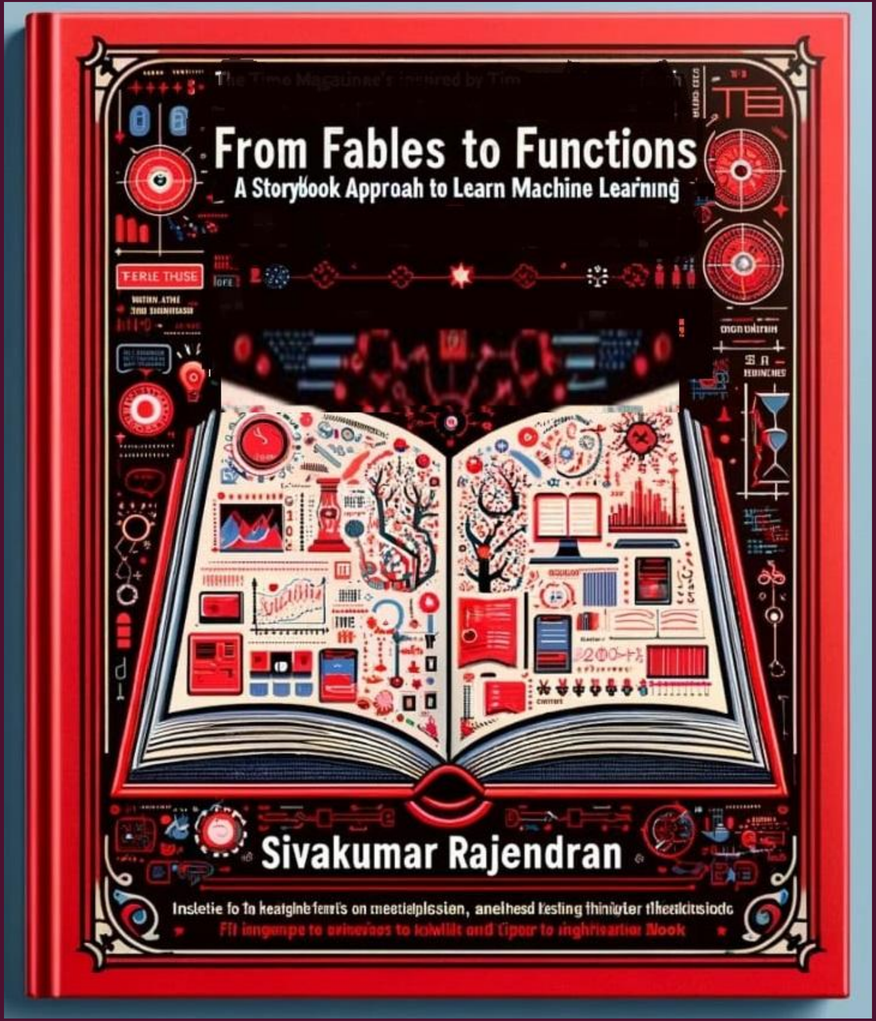

From Fables to Functions
A Storybook Approah to Learn Machine Learning
Sivakumar Rajendran

DAY 1

1. **Old Shelves, New Algorithms: Traditional Methods meets Machine Learning**
   A tale of traditional retail and AI-Powered Mart's Inventory Management

   (AI, Machine Learning, Deep Learning, Generative AI, LLM)

2. **Mysteries of the Menu - A Chef's puzzle**
   In this culinary challenge, chefs decipher both complete and incomplete recipe using their skill and intuition

   (Supervised Learning, Unsupervised learning, Semi-Supervised Learning, Reinforcement Learning)

3. **The Orchard and The Sun**
   Farmer Ada unlocks the secret of her orchard's apple yield by exploring the link between sunlight and fruit production

   (Linear Regression Algorithm)

DAY 2

4. **The Mysterious Case of Disappearing Readers**
   Ellen found why there is a decline in Magazine readership and saved the publication from shutting down the doors

   (Logistic Regression Algorithm)

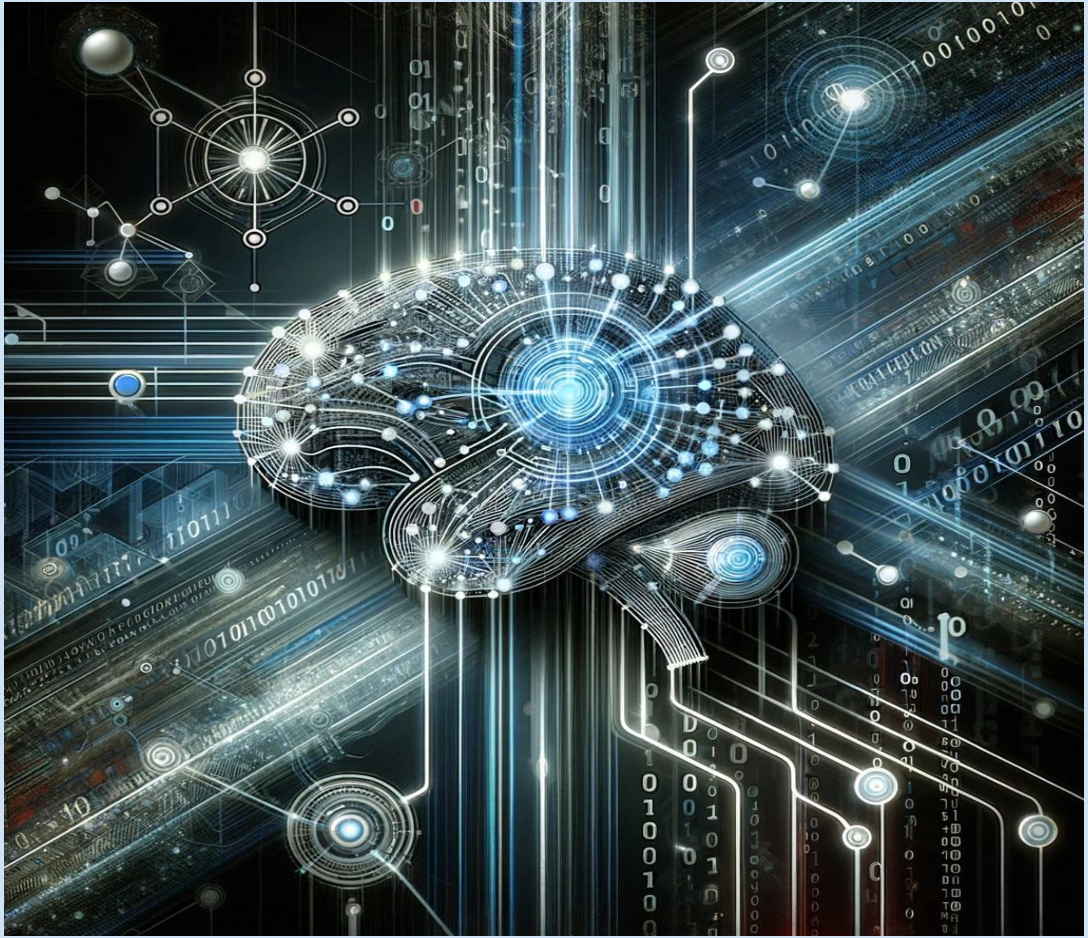
5. Navigating Complex Symptoms: How MediCare Clinic Unraveled the Lyme Disease Mystery
   Medicare clinic's efficient and accurate diagnosis of a patient with Lyme disease through a systematic analysis of symptoms

