Import matplotlib, numpy etc

In [1]:
```
import numpy as np
from matplotlib import pyplot as plt
plt.style.use('ggplot')
%matplotlib inline
```

Import pandas

In [2]:
```
import pandas as pd
```

Create numpy array with your data

In [3]:
```
A = np.array([[1,2,3,4,5], [10,20,30,40,50], [11,22,33,44,55]])
A
```

Out[3]:
```
array([[ 1,  2,  3,  4,  5],
       [10, 20, 30, 40, 50],
       [11, 22, 33, 44, 55]])
```

and a list with your index (row names) and column names

In [4]:
```
index = ['a','b','c']
cols = ['A','B','C','D','E']
```

using pandas you can store all this into a 'DataFrame'

In [22]:
```
df = pd.DataFrame(data=A, index=index, columns=cols)
df
```

Out[22]:

	A	B	C	D	E
a	1	2	3	4	5
b	10	20	30	40	50
c	11	22	33	44	55

Accessing via column by names ([ ] operator)

In [8]:
```
df['B']
```

Out[8]:
```
a     2
b    20
c    22
Name: B, dtype: int64
```

Access via row name (.loc)

In [9]:
```
df.loc['a']
```

Out[9]:
```
A    1
B    2
C    3
D    4
E    5
Name: a, dtype: int64
```

Access via row position (.iloc)

In [10]:
```
df.iloc[1]
```

Out[10]:
```
A    10
B    20
C    30
D    40
E    50
Name: b, dtype: int64
```

Mixed name and position (.ix)

In [31]:
```
df.ix['a',1]
```

Out[31]:
```
2
```

Acessing single elements

In [29]:
```
df.loc['a','B']
```

Out[29]:
```
2
```

In [30]:
```
df.iloc[0,1]
```

Out[30]:
```
2
```

Fast access to single values

In [32]:
```
df.at['a','C']
```
Out[32]: 3

In [33]:
```
df.iat[0,2]
```
Out[33]: 3

Slicing

In [36]:
```
df.iloc[:,0:3]
```
Out[36]:

	A	B	C
a	1	2	3
b	10	20	30
c	11	22	33

Slicing with skipped rows

In [37]:
```
df.iloc[::2,:]
```
Out[37]:

	A	B	C	D	E
a	1	2	3	4	5
c	11	22	33	44	55

or you use boolean indexing!

logical comparison returns a DataFrame with boolean entries

In [19]:
```
df[['A','C']]>10
```
Out[19]:

	A	C
a	False	False
b	False	True
c	True	True

these can be used for indexing

In [38]:
```
df_g2 = df[df[['A','B']]>2]
df_g2
```

Out[38]:

	A	B	C	D	E
a	NaN	NaN	NaN	NaN	NaN
b	10	20	NaN	NaN	NaN
c	11	22	NaN	NaN	NaN

you can drop all rows that have only NaN entries

In [41]:
```
df_g2.dropna( axis=0, how='all')
```

Out[41]:

	A	B	C	D	E
b	10	20	NaN	NaN	NaN
c	11	22	NaN	NaN	NaN

or all columns with at least one NaN entry

In [42]:
```
df_g2.dropna( axis=1, how='any')
```

Out[42]:

a
b
c

selecting rows which contain certain values

In [43]:
```
df[ df["A"].isin([1, 11]) ]
```

Out[43]:

	A	B	C	D	E
a	1	2	3	4	5
c	11	22	33	44	55

Acessing the "raw" numpy data

In [44]:
```
df.values
```

Out[44]:
```
array([[ 1,  2,  3,  4,  5],
       [10, 20, 30, 40, 50],
       [11, 22, 33, 44, 55]])
```

Sorting

In [46]:
```
df.sort_values(by="A", ascending=False)
```

Out[46]:

	A	B	C	D	E
c	11	22	33	44	55
b	10	20	30	40	50
a	1	2	3	4	5

Appending two data frames

In [50]:
```
df2 = pd.DataFrame( np.random.rand(3,5), columns=df.columns )
pd.concat( [df, df2])
```

Out[50]:

	A	B	C	D	E
a	1.000000	2.000000	3.000000	4.000000	5.000000
b	10.000000	20.000000	30.000000	40.000000	50.000000
c	11.000000	22.000000	33.000000	44.000000	55.000000
0	0.285109	0.172316	0.400019	0.344001	0.065652
1	0.686239	0.713619	0.004903	0.223297	0.282492
2	0.786840	0.081758	0.683350	0.364533	0.244403

Dataframes can also be merged (joined)

