

# Databases and Big Data

Big Data

# Where?



# About What?



## My Facebook Was Breached by Cambridge Analytica. Was Yours?

How to find out if you are one of the 87 million victims

ROBINSON MEYER APR 10, 2018



Life-size cutouts of Facebook CEO Mark Zuckerberg are displayed by a progressive advocacy group on the lawn of the U.S. Capitol on Tuesday. (CAROLYN KASTER / REUTERS)

### MORE STORIES

Mark Zuckerberg Says He's Not Resigning  
ROBINSON MEYER



The Cambridge Analytica Scandal, in Three Paragraphs  
ROBINSON MEYER



My Cow Game Extracted Your Facebook Data  
IAN BOOGST



Sudan and the Instagram Tragedy Hustle  
TAYLOR LORENZ



# Big Data

- How BIG is big?

<b>kilo (k)</b>	1,000 (3 zeros)
<b>Mega (M)</b>	1,000,000 (6 zeros)
<b>Giga (G)</b>	1,000,000,000 (9 zeros)
<b>Tera (T)</b>	1,000,000,000,000 (12 zeros)
<b>Peta (P)</b>	1,000,000,000,000,000 (15 zeros)
<b>Exa (E)</b>	1,000,000,000,000,000,000 (18 zeros)
<b>Zetta (Z)</b>	1,000,000,000,000,000,000,000 (21 zeros)
<b>Yotta (Y)</b>	1,000,000,000,000,000,000,000,000 (24 zeros)

# Big Data

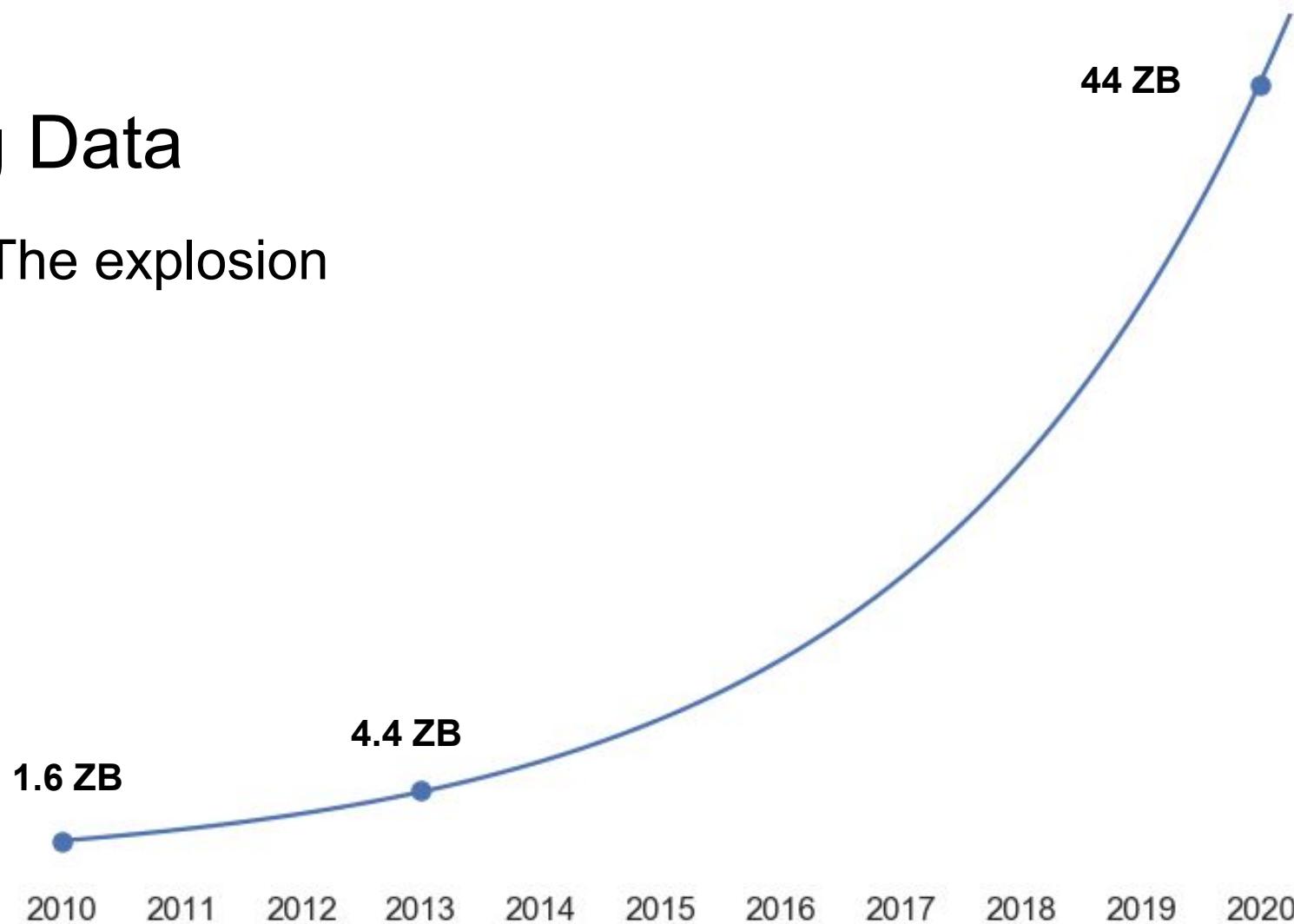
## 2019 *This Is What Happens In An Internet Minute*

- The explosion



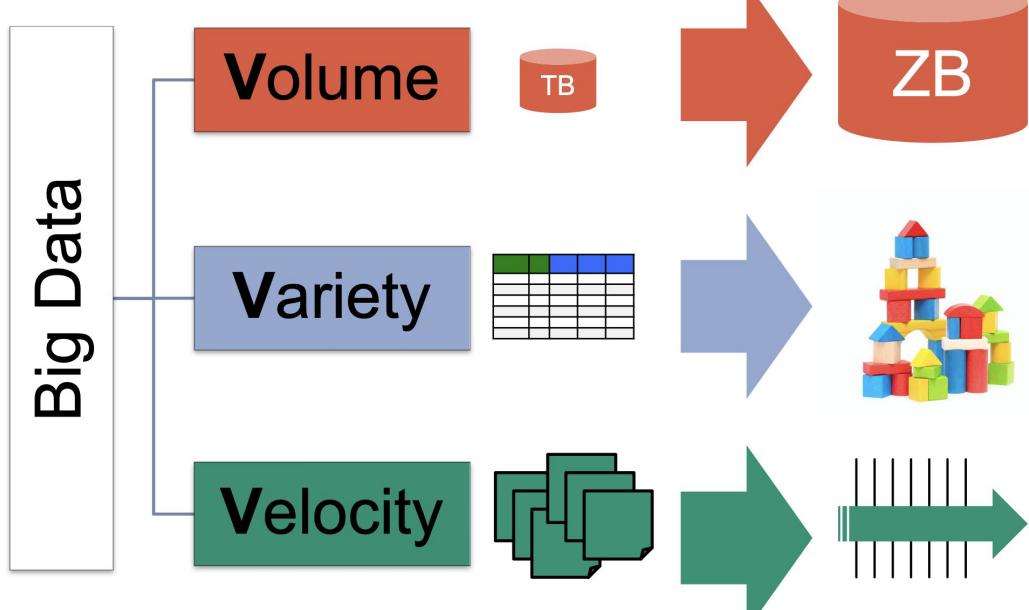
# Big Data

- The explosion



# Big Data

## The Three Vs



# Big Data

- Volume
    - More and more sources
    - Because we CAN!
    - Moore's law on our side
- |  |                          |
|--|--------------------------|
|  | Even better software     |
|  | Better infrastructure    |
|  | Bigger, cheaper hardware |

Web

amazon



Sensor



Science



# Big Data

- Volume

- Because we CAN!
- Moore's law on our side

Even better software

Better infrastructure

Bigger, cheaper hardware

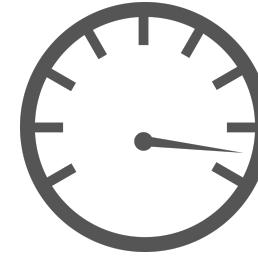
# Big Data

- Volume
  - Because data carries **value**
    - (Most of the time) hard to extract
    - Many people use this to justify keeping more data than needed



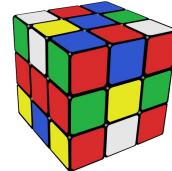
# Big Data

- Velocity
  - Data generated very fast
    - Not manually
    - E.g: 65B whatsapp messages / day
  - You have to handle it in (near) real-time
    - Ingest them all
    - Process them all

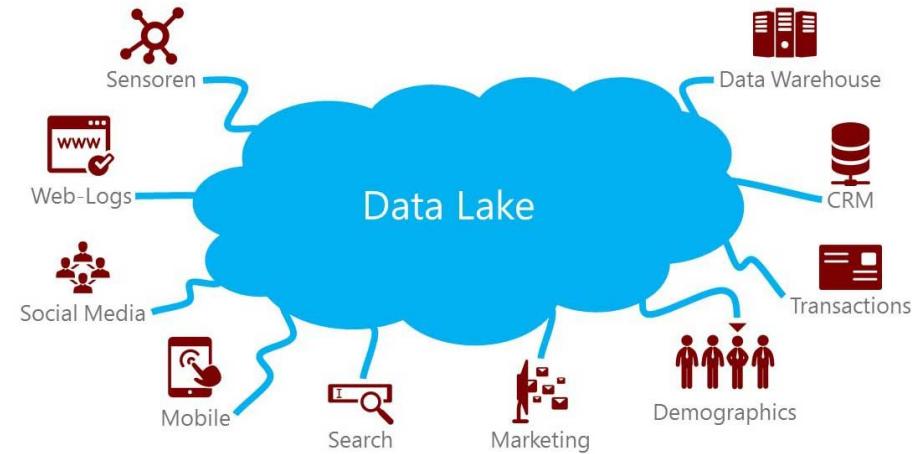
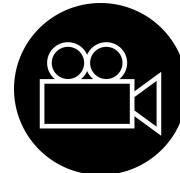


# Big Data

- Variety:
  - All the data models we have learned
  - And more

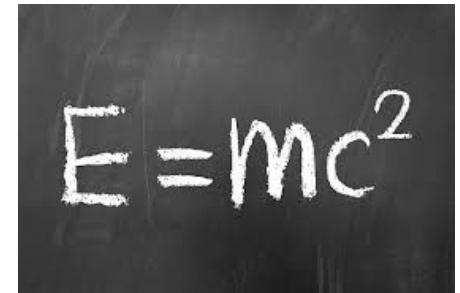


Mr. Bingley was good-looking and gentlemanlike; he had a pleasant countenance, and easy, unaffected manners. His sisters were fine women, with an air of decided fashion. His brother-in-law, Mr. Hurst, merely looked well; but his wife was a very agreeable woman. The general opinion of the room by his fine, tall person, handsome features, noble men, and the report which was in general circulation within five minutes after his entrance, was that he was a most eligible bachelor. When Mr. Weston pronounced him to be a fine figure of a man, the ladies declared he was much handsomer than Mr. Bingley, one who was looked at with great admiration, and who would be a most delightful husband. This was a report which turned the tide of his popularity; for he was discovered to be proud; to be above his company, and above being pleased; and not all this without reason; for he had a haughty, imperious, and most forbidding, disagreeable countenance, and being unworthy to be compared with his friend.



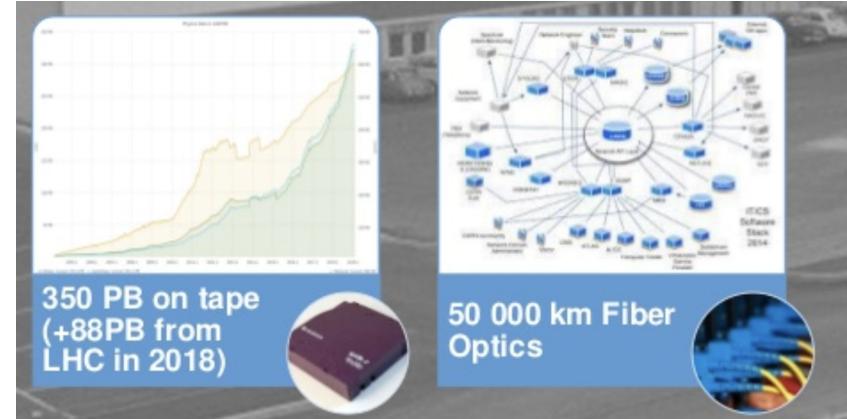
# Why Big Data

- Because we HAVE TO
- 4th scientific paradigm
  - 1st: observation
  - 2nd: theoretical (make hypothesis)
  - 3rd: computational
  - **4th: data-driven**



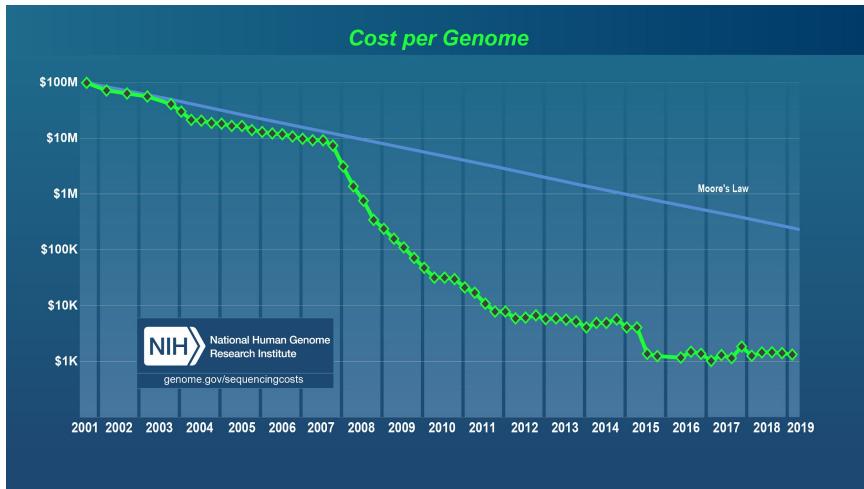
# Big Data

- Data-Driven Science

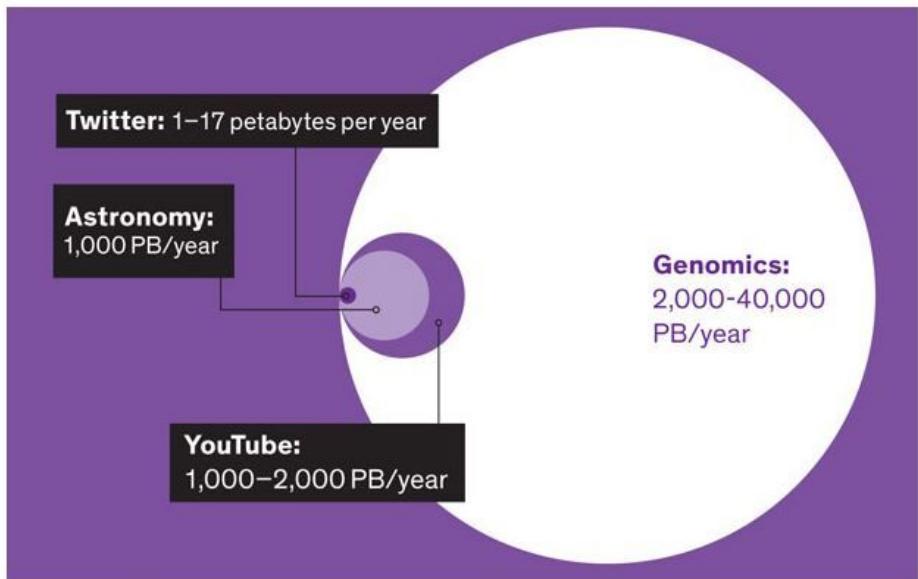


# Big Data

- Data-driven science



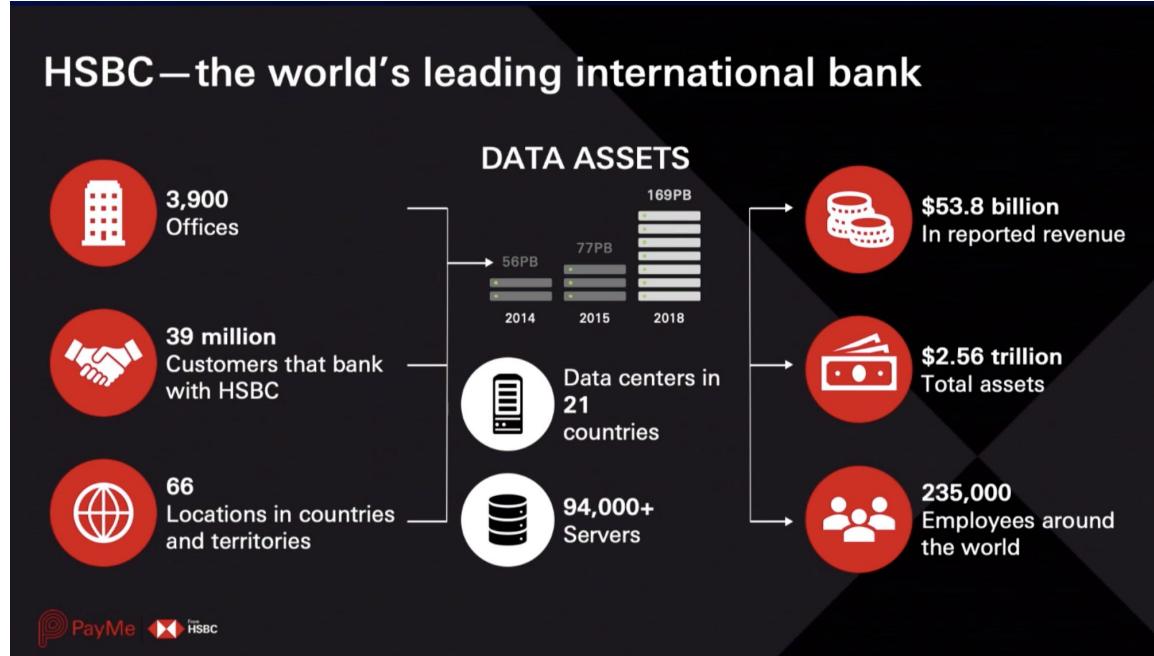
Projected annual storage in 2025



Source: ["Big Data: Astronomical or Genomical?" PLoS Biology, 7 July 2015.](#)

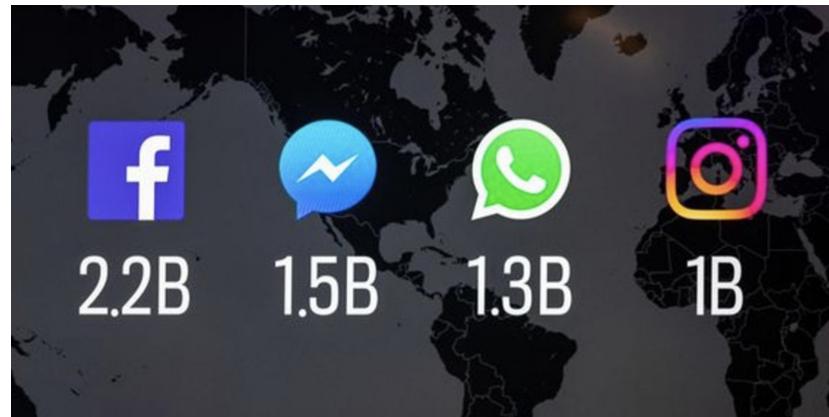
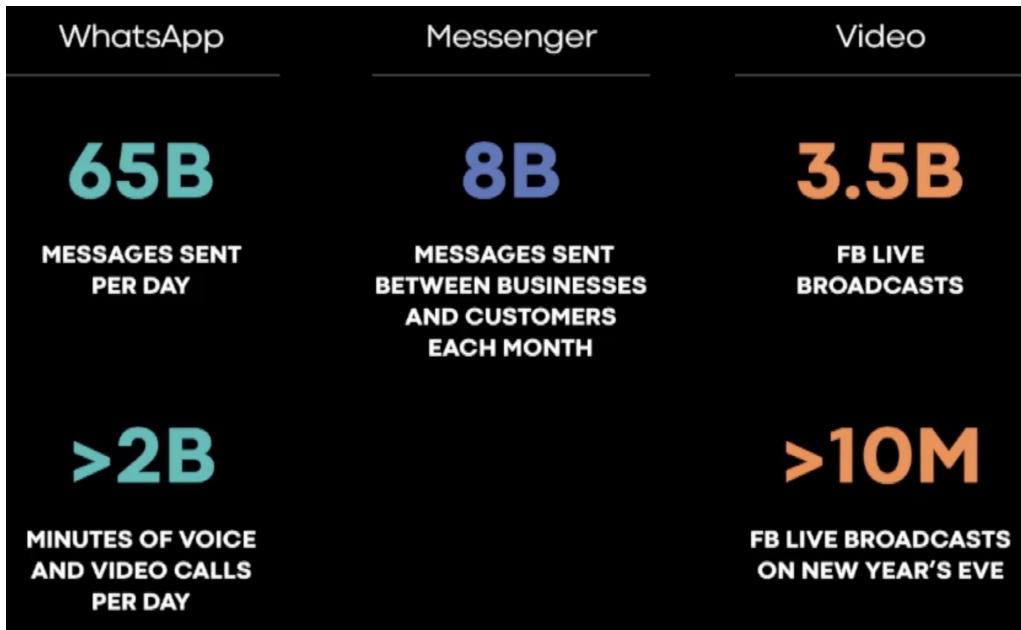
# Big Data

- Finance



# Big Data

- Our lives



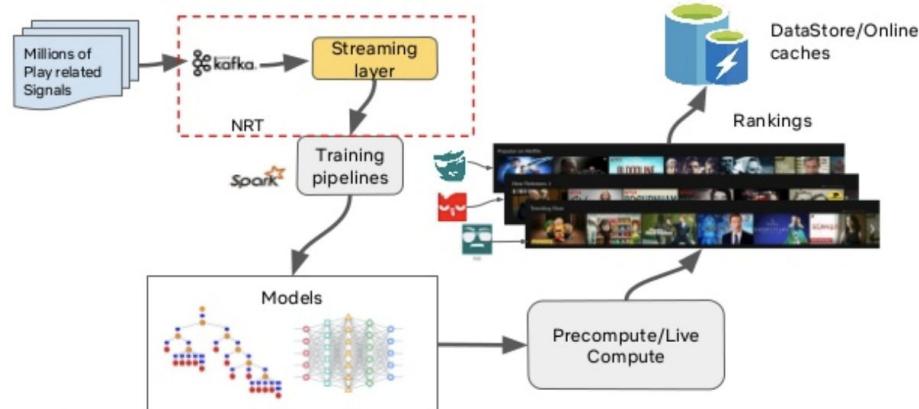
# Big Data - Impact



## Scale @ Netflix

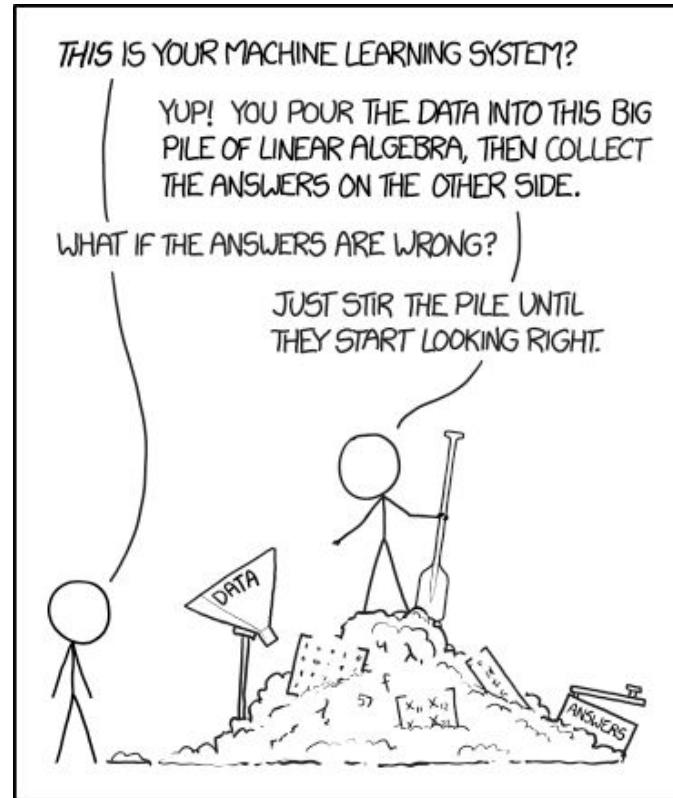
- 125M+ active members
- 190 countries
- 450B+ unique events/day
- 700+ Kafka topics

### NRT Recommendations



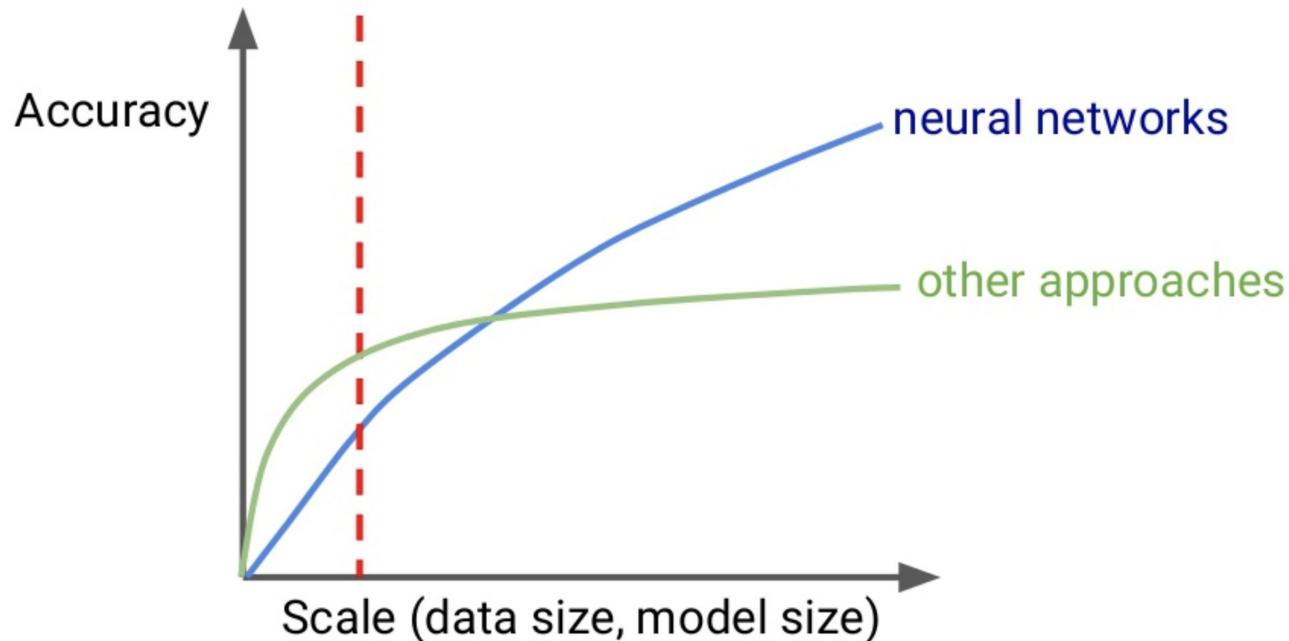
# Big Data

- Machine learning

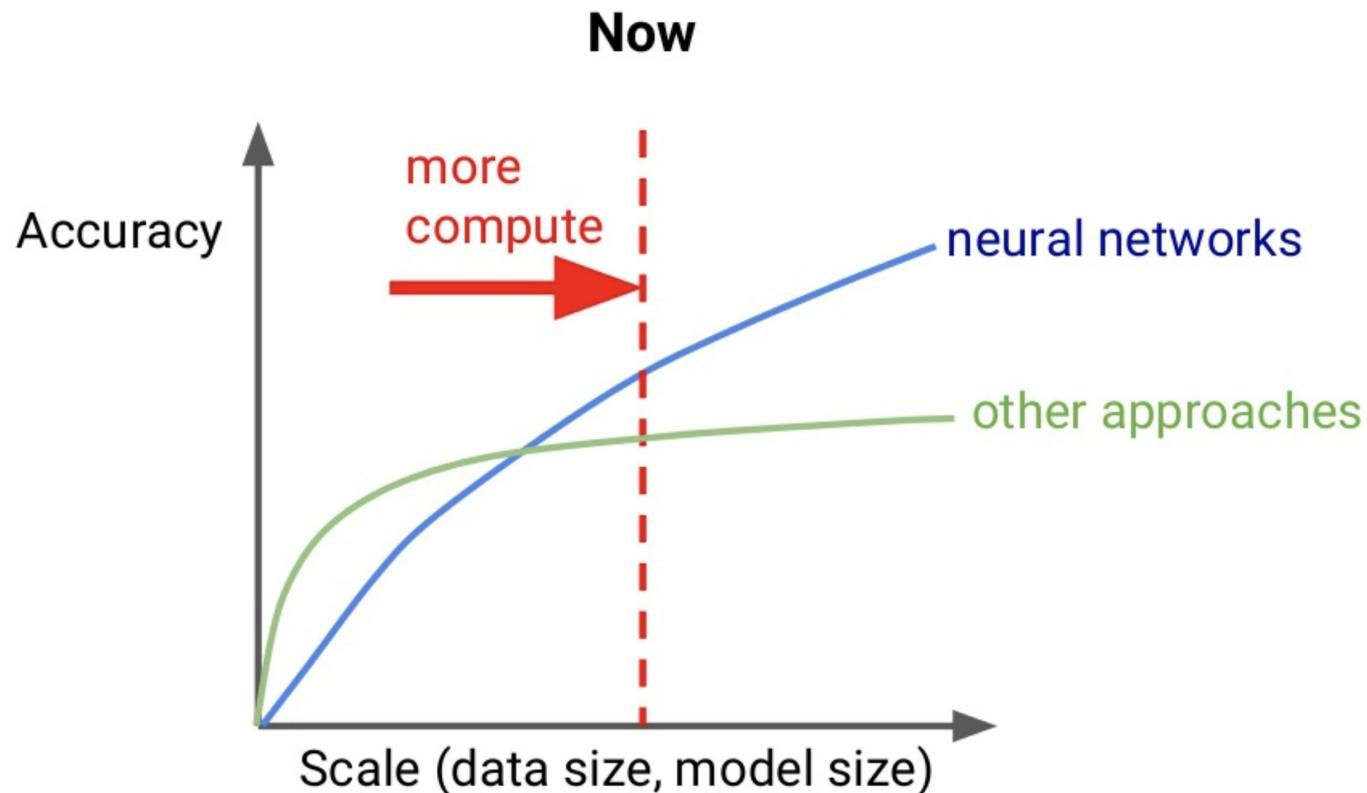


# Big Data

1980s and 1990s

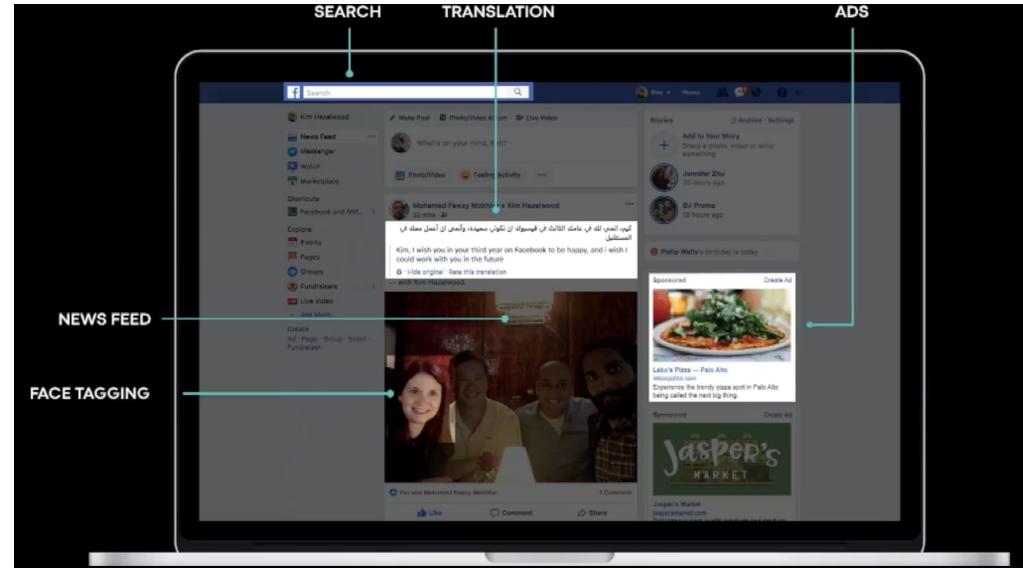
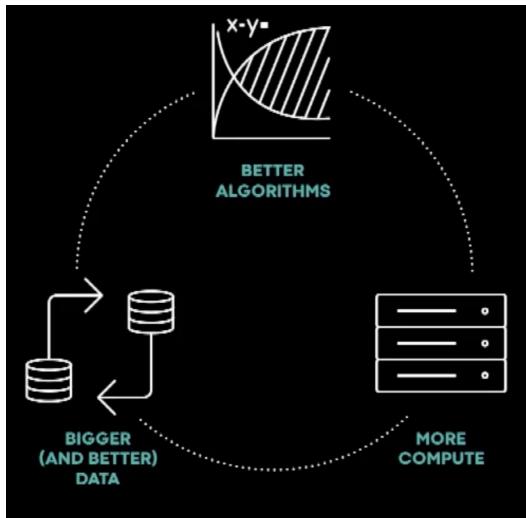


# Big Data

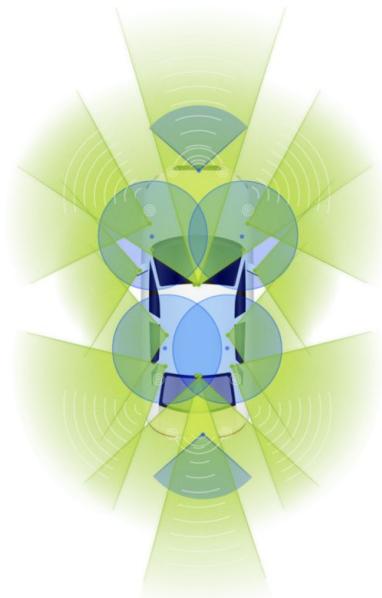


# Big Data - Impact

- Virtuous cycle
- ML becomes ubiquitous



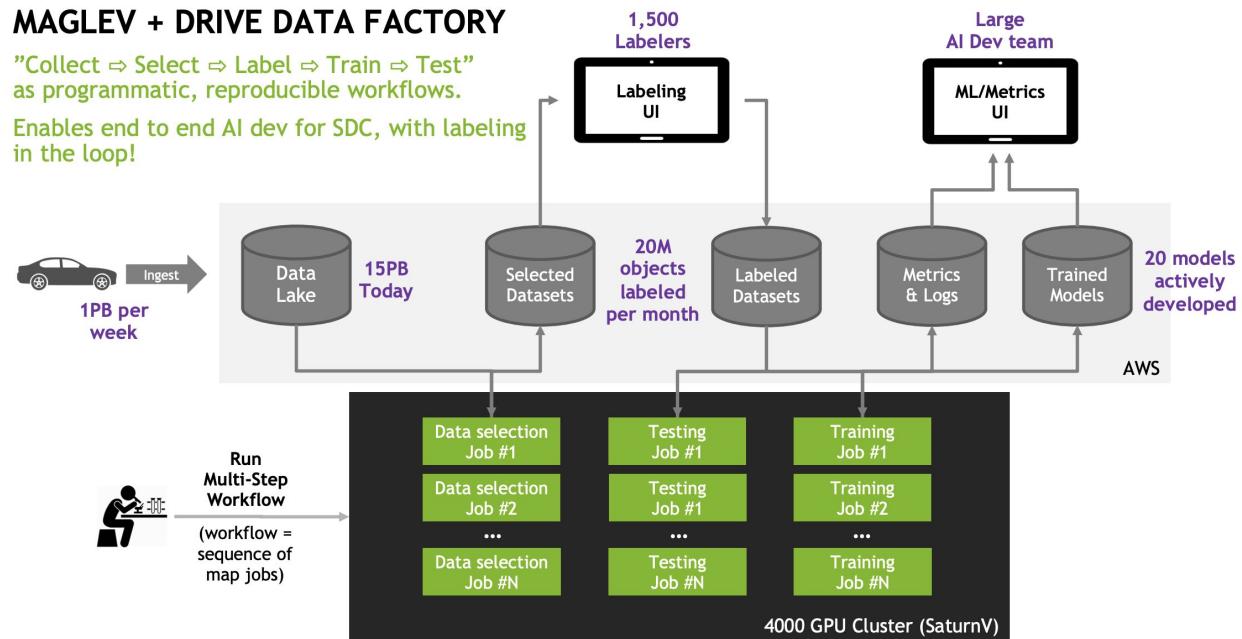
# Big Data - Self Driving Car



## MAGLEV + DRIVE DATA FACTORY

"Collect  $\Rightarrow$  Select  $\Rightarrow$  Label  $\Rightarrow$  Train  $\Rightarrow$  Test" as programmatic, reproducible workflows.

Enables end to end AI dev for SDC, with labeling in the loop!



# Big Data

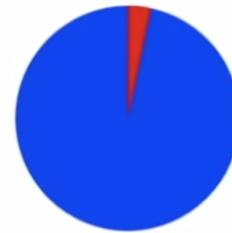


Largest deployment of robots in the world (0.25M)

Make them autonomous.

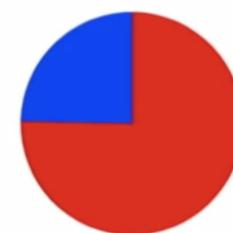
PhD

datasets  
models and algorithms



Tesla

datasets  
models and algorithms



# Big Data - Impact

- Not all good



## Robust De-anonymization of Large Sparse Datasets

Arvind Narayanan and Vitaly Shmatikov

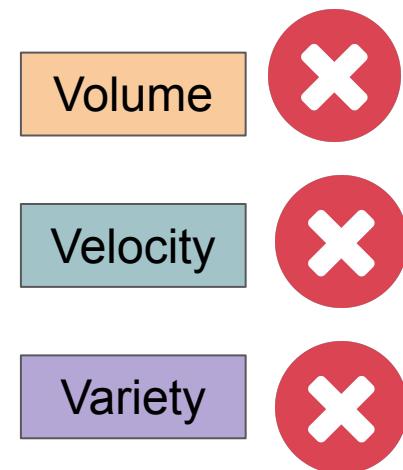
The University of Texas at Austin



# Systems' Perspective

- Remember 3 V's:
  - Volume, Velocity, Variety

Does **not** work at  
BIG DATA scale



# Big Data Systems

- How to judge a big data system

- Capacity
- Throughput
- Latency



How fast we can process a record/request?



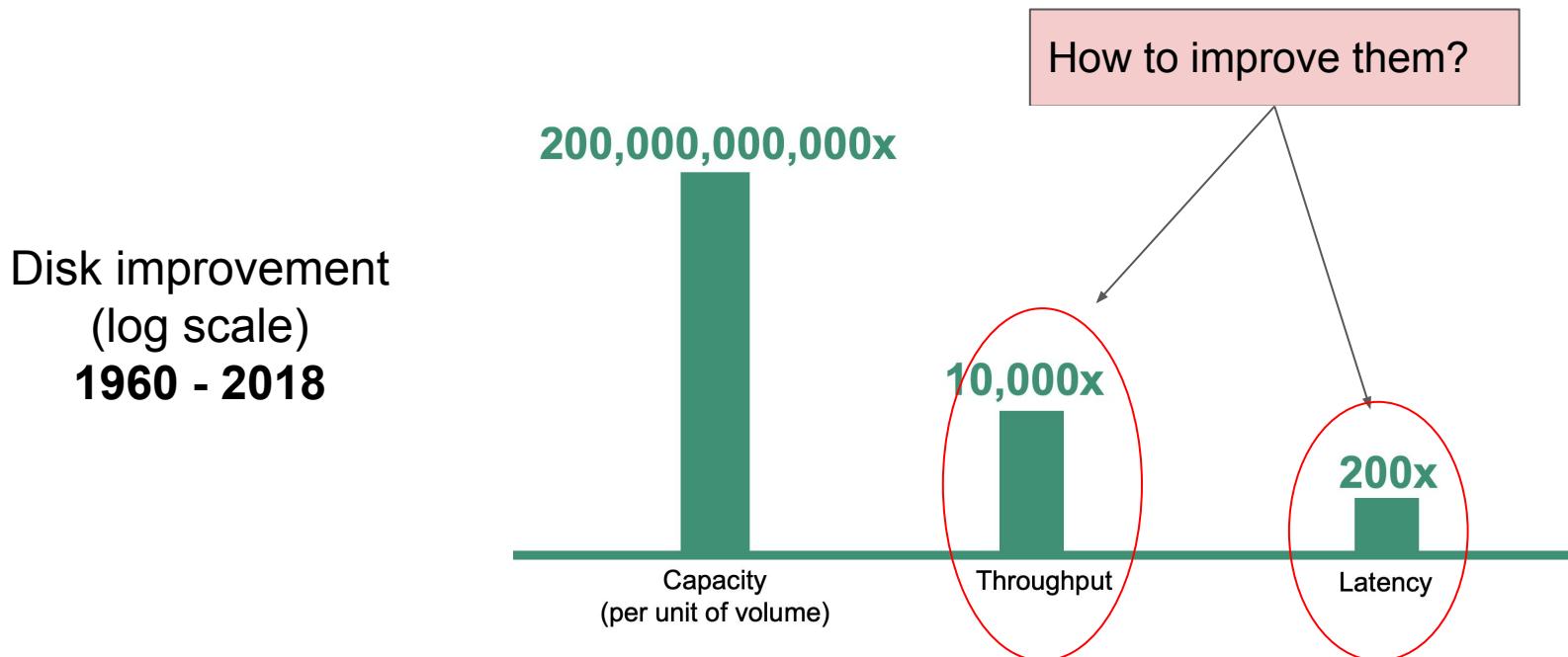
How much we can store?



How much we can process per second?

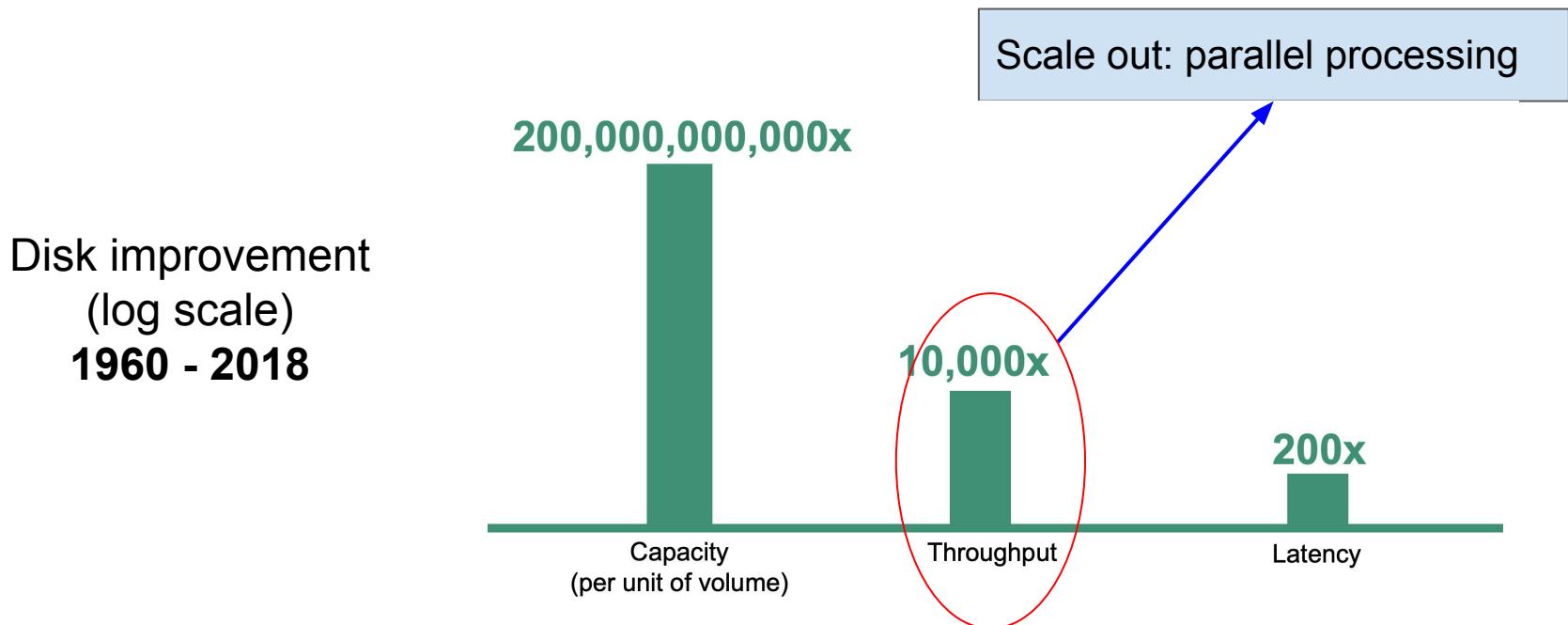
# Big Data Systems

- Moore's law is not equal



# Big Data Systems

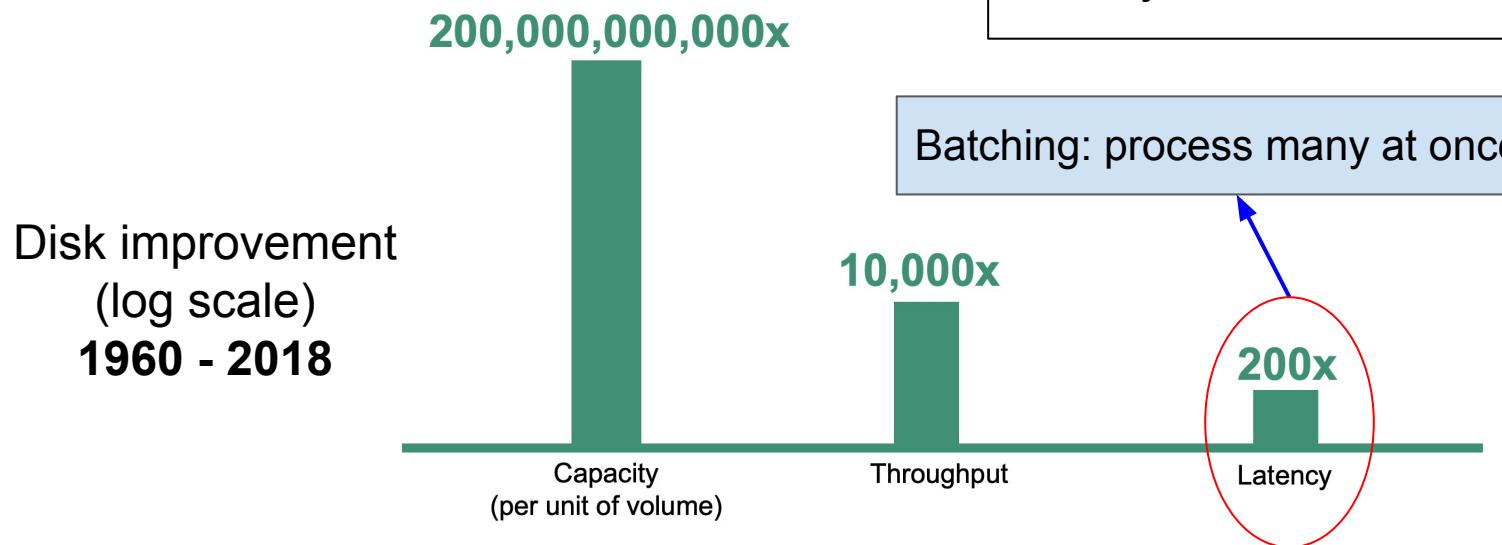
- Moore's law is not equal



*Process in parallel since your throughput is 1000 record/s  
Worst latency you can have is 10ms too  
(avg latency gone down)  
as compared to when you process in the queue one by one  
(avg latency is very high)*

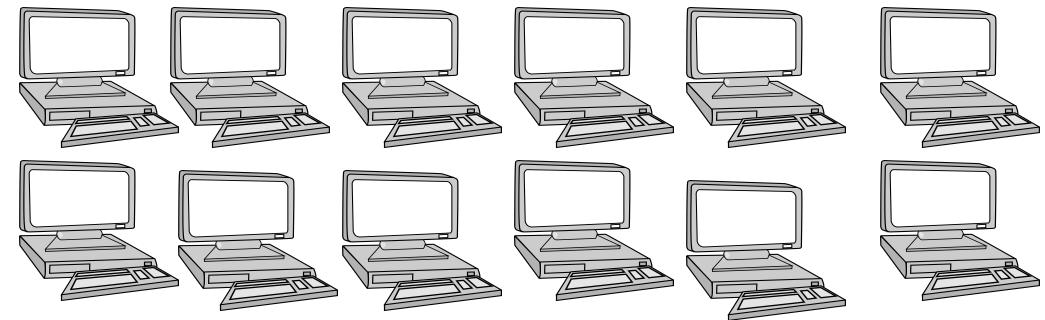
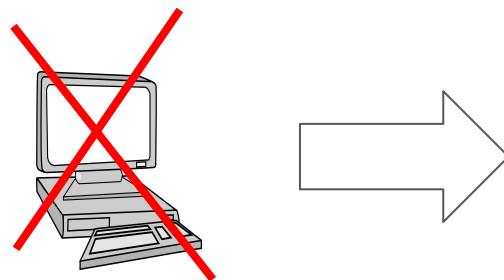
# Big Data Systems

- Moore's law is not equal



# Big Data Challenges

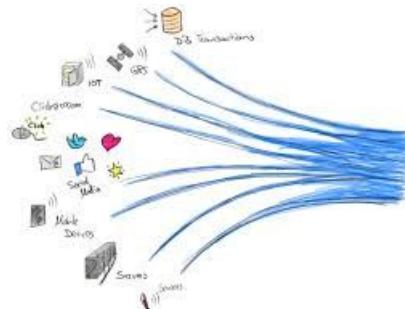
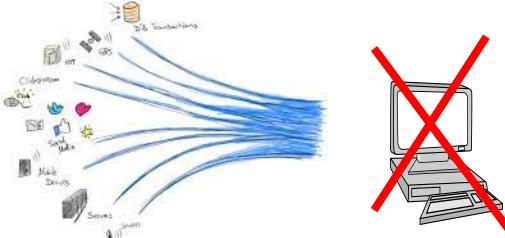
- Challenge 1: **volume**



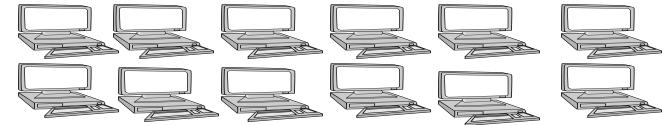
**Approach: Scale OUT**

# Big Data Challenges

- Challenge 2: **velocity**



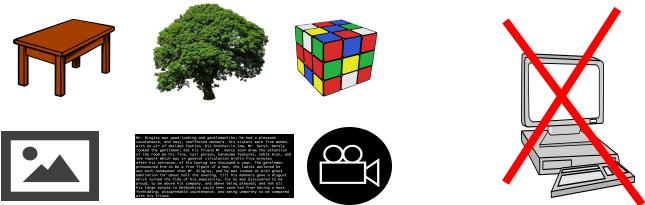
Distributed Streaming System



**Approach:** Scale out + Streaming systems

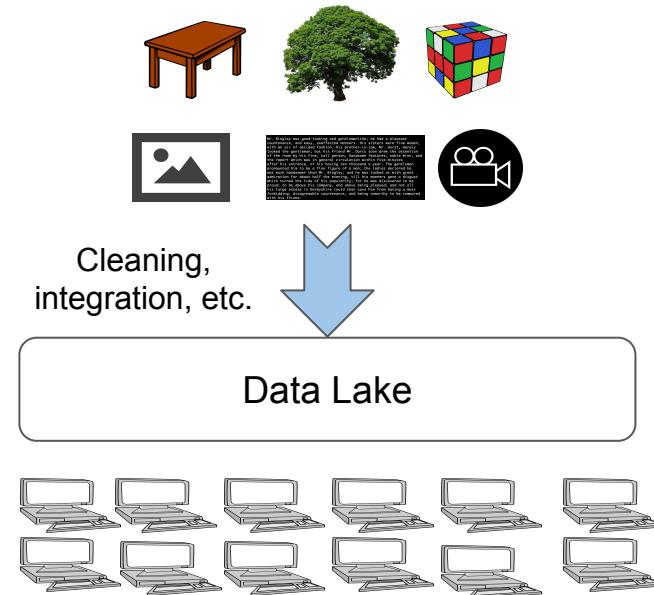
# Big Data Challenge

- Challenge 3: **variety**



**Approach:** collect now, figure out later

**Specialised system:** may work and better perf but not scalable (not sustainable)  
cause new data type always come up



**Approach:** specialized system

# What is Big Data

- Not only about the data
- An ecosystem (suite of technologies) for:

- Storing
- Managing
- Analyzing

Data that is too big to fit  
on a single machine

**At scale**

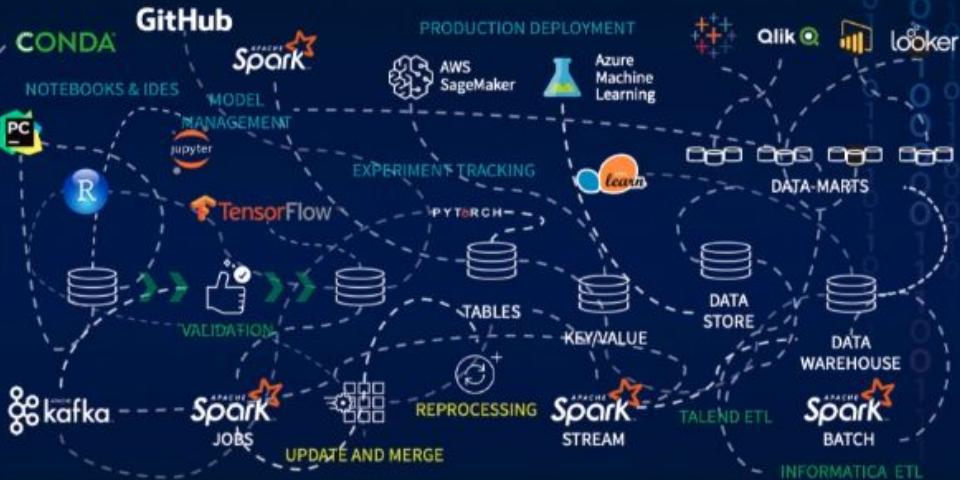
Performance  
Fault tolerance  
Scalability

Applications

## DATA SCIENCE AND MACHINE LEARNING

## BUSINESS ANALYTICS AND REPORTING

Systems



Data

### STREAMS

Kafka | Azure Event Hub | AWS Kinesis

### DATA LAKES

Azure Blob | AWS S3 | HDFS

### NoSQL

Mongo | AWS DynamoDB | Azure Cosmos

BIG DATA & AI LANDSCAPE 2018



V1 - Last updated 6/19/2018

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FIRSTMARK  
EARLY-STAGE VENTURE CAPITAL

# Big Data Storage

- Dynamo

- 2007
- Behind Amazon's S3
- One of the first big data system



**Key-value**

<customer, profile>

...

## Dynamo: Amazon's Highly Available **Key-value** Store

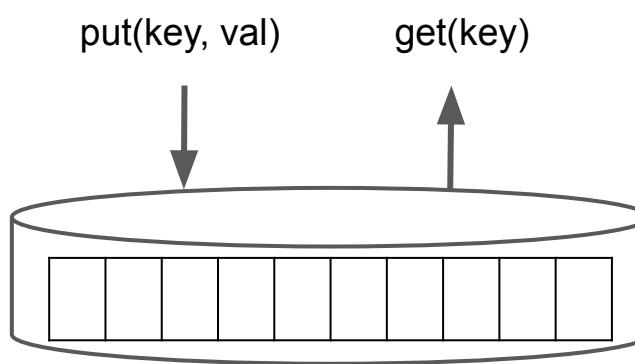
Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, Gunavardhan Kakulapati,  
Avinash Lakshman, Alex Pilchin, Swaminathan Sivasubramanian, Peter Vosshall  
and Werner Vogels

Amazon.com

# Dynamo

- Problems it tries to solve:
  - Store many, many key-value records
    - Doesn't fit on a single machine
  - Efficient search based on key

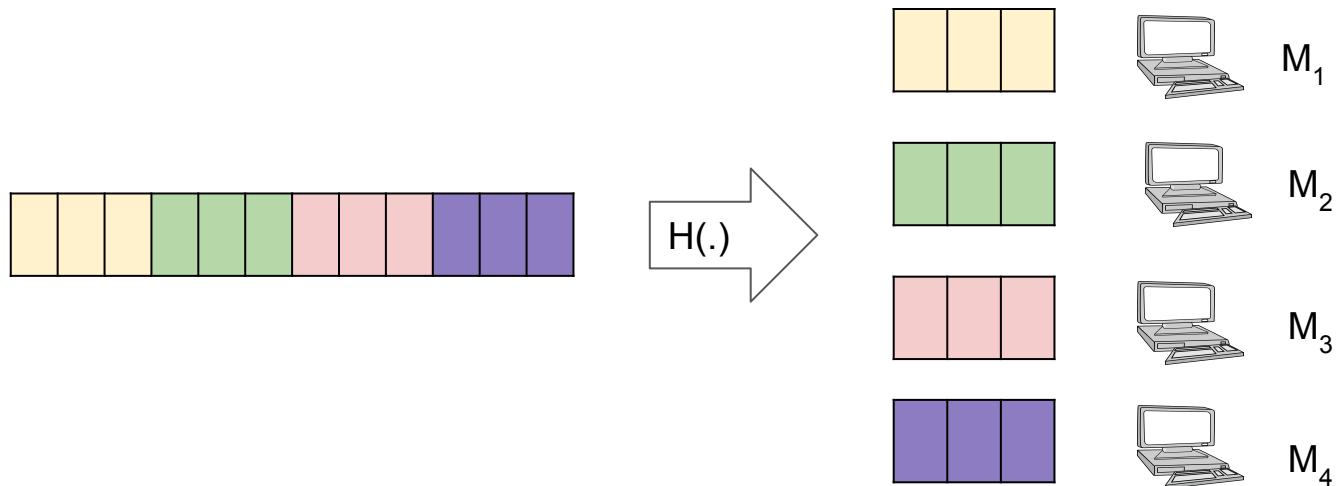
PBs



One  
Giant  
Hash  
Table

# Dynamo

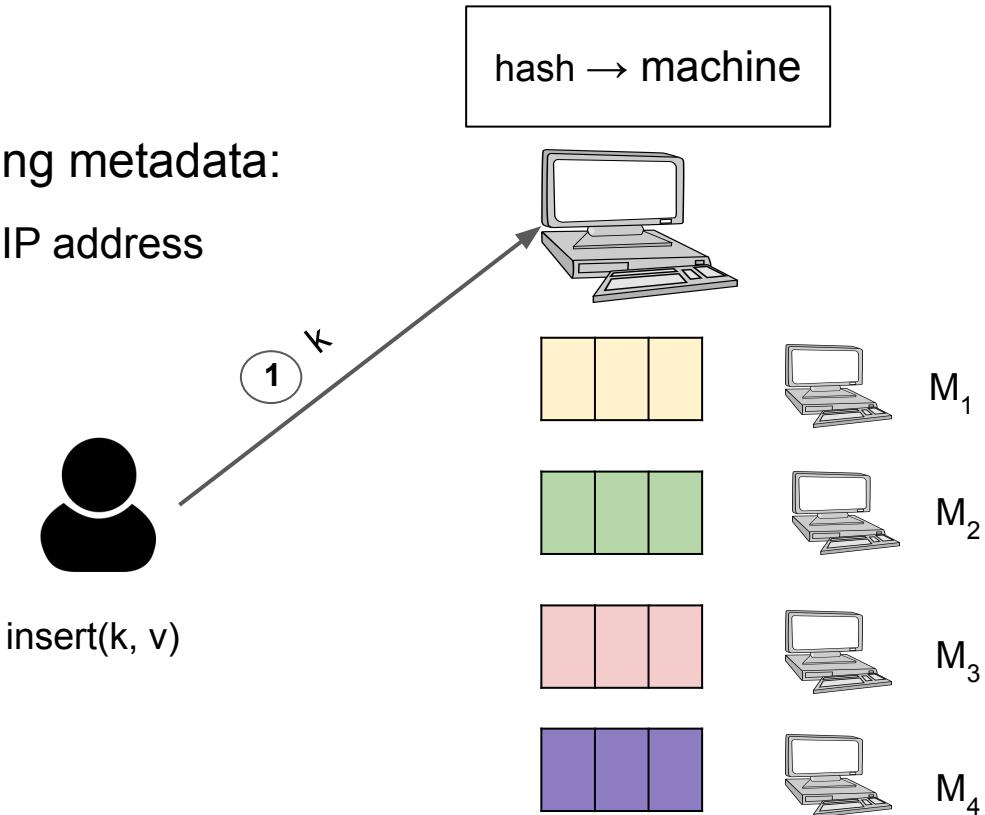
- Strawman
  - Chop up the giant hash table
  - Store pieces on different machines



# Dynamo

- Strawman

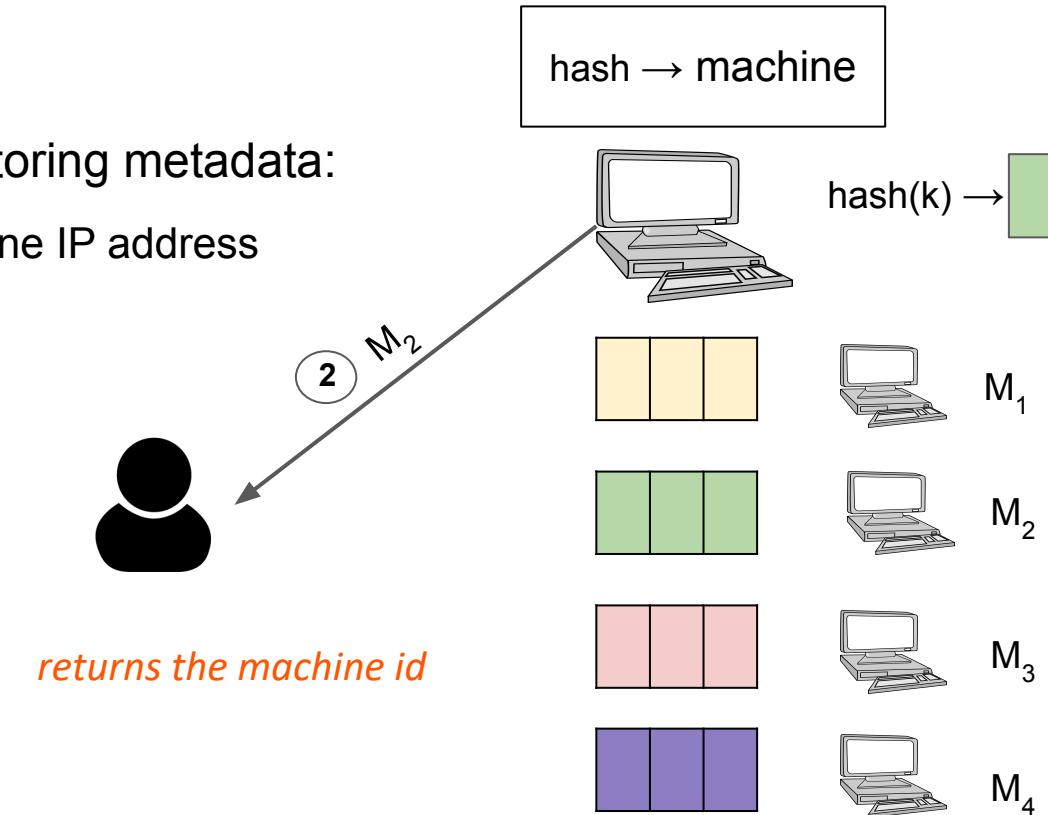
- One master machine storing metadata:
  - Hash value → machine IP address



