Count of private and public colleges

Table of contents

```
from notebookfuncs import *
```

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.pyplot import subplots
import pandas as pd
from ISLP import load_data
import seaborn as sns
from numpy import median
```

```
College = pd.read_csv("College.csv")
College
```

	Unnamed: 0	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.U
0	Abilene Christian University	Yes	1660	1232	721	23	52	2885	537
1	Adelphi University	Yes	2186	1924	512	16	29	2683	122
2	Adrian College	Yes	1428	1097	336	22	50	1036	99
3	Agnes Scott College	Yes	417	349	137	60	89	510	63
4	Alaska Pacific University	Yes	193	146	55	16	44	249	869
...	...	...	...	...	...	...	...	...	...
772	Worcester State College	No	2197	1515	543	4	26	3089	202
773	Xavier University	Yes	1959	1805	695	24	47	2849	110
774	Xavier University of Louisiana	Yes	2097	1915	695	34	61	2793	166
775	Yale University	Yes	10705	2453	1317	95	99	5217	83
776	York College of Pennsylvania	Yes	2989	1855	691	28	63	2988	172

```
college2 = pd.read_csv("College.csv", index_col=0)
college2
```

	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Underg
Abilene Christian University	Yes	1660	1232	721	23	52	2885	537
Adelphi University	Yes	2186	1924	512	16	29	2683	1227
Adrian College	Yes	1428	1097	336	22	50	1036	99
Agnes Scott College	Yes	417	349	137	60	89	510	63
Alaska Pacific University	Yes	193	146	55	16	44	249	869
...	...	...	...	...	...	...	...	...
Worcester State College	No	2197	1515	543	4	26	3089	2029
Xavier University	Yes	1959	1805	695	24	47	2849	1107
Xavier University of Louisiana	Yes	2097	1915	695	34	61	2793	166
Yale University	Yes	10705	2453	1317	95	99	5217	83
York College of Pennsylvania	Yes	2989	1855	691	28	63	2988	1726

```python
College3 = College.rename({"Unnamed: 0": "College"}, axis=1)
College3.set_index("College")
College3
```

	College	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.U
0	Abilene Christian University	Yes	1660	1232	721	23	52	2885	537
1	Adelphi University	Yes	2186	1924	512	16	29	2683	122
2	Adrian College	Yes	1428	1097	336	22	50	1036	99
3	Agnes Scott College	Yes	417	349	137	60	89	510	63
4	Alaska Pacific University	Yes	193	146	55	16	44	249	869
...	...	...	...	...	...	...	...	...	...
772	Worcester State College	No	2197	1515	543	4	26	3089	202
773	Xavier University	Yes	1959	1805	695	24	47	2849	110
774	Xavier University of Louisiana	Yes	2097	1915	695	34	61	2793	166
775	Yale University	Yes	10705	2453	1317	95	99	5217	83
776	York College of Pennsylvania	Yes	2989	1855	691	28	63	2988	172

```python
College = College3
```

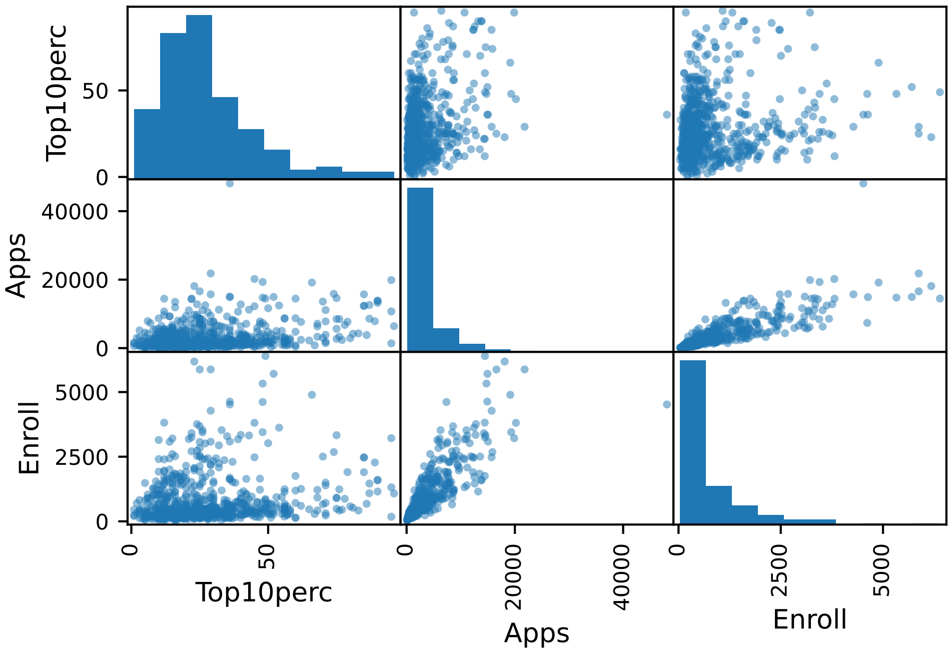
	College	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.U
0	Abilene Christian University	Yes	1660	1232	721	23	52	2885	537
1	Adelphi University	Yes	2186	1924	512	16	29	2683	122
2	Adrian College	Yes	1428	1097	336	22	50	1036	99
3	Agnes Scott College	Yes	417	349	137	60	89	510	63
4	Alaska Pacific University	Yes	193	146	55	16	44	249	869
...	...	...	...	...	...	...	...	...	...
772	Worcester State College	No	2197	1515	543	4	26	3089	202
773	Xavier University	Yes	1959	1805	695	24	47	2849	110
774	Xavier University of Louisiana	Yes	2097	1915	695	34	61	2793	166

	College	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.U
775	Yale University	Yes	10705	2453	1317	95	99	5217	83
776	York College of Pennsylvania	Yes	2989	1855	691	28	63	2988	172

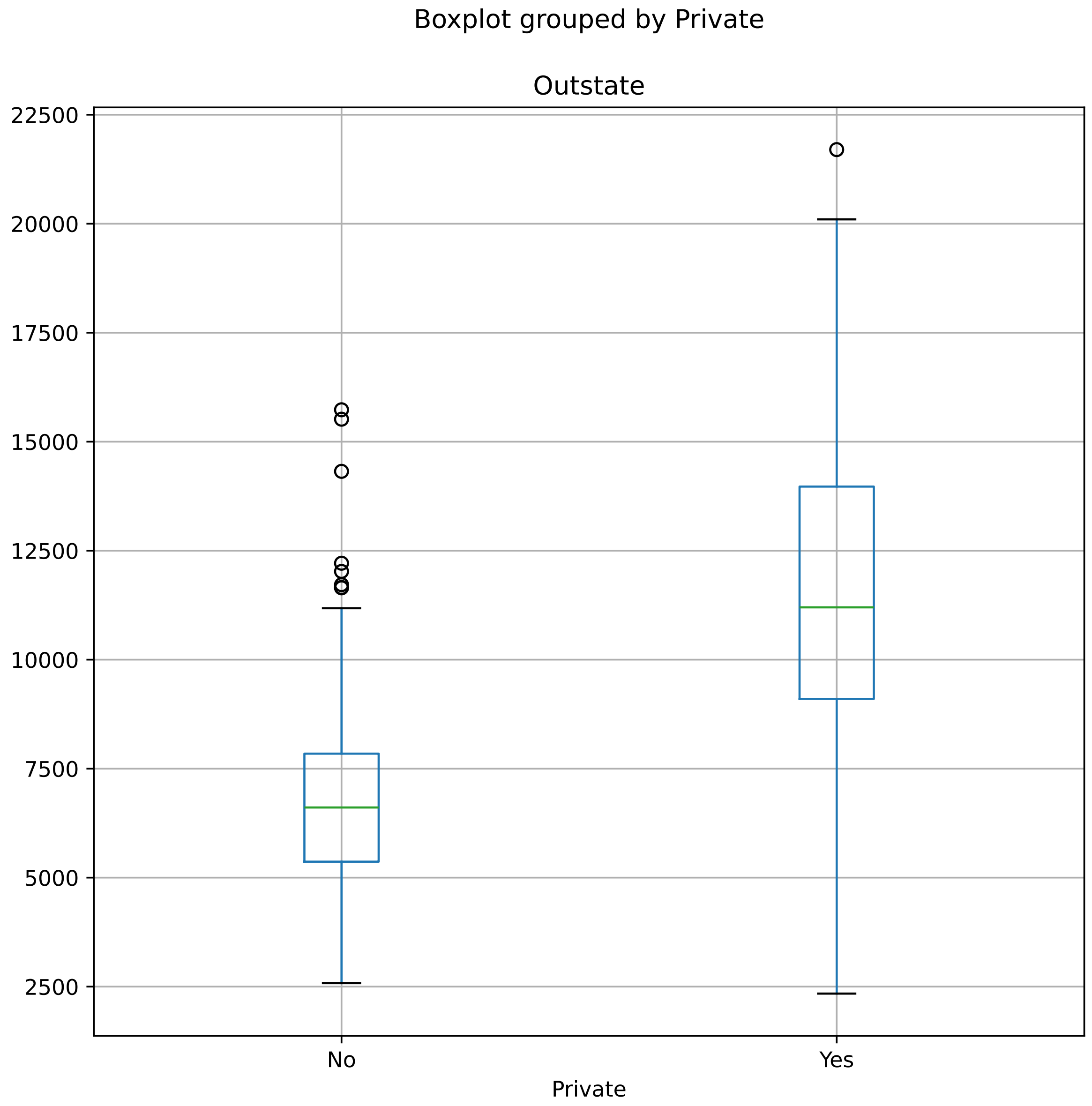
```
College.describe()
```

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outsta
count	777.000000	777.000000	777.000000	777.000000	777.000000	777.000000	777.000000	777.000
mean	3001.638353	2018.804376	779.972973	27.558559	55.796654	3699.907336	855.298584	10440.6
std	3870.201484	2451.113971	929.176190	17.640364	19.804778	4850.420531	1522.431887	4023.01
min	81.000000	72.000000	35.000000	1.000000	9.000000	139.000000	1.000000	2340.00
25%	776.000000	604.000000	242.000000	15.000000	41.000000	992.000000	95.000000	7320.00
50%	1558.000000	1110.000000	434.000000	23.000000	54.000000	1707.000000	353.000000	9990.00
75%	3624.000000	2424.000000	902.000000	35.000000	69.000000	4005.000000	967.000000	12925.0
max	48094.000000	26330.000000	6392.000000	96.000000	100.000000	31643.000000	21836.000000	21700.0

```
pd.plotting.scatter_matrix(College[["Top10perc", "Apps", "Enroll"]]);
```



```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Outstate", by="Private", ax=ax);
```



```
College["Top10perc"]
```

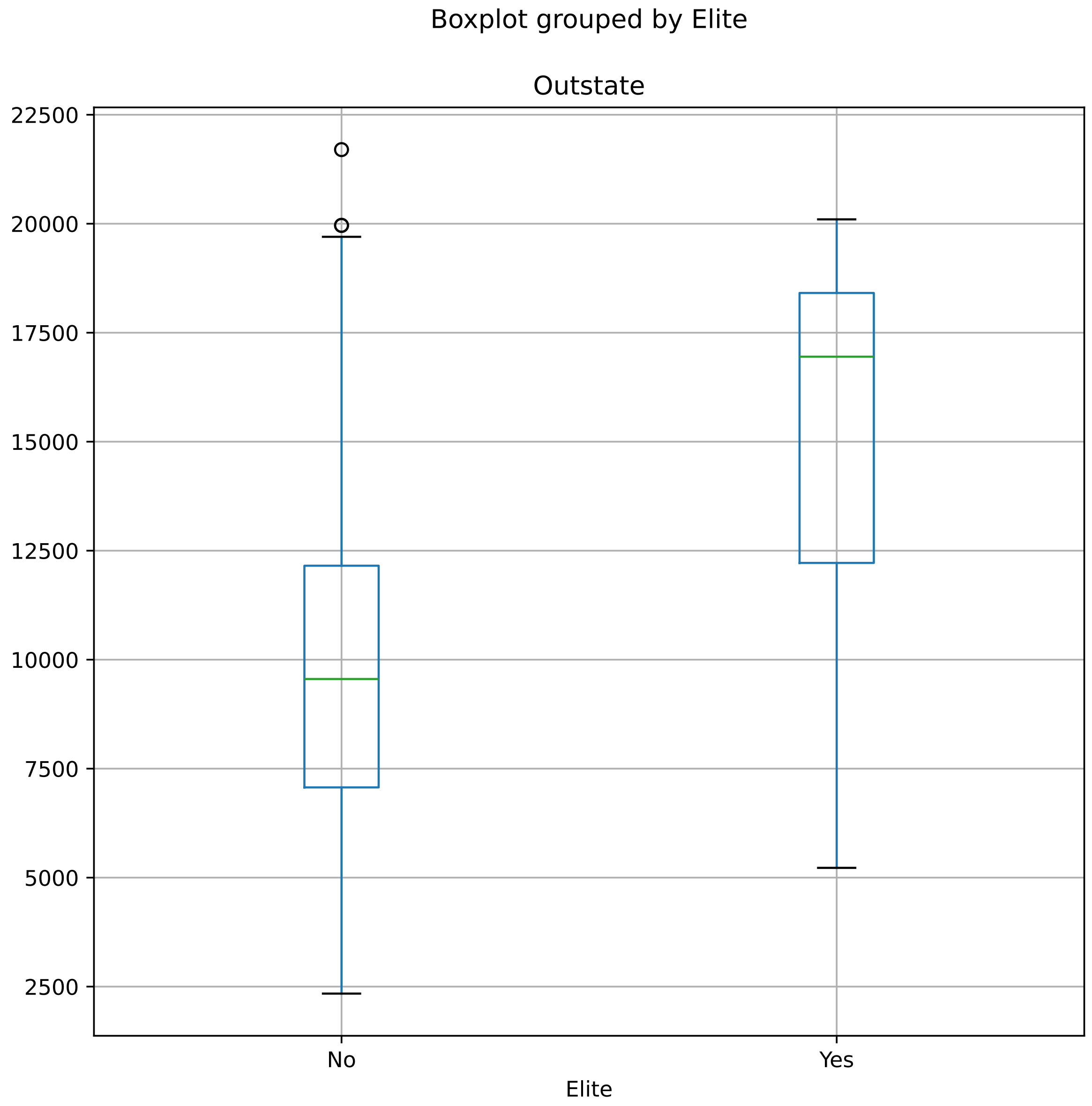
```
0        23
1        16
2        22
3        60
4        16
         ..
```

```
772     4
773    24
774    34
775    95
776    28
Name: Top10perc, Length: 777, dtype: int64
```

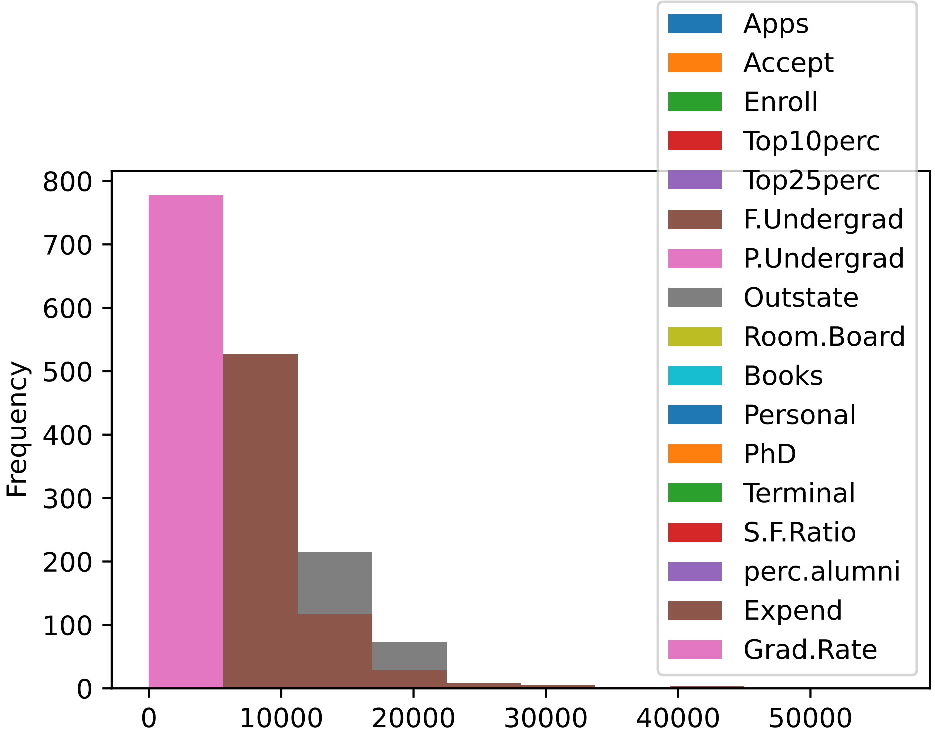
```python
College["Elite"] = pd.cut(College["Top10perc"], [0, 50, 100], labels=["No", "Yes"])
College["Elite"].value_counts()
```

```
Elite
No     699
Yes     78
Name: count, dtype: int64
```

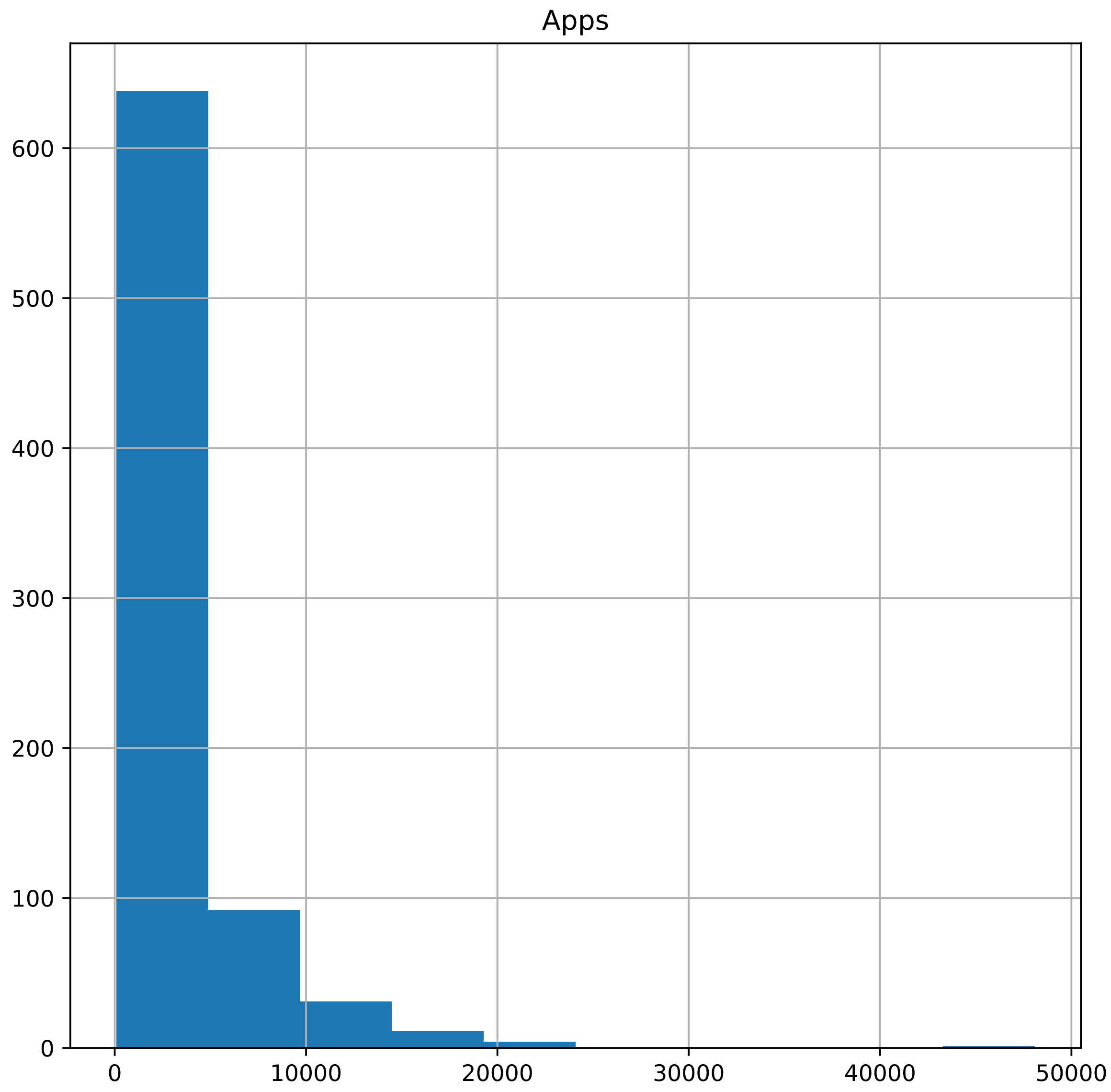
```python
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Outstate", by="Elite", ax=ax);
```



```
College.plot.hist();
```



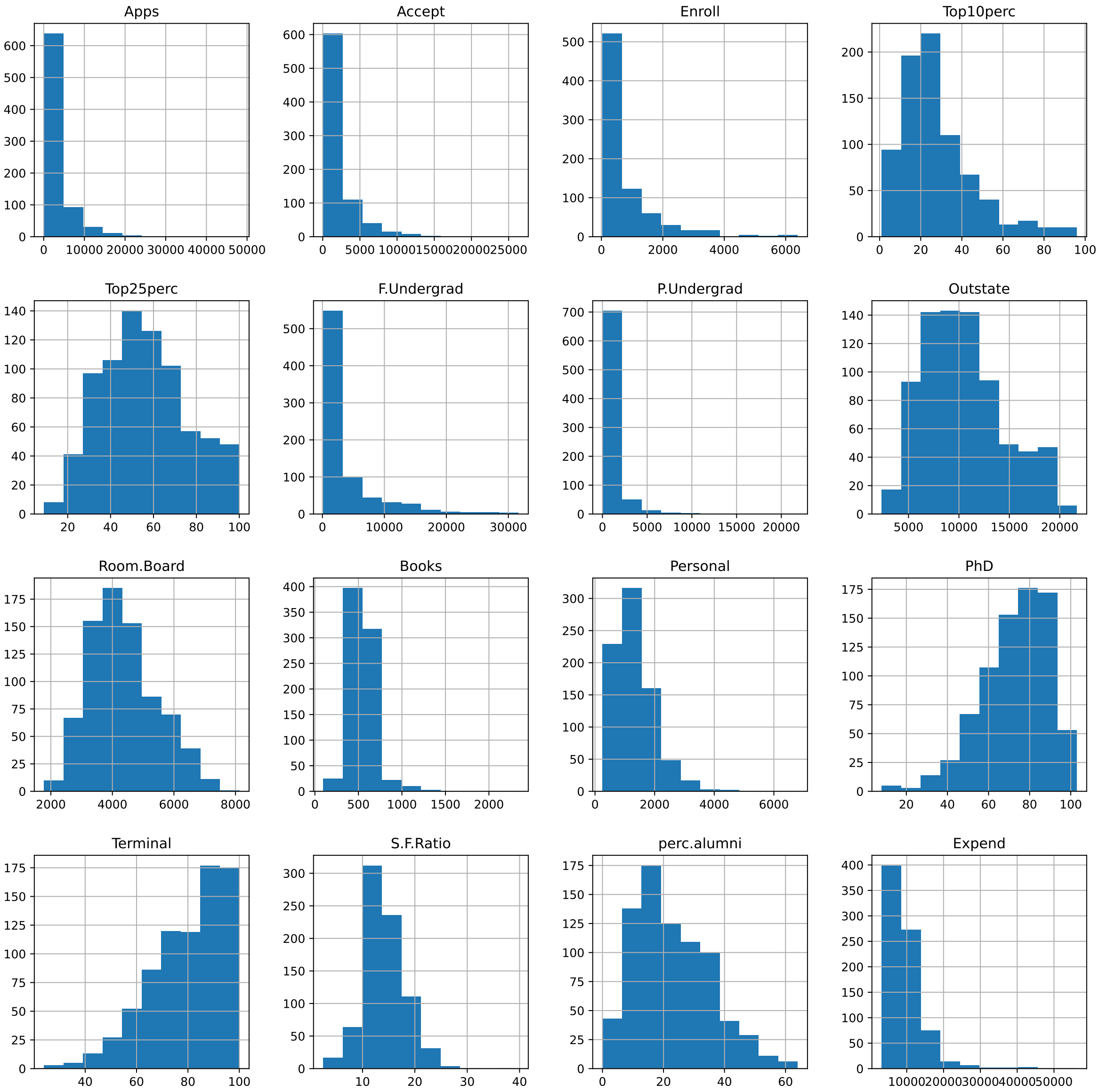
```
fig, ax = subplots(figsize=(8, 8))
College.hist("Apps", ax=ax);
```



```
numeric_columns = College.select_dtypes(include="number").columns.tolist()
numeric_columns
```

```
['Apps',
 'Accept',
 'Enroll',
 'Top10perc',
 'Top25perc',
 'F.Undergrad',
 'P.Undergrad',
 'Outstate',
 'Room.Board',
 'Books',
 'Personal',
 'PhD',
 'Terminal',
 'S.F.Ratio',
 'perc.alumni',
 'Expend',
 'Grad.Rate']
```

```
fig, axs = subplots(4, 4, figsize=(16, 16))
for row in range(0, 4):
    for column in range(0, 4):
        College.hist(numeric_columns[row * 4 + column], ax=axs[row, column])
```



```
College["Private"].value_counts()
```

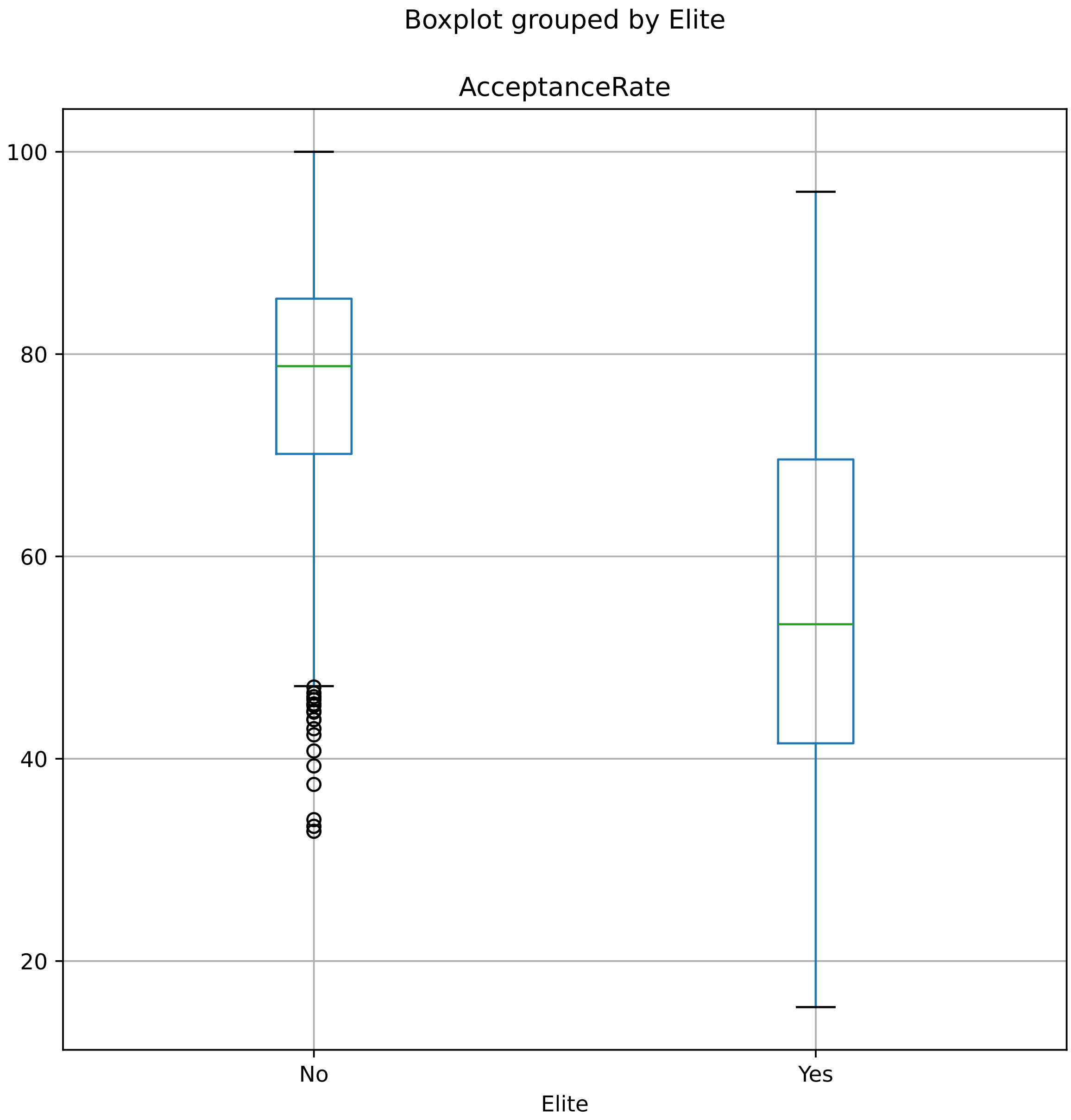
```
Private
Yes    565
No     212
Name: count, dtype: int64
```

```
College["AcceptanceRate"] = round(College["Accept"] / College["Apps"] * 100, 2)
College["AcceptanceRate"]
```

```
0      74.22
1      88.01
2      76.82
3      83.69
4      75.65
       ...
772    68.96
773    92.14
774    91.32
775    22.91
776    62.06
Name: AcceptanceRate, Length: 777, dtype: float64
```

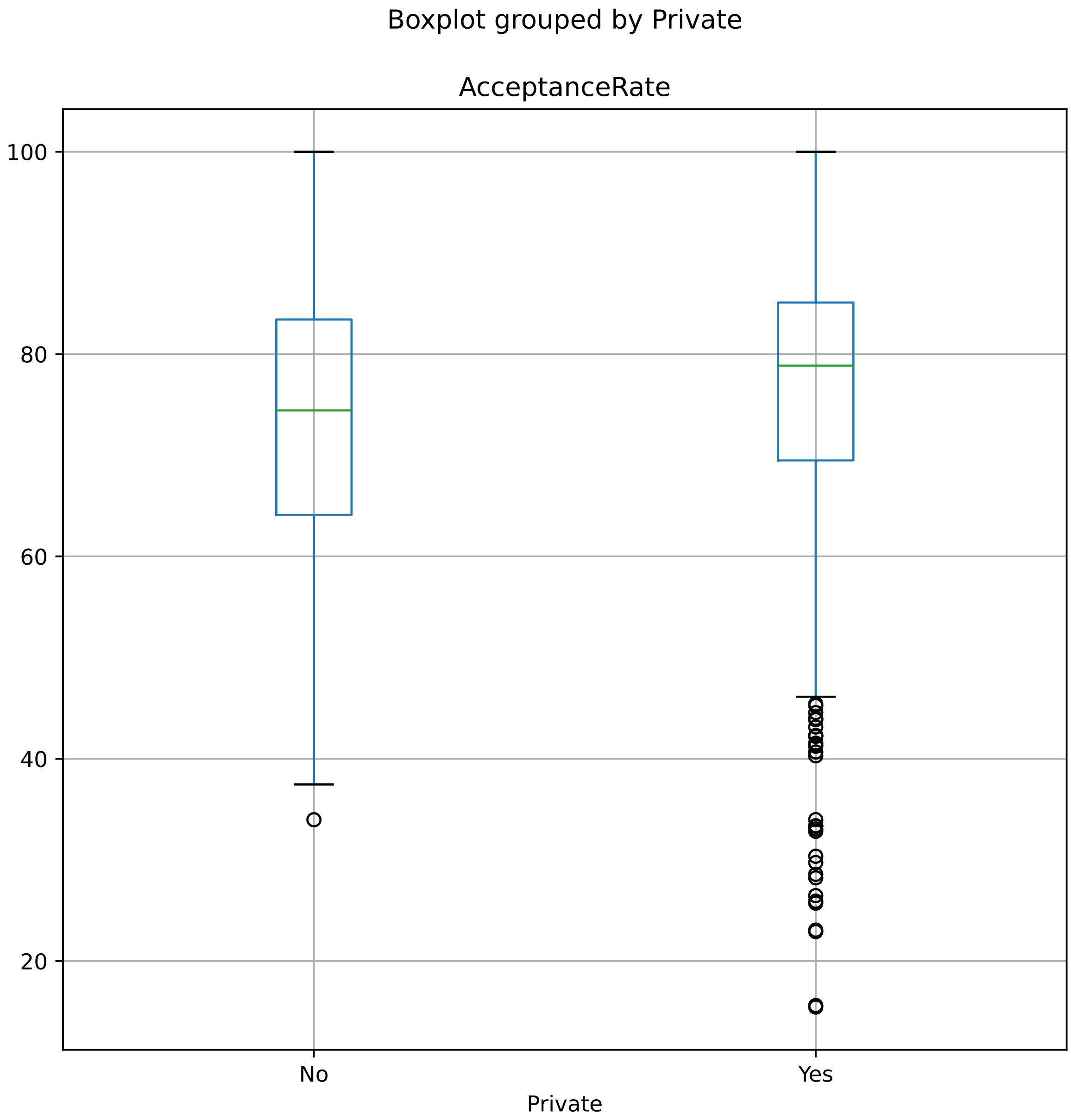
```
### Plot boxplot for acceptance rate by College Type : Elite or not
```

```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("AcceptanceRate", by="Elite", ax=ax);
```



```
### Plot boxplot for acceptance rate for Private colleges or not
```

```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("AcceptanceRate", by="Private", ax=ax);
```

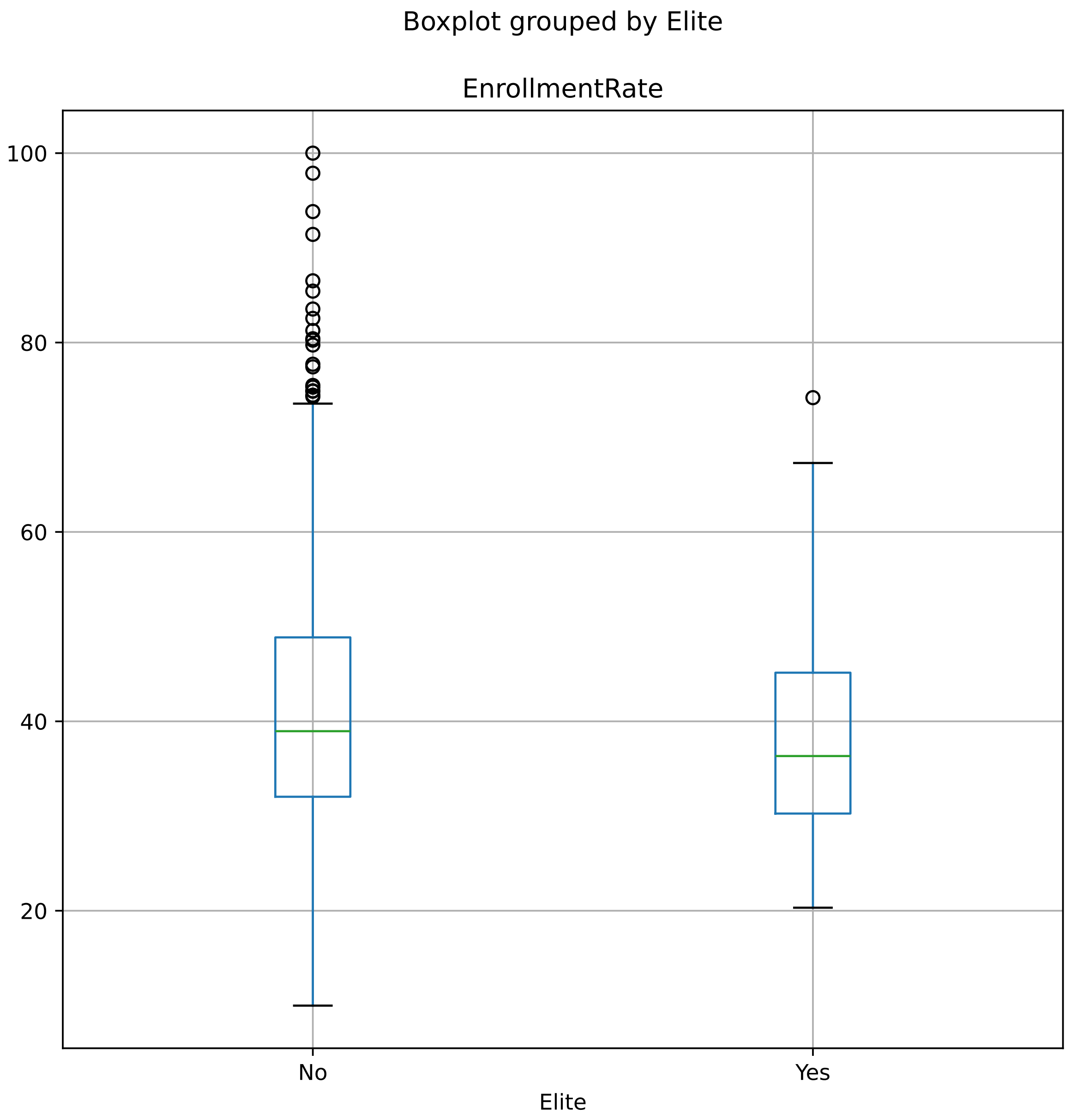


```
College["EnrollmentRate"] = round(College["Enroll"] / College["Accept"] * 100, 2)
College["EnrollmentRate"]
```

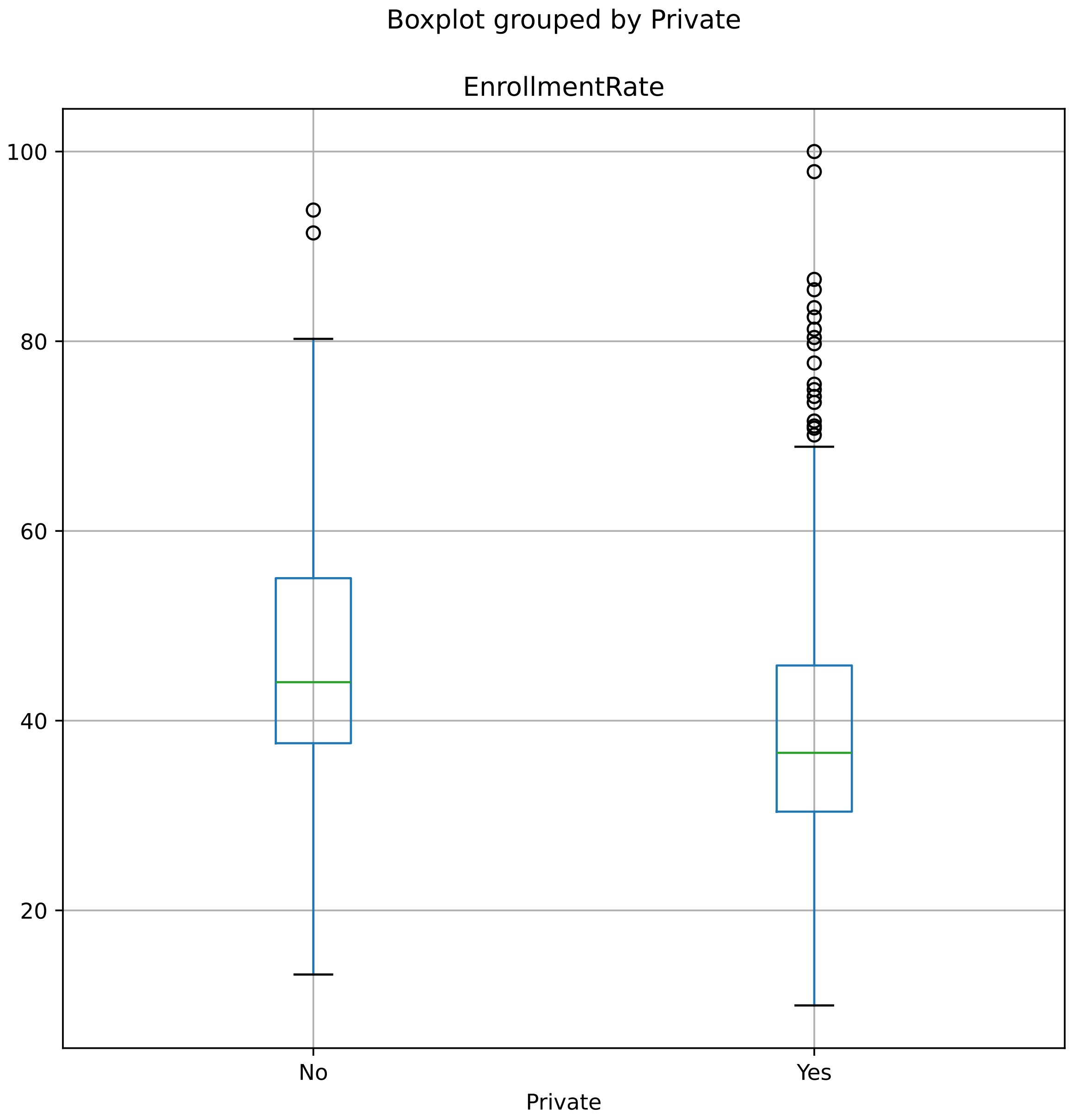
```
0      58.52
1      26.61
2      30.63
3      39.26
```

```
4      37.67
       ...
772    35.84
773    38.50
774    36.29
775    53.69
776    37.25
Name: EnrollmentRate, Length: 777, dtype: float64
```

```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("EnrollmentRate", by="Elite", ax=ax);
```

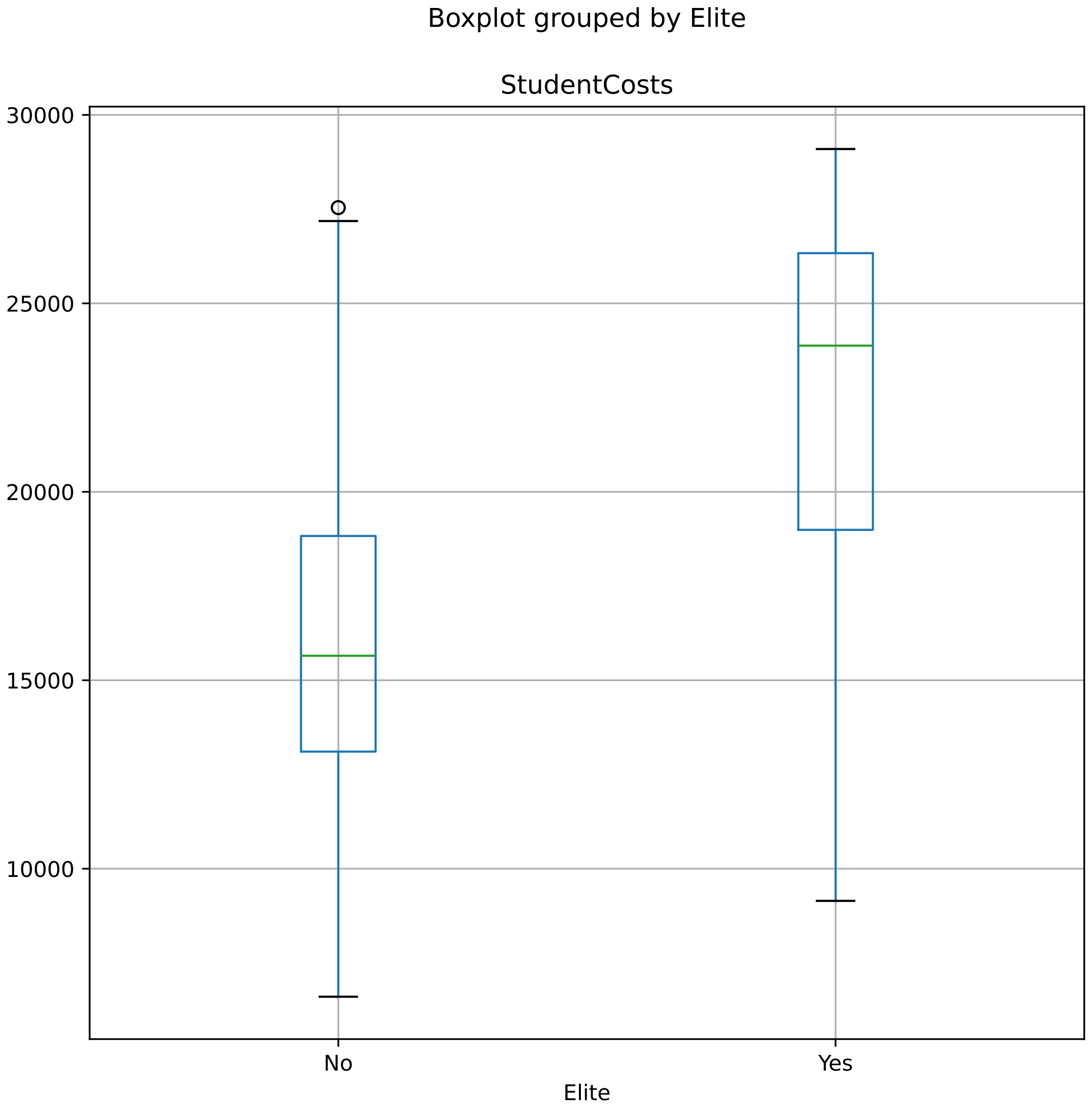


```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("EnrollmentRate", by="Private", ax=ax);
```

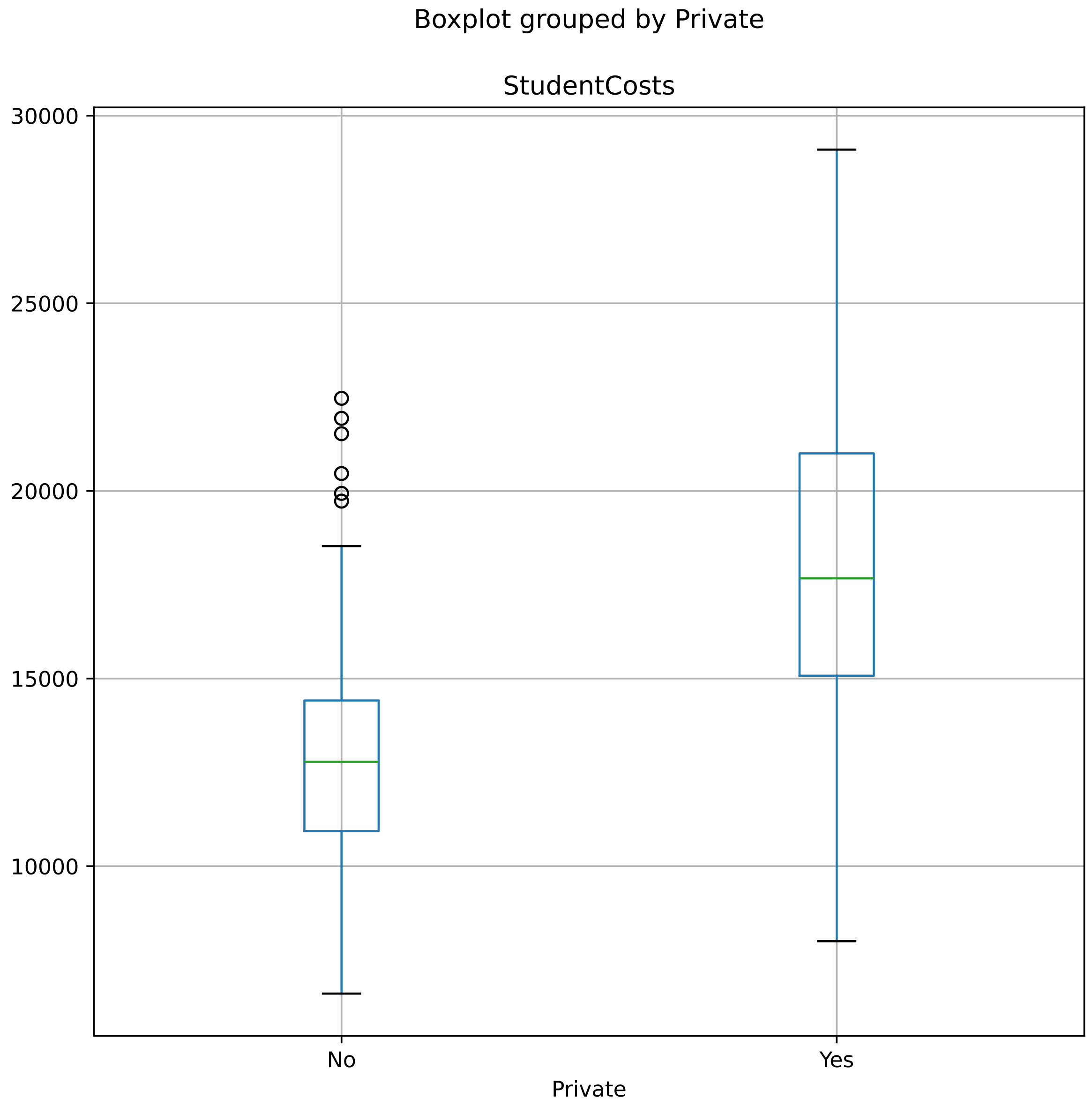


```
College["StudentCosts"] = (
    College["Outstate"] + College["Room.Board"] + College["Books"] +
 ↪  College["Personal"]
)
```

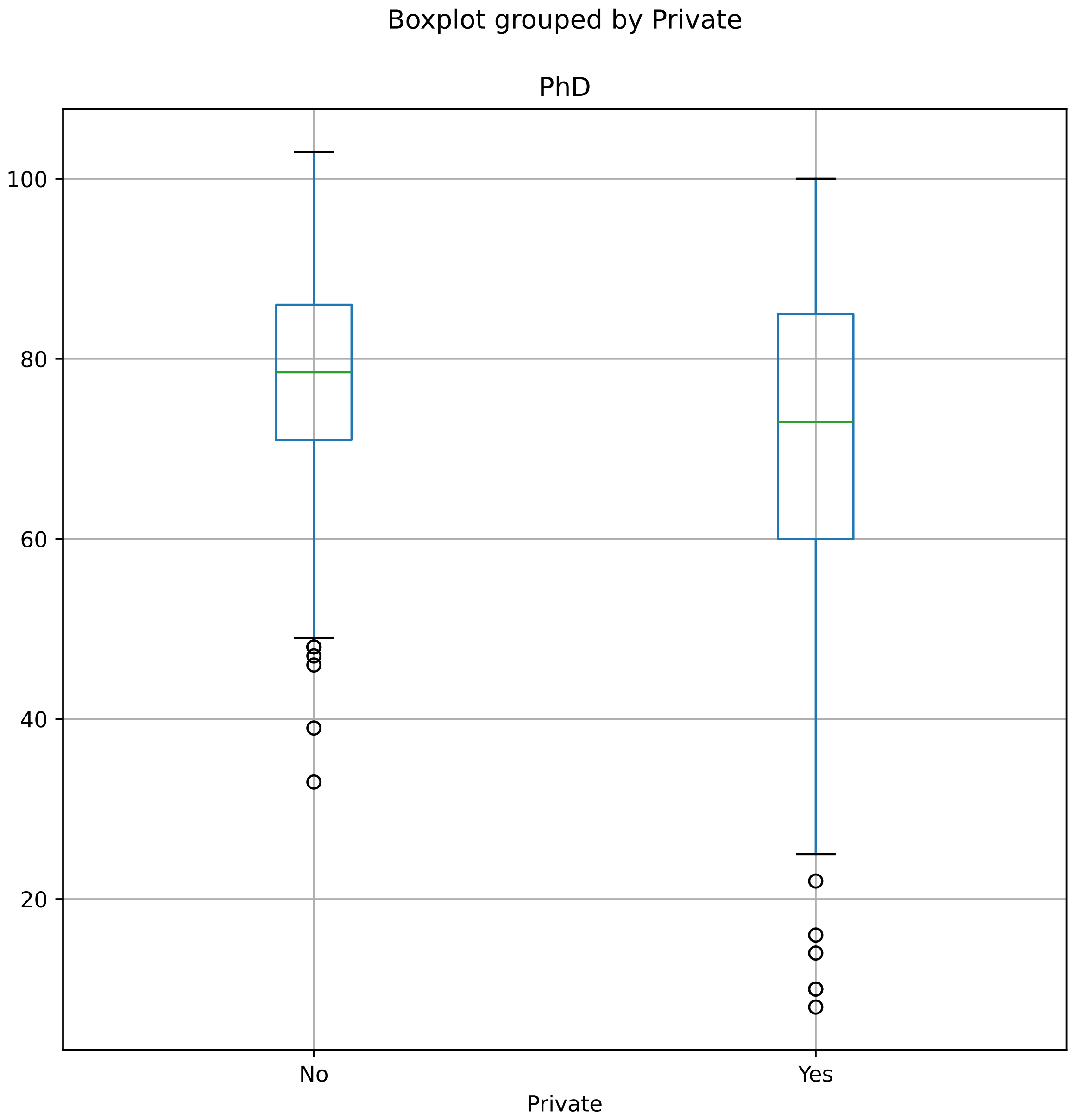
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("StudentCosts", by="Elite", ax=ax);
```



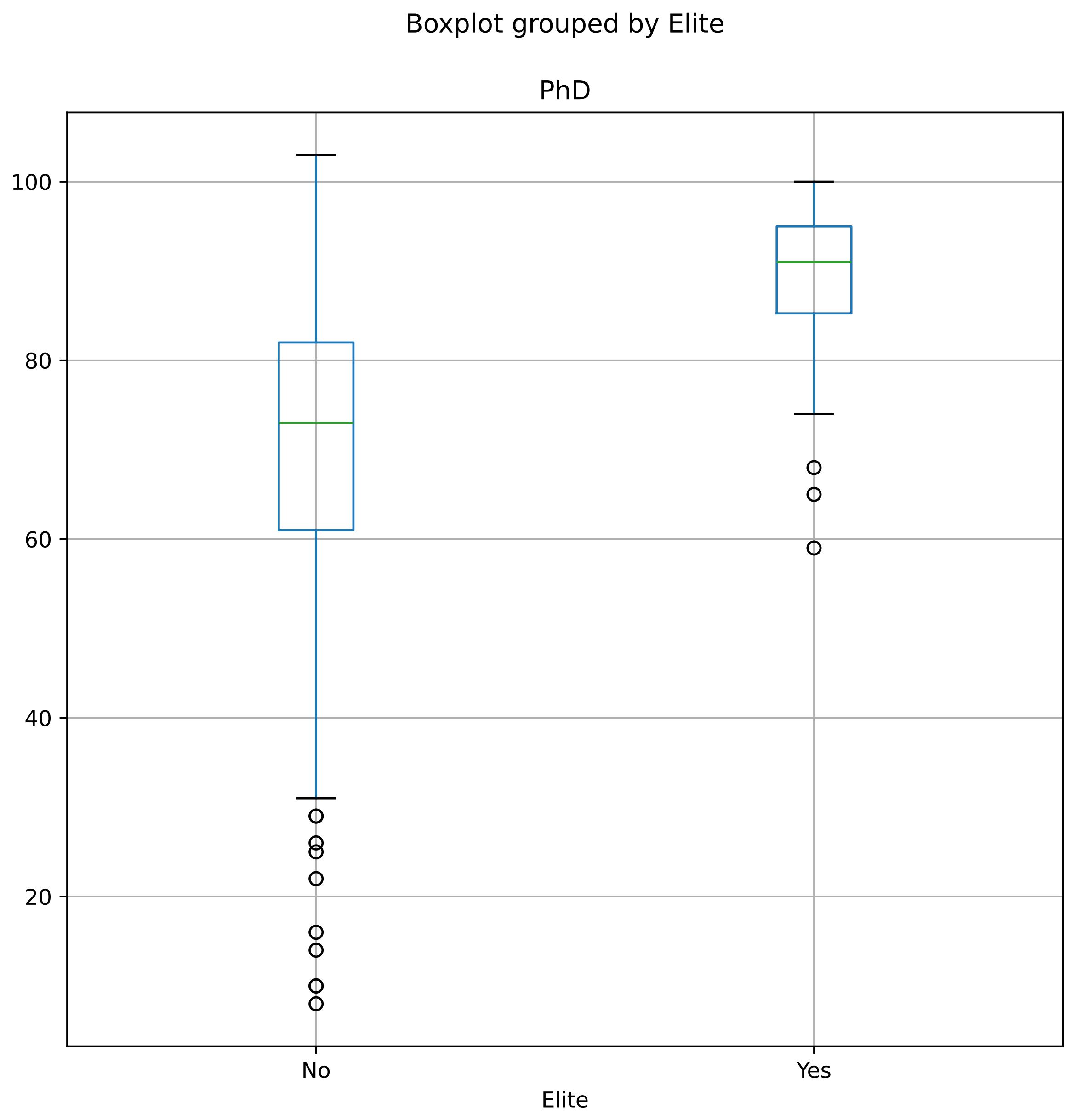
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("StudentCosts", by="Private", ax=ax);
```



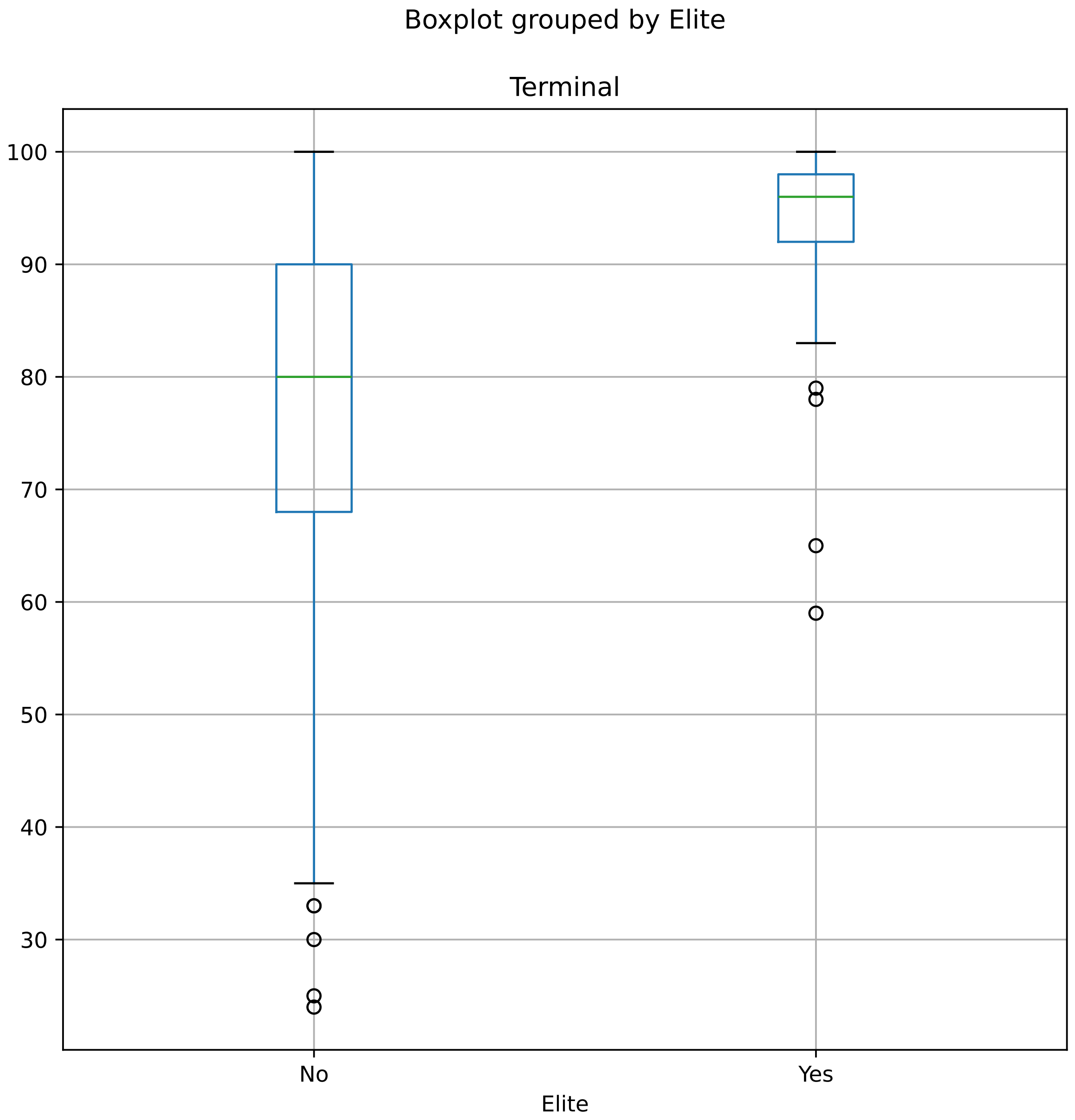
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("PhD", by="Private", ax=ax);
```



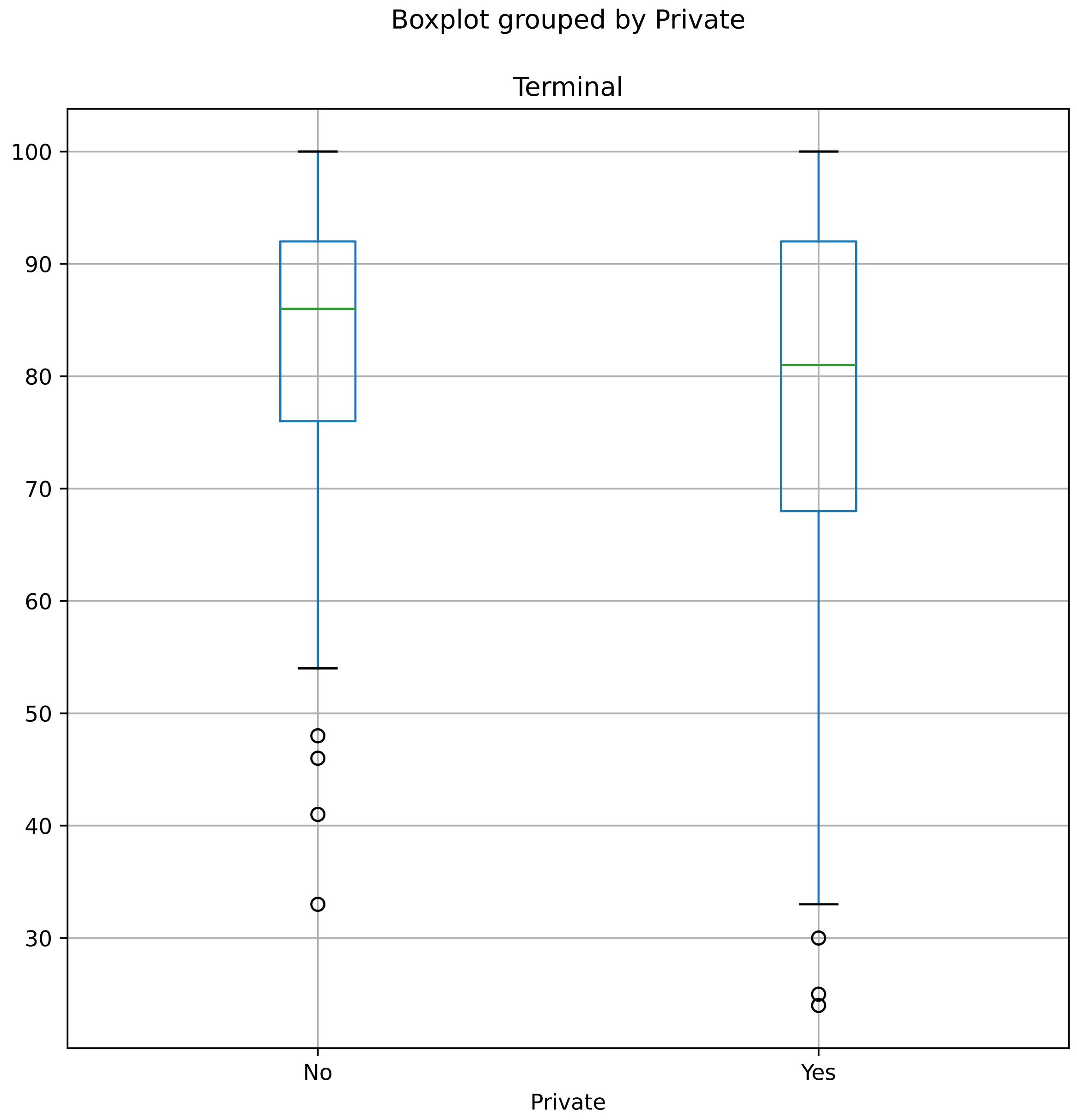
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("PhD", by="Elite", ax=ax);
```



```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Terminal", by="Elite", ax=ax);
```

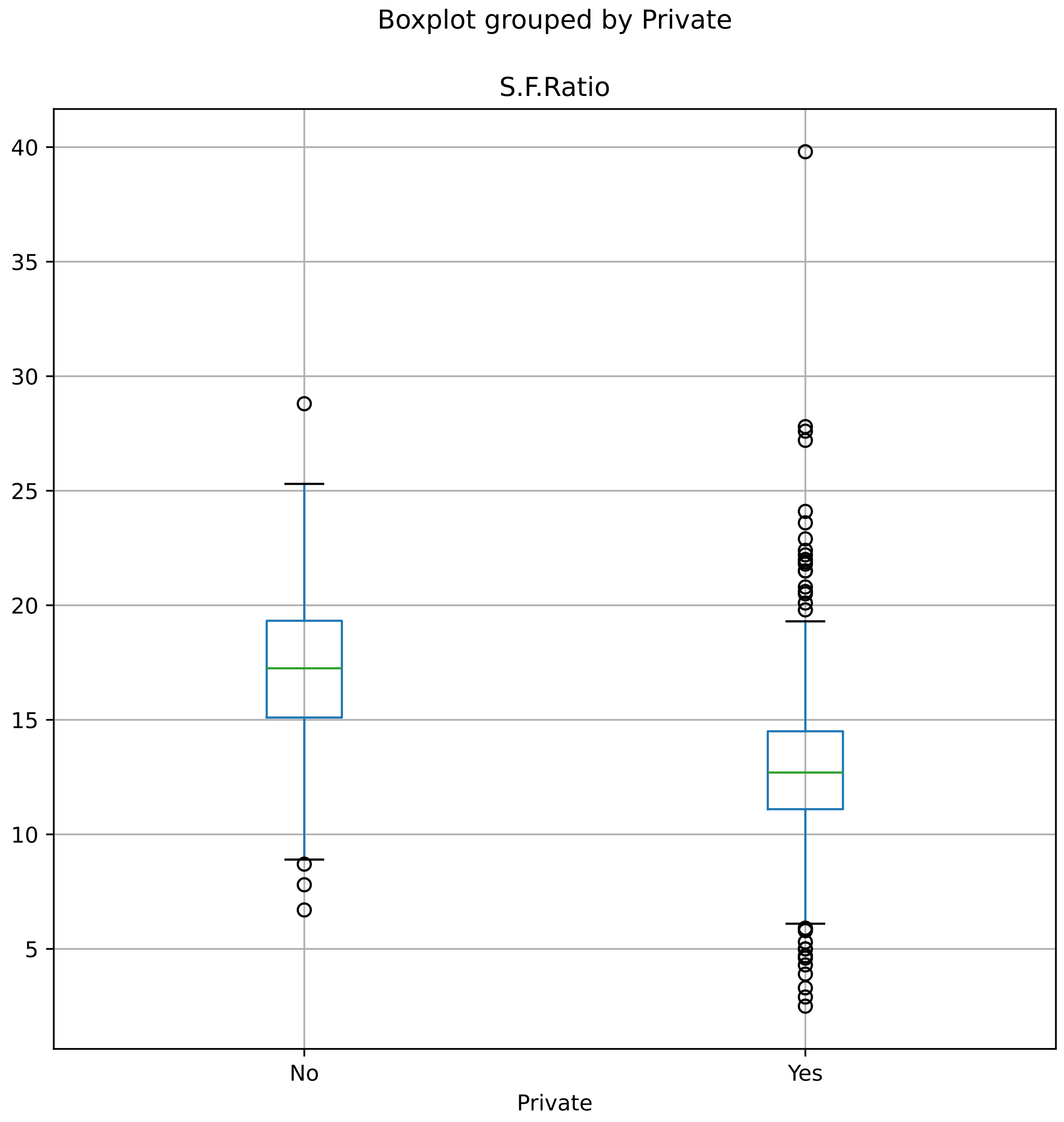


```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Terminal", by="Private", ax=ax);
```

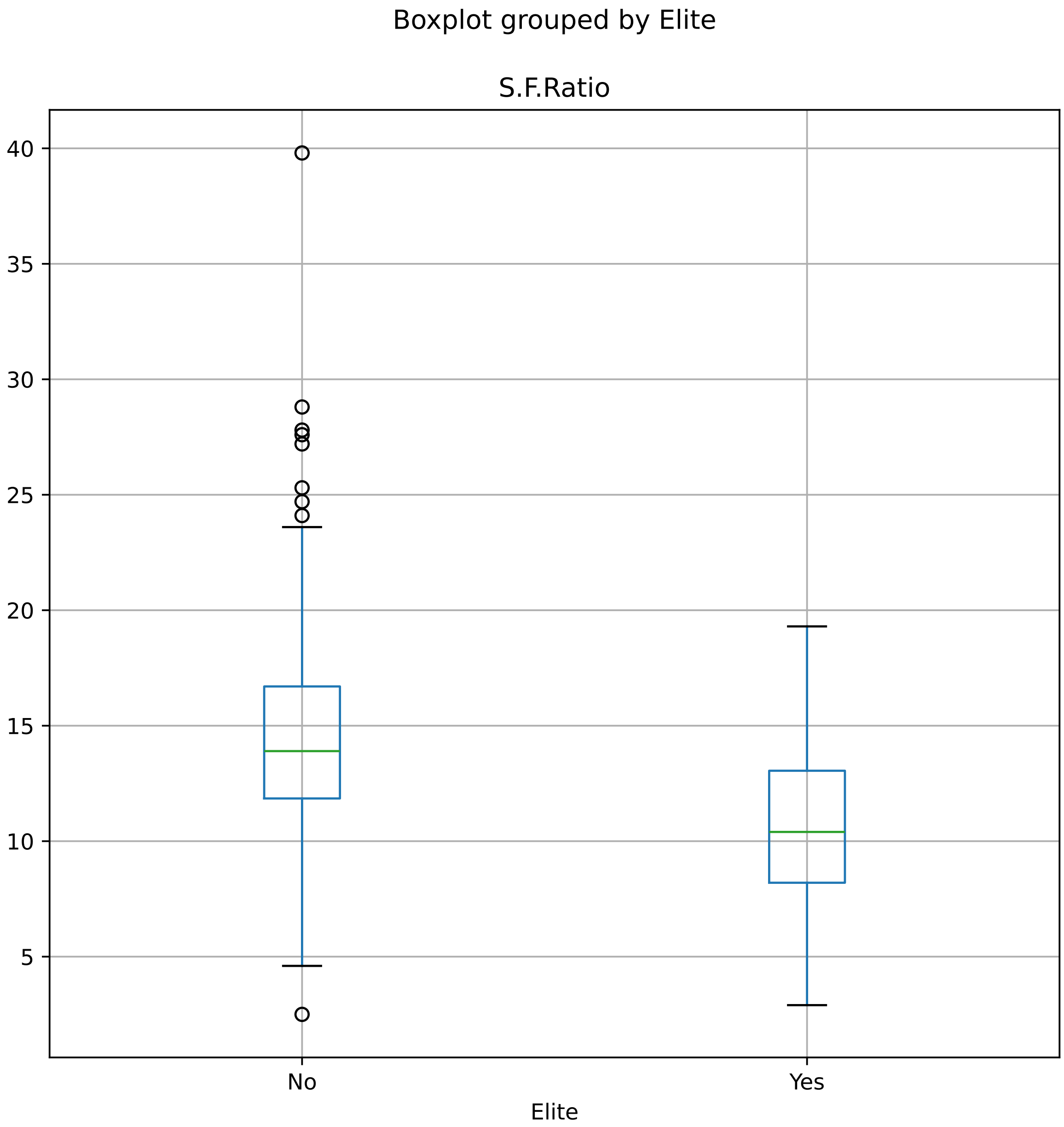


```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("S.F.Ratio", by="Private", ax=ax);
```

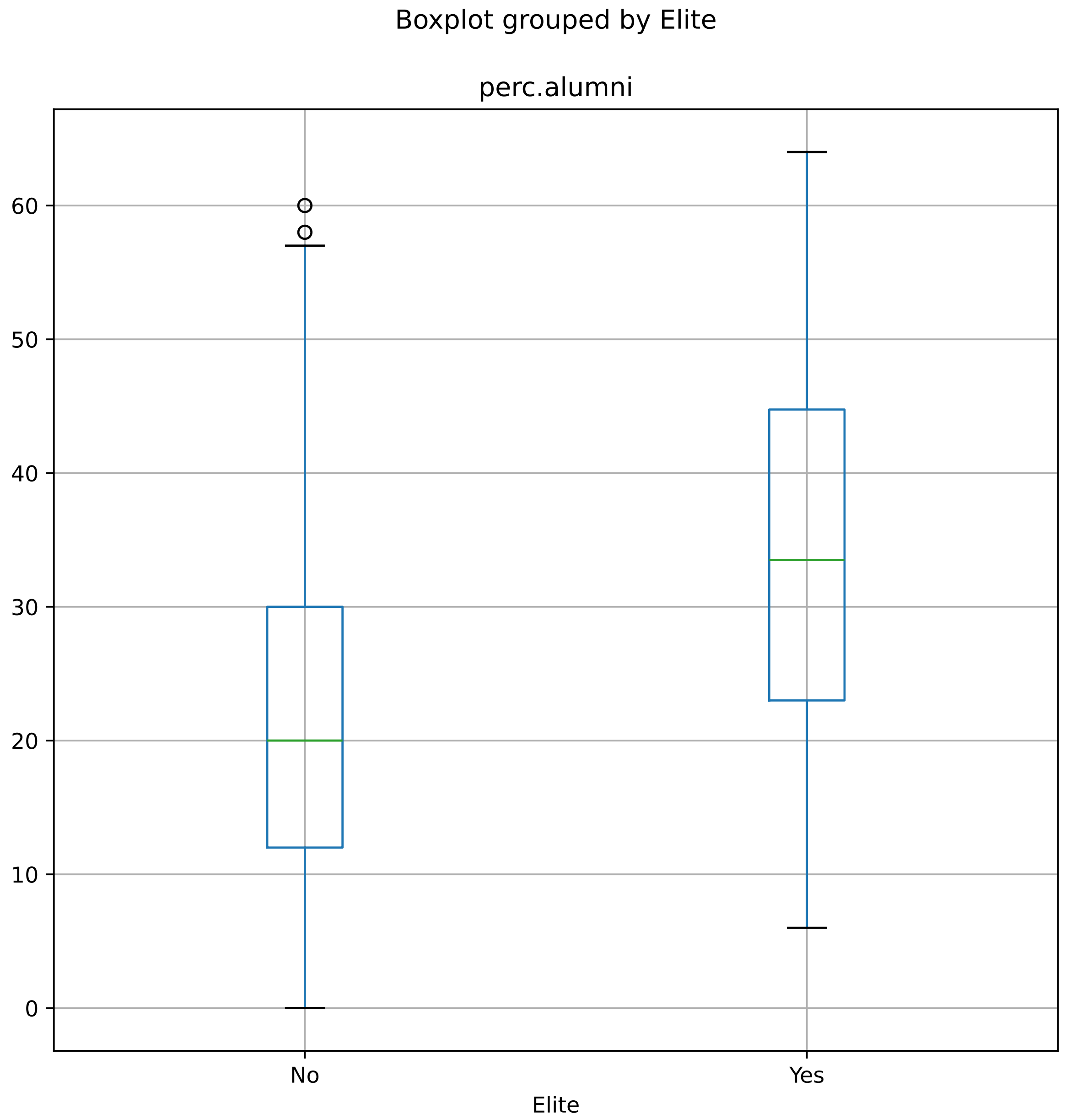
```
Executing <Handle IOLoop._run_callback(functools.par...7a08e5f18d60>)) created at
/home/linus/ISLP/islpenv/lib/python3.12/site-packages/tornado/platform/asyncio.py:235>
took 0.178 seconds
```



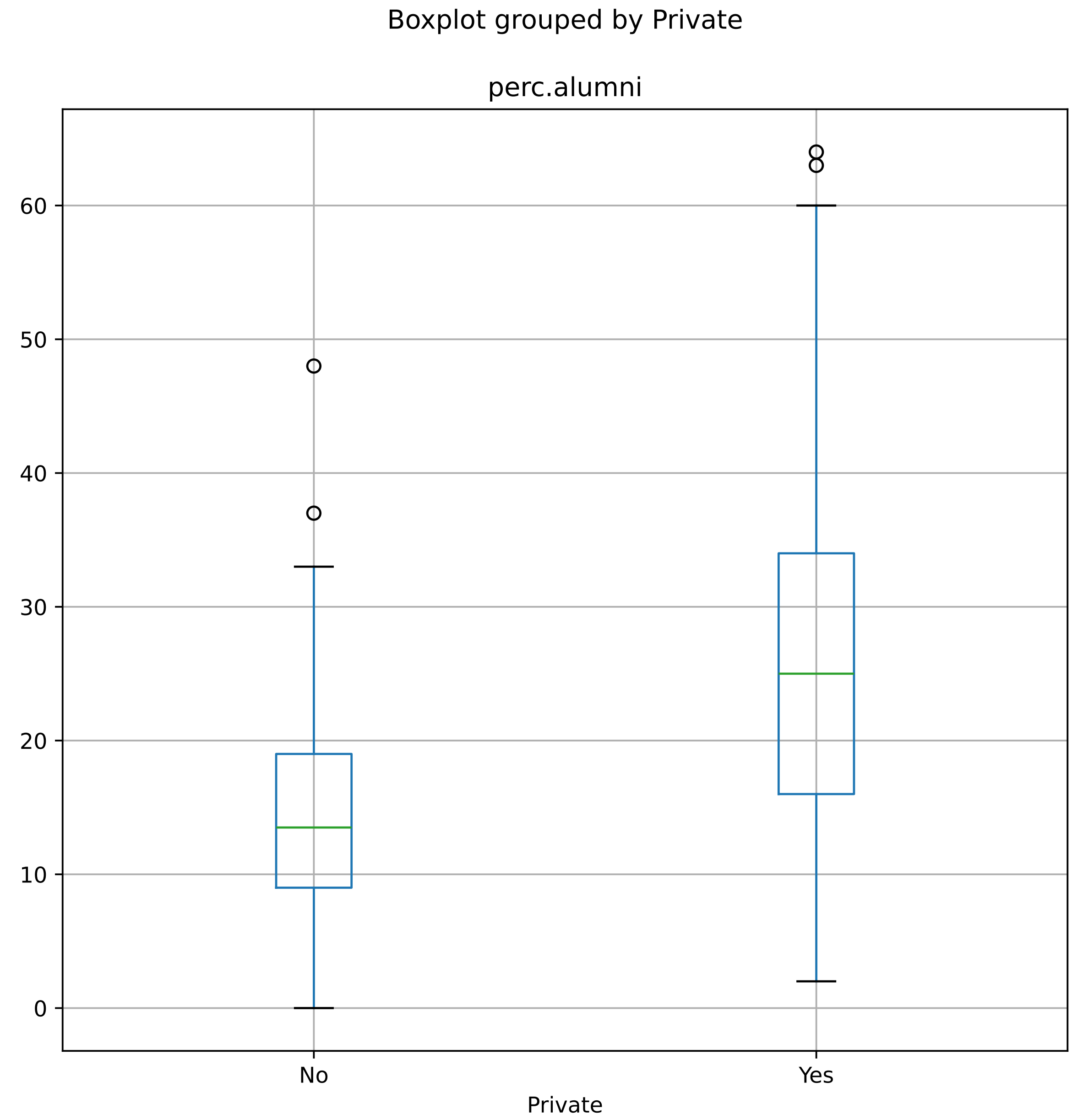
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("S.F.Ratio", by="Elite", ax=ax);
```



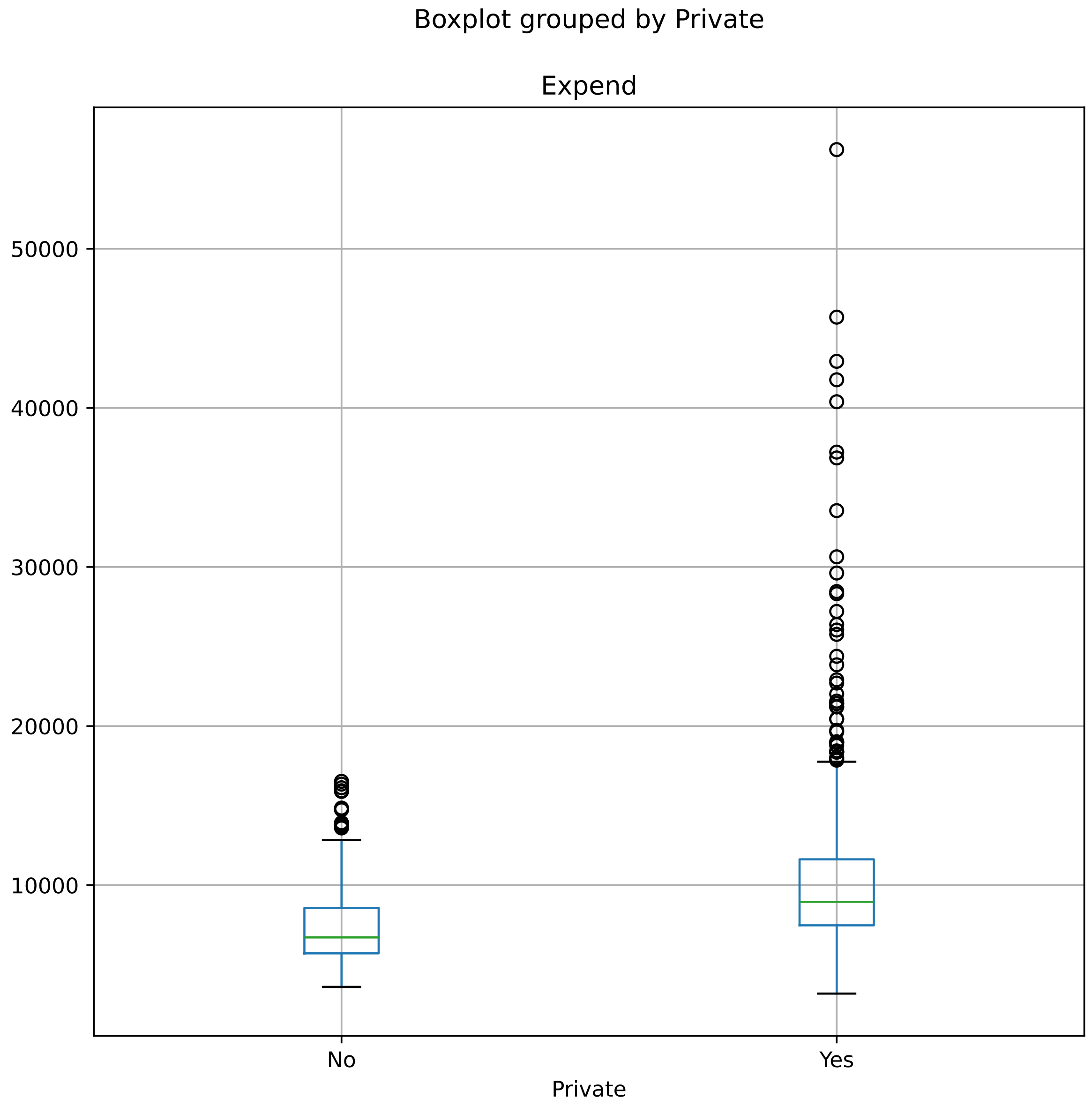
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("perc.alumni", by="Elite", ax=ax);
```



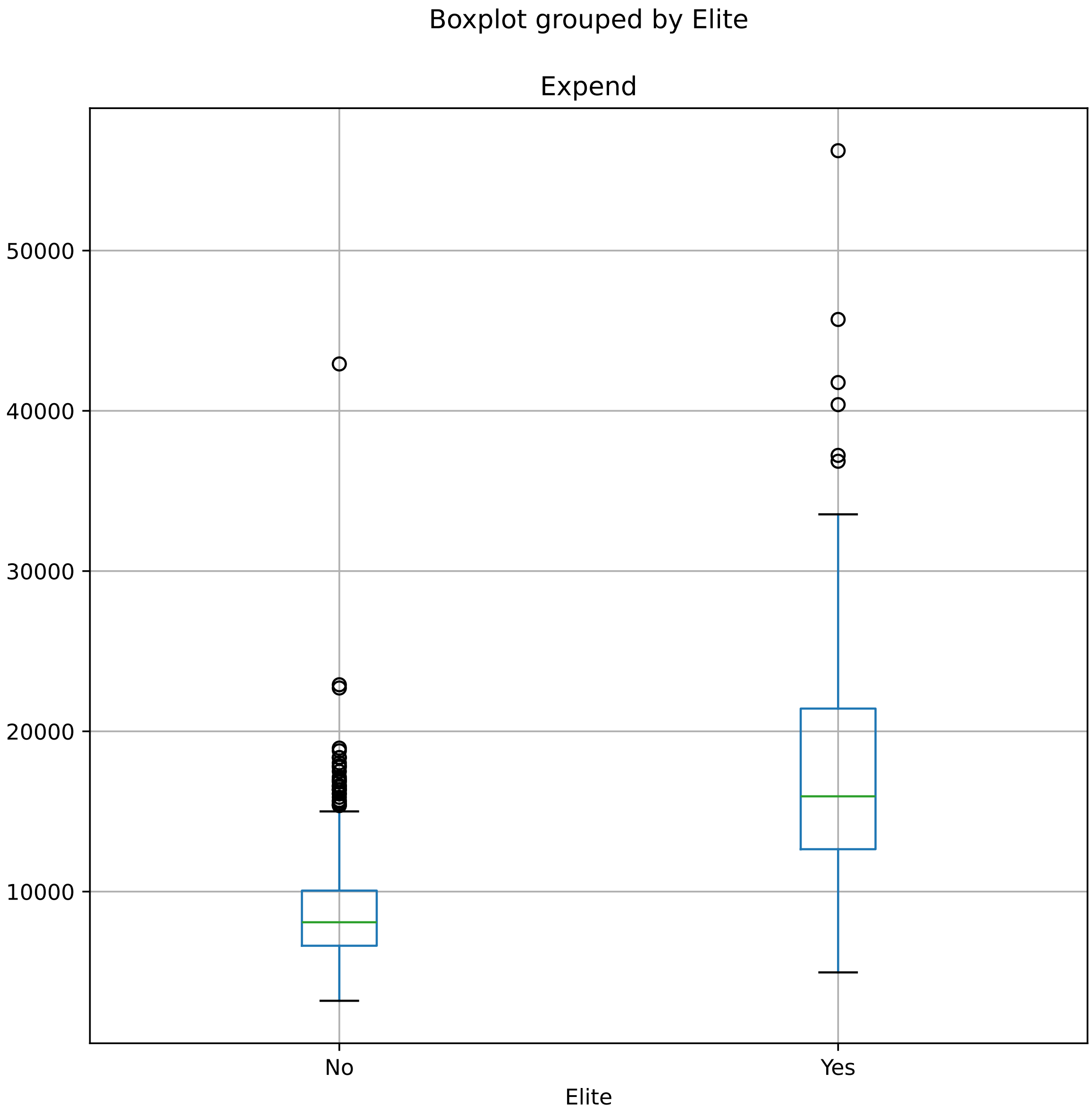
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("perc.alumni", by="Private", ax=ax);
```



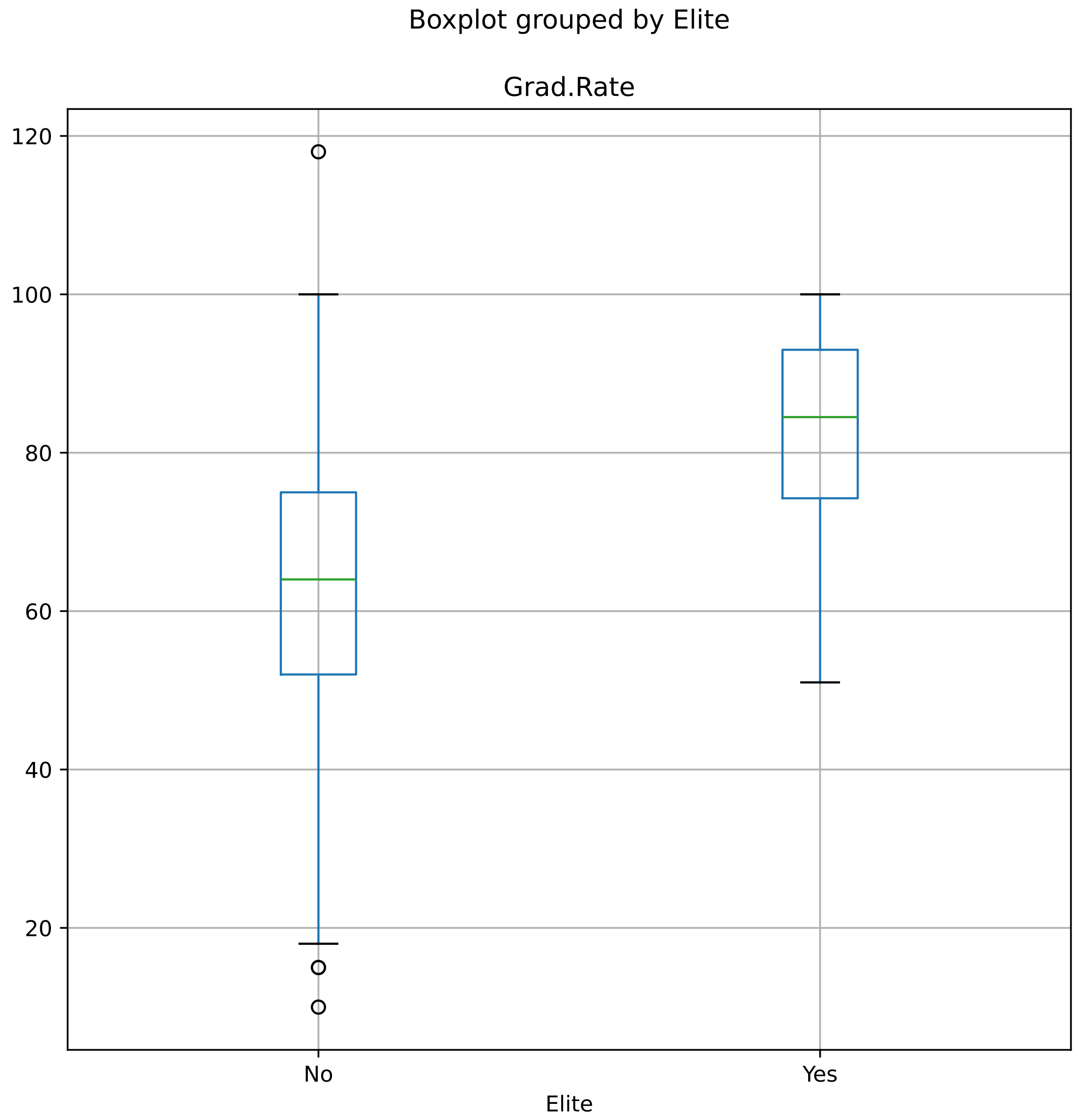
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Expend", by="Private", ax=ax);
```



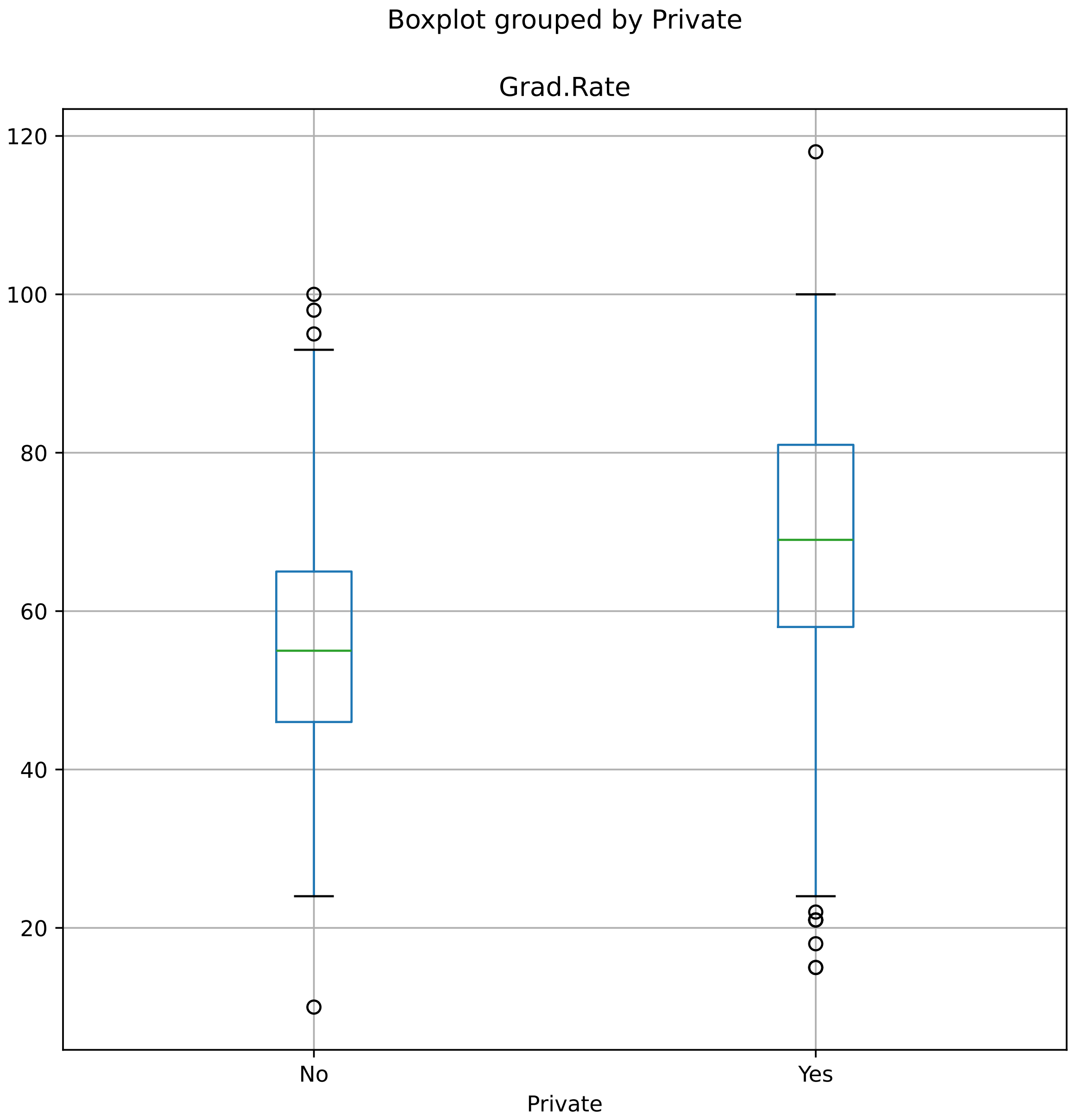
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Expend", by="Elite", ax=ax);
```



```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Grad.Rate", by="Elite", ax=ax);
```



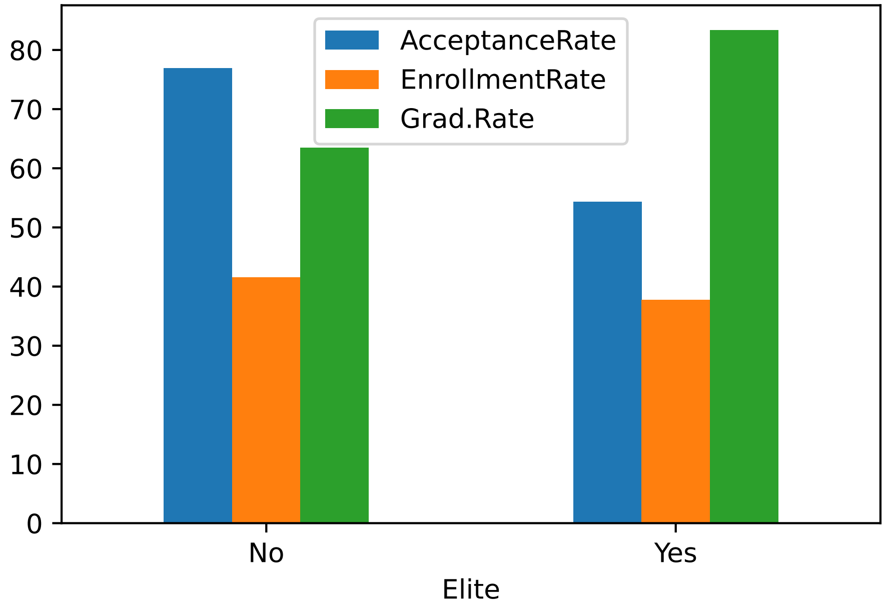
```
fig, ax = subplots(figsize=(8, 8))
College.boxplot("Grad.Rate", by="Private", ax=ax);
```



```
mean_grad_rate = College.groupby("Elite", observed=True)[
    ["AcceptanceRate", "EnrollmentRate", "Grad.Rate"]
].mean()
mean_grad_rate
```

	AcceptanceRate	EnrollmentRate	Grad.Rate
Elite			
No	76.963834	41.586452	63.463519
Yes	54.340128	37.748205	83.384615

```
mean_grad_rate.plot(
    y=["AcceptanceRate", "EnrollmentRate", "Grad.Rate"], kind="bar", rot=0
);
```



```
Auto = pd.read_csv("Auto.csv", na_values={"?"})
print(Auto.shape)
np.unique(Auto["horsepower"])
```

```
(397, 9)

array([ 46.,  48.,  49.,  52.,  53.,  54.,  58.,  60.,  61.,  62.,  63.,
        64.,  65.,  66.,  67.,  68.,  69.,  70.,  71.,  72.,  74.,  75.,
        76.,  77.,  78.,  79.,  80.,  81.,  82.,  83.,  84.,  85.,  86.,
        87.,  88.,  89.,  90.,  91.,  92.,  93.,  94.,  95.,  96.,  97.,
        98., 100., 102., 103., 105., 107., 108., 110., 112., 113., 115.,
       116., 120., 122., 125., 129., 130., 132., 133., 135., 137., 138.,
       139., 140., 142., 145., 148., 149., 150., 152., 153., 155., 158.,
       160., 165., 167., 170., 175., 180., 190., 193., 198., 200., 208.,
       210., 215., 220., 225., 230.,  nan])
```

Which predictors are quantitative and which are qualitative?

Rename the misleading column name acceleration to timetoacceleration since it's a tad misleading.

```
Auto["timetoacceleration"] = Auto["acceleration"]
Auto = Auto.drop("acceleration", axis=1)
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	name	timetoaccelera
0	18.0	8	307.0	130.0	3504	70	1	chevrolet chevelle malibu	12.0
1	15.0	8	350.0	165.0	3693	70	1	buick skylark 320	11.5
2	18.0	8	318.0	150.0	3436	70	1	plymouth satellite	11.0
3	16.0	8	304.0	150.0	3433	70	1	amc rebel sst	12.0
4	17.0	8	302.0	140.0	3449	70	1	ford torino	10.5
...	...	...	...	...	...	...	...	...	...
392	27.0	4	140.0	86.0	2790	82	1	ford mustang gl	15.6
393	44.0	4	97.0	52.0	2130	82	2	vw pickup	24.6
394	32.0	4	135.0	84.0	2295	82	1	dodge rampage	11.6
395	28.0	4	120.0	79.0	2625	82	1	ford ranger	18.6
396	31.0	4	119.0	82.0	2720	82	1	chevy s-10	19.4

```
Auto = Auto.dropna()
Auto.shape
```

```
(392, 9)
```

```
Auto.describe()
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	timetoaccelera
count	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000
mean	23.445918	5.471939	194.411990	104.469388	2977.584184	75.979592	1.576531	15.541327
std	7.805007	1.705783	104.644004	38.491160	849.402560	3.683737	0.805518	2.758864
min	9.000000	3.000000	68.000000	46.000000	1613.000000	70.000000	1.000000	8.000000
25%	17.000000	4.000000	105.000000	75.000000	2225.250000	73.000000	1.000000	13.775000
50%	22.750000	4.000000	151.000000	93.500000	2803.500000	76.000000	1.000000	15.500000
75%	29.000000	8.000000	275.750000	126.000000	3614.750000	79.000000	2.000000	17.025000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	82.000000	3.000000	24.800000

```
Auto["origin"] = Auto.origin.astype("category")
Auto["year"] = Auto.year.astype("category")
Auto["cylinders"] = Auto.cylinders.astype("category")
print(np.unique(Auto["year"]))
print(np.unique(Auto["cylinders"]))
```

```
[70 71 72 73 74 75 76 77 78 79 80 81 82]
[3 4 5 6 8]
```

```
/tmp/ipykernel_9370/803089839.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_9370/803089839.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_9370/803089839.py:3: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
Auto["origin"] = Auto["origin"].cat.rename_categories(
    {1: "American", 2: "European", 3: "Japanese"}
)
np.unique(Auto["origin"])
```

```
/tmp/ipykernel_9370/29212070.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
array(['American', 'European', 'Japanese'], dtype=object)
```

```
Auto.head()
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	name	timetoaccele
0	18.0	8	307.0	130.0	3504	70	American	chevrolet chevelle malibu	12.0
1	15.0	8	350.0	165.0	3693	70	American	buick skylark 320	11.5
2	18.0	8	318.0	150.0	3436	70	American	plymouth satellite	11.0
3	16.0	8	304.0	150.0	3433	70	American	amc rebel sst	12.0
4	17.0	8	302.0	140.0	3449	70	American	ford torino	10.5

```
Auto = Auto.set_index("name")
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	timetoaccelerati
name								
chevrolet chevelle malibu	18.0	8	307.0	130.0	3504	70	American	12.0
buick skylark 320	15.0	8	350.0	165.0	3693	70	American	11.5
plymouth satellite	18.0	8	318.0	150.0	3436	70	American	11.0
amc rebel sst	16.0	8	304.0	150.0	3433	70	American	12.0
ford torino	17.0	8	302.0	140.0	3449	70	American	10.5
...	...	...	...	...	...	...	...	...
ford mustang gl	27.0	4	140.0	86.0	2790	82	American	15.6
vw pickup	44.0	4	97.0	52.0	2130	82	European	24.6
dodge rampage	32.0	4	135.0	84.0	2295	82	American	11.6
ford ranger	28.0	4	120.0	79.0	2625	82	American	18.6
chevy s-10	31.0	4	119.0	82.0	2720	82	American	19.4

```
Auto
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	timetoaccelerati
name								
chevrolet chevelle malibu	18.0	8	307.0	130.0	3504	70	American	12.0
buick skylark 320	15.0	8	350.0	165.0	3693	70	American	11.5
plymouth satellite	18.0	8	318.0	150.0	3436	70	American	11.0
amc rebel sst	16.0	8	304.0	150.0	3433	70	American	12.0
ford torino	17.0	8	302.0	140.0	3449	70	American	10.5
...	...	...	...	...	...	...	...	...
ford mustang gl	27.0	4	140.0	86.0	2790	82	American	15.6
vw pickup	44.0	4	97.0	52.0	2130	82	European	24.6
dodge rampage	32.0	4	135.0	84.0	2295	82	American	11.6
ford ranger	28.0	4	120.0	79.0	2625	82	American	18.6
chevy s-10	31.0	4	119.0	82.0	2720	82	American	19.4

```
Auto_new = Auto.drop(Auto.index[10:86])
Auto_new.describe()
```

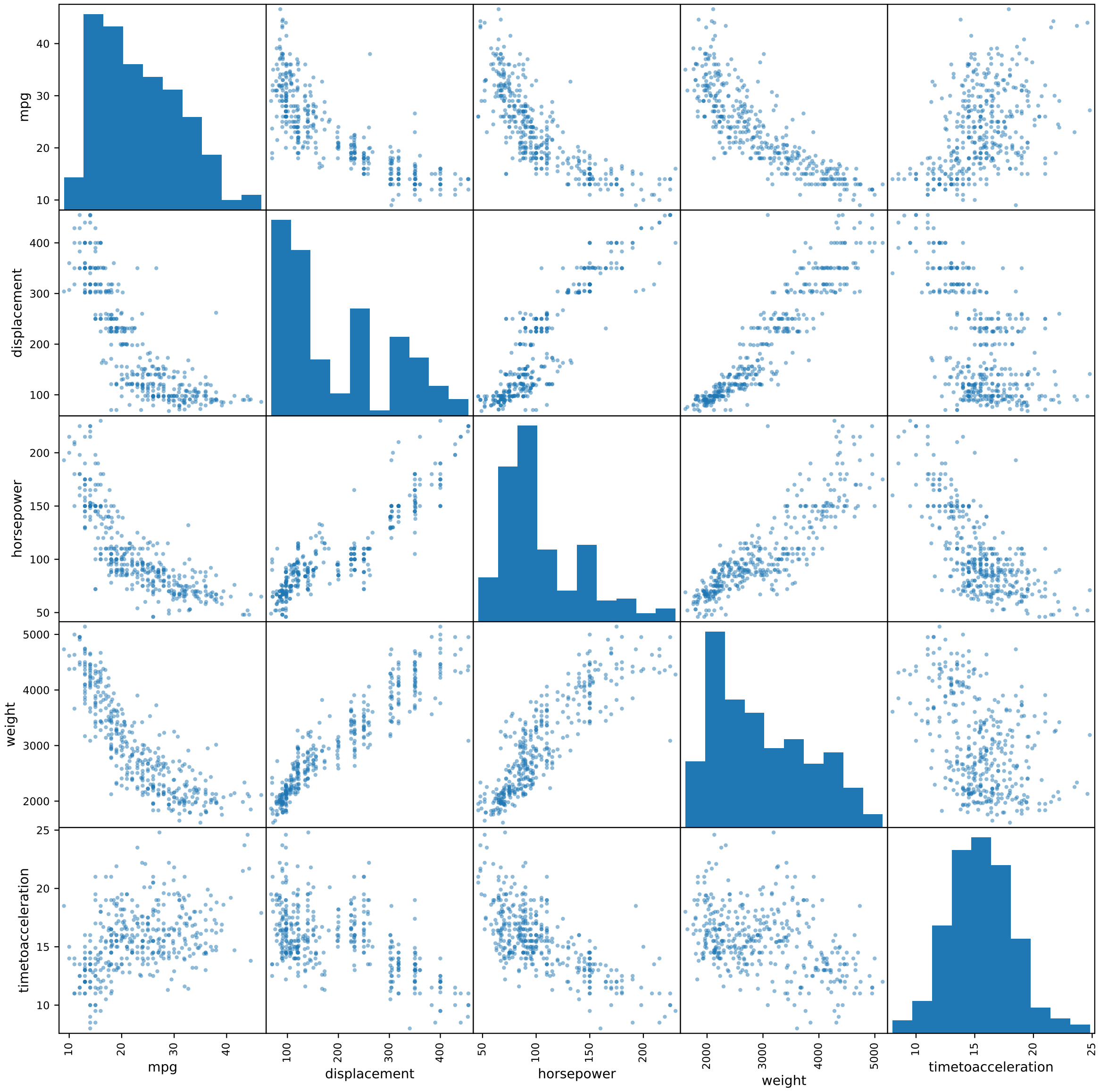
	mpg	displacement	horsepower	weight	timetoacceleration
count	282.000000	282.000000	282.000000	282.000000	282.000000
mean	25.006028	180.120567	99.039007	2884.939716	15.713121
std	7.921384	96.164263	34.197280	793.236373	2.601575
min	11.000000	68.000000	46.000000	1755.000000	8.500000
25%	18.125000	98.000000	74.250000	2188.500000	14.000000
50%	24.500000	140.000000	90.000000	2715.500000	15.500000
75%	31.000000	250.000000	112.000000	3435.250000	17.275000
max	46.600000	455.000000	230.000000	4952.000000	24.600000

```
Auto_new
```

	mpg	cylinders	displacement	horsepower	weight	year	origin	timetoacceleration
name								
buick skylark 320	15.0	8	350.0	165.0	3693	70	American	11.5
plymouth satellite	18.0	8	318.0	150.0	3436	70	American	11.0
amc rebel sst	16.0	8	304.0	150.0	3433	70	American	12.0
ford torino	17.0	8	302.0	140.0	3449	70	American	10.5
amc ambassador dpl	15.0	8	390.0	190.0	3850	70	American	8.5
...	...	...	...	...	...	...	...	...
ford mustang gl	27.0	4	140.0	86.0	2790	82	American	15.6
vw pickup	44.0	4	97.0	52.0	2130	82	European	24.6
dodge rampage	32.0	4	135.0	84.0	2295	82	American	11.6
ford ranger	28.0	4	120.0	79.0	2625	82	American	18.6
chevy s-10	31.0	4	119.0	82.0	2720	82	American	19.4

Using the full data set, investigate the predictors graphically, using scatter plots or other tools of your choice. Create some plots highlighting the relationships among the predictors. Comment on your findings.

```
pd.plotting.scatter_matrix(Auto, figsize=(14, 14));
```



Findings:

1. Weight and displacement seem to be negatively correlated with MPG.
2. timetoacceleration (0–60 mph in seconds) seems to be positively correlated with MPG. As time to acceleration increases, MPG also increases. The longer the time to acceleration, the better the fuel efficiency.
3. weight is also positively correlated with displacement. As weight increases, so does displacement, i.e., as the body weight increases, so does displacement need to increase.

4. Displacement is seen to increase as the number of cylinders increase. This is expected since displacement is a function of the number of cylinders, amongst other components.

We can conclude that MPG can be predicted using the variables weight, displacement and timetoacceleration.

```
mean_mpg_origin = Auto.groupby(["origin"], observed=True)[["mpg"]].mean()
mean_mpg_origin
```

	mpg
origin	
American	20.033469
European	27.602941
Japanese	30.450633

```
mean_mpg_year = Auto.groupby(["year"], observed=True)[["mpg"]].mean()
mean_mpg_year
```

	mpg
year	
70	17.689655
71	21.111111
72	18.714286
73	17.100000
74	22.769231
75	20.266667
76	21.573529
77	23.375000
78	24.061111
79	25.093103
80	33.803704
81	30.185714
82	32.000000

```
mean_mpg_cylinders = Auto.groupby(["cylinders"], observed=True)[["mpg"]].mean()
mean_mpg_cylinders
```

	mpg
cylinders	
3	20.550000
4	29.283920
5	27.366667

	mpg
cylinders	
6	19.973494
8	14.963107

We can also observe that fuel efficiency is affected by the make of the car. Japanese > European > American The year also plays a significant role. Later model cars are more fuel efficient than the earlier models. Cars are also more fuel efficient with lesser number of cylinders. These can also be used as predictors to deduce the MPG.

```
Boston = load_data("Boston")
Boston.columns
```

```
Index(['crim', 'zn', 'indus', 'chas', 'nox', 'rm', 'age', 'dis', 'rad', 'tax',
       'ptratio', 'lstat', 'medv'],
      dtype='object')
```

```
Boston.shape
```

```
(506, 13)
```

The rows represent data for 506 suburbs in Boston. The columns represent housing values and variables of interest that may predict housing values in each suburb.

```
Boston.describe()
```

	crim	zn	indus	chas	nox	rm	age	dis	rad
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.54
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.70
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.00
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.00
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.00
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.0
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.0

```
Boston_quant = Boston.drop("chas", axis=1)
```

	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	lstat	medv
0	0.00632	18.0	2.31	0.538	6.575	65.2	4.0900	1	296	15.3	4.98	24.0
1	0.02731	0.0	7.07	0.469	6.421	78.9	4.9671	2	242	17.8	9.14	21.6
2	0.02729	0.0	7.07	0.469	7.185	61.1	4.9671	2	242	17.8	4.03	34.7
3	0.03237	0.0	2.18	0.458	6.998	45.8	6.0622	3	222	18.7	2.94	33.4
4	0.06905	0.0	2.18	0.458	7.147	54.2	6.0622	3	222	18.7	5.33	36.2

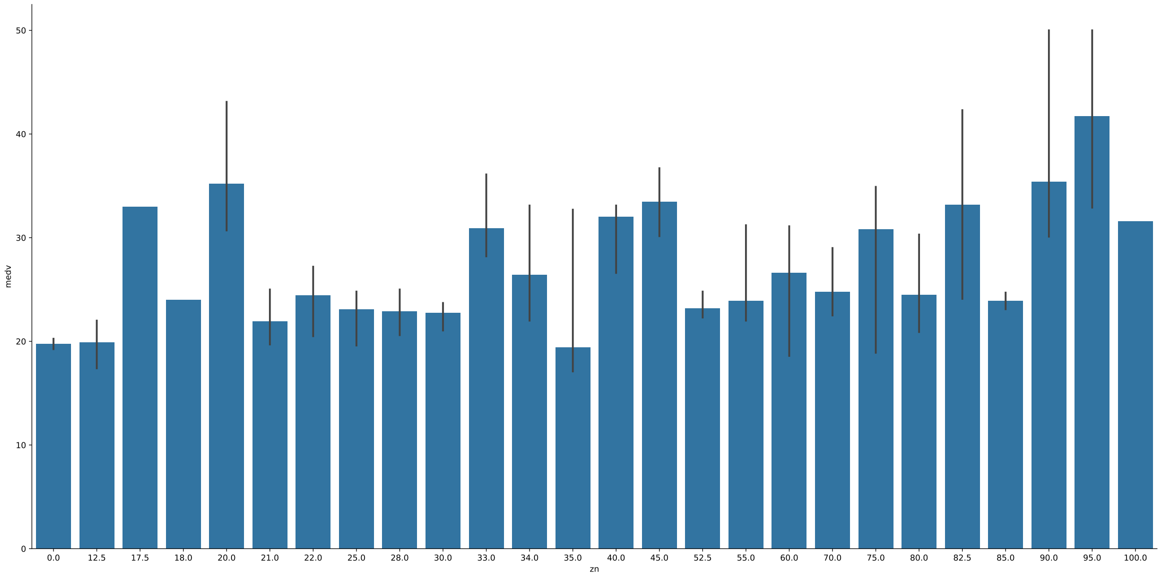
	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	lstat	medv
...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.573	6.593	69.1	2.4786	1	273	21.0	9.67	22.4
502	0.04527	0.0	11.93	0.573	6.120	76.7	2.2875	1	273	21.0	9.08	20.6
503	0.06076	0.0	11.93	0.573	6.976	91.0	2.1675	1	273	21.0	5.64	23.9
504	0.10959	0.0	11.93	0.573	6.794	89.3	2.3889	1	273	21.0	6.48	22.0
505	0.04741	0.0	11.93	0.573	6.030	80.8	2.5050	1	273	21.0	7.88	11.9

```
print(np.unique(Boston_quant["zn"]))
median_medv = Boston_quant.groupby(["zn"], observed=True)[["medv"]].median()
median_medv
```

```
[  0.    12.5  17.5  18.    20.    21.    22.    25.    28.    30.    33.    34.
  35.    40.    45.    52.5  55.    60.    70.    75.    80.    82.5  85.    90.
  95.   100. ]
```

	medv
zn	
0.0	19.75
12.5	19.90
17.5	33.00
18.0	24.00
20.0	35.20
21.0	21.95
22.0	24.45
25.0	23.10
28.0	22.90
30.0	22.75
33.0	30.90
34.0	26.40
35.0	19.40
40.0	32.00
45.0	33.45
52.5	23.20
55.0	23.90
60.0	26.60
70.0	24.80
75.0	30.80
80.0	24.50
82.5	33.20
85.0	23.90
90.0	35.40
95.0	41.70
100.0	31.60

```python
sns.catplot(
    data=Boston_quant,
    x="zn",
    y="medv",
    kind="bar",
    height=10,
    aspect=2,
    estimator=median,
);
```



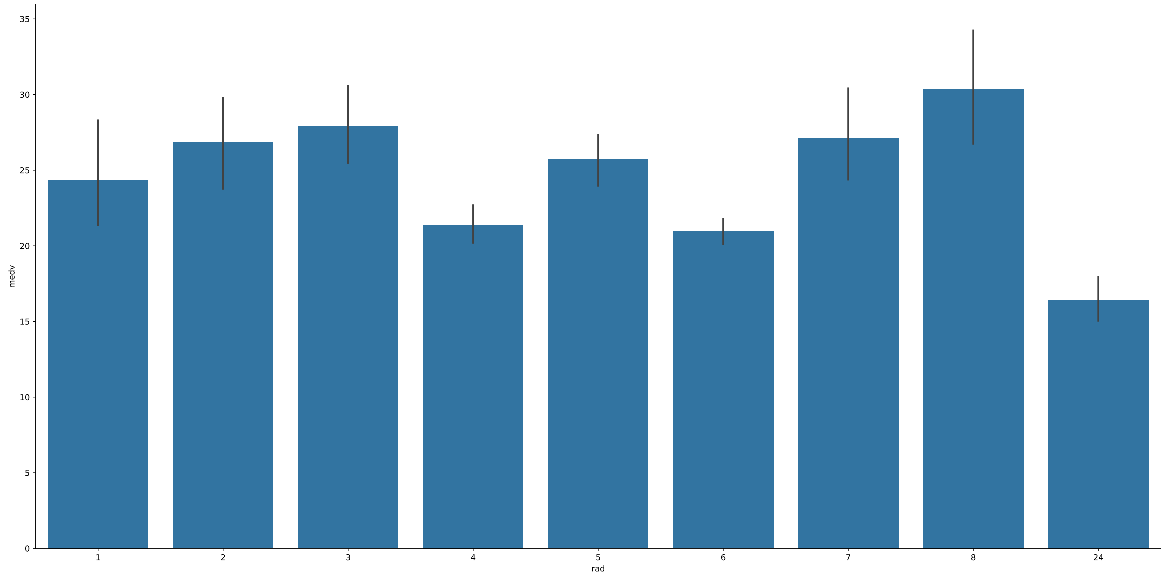
```python
print(np.unique(Boston_quant["rad"]))
mean_rad = Boston_quant.groupby(["rad"], observed=True)[["medv"]].mean()
mean_rad
```

```
[ 1  2  3  4  5  6  7  8 24]
```

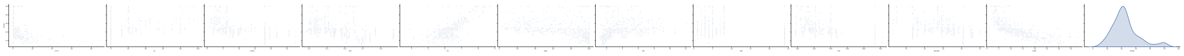
	medv
rad	
1	24.365000
2	26.833333
3	27.928947
4	21.387273
5	25.706957
6	20.976923
7	27.105882
8	30.358333

	medv
rad	
24	16.403788

```
sns.catplot(data=Boston_quant, x="rad", y="medv", kind="bar", height=10, aspect=2);
```



```
sns.set_theme(style="ticks")
g = sns.pairplot(Boston_quant, height=5, aspect=2, diag_kind="kde",
 ↪  y_vars=["medv"]);
```



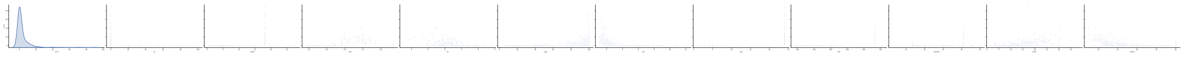
Plotting the other quantitative columns against medv (Median value of owner-occupied homes), we can see that: 1. crim is negatively correlated with medv. i.e., as crime rate increases, median value of homes decrease. 2. indus is negatively correlated with medv which is expected as industrialisation of a town increases, the house prices decrease. 3. nox is negatively correlated with medv which is also expected. 4. as the number of rooms (rm) increase, so does the value of the home. 5. as the proportion of homes built prior to 1940 increase, the value of homes in that area decrease. There are some notable outliers, but that appears to be the general trend. 6. There is a clear relationship in the lsat (lower status of population percent) versus medv where medv decreases with the increase in lstat on the x-axis.

```
Boston_quant["zn"].value_counts()
```

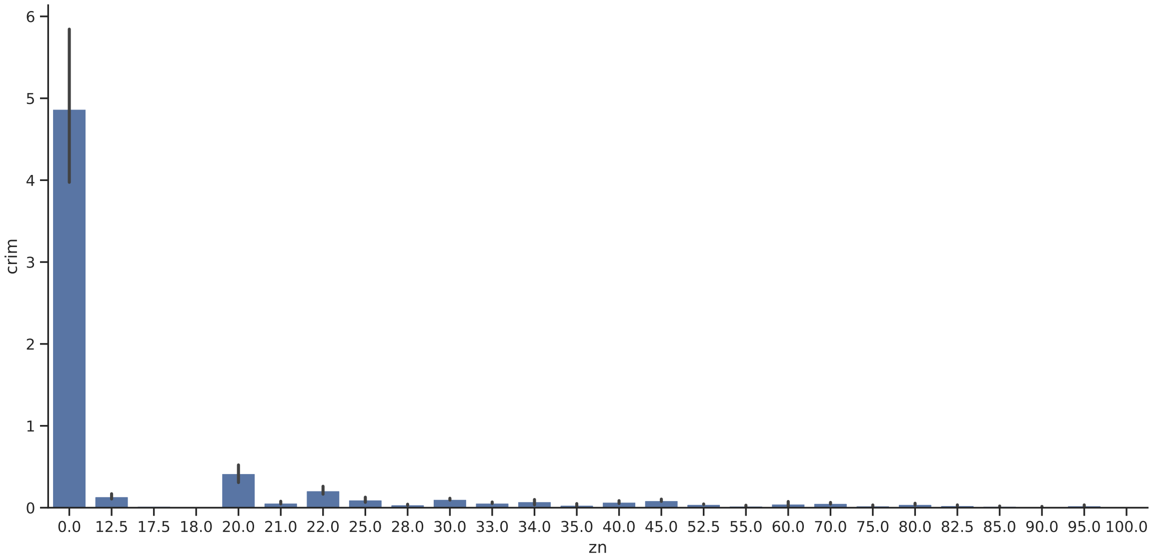
```
zn
0.0      372
```

```
20.0      21
80.0      15
22.0      10
12.5      10
25.0      10
40.0       7
45.0       6
30.0       6
90.0       5
95.0       4
60.0       4
21.0       4
33.0       4
55.0       3
70.0       3
34.0       3
52.5       3
35.0       3
28.0       3
75.0       3
82.5       2
85.0       2
17.5       1
100.0      1
18.0       1
Name: count, dtype: int64
```

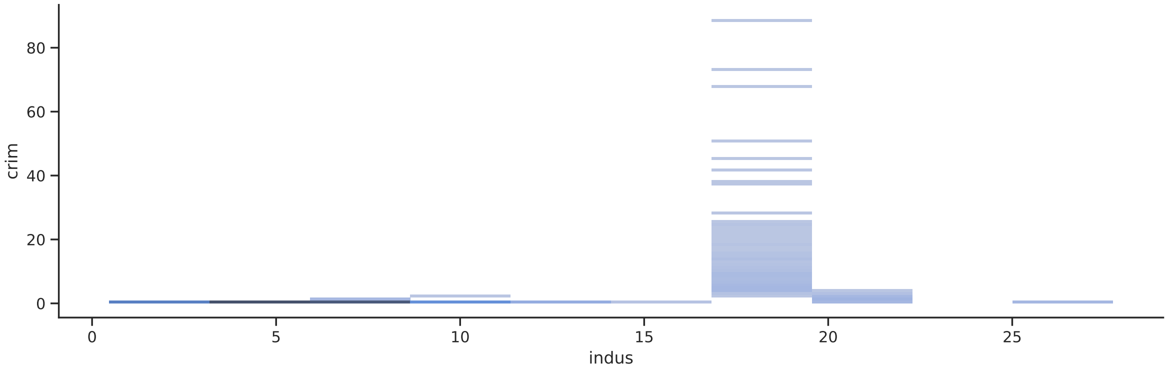
```
g = sns.pairplot(Boston_quant, height=5, aspect=2, diag_kind="kde",
 ↪  y_vars=["crim"]);
```



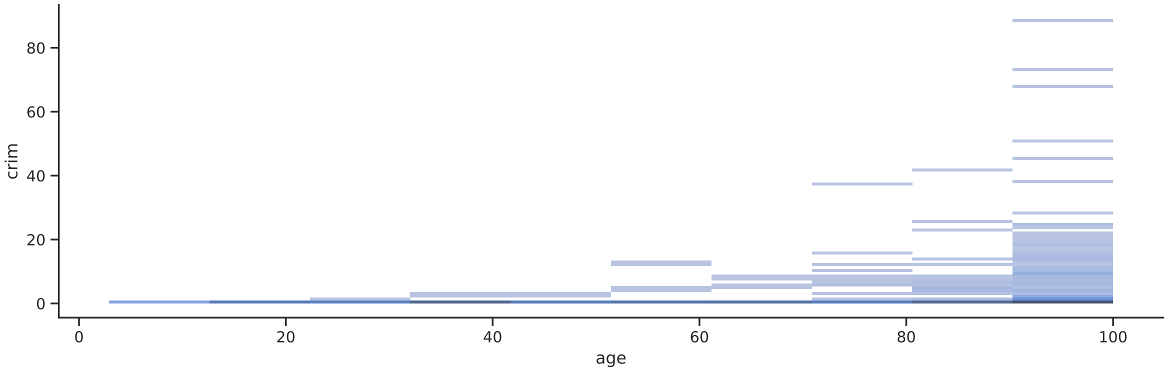
```
sns.catplot(data=Boston_quant, x="zn", y="crim", kind="bar", height=6, aspect=2);
```



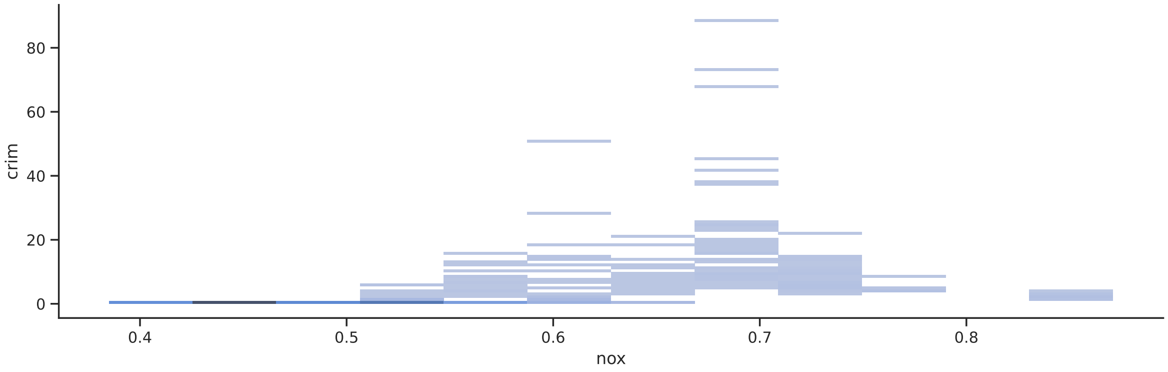
```
sns.displot(data=Boston_quant, x="indus", y="crim", height=4, aspect=3);
```



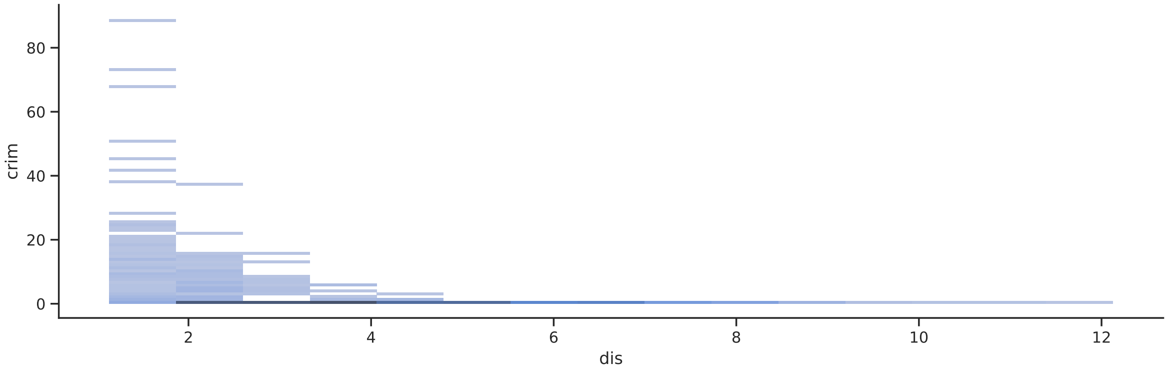
```
sns.displot(data=Boston_quant, x="age", y="crim", height=4, aspect=3);
```



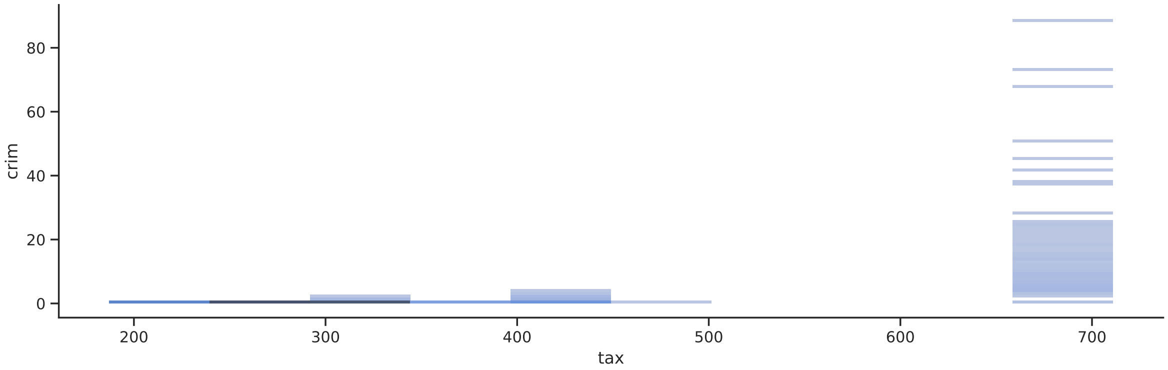
```
sns.displot(data=Boston_quant, x="nox", y="crim", height=4, aspect=3);
```



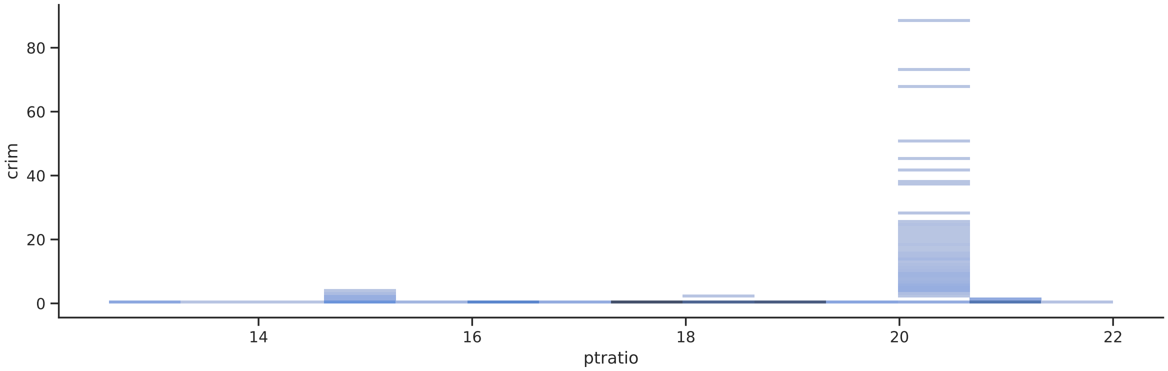
```
sns.displot(data=Boston_quant, x="dis", y="crim", height=4, aspect=3);
```



```
sns.displot(data=Boston_quant, x="tax", y="crim", height=4, aspect=3);
```



```
sns.displot(data=Boston_quant, x="ptratio", y="crim", height=4, aspect=3);
```



We've already seen that there appears to be a relationship b/w crime rate and medv where a higher crime rate is associated with lower property prices. Additionally, plotting the other quantitative variables against crime rate (crim), we can perceive the following: 1. No-zoned areas or towns are associated with higher crime rate compared to all other zoning percentages. 2. For some reason, industrialization of around 18% displays a spike in the crime rate compared to the other suburbs. This might be worth investigating further. 3. Suburbs with nox > 0.55 or so have an elevated crime rate. That could be because lower strata income people live in those areas, and they are more inclined to criminal activities. 4. There also seems to be an increasing relationship b/w crime rate and percentage of homes built prior to 1940. Once that percentage crosses 40%, there is an increasing number of suburbs that exhibit elevated crime rates. 5. Suburbs within a distance to Boston employment centres that range from 1 to 4.5 show an elevated crime rate. This needs to be investigated further. Where are these employment centres located? 6. There seems to be a higher incidence of crimes for areas with tax rate around 670. Why? 7. The crime rate does not seem to have a strong relationship with ptratio, but for around point 20.1 where the crime rate spikes compared to the other areas. 8. Crime rate decreases as the median value of properties rise across suburbs as a whole.

Do any of the suburbs of Boston appear to have particularly high crime rates? Tax rates? Pupil-teacher ratios? Comment on the range of each predictor.

```
Boston_crim = Boston_quant.sort_values(
    by="crim", axis=0, ascending=False, inplace=False
)
top_crim = Boston_crim.head()
print(top_crim)
df = pd.DataFrame((Boston_quant.min(), Boston_quant.max()), index=["Min", "Max"])
df
```

```
        crim   zn  indus    nox     rm    age     dis  rad  tax  ptratio  \
380  88.9762  0.0   18.1  0.671  6.968   91.9  1.4165   24  666     20.2
418  73.5341  0.0   18.1  0.679  5.957  100.0  1.8026   24  666     20.2
405  67.9208  0.0   18.1  0.693  5.683  100.0  1.4254   24  666     20.2
410  51.1358  0.0   18.1  0.597  5.757  100.0  1.4130   24  666     20.2
414  45.7461  0.0   18.1  0.693  4.519  100.0  1.6582   24  666     20.2

     lstat  medv
380  17.21  10.4
418  20.62   8.8
405  22.98   5.0
410  10.11  15.0
414  36.98   7.0
```

	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	lstat	medv
Min	0.00632	0.0	0.46	0.385	3.561	2.9	1.1296	1.0	187.0	12.6	1.73	5.0
Max	88.97620	100.0	27.74	0.871	8.780	100.0	12.1265	24.0	711.0	22.0	37.97	50.0

As we can see from the dataset above, the top five crime rate suburbs are unzoned, have an industrialization rate of 18.1%, nox of 0.671, rooms ranging from 4.5 to 7, percentage of houses built prior to 1940 ranging from 92 to 100%, high tax rate of $666per10,000$ property tax , ptratio of 20.2. The lstat varies from 10.11 rto 36.98 and the median house values from 5.0 to 15.0 which are among the lowest. The index of accessibility to radial highways is 24 which is the best rank amongst all the suburbs.

How many of the suburbs in this data set bound the Charles River?

```
len(Boston.query("chas == 1"))
```

```
35
```

What is the median pupil-teacher ratio among the towns in this data set?

```
median(Boston_quant["ptratio"])
```

```
19.05
```

Which suburb of Boston has lowest median value of owner-occupied homes? What are the values of the other predictors for that suburb, and how do those values compare to the overall ranges for those predictors? Comment on your findings.

```
lowest_medv = Boston_quant[Boston_quant["medv"] == Boston_quant["medv"].min()]
lowest_medv
```

	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	lstat	medv
398	38.3518	0.0	18.1	0.693	5.453	100.0	1.4896	24	666	20.2	30.59	5.0
405	67.9208	0.0	18.1	0.693	5.683	100.0	1.4254	24	666	20.2	22.98	5.0

From the above two data points with the lowest median value for owner-occupied homes, it's evident that crime rate by itself does not determine the median value of homes for those regions. Except for lstat and crim, the other predictors match exactly the two data points. lstat for these two data points are high at 22.98 and 30.59 respectively. In these two cases, the other predictors do a better job of explaining the median value for the homes in these suburbs or these suburbs are neighbouring each other.

In this data set, how many of the suburbs average more than seven rooms per dwelling? More than eight rooms per dwelling? Comment on the suburbs that average more than eight rooms per dwelling.

```
len(Boston_quant[Boston_quant["rm"] > 7])
```

```
64
```

```
eight_rooms = Boston_quant[Boston_quant["rm"] > 8]
print(len(eight_rooms))
eight_rooms
```

```
13
```

	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	lstat	medv
97	0.12083	0.0	2.89	0.4450	8.069	76.0	3.4952	2	276	18.0	4.21	38.7
163	1.51902	0.0	19.58	0.6050	8.375	93.9	2.1620	5	403	14.7	3.32	50.0
204	0.02009	95.0	2.68	0.4161	8.034	31.9	5.1180	4	224	14.7	2.88	50.0
224	0.31533	0.0	6.20	0.5040	8.266	78.3	2.8944	8	307	17.4	4.14	44.8
225	0.52693	0.0	6.20	0.5040	8.725	83.0	2.8944	8	307	17.4	4.63	50.0
226	0.38214	0.0	6.20	0.5040	8.040	86.5	3.2157	8	307	17.4	3.13	37.6
232	0.57529	0.0	6.20	0.5070	8.337	73.3	3.8384	8	307	17.4	2.47	41.7
233	0.33147	0.0	6.20	0.5070	8.247	70.4	3.6519	8	307	17.4	3.95	48.3
253	0.36894	22.0	5.86	0.4310	8.259	8.4	8.9067	7	330	19.1	3.54	42.8
257	0.61154	20.0	3.97	0.6470	8.704	86.9	1.8010	5	264	13.0	5.12	50.0
262	0.52014	20.0	3.97	0.6470	8.398	91.5	2.2885	5	264	13.0	5.91	48.8
267	0.57834	20.0	3.97	0.5750	8.297	67.0	2.4216	5	264	13.0	7.44	50.0
364	3.47428	0.0	18.10	0.7180	8.780	82.9	1.9047	24	666	20.2	5.29	21.9

There are 13 suburbs that average more that 8 rooms per dwelling.

The median value for these dwellings range from 21.9 to 50.0 which is the priciest.

The crime rate in these suburbs is extremely low with the highest at around 3.5%.

Industrialization of these suburbs is also low with 19.58 the maximum.

The percentage of people from the lower income strata tops out at 7.44%

A substantial percentage of dwellings are built prior to 1940 which could explain the higher number of rooms with only one outlier at 8.4%.

```
allDone()
```

```
<IPython.lib.display.Audio object>
```