



2021 HR Analytics Case Study

How “Anonymous” get a better prediction towards their candidates

Purwadhika Jakarta Batch 11

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JOB CONNECTOR

Data Science
&
Machine Learning

The problem

Company

An anonymous company that's dynamic in Big Data and Data Science.

Context

- Needs to enlist data scientists.
- Needs to know which of these candidates are really wants to work for the company or not.

Problem statement

- To predict whether or not candidates alter their occupations after they have completed their training.
- Sorting out candidates that are false predicted

Challenges deep-dive

Challenge 1

Exploratory Data Analysis

A thorough examination meant to uncover the underlying structure of a data set and exposes trends, patterns, and relationships that are not readily apparent.

Challenge 2

Cleaning and Pre-Processing

- Transform the raw dataset into an understandable format.
- Improve data efficiency.

Challenge 3

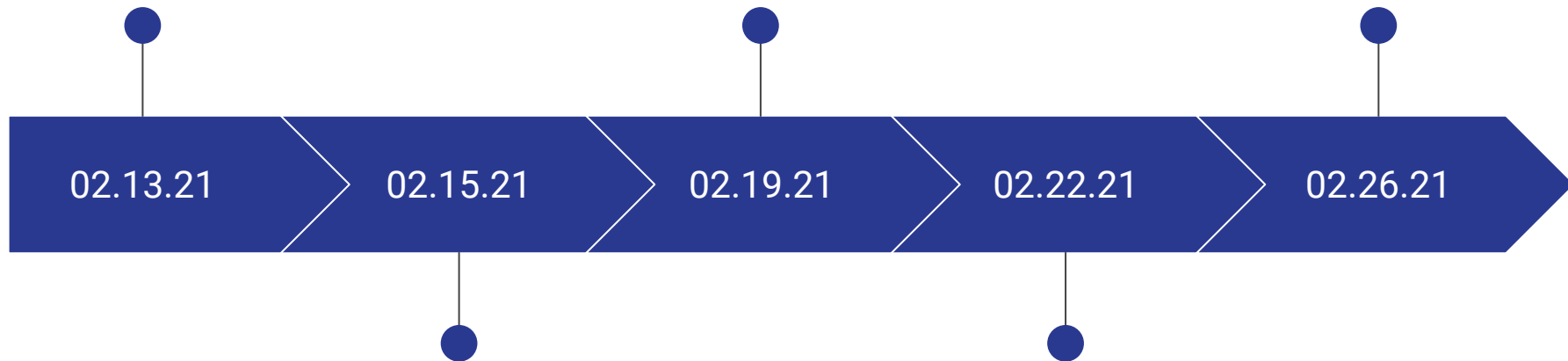
Modeling

Best possible predictive machine learning model to answer those in need.

Start final project

Data Cleaning and
Preprocessing

Due Date 16.00 PM
WIB GMT+7



Exploratory Data
Analysis

Modeling and
Dashboard

Tackle Challenges

Steps

1. Load Dataset
2. EDA
3. Handling Columns
4. Splitting Dataset
5. Handling Missing Values
6. Handling Outliers
7. Handling Imbalanced Data
8. Encoding
9. Feature Selection
10. Building Machine Learning Models
11. Hyperparameter Tuning
12. Evaluating Best Model
13. Saving and Deploy Model

Exploratory Data Analysis

Dataset

<https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists>

| | |
|------------------------|---------------------|
| enrollee_id | city |
| city_development_index | gender |
| relevant_experience | enrolled_university |
| education_level | major_discipline |
| experience | company_size |
| company_type | last_new_job |
| training_hours | target |

Cleaning and Pre-Processing

Steps

1. Drop rows containing ID and training hours of candidates.
2. Impute missing values using their most frequent values.
3. Encode categorical columns of data to numerical using Binary Encoder, and ordinal columns of data to numerical using Ordinal Encoder.
4. Scale numerical column of data using RobustScaler.
5. Generate polynomial and interaction features using PolynomialFeatures for numerical column of data after it's scaled.

Modeling

Supervised Machine Learning Classification

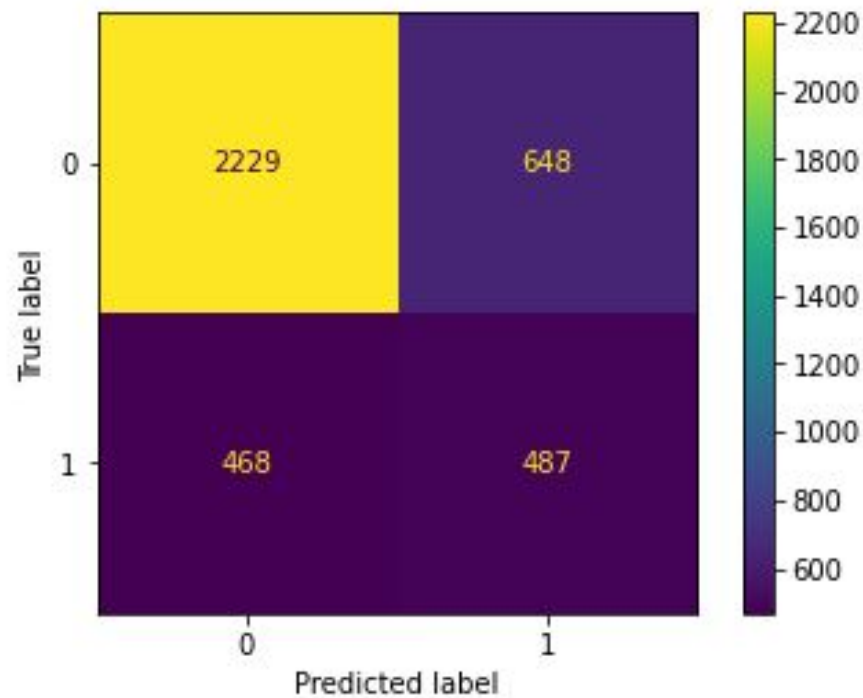
| Model | Before | After |
|------------------------------|--------|-------|
| Logistic Regression | 0.656 | 0.652 |
| Decision Tree Classifier | 0.496 | 0.697 |
| Random Forest Classifier | 0.454 | 0.658 |
| Support Vector Classifier | 0.641 | 0.714 |
| Ada Boost Classifier | 0.576 | 0.580 |
| Gradient Boosting Classifier | 0.582 | 0.607 |
| XGBoost Classifier | 0.584 | 0.612 |
| K Nearest Classifier | 0.650 | 0.521 |

Implementation

Decision Tree Classifier

Confusion Matrix

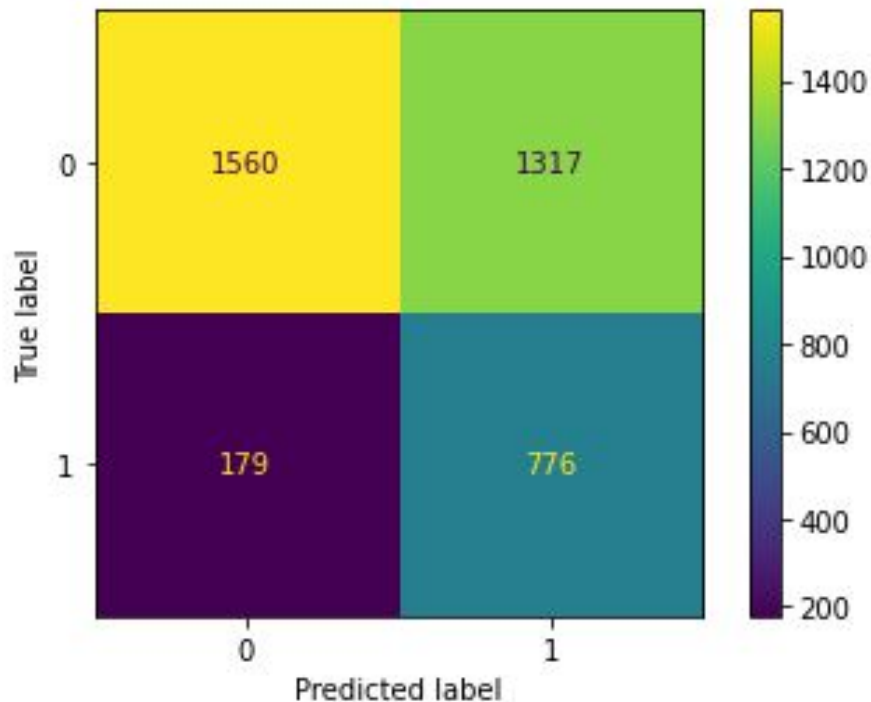
Before Hyperparameter Tuning



Decision Tree Classifier

Confusion Matrix

After Hyperparameter Tuning



Decision Tree Classifier

Comparison

Predicted not changed actually changed

Before : $468/(2229+468)*100 = 17.35\%$

After : $179/(1560+179)*100 = 10.29\%$

Predicted changed actually not

Before : $648/(487+648)*100 = 57.09\%$

After : $1317/(776+1317)*100 = 62.92\%$

Impact

Trade-off

7.06% reduction in predicted not
changed actually changed

5.83% addition in predicted
changed actually not

Problem
Solved!



Thank You