Machine Learning I
60629A

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

Today

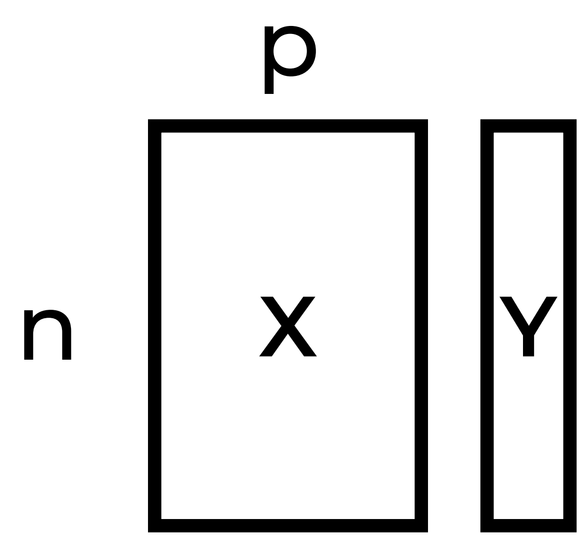
A. Faster computing for machine learning

- Specialized hardware
- Distributed computations
  - Short introduction to MapReduce/Hadoop & Spark

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

Data & Computation

- We generate massive quantities of data
  1. Google 4K searches/s, Twitter: 6K tweets/s, Amazon: 100s sold products/s
     (source: internetlifestats.com)
  2. Banks, insurance companies, etc.
  3. Modestly-sized websites
- 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

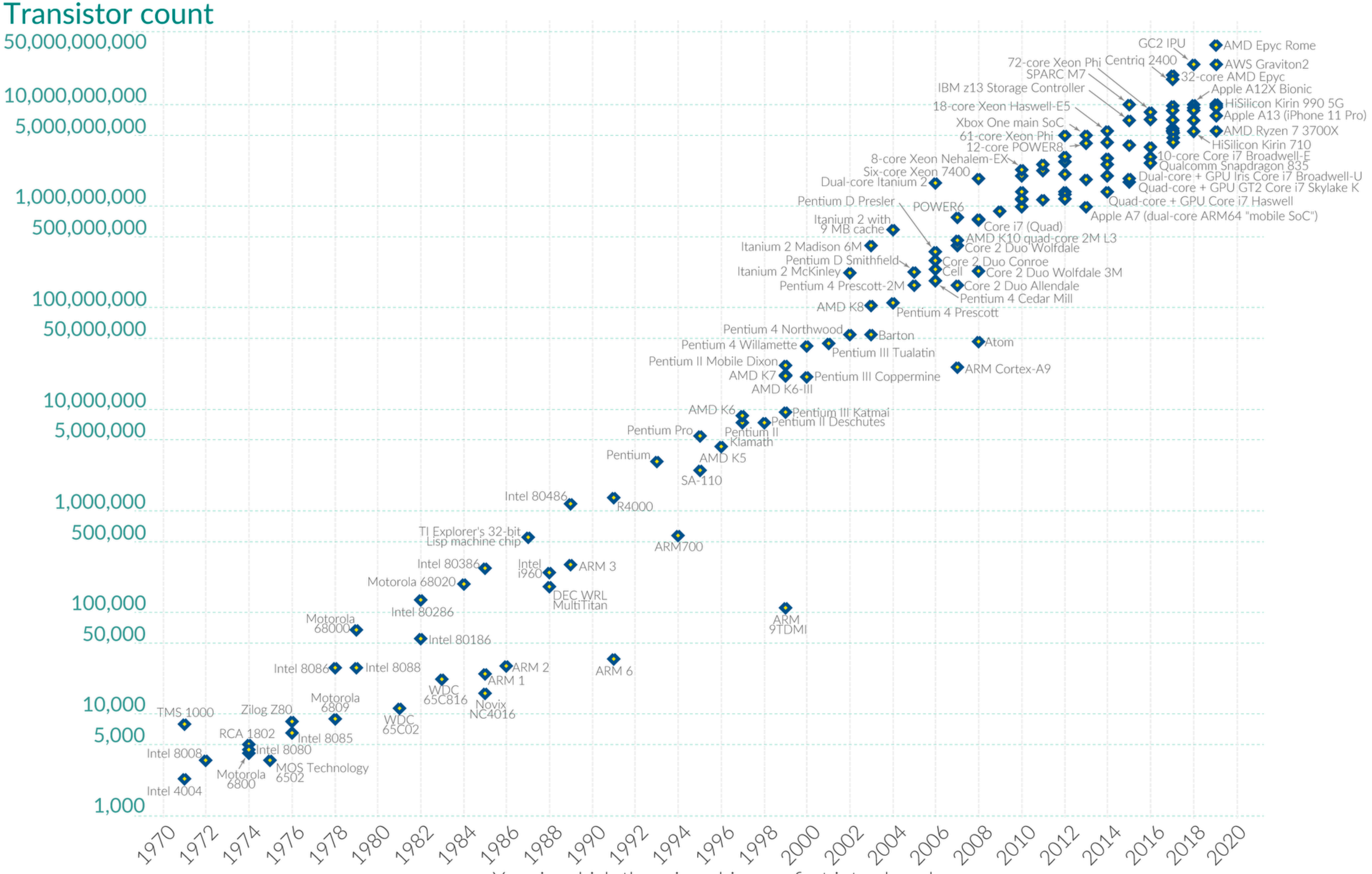
1. Storage

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

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

Modern Computation paradigms

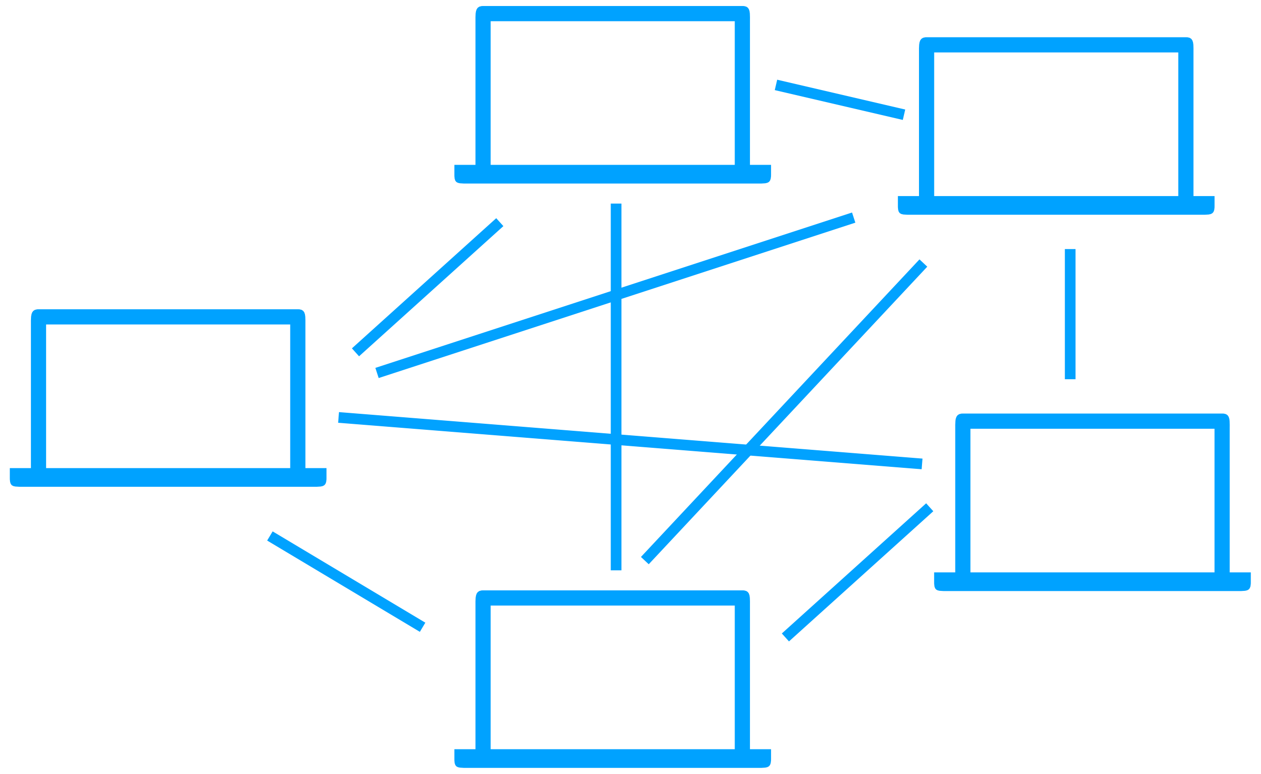
- Floating point operations per second (Flop)
- Smartphone ~ 11 TeraFlops
- 1 Tera: 1,000 Giga, 1 Peta: 1,000 Tera, 1 Exa: 1,000 Peta

1. **"Single" computers**
   - **Large Computers**
     - **1,102 petaFlops***

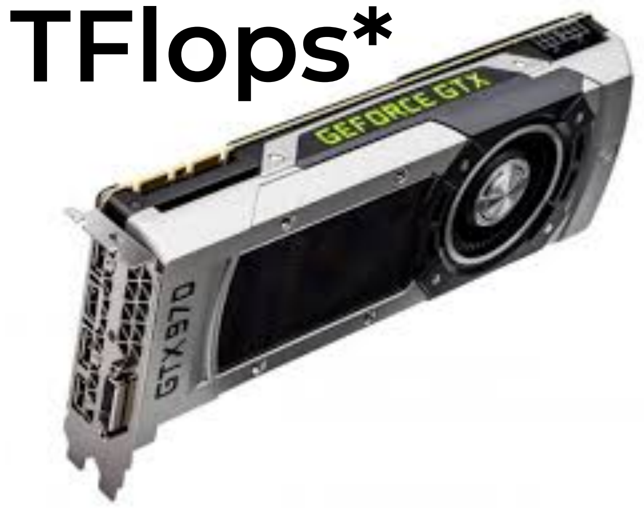
https://www.top500.org/lists/top500/list/2020/06/

Photo from Riken

2. **Distributed computation**
   - **2,3 exaFlops* (Folding@home)**



3. **Specialized hardware**
   - **Focusses on subset of operations**
     - **Graphical Processing Unit (GPU), Field Programmable Gated Array (FPGA)**
     - **~1,000 TFlops***



*: these numbers are given as indications and are subject to changes and precisions.

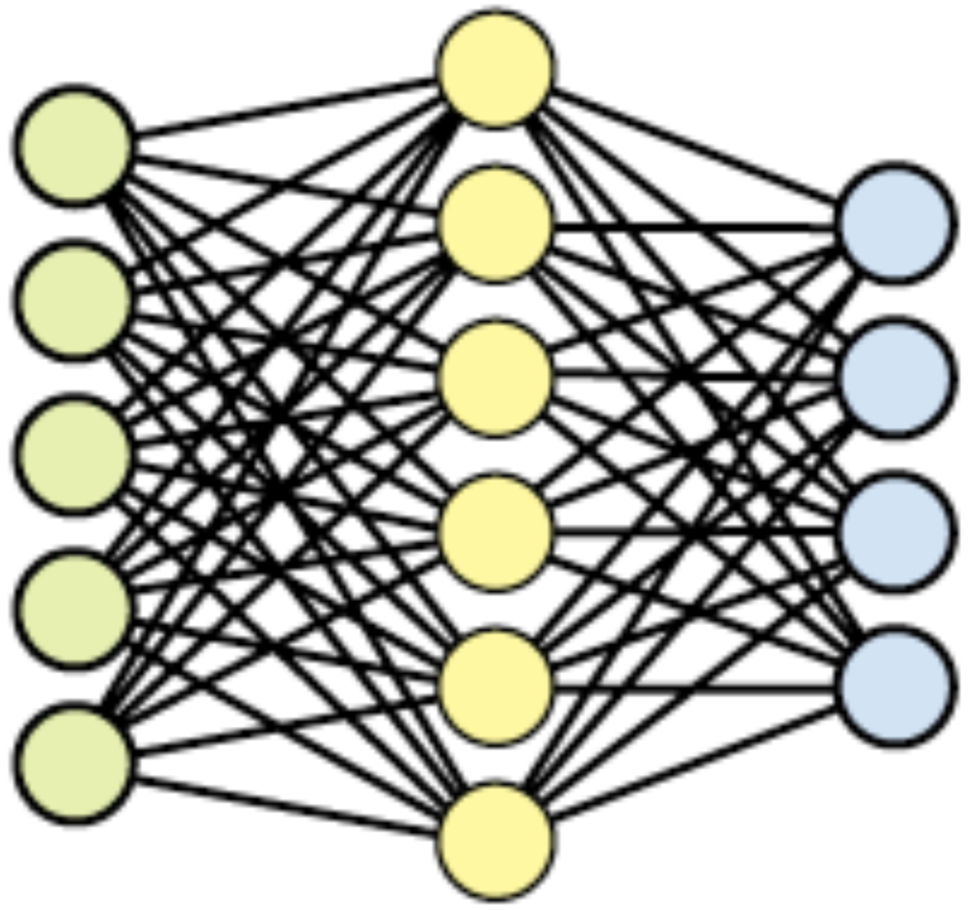
GPUs & other specialized hardware

Hardware

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

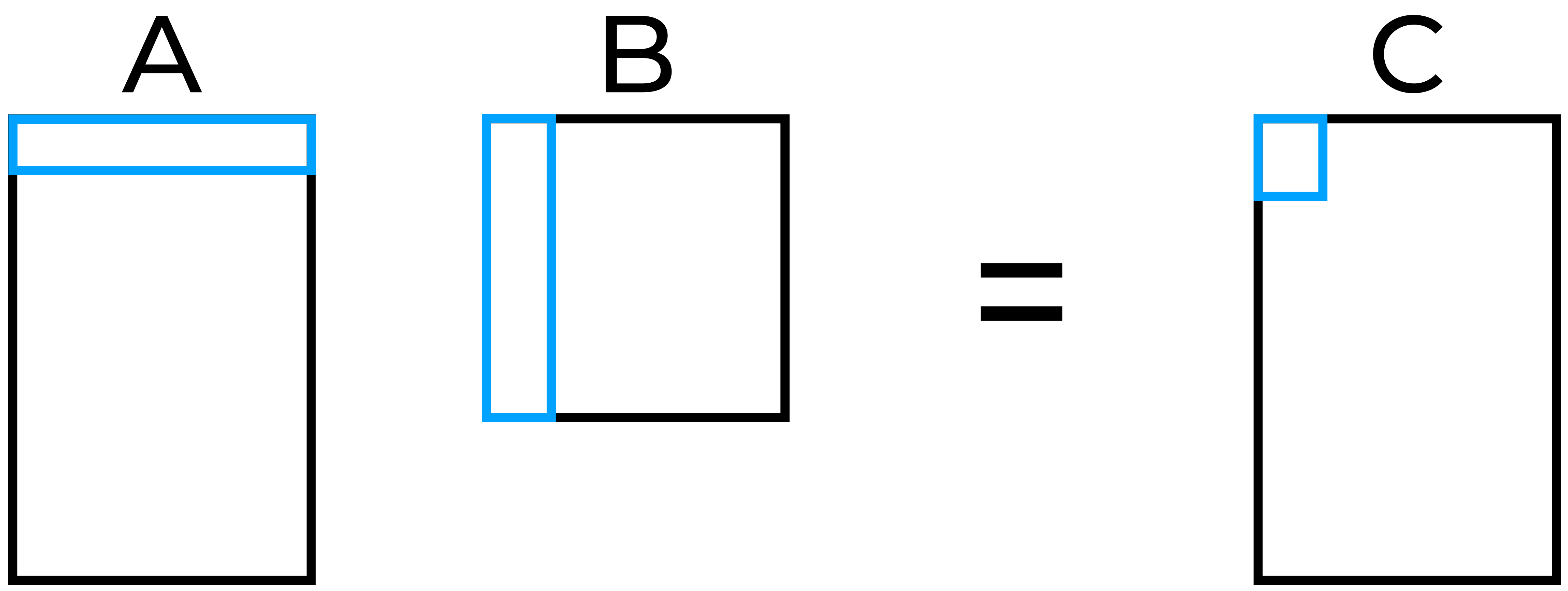
- Central Processing Unit (CPU)
  - Computer's cognition
  - Executes all the instructions from software
    - Arithmetics, read/writes, logic, etc.

Neural Networks

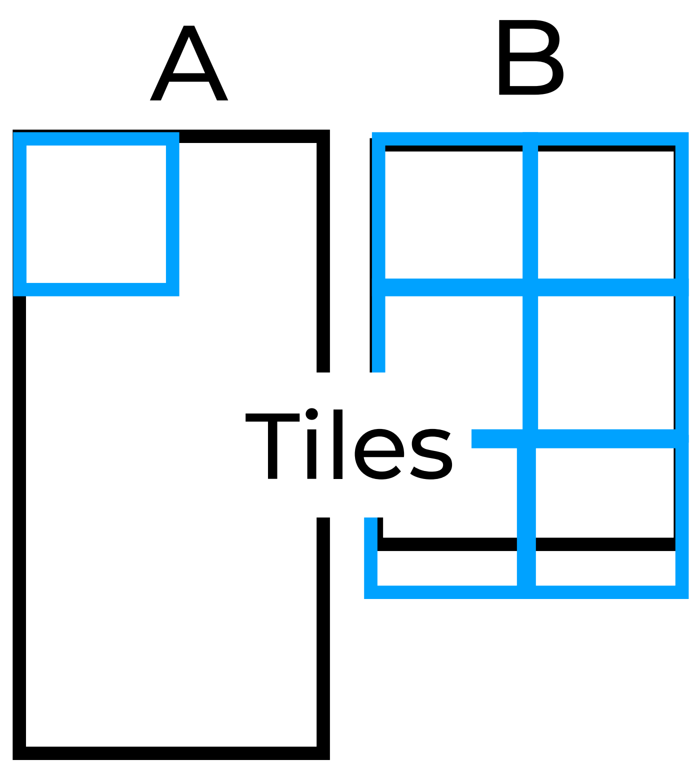


- Linear Algebra:
  - Multiplication *vector X matrix*
    - Neuron activation of multiple neurons
    - Neuron activation for multiple datum
  - Multiplication matrix X matrix
    - Activation of multiple neurons for multiple datum
- The exact dimensions of these vector & matrix depend on the data size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

Parallelizing neural network computations



$C = AB$



- The values of C can be computed **independently** from one another
    - Matrix multiplication can be parallelized
- When parallelizing we can then obtain very significative gains
    - Depend on the size of C
- In practice, divide in tiles
- Note: not all linear algebra operations can be as easily parallelized. Notably, the matrix inverse.

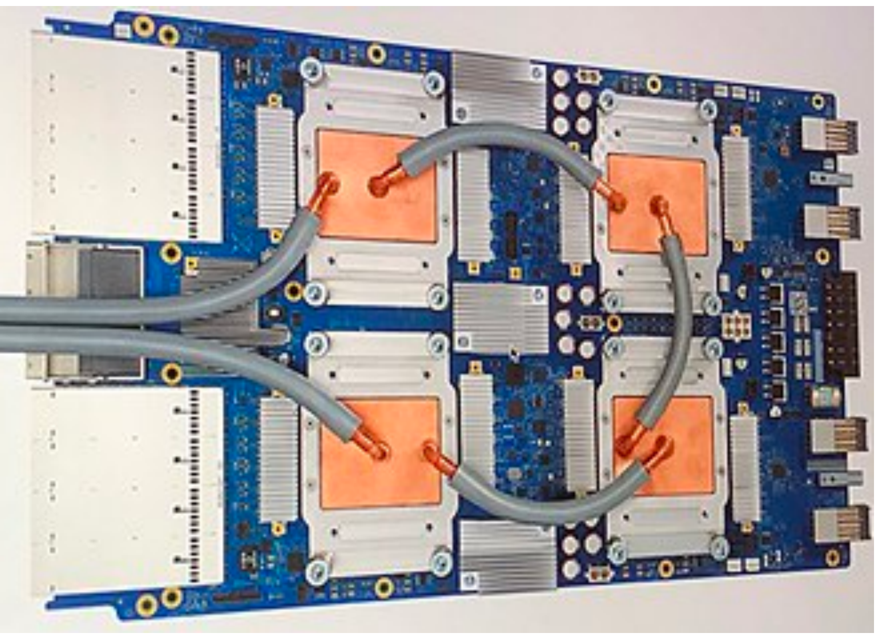
Specialized hardware

NVidia

- 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

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

Even more specialized hardware



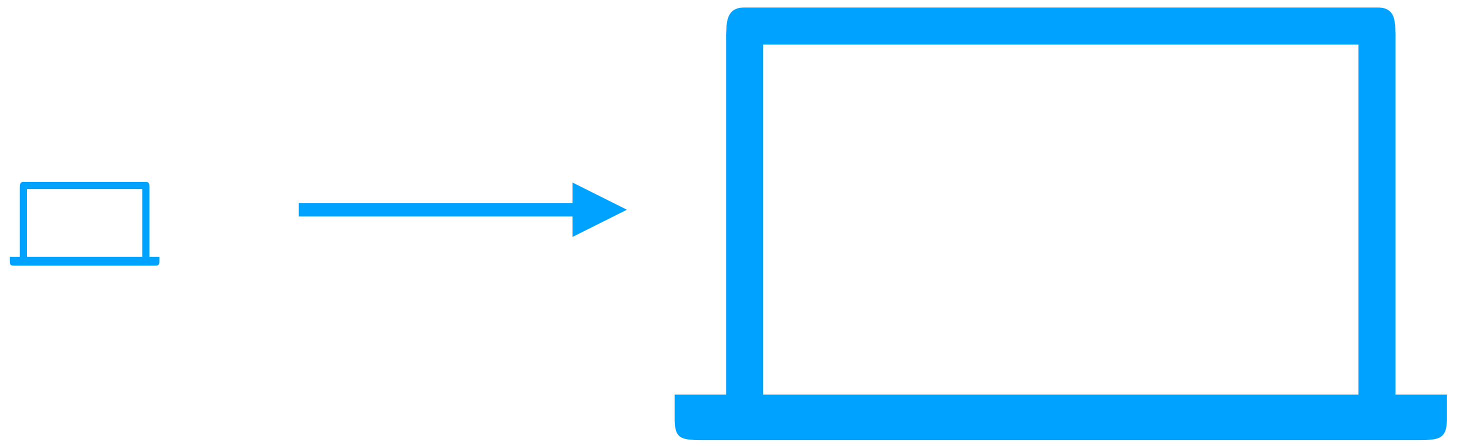
https://en.wikipedia.org/wiki/Tensor_Processing_Unit

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

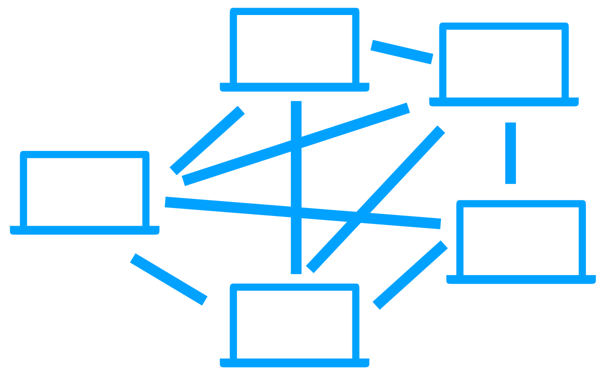
https://colab.research.google.com/github/lcharlin/80-629/blob/master/week10-ParallelComputations/CPU_GPU_TPU.ipynb

- With a few small changes, we can start using a GPU or even a TPU (Google platform only)

Distributed Computing



- Faster computers can help

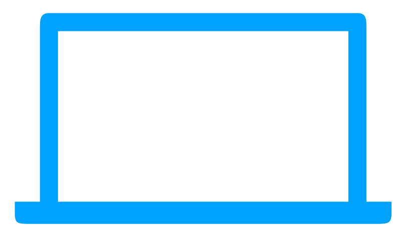


- What about a large of “slow” computers working together?
    - Divide the computation into small problems
        1. All (slow) computers solve a small problem at the same time
        2. Combine the solution of small problems into initial solution

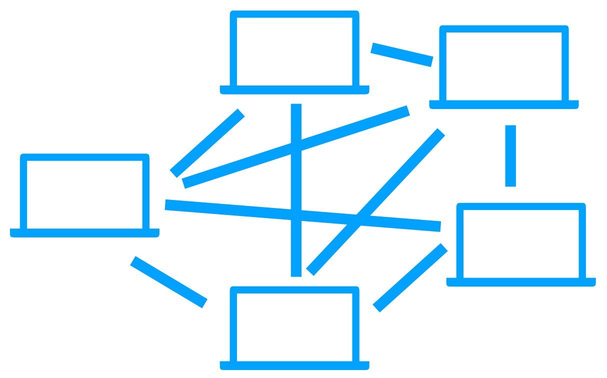
Building our intuition with a simple example

- 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



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



Distributed Computing using MapReduce

Outline

- MapReduce
  - Fundamentals and bag-of-words example
- Spark
  - Fundamentals & MLlib

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

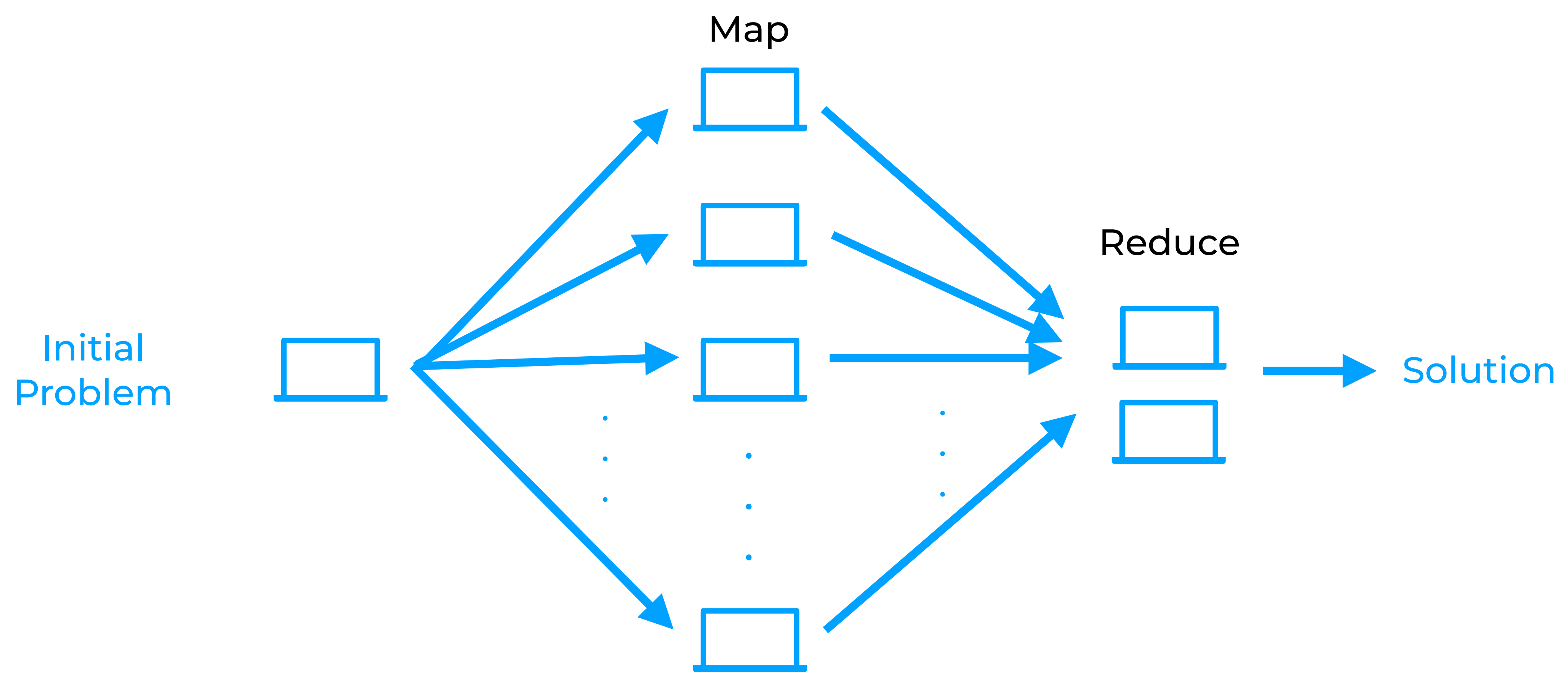
MapReduce

- Two types of tasks:

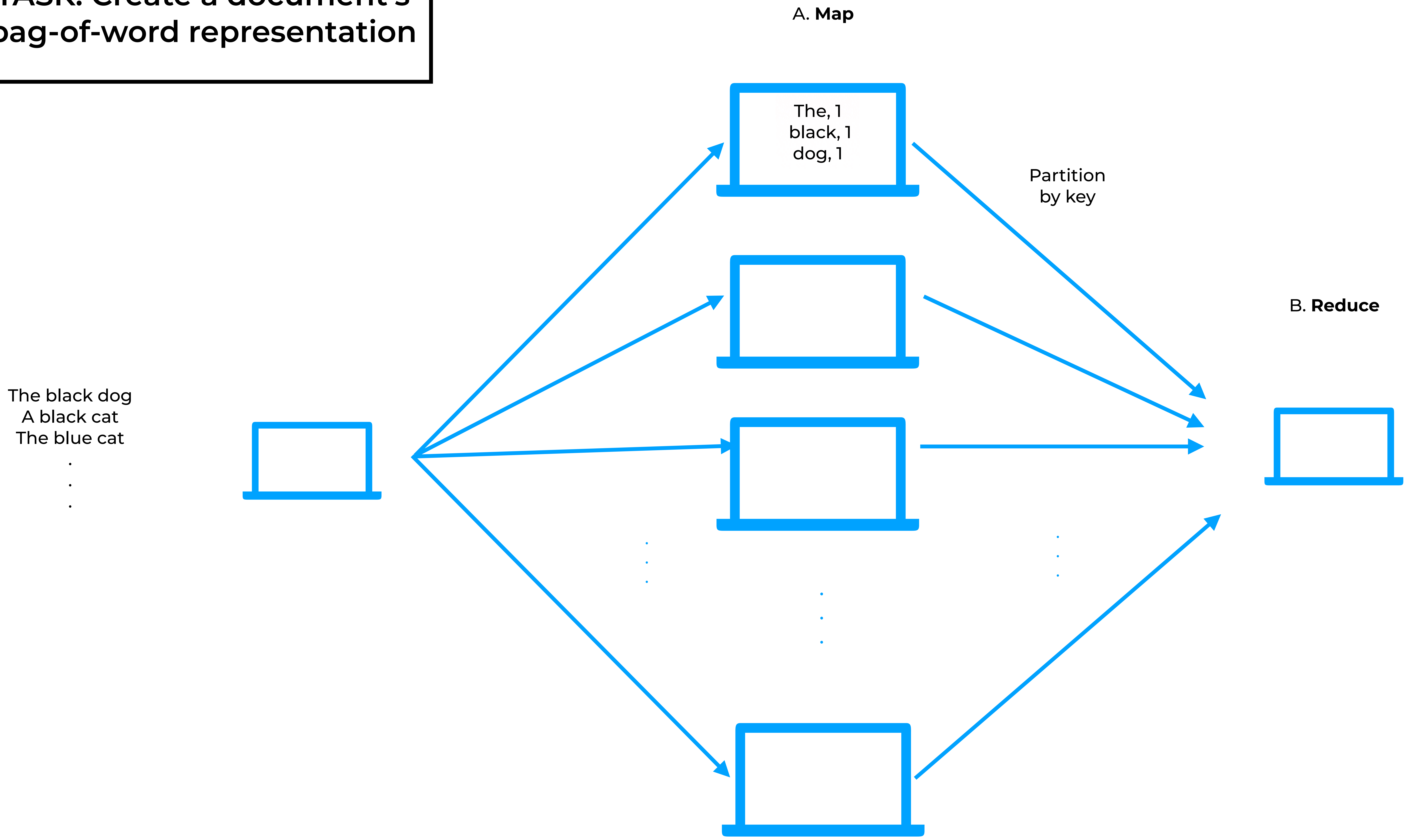
  A. Map: Solve a subproblem (filtering operation)

  - Sorting is then performed

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



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



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 map/reduce
    - Data is written to disk at the end of map/reduce

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

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

$$\mathbf{w} = \Big(\sum_{ij} \mathbf{X}_i^\top \mathbf{X}_j\Big)^{-1} \Big(\sum_{i} \mathbf{X}_i^\top \mathbf{Y}_i\Big)$$

- Each term in the sums can be computer independently

A. **Map**

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

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

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

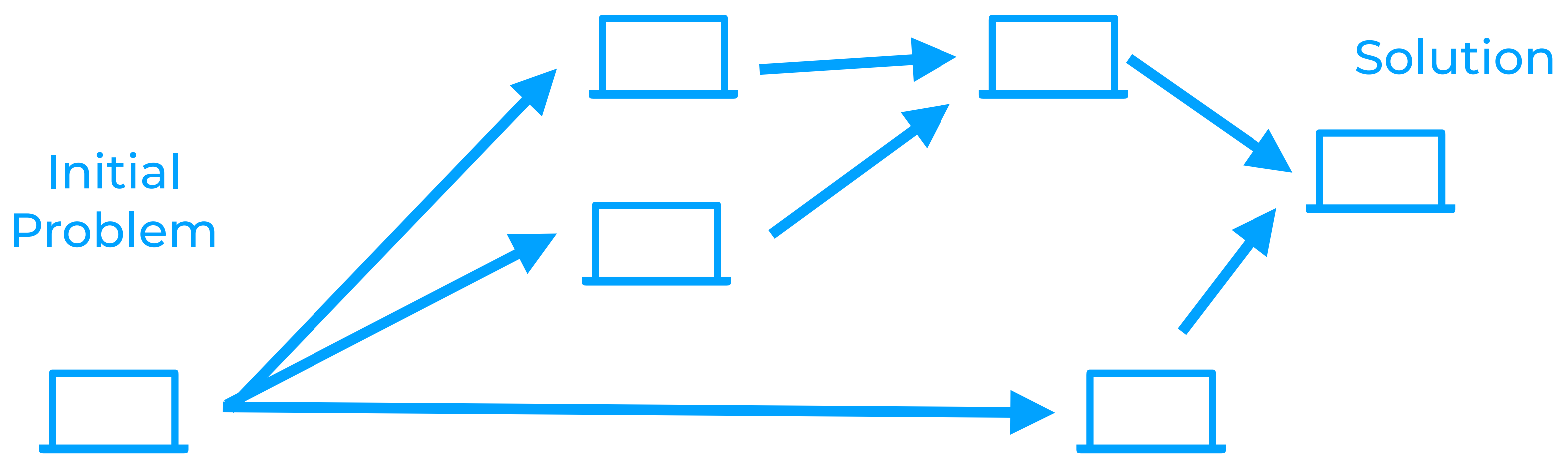
- Many models are fitted with iterative algorithms
  - Gradient descent:
    1. Find the gradient for the current set parameters
    2. Update the parameters with the gradient
- Not ideal for MapReduce
  - Would require several iterations of MapReduce
  - Each time the data is read/written from/to the 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, V3.5.4 September 2024
- Pyton + Spark: pySpark
- Good (current) documentation:
  1. Advanced Analytics with Spark, 2nd edition (2017).
  2. Project docs: https://spark.apache.org/docs/latest/

`DataFrames`

- An extra abstraction on top of RDDs (resilient distributed datasets)
    - 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"

DataFrame

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

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

Estimator

Parallel gradient descent

- Logistic Regression

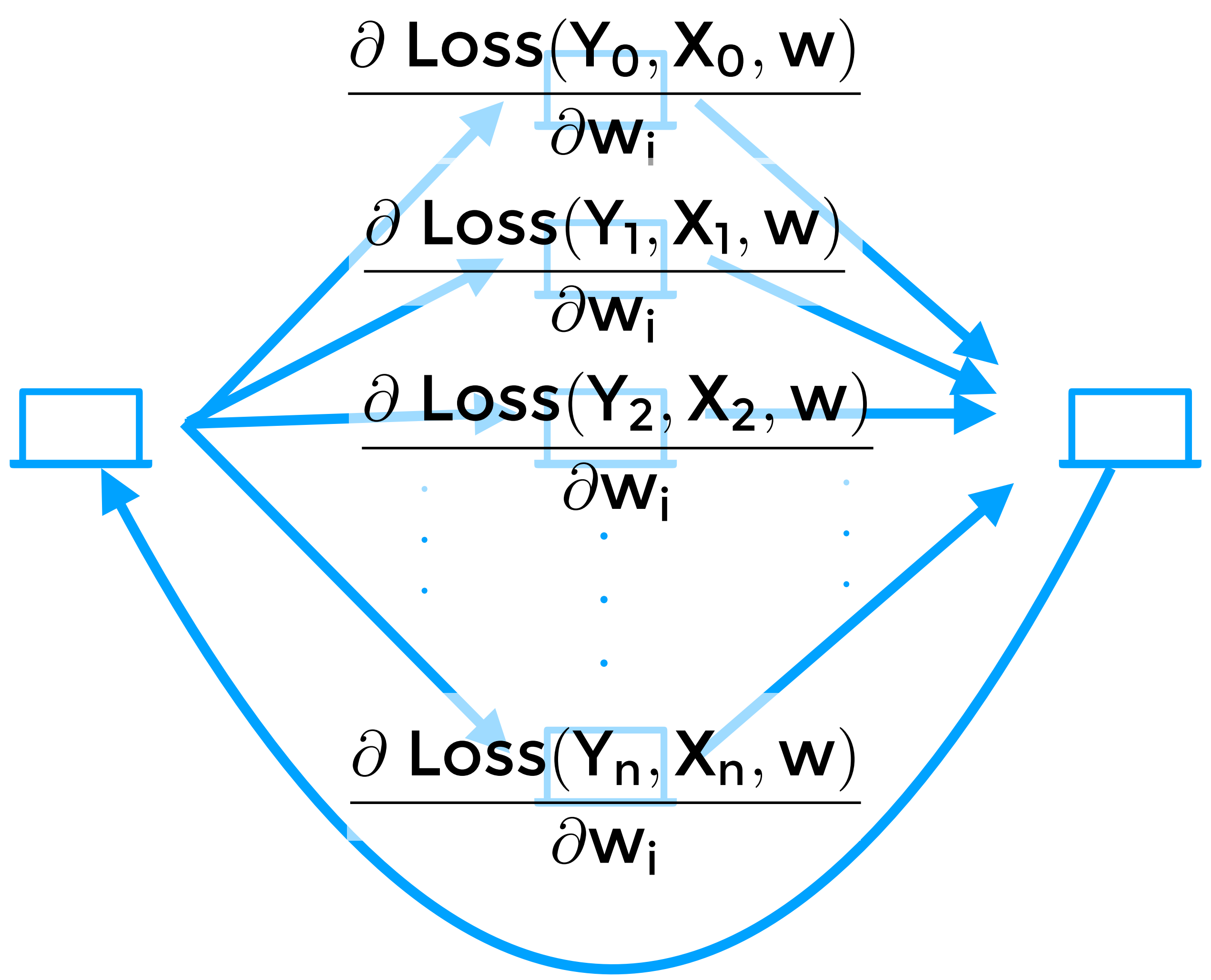
$$y = \frac{1}{1 + \exp(-w_0 - w_1 x_1 - w_2 x_2 - \ldots - w_p x_p)}$$

- No closed-form solution, can use gradients

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

- Loss functions are often decomposable

$$\frac{\partial \sum_j \text{Loss}(Y_j, X_j, w)}{\partial w_i}$$



ML setup

1.

Load your data as a Spark DataFrame

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

- Specialized hardware
  - The go-to method for neural nets training
- Distributed computing is useful:
  - for large-scale data (e.g., data that does not fit on a single computer)
    - for faster computing (when you have multiple available computers)
- 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