In [1]: import pandas as pd In [69]: **import** numpy as np import statistics as s pandas provides two data structures 1. series(1 dimesional array with indexes that can be named) 2. dataframes(2 dimensional array with rows and columns that can be named A series can be create using pd.series() thee input can be a simple dictionary or list In [11]: s1=pd.Series([88,99,75,93,95,93,85]) print('series created using list as input:\n',s1) s2=pd.Series({'a':91, 'b':88, 'c':95, 'd':79, 'e':94}) print('series using dictionary as input:\n',s2) series created using list as input: 0 88 99 1 2 75 3 93 95 5 93 85 dtype: int64 series using dictionary as input: a 91 95 С 79 d 94 dtype: int64 A dataframe can also be created uing simple dictionary with values as a series object(list,tuple) and key(string,charecter,number) keys are shown as column names and the values are the column values respectively or list of lists or list of tuples or tuple of lists or tuple of tuples in the above four cases rows and columns are indexed with number below two cases using dictionary and one of the four cases is shown In [23]: data1={'name':['rohith', 'maruthi', 'gangadhar', 'barghav', 'abhay', 'sudeb', 'tharun', 'abhiram'], 'rollno':[12,3,13,16,63,57,35,33], 'branch':['csd','csm','csm','csd','csd','csd','csm','csd']} In [24]: df=pd.DataFrame(data1) df.head(4)Out[24]: name rollno branch rohith 12 csd maruthi 2 gangadhar 13 csm barghav 16 In [26]: data2=(('rohith', 'maruthi', 'gangadhar', 'barghav', 'abhay', 'sudeb', 'tharun', 'abhiram'), (12,3,13,16,63,57,35,33),('csd','csm','csm','csd','csd','csd','csm','csd')) In [28]: df1=pd.DataFrame(data2) df1 Out[28]: 0 rohith maruthi gangadhar barghav abhay sudeb tharun abhiram 12 63 33 2 csd csm csd csm csd csd csd csm DATA HANDLING In [29]: print('names:\n', df['name']) print('rollno:\n',df.rollno) names: 0 rohith maruthi gangadhar barghav abhay sudeb tharun abhiram Name: name, dtype: object rollno: 12 1 3 13 2 3 16 63 5 57 6 35 33 Name: rollno, dtype: int64 data(dataframe) can be created using 'xlsx', 'csv' files by: pd.read_excel('path of the excel file in your system') pd.read_csv('path of the csv file in your system') In [46]: #current working directory is downloads and the excel workbook is also in downloads (relative path) d1=pd.read_excel('Car Sales Dataset.xlsx') d1.head() Out[46]: brand year selling_price km_driven Number of Owners seats fuel seller_type transmission engine max_power torque 0 Mahindra Bolero Pik-Up Mahindra 2020 679000 5000 Individual Manual 2523 CC 70 bhp 200Nm@ 1400-2200rpm 2 Diesel 1 Mahindra Bolero Pik-Up CBC 1.7T Mahindra 2019 722000 80000 2 Diesel Individual Manual 2523 CC 70 bhp 200Nm@ 1400-2200rpm 2 Tata Nano Cx 45000 10000 Tata 2011 Individual 624 CC 35 bhp 48Nm@ 3000rpm 4 Petrol Manual Maruti 800 Std Maruti 2002 40000 80000 4 Petrol Individual 796 CC 37 bhp 59Nm@ 2500rpm Manual 35 bhp 48@ 3,000+/-500(NM@ rpm) Tata Nano Cx BSIV Tata 2010 55000 50000 4 Petrol Individual Manual 624 CC In [50]: d2=pd.read_csv(r"C:\Users\rohit\Desktop\Data sets\Toy-Sales-dataset - Training.csv") d2.head() Out[50]: Month