

# Data and Artificial Intelligence: Empowering The Future

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# Capabilities of Gen AI

1. **Generative:** Create new text, videos, audio
2. **Interaction:** LLM's are the future of interfaces
3. **Knowledge:** Terabytes of notes, manuals weaponized
4. **Reasoning:** Just getting started; GPT 5 will stun you



# Impact is evolving...rapidly



Solve an advanced math problem

Which came first: the chicken or the egg?

Create a puzzle for me to solve

How many rs are in "strawberry?"

Message ChatGPT

ChatGPT can make mistakes. Check important info.

## Transform your content into engaging AI-generated audio discussions

Start generating

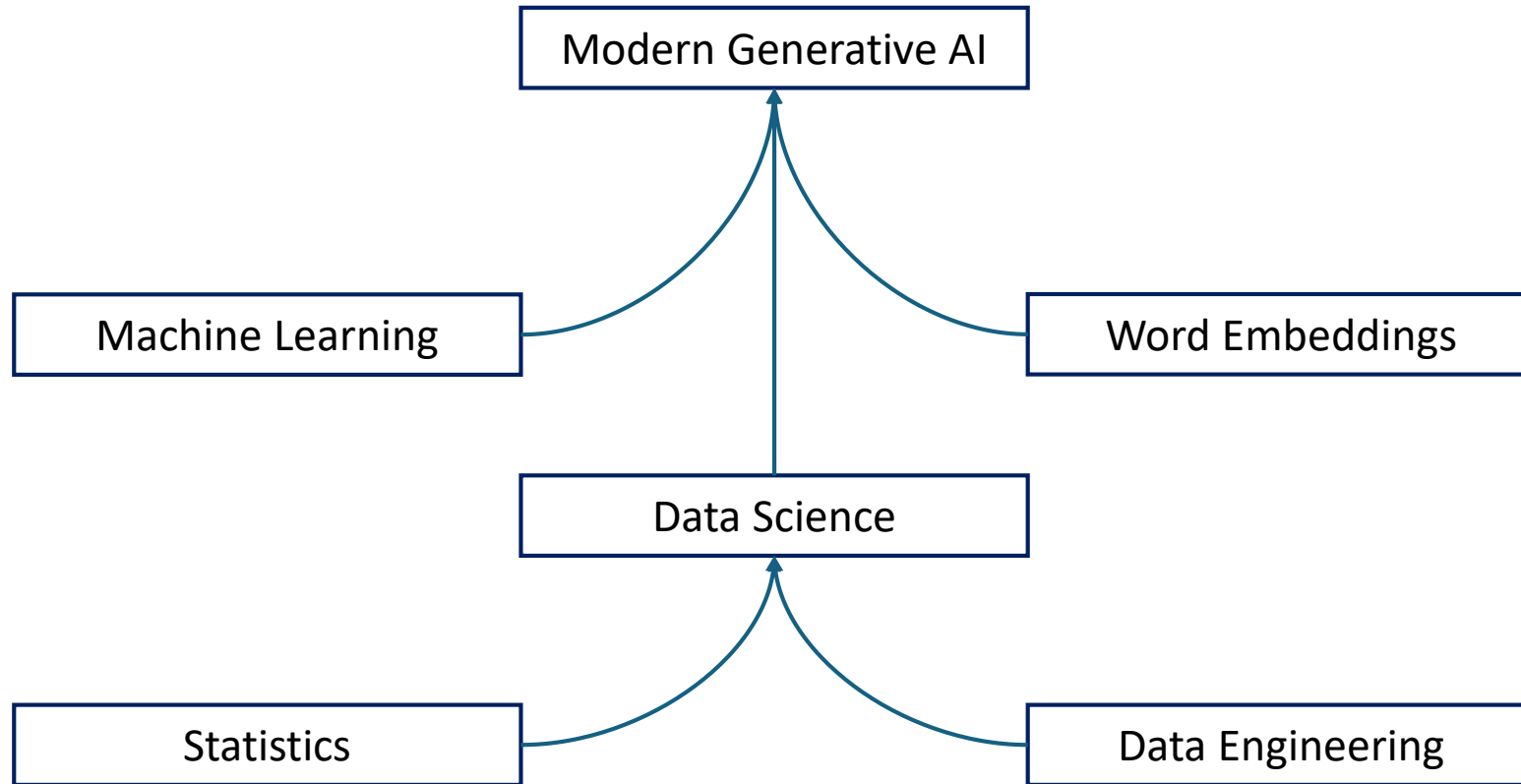
Public

- Attention is All You Need**  
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- PaLM-E: An Embodied Multimodal Language Model**  
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- Position: Levels of AGI for Operationalizing Progress on the Path to AGI**  
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# History of AI

