

1 # Simple ML Model

```
In [ ]: 1 import pandas as pd
        2 import numpy as np
```

```
1 data=pd.read_csv('crx.data',header=None)
```

```
In [26]: 1 #variable engineering or feature engineering
        2 varname=['A'+str(s) for s in range(1,17)]
```

```
In [27]: 1 data.columns=varname
```

```
In [28]: 1 data.head(20)
```

Out[28]:

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16
0	b	30.83	0.000	u	g	w	v	1.250	t	t	1	f	g	00202	0	+
1	a	58.67	4.460	u	g	q	h	3.040	t	t	6	f	g	00043	560	+
2	a	24.50	0.500	u	g	q	h	1.500	t	f	0	f	g	00280	824	+
3	b	27.83	1.540	u	g	w	v	3.750	t	t	5	t	g	00100	3	+
4	b	20.17	5.625	u	g	w	v	1.710	t	f	0	f	s	00120	0	+
5	b	32.08	4.000	u	g	m	v	2.500	t	f	0	t	g	00360	0	+
6	b	33.17	1.040	u	g	r	h	6.500	t	f	0	t	g	00164	31285	+
7	a	22.92	11.585	u	g	cc	v	0.040	t	f	0	f	g	00080	1349	+
8	b	54.42	0.500	y	p	k	h	3.960	t	f	0	f	g	00180	314	+
9	b	42.50	4.915	y	p	w	v	3.165	t	f	0	t	g	00052	1442	+
10	b	22.08	0.830	u	g	c	h	2.165	f	f	0	t	g	00128	0	+
11	b	29.92	1.835	u	g	c	h	4.335	t	f	0	f	g	00260	200	+
12	a	38.25	6.000	u	g	k	v	1.000	t	f	0	t	g	00000	0	+
13	b	48.08	6.040	u	g	k	v	0.040	f	f	0	f	g	00000	2690	+
14	a	45.83	10.500	u	g	q	v	5.000	t	t	7	t	g	00000	0	+
15	b	36.67	4.415	y	p	k	v	0.250	t	t	10	t	g	00320	0	+
16	b	28.25	0.875	u	g	m	v	0.960	t	t	3	t	g	00396	0	+
17	a	23.25	5.875	u	g	q	v	3.170	t	t	10	f	g	00120	245	+
18	b	21.83	0.250	u	g	d	h	0.665	t	f	0	t	g	00000	0	+
19	a	19.17	8.585	u	g	cc	h	0.750	t	t	7	f	g	00096	0	+

```
In [29]: 1 data=data.replace('?',np.nan)
```

In [30]:

```
1 data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
 #   Column  Non-Null Count  Dtype
---  -
 0    A1      678 non-null    object
 1    A2      678 non-null    object
 2    A3      690 non-null    float64
 3    A4      684 non-null    object
 4    A5      684 non-null    object
 5    A6      681 non-null    object
 6    A7      681 non-null    object
 7    A8      690 non-null    float64
 8    A9      690 non-null    object
 9   A10     690 non-null    object
10   A11     690 non-null    int64
11   A12     690 non-null    object
12   A13     690 non-null    object
13   A14     677 non-null    object
14   A15     690 non-null    int64
15   A16     690 non-null    object
dtypes: float64(2), int64(2), object(12)
memory usage: 86.4+ KB
```

In [31]:

```
1 #recast their variables to correct types
2 data['A2']=data['A2'].astype('float')
3 data['A14']=data['A14'].astype('float')
```

In [32]:

```
1 #encode A16 from + - to 1 and 0
2 data['A16']=data['A16'].map({'+':1, '-':0})
```

```
In [33]: 1 data['A16'].head(20)
```

```
Out[33]: 0      1
          1      1
          2      1
          3      1
          4      1
          5      1
          6      1
          7      1
          8      1
          9      1
         10      1
         11      1
         12      1
         13      1
         14      1
         15      1
         16      1
         17      1
         18      1
         19      1
          Name: A16, dtype: int64
```

```
In [34]: 1 #numerical variables
          2 #discrete 3,4
          3 #continuos 1.5,3.5
          4 #categorical variables
          5 #nominal (NAMES)-R,G,B,OOTY
          6 #ORDINAL (ORDERING)-SUNDAY-SATURDAY
```

```
In [35]: 1 cat_columns=[c for c in data.columns if data[c].dtypes=='O']
```

```
In [36]: 1 data[cat_columns].head(20)
```

