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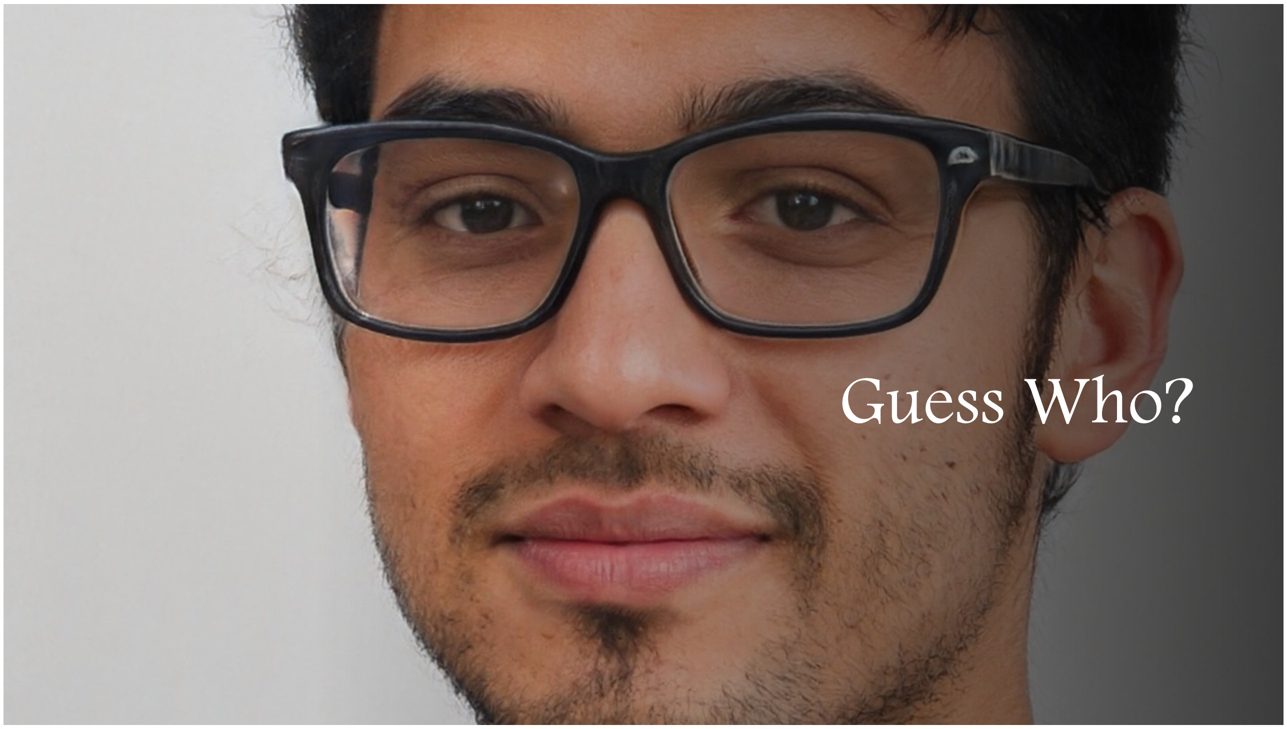
Machine Learning, the mortar of modernization

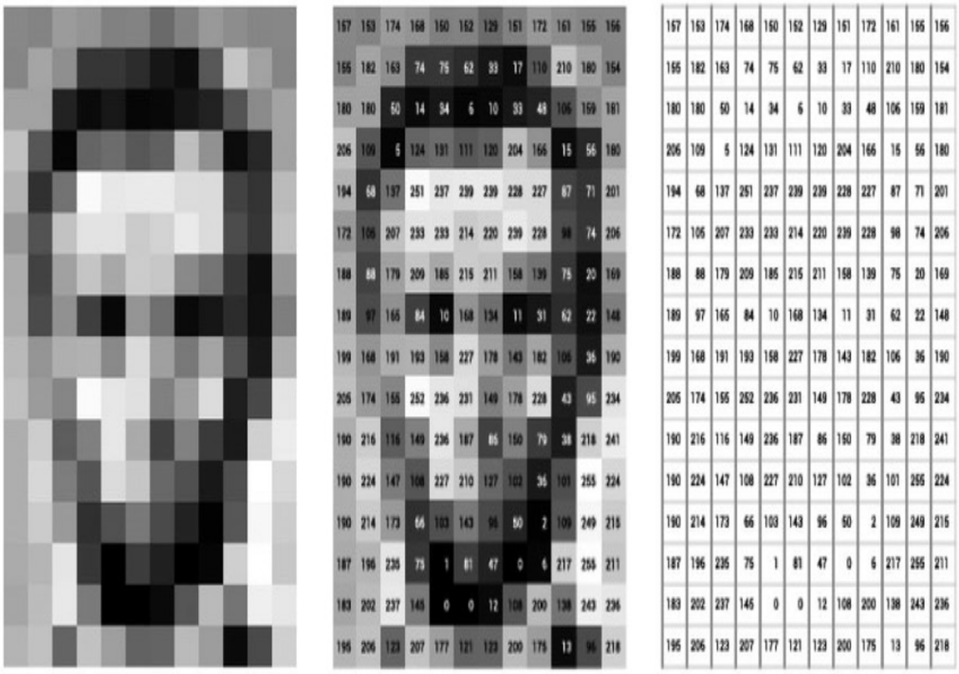
Vishnu S. Pendyala, PhD

Recording: https://www.youtube.com/watch?v=2Uil8cD8UVU&list=PLLsxQYv4DdJk9HSsby8Whox-JhJ0w7Ldk&index=12



Guess Who?

Source: https://thispersondoesnotexist.com/

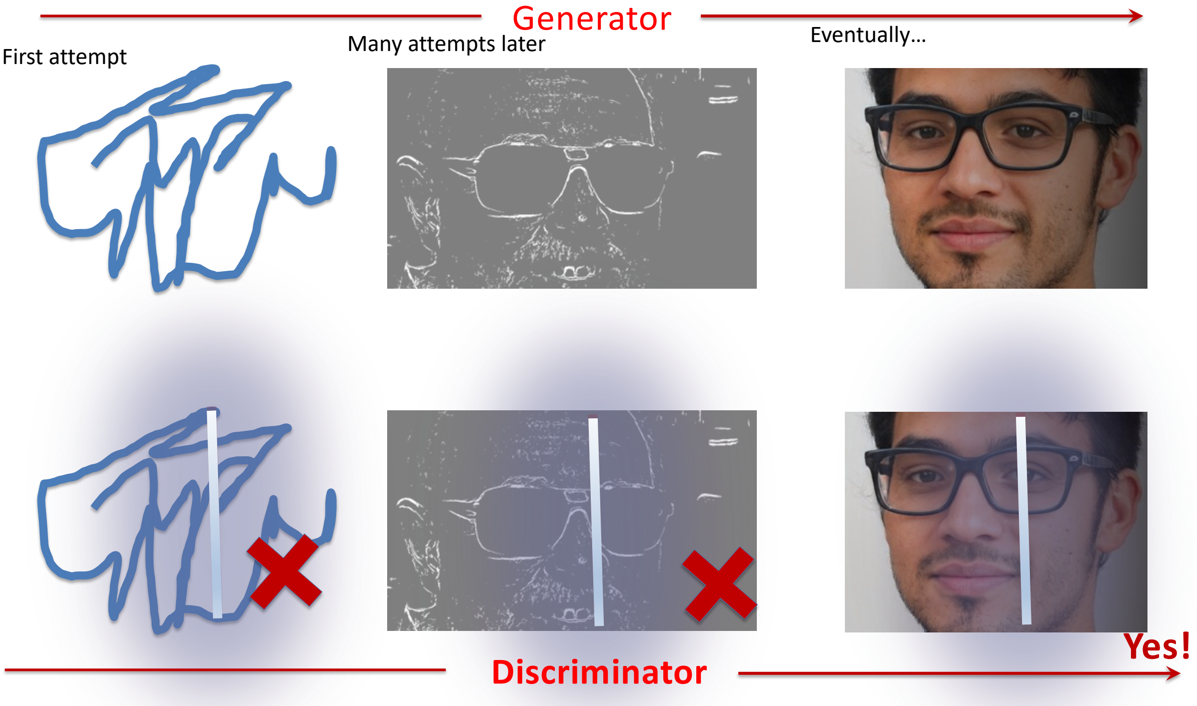


157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Source: Wevers, Melvin, and Thomas Smits. "The visual digital turn: Using neural networks to study historical images." *Digital Scholarship in the Humanities* 35.1 (2020): 194-207.

https://en.akinator.com/

Hello, I am Akinator
Think about a real or fictional character.
I will try to guess who it is
akinator®



Generator

First attempt

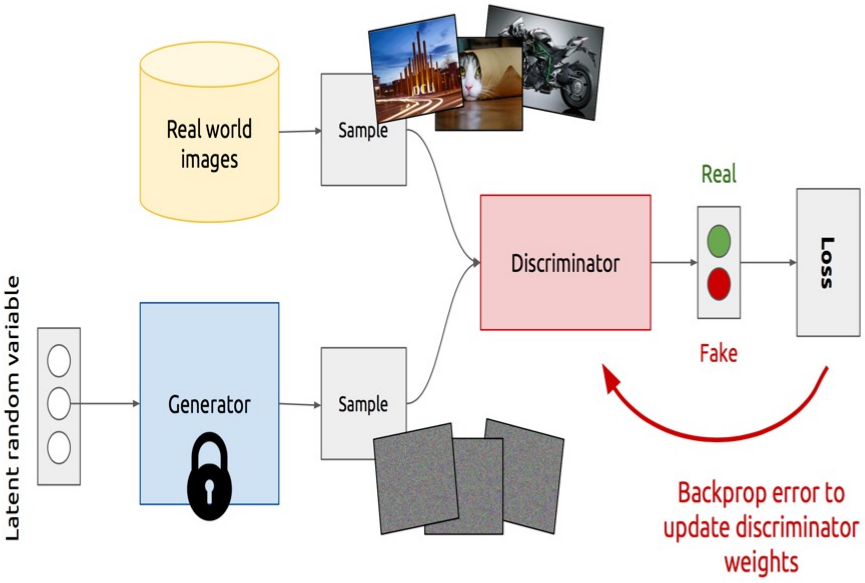
Many attempts later

Eventually…

Discriminator

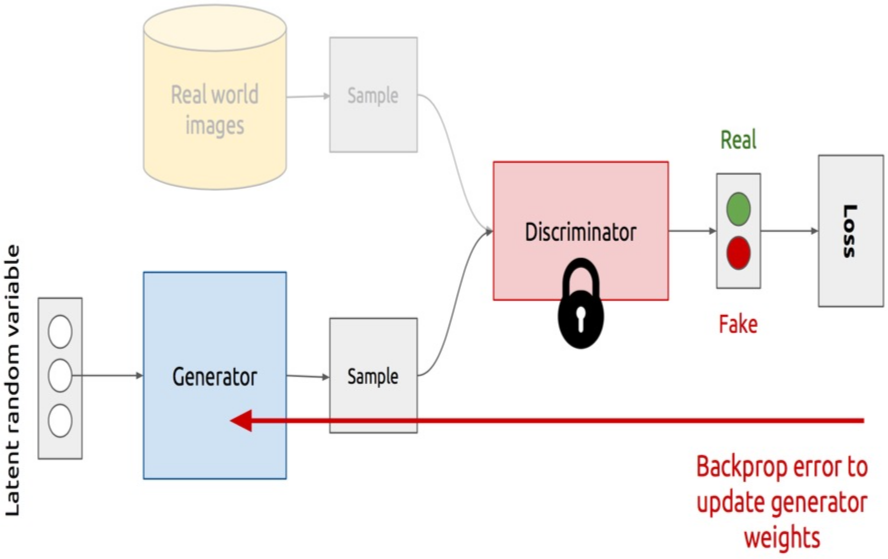
Yes!

GAN: Training Discriminator

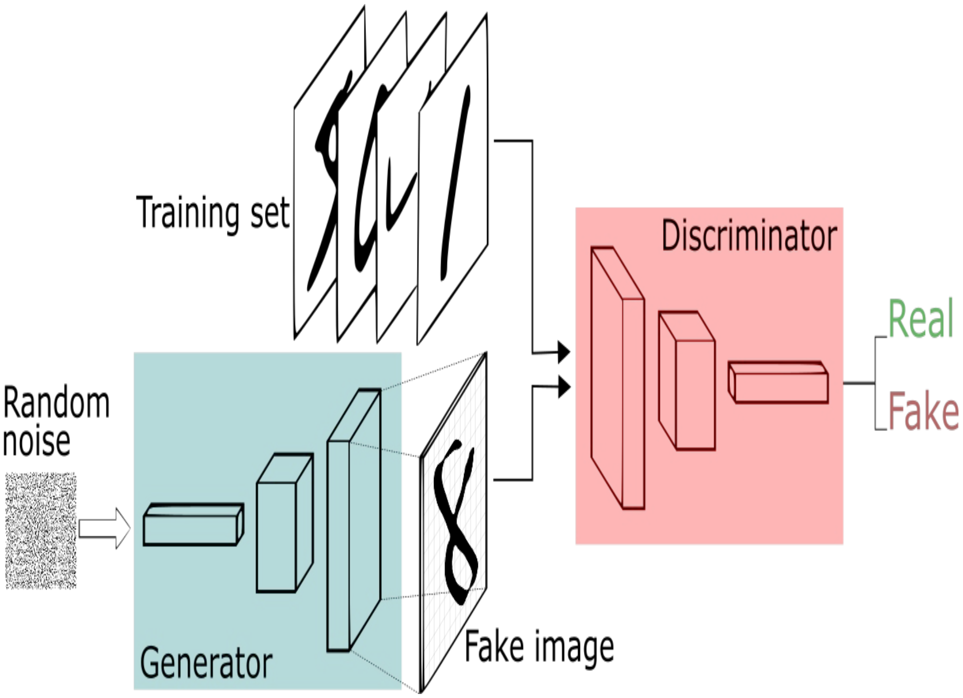


Source: https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

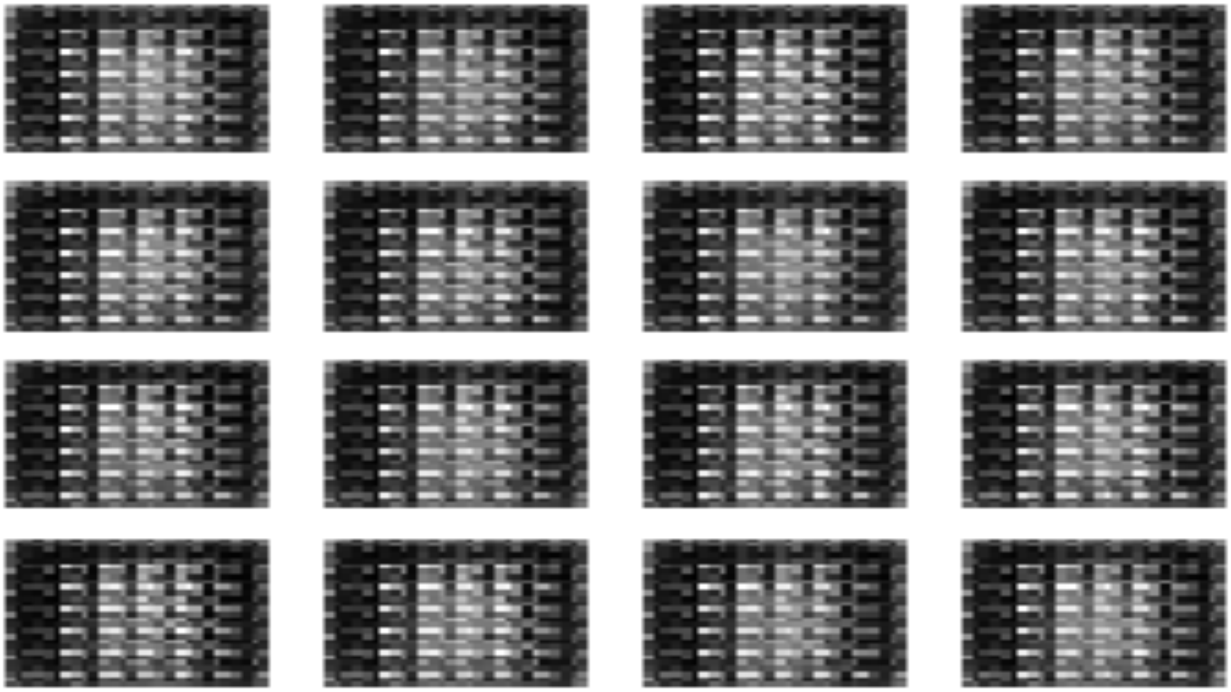
Training Generator



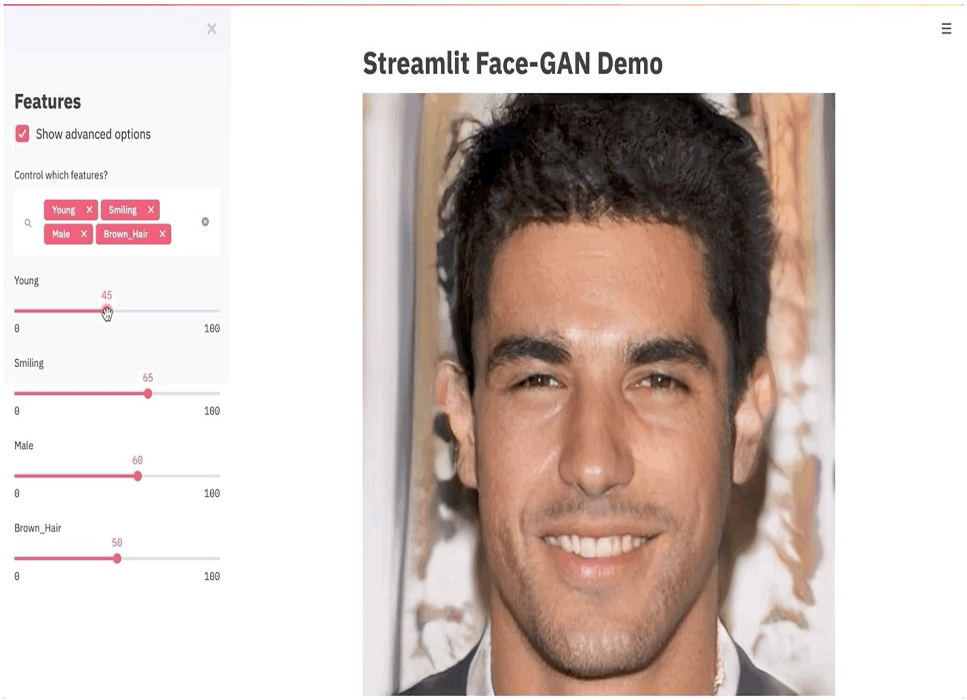
https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016



Source: https://sthalles.github.io/intro-to-gans/



Source: https://www.tensorflow.org/tutorials/generative/dcgan



Streamlit Face-GAN Demo

Features

☑ Show advanced options

Control which features?

Young ✕ Smiling ✕ Male ✕ Brown_Hair ✕

Young: 45 (0–100)

Smiling: 65 (0–100)

Male: 60 (0–100)

Brown_Hair: 50 (0–100)

Soure: https://towardsdatascience.com/build-an-app-to-synthesize-photorealistic-faces-using-tensorflow-and-streamlit-dd2545828021

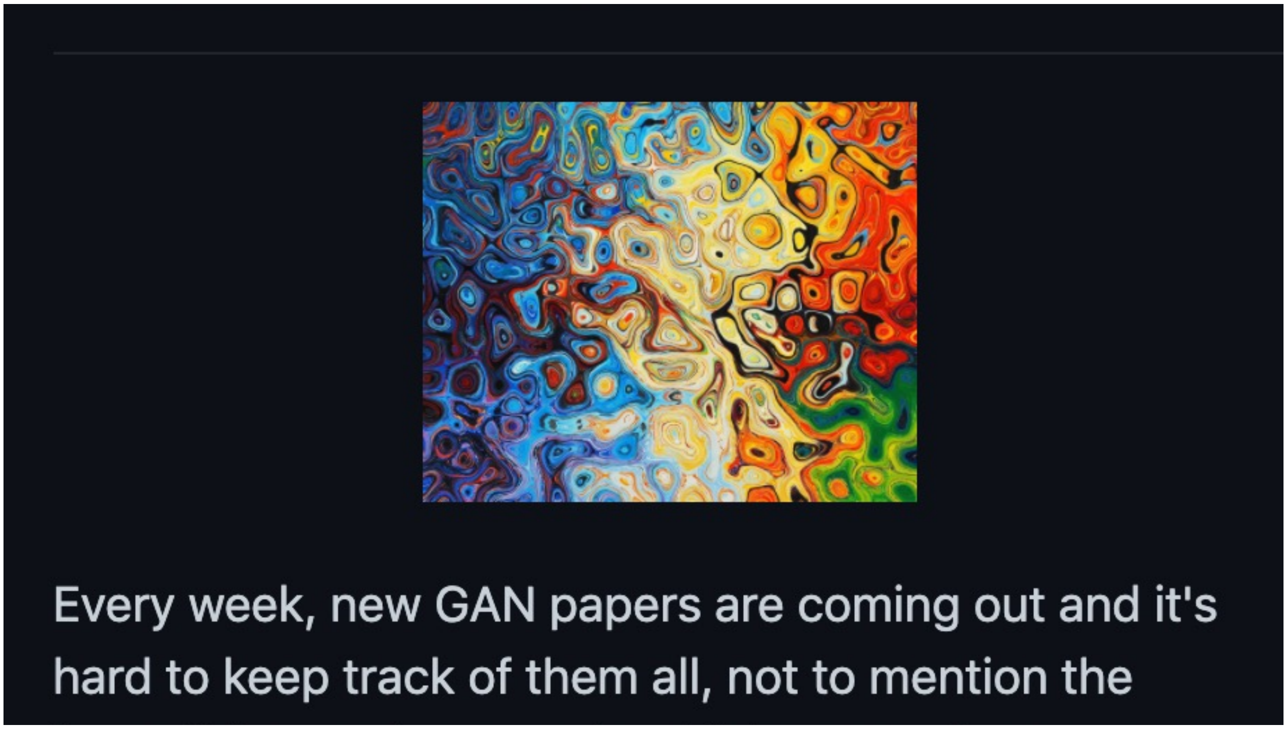
Not just images, AI generated the screenplay for this movie!

"What I cannot create, I do not understand”

Richard Feynman, Nobel Laureate

Generative Adversarial Networks

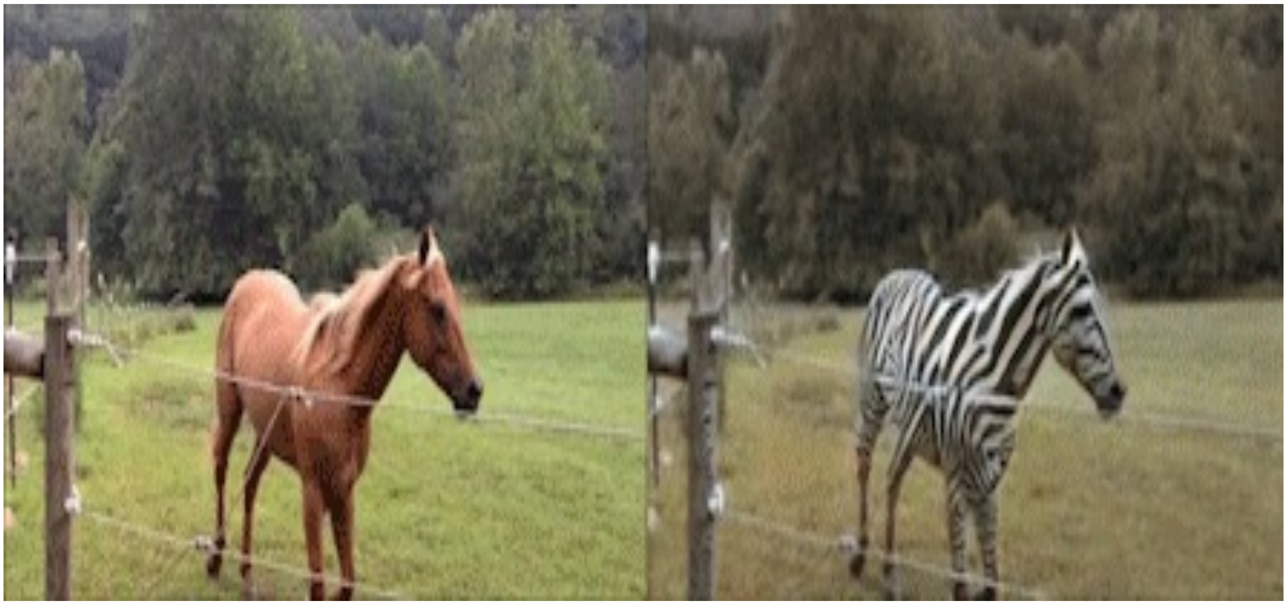
Emerging Trend Alert



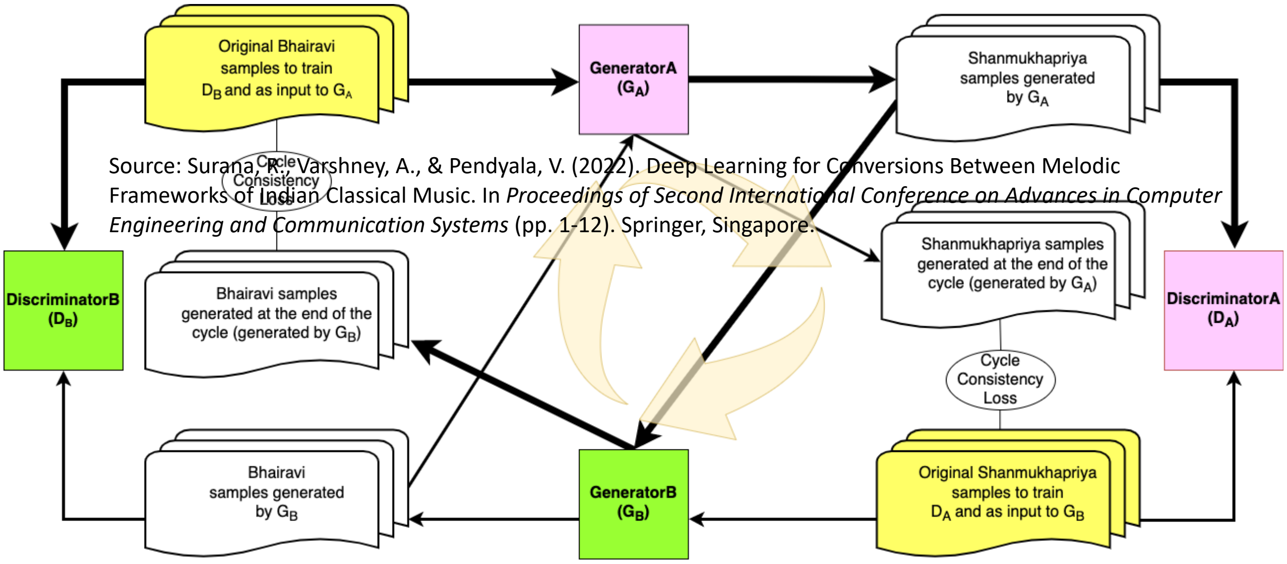
Every week, new GAN papers are coming out and it's hard to keep track of them all, not to mention the

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

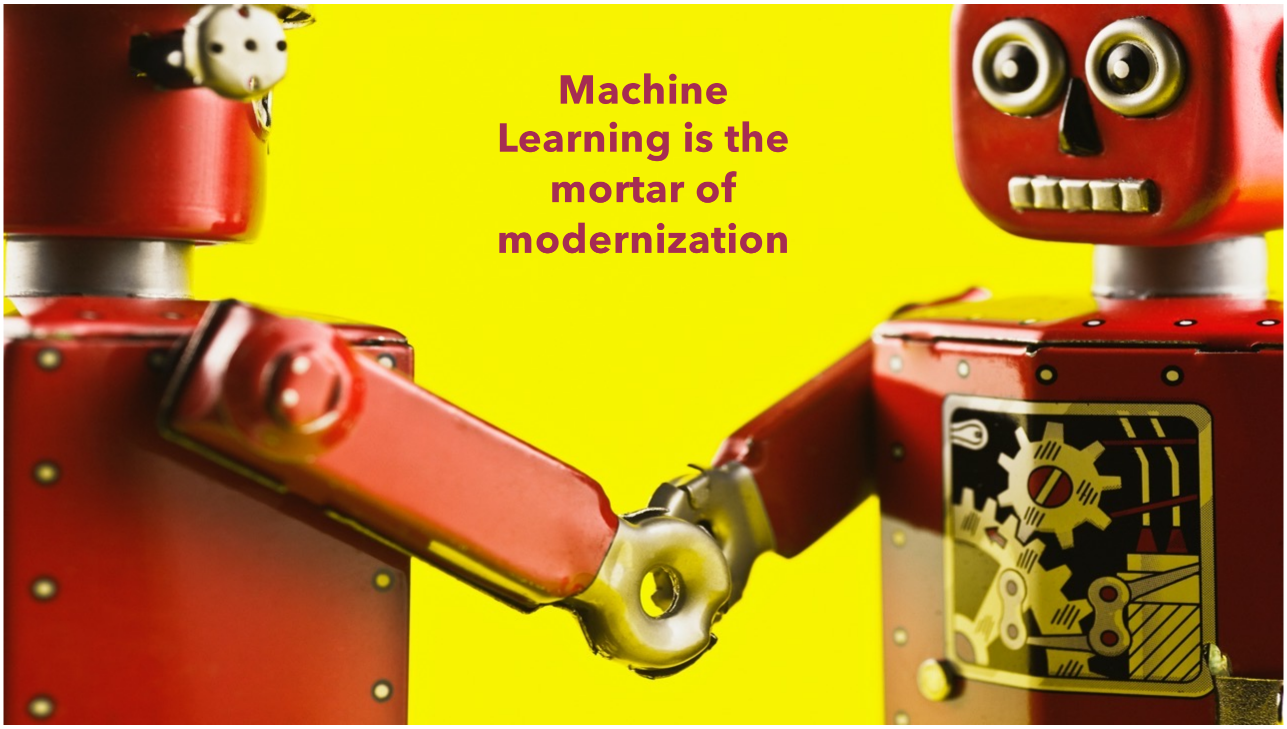
Jun-Yan Zhu*, Taesung Park*, Phillip Isola, Alexei A. Efros
Berkeley AI Research Lab, UC Berkeley



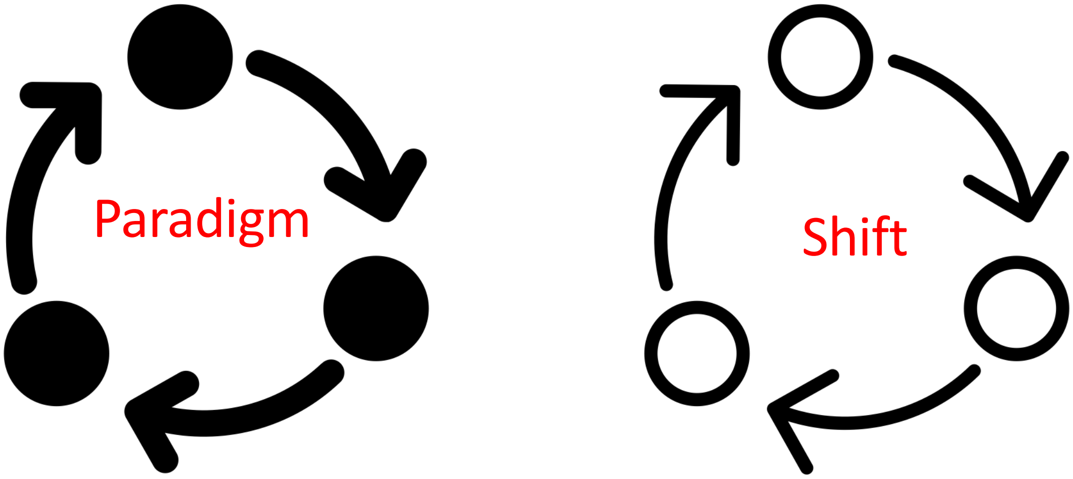
CycleGAN for Conversions Between Melodic Frameworks of Indian Classical Music


Original Bhairavi samples to train D_B and as input to G_A
GeneratorA (G_A)
Shanmukhapriya samples generated by G_A
Cycle Consistency Loss
DiscriminatorB (D_B)
Bhairavi samples generated at the end of the cycle (generated by G_B)
Shanmukhapriya samples generated at the end of the cycle (generated by G_A)
DiscriminatorA (D_A)
Cycle Consistency Loss
Bhairavi samples generated by G_B
GeneratorB (G_B)
Original Shanmukhapriya samples to train D_A and as input to G_B

Source: Surana, R., Varshney, A., & Pendyala, V. (2022). Deep Learning for Conversions Between Melodic Frameworks of Indian Classical Music. In *Proceedings of Second International Conference on Advances in Computer Engineering and Communication Systems* (pp. 1-12). Springer, Singapore.



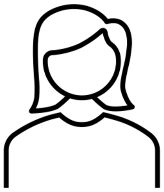
Machine Learning is the mortar of modernization



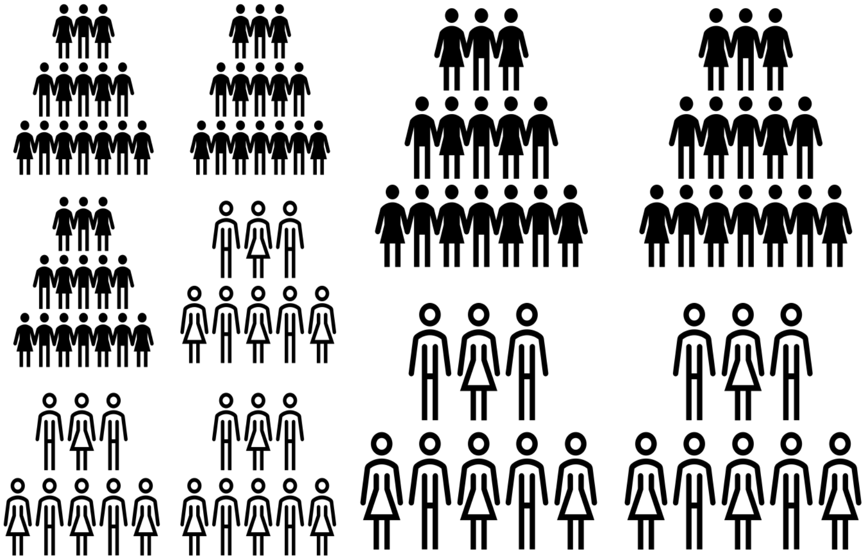
A Paradigm Shift

Traditional Programming: Personal characteristics generalized to many

Analyze one



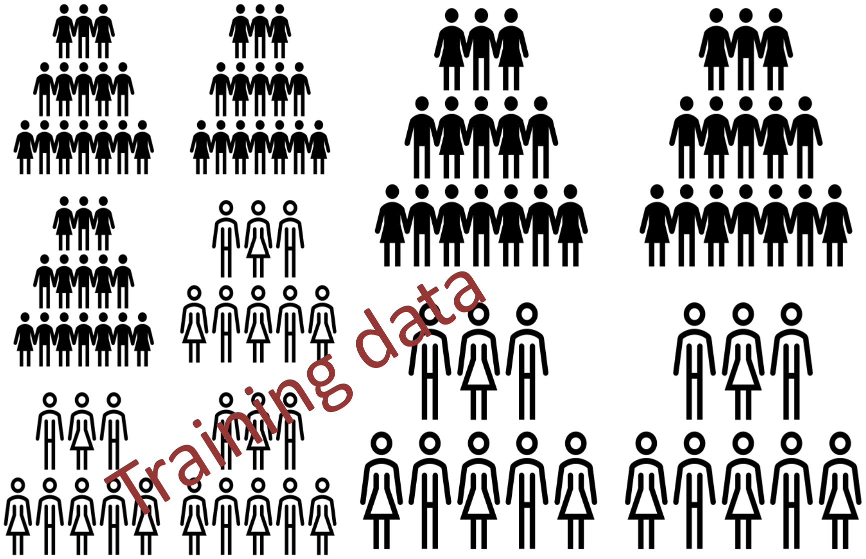
Apply to all



```
If (person X is polite,
magnanimous, …)
then
      good
else
      bad
```

Machine Learning: From Generalization to Personalization

Analyze many

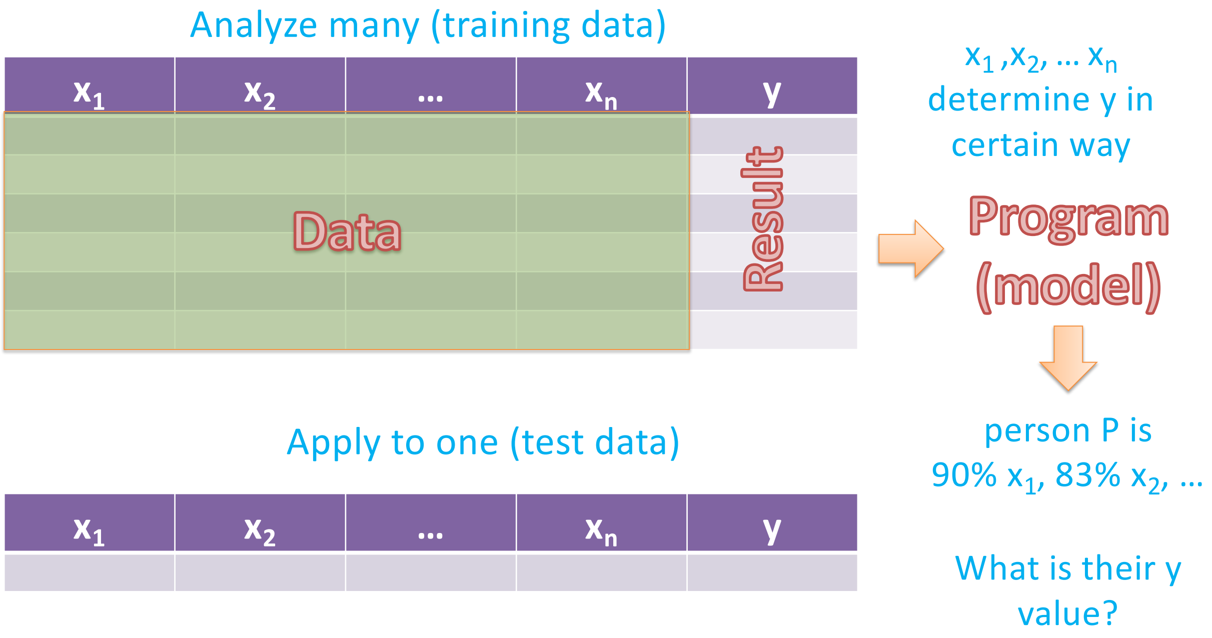


Apply to one

person X is
90% of the time
polite, 83%
magnanimous, …

Are they good or
bad?

Machine Learning: From Generalization to Personalization



Analyze many (training data)

x_1	x_2	…	x_n	y

x_1 ,x_2, … x_n determine y in certain way

Program (model)

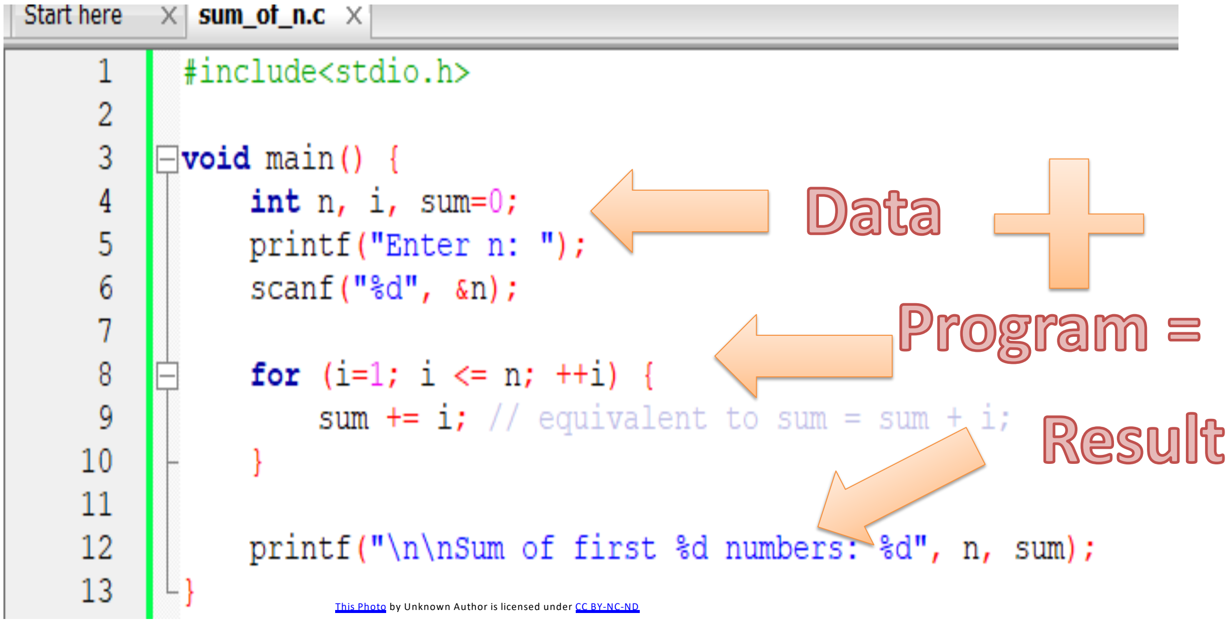
person P is 90% x_1, 83% x_2, …

What is their y value?

Apply to one (test data)

x_1	x_2	…	x_n	y

Compare to traditional programming



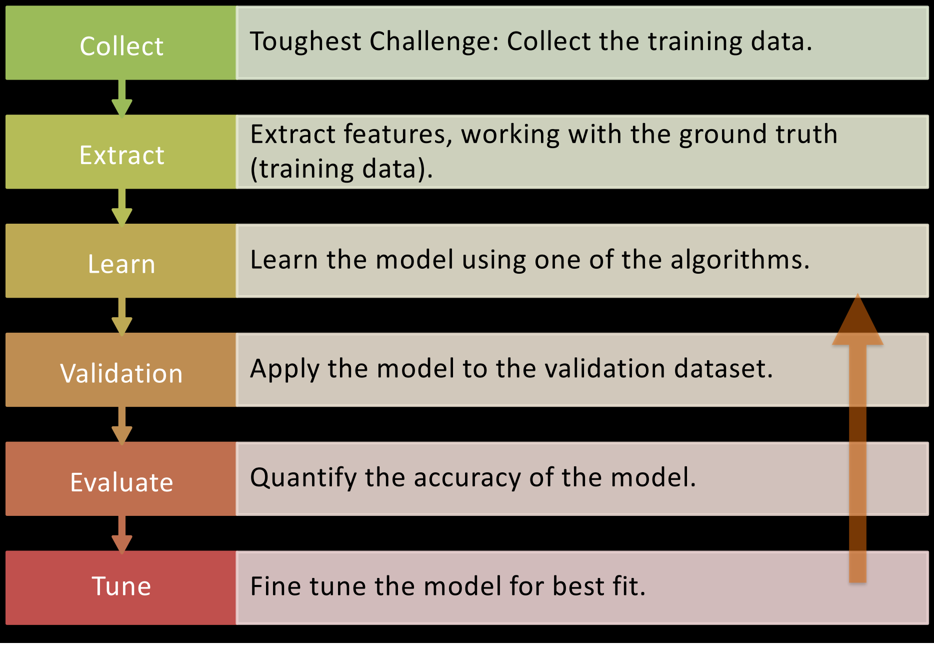
```
#include<stdio.h>

void main() {
    int n, i, sum=0;
    printf("Enter n: ");
    scanf("%d", &n);

    for (i=1; i <= n; ++i) {
        sum += i; // equivalent to sum = sum + i;
    }

    printf("\n\nSum of first %d numbers: %d", n, sum);
}
```

Data + Program = Result

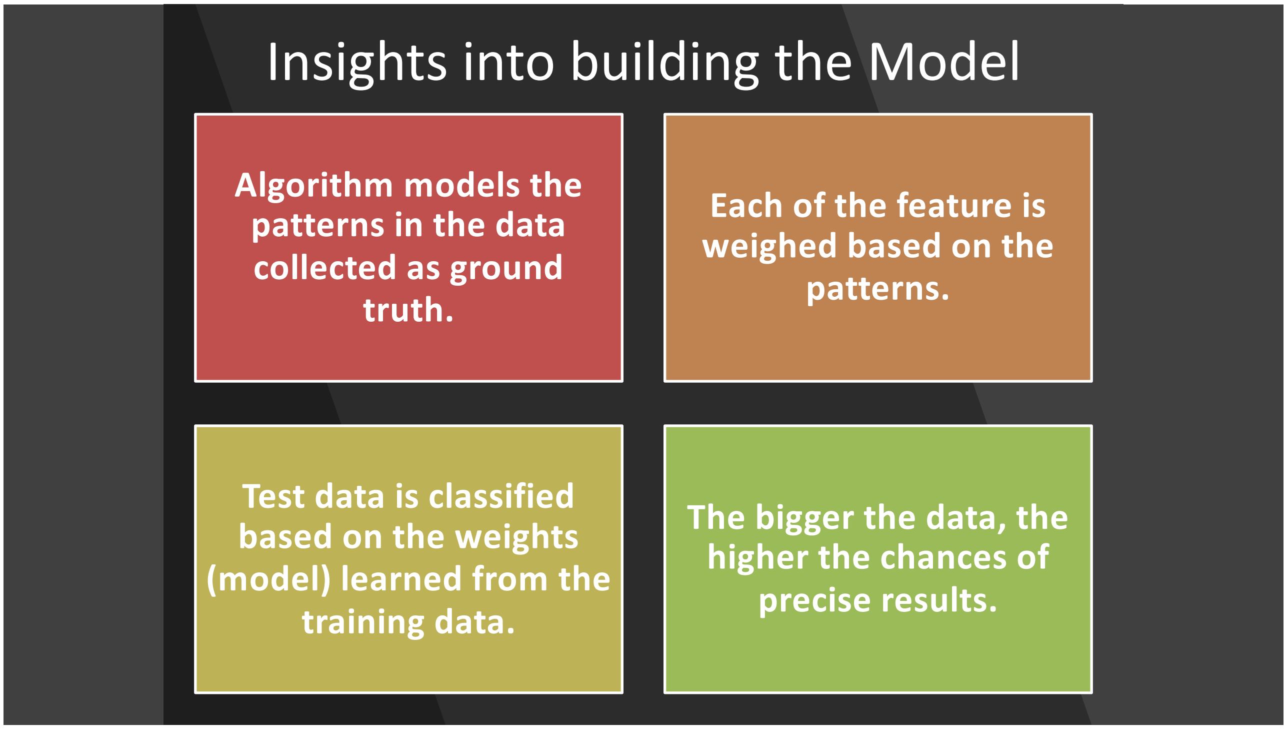
Deductive vs Inductive

Traditional Programming	Machine Learning
• If-then-else rules • Iterations, loops, other programming constructs • deduce conclusions	• Analyze population • Model the characteristics • Apply the model to new samples to induce behavior
• Write MLOC • Static analyzers, debuggers and a whole ecosystem of tools	• Low code / no code • Feature Engineering • Hyperparameter Tuning
• Code intensive • The "Art" of programming	• Data intensive • Data "Science"

The Process: Typical ML Task



Collect	Toughest Challenge: Collect the training data.
Extract	Extract features, working with the ground truth (training data).
Learn	Learn the model using one of the algorithms.
Validation	Apply the model to the validation dataset.
Evaluate	Quantify the accuracy of the model.
Tune	Fine tune the model for best fit.



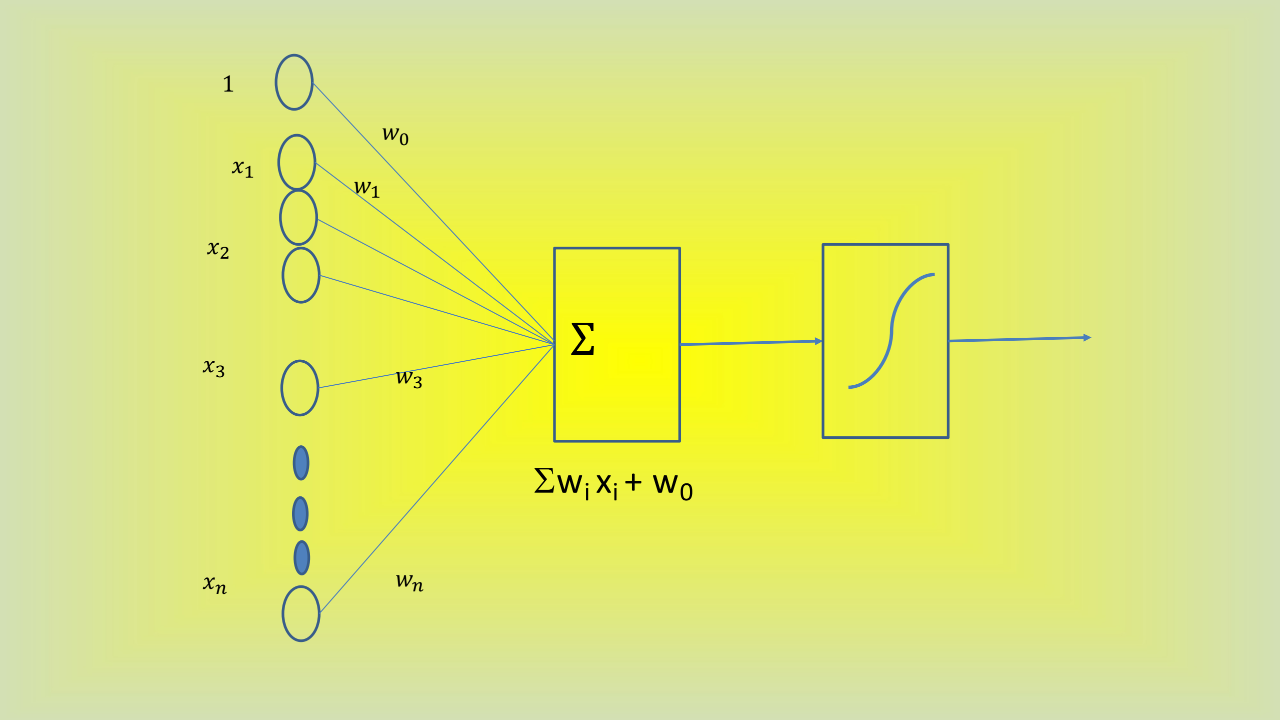
Insights into building the Model

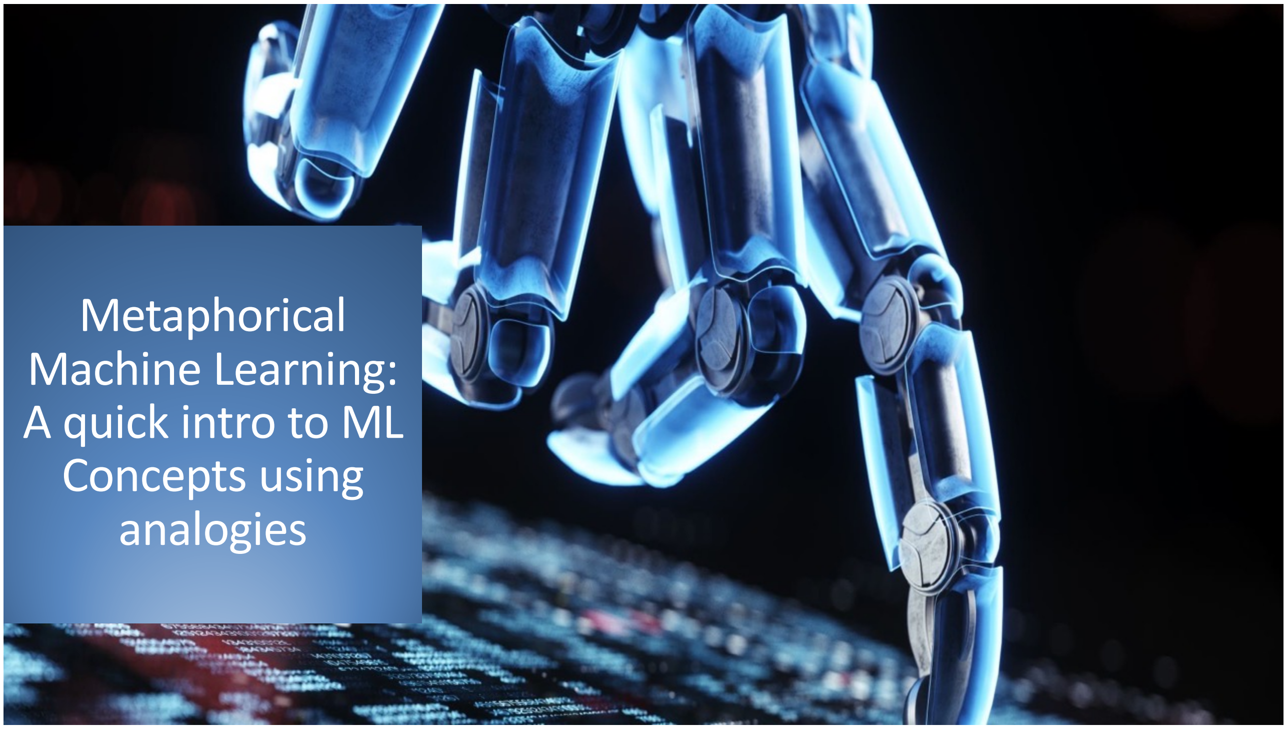
Algorithm models the patterns in the data collected as ground truth.

Each of the feature is weighed based on the patterns.

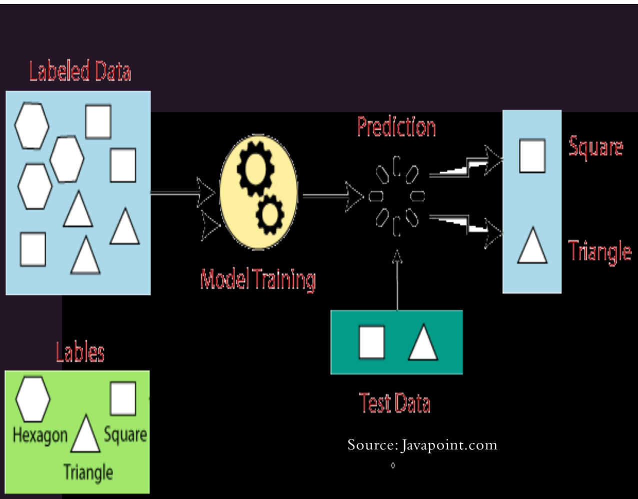
Test data is classified based on the weights (model) learned from the training data.

The bigger the data, the higher the chances of precise results.

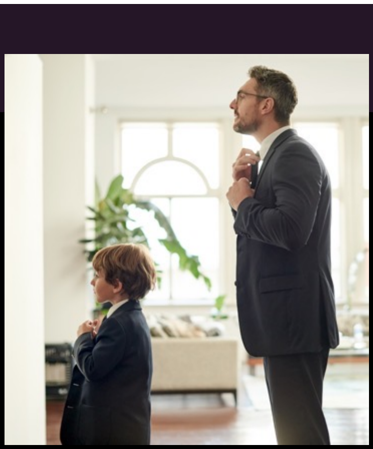




Metaphorical Machine Learning: A quick intro to ML Concepts using analogies



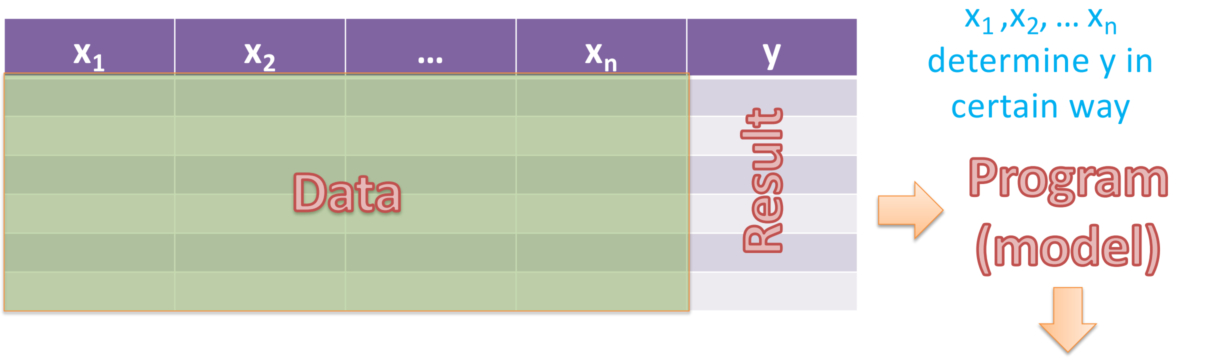
Source: Javapoint.com



Supervised Learning

Parents labeling good and bad for children

Labeled Training Data => Supervised Learning



x_1 x_2 … x_n y

Data

Result

x_1 ,x_2, … x_n determine y in certain way

Program (model)

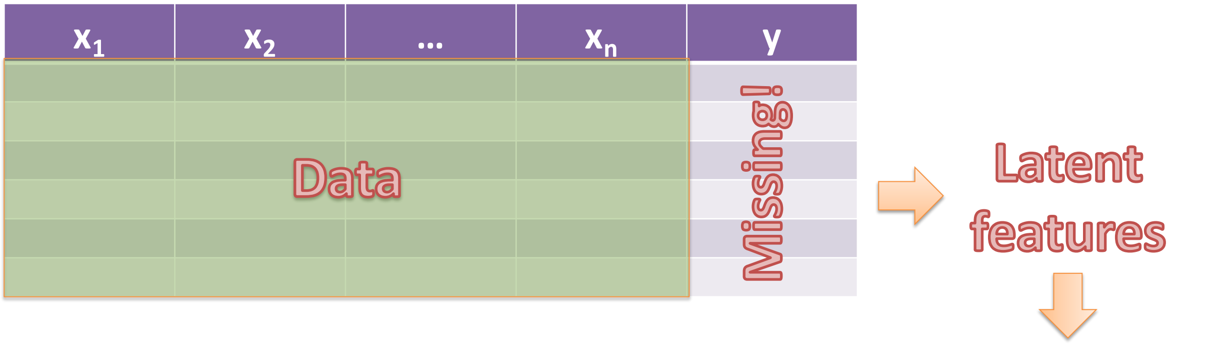
person P is 90% x_1, 83% x_2, …

Apply to one (test data)

x_1	x_2	…	x_n	y

What is their y value?

Unlabeled Training Data => Unsupervised Learning



x_1 x_2 … x_n y

Data

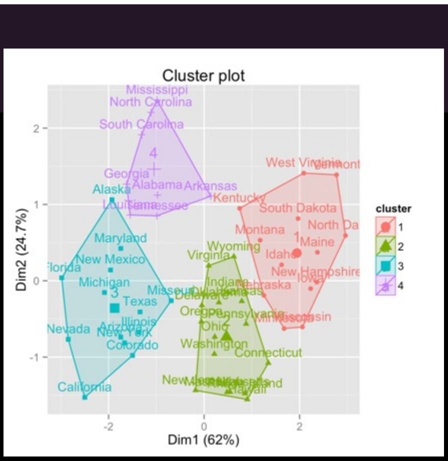
Missing!

Latent features

Group the data into clusters

Generate new data

…



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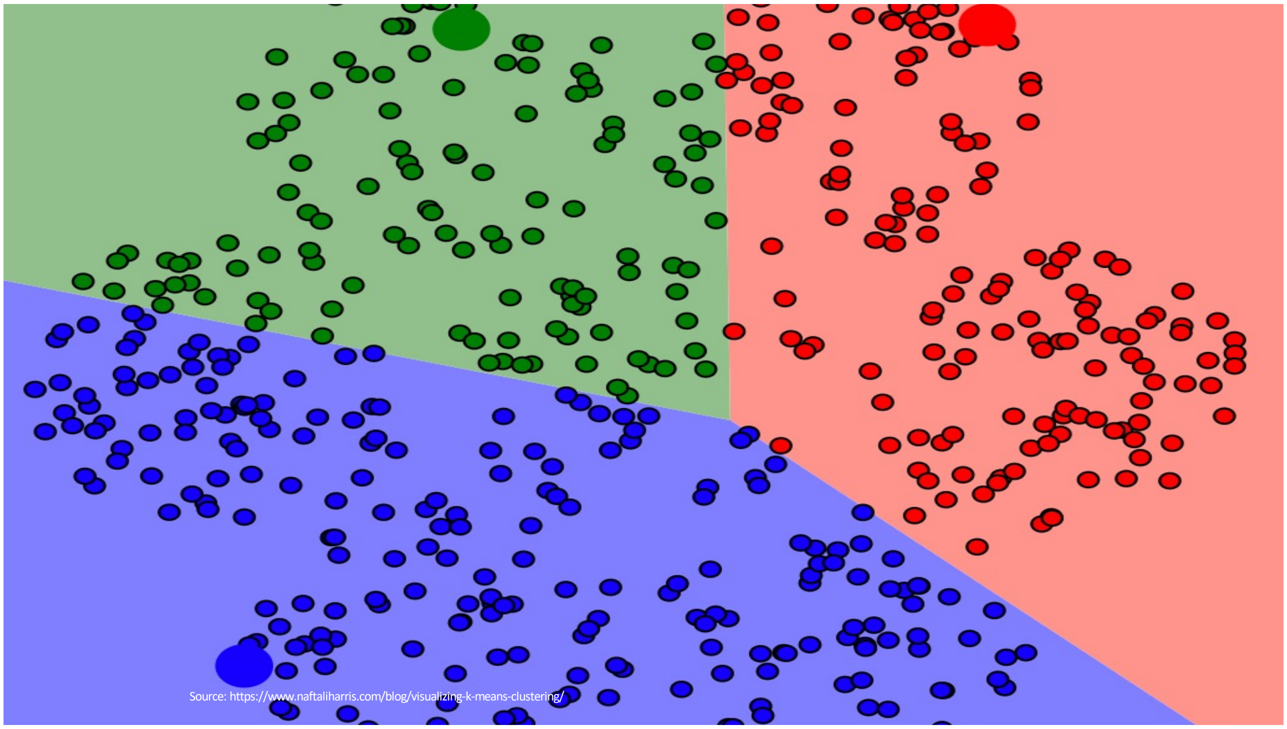
Self or Un supervised Learning of latent features

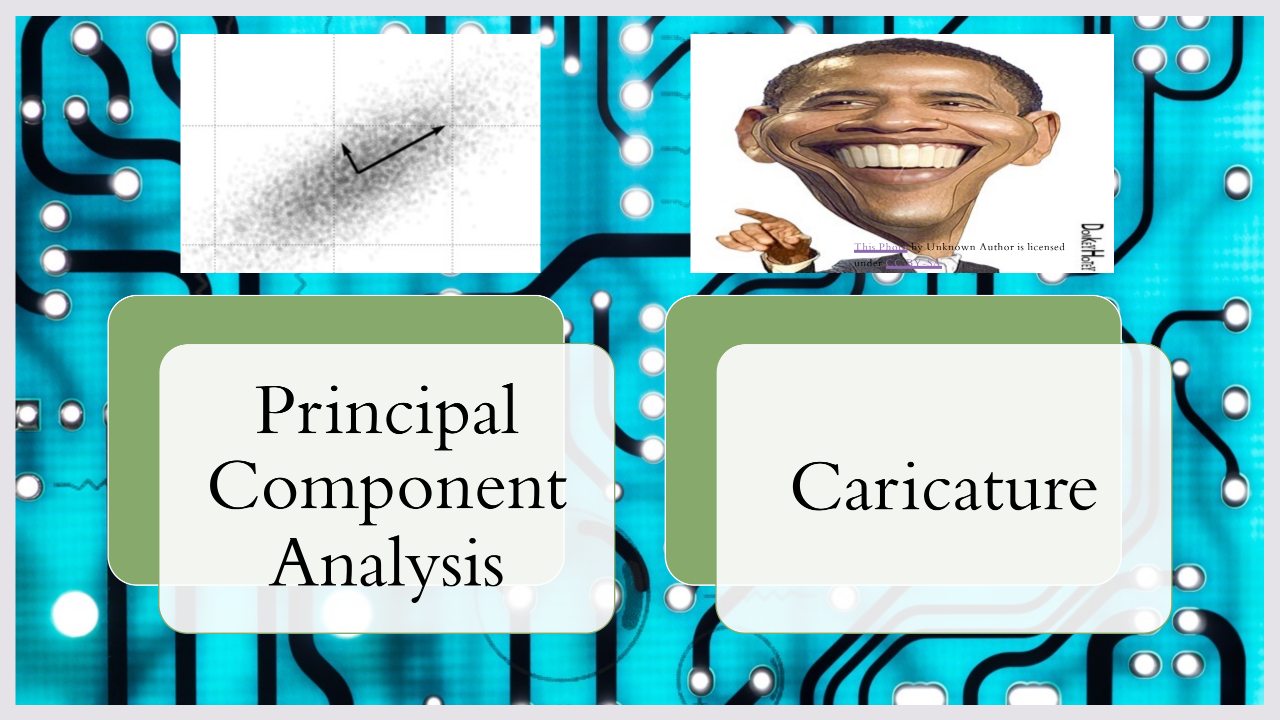
Students forming groups themselves: Clustering



Source: https://www.naftaliharris.com/blog/visualizing-k-means-clustering/

Clustering implicitly identifies latent features

Can we identify them explicitly?



Principal Component Analysis

Caricature

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https://www.sjsu.edu/people/vishnu.pendyala/

@vishnupendyala

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