CSCI 4150U - LAB 2

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In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from pandas.plotting import parallel_coordinates
```

In [2]:
```python
missing_values = [" ?"]
headers =  ["age", "workclass", "fnlwgt", "education", "education-num", "marital-status", "occupation", "relationship",
            "race", "sex", "capital-gain", "capital-loss", "hours-per-week", "native-country", "class"]
data = pd.read_csv('./data/adult.data', header=None, na_values=missing_values, names=headers)
data
```

Out[2]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	class
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=50K
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

Part I:

In [3]:
```
# For each continuous attribute, calculate its average, standard deviation, minimum, and maximum values
for col in data.select_dtypes(exclude=['object']).columns.tolist():
    print('%s:' % (col))
    print('\t Mean = %.2f' % data[col].mean())
    print('\t Standard deviation = %.2f' % data[col].std())
    print('\t Minimum = %.2f' % data[col].min())
    print('\t Maximum = %.2f' % data[col].max())
```

```
age:
	 Mean = 38.58
	 Standard deviation = 13.64
	 Minimum = 17.00
	 Maximum = 90.00
fnlwgt:
	 Mean = 189778.37
	 Standard deviation = 105549.98
	 Minimum = 12285.00
	 Maximum = 1484705.00
education-num:
	 Mean = 10.08
	 Standard deviation = 2.57
	 Minimum = 1.00
	 Maximum = 16.00
capital-gain:
	 Mean = 1077.65
	 Standard deviation = 7385.29
	 Minimum = 0.00
	 Maximum = 99999.00
capital-loss:
	 Mean = 87.30
	 Standard deviation = 402.96
	 Minimum = 0.00
	 Maximum = 4356.00
hours-per-week:
	 Mean = 40.44
	 Standard deviation = 12.35
	 Minimum = 1.00
	 Maximum = 99.00
```

In [4]:

```
# For the discrete attribute, count the frequency for each of its distinct values
for col in data.select_dtypes(include=['object']).columns.tolist():
    print('%s:' % (col))
    print('%s \n' % data[col].value_counts())
```

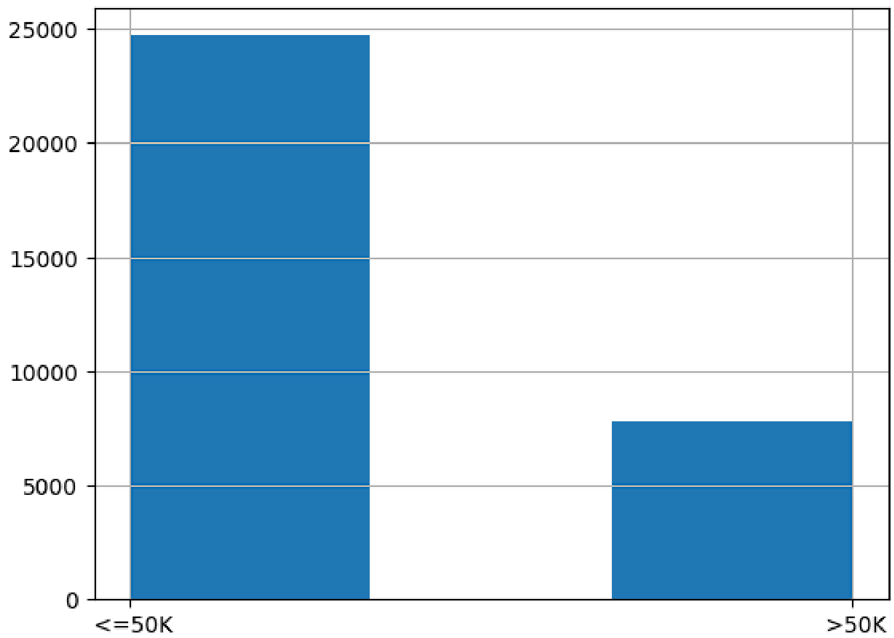
```
workclass:
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64

education:
 HS-grad         10501
 Some-college     7291
 Bachelors        5355
 Masters          1723
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           646
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           333
 1st-4th           168
 Preschool          51
Name: education, dtype: int64
```

```
marital-status:
 Married-civ-spouse       14976
 Never-married            10683
 Divorced                  4443
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: marital-status, dtype: int64

occupation:
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
 Transport-moving     1597
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
 Armed-Forces            9
Name: occupation, dtype: int64

relationship:
 Husband           13193
 Not-in-family      8305
 Own-child          5068
 Unmarried          3446
 Wife               1568
 Other-relative      981
Name: relationship, dtype: int64

race:
 White                 27816
 Black                  3124
 Asian-Pac-Islander     1039
 Amer-Indian-Eskimo      311
 Other                   271
Name: race, dtype: int64

sex:
 Male      21790
 Female    10771
Name: sex, dtype: int64
```

```
native-country:
 United-States                 29170
 Mexico                          643
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Guatemala                        64
 Japan                            62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: native-country, dtype: int64

class:
 <=50K    24720
 >50K      7841
Name: class, dtype: int64
```

In [5]:
```
# Draw histogram of the class variable
%matplotlib inline
data['class'].hist(bins=3)
```

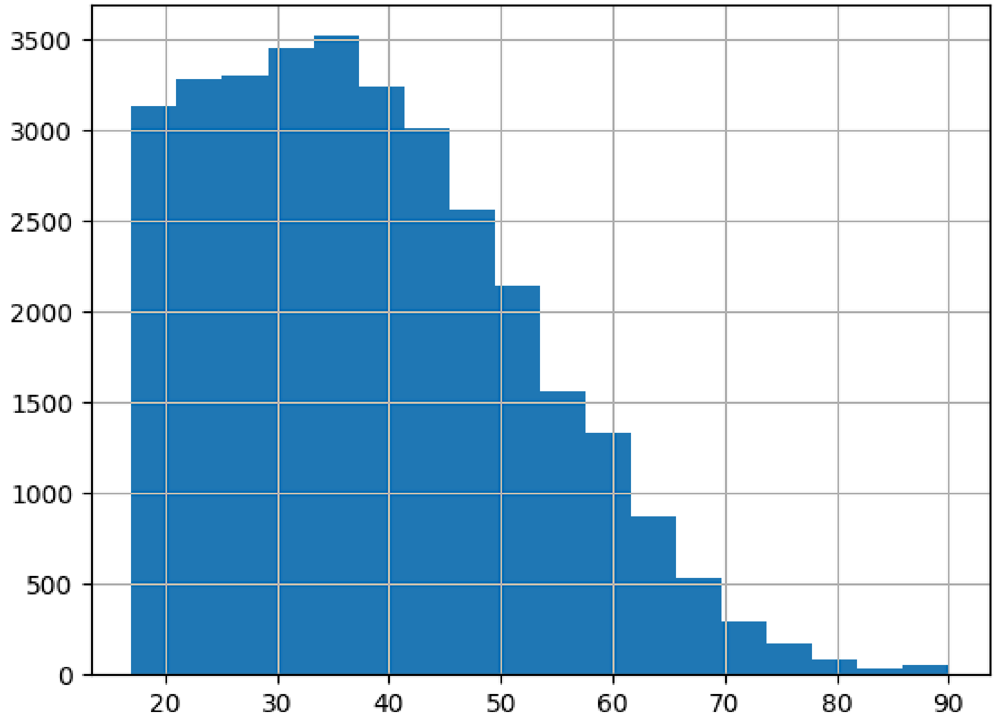
Out[5]: <AxesSubplot: >



In [6]:
```
# Class "<=50K" has significantly more records than class ">50K"
# There are nearly triple amounts of people with income <=50K than people with income >50K
```

In [7]:
```
# Draw the distribution of values for a continuous attribute using a histogram
data['age'].hist(bins=18)
```

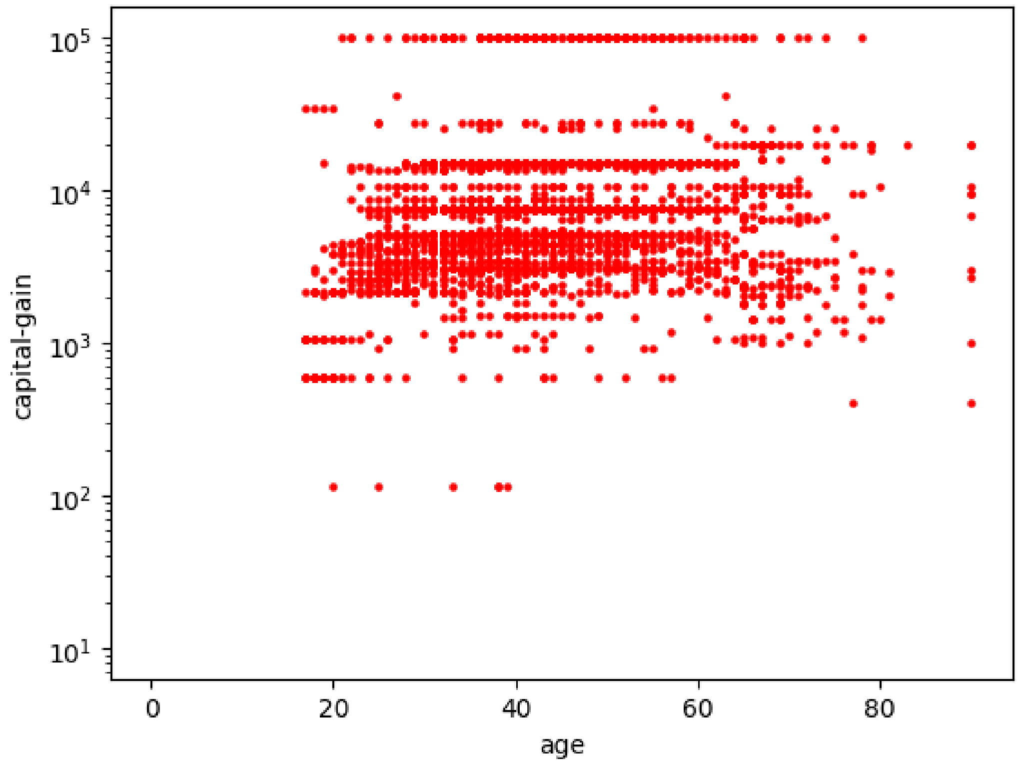
Out[7]: <AxesSubplot: >



In [8]:
```
# People recorded in the datasets are primarily in their 20s to 50s
```

In [9]:
```
plt.scatter(data['age'], data['capital-gain'], s=5, color='red')
plt.xlabel('age')
plt.ylabel('capital-gain')
plt.semilogy(10)
```

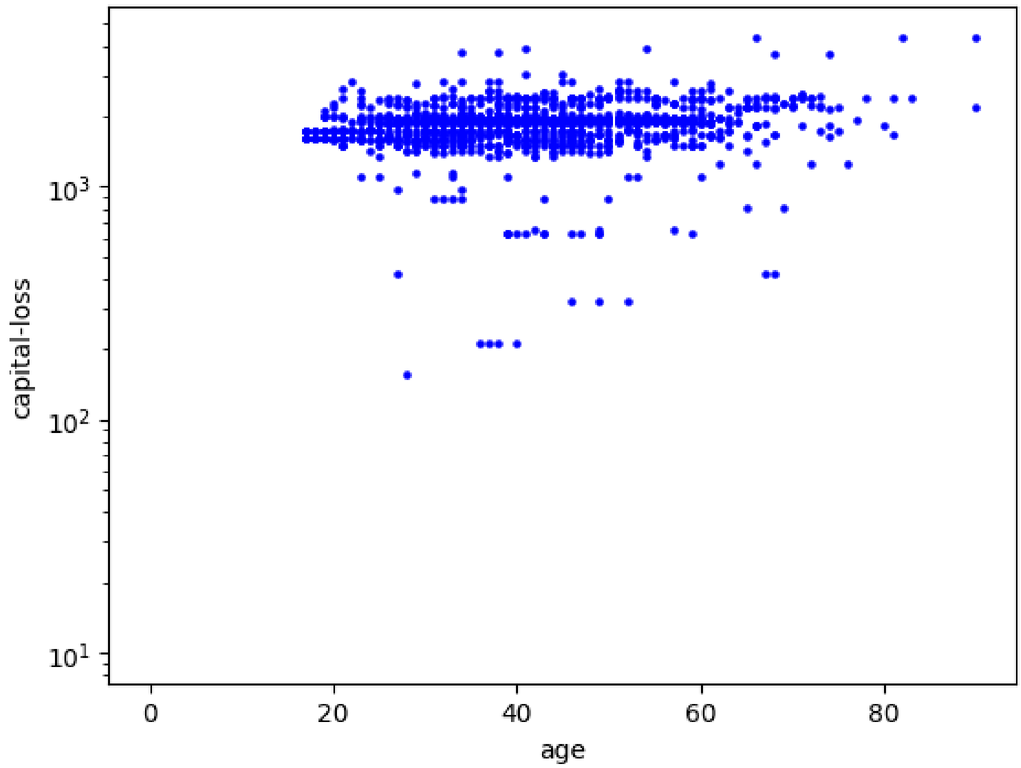
Out[9]:
```
[<matplotlib.lines.Line2D at 0x1f5019b9d30>]
```



In [10]:
```
# There is no relationship between age and capital gain of a person
# Most people recoreded in the datasets have capital gain around 1000 to 10000
```

In [11]:
```
plt.scatter(data['age'], data['capital-loss'], s=5, color='blue')
plt.xlabel('age')
plt.ylabel('capital-loss')
plt.semilogy(10)
```

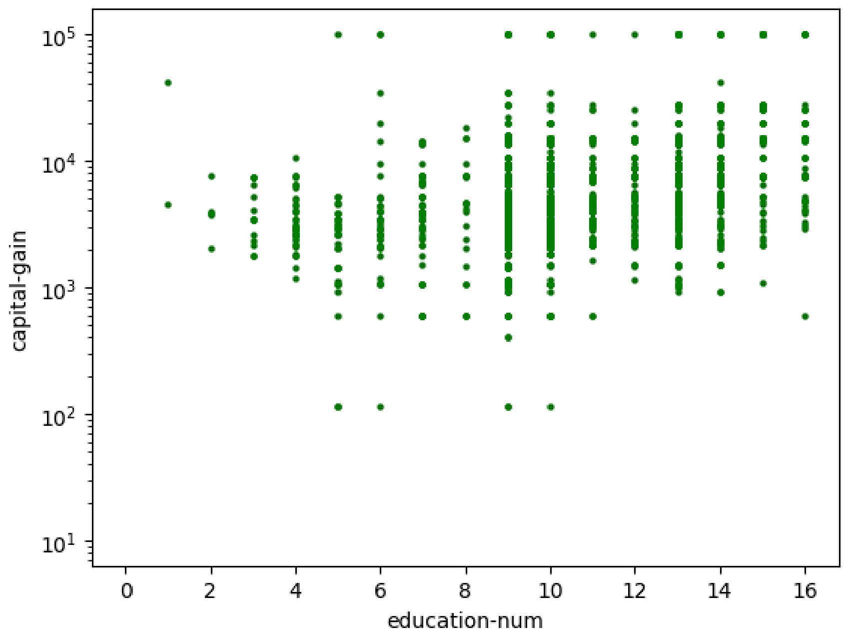
Out[11]: [<matplotlib.lines.Line2D at 0x1f5051b3eb0>]



In [12]:
```
# There is no relationship between age and capital loss of a person
# Most people recoreded in the datasets have capital loss around 1000 to 4000
```

In [13]:
```
plt.scatter(data['education-num'], data['capital-gain'], s=5, color='green')
plt.xlabel('education-num')
plt.ylabel('capital-gain')
plt.semilogy(10)
```

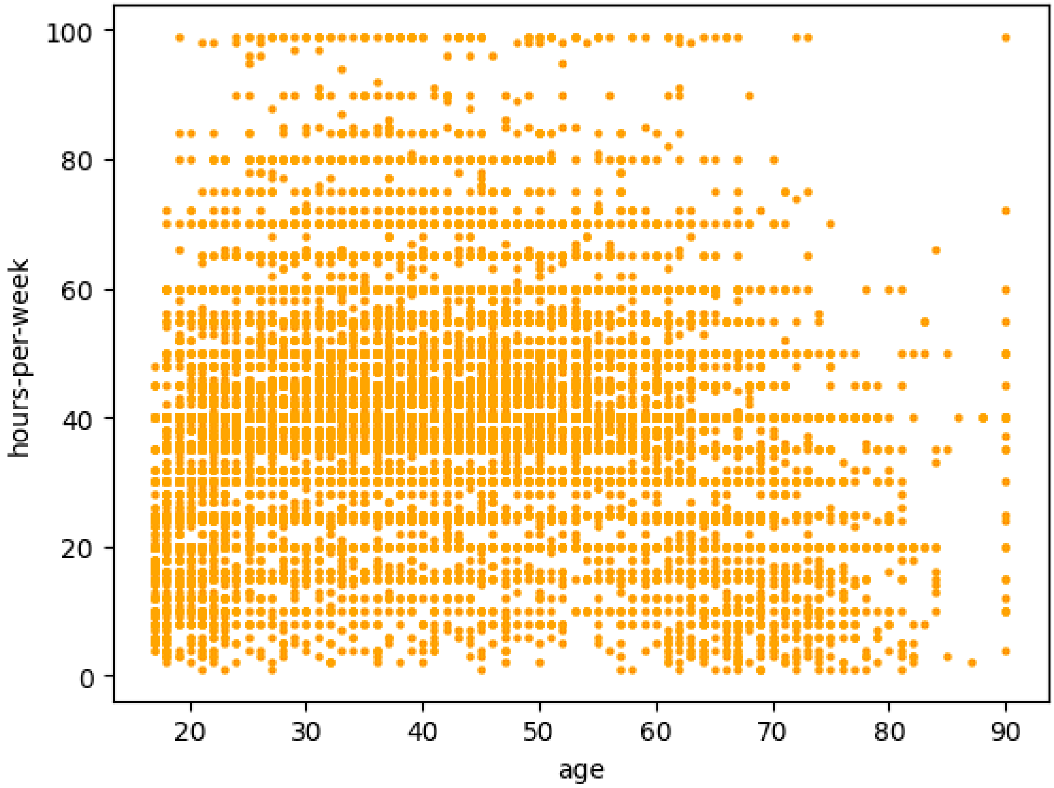
Out[13]:
```
[<matplotlib.lines.Line2D at 0x1f5054525b0>]
```



In [14]:
```
# There is no relationship between the number of years of education and capital gain of a person
# The number of years of education doesn't affect the capital gain of a person
```

In [15]:
```
plt.scatter(data['age'], data['hours-per-week'], s=5, color='orange')
plt.xlabel('age')
plt.ylabel('hours-per-week')
```

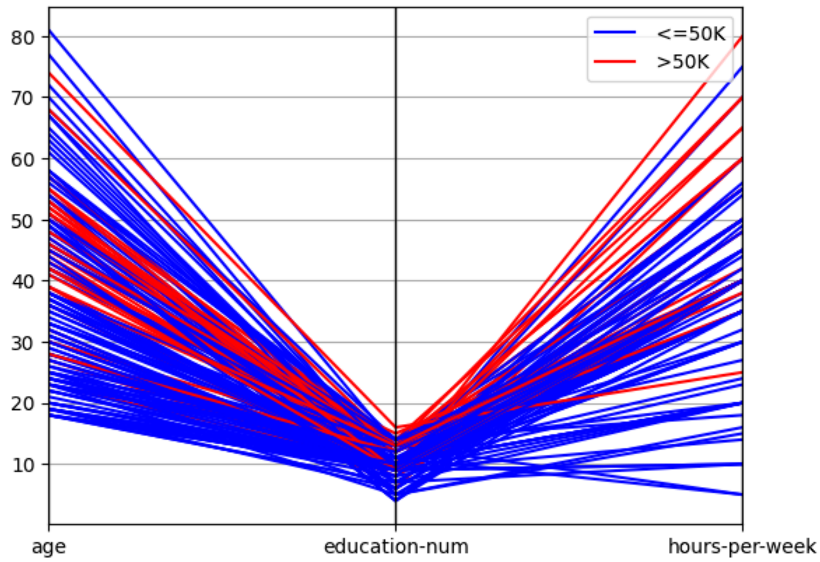
Out[15]: Text(0, 0.5, 'hours-per-week')



In [16]:
```
# Most people recorded in the datasets work around 40 to 50 hours per week
# Most people in their 20s work less, around 20 hours per week
# As age increases, people work fewer hours per week
```

In [17]:
```
# Draw a parallel diagram for some attributes in the data set
plot_data = data[['age', 'education-num', 'hours-per-week', 'class']]
plot_sample = plot_data.sample(frac=.005)
parallel_coordinates(plot_sample, 'class', color=['blue', 'red'])
```

Out[17]: <AxesSubplot: >



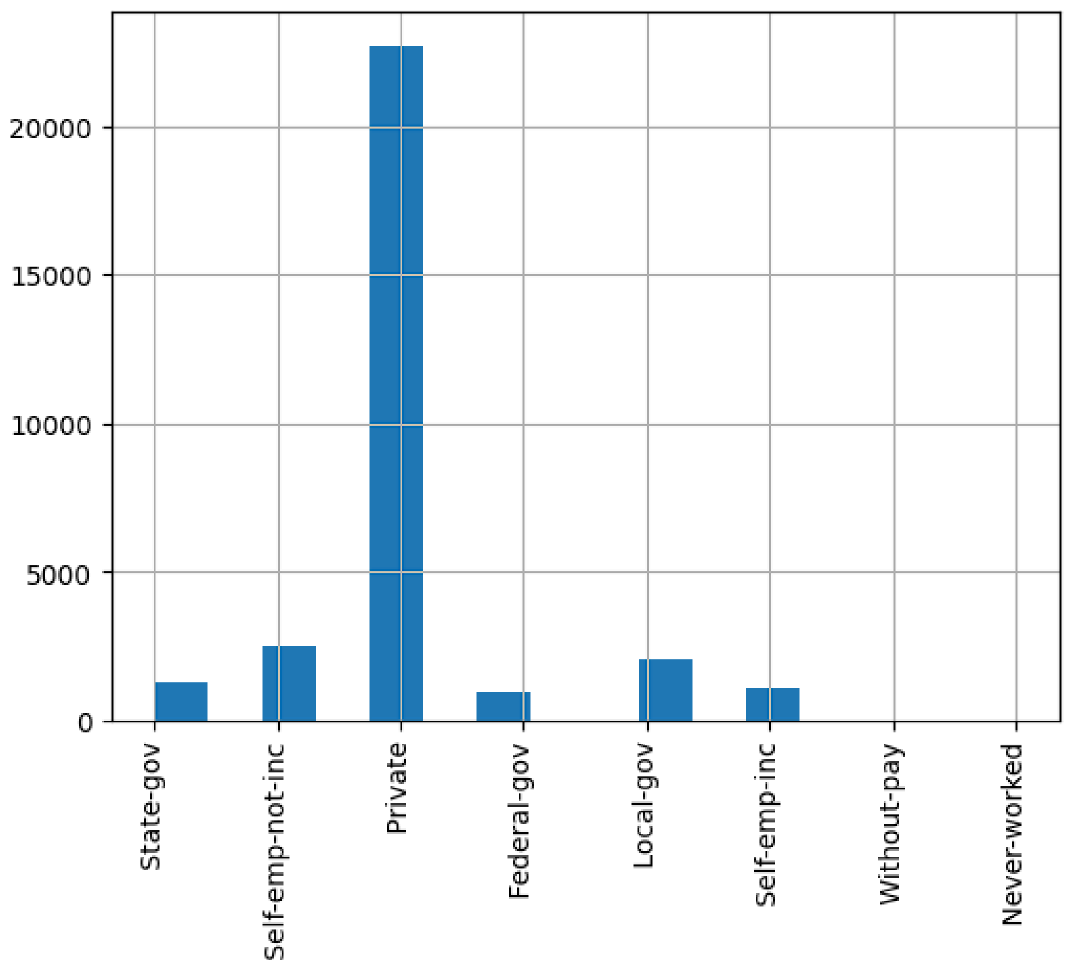
In [18]:
```
# People with income >50K have a higher number of years of education and work more hours per week
# Age doesn't affect the income of a person, a person can have an income >50K with very low years of age
```

Part II:

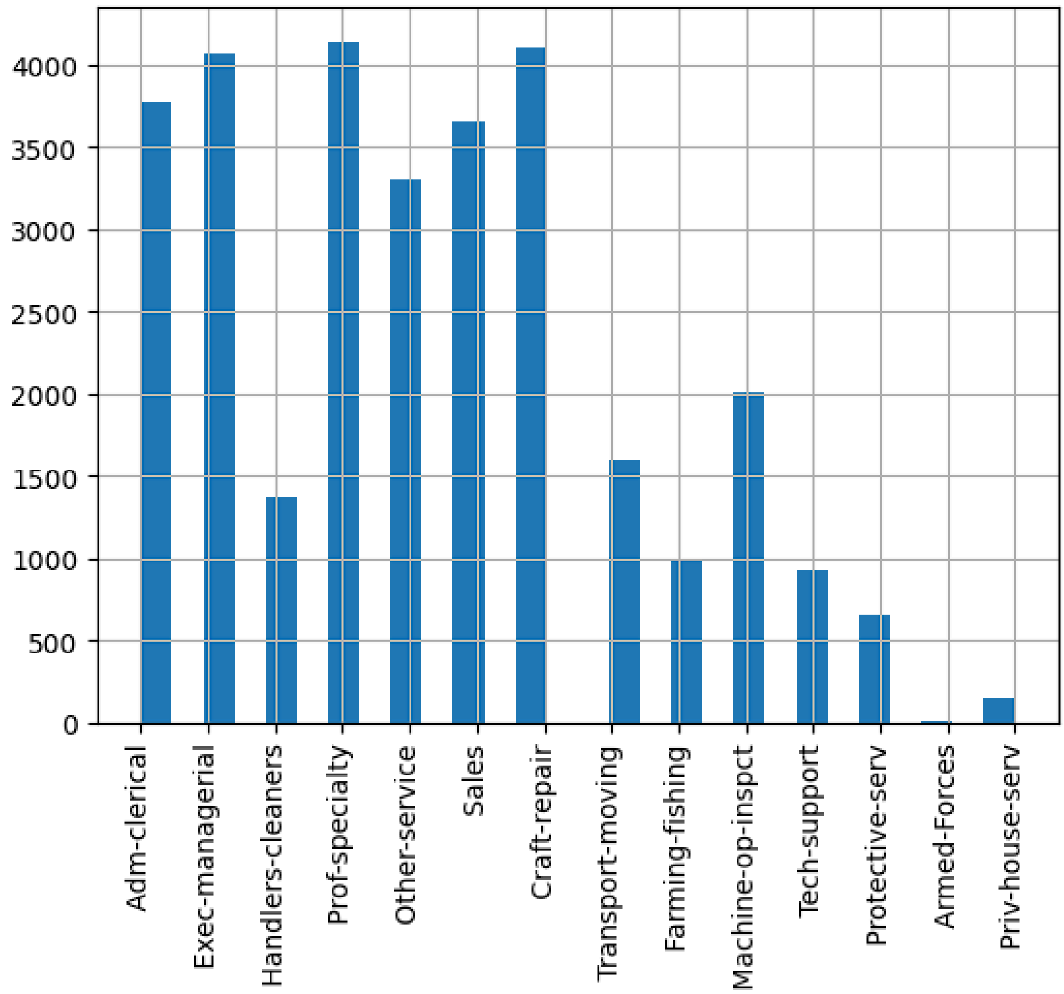
```
In [19]: # Identify which attributes have missing values
         nan_cols = []
         for col in data.columns:
             if data[col].isnull().values.any():
                 nan_cols.append(col)
         print(nan_cols)

         ['workclass', 'occupation', 'native-country']
```

```
In [20]: # Draw a histogram of the attribute before replacing missing values
```

```
In [21]: data['workclass'].hist(bins=data['workclass'].nunique()*2, xrot=90)

Out[21]: <AxesSubplot: >
```

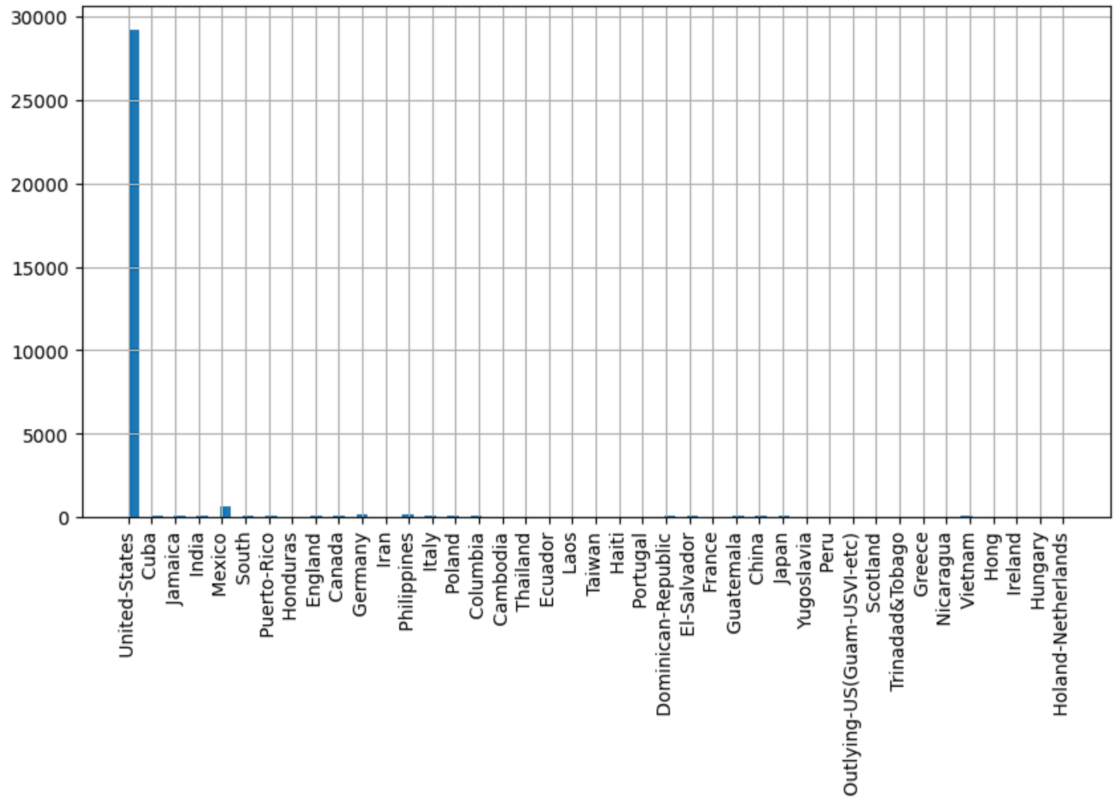


In [22]:
```
data['occupation'].hist(bins=data['occupation'].nunique()*2, xrot=90)
```
Out[22]: <AxesSubplot: >



In [23]:
```
data['native-country'].hist(bins=data['native-country'].nunique()*2, figsize=(10, 5), xrot=90)
```

Out[23]: <AxesSubplot: >

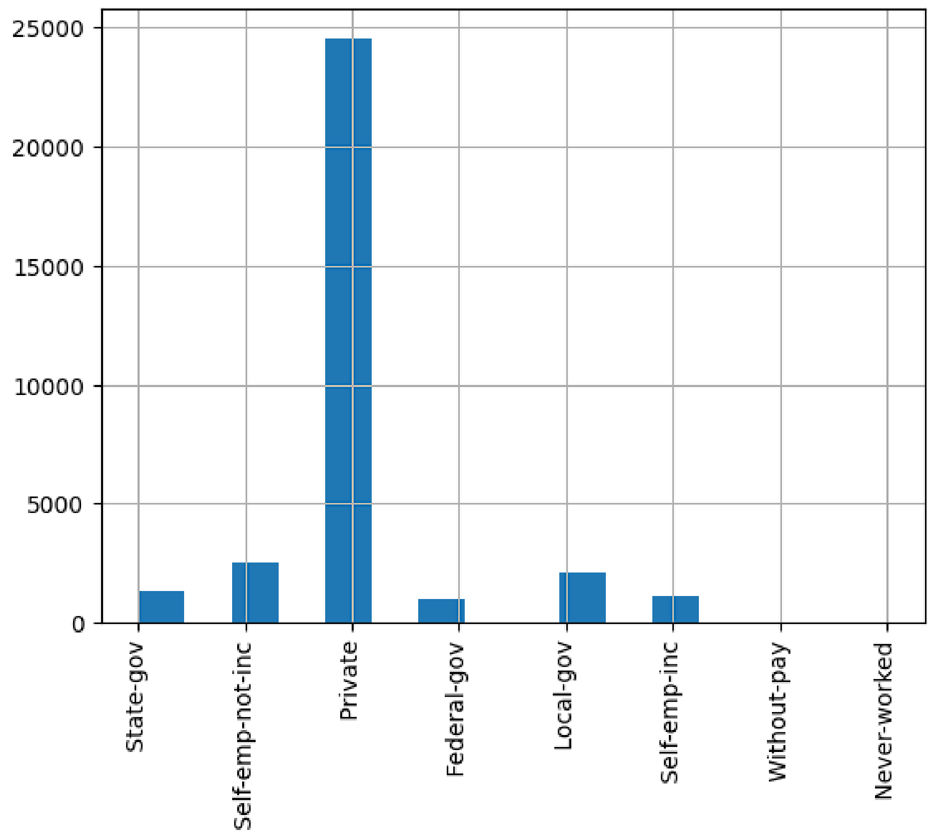


In [24]:
```
# Replacing missing values by the average or mode of the attribute (based on attribute types)
fillna_data = data
for col in nan_cols:
    fillna_data[col].fillna(fillna_data[col].mode()[0], inplace=True)
```

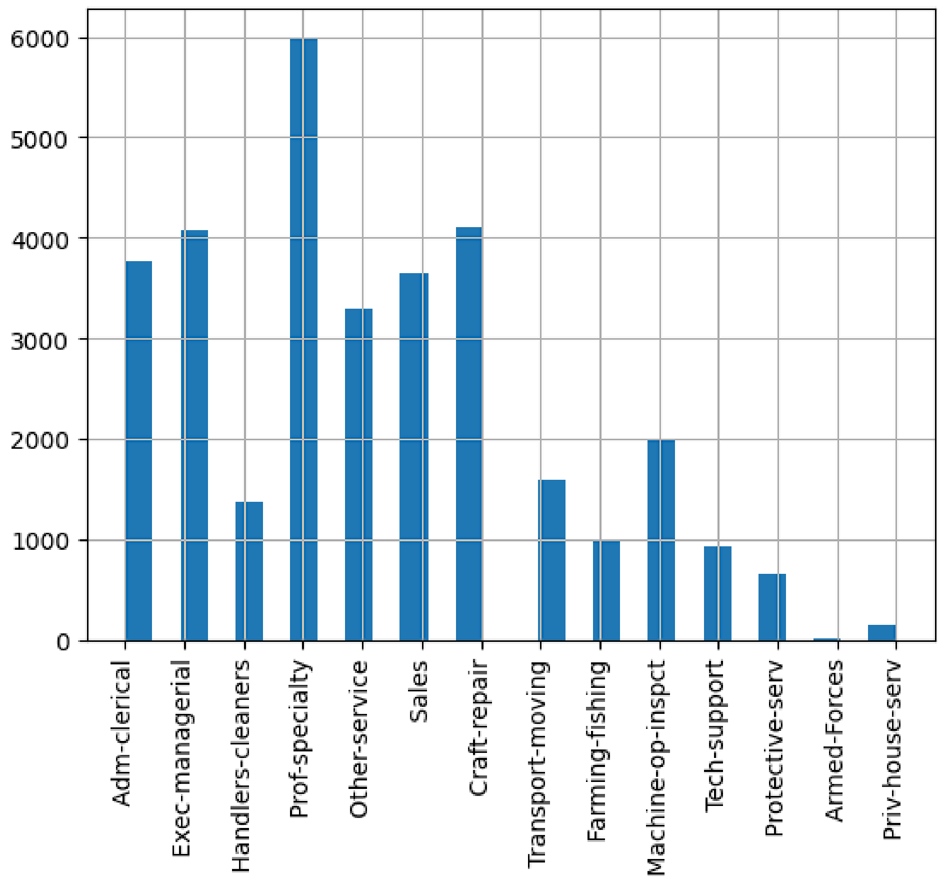
In [25]:
```
# Draw a histogram of the attribute after replacing missing values by the above method
```

In [26]:
```
fillna_data['workclass'].hist(bins=fillna_data['workclass'].nunique()*2, xrot=90)
```

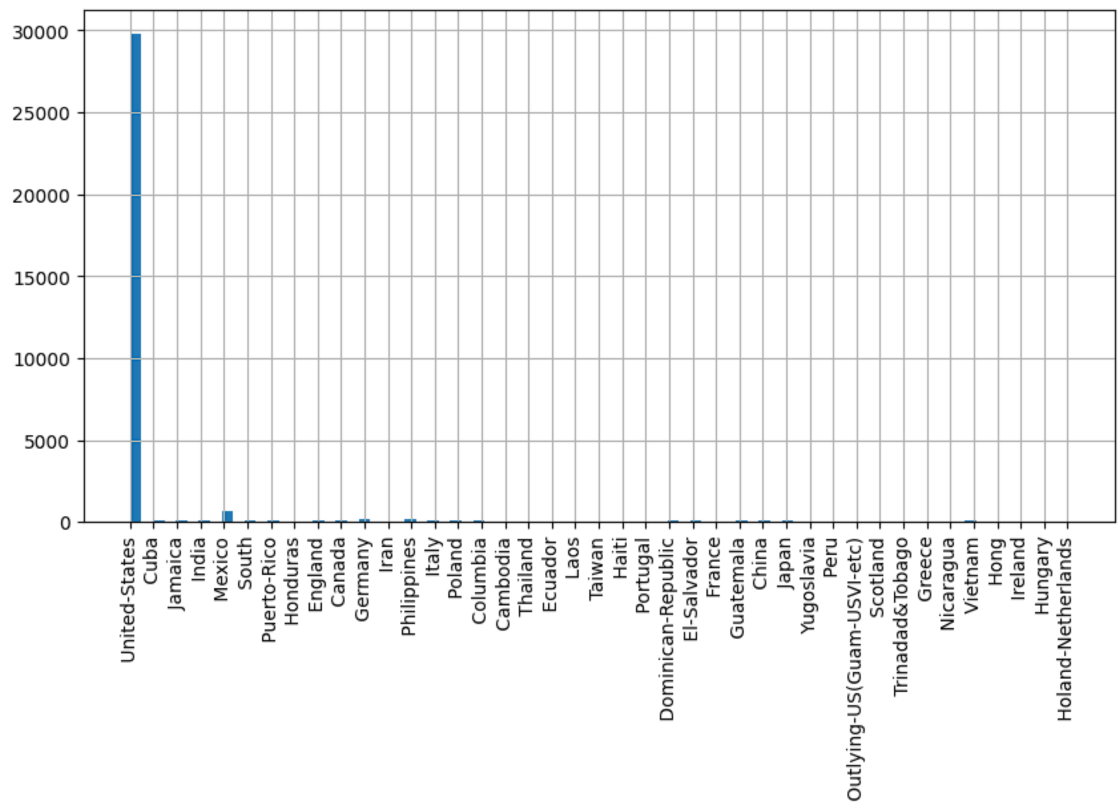
Out[26]: <AxesSubplot: >



In [27]:
```
fillna_data['occupation'].hist(bins=fillna_data['occupation'].nunique()*2, xrot=90)
```
Out[27]: <AxesSubplot: >



In [28]:
```
fillna_data['native-country'].hist(bins=fillna_data['native-country'].nunique()*2, figsize=(10, 5), xrot=90)
```
Out[28]: <AxesSubplot: >



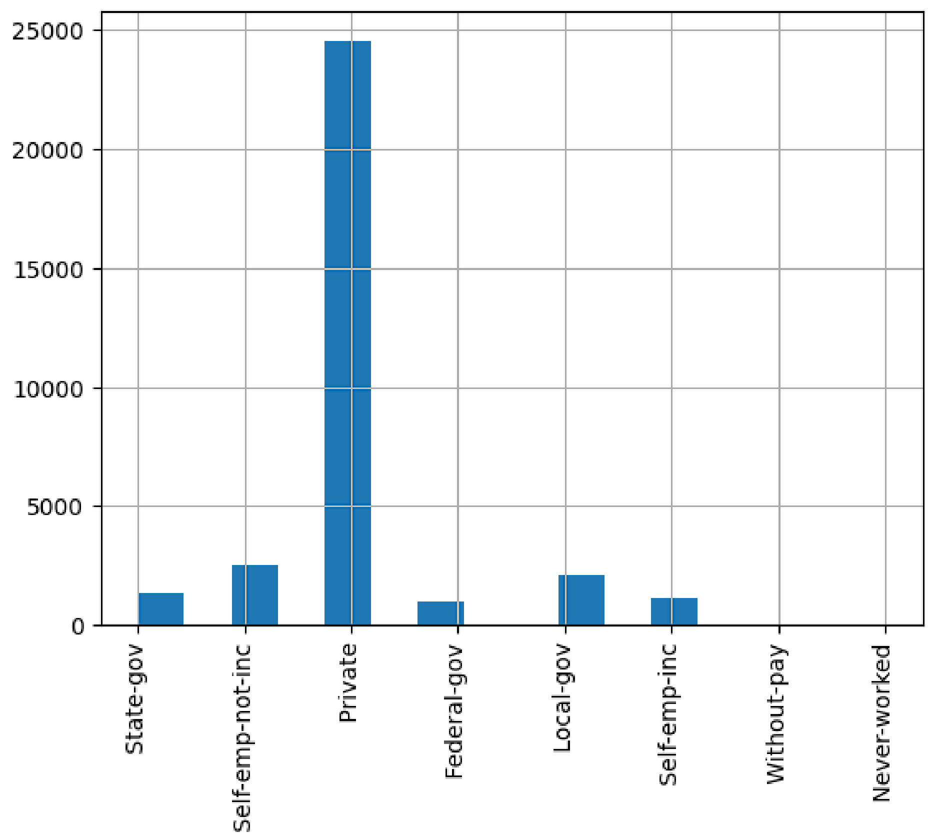
In [29]:
```
data1, data2 = [x for _, x in data.groupby(data['class'])] # Split the data into 2 subsets by classes
```

In [30]:
```
# Replace missing values by the average or mode of the attribute in the particular class to which the instance belongs
for col in nan_cols:
    # Replace missing values by the mode of the attribute in the particular class
    data1[col].fillna(data1[col].mode()[0], inplace=True)
    data2[col].fillna(data2[col].mode()[0], inplace=True)
fillna_data = pd.concat([data1, data2]) # Merge the 2 subsets
```

In [31]:
```
# Draw a histogram of the attribute after replacing missing values by the above method
```

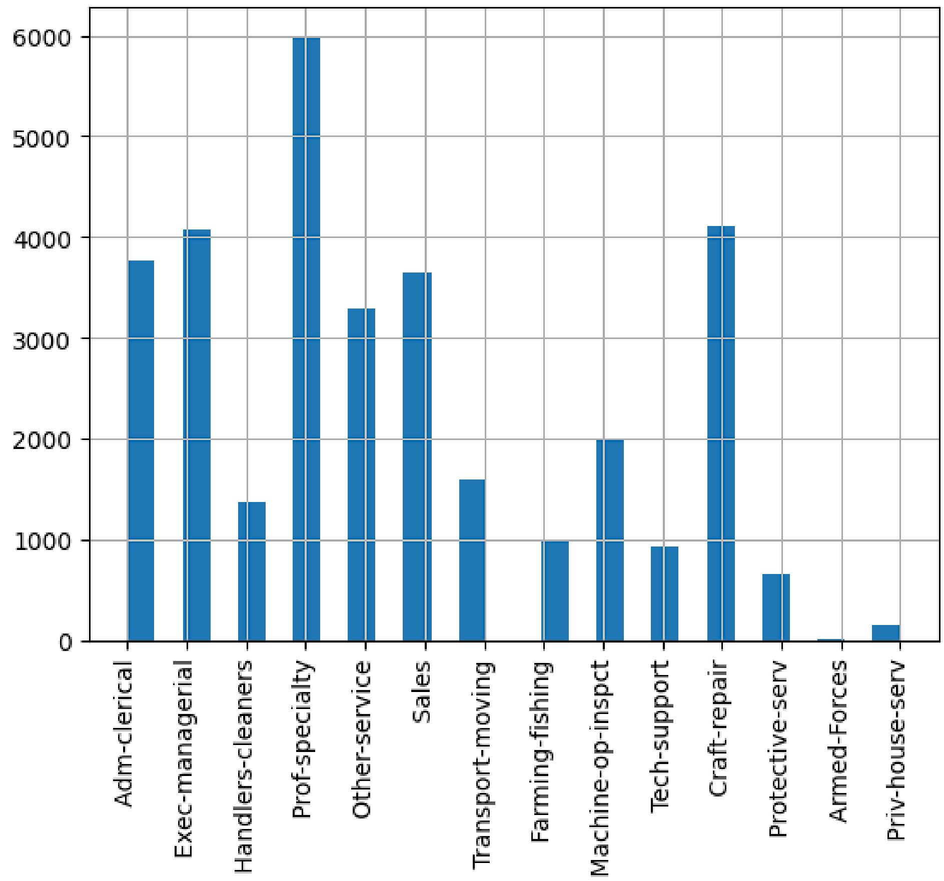
In [32]:
```
fillna_data['workclass'].hist(bins=fillna_data['workclass'].nunique()*2, xrot=90)
```

Out[32]:
```
<AxesSubplot: >
```



In [33]:
```
fillna_data['occupation'].hist(bins=fillna_data['occupation'].nunique()*2, xrot=90)
```

Out[33]: <AxesSubplot: >



In [34]:
```
fillna_data['native-country'].hist(bins=fillna_data['native-country'].nunique()*2, figsize=(10, 5), xrot=90)
```

Out[34]: <AxesSubplot: >