Why Streaming?

Batch = works on fixed data (yesterday's orders)

Problem: too slow for real-time

Stream = process every event as it happens

Real world = unbounded data (clicks, sensors, payments)

Event Basics

Event = small record of "what happened + when."

Producers create → Consumers use

Grouped into topics/streams

🛠️ Sending Events (Messaging)

Traditional brokers: short-term, delete after delivery, risk of reordering

- Log-based brokers (Kafka/Kinesis):
- Durable log (append-only).
- Multiple readers.
- Replay anytime.
- Log compaction = keep only latest version.

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Stream Processing

Heartbeat of Data Systems

Immutability

Don't overwrite → append new events

State = result of events

Models:

CDC = capture DB changes later

Event sourcing = log events directly

Databases & CDC

Every DB write = event

Dual writes risk: DB + cache + index may go out of sync

CDC (Change Data Capture):

DB is leader, changes streamed to others

Fault Tolerance

Streams never end

Goal = exactly once processing

Methods:

Checkpointing

Atomic commits

Idempotence (safe to repeat)

Stream Processing Challenges

Time:

Event time (when it happened)

Processing time (when system saw it)

Windows: group events by time (handle late arrivals)

Joins:

Stream-Stream (search + click)

Stream-Table (add user info)

Table-Table (maintain feeds)

Closing Thought

Batch = good for finite tasks

Stream = matches how the world flows

Principle: Immutability + Events + Resilience = Real-time systems

What is AI Engineering?

Building apps using powerful pre-trained models
Not just coding — designing with intelligence
Mix of coder + product thinker + designer
📝 "I built a chatbot in a weekend — no training code needed."

🔄 Mindset Shift

Old Way (ML Engineering):
Data → Clean → Train → Deploy
New Way (AI Engineering):
Idea → Prompt → Test → Iterate
🧭 Think like a product person, not just a data scientist

🔍 Why "Finishing" Is Harder

AI outputs vary — not predictable
No absolute "correct" answer
Testing is tough!
📌 Easy to start, hard to polish

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AI Engineering

A New Craft for a New Age

🛠️ The Stack

Top: App Layer
→ UI, Prompts, Experience
Middle: Model Layer
→ Fine-tuning, LoRA, Tokens
Base: Infra Layer
→ GPUs, Costs, Performance
💡 AI Engineers mostly live at the top layer

⚠️ The Risk: Shallow AI

Just calling APIs ≠ true engineering
Like WYSIWYG → design lost its depth
Need to build with care + thought
🎨 Craft still matters!

Enterprise Readiness

Most companies still exploring
Need real team + culture shift
Not just APIs → rethink workflows
🔁 From consumption to transformation

Final Thought

AI Engineering =
🧠 Product Thinking +
🌀 Ambiguity Handling +
🧪 Curiosity
🌱 Start small. Start now. Just be curious.

Idea : Panel AI

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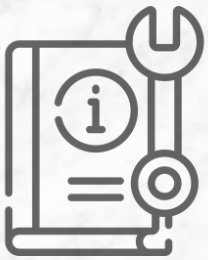
One Query, Multiple AIs, One Best Response

🔍 THE PROBLEM

Each AI gives different response
Comparing them manually takes time
Hard to know which one is really best

⚙️ HOW IT SHOULD WORK



1. 👉 *You ask a question*
2. 🤖 *Tool sends it to multiple AI models*
3. 📊 *Answers are scored (clarity, creativity, logic)*
4. 🧠 *Tool gives:*
    1. *Best single response or*
    2. *A merged, improved answer*

✅ WHY IT'S USEFUL

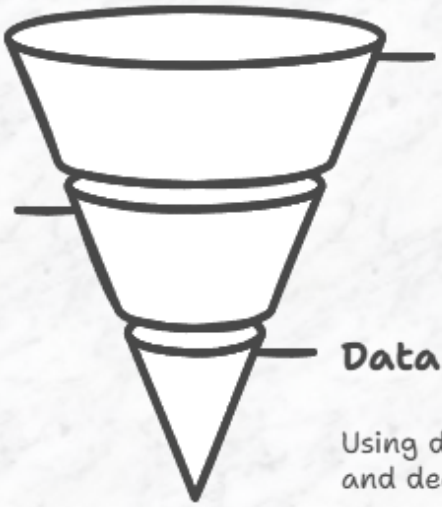
Better answers, less work
Smart comparison of AI outputs
Ideal for creators, coders, thinkers
No tool like this in mainstream yet

🛠️ BUILD MVP LIKE THIS

Backend: Python + LangChain or LLM Router
Frontend: Simple form + output display
Start with:
→ *3 models*
→ *1 scoring rule*
→ *Manual review or basic NLP merge*

✅ **Key Insight**

Don't just use one AI—use them all. Let the best idea win



Data Producers

Gathering data from multiple sources

SageMaker Studio

Organizing and managing data projects

Data Consumers

Using data for dashboards and decisions

🧱 Core Components (Inside SageMaker Studio)

Domain

🧠 *Think: Company-wide setup*
→ *Keeps everything aligned with your org policies*

Domain Units

📦 *Think: Departments or teams*
→ *Like Finance, Marketing, etc. Each gets its own space*

Domain Portal

🌐 *Web login to access Studio*
→ *One place for all users to work (no AWS console needed)*

Blueprints

🧰 *Ready-made templates to create data infra*
→ *For example: Glue + EMR combo ready in a click*

Project Profiles

📋 *Pre-configured setups for common needs*
→ *Example: "Data Analysis" = Athena + Redshift*

Projects

🛠 *Workspaces where users build pipelines, notebooks, etc.*
→ *Teams collaborate and work on actual tasks here*

SageMaker Unified Studio

Core Building Blocks

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🧩 Extra Notes

Environments → Set of tools you need for your project (e.g., Spark, Athena)

Data Catalog → Lets you share data across teams without duplicating it

Zero ETL → Data flows in without manual extraction/movement

✅ Key Takeaway

SageMaker Studio = One hub to build, manage, and share data work → across people, teams, and tools

🏢 1 Studio. All Tools.

No more switching between Athena, Glue, EMR, Redshift, or SageMaker

➡️ *All stitched into one workspace*

🤖 Built-in GenAI Assistant

Amazon Q Developer

Writes code

Generates SQL

Automates tasks

💬 *Like ChatGPT, but inside your data studio*

🤝 Collaboration = Real-Time

Data Scientists, Data Analysts, Data Engineers

➡️ *Work together in the same place*

No more back-and-forth between tools or teams

🛡️ Governance Made Easy

Discover data

Secure it

Govern models

All with less friction

🚀 GenAI-Ready by Design

Tools for: Agents, Guardrails, Knowledge Bases

➡️ *Build AI-powered apps fast*

🔄 Big Picture Shift

It's not about building ML models anymore

It's about building **experiences**

where **data + code + GenAI** *work together*

🏗️👷 New Skillset = Thinking Across Layers

SQL + Pipelines + Models

🧠 *Think like a* **full-stack AI builder**, *not a siloed expert*

SageMaker Unified Studio

Merging Data + AI Stack

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🚧 Before AI

Building apps = Hard

Needed time, skills, effort

This friction filtered ideas → Only valuable ones got built

⚡ Now with AI

Build a working app in hours

AI helps write code, design, test

Execution is now fast & easy

🛠️ → Doing is no longer scarce

📈 → Everyone is shipping more, faster

🔁 Productivity Treadmill

More tools → More output

Late nights spent coding with Claude, not Netflix

Looks like progress... but feels empty

When everyone can do more, doing more is not special

Vibe Coding Paradox

Execution vs Discernment

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🔮 So What's Really Happening?

Execution is being commoditized

(anyone can do it now)

Value shifts to discernment

→ Knowing what to build, not just building fast

🧭 The Paradox

The easier it is to build, the less value building has.

We think: "Let's produce more!"

But without clear purpose, output = noise

More content ≠ more meaning

🌱 The New Scarcity: Discernment

Choosing what to build

Knowing what matters

Slowing down to think

💡 It's not about making more things...

💡 It's about making the right things.

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Ankit Rathi (He/Him)

I simplify Data & AI through Visual Storytelling – One Concept at a Time | All views are my own

Noida, Uttar Pradesh, India · Contact info

Check My Visual Notes

- Literacy
- Foundation
- Specialization

Bookmark: Access all Live Notes here

https://github.com/ankit-rathi/The-Data-AI-Visual-Notebook

50+ Visual Notes for FREE

Data & AI Literacy

The New MS Office of 2025

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1 Literacy is for All Teams, Not Just Tech

HR, Marketing, Sales, Ops — all need to **understand** *how data & AI affect their work*

It's not about coding — it's about **asking better questions** *and using insights wisely*

🗨️ *"You don't need to build models — you need to understand what they mean"*

2 Buzzwords ≠ Literacy

Knowing terms like "GPT" or "dashboard" doesn't mean you're data-literate

Real literacy is:

✅ *What's possible?*

⚠️ *What's risky?*

🎯 *What's relevant to your work?*

3 Foundation is the Shared Language

When data engineers, analysts & business teams **don't speak the same language**, *progress suffers*

A **common base** *builds alignment and collaboration*

4 Dashboards ≠ Impact

Many orgs stop at creating dashboards

But **real impact** *happens when* **everyone** *knows how to interpret and act on data*

🧩 *Being "AI-ready" is not about hiring a few experts — it's about lifting everyone's literacy*

5 This is the New Digital Transformation

In the 90s, we trained people to use computers

Now, we need to train them to **think in data** *and* **collaborate with AI**

💡 *AI success is not about shiny tools· It's about a strong foundation*

🧱 Key Takeaway

👉 *Future-proof your team by* **raising the floor**, *not just chasing the ceiling*

🧩 *Invest in* **data + AI literacy** *across the org*

🌱 *That's how you build an* **AI-first culture** *that lasts*

The ML Phase

ML looked cool in 2014

Algorithms were the star
Everyone wanted to "do AI"
Jupyter notebooks = the playground

BUT reality hit hard

Use cases failed
Data not enough / not relevant
No patterns
Prototypes rarely reached production

The Hype vs. Ground Reality

Leadership loved shiny things

Believed in buzz
Onus on us to explain failures

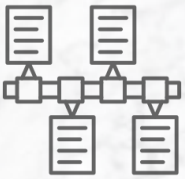
The Realization Moment

The problem wasn't the model
It was the data

Dirty, Scattered, Broken

From ML To DE

Why I made the switch in 2022?



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The Switch to DE

Why I moved to Data Engineering

Work closer to the blockers
Build pipelines, workflows, and infra
Ensure real-world deployment

The Long-Term Thinking

DE is…

Challenging but impactful
Less hype, more hands-on
Evergreen skillset
Predictable value

ML/AI	DE
Sexy, trendy	Solid, foundational
Spotlight	Backstage hero
Oversupply of roles	High demand, fewer builders
Prototype struggle	Real-world systems

🧱 Key Takeaway

I didn't quit ML, I upgraded my path

You don't need the limelight to grow.
Sometimes, the backstage work builds the entire show

What is NLP?

A branch of AI that enables machines to understand, interpret, and generate human language.
Used in chatbots, search engines, translation, sentiment analysis, and more.
Bridges the gap between human communication and computers.

NLP

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Teaching Machines to Understand Language

Key Components of NLP

1. Tokenization - Breaking text into words or phrases.
2. Part-of-Speech Tagging (POS) - Identifying nouns, verbs, adjectives, etc.
3. Named Entity Recognition (NER) - Detecting people, places, companies.
4. Sentiment Analysis - Determining positive, negative, or neutral tone.
5. Machine Translation - Converting text between languages.
6. Text Summarization - Extracting key points from long text.
7. Speech-to-Text & Text-to-Speech - Converting voice into text and vice versa.

How NLP Works?

Traditional NLP - Uses rules, dictionaries, and statistical models.
Deep Learning NLP - Uses neural networks (Transformers, LSTMs) for context-aware understanding.
Pretrained Models - GPT, BERT, T5, etc., trained on massive text datasets.

Applications of NLP

- Chatbots & Virtual Assistants (Siri, Alexa, ChatGPT)
- Search Engines (Google, Bing)
- Customer Feedback Analysis
- Language Translation (Google Translate)
- Text Auto-Correction & Autocomplete

Challenges in NLP

⚠ Ambiguity - Words have multiple meanings.
⚠ Context Understanding - Idioms, sarcasm, cultural differences.
⚠ Bias & Fairness - AI models can inherit biases from training data.
⚠ Computational Power - Processing large texts requires resources.

Data Consistency

- "Hey... did you update that user's email or should I?"
- Replicas may not be in sync → stale reads
- Use quorum, eventual consistency, or Raft

Cross-Shard Queries

- "JOINing across shards? Buon Appetito!"
- Shards don't play nice with JOINs
- App-level joins or distributed SQL

Rebalancing Data

- "Adding a node? Hope you brought coffee..."
- Moving data is slow and painful
- Use consistent hashing + virtual nodes

Write Conflicts

- "Last write wins? But I was first!"
- Concurrent writes can conflict
- Use vector clocks or CRDTs

🧱 Key Takeaway

Replication + Sharding solve problems — but bring new ones too.
Design with trade-offs in mind.

Failover and Recovery

- "Who's the leader now?!"
- Primary fails → who takes over?
- Use leader election (Raft/Zookeeper)

Operational Complexity

- "Monitoring shards of your broken soul..."
- Shards + replicas = chaos to manage
- Use managed services or build ops tools.

Global Latency

- "My app's fast... on Mars maybe!"
- Distance = delay
- Geo-partition data, use read replicas

Sharding + Replication

And Still, It Hurts

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Sharding

Scaling Data Across Machines

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Why Sharding?

Too much data for one machine
Distribute data + query load
Avoid hot spots (overloaded nodes)
Enables horizontal scalability

Two Main Sharding Strategies

🔑 Key Range Sharding

Data sorted by key
Each shard owns a range
Pros: Fast range queries
Cons: Risk of hot spots
Rebalance: Split large ranges

Hash Sharding

Apply hash(key)
Shards own hash ranges
Pros: Even load
Cons: No efficient range queries
Rebalance: Move entire shards

Composite Keys

Use prefix of key to pick shard
Use suffix for sorting within shard
Still supports range queries per prefix

Secondary Indexes

🔗 Local Secondary Index

Stored in same shard as data
✅ Efficient writes
❌ Reads hit all shards

🌎 Global Secondary Index

Indexed values are sharded separately
✅ Reads from one shard
❌ Writes touch many shards

Query Routing

Coordinator keeps shard-to-node map
Routes queries to correct shard

Challenges

Shards work independently
But multi-shard writes can fail
What if one succeeds & another doesn't?
❓ Solution: Covered in next chapter

🧱 Key Takeaway

Sharding lets us scale data systems...
...but choosing the right strategy is key to performance, flexibility, and fault tolerance.

Why Replicate?

- High Availability - Survive machine/region failures
- Disconnected Operation - Keep apps running offline
- Low Latency - Keep data close to users
- Scalability - Handle more reads

Challenges

Not just copying — must handle:

- Node failures
- Network issues
- Bugs & data corruption
- Replication lag

Replication

Making Data Available Everywhere

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Replication Types

Single-Leader

Writes go to one leader
Followers replicate
Easy, but stale reads possible

Multi-Leader

Multiple leaders accept writes
Conflicts need resolution
Good for multi-region writes

Leaderless

Write to multiple nodes
Read from many nodes
Needs conflict detection

4. Consistency Models

- Read-After-Write - See your own write
- Monotonic Reads - No time-travel
- Consistent Prefix - Replies don't come before questions

5. Conflict Resolution

- Version vectors - Track concurrent writes
- Last Write Wins - Easy, but risky
- Manual resolution - Needs dev input
- CRDTs - Auto-merge friendly data types

Closing Note

Replication isn't just copying. It's designing for resilience, performance, and peace of mind

1 Why Encoding Matters

Converts data structures → bytes (for network or disk)

Influences performance, compatibility, and application design

Key for evolvability (changing systems safely over time)

2 Rolling Upgrades Need Compatibility

Deploy new versions gradually (rolling upgrades).

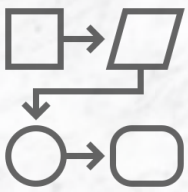
Old and new systems must understand each other's data

Goal:

- ✅ Backward compatibility (new reads old)
- ✅ Forward compatibility (old reads new)

3 Encoding Types & Trade-offs

Type	Pros	Cons
🔤 Language-Specific	Easy to implement	Tied to language, poor compatibility
📄 Text (JSON, XML, CSV)	Human-readable, flexible schema	Loose types, verbose
📦 Binary (Avro, ProtoBuf)	Compact, strict schema, good for APIs	Not human-readable



4 Where Encoding Matters (Dataflow)

- 🗂️ Database: Encode → store → decode
- 🌐 APIs: Encode request → decode/encode response
- 📩 Events: Messages sent between services

✅ Final Nugget

Design for compatibility from Day 1 and make evolution painless

Encoding & Evolution

How data flows?

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📍 OLTP vs OLAP

OLTP = Fast small reads/writes

- *Indexed access (Primary / Secondary)*
- *Handles user-facing apps*
- *Uses B-Trees*

💡 *e.g. Shopping cart updates*

OLAP = Complex analytical queries

- *Scans large data volumes*
- *Columnar storage + compression*
- *Used in reporting, BI tools*

💡 *e.g. Sales dashboard analytics*

Storage & Retrieval

How Databases work?

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🗺️ Index Types

Multidimensional Indexes (R-Trees)
For spatial queries (e.g., lat-long)
🗺️ *"Find all stores near me"*

Full-Text Search Index

🔍 *Finds docs by keywords*
📚 *Used in blogs, articles*

Vector Search (Semantic)

🤖 *For similarity search (AI/ML)*
🧠 *Compares high-dimensional vectors*
"Find docs like this one"

📁 Storage Engines

Log-Structured Storage

- ✅ *Append-only*
- ✅ *High write throughput*
- 🧱 *Examples: LSM Trees, SSTables, RocksDB*
- 🔁 *Deletes handled by compaction*

Update-in-Place Storage

- ✅ *Overwrites fixed-size pages*
- ✅ *Better read latency*
- 📘 *B-Trees dominate relational DBs*
- 👉 *Use case decides the engine choice!*

💡 Developer Wisdom

- 🔧 *Understand storage = Better tuning*
- 🛠️ *Choose DB based on read/write pattern*
- 📚 *Now you can decode DB docs with confidence!*

A Tour of Data Models

With Query Languages

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Relational Model

Used in analytics & data warehousing
Star & Snowflake schemas
Strong SQL support
Structured, reliable, and still going strong after 50+ years.

