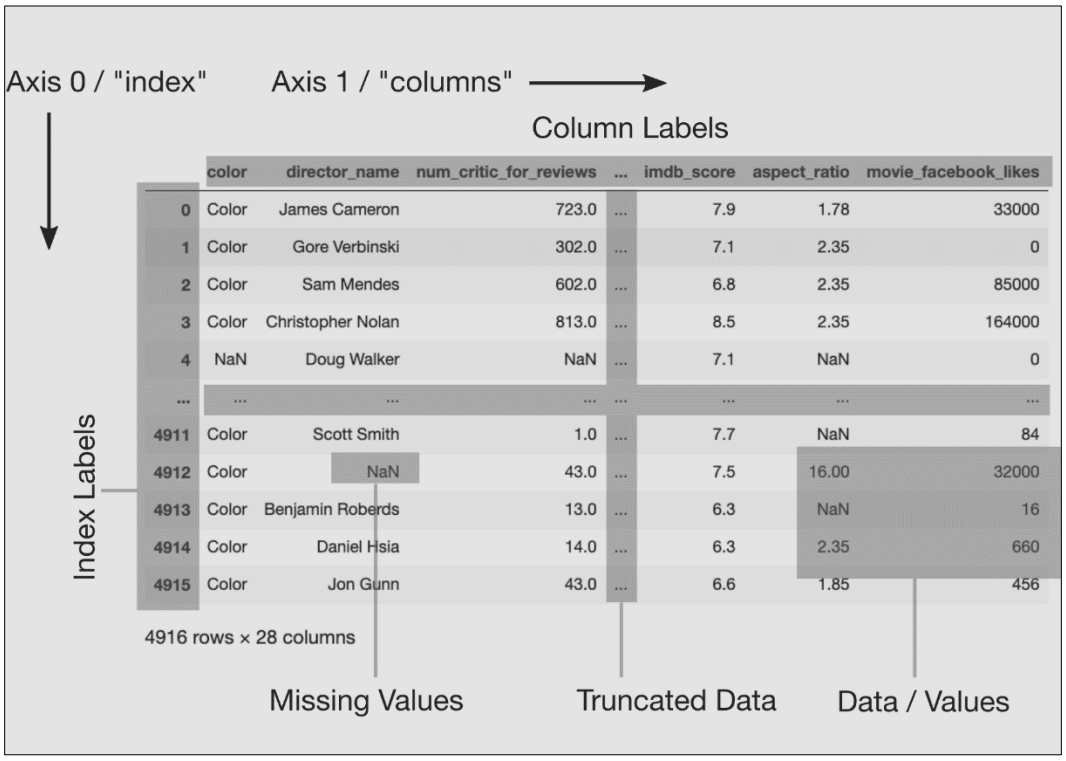
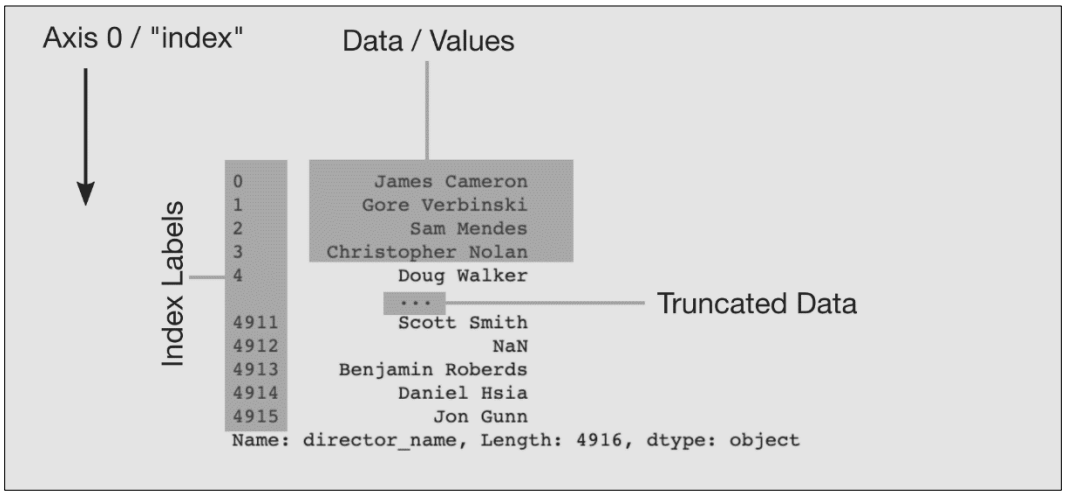
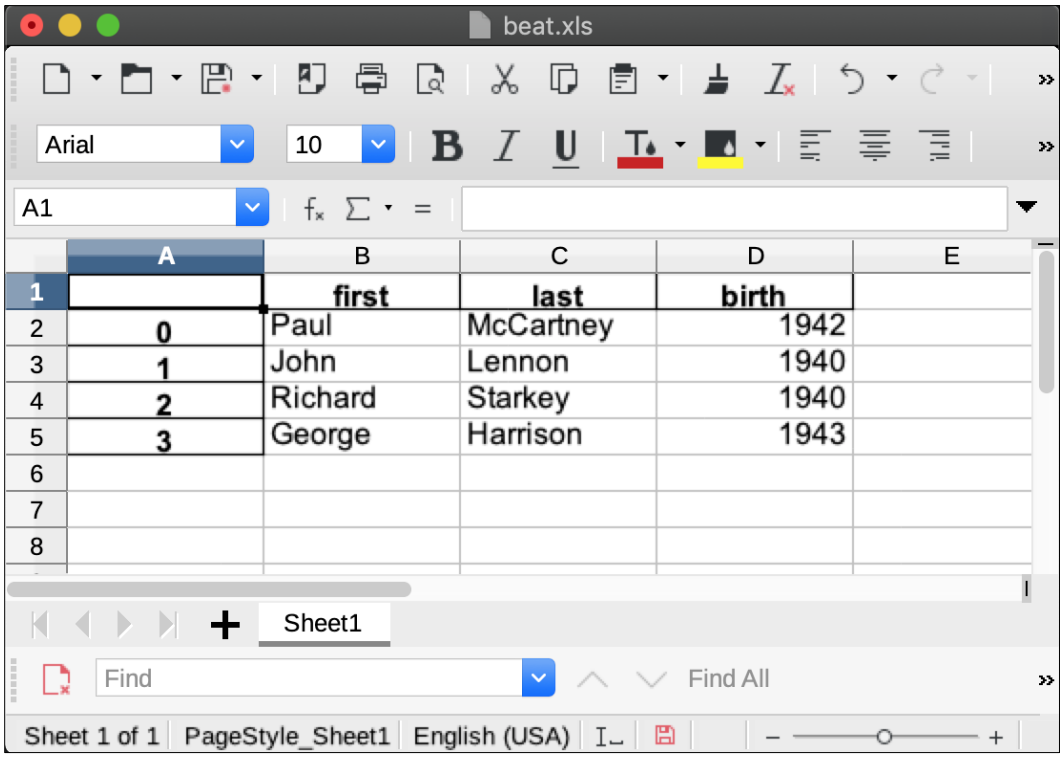
Chapter 1: Pandas Foundations



	color	director_name	num_critic_for_reviews	...	imdb_score	aspect_ratio	movie_facebook_likes
0	Color	James Cameron	723.0	...	7.9	1.78	33000
1	Color	Gore Verbinski	302.0	...	7.1	2.35	0
2	Color	Sam Mendes	602.0	...	6.8	2.35	85000
3	Color	Christopher Nolan	813.0	...	8.5	2.35	164000
4	NaN	Doug Walker	NaN	...	7.1	NaN	0
...	...	...	...	...	...	...	...
4911	Color	Scott Smith	1.0	...	7.7	NaN	84
4912	Color	NaN	43.0	...	7.5	16.00	32000
4913	Color	Benjamin Roberds	13.0	...	6.3	NaN	16
4914	Color	Daniel Hsia	14.0	...	6.3	2.35	660
4915	Color	Jon Gunn	43.0	...	6.6	1.85	456



Chapter 3: Creating and Persisting DataFrames

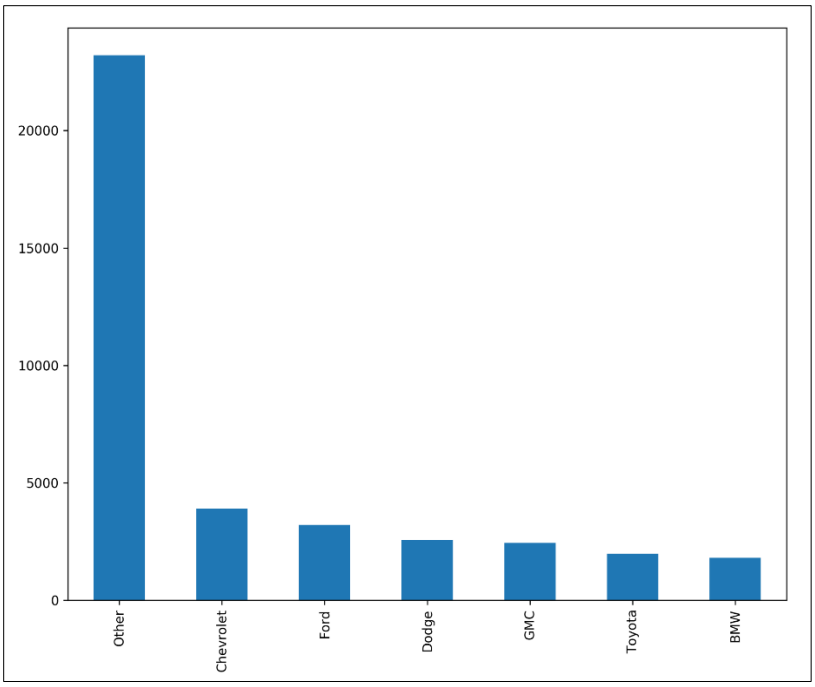


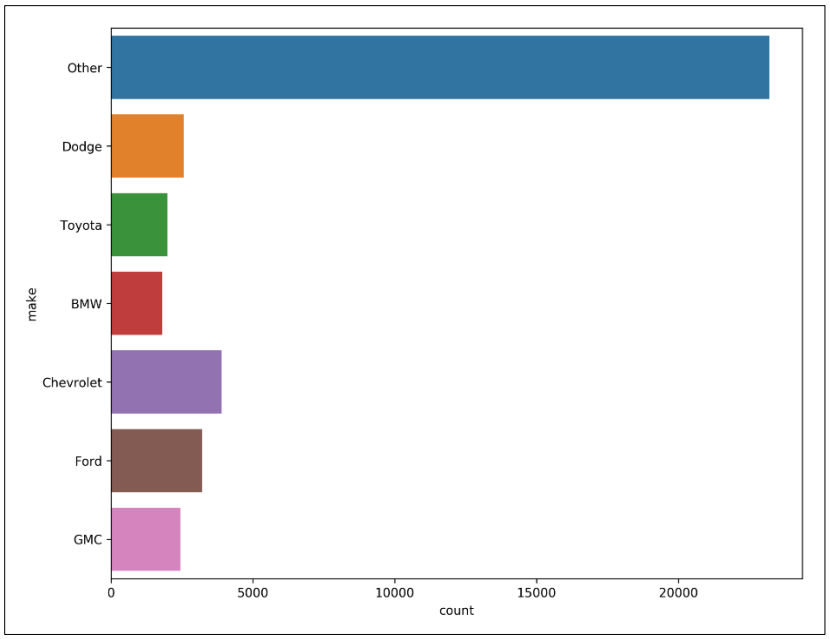
	A	B	C	D	E
1		first	last	birth	
2	0	Paul	McCartney	1942	
3	1	John	Lennon	1940	
4	2	Richard	Starkey	1940	
5	3	George	Harrison	1943	
6					
7					
8					

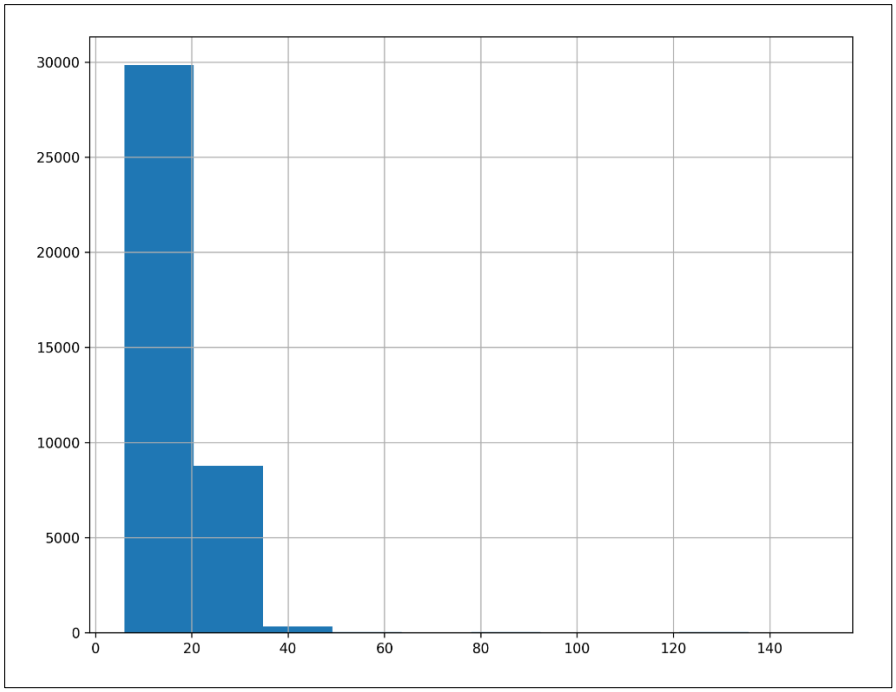
List of studio albums,[A] with selected chart positions and certifications

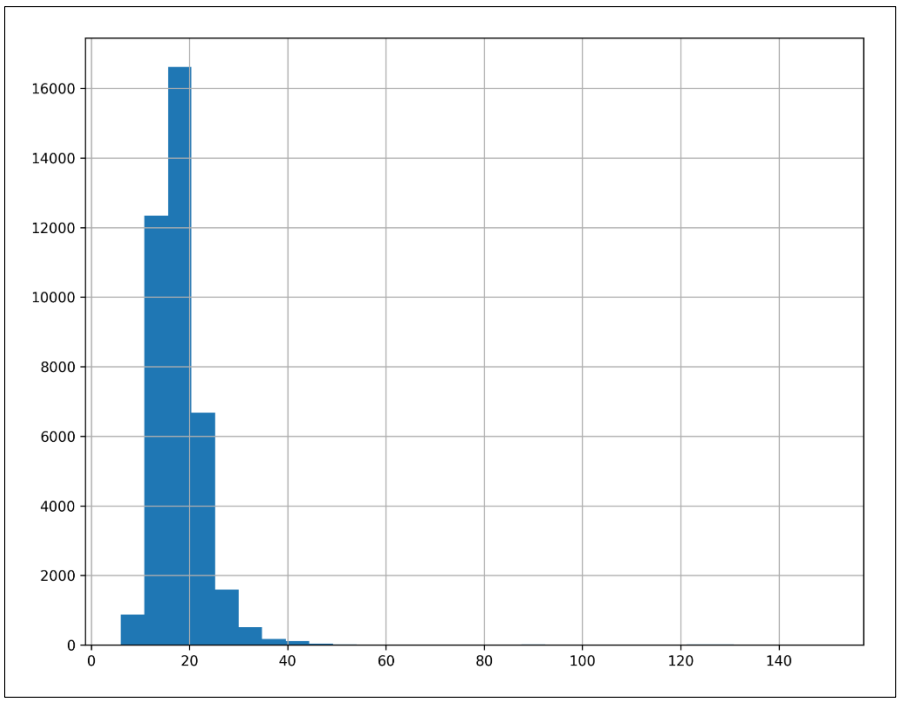
Title	Release	Peak chart positions							Certifications
		UK [1][2]	AUS [3]	CAN [4]	FRA [5]	GER [6]	NOR [7]	US [8][9]	
Please Please Me ‡	• Released: 22 March 1963 • Label: Parlophone (UK)	1	—	—	5	5	—	—	• BPI: Gold[10] • ARIA: Gold[11] • MC: Gold[12] • RIAA: Platinum[13]
With the Beatles[B] ‡	• Released: 22 November 1963 • Label: Parlophone (UK), Capitol (CAN), Odeon (FRA)	1	—	—	5	1	—	—	• BPI: Gold[10] • ARIA: Gold[11] • BVMI: Gold[15] • MC: Gold[12] • RIAA: Gold[13]

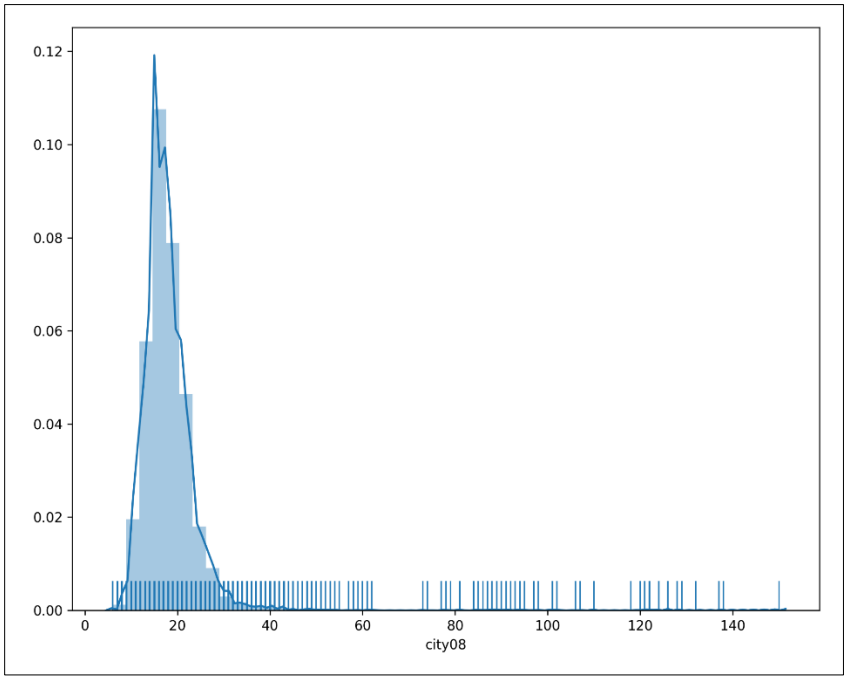
Chapter 5: Exploratory Data Analysis

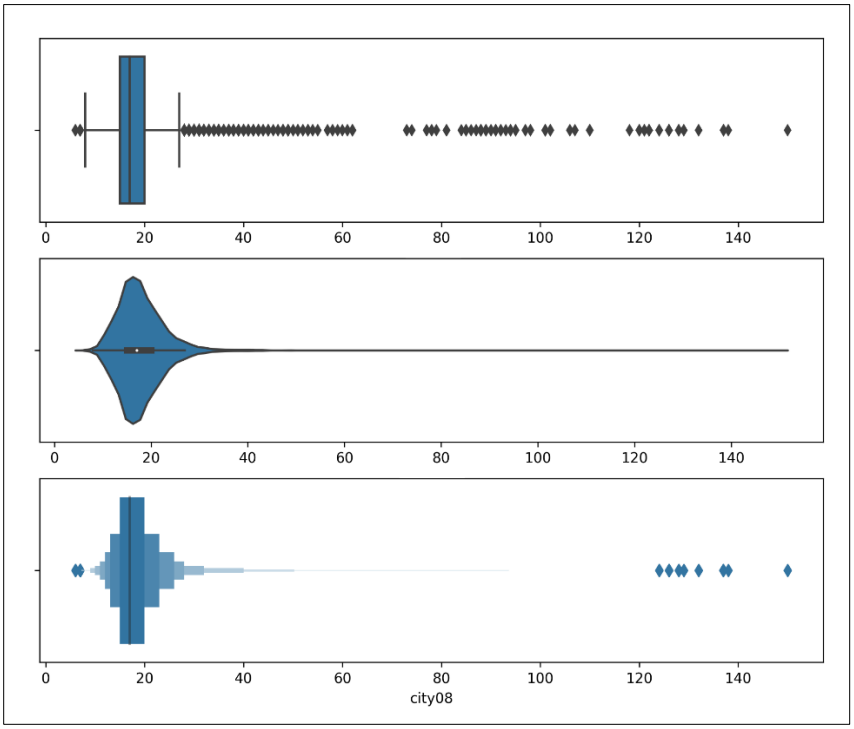


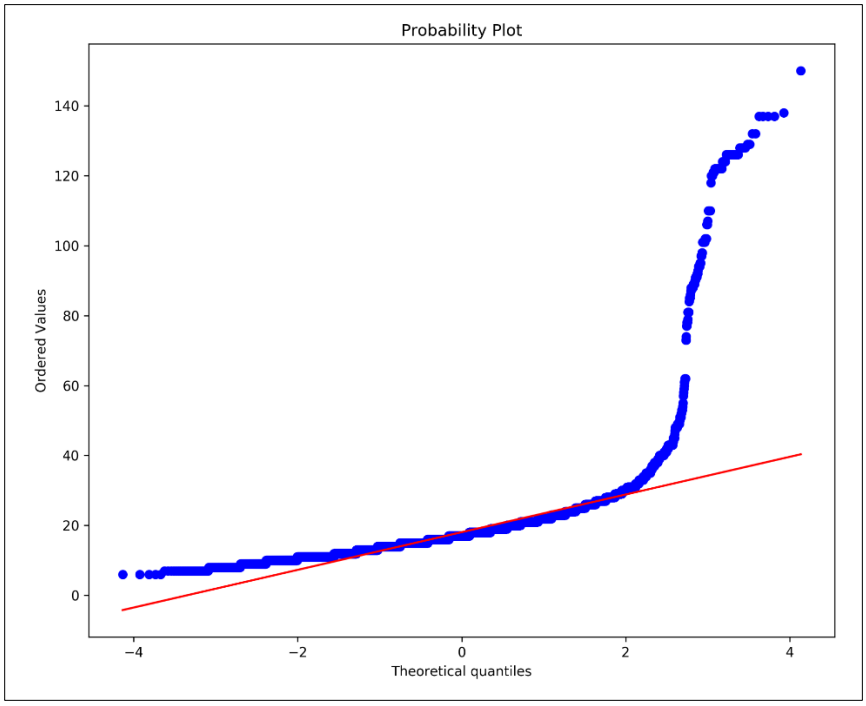


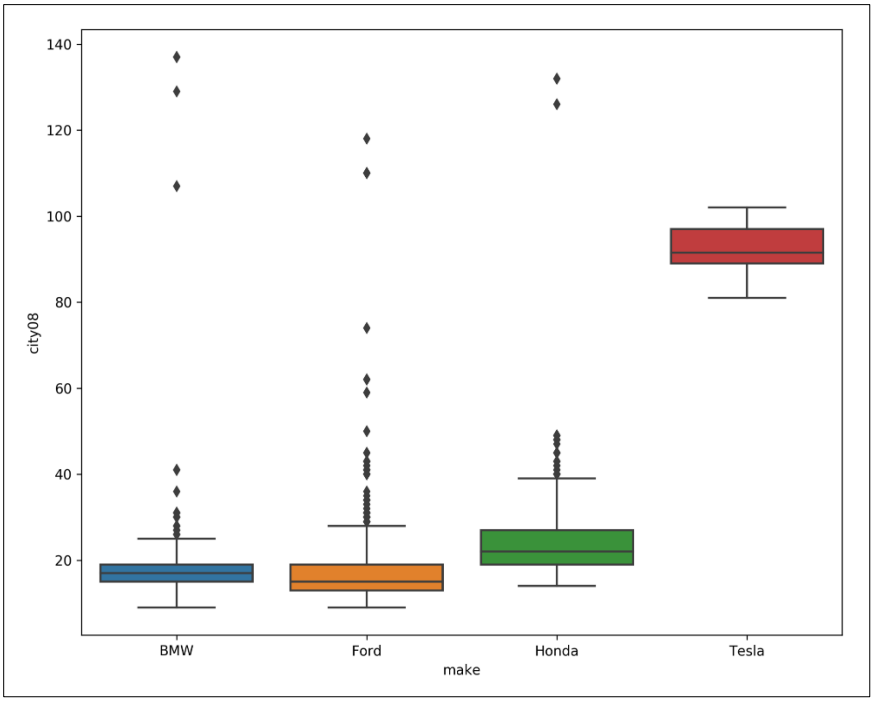

30000
25000
20000
15000
10000
5000
0
0
20
40
60
80
100
120
140

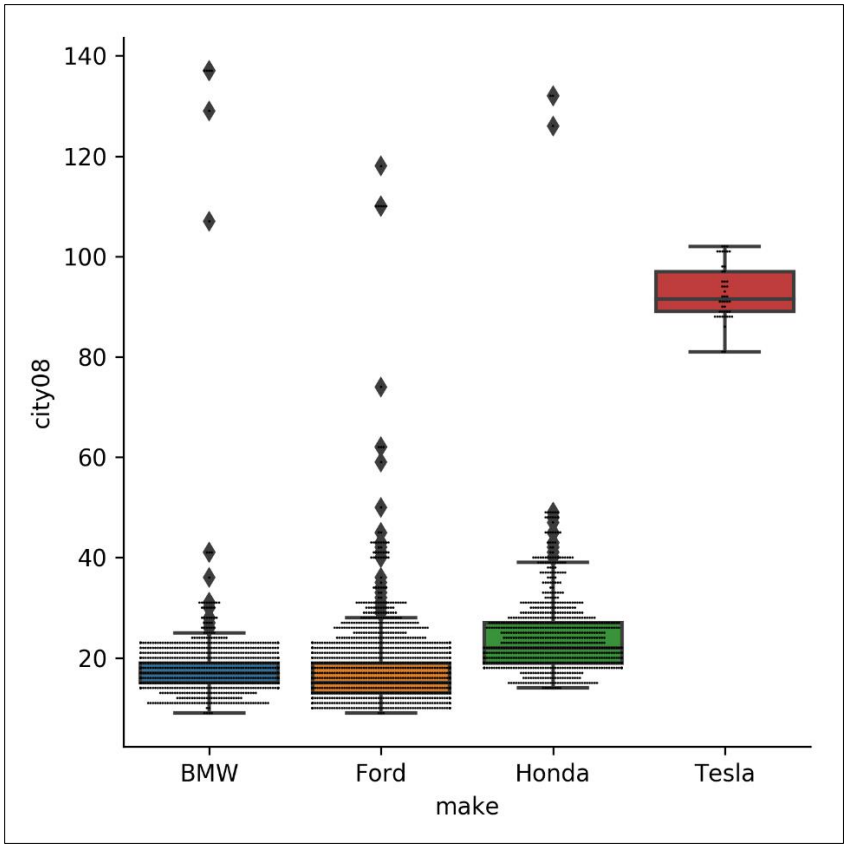

16000
14000
12000
10000
8000
6000
4000
2000
0
0
20
40
60
80
100
120
140

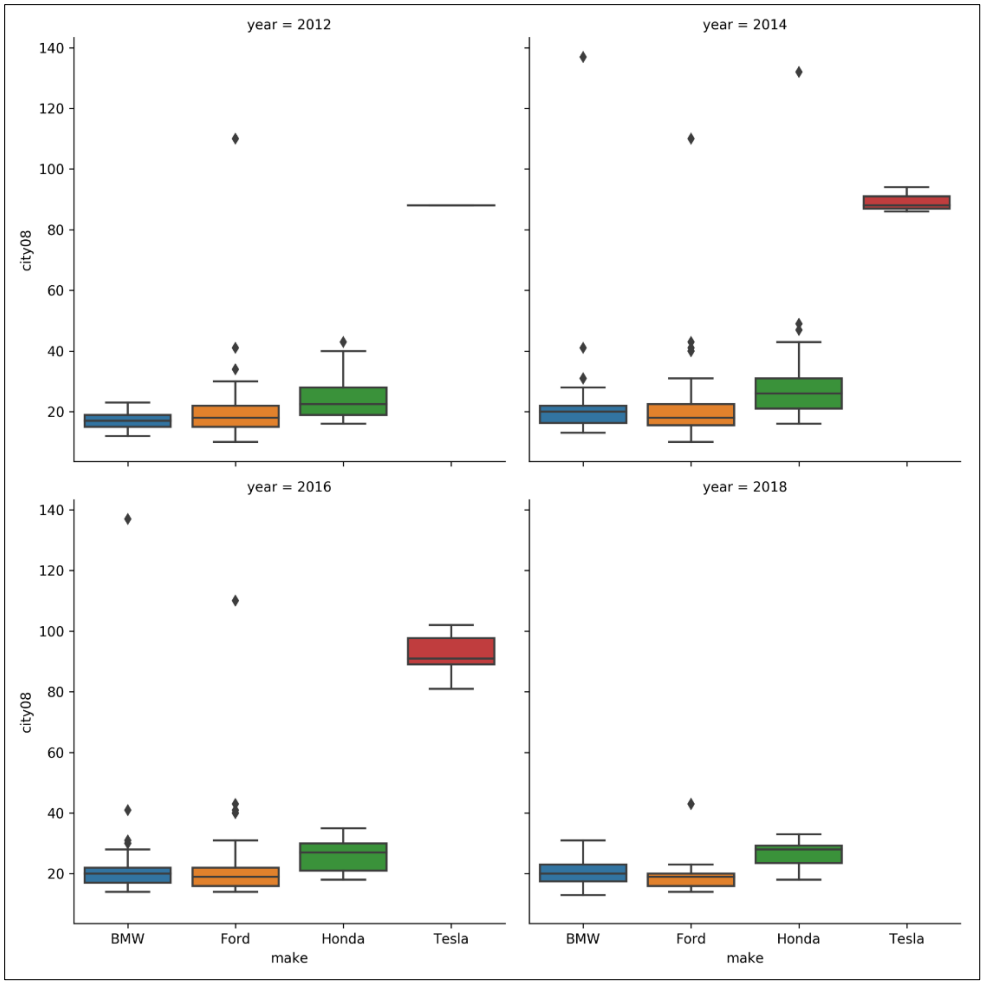

0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
20
40
60
80
100
120
140
city08

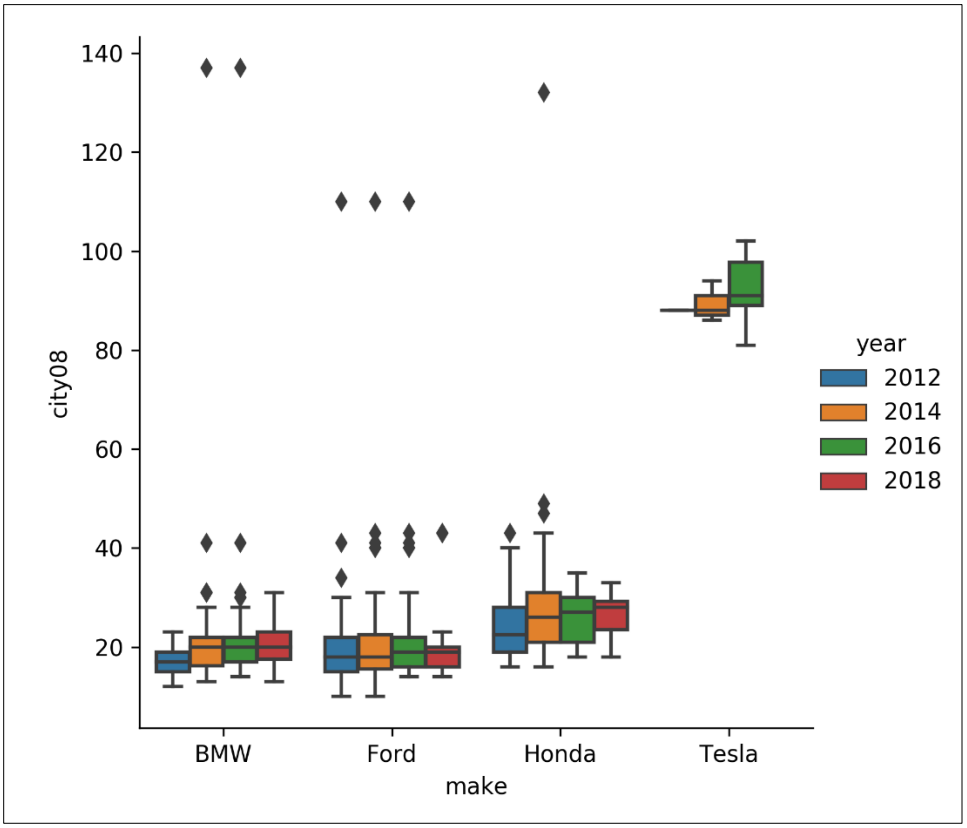

0
20
40
60
80
100
120
140
0
20
40
60
80
100
120
140
0
20
40
60
80
100
120
140
city08


Probability Plot
Ordered Values
Theoretical quantiles
140
120
100
80
60
40
20
0
−4
−2
0
2
4


city08
make
140
120
100
80
60
40
20
BMW
Ford
Honda
Tesla

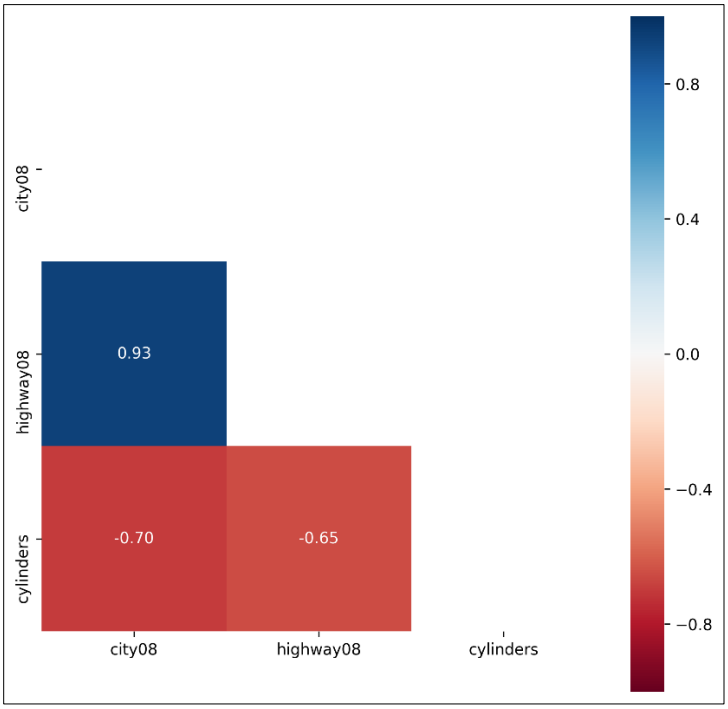

140
120
100
80
60
40
20
city08
BMW
Ford
Honda
Tesla
make

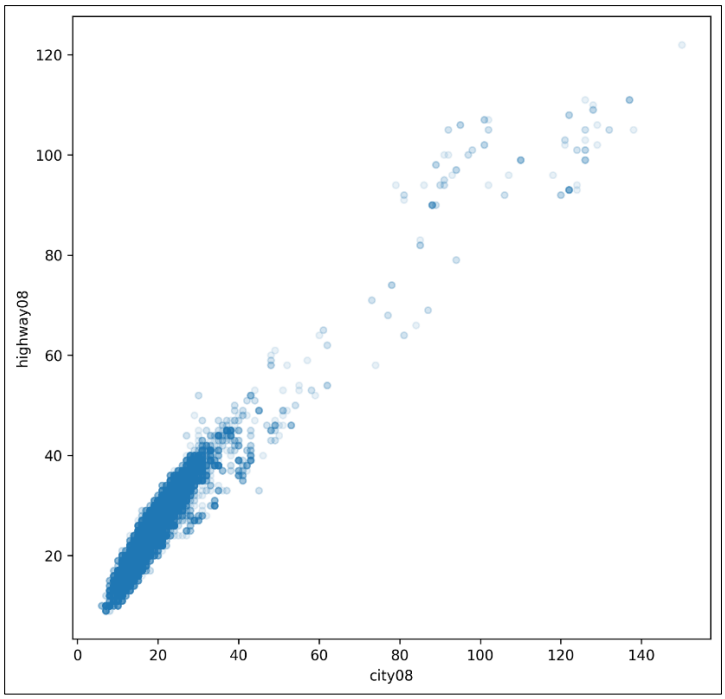

year = 2012
year = 2014
year = 2016
year = 2018
city08
140
120
100
80
60
40
20
BMW
Ford
Honda
Tesla
make

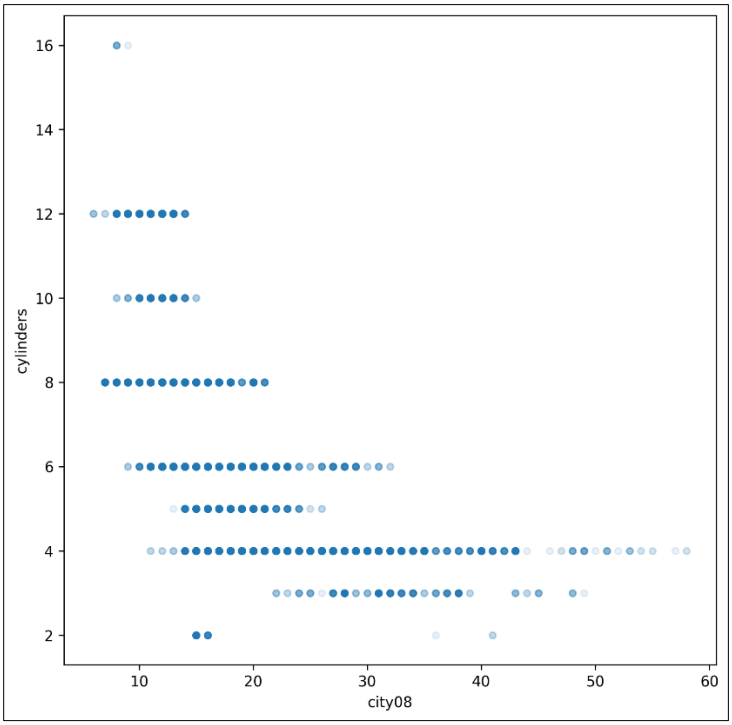


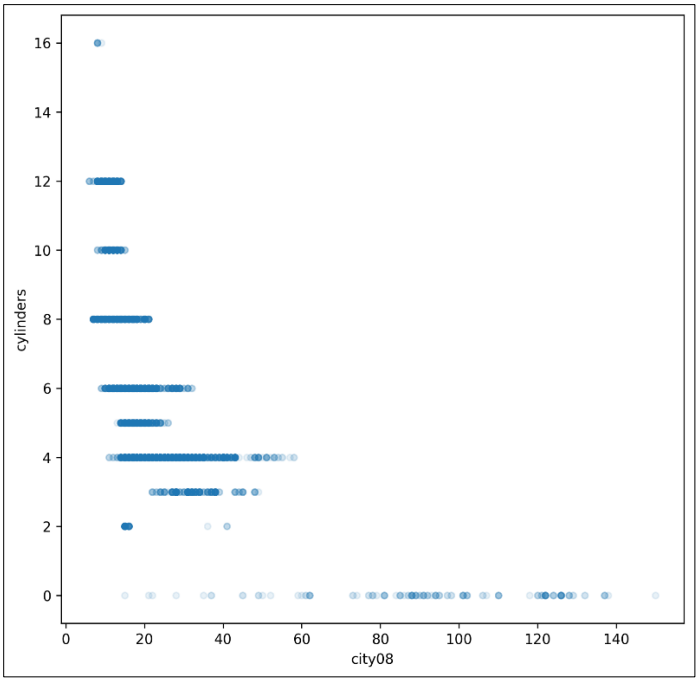
Out[58]:

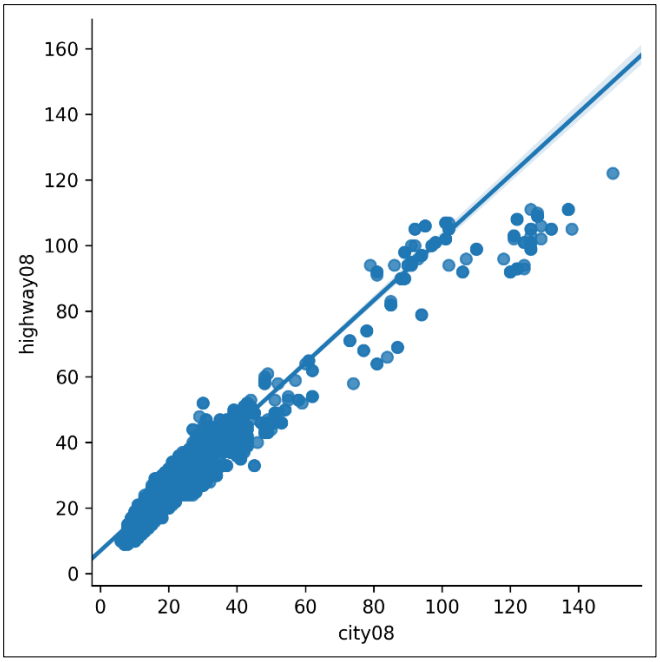
make	mean	std
BMW	17.8174	7.37291
Ford	16.8538	6.70103
Honda	24.373	9.15406
Tesla	92.8261	5.53897

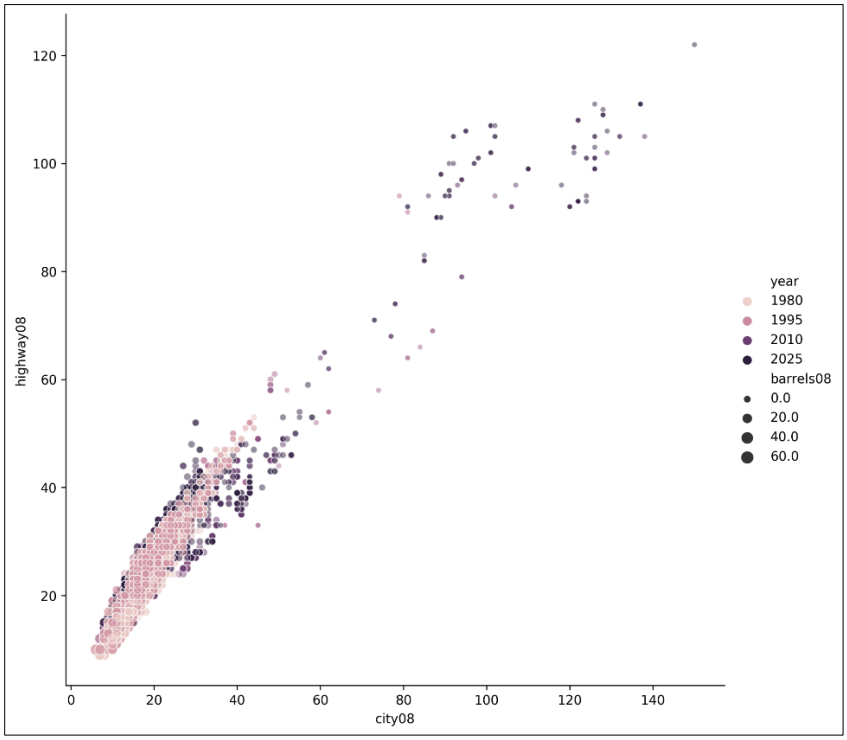

city08
highway08
cylinders
0.93
-0.70
-0.65
city08
highway08
cylinders
0.8
0.4
0.0
−0.4
−0.8

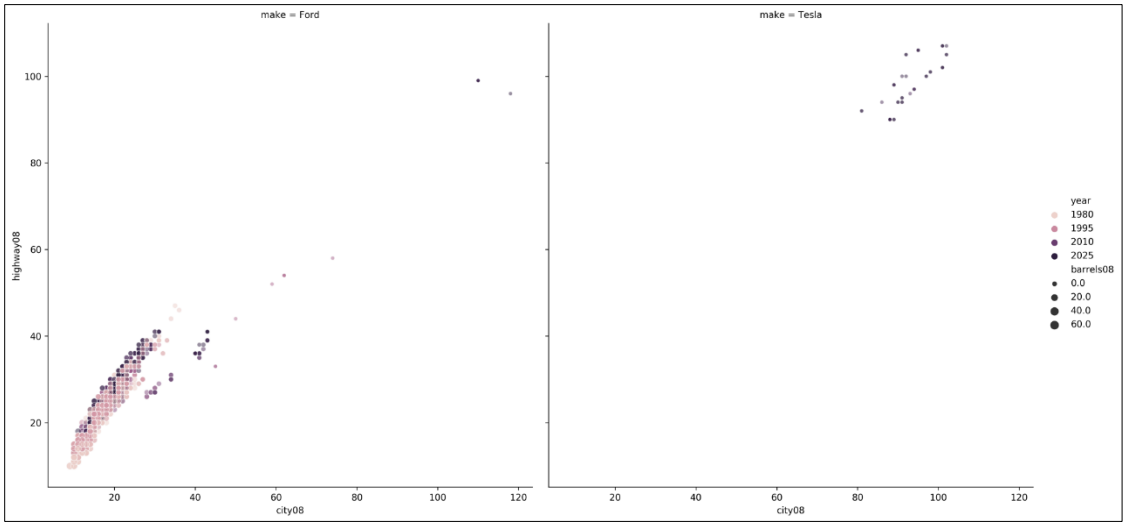

120
100
80
60
40
20
highway08
0
20
40
60
80
100
120
140
city08

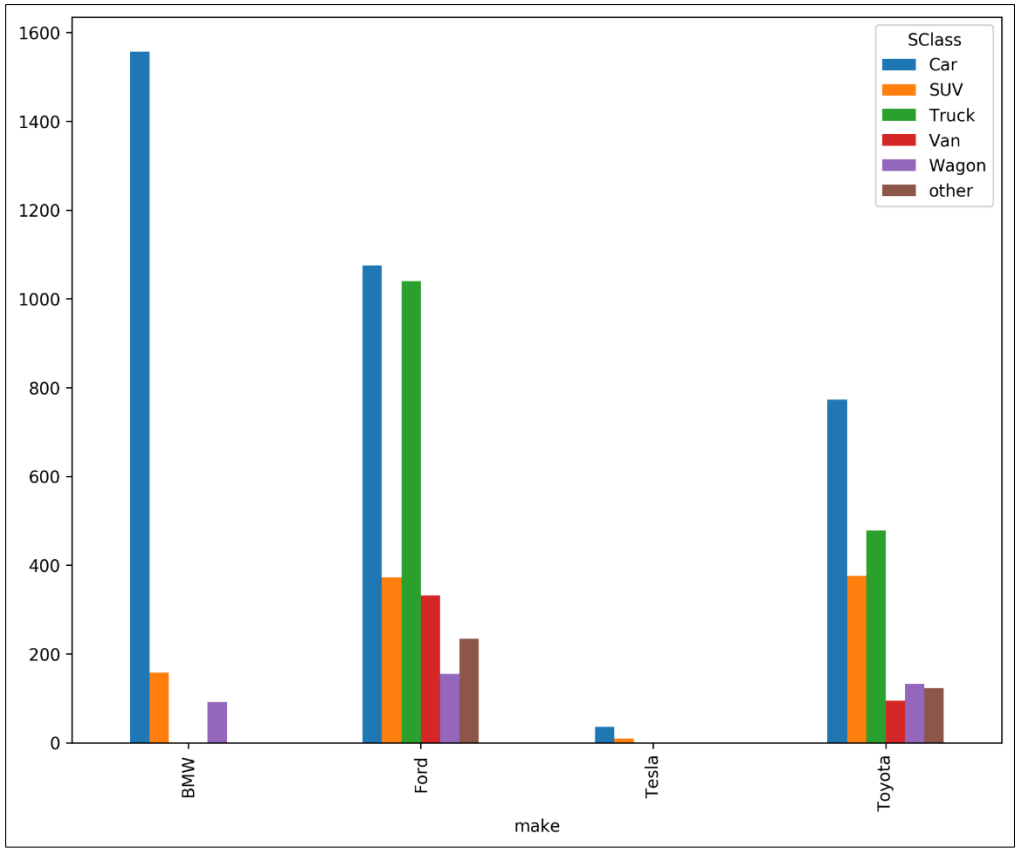

16
14
12
10
8
6
4
2
cylinders
10
20
30
40
50
60
city08

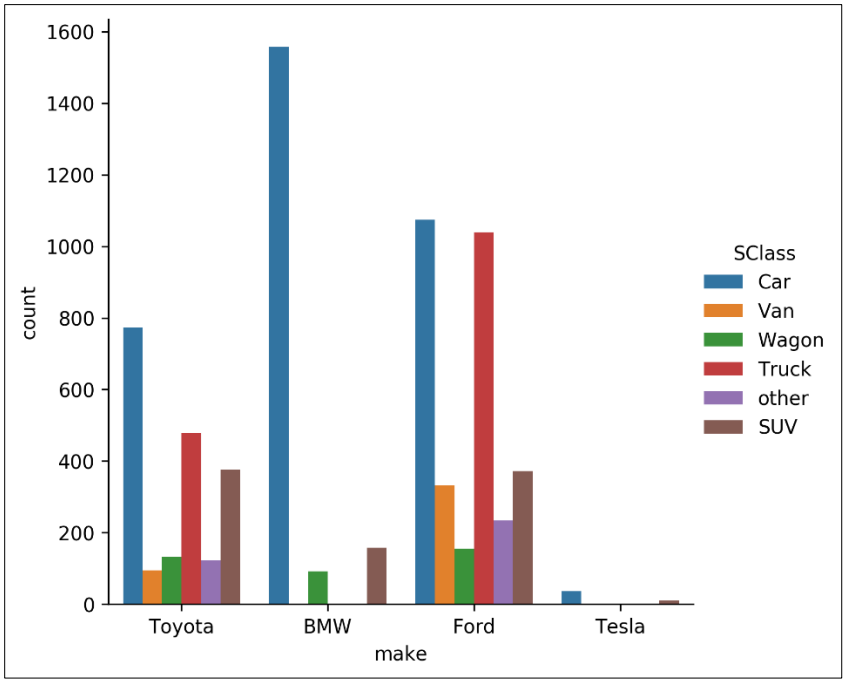

16
14
12
10
8
6
4
2
0
cylinders
0
20
40
60
80
100
120
140
city08

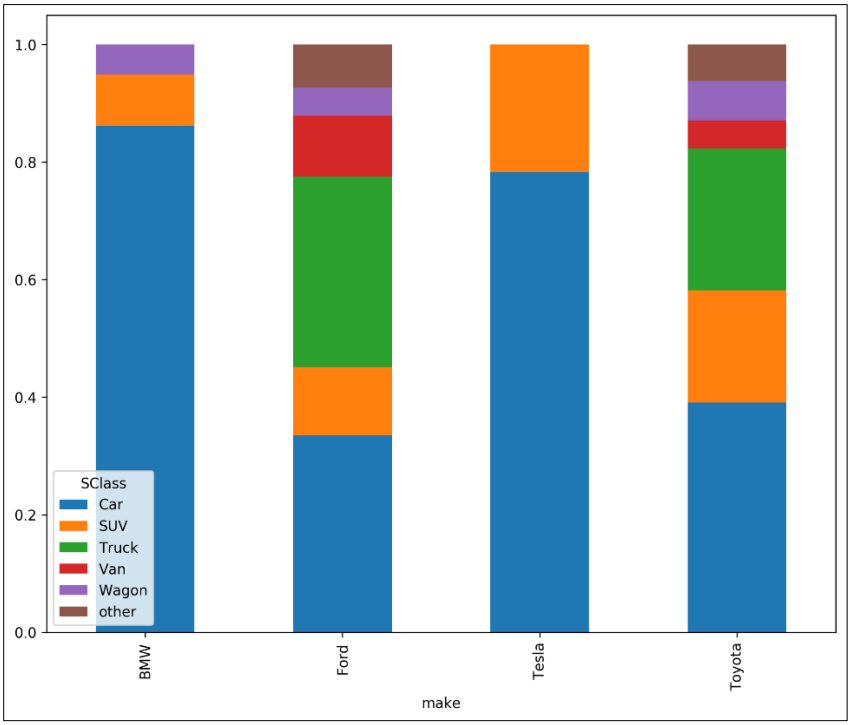

highway08
city08
0
20
40
60
80
100
120
140
160


highway08
city08
year
1980
1995
2010
2025
barrels08
0.0
20.0
40.0
60.0


make = Ford
make = Tesla
highway08
city08
city08
year
1980
1995
2010
2025
barrels08
0.0
20.0
40.0
60.0


SClass
Car
SUV
Truck
Van
Wagon
other
BMW
Ford
Tesla
Toyota
make


1600
1400
1200
1000
800
600
400
200
0
count
Toyota
BMW
Ford
Tesla
make
SClass
Car
Van
Wagon
Truck
other
SUV


1.0
0.8
0.6
0.4
0.2
0.0
SClass
Car
SUV
Truck
Van
Wagon
other
BMW
Ford
Tesla
Toyota
make

Overview

Dataset info

Number of variables	83
Number of observations	39101
Total Missing (%)	13.5%
Total size in memory	24.5 MiB
Average record size in memory	657.0 B

Variables types

Numeric	23
Categorical	23
Boolean	1
Date	0
Text (Unique)	0
Rejected	36
Unsupported	0

Warnings

- `barrelsA08` has 37611 / 96.2% zeros Zeros
- `charge120` has constant value 0 Rejected
- `charge240` has 38903 / 99.5% zeros Zeros
- `city08U` has 29662 / 75.9% zeros Zeros
- `cityA08` has 37611 / 96.2% zeros Zeros
- `cityA08U` is highly correlated with `cityA08` (ρ = 0.94672) Rejected
- `cityCD` is highly skewed (γ1 = 107.76) Skewed
- `cityCD` has 39080 / 99.9% zeros Zeros
- `cityE` has 38880 / 99.4% zeros Zeros
- `cityUF` is highly skewed (γ1 = 25.742) Skewed
- `cityUF` has 39022 / 99.8% zeros Zeros

city08

Numeric

Distinct count	93
Unique (%)	0.2%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	18.078
Minimum	6
Maximum	150
Zeros (%)	0.0%

Statistics | Histogram | Common Values | Extreme Values

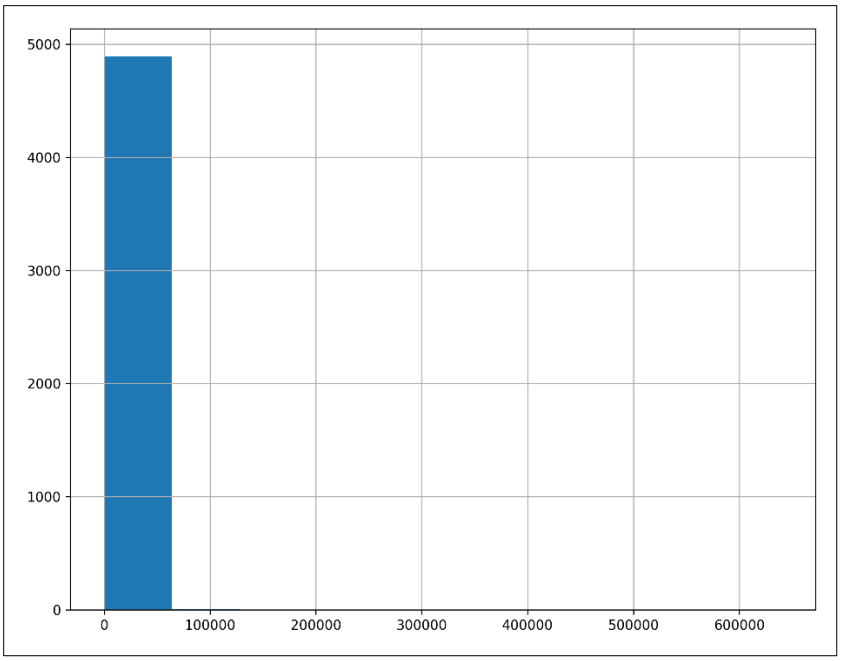
Quantile statistics

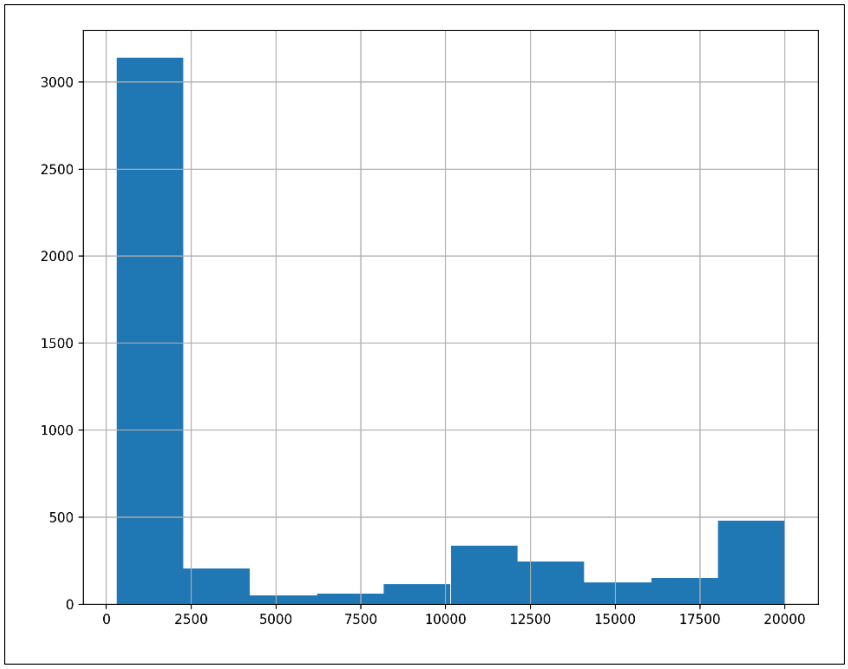
Minimum	6
5-th percentile	11
Q1	15
Median	17
Q3	20
95-th percentile	27
Maximum	150
Range	144
Interquartile range	5

Descriptive statistics

Standard deviation	6.9707
Coef of variation	0.38559
Kurtosis	96.71
Mean	18.078
MAD	3.8648
Skewness	7.4099
Sum	706860
Variance	48.59
Memory size	305.6 KiB

Chapter 7: Filtering Rows





Chapter 8: Index Alignment

```
(df_14 + df_15).head(10).style.highlight_null('yellow')
```

playerID	AB	G	H	HR	R
altuvjo01	1298	nan	425	nan	171
cartech02	898	nan	193	nan	118
castrja01	802	nan	174	nan	81
congeha01	nan	nan	nan	nan	nan
corpoca01	nan	nan	nan	nan	nan
correca01	nan	nan	nan	nan	nan
dominma01	nan	nan	nan	nan	nan
fowlede01	nan	nan	nan	nan	nan
gattiev01	nan	nan	nan	nan	nan
gomezca01	nan	nan	nan	nan	nan

```
(df_14
        .add(df_15, fill_value=0)
        .head(10)
        .style.highlight_null('yellow')
    )
```

playerID	AB	G	H	HR	R
altuvjo01	1298	158	425	15	171
cartech02	898	145	193	24	118
castrja01	802	126	174	11	81
congeha01	201	nan	46	11	25
corpoca01	170	55	40	nan	22
correca01	387	nan	108	22	52
dominma01	564	157	121	nan	51
fowlede01	434	116	120	nan	61
gattiev01	566	nan	139	27	66
gomezca01	149	nan	36	4	19

```
college_n2.loc[unique_max_cols].style.highlight_max()
```

INSTNM	SATVRMID	SATMTMID	UGDS	UGDS_WHITE	UGDS_BLACK	UGDS_HISP	UGDS_ASIAN	UGDS_AIAN	UGDS_NHPI	UGDS_2MOR	UGDS_NRA	UGD
California Institute of Technology	765	785	983	0.2787	0.0153	0.1221	0.4385	0.001	0	0.057	0.0875	
University of Phoenix-Arizona	nan	nan	151558	0.3098	0.1555	0.076	0.0082	0.0042	0.005	0.1131	0.0131	
Mr Leon's School of Hair Design-Moscow	nan	nan	16	1	0	0	0	0	0	0	0	
Velvatex College of Beauty Culture	nan	nan	25	0	1	0	0	0	0	0	0	
Thunderbird School of Global Management	nan	nan	1	0	0	1	0	0	0	0	0	
Cosmopolitan Beauty and Tech School	nan	nan	110	0.0091	0	0.0182	0.9727	0	0	0	0	
Haskell Indian Nations University	430	440	805	0	0	0	0	1	0	0	0	

```
college_ugds.style.highlight_max(axis='columns')
```

INSTNM	UGDS_WHITE	UGDS_BLACK	UGDS_HISP	UGDS_ASIAN	UGDS_AIAN	UGDS_NHPI	UGDS_2MOR	UGDS_NRA	UGDS_UNKN
Alabama A & M University	0.0333	0.9353	0.0055	0.0019	0.0024	0.0019	0	0.0059	0.0138
University of Alabama at Birmingham	0.5922	0.26	0.0283	0.0518	0.0022	0.0007	0.0368	0.0179	0.01
Amridge University	0.299	0.4192	0.0069	0.0034	0	0	0	0	0.2715
University of Alabama in Huntsville	0.6988	0.1255	0.0382	0.0376	0.0143	0.0002	0.0172	0.0332	0.035
Alabama State University	0.0158	0.9208	0.0121	0.0019	0.001	0.0006	0.0098	0.0243	0.0137

Chapter 9: Grouping for Aggregation, Filtration and Transformation

In [111]:
```
from IPython.display import display
for name, group in grouped:
    print(name)
    display(group.head(3))
```

AK

INSTNM	CITY	STABBR	...	MD_EARN_WNE_P10	GRAD_DEBT_MDN_SUPP
University of Alaska Anchorage	Anchorage	AK	...	42500	19449.5
Alaska Bible College	Palmer	AK	...	NaN	PrivacyS...
University of Alaska Fairbanks	Fairbanks	AK	...	36200	19355

3 rows × 26 columns

AL

INSTNM	CITY	STABBR	...	MD_EARN_WNE_P10	GRAD_DEBT_MDN_SUPP
Alabama A & M University	Normal	AL	...	30300	33888
University of Alabama at Birmingham	Birmingham	AL	...	39700	21941.5
Amridge University	Montgomery	AL	...	40100	23370

