US_Census_model

November 29, 2017

At first, since there are no names for the columns of our data, we will start by creating them :

```
In [7]: import pandas as pd
        from sklearn.preprocessing import LabelEncoder
        import matplotlib.pyplot as plt
        import pandas as pd
        import xgboost as xgb
        from sklearn.preprocessing import LabelEncoder
        import numpy as np
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import roc_auc_score,roc_curve,confusion_matrix,precision_score,cla
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import recall_score
        from sklearn.utils import resample
        from sklearn.naive_bayes import GaussianNB
```

```
In [8]: names = ['age',
                 'class of worker',
                 'detailed industry recode',
                 'detailed occupation recode',
                 'education',
                 'wage per hour',
                 'enroll in edu inst last wk',
                 'marital stat',
                 'major industry code',
                 'major occupation code',
                 'race',
                 'hispanic origin',
                 'sex',
                 'member of a labor union',
                 'reason for unemployment',
                 'full or part time employment stat',
                 'capital gains',
                 'capital losses',
                 'dividends from stock',
                 'tax filer stat',
                 'region of previous residence',
                 'state of prevous residence',
```

```
                 'detailed household and family stat',
                 'detailed household summary in household',
                 'instance weight',
                 'migration code-change in msa',
                 'migration code-change in reg',
                 'migration code-move within region',
                 'live in this house 1 year ago',
                 'migration prev res in sunbelt',
                 'num persons worked for employer',
                 'family members under 18',
                 'country of birth father',
                 'country of birth mother',
                 'country of birth self',
                 'citizenship',
                 'own business or self employed',
                 "fill inc questionnaire for veteran's admin",
                 'veterans benefits',
                 'weeks worked in year',
                 'year',
                 'income']

        dftrain=pd.read_csv('census_income_learn.csv',names=names)
        dftest=pd.read_csv('census_income_test.csv',names=names)
        grouped_dftrain=dftrain.groupby("income")
```

1 Preprocessing :

One way to visualize our columns in order to see which ones we should keep, which ones will be beneficial for training our model and which ones will not (i.e. will act like a noise in our data):

We will group our dataframe by income and draw the 'bars' showing each category for a certain feature. In blue is drawn the amount of '-50000' in our category and in orange the one for '50000+'.

Trying to analyse class of worker feature we can notice that the most commun one is 'Not in universe' and we can see that this category comes a lot for other features, we assume that It means that data is not available for some cases where a feature can support many categories or it means that this category is not possible for our element, for example the fourth element has 10 years old , the class of worker has no meaning in this case, Not in universe stands then for 'has no sens'

```
In [9]: dftrain.ix[4]
```

```
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:1: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
```

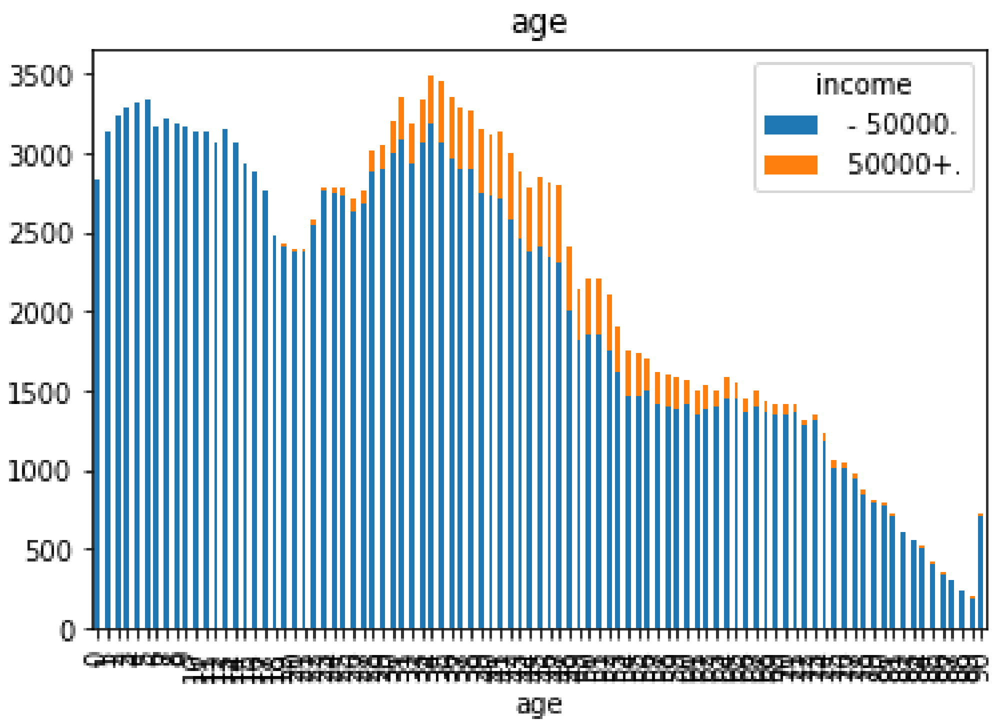
```
  """Entry point for launching an IPython kernel.
```

```
Out[9]: age                                                               10
        class of worker                                    Not in universe
        detailed industry recode                                         0
        detailed occupation recode                                       0
        education                                                 Children
        wage per hour                                                    0
        enroll in edu inst last wk                         Not in universe
        marital stat                                         Never married
        major industry code                    Not in universe or children
        major occupation code                              Not in universe
        race                                                         White
        hispanic origin                                          All other
        sex                                                         Female
        member of a labor union                            Not in universe
        reason for unemployment                            Not in universe
        full or part time employment stat       Children or Armed Forces
        capital gains                                                    0
        capital losses                                                   0
        dividends from stock                                             0
        tax filer stat                                           Nonfiler
        region of previous residence                       Not in universe
        state of prevous residence                         Not in universe
        detailed household and family stat   Child <18 never marr not in subfamily
        detailed household summary in household    Child under 18 never married
        instance weight                                            1069.16
        migration code-change in msa                              Nonmover
        migration code-change in reg                              Nonmover
        migration code-move within region                         Nonmover
        live in this house 1 year ago                                  Yes
        migration prev res in sunbelt                      Not in universe
        num persons worked for employer                                  0
        family members under 18                       Both parents present
        country of birth father                              United-States
        country of birth mother                              United-States
        country of birth self                                United-States
        citizenship                          Native- Born in the United States
        own business or self employed                                    0
        fill inc questionnaire for veteran's admin         Not in universe
        veterans benefits                                                0
        weeks worked in year                                             0
        year                                                            94
        income                                                    - 50000.
        Name: 4, dtype: object
```

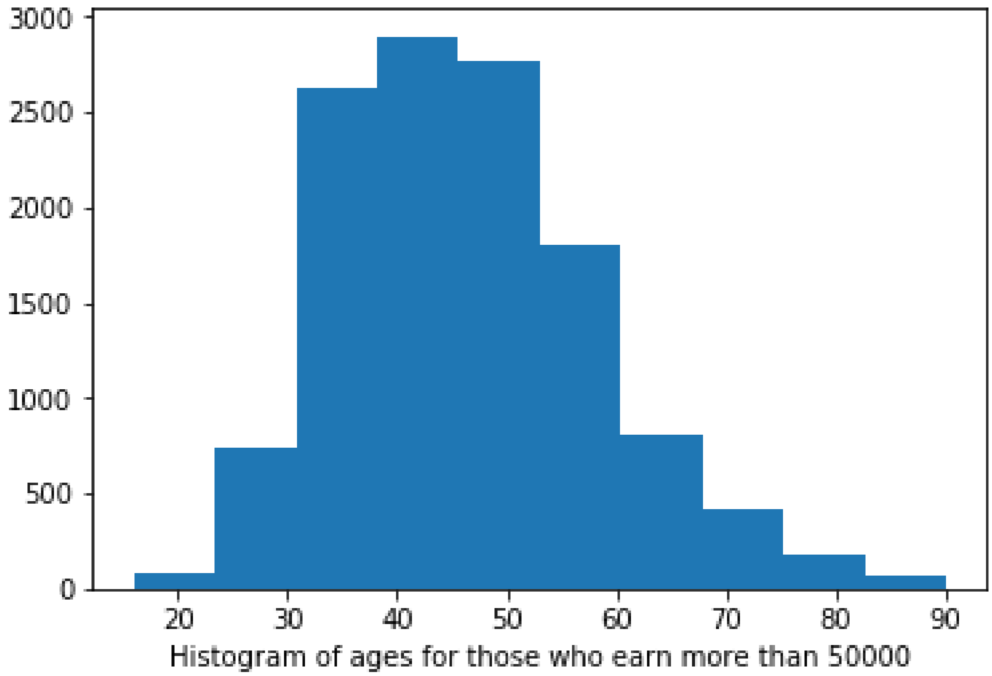
Using this visualisation for each feature and starting with age feature we can notice that most young people earn less than 50000 which is logical

```
In [16]: %matplotlib inline
         dftrain.groupby('income')['age'].value_counts().unstack(level=0).plot(kind='bar',stacke
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f79fa334f60>
```




```
In [12]: plt.hist(dftrain[dftrain['income']==' 50000+.'].age)
         plt.xlabel('Histogram of ages for those who earn more than 50000')
         plt.show()
```



