Google Cloud

Recommendation Systems

Advanced ML with TensorFlow on GCP

End-to-End Lab on Structured Data ML

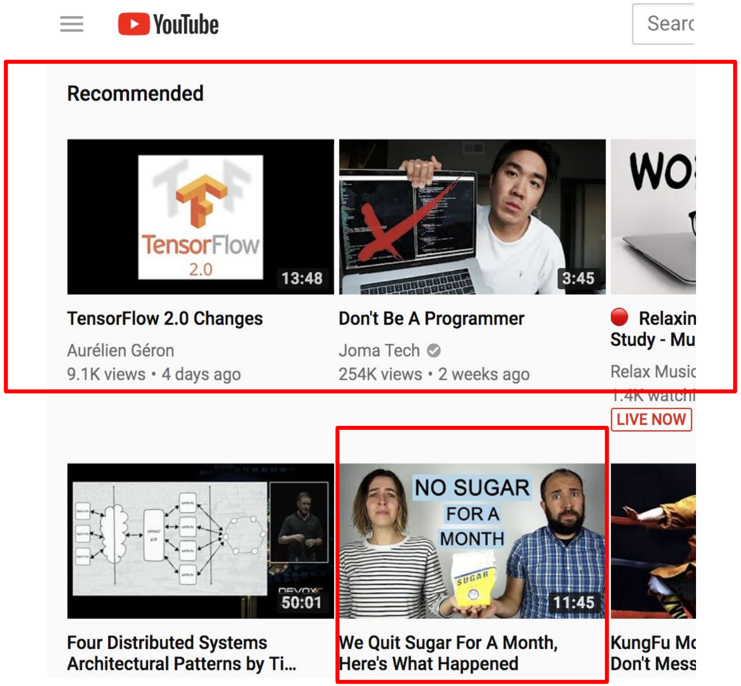
Production ML Systems

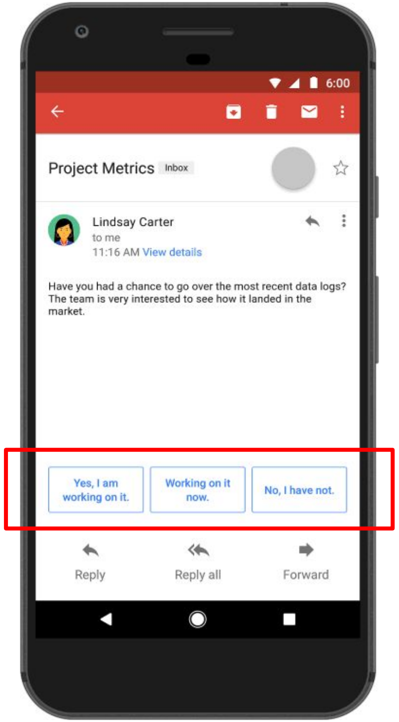
Image Classification Models

Sequence Models

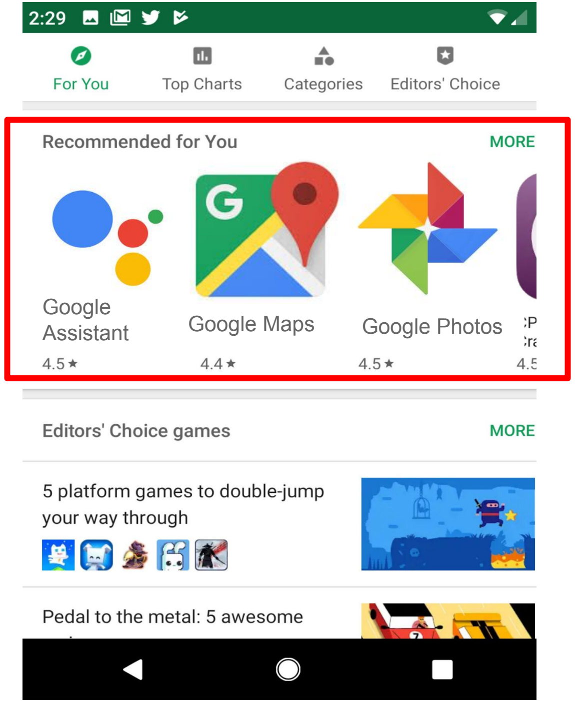
Recommendation Systems

Recommendation engines can make a range of different recommendations



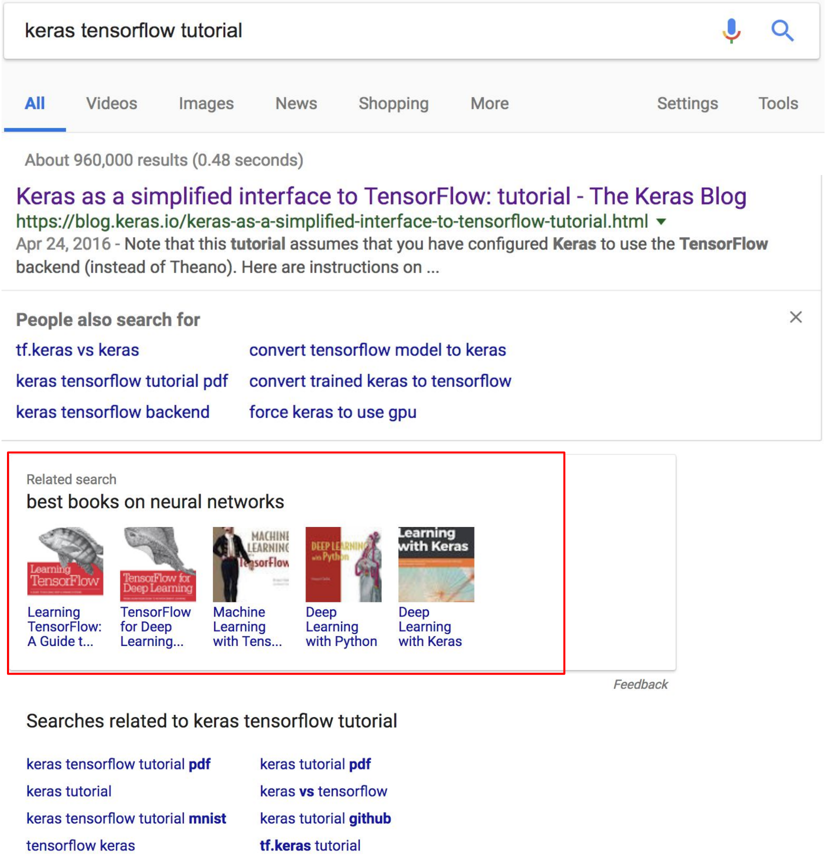


Recommender systems allow us to personalize a user's experience



Google Search is a great example of how recommendation engines provide personalization

Recommenders help you find content that goes together



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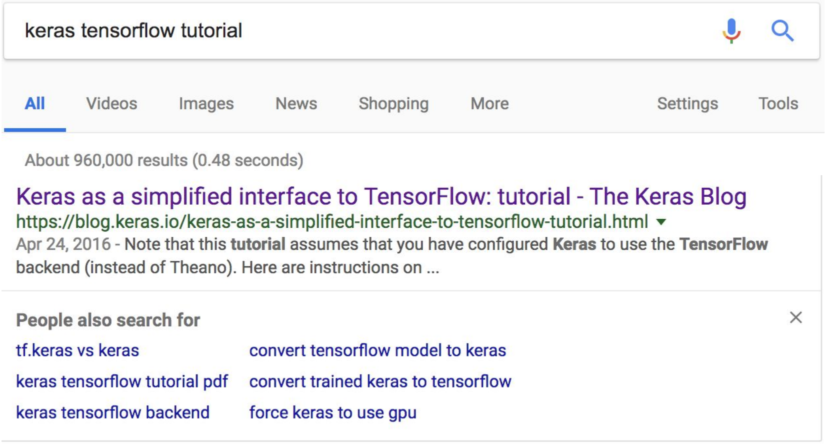
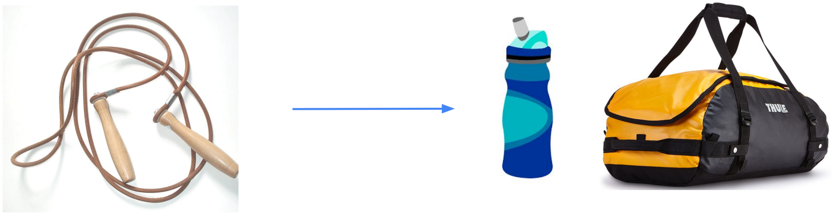
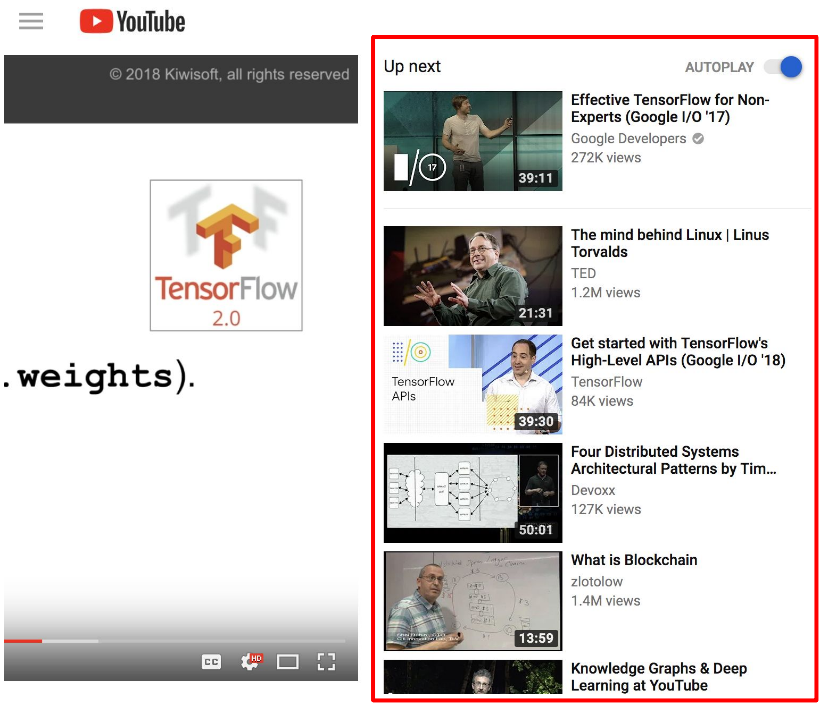
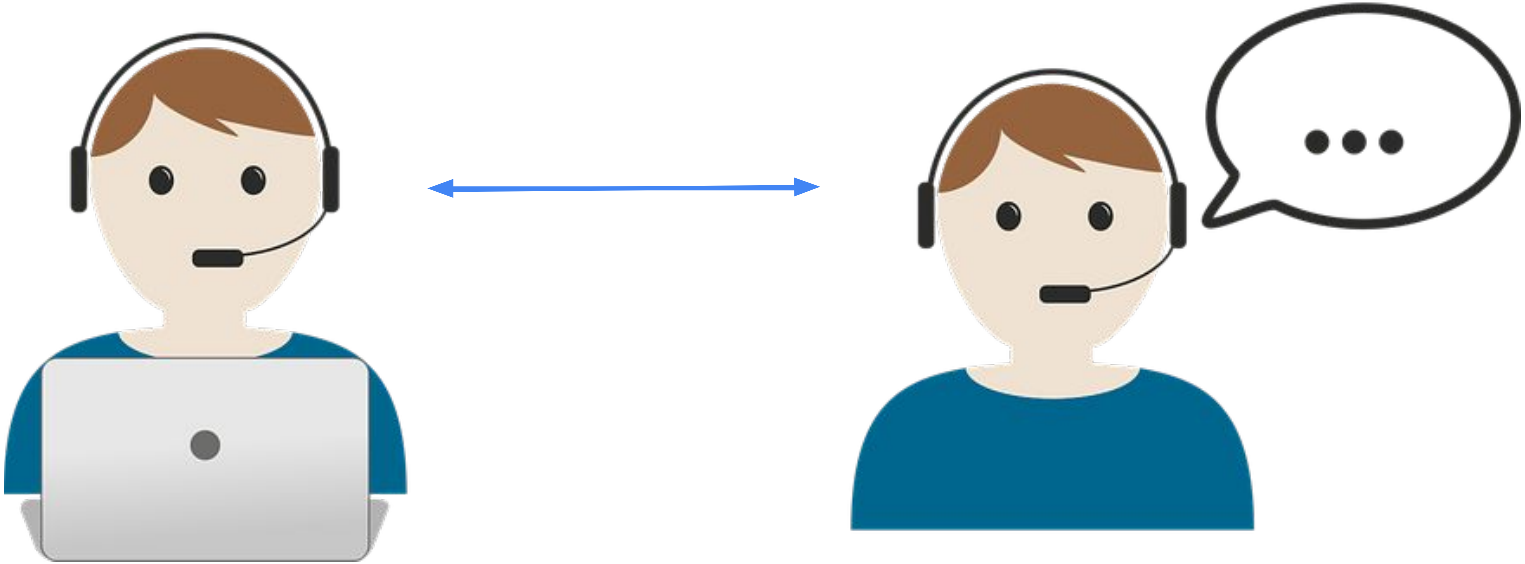




Recommender systems provide a way to keep us engaged



Recommender systems have become an important way for businesses to interact with their customers



Recommender systems provide benefit for both people who provide them and people who use them

1. Help users find related content.
2. Help users explore new items.
3. Improve user decision making.

There are benefits for producers of recommendation systems too

1. Increase user engagement.
2. Learn more about customers.
3. Change user behavior.

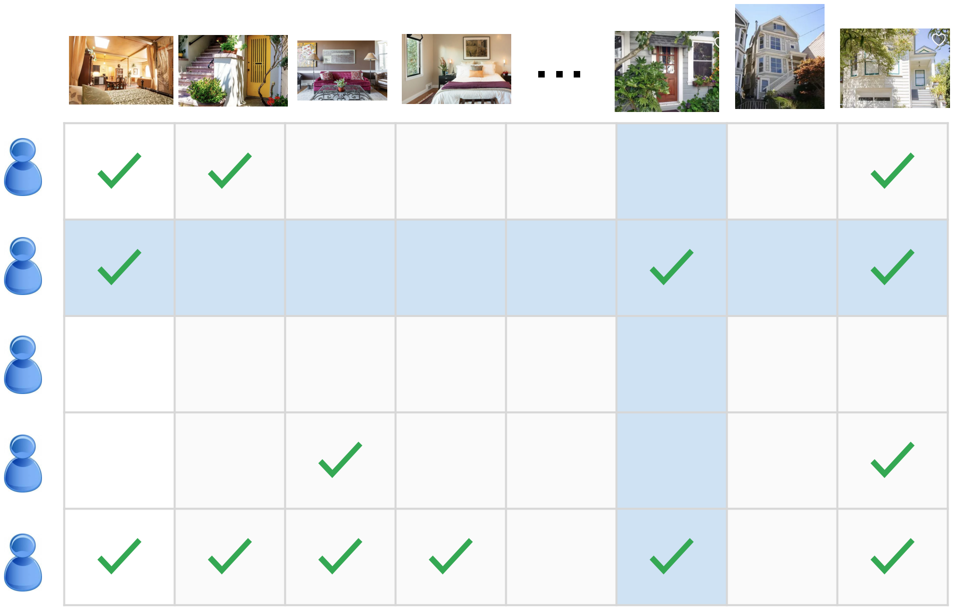
Learn how to...

Distinguish between different type of recommendation engines.

Design and build your own recommendation engine.

Anticipate common problems that arise when developing recommendation engines.

How would you recommend a vacation house to a user?

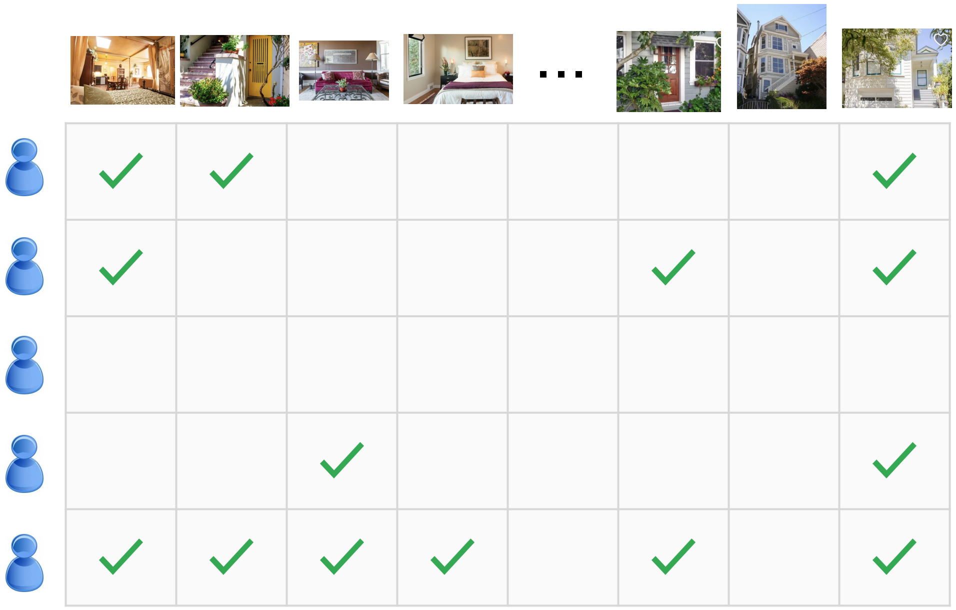


user-item interaction matrix

Lab

Design a recommendation engine for vacation property rentals

How would you recommend a vacation house to a user?



Features

Properties of the user
Properties of the house

Previous rentals of a user
Previous renters of a house

Compare similar users
Compare similar items

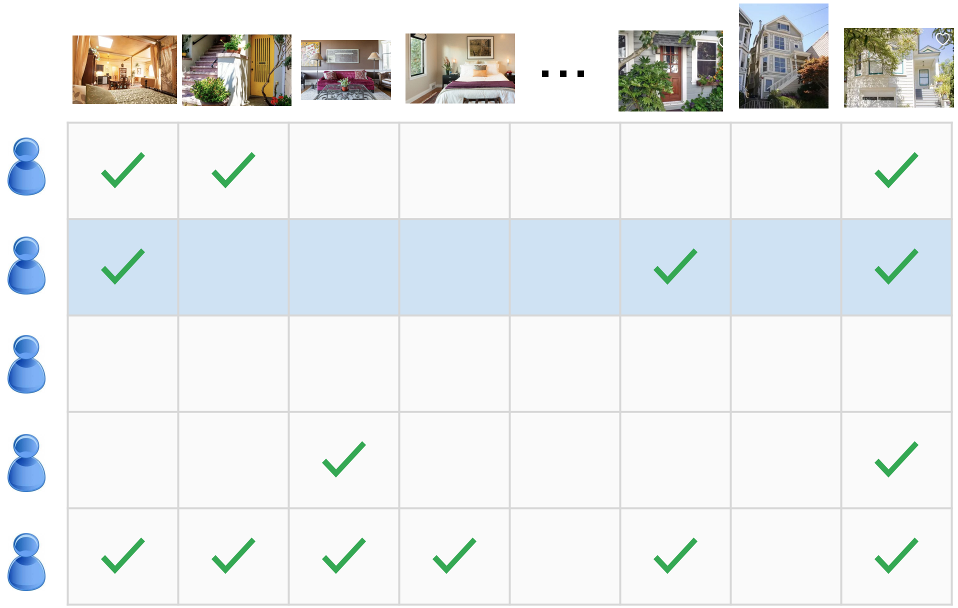
Targets

Rating for unseen properties
Next rental property

Popular types of recommendation engines

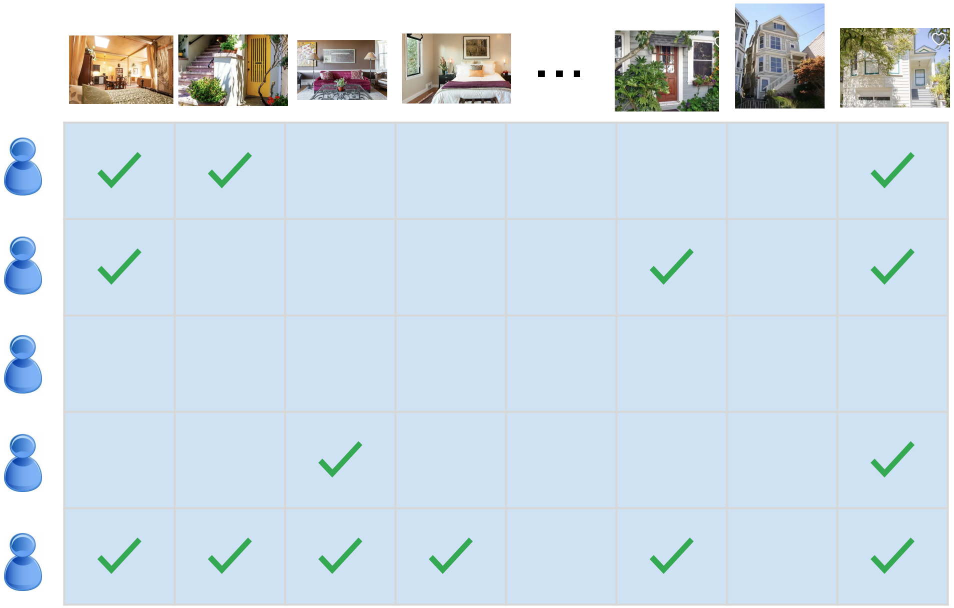
1. Content-based recommender system
2. Collaborative filtering
3. Knowledge-based
4. Deep neural networks

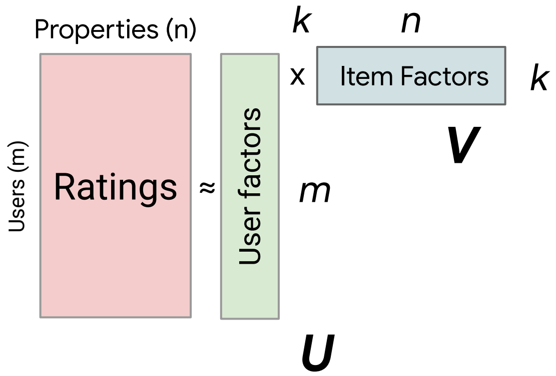
Content-based filtering uses attributes of the items to recommend new items to a user



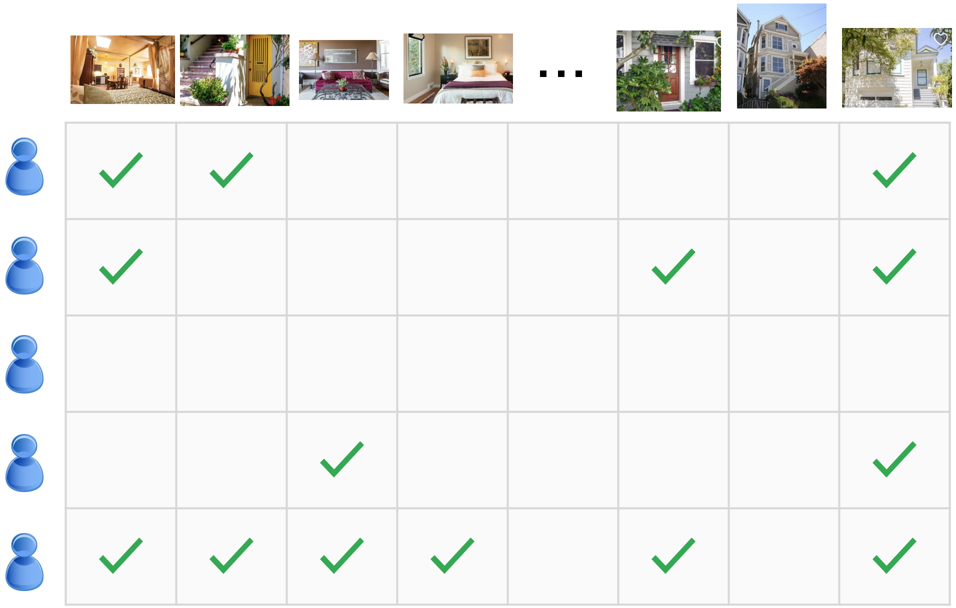
Doesn't take into account the behavior or ratings of other users.

Collaborative filtering uses similarities between users and items simultaneously to determine recommendations





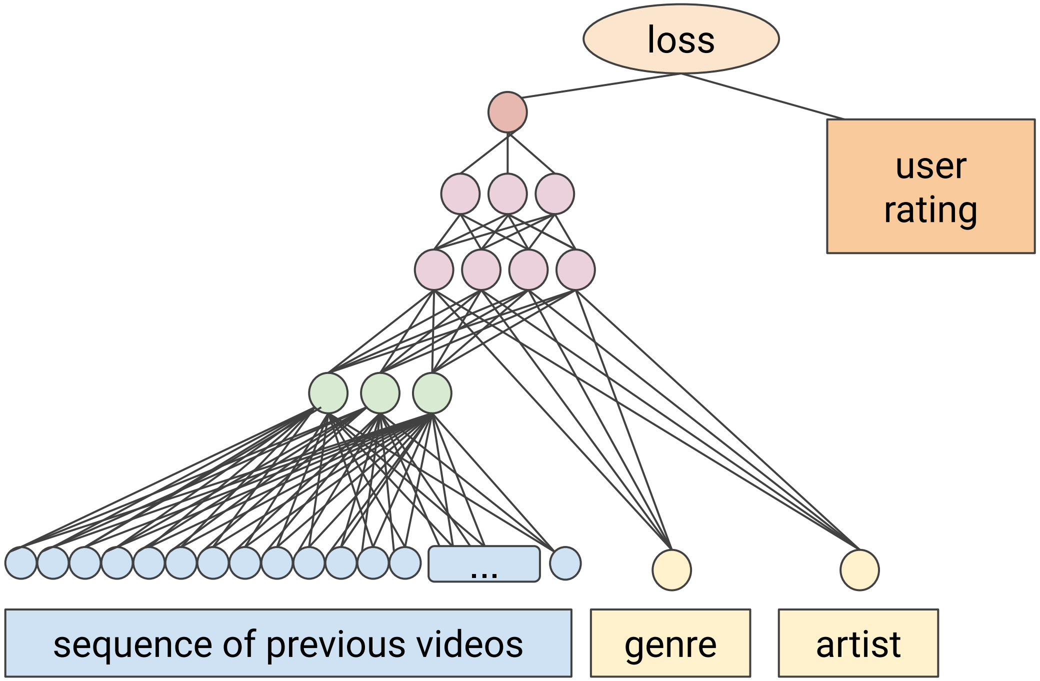
Knowledge-based recommender systems use explicit knowledge



Use explicit knowledge about the users, items, and recommendation criteria.

Often there is value in combining different types of recommendation models into a single hybrid approach

Deep neural networks can be trained to predict ratings based on user and item attributes



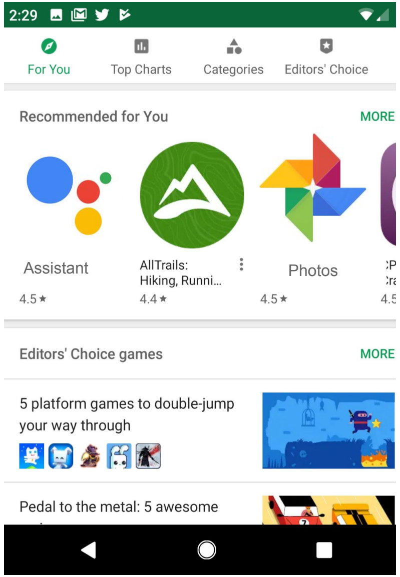
Quiz: The model recommends a hiking app to a user because they recently installed a similar app. This is an example of what kind of filtering?

A. Content-based filtering

B. Collaborative filtering

C. Deep neural network

D. Hybrid approach



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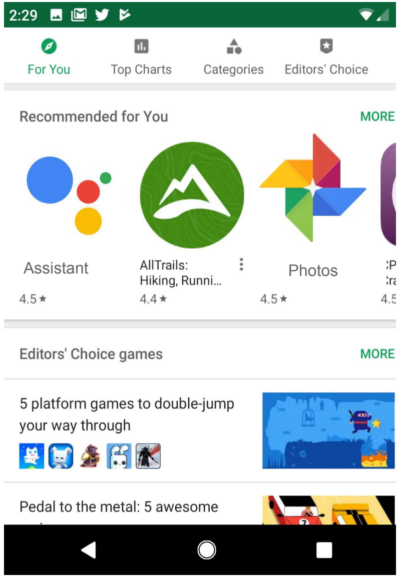

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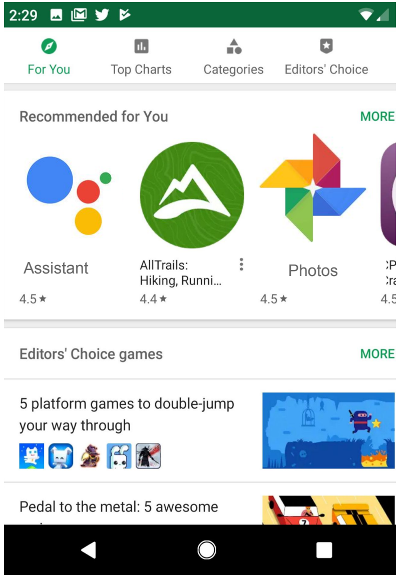
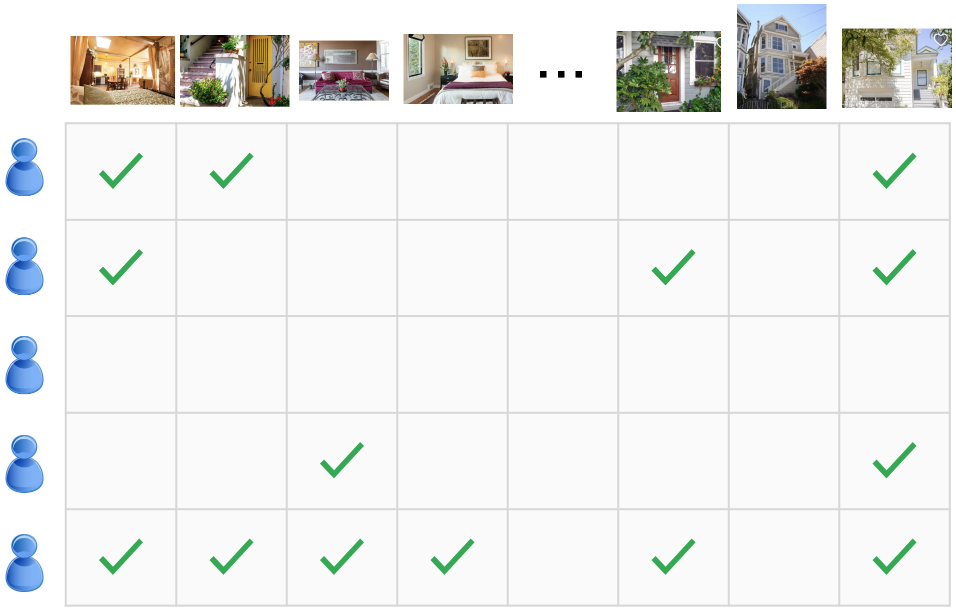


The user space and product space are sparse and skewed



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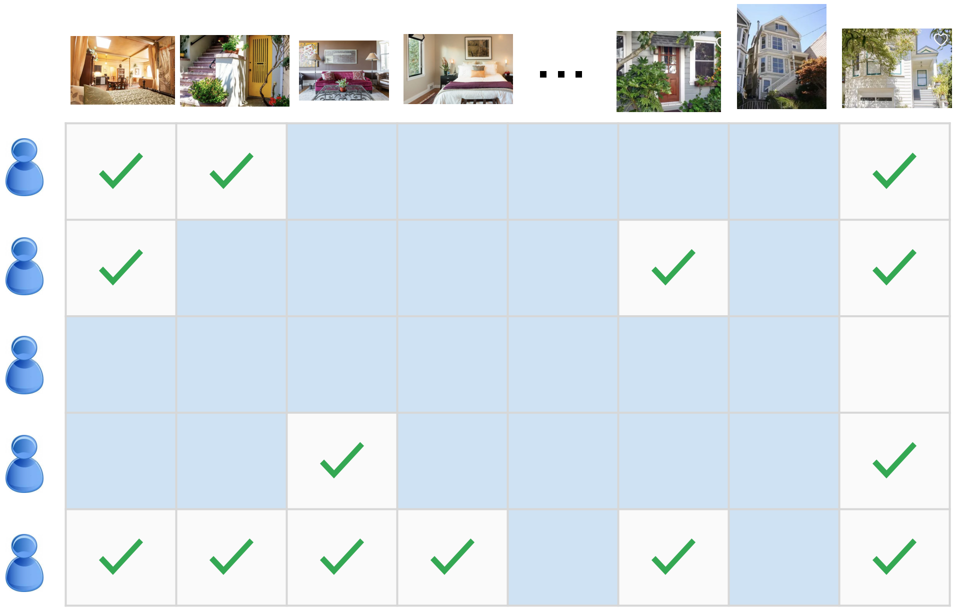
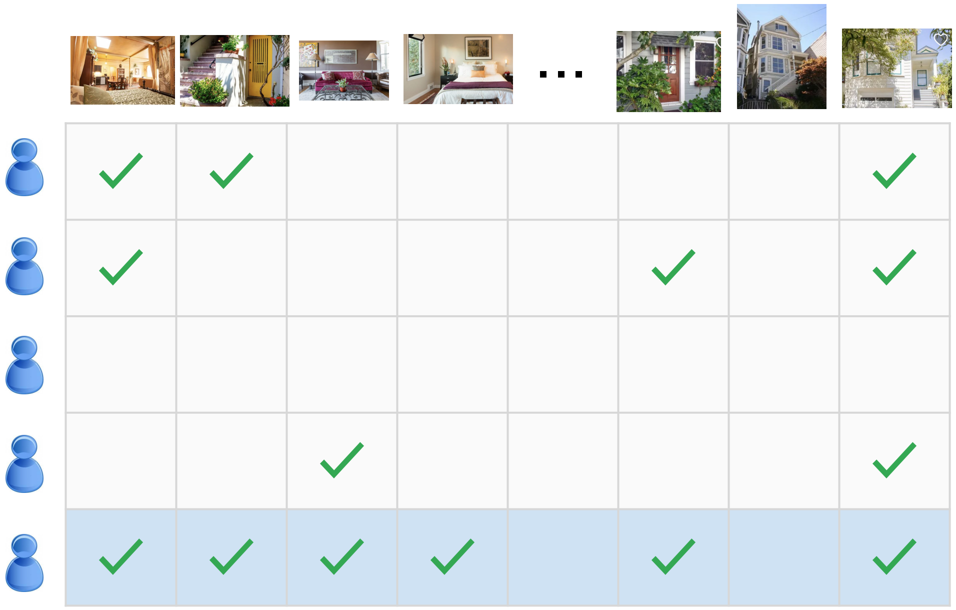


Most items are rated by very few users.

Most users rate only a small fraction of items.

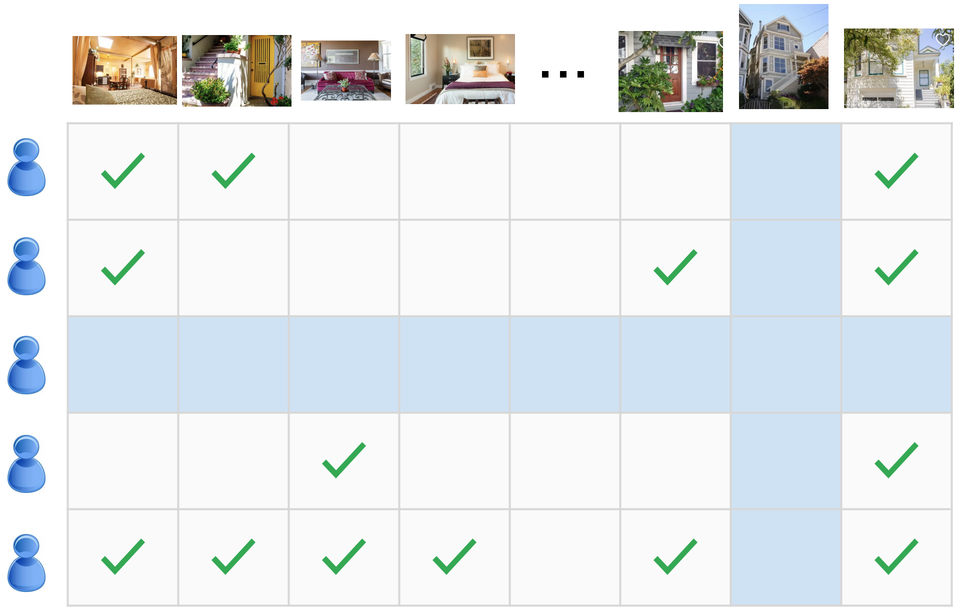
The user space and product space are skewed



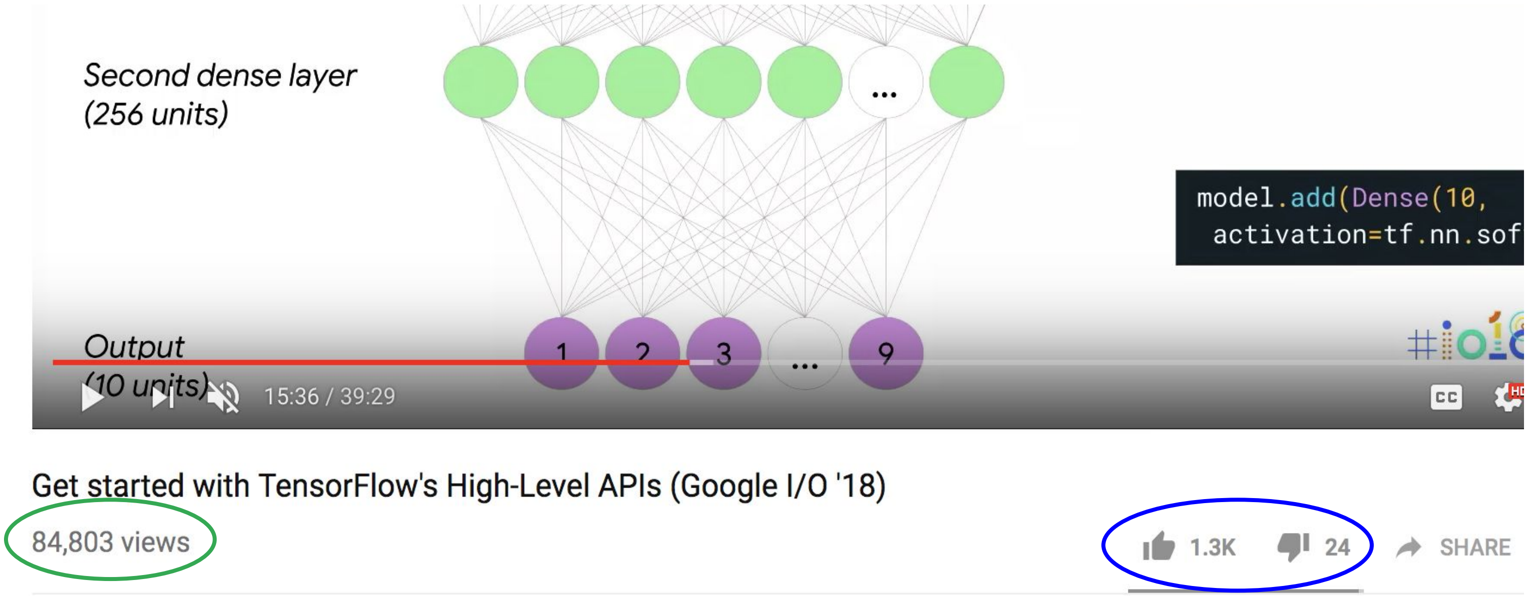
Some properties are very popular.

Some users are very prolific.

The cold start problem occurs when there aren't enough interactions for users or items

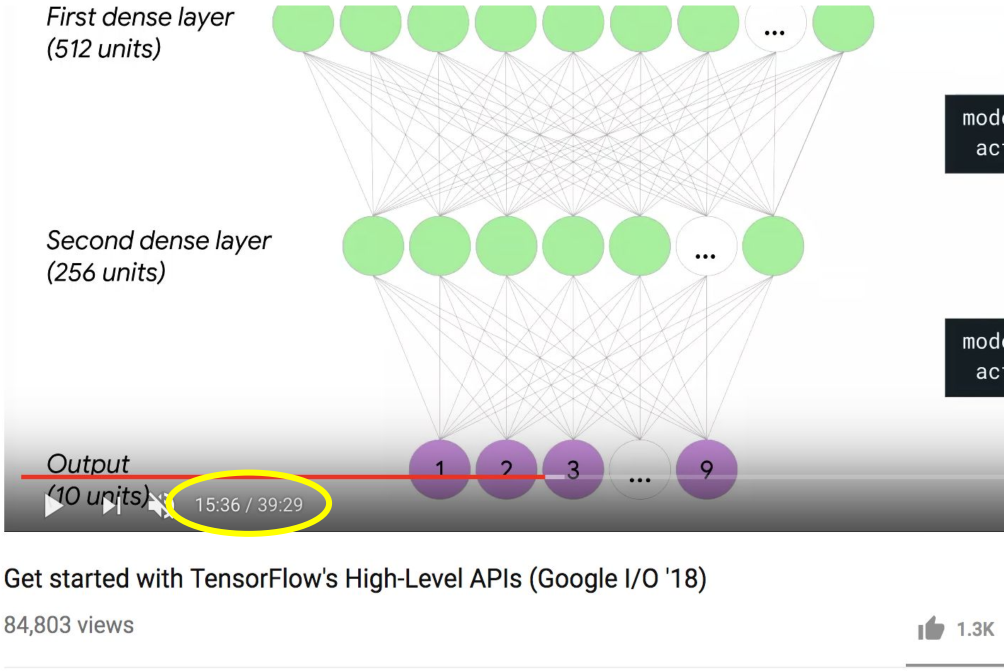


Explicit user feedback is often rare or unobservable



Implicit feedback is much more readily available

- # of clicks
- Play counts
- Fraction of video watched
- Site navigation
- Time spent on page



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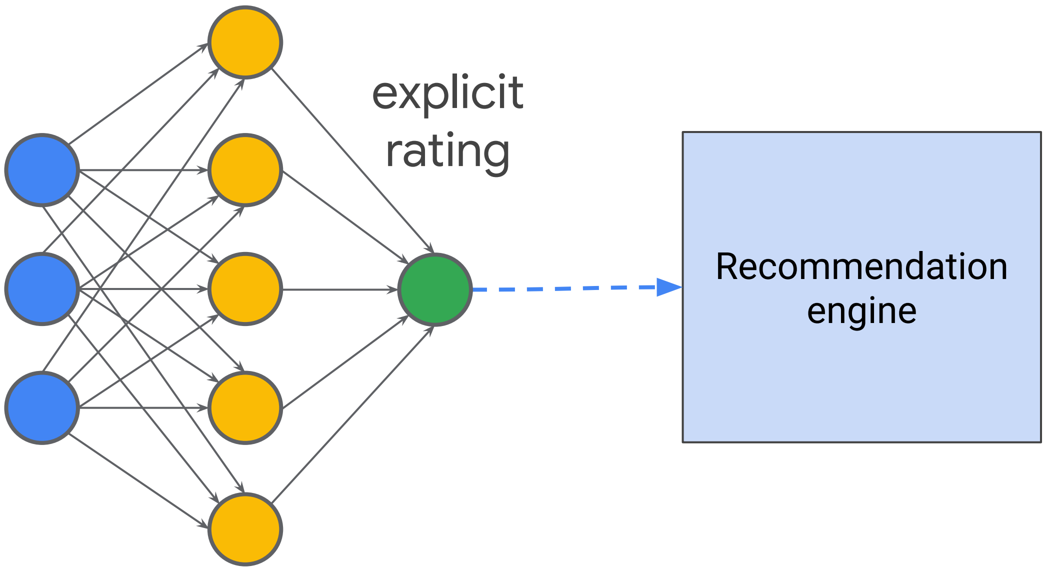

Quiz: Which of the following is NOT a problem that can arise when building a recommendation engine?

A. Sparse user-item rating matrix

B. Not enough user or item interaction information

C. The user-item rating matrix is heavily skewed

D. Too much explicit user feedback data to process

E. Lack of explicit ratings

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Lab

Pick a personalization need for your company and design a recommendation system around it

Quiz: Which of the following are good reasons to build and use a recommendation engine?

A. Everything's better with machine learning

B. To personalize the user's experience

C. To direct users to sponsored items

D. The math behind them is really cool

E. To surface relevant content from possibly millions of items

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Summary

Different types of recommendation engines

How to design your own recommendation engine

Problems that arise when developing recommenders cloud.google.com