# Let’s Start

**Lakshay Kumar**
(lakshaykumar.tech/)

# Initial Thought?

Exploring Generative AI with

# GAN Models

"When it comes to **Generative AI**, the robots are no longer just good at math, they're also fantastic artists!

Let's Explore

**01** Generative AI & **GANs**

**02** Working & **Training GANs**

**03** **Industrial** Applications

lakshaykumar.tech

# GAN Models

**Generative Adversarial Networks**

- GANs and LLMs are the subfield of Deep Learning.
- Set of two algorithms competing with each other.
- Based on self-supervisedly trained models.
- Requires a enormous amount of labeled data

# GAN Algorithm

**Data**

"Enormous!"

**Noise**

"Support the generator"

**Sample**

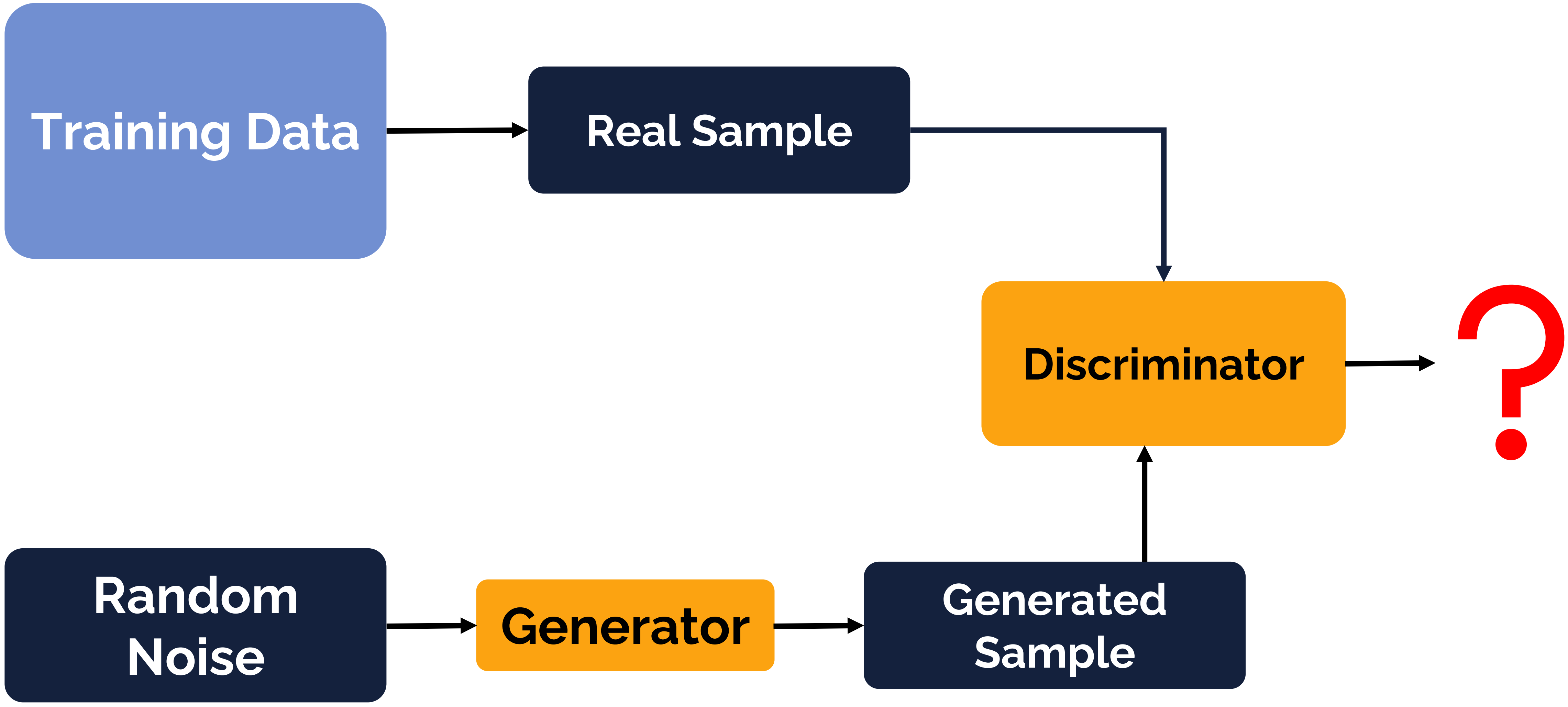
Generated and Real one

**Discriminator**

"Data is fake"

**Generator**

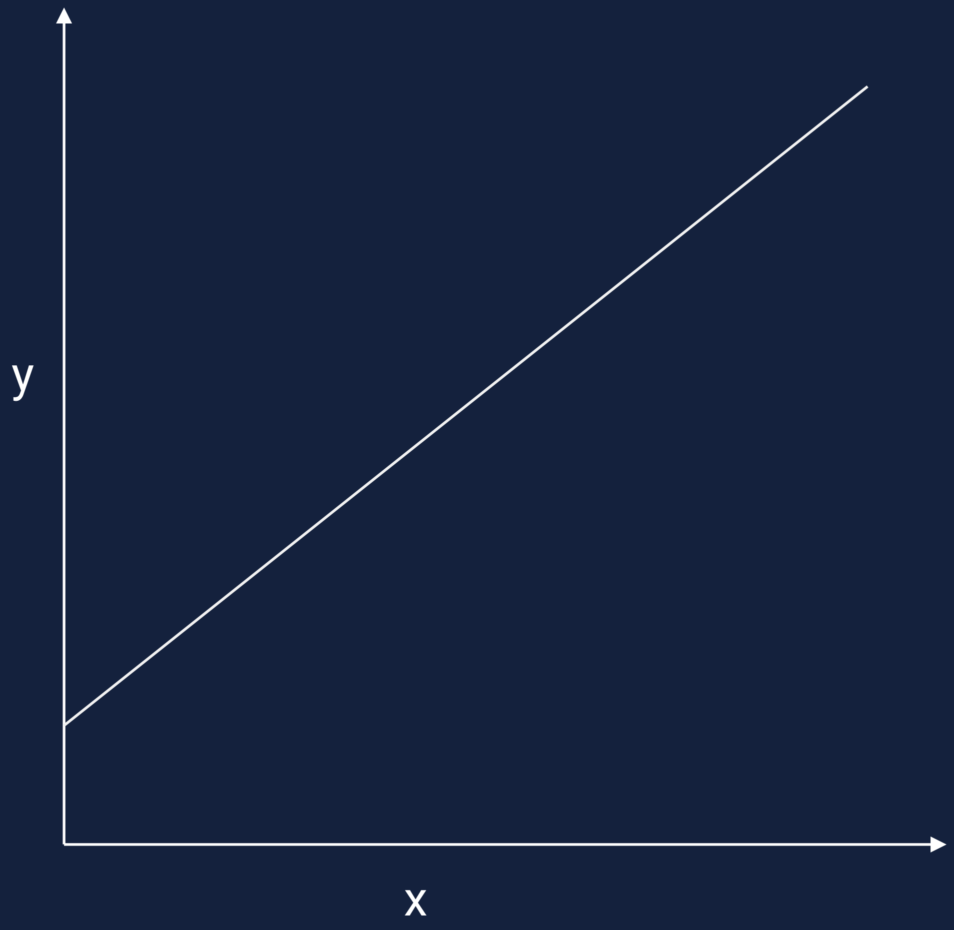
"No, this data is real"


Training Data
Real Sample
Discriminator
?
Random Noise
Generator
Generated Sample

IMP!

# Linear and Logistic Regression

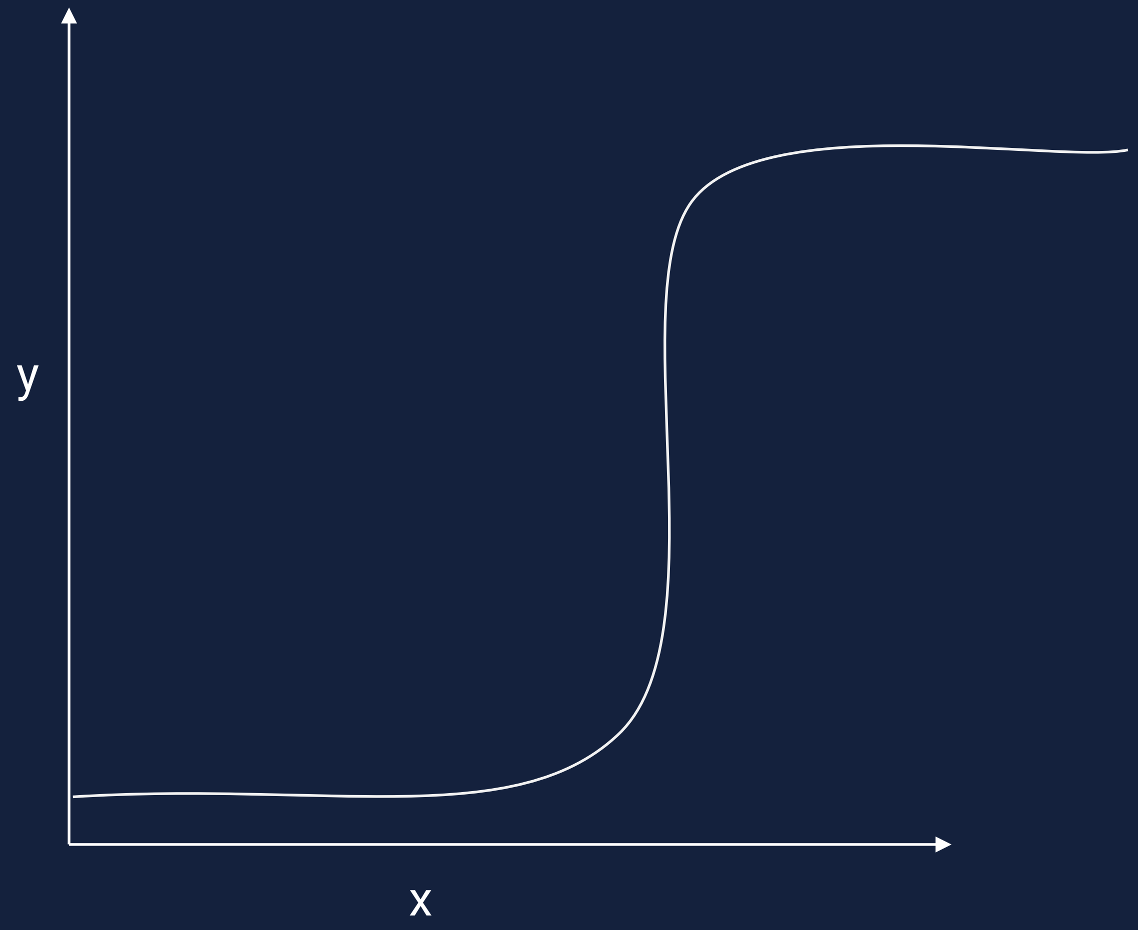
# Linear Regression




$$y = wx + b$$

y = output (prediction)
w = weights
x = input data (unseen)
b = Bias (constant)

# Logistic Regression




**Sigmoid function**

$$S(y) = \frac{1}{1 + e^{-y}}$$

x = variable (prediction)

*Range of S(y) is (0,+1)*

# How do generator and discriminator works?

1

# GANs are Mathematically Represented by :

2

3

Maximizing Discriminator

Log of discriminator output on real data

Log of compliment of Discriminator output of Generator from Random Noise (z).

$$min{\sim}G, max{\sim}D\ V(D,G) = Ex_{\sim Pdata(x)}[\log D(x)] + E_{z\sim p(z)}[\log(1 - D(G(z)))]$$

Minimizing Generator

Expectation value over the probability distribution of real sample

Expectation value over the probability distribution of random noise

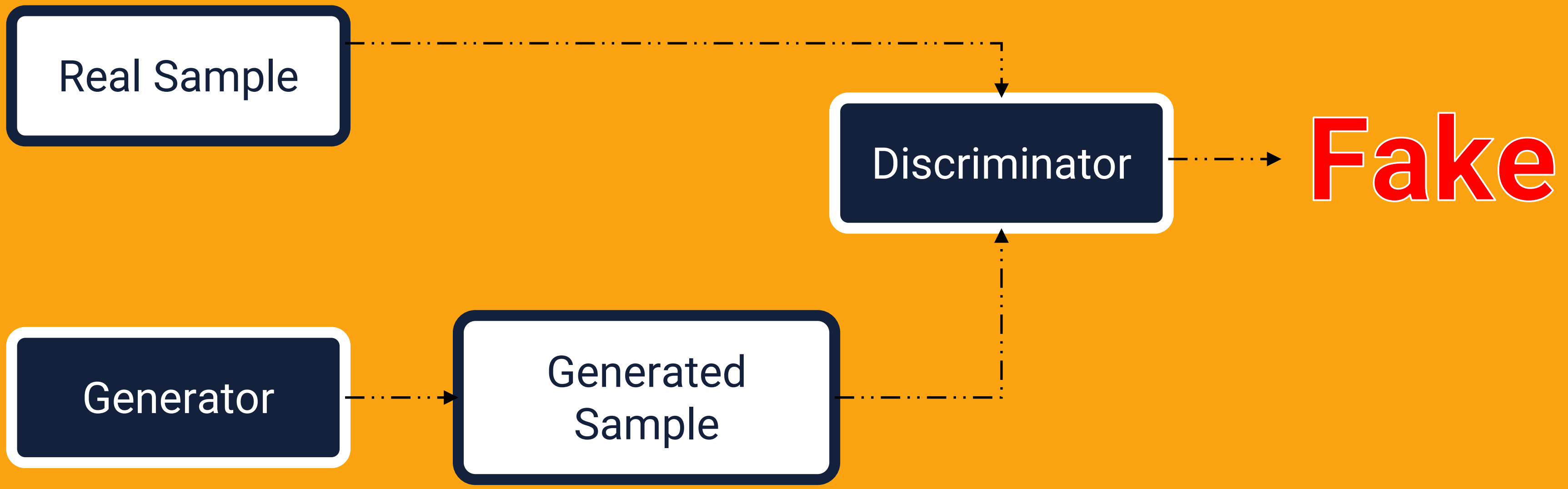
4

This makes sure that generator produces such a output that is difficult for discriminator to catch

1

# "This data is from real sample" - Discriminator

2



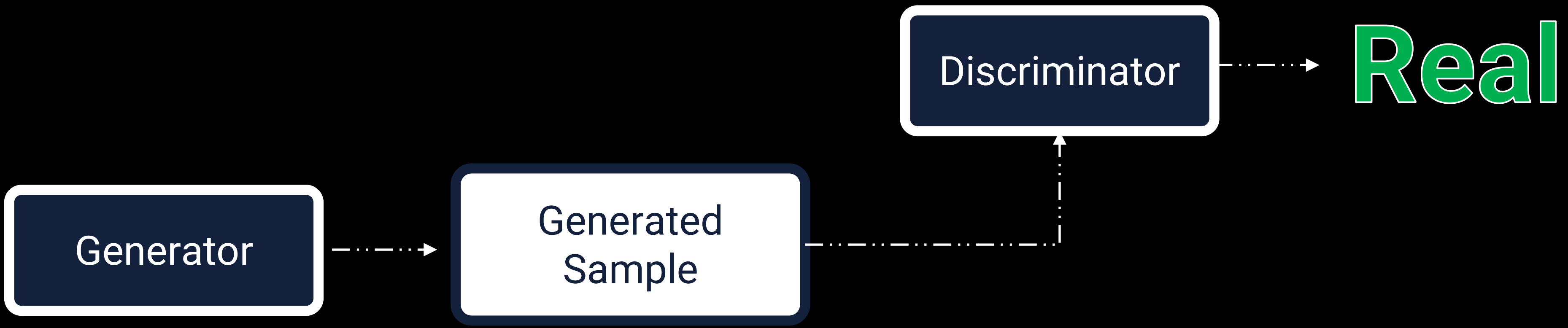

3

$$min{\sim}G, max{\sim}D\; V(D,G) = Ex_{\sim Pdata(x)}[\mathbf{logD(x)}] + \mathbf{E}_{\mathbf{z\sim p(z)}}[\mathbf{log(1 - D(G(z)))}]$$

4

Dominant Discriminator's Loss function makes the generator's learning difficult!

# “No, I generated this data” - Generator




$$min{\sim}G, max{\sim}D\ V(D,G) = \boxed{E_{x\sim Pdata(x)}[\log D(x)]} + E_{z\sim p(z)}[\log(1 - D(G(z)))]$$

**Equilibrium balance where generator fools the discriminator**

# Implementation

# Types of GANs

# Types of Generative Adversarial Networks

**Vanilla GANs** Deep Convolutional GANs Conditional GANs Super Resolution GANs

## Simplest form of GANS

where **generator** and **discriminator** are **simple multi-layer neural network** unit that does certain computations to detect features or business intelligence in the input data.

Text Generation

Data Augmentation

# Types of Generative Adversarial Networks

Vanilla GANs | **Deep Convolutional GANs** | Conditional GANs | Super Resolution GANs

## Combination of GANs and CNNs

DCGANs use convolutional layers to generate realistic images by **learning patterns and features from a training dataset.** The generator network up samples **random noise into images**, while the discriminator network tries to distinguish between real and generated images.

**Realistic Faces generation**

**Deep Fake Images generation**

**Generating variations of images**

# Types of Generative Adversarial Networks

Vanilla GANs | Deep Convolutional GANs | **Conditional GANs** | Super Resolution GANs

## Extension of GANs

CGANs take **input noise along with conditional labels** to generate realistic samples. CGANs take input noise along with conditional labels to **generate realistic samples from same class**. This generates more targeted and controlled outputs.

Image to Image Translation

Text to image synthesis

# Types of Generative Adversarial Networks

Vanilla GANs | Deep Convolutional GANs | Conditional GANs | **Super Resolution GANs**

## Increases the image resolution

The **generator takes a low-resolution image** as input and **generates a high-resolution image.** The **discriminator then tries to distinguish** between the generated high-resolution images and real high-resolution images. This adversarial training process **improves the generator's ability to produce high-quality**, visually appealing, and realistic super-resolved images

Image Resolution Enhancer

# Industrial Applications

- #1 HealthCare
- #2 Gaming
- #3 Fashion
- #4 Marketing
- #5 Manufacturing

# Industrial Applications

## #1 HealthCare

Medical image synthesis for **enhanced diagnosis** and **treatment planning**.

**Drug discovery and development** through generative models.

Generating synthetic patient data for **privacy-preserving research.**

**Augmenting medical education** with interactive virtual simulations.

## #2 Gaming

## #3 Fashion

## #4 Marketing

## #5 Manufacturing

# Industrial Applications

#1 HealthCare

## #2 Gaming

**Procedural generation** of game environments and levels.

AI-generated **music and sound effects** for immersive experiences.

**AI-generated non-player characters** (NPCs) with realistic behaviors

AI-assisted **game design and development tools** for faster iteration.

#3 Fashion

#4 Marketing

#5 Manufacturing

# Industrial Applications

#1 HealthCare

#2 Gaming

## #3 Fashion

**Virtual fashion try-on** for personalized shopping experiences.

**AI-generated designs** for trend forecasting and inspiration.

**Automated fashion styling** recommendations for individual customers.

**Customized pattern generation** for unique garment production.

#4 Marketing

#5 Manufacturing

# Industrial Applications

#1 HealthCare

#2 Gaming

#3 Fashion

## #4 Marketing

**Personalized content** creation for targeted marketing campaigns.

**Automated ad generation** for increased efficiency and scalability.

**AI-powered recommendation systems** for personalized product suggestions.

**Chatbot and virtual assistant** integration for enhanced customer support.

#5 Manufacturing

# Industrial Applications

#1 HealthCare

#2 Gaming

#3 Fashion

#4 Marketing

## #5 Manufacturing

**Product design :** AI-generated prototypes and designs.

**Automated inspection:** AI-powered visual inspection for defects.

**Predictive maintenance:** Identifying equipment failures before they occur.

**Process optimization:** AI-based optimization of manufacturing processes.

# That’s it

DATA ENTHISIAST

# LAKSHAY KUMAR

Project Manager | Data Scientist | Python development | Machine Learning | Community Enthusiast | Speaker

lakshaykumar.tech →