

# Natural Language Processing

## Recommendation Systems

*From the engineering point of view*

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# Readings

- Dan Jurafsky, Stanford University, CS 124, [Recommender Systems lectures](#)

# What recommender systems are?

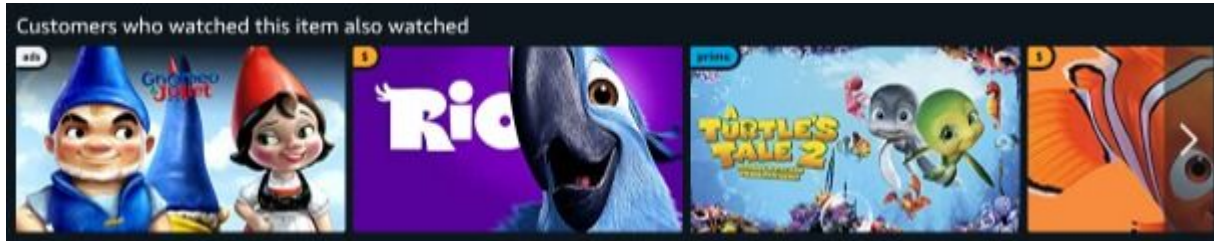
Can you think of examples?

# What recommender systems are?

The most obvious example is "similar items" on shopping sites, or media platforms

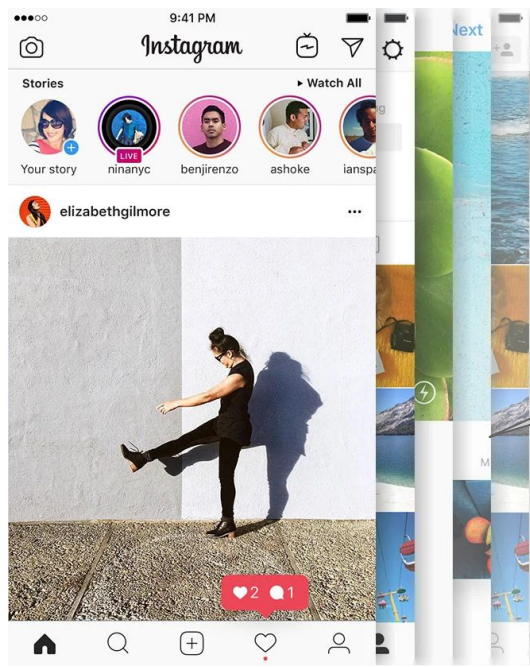


Relatively simple, in most cases not "personalized", i.e. all users see the same recommendation



# What recommender systems are?

## Social media feeds



Personalized for every user

# What recommender systems are?

## Search Ads

digital camera

SafeSearch off ▾

Advanced search

About 272,000,000 results (0.21 seconds)

**Lumix Digital Cameras - Capture the moments that matter** 🔍 👤 Ads  
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[www.jessops.com](http://www.jessops.com) > Cameras > Compact Digital Cameras - Cached  
 20+ items - Compact **Digital Cameras** - Cameras - Jessops. Buy online and ...  
 • Canon Powershot SX210 IS **Digital Camera** in Black - 14x Wide Zoom - 3.0 ...  
 • Canon Powershot S95 **Digital Camera** - 10 Megapixels - 3.8x f2 Optical Zoom  
 • Olympus SZ-20 **Digital Camera** in Black - only at Jessops - 12.5x Super Wide ...

**Amazon.co.uk: Digital Cameras: Point & Shoot Digital Cameras...** 🔍 👤  
[www.amazon.co.uk/Digital-Cameras...Photography-Bundles/b?...](http://www.amazon.co.uk/Digital-Cameras...Photography-Bundles/b?) - Cached  
 Results 1 - 24 of 5287 - Online shopping for **Digital Cameras** from a great selection of  
 Electronics; Point & Shoot **Digital Cameras**. Digital SLRs, Compact System ...

**What Digital Camera. digital camera reviews and photography tips...** 🔍 👤  
[www.whatdigitalcamera.com/](http://www.whatdigitalcamera.com/) - Cached  
 What **Digital Camera** magazine, featuring **digital camera** reviews, **digital camera** best

**1/2 Price Digital Cameras** 🔍 👤 Ads  
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**Amazon Cameras** 🔍 👤  
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 viking-direct.co.uk is rated ★★★★★  
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 Buy Compact or SLR **Digital Camera**,  
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**Digital Cameras At Very** 🔍 👤  
[www.very.co.uk/DigitalCameras](http://www.very.co.uk/DigitalCameras)  
 Buy Now Pay Later **Digital Cameras**  
 at Very & Grab a Great Deal Today!

Customized for user and query

Complicated auction computation

# Search ads auction

## Predicted Click-Through-Rate (pCTR)

The image shows a search engine results page for the query "digital camera". Two callout boxes highlight specific ads and their associated bid and predicted click-through rate (pCTR) values, along with the resulting expected revenue calculation.

**Callout 1 (Left):**

- Bid:** 10¢
- p(click):** 5%
- expected revenue:**  $10 * 0.05 = 0.5c$

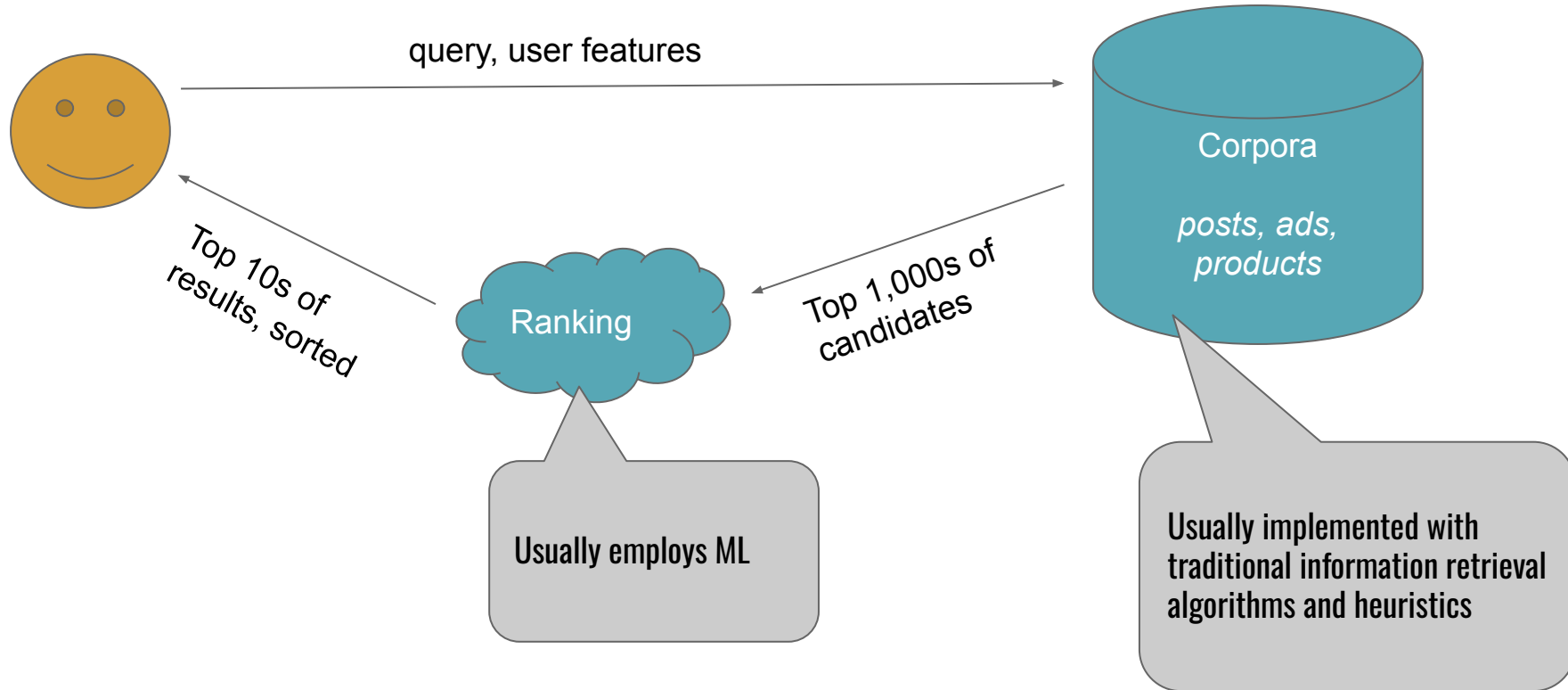
**Callout 2 (Bottom):**

- Bid:** 20¢
- p(click):** 1%
- expected revenue:**  $20 * 0.01 = 0.2c$

**Search Results (Right):**

- 1/2 Price Digital Cameras** (www.money.com/DigitalCameras) - Great Range of Digital Cameras. Buy Now and Pay Later - Littlewoods
- Amazon Cameras** (www.amazon.co.uk/cameras) - Save on Digital Cameras and SLR. Free UK delivery on Amazon Orders
- 10 MP Digital Cameras** (www.viking-direct.co.uk/10MP) - Buy 10MP Digital Cameras at Viking. Buy Now for Next Day Delivery
- Digital Camera Store** (www.connscameras.ie/Digital\_Cameras) - Buy Compact or SLR Digital Camera. Irelands Leading Camera Store!
- Digital Cameras At Very** (www.very.co.uk/DigitalCameras) - Buy Now Pay Later Digital Cameras at Very & Grab a Great Deal Today!

