

Machine Learning Systems Design

Lecture 2: ML and Data Systems Fundamentals



Reply in Zoom chat:

What MLOps tools would you want tutorials on?

Logistics

- 24-hour response policy (except holidays)
- Please prioritize EdStem
- Team search has started!

Search for teammates! #6



Kinbert Chou **STAFF**

14 hours ago in [Project](#)



25
VIEWS



Please use this thread to search for project teammates. You can consider sharing topics such as prior coursework, research or industry experience, and project ideas/topics you are interested in.

[Comment](#) [Edit](#) [Delete](#) [Endorse](#) ...

Zoom etiquettes

- Write questions into Zoom chat
 - Feel free to reply to each other — TAs will also reply
- I will stop occasionally for Q&A

Zoom etiquettes

We appreciate it
if you keep videos on!

- More visual feedback for us to adjust materials
- Better learning environment
- Better sense of who you're with in class!



**WAITING FOR STUDENTS TO TURN VIDEOS ON SO
I DON'T FEEL LIKE I'M TALKING TO AN EMPTY ROOM**

Agenda

1. ML systems fundamentals
2. Decoupling objectives
3. Breakout exercise
4. Data engineering 101

The materials in this course, starting from this lecture, differ significantly from last year

1. ML Systems Fundamentals

ML in production: expectation

1. Collect data
2. Train model
3. Deploy model
- 4.



ML in production: reality

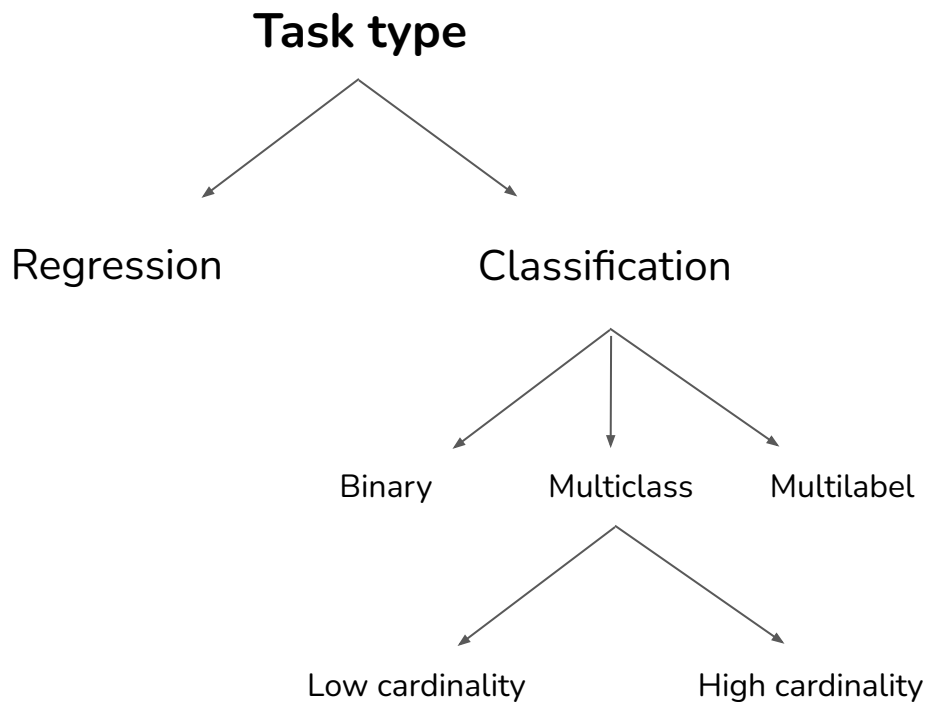
1. Choose a metric to optimize
2. Collect data
3. Train model
4. Realize many labels are wrong -> relabel data
5. Train model
6. Model performs poorly on one class -> collect more data for that class
7. Train model
8. Model performs poorly on most recent data -> collect more recent data
9. Train model
10. Deploy model
11. Dream about \$\$\$
12. Wake up at 2am to complaints that model biases against one group -> revert to older version
13. Get more data, train more, do more testing
14. Deploy model
15. Pray
16. Model performs well but revenue decreasing
17. Cry
18. Choose a different metric
19. Start over

Step 15 and 17 are
essential

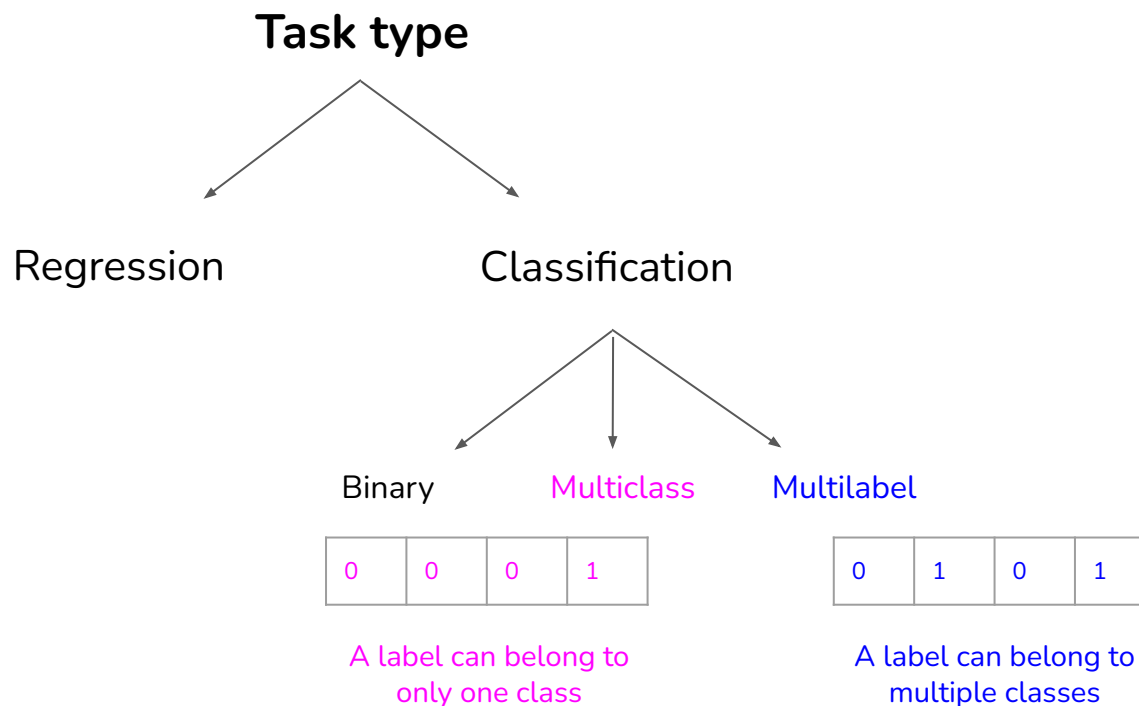
Project considerations

1. Framing
2. Objectives
3. Constraints
4. Phases

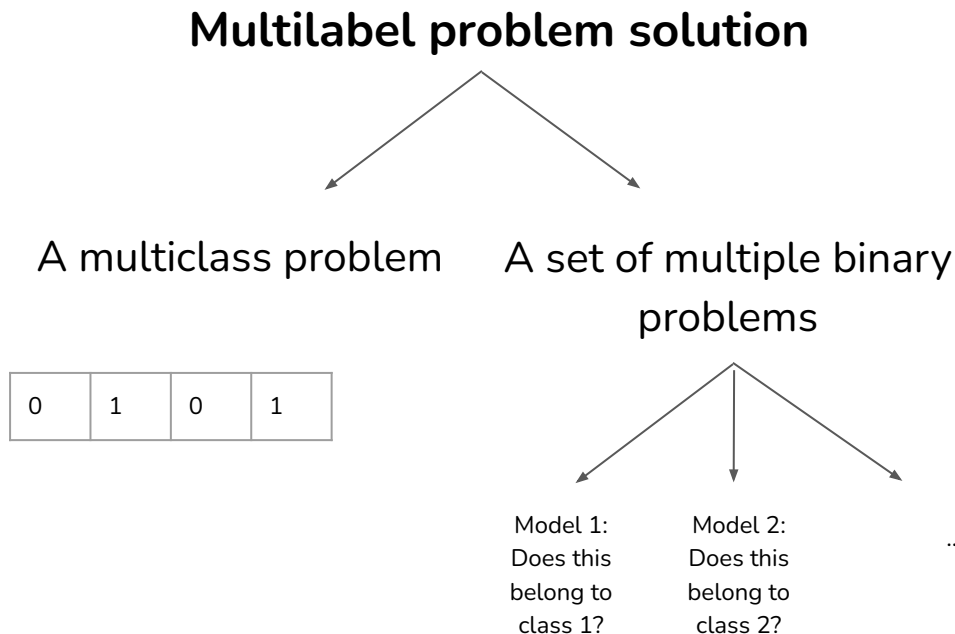
Framing the problem



Multiclass vs. multilabel

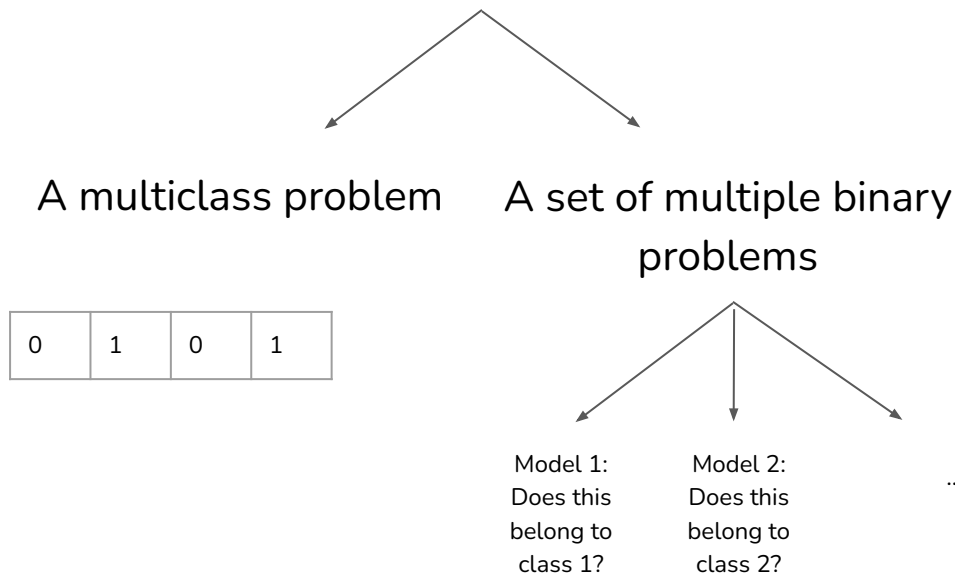


How to handle multilabel tasks



Multilabel is harder than multiclass

Multilabel problem solution



1. How to create ground truth labels?
2. How to decide decision boundaries

Multilabel: decision boundaries

Multilabel problem solution

A multiclass problem

0	1	2	3
0.45	0.33	0.2	0.02

Poll:

Which classes should this example belong to?

1. 0
2. 0, 1
3. 0, 1, 2

A set of multiple binary problems

Model 1:
Does this
belong to
class 1?

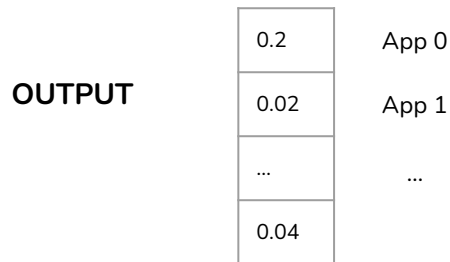
Model 2:
Does this
belong to
class 2?

...

A problem can be framed as different task types

Problem: predict the app users will most likely open next

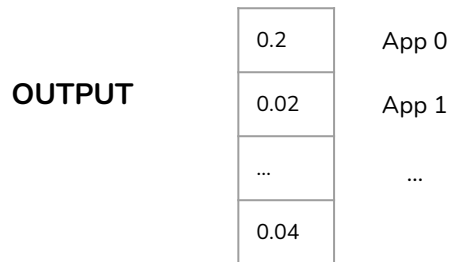
Classification



A problem can be framed as different task types

Problem: predict the app users will most likely open next

Classification



⚠ Every time an app is added/removed, you have to retrain your model ⚠

Framing can make the problem easier/harder

Problem: predict the app users will most likely open next

Regression

									OUTPUT	
INPUT 0	0.072	0.15	0.067	0.154			0.03	App 0
<div><div>User's features</div><div>Environment time, location, etc.</div><div>App's features</div></div>										
INPUT 1	0.072	0.15	0.067	0.154			0.06	App 1
INPUT ...	0.072	0.15	0.067	0.154			0.25	App ...

Framing can make the problem easier/harder

Problem: predict the app users will most likely open next

Very common framing for
recommendations / ads CTR

Regression

										OUTPUT	
INPUT 0	0.072	0.15	0.067	0.154				0.03	App 0
	User's features			Environment time, location, etc.		App's features					
INPUT 1	0.072	0.15	0.067	0.154				0.06	App 1
INPUT ...	0.072	0.15	0.067	0.154				0.25	App ...

Project objectives

- ML objectives
- Business objectives

Project objectives

- ML objectives
 - Performance
 - Latency
 - etc.

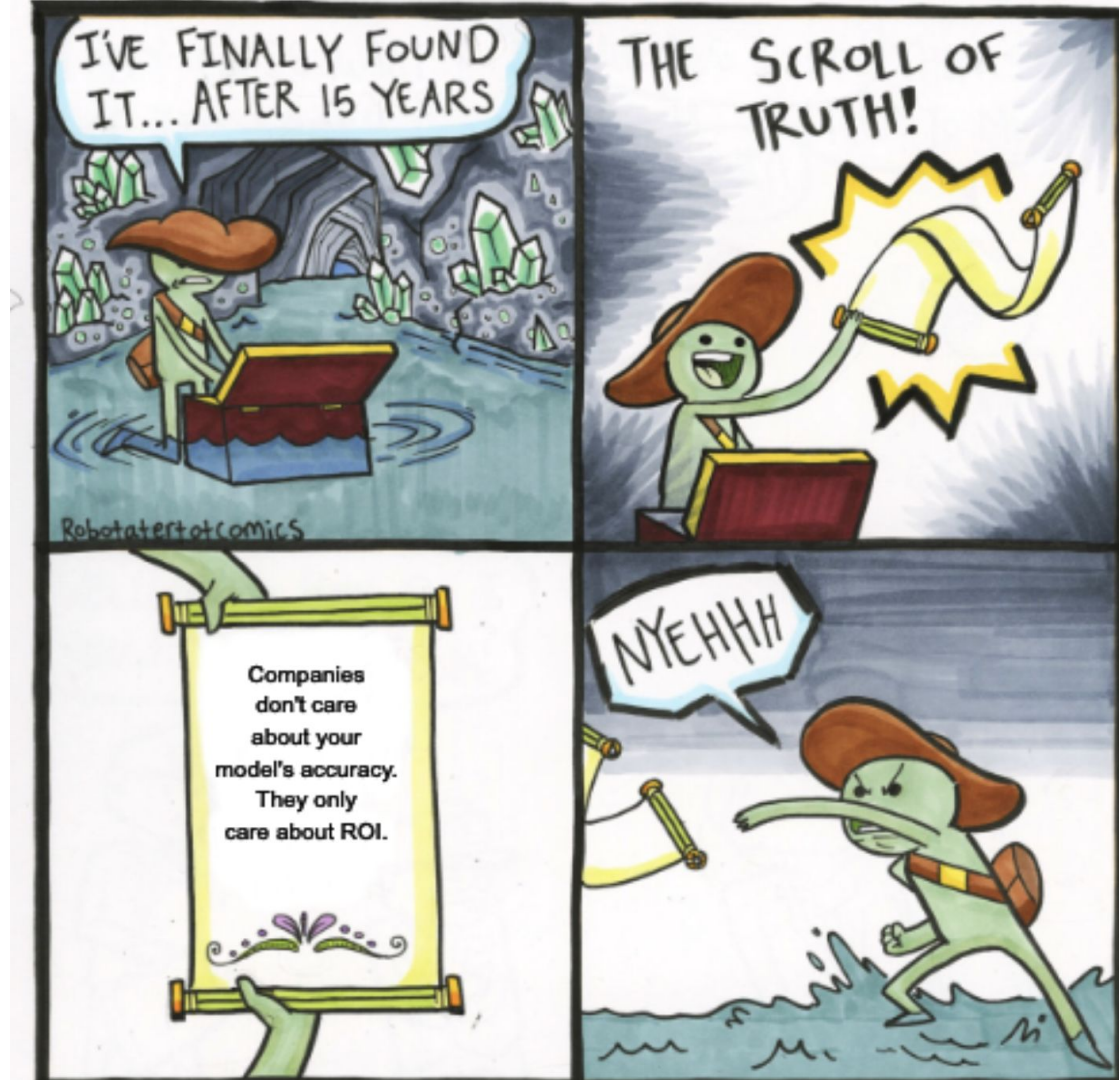
How to evaluate accuracy/F1/etc.
without ground truth labels?

Project objectives

- ML objectives
 - Performance
 - Latency
 - etc.
- Business objectives
 - Cost
 - ROI
 - Regulation & compliance

Project objectives

- ML objectives
 - Performance
 - Latency
 - etc.
- Business objectives
 - Cost
 - ROI
 - Regulation & compliance

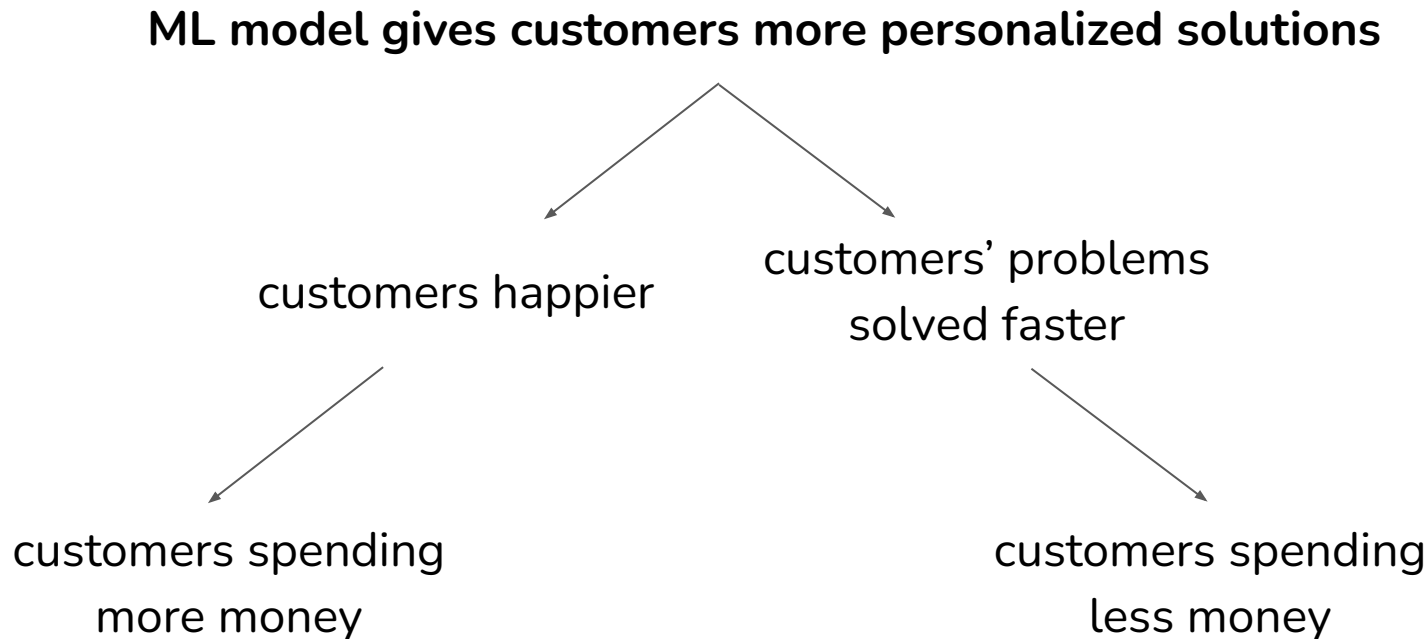


Business objectives

How can this ML project increase profits directly or indirectly?

- Directly: increasing sales (ads, conversion rates), cutting costs
- Indirectly: increasing customer satisfaction, increasing time spent on a website

ML <-> business: can be tricky



ML <-> business: mapping

- Baselines
 - Existing solutions, simple solutions, human experts, competitors solutions, etc.

ML <-> business: mapping

- Baselines
- Usefulness threshold
 - Self-driving needs human-level performance. Predictive texting doesn't.

ML <-> business: mapping

- Baselines
- Usefulness threshold
- False negatives vs. false positives
 - Covid screening: no false negative (patients with covid shouldn't be classified as no covid)
 - Fingerprint unlocking: no false positive (unauthorized people shouldn't be given access)

ML <-> business: mapping

- Baselines
- Usefulness threshold
- False negatives vs. false positives
- Interpretability
 - Does the ML system need to be interpretable? If yes, to whom?

ML <-> business: mapping

- Baselines
- Usefulness threshold
- False negatives vs. false positives
- Interpretability
- Confidence measurement (how confident it is about a prediction)
 - Does it need confidence measurement?
 - Is there a confidence threshold? What to do with predictions below that threshold—discard it, loop in humans, or ask for more information from users?

ML <-> business: mapping

- **Baselines**
 - Existing solutions, simple solutions, human experts, competitors solutions, etc.
- **Usefulness threshold**
 - Self-driving needs human-level performance. Predictive texting doesn't.
- **False negatives vs. false positives**
 - Covid screening: no false negative (patients with covid shouldn't be classified as no covid)
 - Fingerprint unlocking: no false positive (unauthorized people shouldn't be given access)
- **Interpretability**
 - Does it need to be interpretable? If yes, to whom?
- **Confidence measurement (how confident it is about a prediction)**
 - Does it need confidence measurement?
 - Is there a confidence threshold? What to do with predictions below that threshold—discard it, loop in humans, or ask for more information from users?

Constraints: time & budget

- Time
 - Rule of thumb: 20% time to get initial working system, 80% on iterative development
- Budget
 - Data, resources, talent

Time/budget tradeoffs

- Use more (powerful) machines
- Hire more people to label data faster
- Run more experiments in parallel
- Buy existing solutions

Constraints: privacy

- Annotation
 - Can data be shipped outside organizations for annotation?
- Storage
 - What kind of data are you allowed to store? How long can you store it?
- Third-party solutions
 - Can you share your data with a 3rd party (e.g. managed service)?
- Regulations
 - What regulations do you have to conform to?

Technical constraints

- Competitors
- Legacy systems



Four phases of ML adoption

Phase 1: Before ML

“If you think that machine learning will give you a 100% boost, then a heuristic will get you 50% of the way there.”

Martin Zinkevich, Google

Facebook | Home

http://www.facebook.com/home.php

Symbols Ind...s Reference Apple Yahoo! Google Maps YouTube Wikipedia News (4157) Popular POST TO FFFFOUND! Last Genius

Google Mail - Inbox Twitter / Home prehensile's Library Our Team Woolwort Facebook | Home Paparazzi!

facebook Home Profile Friends Inbox 2 Henry Cooke Settings Log out Search

Welcome, Henry. You have 4 event invitations and 3 group invitations.

News Feed London Public Profiles Photos Links Video More

What's on your mind?

Theo Graham - Brown Stuck on riddle 25
http://www.mcgov.co.uk/riddles
17 minutes ago · Comment · Like

Henry Cooke new Facebook design has epic amounts of fail.
27 minutes ago · Comment · Like

Catherine Mellor realised that it wasn't three stretch limos coming to pick up a famous, it was a funeral
50 minutes ago · Comment · Like

Catherine Mellor ooh blimeys
Posted about an hour ago · Comment · Like

Natasha Wisdom > (Silvan Schreuder) Happy Birthday my lovely XXXXX
Posted about an hour ago · See Wall-to-Wall

Ben Bashford
Ben uploaded 9 photos to Flickr
Posted about an hour ago · Comment · Like

Ben Gilmore my thoughts going out to Jonny "rhythm" and Barb... hope your okay mate.
Posted about an hour ago · Comment · Like

Matthew Leydon is so tired :-)
Posted about an hour ago · Comment · Like

Adam Clarkson Wants some fun
Posted about an hour ago · Comment · Like

Tim Poultney has a stinking sore throat
Posted about an hour ago · Comment · Like

2 people like this.
Write a comment...

Matt Thomas Thinking about getting some psychotherapy.
Posted about an hour ago · Comment · Like

Matt Thomas Someone damaged the security gate, had to go home...

TODAY See More
Martin Hewitt's birthday - Send a gift
Silvan Schreuder's birthday - Send a gift
Jemma Butler's birthday - Send a gift

HIGHLIGHTS
Advertise on Facebook
Facebook Ads
Reach over 175 million active users on Facebook. Learn how to connect your business to real customers through Facebook Ads.
Sponsored

Sam's Taste Test ep.3
James Sharpe commented on this.
434

Simbob turns 30
2 friends are tagged.

leam, Jan/feb 09
2 friends are tagged.

Movies
3 friends use this application.

Save ITV Yorkshire
2 friends joined, join this Group

Leavin' Drinks
by Emma Lobb

National book day at school n sam's hair doo
Adrian Bassett is tagged.

POKES
Annakaissa Wallenius - poke back | remove

PEOPLE YOU MAY KNOW See All
Paul Inman
Add as Friend

Stewart Leahy
Add as Friend

Phase 2: Simplest ML models

Start with a simple model that allows visibility into its working to:

- validate hypothesis
- validate pipeline

Phase 3: Optimizing simple models

- Different objective functions
- Feature engineering
- More data
- Ensembling

Phase 4: Complex ML models



2. Decoupling objectives

Decoupling objectives

Possible high-level goals when building a ranking system for newsfeed?

1. minimize the spread of misinformation
2. maximize revenue from sponsored content
3. maximize engagement

Zoom poll: which goal would you choose?

Side note: ethics of maximizing engagement

Several current and former YouTube employees, who would speak only on the condition of anonymity because they had signed confidentiality agreements, said company leaders were obsessed with increasing engagement during those years. The executives, the people said, rarely considered whether the company's algorithms were fueling the spread of extreme and hateful political content.

Employee raises at Facebook depend on engagement, and newly leaked private Zuckerberg recordings show the Groups algorithm prioritizes enragement.

In data terms, anti-vaxx groups and QAnon hysteria are going to get far better engagement than your average drag queen or 'Vote Yes on Proposition Z' groups. Moreover, the group recommendations tool prioritizes the angriest and most out-to-lunch groups, because those tend to get more clicks when they appear in the recommended field

Goal: maximize engagement

Step-by-step objectives:

1. Filter out spam
2. Filter out NSFW content
3. Rank posts by engagement: how likely users will click on them

Wholesome newsfeed

Goal: maximize users' engagement while minimizing the spread of extreme views and misinformation

Step-by-step objectives:

1. Filter out spam
2. Filter out NSFW content
3. Filter out misinformation
4. Rank posts by quality
5. Rank posts by engagement: how likely users will click on them

Decoupling objectives

Goal: maximize users' engagement while minimizing the spread of extreme views and misinformation

Step-by-step objectives:

1. Filter out spam
2. Filter out NSFW content
3. Filter out misinformation
4. Rank posts by quality
5. Rank posts by engagement: how likely users will click on it


How to rank posts by both
quality & engagement?

Multiple objective optimization (MOO)

- Rank posts by quality
 - Predict posts' quality
 - Minimize **quality_loss**: difference between predicted quality and true quality
- Rank posts by how likely users will click on it
 - Predict posts' engagement
 - Minimize **engagement_loss**: difference between predicted clicks and true clicks

One model optimizing combined loss

- Rank posts by quality
 - Predict posts' quality
 - Minimize **quality_loss**: difference between predicted quality and true quality
- Rank posts by how likely users will click on it
 - Predict posts' engagement
 - Minimize **engagement_loss**: difference between predicted clicks and true clicks

$$\text{loss} = \alpha \text{ quality_loss} + \beta \text{ engagement_loss}$$


Train one model to minimize this combined loss
Tune α and β to meet your need

Side note 1: check out Pareto optimization if you
want to learn about how to choose α and β

One model optimizing combined loss

- Rank posts by quality
 - Predict posts' quality
 - Minimize **quality_loss**: difference between predicted quality and true quality
- Rank posts by how likely users will click on it
 - Predict posts' engagement
 - Minimize **engagement_loss**: difference between predicted clicks and true clicks

$$\text{loss} = \alpha \text{ quality_loss} + \beta \text{ engagement_loss}$$

Train one model to minimize this combined loss

Side note 2: this is quite common, e.g. style transfer

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

One model optimizing combined loss

- Rank posts by quality
 - Predict posts' quality
 - Minimize **quality_loss**: difference between predicted quality and true quality
- Rank posts by how likely users will click on it
 - Predict posts' engagement
 - Minimize **engagement_loss**: difference between predicted clicks and true clicks

$$\text{loss} = \alpha \text{ quality_loss} + \beta \text{ engagement_loss}$$

Train one model to minimize this combined loss

⚠ Every time you want to tweak α
and β , you have to retrain your model!



Multiple models: each optimizing one objective

- Rank posts by quality
 - Predict posts' quality
 - Minimize **quality_loss**: difference between predicted quality and true quality
- Rank posts by how likely users will click on it
 - Predict posts' engagement
 - Minimize **engagement_loss**: difference between predicted clicks and true clicks

M_q : optimizes **quality_loss**
 M_e : optimizes **engagement_loss**

Rank posts by $\alpha M_q(\text{post}) + \beta M_e(\text{post})$

Now you can tweak α and β without retraining models

Decouple different objectives

- Easier for training:
 - Optimizing for one objective is easier than optimizing for multiple objectives
- Easier to tweak your system:
 - E.g. α % model optimized for quality + β % model optimized for engagement
- Easier for maintenance:
 - Different objectives might need different maintenance schedules
 - **Spamming techniques** evolve much faster than the way **post quality** is perceived
 - **Spam filtering systems** need updates more frequently than **quality ranking systems**

3. Breakout exercise

10 mins - group of 4

How to build a system to show users trending hashtags?

Aspects to consider

1. Business & ML objectives?
2. How to measure your model's performance?

Do we have ground truths?

3. Constraints
4. What is the simplest possible model?
 - a. Hint: rule-based, count-based

- OK to google
- Don't forget to introduce yourself
- <https://mlops-discord.github.io/blog/designing-twitters-trending-hashtags-solution/>

5. Localization / personalization of trending hashtags?

4. Data Engineering 101

Very basic. For details, take a database class!

Data engineering 101

- Data sources
- Data formats
- Data models
- Data storage engines & processing

Data sources

- User generated
- Systems generated
- Internal databases: users, inventory, customer relationships
- Third-party data

Data sources

Users generated data	Systems generated data
User inputs	Logs, metadata, predictions
Easily mal-formatted	Easier to standardize
Need to be processed ASAP	OK to process periodically (unless to detect problems ASAP)
	Can grow very large very quickly <ul style="list-style-type: none">• Many tools to process & analyze logs: Logstash, DataDog, Logz, etc.• OK to delete when no longer useful

Users' behavioral data (clicks, time spent, etc.) is often system-generated but is considered **user data**

Third-party data: creepy but fascinating

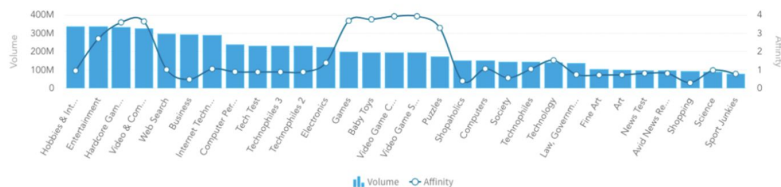
- Types of data
 - social media, income, job
- Demographic group
 - men, age 25-34, work in tech
- More available with Mobile Advertiser ID
- Useful for learning features
 - people who like A also like B

Top interests

They love computing and electronic entertainment. If you want to reach players, try targeting at their top interests.

Data point affinity and volume

Data point intersection volume and affinity, sorted by volume.



61 M profiles

Remote working

Millions of people decided to #stayhome and work remotely to limit the spread of coronavirus. Use our Remote working segment to easily reach them and show software or products that will help them stay effective.

How did we build the segment?

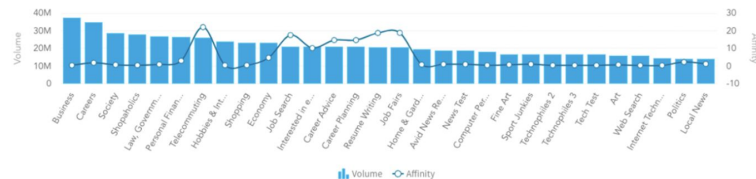
Our segment includes profiles of users who recently read articles, watched videos or used mobile apps which refers to:

- remote working
- effective ways of working from home
- tools for remote workers
- homeschooling and e-learning

If you want to reach remote workers, try to extend your target group by selecting the top interests, which include Telecommuting, Career Planning or Personal Finance.

Data point affinity and volume

Data point intersection volume and affinity, sorted by volume.



The end of tracking IDs ...

EDITORS' PICK | Jun 24, 2020, 12:38am EDT | 685,400 views

Apple Just Crippled IDFA, Sending An \$80 Billion Industry Into Upheaval

[Redacted] would like permission to track you across apps and websites owned by other companies.
Your data will be used to deliver personalized ads to you.

[Allow Tracking](#)

[Ask App Not to Track](#)

Or is this?

In response, the state-backed China Advertising Association, which has 2,000 members, has launched a new way to track and identify iPhone users called CAID, which is being widely tested by tech companies and advertisers in the country.

How to store your data?

Storing your data is only interesting if you want to access it later

- Storing data: **serialization**
- Unloading data: **deserialization**

How to store your data?

Data formats are
agreed upon standards
to serialize your data so that
it can be transmitted & reconstructed later

Data formats: questions to consider

- How to store multimodal data?
 - `{ 'image': [[200,155,0], [255,255,255], ...], 'label': 'car', 'id': 1 }`
- Access patterns
 - How frequently the data will be accessed?
- The hardware the data will be run on
 - Complex ML models on TPU/GPU/CPU

Data formats

Row-major

Column-major

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

Row-major vs. column-major

Column-major:

- stored and retrieved column-by-column
- good for accessing features

	Column 1	Column 2	Column 3
Sample 1
Sample 2
Sample 3

Row-major:

- stored and retrieved row-by-row
- good for accessing samples

Row-major vs. column-major: DataFrame vs. ndarray

Pandas DataFrame: column-major

- accessing a row much slower than accessing a column and NumPy

```
# Get the column `date`, 1000 loops  
%timeit -n1000 df["Date"]  
  
# Get the first row, 1000 loops  
%timeit -n1000 df.iloc[0]
```

```
1.78  $\mu$ s  $\pm$  167 ns per loop (mean  $\pm$  std. dev. of 7 runs, 1000 loops each)  
145  $\mu$ s  $\pm$  9.41  $\mu$ s per loop (mean  $\pm$  std. dev. of 7 runs, 1000 loops each)
```

NumPy ndarray: row-major by default

- can specify to be column-based

```
df_np = df.to_numpy()  
%timeit -n1000 df_np[0]  
%timeit -n1000 df_np[:,0]
```

```
147 ns  $\pm$  1.54 ns per loop (mean  $\pm$  std. dev. of 7 runs, 1000 loops each)  
204 ns  $\pm$  0.678 ns per loop (mean  $\pm$  std. dev. of 7 runs, 1000 loops each)
```

Text vs. binary formats

	Text files	Binary files
Examples	CSV, JSON	Parquet
Pros	Human readable	Compact
Store the number <i>1000000</i> ?	7 characters -> 7 bytes	If stored as int32, only 4 bytes

You can unload the result of an Amazon Redshift query to your Amazon S3 data lake in Apache Parquet, an efficient open columnar storage format for analytics. Parquet format is up to 2x faster to unload and consumes up to 6x less storage in Amazon S3, compared with text formats. This enables you to save data transformation and enrichment you have done in



Data models

- Describe how data is represented
- Two main paradigms:
 - Relational model
 - NoSQL

Relational model (est. 1970)

- Similar to SQL model
- Formats: CSV, Parquet

Tuple (row):
unordered

Column 1	Column 2	Column 3

Heading

Column:
unordered

Relational model: normalization

What if we change “Banana Press” to “Pineapple Press”?

Title	Author	Format	Publisher	Country	Price
Harry Potter	J.K. Rowling	Paperback	Banana Press	UK	\$20
Harry Potter	J.K. Rowling	E-book	Banana Press	UK	\$10
Sherlock Holmes	Conan Doyle	Paperback	Guava Press	US	\$30
The Hobbit	J.R.R. Tolkien	Paperback	Banana Press	US	\$30
Sherlock Holmes	Conan Doyle	Paperback	Guava Press	US	\$15

Original Book
Relation

Relational model: normalization

Title	Author	Format	Publisher ID	Price
Harry Potter	J.K. Rowling	Paperback	1	\$20
Harry Potter	J.K. Rowling	E-book	1	\$10
Sherlock Holmes	Conan Doyle	Paperback	2	\$30
The Hobbit	J.R.R. Tolkien	Paperback	1	\$30
Sherlock Holmes	Conan Doyle	Paperback	2	\$15

Updated Book
Relation

Publisher ID	Publisher	Country
1	Banana Press	UK
2	Guava Press	US

Publisher
Relation

Relational model: normalization

Title	Author	Format	Publisher ID	Price
Harry Potter	J.K. Rowling	Paperback	1	\$20
Harry Potter	J.K. Rowling	E-book	1	\$10
Sherlock Holmes	Conan Doyle	Paperback	2	\$30
The Hobbit	J.R.R. Tolkien	Paperback	1	\$30
Sherlock Holmes	Conan Doyle	Paperback	2	\$15

Publisher ID	Publisher	Country
1	Banana Press	UK
2	Guava Press	US

Pros:

- Less mistakes (standardized spelling)
- Easier to update
- Easier localization

Cons:

- Slow to join across multiple large tables

Relational Model & SQL Model

- SQL model slightly differs from relational model
 - e.g. SQL tables can contain row duplicates. True relations can't.
- SQL is a query language
 - How to specify the data that you want from a database
- SQL is declarative
 - You tell the data system what you want
 - It's up to the system to figure out how to execute
 - Query optimization

SQL

- SQL is an essential data scientists' tool

LEARN SQL!

Problems with SQL

- What if we add a new column?
- What if we change a column type?

SQL to NoSQL

Surprise #2: Hating on RDBMS. There was ample room for free-form response in the survey, and a lot of people took the opportunity to bash on relational database technology. There were some colorful RDBMS-related responses to the question what's your biggest hope for NoSQL in 2012? **And many of them were downright angry.** While NoSQL was for a time the “new shiny thing” that many wanted to play with, it's pretty clear that most of the respondents are looking to NoSQL technology not because it is what the cool kids are doing, but because they are trying to eliminate real pain. What pain you might ask?

Surprise #3: Schema management is the #1 pain driving NoSQL adoption.

NoSQL: No SQL -> Not Only SQL

- Document model
- Graph model

NoSQL

- Document model
 - Central concept: document
 - Relationships between documents are rare
- Graph model
 - Central concept: graph (nodes & edges)
 - Relationships are the priority

Document model: example

- Book data in the document model
- Each book is a document

Document 1: harry_potter.json

```
{
  "Title": "Harry Potter",
  "Author": "J.K. Rowling",
  "Publisher": "Banana Press",
  "Country": "UK",
  "Sold as": [
    {"Format": "Paperback", "Price": "$20"},
    {"Format": "E-book", "Price": "$10"}
  ]
}
```

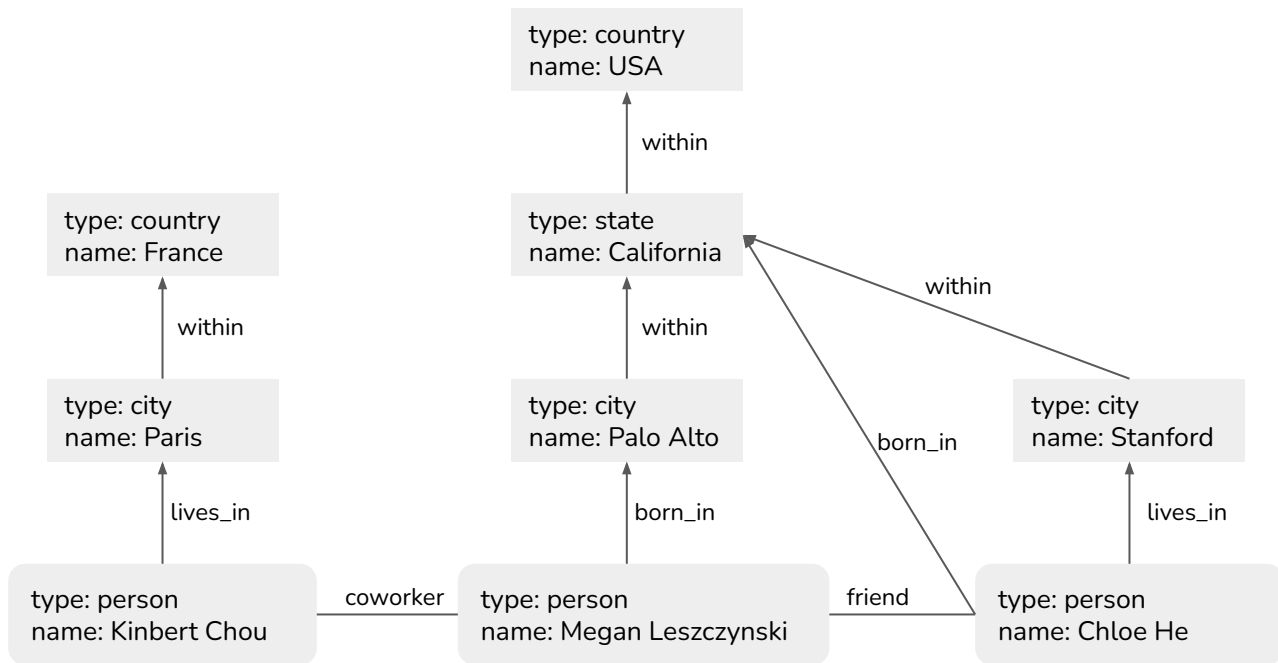
Document 2: sherlock_holmes.json

```
{
  "Title": "Sherlock Holmes",
  "Author": "Conan Doyle",
  "Publisher": "Guava Press",
  "Country": "US",
  "Sold as": [
    {"Format": "Paperback", "Price": "$30"},
    {"Format": "E-book", "Price": "$15"}
  ]
}
```

Document 3: the_hobbit.json

```
{
  "Title": "The Hobbit",
  "Author": "J.R.R. Tolkien",
  "Publisher": "Banana Press",
  "Country": "UK",
  "Sold as": [
    {"Format": "Paperback", "Price": "$30"},
  ]
}
```

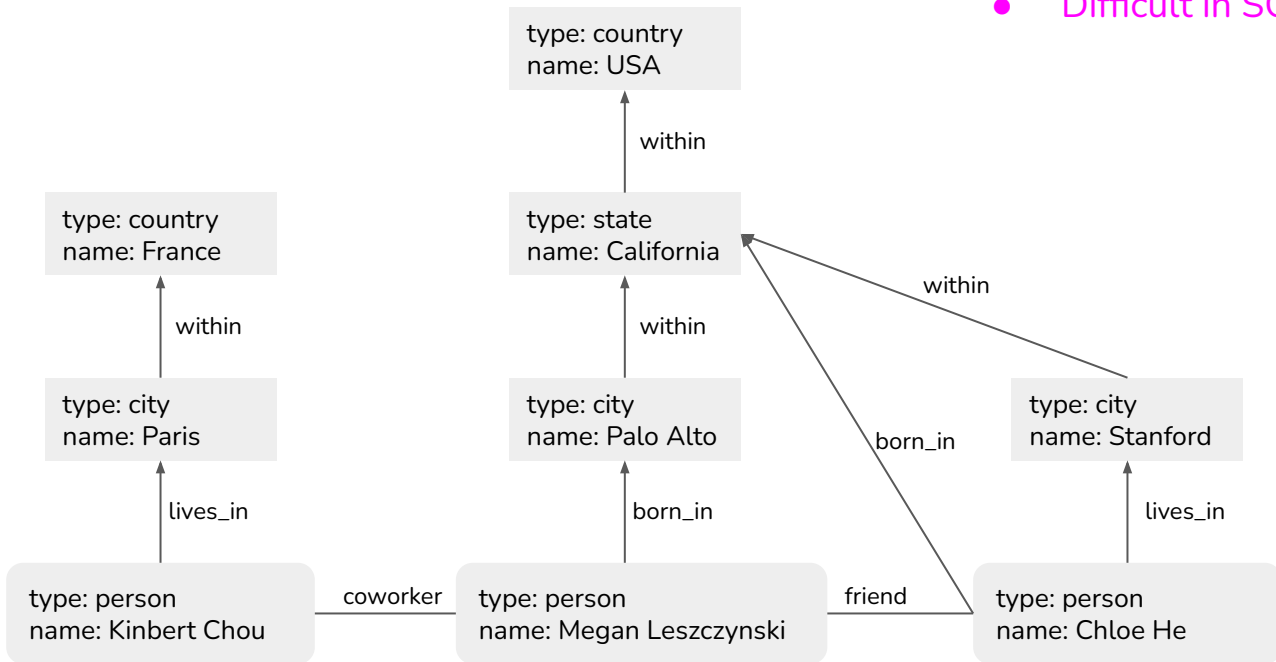
Graph model



Graph model

Query: show me everyone who was born in the USA?

- Easy in graph
- Difficult in SQL



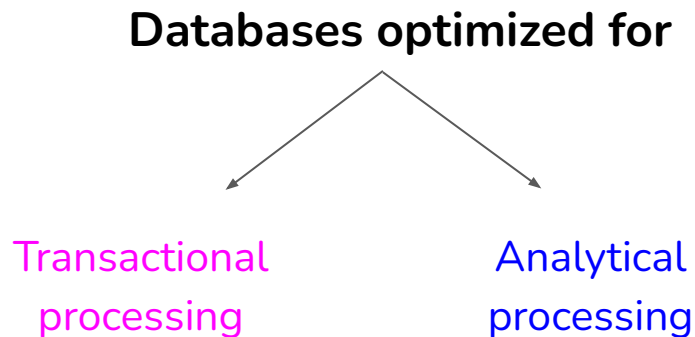
Structured vs. unstructured data

Structured	Unstructured
Schema clearly defined	Whatever
Easy to search and analyze	Fast arrival (e.g. no need to clean up first)
Can only handle data with specific schema	Can handle data from any source
Schema changes will cause a lot of trouble	No need to worry about schema changes
Data warehouses	Data lakes

Structured vs. unstructured data

Structured	Unstructured
Structure is assumed at write	Structure is assumed at read

Data Storage Engines & Processing



OnLine Transaction Processing (OLTP)

- Transactions: tweeting, ordering a Lyft, uploading a new model, etc.
- Operations:
 - Insert when generated
 - Occasional update/delete

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OnLine Transaction Processing

- Transactions: tweeting, ordering a Lyft, uploading a new model, etc.
- Operations:
 - Inserted when generated
 - Occasional update/delete
- Requirements
 - Low latency
 - High availability
 - ACID not necessary
 - **Atomicity**: all the steps in a transaction fail or succeed as a group
 - If payment fails, don't assign a driver
 - **Isolation**: concurrent transactions happen as if sequential
 - Don't assign the same driver to two different requests that happen at the same time

See ACID:
Atomicity,
Consistency,
Isolation,
Durability

OnLine Transaction Processing

- Transactions: tweeting, ordering a Lyft, uploading a new model, etc.
- Operations:
 - Inserted when generated
 - Occasional update/delete
- Requirements
 - Low latency
 - High availability
- Typically row-major

Row

```
INSERT INTO RideTable(RideID, Username, DriverID, City, Month, Price)
VALUES ('10', 'memelord', '3932839', 'Stanford', 'July', '20.4');
```


OnLine Analytical Processing (OLAP)

- How to get aggregated information from a large amount of data?
 - e.g. what's the average ride price last month for riders at Stanford?
- Operations:
 - Mostly SELECT

OnLine Analytical Processing

- Analytical queries: aggregated information from a large amount of data?
 - e.g. what's the average ride price last month for riders at Stanford?
- Operations:
 - Mostly SELECT
- Requirements:
 - Can handle complex queries on large volumes of data
 - Okay response time (seconds, minutes, even hours)

OnLine Analytical Processing

- Analytical queries: aggregated information from a large amount of data?
 - e.g. what's the average ride price last month for riders at Stanford?
- Operations:
 - Mostly SELECT
- Requirements:
 - Can handle complex queries on large volumes of data
 - Okay response time (seconds, minutes, even hours)
- Typically column-major

Column

```
SELECT AVG(Price)
FROM RideTable
WHERE City = 'Stanford' AND Month = 'July';
```

OLTP & OLAP are outdated terms

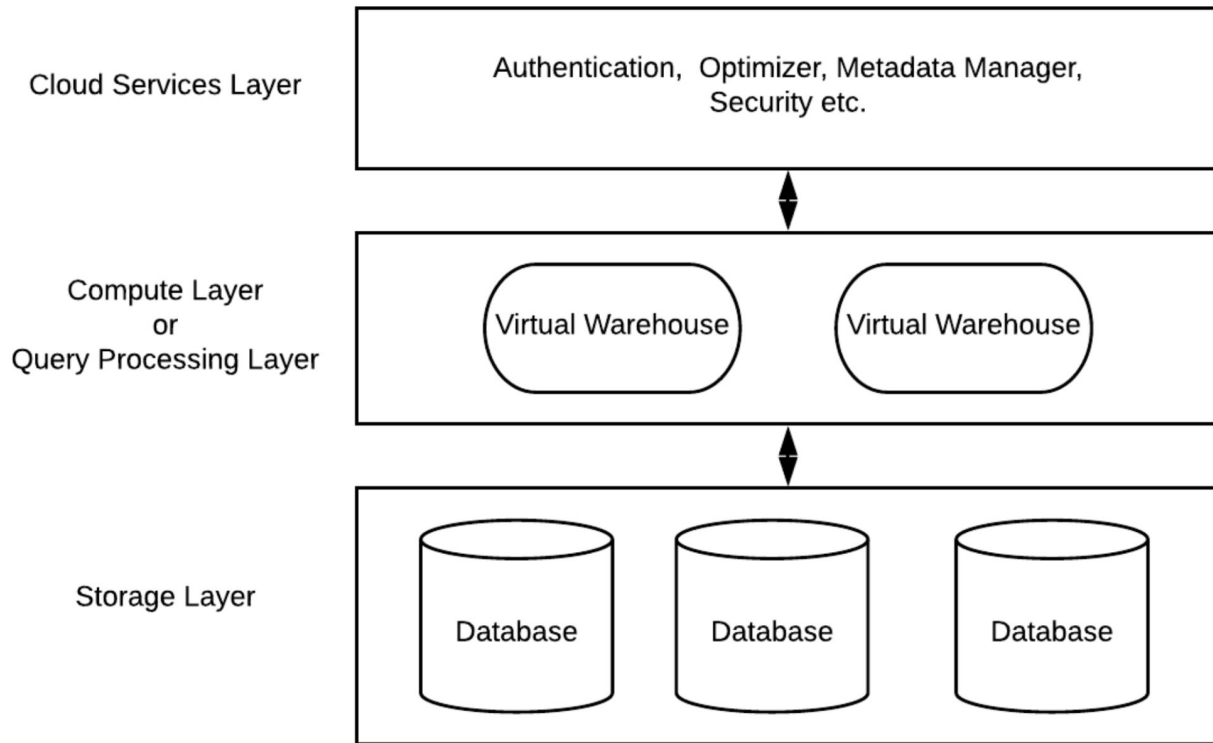


Decoupling storage & processing

- OLTP & OLAP: how data is stored is also how it's processed
 - Same data being stored in multiple databases
 - Each uses a different processing engine for different query types
- New paradigm: storage is decoupled from processing
 - Data can be stored in the same place
 - A processing layer on top that can be optimized for different query types



Decoupling storage & processing

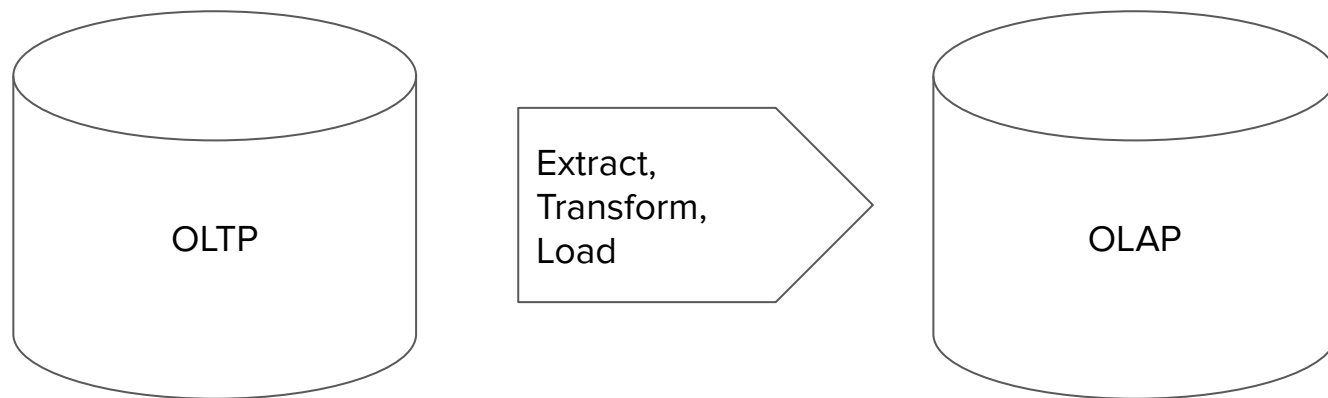


ETL



ETL EVERYWHERE

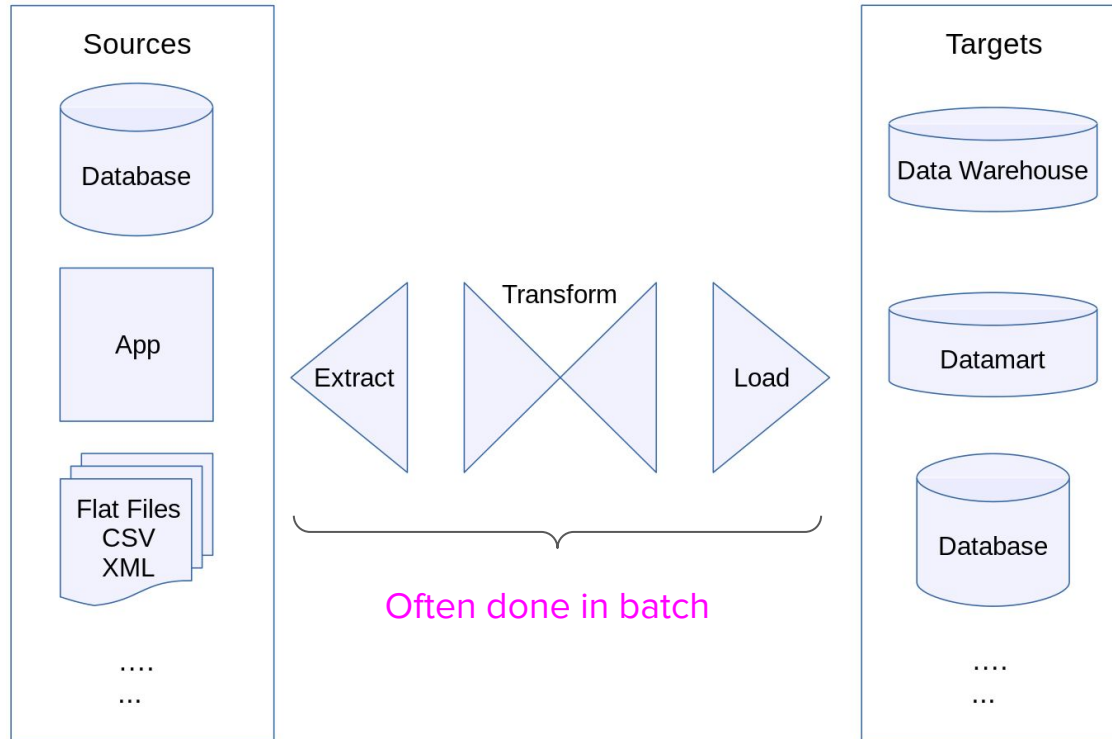
ETL (Extract, Transform, Load)




Transform: the meaty part

- cleaning, validating, transposing, deriving values, joining from multiple sources, deduplicating, splitting, aggregating, etc.

Extract, Transform, Load (ETL)



ETL -> ELT

Structured -> unstructured -> structured

want more flexibility tools & infra standardized

ETL -> ELT -> ETL

Machine Learning Systems Design

Next class: Training Data