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12 Useful Pandas Techniques in Python for Data Manipulation

AARSHAY JAIN ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/AUTHOR/AARSHAY/](https://www.analyticsvidhya.com/blog/author/aarshay/)), JANUARY 3, 2016





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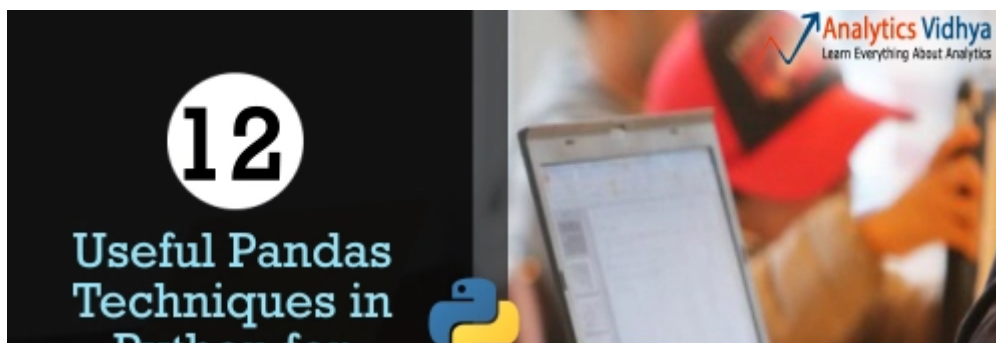
Introduction

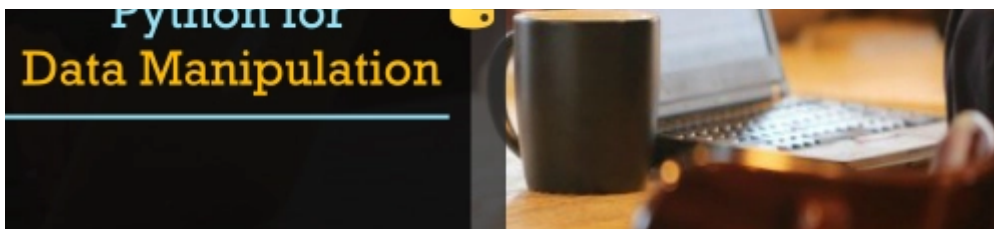
Python is fast becoming the preferred language for data scientists – and for good reasons. It provides the larger ecosystem of a programming language and the depth of good scientific computation libraries. If you are starting to learn Python, have a look at learning path on Python (<https://www.analyticsvidhya.com/learning-paths-data-science-business-analytics-business-intelligence-big-data/learning-path-data-science-python/>).

Among its scientific computation libraries, I found Pandas to be the most useful for data science operations. Pandas, along with Scikit-learn provides almost the entire stack needed by a data scientist. This article focuses on providing **12 ways** for **data manipulation** in Python. I've also shared some **tips & tricks** which will allow you to **work faster**.

I would recommend that you look at the codes for data exploration (<https://www.analyticsvidhya.com/blog/2015/02/data-exploration-preparation-model/>) before going ahead. To help you understand better, I've taken a data set to perform these operations and manipulations.

Data Set: I've used the data set of Loan Prediction (<https://datahack.analyticsvidhya.com/contest/practice-problem-loan-prediction-iii/>) problem. Download the data set and get started.





(https://www.analyticsvidhya.com/wp-content/uploads/2015/12/panda_1.jpg)

Let's get started

I'll start by importing modules and loading the data set into Python environment:

```
import pandas as pd
import numpy as np
data = pd.read_csv("train.csv", index_col="Loan_ID")
```

#1 – Boolean Indexing

What do you do, if you want to filter values of a column based on conditions from another set of columns? For instance, we want a list of all **females who are not graduate** and **got a loan**. Boolean indexing can help here. You can use the following code:

```
data.loc[(data["Gender"]=="Female") & (data["Education"]=="Not Graduate") & (data["Loan_Status"]="Y"), ["Gender","Education","Loan_Status"]]
```

	Gender	Education	Loan_Status
Loan_ID			
LP001155	Female	Not Graduate	Y
LP001669	Female	Not Graduate	Y
LP001692	Female	Not Graduate	Y
LP001908	Female	Not Graduate	Y
LP002300	Female	Not Graduate	Y
LP002314	Female	Not Graduate	Y
LP002407	Female	Not Graduate	Y

LP002489	Female	Not Graduate	Y
LP002502	Female	Not Graduate	Y
LP002534	Female	Not Graduate	Y
LP002582	Female	Not Graduate	Y
LP002731	Female	Not Graduate	Y
LP002757	Female	Not Graduate	Y
LP002917	Female	Not Graduate	Y

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/1.-boolean-indexing.png>)

Read More: Pandas Selecting and Indexing (<http://pandas.pydata.org/pandas-docs/stable/indexing.html>)

#2 – Apply Function

It is one of the commonly used functions for playing with data and creating new variables. *Apply* returns some value after passing each row/column of a data frame with some function. The function can be both default or user-defined. For instance, here it can be used to find the #missing values in each row and column.

```
#Create a new function:
def num_missing(x):
    return sum(x.isnull())

#Applying per column:
print "Missing values per column:"
```

```
print data.apply(num_missing, axis=0) #axis=0 defines that function is to be applied on each column

#Applying per row:
print "\nMissing values per row:"
print data.apply(num_missing, axis=1).head() #axis=1 defines that function is to be applied on each row
```

```
Missing values per column:
Gender          13
Married         3
Dependents      15
Education        0
Self_Employed   32
ApplicantIncome  0
CoapplicantIncome 0
LoanAmount      22
Loan_Amount_Term 14
Credit_History  50
Property_Area    0
Loan_Status      0
dtype: int64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/3-apply.png>)

```
Missing values per row:
Loan_ID
LP001002    1
LP001003    0
LP001005    0
LP001006    0
LP001008    0
dtype: int64
```

Thus we get the desired result.

Note: head() function is used in second output because it contains many rows.

Read More: [Pandas Reference \(apply\) \(http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.apply.html#pandas.DataFrame.apply\)](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.apply.html#pandas.DataFrame.apply)

#3 – Imputing missing files

'fillna()' does it in one go. It is used for updating missing values with the overall mean/mode/median of the column. Let's impute the 'Gender', 'Married' and 'Self_Employed' columns with their respective modes.

```
#First we import a function to determine the mode
from scipy.stats import mode
mode(data['Gender'])
```

Output: *ModeResult(mode=array(['Male'], dtype=object), count=array([489]))*

This returns both mode and count. Remember that mode can be an array as there can be multiple values with high frequency. We will take the first one by default always using:

```
mode(data['Gender']).mode[0]
```

'Male' (<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/4.2-mode2.png>)

Now we can fill the missing values and check using technique #2.

```
#Impute the values:
data['Gender'].fillna(mode(data['Gender']).mode[0], inplace=True)
data['Married'].fillna(mode(data['Married']).mode[0], inplace=True)
data['Self_Employed'].fillna(mode(data['Self_Employed']).mode[0], inplace=True)

#Now check the #missing values again to confirm:
print data.apply(num_missing, axis=0)
```

```
Gender          0
Married         0
Dependents      15
Education       0
Self_Employed   0
ApplicantIncome 0
CoapplicantIncome 0
LoanAmount      22
Loan_Amount_Term 14
Credit_History  50
Property_Area   0
Loan_Status     0
dtype: int64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/4.3-after-impute.png>)

Hence, it is confirmed that missing values are imputed. Please note that this is the most primitive form of imputation. Other sophisticated techniques include modeling the missing values, using grouped averages (mean/mode/median). I'll cover that part in my next articles.

Read More: Pandas Reference (fillna) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.fillna.html#pandas.DataFrame.fillna>)

#4 – Pivot Table

Pandas can be used to create MS Excel style pivot tables. For instance, in this case, a key column is “LoanAmount” which has missing values. We can impute it using mean amount of each ‘Gender’, ‘Married’ and ‘Self_Employed’ group. The mean ‘LoanAmount’ of each group can be determined as:

```
#Determine pivot table
impute_grps = data.pivot_table(values=["LoanAmount"], index=["Gender","Married","Self_Employed"],
                                aggfunc=np.mean)
print impute_grps
```

Gender	Married	Self_Employed	LoanAmount
Female	No	No	114.691176
		Yes	125.800000
	Yes	No	134.222222
		Yes	282.250000
Male	No	No	129.936937
		Yes	180.588235
	Yes	No	153.882736
		Yes	169.395833

[pivot-table.png](#))

More: Pandas Reference (Pivot Table) (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.pivot_table.html#pandas.DataFrame.pivot_table)

#5 – Multi-Indexing

If you notice the output of step #3, it has a strange property. Each index is made up of a combination of 3 values. This is called Multi-Indexing. It helps in performing operations really fast.

Continuing the example from #3, we have the values for each group but they have not been imputed. This can be done using the various techniques learned till now.

```
#iterate only through rows with missing LoanAmount
for i,row in data.loc[data['LoanAmount'].isnull(),:].iterrows():
    ind = tuple([row['Gender'],row['Married'],row['Self_Employed']])
    data.loc[i,'LoanAmount'] = impute_grps.loc[ind].values[0]
```

#Now check the #missing values again to confirm:

```
print data.apply(num_missing, axis=0)
```

```
Gender          0
Married         0
Dependents      15
Education       0
Self_Employed   0
ApplicantIncome 0
CoapplicantIncome 0
LoanAmount      0
Loan_Amount_Term 14
Credit_History  50
Property_Area   0
Loan_Status     0
dtype: int64
```

indexing.png)

Note:

1. Multi-index requires tuple for defining groups of indices in loc statement. This a tuple used in function.
2. The .values[0] suffix is required because, by default a series element is returned which has an index not matching with that of the dataframe. In this case, a direct assignment gives an error.

#6. Crosstab

This function is used to get an initial “feel” (view) of the data. Here, we can validate some basic hypothesis. For instance, in this case, “Credit_History” is expected to affect the loan status significantly. This can be tested using cross-tabulation as shown below:

```
pd.crosstab(data["Credit_History"],data["Loan_Status"],margins=True)
```

Loan_Status	N	Y	All
Credit_History			
0.0	82	7	89
1.0	97	378	475
All	192	422	614

crosstab.png)

These are absolute numbers. But, percentages can be more intuitive in making some quick insights. We can do this using the apply function:

```
def percConvert(ser):
    return ser/float(ser[-1])

pd.crosstab(data["Credit_History"],data["Loan_Status"],margins=True).apply(percConvert, axis=1)
```

Loan_Status	N	Y	All
Credit_History			
0.0	0.921348	0.078652	1
1.0	0.204211	0.795789	1
All	0.312704	0.687296	1

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/7.2-perc-crosstab.png>)

Now, it is evident that people with a credit history have much higher chances of getting a loan as 80% people with credit history got a loan as compared to only 9% without credit history.

But that's not it. It tells an interesting story. Since I know that having a credit history is super important, what if I predict loan status to be Y for ones with credit history and N otherwise. Surprisingly, we'll be right $82+378=460$ times out of 614 which is a whopping 75%!

I won't blame you if you're wondering why the hell do we need statistical models. But trust me, increasing the accuracy by even 0.001% beyond this mark is a challenging task. Would you take this challenge (<http://datahack.analyticsvidhya.com/contest/practice-problem-loan-prediction/>)?

Note: 75% is on train set. The test set will be slightly different but close. Also, I hope this gives some intuition into why even a 0.05% increase in accuracy can result in jump of 500 ranks on the Kaggle leaderboard.

Read More: [Pandas Reference \(crosstab\) \(http://pandas.pydata.org/pandas-docs/version/0.17.0/generated/pandas.crosstab.html\)](http://pandas.pydata.org/pandas-docs/version/0.17.0/generated/pandas.crosstab.html)

#7 – Merge DataFrames

Merging dataframes become essential when we have information coming from different sources to be collated.

Consider a hypothetical case where the average property rates (INR per sq meters) is available for different property types. Let's define a dataframe as:

```
prop_rates = pd.DataFrame([1000, 5000, 12000], index=['Rural', 'Semiurban', 'Urban'], columns=['rates'])
prop_rates
```

	rates
Rural	1000
Semiurban	5000
Urban	12000

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/8.1-rates.png>)

Now we can merge this information with the original dataframe as:

```
data_merged = data.merge(right=prop_rates, how='inner', left_on='Property_Area', right_index=True, sort=False)
data_merged.pivot_table(values='Credit_History', index=['Property_Area', 'rates'], aggfunc=len)
```

```
Property_Area  rates
Rural          1000    179
Semiurban      5000    233
Urban          12000    202
Name: Credit_History, dtype: float64
```

[pivot.png](#))

The pivot table validates successful merge operation. Note that the 'values' argument is irrelevant here because we are simply counting the values.

ReadMore: [Pandas Reference \(merge\)](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.merge.html#pandas.DataFrame.merge) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.merge.html#pandas.DataFrame.merge>)

#8 – Sorting DataFrames

Pandas allow easy sorting based on multiple columns. This can be done as:

```
data_sorted = data.sort_values(['ApplicantIncome', 'CoapplicantIncome'], ascending=False)
data_sorted[['ApplicantIncome', 'CoapplicantIncome']].head(10)
```

	ApplicantIncome	CoapplicantIncome
Loan_ID		
LP002317	81000	0
LP002101	63337	0
LP001585	51763	0
LP001536	39999	0
LP001640	39147	4750
LP002422	37719	0
LP001637	33846	0
LP001448	23803	0
LP002624	20833	6667
LP001922	20667	0

([https://www.analyticsvidhya.com/wp-](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/9.-sort.png)

[content/uploads/2015/12/9.-sort.png](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/9.-sort.png))

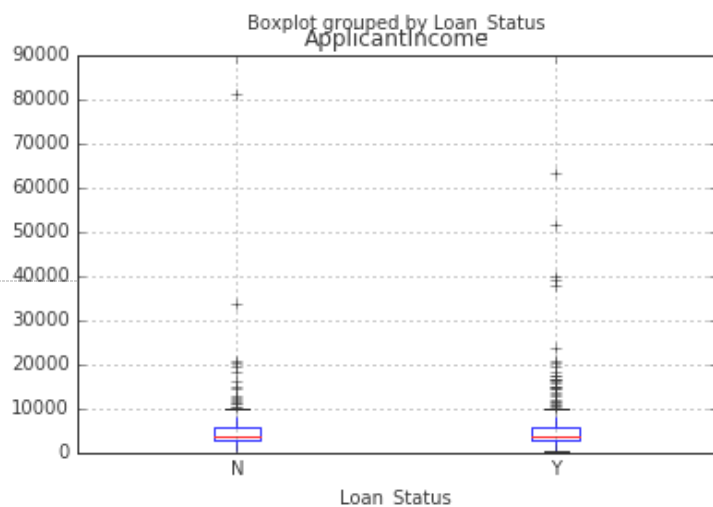
Note: Pandas “sort” function is now deprecated. We should use “sort_values” instead.

More: Pandas Reference (sort_values) (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.sort_values.html#pandas.DataFrame.sort_values)

#9 – Plotting (Boxplot & Histogram)

Many of you might be unaware that boxplots and histograms can be directly plotted in Pandas and calling matplotlib separately is not necessary. It's just a 1-line command. For instance, if we want to compare the distribution of ApplicantIncome by Loan_Status:

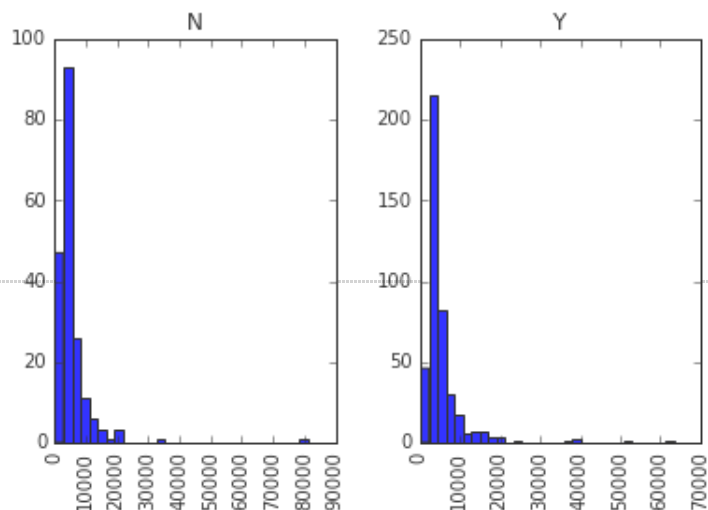
```
import matplotlib.pyplot as plt
%matplotlib inline
data.boxplot(column="ApplicantIncome", by="Loan_Status")
```



([https://www.analyticsvidhya.com/wp-](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/10.1-boxplot.png)

[content/uploads/2015/12/10.1-boxplot.png](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/10.1-boxplot.png))

```
data.hist(column="ApplicantIncome",by="Loan_Status",bins=30)
```



([https://www.analyticsvidhya.com/wp-](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/10.2-hist.png)

[content/uploads/2015/12/10.2-hist.png](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/10.2-hist.png))

This shows that income is not a big deciding factor on its own as there is no appreciable difference between the people who received and were denied the loan.

Read More: Pandas Reference (hist) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.hist.html#pandas.DataFrame.hist>) | Pandas Reference (boxplot) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.boxplot.html#pandas.DataFrame.boxplot>)

#10 – Cut function for binning

Sometimes numerical values make more sense if clustered together. For example, if we're trying to model traffic (#cars on road) with time of the day (minutes). The exact minute of an hour might not be that relevant for predicting traffic as compared to actual period of the day like "Morning", "Afternoon", "Evening", "Night", "Late Night". Modeling traffic this way will be more intuitive and will avoid overfitting.

Here we define a simple function which can be re-used for binning any variable fairly easily.

```
#Binning:
def binning(col, cut_points, labels=None):
    #Define min and max values:
    minval = col.min()
    maxval = col.max()
```

```

#create list by adding min and max to cut_points
break_points = [minval] + cut_points + [maxval]

#if no labels provided, use default labels 0 ... (n-1)
if not labels:
    labels = range(len(cut_points)+1)

#Binning using cut function of pandas
colBin = pd.cut(col,bins=break_points,labels=labels,include_lowest=True)
return colBin

#Binning age:
cut_points = [90,140,190]
labels = ["low","medium","high","very high"]
data["LoanAmount_Bin"] = binning(data["LoanAmount"], cut_points, labels)
print pd.value_counts(data["LoanAmount_Bin"], sort=False)

```

```

low          104
medium       273
high         146
very high     91
dtype: int64

```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/01/eg12.png>)

Read More: [Pandas Reference \(cut\)](http://pandas.pydata.org/pandas-docs/version/0.17.1/generated/pandas.cut.html) (<http://pandas.pydata.org/pandas-docs/version/0.17.1/generated/pandas.cut.html>)

#11 – Coding nominal data

Often, we find a case where we've to modify the categories of a nominal variable. This can be due to various reasons:

1. Some algorithms (like Logistic Regression) require all inputs to be numeric. So nominal variables are mostly coded as 0, 1....(n-1)
2. Sometimes a category might be represented in 2 ways. For e.g. temperature might be recorded as "High", "Medium", "Low", "H", "low". Here, both "High" and "H" refer to same category. Similarly, in "Low" and "low" there is only a difference of case. But, python would read them as different levels.

3. Some categories might have very low frequencies and its generally a good idea to combine them.

Here I've defined a generic function which takes in input as a dictionary and codes the values using 'replace' function in Pandas.

```
#Define a generic function using Pandas replace function
def coding(col, codeDict):
    colCoded = pd.Series(col, copy=True)
    for key, value in codeDict.items():
        colCoded.replace(key, value, inplace=True)
    return colCoded

#Coding LoanStatus as Y=1, N=0:
print 'Before Coding:'
print pd.value_counts(data["Loan_Status"])
data["Loan_Status_Coded"] = coding(data["Loan_Status"], {'N':0,'Y':1})
print '\nAfter Coding:'
print pd.value_counts(data["Loan_Status_Coded"])
```

Before Coding:

```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

After Coding:

```
1    422
0    192
Name: Loan_Status_Coded, dtype: int64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/12.-code.png>)

[code.png](#)

Similar counts before and after proves the coding.

Read More: [Pandas Reference \(replace\)](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.replace.html#pandas.DataFrame.replace) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.replace.html#pandas.DataFrame.replace>)

#12 – Iterating over rows of a dataframe

This is not a frequently used operation. Still, you don't want to get stuck. Right? At times you may need to

iterate through all rows using a for loop. For instance, one common problem we face is the incorrect treatment of variables in Python. This generally happens when:

1. Nominal variables with numeric categories are treated as numerical.
2. Numeric variables with characters entered in one of the rows (due to a data error) are considered categorical.

So it's generally a good idea to manually define the column types. If we check the data types of all columns:

```
#Check current type:
```

```
data.dtypes
```

```
Gender          object
Married         object
Dependents      object
Education       object
Self_Employed   object
ApplicantIncome    int64
CoapplicantIncome float64
LoanAmount      float64
Loan_Amount_Term float64
Credit_History  float64
Property_Area    object
Loan_Status      object
dtype: object
```

([https://www.analyticsvidhya.com/wp-content/uploads/2015/12/2.1-initial-](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/2.1-initial-type.png)

[type.png](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/2.1-initial-type.png))

Here we see that Credit_History is a nominal variable but appearing as float. A good way to tackle such issues is to create a csv file with column names and types. This way, we can make a generic function to read the file and assign column data types. For instance, here I have created a csv file [datatypes.csv](https://www.analyticsvidhya.com/wp-content/uploads/2015/12/datatypes.csv) (<https://www.analyticsvidhya.com/wp-content/uploads/2015/12/datatypes.csv>).

```
#Load the file:
```

```
colTypes = pd.read_csv('datatypes.csv')
```

```
print colTypes
```


	feature	type
0	Gender	categorical
1	Married	categorical
2	Dependents	categorical
3	Education	categorical
4	Self_Employed	categorical
5	ApplicantIncome	continuous
6	CoapplicantIncome	continuous
7	LoanAmount	continuous
8	Loan_Amount_Term	continuous
9	Credit_History	categorical
10	Property_Area	categorical
11	Loan_Status	categorical

([https://www.analyticsvidhya.com/wp-](https://www.analyticsvidhya.com/wp-content/uploads/2016/01/2.2-file-content.png)

[content/uploads/2016/01/2.2-file-content.png](https://www.analyticsvidhya.com/wp-content/uploads/2016/01/2.2-file-content.png))

After loading this file, we can iterate through each row and assign the datatype using column 'type' to the variable name defined in the 'feature' column.

```
#Iterate through each row and assign variable type.
#Note: astype is used to assign types

for i, row in colTypes.iterrows(): #i: dataframe index; row: each row in series format
    if row['type']=="categorical":
        data[row['feature']]=data[row['feature']].astype(np.object)
    elif row['type']=="continuous":
        data[row['feature']]=data[row['feature']].astype(np.float)
print data.dtypes
```

Gender	object
Married	object
Dependents	object
Education	object
Self_Employed	object
ApplicantIncome	float64
CoapplicantIncome	float64
LoanAmount	float64

([https://www.analyticsvidhya.com/wp-](https://www.analyticsvidhya.com/wp-content/uploads/2016/01/2.2-file-content.png)

```
Loan_Amount_Term    float64
Credit_History      object
Property_Area       object
Loan_Status         object
dtype: object
```

[content/uploads/2016/01/2.3-after-changing.png](#))

Now the credit history column is modified to 'object' type which is used for representing nominal variables in Pandas.

Read More: [Pandas Reference \(iterrows\)](#) (<http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.iterrows.html#pandas.DataFrame.iterrows>)

End Notes

In this article, we covered various functions of Pandas which can make our life easy while performing data exploration and feature engineering. Also, we defined some generic functions which can be reused for achieving similar objective on different datasets.

Also See: If you have any doubts pertaining to Pandas or Python in general, feel free to [discuss](http://discuss.analyticsvidhya.com) (<http://discuss.analyticsvidhya.com>) with us.

Did you find the article useful? Do you use some better (easier/faster) techniques for performing the tasks discussed above? Do you think there are better alternatives to Pandas in Python? We'll be glad if you share your thoughts as comments below.

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