Out[36]:

	A1	A4	A5	A6	A7	A9	A10	A12	A13
0	b	u	g	w	v	t	t	f	g
1	a	u	g	q	h	t	t	f	g
2	a	u	g	q	h	t	f	f	g
3	b	u	g	w	v	t	t	t	g
4	b	u	g	w	v	t	f	f	s
5	b	u	g	m	v	t	f	t	g
6	b	u	g	r	h	t	f	t	g
7	a	u	g	cc	v	t	f	f	g
8	b	y	p	k	h	t	f	f	g
9	b	y	p	w	v	t	f	t	g
10	b	u	g	c	h	f	f	t	g
11	b	u	g	c	h	t	f	f	g
12	a	u	g	k	v	t	f	t	g
13	b	u	g	k	v	f	f	f	g
14	a	u	g	q	v	t	t	t	g
15	b	y	p	k	v	t	t	t	g
16	b	u	g	m	v	t	t	t	g
17	a	u	g	q	v	t	t	f	g
18	b	u	g	d	h	t	f	t	g
19	a	u	g	cc	h	t	t	f	g

```
In [37]: 1 num_columns=[c for c in data.columns if data[c].dtypes!='O']
```

In [38]:

```
1 data[num_columns].head(20)
```

Out[38]:

	A2	A3	A8	A11	A14	A15	A16
0	30.83	0.000	1.250	1	202.0	0	1
1	58.67	4.460	3.040	6	43.0	560	1
2	24.50	0.500	1.500	0	280.0	824	1
3	27.83	1.540	3.750	5	100.0	3	1
4	20.17	5.625	1.710	0	120.0	0	1
5	32.08	4.000	2.500	0	360.0	0	1
6	33.17	1.040	6.500	0	164.0	31285	1
7	22.92	11.585	0.040	0	80.0	1349	1
8	54.42	0.500	3.960	0	180.0	314	1
9	42.50	4.915	3.165	0	52.0	1442	1
10	22.08	0.830	2.165	0	128.0	0	1
11	29.92	1.835	4.335	0	260.0	200	1
12	38.25	6.000	1.000	0	0.0	0	1
13	48.08	6.040	0.040	0	0.0	2690	1
14	45.83	10.500	5.000	7	0.0	0	1
15	36.67	4.415	0.250	10	320.0	0	1
16	28.25	0.875	0.960	3	396.0	0	1
17	23.25	5.875	3.170	10	120.0	245	1
18	21.83	0.250	0.665	0	0.0	0	1
19	19.17	8.585	0.750	7	96.0	0	1

In [44]:

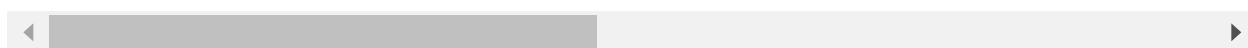
```
1 data1=pd.read_csv('loan.csv')
```

In [45]: 1 data1

Out[45]:

	customer_id	disbursed_amount	interest	market	employment	time_employed	householder
0	0	23201.5	15.4840	C	Teacher	<=5 years	RENT
1	1	7425.0	11.2032	B	Accountant	<=5 years	OWNER
2	2	11150.0	8.5100	A	Statistician	<=5 years	RENT
3	3	7600.0	5.8656	A	Other	<=5 years	RENT
4	4	31960.0	18.7392	E	Bus driver	>5 years	RENT
...
9995	9995	23750.0	11.0019	B	Civil Servant	<=5 years	MORTGAGE
9996	9996	11880.0	10.4923	B	Civil Servant	<=5 years	RENT
9997	9997	19950.0	8.4364	B	Accountant	>5 years	OWNER
9998	9998	4850.0	13.6409	C	Bus driver	>5 years	RENT
9999	9999	25584.0	17.1456	D	Accountant	>5 years	MORTGAGE

10000 rows × 14 columns



In [46]: 1 #continuous
2 data1['disbursed_amount'].unique()

Out[46]: array([23201.5 , 7425. , 11150. , ..., 6279. , 12894.75, 25584.])

In [47]: 1 #discrete
2 data1['number_open_accounts'].unique()

Out[47]: array([4., 13., 8., 20., 14., 5., 9., 18., 16., 17., 12., 15., 6.,
10., 11., 7., 21., 19., 26., 2., 22., 27., 23., 25., 24., 28.,
3., 30., 41., 32., 33., 31., 29., 37., 49., 34., 35., 38., 1.,
36., 42., 47., 40., 44., 43.])

In [49]: 1 data1['target'].unique()

Out[49]: array([0, 1], dtype=int64)

In [50]: 1 data1['time_employed'].unique()

Out[50]: array(['<=5 years', '>5 years', nan], dtype=object)

```
In [51]: 1 data1['householder'].value_counts()
```

```
Out[51]: MORTGAGE    4957
         RENT        4055
         OWNER       988
         Name: householder, dtype: int64
```

```
In [53]: 1 data1[['date_issued', 'date_last_payment']].dtypes
```

```
Out[53]: date_issued    object
         date_last_payment    object
         dtype: object
```

```
In [54]: 1 data1['dateissuedt']=pd.to_datetime(data1['date_issued'])
```

```
In [55]: 1 data1.head()
```

```
Out[55]:
```

	customer_id	disbursed_amount	interest	market	employment	time_employed	householder	ii
0	0	23201.5	15.4840	C	Teacher	<=5 years	RENT	8
1	1	7425.0	11.2032	B	Accountant	<=5 years	OWNER	10
2	2	11150.0	8.5100	A	Statistician	<=5 years	RENT	6
3	3	7600.0	5.8656	A	Other	<=5 years	RENT	10
4	4	31960.0	18.7392	E	Bus driver	>5 years	RENT	9

```
In [57]: 1 data1['month']=data1['dateissuedt'].dt.month
         2 data1['month'].head(10)
```

```
Out[57]: 0    6
         1    5
         2   10
         3    8
         4    7
         5    8
         6    9
         7    3
         8    2
         9   12
         Name: month, dtype: int64
```

```
In [63]: 1 data1['day']=data1['dateissuedt'].dt.day
         2 data1['year']=data1['dateissuedt'].dt.year
```

In [64]:

1	
2	data1['year'].head(10)

Out[64]:

0	2013
1	2014
2	2013
3	2015
4	2014
5	2013
6	2015
7	2015
8	2014
9	2013

Name: year, dtype: int64

In [65]:

1	data1['day'].head(10)
---	-----------------------

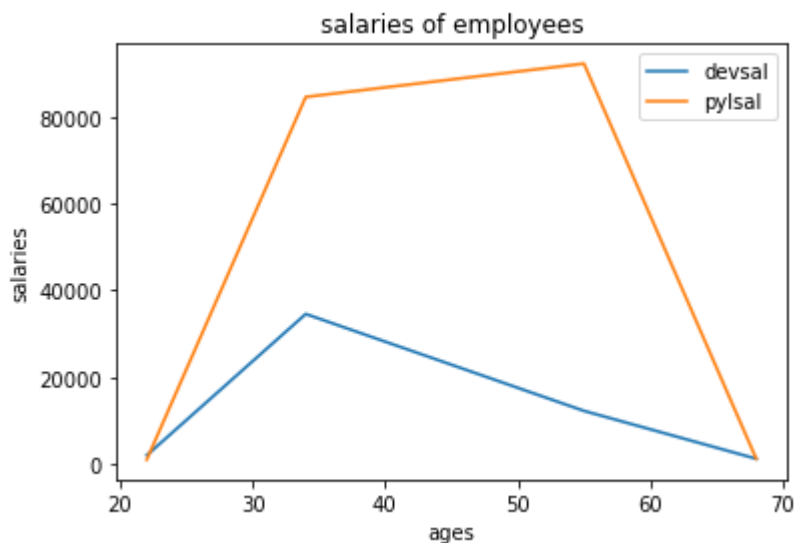
Out[65]:

0	11
1	8
2	26
3	20
4	22
5	21
6	27
7	20
8	14
9	25

Name: day, dtype: int64


```
In [71]: 1 #matplotlib
2 from matplotlib import pyplot as plt
3 plt.title('salaries of employees')
4 plt.xlabel('ages')
5 plt.ylabel('salaries')
6 dev_ages=[22,34,55,68]
7 dev_sal=[2000,34555,12234,1212]
8 py_sal=[1000,84555,92234,1212]
9 plt.plot(dev_ages,dev_sal,label='devsal')
10 plt.plot(dev_ages,py_sal,label='pysal')
11 plt.legend()
```

Out[71]: <matplotlib.legend.Legend at 0x189b46fda60>



```
In [1]: 1 import sklearn.datasets
```

```
In [2]: 1 can=sklearn.datasets.load_breast_cancer()
```

```
In [3]: 1 X=can.data
2 y=can.target
```

```
In [4]: 1 print(X.shape,y.shape)
```

(569, 30) (569,)

```
In [5]: 1 import pandas as pd
2 data=pd.DataFrame(can.data,columns=can.feature_names)
```

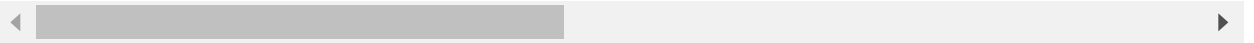
```
In [6]: 1 data["class"]=can.target
```

```
In [7]: 1 data.head()
        2 data.tail(5)
```

Out[7]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587

5 rows × 31 columns

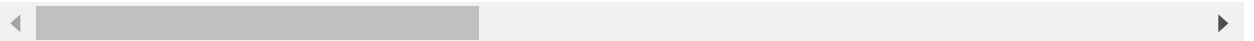


```
In [8]: 1 data.describe()
```

Out[8]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800

8 rows × 31 columns



```
In [9]: 1 data["class"].value_counts()
```

```
Out[9]: 1    357
        0    212
        Name: class, dtype: int64
```

```
In [10]: 1 can.target_names
```

```
Out[10]: array(['malignant', 'benign'], dtype='<U9')
```

In [11]: 1 data.groupby('class').mean()

Out[11]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	cor p
class								
0	17.462830	21.604906	115.365377	978.376415	0.102898	0.145188	0.160775	0.08
1	12.146524	17.914762	78.075406	462.790196	0.092478	0.080085	0.046058	0.02

2 rows × 30 columns

In [12]: 1 data.groupby('mean radius').mean()

Out[12]:

	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	dim
mean radius									
6.981	13.43	43.79	143.5	0.11700	0.07568	0.00000	0.000000	0.1930	0
7.691	25.44	48.34	170.4	0.08668	0.11990	0.09252	0.013640	0.2037	0
7.729	25.49	47.98	178.8	0.08098	0.04878	0.00000	0.000000	0.1870	0
7.760	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.000000	0.1587	0
8.196	16.84	51.71	201.9	0.08600	0.05943	0.01588	0.005917	0.1769	0
...
25.220	24.91	171.50	1878.0	0.10630	0.26650	0.33390	0.184500	0.1829	0
25.730	17.46	174.20	2010.0	0.11490	0.23630	0.33680	0.191300	0.1956	0
27.220	21.87	182.10	2250.0	0.10940	0.19140	0.28710	0.187800	0.1800	0
27.420	26.27	186.90	2501.0	0.10840	0.19880	0.36350	0.168900	0.2061	0
28.110	18.47	188.50	2499.0	0.11420	0.15160	0.32010	0.159500	0.1648	0

456 rows × 30 columns

```
In [13]: 1 from sklearn.model_selection import train_test_split
2 X1=data.drop('class',axis=1)
3 Y1=data['class']
4 x_train,x_test,y_train,y_test=train_test_split(X1,Y1,test_size=0.4,stratify=
5 print(Y1.shape,y_train.shape,y_test.shape)
```

(569,) (341,) (228,)

In [14]: 1 `print(Y1.mean(),y_train.mean(),y_test.mean())`

0.6274165202108963 0.6275659824046921 0.6271929824561403

In [15]: 1 `x_train,x_test,y_train,y_test=train_test_split(X1,Y1,test_size=0.4)#without`
2 `print(Y1.shape,y_train.shape,y_test.shape)`

(569,) (341,) (228,)

In [16]: 1 `print(Y1.mean(),y_train.mean(),y_test.mean())`

0.6274165202108963 0.6187683284457478 0.6403508771929824

In [17]: 1 `x_train,x_test,y_train,y_test=train_test_split(X1,Y1,test_size=0.4,stratify=`
2 `print(Y1.shape,y_train.shape,y_test.shape)`

(569,) (341,) (228,)

In [18]: 1 `print(Y1.mean(),y_train.mean(),y_test.mean())`

0.6274165202108963 0.6275659824046921 0.6271929824561403

In [19]: 1 `print(X1.mean(),x_train.mean(),x_test.mean())`

mean radius	14.127292	
mean texture	19.289649	
mean perimeter	91.969033	
mean area	654.889104	
mean smoothness	0.096360	
mean compactness	0.104341	
mean concavity	0.088799	
mean concave points	0.048919	
mean symmetry	0.181162	
mean fractal dimension	0.062798	
radius error	0.405172	
texture error	1.216853	
perimeter error	2.866059	
area error	40.337079	
smoothness error	0.007041	
compactness error	0.025478	
concavity error	0.031894	
concave points error	0.011796	
symmetry error	0.020542	
fractal dimension error	0.003795	
worst radius	16.269190	
worst texture	25.677223	
worst perimeter	107.261213	
worst area	880.583128	
worst smoothness	0.132369	
worst compactness	0.254265	
worst concavity	0.272188	
worst concave points	0.114606	
worst symmetry	0.290076	
worst fractal dimension	0.083946	
dtype: float64 mean radius		14.167018
mean texture	19.267273	
mean perimeter	92.194839	
mean area	660.770968	
mean smoothness	0.096472	
mean compactness	0.103606	
mean concavity	0.088231	
mean concave points	0.049226	
mean symmetry	0.180840	
mean fractal dimension	0.062770	
radius error	0.414993	
texture error	1.227954	
perimeter error	2.914932	
area error	42.020155	
smoothness error	0.007114	
compactness error	0.025655	
concavity error	0.031797	
concave points error	0.011905	
symmetry error	0.020599	
fractal dimension error	0.003838	
worst radius	16.302003	
worst texture	25.631584	
worst perimeter	107.368065	
worst area	888.655425	

```

worst smoothness      0.131733
worst compactness     0.250276
worst concavity       0.266565
worst concave points  0.113628
worst symmetry        0.288151
worst fractal dimension 0.083792
dtype: float64 mean radius      14.067877
mean texture          19.323114
mean perimeter        91.631316
mean area             646.092105
mean smoothness       0.096193
mean compactness      0.105440
mean concavity        0.089649
mean concave points   0.048461
mean symmetry         0.181643
mean fractal dimension 0.062839
radius error          0.390484
texture error         1.200252
perimeter error       2.792965
area error            37.819846
smoothness error      0.006931
compactness error     0.025214
concavity error       0.032039
concave points error  0.011634
symmetry error        0.020458
fractal dimension error 0.003730
worst radius          16.220114
worst texture         25.745482
worst perimeter       107.101404
worst area            868.510088
worst smoothness      0.133320
worst compactness     0.260231
worst concavity       0.280599
worst concave points  0.116069
worst symmetry        0.292954
worst fractal dimension 0.084175
dtype: float64

```

```

In [44]: 1 x_binarised_train=x_train.apply(pd.cut,bins=2,labels=[1,0])
          2 x_binarised_test=x_test.apply(pd.cut,bins=2,labels=[1,0])

```

```

In [45]: 1 type(x_binarised_train)
          2 x_binarised_train=x_binarised_train.values
          3 x_binarised_test=x_binarised_test.values
          4 type(x_binarised_train)

```

Out[45]: numpy.ndarray

```

In [42]: 1 import numpy as np
          2 from random import randint
          3
          4 b=10
          5 for b in range(x_binarised_train.shape[1]+1):
          6     accurate_rows=0
          7     for x,y in zip(x_binarised_train,y_train):
          8         y_pred=(np.sum(x)>=b)
          9         accurate_rows+=(y==y_pred)
         10     print('b=',b,accurate_rows, accurate_rows/x_binarised_train.shape[0])
         11
         12 '''
         13 i=randint(0,x_binarised_train.shape[0])
         14 b=10
         15
         16 if(np.sum(x_binarised_train[i:])>=b):
         17     print('model prediction is malignant')
         18 else:
         19     print('model prediction is benign')
         20
         21 if(y_train[i]==1):
         22     print('Actual outcome is malignant')
         23 else:
         24     print('Actual outcome is benign')'''
         25
         26
         27
         28

```

```

b= 0 214 0.6275659824046921
b= 1 214 0.6275659824046921
b= 2 214 0.6275659824046921
b= 3 214 0.6275659824046921
b= 4 214 0.6275659824046921
b= 5 214 0.6275659824046921
b= 6 214 0.6275659824046921
b= 7 214 0.6275659824046921
b= 8 214 0.6275659824046921
b= 9 214 0.6275659824046921
b= 10 214 0.6275659824046921
b= 11 214 0.6275659824046921
b= 12 214 0.6275659824046921
b= 13 216 0.6334310850439883
b= 14 218 0.6392961876832844
b= 15 219 0.6422287390029325
b= 16 223 0.6539589442815249
b= 17 226 0.6627565982404692
b= 18 227 0.6656891495601173
b= 19 229 0.6715542521994134
b= 20 238 0.6979472140762464
b= 21 243 0.7126099706744868
b= 22 252 0.7390029325513197
b= 23 264 0.7741935483870968
b= 24 270 0.7917888563049853
b= 25 278 0.8152492668621701
b= 26 289 0.8475073313782991

```

```

b= 27 288 0.844574780058651
b= 28 284 0.8328445747800587
b= 29 272 0.7976539589442815
b= 30 239 0.7008797653958945

```

```

Out[42]: "\ni=randint(0,x_binarised_train.shape[0])\nb=10\n\nif(np.sum(x_binarised_train
[i:])>=b):\n    print('model prediction is malignant')\nelse:\n    print('model
prediction is benign')\n    \nif(y_train[i]==1):\n    print('Actual outcome is
malignant')\nelse:\n    print('Actual outcome is benign')"
```

```

In [47]: 1 b=27
2 accurate_rows=0
3 for x,y in zip(x_binarised_train,y_train):
4     y_pred=(np.sum(x)>=b)
5     accurate_rows+=(y==y_pred)
6     print('b=',b,accurate_rows, accurate_rows/x_binarised_train.shape[0])

```

```

b= 27 269 0.7888563049853372
b= 27 270 0.7917888563049853
b= 27 271 0.7947214076246334
b= 27 271 0.7947214076246334
b= 27 272 0.7976539589442815
b= 27 272 0.7976539589442815
b= 27 273 0.8005865102639296
b= 27 273 0.8005865102639296
b= 27 274 0.8035190615835777
b= 27 275 0.8064516129032258

b= 27 276 0.8093841642228738
b= 27 277 0.8123167155425219
b= 27 278 0.8152492668621701
b= 27 279 0.8181818181818182
b= 27 280 0.8211143695014663
b= 27 281 0.8240469208211144
b= 27 282 0.8269794721407625
b= 27 283 0.8299120234604106
b= 27 284 0.8328445747800587
.  --  ---  -  -----

```



```
In [41]: 1 for b in range(x_binarised_test.shape[1]+1):
2         accurate_rows=0
3         for x,y in zip(x_binarised_test,y_test):
4             y_pred=(np.sum(x)>=b)
5             accurate_rows+=(y==y_pred)
6         print('b=',b,accurate_rows, accurate_rows/x_binarised_train.shape[0])
```

```
b= 0 143 0.41935483870967744
b= 1 143 0.41935483870967744
b= 2 143 0.41935483870967744
b= 3 143 0.41935483870967744
b= 4 143 0.41935483870967744
b= 5 143 0.41935483870967744
b= 6 143 0.41935483870967744
b= 7 143 0.41935483870967744
b= 8 143 0.41935483870967744
b= 9 144 0.4222873900293255
b= 10 144 0.4222873900293255
b= 11 146 0.4281524926686217
b= 12 147 0.4310850439882698
b= 13 149 0.436950146627566
b= 14 149 0.436950146627566
b= 15 150 0.4398826979472141
b= 16 150 0.4398826979472141
b= 17 155 0.45454545454545453
b= 18 161 0.47214076246334313
b= 19 162 0.4750733137829912
b= 20 166 0.4868035190615836
b= 21 172 0.5043988269794721
b= 22 181 0.530791788856305
b= 23 187 0.5483870967741935
b= 24 192 0.5630498533724341
b= 25 197 0.5777126099706745
b= 26 202 0.592375366568915
b= 27 201 0.5894428152492669
b= 28 197 0.5777126099706745
b= 29 178 0.5219941348973607
b= 30 151 0.44281524926686217
```

In [56]:

```

1 b=28
2 accurate_rows=0
3 for x,y in zip(x_binarised_test,y_test):
4     y_pred=(np.sum(x)>=b)
5     accurate_rows+=(y==y_pred)
6     print('b=',b,accurate_rows, accurate_rows/x_binarised_test.shape[0])

```

```

b= 28 175 0.7675438596491229
b= 28 176 0.7719298245614035
b= 28 176 0.7719298245614035
b= 28 177 0.7763157894736842
b= 28 178 0.7807017543859649
b= 28 179 0.7850877192982456
b= 28 180 0.7894736842105263
b= 28 181 0.793859649122807
b= 28 182 0.7982456140350878
b= 28 183 0.8026315789473685
b= 28 184 0.8070175438596491
b= 28 185 0.8114035087719298
b= 28 186 0.8157894736842105
b= 28 187 0.8201754385964912
b= 28 188 0.8245614035087719
b= 28 189 0.8289473684210527

b= 28 190 0.8333333333333334
b= 28 191 0.8377192982456141
b= 28 192 0.8421052631578947

```

In [57]:

```

1 b=27
2 accurate_rows=0
3 for x,y in zip(x_binarised_test,y_test):
4     y_pred=(np.sum(x)>=b)
5     accurate_rows+=(y==y_pred)
6     print('b=',b,accurate_rows, accurate_rows/x_binarised_test.shape[0])

```

```

b= 27 177 0.7763157894736842
b= 27 178 0.7807017543859649
b= 27 179 0.7850877192982456
b= 27 180 0.7894736842105263
b= 27 181 0.793859649122807
b= 27 182 0.7982456140350878
b= 27 183 0.8026315789473685
b= 27 184 0.8070175438596491
b= 27 185 0.8114035087719298
b= 27 186 0.8157894736842105
b= 27 187 0.8201754385964912
b= 27 188 0.8245614035087719
b= 27 189 0.8289473684210527
b= 27 190 0.8333333333333334
b= 27 191 0.8377192982456141
b= 27 192 0.8421052631578947
b= 27 193 0.8464912280701754
b= 27 194 0.8508771929824561
b= 27 195 0.8552631578947368
b= 27 196 0.8596491228070176
b= 27 197 0.8640350877192982

```

In []:

1	
---	--