Achieving AI-driven value creation

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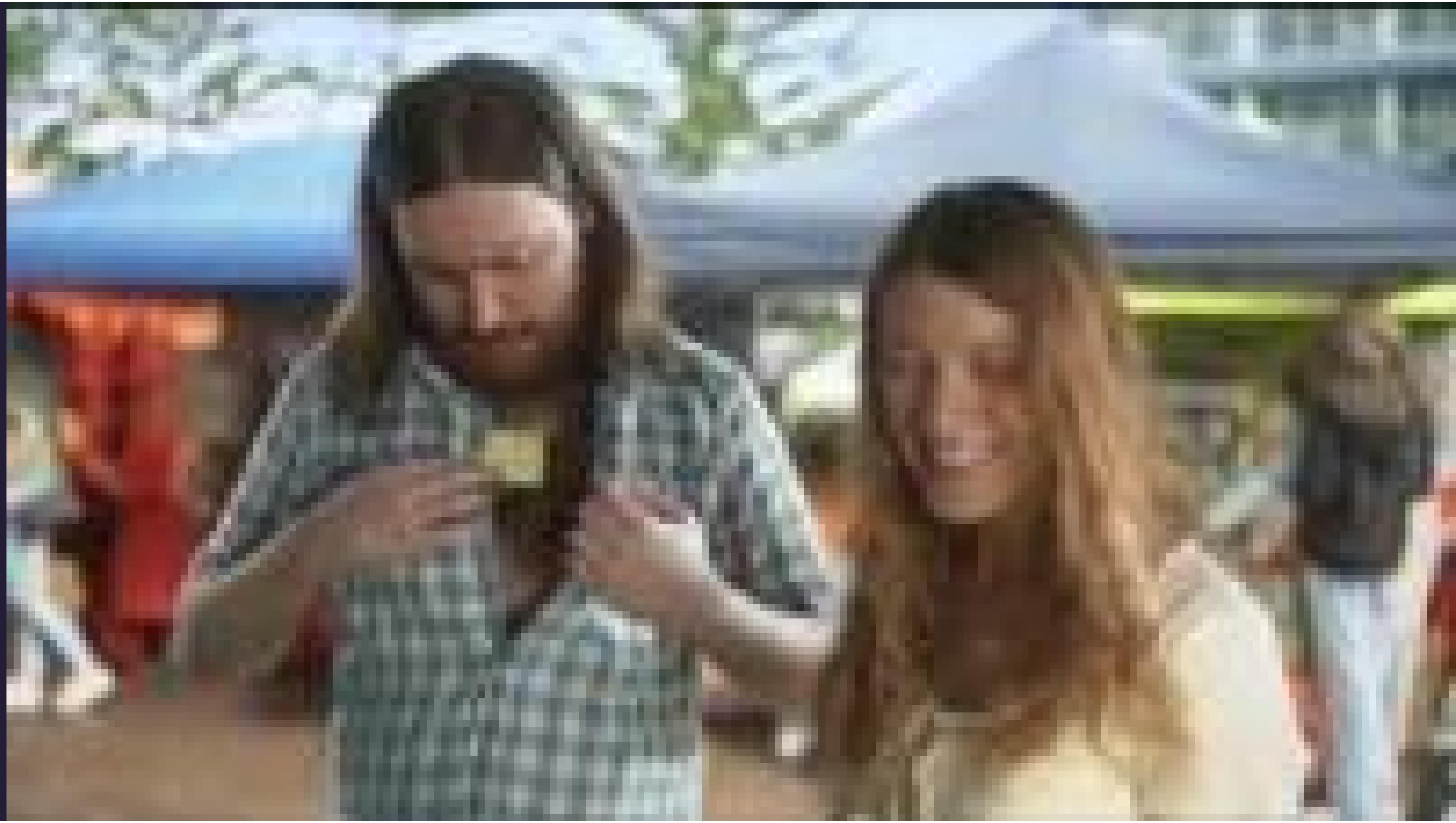
AI, Cyber, Modelling and Simulation for SME growth Symposium
May 2022



Jake An, PhD (Marketing), UNSW Sydney

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Raiz Invest
(Head of Research & Development)

Primary Data Analysis

- Surveys
- Field Experiments
- Lab Experiments

• Launch new products

• Test marketing communication effectiveness

Secondary Data Analysis

Econometric Models
- Difference in difference
- Vector autoregression
- Endogeneity (treatment effects model, control function methods, propensity score, synthetic control)

• Forecast demand
• Optimise marketing resource allocation
• Measure and optimise the impact of new technologies using quasi-field experiments

Machine Learning
- Xgboost
- Neural networks

• Predict churn
• Recommend product and services

	2015	2016	2017	2018	2019	2020	2021	2022
FUM – Year end (Aust only)	-	$43.28m	$148.17m	$254.18m	$444.70m	$605.59m	$1.03bn	$1.01bn (Jan 22)
Active Customer - Year end	-	65,278	133,896	175,345	211,657	343,573	594,992	608,107 (Jan 22)

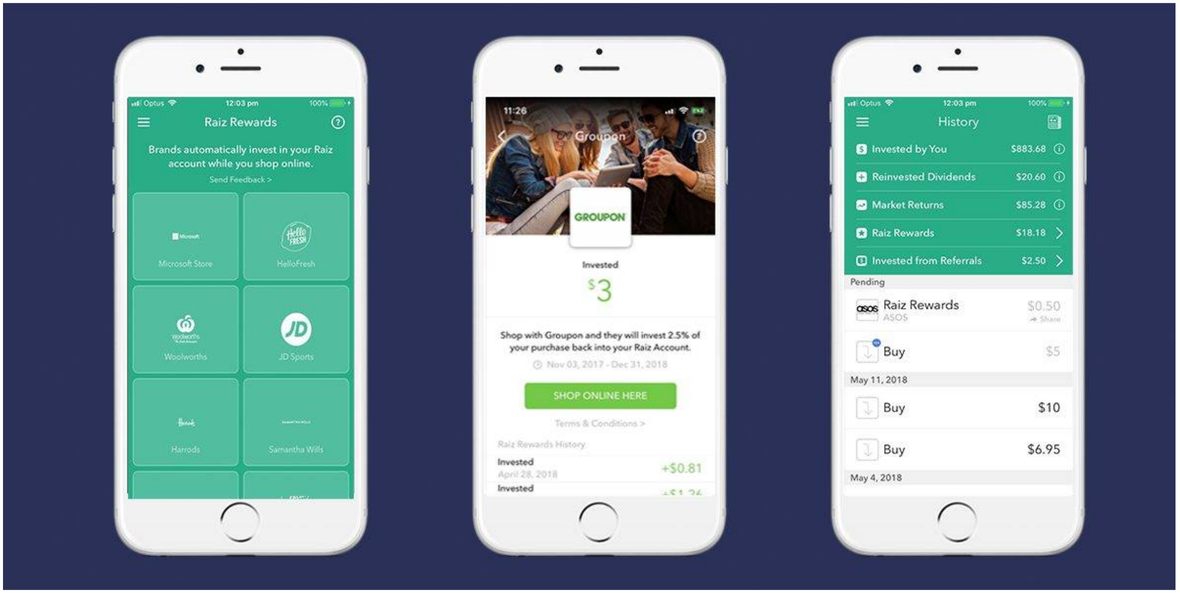
Two Cases of Achieving AI-driven Value Creation

Enhancing customer experience and firm revenue via AI-driven

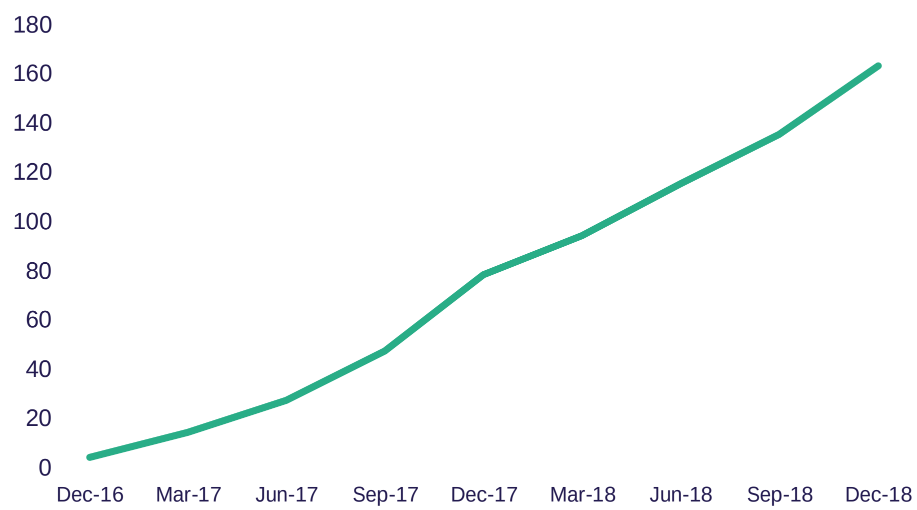
1. Recommender system (with Dr. Lina Yao, Dr. Shuai Zhang, UNSW Sydney)

2. Call centre analytics (with Prof. Oded Netzer, Shin Oblander, Columbia Business School)

1. AI-Driven Recommender System - Raiz Rewards



No. of Raiz Rewards Partners



The Challenge

With over 200+ brands to choose from, which brands should Raiz recommend to whom?

Objective

To develop a state-of-the-art machine learning recommender system that recommends brands and cash rewards to customers based on their transaction data.

Research Context

Recommending the “right” product to the “right” customer is at the heart of marketing, satisfying the unique needs of individual customers.

Two main approaches for recommender systems:

1. “Customers who have bought this product also bought…”
2. “This product is most frequently purchased with…”

Combine both user-based and item-based collaborative filtering algorithms by constructing two parallel neural networks of which the predictions from each neural network are weighted, then summed up for final prediction.

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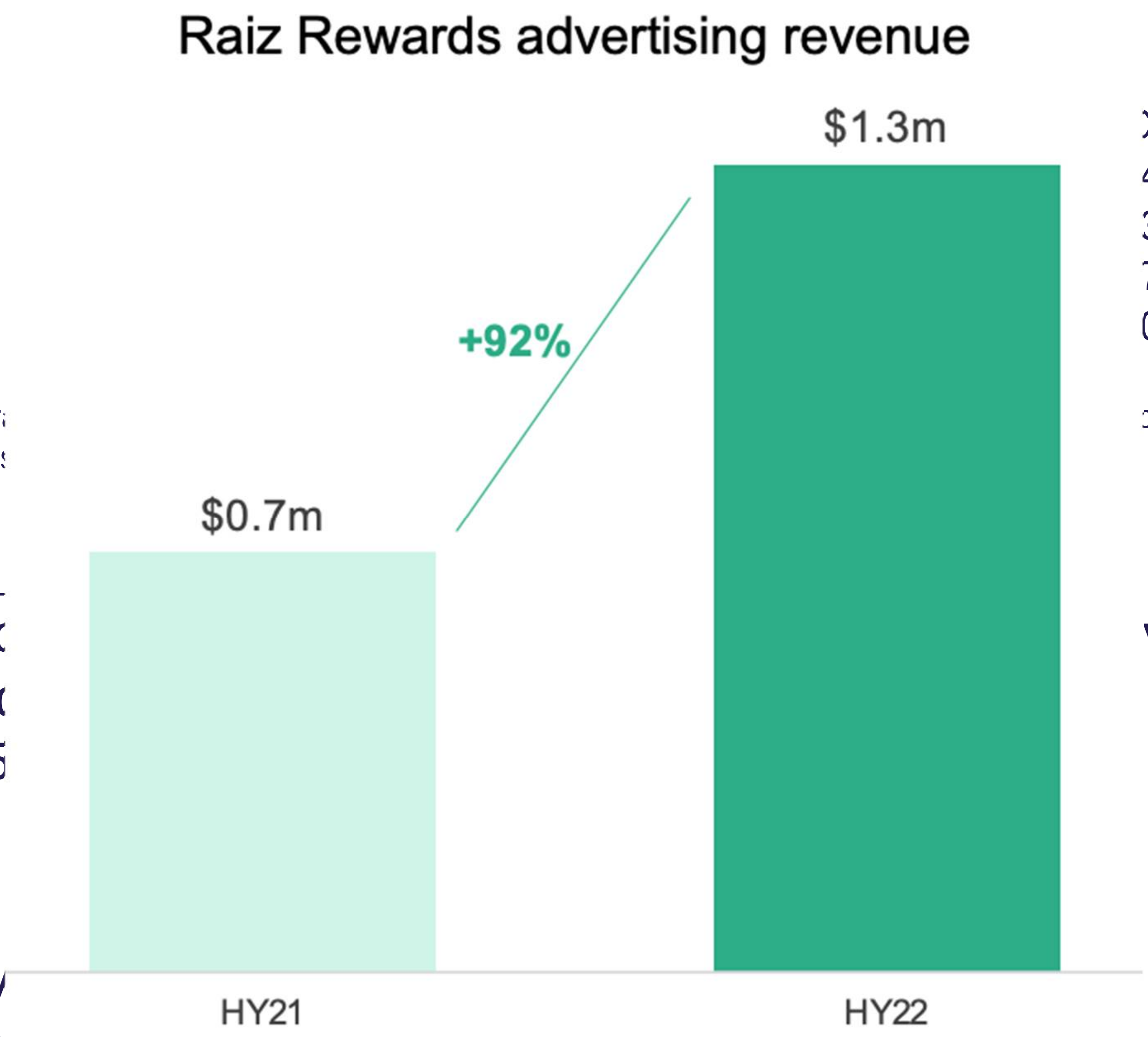
Results

Metrics@10	BPR	ML	Our Model
NDCG	0.4492	4174	**0.4712**
MAP	0.3601	3289	**0.3781**
Recall	0.7406	7032	**0.7651**
Precision	0.0747	0710	**0.0775**

BPR = Bayesian personalised r orisation; NeuMF =
Neural network matrix factoris



<u>Field experiment</u>
The treatment gr ved 40%
more cash rewar cash
rewards = $2,205

Outcomes

- Increased savi
- Improved relev
- Contribution to

2. AI-Driven Call Centre Analytics

Customer service call centres: important but understudied

Consider the **sentiment (emotional valence)** of the customer and service agent during a call

Can speaker sentiment, and dynamics thereof, tell us about customer satisfaction and retention?

A: From what I can see now it's closed. And you got the confirmation email right? Um, but yeah, I'm sorry.

C: Okay, well, anyway, thanks for your help.

A: There's nothing else we can do at this time. Um, thanks for your time.

C: Alright.

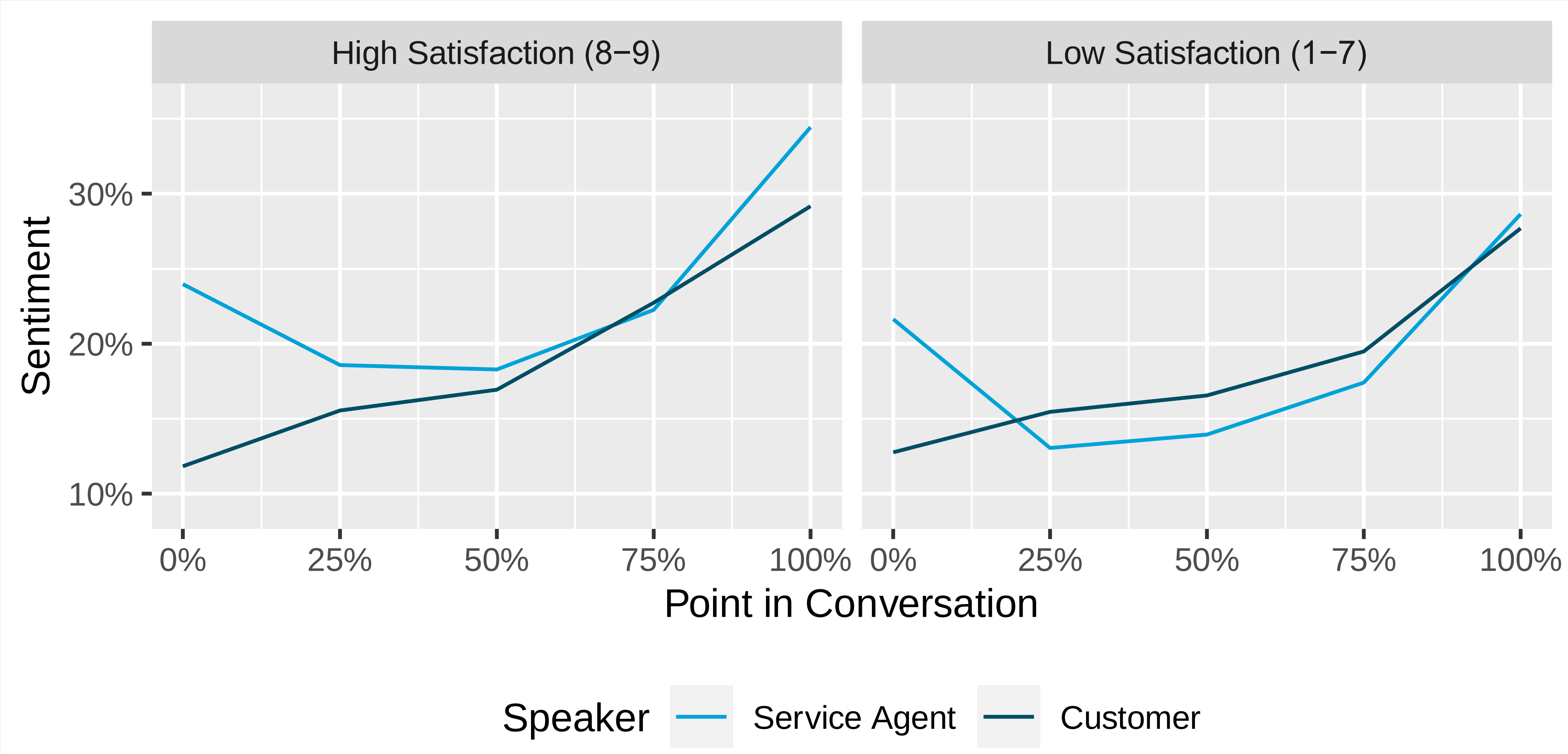
Call B

Agent

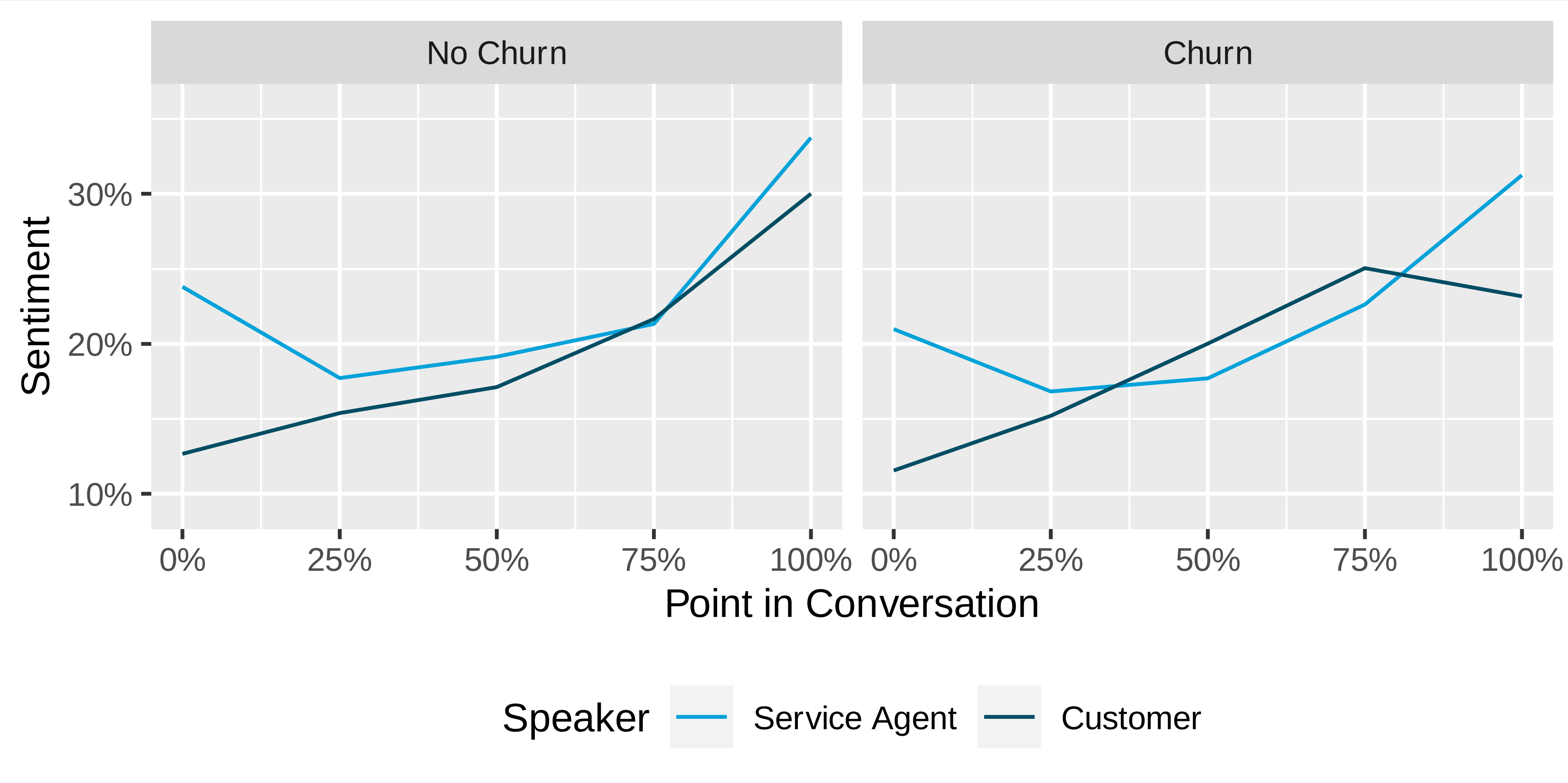
Emotionality is strongly predictive of customer behavior (Rocklage et al. 2021)

Agent word choice affects customer satisfaction (Packard et al. 2018; Li et al. 2020; Packard and Berger 2021)

Sentiment dynamics and CSAT



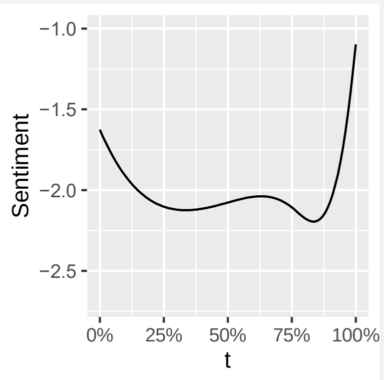
Sentiment dynamics and Churn



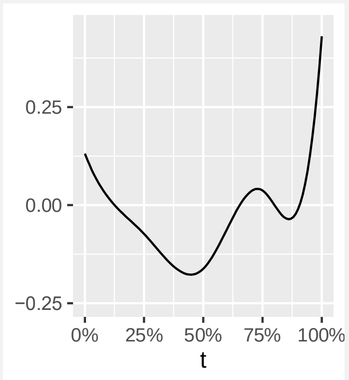
Modeling goal: quantitatively **characterize prototypical shapes/patterns** of sentiment

FUNCTIONAL FACTOR MODEL: INTUITION

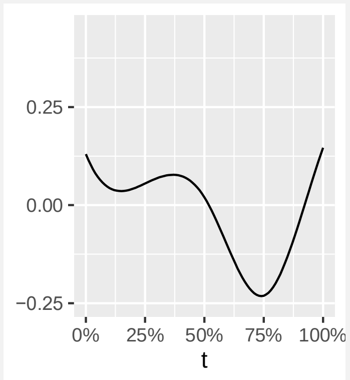
- We want to summarize the **trajectory** of a conversation into interpretable components
- Each function is a **prototypical pattern** of how sentiment may evolve during a conversation
- e.g., consider factorizing agent sentiment into a mixture of 3 functions:



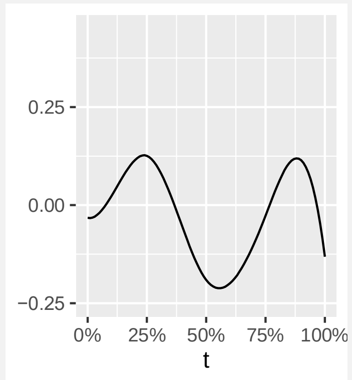
= –2.0 +1.5 ·



+0.9 ·



–0.6 ·



Agent sentiment = Overall + Pleasantries + Deterioration + Troubleshooting

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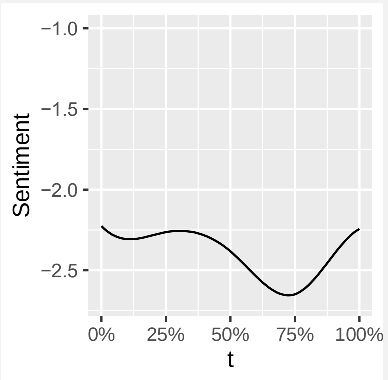
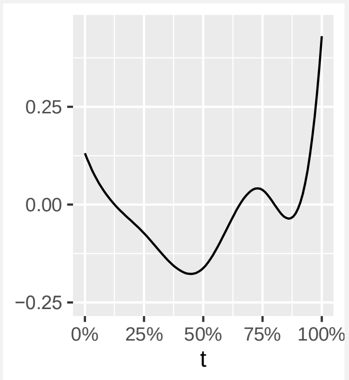
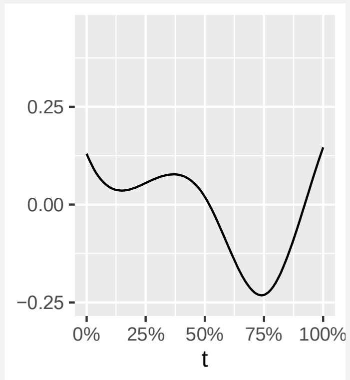


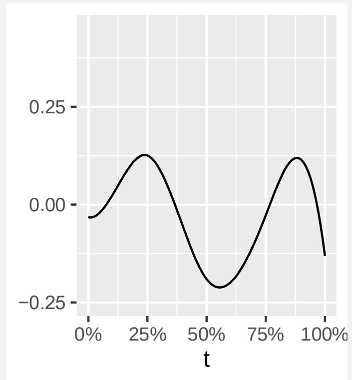
$= -2.4 \; -0.1 \cdot$



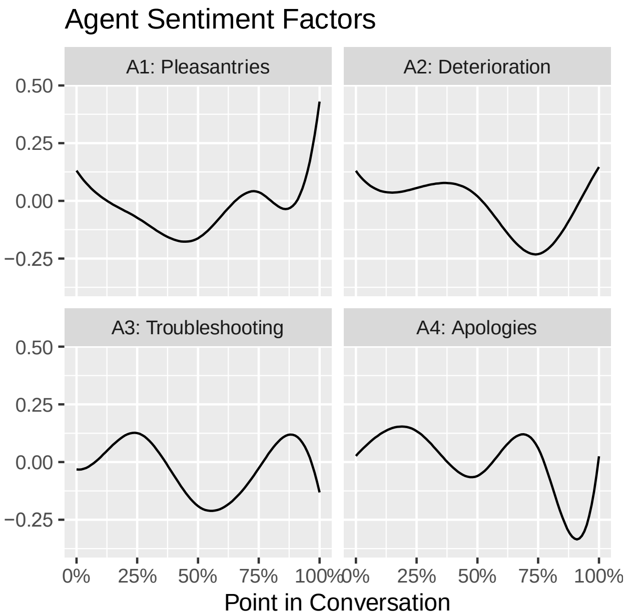
$+1.2 \cdot$

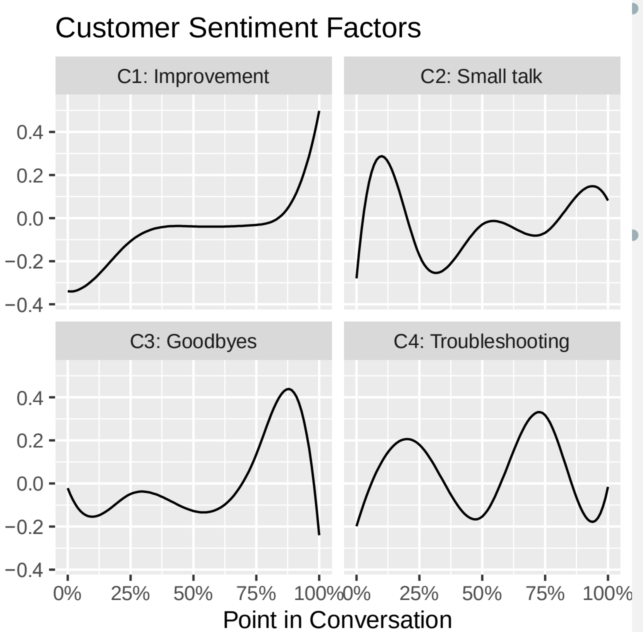


$+0.2 \cdot$



Agent sentiment = Overall + Pleasantries + Deterioration + Troubleshooting





RESULTS: CSAT AND CHURN

- **Agent positivity** good for satisfaction, but not a deteriorating trajectory
- Overall customer sentiment not diagnostic, but the **presence of an upward trajectory** is
- Some evidence of churn effects

Variable	CSAT	Churn
Agent avg. sent. (α_i^A)	1.06 (0.51)*	–0.261 (0.120)*
A1: Pleasantries (ϕ_{i1}^A)	0.07 (0.14)	–0.024 (0.024)
A2: Deterioration (ϕ_{i2}^A)	–0.38 (0.14)**	–0.024 (0.032)
A3: Troubleshooting (ϕ_{i3}^A)	–0.06 (0.13)	–0.025 (0.028)
A4: Apologies (ϕ_{i4}^A)	0.13 (0.12)	0.014 (0.026)
Customer avg. sent. (α_i^C)	0.11 (0.30)	0.049 (0.064)
C1: Improvement (ϕ_{i1}^C)	0.28 (0.14)*	–0.001 (0.028)
C2: Small talk (ϕ_{i2}^C)	–0.10 (0.12)	–0.017 (0.032)
C3: Goodbyes (ϕ_{i3}^C)	–0.05 (0.11)	0.041 (0.030)
C4: Troubleshooting (ϕ_{i4}^C)	0.07 (0.11)	–0.016 (0.029)

** : $p < 0.01$, * : $p < 0.05$, · : $p < 0.1$.
SEs are heteroskedasticity robust. Regressions include LDA topic weights as controls

LET’S COLLABORATE TO ACHIEVE AI-DRIVEN VALUE CO-CREATION

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