

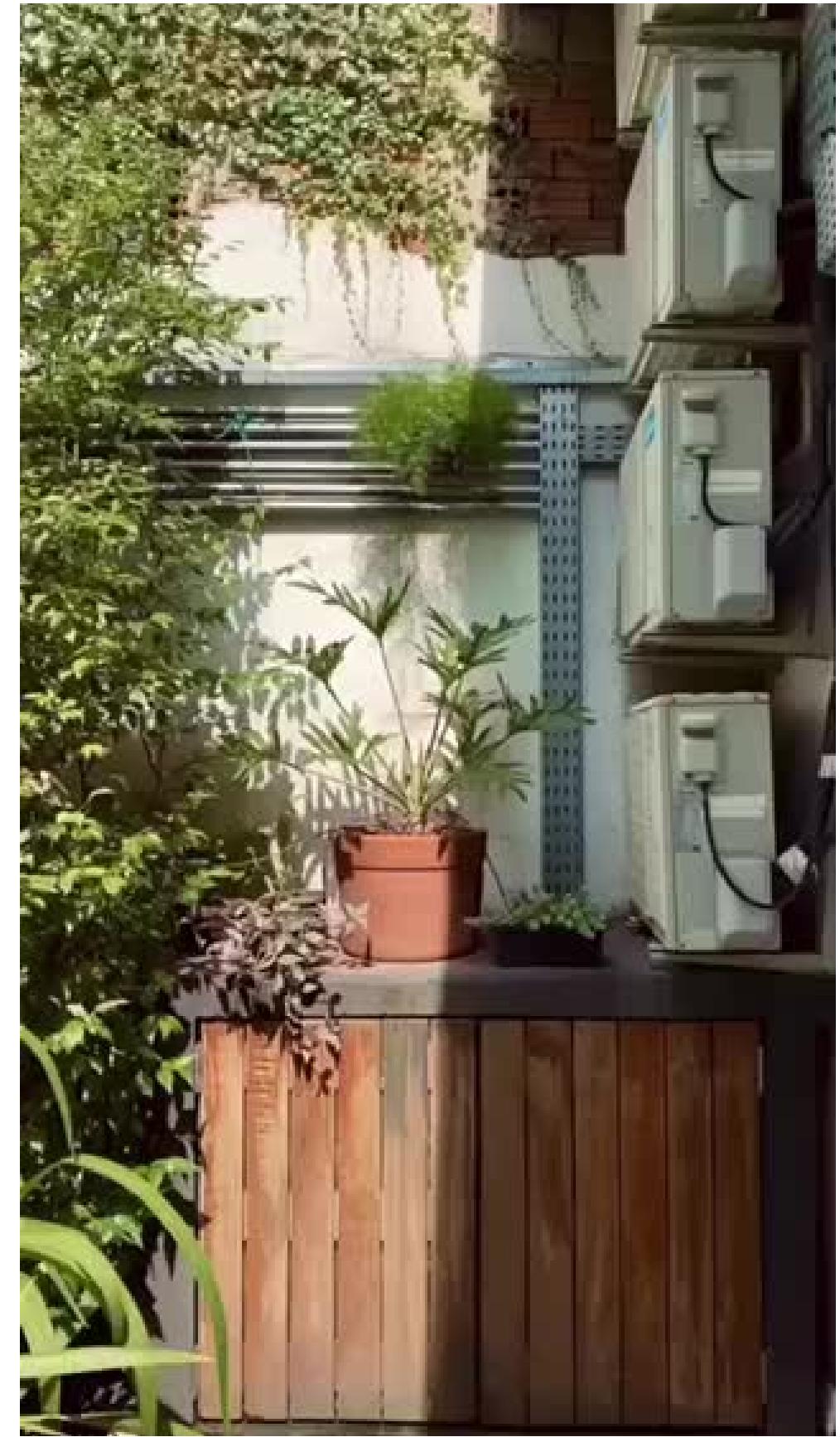
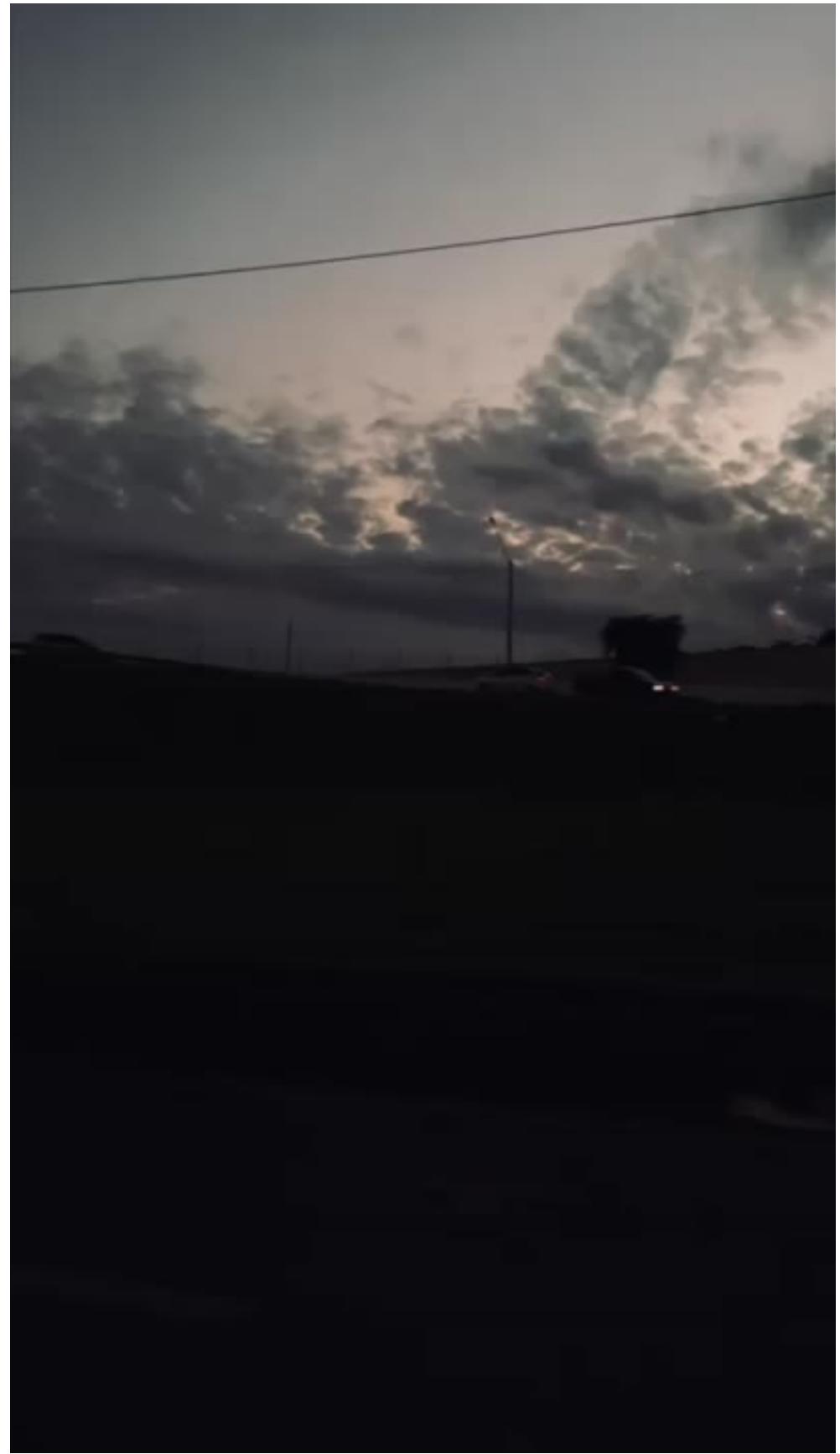


