UNDERSTANDING BEHAVIORS THAT LEAD TO PURCHASING:

A CASE STUDY OF PINTEREST

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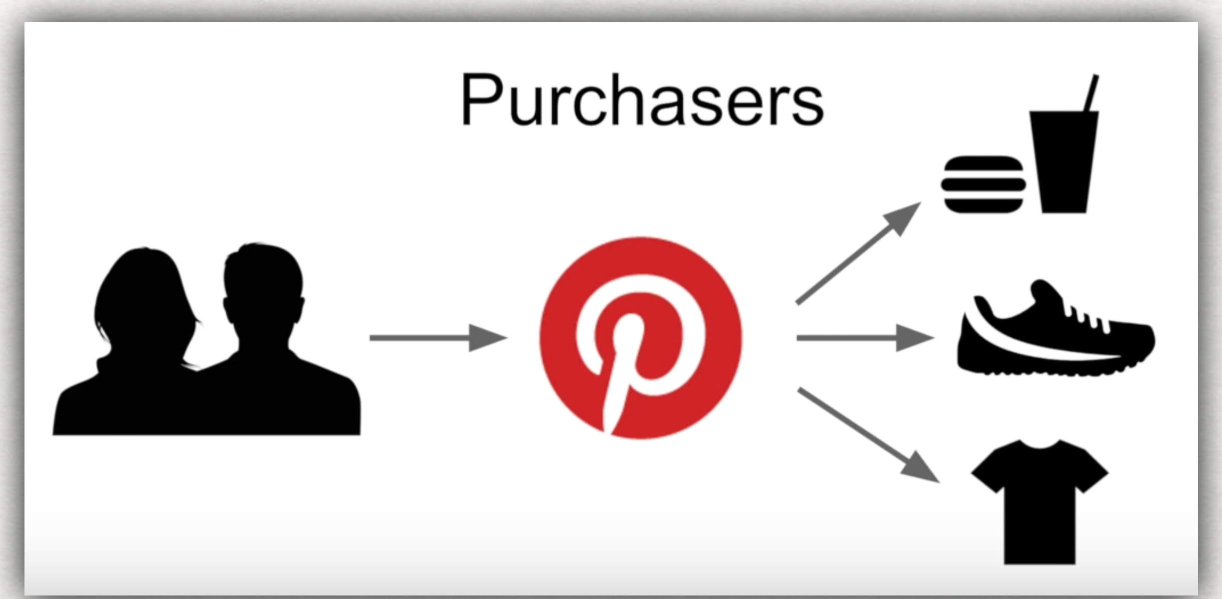
AGENDA

1. Problem Statement
2. Motivation
3. Related Work
4. Dataset
5. Observations
6. Modeling Purchase Intent
7. Conclusion
8. Future Work

PROBLEM STATEMENT

- Understand and Model long term, time varying user purchasing intent using (CDA) Content Discovery Applications.



WHY?

- Online shopping in US alone - 350 bn USD/ year.

    + growing at ~15% annually.

- Improved advertising, search results ranking and personalization

    eg. 1. promote buyable pins to users identified with purchase intent.

    2. target pricing

RELATED WORK

- Collaborative Filtering: Exploit other users' purchase histories
- Content based
  - product reviews, demographic data, previous purchase history
- Using short-term user activity - whether a given user session will result into purchase
  - Task Completion, Hidden Markov Models
- Using external sources
  - social media, email-data, social networks
- Used in combination

DATASET

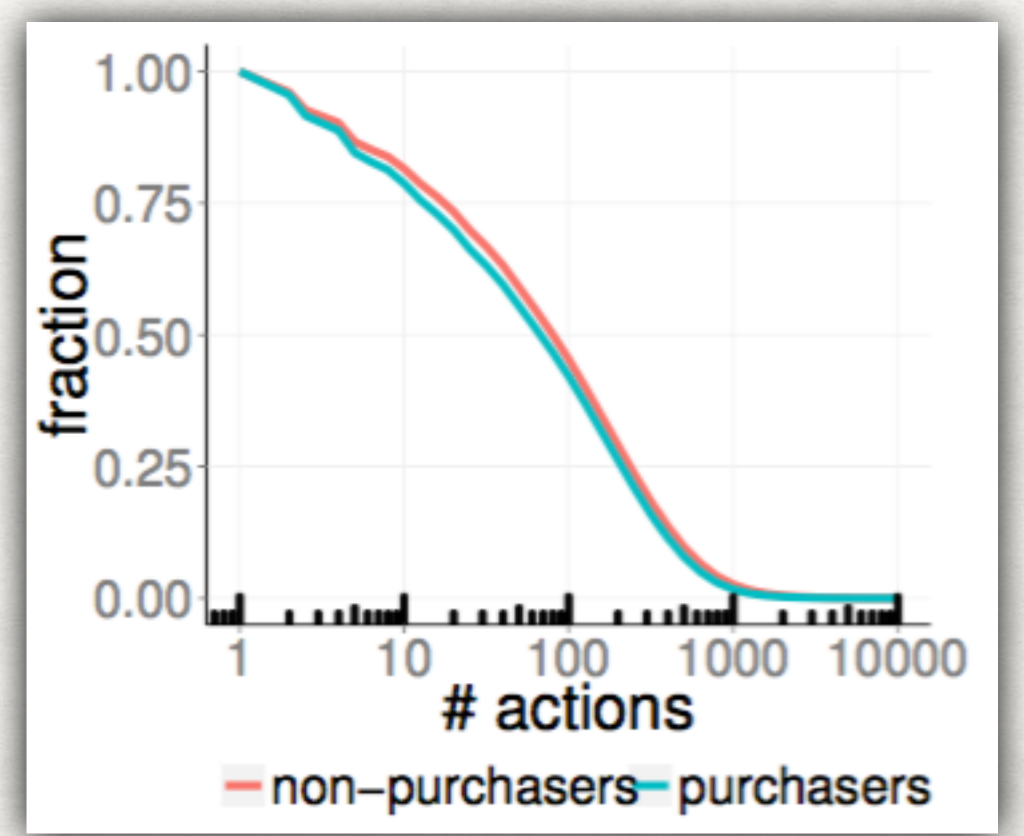
- Content Discovery Application - 4 classes of actions
  - Search
  - Closeup (Engage on-site)
  - Clickthrough (Engage off-site)
  - Save

- Pinterest Dataset

Statistic	Value
Number of purchasers	1.3M
Number of non-purchasers	1.3M
Number of users (total)	2.6M
Number of actions (total)	0.5B
Time duration	28 days
Month when purchases were made	May 2015

- <40% users make >1 purchase in May'15: randomly sampled single purchase
- Each purchaser matched with a non-purchaser by:
  - Registration month
  - #Active days before 28 days (Long term activity)
  - Gender (US based users only)

- User Activity Analysis
    - Purchasers are <u>not</u> more engaged!
    - On the surface purchasers and non-purchasers seem no different.

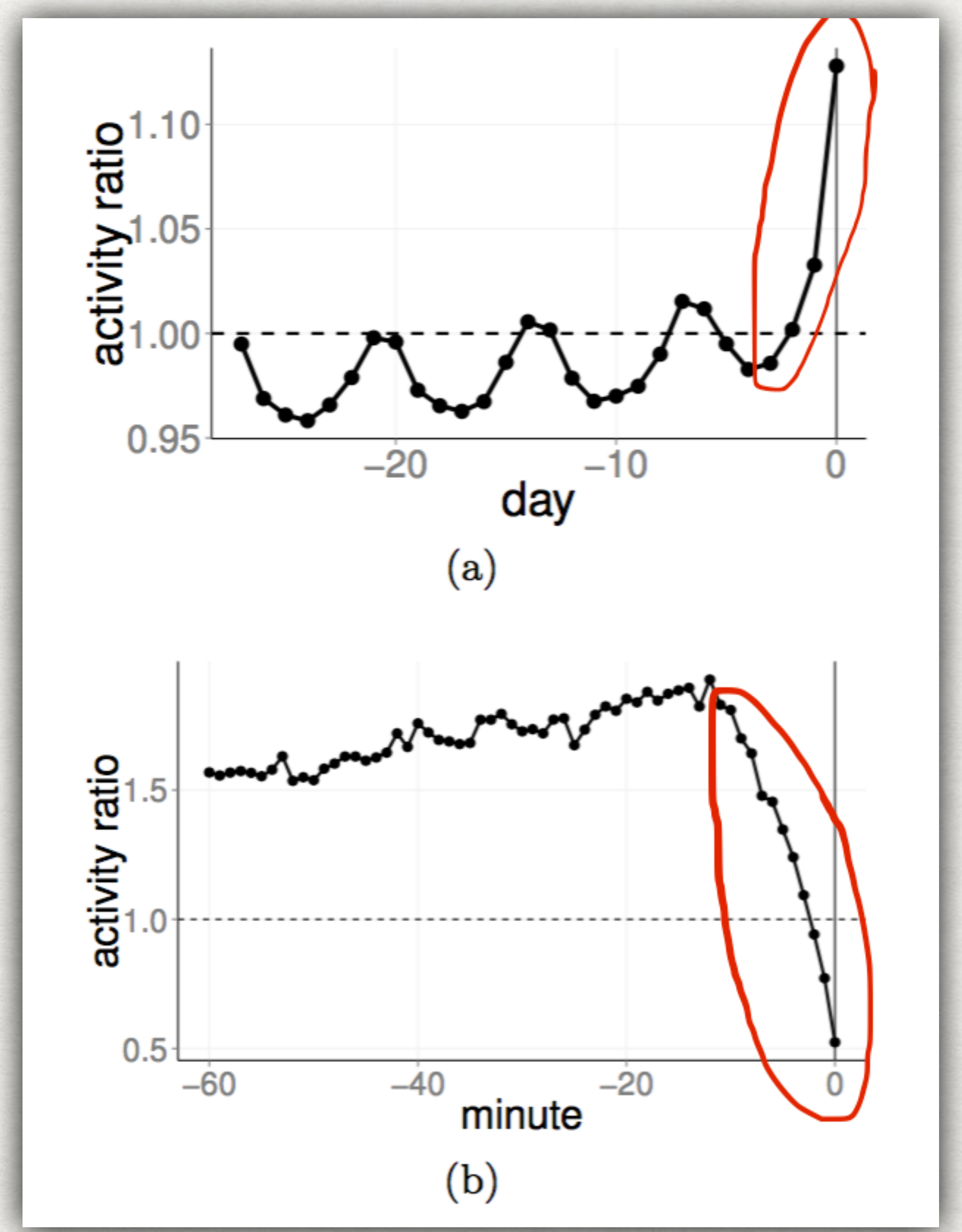


DYNAMICS OF PURCHASE INTENT

HOW DOES IT EVOLVE OVER TIME?

- Overall user activity level
  - Relative activity level of matched purchasers and non-purchasers

$$AR(d) = \frac{\%\ \text{purchasers active on day } d}{\%\ \text{non-purchasers active on day } d}.$$



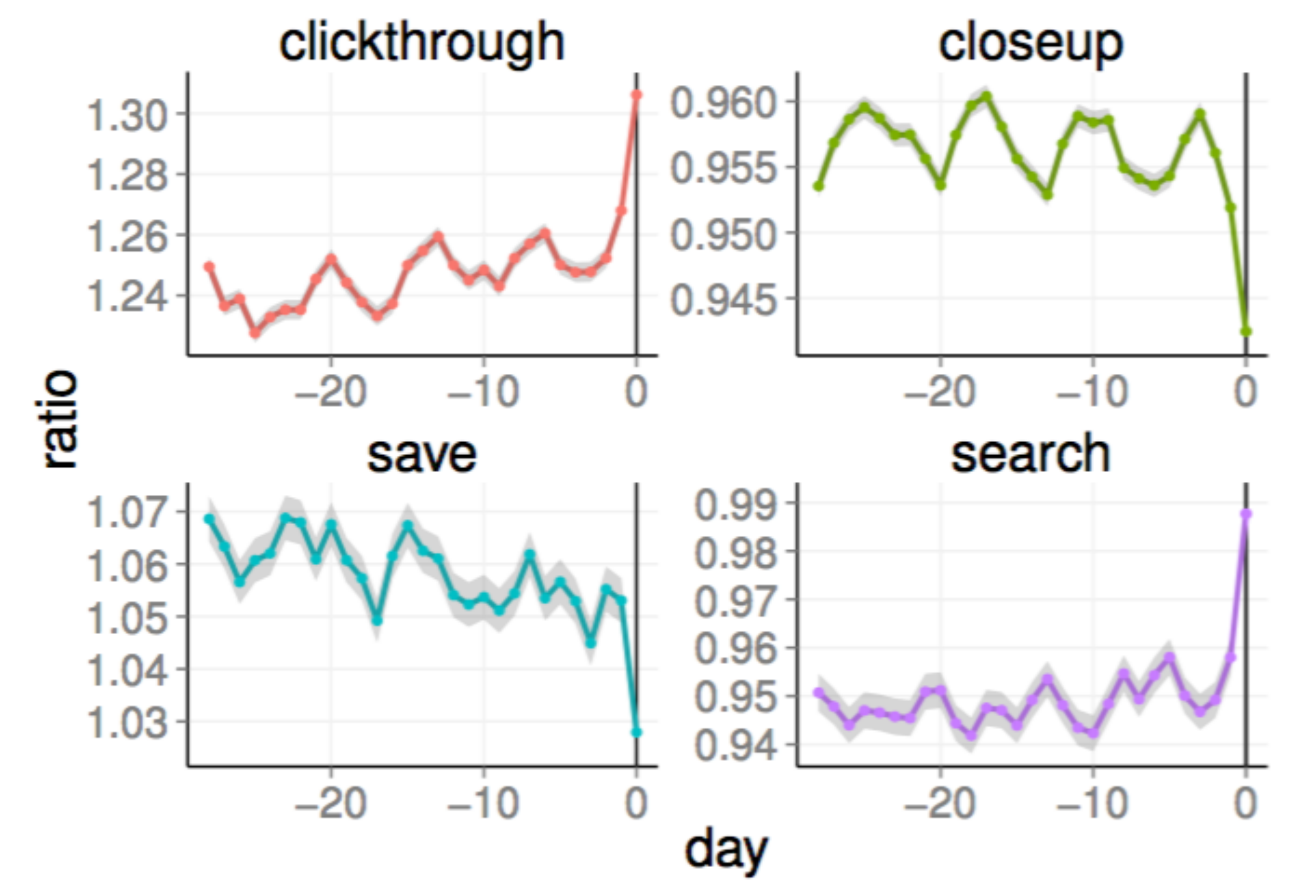
- Specific behavior - user action
  - Intentional actions
  - Action score: prioritize which action?

$$AS(u,d,a) = \frac{\text{\# actions } u \text{ took on day } d \text{ of type } a}{\text{\# actions } u \text{ took overall on day } d}.$$

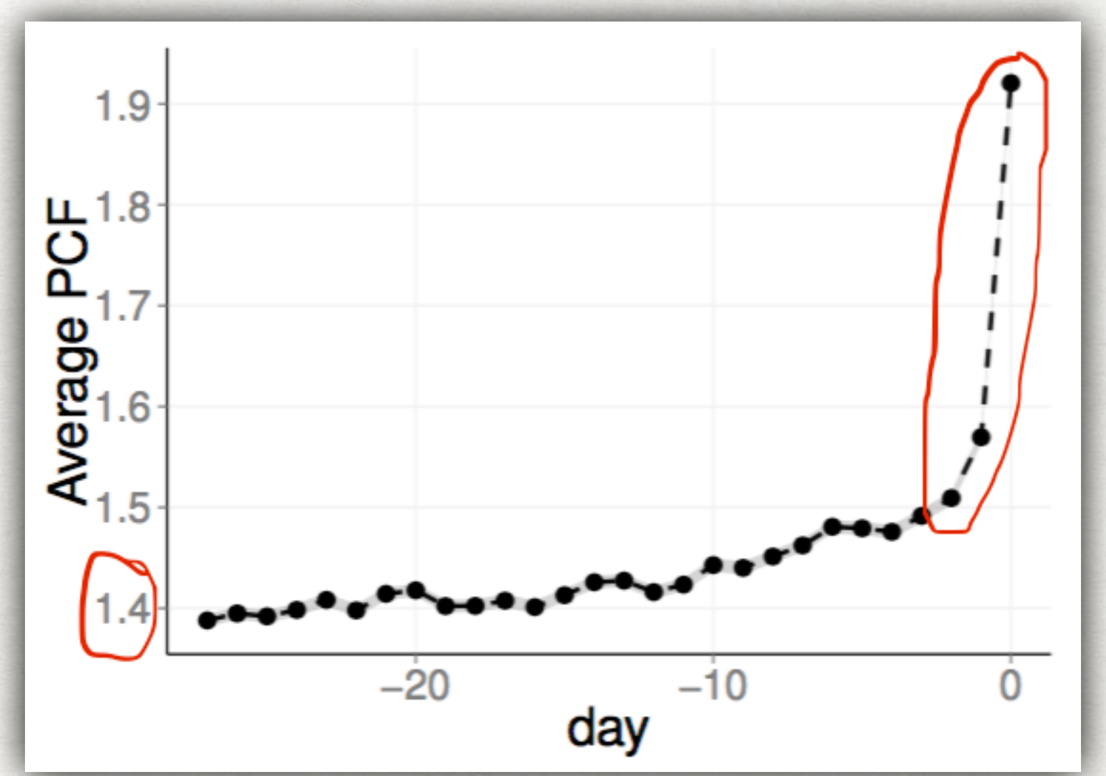
  - AS Ratio: comparing non-purchasers and purchasers.

$$ASR(d,a) = \frac{avg_{u \in \text{purchasers}} AS(u,d,a)}{avg_{u \in \text{non-purchasers}} AS(u,d,a)}.$$

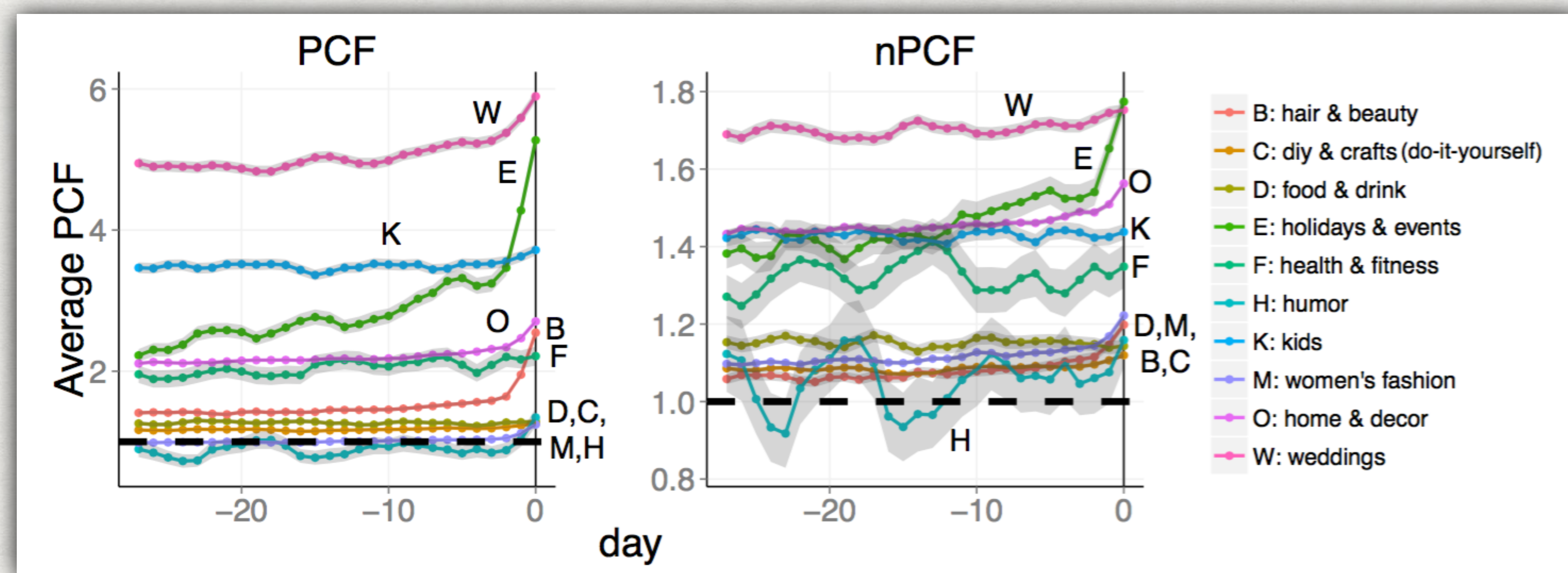
  - Purchaser behavior does change right before day 0!



- Purchasers category focus
  - Pinterest - 32 predetermined high-level categories
  - Partner companies - fall within 10 categories based on pins
  - Category interaction score (I): fraction of actions taken by a user that fall in category c on a day d.
  - Purchase category focus:



$$PCF(p,d,c) = \frac{I(p,d,c)}{avg_{u \in non-purchasers} I(u,d,c)}.$$



- PCF spike before day 0 - differs across categories (Impulsive purchase?)
- nPCF: how interested is a purchaser compared to users already interested in that category?

- Summarizing Purchase Intent Dynamics as Day 0 approaches,
  - Purchaser more likely to be active on CDA.
  - Increased investment in specific content (clickthrough and save) over a lengthy period.
  - Sharp increase in searching for and browsing through on Day 0 compared to other days.
  - Purchaser focuses on content related to their purchase and increasingly so.
  - Extent to which purchase intent is expressed varies across categories.

MODELING PURCHASE INTENT

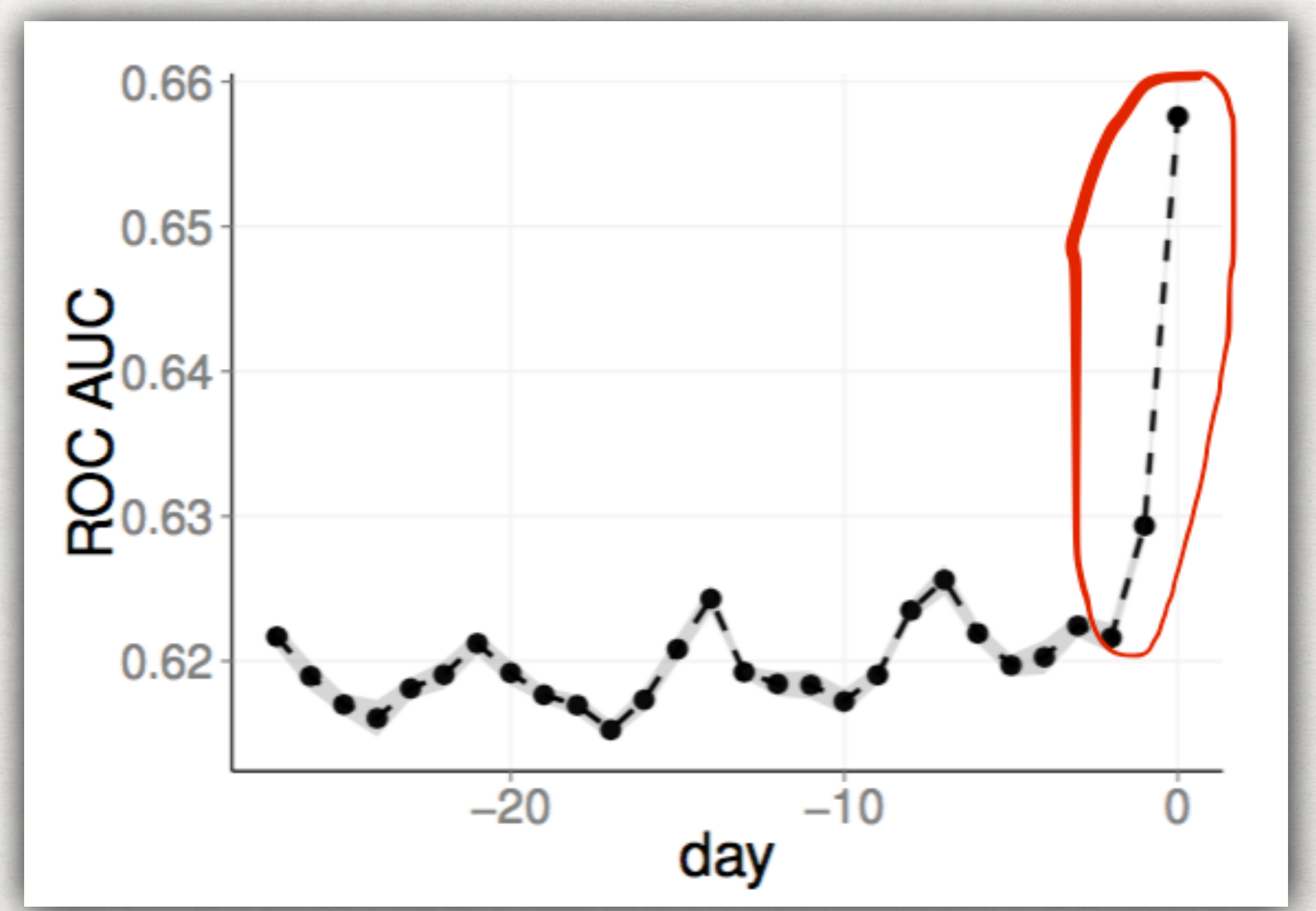
Identifying purchaser based on their behavior on day -k

- Features for learning task
  - Demographics: Gender, Region, #Boards, #Pins
  - Activity: #Active days in last 7 days, #Actions/day
  - Action-type: Action-ratio for each action type, Platform usage
  - Content: Category interaction scores (CIS)
  - Temporal: Difference between Action-type & Content features values over an interval of a) 3 days, b) 30 hours & c) 7 days prior.

- Modeling Purchase Intent Over Time
  - Task 1: How well can purchasers be identified as Day 0 approaches?
    - Sample 250K purchases & non-purchasers, active on -kth day
    - Train separate logistic regression classifiers per day k (0 to -27) and compute the 10-fold cross validated AUC ROC curve.

Observations:

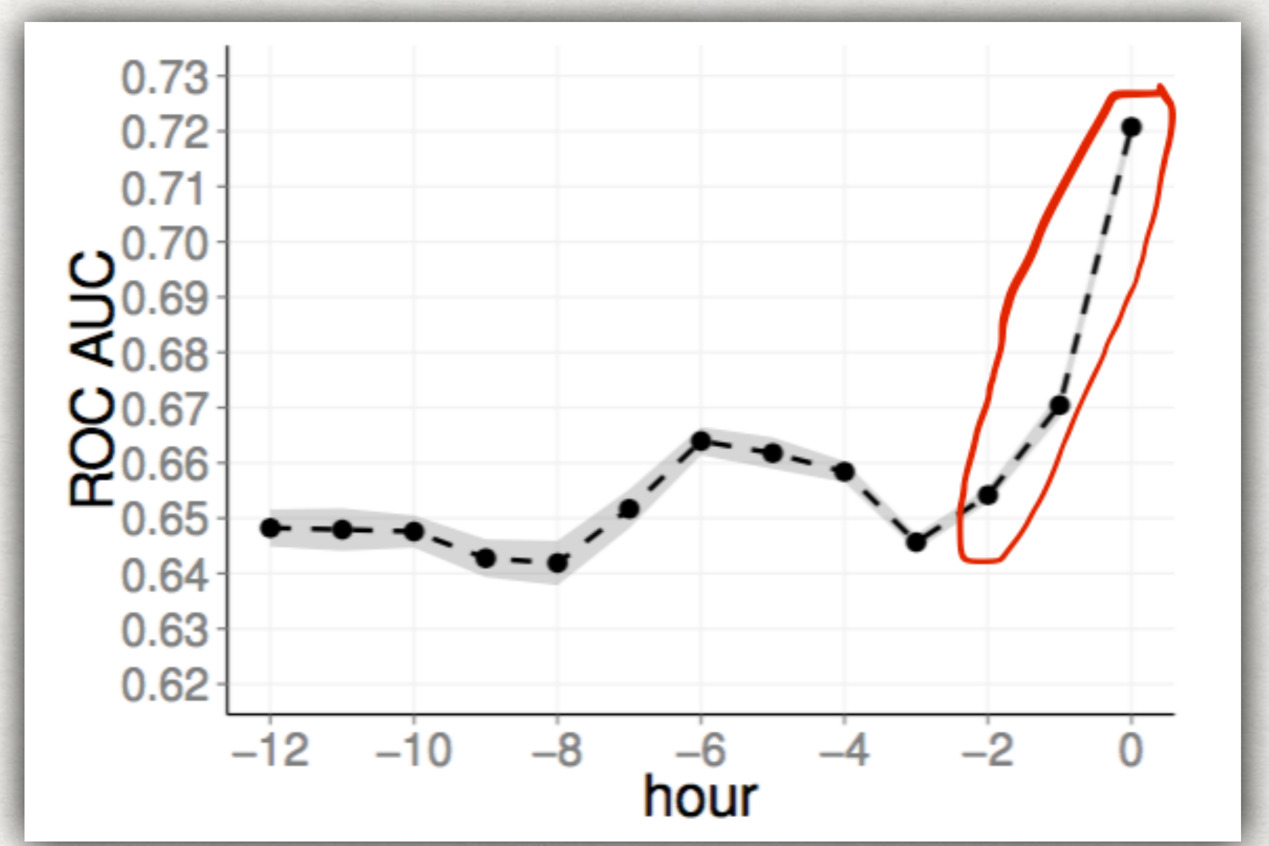
- ROC AUC ~ [0.62, 0.66]
- Purchase intent builds slowly and spikes in the last 3 days



- Task 2: Predict if a user active at -k hours is a purchaser or not?

Observations:

- ROC AUC ~ [0.65, 0.72]
- Short-term differences of purchasers exist shortly before a purchase is made



- Examining Signal Importance
  - Identifying purchasers active on day 0
  - Identifying purchasers active on hour 0

Features	**Day 0**	**Hour 0**
Random Baseline	0.500	0.500
Demographics (d)	0.513 ± 0.0007	0.513 ± 0.0024
Activity (a)	0.591 ± 0.0008	0.625 ± 0.0015
Action-type (A)	0.633 ± 0.0008	0.698 ± 0.0020
Content (C)	0.577 ± 0.0008	0.617 ± 0.0020
Temporal (T)	0.544 ± 0.0007	0.581 ± 0.0019
d + a + A (*how*)	0.642 ± 0.0009	0.702 ± 0.0017
d + a + A + C + T	$\mathbf{0.657} \pm 0.0007$	$\mathbf{0.721} \pm 0.0026$

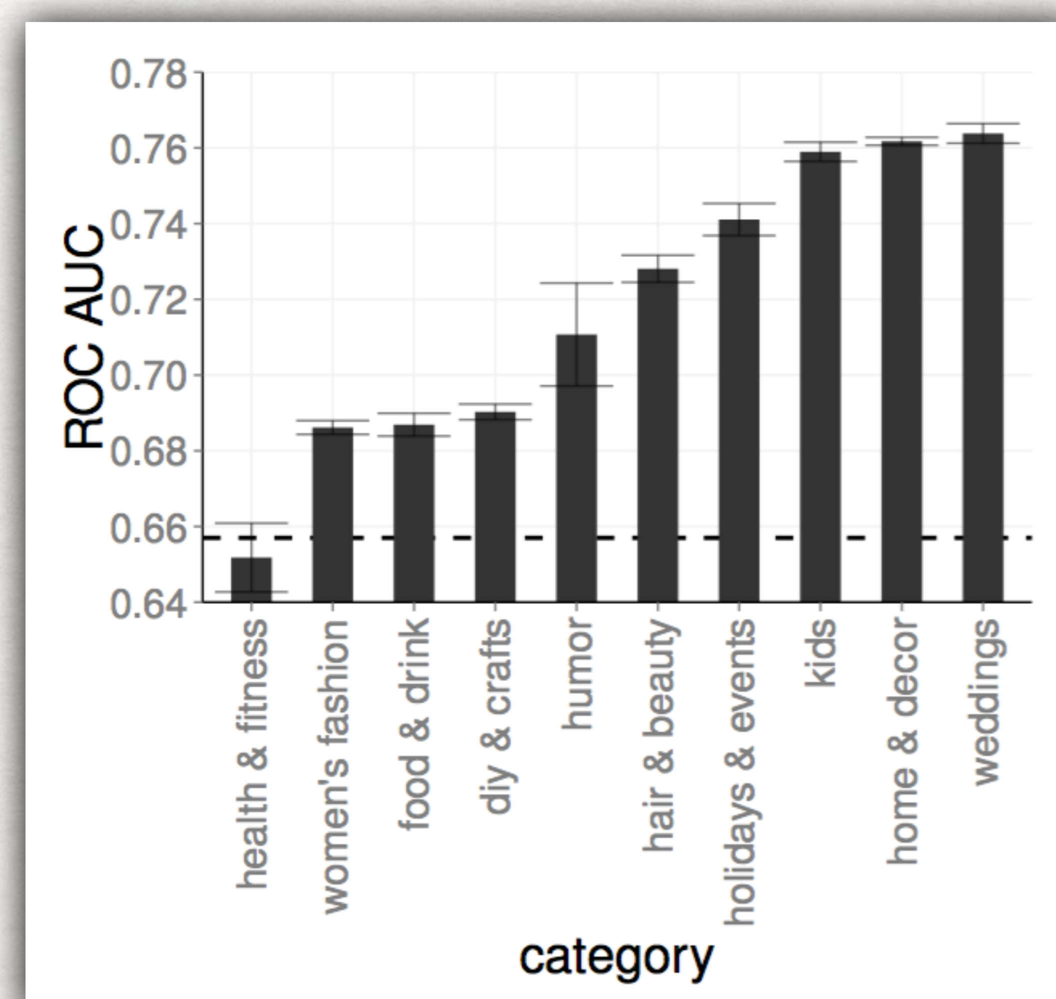
- Modeling per-category purchase intent
    - Task: Predict whether a user will purchase an item in a specific category.
    - Sample active users on the purchase date and build one binary classifier for each category

Observations:

- Differences in ROC values ⇒

  purchase intent is stronger for some categories

- Purchase intent can be modeled both over time, as well as within a specific category

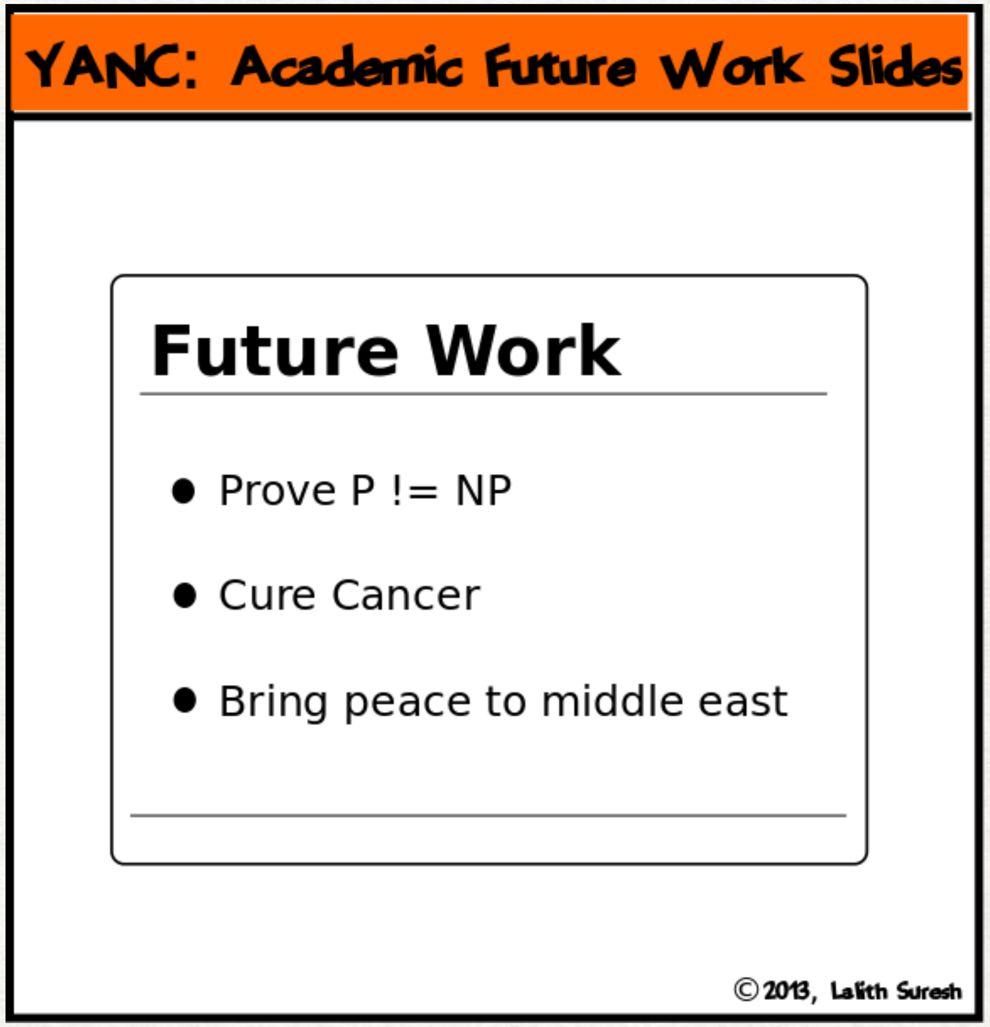


CONCLUSION

- A data-driven, cross-platform approach.
- One of its type -- longitudinal study of the dynamics of user study
- Serves as a basis for future studies on the intersection of online behavior and purchasing patterns
- Results not reproducible - performance on other datasets ?
- Mathematical Relations guided by heuristics rather than previously proven methods

FUTURE WORK

- How to handle impulsive shoppers ?
- Personalize search results based on purchasing intent
- Buyable Pins ?



THANK YOU

QUESTIONS?

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