Final Project

Group 18
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Dataset:

https://archive.ics.uci.edu/ml/datasets/adult

- Classification to predict based on features whether an adult earns over $50K a year or not
- Clustering to find groups and similarities between them

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.

In [1]:
```
# Imports
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn import metrics, model_selection, linear_model, feature_selection, preproces
from sklearn.cluster import KMeans
from sklearn.neighbors import KNeighborsClassifier
from scipy import stats
import plotly.graph_objects as go
import plotly.express as px
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```python
data = pd.read_csv("adult.csv")
display(data.head())
np.shape(data)[0]
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capi g
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	

Out[2]:
```
48842
```

Data Cleaning and EDA

In [3]:
```python
old_value_instances = data.apply(lambda x : dict(x.value_counts()))
```

In [4]:
```python
data.columns = data.columns.str.strip()
data = data.apply(lambda x : x.astype(str).str.strip(' .') if not pd.api.types.is_int64_
```

In [5]:
```python
# Count number of instances of missing values
data.loc[:, (data == '?').any()].apply(lambda x : x.value_counts()).head()
```

Out[5]:

	workclass	occupation	native-country
?	2799.0	2809.0	857.0
Adm-clerical	NaN	5611.0	NaN
Armed-Forces	NaN	15.0	NaN
Cambodia	NaN	NaN	28.0
Canada	NaN	NaN	182.0

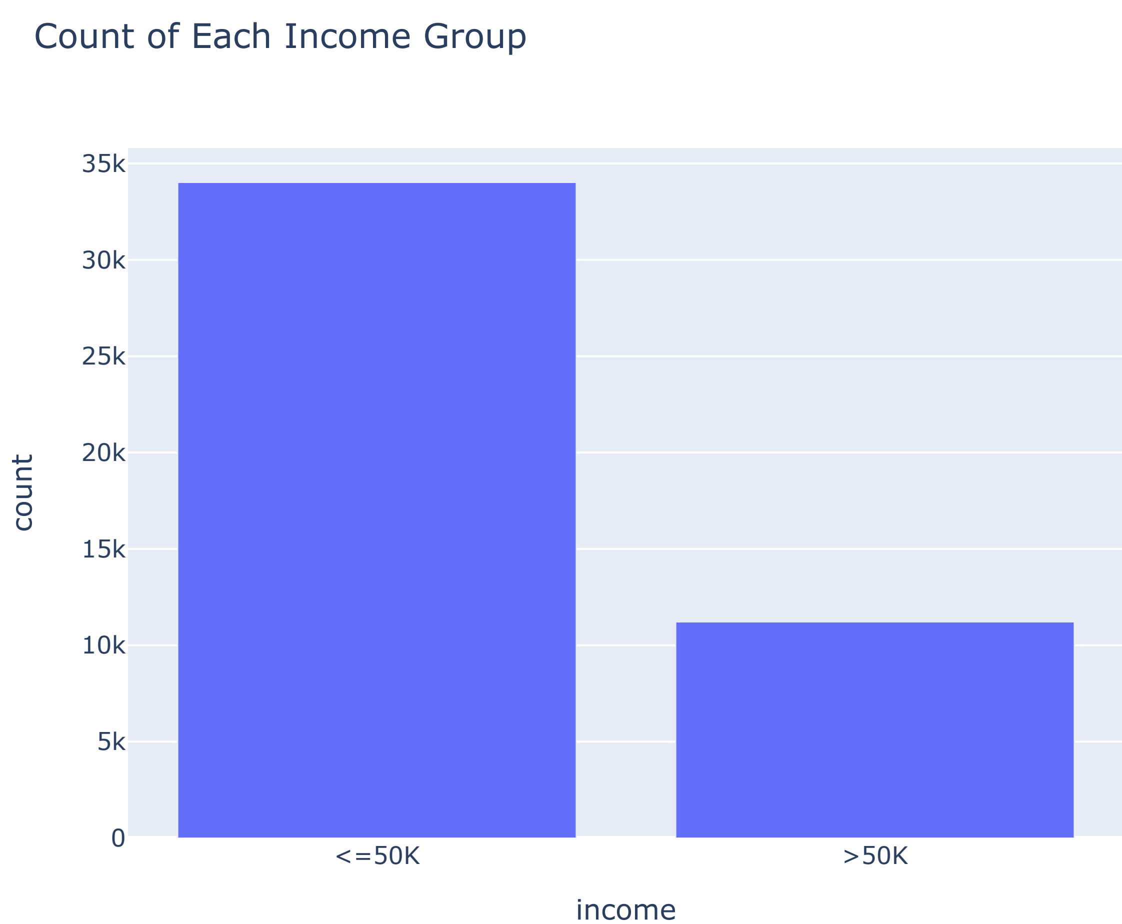
In [6]:
```python
# drop rows with missing values
data = data.replace('?', np.nan).dropna()
display(data.head())
np.shape(data)[0]
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capi g
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	

2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female

Out[6]:
```
45222
```

In [7]:
```
income_count = pd.pivot_table(data, values='workclass', index='income', aggfunc='count')
income_count.rename(columns={'workclass':'count'}, inplace=True)
fig = px.bar(income_count, y='count', title='Count of Each Income Group')
fig.show()
```



From the original dataset, we can see that there is a significant class imbalance. There are much more instances for the majority class, people whose income is less than 50K, than for the minority class, people whose income is more than 50K. Using a dataset with imbalanced classes may result in lower accuracy.

In [8]:
```
data['income-binary'] = pd.get_dummies(data['income'])['>50K']
data.head()
```

Out[8]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capi

0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	

get_dummies() will represent instances with income <=50K as 0 and instances with income >50K as 1.

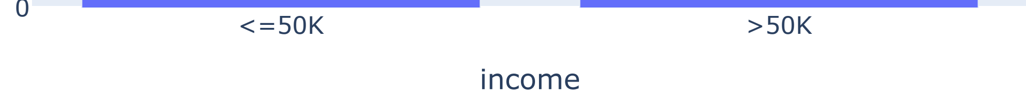
In [9]:

```
minority_class_instances = data[data['income-binary'] == 1]
minority_class_size = data['income-binary'].value_counts()[1]
majority_class_size = data['income-binary'].value_counts()[0]
num_dup = majority_class_size - minority_class_size
duplicates_df = minority_class_instances.sample(n=num_dup, replace=True)
balanced_df = pd.concat([data, duplicates_df], ignore_index=True)
```

Therefore, we can use random duplication of instances in the minority class to make both classes have the same number of instances in our new balanced dataset. This allows us to make the comparison later as to whether using the original dataset or the balanced dataset results in better accuracy for our models.

In [10]:

```
new_income_count = pd.pivot_table(balanced_df, values='workclass', index='income', aggfu
new_income_count.rename(columns={'workclass':'count'}, inplace=True)
fig = px.bar(new_income_count, y='count', title='Count of Each Income Group (after balan
fig.show()
```



Pruning and Correlation Analysis

In [11]:
```
xtrain_edu, xtest_edu, ytrain_edu, ytest_edu = model_selection.train_test_split(np.array
                                                                                  np.arra
                                                                                  test_si
                                                                                  random_
bxtrain_edu, bxtest_edu, bytrain_edu, bytest_edu = model_selection.train_test_split(np.a
                                                                                  np.arra
                                                                                  test_si
                                                                                  random_
```

In [12]:
```
clf_edu = linear_model.LogisticRegression(solver='newton-cg').fit(xtrain_edu.reshape(-1,
bclf_edu = linear_model.LogisticRegression(solver='newton-cg').fit(bxtrain_edu.reshape(-
```

In [13]:
```
predict_edu = clf_edu.predict(xtest_edu.reshape(-1, 1))
print(f"Test: {predict_edu}\nPrediction: {ytest_edu}\n")
print(f"Accuracy: {metrics.accuracy_score(ytest_edu, predict_edu)}")
print(f"Precision: {metrics.precision_score(ytest_edu, predict_edu, average='macro')}")
print(f"Recall: {metrics.recall_score(ytest_edu, predict_edu, average='macro')}")
# print(f"F1: {metrics.f1_score(ytest_edu, predict_edu, average='macro')}")
```

```
Test: ['Masters' 'Bachelors' 'Some-college' ... 'HS-grad' 'Doctorate'
 'Bachelors']
Prediction: ['Masters' 'Bachelors' 'Some-college' ... 'HS-grad' 'Doctorate'
 'Bachelors']

Accuracy: 1.0
Precision: 1.0
Recall: 1.0
```

In [14]:
```
bpredict_edu = bclf_edu.predict(bxtest_edu.reshape(-1, 1))
print(f"Balanced Test: {bpredict_edu}\nPrediction: {bytest_edu}\n")
print(f"Balanced Accuracy: {metrics.accuracy_score(bytest_edu, bpredict_edu)}")
print(f"Balanced Precision: {metrics.precision_score(bytest_edu, bpredict_edu, average='
print(f"Balanced Recall: {metrics.recall_score(bytest_edu, bpredict_edu, average='macro'
# print(f"F1: {metrics.f1_score(ytest_edu, predict_edu, average='macro')}")
```

```
Balanced Test: ['Masters' 'Bachelors' 'Some-college' ... 'HS-grad' 'Doctorate'
 'Bachelors']
Prediction: ['Masters' 'Bachelors' 'Some-college' ... 'HS-grad' 'Doctorate'
 'Bachelors']

Balanced Accuracy: 1.0
Balanced Precision: 1.0
Balanced Recall: 1.0
```

Logistic Regression Analyzing Correlation

- We are trying to determine if `education` and `education-num` are actually correlated and if we can ignore one of them when performing building our models and visualizations. Although based on column names, it's highly likely they are related, we wish to confirm this with correlation analysis.
- Since `education` is categorical and `education-num` is continuous, we cannot perform Pearson's Correlation or Chi2. Instead, we can utilize *Logistic Regression* to see if the two features are correlated. The `newton-cg` sovler is used as it's the one that best matches our dataset given

our sample size and values. We will train this model with `education-num` to classify they're `education`. We'll train it on 80% of the data and test it with the remaining 20%. If the resulting `accuracy`, `precision`, and `recall` is extremely high, we can conclude that `education` and `education-num` are correlated.

Result:

- Accuracy: `1.0`, Balanced = `1.0`
- Precision: `1.0`, Balanced = `1.0`
- Recall: `1.0`, Balanced = `1.0`
- Given that the model was able to predict the test set's `education` with 100% accuracy, we can conclude that our `X` values can accurately classify the values; however, if it's heavily unbalanced, this will be guaranteed near 100%. Precision and recall can be useful as they tell us how relevant our features are at classifying. Given that both of these are `1.0`, we can also determine that our precision-recall is perfect, and that all the features utilized are extremely important in the logistic regression. Moreoever, combining each of these three metrics, it tells us that each of the values in `education-num` is directly translate to a specific value in `education`, i.e. `13` => `Bachelors`. Although with the visible eye, this could seem obvious, this logistic regrssion and the combination of these metrics confirms this hypothesis with all of the values in the dataset. Therefore, we can confirm that `education` and `education-num` are correlated; however, since this value will be important for our kNN model, we will not prune it, rather we will simply ignore it in other usages. The same result can be found with the balanced dataset.

In [15]:
```
display(pd.crosstab(data['marital-status'], data['relationship']))
chi2_mr, p_mr, df_mr, expected_mr = stats.chi2_contingency(pd.crosstab(data['marital-sta
```

relationship marital-status	Husband	Not-in-family	Other-relative	Own-child	Unmarried	Wife
Divorced	0	3435	166	429	2267	0
Married-AF-spouse	11	0	1	1	0	19
Married-civ-spouse	18655	19	184	125	0	2072
Married-spouse-absent	0	282	44	57	169	0
Never-married	0	6691	820	5864	1223	0
Separated	0	588	75	130	618	0
Widowed	0	687	59	20	511	0

In [16]:
```
display(pd.crosstab(balanced_df['marital-status'], balanced_df['relationship']))
bchi2_mr, bp_mr, bdf_mr, bexpected_mr = stats.chi2_contingency(pd.crosstab(balanced_df['
```

relationship marital-status	Husband	Not-in-family	Other-relative	Own-child	Unmarried	Wife
Divorced	0	4282	187	460	2638	0
Married-AF-spouse	16	0	1	1	0	39
Married-civ-spouse	36009	33	229	161	0	4161
Married-spouse-absent	0	354	47	62	193	0
Never-married	0	7892	836	5988	1294	0

Separated	0	710	81	130	682	0
Widowed	0	842	60	23	617	0

In [17]:
```
print(f"Chi2 Value: {chi2_mr}, Balanced = {bchi2_mr}")
```

```
Chi2 Value: 53655.73391361823, Balanced = 80597.71546974855
```

Chi Square for Pruning

- Null Hypothesis: `marital-status` and `relationship` are not correlated
- Significance Level: `0.05`
- DoF: (7-1)(6-1) = `30`
- Critical Value: `43.77`

Result:

- Chi2 Value: `58195.24158415406`, Balanced = `80494.78403003045`
- In order to fail to reject the null hypothesis, we need our Chi2 Value to be less than `43.77`. However, after performing Chi2 analysis, we get `58195.24158415406`, which is much larger than the `43.77`. This means that we **reject our null hypothesis** that `marital-status` and `relationship` are most definitely correlated, and we can prune one of the features. Likewise, `80494.78403003045` is much greater than the Critical Value, which means they are still not correlated.

In [18]:
```
# dropping redundant features
data = data.drop(columns=['relationship'])
balanced_df = balanced_df.drop(columns=['relationship'])
```

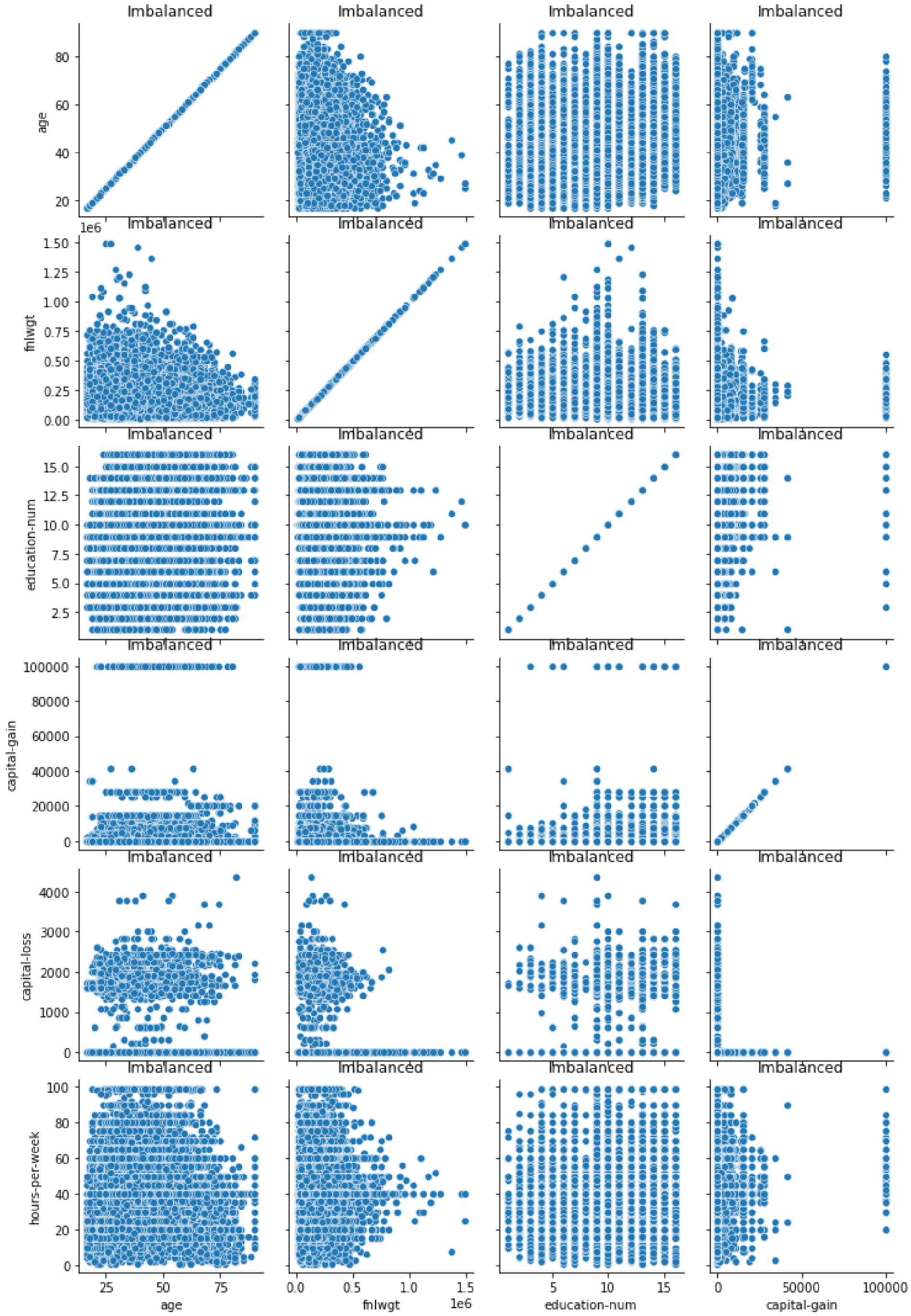
In [19]:
```
value_instances = data.apply(lambda x : dict(x.value_counts()))
bvalue_instances = balanced_df.apply(lambda x : dict(x.value_counts()))
```

Correlation Between Other Numerical Data

In [20]:
```
# Split data between categorical and numerical data
num_data = data.loc[:, data.dtypes == 'int64']
bnum_data = balanced_df.loc[:, data.dtypes == 'int64']
```

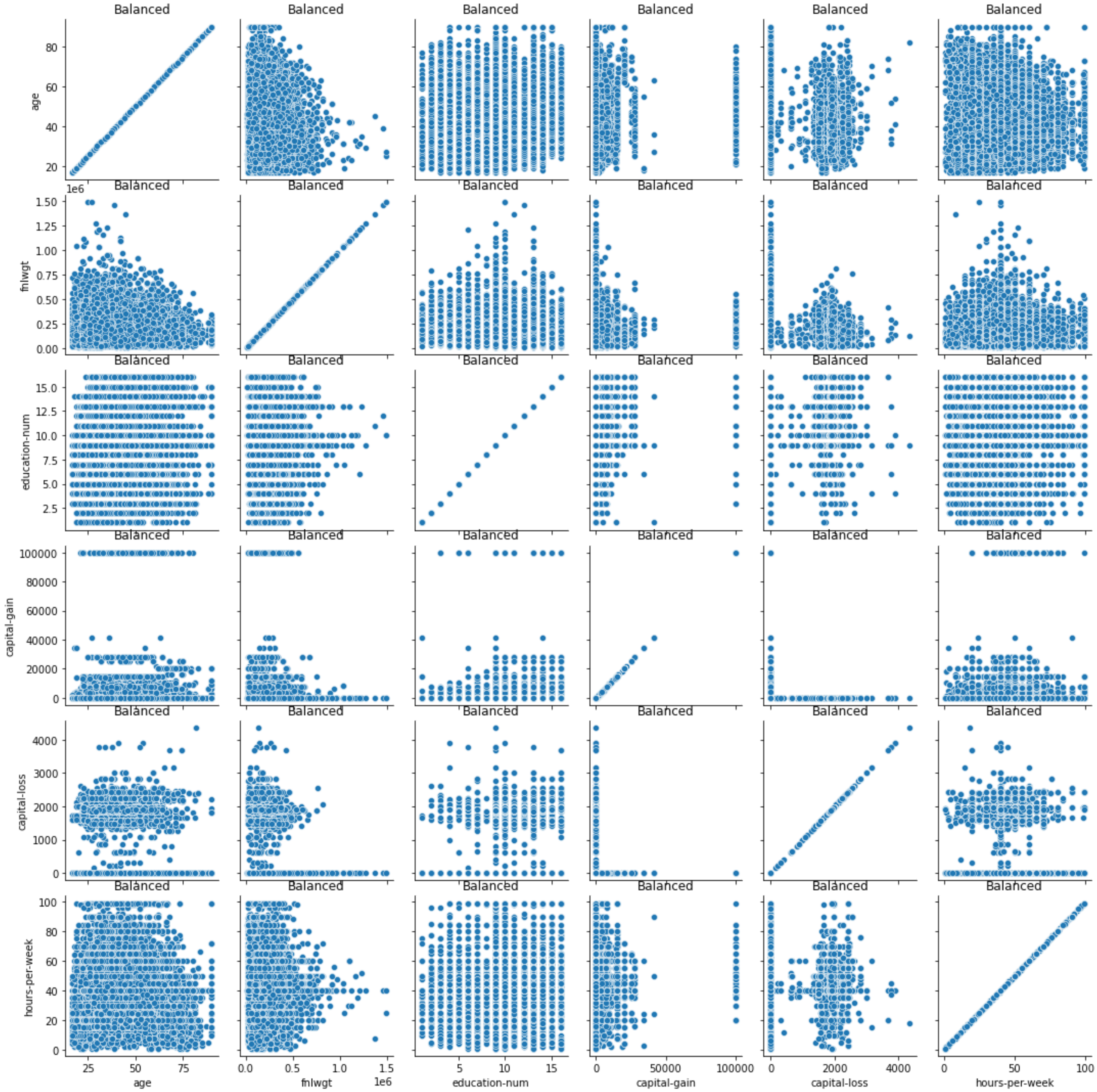
In [21]:
```
fs_pgplot = sns.PairGrid(data.drop(columns='income-binary'))
fs_pgplot.map(sns.scatterplot).set(title='Imbalanced')
```

Out[21]:
```
<seaborn.axisgrid.PairGrid at 0x7f7cd7455700>
```



In [22]:
```
fs_pgplot = sns.PairGrid(balanced_df.drop(columns='income-binary'))
fs_pgplot.map(sns.scatterplot).set(title='Balanced')
```

Out[22]:
```
<seaborn.axisgrid.PairGrid at 0x7f7ca09e20d0>
```




```
In [23]: num_data.corr(method='pearson')
```

Out[23]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
age	1.000000	-0.075792	0.037623	0.079683	0.059351	0.101992
fnlwgt	-0.075792	1.000000	-0.041993	-0.004110	-0.004349	-0.018679
education-num	0.037623	-0.041993	1.000000	0.126907	0.081711	0.146206
capital-gain	0.079683	-0.004110	0.126907	1.000000	-0.032102	0.083880
capital-loss	0.059351	-0.004349	0.081711	-0.032102	1.000000	0.054195
hours-per-week	0.101992	-0.018679	0.146206	0.083880	0.054195	1.000000

```
In [24]: bnum_data.corr(method='pearson')
```

Out[24]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
age	1.000000	-0.071637	0.077153	0.086552	0.061450	0.084949

fnlwgt	-0.071637	1.000000	-0.033181	-0.002869	0.001674	-0.015723
education-num	0.077153	-0.033181	1.000000	0.143448	0.098758	0.164091
capital-gain	0.086552	-0.002869	0.143448	1.000000	-0.051344	0.096742
capital-loss	0.061450	0.001674	0.098758	-0.051344	1.000000	0.062600
hours-per-week	0.084949	-0.015723	0.164091	0.096742	0.062600	1.000000

To see if there is any other correlations between the numerical data, we plotted each numerical feature against each other in a scatter plot to observe any potential correlations. To pair each feature together, `PairGrid` was used with each pair placed in a scatter plot. By looking at the graph, we can see that all the scatter plots show little to no correlation (ignoring the diagonal, which pairs a feature against itself). To confirm the actual values, we also ran Pearson Correlation on each of the pairs and displayed the results in the above matrix. Again, we can see for each pair that there is little to almost no correlation between the two features, with the highest coefficient value in the entire matrix being `0.146206` between `hours-per-week` and `education-num`. With this, we can conclude that none of the *numerical* features are correlated to each other, and that each of these features are relevant. This is the same with the balanced dataset where the highest coefficient is `0.162875`, which is still significantly low.

EDA

Spider Plot Visualization

US vs Non-US in race, education, and marital status

In [25]:
```
#comparing united states race vs race of other countries
race_categories = pd.crosstab(data['race'], data['native-country'])
race_categories
```

Out[25]:

native-country race	Cambodia	Canada	China	Columbia	Cuba	Dominican-Republic	Ecuador	El-Salvador	England	France	...
Amer-Indian-Eskimo	0	0	0	1	0	0	0	0	0	0	...
Asian-Pac-Islander	23	1	110	0	0	1	0	0	2	1	...
Black	1	0	0	0	4	18	1	1	8	1	...
Other	0	2	0	8	3	21	12	8	1	1	...
White	2	160	3	73	126	57	30	138	108	33	...

5 rows × 41 columns

In [26]:
```
#comparing united states race vs race of other countries
brace_categories = pd.crosstab(balanced_df['race'], balanced_df['native-country'])
brace_categories
```

Out[26]:

native-country race	Cambodia	Canada	China	Columbia	Cuba	Dominican-Republic	Ecuador	El-Salvador	England	France	...

Amer-Indian-Eskimo	0	0	0	1	0	0	0	0	0	0	...
Asian-Pac-Islander	36	1	179	0	0	1	0	0	2	1	...
Black	1	0	0	0	7	19	1	1	11	1	...
Other	0	2	0	8	3	21	14	8	2	3	...
White	2	270	6	82	183	62	45	162	196	65	...

5 rows × 41 columns

Race in United-States vs Non United-States

In [27]:

```
#table of race with columns united states vs other
race_categories = pd.crosstab(data['race'], data['native-country'] != 'United-States', n
race_categories = race_categories.rename(columns = {'False' : 'United-States'})
race_categories = race_categories.rename(columns={0: 'United-States', 1: 'Non United-Sta
race_categories
```

Out[27]:

native-country	United-States	Non United-States
race		
Amer-Indian-Eskimo	0.958621	0.041379
Asian-Pac-Islander	0.305449	0.694551
Black	0.937086	0.062914
Other	0.475921	0.524079
White	0.934298	0.065702

In [28]:

```
#table of race with columns united states vs other
brace_categories = pd.crosstab(balanced_df['race'], balanced_df['native-country'] != 'Un
brace_categories = brace_categories.rename(columns = {'False' : 'United-States'})
brace_categories = brace_categories.rename(columns={0: 'United-States', 1: 'Non United-S
brace_categories
```

Out[28]:

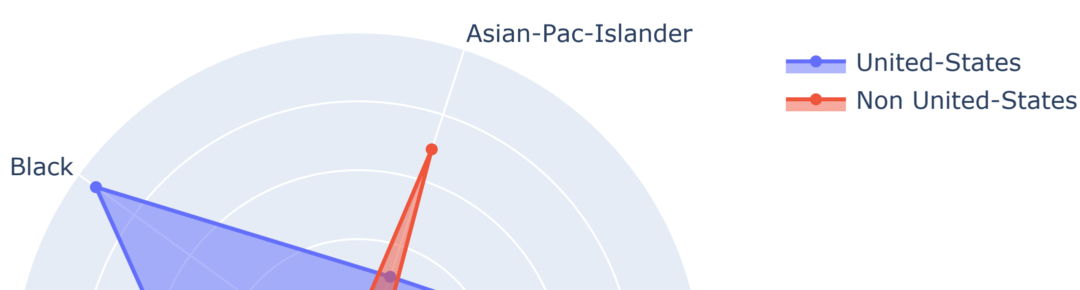
native-country	United-States	Non United-States
race		
Amer-Indian-Eskimo	0.959147	0.040853
Asian-Pac-Islander	0.298676	0.701324
Black	0.938997	0.061003
Other	0.478652	0.521348
White	0.942435	0.057565

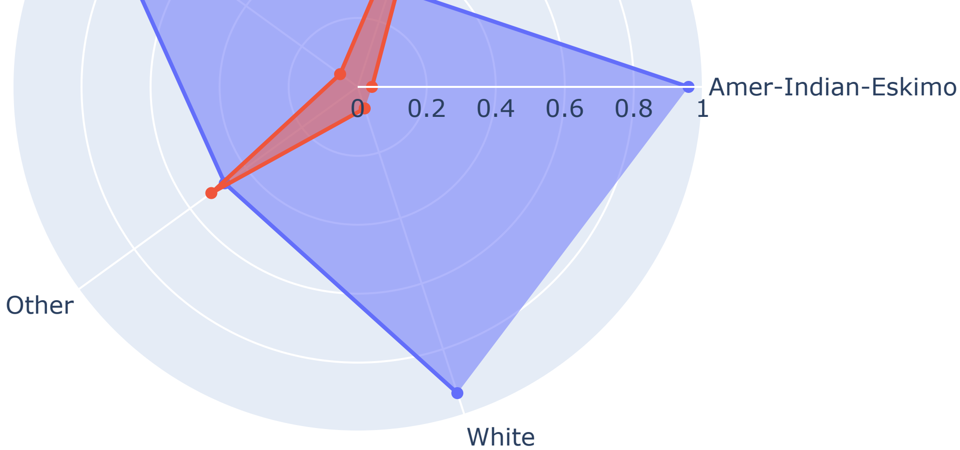
In [29]:

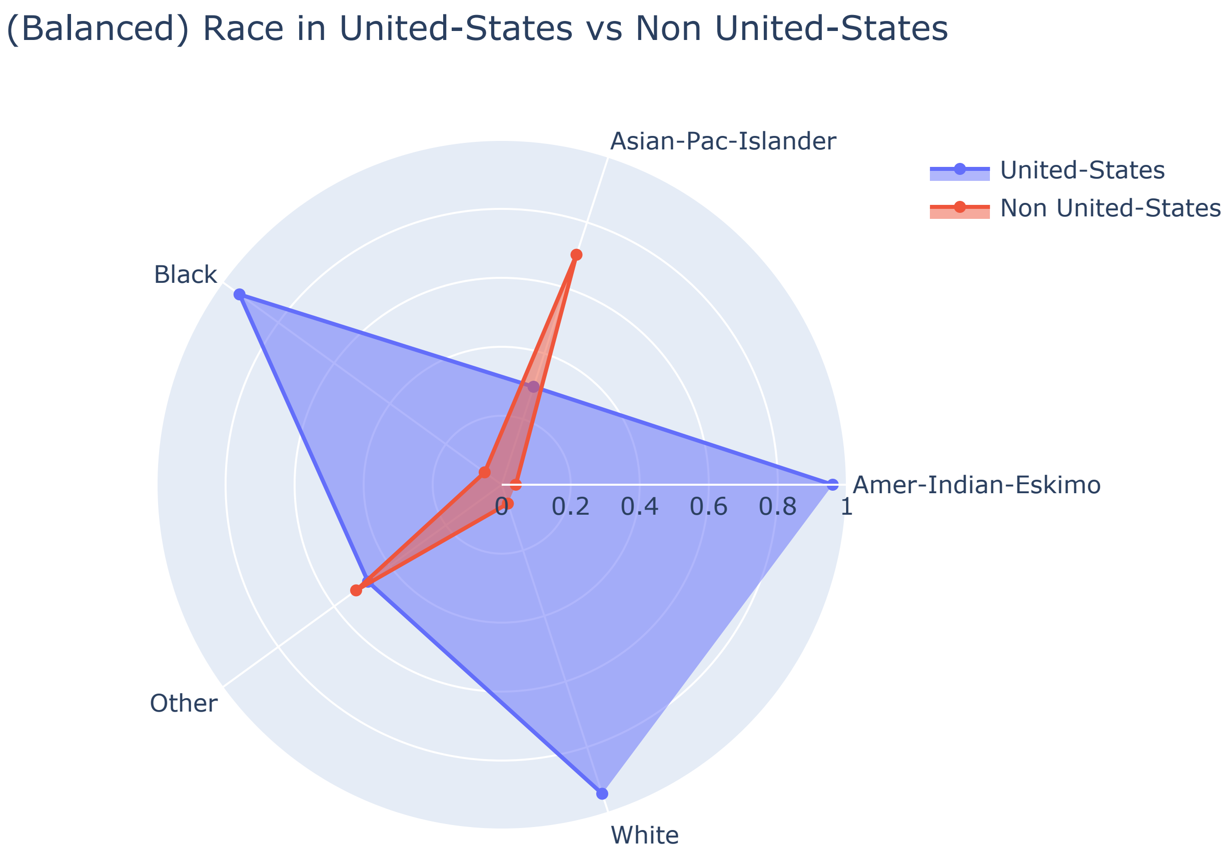
```
# Imbalanced
spider_graph = go.Figure()
spider_graph.add_trace(go.Scatterpolar(
                    r = race_categories['United-States'],
                    theta = ['Amer-Indian-Eskimo','Asian-Pac-Islander','Black' ,'Other',
                    fill = 'toself',
                    name = 'United-States'
))
```

```
spider_graph.add_trace(go.Scatterpolar(
                    r = race_categories['Non United-States'],
                    theta = ['Amer-Indian-Eskimo','Asian-Pac-Islander','Black' ,'Other',
                    fill = 'toself',
                    name = 'Non United-States'
))


spider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
            ),
    title_text = 'Race in United-States vs Non United-States',
    showlegend = True
)

# Balanced
bspider_graph = go.Figure()
bspider_graph.add_trace(go.Scatterpolar(
                    r = brace_categories['United-States'],
                    theta = ['Amer-Indian-Eskimo','Asian-Pac-Islander','Black' ,'Other',
                    fill = 'toself',
                    name = 'United-States'
))

bspider_graph.add_trace(go.Scatterpolar(
                    r = brace_categories['Non United-States'],
                    theta = ['Amer-Indian-Eskimo','Asian-Pac-Islander','Black' ,'Other',
                    fill = 'toself',
                    name = 'Non United-States'
))


bspider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
            ),
    title_text = '(Balanced) Race in United-States vs Non United-States',
    showlegend = True
)

# Show Plots
spider_graph.show()
bspider_graph.show()
```

Race in United-States vs Non United-States







Explanation:

In this dataset, it can been seen that there are large differences in the sizes of racial groups between United-States and all non United-States countries combined. It is shown that there are three racial groups, which are Amer-Indian-Eskimo, Black, and White, that are the predominant racial groups in the United-States, as compared to other countries. However, it can be seen that for non United-States countries that the 'other' racial group and Asian-Pac-Islander are the largest groups in non United-States.

Education in United States vs Non United States

In [30]:
```
education_categories  = pd.crosstab(data['education'], data['native-country'] != 'United
education_categories= education_categories.rename(columns = {'False' : 'United-States'})
education_categories = education_categories.rename(columns={0: 'United-States', 1: 'Non
education_categories
```

Out[30]:

native-country education	United-States	Non United-States
10th	0.914146	0.085854
11th	0.918468	0.081532
12th	0.875217	0.124783
1st-4th	0.234234	0.765766
5th-6th	0.296214	0.703786
7th-8th	0.786148	0.213852
9th	0.778107	0.221893
Assoc-acdm	0.931652	0.068348
Assoc-voc	0.941297	0.058703
Bachelors	0.920079	0.079921
Doctorate	0.849265	0.150735
HS-grad	0.934925	0.065075
Masters	0.910501	0.089499
Preschool	0.277778	0.722222
Prof-school	0.896815	0.103185
Some-college	0.941004	0.058996

In [31]:
```
beducation_categories  = pd.crosstab(balanced_df['education'], balanced_df['native-count
beducation_categories= beducation_categories.rename(columns = {'False' : 'United-States'
beducation_categories = beducation_categories.rename(columns={0: 'United-States', 1: 'No
beducation_categories
```

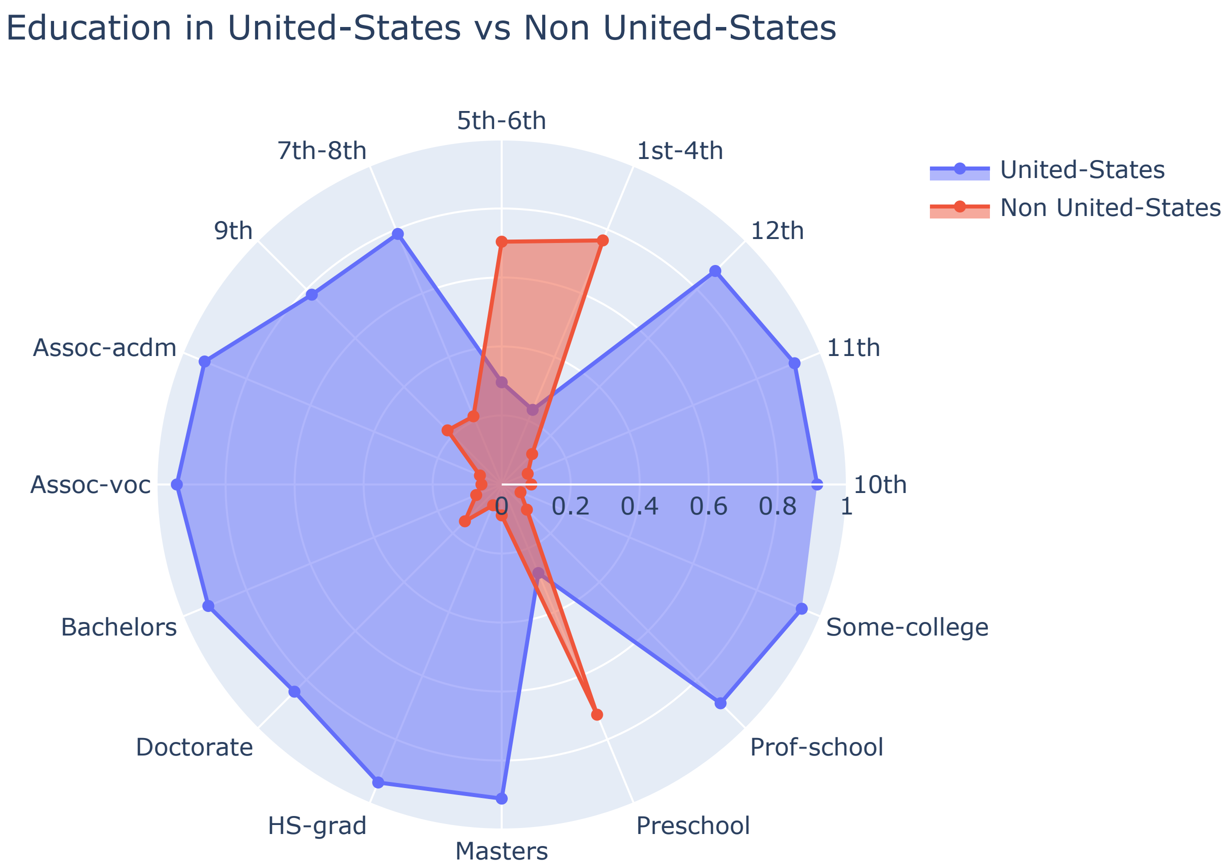
Out[31]:

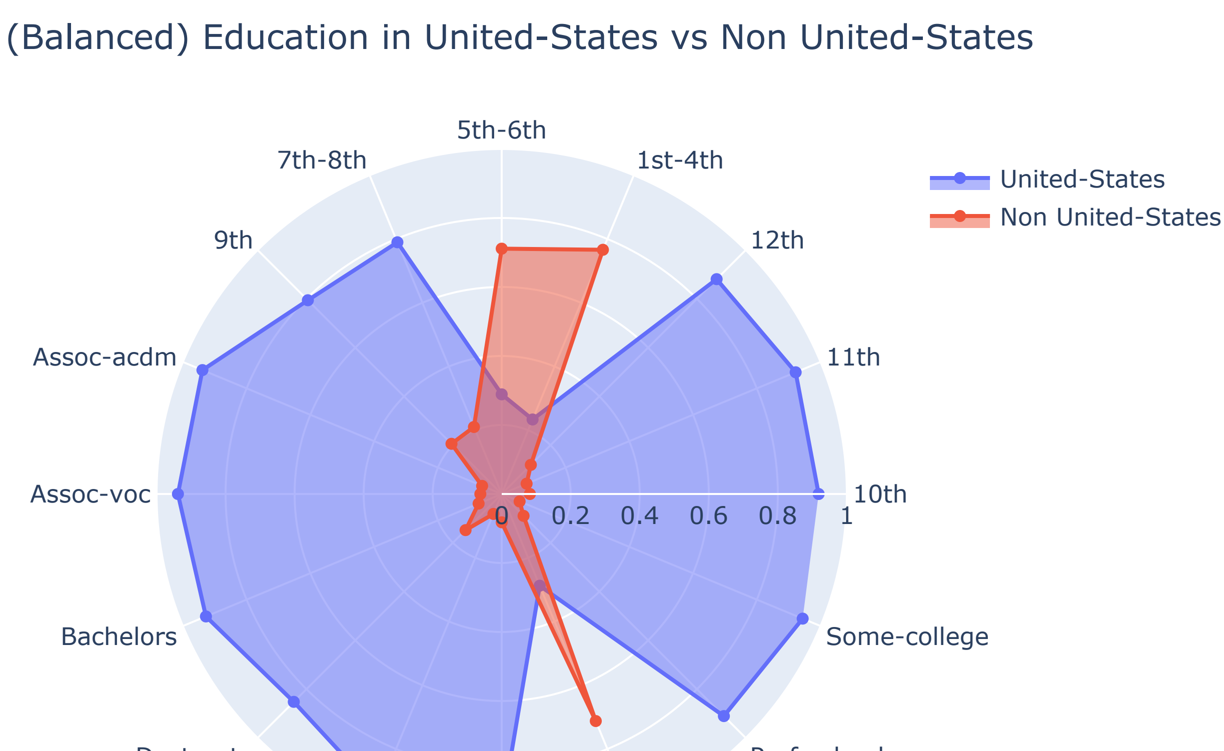
native-country education	United-States	Non United-States
10th	0.918294	0.081706
11th	0.921884	0.078116
12th	0.880665	0.119335
1st-4th	0.233766	0.766234
5th-6th	0.288889	0.711111
7th-8th	0.789755	0.210245
9th	0.794233	0.205767
Assoc-acdm	0.938581	0.061419
Assoc-voc	0.938065	0.061935
Bachelors	0.927539	0.072461
Doctorate	0.851935	0.148065

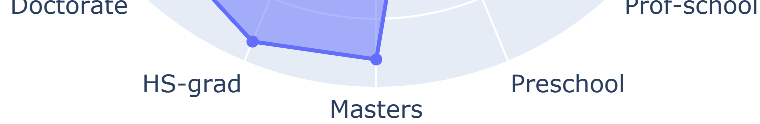
HS-grad	0.937472	0.062528
Masters	0.917987	0.082013
Preschool	0.287671	0.712329
Prof-school	0.910380	0.089620
Some-college	0.943869	0.056131

In [32]:
```
# Imbalanced
spider_graph = go.Figure()
spider_graph.add_trace(go.Scatterpolar(
                    r = education_categories['United-States'],
                    theta = ['10th', '11th','12th', '1st-4th','5th-6th','7th-8th', '9th'
                             'Masters', 'Preschool' , 'Prof-school', 'Some-college'],
                    fill = 'toself',
                    name = 'United-States'
))

spider_graph.add_trace(go.Scatterpolar(
                    r = education_categories['Non United-States'],
                    theta = ['10th', '11th','12th', '1st-4th','5th-6th','7th-8th', '9th'
                             'Masters', 'Preschool' , 'Prof-school', 'Some-college'],
                    fill = 'toself',
                    name = 'Non United-States'
))


spider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
            ),
    title_text = 'Education in United-States vs Non United-States',
    showlegend = True
)

# Balanced
bspider_graph = go.Figure()
bspider_graph.add_trace(go.Scatterpolar(
                    r = beducation_categories['United-States'],
                    theta = ['10th', '11th','12th', '1st-4th','5th-6th','7th-8th', '9th'
                             'Masters', 'Preschool' , 'Prof-school', 'Some-college'],
                    fill = 'toself',
                    name = 'United-States'
))

bspider_graph.add_trace(go.Scatterpolar(
                    r = beducation_categories['Non United-States'],
                    theta = ['10th', '11th','12th', '1st-4th','5th-6th','7th-8th', '9th'
                             'Masters', 'Preschool' , 'Prof-school', 'Some-college'],
                    fill = 'toself',
                    name = 'Non United-States'
))


bspider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
```

```
        ),
    title_text = '(Balanced) Education in United-States vs Non United-States',
    showlegend = True
)

spider_graph.show()
bspider_graph.show()
```







Explanation:

It can be seen that education for United-States is higher than Non United-States countries. Regarding United-States, a citizen tends to have at minimum a 7-8th grade education, and frequently has a college level education. In comparison to Non United-States countries, the most common level of education is either preschool or 5th-6th grade, with few going beyond.

Marital-status in United-States vs Non United-States

In [33]:
```
marital_categories = pd.crosstab(data['marital-status'], data['native-country'] != 'Unit
marital_categories= marital_categories.rename(columns = {'False' : 'United-States'})
marital_categories = marital_categories.rename(columns={0: 'United-States', 1: 'Non Unit
marital_categories
```

Out[33]:

native-country	United-States	Non United-States
marital-status		
Divorced	0.946959	0.053041
Married-AF-spouse	0.968750	0.031250
Married-civ-spouse	0.910330	0.089670
Married-spouse-absent	0.655797	0.344203
Never-married	0.914509	0.085491
Separated	0.884479	0.115521
Widowed	0.916993	0.083007

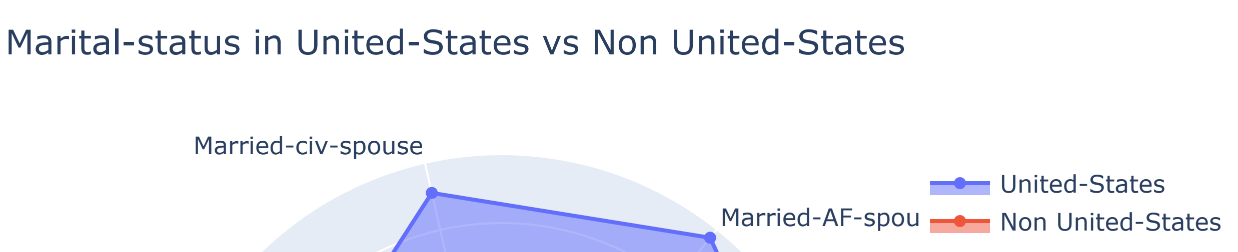
In [34]:
```
bmarital_categories = pd.crosstab(balanced_df['marital-status'], balanced_df['native-cou
bmarital_categories= bmarital_categories.rename(columns = {'False' : 'United-States'})
bmarital_categories = bmarital_categories.rename(columns={0: 'United-States', 1: 'Non Un
bmarital_categories
```

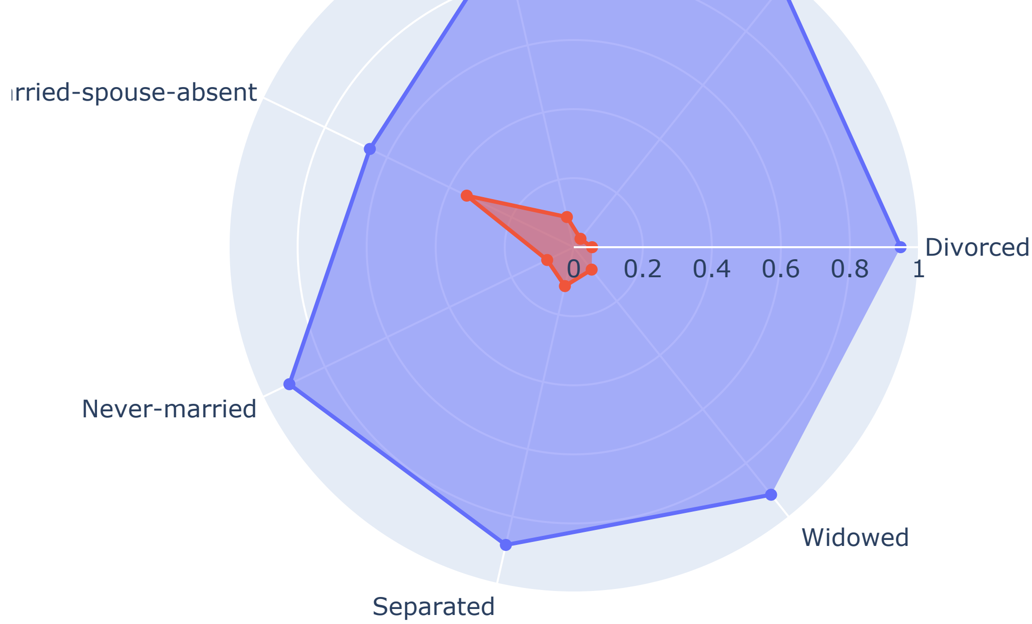
Out[34]:

native-country	United-States	Non United-States
marital-status		
Divorced	0.947139	0.052861
Married-AF-spouse	0.964912	0.035088
Married-civ-spouse	0.921243	0.078757
Married-spouse-absent	0.687500	0.312500
Never-married	0.916864	0.083136
Separated	0.883968	0.116032
Widowed	0.920233	0.079767

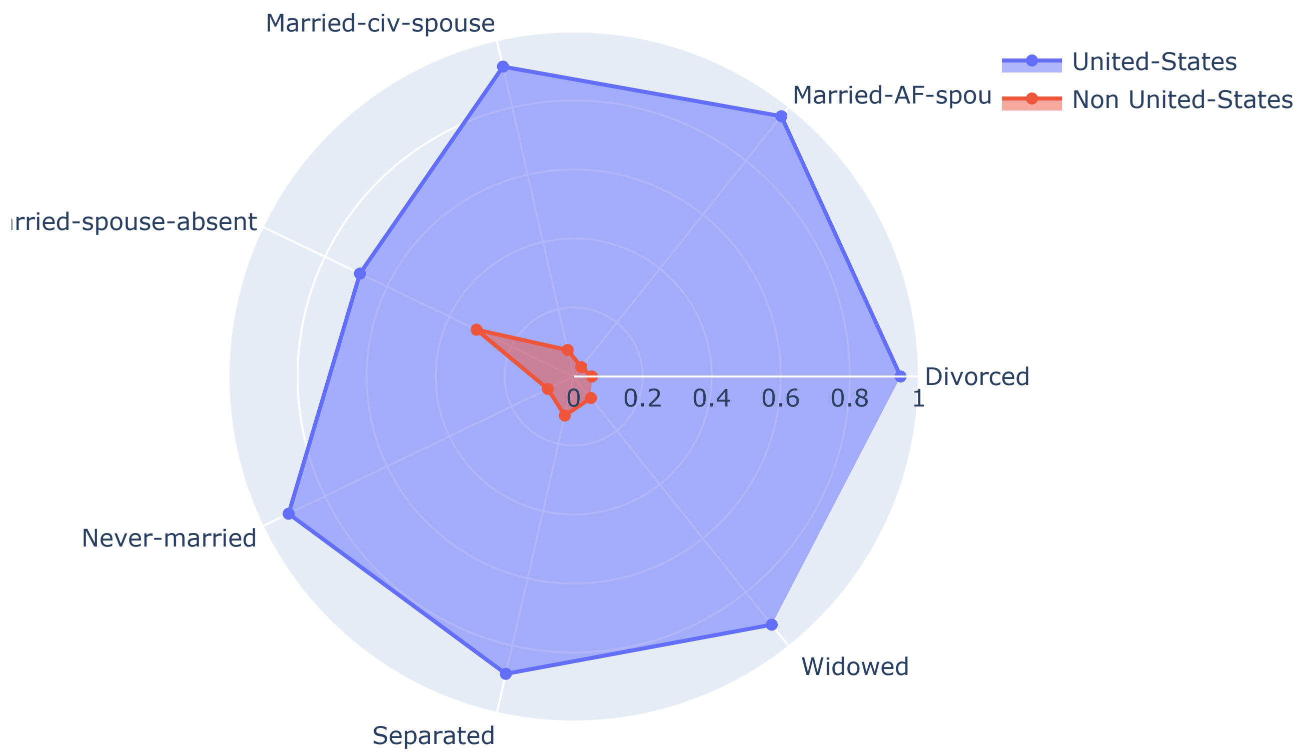
In [35]:
```
# Imbalance
spider_graph = go.Figure()
```

```
spider_graph.add_trace(go.Scatterpolar(
                    r = marital_categories['United-States'],
                    theta = ['Divorced', 'Married-AF-spouse', 'Married-civ-spouse', 'Mar
                    fill = 'toself',
                    name = 'United-States'
))

spider_graph.add_trace(go.Scatterpolar(
                    r = marital_categories['Non United-States'],
                    theta = ['Divorced', 'Married-AF-spouse', 'Married-civ-spouse', 'Mar
                    fill = 'toself',
                    name = 'Non United-States'
))


spider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
            ),
    title_text = 'Marital-status in United-States vs Non United-States',
    showlegend = True
)

# Balanced
bspider_graph = go.Figure()
bspider_graph.add_trace(go.Scatterpolar(
                    r = bmarital_categories['United-States'],
                    theta = ['Divorced', 'Married-AF-spouse', 'Married-civ-spouse', 'Mar
                    fill = 'toself',
                    name = 'United-States'
))

bspider_graph.add_trace(go.Scatterpolar(
                    r = bmarital_categories['Non United-States'],
                    theta = ['Divorced', 'Married-AF-spouse', 'Married-civ-spouse', 'Mar
                    fill = 'toself',
                    name = 'Non United-States'
))


bspider_graph.update_layout(
            polar=dict(
            radialaxis=dict(
                visible = True,
                range = [0, 1]
            ),
            ),
    title_text = '(Balanced) Marital-status in United-States vs Non United-States',
    showlegend = True
)

spider_graph.show()
bspider_graph.show()
```





(Balanced) Marital-status in United-States vs Non United-States



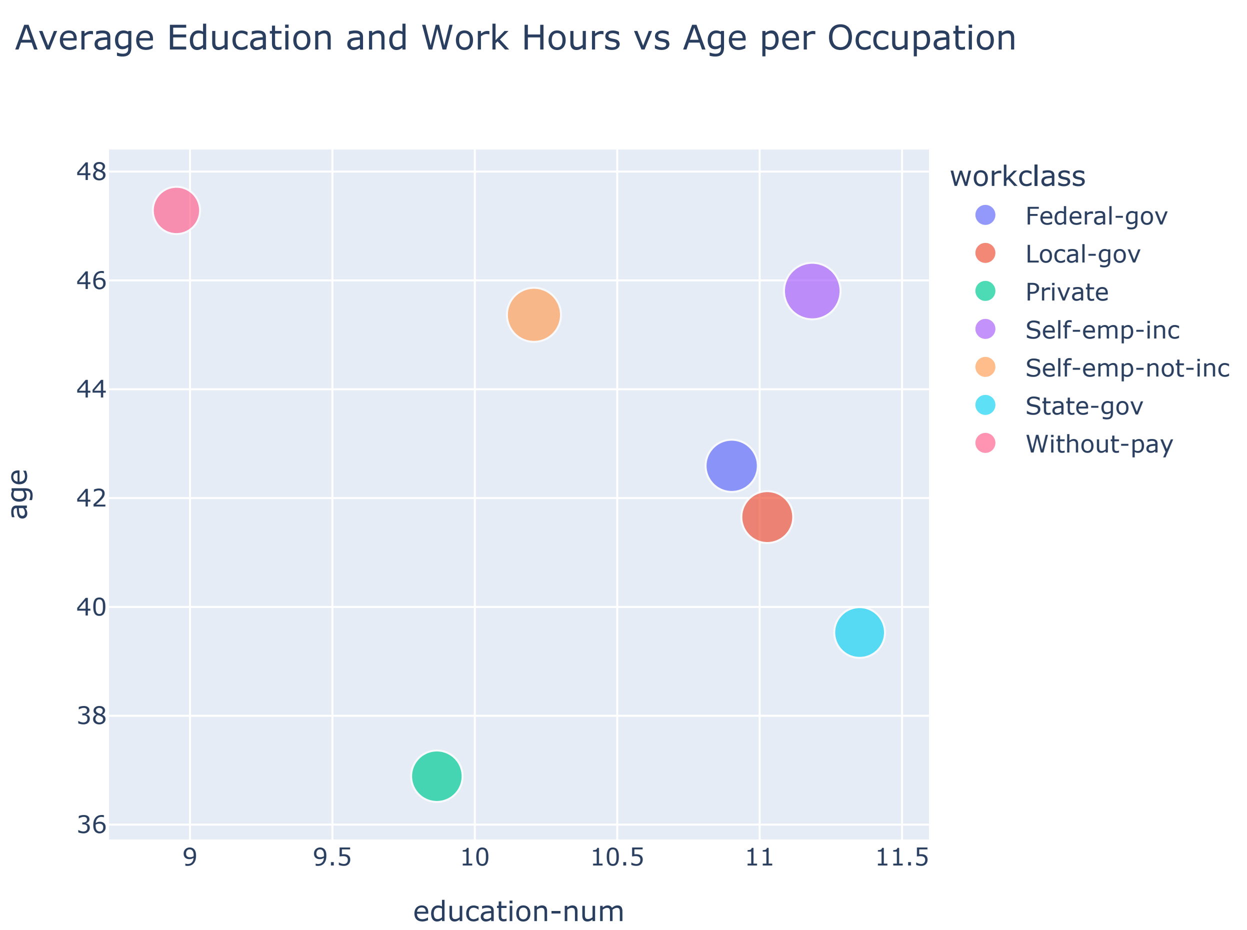
Explanation:

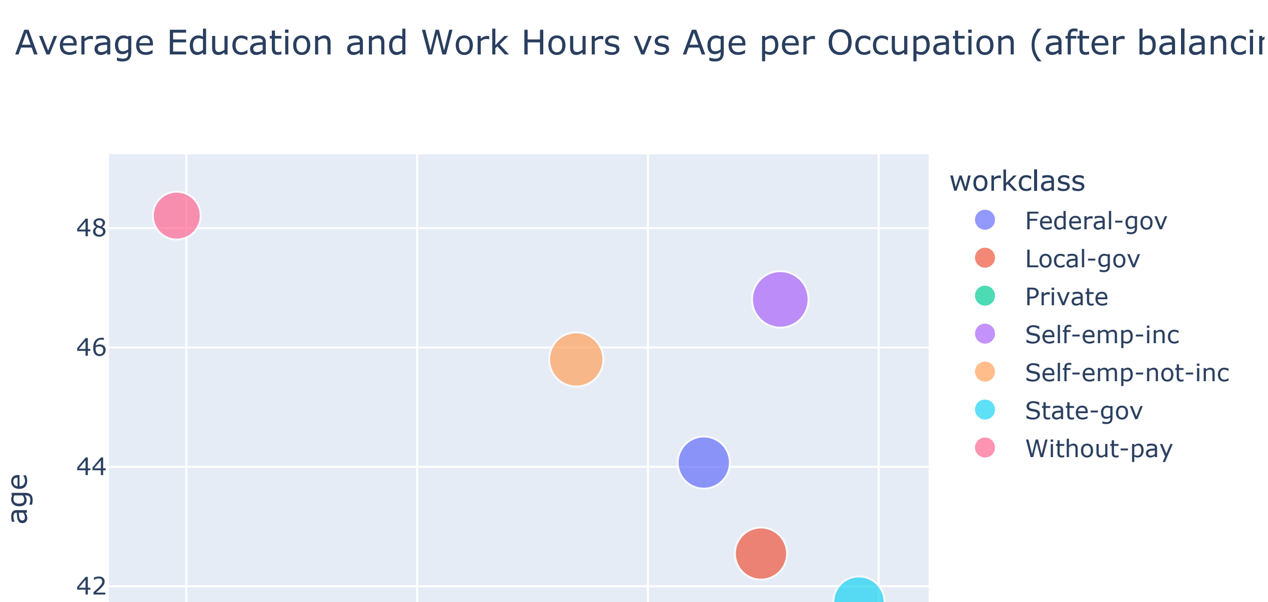
Here we have the Marital status between United-States and Non United-States countries. United-States dominates the graph due to having a huge amount of people, either married or not married. Whereas for Non United-States countries, there is a lower amount of people in general, either married or not married.

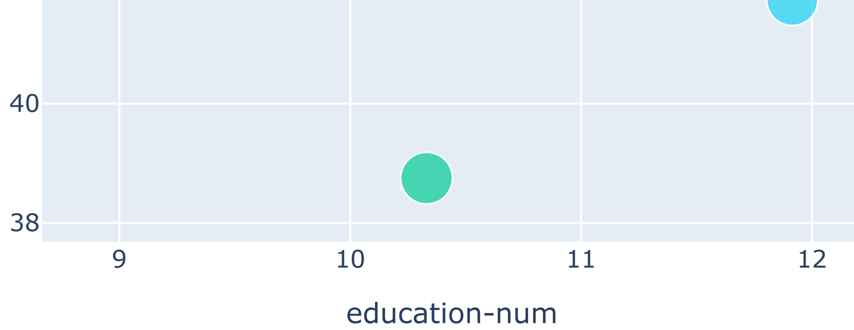
Bubble Chart Visualization

size of bubble: avg hours, axis: edu-num, age, occupation

In [36]:
```
fig = px.scatter((data.groupby('workclass').mean().reset_index()), x='education-num',
                 y='age', size='hours-per-week', color='workclass', title='Average Educa
bfig = px.scatter((balanced_df.groupby('workclass').mean().reset_index()), x='education-
                  y='age', size='hours-per-week', color='workclass', title='Average Educ
fig.show()
bfig.show()
```





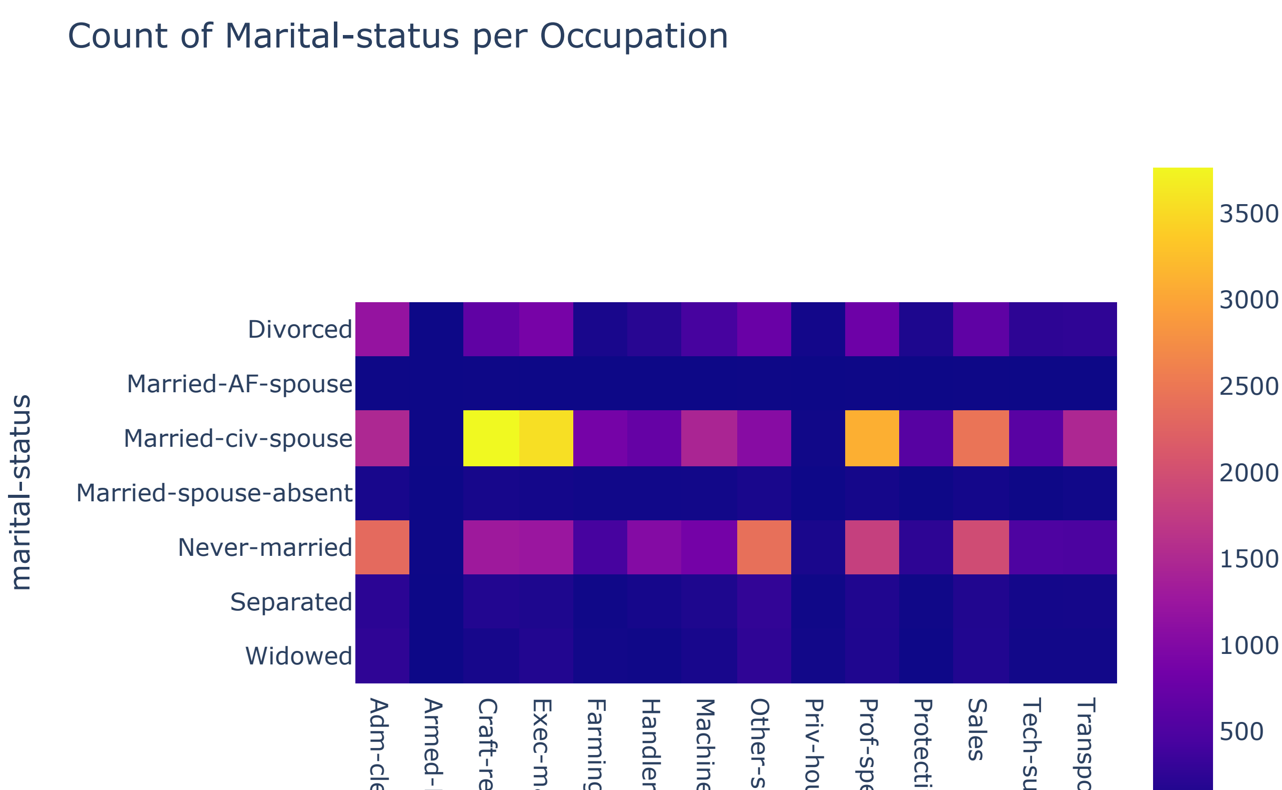


Using a bubble chart with our original dataset, we see that generally as age rises, so does the amount of education for each individual. Self-employed and governmental jobs seem to require more education and higher age, while Private has younger people with slightly less education. People without pay seem to very less education. The bubble sizes are approximately the same as the average for most jobs is at 40 hours per week. When using the same graph with the balanced set, we find that our bubbles and relative positioning have moved with age and education increasing. This is because minority balances have increased the amount of >50K elements, which seem to have higher age and education. This suggests that age and education can be used to predict income.

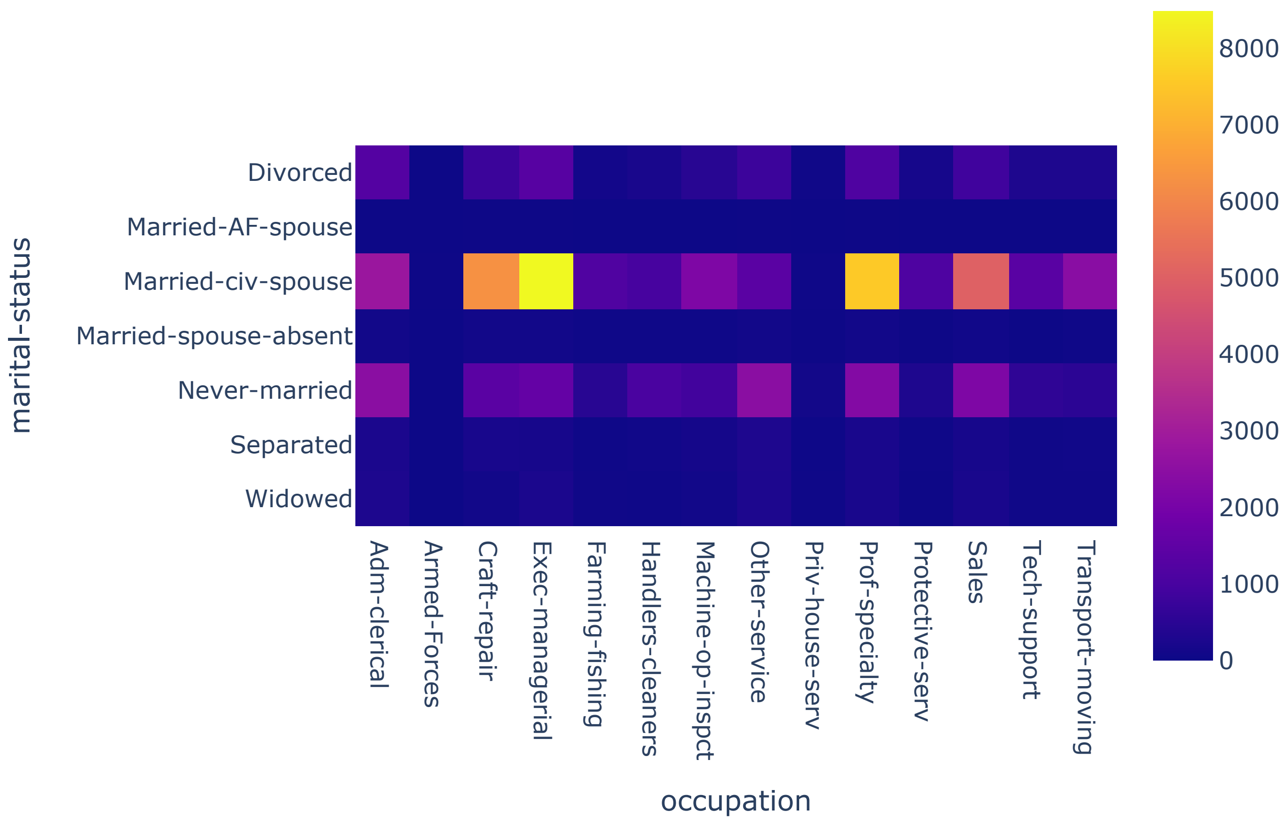
Heatmap Visualization

marital-status, occupation

In [37]:
```
occupation_race_ct = pd.crosstab(data['marital-status'], data['occupation'])
boccupation_race_ct = pd.crosstab(balanced_df['marital-status'], balanced_df['occupation

fig = px.imshow(occupation_race_ct, title='Count of Marital-status per Occupation')
bfig = px.imshow(boccupation_race_ct, title='Count of Marital-status per Occupation (aft

fig.show()
bfig.show()
```



Count of Marital-status per Occupation (after balancing)



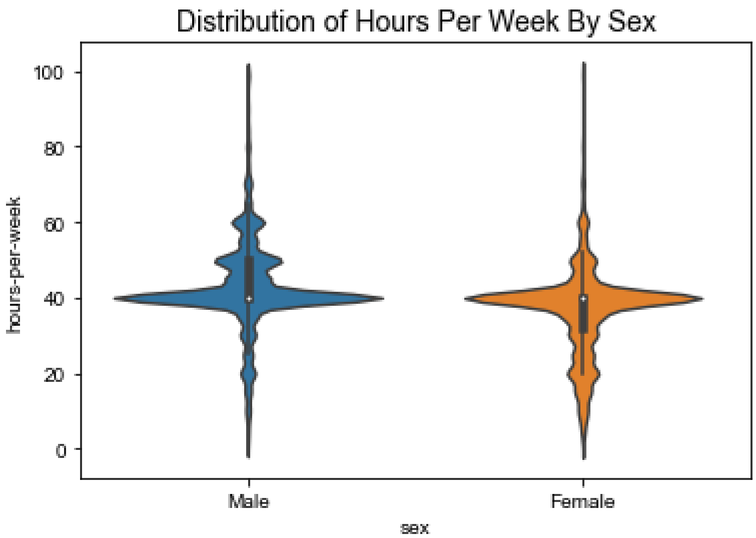
Based on this heatmap, we can see that the dataset is not very even in terms of the number of instances for each type of marital status or with each type of occupation. We can tell that the groups with the most number of instances are people who are married-civ-spouse with an occupation of craft-repair then followed by people who are married-civ-spouse with an occupation of exec-managerial. However, we can also see that in general, there are more people in the category married-civ-spouse than in the other categories for marital status. Based on the second heatmap, we can see that there isn't significant change from the first heatmap. However, the groups with the most number of instances is now people who are married-civ-spouse with an occupation of exec-managerial

Violinplot Visualization

group by sex, distribution of hours per week

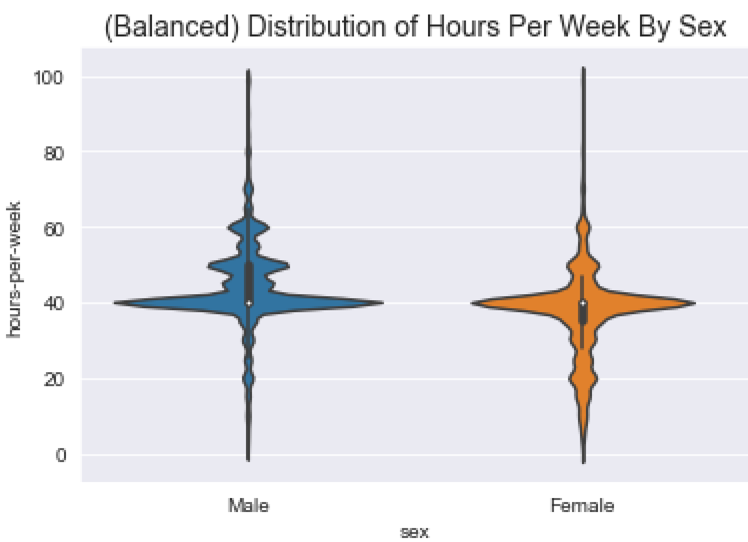
In [38]:
```
Distribution = sns.violinplot(data=data, x="sex", y="hours-per-week")
sns.set_style("darkgrid")
Distribution.set_title('Distribution of Hours Per Week By Sex', fontsize=14)
```

Out[38]:
```
Text(0.5, 1.0, 'Distribution of Hours Per Week By Sex')
```



In [39]:
```python
bDistribution = sns.violinplot(data=balanced_df, x="sex", y="hours-per-week")
sns.set_style("darkgrid")
bDistribution.set_title('(Balanced) Distribution of Hours Per Week By Sex', fontsize=14)
```

Out[39]:
```
Text(0.5, 1.0, '(Balanced) Distribution of Hours Per Week By Sex')
```



Explanation:

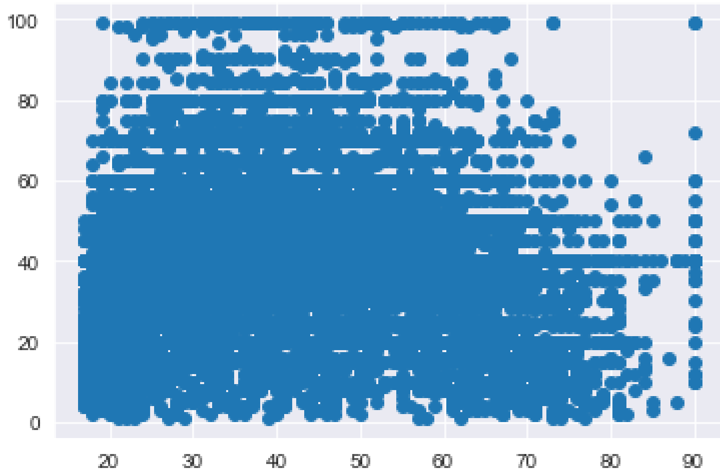
In regards to genders, both seem to have the same distribution for hours per week which is around 40 hours per week. The median for males is lower than the median for females. However, it can be seen that a majority of females work less than 40 hours per week as compared to males. A majority of males tend to work at or more than 40 hours per week compared to females.

Kmeans

Original Graph

In [40]:
```python
#x = age & y = hours per week
#without clustering
plt.scatter(data.age, data['hours-per-week'])
```

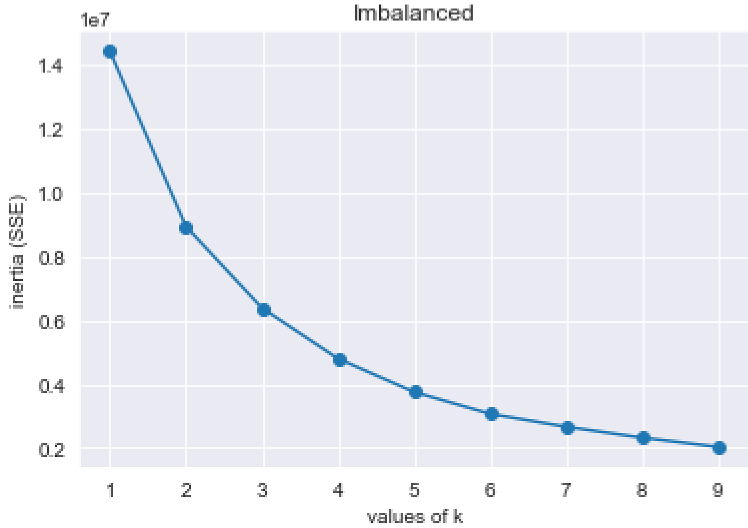
Out[40]:
```
<matplotlib.collections.PathCollection at 0x7f7cc1ef6190>
```

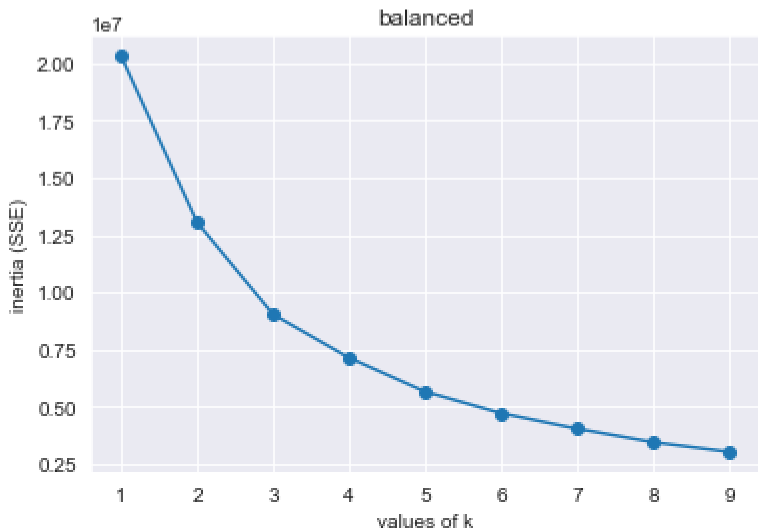


In [41]:
```
plt.scatter(balanced_df.age, balanced_df['hours-per-week'])
```

Out[41]:
```
<matplotlib.collections.PathCollection at 0x7f7cd7d3b9d0>
```

In [42]:
```
#finding the elbow graph
inertias = []
for k in range(1, 10):
    kmeans = KMeans(n_clusters = k)
    kmeans.fit(data[['age','hours-per-week']])
    inertias.append(kmeans.inertia_)


plt.plot(range(1, 10), inertias, 'o-')
plt.xlabel('values of k')
plt.ylabel('inertia (SSE)')
plt.title("Imbalanced")
plt.show()


#balanced
binertias = []
for k in range(1, 10):
    bkmeans = KMeans(n_clusters = k)
    bkmeans.fit(balanced_df[['age','hours-per-week']])
    binertias.append(bkmeans.inertia_)


plt.plot(range(1, 10), binertias, 'o-')
plt.xlabel('values of k')
plt.ylabel('inertia (SSE)')
plt.title("balanced")
plt.show()
```





In [43]:

```
#new dataframe that has the column named "cluster" which will show which group cluster i
k_means = KMeans(n_clusters = 3)
k_means.fit(data[['age','hours-per-week']])
data['cluster'] = k_means.labels_
#data['cluster'] = predict_y
data.head()
```

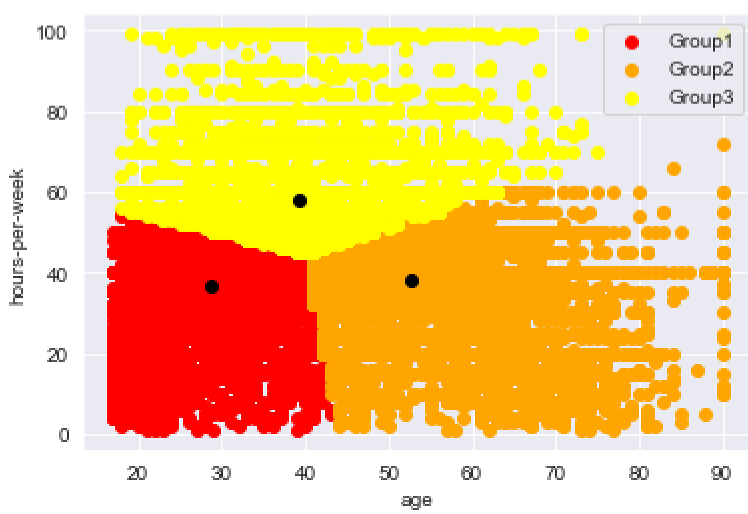
Out[43]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	race	sex	capital-gain	capital-loss
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	White	Male	2174	0
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	White	Male	0	0
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	White	Male	0	0
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Black	Male	0	0
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Black	Female	0	0

Graph with Cluster

In [44]:
```
#assigning the three clusters into groups
dataCluster1 = data[data.cluster == 0]
dataCluster2 = data[data.cluster == 1]
dataCluster3 = data[data.cluster == 2]
#dataCluster4 = data[data.cluster == 3]



#graph the 3 clusters with their group
plt.scatter(dataCluster1.age,dataCluster1['hours-per-week'], color = 'red', label = "Gro
plt.scatter(dataCluster2.age,dataCluster2['hours-per-week'], color = 'orange',label = "G
plt.scatter(dataCluster3.age,dataCluster3['hours-per-week'], color = 'yellow', label = "
#plt.scatter(dataCluster4['hours-per-week'],dataCluster4.age, color = 'black')
centers = k_means.cluster_centers_

plt.scatter(centers[:, 0], centers[:, 1], c = 'black')

#, c = data['cluster']

plt.xlabel('age')
plt.ylabel('hours-per-week')
#plt.legend([dataCluster1, dataCluster2, dataCluster3], ["hours per week","hours per-wee
plt.legend(loc="upper right")
#plt.show()
```

Out[44]: <matplotlib.legend.Legend at 0x7f7cb0052c70>



In [45]:
```
bk_means = KMeans(n_clusters = 3)
bk_means.fit(balanced_df[['age','hours-per-week']])
balanced_df['cluster'] = bk_means.labels_
#data['cluster'] = predict_y
balanced_df.head()
```

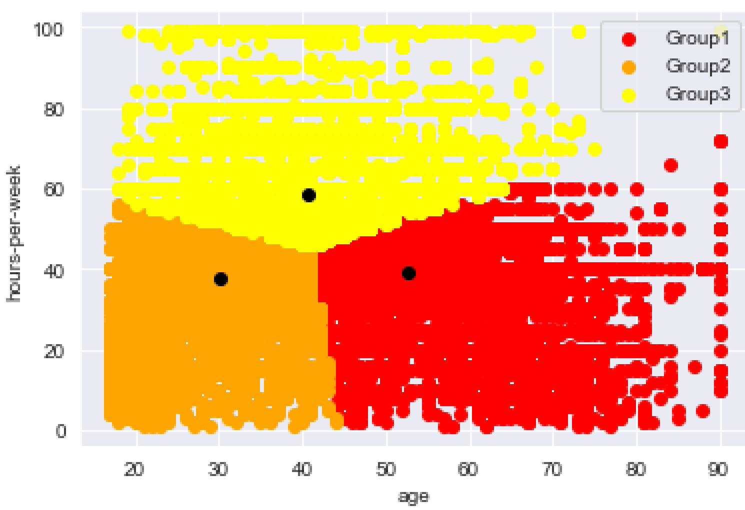
Out[45]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	race	sex	capital-gain	capital-loss
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	White	Male	2174	0
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	White	Male	0	0
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	White	Male	0	0
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Black	Male	0	0

4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Black	Female	0	0

In [46]:
```
#assigning the three clusters into groups
dataCluster1 = balanced_df[balanced_df.cluster == 0]
dataCluster2 = balanced_df[balanced_df.cluster == 1]
dataCluster3 = balanced_df[balanced_df.cluster == 2]
#dataCluster4 = data[data.cluster == 3]



#graph the 3 clusters with their group
plt.scatter(dataCluster1.age,dataCluster1['hours-per-week'], color = 'red', label = "Gro
plt.scatter(dataCluster2.age,dataCluster2['hours-per-week'], color = 'orange',label = "G
plt.scatter(dataCluster3.age,dataCluster3['hours-per-week'], color = 'yellow', label = "
#plt.scatter(dataCluster4['hours-per-week'],dataCluster4.age, color = 'black')
centers = bk_means.cluster_centers_

plt.scatter(centers[:, 0], centers[:, 1], c = 'black')

#, c = data['cluster']

plt.xlabel('age')
plt.ylabel('hours-per-week')
#plt.legend([dataCluster1, dataCluster2, dataCluster3], ["hours per week","hours per-wee
plt.legend(loc="upper right")
#plt.show()
```

Out[46]: `<matplotlib.legend.Legend at 0x7f7cc2271d30>`



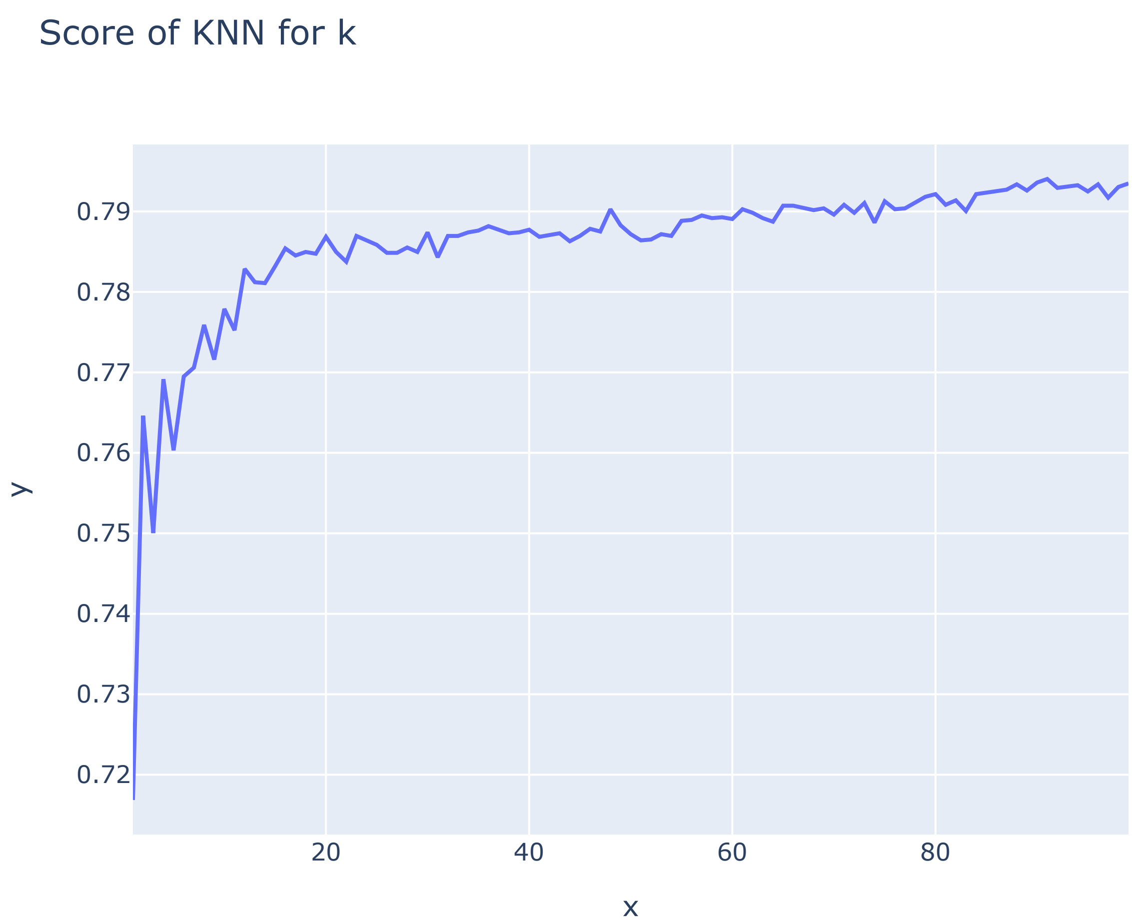
Explanation:

We decided to find the Kmeans in terms of age and hours per week. Comparing the original graph with the new graph with clusters, we can see that there are 3 clusters in regards to hours per week. The first cluster, cluster 0, is shown as the red group1. The second cluster, cluster 1, is shown as the orange group2. Finally the third cluster, cluster 2, is shown as the yellow group3. Each cluster has a black dot which are the centers for each clusters.

kNN

In [47]:
```
X = data[["age", "education-num","hours-per-week"]]
y = data["income"]
```

```
n=100
knnList = []

X_train, X_test, y_train, y_test = model_selection.train_test_split(
             X, y, test_size = 0.2, random_state=42)

for k in range(1,n):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    knnList.append(knn.score(X_test, y_test))

fig = px.line( x=range(1,n), y=knnList, title='Score of KNN for k')
fig.show()
knn = KNeighborsClassifier(n_neighbors=29)
knn.fit(X_train, y_train)
knn.score(X_test, y_test)
```

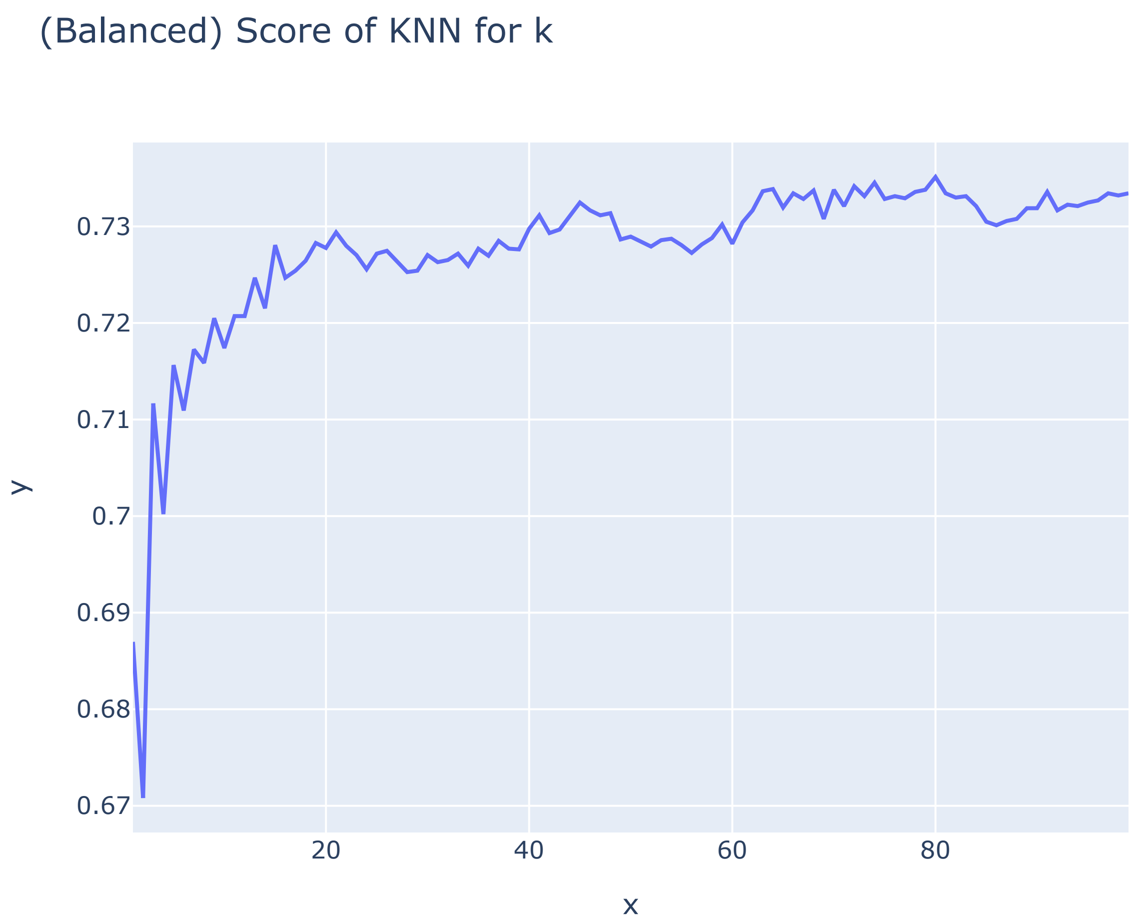


Out[47]: 0.7849640685461581

In [48]:

```
X = balanced_df[["age", "education-num","hours-per-week"]]
y = balanced_df["income"]
n=100
bknnList = []

X_train, X_test, y_train, y_test = model_selection.train_test_split(
             X, y, test_size = 0.2, random_state=42)

for k in range(1,n):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    bknnList.append(knn.score(X_test, y_test))
```

```
bfig = px.line( x=range(1,n), y=bknnList, title='(Balanced) Score of KNN for k')
bfig.show()
bknn = KNeighborsClassifier(n_neighbors=29)
bknn.fit(X_train, y_train)
bknn.score(X_test, y_test)
```



Out[48]:
```
0.7254152579744231
```

Questions

1. Which of the following is NOT a pair of features we were concerned about regarding redundancy?
   a. Education and education-num
   b. **Workclass and occupation**
   c. Relationship and marital-status
2. How did we deal with the problem of imbalance classes?
   a. **Randomly duplicate instances in minority class**
   b. Randomly duplicate instances in majority class
   c. Randomly duplicate instances in both majority and minority classes
3. Why did we use logistic regression for correlation analysis?
   a. The concerned features are both categorical
   b. The concerned features are both continuous
   c. **One feature is categorical and the other is continuous**

Contributions

- Stephen Dong:
  - Data Cleaning
    - Stripping to resolve inconsistant data values
    - Dropped rows with missing values
    - Marked or dropped redundant features
      - Algorithm: Logistic Regression
  - Correlation Analysis Between Numerical Features
    - Pearson's Correlation to see correlation between combinations of pairs of features
    - EDA: Scatterplot pairgrid to visually observe any correlations
- Ellie Cheng:
  - Data Cleaning:
    - Resolved class imbalance:
      - compare counts of classes in original dataset, use random duplication of minority class to fix class imbalance
      - EDA: Bar Chart to visualize class imbalance
  - EDA: Heatmap visualization of Marital-status and occupation
  - Presentation: made questions about project
- Shashvat:
  - EDA: Bubble visualization of education, age, occupation, and hours. Visualization of choosing k-value for KNN.
  - EDA: Line Graph for kNN score per k value
  - Algorithm: KNN model
- Selena Arias:
  - EDA: spider chart visualization of race, sex, and marital for native-country (US vs other)
  - EDA: violinplot visualization - group by sex and its distribution of hours per week
  - Algorithm: K-Means and its visualization

Video Presentation

https://drive.google.com/file/d/1hoB8YU4CtBlRNwJxozmCcJohwaTVwW5B/view?usp=share_link