   (Decision Tree Algorithm)

6. Pitchford Pioneers
   Medicare clinic's efficient and accurate diagnosis of a patient with Lyme disease through a systematic analysis of symptoms

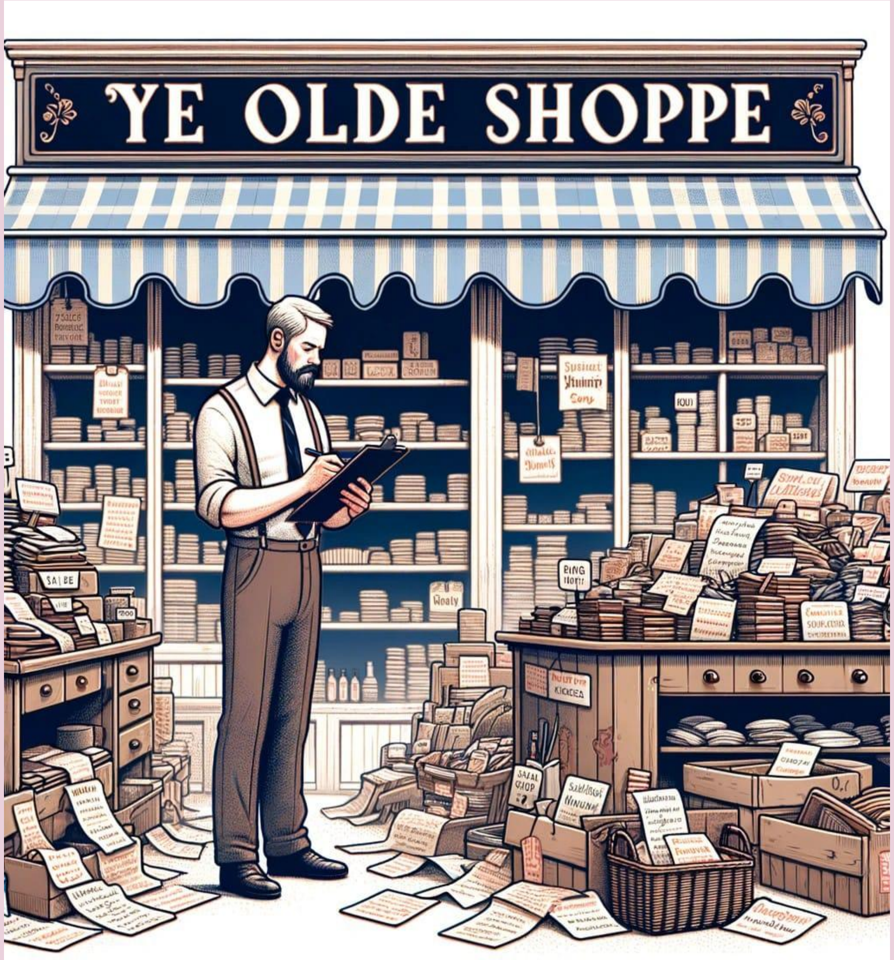
   (K-Means Algorithm)


Story 1



Old Shelves, New Algorithms:
Traditional Methods meets Machine Learning

What is Machine Learning?



Traditionally, Inventory management was largely a manual process.

Store managers would often rely on periodic **physical counts** to determine stock levels. They would order more goods based on factors such as expected seasonal demand, previous sales during similar periods, or just intuition.

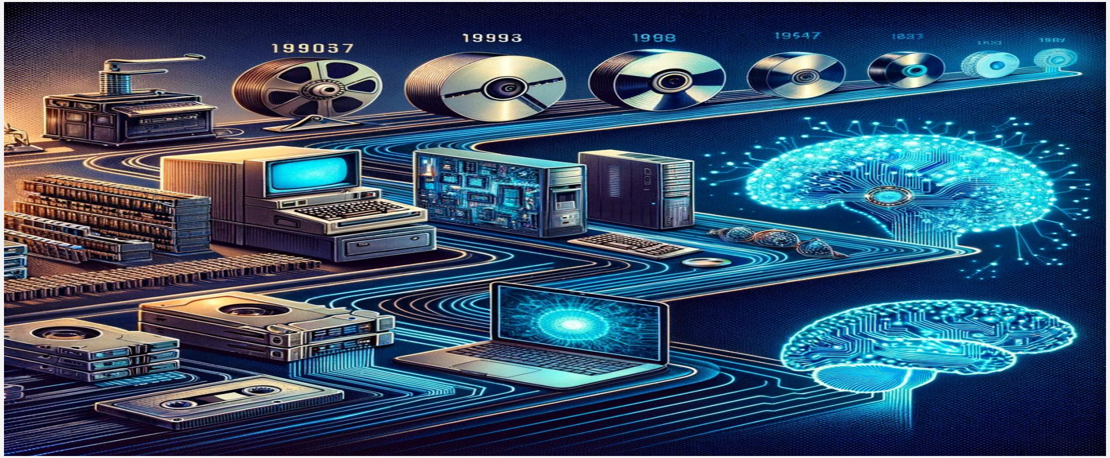
This method was
time-consuming,
prone to human error
and often resulted in either
overstocking (leading to increased storage costs and waste) or
stockouts (leading to missed sales opportunities).

