In [5]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression,LinearRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix,classification_report

from sklearn.model_selection import train_test_split

import warnings
warnings.filterwarnings('ignore')
```

In [6]:

```
ds=pd.read_csv('salary_project.csv')
```

In [9]:

```
ds.head()
```

Out[9]:

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
0	Prof	B	19	18	Male	139750
1	Prof	B	20	16	Male	173200
2	AsstProf	B	4	3	Male	79750
3	Prof	B	45	39	Male	115000
4	Prof	B	40	41	Male	141500

In [11]:

```
ds.shape
```

Out[11]:

```
(397, 6)
```

In [13]:

```
ds.dtypes
```

Out[13]:

```
rank              object
discipline        object
yrs.since.phd      int64
yrs.service        int64
sex               object
salary             int64
dtype: object
```

In [14]:

```
ds.columns
```

Out[14]:

```
Index(['rank', 'discipline', 'yrs.since.phd', 'yrs.service', 'sex', 'salary'],
dtype='object')
```

In [16]:

```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 397 entries, 0 to 396
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   rank           397 non-null    object
 1   discipline     397 non-null    object
 2   yrs.since.phd  397 non-null    int64
 3   yrs.service    397 non-null    int64
 4   sex            397 non-null    object
 5   salary         397 non-null    int64
dtypes: int64(3), object(3)
memory usage: 18.7+ KB
```

In [17]:

```
ds.isnull().sum()
```

Out[17]:

```
rank             0
discipline       0
yrs.since.phd    0
yrs.service      0
sex              0
salary           0
dtype: int64
```

In [18]:

```
ds.describe()
```

Out[18]:

	yrs.since.phd	yrs.service	salary
count	397.000000	397.000000	397.000000
mean	22.314861	17.614610	113706.458438
std	12.887003	13.006024	30289.038695
min	1.000000	0.000000	57800.000000
25%	12.000000	7.000000	91000.000000
50%	21.000000	16.000000	107300.000000
75%	32.000000	27.000000	134185.000000
max	56.000000	60.000000	231545.000000

In [37]:

```
ds.loc[ds['salary']==' ']
```

Out[37]:

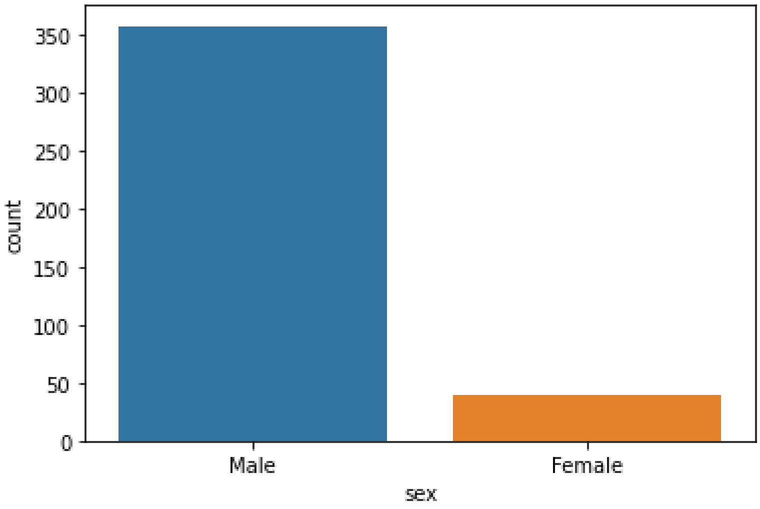
rank	discipline	yrs.since.phd	yrs.service	sex	salary

In [19]:

