kaggle™

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Data Overview

- The data was collected from data professionals in Kaggle survey (2019) .
- This survey received 19,717 usable respondents from 171 countries and territories.
- The results include raw numbers about who is working with data, what's happening with machine learning in different industries, and the best ways for new data scientists to break into the field.
- https://www.kaggle.com/c/kaggle-survey-2019

- External Data Sets

    - Conversion rate table: Merged the conversion rate table to our dataset (https://data.oecd.org/conversion/exchange-rates.htm)

    - Purchasing power parity: To compare economic productivity and standards of living between countries is purchasing power parity. (https://data.worldbank.org/indicator/PA.NUS.PRVT.PP) To bring the salaries of each country at the same scale with that of USA, used this data set. The process is explained later in the analysis.

In [1]:
```
# Print all the outputs in a cell
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import pandas as pd
import re
import seaborn as sns
import sklearn as sk
import sklearn.tree as tree
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

import statsmodels as sm
import numpy as np
import pydotplus
import plotly.express as px
import plotly.offline as py
```

```
py.init_notebook_mode(connected=True)
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.offline as pyo
import plotly.express as px
from IPython.display import Image
from sklearn.cluster import KMeans

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
%pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
```

Load Data

In [3]:

```
# Response data frame has one entry per response. There are 235 columns in the response
response_df = pd.read_csv('multiple_choice_responses_19.csv')
# Purchase parity data
purchase_parity_df = pd.read_csv('purchase_parity.csv', skiprows=4)
# Conversion rate data
currency_rate_df = pd.read_csv('currency_rate.csv')
```

In [4]:

```
response_df.shape
```

Out[4]:

```
(19718, 246)
```

In [5]:

```
response_df.head()
```

Out[5]:

	Time from Start to Finish (seconds)	Q1	Q2	Q2_OTHER_TEXT	Q3	Q4	Q5	Q5_OTHER_TEXT	
0	Duration (in seconds)	What is your age (# years)?	What is your gender? - Selected Choice	What is your gender? - Prefer to self-describe...	In which country do you currently reside?	What is the highest level of formal education ...	Select the title most similar to your current ...	Select the title most similar to your current ...	W the s com wher
1	510	22-24	Male	-1	France	Master’s degree	Software Engineer	-1	emplo
2	423	40-44	Male	-1	India	Professional degree	Software Engineer	-1	> 1 emplo
3	83	55-59	Female	-1	Germany	Professional degree	NaN	-1	
4	391	40-44	Male	-1	Australia	Master’s degree	Other	0	> 1 emplo

5 rows × 246 columns

In [6]:
```
response_df.isna().sum()
```

Out[6]:
```
Time from Start to Finish (seconds)        0
Q1                                         0
Q2                                         0
Q2_OTHER_TEXT                              0
Q3                                         0
                                       ...  
Q34_Part_9                             19238
Q34_Part_10                            19191
Q34_Part_11                            18472
Q34_Part_12                            19430
Q34_OTHER_TEXT                             0
Length: 246, dtype: int64
```

In [7]:
```
response_df.notna().sum()
```

Out[7]:
```
Time from Start to Finish (seconds)    19718
Q1                                     19718
Q2                                     19718
Q2_OTHER_TEXT                          19718
Q3                                     19718
                                       ...  
Q34_Part_9                               480
Q34_Part_10                              527
Q34_Part_11                             1246
Q34_Part_12                              288
Q34_OTHER_TEXT                         19718
Length: 246, dtype: int64
```

There are 246 columns and 19718 rows in the dataset. Each row is a respondent and the columns are the answers to the questions of the survey.

Cleanup Data

Wrote a function to get all the choices that were available for each question. After extracting the choices, created a dictionary to rename all the columns required for our analysis.

In [8]:
```
# Generate a string that can be used as python dictionary to rename columns
for index, value in response_df.T[1:].iterrows():
    v = value[0]
    v = v.strip()
    if v.endswith(' - Text'):
        v = v[:v.rfind(' - Text')]
    multi_choice_idx = v.find('- Selected Choice -')
    if multi_choice_idx != -1:
        v = v[multi_choice_idx + 20:]
    multi_choice_idx = v.rfind('(Include text response) - ')
    if multi_choice_idx != -1:
        v = v[multi_choice_idx + 26:]
    if v.endswith(')'):
        v = v[:v.rfind('(')]
    v = v.lower()
    v = v.strip()
    # Uncomment to generate column_rename_dict. This line will give the question number
    # print(f"'{index}': '{v}'")
```

```
# Column rename map created by copy pasting generated string from
# the code block above, and editing by hand for better column names.
column_rename_dict = {
'Q1': 'age',
'Q2': 'gender',
'Q2_OTHER_TEXT': 'gender_other_text',
'Q3': 'country',
'Q4': 'education',
'Q5': 'title',
'Q5_OTHER_TEXT': 'title_other_text',
'Q6': 'company_size',
'Q7': 'data_team_size',
'Q8': 'employer_uses_ml',
'Q10': 'salary',
'Q11': 'ml_spending',
'Q13_Part_1': 'udacity',
'Q13_Part_2': 'coursera',
'Q13_Part_3': 'edx',
'Q13_Part_4': 'datacamp',
'Q13_Part_5': 'dataquest',
'Q13_Part_6': 'kaggle_courses',
'Q13_Part_7': 'fast.ai',
'Q13_Part_8': 'udemy',
'Q13_Part_9': 'linkedin_learning',
'Q13_Part_10': 'university_courses',
'Q13_Part_11': 'platform_none',
'Q13_Part_12': 'platform_other',
'Q13_OTHER_TEXT': 'platform_other_text',
'Q15': 'coding_exp',
'Q16_Part_1': 'jupyter',
'Q16_Part_2': 'rstudio',
'Q16_Part_3': 'pycharm',
'Q16_Part_4': 'atom',
'Q16_Part_5': 'matlab',
'Q16_Part_6': 'visual_studio',
'Q16_Part_7': 'spyder',
'Q16_Part_8': 'vim/emacs',
'Q16_Part_9': 'notepad++',
'Q16_Part_10': 'sublime',
'Q16_Part_11': 'ide_none',
'Q16_Part_12': 'ide_other',
'Q16_OTHER_TEXT': 'ide_other_text',
'Q18_Part_1': 'python',
'Q18_Part_2': 'r',
'Q18_Part_3': 'sql',
'Q18_Part_4': 'c',
'Q18_Part_5': 'c++',
'Q18_Part_6': 'java',
'Q18_Part_7': 'javascript',
'Q18_Part_8': 'typescript',
'Q18_Part_9': 'bash',
'Q18_Part_10': 'matlab',
'Q18_Part_11': 'programming_language_none',
'Q18_Part_12': 'programming_language_other',
'Q18_OTHER_TEXT': 'programming_language_other_text',
'Q19': 'recommended_language',
'Q19_OTHER_TEXT': 'recommended_language_other_text',
'Q23': 'ml_exp',
}

# Renaming the columns
```

```
response_df = response_df.rename(columns=column_rename_dict)

# Running this mutiple times may result in '0' not found error.
response_df = response_df.drop(0)
```

Dictionary to rename the countries which were not in the readable format

In [9]:

```
# Dictionary to rename the columns of country
country_rename_dict = {
    'United States of America': 'USA',
    'United Kingdom of Great Britain and Northern Ireland': 'UK',
    'Iran, Islamic Republic of...': 'Iran',
    'Hong Kong (S.A.R.)': 'Hong Kong',
    "People 's Republic of China": "China",
    'Republic of Korea': 'South Korea',
    'Iran, Islamic Rep.': 'Iran',
    'Egypt, Arab Rep.': 'Egypt',
    'Hong Kong SAR, China': 'Hong Kong',
    'Russian Federation': 'Russia',
    'Korea, Rep.': 'South Korea',
    'United Kingdom': 'UK',
    'United States': 'USA',
    'Vietnam': 'Viet Nam'
}
# Renaming the country into proper format
response_df.replace(country_rename_dict, inplace=True)
```

In [10]:

```
response_df.head()
```

Out[10]:

	Time from Start to Finish (seconds)	age	gender	gender_other_text	country	education	title	title_other_text	company
1	510	22-24	Male	-1	France	Master's degree	Software Engineer	-1	1000-empl
2	423	40-44	Male	-1	India	Professional degree	Software Engineer	-1	> 1 empl
3	83	55-59	Female	-1	Germany	Professional degree	NaN	-1	
4	391	40-44	Male	-1	Australia	Master's degree	Other	0	> 1 empl
5	392	22-24	Male	-1	India	Bachelor's degree	Other	1	empl

5 rows × 246 columns

Changed the categorical columns into numerical columns

In this dataset, there are not many numerical columns. Columns like **age**, **salary**, **coding experience** are also categorical. These categorical data was not very helpful for our analysis.

Decided to change the categorical column to numerical column. The logic is explained below.

Steps-

1. Wrote functions to convert categorical data into numerical data

2. Clean the data to get only the numbers of the range

3. After cleaning the data, took the mean of the range and added those in another columns

In [11]:

```
# Add a salary_float column by transforming string salary range to mean salary
# Cleaning the characters such as $ and > from the strings. Used different functions
# as all the columns had different format and a single function could not clean it.

response_df.replace(to_replace='$0-999',value='0-999', inplace = True)
response_df.replace(to_replace='> $500,000',value='>500,000', inplace = True)
response_df.replace(to_replace='< 1 years',value='0-1 years', inplace = True)
response_df.replace(to_replace='I have never written code',value='0-0 years', inplace =
response_df.replace(to_replace='> 10,000 employees',value='10000-10000 employees', inpl

salary_float = []
for comp in response_df.salary:
    if not comp or comp != comp:
        salary_float.append(comp)
        continue
    idx = comp.find('-')
    if idx == -1:
        salary_float.append(float(comp[1:].replace(',', '')))
        continue
    low_str = comp[:idx].replace(',', '')
    high_str = comp[idx + 1:].replace(',', '')
    low = int(low_str)
    high = int(high_str)
    salary_float.append((low + high) / 2)
response_df['salary_float'] = salary_float

# Make ml_exp_float column

ml_exp_float = []
for exp in response_df.ml_exp:
    if not exp or exp != exp:
        ml_exp_float.append(exp)
        continue
    idx = exp.find(' years')
    exp = exp[:idx]
    idx = exp.find('-')
    if idx == -1:
        exp = exp[:len(exp) - 1]
        ml_exp_float.append(exp)
        continue
    low = float(exp[:idx])
    high = float(exp[idx + 1:])
    ml_exp_float.append((low + high) / 2)
response_df['ml_exp_float'] = ml_exp_float
response_df['ml_exp_float'] = response_df['ml_exp_float'].astype('float')
```

```
# Make coding_exp_float

coding_exp_float = []
for exp in response_df.coding_exp:
    if not exp or exp != exp:
        coding_exp_float.append(exp)
        continue
    idx = exp.find(' years')
    exp = exp[:idx]
    idx = exp.find('-')
    if idx == -1:
        exp = exp[:len(exp) - 1]
        coding_exp_float.append(exp)
        continue
    low = float(exp[:idx])
    high = float(exp[idx + 1:])
    coding_exp_float.append((low + high) / 2)
response_df['coding_exp_float'] = coding_exp_float
response_df['coding_exp_float'] = response_df['coding_exp_float'].astype('float')

# Make company_size_float

company_size_float = []
for exp in response_df.company_size:
    if not exp or exp != exp:
        company_size_float.append(exp)
        continue
    idx = exp.find(' employees')
    exp = exp[:idx]
    idx = exp.find('-')
    if idx == -1:
        exp = exp[:len(exp) - 1]
        company_size_float.append(exp)
        continue
    low = float(exp[:idx].replace(',', ''))
    high = float(exp[idx + 1:].replace(',', ''))
    company_size_float.append((low + high) / 2)
response_df['company_size_float'] = company_size_float
response_df['company_size_float'] = response_df['company_size_float'].astype('float')
```

Cleaning country exchange rate data.

Cleaning Process -

1. Renamed the countries column in order to merge to the kaggle data.

2. After cleaning the data, merged it with the kaggle dataset.

3. Checked if there are any countries that do not exist in kaggle dataset. Will avoid those countries from our analysis.

In [12]:

```
# Renaming columns to make it easier to merge
code_to_country = {
    'AUS':'Australia',
    'AUT': 'Austria',
    'BEL': 'Belgium',
    'CAN': 'Canada',
    'CZE': 'Czech Republic',
```

```
        'DNK': 'Denmark',
        'FIN': 'Finland',
        'FRA': 'France',
        'DEU': 'Germany',
        'GRC': 'Greece',
        'HUN': 'Hungary',
        'ISL': 'Iceland',
        'IRL': 'Ireland',
        'ITA': 'Italy',
        'JPN': 'Japan',
        'KOR': 'Korea',
        'LUX': 'Luxemburg',
        'MEX': 'Mexico',
        'NLD': 'Netherlands',
        'NZL': 'New Zealand',
        'NOR': 'Norway',
        'POL': 'Poland',
        'PRT': 'Portugal',
        'SVK': 'Slovakia',
        'ESP': 'Spain',
        'SWE': 'Sweden',
        'CHE': 'Switzerland',
        'TUR': 'Turkey',
        'GBR': 'UK',
        'USA': 'USA',
        'BRA': 'Brazil',
        'CHL': 'Chile',
        'CHN': 'China',
        'COL': 'Colombia',
        'EST': 'Estonia',
        'IND': 'India',
        'IDN': 'Indonesia',
        'ISR': 'Israel',
        'RUS': 'Russia',
        'SVN': 'Slovenia',
        'ZAF': 'South Africa',
        'EU28': 'EU',
        'LVA': 'Latvia',
        'LTU': 'Lithuania',
        'SAU': 'Saudi Arabia',
        'EA19': 'EA',
        'ARG': 'Argentina',
        'CRI': 'Costa Rica',
        'BGR': 'Bulgaria',
        'HRV': 'Croatia',
        'CYP': 'Cyprus',
        'MLT': 'Malta',
        'PER': 'Peru',
        'ROU': 'Romania',
        'MKD': 'Macedonia',
        'MDG': 'Madagascar',
        'MAR': 'Morocco',
        'ZMB': 'Zimbabwe',
        'SRB': 'Serbia',
        'HKG': 'Hong Kong',
        'DZA' : 'Algeria',
        'BGD' : 'Bangladesh',
        'BLR' : 'Belarus',
        'EGY' : 'Egypt',
        'IRN' : 'Iran',
        'KEN' : 'Kenya',
```

```
    'MYS' : 'Malaysia',
    'NGA' : 'Nigeria',
    'PAK' : 'Pakistan',
    'PHL' : 'Philippines',
    'SGP' : 'Singapore',
    'KOR' : 'South Korea',
    'THA' : 'Thailand',
    'TUN' : 'Tunisia',
    'UKR' : 'Ukraine',
    'VNM' : 'Viet Nam'

}

cr_df = currency_rate_df.replace(code_to_country).rename(columns={'Country': 'country',
cr_df['country_code'] = currency_rate_df['Country']
cr_df.xchg = cr_df.xchg.astype('float')

# Merging the currency data to kaggle's response_df
response_df = response_df.merge(cr_df, how='left')
rc = response_df.country.unique()
cc = cr_df.country.unique()

# Checking which countries do not exist in kaggle data. We will ignores these countries
print(f'{np.setdiff1d(rc, cc)} will not be included in our analysis.')
```

```
['Other' 'Taiwan'] will not be included in our analysis.
```

Purchase parity data cleaning

Repeat the same process for purchase parity dataset.

In [13]:

```
# Renaming the columns
purchase_parity_df.rename(columns={'Country Name': 'country'}, inplace=True)

# Renaming the country names
purchase_parity_df.replace(country_rename_dict, inplace=True)

# Kaggle and purchase power parity data merged
temp = response_df.merge(purchase_parity_df[['country', '2018']], how='left')
```

In [14]:

```
# Checking countries that do not exist in kaggle data
unique_kaggle_country = temp.country.unique()
unique_purchase_parity_country = purchase_parity_df.country.unique()

# Result is list of countries that competed are present in Kaggle dataset and dont have
print(f'{np.setdiff1d(unique_kaggle_country, unique_purchase_parity_country)} will not
```

```
['Other' 'Taiwan'] will not be included in our analysis.
```

In [15]:

```
# Normalizing the salary to bring every nation at par with USA
response_df = temp
response_df.rename(columns={'2018': 'ppp'}, inplace=True)
response_df.ppp = response_df.ppp.astype('float')
response_df['salary_normalized'] = response_df.salary_float * response_df.xchg / respon
```

Data Overview / Sample Data / Drop Columns

In [16]:

```
response_df.head(2)
```

Out[16]:

	Time from Start to Finish (seconds)	age	gender	gender_other_text	country	education	title	title_other_text	company_
0	510	22-24	Male	-1	France	Master's degree	Software Engineer	-1	1000-9 emplo
1	423	40-44	Male	-1	India	Professional degree	Software Engineer	-1	10000-1(emplo

2 rows × 254 columns

In [17]:

```
# Drop Unnecessary Columns From Dataset.

# Since we are not running any analysis on the 'other' text columns, we will drop those
col_list = []
for c in response_df.columns:
    if c.find("text") != -1:
        col_list.append(c)
response_df = response_df.drop(col_list, axis = 1)
# Dropping other unused columns!!!!!!!!!!!!!!!!!!
```

FINDING 1

Which Countries Have Higher Pay?

Can you name the top 3 countries? Let's see how many were you able to guess?

Decided to analyze which countries have really high pay? If we see the top high paying countries based on the mean salary, as expected, USA is the top paying country. However, we know that earning 1 dollar in USA is different than earning 1 dollar in India. Therefore, we decided to normalize the salary by using the conversion rate and the purchasing power parity for the respective countries. We decided to see if we bring every country's salary on same scale with USA then which country has the best salary?

Normalization Process:

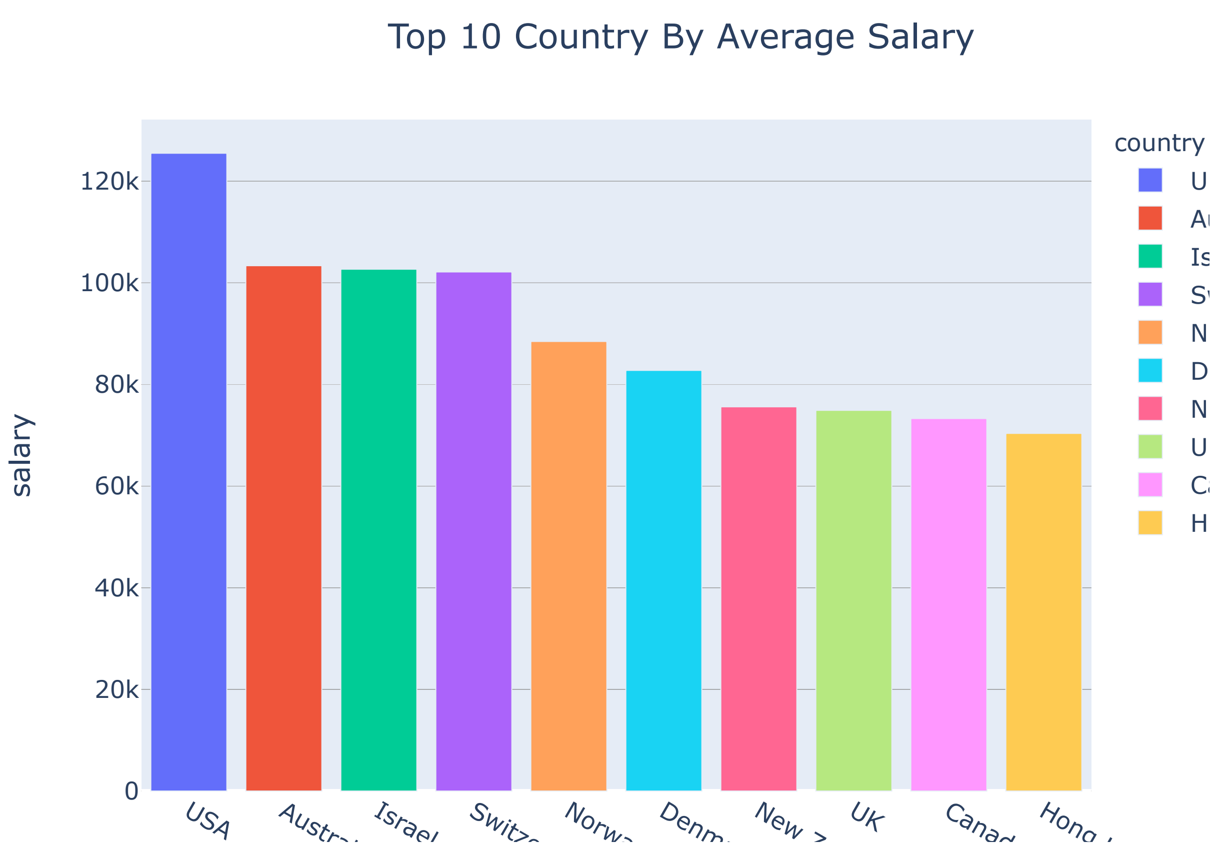
- Conversion rate table: Merged the conversion rate table to our dataset (https://data.oecd.org/conversion/exchange-rates.htm)
- Purchasing power parity: To compare economic productivity and standards of living between countries is purchasing power parity. Then merged another dataset of purchase power parity (https://data.worldbank.org/indicator/PA.NUS.PRVT.PP) to bring the salaries of each country at the same scale with that of USA. PPP will allows us to see which country gives the highest pay according to the economic and financial environment of their country.

The latest data is for 2019. However, decided to use 2018 data as it has information about more countries. For the countries which were not in these external datasets but are present in kaggle dataset, manually adding them to the csv.

Logic to normalize the salary

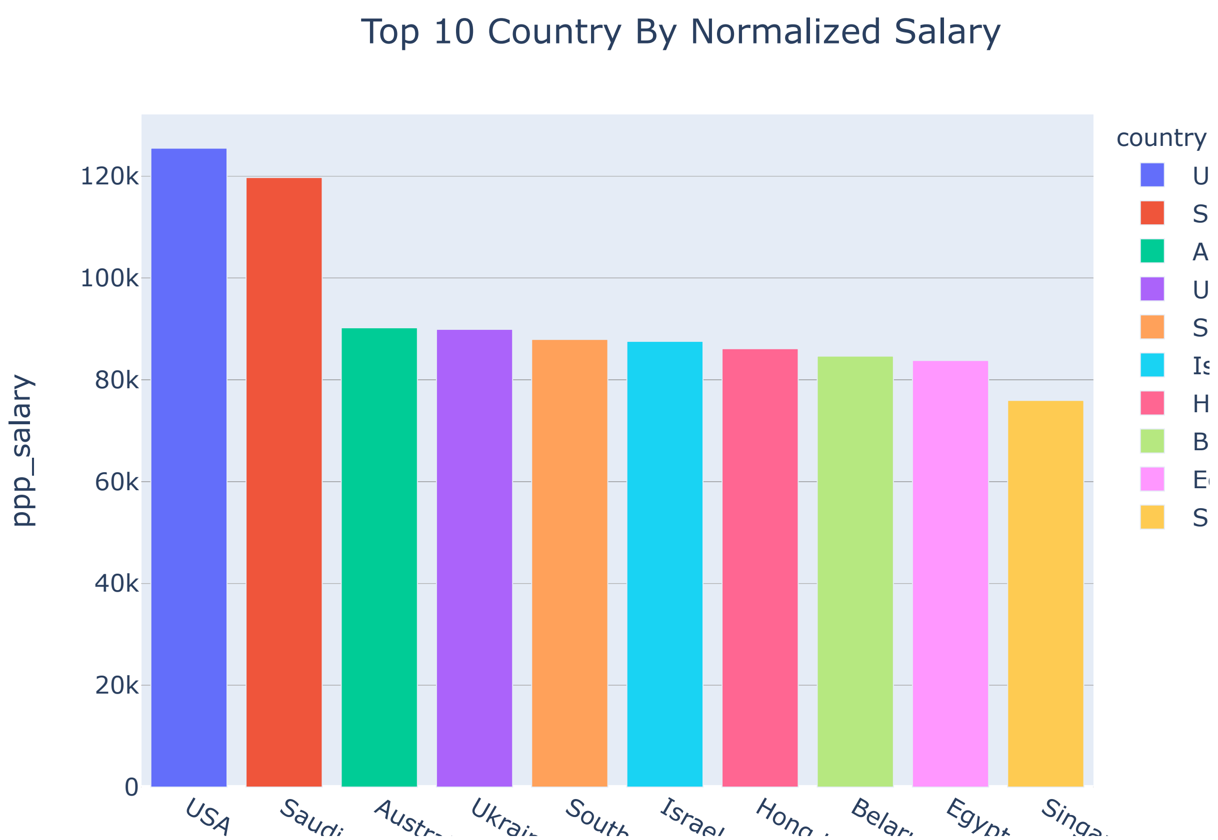
(Salary of respondent * Exchange rate to USA) / Purchase power parity of country

In [18]:
```
# Average Salary Of Each Country
avg_salary_by_country = response_df[(response_df.title != 'Student') & (response_df.tit
groupby(['country', 'country_code']).salary_float.mean().to_frame(name='salary').reset_
top10_country_by_salary = avg_salary_by_country.sort_values(by='salary', ascending=Fals
fig = px.bar(top10_country_by_salary, x='country', y='salary', color='country', title={
        'text': "Top 10 Country By Average Salary",
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})
fig.show()
```



In [19]:
```
avg_ppp_salary_by_country = response_df[(response_df.title != 'Student') & (response_df
groupby(['country', 'country_code']).salary_normalized.mean().to_frame(name='ppp_salary
top10_country_by_ppp_salary = avg_ppp_salary_by_country.sort_values(by='ppp_salary', as
fig = px.bar(top10_country_by_ppp_salary, x='country', y='ppp_salary', color='country',
        'text': "Top 10 Country By Normalized Salary",
```

```
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})
fig.show()
```



In [20]:

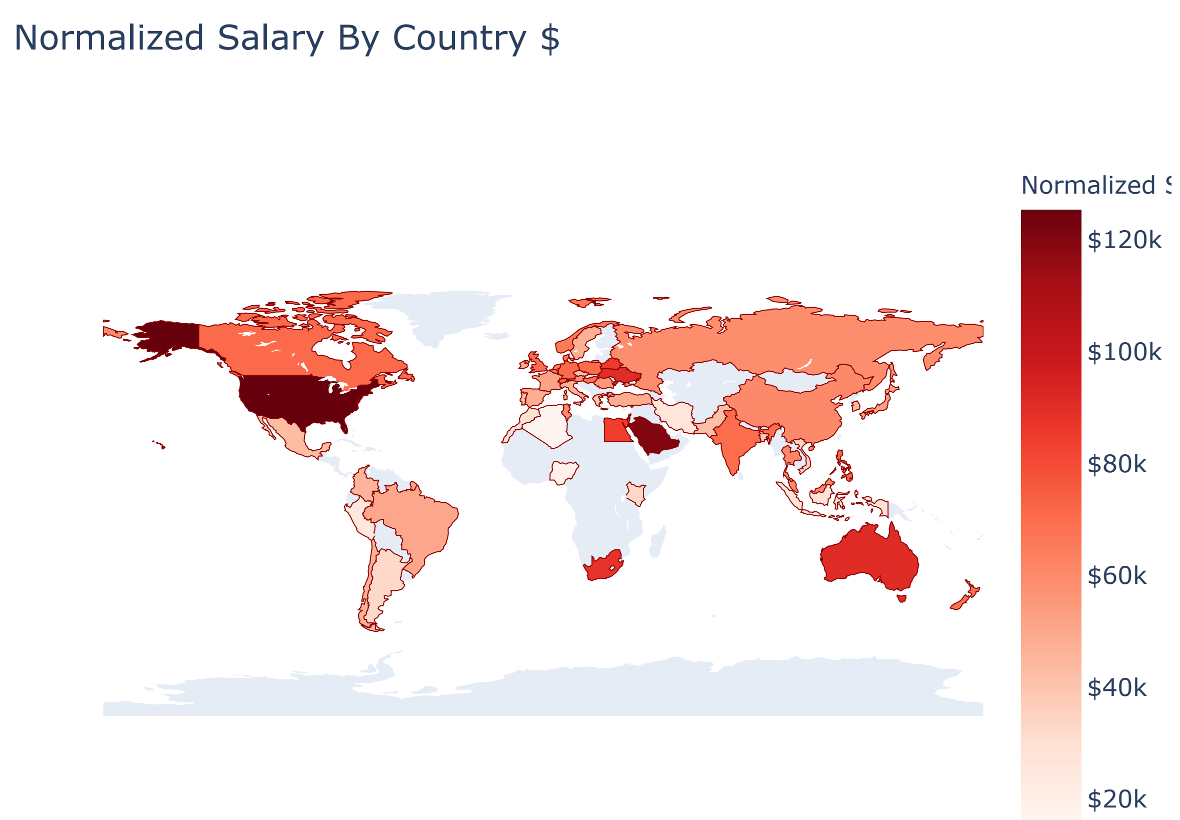
```
df = avg_ppp_salary_by_country

fig0 = go.Figure(data=go.Choropleth(
    locations = df['country_code'],
    z = df['ppp_salary'],
    text = df['country'],
    colorscale="Reds",
    autocolorscale=False,
    reversescale=False,
    marker_line_color='darkred',
    marker_line_width=0.5,
    colorbar_tickprefix = '$',
    colorbar_title = 'Normalized Salary US$',
))

fig0.update_layout(
    title_text='Normalized Salary By Country $',
    geo=dict(
        showframe=False,
        showcoastlines=False,
        projection_type='equirectangular'
```

```
    )
)

# fig.show()
```



Interesting Finding

Interestingly, **Saudi Arabia** which was not even in the Top 10 country became the second highest paying country!!

It is also surprising to see countries such as **South Africa** and **Ukraine** to show up in the list. **United Kingdom** and **Canada** did not even make an appearance in the list.

Managerial Insight

All that glitters is gold!

Competition in developed countries is too high to land you a job with better salaries. You have more places to work with higher salaries other than just USA . The above graph shows the top 10 countries you can land a higher paying jobs to work in.

Finding 2

Countries that pay lower average salary, have higher female ratio of data professionals

2a

Tried to analyze the gender diversity in each country. It is of no surprise that female presence has always been low in science field. However, wanted to analyze in which countries have there is more female presence and find some interesting attributes/pattern in those countries.

Plotted the world map to see which countries have the highest number of female count in data science. As expected **India** and **USA** were the top 2 countries. This is not surprising as they have the highest number of respondents from these countries. They are bound to have a higher female count.

It struck to us that finding out female presence **just by female count** is not the correct way. Then decided to analyze the presence by taking into account the female ratio and not the female count. Calculated female ratio by divinding female count of each country by total number of respondents from that country.

Any guess which country has the highest female count??

Surprisingly, it is **Tunisia** followed by Phillipines and Iran.

USA and **India** did not even make in to the list of top 10!!

Steps of analysis process:

In [21]:
```
# Retrieving Female gender by creating dummies
with_gender_dummy = pd.get_dummies(response_df.copy(), columns=['gender'], dummy_na=Tru
female_by_country = with_gender_dummy.groupby(['country', 'country_code'])['gender_Fema
reset_index()

# Top 10 countries by female count
top10_country_by_female = female_by_country.sort_values(by='female_count', ascending=Fa
```

In [22]:
```
female_by_country.head()
```

Out[22]:

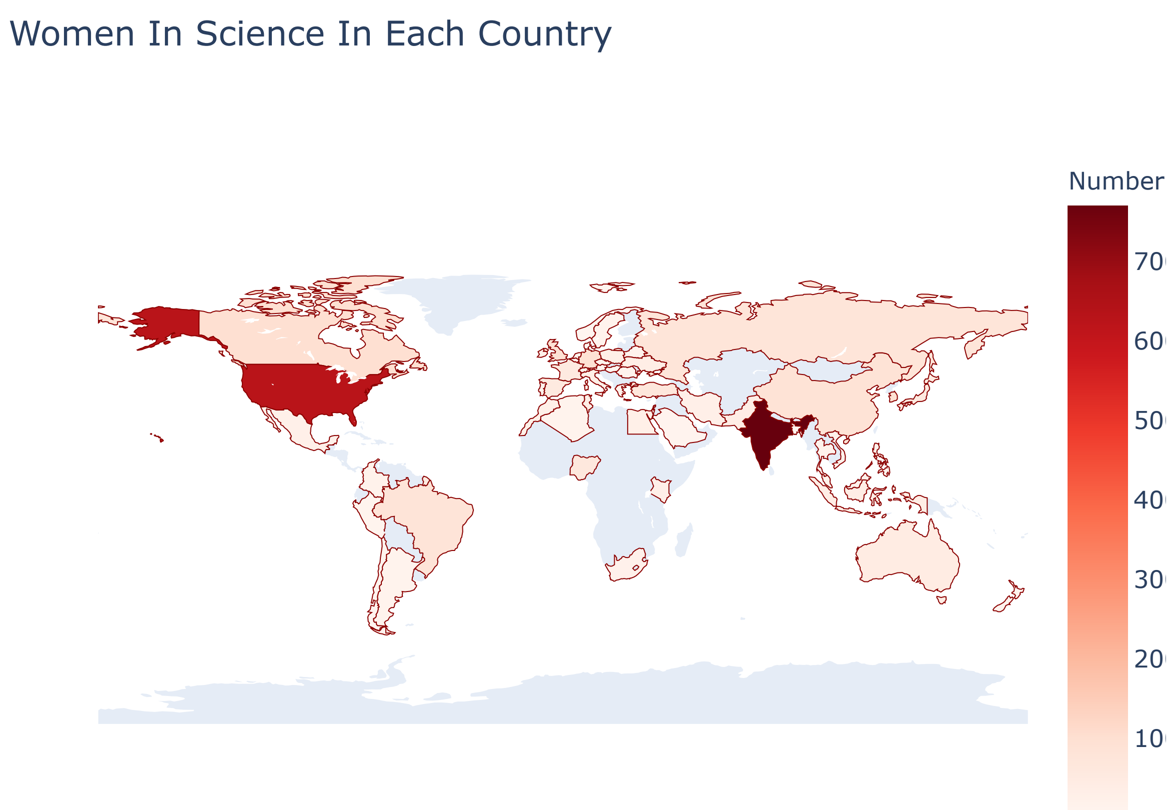
	country	country_code	female_count
0	Algeria	DZA	12.0
1	Argentina	ARG	13.0
2	Australia	AUS	44.0
3	Austria	AUT	5.0
4	Bangladesh	BGD	7.0

In [23]:

```
#Using MapBox for showing Number of female respondents in each country

fig4 = go.Figure(data=go.Choropleth(
    locations = female_by_country['country_code'],
    z = female_by_country['female_count'],
    text = female_by_country['country'],
    colorscale="Reds",
    autocolorscale=False,
    reversescale=False,
    marker_line_color='darkred',
    marker_line_width=0.5,
    colorbar_title = 'Number of Women',
))

fig4.update_layout(
    title_text='Women In Science In Each Country',
    geo=dict(
        showframe=False,
        showcoastlines=False,
        projection_type='equirectangular'
    )
)
```



In [24]:

```
user_by_country = response_df[response_df.country != 'Other'].groupby(['country', 'coun
top10_country_by_user = user_by_country.sort_values(by='user_count', ascending=False).h
top10_country_by_user
```

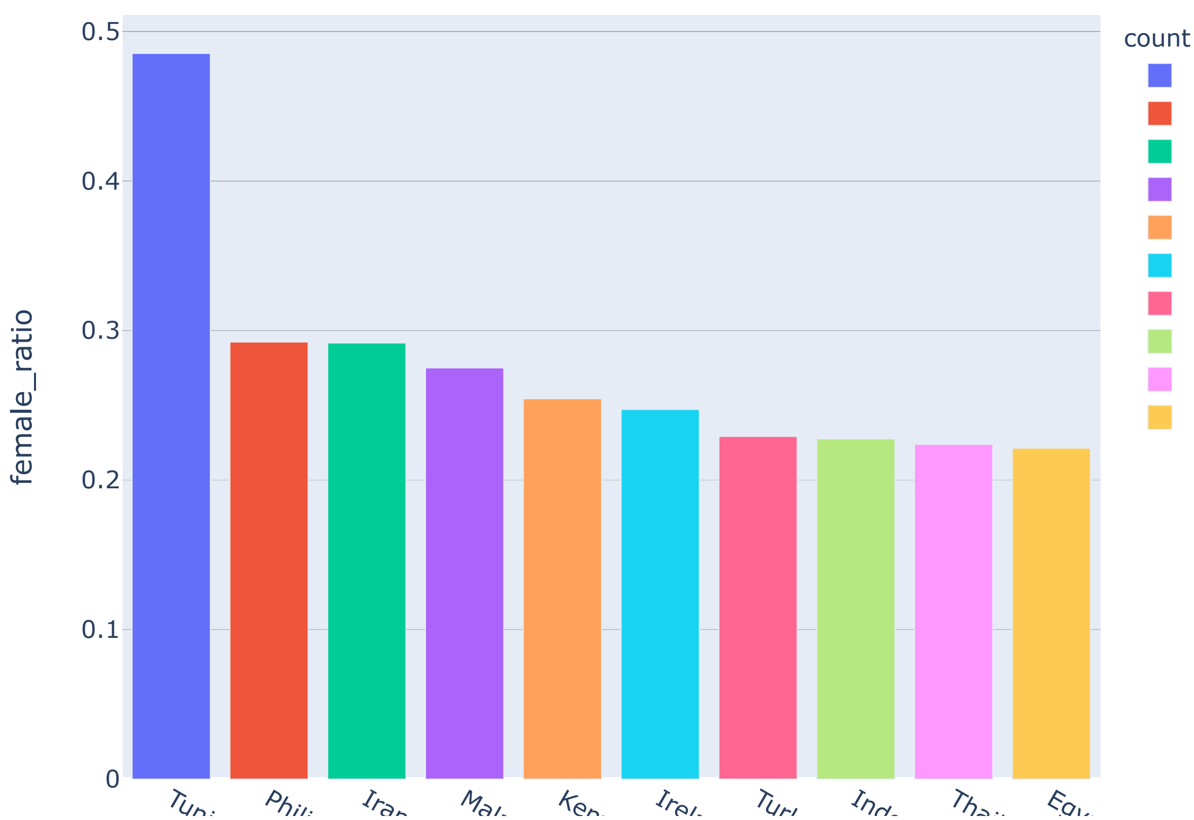
Out[24]:

	country	country_code	user_count
20	India	IND	4786
53	USA	USA	3085
7	Brazil	BRA	728
26	Japan	JPN	673
41	Russia	RUS	626
10	China	CHN	574
16	Germany	DEU	531
45	South Korea	KOR	510
52	UK	GBR	482
8	Canada	CAN	450

In [25]:

```
# Calculating female ratio to get a better picture of presence of female in science.
female_ratio_by_country = \
  female_by_country.set_index('country').female_count / user_by_country.set_index('coun
female_ratio_by_country = female_ratio_by_country.to_frame(name='female_ratio').reset_i

# Top 10 country by female ratio
top10_country_by_female_ratio = female_ratio_by_country.sort_values(by='female_ratio',
px.bar(top10_country_by_female_ratio, x='country', y='female_ratio', color='country')
```



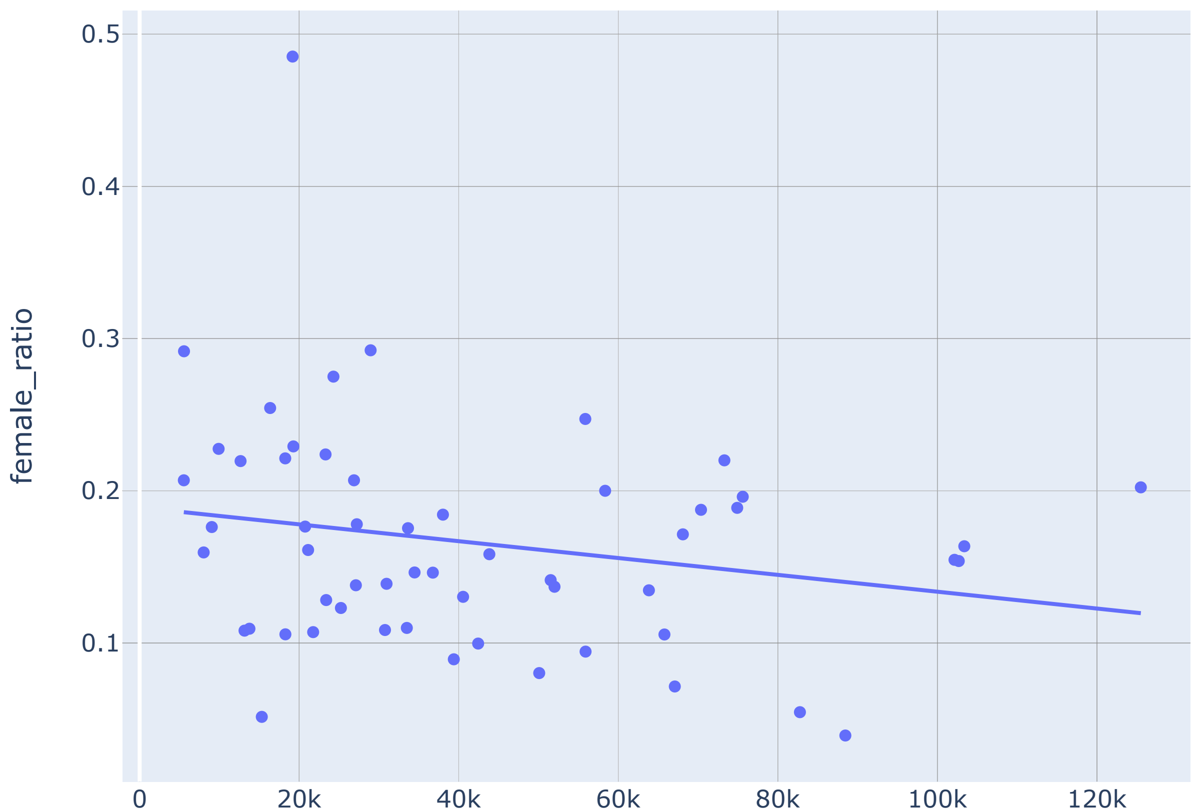
2b

When we saw countries such as 'Tunisia' and 'Kenya' coming up higher in female ratio, decided to dig deep and analyze- is female ratio higher in countries which pay higher average salary?

To our **surprise**, saw that female ratio is much **higher** for countries that have **lower average salary**!! As the average salary increases, female ratio also decreases.

Hover over the graph to see country names

In [26]:
```
female_vs_salary = avg_salary_by_country.merge(female_by_country).merge(female_ratio_by
fig1 = px.scatter(female_vs_salary, x="salary", y="female_ratio", trendline="ols", hove
fig1.show()
```



Interesting Finding

As the average salary increases, number of women in data science decrease!! Women in developing nations see a more direct path to success through data science.

Managerial Insight

If you observe the world map, only USA and India stands out in female count. This indicates that we should try to reach out women who have not participated yet and help them out in education

Further, for countries such as Tunisia and Phillipines that have higher female ratio, we should encourage them to pursue their career with more ferocity!!

Finding 3

Is a higher education degree worth it? Turns out, No!

One of the questions that was asked in the survey was - On which platforms have you begun or completed data science courses? When we saw University courses in the option, we thought of analyzing, whether having a higher degree even worth it? Does it give you a long term salary hike?

For this analysis, taking into consideration only professionals who are employed and earn more than 120k! Divided the respondents into two groups -

* With higher education degree

* Without higher education degree

After that grouped the respondents by age and took a count of average salary of both the groups. After plotting the average salary for each age group, saw that as age increases the average salary of people **without degree is much higher** than respondents who have a higher education degree.

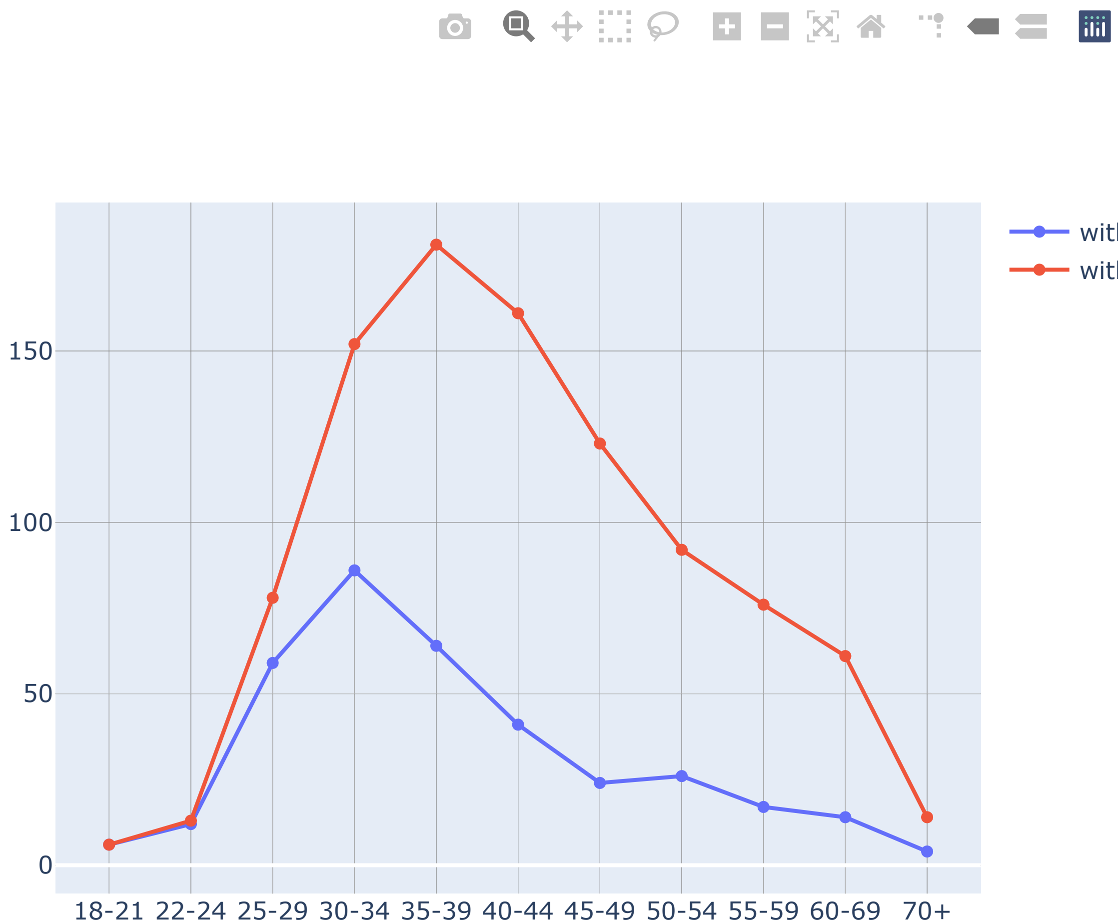
In [27]:
```
# Removing Students and Not Employed and earn more then 120k
education = response_df[~(response_df['title'].isin(["Student", "Not employed"])) & \
                        (response_df['salary_float'] > 120000)]
```

In [28]:
```
# Dividing respondents into two groups
with_higher_degree = education[education.university_courses \
                               =='University Courses (resulting in a university degree)
without_higher_degree = education[education.university_courses \
                               !='University Courses (resulting in a university degree)
```

In [29]:
```
# Grouping by age and taking count of count of people falling within a salary range
avg_salary_with_degree = with_higher_degree.groupby('age')['salary_float'].count().\
                    to_frame(name='Num_People').reset_index()
avg_salary_without_degree = without_higher_degree.groupby('age')['salary_float'].count(
                    to_frame(name='Num_People').reset_index()
```

In [30]:
```
fig2 = go.Figure()
fig3 = fig2.add_trace(go.Scatter(
    x=avg_salary_with_degree.age,
    y=avg_salary_with_degree.Num_People,
    name = 'with degree',
    connectgaps=True
))
fig3.add_trace(go.Scatter(
```

```
    x=avg_salary_without_degree.age,
    y=avg_salary_without_degree.Num_People,
    name='without degree',
))
```



Interesting Finding

People without higher education degree earn more than people with higher education degree.

Managerial Insight

As the data shows that having a higher education degree does not help in earning a higher salary. If you want to earn higher salary over the time, we suggest to improve your skill set. It seems that having good professional experience helps you land a higher paying salary even if you don't have a higher education degree.