WE WILL START AT 1:05 PM

# ML SYSTEMS DESIGN MEETUP GROUP

HETAV PANDYA

# IMPORTANT: THIS WORKSHOP WILL BE RECORDED

HETAV PANDYA

## AGENDA

INTRODUCTION

DATA SOURCES

DATA FORMAT AND COMPRESSION

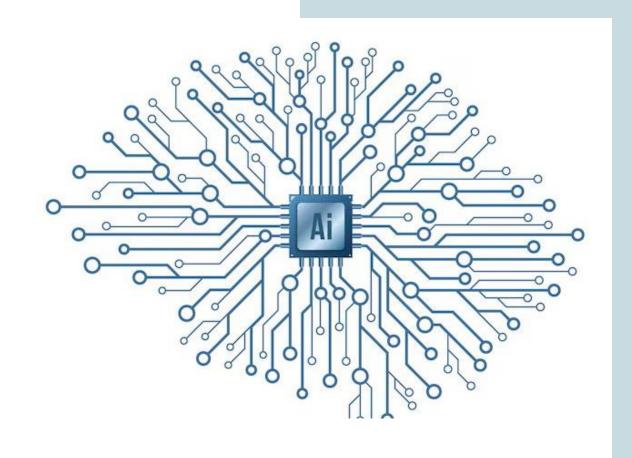
ROW AND COLUMN MAJOR DATABASES

EXTRACT, TRANSFORM, LOAD FRAMEWORK

BATCH AND STREAM PROCESSING

SAMPLING TECHNIQUES

OPEN Q&A





## INTRODUCTION

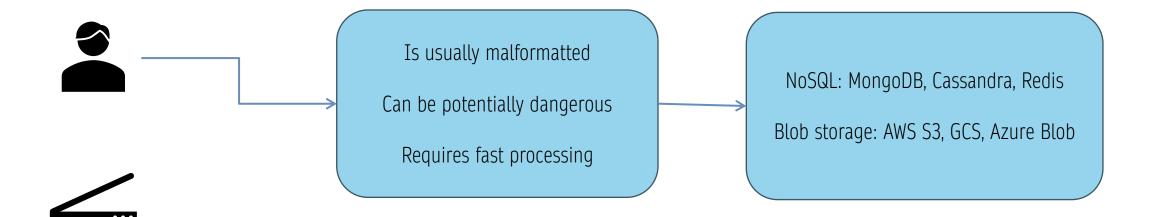
- Welcome to ML Systems Design Meetup Group
- Designing Machine Learning Systems Chip Huyen
- Free Access City Library
- Frequency Biweekly Monthly
- Questions: Meetup Event Chat



# FREE ACCESS



Via Burnaby Public Library

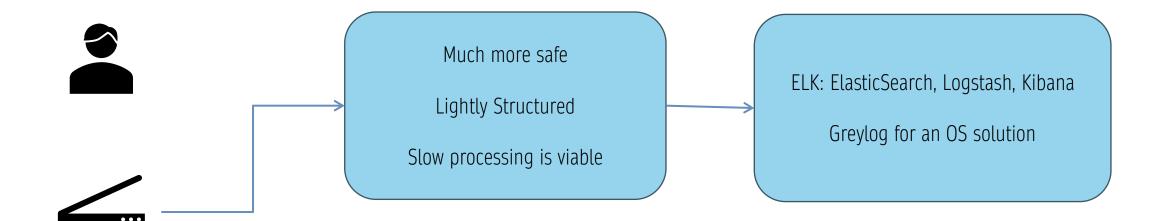








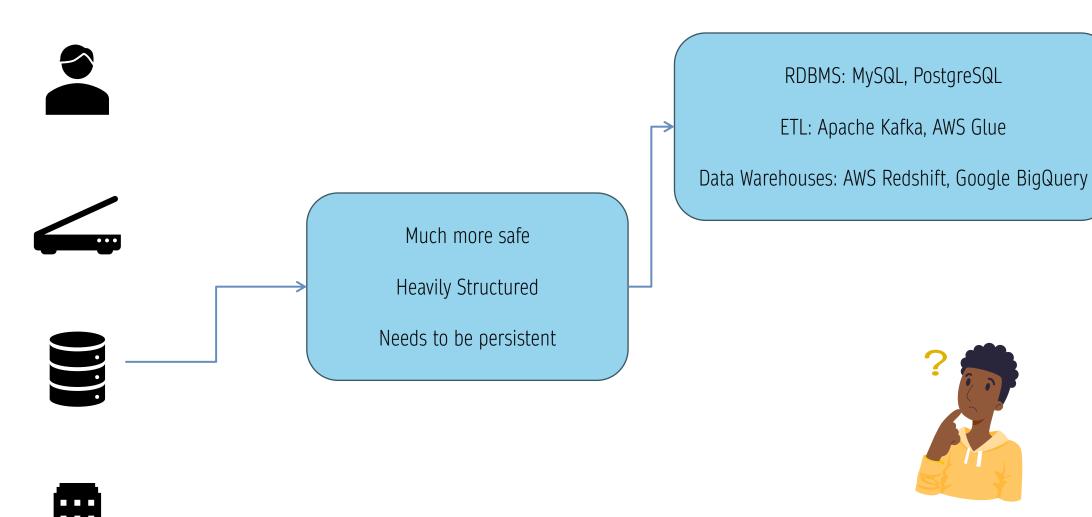
Text inputs, form submissions, video uploads, etc.





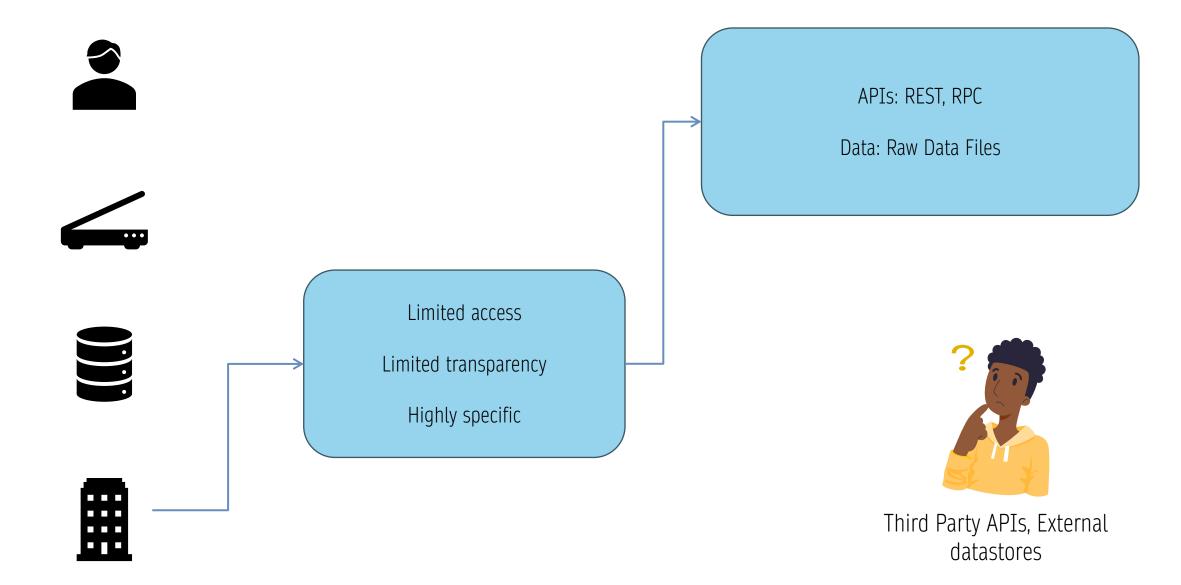






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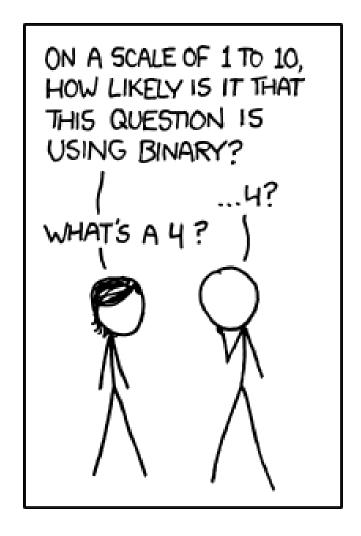
Transactions, orders, static details



#### THE FORMAT MATTERS!

Format	Binary/Text	Human- readable	Example use cases
JSON	Text	Yes	Everywhere
CSV	Text	Yes	Everywhere
Parquet	Binary	No	Hadoop, Amazon Redshift
Avro	Binary primary	No	Hadoop
Protobuf	Binary primary	No	Google, TensorFlow (TFRecord)
Pickle	Binary	No	Python, PyTorch serialization

#### **DEMO TIME**





Google Collab File

### ROW MAJOR VS COLUMN MAJOR

Row Major	Column Major
Faster row reads	Faster column reads
Row data is sequentially stored on disk	Column data is sequentially stored on disk
Example: Numpy (by default)	Example: Pandas

#### SPEED -> TIME -> MONEY

In NumPy, the major order can be specified. When an ndarray is created, it's row-major by default if you don't specify the order.

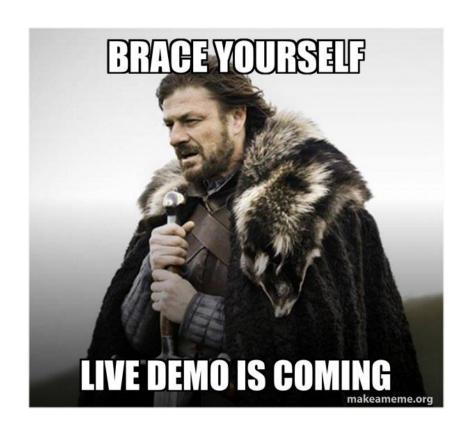
People coming to pandas from NumPy tend to treat DataFrame the way they would ndarray, e.g., trying to access data by rows, and find DataFrame slow.

me: \*gets angry at the code for not doing what I coded it to do\*

the code doing exactly what I coded it to do:



# DEMO TIME (SUBJECT TO TIME)





Google Collab File

#### STRUCTURED VS UNSTRUCTURED



Structured data	Unstructured data
Schema clearly defined	Data doesn't have to follow a schema
Easy to search and analyze	Fast arrival







Schema changes will	No need to worry about schema changes (yet), as	
cause a lot of troubles	the worry is shifted to the downstream	
	applications that use this data	

Can handle data from any source





Can only handle data

with a specific schema

warehouses

### ETL FRAMEWORK

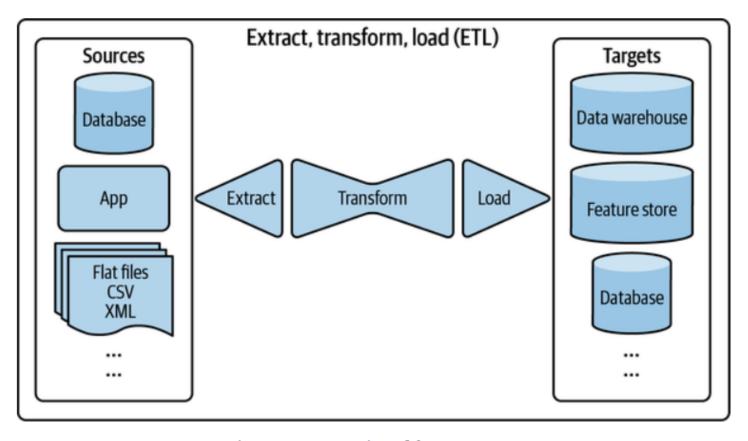
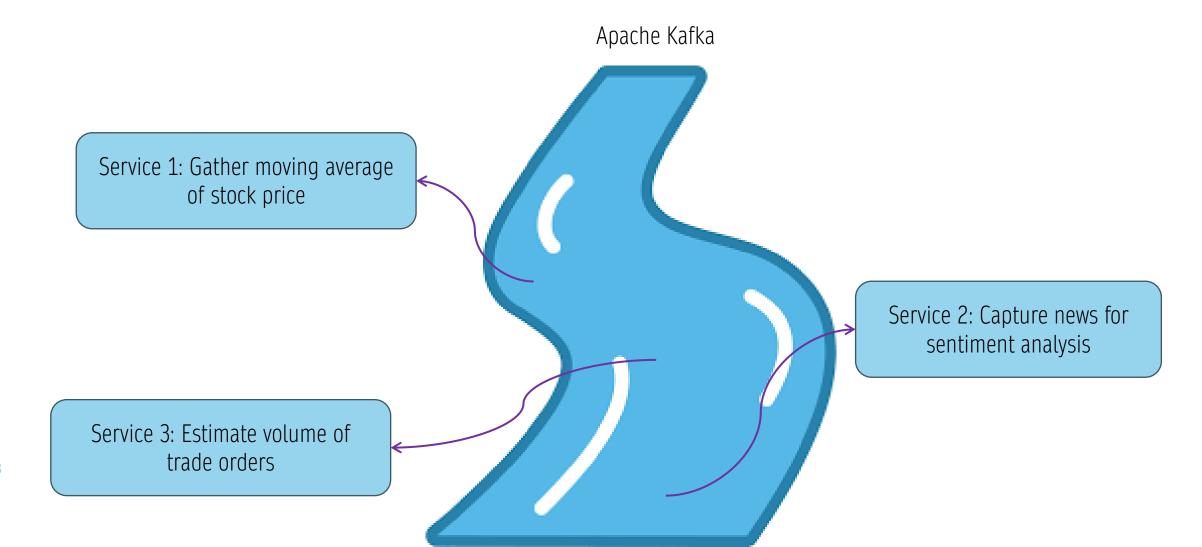


Figure 3-7. An overview of the ETL process

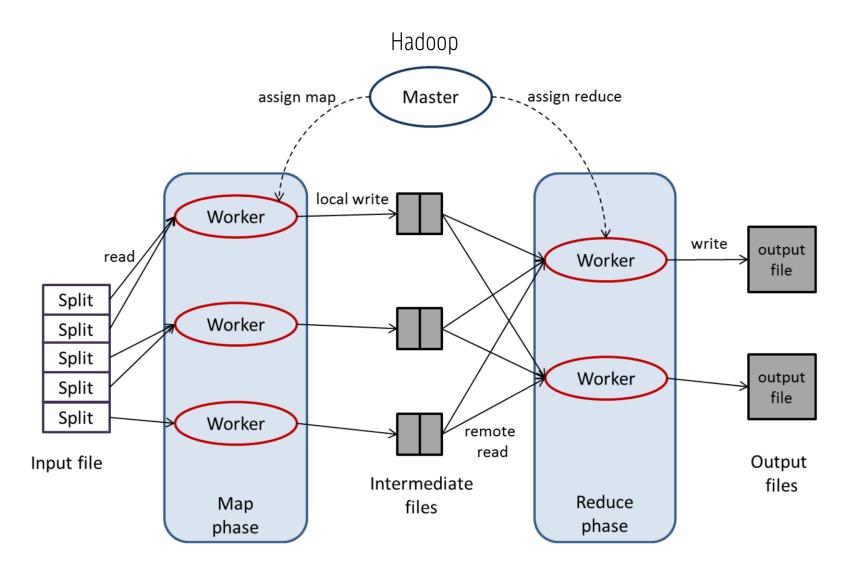
# STREAM VS BATCH PROCESSING

Feature	Batch Processing	Stream Processing
Data Arrival	Data is collected over a period and processed later.	Data is processed in real-time as it arrives.
Processing Latency	High latency; data processed in batches (minutes to hours).	Low latency; data processed near real-time (milliseconds to seconds).
Data Volume	Handles large volumes of data at once (batch sizes).	Handles continuous data streams in small chunks.
Data Structure	Typically structured and stored in databases/files.	Data may be semi-structured or unstructured streams.
Use Cases	Periodic reporting - Historical analysis	Real-time analytics - Fraud detection
Services/Technologies	Hadoop, Spark, Hive	Apache Kafka, AWS Kinesis, Apache Flink, Spark Streaming
Machine Learning	Training models on historical data batches.	Online learning from streaming data. Real-time model inference.

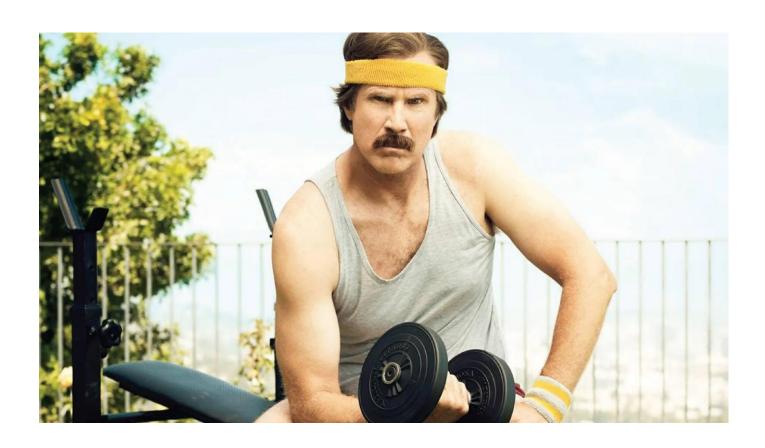
# STREAM PROCESSING



## BATCH PROCESSING



# WHAT DO WE DO WITH THE DATA?



# WHAT DO WE DO WITH THE DATA?

- Your model is as good as your data
- Sampling is a method of gathering data for training
- There are many types of sampling methods
  - Convenience sampling
  - Snowball sampling
  - Judgement sampling
  - Quota sampling
  - Simple random sampling
  - Weighted sampling
  - Reservoir sampling

#### RESERVOIR SAMPLING

Reservoir sampling is a fascinating algorithm that is especially useful when you have to deal with streaming data, which is usually what you have in production.

- 1. Put the first k elements into the reservoir.
- 2. For each incoming  $n^{\text{th}}$  element, generate a random number i such that  $1 \le i \le n$ .
- 3. If  $1 \le i \le k$ : replace the  $i^{\text{th}}$  element in the reservoir with the  $n^{\text{th}}$  element. Else, do nothing.

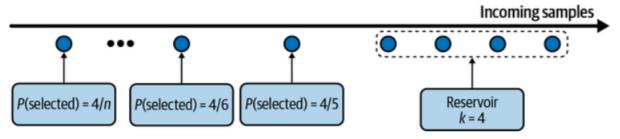


Figure 4-2. A visualization of how reservoir sampling works

#### WHAT TO EXPECT NEXT...

- Data labelling
- Labelling functions
- Natural labelling
- Weak supervision models
- Semi-supervised learning
- Transfer learning
- Class imbalance problems
- ROC curves
- Resampling
- Cost sensitive learning

# YOUR VOICE MATTERS!

Please take some time to fill up our very very short feedback form ©



If you would like to connect with me, feel free to scan this!





Q&A TIME