Sales PromExp Price AdExp 1 73959 0 61.13 8.75 50.04 2 71544 60.19 8.99 50.74 3 78587 59.16 7.50 50.14 4 80364 60.38 7.25 50.27 59.71 7.40 51.25 5 78771 FILTERING THE DATA filtering whole data with branch either csd or csm In [30]: df[df['branch'] == 'csd'] Out[30]: name rollno branch 12 rohith csd 3 barghav 16 63 abhay csd sudeb 57 csd 33 7 abhiram csd In [31]: df[df['branch'] == 'csm'] Out[31]: name rollno branch maruthi 3 csm 2 gangadhar 13 35 tharun csm filtering only names based on the branch In [32]: df.name[df['branch'] == 'csd'] Out[32]: 0 rohith barghav abhay sudeb abhiram Name: name, dtype: object MISSING DATA HANDLING. pandas provide functions like -> isna() -> notna() -> fillna() -> dropna() to handle with missing data null values are represented as "np.nan" or "NaN" and it is a float data type In [52]: df['age']=[21, 21, 23, 20, np.nan, 21, np.nan, 20] In [57]: df[df.age.isna()] Out[57]: name rollno branch age 4 abhay 63 csd NaN 6 tharun 35 csm NaN In [58]: df[df.age.notna()] name rollno branch age 12 csd 21.0 rohith csm 21.0 maruthi 2 gangadhar 13 csm 23.0 csd 20.0 57 csd 21.0 sudeb 33 csd 20.0 fillna has two parameter which decides the value to be filled 1. value ->you can fill it with a variable or output of an statistical measure(mean,median,mode) 2. method ->ffill,bfill 3. it has parameter 'limit' to limit no of values to be filled consecutively In [75]: df.age.fillna(s.mode(df.age)) #if u want to fill a specic value use ->fillna(value) i.e fillna(21) Out[75]: 0 21.0 23.0 20.0 21.0 21.0 21.0 20.0 Name: age, dtype: float64 In [80]: df.fillna(method='ffill',limit=1) C:\Users\rohit\AppData\Local\Temp\ipykernel_23908\393035141.py:1: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill df.fillna(method='ffill',limit=1) Out[80]: name rollno branch age rohith 12 csd 21.0 maruthi csm 21.0 2 gangadhar 13 csm 23.0 csd 20.0 barghav abhay csd 20.0 csd 21.0 sudeb csm 21.0 tharun abhiram 33 csd 20.0 In [82]: df.ffill(limit=1) Out[82]: name rollno branch age 0 rohith 12 csd 21.0 csm 21.0 maruthi 2 gangadhar 13 csm 23.0 abhay csd 20.0 csd 21.0 sudeb tharun csm 21.0 abhiram csd 20.0 In [73]: df.dropna() Out[73]: name rollno branch age 12 csd 21.0 rohith maruthi csm 21.0 2 gangadhar csm 23.0 csd 20.0 csd 21.0 sudeb csd 20.0 abhiram 33 ->in the above examples only a single feature has null values ->all the four functions are applicable even if the data has null values in multiple columns ->you can filter the data by a particular columns null values ->fillna fills data based on that particular column values MERGING, JOINING AND CONCATENATING DATAFRAMES ->merge and join are almost same in crating output/result -megre takes separate key parameter -join considers index as key parameter these features are used to combine two dataframes with different features(columns) In [118... m1=pd.DataFrame({'key':['A','B','C'],'value':[10,20,30]}) m2=pd.DataFrame({'key':['B','C','D'],'value':[35,45,55]}) m3=pd.merge(m1, m2, on='key', how='inner') m4=pd.merge(m1, m2, on='key', how='left') m5=pd.merge(m1, m2, on='key', how='outer') In [119... **m3** Out[119... key value_x value_y 35 In [120... **m4** Out[120... key value_x value_y NaN 10 35.0 **2** C 30 45.0 In [121... **m5** Out[121... key value_x value_y 10.0 NaN 20.0 35.0 30.0 45.0 D NaN 55.0 ->concatenating two dataframes In [126... df['scores']=[94,89,84,98,80,79,93,90] In [127... newdata=pd.DataFrame({'name':['teja','sathwik','madhu','lokesh'], 'rollno':[49,6,51,30], 'branch':['csm','csd','csm','csd'], 'age':[21,21,22,21], 'scores':[89,96,93,90]}) In [135... | df=pd.concat([df,newdata],ignore_index=True) Out[135... name rollno branch age scores 12 csd 21.0 94 0 rohith maruthi csm 21.0 89 2 gangadhar 13 csm 23.0 84 barghav csd 20.0 98 80 csd NaN 63 abhay 79 sudeb 57 csd 21.0 tharun 35 93 csm NaN abhiram csd 20.0 90 csm 21.0 89 teja sathwik csd 21.0 96 csm 22.0 93 10 madhu 51 lokesh 30 csd 21.0 90 12 49 csm 21.0 89 teja 96 sathwik csd 21.0 csm 22.0 93 madhu lokesh 30 csd 21.0 90 DATA ANALYSIS WITH PANDAS ->pivottable for data aggreagation ->groupby for data grouping these two features are vastly used for eploratory data analysis(EDA) consider car sales dataset for pivottable and df dataframe for groupby In [88]: d1.pivot_table(index='brand',columns='Number of Owners',values=['selling_price','km_driven'],aggfunc='mean').fillna(0) Out[88]: km_driven selling_price Number of Owners 2 brand 83333.333333 0.0 Ambassador 0.000000 80000.000000 0.000000 0.0 0.000000e+00 9.866667e+04 2.000000e+05 0.000000 Ashok 0.0 0.000000 200000.000000 0.000000 0.000000 0.0 0.000000e+00 3.000000e+05 0.000000e+00 0.000000 Audi 14300.0 53109.357143 58271.428571 120000.000000 98000.000000 6223000.0 2.544786e+06 1.818571e+06 1.025000e+06 810000.000000 **BMW** 0.0 19110.247525 95680.000000 60000.000000 110000.000000 0.0 4.641733e+06 1.335000e+06 8.300000e+05 480000.000000 Chevrolet 72047.088496 82621.172840 92400.000000 109727.272727 0.0 2.885002e+05 2.754691e+05 2.135600e+05 248818.090909 Daewoo 0.0 81317.000000 0.000000 0.000000 0.000000 0.0 7.700000e+04 0.000000e+00 0.000000e+00 0.000000 35478.701754 43571.428571 35000.000000 0.000000 0.0 3.102807e+05 3.575713e+05 2.600000e+05 0.000000 Datsun Fiat 75974.916667 86333.333333 110000.000000 0.000000 0.0 3.700000e+05 2.220832e+05 2.919998e+05 0.000000 16500.000000 133639.500000 0.000000 0.000000 0.0 9.800000e+05 7.025000e+05 0.000000e+00 0.000000 Force Ford 0.0 63805.357143 88934.376147 90061.727273 72798.800000 0.0 6.125714e+05 3.618990e+05 3.035000e+05 321400.000000 Honda 24857.0 48728.764706 86674.300000 99400.000000 161000.000000 2000000.0 6.737147e+05 4.056683e+05 3.091470e+05 81000.000000 Hyundai 0.0 51645.801587 85182.809392 86419.910256 95567.567568 0.0 5.470793e+05 3.598204e+05 2.829807e+05 234864.810811 45560.000000 0.000000 0.000000 0.000000 0.0 1.942000e+06 0.000000e+00 0.000000e+00 0.000000 Isuzu 29578.571429 70000.000000 0.000000 0.000000 0.0 2.914257e+06 3.000000e+06 0.000000e+00 0.000000 Jaguar Jeep 37704.100000 20000.000000 0.000000 0.000000 0.0 2.157267e+06 1.920000e+06 0.000000e+00 0.000000 Kia 0.0 10000.000000 0.000000 0.000000 0.000000 0.0 1.504500e+06 0.000000e+00 0.000000e+00 0.000000 0.000000 