)
Data Ingestion → Data Cleaning & Transformation → Model-Training → Testing & Validation → Deployment.
Model Selection

* Start with a business problem: (✓)
1) Business Problem → Narrow down to the stakeholders.
2). Data → Availability, refresh, pipeline development.
3). Model Building → Feature Extraction, tuning, Benchmarking
4). Deploy & Measure → A/B Test, integration.
5). Active learning & Tuning → Bias mitigation, ground truth & success, monitoring, version control.

Business Needs: Production systems actively learn from human
Business Case: Adobe Stock Photo:
Job → Find a stock photo for marketing collateral which is likely to drive improved search.
5) Generate appropriate search query.
6) Enter search Query.
7) Apply filters to narrow results.
8) Identify images with the corresponding visual aesthetic qualities.

Project Statement
" Adobe Stock

I. What problem are we solving?
II. How does AI add value?
III. What data are needed?
IV. Scope?
V. How do we measure success?

→ What makes a metric effective?
↳ i). Easily measurable.
ii). Directly correlated to business performance.
iii). Predictive of future business outcomes.
iv). Isolated to factors controlled by the group its measuring
v). Comparable to competitor's metrics or industry benchmarks

* I. We're helping marketers find the right stock images for marketing collateral, in order to improve sales.

* II. The AI can tag images with their right qualities, thus making image search more efficient.

* III. Stock images tagged with aesthetic qualities as Data.

* IV. When the user needs to find a stock photo for making marketing collateral, based on the best option out there.

* V. User can find the best stock image quickly.
(metric)

–	3	10	17	24
–	4	11	18	25
–	5	12	19	26
–	6	13	20	27
–	7	14	21	28
1	8	15	22	29
2	9	16	23	–

Liberation Day (Angola)

Using AI in Business :-

1). Deploy for targeted use cases : To realize business value, AI technologies must be deployed to delivar specific, measurable business outcomes for dargeted use-cases. [Gartner]

2). Business Problem before Data : It's rarely a good idea to start with a decision to clean up data. It's almost always better to start with a business ~~case~~ case and then evaluate options for how to achieve success in that special case. [PWC]

3). Success depends on the data : Our AI systems are as good as the data we put into them. [IBM Think]

* Adobe Stock Photo Metric → Time spent b/w searching & purchase
* LinkedIn Metric → using NLP.
  1). Increased collective Inmail response rates.
  2). No. of two way conversation started

Need of AI / Key Considerations :-

i) Is the problem is an impactful enough worth solving ?
ii) Can it be quantified the business value simply.
iii) Does the problem have a large volume of associated data that ml can actually learn from ?

A> Deep learning V/S. Traditional ML

Deep learning	Traditional ML
i) Deep learning out performs with large datasets.	i). ML will work better with smaller datasets.
ii) DL techniques will require more powerfull infrastructure.	ii) ML will require relatively less.
iii). DL is about learning features. ~~rather than~~	iii) ML will rather stands on manually engineering them.
iv) DL shines with when applied to complex/multi-dimen-tional problems: image classification, NLP, Speech recog. etc.	iv). If the data is moderate size & it doesn't contain too many features, and the hypothesis func. is non-linear then we try ML.

1). Start with the business value: Break your thoughts down into a small & specific component of the process of that you want to improve.

2). Get real with the data: Use production data to ensure that the training data match the reality of the real-world deployment. (Kaggle)

3). Learning is key to value: Learning from new data ensures constant improvement.

⇒ Key Roles ↓

Product Owner	Data Engineer	DevOPS
Designer	Data Scientist	↳ Development
Software Engineer	Quality Assuarance	& Operations.

Summary:

>> Start with a business problem >> Make sure of right data >> Build an interdisciplinary team.

>> Learn & iterate fast.

Creating A Dataset

Data fit & Annotation

Answer ques. with Data → Improve Search Results
↳ 1) Return relevant results
2). Return tailored & individual preferences

While building a dataset
↳ Check → 1) Does the dataset fit the problem?
2). Is the dataset complete?
3) How can you annotate the dataset & ensure the quality of the data & UX over time.

* Production Data → Data that is generated by users.

Ensure Data fit using Confusion Matrix :
↳ Precision
↳ Recall
↳ F1 Score

n=10	Predicted No.	Predicted Yes
Actual No	35 TN	15 FP
Actual Yes	5 FN	45 TP

Hence;

$$F1\ Score = \frac{Precision * Recall}{Precision + Recall} * 2$$

* Precision = $\frac{True\ Pos.}{Total\ Predicted\ Pos} = \frac{45}{45+15}$ (75%)

* Recall = $\frac{True\ Pos.}{Total\ Actual\ Pos.} = \frac{45}{45+5}$ (90%)

$$= \frac{75 * 90}{75+90} \times 2 = 0.82$$

* TN → True Positive
FN → False Neg.
& vice-versa

Precision indicates how often the models correct when it predicts the positive label.
Recall indicates how many of the true positives your model predicted.

* Data Completeness : 1). The problem, 2). Use combination of richly labelled of data, 3). Conduct research to get best data.

: Build A Model :

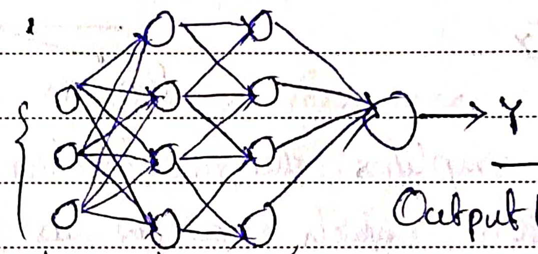
Training & Evaluating a Model

* Key elements of ML - { i). Model Architecture. ii). Training Data. iii). Model Evaluation }

A> Concepts :

a). Overview of Modelling
b). Training Data - currency of ML.
c). Model Evaluation - Key metrics.
d). Transfer Learning & Automated ML - sounds interesting.

A> Neural Network :



* Layers of knowledge made up of nodes...

input layer   hidden layer   Output layer

* Neural Network is a series of ~~networks~~ layers, each of which contains different nodes which will perform various calculations.

* The structure of these nodes & layers as well as how they're connected is what known as Network Architecture.

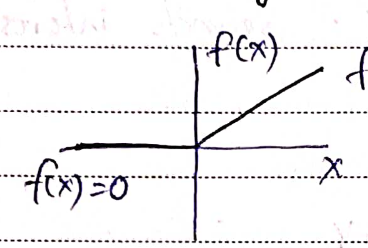
A> Activation Functions : → Sigmoid, → Relu, → Leaky Relu

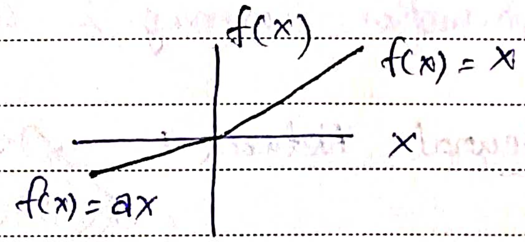
→ It serve as the individual decision boundary to pass on info.
→ Activation functions are ~~crucial~~ crusial for data flow in model.
→ An ideal activation function, would return a range of values which will allow us to scale the nodes output instead of binary 0 or 1.

Activation Functions

◉ Activation Functions are functions that we can use as decision boundaries to tell us wheather or not to send a signal to subsequent layers in the network. ✓ e.g. → sigmoid.

→ Relu & Leaky Relu (Relu - Rectified Linear Unit)





* These two simplifies the activation functions to a linear equation which allow us for faster & less complex training.

✓ Here we don't pay attention to the negative input (i.e. → f(x)=0 or ax) which reduces the no. of nodes therefore less complexity.

* Back-Propagation : It's an algorithm that automatically updates those weights ($w_1, w_2, \ldots w_n$) on the inputs in each node (perceptron).

1) Step 1 : Looking @ the o/p of a model & goes backward through the nodes & layers to find the source of error.

2) Step-2 : Then it updates the weights such that their value is either increased or decreased, in response to the error they caused.

→ Basically, Back-propagation is the reverse cycle of Forward Propagation & it continues untill the model is trained.

Training Data

Modelling Key Points:

i) Neural Networks are a series of layers comprised of computational nodes.

ii) Activation functions act as decision boundaries for a node.

iii) Weights on the inputs are tuned during training.

iv) Different node types & architectures are used for specific problem types.

Data is key to model performance:

i) Data defines model performance as the parameters are updated based on that, hence it requires standard data (e.g. → Kaggle).

* Model Performance:

Robust metrics to get model evaluation → Precision, Recall.

Labelled Data: 80% → training data; 20% → Validation data (10%), test data (10%)

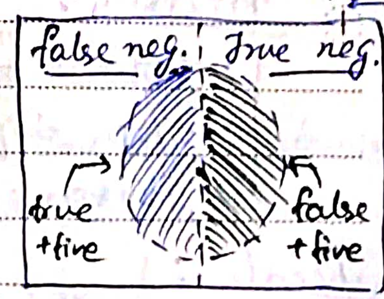
The validation data is used during training to help to inform updates to model parameters.

