12 Useful Pandas Techniques in Python for Data Manipulation

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Introduction

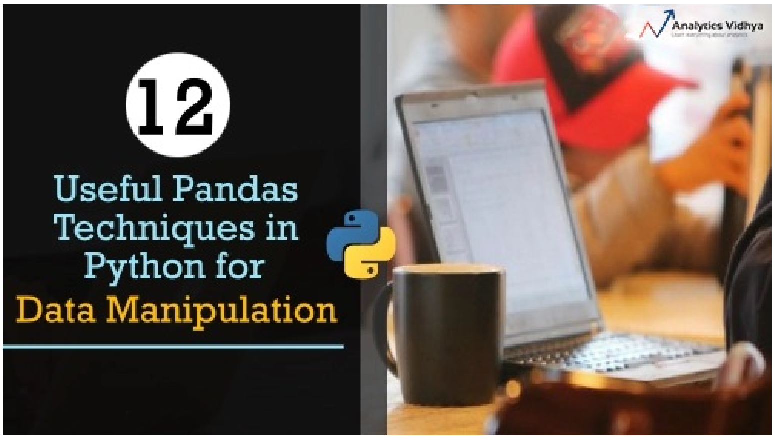
Python is fast becoming the preferred language in data science – and for good reason(s). It provides the larger ecosystem of a programming language and the depth of good scientific computation libraries. If you are starting to learn Python, have a look at learning path on Python.

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 before going ahead. To help you understand better, I've taken a data set to perform these operations and manipulations.

If you're just starting out your data science journey, they you'll love the 'Introduction to Data Science' course. It covers the basics of Python, comprehensive introduction to statistics and several machine learning algorithms. A must-have course!

Data Set: I've used the data set of Loan Prediction problem. Download the dataset and get started.



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

Read More: [Pandas Selecting and Indexing]

#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

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)]

#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'
```

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
```

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)]

#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
```

```
                             LoanAmount
Gender Married Self_Employed
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
```

More: [Pandas Reference (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
```

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

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

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?

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)

#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

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
```

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)]

#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

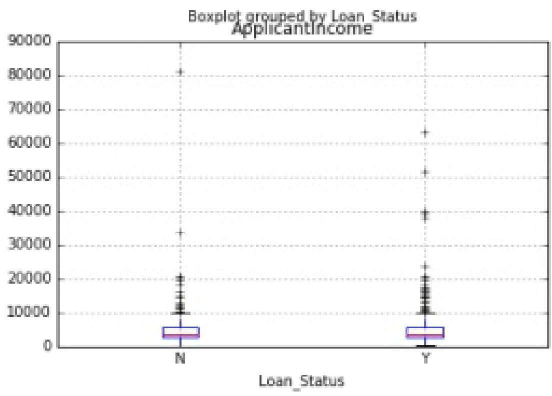
Note: Pandas "sort" function is now deprecated. We should use "sort_values" instead.

More: [Pandas Reference (sort_values)]

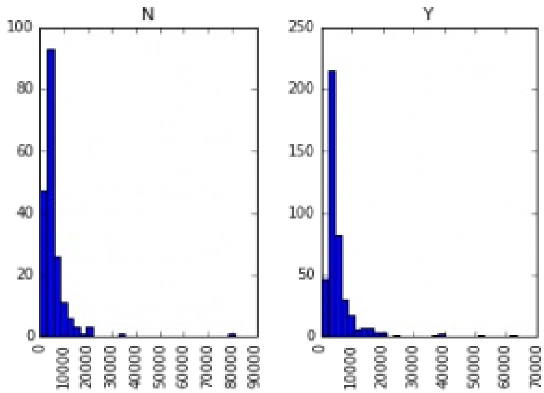
#9 – Plotting (Boxplot & Histogram)

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")
```



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



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)] | [Pandas Reference (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
```

Read More: [Pandas Reference (cut)]

#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
```

Similar counts before and after proves the coding.

Read More: [Pandas Reference (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
```

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.

```
#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

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
```

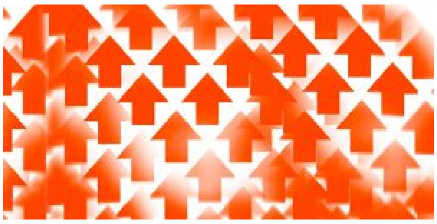
```
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome      float64
CoapplicantIncome    float64
LoanAmount           float64
```

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

Now the credit history column is modified to 'object' type which is used for representing nominal variables in Pandas.
Read More: [Pandas Reference (iterrows)]

Projects

Now, its time to take the plunge and actually play with some other real datasets. So are you ready to take on the challenge? Accelerate your data science journey with the following Practice Problems:

	Practice Problem: Food Demand Forecasting Challenge	Predict the demand of meals for a meal delivery company
	Practice Problem: HR Analytics Challenge	Identify the employees most likely to get promoted
	Practice Problem: Predict Number of Upvotes	Predict number of upvotes on a query asked at an online question & answer platform

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 todiscuss 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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