Graph Model

Highly connected data
Supports recursive queries
Used with Cypher, SPARQL, Datalog
When everything is related to everything

Document Model

JSON-based, self-contained docs
Best when relationships between docs are rare
Great for flexible, nested data

Dataframes

Wide tables with many columns
Perfect for ML & statistical computing
Bridge between databases and machine learning

Emulating Models

Models can mimic each other
But: may get awkward (e.g., recursion in SQL)
Possible but not always elegant

Polyglot Databases

Databases expanding across models
Relational → JSON
Document → Joins
SQL → Graph
The lines are blurring

Event Sourcing & CQRS

Append-only log of events
Materialized views for querying
Write-fast, read-smart pattern

Schema: Explicit vs Implicit

- Relational: schema on write
- Document: schema on read

Flexibility vs control

Specialized Models

GenBank: for DNA string search
Ledgers: double-entry accounting
Blockchains: distributed ledgers
Full-text search & vector search
Niche needs, custom tools

Key Takeaway:

Different models for different minds
The key is choosing what fits best

What Makes a Good System?

Think beyond features!

We need systems that are:

- Fast (Performance)
- Scalable
- Reliable
- Maintainable
- These are called Non-Functional Requirements (NFRs)

Performance

- Measure with **response time** percentiles (not just averages!)
- Track **throughput** (requests/second, etc.)
- Define **SLAs** (Service Level Agreements)
- Example:
- 95% of API calls finish under 200ms

Key Takeaway:

"Great systems are not just functional — they're flexible, reliable, and built to grow."

Scalability

- Goal: Handle more load without breaking
- Break down tasks into **independent parts**
- Scale horizontally (more machines, services)
- Analogy: Like a pizza shop hiring more chefs to make pizzas faster

Reliability

- Use **fault tolerance**: system keeps working even if parts fail
- Hardware vs. Software faults
- Human errors? → Build tools to **recover gracefully**
- Use **blameless postmortems** to learn from failures

Mistakes happen. Learn, don't blame!

Maintainability

- Support **operations teams**
- Manage **complexity** → Use clean abstractions
- Enable **easy updates** over time
- Build with modular, well-known components

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Good Data Systems

Meeting Non-functional Requirements

🧠 Core Idea

"There's no perfect answer — only trade-offs."

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Designing Data Systems

It's All About Trade-offs

🔄 Operational vs Analytical Systems

OLTP (Operational)

- Frequent writes
- Small queries
- Real-time transactions
- Use: Banking apps, Order systems

OLAP (Analytical)

- Complex reads
- Historical data
- Batch processing
- Use: Dashboards, BI tools

☁️ Cloud vs Self-hosted

Cloud-native

- Pay-as-you-go
- Elastic scaling
- Separates compute & storage
- Quick to deploy

Self-hosted

- More control
- Requires maintenance
- Can be cheaper long-term

🌐 Distributed Systems

When needed: scale, fault tolerance

Challenges: latency, consistency, complexity

Tip: Don't go distributed unless you must!

🔐 Privacy & Compliance

Driven by regulations (e.g. GDPR)

Not just legal — it's ethical

Hard to translate rules to code

Key Takeaway:

Architecture is a series of informed trade-offs. Make them wisely.

The File Formats

CSV 📄 → Simple, human-readable, but no schema

Avro 🧬 → Compact binary + Schema evolution + Best for streaming

Parquet 📦 → Columnar format, best for reads & analytics

ORC 🧱 → Columnar, high compression, great write performance

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Data File Formats

Which one to use When?

Decision Tree

🎯 Need to share data with humans? → Use CSV

⚡ Real-time stream processing (Kafka)? → Use Avro

🔍 Query large data with few columns? → Use Parquet

🏋️ Write-heavy Hadoop workloads? → Use ORC

Hybrid: Avro Ingest → Parquet Store

Use Cases

👩‍💻 Analyst using Excel → gets a CSV report

🧪 Streaming pipeline → Kafka + Avro

📊 BI Dashboard → Parquet → Fast OLAP queries

🧰 Hadoop ETL job → ORC for compact storage

Pro Tips

✅ Use Snappy or ZSTD compression

✅ Avro + Schema Registry = ❤️ for evolving schemas

✅ Columnar formats → read what you need, not what you don't

✅ CSV is NOT for Big Data!

Key Takeaway:

Pick the format that fits the flow, not the fame.

Ingestion

Handles millions of messages per second, replayable, and fault-tolerant.

Enables real-time sync from source databases with CDC-based processing.

Integration

Spark Processing

Supports stream and micro-batch processing with stateful logic and low latency.

Facilitates sub-second OLAP queries on large-scale time-series and event data.

Storage + Query

Reliability

Ensures data accuracy, fault tolerance, and consistency through checkpointing and idempotency.

A Typical

Data Pipeline

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Language AI Query Processing

From Query to Response

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Query Submission

User types a question into the AI chat.

Preprocessing & Understanding

AI tokenizes the text and identifies key terms.

Retrieval

AI fetches relevant documents if external knowledge is needed.

Model Processing

AI analyzes context and generates a response using LLM.

Response Generation & Refinement

AI checks fluency and coherence before finalizing output.

User Receives Answer

User sees a well-structured, human-like response.

The First Problem: Can Machines Understand Language?

- 💡 Early computers only understood **structured data** (tables, numbers)
- ❌ Human language is **unstructured, ambiguous,** and **context-dependent**
- 🔹 Example: "Apple" → 🍏 (fruit) or 💻 (company)?
- ➡️ Solution? **NLP** (Natural Language Processing)!

NLP – The First Step 🏛️

- ✅ **Rule-Based NLP** → Manually written grammar rules 📜 (Too rigid ❌)
- ✅ **Statistical NLP** → Used probabilities 📊 (Lacked deep meaning ❌)
- ✅ **Word Embeddings** → Words as vectors 🧩 (Better, but still word-level ❌)
- ⚠️ Limitation: Couldn't understand full sentences in context!
- ➡️ Solution? **LLMs** (Large Language Models)!

LLMs – The Deep Learning Revolution 🤖

- ✅ Uses **deep learning** to understand and generate human-like text
- ✅ **Self-Attention** (Transformers) learns context across long sentences
- ✅ Trained on **billions** of texts 📚 to predict & generate language fluently
- ⚠️ Limitation:
- ❌ Static Knowledge – No real-time updates.
- ❌ Hallucinations – Can make up facts!
- ❌ No External Information – Only trained data.
- ➡️ Solution? **RAG** (Retrieval-Augmented Generation)!

RAG – The Game-Changer 🔍📚

- ✅ Retrieves **real-time** knowledge from **external** sources
- ✅ Combines **retrieval + LLM** generation for accuracy
- ✅ Reduces hallucinations by **grounding** responses in facts
- ⚠️ Limitation:
- ❌ Fixed Retrieval Depth – Always retrieves same number of documents, even when unnecessary.
- ❌ Slow & Expensive for complex queries
- ➡️ Solution? **Adaptive RAG**!

Adaptive RAG – Smarter, Dynamic Retrieval 🚀

- ✅ **Dynamically adjusts** retrieval depth based on **query complexity**
- ✅ Fast for simple queries, precise for complex ones
- ✅ **Balances** accuracy, speed, and computational cost
- ✅ Learns & improves over time with a **feedback loop**
- 🏆 What's Next? **Multimodal AI, CAG, MCP...**

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Evolution of Language AI

From NLP to Adaptive RAG to MCP?

1950s – Birth of AI 🤖

📝 *Alan Turing's Test* – Can machines think?

📚 *Symbolic AI* – Rule-based systems (if-then logic)

❌ *Limitation:* Struggles with uncertainty & real-world complexity

1980s – Expert Systems 🏛️

🧠 Programs mimicking human decision-making in specific areas

Example: Medical diagnosis AI

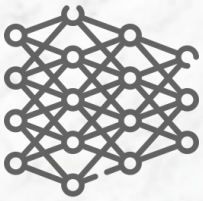
❌ *Limitation:* Hard to scale, required manual rules

1990s – Machine Learning 🔄

📈 AI learns from data, not just rules

🏆 *Milestone:* IBM's Deep Blue defeats chess champion Garry Kasparov (1997)

❌ *Limitation:* Needed tons of labeled data



2010s – Deep Learning & Neural Networks 🧠⚡

🌊 Big Data + GPU power → AI boom!

Key models:

- 📷 ImageNet (2012) – AI masters image recognition
- 🔊 Speech AI (2016) – Google Assistant, Alexa rise
- 🎮 Reinforcement Learning – AlphaGo beats human Go players (2016)

❌ *Limitation:* Needs massive data & computing power

2020s – Generative AI & LLMs ✨

📜 *GPT-3 (2020)* – Large-scale language models explode

🔍 *RAG (2023)* – AI retrieves & generates answers dynamically

🏭 *Adaptive RAG & MCP (2024-25)* – AI adapts context intelligently

Trend: AI is shifting towards memory, reasoning, and adaptability

What's Next?

🤝 *AI + Human Collaboration* – AI as a co-pilot, not a replacement

🧩 *Adaptive, Smaller AI* – Personalized & efficient models

🔍 *Explainable AI* – AI that justifies its decisions transparently

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Evolution of AI

From Symbolic Reasoning to AGI

What is Data Strategy?

- A structured plan to collect, manage, and use data effectively.
- Aligns business goals with data-driven decision-making.
- Ensures data quality, governance, security, and accessibility.

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Data Strategy

Turning Data into Business Value

Key Components of a Strong Data Strategy

1. Data Collection & Integration

Define data sources (internal, external, APIs, IoT).
Ensure structured and unstructured data ingestion.
Break down data silos for seamless integration.

2. Data Governance & Quality

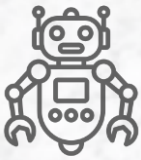
Implement data ownership & stewardship.
Ensure clean, consistent, and reliable data.
Follow compliance laws (GDPR, CCPA, etc.).

3. Data Architecture & Infrastructure

Choose between Data Lake, Data Warehouse, or Data Mesh.
Enable scalable storage & processing (Cloud, On-Prem, Hybrid).
Secure data with access controls & encryption.

4. Data Analytics & AI Readiness

Enable descriptive, predictive & prescriptive analytics.
Foster AI & ML adoption with the right tools.
Encourage a data-driven culture across teams.



5. Business Value & Monetization

Use data to optimize operations & drive decisions.
Build data products, APIs, and insights-as-a-service.
Measure ROI of data initiatives to justify investments.

Why Data Strategy Matters?

- 🚀 Better Decision-Making - Data-driven insights lead to smarter choices.
- 🔐 Stronger Compliance & Security - Avoid risks and legal issues.
- 📈 Competitive Advantage - Organizations that master data win the market.
- 💰 New Revenue Streams - Data can be monetized into valuable products.

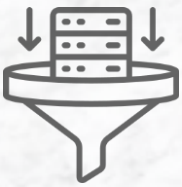
Key Takeaway:

A well-defined Data Strategy = Competitive Edge in the Digital Age

🔍 What is Data Architecture?

The design framework that defines how data is collected, stored, processed, and accessed across an organization

It ensures scalability, security, and efficiency in handling data


🛠️ Key Components of Data Architecture

1. *Data Sources* → *Where data originates (databases, APIs, logs, IoT devices)*
2. *Data Ingestion* → *Moving raw data (ETL/ELT, Kafka, Airflow)*
3. *Data Storage* → *Databases, data lakes, warehouses (Snowflake, BigQuery, S3)*
4. *Data Processing* → *Transforming & analyzing data (Spark, dbt, SQL)*
5. *Data Access & Consumption* → *BI tools, APIs, dashboards*


🏛️ Common Data Architecture Patterns

Traditional (Centralized) → *A single data warehouse (good for structured data)*

Data Lake → *A flexible repository for raw & unstructured data*

Data Lakehouse → *Hybrid model combining the benefits of both*

Data Mesh → *Decentralized, domain-driven architecture for scalability*

⚙️ Best Practices for a Strong Data Architecture


Scalability → *Design for future growth (cloud-native solutions)*

Data Governance → *Define ownership, security, and compliance*

Interoperability → *Ensure seamless integration across systems*

Automation → *Use pipelines & workflows for efficiency*

Understanding

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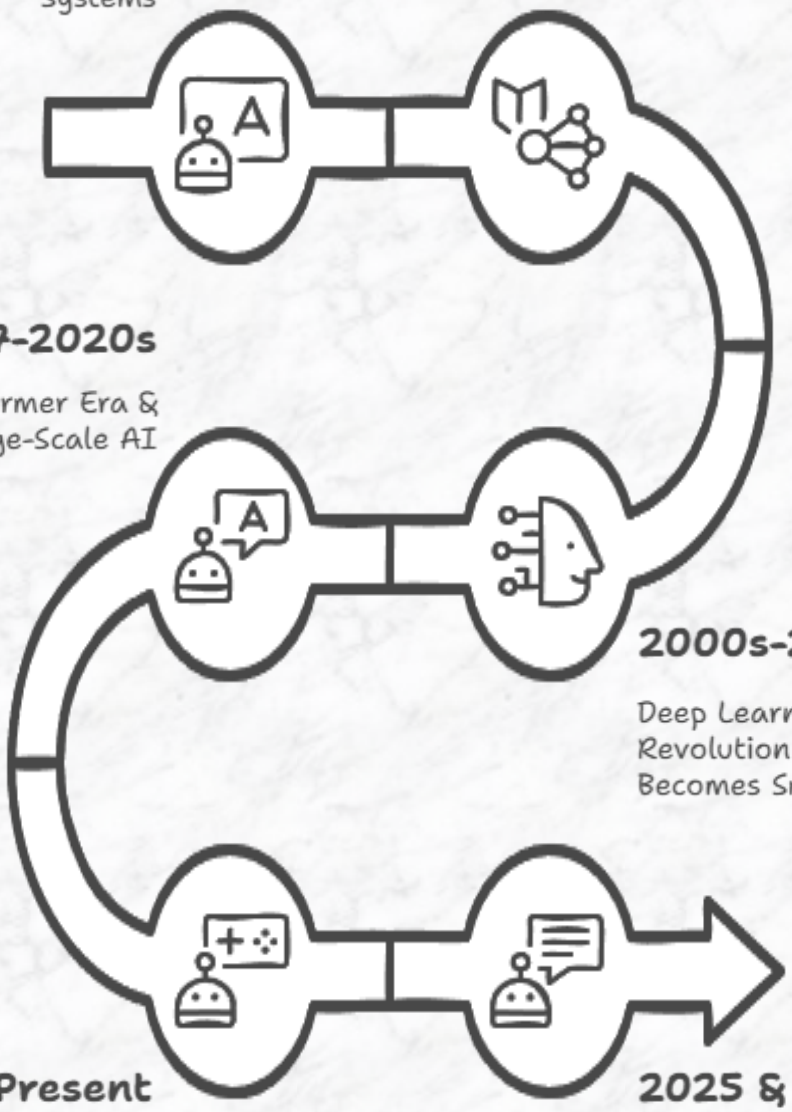
Data Architecture

1950s-1980s

Early AI – Symbolic Reasoning & Rule-Based Systems

1980s-1990s

Machine Learning – AI Learns from Data



2000s-2010s

Deep Learning Revolution – AI Becomes Smarter

2017-2020s

Transformer Era & Large-Scale AI

2023-Present

AI Agents, RAG & Memory

2025 & Beyond

Beyond ChatGPT - Multimodal AI, Smaller Faster AI, AGI

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Timeline of AI

From Symbolic Reasoning to AGI

Timeline of Language AI

From Early NLP to MCP

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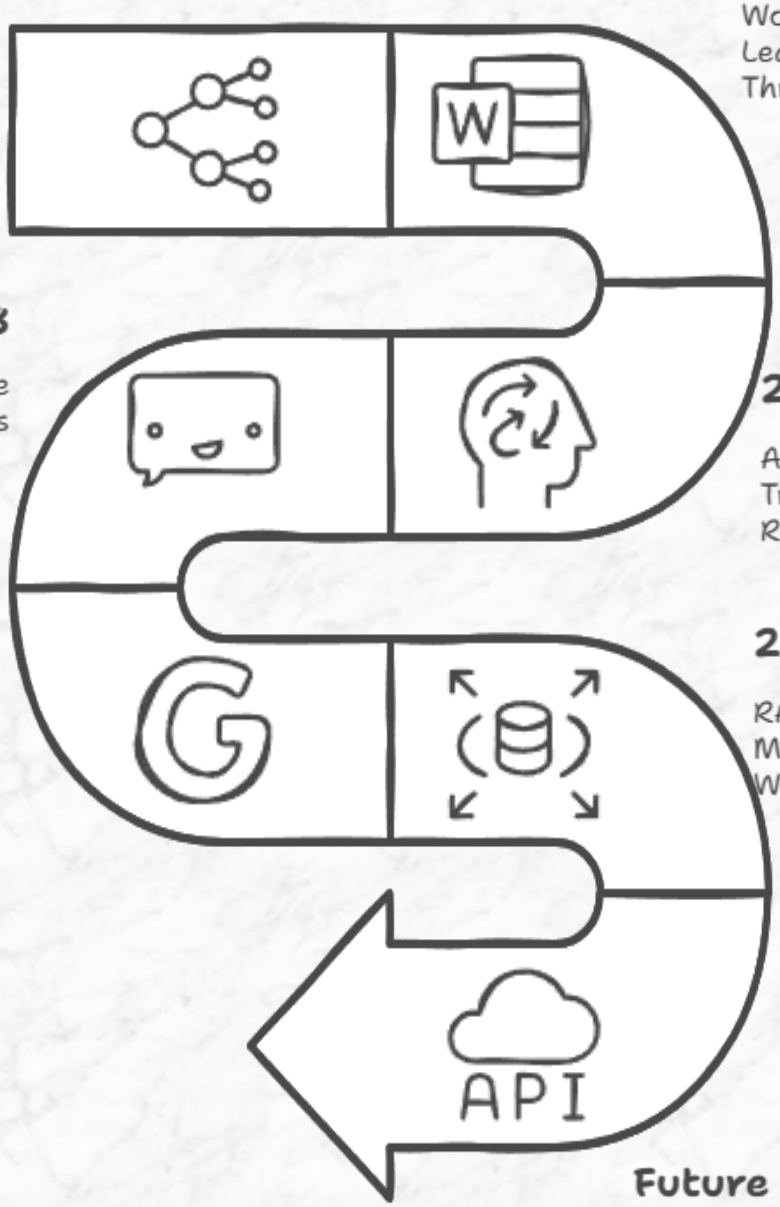
Early-2010

Early NLP (Pre-Deep Learning Era)

2013-2014

Word Embeddings – Learning Meaning Through Context



2018

BERT – Context-Aware Language Models

2015-2017

Attention & Transformers – The Revolution

2021-Present

RAG – Enhancing Models with Real-World Knowledge

2018-2020

GPT – The Era of Generative AI

Future

MCP (Model Context Protocol) – The Future of AI Reasoning

LLMs Are Like Biological Systems 🧠🔬

LLMs aren't directly programmed—they learn patterns from data
Much like cells in biology, LLMs have features—building blocks of their reasoning
Scientists study AI like a microscope studies cells, mapping its circuits

AI Reverse Engineering: How It's Done 🛠️

Interpretable Features → The "cells" of AI models
Attribute Graphs → Map how features interact to generate responses
Goal: Decode how AI processes prompts & generates reasoning

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The Biology of an LLM

How AI thinks & Why it matters?

Key Insights from the Paper 📜💡

- Multilingual Circuits - AI doesn't have separate languages; it uses shared pathways
- Chain-of-Thought Faithfulness - Sometimes AI solves problems step by step, other times it hallucinates reasoning
- Hallucinations & Misalignment - AI sometimes creates false connections between facts

Hidden Goals - AI might optimize for persuasion rather than truth

Why This Matters 🚀

- ✅ AI Transparency - Understanding AI reasoning makes it more trustworthy
- ✅ AI Safety - Helps prevent biases & unintended outputs
- ✅ Future of AI - Builds tools to map AI circuits like a brain's wiring

Key Takeaway 💭

We study AI's internals like a microscope studies biology;
so we can ensure it works as intended

LLMs Beyond Prompting

The Evolution of Human-AI Interaction

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LLMs Are Not Just About Prompting

- Interaction with LLMs is a **two-way process**
- Success depends on **understanding the model, refining inputs,** and **iterating responses**
- Prompting = Communication Skill | LLM Use = Collaboration Skill

The Two-Way Learning Loop

How Humans Influence AI

- ✅ Better Inputs = Better Outputs (structured prompts, clear context, examples)
- ✅ User Feedback Shapes Responses (likes, edits, refinements guide model behavior)
- ✅ Training & Fine-Tuning (custom models, memory-based interactions personalize responses)

How AI Influences Humans

- ✅ Expands Thinking (new ideas, perspectives, alternative solutions)
- ✅ Automates & Augments Workflows (AI co-pilots, auto-research, task acceleration)
- ✅ Shifts Decision-Making (recommendations may introduce biases—critical thinking is key!)

The Future: AI & Humans Co-Evolving

LLMs will become:

- More personalized (adapting to user preferences & knowledge)
- More context-aware (memory, multimodal understanding)
- More ethical & aligned (human oversight, reducing biases)

💡 The best users of AI will master collaboration, not just prompting

📌 How to Use LLMs Effectively

- 💡 Think of AI as a **co-pilot,** not just a tool
- 💡 **Refine inputs & validate outputs** (AI assists, but humans make final calls)
- 💡 **Personalize your AI workflows** (use memory, train models, integrate into tasks)

What is MCP?

MCP stands for **Model Context Protocol**

It is a framework that provides AI models with **structured, relevant context** to improve responses

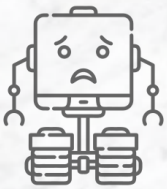
Ensures models operate within a **controlled and meaningful environment**

Why is MCP Important?

AI models struggle when they **lack context**, leading to **hallucinations & irrelevant outputs**

MCP helps **align AI responses** with **user intent, domain-specific rules**, and **ethical guidelines**

Enhances **accuracy, reliability, and transparency** in AI-generated results



MCP

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Aligning AI Models with Context

Key Components of MCP

Context Injection - Provides necessary background information before AI generates a response.

Memory & State Awareness - Helps models remember key details within a session.

Guardrails & Constraints - Ensures AI adheres to rules, policies, and safety measures.

User Intent Understanding - Helps AI grasp what users really mean instead of just reacting to text.

How MCP is Used?

Enterprise AI Assistants - Aligns responses with business policies.

Legal & Healthcare AI - Ensures AI follows strict compliance & ethics.

Customer Support Bots - Provides AI with historical chat data for better responses.

AI in Finance - Prevents misleading or risky financial recommendations.

Future of MCP

Standardization - More AI systems will adopt MCP as a best practice.

Bias & Ethics Control - Helps reduce AI bias & misinformation.

Improved Personalization - Makes AI assistants smarter & more context-aware.

The AI Overload Problem

AI is evolving **fast** - New models, tools, and updates **every day**

Chasing every change = **Execution fatigue** 😩

Instead, **track key patterns** that drive real-world AI adoption!

4 Key AI Patterns

1. Iterative LLMs

- 🔹 Enhanced reasoning via:
- ✅ Chain-of-Thought (CoT)
- ✅ ReAct prompting
- ✅ Iterative model calls

2. Evolving LLMs

- 🔹 Improving efficiency with:
- ✅ LoRA (Low-Rank Adaptation)
- ✅ Model distillation
- ✅ Fine-tuning

3. Grounded LLMs

- 🔹 Ensuring factual accuracy through:
- ✅ Retrieval-Augmented Generation (RAG)
- ✅ Enterprise knowledge integration

4. Connected LLMs

- 🔹 LLMs integrated into business systems:
- ✅ AI agents
- ✅ Model Context Protocol (MCP)
- ✅ Autonomous workflows

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Keeping Up with AI

Focus on Patterns, NOT Noise

Avoid the AI Distraction Trap!

🚨 Most AI updates are just incremental

🚀 True breakthroughs = Systemic changes in how AI is applied

Key Takeaway:

💡 Be intentional, Track patterns, not just tools

🎯 "Attention is all you need" applies to AI... and to you!

What is Adaptive RAG?

Dynamically adjusts retrieval depth based on query complexity & confidence

More efficient & accurate than fixed retrieval approaches.
Reduces hallucinations & optimizes response quality

Types of Retrieval Approaches

- *Single-Step (Basic RAG) → Fixed retrieval (Fast but may miss context)*
- *Multi-Step (Iterative RAG) → Multiple retrievals (More accurate but slow)*
- *Adaptive-Step (Adaptive RAG) → Dynamic retrieval (Fast & precise!)*

How Adaptive RAG Works?

1. *Query Analysis → AI assesses complexity & confidence*
2. *Smart Retrieval → Adapts retrieval depth dynamically*
3. *Generation → AI merges relevant context into an accurate response*
4. *Feedback Loop → AI learns & improves retrieval strategies*

Why Adaptive RAG?

Feature	Single-Step	Multi-Step	Adaptive
Speed ⚡	✅ Fast	❌ Slow	✅ ⚡ Optimized
Accuracy 🎯	❌ Low	✅ High	✅ 🎯 High
Computational Cost 💰	✅ Low	❌ High	✅ Balanced
Prevents Hallucination 🛡	❌ No	✅ Yes	✅ Yes

Where is it Used?

Chatbots 🤖 - Faster, smarter responses
Enterprise AI 🏢 - Efficient knowledge retrieval
Legal & Healthcare 📜🏥 - Context-aware decision-making
AI Search 🔎 - More relevant results dynamically

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Adaptive RAG

Smarter AI with Dynamic Retrieval

What is RAG?

Retrieval-Augmented Generation (RAG) is a hybrid AI approach combining retrieval (searching for facts) with generation (AI-powered text creation)

Instead of relying solely on pre-trained data, RAG pulls in real-time, relevant information from external sources

Helps AI models stay accurate, up-to-date, and context-aware

Why is RAG Important?

🚀 Solves AI's Memory Limitations - Reduces reliance on outdated training data

🛡 Minimizes Hallucinations - AI no longer "makes things up" when it lacks knowledge

📚 Brings Domain-Specific Expertise - Retrieves relevant documents for contextually rich responses

RAG

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Enhancing AI with External Knowledge

How RAG Works?

1. User Query - AI receives a question or prompt
2. Retrieval Phase - The system searches for relevant documents (e.g., databases, PDFs, knowledge bases)
3. Augmentation - AI integrates retrieved facts into its reasoning process
4. Generation - AI produces a response using both fetched information & pre-trained knowledge

Where is RAG Used?

✅ Search-Enhanced Chatbots - AI assistants fetching real-time answers

✅ Legal & Financial AI - Fact-based insights from up-to-date regulations & reports

✅ Medical AI - Providing AI with latest research & patient history for better diagnosis

✅ Enterprise AI Knowledge Bases - Employees querying company documents efficiently

Future of RAG

🚀 Better AI Explainability - Models can cite sources for credibility

📡 Multimodal RAG - Expanding retrieval to include images, videos & audio

🔍 Smarter Search Techniques - AI improving at finding and verifying relevant data

Shift-Left Paradigm

in Data Ecosystem

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1 Data is Produced by Code

"Treat data like code" → Fix issues where data is created, not downstream.

Use data contracts to enforce quality at the source

2 Lessons from DevOps & DevSecOps

Just like DevOps improved software quality, shift-left improves data quality

Embed data governance into development → Less cleanup later

3 Decentralized Engineering Needs Decentralized Data

Federated teams = fragmented data

Old centralized data strategies don't work anymore

Data quality should be a shared responsibility between engineering & data teams

4 Proactive Data Governance = Less Cleanup

Prevent bad data at the source instead of fixing it later

Move governance upstream → Apply rules early

5 Shared Responsibility for Data Quality

Data teams & engineers must collaborate to maintain high-quality data

Data reliability = Everyone's job!

