

Recent Challenges and Advances in Industrial Recommender Systems

Liangjie Hong

1st International Workshop on Industrial Recommendation Systems@KDD 2020



August 24th, 2020



Agenda

- 1** Industrial Recommender Systems with Their Ecosystems
- 2** Case I: Understanding The Interplay between Recommender Systems and Search Systems
- 3** Case II: The Journey of Long-term Engagement Optimization



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- 1** Industrial Recommender Systems with Their Ecosystems
- 2** Case I: Understanding The Interplay between Recommender Systems and Search Systems
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Industrial Recommender Systems are more than Matrix Factorization and Neural Models.

Recommender systems are parts of a larger **ecosystem**, serving the overall **product strategy** for a **business**.

Modules and Pages

Down-funnel decisions (e.g., subscriptions, purchases, conversions and etc.) are outcomes of interactions of multiple modules and pages across sessions.

The image shows a composite of two web pages. On the left is a LinkedIn profile for Liangjie Hong, Director of Engineering, AI at LinkedIn. The profile includes a 'PREMIUM' badge, a profile picture, and statistics such as 'Who viewed your profile 2,056' and 'Views of your post 30,399'. Below the profile are sections for 'Recent' (LinkedIn Company Group, Yahoo Research at the W...), 'Groups' (LinkedIn Company Group, Yahoo Research at the W..., Yahoo Employees and AI...), 'Events', and 'Followed Hashtags' (#analytics, #restaurants, #businesstravel). On the right is an Etsy storefront. The top navigation bar includes 'Home', 'My Network', 'Jobs', 'Messaging', 'Notifications', 'Me', 'Work', and 'Learning'. The main content area features a 'Start a post' button, a 'Photo' upload option, and a 'Write article' button. Below this is a post by Najla Elmachtoub, Engineering Manager at Etsy, with a caption: 'Hi #engineeringmanagers. Etsy is looking to fill a few roles. I'm particularly excited about this drop, because leadership team have exciting plans in store.' The post includes a photo of an office scene and a 'Careers at Etsy' link. To the right of the post is a 'LinkedIn News' section with articles like 'America's confidence splits' and 'Bracing for the end of benefits'. Below the post is a 'Welcome back, Liangjie!' message with 'Suggested searches' for 'knight baby shower', 'dragon art', 'big dipper print', and 'big dipper little di...'. The main product grid shows 'Our picks for you' with items like 'CRAFTSMAN SOAP CO. BEER SOAP 6-PACK SAMPLER' for \$15.00, 'Inalka Design' floral art for \$8.50 (15% off), 'MOROCAN MUD' for \$8.00, and 'Great Changes in Tibet' for \$24.95 (FREE shipping). The 'Recently favored' section shows a checkered pattern for \$30.00, 'Great Changes in Tibet' for \$24.95 (FREE shipping), a boat illustration for \$30.00, and another boat illustration for \$30.00. The 'New from shops you like' section features colorful, detailed illustrations of towns like 'NATICK', 'SOMERVILLE', and 'BLOCK ISLAND'.

Product and Business Needs

Recommender systems have to fit into the overall product and business strategy. Sometimes, it is hard to link the success of a module to the overall business.

Great companies are built with great people



Find and engage the right candidates, build your brand, and make even smarter talent decisions.

Contact sales

69
active members
growing

NETFLIX

Home TV Shows Movies Latest My List

FEAR CITY NEW YORK vs. THE MAFIA

TOP 10 #2 in the U.S. Today

Gambino. Bonanno. Colombo. Lucchese. Genovese. No one dared cross the feared mob families — until one agency finally did.

▶ Play

ⓘ More Info

Documentaries



A Collection of Software Services.

In large-scale recommender systems, any of data, features, tools, pipelines, online servings and etc. can be owned and operated by different teams with different goals.

TEAMWORK



Industrial Recommender Systems are more than Matrix Factorization and Neural Models.

Recommender systems are parts of a larger **ecosystem**, serving the overall **product strategy** for a **business**.

- A typical web application has many pages with different types of modules to serve the product need. The interplay between these modules is complex.
- A product with recommender systems needs to serve a set of business purposes, including long-term and short-term goals.
- A recommender system is a product of large-scale engineering practices involving many teams and organizations. End-to-end optimization is challenging.

