Data Inputation Techniques

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1 Mean/Median Imputation

Mean or median imputation replaces missing values in a data set with the mean (average) or median (middle value) of the missing values for the corresponding value. This process is simple and easy to use, but it can affect the change of data, especially if missing values are not distributed.

1.1 Advantages

Ease of Implementation
 Requires minimum computation and no complex algorithms.
 Fast Execution
 Suitable for lagre dataset

1.2 Disadvantages

Reduction in Variability

1.3 Case Study

Consider a dataset with missing values in the 'Blood Pressure' and 'Cholesterol' columns. We will demonstrate mean and median imputation using Python.

1.4 code

import pandas as pd import numpy as np # Sample data creation data = 'Age': [25, 30, 22, 28, 35, 40], 'Blood Pressure': [120, 130, np.nan, 140, np.nan, 135], 'Cholesterol': [200, np.nan, 180, 190, np.nan, 210]

```
df = pd.DataFrame(data)
print("Original Data:")
print(df)
# Mean Imputation
df_m ean_i mputed = df.copy()
df_m ean_i mputed['BloodPressure'].fillna(df['BloodPressure'].mean(), inplace = fillna(df['BloodPressure'].mean(), inplace = fillna(df['BloodPressure'].me
df_mean_imputed['Cholesterol'].fillna(df['Cholesterol'].mean(),inplace = True)
print("afterMeanImputation:")
print(df_mean_imputed)
                     Median Imputation
df_m edian_i mputed = df.copy()
df_median_imputed['BloodPressure'].fillna(df['BloodPressure'].median(),inplace =
True)
df_median_imputed['Cholesterol'].fillna(df['Cholesterol'].median(),inplace = True)
print("afterMedianImputation:")
print(df_median_imputed)
```

2 Mode Imputation

Mode imputation involves replacing missing values in a dataset with the mode. This technique is generally used for categorical data but can also be used for numerical data when appropriate.

2.1 Advantages

Fast Execution
 Suitable for large dataset
 Ease of Implementation

2.2 Disadvantages

1. Not Suitable for All Data Types Less affective for numerical data 2. Reduction in Variability

2.3 Case Study

Consider a dataset with missing values in the 'Gender' and 'Smoker' columns. We will demonstrate mode imputation using Python.

2.4 code

```
import pandas as pd
import numpy as np
Sample data creatio
data =
'Age': [25, 30, 22, 28, 35, 40],
'Gender': ['Male', 'Female', np.nan, 'Female', 'Male', np.nan],
'Smoker': ['No', 'Yes', 'No', np.nan, 'Yes', np.nan]
df = pd.DataFrame(data)
print("Original Data:")
print(df)
# Mode Imputation
df_m ode_i mputed = df.copy()
\#Function to impute mode
defimpute_mode(series):
mode = series.mode()[0]
returnseries. fillna(mode)
   # Apply mode imputation
df_m ode_i mputed['Gender'] = impute_m ode(df['Gender'])
df_mode_imputed['Smoker'] = impute_mode(df['Smoker'])
print("afterModeImputation:")
print(df_mode_imputed)
```

3 K-Nearest Neighbors (KNN) Imputation

K-nearest neighbor (KNN) imputation is a method of imputing missing values by looking at the "k" closest points (neighbours) to missing data already in the feature space. Missing values are then imputed to the nearest neighbor's values

3.1 Advantages

1. Flexible

Can handle different types of data

2. Can capture non-linear relationships between features

3.2 Disadvantages

1. Scalability Issues

Not suitable for large dataset

3.3 Case Study

A real estate company want to develop a model to predict house prices based on various features such as size, no. of bedrooms, no. of bathrooms, etc. The dataset contains missing values in some features, which we need to handle to build a model.

3.4 code

```
# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
# Step 2: Load the dataset
data =
'Size': [2100, 1600, np.nan, 2400, 1800],
'Bedrooms': [3, np.nan, 4, 3, 2],
'Bathrooms': [2, 2, 3, 2, 1],
'Location': [1, 2, 3, np.nan, 2],
'Age': [10, 5, 8, 20, 15],
'Price': [500000, 350000, 450000, 600000, 400000]
df = pd.DataFrame(data)
   # Step 3: Preprocess the data
# Convert categorical variables to numerical format if necessary
# In this example, 'Location' is already numerical
# Standardize the data (excluding the target variable 'Price')
scaler = StandardScaler()
scaled_f eatures = scaler.fit_t ransform(df.drop('Price', axis = 1))
\#Step 4: Apply KNN Imputation
imputer = KNNImputer(n_n eighbors = 3)
imputed_data = imputer.fit_transform(scaled_features)
\#Convert the imputed databack to the original scale
imputed_data = scaler.inverse_transform(imputed_data)
\#Create a new Data Frame with the imputed data
imputed_d f = pd.DataFrame(imputed_data, columns = df.columns[: -1])
imputed_d f['Price'] = df['Price']
```

```
print("Original Data Frame with Missing Values:") \\ print(df) \\ print("after KNN Imputation:") \\ print(imputed_d f) \\ \#Step 5: Evaluate the result \\ \#For this case study, we simply print the before and after data. \\ \#In a real - world scenario, further analysis and modeling would follow.
```

4 Multiple Imputation by Chained Equations (MICE)

Multiple Imputation by Chained Equations (MICE) is a method for handling missing data by creating multiple complete datasets, each with a different imputed values. These datasets are then analyzed separately and the results are combined to create final estimate. This imputation process use chained equations which means each variable with missing values is imputed according to the model that includes other variables as predictors.

4.1 Advantages

- 1. Versatility
- It Can be applied to a wide range of data types and structures
- 2. Flexibility

4.2 Disadvantages

1. Complex

4.3 Case Study

Consider a healthcare dataset with missing values in the 'Age' and 'BMI' columns. We will demonstrate MICE imputation using Python.

4.4 code

```
\# Step 1: Import necessary libraries import pandas as pd import numpy as np from sklearn.experimental import enable iterative_i mputer \#noqa from sklearn.imputeimport Iterative Imputer
```

```
\#Step2: Load the data set \\ data = 'Age': [25, 45, np.nan, 35, 50], 'Gender': [1, 0, 1, 0, 1], 'BMI': [22.5, np.nan, 24.7, 26.8, np.nan], 'Blood F \\ df = pd. Data Frame (data) \\ \#Step3: Apply MICE Imputation \\ imputer = Iterative Imputer (max_iter = 10, random_state = 0) \\ imputed_data = imputer. fit_t rans form (df) \\ \#Convert the imputed data back to a Data Frame \\ imputed_df = pd. Data Frame (imputed_data, columns = df. columns) \\ \#Step4: Evaluate the result \\ print ("Original Data Frame with Missing Values:") \\ print (df) \\ print ("after MICE Imputation:") \\ print (imputed_df)
```

5 Regression Imputation

Regression imputation is a method of identifying missing values by using a regression mode to estimate missing values. In this method, the missing value of the variable is estimated based on the observed values of the other variables. These model uses the relationships between variables to produce imputed values that are consistent with the observed data.

5.1 Advantages

- 1. predictive Power
- It Can improve the quality of the dataset
- 2. Single Imputation

Reduces complexity

5.2 Disadvantages

1. Model Dependency

5.3 Case Study

Consider a dataset with missing values in the 'BMI' column. We will demonstrate regression imputation using Python.

5.4 code

```
# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model<sub>s</sub> election import train_t est_s plit
from sklear n. linear_model import Linear Regression
\#Step2: Load the dataset (assuming' data.csv' is your dataset file)
df = pd.read_csv('data.csv')
\#Step 3: Splitthe data set into training and test sets
\#Assume'BMI' is the column with missing values
train = df.dropna(subset = ['BMI'])Userowswhere'BMI'isnotNaN for training
test = df[df['BMI'].isnull()]Rowswithmissing'BMI'values for imputation
\#Separate features and target
X_t rain = train.drop(['BMI'], axis = 1)
y_t rain = train['BMI']
X_test = test.drop(['BMI'], axis = 1)
\#Step4: Trainare gression model on non-missing data
model = LinearRegression()
model.fit(X_train, y_train)
\#Step5: Predictmissing'BMI' values using the trained model
predicted_bmi = model.predict(X_test)
\#Step 6: Impute them is singular sin the original dataset
df.loc[df['BMI'].isnull(),'BMI'] = predicted_bmi
\#Step7: Evaluate the imputed dataset (optional)
print("Original Data Frame with Missing Values:")
print(df)
```

6 Github Link

https://github.com/Sakshamnandanwar/Assignment