

MULTI-OBJECTIVE OPTIMIZATION TO BOOST EXPLORATION IN RECOMMENDER SYSTEMS

SERDAR KADIOGLU
VP of AI, Fidelity Investments
Adjunct Faculty, Brown University



skadio.github.io



*Building new applications
with limited or no training data
remains a common challenge in the industry.*

*Apriori decision in any recommender system:
what is the universe of items \mathcal{I} to consider?*

— Trade-offs: Item Selection Matters

- Number of items vs. experimentation time
- Number of items vs. diversity and learning objectives
- Item mixture and coverage of outcomes and audience
- Time-to-market and onboarding effort: review, publish, register etc.

Question: What is the right mix of items to start the initial experimentation?

Answer: Principled approach for Item Selection

— Today's Talk

Discrete
Optimization

Natural
Language
Processing

Item
Selection
Problem (ISP)

Unsupervised
Learning

Roadmap

1. Problem Definition

Introduce the ISP problem
Illustrative example



3. Solution Approach

Multi-objective
Optimization Framework



5. Human-in-the Loop Decision Making

Empower business users with
interactive item selection



2. High-Level System Design

ISP in the context of
Recommender system pipelines



4. Benefits of the Approach

Numerical results on
recommendation benchmarks



– Item Selection Problem

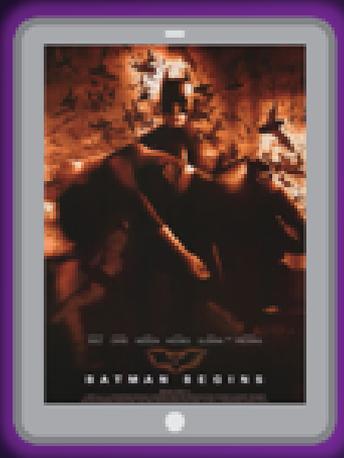
Illustrative Example

Problem Definition

High-Level System Design



— Illustrative Example



— Item Metadata Categories and Labels

| Category | Label |
|-----------|--|
| Title | Spectre - 007 |
| Storyline | A cryptic message sends James Bond on a trail to uncover the existence of .. |
| Genre | Spy |
| Language | English |
| Director | Sam Mendes |
| Producer | MGM |
| Stars | Daniel Craig, Christoph Waltz, Monica Bellucci, .. |

— Item Selection Problem (ISP)