# Recommender system task definition





# Serving scale challenges

Typical usage stats for popular social media platforms:

- Over a billion of users
- Peaks at >500K requests per second
- Has >1,000 candidates to score for each request
- Needs to perform >500M inferences per second to serve the global user traffic

**Serving infrastructure costs many millions of dollars. Must be deployed all over the world, including in countries under sanctions.**

**Cannot naively use big NLP models, such as BERT, GPT-3, etc.**

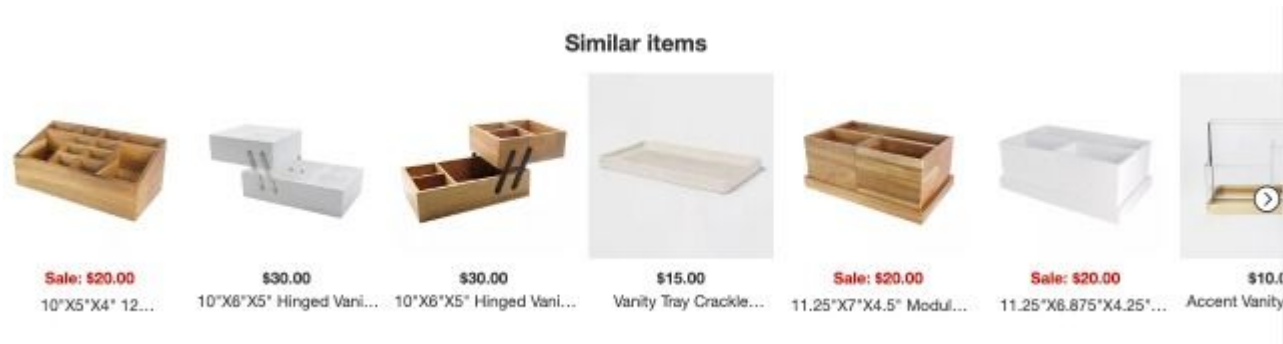


# Objective function

When using ML you need to figure out the objective function

For shopping recommendations it is relatively simple:

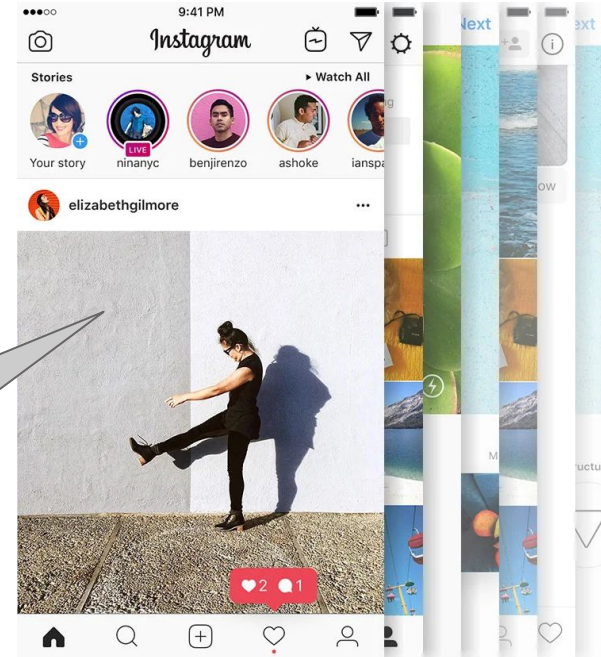
*What items are purchased after viewing this item*



# Objective function

How do you define the objective function for ranking social media posts?

How would a human select the best TikTok videos for me to watch?  
What would you need to know about me?