In [53]:
```
df2 = pd.DataFrame( [[50, 'eins'], [5, 'zwei'], [55, 'drei']], colu
mns=["E2", "no"])
df3 = pd.merge(df, df2, left_on="E", right_on="E2")
df3.drop("E2", axis=1, inplace=True)
df3
```

Out[53]:

	A	B	C	D	E	no
0	1	2	3	4	5	zwei
1	10	20	30	40	50	eins
2	11	22	33	44	55	drei

Importing data using pandas (repetition from Data I/O session)

In [60]:
```
diamonds = pd.read_csv('diamonds.csv',index_col=0)
```

Show only the first 5 rows of this huge data set

In [61]:
```
diamonds.head()
```

Out[61]:

	carat	cut	color	clarity	depth	table	price	x	y	z
1	0.23	Ideal	E	SI2	61.5	55	326	3.95	3.98	2.43
2	0.21	Premium	E	SI1	59.8	61	326	3.89	3.84	2.31
3	0.23	Good	E	VS1	56.9	65	327	4.05	4.07	2.31
4	0.29	Premium	I	VS2	62.4	58	334	4.20	4.23	2.63
5	0.31	Good	J	SI2	63.3	58	335	4.34	4.35	2.75

or the last 5

In [62]:
```
diamonds.tail()
```

Out[62]:

	carat	cut	color	clarity	depth	table	price	x	y	z
53936	0.72	Ideal	D	SI1	60.8	57	2757	5.75	5.76	3.50
53937	0.72	Good	D	SI1	63.1	55	2757	5.69	5.75	3.61
53938	0.70	Very Good	D	SI1	62.8	60	2757	5.66	5.68	3.56
53939	0.86	Premium	H	SI2	61.0	58	2757	6.15	6.12	3.74
53940	0.75	Ideal	D	SI2	62.2	55	2757	5.83	5.87	3.64

get some infos about the DataFrame

In [63]:
```
diamonds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 53940 entries, 1 to 53940
Data columns (total 10 columns):
carat      53940 non-null float64
cut        53940 non-null object
color      53940 non-null object
clarity    53940 non-null object
depth      53940 non-null float64
table      53940 non-null float64
price      53940 non-null int64
x          53940 non-null float64
y          53940 non-null float64
z          53940 non-null float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.5+ MB
```

or some basic statistics

In [64]:
```
diamonds.describe()
```

Out[64]:

	carat	depth	table	price	x	y
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	539
mean	0.797940	61.749405	57.457184	3932.799722	5.731157	5.7
std	0.474011	1.432621	2.234491	3989.439738	1.121761	1.1
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.0
25%	0.400000	61.000000	56.000000	950.000000	4.710000	4.7
50%	0.700000	61.800000	57.000000	2401.000000	5.700000	5.7
75%	1.040000	62.500000	59.000000	5324.250000	6.540000	6.5
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.

or even the correlation between the columns

In [65]:
```
diamonds.corr()
```

Out[65]:

	carat	depth	table	price	x	y	z
carat	1.000000	0.028224	0.181618	0.921591	0.975094	0.951722	0.953387
depth	0.028224	1.000000	-0.295779	-0.010647	-0.025289	-0.029341	0.094924
table	0.181618	-0.295779	1.000000	0.127134	0.195344	0.183760	0.150929
price	0.921591	-0.010647	0.127134	1.000000	0.884435	0.865421	0.861249
x	0.975094	-0.025289	0.195344	0.884435	1.000000	0.974701	0.970772
y	0.951722	-0.029341	0.183760	0.865421	0.974701	1.000000	0.952006
z	0.953387	0.094924	0.150929	0.861249	0.970772	0.952006	1.000000

Compute mean values for each cut

In [69]:
```
diamonds.groupby("cut").mean()
```

Out[69]:

