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1 Get Vehicle Resale Price and Specs

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1.1 Abstract

We are working on a vehicle dataset with information gathered from web scrapping, open api and downloadable csv file. We will munging the data and perform several operations to reform the dataset into an Entity-Relationship structure. After auditing and cleaning data, we will visualize the dataset and conclude the result we could get.

1.2 Data

- Open data(Downloadable csv file):
 - NHTSA vPIC Database: Manufacture(top30).csv > Dataset include name of manufacutres in United States market. Link: https://vpic.nhtsa.dot.gov/api/vehicles/GetMakesForVehicleType/car?format=csv
 - United States Environmental Protection Agency(EPA): all_alpha_20.csv
 Dataset include vehicle specs and EPA air pollution score. Link: https://www.fueleconomy.gov/feg/download.shtml
- API: NHTSA Open API: > Dataset include all the veichle models made the by manufactures. Link: https://vpic.nhtsa.dot.gov/api/
- Web Scrapping: https://www.truecar.com > Searching for the new car price and the used car trade-in price.

1.2.1 Importing Libraries

```
[84]: import urllib
  import requests
  import json
  from bs4 import BeautifulSoup
  import re
  import pandas as pd
  import numpy as np
  import matplotlib.pyplot as plt
```

- 1.3 Datasource1 NHTSA Vehicle Api
- 1.3.1 Fetch the vehicle models based on the manufacture, year and vehicle type.

API Example: Here is the example of json farmat returned from NHTSA Api.

```
[87]: url = "https://vpic.nhtsa.dot.gov/api/vehicles/GetModelsForMakeIdYear/makeId/
      ⇒474/modelyear/2015?format=json"
      req = urllib.request.Request(url=url)
      json_obj = urllib.request.urlopen(req)
      data = json.load(json_obj)
      result = (data)['Results']
      print (result[0])
     {'Make_ID': 474, 'Make_Name': 'Honda', 'Model_ID': 1861, 'Model_Name': 'Accord'}
     Relavent Code:
 []: def get_data(make):
          headers = {'User-Agent': 'Mozilla/5.0 (Windows NT 6.1; WOW64; rv:23.0)_
      →Gecko/20100101 Firefox/23.0'}
          url = "https://vpic.nhtsa.dot.gov/api/vehicles/GetModelsForMakeYear/make/"
      →+ make + "/vehicletype/passenger%20car?format=json"
          reg = urllib.request.Request(url=url, headers=headers)
          json_obj = urllib.request.urlopen(req)
          data = json.load(json_obj)
          result = (data)['Results']
          return result
```

- 1.4 Datasource2 Truecar.com Website Scrapping
- 1.4.1 Fetch MSRP (Manufacturer's Suggested Retail Price) and Resale Price based on models.

Website Example: Check the model: BMW M4 search result:

Extract the model name and the price

```
[15]: card=soup.find_all(attrs={"data-test" : "vehicleListing"})
for item in card:
    name = item.find('h4',{"data-test":"vehicleListingCardTitle"}).get_text()
    price = item.find('h4',{"data-test":"vehicleListingPriceAmount"}).get_text()
    price = price.replace('$', '')# Reforant for the next processing
```

```
price = price.replace(',', '')# Reforant for the next processing
print(name,price)
```

```
2020 BMW M4 CS Coupe 106295
2020 BMW M4 Convertible 98530
2020 BMW M4 Coupe 86120
2020 BMW M4 CS Coupe 106295
2020 BMW M4 CS Coupe 106295
2020 BMW M4 Coupe 87485
2020 BMW M4 CS Coupe 113895
2020 BMW M4 Coupe 86795
2020 BMW M4 Coupe 83895
```

Relavent Code: (Fetch new car price)

```
[]: def fetch_price(brand, model):
         sum=0
         count=0
         url = "https://www.truecar.com/new-cars-for-sale/listings/" + brand+ "/
      →"+model + "/location-boston-ma/"
         print(url)
         html= urllib.request.urlopen(url).read()
         soup= BeautifulSoup(html, features="html.parser")
         avail = soup.find('h4',{'data-qa':'Heading'}).get_text()
         if avail == "You filtered out all available listings.":
             print(url, "No Price Available")
             return
         card=soup.find_all(attrs={"data-test" : "vehicleListing"})
         for item in card:
             name = item.find('h4',{"data-test":"vehicleListingCardTitle"}).
      →get_text()
             price = item.find('h4',{"data-test":"vehicleListingPriceAmount"}).

    get_text()

             if re.search(model,name, re.IGNORECASE): #Make sure the model retured_
      \rightarrow is correct.
                 price = price.replace('$', '')
                 price = price.replace(',', '')
                 sum=sum+int(price)
                 count=count+1
             else:
                 print(url, "error")
         if count == 0:
             print(url, "No available price")
```

```
return
else:
return sum/count
```

Relavent Code: (Fetch used car price)

```
[]: def fetch_used_price(brand,model):
         count=0
         url = "https://www.truecar.com/used-cars-for-sale/listings/" + brand+ "/
      →"+model + "/location-boston-ma/"
         html= urllib.request.urlopen(url).read()
         soup= BeautifulSoup(html, features="html.parser")
         avail = soup.find('h4',{'data-qa':'Heading'}).get text()
         if avail == "You filtered out all available listings.":
             print(url, "No Price Available")
             return "-"
         card=soup.find_all(attrs={"data-test" : "vehicleListing"})
         year = list()
         price_set = list()
         for item in card:
             name = item.find('h4',{"data-test":"vehicleListingCardTitle"}).

    get_text()

             price = item.find('h4',{"data-test":"vehicleListingPriceAmount"}).
      →get_text()
             if re.search(model,name, re.IGNORECASE):
                 price = price.replace('$', '')
                 price = price.replace(',', '')
                 if price != "N/A":
                     count=count+1
                     #print(name[0:4],price)
                     year.append(str(name[0:4]))
                     price set.append(int(price))
                     #print(year, price_set)
                     dict = {"year": year, "price": price_set}
                     data = pd.DataFrame(dict)
             else:
                 print(url,"error")
         if count == 0:
             print(url, "No available price")
             return "-"
         else:
             r_year = data.groupby('year').mean() # Group the resale price by year, _
      → and calculate the mean.
             r_year = pd.DataFrame(r_year)
             y= r_year['price'].index.tolist()
```

1.5 Datasource3 - EPA Fuel Economy Data

1.5.1 Fetch vehicle specs and EPA economy score.

Relavent Code:

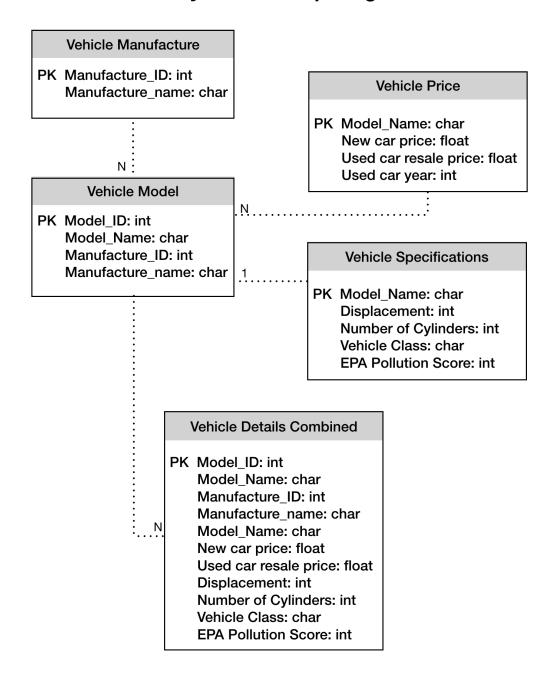
```
[]: spec = item['Make_Name'].upper() + " " + item['Model_Name']
with open('all_alpha_20.csv')as m:
    m_csv = csv.reader(m)
    headers = next(m_csv)
    for info in m_csv:
        if spec in info[0]:
            row.append(info[1])
            row.append(info[2])
            row.append(info[10])
            row.append(info[11])
            break
```

1.6 Conceptual Model

```
[108]: from IPython.display import Image
Image('ERD.png')
```

[108]:

Entity Relationship Diagram



1.7 Munging the data, reformatting and saving in csv file:

```
Relavent Code:
```

```
for item in result:
    brand = item['Make_Name'].lower()
```

```
model = item['Model_Name'].lower()
    brand = brand.replace(" ","-")
    model = model.replace(" ",'-')
    new = fetch_price(brand, model)
    row = [item['Make_ID'], item['Make_Name'], item['Model_ID'],__
 →item["Model_Name"]]
    if new != None:
        used = fetch_used_price(brand,model)
 → [item['Make_ID'],item['Make_Name'],item['Model_ID'],item["Model_Name"], new]
        for i in used:
            row.extend(i)
    with open('model.csv', 'a')as f:
        f_csv = csv.writer(f)
        f_csv.writerow(row)
with open('record.csv', 'a')as r: # saving web scrapping progress, avoid_
 \rightarrow getting duplicated data.
    r_csv = csv.writer(r)
    r_csv.writerow([make])
```

1.8 Data Cleaning

Open CSV file with the result of data mugging:

```
[106]: data = pd.read_csv("model.csv", index_col=3)
    data.head()
```

```
[106]:
                    Make_ID Make_Name Model_ID
                                                                      2020
                                                                                     2019 \
                                                            MSRP
       Model_Name
                                             5354
       TLX
                        475
                                 Acura
                                                    38719.333333
                                                                   26799.5
                                                                             30921.500000
       R.L.X
                        475
                                 Acura
                                             2149
                                                    62995.000000
                                                                       NaN
                                                                                      NaN
       ILX
                        475
                                                    29215.952381
                                 Acura
                                             2150
                                                                       {\tt NaN}
                                                                             22383.333333
       R.I.
                        475
                                 Acura
                                             1872
                                                             NaN
                                                                       NaN
                                                                                      NaN
       TL
                        475
                                 Acura
                                             1873
                                                             NaN
                                                                       NaN
                                                                                      NaN
                             2018
                                            2017
                                                           2016
                                                                      2015
                                                                                    2013 \
       Model_Name
       TLX
                    30344.000000 21031.153846 18514.000000
                                                                 18422.25
                                                                                     {\tt NaN}
       RLX
                    33086.428571 23564.000000
                                                  23100.000000
                                                                  20308.00
                                                                                     {\tt NaN}
       ILX
                    19085.000000 17201.714286 16563.333333
                                                                  10995.00
                                                                            ... 11533.25
       RL
                              NaN
                                             NaN
                                                            {\tt NaN}
                                                                       {\tt NaN}
                                                                                     NaN
       TL
                              NaN
                                             NaN
                                                            NaN
                                                                                     NaN
                                                                       {\tt NaN}
                    2012 2011 2010 2009 2008 Displacement Cylinder \
       Model_Name
```

TLX	NaN	NaN	NaN	NaN	NaN		2.4	4.0	
RLX	NaN	NaN	NaN	NaN	NaN		3.5	6.0	
ILX	NaN	NaN	NaN	NaN	NaN		2.4	4.0	
RL	NaN	NaN	NaN	NaN	NaN		NaN	NaN	
TL	NaN	NaN	NaN	NaN	NaN		NaN	NaN	
	Vehic	le Clas	ss EPA	Air P	ollution	Score			
Model_Name									
TLX	sı	small car				3.0			
RLX	mids	midsize car				7.0			
ILX	sı	small car				3.0			
RL		NaN				NaN			
TL		NaN				NaN			
[5 rows x	21 colur	nns]							
: data.shape	!								
: (694, 21)									
: data.dtype	S								
: Make_ID				int64					
Make_Name		object							
Model_ID		int64							
MSRP		float64							
2020		float64							
2019		float64							
2018				oat64					
2017				pat64					
2016				oat64					
2015				oat64					
2014		float64							
2013		float64							
2012		float64							
2011				oat64					
2010				pat64					
2009	float64								
2008	float64								
Displaceme									
Cylinder	0	float64							
Vehicle Cl	ass			oject					
ACTITION OF	22	a	67						

[107]

[107]

[21]

[21]

Select the model with valid new car price (MSRP): (Keep data accuracy)

float64

EPA Air Pollution Score

dtype: object

```
[30]: valid = data.loc[:,'MSRP']>0
      v_df = data.loc[valid,:]
      v_df.info()
     <class 'pandas.core.frame.DataFrame'>
     Index: 139 entries, TLX to XC40
     Data columns (total 21 columns):
     Make_ID
                                 139 non-null int64
     Make_Name
                                 139 non-null object
                                 139 non-null int64
     Model_ID
     MSR.P
                                 139 non-null float64
                                 10 non-null float64
     2020
     2019
                                 106 non-null float64
     2018
                                 102 non-null float64
                                 121 non-null float64
     2017
     2016
                                 106 non-null float64
                                 90 non-null float64
     2015
                                 88 non-null float64
     2014
                                 71 non-null float64
     2013
     2012
                                 55 non-null float64
     2011
                                 34 non-null float64
                                 37 non-null float64
     2010
     2009
                                 25 non-null float64
                                 21 non-null float64
     2008
                                 89 non-null float64
     Displacement
     Cylinder
                                 89 non-null float64
     Vehicle Class
                                 91 non-null object
                                 91 non-null float64
     EPA Air Pollution Score
     dtypes: float64(17), int64(2), object(2)
     memory usage: 23.9+ KB
     Drop the rows with too little information:
[59]: dp = v_df.dropna(thresh = 12)
      dp.shape
[59]: (96, 21)
     Calculate the vehicle resale price change percentage per year:
[60]: price = dp.iloc[:,4:14]#18
      percent = price.pct_change(axis='columns',fill_method='backfill')
      percent.head()
[60]:
                  2020
                             2019
                                       2018
                                                 2017
                                                            2016
                                                                      2015
                                                                                2014 \
     Model_Name
      X.IT
                        0.153809 -0.018676 -0.306909 -0.119687 -0.004956
                   NaN
                                                                                 NaN
      RLX
                        0.000000 0.000000 -0.287805 -0.019691 -0.120866 0.006828
```

NaN

```
ILX
               {\tt NaN}
                     0.000000 - 0.147357 - 0.098679 - 0.037111 - 0.336184 0.336971
Α4
                     0.000000 \quad 0.000000 \quad -0.036446 \quad -0.199000 \quad -0.260069 \quad -0.051160
               {\tt NaN}
A6
                     0.000000 - 0.072015 0.000000 - 0.180935 - 0.261664 - 0.084622
                   2013
                               2012
                                           2011
Model_Name
TLX
                    NaN
                                NaN
                                            NaN
RLX
                    NaN
                                {\tt NaN}
                                            NaN
ILX
             -0.215425
                                {\tt NaN}
                                            NaN
Α4
             -0.111173 -0.377736 0.304724
              0.176149 -0.428725 -0.087555
A6
```

Calculate the vehicle resale price average change percentage from 2020 to 2008:

```
[61]: percent.mean(1).head()
```

```
[61]: Model_Name

TLX -0.059284

RLX -0.070256

ILX -0.071112

A4 -0.081207

A6 -0.104374
```

dtype: float64

```
Combine the change percentage table with original table
```

/usr/local/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1: FutureWarning: The join_axes-keyword is deprecated. Use .reindex or .reindex_like on the result to achieve the same functionality.
"""Entry point for launching an IPython kernel.

Sort the models with the average percent change.

```
Top 10 models with least resale price drop:
```

```
[63]: print(res.sort_values(by='ave',ascending=False)['ave'].head(10))
```

