Project #3

SDS348 Spring 2021

Julia Capelli (jcc5625)

```
In [ ]:
```

```
#Import Packages
import numpy as np
Let's use some `pandas` functions in Python that are equivalent
to `tidyr` functions in R for data wrangling:
![image.png](attachment:image.png)import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(color_codes=True)
```

This dataset was taken from Professor Layla Guyots Github website. This dataset is orginally from the Mass package. It is a dataset that covers breastcancer patients from the University of Wisconsin Hospitals. In this dataset Dr.William H. Wolberg assesed biopsies of breast tumors in 699 paitients and 11 varibles. There were nine variables that were scored on a scale of 1 to 10. All of the variables were compared to the outcome variable which was if the cells were benign or malignant.

```
In [27]:
```

```
# Import dataset
Biopsy = pd.read_csv("https://raw.githubusercontent.com/laylaguy
ot/datasets/main//Biopsy.csv")
```

```
In [101]:
```

```
#View Dataset
Biopsy.head
```

```
Out[101]:
```

<pre><bound method="" ndframe.head="" of<="" th=""></bound></pre>				
uniform_cell_size	uniform_cell_s	shape marg_adhesion		
0	5	1		
1 1	-			
1	5	4		
4 5				
2	3	1		
1 1				
3	6	8		
8 1		_		
4	4	1		
1 3	0	1.0		
5 10 8	8	10		
6	1	1		
1 1	1	1		
7	2	1		
2 1	_	_		
8	2	1		
1 1				
9	4	2		
1 1				
10	1	1		
1 1				
11	2	1		
1 1	_	•		
12	5	3		
3 13	1	1		
1 1	1	1		
14	8	7		
5 10	· ·	,		
15	7	4		
6 4				
16	4	1		
1 1				
17	4	1		
1 1				
18	10	7		
7 6	_	_		
19	6	1		
1 1	7	2		
20	7	3		

2	10	
21	10	5
5	3	
22	3	1
1	1	
23	1	1
1	1	2
24 3	5 4	2
25	3	2
1	1	-
26	5	1
1	1	
27	2	1
1	1	
28	1	1
3	1	1
29 1	3 1	1
••	1	
••	•••	• • •
653	5	10
10	8	
654	3	10
7	8	
655	3	2
1	2	4
656	2 1	1
1 657	5	3
2	1	J
658	1	1
1	1	
659	4	1
4	1	
660	1	1
2	1 -	
661	5	1
1 662	1	1
1	1	1
663	2	1
1	1	_
664	10	10
10	10	
	_	

665		5	10	
10	10			
666		5	1	
1	1			
667		1	1	
1	1			
668		1	1	
1	1			
669		1	1	
1	1			
670		1	1	
1	1			
671		3	1	
1	1			
672		4	1	
1	1			
673		1	1	
1	1			
674		1	1	
1	3			
675		5	10	
10	5			
676		3	1	
1	1			
677		3	1	
1	1			
678		3	1	
1	1			
679		2	1	
1	1			
680		5	10	
10	3			
681		4	8	
6	4			
682		4	8	
8	5			
			bare_nuclei	bland_chroma
tin	normal_nucleo	li \		
0		2	1	
3	1			
1		7	10	
3	2			
2		2	2	
_				

3	1		
3 3 4 3 5 9 6 3 7 3 8 1 9	7	3	4
3	7	2	1
4	1	2	1
5 5	1	7	10
9	7	,	10
6		2	10
3	1		
7		2	1
3	1		_
8	1	2	1
9	1	2	1
2	1	2	_
10		1	1
3	1		
11		2	1
2	1		_
12	4	2	3
4 13	4	2	3
3	1	L	3
14	_	7	9
5	5		
15		6	1
4	3		
16	1	2	1
2 17	1	2	1
3	1	2	1
18	_	4	10
4	1		
19		2	1
3	1	_	
20	4	5	10
5 21	4	6	7
7	10	O	/
22	10	2	1
2	1		_
23 3 24		2	1
3	1		
24	-	2	7
3	6	_	_

25		1	1
2	1		
26	1	2	1
2	1	2	_
27	-	2	1
2	1		
28		2	1
1	1		
29 2		1	1
2	1		
• •		• • •	• • •
	• • •	-	-
653	1.0	5	5
7 654	10	5	8
7	4	J	0
, 655	1	2	1
3	1	_	_
656		2	1
3	1		
657		3	1
1	1		
658		2	1
2	1	•	
659	1	2	1
1 660	1	2	1
2	1	2	1
661	-	2	1
1	1	_	_
662		2	1
1	1		
663		2	1
1	1		
664		5	10
10	10		4.0
665	6	4	10
5	6	2	1
666 3	2	2	1
667	2	2	1
1	1	2	±
668	-	2	1
1	1		
6.60		•	_

669			2	1
1		1		
670			2	1
1		1		
671			2	1
2		3		
672			2	1
1		1		
673			2	1
1		1		
674			2	1
1		1		
675			4	5
4		4		
676			2	1
1		1		
677			2	1
2		1		
678			3	2
1		1		
679			2	1
1		1		
680			7	3
8		10		
681			3	4
10		6		
682			4	5
10		4		
	mitoses	outcome		
0	1	benign		
1	1	benign		
2	1	benign		
3 4	1	benign		
4	1	benign		
5	1	malignant		
6	1	benign		
7	1	benign		
8	5	benign		
9	1	benign		
10	1	benign		
11	1	benign		
12	1	malignant		
13	1	benign		
14	4	malignant		
		- .		

15	1	malignant
16	1	benign
17	1	benign
18	2	malignant
19	1	benign
20	4	malignant
21	1	malignant
22	1	benign
23	1	benign
24	1	malignant
25	1	benign
26	1	benign
27	1	benign
28	1	benign
29	1	benign
23		Schigh
653	1	malignant
654	1	malignant
655	1	benign
656	1	benign
657	1	benign
658	1	benign
659	1	benign
660	1	benign
661	1	benign
662	1	benign
663	1	benign
664	7	malignant
665	3	malignant
666	1	benign
667	1	benign
668	1	benign
669	1	benign
670	1	benign
671	1	benign
672	1	benign
673	8	benign
674	1	benign
675	1	malignant
676	1	benign
677	2	benign
678	1	benign
679	1	benign
680	2	malignant
601	-	

```
malignant
682
           1
[683 rows x 10 columns]>
In [102]:
#Show info about dataset
Biopsy.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 683 entries, 0 to 682
Data columns (total 10 columns):
clump thickness
                        683 non-null int64
uniform cell_size
                        683 non-null int64
uniform cell shape
                        683 non-null int64
marg adhesion
                        683 non-null int64
epithelial cell size
                        683 non-null int64
bare nuclei
                        683 non-null int64
bland chromatin
                        683 non-null int64
normal nucleoli
                        683 non-null int64
                        683 non-null int64
mitoses
                        683 non-null object
outcome
dtypes: int64(9), object(1)
memory usage: 78.7+ KB
In [29]:
Biopsy.shape
```

Out[29]:

68T

1 malignant

(683, 10)

From the output we can see the table contains 683 rows and 10 columns.

In [61]:

#Info about the data set
Biopsy.describe()

Out[61]:

	clump_thickness	uniform_cell_size	uniform_cell_shape	marg_adh
count	683.000000	683.000000	683.000000	683.00
mean	4.442167	3.150805	3.215227	2.83
std	2.820761	3.065145	2.988581	2.86
min	1.000000	1.000000	1.000000	1.00
25%	2.000000	1.000000	1.000000	1.00
50%	4.000000	1.000000	1.000000	1.00
75%	6.000000	5.000000	5.000000	4.00
max	10.000000	10.000000	10.000000	10.00

This a summary statistics for all of the numeric variables in this dataset. All of the variables were scored on a scale of 1-10 which explains why all the variables have a min and max of 10 and why they will all have the same range. Clump Thickness has the highest mean of 4.4 and mitoses has the lowest means of 1.6.

```
In [62]:
```

```
#Drop missing values
Biopsy = Biopsy.dropna()
Biopsy.count()
```

Out[62]:

```
clump thickness
                         683
uniform cell size
                         683
uniform cell shape
                         683
marg adhesion
                         683
epithelial_cell_size
                         683
bare nuclei
                         683
bland chromatin
                         683
normal nucleoli
                         683
mitoses
                         683
                         683
outcome
dtype: int64
```

In [43]:

```
#Show all the variables
Biopsy.columns
```

Out[43]:

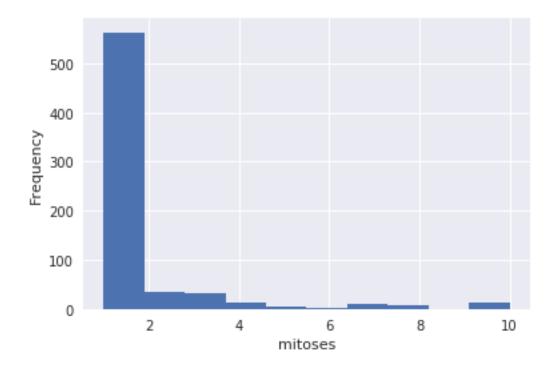
There are 10 variables tested for in this dataset

In [92]:

```
# Create a histogram
Biopsy['mitoses'].plot(kind = "hist")
plt.xlabel('mitoses') # add a label
```

Out[92]:

Text(0.5,0,'mitoses')



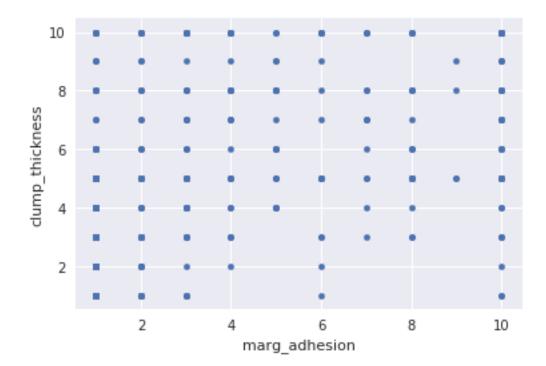
From this hisogram we can clearly see that there is a dramtic skew to the right, this is mostly likely caused by a few outlier that may have altered the data.

In [89]:

```
# Use pandas to create a scatterplot
Biopsy.plot.scatter(x = 'marg_adhesion', y = 'clump_thickness')
```

Out[89]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fe713ce
4630>



Marge Adhesion and clump thickness are two factors that both predicted to contribute cancer cells. Marg adhesions is the the mechanism by which two cells are able to stick to eachother. If cells loose their adhesive propertiies then this can lead to cells breaking aways and spreading cancer. Clump thickness is also a predictive propertie of cancer, since breast cancer is uncontrolled growth of breast cells, if there is clump thickness of many cells then there is a higher chance a patient will have breast cancer. However, while both of these variables can be linked to breat cancer predictions they are not related to eachother. The data in the scatterplot is not uniformed which shows no signinficant relationship

In [94]:

```
#Get a count of the number of 'M' & 'B' cells
Biopsy['outcome'].value_counts()
```

Out[94]:

benign 444 malignant 239

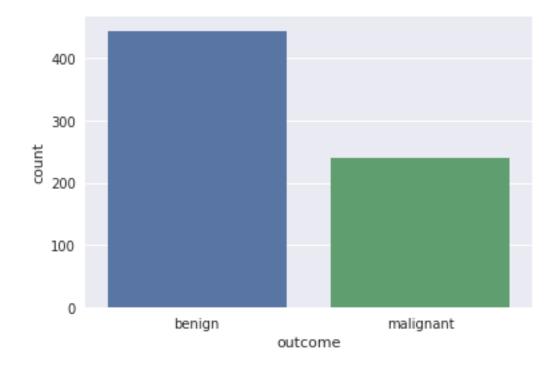
Name: outcome, dtype: int64

In [93]:

```
#Visualize this count
sns.countplot(Biopsy['outcome'],label="Count")
```

Out[93]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fe71342
c550>



There are 444 Beign and 239 Malignant tumors present in this dataset

```
In [82]:
```

```
Biopsy['outcome'].value_counts()
```

Out[82]:

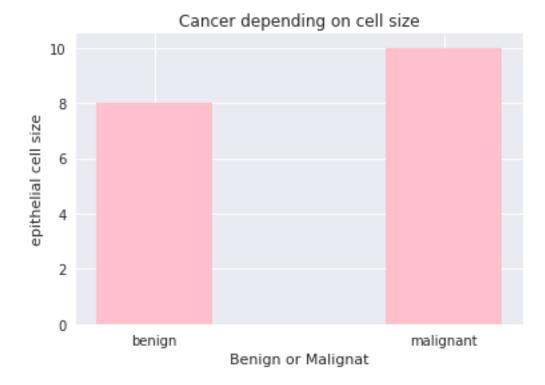
benign 444 malignant 239

Name: outcome, dtype: int64

In [85]:

```
plt.bar(Biopsy.outcome, Biopsy.clump_thickness, color= 'pink', w
idth = 0.4)

plt.xlabel("Benign or Malignat")
plt.ylabel("Clump Thickness")
plt.title("Cancer depending on Clump Thickness")
plt.show()
```



After creating this graph one can determine that the greater the clump thickness is in paitents then the most likely they will have cancer. Paitients will more clump thickness had more malignant cells.

In []:			