Precision & Recall as metric:

Dogs Vs. Cats — 2 cat predicted out of 3.

▷ Precision → $\frac{\text{true +ive}}{\text{model pred.}} = \frac{\text{true +ive}}{(\text{true +ive} + \text{false +ive})}$

▷ Recall → $\frac{\text{true +ive}}{\text{Ground truth}} = \frac{\text{true +ive}}{(\text{true +ive} + \text{false neg.})}$



O → Model Pred.
□ → Ground Truth

Hence, True +ive → 2 cats; False Neg. → 1 cat!
False +ive → 1 Dog as Cat;

Model Evaluation

Importance:

1) Model Precision, tells us when a model makes the prediction, how likely is that going to be correct?

2). Model Recall, tells us how good is a model at identifying actual occurances of objects in the data? i.e. → wheather or not the model can recognize these objects?

* Get back to the examples from video + F1 score!

Δ Confusion Matrix:

		Predicted label: A	B	Z
True label	A	100%		
	B		100%	
	Z		100%	

Δ Quiz - model Evaluation: Calculate F1 score:

True Label ↓	Predicted Label: Car	Stop Sign	Person
Car	15	2	3
Stop sign	6	12	
Person		4	22

Precision:

→ Car $= \frac{15}{(15+6)} = 15/21 = 0.71$

→ Stop Sign $= \frac{12}{(12+2+4)} = 12/18 = 0.66$

→ Person $= \frac{22}{(22+3)} = 22/25 = 0.88$

∴ avg. $= \frac{0.71 + 0.66 + 0.88}{3} = 75\%$

Recall:

→ Car $= 15/(15+2+3) = 15/20 = 0.75$; Stop Sign $= 12/18 = 0.66$

→ Person $= 22/26 = 0.85$

∴ avg. $= 75\%$

Hence, F1 Score $= \frac{.75 \times .75}{.75 + .75} \times 2 = 0.75$

: Transfer Learning :

Transfer learning is when we use the knowledge from an already trained network, with a similar use case which is stored in the architecture of the network as well as the weights and adapt that to the new use case, which requires different classes.

i.e. → leveraging existing trained models to solve new use cases.

Step-1 → Take the first n layers of a pre-trained network like → ResNet50.

Step-2 → Then attach or replace with new layers. (i.e. → output layers with desired new classes & retrain)

Automated ML : This allows us to build relatively robust & scalable models without much machine learning experience. (i.e. → services like gcloud to create models automatically from data)

- → Allows quick proto-typing.
- → Benefit of enterprise support.
- → Much less hassle & complexity.

Automated ML	vs. Custom Modelling
Pro's: Easy, cheap & quick + Robust Enterprise Support.	Pro's : Full control, customizable & Unlimited Use-Cases.
Con's : Non-scalable, limited Use-cases & Data is open to 3rd party.	Con's : Expensive, Limited support & Requires ML expertise.

Measuring Business Impact
II

1). Improving automations & 2). Delivering superior customer experience.

✓ E-commerce / Netflix + Agriculture + Manufacturing = AI Values.

* Business Goal → Revisit success Metrics.
  - i). Customer Experience.
  - ii) Revenue Gain.
  - iii). Customer Engagement. (UI/UX)
  - iv). Business Process Automation.
  - v). Better & faster decision making.

Outcome >> Output

Outcome		Output
Generate Revenue		Accuracy
Improve UX	vs.	Execution time
Increase satisfaction		Recall
Automate & save cost		Precision

* Best outcomes doesn't count if it's doesn't provide intended outcomes.

A> Chatbot Case Study : 1). Measure outputs
2). learn corresponding outcomes
3). Evolve & improve.

B> A/B Testing for models :

||Production Traffic|| —100%→ (Split based on 'x' criteria)
- —80%→ || Model A || (Controlled model)
- —20%→ || Model B || (Challenger model)

* Then, after tracking the performance metrics, we conclude to replace model A with B.

