machine learning conference

Repeat Purchase Recommendations: Contextual Reranking, Customer Cohorts, and Impressions Feedback

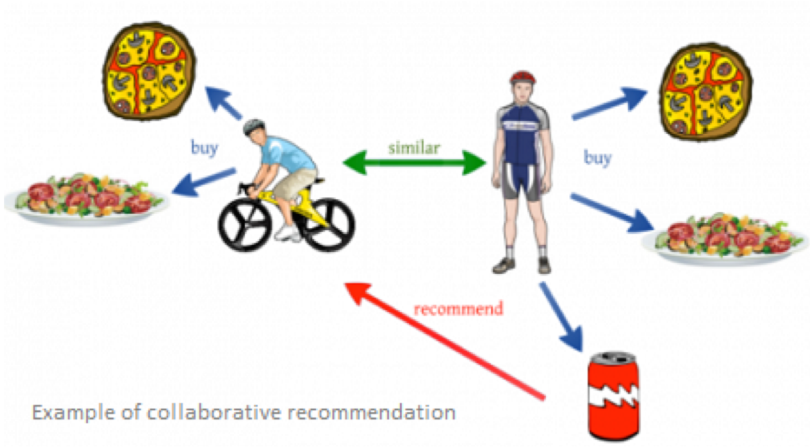
Srevatsan Muralidharan @srevatsa
Applied Scientist II | Personalization

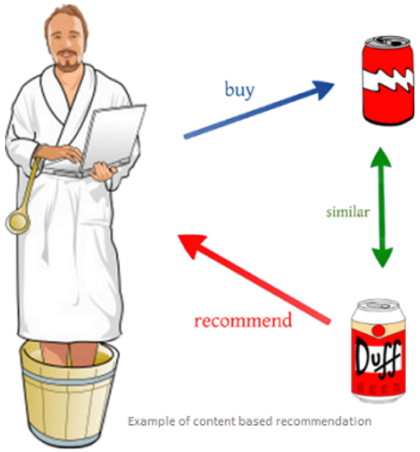
Rahul Bhagat
Sr. Applied Sciences Manager
Social Shopping Tech

Won Jae Lee
Software Development Engineer
Personalization

Yu Liu
Applied Science Intern
Personalization

Common recommendation strategies





Collaborative filtering

Content-based filtering

Central idea: Recommend new items to customers based on customer's past behavior (purchases, views, ratings, etc.) or explicit preferences

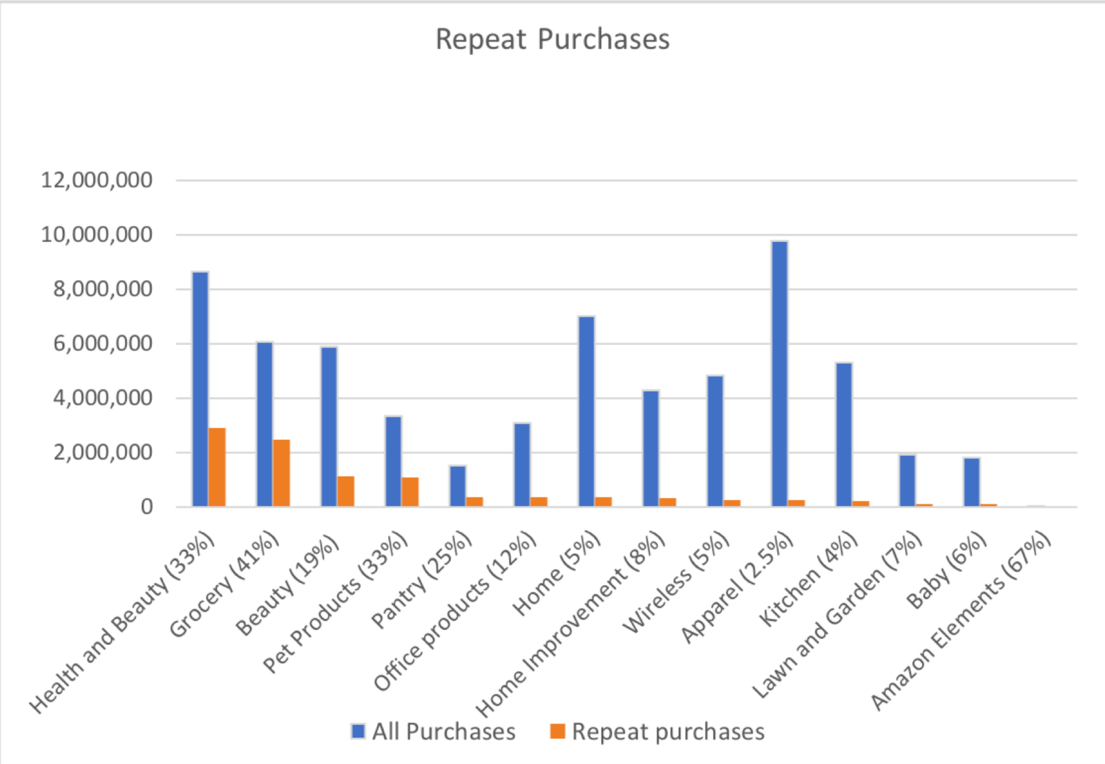
Image source: https://www.quora.com/What-is-the-difference-between-content-based-filtering-and-collaborative-filtering

What about recommending items to customers that they have already bought before?

What about recommending items to customers that they have already bought before?

Groceries, everyday essentials, etc.

Repeat Purchase Recommendations



- 10% of purchases in Amazon are repeat purchases
- 28% in various consumable categories

Buy it again (BIA)

Buy it again

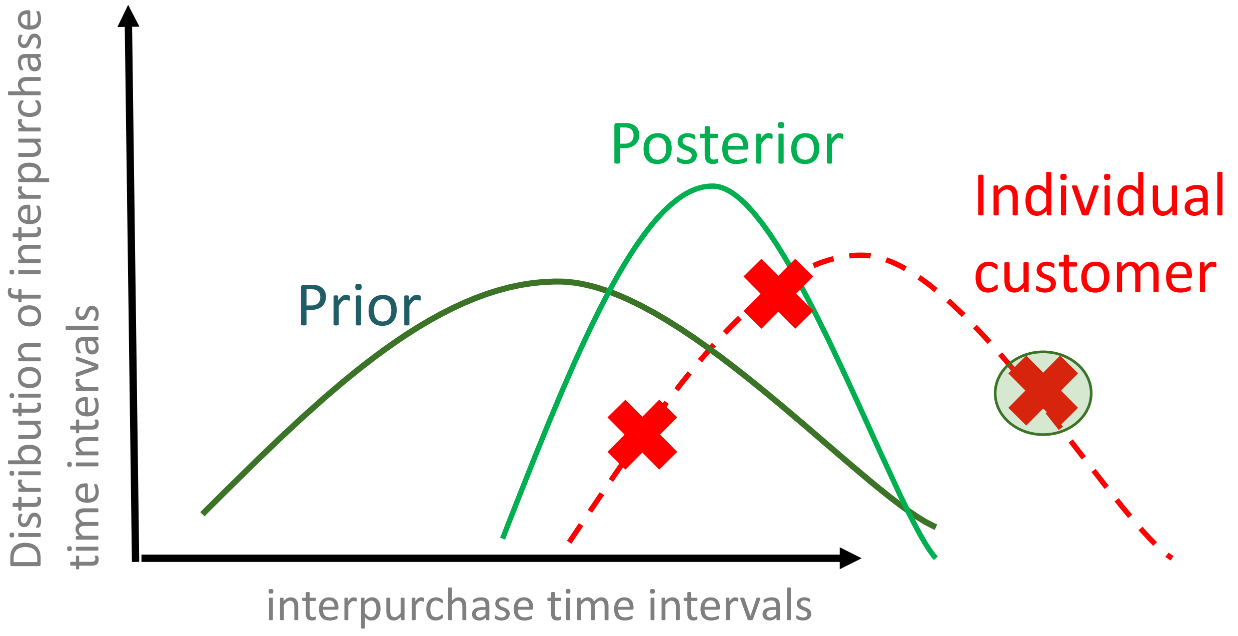
Customer benefit: Provide timely recommendations of products that they may wish to purchase again

- What type of items are repeat purchasable?

- When is the right time to remind them of it?

1) Rahul Bhagat, ‘Buy it again’: Modeling repeat purchase recommendations, AMLC (2015)
2) Srevatsan Muralidharan and Rahul Bhagat, A Bayesian lognormal model of repeat purchase recommendations, AMLC (2017)

Buy it again: Bayesian Lognormal Models



- Evidence: Customer specific repeat interval history
- Prior: Time interval distribution of an ASIN across all customers
- Assumption: Lognormally distribution

Srevatsan Muralidharan and Rahul Bhagat, A Bayesian lognormal model of repeat purchase recommendations AMLC (2017)

Buy it again

Over million ASINS

Over 150 million customers world-wide

Over a billion dollars attributed OPS

Buy it again: refining the models

- Contextual relevance: should we rerank the recommendations based on most recently added item?
- Household size: Should we account for the family sizes?
- Impressions feedback: Should we account for the view signals.

Buy it again: contextual reranking

Guitar string winder

BIA ranking independent of customer context

- Two competing hypothesis: to contextualize or not
- Context: Product Group (e.g. musical instruments) of the last added ASIN to cart

Buy it again: contextual reranking

Scoring function: $S_{A_{BIA}}(t_{k+1}|t_k, t_{k-1}, \ldots t_1, A_{context}) \approx \underbrace{P^f(t_{k+1})}_{\text{Time models}} \mathrm{x} \underbrace{P(PG_{BIA}|PG_{context})}_{\text{Contextual relevance (Markov Chain)}}$

Buy it again: contextual reranking

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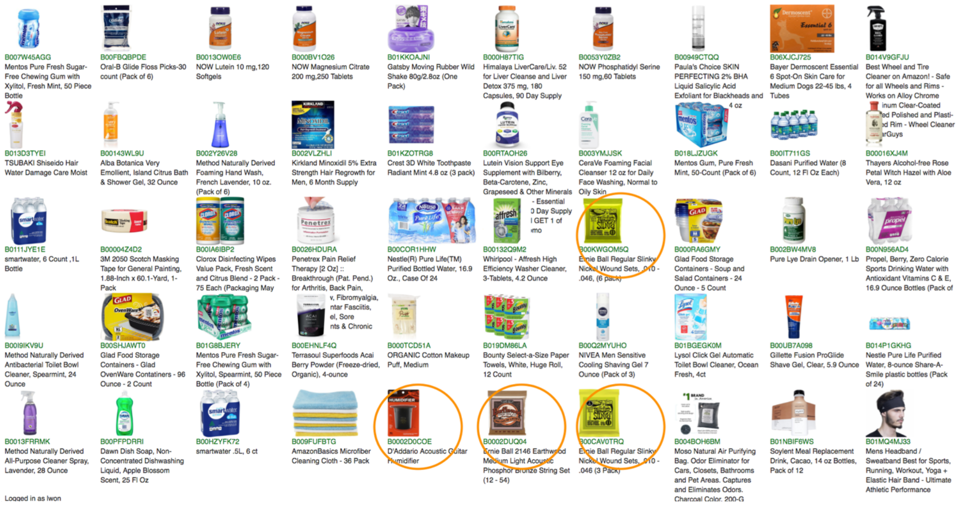
Without contextual signals



Buy it again: contextual reranking

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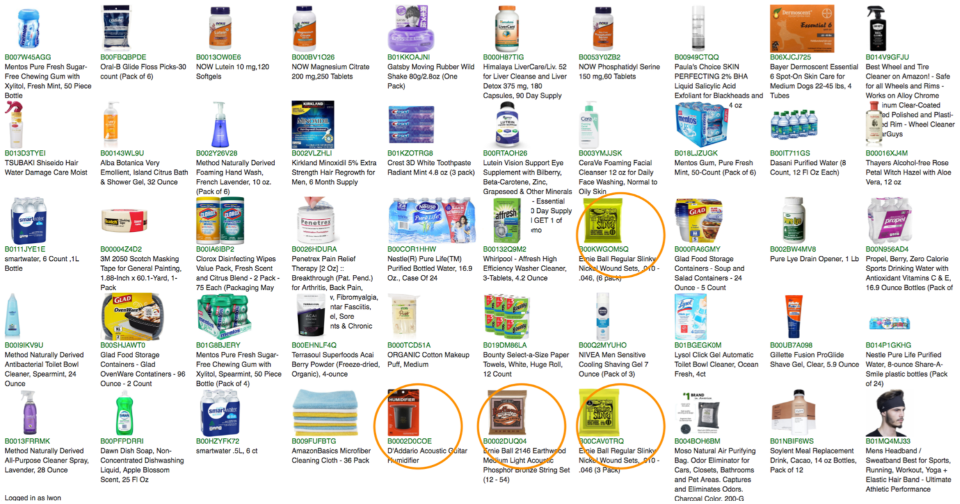
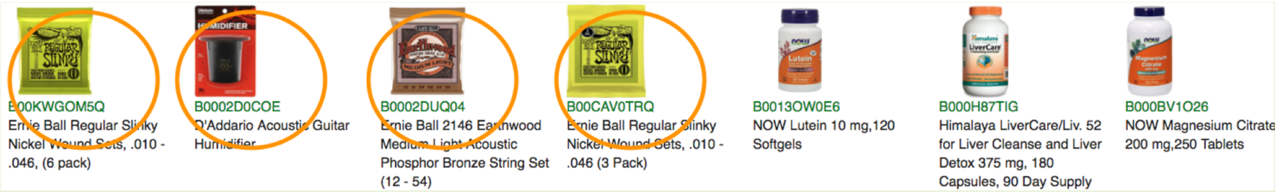
Without contextual signals



With contextual reranking (f=0.25)



With contextual reranking (f=0.10)

Buy it again: contextual reranking

Online results

Info			C_CP in Progress (Shipped in 9 Days) [Beta]	
Marketplace	Days	Customers	% Impact	p-value
US	14	6,581,057	0.24% (0.03%, 0.46%)	0.057

CCP: Composite Contribution Profits

- Launched or being experimented in a number of context heavy pages: High-Upsell Cart, Detail Pages, Cart, etc.
- Improves freshness for returning customers
- Context is an important signal to account for

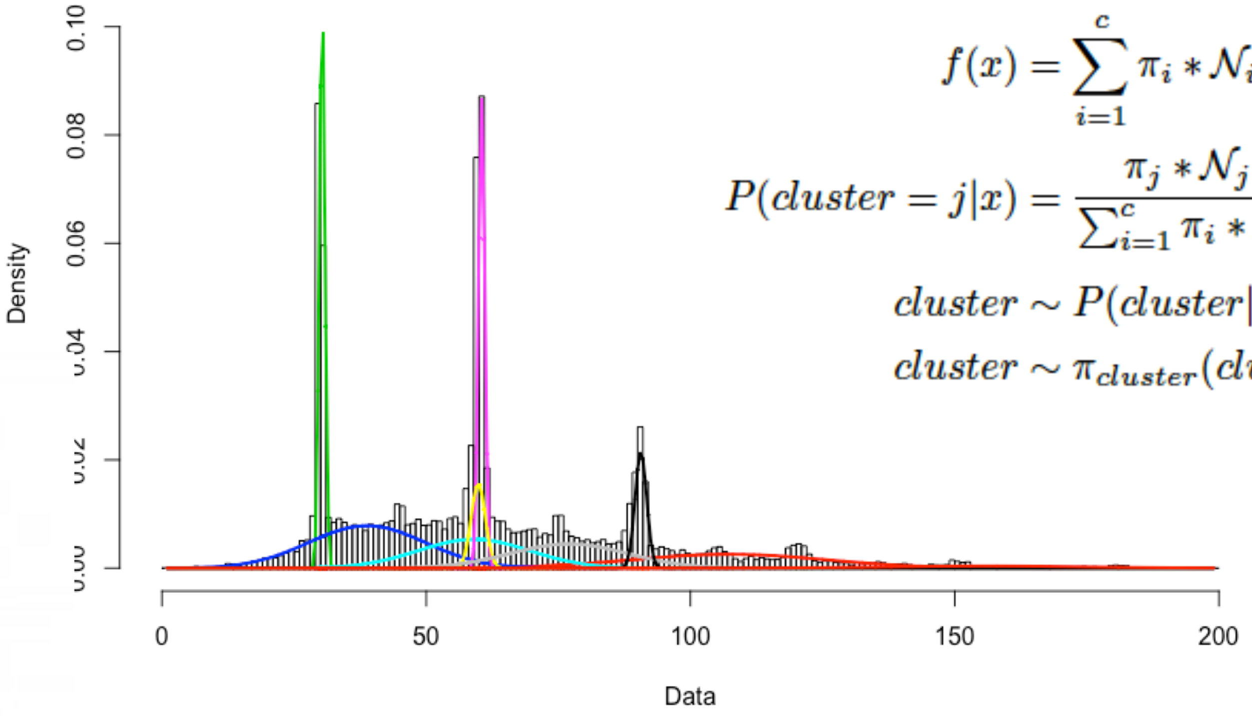
Buy it Again: household size

Buy

Consume

Buy it again: household size

Gaussian mixture models



$$f(x) = \sum_{i=1}^{c} \pi_i * \mathcal{N}_i(x|\mu_i, \sigma_i^2)$$

$$P(cluster = j|x) = \frac{\pi_j * \mathcal{N}_j(x|\mu_j, \sigma_j^2)}{\sum_{i=1}^{c} \pi_i * \mathcal{N}_i(x|\mu_i, \sigma_i^2)}$$

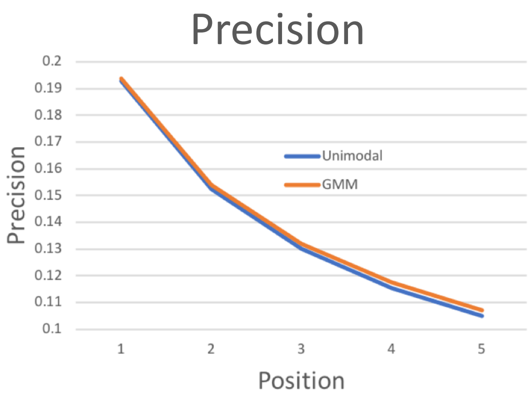
$$cluster \sim P(cluster|x)$$

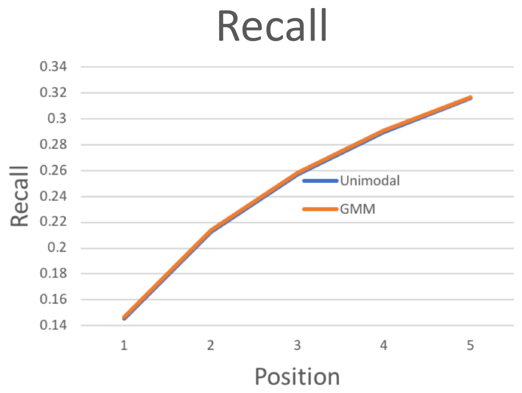
$$cluster \sim \pi_{cluster}(cluster|x)$$

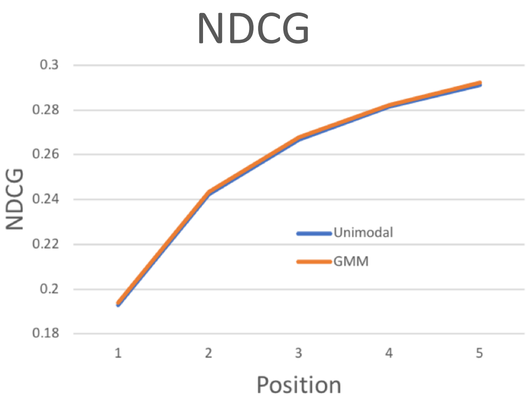
Buy it again: household size

Qualitative comparison

Quantitative comparison







- Offline metrics are relatively flat
- Qualitative comparison of recommendation rankings were not very different
- Did not proceed with online testing

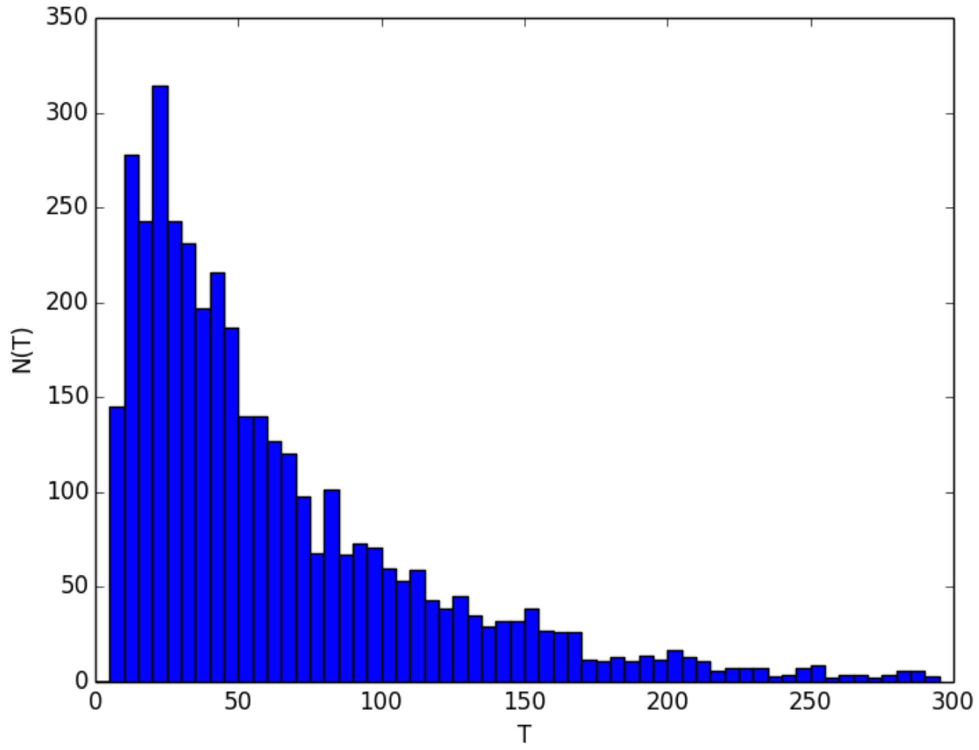
Buy it again: impressions feedback

Customer Problem

- Recommendation staleness

Reasons

- Recommendations are fixed (customer's past purchases)
- Time distributions are wide and the purchase propensities do not change day to day.

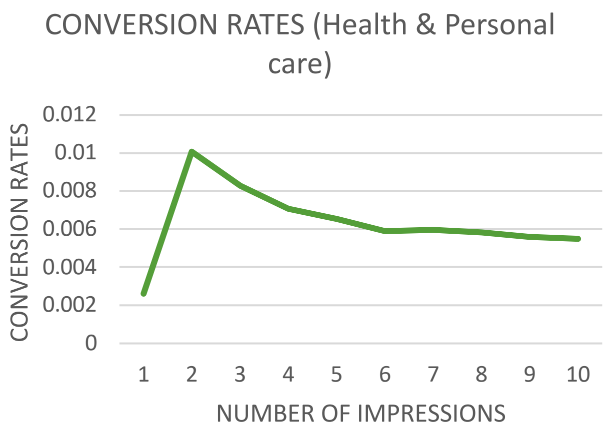


Staleness → Customer fatigue

Buy it again: impressions feedback

Conversion factor as a β-distribution

ASIN-Impression	Count of customers (N_{I_c})	Count of purchasing customers (N_{p_c})
1,B019DM86LA-1	24519	1127
1,B019DM86LA-2	12633	510
1,B019DM86LA-3	7472	236



Scoring function

$$S(t_{n+1} = t | t_1, t_2, t_3, ...t_n, ; k) = I(ASIN, k) \times P(t_{n+1} = t | t_1, t_2, t_3, ...t_n)$$

$$\alpha_0 = \o N_{p_c}(ASIN, k+1) + (1 - \o) * N_{p_c}(PG, k+1);$$
$$\beta_0 = [\o * N_{I_c}(ASIN, k+1) + (1 - \o) * N_{I_c}(PG, k+1)] - \alpha_0;$$
$$I(ASIN, k) \in \beta(\alpha_0, \beta_0);$$

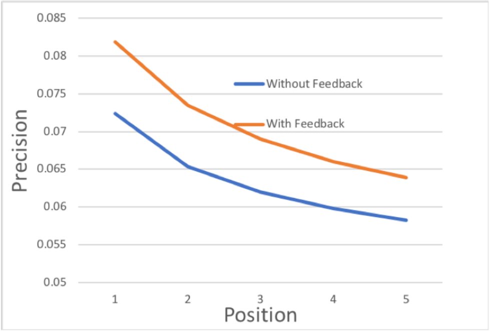
Sparsity: Use Product Group based priors

k is the number of impressions

Impressions feedback

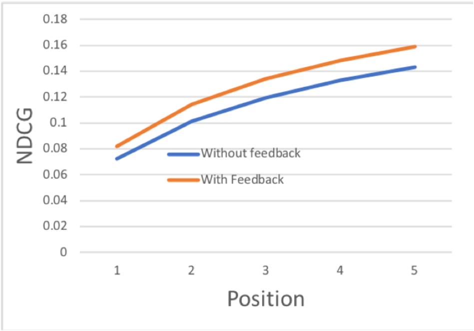
Offline metrics:

Precision



Recall

NDCG



Online metrics:

Info			C_CP (Shipped in 28 days)	
Marketplace	Days	Customers	%impact	p-value
JP	21	2,037,034	0.59% (0.12%,1.06%)	0.014
US	21	13,138,557	0.07% (-0.10%,0.23%)	0.438

Impressions is an important signal to account for!

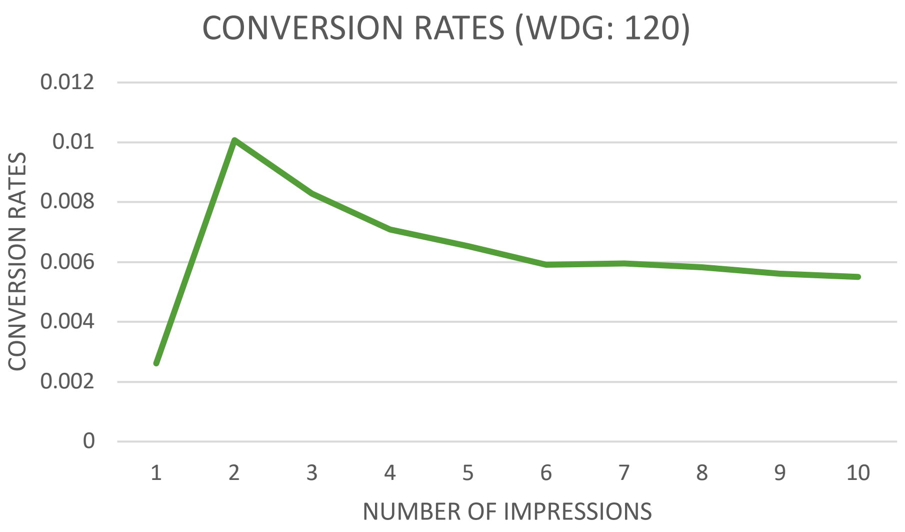
Conclusion and future work

- Explored three model refinements
  - Contextual reranking
  - Household size
  - Impressions feedback
- Machine learning model that combines these different signals

Thank you!

Back up slides

NEED FOR COUNTERFACTUAL SIGNALS



Online metrics

Weblab results of the BLN model

Info			OPS		Paid Units		Log OPS		Projected impact
Market	Days	Customers	% impact	p -value	% impact	p -value	% impact	p -value	Annualized $
JP-NAV	35	5,280,600	0.31	0.109	**0.48**	**0.004**	**0.13**	**0.015**	**+19 MM**
JP-Mobile	28	8,014,164	-0.02	0.909	0.10	0.475	-0.07	0.183	-1 MM
US-NAV	7	13,419,868	-0.04	0.812	-0.07	0.562	0.0	0.976	-12 MM
US-Mobile	21	33,461,001	0.07	0.320	0.08	0.173	**0.06**	**0.026**	**+44 MM**
B2B	14	253,448	1.54	0.175	**2.45**	**0.021**	0.25	0.399	**+37 MM**

Srevatsan Muralidharan and Rahul Bhagat, A Bayesian lognormal model of repeat purchase recommendations AMLC (2017)

Buy it Again

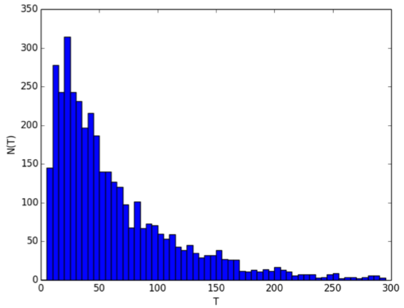
- 3 million ASINs to more than 150 million customers
- Accounts for over 1.1% of attributed OPS
- Spans a number of Amazon pages such as high-upsell-cart, cart, nav-fly-out, mobile gateway, desktop gateway, thank you page, email confirmation

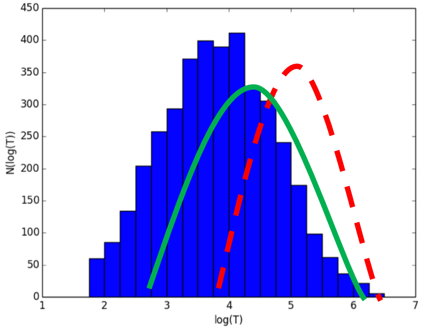
Overview

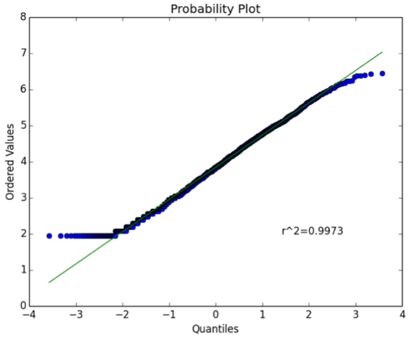
- Motivation
- Core Model
- Model refinements
  - Contextual reranking
  - Customer cohorts
  - Impressions feedback
- Remarks

Bayesian Lognormal Model (BLN)

Time Factor

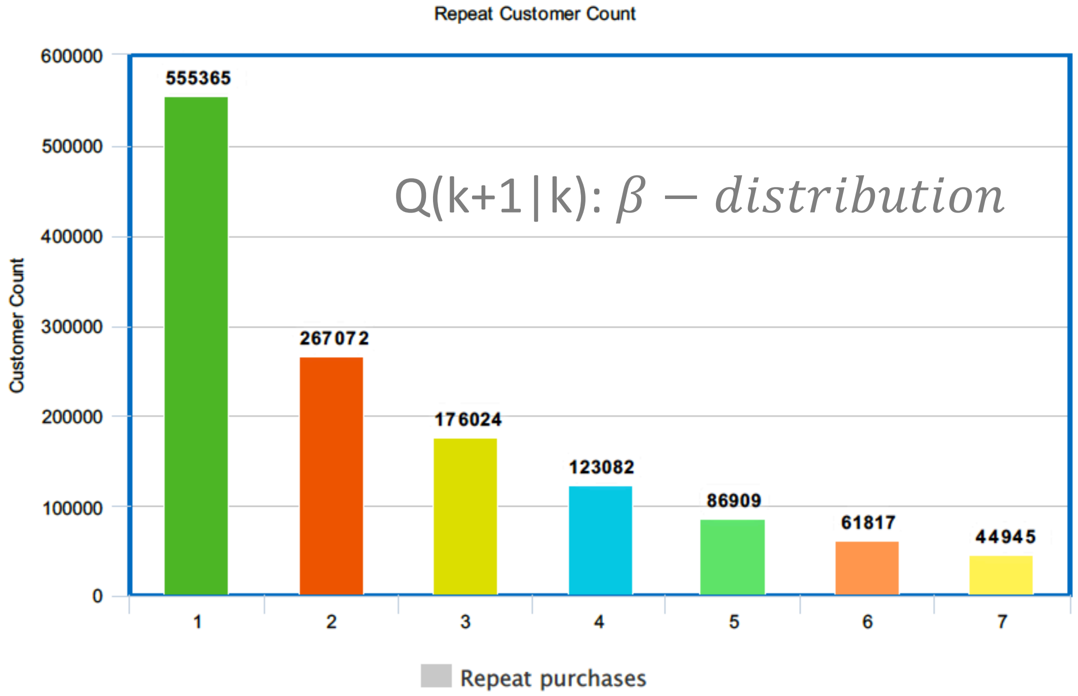






$T(t)$: Lognormally distributed!

Item Factor



Q(k+1|k): $\beta - distribution$

$$P(t_{k+1}|t_k, t_{k-1}, \dots t_1) \approx \underbrace{T(t_{k+1} = |t_k, t_{k-1}, \dots t_1)}_{\text{Time factor}} * \underbrace{Q(k+1|k)}_{\text{Item factor}}$$

Collaborators

Rahul Bhagat

Sr. Applied Sciences Manager
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Won Jae Lee

Software Development Engineer II
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Yu Liu

Applied Sciences Intern
Personalization

Acknowledgements: Mahae Koh (SDM@P13N)

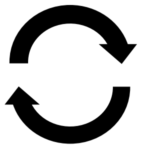
But why no difference?

Buy

Consume

Hypothesis

Buy



Consume