= Big Data + Big Stats + Big Vectors

# A Historical Confluence



# Where does the word “data: come from?

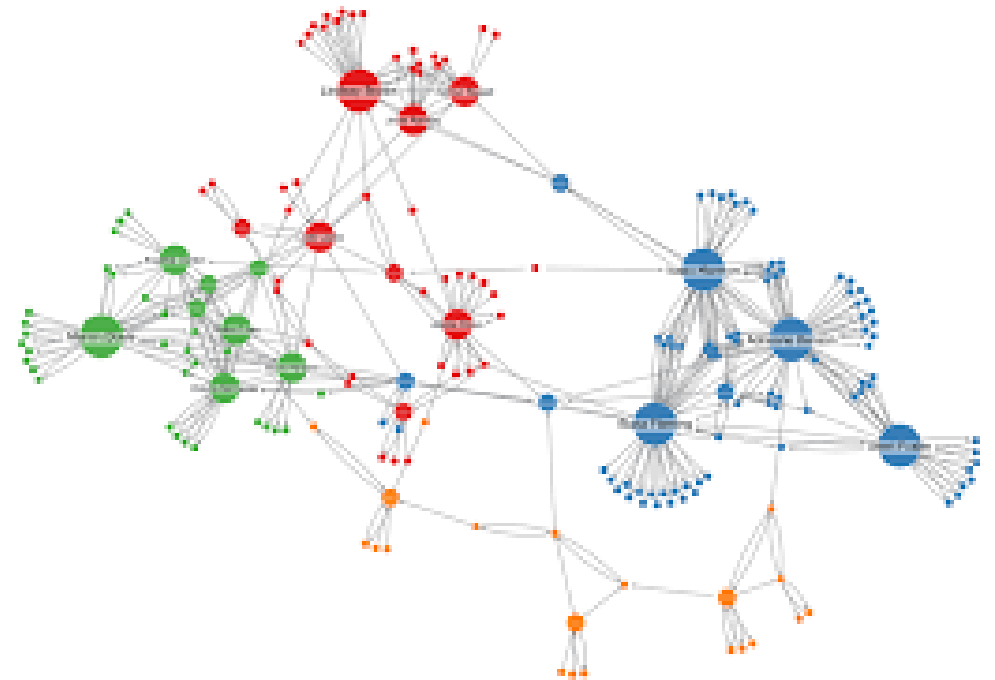
- Data: 1640s, "a fact given or granted," classical plural of datum.
- From Latin datum. Proto-Indo-European (Sanskrit: Data, Dana)
- 1897 as "numerical facts collected for future reference."
- Transmission: 1946.
- *Data-processing* 1954;
- *database* 1962;
- *data-entry* is by 1970.

# History of “Statistics”

- Comes from ancient civilizations such as Babylon
  - Counting was the beginning: hexagesimal, decimal
- The term comes from the word for “state” (like statecraft)
  - Counts of goods, estimation of taxes
  - Census taking, mortality (John Graunt 1662)
- Probability Theory
  - Pascal, Fermat, Bernoulli, de Moivre
- Pre-modern stats: 1850-1945
  - Gauss, Nightingale, Pearson, Fisher, (Egon) Pearson, Bayes, von Neumann, Tukey
- Modern stats
  - Pearson, Bayesian, Ulam, Bradley, Efrom

# Modern statistics

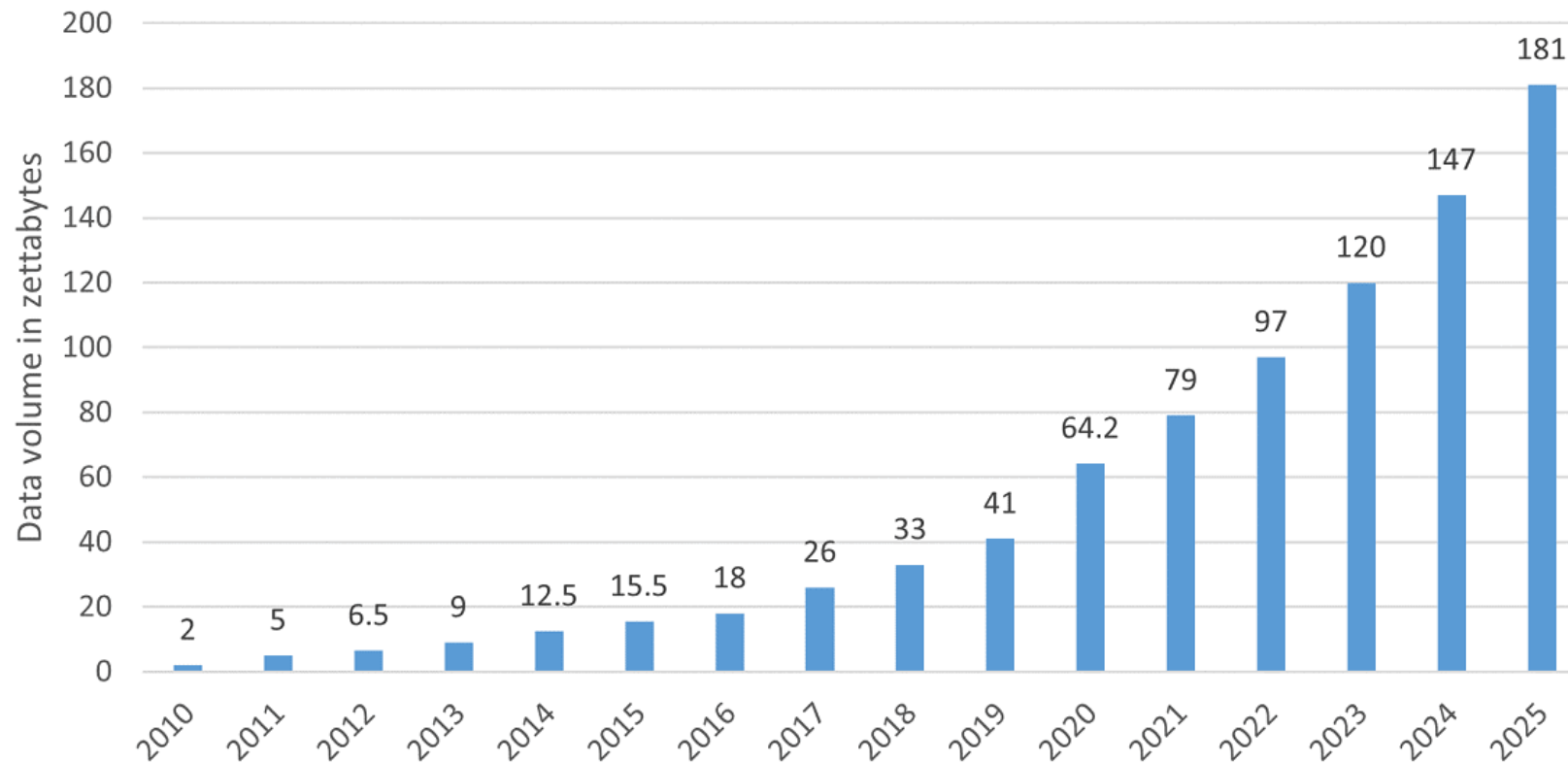
- Basic statistics (descriptive, exploratory)
- Data pre-processing and cleaning
- Unsupervised learning and clustering
- Supervised learning:
  - Regression, linear and logistic
  - Decision trees
  - Random forests
  - Support vector machines
  - K-Nearest Neighbors
  - *etc.*





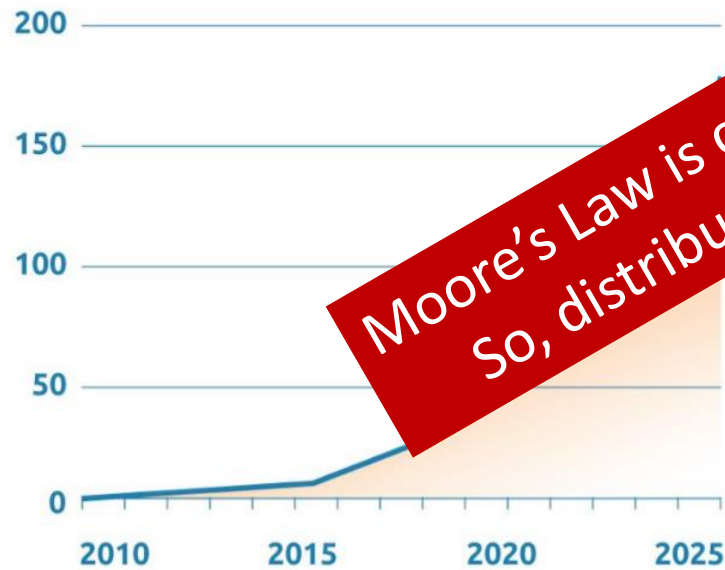
# Enter Big Data

Volume of data created and replicated worldwide (source: IDC)

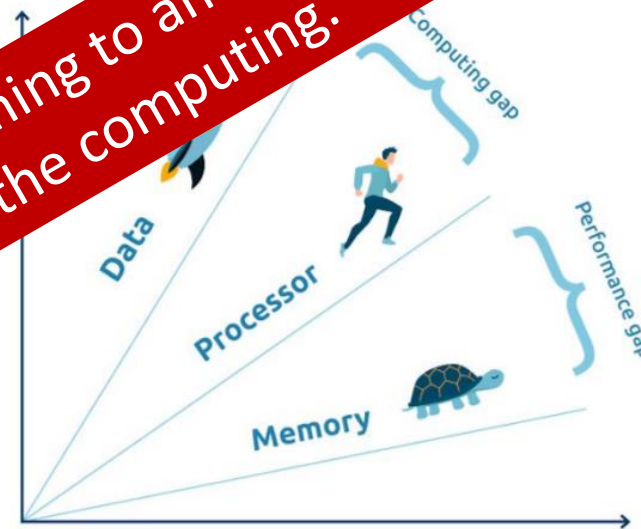


# Data outcompetes processing

**VOLUME OF DATA CREATED  
GLOBALLY 2010-2025**  
(IN ZETABYTES)

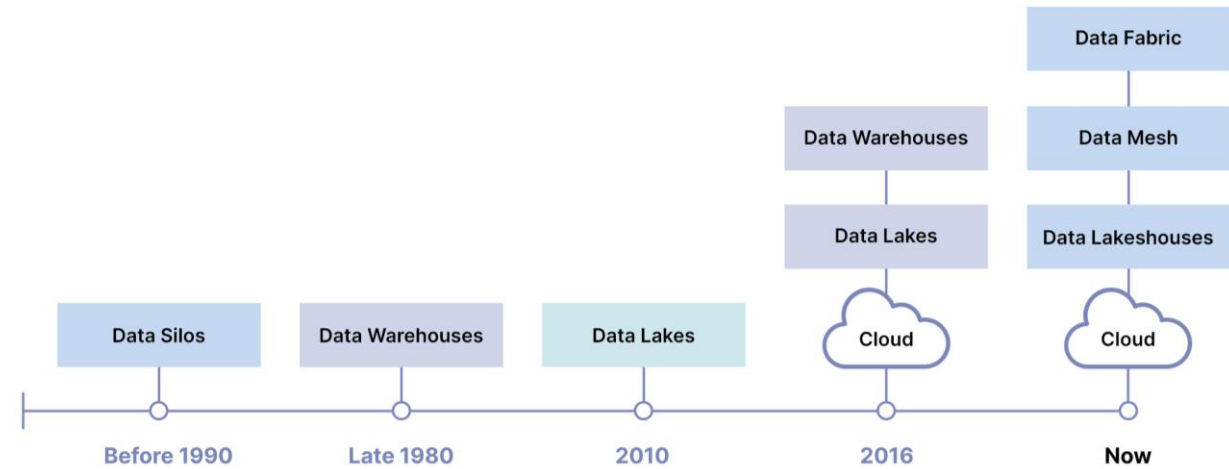


Moore's Law is coming to an end.  
So, distribute the computing.