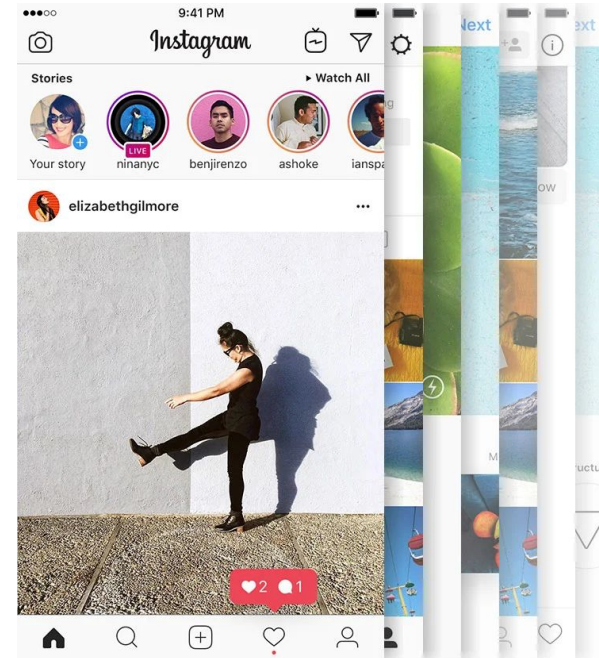
# Objective function

How do you define the objective function for ranking social media posts?

**What are we optimizing for?**

Possible candidates

- Maximize the time spent in the app scrolling the posts
- User spent more time reading the post
- Maximize user engagement, such as "like" button clicks, comments/replies



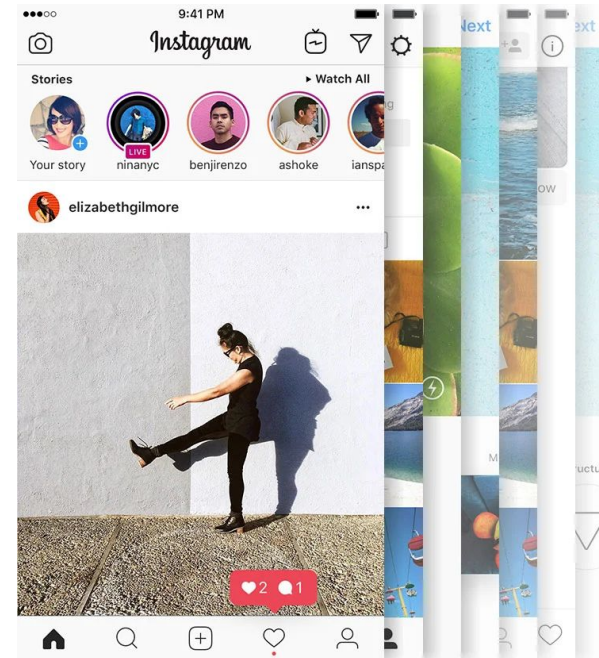
# Objective function

Usually requires complicated models with lots of features and multi-objective functions, which are kept in secret.

**If users spend a few minutes longer per day in the app, the company will make many billions more \$\$\$ in advertising revenues**

**It's important to optimize for long-term user happiness.**

**Companies fight hard to hire ML researchers and infrastructure people**



# Non-stationary problem

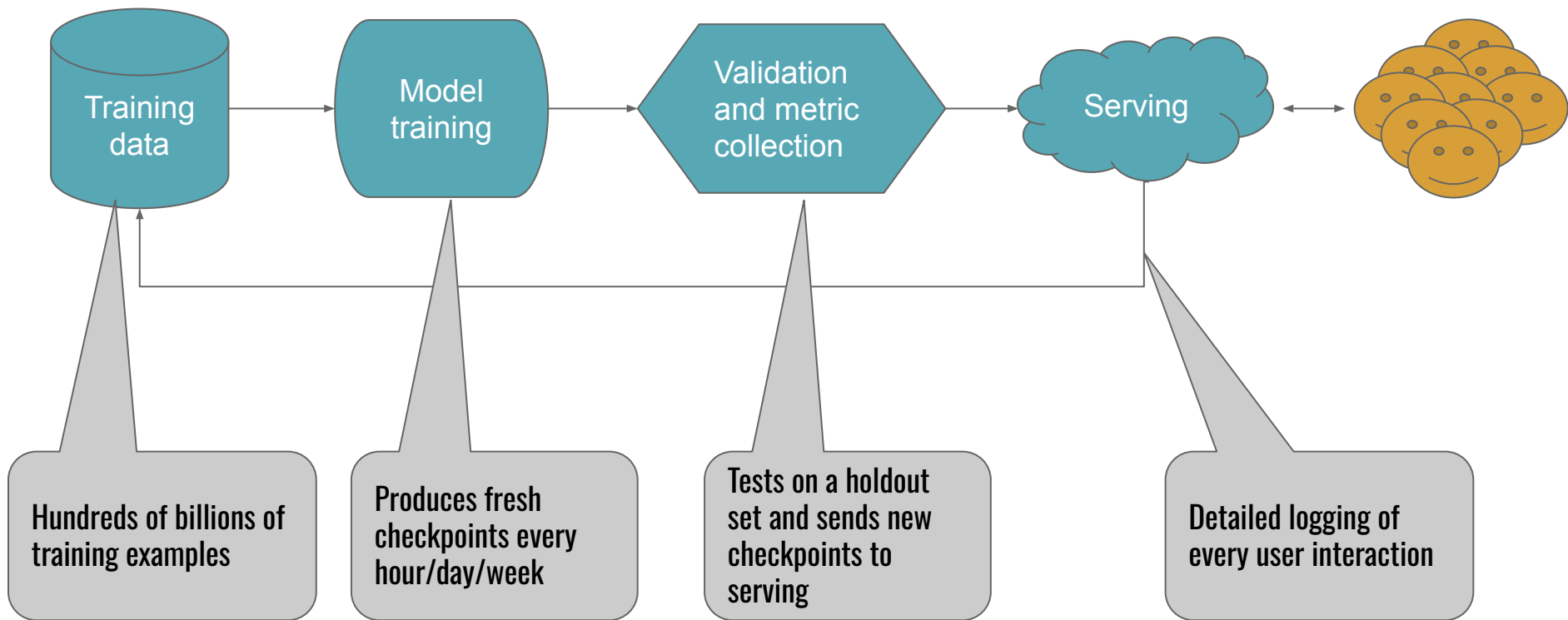
User behavior and the meaning of keywords changes very rapidly.