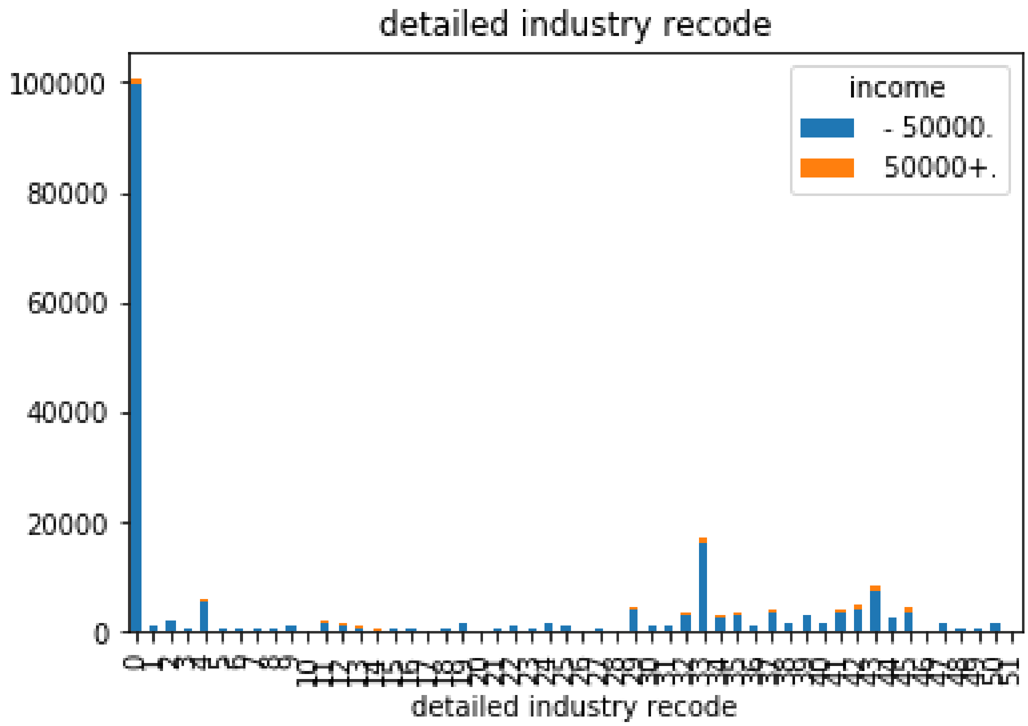
This histogram can show us that the large majority of people who earn more than 50000 are more than 12 years old,we choose to drop from our data elements that have less than 12 years old which would help us create some balance for later since we can notice from the start that elements with more than 50000 elements as income are way more available than those with less than 50000

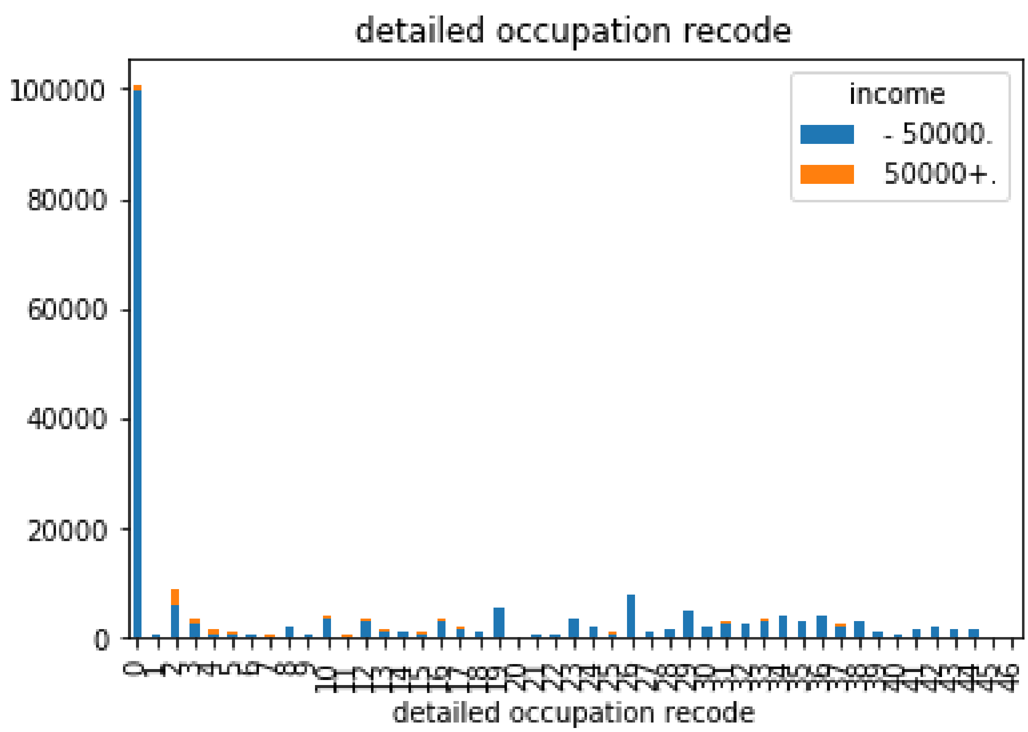
```
In [13]: dftrain_age=dftrain[dftrain.age>12]
```

Next, we assume that detailed industry recode,detailed occupation recode won't provide efficient information to our data since even if they are numerical values, they are quantified and spread all over the categories (i.e. for each detailed recode we may find both kind of incomes > and < 50000,we will drop it later in order to have less noise. We also assume that other codes such as major industry code,major occupation code,migration code-change in reg,migration code-move within region

```
In [14]: indexesofrecodes=[2,3]
```

```
In [17]: %matplotlib inline
         for n in indexesofrecodes:
             dftrain.groupby('income')[names[n]].value_counts().unstack(level=0).plot(kind='bar'
```


detailed industry recode
income
- 50000.
50000+.
detailed industry recode

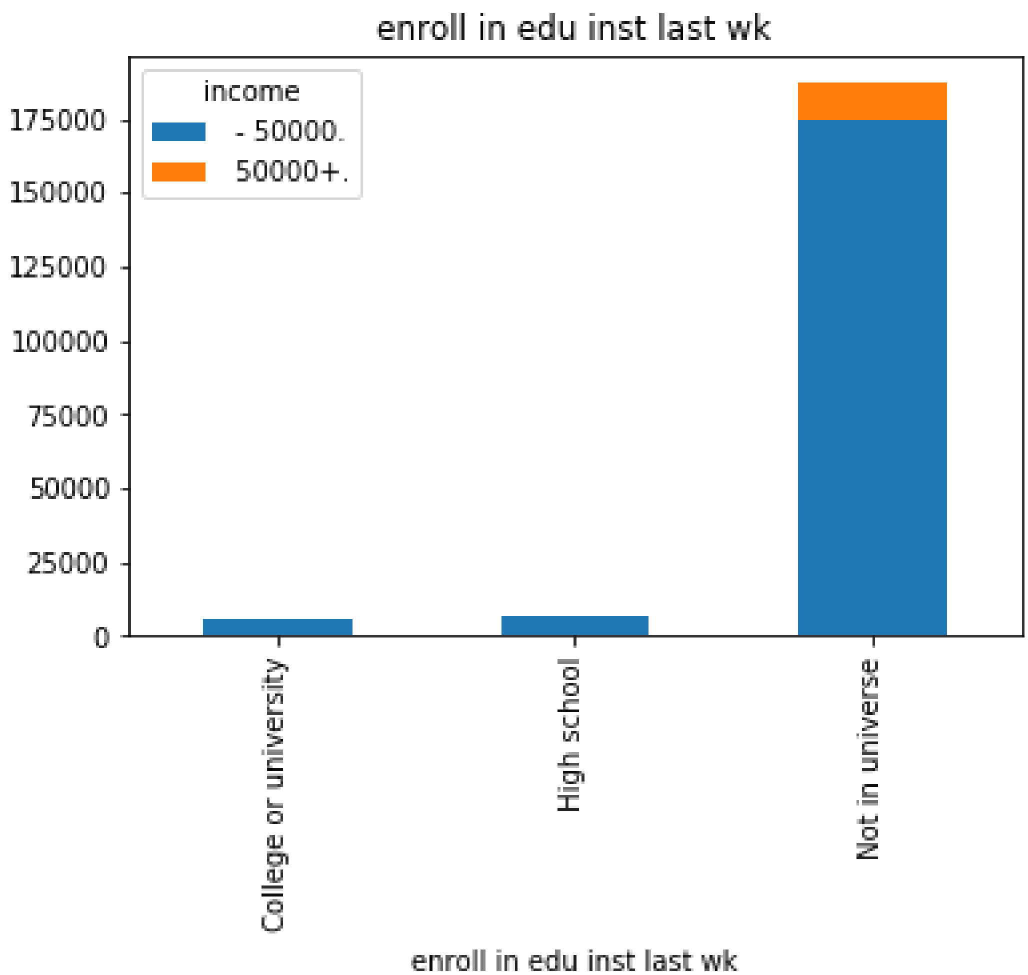

detailed occupation recode
income
- 50000.
50000+.
detailed occupation recode

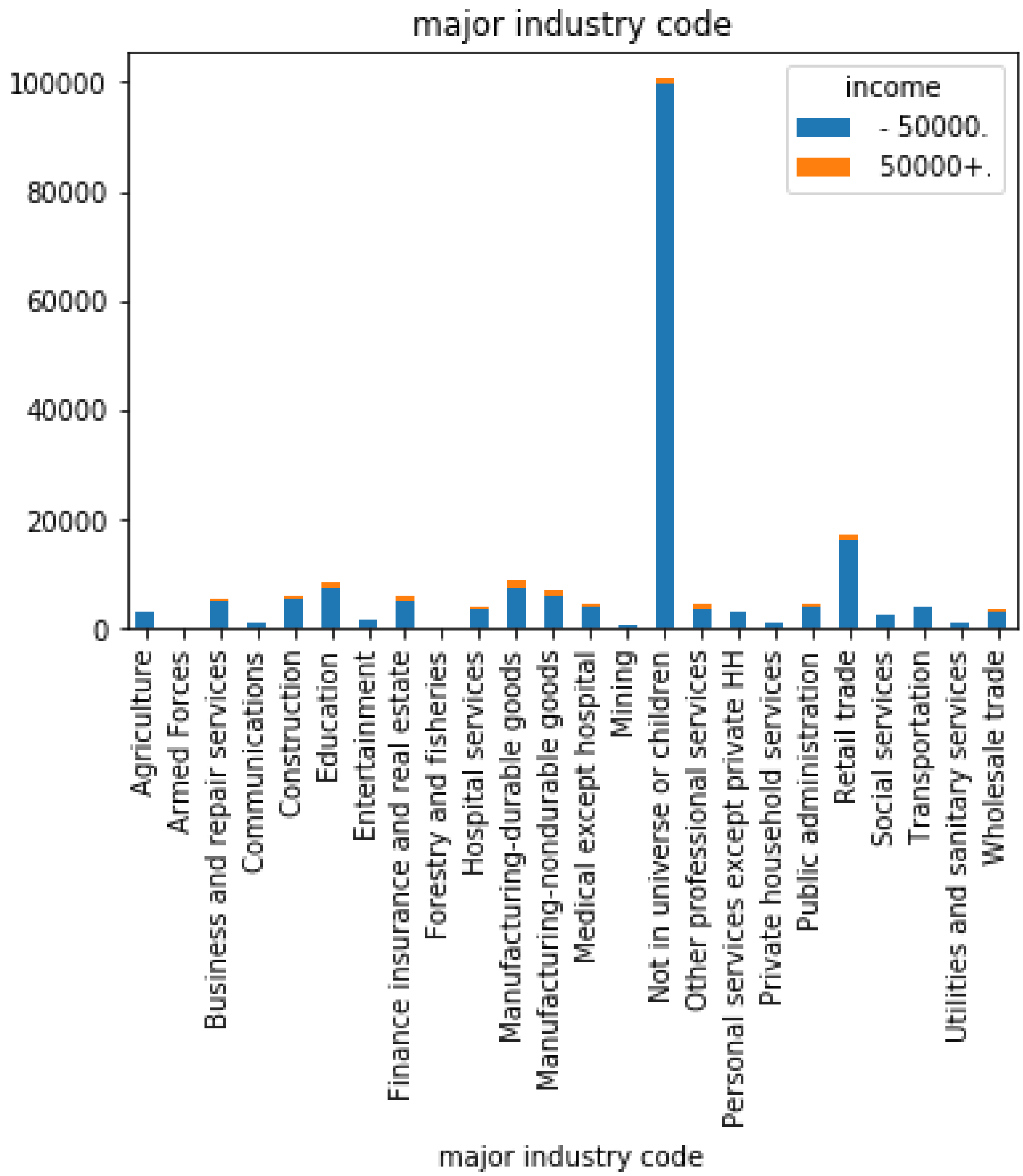
With the same logic for the other features, we decided to drop the features below:

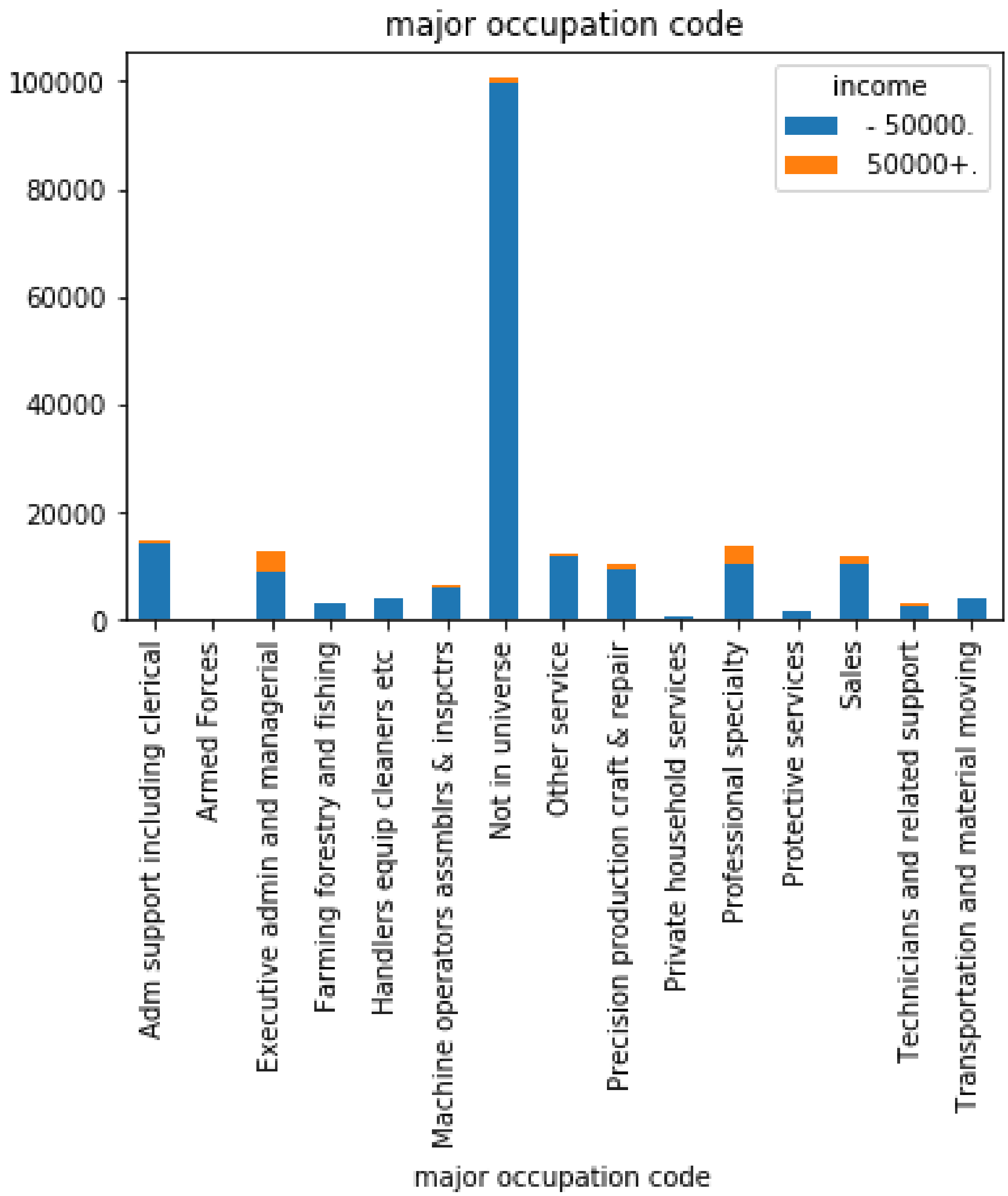
Now for those indexes_todrop below we have the opposite case of what we had before, here either we find that both kind of incomes are in Not in universe category or/and Not in universe category is way more available than other categories which is the case for 'member of a labor union' which would introduce more noise to our data than it would be beneficial for it

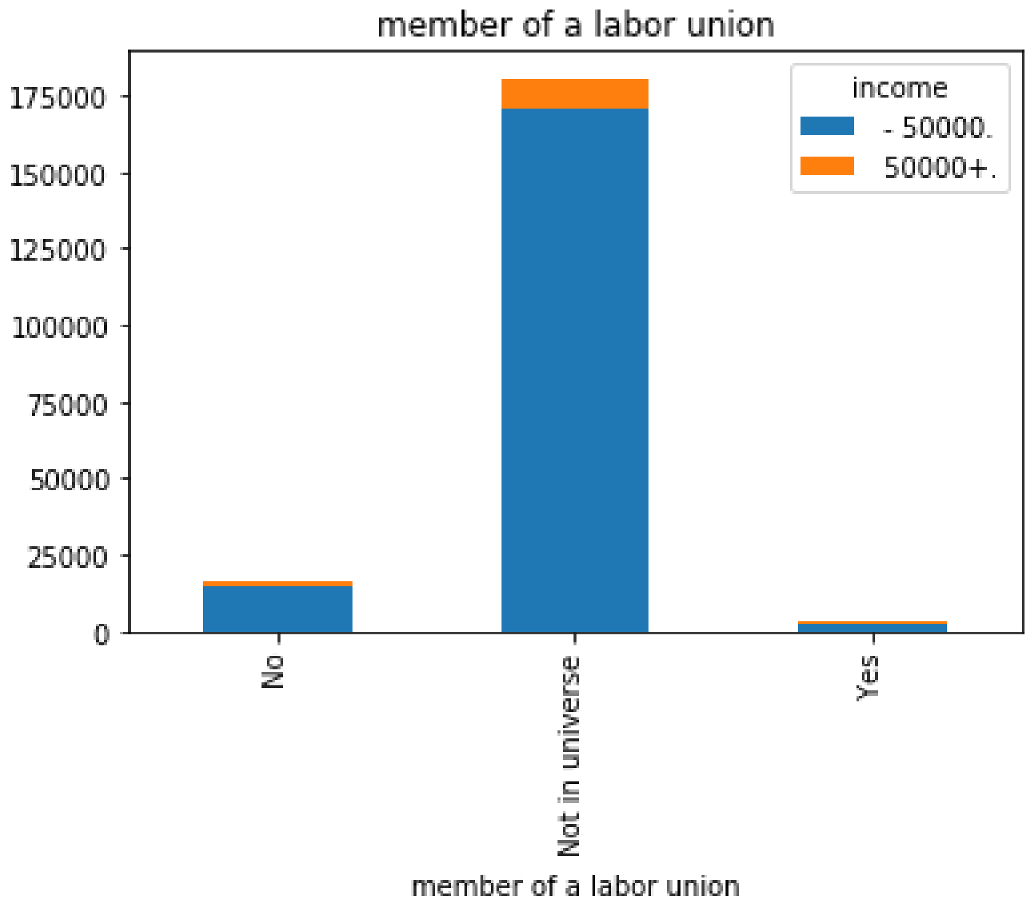
In [19]:
```
col=dftrain.columns
indexes_todrop=[6,8,9,13,14,20,25,26,27,29,31,37]
```

