Project data analysis

(Income Data Set)

Understanding the Data Science Lifecycle

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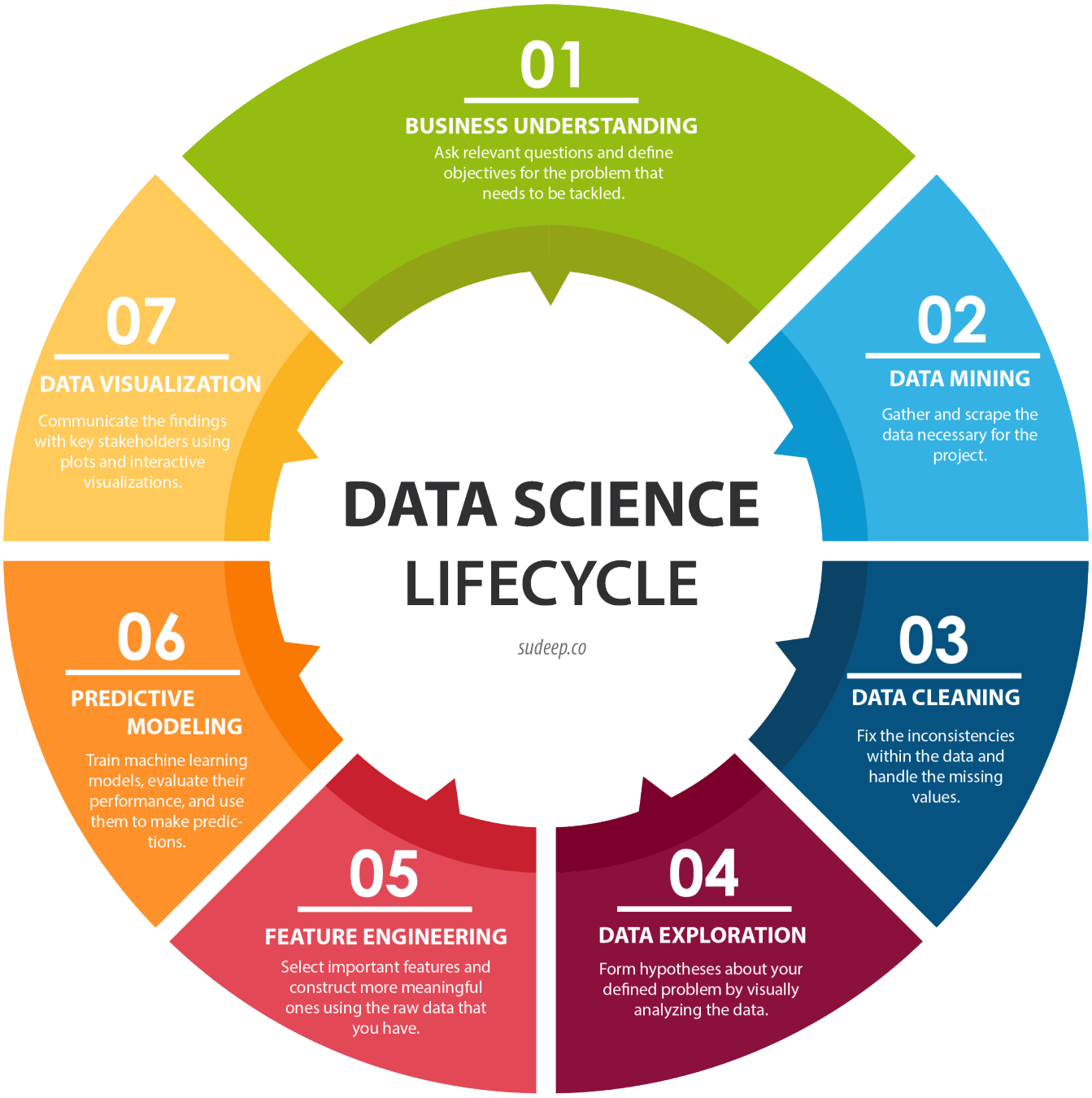
Understanding the Data Science Lifecycle

In this science project, we used the data science lifecycle that indicates seven steps taken to build, deliver and maintain the "test" data for the income product through extraction, preparation, cleansing, modelling, and evaluation for several independent variables, etc. (*see figure1*)



Step 1: Business understand

Before we make collecting the data, we need to understand the objectives in the project. To reduce the put the suitable variables, and reduce time of collecting and understanding of data.

The income data set is an individual's annual income results from various factors. The train dataset provided predictive feature like education num, occupation, work class, marital status and so on, to predict whether or not these factors can influence the income of the employees.

We explored the possibility in predicting income level (more than or less than 50 K) based on the individual's personal information through practicing machine learning problem like classification and regression (Customers income prediction)

This is a supervised machine learning problem because here we have a labeled data set.

The dependent variable (Y) is the income.

- The income is divided into two classes: <=50K and >50K

The independent Variables (X) are: Age, education type, occupation and so on.

Number of attributes: 14

- These are the demographics and other features to describe a person

Respiratory data used is: Income datasets (train set) from:

https://www.kaggle.com/datasets/mastmustu/income

Step 2: Data Mining

We collect data based on variables (age, gender, type of job, income, education level, hours per week, race)

Open file (lab work)

In [1]

```
import numpy as np # linear algebra

import pandas as pd # data processing, CSV file
```

In [2]

```
# Import data
data = pd.read_csv("../input/income/train.csv")
data.shape
```

Out [2]

```
(43957,15)
```

In [3]

```
data.columns
```

Out [3]:

```
Index(['age', ' workclass', ' fnlwgt', ' education', ' education-num',
       ' marital-status', ' occupation', ' relationship', ' race', ' sex',
       ' capital-gain', ' capital-loss', ' hours-per-week', ' native-country',
       ' income'],
      dtype='object')
```

Step 3: Data Cleaning

The data I chose is the income dataset for binary classification (https://www.kaggle.com/mastmustu/income). This data set offers a vast array of features. Some columns have a missing value as ? we need to convert actual None.

In[4]

```
data = data.replace('?', np.nan)

# Chechking null values
def about_data(df):
    total_missing_values = df.isnull().sum().reset_index()
    total_missing_values = total_missing_values.rename(columns={'inde
x':'columns',0:'total missing'})
    total_missing_values['ration of missing'] = total_missing_values[
'total missing']/len(df)
    return total_missing_values
```

We find out, there are 3 columns have null value. we can drop it because of percentage of missing value very low.

In[5]

```
about_data(data)
```

Out[5]

	columns	total missing	ration of missing
0	age	0	0.000000
1	workclass	1836	0.056386
2	fnlwgt	0	0.000000
3	education	0	0.000000
4	education-num	0	0.000000
5	marital-status	0	0.000000
6	occupation	1843	0.056601
7	relationship	0	0.000000
8	race	0	0.000000
9	sex	0	0.000000
10	capital-gain	0	0.000000
11	capital-loss	0	0.000000
12	hours-per-week	0	0.000000
13	native-country	583	0.017905

As we see we found some null value . and we will write the below code to delete null value from our data:

In[6]

```
data.dropna(inplace=True,axis=0)
about_data(data)
```

Out [6]

	columns	total missing	ration of missing
0	age	0	0.000000
1	workclass	0	0.000000
2	fnlwgt	0	0.000000
3	education	0	0.000000
4	education-num	0	0.000000
5	marital-status	0	0.000000
6	occupation	0	0.000000
7	relationship	0	0.000000
8	race	0	0.000000
9	sex	0	0.000000
10	capital-gain	0	0.000000
11	capital-loss	0	0.000000
12	hours-per-week	0	0.000000
13	native-country	0	0.000000

as we see we have a clean data

Step 4: Exploratory Analysis

For this part, we can observe relationships with the data while having fun with functions. In this example, the dataset provided predictive feature like age, education num, employment status, marital status to predict if the income is greater than $50K. It can be used to practice machine learning problem like binary classification. So, we need to accurately predict whether or not someone is making more or less than $50,000 a year.,

Also before start we will explain the name for our columns :

In [7]
```
data.columns
```

Out [7]
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income_>50K'],
      dtype='object')
```

Columns	Definition
age	Age of Persons
workclass	Describe work type
fnlwgt	Financial Weight
education	Person's education level
educational-num	Experience of Years
martial status	Person's martial status
occupation	Person's usual or principal work or business
gender	Gender of Person
race	Person's race
capital gain	Person's capital gain
capital loss	Person's capital loss
hours per hour	Earn per hour
native country	Persons native country
income_>50K'	Whether <50k or not

In [8]

```
data.info()
```

Out [8]

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              32561 non-null  int64
 1    workclass       32561 non-null  object
 2    fnlwgt          32561 non-null  int64
 3    education       32561 non-null  object
 4    education-num   32561 non-null  int64
 5    marital-status  32561 non-null  object
 6    occupation      32561 non-null  object
 7    relationship    32561 non-null  object
 8    race            32561 non-null  object
 9    sex             32561 non-null  object
 10   capital-gain    32561 non-null  int64
 11   capital-loss    32561 non-null  int64
 12   hours-per-week  32561 non-null  int64
 13   native-country  32561 non-null  object
 14   income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In[9]

```
data.describe()
```

Out[9]

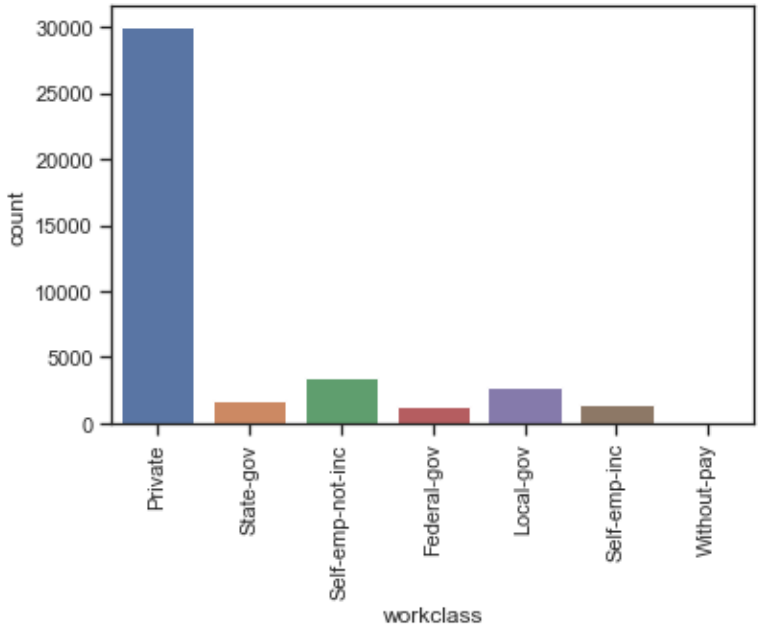
	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000

we will show some diagram from our database :

In[10]:

```
data["workclass"] = [cols.replace(' ', '') for cols in
data["workclass"]]
sns.countplot(data=data,x='workclass')
plt.xticks(rotation=90)
```

Out [10]:

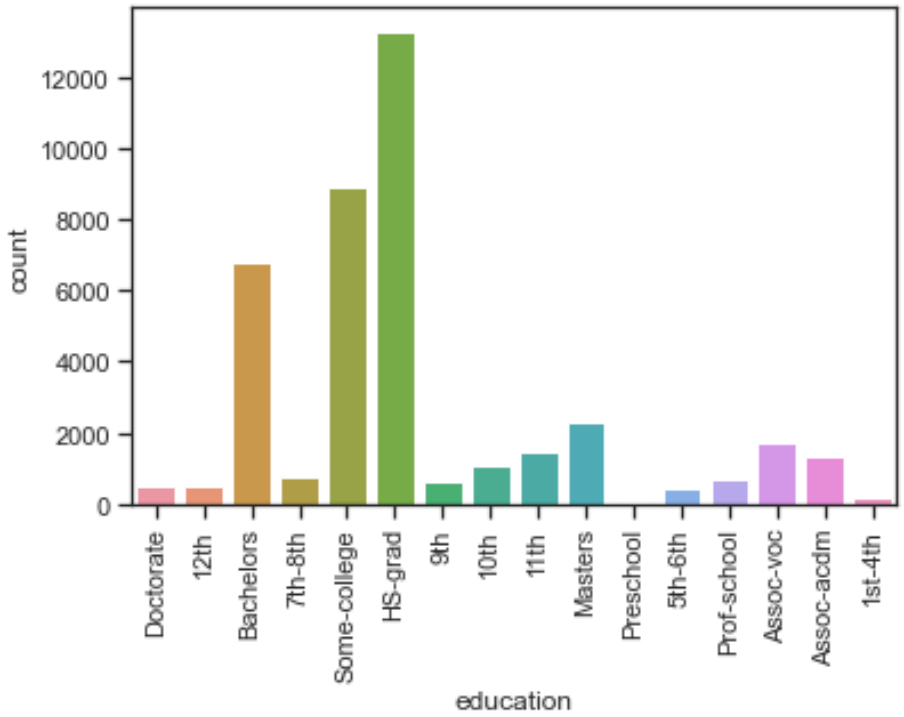


As we see this diagram show for us how many people in workclass and we see the big workclass is a private .

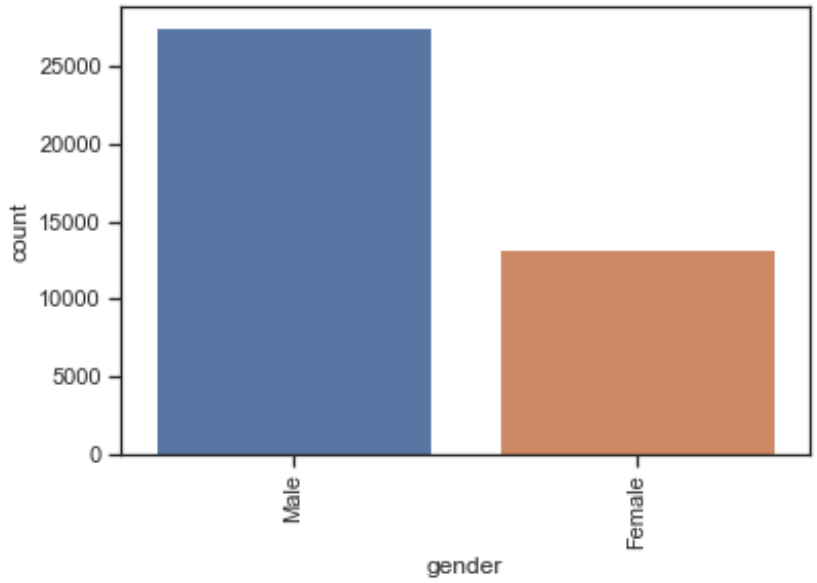
In[11]

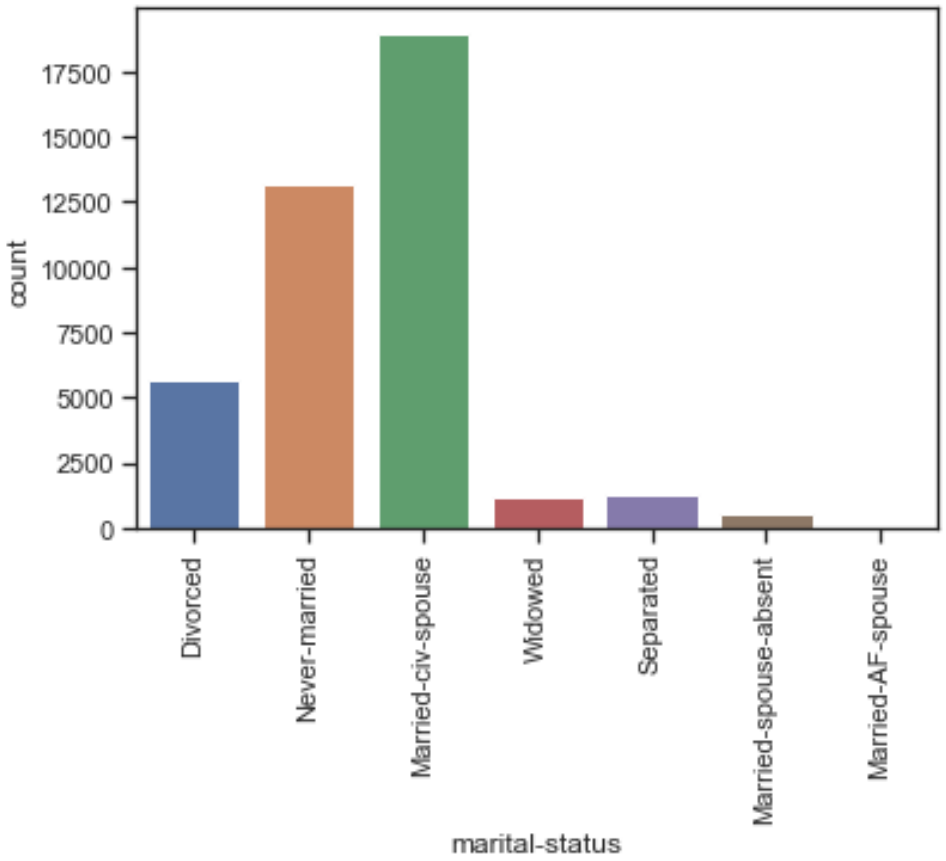
```
data["education"] = [cols.replace(' ', '') for cols in
data["education"]]
sns.countplot(data=data,x='education')
plt.xticks(rotation=90)
```

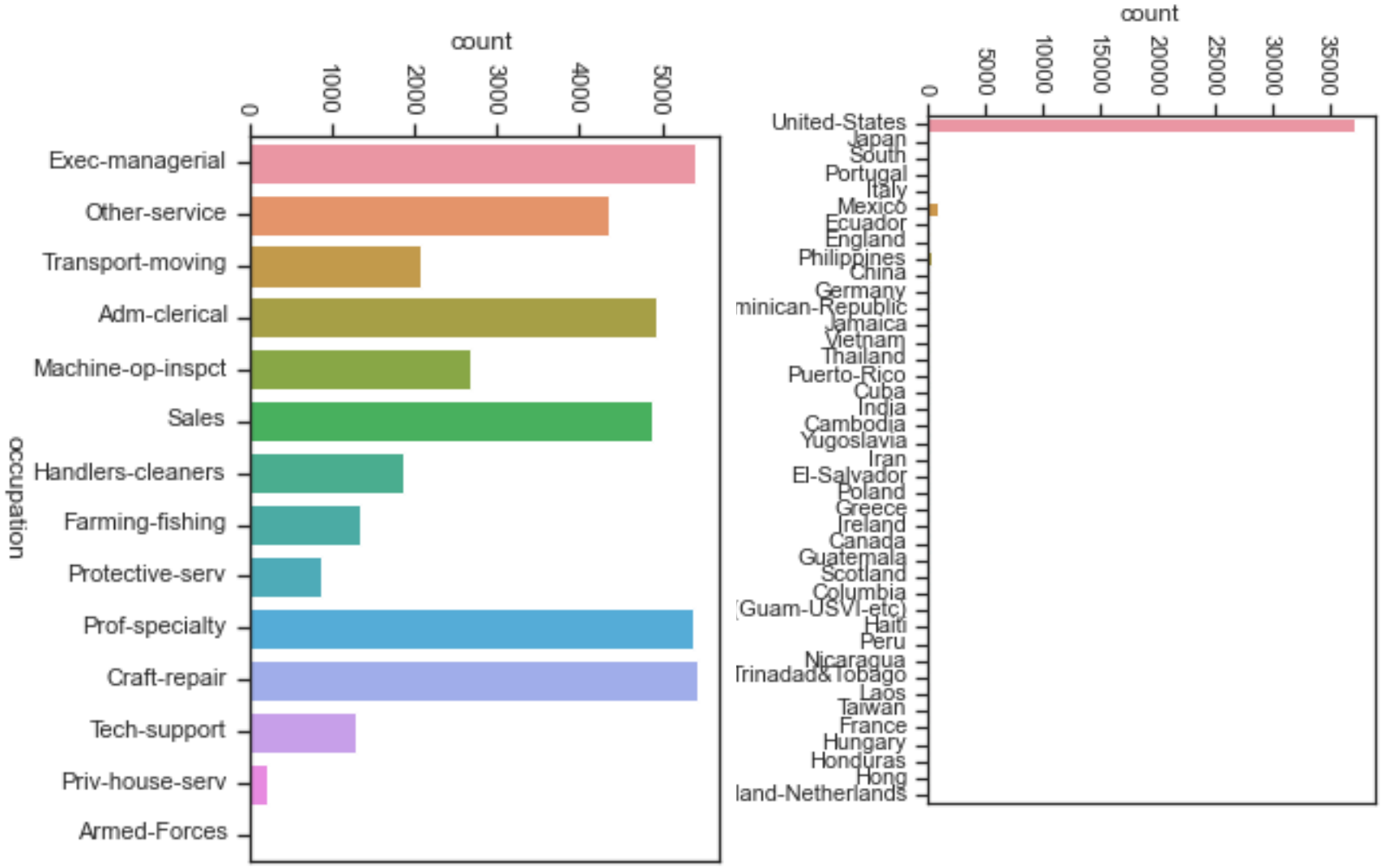
Out [11] :

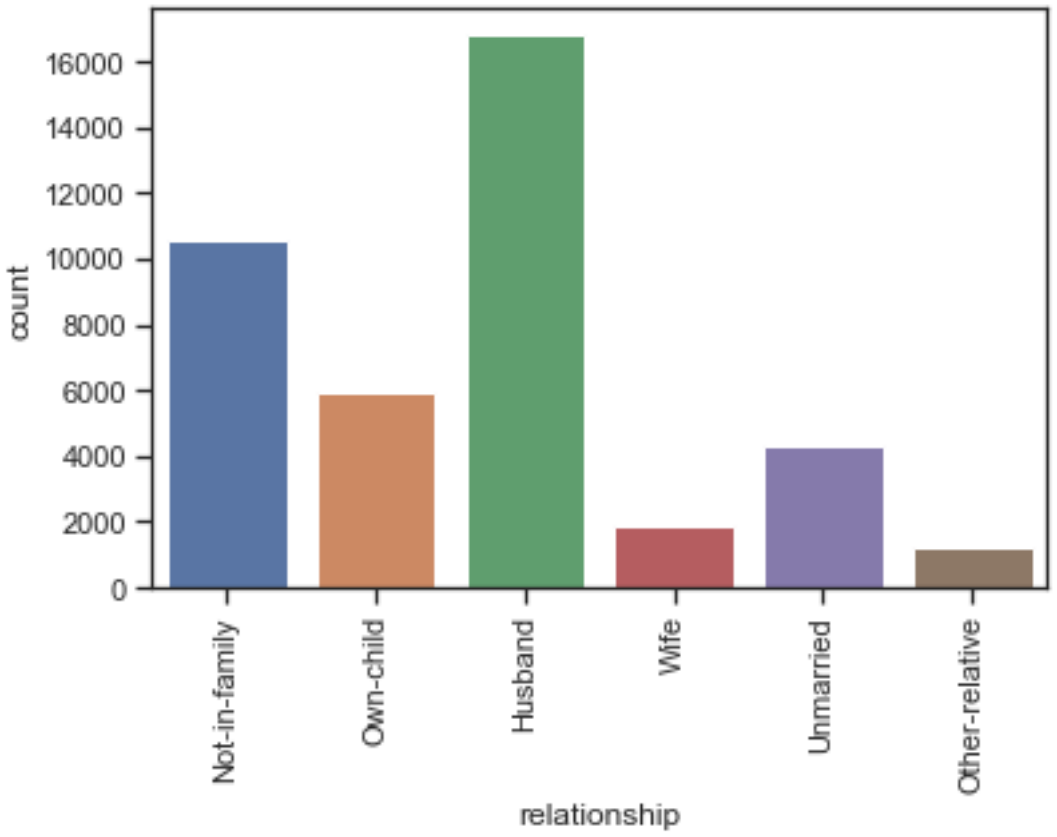


And we will show for all the other diagram but we don't write the code because it's same the last code:






count
0
1000
2000
3000
4000
5000
occupation
Exec-managerial
Other-service
Transport-moving
Adm-clerical
Machine-op-inspct
Sales
Handlers-cleaners
Farming-fishing
Protective-serv
Prof-specialty
Craft-repair
Tech-support
Priv-house-serv
Armed-Forces
count
0
5000
10000
15000
20000
25000
30000
35000
United-States
Japan
South
Portugal
Italy
Mexico
Ecuador
England
Philippines
China
Germany
minican-Republic
Jamaica
Vietnam
Thailand
Puerto-Rico
Cuba
India
Cambodia
Yugoslavia
Iran
El-Salvador
Poland
Greece
Ireland
Canada
Guatemala
Scotland
Columbia
(Guam-USVI-etc)
Haiti
Peru
Nicaragua
Trinadad&Tobago
Laos
Taiwan
France
Hungary
Honduras
Hong
land-Netherlands


16000
14000
12000
10000
8000
6000
4000
2000
0
count
Not-in-family
Own-child
Husband
Wife
Unmarried
Other-relative
relationship

Step5: Feature Engineering

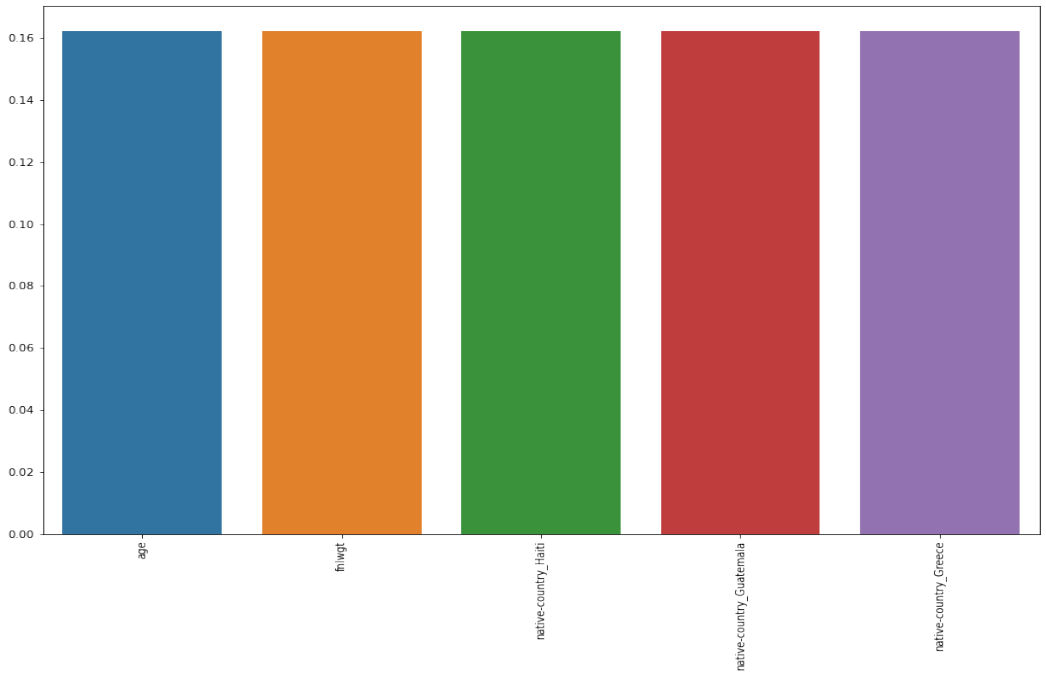
In machine learning, a feature is a measurable property or attribute of a phenomenon being observed. If we were predicting the income of customers, a possible feature is the amount of income they get. We typically perform two types of tasks in feature engineering - feature selection and construction. in this example, I select the top five feature selection.

In [12]

```
coefs = pd.Series(index=X.columns,data=tuned_model_rf.feature_importances_[0])
coefs = coefs.sort_values(ascending=False)[:5]
plt.figure(figsize=(15,10))
sns.barplot(x=coefs.index,y=coefs.values)
plt.xticks(rotation=90)
```

Out [12]

```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'age'),
  Text(1, 0, 'fnlwgt'),
  Text(2, 0, 'native-country_Haiti'),
  Text(3, 0, 'native-country_Guatemala'),
  Text(4, 0, 'native-country_Greece')])
```



Step 6: Predictive Modeling

I used the predictive modeling to ensure that the outcomes from the model actually make sense and are significant. Then, it is critical that you evaluate its success. A process called k-fold cross validation. This allows the model to be trained on all the data instead of using a typical train-test split.

In this example, I used (logisticRegression(LR), KNeighborsClassifier(KNN), DecisionTreeClassifier(DTC), RandomForestClassifier(RFC)).

In [13]

```
trees = 100
max_features = 3
results = []
names_of_models = []

model_list =[('LR', LogisticRegression()),
             ('KNN', KNeighborsClassifier()),
             ('DTC', DecisionTreeClassifier()),
             ('RFC', RandomForestClassifier(n_estimators=trees,max_features=3))]


for name, model in model_list:
    kfold = KFold(n_splits=10, random_state=None)
    cv_results = cross_val_score(model, scaled_X_train, y_train, cv=kfold,
scoring='accuracy')
    results.append(cv_results)
    names_of_models.append(name)
    res = "{}: {} ({})".format(name, cv_results.mean(), cv_results.std())
    print(res)
```

Out [13]

```
LR: 0.8195238593199343 (0.006410311684477739)
KNN: 0.8247283318387449 (0.004367257918147866)
DTC: 0.9133345796457777 (0.0037535594855644784)
RFC: 0.9258656297610204 (0.0032177164323382765)
```

As indicated above, Random Forest has highest accuracy. Then, we choose random forest model and tune params

Step7: Data visualization

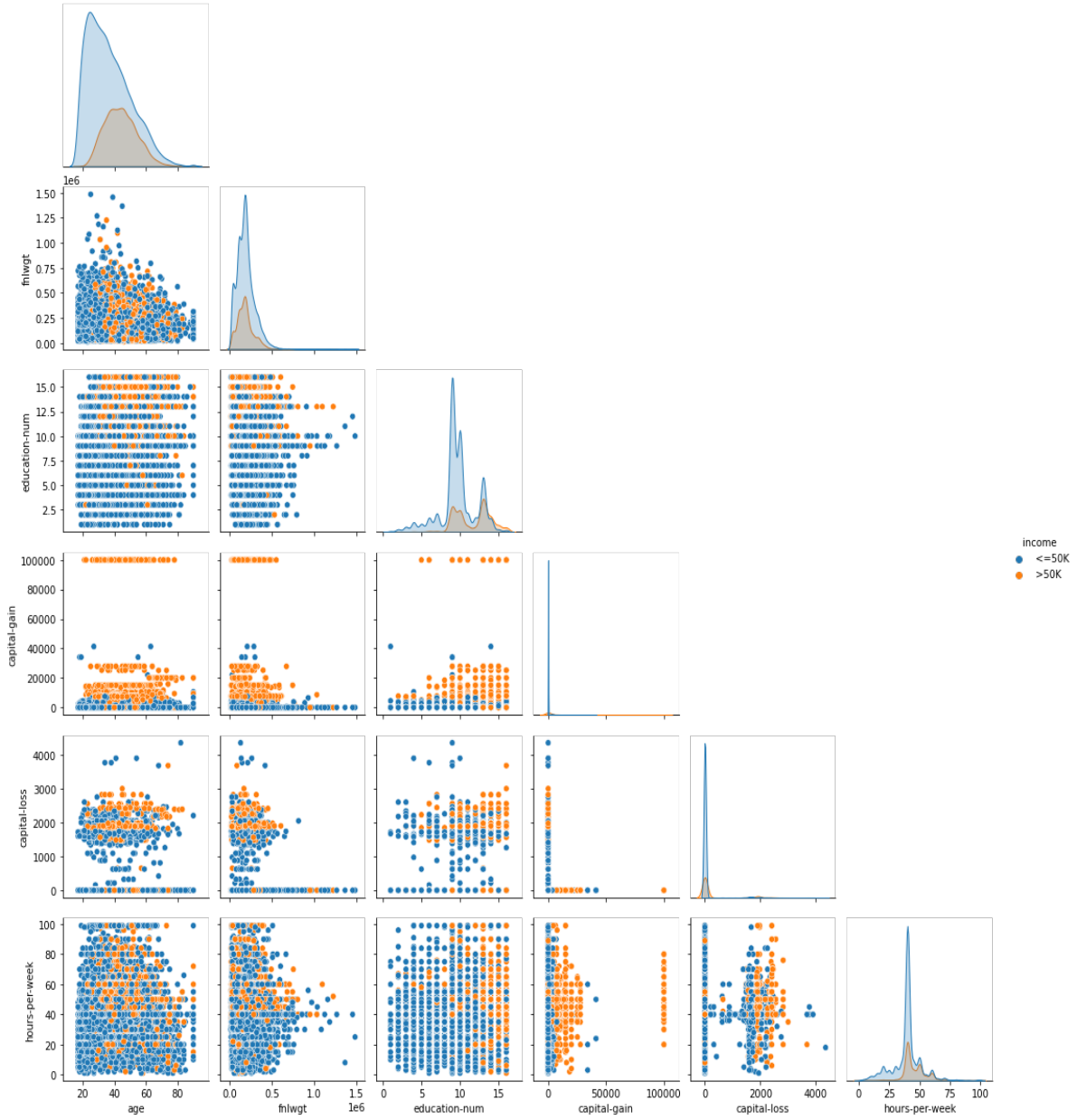
Here we represent the model in way that the different stakeholders in the project can understand.

In [13]

```
sns.pairplot(data,hue='income_>50K',corner=True)
```

Out[14]

```
<seaborn.axisgrid.PairGrid at 0x1e0e4114be0>
```

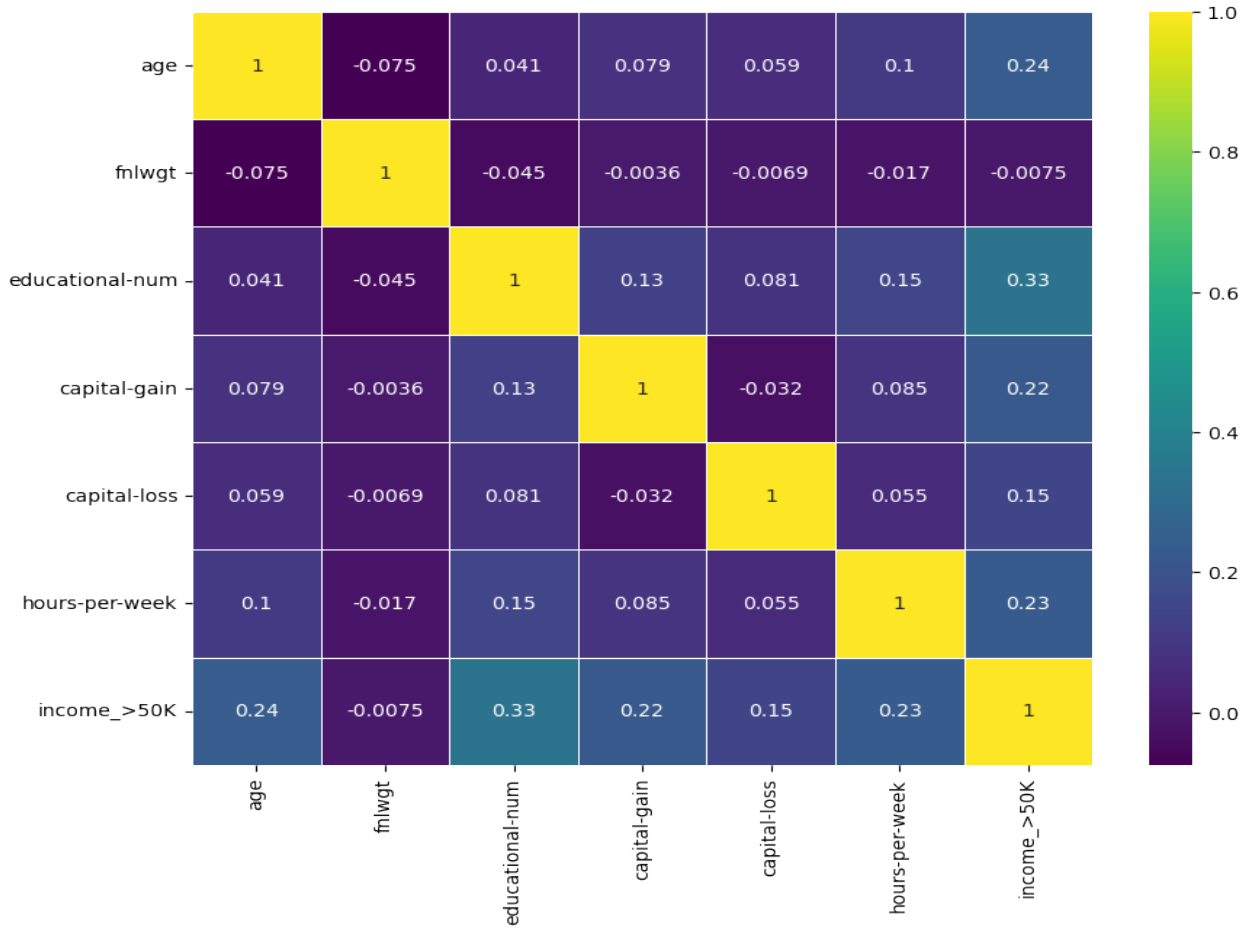


In [15]

```
plt.figure(figsize=(10,8),dpi=100)
sns.heatmap(data.corr(),cmap="viridis",annot=True,linewidth=0.5)
```

out [15]

```
<AxesSubplot:>
```



In one hand, the positive relationship with the income are:Age, Workclass Federal-, Workclass private, fnlwgt, ..all the variables in blue color.

While the negative relationship with the income are: Workclass never worked, Education 7th – 8 th, Martial status never married, Occupation family finshing …. All the variables in green colors.

On other hand, there are some variables such as: educationPreschool , relationshipUnmarried , and occupationTransport-moving… all the variables in black color. These are not influence the income at all.

Conclusion

There are little number of employees make more than 50 K. We recommended to increase the hours per week to 40., also we can employee the worker with bachelors and master degree (need to increase) for income less than 50 K. Prefer work in private class for high income. In sum, employees should encourage to increase their income with the variables that are related to increase the income such as age and avoid all other variables that are not impact the income or has a negative impact on it.

Our file :

https://github.com/Hussain-Almansour/mywebsit/tree/master/Project