# Dynamo

- Strawman

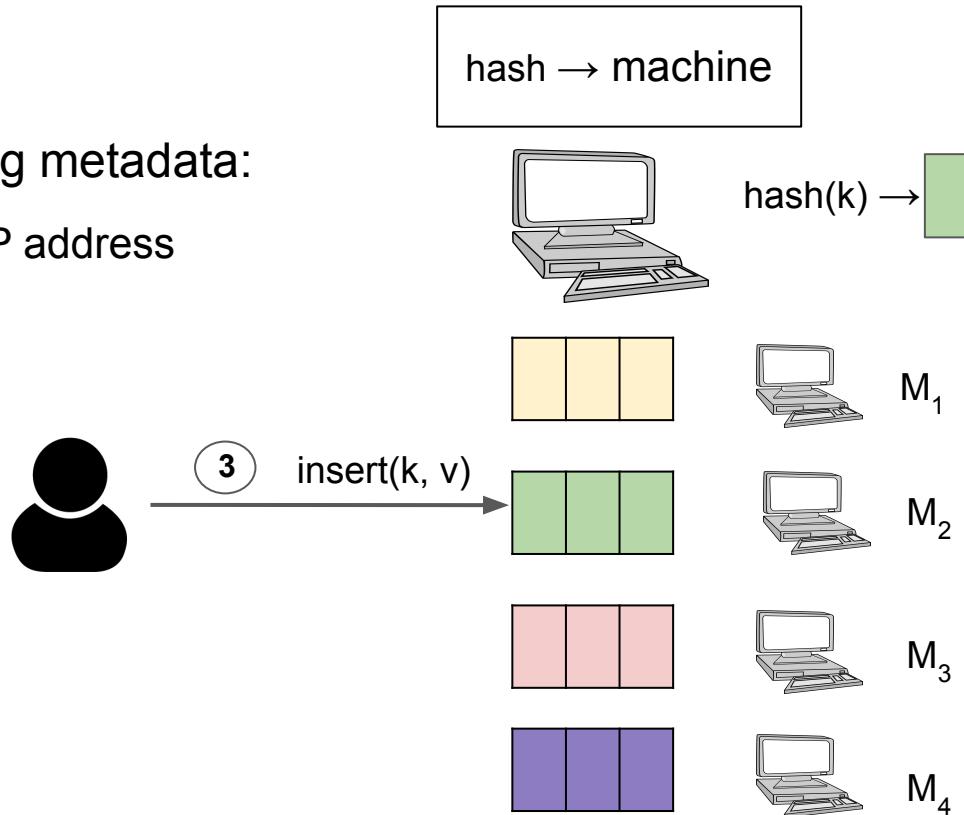
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# Dynamo

- Strawman

- One master machine storing metadata:
  - Hash value → machine IP address



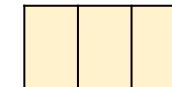
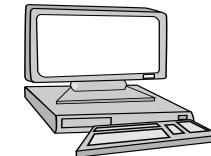
# Dynamo

- Strawman

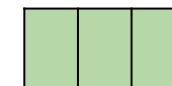
- Problem:

- What happen if I want to add new machine?
    - (or if one machine fails)?

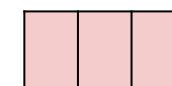
hash → machine



$M_1$



$M_2$



$M_3$

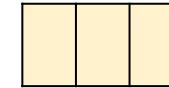
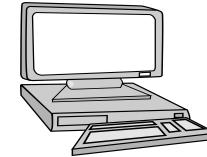


$M_4$

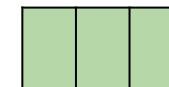
# Dynamo

- Strawman

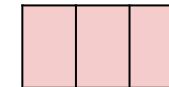
hash → machine



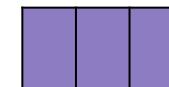
$M_1$



$M_2$



$M_3$



$M_4$

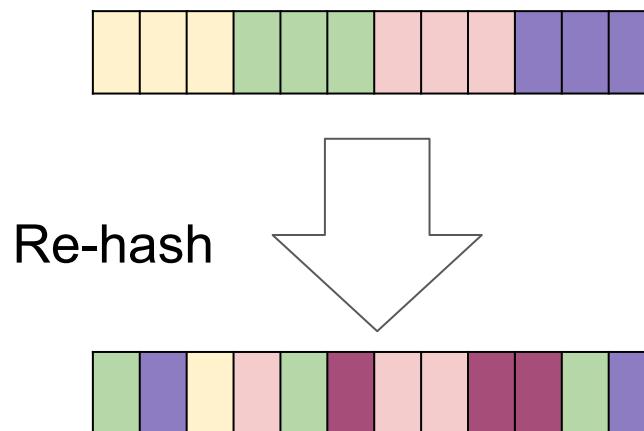
?



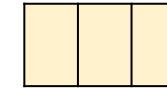
$M_5$

# Dynamo

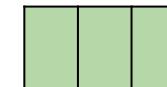
- Strawman



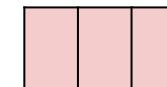
hash → machine



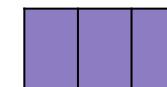
$M_1$



$M_2$



$M_3$



$M_4$

?



$M_5$

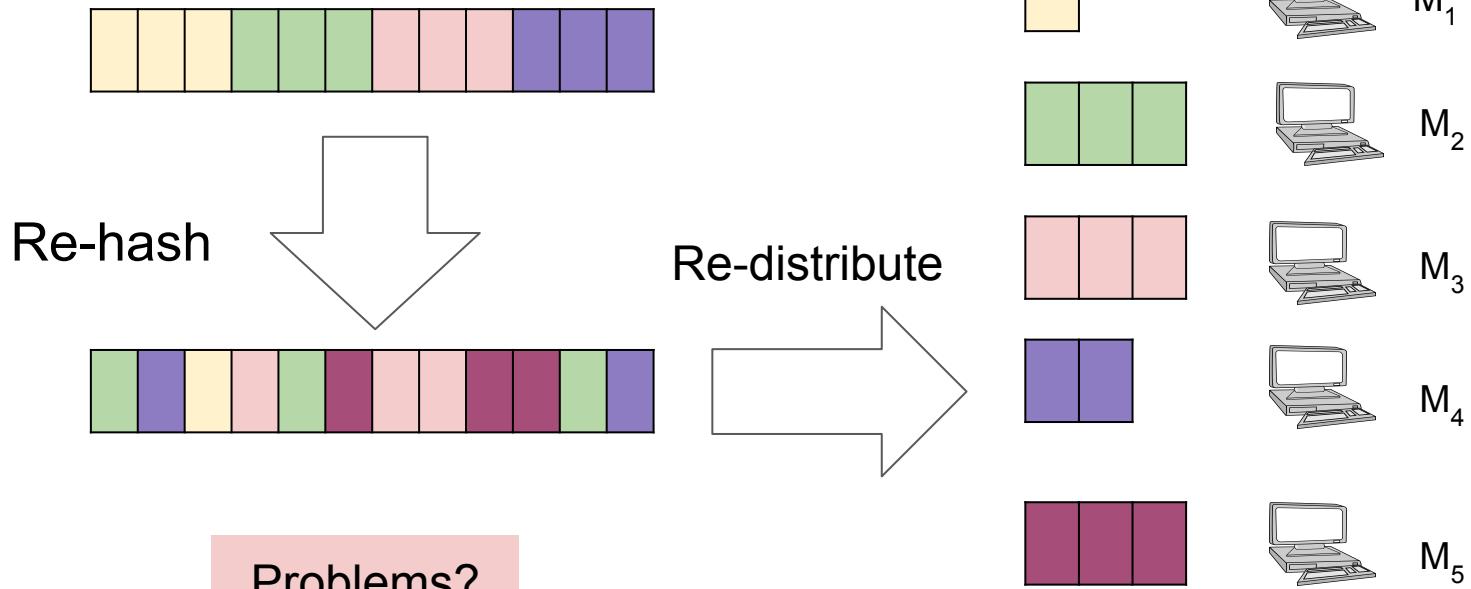
*modulus 5 instead of modulus 4 ??*

# Dynamo

- Strawman

*when you wanna add a new machine,  
need to go back to your original data  
and rehash and redistribute again. -->  
very expensive*

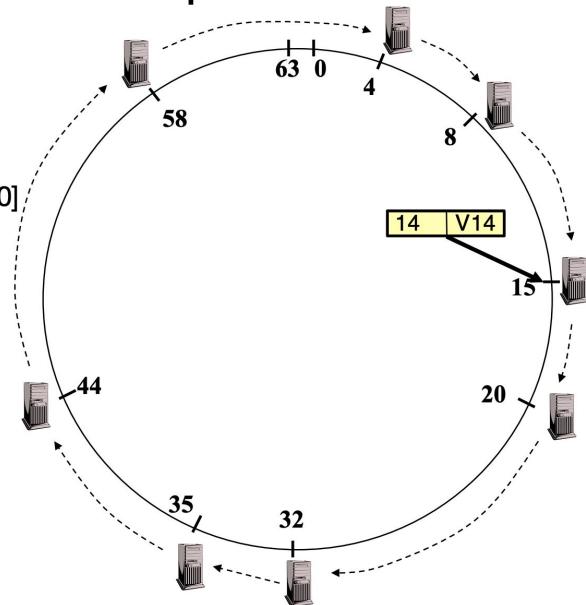
hash → IP address



# Dynamo

- Consistent Hashing
  - Machines and keys get their IDs from the same space:  
 $[0, \dots, 2^m)$

$m = 6 \rightarrow$  ID space: 0..63  
Node 8 maps keys [5,8]  
Node 15 maps keys [9,15]  
Node 20 maps keys [16, 20]  
...  
Node 4 maps keys [59, 4]



Very important idea in  
modern computing systems

# Dynamo

- Consistent Hashing:
  - IDs is a circle
  - Node stores only keys in the range between itself and the previous node (clockwise)

$m = 6 \rightarrow$  ID space: 0..63

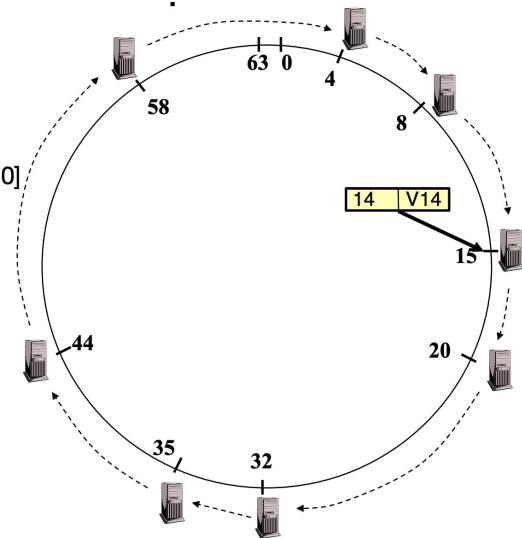
Node 8 maps keys [5,8]

Node 15 maps keys [9,15]

Node 20 maps keys [16, 20]

...

Node 4 maps keys [59, 4]



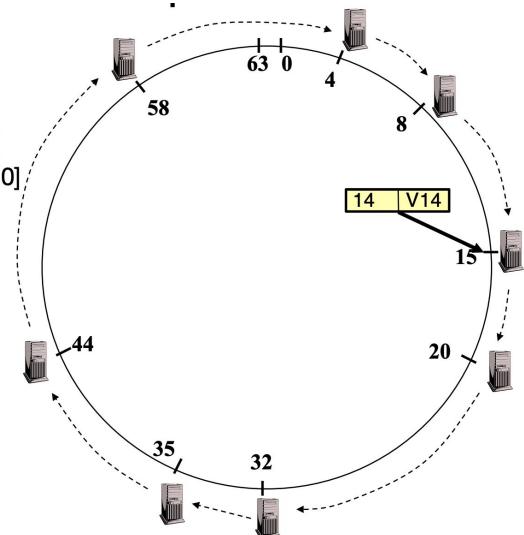
Node 15 stores keys in the range (8, 15]

Node 32 stores keys in the range (32,35]

# Dynamo

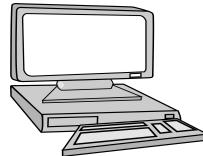
- Consistent Hashing:
  - Example: `insert(30, val)`
    - `val` stored at node 32

$m = 6 \rightarrow$  ID space: 0..63  
Node 8 maps keys [5,8]  
Node 15 maps keys [9,15]  
Node 20 maps keys [16, 20]  
...  
Node 4 maps keys [59, 4]



Node ID → IP address

Master  
server



# Dynamo

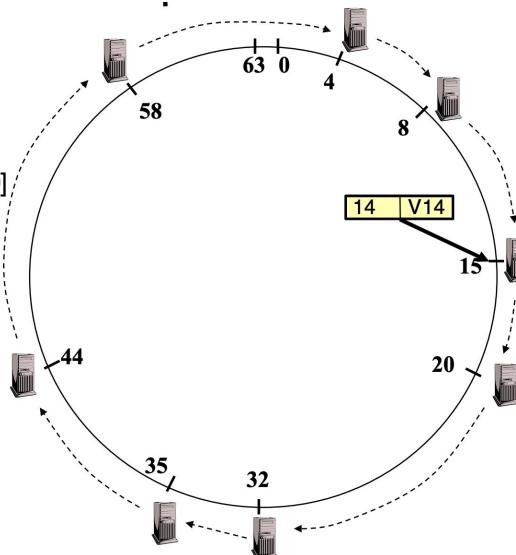
- Consistent Hashing:
  - Why better?
  - What happens when a new node joins?
    - Get a new node ID
    - Then....?

*insert node 40*

*only need to redistribute key range in  
node 44*

*if node 44 fails, the only node that is  
affected is node after it.*

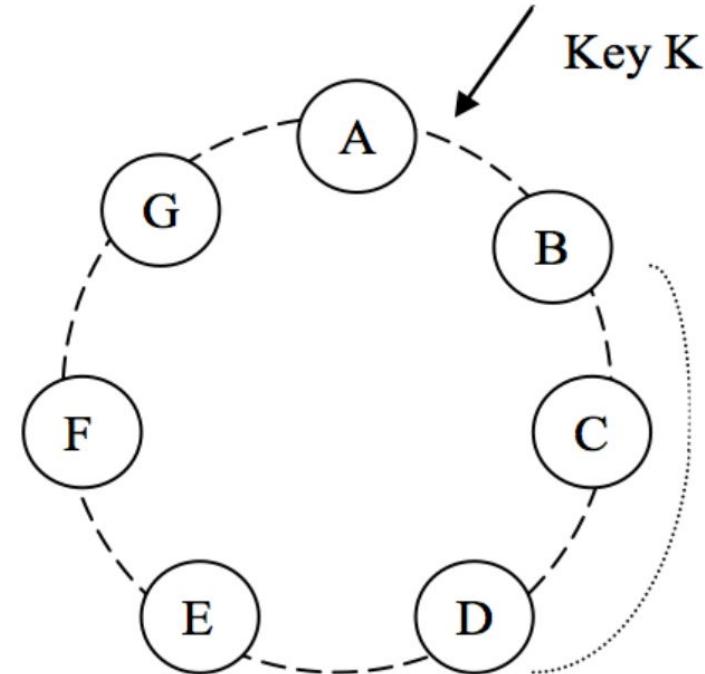
$m = 6 \rightarrow$  ID space: 0..63  
Node 8 maps keys [5, 8]  
Node 15 maps keys [9, 15]  
Node 20 maps keys [16, 20]  
...  
Node 4 maps keys [59, 4]



# Dynamo

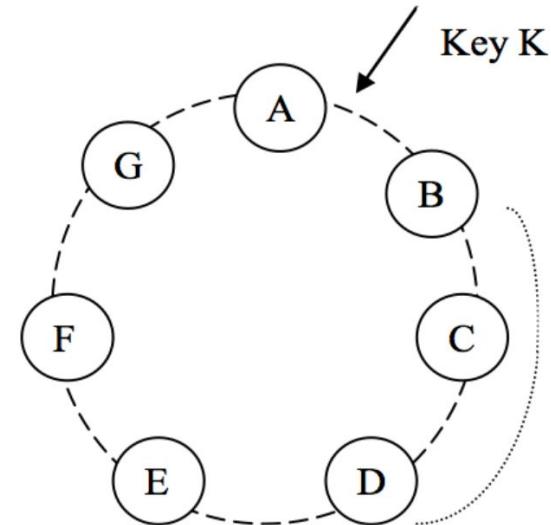
*if bottle neck at node b, you replicate and get the same data into node c and d.*

- Replication:
  - Usually 3 successive nodes in the ring
    - Not physically close to each other
  - E.g. node B, C, D stores K
- Write operation
  - Sent to any of these replicas
- Read
  - From any of these replicas



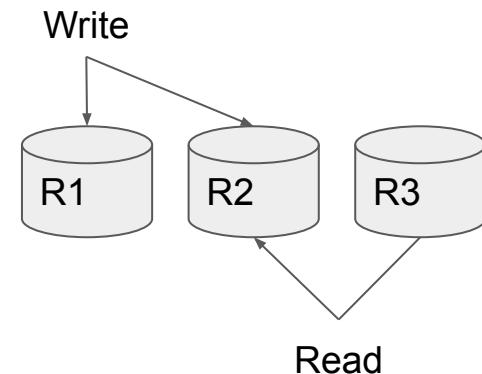
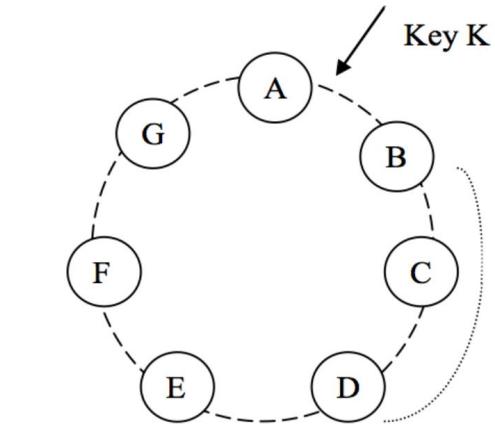
# Dynamo

- Problem: **eventual consistency**
  - Example:
    - Write to B
    - B starts replicating to C and D
    - Read from D, when previous step hasn't finished
  - Eventual consistency: no guarantee that read returns the latest write
  - What happen when 2 users read from 2 different replicas?



# Dynamo

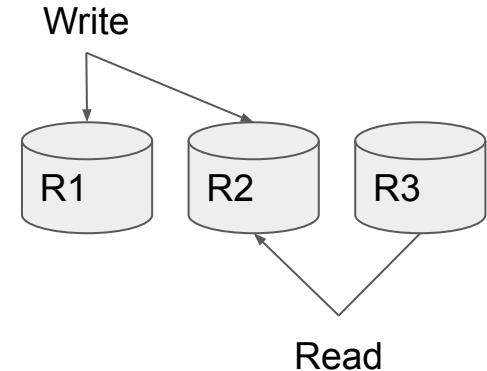
- Problem: eventual consistency
  - Amazon say it's OK!
    - User can add to items to cart, only later find out that item no longer available
  - Sacrificing correctness for performance
- A middle ground: sloppy quorum
  - N replicas
  - Write waits for W replicas to finish ( $W < N$ )
  - Read waits for R replicas to finish ( $R < N$ )



# Dynamo

- A middle ground: sloppy quorum
  - $N$  replicas
  - Write waits for  $W$  replicas to finish ( $W < N$ )
  - Read waits for  $R$  replicas to finish ( $R < N$ )
- When  $R + W > N$ 
  - Set of write and read replicas overlap at least 1 server
  - Meaning that at least 1 replica contains the latest write

How do we know which one?



Example:  $N=3$

- $W = 2$
- $R = 2$

# Summary

- Big data is
  - Volume, Velocity, Variety
  - Many specialized systems put together
- Making real impact
  - Necessity, no longer a choice, for large enterprises
- Few examples: key-value store, stream, graph
- Next: Cloud computing
  - Key enabler of Big data