A Multi-Armed Bandit Framework for Recommendations at Netflix

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Elliot Chow

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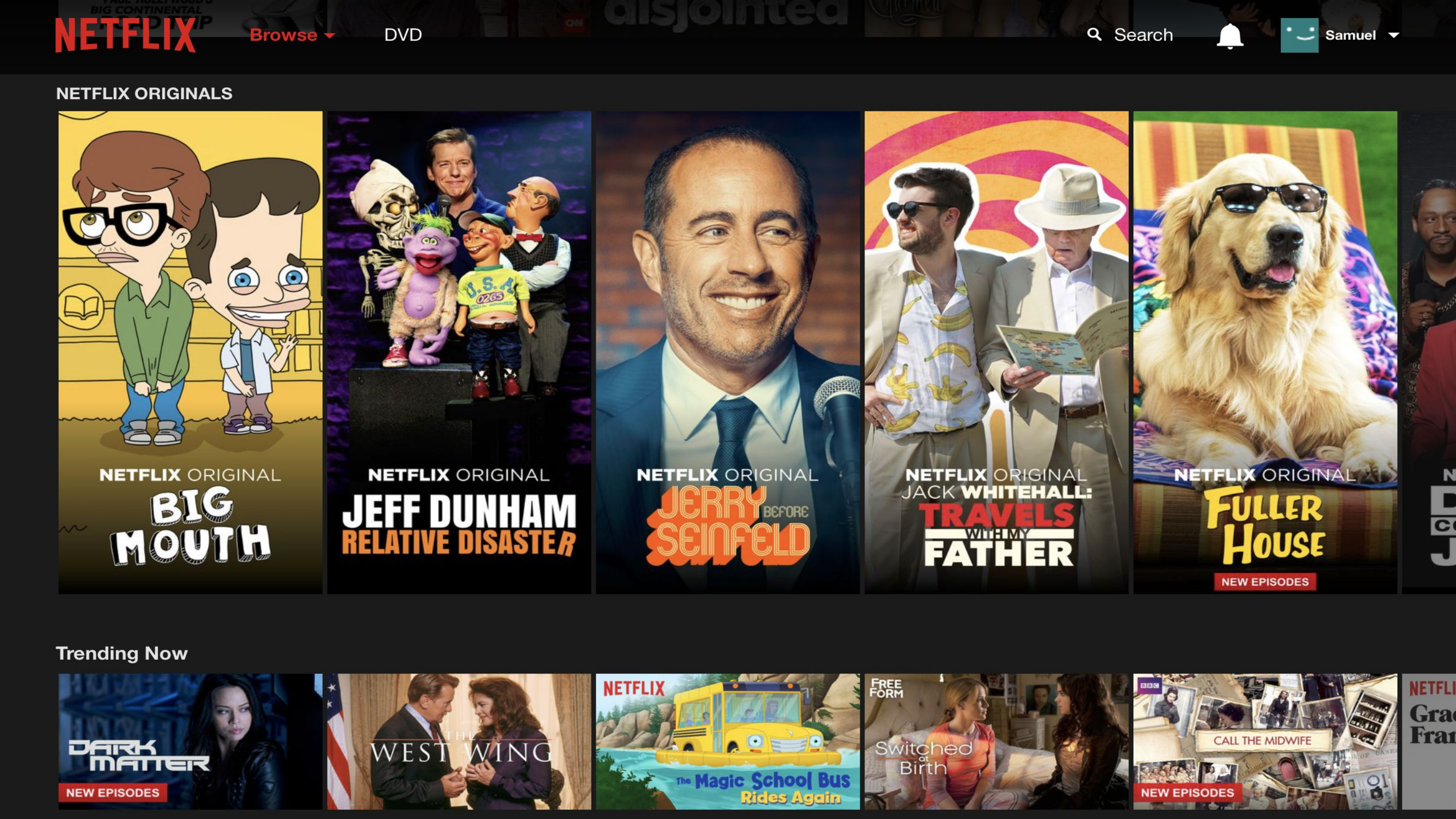
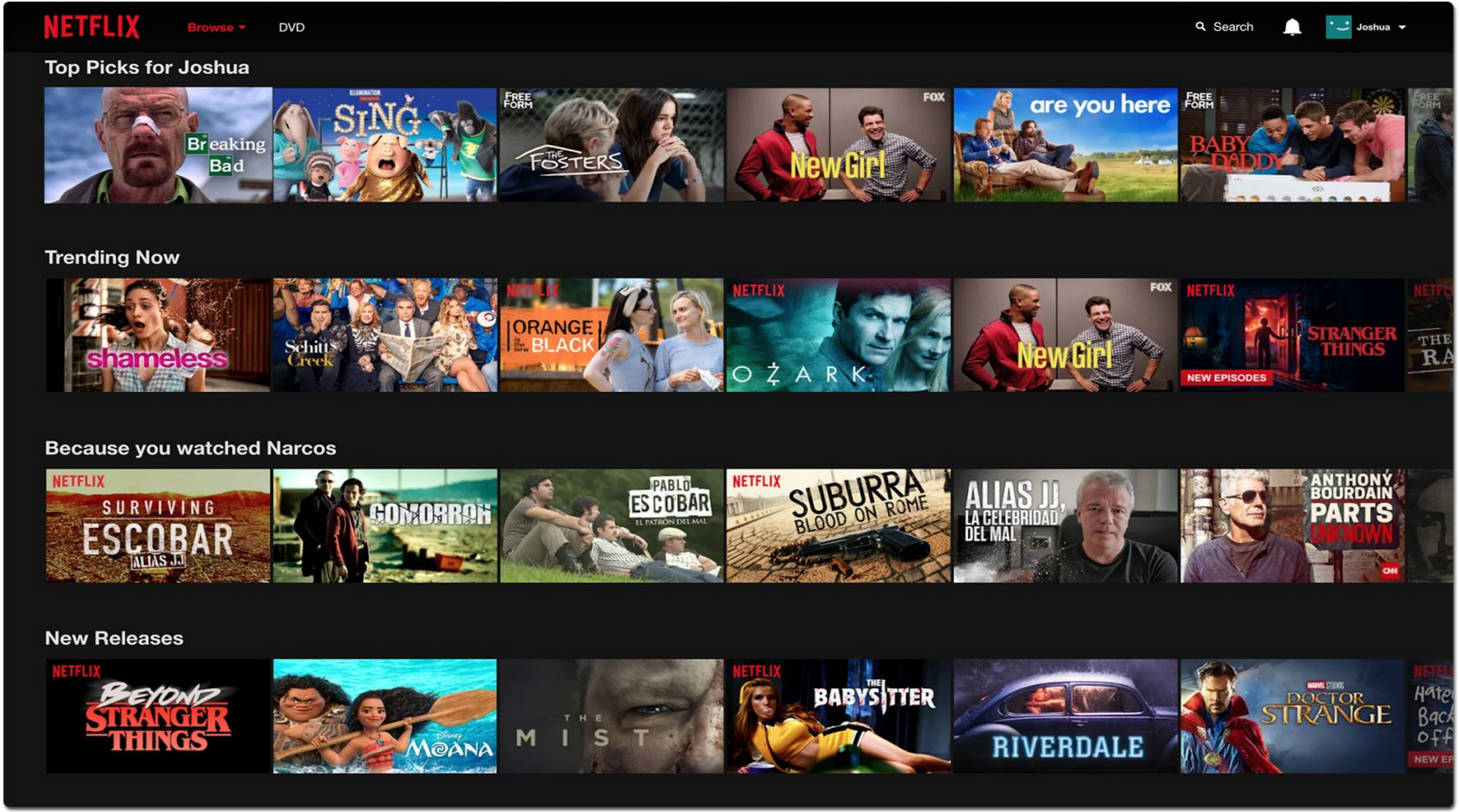

NETFLIX
Browse
DVD
Search
Samuel
NETFLIX ORIGINALS
NETFLIX ORIGINAL
BIG MOUTH
NETFLIX ORIGINAL
JEFF DUNHAM
RELATIVE DISASTER
NETFLIX ORIGINAL
JERRY BEFORE SEINFELD
NETFLIX ORIGINAL
JACK WHITEHALL:
TRAVELS WITH MY FATHER
NETFLIX ORIGINAL
FULLER HOUSE
NEW EPISODES
Trending Now
DARK MATTER
NEW EPISODES
THE WEST WING
NETFLIX
The Magic School Bus Rides Again
FREE FORM
Switched at Birth
BBC
CALL THE MIDWIFE
NEW EPISODES

Recommendations at Netflix

Personalized Homepage for each member

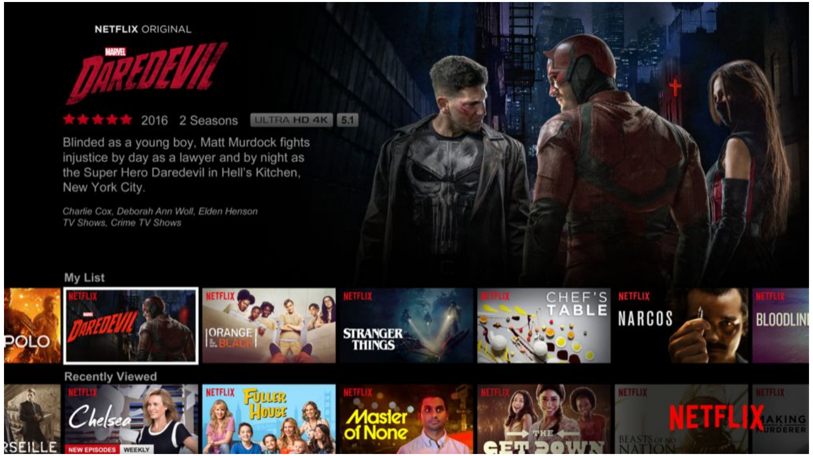
- **Goal**: Quickly help members find content they'd like to watch
- **Risk**: Member may lose interest and abandon the service
- **Challenge**: 117M+ members
- Recommendations Valued at: $1B*

*Carlos A. Gomez-Uribe, Neil Hunt: The Netflix Recommender System: Algorithms, Business Value, and Innovation. ACM Trans. Management Inf. Syst. 6(4): 13:1-13:19 (2016)


NETFLIX
Browse
DVD
Search
Joshua
Top Picks for Joshua
Breaking Bad
SING
FREE FORM
THE FOSTERS
FOX
New Girl
are you here
BABY DADDY
Trending Now
shameless
Schitt's Creek
NETFLIX
ORANGE is the new BLACK
OZARK
STRANGER THINGS
NEW EPISODES
Because you watched Narcos
SURVIVING ESCOBAR ALIAS JJ
GOMORRAH
PABLO ESCOBAR EL PATRÓN DEL MAL
SUBURRA BLOOD ON ROME
ALIAS JJ, LA CELEBRIDAD DEL MAL
ANTHONY BOURDAIN PARTS UNKNOWN
CNN
New Releases
BEYOND STRANGER THINGS
MOANA
THE MIST
THE BABYSITTER
RIVERDALE
DOCTOR STRANGE

Our Focus: Billboard Recommendation

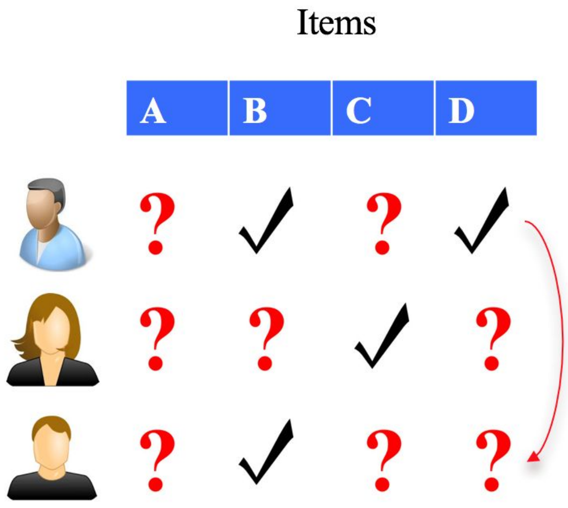
Goal: Recommend a **single relevant title** to each member at the right time and **respond quickly** to member feedback.



Example Billboard of Daredevil on the Netflix homepage

Traditional Approaches for Recommendation

- Collaborative Filtering based approaches most popularly used.
  - Idea is to use the “wisdom of the crowd” to recommend items
  - Well understood and various algorithms exist (e.g. Matrix Factorization)



Collaborative Filtering

Challenges for Traditional Approaches

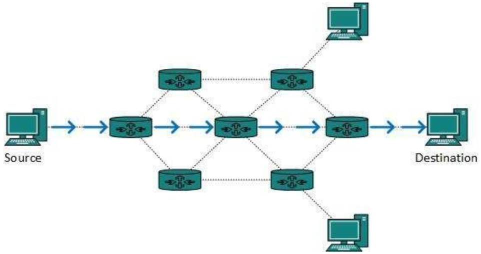
Challenges for traditional approaches for recommendation:

- Scarce feedback
- Dynamic catalog
- Non-stationary member base
- Time sensitivity
    - Content popularity changes
    - Member interests evolves
    - Respond quickly to member feedback

Multi-Armed Bandits

Increasingly successful in various practical settings where these challenges occur

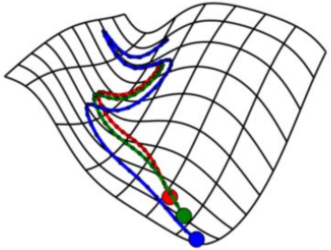
Clinical Trials



Network Routing

Online Advertising

AI for Games

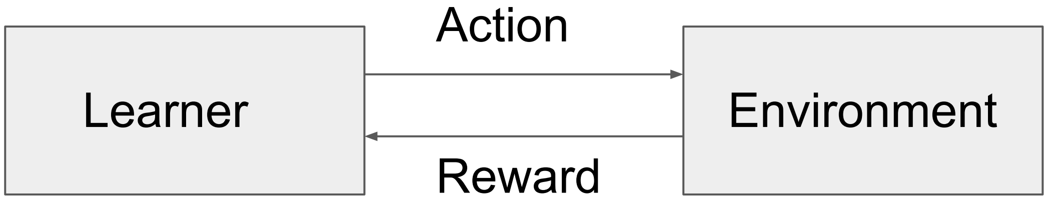


Hyperparameter Optimization

Multi-Armed Bandit For Recommendation

- Multiple slot machines with unknown reward distribution
- A gambler with multiple arms
- Which machine to play in order to maximize the reward ?

Bandit Algorithms Setting



For each round

- Learner chooses an **action** from a set of available actions
- The environment generates a response in the form of a real-valued **reward** which is sent back to the learner
- Goal of the learner is to **maximize the cumulative reward** or **minimize the cumulative regret** which is the difference in total reward gained in n rounds and the total reward that would have been gained w.r.t to the optimal action.

Multi-Armed Bandit For Recommendation

Exploration-Exploitation tradeoff : Recommend the optimal title given the evidence i.e. **exploit** or recommend other titles to gather feedback i.e. **explore**.

Principles of Exploration

- The best long-term strategy ***may involve short-term sacrifices***.

- Gather information to make the best overall decision.
  - **Naive Exploration**: Add a noise to the greedy policy. [ϵ-greedy]
  - **Optimism in the Face of Uncertainty**: Prefer actions with uncertain values. [Upper Confidence Bound (UCB)]
  - **Probability Matching**: Select the actions according to the probability they are the best. [Thompson Sampling]

Numerous Variants

- Different Environments :
    - **Stochastic and stationary**: Reward is generated i.i.d. from a distribution specific to the action. No payoff drift.
    - **Adversarial**: No assumptions on how rewards are generated.
- Different objectives: **Cumulative** regret, **tracking** the best expert
- **Continuous or discrete** set of actions, finite vs infinite
- Extensions: Varying set of arms, Contextual Bandits, etc.

Epsilon Greedy for MABs

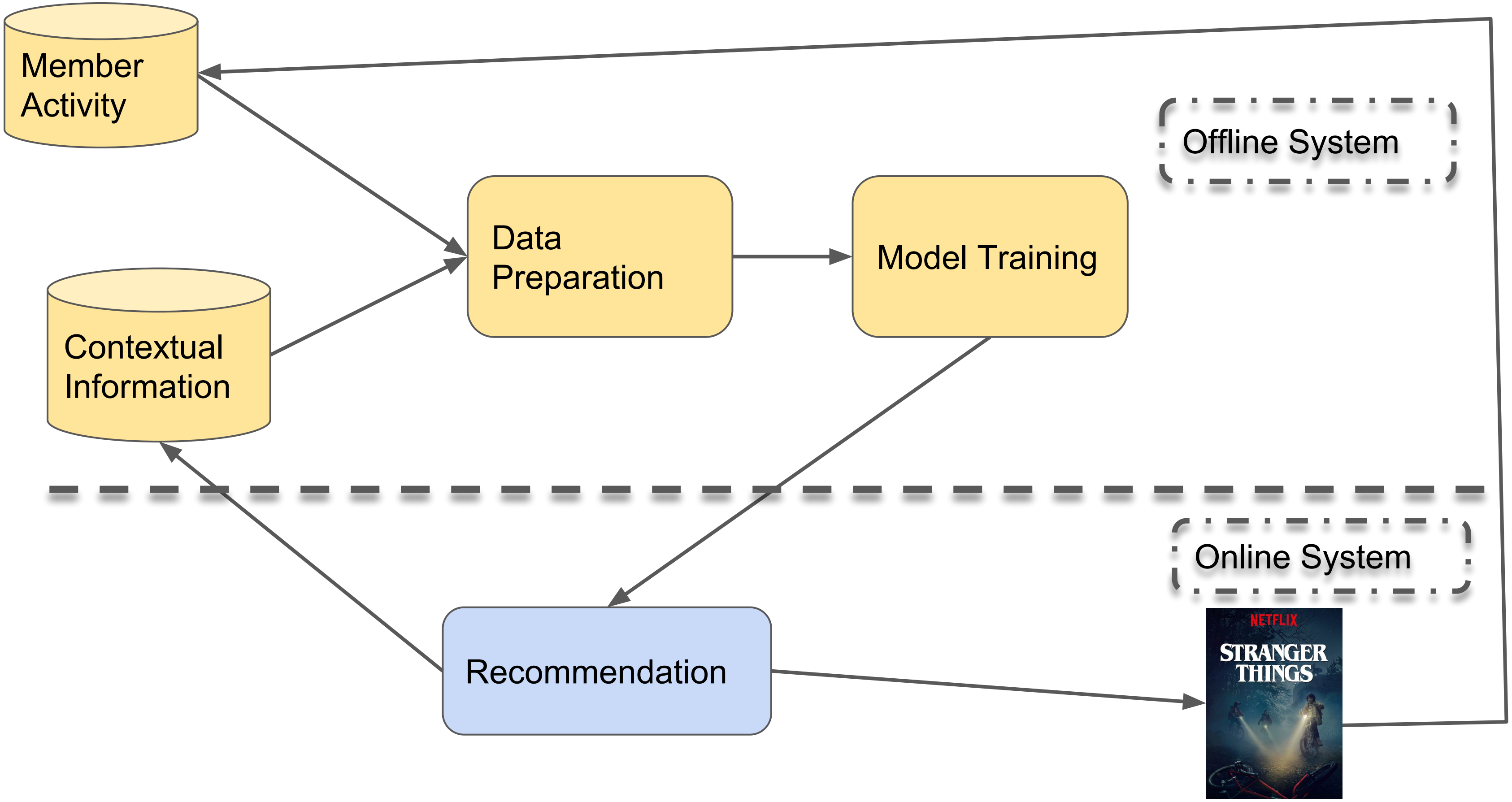
Epsilon Greedy

- **Exploration**:
  - Uniformly explore with a probability ϵ
  - Provides **unbiased data** for training.
- **Exploitation**: Select the optimal action with a probability $(1 - \epsilon)$

Key Aspects of Our Framework

- Can support **different contextual bandit algorithms** i.e., Epsilon Greedy, Thompson Sampling, UCB, etc.
- **Closed-loop system** that establishes a link between how recommendations are made and how our members respond to them, important for online algorithms.
- Supports **snapshot logging** to log facts to generate features for offline training.
- Supports **regular updates** of policies.

System Architecture


Member Activity
Contextual Information
Data Preparation
Model Training
Offline System
Online System
Recommendation
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STRANGER THINGS

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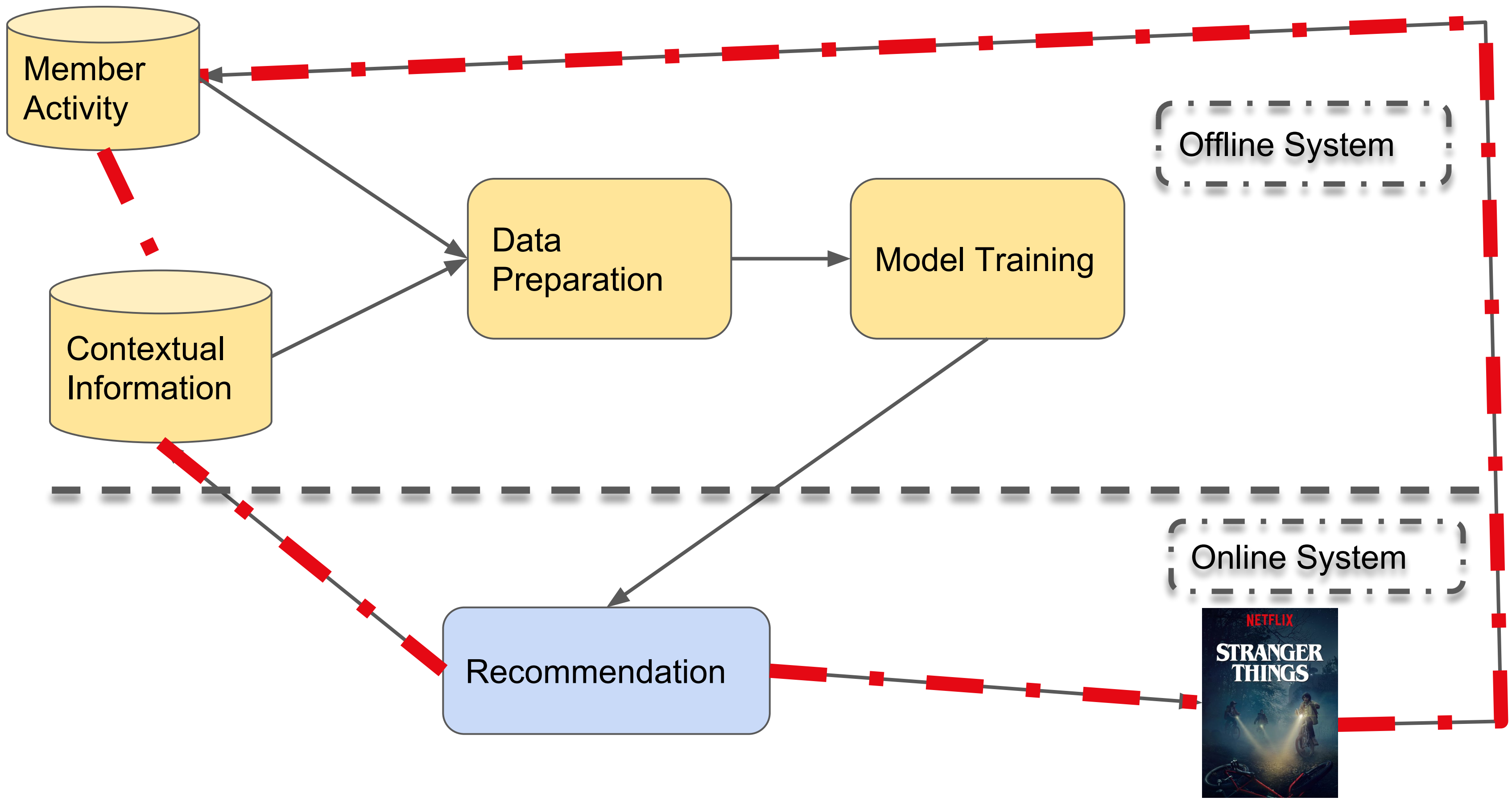

Member Activity
Offline System
Data Preparation
Model Training
Contextual Information
Online System
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Recommendation

Key Components

Online

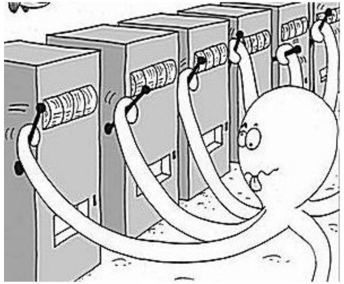
- Apply explore/exploit policy
- Log contextual information
- Score and generate recommendations

Offline

- Attribution assignment
- Model training

Apply Explore/Exploit Policy

- **Generate** the candidate pool of titles
- **Select** a title from candidate pool
  - For uniform exploration, randomly select a title uniformly from the candidate pool

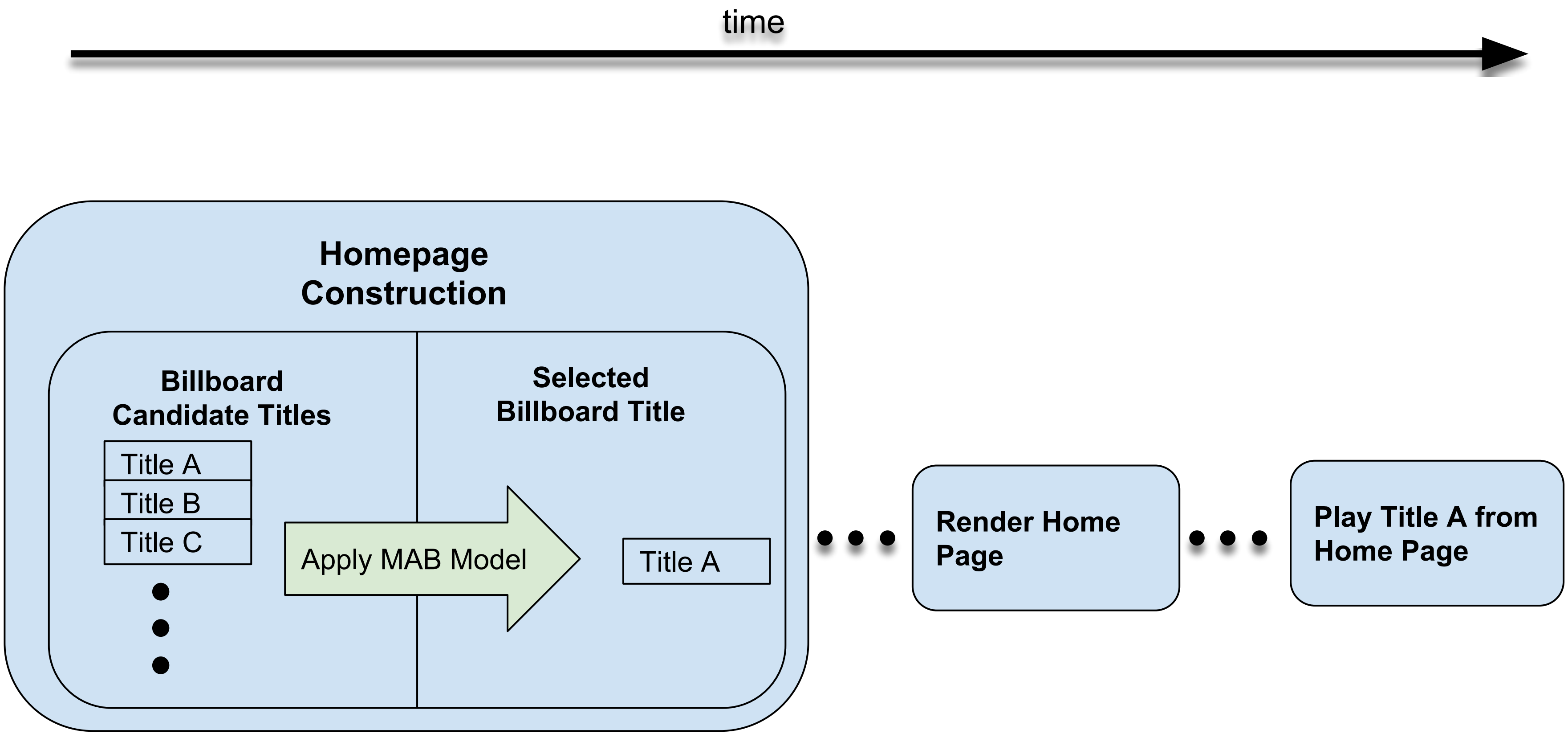


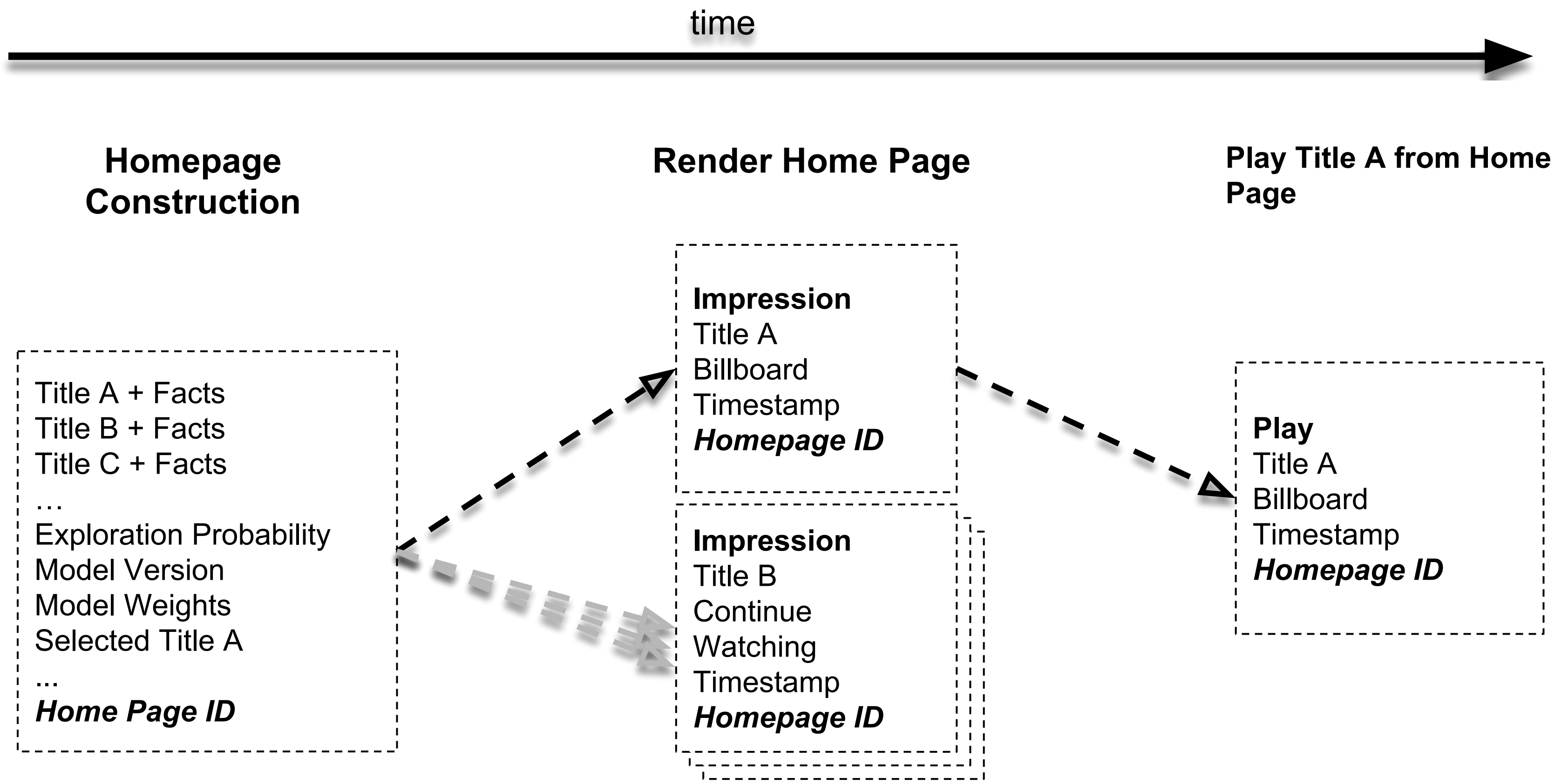
Log Contextual Information

- Exploration Probability
- Candidate pool
- Selected title
- Snapshot facts for feature generation

Attribution Assignment

- **Filter** for relevant member activity
- **Join** with explore/exploit information
- **Define** and construct sessions
- **Generate** labels


time
Homepage Construction
Billboard Candidate Titles
Title A
Title B
Title C
Apply MAB Model
Selected Billboard Title
Title A
Render Home Page
Play Title A from Home Page


time
Homepage Construction
Render Home Page
Play Title A from Home Page
Title A + Facts
Title B + Facts
Title C + Facts
…
Exploration Probability
Model Version
Model Weights
Selected Title A
...
Home Page ID
Impression
Title A
Billboard
Timestamp
Homepage ID
Impression
Title B
Continue
Watching
Timestamp
Homepage ID
Play
Title A
Billboard
Timestamp
Homepage ID

Feature Generation

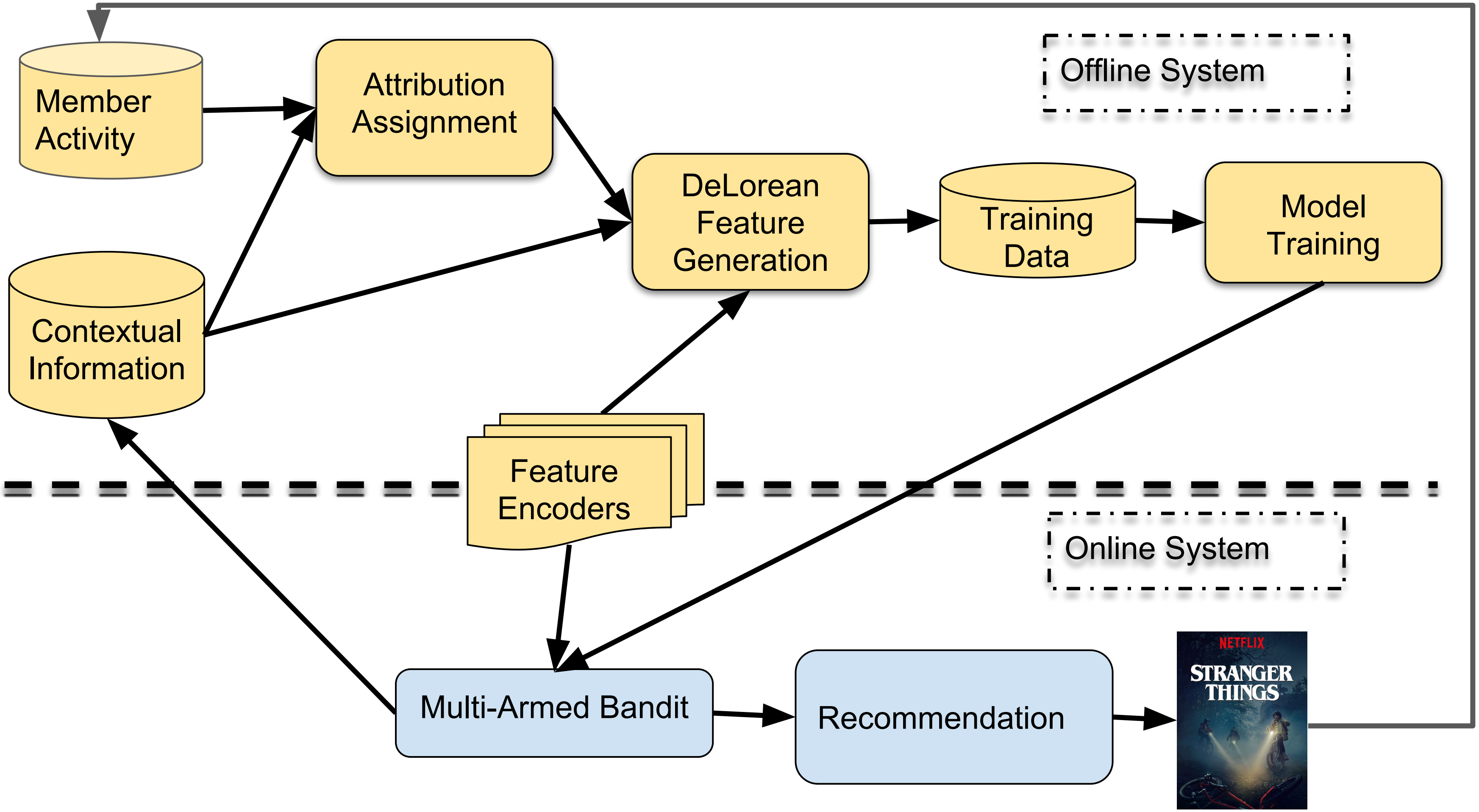
- **Join** labels with snapshotted facts
- **Generate** features using DeLorean
    - Feature encoders are shared online and offline

Model Training and Publishing

- **Train** and validate model
- **Publish** the model to production

Metrics and Monitoring

- A/B test metrics
- Distribution of arm pulls
  - Stability
  - Explore vs. Exploit
- Take Rate
  - Convergence
  - Online v.s. Offline
  - Explore v.s. Exploit


Member Activity
Attribution Assignment
Offline System
DeLorean Feature Generation
Training Data
Model Training
Contextual Information
Feature Encoders
Online System
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Multi-Armed Bandit
Recommendation

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Example Bandit Policies For Recommendation

Background and Notation

- Let k = 1, … K denote the set of titles in the candidate pool when a member arrives on the Netflix homepage
- Let $x_{ik} \in \mathbb{R}^d$ be the context vector for member i and title k.
- Let y_{ik} represent the label when member i was shown the title k.

Greedy Exploit Policy

- Learn a **model per title in the candidate pool** to predict the **likelihood of play on the title**

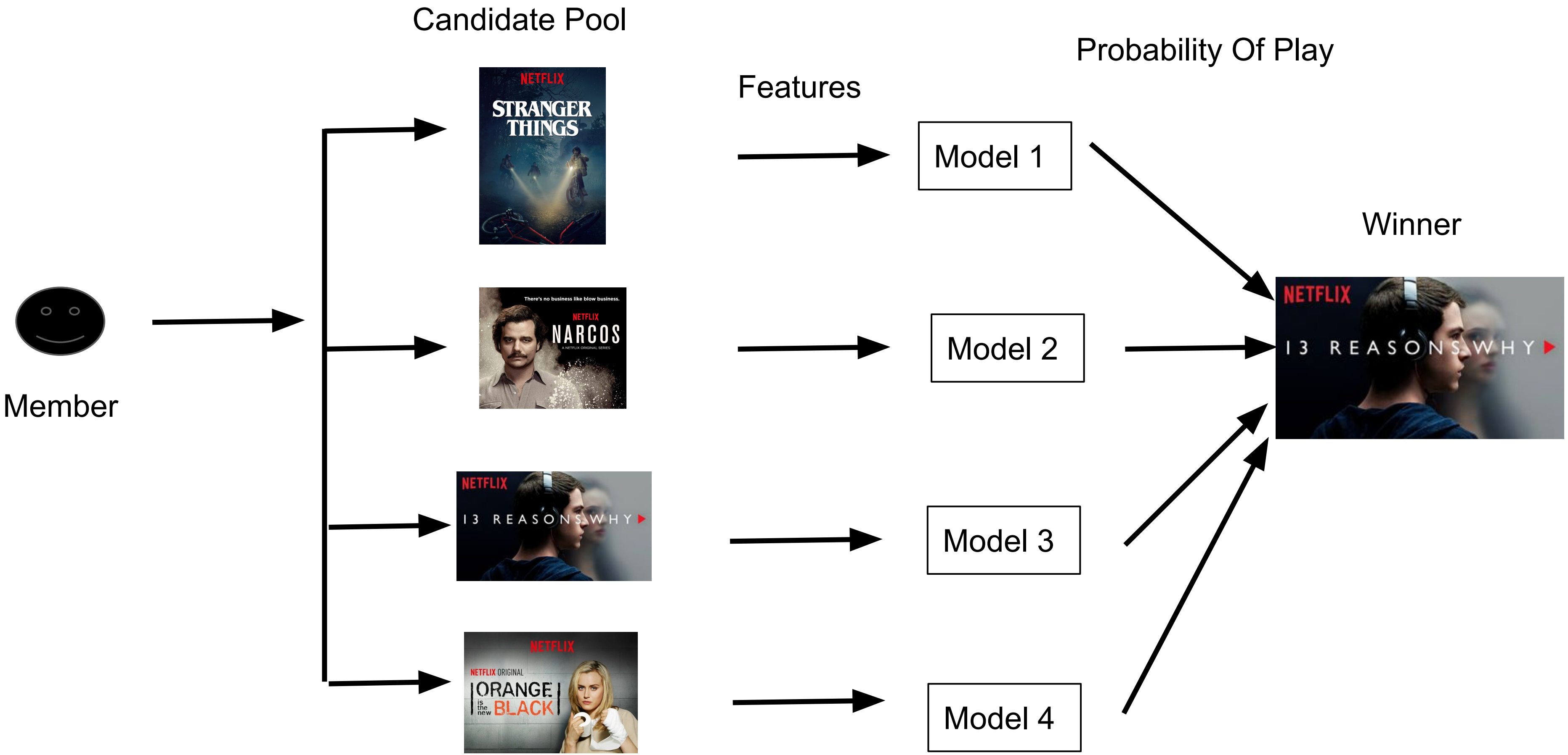
$$Pr(y_{ik} = 1 | x_{ik}, K) = \sigma(f(x_{ik}, \Theta))$$

- Pick a winning title:

$$k = \arg\max Pr(y_{ik} = 1 | x_{ik}, K)$$

- Various models can be used to learn to predict the probability, for example, logistic regression, neural networks or gradient boosted decision trees.

Greedy Exploit Policy

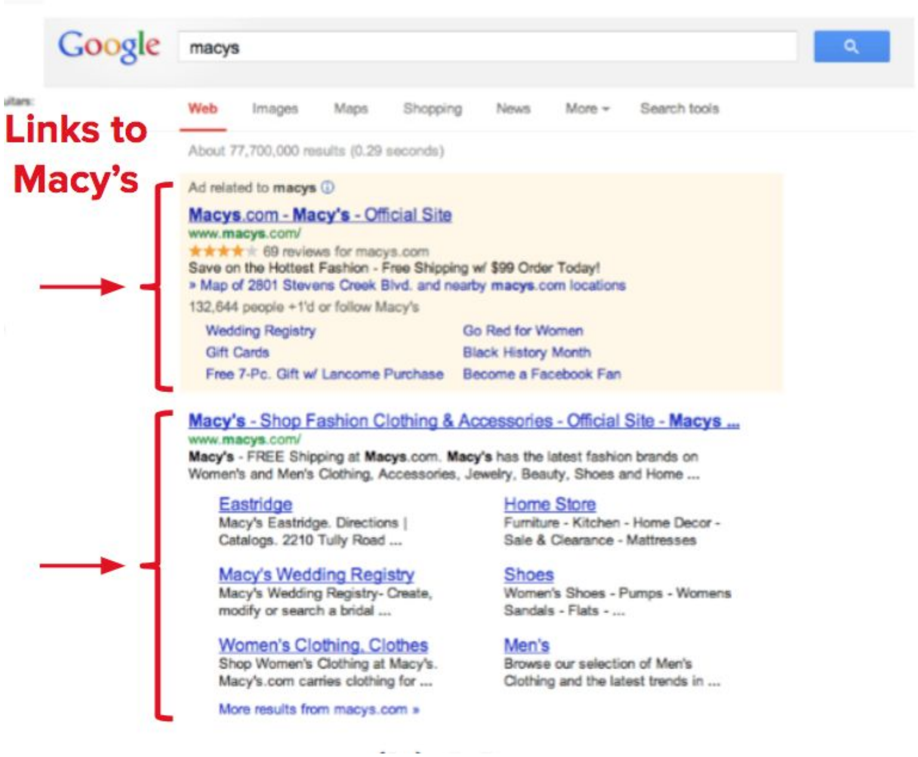


Would the member have played the title anyways?

Causal Effect of an Advertisement

- Advertising: Target the user to increase the conversion.

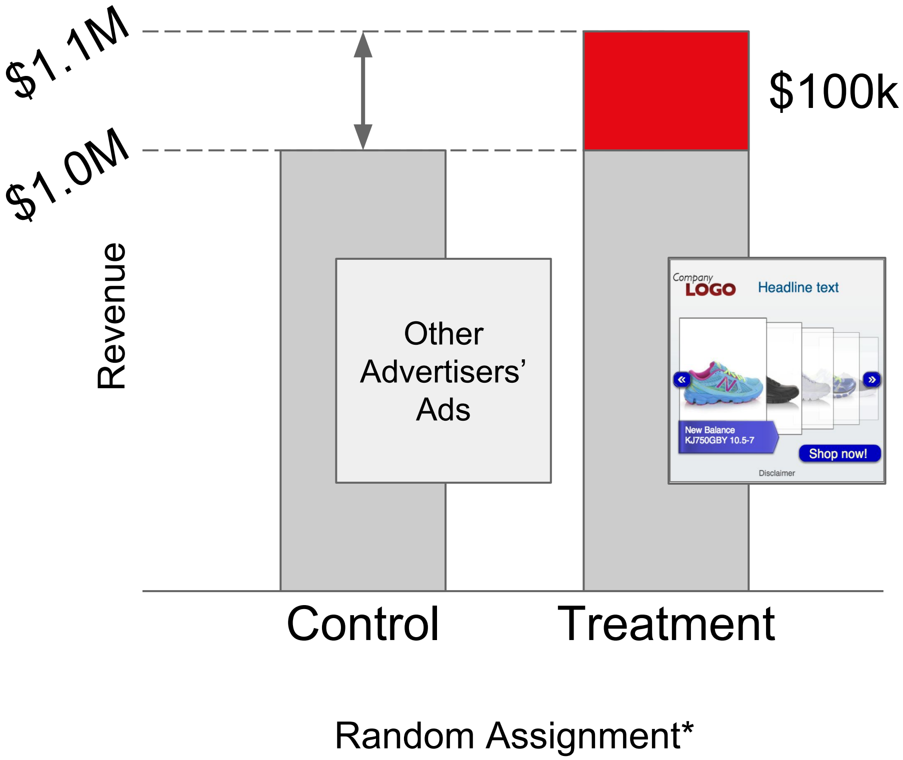
- Causal Question: Would the user have converted anyways ?*



*Johnson, Garrett A. and Lewis, Randall A. and Nubbemeyer, Elmar I, Ghost Ads: Improving the Economics of Measuring Online Ad Effectiveness (January 12, 2017). Simon Business School Working Paper No. FR 15-21. Available at SSRN: https://ssrn.com/abstract=2620078

Incrementality from Advertising

- Goal: Measure ad effectiveness.
- **Incrementality**: The **difference in the outcome because the ad was shown**; the causal effect of the ad.



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Incrementality Based Policy on Billboard

- Goal: Recommend title which has the **largest additional benefit from being presented on the Billboard**
  - Member could have played the title **from anywhere else on the homepage or from search**
  - Popular titles likely to appear on the homepage via other rows e.g., Trending Now
  - Better to **utilize the real estate on the homepage** for recommending other titles.

- Define Policy to be **incremental with respect to probability of play**.

Incrementality Based Policy on Billboard

- Goal: Recommend title which has the **largest additional benefit from being presented on the Billboard**

$$argmax P(y_{ik} = 1 | x_{ik}, K, b = 1) - P(y_{ik} = 1 | x_{ik}, K, b = 0)$$

Where b=1 → Billboard was shown for the title and b=0 → not shown.

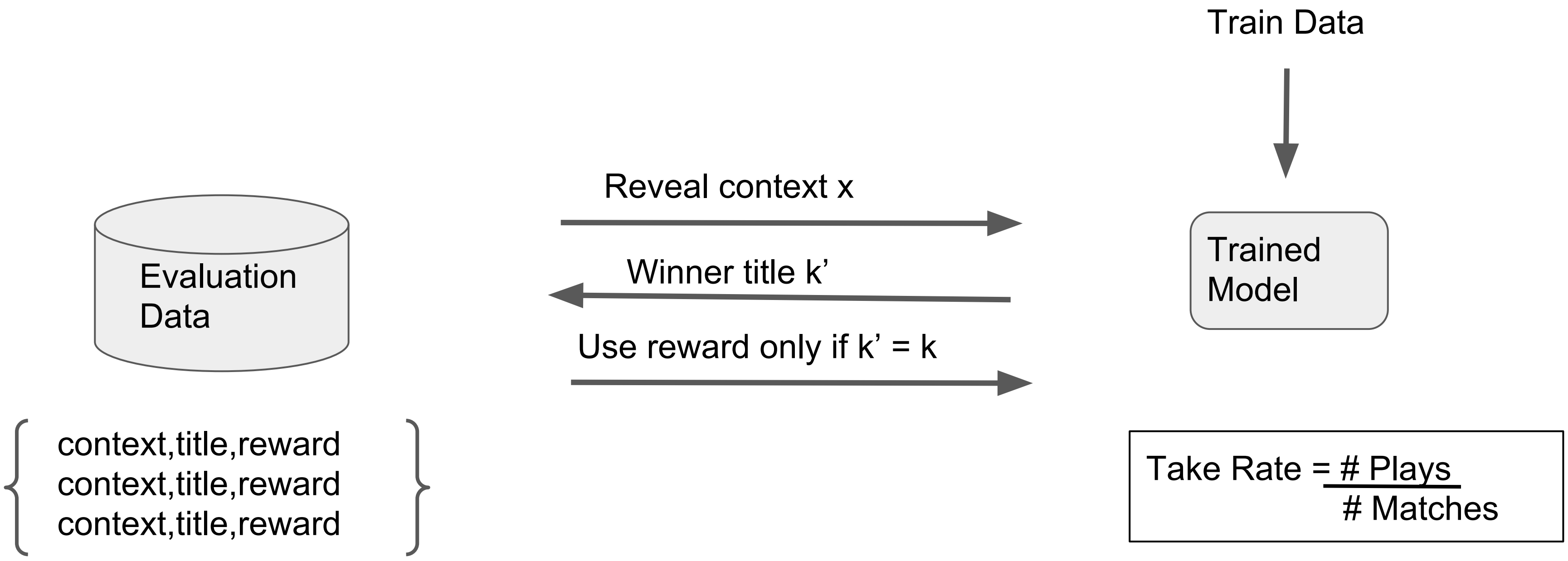
Offline Evaluation: Replay [Li et al, 2010]

- Relies upon **uniform exploration data**. For every record in the uniform exploration log {context, title k shown, reward, list of candidates}

- Offline Evaluation: For every record
  - Evaluate the trained model **for all the titles** in the candidate pool.
  - Pick the winning title k’
  - Keep the record in history if **k’ = k** (the title impressed in the logged data) else discard it.
  - Compute the metrics from the history.

Offline Evaluation: Replay [Li et al, 2010]

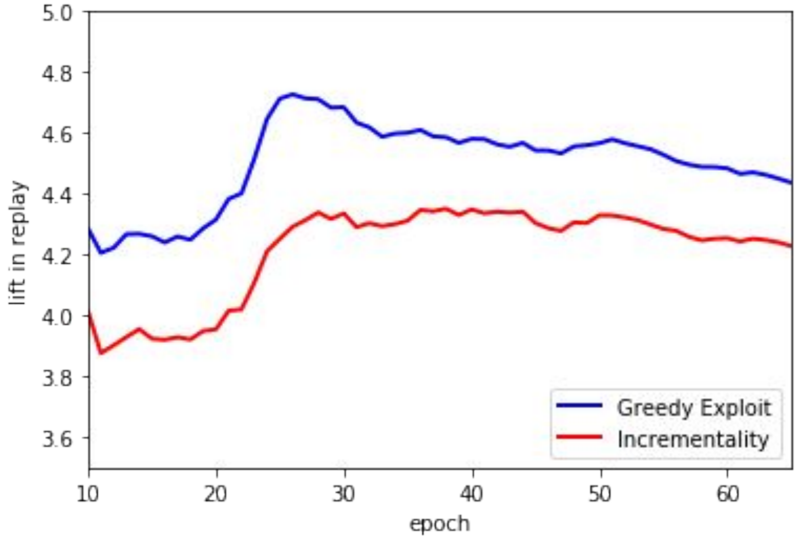
Uniform Exploration Data - Unbiased evaluation



Offline Replay

Exploit has higher replay take rate as compared to incrementality.

Incrementality Based Policy sacrifices replay by selecting a lesser known title that would benefit from being shown on the Billboard.

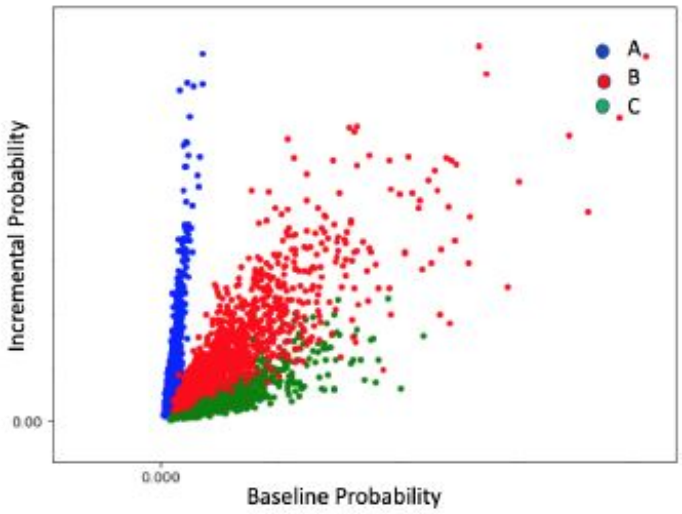


Lift in Replay in the various algorithms as compared to the Random baseline

Which titles benefit from Billboard ?

Title A has a **low baseline probability of play**, however when the billboard is shown the **probability of play increases substantially**!

Title C has higher baseline probability and **may not benefit as much** from being shown on the Billboard.



Scatter plot of incremental vs baseline probability of play for various members.

Online Observations

- Online take rates for take rates follow the offline patterns.

- Our implementation of incrementality is able to shift engagement within the candidate pool.

Future Work

- Framework allows for easily plugging in different policies. Enables -
  - Policy exploration:
    - Different MAB policies TS, UCB, etc.
    - Other ways of combining causal inference with MABs.
  - Model exploration:
    - Different models like NN, LR, GBDT, etc.
  - Reward exploration.
    - Consider long term reward
    - Different kinds of rewards

Thank you.

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