Anaconda

Online Shoppers Purchasing Intention

Background **Story**

As a Data Scientist team at e-commerce company at PT Anaconda, responsible for analyze data related to current visitor behavior and potential improvements purchase amount

Meet with our team

Muhammad **Irfan** Fadlurahman

Ramado Dipradelana

Bima Purnomo Sandi

Deni Indra Permana

TABLE OF CONTENTS

STEP 01 — PROBLEM STATEMENT
Bima Purnomo Sandi

STEP 02 — EDA DAN INSIGHT
Ramado Dipradelana

STEP 03 — DATA PRE-PROCESSING
M. Irfan Fadhlurrahman

STEP 04 — MODELING
M. Irfan Fadhlurrahman

STEP 05 — RECOMMENDATION
Deni Indra Permana

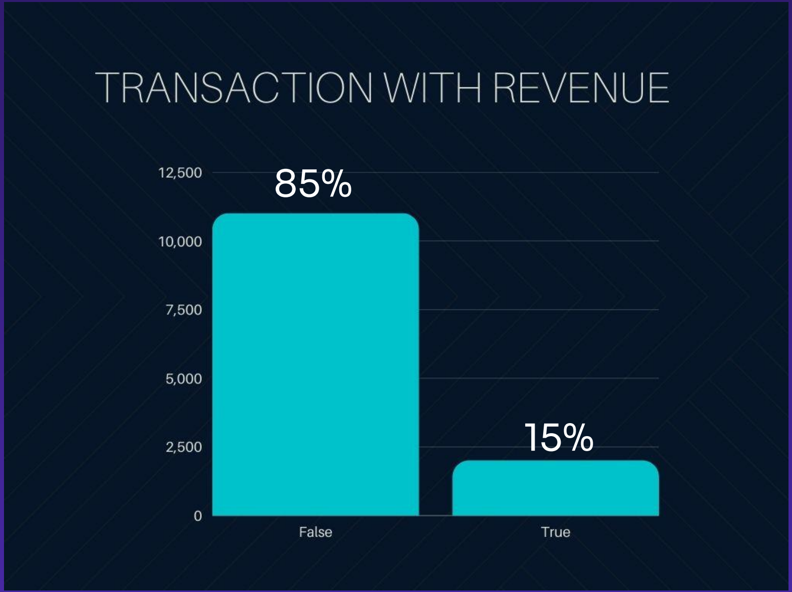
01

Problem Statement

Problem Statement

Out of all visitors only 15% converted and make purchase. Based on the most updated reference, average ecommerce conversion/purchase rate is between 2-5%

Then why this is a problem?



Based on **Data...**

On 2021, consumers who shop online increase up to 88%*. **15% of Purchase Rate** is too small.

*CNN Indonesia, Konsumen Belanja Online RI Melonjak 88 Persen pada 2021

CVR*

Actual :15%
Reference : 2-5%

*CVR(Conversion Rate) or Purchase Rate: the percentage of website visitors who buy something on the site.

BOUNCE RATE*

Actual :Up to 20%
Reference : 26%-70%

*Bounce Rate: the rate at which new visitors visit a site and immediately click away without doing anything

EXIT RATE*

Actual :Up to 20%
Reference : 26%-70%

*Exit Rate: The percentage of pageviews on the website that end at that specific page

Compared to the low bounce rate and exit rate, our conversion rate 15% would be relatively low. With such a low bounce rate & exit rate, we should have achieved more conversion.

*Reference: https://guidingmetrics.com/content/ecommerce-industry-most-critical-metrics-kpis/

Our Objective

- Giving insights and action recommendation to increase conversion rate
- Build a machine learning model to automatically predict which visitor will purchase
- Analyze Visitors behavior for better understanding

Now

15%

Conversion Rate

Goal!

20%

Conversion Rate

Metric

$$\text{Conversion Rate} = \frac{\text{Number of Transaction}}{\text{Number of Web Visit}} \times 100\%$$

02

EDA & Insight

EDA & Insight

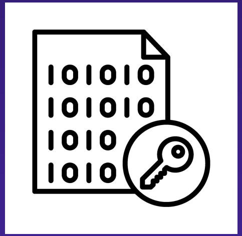
There are 12.330 rows and 18 column of online shopper customers sessions data in a one-year period.

- Administrative
- Administrative Duration
- Informational
- Informational Duration
- Product Related
- Product Related Duration
- Bounce Rate
- Exit Rate
- Page Values
- Special Day
- Month
- Operating Systems
- Browser
- Region
- Traffic Type
- Visitor Type
- Weekend
- **Revenue**

EDA & Insight

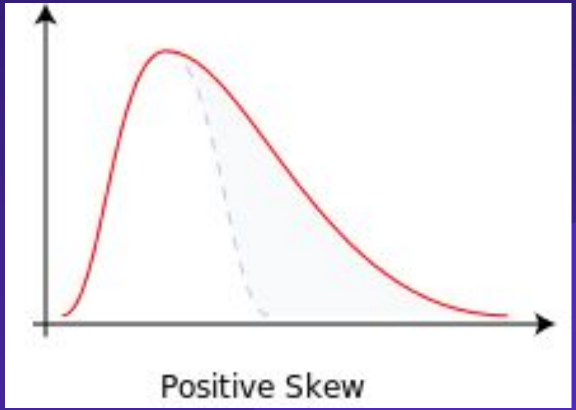
Low-Variance numeric feature:

- Visitor Type
- Special Day



No actual categories :

- Operating System
- Region
- Browser
- Traffic Type

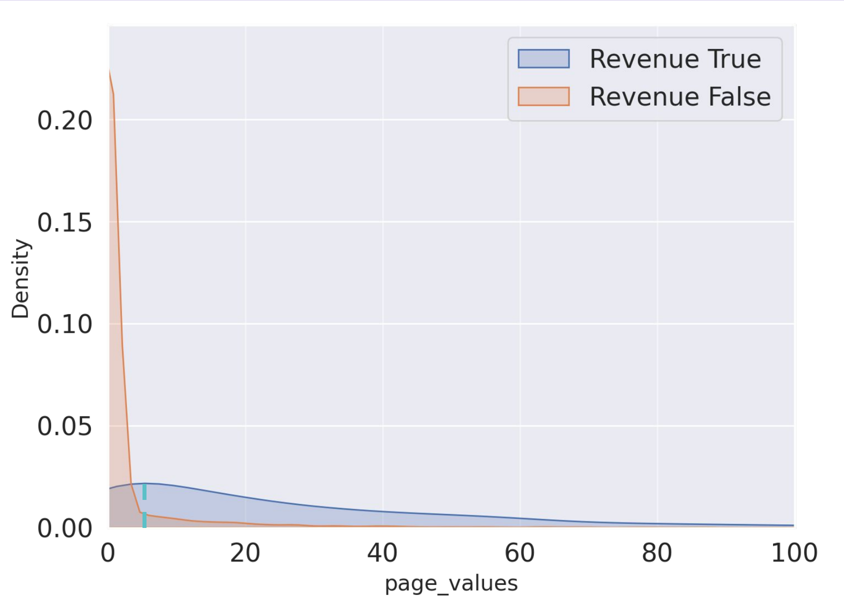


10 numerical features are positive Skew

EDA & Insight

Product related duration

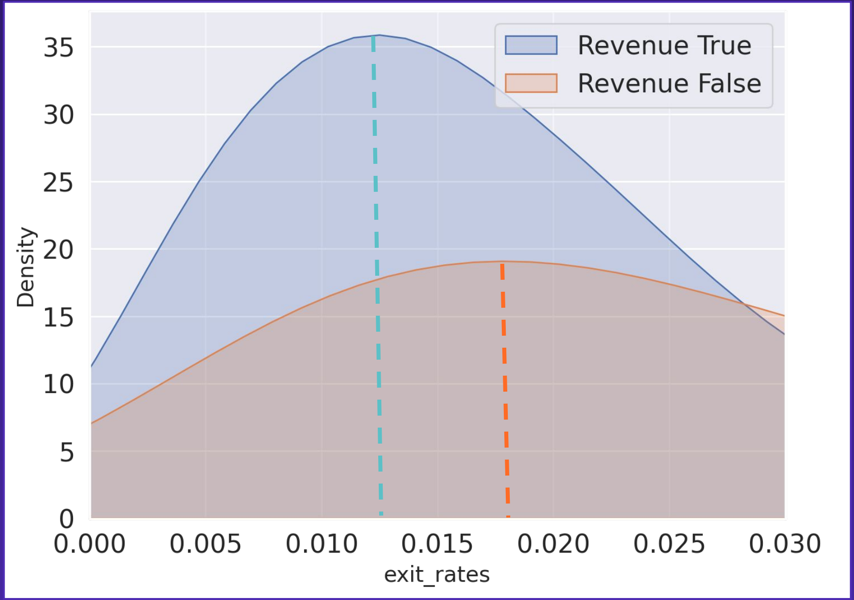
Page values



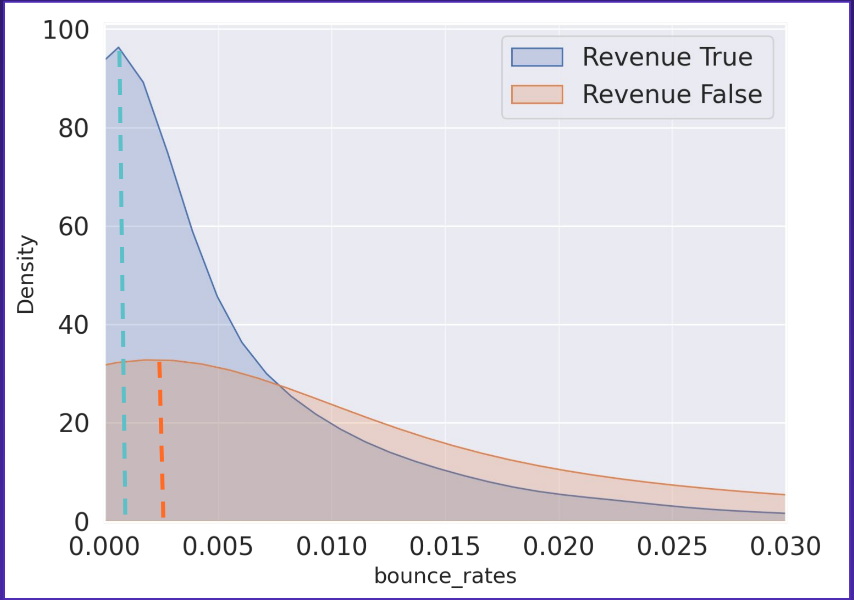
Visitor with higher page values and higher product related duration tend to make a purchase.

EDA & Insight

Exit rates



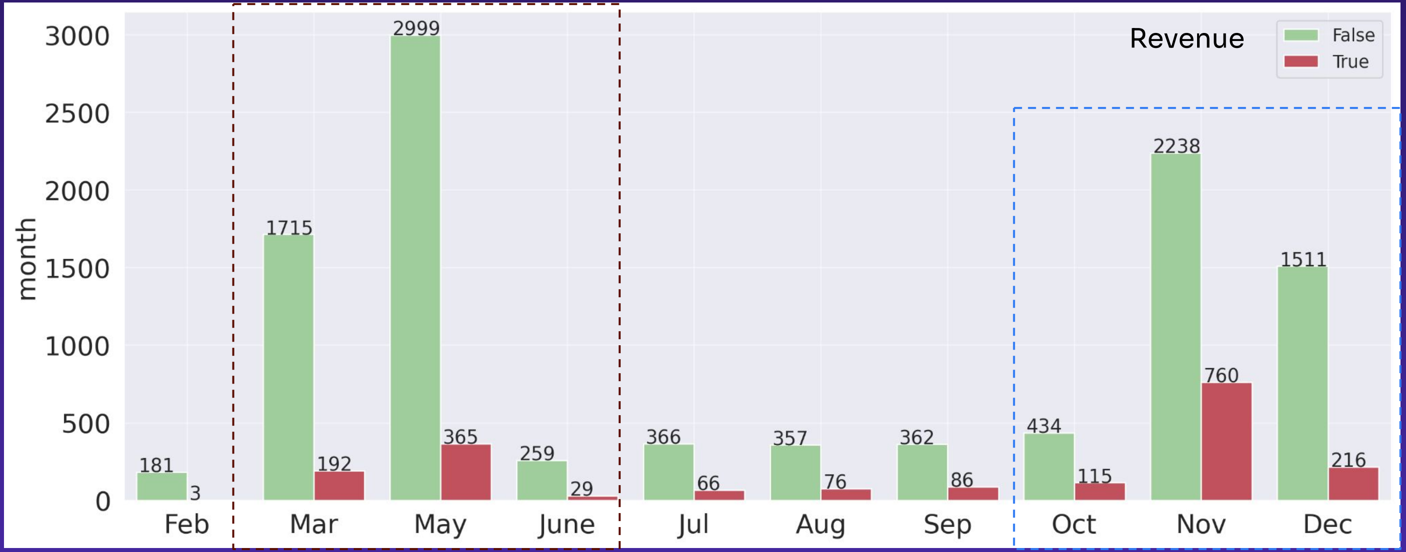
Bounce rates



Visitor with lower exit rates and lower bounce rates tend to make a purchase.

EDA & Insight

Month



The highest amount of web traffic is at March - June but the conversion rate is lower compared to October - December. There is a potential to increase the conversion rate at March - June.

03

Data Pre-Processing

Data Preprocessing

Missing Value

There is no missing value in the dataset so nothing to handle

Handling Outliers

There are numerical features that indicates outliers, handled using Log Transformer

Categorical Feature Encoding

Month: Quarter Binning*
Weekend & Visitor type::One Hot

Duplicated Data

There are 125 rows of duplicated data, it must be dropped

Numeric Feature Scaling

RobustScaler

Handling Class Imbalance

SMOTE

*quarter binning encoded in order to represents whole months

Feature Engineering

Feature Selection

Drop Features* :

- Operating System
- Browser
- Region
- Traffic Type

Feature Extraction

There are 3 additional features
Average administrative duration per page
Average informational duration per page
Average product related duration per page

Split Dataset

80% Data Train, 20% Data Test

*Already encoded and no additional informations that represents actual categories

04

Modelling & Evaluation

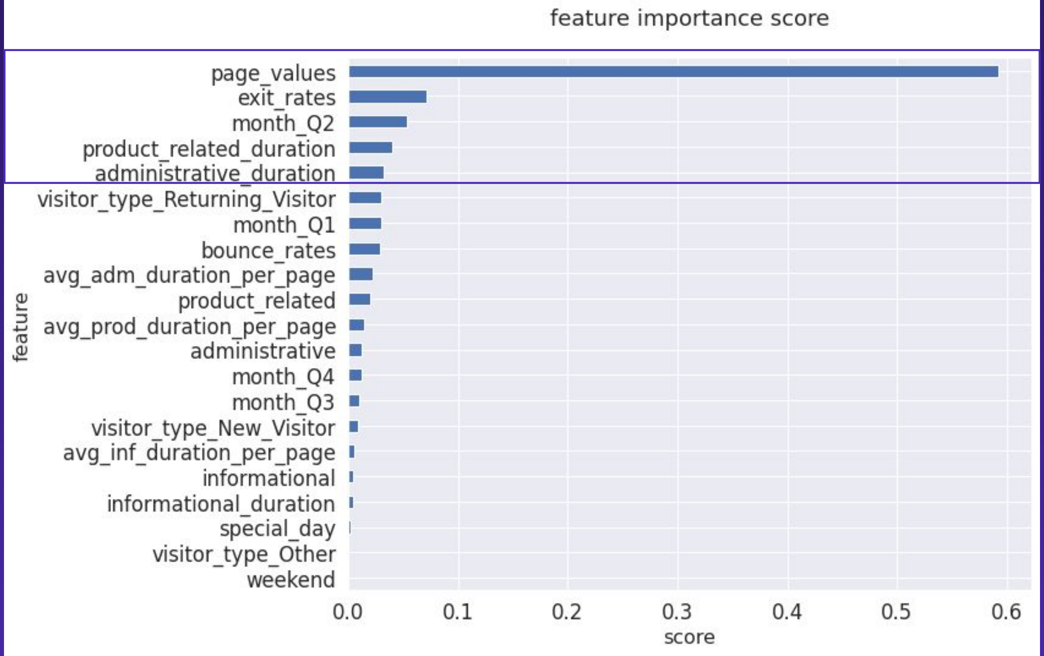
Modelling & Evaluation

Model	ROC-AUC		Precision		Recall	
	Train	Test	Train	Test	Train	Test
Random Forest	**0.94**	**0.92**	**0.63**	**0.62**	**0.80**	**0.78**
Extra Trees	0.82	0.81	0.35	0.35	0.57	0.54
XGBoost	0.98	0.92	0.75	0.60	0.90	0.73

The primary metric is **Precision**. We try to minimize the false positive, which is predicted make a purchase but actually not purchase, is costly to our revenue. We do not want the visitor who actually does not make a purchase, not detected by our model.

The best model we choose is **Random Forest** because the difference between train and test metrics are lowest compared to other model. After experimenting with hyperparameter tuning and cross validation, the model performance did not improve and they overfitted so we use the model before hyperparameter tuning with parameter **max_depth = 7** and **class_weight = balanced_subsample** .

Feature Importance



Top Five Feature Importance:

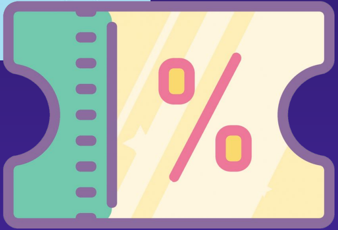
- Page Value
- Exit Rates
- Month: May and June
- Product Related Duration
- Administrative Duration

Visitors with high number of visited pages are likely to make a purchase.

05

Business Recommendation

Page Value



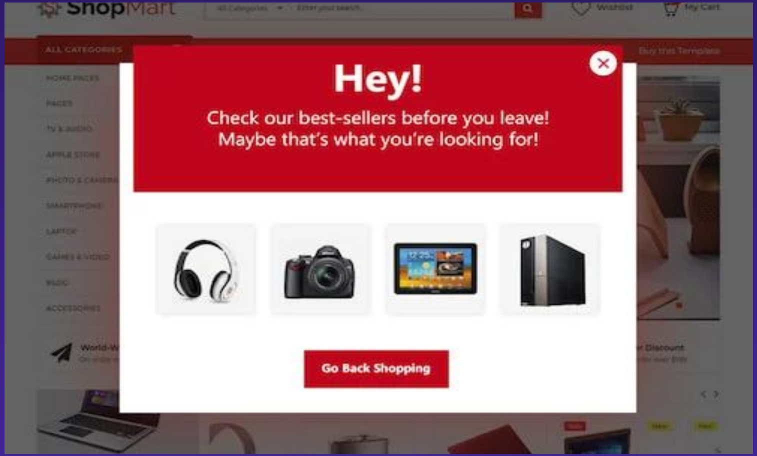
Page value can be increased by increasing traffic count quality. Page value can be optimized with Search Engine Optimization (SEO) or giving voucher per category product.

Month

Give some vouchers and holding an event in May.

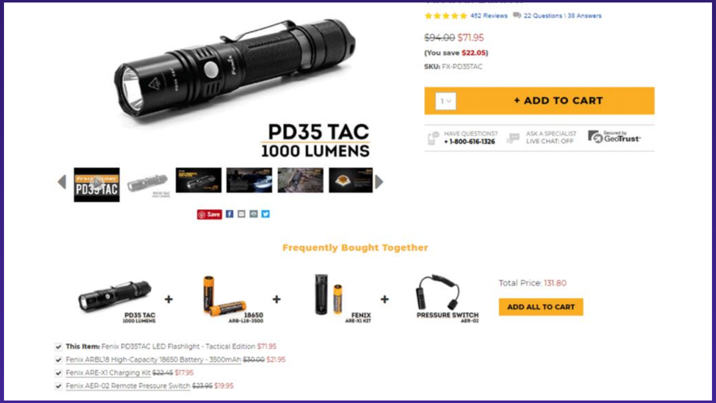
Reference :
https://www.wordtracker.com/academy/seo/page-optimization/how-to-optimize-web-page

Exit Rate



Optimize pages with a high exit rate. Add Exit Intent Popups, CTA in the right place, and provide a live chat feature.

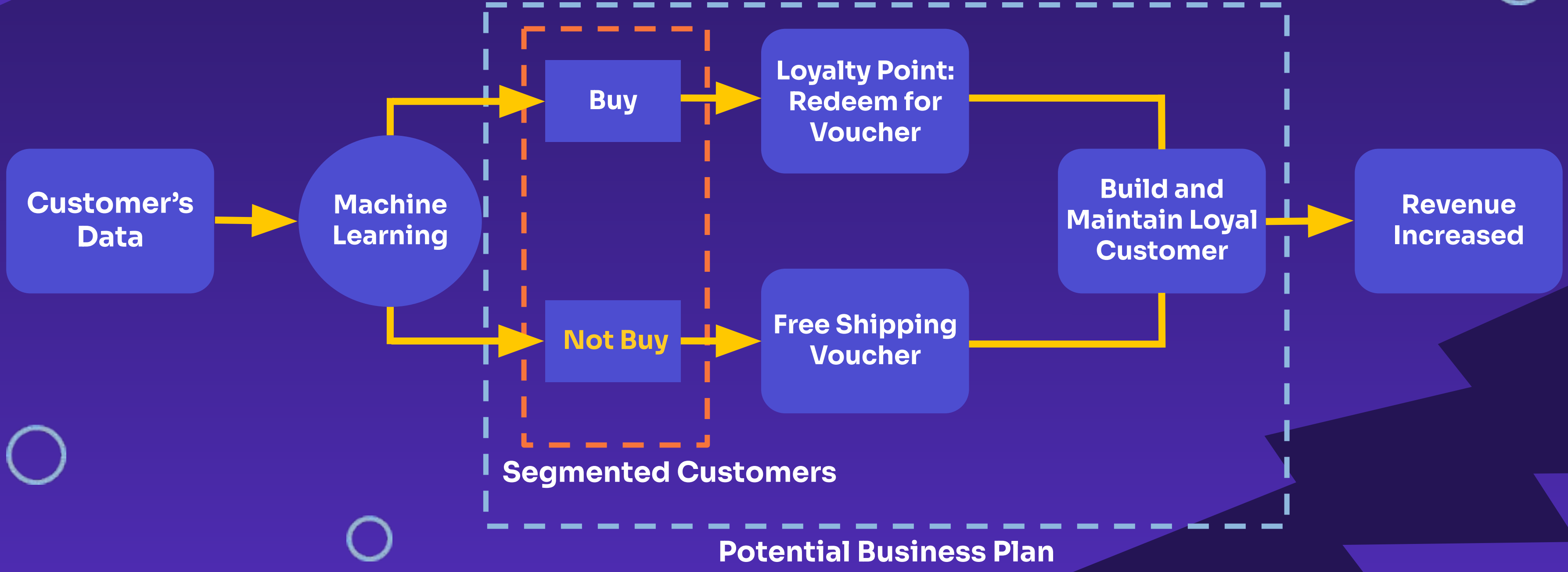
Product Related Duration



Improvements in terms of interface, ease of access, clarity of information, and product demonstration on Related Products.

Reference : https://databox.com/lower-exit-ratee

Business Recommendation Flow



Our **Strategies**

Our Focused Program

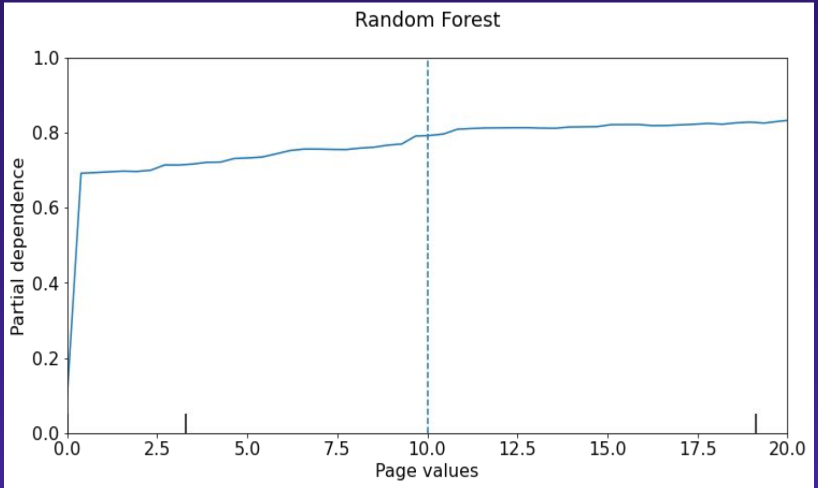
Voucher: Free Shipping

Mechanism:

- Customer get free shipping voucher.

Reference : https://www.invespcro.com/blog/free-shipping/

Business Simulation



Visitors who are predicted not to make a transaction will get a voucher. When these visitors get a voucher, they tend to explore more in our e-commerce so that the page values will likely to increase. As per the left plot, we can assume the average page values of these visitors increase to 10 pages. From this increase in page values, the conversion rate increases 75%.

Visitor predicted not make a Transaction → **Send them Free Shipping Voucher** → **Page Value Increased** → **75% Conversion Rate**

Potential Revenue

15% Conversion **Rate** ▶▶▶▶ **75%** Conversion **Rate**

15% Conversion Rate		75% Conversion Rate
Rp.30.000*		Rp.30.000*
382 ×	▶▶▶▶	1849 ×
Rp.11.460.000		**Rp.55.470.000**

Potential **Revenue** ↑ **Increased 4.8X**

*Assumption: Average revenue per online shopper per transaction in Indonesia

Danke!

Do you have any questions?

Appendix

Feature Selection

Evaluation Metric	Before Selection (%)	After Selection (%)
ROC-AUC	92.2	91.1
Precision	61.8	60.2
Recall	78.0	77.2

The model with **5 most important features** have **slightly lower** precision and ROC-AUC score on test set then the model with all features.

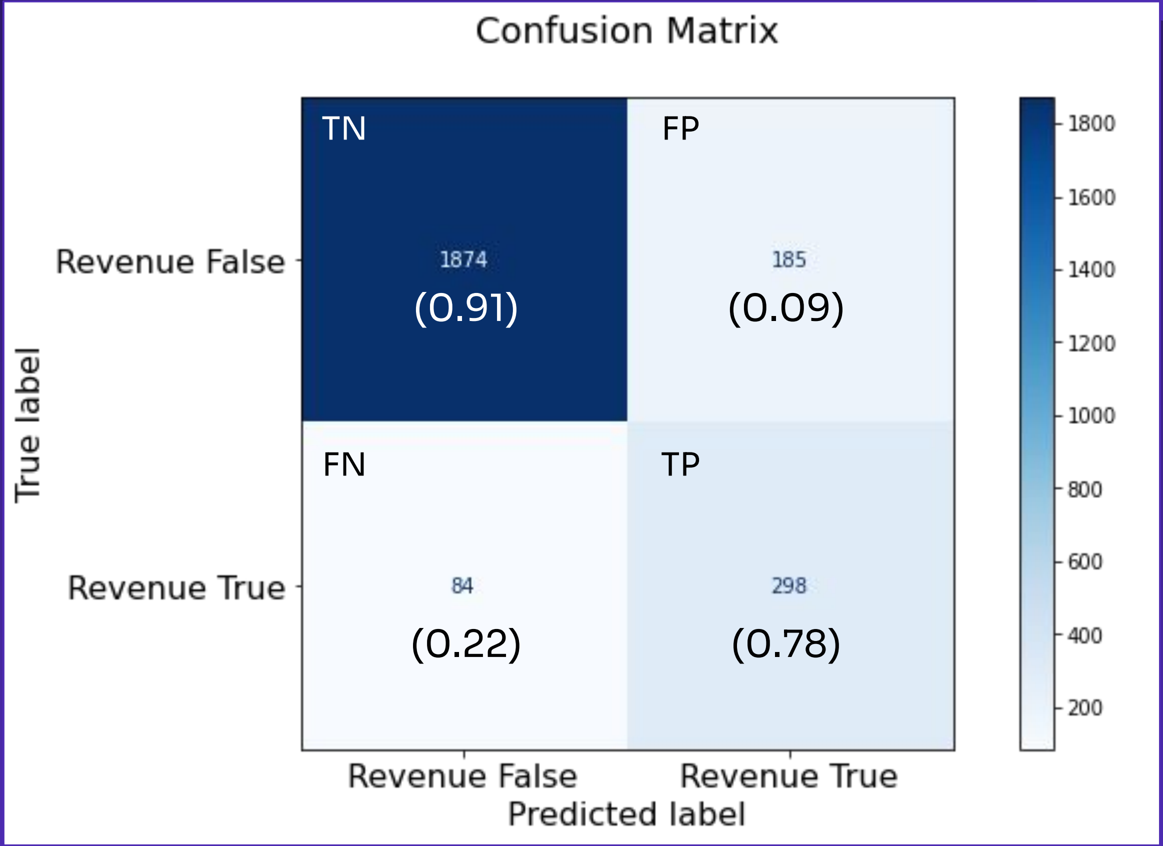
Notebook for simulation: link

```python
# select the threshold based on PDP
page_values_threshold = 10

# change the page_values data for page_values <= 5
filter_for_revenue_false = X_test_new['revenue'] == 0
func = lambda x: page_values_threshold if x <= page_values_threshold else x
X_test_new.loc[filter_for_revenue_false, 'page_values'] = X_test_new.loc[filter_for_revenue_false, 'page_values'].apply(func)

# prediction on test data
y_proba = model.predict_proba(X_test_new.drop('revenue', axis=1))[:, 1]
y_pred = (y_proba >= 0.5).astype(int)

# calculate convert visitors
total_treated_visitors = X_test[filter_for_revenue_false].shape[0]
potential_convert_visitors = ((X_test_new['revenue'] == 0) & (y_pred == 1)).sum()
purchase_rate_after_treatment = potential_convert_visitors * 100 / X_test_new.shape[0]

# display the results
print(f"Page values threshold: {page_values_threshold}")
print(f"Total visitors who get a treatment: {total_treated_visitors} visitors")
print(f"Convert-to-purchase visitors after get a treatment: {potential_convert_visitors} visitors")
print(f"Purchase Rate After Treatment: {purchase_rate_after_treatment:.2f}%")
```

```
Page values threshold: 10
Total visitors who get a treatment: 2059 visitors
Convert-to-purchase visitors after get a treatment: 1849 visitors
Purchase Rate After Treatment: 75.75%
```

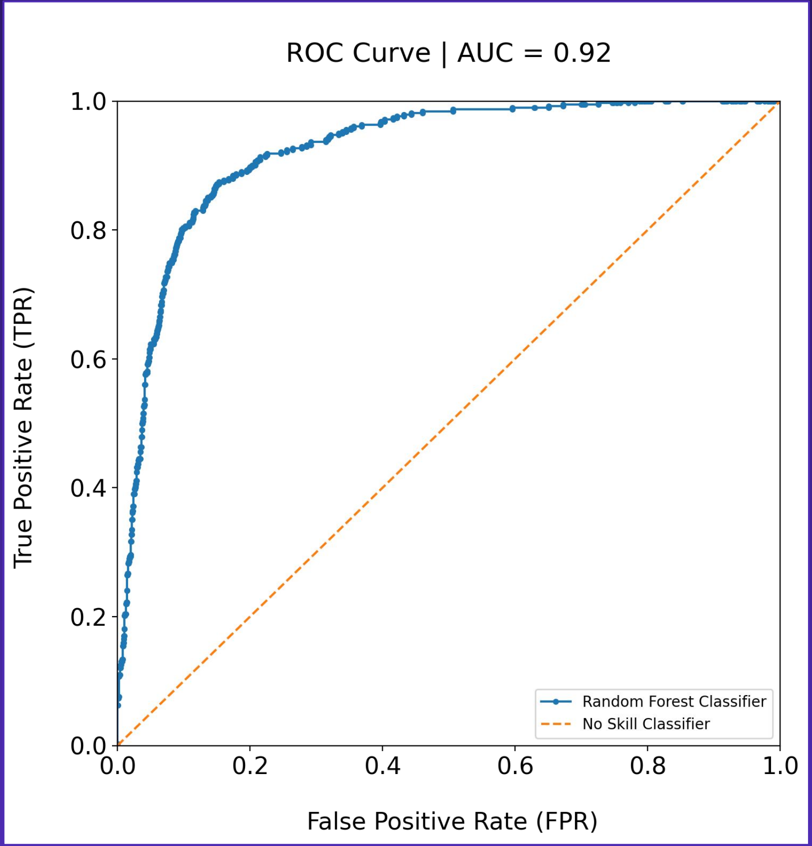
Confusion Matrix (Random Forest)

For Test Data



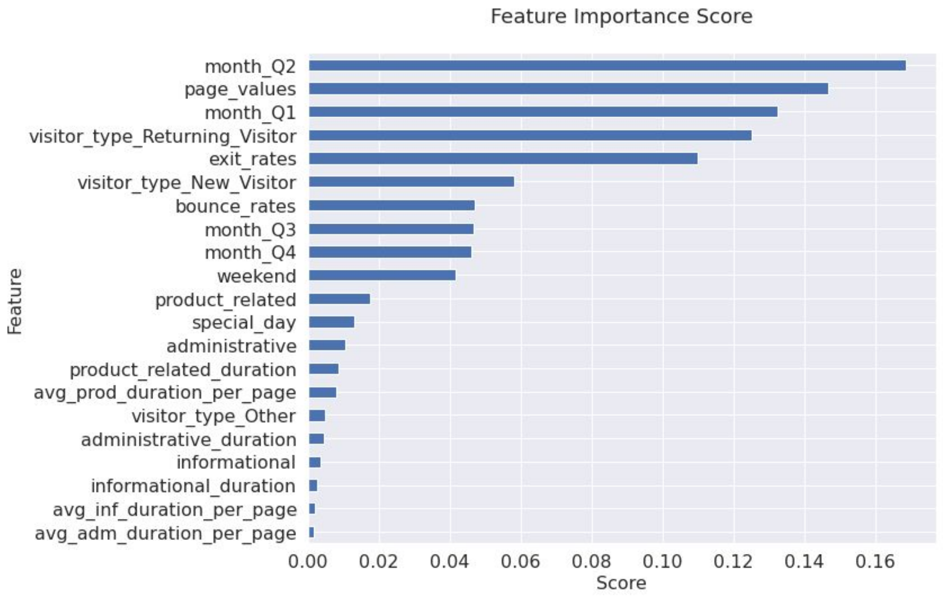
ROC (Random Forest)

For Test Data



	threshold	tpr	fpr
0	0.146	0.110	0.002
1	0.158	0.154	0.009
2	0.329	0.649	0.061
3	0.377	0.702	0.068
4	0.611	0.819	0.114
5	0.704	0.859	0.146
6	0.826	0.963	0.369
7	0.839	0.971	0.403
8	0.958	1.000	0.801
9	0.990	1.000	0.938

Extra Trees



XGBoost