

# Data Science Portofolio

MOCHAMAD CHOIRIL IMAN

# About Me



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Bachelor of Electrical Engineering from Brawijaya University with GPA 3.57/4.00. Experience with instrumentation, testing, programming, product development, electrical design etc. Loves new things and experience leading a team. Also have experience at data processing, data visualization, tools mastery (Ms. Excel, PostgreSQL, Python, Google Data Studio) and machine learning

#### Tools Mastery **Hectronics Design**













#### **Data Processing**









## Latar Belakang Masalah



Tingkat pembatalan hotel secara global

Penurunan revenue

Kebiasaan cancel





37%

Tingkat
pembatalan hotel
di Portugal
(City Hotel &
Resort Hotel)

## Asumsi kerugian per tahun

**Resort Hotel** 



€ 484k
\*Diambil dari kolom ADR

7 Miliar Rupiah

**City Hotel** 



€ 1,500k
\*Diambil dari kolom ADR

23 Miliar Rupiah





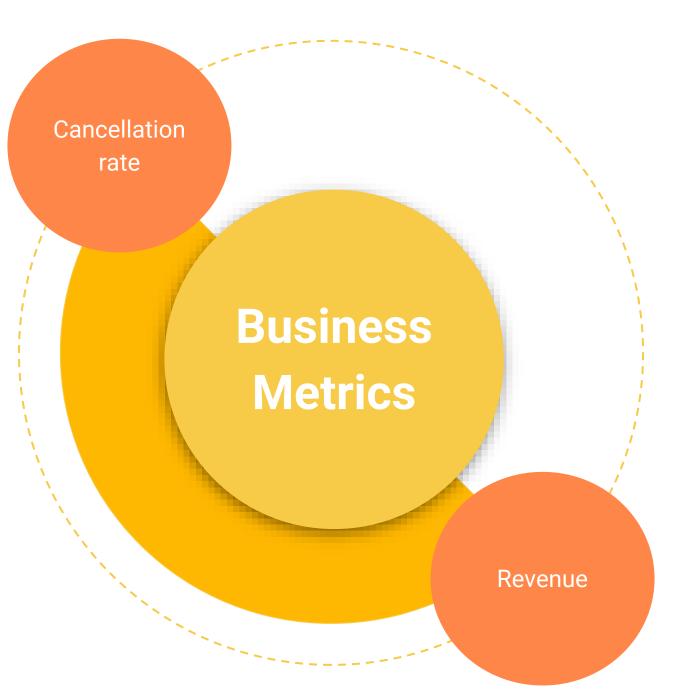
# Solusi?

# CANCELLATION RATE PREDICTION



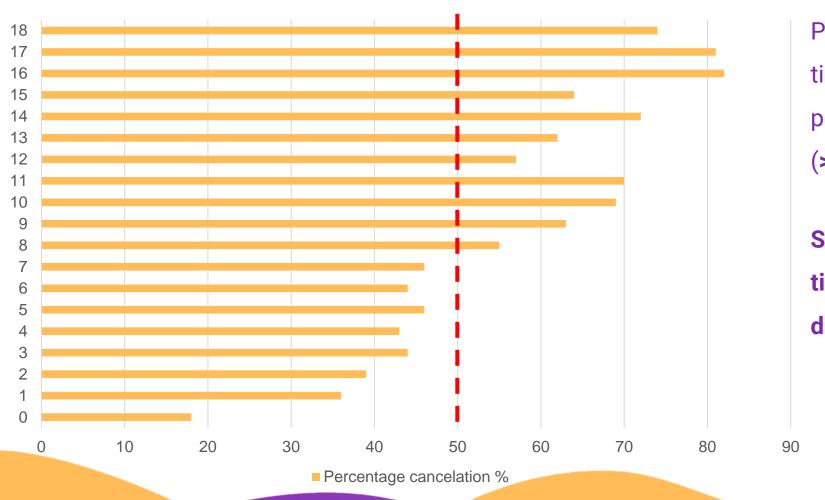
# **Target**







#### **Lead time**



Pemesanan hotel dengan lead time lebih dari **7 bulan** memiliki peluang pembatalan lebih besar (>50%)

Semakin lama Lead time semakin tinggi kemungkinan pemesanan dibatalkan

#### **Parking Space & Cancelled Rate**



Pemesanan yang memerlukan tempat parkir tidak melakukan pembatalan pesanan

#### **Cancellation rate by market segment**



#### Berikut persentase tingkat pembatalan :

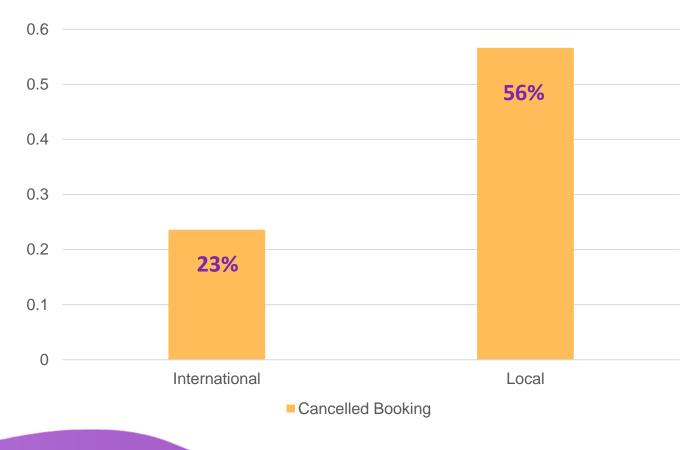
**Groups 61% (tertinggi)** 

Aviation, Complementary, Corporate, Direct 18 - 22%

**Travel Agent 34 - 36 %** 



#### **Guest location**



Pemesan turis lokal memiliki kemungkinan lebih tinggi untuk pembatalan pemesanan



#### Cancellation rate for previously cancelled booking



Pemesan yang sebelumnya pernah melakukan pembatalan pemesanan, memiliki kemungkinan lebih tinggi untuk membatalkan pesanan nya



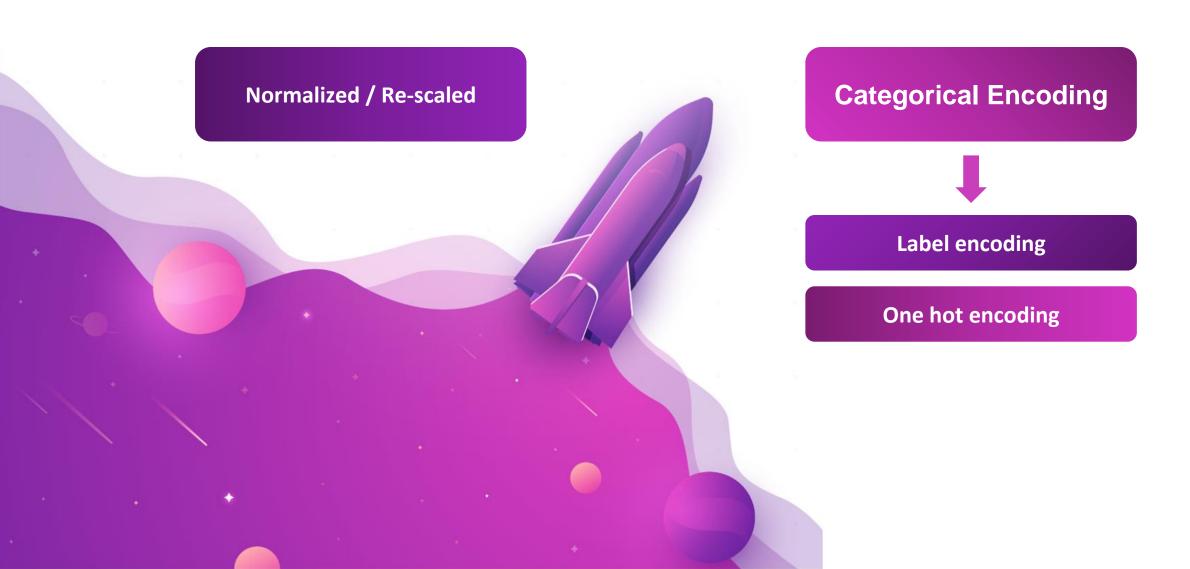
### **Data Cleansing and Pre Processing**



