In [1]:

```python
from pandas import read_csv
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
import warnings
from sklearn.metrics import accuracy_score
warnings.filterwarnings('ignore')
```

In [2]:

```python
train = pd.read_csv('/Users/SAURABH/Saurabh patil/DATA SCIENCE/Forecasting/SalaryData_Train(1).csv')
train
```

Out[2]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
30156	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
30157	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
30158	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
30159	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=50K
30160	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

30161 rows × 14 columns

In [3]:

```python
test = pd.read_csv('/Users/SAURABH/Saurabh patil/DATA SCIENCE/Forecasting/SalaryData_test(1).csv')
test
```

Out[3]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
15055	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	40	United-States	<=50K
15056	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	United-States	<=50K
15057	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	United-States	<=50K
15058	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	United-States	<=50K
15059	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	United-States	>50K

15060 rows × 14 columns

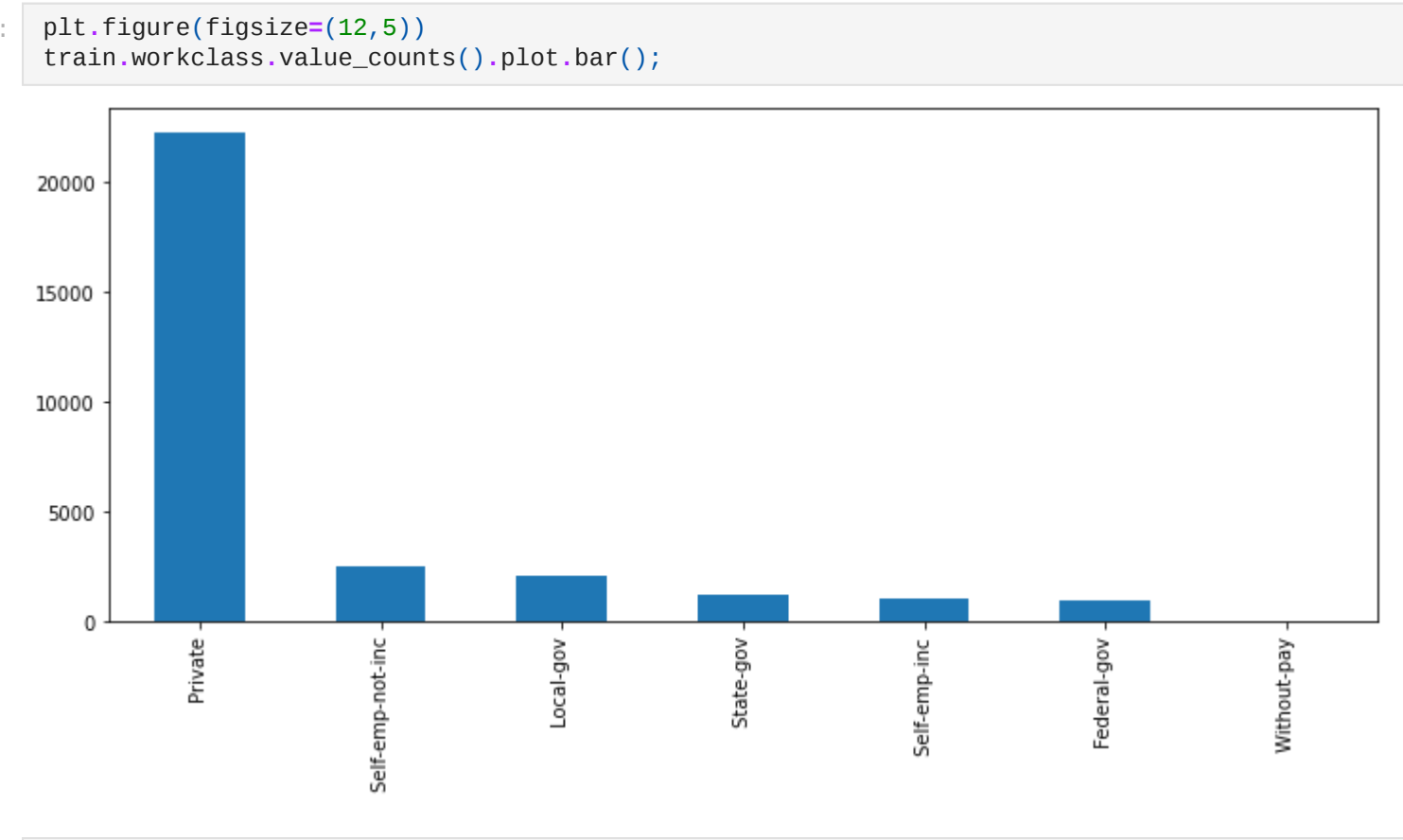
In [4]:

```python
#Checking for null values & data types
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            30161 non-null  int64 
 1   workclass      30161 non-null  object
 2   education      30161 non-null  object
 3   educationno    30161 non-null  int64 
 4   maritalstatus  30161 non-null  object
 5   occupation     30161 non-null  object
 6   relationship   30161 non-null  object
 7   race           30161 non-null  object
 8   sex            30161 non-null  object
 9   capitalgain    30161 non-null  int64 
 10  capitalloss    30161 non-null  int64 
 11  hoursperweek   30161 non-null  int64 
 12  native         30161 non-null  object
 13  Salary         30161 non-null  object
dtypes: int64(5), object(9)
memory usage: 2.2+ MB
```

