LESSONS FROM LIVE APPLICATION OF DEEP LEARNING CONTINUOUS PRICING SYSTEM IN AN AIRLINE

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Co-Founder & Chief AI, PhD

AGIFORS – Sep 2022

SPEAKER BIO

- Co-founder & Chief AI Officer, Fetcherr.io
- PhD in Computational Neuroscience.
- Former Head of AI of major US algo trading firm.
- 30+ years of experience developing AI based SW products.
- Specializing in development of algo trading systems & models.

DR. URI YERUSHALMI

AGENDA

Lessons based on 3M+3M live application

01 FROM WALL STREET QUANT TRADING TO AIRLINE CONTINUOUS PRICING

02 SYSTEM ARCHITECTURE & COMPONENTS

03 MODELS SPARSITY REQUIREMENTS

04 MODELS MULTITYPE NEEDS

05 XAI AS A R&D TOOL

06 LIVE A/B TESTING METHODOLOGY & RESULTS

07 LESSONS SUMMARY

08 Q&A

IMPACT OF APPLYING A DL PRICING SYSTEM

From a quant perspective

Return

$$E(r_a - r_b)$$

Sharpe

$$\frac{E(r_a - r_b)}{\sqrt{Var(r_a - r_b)}}\sqrt{N}$$

Equity Value

Trading Volume

To a pricing analyst perspective…

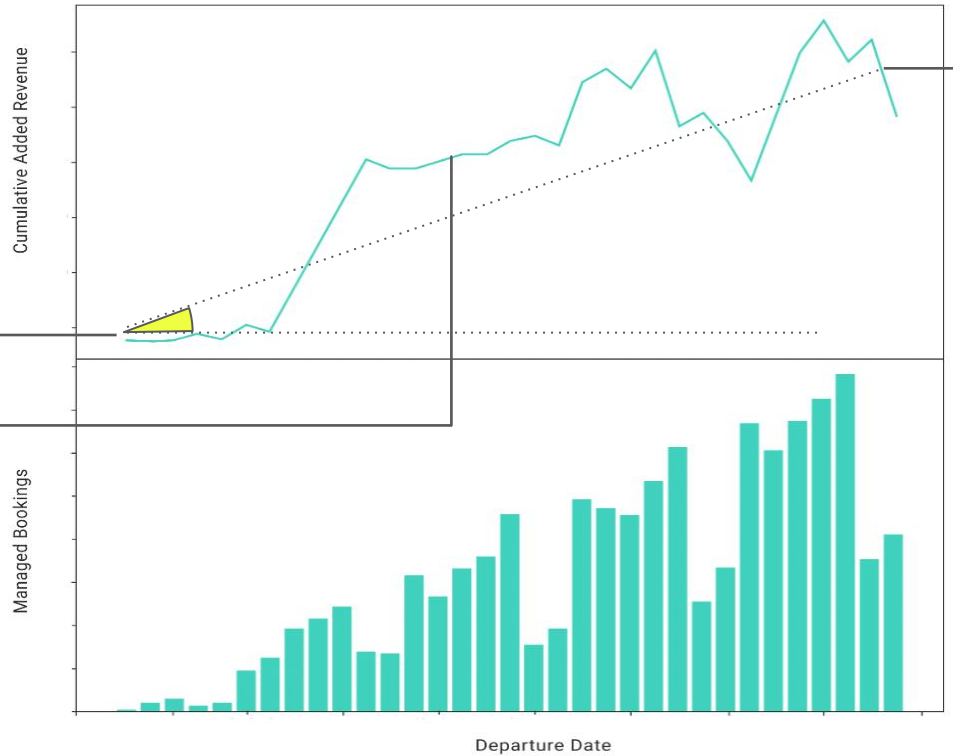
IMPACT OF APPLYING A DL PRICING SYSTEM

Return

$E(r_a - r_b) = 13\%$

Sharpe

$$\frac{E(r_a - r_b)}{\sqrt{Var(r_a - r_b)}}\sqrt{N} = 8.1$$

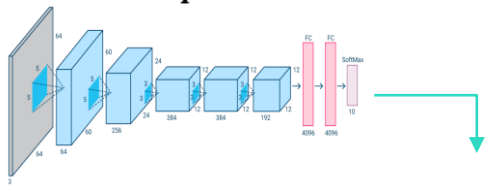


Cumulative added revenue

PRICING SYSTEM ARCHITECTURE-1

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$



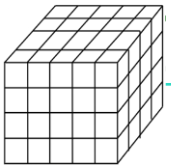
Optimal Prices

$$P = g(B)$$

Reward

$$r = h(B,P)$$

Market Data



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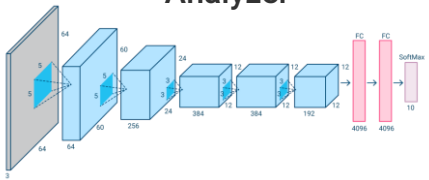
Market Analyzer



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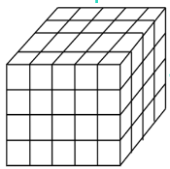
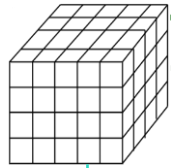
Market Behavior



$B = f(D)$



Simulator

h

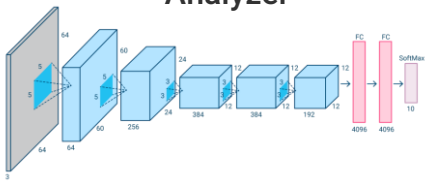
PRICING SYSTEM ARCHITECTURE-2

Ticketing, Booking, Availability,
Competitors prices, ATPCO,
Events, Fares, Capital Markets,
Weather, News,
Flight Schedules…

Market Data

D

Market Analyzer



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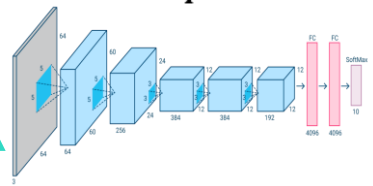
Market Behavior

$B = f(D)$

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$

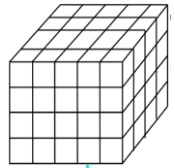


Reward (RL)

$r = h(B,P)$

Optimal Prices

$P = g(B)$



Simulator

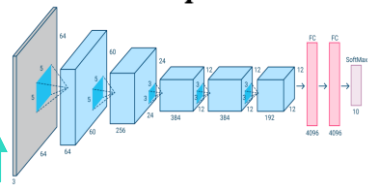
h

PRICING SYSTEM ARCHITECTURE-3

Granular demand size & elasticity, competition aggressiveness

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$



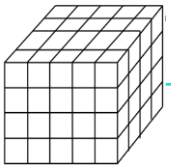
Optimal Prices

$$P = g(B)$$

Reward (RL)

$$r = h(B,P)$$

Market Data



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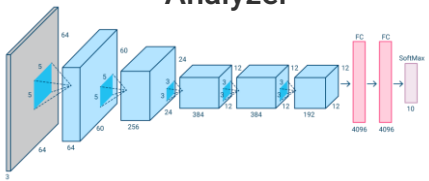
Market Analyzer



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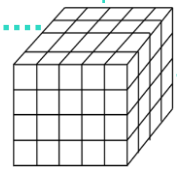
Market Behavior



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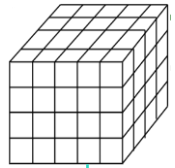


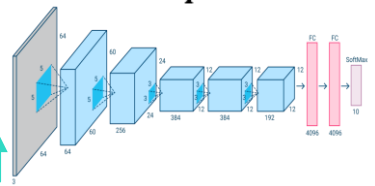
Simulator

h

PRICING SYSTEM ARCHITECTURE-3

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$



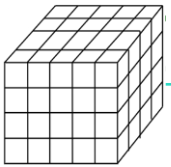
Optimal Prices

$$P = g(B)$$

Reward (RL)

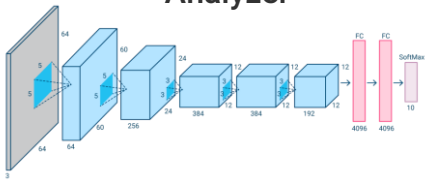
$$r = h(B,P)$$

Market Data



D

Market Analyzer



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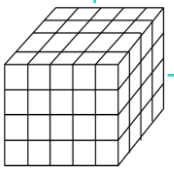
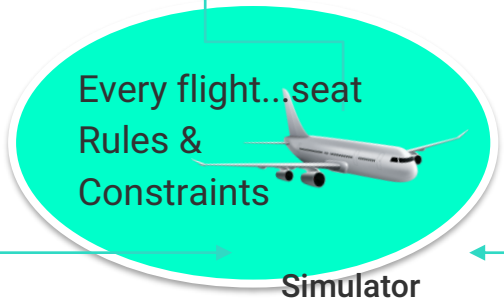
Market Behavior



$B = f(D)$



Simulator

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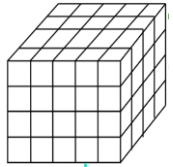
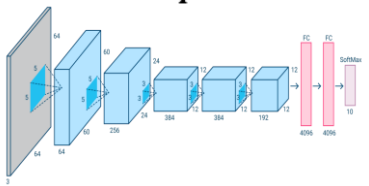


PRICING SYSTEM ARCHITECTURE-4

Revenue, Market Share, LF

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$



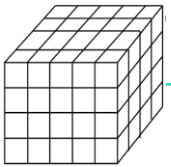
Optimal Prices

$$P = g(B)$$

Reward (RL)

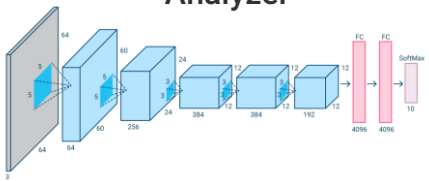
$$r = h(B,P)$$

Market Data



D

Market Analyzer



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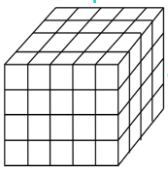
Market Behavior



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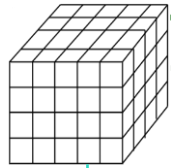


Simulator

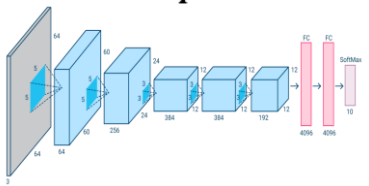
h

PRICING SYSTEM ARCHITECTURE-5

As granular as airline permits

Price Optimizer

$$g(B) \approx \underset{P}{argmax}\, h(B,P)$$



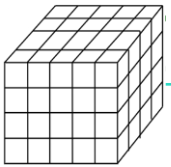
Optimal Prices

$$P = g(B)$$

Reward

$$r = h(B,P)$$

Market Data



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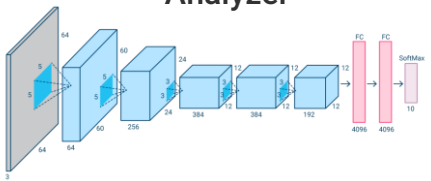
Market Analyzer



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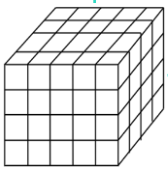
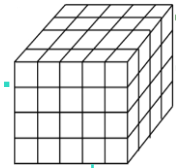
Market Behavior



$B = f(D)$



Simulator

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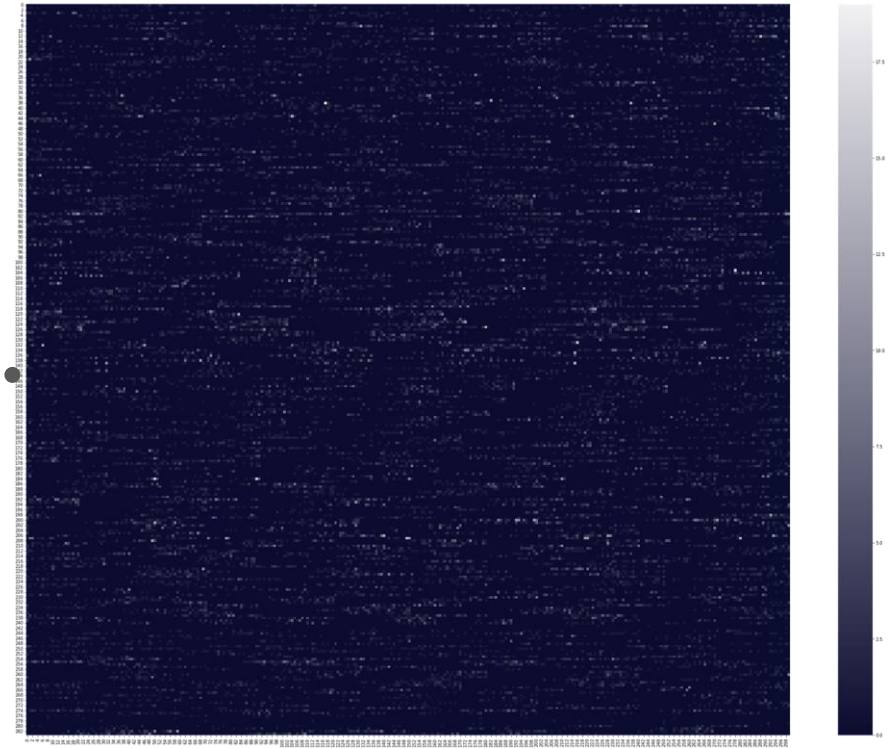
DATA SPARSITY

High Granularity
High Resolution

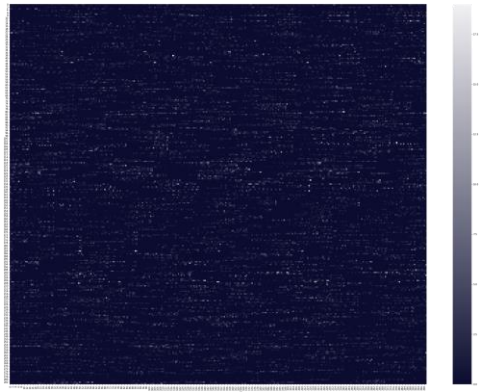


Sparse booking data $\in D$

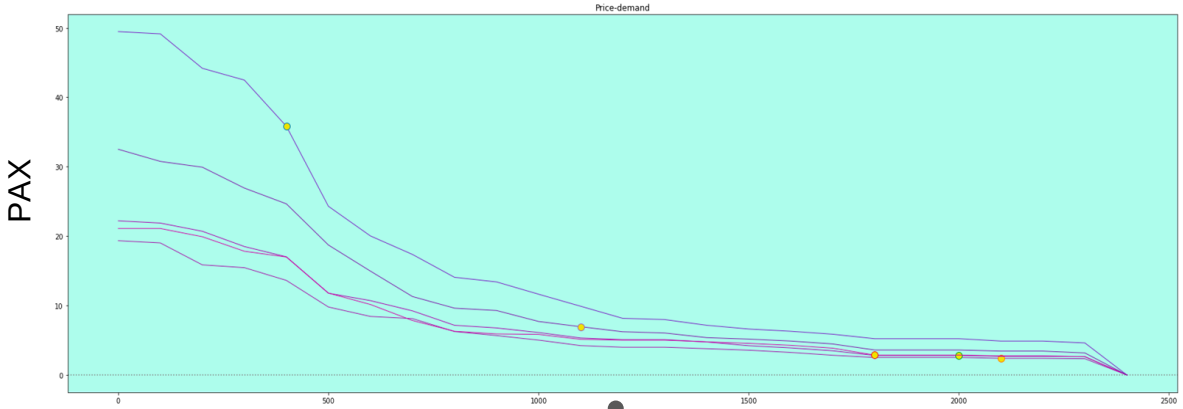
ML MODEL & DATA SPARSITY

D is High Resolution

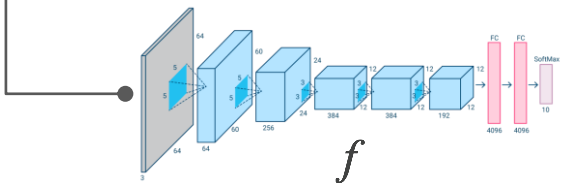
Sparse booking data $\in D$



Accurate demand curves $\in B$



price



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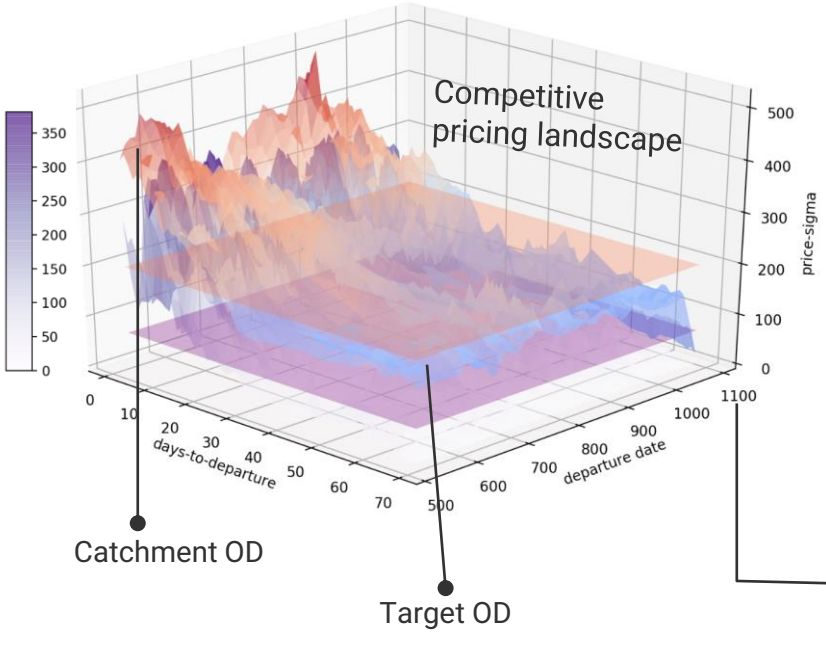
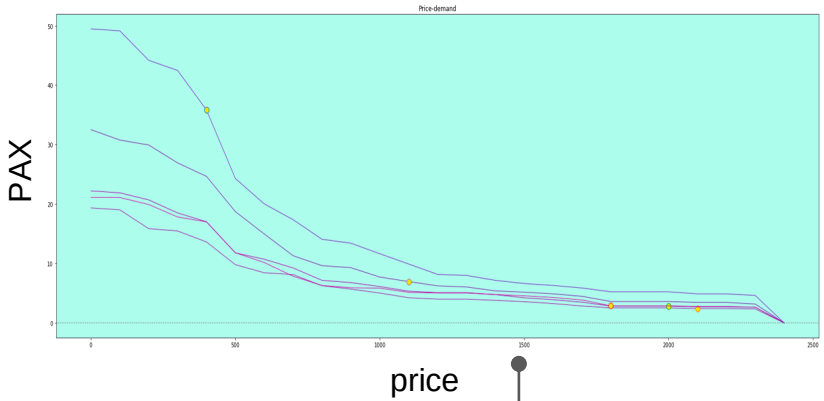
ML MODEL & MULTITYPE DATA

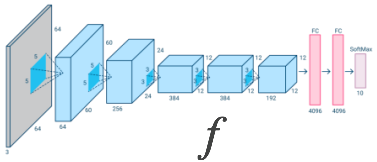
D is multitype

SpatioTemporal Data $\in D$



Accurate demand curves $\in B$





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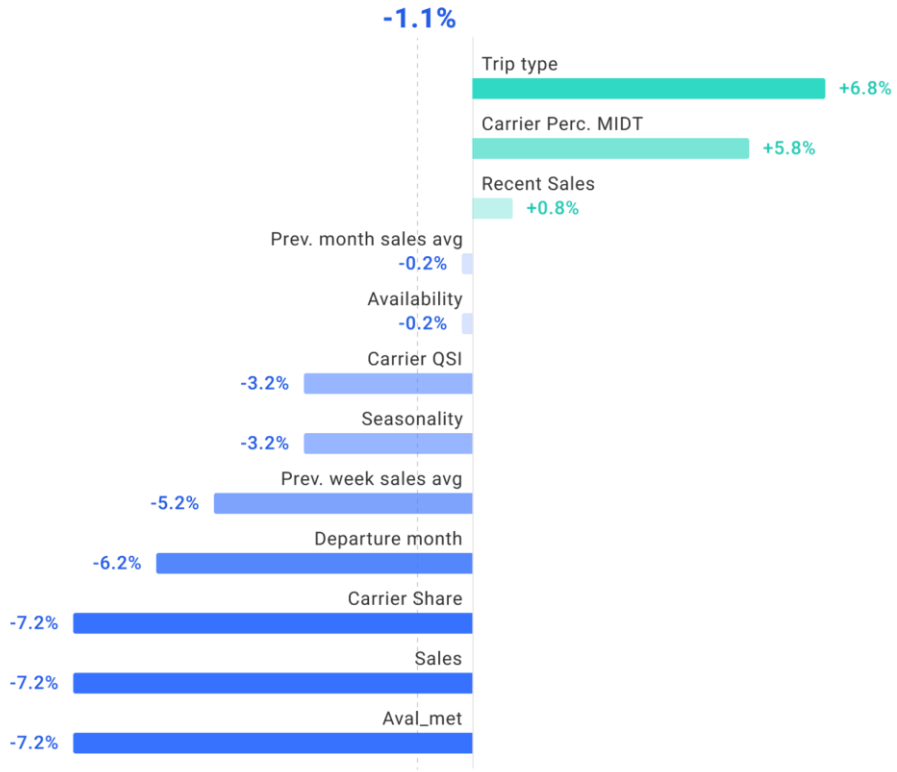
Explainable AI

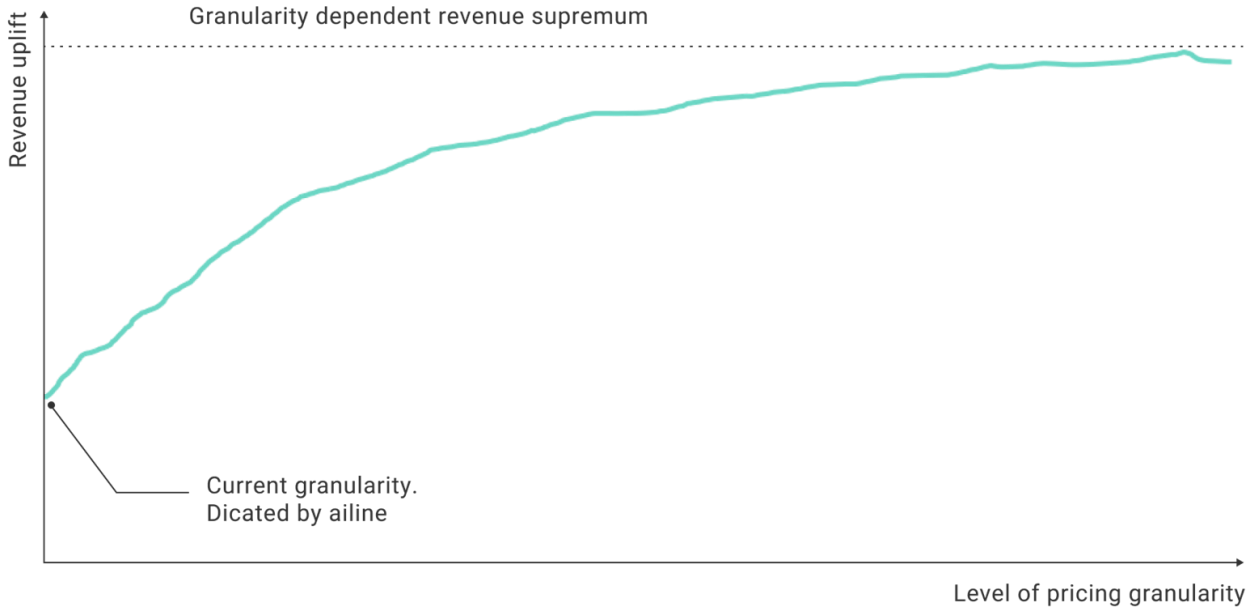
- Need to make sure ML learned the right logic.
- XAI used both for R&D and for End User.
- XAI libs are less optimization oriented.
- In house shap built for optimization.

$$\phi_i(p) = \sum_{S \subseteq N/i} \frac{|S|!(n - |S| - 1)!}{n!} (p(S \cup i) - p(S))$$

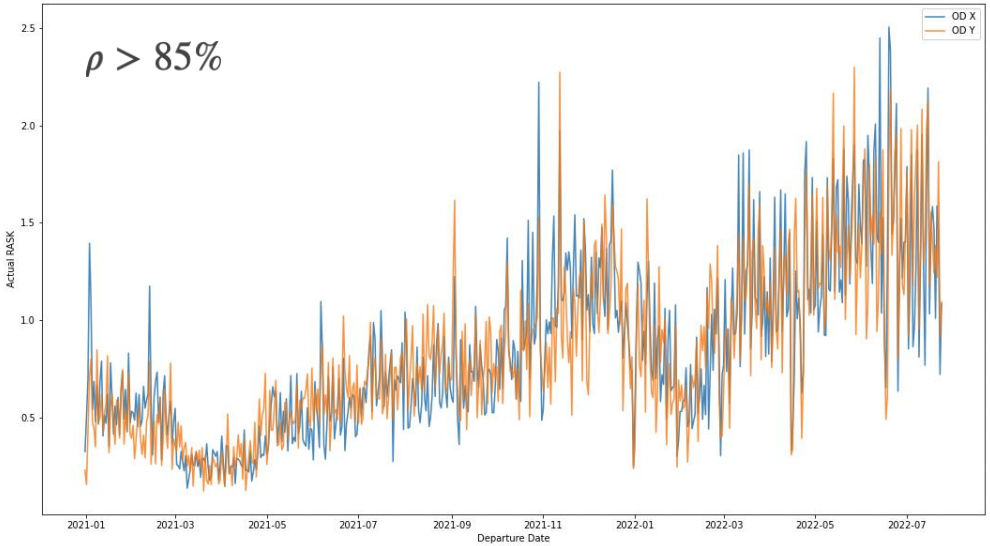


IMPACT OF GRANULAR PRICE CONTROL

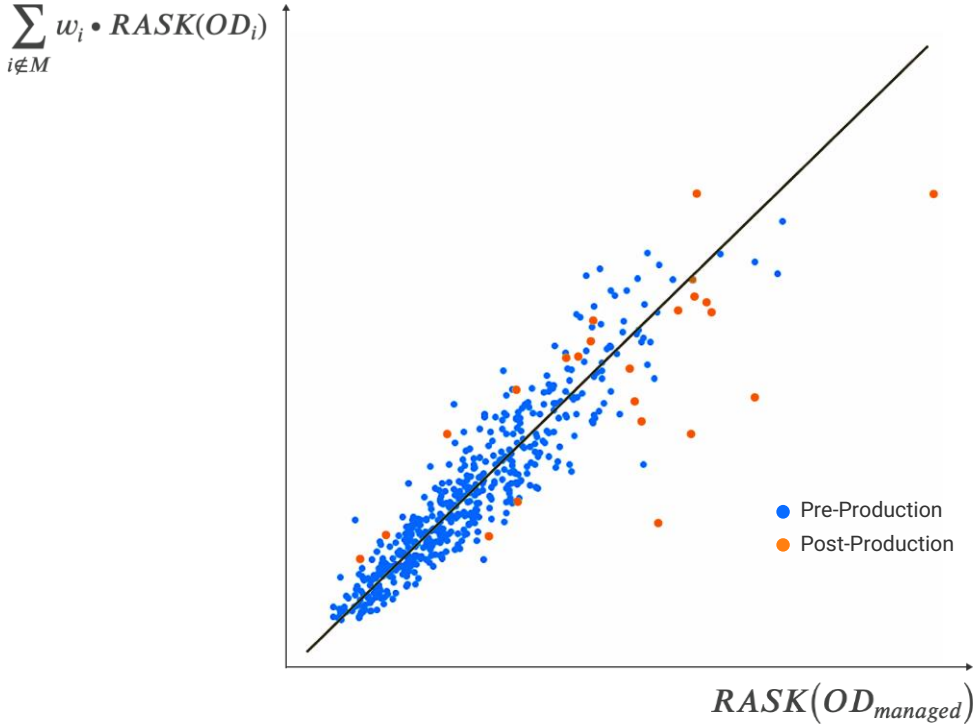
Pricing granularity
Level of segmentation of products and passengers



RASKS ARE CORRELATED



LIVE PERFORMANCE MEASUREMENT METHODOLOGY

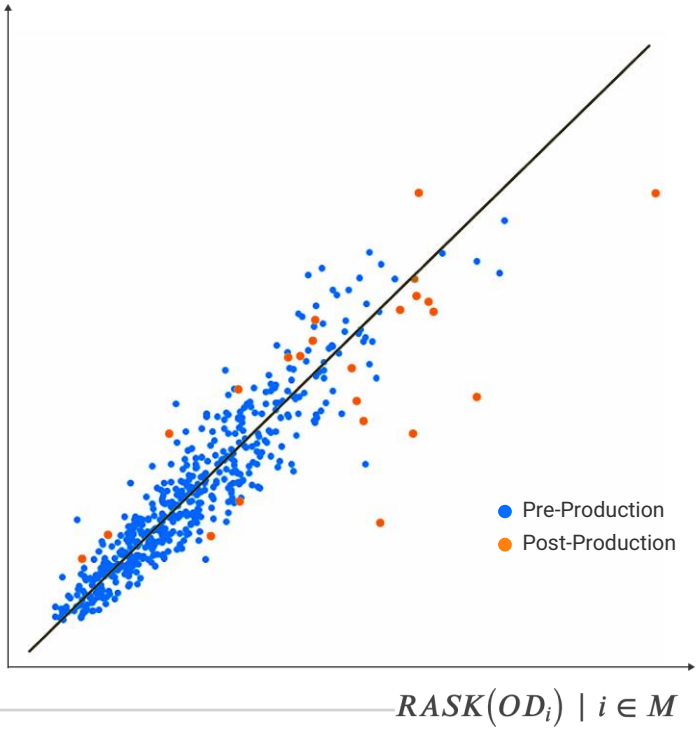


LIVE PERFORMANCE MEASUREMENT METHODOLOGY

$$\text{Revenue ascribed to new pricing} = r_a - r_b$$

r_a: Actual revenue

r_b: $\sum_{i \notin M} w_i \bullet RASK(OD_i)$ — Expected revenue Projected By correlated ODs

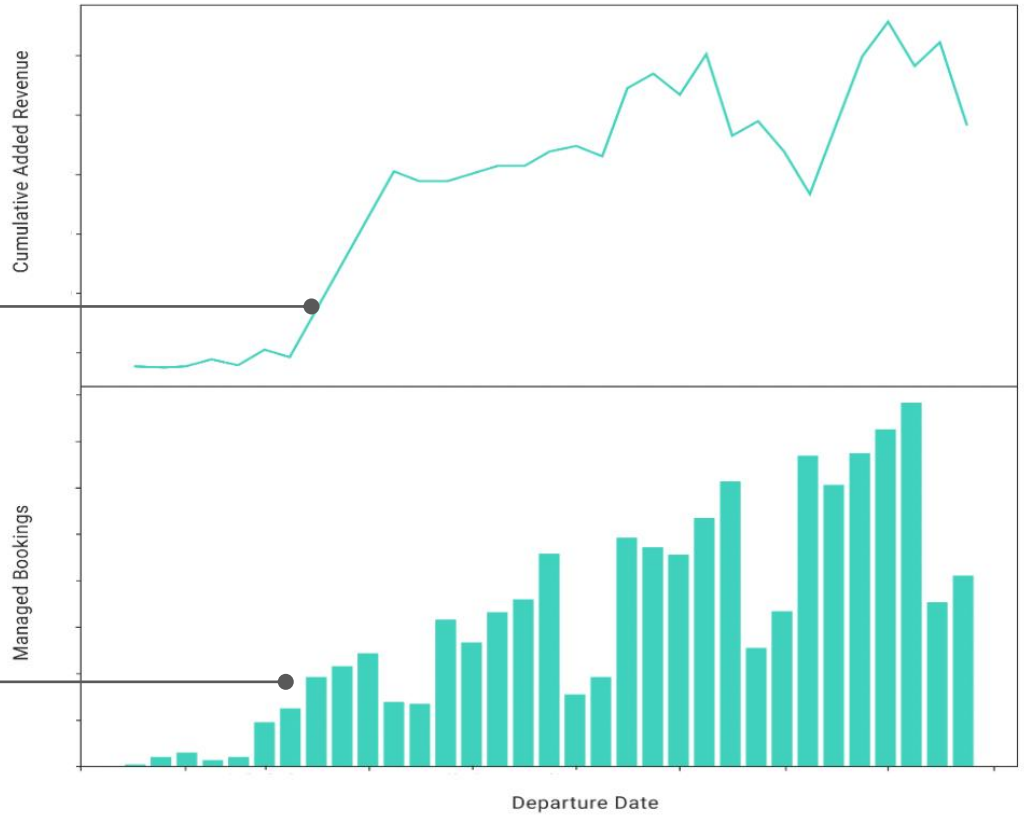


LIVE RESULTS

$r_a - r_b$

RASK increase of
18%-7%

Gradual deployment



CONCLUSIONS

1. Trading methodologies are applicable.
2. Results that are statistically significant
3. Models' capability to work with data that is: Sparse, Multitype, Spatio-Temporal, Volatile & NonStationary.
4. High potential in giving the AI granular, high resolution price control.
5. XAI utilization both for dev and for user acceptance.
6. Gradual deployment is essential.
7. A/B testing is possible.
8. Applicable to other areas: NW planning, ancillaries management, loyalty programs…

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