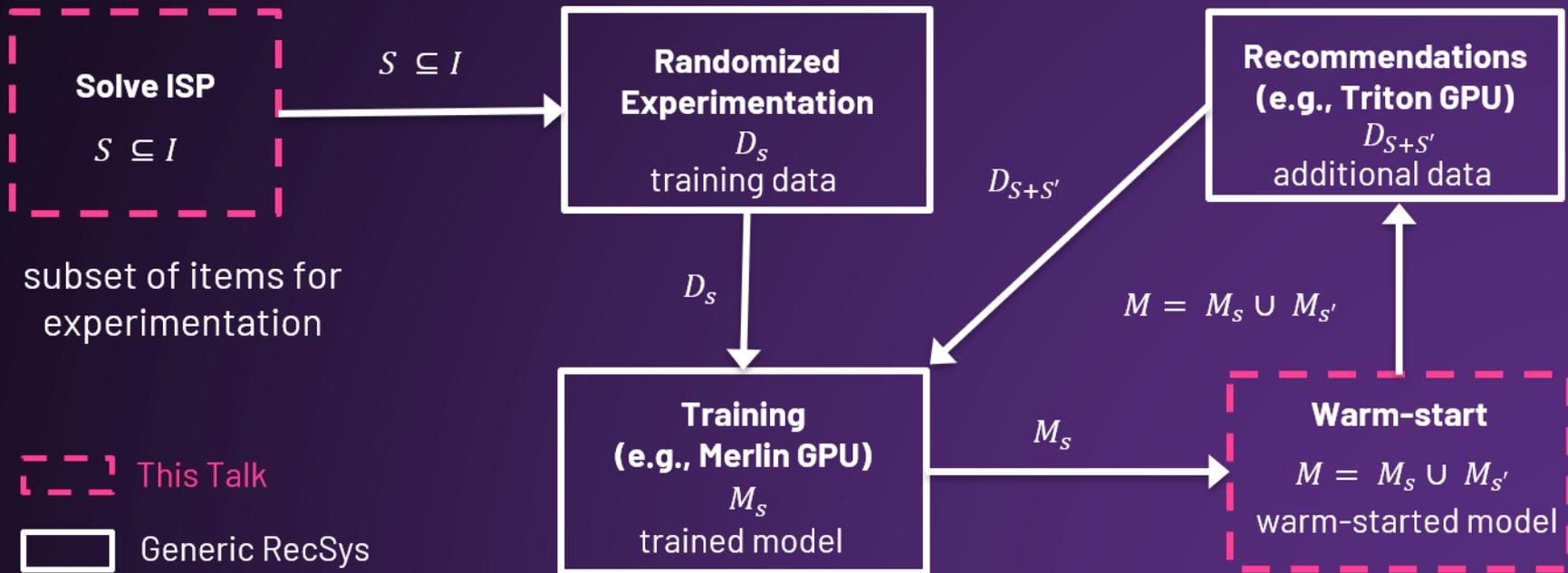
Movie Recommenders

- I : All available movies
- S : Subset of movies $S \subset I$ for experimentation
- C : Categories e.g., language, genre, producer
- L_c : Labels within each category e.g., action, comedy for genre
- $E(I)$: Deep latent representation powered by GPU Technology
text e.g., movie reviews, image e.g., cover art,
audio e.g., soundtrack, video e.g., trailer
- **Goal**: find a minimum subset and maximize label coverage and diversity

IJCAI 2021, Item Selection meets Active Learning, [Kadioglu et. al.](#)

CPAIOR 2021, Optimized Item Selection for Recommender Systems, [Kadioglu et. al.](#)

— High-Level System Design

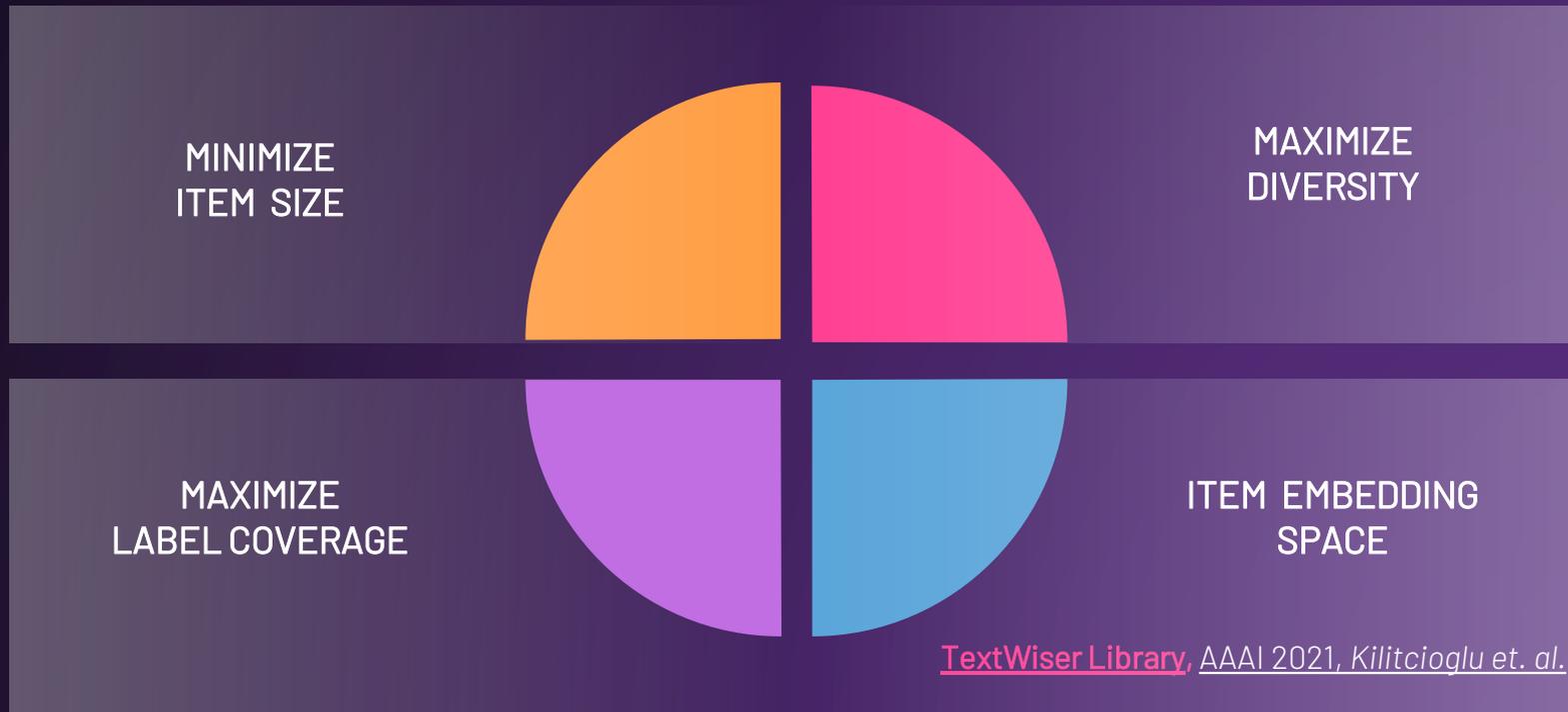


– **Solution Approach**

Multi-objective optimization
framework with cover formulation



— Multi-Objective Optimization Framework



— Multi-Objective Optimization Framework

1

Minimizing the Subset Size

Use standard set covering formulation to select subset of items that cover all predefined labels

2

Maximizing Diversity

Reformulate the loss function to consider items that are most spread out in embedding space $E(I)$ while still covering all labels

3

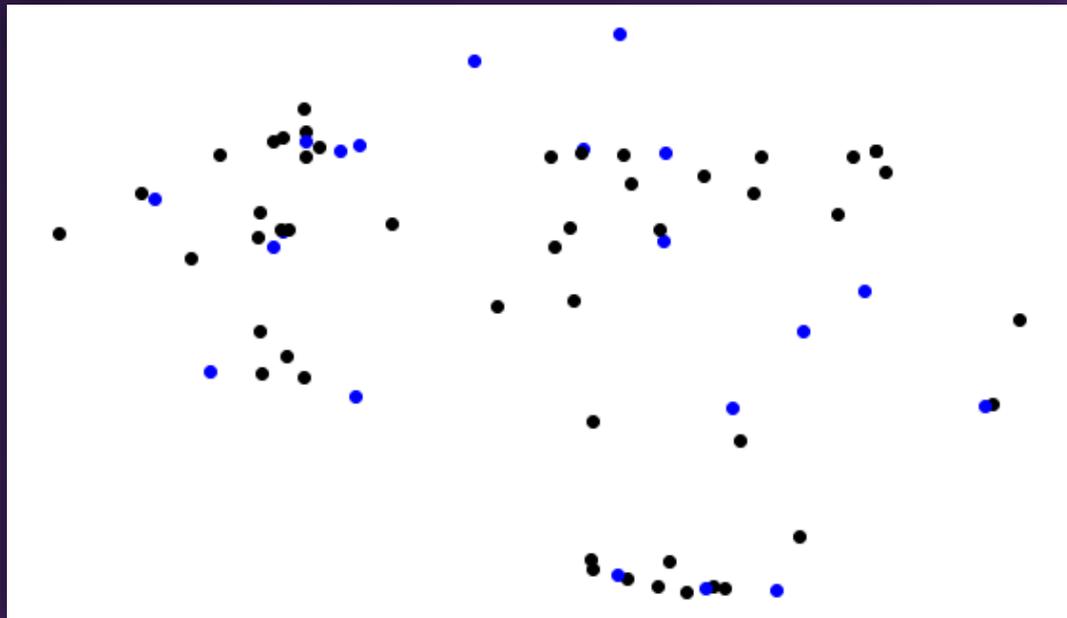
Bounded Experiment Time

Constrain number of selected items from #2 while maximizing the number of labels covered

— The High Level Idea

$$\begin{aligned} \min \sum_i^I c_i x_i \\ \sum_{i \in I} M_{l,i} x_i \geq 1 \quad \forall l \in L_c, \forall c \in C \\ x_i \in \{0, 1\}, c_i = 1 \quad \forall i \in I \end{aligned}$$

$$\begin{aligned} \max \sum_{l \in L_c, c \in C} is_label_covered_l \\ \sum_{i \in I} x_i \leq t \\ M_{l,i} x_i \leq is_label_covered_l \quad \forall l \in L_c, \forall c \in C \forall i \in I \\ \sum_{i \in I} M_{l,i} x_i \geq is_label_covered_l \quad \forall l \in L_c, \forall c \in C \\ x_i \in \{0, 1\} \quad \forall i \in I \\ is_label_covered_l \in \{0, 1\} \quad \forall l \in L_c, \forall c \in C \end{aligned}$$



– Benefits of the Approach

[Q1] How much speed-up is possible?

[Q2] How sensitive is the embedding space?



— Movie and Book Recommenders

| | Items | Categories | Unique Labels |
|--|-----------------|---|---------------|
| MovieLens Movie Recommenders ^[1] | 1,000 10,000 | Genre, Producer, Language, Genre x Language | 473 1,011 |
| Goodreads Book Recommenders ^[2] | 1,000 10,000 | Genre, Publisher, Genre X Publisher | 574 1,322 |

[1] Harper, F., Konstan, J.: The movielens datasets: History and context.

[2] Wan, M., McAuley, J.J.: Item recommendation on monotonic behavior chains.

[Q1] How much speed-up?

Significantly less number of items *while covering all labels* against Randomized, Greedy and Clustering baselines

~75% Reduction (4X faster)

Small dataset with 1000 items

~90% Reduction (10X faster)

Large dataset with 1000 items



[Q2] Sensitivity of Embeddings

Similar unit coverage for different embedding methods

Deep/GPU methods lead to rich latent representations

| TextWiser Embedding ^[1] | 1K | 10K |
|------------------------------------|-----|-----|
| TFIDF ^[2] | 1.2 | 0.5 |
| Word2Vec ^[3] | 1.4 | 0.7 |
| GloVe ^[4] | 1.4 | 0.6 |
| Byte-Pair ^[5] | 1.3 | 0.6 |

[1] Kilitcioglu, D., Kadioglu, S. Representing the Unification of Text Featurization using a Context-Free Grammar. AAAI 2021

[2] Jones, K.S.: A statistical interpretation of term specificity and its application in retrieval.

[3] Grave, E., Bojanowski, P., Gupta, P., Joulin, A., Mikolov, T.: Learning word vectors for 157 languages. ACL 2018

[4] Pennington, J., Socher, R., Manning, C.D.: Glove: Global vectors for word representation. ACL 2014

[5] Sennrich, R., Haddow, B., Birch, A.: Neural machine translation of rare words with subword units. ACL 2016

Human-in-the-Loop Decision Making

Interactive item selection

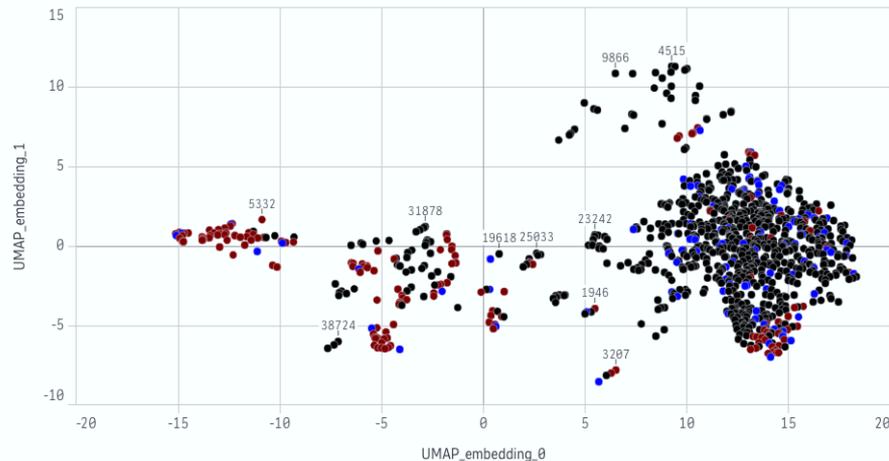
Dynamic settings

Active learning



Optimized Content Selection

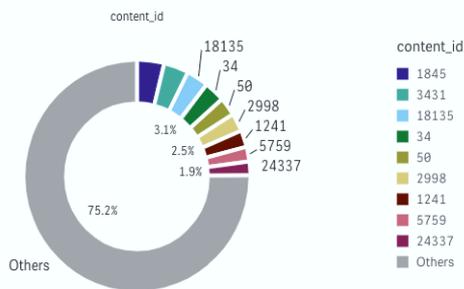
2D embeddings of contents



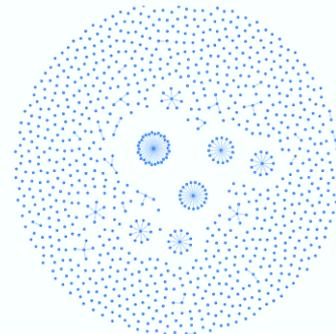
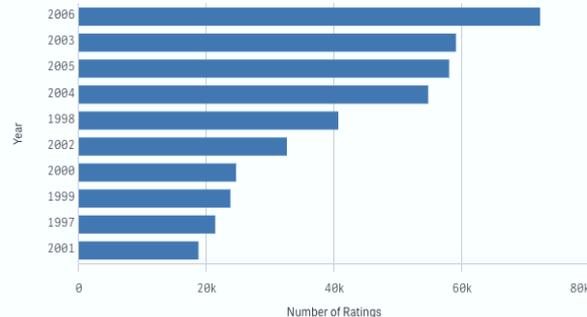
Content data

| conte... | Genre | Title | Description |
|----------|----------|-------------------------------------|--|
| 19173 | poetry | The Divine Comedy Vol. 2: Purgatory | ...The Divine Comedy... is perhaps the greatest Christian classic ever written, and probably the greatest adventure story ever told. Dante wrote |
| 28716 | fiction | Blood Meridian | 'Blood Meridian' presents an epic novel of the violent American West. The story is loosely based on accounts of murder along the border |
| 45205 | fiction | No Name | 'Mr Vanstone's daughters are Nobody's Children'. Magdalen Vanstone and her sister Norah learn |
| 10404 | fiction | Doctor Who: Cat's Cradle-Witch Mark | 'Spare no sympathy for those creatures. They were witches, they deserved to die.' A coach crashes on the M40. All the passengers |
| 11499 | fiction | The Promise | "A superb mirror of a place, a time, and a group of people who capture our immediate interest and hold it tightly." —The Philadelphia Inquirer |
| 45066 | fiction | The Mill on the Floss | "Backgrounds" includes fifteen letters from the 1859-69 period centering on the novel's content and composition; "Brother and Sister" |
| 35958 | children | Sagwa the Chinese Siamese Cat | "Before you go out into the world," Ming Miao told her five kittens, "you must know the true story of your ancestors..." |
| 38700 | fiction | Rabbit Hole | "David Lindsay-Abaire has crafted a drama that's not just a departure but a revelation—an intensely emotional examination of grief, laced |

Number of Ratings



Number of Ratings v.s. Year Published



— Special thanks to our collaborators!

- [IJCAI'21] Active learning meets optimized item selection
- [CPAIOR'21] Optimized item selection to boost exploration for recommender systems
- [AAAI'21] Representing the unification of text featurization using a context-free grammar
- [AAAI'22] Seq2Pat: Sequence-to-Pattern generation
- [AAAI'22] Dichotomic pattern mining for prediction from clickstream datasets
- [ICMLA'21] Surrogate ground truth to enhance binary fairness in uplift modelling
- [IJAIT'21] Parallelizable contextual multi-armed bandits
- [JDSA'21] Modeling uncertainty to improve personalized recommendations via Bayesian DL
- [ICTAI'19] Bayesian DL-based exploration-exploitation for personalized recommendations
- [Pixsellz\(CC\)BY 4.0](#) and [SlidesCarnival\(CC\)BY 4.0](#)

- **Recommenders** **Mab2Rec:** <https://github.com/fidelity/mab2rec>
- **Multi-armed Bandits** **MABWiser:** <https://github.com/fidelity/mabwiser>
- **Text/NLP** **TextWiser:** <https://github.com/fidelity/textwiser>
- **Pattern Mining** **Seq2Pat:** <https://github.com/fidelity/seq2pat>
- **Feature Selection** **Selective:** <https://github.com/fidelity/selective>
- **AI Fairness & Bias** **Jurity:** <https://github.com/fidelity/jurity>



skadio.github.io



**Du
Cheng**

**Doruk
Kilitcioglu**



**Bernard
Kleynhans**

**Filip
Michalsky**

**Xin
Wang**

