From Cold-Start to Warm Reception: The Impact of Knowledge Contribution as a Signaling Mechanism

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Introduction

- Reputation and feedback systems have played a pivotal role in enhancing trust and mitigating information asymmetries between anonymous sellers and buyers in online marketplaces
  - Sellers with higher user-generated review ratings experience price premiums (Jin and Kato 2006; Jolivet et al. 2016), and increased revenues (Liu et al. 2016; Luca 2016)

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- While reputation systems can benefit existing firms that have been able to build a track record, they can pose a new challenge for entrants who typically must start out operations without any pre-existing reputation
  - New sellers may opt to accept initial losses to build a favorable reputation (Shapiro 1983), and this short-run loss could jeopardize their long-term business survival prospects (Fan et al. 2016)

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  - New sellers may opt to accept initial losses to build a favorable reputation (Shapiro 1983), and this short-run loss could jeopardize their long-term business survival prospects (Fan et al. 2016)
- Reputation systems can create an entry barrier for qualified newcomers who have not yet established their reputations
  - This challenge is commonly referred to as the **cold-start problem**

Freelance Platforms

upwork freelancer

Mobile App Stores

Google Play App Store

E-commerce Platforms

ebay Etsy amazon

First time? Recommender Systems and the 'Cold Start' Problem

Assad Abbas
Associate Professor of Computer Science | Fact Checked by Eddie Wrenn

Disclosure

Hypebot

The Cold Start Problem and What Spotify Algorithms Mean for Musicians

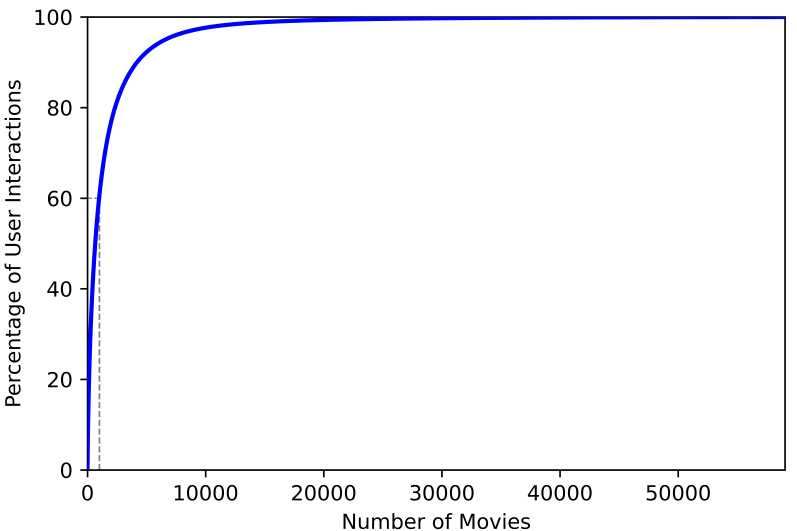
The Cold Start Problem and What Spotify Algorithms Mean for Musicians · Layer 1: Collaborative Filtering, which looks at when a song is played...

HackerNoon

Solving the Cold Start Problem with Pre-Trained AI Algorithms

Pre-trained search algorithms can be leveraged to speed up the development process solving the cold start problem and reduce risk. These...

Figure. 1. Cumulative Percentage of User Interactions from a Movielens Dataset



Overview of the Paper

1. We identify the clear understanding of where the underlying sources of reputation that causes struggle to young sellers
    - The cold-start problem hinges on **On-Platform reputation** (that attorneys begin to establish *after* joining the platform), as opposed to **Off-Platform reputation** (that attorneys has established *before* they join the platform)
    - The market's administrative data allows us to distinguish the cold-start period into two phases

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   - The market's administrative data allows us to distinguish the cold-start period into two phases
2. The first phase is the period during which attorneys were required to wait until they meet the first customer
   - Attorneys who contributed knowledge take one and a half months less to transact with the first customer, but not for the low-quality attorneys
   - Introducing a less history-dependent quality signal can mitigate the cold-start problem (Hui et al. (2021))

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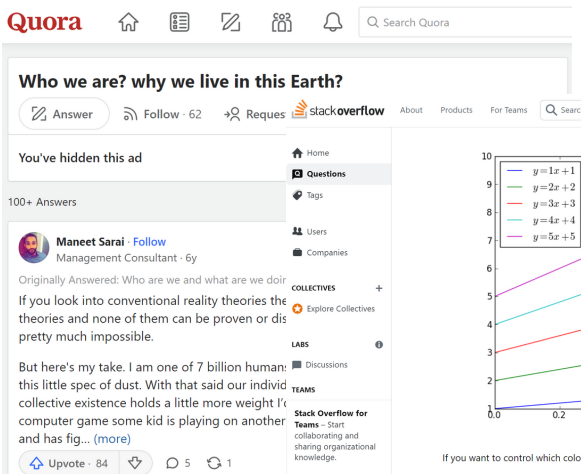
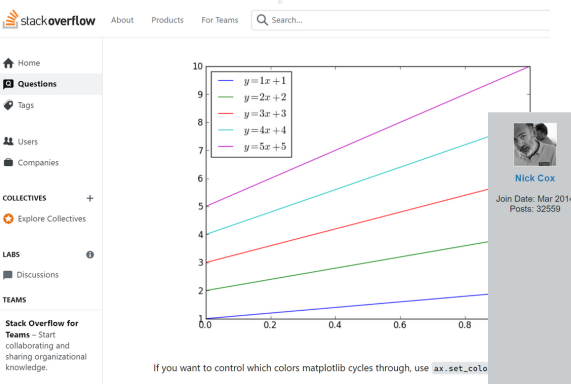
3. The second phase is the time after they have completed their first transaction but have yet to receive important market signal, the first customer review (Pallais 2014; Liang et al. 2016; Li et al. 2020)
   - Obtaining the first review increases the revenue of next period by 35%, and additional 15% to those who contributed their knowledge
   - High- and low-quality attorneys send indifferent number of signals in the cold-period, potentially because marginal benefit of signaling lower than the warm-period

Knowledge Contribution in Q&A session

KNOWLEDGE CONTRIBUTION IN Q&A SESSION





If you want to control which colors matplotlib cycles through, use `ax.set_colo`

```
import matplotlib.pyplot as plt
import numpy as np

x = np.linspace(0, 1, 10)
fig, ax = plt.subplots()
ax.set_color_cycle(['red', 'black', 'yellow'])
for i in range(1, 6):
    plt.plot(x, i * x + i, label='$y = {i}x + {i}$'.format(i=i))
plt.legend(loc='best')
plt.show()
```

Nick Cox

Join Date: Mar 2014
Posts: 32559

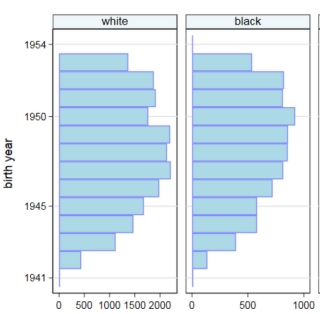
05 Sep 2017, 05:21

I looked for an example all can play with in which there were 3 predictor categories an

Code:

```
webuse nlswork
twoway histogram birth_yr, by(race, note("") xrescale row(1)) horiz
```

My point is not to make a claim about what's best, but to underline that there are choic



Knowledge Contribution as a Signaling Mechanism

- In the context of the cold-start problem within the legal consultation market, lawyers can voluntarily participate in Question & Answer (Q&A) sessions
  - Consumers post the lawsuits they are involved, covering the detailed legal and circumstantial issues; Attorneys actively address potential clients' inquiries

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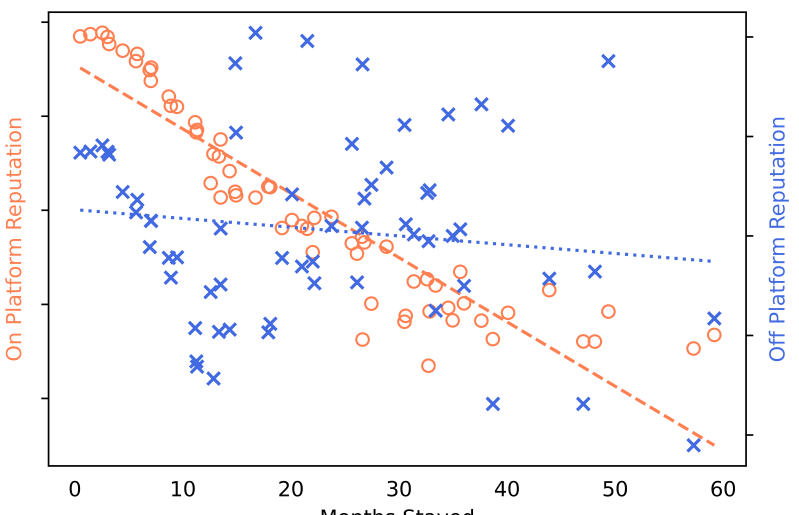
- In the context of the cold-start problem within the legal consultation market, lawyers can voluntarily participate in Question & Answer (Q&A) sessions
  - Consumers post the lawsuits they are involved, covering the detailed legal and circumstantial issues; Attorneys actively address potential clients' inquiries
- The purpose of providing answers is to signal to potential clients that the attorney has the necessary skills and knowledge to handle their legal matters
  - Attorneys have the opportunity to showcase their expertise by providing detailed and insightful answers to legal inquiries.
  - Q&A sessions allow direct interaction between attorneys and potential clients.
  - Attorneys can address specific concerns and provide tailored responses, enhancing the perceived quality of their services.

Q1. Reputation Sources of Cold-Start Problem

Figure. 2. Platform vs. Non-Platform Reputation on Stayed Duration of Attorneys



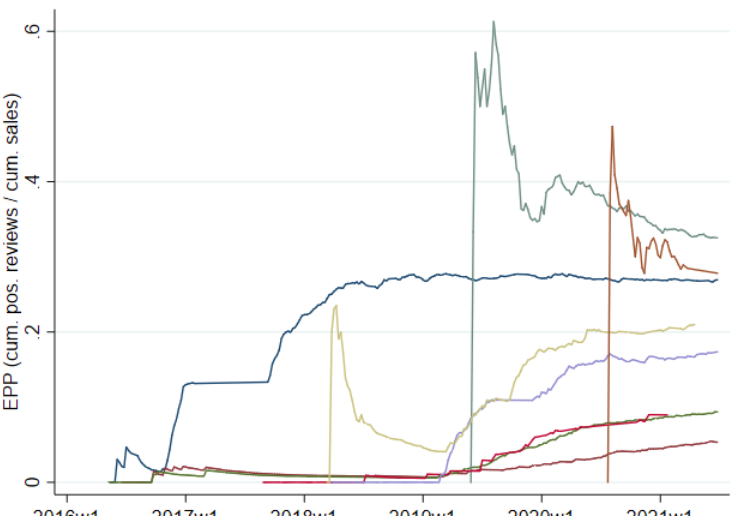
Quality Measure

Quality Measure

	N	Mean	Std.	10%	Median	90%
Quality Measures						
Review rating (total satisfaction)	25,269	4.787	0.779	4.7	5	5
Review rating (average) (average of four metrics)	25,269	4.205	1.515	1.225	4.95	5
Percent Review (PR) (=cum. reviews / cum. sales)	25,269	0.344	0.152	0.163	0.344	0.533
Percent Positive (PP) (=cum. pos. reviews / cum. reviews)	24,267	0.700	0.356	0.054	0.884	1
Effective Percent Positive (EPP) (=cum. pos. reviews / cum. sales)	25,269	0.244	0.182	0.008	0.234	0.5

- EPP is unobservable, so buyers cannot select on it, which means its potentially exogenous (Nosko and Tadelis 2015)
- We conjecture that a seller with a lower propensity of positive feedback will be more likely to deliver a worse experience
- Our data confirms that EPP well represents the seller quality measure

Figure. 3. Trends in Effective Percent Positive (EPP)



Q2. Pre-Transaction Period Model

$$
\begin{aligned}
y_i = \quad & \beta_1 High_i + \beta_2 High_i \times Signal_i + \beta_3 Low_i \times Signal_i \\
& + \alpha_1 Rent_i + \alpha_2 Exp_i + \alpha_3 Cert_i + \sum_{j=1}^{5} \gamma_j Rank_i \\
& + \tau_t + \epsilon_i
\end{aligned}
$$

- y_i is the months elapsed since the sign-up date to the first transaction for attorney i
- $High_i$ is an indicator variable equal to 1 if $UEPP_i > med$
- $Signal_i$ is an indicator variable equal to 1 if attorney i have answered before the first transaction
- τ_t is year fixed effects

Q2. Pre-Transaction Period Analysis

	Dependent variable: Months sign-up date to the 1st trans.		
	(1)	(2)	(3)
High	-2.701***	-2.043**	-1.997*
	[0.767]	[1.031]	[1.038]
Signal	-1.448*		
	[0.739]		
High × Signal		-2.169**	-1.933*
		[1.056]	[1.059]
Low × Signal		-0.751	-0.376
		[1.039]	[1.047]
Rent fee			-0.160**
			[0.065]
Years of exp.			0.07
			[0.062]
KBA certificates			0.414
			[0.447]
College ranking (Base: Tier1)			
Tier 2			0.798
			[1.149]
Tier 3			1.597
			[1.260]
Tier 4			0.902
			[1.184]
Tier 5			1.593
			[1.876]
Year fixed effects	Yes	Yes	Yes
Observations	789	789	789
R-squared	0.496	0.496	0.504

The Impact of Reputation on Signaling Decisions

	Dependent variable: frequency of answers at $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
EPP	26.268***	26.301***	9.728*	10.418**	12.035**	13.617***
	[2.002]	[2.004]	[5.637]	[5.193]	[5.284]	[4.718]
Cold: review=0	4.918***	5.763***	3.968	4.132*	6.473***	7.122***
	[1.291]	[1.297]	[2.436]	[2.322]	[2.350]	[2.052]
Review rating	0.092	0.094	-0.288	-0.298	0.068	0.081
	[0.287]	[0.287]	[0.470]	[0.480]	[0.464]	[0.459]
Control Variables						
Advertisement	-9.002***	-8.733***	-5.682**	-5.642**	-4.558*	-4.569*
	[1.202]	[1.204]	[2.416]	[2.455]	[2.731]	[2.753]
Cum. # of reviews		0.009***		-0.008		-0.009
		[0.001]		[0.012]		[0.013]
Experience	0.289***	0.315***	-0.231	-0.166		
	[0.052]	[0.052]	[0.400]	[0.375]		
Certified expertise	-3.305***	-3.439***	-3.499	-3.116		
	[0.421]	[0.419]	[2.672]	[2.881]		
Other license	1.469***	1.326***	5.947	6.008		
	[0.433]	[0.430]	[4.164]	[4.225]		
Rent ($\$/m^2$)	0.415***	0.390***	-0.478	-0.382		
	[0.048]	[0.048]	[0.330]	[0.404]		
College ranking	0.521***	0.526***	0.318	0.342		
	[0.044]	[0.044]	[0.263]	[0.260]		
Constant	-22.604***	-23.087***	-37.727	-39.552	-44.749	-45.506
	[3.921]	[3.988]	[30.544]	[30.603]	[31.297]	[31.197]
Law firm fixed effects	No		Yes		No	
Attorney fixed effects	No		No		Yes	
Week fixed effects	Yes		Yes		Yes	
Std. errors clustering	Attorney		Law firm		Attorney	
Number of law firms	551	551	551	551	551	551
Number of attorneys	741	741	741	741	741	741
Observations	24,480	24,480	24,480	24,480	24,480	24,480
Adj. R-squared	0.056	0.057	0.384	0.385	0.421	0.421

Q3. Post-Transaction Period Analysis

	Dependent variable: log of revenue at $t+1$			
	(1)	(2)	(3)	(4)
Cold: review=0	-0.512***	-0.511***	-0.341***	-0.346***
	[0.057]	[0.057]	[0.060]	[0.061]
Answers (10s)	0.165***	0.207***	0.146***	0.255***
	[0.034]	[0.053]	[0.024]	[0.044]
EPP	0.624***	0.715***	0.527***	0.814***
	[0.136]	[0.168]	[0.154]	[0.187]
Answers (10s) × EPP		0.320**		0.756***
		[0.145]		[0.214]
Control Variables				
Advertisement	0.352***	0.350***	0.171***	0.170***
	[0.052]	[0.053]	[0.049]	[0.048]
Review rating	0.011	0.012	-0.016	-0.016
	[0.012]	[0.012]	[0.013]	[0.013]
Number of reviews	0.230***	0.230***	0.041	0.039
	[0.024]	[0.024]	[0.026]	[0.025]
Experience	-0.001	-0.001		
	[0.004]	[0.004]		
Certified expertise	-0.045	-0.048		
	[0.049]	[0.049]		
Other license	-0.018	-0.018		
	[0.049]	[0.049]		
Rent ($/m2)	0.014***	0.014***		
	[0.004]	[0.005]		
College ranking	-0.003	-0.003		
	[0.002]	[0.002]		
Constant	10.191***	10.148***	10.895***	10.807***
	[0.205]	[0.203]	[0.100]	[0.093]
Attorney fixed effects	No	No	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Std. errors clustering	Attorney	Attorney	Attorney	Attorney
Number of attorneys	741	741	741	741
Observations	24,480	24,480	24,480	24,480
Adj. R-squared	0.262	0.262	0.533	0.534

Final remark to cold-starters in academia....