CS 265

Stratos Idreos

BIG DATA SYSTEMS

NoSQL | Neural Networks | Image AI | LLMs | Data Science

Today:
Go quickly over logistics again

Intro to self-designing systems concept

Very high-level intro into NoSQL Big Data Systems (key-value stores)

algorithm/system design = not just computation

data movement is the key

50-80% of end-to-end time is due to storage-related decisions

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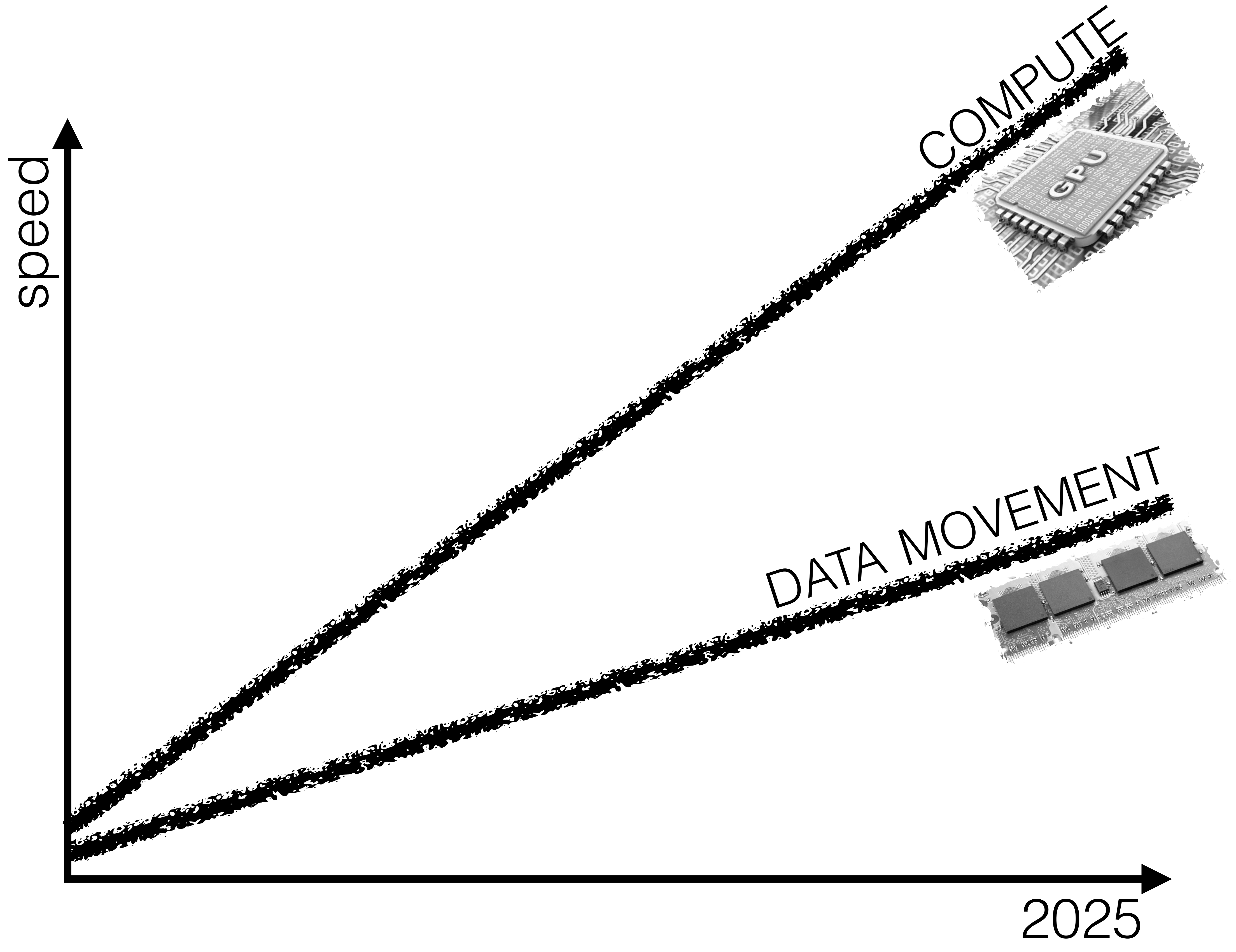
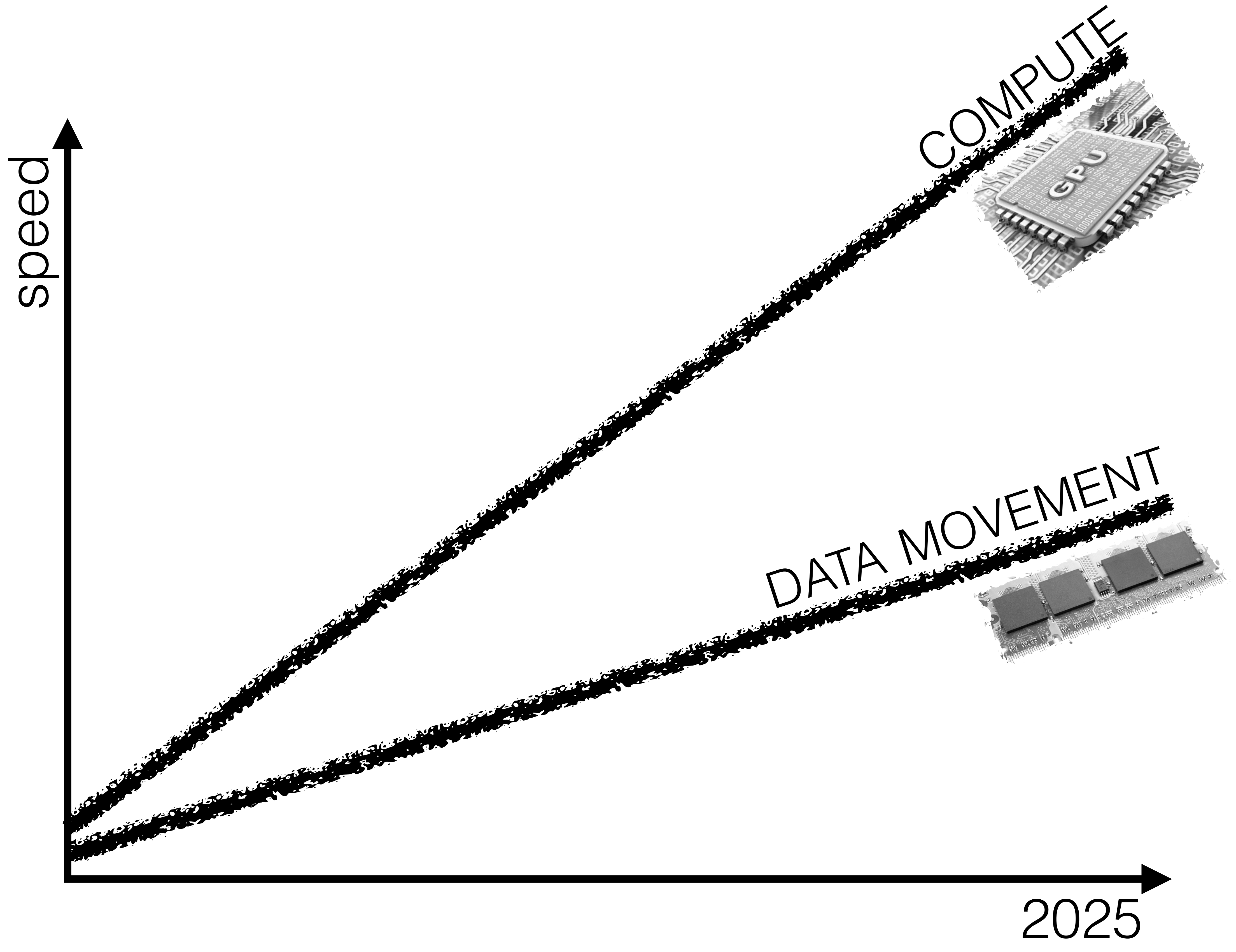
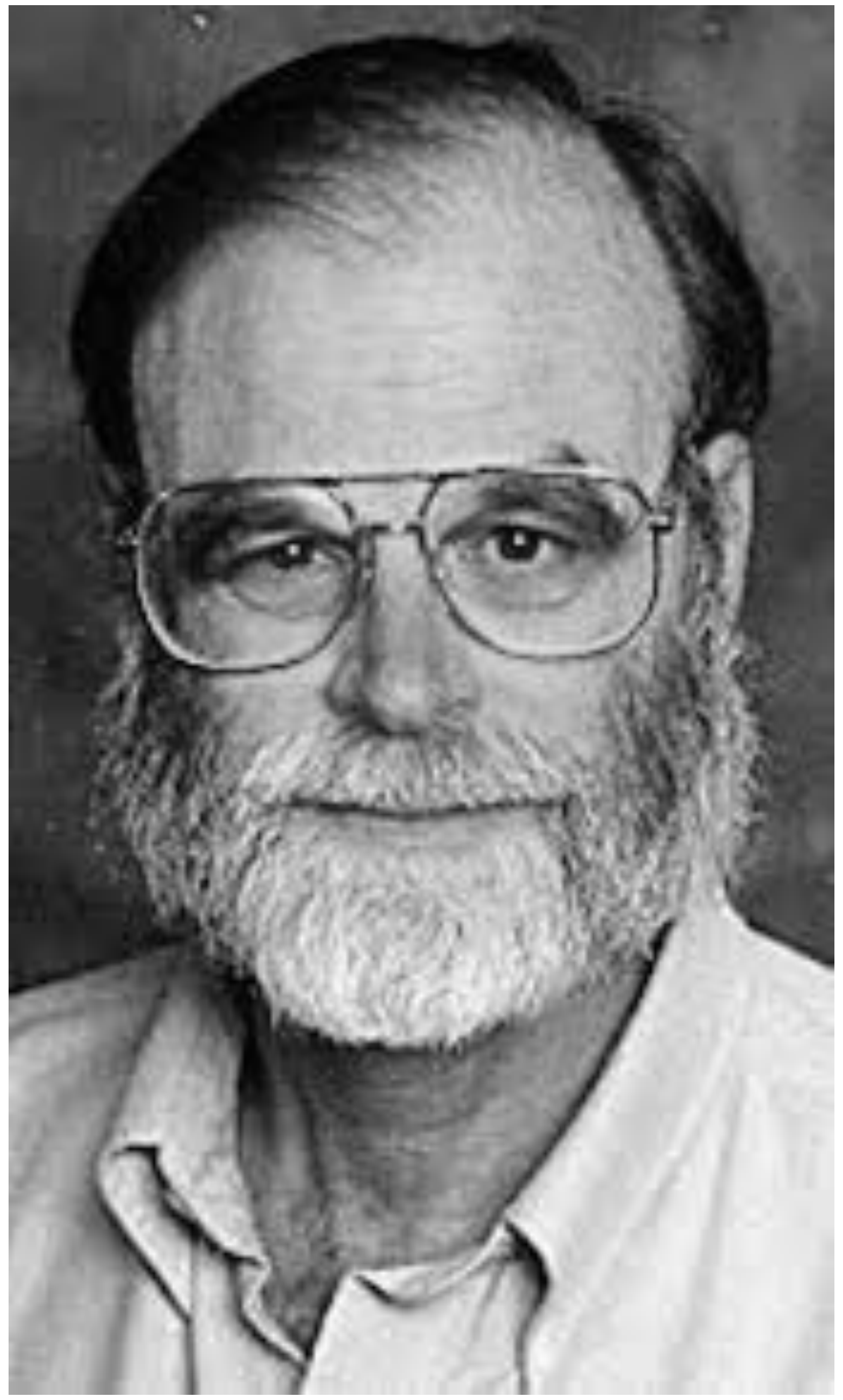
cloud cost



DATA STRUCTURES DEFINE PERFORMANCE





register = this room

caches = this city

memory = nearby city

disk = Pluto

Jim Gray, Turing Award 1998

What is a data system?

A data system is an end-to-end software system that:
manages storage, data movement, and provides access to data

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A system is a complex set of components

interacting in harmony depending on the context

exposing as little as possible complexity to users

declarative interface

ask ''what'' you want

data* system

the system decides
"how" to best store
and access data

How do I make my **data system** run x times as fast?  (sql,nosql,bigdata, …)

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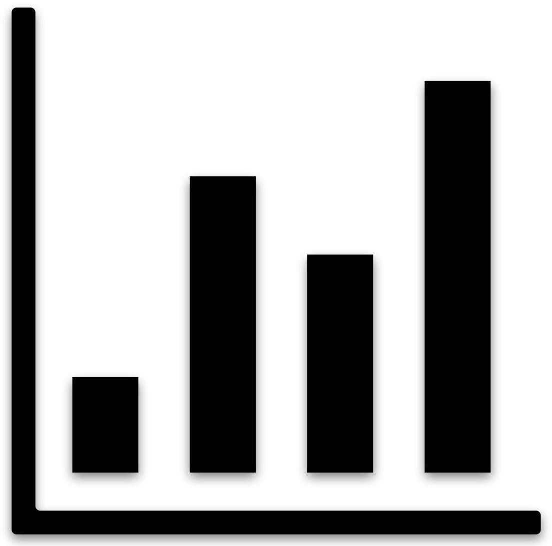
How to accelerate **statistics** computation for data science/ML? 

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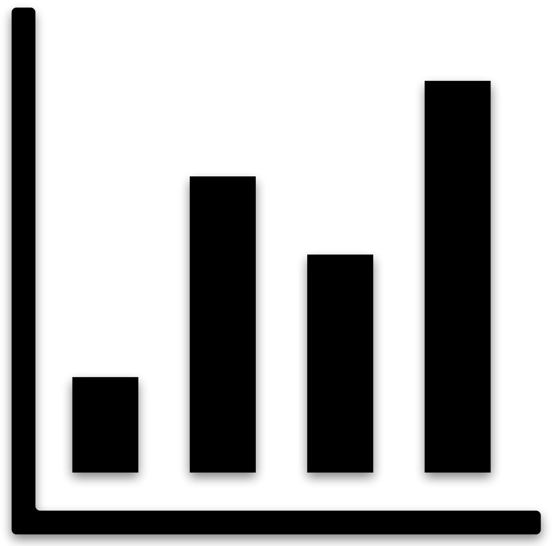
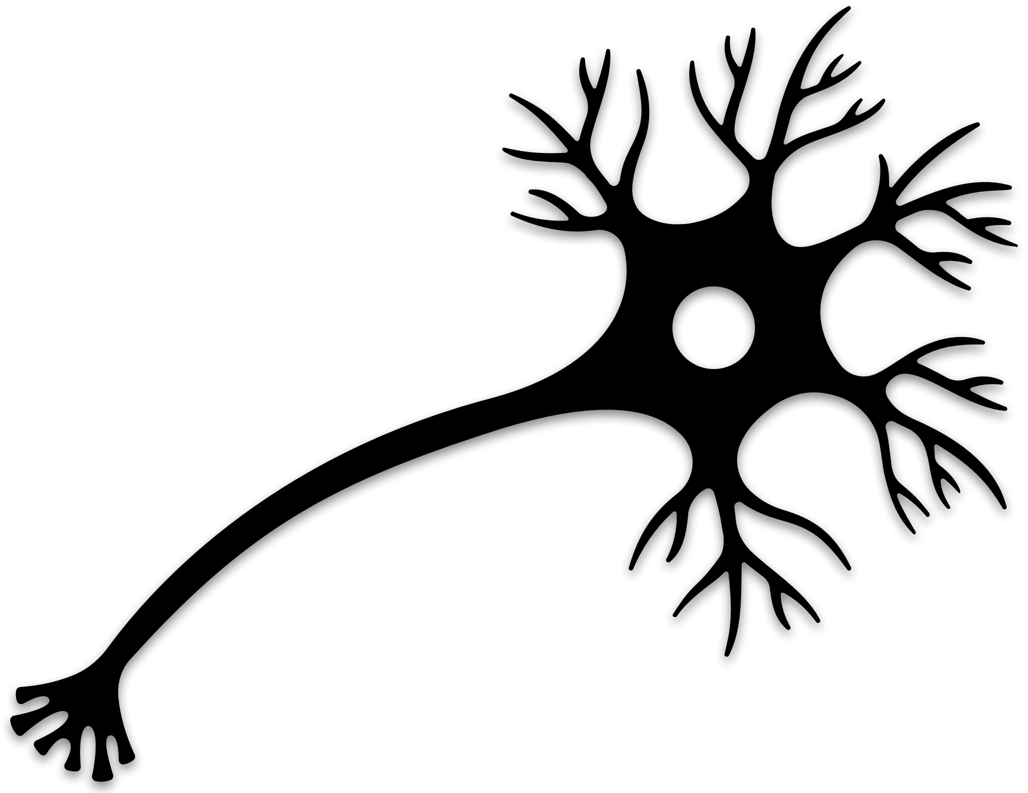
How to accelerate **statistics** computation for data science/ML? 



How do I train my **neural network/LLM** x times faster?

DASlab @ Harvard SEAS

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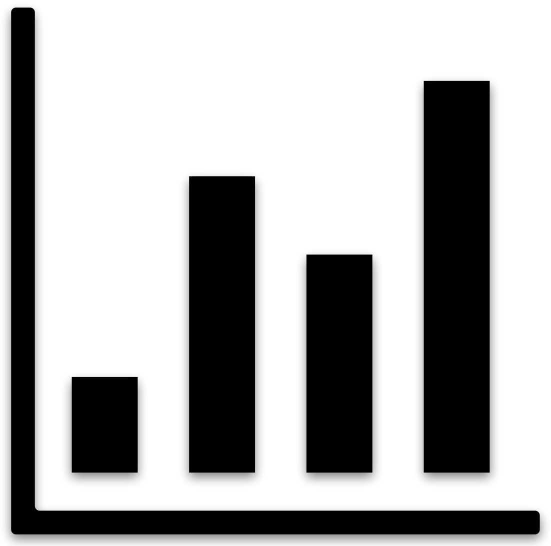
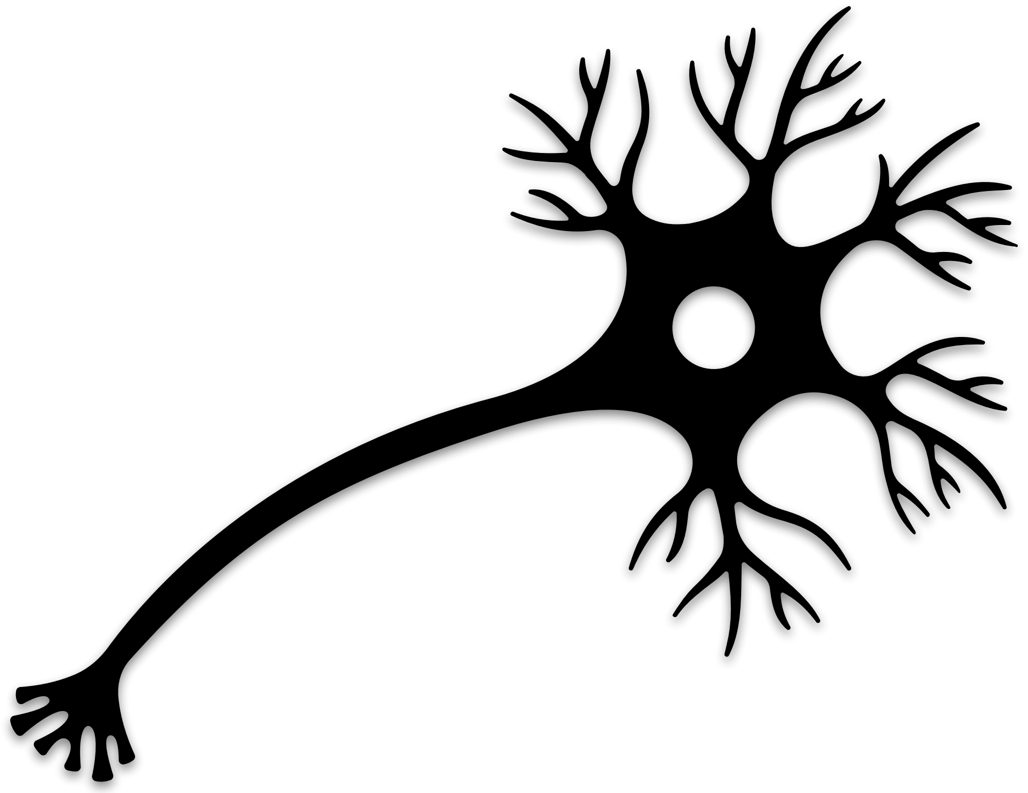
How to accelerate **statistics** computation for data science/ML? 



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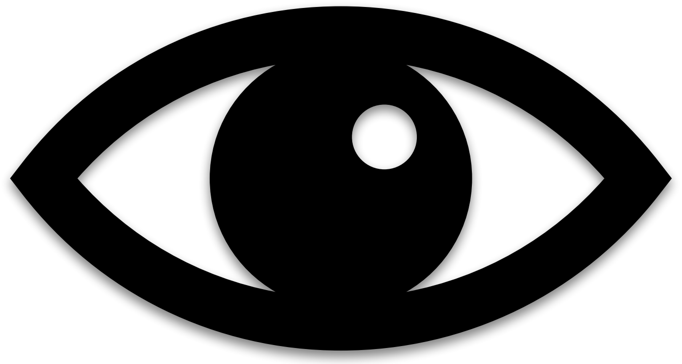
How can I do 10x **Image AI inference**? 

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Is there maybe a perfect system? Nope…

learning outcome
Fundamentals of storage

data structures, SQL, NoSQL, Neural Networks, Data Science, Images, LLMs

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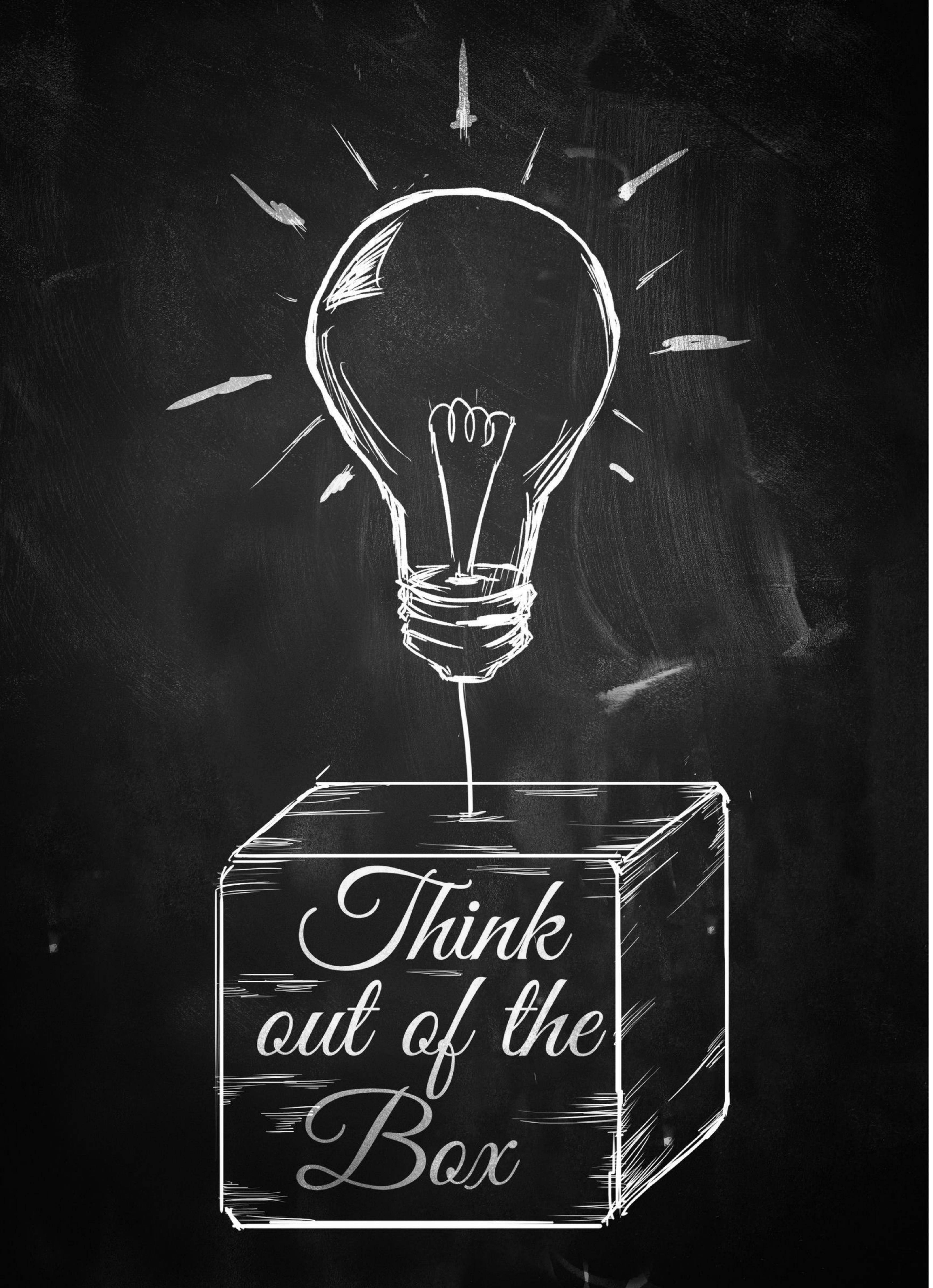
Self-designing systems

Automated system design: cloud cost, hardware, data & app requirements



first 4-5 weeks: Stratos/Sanket/Utku
Basic background
Self-designing systems
Neural network systems
Image AI systems
Research thinking

afterwards:
Students present research papers
One paper per class (ML systems)
In-class research/systems discussion
Research reviews
Research/systems projects

Recent Research Papers

Each student:

2 reviews per week/1 presentation

review and slides should focus on

what is the problem
why is it important
why is it hard
why existing solutions do not work
what is the core intuition for the solution
solution step by step
does the paper prove its claims
exact setup of analysis/experiments
are there any gaps in the logic/proof
possible next steps

* follow a few citations to gain more background

learn to judge constructively

learn to present

learn to prepare slides

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systems project

research project

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NoSQL, in c/c++

MLsys, in pytorch

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groups of max three

Adaptivity/Performance
Across all subject areas

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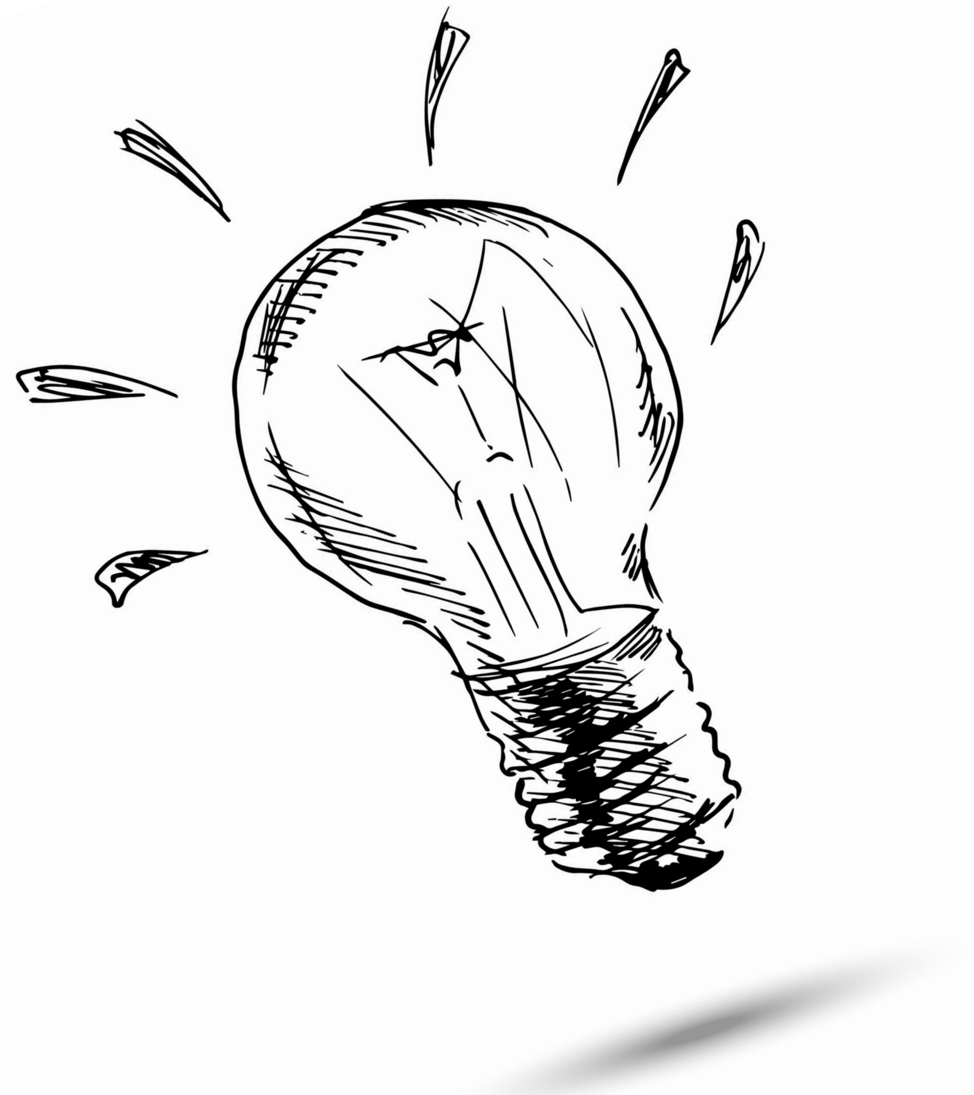
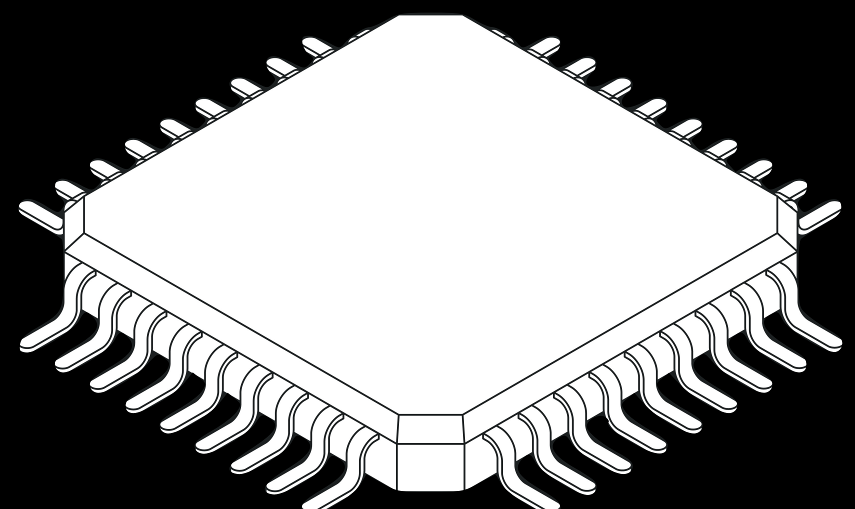
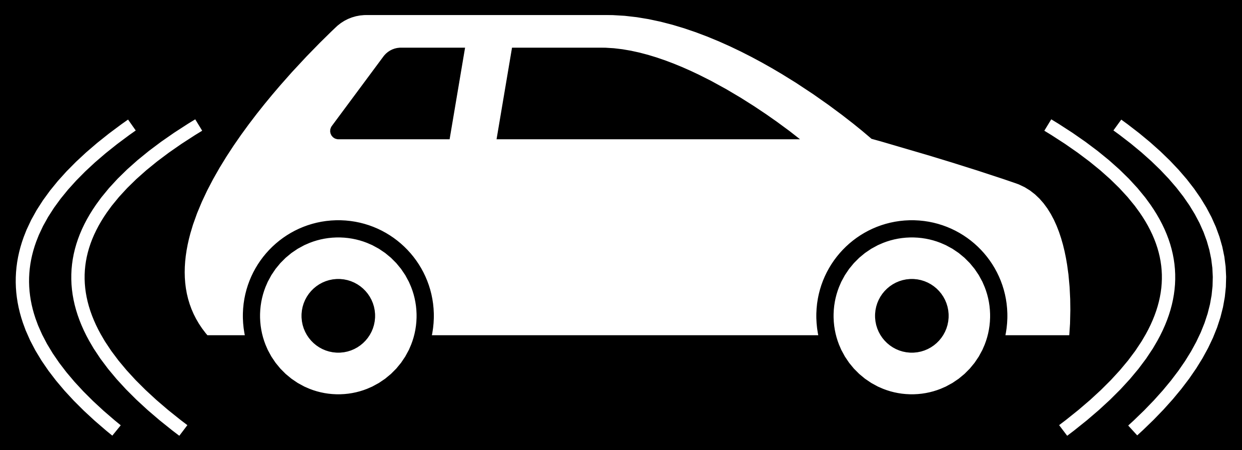


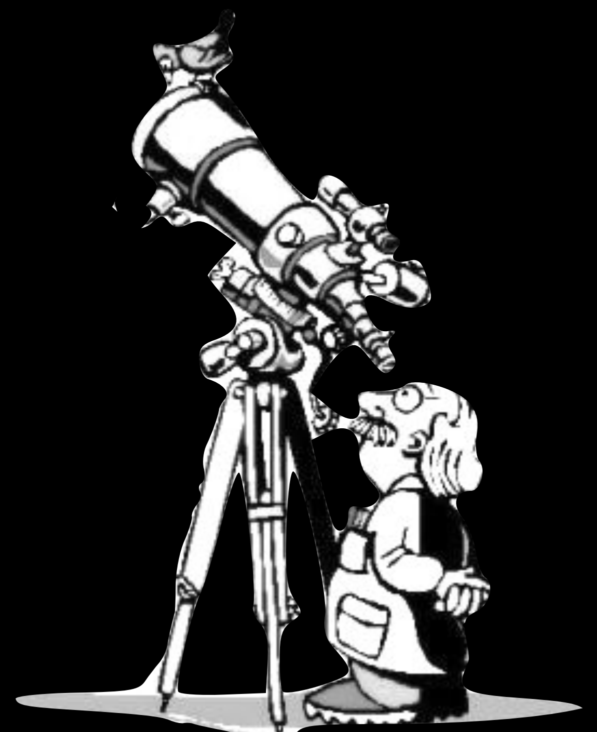
Questions on logistics?

Self-designing Systems

The problem: as the big data/AI world keeps changing…

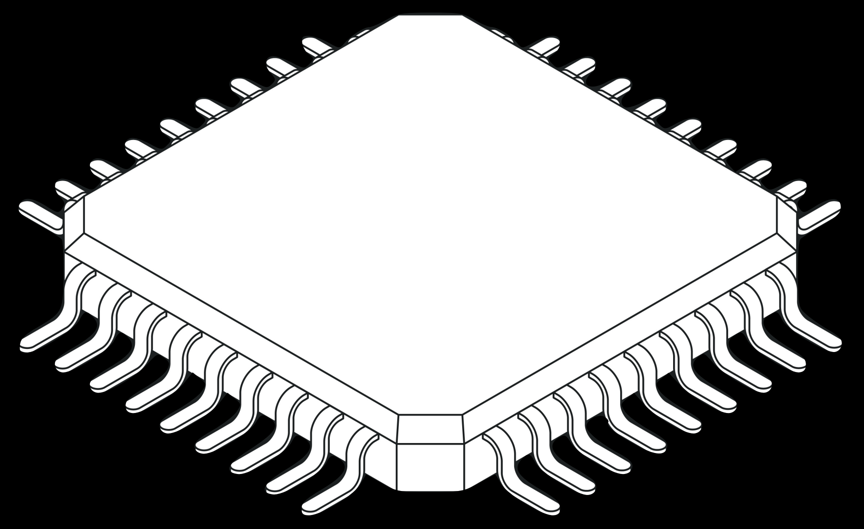


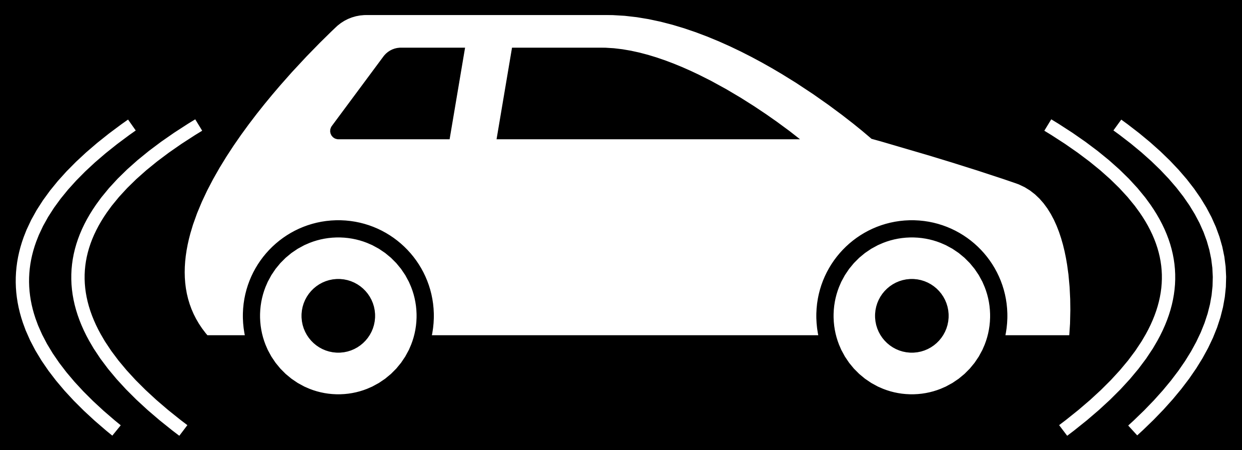


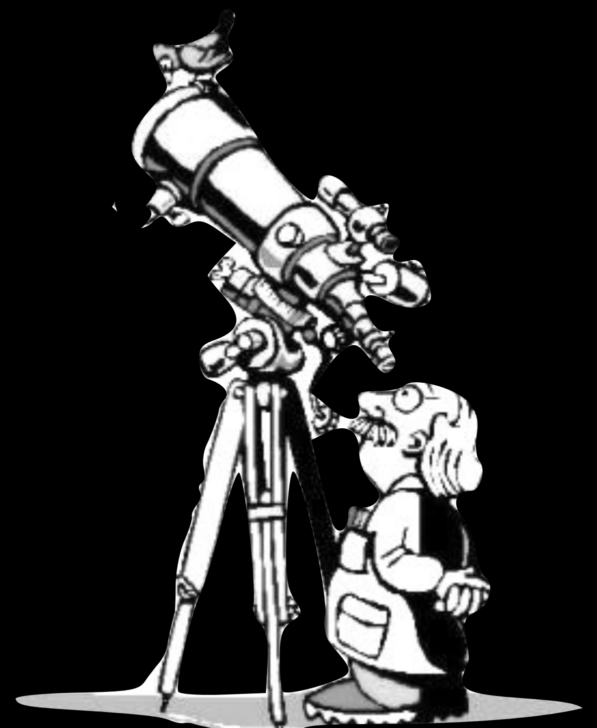


The problem: as the big data/AI world keeps changing…

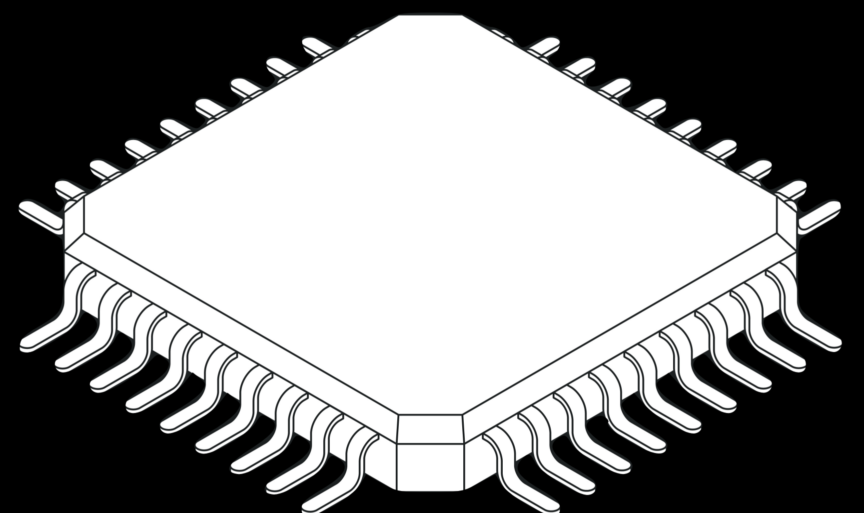
there is a continuous need for new data systems
but it is **extremely hard to design & build new systems**

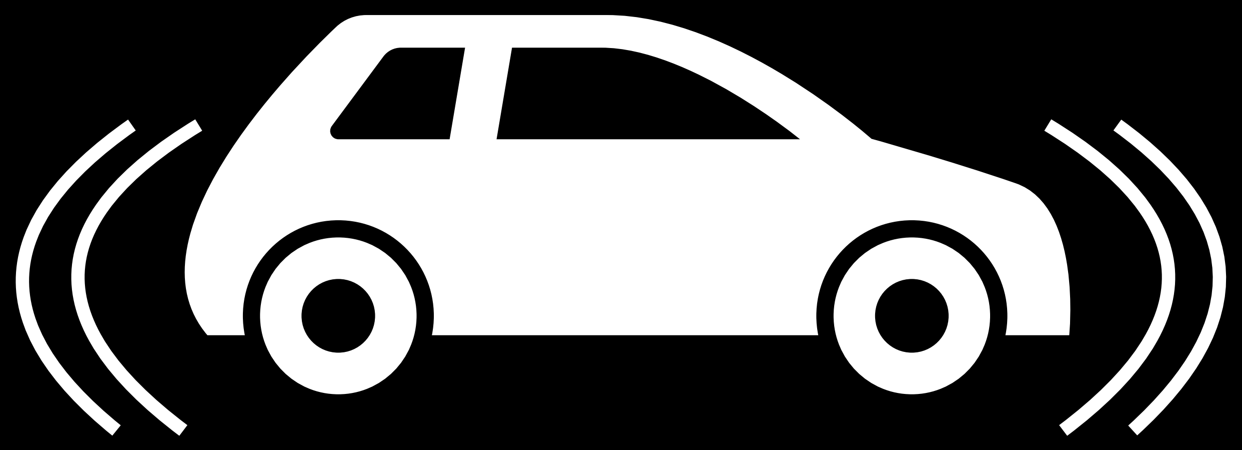


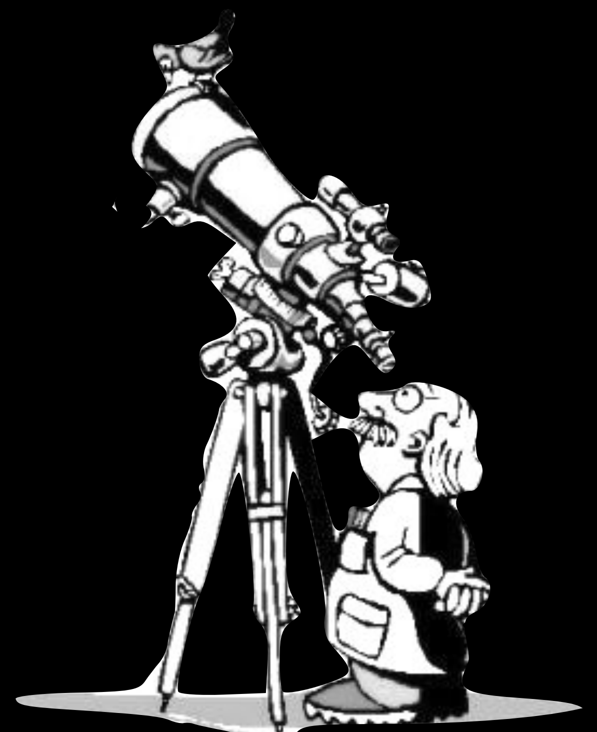




How do we design a data system that is **X times faster for a workload W**?







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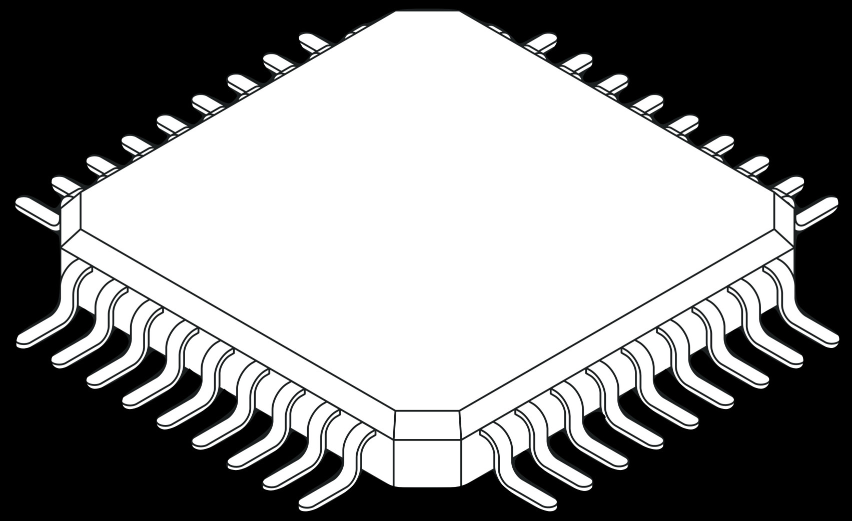

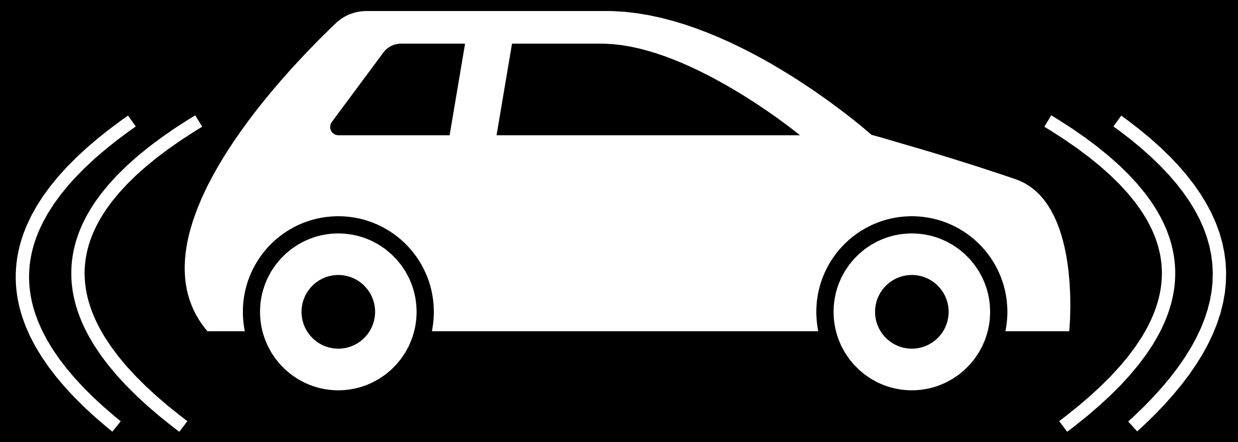

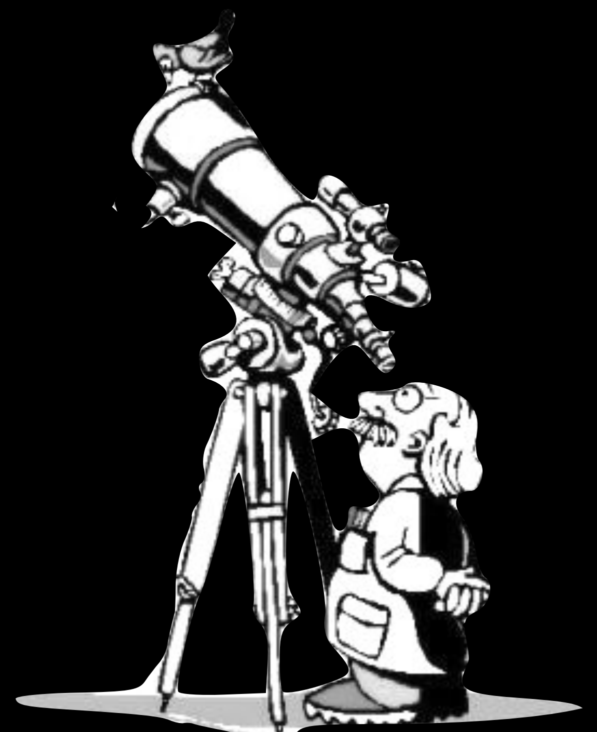

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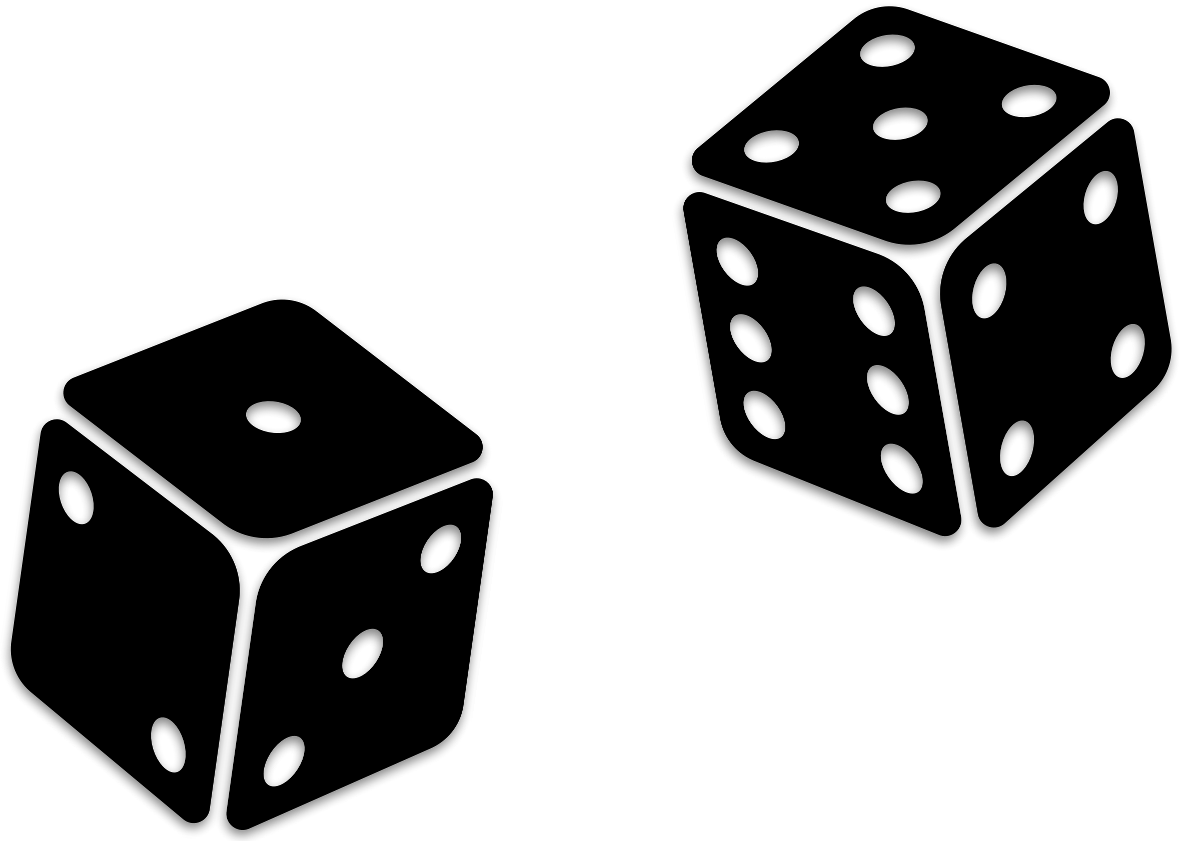
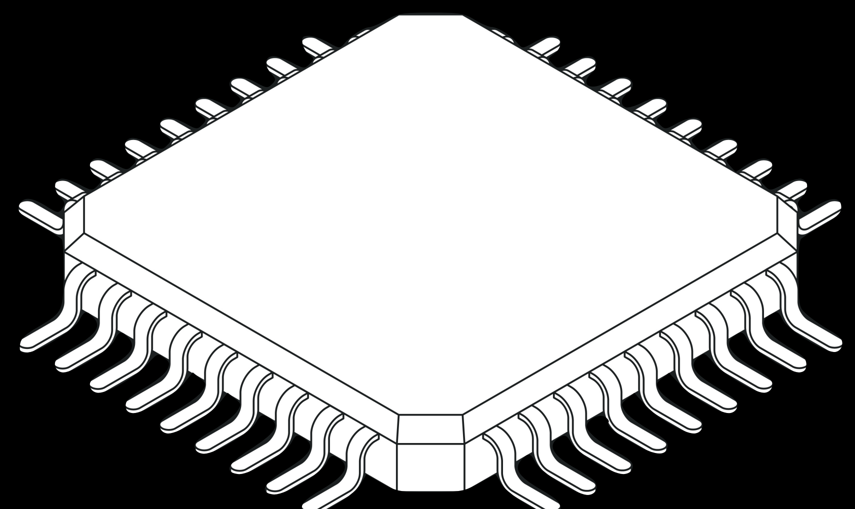
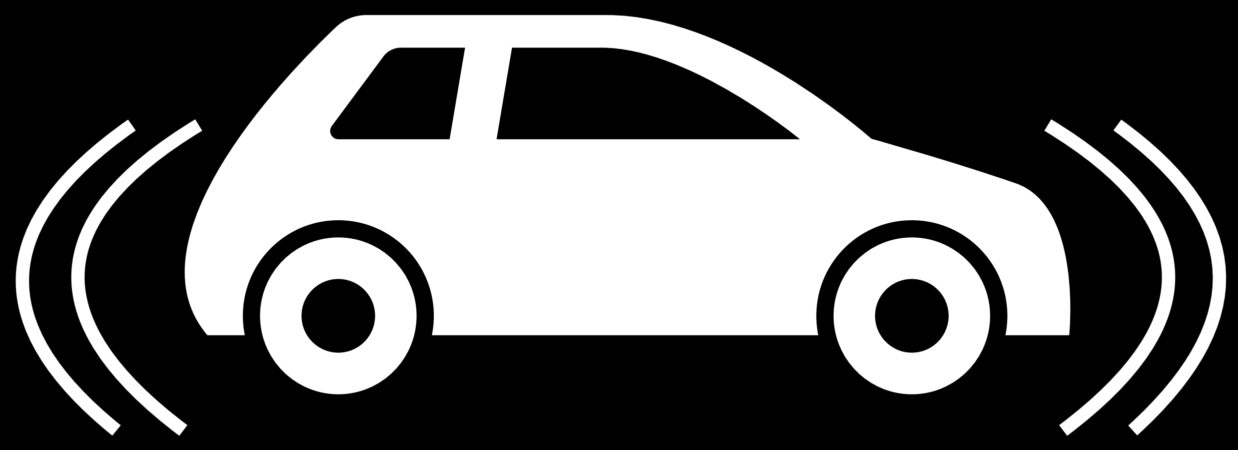
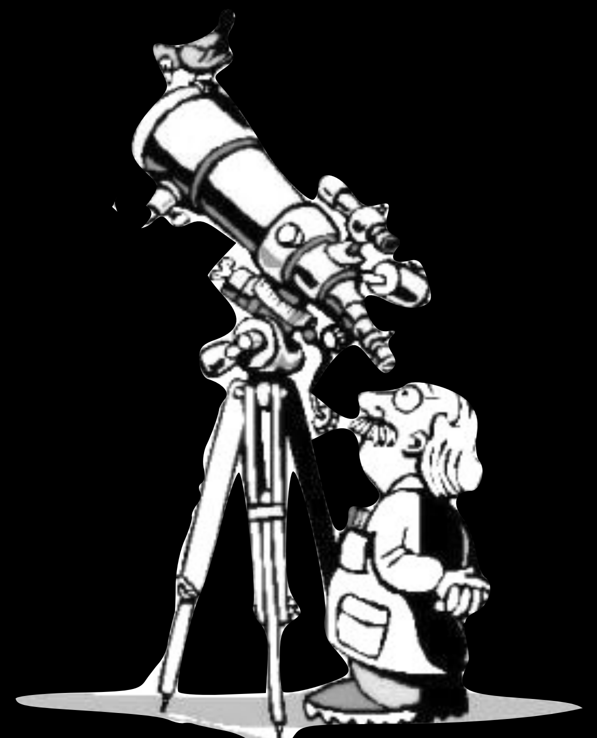


Should we **upgrade** to new version Z?

What will **break** our system?







BOTTLENECK: SUB-OPTIMAL DATA SYSTEMS

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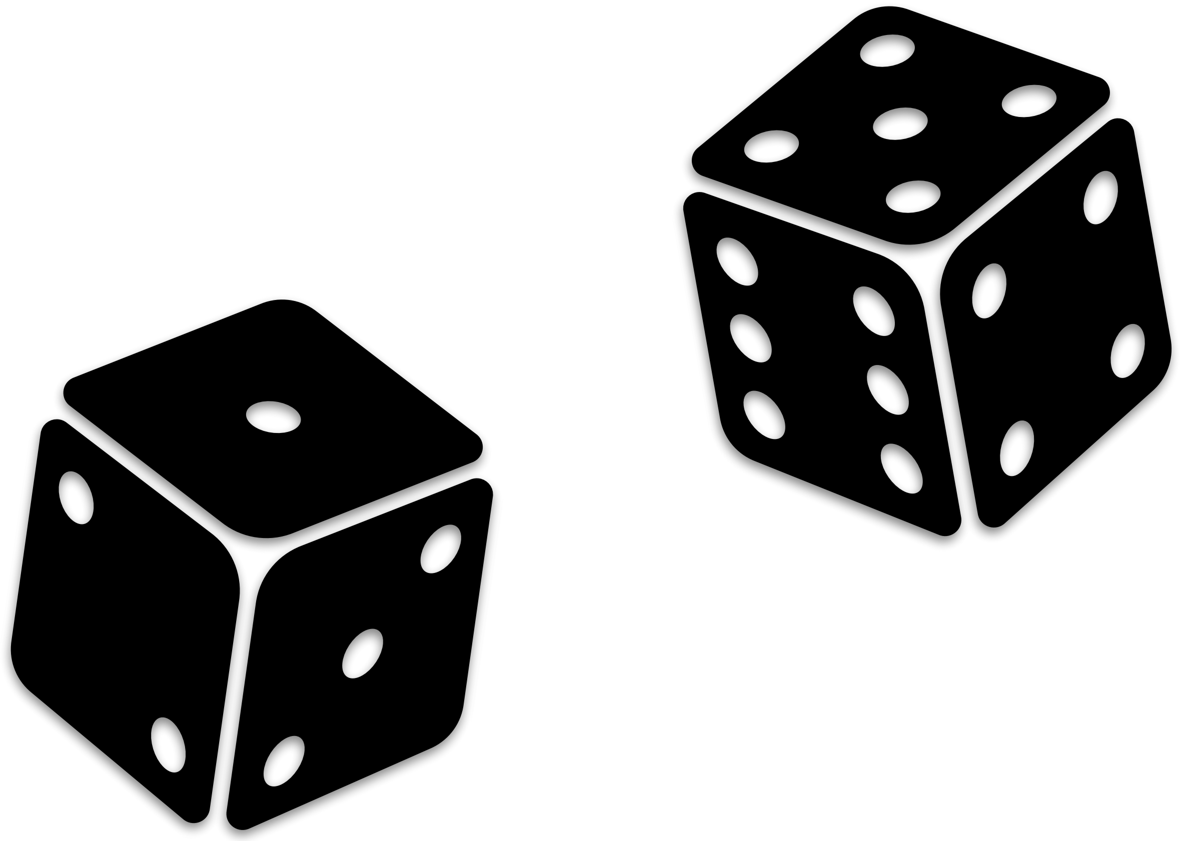
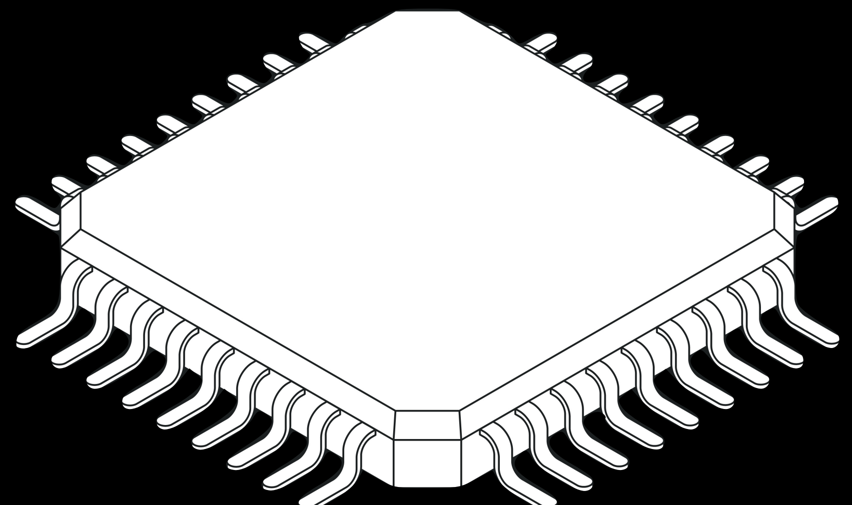
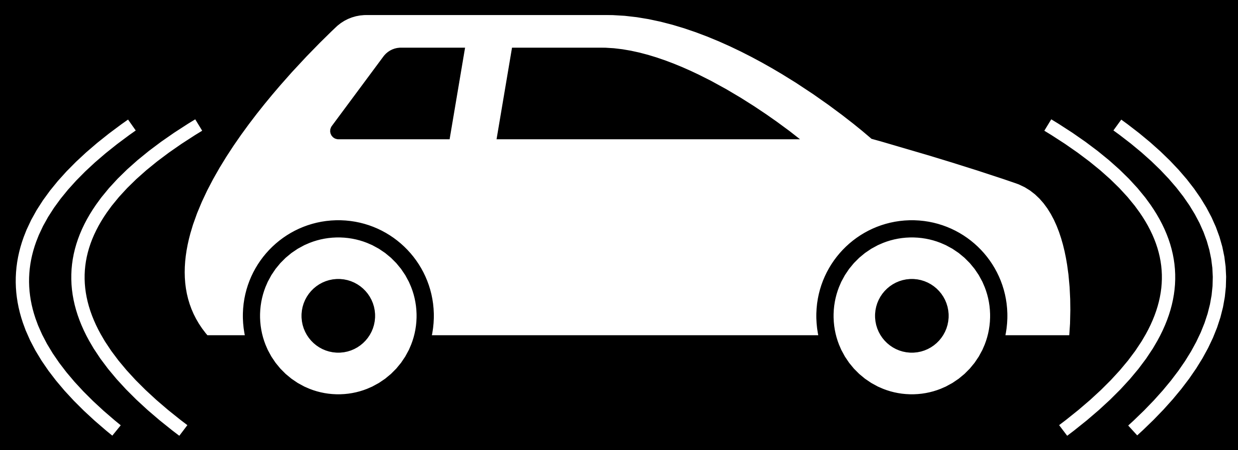
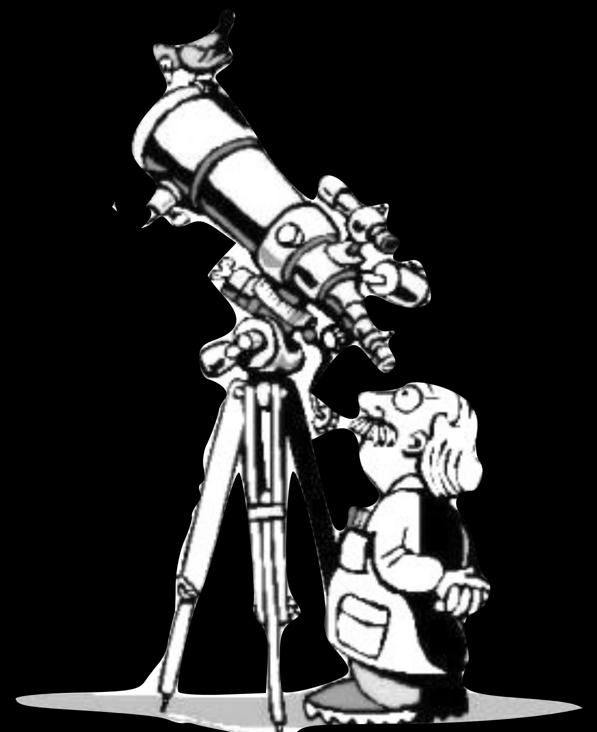




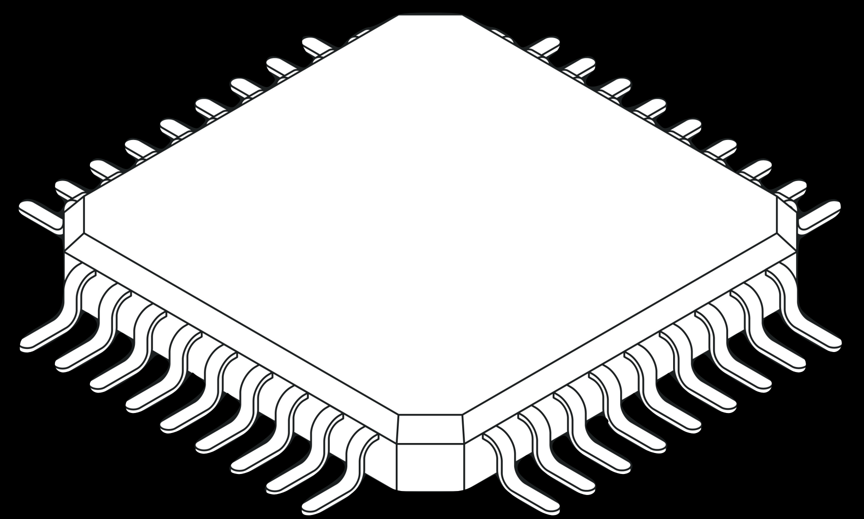


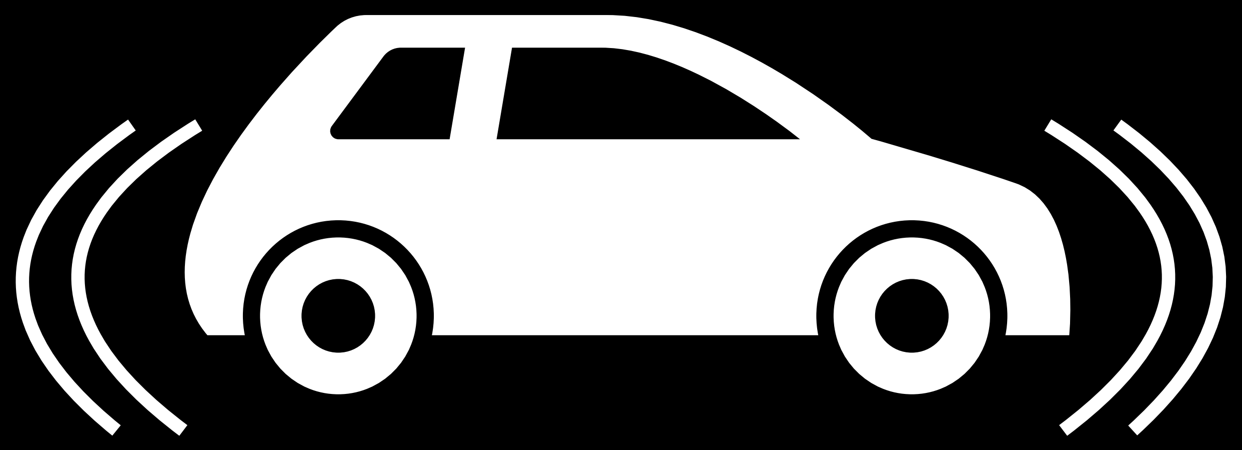


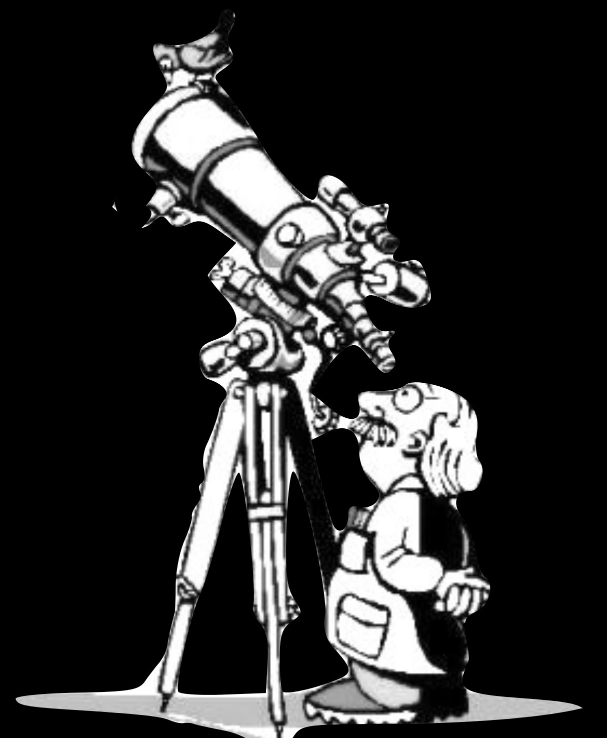
BOTTLENECK: SUB-OPTIMAL DATA SYSTEMS

huge cloud cost

environmental impact





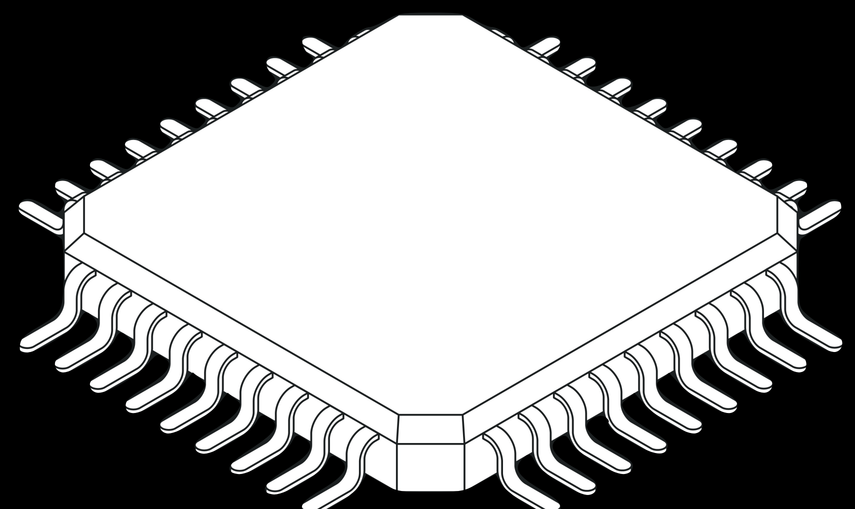


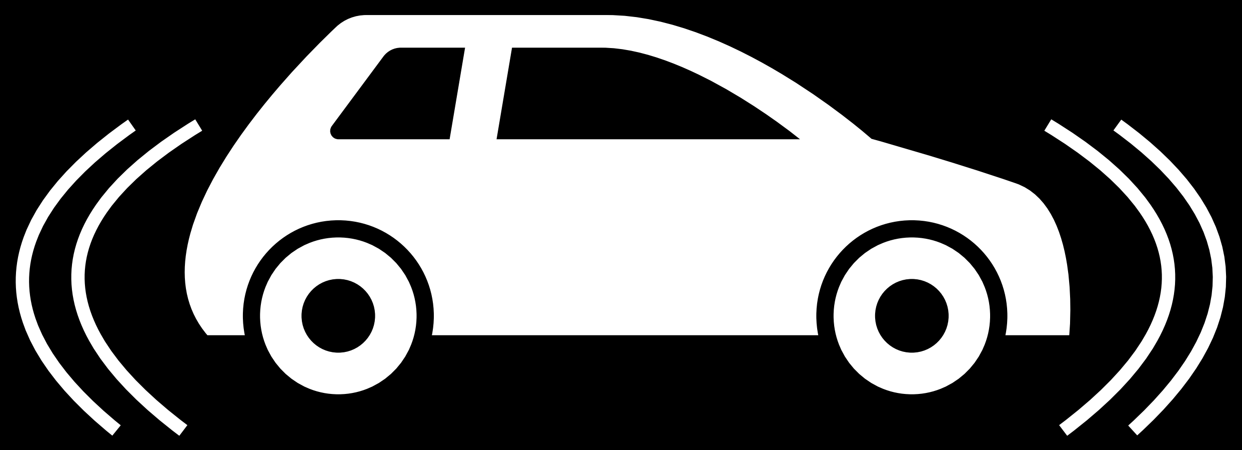
BOTTLENECK: SUB-OPTIMAL DATA SYSTEMS

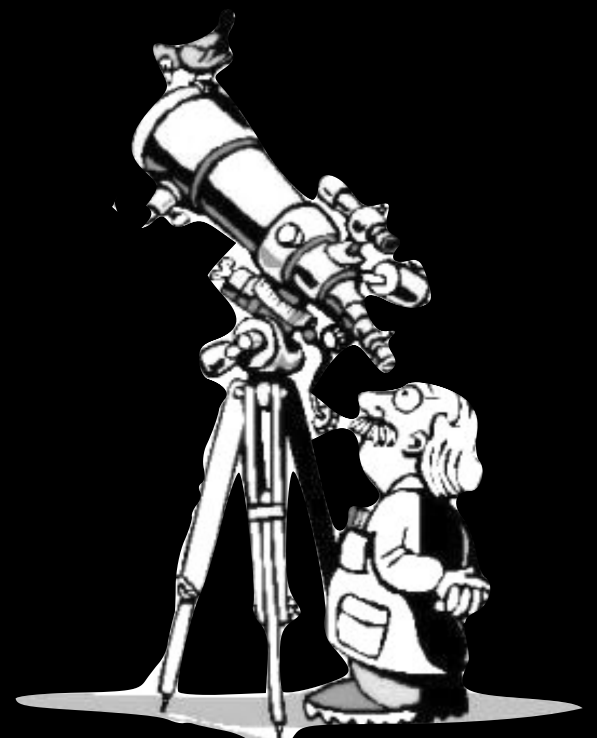
expensive transitions

huge cloud cost

environmental impact







BOTTLENECK: SUB-OPTIMAL DATA SYSTEMS

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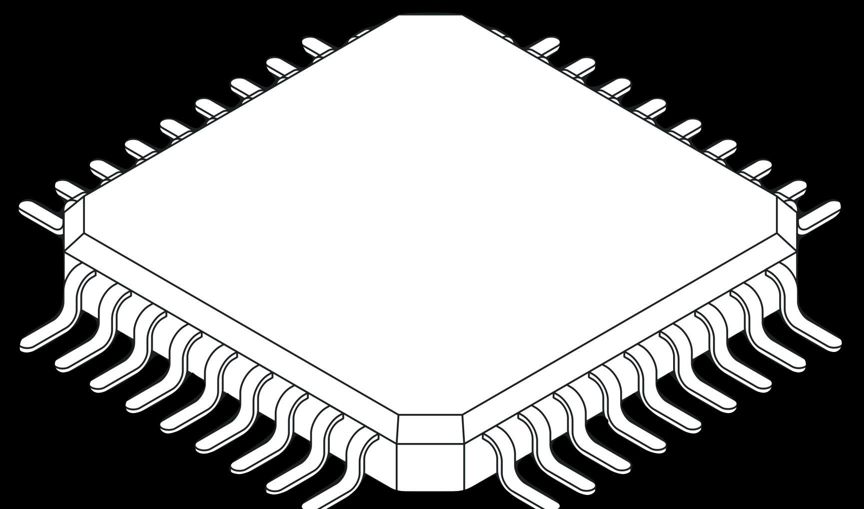
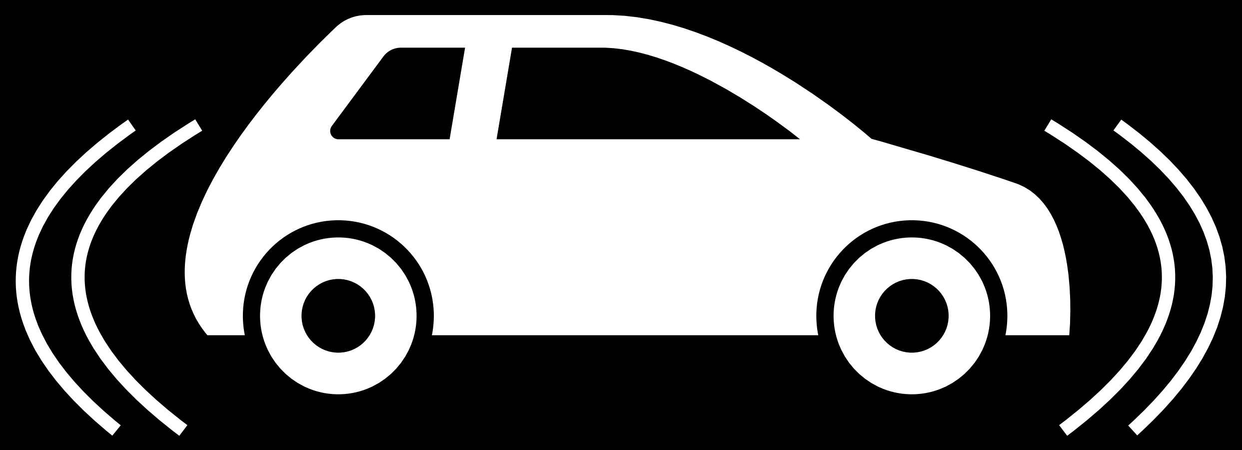
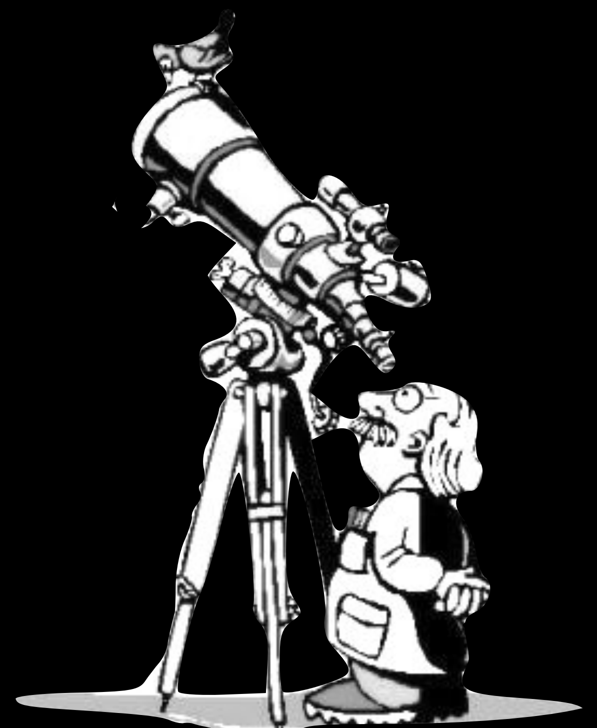
huge cloud cost

application feasibility

environmental impact





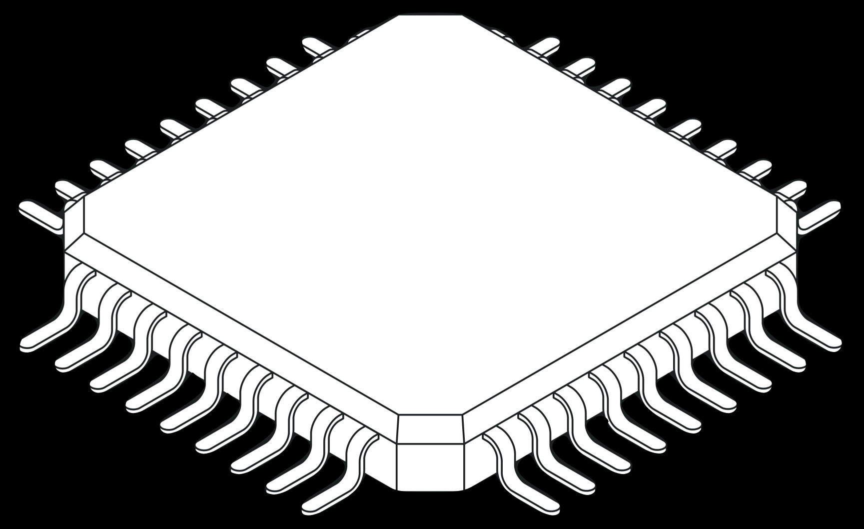


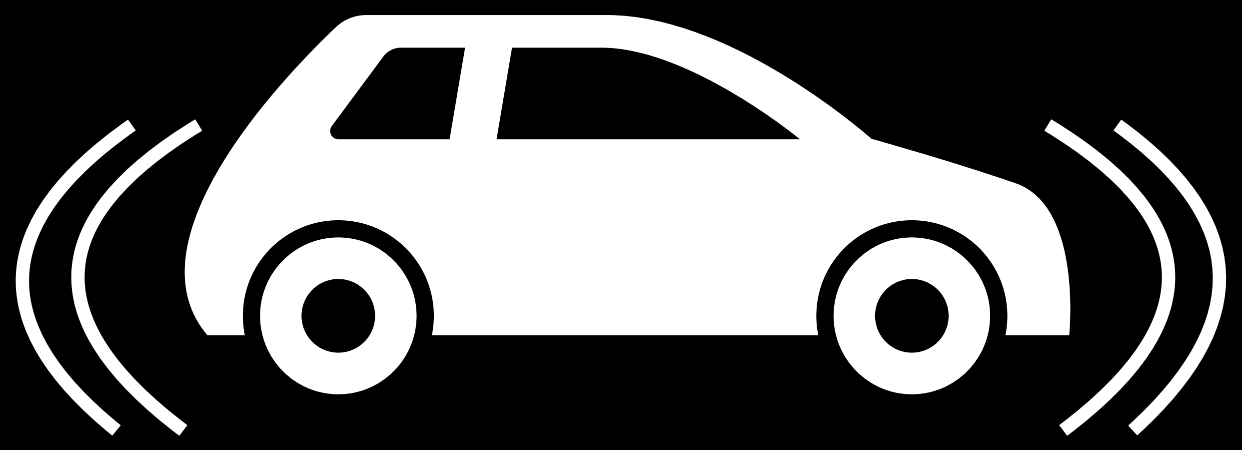
BOTTLENECK: SUB-OPTIMAL DATA SYSTEMS

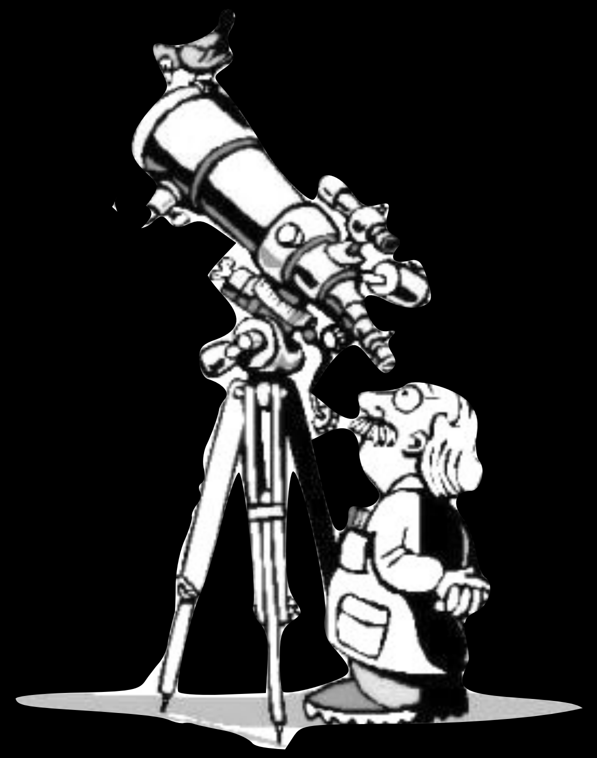
huge cloud cost expensive transitions application feasibility environmental impact

complexity

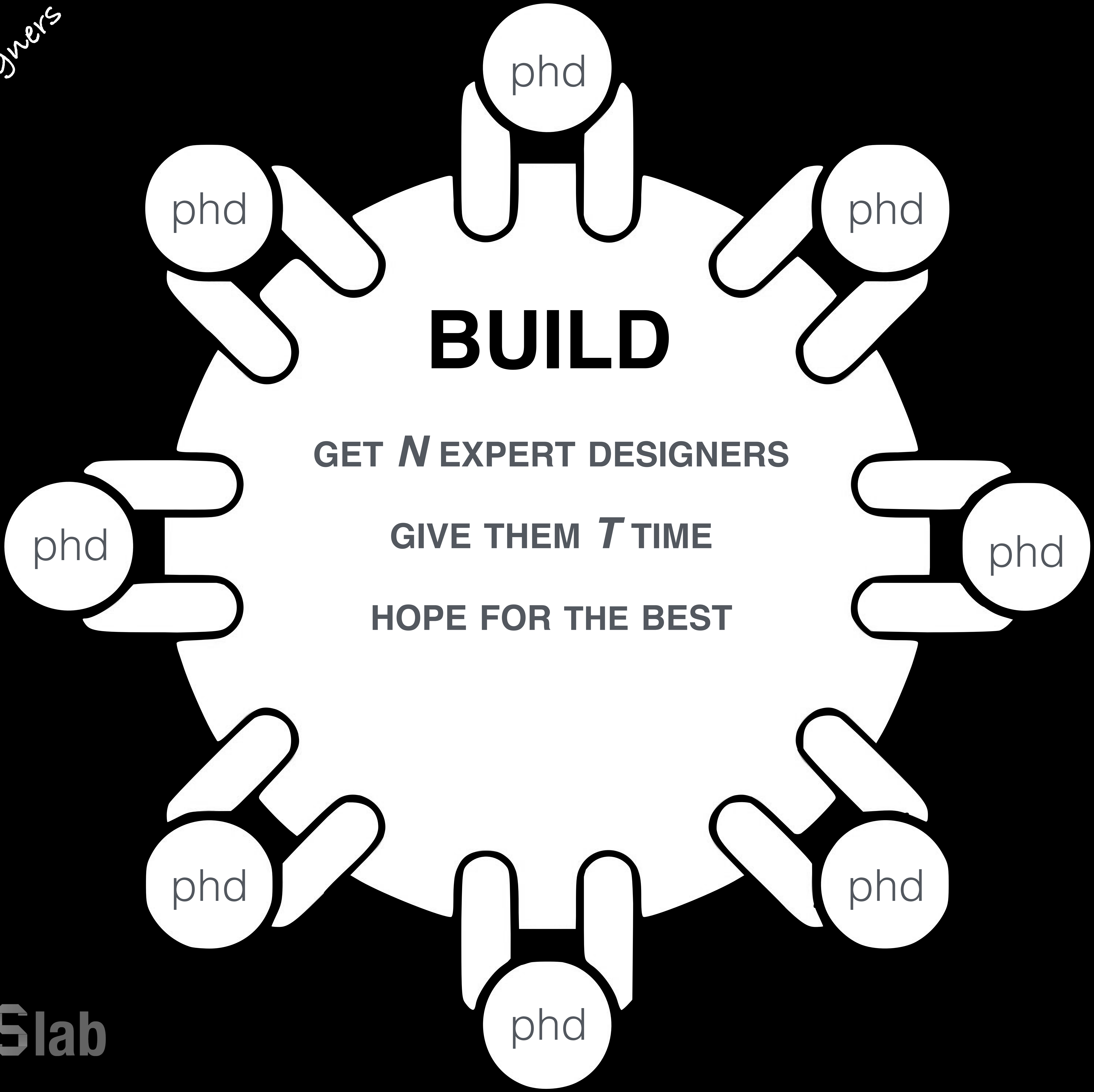
how we **BUILD** systems







the dinning
systems designers



BUILD

GET *N* EXPERT DESIGNERS

GIVE THEM *T* TIME

HOPE FOR THE BEST

the dinning
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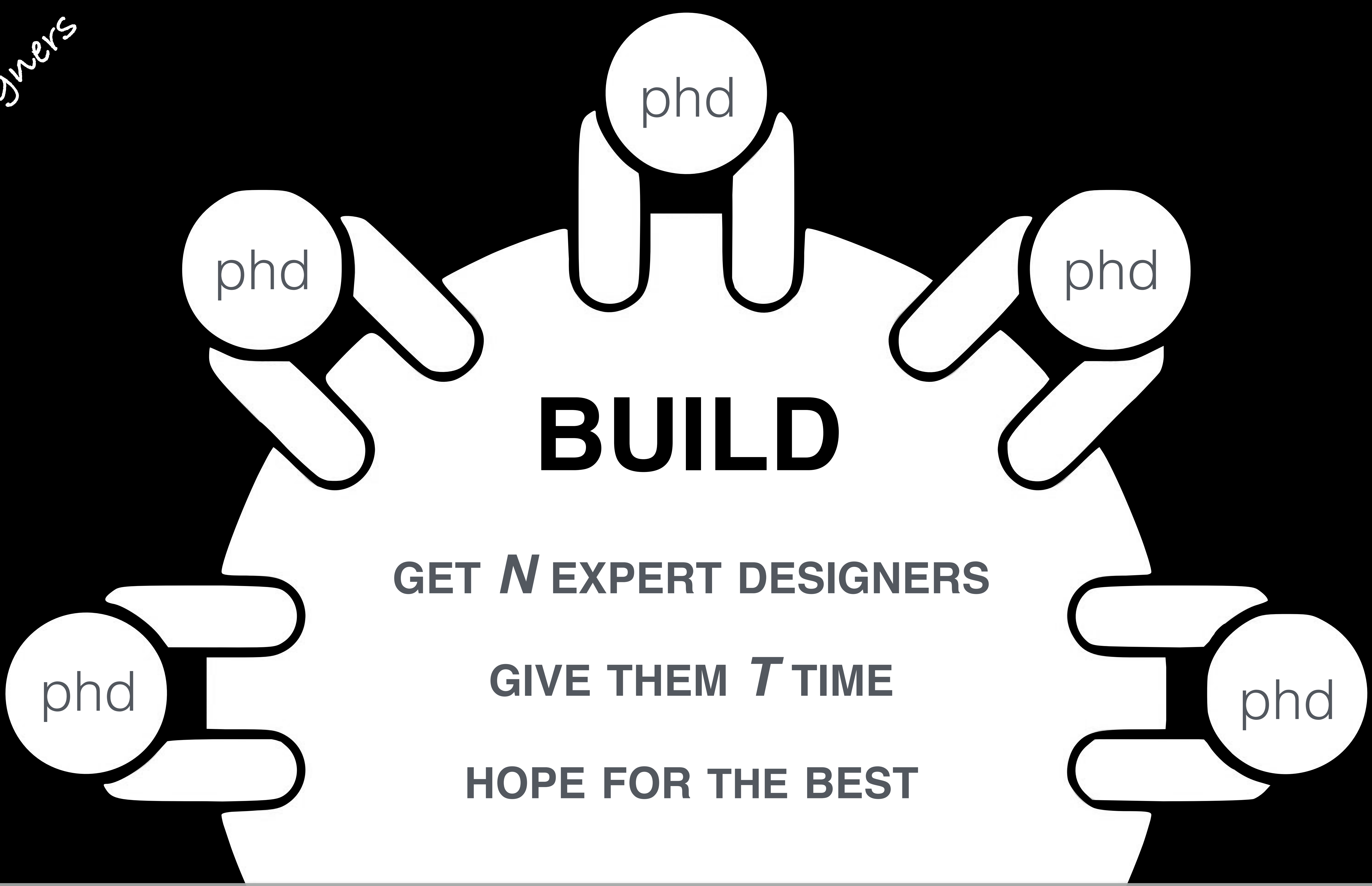

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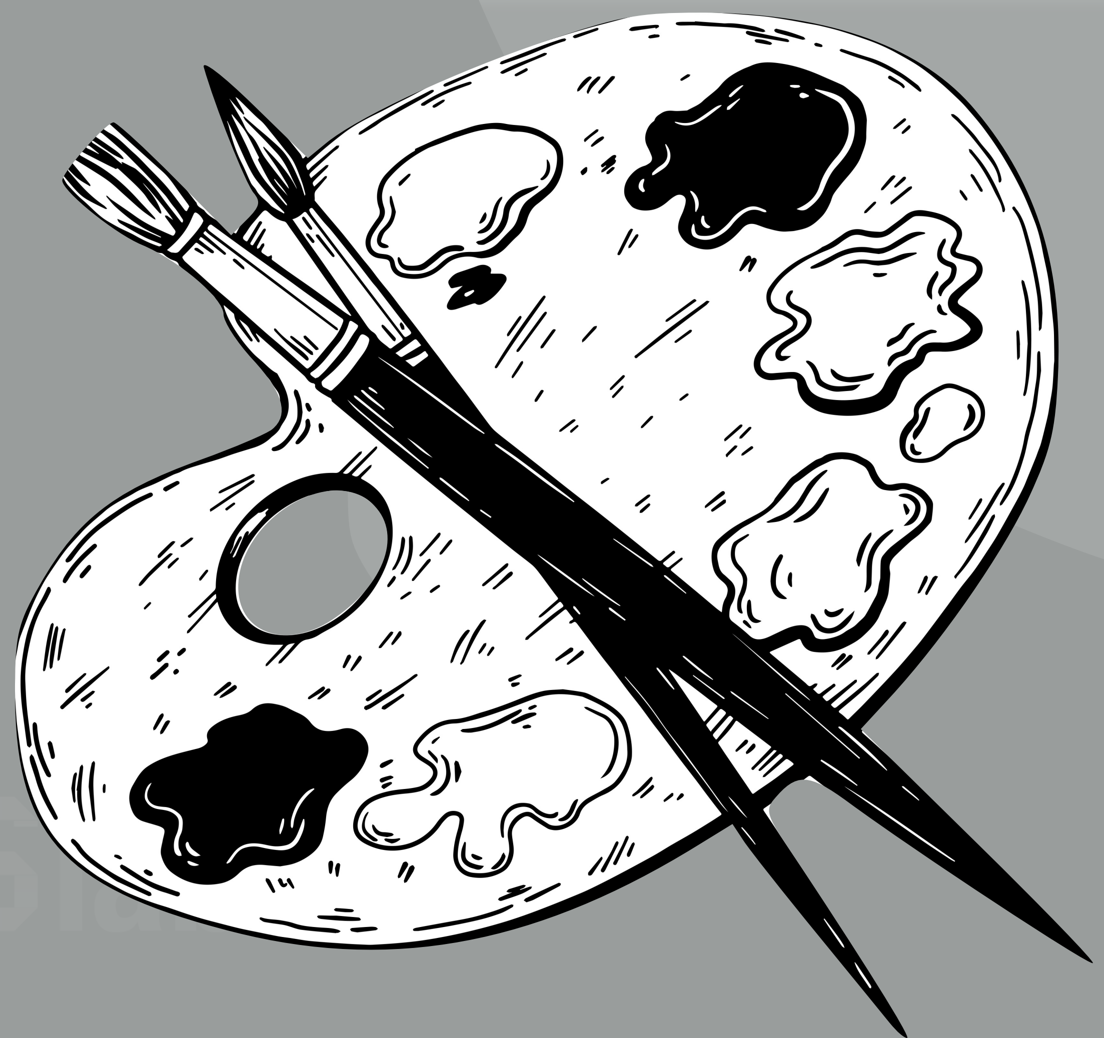
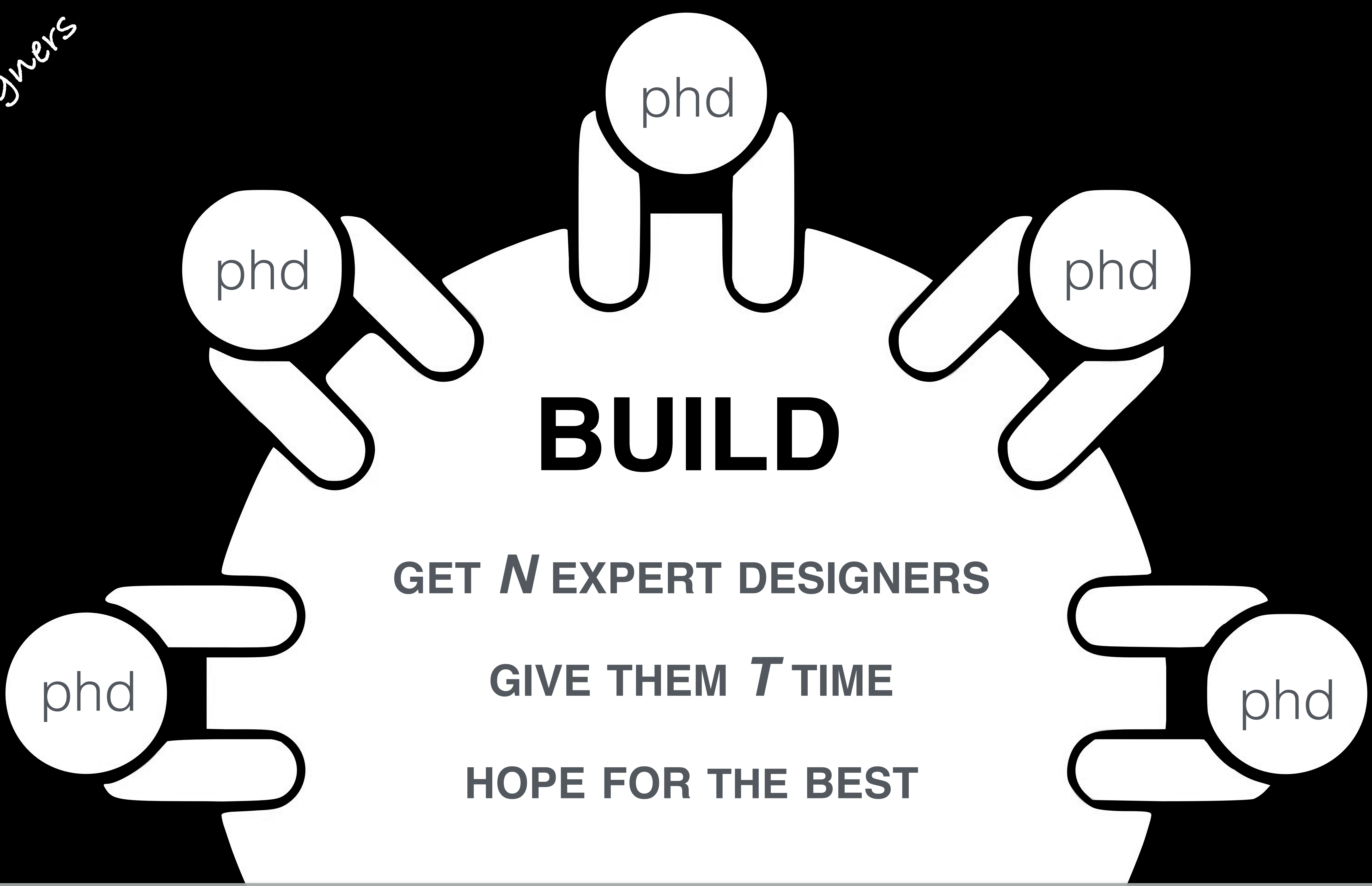
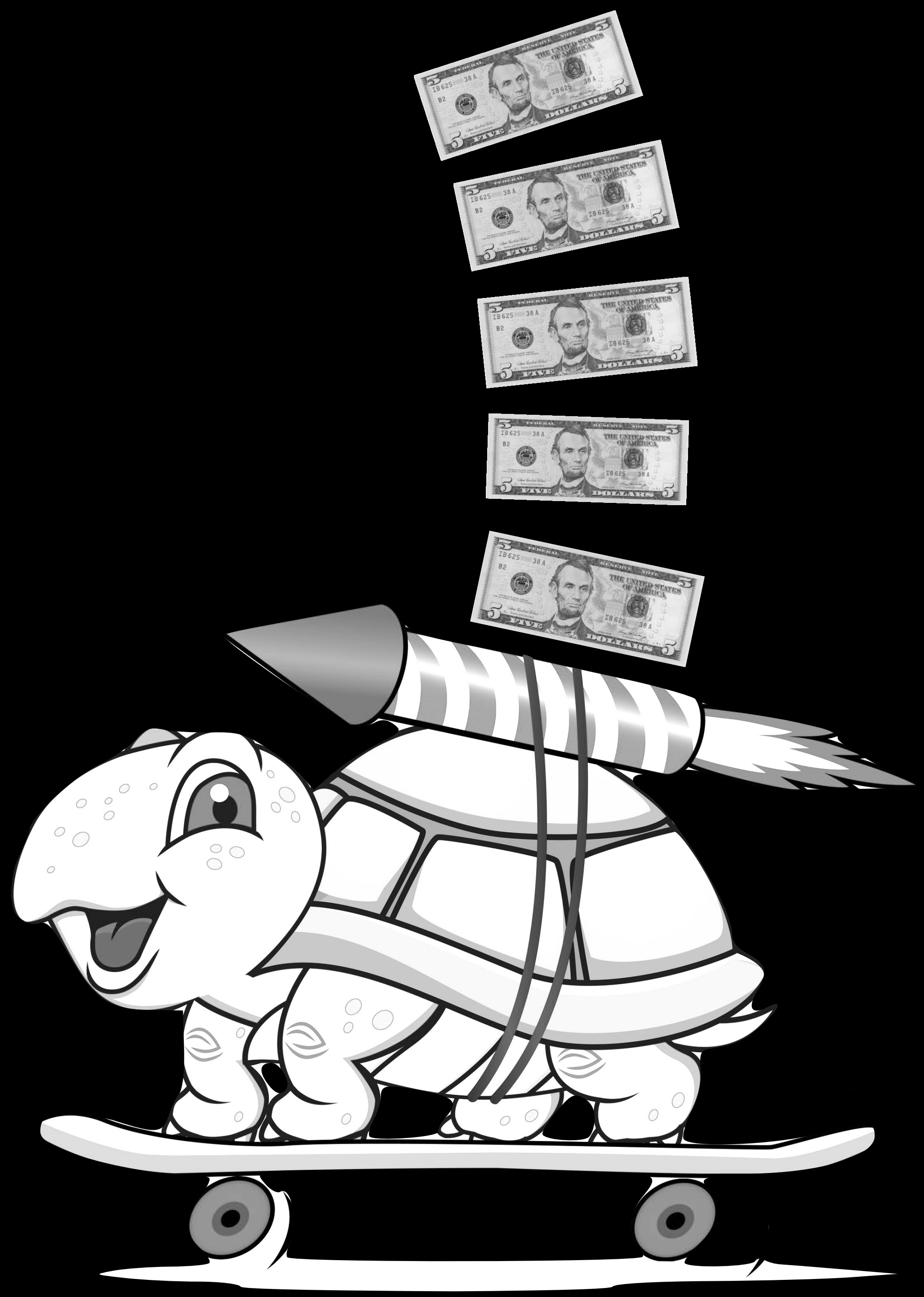
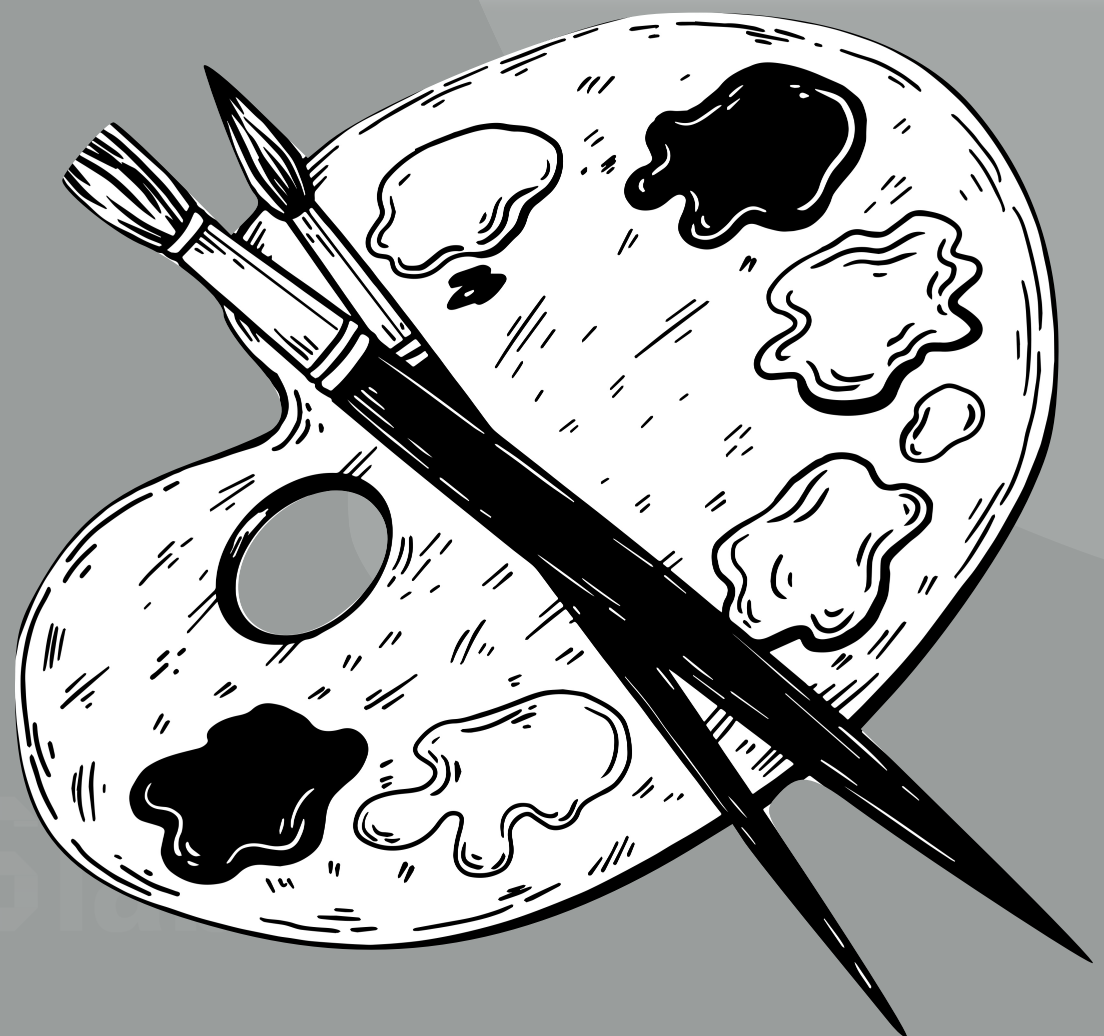


design is an art

the dinning
systems designers







design is an art

Design: 6-7 years
Reasoning: months/impossible

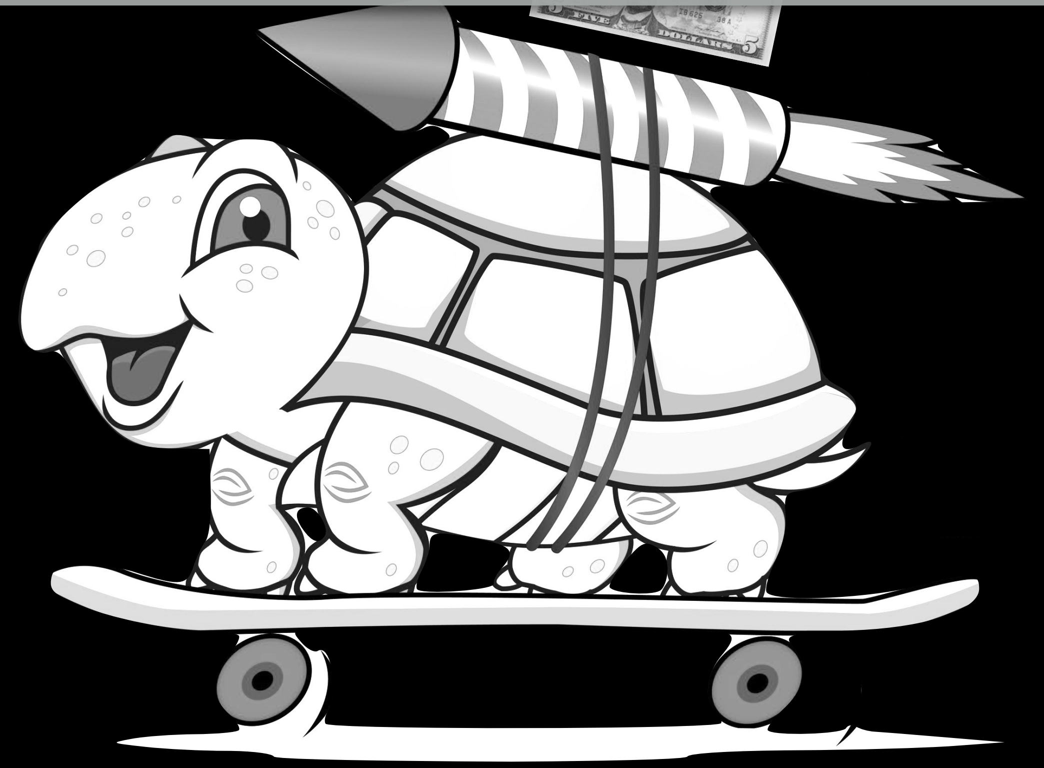
GET *N* EXPERT DESIGNERS

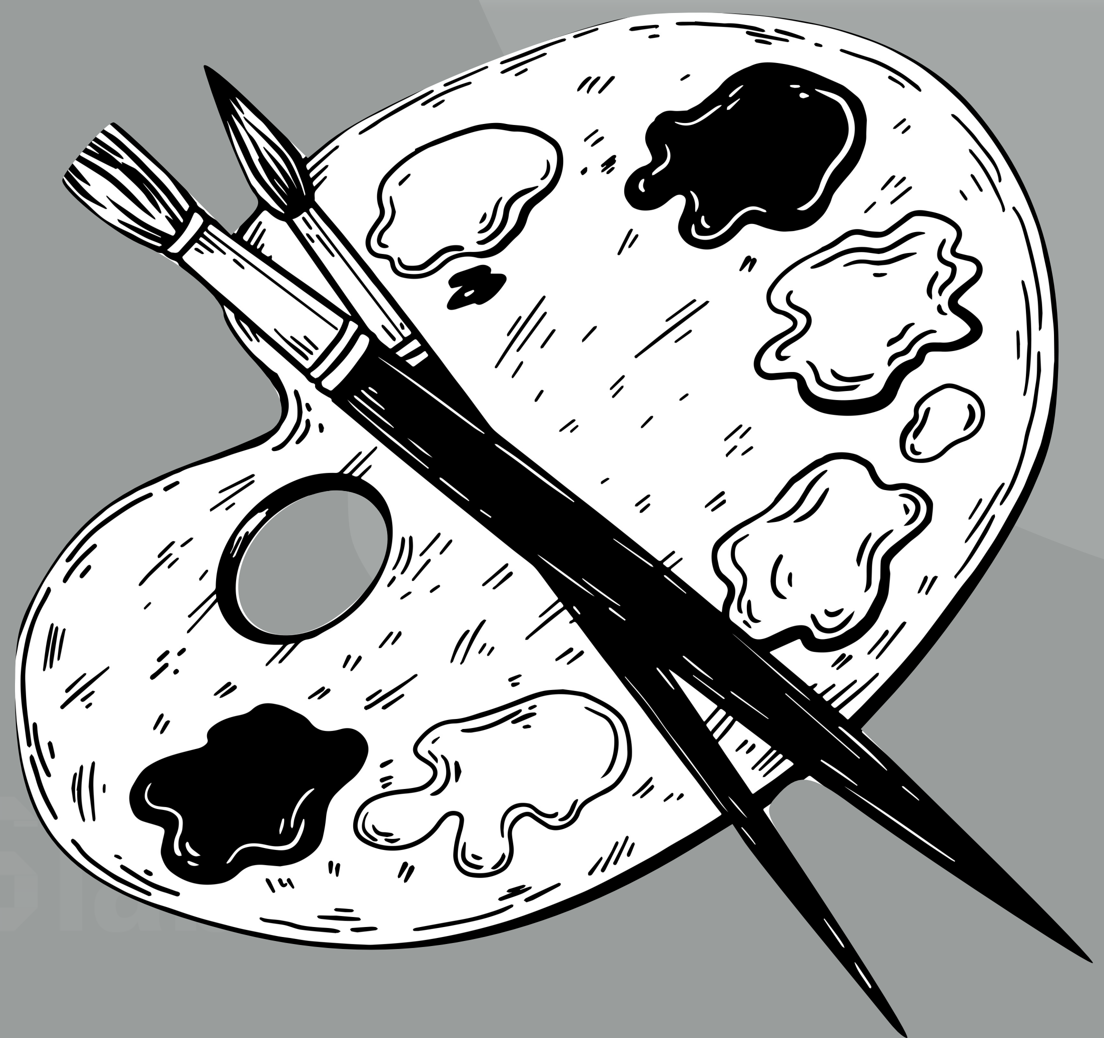
GIVE THEM *T* TIME

HOPE FOR THE BEST

phd

phd

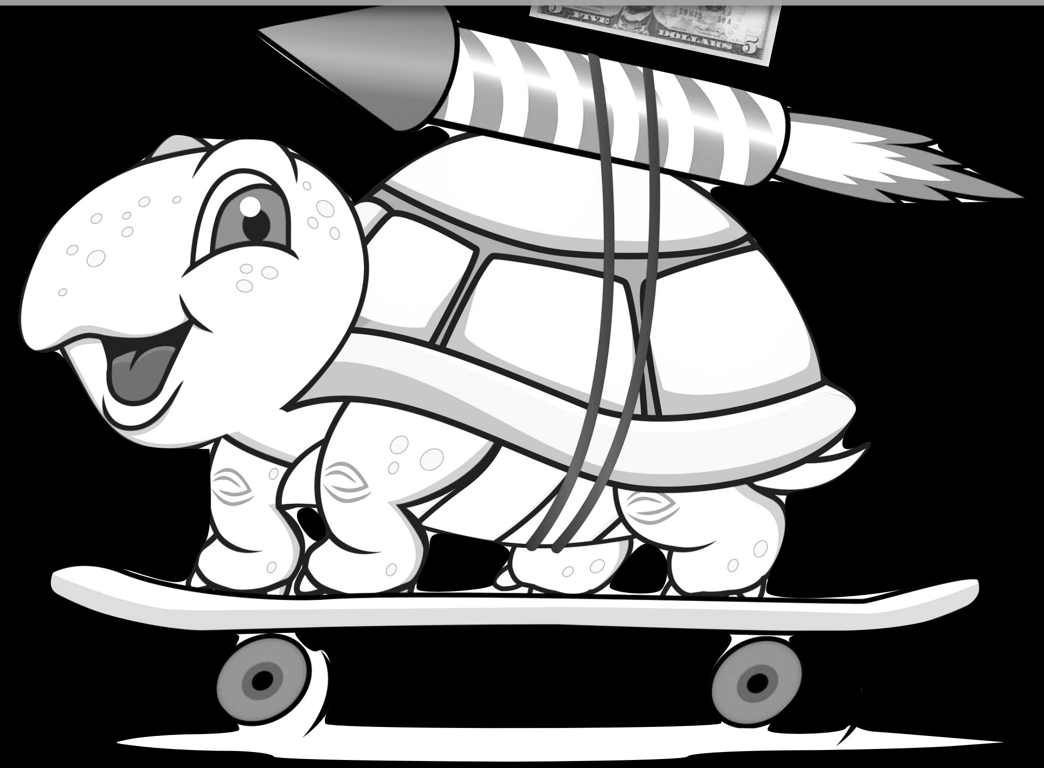




design is an art

sign: … s

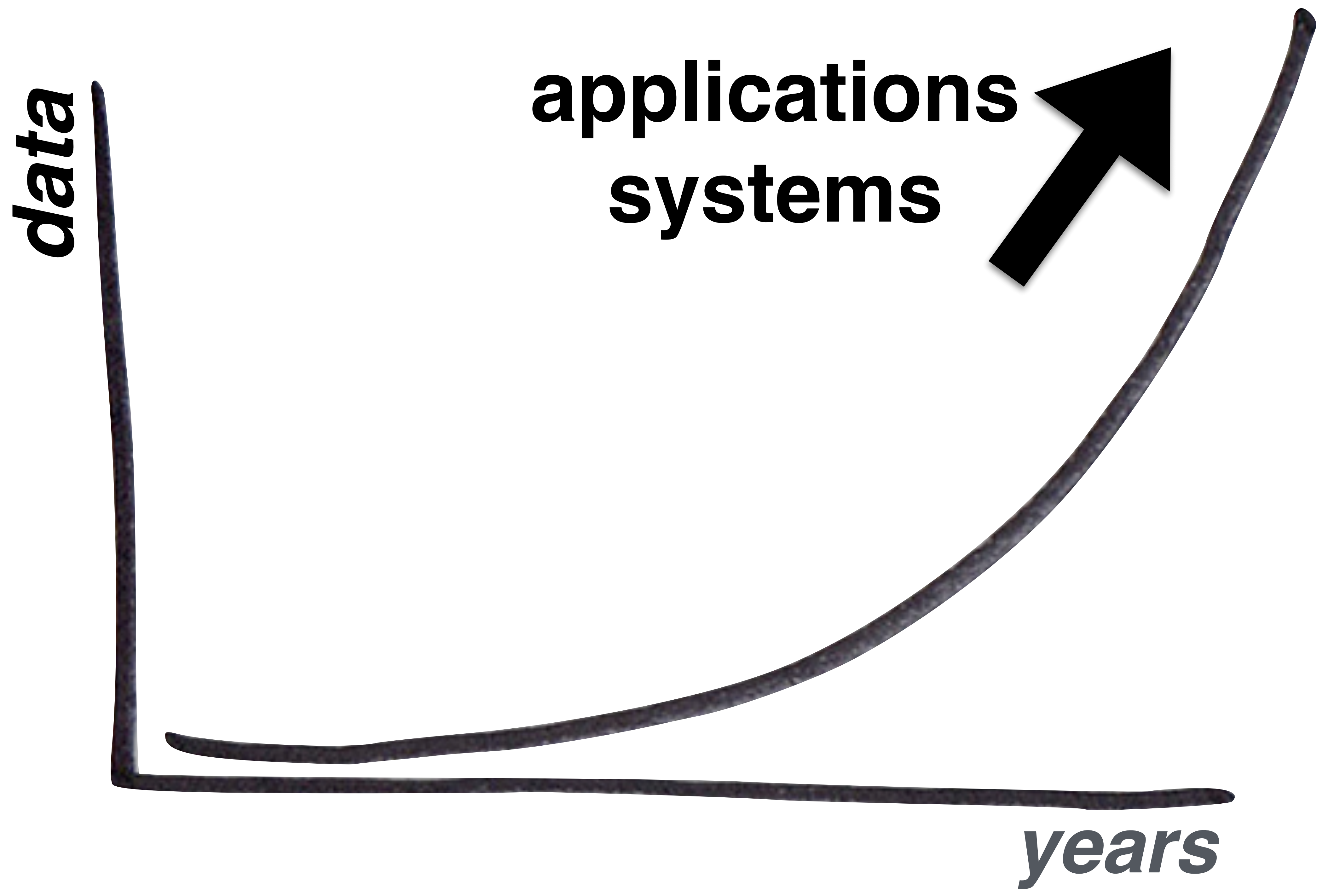
Re … : … mpossible

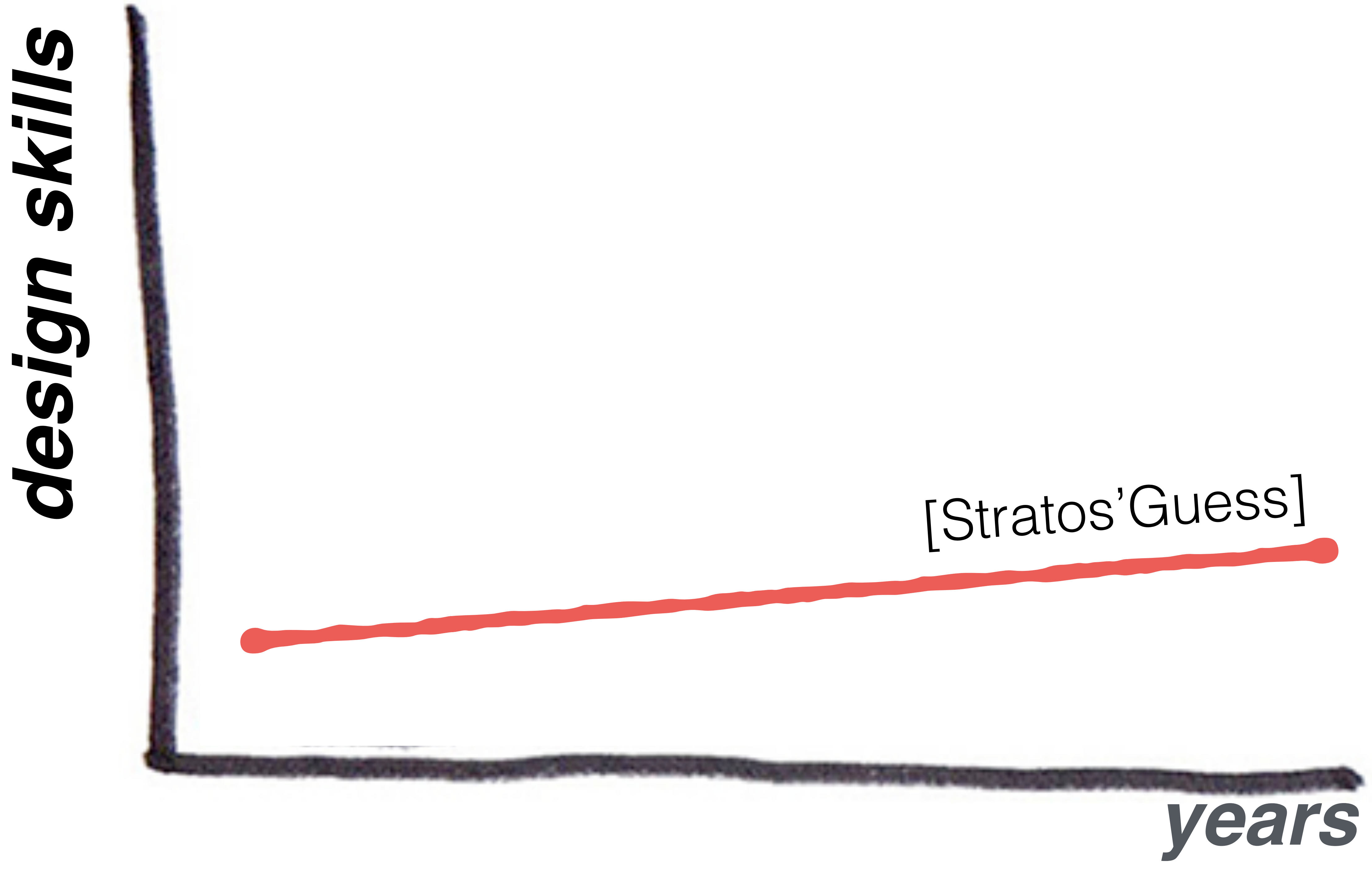


is an art

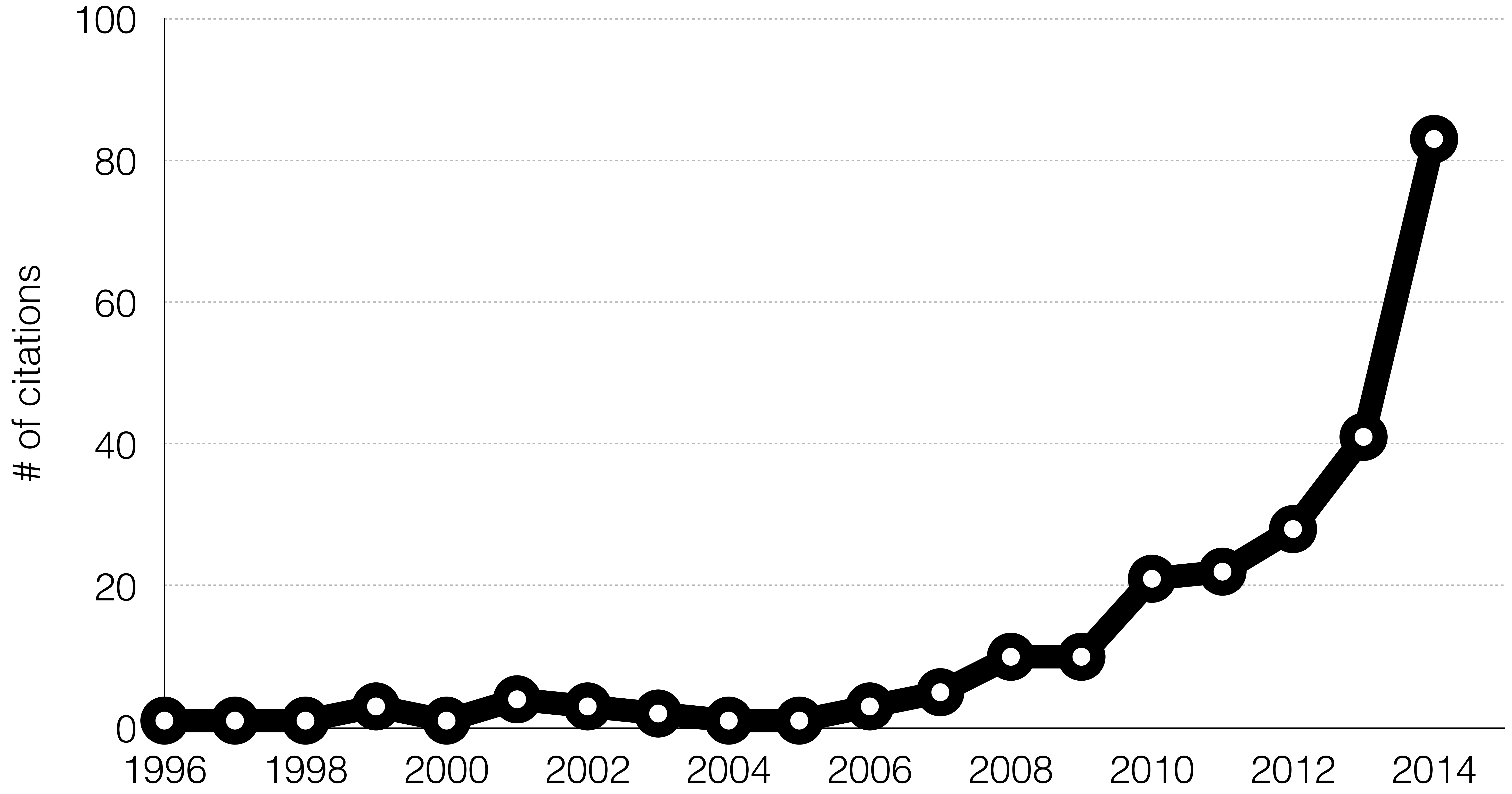

data
hardware
applications
years
phd
phd
is an art

1 design/research skills do not scale





2 no one knows everything out there



NoSQL storage

P. O'Neil, E. Cheng, D. Gawlick, E, O'Neil
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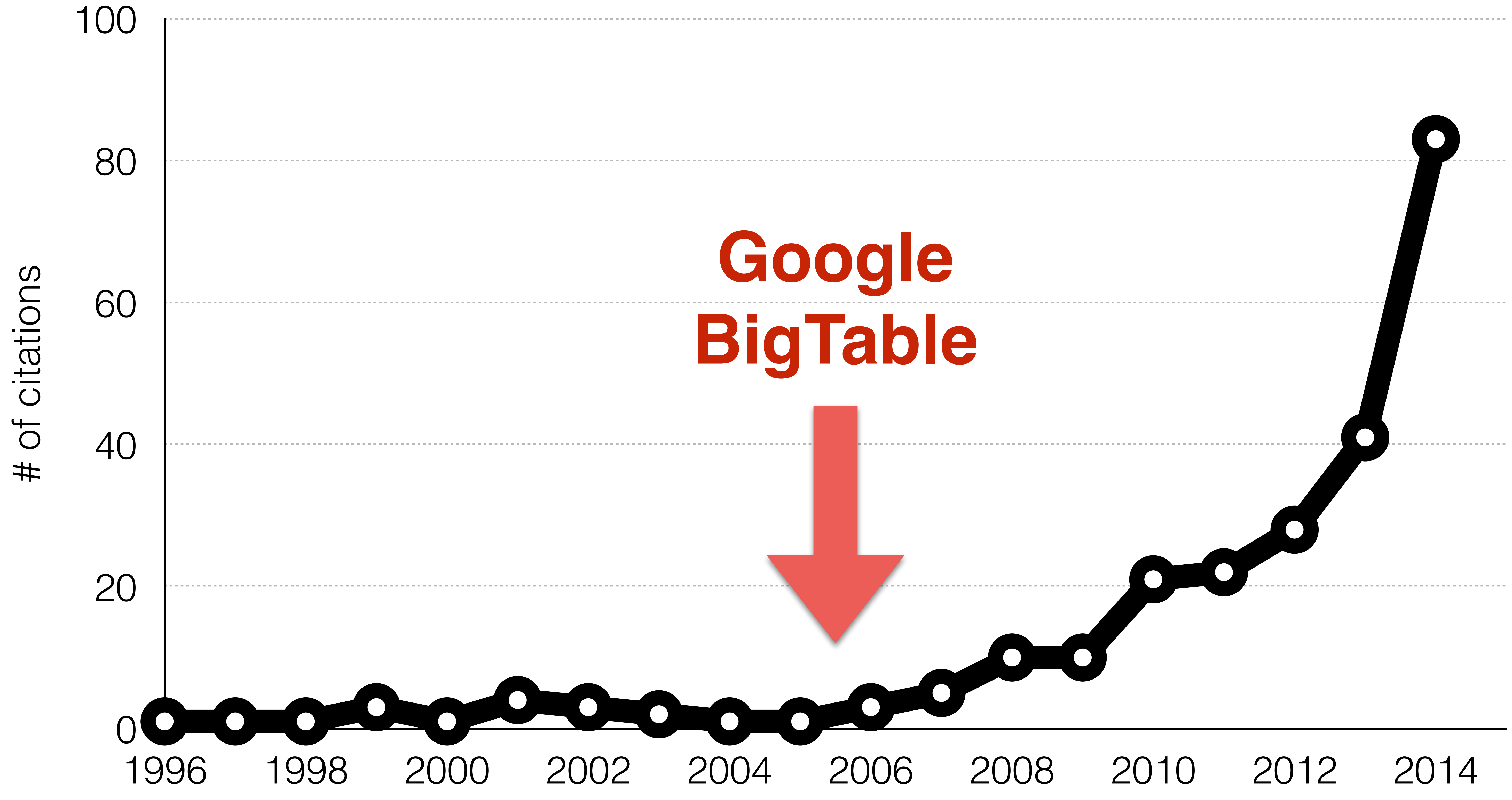

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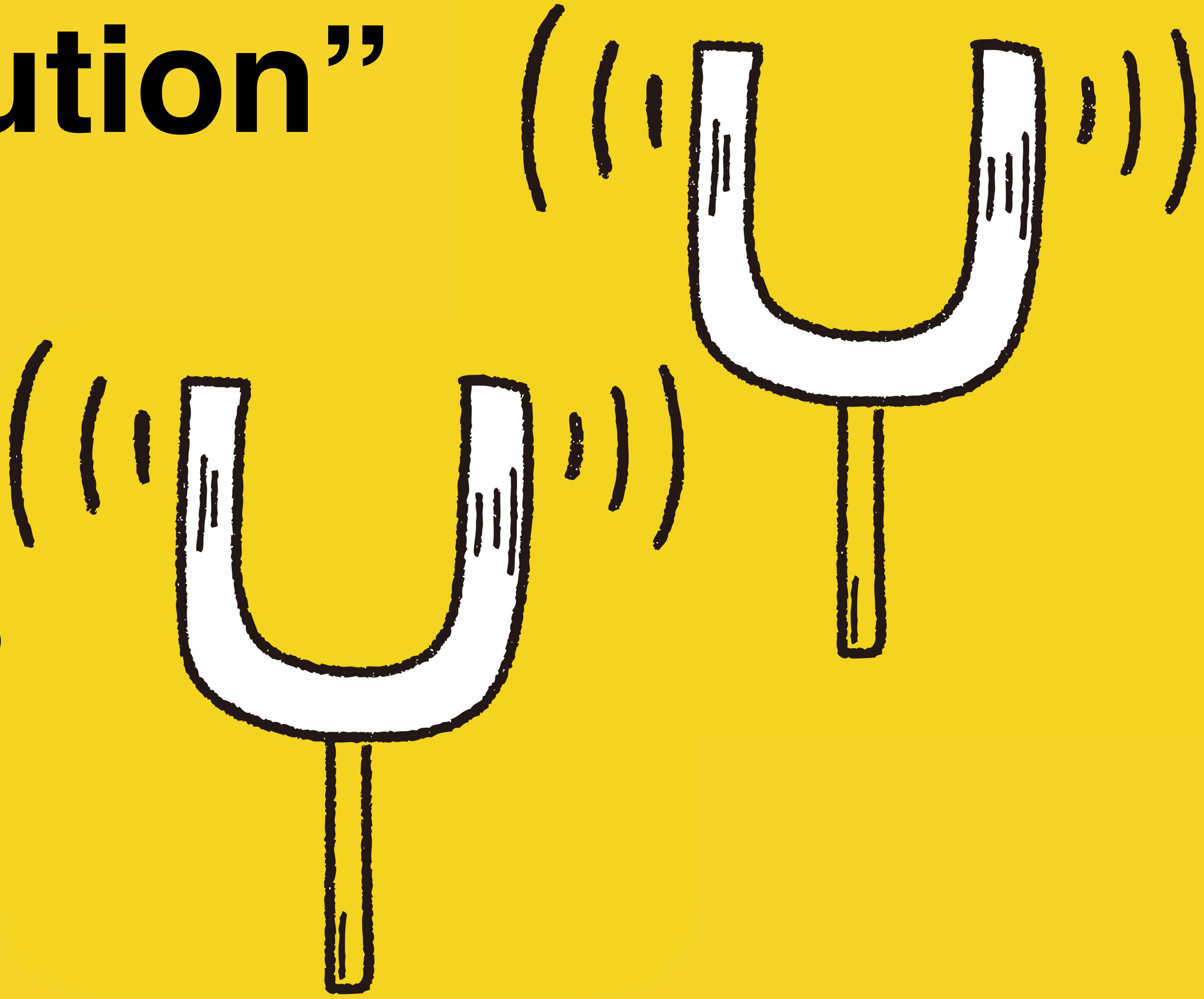
The HIPPO method

"Highest Paid Person's Opinion"

standard “solution”



expose knobs

Some possible ideas

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Some possible ideas

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   Yes, but only around a narrow design space.

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1. **Aren't data systems already "adaptive", e.g., optimizer makes the best online decision?**
   Yes, but only around a narrow design space.

2. **Aren't adaptive data systems architectures able to adapt to new applications?**

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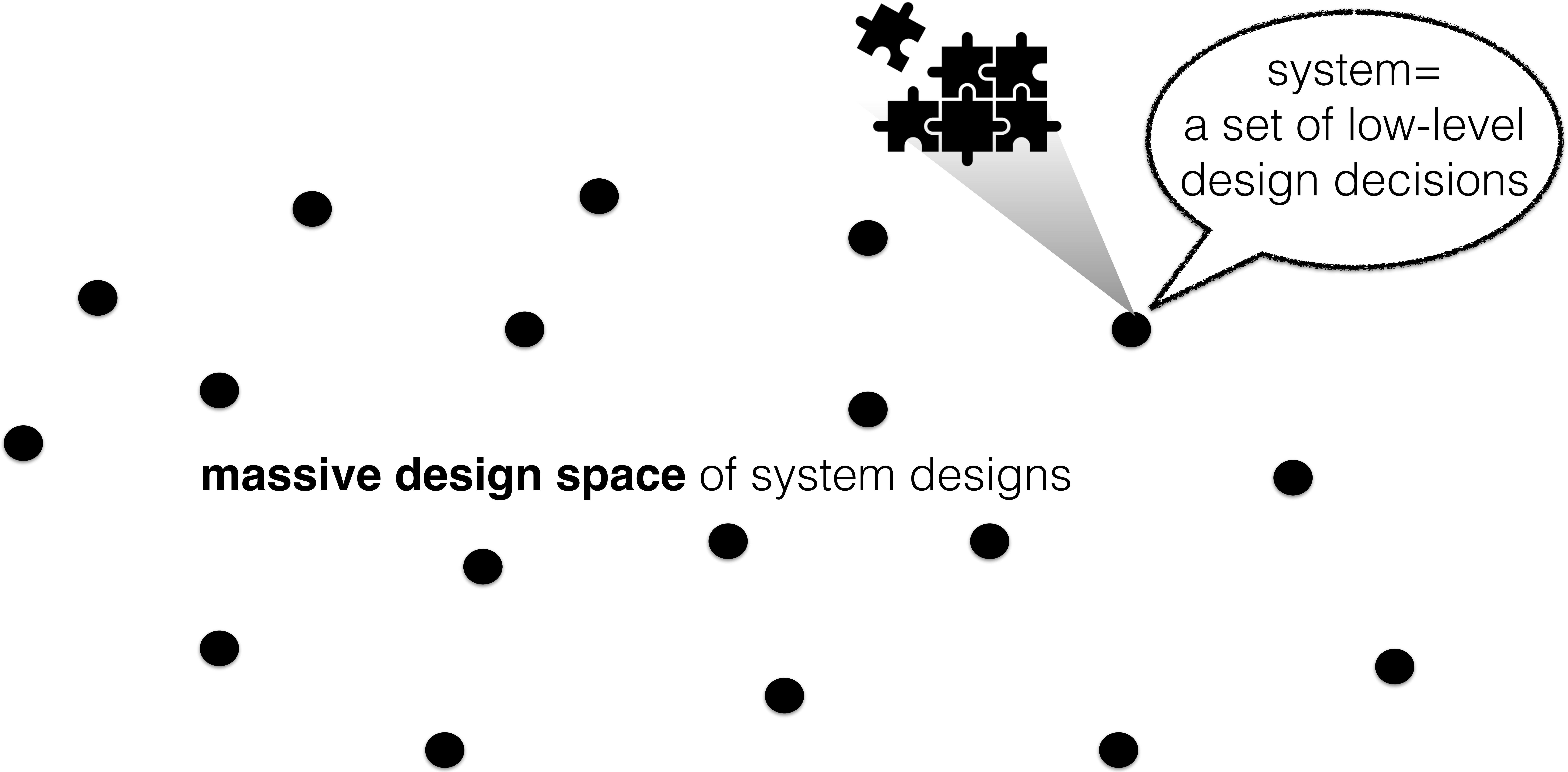
These ideas can lead to better systems but we need something more to

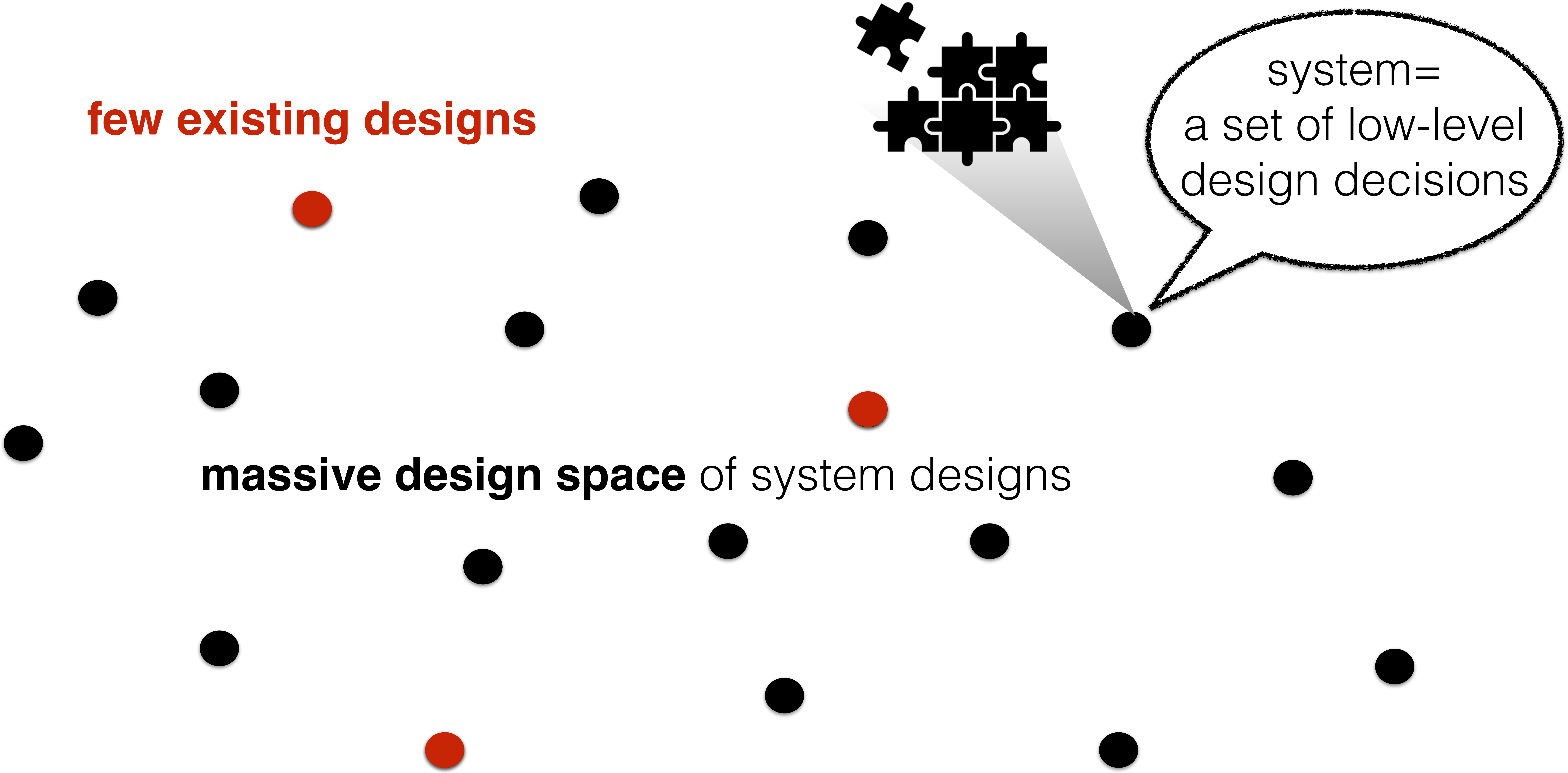
FIND FAST THE BEST POSSIBLE DESIGN

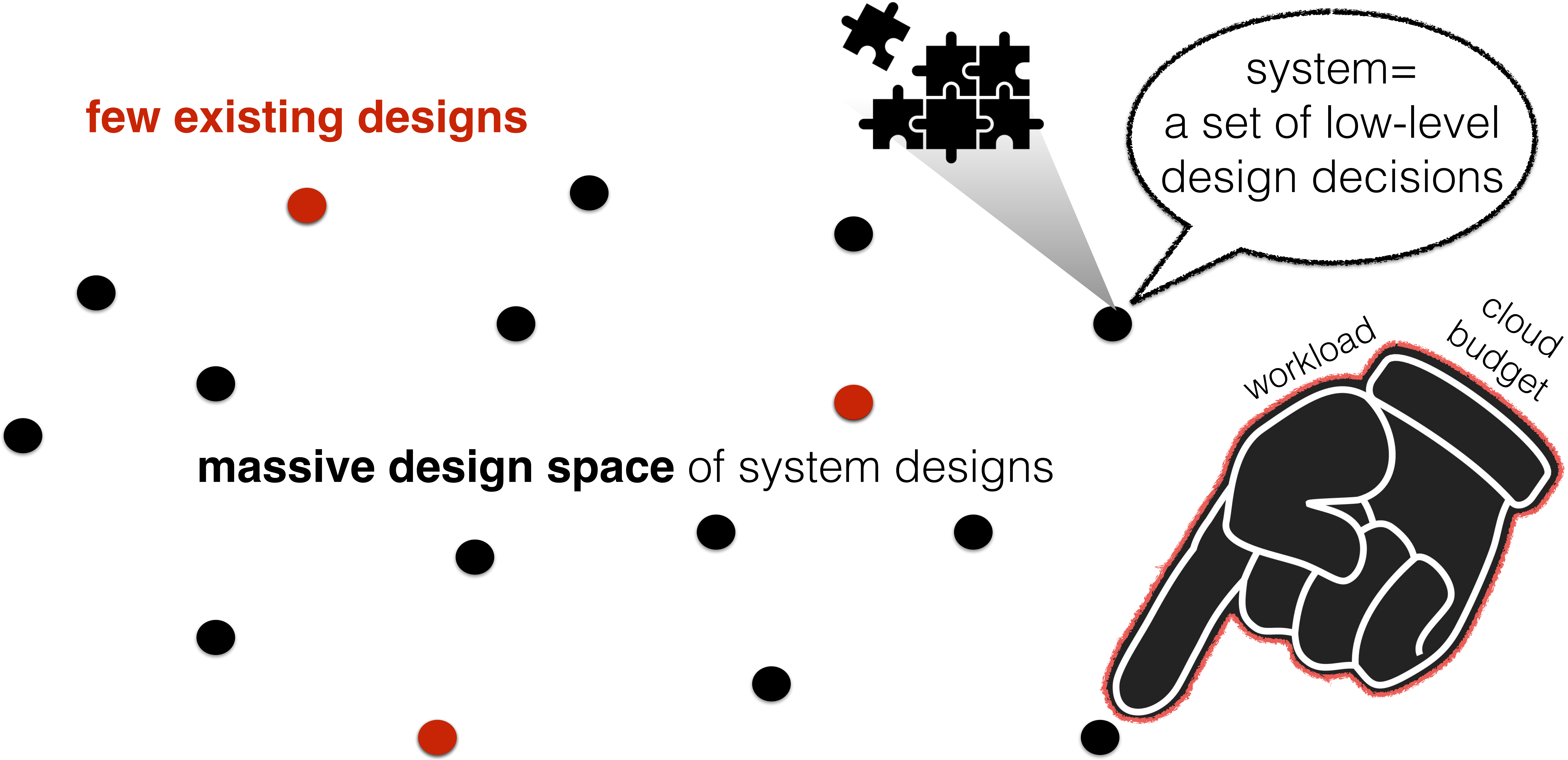
SELF-DESIGNING SYSTEMS

Automatically invent & build the perfect system for any new application

massive design space of system designs


system=
a set of low-level
design decisions
massive design space of system designs


few existing designs
system=
a set of low-level
design decisions
massive design space of system designs



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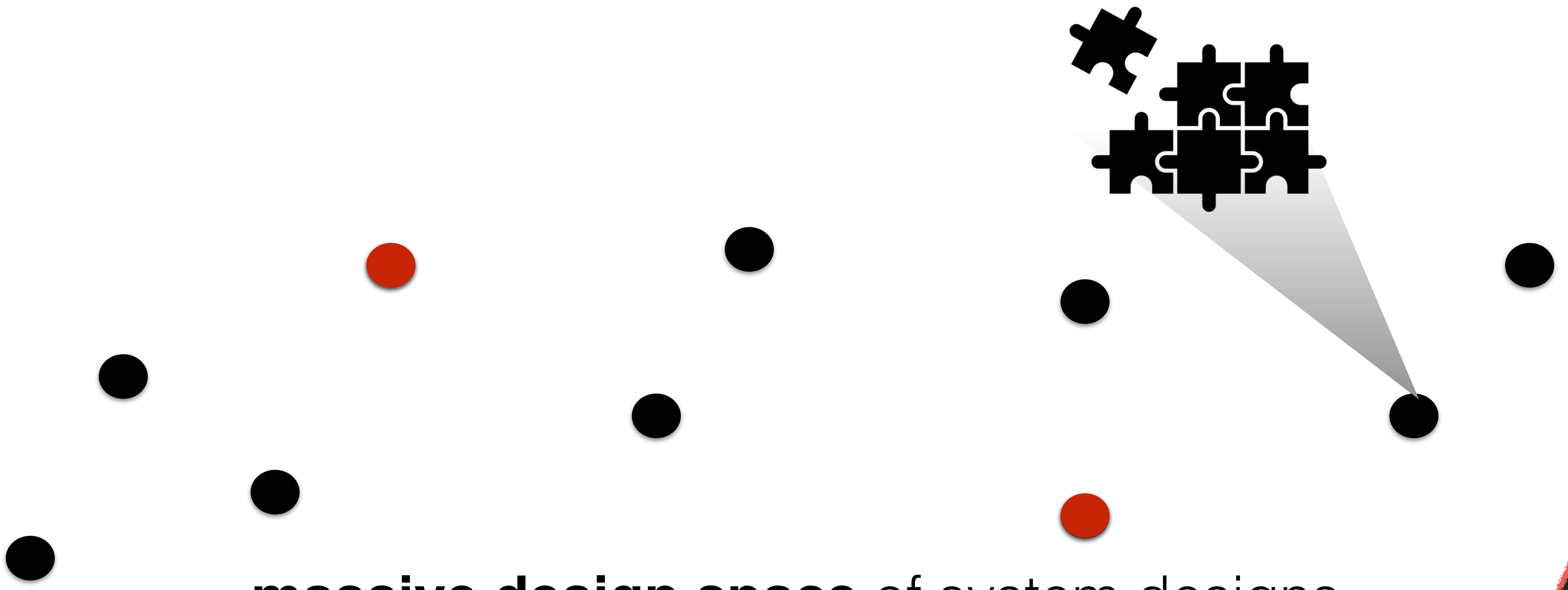


massive design space of system designs

reasoning: understand all the design decisions & their impact

HOW
DO WE
START

SLAs

robustness

concurrency

multi-tenancy

data types

HOW DO WE START

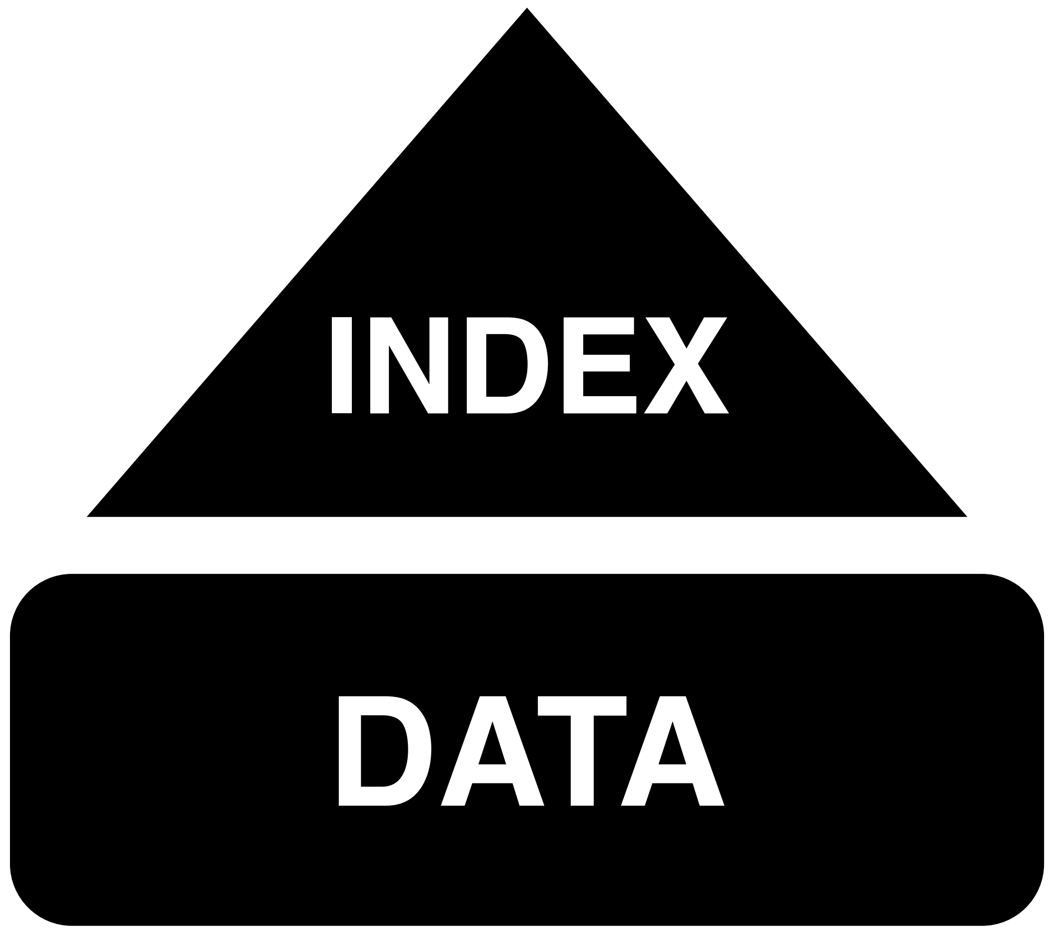
indexing

complex operations

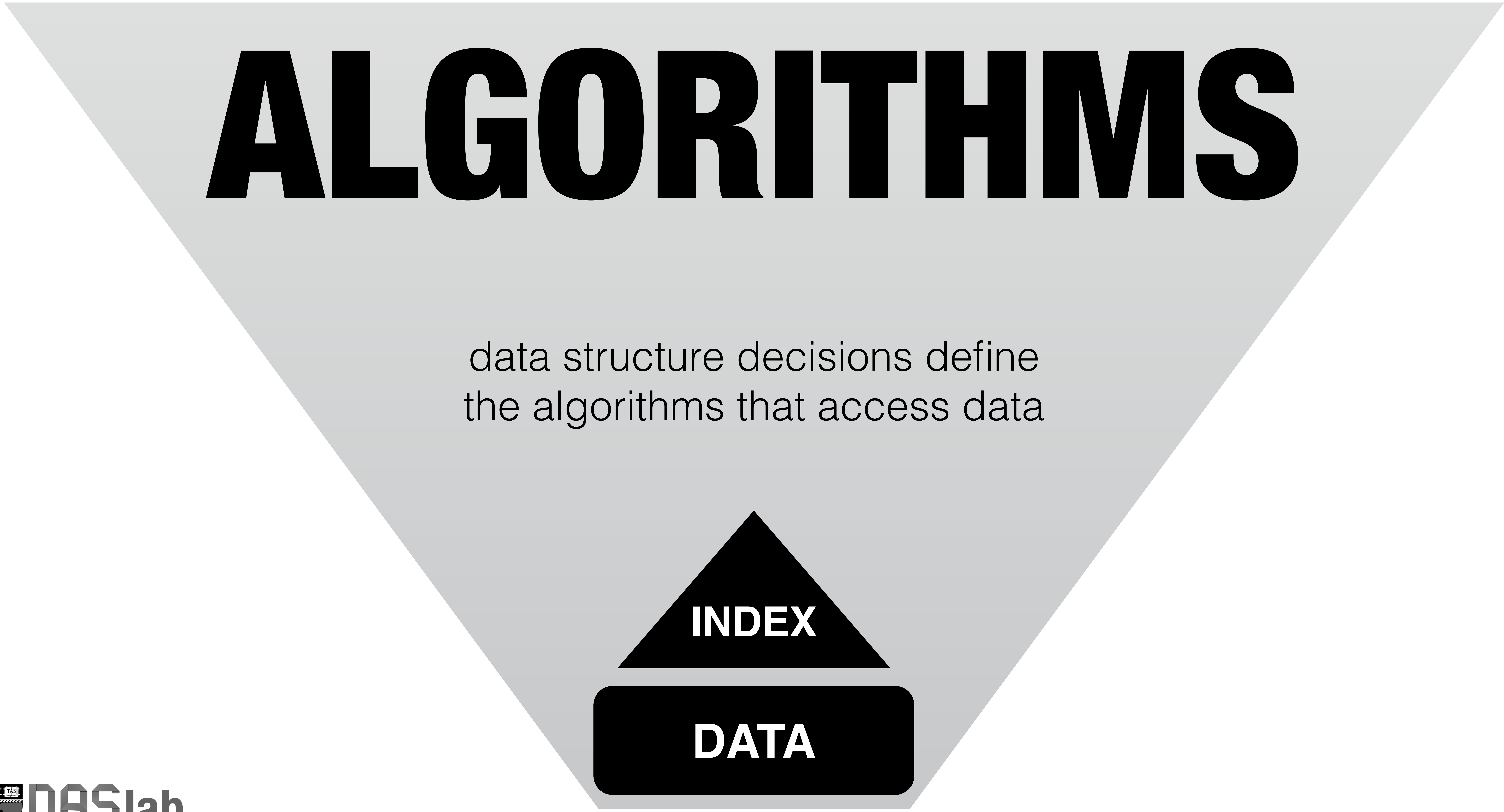
optimizer

cloud

hardware



HOW DO WE START



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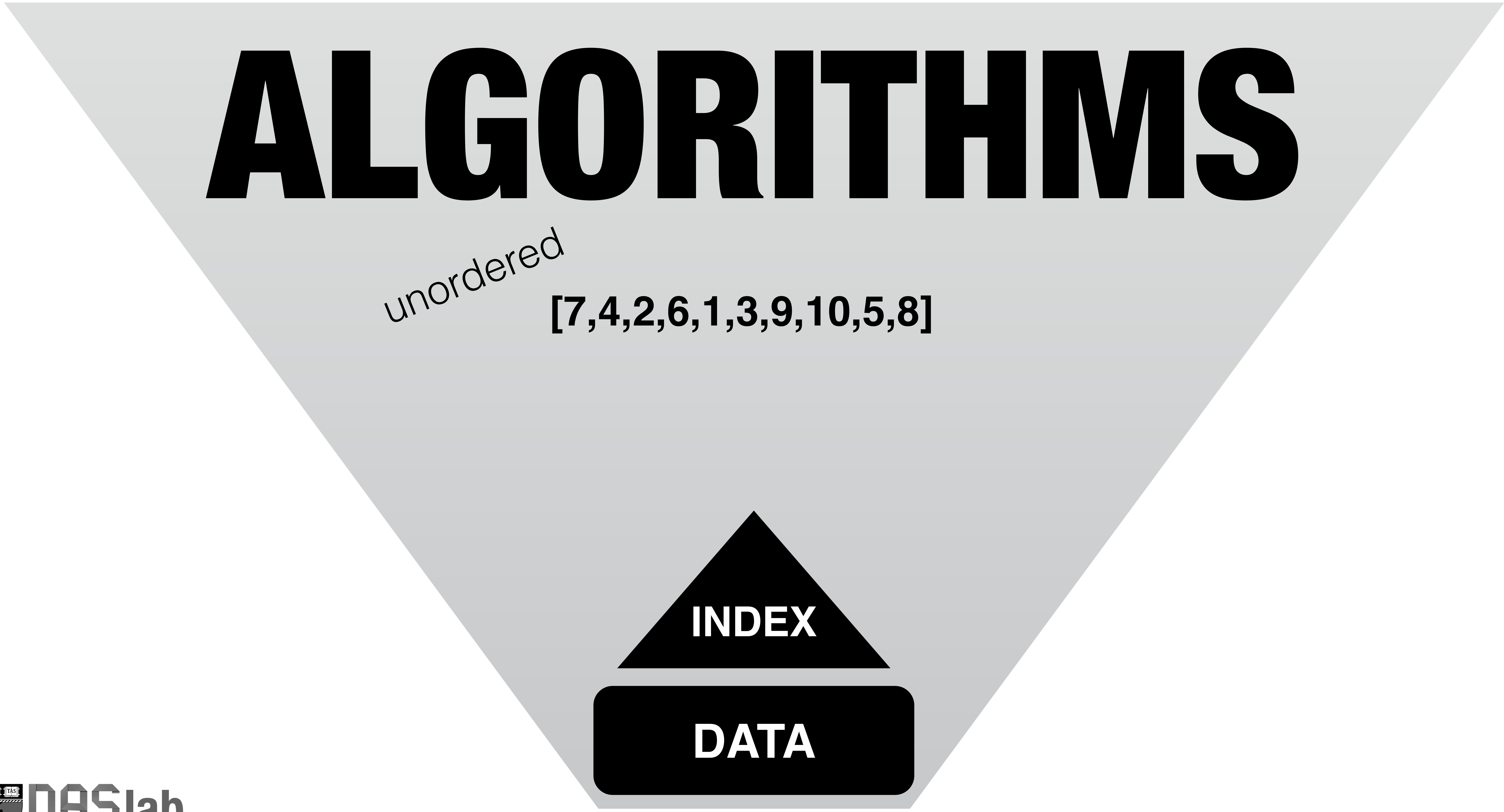
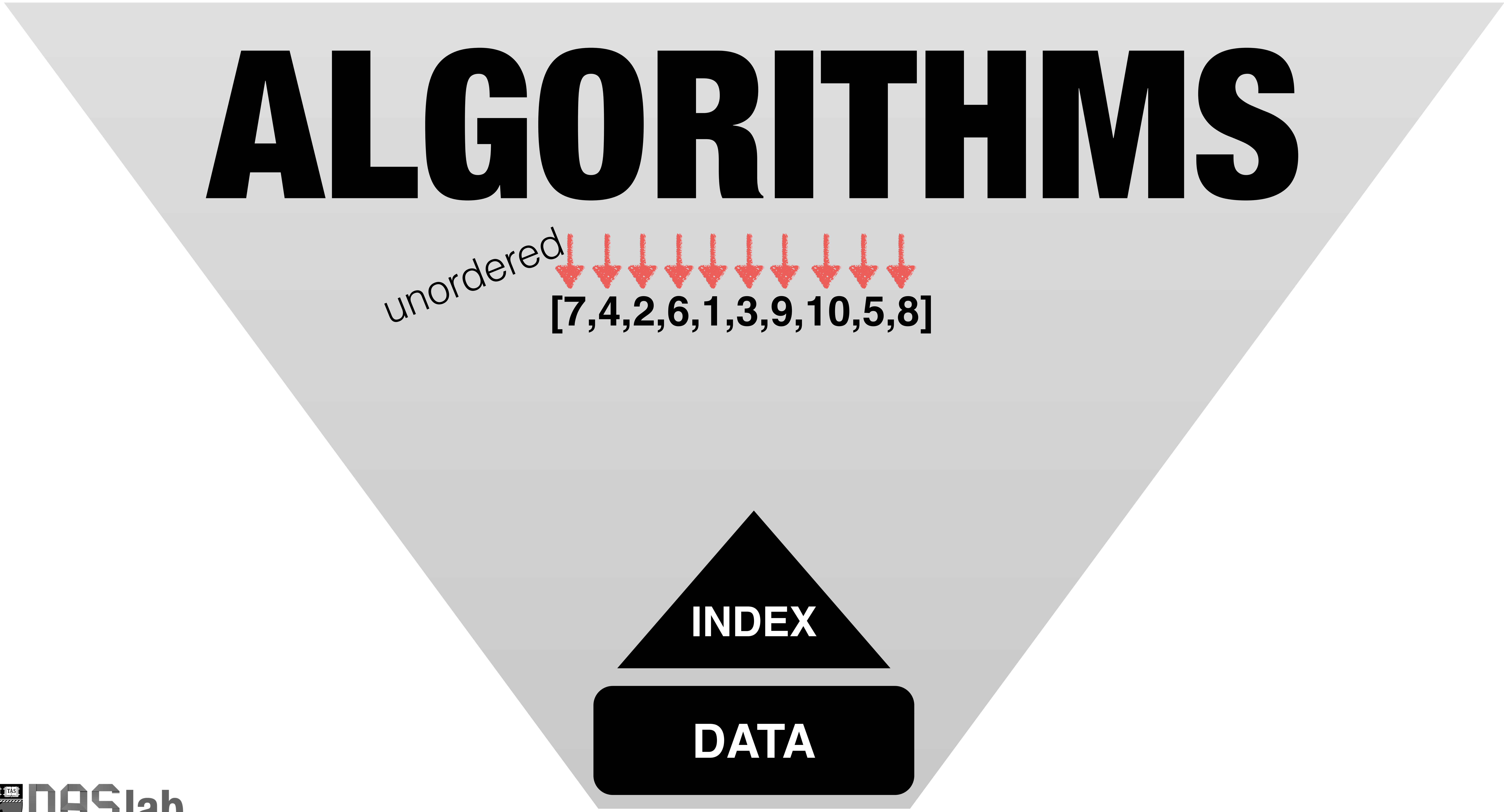

ALGORITHMS
unordered
[7,4,2,6,1,3,9,10,5,8]
INDEX
DATA



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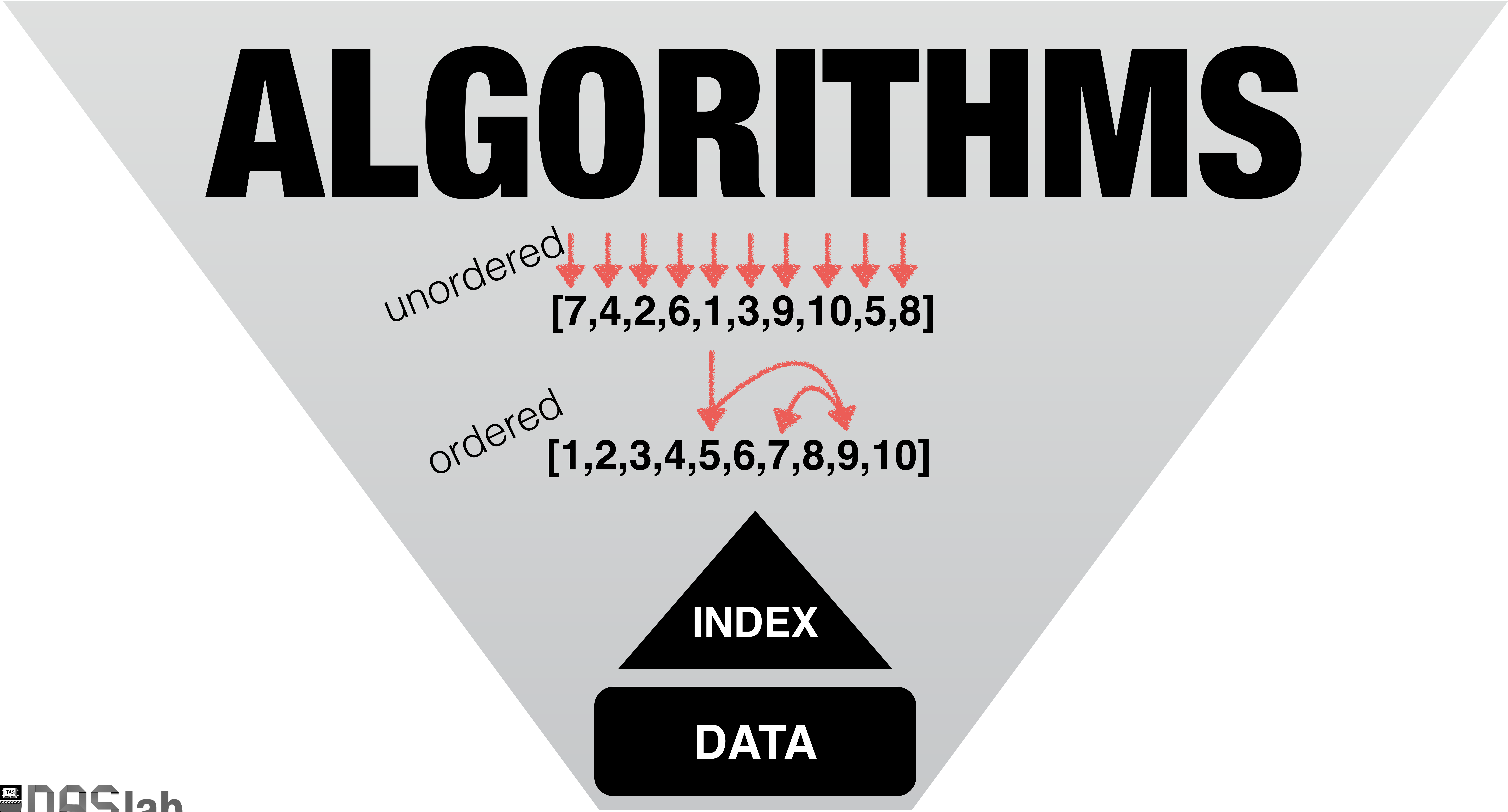

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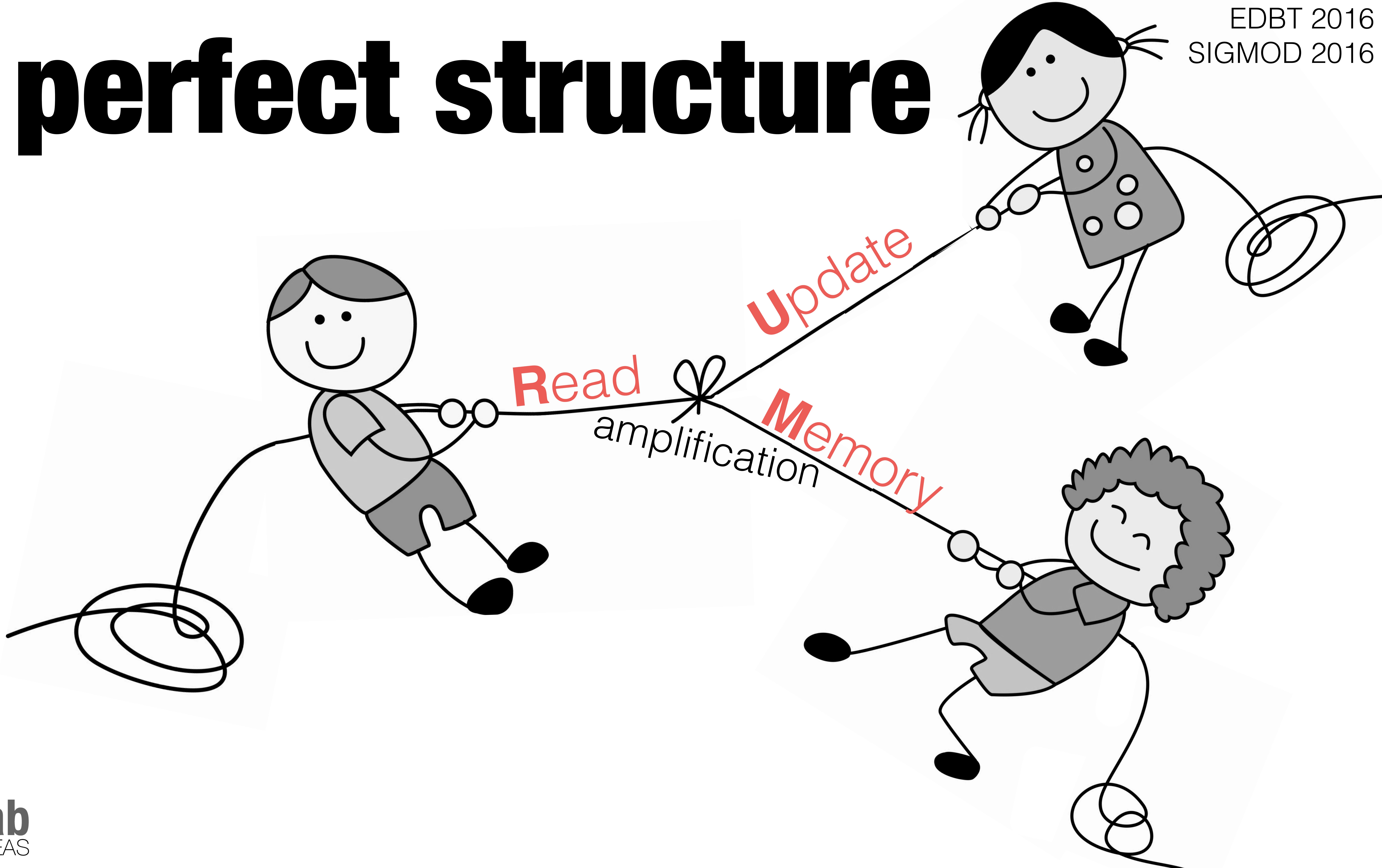
no perfect structure

EDBT 2016
SIGMOD 2016



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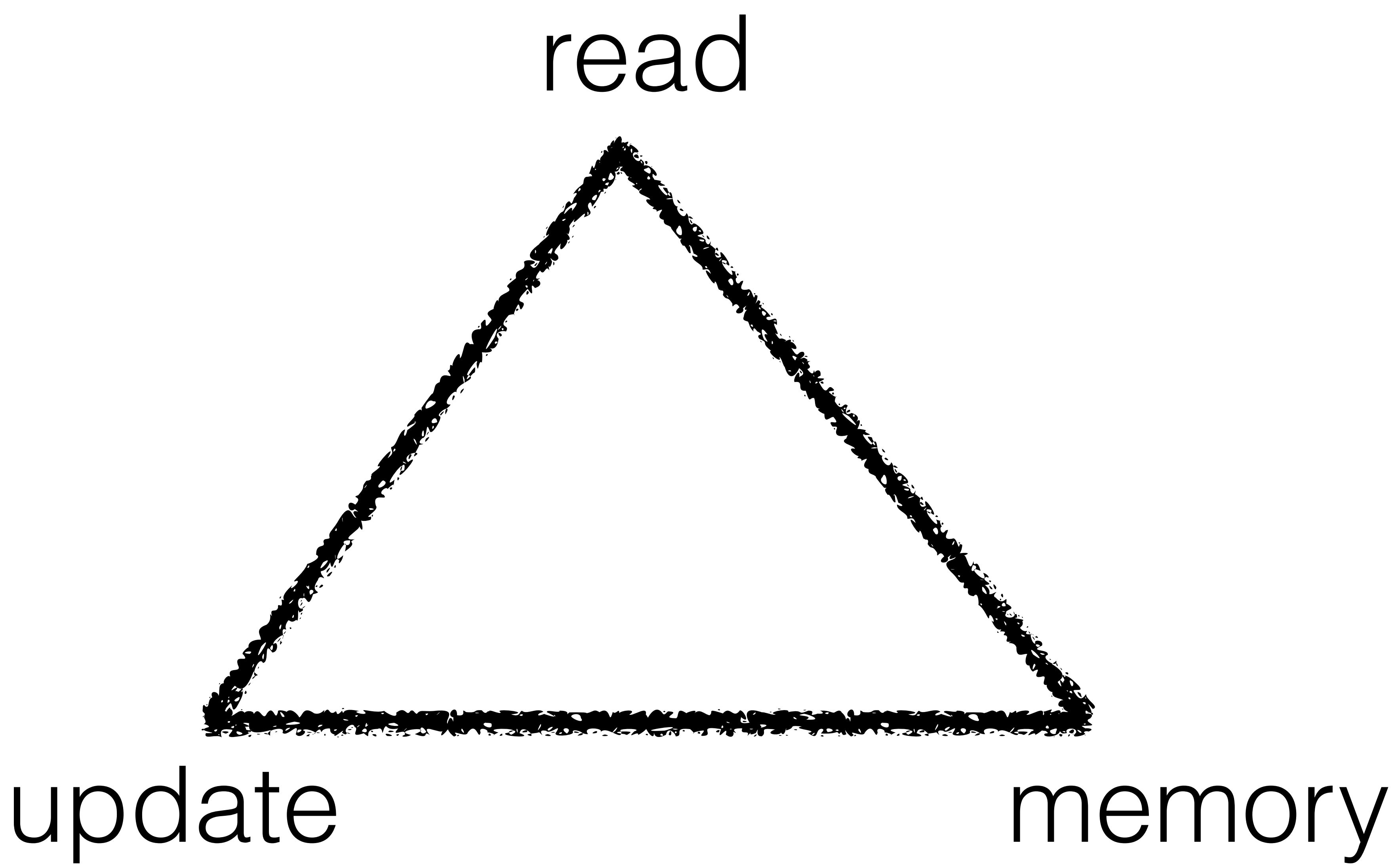
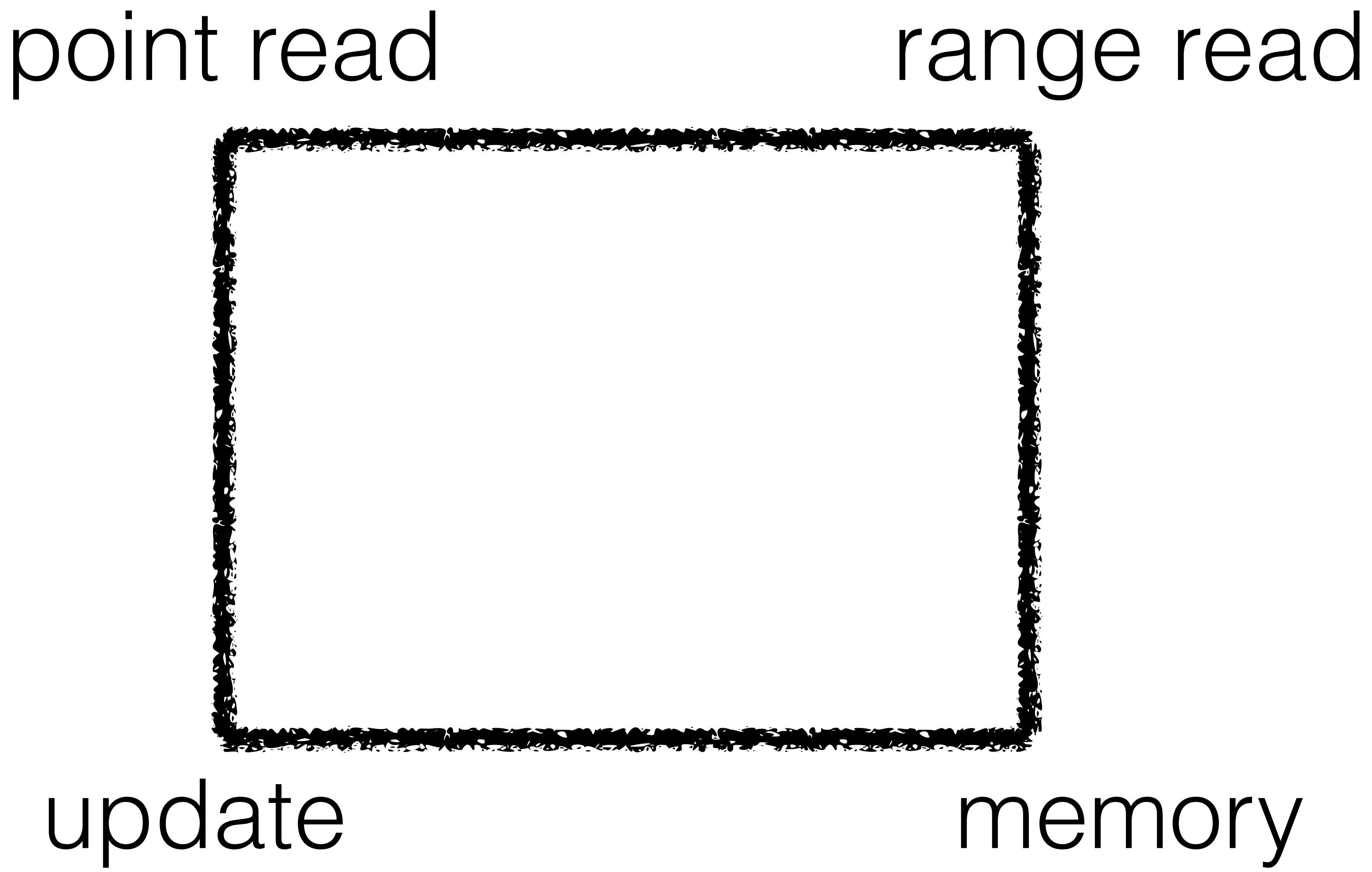
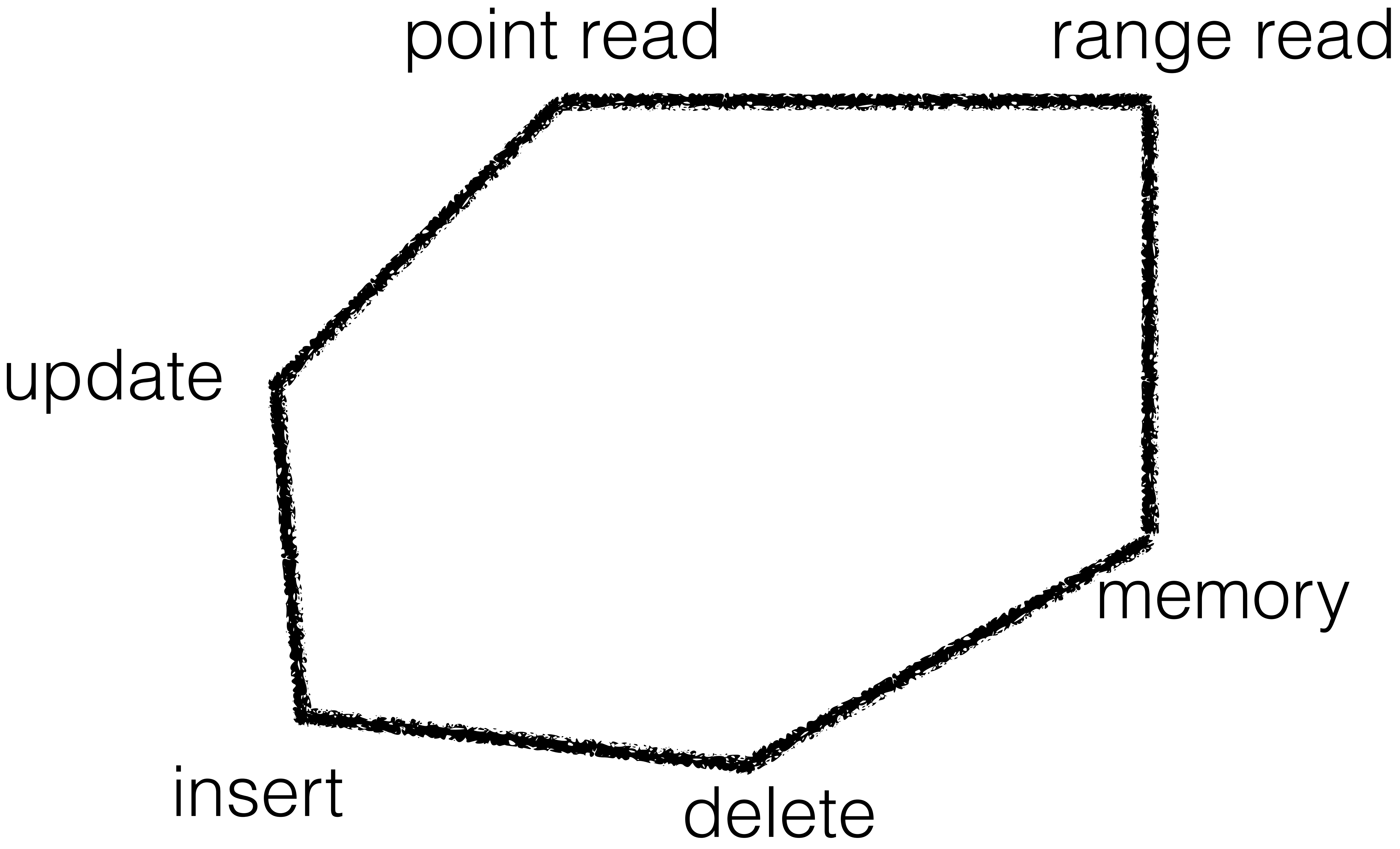

read
update
memory


point read
range read
update
memory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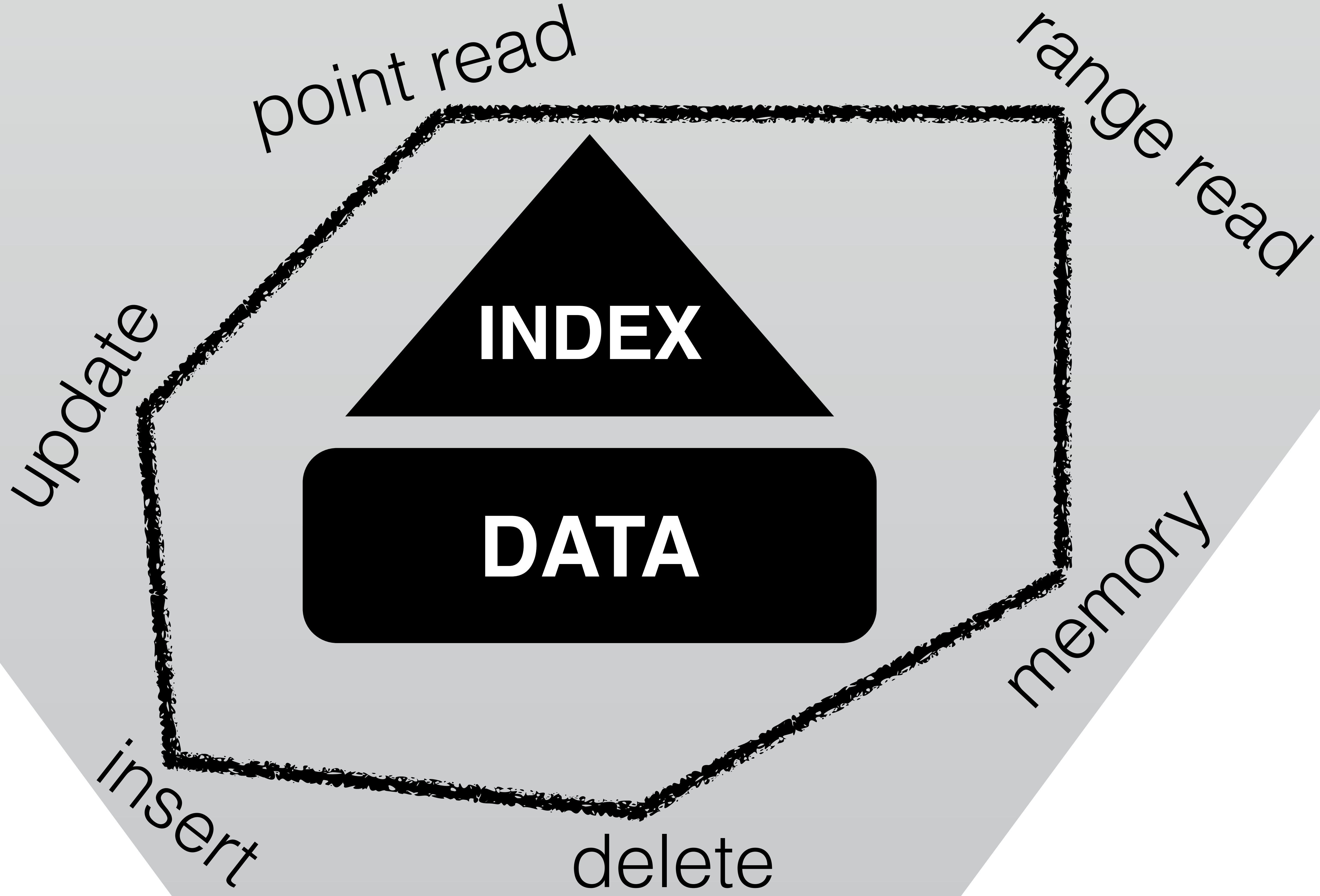
ALGORITHMS



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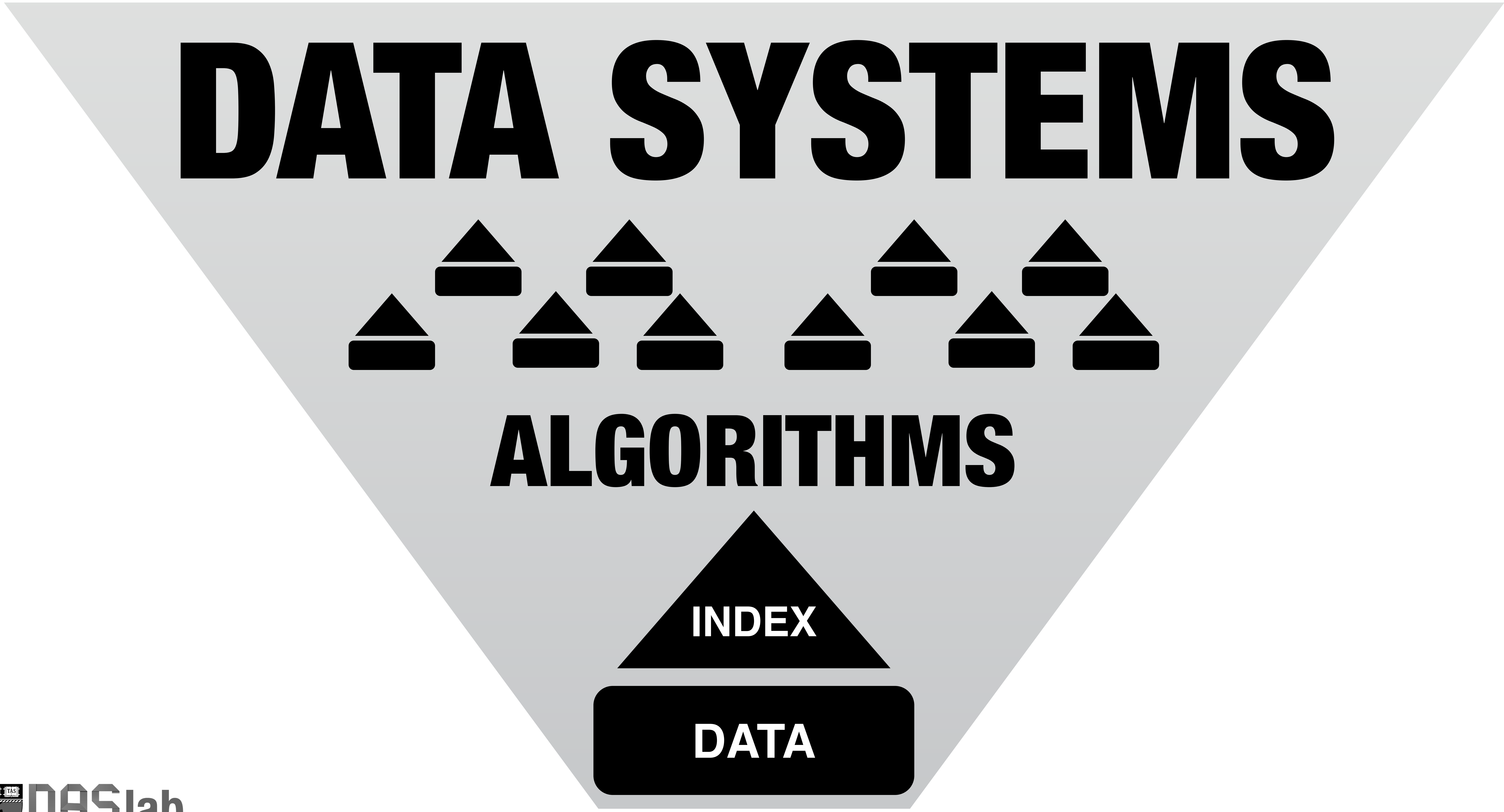
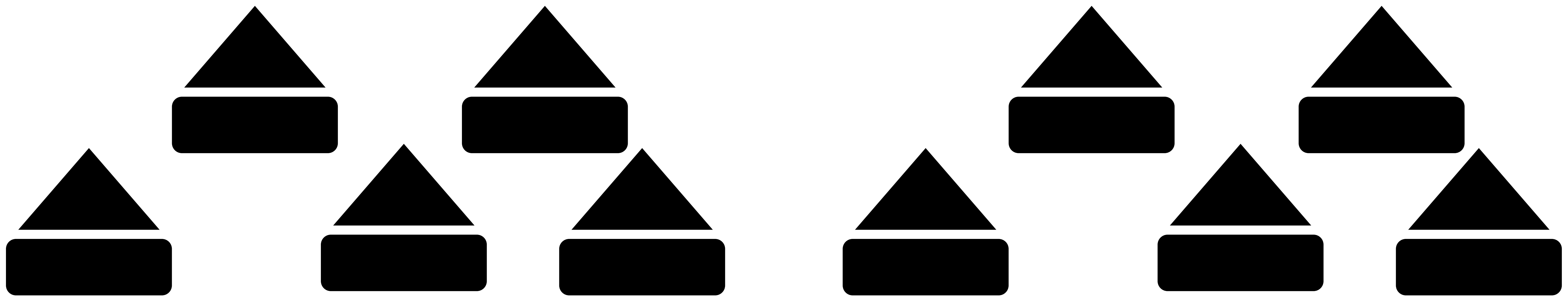

DATA SYSTEMS
ALGORITHMS
INDEX
DATA

NoSQL systems are the backbone of the BigData and AI era

LSM-tree
KV-stores

FACEBOOK, AMAZON, GOOGLE, TWITTER, LINKEDIN

MACHINE LEARNING, SQL, CRYPTO, SCIENCE



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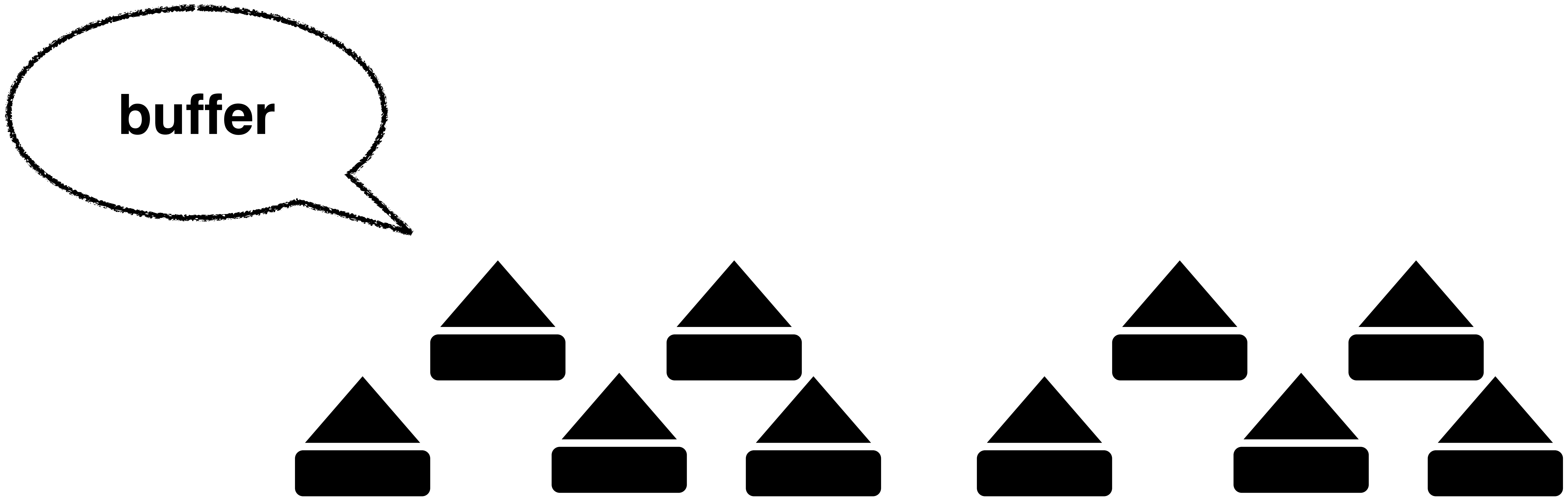

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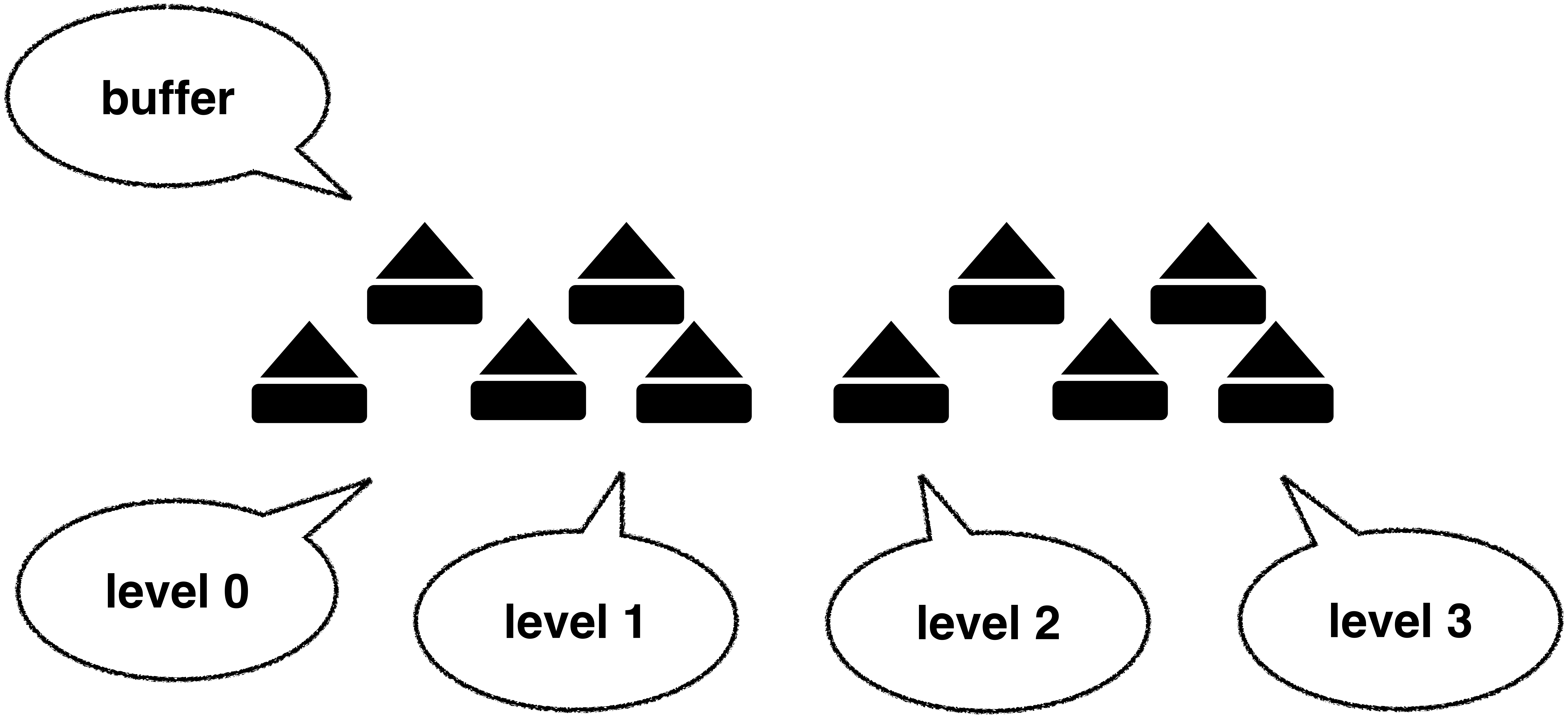

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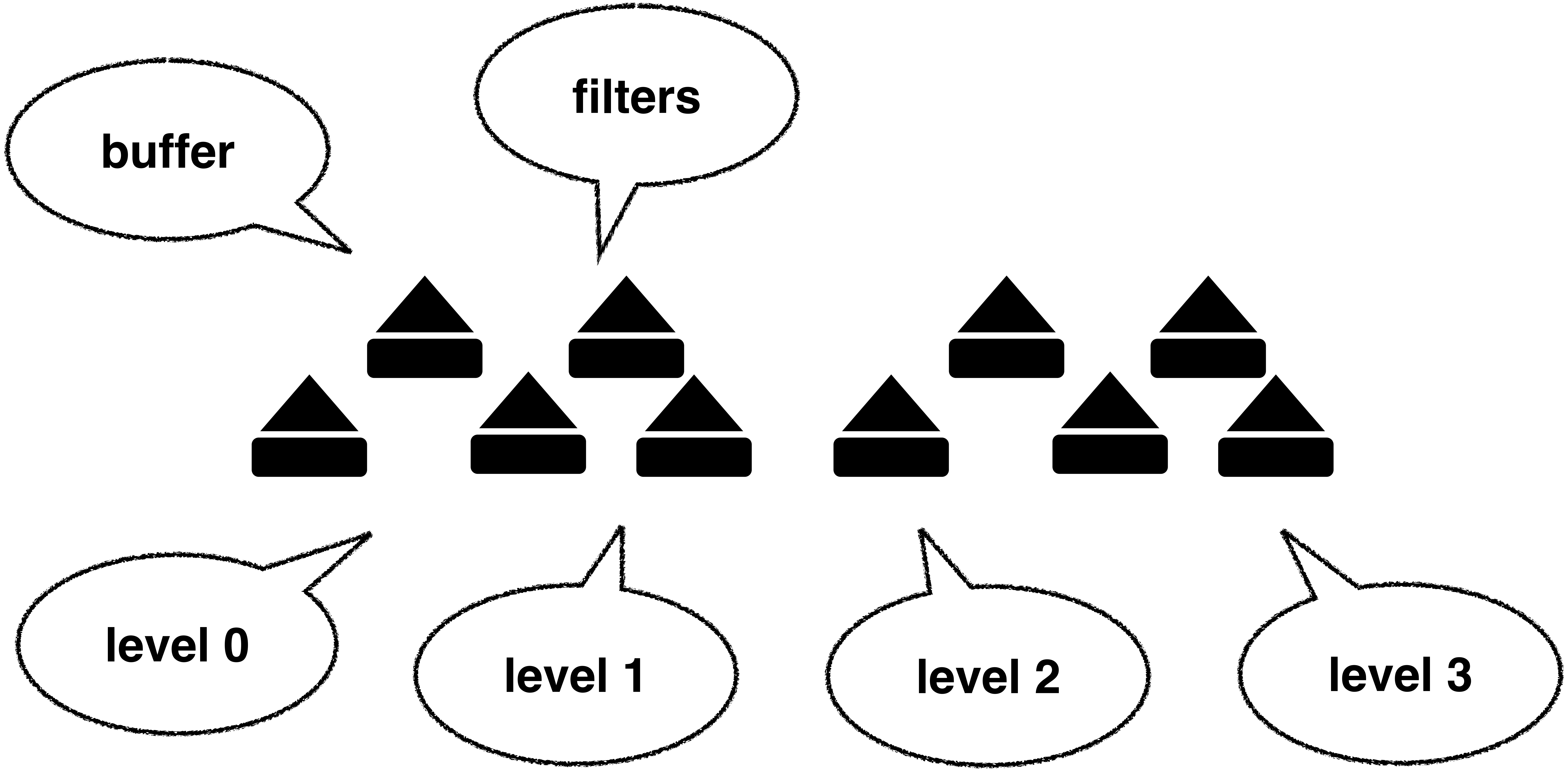

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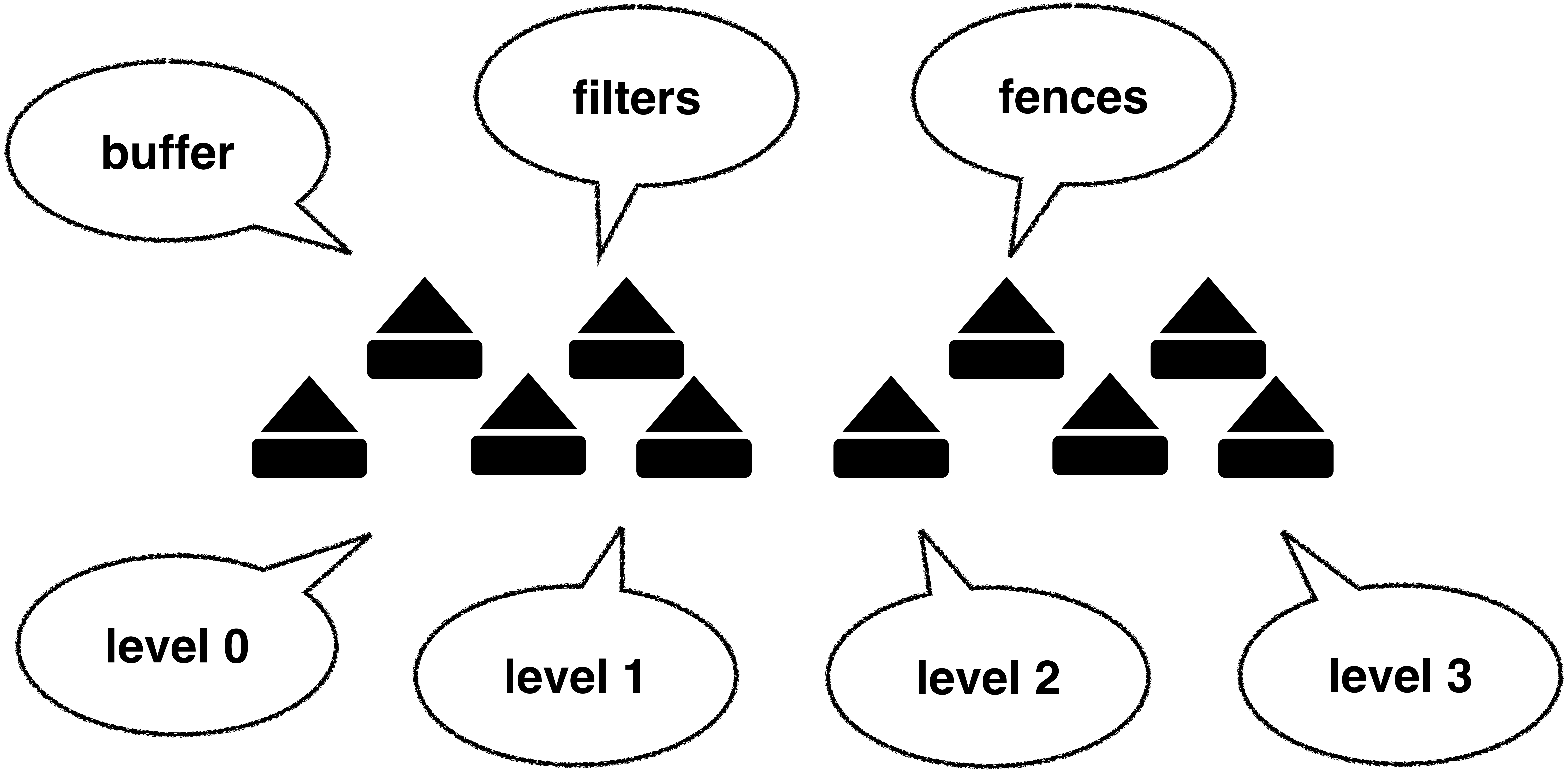

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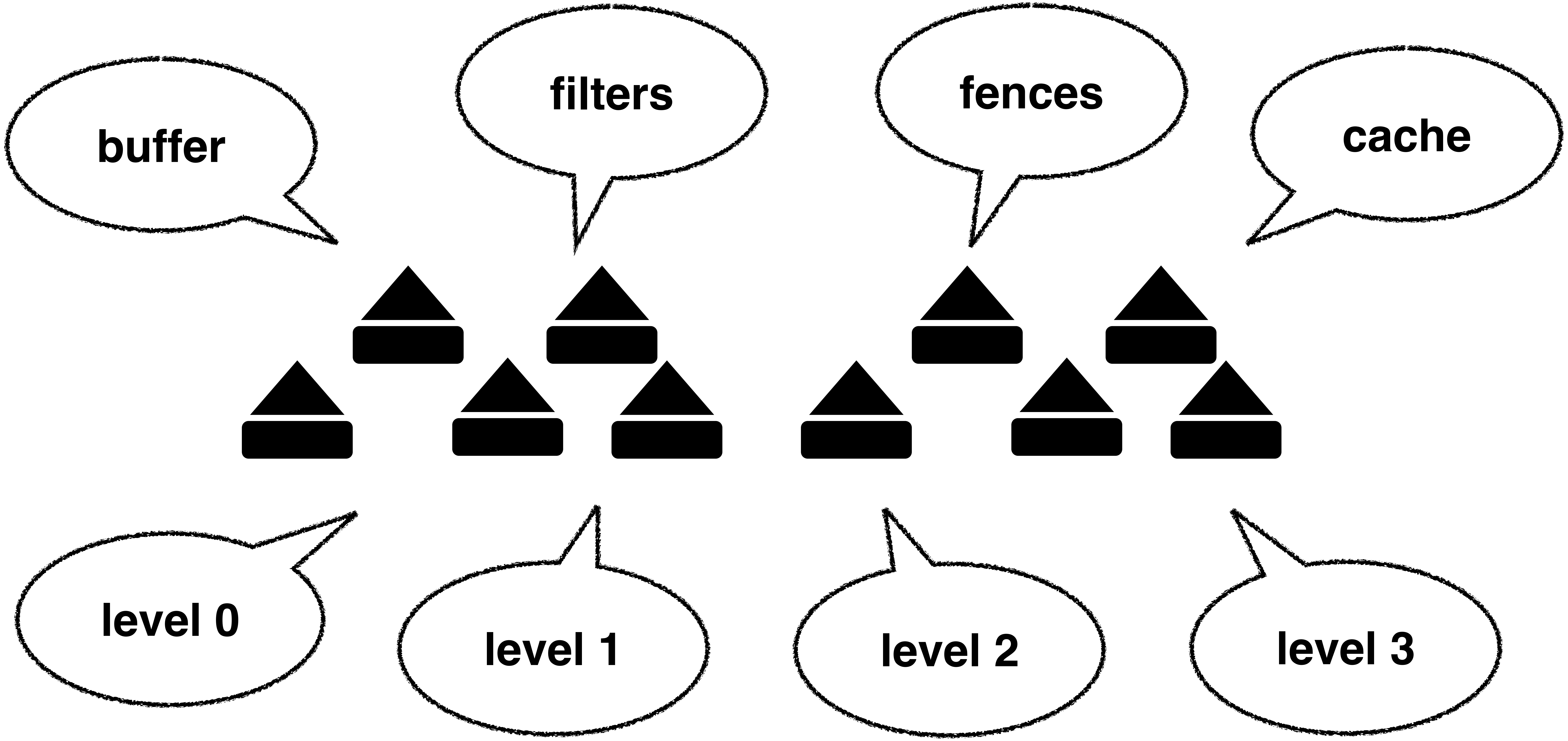

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buffer

filters

fences

cache

diverse data structures

interactions

hardware

level 0

level 1

level 2

level 3

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diverse data structures | interactions | hardware | parallelism | robustness cloud cost SLAs

level 0

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buffer **filters** **fences** **cache**

diverse data structures	interactions	hardware	parallelism	robustness cloud cost SLAs

There exist numerous variations of NoSQL KV-stores

LSM-tree variants, B-trees (MongoDB), Hash-index (Microsoft)

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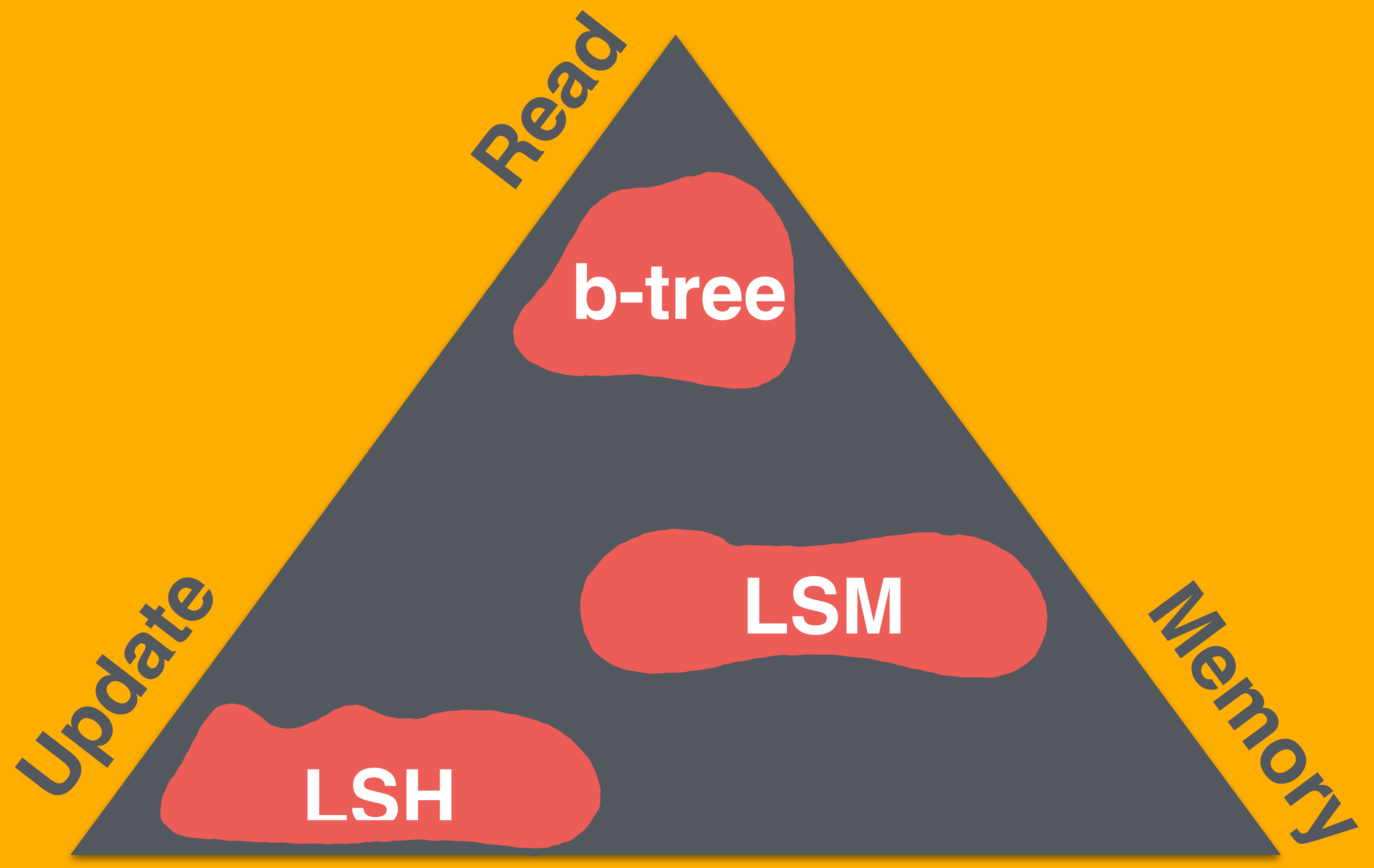

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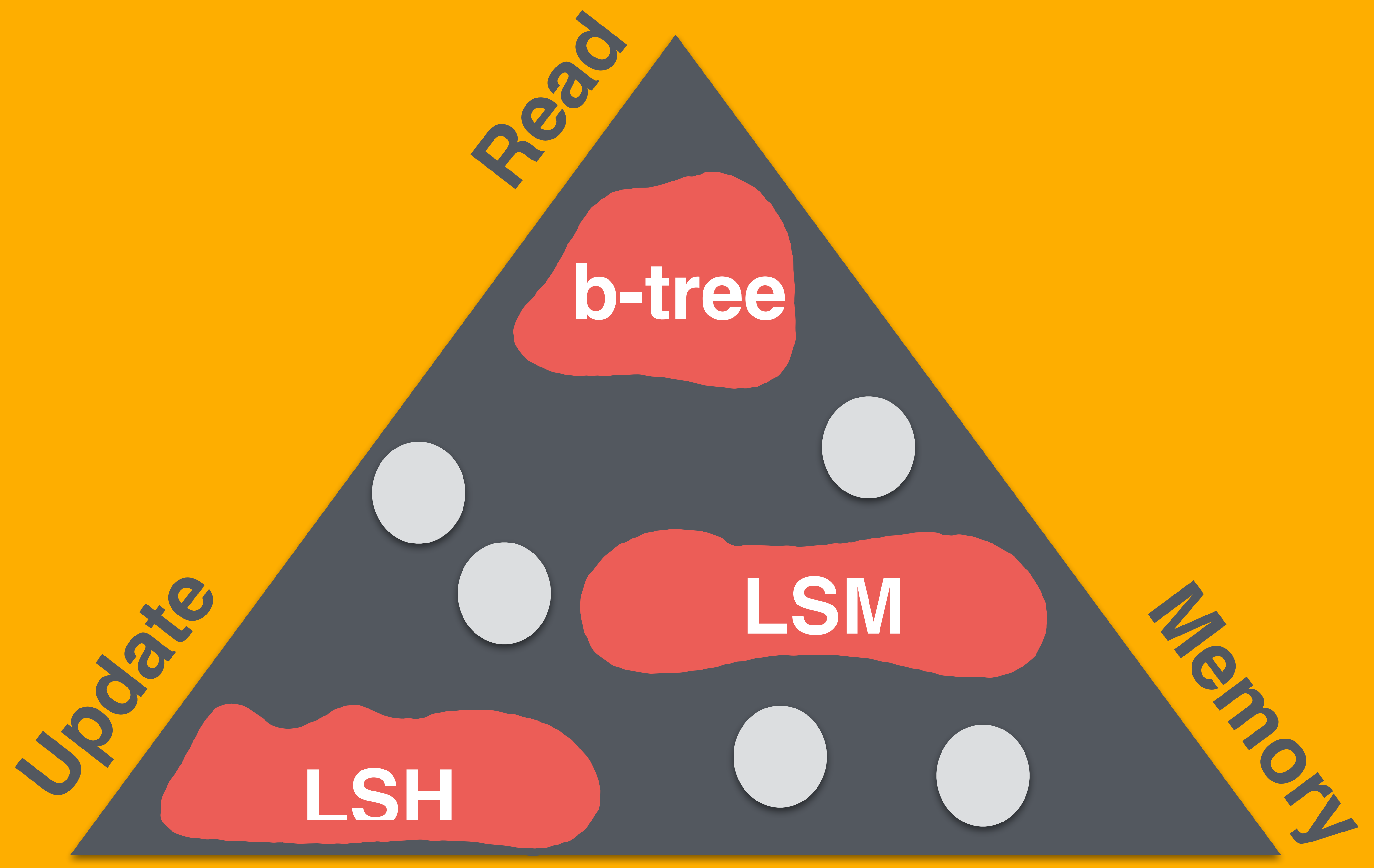

Constant and increasing efforts for new system designs as applications & hardware change

diverse data structures	interactions	hardware	parallelism	robustness cloud cost SLAs

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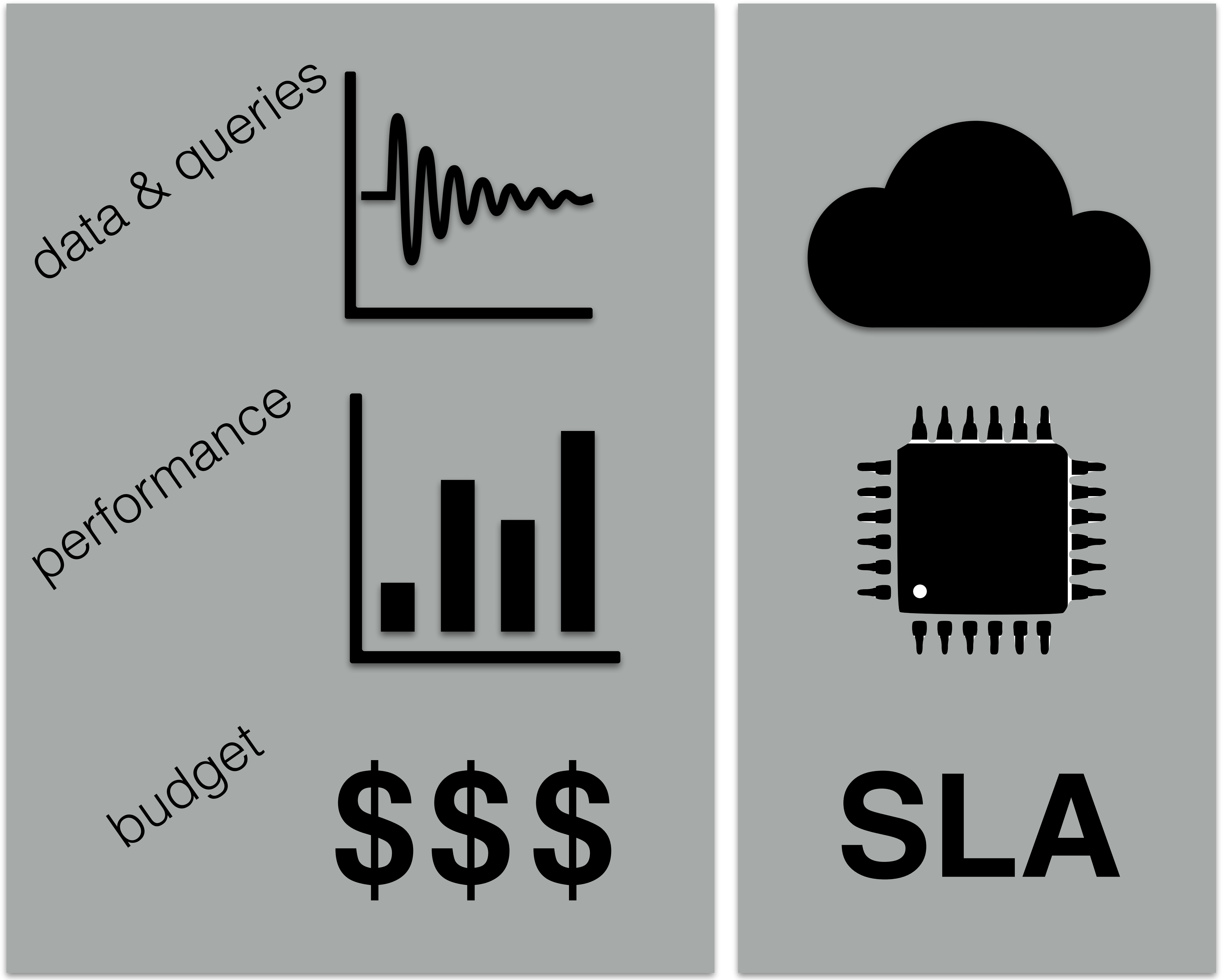
diverse data structures | interactions | hardware | parallelism | robustness cloud cost SLAs

Requirements/Goals

diverse data structures | interactions | hardware | parallelism | robustness cloud cost SLAs

Requirements/Goals

Context



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diverse data structures | interactions | hardware | parallelism | robustness cloud cost SLAs

Requirements/Goals

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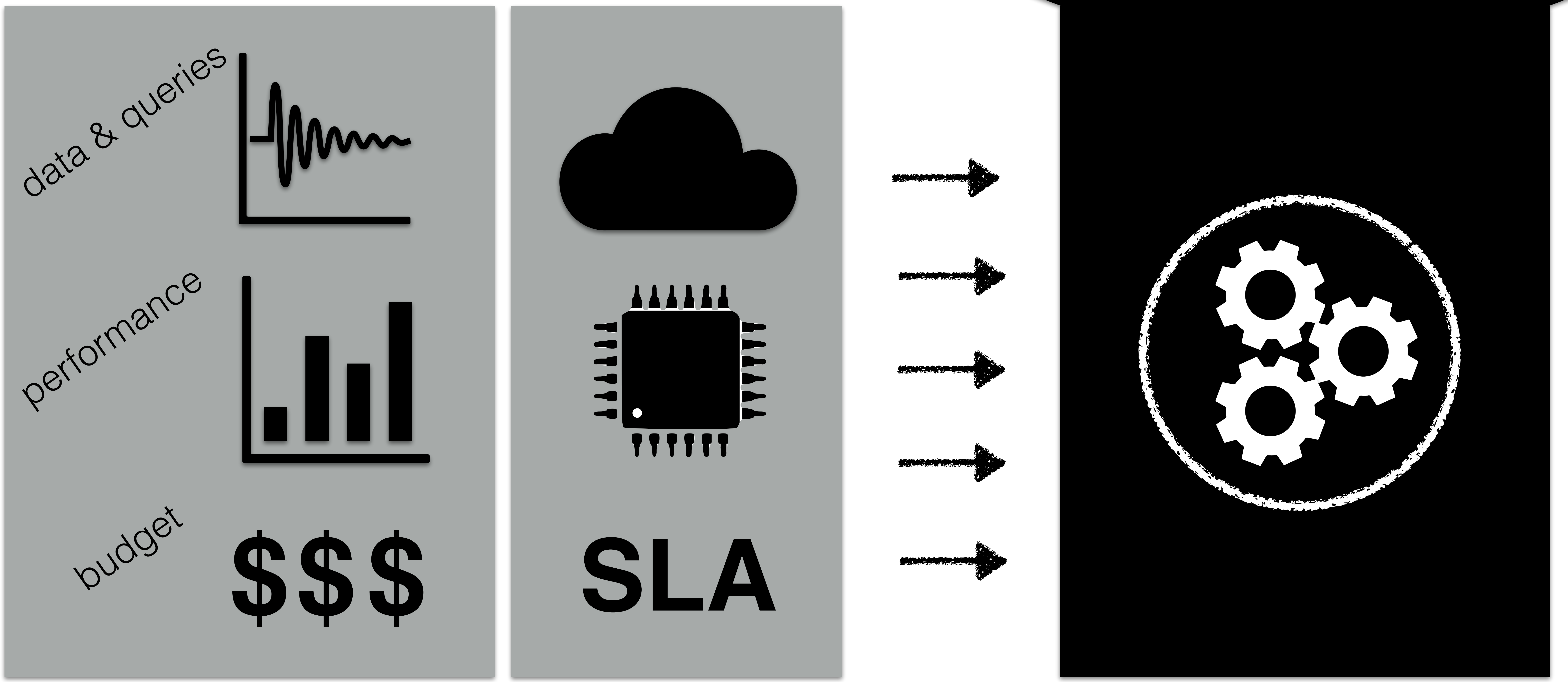

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diverse
data structures
interactions
hardware
parallelism
robustness
cloud cost
SLAs
Requirements/Goals
Context
data & queries
performance
budget
$$$
SLA
best
DATA
SYSTEM
design & code
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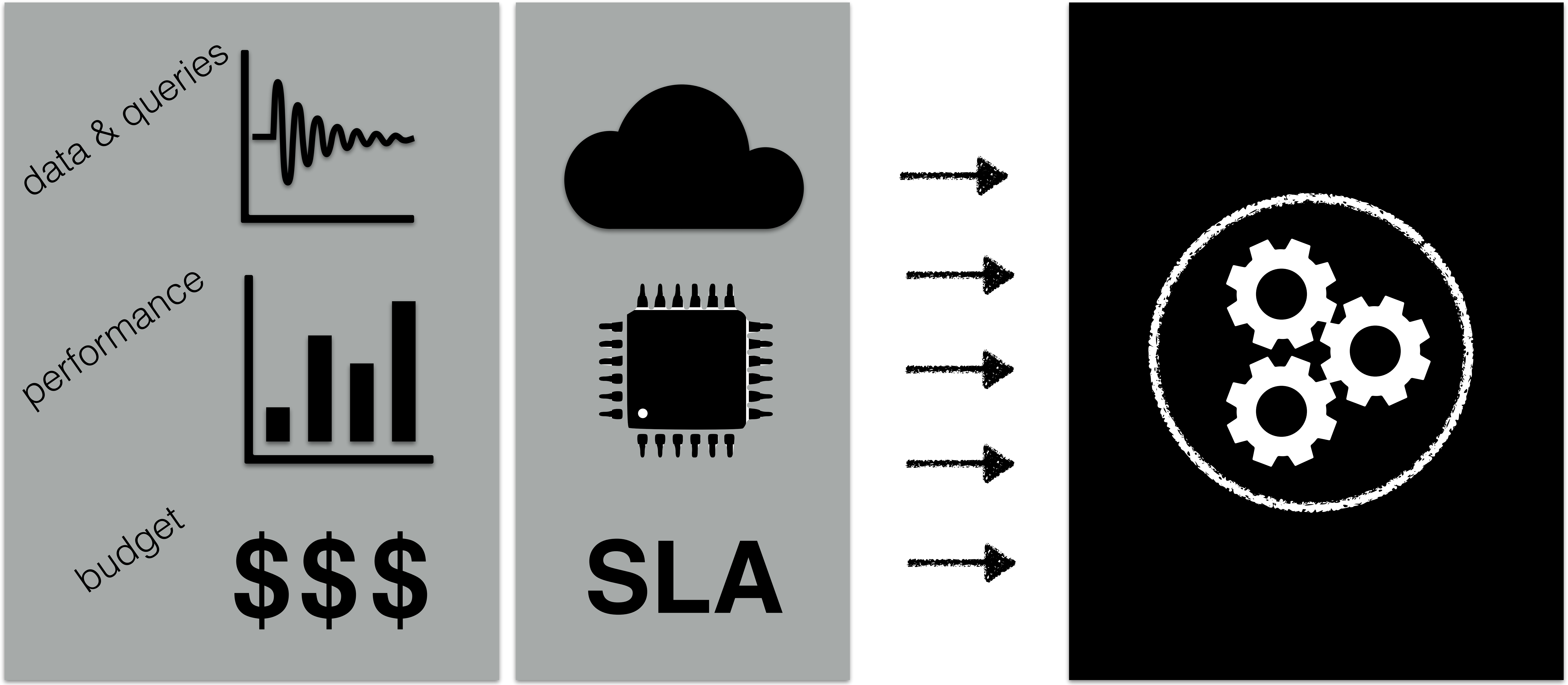

what-if reasoning

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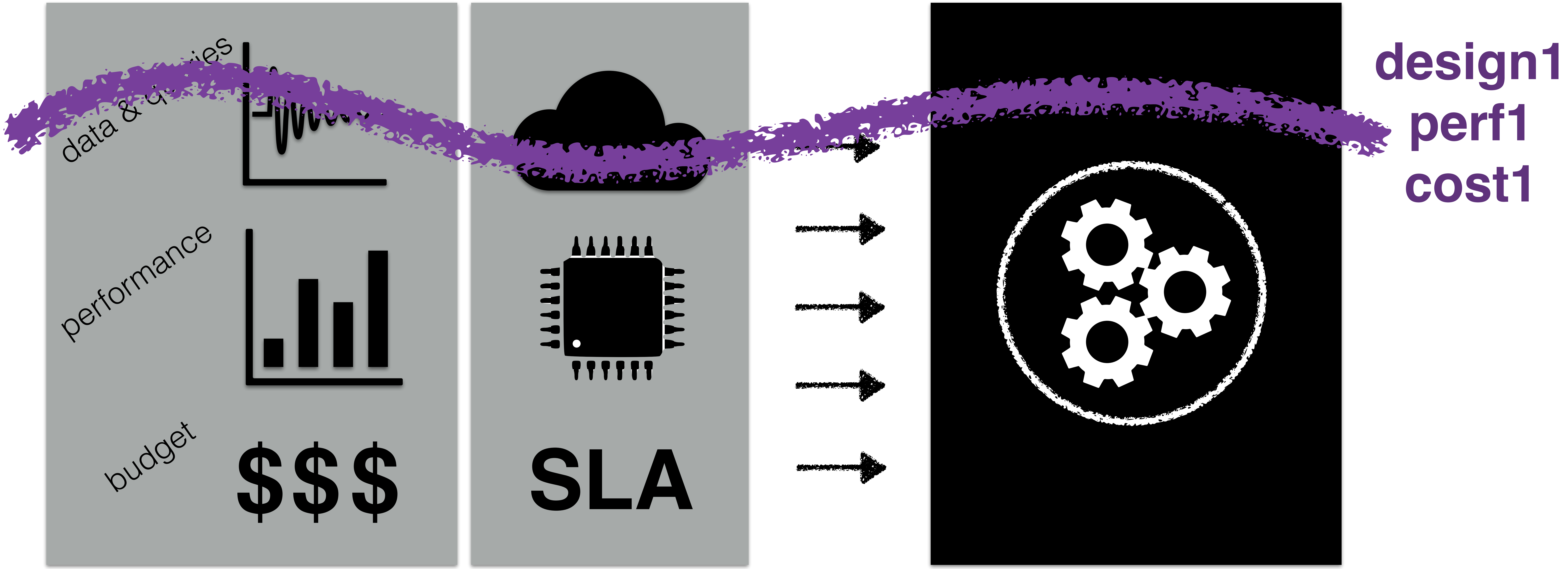

what-if reasoning

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what-if reasoning

AUTO DESIGN

Rob Tarjan, Turing Award 1986

"**IS THERE A CALCULUS OF DATA STRUCTURES**

by which one can choose the appropriate representation and techniques for a given problem?" (SIAM,1978)

[*P* vs *NP, average case, constant factors vs asymptotic, low bounds*]

DASlab @ Harvard SEAS

IS THERE A CALCULUS OF DATA SYSTEMS?

Rob Tarjan, Turing Award 1986

“IS THERE A CALCULUS OF DATA STRUCTURES

by which one can choose the appropriate representation and techniques for a given problem?” (SIAM,1978)

[*P* vs *NP, average case, constant factors vs asymptotic, low bounds*] the **grammar** of data systems design

Nikos Kazantzakis, philosopher

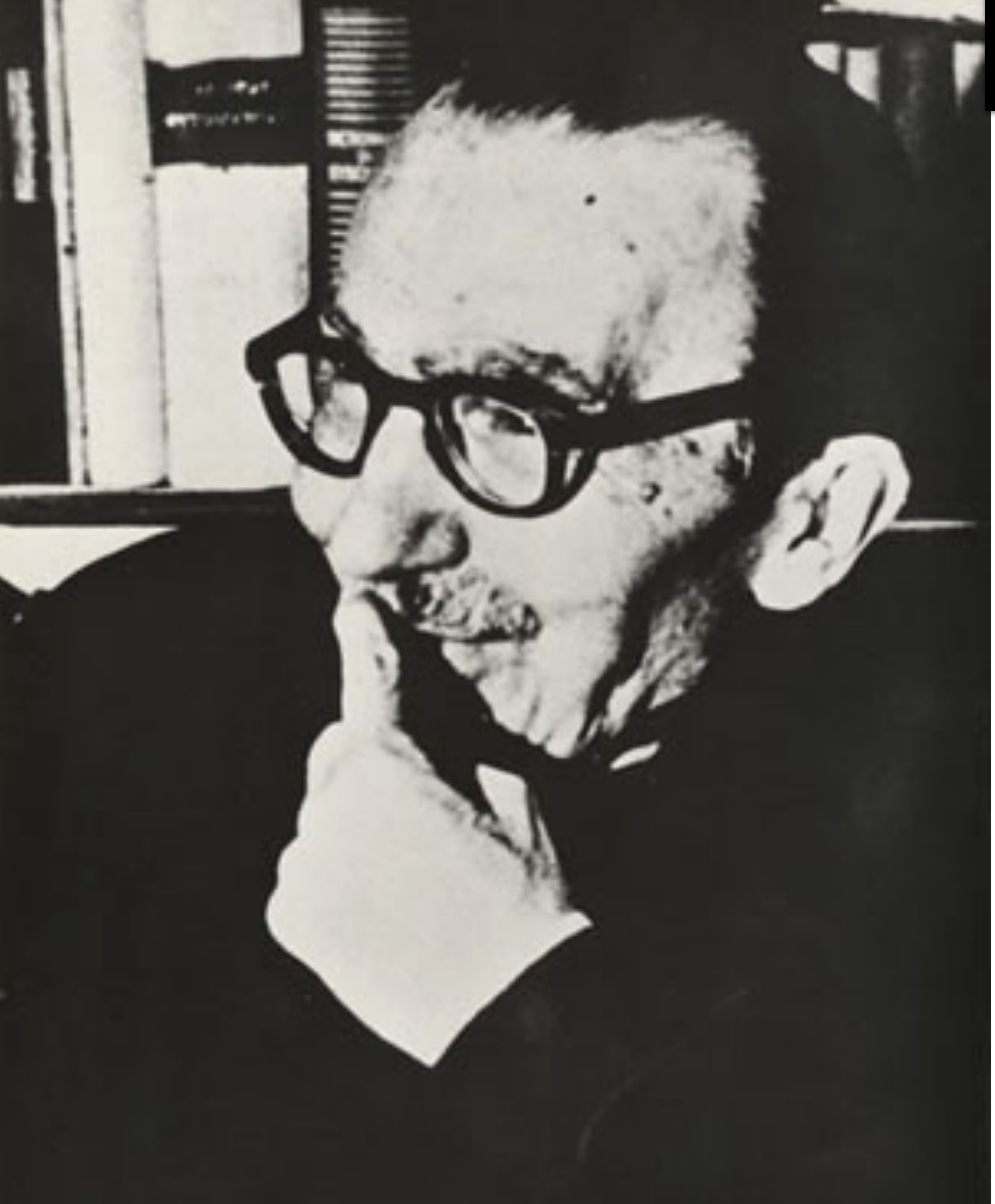
action is for nothing holy

hope the most of

fear form

am free

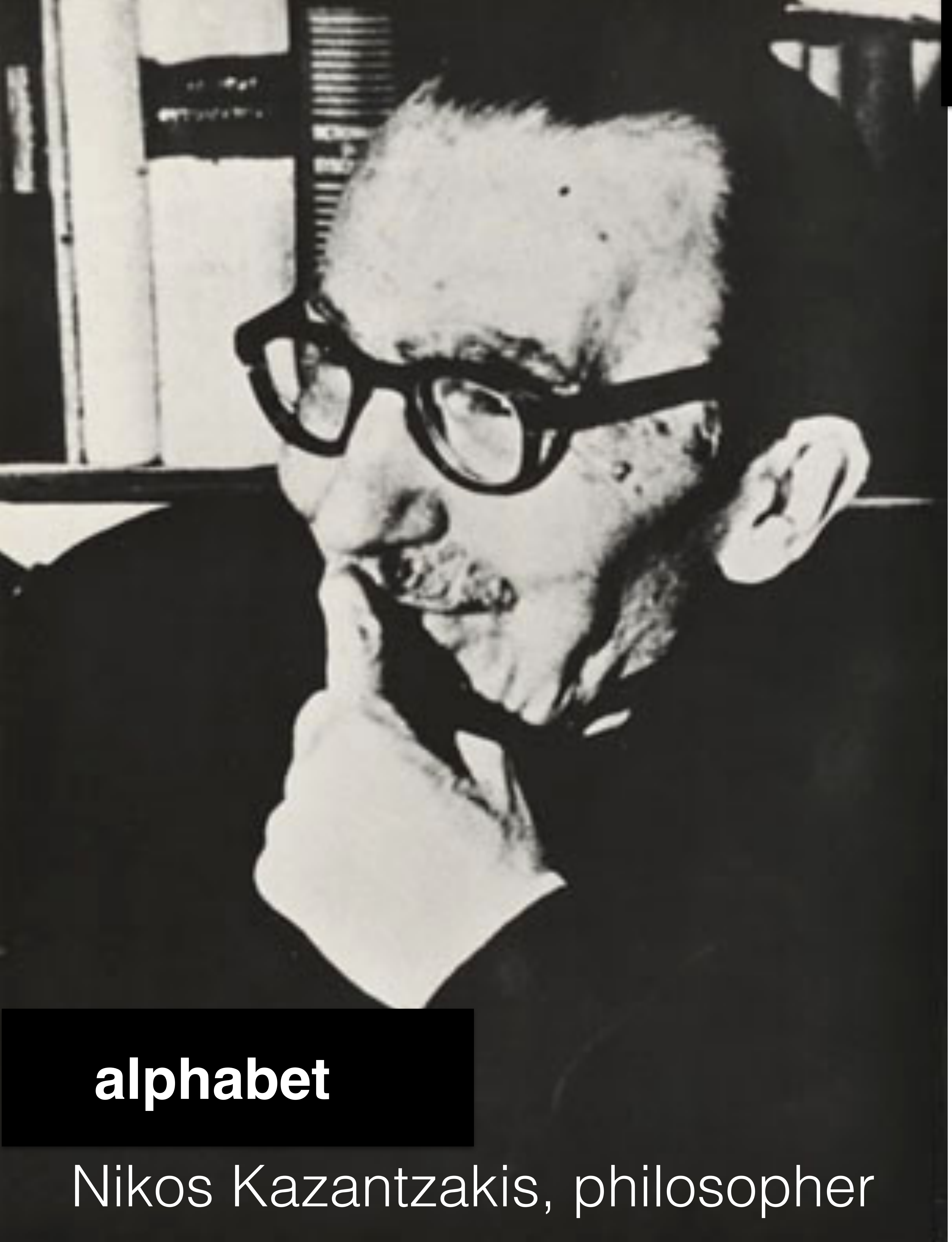
ultimate I theory



Nikos Kazantzakis, philosopher

action is the ultimate most holy form of theory

I hope for nothing
I fear nothing
I am free



alphabet

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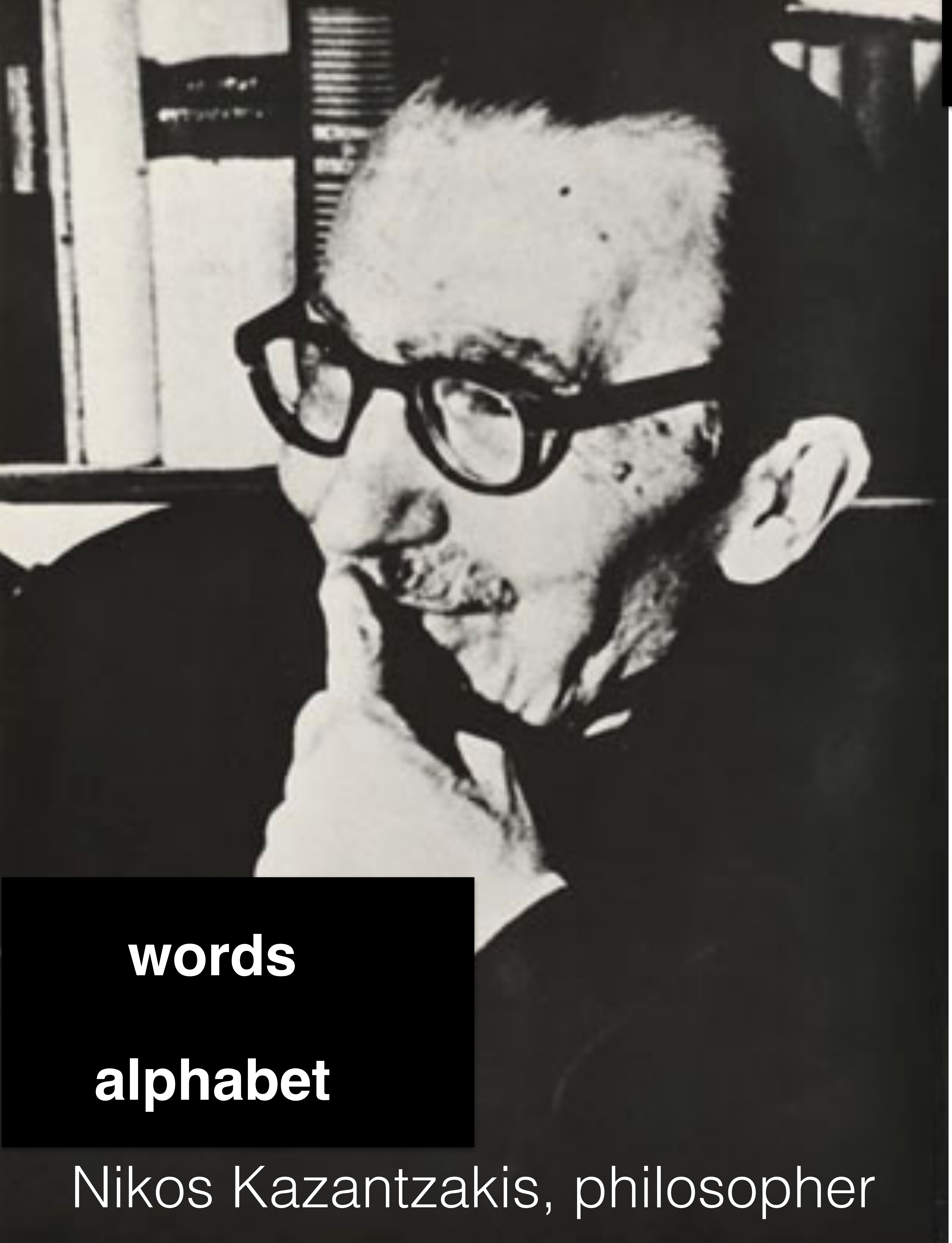

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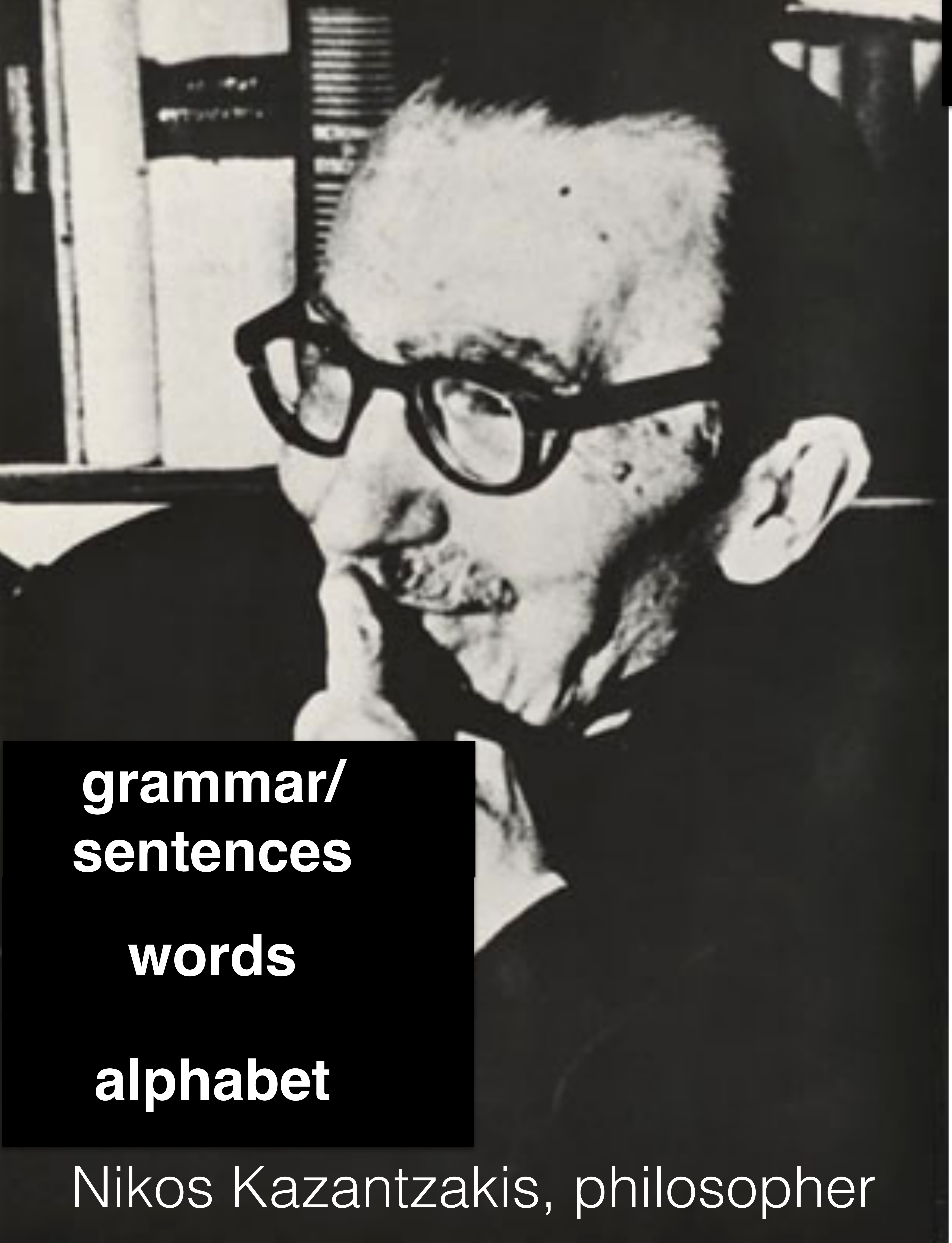

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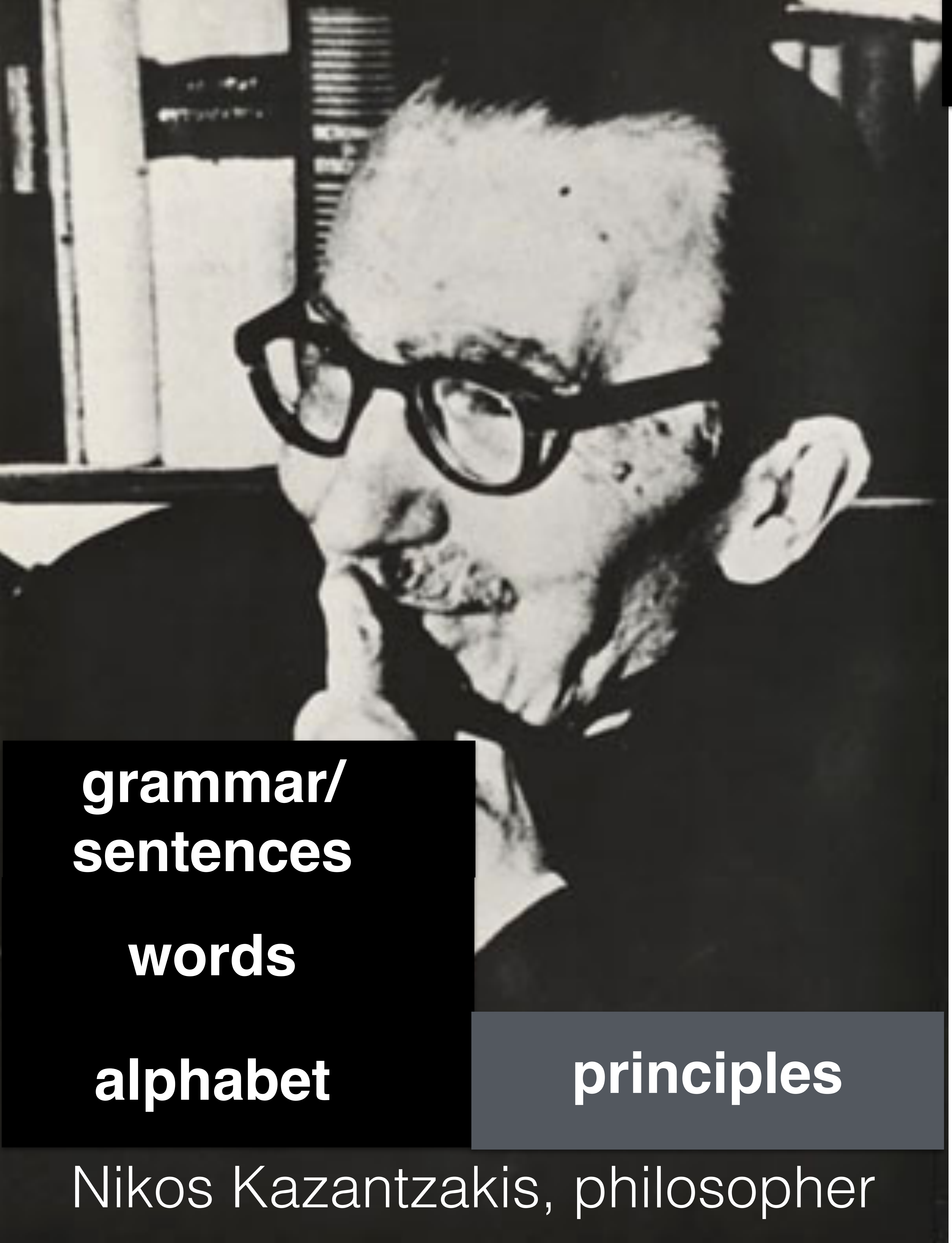

grammar/ sentences

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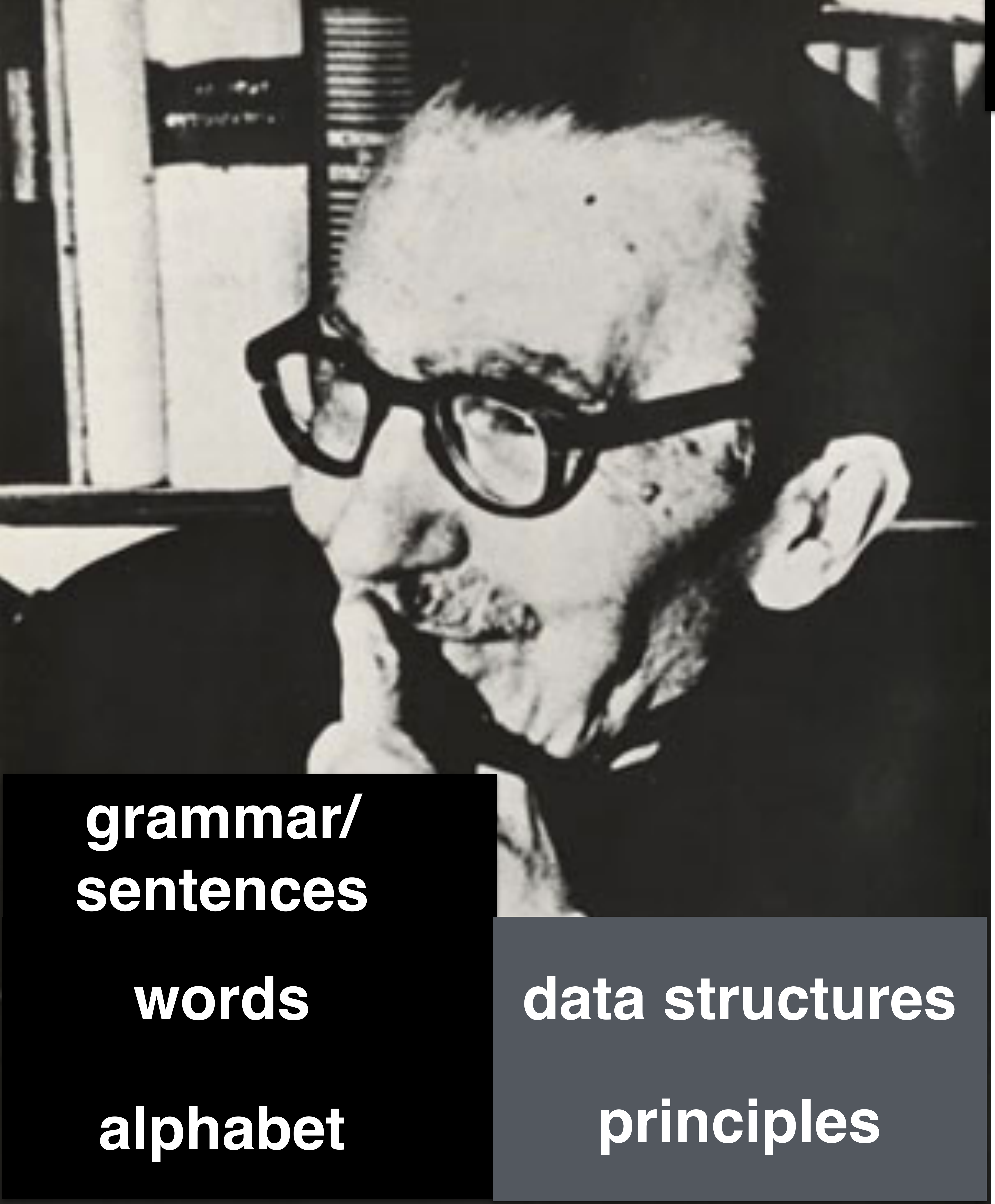

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grammar/ sentences	**interactions**
words	**data structures**
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the **grammar** of data systems design

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which are “all”
possible *data systems*
we may ever invent?

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Trillions of possible data structures

Data Calculator @SIGMOD 2018

Trillions of possible data structures

Data Calculator @SIGMOD 2018

New NoSQL systems: 1000x faster

Cosine @PVLDB 2022 and Limousine @SIGMOD 2024

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10x faster Image AI

Image Calculator, SIGMOD 2024

Get familiar with the very basics of traditional database architectures:
Architecture of a Database System. By J. Hellerstein, M. Stonebraker and J. Hamilton. Foundations and Trends in Databases, 2007

Get familiar with very basics of modern database architectures:
The Design and Implementation of Modern Column-store Database Systems. By D. Abadi, P. Boncz, S. Harizopoulos, S. Idreos, S. Madden. Foundations and Trends in Databases, 2013

Get familiar with the very basics of modern large scale systems:
Massively Parallel Databases and MapReduce Systems. By Shivnath Babu and Herodotos Herodotou. Foundations and Trends in Databases, 2013

Check out: syllabus, preparation readings, project 0, systems project 1, online sections

http://daslab.seas.harvard.edu/classes/cs265/

Here is my data and inference requests.
Design and implement and implement an LLM for my budget?

Nvidia released a new GPU.
Should we invest in the new hardware for our cluster of Image AI systems?

We are preparing to release a new feature for our social network application.
Should we redesign and reimplement our underlying key-value store?

….

CS 265

Stratos Idreos

BIG DATA SYSTEMS

NoSQL | Neural Networks | Image AI | LLMs | Data Science