```
sns.countplot(x='sex',data=ds)
```

Out[19]:

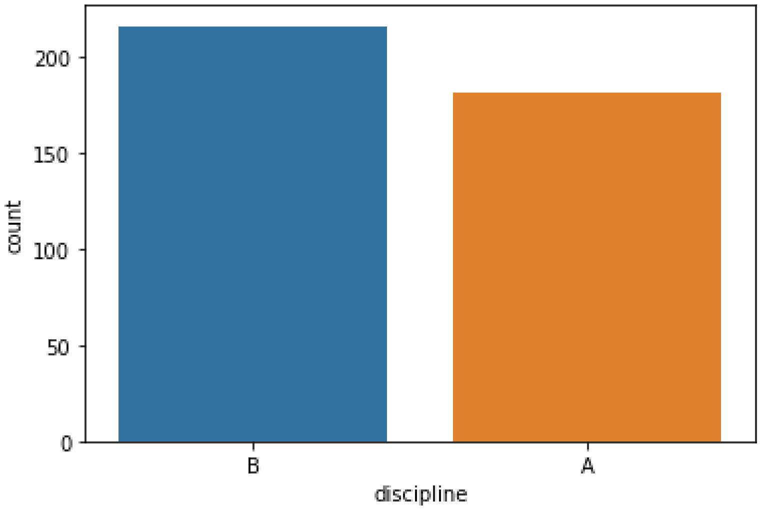
```
<AxesSubplot:xlabel='sex', ylabel='count'>
```



The gender in the data is not evenly distributed

In [25]:
```
sns.countplot(x='discipline',data=ds)
```

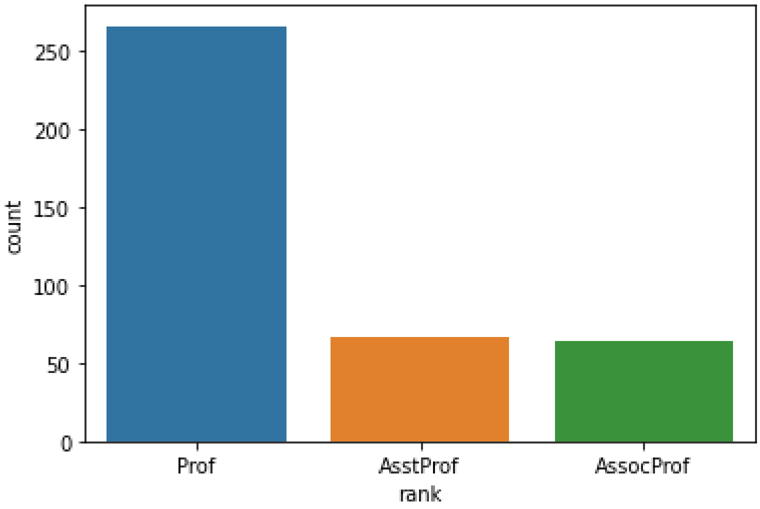
Out[25]:
```
<AxesSubplot:xlabel='discipline', ylabel='count'>
```



There is a fair distribution in discipline

In [26]:
```
sns.countplot(x='rank',data=ds)
```

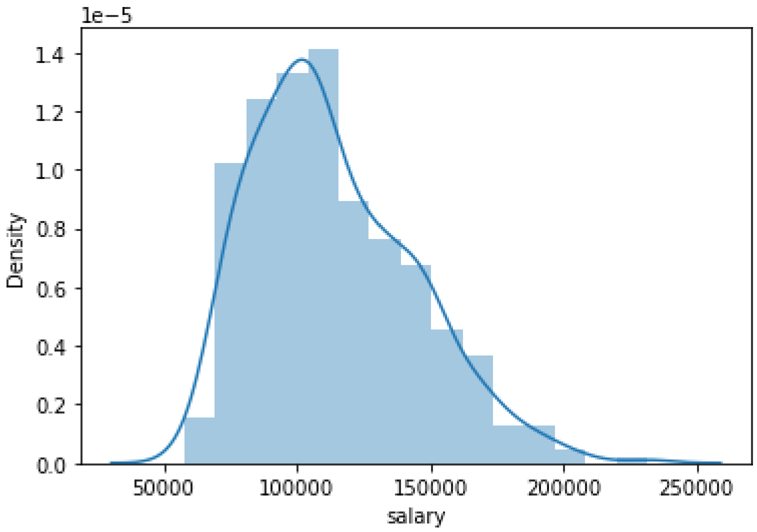
Out[26]:
```
<AxesSubplot:xlabel='rank', ylabel='count'>
```



The data has is heavily skewed in favor of professors as against assistant and associate professors

In [22]:
```
sns.distplot(ds['salary'])
```

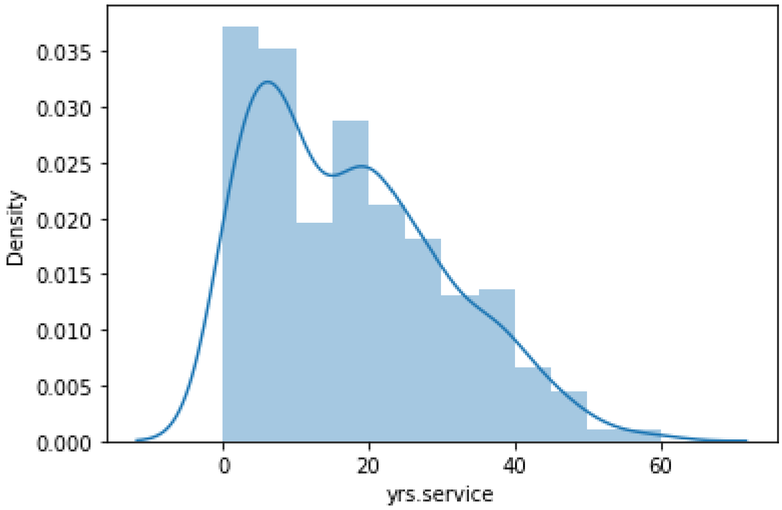
Out[22]:
```
<AxesSubplot:xlabel='salary', ylabel='Density'>
```



The data does not follow a fair distribution curve

In [23]:
```
sns.distplot(ds['yrs.service'])
```

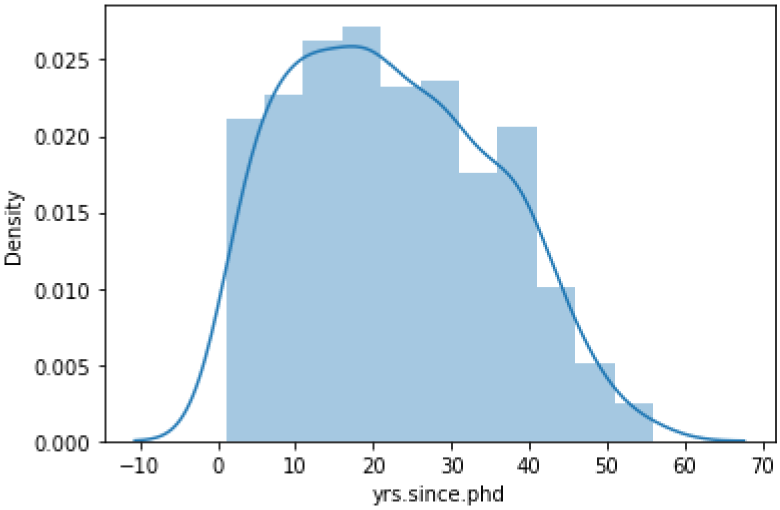
Out[23]:
```
<AxesSubplot:xlabel='yrs.service', ylabel='Density'>
```



The data is not fairly distrinuted

In [24]:
```
sns.distplot(ds['yrs.since.phd'])
```

Out[24]:
```
<AxesSubplot:xlabel='yrs.since.phd', ylabel='Density'>
```



The data seem well distributed

In [30]:

```
ds=pd.DataFrame(ds)
ds
```

Out[30]:

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
0	Prof	B	19	18	Male	139750
1	Prof	B	20	16	Male	173200
2	AsstProf	B	4	3	Male	79750
3	Prof	B	45	39	Male	115000
4	Prof	B	40	41	Male	141500
...	...	...	...	...	...	...
392	Prof	A	33	30	Male	103106
393	Prof	A	31	19	Male	150564
394	Prof	A	42	25	Male	101738
395	Prof	A	25	15	Male	95329
396	AsstProf	A	8	4	Male	81035

397 rows × 6 columns

In [38]:

```
from sklearn.preprocessing import OrdinalEncoder
enc=OrdinalEncoder()
```

In [39]:

```
for i in ds.columns:
    if ds[i].dtypes=='object':
        ds[i]=enc.fit_transform(ds[i].values.reshape(-1,1))
```

In [40]:

```
ds
```

Out[40]:

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
0	2.0	1.0	19	18	1.0	139750
1	2.0	1.0	20	16	1.0	173200

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
2	1.0	1.0	4	3	1.0	79750
3	2.0	1.0	45	39	1.0	115000
4	2.0	1.0	40	41	1.0	141500
...	...	...	...	...	...	...
392	2.0	0.0	33	30	1.0	103106
393	2.0	0.0	31	19	1.0	150564
394	2.0	0.0	42	25	1.0	101738
395	2.0	0.0	25	15	1.0	95329
396	1.0	0.0	8	4	1.0	81035

397 rows × 6 columns

```
In [42]: ds.dtypes
```

```
Out[42]: rank              float64
         discipline        float64
         yrs.since.phd       int64
         yrs.service         int64
         sex               float64
         salary              int64
         dtype: object
```

```
In [45]: ds.describe()
```

Out[45]:

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
count	397.000000	397.000000	397.000000	397.000000	397.000000	397.000000
mean	1.508816	0.544081	22.314861	17.614610	0.901763	113706.458438
std	0.757486	0.498682	12.887003	13.006024	0.298010	30289.038695
min	0.000000	0.000000	1.000000	0.000000	0.000000	57800.000000
25%	1.000000	0.000000	12.000000	7.000000	1.000000	91000.000000
50%	2.000000	1.000000	21.000000	16.000000	1.000000	107300.000000
75%	2.000000	1.000000	32.000000	27.000000	1.000000	134185.000000
max	2.000000	1.000000	56.000000	60.000000	1.000000	231545.000000

```
In [41]: ds.corr()
```

Out[41]:

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
rank	1.000000	-0.086266	0.525500	0.447499	0.132492	0.522207
discipline	-0.086266	1.000000	-0.218087	-0.164599	0.003724	0.156084
yrs.since.phd	0.525500	-0.218087	1.000000	0.909649	0.148788	0.419231
yrs.service	0.447499	-0.164599	0.909649	1.000000	0.153740	0.334745
sex	0.132492	0.003724	0.148788	0.153740	1.000000	0.138610

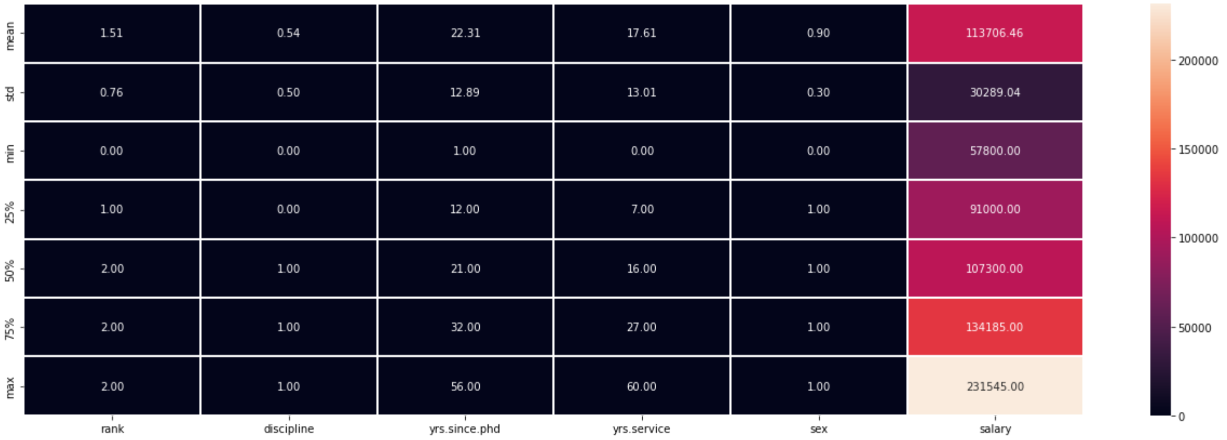
	rank	discipline	yrs.since.phd	yrs.service	sex	salary
salary	0.522207	0.156084	0.419231	0.334745	0.138610	1.000000

In [54]:

```
plt.figure(figsize=(22,7))
sns.heatmap(ds.describe()[1:],annot=True,linewidths=0.1,linecolor='white',fmt
```

Out[54]:

```
<AxesSubplot:>
```

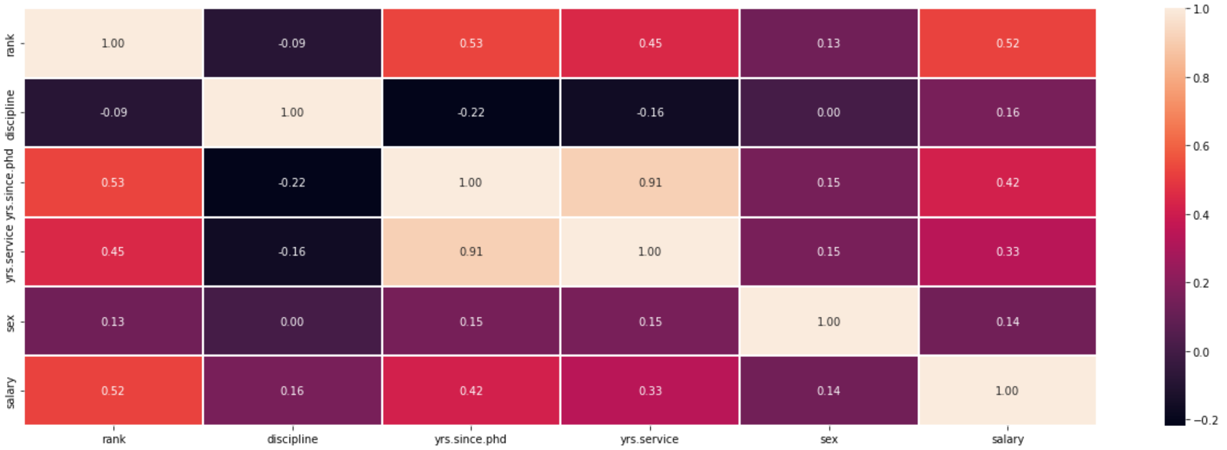


In [52]:

```
plt.figure(figsize=(22,7))
sns.heatmap(ds.corr(),annot=True,linewidths=0.1,linecolor='white',fmt='0.2f')
```

Out[52]:

```
<AxesSubplot:>
```



From the above, salary seems not to have a good correlation with the other variables. The correlation is seen to be lowest with sex and discipline.

In [55]:

```
# Correlation with the target column:
```

In [56]:

```
ds.corr()['salary'].sort_values()
```

Out[56]:

```
sex              0.138610
discipline       0.156084
yrs.service      0.334745
yrs.since.phd    0.419231
rank             0.522207
salary           1.000000
Name: salary, dtype: float64
```

In [58]:

```
ds.skew().sort_values(ascending=False)
```

Out[58]:

```
salary            0.714568
yrs.service       0.650569
yrs.since.phd     0.300880
discipline       -0.177684
rank             -1.151164
sex              -2.709958
dtype: float64
```

Keeping +/-0.65 as the range for skewness, here are the columns which does not lie within this range;

- salary
- rank
- sex

In [59]:

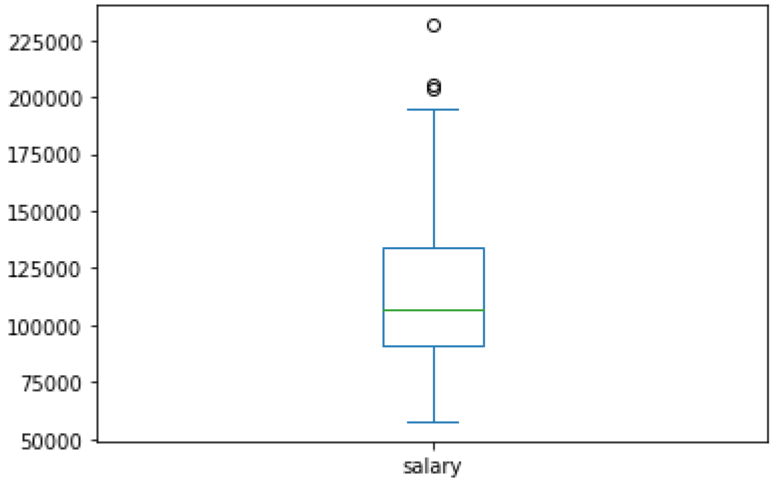
```
#Checking Outliers:
```

In [60]:

```
ds['salary'].plot.box()
```

Out[60]:

```
<AxesSubplot:>
```

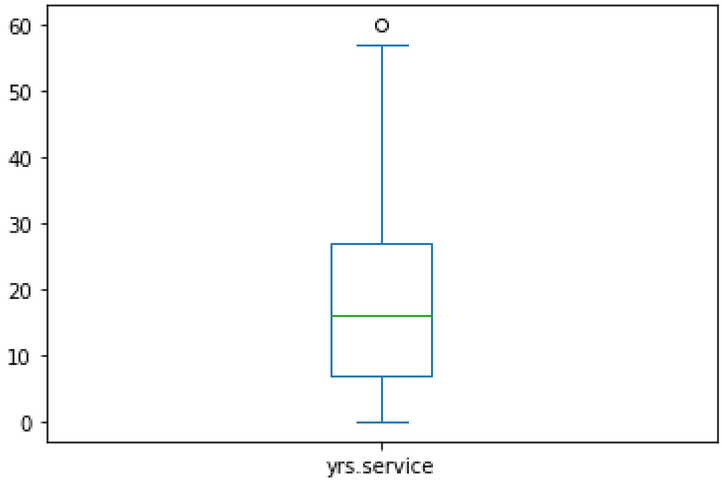


In [61]:

```
ds['yrs.service'].plot.box()
```

Out[61]:

```
<AxesSubplot:>
```

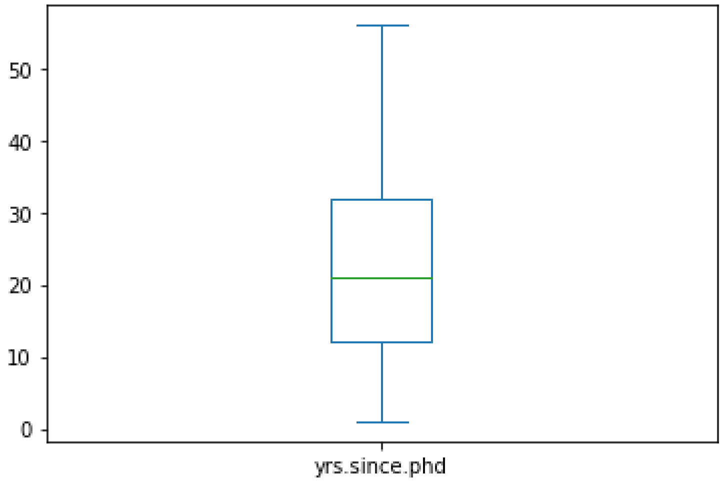


In [62]:

```
ds['yrs.since.phd'].plot.box()
```

Out[62]:

```
<AxesSubplot:>
```

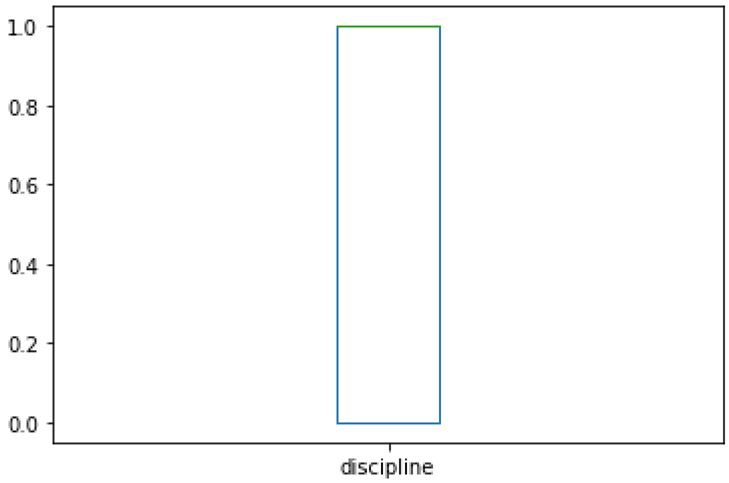


In [63]:

```
ds['discipline'].plot.box()
```

Out[63]:

```
<AxesSubplot:>
```

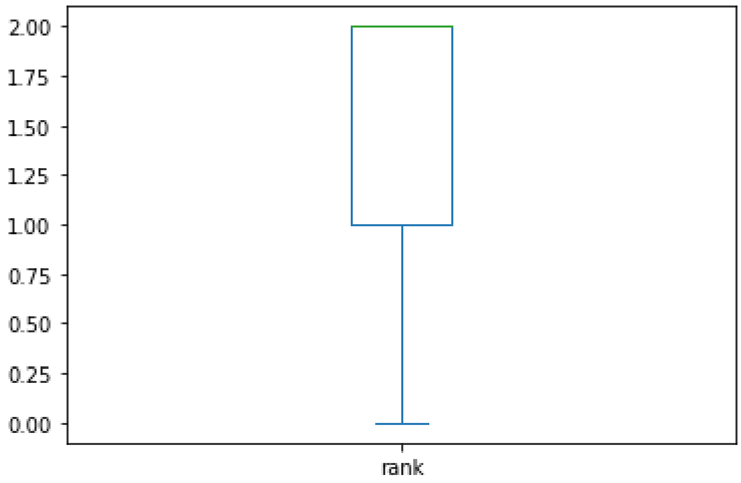


In [64]:

```
ds['rank'].plot.box()
```

Out[64]:

```
<AxesSubplot:>
```

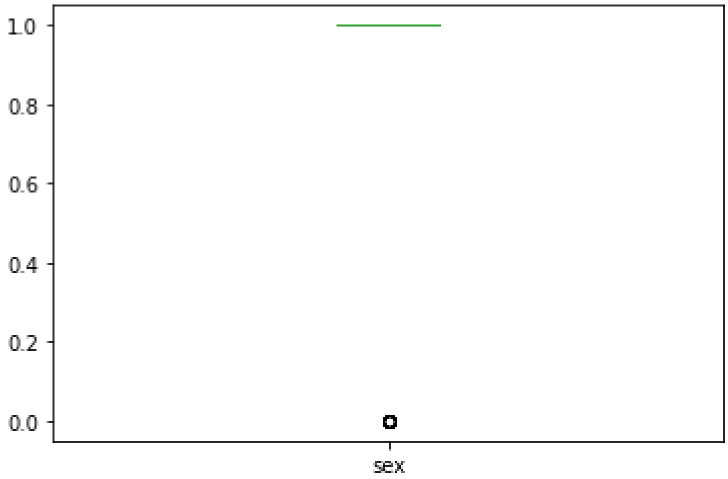


In [65]:

```
ds['sex'].plot.box()
```

Out[65]:

```
<AxesSubplot:>
```



In [66]:

```
ds.shape
```

Out[66]:

```
(397, 6)
```

In [67]:

```
#Removing Outliers:
```

In [69]:

```
from scipy.stats import zscore
import numpy as np
z=np.abs(zscore(ds))
threshold=3
np.where(z>3)
```

Out[69]:

```
(array([  9,  19,  24,  34,  35,  43,  47,  48,  52,  63,  68,  84,  90,
        103, 114, 119, 123, 127, 131, 132, 133, 148, 153, 179, 186, 218,
        230, 231, 233, 237, 245, 253, 254, 274, 316, 323, 330, 332, 334,
        341, 358, 361, 364]),
 array([4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4,
        4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 4, 4, 5]))
```

In [70]:

```
ds_new=ds[(z<3).all(axis=1)]
```

In [71]:

```
ds.shape
```

Out[71]:

```
(397, 6)
```

In [72]:

```
ds_new.shape
```

Out[72]:

```
(354, 6)
```

In [73]:

```
x=ds_new.iloc[:,0:-1]
```

In [74]:

```
x
```

Out[74]:

	rank	discipline	yrs.since.phd	yrs.service	sex

	rank	discipline	yrs.since.phd	yrs.service	sex
0	2.0	1.0	19	18	1.0
1	2.0	1.0	20	16	1.0
2	1.0	1.0	4	3	1.0
3	2.0	1.0	45	39	1.0
4	2.0	1.0	40	41	1.0
...	...	...	...	...	...
392	2.0	0.0	33	30	1.0
393	2.0	0.0	31	19	1.0
394	2.0	0.0	42	25	1.0
395	2.0	0.0	25	15	1.0
396	1.0	0.0	8	4	1.0

354 rows × 5 columns

In [75]:
```
y=ds_new.iloc[:,-1]
```

In [76]:
```
y
```

Out[76]:
```
0      139750
1      173200
2       79750
3      115000
4      141500
        ...  
392    103106
393    150564
394    101738
395     95329
396     81035
Name: salary, Length: 354, dtype: int64
```

In [77]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=20,random_state=
```

In [78]:
```
x_train.shape
```

Out[78]:
```
(334, 5)
```

In [79]:
```
x_test.shape
```

Out[79]:
```
(20, 5)
```

In [80]:
```
y_train.shape
```

Out[80]:
```
(334,)
```

In [81]:
```
y_test.shape
```

```
Out[81]: (20,)
```

```
In [82]: lr=LinearRegression()
```

```
In [83]: lr.fit(x_train,y_train)
```

```
Out[83]: LinearRegression()
```

```
In [84]: ds.columns
```

```
Out[84]: Index(['rank', 'discipline', 'yrs.since.phd', 'yrs.service', 'sex', 'salary'],
dtype='object')
```

```
In [85]: pred=lr.predict(x_test)
         print('Predicted Salary: ',pred)
         print('Actual Salary: ',y_test)
```

```
Predicted Salary:  [119800.41922748 117784.53516541 122164.23129701  89609.339
37947
 117961.82571662 126641.2874388  126111.94560093 115680.00582773
 100657.20462655 124007.41626325 131552.85522404 105566.24259602
 113659.53031027 104338.98310365 118839.09556194 117695.8898898
 122688.9816795  103788.60453441 123130.14641794  88361.5113319 ]
Actual Salary:  22      93904
305    111350
85     132825
376     74856
113    104279
238     77202
320    104428
116    148500
61      75243
155    118971
4      141500
11      79800
110    112429
83      88825
250    109000
105    113543
235     81700
162     98510
44      94384
54     103760
Name: salary, dtype: int64
```

```
In [ ]:
```