

## A. Data Engineer

- Builds and maintains data pipelines and infrastructure (ETL: Extract, Transform, Load).
- Ensures that data is clean, accessible, and organized for further use.

## B. Data Analyst / BI Analyst

- Cleans, explores, and visualizes data (e.g. using SQL, Excel, Tableau).
- Produces dashboards and reports to inform stakeholders and support decision-making.

## C. Data Scientist

- Goes beyond analysis to design and implement predictive models using machine learning.
- Involves statistical modeling, hypothesis testing (A/B tests), and model tuning.

## D. ML/Ops Engineer or Applied Scientist

- Focuses on taking data science models into production (serving, monitoring, maintenance).
- In larger organizations, combines engineering with machine learning to operationalize models.

## E. Data Architect / Strategist / Product Manager

- **Data Strategist:** Defines business objectives and aligns data collection/insight efforts accordingly.
- **Data Architect:** Designs high-level data systems and ensures proper database schemas.
- **Data Product Manager:** Oversees the delivery and success of data-driven products from conception to deployment.

## 4. Skills & Communication

- These roles require both **hard skills** (statistics, ML, programming, databases) and **soft skills** (communication, business understanding).
- Critical to explain insights to non-technical stakeholders to drive action—being a data storyteller is key.

## 5. Organizational Context & Role Overlap

- In **smaller teams**, roles might overlap (e.g., a data scientist handling infrastructure).
- In **large organizations**, roles are more siloed and specialized.
- The broad and evolving nature of “data scientist” means titles aren’t standardized across companies.

## 6. Career Implications & Starting Strategy

- If you enjoy **building systems**, lean toward Data Engineering or ML/Ops.
- If **analysis and visualization** interest you, aim for Data Analyst / BI roles.
- For those wanting to **research and build predictive models**, pursue Data Scientist or Applied Scientist positions.
- Understand where your passion lies to choose the right path and job title.

## 1. What Is a Tensor?

- A **tensor** is a generalization of scalars, vectors, and matrices — visualized as a **multi-dimensional array**.
- **Scalar:** 0-dimensional (e.g., a single number).
- **Vector:** 1-dimensional (e.g., a list of numbers along a line).
- **Matrix:** 2-dimensional (e.g., grid of rows and columns).

- **N-dimensional tensor (nd-tensor)**: Extends this concept to any number of dimensions, enabling representation of complex data structures.

## 2. Tensor Rank & Shape

- **Rank** = Number of dimensions (axes).
  - Rank 0 = scalar, Rank 1 = vector, Rank 2 = matrix, etc
  - Shape = Size of each dimension (e.g., shape [3,4,5] means  $3 \times 4 \times 5$  elements).

## 3. Role in Machine Learning & Computation

- Tensors are the **fundamental data structure** in machine learning frameworks like TensorFlow and PyTorch.
- They allow high-dimensional data (images, text, time-series) to be represented and processed efficiently.

## 4. Tensor Algebra

- Supports **linear algebra operations** like addition, multiplication, dot products, reshaping, transposing, slicing.
- These operations generalize vector and matrix math to higher dimensions and are integral to ML and deep learning workflows.

## 5. Interpreting Dimensions

- Each axis carries specific meaning:
  - **Rank 1**: a list of features.
  - **Rank 2**: rows as samples, columns as features.
  - **Rank 3+**: e.g., color image (Height  $\times$  Width  $\times$  Channels).
- What counts as a meaningful axis depends on context.

## 6. Why Tensors Matter

- Enable **uniform, efficient computation** across diverse data types.
- Form the core of **gradient-based optimization** and computation graphs in deep learning.



## Key Takeaways

- Tensors generalize scalars, vectors, matrices to any dimensions.
- Rank denotes how many axes; shape gives size along each axis.
- They're the backbone of machine learning frameworks for data representation and computation.
- Understanding tensors is essential for working with neural networks, convolutional architectures, and other ML models.