

The background is a dark navy blue. On the left side, there are several parallel teal lines that form a corner-like shape, extending from the top left towards the bottom. In the bottom right corner, there are three parallel teal lines that extend diagonally upwards from the bottom left towards the top right. The main text is centered in the upper half of the image.

ARTIFICIAL INTELLIGENCE

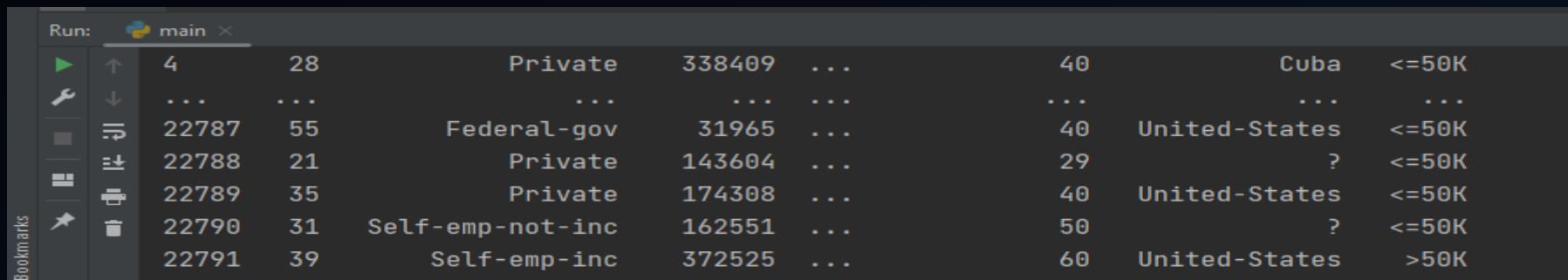
EMPLOYEE SALARY PREDICTION

Team members

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Preprocessing

If we look in the data, we will see a lot of (“?”)



The screenshot shows a Jupyter Notebook console with a table of data. The table has 10 columns. The 9th column contains several missing values represented by "?".

Run:	main								
4	28	Private	338409	...		40	Cuba	<=50K	
...	
22787	55	Federal-gov	31965	...		40	United-States	<=50K	
22788	21	Private	143604	...		29	?	<=50K	
22789	35	Private	174308	...		40	United-States	<=50K	
22790	31	Self-emp-not-inc	162551	...		50	?	<=50K	
22791	39	Self-emp-inc	372525	...		60	United-States	>50K	

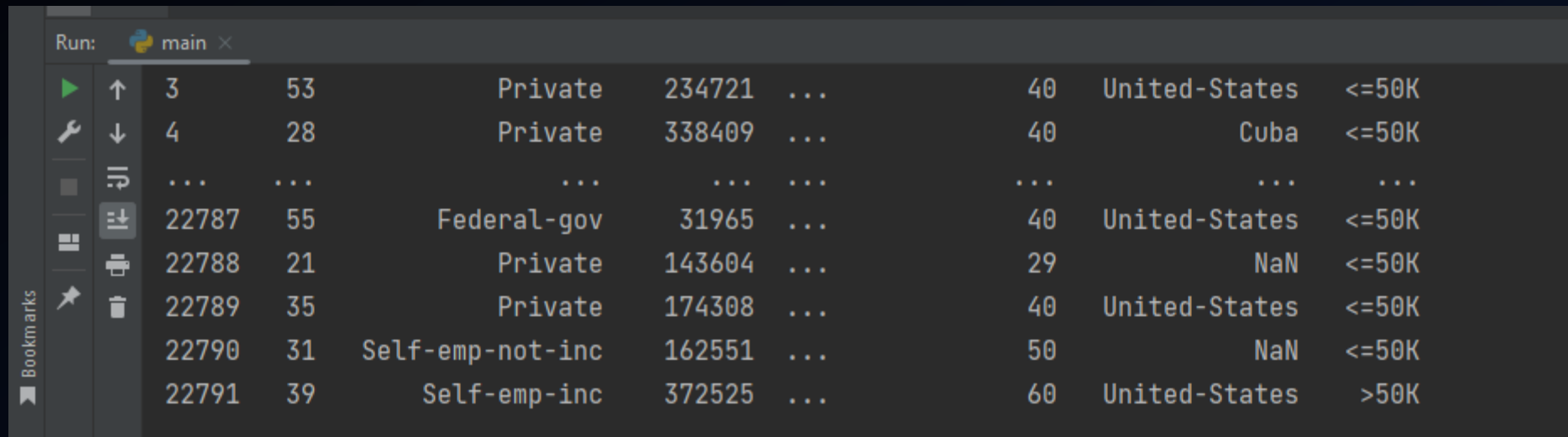
so, we replace it to **NAN** values using this line of code :

```
d.replace(" ?", np.nan, inplace=True)
```

