Imputing using fancyimpute

DEALING WITH MISSING DATA IN PYTHON

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fancyimpute package

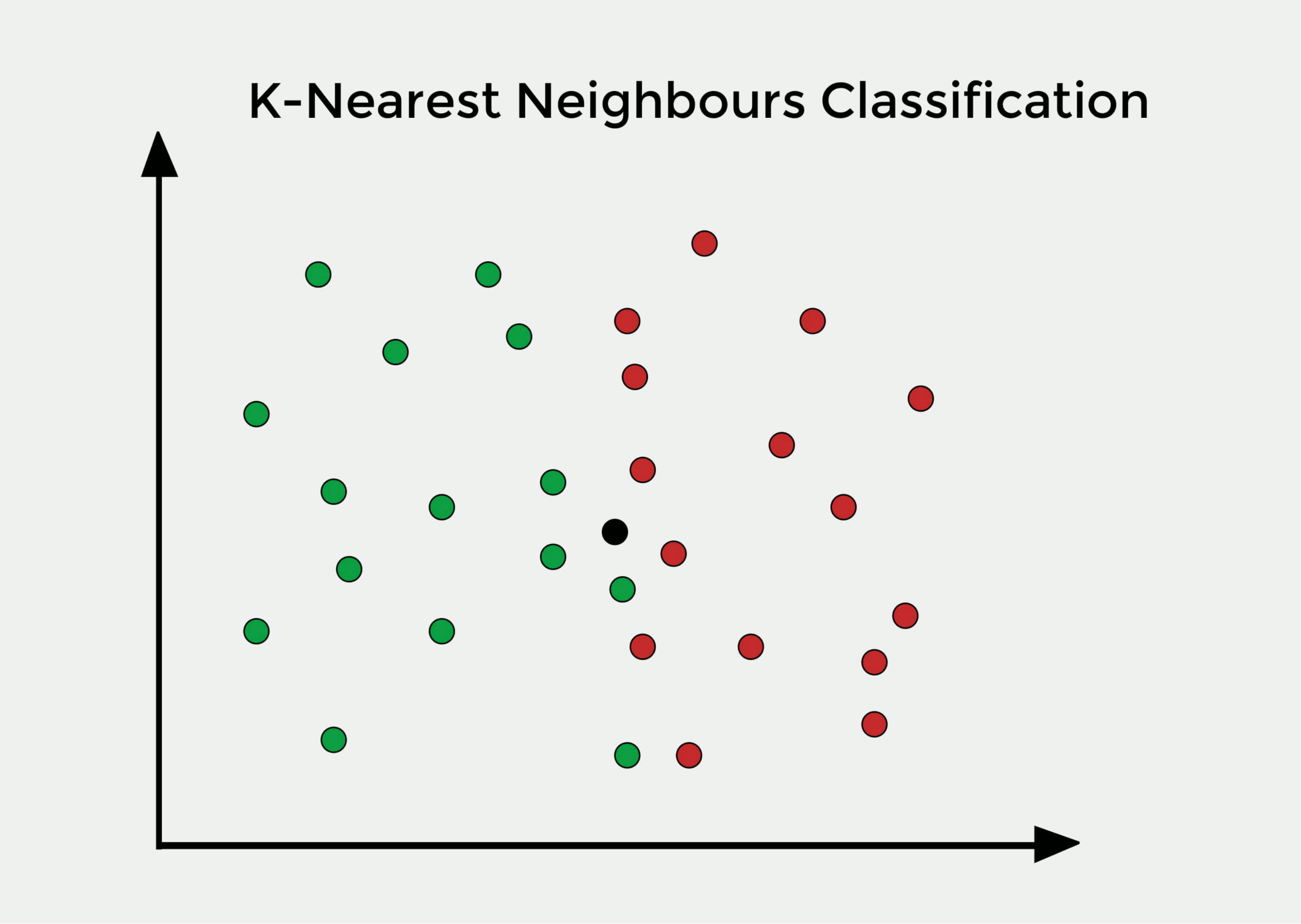
- Package contains advanced techniques
- Uses machine learning algorithms to impute missing values
- Uses other columns to predict the missing values and impute them

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
diabetes_knn = diabetes.copy(deep=True)
knn_imputer = KNN()
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
diabetes_MICE = diabetes.copy(deep=True)
MICE_imputer = IterativeImputer()
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

```python
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()
    col = users[col_name]

    # Select the non-null values in the column
    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)

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

Imputing with KNN

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

# Create KNN imputer
KNN_imputer = KNN()

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

for col_name in users_KNN_imputed:
    # Reshape the values to 2-dimensions to
    # avoid errors while storing in the DataFrame
    reshaped = users_KNN_imputed[col_name].values.reshape(-1, 1)
    users_KNN_imputed[col_name] = \
    ordinal_enc_dict[col_name].inverse_transform(reshaped)
```

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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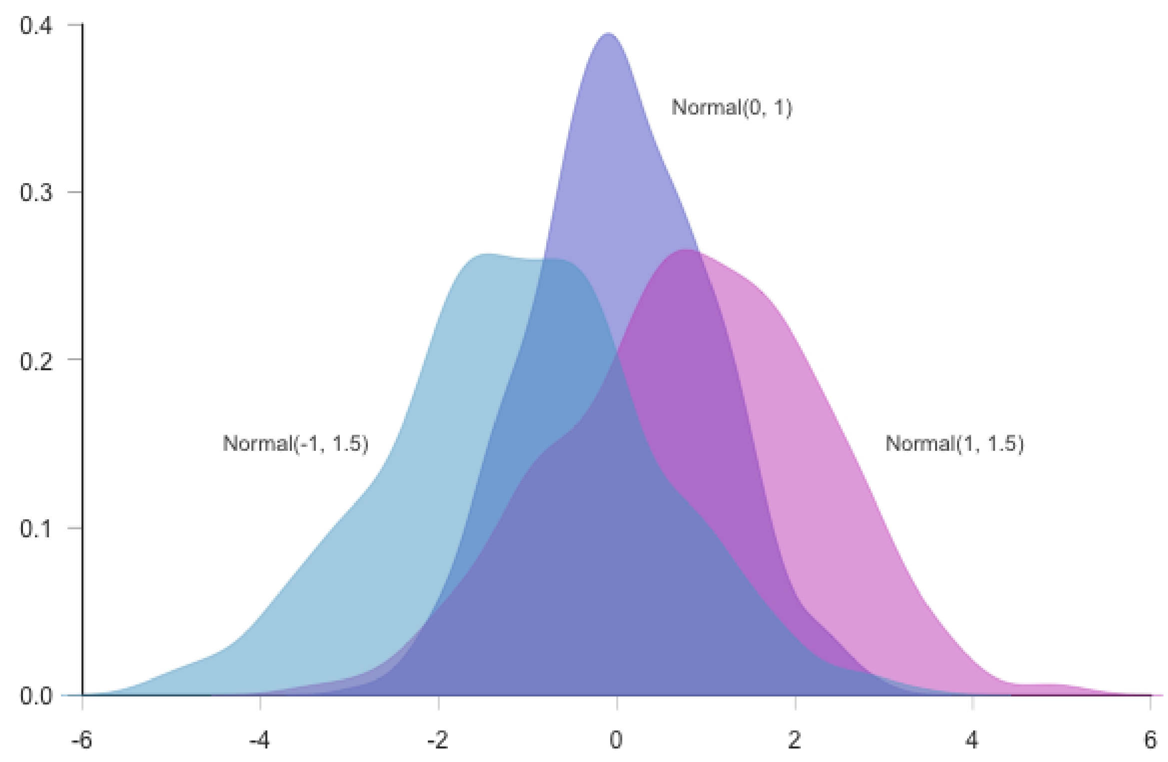
Evaluation techniques

- 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

```python
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()
```

```python
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]
<hr />----------------------------------------------------------------------------------
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
```

> **Note:** The metrics used here is for linear correlations only. You must use the metrics that are reflective of the data.

Comparing coefficients of different imputations

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

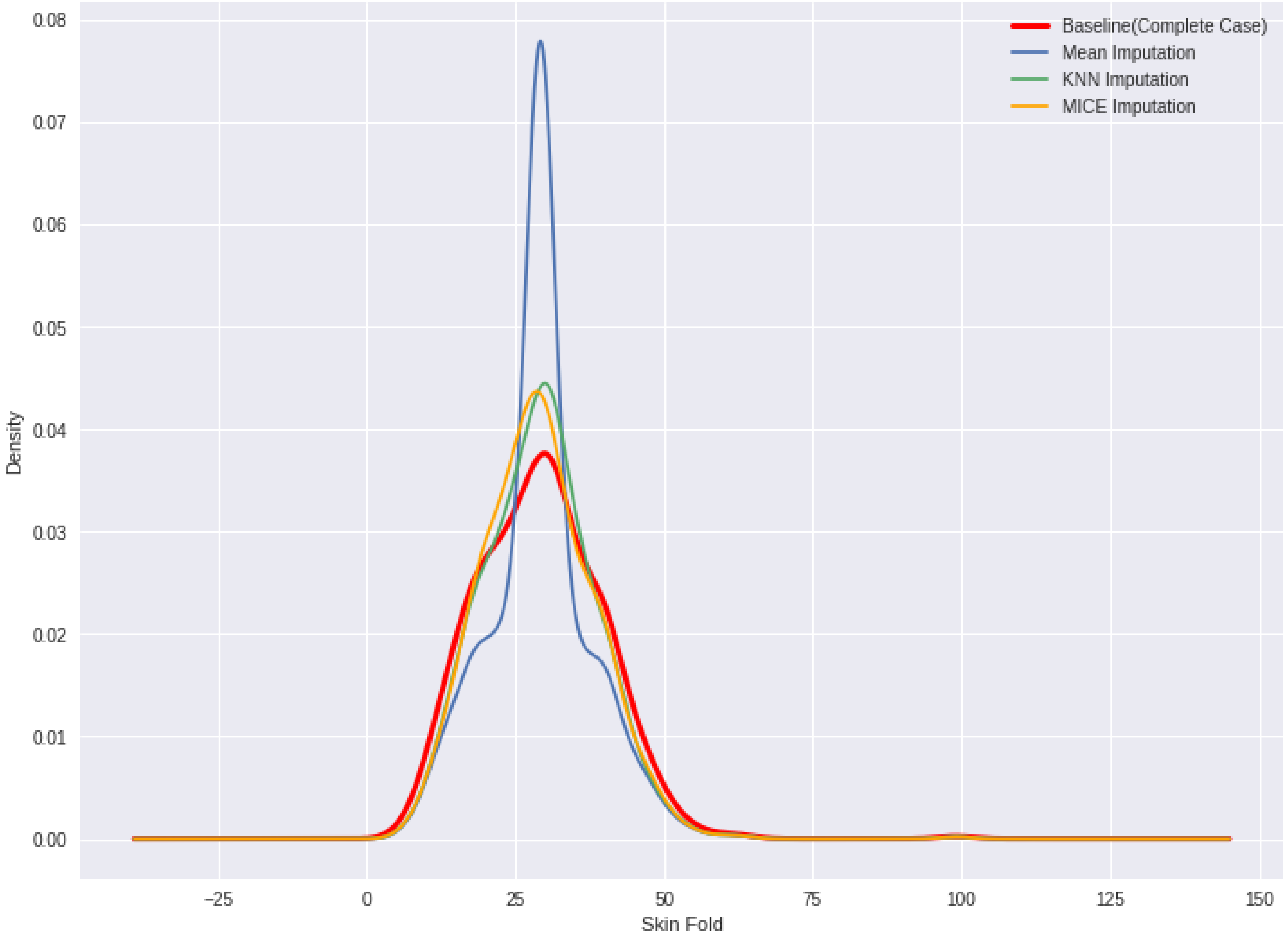
```
                   Complete  Mean Imp.  KNN Imp.  MICE Imp.
const             -1.102677  -1.024005  -1.028035  -1.050023
Pregnant           0.012953   0.020693   0.020047   0.020295
Glucose            0.006409   0.006467   0.006614   0.006871
Diastolic_BP       0.000055  -0.001137  -0.001196  -0.001317
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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