

TASK 1:

SUMMARIZING THE DATASET:

Observation Of the Data

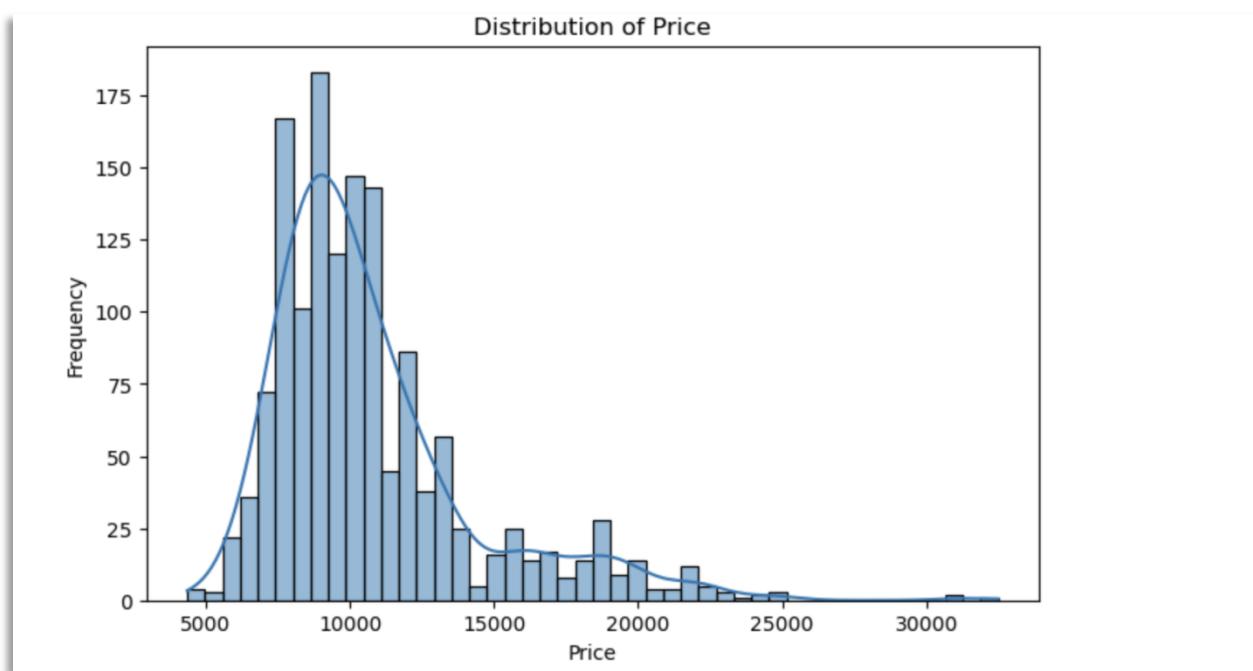
	Id	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	HP	Met_Color	Automatic	CC
count	1436.00	1436.00	1436.00	1436.00	1436.00	1436.00	1436.00	1436.00	1436.00	1436.00
mean	721.56	10730.82	55.95	5.55	1999.63	68533.26	101.50	0.67	0.06	1576.86
std	416.48	3626.96	18.60	3.35	1.54	37506.45	14.98	0.47	0.23	424.39
min	1.00	4350.00	1.00	1.00	1998.00	1.00	69.00	0.00	0.00	1300.00
25%	361.75	8450.00	44.00	3.00	1998.00	43000.00	90.00	0.00	0.00	1400.00
50%	721.50	9900.00	61.00	5.00	1999.00	63389.50	110.00	1.00	0.00	1600.00
75%	1081.25	11950.00	70.00	8.00	2001.00	87020.75	110.00	1.00	0.00	1600.00
max	1442.00	32500.00	80.00	12.00	2004.00	243000.00	192.00	1.00	1.00	16000.00

1. Price: The average car price is \$10,730.82, with prices ranging from \$4,350 to \$32,500. A standard deviation of \$3,626.96 indicates a significant variation in prices.
2. Age: The average age of the cars (as of August 2004) is 55.95 months, with most cars between 44 and 70 months old.
3. Manufacturing Year: The average manufacturing year is 1999.63, with cars manufactured between 1998 and 2004, and 75% of cars manufactured before 2001.
4. Kilometers (KM): The average mileage is 68,533 km, with cars ranging from as low as 1 km to 243,000 km. The interquartile range shows that most cars have driven between 43,000 and 87,000 km.
5. Horsepower (HP): The cars have an average horsepower of 101.5, ranging from 69 to 192 horsepower, indicating a variety of vehicle power levels.
6. Metallic Color: 67% of the cars have metallic paint, based on the binary variable.
7. Automatic Transmission: Only 6% of the cars are automatic, as shown by the low average of this binary feature.
8. Engine Capacity (CC): The average engine capacity is 1,576.86 cc, with most cars having engine sizes between 1,400 and 1,600 cc.

DISTRIBUTION OF PRICE:

Mean of Price: 10730.824512534818

Median of Price: 9900.0



INFERENCE:

The median price is 9,900, which suggests that half of the cars are priced below 9,900 and half are priced above.