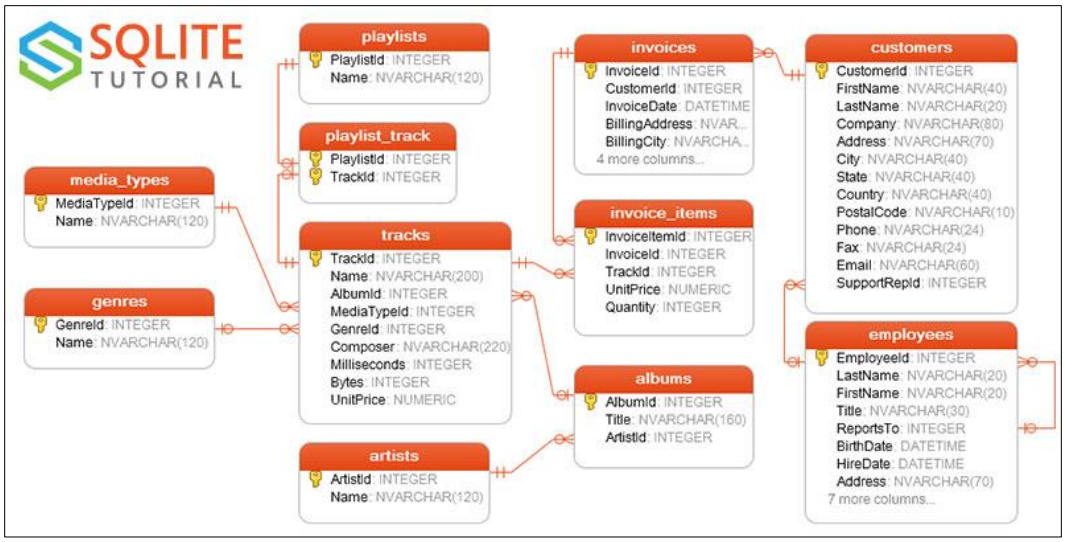
3 rows × 26 columns

In [112]:
```
(weight_loss
    .assign(percent_loss=(weight_loss
        .groupby(['Name', 'Month'])
        ['Weight']
        .transform(percent_loss)
        .round(1)))
    .query('Week == "Week 4"')
    .pivot(index='Month', columns='Name',
           values='percent_loss')
    .assign(winner=lambda df_:
            np.where(df_.Amy < df_.Bob, 'Amy', 'Bob'))
    .style.highlight_min(axis=1)
)
```

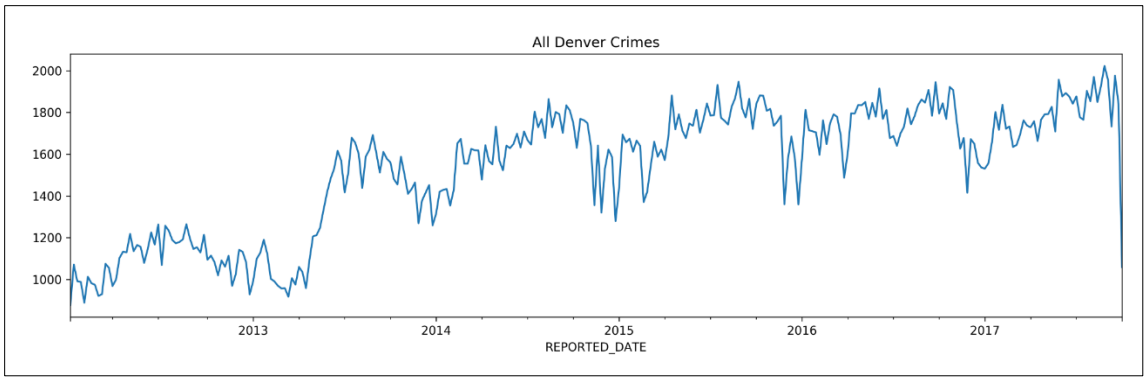
Out[112]:

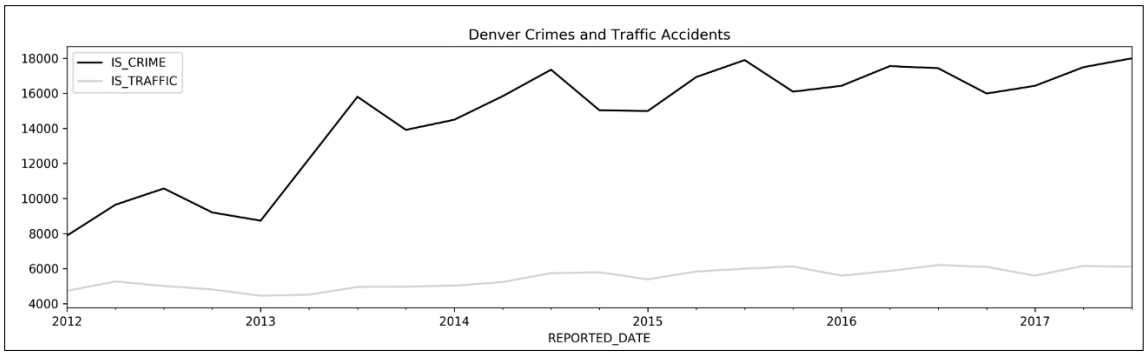
Name	Amy	Bob	winner
Month			
Apr	-5.3	-4.2	Amy
Feb	-8.9	-5.3	Amy
Jan	-3.6	-2.7	Amy
Mar	-1.7	-2.6	Bob

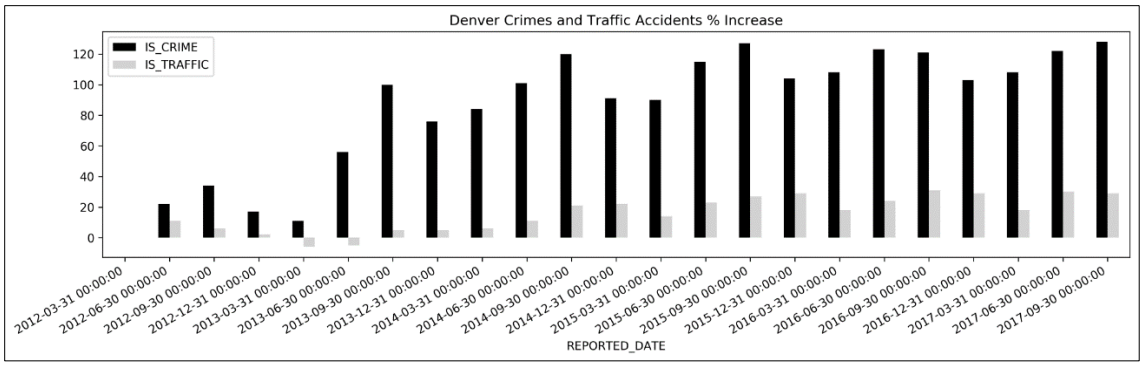
Chapter 11: Combining Pandas Objects

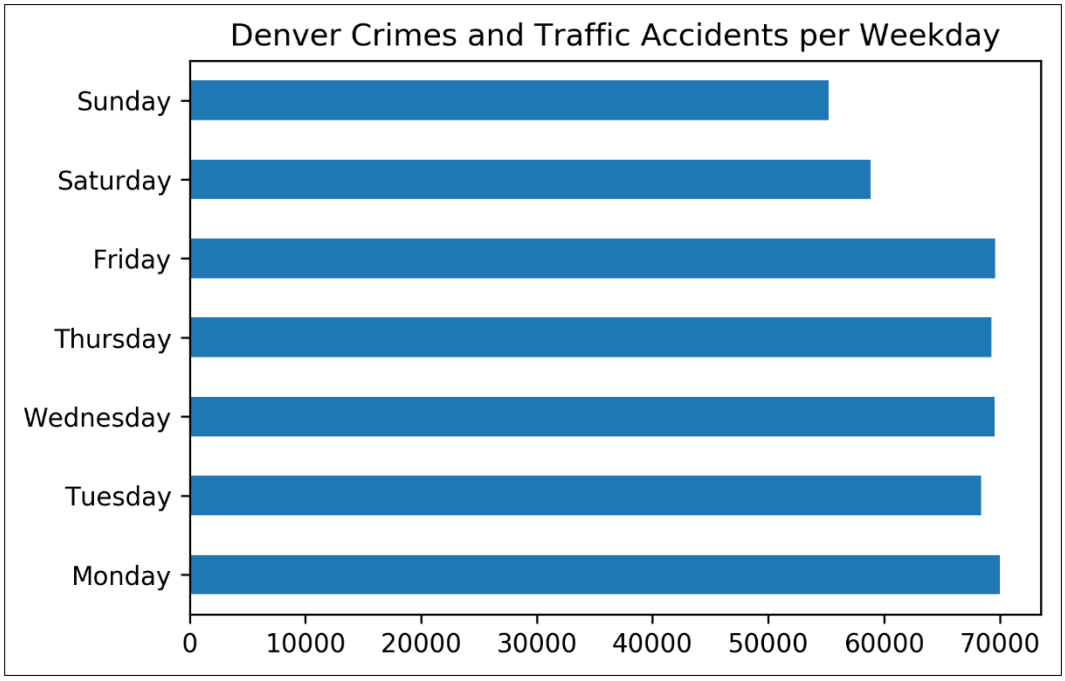


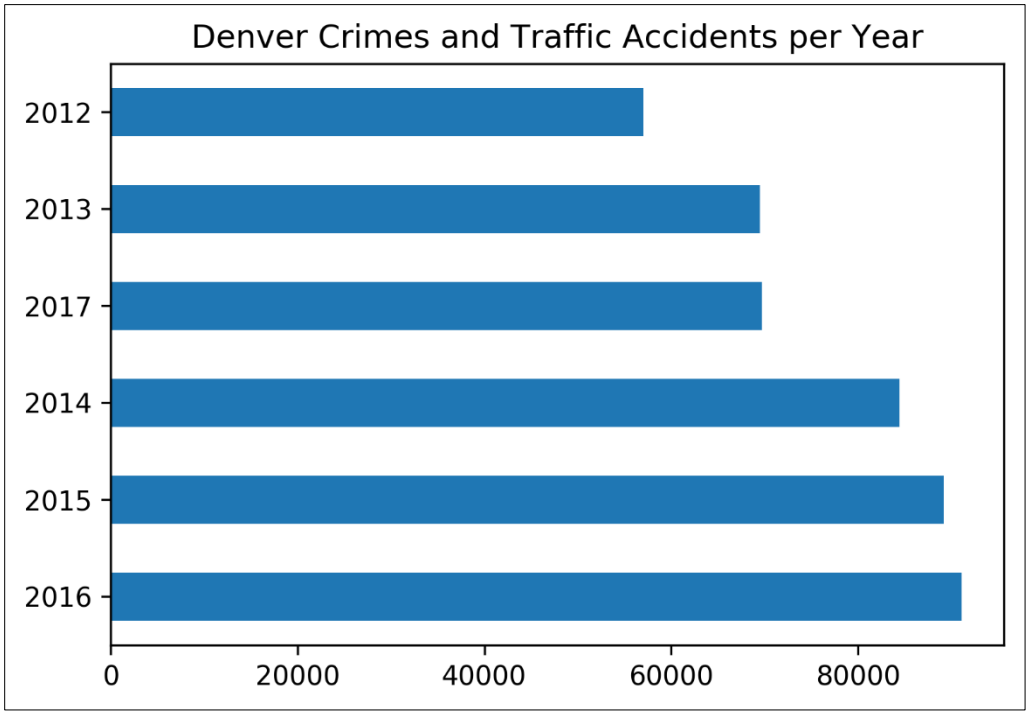
Chapter 12: Time Series Analysis

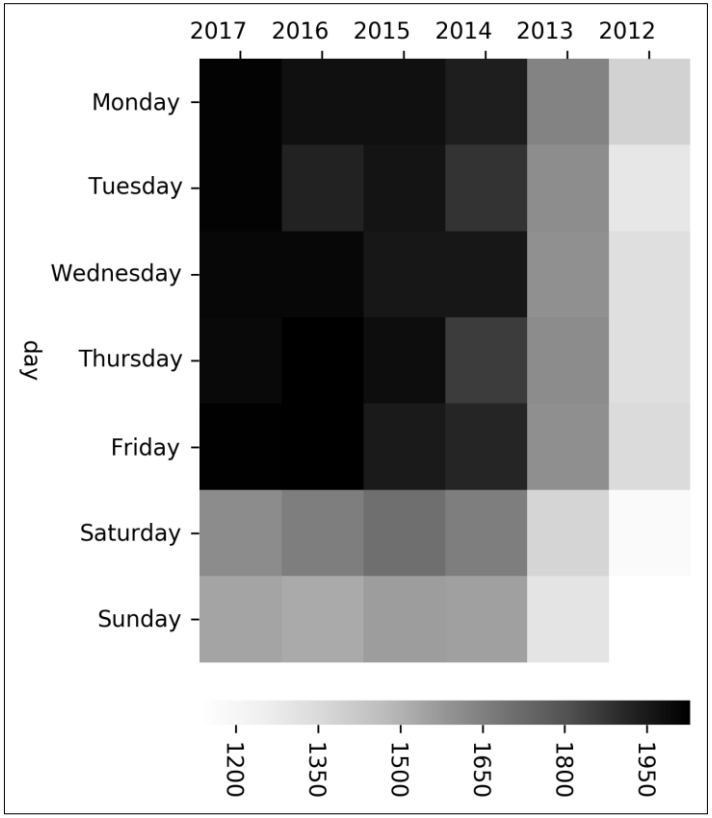


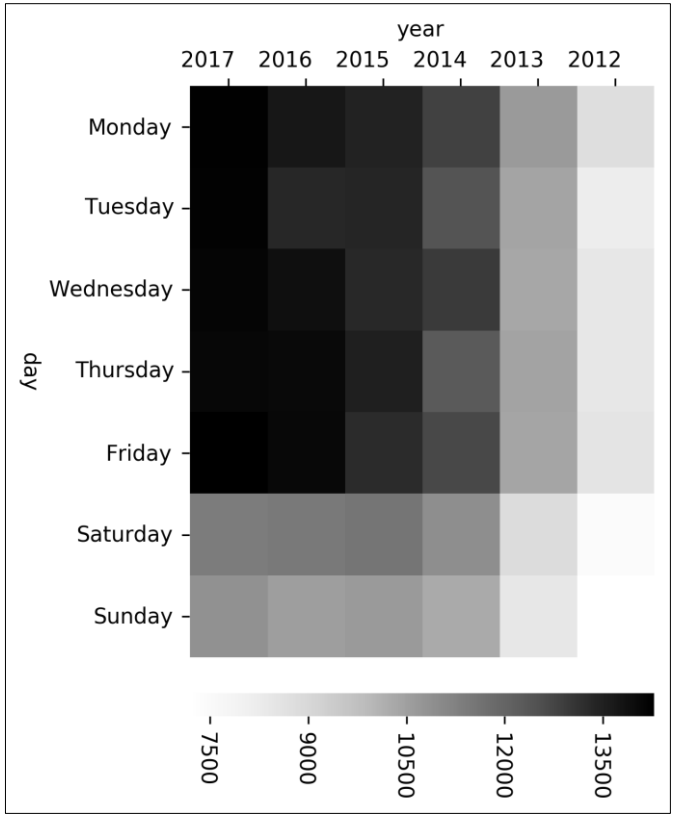





Denver Crimes and Traffic Accidents per Weekday
Sunday
Saturday
Friday
Thursday
Wednesday
Tuesday
Monday
0
10000
20000
30000
40000
50000
60000
70000

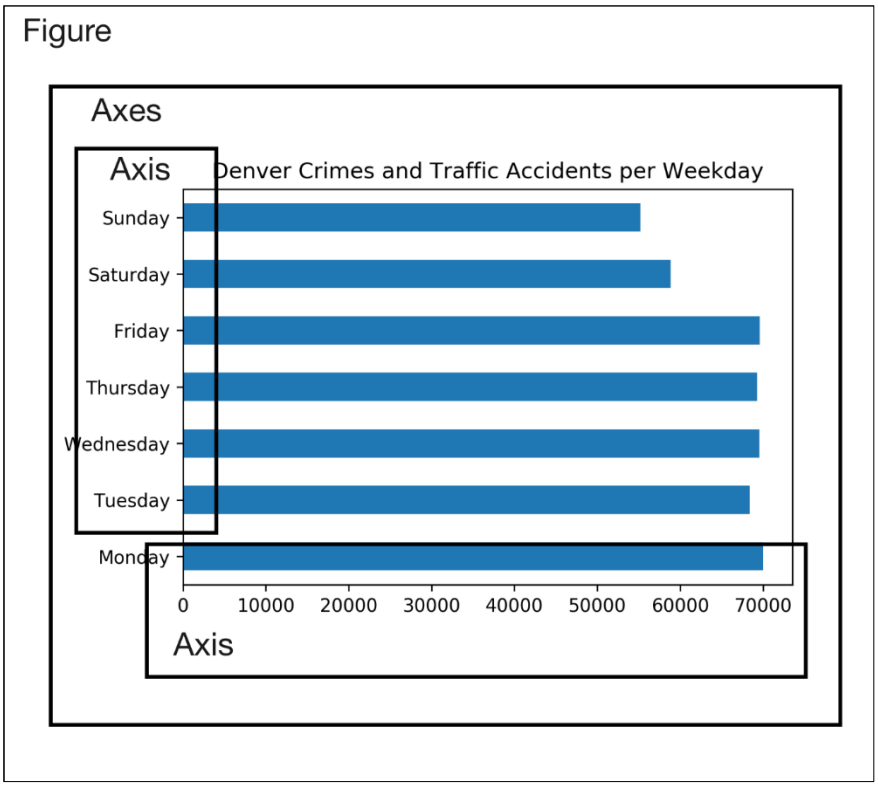

Denver Crimes and Traffic Accidents per Year
2012
2013
2017
2014
2015
2016
0
20000
40000
60000
80000

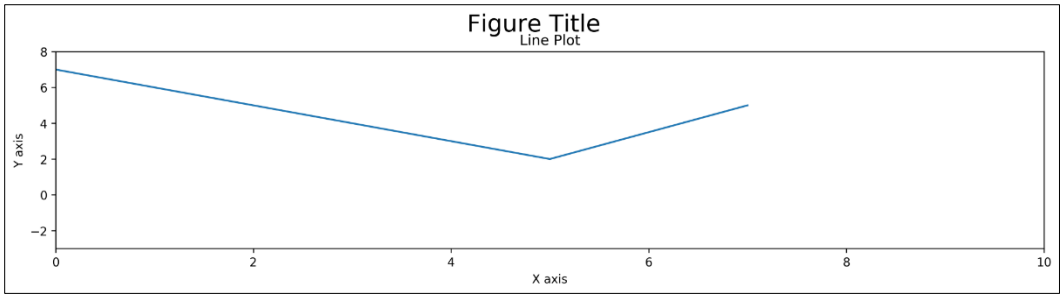

2017
2016
2015
2014
2013
2012
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
day
1200
1350
1500
1650
1800
1950

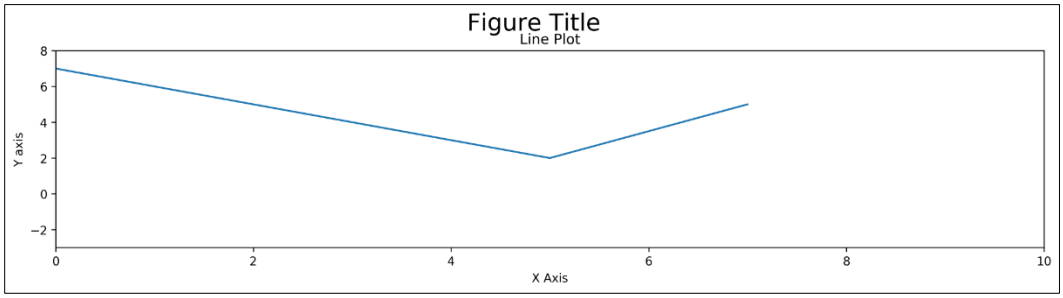

year
2017
2016
2015
2014
2013
2012
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
day
7500
9000
10500
12000
13500

	IS_CRIME						IS_TRAFFIC					
	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
0	2422	4040	5649	5649	5377	3811	919	792	978	1136	980	782
2	1888	3214	4245	4050	4091	3041	718	652	779	773	718	537
4	1472	2181	2956	2959	3044	2255	399	378	424	471	464	313
6	1067	1365	1750	2167	2108	1567	411	399	479	494	593	462
8	2998	3445	3727	4161	4488	3251	1957	1955	2210	2331	2372	1828
10	4305	5035	5658	6205	6218	4993	1979	1901	2139	2320	2303	1873
12	4496	5524	6434	6841	7226	5463	2200	2138	2379	2631	2760	1986
14	4266	5698	6708	7218	6896	5396	2241	2245	2630	2840	2763	1990
16	4113	5889	7351	7643	7926	6338	2714	2562	3002	3160	3527	2784
18	3660	5094	6586	7015	7407	6157	3118	2704	3217	3412	3608	2718
20	3521	4895	6130	6360	6963	5272	1787	1806	1994	2071	2184	1491
22	3078	4318	5496	5626	5637	4358	1343	1330	1532	1671	1472	1072

Chapter 13: Visualization with Matplotlib, Pandas, and Seaborn



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Line Plot
Y axis
X Axis
8
6
4
2
0
−2
0
2
4
6
8
10