# Data Engineering

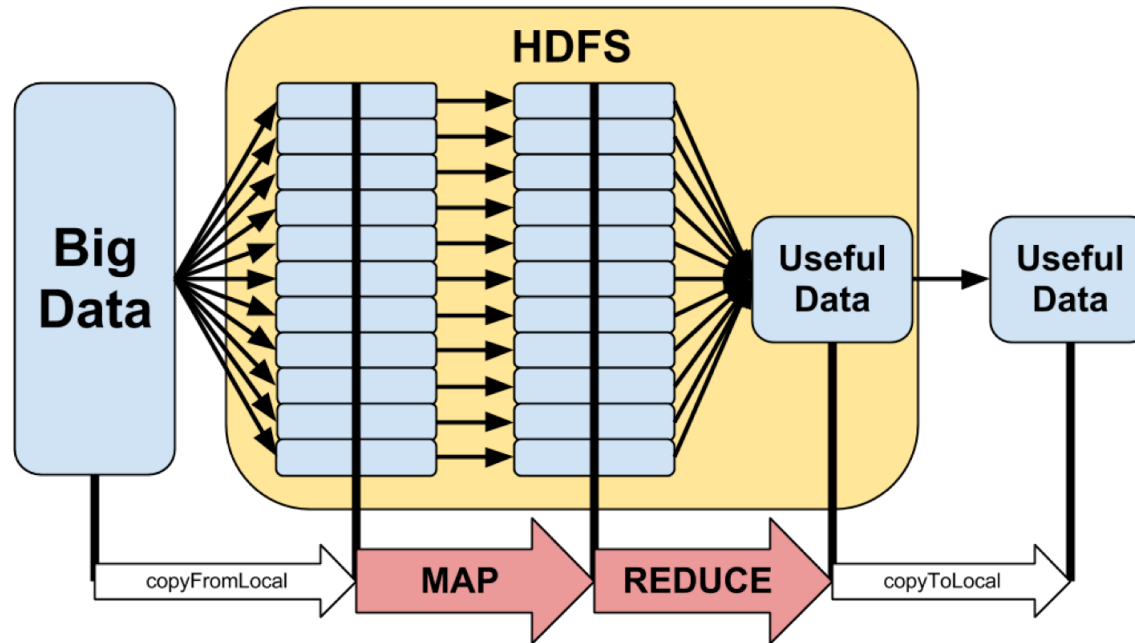
# New distributed data architectures

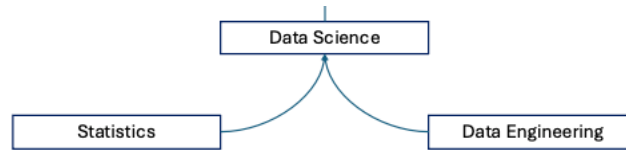


<https://www.zdnet.com/article/cloud-computing-will-virtually-replace-traditional-data-centers-within-three-years/>

<https://www.infocepts.ai/blog/dont-decide-on-a-data-architecture-until-you-read-this/>

# New Distributed Computation: Hadoop



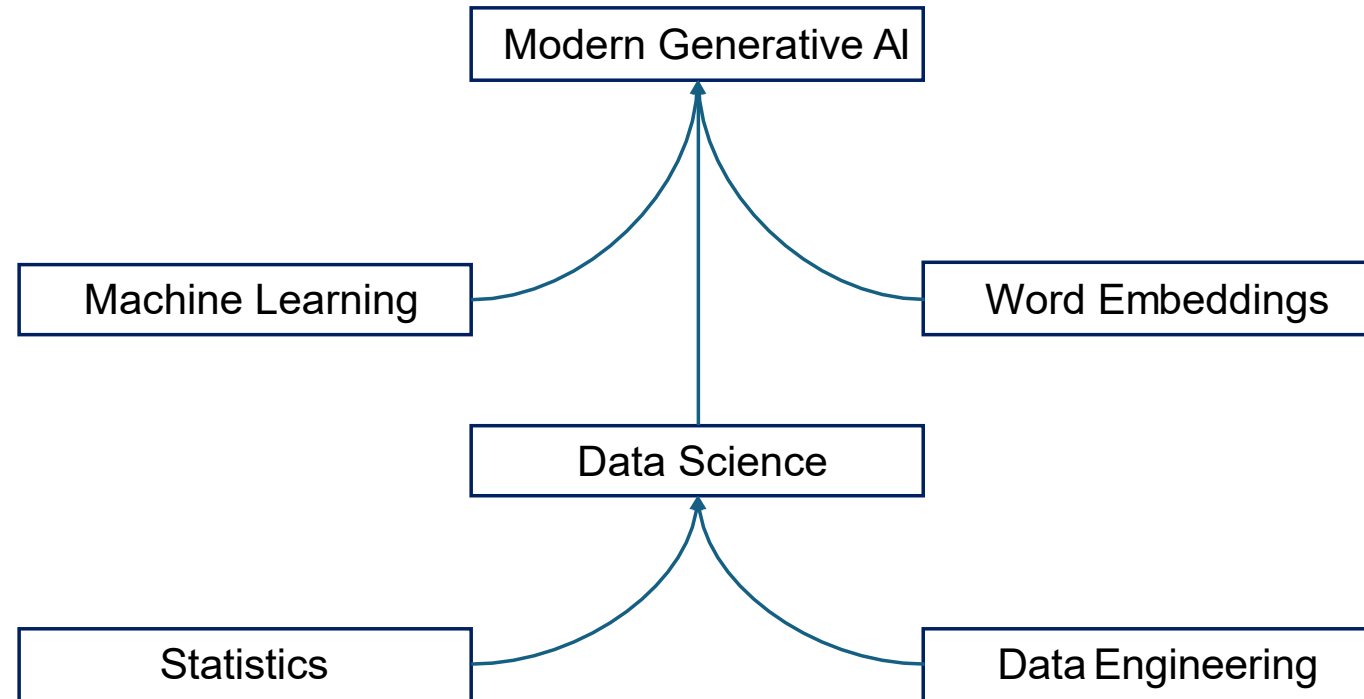


And that is  
Data Science

C. F. Jeff Wu suggested rebranding statistics as data science.

*“Statistics = Data Science?”*

# Back to our map



# Machine Learning

Start with the data

Labeled (supervised)

Unlabeled (unsupervised)



# 3 Waves of AI

GPU's, Large Datasets

## Wave 1: Neural Networks *1940s -1990s*

- Neural Networks
- Expert Systems

**IBM**  
Deep Blue



## Wave 2: Deep Learning: *2011 - present*

- Deep Neural Networks
- Pattern Recognition
- Matching, Prediction



Siri



Google  
Lens

## Wave 3: Generative AI *2017 - present*

- Large Language Models (“LLMs”)
- Text, Image, Video, Science Generation



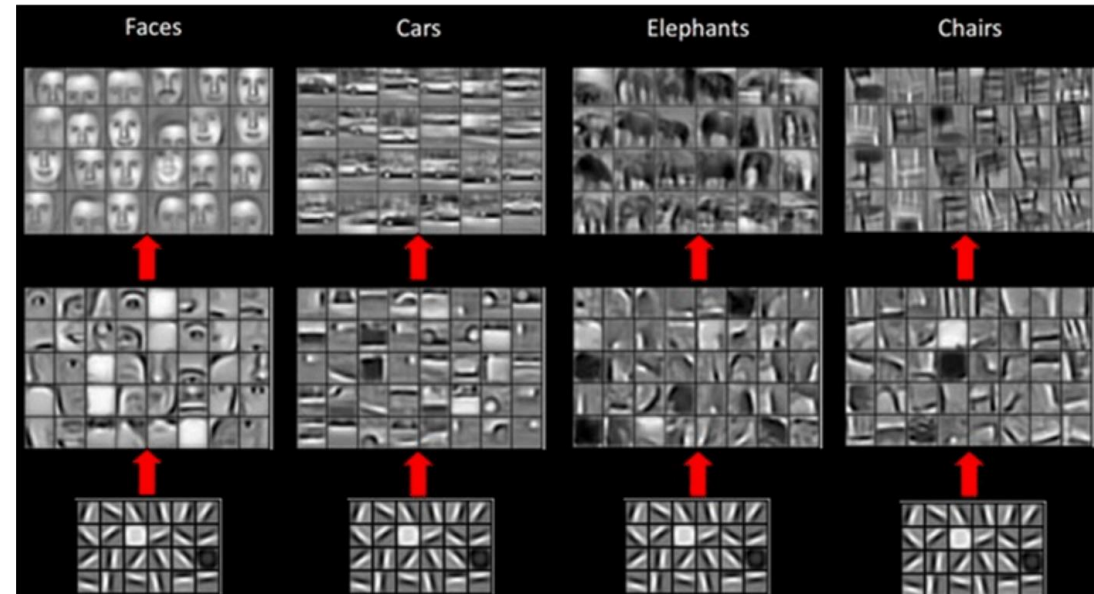
ChatGPT



MS Copilot

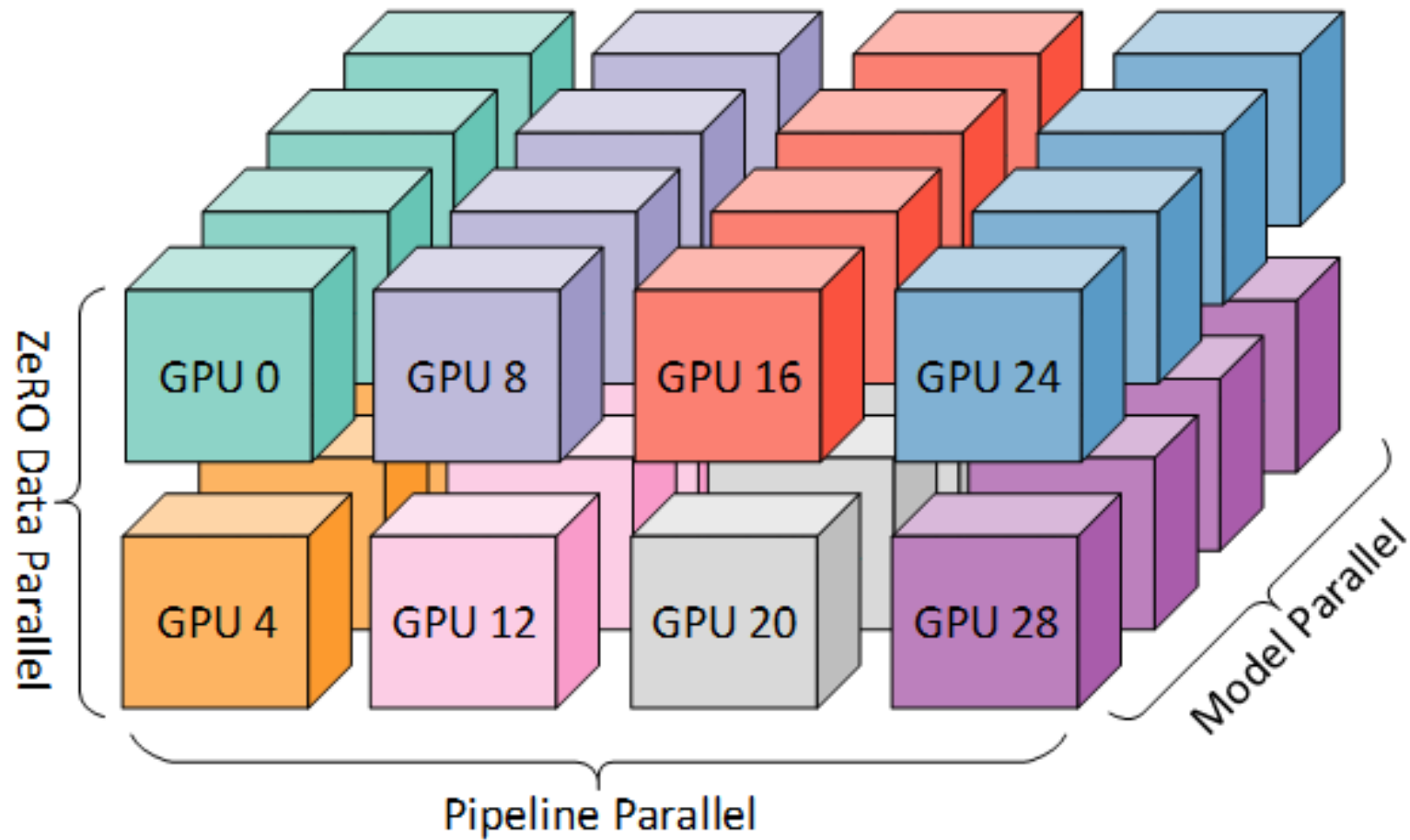
# Neural Networks are not Regression

1. Non-Linearity and Complexity
  - Non-linear activation functions: ReLU, sigmoid, or tanh
2. Representation Learning
  - No need to handcraft features
3. Universal Approximation
  - Hornik, K., Stinchcombe, M., & White, H. (1989). *Multilayer feedforward networks are universal approximators*. *Neural Networks*, 2(5), 359-366.
4. Architecture Variability
  - CNN, RNN's, Transformers
5. Scalability through parallelization, big data
  - Cloud, Hadoop, GPU's, TPU's, transfer learning,



<https://towardsdatascience.com/simple-introduction-to-convolutional-neural-networks-cdf8d3077bac>

# More Engineering How GPU's parallelize AI

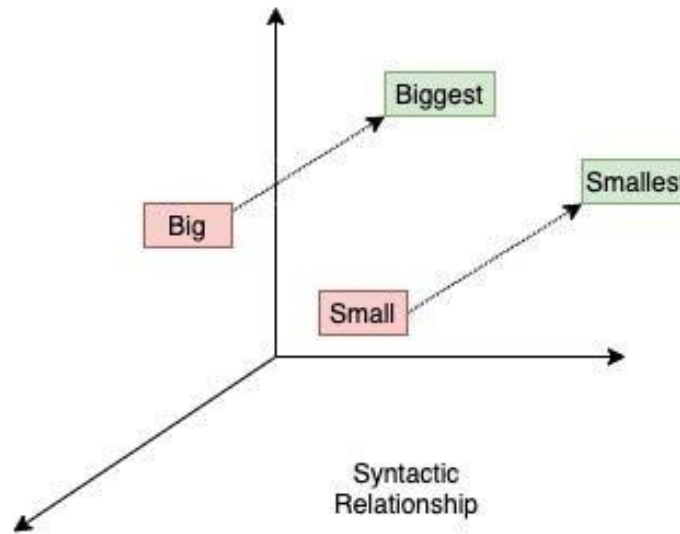
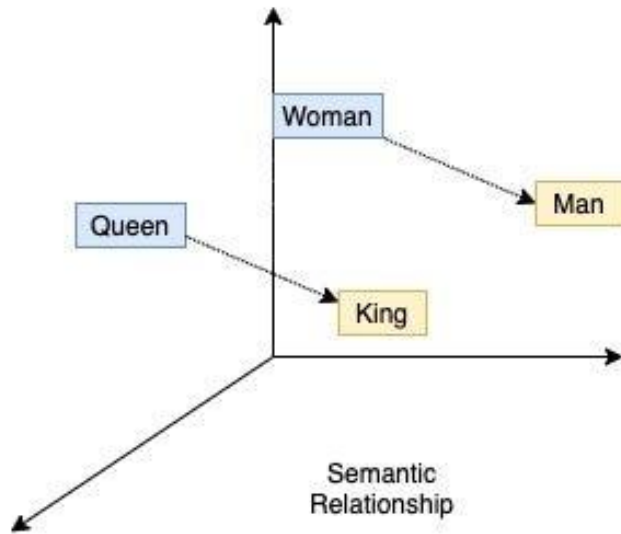


Large Language Models  
*are based on*  
Word Embeddings

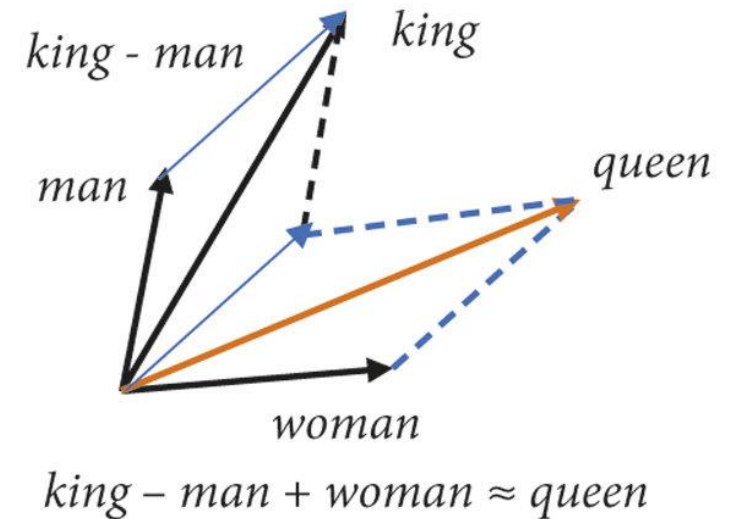
Reducing words to numbers

# Words as Vectors

- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. *Proceedings of International Conference on Learning Representations (ICLR)*.
- Tomas Mikolov, Wen tau Yih, and Geoffrey Zweig. 2013b. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT-2013)*. Association for Computational Linguistics.