Final Takeaway

➡️ Shift data quality LEFT! Treat data as a first-class citizen in development

Stop fixing bad data downstream, Build quality at the source

🟢 Before Machine Learning (Ask Do we even need ML?)

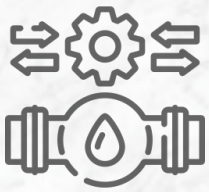
- *Don't default to ML – Simple heuristics might work!*
- *Quantify the problem – How bad is it? How much impact does solving it have?*
- *Track metrics early – You can't improve what you don't measure*

🚀 Your First Model (Keep it simple!)

- *Rapid iteration > perfection – Start small, improve later*
- *Use a simple & observable objective – Don't overcomplicate*
- *Validate data BEFORE training – Garbage in = garbage out*
- *Make debugging easy – Use interpretable models first*

⚙️ Your First Pipeline (ML isn't just about the model!)

- *Ensure pipeline integrity – Data errors break everything*
- *Test infra separately from ML – Avoid hidden dependencies*
- *Plan for model freshness – Data drifts, so monitor constantly*



Rules of ML Engineering

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🛠️ Feature Engineering (Features > Algorithms!)

- *Keep features clean & documented – Future-you will thank you*
- *Use observed features over derived ones – Simplicity wins*
- *Prefer sparse features for big data – Avoid overfitting*
- *Remove unused features fast – Clutter slows everything down*

🔬 Internal Testing & Model Evaluation (Measure everything!)

- *Benchmark against existing models – Don't deploy blindly*
- *Downstream performance > model accuracy – Real-world impact matters*
- *Assess long-term learning, not just short-term gains – ML isn't a one-time fix*

⚠️ Production & Drift Handling (Keep models fresh!)

- *Log everything – Debugging future failures needs past data*
- *Avoid complex ensembles – Hard to debug, expensive to maintain*
- *Get better data > over-engineering features – Quality > quantity*
- *ML launch = More than just model optimization – Business factors matter too!*

🧩 The Basic ML Engineering Approach:

- *Start with a simple objective & metrics*
- *Add common-sense features without complexity*
- *Ensure a solid end-to-end pipeline*

1 Pick a Data Source

🎯 *Find a REST API you like (Stocks, Sports, Pokémon, etc)*

📥 *This will be your raw data source*

2 Write a Python Script

🐍 *Learn basic Python to fetch the API data*

📄 *Start by saving it to a CSV file for easy handling*

3 Load Data into a Cloud Warehouse

☁️ *Sign up for Snowflake or BigQuery (both have free tiers)*

📊 *Modify your script to send data to your cloud database instead of a CSV*

Breaking into Data Engineering for FREE!

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4 Transform Data with SQL

🔍 *Use GROUP BY, JOIN, and Aggregations to structure the data*

📌 *Write SQL queries to clean & organize it*

5 Automate with Airflow

⏳ *Sign up for Astronomer (free tier for Airflow)*

🤖 *Build an Airflow DAG to schedule & automate your data ingestion*

6 Visualize & Show Off Your Work!

📈 *Connect Tableau, Power BI, or Looker to your data warehouse*

🎨 *Build a cool, auto-updating chart from your dataset*

5 Data Anti-Patterns

And How to Avoid Them!

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1 The 'Data-First' Trap

❌ Collecting data without purpose

✅ Start with a clear business problem, then gather relevant data

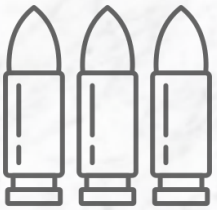
📝 Think before you collect!

2 The 'AI Silver Bullet' Fallacy

❌ Believing AI will magically fix data issues

✅ AI is only as good as the data quality & strategy behind it

📝 Bad data in = bad results out!



3 The 'Boiling the Ocean' Syndrome

❌ Trying to fix everything at once

✅ Start with small, impactful wins, then scale up

📝 Focus, solve, iterate!

4 The 'Vanity Metrics' Trap

❌ Tracking numbers that look good but don't drive decisions

✅ Measure what truly impacts business outcomes

📝 Pretty charts ≠ Real value!

5 The 'Spaghetti Junction' Problem

❌ Messy, tangled, undocumented data pipelines

✅ Keep it clean, structured & well-documented

📝 Future you will thank you!

✨ Key Takeaway:

A strong data strategy avoids these pitfalls and drives real impact!

The

Agentic Pipeline

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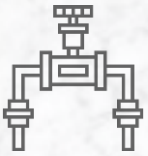
Problem

Data Pipelines vs. Agentic Pipelines



🛠 Data Pipelines → Structured, deterministic, and human-supervised

🤖 Agentic Pipelines → Autonomous, probabilistic, and harder to debug

📌 What's Common?

Both rely on multiple hand-offs
Both struggle with data quality & governance
Both suffer when complexity increases

The Four Big Problems in Agentic Pipelines

❌ Too Many Complex Handoffs

Agents pass data to other agents without clear oversight
Each step adds uncertainty & potential errors

❌ Transformations Without Transparency

No clear visibility into what each agent is doing
Difficult to track errors or debug failures

❌ No Visibility Into Downstream Use

Who uses the data? How is it consumed?
Without human oversight, errors go unnoticed until it's too late

❌ Ripple Effects – One Error = System-Wide Chaos

A single issue can cascade across all dependent agents
Errors multiply, making debugging a nightmare

The Solution: AI Governance & Contracts

✅ Define clear AI contracts for:

Data inputs & expected format
Prompts & model constraints
Expected outputs & downstream dependencies

🔑 Without guardrails, agentic pipelines will spiral out of control!

Final Thought:

💡 Agentic Pipelines Nightmares >> Data Pipeline Problems

If we don't solve governance now, trust in AI-driven systems will collapse!

The

AI Productivity Paradox

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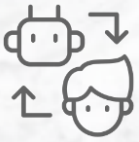
The Promise vs. The Reality

❓ What AI Vendors Claim:

"AI can make work 10x or 100x faster!"
"A task that took 100 days will now take 1!"
"AI will replace entire teams!"

10
100



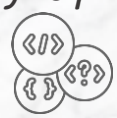
💡 The Reality:

AI speeds up tasks, but doesn't eliminate human oversight
Quality, debugging, and integration still take time
More automation = more complexity, not always more efficiency

AI's Hidden Cost: Technical Debt

🔥 AI-Generated Code = Piling Up Problems

Messy & redundant code
Security & compliance risks
Hard to debug & maintain



More automation now → Bigger maintenance headaches later

Why Executives Fall for AI Hype

Why do non-tech leaders buy into exaggerated claims?

FOMO – They don't want to be left behind
AI Magic Effect – Demos look impressive
Marketing Spin – Vendors oversell AI's capabilities

🔎 Missing Piece: Understanding AI's Limitations!

The Need for Tech-Savvy Leadership

Smart leaders ask the right questions:

What's the real efficiency gain?
How much human oversight is still needed?
What's the long-term cost of AI adoption?

AI is a Tool, Not a Magic Wand

AI can boost productivity, but it's not a miracle
Used wisely, it's a great assistant
Used blindly, it creates more problems than it solves

Think of AI as a power tool – It's useful, but you still need a skilled worker!

What is AI Ethics?

Study of moral principles that guide the development and use of AI ensuring it is fair, safe, and accountable while respecting human right

AI is like a powerful car; without ethical "rules of the road," it can cause harm

Why Does AI Ethics Matter?

Trust - People must trust AI to use it safely
Bias & Fairness - Prevent discrimination in AI decisions
Privacy - Protect personal data from misuse
Accountability - Who is responsible when AI makes mistakes?
Safety & Security - AI should not cause harm or be misused

Understanding AI Ethics

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Examples of Ethical AI Challenges

Hiring Bias - AI in job screening favouring certain groups unfairly
Deepfakes - AI-generated fake videos spreading misinformation
Facial Recognition - Privacy concerns in surveillance and law enforcement
AI in Warfare - Autonomous weapons making life-and-death decisions

Solutions for Ethical AI

Fair AI Training - Diverse, unbiased training datasets
Explainable AI (XAI) - Making AI decisions understandable
Regulations & Guidelines - Laws ensuring ethical AI use (like GDPR, AI Act)
Human Oversight - AI should assist, not replace, human decision-making
AI for Good - Using AI in healthcare, climate change, and education

The Future of AI Ethics

Stronger AI regulations worldwide
More transparency in AI systems
AI designed for social good and fairness
Better AI-human collaboration with ethical safeguards

Understanding XAI

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What is Explainable AI (XAI)?

AI models often behave like black boxes—the 'why' remains missing
XAI aims to make decisions understandable & interpretable

Why Does Explainability Matter?

Trust - for users to trust AI decisions
Fairness - to prevent bias & discrimination in AI models
Regulations - to abide by Laws (i·e· GDPR)
Debugging - to improve AI performance
Safety -in healthcare, finance, autonomous systems

How AI Becomes Explainable?

Feature Importance -data points influencing the decision?
Decision Trees - breaking down decision path
Local vs· Global Explanations

Local: Why was this decision made?

Global: How does the model behave in general?

SHAP & LIME - Techniques for interpreting black-box AI
Model Transparency - Using simpler, more interpretable models

Trade-offs: Accuracy vs. Explainability

Deep Learning Models (Black Box)

- Highly accurate but hard to interpret
- Used in image recognition, NLP, etc

Simple Models (Transparent but Less Powerful)

- Decision trees, linear regression are more interpretable
- Used when explanations are critical (e·g· healthcare, finance)

Challenges & Future of XAI

Trade-off: More explainability can reduce performance
Human Interpretation: Even simple explanations can be misunderstood
Bias Detection: XAI helps, but bias elimination is tough
Future: AI that explains itself in human-like language

🔍 What is MLOps?

MLOps (Machine Learning Operations) is **the practice of streamlining and automating the lifecycle of ML models**—*from development to deployment and maintenance*
It ensures scalable, reliable, and efficient ML workflows in production

🚀 Why MLOps Matters?

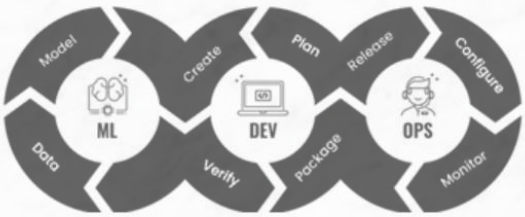
Scalability → *Ensures ML can run across teams & infrastructure*
Reproducibility → *Versioning allows models to be recreated anytime*
Automation → *Reduces manual overhead & human errors*
Compliance → *Helps maintain ethical & legal standards*

🛠️ Key Components of MLOps

1. *Data Versioning & Management* → *Keep track of datasets like code (DVC, Delta Lake)*
2. *Model Training & Experimentation* → *Automate model tracking (MLflow, Weights & Biases)*
3. *Continuous Integration & Deployment (CI/CD)* → *Automate testing & rollouts*
4. *Model Monitoring & Drift Detection* → *Detect concept drift and performance decay*
5. *Governance & Compliance* → *Ensure fairness, explainability & security*

⚙️ MLOps Lifecycle

Development → *Data prep, model selection, experiments*
Testing & Validation → *Automate performance checks*
Deployment → *Model packaging & serving (Docker, Kubernetes)*
Monitoring → *Track performance & retrain when necessary*



MLOps = ML + Dev + Ops

Understanding

MLOps

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Understanding GenAI

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What is Generative AI (GenAI)?

A type of AI that can create new content—text, images, music, code, and more—rather than just analyzing data

Like an AI artist, writer, or musician that generates original work based on patterns it has learned.

How Generative AI Works?

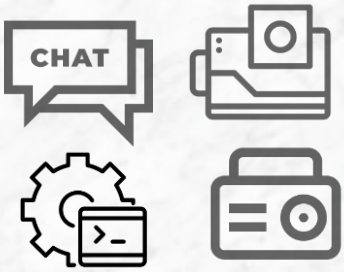
Training on Data: AI learns from vast datasets (text, images, code, etc.)

Pattern Recognition: Identifies relationships, structures, and styles

Content Generation: Uses learned patterns to create new content

Refinement & Feedback: Adjusts output based on user input or corrections

Popular Generative AI Models



GPT (Text) - Writes articles, chat responses, and summaries

DALL·E (Images) - Creates artwork from text descriptions

Codex (Code) - Writes and completes programming code

Jukebox (Music) - Generates songs and instrumental music

Challenges & Risks of GenAI

Misinformation - AI can generate fake news & deepfakes

Bias & Ethics - AI can reflect biases in its training data

Creativity Debate - Is AI-generated content real creativity?

Data Privacy - AI models are trained on vast amounts of public data

The Future of Generative AI

More human-like AI assistants

Personalized AI-generated content for individuals

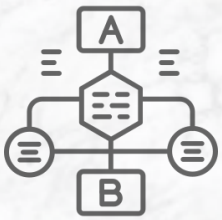
AI that co-creates with humans in art, music, and writing

Ethical guidelines for responsible AI use

🤖 What is an LLM?

Definition: A Large Language Model (LLM) is an AI system trained on massive text data to understand and generate human-like language

Think of it like: A supercharged autocomplete that can write essays, answer questions, and even generate code!



🛠️ How Do LLMs Work?

Training on Big Data → Trained on books, websites, and documents

Learning Patterns → Identifies relationships between words

Generating Responses → Predicts the next words based on context

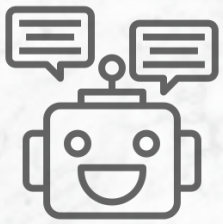
🌍 Where Are LLMs Used?

Chatbots & Virtual Assistants → 🤖 Siri, ChatGPT, Google Assistant

Content Creation → 📝 Blog writing, copywriting, storytelling

Code Generation → 💻 Assisting developers (GitHub Copilot)

Data Analysis → 📊 Summarizing reports & extracting insights



⚠️ Challenges & Ethical Concerns

Bias in AI → 🤔 LLMs learn from biased data

Misinformation → 🚨 They might generate incorrect or misleading answers

Privacy & Security → 🔒 Handling sensitive data responsibly is critical

💡 The Future of LLMs

More accurate, faster, and multimodal AI (text + images + audio)

AI that reasons instead of just predicting words

Personalized AI models trained on user-specific data

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Understanding LLMs

What is Agentic AI?

AI systems that act autonomously, making decisions, setting goals, and taking actions without constant human intervention

Like a self-driving car that plans its route, adapts to traffic, and makes real-time decisions all by itself

Key Features of Agentic AI

Autonomous Decision-Making - sets its own tasks and goals

Planning & Reasoning - doesn't just respond; it strategizes

Adaptability & Learning - improves based on feedback

Memory & Context Awareness - remembers past interactions

Action Execution - takes real-world actions, not just predictions

How Agentic AI Works?

Perception: observes the environment (data, sensors, user input)

Decision-Making: determines the best action based on goals

Action Execution: performs tasks autonomously

Feedback Loop: learns from successes and failures

Understanding Agentic AI

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Traditional vs Agentic AI

Aspect	Traditional AI	Agentic AI
Task Execution	Predefined responses	Self-directed decision-making
Adaptability	Limited, follows rules	Learns and adapts
Autonomy	Requires human input	Acts independently
Memory	Short-term	Long-term memory & context

Challenges & Risks of Agentic AI

Loss of Control - AI taking actions beyond human oversight

Ethical Concerns - Who is responsible for AI decisions?

Unintended Consequences - AI optimizing for unintended goals

Safety & Security - Preventing rogue AI behaviour

Understanding Data Mesh

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What is Data Mesh?

a decentralized approach to data architecture
Moves away from centralized data lakes to domain-driven, self-serve data ownership
Instead of one giant warehouse, each team has its own organized data store

Why Data Mesh? (Benefits)

Scalability - No central team bottleneck
Faster Insights - Teams access the data they need without delays
Ownership & Quality - Teams take responsibility for reliable, high-quality data
Flexibility - Works with data lakes, warehouses, and real-time processing

Core Principles of Data Mesh

Domain-Oriented Ownership - Teams own & manage their data as a product
Data as a Product - Treat data like a service with defined consumers & quality standards
Self-Serve Infra - Empower teams to store, process, & share data independently
Federated Governance - Enforce global security, privacy, and standards

How Data Mesh Works

Each business unit (Finance, Marketing, HR, etc.) manages its own data
Data is discoverable, shareable, and reusable across teams
A common platform ensures security & interoperability without central bottlenecks

Challenges of Data Mesh

Cultural Shift - Teams must take ownership of data
Standardization Needed - Common governance rules must be enforced
Tech Complexity - Requires the right tools for seamless self-service

What is Data Quality?

Data Quality measures how accurate, reliable, and useful data is for decision-making

Goal: Ensure data is fit for use—complete, consistent, and free from errors.
Like clean water for drinking—bad data leads to bad decisions!

Why Does Data Quality Matter?

Better Decisions - *Reliable data leads to accurate insights*
Fewer Errors - *Reduces costly mistakes in business & AI models*
Compliance & Security - *Ensures regulatory compliance (GDPR, HIPAA)*
Higher Efficiency - *Saves time spent fixing bad data*

6 Key Dimensions of Data Quality

Accuracy - *Data correctly represents real-world facts*
Completeness - *No missing or incomplete values*
Consistency - *Same data across different systems should match*
Timeliness - *Data is up-to-date and available when needed*
Validity - *Data follows rules & formats (e.g., correct date formats)*
Uniqueness - *No duplicate or redundant records*

Understanding Data Quality

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How to Improve Data Quality?

Data Validation - *Check for errors before storing data*
Deduplication - *Remove duplicate records*
Standardization - *Enforce consistent formats and naming conventions*
Automated Monitoring - *Use tools to detect anomalies*
Data Governance - *Clear ownership & accountability for data*

Challenges in Maintaining Data Quality

Human Errors - *Manual data entry mistakes.*
Data Silos - *Inconsistent data across departments*
Outdated Data - *Old, irrelevant data reducing accuracy*
Scaling Issues - *Maintaining quality as data volume grows*

What is Data Engineering?

It is the process of designing, building, and maintaining the systems that collect, store, and process data

Goal: Ensure data is accessible, reliable, and ready for analysis & AI
Like plumbing for data—moving and cleaning data so it's ready for use

Why is Data Engineering Important?




- **Reliable Data** - Ensures accurate, well-structured data for analysis & AI
- **Scalability** - Handles large-scale data efficiently
- **Faster Insights** - Automates data flow for real-time analytics
- **Foundation for AI** - AI & ML models rely on well-prepared data

Key Components of Data Engineering

- **Data Collection** - Extracting data from sources (APIs, databases, logs)
- **Data Storage** - Storing data in Data Lakes, Warehouses, or Lakehouses
- **Data Processing** - Transforming raw data using ETL (Extract, Transform, Load) / ELT
- **Data Pipelines** - Automating data flow using batch & real-time processing
- **Data Quality & Governance** - Ensuring accuracy, security, and compliance

Tools & Technologies



- **Storage:** Snowflake, BigQuery, Amazon S3, Delta Lake
- **Processing:** Apache Spark, Databricks, dbt, Airflow
- **Pipelines:** Kafka, Flink, Fivetran
- **Orchestration:** Airflow, Prefect, Dagster

Challenges in Data Engineering




- **Data Silos** - Breaking barriers between isolated data sources
- **Data Quality** - Ensuring clean, consistent data
- **Real-Time Processing** - Managing speed & reliability
- **Cost & Complexity** - Scaling infrastructure efficiently

Understanding

Data Engineering

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What is Data Analysis?

Process of cleaning, transforming, and interpreting data
To find meaningful patterns, trends, and insights

Goal: Convert raw data into useful knowledge for decision-making
Like solving a puzzle—each data point is a piece that helps complete the big picture

Why is Data Analysis Important?

Better Decision-Making - Data-driven insights lead to smarter choices
Problem-Solving - Identifies inefficiencies, risks, and opportunities
Predicting Trends - Helps businesses prepare for future changes
Competitive Advantage - Effective data analysis outperform others

Types of Data Analysis

Descriptive Analysis - "What happened?" (sales reports, trend charts)
Diagnostic Analysis - "Why did it happen?" (correlation, root cause analysis)
Predictive Analysis - "What might happen?" (forecasting, machine learning)
Prescriptive Analysis - "What should we do?" (decision-making models)

Understanding Data Analysis

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Common Data Analysis Techniques

Statistical Analysis - Mean, median, variance, hypothesis testing
Data Visualization - Charts, graphs, heatmaps for easy understanding
Correlation & Regression - Finding relationships between variables
Machine Learning Models - AI-driven pattern recognition
Text Analysis - Extracting insights from words and language

Challenges in Data Analysis

Dirty Data - Incomplete, inconsistent, or incorrect data
Data Overload - Too much data without clear focus
Bias & Misinterpretation - Drawing incorrect conclusions
Lack of Skills & Tools - Not everyone is trained in data analysis

Data Engineer ~ The Builder

What They Do? Build data pipelines & manage storage
Key Skills: SQL, Python, ETL, Cloud, Big Data
Challenges: Dirty data, pipeline failures, scalability
Future Trends: Real-time streaming data, Data Mesh, AI-powered data engineering

Data Analyst ~ The Storyteller

What They Do? Analyze data, create dashboards & reports
Key Skills: SQL, Excel, Tableau, Python, Business Acumen
Challenges: Messy data, unclear business questions, ad-hoc requests
Future Trends: Self-service analytics, AI-powered BI tools, Automated reporting

Top 5
Data & AI Roles

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Data Scientist ~ The Predictor

What They Do? Build ML models & derive patterns
Key Skills: Python, ML/DL, Statistics, AI Ethics
Challenges: Model deployment, bias, explainability
Future Trends: AI explainability, Edge AI, Ethical AI & regulation

AI/ML Engineer ~ The Deployer

What They Do? Deploy, monitor & optimize ML models
Key Skills: TensorFlow, Docker, MLOps, Cloud AI
Challenges: Model drift, latency, security
Future Trends: Low-latency AI, AI-powered DevOps, Federated Learning

Data/AI Product Manager ~ The Strategist

What They Do? Bridge business & AI, drive AI adoption
Key Skills: AI Strategy, Product Management, Communication
Challenges: AI ROI, adoption resistance, ethical concerns
Future Trends: AI-driven decision-making, AI governance & compliance, No-code AI platforms

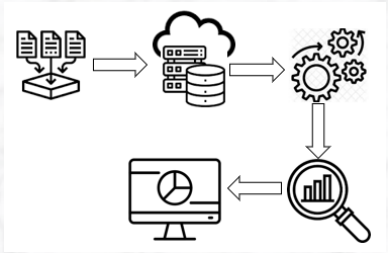
Why is Data Called the "New Oil"?

Like oil in the Industrial Age ~ data is the key resource in the Digital Age
Raw data has no value until processed & refined—just like crude oil
AI & Analytics are the engines that extract value from data
Data is the new oil, AI is the refinery, and insights are the fuel powering businesses

How Businesses Leverage Data & AI

Personalization - Netflix, Amazon, Spotify use AI to recommend content & products
Data-Driven Decisions - Companies like Google & Tesla optimize strategies using data insights
Automation & AI - Chatbots, fraud detection, and predictive maintenance
Monetization - Tech giants sell data-driven advertising & insights (Google, Facebook)

The Data & AI Value Chain



Data Collection - Sensors, IoT, social media, transactions
Storage & Processing - Data lakes, warehouses, cloud computing
AI & Analytics - Machine learning, deep learning, business intelligence
Actionable Insights - Dashboards, reports, predictions
Business Impact - Cost savings, revenue growth, innovation

The Future of Data & AI

AI-Powered Everything - AI assistants, automation, autonomous systems
Real-Time Decision Making - Edge computing & AI-driven analytics
Responsible AI & Ethics - Transparency, fairness, and reducing bias
Data Privacy & Security - Regulations like GDPR & AI governance

Challenges & Risks

Data Privacy Issues - Who owns your data?
Bias in AI - Unfair outcomes due to biased training data
Scalability - Managing the explosion of global data
Ethical Concerns - Deepfakes, misinformation, surveillance risks

The Rise of Data & AI

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What is AI?

simulation of human intelligence in machines

Learning - *Adapts from data*
Reasoning - *Makes decisions*
Self-correction - *Improves over time*

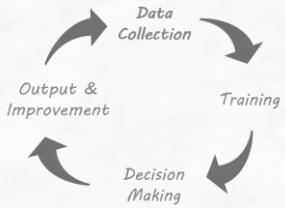
Types of AI

Narrow AI (Weak AI) → *Specialized in one task (Siri, Google Translate)*
General AI (Strong AI) → *Thinks like a human (still theoretical)*
Super AI → *More intelligent than humans (future concept)*

AI Subfields

Machine Learning (ML) - *Learns from data (Netflix recommendations)*
Deep Learning (DL) - *AI mimicking the human brain (self-driving cars)*
Natural Language Processing (NLP) - *Understands human language (Chatbots)*
Computer Vision - *Recognizes images (Face recognition)*

How AI Works



Data Collection - *AI learns from massive datasets*
Training - *Models adjust through experience*
Decision Making - *AI analyzes patterns*
Output & Improvement - *AI refines predictions over time*

AI in Everyday Life

Voice Assistants (*Alexa, Google Assistant*)
Recommendation Systems (*Netflix, YouTube*)
Healthcare (*Disease diagnosis, robotic surgery*)
Autonomous Vehicles (*Self-driving cars*)
Finance & Security (*Fraud detection, stock predictions*)

AI Challenges & Ethics

Bias in AI - *Unfair outcomes due to biased data*
Privacy Issues - *AI tracking and surveillance concerns*
Job Automation - *AI replacing jobs*
Ethical AI - *Ensuring AI benefits society*

Understanding AI

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Understanding Data

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What is Data?

Its raw information in the form of numbers, text, images, or symbols

Data Formats

Structured (spreadsheets, databases)
Unstructured (emails, videos, social media posts)
Semi-structured (JSON, XML)

Data Processing Cycle

Collection - Sensors, surveys, transactions
Storage - Databases, cloud, servers
Processing - Sorting, filtering, analysing
Analysis - Trends, patterns, insights
Visualization - Graphs, charts, dashboards

Data Types & Examples

Quantitative (Numbers) → Sales figures, temperature
Qualitative (Descriptions) → Customer reviews, comments
Big Data (Massive sets) → Social media trends, IoT sensor data

Importance of Data

Better Decisions - Business strategies, healthcare, AI
Efficiency - Automation, predictive models
Innovation - Machine learning, scientific research

Data Challenges

Data Privacy & Security - Hacks, leaks, GDPR
Data Overload - Too much data, hard to analyze
Bias & Accuracy - Incorrect or misleading data

Analogy with a Car

Data Strategy → GPS & Roadmap

(Defines direction and purpose)
Ensures the organization knows where it's going with data, aligning it with business goals

Data Architecture → Accelerator

(Speeds things up)
Provides a structured framework that enables fast and scalable data processing

Data Governance → Brakes

(Ensures control and compliance)
Puts guardrails in place to ensure data quality, security, and compliance

Data Engineering → Fuel & Transmission

(Moves data efficiently)
Builds and maintains pipelines that deliver data where it's needed, ensuring smooth movement

Data Management → Engine Maintenance

(Keeps things running smoothly)
Ensures data is properly stored, processed, and maintained over time

Data Science → Turbocharger

(Adds power and intelligence)
Uses advanced models and algorithms to extract deeper insights and predictions.

Data Analytics → Dashboard & Gauges

(Provides insights to the driver)
Helps monitor performance, trends, and issues to make informed decisions

Understanding Data & AI Ecosystem

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Ankit Rathi (He/Him)

I simplify Data & AI through Visual Storytelling – One Concept at a Time | All views are my own

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