



Machine

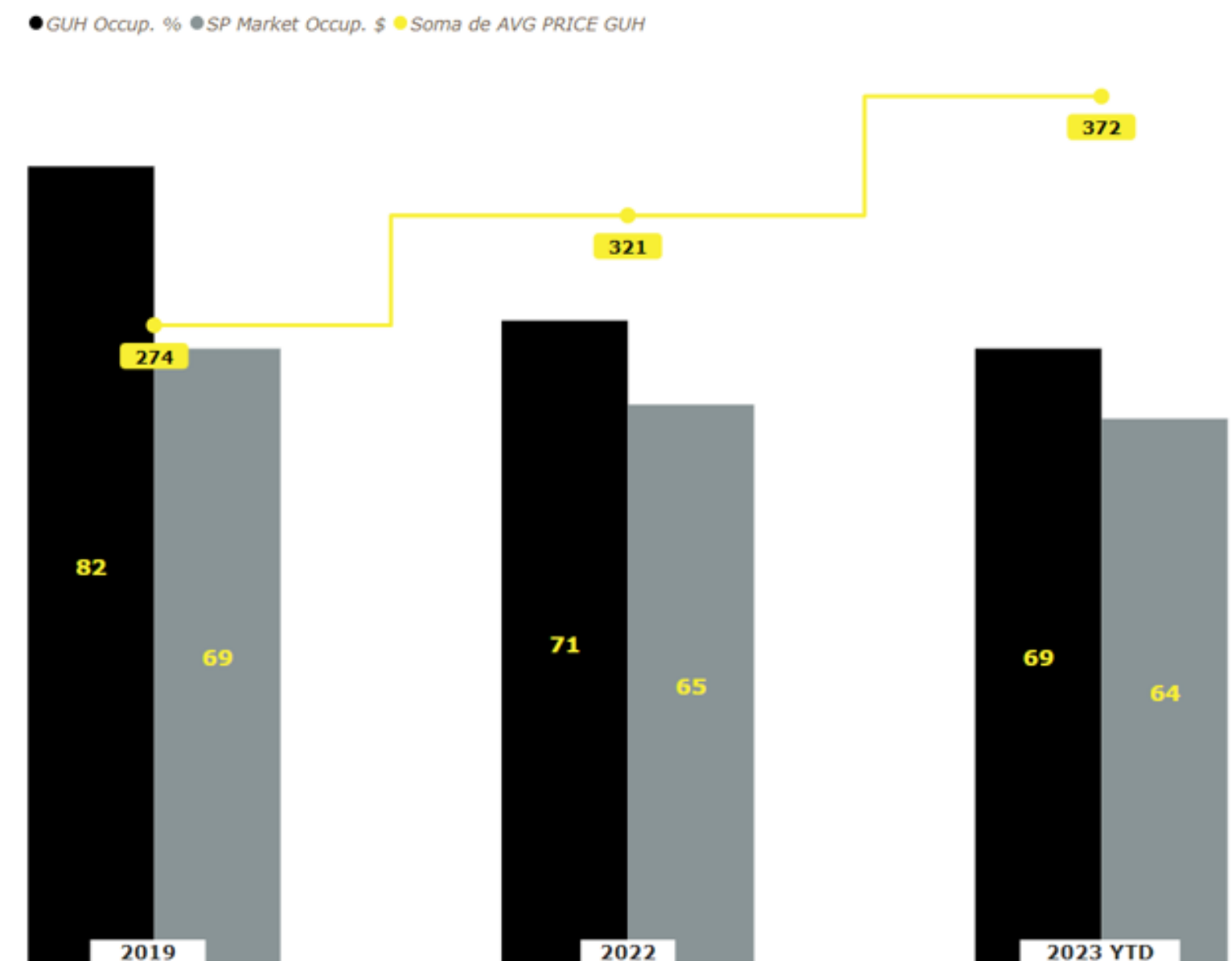
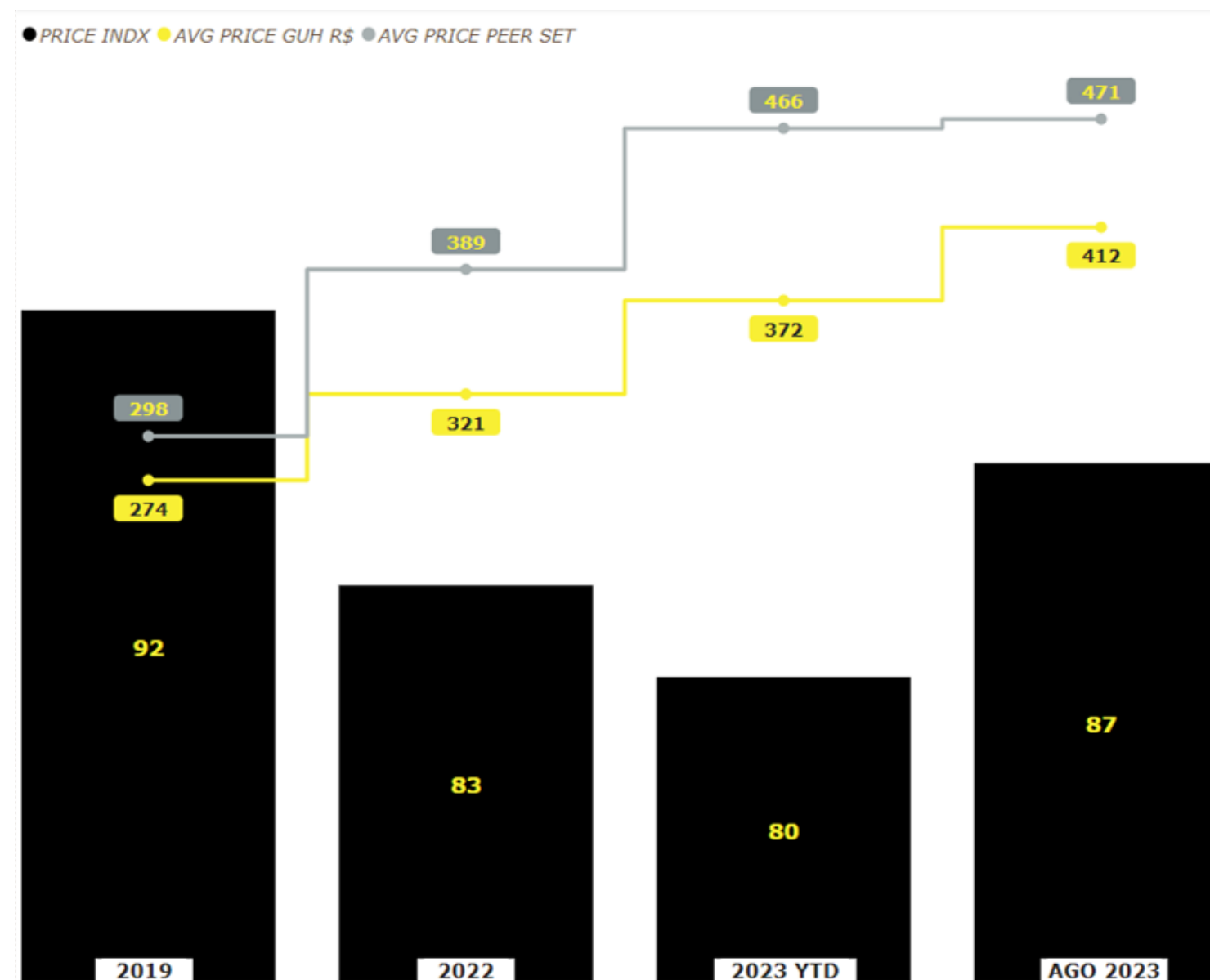
Learning

