Handling Categorical Data in Python

Last Updated : 01 Dec, 2022

Categorical data is a set of predefined categories or groups an observation can fall into. Categorical data can be found everywhere. For instance, survey responses like marital status, profession, educational qualifications, etc. However, certain problems can arise with categorical data that must be dealt with before proceeding with any other task. This article discusses various methods to handle categorical data. So, let us take a look at some problems posed by categorical data and how to handle them.

As mentioned earlier, categorical data can only take up a finite set of values. However, due to human error, while filling out a survey form, or any other reason, some bogus values could be found in the dataset.

Importing Libraries

Python libraries make it very easy for us to handle the data and perform typical and complex tasks with a single line of code.

- **Pandas** – This library helps to load the data frame in a 2D array format and has multiple functions to perform analysis tasks in one go.
- **Numpy** – Numpy arrays are very fast and can perform large computations in a very short time.
- **Matplotlib**/**Seaborn** – This library is used to draw visualizations.
- Sklearn – This module contains multiple libraries having pre-implemented functions to perform tasks from data preprocessing to model development and evaluation.

Python3

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

from sklearn.preprocessing import LabelEncoder
```

Now let's load the dataset into the pandas dataframe.

Python3

```
main_data = pd.read_csv('demographics.csv')
main_data.head()
```

Output:

	first_name	last_name	blood_type	marriage_status	income	device
0	Abdul	Colon	A+	married	145000	AndroidOS
1	Abdul	Pierce	B+	married	85000	MacOS
2	Desirae	Pierce	B+	MARRIED	130000	iOS
3	Shannon	Gibson	A+	married	175000	MacOS
4	Desirae	Little	B+	unmarried	130000	MacOS

First five rows of the dataset

To understand membership constraints, consider the feature, and blood type. We need to verify whether the blood type feature consists of bogus values or not. First, we need to create a data frame with all possible values of blood type that are valid.

Python3

```
# create a new dataframe with possible values for blood type
blood_type_categories = pd.DataFrame({
    'blood_type': ['A+', 'A-', 'B+', 'B-', 'AB+', 'AB-', 'O+', 'O-']
})
blood_type_categories
```

Output:

	blood_type
0	A+
1	A-
2	B+
3	B-
4	AB+
5	AB-
6	O+
7	O-

Now, the bogus values can be found using the difference method.

Python3

```
# finding bogus categories
unique_blood_types_main = set(main_data['blood_type'])
bogus_blood_types = unique_blood_types_main.difference(
    blood_type_categories['blood_type']
)
bogus_blood_types
```

Output:

```
{'C+', 'D-'}
```

Once the bogus values are found, the corresponding rows can be dropped from the dataset. In some scenarios, the values could be replaced with other values if there is information available. However, since there is no information available regarding the true blood type, they will be dropped.

Python3

```
# extracting records with bogus blood types
bogus_records_index = main_data['blood_type'].isin(bogus_blood_types)

# drop the records with bogus blood types
without_bogus_records = main_data[~bogus_records_index]
without_bogus_records['blood_type'].unique()
```

Output:

```
array(['A+', 'B+', 'A-', 'AB-', 'AB+', 'B-', 'O-', 'O+'], dtype=object)
```

Inconsistent Categories

Inconsistencies could arise in categorical data quite often. Consider the feature, marriage status. Let us take a look at all the unique values of marital status.

Python3

```
# exploring inconsistencies in marriage status category
main_data['marriage_status'].unique()
```

Output:

```
array(['married', 'MARRIED', ' married', 'unmarried ', 'divorced',
       'unmarried', 'UNMARRIED', 'separated'], dtype=object)
```

It is quite evident that there are redundant categories due to leading and trailing spaces as well as capital letters. First, let us deal with capital letters.

Python3

```
# removing values with capital letters
inconsistent_data = main_data.copy()
inconsistent_data['marriage_status'] = inconsistent_data['marriage_status']\
    .str.lower()
inconsistent_data['marriage_status'].unique()
```

Output:

```
array(['married', ' married', 'unmarried ', 'divorced', 'unmarried',
       'separated'], dtype=object)
```

Next, we will deal with leading and trailing spaces.

Python3

```
inconsistent_data['marriage_status'] = inconsistent_data['marriage_status']\
    .str.strip()
inconsistent_data['marriage_status'].unique()
```

Output:

```
array(['married', 'unmarried', 'divorced', 'separated'], dtype=object)
```

Remapping Categories

Numerical data like age or income can be mapped to different groups. This helps in getting more insights about the dataset. Let us explore the income feature.

Python3

```
# range of income in the dataset
print(f"Max income - {max(main_data['income'])},\
      Min income - {min(main_data['income'])}")
```

Output:

```
Max income - 190000, Min income - 40000
```

Now, let us create the range and labels for the income feature. Pandas' cut method is used to achieve this.

Python3

```
# create the groups for income
range = [40000, 75000, 100000, 125000, 150000, np.inf]
labels = ['40k-75k', '75k-100k', '100k-125k', '125k-150k', '150k+']

remapping_data = main_data.copy()
remapping_data['income_groups'] = pd.cut(remapping_data['income'],
                                         bins=range,
                                         labels=labels)
```

```
remapping_data.head()
```

Output:

	first_name	last_name	blood_type	marriage_status	income	device	income_groups
0	Abdul	Colon	A+	married	145000	AndroidOS	125k-150k
1	Abdul	Pierce	B+	married	85000	MacOS	75k-100k
2	Desirae	Pierce	B+	MARRIED	130000	iOS	125k-150k
3	Shannon	Gibson	A+	married	175000	MacOS	150k+
4	Desirae	Little	B+	unmarried	130000	MacOS	125k-150k

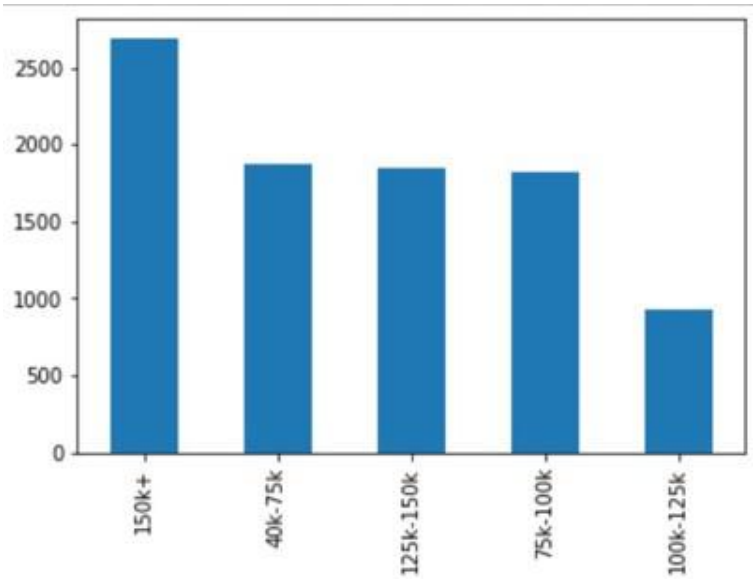
First five rows of the dataset.

Now, it is easier to visualize the distribution.

Python3

```
remapping_data['income_groups'].value_counts().plot.bar()
```

Output:



Barplot for the count of each income category

Cleaning Categorical Data

To understand this problem, a new data frame with just one feature, phone numbers are created.

Python3

```
phone_numbers = []
```

```
for i in range(100):
  # phone numbers could be of length 9 or 10
  number = random.randint(100000000, 9999999999)

  # +91 code is inserted in some cases
  if(i % 2 == 0):
    phone_numbers.append('+91 ' + str(number))
  else:
    phone_numbers.append(str(number))

phone_numbers_data = pd.DataFrame({
    'phone_numbers': phone_numbers
})

phone_numbers_data.head()
```

Output:

	phone_numbers
0	+91 707631849
1	6315742874
2	+91 1584173083
3	3389343099
4	+91 3970692379

Based on the use case, the code before numbers could be dropped or added for missing ones. Similarly, phone numbers with less than 10 numbers should be discarded.

Python3

```
phone_numbers_data['phone_numbers'] = phone_numbers_data['phone_numbers']\
    .str.replace('\+91 ', '')

num_digits = phone_numbers_data['phone_numbers'].str.len()
invalid_numbers_index = phone_numbers_data[num_digits < 10].index
phone_numbers_data['phone_numbers'] = phone_numbers_data.drop(
    invalid_numbers_index)
phone_numbers_data = phone_numbers_data.dropna()

phone_numbers_data.head()
```

Output:

	phone_numbers
0	5377617628
2	7152234401
3	2839400071
4	7651215019
5	4451571165

Finally, we can verify whether the data is clean or not.

Python3

```
assert phone_numbers_data['phone_numbers'].str.contains('\+91 ').all() == False
assert (phone_numbers_data['phone_numbers'].str.len() != 10).all() == False
```

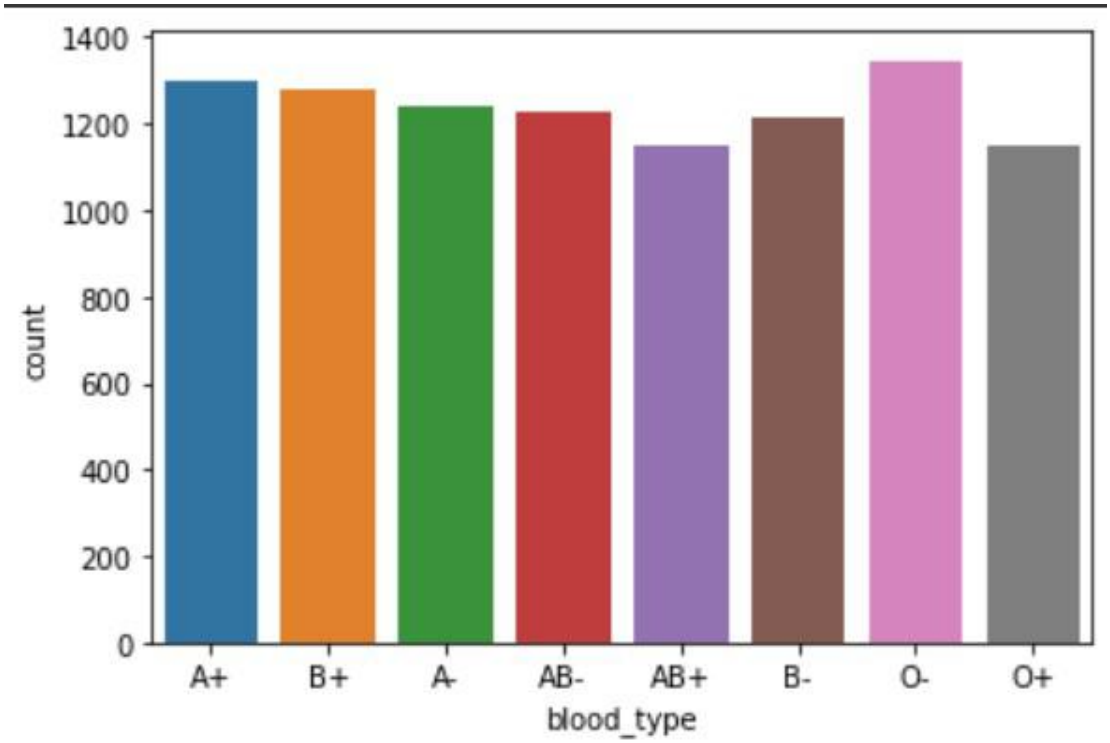
Visualizing Categorical Data

Various plots could be used to visualize categorical data to get more insights about the data. So, let us visualize the number of people belonging to each blood type. We will make use of the seaborn library to achieve this.

Python3

```
sns.countplot(x='blood_type',
              data=without_bogus_records)
```

Output:



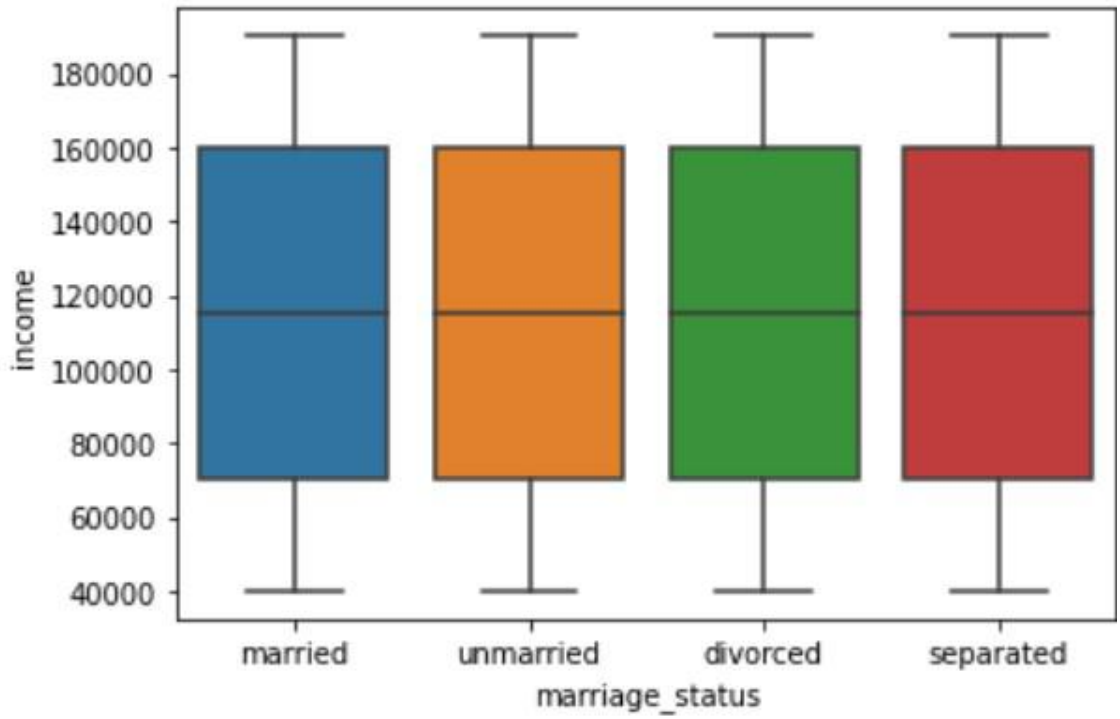
Countplot for blood_type category

Furthermore, we can see the relationship between income and the marital status of a person using a boxplot.

Python3

```
sns.boxplot(x='marriage_status',
            y='income',
            data=inconsistent_data)
```

Output:



Boxplot for marriage_status with income

Encoding Categorical Data

Certain learning algorithms like regression and neural networks require their input to be numbers. Hence, categorical data must be converted to numbers to use these algorithms. Let us take a look at some encoding methods.

Label Encoding

With label encoding, we can number the categories from 0 to num_categories – 1. Let us apply label encoding on the blood type feature.

Python3

```
le = LabelEncoder()
without_bogus_records['blood_type'] = le.fit_transform(
    without_bogus_records['blood_type'])
without_bogus_records['blood_type'].unique()
```

Output:

```
array([0, 4, 1, 3, 2, 5, 7, 6])
```

One-hot Encoding

There are certain limitations of label encoding that are taken care of by one-hot encoding.

Python3

```
inconsistent_data = pd.get_dummies(inconsistent_data,
                                   columns=['marriage_status'])
inconsistent_data.head()
```

Output:

	first_name	last_name	blood_type	income	device	marriage_status_divorced	marriage_status_married	marriage_status_separated	marriage_status_unmarried
0	Abdul	Colon	A+	145000	AndroidOS	0	1	0	0
1	Abdul	Pierce	B+	85000	MacOS	0	1	0	0
2	Desirae	Pierce	B+	130000	iOS	0	1	0	0
3	Shannon	Gibson	A+	175000	MacOS	0	1	0	0
4	Desirae	Little	B+	130000	MacOS	0	0	0	1

Ordinal Encoding

Categorical data can be ordinal, where the order is of importance. For such features, we want to preserve the order after encoding as well. We will perform ordinal encoding on income groups. We want to preserve the order as 40K-75K < 75K-100K < 100K-125K < 125K-150K < 150K+

Python3

```
custom_map = {'40k-75k': 1, '75k-100k': 2, '100k-125k': 3,
              '125k-150k': 4, '150k+': 5}
remapping_data['income_groups'] = remapping_data['income_groups']\
    .map(custom_map)
remapping_data.head()
```

Output:

	first_name	last_name	blood_type	marriage_status	income	device	income_groups
0	Abdul	Colon	A+	married	145000	AndroidOS	4
1	Abdul	Pierce	B+	married	85000	MacOS	2
2	Desirae	Pierce	B+	MARRIED	130000	iOS	4
3	Shannon	Gibson	A+	married	175000	MacOS	5
4	Desirae	Little	B+	unmarried	130000	MacOS	4

Similarly, different encodings can be applied according to the use case.

Related Articles

1. Handling Categorical Data with Bokeh - Python
2. How to convert categorical data to binary data in Python?
3. How to convert categorical string data into numeric in Python?
4. Exploring Categorical Data
5. Pandas – Filling NaN in Categorical data

6. ML | One Hot Encoding to treat Categorical data parameters
7. Python | Pandas.Categorical()
8. Python | Pandas Categorical DataFrame creation
9. Python – Categorical Encoding using Sunbird
10. How to handle missing values of categorical variables in Python?

Previous Next

Article Contributed By :

aayushhyadav
@aayushhyadav

Vote for difficulty

Easy | Normal | Medium | Hard | Expert

Article Tags : Picked, Technical Scripter 2022, Python, Technical Scripter

Practice Tags : python

Improve Article | Report Issue

GeeksforGeeks
A-143, 9th Floor, Sovereign Corporate Tower,
Sector-136, Noida, Uttar Pradesh - 201305

feedback@geeksforgeeks.org

Data Structures

Algorithms

Web Development

Write & Earn

Computer Science

Data Science & ML

Interview Corner

Python

Preparation for SDE

Company Interview Corner

Experienced Interview

Internship Interview

Competitive Programming

Aptitude

Python Programming Examples

Django Tutorial

Python Projects

Python Tkinter

OpenCV Python Tutorial

GfG School

CBSE Notes for Class 8

CBSE Notes for Class 9

CBSE Notes for Class 10

CBSE Notes for Class 11

CBSE Notes for Class 12

English Grammar

UPSC/SSC/BANKING

SSC CGL Syllabus

SBI PO Syllabus

IBPS PO Syllabus

UPSC Ethics Notes

UPSC Economics Notes

UPSC History Notes