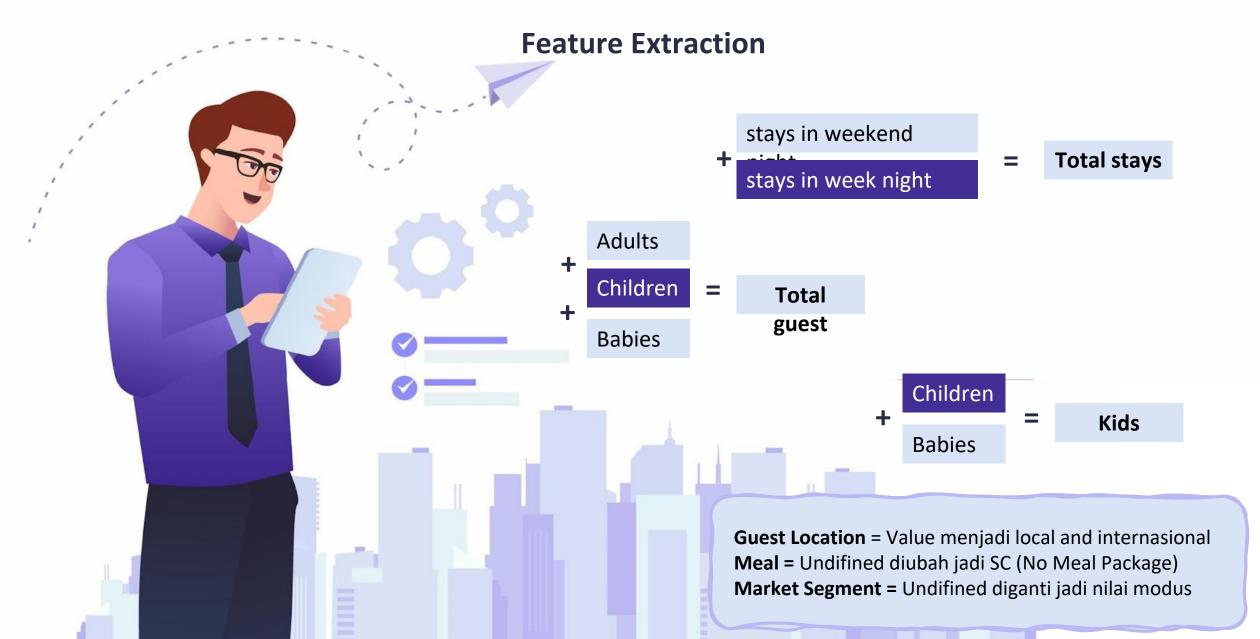
- Mengubah outlier menjadi batas atas (High Limit)
- Ganti nilai outlier dari feature yang memiliki nilai low limit dan high limit yang sama, menjadi nilai terdekat

## **Feature Engineering**

Feature Transformation



### **Feature Engineering**



## **Feature Engineering**

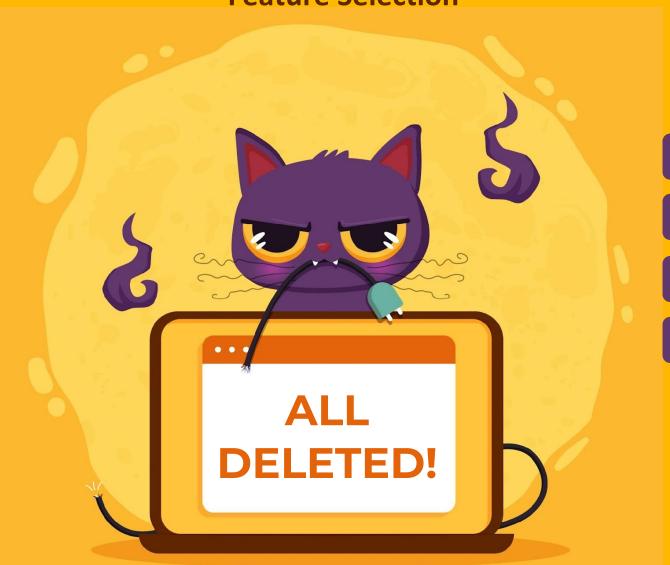
**Feature Selection** 

Name

**Email** 

**Phone Number** 

**Credit card** 

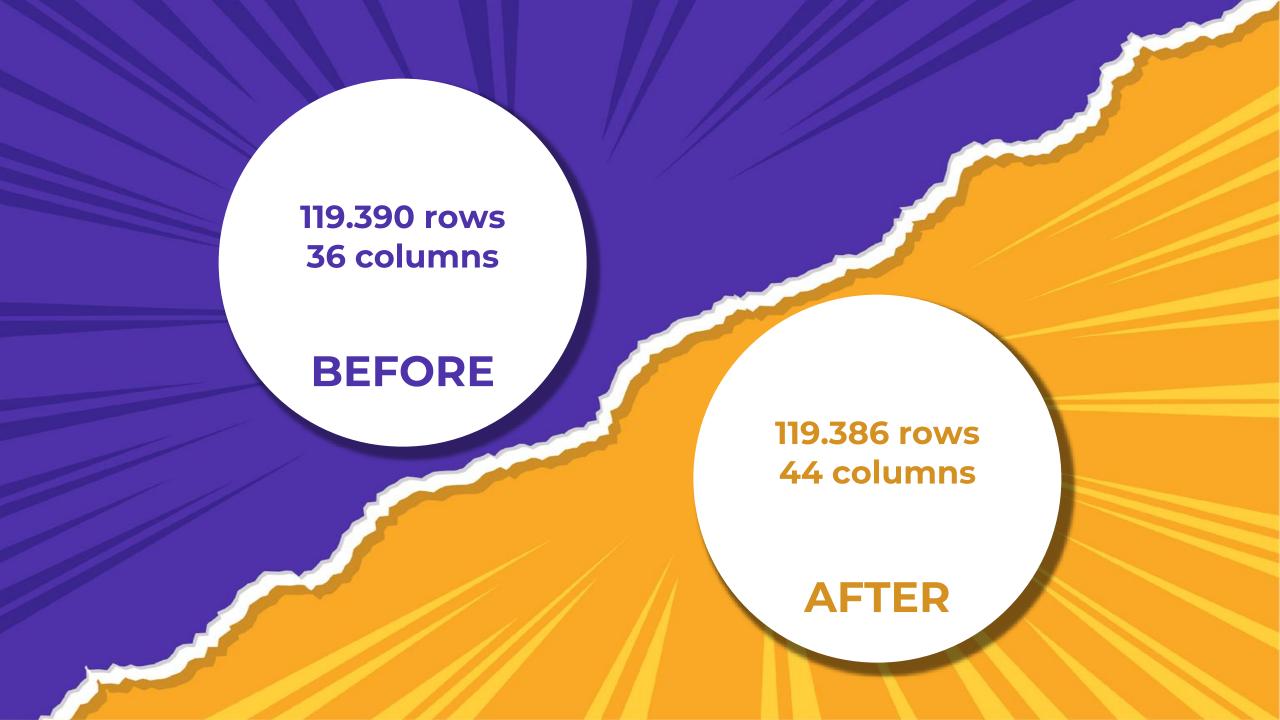


Children

**Babies** 

Stay in weekend nights

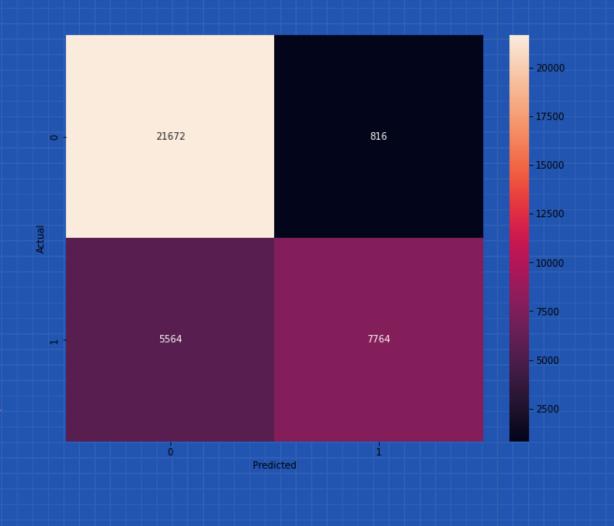
Stay in week nights



# Modelling Selection

Algoritma	Accuracy	Precision	Recall	F1 – Score	AUC
Logistic Regression	80%	81%	62%	70%	88%
XGBoost	84%	83%	71%	77%	92%
KNN	84%	79%	76%	78%	90%
Adaboost	82%	81%	68%	74%	90%
LightGBM	82%	91%	58%	71%	90%
Random Forest	89%	88%	81%	84%	95%
Decision Tree	84%	79%	80%	79%	84%

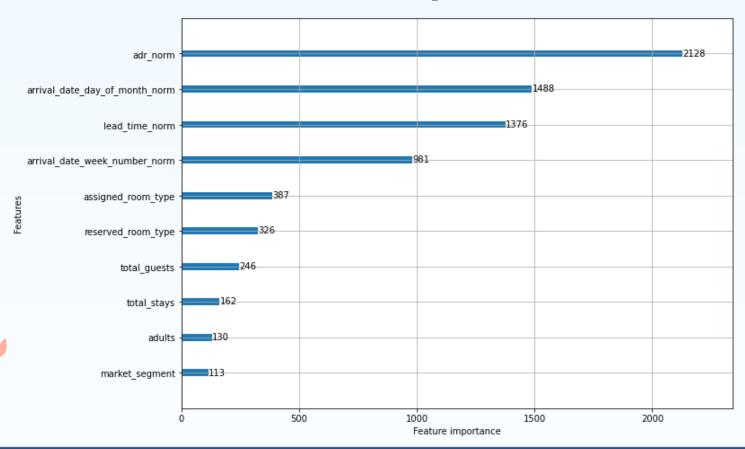
#### **Confusion Matrix**



Fokus pada predictive model yang paling bagus dalam menurunkan false positif

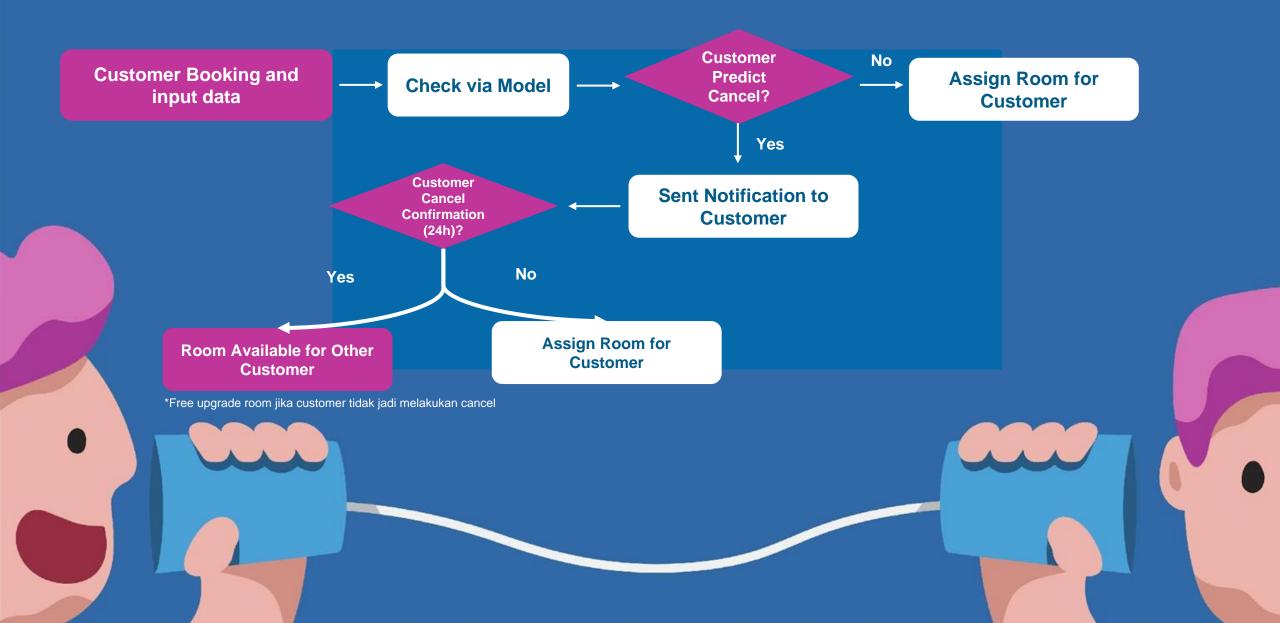
False Positif: Hasil prediksi customer melakukan cancellation tetapi kenyataanya customer tetap menginap

### Feature importance



Feature yang paling berpengaruh terhadap cancelation adalah adr

## **Implementasi**



**Business** recommendations

Non refund policy applied if lead time > 210 days

**VIP Parking/Vallet** 

Special offer for local customer

Customer loyalty point

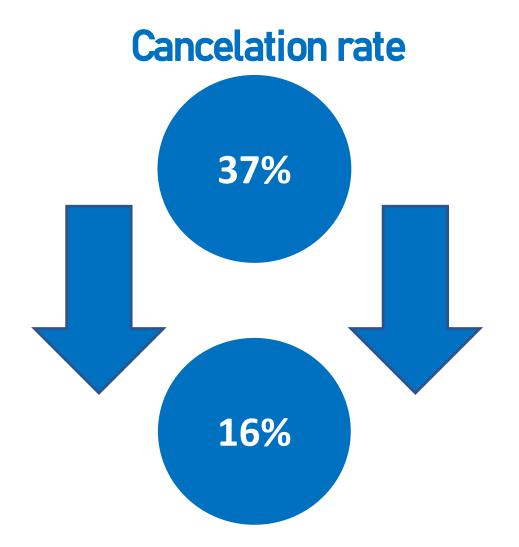
**Check in Online** 

**Phone reminder** 

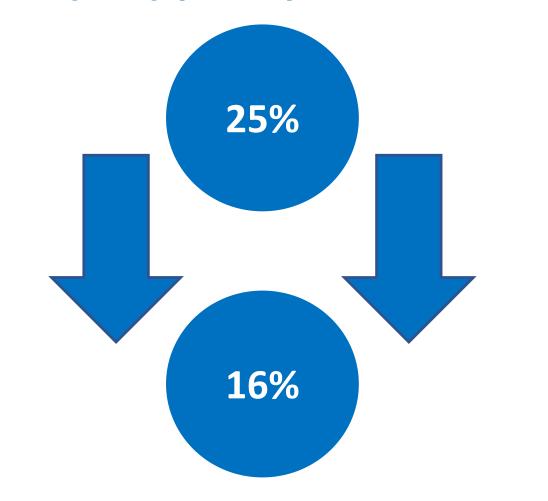
**Hotel partnership** 

Travel agent partnership

## Simulation Result



Mengurangi potensi penurunan revenue





# THANKYOU