

Recommender Systems || Lecture 13

Summer 2022

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UW, Seattle

August 17, 2022

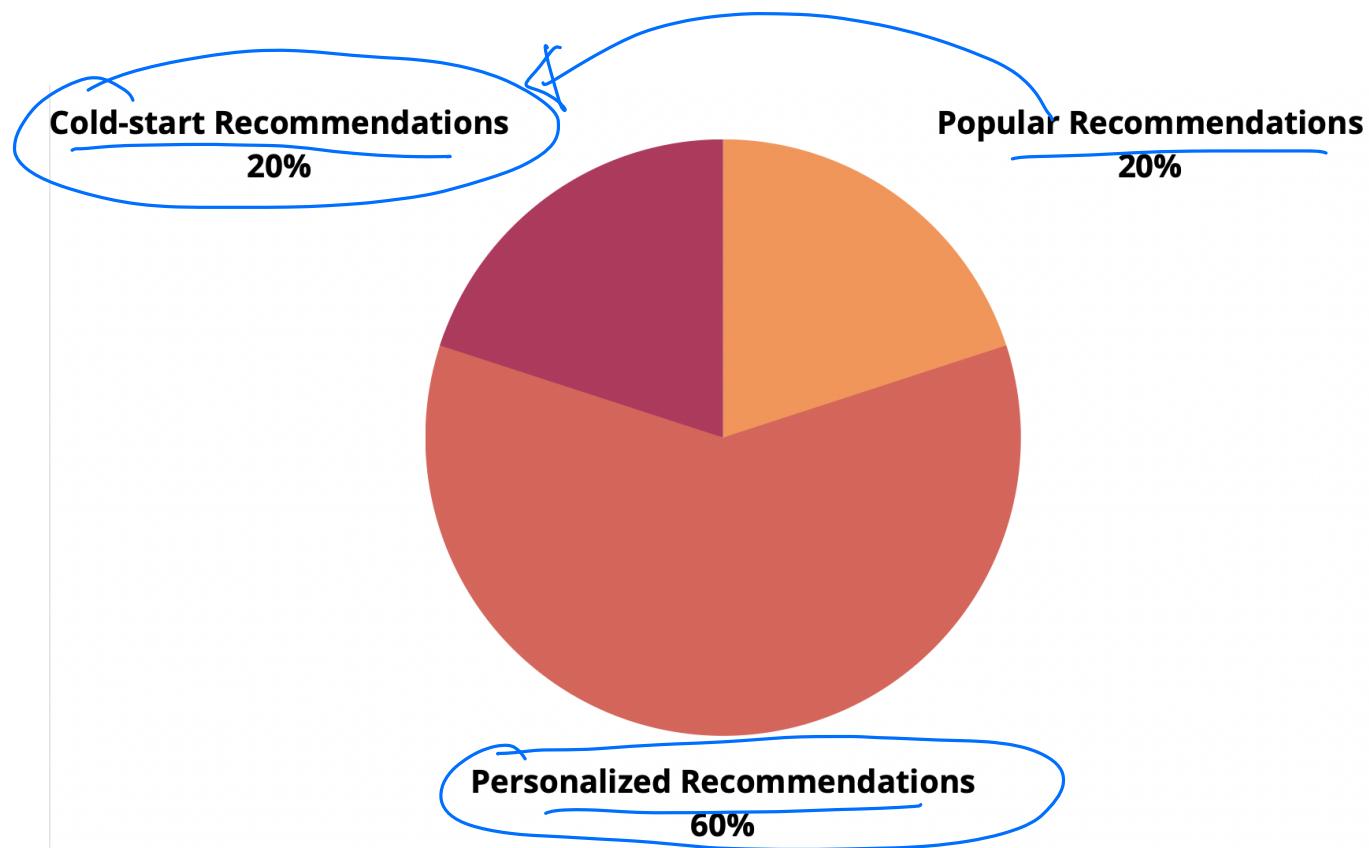
Today

- ① Recap and Review of Recommender Systems

Recommender Systems are Ubiquitous



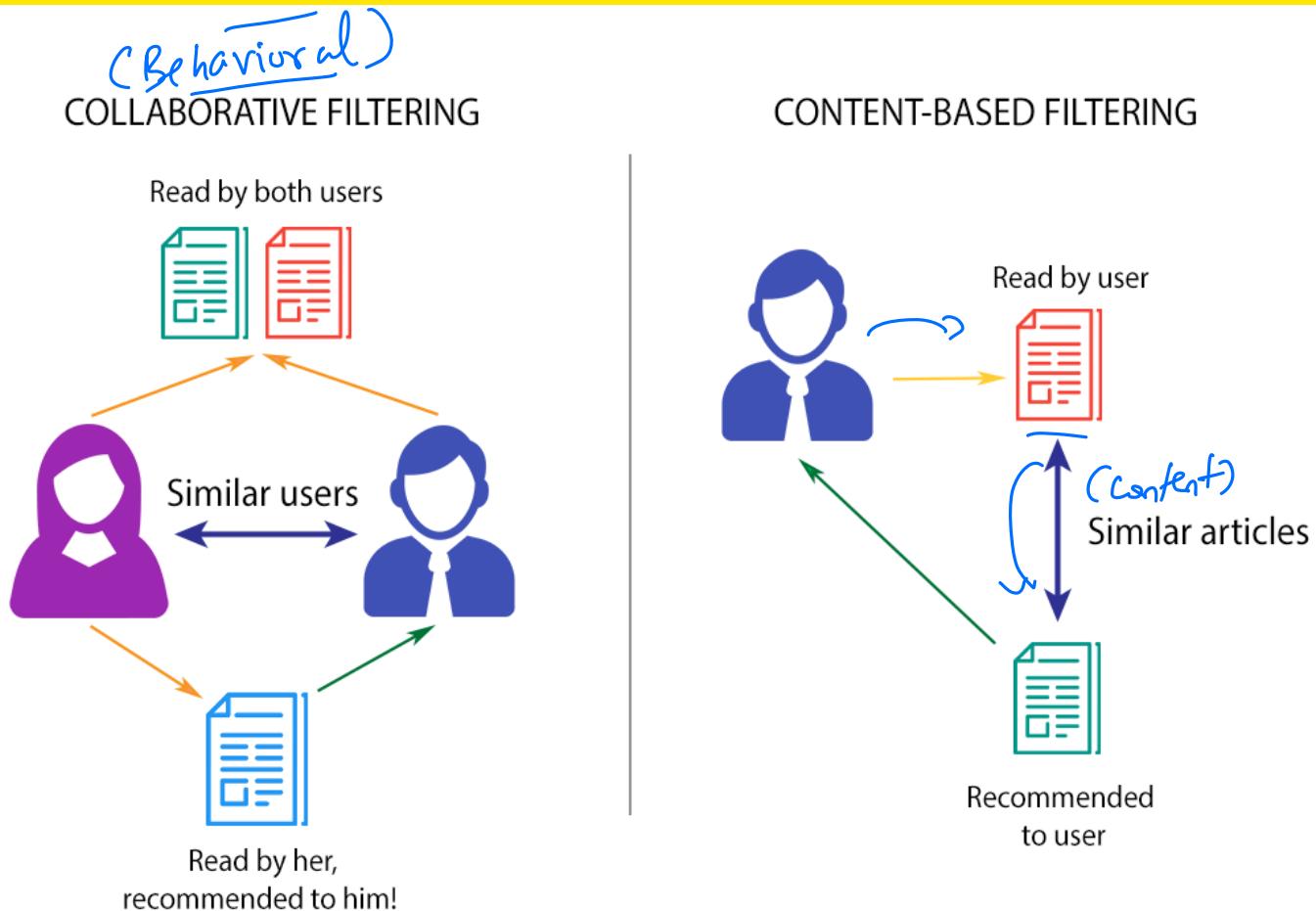
Recommender Types



Recommender Types

- ① Batch Recommender (*offline*) → Compute Recs before a customer shows up
- ② Online/Sessions Recommender → Recs Can change during session

Collaborative filtering vs Content Based Filtering



Item based recommendations

amazon.com

Recommended for You

Amazon.com has new recommendations for you based on items you purchased or told us you own.

LOOK INSIDE!

[Google Apps Deciphered: Compute in the Cloud to Streamline Your Desktop](#)

LOOK INSIDE!

[Google Apps Administrator Guide: A Private-Label Web Workspace](#)

LOOK INSIDE!

[Googlepedia: The Ultimate Google Resource \(3rd Edition\)](#)

Amazon Recommendations

Recommended for you, Thomas

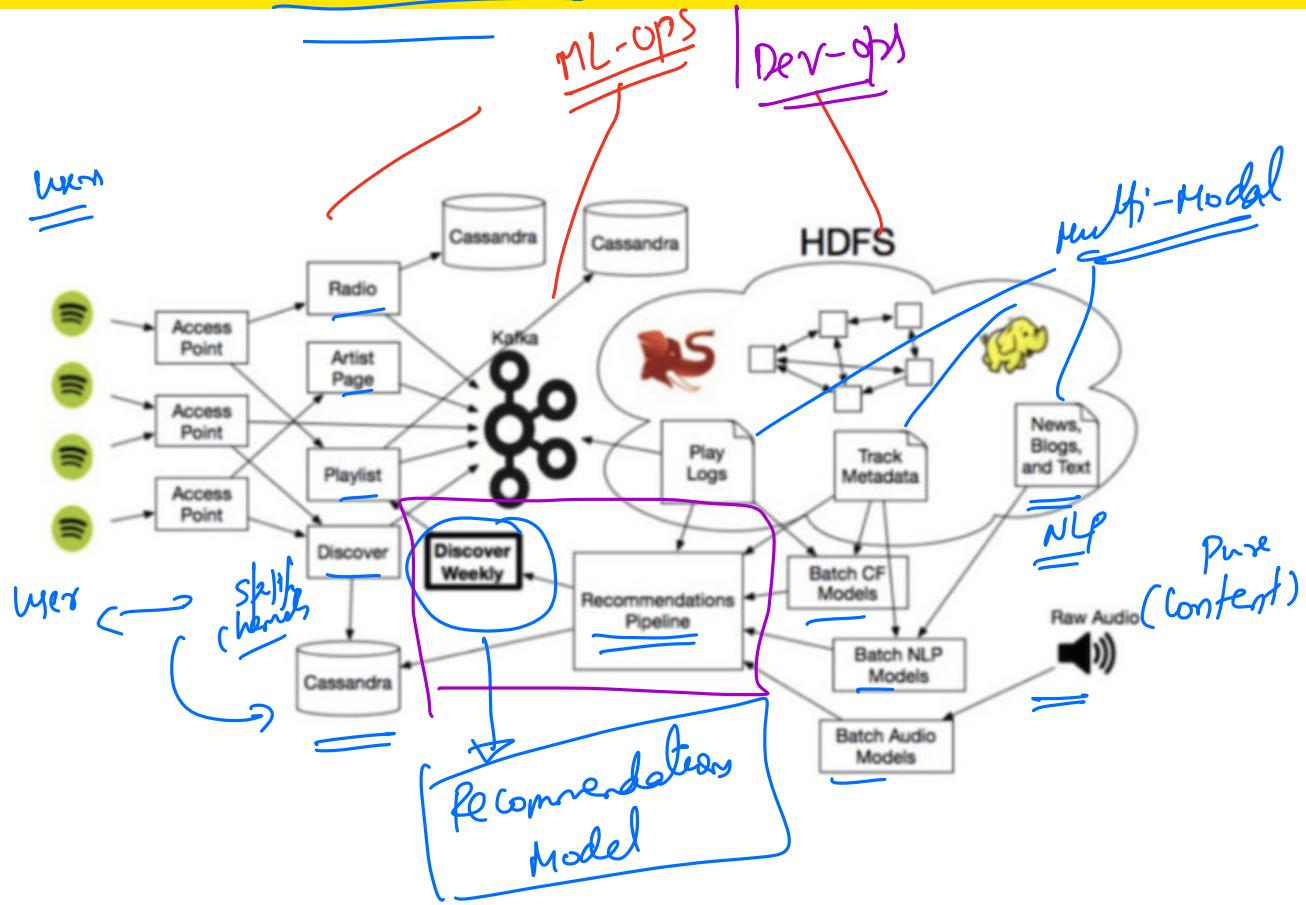
 <p>Literature & Fiction 62 ITEMS</p>	 <p>Exercise & Fitness Equipment 8 ITEMS</p>	 <p>Health, Fitness & Dieting Books 37 ITEMS</p>	 <p>Tableware 12 ITEMS</p>
 <p>Prime Video – Unlimited Streaming for Prime Members 12 ITEMS</p>	 <p>Coffee, Tea & Espresso 98 ITEMS</p>	 <p>Biographies & Memoirs 17 ITEMS</p>	 <p>Engineering Books 7 ITEMS</p>