Analogical Reasoning

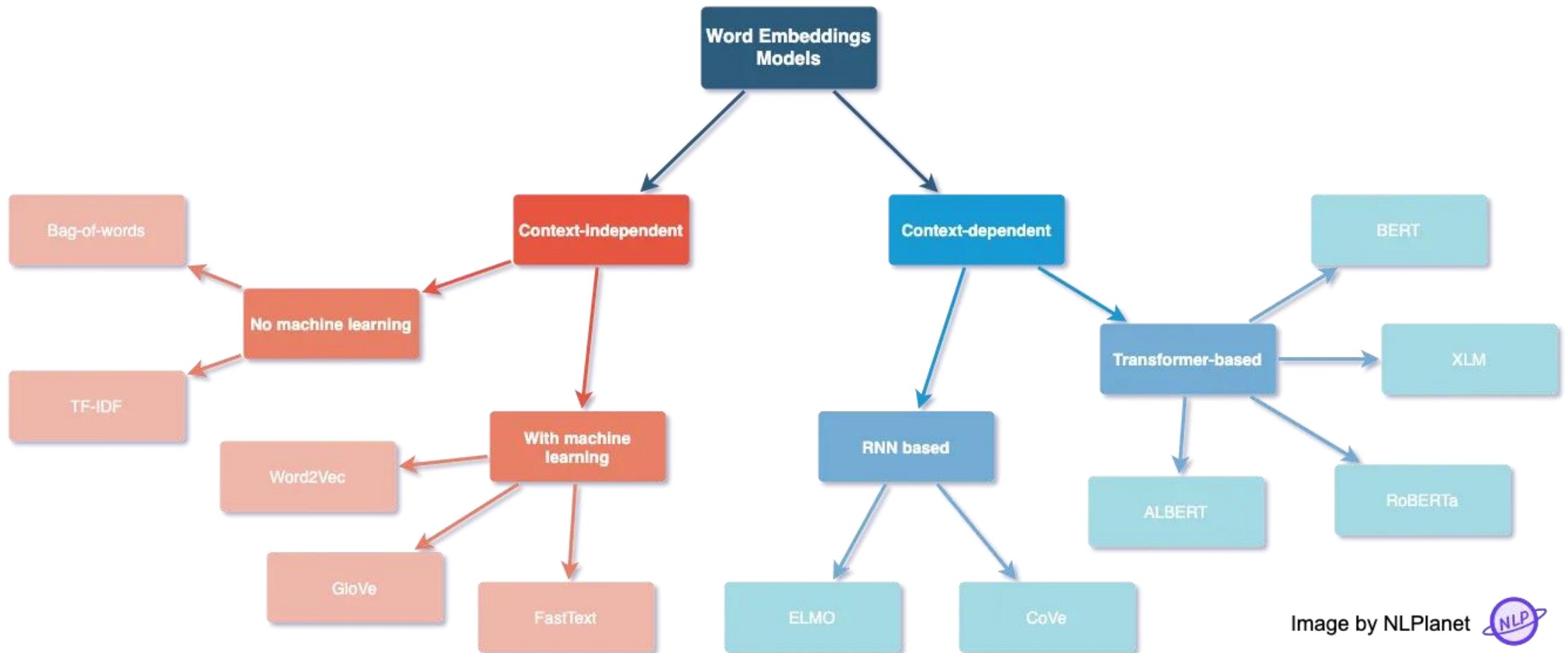


<https://towardsdatascience.com/word2vec-research-paper-explained-205cb7eccc30>

Liang, Wentao, Lu Wang, Jialuo She, and Yuqing Liu. "Detecting Resource Release Bugs with Analogical Reasoning." *Scientific Programming* 2022, no. 1 (2022): 3518673.

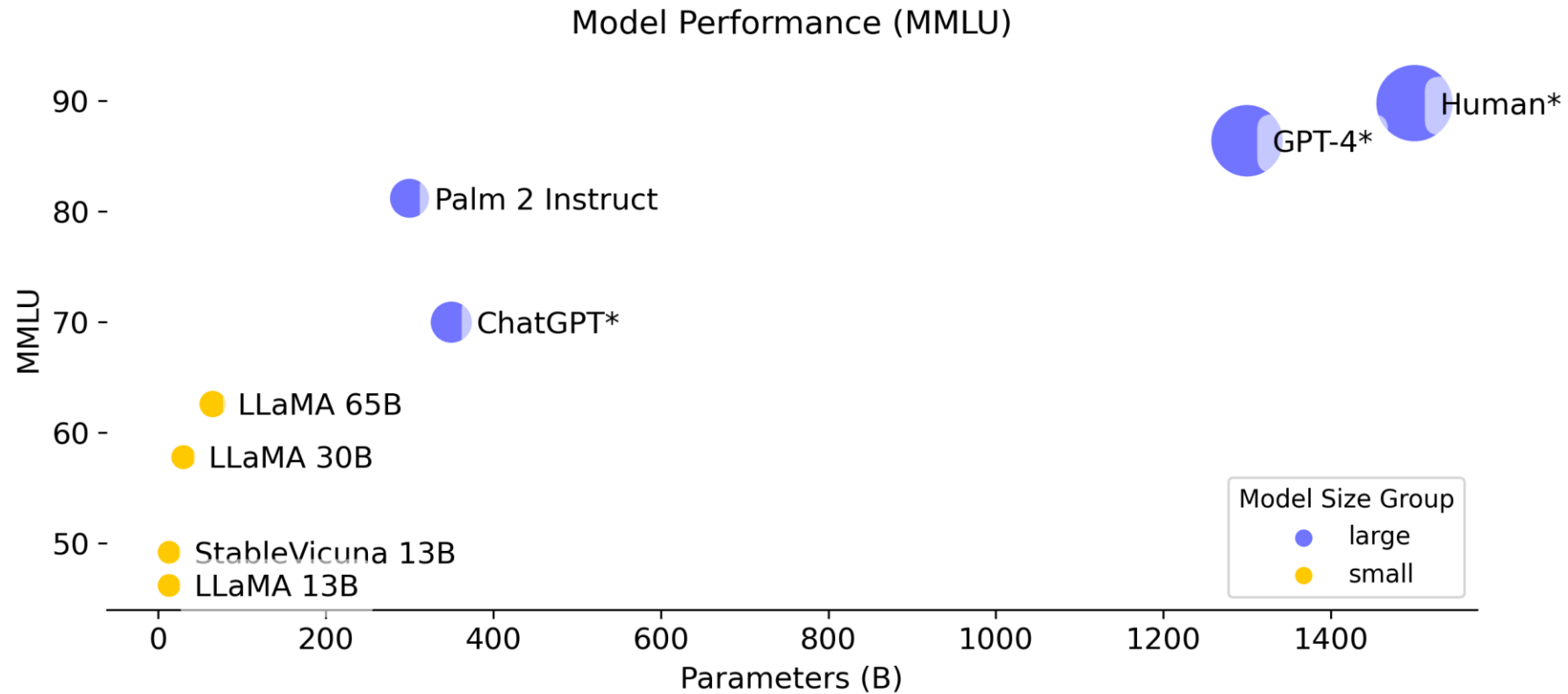
# Words become numbers

<https://medium.com/nlplanet/two-minutes-nlp-11-word-embeddings-models-you-should-know-a0581763b9a9>



# Massive Multitask Language Understanding

## MMLU tests models on 57 different subjects



\*Exact model size is unknown. | Data from InstructEval GitHub.

<https://newsletter.victordibia.com/p/understanding-size-tradeoffs-with>

Conclusion



# Barriers Being Breached by Gen AI

**Content**    **Structured vs Unstructured**    80% of data is unstructured

**Old AI**    **Supervised vs Unsupervised**    Passive information unleashed

## Robots learn to perform chores by watching YouTube

Brian Heater / 9:09 AM PDT • June 22, 2023

 Comment



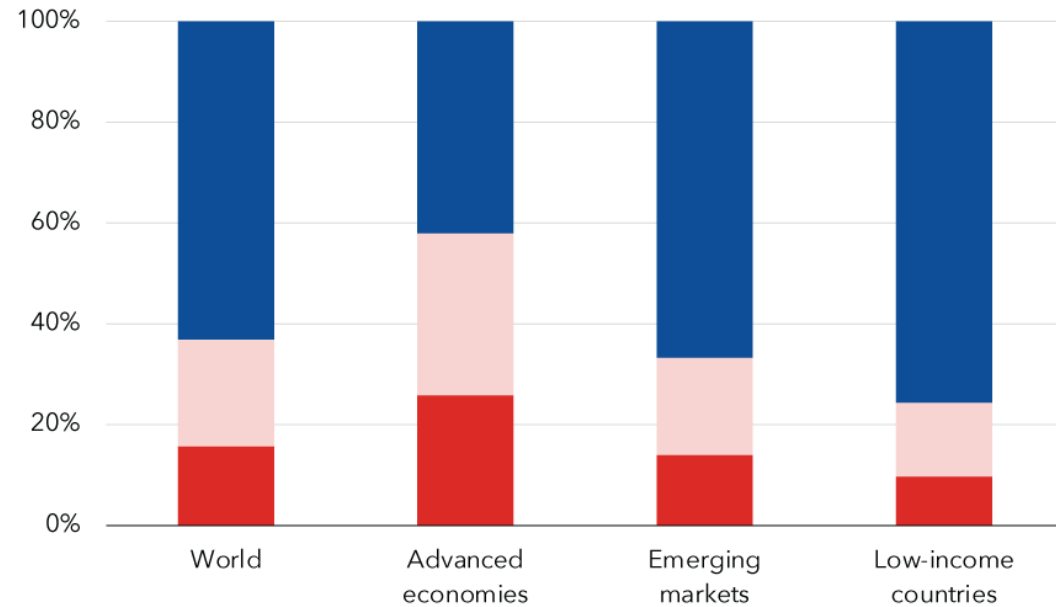
# Impact on jobs, economy

## AI's impact on jobs

Most jobs are exposed to AI in advanced economies, with smaller shares in emerging markets and low-income countries.

### Employment shares by AI exposure and complementarity

■ High exposure, high complementarity   ■ High exposure, low complementarity  
■ Low exposure



Source: International Labour Organization (ILO) and IMF staff calculations

Note: Share of employment within each country group is calculated as the working-age-population-weighted average.