This means that a significant portion of the cars are priced lower than the average price, i.e., 10730. Therefore, most cars are likely to be more affordable than the average is suggesting.

The average price could have been influenced by a few high-priced cars(outliers), making it appear that cars are generally more expensive than they are.

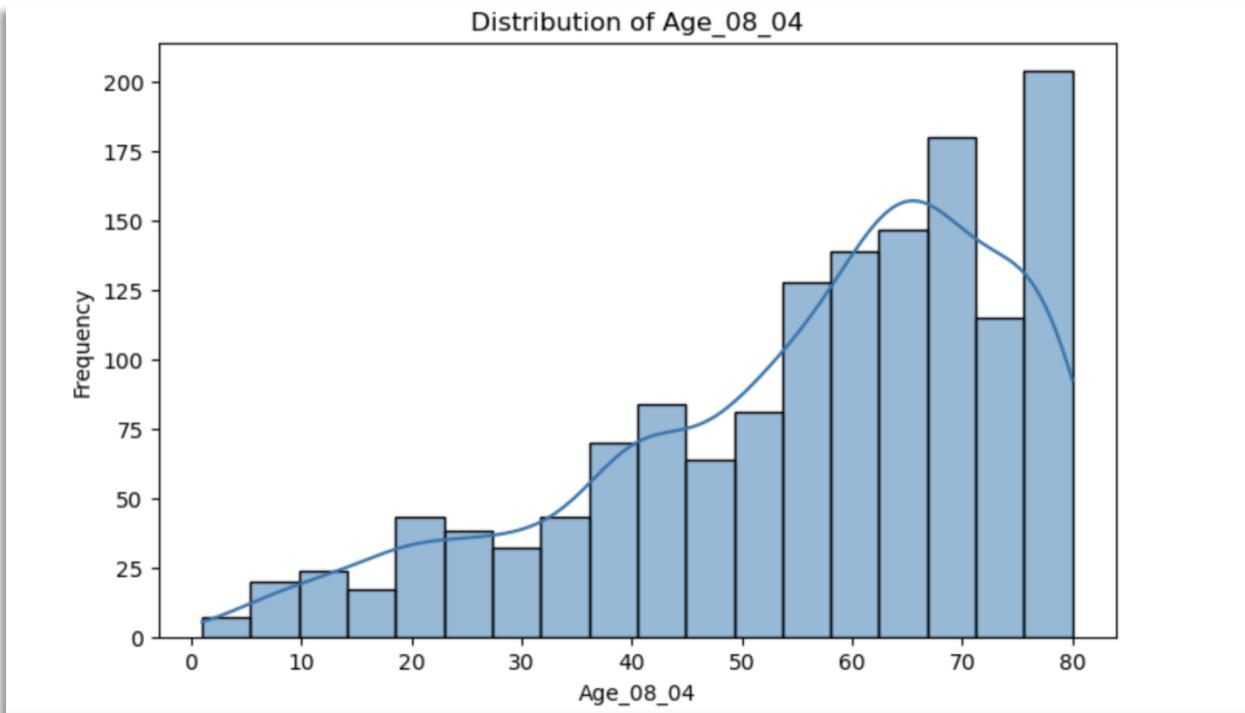
We can also look at Skewness to understand the asymmetry of the distribution.

In this Mean > Median therefore it means it's Right Skewed – implying that there are many cheap cars but only few expensive ones.

DISTRIBUTION OF AGE:

Mean of Age: 55.94707520891365

Median of Age: 61.0



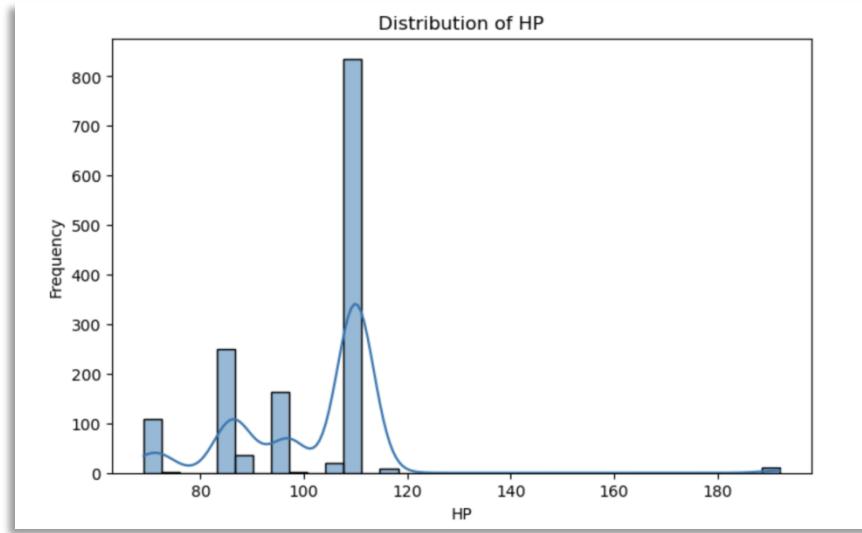
INFERENCE:

In this Mean < Median which means it's Left Skewed – implying that there are a few newer cars in the dataset but the majority of cars are older.

DISTRIBUTION OF HP:

Mean of HP: 101.50208913649026

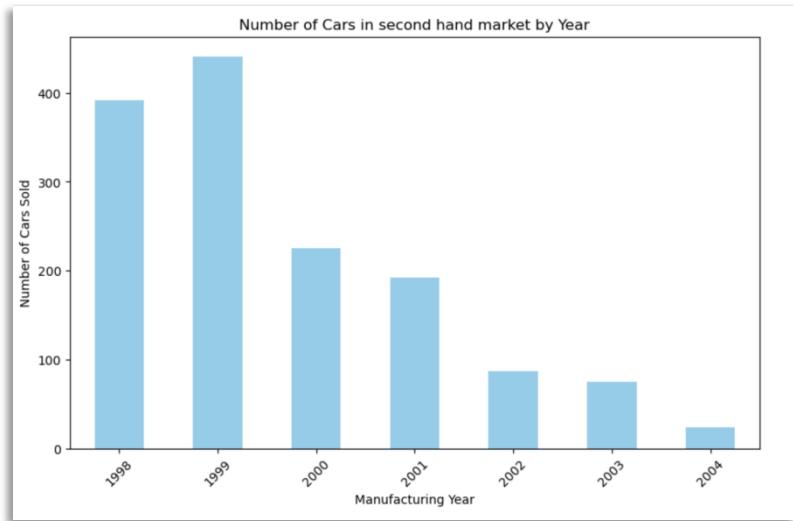
Median of HP: 110.0



INFERENCE:

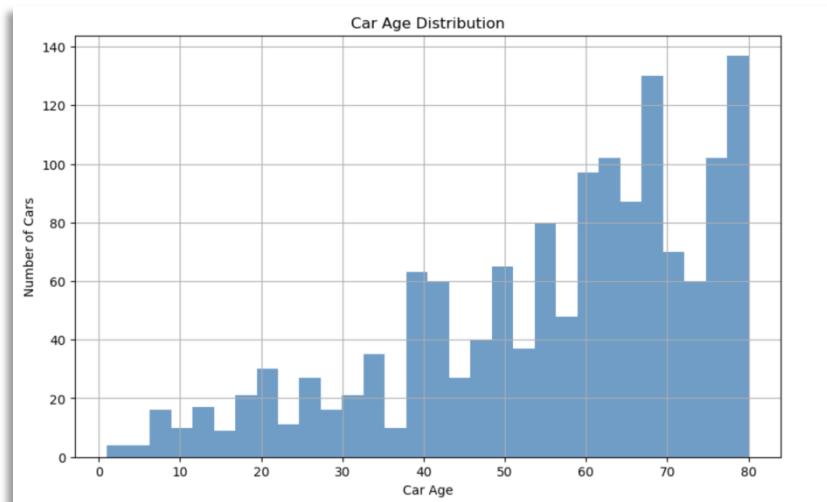
So, from the above we can assume that Left Skewed - Mean < Median but it is also important that we look at the graph and the skewness calculation which is a better indicator of the distribution shape. So, though the mean < median, it follows a Right skewed distribution.

UNDERSTANDING CARS BY YEAR:



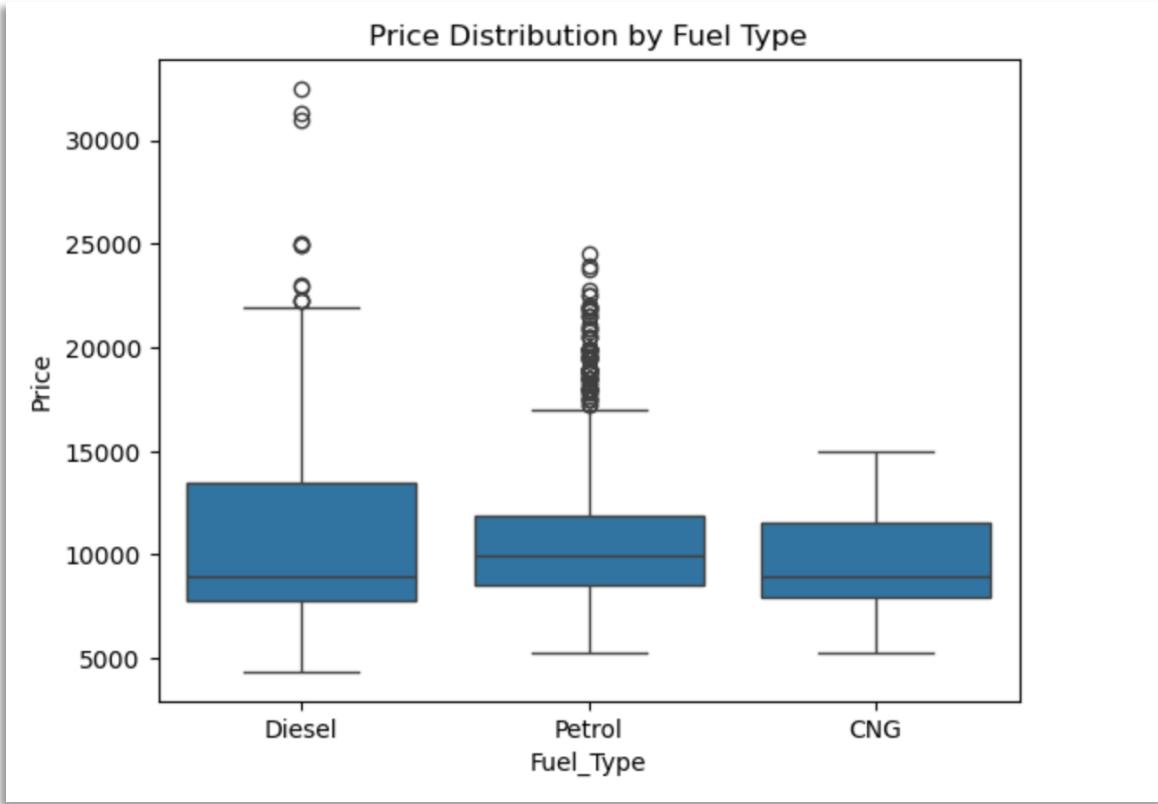
There was a greater presence of 1998 and 1999 Toyota Corolla models in the second-hand market, while newer models were less commonly available. This trend is clearly illustrated in the graph, with the most recent data available up to 2004.

CAR AGE DISTRIBUTION:



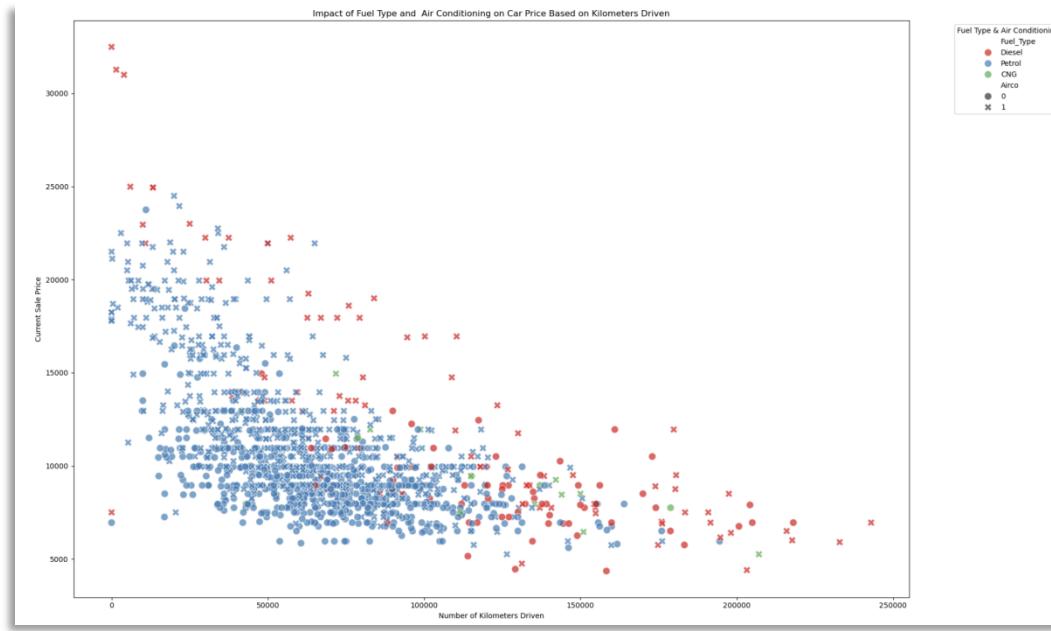
The Bar graph shows us that the number of cars is higher with age greater than 40 months. As the car age declines the number of cars gets less. Thats why the median price of car is less than mean price.

PRICE DISTRIBUTION BY FUEL TYPE:



The box plot shows that the price distribution of cars based on fuel type, showing that Diesel cars generally have higher prices and more outliers, with a median of around 10,000 and outliers up to 30,000. Petrol cars have a median price just below 10,000, with outliers reaching up to 25,000. CNG cars are the most consistently priced, with a median around 7,500 and no significant outliers.

IMPACT OF FUEL TYPE & AC ON CAR PRICE BASED ON THE KM DRIVEN:



Diesel cars (red) tend to cluster at higher price points compared to Petrol (blue) and CNG (green), particularly when the car has driven fewer kilometers. However, this gap closes as kilometers driven increases

Petrol cars (blue) dominate the lower price range across the spectrum, and their prices drop more quickly with kilometers driven increases

CNG cars (green) appear sparsely and are mostly concentrated in the middle price range, with fewer data points overall

Cars with air conditioning (cross markers) tend to have higher sale prices compared to cars without air conditioning (circle markers). This is noticeable across different fuel types.

This impact is especially pronounced in the lower Kilometer driven cars, where the price difference between cars with and without air conditioning is more visible.

2. NORMALIZING THE VARIABLE KILOMETERS:

```
Original KM values:
```

```
0    46986
1    72937
2    41711
3    48000
4    38500
Name: KM, dtype: int64
```

```
Standard Normalized KM values:
```

```
0   -0.574695
1    0.117454
2   -0.715386
3   -0.547650
4   -0.801028
Name: KM, dtype: float64
```

3. CREATING DUMMIES FOR FUEL TYPES:

```
Original Fuel_Type values:
```

```
0   Diesel
1   Diesel
2   Diesel
3   Diesel
4   Diesel
Name: Fuel_Type, dtype: object
```

```
DataFrame with Fuel_Type dummies:
```

```
   Id          Model  Price  Age_08_04 \
0  1  TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors  13500    23
1  2  TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors  13750    23
2  3  TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors  13950    24
3  4  TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors  14950    26
4  5  TOYOTA Corolla 2.0 D4D HATCHB SOL 2/3-Doors  13750    30

   Mfg_Month  Mfg_Year      KM Fuel_Type  HP Met_Color ... Radio \
0       10     2002 -0.574695  Diesel   90      1 ...  0
1       10     2002  0.117454  Diesel   90      1 ...  0
2        9     2002 -0.715386  Diesel   90      1 ...  0
3        7     2002 -0.547650  Diesel   90      0 ...  0
4        3     2002 -0.801028  Diesel   90      0 ...  0

   Mistlamps  Sport_Model  Backseat_Divider  Metallic_Rim  Radio_cassette \
0         0            0                  1                  0                  0
1         0            0                  1                  0                  0
2         0            0                  1                  0                  0
3         0            0                  1                  0                  0
4         1            0                  1                  0                  0

   Parking_Assistant  Tow_Bar  Fuel_Type_Diesel  Fuel_Type_Petrol
0                 0         0           True        False
1                 0         0           True        False
2                 0         0           True        False
3                 0         0           True        False
4                 0         0           True        False
```

```
[5 rows x 41 columns]
```

4. PARTITIONING THE DATASET:

Training : (718, 39)
Validation : (431, 39)
Test : (287, 39)

Training : (718, 39)
Validation : (430, 39)
Test : (288, 39)

TASK 2:

SUMMARY OF THE CASE STUDY: MARKET STREET WINE CASE

CHANGES IN CUSTOMER BASE:

- It varied from people who wanted an experience with wines from classic regions to people who are curious about local and organic wines.
- The age group used to be mid 40s and 50s which shifted to 30s and 40s.
- Types of customers:
 1. Knowledgeable and enthusiasts.
 2. Curious but not widely informed.
 3. Who just came to grab something.

CHANGES IN REGULATIONS:

- In 1933, a “Three tier system” was introduced: Manufacturers, Wholesalers and retailer (all require license)
- If a retailer/restaurant want to do business with a winery(manufacturer) – they need to obtain license in whole of Virginia to open their warehouses and then send their representatives to the endpoint which is retailer/ restaurants.
- Retailers have to only buy from reps.

CHANGE IN WINE TRENDS:

- In 2006 wine with high alcohol was preferred.
- A movement called “In pursuit of balance”, pushed to prefer lower alcohol which meant now grapes had to be picked earlier for heartier wines
- Rose wines were less popular but now there is sharp increase in popularity especially those that from Provence, France.

- To better understand the growth: Rose wine grew 118% times in 5 years whereas still wine grew 1.5%.
- In 2021, it came to a stop. Now the focus is on few high-quality labels.
- Rose wine sales according to places: Cold – seasonality, warm- all through the year.
- One more shift was Bordeaux was shifting to local Burgundy, Champagne, California etc.

ANOTHER SHIFT:

- Shift towards sustainability in US led to an interest in natural wines.
- Natural wines are now ahead of organic and sparkling wines.
- Millennials were actually converting them into something more than just buzz words.
- They are coming into the store and persistently asking for those wines.
- But understanding what exactly is organic is proving difficult. Does it mean wines low on sulphate?

COVID 19 TRENDS:

- Covid 19 led to supply chain issues like importing French produced sparkling wine was now difficult. Many hoped that these issues short term, but they went on for several years.
- Hence US produced prosecco and sparkling wine, the local substitutes. Now they became less of a holiday thing and more of an everyday thing.
- There was a new energy to the domestic production therefore sparkling wine category grew 13% among US drinkers in 2022.
- As the supply chain issues continued it gave opportunity for wines from lesser-known regions like Washington, Oregon, New York, Finger Lakes-Food and drinks from Idaho, Colorado and Virginia.
- But still many Charlottesville wine consumers preferred old world options.

CHANGES IN PURCHASING WINES:

- Apart from the supply chain issues, method of purchasing has also changed now.
- They have started using ecommerce platforms, stores became warehouses and hence there is no issue of space.
- But it would be difficult to retain the customers they have gained during pandemic “online only” shopping.
- This digital engagement allowed to collect more data on customer behaviors
- Millennials were buying more age than any other age.

BUSINESS PROBLEMS:

The below are the business problems to be addressed:

1. While classic wines (French and Italian) have become difficult to obtain. What other alternatives consumers might be open to trying?

2. Were there wine producing regions more easily available in US? That consumers might be interested in?
3. Could we find good ones that hit the popular price point of under 20\$?
4. Should they think about additional strategies to entice millennials?
5. What other wine trends would it be beneficial to consider?

**BREIF ANALYSIS OF THE DATASET
THROUGH EXCEL USING POWER QUERY:
INFERENCE 1:**

A	B	C	D	E	F	G	H	I	J	K	L	M
title	points	badge	price_usd	organic*	vintage_year	alcohol_content	bottle_size	wine_style	grape_variety	designation	vineyard_state	vineyard_region
2 Frey NV Organic Red (California)	86	Best Buy	9	1		0.139 750 ml	Red	Red Blends	Organic	California	California	
3 Dark Horse 2018 Sauvignon Blanc (California)	90	Best Buy	8	0	2018	0.13 750 ml	White	Sauvignon Blanc		California	California	
4 Dark Horse 2016 Merlot (California)	89	Best Buy	8	0	2016	0.135 750 ml	Red	Merlot		California	California	
5 Dark Horse 2019 Chardonnay (California)	89	Best Buy	8	0	2019	0.145 750 ml	White	Chardonnay		California	California	
6 Dark Horse 2019 Sauvignon Blanc (California)	89	Best Buy	8	0	2019	0.13 750 ml	White	Sauvignon Blanc		California	California	
7 Dark Horse 2018 Rosé (California)	84	Best Buy	8	0	2019	0.13 750 ml	Rose	Rosé		California	California	
8 Dark Horse 2020 Pinot Grigio (California)	88	Best Buy	8	0	2020	0.13 750 ml	White	Pinot Grigio		California	California	
9 Dark Horse NV Double Down (California)	88	Best Buy	8	0		0.145 750 ml	Red	Red Blends	Double Down	California	California	
10 Dark Horse 2017 Pinot Noir (California)	89	Best Buy	8	0	2017	0.14 750 ml	Red	Pinot Noir		California	California	
11 Sutter Home NV Pinot Grigio (California)	88	Best Buy	8	0		0.13 750 ml	White	Pinot Grigio		California	California	
12 Dark Horse 2019 Merlot (California)	88	Best Buy	8	0	2019	0.145 750 ml	Red	Merlot		California	California	
13 Dark Horse NV Big Red (California)	87	Best Buy	8	0		0.135 750 ml	Red	Red Blends	Big	California	California	
14 Dark Horse 2017 Cabernet Sauvignon (California)	87	Best Buy	8	0	2017	0.135 750 ml	Red	Cabernet Sauvignon		California	California	
15 Dark Horse 2018 Chardonnay (California)	87	Best Buy	8	0	2016	0.135 750 ml	White	Chardonnay		California	California	
16 Twisted 2015 Pinot Grigio (California)	87	Best Buy	8	0	2015	0.13 750 ml	White	Pinot Grigio		California	California	
17 Dark Horse 2017 Sauvignon Blanc (California)	87	Best Buy	8	0	2017	0.13 750 ml	White	Sauvignon Blanc		California	California	

With the help of power query, we have sorted the “Best buy” badge data in excel. First, we sorted the price column in ascending order and then we sorted the points column in descending order. We have also moved organic column next to the price_usd column, after that we sorted the organic column. After the sorting we can understand the data better.

As there was a trend of organic wine we can see that the only best buy badged wine which is also organic is Frey NV which is of 9\$ and has 86 points. All other wine has the best badge but are not organic, but they have higher points and still many of the wines come under 20\$.

INFERENCE 2:

A	B	C	D	E	F	G	H	I	J	
title	points	badge	price_usd	natural*	vintage_year	alcohol_content	bottle_size	wine_style	grape_variety	designation
2 Halcyon 2019 L'Espresso Vineyard Cabernet Franc (El Dorado)	93	Cellar Selection	35	1	2019	0.137 750 ml	Red	Cabernet Franc	Camino Alto Vineyard	
3 Rutherford 2013 Louis Vintner's Reserve Pinot Noir (Santa Barbara County)	94	Cellar Selection	58	1	2013	0.135 750 ml	Red	Pinot Noir	Louis Vintner's Reserve	
4 Roche 2016 White End Vineyard Chardonnay (Chehalis Mountains)	93	Cellar Selection	60	1	2016	0.135 750 ml	White	Chardonnay	White End Vineyard	
5 Patricia Green Cellars 2016 Freedom Hill Vineyard Côte Pinot Noir (Willamette Valley)	95	Cellar Selection	75	1	2016	0.14 750 ml	Red	Pinot Noir	Freedom Hill Vineyard Côte Cl	
6 The Erie Vineyards 2013 Original Vines Estate Pinot Noir (Willamette Valley)	94	Cellar Selection	80	1	2013	0.13 750 ml	Red	Pinot Noir	Original Vines Estate	
7 Kendall-Jackson 2013 Vintner's Reserve Summation Red (Dundee Hills)	91	Cellar Selection	17	0	2013	0.145 750 ml	Red	Red Blends	Vintner's Reserve Summation	
8 Styling 2014 Whimsy Estate Riesling (Ribbon Ridge)	95	Cellar Selection	20	0	2014	0.12 750 ml	White	Riesling	Whimsy Estate	
9 McNamara 2017 Petite Sirah (Mendocino)	92	Cellar Selection	20	0	2017	0.148 750 ml	Red	Petite Sirah		
10 Long Shadows 2019 Poet's Leap Riesling (Columbia Valley (WA))	92	Cellar Selection	20	0	2019	0.123 750 ml	White	Riesling	Poet's Leap	
11 Soos Creek 2017 Soleil Red (Columbia Valley (WA))	91	Cellar Selection	20	0	2017	0.141 750 ml	Red	Bordeaux-style Red Blend	Soleil	
12 St. Amant 2018 Mohr-Fry Ranch Petite Sirah (Lodi)	94	Cellar Selection	21	0	2018	0.143 750 ml	Red	Petite Sirah	Mohr-Fry Ranch	
13 Barra of Mendocino 2016 Estate Grown Petite Sirah (Mendocino)	93	Cellar Selection	22	0	2016	0.145 750 ml	Red	Petite Sirah	Estate Grown	
14 Sokol Blosser 2015 Pinot Gris (Dundee Hills)	91	Cellar Selection	22	0	2015	0.13 750 ml	White	Pinot Gris		
15 Barra of Mendocino 2011 Estate Grown Petite Sirah (Mendocino)	89	Cellar Selection	22	0	2011	0.145 750 ml	Red	Petite Sirah	Estate Grown	
16 Keuka Spring 2014 Humphreys Vineyard Riesling (Finger Lakes)	88	Cellar Selection	22	0	2014	0.12 750 ml	White	Riesling	Humphreys Vineyard	
17 Tolosa 2019 No Oak Heritage Chardonnay (Central Coast)	91	Cellar Selection	23	0	2019	0.134 750 ml	White	Chardonnay	No Oak Heritage	

In this image, we have filtered the Cellar Selection badge data. as we are focusing on the natural wine we sorted the natural column in descending order, then sorted the price column in ascending order, after that, we sorted the points column in descending order so that we can get a clear view on our data.

As we can see that there are 5 natural wine with the price range of \$35 - \$80 and with points range of 92-95. If the wine is not natural then the price range is \$17 - \$525 and the point ranges from 88 - 100.

INFERENCE 3:

A	B	C	D	E	F	G	H	I	J	
title	points	badge	price_usd	natural*	vintage_year	alcohol_content	bottle_size	wine_style	grape_variety	designation
6 J. Scott Cellars 2017 Sauvignon Blanc (Oregon)	91	Editors' Choice	18	1	2017	0.138 750 ml	White	Sauvignon Blanc		
7 Hawk 2020 Grenache Rose (Rogue Valley)	91	Editors' Choice	18	1	2020	0.127 750 ml	Rose	Rosé	Grenache	
8 Barra of Mendocino 2016 Estate Grown Cabernet Sauvignon (Mendocino)	91	Editors' Choice	20	1	2016	0.145 750 ml	Red	Cabernet Sauvignon	Estate Grown	
9 Owen Roe 2020 Crawford-Beck Vineyard Pinot Gris (Eola-Amity Hills)	92	Editors' Choice	22	1	2020	0.13 750 ml	White	Pinot Gris	Crawford-B	
10 Charlie & Echo 2019 Witherfall Tempest Red (San Diego County)	91	Editors' Choice	25	1	2019	0.118 750 ml	Red	Red Blends	Witherfall I	
11 J. Scott Cellars 2016 Syrah (Rogue Valley)	91	Editors' Choice	28	1	2016	0.149 750 ml	Red	Syrah		
12 Amador Cellars 2015 Estate Reserve Grenache Noir (Amador County)	93	Editors' Choice	30	1	2015	0.15 750 ml	Red	Grenache Noir	Estate Reserve	
13 Fields Family 2013 Lodi Native Stampede Vineyard Zinfandel (Clements Hills)	91	Editors' Choice	30	1	2013	0.139 750 ml	Red	Zinfandel	Lodi Native	
14 Troon 2014 Estate Tannat (Applegate Valley)	90	Editors' Choice	35	1	2014	0.144 750 ml	Red	Tannat	Estate	
15 Thacher 2020 Hastings Ranch Viognier (Paso Robles)	92	Editors' Choice	36	1	2020	0.129 750 ml	White	Viognier	Hastings Ra	
16 Davies 2015 Pinot Noir (Anderson Valley)	94	Editors' Choice	40	1	2015	0.143 750 ml	Red	Pinot Noir		
17 Birchino 2019 Mr. Natural No. 3 Enz Vineyard Old Vine Mourvèdre (Lime Kiln Valley)	93	Editors' Choice	40	1	2019	0.125 750 ml	Red	Mourvèdre	Mr. Natural	
18 Ricochet 2019 Pinot Noir (Willamette Valley)	91	Editors' Choice	40	1	2019	0.13 750 ml	Red	Pinot Noir		
19 Day 2019 Belle Pente Vineyard Chardonnay (Yamhill-Carlton)	94	Editors' Choice	48	1	2019	0.123 750 ml	White	Chardonnay	Belle Pente	
20 Brooks 2015 Cinnella Pinot Noir (Eola-Amity Hills)	93	Editors' Choice	48	1	2015	0.135 750 ml	Red	Pinot Noir	Cinnella	
21 Winderlea 2013 Crawford Beck Vineyard Pinot Noir (Eola-Amity Hills)	91	Editors' Choice	48	1	2013	0.128 750 ml	Red	Pinot Noir	Crawford Bi	
22 King Estate 2013 Antiquum Vineyards Pinot Noir (Willamette Valley)	92	Editors' Choice	55	1	2013	0.135 750 ml	Red	Pinot Noir	Antiquum I	
23 Dutton-Goldfield 2014 Fox Den Vineyard Pinot Noir (Green Valley)	94	Editors' Choice	62	1	2014	0.135 750 ml	Red	Pinot Noir	Fox Den Vir	
24 Brick & Mortar 2017 Rosé (California)	91	Editors' Choice	8	0	2017	0.115 375 ml	Rose	Rosé		
25 Brick & Mortar 2018 Rosé (California)	91	Editors' Choice	8	0	2018	0.115 375 ml	Rose	Rosé		
26 Maker 2020 Ser Winery Rosé of Grenache (Monterey)	90	Editors' Choice	8	0	2020	0.13 250 ml	Rose	Grenache	Ser Winery	
27 Al 2016 Sauvignon Blanc (Monterey County)	88	Editors' Choice	8	0	2016	0.129 375 ml	White	Sauvignon Blanc		
28 Maker 2019 Nicole Walsh Cabernet Pfeffer (Cienega Valley)	91	Editors' Choice	12	0	2019	0.13 250 ml	Red	Cabernet Pfeffer	Nicole Wal	
29 Coopers Hall 2018 Rosé of Pinot Noir (Willamette Valley)	90	Editors' Choice	12	0	2018	0.139 500 ml	Rose	Pinot Noir	Rosé of	
30 Castle Rock 2014 Pinot Noir (Mendocino County)	87	Editors' Choice	13	0	2014	0.135 750 ml	Red	Pinot Noir		
31 Vinum 2015 Chenin Blanc (Clarksburg)	91	Editors' Choice	14	0	2015	0.135 750 ml	White	Chenin Blanc		
32 J. Lohr 2018 Riverstone Chardonnay (Arroyo Seco)	88	Editors' Choice	14	0	2018	0.14 750 ml	White	Chardonnay	Riverstone	
33 Bonny Doon 2020 Le Cigare Volant Red (Central Coast)	92	Editors' Choice	15	0	2020	0.136 750 ml	Red	Rhône-style Red Blend	Le Cigare Vi	

The last Badge is the Editor's choice in this data, we have more natural options with the prices ranging from \$18 - \$62 and points ranging from 91 - 94. if we talk about non-natural options the prices are higher ranging from \$8 - \$475 with points ranging from 87 - 100.

THROUGH PYTHON:

UNDERSTANDING ROWS AND COLUMNS:

```
(41731, 65)
Index(['title', 'points', 'badge', 'price_usd', 'vintage_year',
       'alcohol_content', 'bottle_size', 'wine_style', 'grape_variety',
       'designation', 'vineyard_state', 'vineyard_region_1',
       'vineyard_region_2', 'winery', 'winery_longitude', 'winery_latitude',
       'winery_state', 'review_url', 'review_year', 'taster_name', 'natural*',
       'organic*', 'cherr*', 'sweet*', 'tanni*', 'earth*', 'fresh*', 'melon',
       'yeast', 'tart', 'bright*', 'jam', 'plum*', 'perfume*', 'fruit*',
       'toast*', 'dry*', 'crisp*', 'acid*', 'vanilla', 'apple', 'lime', 'oak*',
       'spic*', 'strawberr*', 'tropical*', 'smok*', 'meat*', 'berr*',
       'mineral', 'apricot', 'tobacco', 'leather*', 'forest', 'pepper*',
       'herb*', 'floral', 'rich*', 'citrus*', 'nut*', 'grass*', 'lemon*',
       'cream*', 'wood*', 'honey'],
      dtype='object')
```

The dataset has 41,731 rows and 65 columns. The columns represent various attributes of wine, including details like title, points, price, vintage year, and winery location, along with tasting notes (e.g., fruit, tannin, oak) and descriptors. The data spans a wide range of characteristics used for wine reviews and analysis.

CHECKING FOR NULL VALUES:

```
title          0
points         0
badge        35138
price_usd     334
vintage_year   470
...
grass*         0
lemon*         0
cream*         0
wood*          0
honey          0
Length: 65, dtype: int64
```

The output shows the count of missing values for each column in the `wine_df` DataFrame. Notably, the 'badge' column has 35,138 missing entries, while 'price_usd' and 'vintage_year' have 334 and 470 missing values, respectively, indicating areas where data may need to be handled before analysis.

CHECKING FOR DUPLICATE ROWS:

```
print(wine_df.duplicated().sum())
```

```
0
```

The output indicates that there are no duplicate entries in the `wine_df` DataFrame