Final Project Presentation

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Machine Learning Class

Program Studi Independen Bersertifikat
Zenius Bersama Kampus Merdeka

Latar Belakang

Latar Belakang Project

Sumber Data: Walmart Dataset
https://www.kaggle.com/datasets/yasserh/walmart-dataset

Problem: **Regression**

Tujuan:

- Memprediksi penjualan mingguan di Walmart

Eksplorasi Data dan Visualisasi

Business Understanding

Walmart merupakan salah satu perusahaan *retail* multinasional terbesar di dunia. Walmart memiliki banyak pesaing yang bergerak di bidang *retail* sehingga diperlukan keputusan yang strategis agar bisa mempertahankan posisinya.

Business Understanding

Resource/Dataset:

- Gabungan data dari 45 toko termasuk informasi toko dan penjualan mingguan.
- Data disediakan setiap minggu
- Terdapat 4 minggu liburan (Natal, Thanksgiving, Super bowl, Hari Buruh)

Business Understanding

Business Objectives:

- Apakah terdapat insights pada data? Sehingga kita bisa...

Increase Profit

Reduce Cost

Reduce Future Loss

Side Questions: Bagaimana faktor waktu dan perekonomian negara bisa mempengaruhi Weekly Sales?

Data Cleansing

Dimensi data: **6435 baris dan 8 kolom**

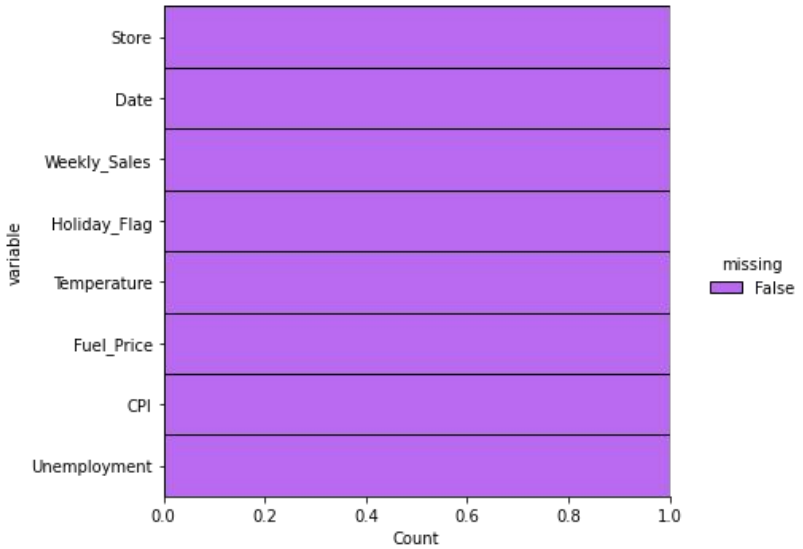
Kolom target: **Weekly_Sales**

Missing values: **0**

Duplicated values: **0**

Jumlah toko: **45**

Hari unik: **Jum'at***



*Pencatatan data dilakukan setiap hari Jum'at

Data Cleansing

Info Hari Libur Besar dari tahun 2010-2012:

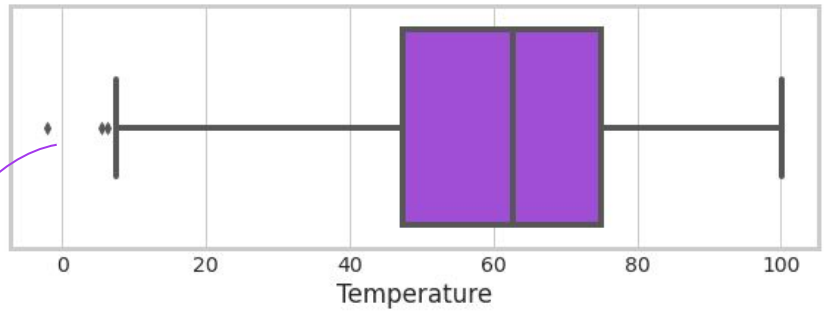
- Super Bowl: Seluruhnya terdapat dalam dataset
- Labor Day: Seluruhnya terdapat dalam dataset
- Thanksgiving: **Tidak ada data tahun 2012*** — Harusnya ada di bulan November 2012
- Christmas: **Tidak ada data tahun 2012*** — Harusnya ada di bulan Desember 2012

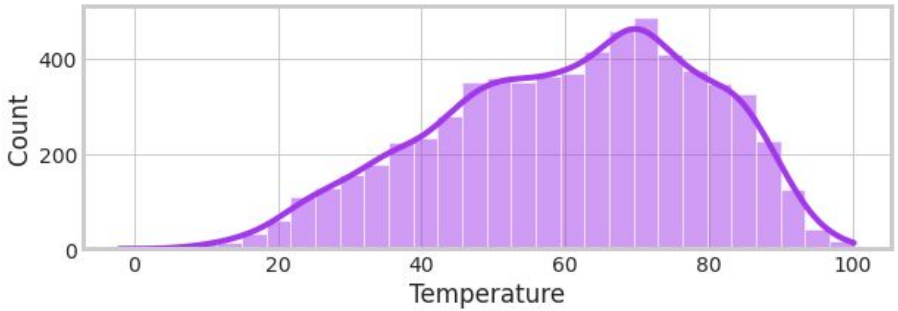
Range data: **5 Februari 2010 - 6 Oktober 2012**

*akibat dari range data yang kurang lengkap. Hari libur besar tersebut berada di luar range data

Data Cleansing

Outliers: Kolom Temperature = **3** data





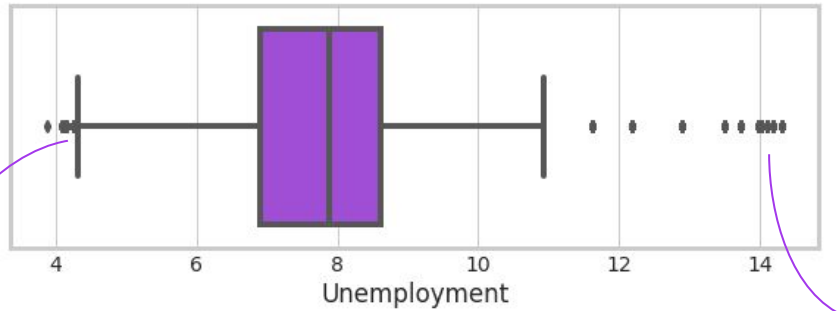
Wajar. Outliers ada di suhu terendah dan berada di Bulan Januari dan Februari.

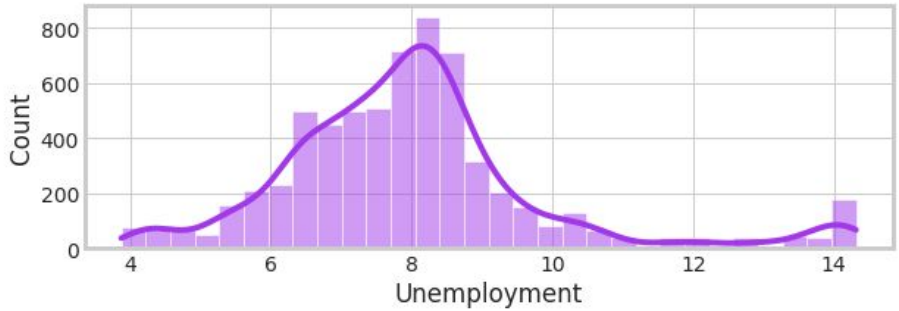
Asumsi: Data temperatur pada hari itu diambil ketika musim dingin

Data Pendukung: Pada tahun 2011, musim dingin dimulai dari awal Desember 2010 dan berakhir di akhir Februari 2011

Data Cleansing

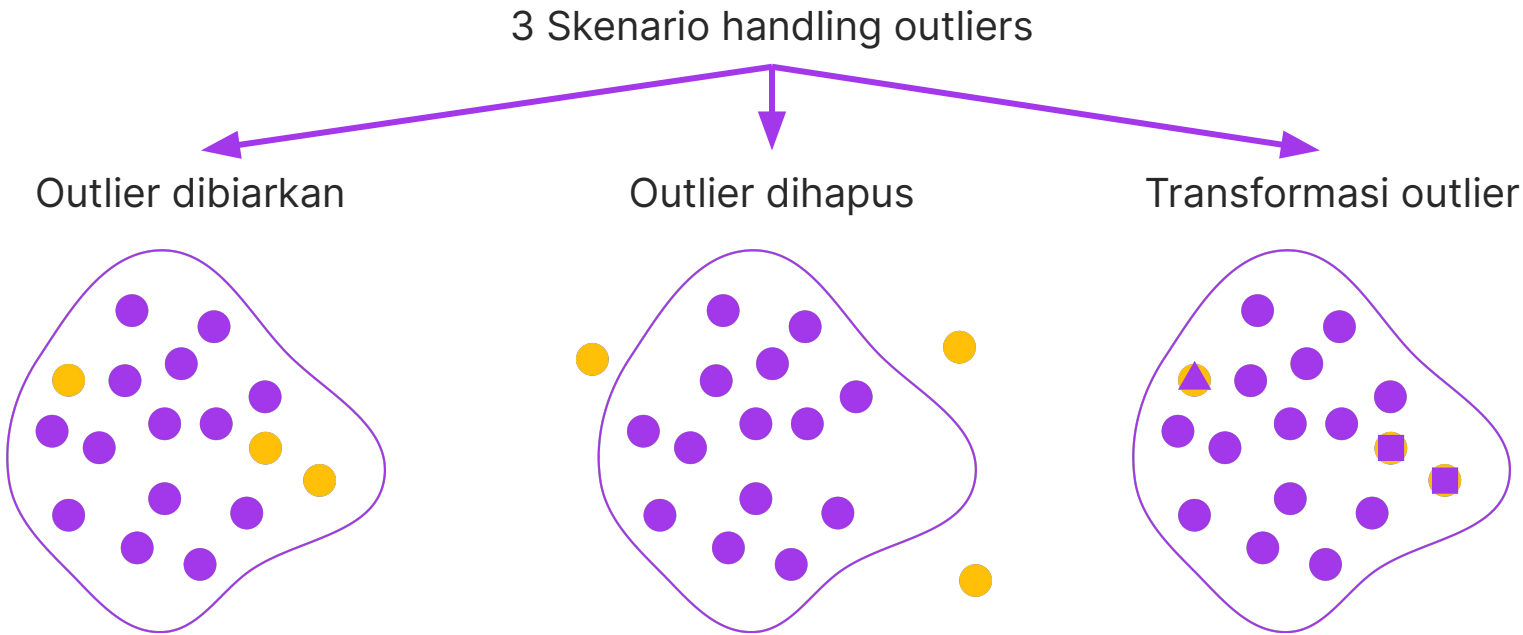
Outliers: Kolom Unemployment = **481** data



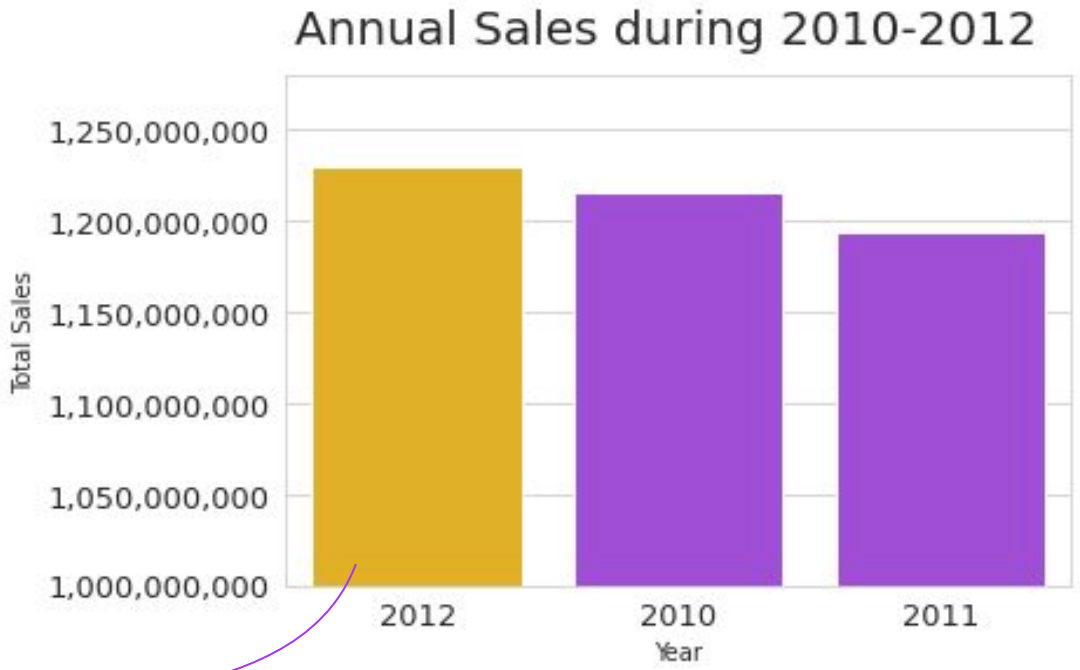


Unemployment **rendah** terdapat pada tahun **2012**. Sementara itu, Unemployment **tinggi** terdapat pada **semua tahun**. Sehingga, **perlu dilakukan handling outlier lebih jauh**

Handling Outliers



Exploratory Data Analysis



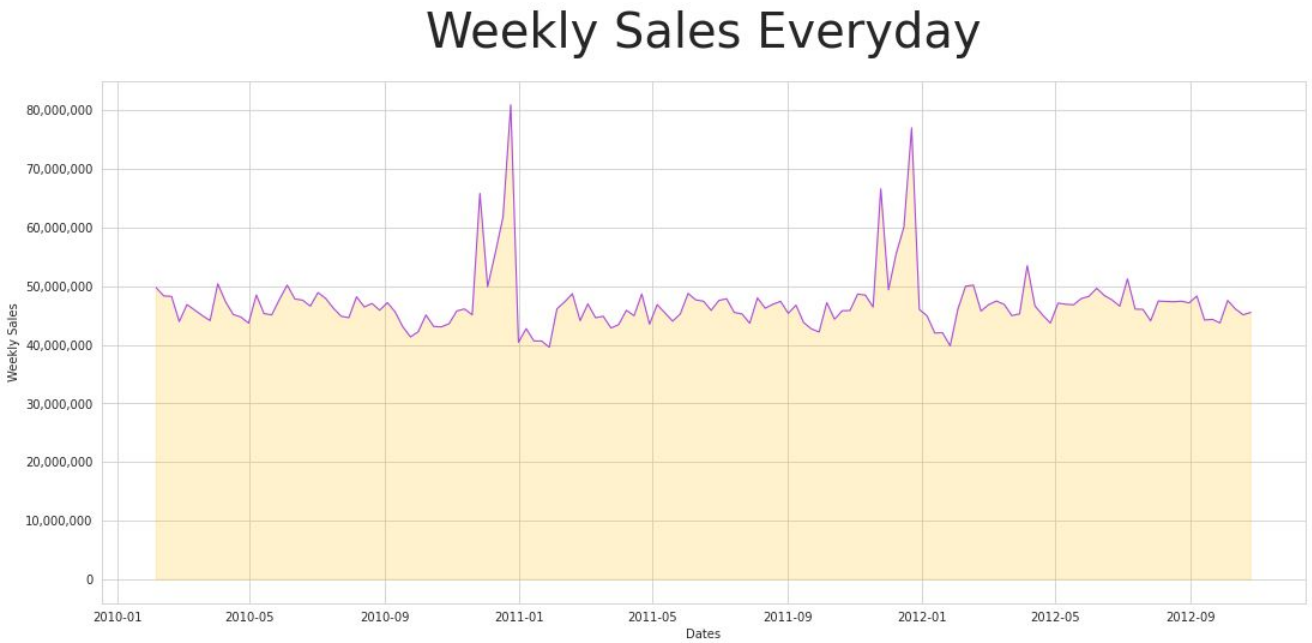
Insight: Annual Sales terbesar terjadi pada tahun **2012**.

Notes: Karena range data setiap tahun tidak seimbang, Total Weekly Sales dihitung dari bulan **Februari hingga Juli** saja untuk melihat perbandingannya.

Exploratory Data Analysis

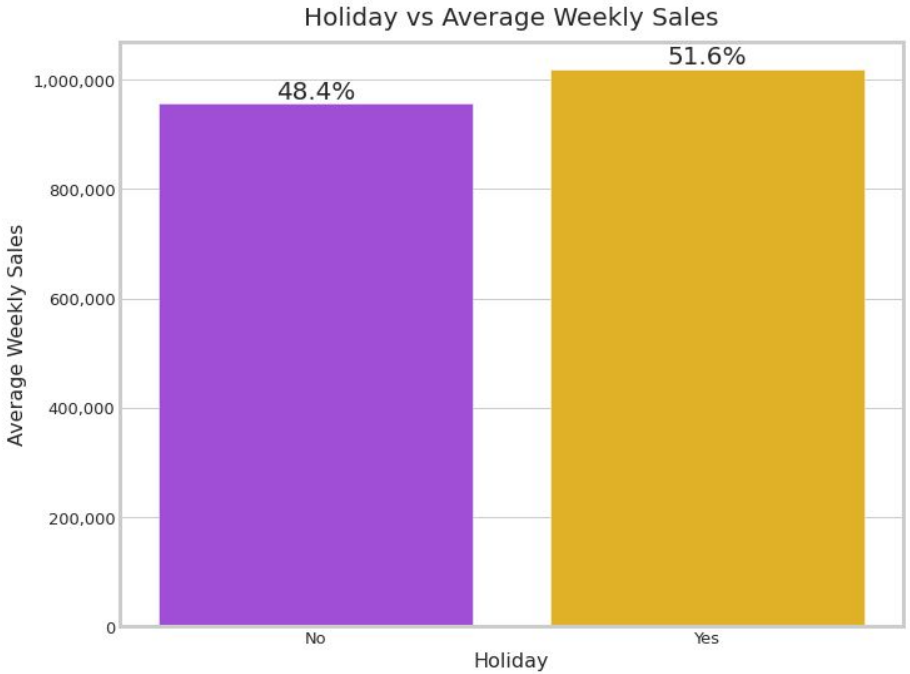
Insight: Average Weekly Sales terbesar terjadi pada bulan **Desember**.

Exploratory Data Analysis



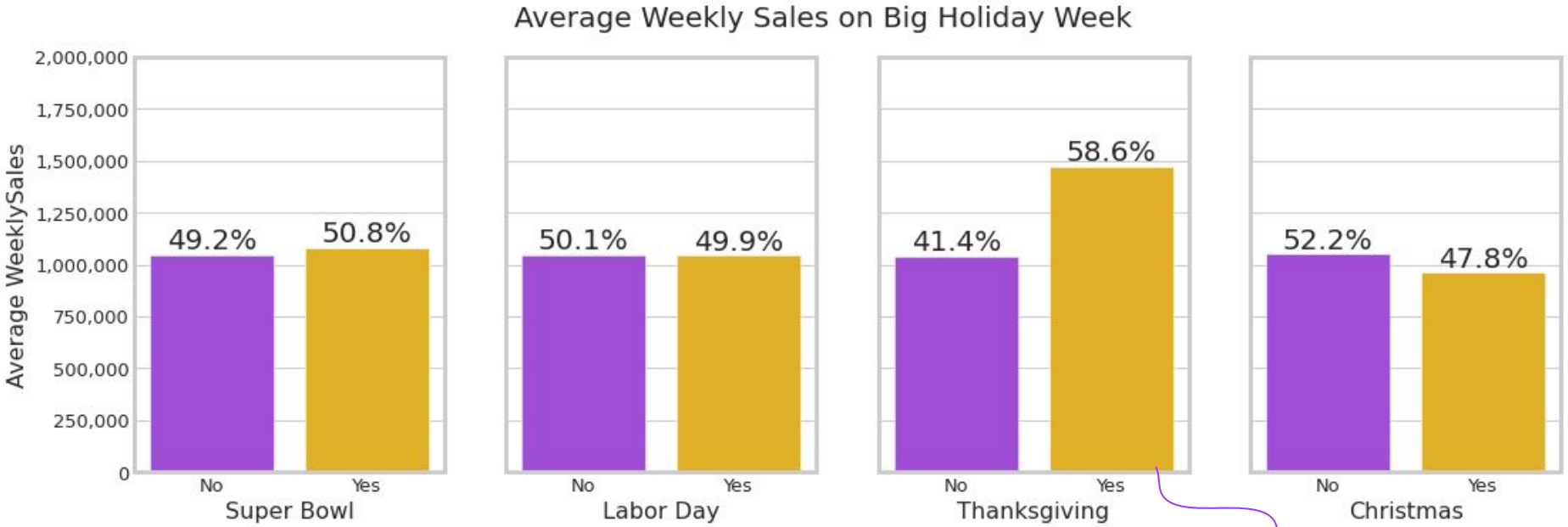
Insight: Terdapat pola tahunan dimana penjualan meningkat signifikan di bulan **November** dan **Desember**.

Exploratory Data Analysis



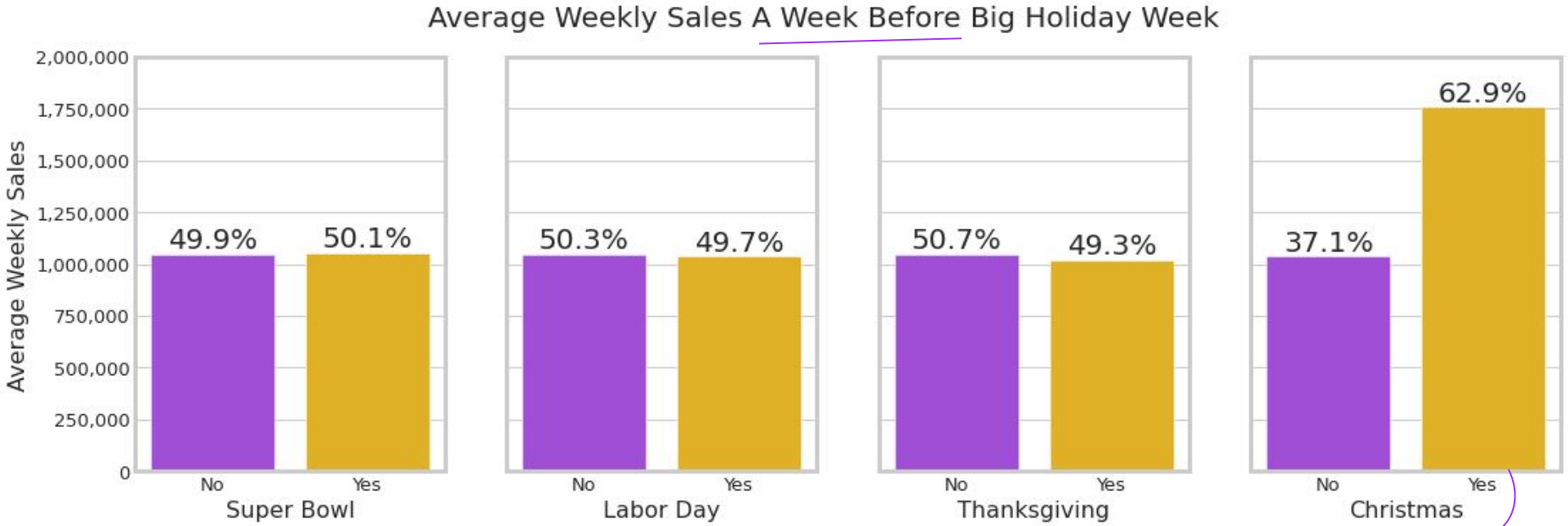
Insight: Terdapat selisih Average Weekly Sales sebesar **3,2 %** lebih tinggi pada **Holiday** dibandingkan **Hari Biasa**.

Exploratory Data Analysis



Insight: Average Weekly Sales tertinggi **ketika** Holiday Week terjadi di **Thanksgiving**.
Dimana perbandingannya sebesar **17,2 %** lebih tinggi dibandingkan Hari Biasa

Exploratory Data Analysis

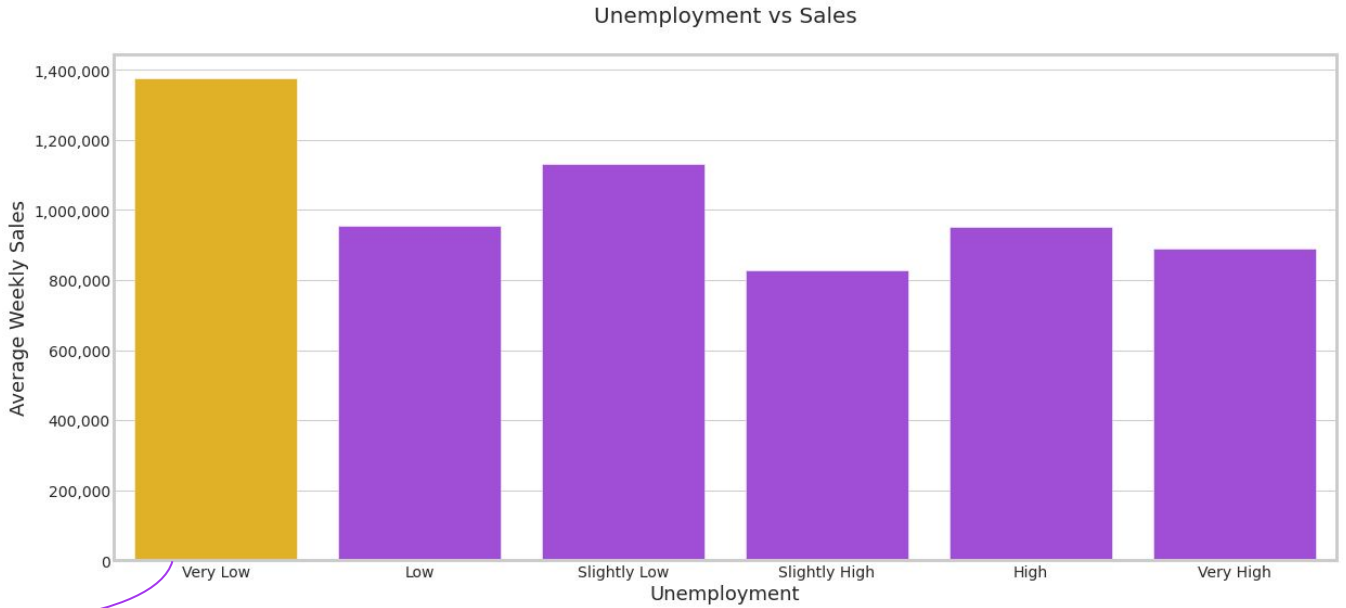


Insight: Average Weekly Sales tertinggi **1 minggu sebelum** Holiday Week terjadi di **Christmas.**
Dimana perbandingannya sebesar **25,8 %** dibandingkan Hari Biasa

Exploratory Data Analysis

Kategori Unemployment Rate:
8.0 - 9.9 : 1 (Very Low)
10.0 - 10.9 : 2 (Low)
11.0 - 11.9 : 3 (Slightly Low)
12.0 - 12.9 : 4 (Slightly High)
13.0 - 13.9 : 5 (High)
14.0 - 14.9 : 6 (Very High)

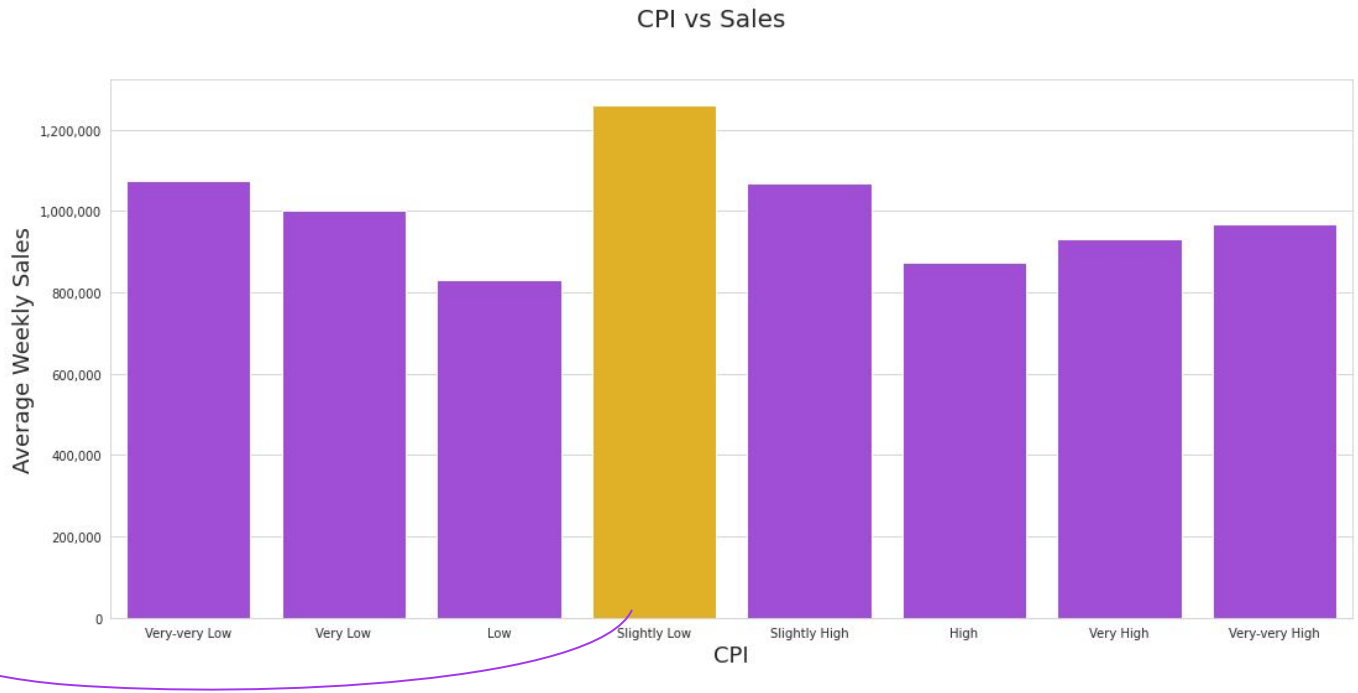
Insight: Average Weekly Sales tertinggi terjadi ketika Unemployment Rate **Sangat Rendah**.



Exploratory Data Analysis

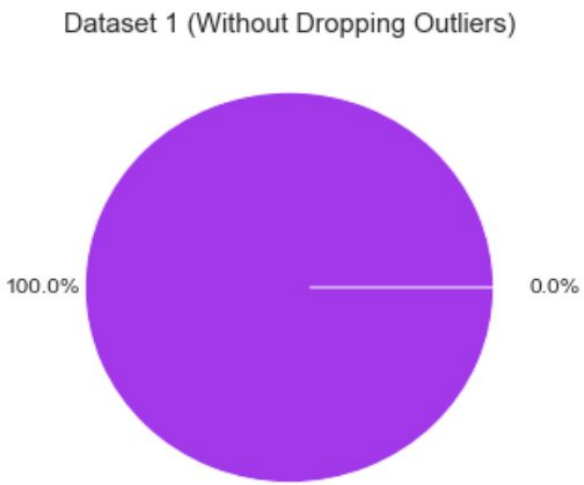
Kategori CPI:
211.0 - 211.4 : 1 (Very-very Low)
211.5 - 211.9 : 1 (Very Low)
212.0 - 212.4 : 2 (Low)
212.5 - 212.9 : 3 (Slightly Low)
213.0 - 213.4 : 4 (Slightly High)
213.5 - 213.9 : 5 (High)
214.0 - 214.4 : 6 (Very High)
214.5 - 214.9 : 6 (Very High)

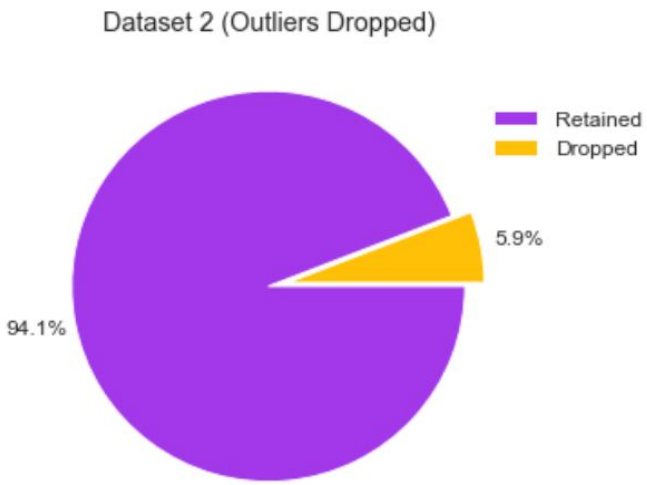
Insight: Average Weekly Sales tertinggi terjadi ketika CPI **Sedikit Rendah**.

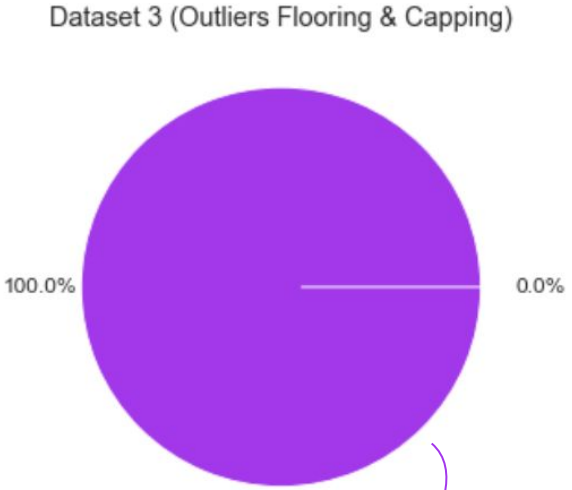


Modelling

Final Dataset







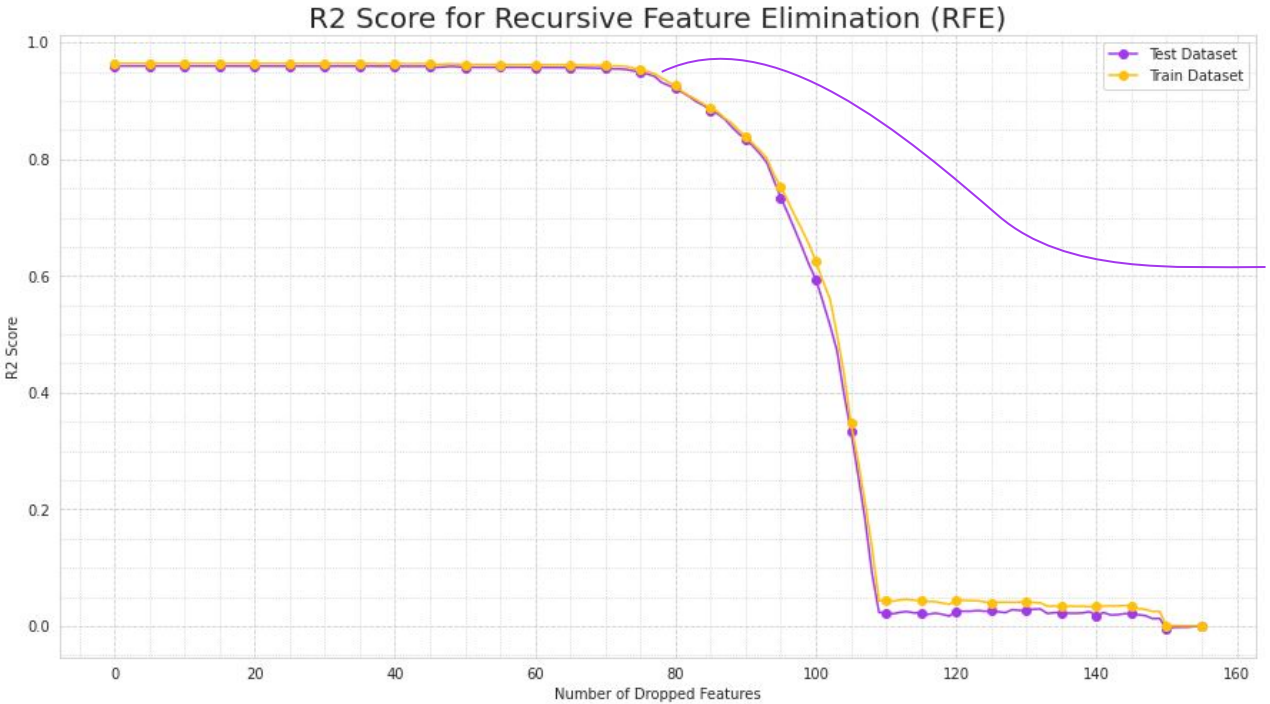
Floor: 10th percentile
Cap: 90th percentile

Feature Selection & Decomposition

1. **Recursive Feature Elimination (RFE)**
   menyeleksi fitur berdasarkan **estimator** secara rekursif
   - (+) Mudah diinterpretasikan
   - (-) Sangat bergantung pada estimator
   - (-) Fitur yang berpotensi bisa saja tidak lolos seleksi

2. **Principal Component Analysis (PCA)**
   mereduksi fitur dengan melakukan **kombinasi** berdasarkan nilai varians
   - (+) Fitur akan dikombinasikan, bukan dieliminasi
   - (-) Hasil sulit diinterpretasikan

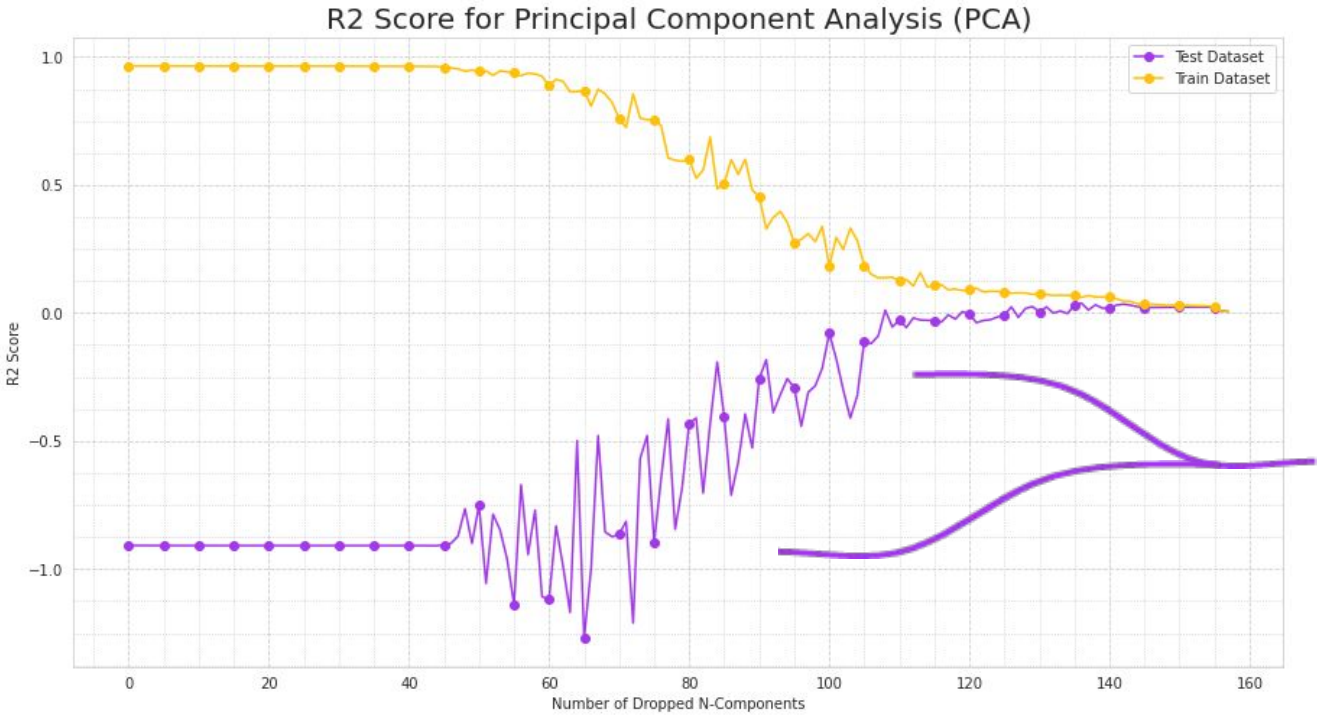
Feature Selection & Decomposition



Jumlah fitur optimal: 76

R2 Score mulai jatuh secara drastis setelah jumlah fitur yang di-drop melebihi 75, sehingga jumlah fitur yang terbaik adalah 76 (151-75)

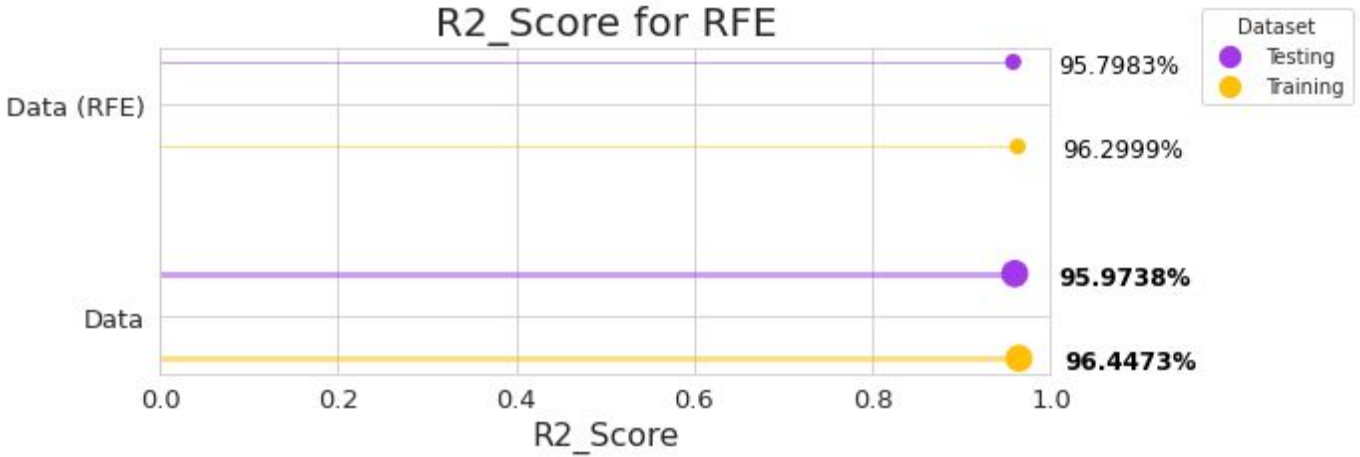
Feature Selection & Decomposition



PCA mengalami overfitting

Nilai R2 sangat baik pada training dataset, tetapi bernilai negatif dan naik turun secara drastis pada testing dataset

Feature Selection & Decomposition



Insight: Data tanpa seleksi fitur memiliki R2 score yang sedikit lebih baik

Setelah diukur waktu komputasinya, untuk 1x iterasi, proses training data tanpa RFE memakan waktu 0.128 s, sedangkan dengan RFE 0.124 s, selisih waktu 0.003s tidak terlalu signifikan karena jumlah datanya masih sedikit.

Model Selection

Dataset Splitting
- Train: 60%
- Test: 40%

Model:

1. **Linear Regression**
   Tidak ada penalti yang diberikan untuk tiap nilai bobot (weight).
2. **Lasso Regression**
   Penalti diberikan sebesar jumlah dari nilai absolut bobot.
3. **Ridge Regression**
   Penalti diberikan sebesar jumlah dari nilai kuadrat bobot.
4. **ElasticNet Regression**
   Penalti diberikan menggunakan kombinasi Lasso dan Ridge.

Evaluation Metric

- **R2-Score**
- MAE (Mean Absolute Error)
- MSE (Mean Squared Error)
- RMSE (Root Mean Squared Error)
- MAPE (Mean Absolute Percentage Error)
- **NRMSE (Normalized Root Mean Squared Error)**

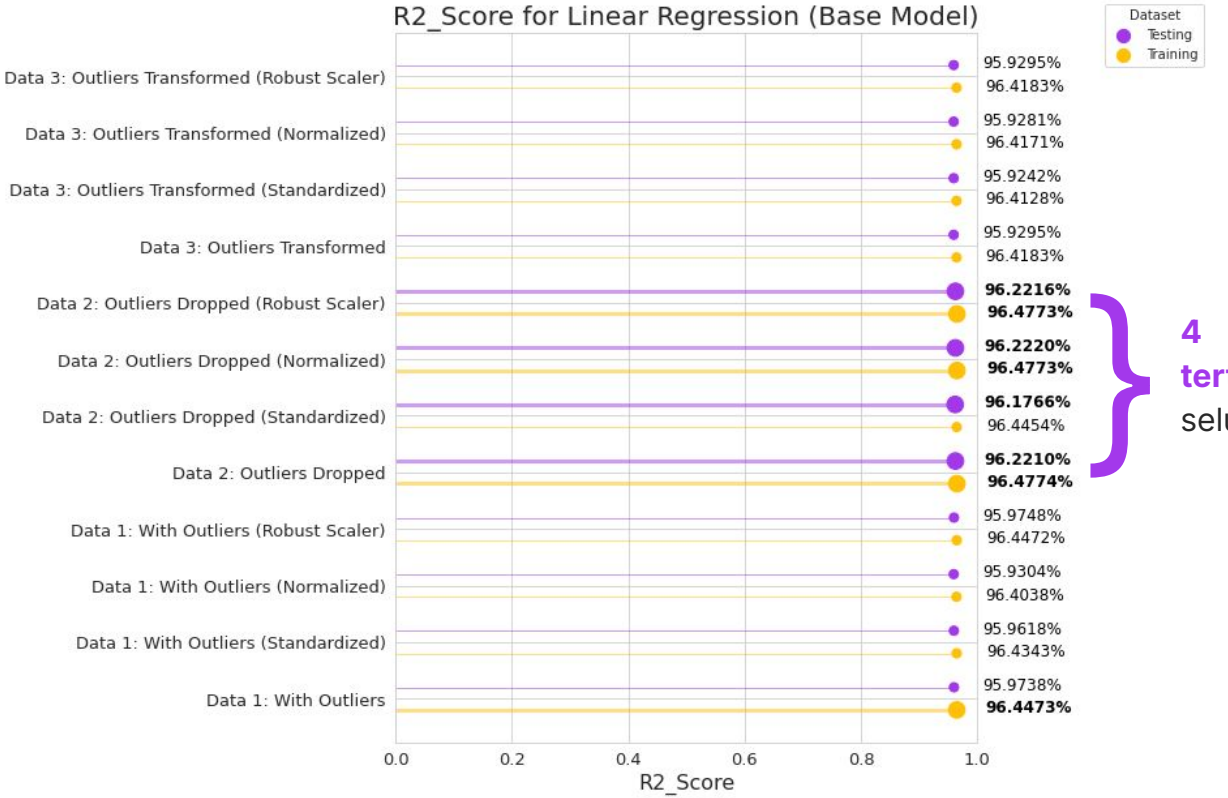
RMSE/standard deviation

(+) widely used
(–) scale-dependent*

(+) scale-independent
(–) asymmetric**

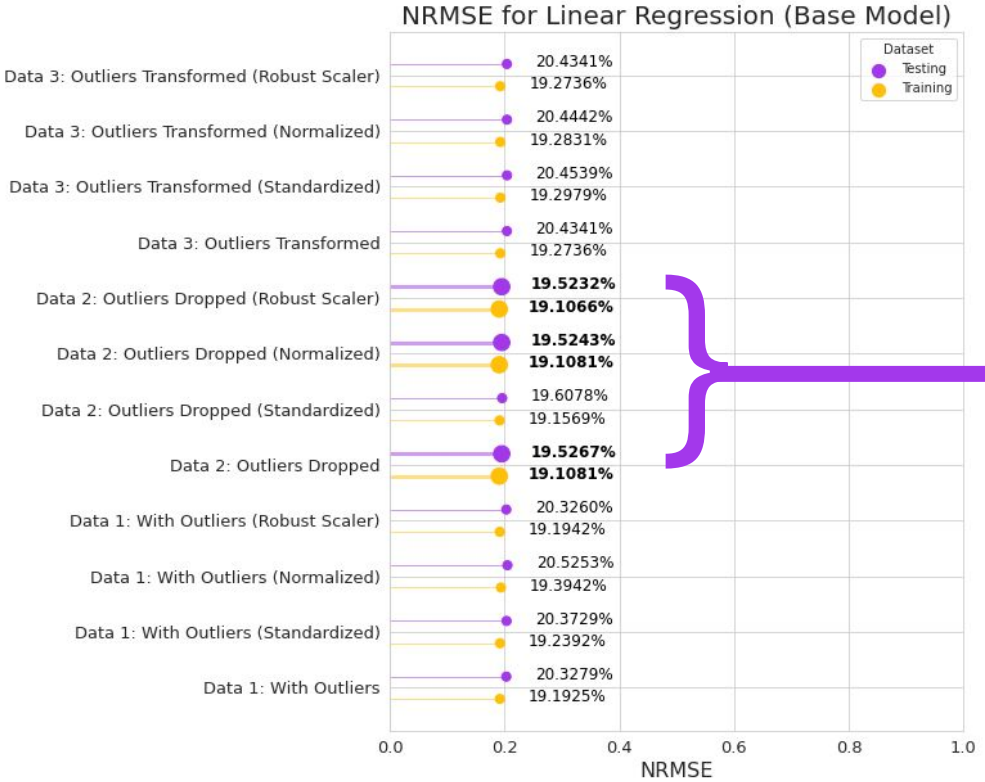
* Supporting detail: End-to-End Introduction to Evaluating Regression Models - AnalyticsVidhya
** Stack Exchange: Is MAPE a good error measurement statistics?

Model: Linear Regression



4 data dengan R2 Score tertinggi, dimiliki hampir seluruh **dataset kedua**

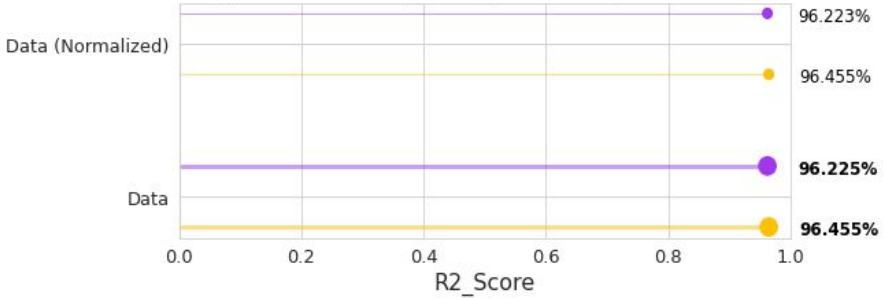
Model: Linear Regression

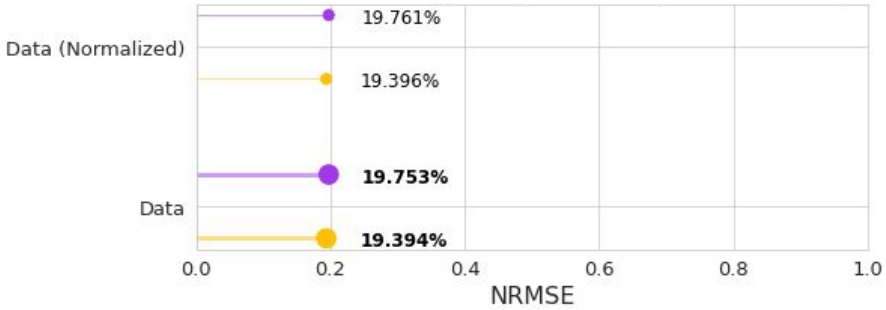


4 data dengan nilai NMRSE terendah dimiliki hampir seluruh **dataset kedua**

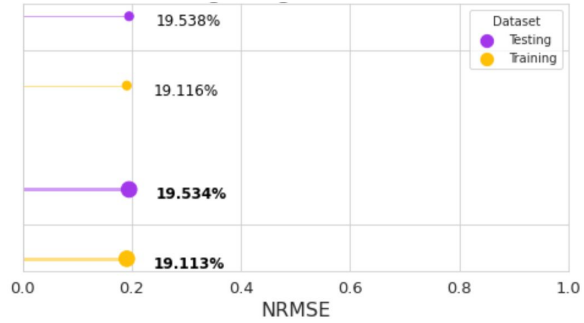
Model: Ridge Regression

Base Model



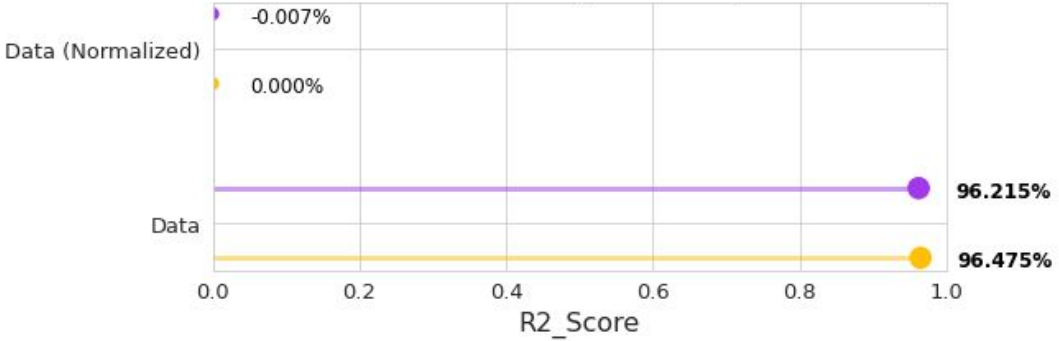


Tuned Model

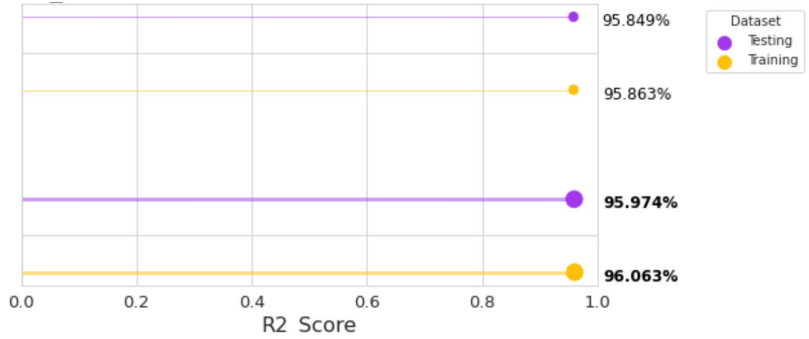


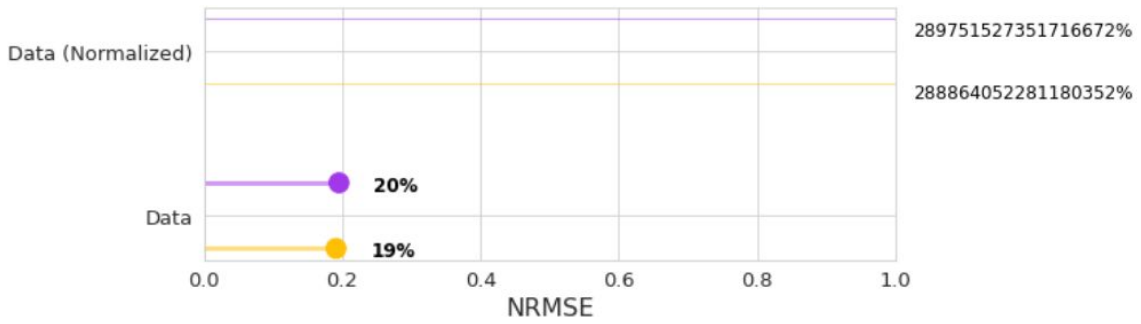
Model: Lasso Regression

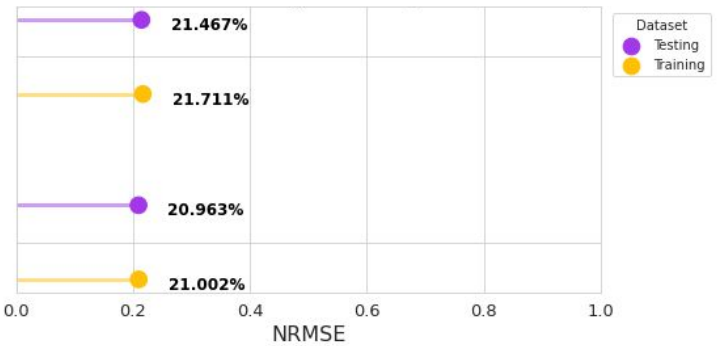
Base Model



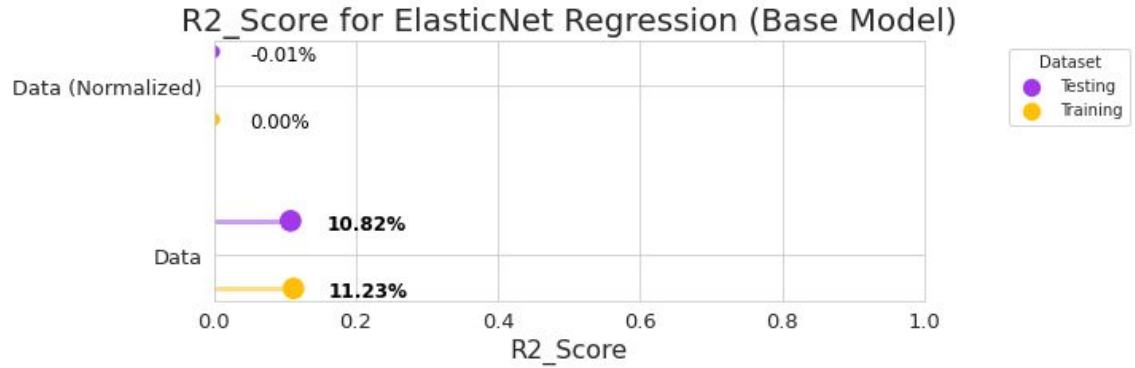
Tuned Model

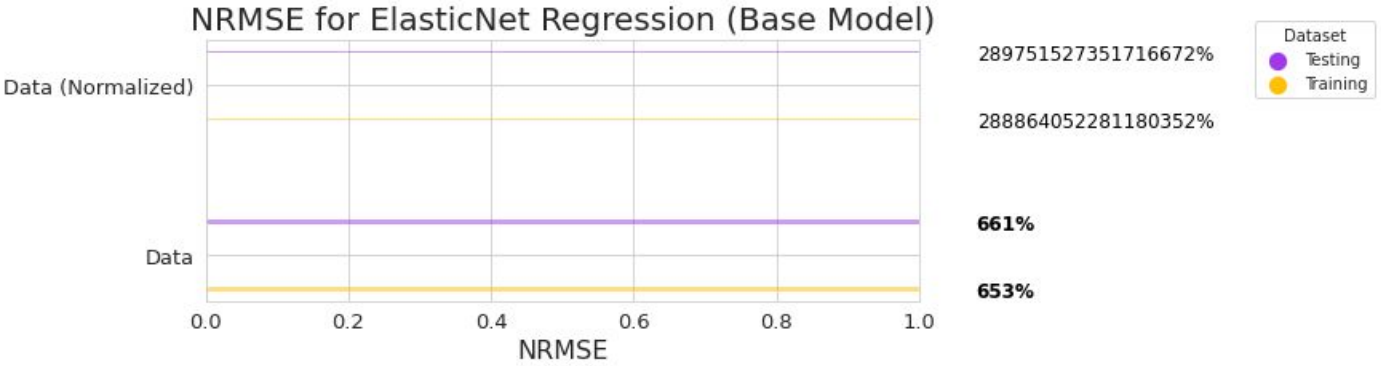




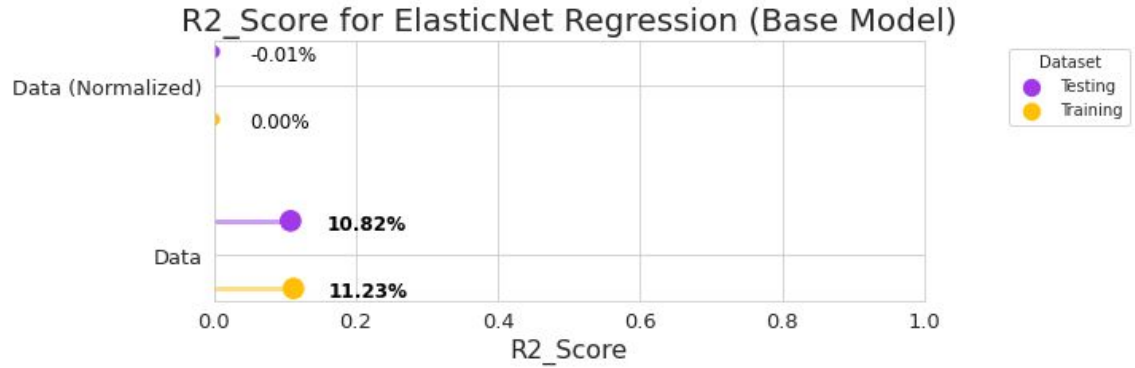


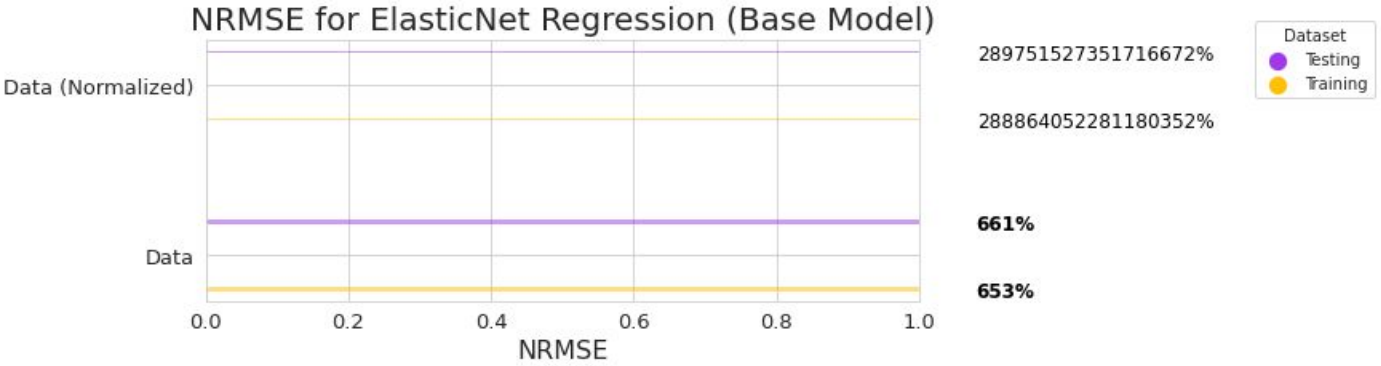
Model: Elastic Net



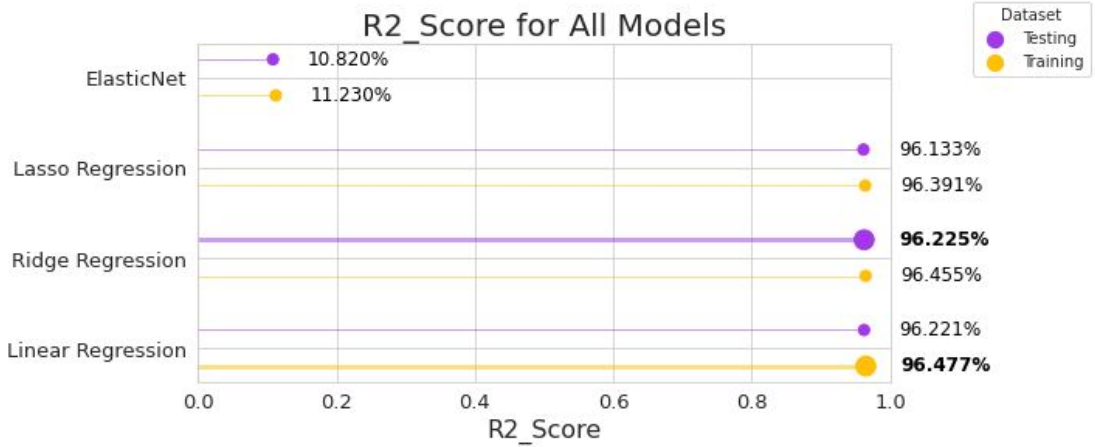


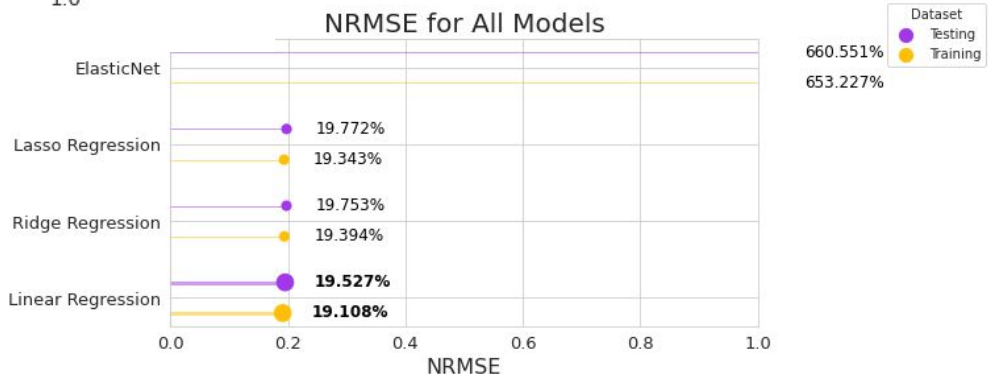
Model: Elastic Net





Model Comparison





Conclusion

Conclusion

- Model terbaik untuk memprediksi penjualan mingguan adalah Ridge Regression. Model ini dapat memberikan informasi yang membantu manajer bisnis mengidentifikasi dan memahami kelemahan dalam perencanaan bisnis.

Rekomendasi:

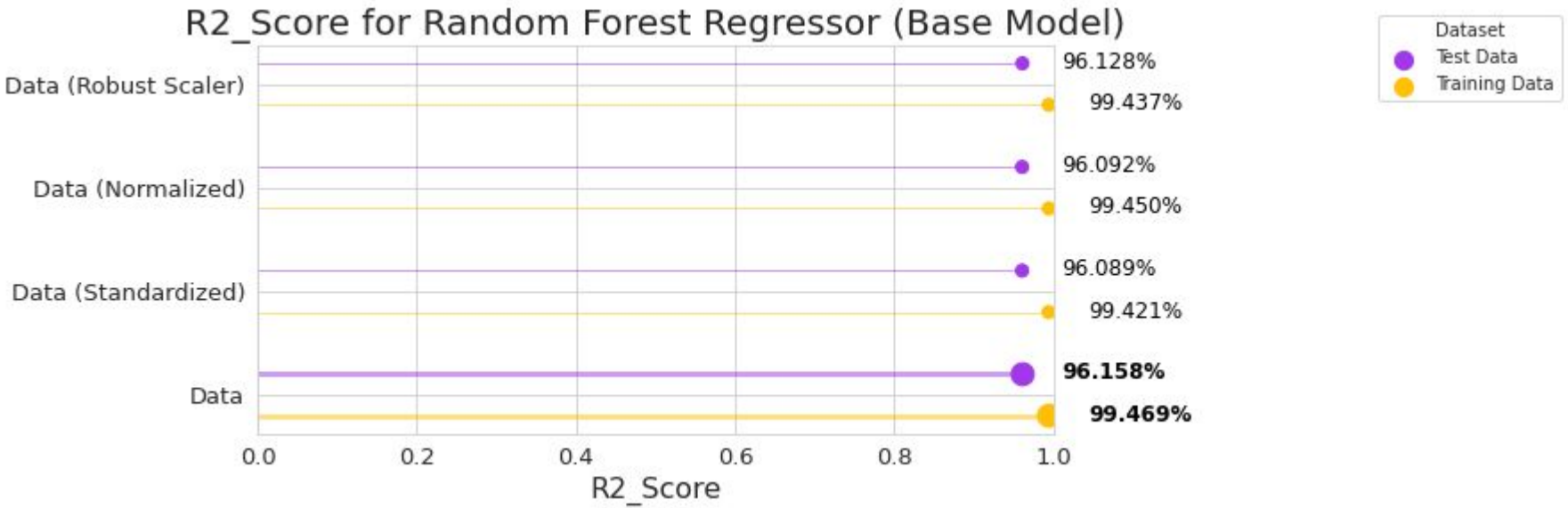
- Divisi Marketing sebaiknya meningkatkan advertising ketika Minggu-minggu sebelum Christmas dan saat Thanksgiving.
- Perlu penambahan orang dari divisi Logistik di bulan November-Desember karena penjualannya meningkat signifikan dibandingkan bulan-bulan lainnya.
- Melakukan re-stock barang secukupnya di hari biasa untuk meminimalkan production cost.

Terima kasih!

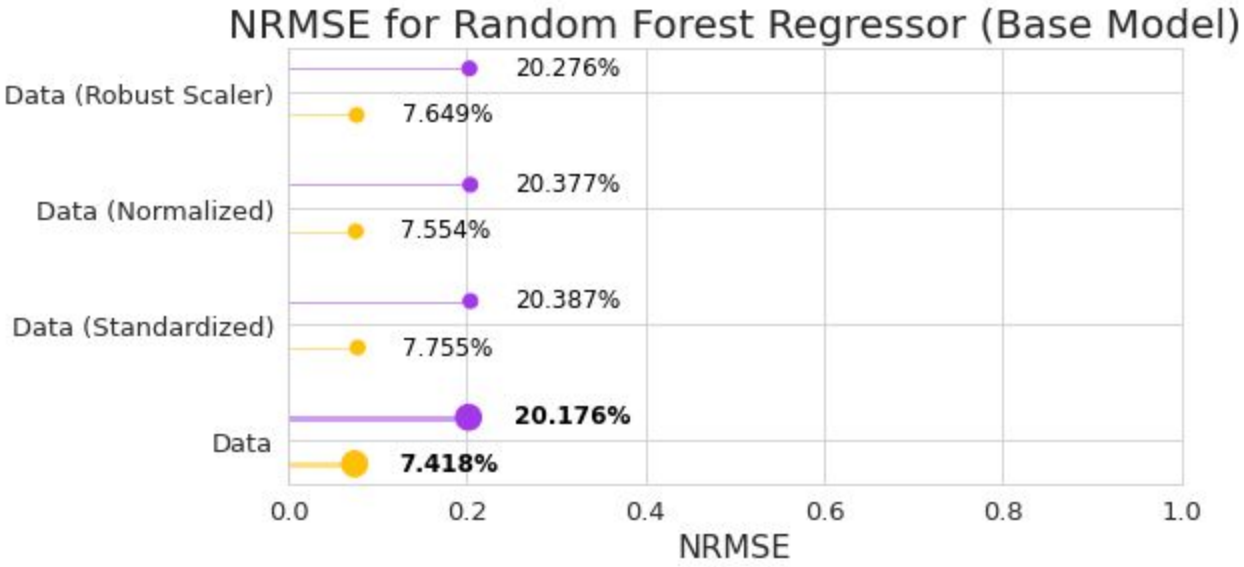
Ada pertanyaan?

LAMPIRAN

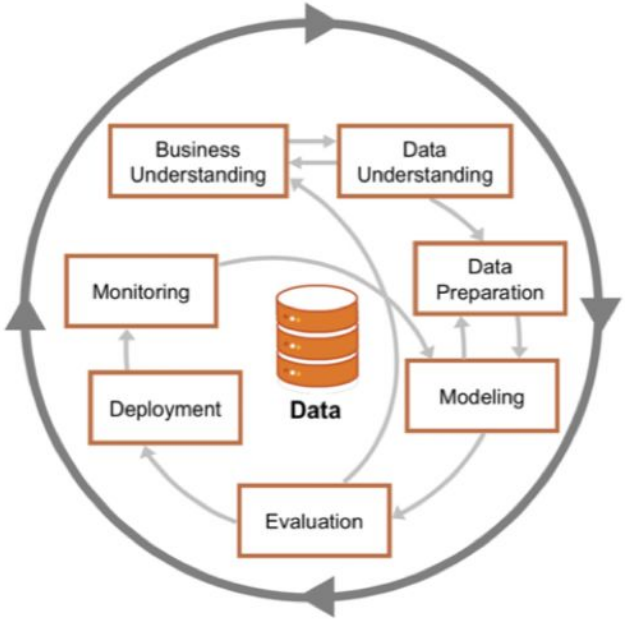
Model: Random Forest Regressor



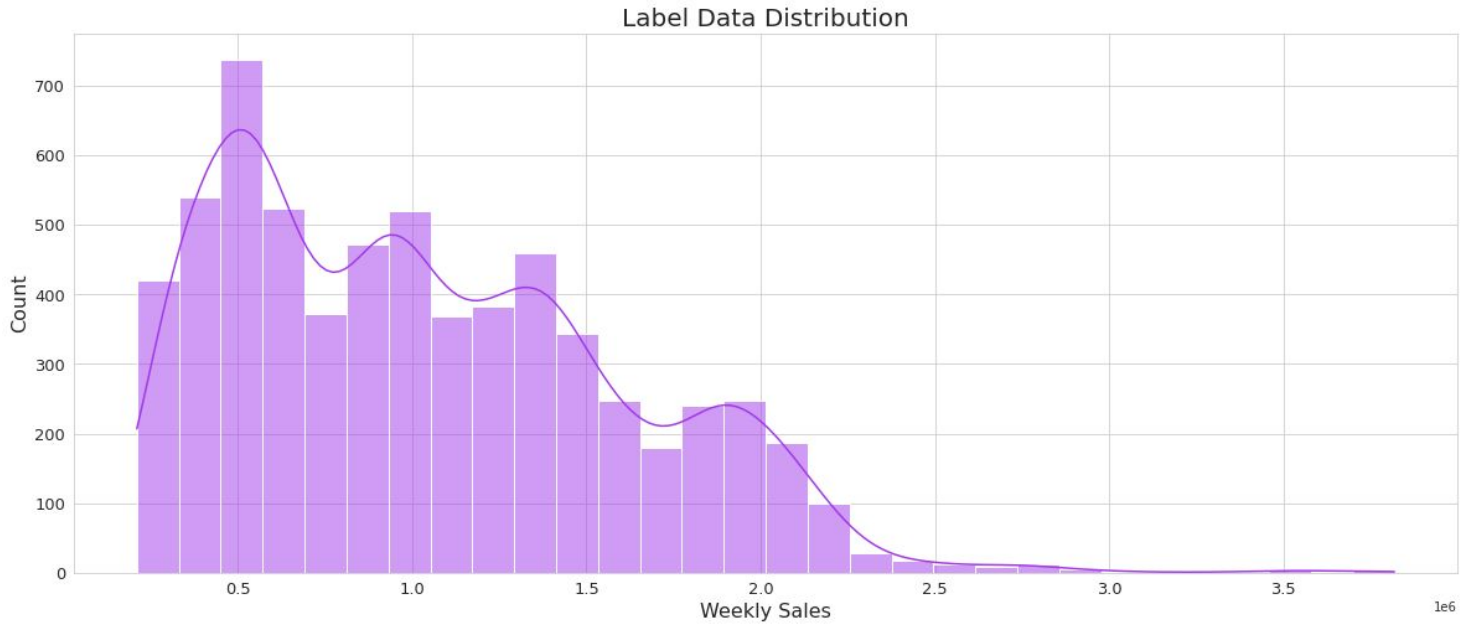
Model: Random Forest Regressor



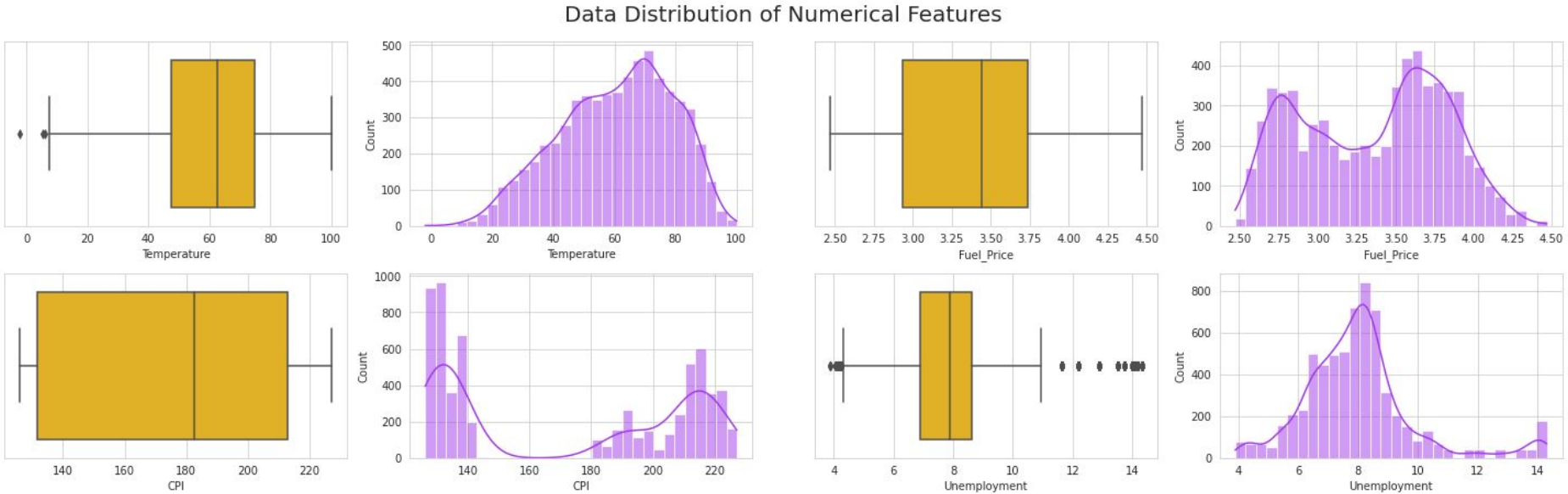
CRISP-DM Methodology



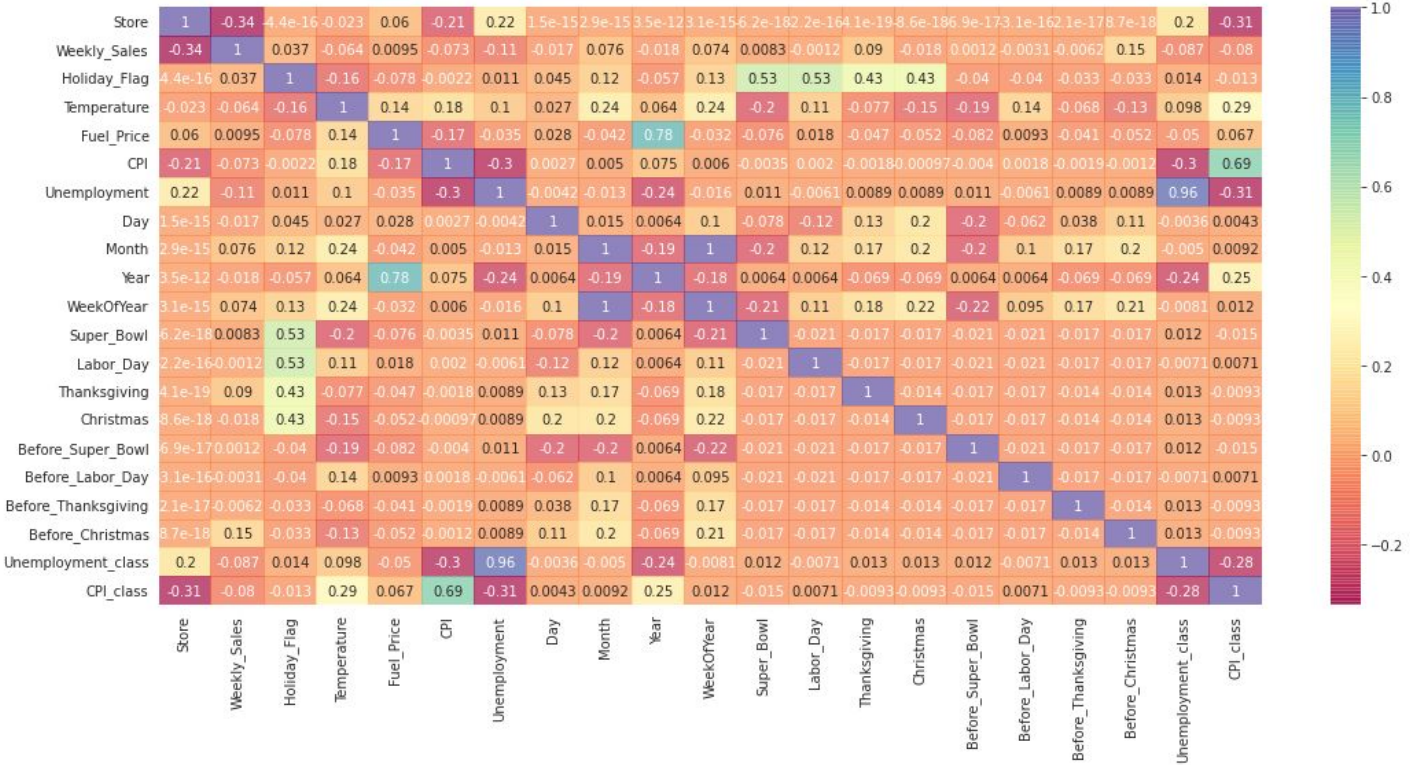
Univariate Analysis (Target)



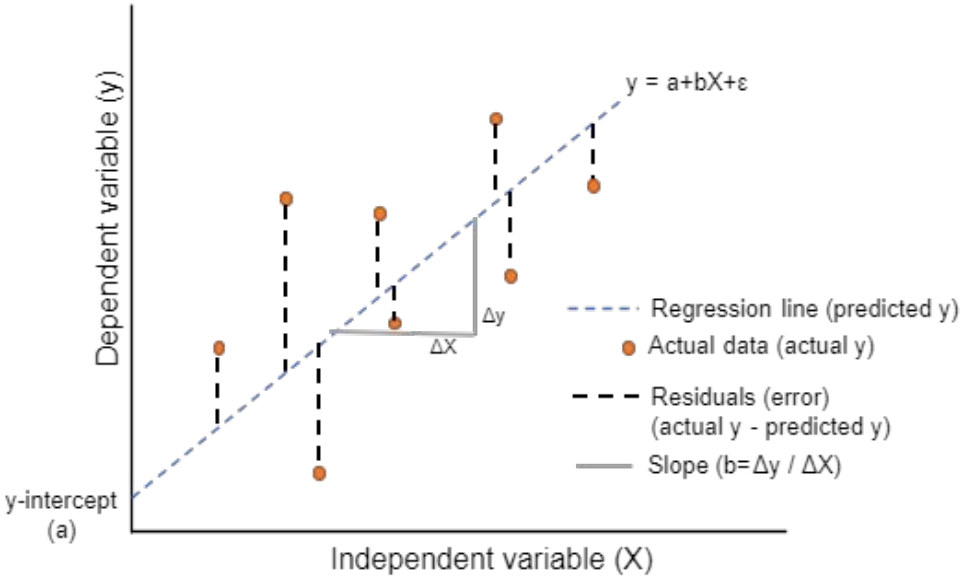
Univariate Analysis (Numerical)

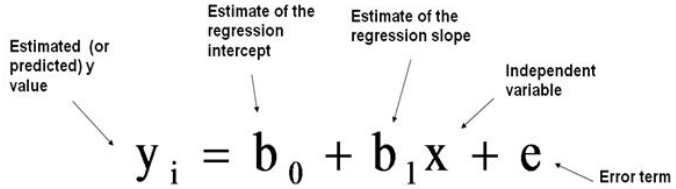


Correlation Matrix

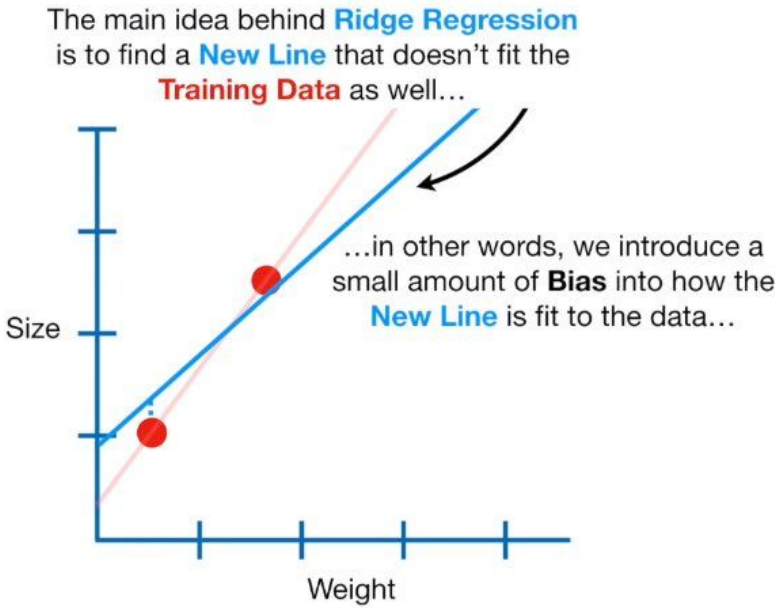


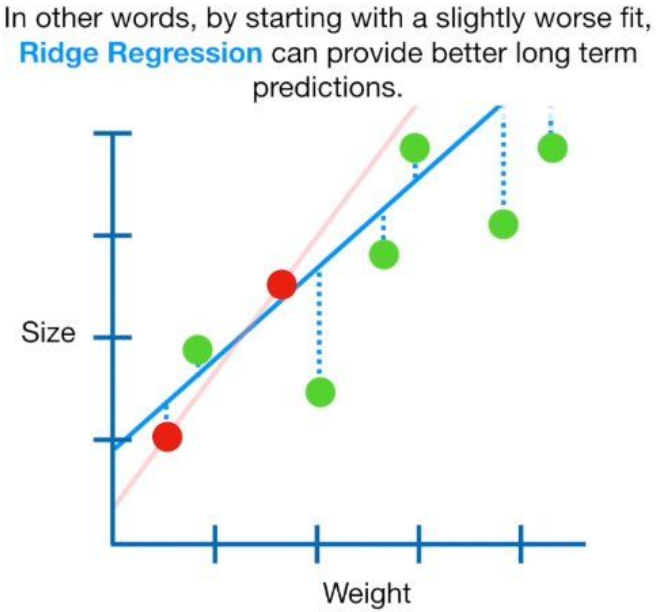
Linear Regression Explained



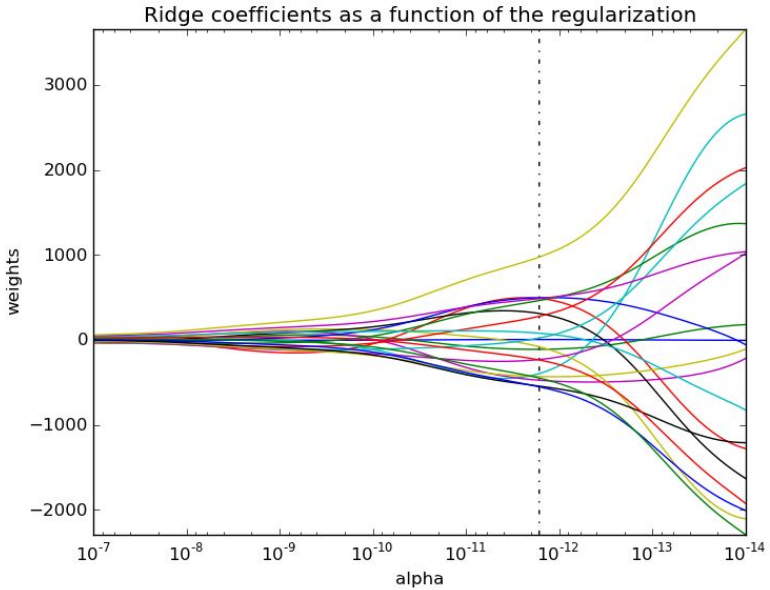


Ridge Regression Explained

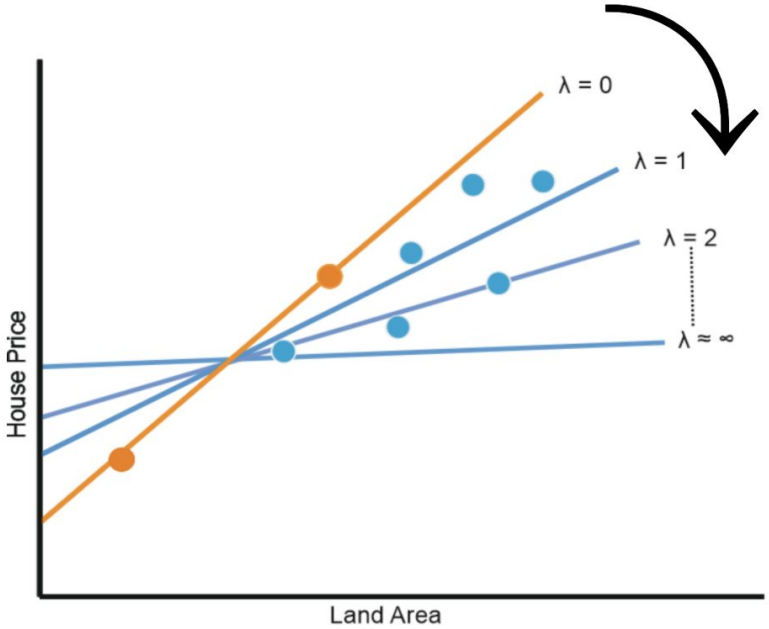




Ridge Regression Explained



Lasso Explained



Lasso Explained

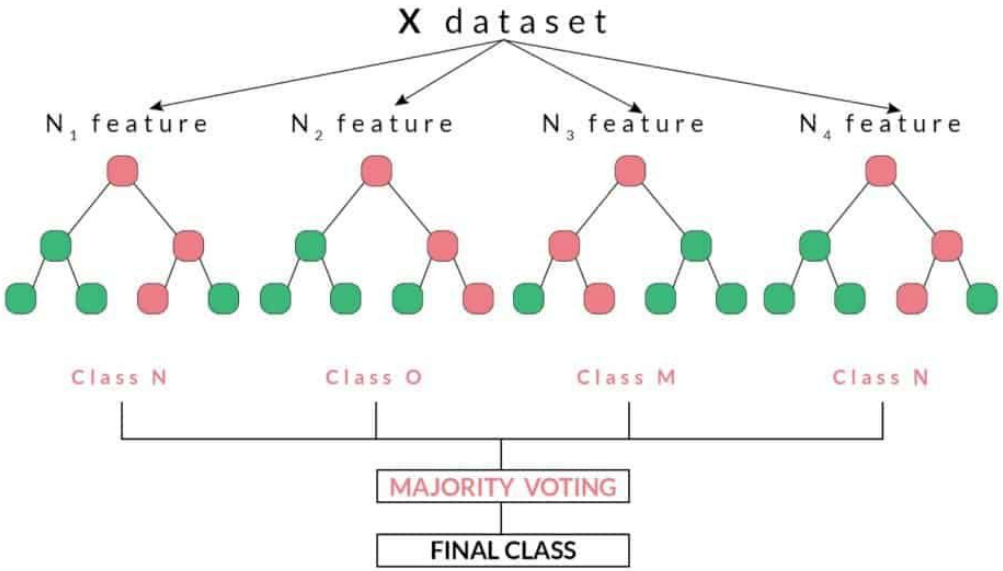
Base model dari Lasso memiliki *performance* yang bisa dibilang buruk. Dataset yang kita olah memiliki banyak *categorical predictor* seperti Store, Holiday_Flag, Month, Week, WeekOfYear, Day, dan yang lainnya. Berdasarkan hasil *feature importance* yang didapatkan dari koefisien regresor, pada dataset ini *numerical predictor* justru memiliki nilai *importance* yang sangat rendah dibandingkan *categorical predictor*.

Algoritma Lasso dari ScikitLearn sepertinya tidak bisa menangani masalah ini karena Lasso memberikan nilai *penalty* terhadap fitur yang memiliki kontribusi minor sehingga koefisiennya mendekati/menjadi nol [[1]], sedangkan untuk *categorical predictor* yang telah di-encode akan terpecah menjadi beberapa variabel (Contoh: fitur "Store" akan menjadi "Store_1", "Store_2", ... "Store N") dan tidak masuk akal untuk mengambil sebagian variabel saja dari *categorical predictor*. Misalnya, setelah diketahui nilai koefisiennya, "Store_27" dan "Store_31" tidak diberikan penalti karena memiliki kontribusi lebih besar, tetapi "Store _44" memiliki kontribusinya yang sangat kecil sehingga Lasso memberi penalti dengan menjadikan koefisiennya 0, padahal tidak bisa begitu karena mereka merupakan satu kesatuan dan seharusnya seluruh fitur-fitur yang telah di-encode dari fitur "Store" diambil semua atau tidak dipakai semua) sehingga diperlukan *treatment* khusus (modifikasi Lasso) untuk masalah seperti ini. [2] [3]. Sementara, untuk alasan mengapa Lasso memiliki *performance* yang baik pada dataset tanpa *feature scaling* belum kami temukan karena berdasarkan sumber yang ada Lasso seharusnya memiliki *performance* yang baik jika skala datanya sama [[4]](https://stats.stackexchange.com/questions/86434/is-standardisation-before-lasso-really-necessary).

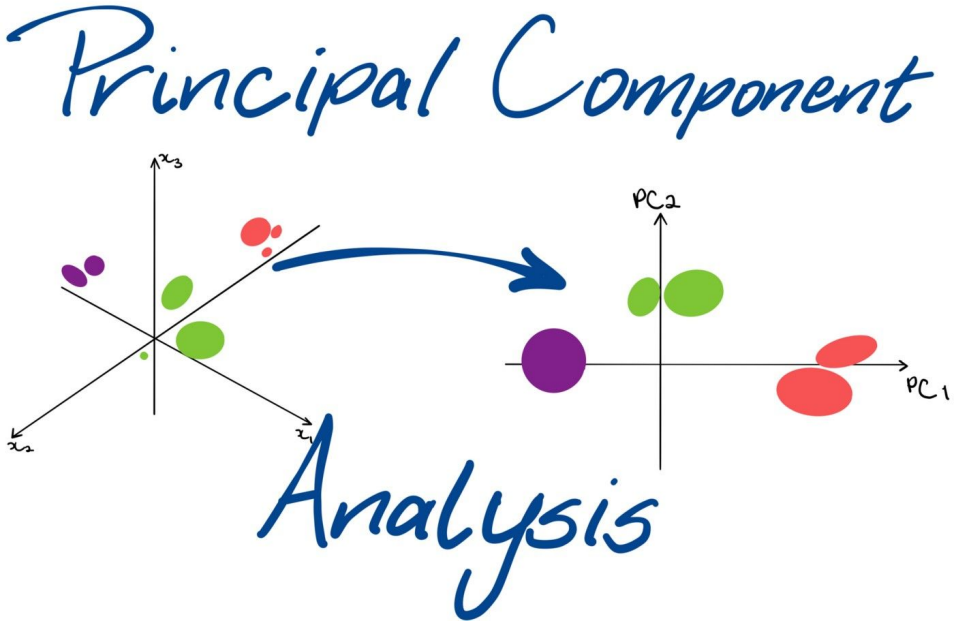
Lasso Explained

Sementara setelah dilakukan hyperpameter tuning, dengan alpha yang mendekati 0, **performance** model langsung meningkat karena semakin kecil alpha maka semakin kecil penalti yang diberikan oleh Lasso. Berdasarkan dokumentasi dari Scikit Learn [[5]](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html), jika nilai alpha di-set mendekati atau sama dengan nol, maka cara kerja Lasso secara esensinya sama saja dengan Linear Regression standard karena efek penalti yang diberikan hampir tidak ada. Oleh karena itu saat tuning dengan alpha mendekati 0, **performance** model baik nilai R2 score dan NRMSE-nya langsung berubah drastis.

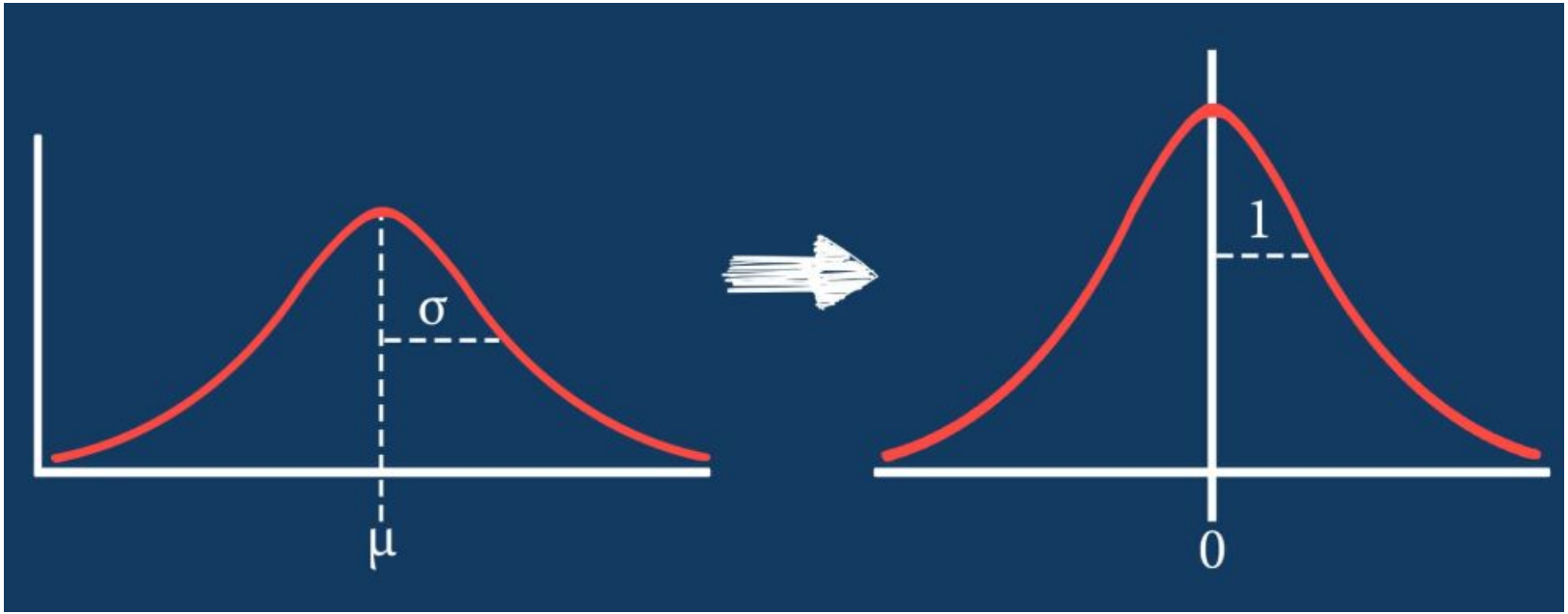
Random Forest Explained



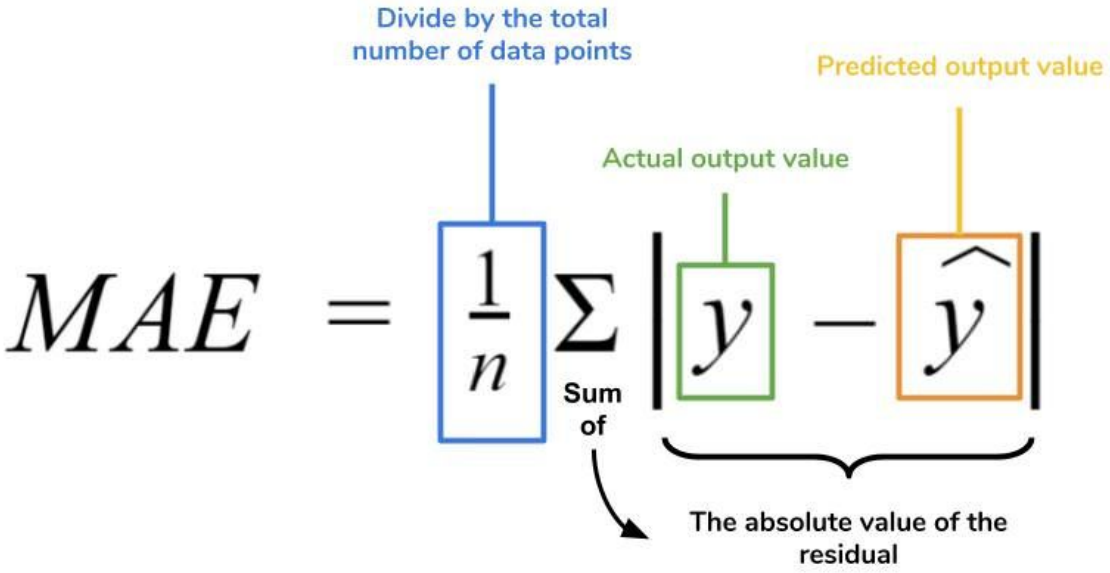
Principal Component Analysis



Standardization



Evaluation Metric: MAE (Mean Absolute Error)



Evaluation Metric: MSE (Mean Squared Error)

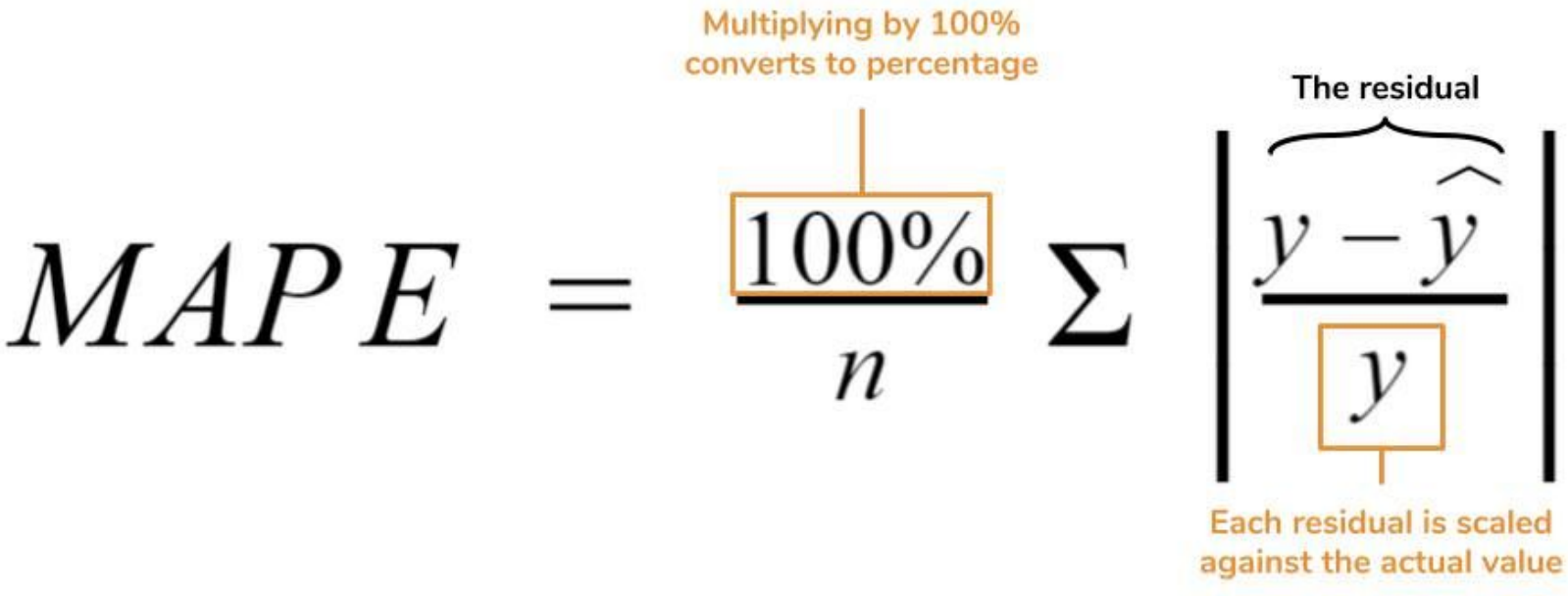
$$MSE = \frac{1}{n}\Sigma\underbrace{\left(y - \hat{y}\right)}^{2}$$

The square of the difference between actual and predicted

Evaluation Metric: RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

Evaluation Metric: MAPE (Mean Absolute Percentage Error)



Evaluation Metric: NRMSE (Normalized Root Mean Squared Error)

$$NRMSE = \frac{RMSE}{mean(y)} \quad OR \quad NRMSE = \frac{RMSE}{y_{max} - y_{min}}$$

Evaluation Metric: R2-Score

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2}$$

Feature Selection & Decomposition

- **Recursive Feature Elimination (RFE)**
  menyeleksi fitur berdasarkan estimator secara rekursif

- **Principal Component Analysis (PCA)**
  mereduksi fitur dengan melakukan kombinasi berdasarkan nilai varians