- World news
  - Science, politics, wars, pandemics, economic and social issues
- Popular events
  - Black Friday, Back-to-School, Oscars, Grammys, Worldcup, Super Bowl
- Trends
  - Fashion, Flashmobs, New art releases

Model quality degrades within days



# Online training



# Common issues with model quality

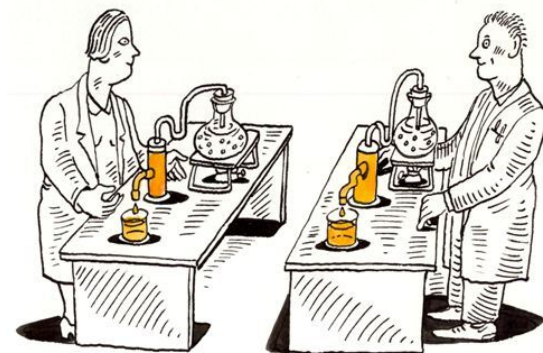
- Model instability
  - Hyperparameters, such as learning rate, are tuned very close to the breaking point to pick up user behavior changes very quickly
  - Usually requires some form of weight normalization and gradient clipping





# Common issues with model quality

- Reproducibility
  - A retrain of a model should yield the same accuracy up to 0.01%, otherwise ML researchers can't experiment with new models
  - Due to the distributed nature of training infrastructure the training sample visitation is not deterministic
  - Non-stochastic properties of Deep Neural Networks
  - See [Reproducibility in Deep Learning and Smooth Activations](#)



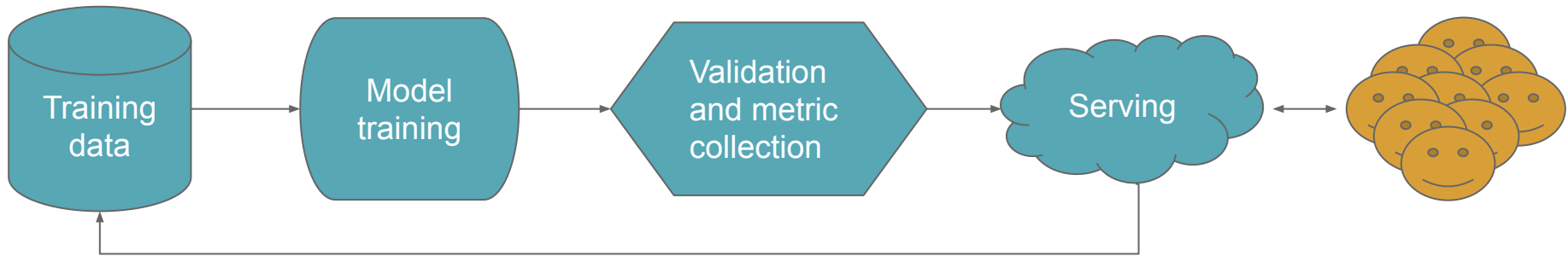
# Common issues with model quality

- Ingestion of bad data + ripple effects
  - Happens when an upstream system misbehaves, e.g. the "buy" button gets broken for several hours, which skews the training data
  - The model starts making wrong predictions and new logs get poisoned as well
  - This creates a ripple effect that is very hard to deal with. Usually requires reverting to older checkpoints and isolating large ranges of training data.



# Common issues with model quality

- Feedback loop problem
  - A freshly-trained model performs poorly when it starts serving user traffic for the first time
  - It has not seen enough bad examples, because it was trained only on data that was filtered by previous iterations of the model



# Training data

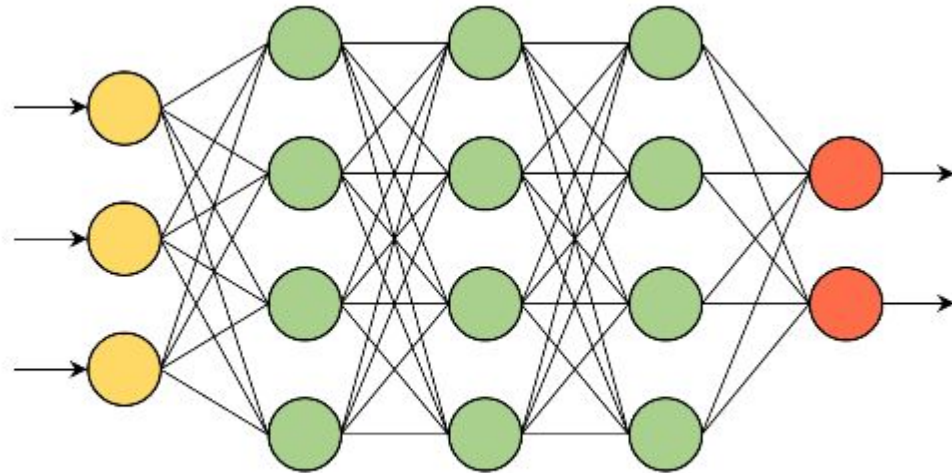
## Input data

User:

*User preferences,  
Language, Region,  
Browser, device, ...*

Post/Ad/Product:

*Creators, title,  
content, price, rating*



**Input layer**

**Hidden layers**

**Output layer**

## Labels

User interactions:

*Post viewed  
Time spent viewing  
the post  
Like button clicked  
Comment left*

# Training data

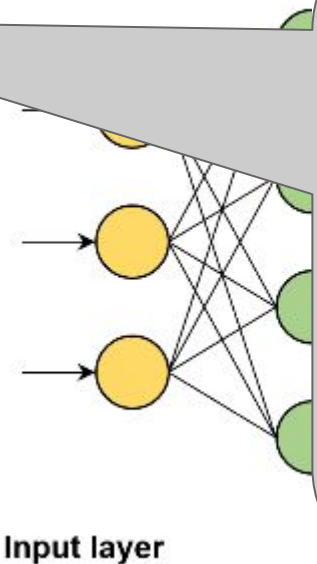
## Input data

User:

*User preferences,  
Language, Region,  
Browser, device, ...*

Post/Ad/Product:

*Creators, title,  
content, price, rating*



Hundreds of features, a lot of textual information.

Need to make sure that features are available at serving time. E.g. whether the user clicked on the post is not a good feature.

Deep Neural Networks work with vectors of floating point numbers, not with text, especially not with variable-length features

Heavy usage of embedding tables

If computation capacity allows in serving sequences can be processed using large language models, such as Bert, GPT-2/3

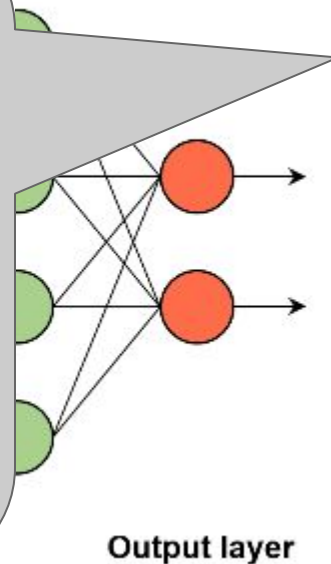
Embeddings are also useful for memorizing non-textual information

# Training data

Labels are often binary indicator whether an event happened or not.  
E.g. whether the user clicked on the "like" button.

However, the model outputs the probability of an event.  
E.g. the probability that the user clicks on the like button is 0.0343

This means that the losses are always high, even when the model is well trained.



## Labels

User interactions:

*Post viewed*

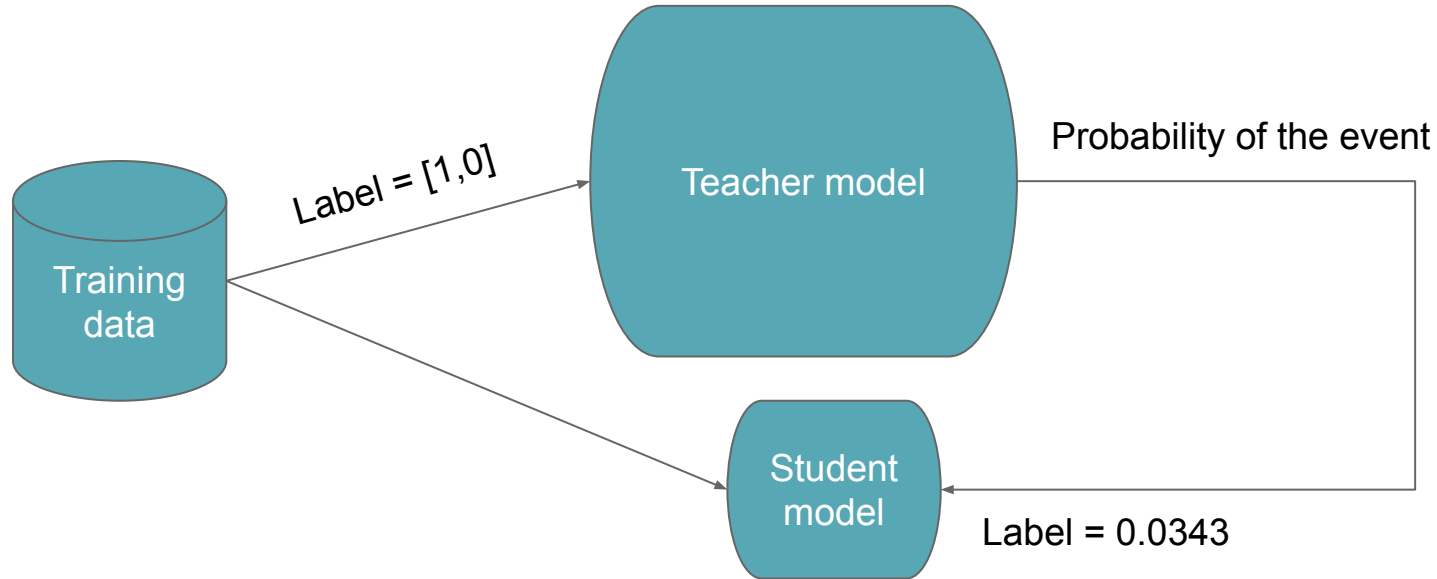
*Time spent viewing  
the post*

*Like button clicked*

*Comment left*

# Teacher - student

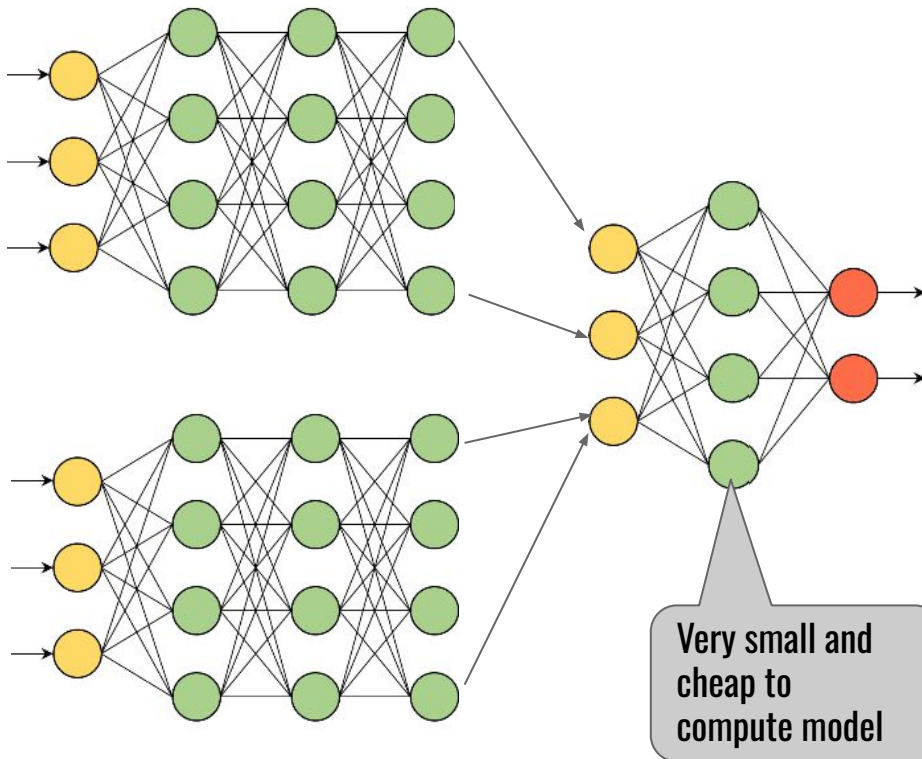
We can train a much bigger model that is unviable for serving and use it as a "teacher" for a production model.



