Mastering Preprocessing Data

Data Engineering Week 4

25 Mei 2023

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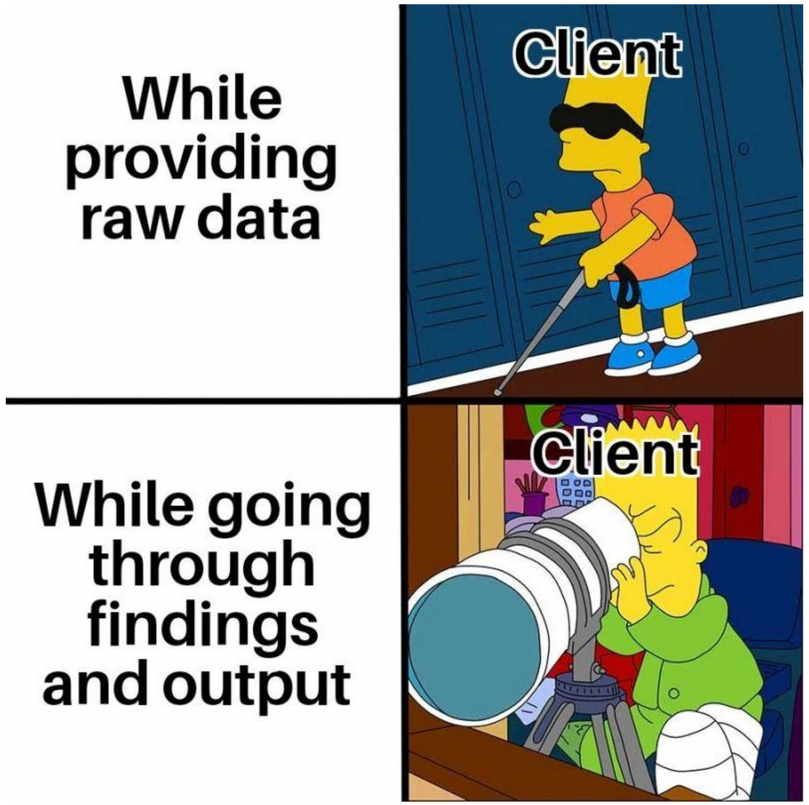
What ~~you~~ we will learn

1. What is Data Preprocessing
2. Why Preprocess Data?
3. What is Data Quality?
4. Dimensions of Data Quality
5. Data Preprocessing Pillar
6. Data Preprocessing Steps
7. Data Preprocessing Best Practices
8. Importance of Data Preprocessing
9. Data Preprocessing Hands On
10. Data Preprocessing in Machine Learning Competition

What is Data Preprocessing

Data preprocessing is a **critical step** in the data science **process**, and it often **determines** the **success** or **failure** of a **project**.

Real-world data are highly susceptible to noisy, missing, and inconsistent data due to their typically huge size and their likely origin from multiple, heterogenous sources



Why Preprocess the Data?

The **goal** of preprocessing data is to **ensure data quality**. Low-quality data will **lead** to low-quality mining results.

What is Data Quality

Data quality **measures** how **well** a **dataset** meets **criteria**. There are many factors comprising data quality.

These include:

1. Accuracy
2. Completeness
3. Consistency
4. Uniqueness
5. Timeliness
6. Validity
7. Integrity
8. Precision
9. Currency
10. Conformity

Dimensions of Data Quality

- **Accuracy**

  This dimension refers to the correctness of the data values based on the agreed upon "source of truth." it's important to designate a primary data source; other data sources can be used to confirm the accuracy of the primary one.

- **Completeness**

  This represents the amount of data that is usable or complete. If there is a high percentage of missing values, it may lead to a biased or misleading analysis if the data is not representative of a typical data sample.

- **Consistency**

  Consistent data can be explained as how close your data aligns or is in uniformity with another dataset. Using different sources to check for consistent data trends and behavior.

- **Uniqueness**

  The occurrence of an object or an event gets recorded multiple times in a dataset. For example, when reviewing customer data, you should expect that each customer has a unique customer ID.

- **Timeliness**

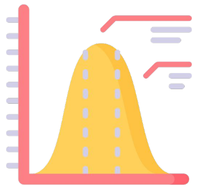
  This dimension refers to the readiness of the data within an expected time frame. For example, customers expect to receive an order number immediately after they have made a purchase, and that data needs to be generated in real-time.

- **Validity**

  How much data matches the required format for any business rules. Formatting usually includes metadata, such as valid data types, ranges, patterns, and more.

Data Preprocessing Pillar

Data Cleaning



Data Transformation

Data Reduction

Data Integration

Data Augmentation

Data Cleaning

This involves **detecting** and rectifying errors, **inconsistencies**, and **anomalies** within the dataset.

Common techniques include **handling missing values**, **removing duplicates**, and **correcting inaccuracies/ outlier**.

	Nama	Usia	Negara Asal	Kapal	Jumlah Harta Karun (USD)
0	Blackbeard	45.0	England	Queen Anne"s Revenge	500000.0
1	Anne Bonny	32.0	Ireland	Unknown	300000.0
2	Jack Sparrow	NaN	Caribbean	Black Pearl	1000000.0
3	Barbarossa	55.0	Spain	Queen Anne"s Revenge	700000.0
4	Ghost	10000.0	None	Unknown	NaN
5	Anne Bonny	32.0	Ireland	Unknown	300000.0

Handling Missing Values

Type of Missing Values

- Missing Completely At Random (MCAR)
  This type of missing data is purely random and lacks any discernible pattern.
  ex: data yang hilang mungkin terjadi karena masalah teknis saat memasukkan data survei, seperti kegagalan sistem komputer.

- Missing at Random (MAR)
  There is a pattern in the missing values, but this pattern can be explained by other observed variables.
  ex: Data kesehatan mental yang hilang hanya berasal dari responden berusia lanjut tanpa hubungan langsung dengan status kesehatan mental.

- Missing Not At Random (MNAR)
  This type of missing data has a specific pattern that cannot be explained by observed variables.
  ex: responden dengan gaji tinggi enggan memberikan informasi gaji dalam survei, mempengaruhi keberadaan data yang hilang

Understanding the type of missing data is crucial because it determines the appropriate strategy for handling missing values and ensuring the integrity of statistical analyses.

How to Handle

1. Deletion

   This involves removing rows or columns with missing values.
   This is a straightforward method, but it can be problematic if a significant portion of your data is missing.

2. Imputation
   - **Mean/Median/Mode**
     values can be replaced with the mean, median, or mode of remaining values in the column.
   - **Last/Baseline Observation Carried Forward (L/B-OCF)**
     the last/first known value from the same subject is used to fill in missing values for subsequent observations.
   - **Prediction of Missing Value**
     - **KNN Imputer** (Univariate)
     - **Ittereative Imputer** (Multi Variate)
     - **Deep Learning Library** (Datawig)
   - **Constant Value (MCAR)**
     replace the missing values with the defined constant values
     ex: -9999, unknown

Handling Outliers

Type of Outlier

- Global Outliers (Point Anomalies)
  A value is considered a global outlier if it is far outside the entire data set in which it is found.
  ex: People with a height of 1 cm

- Conditional Outliers
  A value is considered a contextual outlier if the value is within a certain context, but not as a whole.
  ex: People with a height of 215 cm (possible, but rare in Asia)

- Collective Outliers
  Subset of data points deviating significantly from the overall pattern without individual anomalies.
  ex: Sales data for stores with stable sales patterns that suddenly have significantly different total sales on a particular day,