77500.000000 0.0 29757.600000 0.000000 0.0 3.930000e+06 0.000000e+00 2.000000e+06 0.000000 Land 0.0 20000.000000 0.000000 0.000000 0.000000 0.0 5.150000e+06 0.000000e+00 0.000000e+00 0.000000 Lexus MG 0.000000 0.000000 0.0 12366.666667 0.000000 0.0 1.783333e+06 0.000000e+00 0.000000e+00 0.000000 Mahindra 0.0 81442.209446 97647.697115 138749.081633 139963.357143 0.0 7.116488e+05 4.989326e+05 4.490816e+05 371428.571429 Maruti 52256.656785 80818.193126 91023.966480 93222.868852 0.0 4.841598e+05 2.990833e+05 2.277031e+05 161901.622951 Mercedes-Benz 0.0 44310.162162 62664.642857 100000.000000 0.000000 0.0 2.899054e+06 1.552786e+06 1.466667e+06 0.000000 Mitsubishi 0.0 105081.833333 186000.000000 110000.000000 0.000000 0.0 1.258333e+06 5.958333e+05 1.600000e+05 0.000000 Nissan 65943.264151 82748.428571 90000.000000 91000.000000 0.0 5.123396e+05 4.009047e+05 3.008333e+05 320000.000000 Opel 0.0 0.000000 0.000000 110000.000000 0.000000 0.0 0.000000e+00 0.000000e+00 6.800000e+04 0.000000 Renault 0.0 50693.383333 90733.750000 88825.000000 0.000000 0.0 4.690166e+05 4.596000e+05 3.337499e+05 0.000000 0.0 7.378088e+05 4.028571e+05 2.450000e+05 51234.970588 106035.035714 117500.000000 0.000000 0.000000 Skoda Tata 69604.760776 98427.124352 110089.142857 102084.615385 0.0 4.432909e+05 2.281826e+05 1.729219e+05 151807.615385 0.0 1.183630e+06 8.003986e+05 5.418636e+05 430777.555556 Toyota 82989.461538 118886.405405 171454.545455 181791.000000 5400.0 60387.425926 88630.839286 91714.285714 89333.33333 1350000.0 5.641296e+05 3.915000e+05 3.407142e+05 276666.500000 Volkswagen 13287.878788 72500.000000 Volvo 0.000000 0.000000 0.0 3.303409e+06 1.200000e+06 0.000000e+00 0.000000 In [136... df.groupby(by=['branch', 'name']).size() #size represents the count Out[136... branch name csd abhay abhiram 1 barghav 1 lokesh 2 rohith 1 sathwik 2 sudeb 1 gangadhar madhu 2 maruthi 1 teja 2 tharun 1 dtype: int64 In [137... df.groupby(by=['age', 'name']).size() Out[137... age name 20.0 abhiram 1 barghav 1 21.0 lokesh maruthi rohith 1 sathwik 2 sudeb 1 teja 22.0 madhu 23.0 gangadhar 1 dtype: int64 In [138... df.groupby(by=['branch'])['scores'].mean() Out[138... branch csd 90.333333 csm 90.000000 Name: scores, dtype: float64 PANDAS (SERIES, DATAFRAME) VS REGULAR PYTHON DATA STRUCTURES 1.pandas numerical computation speed is faster than regular datastructures 2.no use of lopp control statements for iterating throung a series object 3.-pandas vast inbuit functions to peform larger tasks(agrregation) -using regular data structures new code with logic must be developed to perform such tasks 4.large data is easy to use and handle using pandas PANDAS APPLICATIONS IN DATA SCIENCE pandas is built on top of the numpy package, pandaas provides even more vast features including the features of numpy pandas provide features to handle categorical data unlike numpy pandas provide these applications in data science ->handling missing values(step of data pre processing) ->for summary statistics using pivot tables and grouping (EDA) ->data preparation for machine learning model fillting(PCA,kmeans,etc)