For both files (Train , Test)

Preprocessing

The result is :



Run: main	3	53	Private	234721	...	40	United-States	<=50K
	4	28	Private	338409	...	40	Cuba	<=50K

	22787	55	Federal-gov	31965	...	40	United-States	<=50K
	22788	21	Private	143604	...	29	NaN	<=50K
	22789	35	Private	174308	...	40	United-States	<=50K
	22790	31	Self-emp-not-inc	162551	...	50	NaN	<=50K
	22791	39	Self-emp-inc	372525	...	60	United-States	>50K

when we got **NAN** values , We can handle it with known techniques such as `fillna()` or `dropna()` method .

Preprocessing

We used both to trying to achieve the best score :

```
d = d.dropna(axis=0, how='any')
```

```
d.fillna(method='ffill', inplace=True) # ffill backfill bfill pad
```

We change value on **education** from integers and string's to strings only to make best encoder on this column

```
# Convert "education" to string  
d = d.astype({'education': 'string'})
```

Preprocessing

- prediction want column have the same name, so We change the column name in **test** data to the same in **train** data for prediction :

```
d.rename(columns={'workclass': 'work-class'}, inplace=True)
d.rename(columns={'fnlwgt': 'work-fnl'}, inplace=True)
d.rename(columns={'occupation': 'position'}, inplace=True)
```

Then we apply the **labelencoder technique** to convert the columns have strings to integer

```
99 # ===== #
100
101 FE_train_columns = ['work-class', 'education', 'marital-status', 'position', 'relationship', 'race', 'sex', 'native-country', 'salary']
102 FE_test_columns = ['work-class', 'education', 'marital-status', 'position', 'relationship', 'race', 'sex', 'native-country']
103
104 # ===== #
105
106 label_encoder = preprocessing.LabelEncoder()
107 for i in FE_train_columns:
108     final_train[i] = label_encoder.fit_transform(final_train[i])
109
110 test_label_encoder = preprocessing.LabelEncoder()
111 for c in FE_test_columns:
112     final_test[c] = label_encoder.fit_transform(final_test[c])
113
```

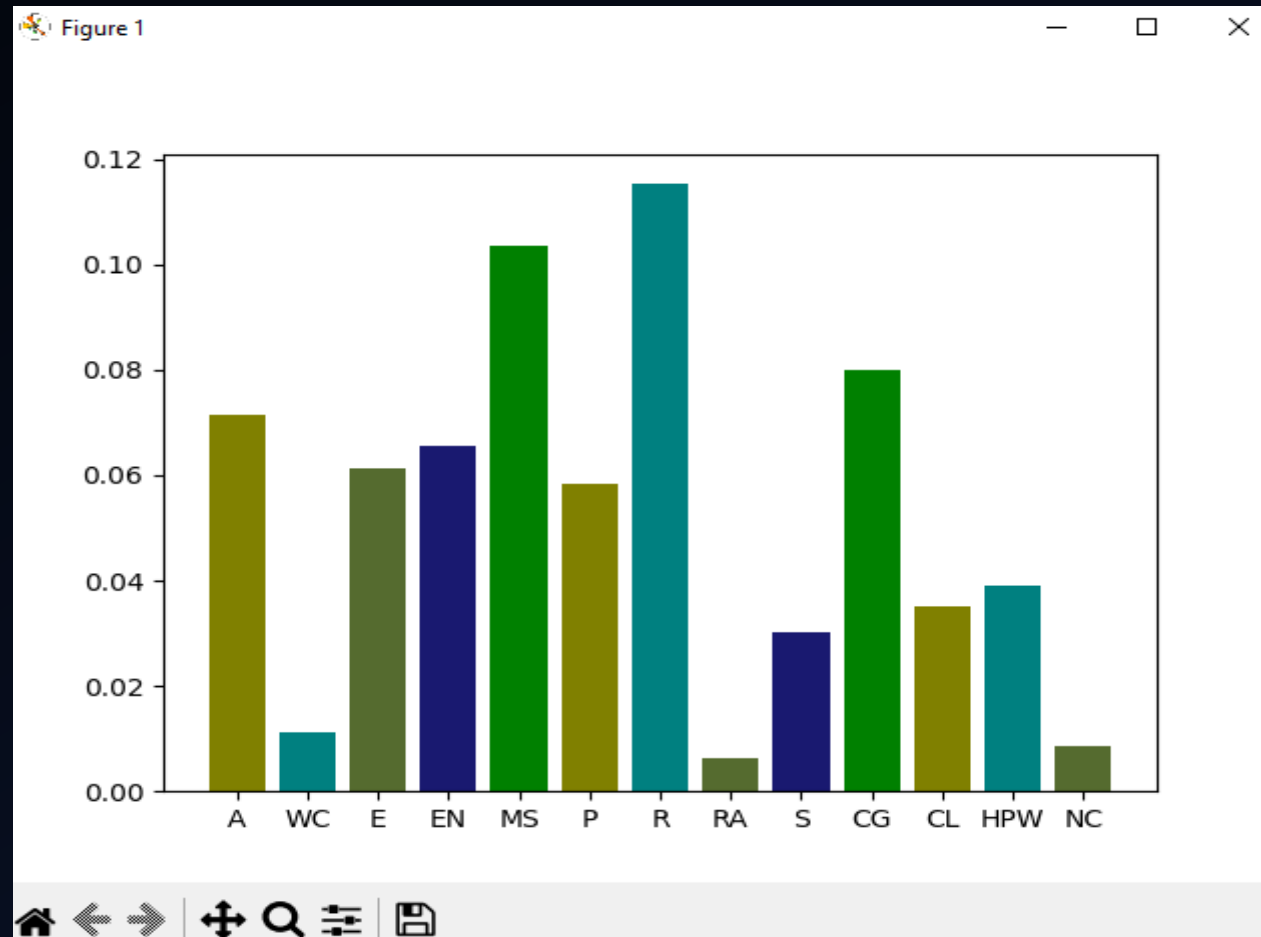
Preprocessing

We searched for the best feature selection for categorical data and found that the **mutual information** technique is the best one for our data :

```
135 X=X.drop('salary', axis=1)
136 mutual_info = mutual_info_classif(X, Y)
137 mutual_info = pd.Series(mutual_info)
138 mutual_info.index = X.columns
139 mutual_info.sort_values(ascending=False)
140
141 # mutual_info_classif plot
142 listtt = list(mutual_info)
143 names = ['A', 'WC', 'E', 'EN', 'MS', 'P', 'R', 'RA', 'S', 'CG', 'CL', 'HPW', 'NC']
144 c = ['olive', 'teal', 'darkolivegreen', 'midnightblue', 'green']
145 plt.bar(names, listtt, color = c)
146 plt.show()
147
148 sel_five_cols = SelectKBest(mutual_info_classif , k = 12)#8 9 10 13 XGB
149 sel_five_cols.fit(X, Y)
150 train = X.columns[sel_five_cols.get_support()]
151
```

Preprocessing

The mutual information plotting :



Preprocessing

We use `train test split()` function to split the data to 20% test and 80% train data and store the result of this function in :

`X_train`

`X_valid`

`Y_train`

`Y_valid`

```
# ===== #  
  
X_train, X_valid, y_train, y_valid = train_test_split(X, Y, random_state = 10 , test_size = 0.2, shuffle=True)  
  
# ===== (LR) ===== #
```

The models

The best model achieved the best two accuracy on Kaggle was (**XGBOOST**) with the next csv files:

1) XGB(The best).csv : 0.87235

With parameters :

Dropna (train data)

Drop fnl-work column

Fillna('ffil') , (test data)

K=13 , Random State =10

The models

2) XGB(the second best).csv : 0.86996

With parameters :

Dropna (train data)

Drop fnl-work column

Fillna('ffil') , (test data)

K=13 , Random State =8

Train & predict time for all algorithms