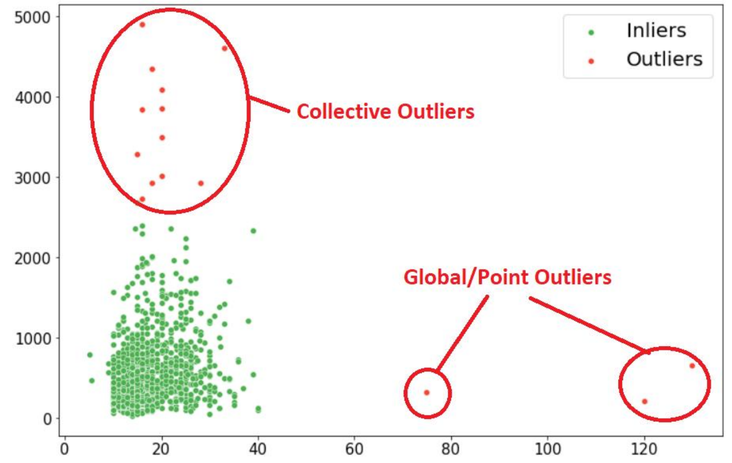
How to Detect an Outlier

- IQR Method
- Z-Score Method
- Boxplot Analysis

If outliers have been identified, the next thing that needs to be done is to determine whether the identified data needs to be deleted, modified, or used as new insight in data analysis. Consider Dataset Size & Existence of Influential Observations (Model/ Analysis) Result

How to Handle Outlier

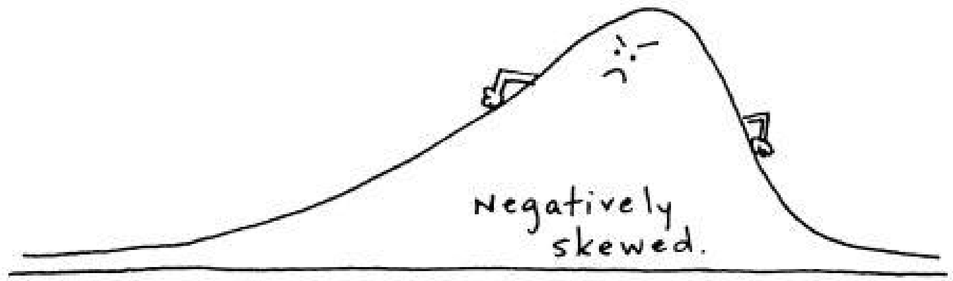
- Remove Outlier
- Change the Scale (Normalization)
- Imputation
  - Quantile Based Flooring and Capping (Define min/max threshold)
  - Mean/Median/Mode

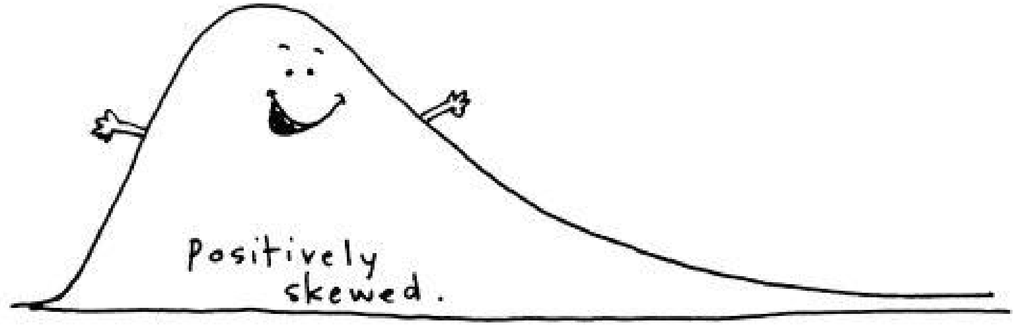


Data Transformation

Data often comes in various formats and scales, necessitating standardisation or normalisation to ensure uniformity and comparability across features.

Transformation techniques such as **scaling**, e**ncoding categorical variables**, and **feature engineering** play a pivotal role in this stage.





	Nama	Umur	Tanggal Lahir	Gaji	Aktif	Penilaian	Review Date	Kode Pos
0	Andi	23	2000-05-17	5000000	True	3.9	2022-04-01 11:24:41.075660	12345
1	Budi	30	1993-08-25	7000000	False	4.2	2021-05-17 11:24:41.076756	67890
2	Citra	25	1998-03-14	6000000	True	4.5	2016-09-27 11:24:41.076756	54321
3	Dewi	22	2001-01-30	5500000	True	3.8	2015-12-26 11:24:41.076756	09876
4	Eka	28	1995-06-05	6500000	False	4.0	2011-06-09 11:24:41.076756	11223

Data Transformation

Numeric Transformation

- Normalisation

  Scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1.
  change num values to maintain a consistent scale without distorting differences or losing information.
- Scaling

  Scaling is a method used to normalise the range of independent variables or features of data within a particular range.
  scaling doesn't necessarily preserve the original distribution or relative differences between values.
- Binning

  Binning is used for the transformation of a continuous or numerical variable into a categorical feature.
  It helpfull, but the bin sizes need to be chosen correctly.

Encoding Categorical

- One-Hot Encoding

	warna
0	merah
1	hijau
2	biru
3	merah
4	biru

biru	hijau	merah
0.0	0.0	1.0
0.0	1.0	0.0
1.0	0.0	0.0
0.0	0.0	1.0
1.0	0.0	0.0

- Label Encoding

```
['merah', 'hijau', 'biru', 'merah', 'biru']
[2 1 0 2 0]
```

- Ordinal Encoding

```
# Definisikan urutan kategori
urutan_kategori = ['merah', 'hijau', 'biru']
kategori = ['merah', 'hijau', 'biru', 'merah', 'biru']
kategori_array = np.array(kategori).reshape(-1, 1)

# Buat objek OrdinalEncoder dengan spesifikasi urutan
ordinal_encoder = OrdinalEncoder(categories=[urutan_kategori])

# Terapkan Ordinal Encoding pada data kategori
kategori_ordinal_encoded = ordinal_encoder.fit_transform(kategori_array)
```

Feature Engineering

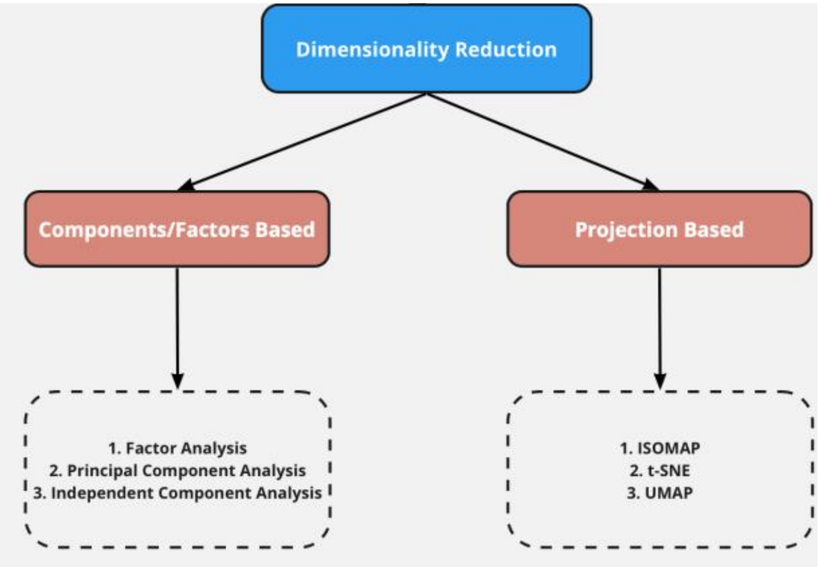
Process for developing and selecting features or attributes that will be used to carry out data analysis or create a machine learning model.

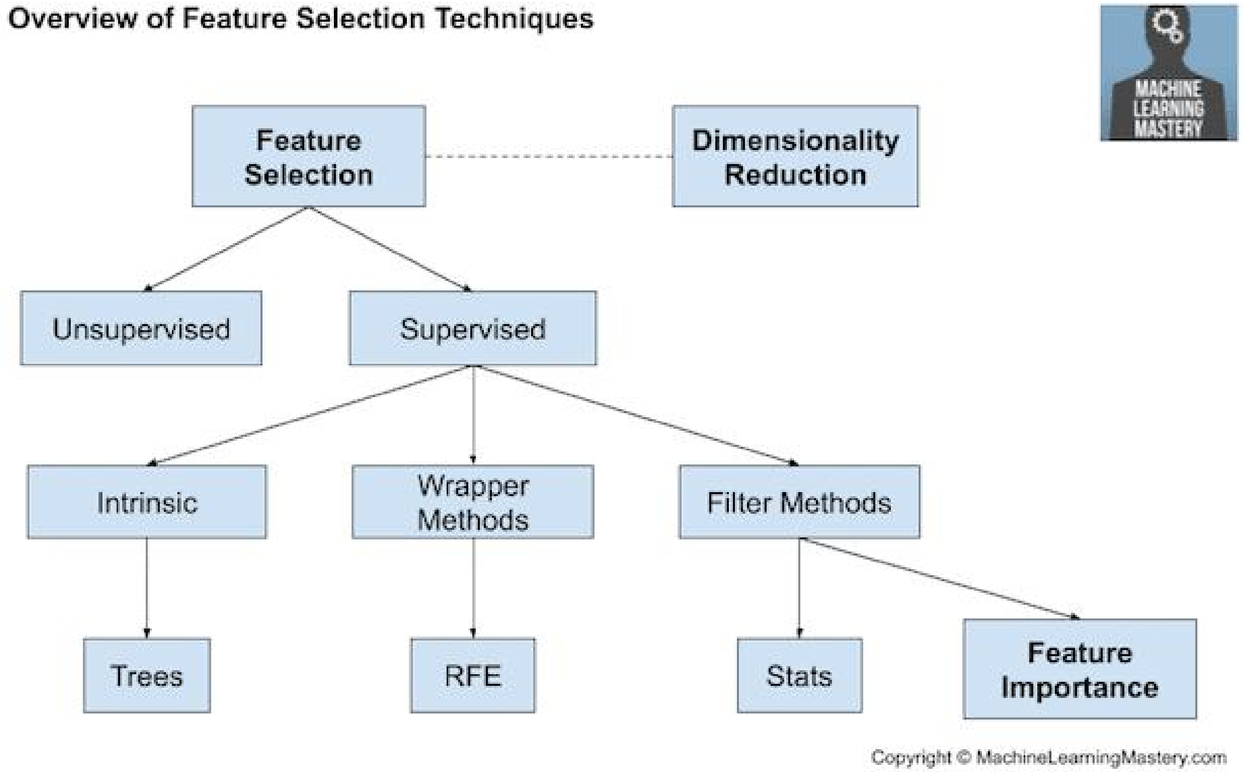
belanja_buah	belanja_daging	belanja_ikan	belanja_kue
50575.0	260967.0	50575.0	20230.0
6069.0	44506.0	80920.0	20230.0
117611.0	265460.0	96341.0	145573.0
206346.0	1613901.0	27725.0	125868.0
90563.0	311757.0	40358.0	33875.0

Data Reduction

In instances where the dataset is excessively large or contains redundant features.

data reduction techniques like dimensionality reduction or feature selection can streamline the dataset without sacrificing critical information.





feature importance

recursive feature elimination

chi square
fisher score

information gain

Data Integration

Integrate data from multiple sources or datasets by combining them based on common identifiers or keys, ensuring consistency and completeness in the merged dataset.

	tanggal	ot	eventID	datetime	latitude	longitude
0	2008-11-01	00:31:25.143	bmg2008vkye	2008-11-01 00:31:25.143741+00:00	-0.604440	98.895531
1	2008-11-01	01:34:29.660	bmg2008vlag	2008-11-01 01:34:29.660856+00:00	-6.611860	129.387220
2	2008-11-01	01:38:14.802	bmg2008vlaj	2008-11-01 01:38:14.802129+00:00	-3.650586	127.990680
3	2008-11-01	02:20:05.909	bmg2008vlbt	2008-11-01 02:20:05.909515+00:00	-4.198925	128.097000
4	2008-11-01	02:32:18.756	bmg2008vlcd	2008-11-01 02:32:18.756155+00:00	-4.091891	128.200470

latitude	longitude	magnitude	mag_type	depth_y	phasecount	azimuth_gap	location
-0.604440	98.895531	2.989742	MLv	20	6.0	146.70738	Southern Sumatra, Indonesia
-6.611860	129.387220	5.507549	mb	30	62.0	45.46764	Banda Sea
-3.650586	127.990680	3.539674	MLv	5	4.0	331.97404	Seram, Indonesia
-4.198925	128.097000	2.424314	MLv	5	5.0	326.37993	Banda Sea
-4.091891	128.200470	2.410045	MLv	10	5.0	314.65474	Banda Sea

	Unnamed: 0	eventID	datetime	latitude	longitude	magnitude	mag_type	depth	phasecount	azimuth_
0	0	bmg2008vkye	2008-11-01 00:31:25.143741+00:00	-0.604440	98.895531	2.989742	MLv	20	6.0	146.70
1	1	bmg2008vlag	2008-11-01 01:34:29.660856+00:00	-6.611860	129.387220	5.507549	mb	30	62.0	45.46
2	2	bmg2008vlaj	2008-11-01 01:38:14.802129+00:00	-3.650586	127.990680	3.539674	MLv	5	4.0	331.97
3	3	bmg2008vlbt	2008-11-01 02:20:05.909515+00:00	-4.198925	128.097000	2.424314	MLv	5	5.0	326.37
4	4	bmg2008vlcd	2008-11-01 02:32:18.756155+00:00	-4.091891	128.200470	2.410045	MLv	10	5.0	314.65

	tgl	ot	lat	lon	depth	mag	remark	strike1	dip1	rake1	strike2	dip2	rake2
0	2008/11/01	21:02:43.058	-9.18	119.06	10	4.9	Sumba Region - Indonesia	NaN	NaN	NaN	NaN	NaN	NaN
1	2008/11/01	20:58:50.248	-6.55	129.64	10	4.6	Banda Sea	NaN	NaN	NaN	NaN	NaN	NaN
2	2008/11/01	17:43:12.941	-7.01	106.63	121	3.7	Java - Indonesia	NaN	NaN	NaN	NaN	NaN	NaN
3	2008/11/01	16:24:14.755	-3.30	127.85	10	3.2	Seram - Indonesia	NaN	NaN	NaN	NaN	NaN	NaN
4	2008/11/01	16:20:37.327	-6.41	129.54	70	4.3	Banda Sea	NaN	NaN	NaN	NaN	NaN	NaN

Data Augmentation

Generate synthetic samples or variations of existing data instances to augment the dataset, particularly in scenarios with limited data availability, to enhance model robustness and generalisation.

Tabular

- Smote (Synthetic Minority Over-sampling Tehnique)
- Random Sampling

Image

- Change Contras/ Rotation/ Brightness etc (modified image property)

Text

- Retrieval Augmented Generation (RAG)

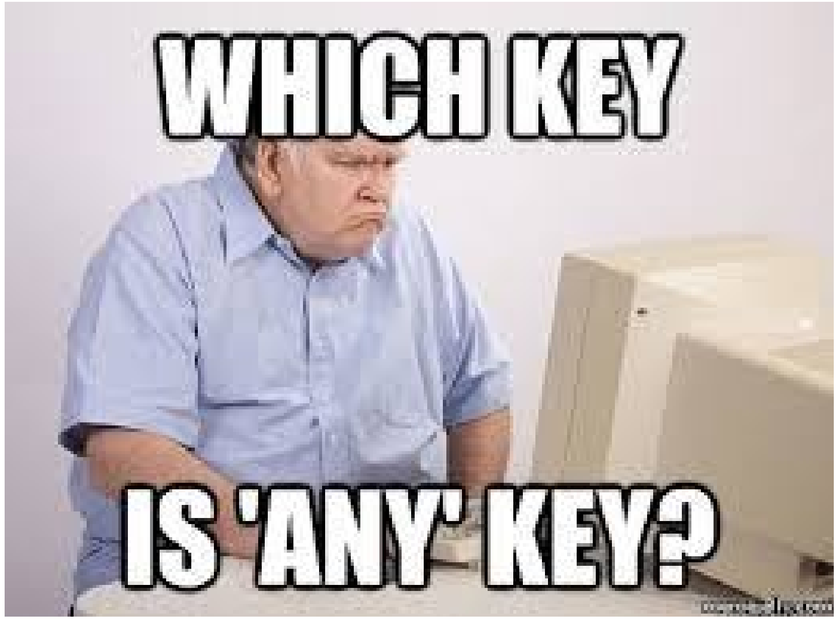
Key of Data Processing

- **Data Understanding**
  - Type of Data
  - Structure
  - Features
  - Potential Issues

- **Trial and Errors**

  Try any method you know and choose the best result

But when you understand the characteristics of each existing data preprocessing technique, you can save more time than trying repeatedly which wastes a lot of time



Refference

https://www.analyticsvidhya.com/blog/2021/10/handling-missing-value/

https://www.kaggle.com/discussions/general/451606

https://www.analyticsvidhya.com/blog/2021/05/detecting-and-treating-outliers-treating-the-odd-one-out/

https://towardsdatascience.com/outliers-analysis-a-quick-guide-to-the-different-types-of-outliers-e41de37e6bf6d

https://medium.com/@vikakbary/outlier-definition-classification-handling-461037eb18be

https://towardsdatascience.com/7-ways-to-handle-missing-values-in-machine-learning-1a6326adf79e

https://www.analyticsvidhya.com/blog/2020/08/types-of-categorical-data-encoding/

https://medium.com/@myskill.id/feature-engineering-327d64277211

https://www.analyticsvidhya.com/blog/2020/10/feature-selection-techniques-in-machine-learning/

https://www.analyticsvidhya.com/blog/2020/08/types-of-categorical-data-encoding/

https://timespro.com/blog/what-is-data-processing-know-the-importance-and-best-practices

https://medium.com/analytics-vidhya/data-augmentation-for-tabular-data-f75c94398c3e

https://www.blog.trainindata.com/mastering-data-preprocessing-techniques/

https://www.analyticsvidhya.com/blog/2021/05/feature-transformations-in-data-science-a-detailed-walkthrough/

https://medium.com/analytics-vidhya/a-guide-to-data-transformation-9e5fa9ae1ca3

Importance of Data Pre-processing

- **Ehanced Data Quality**

  Raw data often contains errors, inconsistencies, and missing values that can distort analysis and lead to erroneous conclusions. Data preprocessing addresses these issues, ensuring the dataset is clean, accurate, and anomalies-free.

- **Improved Model Performance**

  High-quality data is indispensable for training accurate and robust machine learning models. By preprocessing the data to remove noise, outliers, and irrelevant features, the model can focus on learning meaningful patterns

- **Facilitates Feature Engineering**

  Feature engineering, the process of selecting, extracting, or creating relevant features from the raw data, is a crucial aspect of model development. Data preprocessing lays the groundwork for effective feature engineering by standardising, transforming, and encoding the features to make them suitable for analysis and model training.

- **Mitigates Overfitting and Underfitting**

  Overfitting and underfitting in machine learning result from a mismatch between model complexity and available data. Data preprocessing helps balance this by ensuring models are trained on representative, well-structured datasets, reducing these risks.

- **Enables Data Exploration and Visualizations**

  Preprocessed data is more amenable to exploratory data analysis and data visualisation, allowing data scientists to gain valuable insights into the underlying patterns, trends, and relationships within the data, visualising preprocessed data aids in identifying outliers, detecting correlations, and informing subsequent modelling decisions.

Let’s Hands On

Penugasan

Dari hasil scraping data kemarin, lakukan preprocessing data, sebutkan langkah apa saja yang dilakukan dan apa yang jadi dasaran dalam melakukannya

output: .ipynb, raw.csv, cleaned.csv

kelompok: sama seperti case web scraping

Deadline: 1 Juni 2024

Absensi

https://s.id/mdp-w4

Feedback Form

https://s.id/ff-de23

Quote

”Don't compare yourself with other people; compare yourself with who you were yesterday.”

– Jordan Peterson

Thank you