Machine Learning I
60629A

Parallel computational paradigms for large-scale data processing
— Week #10

Today

A. Distributed computing for machine learning

- Background
- Short introduction to MapReduce/Hadoop & Spark

B. Summary of material seen so far

Note: Most lectures so far used stats concepts. Today we'll turn to computer science.

Distributed Computation for Machine Learning

Data & Computation

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- **We generate massive quantities of data**

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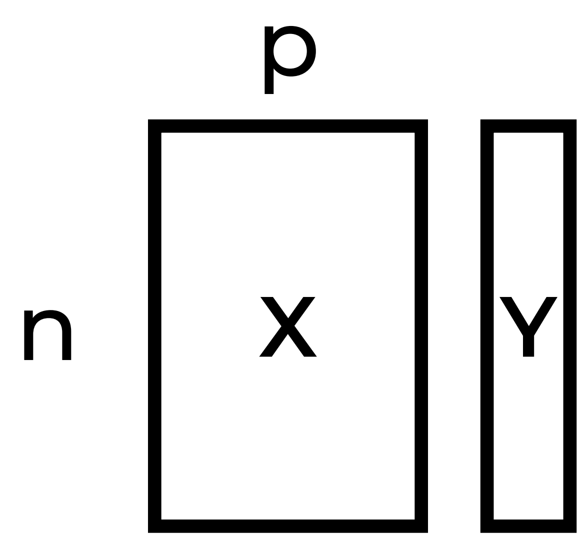
- Both large n and large p



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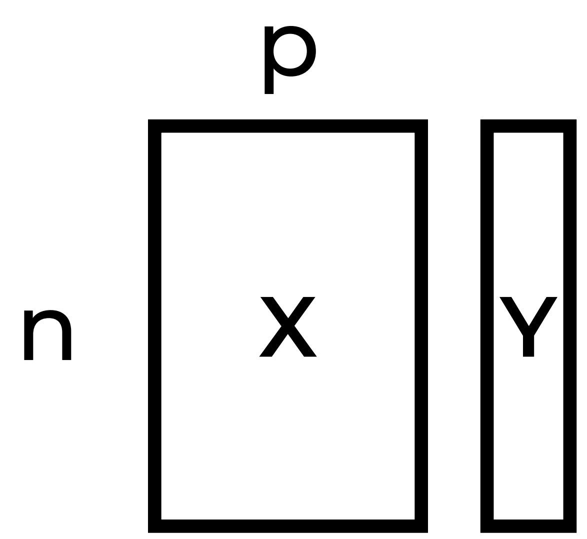

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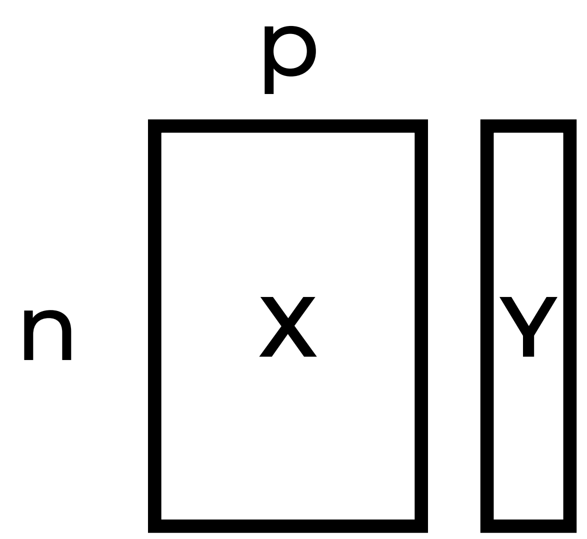


- Both large n and large p

- In general computation will scale up with the data

  - Often fitting an ML models requires one or multiple operations that looks at the whole dataset

e.g., Linear regression $\mathbf{w} = (\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X}^\top \mathbf{Y}$

Issues with massive datasets

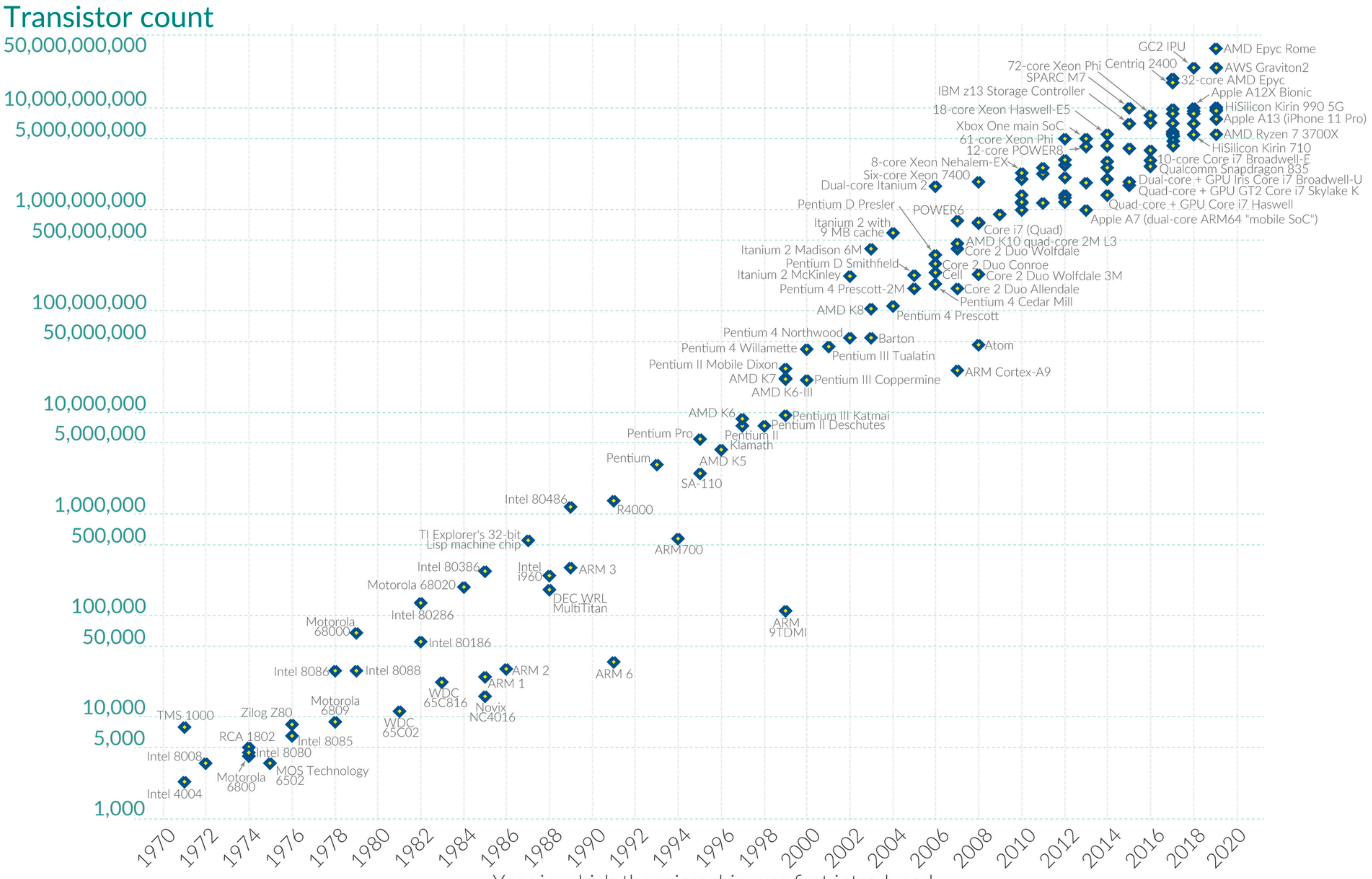
1. Storage

2. Computation

Moore's Law: The number of transistors on microchips doubles every two years

Our World in Data

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.



Data source: Wikipedia (wikipedia.org/wiki/Transistor_count)

[https://en.wikipedia.org/wiki/Moore%27s_law]

OurWorldinData.org – Research and data to make progress against the world's largest problems.

Modern Computation paradigms

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- Floating point operations per second (Flop)
- Smart phone ~ 0.6 TFlops
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1. **“Single” computers**

- **Large Computers**
  - **513, 855 TFlops**

https://www.top500.org/lists/top500/list/2020/06/

Photo from Riken

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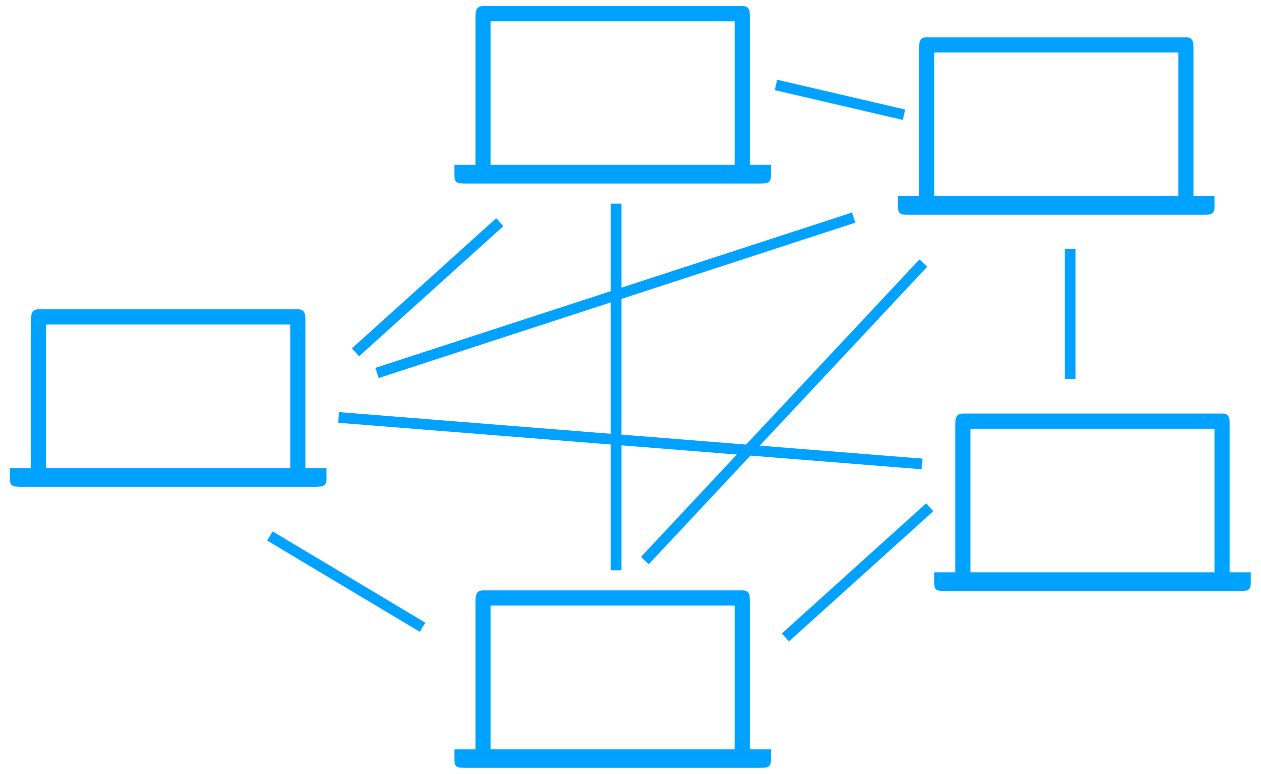
2. Distributed computation