Spotify Recommendations

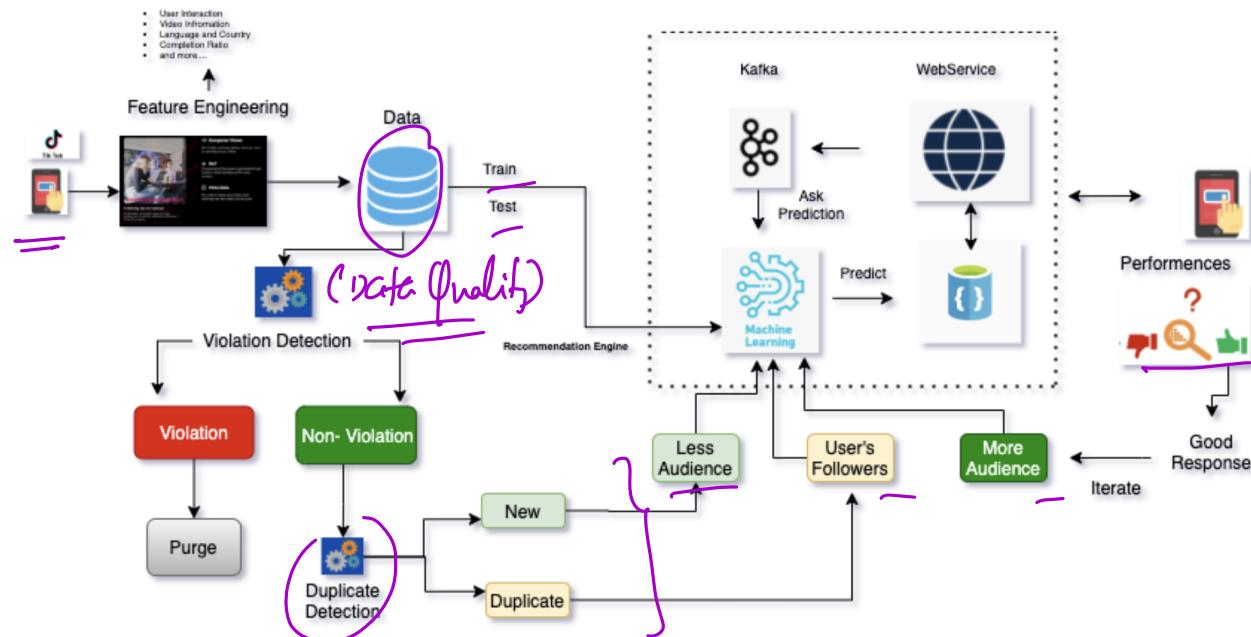
The screenshot shows a Spotify 'Discover Weekly' playlist page. At the top, there are four album covers: 'SICK IN THE HEAD' by Jackson Penn, 'Bad News' by Pat Muresan, 'LIONHEIR All My Life', and 'WITH YOU WITH ME' by Fosternicole. Below the covers, the title 'Discover Weekly' is displayed in large white letters, followed by the subtitle 'New Music For You To Discover!' and the creator information 'Created by Lori Pineda • 25 songs, 1 hr 22 min'. A green 'PLAY' button is on the left, and a 'FOLLOWERS 21,056' link is on the right. Below the main title, there is a 'Filter' input field and a table of song details.

TITLE	ARTIST	ALBUM	DATE
Sick in the Head	Jackson Penn	Sick in the Head	2019-10-03
Bad News	Pat Muresan	Bad News	11 days ago
All My Life	LIONHEIR	All My Life	3 days ago
Whisper Wait	Fosternicole	With You With ...	2019-10-03

Spotify Pipeline System Design



TikTok Recommendations



Recommender Modeling Pipeline Considerations

- ① Data Quality ✓
 ↳ Log Data → Filter
 → Denoise
 → Extract features, etc.
- ② Freshness of Recommendations
- ③ Relevance
- ④ Diversity
- ⑤ Personalized vs Popular
- ⑥ Offline vs Online Evaluation
- ⑦ Recommendation Metrics vs Business Metrics

High Data quality

Recommender Modeling Pipeline Considerations — Data Quality

- ① Often Noisy
 - ② Multiple Data streams - E.g. video meta data, video content, video text description, etc for video recommendations
 - ③ Click Data vs Engagement Data
 - useful
 - not useful
 - Bots
- video-user interaction data (behavioral)*