Algorithms **analyze historical sales data, seasonal trends, promotions, local events, and even weather forecasts to predict future demand with high accuracy.** Rather than relying on human estimates, the system continuously learns and adjusts its predictions based on real-time sales data.

For example, a machine learning model might predict an **increase in the sale of umbrellas by analyzing weather patterns**, rather than a store manager making a guess based on the onset of the rainy season. The algorithm can also identify subtle patterns, like a spike in the sale of baking ingredients in certain localities when a cooking show airs.

As a result, stores maintain **optimal stock levels, minimize waste, and improve customer satisfaction** because products are available when customers want them. The **efficiency** gained from machine learning not only cuts down on operational costs but also frees up staff to focus on customer service and other areas of improvement.

From the era of traditional approach,
what are the advancements that aid the Machine Learning?



DATA

Massive amount of data that has patterns and that leads to lot of discovery

STORAGE

Technologies to store and quickly retrieve the massive data from anywhere in the universe

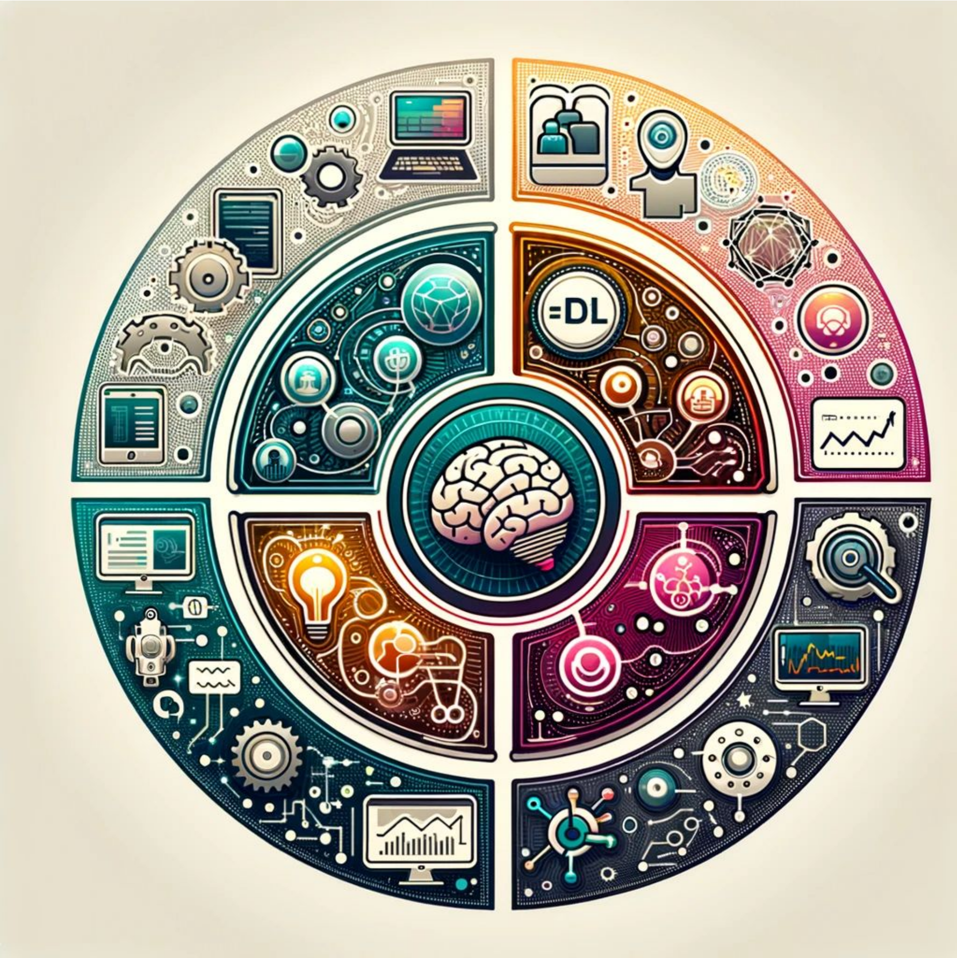
TECHNOLOGY

High processing power units (GPU, TPU) that enabled the data processing, programming as more efficient and quick turnaround

ALGORITHMS

Evolution in Data, Storage, Technology fosters the innovation

AI Vs ML Vs DL *and the new kid*



The hierarchy can be visualized as:

- AI (Largest Circle): All encompassing, covering any technique that enables computers to mimic human behavior.
- ML (Within AI): A type of AI that enables a system to learn from data rather than through explicit programming.
- DL (Within ML): A specialized ML technique dealing with deep neural networks.

ML is AI, not all AI is ML.

Similarly, all DL is ML, but not all ML is DL.

The progression from AI to ML to DL represents a move from broad, rule-based intelligent systems to more specific, data-driven learning systems, and then to even more refined, deep neural network-based learning.

Applications of Machine Learning


Smart Car
Canerera Recommentions
Swartphore
Smathare Warencies
Healthcare Wearbple


SELES PREDICE
MACHINE LEARNING


Voice Commads
Recegnation
AI
Aumorty AI
Hacial recegetion
Recegiration

Does Machine learning is only to FIND (or) PREDICT?

Healthcare

- Diagnosis and Prognosis: Machine learning models can analyze medical images (like X-rays, MRIs) to detect diseases like cancer, pneumonia, or brain tumors. They can also predict disease progression and patient outcomes.
- Drug Discovery and Development: ML algorithms help in identifying potential drug candidates and in optimizing the drug development process.

Finance

- Fraud Detection: Machine learning is used to detect unusual patterns indicating fraudulent transactions in banking and finance.
- Algorithmic Trading: ML algorithms can analyze market data to make automated trading decisions based on patterns and trends.

Retail and E-Commerce

- Recommendation Systems: Machine learning powers recommendation engines used by companies like Amazon and Netflix to suggest products or movies to users.
- Inventory Management: Predictive analytics help in forecasting demand and optimizing stock levels.

Manufacturing

- Predictive Maintenance: Machine learning models predict when equipment needs maintenance, reducing downtime and saving costs.
- Quality Control: Automated inspection systems use ML to identify defects or anomalies in products.

Autonomous Vehicles

- Navigation and Control: Machine learning algorithms help self-driving cars interpret sensor data to make real-time navigation decisions.
- Traffic Analysis and Management: Analyzing traffic patterns to optimize routes and reduce congestion.

Energy Sector

- Smart Grid Management: Machine learning aids in optimizing energy distribution and predicting energy demand.
- Renewable Energy Optimization: Algorithms predict wind or solar energy generation to optimize their integration into the power grid.

Environmental Monitoring

- Climate Modeling: Machine learning helps in predicting climate changes and extreme weather events.
- Wildlife Conservation: Analyzing satellite images and sensor data for monitoring wildlife populations and habitats.

Education

- Personalized Learning: Adapting learning content and approaches to individual student needs and learning styles.
- Grading and Assessment: Automating the grading of standardized tests or essays.

Agriculture

- Crop Monitoring and Analysis: Using satellite images and sensors to monitor crop health, predict yields, and optimize farming practices.
- Pest and Disease Detection: Identifying potential outbreaks of pests or diseases in crops.

Art and Entertainment

- Music and Art Generation: Creating new pieces of art or music through generative algorithms.
- Game Development: Enhancing gaming experiences by adapting game difficulty or storyline based on player behavior.

Space Exploration

- Rover Navigation and Control: On Mars or other celestial bodies, ML is used for navigation and data collection.
- Astronomical Data Analysis: Analyzing vast amounts of data from telescopes to identify celestial objects and phenomena.

Law and Public Policy

- Predictive Policing: Using historical data to predict areas and times with high crime risk.
- Policy Analysis: Simulating and predicting the effects of policy decisions.

Cybersecurity

- Intrusion Detection Systems: Identifying unusual network activity that could indicate a cyber attack.
- Malware Analysis: Automatically identifying and categorizing malware samples.

Yes, the new kid

Generative AI

Generative AI

Generative AI refers to a **category of artificial intelligence** that can generate new content, often mimicking human-like creativity. This content can include **text, images, music, and even code**.

The AI systems behind generative AI are typically trained on **large datasets** and use sophisticated algorithms to create output that is similar in style or content to their training data.

Large Language Models (LLM)

A Large Language Model (LLM), is a type of artificial intelligence (or) Generative AI model designed to understand, generate and sometimes translate human language. These models are "large" both in terms of the size of their neural network and the amount of data they have been trained on. Key characteristics include:

Neural Network Architecture: LLMs are typically built using a variant of the transformer architecture, which excels in handling sequential data like text.

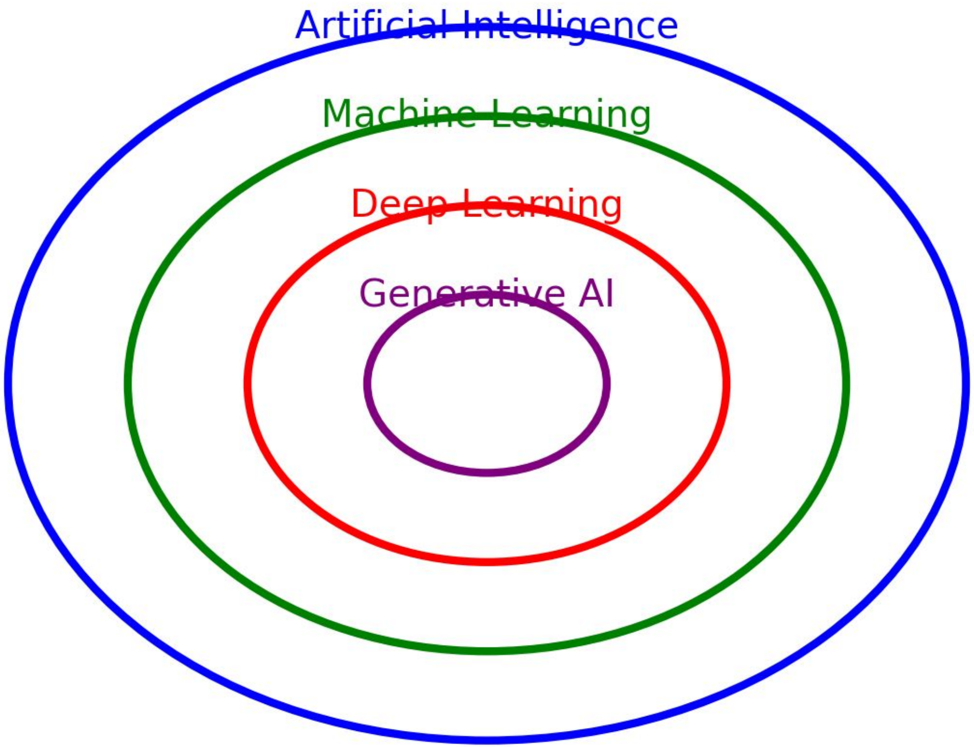
Training Data: They are trained on vast datasets comprising text from books, articles, websites, and other written sources. This training enables them to understand and generate language in a way that is often contextually relevant and syntactically correct.

Capabilities: LLMs are capable of performing a variety of language-related tasks, such as text completion, question answering, text summarization, translation, and even creative writing. They can also assist in more specialized tasks like coding, data analysis, and educational tutoring.

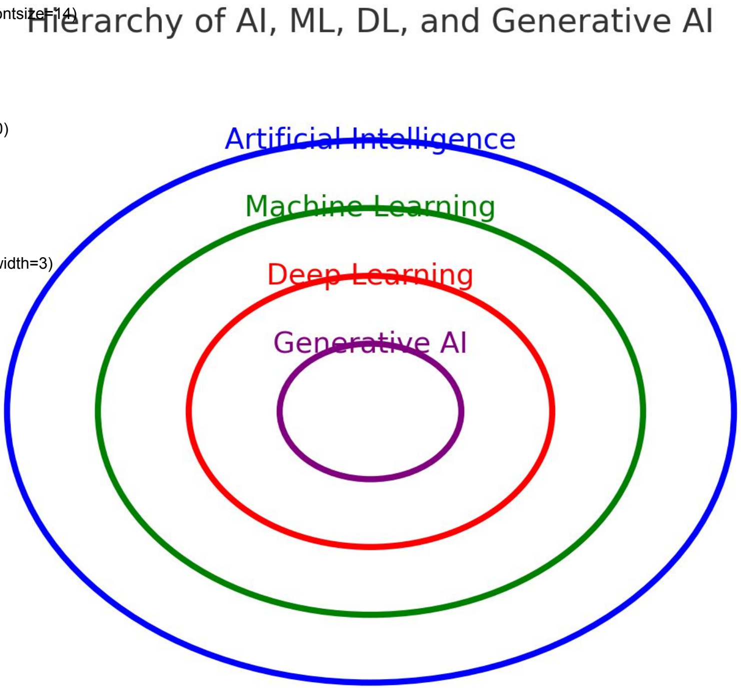
Challenges and Limitations: While powerful, LLMs have limitations. They can sometimes generate incorrect or nonsensical responses, they may perpetuate biases present in their training data, and they lack true understanding or consciousness.

Applications: These models are used in a wide range of applications, from chatbots and virtual assistants to tools for writers, researchers, and software developers.Examples: Some well-known LLMs include OpenAI's GPT series (like this one, GPT-4), Google's BERT and T5, and Facebook's BART and RoBERTa.

Hierarchy of AI, ML, DL, and Generative AI



```
import numpy as np

# Function to add curved text
def add_curved_text(text, center, radius, angle, color):
    theta = np.radians(angle)
    x = center[0] + radius * np.cos(theta)
    y = center[1] + radius * np.sin(theta)
    ax.text(x, y, text, rotation=angle-90, color=color, ha='center', va='center', fontsize=14)

# Create figure and axis
fig, ax = plt.subplots(figsize=(8, 6))

# Set the title and background color
ax.set_title('Hierarchy of AI, ML, DL, and Generative AI', fontsize=16, pad=20)
fig.patch.set_facecolor('white')

# Define circles
circle_ai = plt.Circle((0.5, 0.5), 0.4, color='blue', fill=False, linewidth=3)
circle_ml = plt.Circle((0.5, 0.5), 0.3, color='green', fill=False, linewidth=3)
circle_dl = plt.Circle((0.5, 0.5), 0.2, color='red', fill=False, linewidth=3)
circle_generative_ai = plt.Circle((0.5, 0.5), 0.1, color='purple', fill=False, linewidth=3)

# Add circles to the plot
ax.add_artist(circle_ai)
ax.add_artist(circle_ml)
ax.add_artist(circle_dl)
ax.add_artist(circle_generative_ai)

# Add curved text labels
add_curved_text('Artificial Intelligence', (0.5, 0.5), 0.4, 90, 'blue')
add_curved_text('Machine Learning', (0.5, 0.5), 0.3, 90, 'green')
add_curved_text('Deep Learning', (0.5, 0.5), 0.2, 90, 'red')
add_curved_text('Generative AI', (0.5, 0.5), 0.1, 90, 'purple')

# Remove axis and adjust plot limits
ax.set_axis_off()
ax.set_xlim(0, 1)
ax.set_ylim(0, 1)

plt.show()
```




Story2

Mysteries of the Menu - A Chef’s puzzle

Machine Learning Types

Supervised Learning:
Think of supervised learning as a cooking class where the instructor provides a detailed recipe for the students to follow. **Each recipe clearly lists the ingredients and the steps required to make a specific dish. T**he instructor also shows a picture of what the finished dish should look like.

In machine learning, this is akin to having a labeled dataset where the model is trained on both the input data and the output it should predict, much like following a recipe to get a specific dish.

Semi-supervised Learning:
In this scenario, students are given a recipe with the list of ingredients **but only a few steps are described**. They need to use their prior knowledge and intuition to fill in the missing steps and complete the dish.

Similarly, in semi-supervised learning, the algorithm is trained on a dataset that includes both labeled and unlabeled data, helping improve learning accuracy with less than complete information.

Unsupervised Learning:
Imagine a mystery box cooking challenge. Chefs are given a box of ingredients **without any recipe or picture of the final dish**. They must rely on their experience and creativity to combine the ingredients in a way that makes a delicious dish.

In unsupervised learning, the algorithm is given data without any labels or instructions and must find patterns and relationships within the data itself to form conclusions or groupings, like clustering similar ingredients to decide which ones might go well together.

Learning Type	Use Case	Description
Supervised Learning	**Email Spam Detection**	A model is trained on labeled emails to classify them as spam or not spam based on content and sender.
	Credit Scoring	Financial institutions use past loan data to predict creditworthiness of applicants.
	Medical Diagnosis	Machine learning models predict diseases based on symptoms and test results.
Semi-Supervised Learning	**Language Translation**	Models are trained on a limited set of labeled data and then apply this learning to translate new languages.
	Image Recognition with Limited Labels	Training on a small set of labeled images, then applying the model to a larger set of unlabeled images.
	Content Categorization	With a small set of labeled documents, categorize a large volume of similar documents.
Unsupervised Learning	**Market Segmentation**	Identifying different customer groups for targeted marketing based on buying patterns and preferences.
	Anomaly Detection in Network Security	Identifying unusual patterns or anomalies in network traffic that could indicate security threats.
	Recommendation Systems	E-commerce platforms use customer browsing and purchasing history to recommend products.

In supervised learning, the model is trained on a labeled dataset, where each instance of the data is paired with the correct answer or outcome. Let's delve into how each of these use cases applies supervised learning:

1. Email Spam Detection

- Data: A collection of emails that have been labeled as "spam" or "not spam."
- Supervised Learning Process:
  - The model is trained on this labeled dataset, learning to identify features of emails that are typically associated with spam, such as certain keywords, sender's email address, the presence of attachments, etc.
  - The algorithm uses this training to build a model that can predict whether a new, unseen email is spam or not.
- Outcome: When a new email arrives, the model can classify it as spam or not based on the features it learned during training.

2. Credit Scoring

- Data: Historical data of borrowers which includes their credit history, repayment history, income, debts, and whether they defaulted or were consistent in repayments (labeled as “good credit” or “bad credit”).
- Supervised Learning Process:
  - The model is trained to understand the patterns and characteristics of borrowers who have either defaulted or successfully paid back loans.
  - It learns to associate certain features (like income level, debt-to-income ratio, etc.) with the likelihood of defaulting on a loan.
- Outcome: The model can then predict the creditworthiness of new loan applicants, helping financial institutions make informed lending decisions.

3. Medical Diagnosis

- Data: Patient data, including symptoms, test results, medical histories, and the diagnosis (e.g., type of disease).
- Supervised Learning Process:
  - The model is trained on this dataset, learning to correlate specific symptoms, test results, and medical history with certain diagnoses.
  - It identifies patterns and relationships that are indicative of various medical conditions.
- Outcome: For new patients, the model can assist healthcare professionals in diagnosing diseases based on the learned patterns.

Semi-supervised learning is a machine learning approach that combines a small amount of labeled data with a large amount of unlabeled data during training. This approach is particularly useful when acquiring labeled data is expensive or time-consuming, but there is an abundance of unlabeled data. Let's explore how semi-supervised learning applies to language translation, image recognition with limited labels, and content categorization:

1. Language Translation

- Data: A small set of texts where each sentence or phrase is translated between two languages (labeled data), along with a large corpus of text in each language that isn't translated (unlabeled data).
- Semi-Supervised Learning Process:
    - The model initially learns from the small set of translated texts, grasping basic grammar and vocabulary correspondences between the two languages.
    - It then uses this understanding to make sense of the larger corpus of unlabeled text, refining its understanding of the languages' structures and nuances.
- Outcome: The model becomes capable of translating new texts between the languages more accurately, even though it was initially trained with a limited amount of direct translation examples.

2. Image Recognition with Limited Labels

- Data: A small set of images where each is labeled with the correct category (e.g., cats, dogs, cars) and a much larger set of unlabeled images.
- Semi-Supervised Learning Process:
    - The model learns to recognize and categorize images from the small labeled dataset.
    - It then applies and refines this learning on the larger dataset of unlabeled images, improving its ability to identify and categorize images based on the learned features.
- Outcome: Enhanced accuracy in recognizing and categorizing new images, even though the model had limited labeled examples to start with.

3. Content Categorization

- Data: A small number of documents or articles that have been categorized (e.g., sports, politics, technology) and a large volume of uncategorized documents.
- Semi-Supervised Learning Process:

In unsupervised learning, the data used to train models does not come with predefined labels or specific outcomes. The algorithm tries to identify patterns and relationships in the data on its own. Let's break down how this applies to the use cases you mentioned: buying patterns, network traffic, and purchasing history.

1. Buying Patterns (Market Segmentation)

- Data: Customer transaction histories, browsing behaviors, demographic information.
- Unsupervised Learning: The algorithm groups customers into segments based on similarities in their data. These similarities are not predefined but are identified by the algorithm based on patterns such as frequency of purchases, average spending, types of products bought, etc.
- Outcome: Distinct customer segments that businesses can target with tailored marketing strategies. This segmentation is not based on any labeled outcome but on the natural clustering of customer behaviors and characteristics.

2. Network Traffic (Anomaly Detection)

- Data: Logs of network activity, including details like IP addresses, time stamps, data volume, type of traffic, etc.
- Unsupervised Learning: The algorithm learns what 'normal' network traffic looks like and then identifies anomalies or deviations from this norm. It does this without prior knowledge of what constitutes a security threat or an anomaly; it simply looks for patterns that differ significantly from the established baseline.
- Outcome: Identification of potential security threats or issues like data breaches, malware, or other cyber attacks, based on unusual traffic patterns.

3. Purchasing History (Recommendation Systems)

- Data: Historical data on customer purchases, browsing history, product ratings, etc.
- Unsupervised Learning: Algorithms like collaborative filtering identify products that similar customers have liked or bought and recommend them to others. These recommendations are not based on explicit labels but on the patterns and relationships the algorithm finds in the data – such as correlations between products or similarities in customer preferences.
- Outcome: Personalized product recommendations that can improve customer experience and increase sales.

In each case, the unsupervised learning approach is key because it discovers hidden structures or patterns in the data without relying on predefined categories or labels. This makes it particularly useful for exploring and understanding complex datasets where the relationships or anomalies are not initially


STORY 3

The Orchard and The Sun

Once upon a time, in a land filled with rolling hills and lush orchards, there was a curious farmer named Ada. Ada loved her apple orchard, but she always wondered how much sunlight each tree needed to produce the juiciest apples.

One spring, Ada decided to conduct an experiment. She measured how many hours of sunlight each of her apple trees received daily. Then, in the fall, she carefully counted the number of apples each tree produced.

Using a large parchment, Ada plotted a graph. Each point on this graph represented a tree, with its sunlight hours on one axis and the number of apples on the other. Ada noticed a pattern: trees that received more sunlight tended to produce more apples. This relationship wasn't perfect—some trees with lots of sunlight didn't produce as many apples as expected, and some with less sunlight produced more. But overall, the trend was clear.

Ada realized she could predict the apple yield of a tree based on how much sunlight it got. She drew a straight line through her points on the graph, trying to keep the line as close to all the points as possible. This line was her model, and the slope of the line represented how apple production increased with sunlight. The intercept of the line indicated how many apples a tree might produce with no sunlight at all—a theoretical starting point.