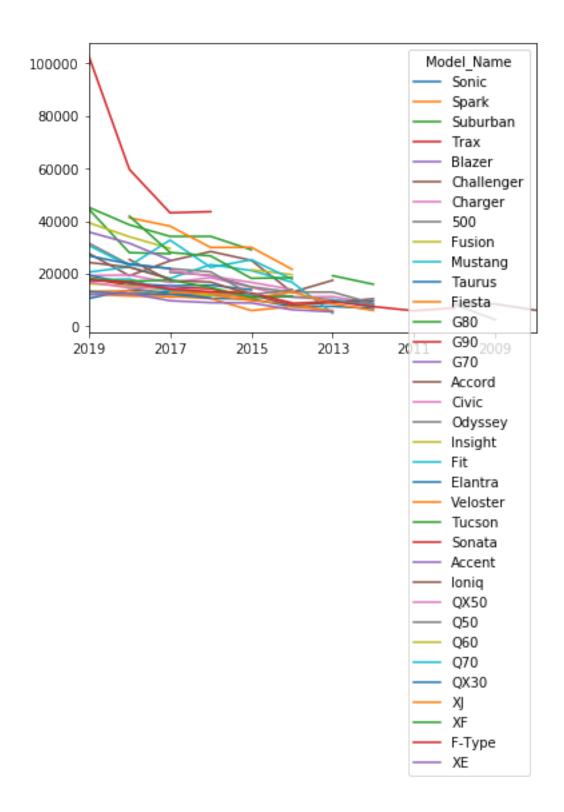
```
Model_Name
Camaro -0.005865
Corvette -0.013544
Challenger -0.017358
Optima -0.021918
Rio -0.025721
```

370Z -0.039929
Sonic -0.041635
TTS -0.041867
Impreza -0.045470
Camry -0.046822
Name: ave, dtype: float64

1.9 Data Visualization.

Now we could easily picture various plots to analyse the dataset. ### Line plot with Resale Value in time series:

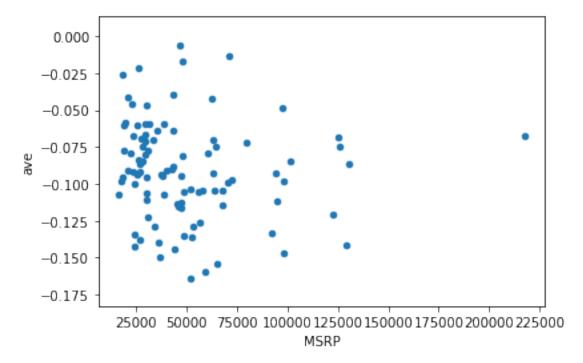
```
[97]: p_y = res.iloc[35:70,5:17].T
    p_y.plot()
    plt.show()
```



Conclusion: The trade-in value of used car drops fast in first ${\bf 2}$ years, and drops slower in next few years.

1.9.1 Scatter plot with Resale Price Average Change Percentage v.s. MSRP (Manufacturer's Suggested Retail Price)

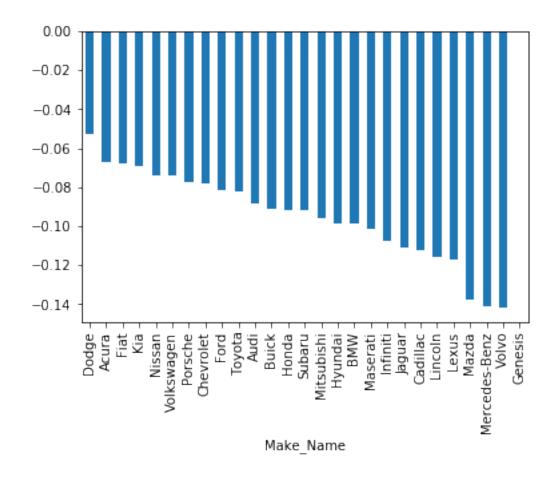
```
[96]: n_u= res.sort_values(by ='ave',ascending=False)
    p_nu=n_u.iloc[:,[3,-1]]
    p_nu.plot(kind='scatter', x='MSRP', y='ave')
    plt.show()
```



Conclusion: There's no strong relationship between the new car price and the average resale price drop percentage.