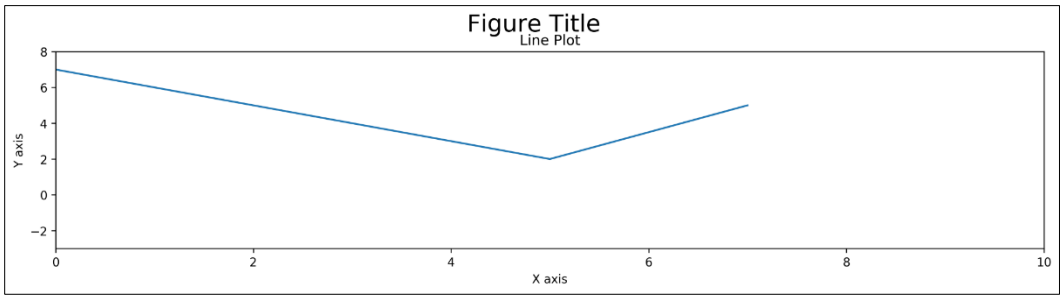
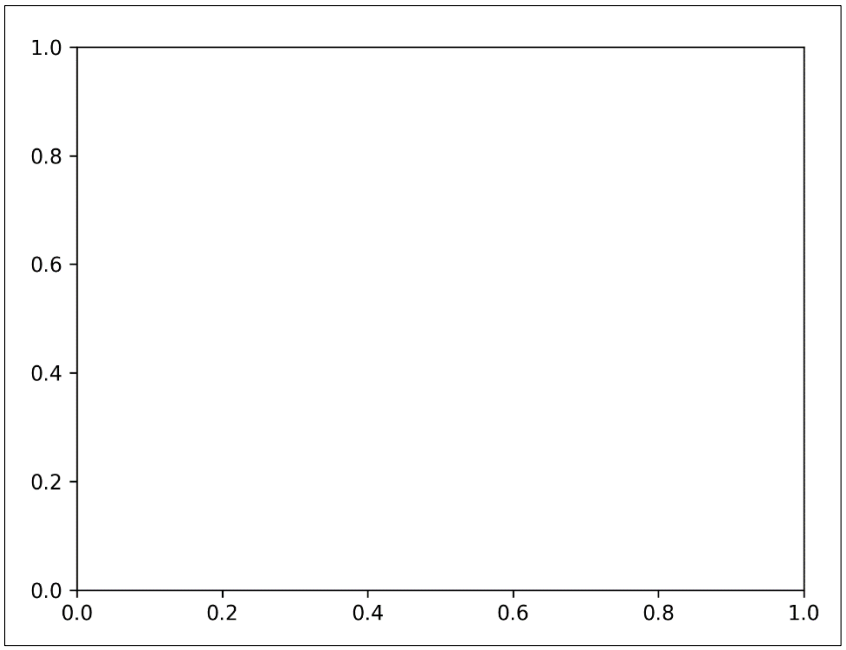


Figure Title
Line Plot
Y axis
X axis
8
6
4
2
0
−2
0
2
4
6
8
10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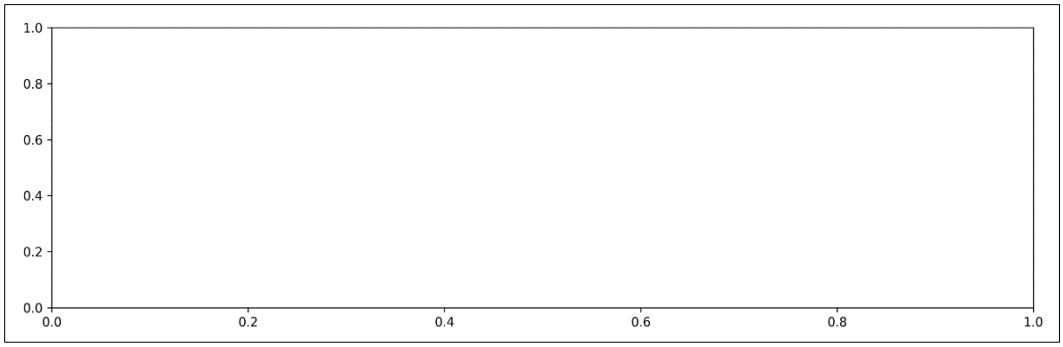
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0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0.8
0.6
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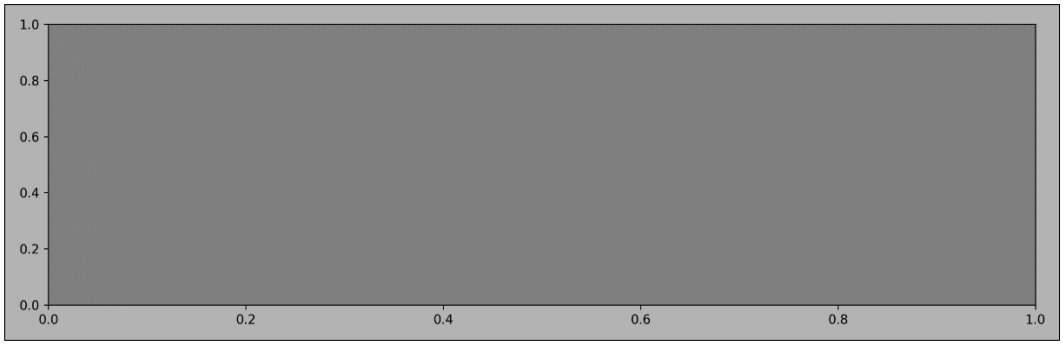
0.2
0.4
0.6
0.8
1.0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0.6
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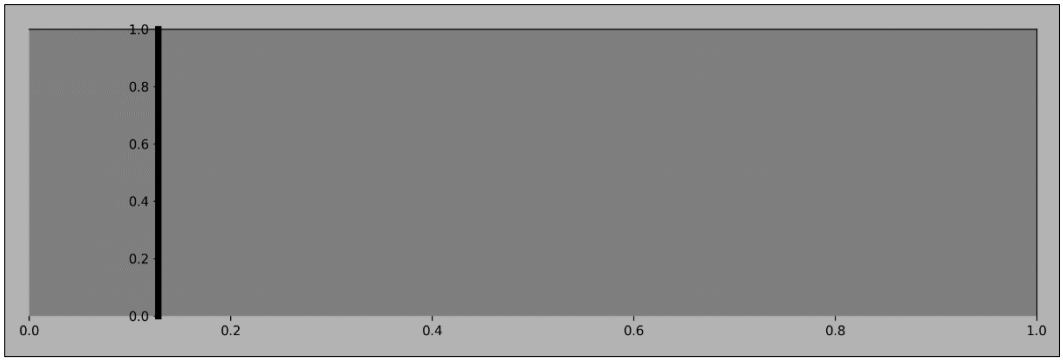
0.0
0.0
0.2
0.4
0.6
0.8
1.0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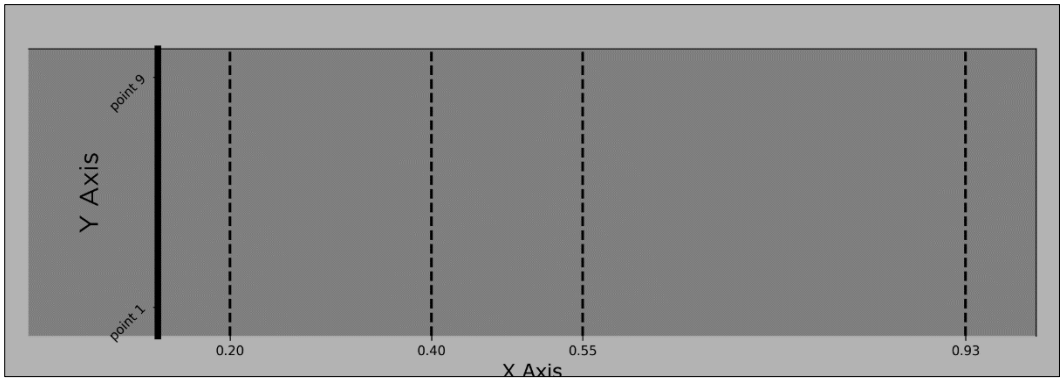
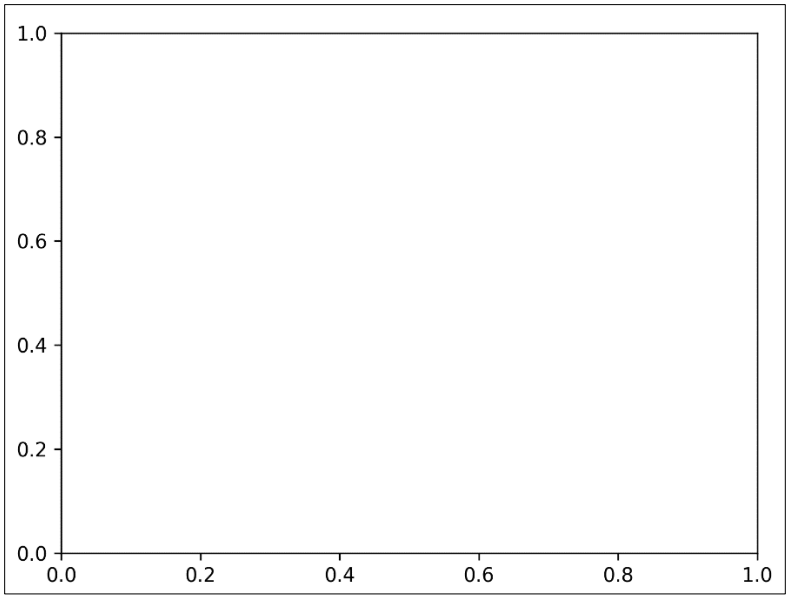
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


point 9
Y Axis
point 1
0.20
0.40
0.55
0.93
X Axis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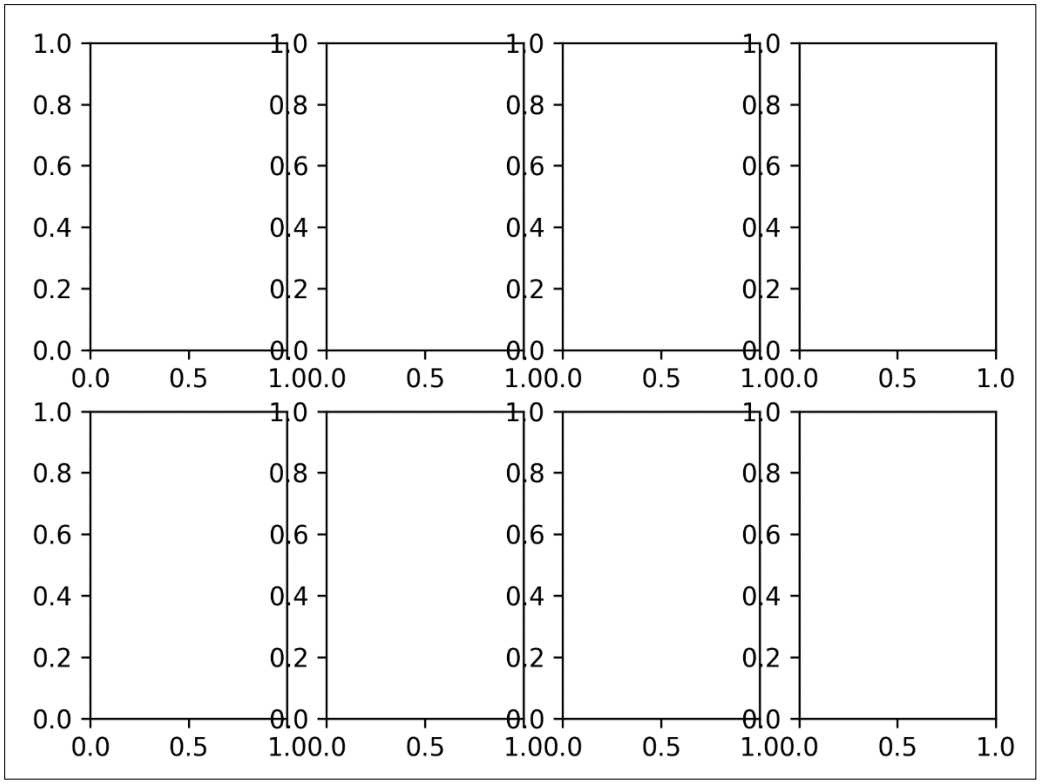
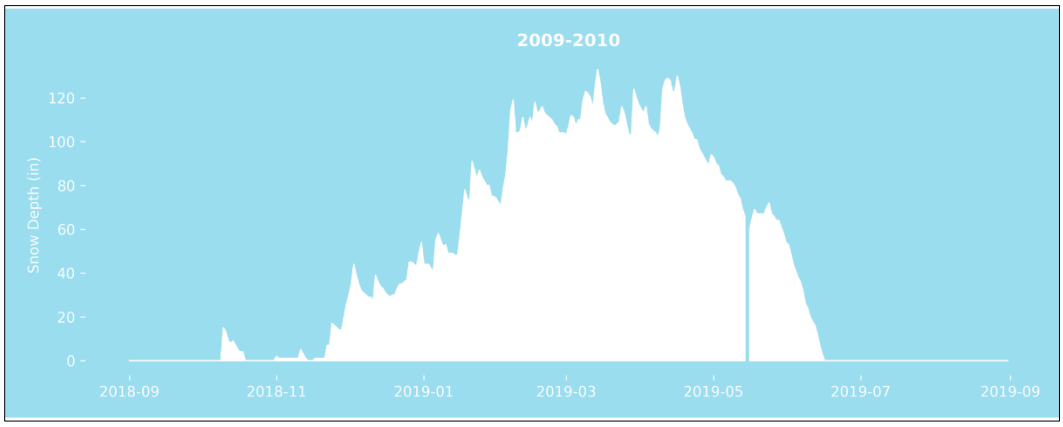
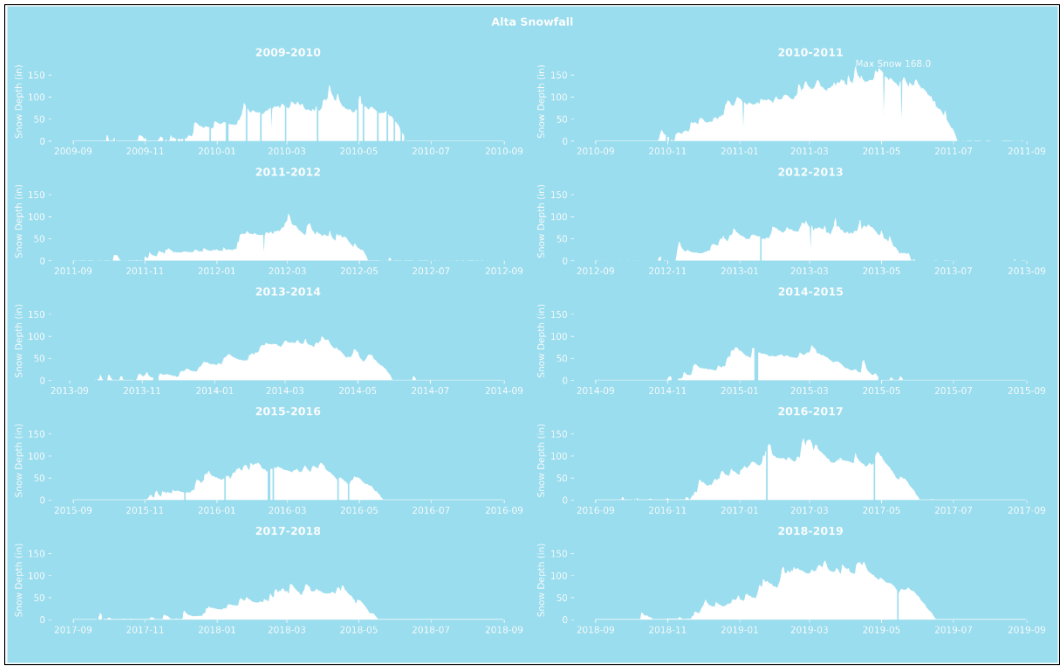
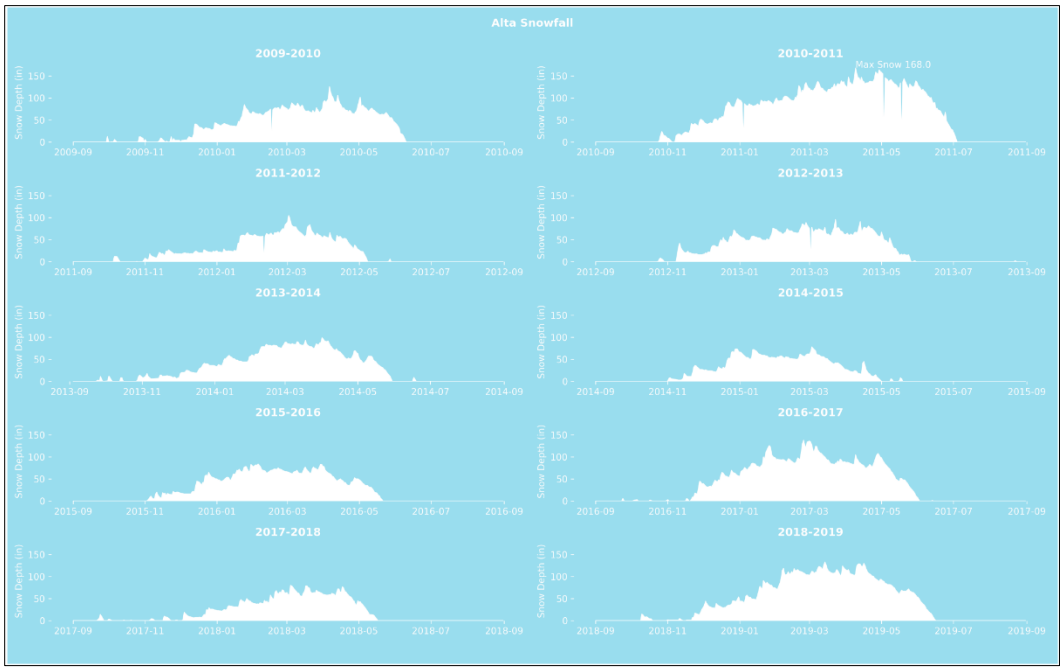
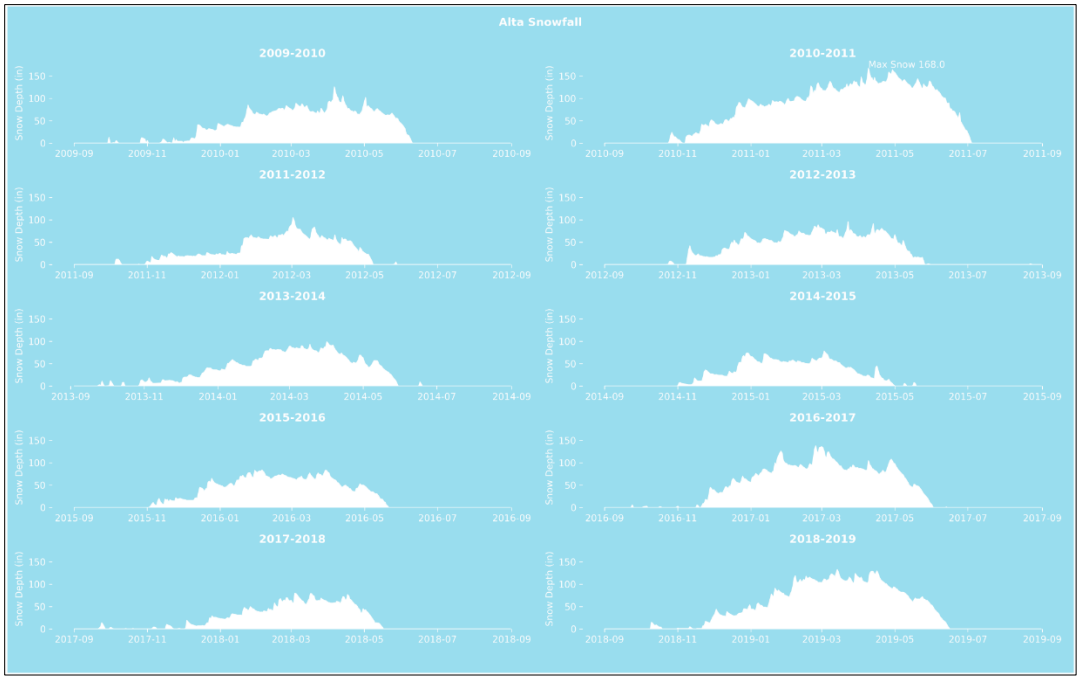
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

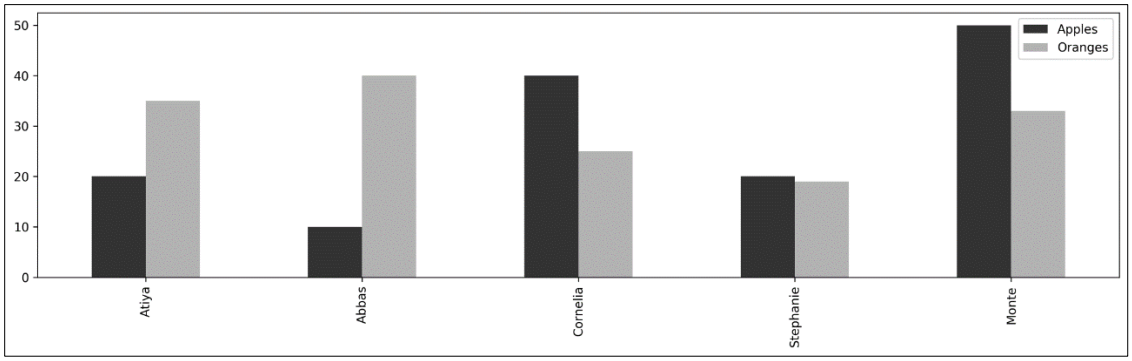

1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0

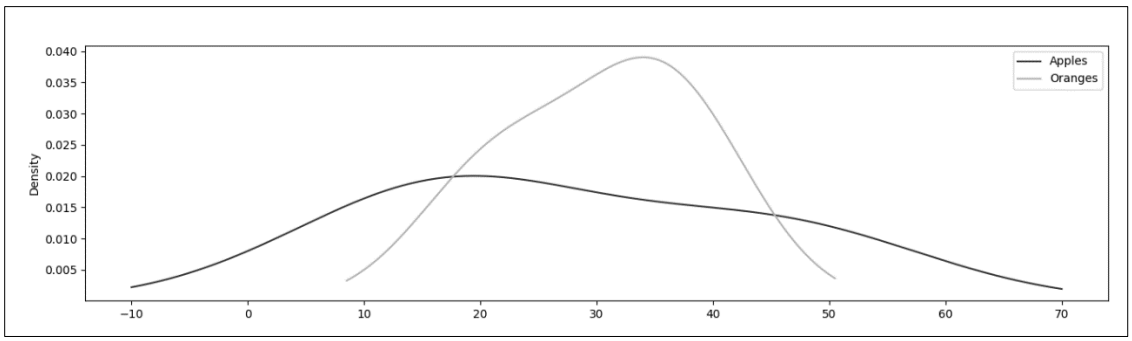

2009-2010
Snow Depth (in)
120
100
80
60
40
20
0
2018-09
2018-11
2019-01
2019-03
2019-05
2019-07
2019-09

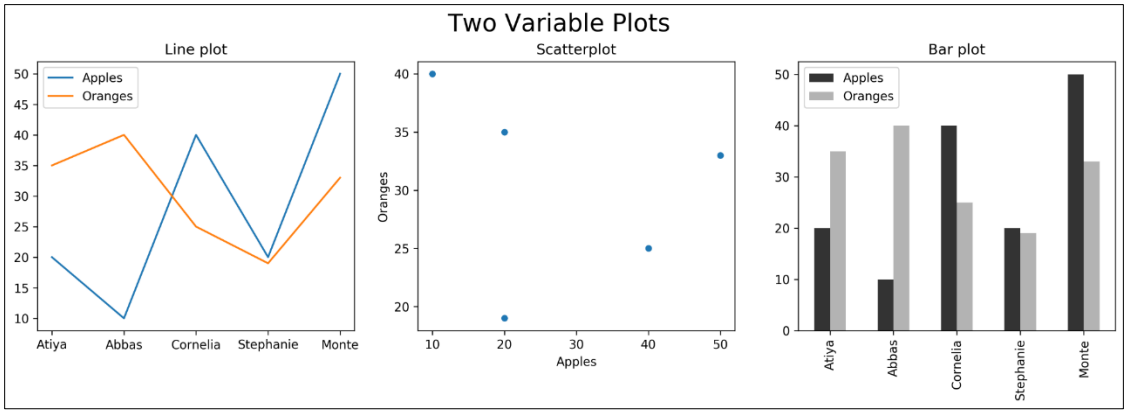

Alta Snowfall
2009-2010
2010-2011
Max Snow 168.0
2011-2012
2012-2013
2013-2014
2014-2015
2015-2016
2016-2017
2017-2018
2018-2019
Snow Depth (in)

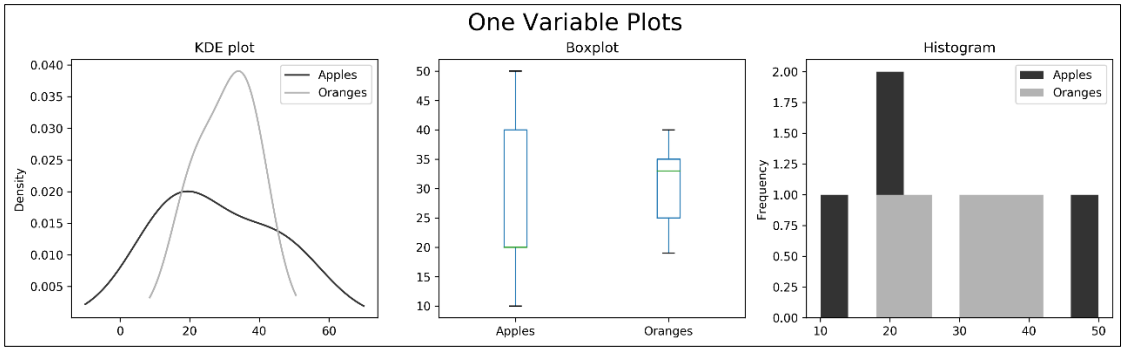

Alta Snowfall
2009-2010
2010-2011
Max Snow 168.0
2011-2012
2012-2013
2013-2014
2014-2015
2015-2016
2016-2017
2017-2018
2018-2019
Snow Depth (in)

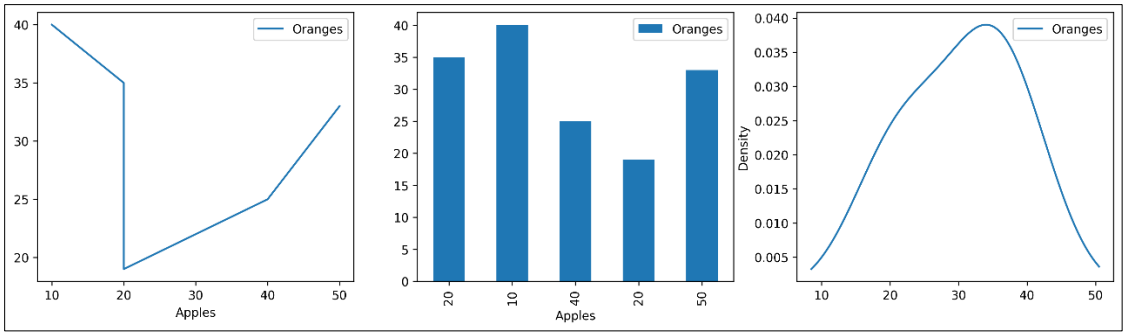

Alta Snowfall
2009-2010
2010-2011
Max Snow 168.0
2011-2012
2012-2013
2013-2014
2014-2015
2015-2016
2016-2017
2017-2018
2018-2019
Snow Depth (in)

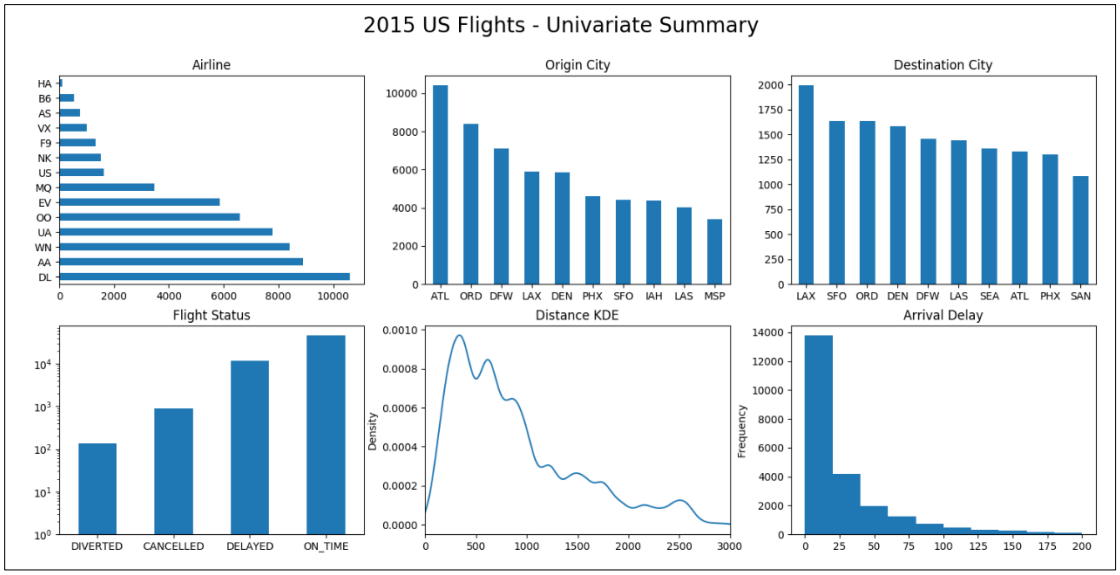

Apples
Oranges
Atiya
Abbas
Cornelia
Stephanie
Monte

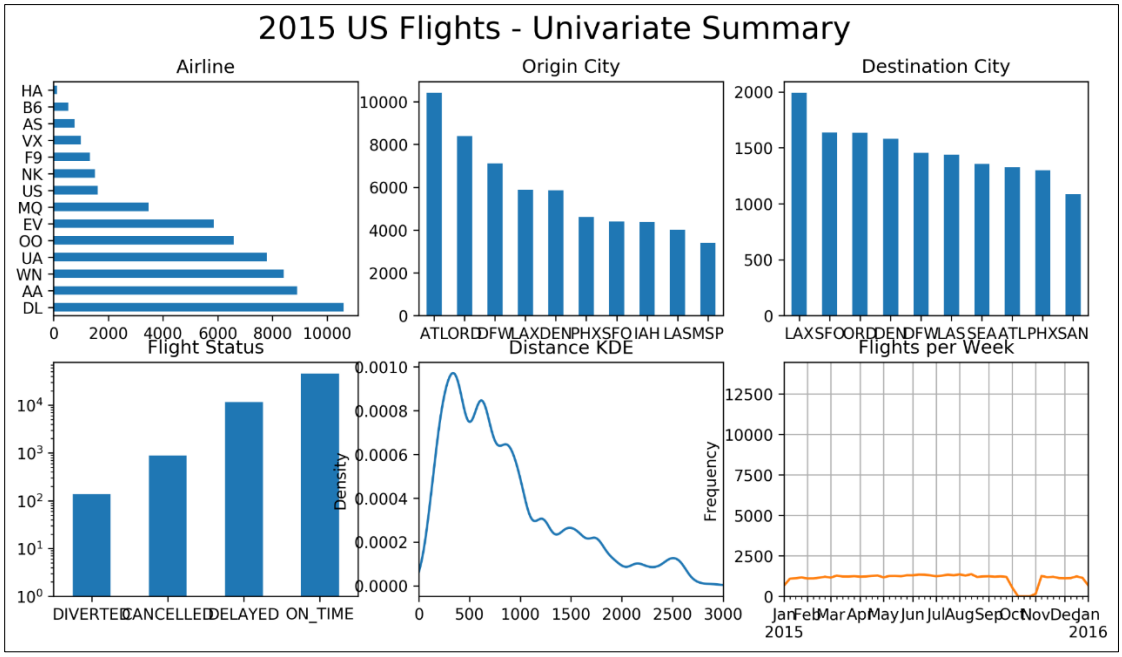

Apples
Oranges
Density

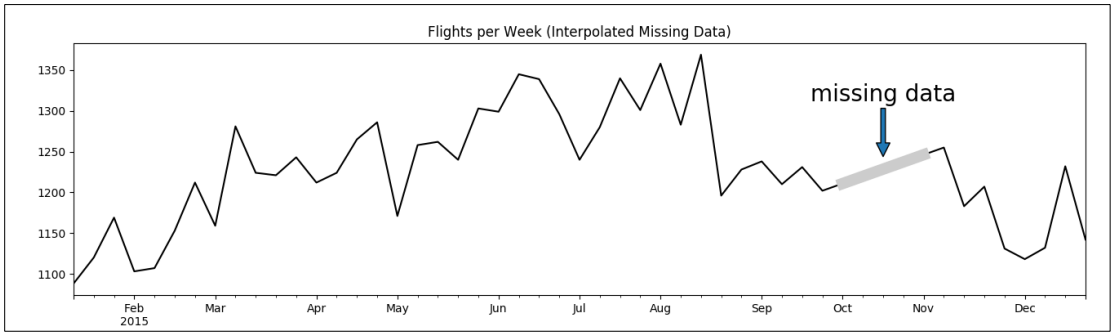

Two Variable Plots
Line plot
Apples
Oranges
Atiya
Abbas
Cornelia
Stephanie
Monte
Scatterplot
Oranges
Apples
Bar plot
Apples
Oranges
Atiya
Abbas
Cornelia
Stephanie
Monte

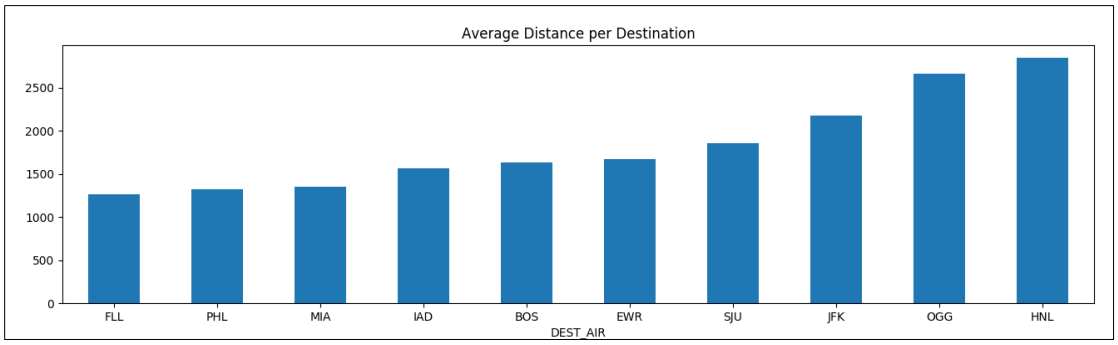

One Variable Plots
KDE plot
Apples
Oranges
Density
Boxplot
Apples
Oranges
Histogram
Apples
Oranges
Frequency

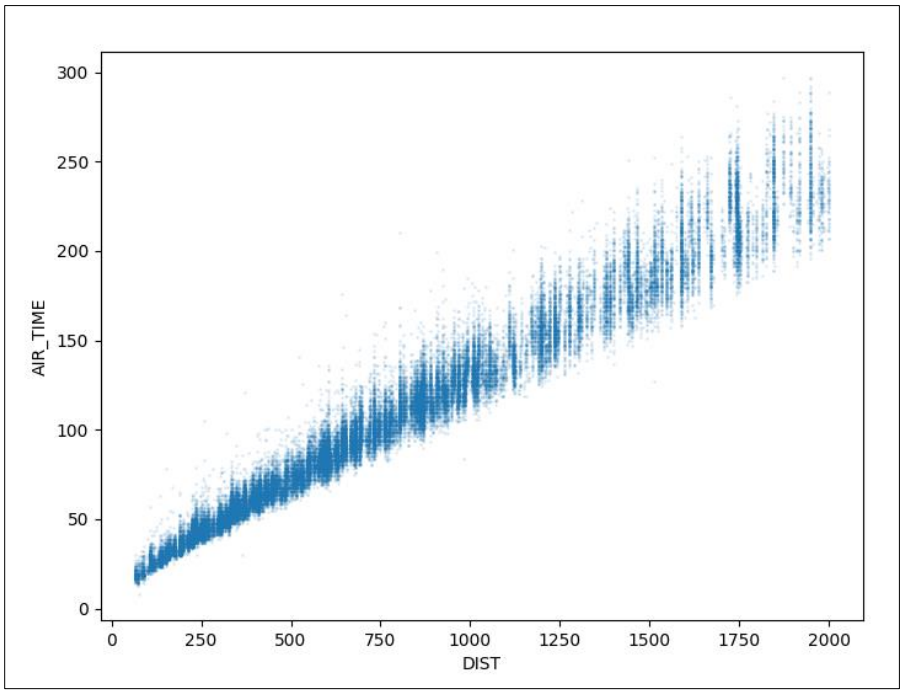

Oranges
Apples
Oranges
Apples
Oranges
Density

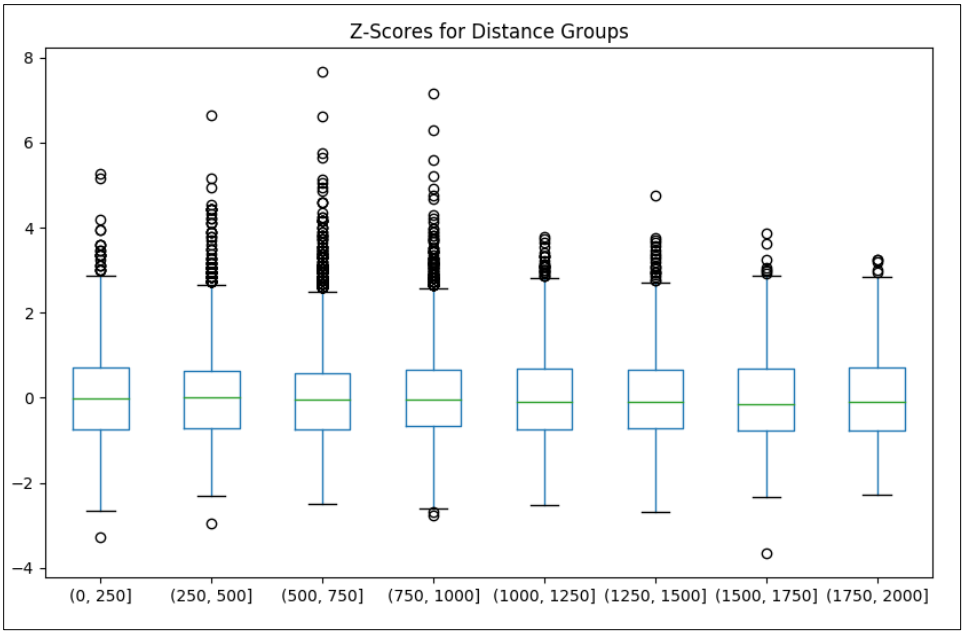

2015 US Flights - Univariate Summary
Airline
HA
B6
AS
VX
F9
NK
US
MQ
EV
OO
UA
WN
AA
DL
0
2000
4000
6000
8000
10000
Origin City
ATL
ORD
DFW
LAX
DEN
PHX
SFO
IAH
LAS
MSP
Destination City
LAX
SFO
ORD
DEN
DFW
LAS
SEA
ATL
PHX
SAN
Flight Status
DIVERTED
CANCELLED
DELAYED
ON_TIME
Distance KDE
Density
Arrival Delay
Frequency

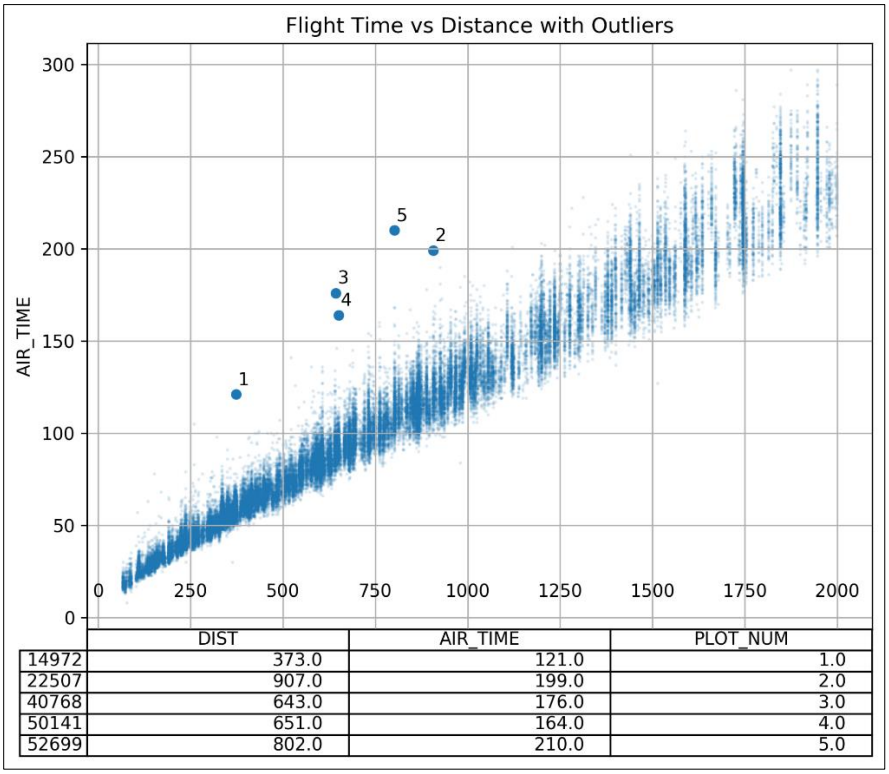

2015 US Flights - Univariate Summary
Airline
HA
B6
AS
VX
F9
NK
US
MQ
EV
OO
UA
WN
AA
DL
Origin City
ATL
ORD
DFW
LAX
DEN
PHX
SFO
IAH
LAS
MSP
Destination City
LAX
SFO
ORD
DEN
DFW
LAS
SEA
ATL
PHX
SAN
Flight Status
DIVERTED
CANCELLED
DELAYED
ON_TIME
Distance KDE
Density
Flights per Week
Frequency
Jan
2015
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2016


Flights per Week (Interpolated Missing Data)
missing data
1350
1300
1250
1200
1150
1100
Feb
2015
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

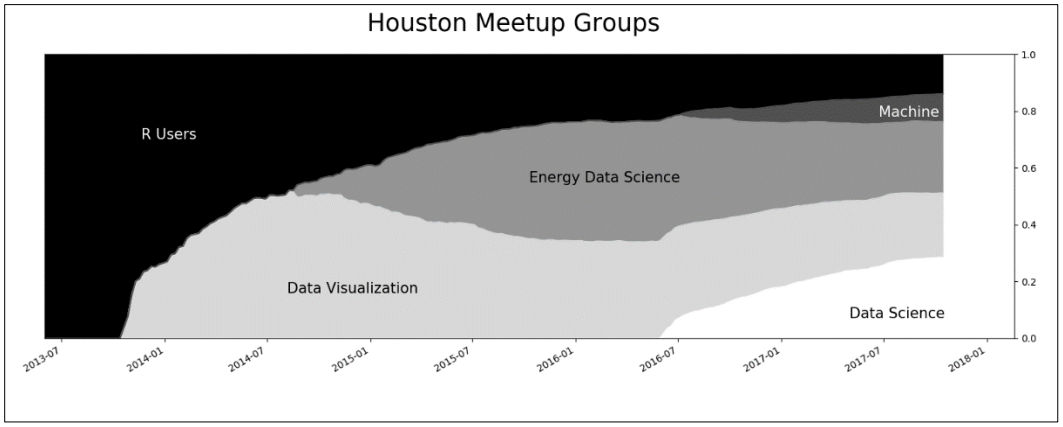

Average Distance per Destination
2500
2000
1500
1000
500
0
FLL
PHL
MIA
IAD
BOS
EWR
SJU
JFK
OGG
HNL
DEST_AIR

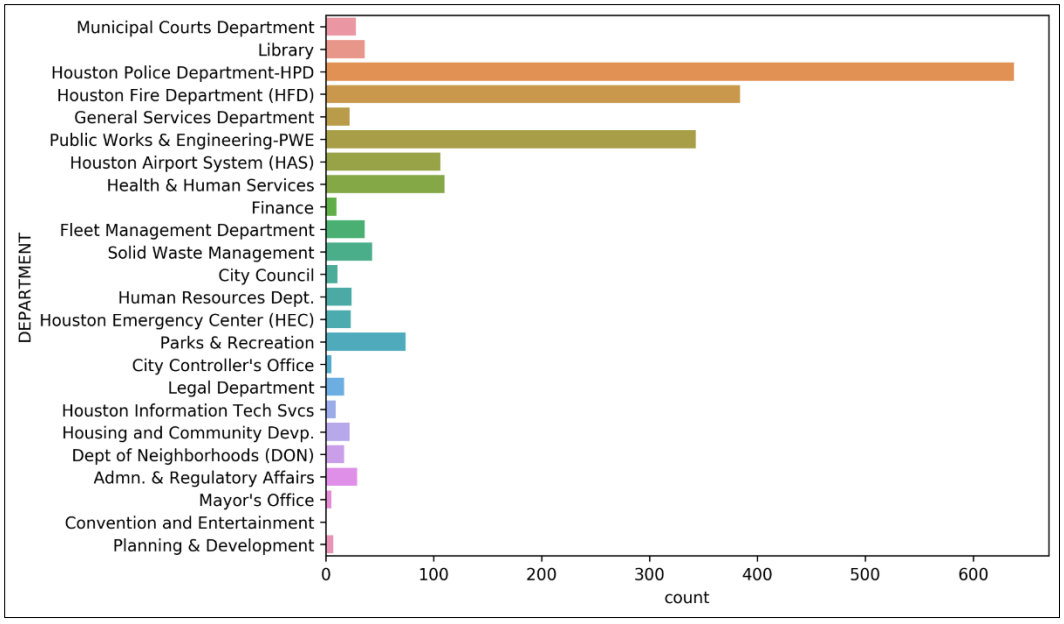

AIR_TIME
300
250
200
150
100
50
0
0
250
500
750
1000
1250
1500
1750
2000
DIST

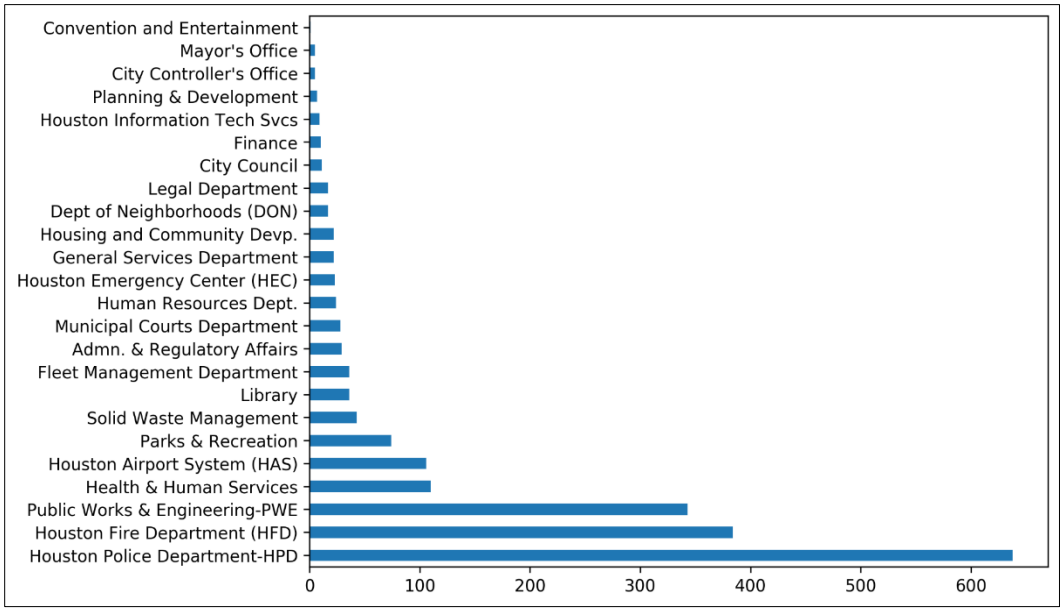


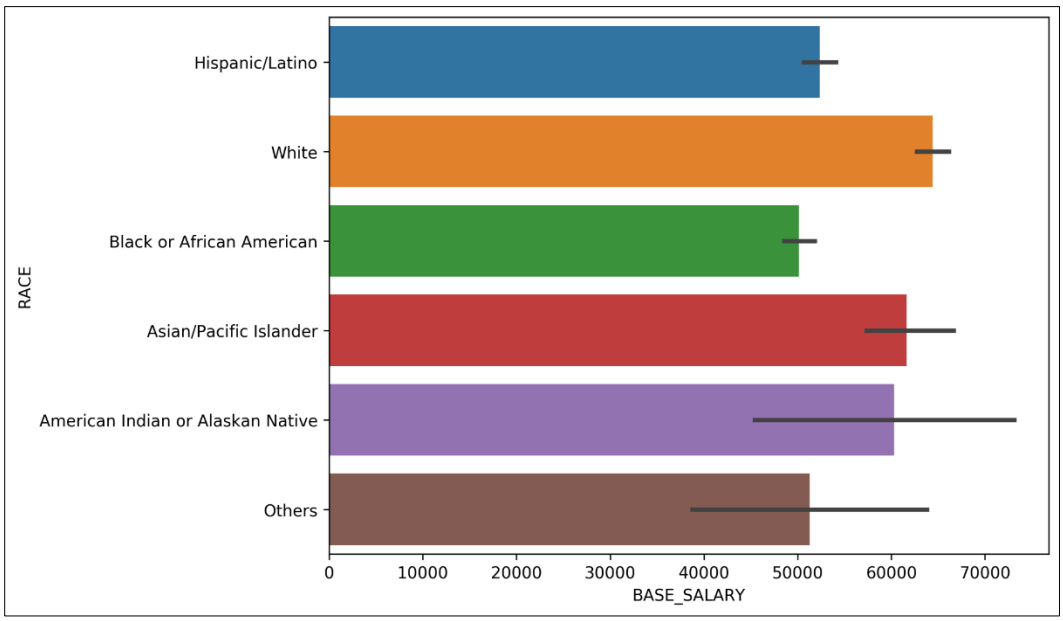


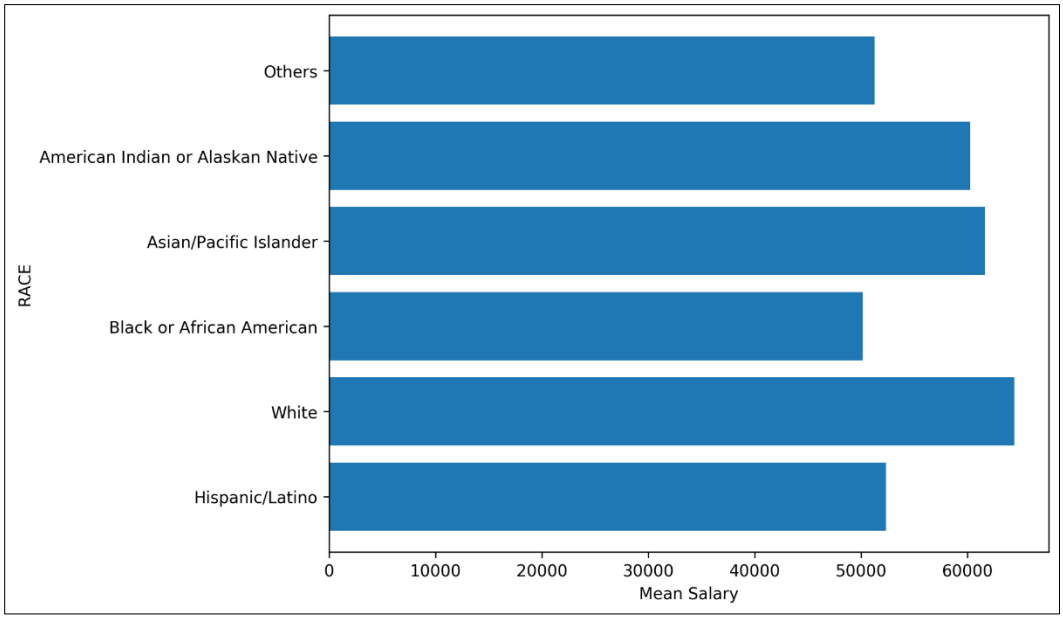
	DIST	AIR_TIME	PLOT_NUM
14972	373.0	121.0	1.0
22507	907.0	199.0	2.0
40768	643.0	176.0	3.0
50141	651.0	164.0	4.0
52699	802.0	210.0	5.0

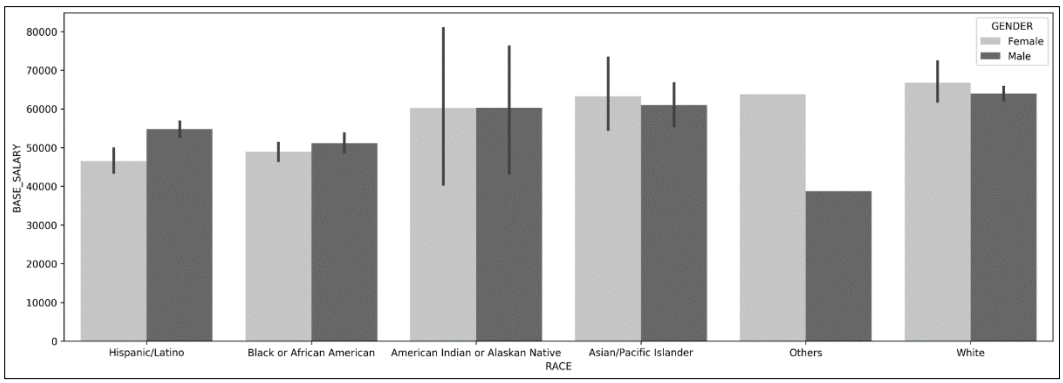

Houston Meetup Groups
R Users
Machine
Energy Data Science
Data Visualization
Data Science
1.0
0.8
0.6
0.4
0.2
0.0
2013-07
2014-01
2014-07
2015-01
2015-07
2016-01
2016-07
2017-01
2017-07
2018-01

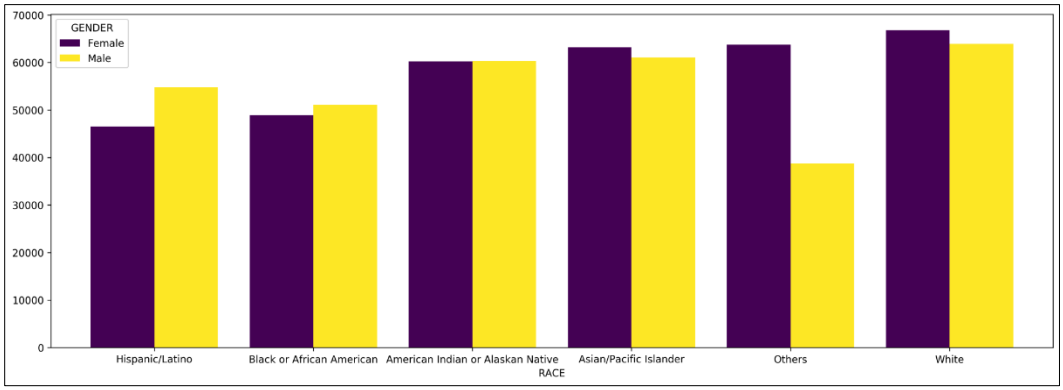

Municipal Courts Department
Library
Houston Police Department-HPD
Houston Fire Department (HFD)
General Services Department
Public Works & Engineering-PWE
Houston Airport System (HAS)
Health & Human Services
Finance
Fleet Management Department
Solid Waste Management
City Council
Human Resources Dept.
Houston Emergency Center (HEC)
Parks & Recreation
City Controller's Office
Legal Department
Houston Information Tech Svcs
Housing and Community Devp.
Dept of Neighborhoods (DON)
Admn. & Regulatory Affairs
Mayor's Office
Convention and Entertainment
Planning & Development
DEPARTMENT
0
100
200
300
400
500
600
count

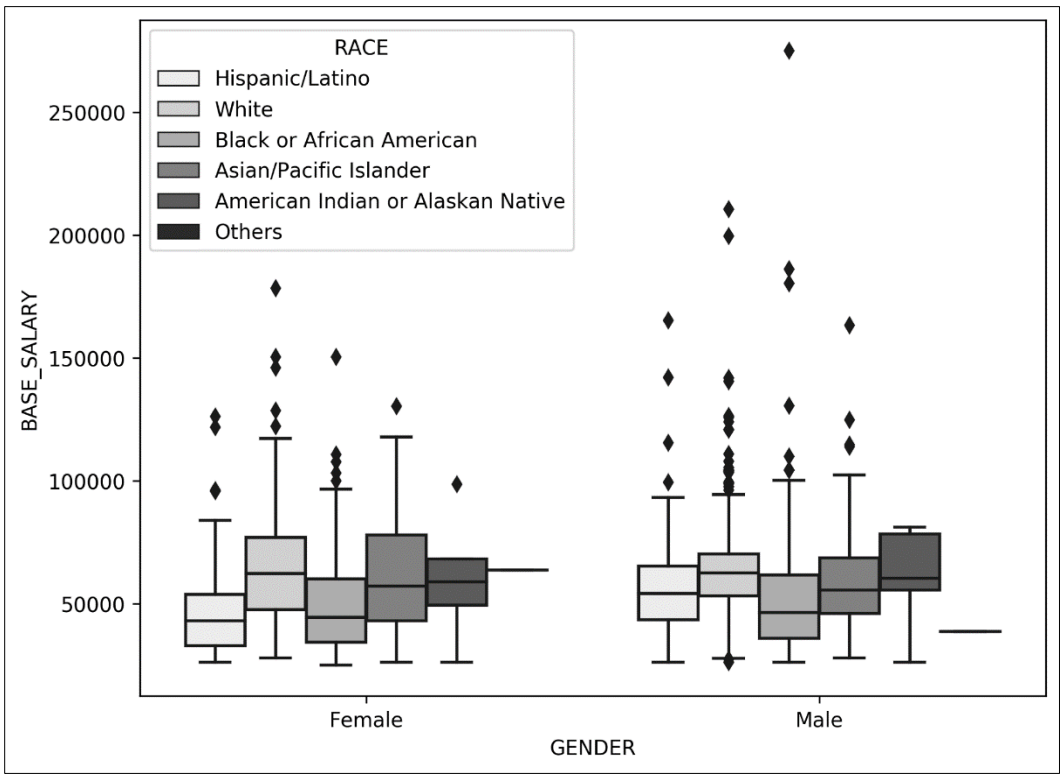

Convention and Entertainment
Mayor's Office
City Controller's Office
Planning & Development
Houston Information Tech Svcs
Finance
City Council
Legal Department
Dept of Neighborhoods (DON)
Housing and Community Devp.
General Services Department
Houston Emergency Center (HEC)
Human Resources Dept.
Municipal Courts Department
Admn. & Regulatory Affairs
Fleet Management Department
Library
Solid Waste Management
Parks & Recreation
Houston Airport System (HAS)
Health & Human Services
Public Works & Engineering-PWE
Houston Fire Department (HFD)
Houston Police Department-HPD
0
100
200
300
400
500
600

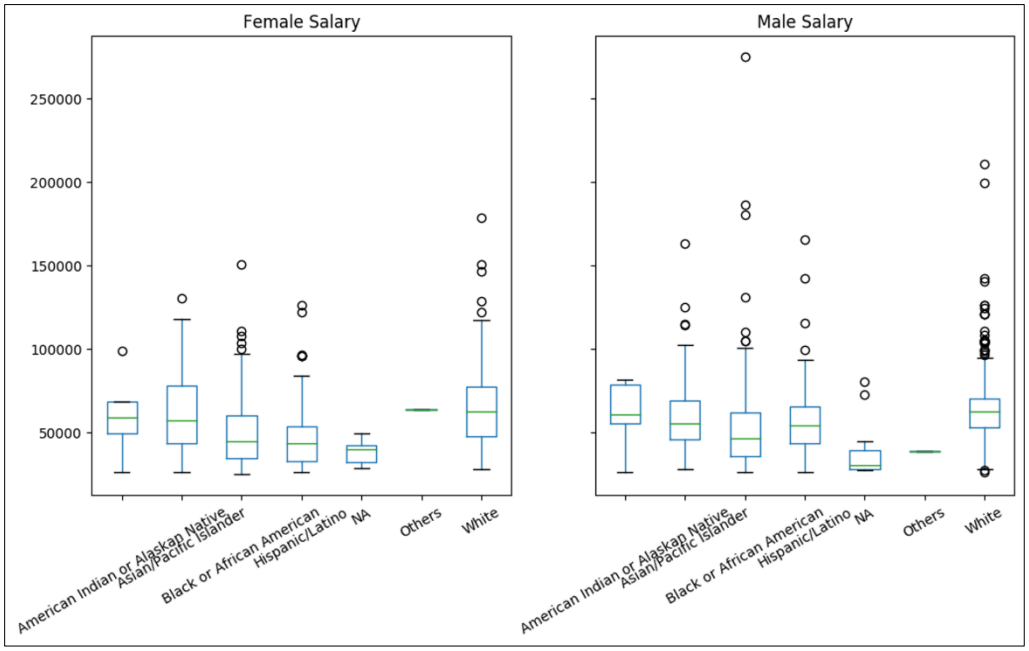

Hispanic/Latino
White
Black or African American
Asian/Pacific Islander
American Indian or Alaskan Native
Others
RACE
0
10000
20000
30000
40000
50000
60000
70000
BASE_SALARY

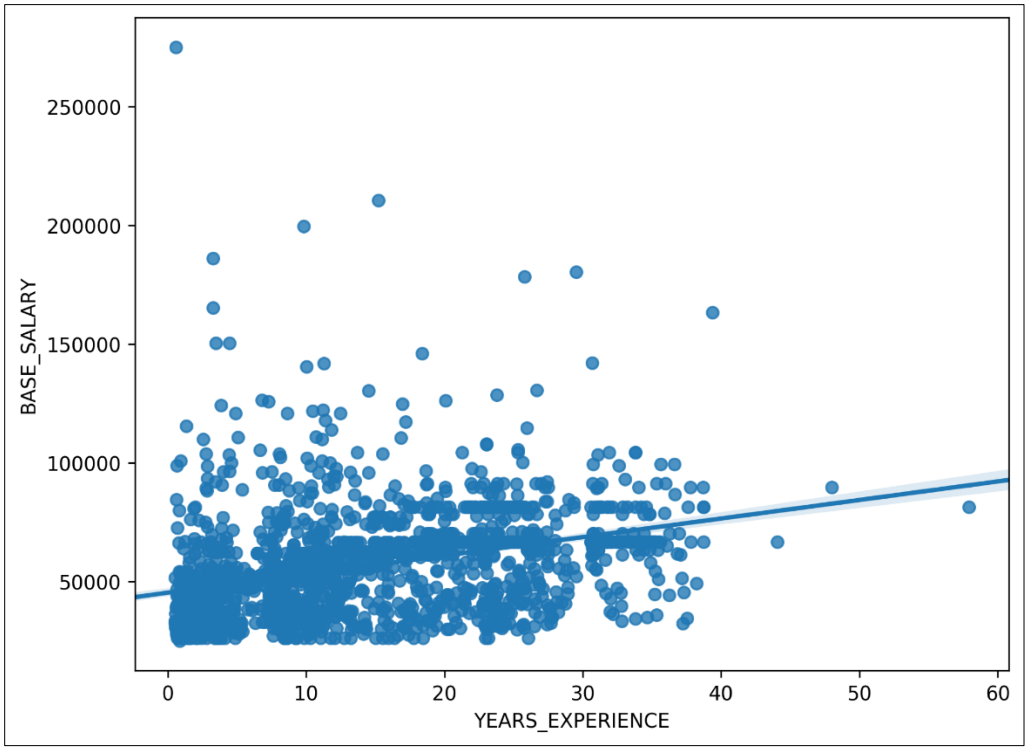

Others
American Indian or Alaskan Native
Asian/Pacific Islander
Black or African American
White
Hispanic/Latino
RACE
0
10000
20000
30000
40000
50000
60000
Mean Salary

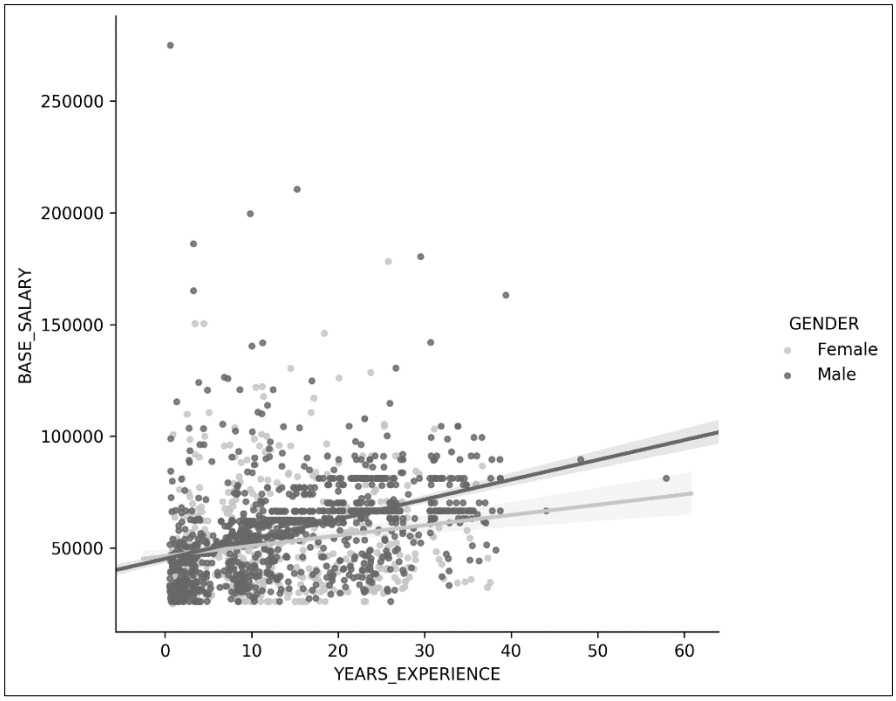

GENDER
Female
Male
BASE_SALARY
80000
70000
60000
50000
40000
30000
20000
10000
0
Hispanic/Latino
Black or African American
American Indian or Alaskan Native
Asian/Pacific Islander
Others
White
RACE

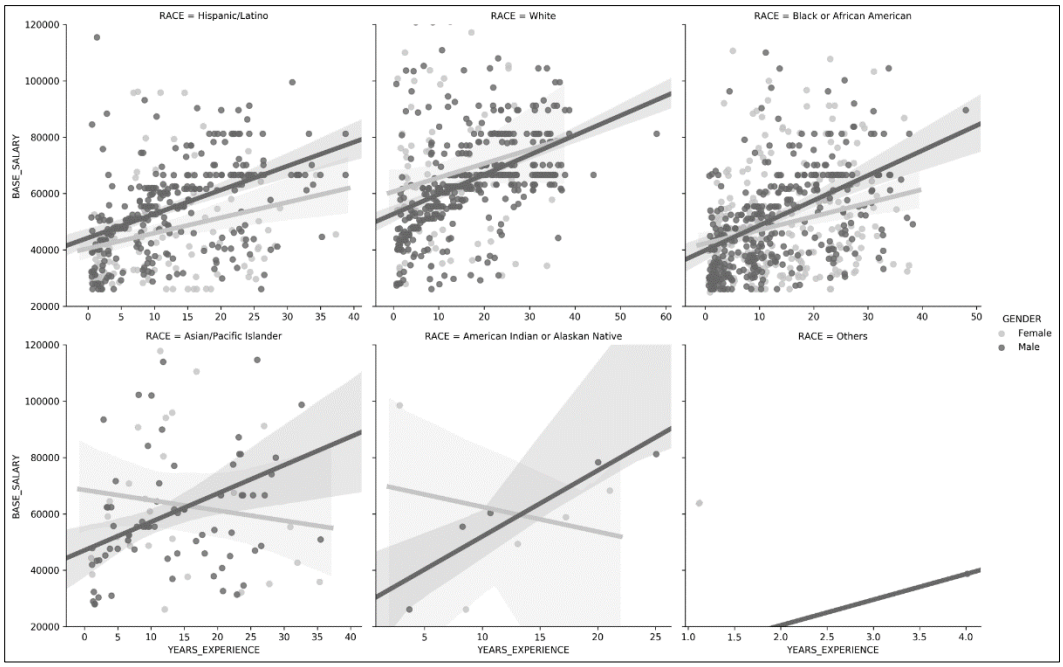

GENDER
Female
Male
70000
60000
50000
40000
30000
20000
10000
0
Hispanic/Latino
Black or African American
American Indian or Alaskan Native
Asian/Pacific Islander
Others
White
RACE

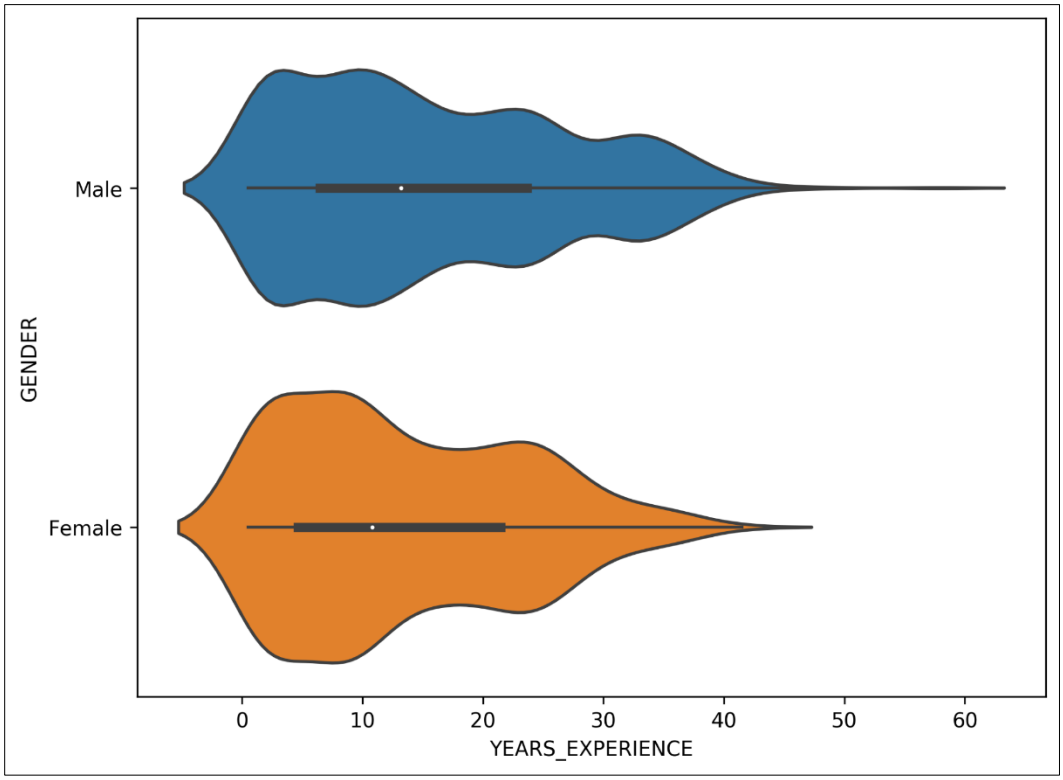

RACE
Hispanic/Latino
White
Black or African American
Asian/Pacific Islander
American Indian or Alaskan Native
Others
250000
200000
150000
100000
50000
BASE_SALARY
Female
Male
GENDER

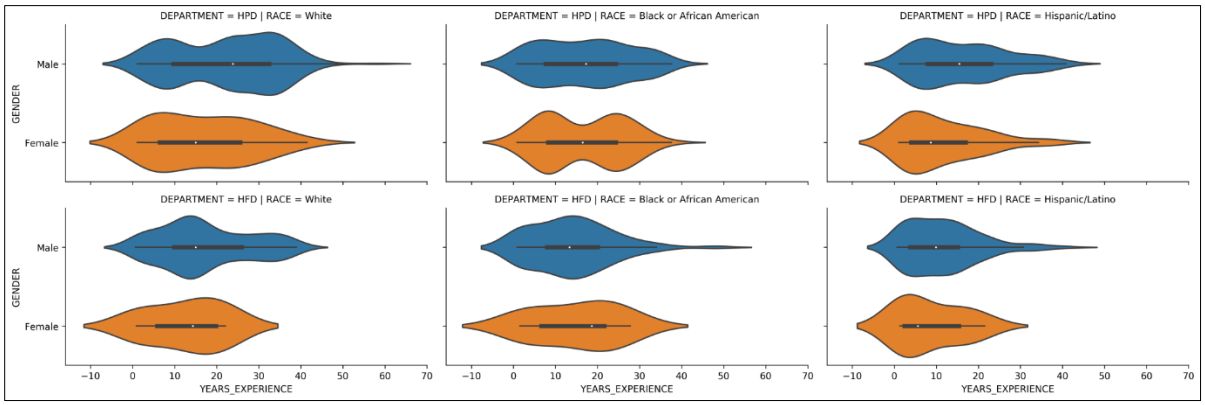

Female Salary
Male Salary
250000
200000
150000
100000
50000
American Indian or Alaskan Native
Asian/Pacific Islander
Black or African American
Hispanic/Latino
NA
Others
White


BASE_SALARY
YEARS_EXPERIENCE
250000
200000
150000
100000
50000
0
10
20
30
40
50
60

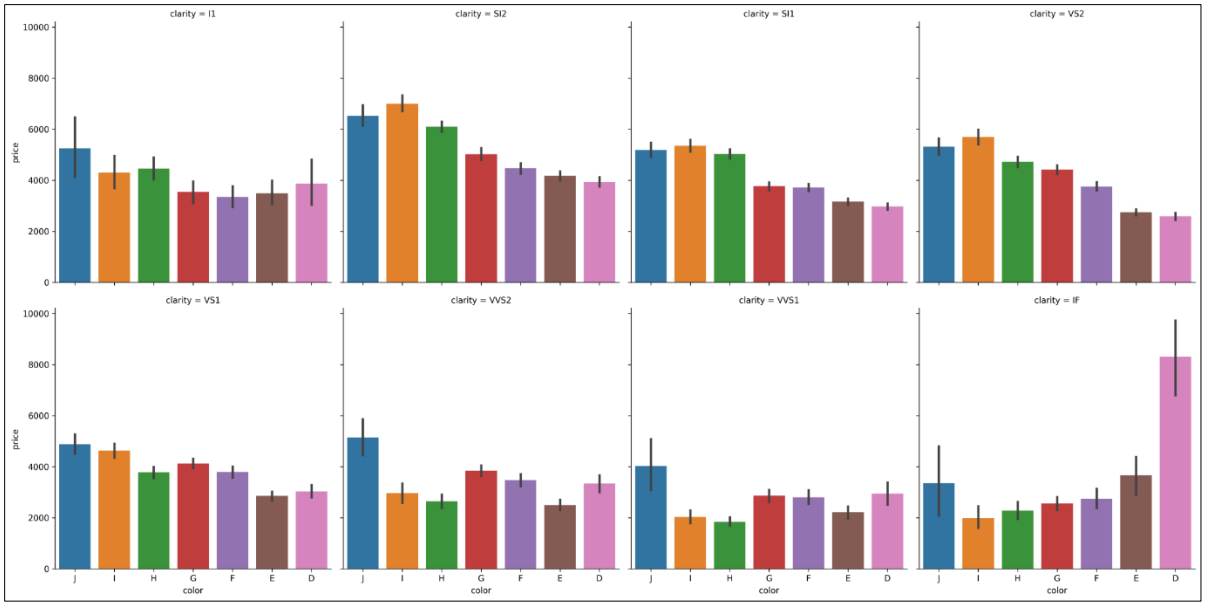

BASE_SALARY
250000
200000
150000
100000
50000
0
10
20
30
40
50
60
YEARS_EXPERIENCE
GENDER
Female
Male

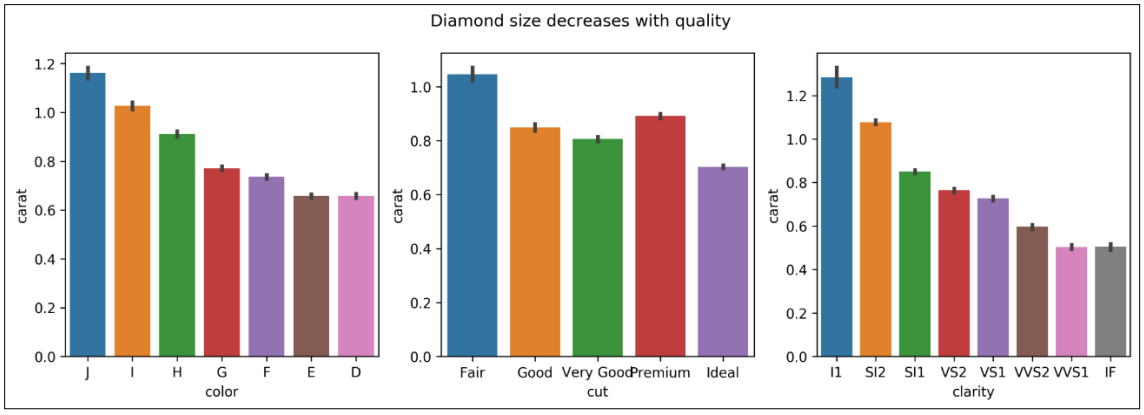

RACE = Hispanic/Latino
RACE = White
RACE = Black or African American
RACE = Asian/Pacific Islander
RACE = American Indian or Alaskan Native
RACE = Others
BASE_SALARY
YEARS_EXPERIENCE
GENDER
Female
Male

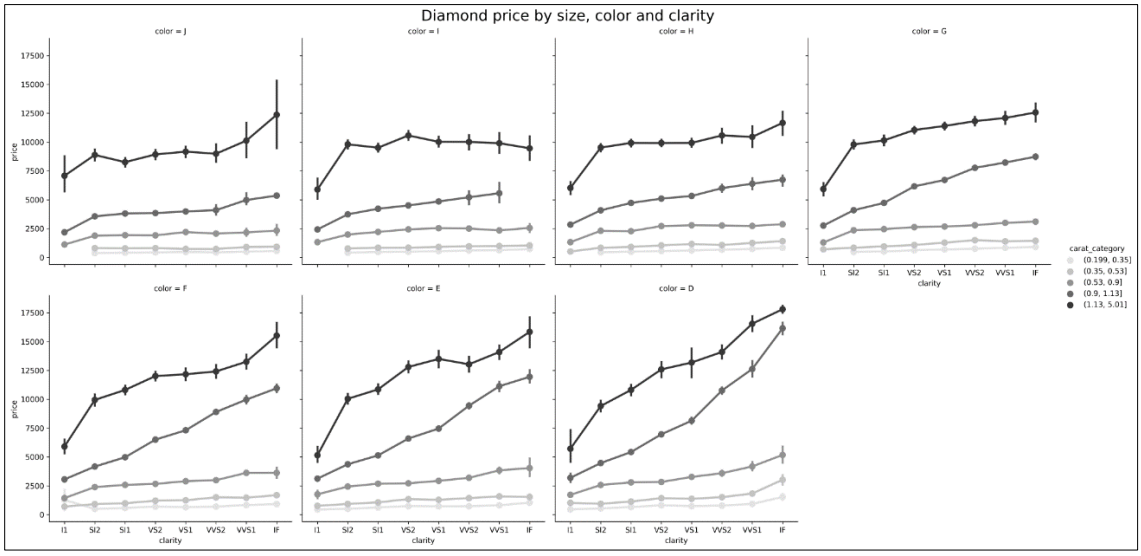

Male
Female
GENDER
0
10
20
30
40
50
60
YEARS_EXPERIENCE

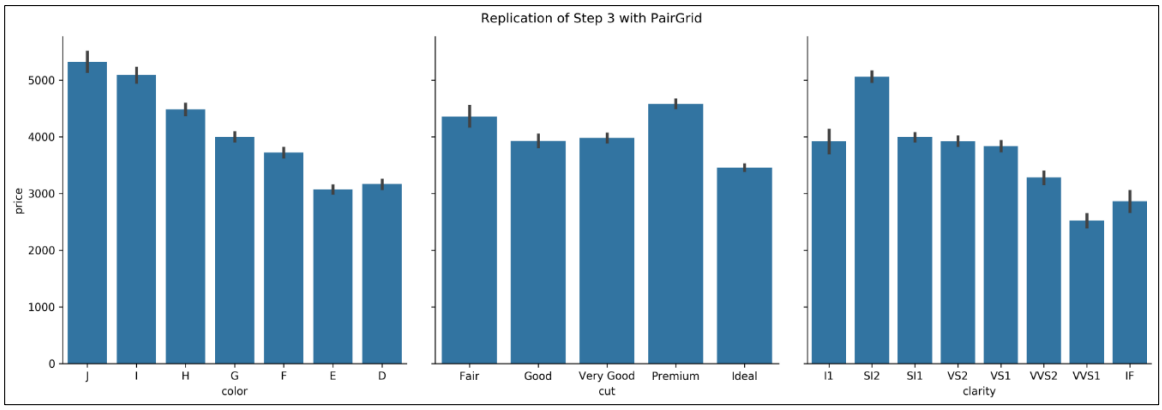

DEPARTMENT = HPD | RACE = White
DEPARTMENT = HPD | RACE = Black or African American
DEPARTMENT = HPD | RACE = Hispanic/Latino
DEPARTMENT = HFD | RACE = White
DEPARTMENT = HFD | RACE = Black or African American
DEPARTMENT = HFD | RACE = Hispanic/Latino
Male
Female
GENDER
−10
0
10
20
30
40
50
60
70
YEARS_EXPERIENCE


Price Decreasing with Increasing Quality?
price
color
J I H G F E D
cut
Fair Good Very Good Premium Ideal
clarity
I1 SI2 SI1 VS2 VS1 VVS2 VVS1 IF


clarity = I1
clarity = SI2
clarity = SI1
clarity = VS2
clarity = VS1
clarity = VVS2
clarity = VVS1
clarity = IF
price
color


Diamond size decreases with quality
carat
color
J I H G F E D
cut
Fair Good Very Good Premium Ideal
clarity
I1 SI2 SI1 VS2 VS1 VVS2 VVS1 IF


Diamond price by size, color and clarity
color = J
color = I
color = H
color = G
color = F
color = E
color = D
price
clarity
carat_category
(0.199, 0.35]
(0.35, 0.53]
(0.53, 0.9]
(0.9, 1.13]
(1.13, 5.01]


Replication of Step 3 with PairGrid
price
color
J I H G F E D
cut
Fair Good Very Good Premium Ideal
clarity
I1 SI2 SI1 VS2 VS1 VVS2 VVS1 IF

Chapter 14: Debugging and Testing Pandas

```
<ipython-input-9-6ce28d2fea57> in add1(x)
      1 def add1(x):
----> 2     return x + 1
      3
      4 df.Q3.apply(add1)

TypeError: must be str, not int
```

```
In [*]: %debug

> <ipython-input-9-6ce28d2fea57>(2)add1()
      1 def add1(x):
----> 2     return x + 1
      3
      4 df.Q3.apply(add1)

ipdb> p x
'United States of America'
ipdb> u
> /Users/matt/.env/364/lib/python3.6/site-packages/pandas/core/series.py(4045)apply()
   4043             else:
   4044                 values = self.astype(object).values
-> 4045                 mapped = lib.map_infer(values, f, convert=convert_dtype)
   4046
   4047         if len(mapped) and isinstance(mapped[0], Series):

ipdb> p self
1        United S...
2          Indonesia
3        United S...
4        United S...
5              India
              ...
23855         France
23856         Turkey
23857         Turkey
23858    United K...
23859          Spain
Name: Q3, Length: 23859, dtype: object

ipdb>
```

```
from IPython.core.debugger import set_trace

def add1(x):
    set_trace()
    return x + 1

df.Q3.apply(add1)
```

```
> <ipython-input-11-cb997d0cb281>(5)add1()
      3 def add1(x):
      4     set_trace()
----> 5     return x + 1
      6
      7 df.Q3.apply(add1)


ipdb>
```