GUEST URBAN  
HTL  
SAO PAULO

# Machine Learning

Price Prediction for Guest Urban  
Hotel Rates

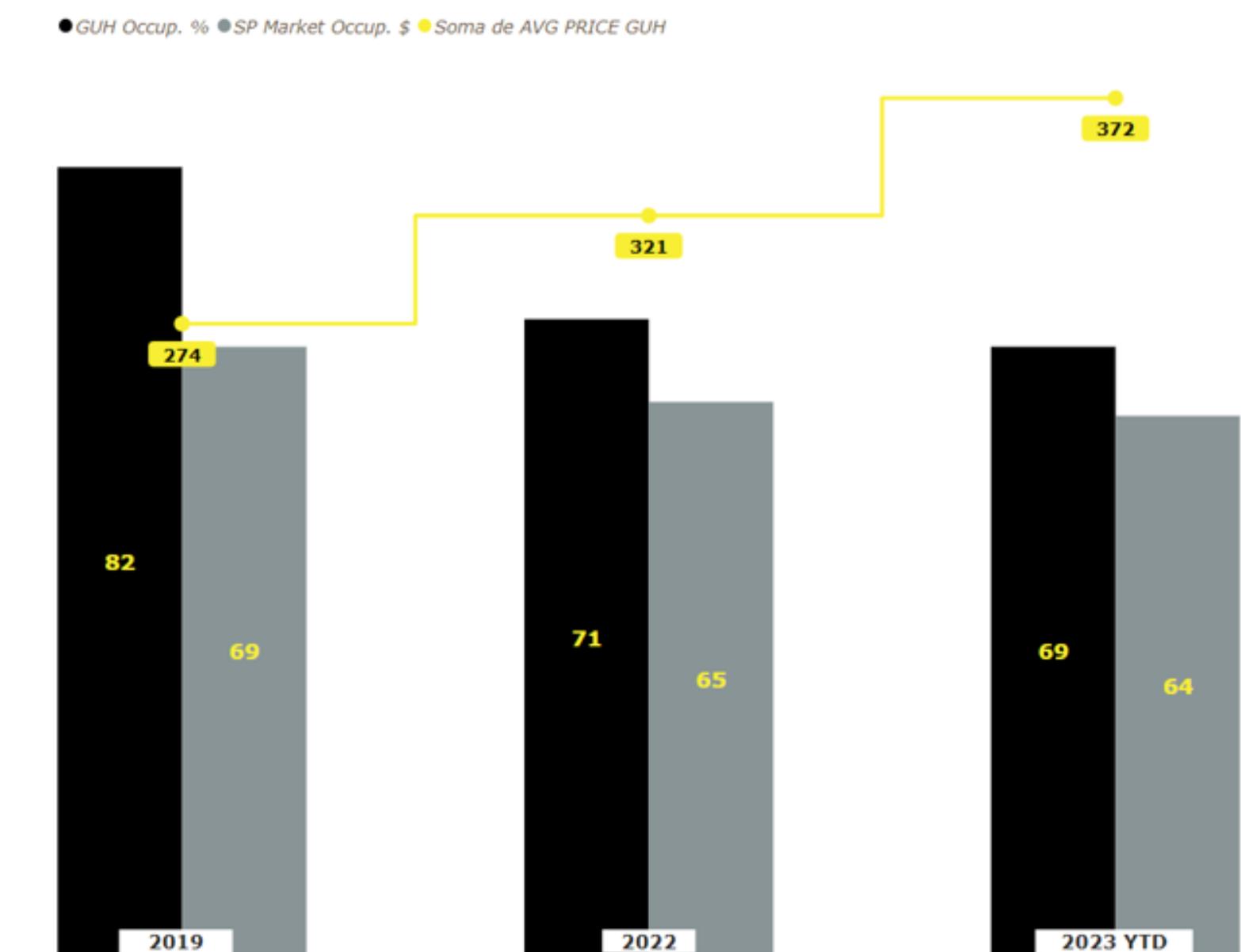
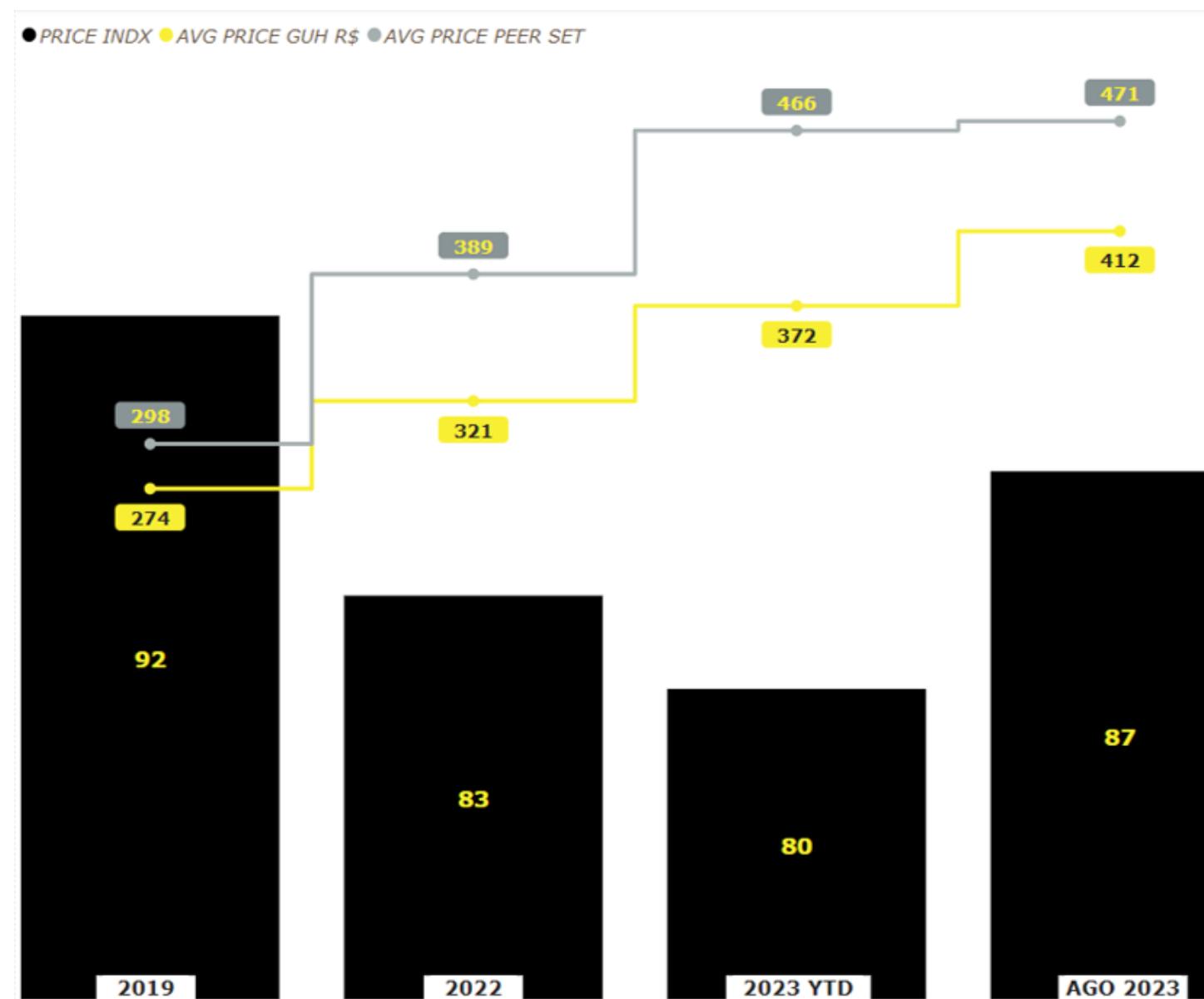




By Demian Figueredo

# THE PROBLEM

After pandemic, market price of São Paulo hotel rates and occupancy rates has changed drastic.  
It's been difficult to apply with efficiency a well planned price strategy.



# ML PROBLEM SOLVING ROUTES



**Demand forecasting**

Competitive analysis

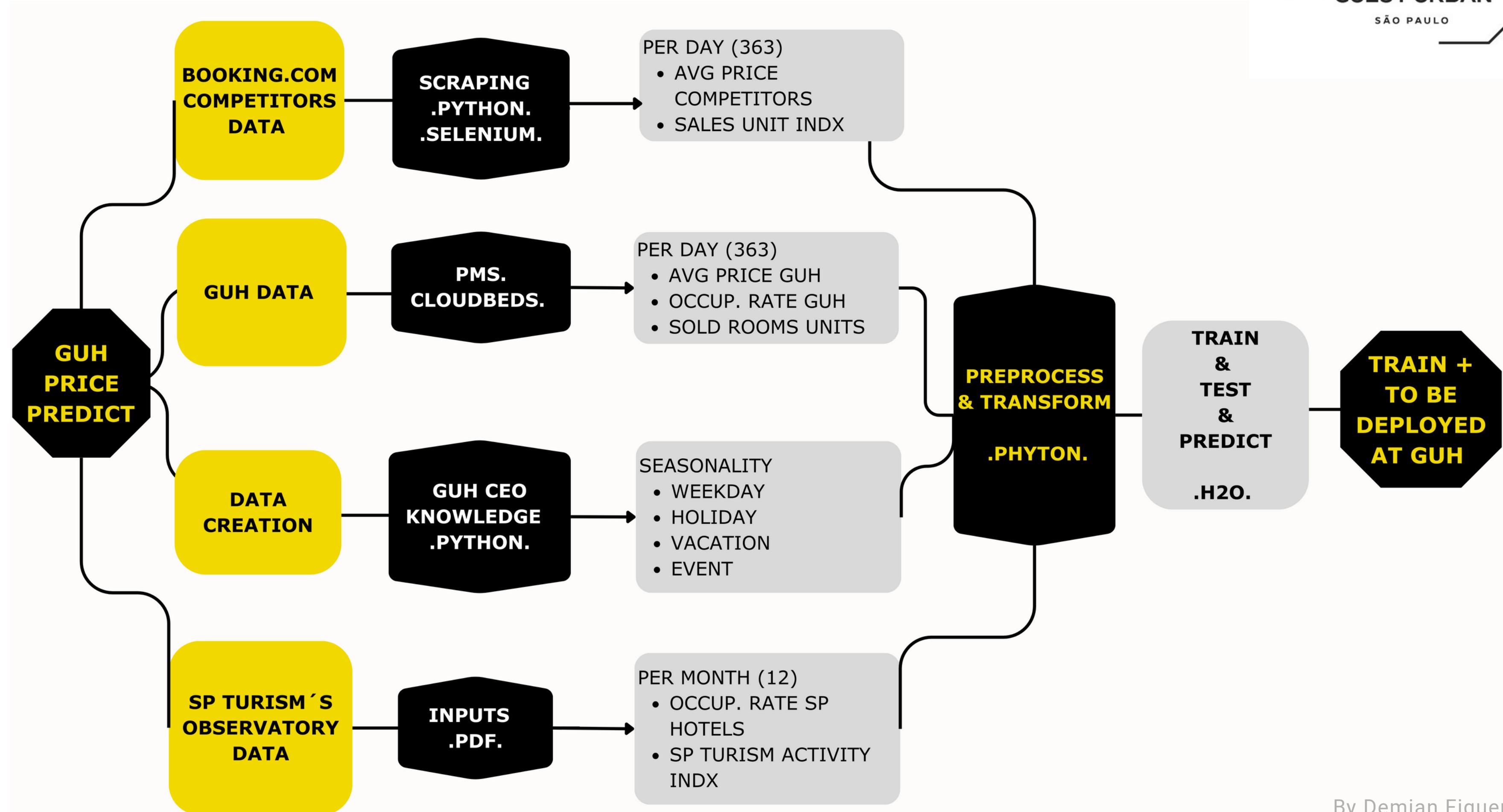
**Personalized pricing**

Price optimization

**Dynamic pricing**

best price points by considering factors like occupancy rates, , historical data, and revenue goals

# ML PROCESS



# ML TRAIN PREP

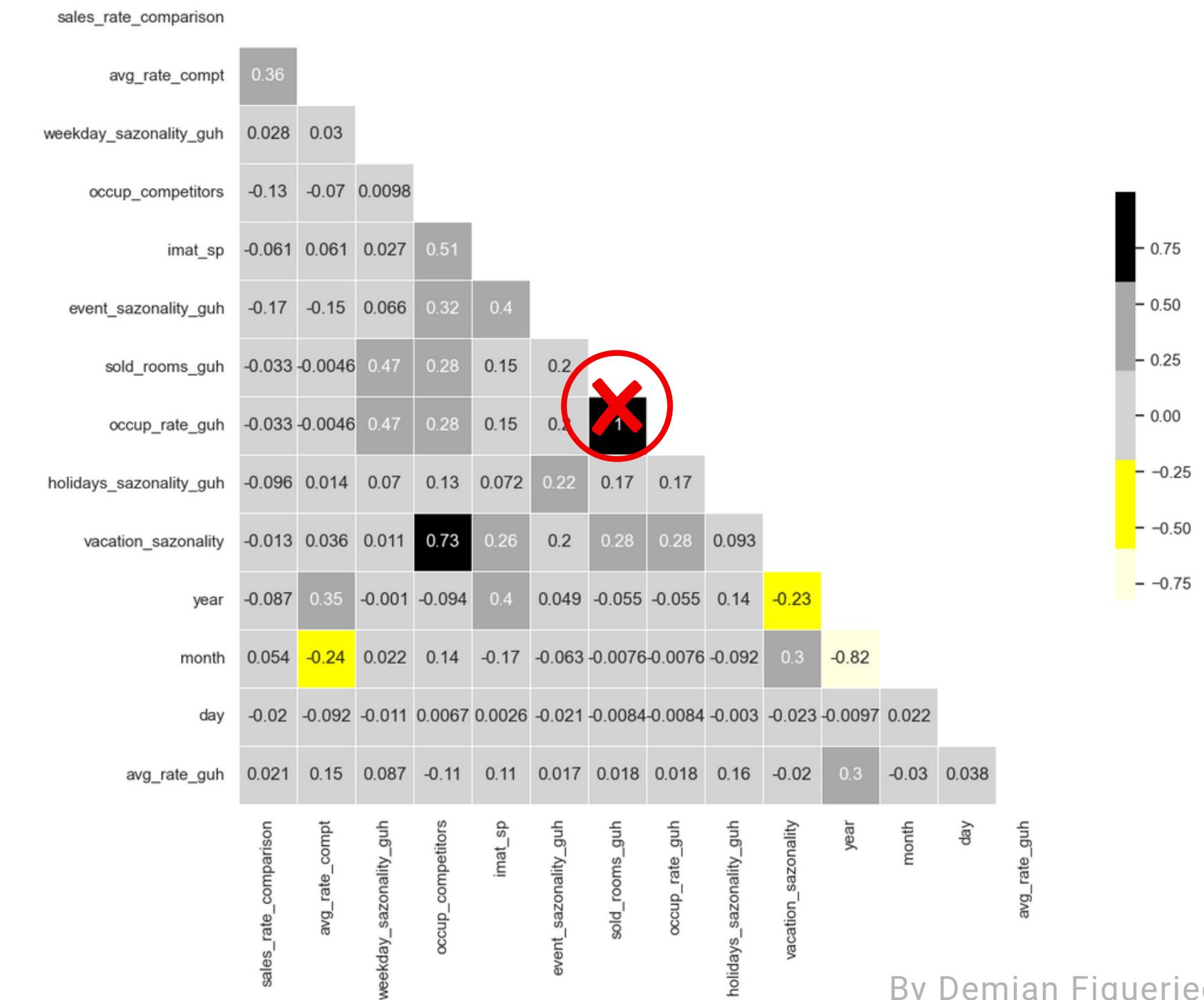
DATA TRAIN - Sept 2022 - Aug 2023

```
4
5 train.head(50)
```

Out[118]:

	sales_rate_comparison	avg_rate_compt	weekday_sazonality_guh	occup_competitors	imat_sp	event_sazonality_guh	occup_rate_guh	holidays_saz
0	-0.5039	410.93	5.0	0.6922	0.959	0.0	1.0000	
1	0.0000	390.67	1.0	0.6922	0.959	0.0	0.6923	
2	-0.3103	398.69	2.0	0.6922	0.959	0.0	0.5385	
3	-0.8272	432.25	3.0	0.6922	0.959	0.0	0.4615	
4	-0.5062	442.07	3.0	0.6922	0.959	0.0	0.6923	
5	-0.6033	441.27	4.0	0.6922	0.959	1.0	0.8462	
6	-0.6089	406.09	5.0	0.6922	0.959	0.0	0.9231	
7	-0.6471	408.77	5.0	0.6922	0.959	0.0	0.6923	
8	-0.8049	422.12	1.0	0.6922	0.959	0.0	0.4615	
9	-0.8316	386.19	2.0	0.6922	0.959	0.0	0.5385	
10	-0.6000	429.16	3.0	0.6922	0.959	0.0	1.0000	
11	-0.5556	464.14	3.0	0.6922	0.959	0.0	1.0000	
12	-0.6418	481.69	4.0	0.6922	0.959	0.0	1.0000	
13	-0.6364	473.43	5.0	0.6922	0.959	0.0	0.8462	
14	-0.8033	424.48	5.0	0.6922	0.959	0.0	1.0000	
15	-0.7555	422.09	1.0	0.6922	0.959	0.0	0.8462	
16	-0.6226	369.23	2.0	0.6922	0.959	0.0	0.6154	
17	-0.7333	402.63	3.0	0.6922	0.959	0.0	1.0000	
18	-0.4563	442.92	3.0	0.6922	0.959	0.0	1.0000	
19	-0.7064	461.12	4.0	0.6922	0.959	0.0	1.0000	

Shape 363 x 12



# TRAIN & TESTS RESULTS

## H2O

Leader Model  
Distributed Random Forest

## TRAIN

RMSE                    R\$ 27,15  
 MAE                    R\$ 18,95  
 Metrics AVG    R\$ 23,05

## TEST

RMSE                    R\$ 26,94  
 MAE                    R\$ 18,54  
 Metrics AVG    R\$ 22,74

Variable Importances:

variable	relative_importance	scaled_importance	percentage
imat_sp	1459657.7500000	1.0	0.1811754
occup_competitors	1104379.7500000	0.7566018	0.1370777
day	1019247.6250000	0.6982785	0.1265109
avg_rate_compt	894215.8125000	0.6126202	0.1109917
occup_rate_guh	861226.8125000	0.5900197	0.1068971
sales_rate_comparison	740664.9375000	0.5074237	0.0919327
month	666133.8750000	0.4563631	0.0826818
weekday_sazonality_guh	504431.1875000	0.3455818	0.0626109
holidays_sazonality_guh	342944.9062500	0.2349488	0.0425670
year	218149.8906250	0.1494528	0.0270772
event_sazonality_guh	141117.5156250	0.0966785	0.0175158
vacation_sazonality	104428.4531250	0.0715431	0.0129619

R\$ 342

-6.3%

R\$ 365

Avg GUH price  
Sept22 - Aug23

R\$ 387

+6.3%

# PREDICT

Due to GUH's drastic price increases in Jul, Aug and Sept 2023, TRAIN model needs to be fed with months' prices.



	predict	avg_rate_guh	Date
0	362.867928	436.69	2023-09-01
1	367.221548	439.37	2023-09-02
2	334.686727	427.36	2023-09-03
3	337.098624	374.63	2023-09-04
4	348.288622	376.97	2023-09-05
5	363.034139	400.62	2023-09-06
6	372.053621	431.20	2023-09-07
7	370.622413	435.40	2023-09-08

```
In [145]: 1 mean_GUH = prediction['avg_rate_guh'].mean()
2 mean_PREDICT = prediction['predict'].mean()
3
4 print("Mean GUH rate Sept 2023:", mean_GUH)
5 print("Mean predict Sept 2023: {:.2f}".format(mean_PREDICT))
```

Mean GUH rate Sept 2023: 415.28  
Mean predict Sept 2023: 356.98

## NEXT STEPS

01

**Update TRAIN,  
with new price  
increase**

03

**Use other ML's  
routes for GUH  
problem**

02

**Deploy model  
to GUH**



Thank  
You

By Demian Figueriedo