Recommender Modeling Pipeline Considerations — Freshness

- ① Fashion ↴
- ② Music ✓ (Pending)
- ③ News

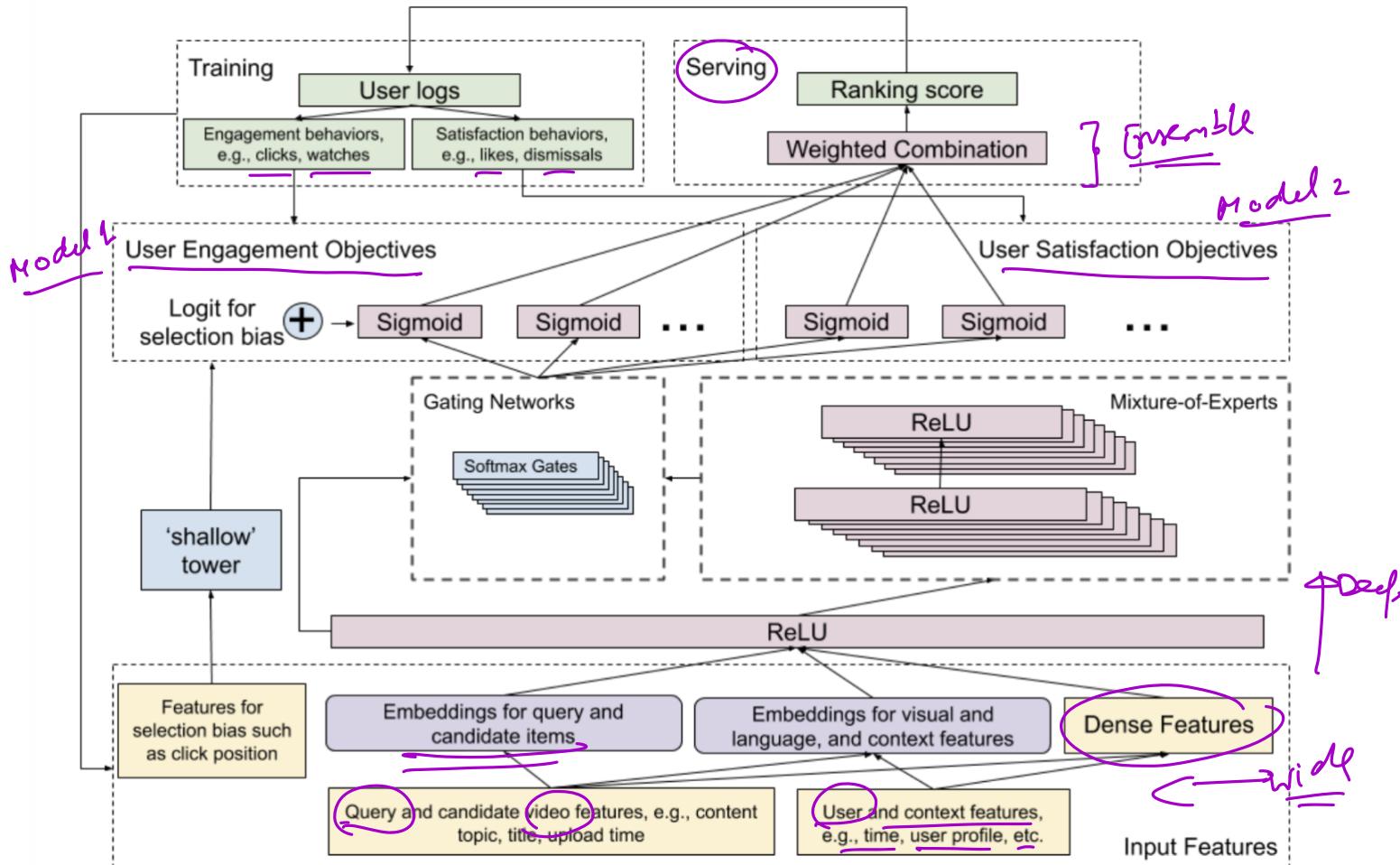
Recommender Modeling Pipeline Considerations — Relevance

- ① Bread and butter of recommendations modeling
- ② Relevance to the point of “The app understands me”
- ③ Relevance models for both cold start and regular customers
- ④ Deep Relevance models - Using deep learning for Relevance modeling

Recommender Modeling Pipeline Considerations — Deep Relevance

- ① AutoRec
- ② DeepRec
- ③ Multi-Layer perceptron
- ④ Session based recommendations: Uses LSTM/Sequential models
- ⑤ YouTube Recommendations is a good example of multi-modal, multi-objective, ensemble based deep and wide recommendations model

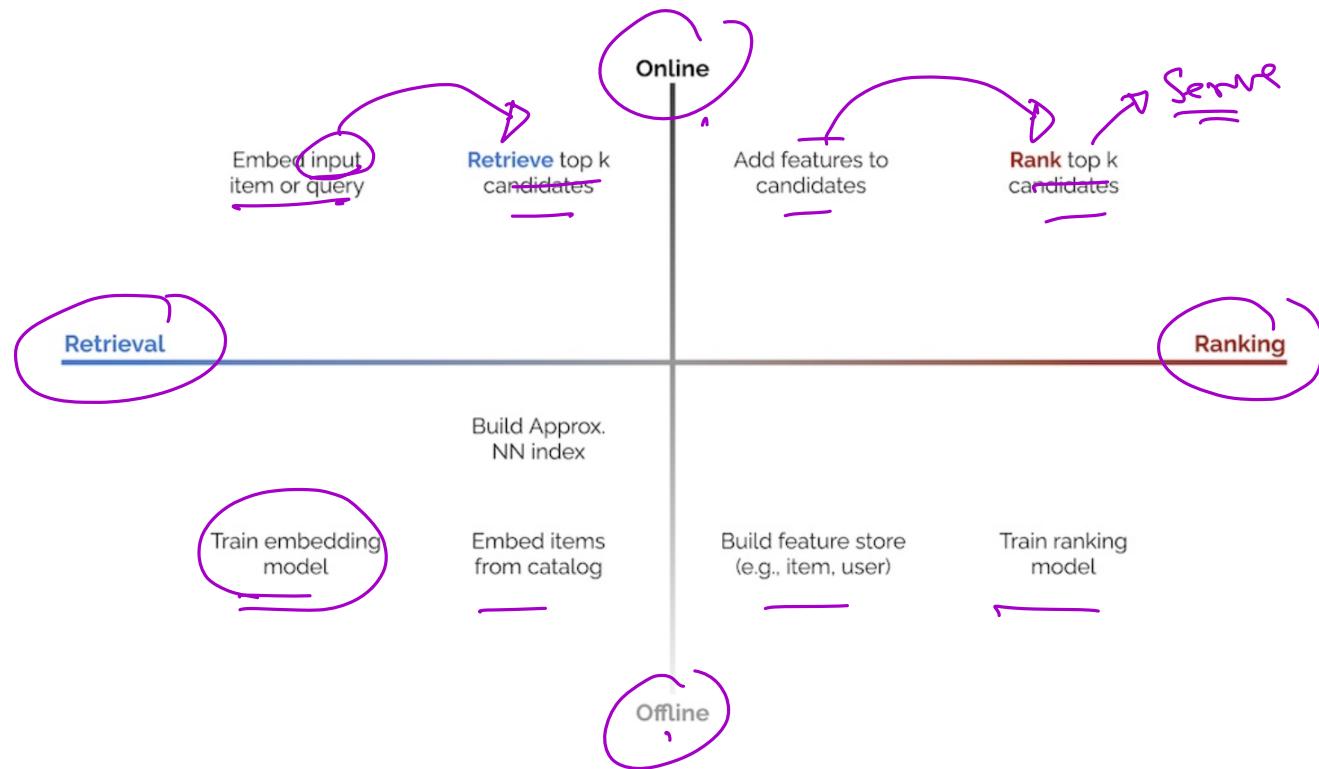
YouTube Recommender Design



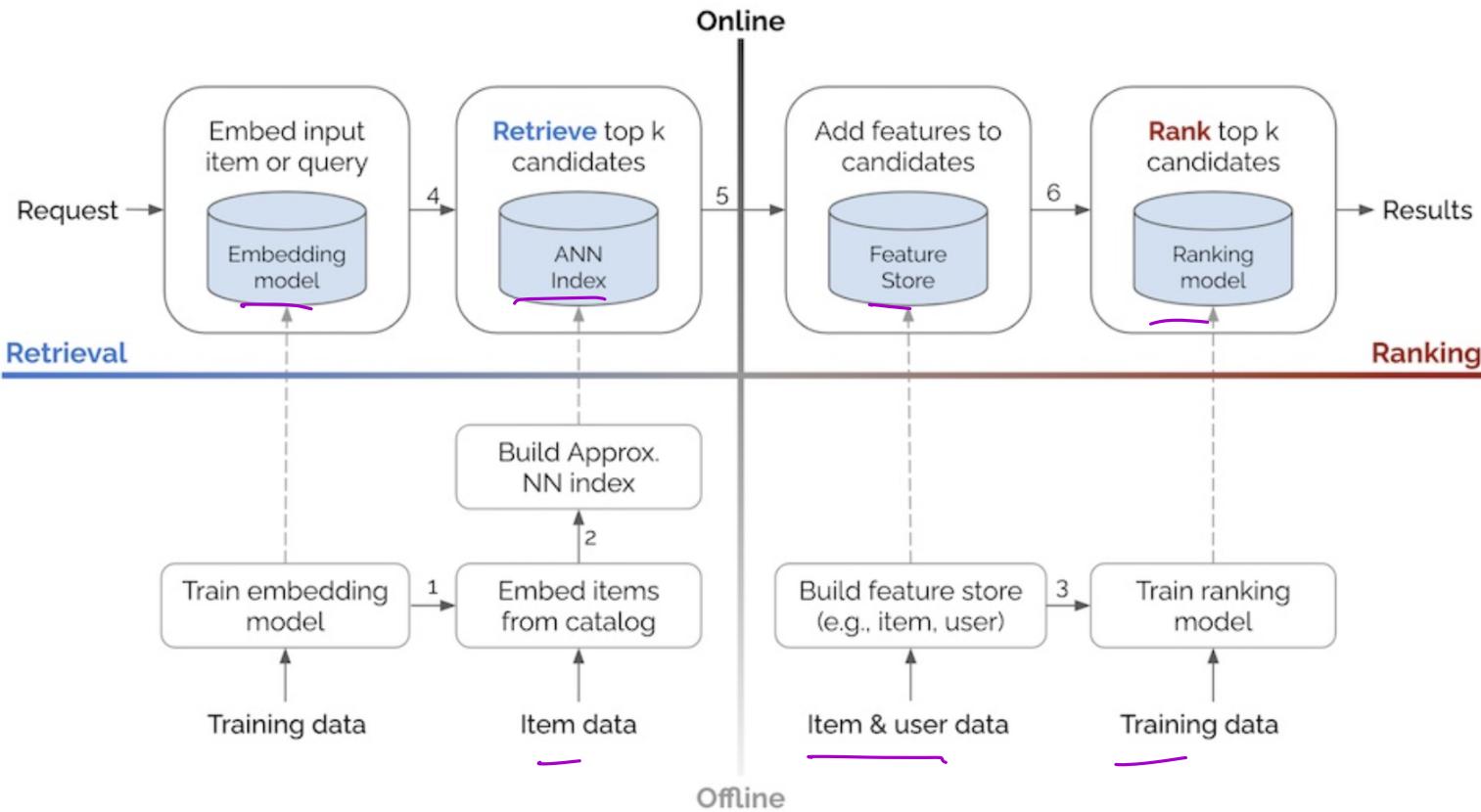
Recommender Modeling Pipeline Considerations

- ① Data Quality
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Recommender System Design High-level



Recommender System Design High-level



Recommender System Level Considerations

① Scalability for Model Training and Model Serving



Recommender System Level Considerations

- ① Scalability for Model Training and Model Serving
- ② Latency for Model Serving

Recommender System Level Considerations

- ① Scalability for Model Training and Model Serving
- ② Latency for Model Serving
- ③ Data integration after data quality checks

(Continuous)

Recommender System Level Considerations

- ① Scalability for Model Training and Model Serving
 - ② Latency for Model Serving
 - ③ Data integration after data quality checks
 - ④ More on this in ML Ops Guest Lecture tomorrow!
-

Metrics for Recommender Systems

Recommendation vs Ranking Metrics

- ① Offline Recommendation metrics help us understand how well offline recommendations are on test set

Recommendation vs Ranking Metrics

- 
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 - ② Ranking metrics in addition help us understand how well the offline recommendations are ordered/ranked

Recommendation vs Ranking Metrics

- ① Offline Recommendation metrics help us understand how well offline recommendations are on test set
 - ② Ranking metrics in addition help us understand how well the offline recommendations are ordered/ranked
 - ③ In practice - Combination of Recommendation and Ranking metrics used
-

Summary of Offline Metrics for Recommender Systems

Rec metrics
Ranking metrics

Metric	Description
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
Precision @ k	$\frac{TP@k}{k}$
Recall @ k	$\frac{TP@k}{N}$
F-score	HM of Precision, Recall
Average Precision @ k	Average of ' <u>active</u> ' precisions in k
DCG @ k	Discounted Cumulative Gain
NDCG @ k	Normalized DCG

- 1) Recommendation Bias:-
2) click bias:-

Online Evaluation

- ① Internal Testing
- ② A/B Testing - Control vs Treatment
- ③ A/B Testing Example - Existing Page for Groceries (Control) vs Existing Page + Your Recommendations widget (Treatment)
- ④ Bandit Testing (Recent development) - Testing multiple options simultaneously instead of just 2

Online Metrics

- ① Usually business metrics
- ② Number of purchases
- ③ Increase in customers?
- ④ Revenue/Sales?

Offline-Online Gap

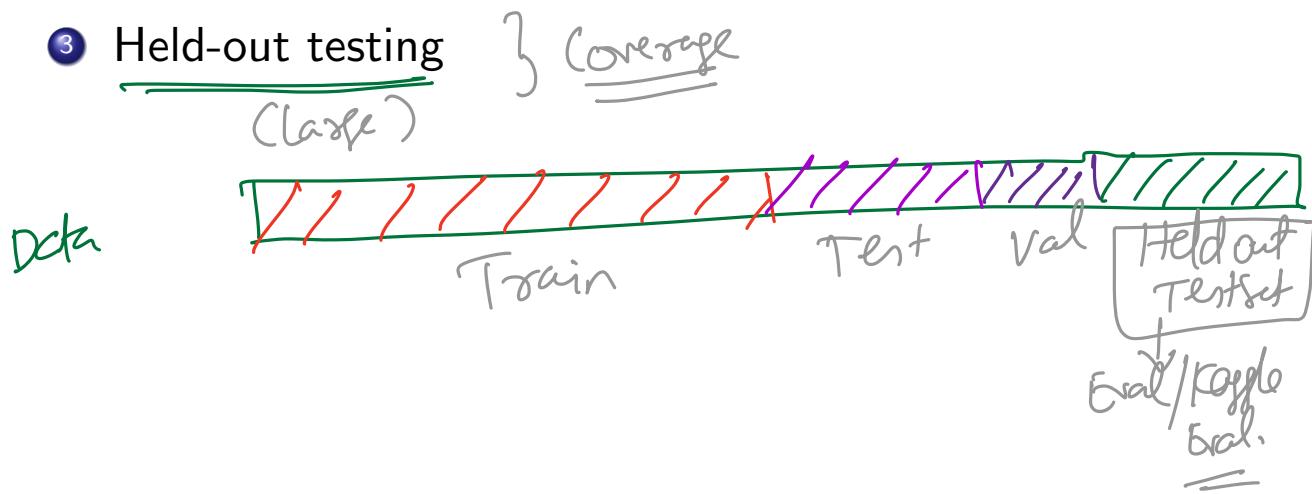
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 - ② How to correct for this?
- 

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- ③ Held-out testing

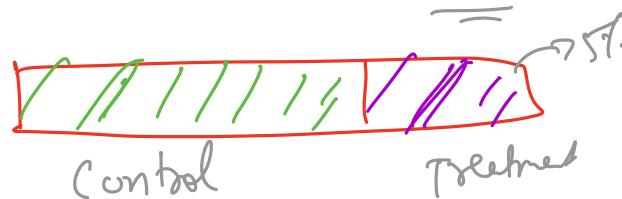


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Offline-Online Gap

- ① There is always some gap between offline and online metrics
 - ② How to correct for this?
 - ③ Held-out testing
 - ④ Internal testing
 - ⑤ 5% A/B test - Can do fixes if something is off
 - ⑥ Gradually increase the percentage as confidence builds
- 

Building your Recommender System!

① Data sources?

Labels
Project
How much init??
multi-model??

Building your Recommender System!

- ① Data sources?
- ② Data quality checks

Building your Recommender System!

- ① Data sources?
- ② Data quality checks
- ③ Offline vs online recommendations] Rec Design

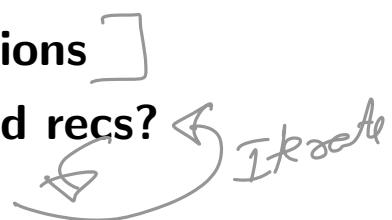
Building your Recommender System!

- ① Data sources?
- ② Data quality checks
- ③ Offline vs online recommendations
- ④ Collaborative, content or hybrid recs? Modeling

Building your Recommender System!

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- ④ Collaborative, content or hybrid recs?
- ⑤ Baseline and gaps in baseline?


Building your Recommender System!

- ① Data sources?
 - ② Data quality checks
 - ③ Offline vs online recommendations
 - ④ Collaborative, content or hybrid recs?
Ikaoete
 - ⑤ Baseline and gaps in baseline?
 - ⑥ Evaluating your system right
- 
- A series of handwritten annotations in blue ink. An arrow points from the bracket under 'Offline vs online recommendations' to the word 'online'. Another arrow points from the bracket under 'Collaborative, content or hybrid recs?' to the word 'hybrid'. A large, loopy arrow labeled 'Ikaoete' points from the bracket under 'Collaborative, content or hybrid recs?' to the word 'content'. A horizontal line with a bracket underneath groups the last two items, 'Baseline and gaps in baseline?' and 'Evaluating your system right'.

Building your Recommender System!

- ① Data sources?
- ② Data quality checks
- ③ Offline vs online recommendations
- ④ Collaborative, content or hybrid recs?
- ⑤ Baseline and gaps in baseline?
- ⑥ Evaluating your system right
- ⑦ Use cases where your model needs improvement?

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- ⑤ Baseline and gaps in baseline?
- ⑥ Evaluating your system right
- ⑦ Use cases where your model needs improvement?
- ⑧ Scalability and latency considerations

System Design

Questions/Thoughts??