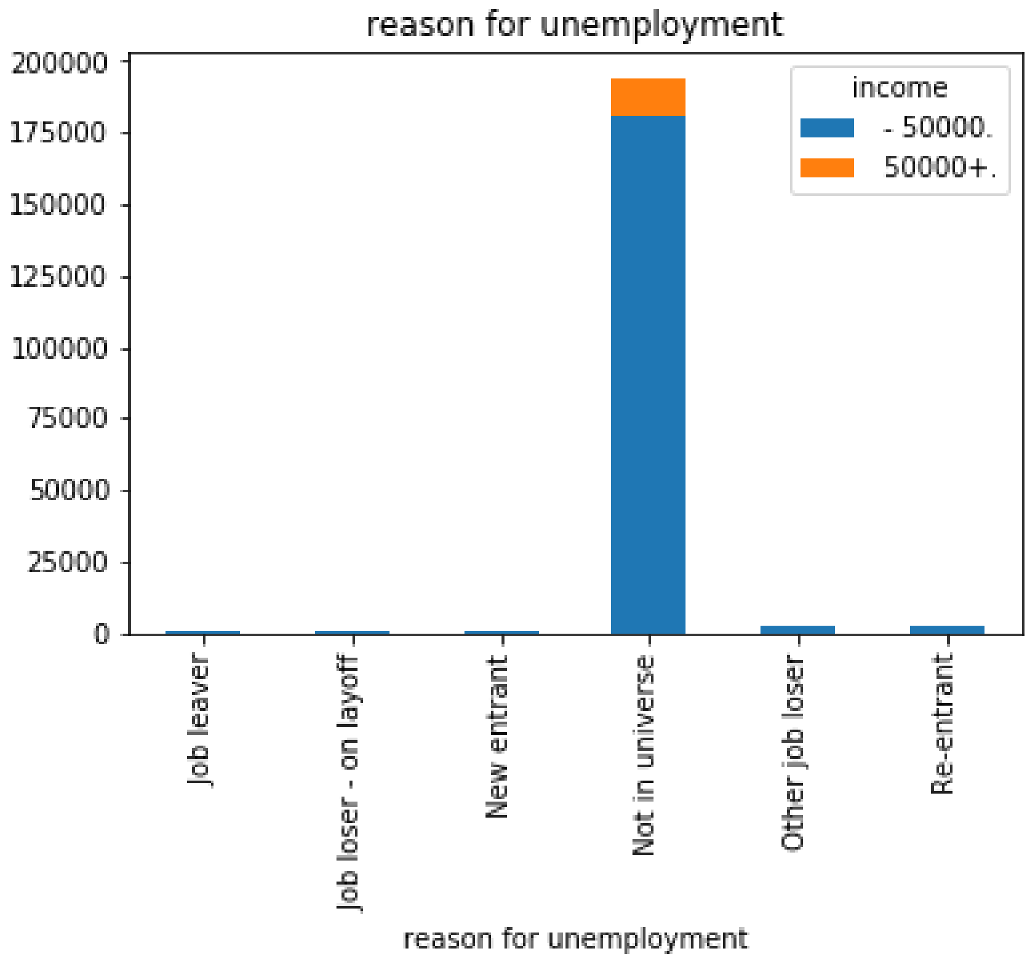
In [20]:
```
%matplotlib inline
for ind in indexes_todrop:
    dftrain.groupby('income')[col[ind]].value_counts().unstack(level=0).plot(kind='bar'
```

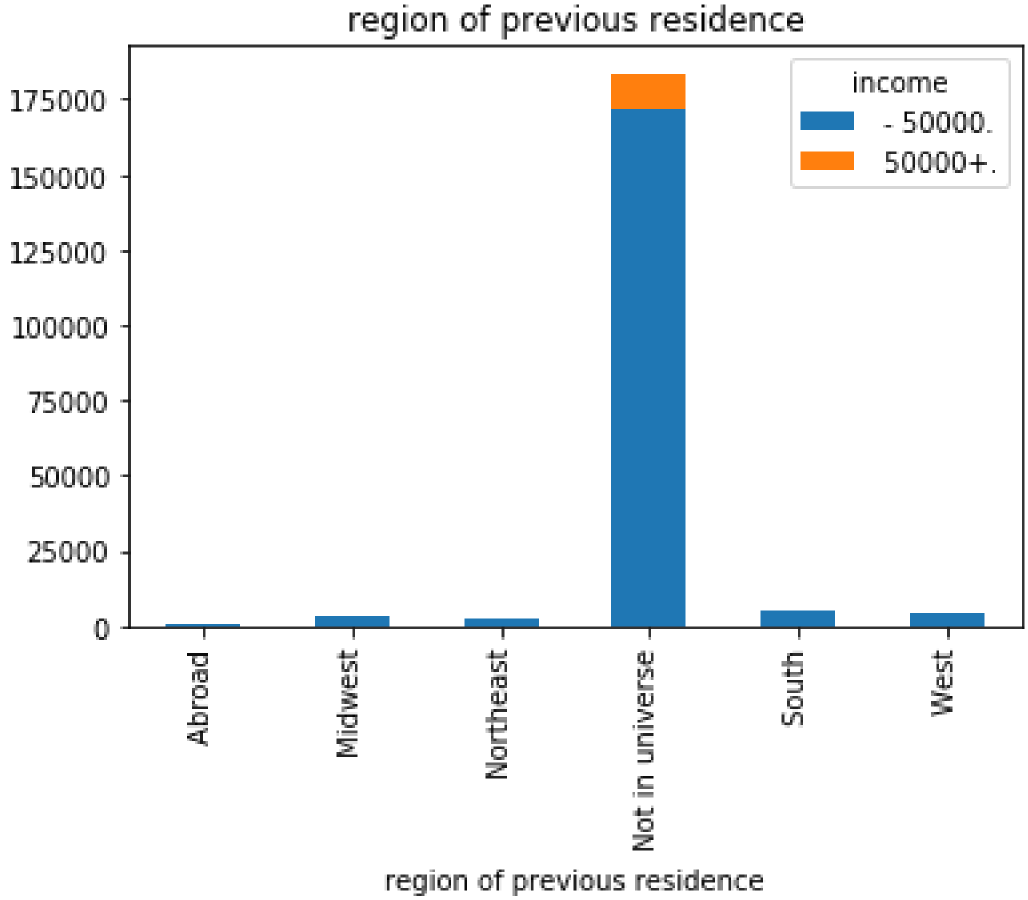


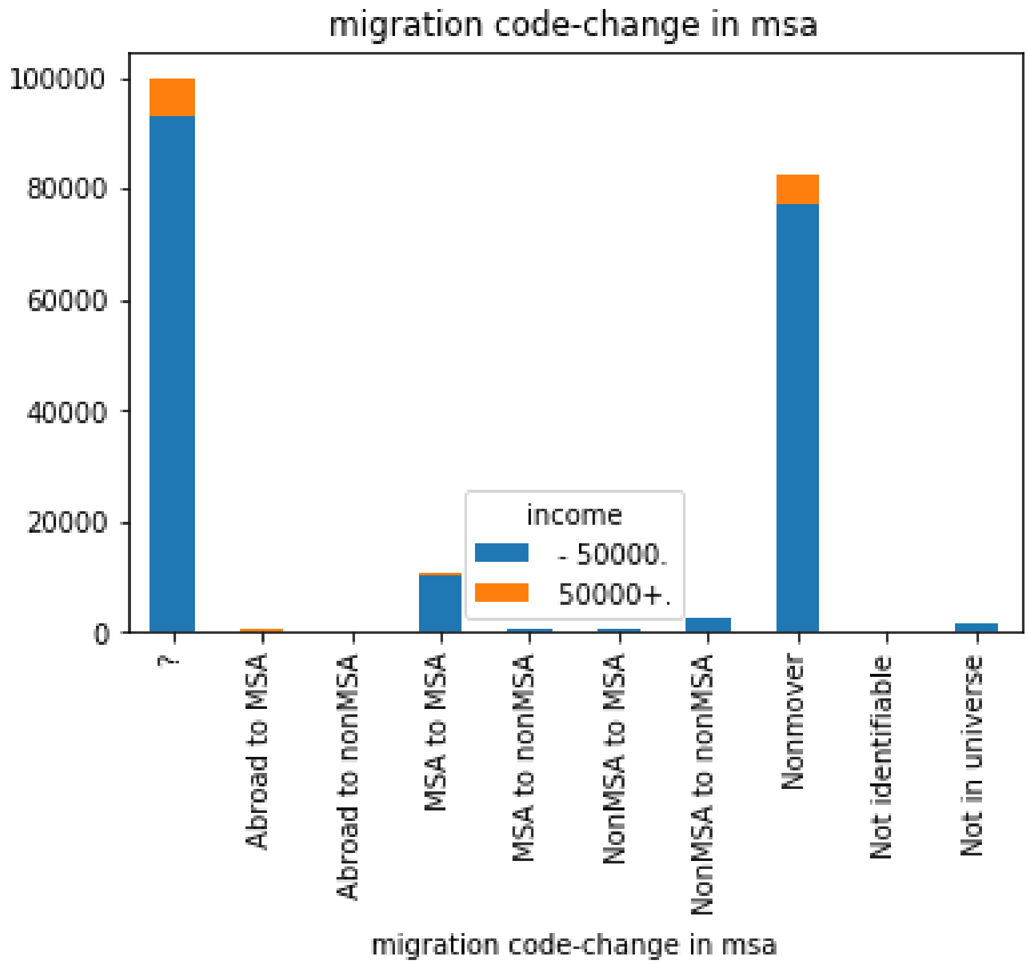

major industry code
income
- 50000.
50000+.
100000
80000
60000
40000
20000
0
Agriculture
Armed Forces
Business and repair services
Communications
Construction
Education
Entertainment
Finance insurance and real estate
Forestry and fisheries
Hospital services
Manufacturing-durable goods
Manufacturing-nondurable goods
Medical except hospital
Mining
Not in universe or children
Other professional services
Personal services except private HH
Private household services
Public administration
Retail trade
Social services
Transportation
Utilities and sanitary services
Wholesale trade
major industry code

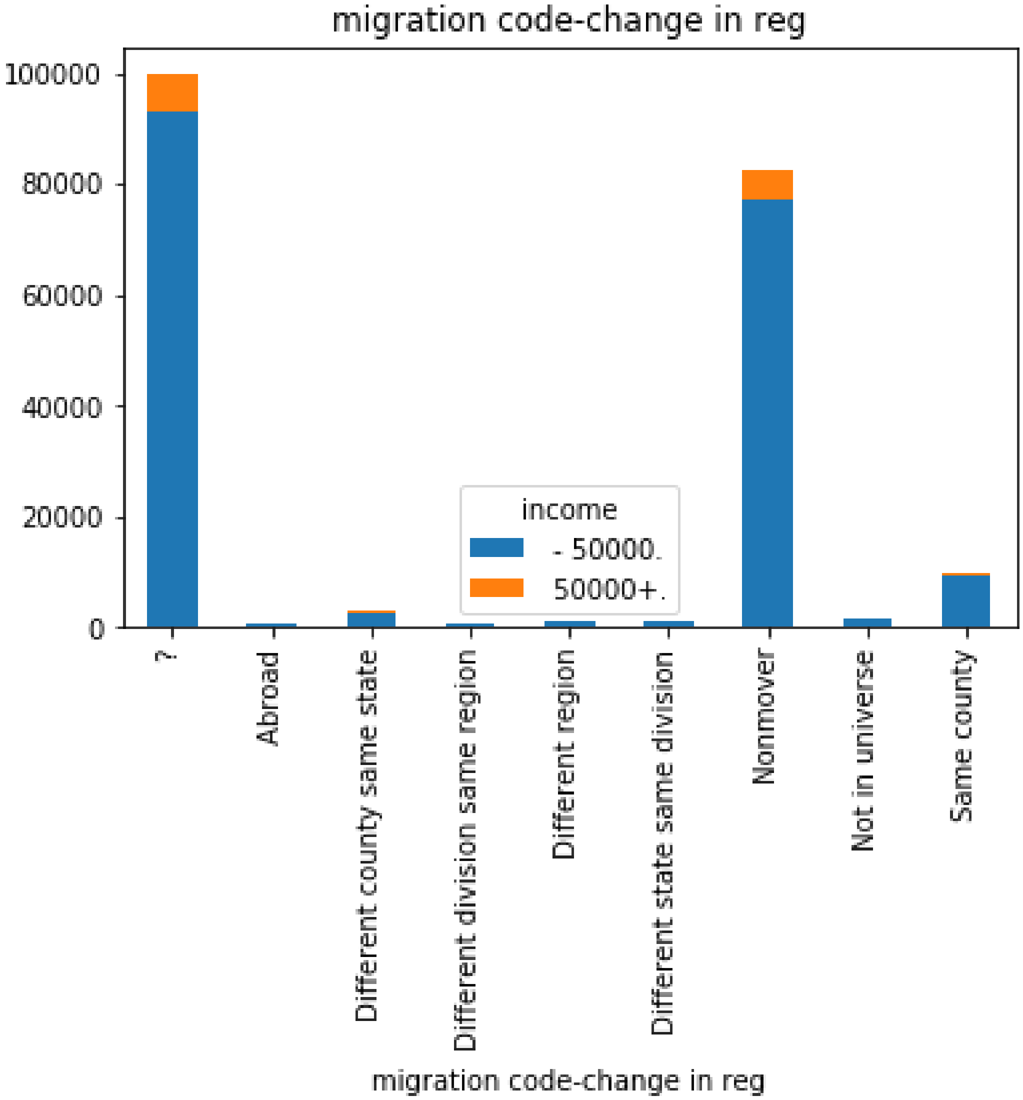

major occupation code
income
- 50000.
50000+.
100000
80000
60000
40000
20000
0
Adm support including clerical
Armed Forces
Executive admin and managerial
Farming forestry and fishing
Handlers equip cleaners etc
Machine operators assmblrs & inspctrs
Not in universe
Other service
Precision production craft & repair
Private household services
Professional specialty
Protective services
Sales
Technicians and related support
Transportation and material moving
major occupation code

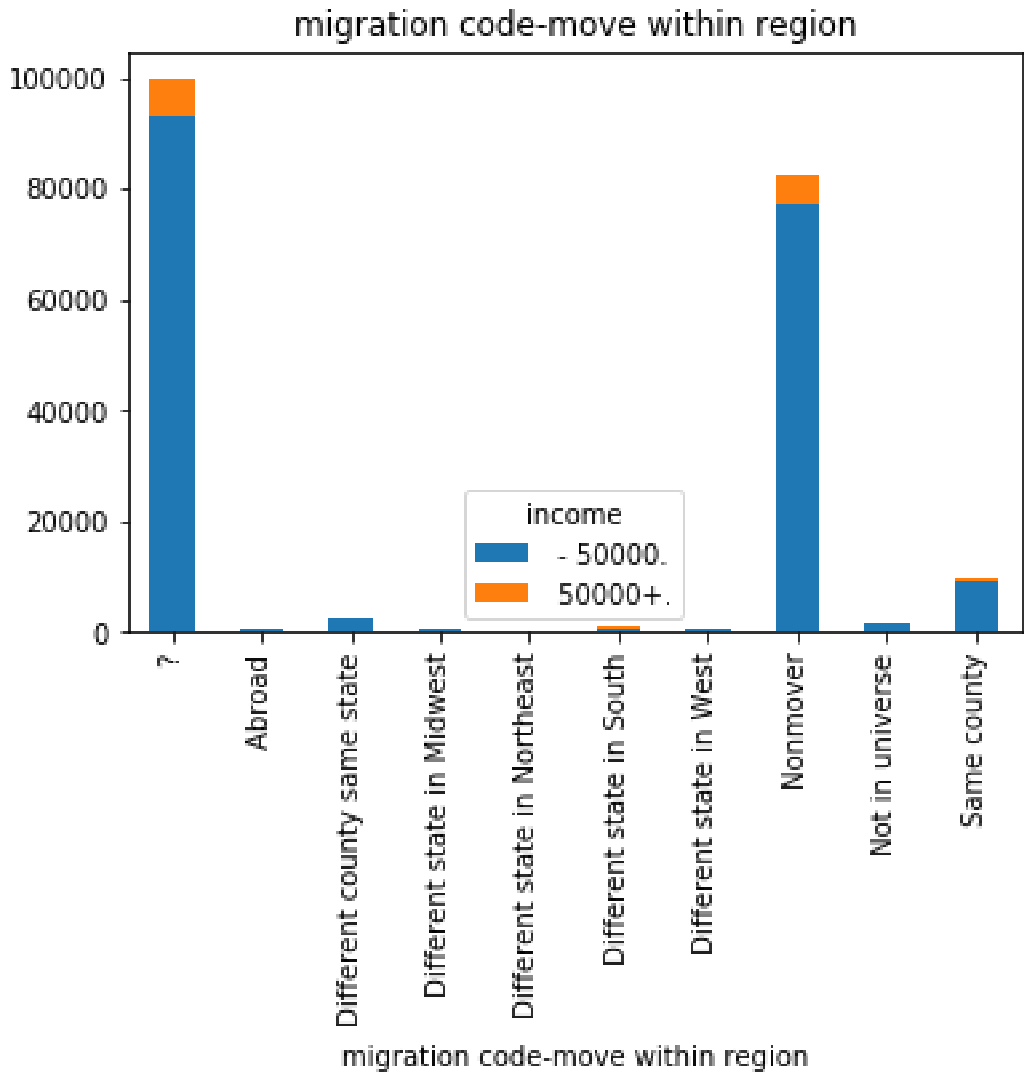

member of a labor union
income
- 50000.
50000+.
175000
150000
125000
100000
75000
50000
25000
0
No
Not in universe
Yes
member of a labor union


reason for unemployment
200000
175000
150000
125000
100000
75000
50000
25000
0
income
- 50000.
50000+.
Job leaver
Job loser - on layoff
New entrant
Not in universe
Other job loser
Re-entrant
reason for unemployment

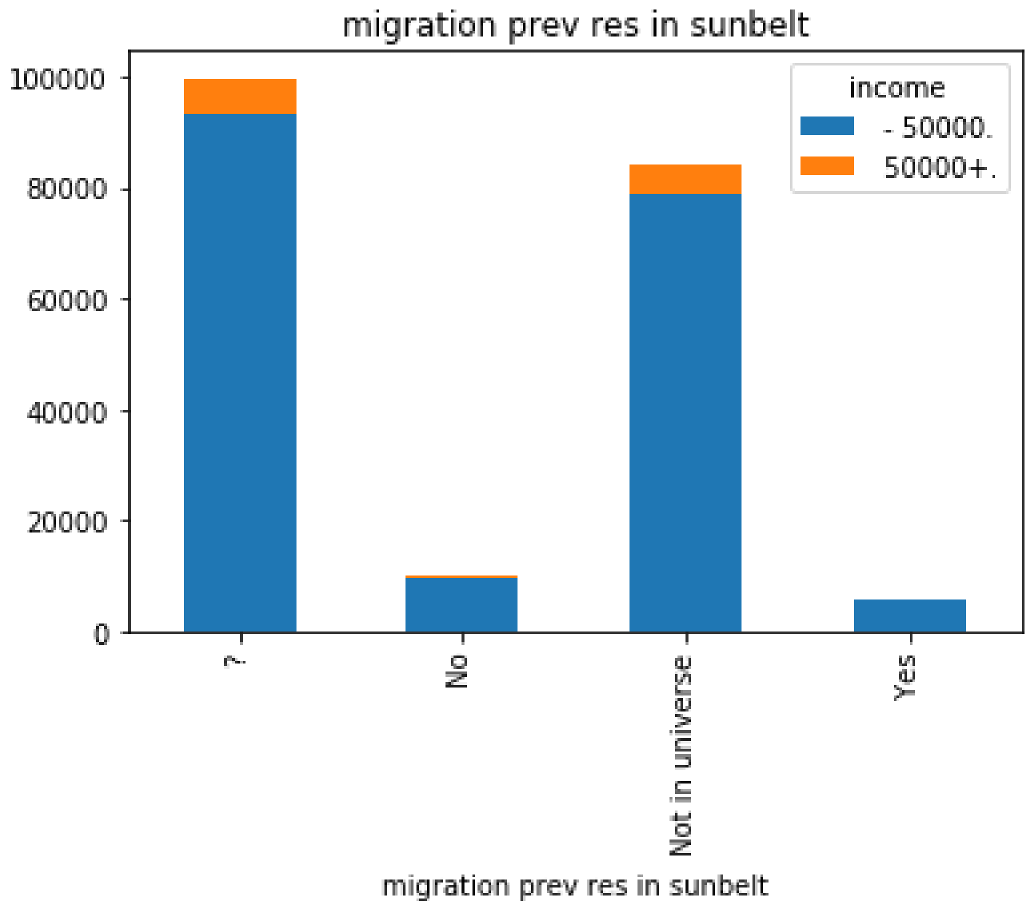

region of previous residence
175000
150000
125000
100000
75000
50000
25000
0
income
- 50000.
50000+.
Abroad
Midwest
Northeast
Not in universe
South
West
region of previous residence

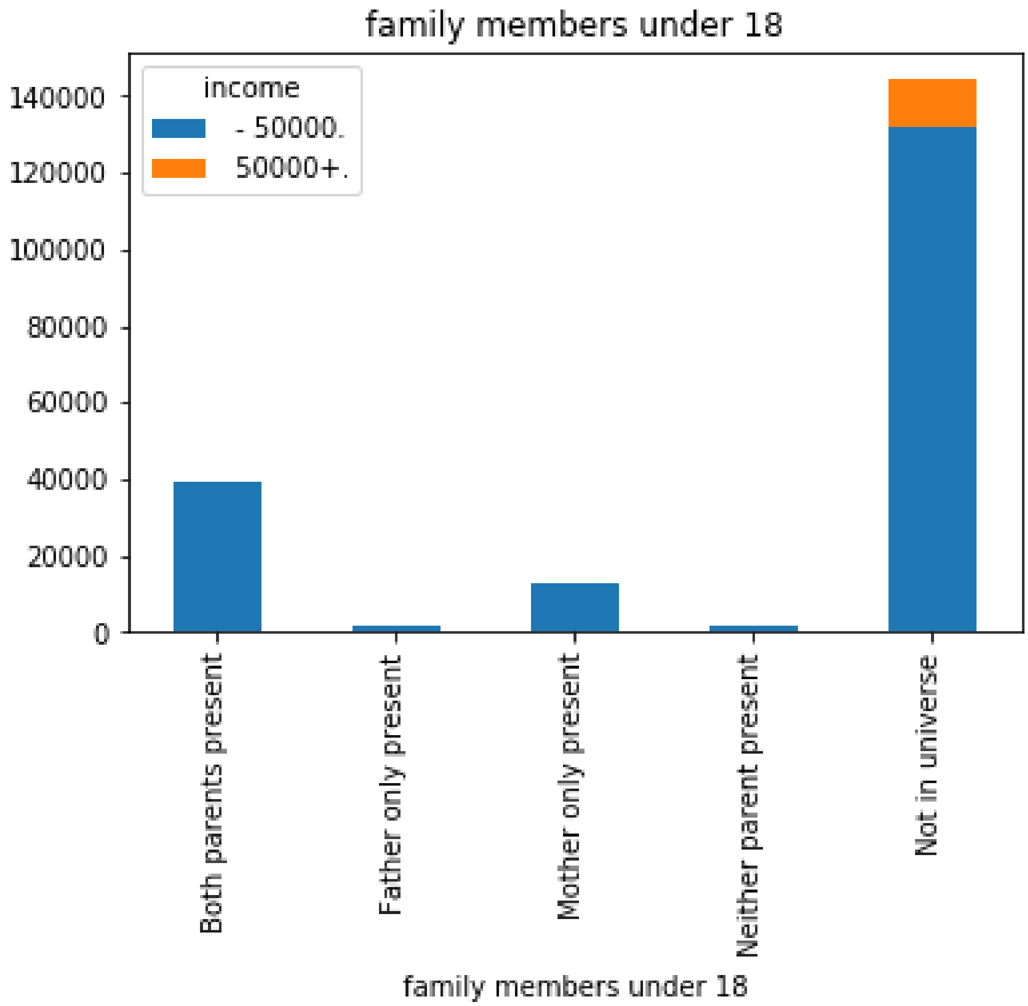

migration code-change in msa
100000
80000
60000
40000
20000
0
income
- 50000.
50000+.
?
Abroad to MSA
Abroad to nonMSA
MSA to MSA
MSA to nonMSA
NonMSA to MSA
NonMSA to nonMSA
Nonmover
Not identifiable
Not in universe
migration code-change in msa

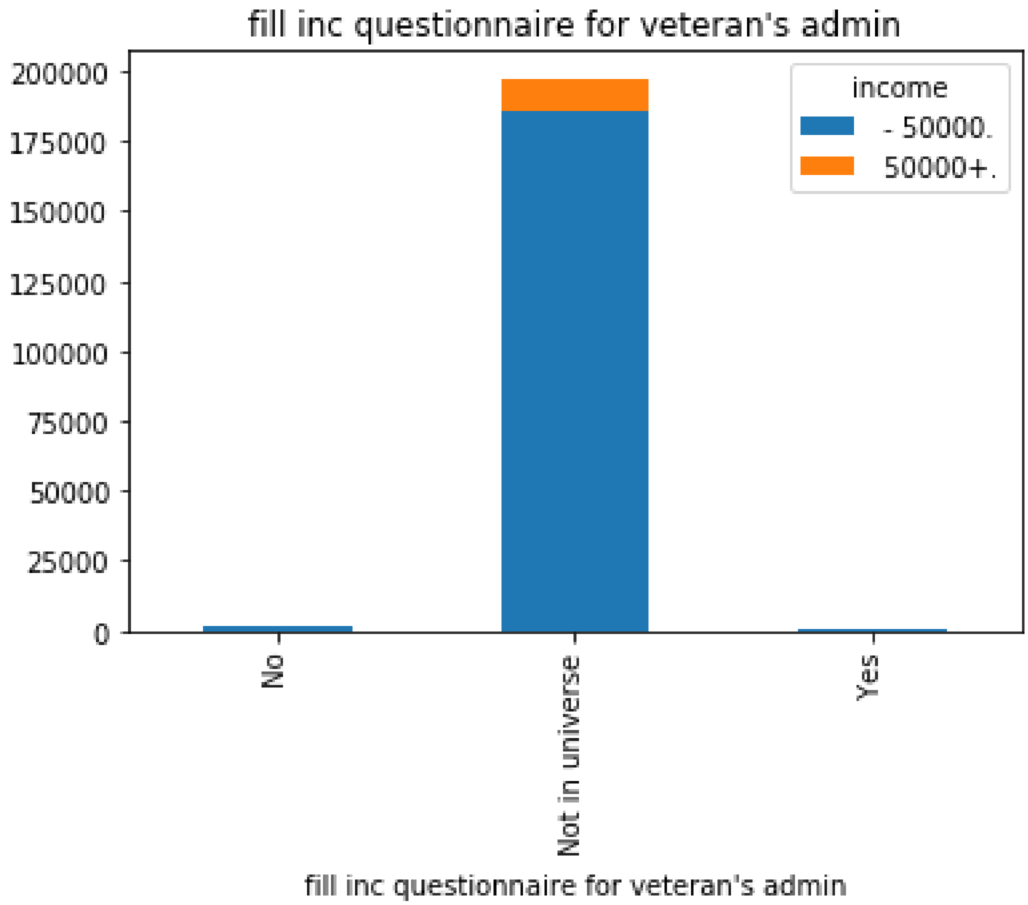

migration code-change in reg
100000
80000
60000
40000
20000
0
income
- 50000.
50000+.
?
Abroad
Different county same state
Different division same region
Different region
Different state same division
Nonmover
Not in universe
Same county
migration code-change in reg



migration code-move within region
100000
80000
60000
40000
20000
0
income
- 50000.
50000+.
?
Abroad
Different county same state
Different state in Midwest
Different state in Northeast
Different state in South
Different state in West
Nonmover
Not in universe
Same county
migration code-move within region


migration prev res in sunbelt
100000
80000
60000
40000
20000
0
income
- 50000.
50000+.
?
No
Not in universe
Yes
migration prev res in sunbelt

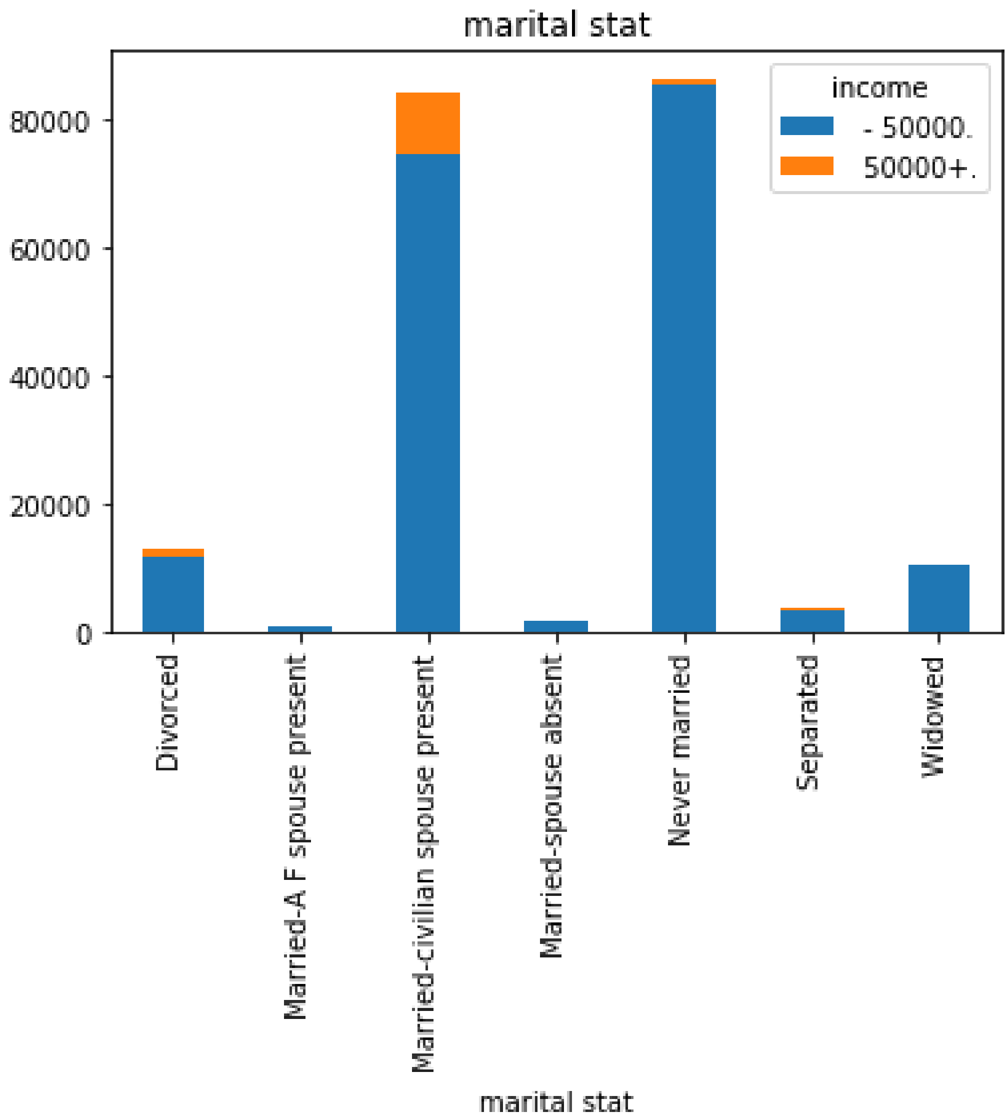

family members under 18
income
- 50000.
50000+.
140000
120000
100000
80000
60000
40000
20000
0
Both parents present
Father only present
Mother only present
Neither parent present
Not in universe
family members under 18



Since 'Not in universe' is a category that we have in many features, we assume that It means that data is not available (i.e. NAN). For this case, we can see that the most commun category is 'Not in universe' and in addition to that, the minority class (50 000+) is only available in this category, we can then drop this column since It won't give any new and interesting information/insights for training our model.

Meanwhile, there are features that would definitely be very beneficial for our model like 'education' which will clearly impact the income or marital stat (a married person may be more productive and then have a better income),while a never married person has more chances to earn less than 50000 as shows this plot

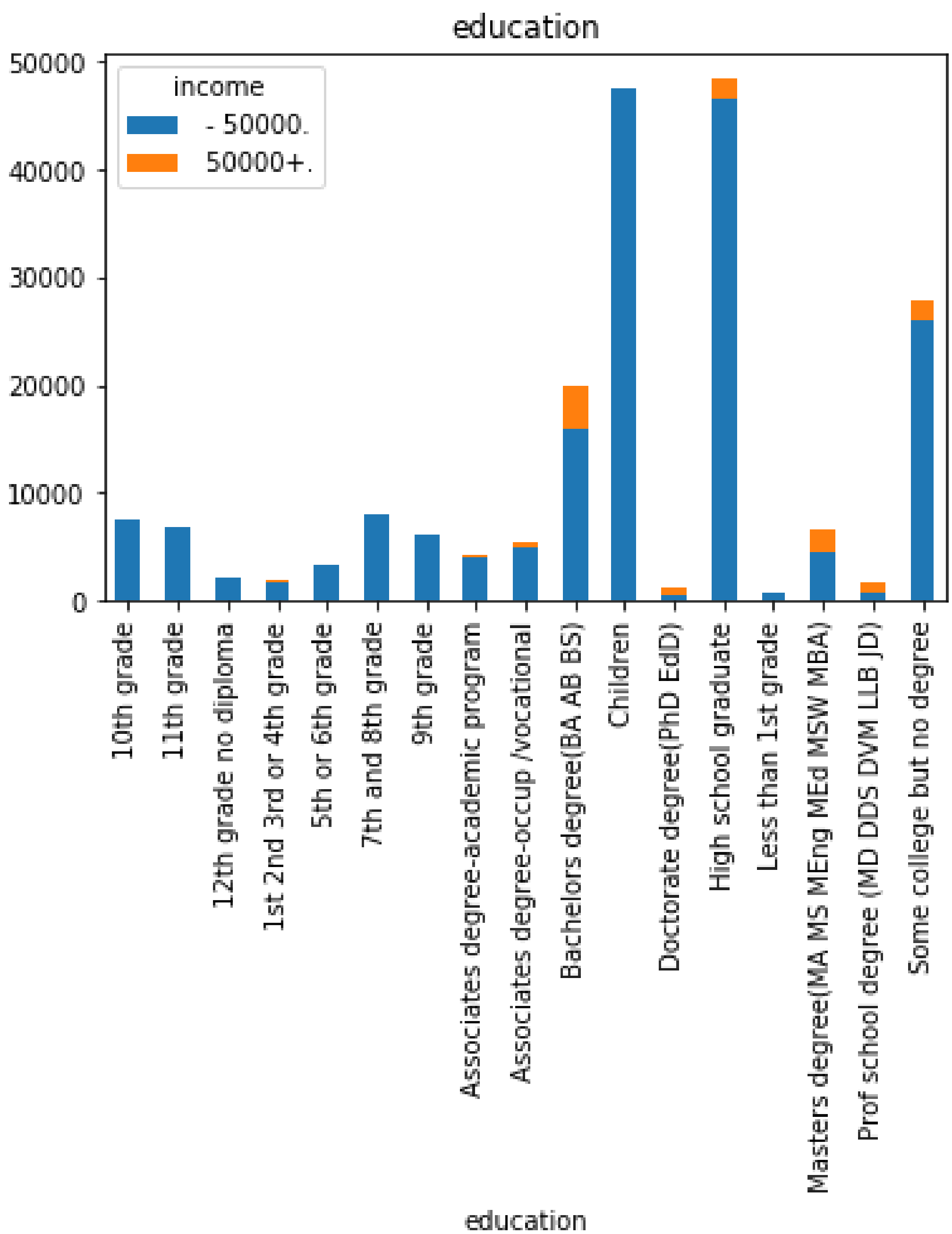
```
In [22]: dftrain.groupby('income')[col[7]].value_counts().unstack(level=0).plot(kind='bar',stack

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6a18cc4128>
```



Education will definitely be good for our model because it is usual to find that people who earn more money are the one with better education even if it is not always the case

```
In [23]: dftrain.groupby('income')[col[4]].value_counts().unstack(level=0).plot(kind='bar',stack
```

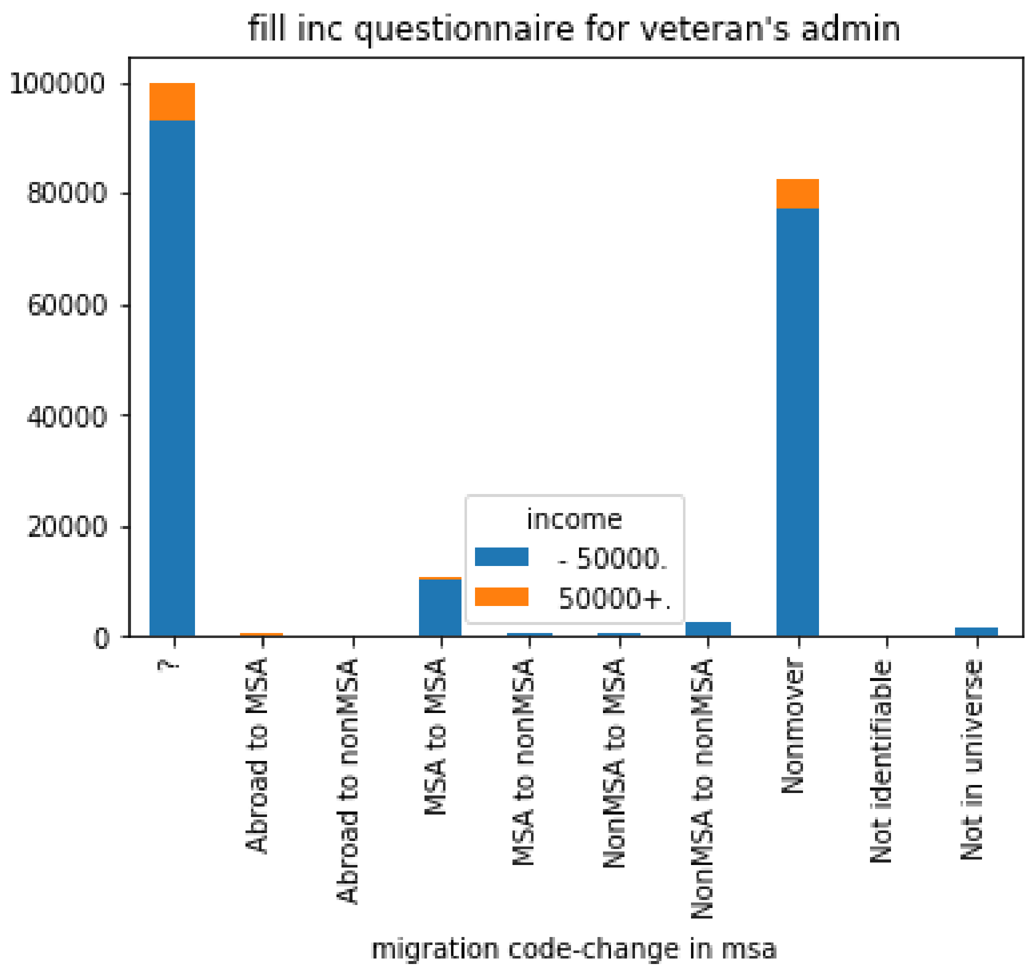
```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6a18c8e748>
```



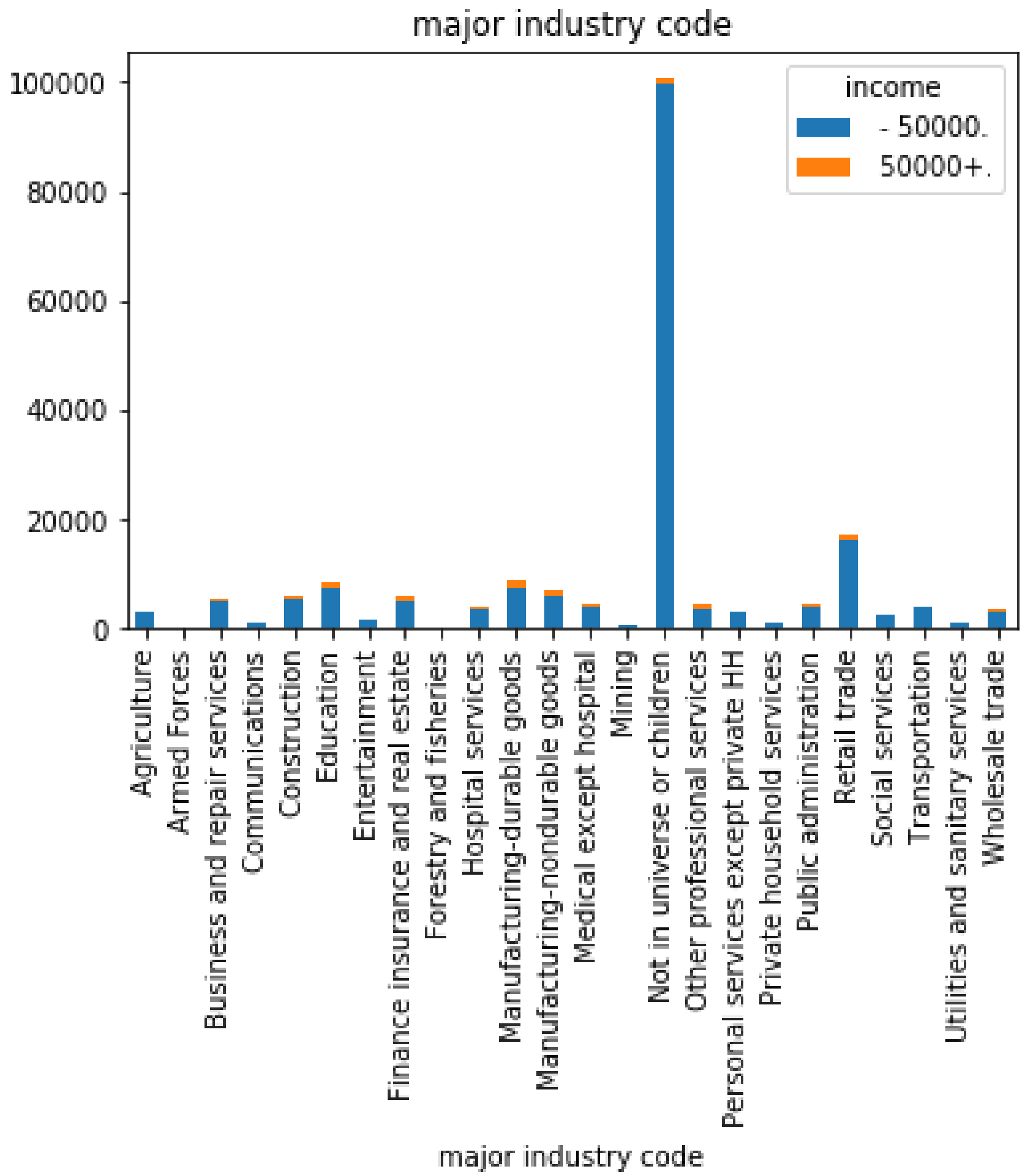
We chose to keep some features where 'Not in universe' is the most commun with a very high percentage compared to others for the simple reason that we have data for both kind of incomes all over the other categories, which may be interesting for our model. An example is shown below:

```
In [24]: dftrain.groupby('income')['migration code-change in msa'].value_counts().unstack(level=
```

```
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6a184ff2e8>
```




```
In [25]: ind=8
         dftrain.groupby('income')[col[ind]].value_counts().unstack(level=0).plot(kind='bar',sta

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6a10fabd30>
```



In [26]:
```
dftrain_filtred=dftrain_age.drop(col[indexes_todrop+indexesofrecodes],axis=1)
dftest_filtred=dftest.drop(col[indexes_todrop+indexesofrecodes],axis=1)
```

In [27]:
```
categoricals = dftrain_filtred.select_dtypes(include=[np.object]).columns.tolist()
print(categoricals)
```

```
['class of worker', 'education', 'marital stat', 'race', 'hispanic origin', 'sex', 'full or part
```

These are the categorical features in our data that we are planning to convert to numerical values using labelencoding, even if Label encoding could perform very badly when using it with tree models for example since we assume that some categories are better than others when assigning sorted discrete values to them.

2 Onehotencoding for categorical data

```
In [28]: from sklearn.preprocessing import OneHotEncoder
```

```
In [29]: big_X=dftrain_filtred.append(dftest_filtred)
```

```
In [30]: def one_hot_encode(df):
             categorical = df.select_dtypes(include=[np.object]).columns.tolist()
             numerical= df.drop(categorical, axis=1, inplace=False, errors='ignore')
             dummies = pd.get_dummies(df[categorical])
             concat_= pd.concat([numerical,dummies],axis=1)
             return concat_
```

```
In [31]: big_y=big_X['income']
         big_X_=one_hot_encode(big_X.drop('income',axis=1,inplace=False))
```

```
In [32]: train_X = big_X_[0:dftrain_filtred.shape[0]]
         test_X = big_X_[len(train_X):]
```

```
In [33]: le=LabelEncoder()
         big_y_=le.fit_transform(big_y)
         train_y=big_y_[0:dftrain_filtred.shape[0]]
         test_y=big_y_[len(train_y):]
```

3 Machine Learning Models Dealing with Class Imbalance

4 Logistic regression

```
In [34]: def transform(predictions,threshold):
             for k in range(len(predictions)):
                 if predictions[k]>threshold:
                     predictions[k]=1
                 else:
                     predictions[k]=0
```

```
In [35]: train_X=np.array(train_X)
```

We will do a cross validation to choose a threshold for predict_proba, changing this threshold will definitely impact our prediction in a way that will allow us to deal with this class imbalance.

```
In [ ]: from sklearn.model_selection import KFold
        kf = KFold(n_splits=5)
        thresholds=[]
        precisions=[]
        recalls=[]
        f1scores=[]
        aucscores=[]
        for train_index, test_index in kf.split(train_X):
```

```
    for threshold in [0.2,0.3,0.5,0.6,0.7,0.8,0.85,0.9]:
        X_train, X_test = train_X[train_index], train_X[test_index]
        y_train, y_test = train_y[train_index], train_y[test_index]
        clf = LogisticRegression(class_weight='balanced')
        clf.fit(X_train,y_train)
        predictions=[x[1] for x in clf.predict_proba(X_test)]
        transform(predictions,threshold)
        thresholds+=[threshold]
        precisions+=[precision_score(y_test,predictions)]
        recalls+=[recall_score(y_test,predictions)]
        f1scores+=[f1_score(y_test,predictions)]
        aucscores+=[roc_auc_score(y_test,predictions)]
```

Running this code we find that the best value is 0.8 for our threshold from the values we have chosen manually

```
In [36]: threshold=0.8
         clf = LogisticRegression(class_weight='balanced')
         clf.fit(train_X,train_y)
         predictions=[x[1] for x in clf.predict_proba(test_X)]
         transform(predictions,threshold)
```

```
In [37]: print(classification_report(test_y,predictions, target_names=['-50000', '+50000']))
```

```
             precision    recall  f1-score   support

     -50000       0.97      0.97      0.97     93576
     +50000       0.53      0.58      0.55      6186

avg / total       0.94      0.94      0.94     99762
```

5 Random Forest

```
In [39]: from sklearn.ensemble import RandomForestClassifier
```

```
In [ ]: kf = KFold(n_splits=5)
        thresholds=[]
        precisions=[]
        recalls=[]
        f1scores=[]
        aucscores=[]
        for train_index, test_index in kf.split(train_X):
            for threshold in [0.2,0.3,0.5,0.6,0.7,0.8,0.85,0.9]:
                X_train, X_test = train_X[train_index], train_X[test_index]
                y_train, y_test = train_y[train_index], train_y[test_index]
                clf_rf = RandomForestClassifier(n_estimators = 100, criterion='gini',random_stat
```

```
            clf_rf.fit(X_train,y_train)
            predictions=[x[1] for x in clf_rf.predict_proba(X_test)]
            transform(predictions,threshold)
            thresholds+=[threshold]
            precisions+=[precision_score(y_test,predictions)]
            recalls+=[recall_score(y_test,predictions)]
            f1scores+=[f1_score(y_test,predictions)]
            aucscores+=[roc_auc_score(y_test,predictions)]
```

Running this code we find that the best threshold from the ones chosen manually is 0.3

```
In [40]: threshold=0.3
         clf_rf = RandomForestClassifier(n_estimators = 100, criterion='gini',random_state=0, cl
         clf_rf.fit(train_X,train_y)
         predictions=[x[1] for x in clf_rf.predict_proba(test_X)]
         transform(predictions,threshold)
```

```
In [41]: print(classification_report(test_y,predictions, target_names=['-50000', '+50000']))

             precision    recall  f1-score   support

     -50000       0.97      0.97      0.97     93576
     +50000       0.55      0.56      0.56      6186

avg / total       0.95      0.94      0.94     99762
```

6 XgBoost

```
In [42]: import xgboost as xgb
```

```
In [43]: train_X=np.array(train_X)
         test_X=np.array(test_X)
```

```
In [ ]: kf = KFold(n_splits=5)
        thresholds=[]
        precisions=[]
        recalls=[]
        f1scores=[]
        aucscores=[]
        for train_index, test_index in kf.split(train_X):
            for threshold in [0.2,0.3,0.5,0.6]:
                X_train, X_test = train_X[train_index], train_X[test_index]
                y_train, y_test = train_y[train_index], train_y[test_index]
                gbm = xgb.XGBClassifier(max_depth=3, n_estimators=300, learning_rate=0.05).fit(X
                predictions=[x[1] for x in gbm.predict_proba(X_test)]
                transform(predictions,threshold)
```

```
                thresholds+=[threshold]
                precisions+=[precision_score(y_test,predictions)]
                recalls+=[recall_score(y_test,predictions)]
                f1scores+=[f1_score(y_test,predictions)]
                aucscores+=[roc_auc_score(y_test,predictions)]
```

Same as before we will take 0.3 as threshold

```
In [44]: threshold=0.3
         gbm = xgb.XGBClassifier(max_depth=3, n_estimators=300, learning_rate=0.05).fit(train_X,
         predictions=[x[1] for x in gbm.predict_proba(test_X)]
         transform(predictions,threshold)
```

```
In [45]: print(classification_report(test_y,predictions, target_names=['-50000', '+50000']))
```

```
             precision    recall  f1-score   support

     -50000       0.97      0.98      0.97     93576
     +50000       0.61      0.57      0.59      6186

avg / total       0.95      0.95      0.95     99762
```