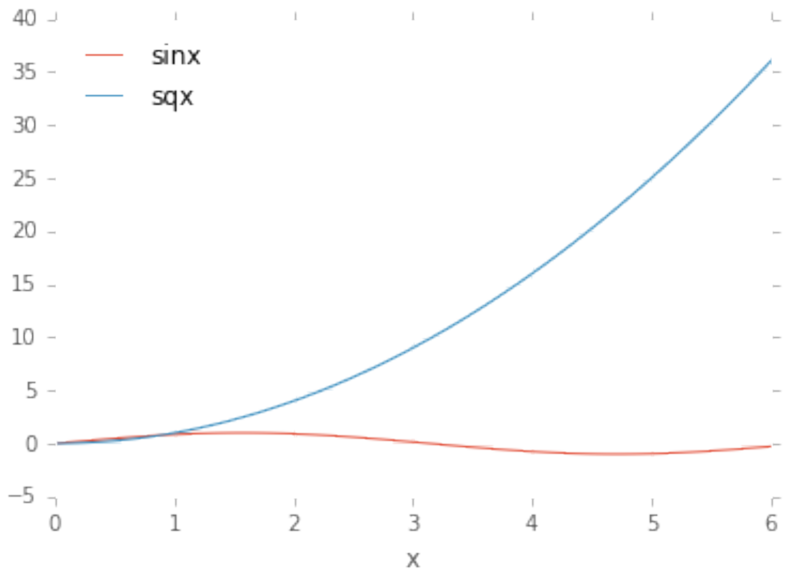
	carat	depth	table	price	x	y	z
cut							
Fair	1.046137	64.041677	59.053789	4358.757764	6.246894	6.182652	3.98277
Good	0.849185	62.365879	58.694639	3928.864452	5.838785	5.850744	3.6395(
Ideal	0.702837	61.709401	55.951668	3457.541970	5.507451	5.520080	3.4014
Premium	0.891955	61.264673	58.746095	4584.257704	5.973887	5.944879	3.6471
Very Good	0.806381	61.818275	57.956150	3981.759891	5.740696	5.770026	3.5598(

Plotting

Pandas DataFrames have include the pyplot.plot function

In [70]:
```
x = np.linspace(0, 6, 100)
a = np.array( [x, np.sin(x), x*x] ).transpose()
df = pd.DataFrame( a, columns=["x", "sinx", "sqx"] )
df.plot(x="x", y=["sinx", "sqx"])
```

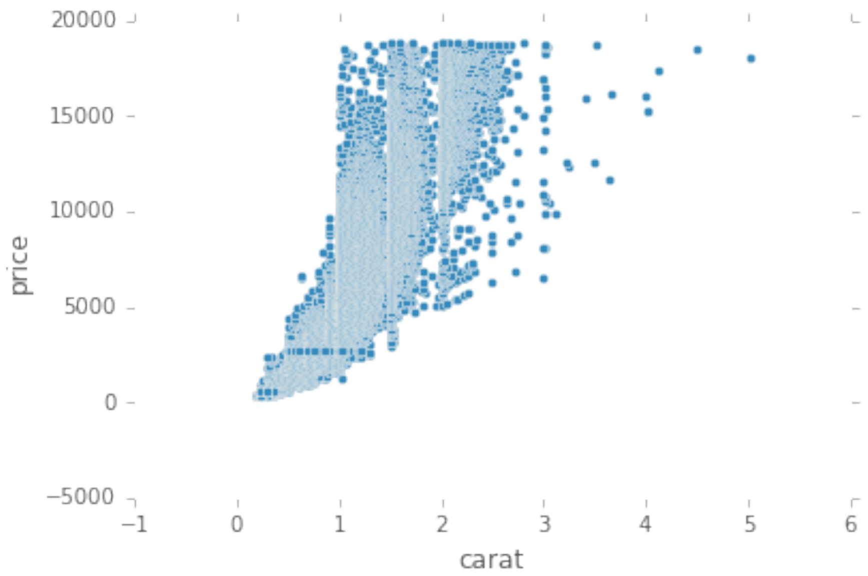
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7756729f98>



Scatterplot

```
In [71]: diamonds.plot(x="carat", y="price", kind='scatter')
```

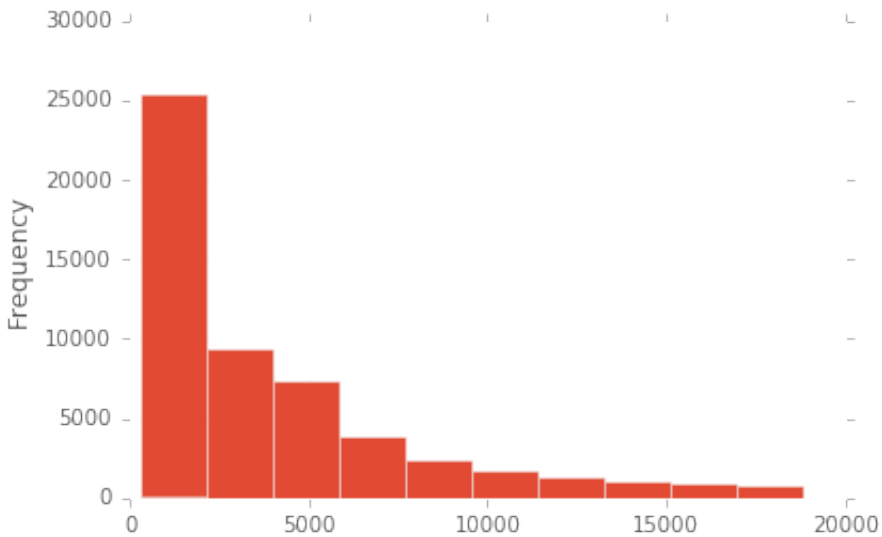
Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7756729d30>



Histogramm of diamond prices

```
In [72]: diamonds["price"].plot(kind="hist")
```

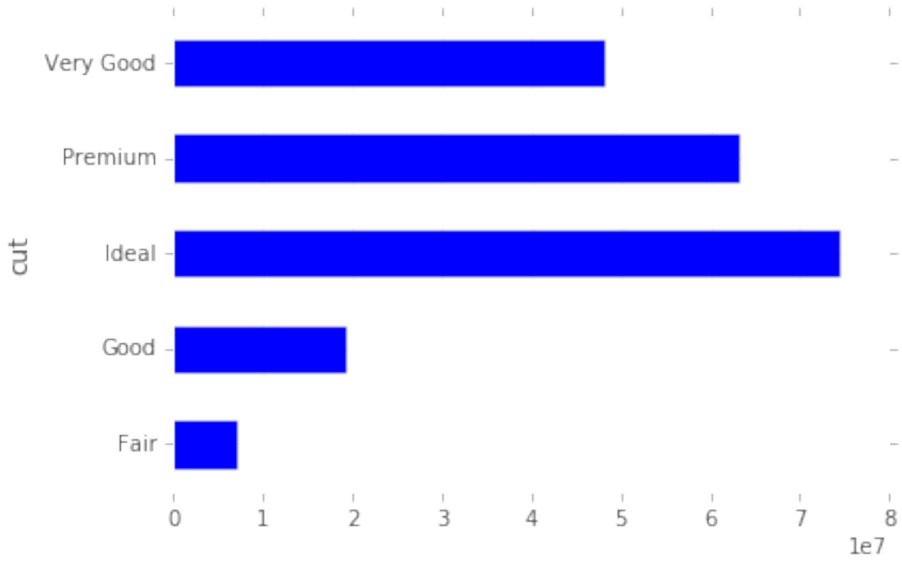
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x7f775651c6a0>



Bar plot

In [77]:
```
diamonds.groupby("cut")["price"].sum().plot(kind="barh")
```

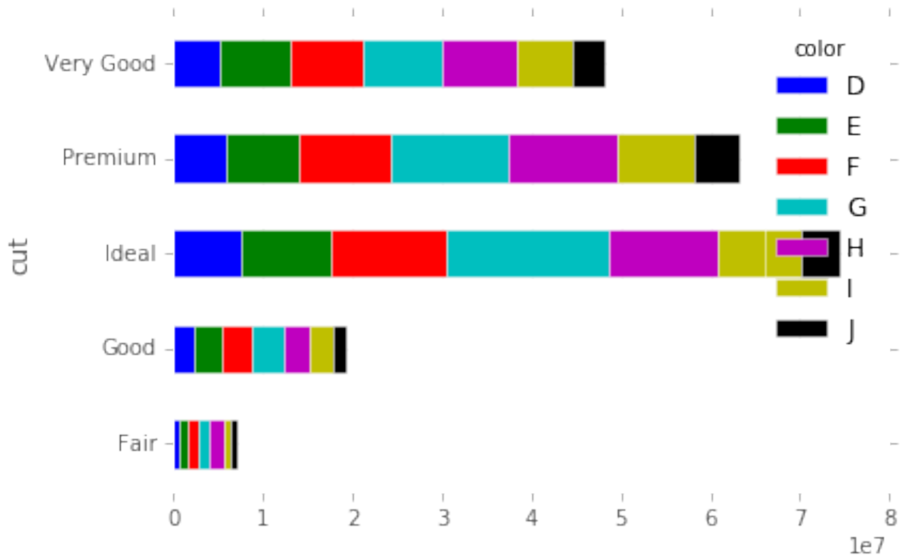
Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x7f77564436d8>



Stacked bar plot

In [40]:
```
price_per_color = diamonds.groupby( ["cut", "color"] )["price"].sum
().unstack()
price_per_color.plot(kind="barh", stacked=True)
#price_per_color
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2e6ff7f28>



In [81]:
```
price_per_color = diamonds.groupby( ["cut", "color"] )["price"].sum
().unstack()
price_per_color
```

Out[81]:

color	**D**	**E**	**F**	**G**	**H**	**I**	**J**
cut							
Fair	699443	824838	1194025	1331126	1556112	819953	592103
Good	2254363	3194260	3177637	3591553	3001931	2650994	1404271
Ideal	7450854	10138238	12912518	18171930	12115278	9317974	4406695
Premium	5820962	8270443	10081319	13160170	12311428	8491146	5086030
Very Good	5250817	7715165	8177367	8903461	8272552	6328079	3460182

In [ ]: