Econ Salary Prediction by beginners-newbies

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1. Introduction

People are interested in predicting salary in the fields of Economics. However, there are numerous features that play roles of determining individual's income. According to U.S. Bureau of Labor Statistics, features such as higher educational attainment usually correlate with higher income. Since the number of social-economics factors are large, it would be great that we could come-up with a prediction model that predicts individual's salary based on their unique features. In this project, we were utilizing IPUMS CPS(https://cps.ipums.org/cps/index.shtml) data to achieve our goal.

Something to notice is the language we will use below. Before running statistical testing on the ceteris paribus causal inference, we shall never use the word "causes" in our conclusion. In fact, it is hard to draw causal inference because we need apple-to-apple comparison to the potential outcomes of treated and untreated of same individual. For example, we need data of same individual's salary if he has a master degree vs if he only have a high school diploma. However, one of the potential outcome is never observed, which made such comparison impossible. Thus, to draw this ceteris paribus causal inference, we need to compute the Average treatment Effect.

2. Data Cleaning & Preprocessing, Feature Engineering

First, we noticed that the data set has 29 columns:

```
['YEAR', 'SERIAL', 'MONTH', 'HWTFINL', 'CPSID',
'ASECFLAG', 'HFLAG', 'ASECWTH', 'REGION', 'STATEFIP',
'NFAMS', 'PERNUM', 'WTFINL', 'CPSIDP', 'ASECWT', 'AGE',
'SEX', 'RACE', 'MARST', 'BPL', 'EMPSTAT', 'OCC',
'UHRSWORKT', 'WKSTAT', 'JOBCERT', 'EDUC', 'EDDIPGED',
'INCWAGE', 'OINCWAGE']
```

where the `INCWAGE` column describes the salaries we are interested in.

1. Clean Data

But after looking at values in the `INCWAGE` column, we found many `nan`s and abnormal values like `99999999` (according to the IPUMS source, `99999999` stands for "not in universe").

```
total surveys: 54737
number of N.I.U wage: 5543
number of NaN wage: 30160
number of 0 wage: 7496
number of wage > 0: 11538
number of wage >= 0: 19034
```

We exclude these data from our dataframe since they cannot help us make predictions: (`data` is the raw data set, `NIU` equals to 99999999)

```
raw_data = pd.read_csv('../data/beginner.csv')
clean_data = raw_data[(raw_data["INCWAGE"] != 99999999.0)
& (raw_data["INCWAGE"] != 0.0)]
clean_data = clean_data.dropna(subset = ['INCWAGE'])
clean_data = clean_data.dropna(how = 'all', axis = 1)
clean_data = clean_data.drop(columns = ['HFLAG',
'ASECFLAG', 'MONTH', 'CPSID', 'SERIAL', 'CPSIDP'])
clean_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11538 entries, 0 to 54733
Data columns (total 19 columns):
#    Column      Non-Null Count  Dtype
---  ------      --------------  -----
0    YEAR        11538 non-null  int64
1    ASECWTH     11538 non-null  float64
2    REGION      11538 non-null  int64
3    STATEFIP    11538 non-null  int64
4    NFAMS       11538 non-null  int64
5    PERNUM      11538 non-null  int64
6    ASECWT      11538 non-null  float64
7    AGE         11538 non-null  int64
8    SEX         11538 non-null  int64
9    RACE        11538 non-null  int64
```

```
10  MARST      11538 non-null  int64
11  BPL        11538 non-null  int64
12  EMPSTAT    11538 non-null  int64
13  OCC        11538 non-null  int64
14  UHRSWORKT  11538 non-null  int64
15  WKSTAT     11538 non-null  int64
16  EDUC       11538 non-null  int64
17  INCWAGE    11538 non-null  float64
18  OINCWAGE   11538 non-null  float64
dtypes: float64(4), int64(15)
memory usage: 1.8 MB
```

2. Adjust income for inflation

> *https://cps.ipums.org/cps/cpi99.shtml*

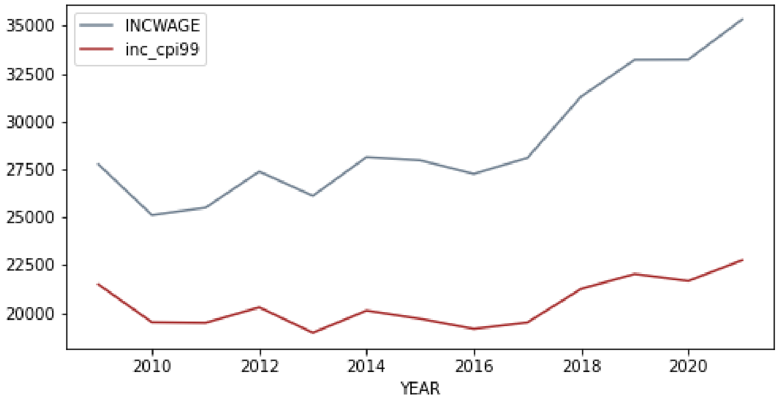
We need to inflate or deflate the dollar amounts of `INCWAGE` in order to make them comparable, so we convert the dollar amounts to constant 1999 dollars by multiplying the CPI99 constants of that data year to the `INCWAGE` values:

We first record these constants in a static `.json` file so that it can be easily loaded as a dictionary:

```
with open(data_pth / 'cpi99_cons.json', 'w') as fout:
    json.dump(cpi99_cons, fout)
```

Then, generate a series of the corresponding CPI99 constants of that data year and multiply the constants to the raw dollar amounts of `INCWAGE`:

```
def clean_incwage(df):
    cpi99 = df['YEAR'].apply(lambda yr :
cpi99_cons[str(yr)])
    df['inc_cpi99'] = df['INCWAGE'] * df['cpi99']

    df.groupby('YEAR').mean()['INCWAGE'].plot(legend=True)
    df.groupby('YEAR').mean()
['inc_cpi99'].plot(legend=True)

clean_wage(clean_data)
```



As shown, the adjusted values are deflated as they are after 1999.

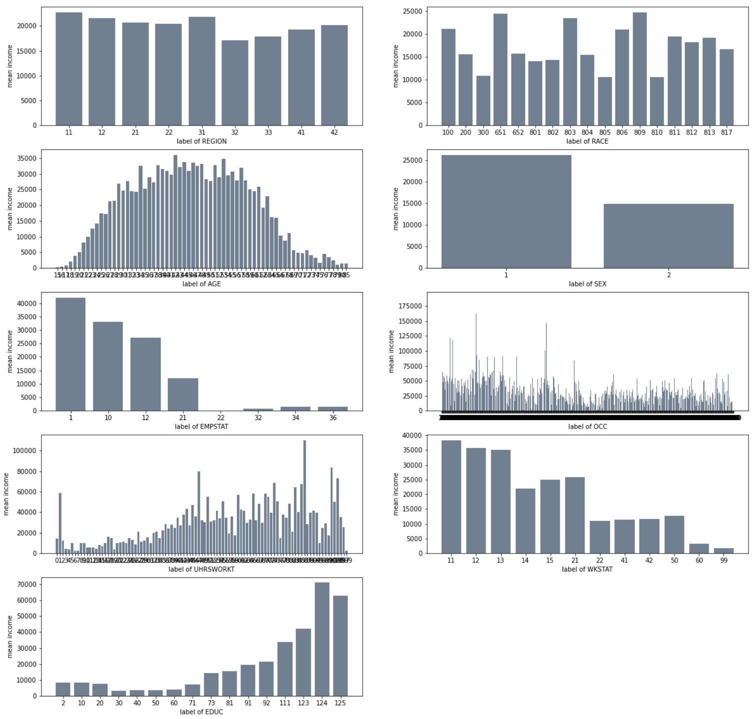
3. Choose & Adjust appropriate factors

Then, after exploring these columns and the descriptions (e.g. https://cps.ipums.org/cps-action/variables/BPL#description_section), we decided to focus on columns as below:

```
['REGION', 'RACE', 'AGE', 'SEX', 'EMPSTAT', 'OCC',
'UHRSWORKT', 'WKSTAT', 'EDUC']
```

Visualize the relations between each factor and `INCWAGE` (note that some factors have the labels as codes)

```
def display_categ(df):
    indices = ['REGION', 'RACE', 'AGE', 'SEX', 'EMPSTAT',
'OCC', 'UHRSWORKT', 'WKSTAT', 'EDUC']

    fig, axs = plt.subplots(5, 2, figsize=(20, 20),
constrained_layout=False)

    for i in range(len(indices)):
        ax = axs.flat[i]
        it = indices[i]
        ser = df.groupby(it).mean()['inc_cpi99']
        ax.bar(list(map(str, ser.index)),
ser.values.tolist(), color='slategrey')

        ax.set_ylabel("mean income")
        ax.set_xlabel(f"label of {it}")

    return fig, axs

fig, axs = display_categ(clean_data)
```



1. Region, Race, Occupation

According to the IPUMS, region codes are:

Code	Label
	NORTHEAST REGION
11	New England Division
12	Middle Atlantic Division
	MIDWEST REGION
21	East North Central Division
22	West North Central Division
	SOUTH REGION
31	South Atlantic Division
32	East South Central Division
33	West South Central Division
	WEST REGION
41	Mountain Division
42	Pacific Division
	STATE UNKNOWN
97	State not identified

Connected to our graph, Mean income in New England Division (11) and South Atlantic Division (31) are higher, while East South Central Division (32) has the lowest mean.

We sort the region labels by the mean income value and give them ordinal numbers:

```
ser = clean_data.groupby('REGION').mean()
['inc_cpi99'].sort_values()
region_ord = ser.reset_index()['REGION']
region_ord = {region_ord.loc[i] : i  for i in
region_ord.index}
clean_data['region_ord'] =
clean_data['REGION'].apply(lambda x : region_ord[x])
```

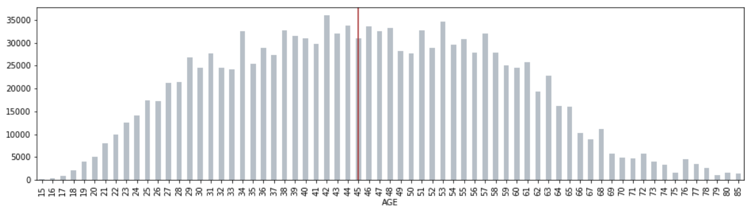
We apply the same approach to `RACE` and `OCC` columns.

2. Age

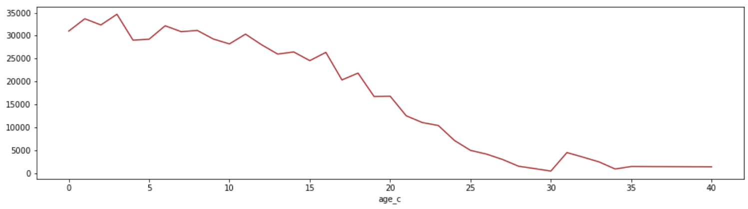
The relationship between age and salary can be described by a bell-shaped pattern that emphasizes a peaked salary around the age of 40 to 50. It can be observed that at an age before 40, salaries are clearly less than that who have reached their 40 to 50. Moreover, there experiences a gradual upward trend as age increases in the quantification of salary. Similarly, it can be observed that at an age after 50, salaries also becomes less than those who are at their 40 to 50. In addition, a gradual, downward trend can be observed from the display of the relationship between age and salary.

We choose a centered age of 45 (where the area left to 45 is equal to the area right to 45):

```
def age_score(df):
    salary_vs_age = df[['AGE', 'inc_cpi99']]
    plt.rcParams["figure.figsize"] = (16,4)

    mean_inc_by_age = df.groupby('AGE').mean()
['inc_cpi99']
    mean_inc_by_age.plot(kind='bar', color='slategrey',
alpha=.5)

    age_lst = mean_inc_by_age.index.tolist()

    l = np.min(age_lst)
    r = np.max(age_lst)
    while l <= r:
        mid = (l + r) >> 1
        lower = mean_inc_by_age.iloc[:mid].sum()
        upper = mean_inc_by_age.iloc[mid:].sum()
        if lower >= upper:
            r = mid - 1
        else:
            l = mid + 1

    plt.axvline(r, color='brown')
    plt.savefig('age_centered.png')

age_score(clean_data)
```




```
clean_data['age_c'] = abs(filtered['AGE'] - 45)
clean_data.groupby('age_c').mean()
['inc_cpi99'].plot(color='brown')
plt.savefig('age_centered_plot.png')
```



3. Other indices

Other indices, including `EDUC` (education) and `WKSTAT` have been properly ordered by their codes. We leave them unchanged.

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3. Models

3.1 Linear Regression With Ordinal Columns

We use the adjusted columns to run a linear regression:

```
def least_squares_regression(X, y):
    """ Find the least squares regression plane using the
normal equations """
    return np.linalg.solve(X.T @ X, X.T @ y)

def mse_with_vars(df, ob, vars, f=None) :
    data = df.get(vars).values.tolist()

    design_mat = np.array([[1, *row] for row in data])
    observ_vec = np.array(df[ob].values)

    w = least_squares_regression(design_mat, observ_vec)

    err_vec = observ_vec - design_mat @ w
    mse = np.dot(err_vec, err_vec) / len(data)
```

```
    return w, mse

mse_with_vars(
    clean_data, 'inc_cpi99',
    ['region_ord', 'race_ord', 'age_c', 'SEX', 'EMPSTAT',
'occ_ord', 'UHRSWORKT', 'WKSTAT', 'EDUC']
)
```

```
<class 'numpy.ndarray'>
(array([ 8.72228854e+02,  2.04811704e+02,
2.45518832e+02, -2.56547011e+02,
     -5.45191102e+03,  3.09293242e+02,
8.93171050e+01,  2.76527878e-01,
     -1.32927802e+02,  1.43378040e+02]),
879818925.1034607)
```

where the mse is approximately 8.8×10^8.

3.2 Sklearn Linear Regression

Alternatively, we split our dataset into training data and test data, and apply `sklearn` linear regression:

```
from sklearn.linear_model import RidgeCV
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Ridge

model_data = clean_data[['EDUC', 'AGE',
'WKSTAT']].astype(str)
model_data = pd.get_dummies(data = model_data)

X = model_data.to_numpy()
y = clean_data['INCWAGE'].to_numpy()
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size = 0.1)

model = LinearRegression(normalize = True)
model.fit(X_train, y_train)
weight = model.coef_
bias = model.intercept_
X_predict = model.predict(X_test)
model_error = mean_squared_error(y_test, X_predict)
model.score(X_test, y_test), model_error

clf = RidgeCV(alphas=[1e-3]).fit(X_train, y_train)
clf.score(X_test, y_test), model_error
```

```
(0.23010189890711807, 2419350257.9956675)
```

where the accuracy is about 0.23 and the error is 2.4×10^9.

---

4. Conclusion

Although our MSE is relatively high, we believe it is reasonable because it is hard for the model to predict accurately so that it could guess all decimals of the testing salaries. However, we were still able to reach above 20% accuracy on the testing set in most trials.

A limitation on the dataset is that due to the nature of how this data was collected, most of our statistics obtained are solely from March and restricted to March. Such constraint limits us to explore further into factors like whether there exists a traceable pattern to define relationship between month and salary.

Additionally, the dataset raises challenges intrinsically when it contains almost at least one null value for each observation. While such circumstance would be often-time anticipated, it still introduces a limitation because I believe if we were to have less incomplete data, the accuracy of model trained would've been better. Also, some potential future improvement could be cleaning the data better.