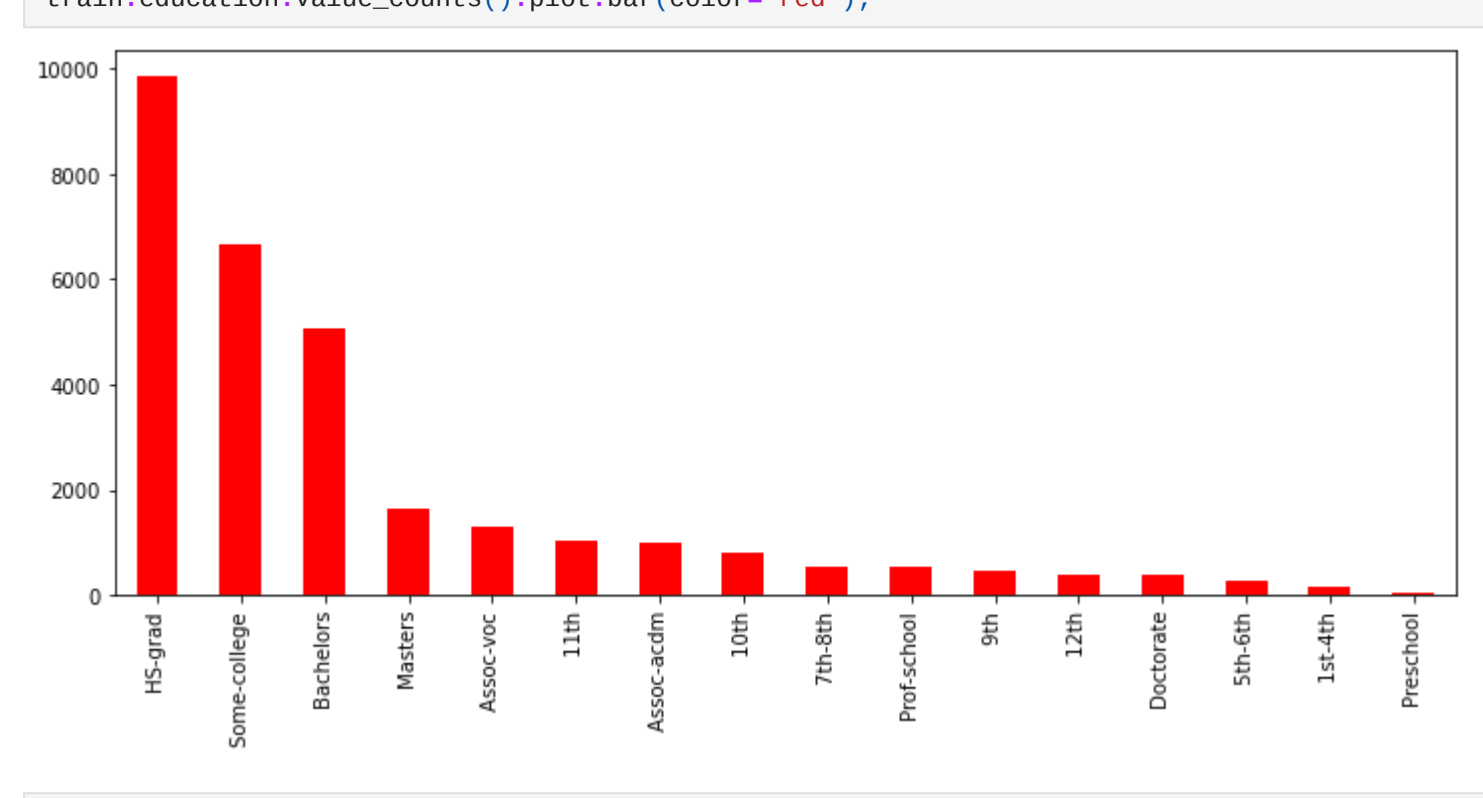
In [5]:

```python
plt.figure(figsize=(12,5))
train.workclass.value_counts().plot.bar();
```



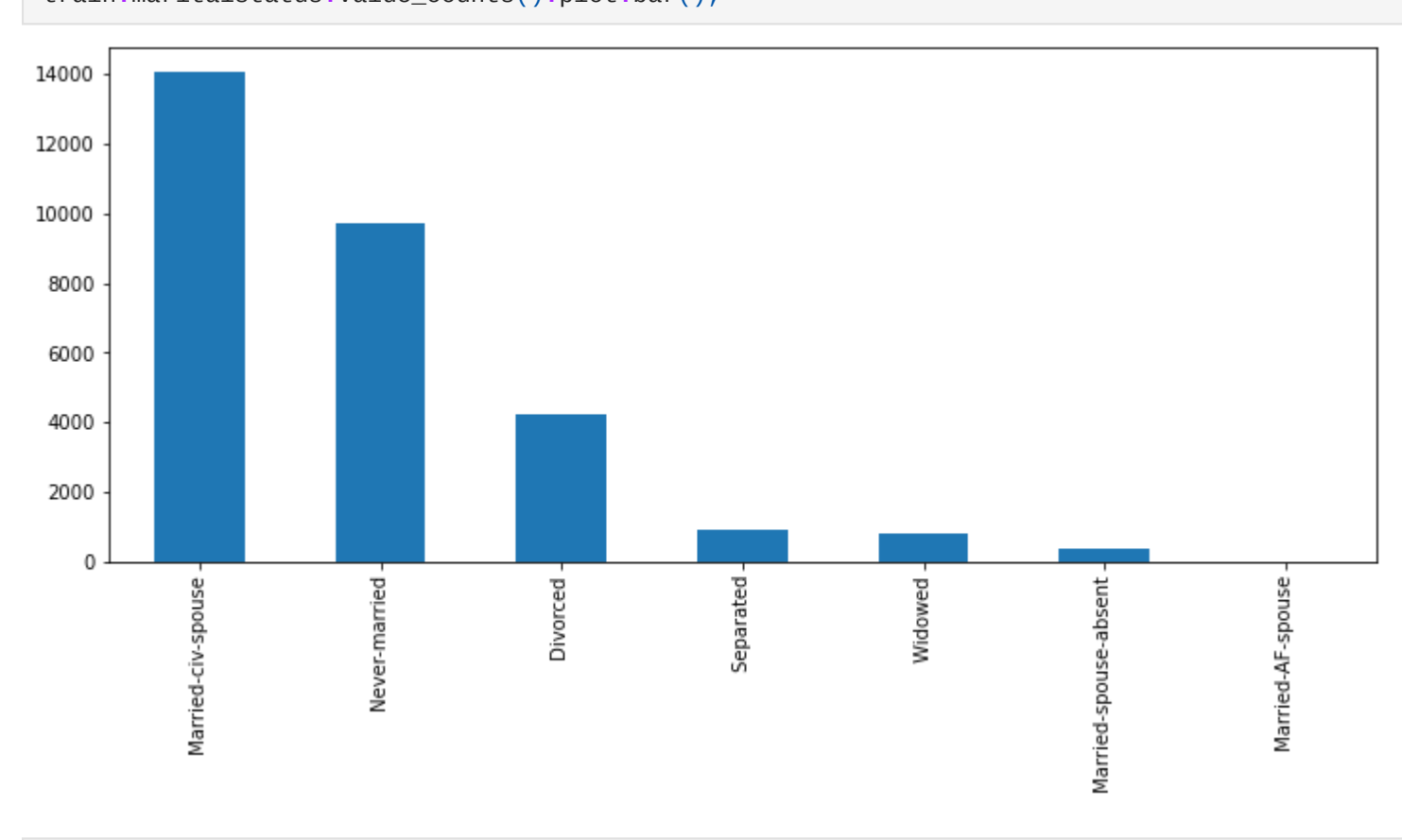
In [6]:

```python
plt.figure(figsize=(12,5))
train.education.value_counts().plot.bar(color='red');
```



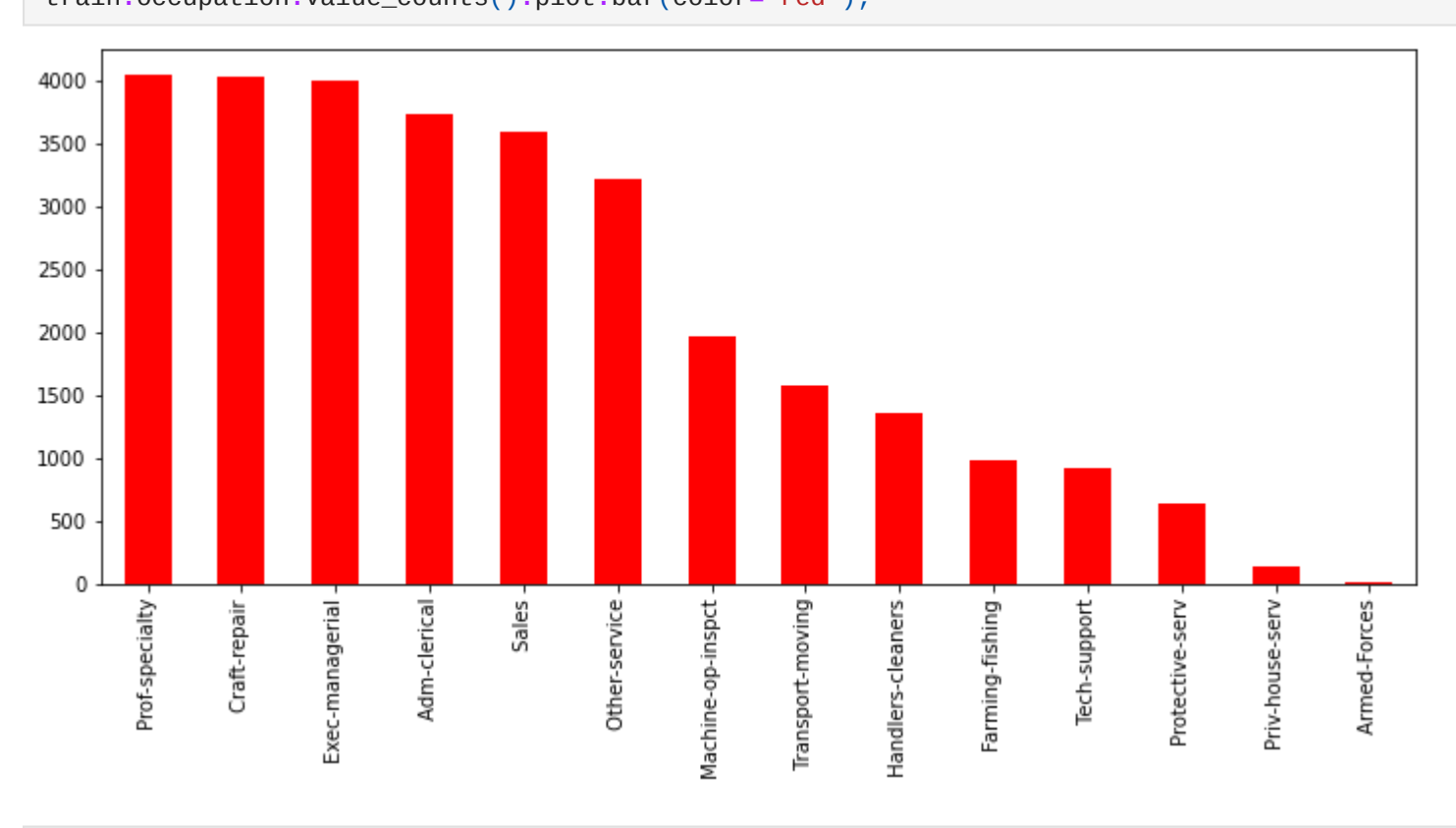
In [7]:

```python
plt.figure(figsize=(12,5))
train.maritalstatus.value_counts().plot.bar();
```



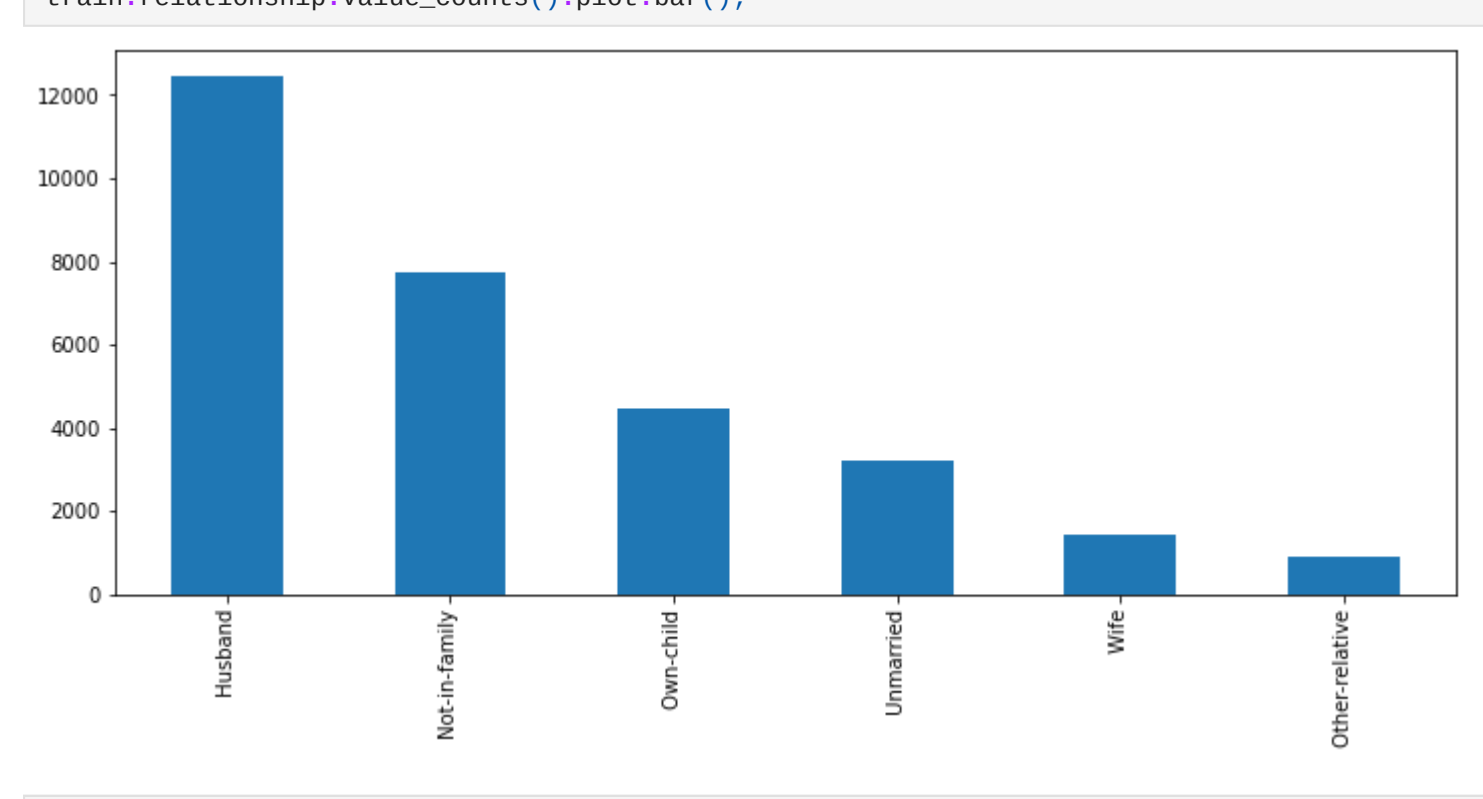
In [8]:

```python
plt.figure(figsize=(12,5))
train.occupation.value_counts().plot.bar(color='red');
```



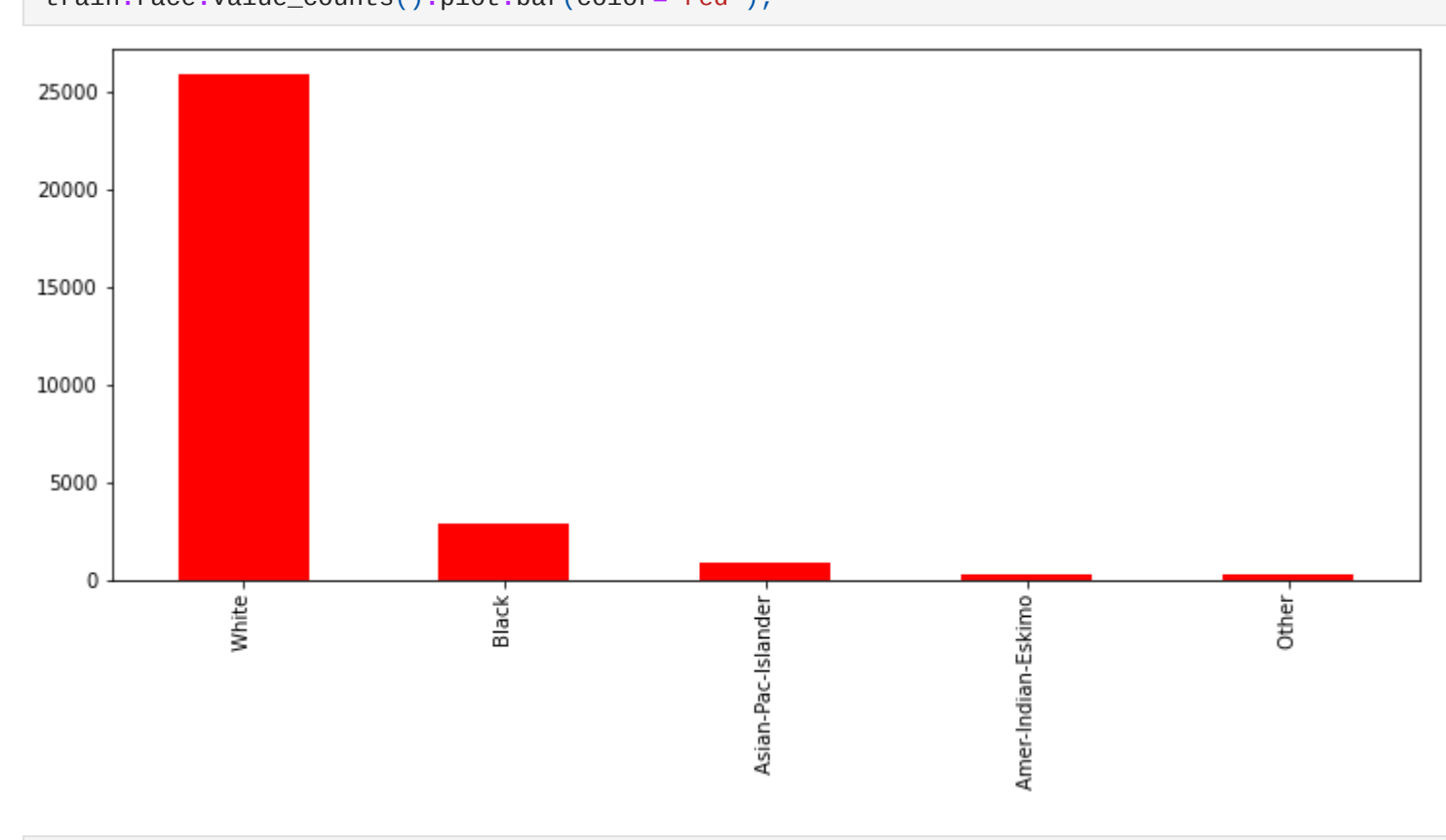
In [9]:

```python
plt.figure(figsize=(12,5))
train.relationship.value_counts().plot.bar();
```



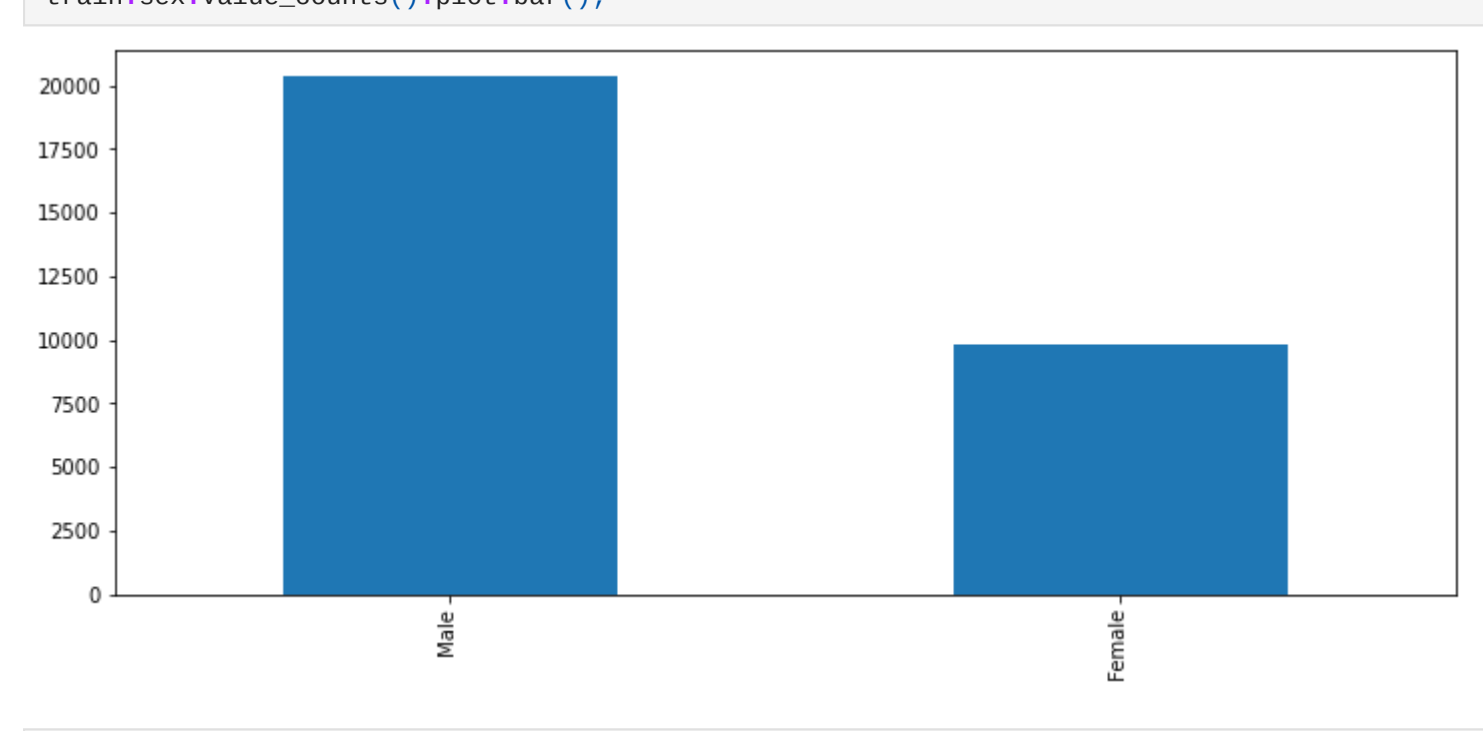
In [10]:

```python
plt.figure(figsize=(12,5))
train.race.value_counts().plot.bar(color='red');
```



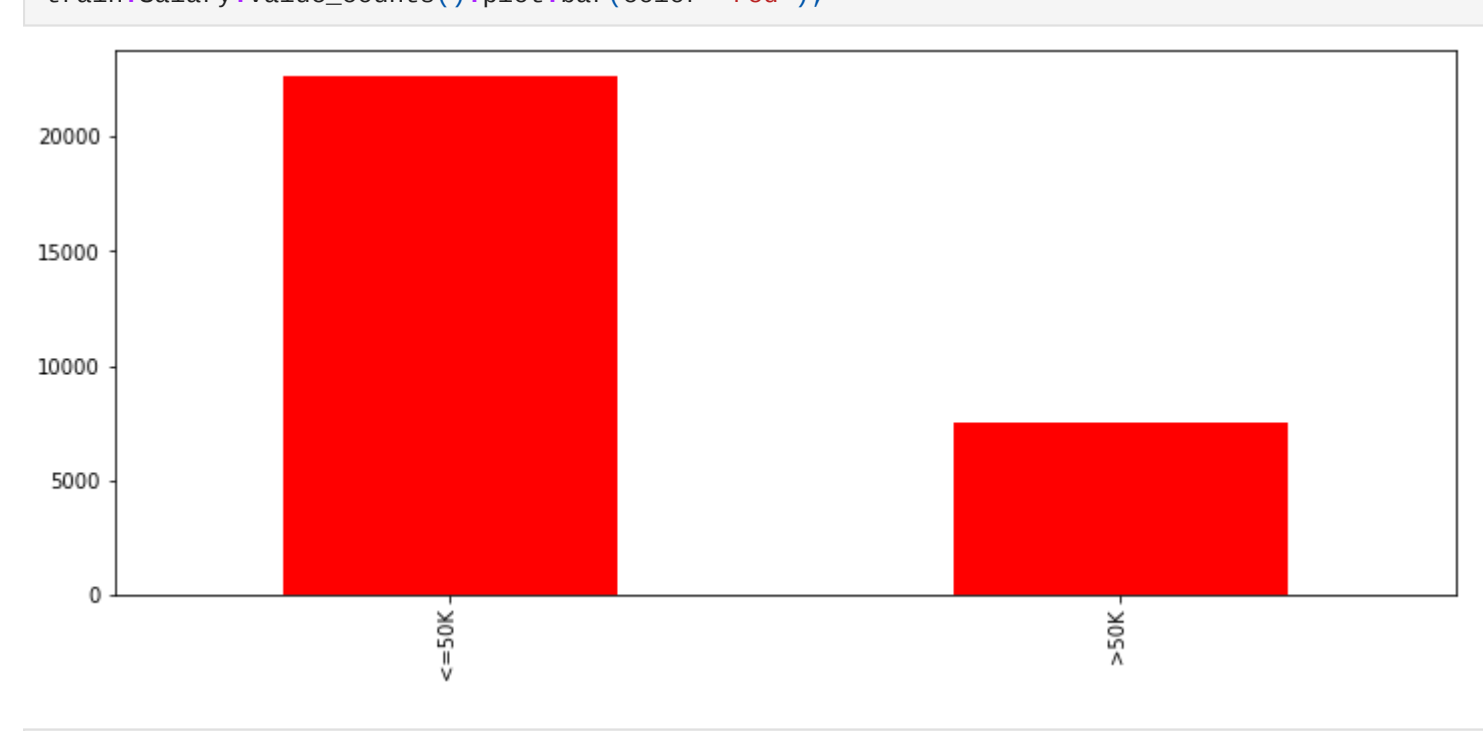
In [11]:

```python
plt.figure(figsize=(12,5))
train.sex.value_counts().plot.bar();
```



In [12]:

```python
plt.figure(figsize=(12,5))
train.Salary.value_counts().plot.bar(color='red');
```



In [14]:

```python
train1 = train.iloc[:,0:13]

train1 = pd.get_dummies(train1)
train1
```

Out[14]:

	age	educationno	capitalgain	capitalloss	hoursperweek	workclass_ Federal-gov	workclass_ Local-gov	workclass_ Private	workclass_ Self-emp-inc	workclass_ Self-emp-not-inc	...	native_ Portugal	native_ Puerto-Rico	native_ Scotland	native_ South	native_ Taiwan	native_ Thailand	na Trinadad&To
0	39	13	2174	0	40	0	0	0	0	0	...	0	0	0	0	0	0	
1	50	13	0	0	13	0	0	0	0	1	...	0	0	0	0	0	0	
2	38	9	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
3	53	7	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
4	28	13	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
30156	27	12	0	0	38	0	0	1	0	0	...	0	0	0	0	0	0	
30157	40	9	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
30158	58	9	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
30159	22	9	0	0	20	0	0	1	0	0	...	0	0	0	0	0	0	
30160	52	9	15024	0	40	0	0	0	1	0	...	0	0	0	0	0	0	

30161 rows × 102 columns

In [15]:

```python
test1 = test.iloc[:,0:13]

test1 = pd.get_dummies(test1)
test1
```

Out[15]:

	age	educationno	capitalgain	capitalloss	hoursperweek	workclass_ Federal-gov	workclass_ Local-gov	workclass_ Private	workclass_ Self-emp-inc	workclass_ Self-emp-not-inc	...	native_ Portugal	native_ Puerto-Rico	native_ Scotland	native_ South	native_ Taiwan	native_ Thailand	na Trinadad&To
0	25	7	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
1	38	9	0	0	50	0	0	1	0	0	...	0	0	0	0	0	0	
2	28	12	0	0	40	0	1	0	0	0	...	0	0	0	0	0	0	
3	44	10	7688	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
4	34	6	0	0	30	0	0	1	0	0	...	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
15055	33	13	0	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
15056	39	13	0	0	36	0	0	1	0	0	...	0	0	0	0	0	0	
15057	38	13	0	0	50	0	0	1	0	0	...	0	0	0	0	0	0	
15058	44	13	5455	0	40	0	0	1	0	0	...	0	0	0	0	0	0	
15059	35	13	0	0	60	0	0	0	1	0	...	0	0	0	0	0	0	

15060 rows × 102 columns

Since number of columns are more, let's use PCA

In [16]:

```python
#Scaling the data

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

sc.fit(train1)
train_norm = sc.transform(train1)
train_norm                     #Normalised dataset
```

Out[16]:

```
array([[ 0.04277892,  1.12889813,  0.14608503, ...,  0.31081205,
        -0.04611353, -0.0230384 ],
       [ 0.88026081,  1.12889813, -0.14744712, ...,  0.31081205,
        -0.04611353, -0.0230384 ],
       [-0.0333558 , -0.4397325 , -0.14744712, ...,  0.31081205,
        -0.04611353, -0.0230384 ],
       ...,
       [ 1.48933854, -0.4397325 , -0.14744712, ...,  0.31081205,
        -0.04611353, -0.0230384 ],
       [-1.25151126, -0.4397325 , -0.14744712, ...,  0.31081205,
        -0.04611353, -0.0230384 ],
       [ 1.03253024, -0.4397325 ,  1.88108414, ...,  0.31081205,
        -0.04611353, -0.0230384 ]])
```

In [17]:

```python
#Scaling the data

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

sc.fit(test1)
test_norm = sc.transform(test1)
test_norm                     #Normalised dataset
```

Out[17]:

```
array([[-1.02900513, -1.2165628 , -0.14543845, ...,  0.30373366,
        -0.03554172, -0.02156441],
       [-0.05742253, -0.43489824, -0.14543845, ...,  0.30373366,
        -0.03554172, -0.02156441],
       [-0.80479376,  0.73759862, -0.14543845, ...,  0.30373366,
        -0.03554172, -0.02156441],
       ...,
       [-0.05742253,  1.1284309 , -0.14543845, ...,  0.30373366,
        -0.03554172, -0.02156441],
       [ 0.39100021,  1.1284309 ,  0.562734  , ...,  0.30373366,
        -0.03554172, -0.02156441],
       [-0.2816339 ,  1.1284309 , -0.14543845, ...,  0.30373366,
        -0.03554172, -0.02156441]])
```

In [18]:

```python
from sklearn.decomposition import PCA

train_pca = PCA(n_components = 102)
train_pca_values = train_pca.fit_transform(train_norm)
train_pca_values
```

Out[18]:

```
array([[-5.50838008e-01, -2.38164986e+00, -5.91921169e-01, ...,
         1.98192284e-15, -1.50196153e-15, -7.30126458e-16],
       [ 2.81915829e+00, -1.37085459e+00, -4.81126421e-02, ...,
         8.82338243e-15,  1.14590083e-15, -1.01199274e-16],
       [-7.93831525e-01,  8.71803957e-01, -1.20213150e+00, ...,
         3.53912850e-15,  1.84468024e-15, -8.83012194e-17],
       ...,
       [-2.37835145e+00, -7.98690413e-01,  3.39105780e-01, ...,
        -1.02601066e-17, -5.84665906e-17,  3.86829768e-17],
       [-1.97547719e+00,  1.19305162e+00, -1.82899406e+00, ...,
        -9.59259949e-17,  8.22882930e-17, -2.13795590e-17],
       [ 7.62131786e-01, -1.77200870e+00,  5.36971989e-01, ...,
         1.00544222e-15,  1.69243804e-16, -2.19423520e-16]])
```

In [19]:

```python
from sklearn.decomposition import PCA

test_pca = PCA(n_components = 102)
test_pca_values = test_pca.fit_transform(test_norm)
test_pca_values
```

Out[19]:

```
array([[-2.24293780e+00,  2.60318091e+00, -3.27616503e-01, ...,
         2.22865956e-15, -1.93441853e-16, -1.40523811e-15],
       [ 2.22690391e+00,  1.59471521e+00, -7.32082794e-01, ...,
         1.57312732e-14, -5.28900647e-15, -6.51646966e-16],
       [ 2.30704416e+00, -1.16883181e+00, -2.00521481e-01, ...,
         2.21130876e-15, -1.35451566e-15, -1.66172696e-16],
       ...,
       [ 2.39583218e+00, -1.46859740e+00, -2.09424792e-01, ...,
         1.19081856e-16, -4.65121998e-17, -3.92763648e-17],
       [-1.14039506e+00, -1.03678137e+00,  2.58079490e+00, ...,
        -6.75359491e-17,  5.15886796e-17,  8.24715591e-17],
       [ 3.38445120e+00, -1.95481575e+00, -1.72791531e-01, ...,
         9.74504929e-17,  2.53899703e-17, -1.56758340e-17]])
```

In [20]:

```python
# The amount of variance that each PCA explains is
var = train_pca.explained_variance_ratio_
var
```

Out[20]:

```
array([4.47952203e-02, 3.03018755e-02, 2.56772664e-02, 2.30740938e-02,
       1.90544461e-02, 1.75159608e-02, 1.66112958e-02, 1.51765356e-02,
       1.40918479e-02, 1.37139289e-02, 1.30161578e-02, 1.27145892e-02,
       1.22845420e-02, 1.20633855e-02, 1.19277829e-02, 1.17776199e-02,
       1.15732784e-02, 1.14595050e-02, 1.12290572e-02, 1.10955712e-02,
       1.09763472e-02, 1.09664173e-02, 1.08013630e-02, 1.07163253e-02,
       1.06965233e-02, 1.06243926e-02, 1.05150466e-02, 1.04401201e-02,
       1.04195534e-02, 1.03772631e-02, 1.02585913e-02, 1.02518285e-02,
       1.02343018e-02, 1.02011311e-02, 1.01746044e-02, 1.00893885e-02,
       1.00693090e-02, 1.00007488e-02, 9.97967518e-03, 9.93621541e-03,
       9.91132587e-03, 9.87257873e-03, 9.85864172e-03, 9.85346688e-03,
       9.83507641e-03, 9.82654639e-03, 9.82141035e-03, 9.81950938e-03,
       9.81361594e-03, 9.80760489e-03, 9.80531422e-03, 9.80056163e-03,
       9.79178710e-03, 9.77352236e-03, 9.77198782e-03, 9.75826765e-03,
       9.72396821e-03, 9.71129292e-03, 9.68894621e-03, 9.68294717e-03,
       9.66009263e-03, 9.63768491e-03, 9.62281079e-03, 9.58462673e-03,
       9.56141726e-03, 9.52463771e-03, 9.42925368e-03, 9.41301408e-03,
       9.36144053e-03, 9.30687373e-03, 9.28398704e-03, 9.11455862e-03,
       9.07861857e-03, 9.01571083e-03, 8.94583330e-03, 8.83778340e-03,
       8.72770250e-03, 8.59927945e-03, 8.45704067e-03, 8.40278797e-03,
       8.31065450e-03, 7.87100230e-03, 7.65417979e-03, 7.17339353e-03,
       7.15472018e-03, 6.46609230e-03, 6.11577048e-03, 5.95158857e-03,
       5.31995594e-03, 4.76166961e-03, 4.27250537e-03, 2.37624831e-03,
       1.95586706e-04, 4.46131361e-32, 2.23683176e-32, 1.45808620e-32,
       8.35283580e-33, 8.27375302e-33, 7.32353682e-33, 4.67062116e-33,
       2.40856401e-33, 1.54366455e-34])
```

In [21]:

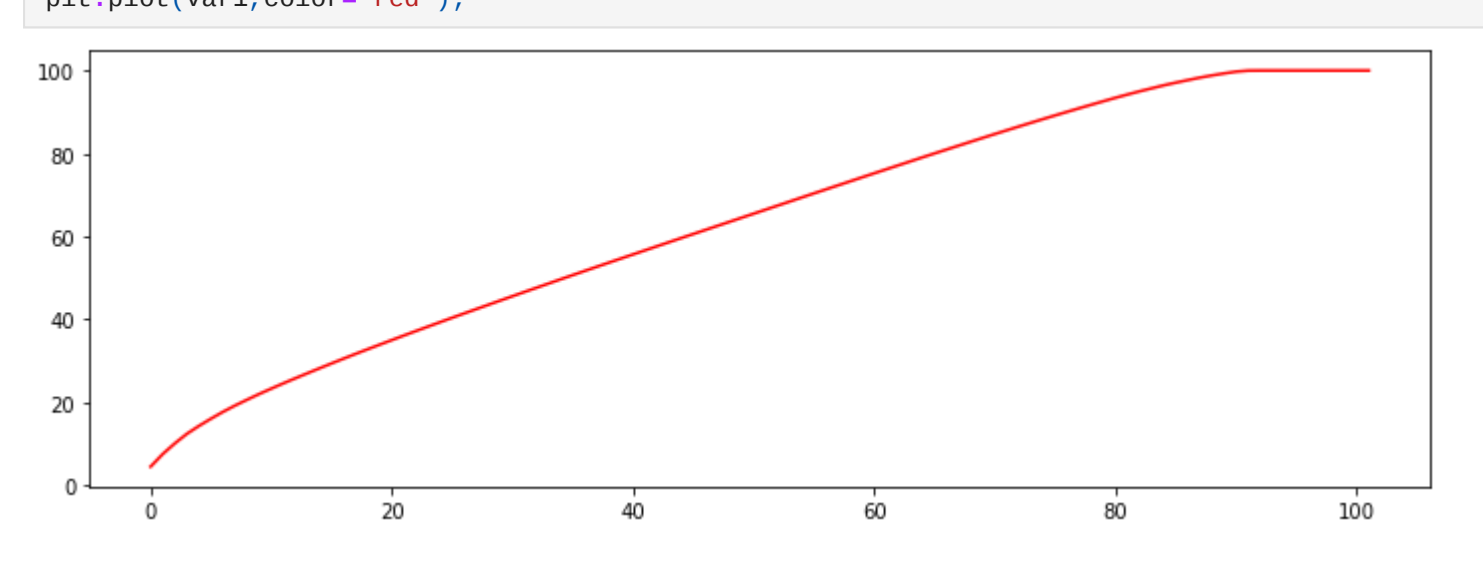
```python
# Cumulative variance
var1 = np.cumsum(np.round(var,decimals = 4)*100)
var1
```

Out[21]:

```
array([  4.48,   7.51,  10.08,  12.39,  14.3 ,  16.05,  17.71,  19.23,
        20.64,  22.01,  23.31,  24.58,  25.81,  27.02,  28.21,  29.39,
        30.55,  31.7 ,  32.82,  33.93,  35.03,  36.13,  37.21,  38.28,
        39.35,  40.41,  41.46,  42.5 ,  43.54,  44.58,  45.61,  46.64,
        47.66,  48.68,  49.7 ,  50.71,  51.72,  52.72,  53.72,  54.71,
        55.7 ,  56.69,  57.68,  58.67,  59.65,  60.63,  61.61,  62.59,
        63.57,  64.55,  65.53,  66.51,  67.49,  68.47,  69.45,  70.43,
        71.4 ,  72.37,  73.34,  74.31,  75.28,  76.24,  77.2 ,  78.16,
        79.12,  80.07,  81.01,  81.95,  82.89,  83.82,  84.75,  85.66,
        86.57,  87.47,  88.36,  89.24,  90.11,  90.97,  91.82,  92.66,
        93.49,  94.28,  95.05,  95.77,  96.49,  97.14,  97.75,  98.35,
        98.88,  99.36,  99.79, 100.03, 100.05, 100.05, 100.05, 100.05,
       100.05, 100.05, 100.05, 100.05, 100.05, 100.05])
```

In [22]:

```python
# Variance plot for PCA components obtained
plt.figure(figsize=(12,4))
plt.plot(var1,color="red");
```



Selecting first 90 PCAs out of total 102

In [23]:

```python
finaltrain = pd.concat([pd.DataFrame(train_pca_values[:,0:90]),
                     train[['Salary']]], axis = 1)
finaltrain
```

Out[23]:

	0	1	2	3	4	5	6	7	8	9	...	81	82	83	84	85	86	87	
0	-0.550838	-2.381650	-0.591921	1.433211	0.340516	1.940931	-0.055056	0.515267	-0.603118	-1.349744	...	0.925827	0.366843	0.762292	0.955908	-0.431471	-0.253518	-0.090683	1.44
1	2.819158	-1.370855	-0.048113	0.060772	0.148609	0.494097	0.971070	0.977166	-1.058340	1.543212	...	1.715245	-0.684681	0.173783	-1.120804	1.043838	-1.127099	0.538383	-0.17
2	-0.793832	0.871804	-1.202131	-0.513685	0.452004	0.675599	-2.665003	0.041210	0.966047	-0.942719	...	0.666397	-0.126942	-0.368158	0.399572	0.094164	-0.001750	-0.622668	0.11
3	0.732942	2.502494	0.763990	-0.149514	-3.056486	0.166519	0.140931	-2.430582	0.155941	1.066790	...	0.058897	0.409911	0.952768	0.193645	0.292208	0.033568	-0.226799	-0.77
4	-1.070350	-1.638424	4.542395	0.260940	0.650488	-2.473710	2.483233	-2.795740	-0.249688	1.001833	...	-1.388747	0.857151	-1.132278	0.924125	0.087501	-0.409813	-0.711475	0.56
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
30156	-0.766825	-1.596732	-0.037113	-0.576608	0.331904	-3.490439	2.320920	-0.117277	-0.388185	-1.112954	...	-0.680328	0.177364	-0.265304	-0.170305	0.307492	-0.087299	-0.407937	1.07
30157	1.704432	1.785328	-0.594925	-0.692498	-0.411458	-1.251061	-0.505186	-0.513443	1.286209	-0.530841	...	0.603116	-0.279650	0.035936	0.532717	-0.070438	-0.160400	0.100112	-0.12
30158	-2.378351	-0.798690	0.339106	-4.067833	0.281604	-1.215646	-0.253538	1.090962	0.960431	0.065679	...	-1.205160	0.177494	0.668585	0.528450	0.580482	0.156868	-0.442096	0.75
30159	-1.975477	1.193052	-1.828994	1.598638	-0.633416	-0.187607	0.789310	0.860548	0.808205	-0.906124	...	1.329776	-0.312235	0.180269	-1.124998	0.500770	-0.047237	-0.227867	0.99
30160	0.762132	-1.772009	0.536972	-2.417460	0.352371	-1.720856	2.466035	1.201089	0.049580	2.336657	...	-0.101924	-0.081743	-1.601187	-0.338971	0.643763	-0.635779	0.200448	0.64

30161 rows × 91 columns

In [24]:

```python
finaltest = pd.concat([pd.DataFrame(test_pca_values[:,0:90]),
                     test[['Salary']]], axis = 1)
finaltest
```

Out[24]:

	0	1	2	3	4	5	6	7	8	9	...	81	82	83	84	85	86	87	
0	-2.242938	2.603181	-0.327617	2.062024	-3.245808	0.812560	-0.442784	-1.685650	0.924250	1.891991	...	0.322344	-0.266021	0.252272	-0.426056	0.051791	0.853665	-0.773508	0.46
1	2.226904	1.594715	-0.732083	-0.582928	0.054350	0.429844	-0.039662	1.000275	0.209847	0.679798	...	-1.039511	0.061724	-0.355513	1.642111	-1.653340	-0.382266	-0.152825	-0.39
2	2.307044	-1.168832	-0.200521	0.097952	-1.635067	2.571033	1.024094	-0.651146	-1.099703	-3.652572	...	-0.314783	0.077195	-0.472801	0.653684	1.100821	-0.205823	0.020513	-0.19
3	1.080755	1.260533	0.937857	-0.024262	-3.174398	-0.970844	-0.340336	-1.973938	-0.711191	1.075373	...	0.651033	0.491425	0.776518	0.289192	0.192050	-0.267516	-0.415089	-0.48
4	-1.759546	1.778058	-1.256430	0.402017	0.646302	1.112461	-0.656860	0.304387	1.071483	0.751177	...	-0.341200	0.427165	0.069133	-0.864467	0.492786	-0.925634	0.280922	0.99
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
15055	-0.603437	-1.380653	-1.217944	3.023232	0.463631	0.320846	0.117746	-0.907320	1.101617	0.372391	...	-0.188856	0.102889	0.003352	0.969400	0.325052	1.506765	-0.047672	0.31
15056	-1.670443	-3.020764	0.059822	-0.326201	1.744026	-0.876546	-1.136618	-0.761872	0.720123	-0.079865	...	-0.158983	0.387623	-0.149291	0.919562	0.137806	0.821065	-0.053937	-1.40
15057	2.395832	-1.468597	-0.209425	1.122402	0.364606	-0.944486	0.190120	-1.382649	0.773748	0.171544	...	-0.488672	-0.211695	0.427440	0.216012	0.330597	0.638795	0.215296	-0.53
15058	-1.140395	-1.036781	2.580795	2.251643	-1.495169	-1.684794	-0.913144	2.031935	-0.905050	-0.245674	...	1.018273	2.174690	-0.425788	0.167408	0.560413	2.514837	-0.992345	1.51
15059	3.384451	-1.954816	-0.172792	0.603588	0.377618	0.007115	-0.009551	-0.042785	-1.856118	1.845860	...	-0.667836	-0.282967	-0.036093	-0.108368	1.204187	0.330331	-0.194209	-0.17

15060 rows × 91 columns

In [25]:

```python
#Since the training dataset is huge, we'll use some part of it for the training purpose, to reduce time consumed.
array = finaltrain.values
X = array[0:1000,0:90]
Y = array[0:1000,90]
```

Since the training and test datasets are separately given in the problem, so we'll use them separately for model validation

SVM Classification

Let's use Grid search CV to find out best value for params

In [26]:

```python
# SVM Classification
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report


from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split, cross_val_score
```

In [27]:

```python
clf = SVC()
param_grid = [{'kernel':['rbf'],'gamma':[0.9,0.5,0.1],'C':[1,10,100] },
             {'kernel':['linear'],'C':[1,10,100]}]
gsv = GridSearchCV(clf,param_grid,cv=10,n_jobs=-1)
gsv.fit(X,Y)

gsv.best_params_ , gsv.best_score_
```

Out[27]:

```
({'C': 10, 'kernel': 'linear'}, 0.8220000000000001)
```

In [28]:

```python
#Since the testing dataset is huge, we'll use some part of it for the test purpose, to reduce the time consumed.
x = finaltest.values[0:1000,0:90]
y = finaltest.values[0:1000,90]
```

In [29]:

```python
#SVM Clasification
clf = SVC(C=10, kernel='linear')
clf.fit(x,y)
results = clf.score(x,y)
print(np.round(results, 4))
```

```
0.846
```

Now, let's try some Ensemble methods to see if we can further increase the accuracy of the model

Trial-1: Bagging

In [30]:

```python
# Bagged Decision Trees for Classification
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

seed = 7
cart = DecisionTreeClassifier()
num_trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_state=seed)
model.fit(x,y)
results = model.score(x,y)
print(np.round(results, 4))
```

```
0.999
```

Trial-2: Random Forest

In [31]:

```python
# Random Forest Classification

from sklearn.ensemble import RandomForestClassifier

num_trees = 100
max_features = 3
model = RandomForestClassifier(n_estimators=num_trees, max_features=max_features)
model.fit(x,y)
results = model.score(x,y)
print(np.round(results, 4))
```

```
0.999
```

Trial-3: Boosting

In [32]:

```python
# AdaBoost Classification

from sklearn.ensemble import AdaBoostClassifier
num_trees = 100
seed=7

model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
model.fit(x,y)
results = model.score(x,y)
print(np.round(results, 4))
```

```
0.942
```

Trial-5: Stacking

In [33]:

```python
# Stacking Ensemble for Classification
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
```

In [34]:

```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = DecisionTreeClassifier()
estimators.append(('cart', model))
model = SVC()
estimators.append(('svm', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(x,y)
results = ensemble.score(x,y)
print(np.round(results, 4))
```

```
0.886
```

In [35]:

```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = DecisionTreeClassifier()
estimators.append(('cart', model))
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('Boosting', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(x,y)
results = ensemble.score(x,y)
print(np.round(results, 4))
```

```
0.952
```

Hence, we can say that Bagging/Random Forest- any of them is equally best predicting model for this dataset

In [ ]:

In [ ]: