

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

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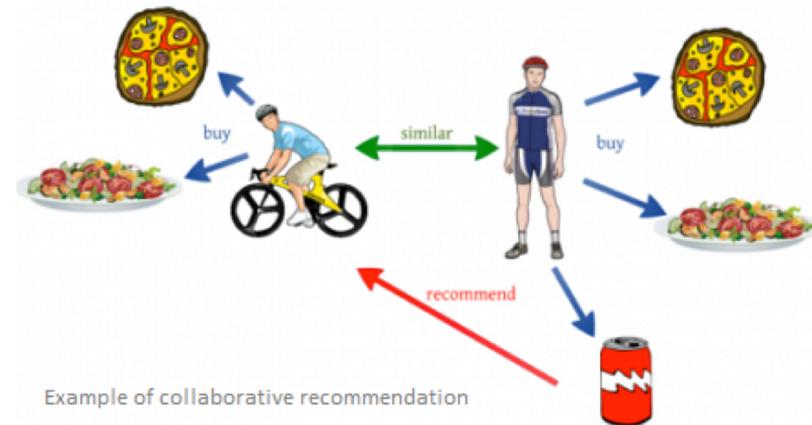
Software Development Engineer
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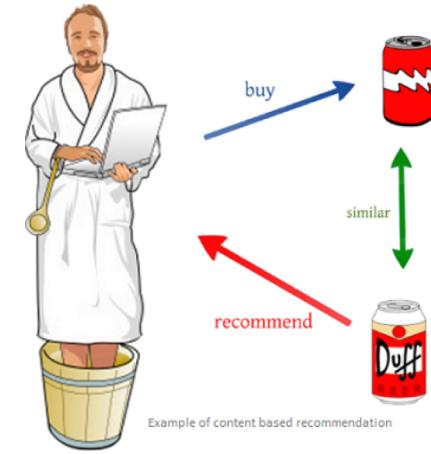
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Common recommendation strategies



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



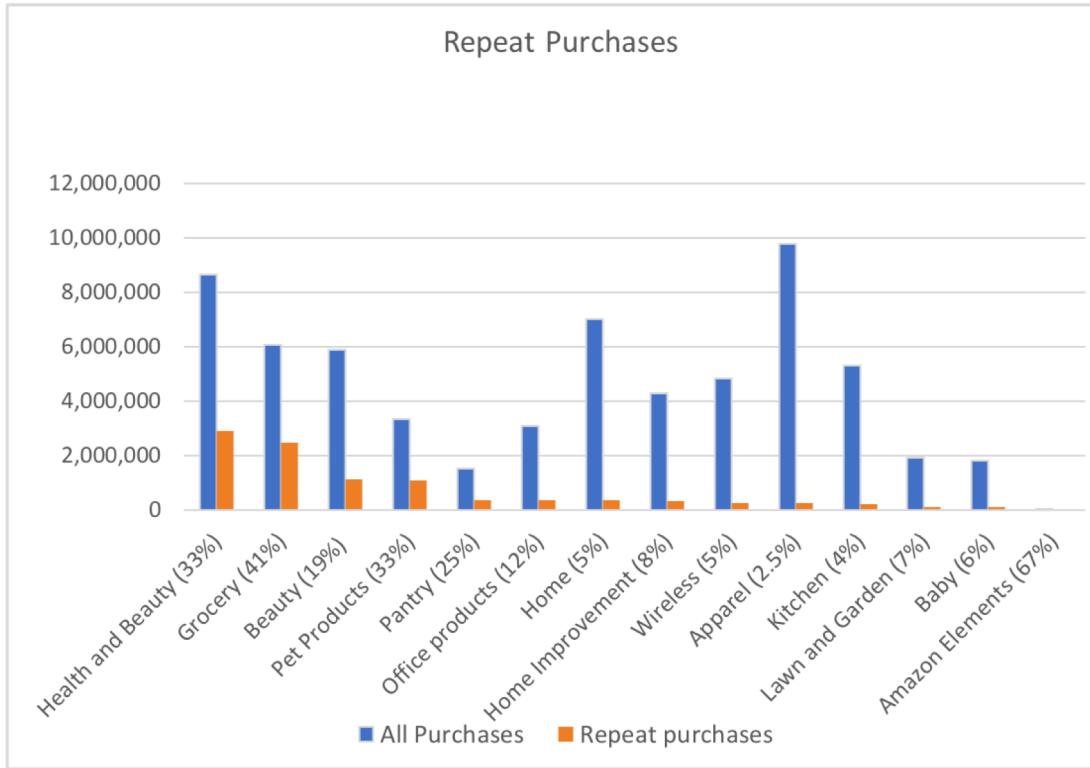
What about recommending items to
customers that they have already
bought before?



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

Groceries, everyday essentials, etc.

Repeat Purchase Recommendations



Buy it again (BIA)



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



Buy it again

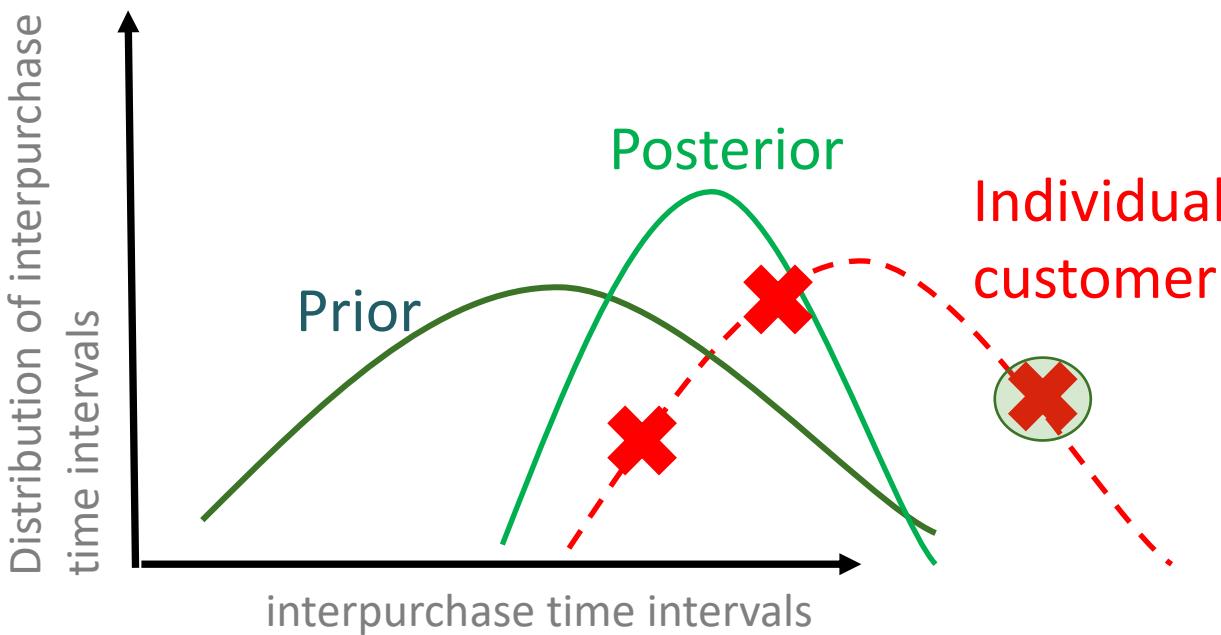
Customer benefit: Provide timely recommendations of products that they may wish to purchase again

- 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

Buy it again



Over million ASINS

Over 150 million customers
world-wide

Over a billion dollars
attributed OPS

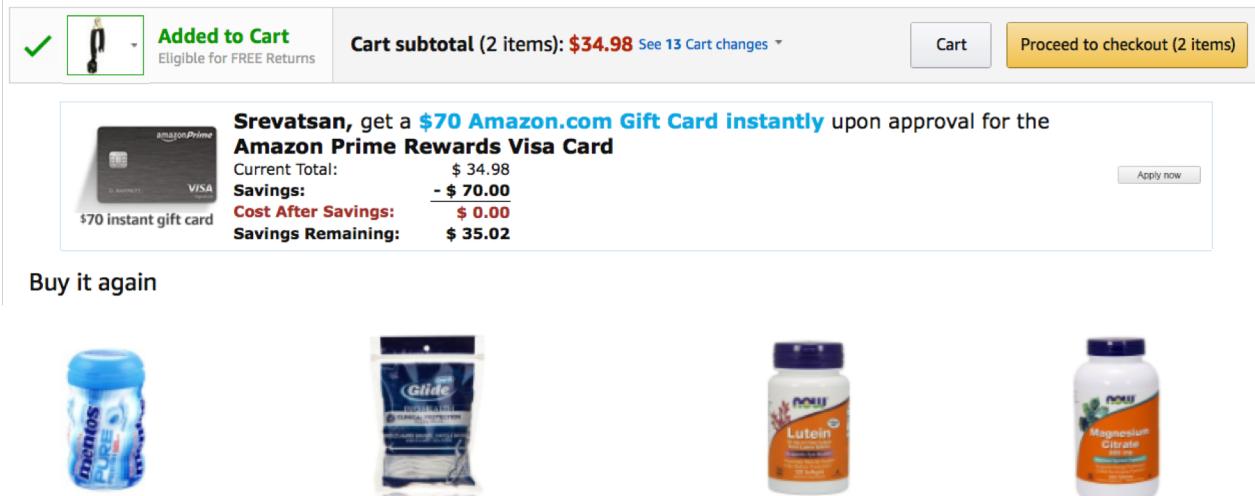


Buy it again: refining the models

- 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



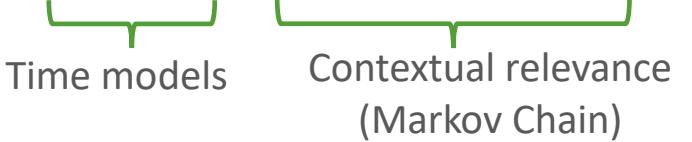
The image shows a screenshot of an Amazon shopping cart. At the top, there is a green checkmark icon followed by a small image of a guitar string winder, with the text "Added to Cart" and "Eligible for FREE Returns". To the right, it says "Cart subtotal (2 items): \$34.98 See 13 Cart changes" with a "Cart" button and an "Proceed to checkout (2 items)" button. Below this, a promotional box for an Amazon Prime Rewards Visa Card is displayed, showing a card image and the text "Srevatsan, get a \$70 Amazon.com Gift Card instantly upon approval for the Amazon Prime Rewards Visa Card". It also shows current totals and savings: "Current Total: \$ 34.98", "Savings: - \$ 70.00", "Cost After Savings: \$ 0.00", and "Savings Remaining: \$ 35.02". A "Buy it again" button is located below the promotional box. At the bottom, there are four product images: a container of Swiffer pads, a pack of Glide dental floss, a bottle of Now Lutein, and a bottle of Now Magnesium Citrate.

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

BIA ranking independent of customer context

Buy it again: contextual reranking

Scoring function: $S_{A_{BIA}}(t_{k+1}|t_k, t_{k-1}, \dots, t_1, A_{context}) \approx P^f(t_{k+1}) \times P(PG_{BIA}|PG_{context})$



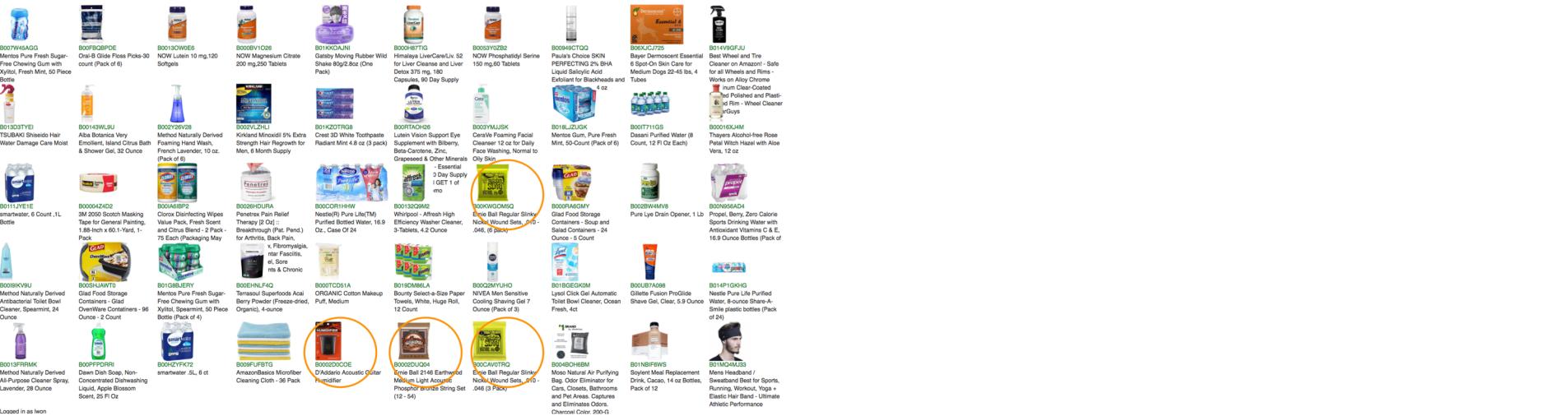
Time models Contextual relevance
(Markov Chain)

Buy it again: contextual reranking

Scoring function: $S_{ABIA}(t_{k+1}|t_k, t_{k-1}, \dots, t_1, A_{context}) \approx P^f(t_{k+1}) \times P(PG_{BIA}|PG_{context})$

Time models Contextual relevance
(Markov Chain)

Without contextual signals

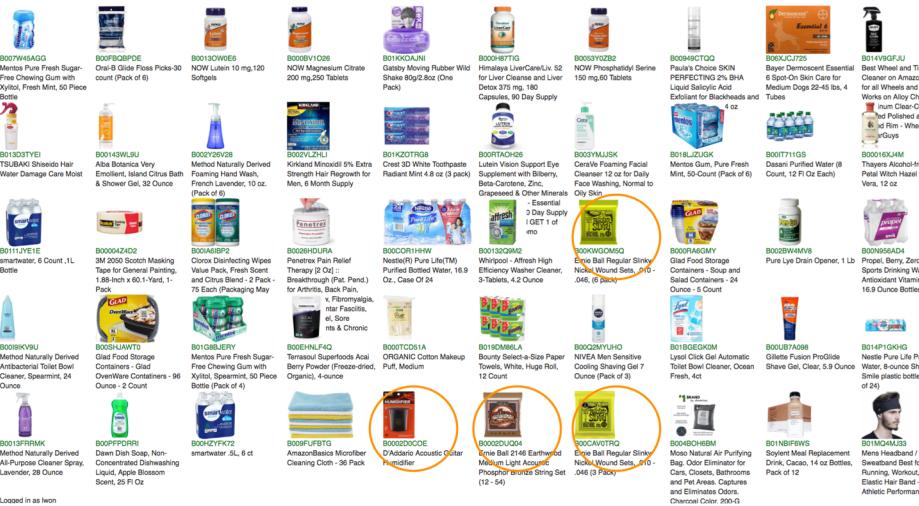


Buy it again: contextual reranking

Scoring function: $S_{ABIA}(t_{k+1}|t_k, t_{k-1}, \dots, t_1, A_{context}) \approx P^f(t_{k+1}) \times P(PG_{BIA}|PG_{context})$

Time models Contextual relevance
(Markov Chain)

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



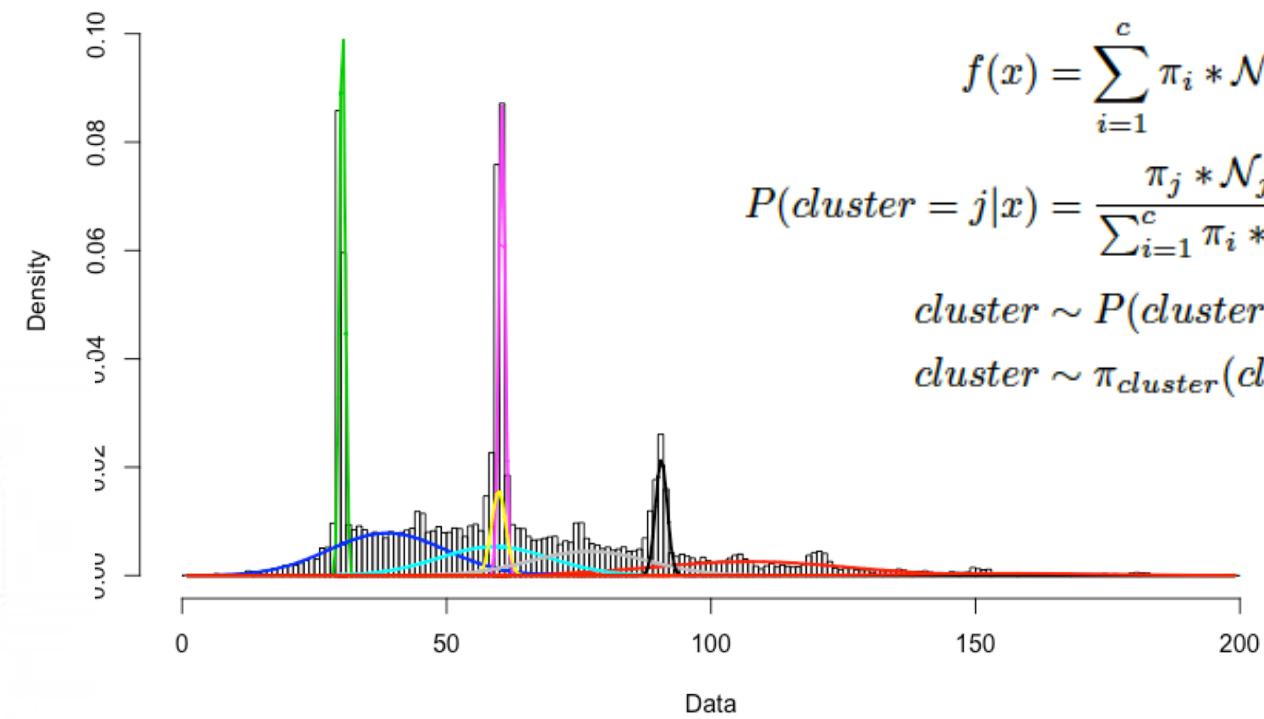
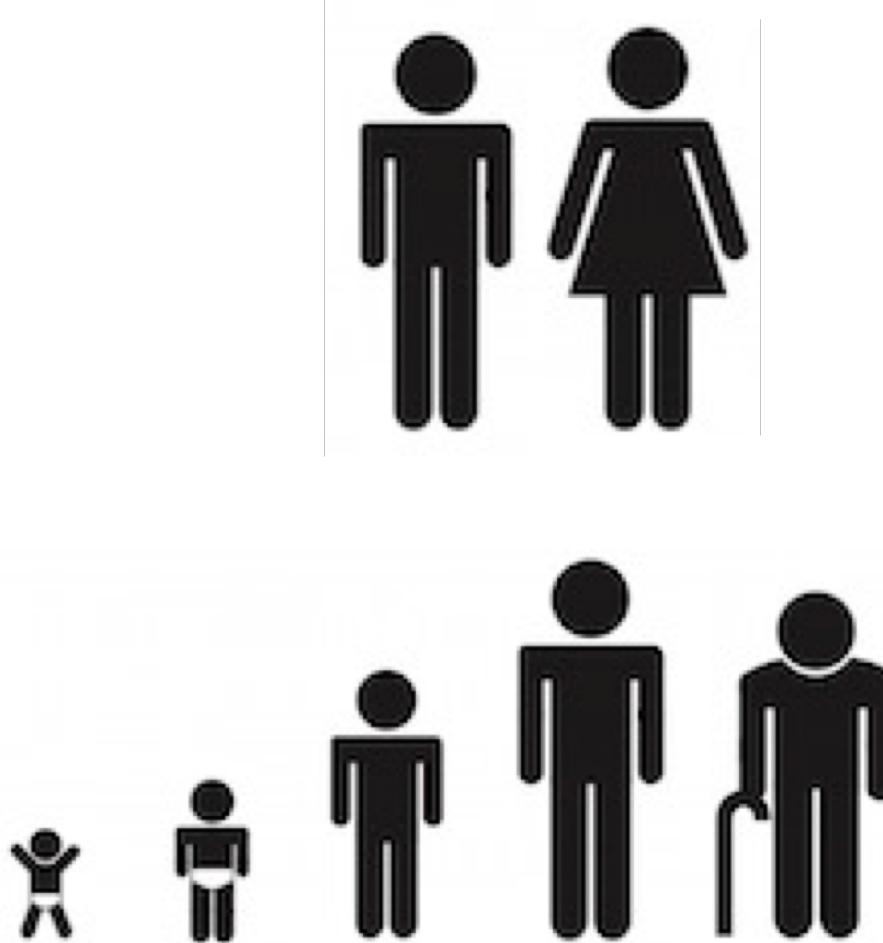
Buy



Consume



Buy it again: household size

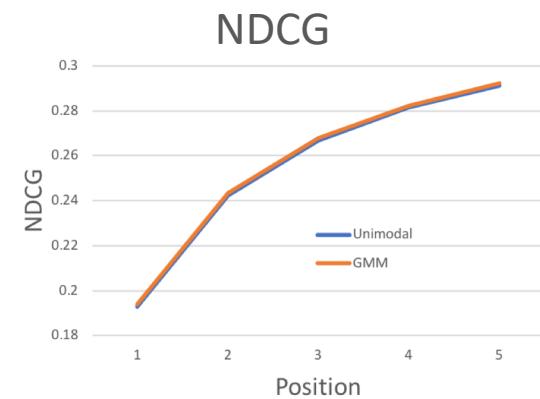
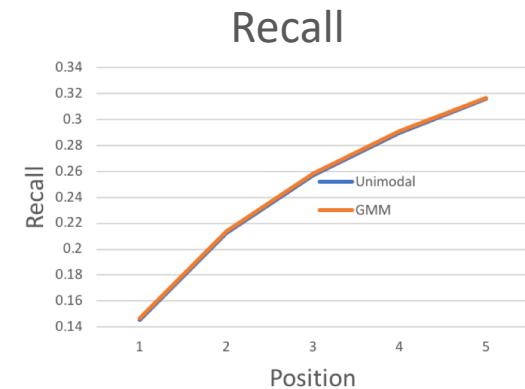
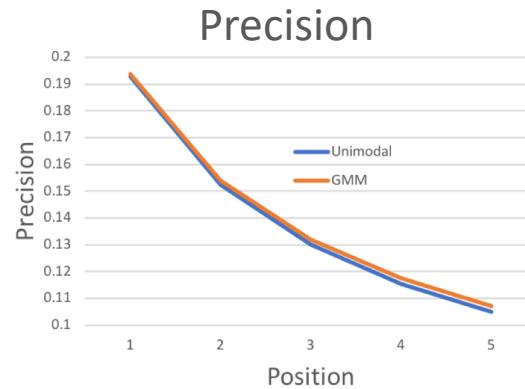


Buy it again: household size

Qualitative comparison

has 26 sims in db3: NOT RELEVANT unique		has 26 sims in db4: NOT RELEVANT unique			
1.		Dove Men+Care Antiperspirant Deodorant Stick, Extra Fresh, 2.7 oz (Pack of 2) 4.3 out of 5 stars (1,089) \$7.37 B0061JPJ28, 588169	1.		Dove Men+Care Antiperspirant Deodorant Stick, Extra Fresh, 2.7 oz (Pack of 2) 4.3 out of 5 stars (1,089) \$7.37 B0061JPJ28, 588966
2.		Brita Pitcher Replacement Filter (Pack of 2) 4.3 out of 5 stars (93) \$14.46 B0062A4JHC, 573708	2.		Colgate 360 Adult Full Head Soft Toothbrush (4 Count) 4.3 out of 5 stars (539) \$8.97 B002YXXZQM, 571248
3.		Colgate 360 Adult Full Head Soft Toothbrush (4 Count) 4.3 out of 5 stars (539) \$8.97 B002YXXZQM, 570875	3.		Brita Pitcher Replacement Filter (Pack of 2) 4.3 out of 5 stars (93) \$14.46 B0062A4JHC, 568852
4.		Softsoap Hand Soap Soothing Aloe Vera Moisturizing Hand Soap Refreshing Fluid Ounce ... 4.3 out of 5 stars (234) \$16.19 B005MQ3Y3M, 567727	4.		Softsoap Hand Soap Soothing Aloe Vera Moisturizing Hand Soap Refreshing Fluid Ounce ... 4.3 out of 5 stars (234) \$16.19 B005MQ3Y3M, 566137
5.		HERBALIFE HERBAL TEA CONCENTRATE - ORIGINAL FLAVOR 3.53 OZ 4.4 out of 5 stars (107) \$42.33 B007B23KGG, 510977	5.		HERBALIFE HERBAL TEA CONCENTRATE - ORIGINAL FLAVOR 3.53 OZ 4.4 out of 5 stars (107) \$42.33 B007B23KGG, 511400

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

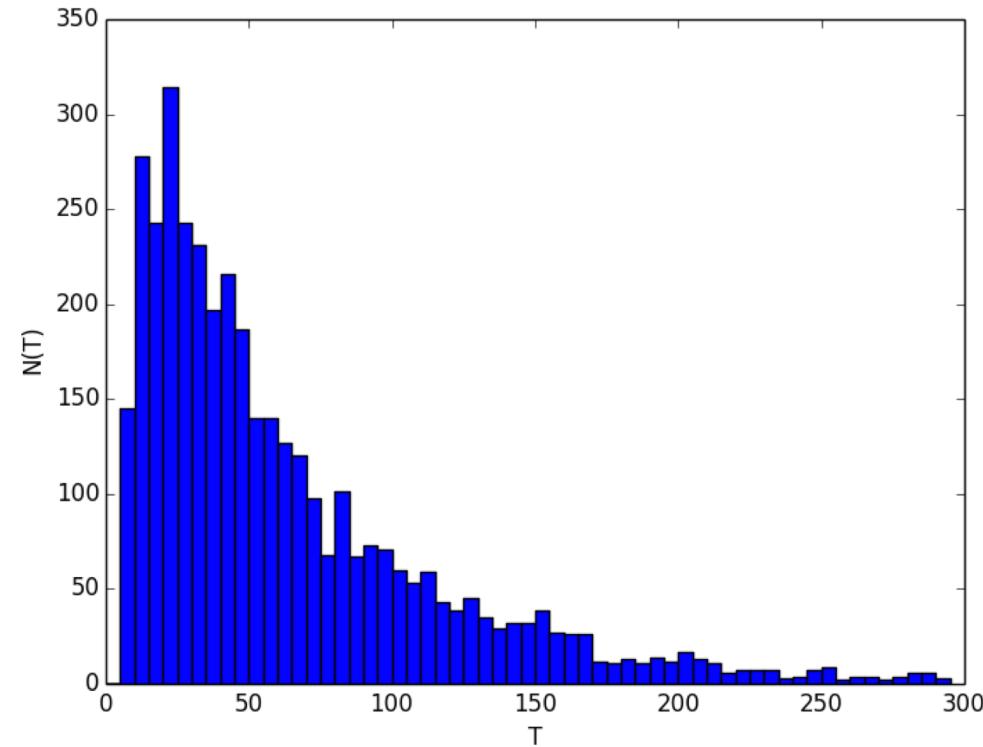
Reasons

- 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

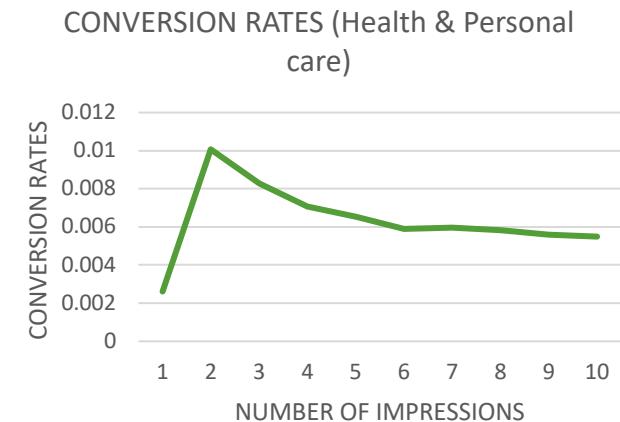
ASIN-Impression	Count of customers (N_{I_c})	Count of purchasing customers (N_{p_c})
1,B019DM86LA-1	24519	1127
1,B019DM86LA-2	12633	510
1,B019DM86LA-3	7472	236

Scoring function

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

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

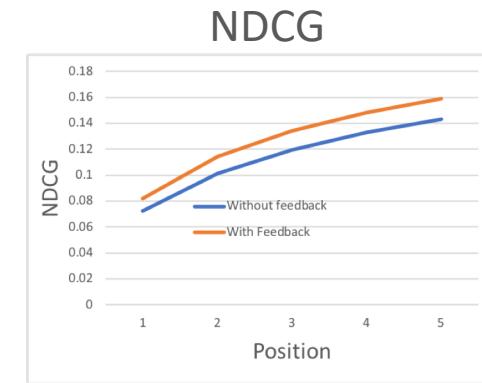
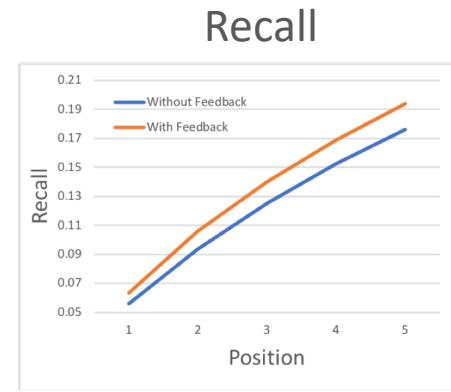
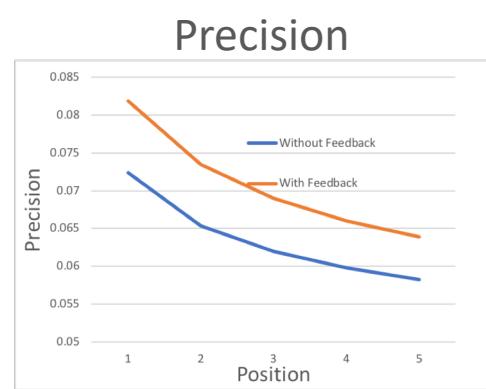
k is the number of impressions



Sparsity: Use Product Group based priors

Impressions feedback

Offline metrics:



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



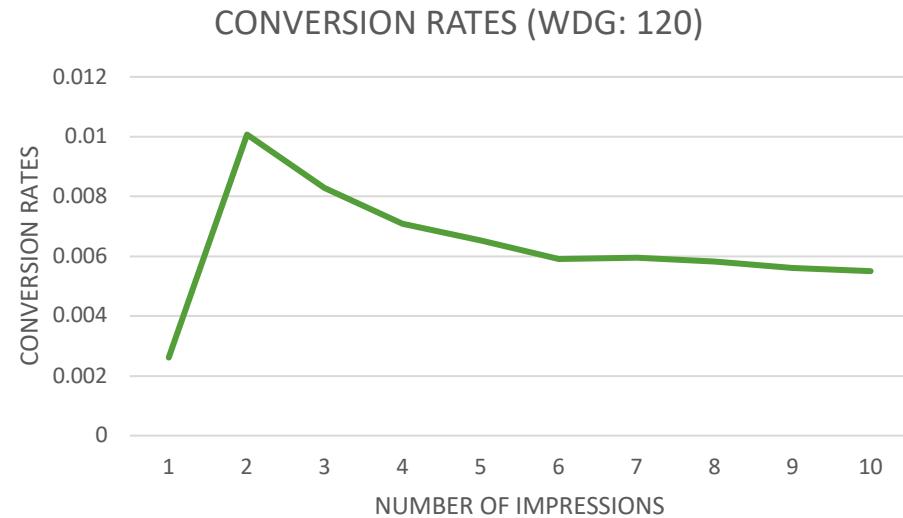
Thank you!





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

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

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

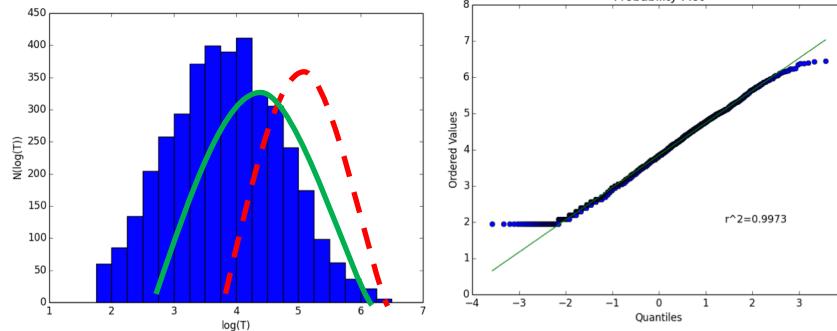
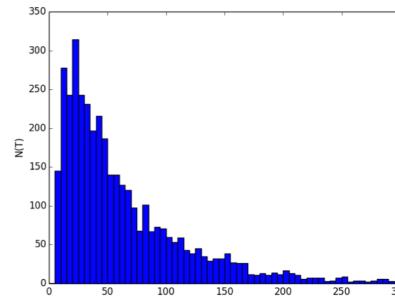


Overview

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

Bayesian Lognormal Model (BLN)

Time Factor

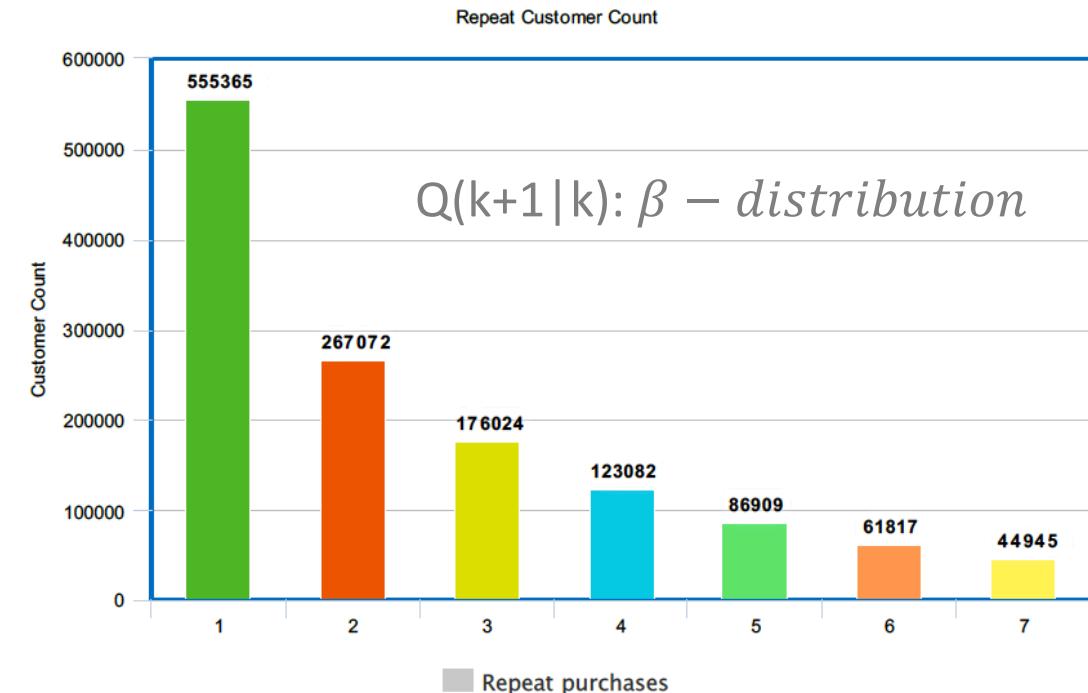


$T(t)$: Lognormally distributed!

$$P(t_{k+1}|t_k, t_{k-1}, \dots, t_1) \approx T(t_{k+1} = |t_k, t_{k-1}, \dots, t_1) * Q(k+1|k)$$

Time factor
}
Item factor

Item Factor



Collaborators



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Software Development Engineer II
Personalization



Yu Liu

Applied Sciences Intern
Personalization

Acknowledgements: Mahae Koh (SDM@P13N)

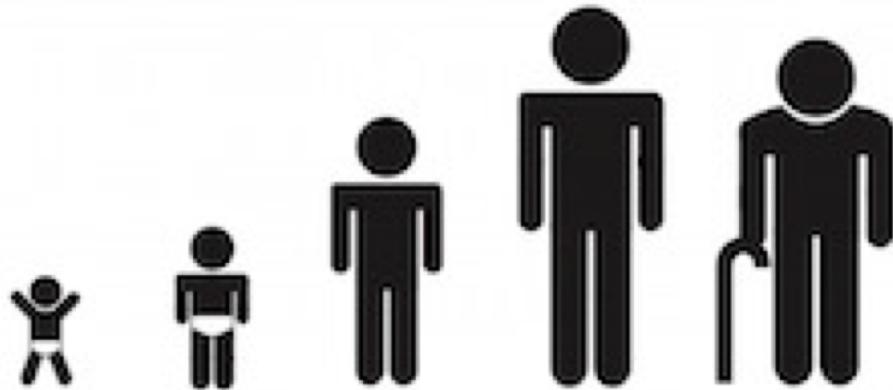
But why no difference?



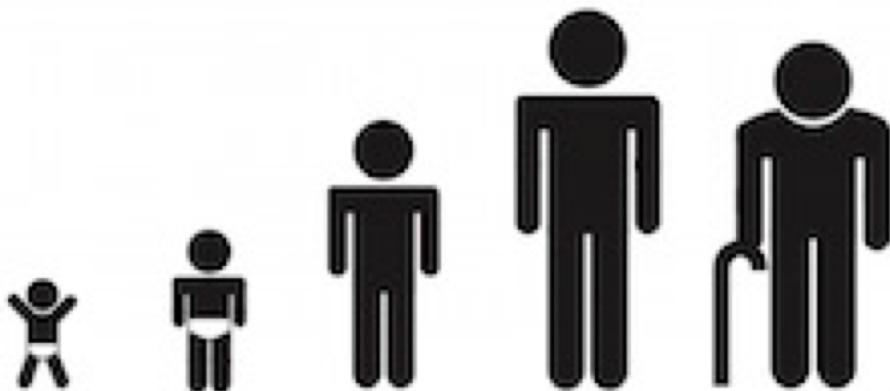
Buy



Consume



Hypothesis



Consume

