

Data Science Team, Hunky Dory

Shipping Prediction

"Reduce the products are delivered **not on time** & customer care calls to Improve Company's Revenue"



About Us

Hunky-Dory is a Data Science Team in **Hunky**, which is a growing **e-commerce**.



Arif Romadhan
Tutor

Team



Boma Wikanthyasa I

will present about:

Problem Statement



Andriana Butar-butar

will present about:

Insight & Data Pre Processing

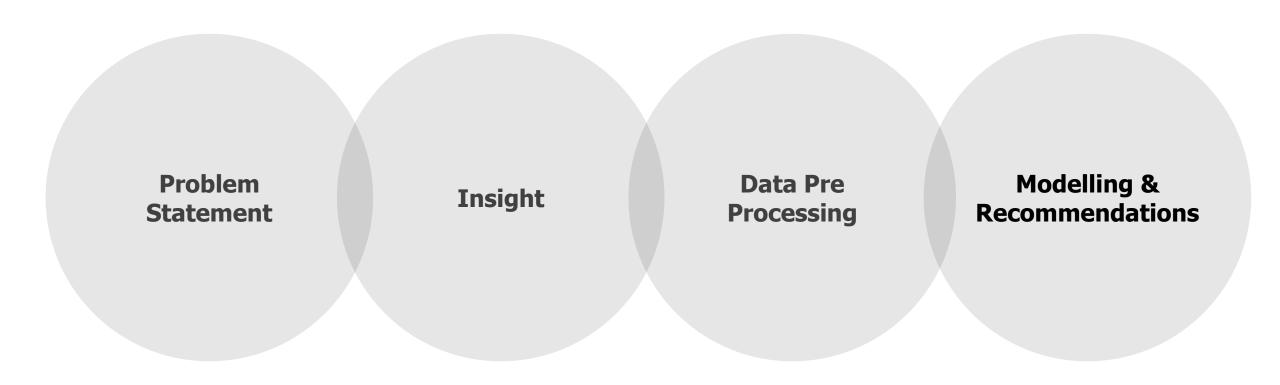


Reny Nur Hidayah

will present about:

Modelling & Recommendations

Contents of The Report





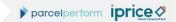
BACKGROUND



The e-commerce business in Indonesia is increasingly promising. In the midst of a pandemic, this digital-based trading business is even projected to grow 33.2 percent from 2020, which reached IDR253 trillion to IDR337 trillion this year.

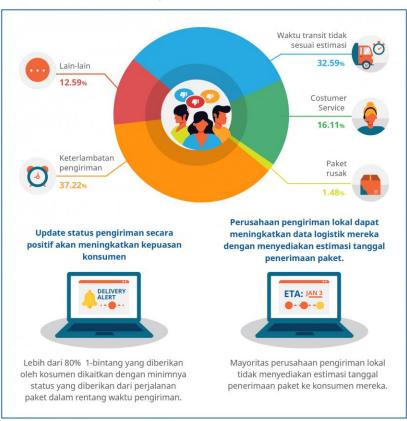
PENGIRIMAN PAKET

Rataan Estimasi Waktu Pengiriman Paket di Asia Tenggara



Lebih dari 90% keluhan negatif konsumen adalah seputar keterlambatan waktu penerimaan paket dari estimasi waktu yang dijanjikan.

Di Asia Tenggara, positive review dari konsumen biasanya cenderung lebih pendek, konsumen gemar menggunakan emoji untuk mengekspresikan respon positifnya. Sebalikanya, untuk keluhan yang bersifat negatif, konsumen akan lebih detail, komprehensif dan emosional.



(Based on iprice, 2018)

Delivery service is a biggest problem on e-commerce

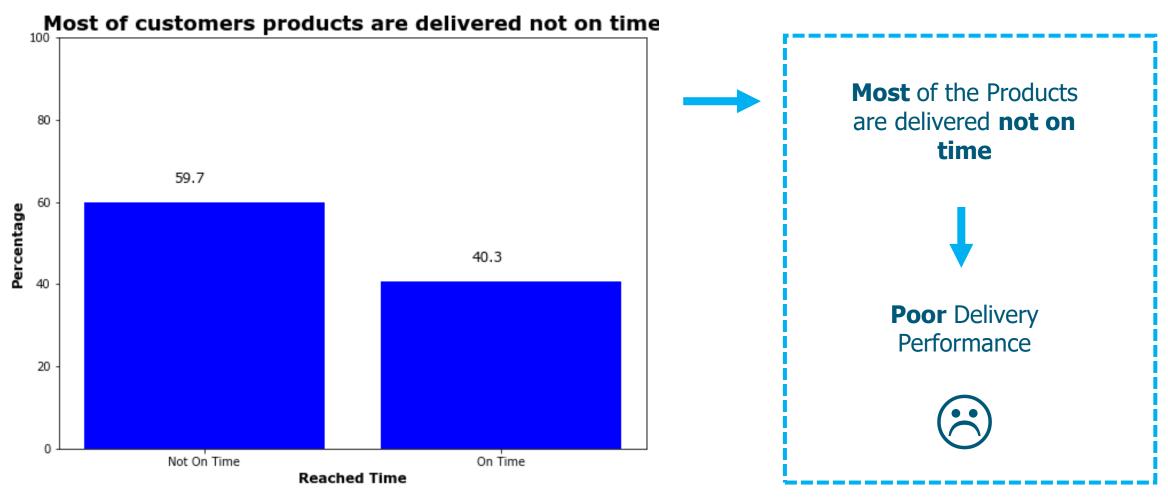
Late shipment 37.22%

Transit time does not match estimates 32.59%



Customer care calls

Internal issues





38% Customer Will not shop at the same store due to a negative shipping experience



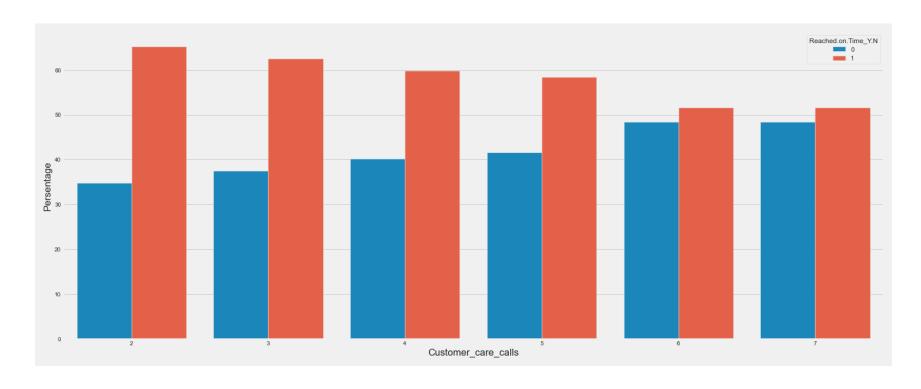
https://www.shipbob.com/blog/ecommerce-shipping/

Potential of **4,180** customer who will not shop at our store



" Shipping Prediction "

Internal issues



Customers who frequently make customer care calls tend to be more on time



Customers must often make customer care calls so that the products delivered on time

Goals

Reduce the products that delivered not on time



Increase Company's revenue

Impact:

1. Prevent Potential of customer who will not shop at our store



Reduce customer care calls

Matrics

Late shipment rate



Customer care calls rate

Objective



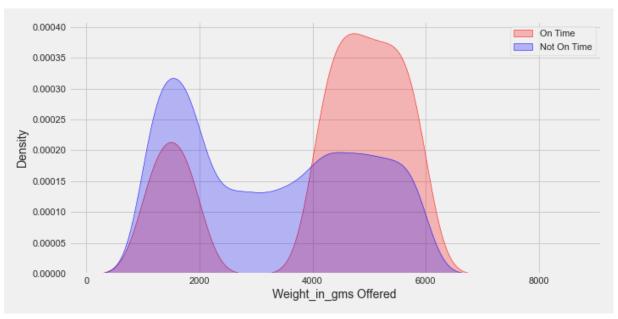
Modelling "Creating a prediction model"



Discount offered



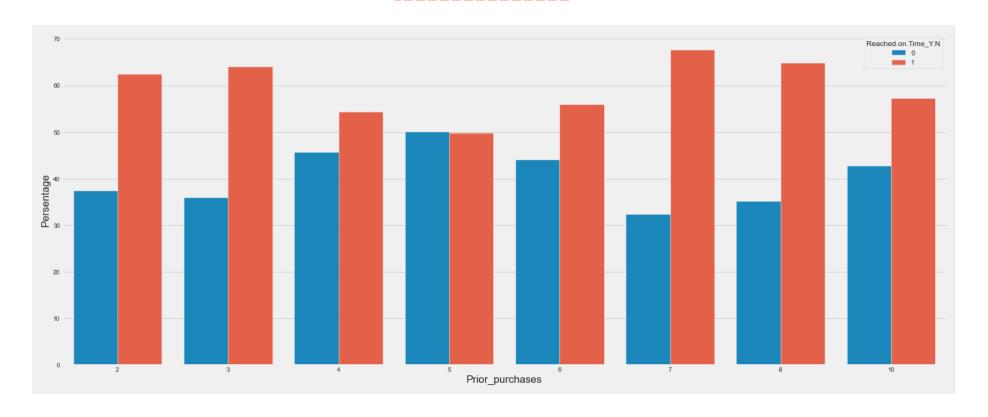
Weight



The most On-time products have a discount in the range of 1-15 USD, while discounts above 15 USD tend not to be on time

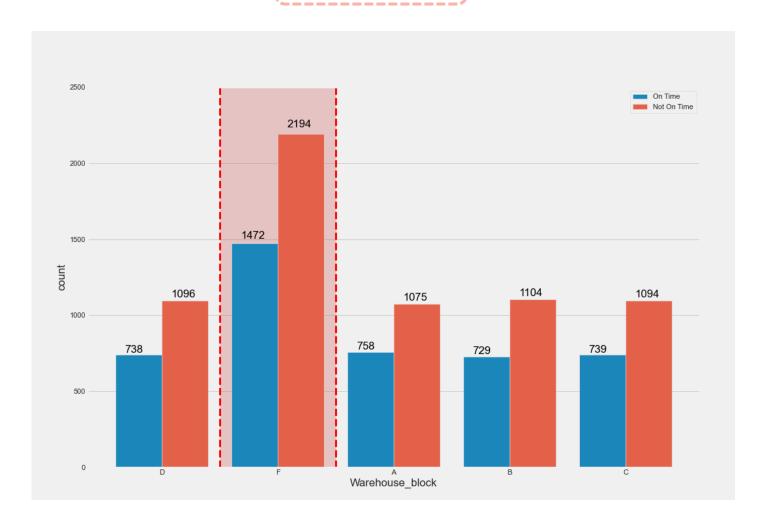
The most On-time products have a weight in the range of 4-6 kg, while weight in the range 1-4 kg tend not to be on time

Prior Purchase



Customers having prior purchases below 5 tend not to be on time and after more than 5 products ordered are no longer on time

Warehouse block

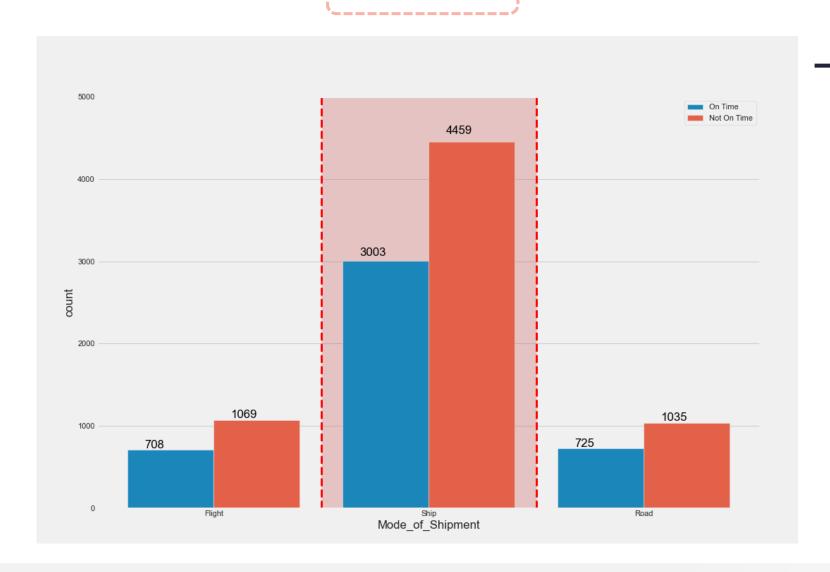


About **30%** of the product ships from **Warehouse F**

Evaluate each warehouse

- 1. Optimizing Warehouse Management System
- 2. Are we short on employees at every warehouse?

Mode of Sipment



Most of the products are shipped via ship

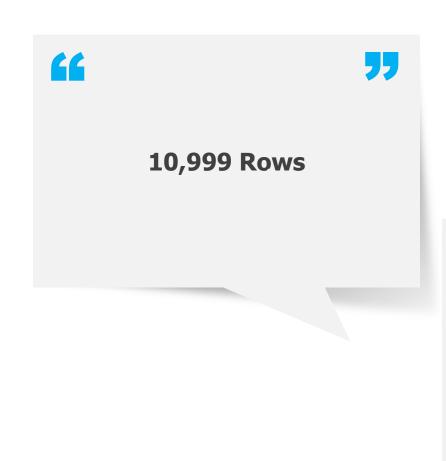
Prioritas = Ship

WHY SHIP?

- Efficient in terms of shipping costs
- 2. There is **More Cargo Space** in Ocean Shipping
- **3. Flexible** in receiving goods sent via sea shipping



Our Dataset





Features

- ID
- Warehouse_block
- Mode_of_Shipment
- Customer_care_calls
- Customer_rating
- Cost_of_the_Product
- Prior_purchases
- Product_importance
- Gender
- Discount_offered
- Weight_in_gms
- Reached.on.Time_Y.N

Duplicated Data

Missing Value

Outliers

No duplicate values found

No missing value found

- Discount Offered
- Prior Purchases
- But we using data whose outliers haven't been removed, because there is no significant difference

FeaturesEngineering

- Discount_group
- Weight_group
- Cost_group

Delete Columns

Customer care calls

Customer_rating

ID

Label Encoding

Gender (F:0, M:1)

One hot Endcoding

- Product_importance
- Warehouse_block
- Mode_of_shipment

MODELLING & RECOMMENDATIONS

Modelling

No	Method	Accuracy	Precision	Recall	AUC
1	Logistic Regression	0.68	0.78	0.64	0.69
2	Decision Tree Classifier	0.69	0.88	0.54	0.72
3	Random Forest Classifier	0.68	0.86	0.55	0.71
4	XGB Classifier	0.68	0.88	0.54	0.72
5	AdaBoost Classifier	0.678	0.82	0.59	0.70
6	LGBM Classifier	0.68	0.87	0.55	0.72

Final model decision



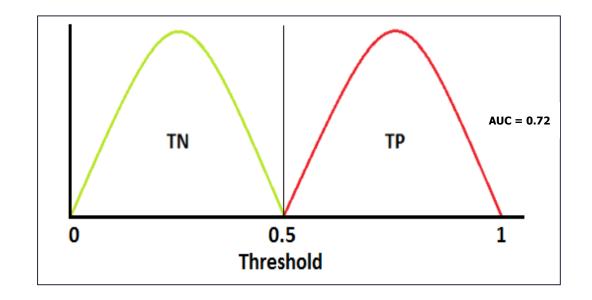


Why?

- 1. AUC & Precission (Higest Score)
- 2. Small Data → stick to simple methods

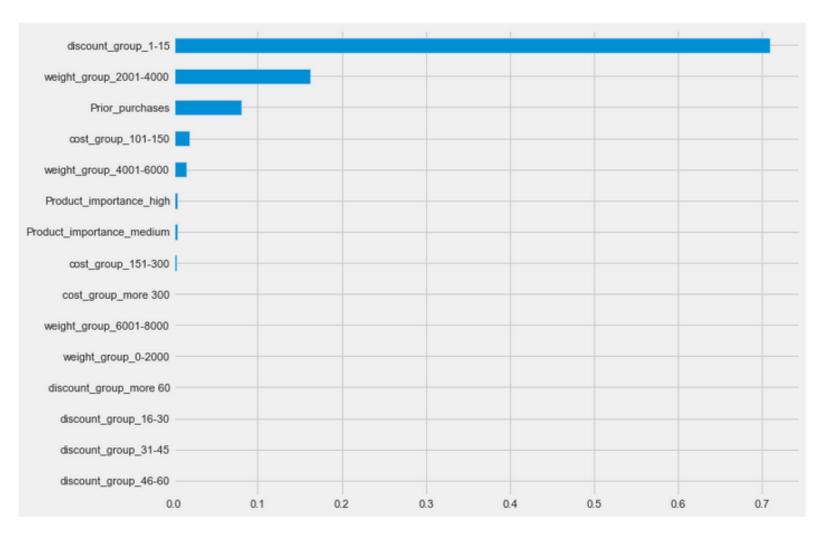
Modelling

Final model decision —— Decission Tree Classifier



AUC Score = 0.72, which shows that the model **can predict both on-time and late shipment by 72%** (can provide a class separation correctly by 72%)

Feature Importance



Recommendations

Recommendation Actionable

- 1. Using the mode of shipment via **Liner**
- Because it has a fixed route and schedule so it arrives faster than the trump service ship
- Loading and unloading only takes 2 - 3 hours
- Reducing the products are delivered not on time

- 2. **Notify** the delivery status
- Reducing the number of customer care calls

Recommendations

Recommendation Actionable

3. **Free Shipping** on the next transaction

- For those who are predict to be late
- So that customers don't leave the store because of a negative shipping experience



74% Free shipping may affect checkout

https://www.shipbob.com/blog/ecommerce-shipping/



4. **Evaluation** at each warehouse

 Evaluation at each warehouse in order to further optimize the warehouse management system, by giving importance to designing a data warehouse model.

Comparison before & after modelling

"Reduce products are delivered **not on time** & customer care calls"

Reduce the products are delivered "not on time"

□ 6563 products are not on time

After

□ 72% (accurately predict) so we could Reduce 4726 the products are delivered not on time

Reduce customer care calls

Before

- Mean of customer care calls 4
- □ **37.2%** Complaint of delay (based on survey)
- \Box 10,999 x 4 = 43,996 calls/day
- \square 37,2% x 43,996 = 16,367 calls (Complaint of delay calls)
- □ 72% x 16,367 = **11,784** calls
- \square 80*21 = 1,680 calls/day
- □ 43.996 / 1680 = **26 Customer Care**

After

- → 72% (accurately predict) so we could possibly reduce 11,784 customer care calls
- \Box 43,996 11,784 = 32,212 calls/day
- \square 80*21 = 1,680 calls/day
- □ 32,212 / 1,680 = **19** Customer Care

Reduce 7 staff customer care

1 Customer care = Rp 4.400.000 (UMR Jakarta)

Rp 30.800.000 Save/bulan

1 Customer Care = 80 calls/day Estimating cargo = 21 days

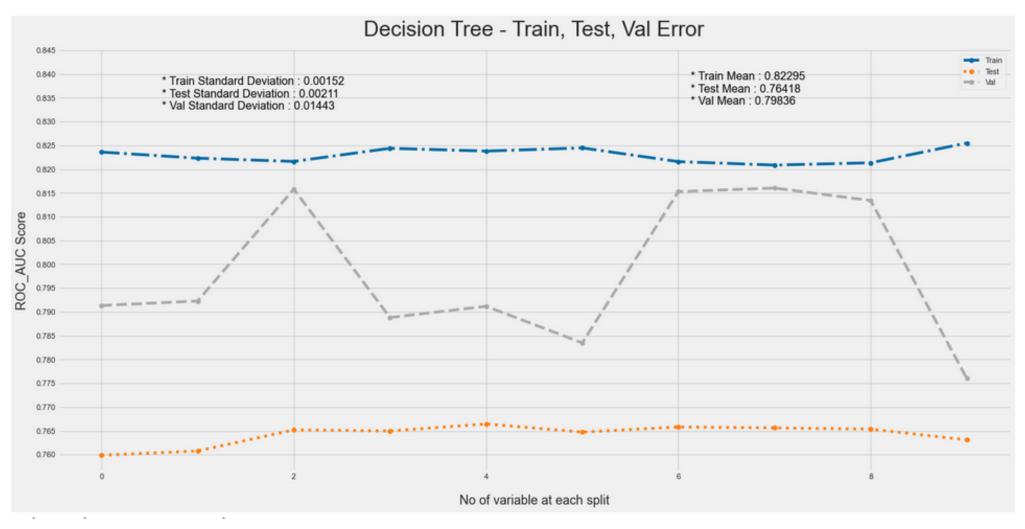




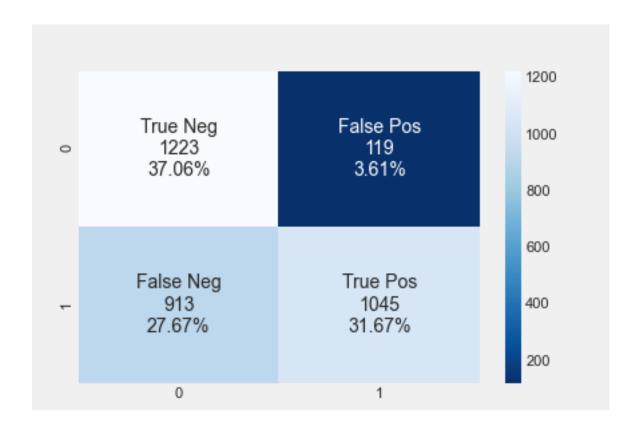
DecisionTreeClassifier Tuning

```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42),
                   param distributions={'max_depth': [1, 4, 8, 12, 16, 19, 23,
                                                      27, 31, 34, 38, 42, 46,
                                                      49, 53, 57, 61, 64, 68,
                                                      72, 76, 79, 83, 87, 91,
                                                      94, 98, 102, 106, 110],
                                        'max features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4, 10, 20,
                                        'min_samples_split': [2, 5, 10, 100]},
                   random state=42, scoring='roc auc')
                  best_params = model.best_params_
                  best_params
                  {'min_samples_split': 10,
                   'min_samples_leaf': 20,
                   'max_features': 'sqrt',
                   'max depth': 23}
```

Cross Validation



Confussion Matrics



Decision Tree Classifier

AUC: 712%