Price Prediction for Guest Urban
Hotel Rates



THE PROBLEM

After pandemic market price o São Paulo hotel rates and occupancy rates has changed drastic.
It ´s been difficult to apply with efficiency a well planned price policy.



ML PROBLEM SOLVING ROUTES



Demand forecasting

Competitive analysis

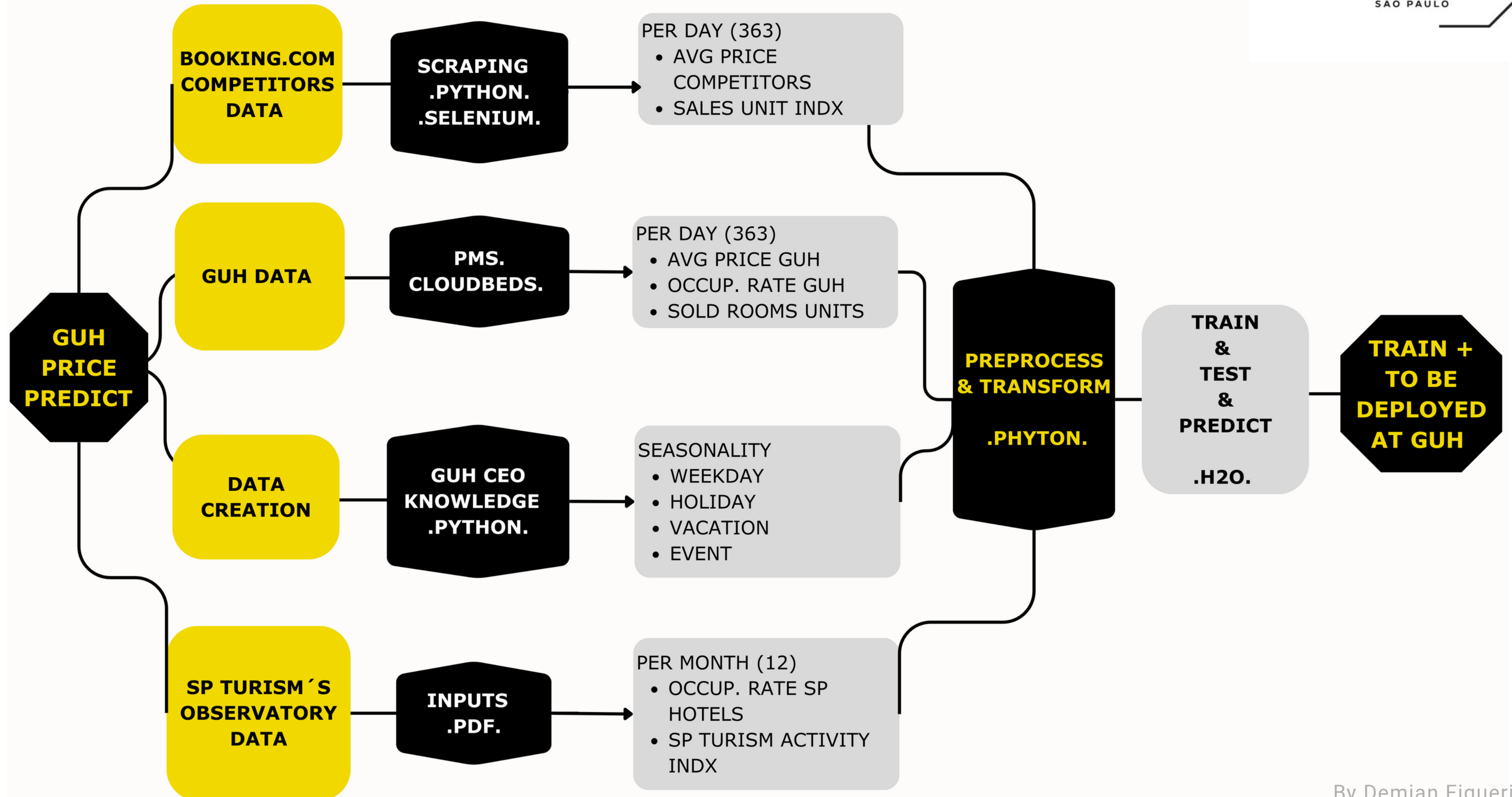
Personalized pricing

Price optimization

Dynamic pricing

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

ML PROCESS



ML TRAIN PREP

DATA TRAIN - Sept 2022 - Aug 2023

4

5

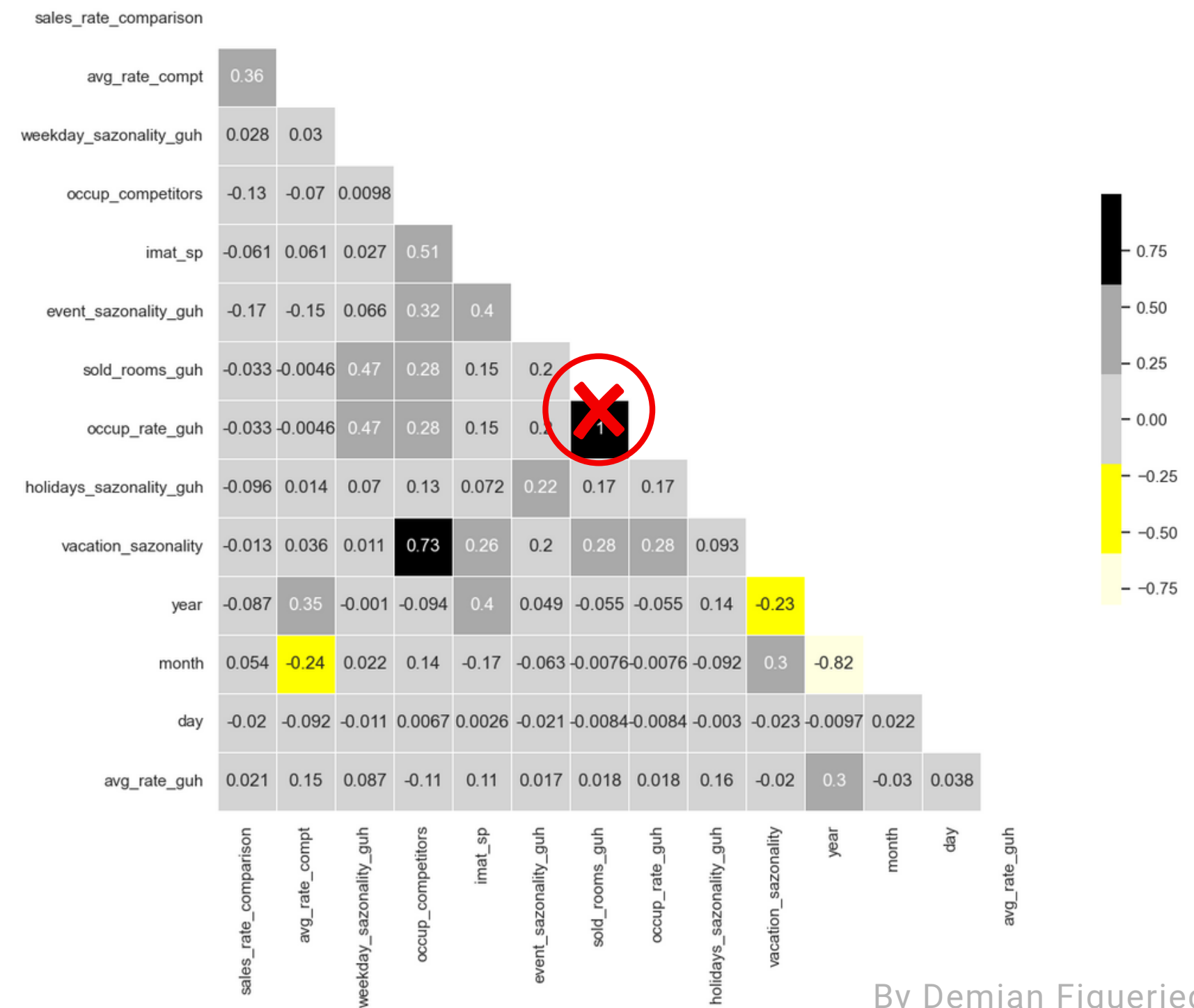
train.head(50)

Shape 363 x 12

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	

CORRELATION MATRIX



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

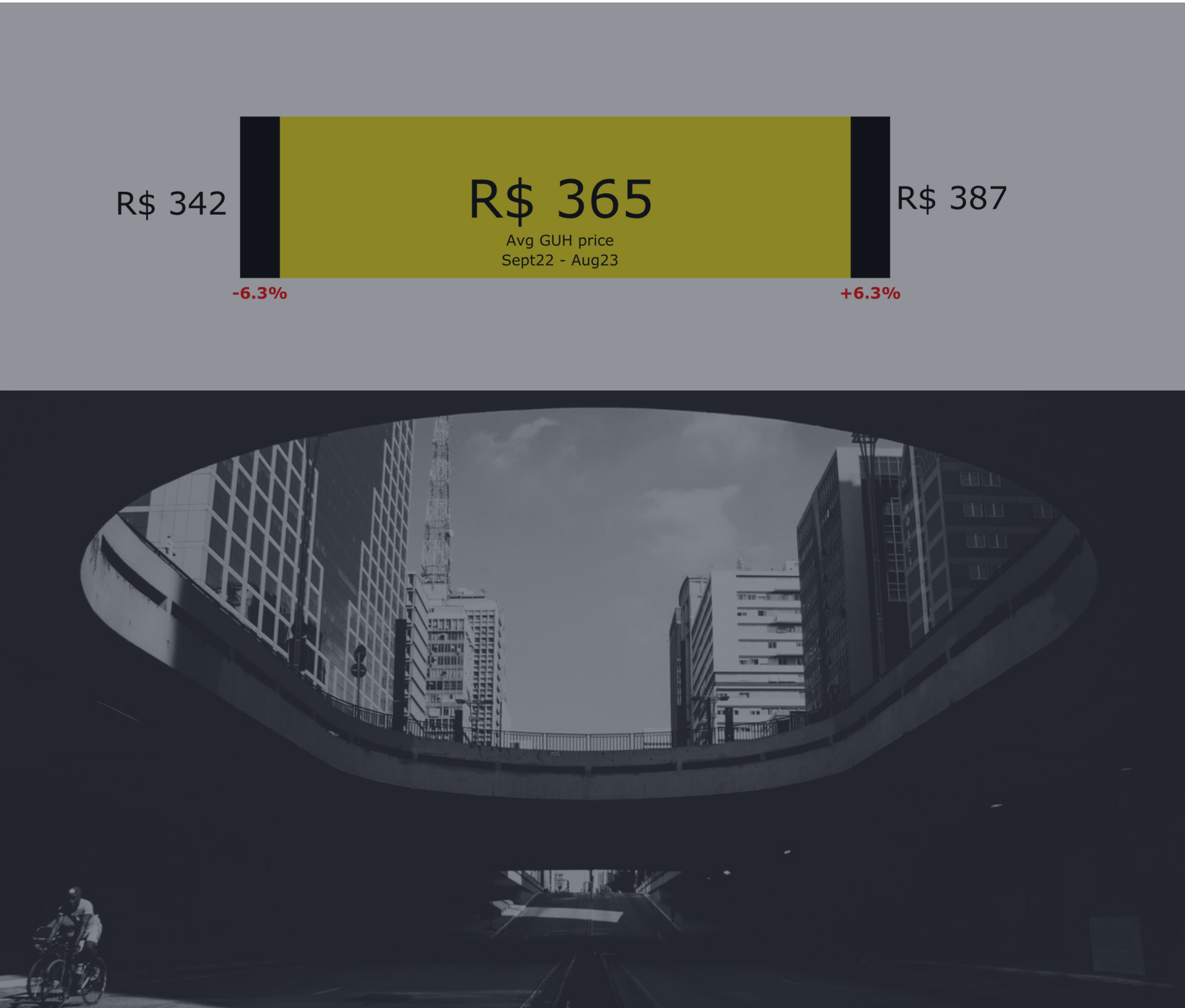
R\$ 387

+6.3%

PREDICT



Do to the GUH's drasctic prices increases in Jul, Aug and Sept 2023, TRAIN model needs to b more up to date 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))
```

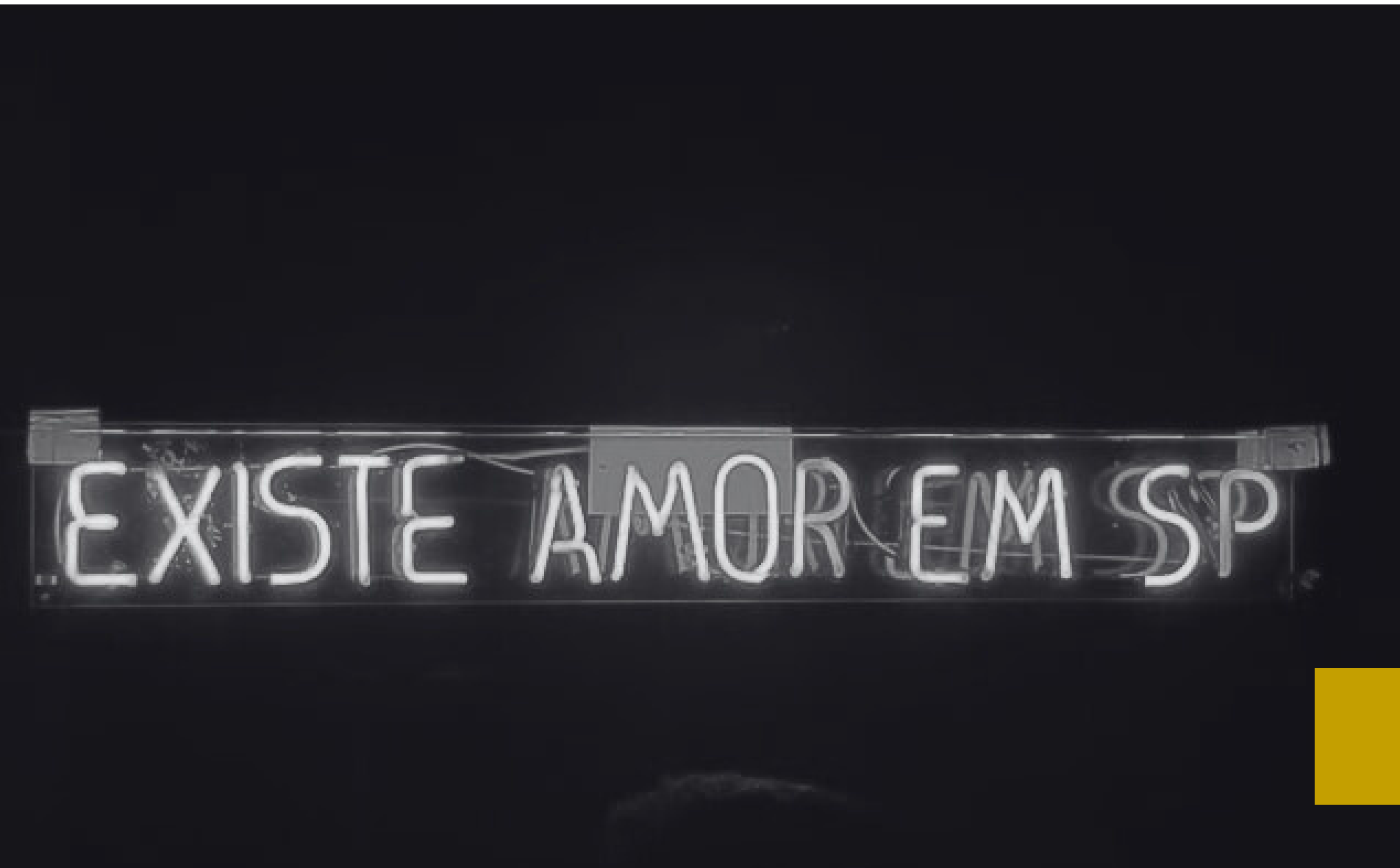
Mean GUH rate Sept 2023: 415.28
Mean predict Sept 2023: 356.98

NEXT STEPS

01 Update TRAIN,
with new price
increase

02 Deploy model
to GUH

03 Use other ML's
routes for GUH
problem



**Thank
You**