What Ada had created was a linear regression model. By extending her line, she could estimate the apple production of a tree that wasn't in her original experiment. Ada's neighbors were amazed. They used her model to predict their own apple yields, adjusting for differences in their orchards.

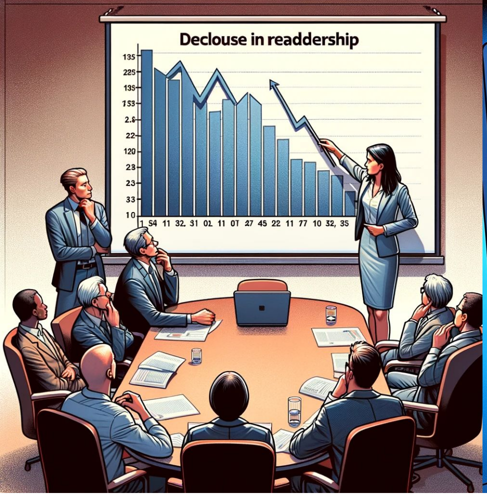
The story of Ada's orchard teaches us about linear regression. It's a way to understand and predict relationships between variables. Ada's sunlight and apple counts were her data, the plotted points her observations, and the line she drew was her regression model. It wasn't perfect—nature is full of surprises—but it was a powerful tool for making informed predictions. And so, Ada's orchard thrived, guided by the light of her knowledge and the warmth of the sun.

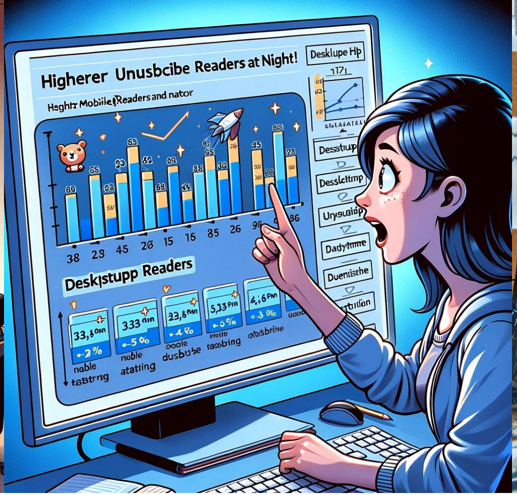
[Link to Notebook]


STORY 4

The Mysterious Case of Disappearing Readers

(Logistics Regression)

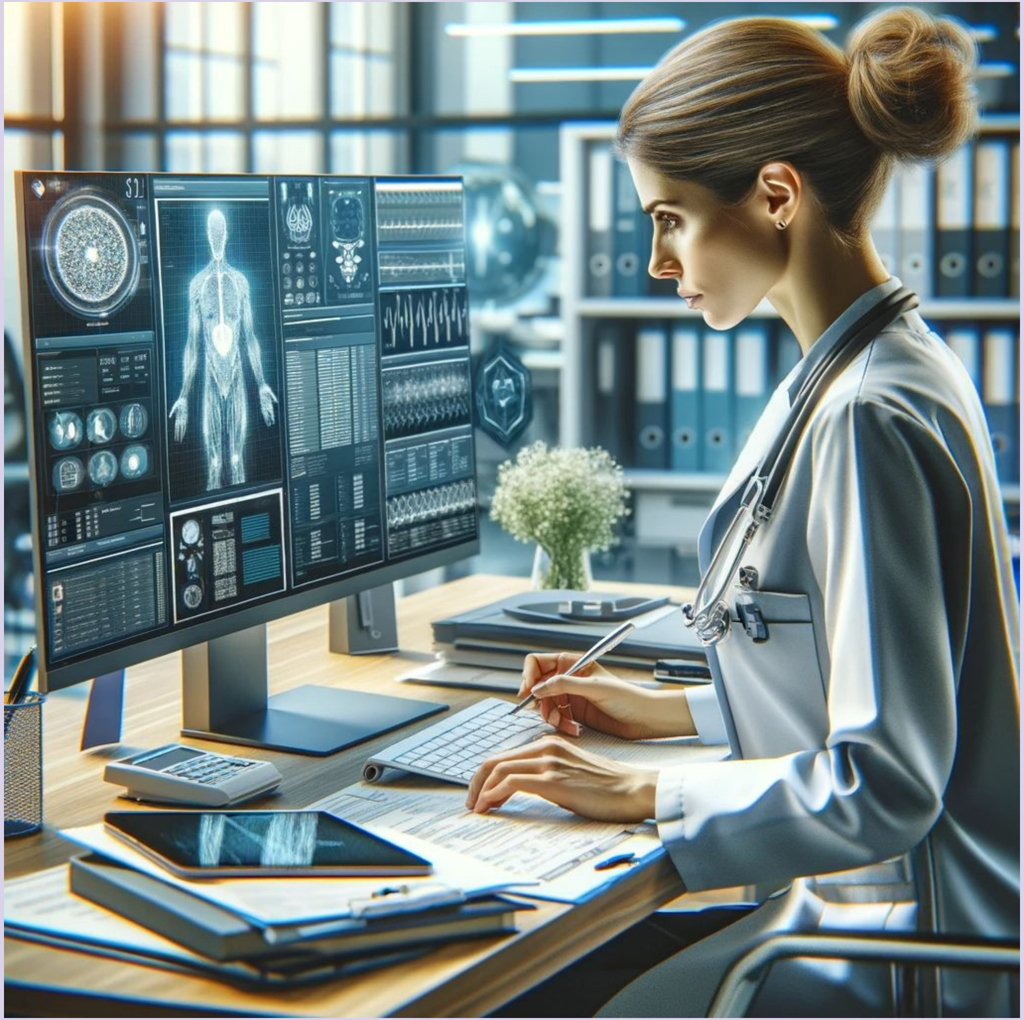




There is a decline in Magazine readership. Firm's Data Scientist Ellen scans the readership data to find any pattern behind this decline and found that the readers who read with Dark Mode is the major population there. On validating the product feature it was found that in dark mode, text is blurred and causes eye strain to the readers. Issue was fixed. Next month Sales report has a reason to celebrate


[Link to Notebook]


