



A Data-Driven Approach for Golf Resort Revenue Management

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Business Context

- Golf Resort: **Hotel, Golf, Pub, Bar, Shop**

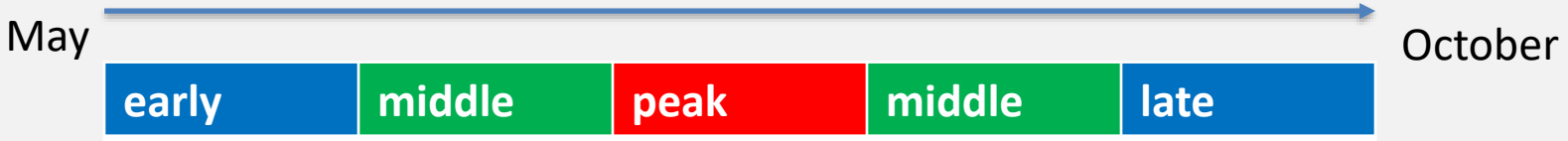




- Regular Revenues (**certain**) + Auxiliary Revenues (**uncertain**)
- 7 ordered **service levels** (room categories):

$$CD \leq CK \leq DD \leq DK \leq DKB \leq 2BV \leq 4BV$$

- Open Season: from **May** to **October**.
- Price categories are **fixed** in advance: $early \leq middle \leq peak$



The Story

- A guest books **single hotel night**.
- Maximum accommodation price is **$CAD 3K**, minimum is **$CAD 0.25K.**
- Then spends **$CAD 5K** for a bottle of wine.

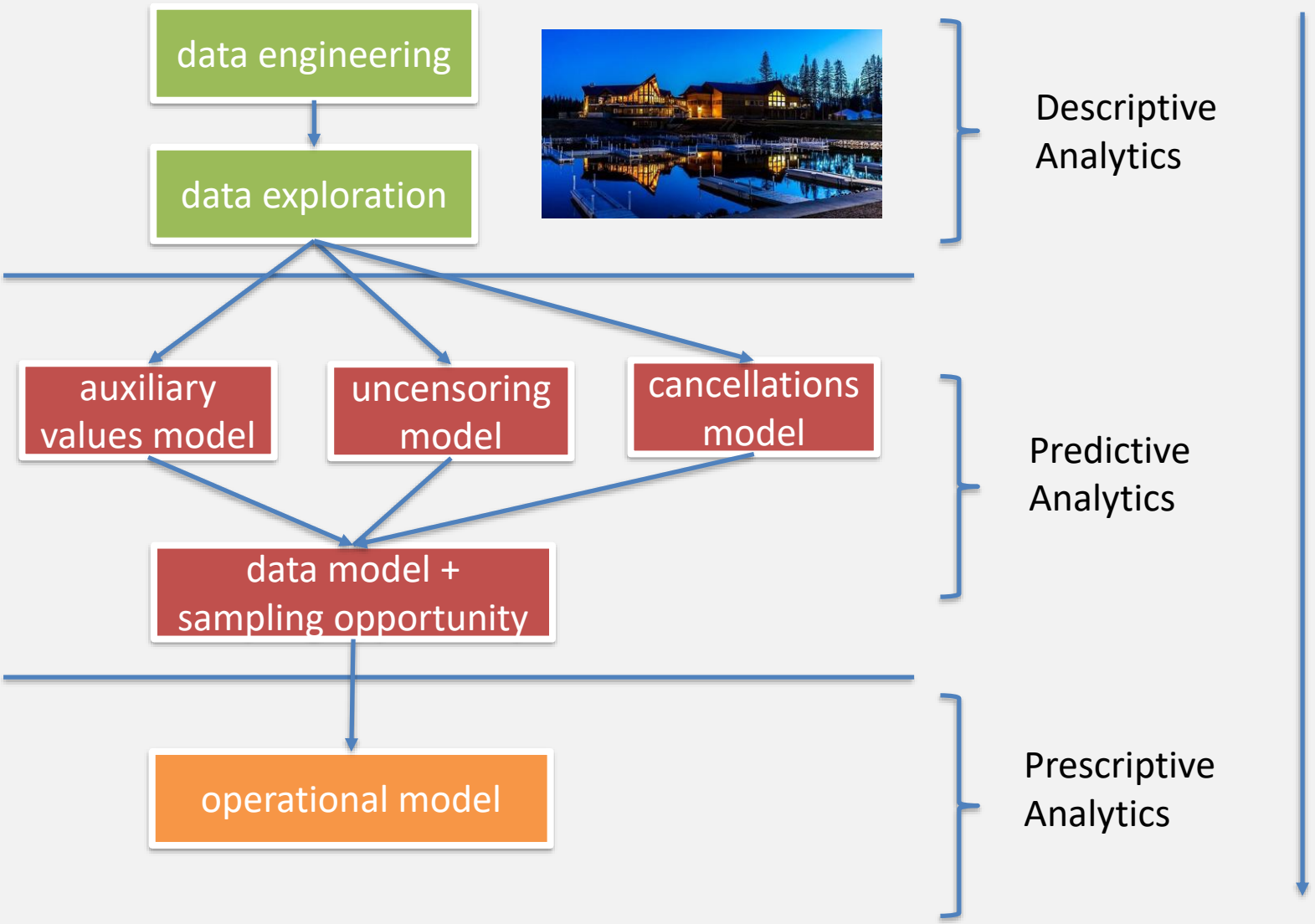






- **Who are such clients?**
  Resort likes them!
- Opportunity: **10 guests**, **5 days** $\Rightarrow$ **$CAD 250K** in less than a **week**!

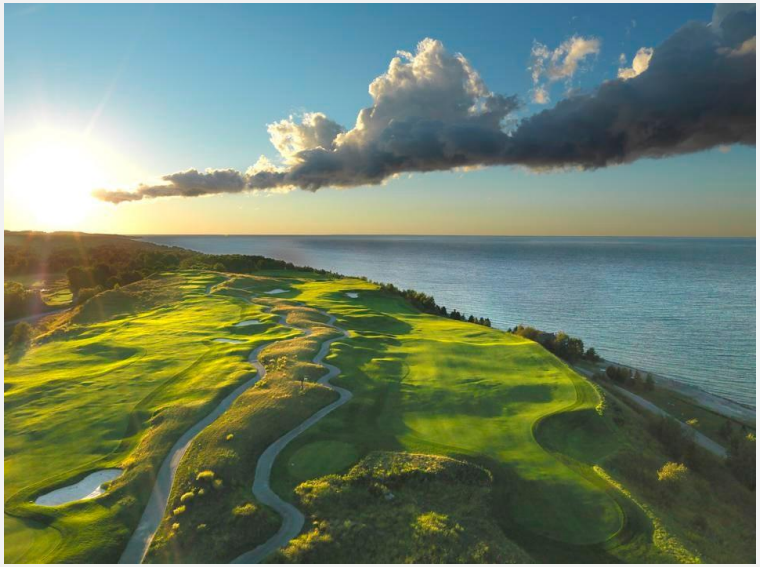
System Overview



Agenda

- **Introduction**
  - Business Context
  - Story
  - System Overview
- **Theory**
  - Scope
  - Model
  - Questions
  - Approach
  - Results
- **Practice**
  - Data and Lift
  - Visualizations





Theory Scope

Skip In What Follows
Due to Time Limits

Theory

Uncensoring

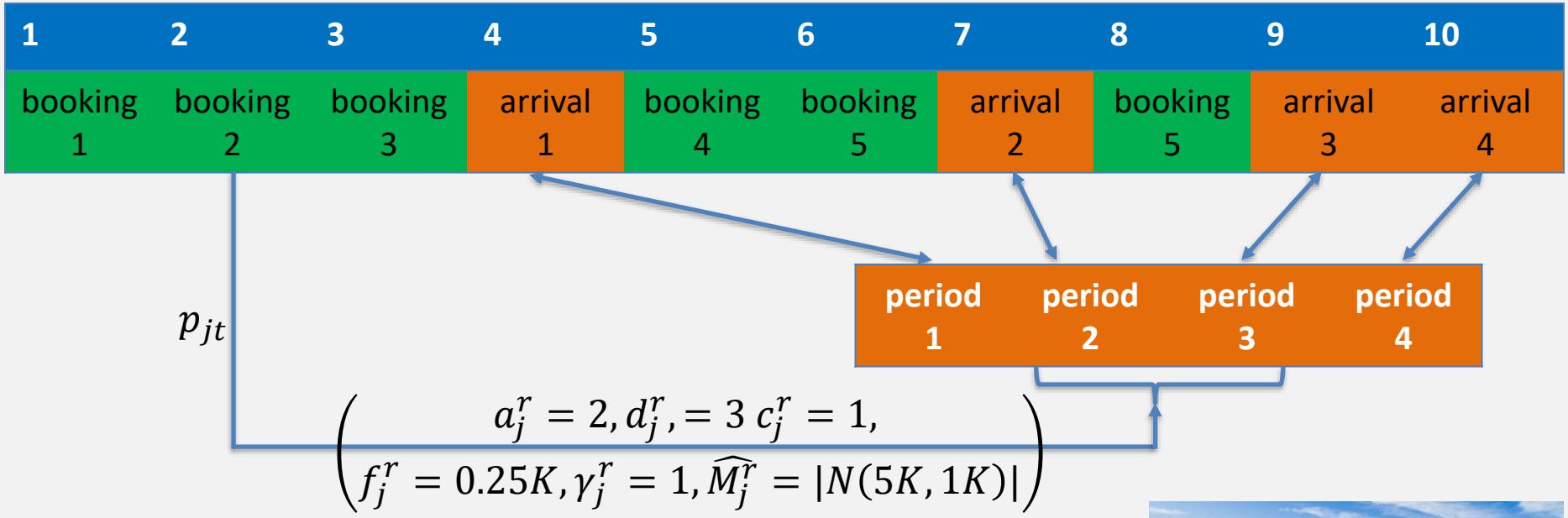
- GLM (generalized linear models)
- Parametric EM (Expectation-Maximization)

Operational Model

- RLP (Randomized Linear Programming)



Operational Model





- Two types of events: **booking** and **arrival**.
- At **most one reservation** during each booking event.
- R reservation request types.
- **Request**: $\left(a_j^r, d_j^r, c_j^r, f_j^r, \gamma_j^r, \widehat{M_j^r}\right) =$ (stay begin, stay end, category, fare, refund rate, auxiliary value).
- p_{jt} - probability to get **request *j* at time *t***. $\widehat{D_{jt}}$ - corresponding RV.

Operational Model

Client Behavior:

- Cancellation RV is $\hat{S}^c$, No-Show RV is $\hat{S}^n$, Show RV is $\hat{S}^s$.
- Natural to introduce overbooking and free upgrades.
- Free upgrade cost $\theta_{j,k}^{upgr}$, decline cost θ_j^{decl}.

Decision Variables:

- y^t: accepted requests (decision at booking events).
- w^t: allocated requests (decision at arrival events).



Operational Model

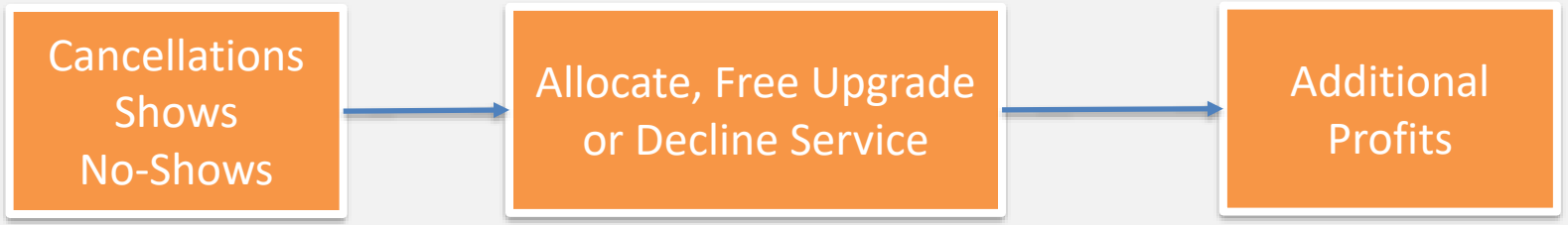
Process as Dynamic Program:

- $JR_t(x^t, v^t)$ – optimal revenue to go with accepted requests x^t and allocations v^t.
- **Terminal Condition**: $JR_{T+1}(x^{T+1}, y^{T+1}) = 0$.
- **Booking Event**:





- **Arrival Event:**



Rolling Horizon DP

Booking Event:

$$JR_t(x^t, v^t) = \mathop{\mathbb{E}}_{\widehat{D}^t} \left[\max_{\substack{0 \le y^t \le \widehat{D}^t \\ y^t \in \{0,1\}}} \left\{ \sum_{j=1}^{R} y_{jt} f_j^r + JR_{t+1}(x^t \oplus y^t, v^t) \right\} \right]$$

Arrival Event:

$$JR_t(x^t, v^t) = \mathop{\mathbb{E}}_{\widehat{S}} \Bigg[-\gamma_j^r f_j^r \widehat{S}_{j\tau}^c x_{j\tau} + \max_{w_{[arr=t]} \in \{0,1\}} \mathop{\mathbb{E}}_{\widehat{M}} \left(JR_{t+1}(x^t, v^t \oplus w_{[arr=t]}) + \sum_{(j,\tau) \in \mathcal{R}_t^*} [-w_{j\tau}^{decl} \theta_j^{decl} + \sum_{k \ge c_j^r} w_{jk}^{upgr,\tau} (\widehat{M}_{j\tau} - \theta_{jk}^{upgr})] \right) \Bigg]$$



subject to:

$$\begin{cases} \forall (j,\tau) \in \mathcal{R}_t^* : \sum\limits_{k \ge c_j^r} w_{jk}^{upgr,\tau} + w_{j\tau}^{decl} = x_{j\tau} \widehat{S}_{j\tau}^s \\ \forall i = \overline{1,A},\ k = \overline{1,L} : \sum\limits_{\substack{(j,\tau) \in \mathcal{R}_{<t}^* \\ a_j^r \le i \le d_j^r}} v_{jk}^{upgr,\tau} + \sum\limits_{\substack{(j,\tau) \in \mathcal{R}_t^* \\ a_j^r \le i \le d_j^r}} w_{jk}^{upgr,\tau} \le c_k \end{cases}$$

Questions and Targets

1. How to **Lift The Profit**?
2. How to make a decision approach? that:
   - **Asymptotically optimal**
   - **Computationally tractable**
   - **Provable bounds**
   - **Sellable**



Randomized LP is:

- Computationally tractable.
- Native demonstration on samples.
- Induced bids are easily interpretable.
- More promising than deterministic LP, since captures moments of RV beyond 1^{st} .



Original Plan

1. Inequality $JR \leq RH - RLP \leq DLP$ (deterministic LP).
2. From $JR \leq DLP$, by coupling argument $JR \sim DLP$.
3. Therefore $RH - RLP \sim DLP$.

Problem: RH-RLP <= DLP?

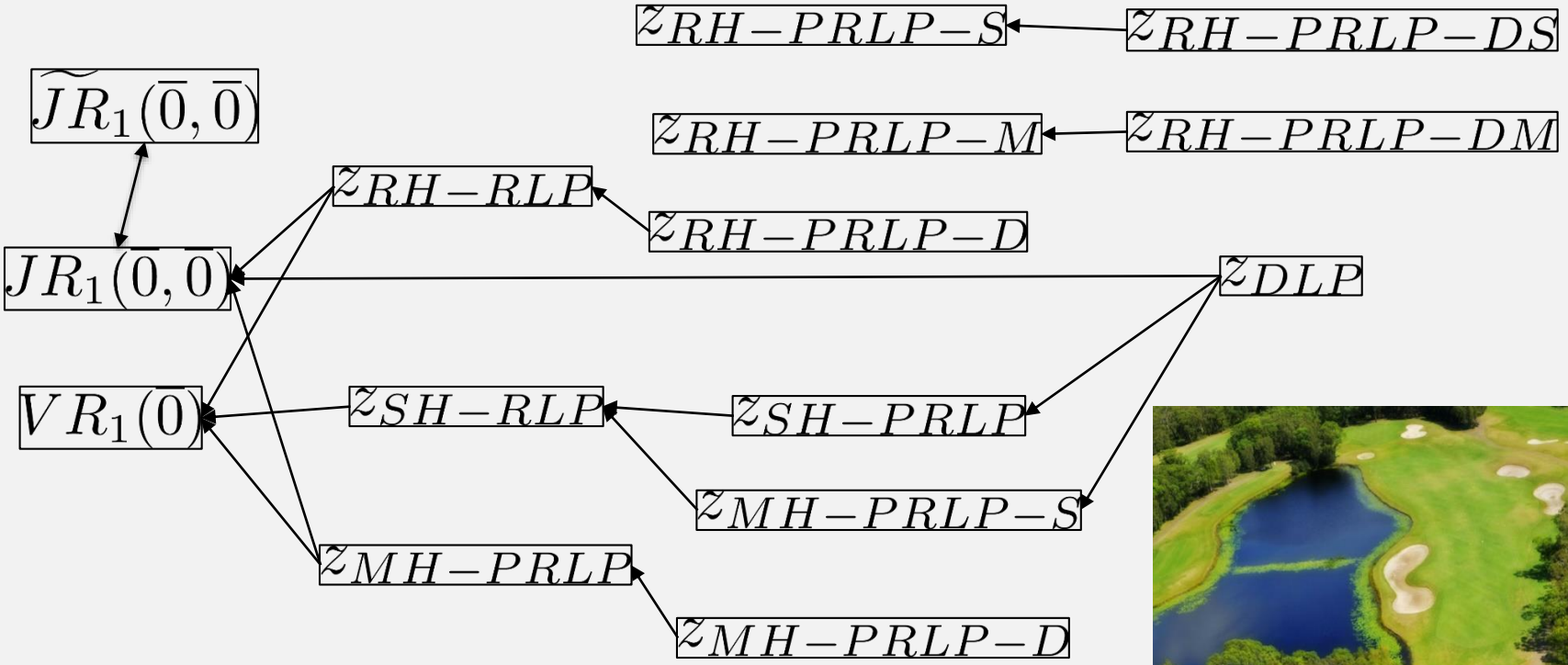


Working Plan

1. Inequality $JR \leq DLP$.
2. From $JR \leq DLP$, by coupling argument $JR \sim DLP$.
3. Introduce Static Horizon setting VR, where all decisions are postponed until the end of time horizon.
4. Inequality $VR \leq SH - RLP \leq DLP$.
5. From $VR \leq DLP$, by coupling argument $VR \sim DLP$.
6. Finally, $SH - RLP \sim JR$.

Results

Theorem. The figure below depicts all the established inequalities together, where each arrow ← represents ≤ inequality. Policies SH-RLP, MH-PRLP-S and SH-PRLP are asymptotically optimal.





Practice

Dataset:

- Golf Resort Private Data, 3 years.
- Semi-Real Data, Artificially expanded, 3 years.

Restrictions:

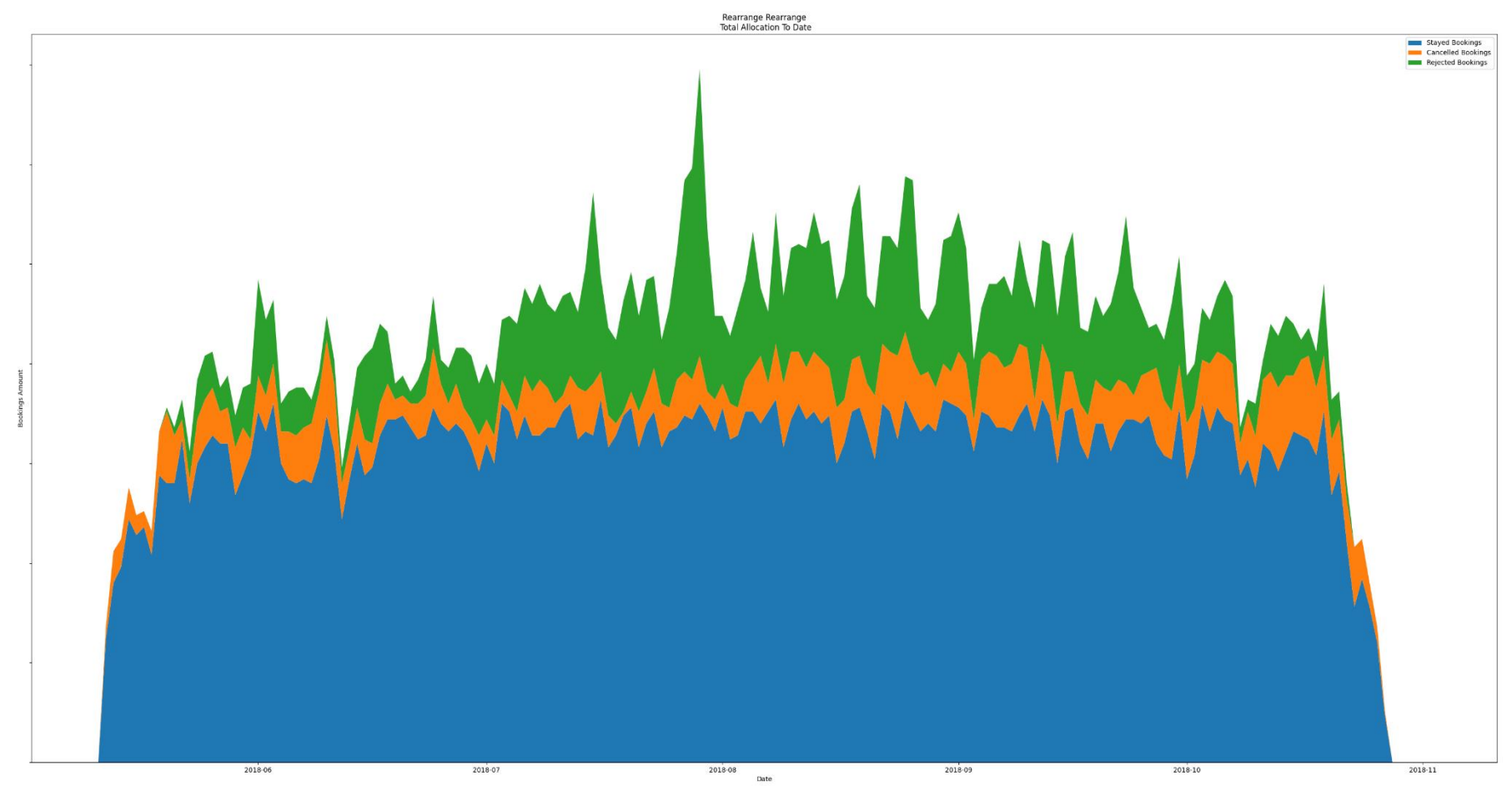
- No decline of service (free upgrades are OK).
- Prices are fixed one year before the next season starts.



Lift:

Setting	Lift
Private-EM-2018	8.6%
Private-EM-2017	6.7%
Private-EM-2016	7.2%
Private-GLM-2018	4.7%
Private-GLM-2017	3.9%
Private-GLM-2016	3.0%
Artificial-GLM-2015	4.6%
Artificial-GLM-2016	4.1%
Artificial-GLM-2017	4.9%

Visualization: Room Allocation



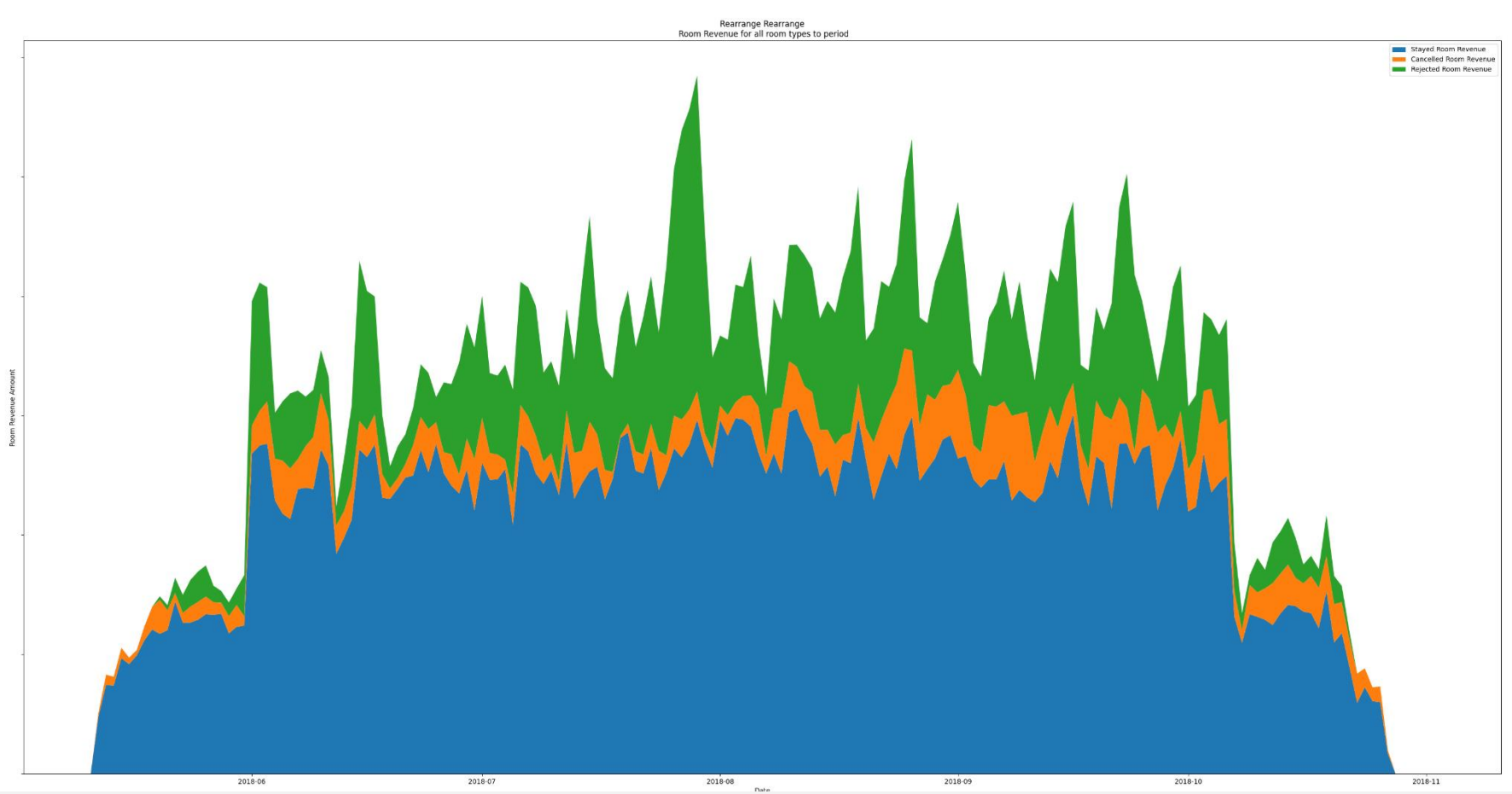
Blue – Arrived

Orange – Cancelled

Green - Rejected



Visualizations: Room Revenue



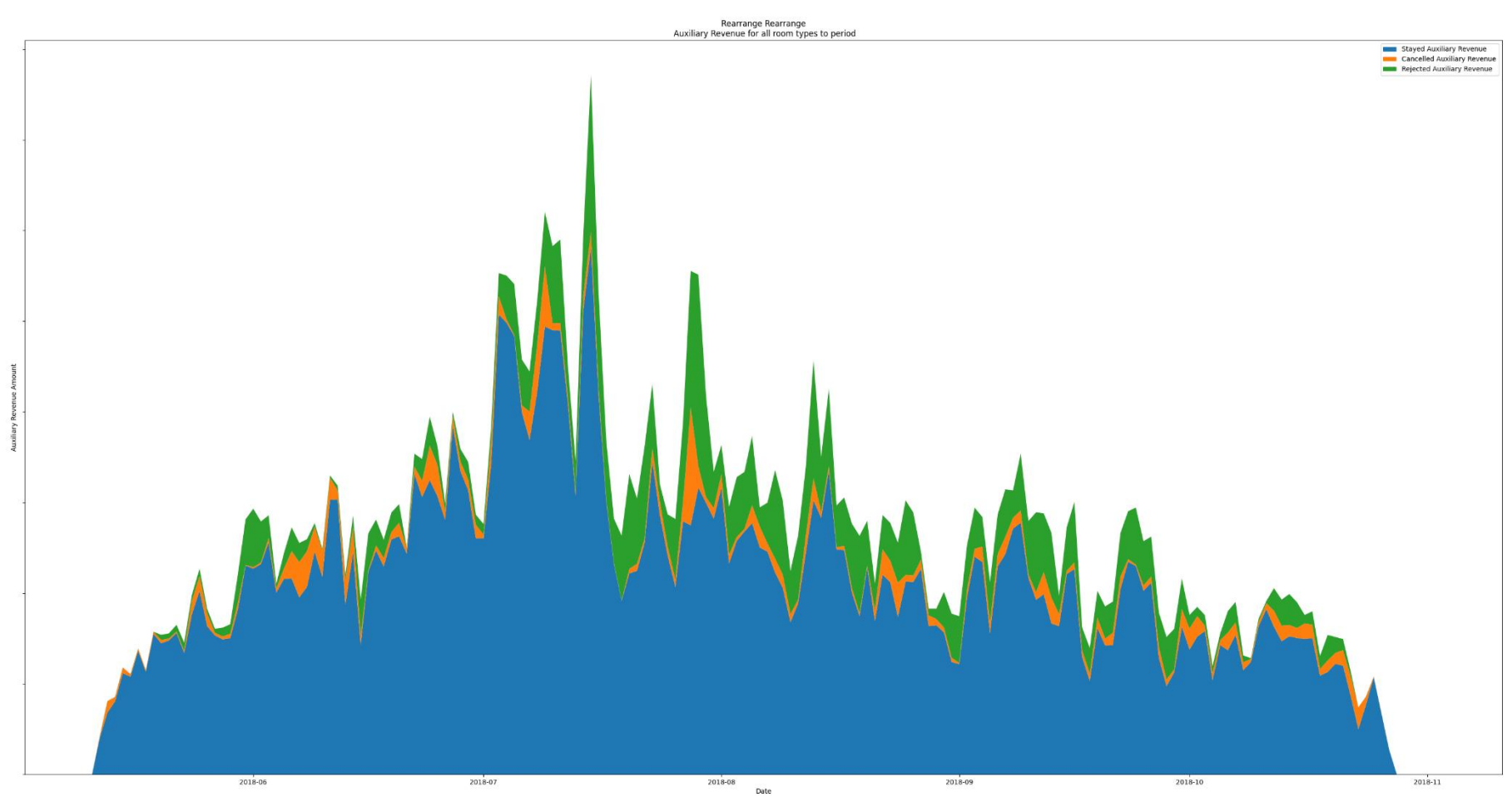
Blue – Arrived

Orange – Cancelled

Green - Rejected



Visualization: Auxiliary Revenue



Blue – Arrived

Orange – Cancelled

Green - Rejected



Summary

1. Full practical implementation from raw data to profit-demonstrating project POC.
2. Theory for operations management and uncensoring stages.
3. Multiple RLP approaches for Rolling Horizon, Mixed Horizon and Static Horizon configurations. Some of them are asymptotically optimal and have provable inequalities.

Bonus! Have shown you many beautiful and relaxing golf resort pictures all over the world.





Thank you for your attention! (or patience)
Feel free to express your opinion.