

Imputing using fancyimpute

DEALING WITH MISSING DATA IN PYTHON



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fancyimpute package

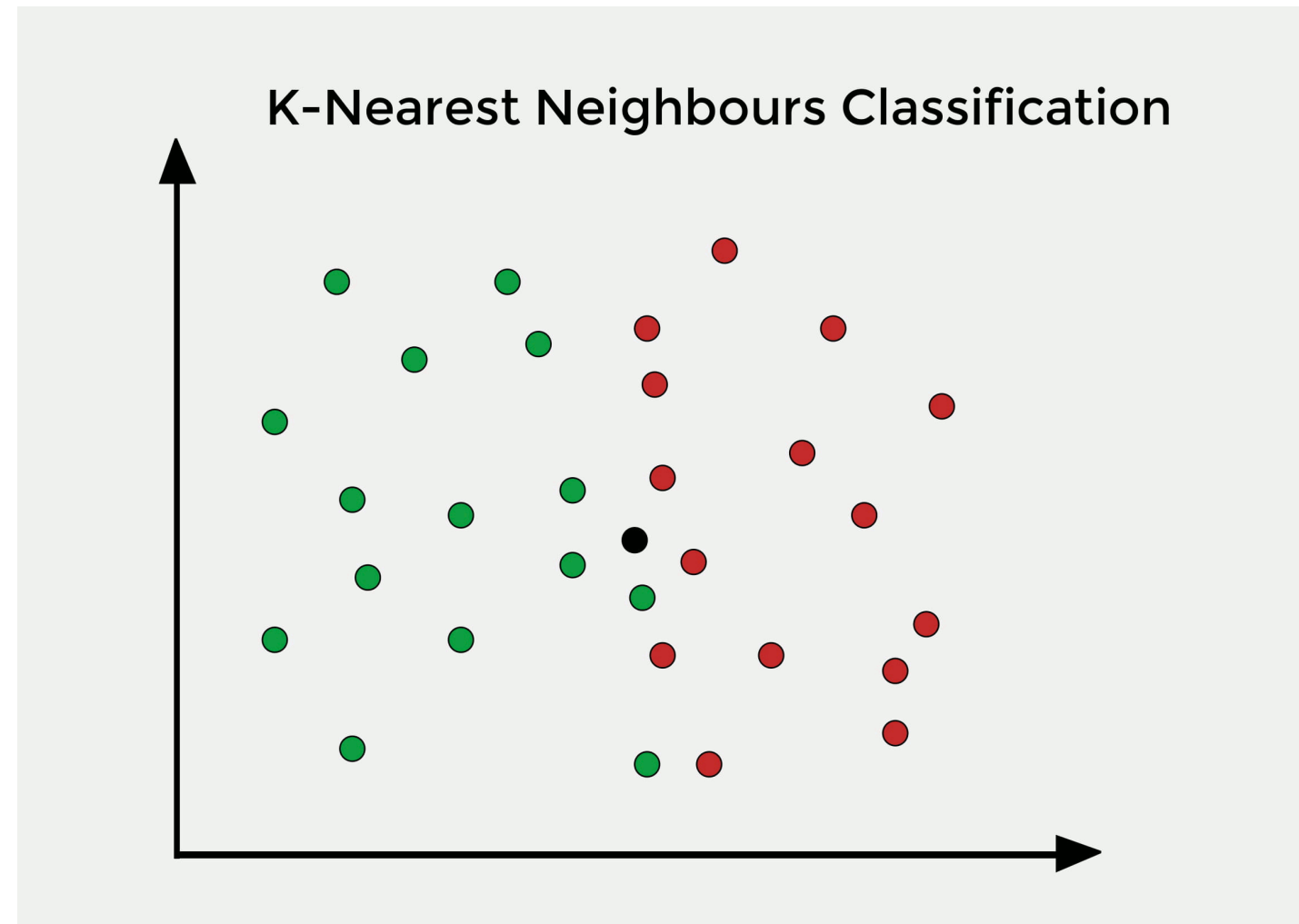
- Package contains advanced techniques
- Uses machine learning algorithms to impute missing values
- Uses other columns to predict the missing values and impute them

Fancyimpute imputation techniques

- KNN or K-Nearest Neighbor
- MICE or Multiple Imputation by Chained Equations

K-Nearest Neighbor Imputation

- Select K nearest or similar data points using all the non-missing features
- Take average of the selected data points to fill in the missing feature



K-Nearest Neighbor Imputation

```
from fancyimpute import KNN
knn_imputer = KNN()
diabetes_knn = diabetes.copy(deep=True)
diabetes_knn.iloc[:, :] = knn_imputer.fit_transform(diabetes_knn)
```

Multiple Imputations by Chained Equations (MICE)

- Perform multiple regressions over random sample of the data
- Take average of the multiple regression values
- Impute the missing feature value for the data point

Multiple Imputations by Chained Equations(MICE)

```
from fancyimpute import IterativeImputer  
  
MICE_imputer = IterativeImputer()  
diabetes_MICE = diabetes.copy(deep=True)  
diabetes_MICE.iloc[:, :] = MICE_imputer.fit_transform(diabetes_MICE)
```

Summary

- Using Machine Learning techniques to impute missing values
- KNN finds most similar points for imputing
- MICE performs multiple regression for imputing
- MICE is a very robust model for imputation

Let's practice!

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Imputing categorical values

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Complexity with categorical values

- Most categorical values are strings
- Cannot perform operations on strings
- Necessity to convert/encode strings to numeric values and impute

Conversion techniques

ONE-HOT ENCODER

Color	Color_Red	Color_Green	Color_Blue
Red	1	0	0
Green	0	1	0
Blue	0	0	1
Red	1	0	0
Blue	0	0	1
Blue	0	0	1

ORDINAL ENCODER

Color	Value
Red	0
Green	1
Blue	2
Red	0
Blue	2
Blue	2

Imputation techniques

- Fill with most frequent category
- Impute using statistical models like KNN

Users profile data

```
users = pd.read_csv('userprofile.csv')
users.head()
```

	smoker	drink_level	dress_preference	ambience	hijos	activity	budget
0	False	abstemious	informal	family	independent	student	medium
1	False	abstemious	informal	family	independent	student	low
2	False	social drinker	formal	family	independent	student	low
3	False	abstemious	informal	family	independent	professional	medium
4	False	abstemious	no preference	family	independent	student	medium

Ordinal Encoding

```
from sklearn.preprocessing import OrdinalEncoder

# Create Ordinal Encoder
ambience_ord_enc = OrdinalEncoder()

# Select non-null values in ambience
ambience = users['ambience']
ambience_not_null = ambience[ambience.notnull()]
reshaped_vals = ambience_not_null.values.reshape(-1, 1)

# Encode the non-null values of ambience
encoded_vals = ambience_ord_enc.fit_transform(reshaped_vals)

# Replace the ambience column with ordinal values
users.loc[ambience.notnull(), 'ambience'] = np.squeeze(encoded_vals)
```

Ordinal Encoding

```
# Create dictionary for Ordinal encoders
ordinal_enc_dict = {}

# Loop over columns to encode
for col_name in users:
    # Create ordinal encoder for the column
    ordinal_enc_dict[col_name] = OrdinalEncoder()

    # Select the non-null values in the column
    col = users[col_name]
    col_not_null = col[col.notnull()]
    reshaped_vals = col_not_null.values.reshape(-1, 1)

    # Encode the non-null values of the column
    encoded_vals = ordinal_enc_dict[col_name].fit_transform(reshaped_vals)
```


Imputing with KNN

```
users_KNN_imputed = users.copy(deep=True)

# Create MICE imputer
KNN_imputer = KNN()

users_KNN_imputed.iloc[:, :] = np.round(KNN_imputer.fit_transform(imputed))

for col in imputed:
    reshaped_col = imputed[col].values.reshape(-1, 1)
    users_KNN_imputed[col] = ordinal_enc[col].inverse_transform(reshaped_col)
```

Summary

Steps to impute categorical values

- Convert non-missing categorical columns to ordinal values
- Impute the missing values in the ordinal DataFrame
- Convert back from ordinal values to categorical values

Let's practice!

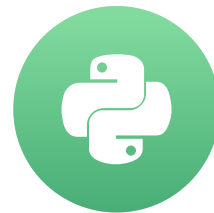
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Evaluation of different imputation techniques

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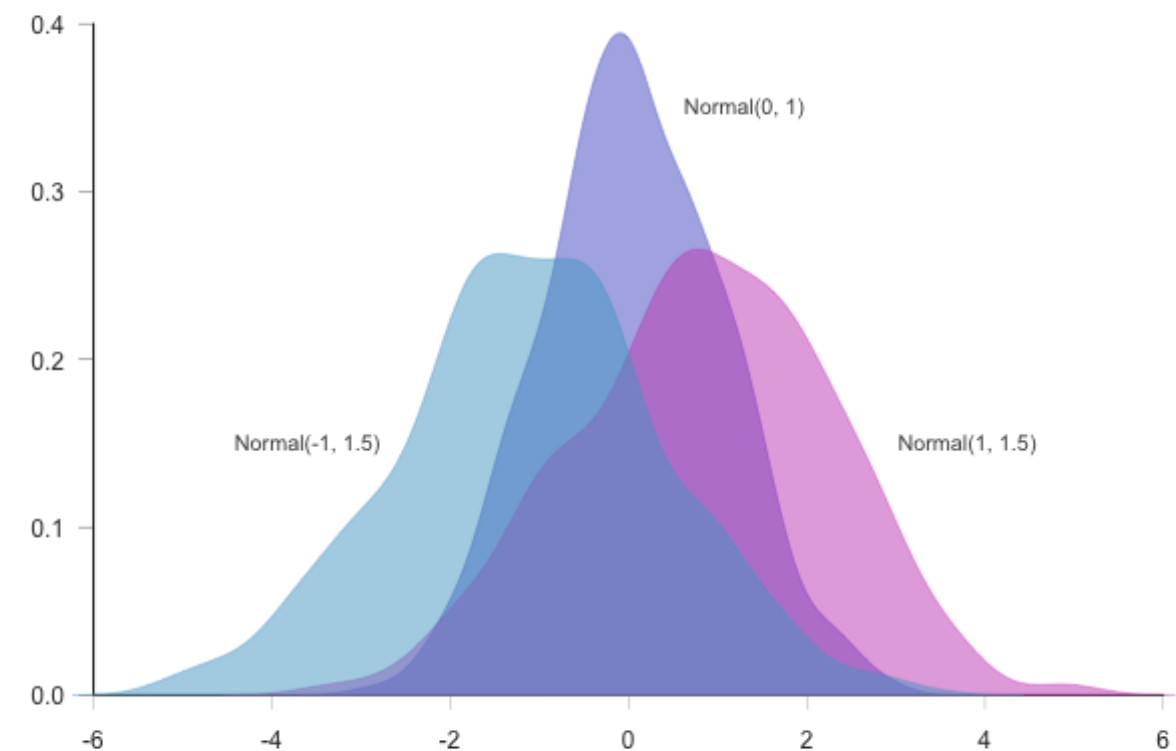
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Evaluation techniques

- Imputations are used to improve model performance.
- Imputation with maximum machine learning model performance is selected.

- Density plots explain the distribution in the data.
- A very good metric to check bias in the imputations.



Fit a linear model for statistical summary

```
import statsmodels.api as sm

diabetes_cc = diabetes.dropna(how='any')
X = sm.add_constant(diabetes_cc.iloc[:, :-1])
y = diabetes_cc['Class']
lm = sm.OLS(y, X).fit()
```

```
print(lm.summary())
```

```
Summary:                                OLS Regression Results
=====
Dep. Variable:          Class    R-squared:                0.346
Model:                  OLS      Adj. R-squared:         0.332
Method:                 Least Squares    F-statistic:           25.30
Date:                  Wed, 10 Jul 2019    Prob (F-statistic):    2.65e-31
Time:                  15:03:19    Log-Likelihood:        -177.76
No. Observations:      392    AIC:                   373.5
Df Residuals:          383    BIC:                   409.3
Df Model:              8
Covariance Type:       nonrobust
=====
               coef    std err          t      P>|t|      [0.025    0.975]
-----
const         -1.1027     0.144    -7.681     0.000    -1.385    -0.820
Pregnant         0.0130     0.008     1.549     0.122    -0.003     0.029
Glucose          0.0064     0.001     7.855     0.000     0.005     0.008
Diastolic_BP    5.465e-05     0.002     0.032     0.975    -0.003     0.003
Skin_Fold         0.0017     0.003     0.665     0.506    -0.003     0.007
Serum_Insulin   -0.0001     0.000    -0.603     0.547    -0.001     0.000
BMI              0.0093     0.004     2.391     0.017     0.002     0.017
Diabetes_Pedigree 0.1572     0.058     2.708     0.007     0.043     0.271
Age              0.0059     0.003     2.109     0.036     0.000     0.011
```

R-squared and Coefficients

```
lm.rsquared_adj
```

```
0.33210
```

```
lm.params
```

```
const          -1.102677
Pregnant        0.012953
Glucose         0.006409
Diastolic_BP   0.000055
Skin_Fold       0.001678
Serum_Insulin  -0.000123
BMI             0.009325
Diabetes_Pedigree 0.157192
Age            0.005878
dtype: float64
```


Fit linear model on different imputed DataFrames

```
# Mean Imputation
X = sm.add_constant(diabetes_mean_imputed.iloc[:, :-1])
y = diabetes['Class']
lm_mean = sm.OLS(y, X).fit()

# KNN Imputation
X = sm.add_constant(diabetes_knn_imputed.iloc[:, :-1])
lm_KNN = sm.OLS(y, X).fit()

# MICE Imputation
X = sm.add_constant(diabetes_mice_imputed.iloc[:, :-1])
lm_MICE = sm.OLS(y, X).fit()
```

Comparing R-squared of different imputations

```
print(pd.DataFrame({'Complete': lm.rsquared_adj,  
                    'Mean Imp.': lm_mean.rsquared_adj,  
                    'KNN Imp.': lm_KNN.rsquared_adj,  
                    'MICE Imp.': lm_MICE.rsquared_adj},  
              index=[ 'R_squared_adj' ]))
```

	Complete	Mean Imp.	KNN Imp.	MICE Imp.
R_squared_adj	0.332108	0.313781	0.316543	0.317679

Comparing coefficients of different imputations

```
print(pd.DataFrame({'Complete': lm.params,  
                    'Mean Imp.': lm_mean.params,  
                    'KNN Imp.': lm_KNN.params,  
                    'MICE Imp.': lm_MICE.params}))
```

	Complete	Mean Imp.	KNN Imp.	MICE Imp.
const	-1.102677	-1.024005	-1.028035	-1.050023
Pregnant	0.012953	0.020693	0.020047	0.020295
Glucose	0.006409	0.006467	0.006614	0.006871
Diastolic_BP	0.000055	-0.001137	-0.001196	-0.001317
Skin_Fold	0.001678	0.000193	0.001626	0.000807
Serum_Insulin	-0.000123	-0.000090	-0.000147	-0.000227
BMI	0.009325	0.014376	0.013239	0.014203
Diabetes_Pedigree	0.157192	0.129282	0.128038	0.129056
Age	0.005878	0.002092	0.002046	0.002097

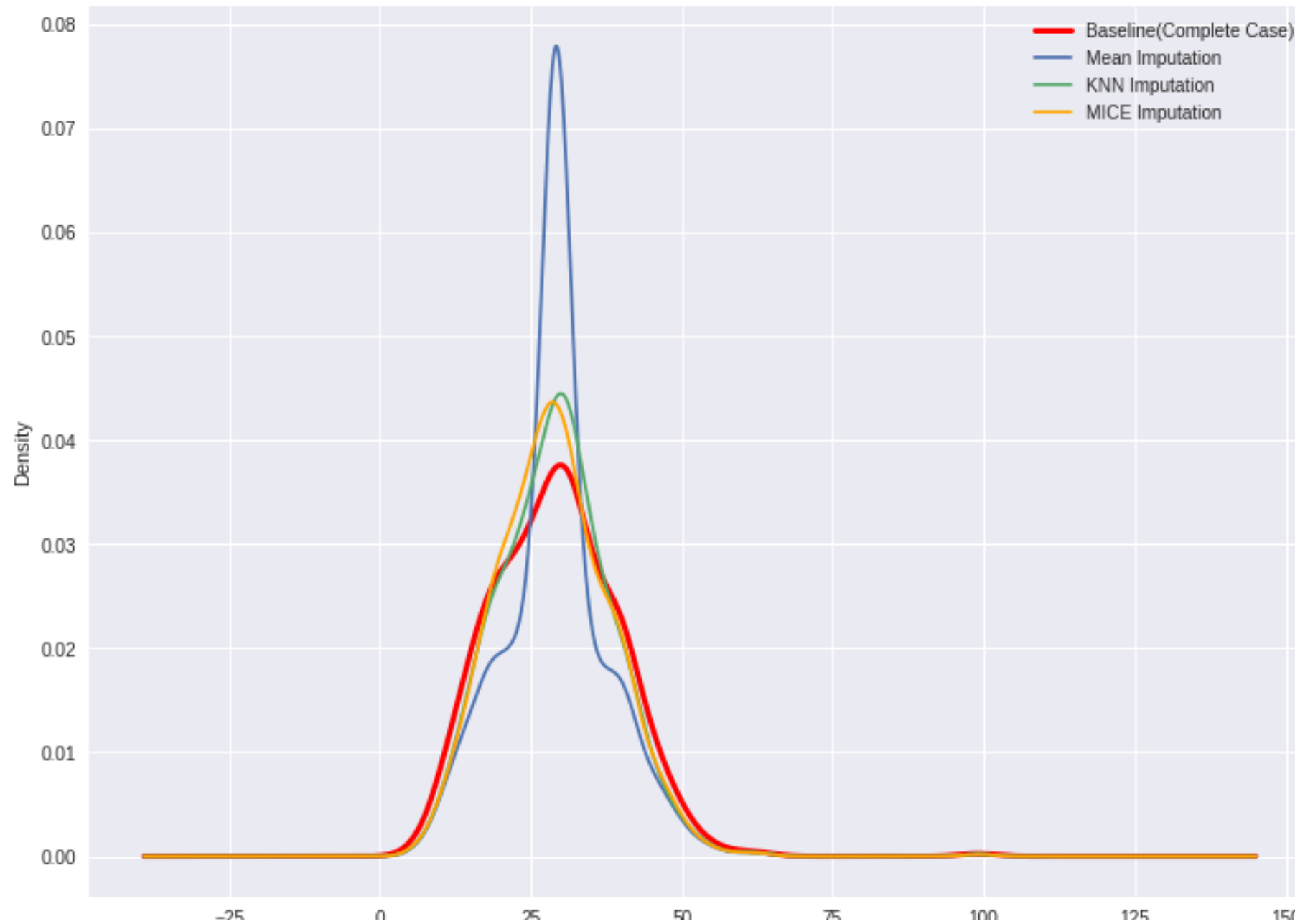
Comparing density plots

```
diabetes_cc['Skin_Fold'].plot(kind='kde', c='red', linewidth=3)
diabetes_mean_imputed['Skin_Fold'].plot(kind='kde')
diabetes_knn_imputed['Skin_Fold'].plot(kind='kde')
diabetes_mice_imputed['Skin_Fold'].plot(kind='kde')

labels = ['Baseline (Complete Case)', 'Mean Imputation', 'KNN Imputation',
          'MICE Imputation']

plt.legend(labels)
plt.xlabel('Skin Fold')
```

Comparing density plots



Summary

- Applying linear model from the statsmodels package
- Comparing the coefficients and standard errors
- Comparing density plots

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Conclusion

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Chapter 1

- Null Value operations
- Detecting missing values
- Replacing missing values
- Analyzing amount of missingness

Chapter 2

- Types of missingness
 - MCAR
 - MAR
 - MNAR
- Correlations of missingness
 - Heatmaps
 - Dendrograms
- Visualize missingness across a variable
- Deleting missing values

Chapter 3

- Imputation techniques
- Treating time-series data
- Graphical comparison of imputed time-series data

Chapter 4

- Advanced imputation techniques
 - KNN
 - MICE
- Imputing categorical data
- Evaluating and comparing the different imputations

Congratulations!!

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