- **~200, 000 TFlops (Folding@home)**



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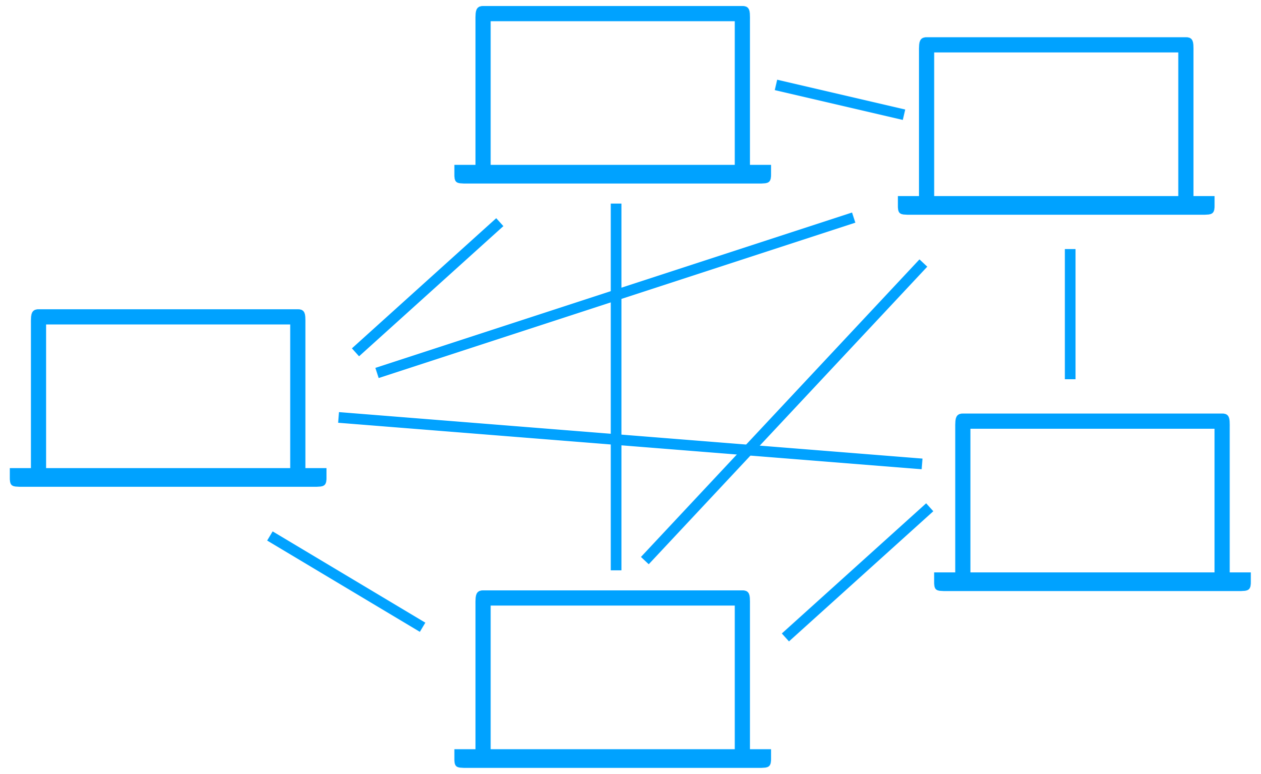


3. **Specialized hardware**
   - **Focusses on subset of operations**
     - **Graphical Processing Unit (GPU), Field Programmable Gated Array (FPGA)**
     - **~100 TFlops**

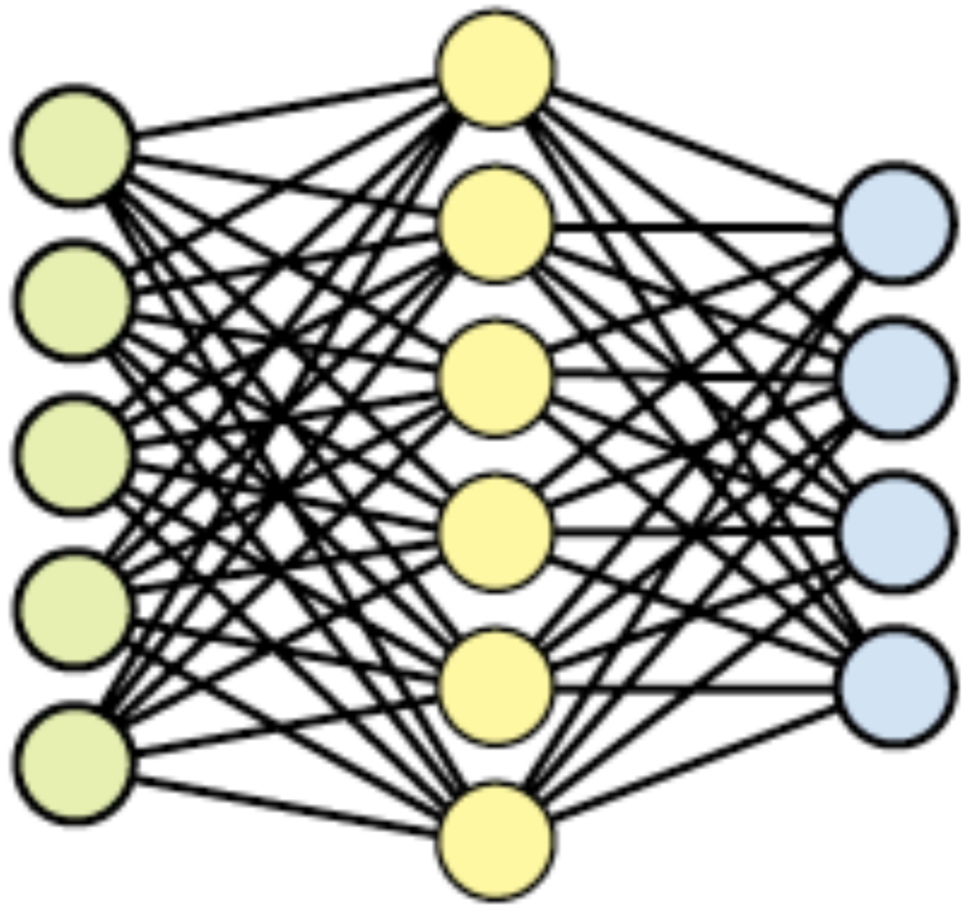
GPUs & other specialized hardware

Hardware

http://www.personal.psu.edu/users/d/l/dlm99/cpu.html

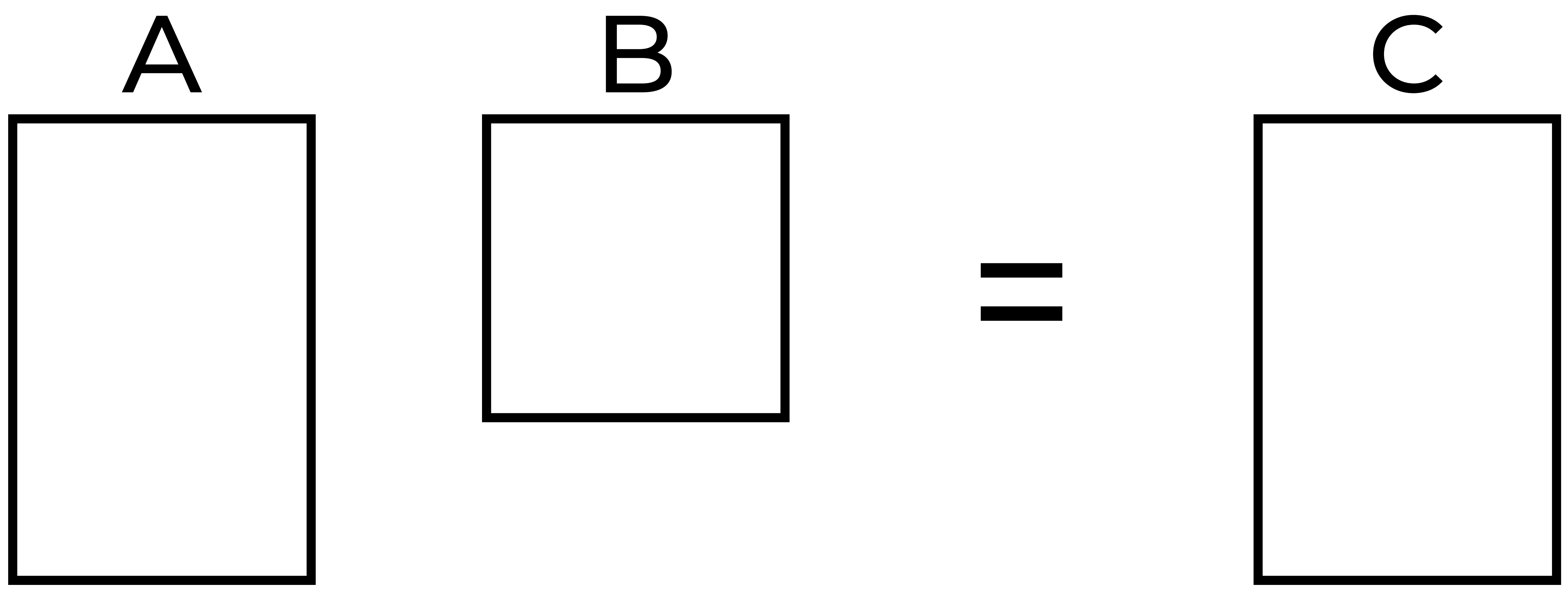
- Central Processing Unit (CPU)
  - Computer's cognition
  - Executes all the instructions from software
    - Arithmetics, read/writes, logic, etc.

Neural Networks

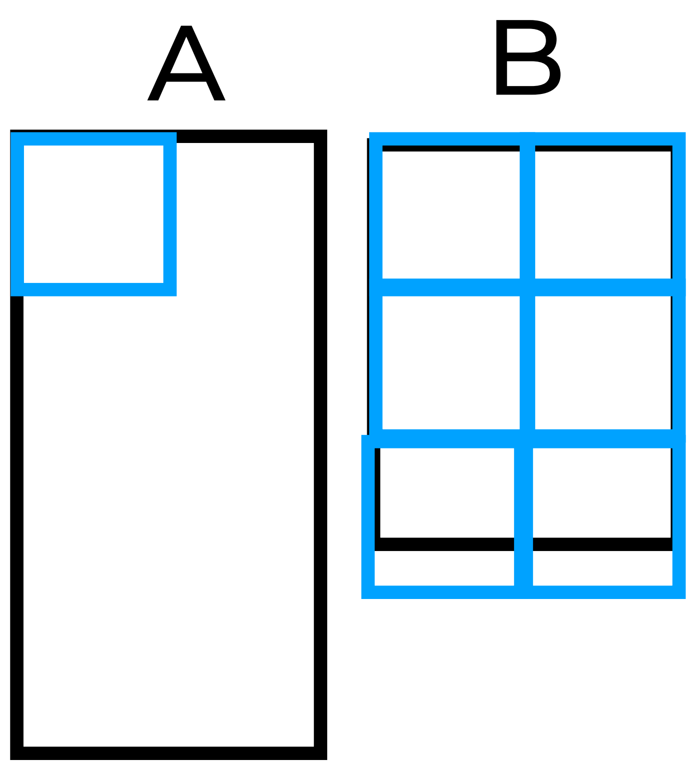


- Linear Algebra:
  - Multiplication *vector X matrix*
    - Neuron activation of multiple neurons
    - Neuron activation for multiple datum
  - Multiplication matrix X matrix
    - Activation of multiple neurons for multiple datum
- The exact dimensions of these vector & matrix depend on the data size (mini batch) and the number of neurons