SSTORLE
STORY
5



Navigating Complex Symptoms:
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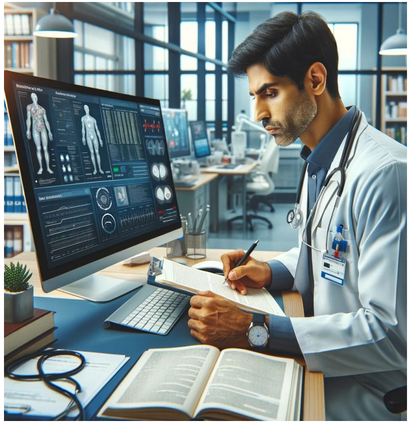

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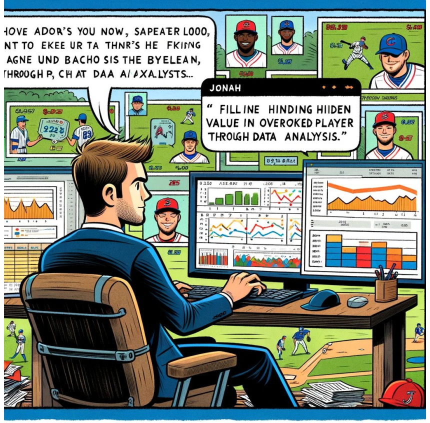
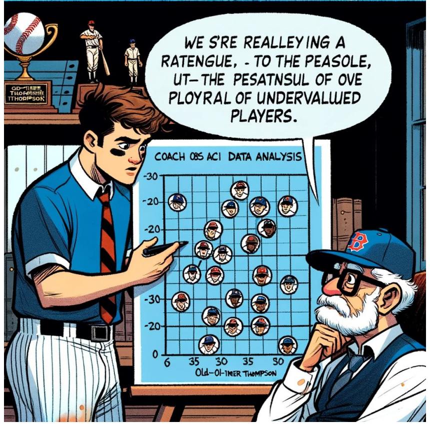
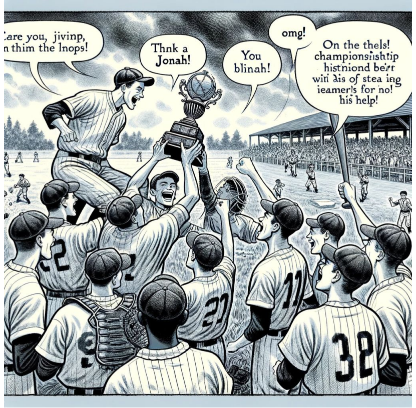
STORY 6


ITCHFORD PIONOEER
PRINEBALT
PISEBALL







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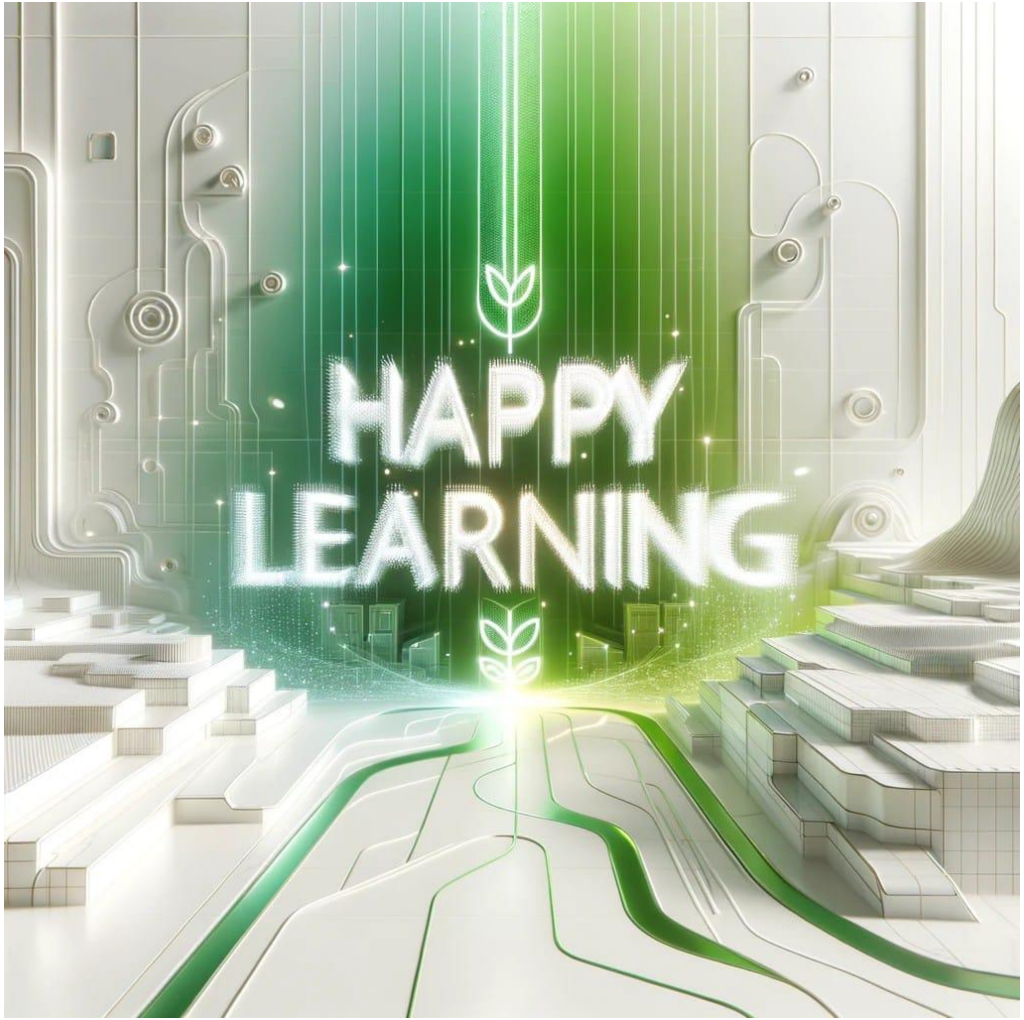
HAPPY
LEARNING