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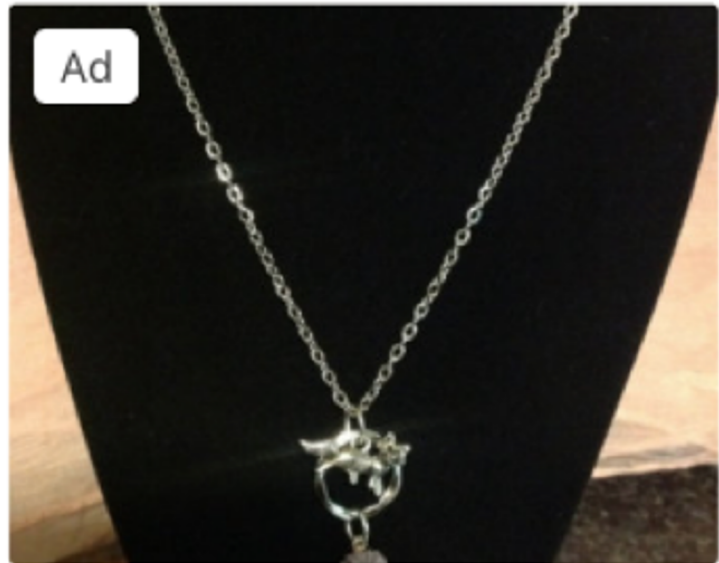
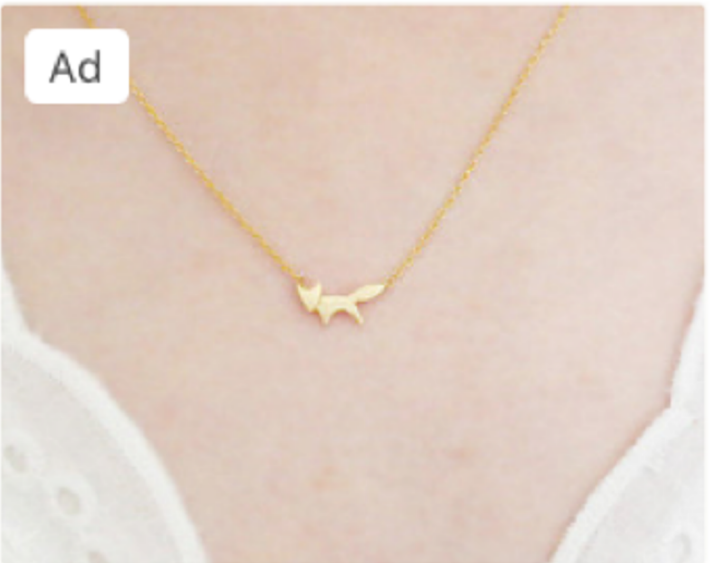
Shop sales and save on unique finds.

Etsy Sell Sign in

fox necklace Search

silver fox necklace gold fox necklace

All categories > "fox necklace" (7,148 Results)

Ad  Ad 

Fox flower necklace Fox Necklace Animal Pe...

Etsy Sell Sign in

Search for items or shops

If it's handcrafted, vintage, custom, or unique, it's on Etsy.

Our Cyber Sales Weekend

Save on original accents, crafted by creators.

Example I: An A/B Test Result for A New Recommendation Algorithm

	% Change
Recommendation Clicks	+5%
Search Clicks	-3%
Revenue	~

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Notes:

- Improvements might come as a result of a series of A/B testing results.
- Not shipping early corner-stone results might lead to a sub-optimal user experience in a long run.
- Shipping placebo results might lead to a sub-optimal user experience in a long run.

Example II: An A/B Test Result for A New Recommendation Algorithm

	% Change
Recommendation Clicks	-10%
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Revenue	+1%

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Notes:

- Deteriorations might come as a result of a series of A/B testing results.
- Once damage is done, it might impact machine learning algorithms in many ways (e.g., training bias).
- Not shipping early corner-stone results might lead to a sub-optimal user experience in a long run.
- Shipping placebo results might lead to a sub-optimal user experience in a long run.

We need to understand the **interplay** between recommendation and search modules as well as their whole **ecosystem** to create a **coherent** user experience and optimize user engagement.

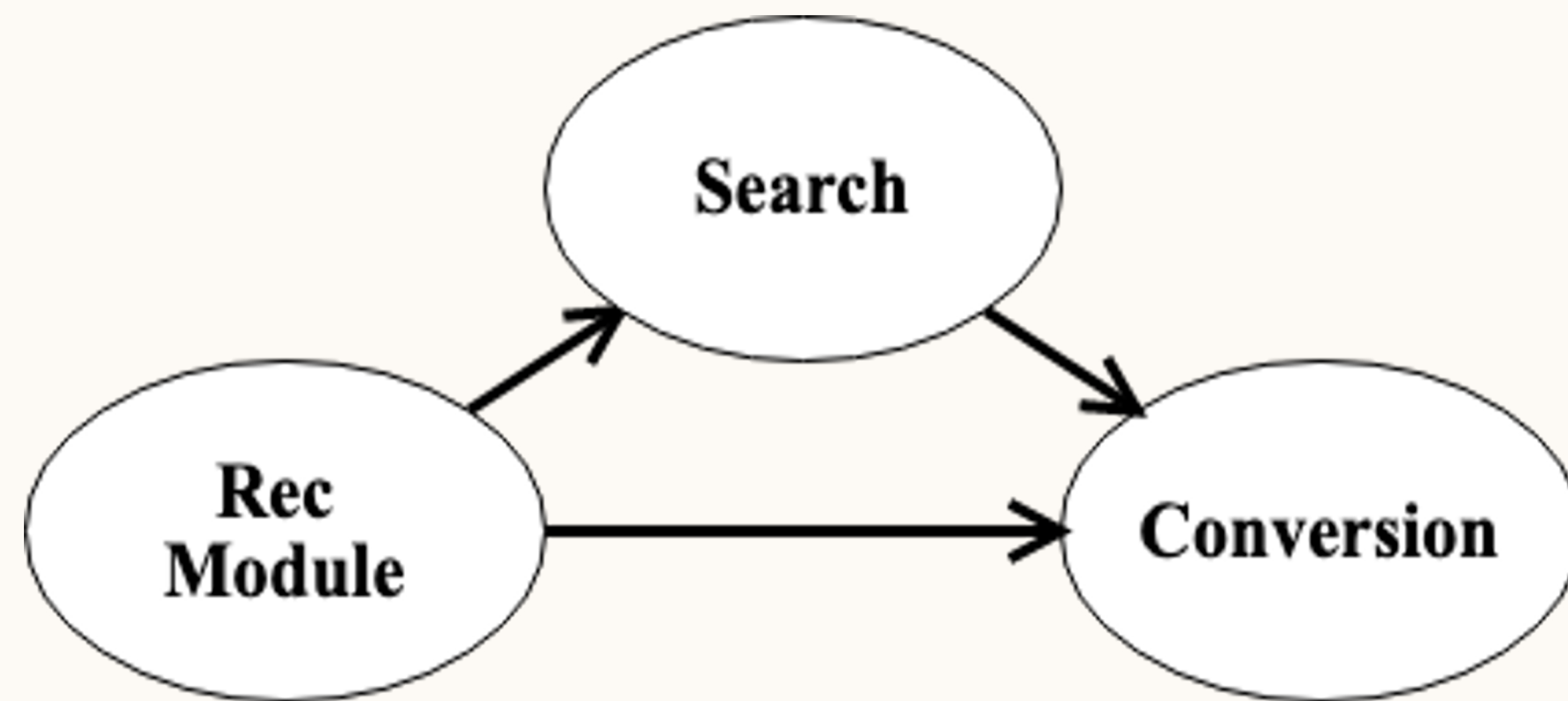
- Opportunity 1:
Understand experimental results while multiple teams work on different recommendation and search modules.
- Opportunity 2:
Develop and implement strategies to improve multiple modules and possibly optimize overall user engagement.
- Opportunity 3:
Develop machine learning models to directly optimize user engagement from a whole user journey perspective.

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X. Yin and L. Hong. **The Identification and Estimation of Direct and Indirect Effects in A/B Tests through Causal Mediation Analysis**. KDD 2019.

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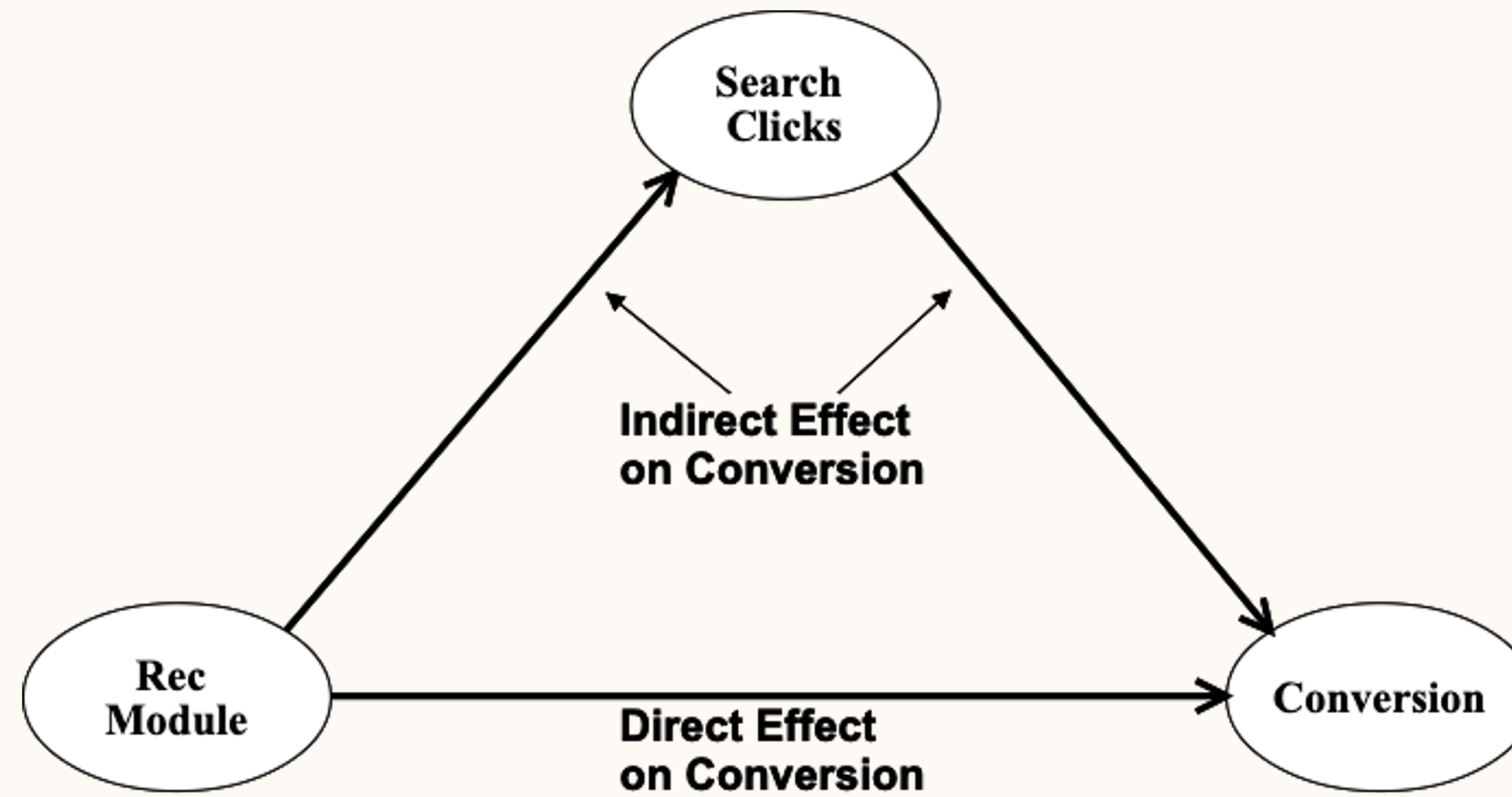
A product change could *induce* changes in user interaction with other products.



- An improved recommendation module could effectively suggest items that satisfy users' needs so that users don't need to search as much as usual.
- The overall performance of an improved recommendation module could be cannibalized by the induced reduction of user engagement in search.
- The performance of search could be cannibalized by an improved recommendation module.

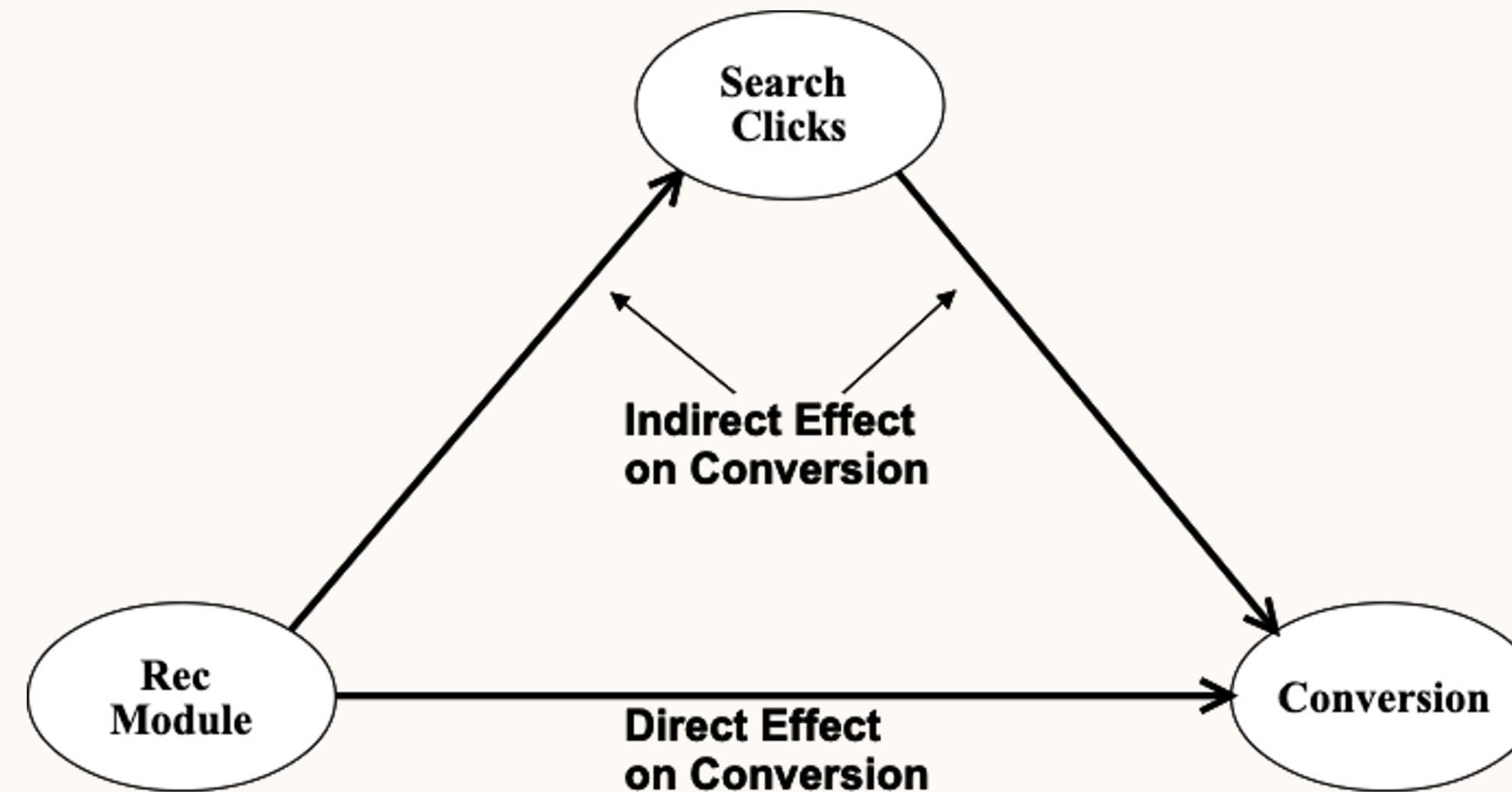
Common Solution

Splitting Average Treatment Effect (ATE) into Two Parts:
Direct Effect and Indirect Effect



Common Solution

Splitting Average Treatment Effect (ATE) into Two Parts: Direct Effect and Indirect Effect



Notes:

- Causal Mediation Analysis (CMA) is a formal statistical framework to conduct such analysis.
- Average Direct Effect (ADE) is the direct impact of new recommendations while keeping search behavior fixed.
- Average Causal Mediation Effect (ACME) is the impact of induced changes in search behavior due to changes in recommendation algorithm.

Common Solution

Splitting Average Treatment Effect (ATE) into Two Parts: Direct Effect and Indirect Effect

Notes:

- ATE, ADE and ACME has been studied extensively in the literature.
- Existing methodologies cannot be easily utilized due to violations of the key assumptions in the literature: no unmeasured causally-dependent mediator.
- A typical E-commerce site could have hundreds of web-pages and modules, and all of them could be mediators. It is difficult to measure all of them.
- We extended ADE and ACME to Generalized ADE (GADE) and Generalized ACME (GACME) respectively.
- It is easy to implement and only requires solving two linear regression equations simultaneously.
- Git Repo: <https://github.com/xuanyin/causal-mediation-analysis-for-ab-tests>

Case I: RecSys Listing Page Same-Shop Experiment

Effect	% Change	
	Conversion Rate	GMV
GADE Direct Effect of the Change of Rec Module	0.4959%*	0.1681%
GACME The Effect of the Induced Change of Search	-0.2757%***	-0.4200%***
ATE	0.2202%	-0.2518%

Notes:

1. % Change = Effect/Mean of Control
2. ‘***’ p<0.001, ‘**’ p<0.01, ‘*’ p<0.05, ‘.’ p<0.1. Two-tailed p-value is derived from z-test for H₀: the effect is zero, which is based on asymptotic normality.

Case II: RecSys Listing Page Internal-Bottom Desktop Experiment

Effect	% Change	
	Conversion Rate	GMV
GADE Direct Effect of the Change of Rec Module	0.3448%*	0.0659%
GACME The Effect of the Induced Change of Search	-0.0570%.	-0.0926%.
ATE	0.2878%.	-0.0267%

Notes:

1. % Change = Effect/Mean of Control
2. ‘***’ p<0.001, ‘**’ p<0.01, ‘*’ p<0.05, ‘.’ p<0.1. Two-tailed p-value is derived from z-test for H₀: the effect is zero, which is based on asymptotic normality.

Takeaways

- Understanding direct vs. indirect effects enables us to understand the competition between recommendation modules and search results; and give more informed decisions during roll-outs
- Develop better recommendation strategies such as suggesting items and categories not searched organically or diverse information shown in different surfaces.
- Develop better offline evaluation framework to incorporate both search and recommendation results.



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Measuring Product and Business Success

Business tends to not focus on immediate user engagement improvements but longer term successes (e.g., confirmed hires, GMS, user retention and etc.).

The image shows two screenshots side-by-side. The top screenshot is a LinkedIn job search results page for 'Software engineer in United States' with 145,645 results. It lists several job postings, including 'Software Development Engineer' at Apple, 'Software Engineer' at Amazon Web Services (AWS), 'Software Engineer, Tiktok Monetization' at TikTok, and 'Software Engineer' at Facebook. The bottom screenshot is an Etsy search for 'ancient maps', showing various map-related products like 'An Ancient Mappe of Fairyland Gall...', 'Vintage Mumbai Bombay India post...', 'Vintage Compass | Multi Panel | Gall...', 'Antique world maps, Old world map...', 'Antique map of Roman Empire, 1709...', and another 'An Ancient Mappe of Fairyland Gall...'.

Internal Feedback Turn On Alpha

There are non-trivial gaps between what we could optimize and what we should optimize.

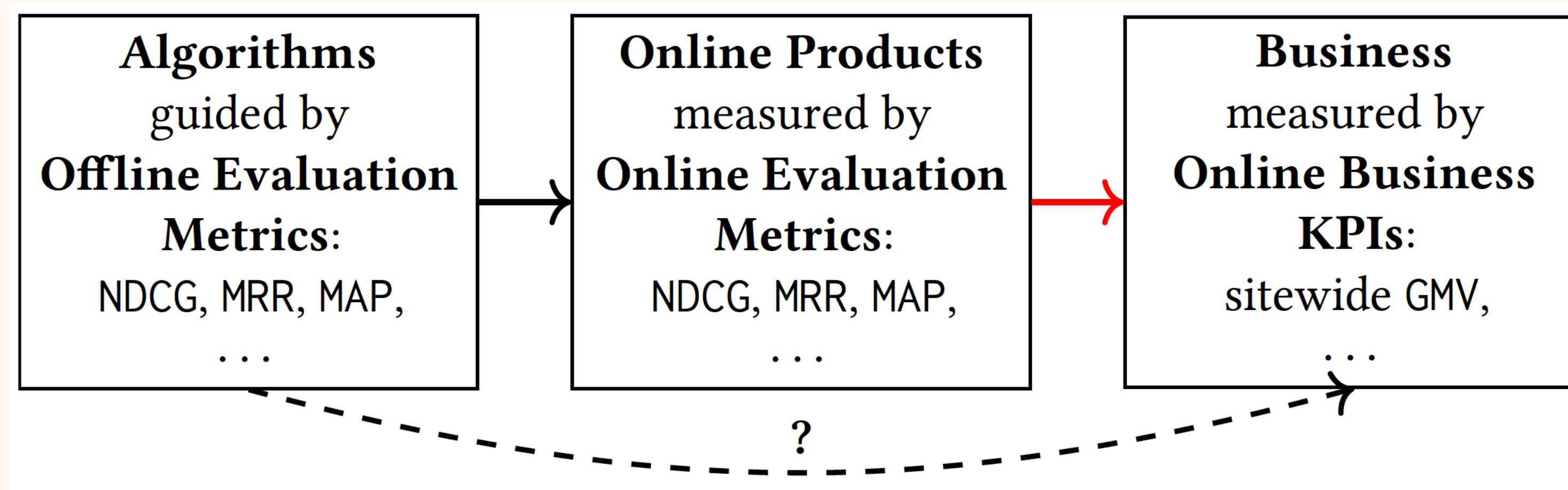
- Opportunity 1:
Optimize short-term metrics and seek to establish relationships between short-term metrics and long-term metrics.
- Opportunity 2:
Directly optimize long-term metrics.
- Opportunity 3:
Accelerate experimentation and directly optimize long-term metrics.

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Causal Meta-Mediation Analysis

The Causal Path from Algorithms to Business

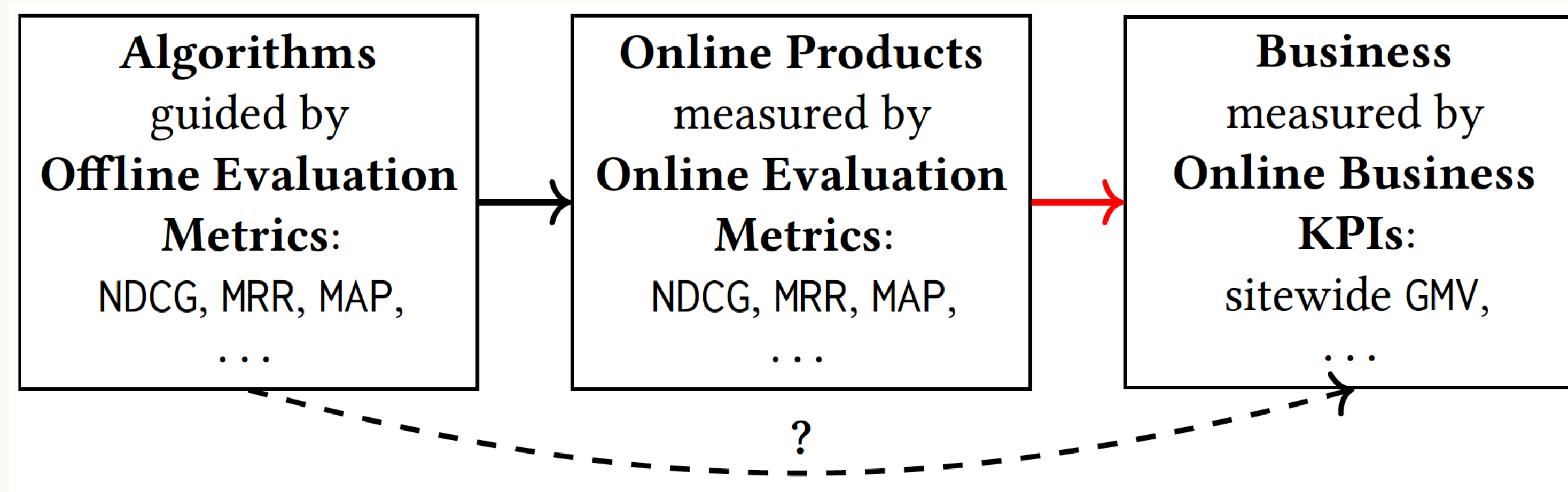


Notes:

- First part (the black arrow): counterfactual estimators of offline evaluation metrics to bridge the inconsistency between changes of offline and online evaluation metrics.
- Second part (the red arrow): the causality between online products (assessed by online evaluation metrics) and the business (assessed by online business KPIs).
e.g. how business KPIs would change for a 10% increase in an online evaluation metric.

Causal Meta-Mediation Analysis

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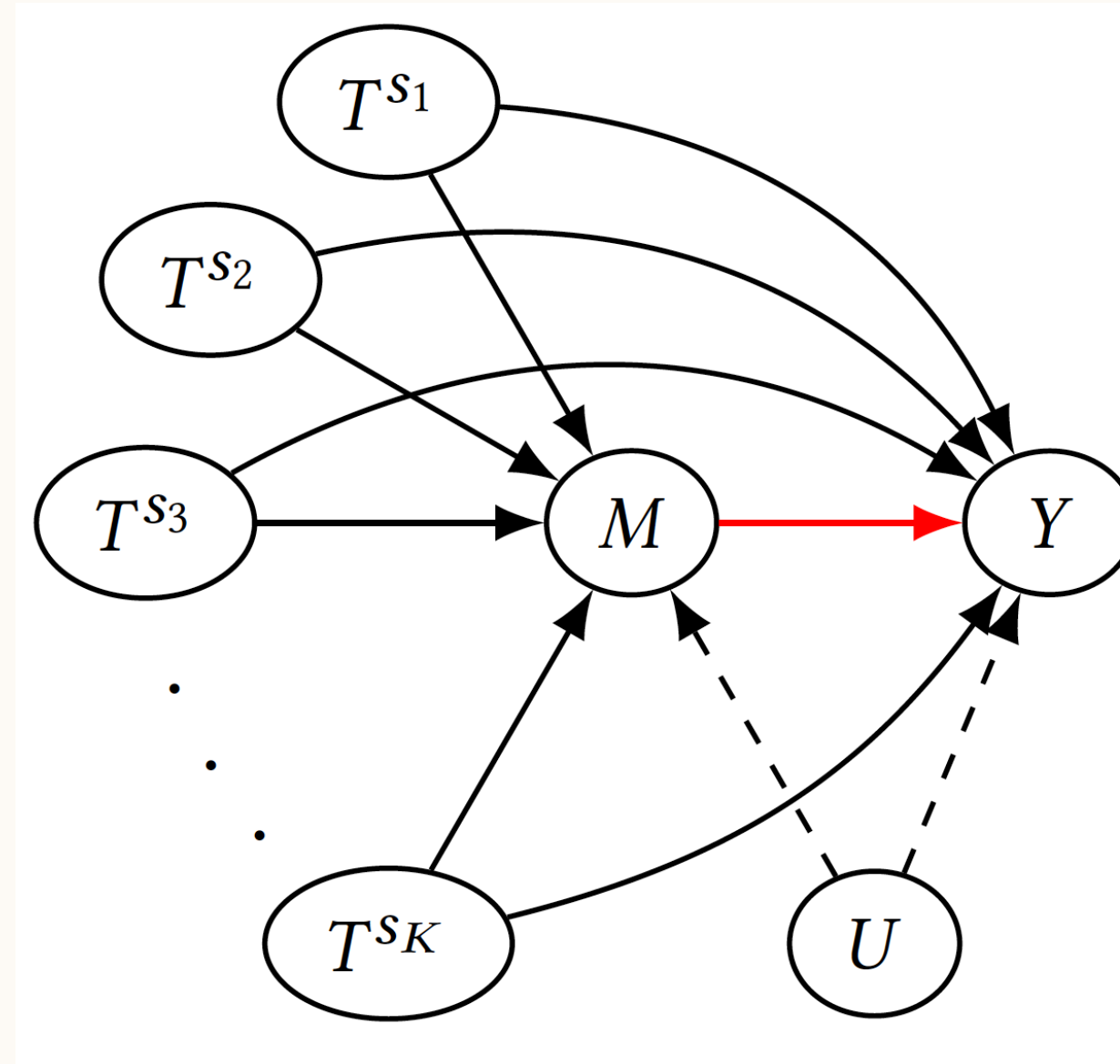


Key Ideas:

- We model the causality between online evaluation metrics and business KPIs by *dose-response function* (DRF) in potential outcome framework.
- Instead of conducting online tests, we use results from historical A/B experiments to conduct Meta-Analysis.
- Online evaluation metrics could be mediators that (partially) transmit causal effects of treatments on business KPIs in experiments where treatments are not necessarily algorithm-related.

Causal Meta-Mediation Analysis

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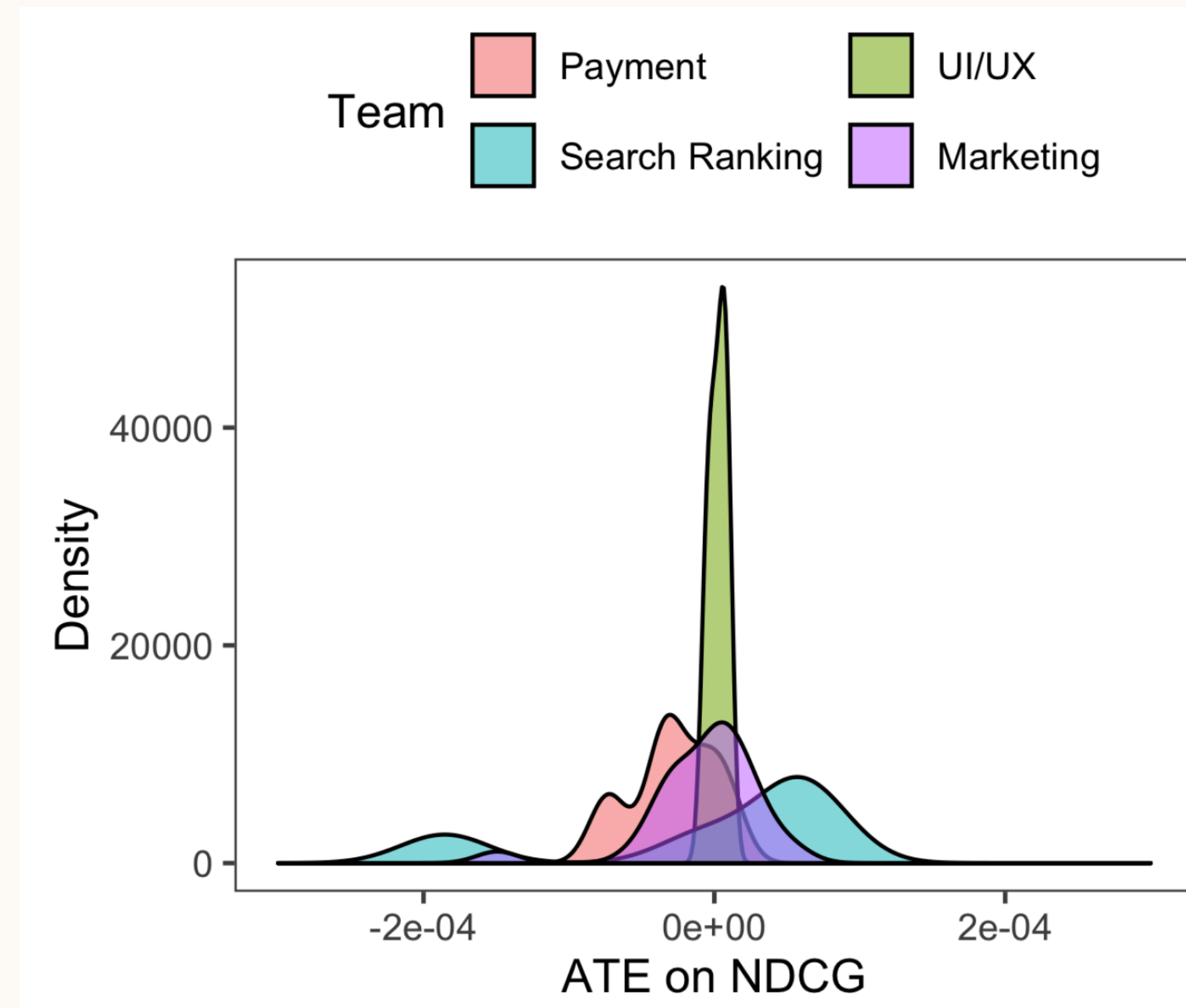


Key Ideas:

- T s are treatments; M is a mediator; Y is a outcome; U is unobserved and unmeasured.
- M is online evaluation metric. Y is online business KPI.

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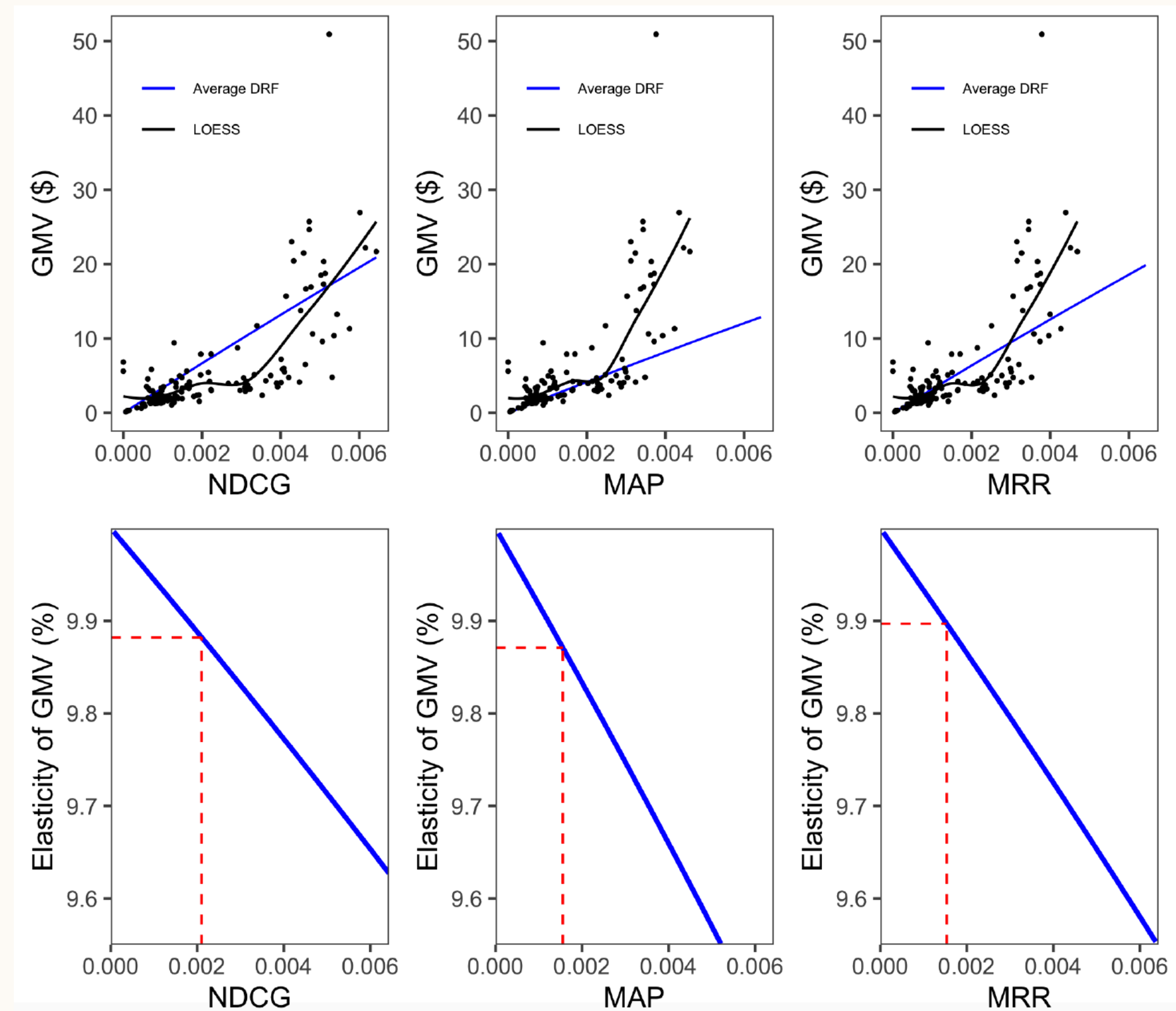


Data:

- 190 experiments from different teams.
- The figure shows that basic assumptions used by the method holds: enough variations.

Causal Meta-Mediation Analysis

The Causal Path from Algorithms to Business



Results:

- NDCG, MAP, MRR all have positive casual relationships with GMV.
- We could utilize *elasticity* to choose a better metric.

Takeaways

- We model the causality between online evaluation metrics and business KPIs by dose-response function (DRF) in potential outcome framework.
- Instead of conducting online tests, we use results from historical A/B experiments to conduct Meta-Analysis.
- From 190 experiments' data, we have established positive causal relationships between offline metrics and business KPIs and also could choose which metric is better.



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Thank you