# Splitting models

## User model:

*User preferences,  
Language, Region,  
Browser, device, ...*



## Post/Ad/Product model:

*Creators, title,  
content, price, rating*

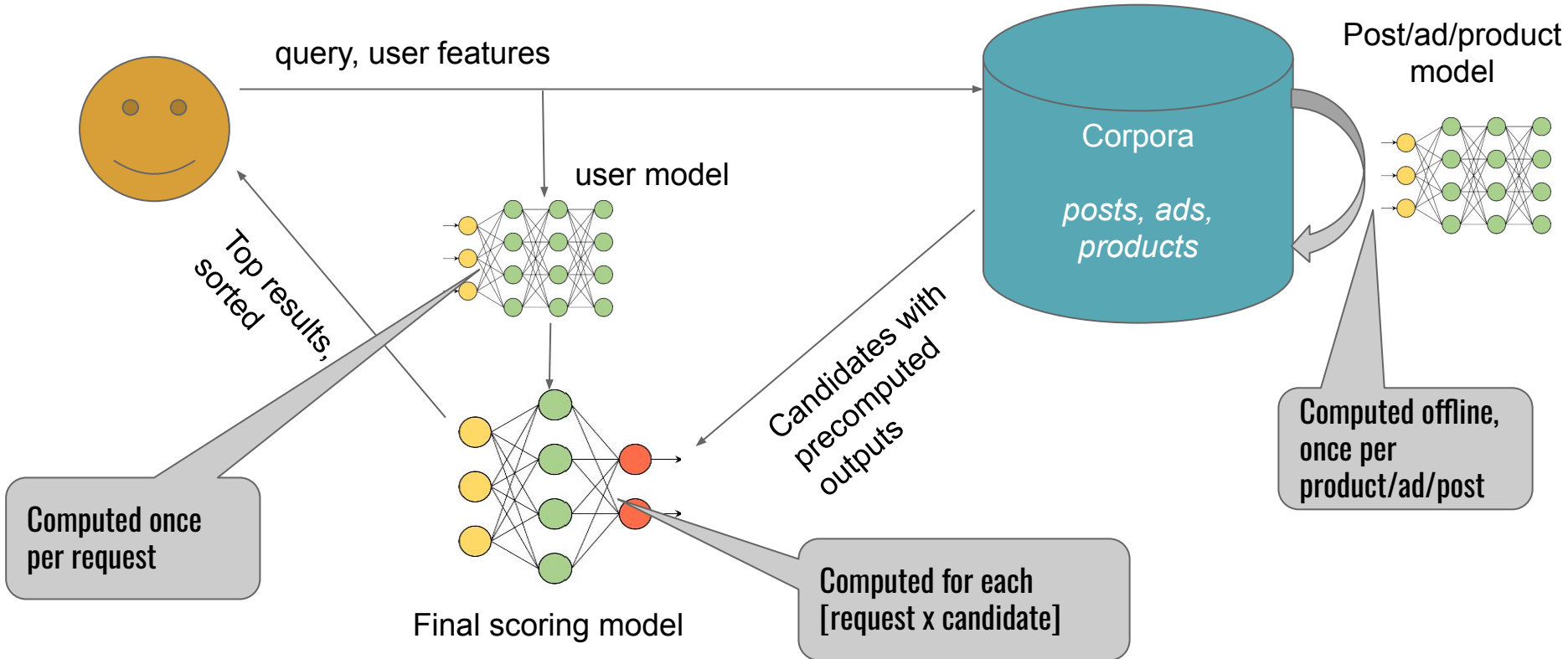
## Labels

### User interactions:

- Post viewed*
- Time spent viewing the post*
- Like button clicked*
- Comment left*



# Splitting models



# Splitting models

- Greatly reduces serving cost
- Usually worsens the quality, because user and candidate post features aren't mixed in the neural network
- Adds a lot to system complexity

# Parting words

We briefly discussed some interesting issues with building and deploying ML models

Here are some topics that we haven't talked about:

- Privacy issues and protections
- How to evaluate model quality
- Additional model distillation techniques
- Special optimizers and other techniques for asynchronous distributed training
- How to deal with late arriving data
- How to maintain models that train for months
- How to maintain feature definitions
- And many other topics

# Thank you!

## Questions?