Parallelizing neural network computations



$$C = AB$$



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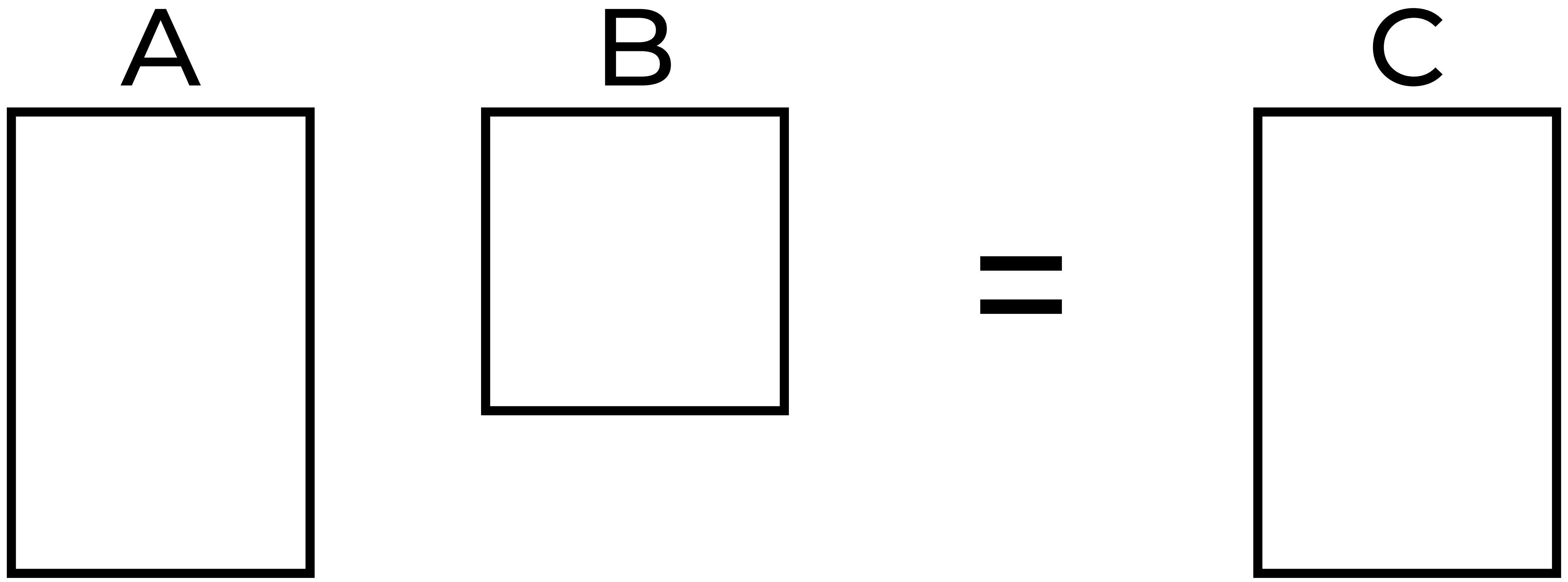
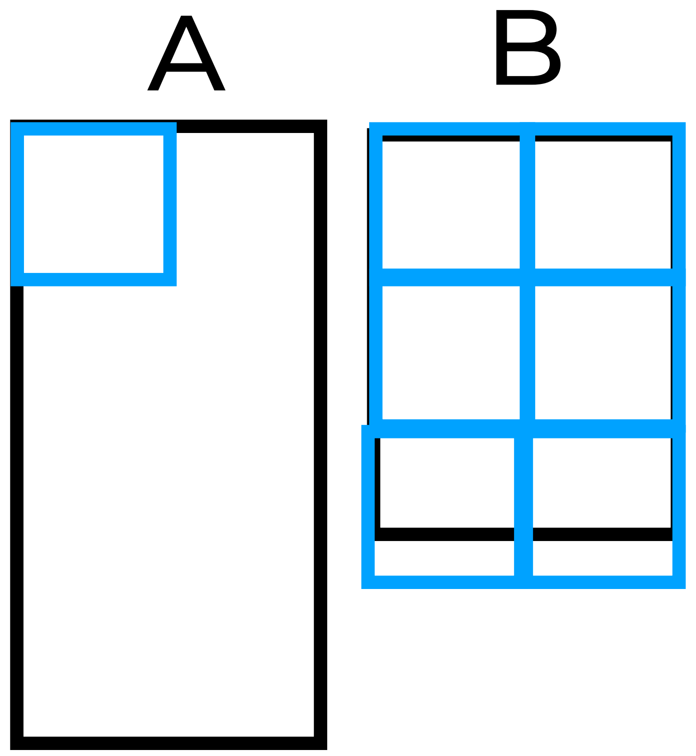


$$C = AB$$

$$C_{ij} = \sum_k A_{ik} B_{kj}$$



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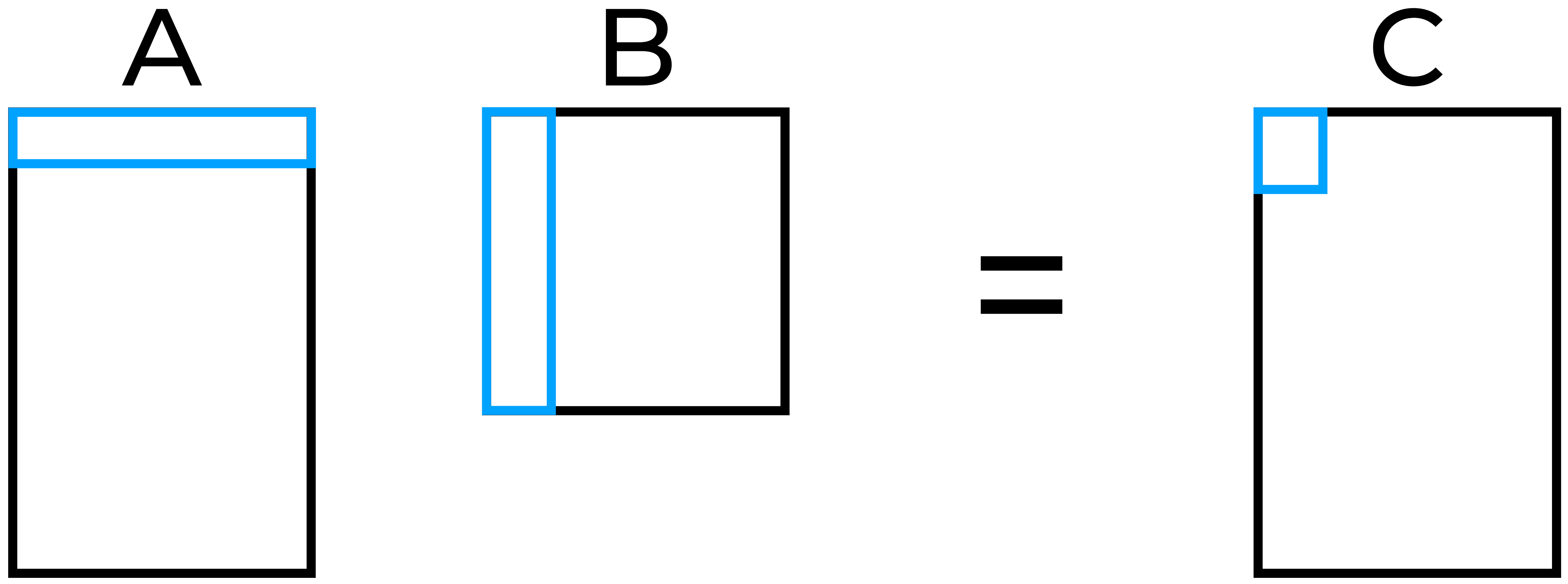

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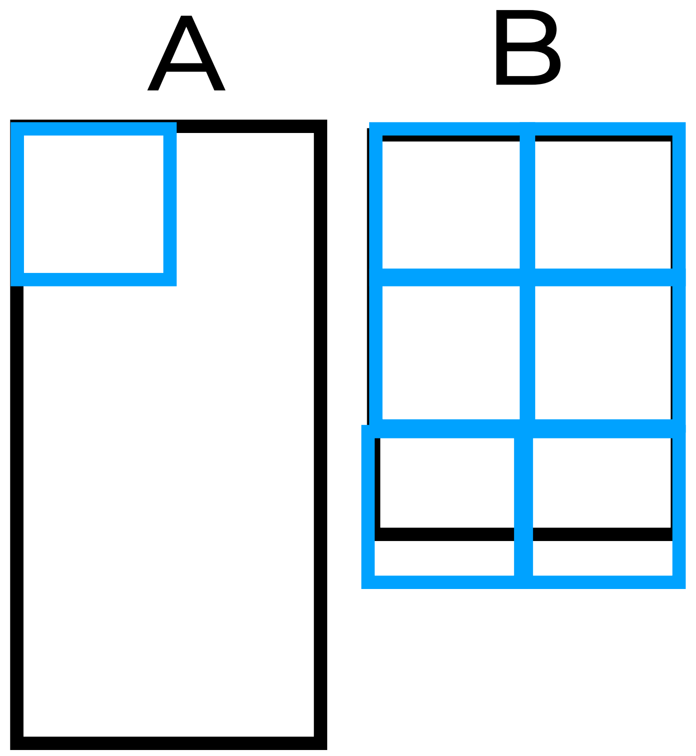

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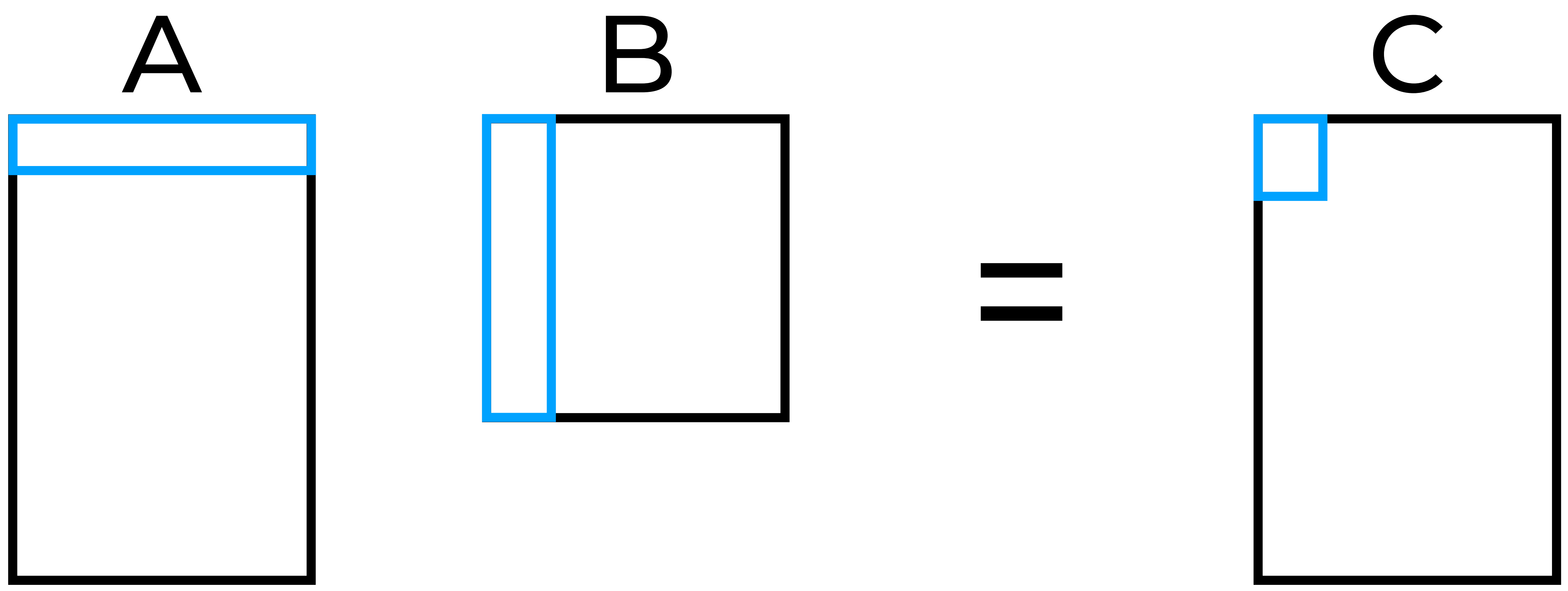

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  - Matrix multiplication can be parallelized

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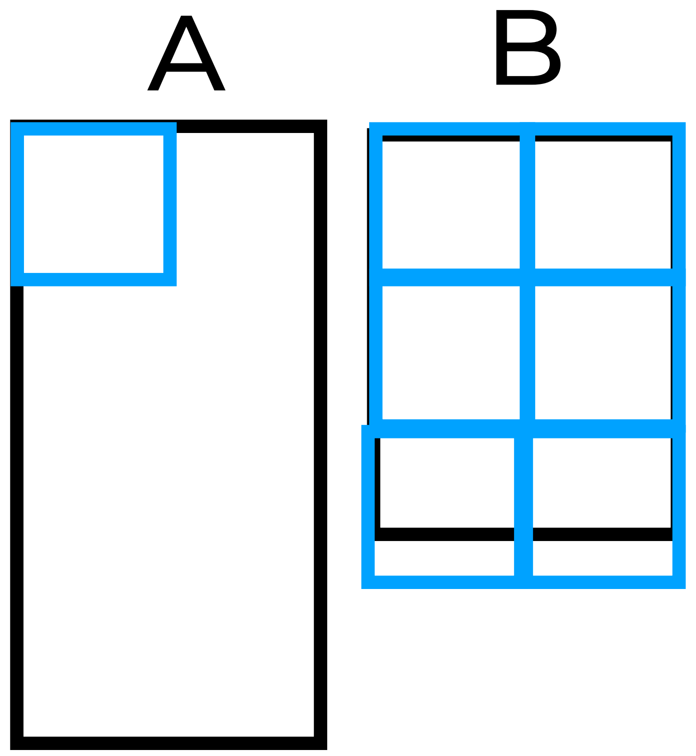

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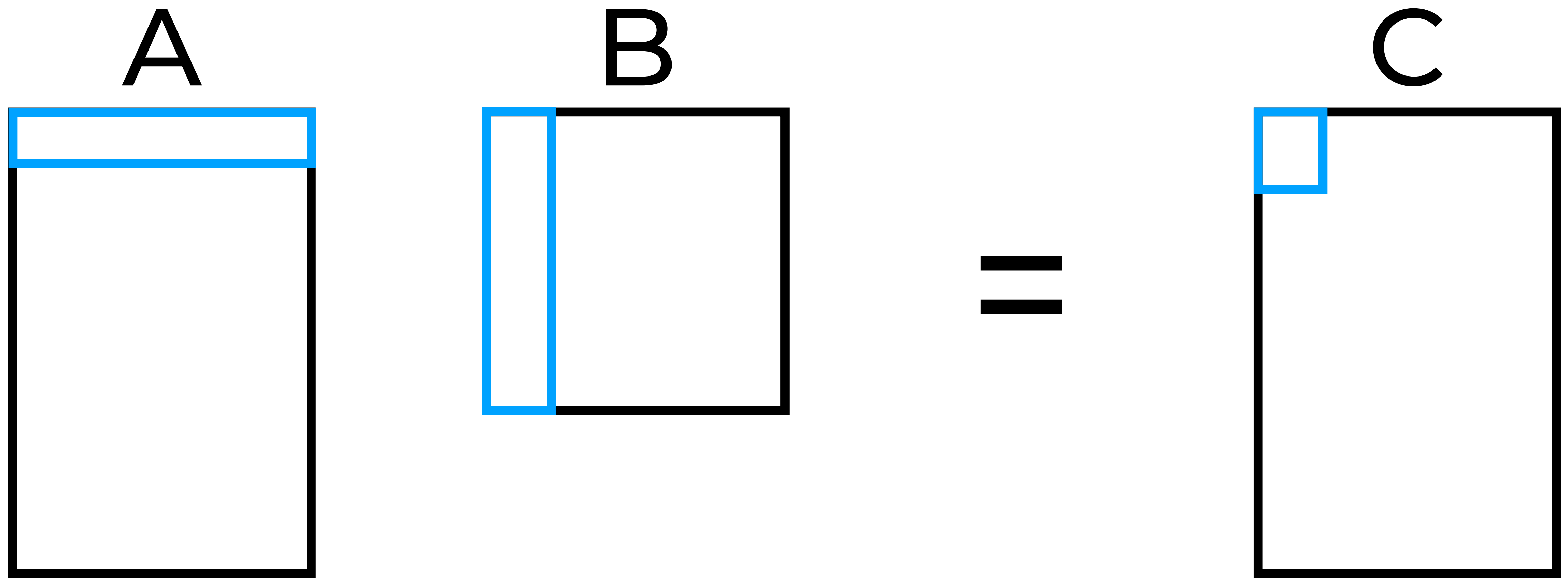

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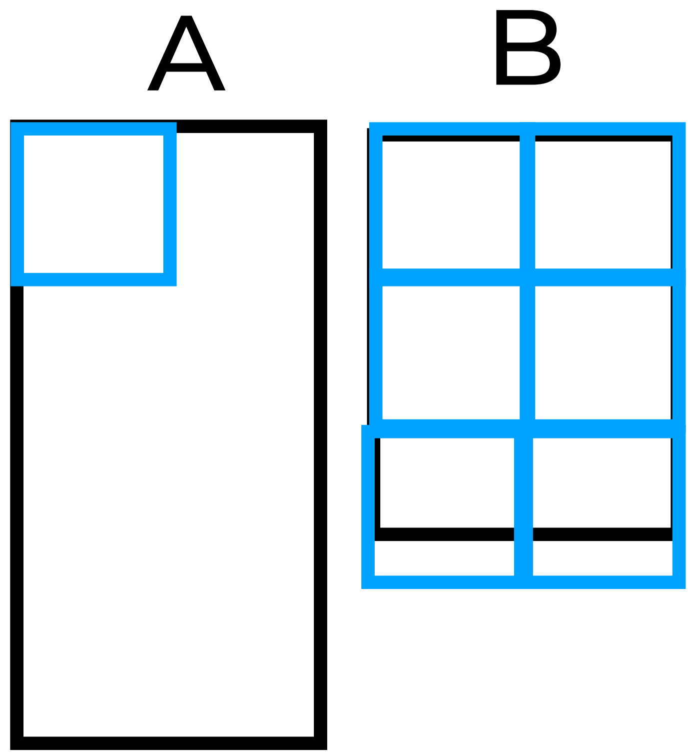

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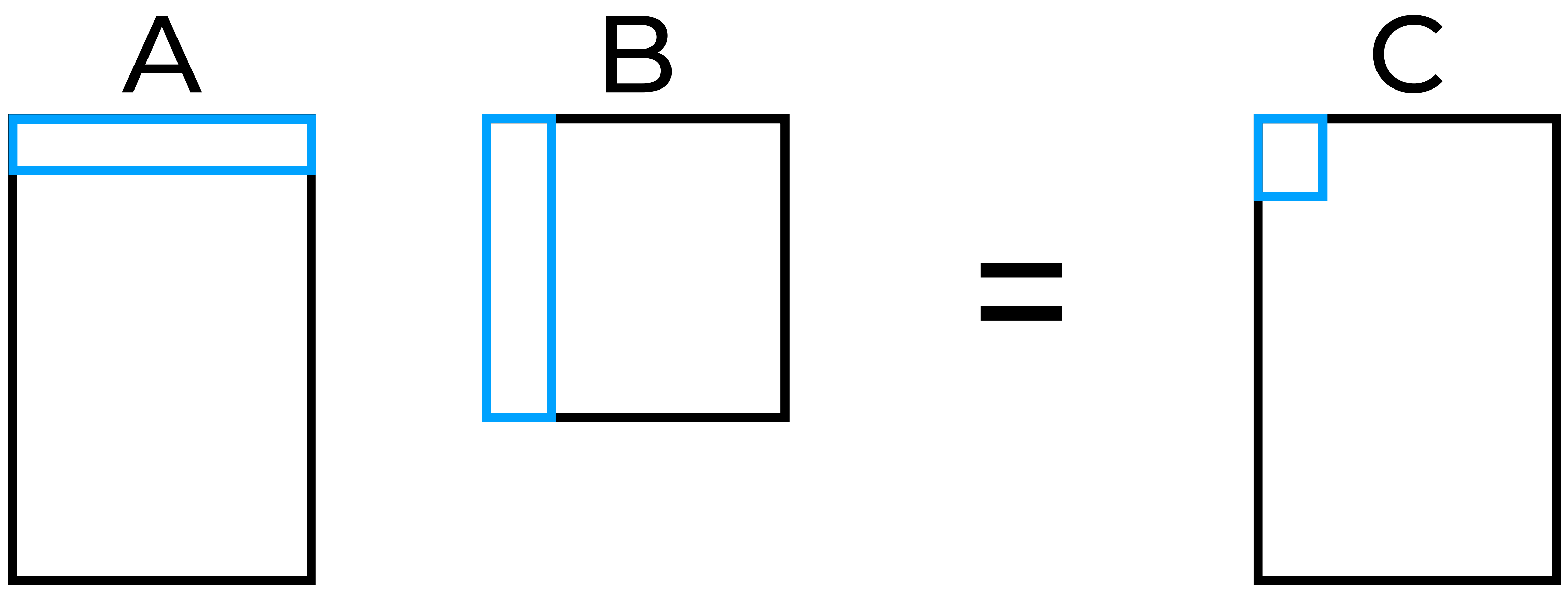

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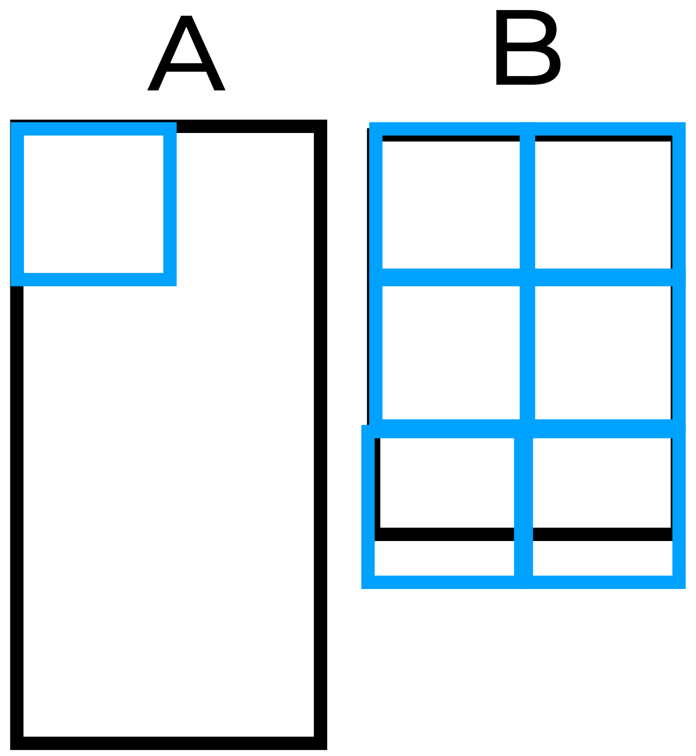

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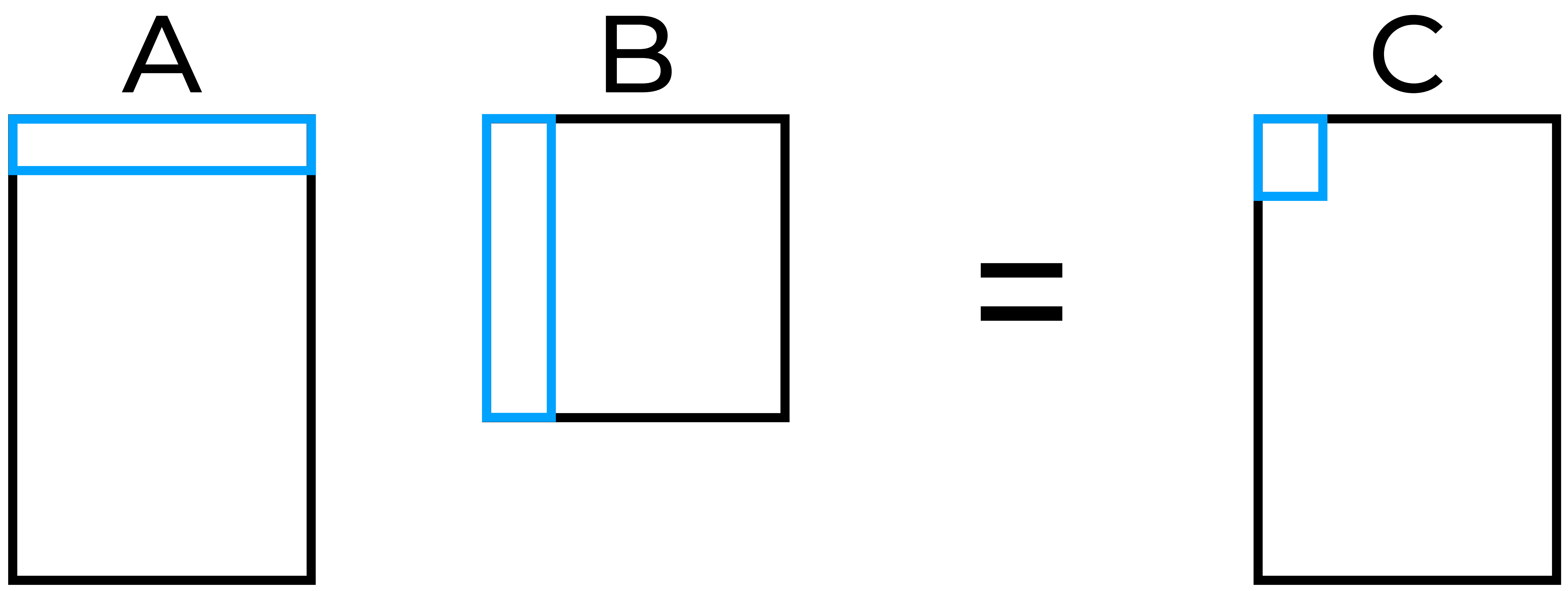

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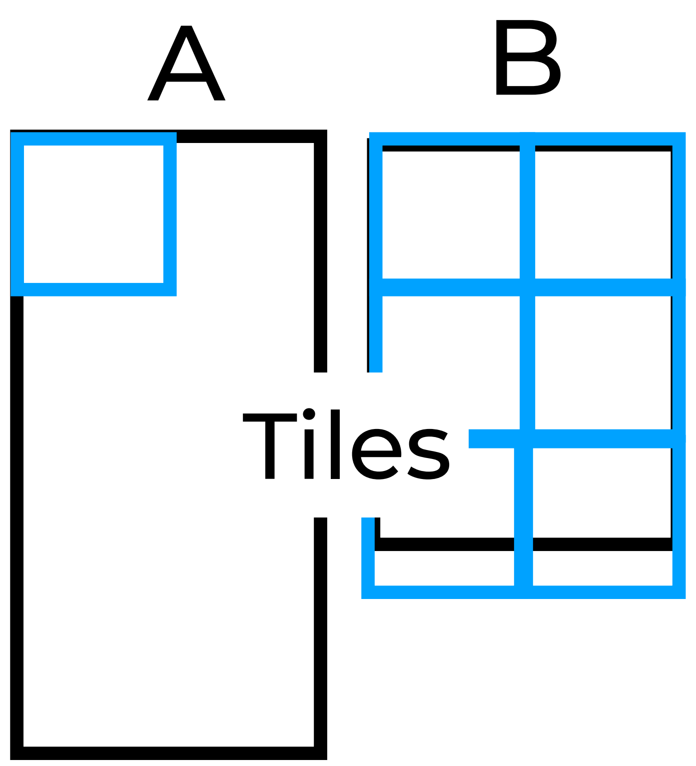

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- Note: not all linear algebra operations can be as easily parallelized. Notably, the matrix inverse.

Specialized hardware

- Graphical Processing Unit (GPU)
  - Initially designed for 3D games
  - Specialized for linear algebra operations
    - Thousands of cores (vs. a few tens for CPUs)
    - Fast access to memory
  - Multi-GPUs for a single computer

NVidia

https://cryptomining-blog.com/tag/multi-gpu-mining-rig/

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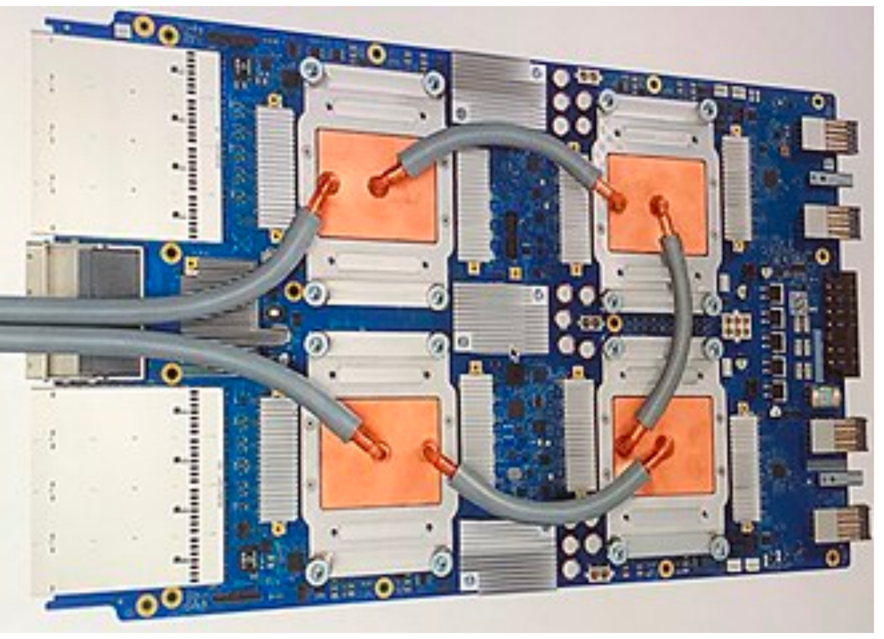
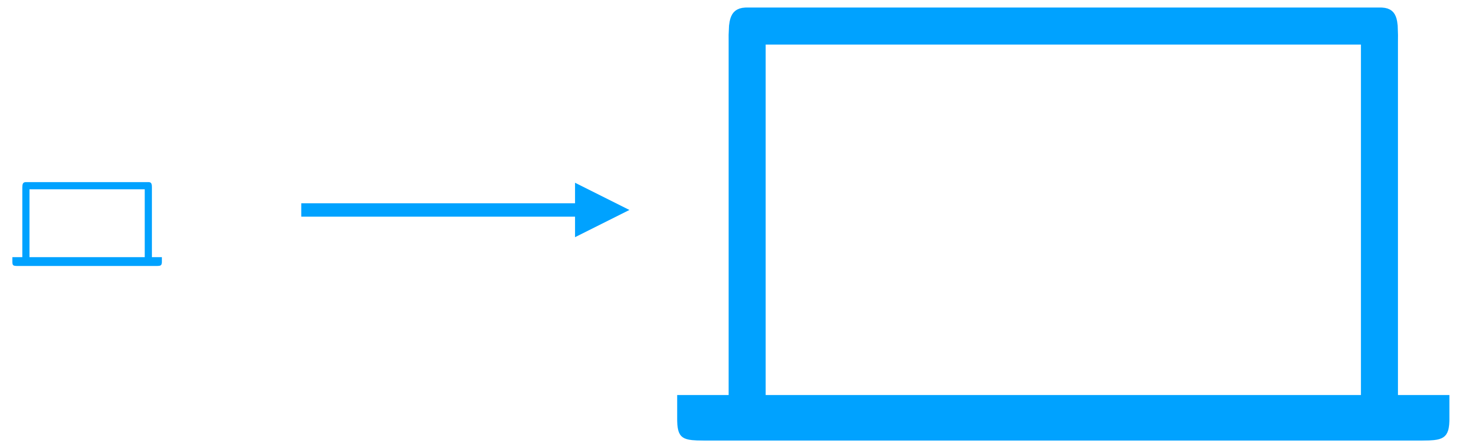
Even more specialized hardware



https://en.wikipedia.org/wiki/Tensor_Processing_Unit

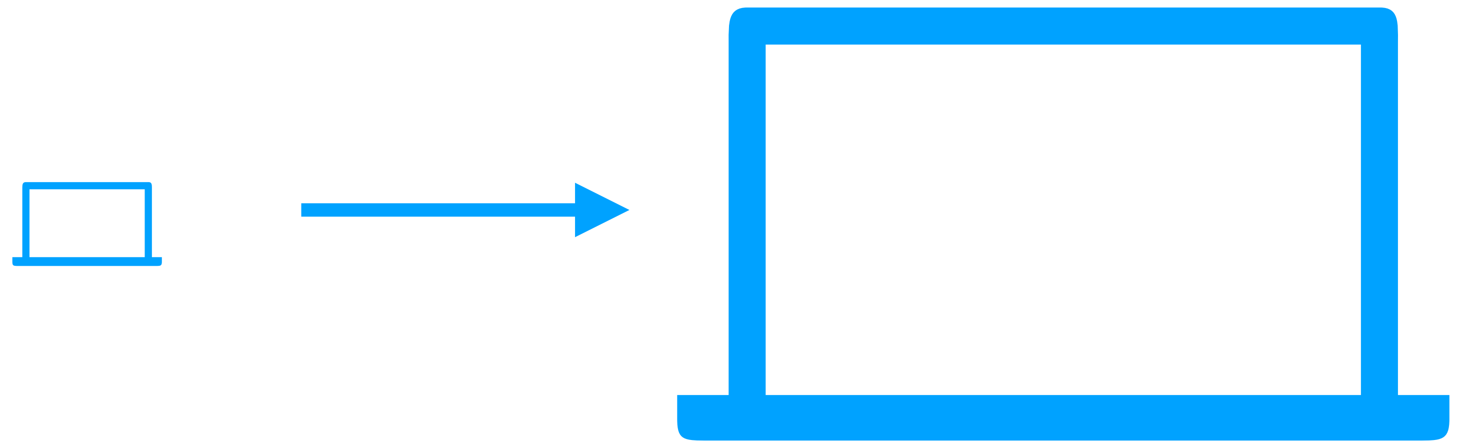
- Tensorflow Processing Unit (TPU)
  - Developed by Google for neural networks (ASIC)
    - Supports matrix multiplication operations
    - Training & Test
  - Precision of operations is lower compared to GPUs
  - Multiple TPUs per “machine”

Distributed Computing



Distributed Computing

- Faster computers can help



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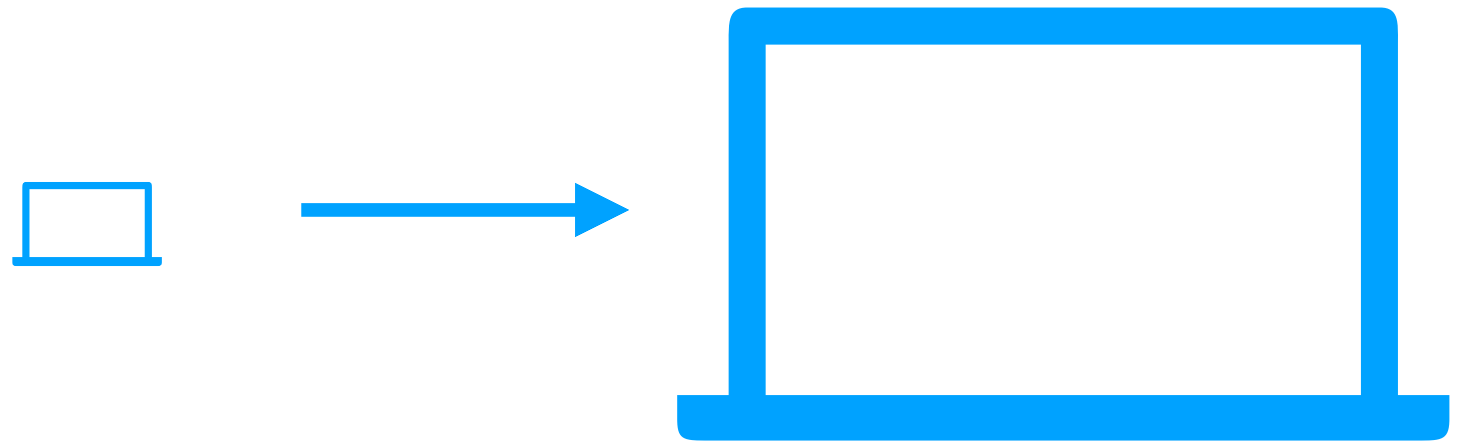

- Faster computers can help
- What about a large of “slow” computers working together?
  - Divide the computation into small problems
    1. All (slow) computers solve a small problem at the same time
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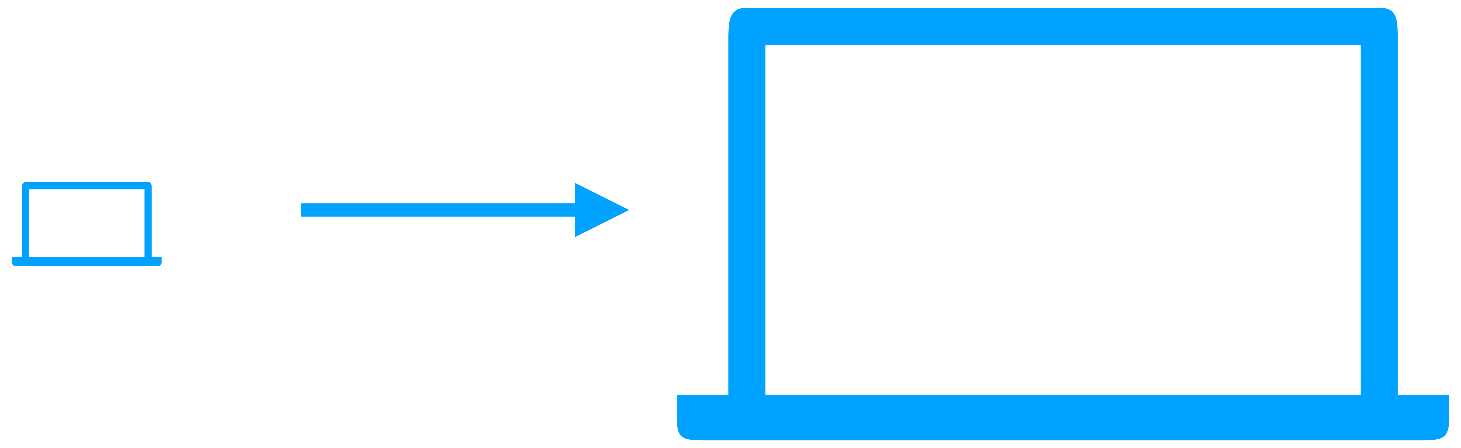

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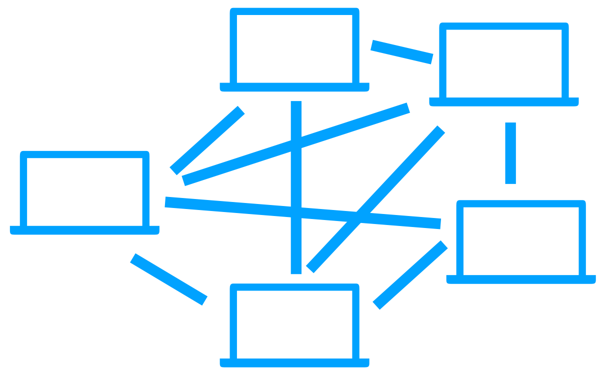

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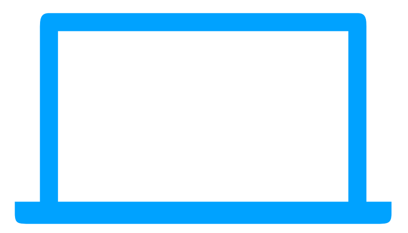
Building our intuition with a simple example

- You are tasked with counting the number of houses in Montreal

  1. Centralized (single computer):

     - Ask a marathon runner to jog around the city and count
     - Build a system to count houses from satellite imagery



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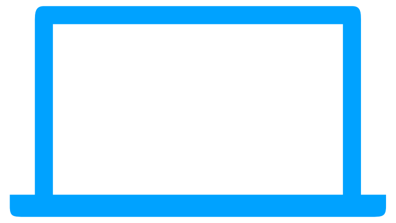
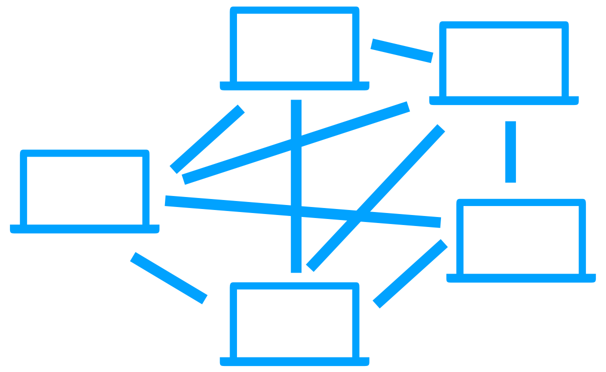


  2. Distributed (many computers):

     - Ask 1,000 people to each count houses from a small geographical area
     - Once they are done they report their result at your HQ



Tool for distributed computing (for machine learning)

- Apache Spark (https://spark.apache.org/)
  - Builds on MapReduce ideas
    - More flexible computation graphs
  - High-level APIs
    - MLlib

Distributed Computing using MapReduce

MapReduce

- From Google engineers

  "MapReduce: Simplified Data Processing on Large Clusters", Jeffrey Dean and Sanjay Ghemawat, 2004

  - Now also known as (Apache) Hadoop
  - Google built large-scale computation from commodity hardware

- Specific distributed interface

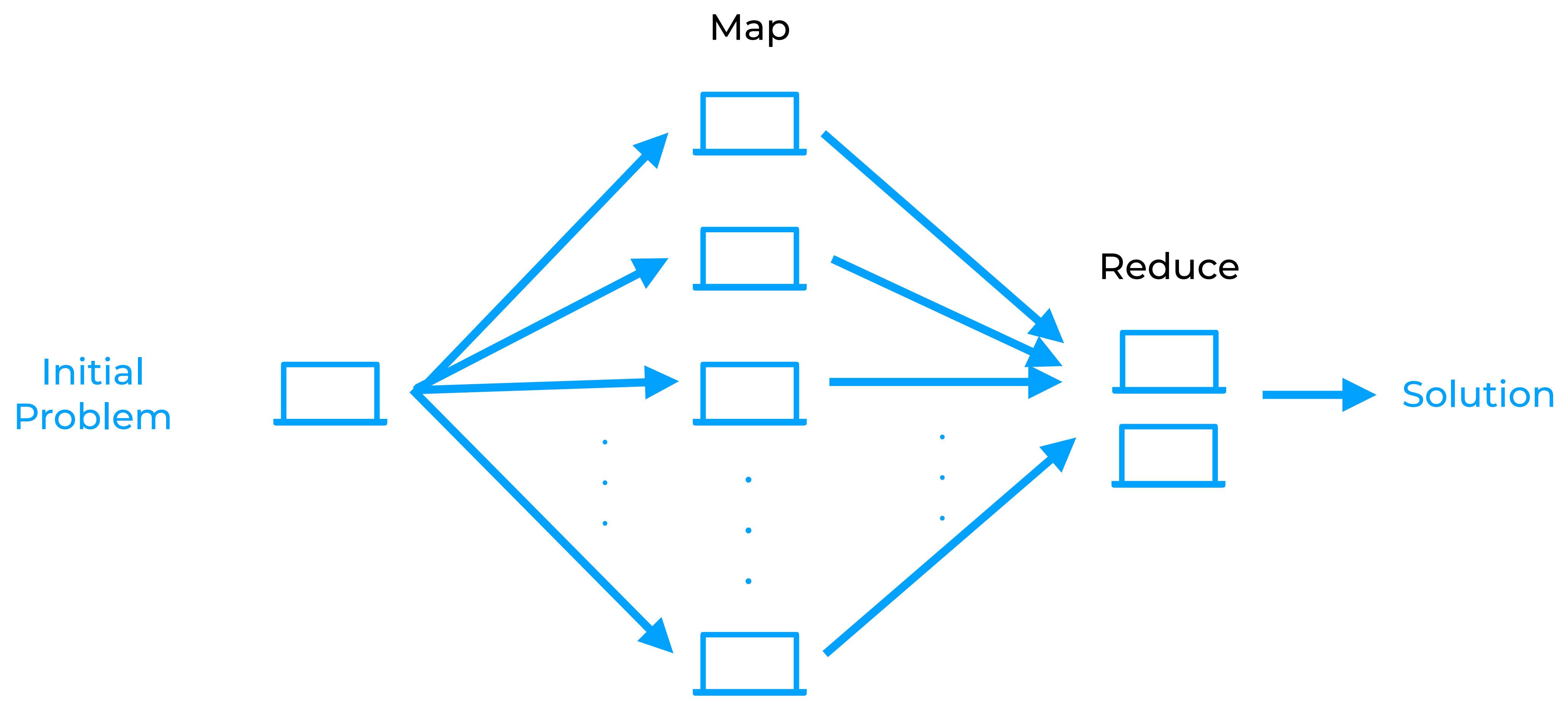
  - Useful for algorithms that can be expressed using this interface

MapReduce

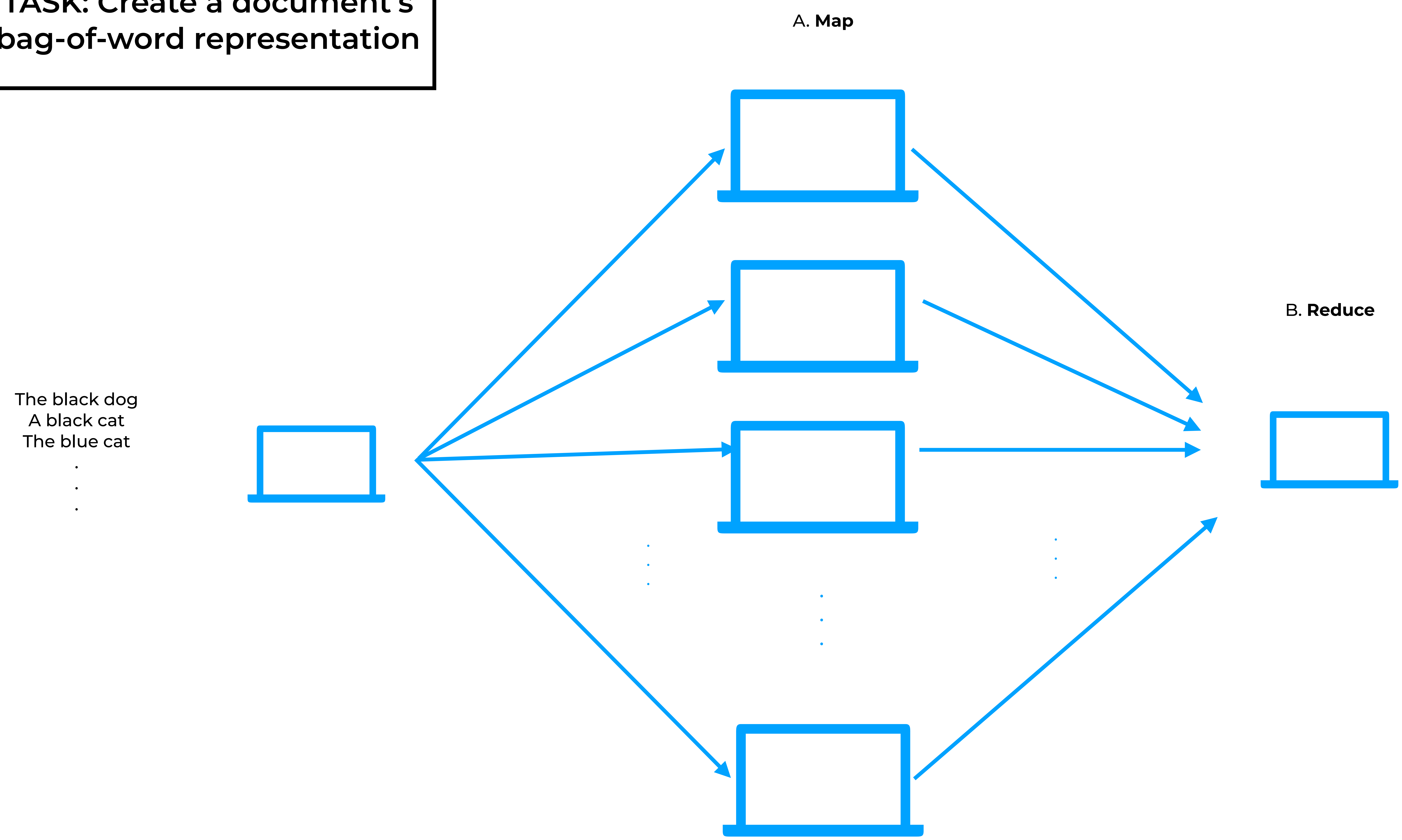
- Two types of tasks:

   A. Map: Solve a subproblem (filtering operation)

   B. Reduce: Combine the results of map workers (summary operation)



TASK: Create a document's bag-of-word representation



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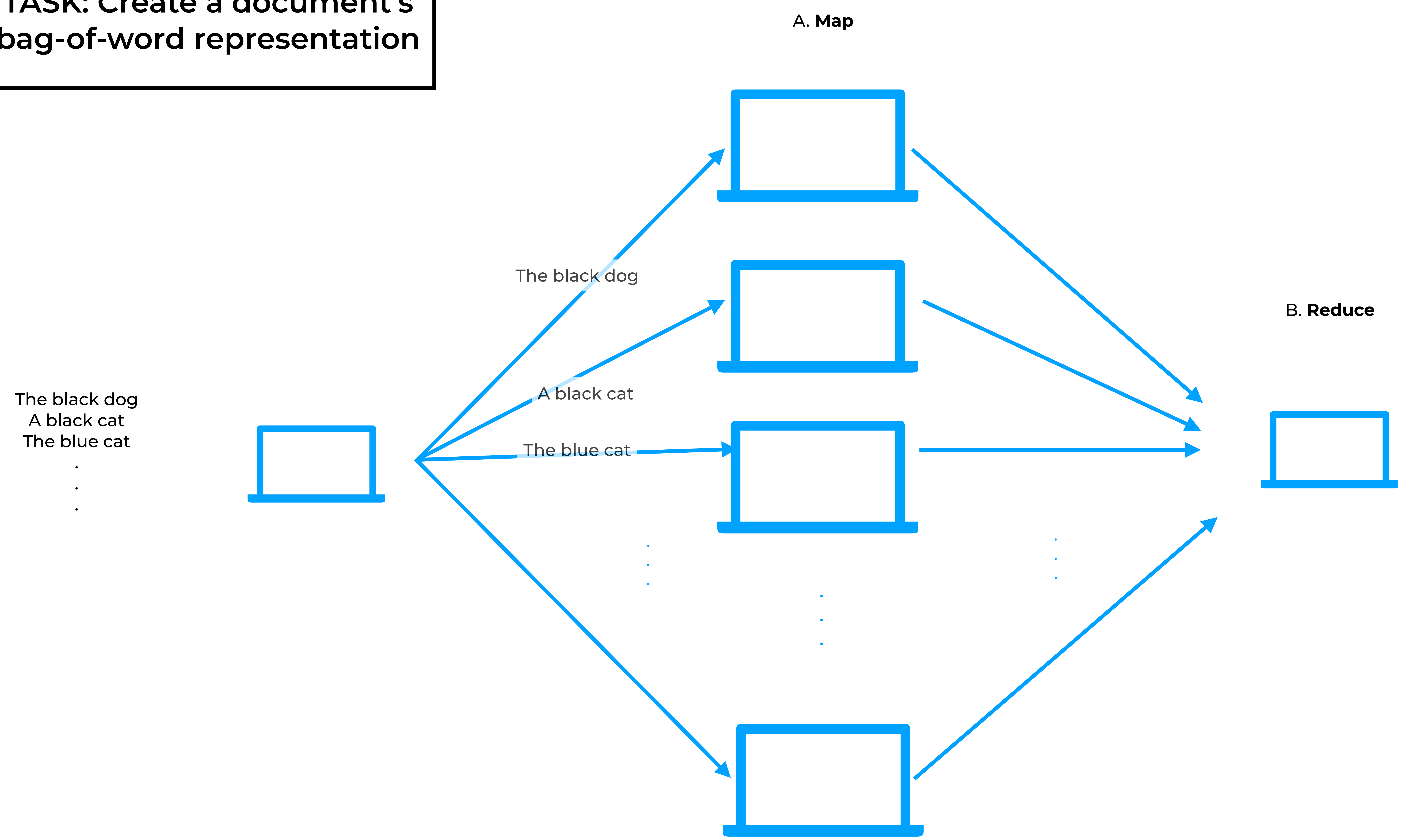

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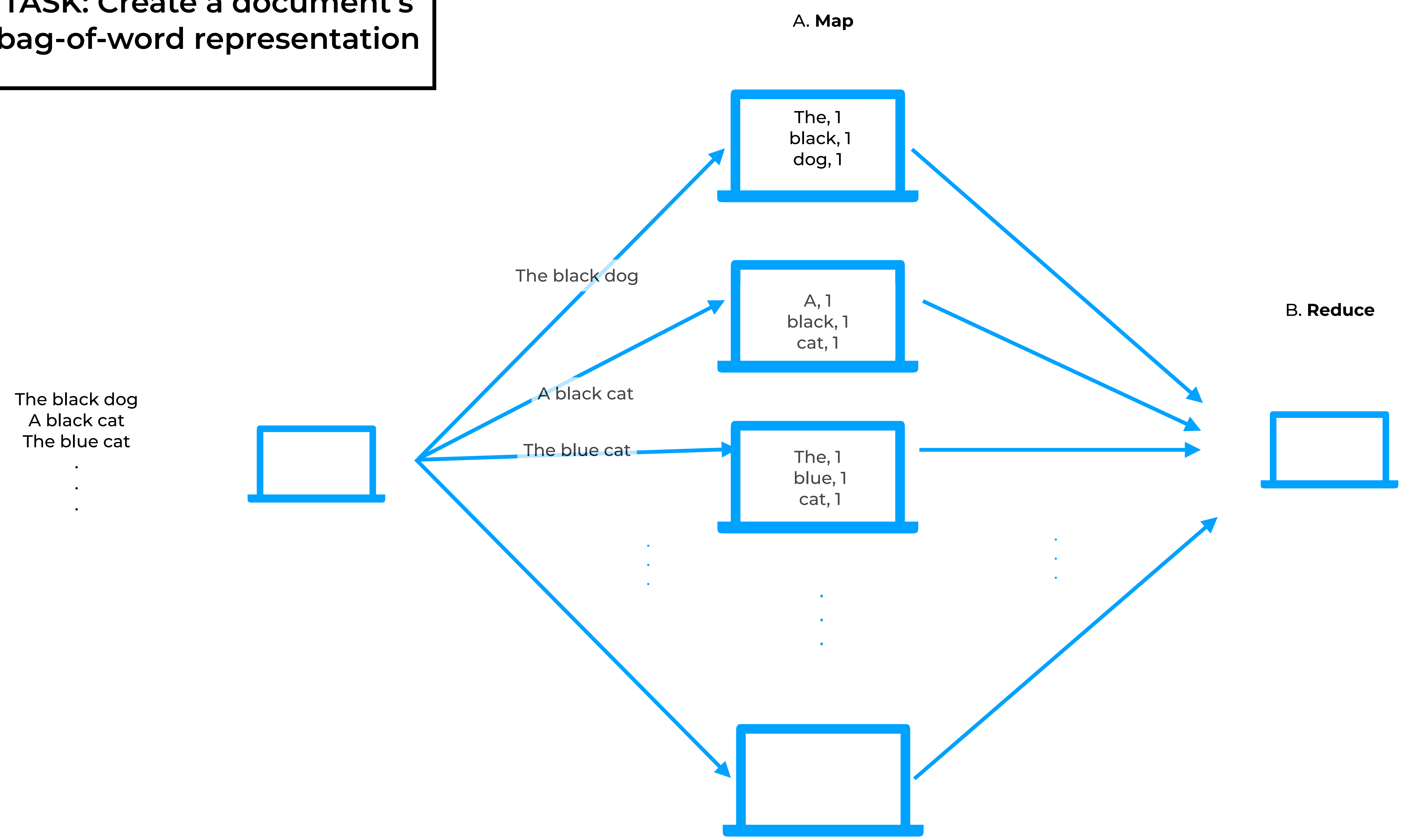

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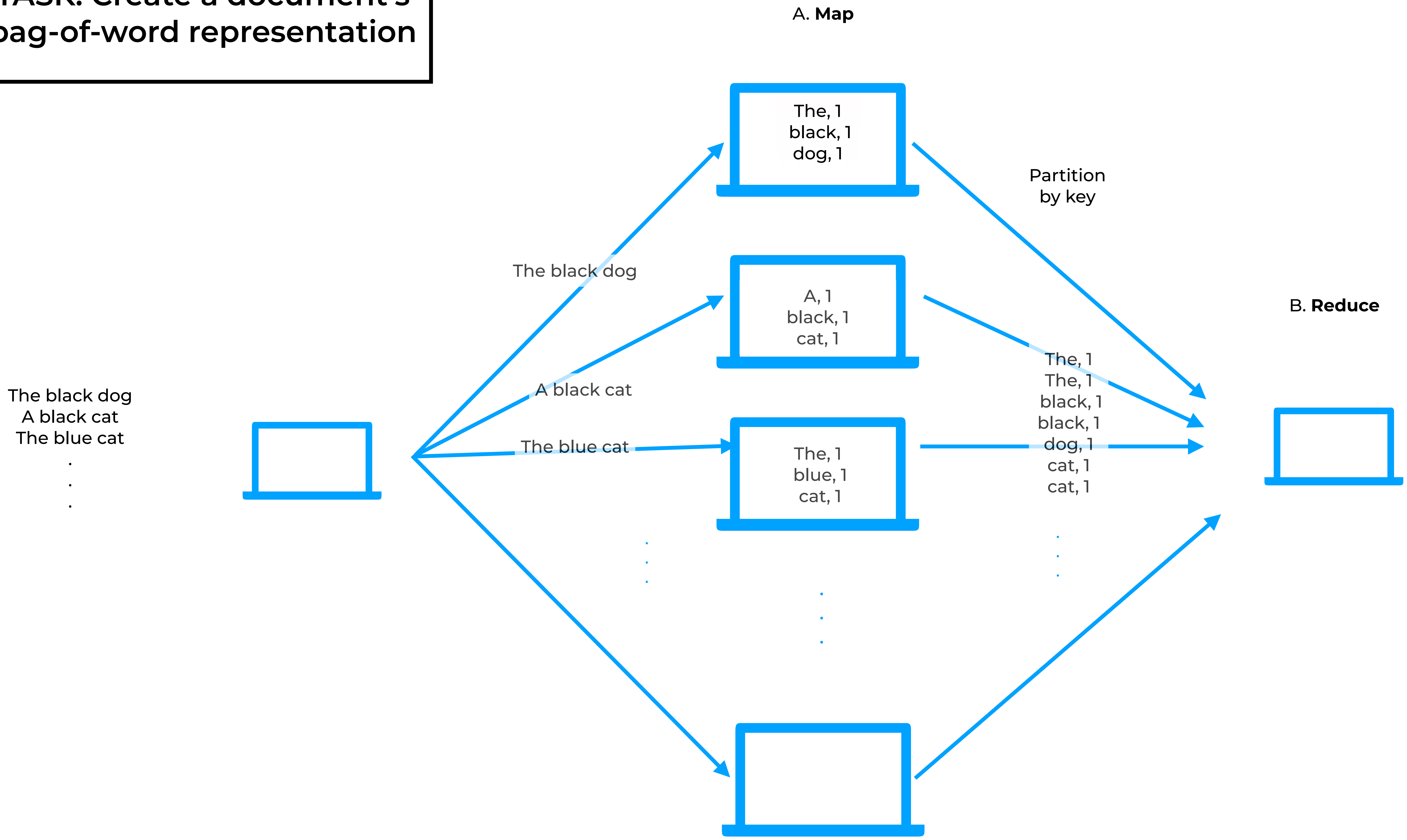

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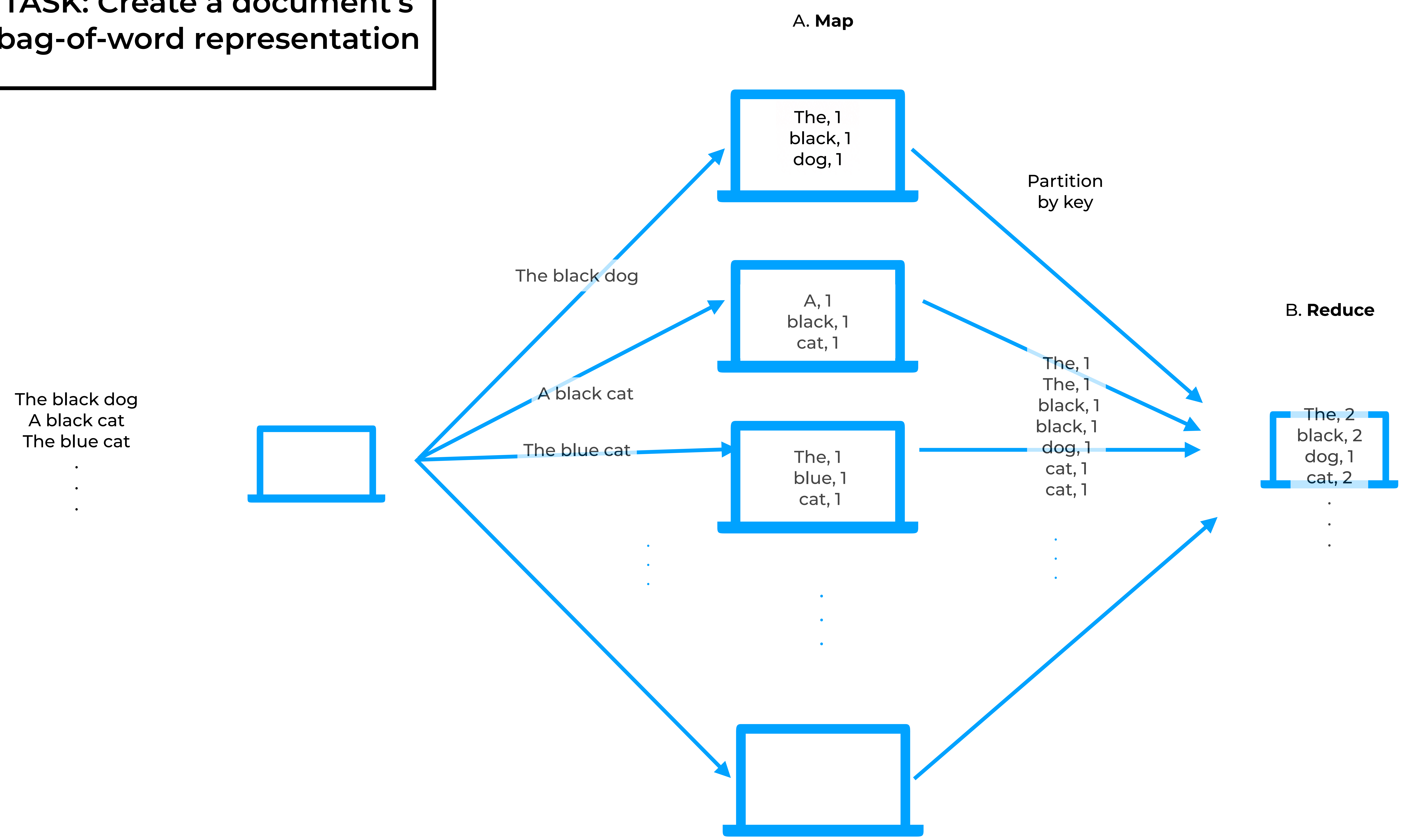

Some details

- Typically the number of subproblems is higher than the number of available machines
  - ~linear speed-up wrt to the number of machines
- If a node crashes, need to recompute its subproblem
- Input/Output
  - Data is read from disk when beginning
  - Data is written to disk at the end

MapReduce is quite versatile

- When I was at Google the saying was (roughly):

“If your problem cannot be framed as MapReduce you haven’t thought hard enough about your problem.”

- A few examples of “map-reduceable” problems:
  - Intuition: Your problem needs to be decomposable into map functions and reduce functions
  - Sorting, filtering, distinct values, basic statistics
  - Finding common friends, sql-like queries, sentiment analysis

MapReduce for machine learning

1. Training linear regression

   - Reminder: there is a closed-form solution

$$\mathbf{w} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Y}$$

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A. **Map**

$$\boxed{\mathbf{X}_0^\top \mathbf{X}_1}$$

MapReduce for machine learning

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A. **Map**

$$X_0^\top X_1$$

2. Other models we studied have a closed form solution (e.g., Naive Bayes and LDA)

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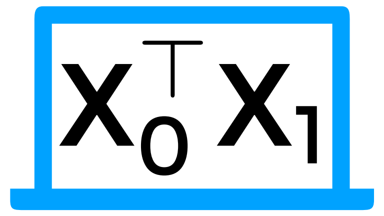
A. Map



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3. Hyper-parameter search
    - A neural network with 2 hidden layers and 5 hidden units per layer and another with 3 hidden layers and 10 hidden units

Shortcomings of MapReduce

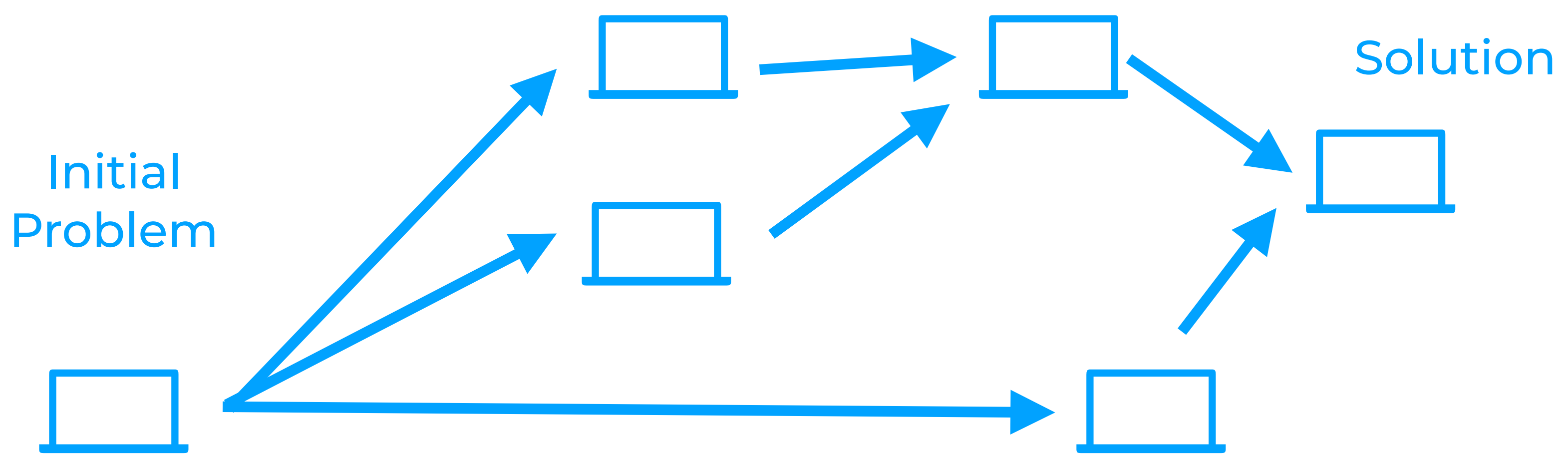
- Many models are fitted with iterative algorithms
  - Gradient descent:
    1. Find the gradient for the current set parameters
    2. Update the parameters with the gradient
- Not ideal for MapReduce
  - Would require several iterations of MapReduce
  - Each time the data is read/written from/to the disk

Distributed computing using Apache Spark

(Apache) Spark

- Advantages over MapReduce

  1. Less restrictive computations graph (DAG instead of Map then Reduce)



     - Doesn't have to write to disk in-between operations

  2. Richer set of transformations

     - map, filter, cartesian, union, intersection, distinct, etc.

  3. In-memory processing

Spark History

- Started in Berkeley's AMPLab (2009)
- Version 1.0 2014
  - Based on Resilient Distributed Datasets (RDDs)
- Version 2.0 June 2016
  - V2.3 February 2018, V2.4.4 September 2019, V3.3.1 October 2022
- Pyton + Spark: pySpark
- Good (current) documentation:
  1. Advanced Analytics with Spark, 2nd edition (2017).
  2. Project docs: https://spark.apache.org/docs/latest/

Resilient Distributed Datasets (RDDs)

- A data abstraction
  - Collection of partitions. Partitions are the distribution unit.
  - Operations on RDDs are (automatically) distributed.
- RDDs support two types of operations:
  1. Transformations
     - Transform a dataset and return it
  2. Actions
     - Compute a result based on an RDD
  - These operations can then be "chained" into complex execution flows

DataFrames

- An extra abstraction on top of RDDs
  - Encodes rows as a set of columns
    - Each column has a defined type
  - Useful for (pre-processed) machine learning datasets
- Same name as `data.frame` (R) or `pandas.DataFrame`
  - Similar type of abstraction but for distributed datasets
- Two types of operations (for our needs): transformers, estimators.

Spark’s “Hello World”

```
data = spark.read.format("libsvm").load("hdfs://...")

model = LogisticRegression(regParam=0.01).fit(data)
```

Spark’s “Hello World”

DataFrame →

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Spark's "Hello World"

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Estimator

Parallel gradient descent

- Logistic Regression

$$y = \frac{1}{1 + \exp(-w_0 - w_1 x_1 - w_2 x_2 - \ldots - w_p x_p)}$$

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- No closed-form solution, can use gradients

$$\frac{\partial \text{ Loss}(Y, X, w)}{\partial w_i}$$

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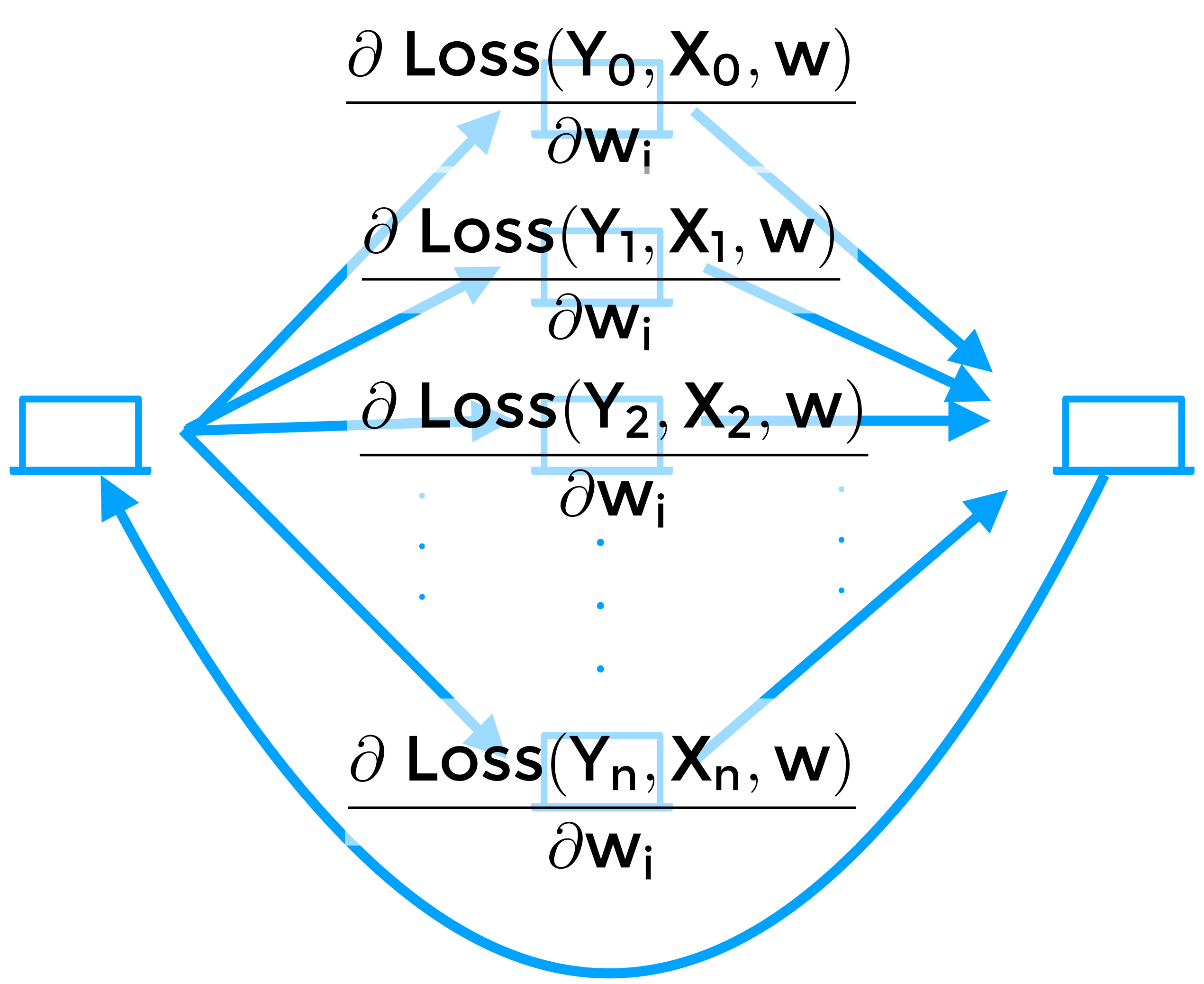

ML setup

1.

Load your data as an RDD

2.

Machine Learning Library (MLlib) Guide

MLlib is Spark's machine learning (ML) library. Its goal is to make practical machine learning scalable and easy. At a high level, it provides tools such as:

- ML Algorithms: common learning algorithms such as classification, regression, clustering, and collaborative filtering
- Featurization: feature extraction, transformation, dimensionality reduction, and selection
- Pipelines: tools for constructing, evaluating, and tuning ML Pipelines
- Persistence: saving and load algorithms, models, and Pipelines
- Utilities: linear algebra, statistics, data handling, etc.

Classification and Regression - RDD-based API

The `spark.mllib` package supports various methods for binary classification, multiclass classification, and regression analysis. The table below outlines the supported algorithms for each type of problem.

Problem Type	Supported Methods
Binary Classification	linear SVMs, logistic regression, decision trees, random forests, gradient-boosted trees, naive Bayes
Multiclass Classification	logistic regression, decision trees, random forests, naive Bayes
Regression	linear least squares, Lasso, ridge regression, decision trees, random forests, gradient-boosted trees, isotonic regression

https://spark.apache.org/docs/latest/ml-guide.html

Takeaways

- Distributed computing is useful:
  - for large-scale data
  - for faster computing
- Current frameworks (e.g., spark) offer easy access to popular ML models + algorithms
  - Useful speedups by decomposing the computation into a number of identical smaller pieces
  - Still requires some engineering/coding