1.9.2 Resale price average drop rate v.s. Manufacture

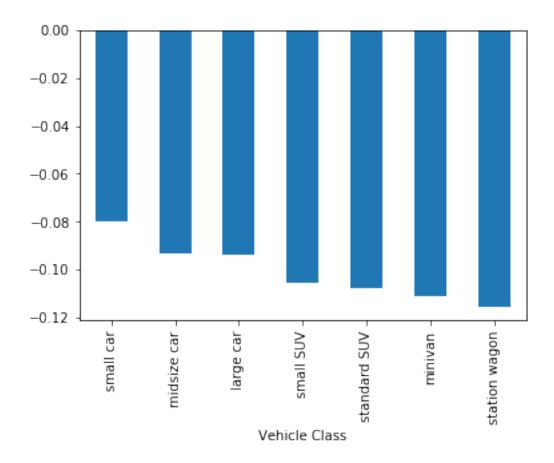
```
[75]: bran_ave=n_u.groupby('Make_Name').mean()
    bran_ave= bran_ave.sort_values(by ='ave',ascending=False)
    bran_ave = bran_ave['ave']
    bran_ave.plot(kind='bar')
    plt.show()
```



Conclusion: Top 5 brand with least trade-in value drop in US market is : Dodge, Acura, Fiat, Kia, and Nissan.

1.9.3 Resale price average drop rate v.s. Vehicle Class

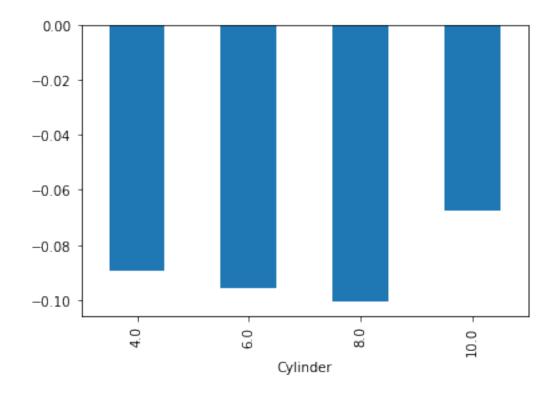
```
[76]: bran_ave=res.groupby('Vehicle Class').mean()
    bran_ave= bran_ave.sort_values(by ='ave', ascending=False)
    bran_ave = bran_ave['ave']
    bran_ave.plot(kind='bar')
    plt.show()
```



Conclusion: The most popular vehicle type in US market is: Small Car

1.9.4 Resale price average drop rate v.s. number of cylinders

```
[77]: bran_ave=res.groupby('Cylinder').mean()
bran_ave = bran_ave['ave']
bran_ave.plot(kind='bar')
plt.show()
```



1.10 Audit Accuracy

Since not all the models have valid sale price on the website, we have code to return Null value when no price available or wrong price get. Also, we use commands like dropna, check price>0 to confirm the data accuracy.

1.11 Audit Consistency

The datasets which have been used in this assignment show a uniform relationship between each of the dataset since they are linked to each other by a common attribute.

1.12 Report

- Files:
 - Files used: Manufacture(top30).csv, all_alpha_20.csv
 - Files generated: model.csv, record.csv
- Codes:
 - Step 1: Extraction of Data
 - 1. Using the API: Using urllib.request to access the website, changing variables in the url to get models from different manufactures. json library to read the data.
 - 2. Using the website to scrap the data: Using urllib.request to access the website BeautifulSoup library helps to scrap the contents of the

- web page. find_all() method were used to extract the information we need.
- 3. Loading the csv file: Using csv library to read, write and append the csv file. Pandas to read the csv file and load into data frames.
- Step 2: Auditing and cleaning the data: To gain information about the dataset, we used method like shape, info, iloc, isnull, etc, concat data frames and reindex, dropna to cleaning the data.

1.13 Conclusion

The assignment focusing on learning getting the data from various sources, munging the data and reformat the data to fit the conceptual database model, cleaning and auditing to make the dataset accurate. and visualizing the dataset to get useful conclusion. ## Contribution

We contributed by own: 70% By external sources: 30% ## Citations

https://github.com/nikbearbrown/INFO_6210/blob/master/Movie_DB_Example/Pandas_Data_Cleaning_Wrantyhttps://blog.csdn.net/u014662865/article/details/59058039

https://morvanzhou.github.io/tutorials/data-manipulation/np-pd/3-2-pd-indexing/

https://zhuanlan.zhihu.com/p/32572237 https://blog.csdn.net/guoziqing506/article/details/52014

[]: