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Airline offer optimization with the Markov chain choice model

Kevin Wang (MIT)

Michael Wittman & Thomas Fiig (Amadeus)

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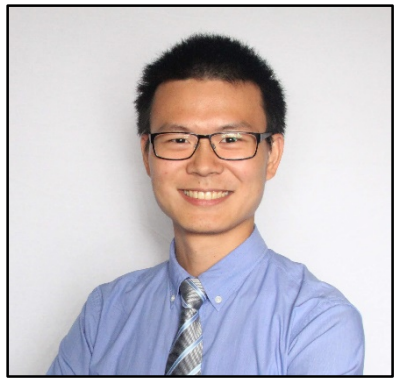
Speaker



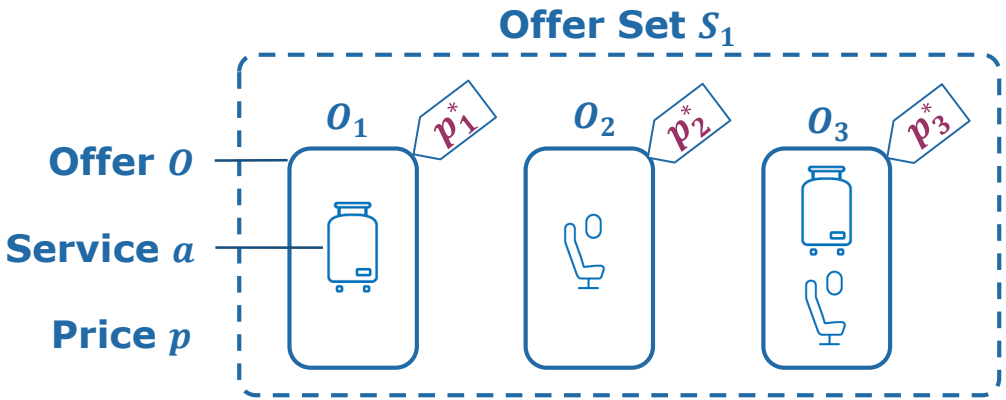
Kevin Wang is a Ph.D. student at the Massachusetts Institute of Technology. Within the MIT/PODS Revenue Management Consortium, his research focuses on dynamic offer generation, ancillary revenue management and bundle pricing. He holds an M.Eng. and B.A. in Aeronautical Engineering from the University of Cambridge.

Airline Offer Optimization

NDC enables the dynamic creation of offers that include bundles of flights and ancillary services

Customer choices between offers become more relevant for price optimization

Optimized bundling of services can represent a new revenue opportunity



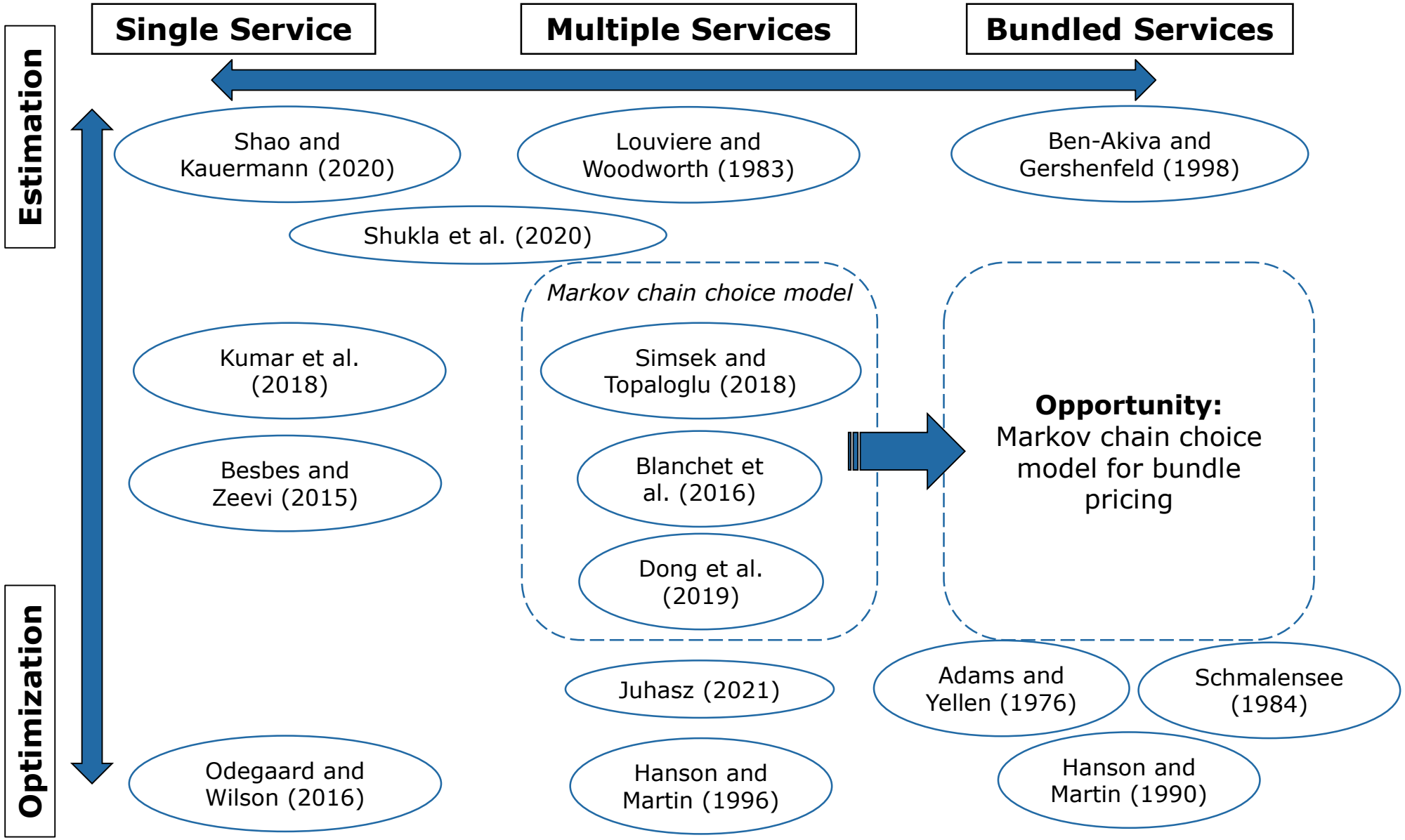
Naïve A La Carte Pricing: p_1^* constant (e.g. equal to mean valuation)

Myopic A La Carte Pricing: $p_1^* = \arg\max_{p_1} \ (p_1 - c_1) \cdot \Pr_1(p_1)$

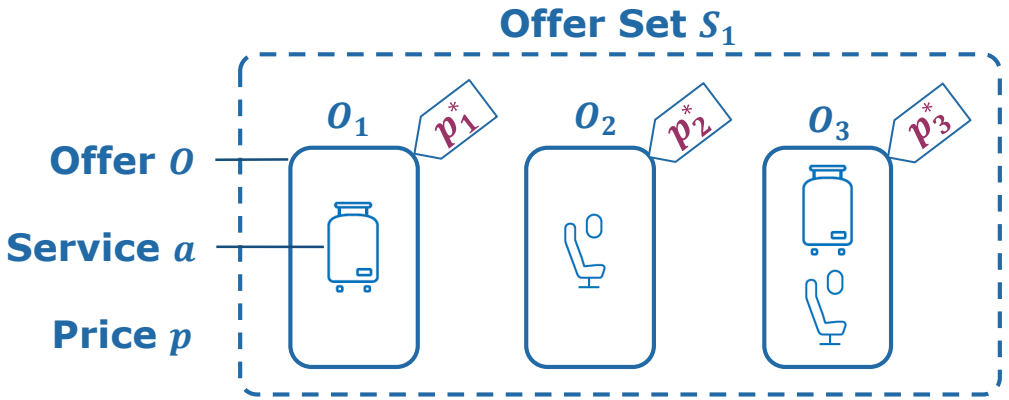
Joint Optimal Pricing: $\boldsymbol{p}^* = \arg\max_{\boldsymbol{p}^*} \{\sum_{o_i \in S} (p_i - c_i) \cdot \Pr_i(p_1, p_2, p_3)\}$

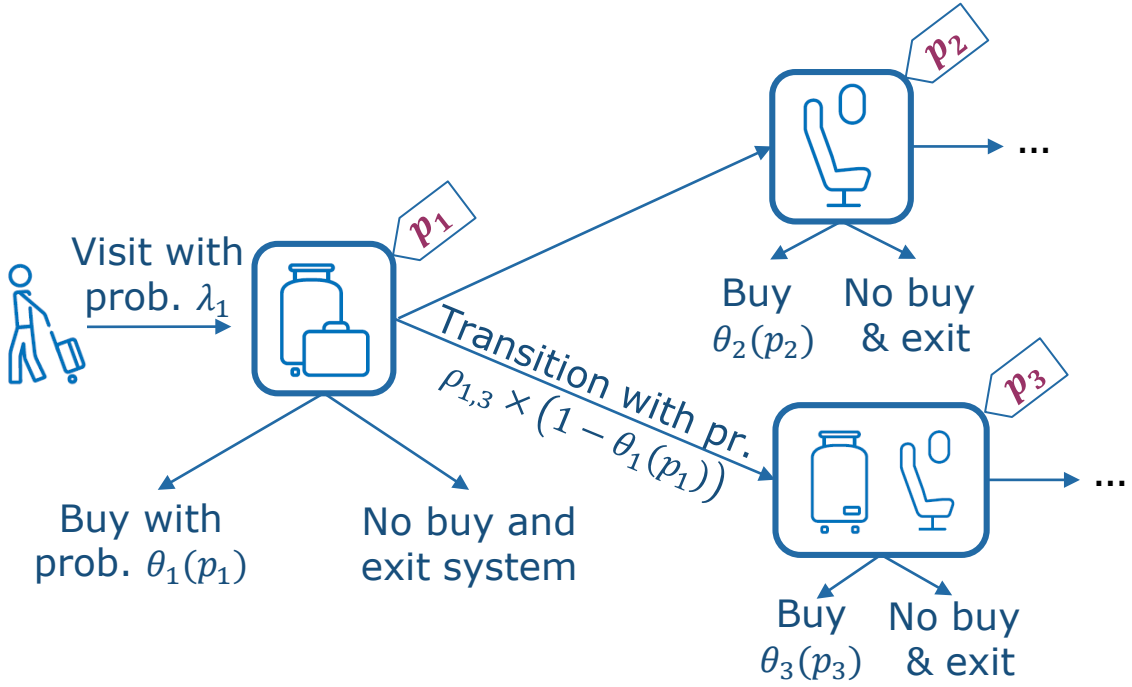
Joint offer set selection and pricing represents a new optimization problem in airline revenue management

Literature Review – Price Optimization



The Markov Chain Choice Model (MCCM)





The MCCM[1] has several advantages for price optimization:

- Any random utility model can be modeled as a MCCM[1,2]
- IIA property not necessarily present (no constant markup problem[3] for price optimization)
- Optimal prices can be computed through a series of <u>one-dimensional</u> optimizations[4]

[1]Blanchet et al., 2016; [2]Berbeglia, 2016; [3]Gallego and Wang, 2014; [4]Dong et al., 2019

Non-PODS Simulation of Ancillary Purchases

Comparing MCCM Bundle Pricing Against A La Carte Pricing Strategies

- Customers choose the Offer i that maximizes their utility $U_i = V_i - p_i$
- Airline models customer behavior with the MCCM
- Compare MCCM prices Naïve A La Carte Pricing (price = μ_a) and Myopic A La Carte Pricing

Offer Set S with three services

1 | 2 | 3 | 12 | 13 | 23 | 123

$$V_{12} = \begin{cases} V_1 + V_2 & if\ r_1 = 1 \wedge r_2 = 1 \\ V_1 & if\ r_1 = 1 \wedge r_2 = 0 \\ V_2 & if\ r_1 = 0 \wedge r_2 = 1 \\ 0 & if\ r_1 = 0 \wedge r_2 = 0 \end{cases}$$

	V_a	**1**	**2**	**3**
Mean (Gaussian Dist.)	μ_a	\$10	\$20	\$20
Standard Deviation	σ_a	\$3	\$6	\$6
Relevance	r_a	75%	75%	75%
Cost of Provision	c_a	\$0	\$0	\$0

MCCM Parameters

$\theta(p) = \Pr(V(\mu, \sigma, r) \geq p)$

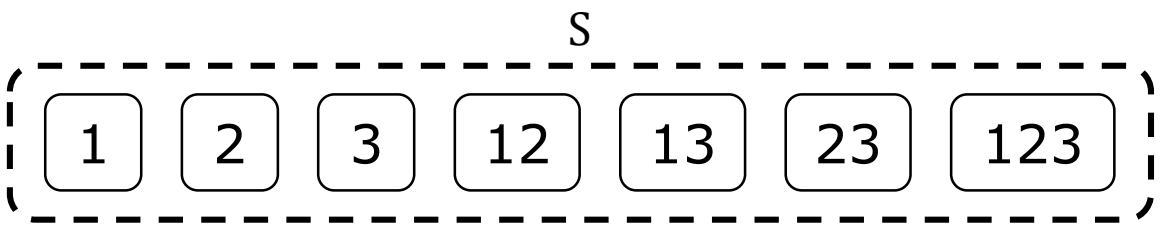
$\lambda_i = 1/7$

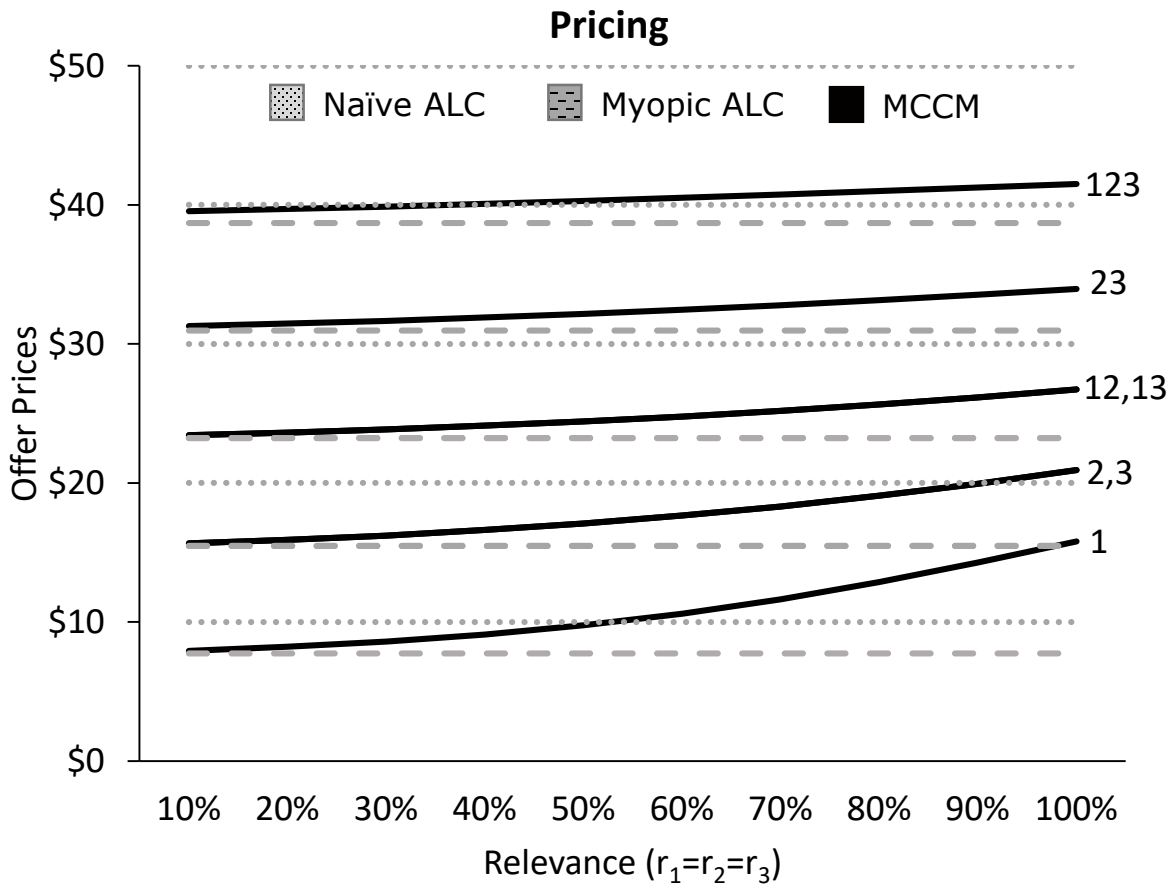
$\rho_{ij} = 10\%$

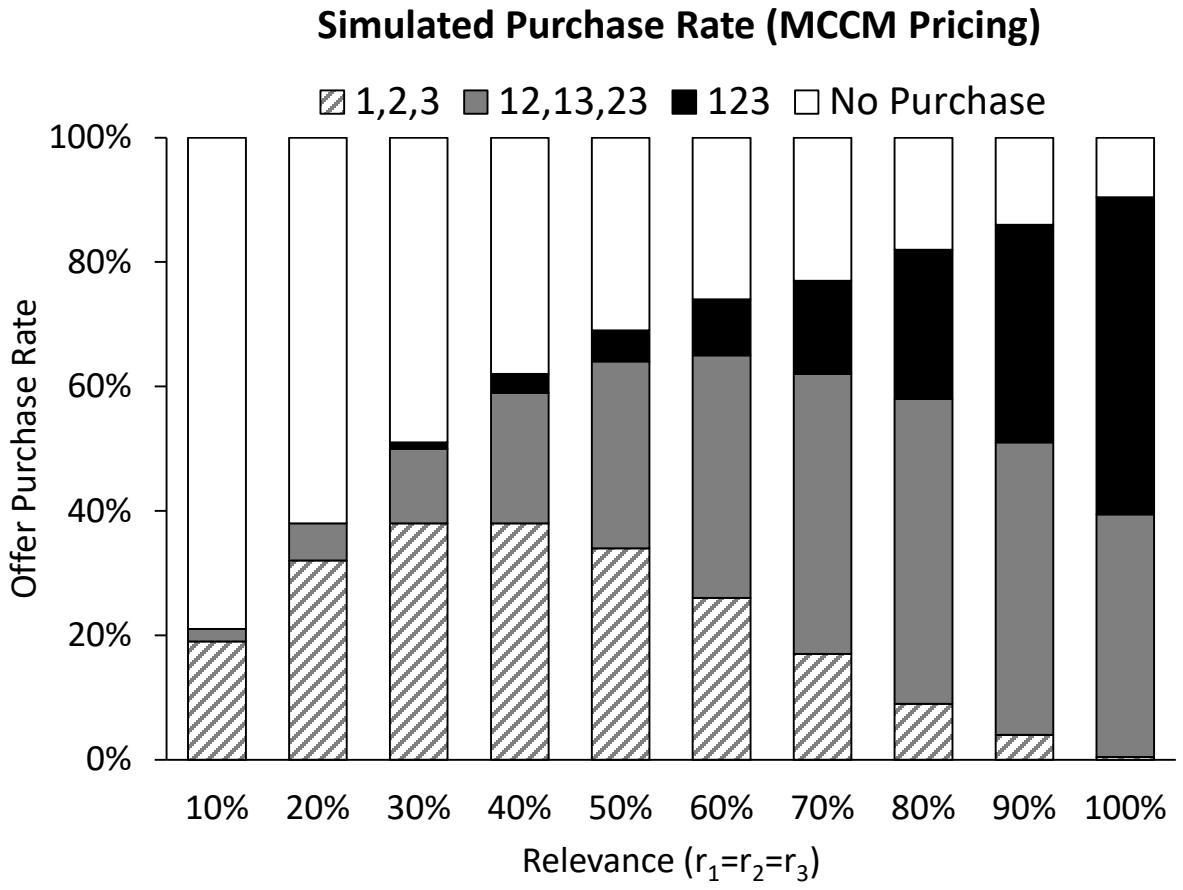
MCCM Prices with Relevance

When relevance is low, MCCM reduces the bundle discount and offers myopic ALC prices

Relevance r	Cost c
Variable	$0







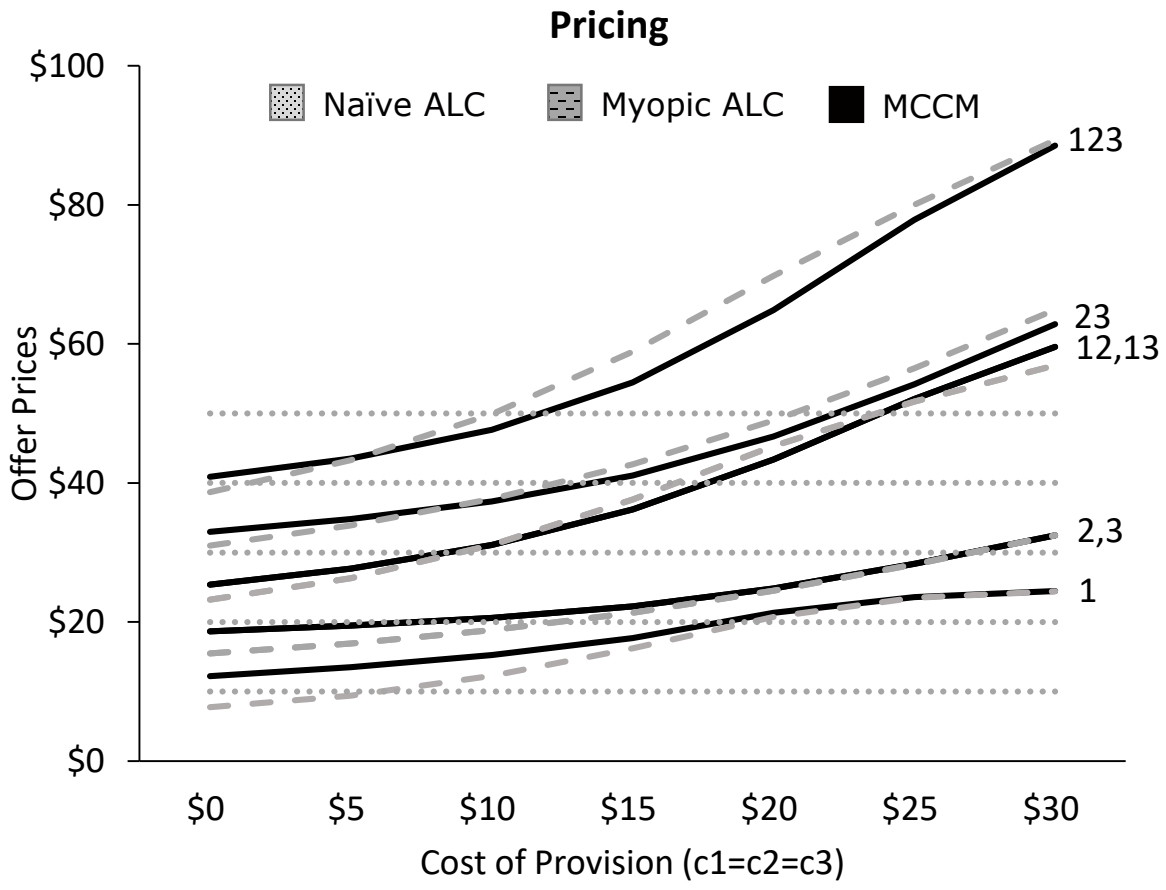
MCCM Prices with Cost of Provision

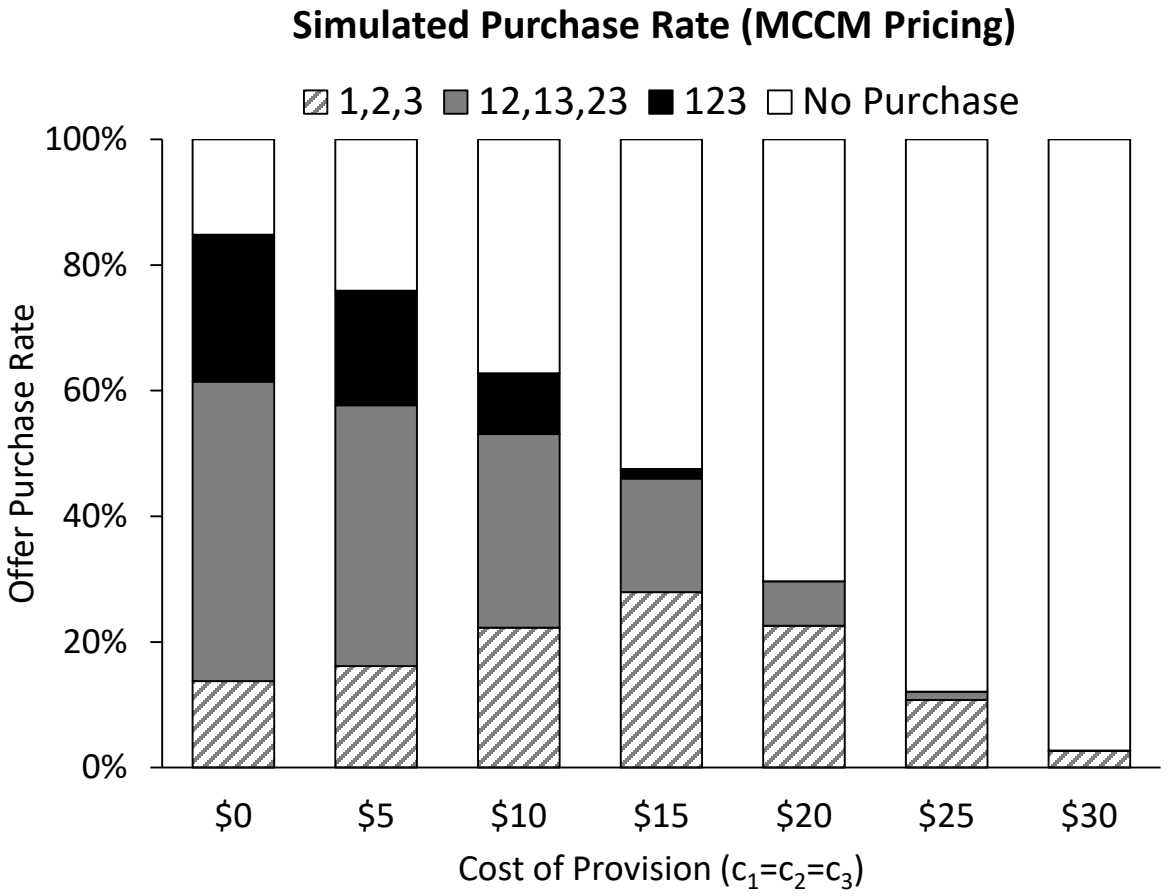
When cost is low, the optimized prices reduce and more ancillaries are sold

Relevance r	Cost c
75%	Variable

S

1 2 3 12 13 23 123





Maximum Likelihood Estimation of MCCM Parameters

Change in Revenue compared to Baseline Naïve Pricing

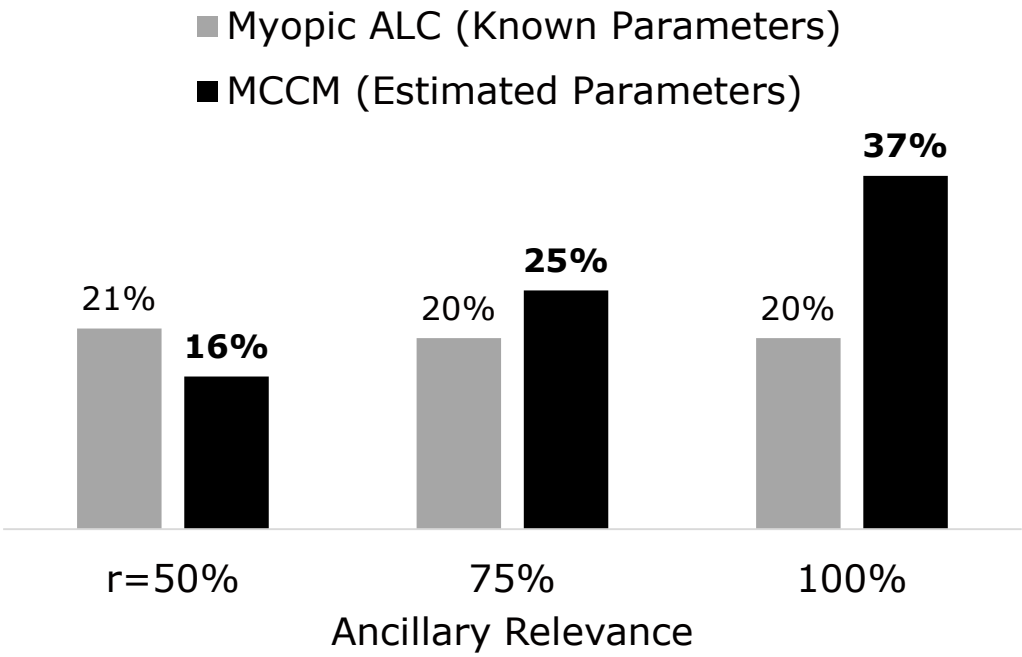
- **Dataset:** 100,000 observed bookings over 200 randomly sampled price combinations from artificially simulated passengers with the same V_a distributions
- **Model:** Constrained MCCM with 10 free parameters
- **Optimization:** Local optimization to maximize log-likelihood

Relevance r	Cost c
Variable	$0

Outcome of Parameter Estimation[1]

Offer	Price p_i^* Est. Params	Estimated Purch Prob	Simulated Purch Prob
1	$22.05	0%	0%
2	$24.93	2%	1%
3	$24.87	2%	1%
12	$27.28	11%	10%
13	$27.24	11%	10%
23	$31.05	22%	13%
123	$35.32	30%	38%

Ancillary Revenue vs. Baseline "Naïve" Pricing[2]



[1]Example Results for Relevance=75% and Cost=$0, [2]Naïve pricing sets prices equal to the true mean valuation

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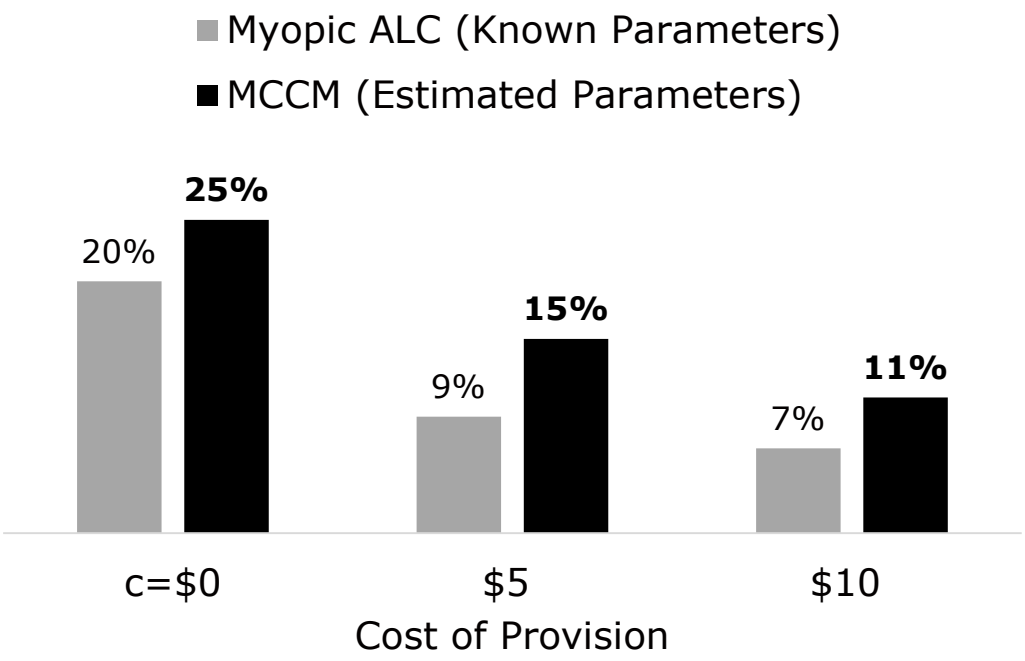

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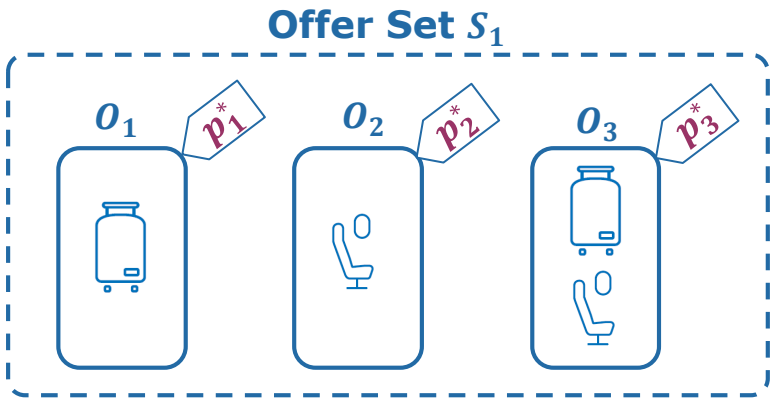
Conclusions

- Goal: Jointly optimize the prices of any number of Offers in an Offer Set
  - Computationally infeasible for realistic choice models and Offer Set sizes

- MCCM is a relatively new model with attractive properties for the Offer Set Pricing problem
  - Computationally efficient & can mimic any random utility model
  - Optimal prices do not have constant markup (price - cost) property



- MCCM produces reasonable prices and is tractable
  - Revenue benefits from bundle pricing over myopic ALC pricing (+4% at r=0.75)
  - Good ancillary revenue improvements over naïve ALC pricing (+25% at r=0.75)
  - Parameter estimation is feasible using log-likelihood optimization

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Contact: kevini@mit.edu