

Innovaccer | IIT Madras | Decision Scientist-Test | Report

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* column = variable, variable = column

Data Preprocessing:

1. Data Type change

- Some of the missing values in the data are represented by 'N/A'(instead of NaN) which is a **string**, and as result of which the columns with have float values along with 'N/A' have their data type as **object** (non-numeric data type)
- This will result in issue when handling non-numeric(categorical) data types. So, we have change those columns data type to a numeric data type(float64)

2. Missing Values

- a. **Target variable**('per_capita_exp_total_py')
 - Delete the rows in which target column value is missing
- b. **Numeric variables**
 - Replace the missing values in column with **mean** of the available values
- c. **Non-numeric variables**
 - Replace the missing values in column with **mode** of the available values
- d. **Majority missing**
 - If a column has missing values in majority(90%) rows, delete the column

3. Majority variables

- Delete columns if majority(90%) rows have same value as the model won't learn anything from a feature in which change isn't much.

4. Categorical variables

- Delete categorical variables as there are too many levels in each variable
- Alternative is to cluster them(levels) based on their frequency -- didn't implement it

5. Splitting

- Divide the data into ~85% train , ~7% valid, ~8% train data

Model building:

Linear Regression:

1. No regularization

- Without regularization the model exactly(nearly) fits the data as the available training data is low

2. Regularization(L2 -- Ridge)

- Use high values of alpha to avoid overfitting, since we have very low data
- Optimal alpha -- alpha for which the model performs better on valid data
- Even though in some of the data split scenarios the optimal model performance on test data is low, it's very high when compared to the no regularization model.