Bias in AI

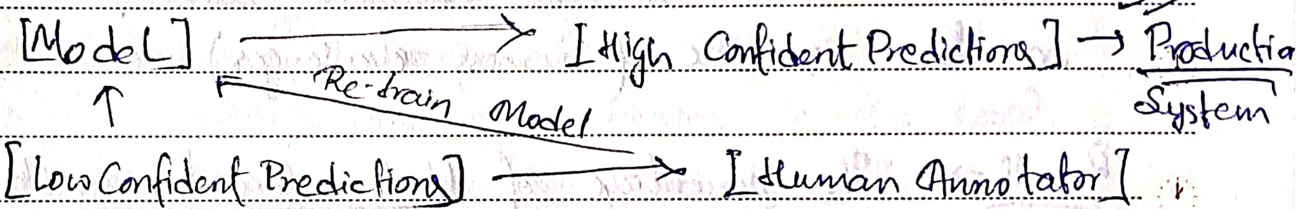
There will always be bias in the data as it's collected from humans, for context.

How to resolve biases? → 1). Awareness about the dataframe.

2). Get a diverse set of data

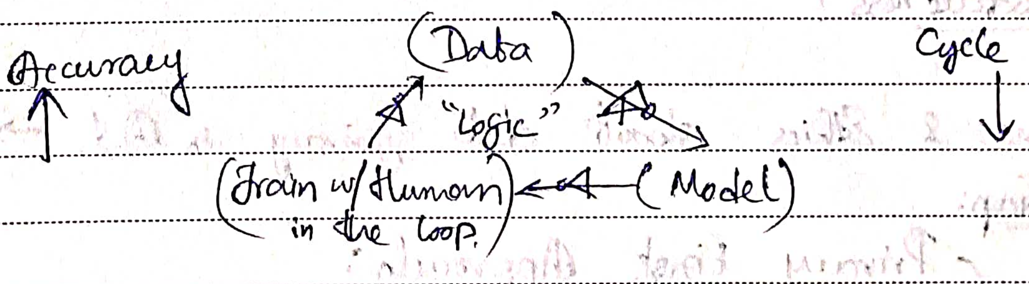
3). Iterate & learn keeping UX in mind!

⇒ Active Learning / Continues Learning :



* Always keeping human in the loop for +ive feedback.
i.e. → to tune the parameters towards better model.

We reduce the cost of this by → Smart Selection:



Smart Selection for training data →

1). Identifying most valuable data for training.
2). Class importance + Novelty + Uncertainty & low confidence.

Case Study → Spam filter (Using continuous learning).

Repeat
1). Filter spams with ML model
2). User will correct the mislabled ones.
3). Retrain the model with user data.
4). Accuracy will improve with time.

Accuracy vs. Recall vs. Precision :-

* Should we build the most accurate model? - depends on the use-case (business challenges) we're solving.

Recall → The percentage of total relevant results correctly classified by the algorithm.

Precision → The proportion of data points model says were relevant actually were relevant.

* Model Staleness?

* Compliance & Ethics about data privacy in A.I. → Huge Gap:

Privacy First Approach:
- Data law & AI coexist.
- Deeper understanding & Governance of data.
- Understand the sensivity of data (PII?, PHI?)
- Appropriate control & security measures.
- Obtain explicit concent & explanation to customer

Scaling AI Product

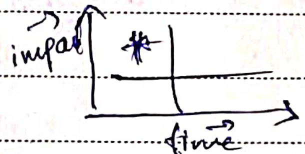
▷ Organize for Scale → { 1). Machine Architecture.
2). Organization Structure.

Blockages ↳ 1). Storage Challenges. (Big Data)
2). Network Challenges. (Model Performation)
3). Compute Challenges. (Powerful Infrastructure)

Summary:
AI brings a lot of business benefits.
Measuring success metric.
Contineous learning of model
(i.e.→ keeping human in the loop).
Monitoring & migating bias.
Security & data privacy.

-: AI Product Development :-

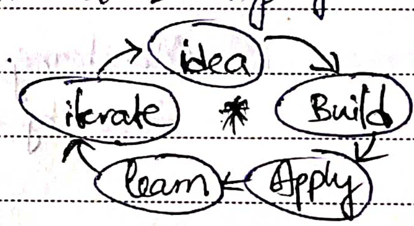
AI product cycle
1). Identify the business problem & ideate the solution.
2). Prototype, test & Refine.
3). Release, Measure & Update.



Problem → Solution → Discovery

* Impact VS. Time → Go with the solution idea that has the biggest return on investment
  i.e. → The most impact for the least amount of work.

Real-Data Proto-type :-
- → Build out a small version of the product & deploy.
- → It's okay if it's ugly & broken.
- → Measure twice, cut once.



D) Test, Refine → Final Product.
Prototyping

A) Release, Measure, Update
- → 1). Build the product.
- → 2). Launch the product.
- → 3). React to new info as you realease.

* Linear Interpolation.

— Done ✓ —