Main

December 5, 2018

1 Program overview

- Look at relationships between income & different attributes.
- Extract important features from a Random Forest Model.

```
In [1]: import os
        os.chdir(r"C:\Users\Arnold\OneDrive\R_Python_working_directory")
        import pandas as pd
        import numpy as np
        from plotnine import *
        %matplotlib inline
        (theme_update(plot_background = element_rect(fill = "gold"),panel_background = element_
        colour = "blue",size = 1.99,linetype = "solid"),plot_title = element_text(hjust = 0.5))
```

2 Read in data

```
In [2]: df=pd.read_csv('cencus income.csv',na_values='?')
```

3 Data preview

```
In [3]: df.head()
```

```
Out[3]:    age  workclass  fnlwgt     education  educational-num      marital-status  \
        0   25    Private  226802          11th                7       Never-married
        1   38    Private   89814       HS-grad                9  Married-civ-spouse
        2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-spouse
        3   44    Private  160323  Some-college               10  Married-civ-spouse
        4   18        NaN  103497  Some-college               10       Never-married

                  occupation relationship   race  gender  capital-gain  capital-loss  \
        0  Machine-op-inspct    Own-child  Black    Male             0             0
        1    Farming-fishing      Husband  White    Male             0             0
        2    Protective-serv      Husband  White    Male             0             0
        3  Machine-op-inspct      Husband  Black    Male          7688             0
        4                NaN    Own-child  White  Female             0             0
```

```
   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K
```

4 Data summary

In [4]:
```
df.describe().T
```

Out[4]:
```
                  count           mean            std      min        25%  \
age             48842.0      38.643585      13.710510     17.0       28.0
fnlwgt          48842.0  189664.134597  105604.025423  12285.0   117550.5
educational-num 48842.0      10.078089       2.570973      1.0        9.0
capital-gain    48842.0    1079.067626    7452.019058      0.0        0.0
capital-loss    48842.0      87.502314     403.004552      0.0        0.0
hours-per-week  48842.0      40.422382      12.391444      1.0       40.0

                     50%       75%        max
age                 37.0      48.0       90.0
fnlwgt          178144.5  237642.0  1490400.0
educational-num     10.0      12.0       16.0
capital-gain         0.0       0.0    99999.0
capital-loss         0.0       0.0     4356.0
hours-per-week      40.0      45.0       99.0
```

5 Check the shape

In [5]:
```
df.shape
```

Out[5]: (48842, 15)

6 Check % of rows with missing values

In [6]:
```
np.mean(pd.isnull(df).any(axis=1))*100
```

Out[6]: 7.411653904426519

7% is low, so I'll drop the rows with missing values

7 Drop rows with missing values

In [7]:
```
df.dropna(inplace=1==1)
```

8 Age binning

```
In [8]: df.age=pd.cut(df.age,bins=[16,20,30,40,50,60,70,100])
```

9 Remove columns that I'm not going to use

```
In [9]: df.drop(columns=['relationship','capital-gain','capital-loss','hours-per-week'],inplac
```

9.1 Function to look at the relationships between different attributes & income

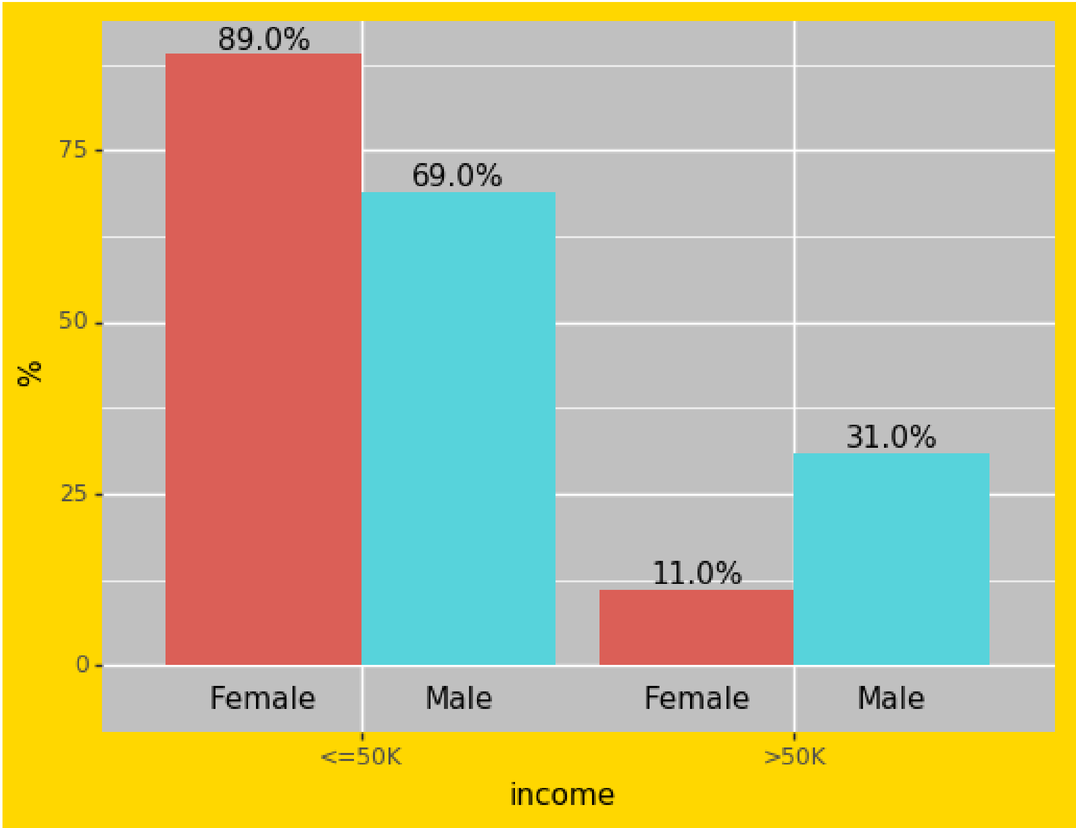
9.1.1 This function only works with categorical variables.

```
In [ ]: def relation(attr):
            tdf=df.pivot_table(values='fnlwgt',columns=['income'],index=attr,aggfunc=len,margi
            tdf.iloc[:-1,0]=tdf.iloc[:-1,0].values/(tdf.All[:-1]).values
            tdf.iloc[:-1,1]=1-tdf.iloc[:-1,0].values
            tdf.sort_values(by=['>50K'],inplace=1==1,ascending=1==0)
            tdf.iloc[1:,:2]=tdf.iloc[:,:2].applymap(lambda x: round(x*100))
            tdf=tdf.iloc[1:,:-1].stack().reset_index()
            tdf.rename(columns={0:'%'},inplace=1==1)
            return tdf
        def rggplot(attr,size=8):
            graph=ggplot(tdf,aes(x=attr,y='%',fill=attr))+geom_bar(stat='identity',show_legend
            size=size,format_string='{}%')+coord_flip()+ggtitle('% of income > 50K')
            return graph
```

10 Gender vs Income

```
In [37]: tdf=relation('gender')
         tdf
```

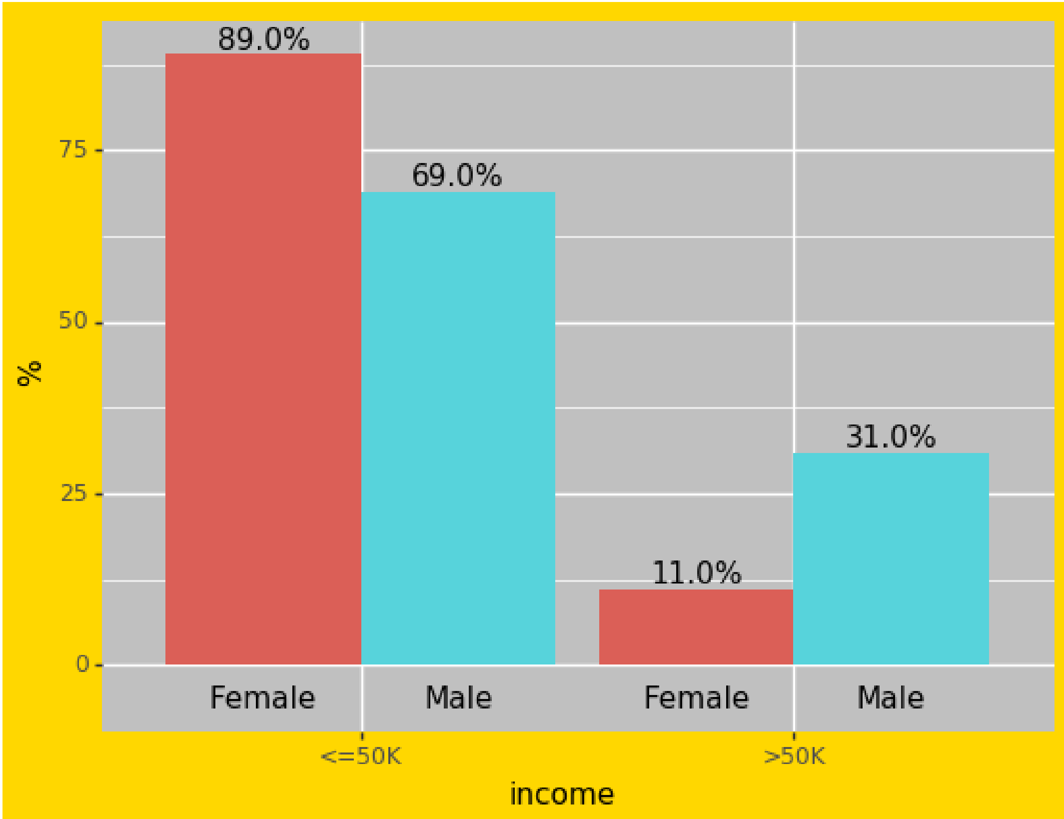
```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```




```
Out[37]: <ggplot: (-9223371902897112309)>

In [13]: (ggplot(tdf,aes(x='income',y='%',fill='gender'))+geom_bar(stat='identity',position='do
         geom_text(aes(y=-5,label='gender'),position=position_dodge(width=0.9))+geom_text(aes(l
         position_dodge(width=0.9),va='bottom', format_string='{}%'))

C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```



Out[13]: <ggplot: (133955488583)>

We can see that males are more likely to have high income than females.

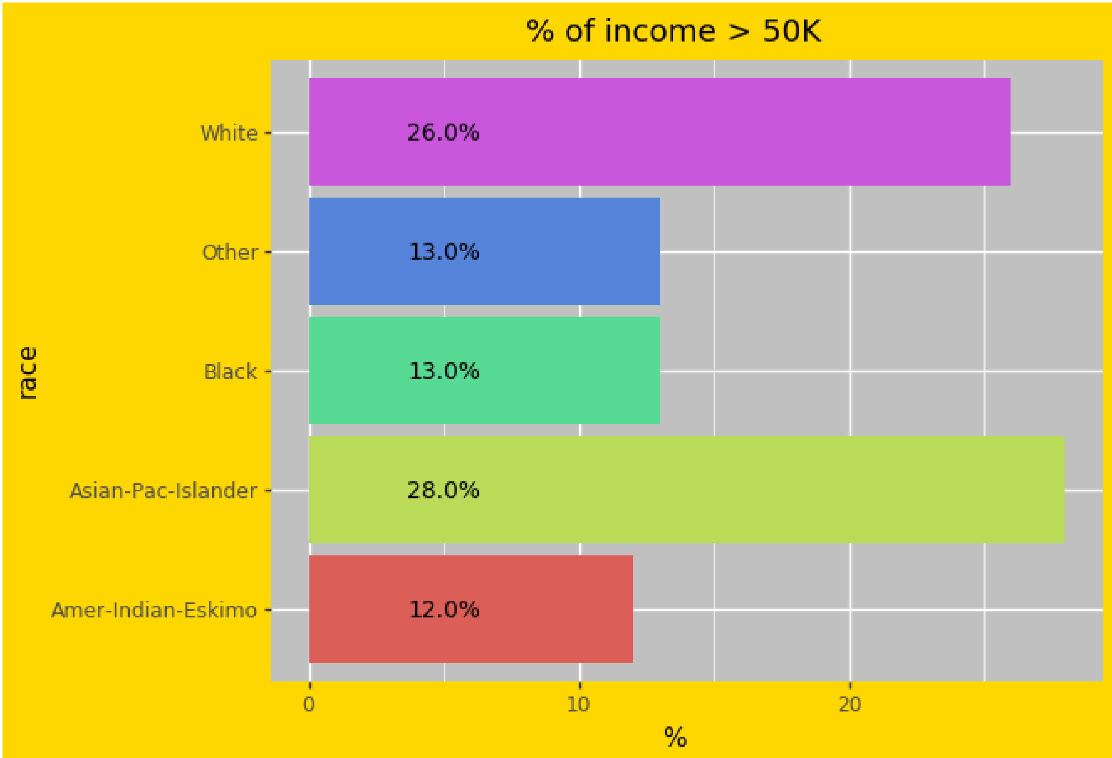
11 Race VS Income

```
In [14]: tdf=relation('race')
         tdf=tdf[tdf.income=='>50K']
         tdf
```

```
Out[14]:                  race income     %
         1  Asian-Pac-Islander   >50K  28.0
         3               White   >50K  26.0
         5               Other   >50K  13.0
         7               Black   >50K  13.0
         9  Amer-Indian-Eskimo   >50K  12.0
```

```
In [15]: rggplot('race',10)
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```




```
Out[15]: <ggplot: (133955726326)>
```

We can see that Asian-Pac-Islander & White races are more likely to have high income than other races.

12 Occupation VS Income

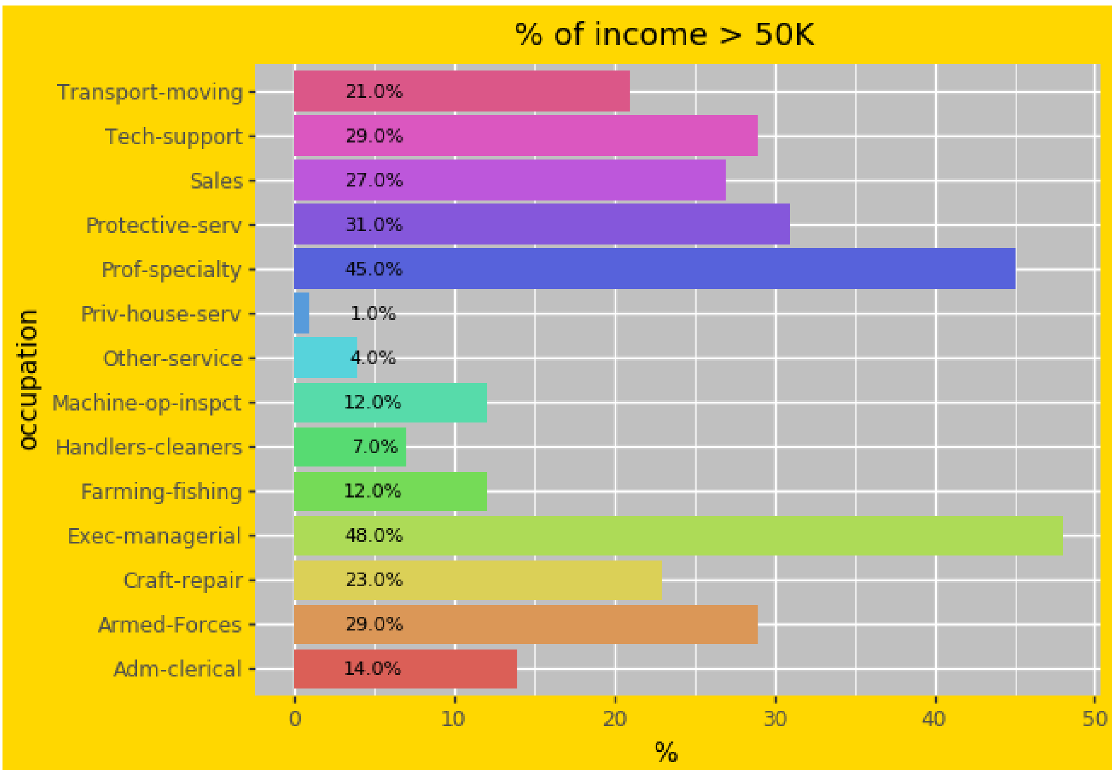
```
In [16]: tdf=relation('occupation')
         tdf=tdf[tdf.income=='>50K']
         tdf
```

```
Out[16]:            occupation income     %
         1     Exec-managerial   >50K  48.0
         3      Prof-specialty   >50K  45.0
         5     Protective-serv   >50K  31.0
         7        Tech-support   >50K  29.0
         9        Armed-Forces   >50K  29.0
         11              Sales   >50K  27.0
         13       Craft-repair   >50K  23.0
         15   Transport-moving   >50K  21.0
         17       Adm-clerical   >50K  14.0
         19  Machine-op-inspct   >50K  12.0
         21    Farming-fishing   >50K  12.0
```

```
23  Handlers-cleaners    >50K   7.0
25      Other-service    >50K   4.0
27     Priv-house-serv   >50K   1.0
```

In [17]:
```
rggplot('occupation')
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```



Out[17]: <ggplot: (-9223371902899033207)>

We see that Exec-managerial, Prof-specialty, & Protective-serv are more likely to have high income than other occupations.

13 Workclass VS Income

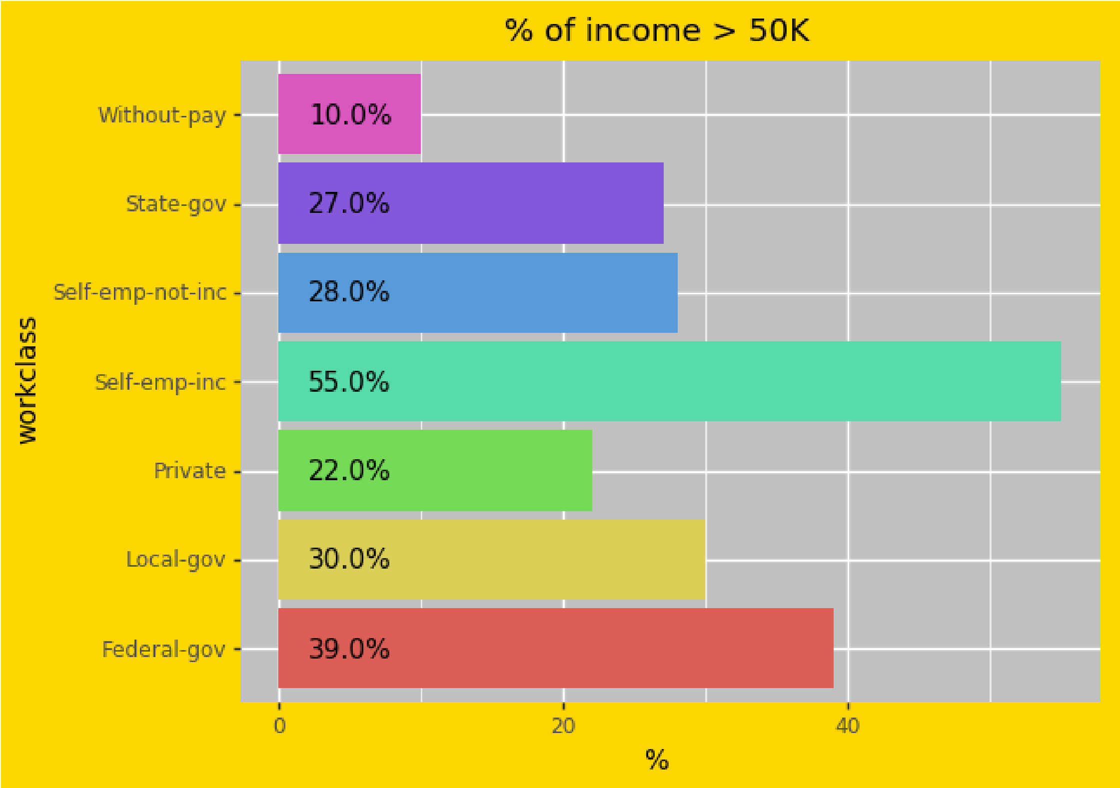
In [18]:
```
tdf=relation('workclass')
tdf=tdf[tdf.income=='>50K']
tdf
```

Out[18]:
```
         workclass income     %
1     Self-emp-inc   >50K  55.0
```

```
3          Federal-gov   >50K  39.0
5            Local-gov   >50K  30.0
7     Self-emp-not-inc   >50K  28.0
9            State-gov   >50K  27.0
11             Private   >50K  22.0
13         Without-pay   >50K  10.0
```

In [19]:
```
(ggplot(tdf,aes('workclass','%',fill='workclass'))+geom_bar(stat='identity',show_legen
format_string='{}%')+coord_flip()+ggtitle('% of income > 50K'))
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```



Out[19]: <ggplot: (-9223371902898882921)>

We see that Self-emp-inc, Federal-gov, Local-gov are more likely to have high income than other workclass.

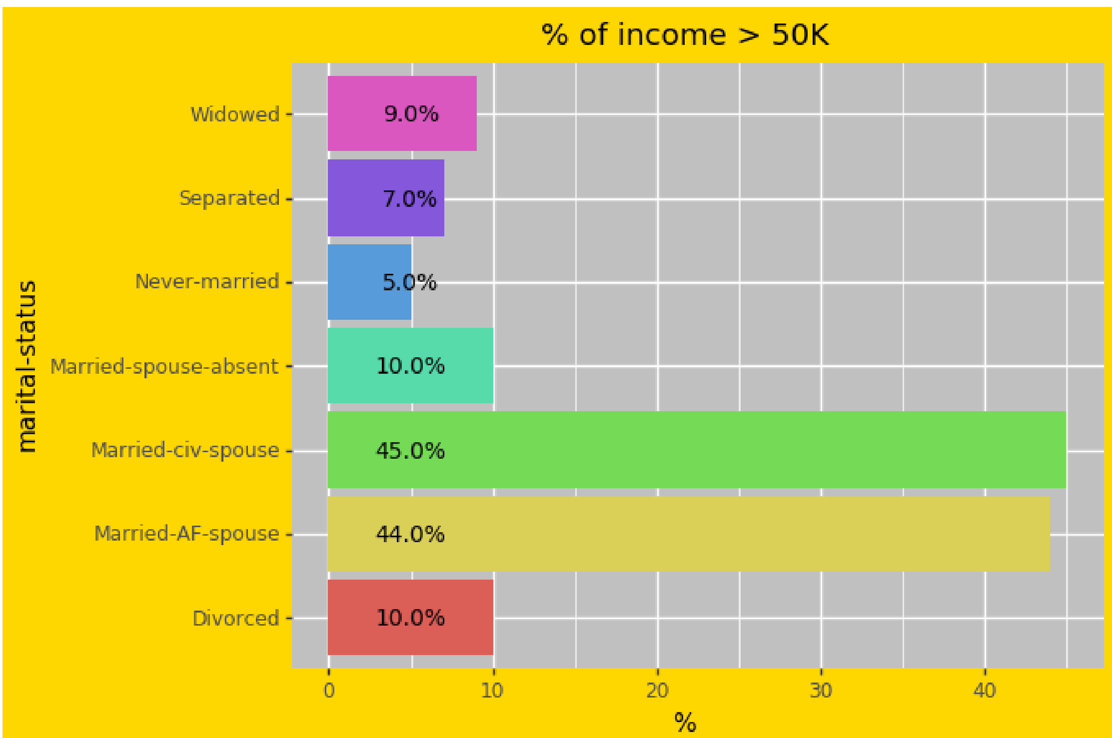
14 Marital-status VS Income

In [20]:
```
tdf=relation('marital-status')
tdf=tdf[tdf.income=='>50K']
tdf
```

```
Out[20]:           marital-status income     %
        1      Married-civ-spouse   >50K  45.0
        3       Married-AF-spouse   >50K  44.0
        5                Divorced   >50K  10.0
        7   Married-spouse-absent   >50K  10.0
        9                 Widowed   >50K   9.0
        11              Separated   >50K   7.0
        13          Never-married   >50K   5.0
```

```
In [21]: rggplot('marital-status',10)
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```




```
Out[21]: <ggplot: (133955472946)>
```

We see people who has the marital status of Married-civ-spouse, or Married-AF-spouse are much more likely to have high income than others.

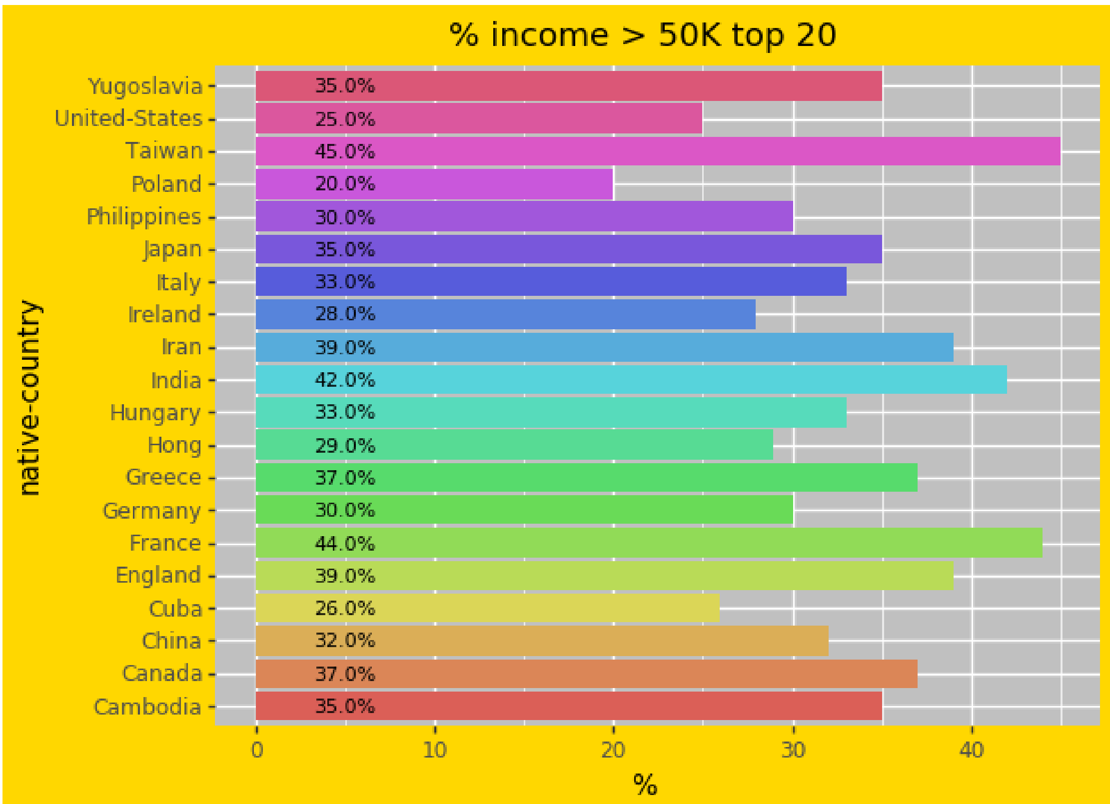
15 Native-country VS Income

```
In [22]: tdf=relation('native-country')
         tdf=tdf[tdf.income=='>50K']
```

```
tdf
tdf=tdf.iloc[:20,:]
```

```
In [23]: rggplot('native-country')+ggtitle('% income > 50K top 20')
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```




```
Out[23]: <ggplot: (133955817494)>
```

- We see that top 3 native country that have higher % of high income individuals are Taiwan, France, & India.
- U.S.A. as native country is ranked in the middle with 25% of people with high income.

16 Random Forest model

```
In [24]: from custom import tts
         from sklearn.ensemble import RandomForestClassifier as rfc
```

16.1 Getting data ready for modeling

```
In [25]: from sklearn.preprocessing import LabelEncoder as le
         from pandas import get_dummies as getd
```

```
In [26]: tdf=df.loc[:,['educational-num','workclass','marital-status','occupation','race','gend
```

```
In [27]: tdf.loc[:,'age']=le().fit_transform(df.age)
         clm=['workclass','marital-status','occupation','race','gender','native-country','incom
         tdf=getd(tdf,columns=clm,prefix=clm,drop_first=1==1)
```

16.2 Split data into training and testing group

```
In [28]: xtr,xte,ytr,yte=tts(tdf,dep='income_>50K')
```

```
C:\Anocanda\lib\site-packages\sklearn\model_selection\_split.py:2069: FutureWarning: From versi
  FutureWarning)
```

16.3 Model fitting

```
In [29]: mod=rfc(n_estimators=100).fit(xtr,ytr)
```

16.4 Look at feature importance

```
In [30]: imp=pd.DataFrame({'Attribute':tdf.columns[:-1],'Score':mod.feature_importances_.round
```

16.5 Clean up

```
In [31]: def clean(string):
             if '_' in string:
                 return string[:string.find('_')]
             return string
```

```
In [32]: imp.Attribute=imp.Attribute.map(clean)
```

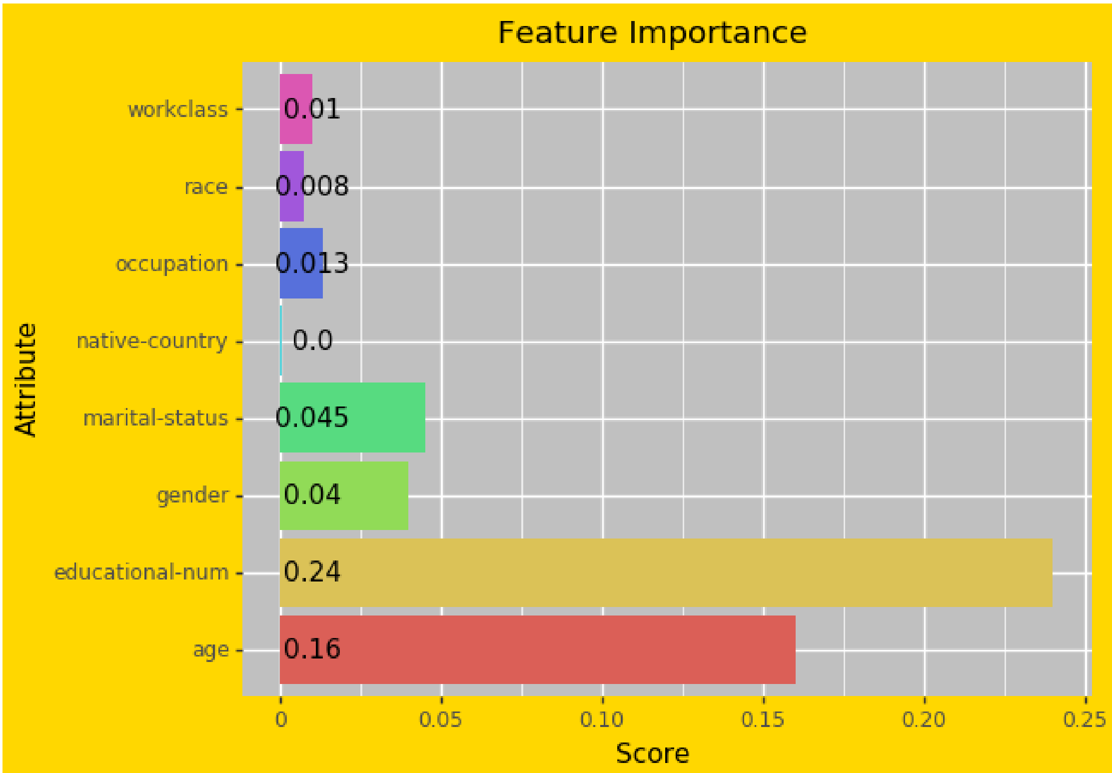
```
In [33]: tdf=imp.groupby('Attribute').mean().reset_index().sort_values('Score',ascending=1==0)
         tdf
```

Out[33]:

	Attribute	Score
1	educational-num	0.240000
0	age	0.160000
3	marital-status	0.045000
2	gender	0.040000
5	occupation	0.013077
7	workclass	0.010000
6	race	0.007500
4	native-country	0.000250

```
In [34]: ggplot(tdf,aes('Attribute','Score',fill='Attribute'))+geom_bar(stat='identity',show_le
         (label='round(Score,3)',y=.01))+coord_flip()+labs(title='Feature Importance',caption=
```

```
C:\Anocanda\lib\site-packages\plotnine\layer.py:517: MatplotlibDeprecationWarning: isinstance(
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
```




```
Out[34]: <ggplot: (133957643030)>
```

We see that education & age are by far the most important features according to this model.

16.6 Accuracy of the model

```
In [35]: mod.score(xte,yte)

Out[35]: 0.8231869103773585

In [36]: tdf.Attribute.unique()

Out[36]: array(['educational-num', 'age', 'marital-status', 'gender', 'occupation',
                'workclass', 'race', 'native-country'], dtype=object)
```