Assignment_25_Data_Science_Masters

February 18, 2019

1 Session 25 - Assignment Machine learning 6

Predict whether a person makes over 50K per year or not from classic adult dataset using XGBoost.

Data Set Information: Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0))

Attribute Information:

Listing of attributes: >50K, <=50K. age: continuous. workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked. fnlwgt: continuous. education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool. education-num: continuous. marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces. relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried. race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black. sex: Female, Male. capital-gain: continuous. capital-loss: continuous. hours-per-week: continuous. native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India,Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

1.0.1 Load libraries

```
In [0]: # Core Libraries - Data manipulation and analysis
        import pandas as pd
        import numpy as np
        import math
        from math import sqrt
        import matplotlib.pyplot as plt
        import seaborn as sns

        # Core Libraries - Machine Learning
        import sklearn
        import xgboost as xgb
```

```
# Importing Classifiers - Modelling
from sklearn.linear_model import LogisticRegression
from xgboost.sklearn import XGBClassifier

## Importing train_test_split,cross_val_score,GridSearchCV,KFold - Validation and Opti
from sklearn.model_selection import  train_test_split, cross_val_score, GridSearchCV, K


# Importing Metrics - Performance Evaluation
from sklearn import metrics

# Warnings Library - Ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

1.1 Load Data

```
In [0]: train_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adul
        test_set =  pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adul
                        header = None)
        col_labels = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_sta
                          'race', 'sex', 'capital_gain', 'capital_loss', 'hours_per_week', 'na
        train_set.columns = col_labels
        test_set.columns = col_labels
```

1.2 Understand the Dataset and Data

```
In [3]: train_set.shape,test_set.shape

Out[3]: ((32561, 15), (16281, 15))

In [4]: train_set.columns

Out[4]: Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
               'marital_status', 'occupation', 'relationship', 'race', 'sex',
               'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
               'wage_class'],
              dtype='object')

In [5]: train_set.head()

Out[5]:    age          workclass  fnlwgt   education  education_num  \
        0   39          State-gov   77516   Bachelors             13
        1   50   Self-emp-not-inc   83311   Bachelors             13
        2   38            Private  215646     HS-grad              9
        3   53            Private  234721        11th              7
        4   28            Private  338409   Bachelors             13
```

```
       marital_status          occupation    relationship    race      sex  \
0       Never-married        Adm-clerical   Not-in-family   White     Male
1  Married-civ-spouse     Exec-managerial         Husband   White     Male
2            Divorced   Handlers-cleaners   Not-in-family   White     Male
3  Married-civ-spouse   Handlers-cleaners         Husband   Black     Male
4  Married-civ-spouse      Prof-specialty            Wife   Black   Female

   capital_gain  capital_loss  hours_per_week  native_country wage_class
0          2174             0              40   United-States      <=50K
1             0             0              13   United-States      <=50K
2             0             0              40   United-States      <=50K
3             0             0              40   United-States      <=50K
4             0             0              40            Cuba      <=50K
```

```
In [7]: test_set.columns
```

```
Out[7]: Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
               'marital_status', 'occupation', 'relationship', 'race', 'sex',
               'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
               'wage_class'],
              dtype='object')
```

```
In [8]: test_set.head()
```

```
Out[8]:    age   workclass  fnlwgt      education  education_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           ?  103497   Some-college             10        Never-married

                  occupation relationship    race      sex  capital_gain  \
        0  Machine-op-inspct    Own-child   Black     Male             0
        1    Farming-fishing      Husband   White     Male             0
        2    Protective-serv      Husband   White     Male             0
        3  Machine-op-inspct      Husband   Black     Male          7688
        4                  ?    Own-child   White   Female             0

           capital_loss  hours_per_week  native_country wage_class
        0             0              40   United-States     <=50K.
        1             0              50   United-States     <=50K.
        2             0              40   United-States      >50K.
        3             0              40   United-States      >50K.
        4             0              30   United-States     <=50K.
```

```
In [9]: train_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
```

```
Data columns (total 15 columns):
age               32561 non-null int64
workclass         32561 non-null object
fnlwgt            32561 non-null int64
education         32561 non-null object
education_num     32561 non-null int64
marital_status    32561 non-null object
occupation        32561 non-null object
relationship      32561 non-null object
race              32561 non-null object
sex               32561 non-null object
capital_gain      32561 non-null int64
capital_loss      32561 non-null int64
hours_per_week    32561 non-null int64
native_country    32561 non-null object
wage_class        32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
In [10]: test_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
age               16281 non-null int64
workclass         16281 non-null object
fnlwgt            16281 non-null int64
education         16281 non-null object
education_num     16281 non-null int64
marital_status    16281 non-null object
occupation        16281 non-null object
relationship      16281 non-null object
race              16281 non-null object
sex               16281 non-null object
capital_gain      16281 non-null int64
capital_loss      16281 non-null int64
hours_per_week    16281 non-null int64
native_country    16281 non-null object
wage_class        16281 non-null object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
```

```
In [11]: train_set.get_dtype_counts()
```

```
Out[11]: int64     6
         object    9
         dtype: int64
```

```
In [12]: test_set.get_dtype_counts()
```

```
Out[12]: int64     6
         object    9
         dtype: int64
```

1.3 Clean the data

1.4 Clean Column Names

```
In [13]: train_set.columns
```

```
Out[13]: Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
                'marital_status', 'occupation', 'relationship', 'race', 'sex',
                'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
                'wage_class'],
               dtype='object')
```

```
In [14]: test_set.columns
```

```
Out[14]: Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
                'marital_status', 'occupation', 'relationship', 'race', 'sex',
                'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
                'wage_class'],
               dtype='object')
```

The columns don't have any nonsensical values, therefore there is no need to clean or change column names

1.5 Clean Numerical Columns

1.5.1 Null values

```
In [0]: num_cols = train_set.select_dtypes(include="int64").columns.values
        # num_cols = test_set.select_dtypes(include="int64").columns.values can also be used b
```

```
In [16]: train_set[num_cols].isna().sum()
```

```
Out[16]: age               0
         fnlwgt            0
         education_num     0
         capital_gain      0
         capital_loss      0
         hours_per_week    0
         dtype: int64
```

```
In [17]: test_set[num_cols].isna().sum()
```

```
Out[17]: age               0
         fnlwgt            0
```

```
education_num     0
capital_gain      0
capital_loss      0
hours_per_week    0
dtype: int64
```

No null values in the numerical columns of both the train_set and test_set

1.5.2 Zeros

Check if there are any rows with all row values = zero that need our consideration so that we can decide to study those rows

```
In [18]: train_set.loc[(train_set==0).all(axis=1),num_cols].shape

Out[18]: (0, 6)

In [19]: test_set.loc[(train_set==0).all(axis=1),num_cols].shape

Out[19]: (0, 6)
```

There are no rows which have all row values == 0

Check if there are any rows with any row values = zero that need our consideration so that we can decide to study those rows

```
In [20]: train_set.loc[(train_set==0).any(axis=1),num_cols].shape

Out[20]: (32561, 6)

In [21]: train_set.loc[(train_set==0).any(axis=1),num_cols].head()

Out[21]:    age  fnlwgt  education_num  capital_gain  capital_loss  hours_per_week
         0   39   77516             13          2174             0              40
         1   50   83311             13             0             0              13
         2   38  215646              9             0             0              40
         3   53  234721              7             0             0              40
         4   28  338409             13             0             0              40

In [0]: train_set.loc[(train_set.drop(["capital_gain", "capital_loss"],axis=1)==0).any(axis=1)

Out[0]: (0, 6)

In [0]: test_set.loc[(train_set==0).any(axis=1),num_cols].shape

Out[0]: (16281, 6)

In [0]: test_set.loc[(test_set.drop(["capital_gain", "capital_loss"],axis=1)==0).any(axis=1),nu

Out[0]: (0, 6)
```

There are no rows which have any row values == 0, except in captital_gain, capital_loss columns(where 0 is a valid value)

1.5.3 Nonsensical values

1.6 Clean Categorical Columns

1.6.1 Null values

```
In [0]: cat_cols = train_set.select_dtypes(include="object").columns.values
        cat_cols
```

```
Out[0]: array(['workclass', 'education', 'marital_status', 'occupation',
               'relationship', 'race', 'sex', 'native_country', 'wage_class'],
              dtype=object)
```

```
In [0]: train_set[cat_cols].isna().sum()
```

```
Out[0]: workclass         0
        education         0
        marital_status    0
        occupation        0
        relationship      0
        race              0
        sex               0
        native_country    0
        wage_class        0
        dtype: int64
```

```
In [0]: test_set[cat_cols].isna().sum()
```

```
Out[0]: workclass         0
        education         0
        marital_status    0
        occupation        0
        relationship      0
        race              0
        sex               0
        native_country    0
        wage_class        0
        dtype: int64
```

1.6.2 Empty Values

```
In [0]: train_set.loc[(train_set=="").any(axis=1),cat_cols].shape
```

```
Out[0]: (0, 9)
```

```
In [0]: test_set.loc[(train_set=="").any(axis=1),cat_cols].shape
```

```
Out[0]: (0, 9)
```

There are no empty strings in any of the rows

1.6.3 Nonsensical values

In [0]:
```
train_set[cat_cols].nunique()
```

Out[0]:
```
workclass          9
education         16
marital_status     7
occupation        15
relationship       6
race               5
sex                2
native_country    42
wage_class         2
dtype: int64
```

In [0]:
```
for col in cat_cols:
    print(train_set[col].unique(),"\n")
```

```
[' State-gov' ' Self-emp-not-inc' ' Private' ' Federal-gov' ' Local-gov'
 ' ?' ' Self-emp-inc' ' Without-pay' ' Never-worked']

[' Bachelors' ' HS-grad' ' 11th' ' Masters' ' 9th' ' Some-college'
 ' Assoc-acdm' ' Assoc-voc' ' 7th-8th' ' Doctorate' ' Prof-school'
 ' 5th-6th' ' 10th' ' 1st-4th' ' Preschool' ' 12th']

[' Never-married' ' Married-civ-spouse' ' Divorced'
 ' Married-spouse-absent' ' Separated' ' Married-AF-spouse' ' Widowed']

[' Adm-clerical' ' Exec-managerial' ' Handlers-cleaners' ' Prof-specialty'
 ' Other-service' ' Sales' ' Craft-repair' ' Transport-moving'
 ' Farming-fishing' ' Machine-op-inspct' ' Tech-support' ' ?'
 ' Protective-serv' ' Armed-Forces' ' Priv-house-serv']

[' Not-in-family' ' Husband' ' Wife' ' Own-child' ' Unmarried'
 ' Other-relative']

[' White' ' Black' ' Asian-Pac-Islander' ' Amer-Indian-Eskimo' ' Other']

[' Male' ' Female']

[' United-States' ' Cuba' ' Jamaica' ' India' ' ?' ' Mexico' ' South'
 ' Puerto-Rico' ' Honduras' ' England' ' Canada' ' Germany' ' Iran'
 ' Philippines' ' Italy' ' Poland' ' Columbia' ' Cambodia' ' Thailand'
 ' Ecuador' ' Laos' ' Taiwan' ' Haiti' ' Portugal' ' Dominican-Republic'
 ' El-Salvador' ' France' ' Guatemala' ' China' ' Japan' ' Yugoslavia'
 ' Peru' ' Outlying-US(Guam-USVI-etc)' ' Scotland' ' Trinadad&Tobago'
 ' Greece' ' Nicaragua' ' Vietnam' ' Hong' ' Ireland' ' Hungary'
 ' Holand-Netherlands']
```

```
[' <=50K' ' >50K']
```

The columns workclass, occupation and native_country have rows that have garbage values which need to be imputed or dropped in the train_set

```
In [0]: test_set['workclass'].unique()
```

```
Out[0]: array([' Private', ' Local-gov', ' ?', ' Self-emp-not-inc',
               ' Federal-gov', ' State-gov', ' Self-emp-inc', ' Without-pay',
               ' Never-worked'], dtype=object)
```

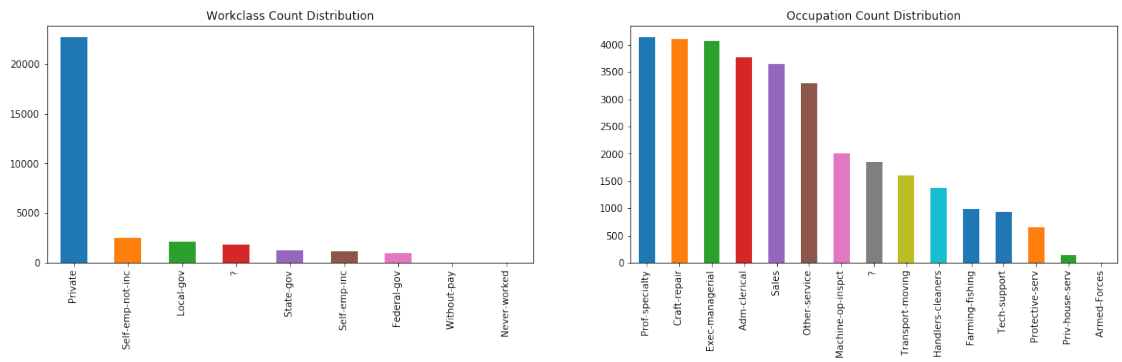
```
In [0]: for col in cat_cols:
            print(test_set[col].unique(),"\n")
```

```
[' Private' ' Local-gov' ' ?' ' Self-emp-not-inc' ' Federal-gov'
 ' State-gov' ' Self-emp-inc' ' Without-pay' ' Never-worked']

[' 11th' ' HS-grad' ' Assoc-acdm' ' Some-college' ' 10th' ' Prof-school'
 ' 7th-8th' ' Bachelors' ' Masters' ' Doctorate' ' 5th-6th' ' Assoc-voc'
 ' 9th' ' 12th' ' 1st-4th' ' Preschool']

[' Never-married' ' Married-civ-spouse' ' Widowed' ' Divorced'
 ' Separated' ' Married-spouse-absent' ' Married-AF-spouse']

[' Machine-op-inspct' ' Farming-fishing' ' Protective-serv' ' ?'
 ' Other-service' ' Prof-specialty' ' Craft-repair' ' Adm-clerical'
 ' Exec-managerial' ' Tech-support' ' Sales' ' Priv-house-serv'
 ' Transport-moving' ' Handlers-cleaners' ' Armed-Forces']

[' Own-child' ' Husband' ' Not-in-family' ' Unmarried' ' Wife'
 ' Other-relative']

[' Black' ' White' ' Asian-Pac-Islander' ' Other' ' Amer-Indian-Eskimo']

[' Male' ' Female']

[' United-States' ' ?' ' Peru' ' Guatemala' ' Mexico'
 ' Dominican-Republic' ' Ireland' ' Germany' ' Philippines' ' Thailand'
 ' Haiti' ' El-Salvador' ' Puerto-Rico' ' Vietnam' ' South' ' Columbia'
 ' Japan' ' India' ' Cambodia' ' Poland' ' Laos' ' England' ' Cuba'
 ' Taiwan' ' Italy' ' Canada' ' Portugal' ' China' ' Nicaragua'
 ' Honduras' ' Iran' ' Scotland' ' Jamaica' ' Ecuador' ' Yugoslavia'
 ' Hungary' ' Hong' ' Greece' ' Trinadad&Tobago'
 ' Outlying-US(Guam-USVI-etc)' ' France']

[' <=50K.' ' >50K.']
```

The columns workclass, occupation and native_country have rows that have garbage values which need to be imputed or dropped in the test_set

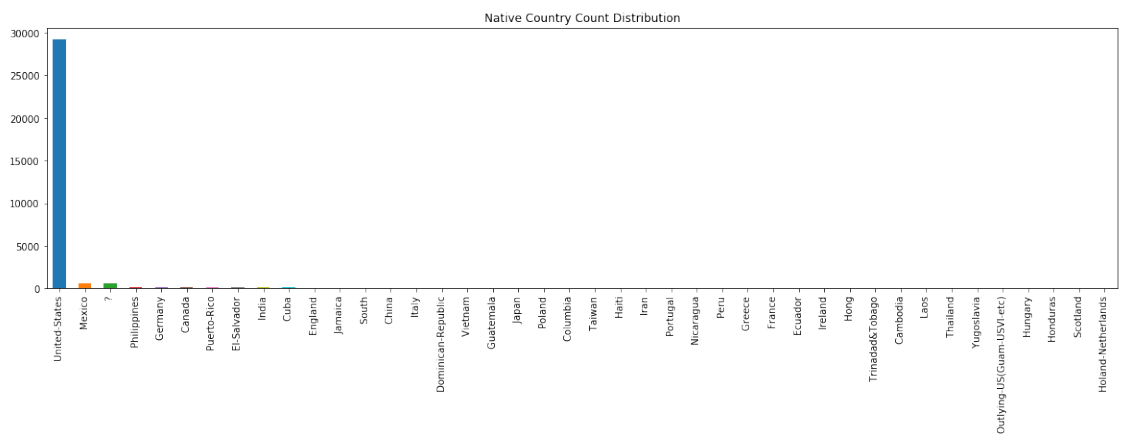
```
In [0]: plt.figure(figsize=(20,10))
        plt.subplot(2,2,1)
        plt.title("Workclass Count Distribution")
        train_set['workclass'].value_counts().plot.bar()

        plt.subplot(2,2,2)
        plt.title("Occupation Count Distribution")
        train_set['occupation'].value_counts().plot.bar()
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x2262fd9cf98>
```



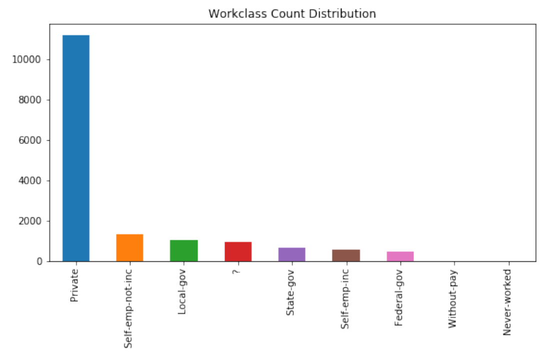

```
In [0]: plt.figure(figsize=(20,5))
        plt.subplot(1,1,1)
        plt.title("Native Country Count Distribution")
        train_set['native_country'].value_counts().plot.bar()
```

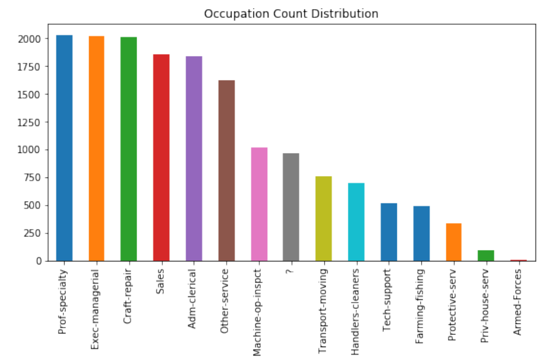
```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x2262fb0aef0>
```



```
In [0]: plt.figure(figsize=(20,10))
        plt.subplot(2,2,1)
        plt.title("Workclass Count Distribution")
        test_set['workclass'].value_counts().plot.bar()

        plt.subplot(2,2,2)
        plt.title("Occupation Count Distribution")
        test_set['occupation'].value_counts().plot.bar()
```

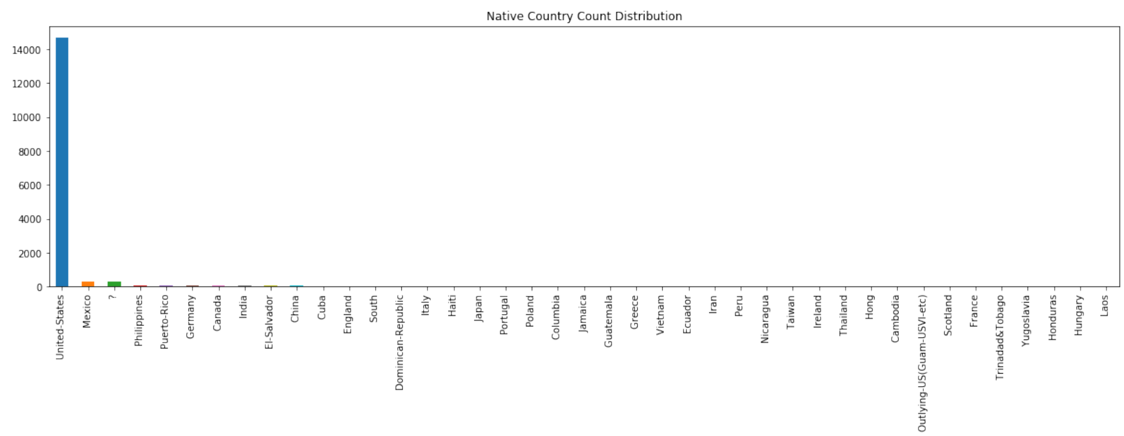
```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x22630b18048>
```






```
In [0]: plt.figure(figsize=(20,5))
        plt.subplot(1,1,1)
        plt.title("Native Country Count Distribution")
        test_set['native_country'].value_counts().plot.bar()
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x2263074a5f8>
```




```
In [0]: train_set[train_set.workclass.str.contains("\?")].head()
```

```
Out[0]:      age workclass  fnlwgt      education  education_num  \
        27    54         ?  180211   Some-college             10
        61    32         ?  293936        7th-8th              4
        69    25         ?  200681   Some-college             10
        77    67         ?  212759           10th              6
        106   17         ?  304873           10th              6

                    marital_status occupation    relationship                race  \
        27      Married-civ-spouse          ?         Husband  Asian-Pac-Islander
        61   Married-spouse-absent          ?   Not-in-family               White
        69           Never-married          ?       Own-child               White
        77      Married-civ-spouse          ?         Husband               White
        106          Never-married          ?       Own-child               White

                sex  capital_gain  capital_loss  hours_per_week  native_country  \
        27     Male             0             0              60           South
        61     Male             0             0              40               ?
        69     Male             0             0              40   United-States
        77     Male             0             0               2   United-States
        106  Female         34095             0              32   United-States

            wage_class
        27        >50K
        61       <=50K
        69       <=50K
        77       <=50K
        106      <=50K
```

```
In [0]: test_set[test_set.workclass.str.contains("\?")].head()
```

```
Out[0]:     age workclass  fnlwgt      education  education_num      marital_status  \
        4    18         ?  103497   Some-college             10       Never-married
        6    29         ?  227026        HS-grad              9       Never-married
        13   58         ?  299831        HS-grad              9  Married-civ-spouse
        22   72         ?  132015        7th-8th              4            Divorced
        35   65         ?  191846        HS-grad              9  Married-civ-spouse

           occupation    relationship   race     sex  capital_gain  capital_loss  \
        4           ?       Own-child  White  Female             0             0
        6           ?       Unmarried  Black    Male             0             0
        13          ?         Husband  White    Male             0             0
        22          ?   Not-in-family  White  Female             0             0
        35          ?         Husband  White    Male             0             0

            hours_per_week  native_country wage_class
        4               30   United-States     <=50K.
        6               40   United-States     <=50K.
        13              35   United-States     <=50K.
```

```
22                6   United-States     <=50K.
35               40   United-States     <=50K.
```

In [0]:
```
(train_set.loc[(train_set==" ?").any(axis=1),cat_cols].shape[0]/train_set.shape[0])*100
```

Out[0]:
```
7.367709836921471
```

In [0]:
```
(test_set.loc[(test_set==" ?").any(axis=1),cat_cols].shape[0]/test_set.shape[0])*100
```

Out[0]:
```
7.499539340335361
```

If we drop the rows containing ? values, we incur a data loss of approximately 7.5% data loss in the train_set and the test_set. Therefore we choose to drop it

In [0]:
```
train_set.drop(train_set.loc[(train_set==" ?").any(axis=1)].index, inplace= True)
train_set.shape[0]
```

Out[0]:
```
30162
```

In [0]:
```
test_set.drop(test_set.loc[(test_set==" ?").any(axis=1)].index, inplace= True)
test_set.shape[0]
```

Out[0]:
```
15060
```

In [0]:
```
test_set.loc[(test_set==" ?").any(axis=1),cat_cols].shape[0]/test_set.shape[0]
```

Out[0]:
```
0.0
```

2 Get Basic Statistical Information

In [0]:
```
train_set.describe()
```

Out[0]:
```
                age        fnlwgt  education_num  capital_gain  capital_loss  \
count  30162.000000  3.016200e+04   30162.000000  30162.000000  30162.000000
mean      38.437902  1.897938e+05      10.121312   1092.007858     88.372489
std       13.134665  1.056530e+05       2.549995   7406.346497    404.298370
min       17.000000  1.376900e+04       1.000000      0.000000      0.000000
25%       28.000000  1.176272e+05       9.000000      0.000000      0.000000
50%       37.000000  1.784250e+05      10.000000      0.000000      0.000000
75%       47.000000  2.376285e+05      13.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

       hours_per_week
count    30162.000000
mean        40.931238
std         11.979984
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

```
In [0]: train_set.describe(include='object')
```

```
Out[0]:        workclass education       marital_status       occupation relationship  \
count      30162     30162                30162            30162        30162
unique         7        16                    7               14            6
top      Private   HS-grad   Married-civ-spouse   Prof-specialty      Husband
freq       22286      9840                14065             4038        12463

          race    sex  native_country wage_class
count    30162  30162           30162      30162
unique       5      2              41          2
top      White   Male   United-States      <=50K
freq     25933  20380           27504      22654
```

```
In [0]: test_set.describe()
```

```
Out[0]:                 age        fnlwgt  education_num  capital_gain  capital_loss  \
count  15060.000000  1.506000e+04   15060.000000  15060.000000  15060.000000
mean      38.768327  1.896164e+05      10.112749   1120.301594     89.041899
std       13.380676  1.056150e+05       2.558727   7703.181842    406.283245
min       17.000000  1.349200e+04       1.000000      0.000000      0.000000
25%       28.000000  1.166550e+05       9.000000      0.000000      0.000000
50%       37.000000  1.779550e+05      10.000000      0.000000      0.000000
75%       48.000000  2.385888e+05      13.000000      0.000000      0.000000
max       90.000000  1.490400e+06      16.000000  99999.000000   3770.000000

       hours_per_week
count    15060.000000
mean        40.951594
std         12.062831
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

```
In [0]: test_set.describe(include='object')
```

```
Out[0]:        workclass education       marital_status        occupation  \
count      15060     15060                15060             15060
unique         7        16                    7                14
top      Private   HS-grad   Married-civ-spouse   Exec-managerial
freq       11021      4943                 6990              1992

       relationship   race    sex  native_country wage_class
count         15060  15060  15060           15060      15060
unique            6      5      2              40          2
top         Husband  White   Male   United-States     <=50K.
freq           6203  12970  10147           13788      11360
```

In [0]:
```
train_set.corr()
```

Out[0]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
age	1.000000	-0.076511	0.043526	0.080154	0.060165	0.101599
fnlwgt	-0.076511	1.000000	-0.044992	0.000422	-0.009750	-0.022886
education_num	0.043526	-0.044992	1.000000	0.124416	0.079646	0.152522
capital_gain	0.080154	0.000422	0.124416	1.000000	-0.032229	0.080432
capital_loss	0.060165	-0.009750	0.079646	-0.032229	1.000000	0.052417
hours_per_week	0.101599	-0.022886	0.152522	0.080432	0.052417	1.000000

In [0]:
```
test_set.corr()
```

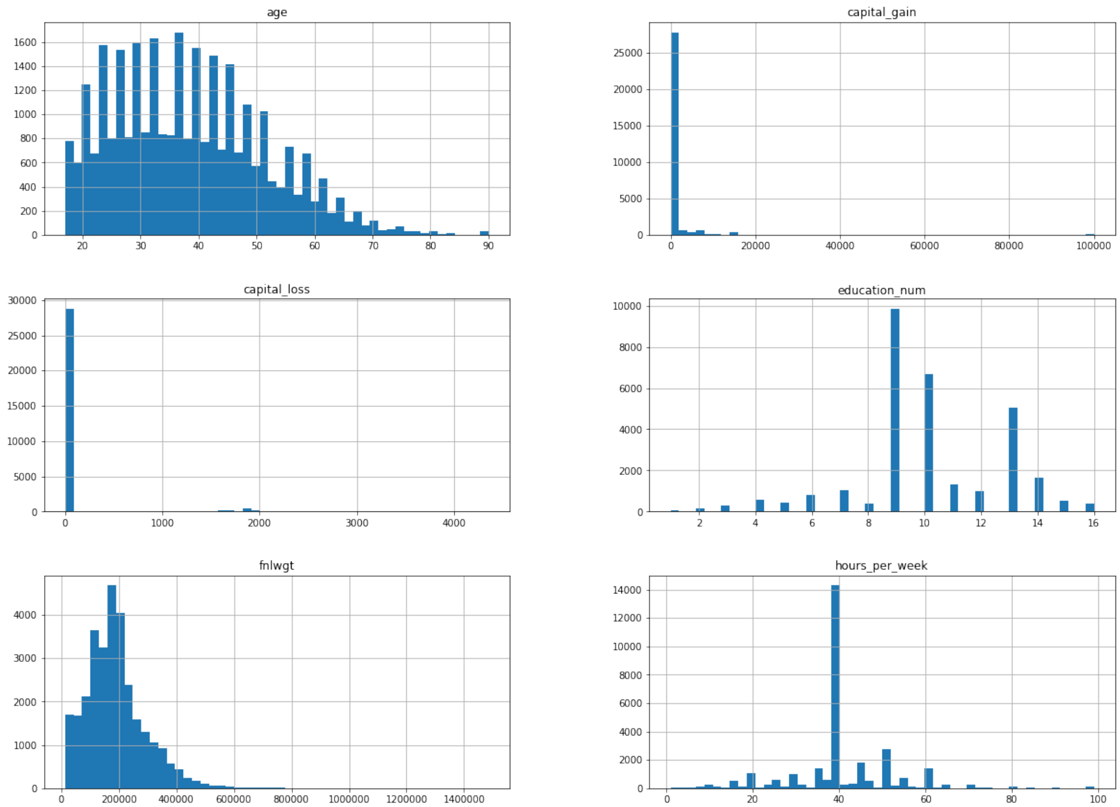
Out[0]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
age	1.000000	-0.074375	0.026123	0.078760	0.057745	0.102758
fnlwgt	-0.074375	1.000000	-0.036010	-0.012839	0.006421	-0.010306
education_num	0.026123	-0.036010	1.000000	0.131750	0.085817	0.133691
capital_gain	0.078760	-0.012839	0.131750	1.000000	-0.031876	0.090501
capital_loss	0.057745	0.006421	0.085817	-0.031876	1.000000	0.057712
hours_per_week	0.102758	-0.010306	0.133691	0.090501	0.057712	1.000000

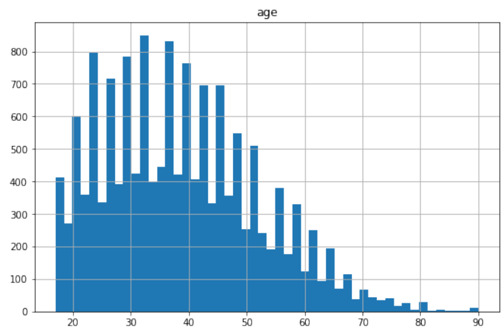
3 Explore Data

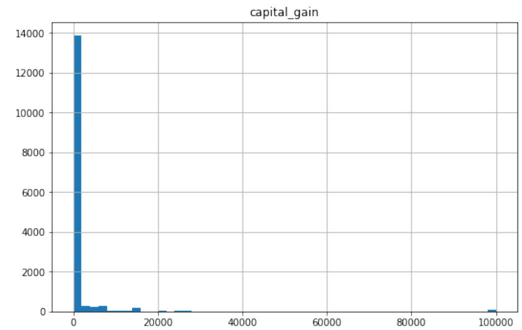
3.1 Uni-variate

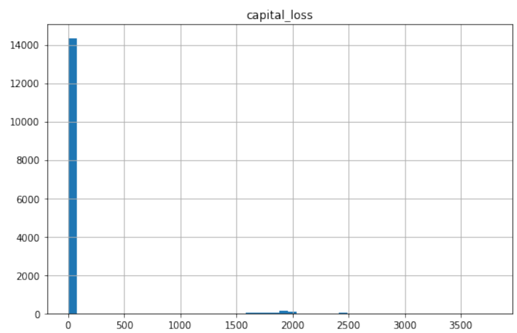
In [0]:
```
train_set[num_cols].hist(bins=50, figsize=(20,20), layout=(4,2))
plt.show()
```

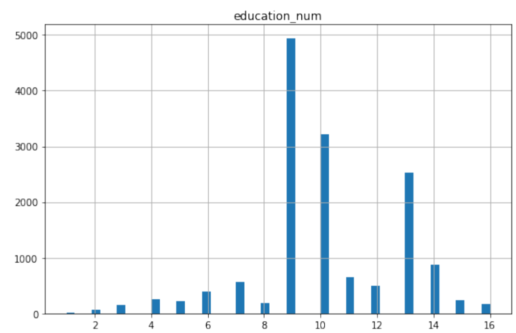


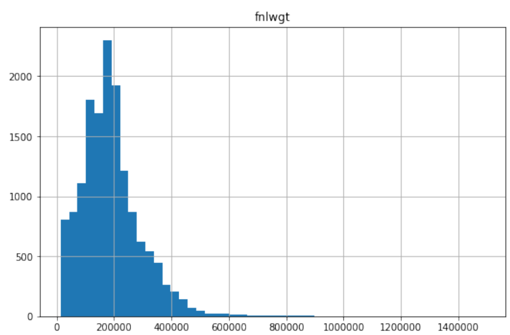
In [0]:
```
test_set[num_cols].hist(bins=50, figsize=(20,20), layout=(3,2))
plt.show()
```

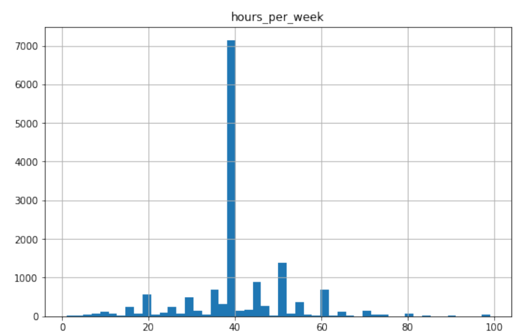






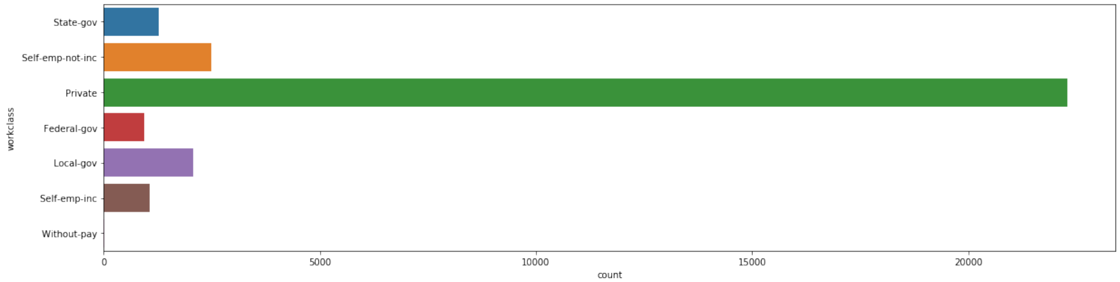


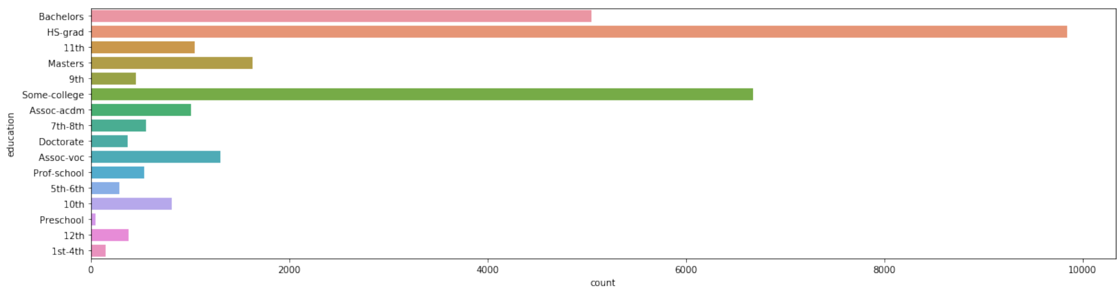


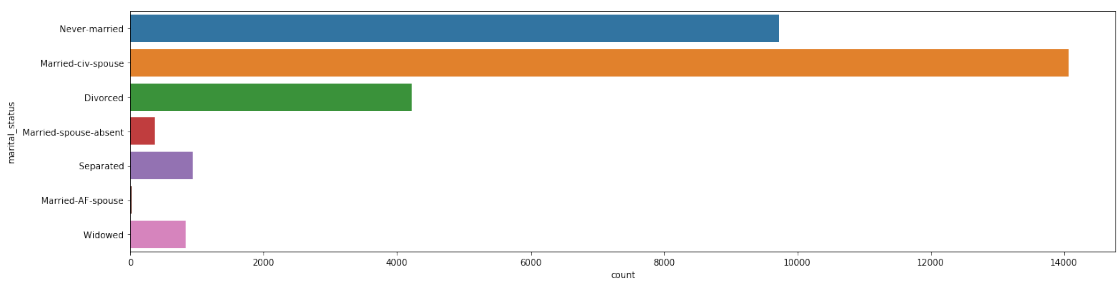


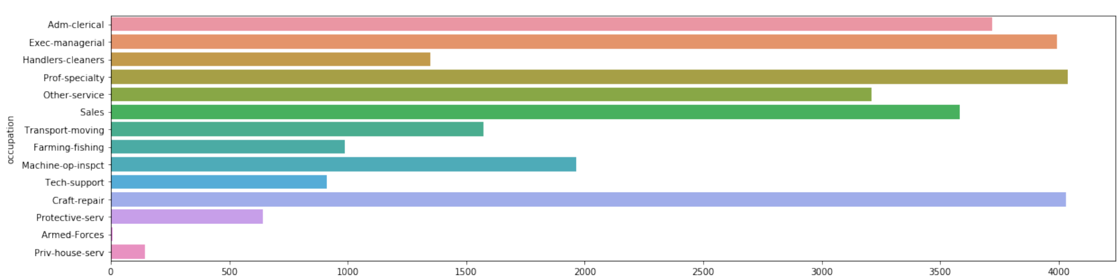
3.1.1 Categorical Columns

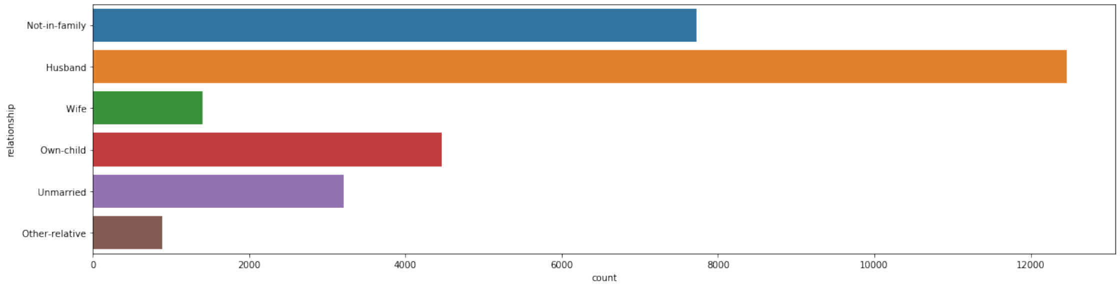
```
In [0]: for i, col in enumerate(cat_cols):
            if(col!='native_country'):
                plt.figure(i,figsize = (20,5))
                sns.countplot(y=col, data=train_set,)
            else:
                plt.figure(i,figsize = (20,10))
                sns.countplot(y=col, data=train_set)
```

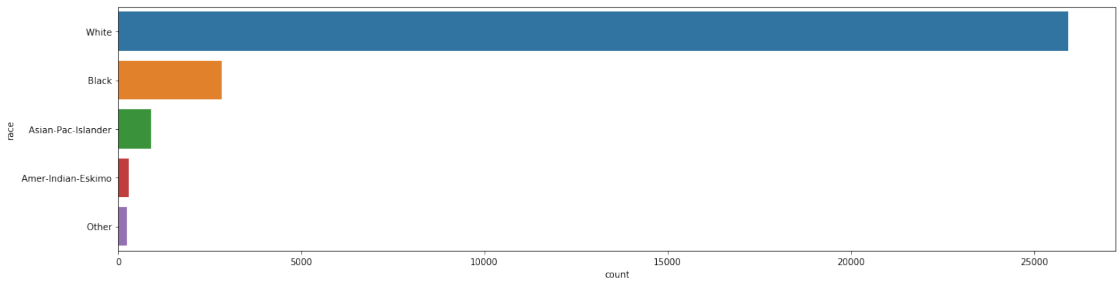

State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
Self-emp-inc
Without-pay
workclass
0
5000
10000
15000
20000
count

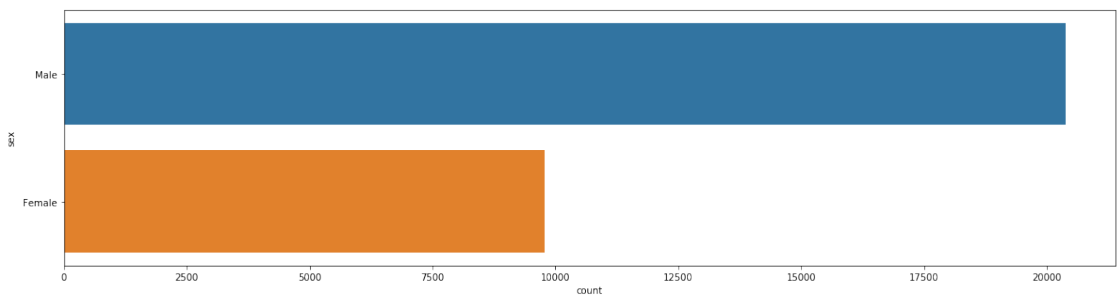

Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
7th-8th
Doctorate
Assoc-voc
Prof-school
5th-6th
10th
Preschool
12th
1st-4th
education
0
2000
4000
6000
8000
10000
count

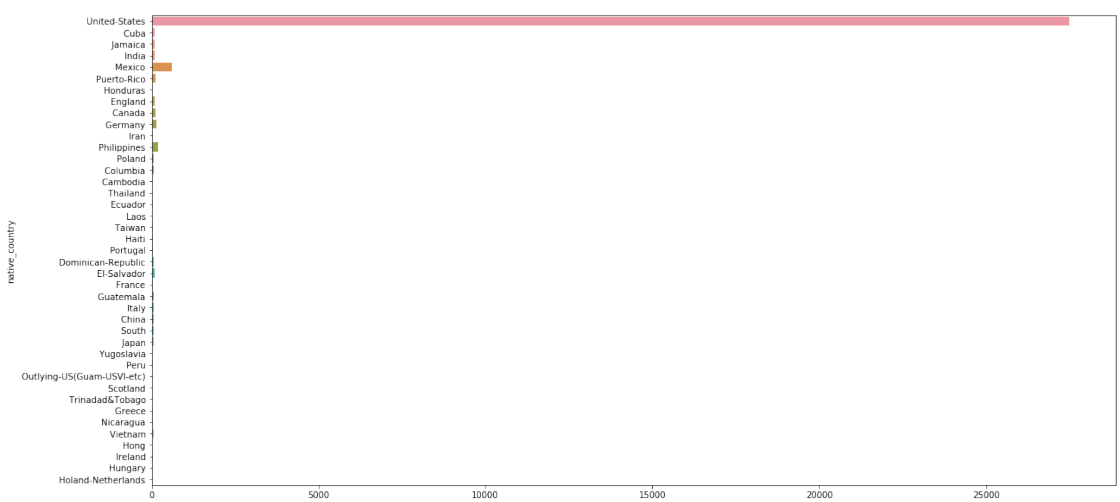

Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
marital_status
0
2000
4000
6000
8000
10000
12000
14000
count

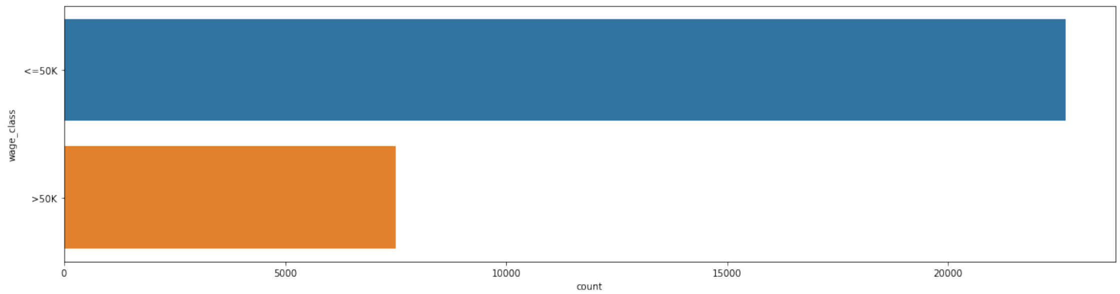

Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Craft-repair
Protective-serv
Armed-Forces
Priv-house-serv
occupation
0
500
1000
1500
2000
2500
3000
3500
4000
count


relationship
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
0
2000
4000
6000
8000
10000
12000
count

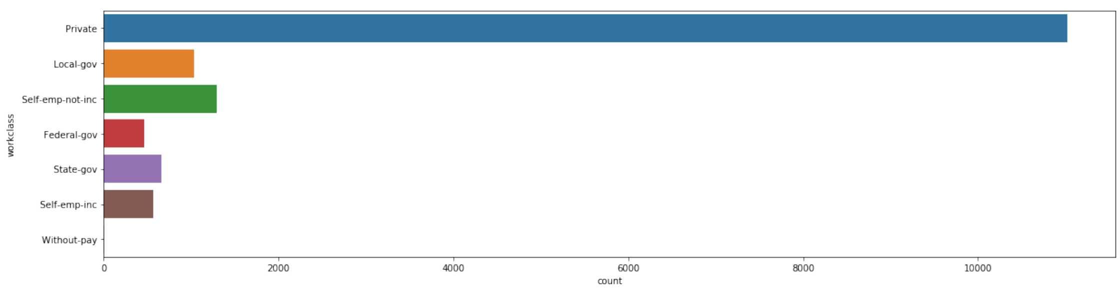

race
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
0
5000
10000
15000
20000
25000
count

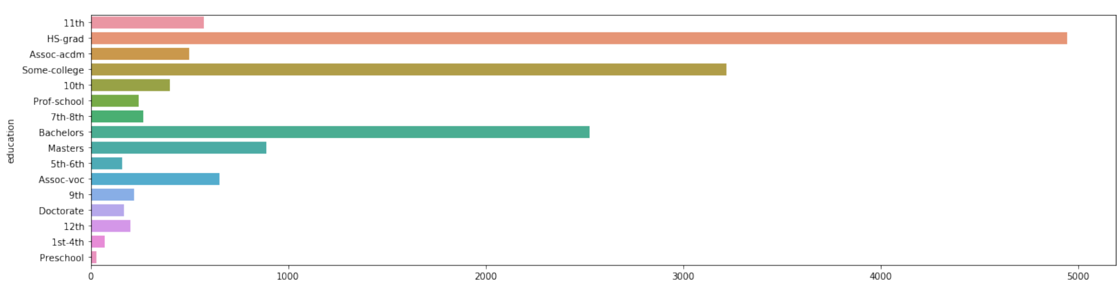

sex
Male
Female
0
2500
5000
7500
10000
12500
15000
17500
20000
count

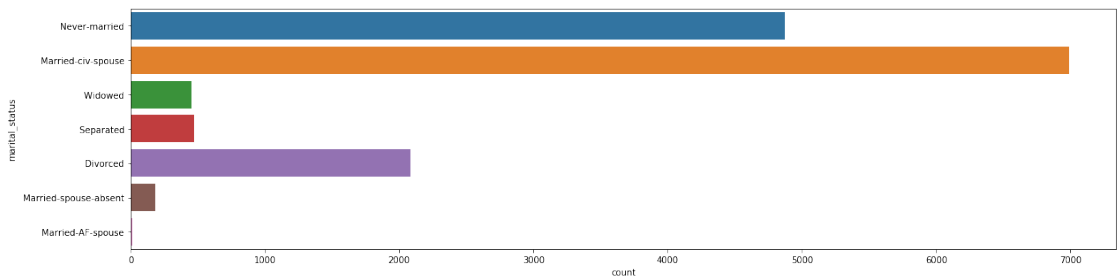

native_country
United-States
Cuba
Jamaica
India
Mexico
Puerto-Rico
Honduras
England
Canada
Germany
Iran
Philippines
Poland
Columbia
Cambodia
Thailand
Ecuador
Laos
Taiwan
Haiti
Portugal
Dominican-Republic
El-Salvador
France
Guatemala
Italy
China
South
Japan
Yugoslavia
Peru
Outlying-US(Guam-USVI-etc)
Scotland
Trinadad&Tobago
Greece
Nicaragua
Vietnam
Hong
Ireland
Hungary
Holand-Netherlands
0
5000
10000
15000
20000
25000
count

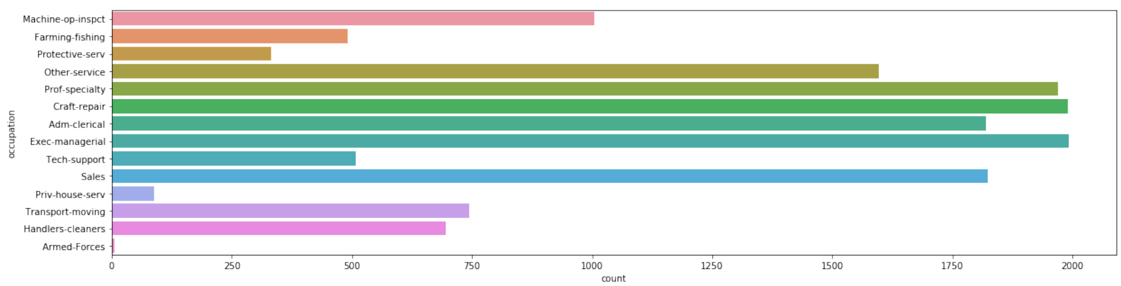


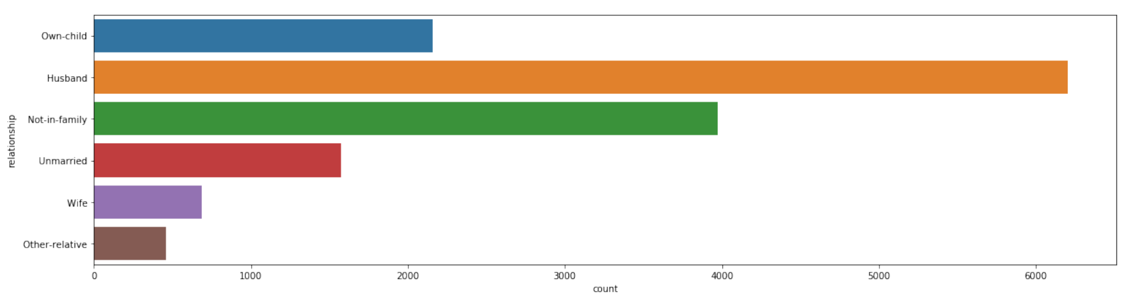

```
In [0]: for i, col in enumerate(cat_cols):
            if(col!='native_country'):
                plt.figure(i,figsize = (20,5))
                sns.countplot(y=col, data=test_set)
            else:
                plt.figure(i,figsize = (20,10))
                sns.countplot(y=col, data=test_set)
```

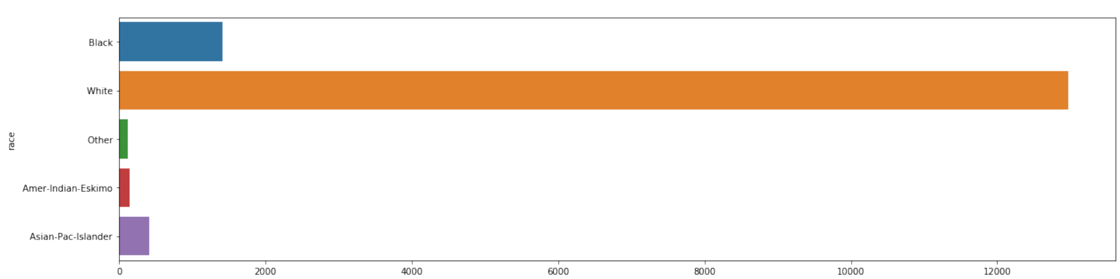


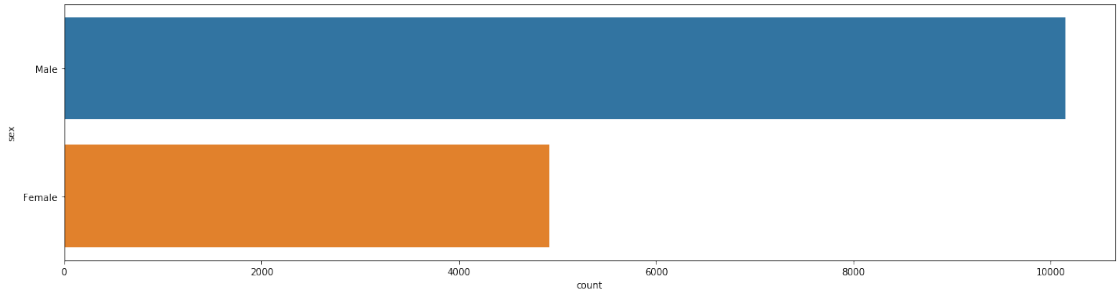


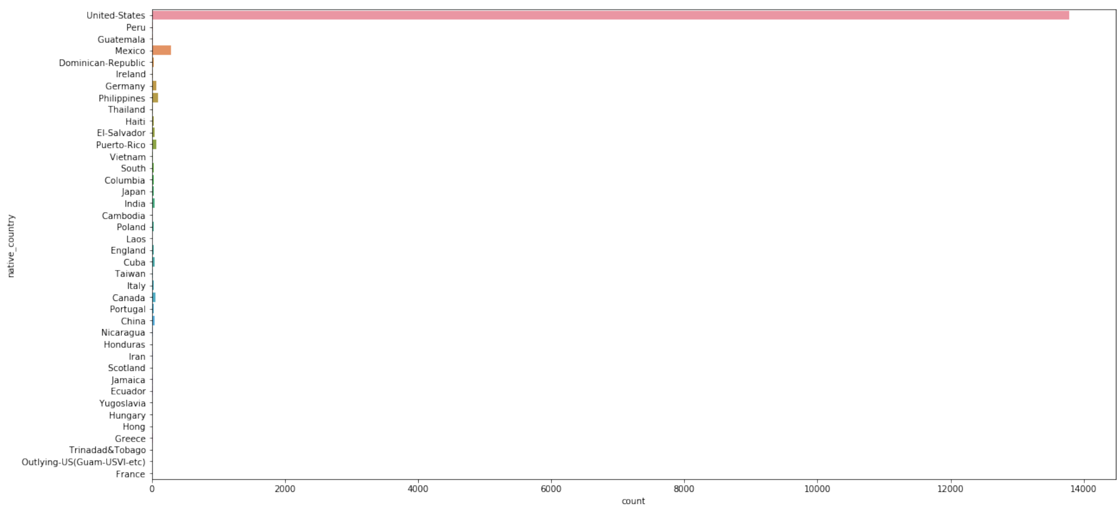

marital_status
Never-married
Married-civ-spouse
Widowed
Separated
Divorced
Married-spouse-absent
Married-AF-spouse
0
1000
2000
3000
4000
5000
6000
7000
count

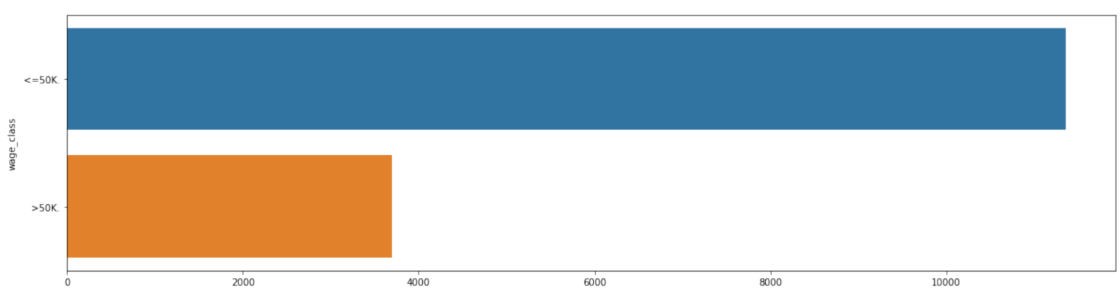

occupation
Machine-op-inspct
Farming-fishing
Protective-serv
Other-service
Prof-specialty
Craft-repair
Adm-clerical
Exec-managerial
Tech-support
Sales
Priv-house-serv
Transport-moving
Handlers-cleaners
Armed-Forces
0
250
500
750
1000
1250
1500
1750
2000
count


relationship
Own-child
Husband
Not-in-family
Unmarried
Wife
Other-relative
0
1000
2000
3000
4000
5000
6000
count


race
Black
White
Other
Amer-Indian-Eskimo
Asian-Pac-Islander
0
2000
4000
6000
8000
10000
12000
count

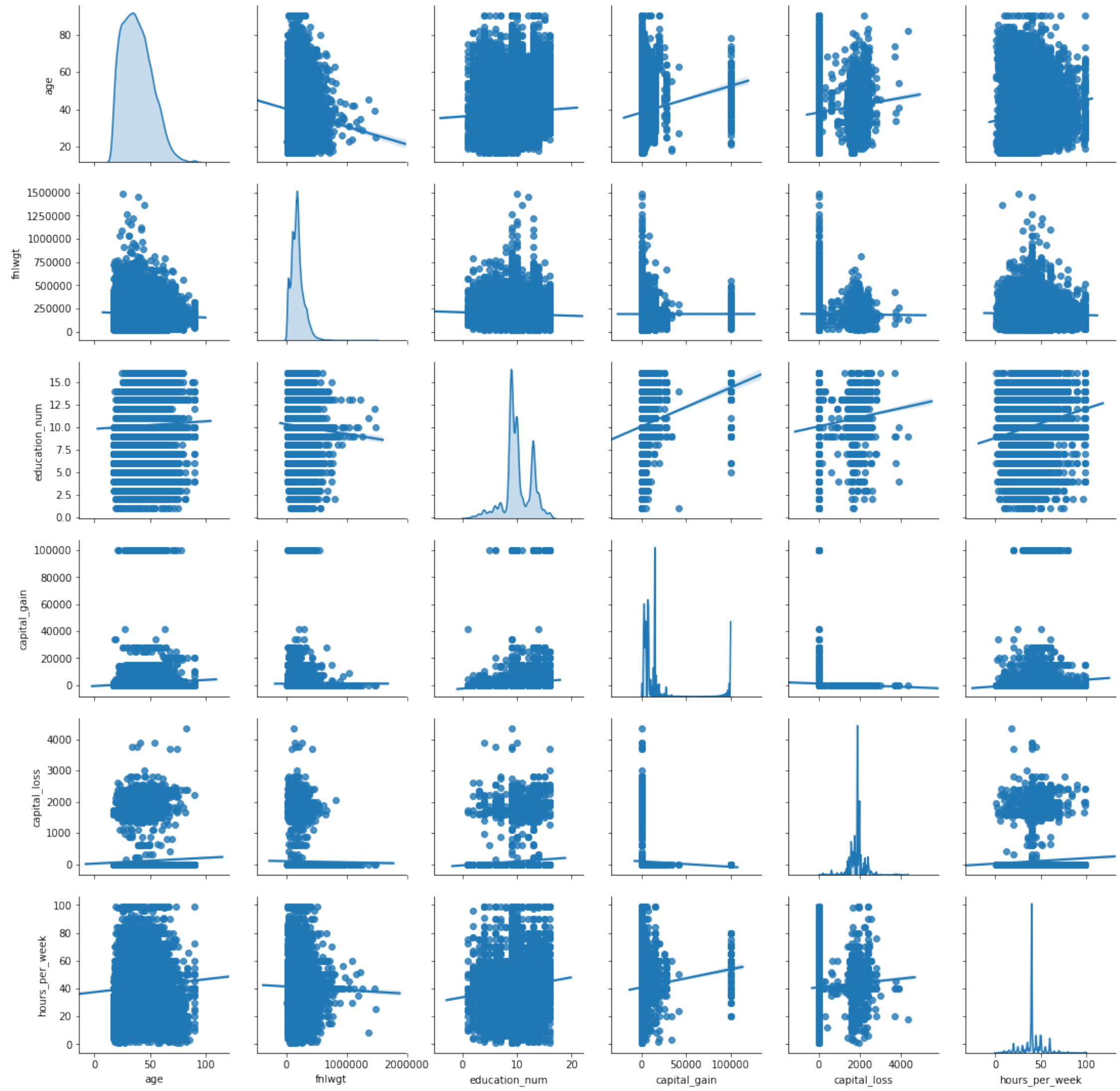




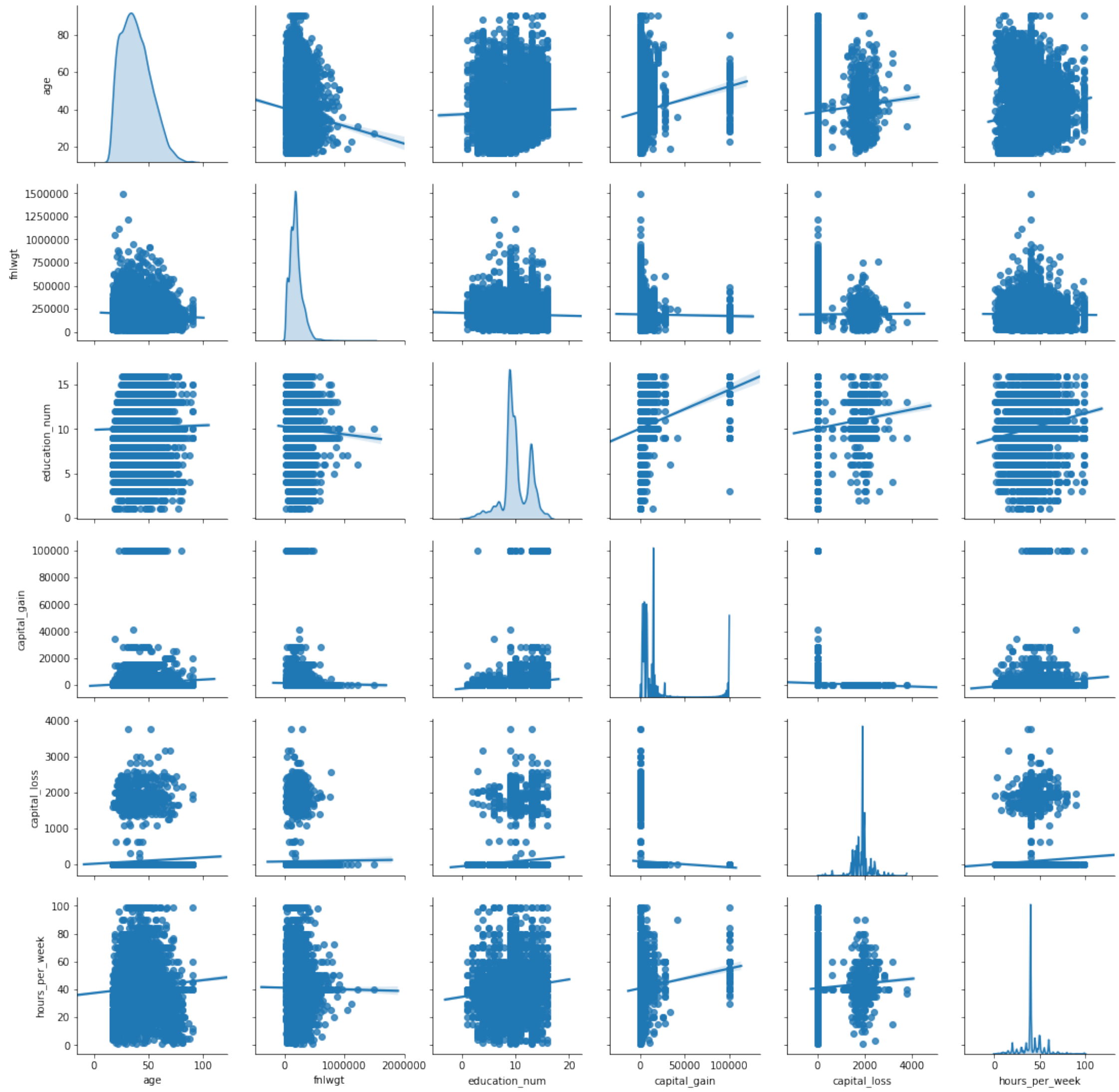


3.2 Bi-variate

```
In [0]: sns.pairplot(train_set[num_cols],kind ='reg',diag_kind='kde')

Out[0]: <seaborn.axisgrid.PairGrid at 0x226308c5ba8>
```

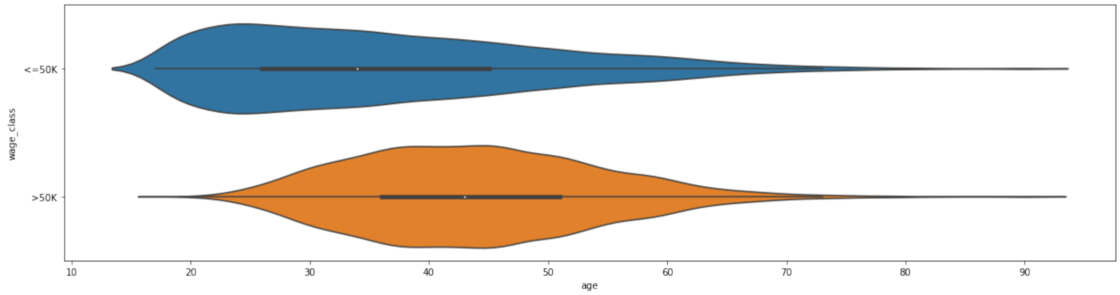



```
In [0]: sns.pairplot(test_set[num_cols],kind ='reg',diag_kind='kde')

Out[0]: <seaborn.axisgrid.PairGrid at 0x22631fb0208>
```

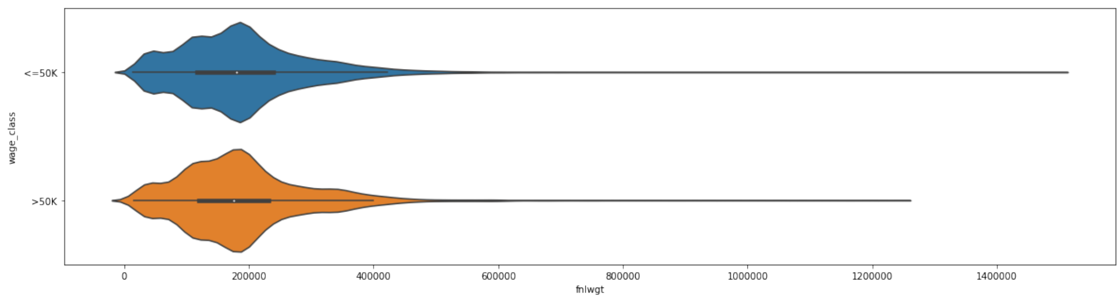


None of the numerical columns are strongly correlated with each other, either in train_set or test_set. However, it is interesting to note that education is more correlated with capital_gain than capital_loss

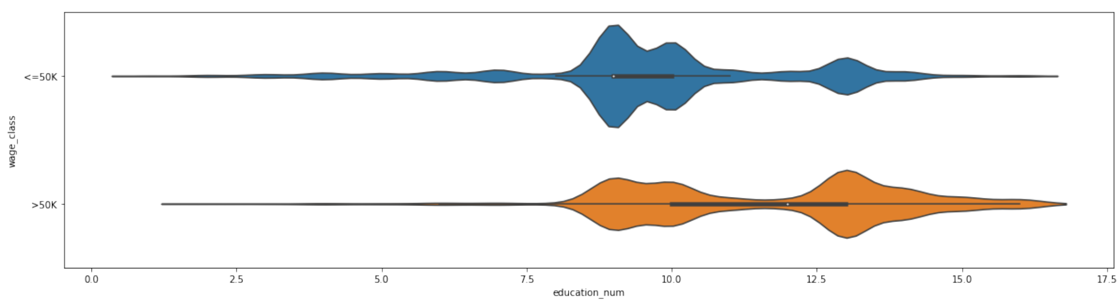
```
In [0]: for i, col in enumerate(num_cols):
            plt.figure(i,figsize = (20,5))
            sns.violinplot(x=col,y='wage_class', data=train_set)
```



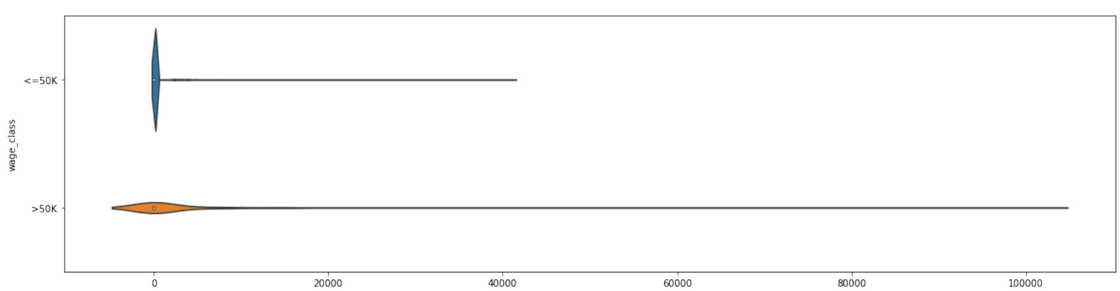
<=50K
>50K
wage_class
10
20
30
40
50
60
70
80
90
age



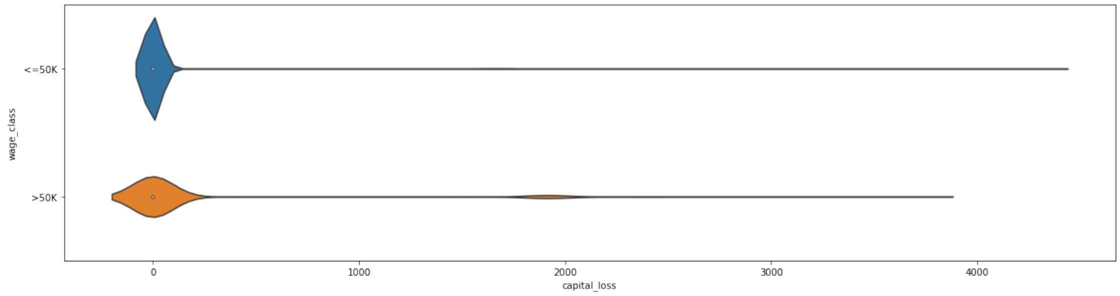
<=50K
>50K
wage_class
0
200000
400000
600000
800000
1000000
1200000
1400000
fnlwgt

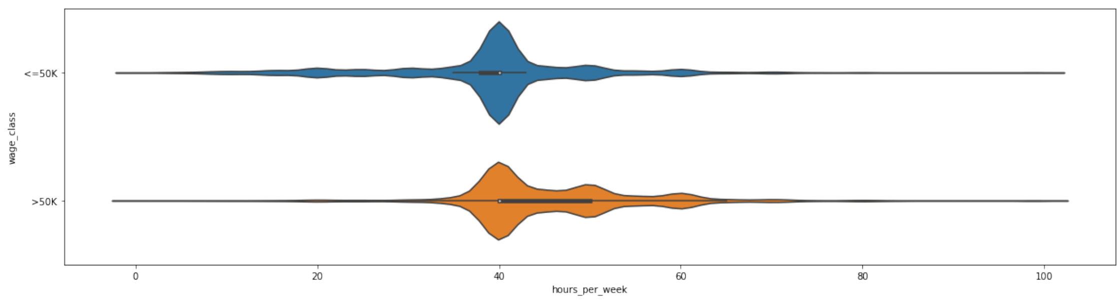


<=50K
>50K
wage_class
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
education_num

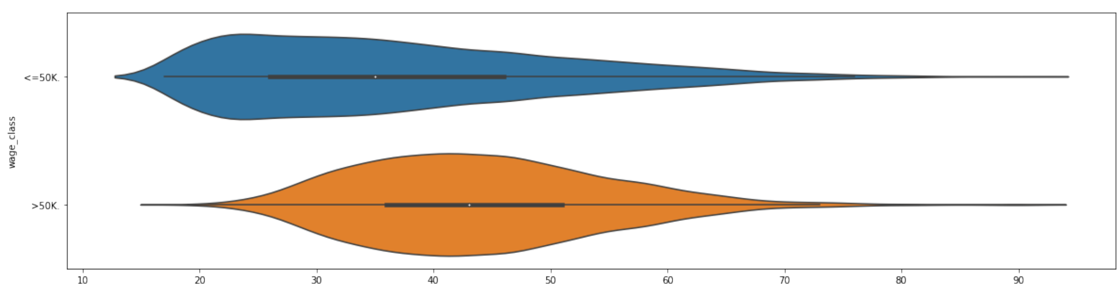


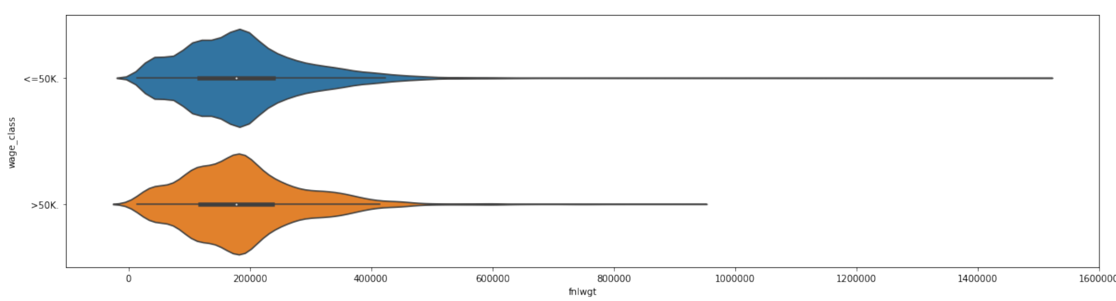
<=50K
>50K
wage_class
0
20000
40000
60000
80000
100000
capital_gain

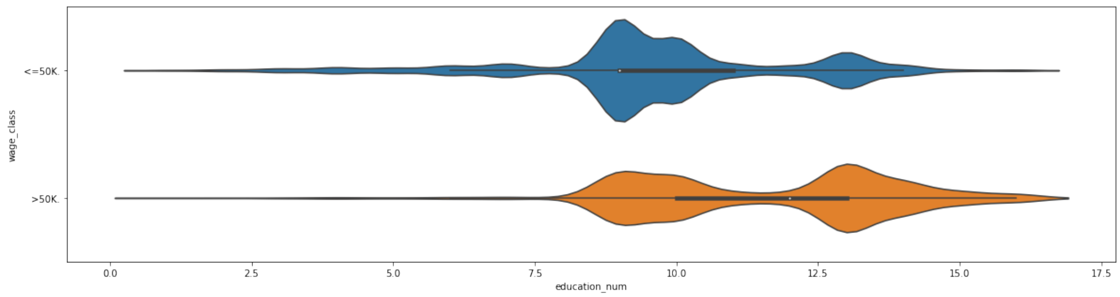




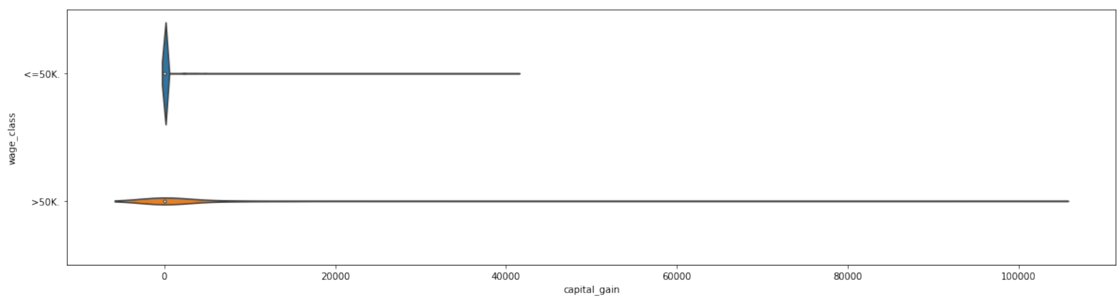
In [0]:
```
for i, col in enumerate(num_cols):
    plt.figure(i,figsize = (20,5))
    sns.violinplot(x=col,y='wage_class', data=test_set)
```



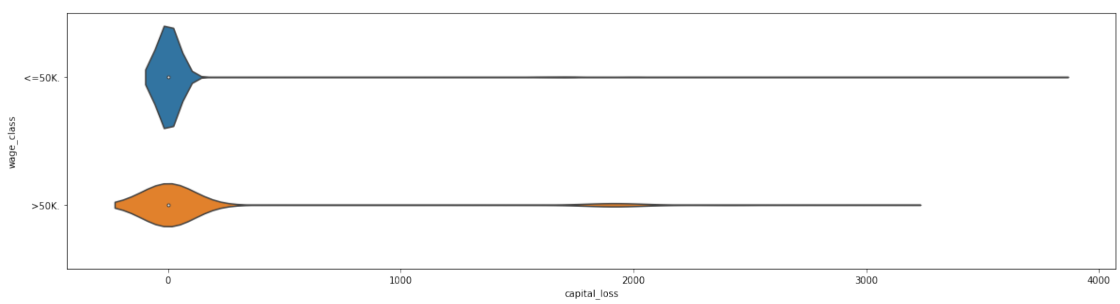




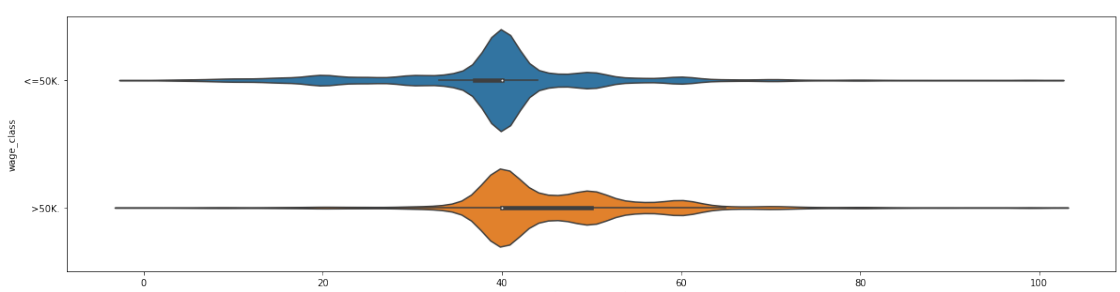
<=50K.
>50K.
wage_class
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
education_num



<=50K.
>50K.
wage_class
0
20000
40000
60000
80000
100000
capital_gain



<=50K.
>50K.
wage_class
0
1000
2000
3000
4000
capital_loss

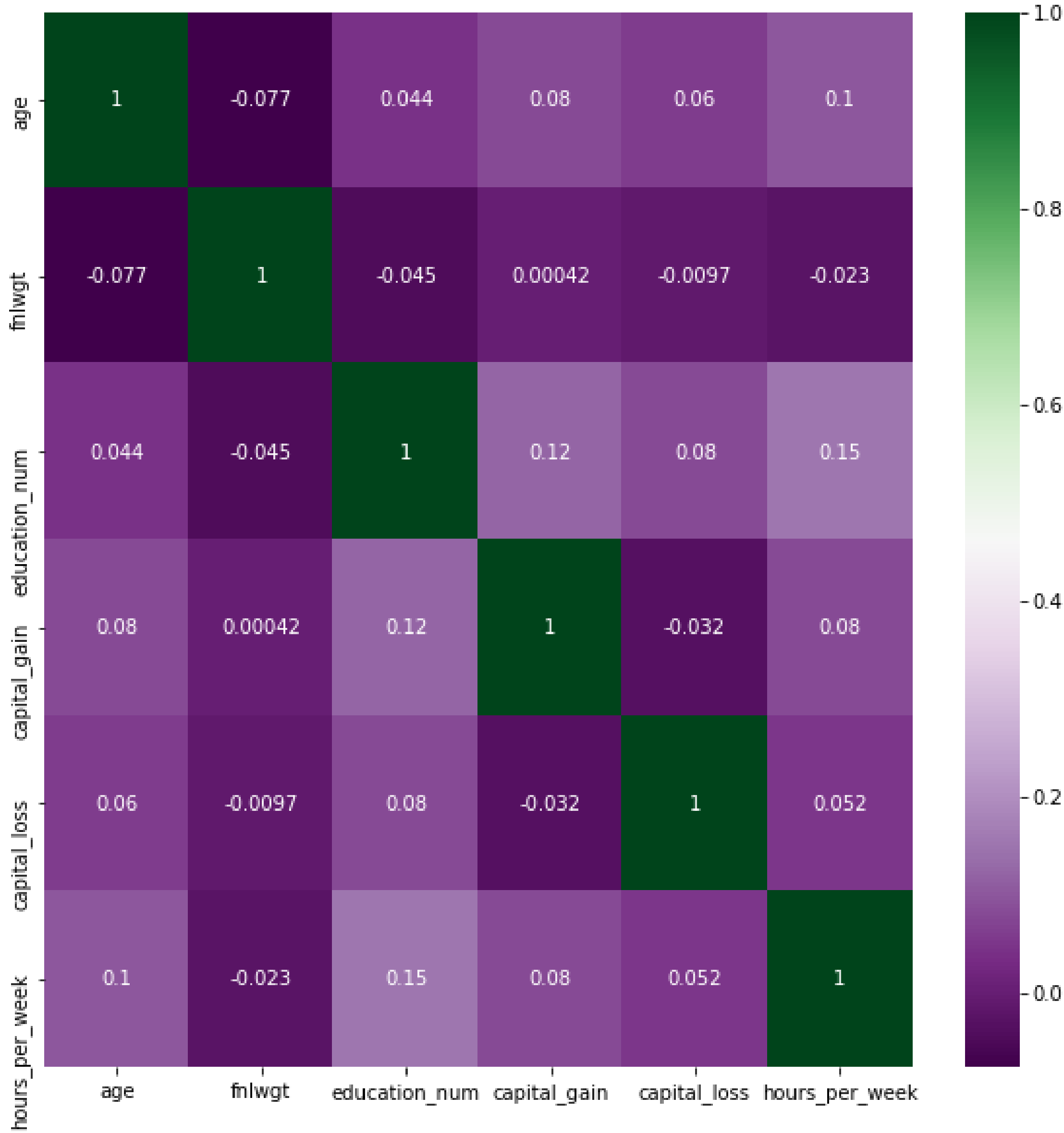


<=50K.
>50K.
wage_class
0
20
40
60
80
100
hours_per_week

3.3 Multi-variate

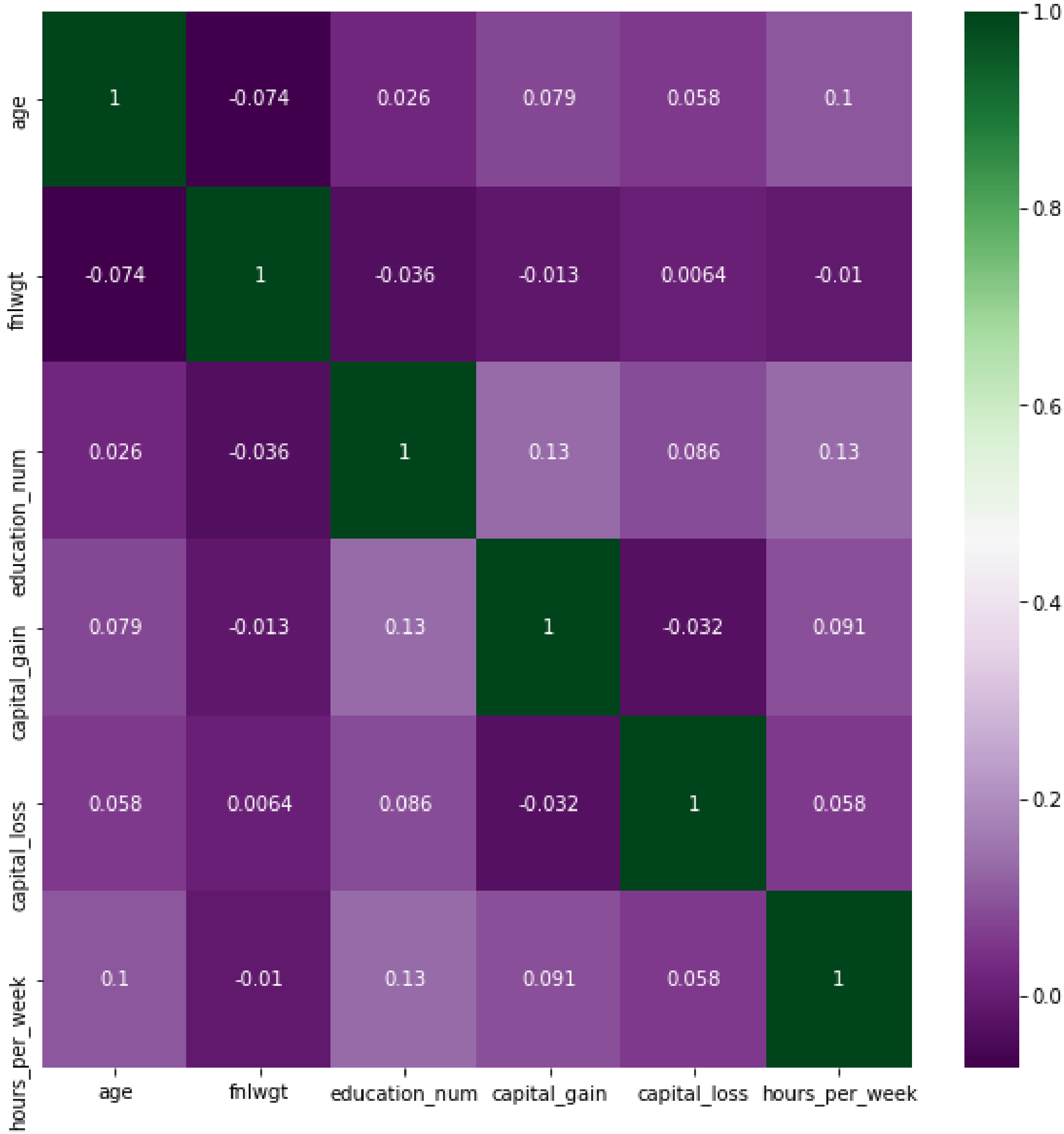
```
In [0]: plt.figure(figsize=(10,10))
        sns.heatmap(train_set.corr(), annot = True,cmap= "PRGn")
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x226375b8be0>
```




```
In [0]: plt.figure(figsize=(10,10))
        sns.heatmap(test_set.corr(), annot = True,cmap= "PRGn")
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x22637cd01d0>
```



4 Engineer Features

4.1 Encode Categorical Columns

```
In [0]: for col in train_set.columns: # Loop through all columns in the dataframe
            if train_set[col].dtype == 'object': # Only apply for columns with categorical str
                train_set[col] = pd.Categorical(train_set[col]).codes # Replace strings with a
```

```
In [0]: for col in test_set.columns: # Loop through all columns in the dataframe
            if test_set[col].dtype == 'object': # Only apply for columns with categorical stri
                test_set[col] = pd.Categorical(test_set[col]).codes # Replace strings with an
```

5 Generate Input Vector X and Output Y, and Split the Data for Training and Testing

```
In [0]: x_train = train_set.drop('wage_class', axis =1)
        y_train = train_set['wage_class']
        x_test = test_set.drop('wage_class', axis =1)
        y_test = test_set['wage_class']
```

```
In [0]: x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

```
Out[0]: ((30162, 14), (30162,), (15060, 14), (15060,))
```

6 Fit the Base Models and Collect the Metrics

6.1 Logistic Regression

```
In [0]: log_res = LogisticRegression()
        model_lr = log_res.fit(x_train, y_train)

        y_test_pred = model_lr.predict(x_test)

        y_test_pred_prob = model_lr.predict_proba(x_test)

        model_lr.score(x_test,y_test)
```

```
Out[0]: 0.7847941567065073
```

```
In [0]: # Generate model evaluation metrics for the Logistic Regression
        print("Performance metrics of the model for the Logistic Regression")
        print("-"*100)
        print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))
        print("Precision Score: ",metrics.precision_score(y_test, y_test_pred))
        print("Recall Score: ",metrics.recall_score(y_test, y_test_pred))
        print("AUROC Score: ",metrics.roc_auc_score(y_test,  y_test_pred_prob[:,1]))
        print()
        print("Confusion Matrix:  \n ",metrics.confusion_matrix(y_test, y_test_pred))
        print()
        print("Classification Report:\n ",metrics.classification_report(y_test, y_test_pred))
```

```
Performance metrics of the model for the Logistic Regression
-----------------------------------------------------------------------------------------------
Accuracy:  0.7847941567065073
Precision Score:  0.6284275321768327
Recall Score:  0.3035135135135135
AUROC Score:  0.7567870551008756

Confusion Matrix:
  [[10696   664]
```

```
 [ 2577  1123]]

Classification Report:
              precision    recall  f1-score   support

          0       0.81      0.94      0.87     11360
          1       0.63      0.30      0.41      3700

avg / total       0.76      0.78      0.76     15060
```

6.2 XGBoost Base Model

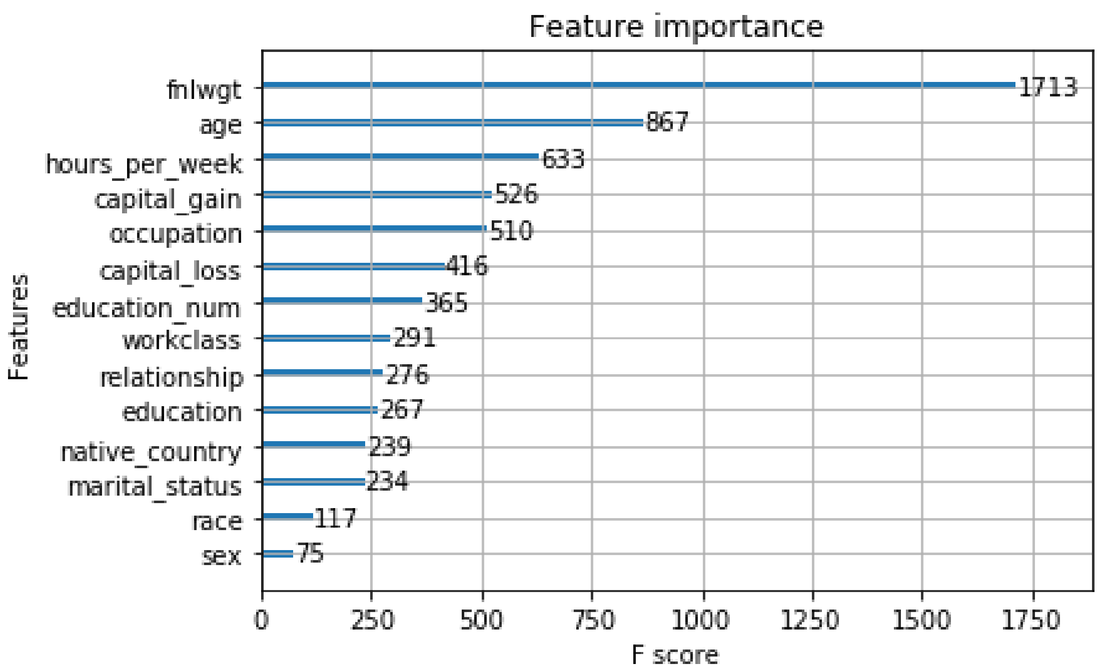
```
In [0]: params = {'learning_rate': 0.1, 'n_estimators': 1000, 'seed':0, 'subsample': 0.8, 'cols
                     'objective': 'binary:logistic'}
        XGB_base = XGBClassifier(**params)

        XGB_base.fit(x_train, y_train)

        y_test_pred = XGB_base.predict(x_test)
        y_test_pred_prob = XGB_base.predict_proba(x_test)

        XGB_base.score(x_test,y_test)

Out[0]: 0.8663346613545817

In [0]: # Generate model evaluation metrics for the XGBOOST- Base Model
        print("Performance metrics of the model for the XGBOOST- Base Model")
        print("-"*100)
        print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))
        print("Precision Score: ",metrics.precision_score(y_test, y_test_pred))
        print("Recall Score: ",metrics.recall_score(y_test, y_test_pred))
        print("AUROC Score: ",metrics.roc_auc_score(y_test,  y_test_pred_prob[:,1]))
        print()
        print("Confusion Matrix:  \n ",metrics.confusion_matrix(y_test, y_test_pred))
        print()
        print("Classification Report:\n ",metrics.classification_report(y_test, y_test_pred))

Performance metrics of the model for the XGBOOST- Base Model
----------------------------------------------------------------------------------------------------
Accuracy:  0.8663346613545817
Precision Score:  0.8172245204964272
Recall Score:  0.5872972972972973
AUROC Score:  0.9248164969547013

Confusion Matrix:
  [[10874   486]
 [ 1527  2173]]
```

```
Classification Report:
              precision    recall  f1-score   support

          0       0.88      0.96      0.92     11360
          1       0.82      0.59      0.68      3700

avg / total       0.86      0.87      0.86     15060
```

7 Select Features

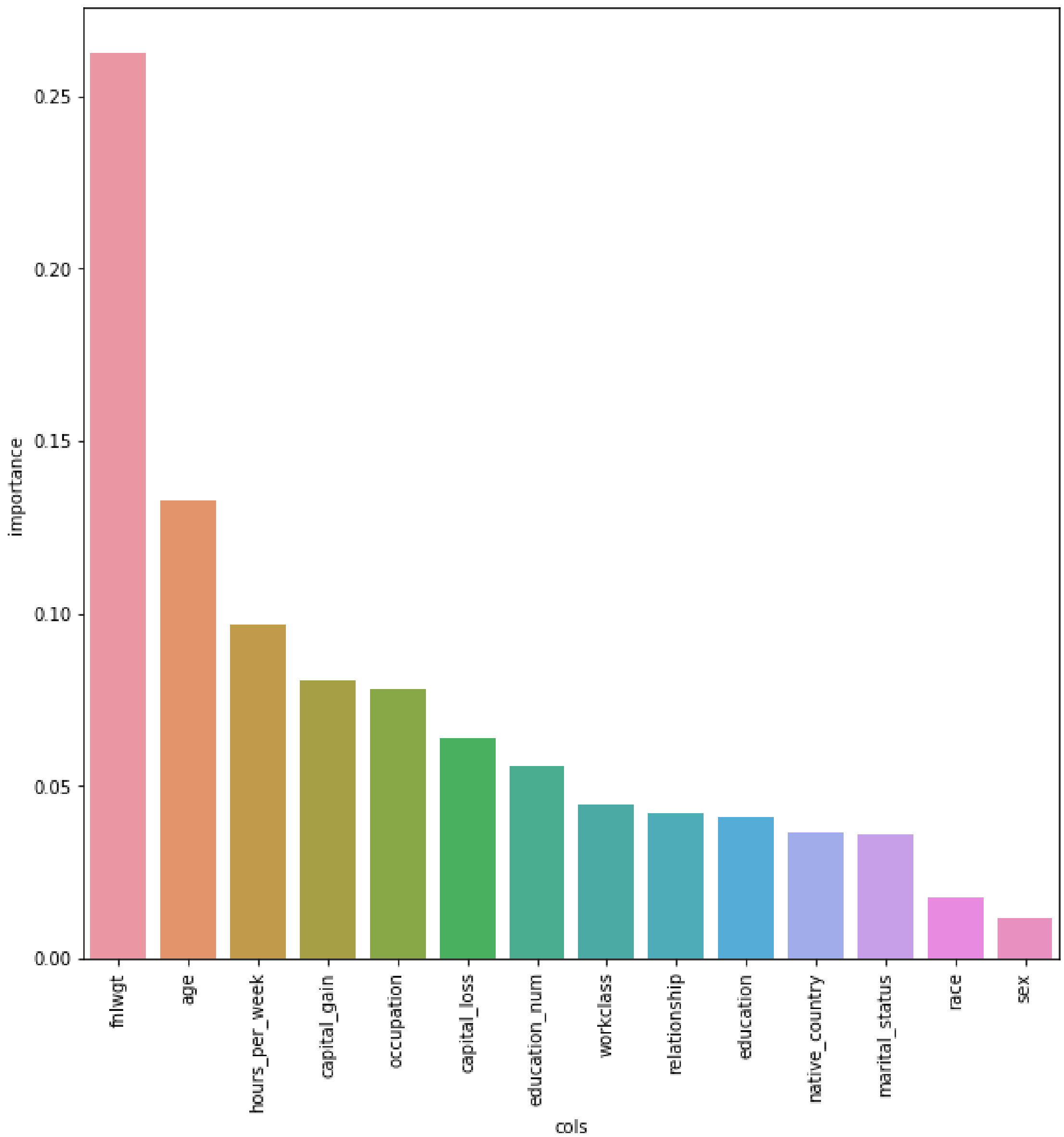
In [0]:
```
xgb.plot_importance(XGB_base)
```

Out[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x226385bd518>
```



In [0]:
```
importance = pd.DataFrame.from_dict({'cols':x_train.columns, 'importance': XGB_base.fea
importance = importance.sort_values(by='importance', ascending=False)
plt.figure(figsize=(10,10))
sns.barplot(importance.cols, importance.importance)
plt.xticks(rotation=90)
```

Out[0]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 <a list of 14 Text xticklabel objects>)
```




```
In [0]: imp_cols = importance[importance.importance >= 0.03].cols.values
        imp_cols
```

```
Out[0]: array(['fnlwgt', 'age', 'hours_per_week', 'capital_gain', 'occupation',
               'capital_loss', 'education_num', 'workclass', 'relationship',
               'education', 'native_country', 'marital_status'], dtype=object)
```

```
In [0]: params = {'learning_rate': 0.1, 'n_estimators': 1000, 'seed':0, 'subsample': 0.8, 'cols
                  'objective': 'binary:logistic'}
        XGB_feat_rem1 = XGBClassifier(**params)
```

```
XGB_feat_rem1.fit(x_train[imp_cols], y_train)

y_test_pred = XGB_feat_rem1.predict(x_test[imp_cols])
y_test_pred_prob = XGB_feat_rem1.predict_proba(x_test[imp_cols])

XGB_feat_rem1.score(x_test[imp_cols],y_test)
```

Out[0]: 0.8667994687915007

```
In [0]: # Generate model evaluation metrics for the XGBOOST- Feature Importance Threshold = 0.
        print("Performance metrics of the model for the XGBOOST- Feature Importance Threshold =
        print("-"*100)
        print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))
        print("Precision Score: ",metrics.precision_score(y_test, y_test_pred))
        print("Recall Score: ",metrics.recall_score(y_test, y_test_pred))
        print("AUROC Score: ",metrics.roc_auc_score(y_test,  y_test_pred_prob[:,1]))
        print()
        print("Confusion Matrix:  \n ",metrics.confusion_matrix(y_test, y_test_pred))
        print()
        print("Classification Report:\n ",metrics.classification_report(y_test, y_test_pred))
```

```
Performance metrics of the model for the XGBOOST- Feature Importance Threshold = 0.03
----------------------------------------------------------------------------------------------
Accuracy:  0.8667994687915007
Precision Score:  0.8245210727969349
Recall Score:  0.5816216216216217
AUROC Score:  0.9254073681956604

Confusion Matrix:
  [[10902   458]
 [ 1548  2152]]

Classification Report:
               precision    recall  f1-score   support

          0       0.88      0.96      0.92     11360
          1       0.82      0.58      0.68      3700

avg / total       0.86      0.87      0.86     15060
```

Our base model with all the features performs better than the model for which features were removed with a feature importance threshold of 0.03. So we stick with the model with all the features

8 Validate Model

In [0]:
```
scoring = 'neg_mean_squared_error'

kfold = KFold(n_splits=10, random_state=7)
cv_results = cross_val_score(XGB_base, x_train,y_train, cv=kfold, scoring=scoring)
print("xGB_Base CV Scores:","\n\t CV-Mean:", cv_results.mean(),
                    "\n\t CV-Std. Dev:",  cv_results.std(),"\n")
```

```
xGB_Base CV Scores:
         CV-Mean: -0.13155633769382874
         CV-Std. Dev: 0.00493050943479764
```

We have good CV mean and Std deviation score for XGB_base, however, we still need to optimize the hyper-parameters.

9 Optimize or Tune Model for better Performance

In [0]:
```
XGBClassifier()
```

Out[0]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [0]:
```
param_grid = {
              'colsample_bylevel':[0.8],
              'colsample_bytree':[0.8],
              'learning_rate':[0.1, 0,2, 0.3],
              'max_depth':[2, 4, 7],
              'min_child_weight':[1, 3],
              'n_estimators':[200],
              'n_jobs':[-1],
              'objective':['binary:logistic'],
              'random_state':[100],
              'reg_alpha':[0.1, 1, 10],
              'scale_pos_weight':[1],
              'silent':[True]}

XGB_grid = GridSearchCV(XGBClassifier(), param_grid=param_grid,cv = 5, verbose=1)
```

In [0]:
```
XGB_grid.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
```

```
[Parallel(n_jobs=1)]: Done 360 out of 360 | elapsed: 11.8min finished
```

```
Out[0]: GridSearchCV(cv=5, error_score='raise',
               estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
               colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
               max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
               n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
               reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
               silent=True, subsample=1),
               fit_params=None, iid=True, n_jobs=1,
               param_grid={'colsample_bylevel': [0.8], 'colsample_bytree': [0.8], 'learning_ra
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring=None, verbose=1)
```

```
In [0]: XGB_grid.best_params_
```

```
Out[0]: {'colsample_bylevel': 0.8,
         'colsample_bytree': 0.8,
         'learning_rate': 0.1,
         'max_depth': 7,
         'min_child_weight': 3,
         'n_estimators': 200,
         'n_jobs': -1,
         'objective': 'binary:logistic',
         'random_state': 100,
         'reg_alpha': 0.1,
         'scale_pos_weight': 1,
         'silent': True}
```

```
In [0]: model = XGB_grid.best_estimator_
        model.fit(x_train, y_train)
        y_test_pred = model.predict(x_test)
```

```
In [0]: model.score(x_test, y_test)
```

```
Out[0]: 0.8686586985391767
```

```
In [0]: # Generate model evaluation metrics for the XGBOOST - Hyperparameter tuned
        print("Performance metrics of the model for the XGBOOST - Hyperparameter tuned")
        print("-"*100)
        print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))
        print("Precision Score: ",metrics.precision_score(y_test, y_test_pred))
        print("Recall Score: ",metrics.recall_score(y_test, y_test_pred))
        print("AUROC Score: ",metrics.roc_auc_score(y_test,  y_test_pred_prob[:,1]))
        print()
        print("Confusion Matrix:  \n ",metrics.confusion_matrix(y_test, y_test_pred))
        print()
        print("Classification Report:\n ",metrics.classification_report(y_test, y_test_pred))
```

```
Performance metrics of the model for the XGBOOST - Hyperparameter tuned
-----------------------------------------------------------------------------------------------
Accuracy:  0.8686586985391767
Precision Score:  0.7910750507099391
Recall Score:  0.6324324324324324
AUROC Score:  0.9254073681956604

Confusion Matrix:
  [[10742   618]
 [ 1360  2340]]

Classification Report:
              precision    recall  f1-score   support

          0       0.89      0.95      0.92     11360
          1       0.79      0.63      0.70      3700

avg / total       0.86      0.87      0.86     15060
```

10 Choose the model for deployment

We chose the hyperparameter tuned model because it has the better accuracy score as all other average metrics(from classification report) are the same.

In [0]:
```
model
```

Out[0]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=0.8,
       colsample_bytree=0.8, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=7, min_child_weight=3, missing=None, n_estimators=200,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=100, reg_alpha=0.1, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=1)
```

In [0]:
```
import pickle
chosen_model = pickle.dumps(model)
```

pickle.loads(chosen_model)