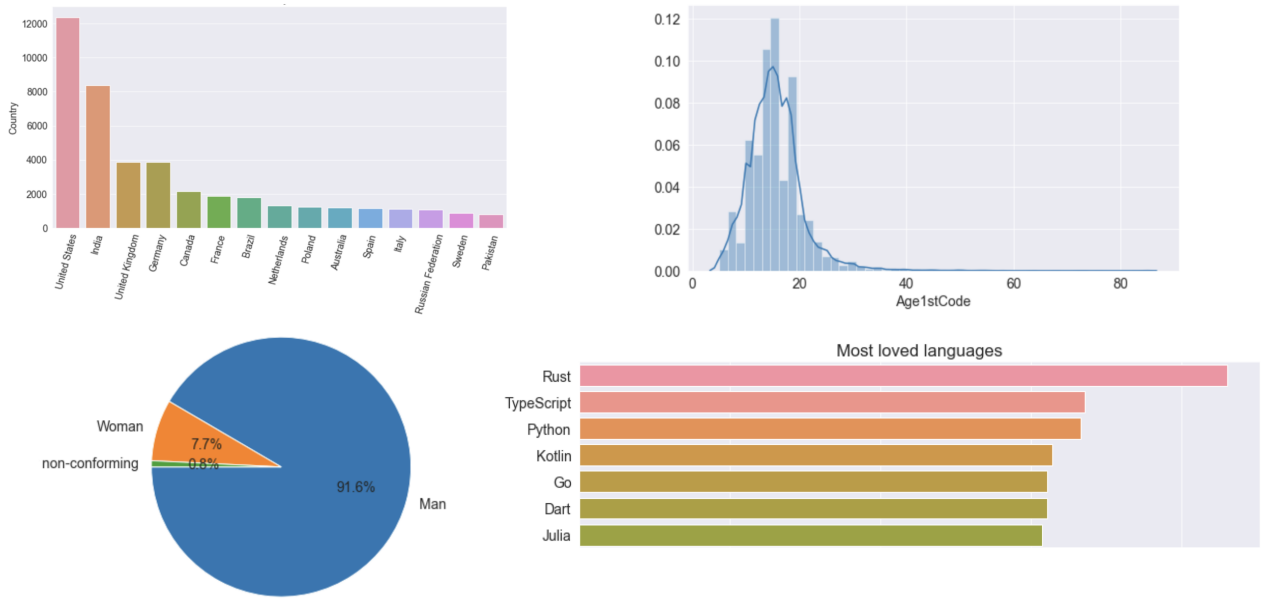
Exploratory Data Analysis using Python - A Case Study

Analyzing responses from the Stack Overflow Annual Developer Survey 2020



Part 9 of "Data Analysis with Python: Zero to Pandas"

This tutorial series is a beginner-friendly introduction to programming and data analysis using the Python programming language. These tutorials take a practical and coding-focused approach. The best way to learn the material is to execute the code and experiment with it yourself. Check out the full series here:

1. First Steps with Python and Jupyter
2. A Quick Tour of Variables and Data Types
3. Branching using Conditional Statements and Loops
4. Writing Reusable Code Using Functions
5. Reading from and Writing to Files
6. Numerical Computing with Python and Numpy
7. Analyzing Tabular Data using Pandas
8. Data Visualization using Matplotlib & Seaborn
9. Exploratory Data Analysis - A Case Study

The following topics are covered in this tutorial:

- Selecting and downloading a dataset
- Data preparation and cleaning
- Exploratory analysis and visualization
- Asking and answering interesting questions
- Summarizing inferences and drawing conclusions

How to run the code

This tutorial is an executable Jupyter notebook hosted on Jovian. You can *run* this tutorial and experiment with the code examples in a couple of ways: *using free online resources* (recommended) or *on your computer*.

Option 1: Running using free online resources (1-click, recommended)

The easiest way to start executing the code is to click the **Run** button at the top of this page and select **Run on Binder**. You can also select "Run on Colab" or "Run on Kaggle", but you'll need to create an account on Google Colab or Kaggle to use these platforms.

Option 2: Running on your computer locally

To run the code on your computer locally, you'll need to set up Python, download the notebook and install the required libraries. We recommend using the Conda distribution of Python. Click the **Run** button at the top of this page, select the **Run Locally** option, and follow the instructions.

> **Jupyter Notebooks**: This tutorial is a Jupyter notebook - a document made of *cells*. Each cell can contain code written in Python or explanations in plain English. You can execute code cells and view the results, e.g., numbers, messages, graphs, tables, files, etc., instantly within the notebook. Jupyter is a powerful platform for experimentation and analysis. Don't be afraid to mess around with the code & break things - you'll learn a lot by encountering and fixing errors. You can use the "Kernel > Restart & Clear Output" menu option to clear all outputs and start again from the top.

Introduction

In this tutorial, we'll analyze the StackOverflow developer survey dataset. The dataset contains responses to an annual survey conducted by StackOverflow. You can find the raw data & official analysis here: https://insights.stackoverflow.com/survey.

There are several options for getting the dataset into Jupyter:

- Download the CSV manually and upload it via Jupyter's GUI
- Use the `urlretrieve` function from the `urllib.request` to download CSV files from a raw URL
- Use a helper library, e.g., `opendatasets`, which contains a collection of curated datasets and provides a helper function for direct download.

We'll use the `opendatasets` helper library to download the files.

```
!pip install jovian opendatasets --upgrade --quiet
```

```
import opendatasets as od
```

```
od.download('stackoverflow-developer-survey-2020')
```

```
Downloading https://raw.githubusercontent.com/JovianML/opendatasets/master/data/stackoverflow-
```

developer-survey-2020/survey_results_public.csv to ./stackoverflow-developer-survey-2020/survey_results_public.csv

94609408it [00:04, 21555760.40it/s]

Downloading https://raw.githubusercontent.com/JovianML/opendatasets/master/data/stackoverflow-developer-survey-2020/survey_results_schema.csv to ./stackoverflow-developer-survey-2020/survey_results_schema.csv

16384it [00:00, 67386.17it/s]

Downloading https://raw.githubusercontent.com/JovianML/opendatasets/master/data/stackoverflow-developer-survey-2020/README.txt to ./stackoverflow-developer-survey-2020/README.txt

8192it [00:00, 44570.36it/s]

Let's verify that the dataset was downloaded into the directory `stackoverflow-developer-survey-2020` and retrieve the list of files in the dataset.

```
import os
```

```
os.listdir('stackoverflow-developer-survey-2020')
```

```
['survey_results_schema.csv', 'survey_results_public.csv', 'README.txt']
```

You can through the downloaded files using the "File" > "Open" menu option in Jupyter. It seems like the dataset contains three files:

- `README.txt` - Information about the dataset
- `survey_results_schema.csv` - The list of questions, and shortcodes for each question
- `survey_results_public.csv` - The full list of responses to the questions

Let's load the CSV files using the Pandas library. We'll use the name `survey_raw_df` for the data frame to indicate this is unprocessed data that we might clean, filter, and modify to prepare a data frame ready for analysis.

```
import pandas as pd
```

```
survey_raw_df = pd.read_csv('stackoverflow-developer-survey-2020/survey_results_public.
```

```
survey_raw_df
```

	Respondent	MainBranch	Hobbyist	Age	Age1stCode	CompFreq	CompTotal	ConvertedComp	Country	C
0	1	I am a developer by profession	Yes	NaN	13	Monthly	NaN	NaN	Germany	

	Respondent	MainBranch	Hobbyist	Age	Age1stCode	CompFreq	CompTotal	ConvertedComp	Country	C
1	2	I am a developer by profession	No	NaN	19	NaN	NaN	NaN	United Kingdom	
2	3	I code primarily as a hobby	Yes	NaN	15	NaN	NaN	NaN	Russian Federation	
3	4	I am a developer by profession	Yes	25.0	18	NaN	NaN	NaN	Albania	
4	5	I used to be a developer by profession, but no...	Yes	31.0	16	NaN	NaN	NaN	United States	
...	...	...	...	...	...	...	...	...	...	
64456	64858	NaN	Yes	NaN	16	NaN	NaN	NaN	United States	
64457	64867	NaN	Yes	NaN	NaN	NaN	NaN	NaN	Morocco	
64458	64898	NaN	Yes	NaN	NaN	NaN	NaN	NaN	Viet Nam	
64459	64925	NaN	Yes	NaN	NaN	NaN	NaN	NaN	Poland	
64460	65112	NaN	Yes	NaN	NaN	NaN	NaN	NaN	Spain	

64461 rows × 61 columns

The dataset contains over 64,000 responses to 60 questions (although many questions are optional). The responses have been anonymized to remove personally identifiable information, and each respondent has been assigned a randomized respondent ID.

Let's view the list of columns in the data frame.

```
survey_raw_df.columns
```

```
Index(['Respondent', 'MainBranch', 'Hobbyist', 'Age', 'Age1stCode', 'CompFreq',
       'CompTotal', 'ConvertedComp', 'Country', 'CurrencyDesc',
       'CurrencySymbol', 'DatabaseDesireNextYear', 'DatabaseWorkedWith',
       'DevType', 'EdLevel', 'Employment', 'Ethnicity', 'Gender', 'JobFactors',
       'JobSat', 'JobSeek', 'LanguageDesireNextYear', 'LanguageWorkedWith',
       'MiscTechDesireNextYear', 'MiscTechWorkedWith',
       'NEWCollabToolsDesireNextYear', 'NEWCollabToolsWorkedWith', 'NEWDevOps',
       'NEWDevOpsImpt', 'NEWEdImpt', 'NEWJobHunt', 'NEWJobHuntResearch',
       'NEWLearn', 'NEWOffTopic', 'NEWOnboardGood', 'NEWOtherComms',
       'NEWOvertime', 'NEWPurchaseResearch', 'NEWPurpleLink', 'NEWSOSites',
       'NEWStuck', 'OpSys', 'OrgSize', 'PlatformDesireNextYear',
```

```
       'PlatformWorkedWith', 'PurchaseWhat', 'Sexuality', 'SOAccount',
       'SOComm', 'SOPartFreq', 'SOVisitFreq', 'SurveyEase', 'SurveyLength',
       'Trans', 'UndergradMajor', 'WebframeDesireNextYear',
       'WebframeWorkedWith', 'WelcomeChange', 'WorkWeekHrs', 'YearsCode',
       'YearsCodePro'],
      dtype='object')
```

It appears that shortcodes for questions have been used as column names.

We can refer to the schema file to see the full text of each question. The schema file contains only two columns: `Column` and `QuestionText`. We can load it as Pandas Series with `Column` as the index and the `QuestionText` as the value.

```
schema_fname = 'stackoverflow-developer-survey-2020/survey_results_schema.csv'
```

```
schema_raw = pd.read_csv(schema_fname, index_col='Column').QuestionText
```

```
schema_raw
```

```
Column
Respondent             Randomized respondent ID number (not in order ...
MainBranch             Which of the following options best describes ...
Hobbyist                                        Do you code as a hobby?
Age                    What is your age (in years)? If you prefer not...
Age1stCode             At what age did you write your first line of c...
                                              ...
WebframeWorkedWith     Which web frameworks have you done extensive d...
WelcomeChange          Compared to last year, how welcome do you feel...
WorkWeekHrs            On average, how many hours per week do you wor...
YearsCode              Including any education, how many years have y...
YearsCodePro           NOT including education, how many years have y...
Name: QuestionText, Length: 61, dtype: object
```

```
schema_raw
```

```
Column
Respondent             Randomized respondent ID number (not in order ...
MainBranch             Which of the following options best describes ...
Hobbyist                                        Do you code as a hobby?
Age                    What is your age (in years)? If you prefer not...
Age1stCode             At what age did you write your first line of c...
                                              ...
WebframeWorkedWith     Which web frameworks have you done extensive d...
WelcomeChange          Compared to last year, how welcome do you feel...
WorkWeekHrs            On average, how many hours per week do you wor...
YearsCode              Including any education, how many years have y...
YearsCodePro           NOT including education, how many years have y...
Name: QuestionText, Length: 61, dtype: object
```

We can now use `schema_raw` to retrieve the full question text for any column in `survey_raw_df`.

```
schema_raw['YearsCodePro']
```

```
'NOT including education, how many years have you coded professionally (as a part of your work)?'
```

We've now loaded the dataset. We're ready to move on to the next step of preprocessing & cleaning the data for our analysis.

Save and upload your notebook

Whether you're running this Jupyter notebook online or on your computer, it's essential to save your work from time to time. You can continue working on a saved notebook later or share it with friends and colleagues to let them execute your code. Jovian offers an easy way of saving and sharing your Jupyter notebooks online.

```
# Select a project name
project='python-eda-stackoverflow-survey'
```

```
# Install the Jovian library
!pip install jovian --upgrade --quiet
```

```
import jovian
```

```
jovian.commit(project=project)
```

```
[jovian] Updating notebook "tarif9351/python-eda-stackoverflow-survey" on https://jovian.com
[jovian] Committed successfully! https://jovian.com/tarif9351/python-eda-stackoverflow-survey
```

```
'https://jovian.com/tarif9351/python-eda-stackoverflow-survey'
```

The first time you run `jovian.commit`, you'll be asked to provide an API Key to securely upload the notebook to your Jovian account. You can get the API key from your Jovian profile page after logging in / signing up.

`jovian.commit` uploads the notebook to your Jovian account, captures the Python environment, and creates a shareable link for your notebook, as shown above. You can use this link to share your work and let anyone (including you) run your notebooks and reproduce your work.

Data Preparation & Cleaning

While the survey responses contain a wealth of information, we'll limit our analysis to the following areas:

- Demographics of the survey respondents and the global programming community
- Distribution of programming skills, experience, and preferences
- Employment-related information, preferences, and opinions

Let's select a subset of columns with the relevant data for our analysis.

```
selected_columns = [
    # Demographics
    'Country',
    'Age',
    'Gender',
    'EdLevel',
    'UndergradMajor',
    # Programming experience
    'Hobbyist',
    'Age1stCode',
    'YearsCode',
    'YearsCodePro',
    'LanguageWorkedWith',
    'LanguageDesireNextYear',
    'NEWLearn',
    'NEWStuck',
    # Employment
    'Employment',
    'DevType',
    'WorkWeekHrs',
    'JobSat',
    'JobFactors',
    'NEWOvertime',
    'NEWEdImpt'
]
```

```
len(selected_columns)
```

```
20
```

Let's extract a copy of the data from these columns into a new data frame `survey_df`. We can continue to modify further without affecting the original data frame.

```
survey_df = survey_raw_df[selected_columns].copy()
```

```
schema = schema_raw[selected_columns]
```

Let's view some basic information about the data frame.

```
survey_df.shape
```

```
(64461, 20)
```

```
survey_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64461 entries, 0 to 64460
```

```
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Country                 64072 non-null  object 
 1   Age                     45446 non-null  float64
 2   Gender                  50557 non-null  object 
 3   EdLevel                 57431 non-null  object 
 4   UndergradMajor          50995 non-null  object 
 5   Hobbyist                64416 non-null  object 
 6   Age1stCode              57900 non-null  object 
 7   YearsCode               57684 non-null  object 
 8   YearsCodePro            46349 non-null  object 
 9   LanguageWorkedWith      57378 non-null  object 
 10  LanguageDesireNextYear  54113 non-null  object 
 11  NEWLearn                56156 non-null  object 
 12  NEWStuck                54983 non-null  object 
 13  Employment              63854 non-null  object 
 14  DevType                 49370 non-null  object 
 15  WorkWeekHrs             41151 non-null  float64
 16  JobSat                  45194 non-null  object 
 17  JobFactors              49349 non-null  object 
 18  NEWOvertime             43231 non-null  object 
 19  NEWEdImpt               48465 non-null  object 
dtypes: float64(2), object(18)
memory usage: 9.8+ MB
```

Most columns have the data type `object`, either because they contain values of different types or contain empty values (`NaN`). It appears that every column contains some empty values since the Non-Null count for every column is lower than the total number of rows (64461). We'll need to deal with empty values and manually adjust the data type for each column on a case-by-case basis.

Only two of the columns were detected as numeric columns (`Age` and `WorkWeekHrs`), even though a few other columns have mostly numeric values. To make our analysis easier, let's convert some other columns into numeric data types while ignoring any non-numeric value. The non-numeric are converted to `NaN`.

```
survey_df['Age1stCode'] = pd.to_numeric(survey_df.Age1stCode, errors='coerce')
survey_df['YearsCode'] = pd.to_numeric(survey_df.YearsCode, errors='coerce')
survey_df['YearsCodePro'] = pd.to_numeric(survey_df.YearsCodePro, errors='coerce')
```

Let's now view some basic statistics about numeric columns.

```
survey_df.describe()
```

	Age	Age1stCode	YearsCode	YearsCodePro	WorkWeekHrs
count	45446.000000	57473.000000	56784.000000	44133.000000	41151.000000

	Age	Age1stCode	YearsCode	YearsCodePro	WorkWeekHrs
mean	30.834111	15.476572	12.782051	8.869667	40.782174
std	9.585392	5.114081	9.490657	7.759961	17.816383
min	1.000000	5.000000	1.000000	1.000000	1.000000
25%	24.000000	12.000000	6.000000	3.000000	40.000000
50%	29.000000	15.000000	10.000000	6.000000	40.000000
75%	35.000000	18.000000	17.000000	12.000000	44.000000
max	279.000000	85.000000	50.000000	50.000000	475.000000

There seems to be a problem with the age column, as the minimum value is 1 and the maximum is 279. This is a common issue with surveys: responses may contain invalid values due to accidental or intentional errors while responding. A simple fix would be to ignore the rows where the age is higher than 100 years or lower than 10 years as invalid survey responses. We can do this using the `.drop` method, as explained here.

```
survey_df.drop(survey_df[survey_df.Age < 10].index, inplace=True)
survey_df.drop(survey_df[survey_df.Age > 100].index, inplace=True)
```

The same holds for `WorkWeekHrs`. Let's ignore entries where the value for the column is higher than 140 hours. (~20 hours per day).

```
survey_df.drop(survey_df[survey_df.WorkWeekHrs > 140].index, inplace=True)
```

The gender column also allows for picking multiple options. We'll remove values containing more than one option to simplify our analysis.

```
survey_df['Gender'].value_counts()
```

```
Man                                                            45895
Woman                                                           3835
Non-binary, genderqueer, or gender non-conforming                385
Man;Non-binary, genderqueer, or gender non-conforming            121
Woman;Non-binary, genderqueer, or gender non-conforming           92
Woman;Man                                                         73
Woman;Man;Non-binary, genderqueer, or gender non-conforming       25
Name: Gender, dtype: int64
```

```
import numpy as np
```

```
survey_df.where(~(survey_df.Gender.str.contains(';', na=False)), np.nan, inplace=True)
```

We've now cleaned up and prepared the dataset for analysis. Let's take a look at a sample of rows from the data frame.

```
survey_df['Gender'].value_counts()
```

```
Man                                                            45895
```

```
Woman                                                 3835
Non-binary, genderqueer, or gender non-conforming      385
Name: Gender, dtype: int64
```

```
survey_df.sample(10)
```

	Country	Age	Gender	EdLevel	UndergradMajor	Hobbyist	Age1stCode	YearsCode	YearsCodePro	
18918	United Kingdom	NaN	NaN	NaN	NaN	Yes	NaN	NaN	NaN	Bas
6371	India	33.0	Man	Bachelor's degree (B.A., B.S., B.Eng., etc.)	NaN	Yes	13.0	17.0	8.0	
34004	Italy	18.0	Man	Secondary school (e.g. American high school, G...	NaN	Yes	12.0	6.0	NaN	I
61027	United States	24.0	Man	Bachelor's degree (B.A., B.S., B.Eng., etc.)	Computer science, computer engineering, or sof...	Yes	13.0	8.0	2.0	Ba
57907	United States	29.0	Man	Other doctoral degree (Ph.D., Ed.D., etc.)	Fine arts or performing arts (such as graphic ...	Yes	21.0	8.0	5.0	Basl
38143	India	NaN	NaN	Bachelor's degree (B.A., B.S., B.Eng., etc.)	Computer science, computer engineering, or sof...	Yes	NaN	NaN	NaN	
14076	France	26.0	Man	Master's degree (M.A., M.S., M.Eng., MBA, etc.)	Computer science, computer engineering, or sof...	No	15.0	9.0	7.0	Bash/
27883	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
29754	Canada	59.0	Man	Bachelor's degree (B.A., B.S., B.Eng., etc.)	A natural science (such as biology, chemistry,...	Yes	14.0	45.0	25.0	Basl
9110	Germany	33.0	Man	NaN	Computer science, computer engineering, or sof...	Yes	14.0	13.0	6.0	

Let's save and commit our work before continuing.

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "tarif9351/python-eda-stackoverflow-survey" on https://jovian.com
[jovian] Committed successfully! https://jovian.com/tarif9351/python-eda-stackoverflow-survey
```

```
'https://jovian.com/tarif9351/python-eda-stackoverflow-survey'
```

Exploratory Analysis and Visualization

Before we ask questions about the survey responses, it would help to understand the respondents' demographics, i.e., country, age, gender, education level, employment level, etc. It's essential to explore these variables to understand how representative the survey is of the worldwide programming community. A survey of this scale generally tends to have some selection bias.

Let's begin by importing `matplotlib.pyplot` and `seaborn` .

```
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (9, 5)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

Country

Let's look at the number of countries from which there are responses in the survey and plot the ten countries with the highest number of responses.

```
schema.Country
```

```
'Where do you live?'
```

```
survey_df.Country.nunique()
```

```
183
```

We can identify the countries with the highest number of respondents using the `value_counts` method.

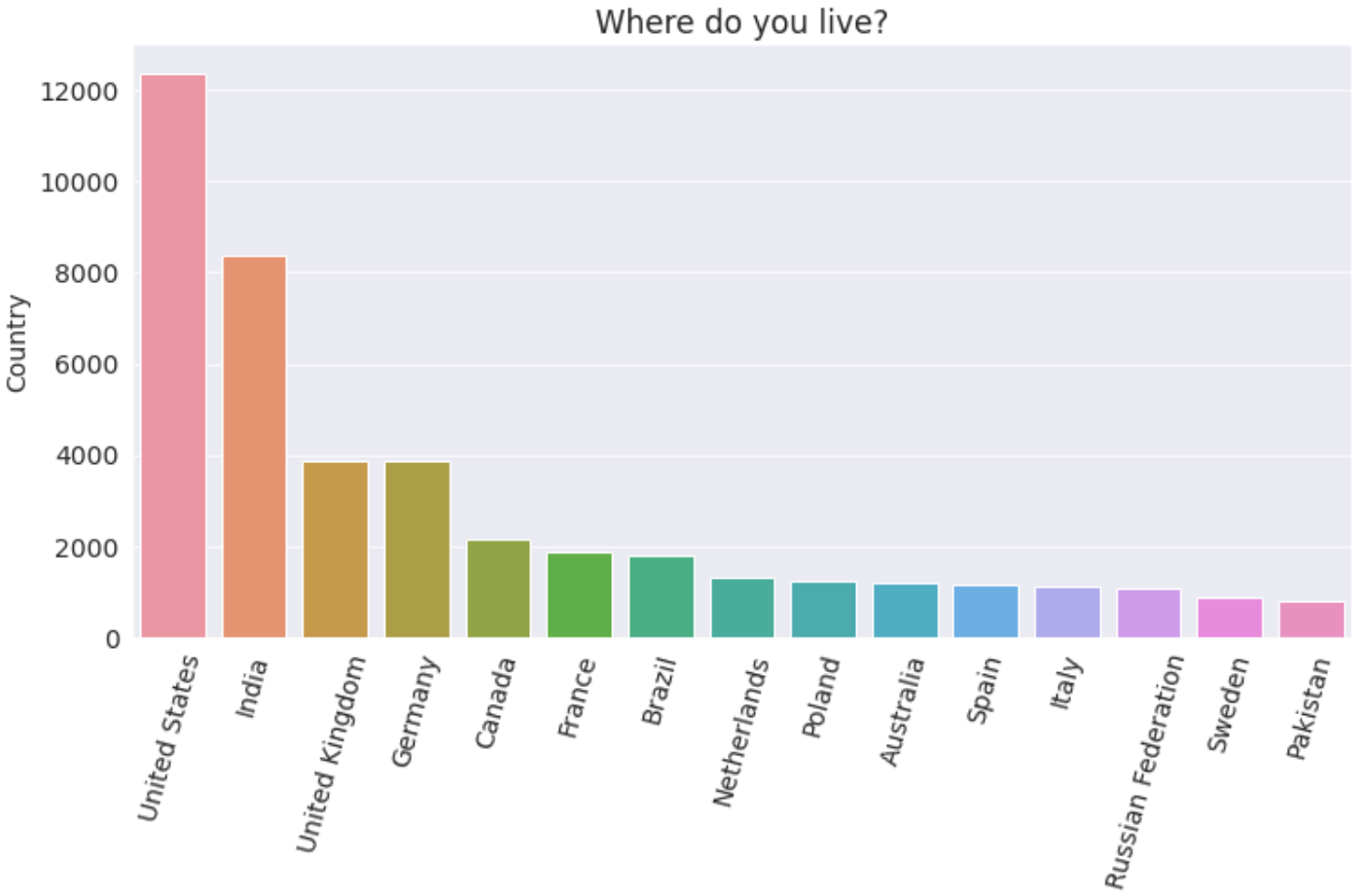
```
top_countries = survey_df.Country.value_counts().head(15)
top_countries
```

```
United States          12371
India                   8364
United Kingdom          3881
Germany                 3864
```

```
Canada                   2175
France                   1884
Brazil                   1804
Netherlands              1332
Poland                   1259
Australia                1199
Spain                    1157
Italy                    1115
Russian Federation       1085
Sweden                    879
Pakistan                  802
Name: Country, dtype: int64
```

We can visualize this information using a bar chart.

```
plt.figure(figsize=(12,6))
plt.xticks(rotation=75)
plt.title(schema.Country)
sns.barplot(x=top_countries.index, y=top_countries);
```



It appears that a disproportionately high number of respondents are from the US and India, probably because the survey is in English, and these countries have the highest English-speaking populations. We can already see that the survey may not be representative of the global programming community - especially from non-English speaking countries. Programmers from non-English speaking countries are almost certainly underrepresented.

Exercise: Try finding the percentage of responses from English-speaking vs. non-English speaking countries. You can use this list of languages spoken in different countries.

```
listed_countries = ['United States',
                    'United Kingdom',
                    'Canada',
                    'Australia']
```

```
len(listed_countries)
```

4

```
english_speakers = survey_df[survey_df['Country'].isin(listed_countries)].Country.value
```

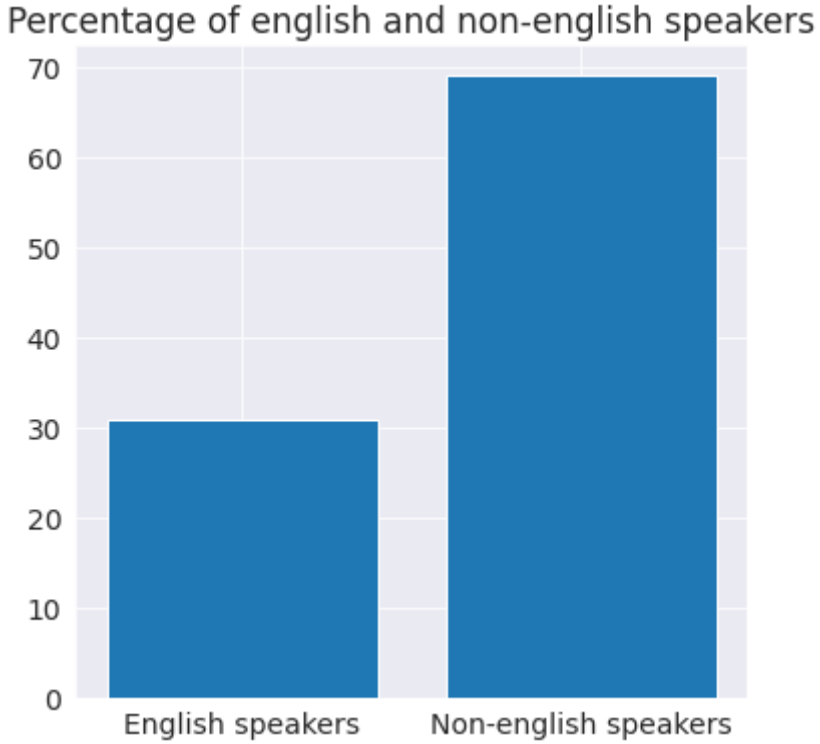
```
non_english_speakers =survey_df.Country.value_counts().sum() - english_speakers
```

```
total_speakers =  english_speakers.sum() + non_english_speakers.sum()
```

```
speakers = [english_speakers * 100 /total_speakers , non_english_speakers *100 /total_s
```

```
speakers_name = [ 'English speakers', 'Non-english speakers']
```

```
plt.figure(figsize=(6,6))
plt.title("Percentage of english and non-english speakers")
plt.bar(speakers_name, speakers);
```

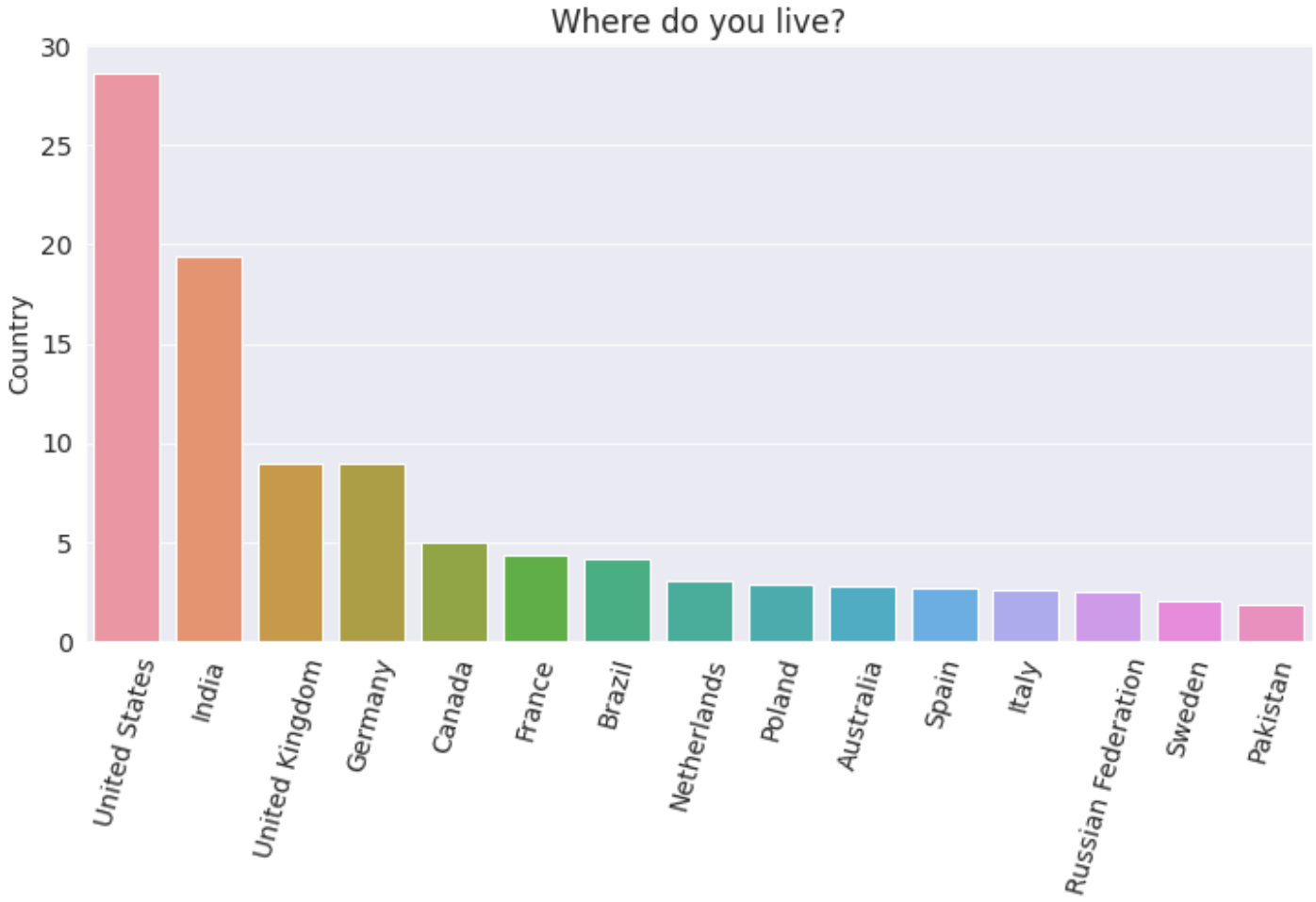



```
top__countries = top_countries * 100/ top_countries.sum()

plt.figure(figsize=(12,6))
plt.xticks(rotation=75)
```

```
plt.title('Where do you live?')

plt.ylabel('Percentage')
sns.barplot(x=top_countries.index, y=top__countries);
```



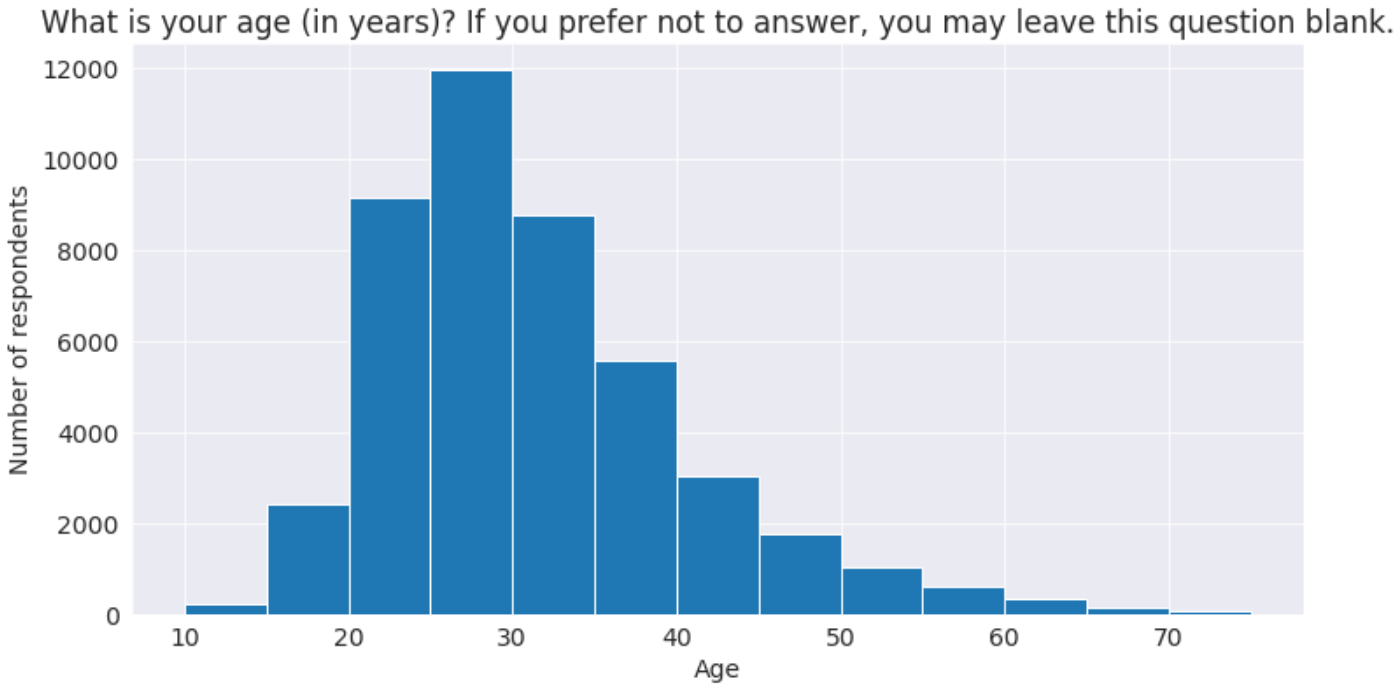
Age

The distribution of respondents' age is another crucial factor to look at. We can use a histogram to visualize it.

```
plt.figure(figsize=(12, 6))
plt.title(schema.Age)
plt.xlabel('Age')
plt.ylabel('Number of respondents')

plt.hist(survey_df.Age, bins=np.arange(10,80,5))
```

```
(array([  209.,  2419.,  9135., 11938.,  8739.,  5582.,  3031.,  1756.,
         1038.,   622.,   333.,   143.,    75.]),
 array([10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75]),
 <BarContainer object of 13 artists>)
```



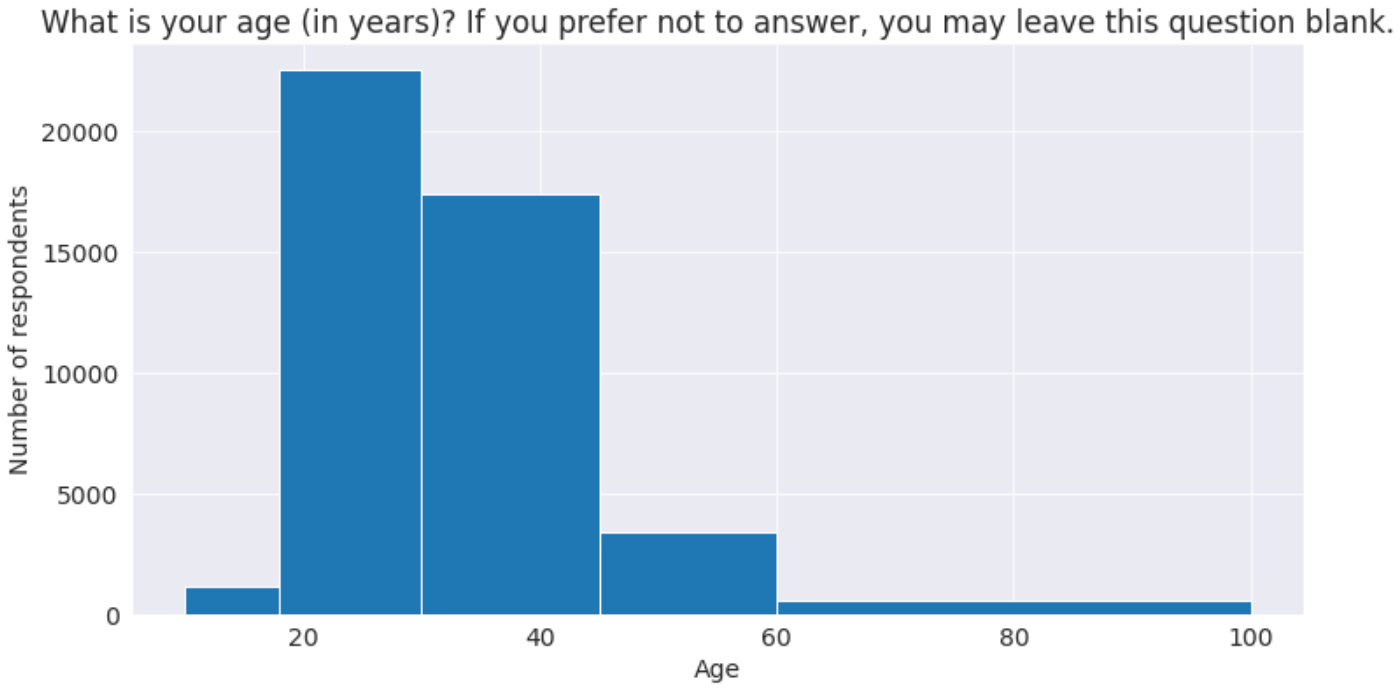
It appears that a large percentage of respondents are 20-45 years old. It's somewhat representative of the programming community in general. Many young people have taken up computer science as their field of study or profession in the last 20 years.

Exercise: You may want to filter out responses by age (or age group) if you'd like to analyze and compare the survey results for different age groups. Create a new column called AgeGroup containing values like `Less than 10 years`, `10-18 years`, `18-30 years`, `30-45 years`, `45-60 years` and `Older than 60 years`. Then, repeat the analysis in the rest of this notebook for each age group.

```
plt.figure(figsize=(12, 6))
plt.title(schema.Age)
plt.xlabel('Age');
plt.ylabel('Number of respondents');

plt.hist(survey_df.Age, bins=[10,18,30,45,60,100])
```

```
(array([ 1181., 22520., 17352.,  3416.,   599.]),
 array([ 10,  18,  30,  45,  60, 100]),
 <BarContainer object of 5 artists>)
```



Gender

Let's look at the distribution of responses for the Gender. It's a well-known fact that women and non-binary genders are underrepresented in the programming community, so we might expect to see a skewed distribution here.

```
schema.Gender
```

```
'Which of the following describe you, if any? Please check all that apply. If you prefer not to answer, you may leave this question blank.'
```

```
gender_counts = survey_df.Gender.value_counts()
gender_counts
```

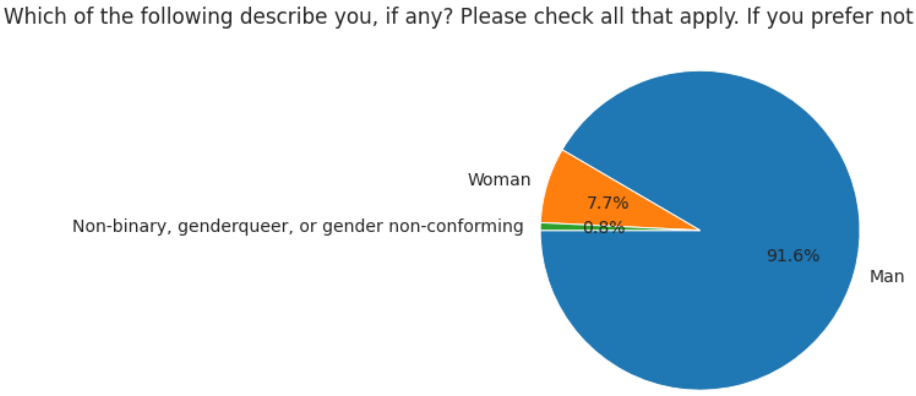
```
Man                                                 45895
Woman                                                3835
Non-binary, genderqueer, or gender non-conforming     385
Name: Gender, dtype: int64
```

A pie chart would be a great way to visualize the distribution.

```
import numpy as np
```

```
survey_df.where(~(survey_df.Gender.str.contains(';', na=False)), np.nan, inplace=True)
```

```
plt.figure(figsize=(12,6))
plt.title(schema.Gender)
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=180);
```

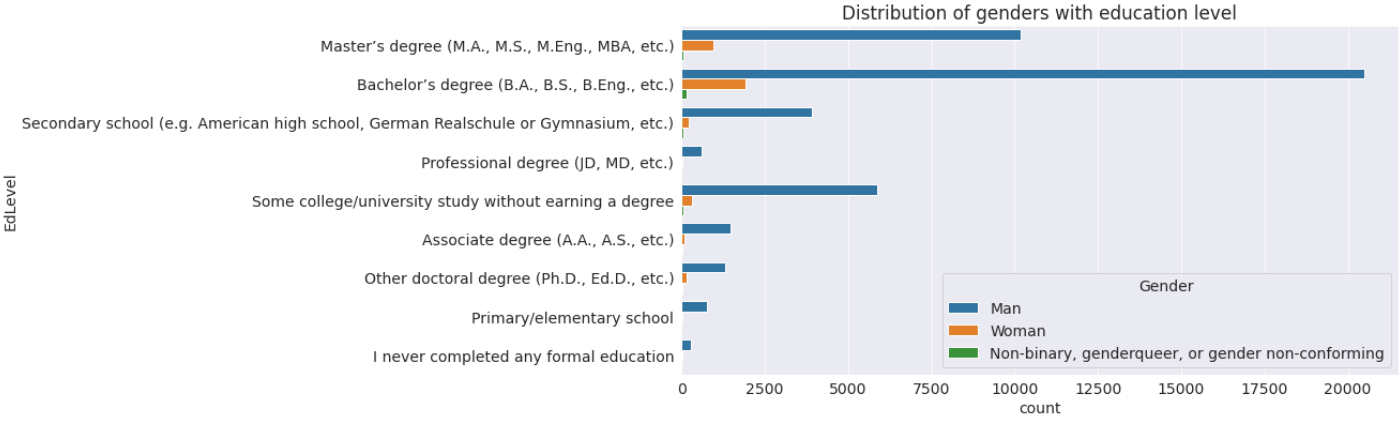


Only about 8% of survey respondents who have answered the question identify as women or non-binary. This number is lower than the overall percentage of women & non-binary genders in the programming community - which is estimated to be around 12%.

Exercise: It would be interesting to compare the survey responses & preferences across genders. Repeat this analysis with these breakdowns. How do the relative education levels differ across genders? How do the salaries vary? You may find this analysis on the Gender Divide in Data Science useful.

```
plt.figure(figsize=(12,6))
sns.countplot(data=survey_df, x=None, y=survey_df.EdLevel, hue= survey_df.Gender)
plt.title("Distribution of genders with education level")
```

```
Text(0.5, 1.0, 'Distribution of genders with education level')
```

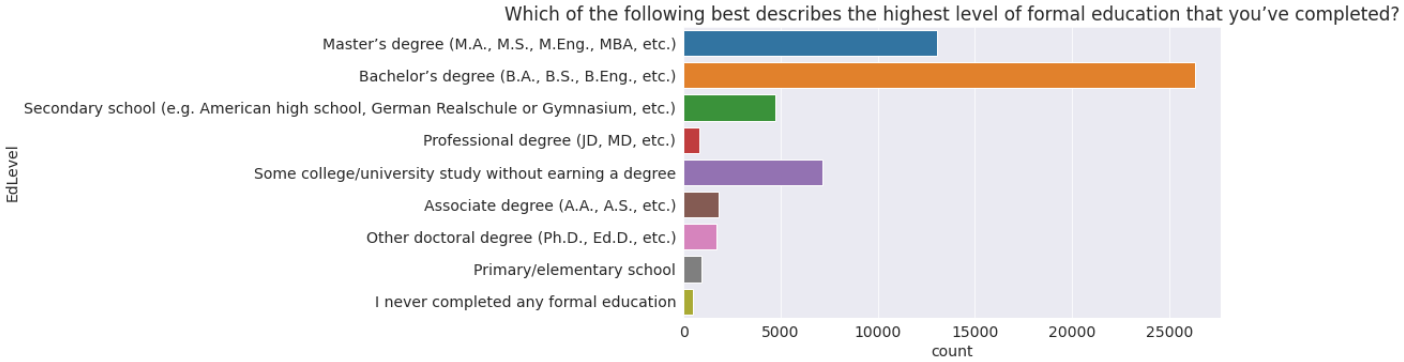


Education Level

Formal education in computer science is often considered an essential requirement for becoming a programmer. However, there are many free resources & tutorials available online to learn programming. Let's compare the education levels of respondents to gain some insight into this. We'll use a horizontal bar plot here.

```
sns.countplot(data=survey_df, x=None, y=survey_df.EdLevel)
plt.title(schema.EdLevel)
```

```
Text(0.5, 1.0, 'Which of the following best describes the highest level of formal
education that you've completed?')
```



It appears that well over half of the respondents hold a bachelor's or master's degree, so most programmers seem to have some college education. However, it's not clear from this graph alone if they hold a degree in computer science.

Exercises: The graph currently shows the number of respondents for each option. Can you modify it to show the percentage instead? Further, try comparing the percentages for each degree for men vs. women.

```
edlevel= survey_df.EdLevel.value_counts()
```

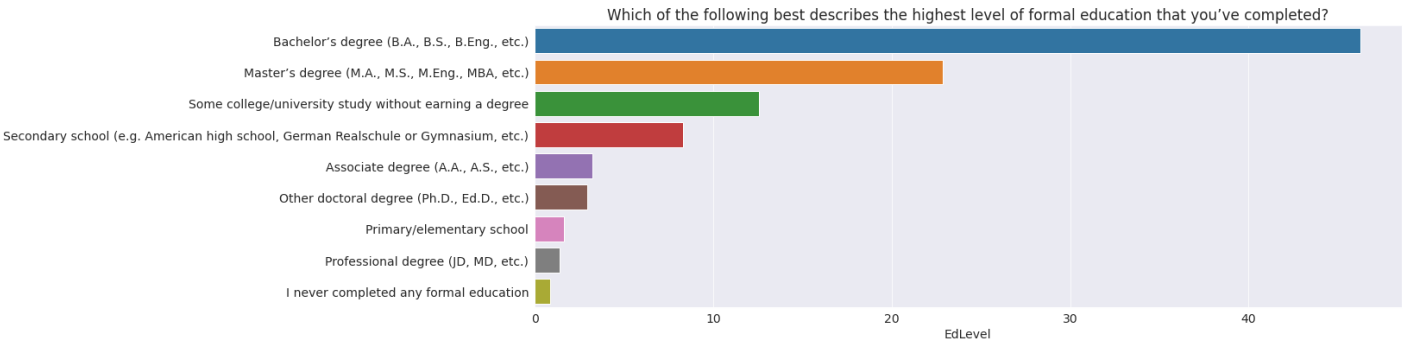
```
edlevel.index
```

```
Index(['Bachelor's degree (B.A., B.S., B.Eng., etc.)',
       'Master's degree (M.A., M.S., M.Eng., MBA, etc.)',
       'Some college/university study without earning a degree',
       'Secondary school (e.g. American high school, German Realschule or Gymnasium,
etc.)',
       'Associate degree (A.A., A.S., etc.)',
       'Other doctoral degree (Ph.D., Ed.D., etc.)',
       'Primary/elementary school', 'Professional degree (JD, MD, etc.)',
       'I never completed any formal education'],
      dtype='object')
```

```
ed_level = edlevel * 100/ edlevel.sum()
```

```
plt.figure(figsize=(18,6))
sns.barplot(y= edlevel.index,x=ed_level)
plt.title(schema.EdLevel)
```

```
Text(0.5, 1.0, 'Which of the following best describes the highest level of formal
education that you've completed?')
```



```
df = survey_df.EdLevel.value_counts()
df
```

```
Bachelor's degree (B.A., B.S., B.Eng., etc.)
26356
Master's degree (M.A., M.S., M.Eng., MBA, etc.)
13024
Some college/university study without earning a degree
7163
Secondary school (e.g. American high school, German Realschule or Gymnasium, etc.)
4724
Associate degree (A.A., A.S., etc.)
1831
Other doctoral degree (Ph.D., Ed.D., etc.)
1681
Primary/elementary school
929
Professional degree (JD, MD, etc.)
793
I never completed any formal education
480
Name: EdLevel, dtype: int64
```

Let's also plot undergraduate majors, but this time we'll convert the numbers into percentages and sort the values to make it easier to visualize the order.

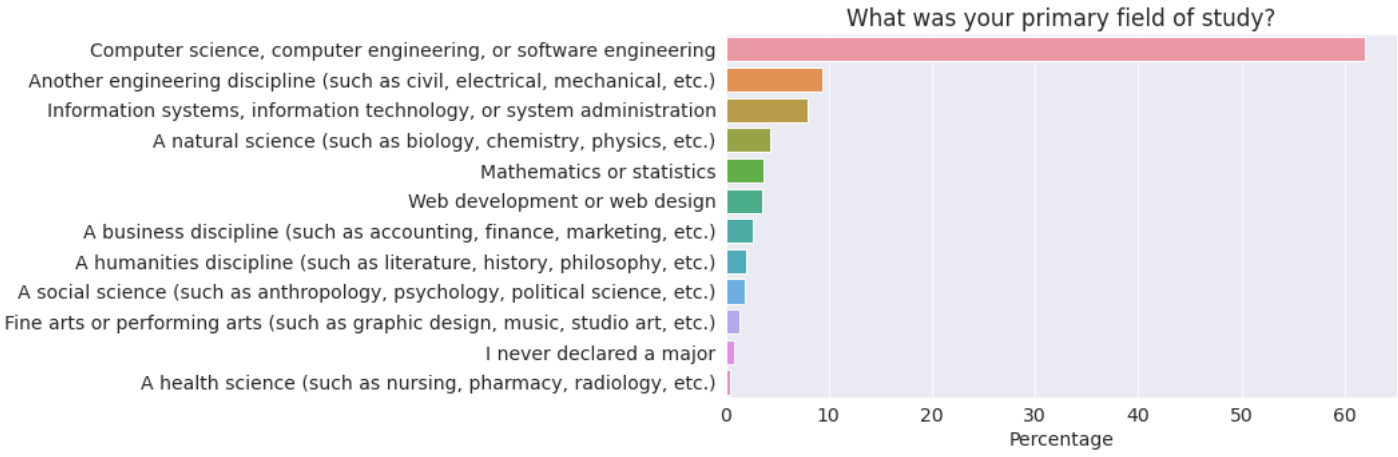
```
schema.UndergradMajor
```

```
'What was your primary field of study?'
```

```
undergrad_pct = survey_df.UndergradMajor.value_counts() * 100 / survey_df.UndergradMajc

sns.barplot(x=undergrad_pct, y=undergrad_pct.index)

plt.title(schema.UndergradMajor)
plt.ylabel(None);
plt.xlabel('Percentage');
```



It turns out that 40% of programmers holding a college degree have a field of study other than computer science - which is very encouraging. It seems to suggest that while a college education is helpful in general, you do not need to pursue a major in computer science to become a successful programmer.

Exercises: Analyze the `NEWEdImpt` column for respondents who hold some college degree vs. those who don't. Do you notice any difference in opinion?

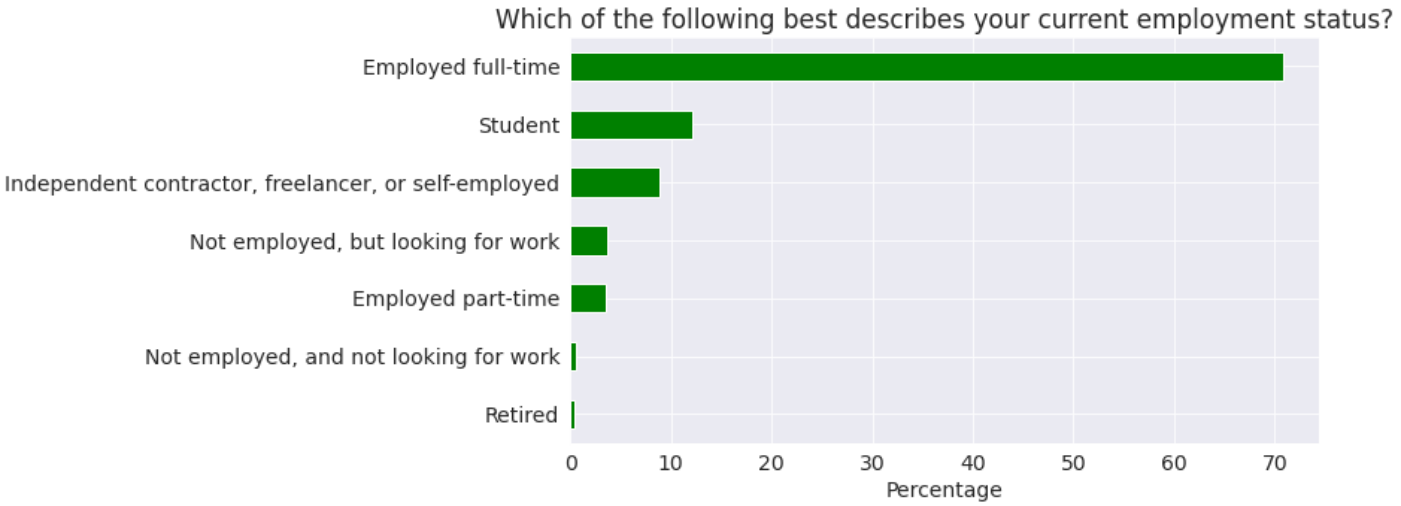
Employment

Freelancing or contract work is a common choice among programmers, so it would be interesting to compare the breakdown between full-time, part-time, and freelance work. Let's visualize the data from the `Employment` column.

```
schema.Employment
```

```
'Which of the following best describes your current employment status?'
```

```
(survey_df.Employment.value_counts(normalize=True, ascending=True)*100).plot(kind='barh
plt.title(schema.Employment)
plt.xlabel('Percentage');
```



It appears that close to 10% of respondents are employed part time or as freelancers.

Exercise: Add a new column `EmploymentType` containing the values `Enthusiast` (student or not employed but looking for work), `Professional` (employed full-time, part-time or freelancing), and `Other` (not employed or retired). For each of the graphs that follow, show a comparison between `Enthusiast` and `Professional`.

The `DevType` field contains information about the roles held by respondents. Since the question allows multiple answers, the column contains lists of values separated by a semi-colon `;`, making it a bit harder to analyze directly.

```
schema.DevType
```

```
'Which of the following describe you? Please select all that apply.'
```

```
survey_df.DevType.value_counts()
```

```
Developer, full-stack
```

```
4396
Developer, back-end
3056
Developer, back-end;Developer, front-end;Developer, full-stack
2214
Developer, back-end;Developer, full-stack
1465
Developer, front-end
1390

...
Database administrator;Developer, back-end;Developer, front-end;Developer, full-
stack;Developer, QA or test;Senior executive/VP
1
Database administrator;Developer, back-end;Developer, front-end;Developer, full-
stack;Product manager;Senior executive/VP
1
Developer, back-end;Developer, full-stack;Developer, mobile;DevOps
specialist;Educator;System administrator
1
Data or business analyst;Database administrator;Developer, back-end;Developer, desktop
or enterprise applications;Developer, front-end;Developer, mobile;Engineering manager
1
Data or business analyst;Developer, mobile;Senior executive/VP;System administrator
1
Name: DevType, Length: 8213, dtype: int64
```

Let's define a helper function that turns a column containing lists of values (like `survey_df.DevType`) into a data frame with one column for each possible option.

```
def split_multicolumn(col_series):
    result_df = col_series.to_frame()
    options = []
    # Iterate over the column
    for idx, value  in col_series[col_series.notnull()].iteritems():
        # Break each value into list of options
        for option in value.split(';'):
            # Add the option as a column to result
            if not option in result_df.columns:
                options.append(option)
                result_df[option] = False
            # Mark the value in the option column as True
            result_df.at[idx, option] = True
    return result_df[options]
```

```
dev_type_df = split_multicolumn(survey_df.DevType)
```

```
dev_type_df
```

	Developer, desktop or enterprise applications	Developer, full-stack	Developer, mobile	Designer	Developer, front-end	Developer, back-end	Developer, QA or test	DevOps specialist	Developer, game or graphics	Data administ
0	True	True	False	False	False	False	False	False	False	
1	False	True	True	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	
64456	False	False	False	False	False	False	False	False	False	
64457	False	False	False	False	False	False	False	False	False	
64458	False	False	False	False	False	False	False	False	False	
64459	False	False	False	False	False	False	False	False	False	
64460	False	False	False	False	False	False	False	False	False	

64451 rows × 23 columns

The `dev_type_df` has one column for each option that can be selected as a response. If a respondent has chosen an option, the corresponding column's value is `True`. Otherwise, it is `False`.

We can now use the column-wise totals to identify the most common roles.

```
dev_type_totals = dev_type_df.sum().sort_values(ascending=False)
dev_type_totals
```

```
Developer, back-end                                26996
Developer, full-stack                              26915
Developer, front-end                               18128
Developer, desktop or enterprise applications      11687
Developer, mobile                                   9406
DevOps specialist                                   5915
Database administrator                              5658
Designer                                            5262
System administrator                                5185
Developer, embedded applications or devices         4701
Data or business analyst                            3970
Data scientist or machine learning specialist       3939
Developer, QA or test                               3893
Engineer, data                                      3700
Academic researcher                                 3502
Educator                                            2895
Developer, game or graphics                         2751
Engineering manager                                 2699
Product manager                                     2471
Scientist                                           2060
Engineer, site reliability                          1921
```

```
Senior executive/VP                          1292
Marketing or sales professional               625
dtype: int64
```

As one might expect, the most common roles include "Developer" in the name.

Exercises:

- Can you figure out what percentage of respondents work in roles related to data science?
- Which positions have the highest percentage of women?

```
respondents1 = ['Data or business analyst',
                'Data scientist or machine learning specialist',
                'Engineer, data']
```

```
df1 = dev_type_df[respondents1]
```

```
df1
```

	Data or business analyst	Data scientist or machine learning specialist	Engineer, data
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
...	...	...	...
64456	False	False	False
64457	False	False	False
64458	False	False	False
64459	False	False	False
64460	False	False	False

64306 rows × 3 columns

```
df1.any(axis= 1).sum()
```

8635

```
df2 = 64306 - df1.any(axis= 1).sum()
```

```
df2
```

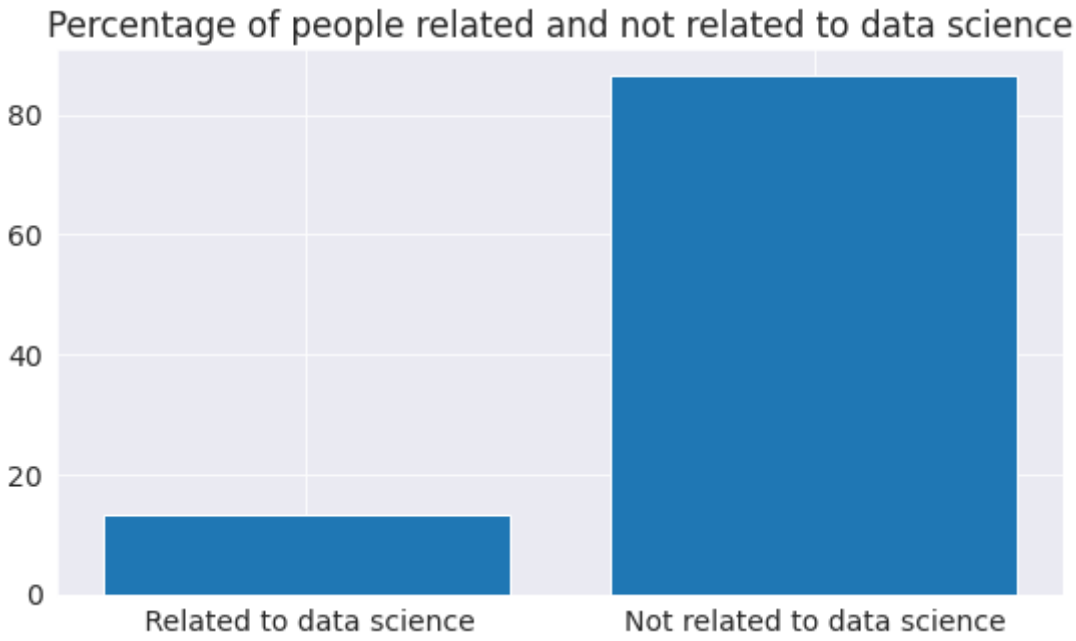
55671

```
values = [ df1.any(axis= 1).sum()* 100/ 64306 , df2 * 100/ 64306]
```

```
respondent = [ ' Related to data science' , 'Not related to data science']
```

```
plt.title('Percentage of people related and not related to data science')
plt.bar(respondent,values)
```

```
<BarContainer object of 2 artists>
```




```
female_df = survey_df[survey_df.Gender== 'Woman']
```

```
female_df
```

	Country	Age	Gender	EdLevel	UndergradMajor	Hobbyist	Age1stCode	YearsCode	YearsCodePro
34	United States	16.0	Woman	Bachelor's degree (B.A., B.S., B.Eng., etc.)	Information systems, information technology, o...	Yes	13.0	3.0	NaN
39	United States	20.0	Woman	Associate degree (A.A., A.S., etc.)	NaN	Yes	14.0	6.0	NaN
55	United States	27.0	Woman	Bachelor's degree (B.A., B.S., B.Eng., etc.)	A natural science (such as biology, chemistry,...	Yes	21.0	6.0	4.0
65	Canada	21.0	Woman	NaN	Computer science, computer engineering, or sof...	Yes	9.0	12.0	NaN
84	United States	21.0	Woman	Some college/university study without earning ...	Web development or web design	Yes	15.0	6.0	1.0
...	...	...	...	...	...	...	...	...	...

	Country	Age	Gender	EdLevel	UndergradMajor	Hobbyist	Age1stCode	YearsCode	YearsCodePro
64342	Nigeria	NaN	Woman	Some college/university study without earning ...	Web development or web design	Yes	20.0	4.0	3.0
64365	Iran	26.0	Woman	Bachelor's degree (B.A., B.S., B.Eng., etc.)	Computer science, computer engineering, or sof...	Yes	15.0	11.0	NaN
64373	Australia	19.0	Woman	Some college/university study without earning ...	Computer science, computer engineering, or sof...	Yes	14.0	7.0	1.0
64401	Poland	NaN	Woman	I never completed any formal education	NaN	Yes	NaN	NaN	NaN
64415	Myanmar	NaN	Woman	Secondary school (e.g. American high school, G...	NaN	Yes	11.0	5.0	29.0

3843 rows × 20 columns

```
fem_df = split_multicolumn(female_df.DevType)
```

```
fem_df.mean().sort_values(ascending=False) * 100
```

```
Developer, full-stack                             38.459537
Developer, back-end                               34.686443
Developer, front-end                              31.147541
Developer, mobile                                 11.969815
Developer, desktop or enterprise applications     11.293260
Designer                                           8.665105
Data scientist or machine learning specialist      7.962529
Data or business analyst                           7.338017
Developer, QA or test                              6.531356
Database administrator                             5.776737
Academic researcher                                5.568566
Engineer, data                                     4.839969
Educator                                           4.631798
Developer, embedded applications or devices        4.007286
DevOps specialist                                  4.007286
System administrator                               3.564923
Scientist                                          3.122560
Product manager                                    2.940411
Developer, game or graphics                        2.732240
Engineering manager                                2.524070
Marketing or sales professional                    1.665366
Engineer, site reliability                         1.587302
```

```
Senior executive/VP                                1.196982
dtype: float64
```

Highest percentage of woman are full stack web developer

We've only explored a handful of columns from the 20 columns that we selected. Explore and visualize the remaining columns using the empty cells below.

```
survey_raw_df.Ethnicity.value_counts().head(20)
```

```
White or of European descent
29318
South Asian
4467
Hispanic or Latino/a/x
2256
Black or of African descent
1690
Southeast Asian
1686
East Asian
1681
Middle Eastern
1622
Hispanic or Latino/a/x;White or of European descent
763
Middle Eastern;White or of European descent
378
Multiracial
292
Biracial
149
White or of European descent;Indigenous (such as Native American, Pacific Islander, or
Indigenous Australian)      102
South Asian;Southeast Asian
86
East Asian;Southeast Asian
70
White or of European descent;Multiracial
66
East Asian;White or of European descent
63
Indigenous (such as Native American, Pacific Islander, or Indigenous Australian)
61
Hispanic or Latino/a/x;White or of European descent;Multiracial
56
Black or of African descent;White or of European descent;Biracial
51
East Asian;South Asian
```

```
50
Name: Ethnicity, dtype: int64
```

What are the top DBMS ?

```
survey_raw_df.DatabaseWorkedWith.value_counts().head(5)
```

```
MySQL                          3827
Microsoft SQL Server           3298
PostgreSQL                     1937
SQLite                         1313
Microsoft SQL Server;MySQL     1158
MySQL;SQLite                   1080
MongoDB                         975
MariaDB;MySQL                   883
MySQL;PostgreSQL                864
MongoDB;MySQL                   819
Name: DatabaseWorkedWith, dtype: int64
```

What are the top programming languages ?

```
survey_raw_df.LanguageWorkedWith.value_counts().head(5)
```

```
HTML/CSS;JavaScript;PHP;SQL              1073
HTML/CSS;JavaScript                       900
C#;HTML/CSS;JavaScript;SQL                856
C#;HTML/CSS;JavaScript;SQL;TypeScript     754
HTML/CSS;JavaScript;TypeScript            697
Name: LanguageWorkedWith, dtype: int64
```

Let's save and upload our work before continuing.

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "tarif9351/python-eda-stackoverflow-survey" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/tarif9351/python-eda-stackoverflow-
survey
```

```
'https://jovian.com/tarif9351/python-eda-stackoverflow-survey'
```

Asking and Answering Questions

We've already gained several insights about the respondents and the programming community by exploring individual columns of the dataset. Let's ask some specific questions and try to answer them using data frame operations and visualizations.

Q: What are the most popular programming languages in 2020?

To answer, this we can use the `LanguageWorkedWith` column. Similar to `DevType`, respondents were allowed to choose multiple options here.

```
survey_df.LanguageWorkedWith
```

```
0                                    C#;HTML/CSS;JavaScript
1                                          JavaScript;Swift
2                                  Objective-C;Python;Swift
3                                                       NaN
4                                       HTML/CSS;Ruby;SQL
                                ...
64456                                                   NaN
64457    Assembly;Bash/Shell/PowerShell;C;C#;C++;Dart;G...
64458                                                   NaN
64459                                                HTML/CSS
64460                      C#;HTML/CSS;Java;JavaScript;SQL
Name: LanguageWorkedWith, Length: 64306, dtype: object
```

First, we'll split this column into a data frame containing a column of each language listed in the options.

```
languages_worked_df = split_multicolumn(survey_df.LanguageWorkedWith)
```

```
languages_worked_df
```

	C#	HTML/CSS	JavaScript	Swift	Objective-C	Python	Ruby	SQL	Java	PHP	...	VBA	Perl	Scala
0	True	True	True	False	False	False	False	False	False	False	...	False	False	False
1	False	False	True	True	False	False	False	False	False	False	...	False	False	False
2	False	False	False	True	True	True	False	False	False	False	...	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False
4	False	True	False	False	False	False	True	True	False	False	...	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
64456	False	False	False	False	False	False	False	False	False	False	...	False	False	False
64457	True	True	True	True	True	True	True	True	True	True	...	True	True	True
64458	False	False	False	False	False	False	False	False	False	False	...	False	False	False
64459	False	True	False	False	False	False	False	False	False	False	...	False	False	False
64460	True	True	True	False	False	False	False	True	True	False	...	False	False	False

64306 rows × 25 columns

It appears that a total of 25 languages were included among the options. Let's aggregate these to identify the percentage of respondents who selected each language.

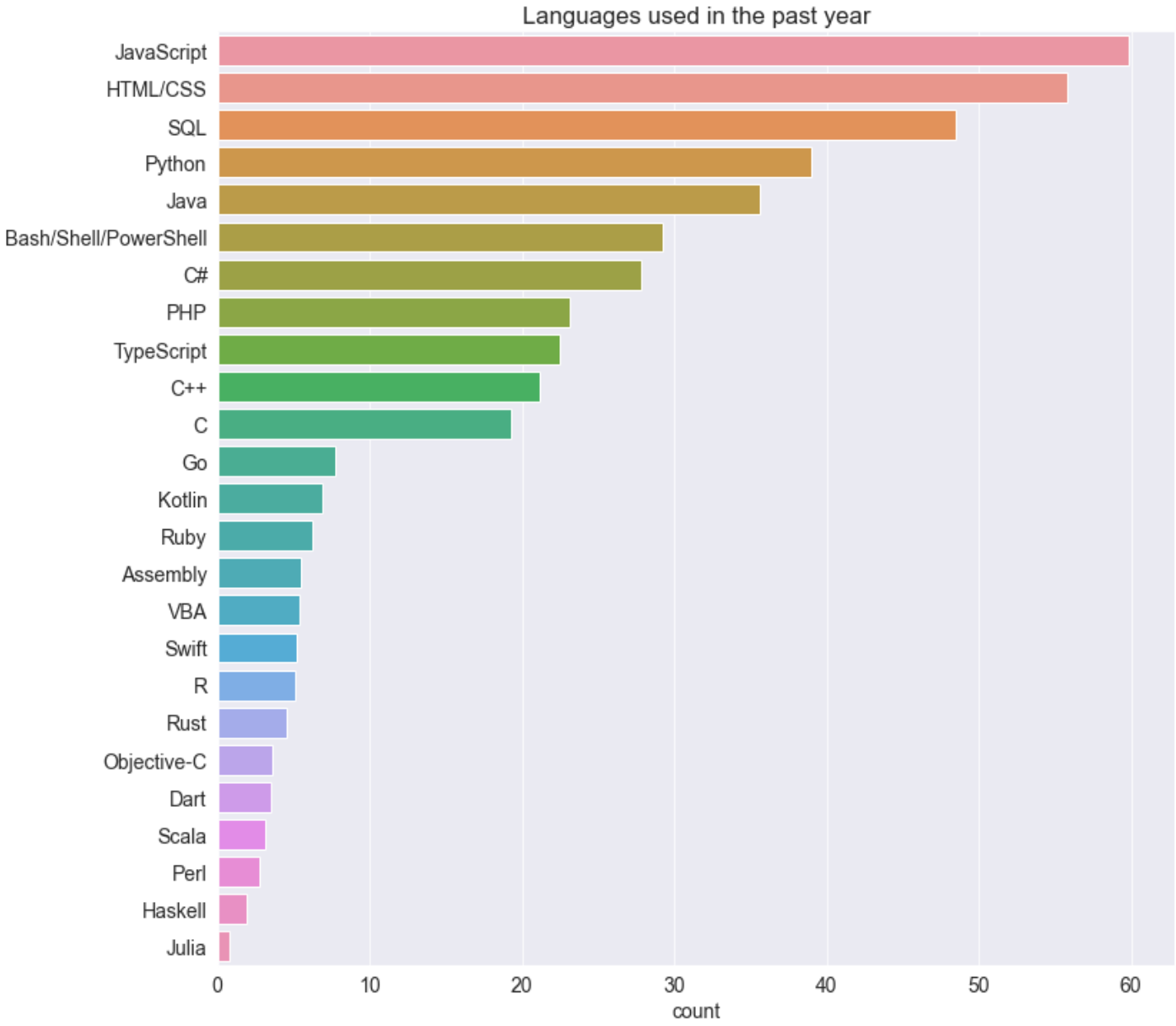
```
languages_worked_percentages = languages_worked_df.mean().sort_values(ascending=False)
languages_worked_percentages
```

```
JavaScript                59.893323
```

```
HTML/CSS                55.801947
SQL                     48.444935
Python                  39.001026
Java                    35.618760
Bash/Shell/PowerShell   29.239884
C#                      27.803004
PHP                     23.130035
TypeScript              22.461357
C++                     21.114670
C                       19.236152
Go                       7.758219
Kotlin                   6.887382
Ruby                     6.229590
Assembly                 5.447392
VBA                      5.394520
Swift                    5.226573
R                        5.064846
Rust                     4.498803
Objective-C              3.603085
Dart                     3.517557
Scala                    3.150561
Perl                     2.757130
Haskell                  1.861413
Julia                    0.782198
dtype: float64
```

We can plot this information using a horizontal bar chart.

```
plt.figure(figsize=(12, 12))
sns.barplot(x=languages_worked_percentages, y=languages_worked_percentages.index)
plt.title("Languages used in the past year");
plt.xlabel('count');
```



Perhaps unsurprisingly, Javascript & HTML/CSS comes out at the top as web development is one of today's most sought skills. It also happens to be one of the easiest to get started. SQL is necessary for working with relational databases, so it's no surprise that most programmers work with SQL regularly. Python seems to be the popular choice for other forms of development, beating out Java, which was the industry standard for server & application development for over two decades.

Exercises:

- What are the most common languages used by students? How does the list compare with the most common languages used by professional developers?
- What are the most common languages among respondents who do not describe themselves as "Developer, front-end"?
- What are the most common languages among respondents who work in fields related to data science?
- What are the most common languages used by developers older than 35 years of age?
- What are the most common languages used by developers in your home country?

Most Common language for students

```
employment_df = survey_df[survey_df.Employment == "Student"]
```

```
student_language_df = employment_df.LanguageWorkedWith
```

```
student_language_df1 = split_multicolumn(survey_df.LanguageWorkedWith)
```

```
student_language_df1.mean().sort_values(ascending=False) * 100
```

```
JavaScript              59.893563
HTML/CSS                55.805185
SQL                     48.455416
Python                  38.987758
Java                    35.622411
Bash/Shell/PowerShell   29.239267
C#                      27.813378
PHP                     23.140060
TypeScript              22.477541
C++                     21.109060
C                       19.234767
Go                       7.756280
Kotlin                   6.885851
Ruby                     6.224884
Assembly                 5.450652
VBA                      5.397899
Swift                    5.224124
R                        5.065864
Rust                     4.491784
Objective-C              3.602737
Dart                     3.517401
Scala                    3.154334
Perl                     2.758685
Haskell                  1.860328
Julia                    0.783541
dtype: float64
```

Most common language for students is javascript

Most Common language for People related to data science

```
most_used_language_df = survey_df[survey_df['DevType'].isin(respondents1)]
```

```
most_used_language_df1 = split_multicolumn(most_used_language_df.LanguageWorkedWith)
```

```
most_used_language_df1.mean().sort_values(ascending=False) * 100
```

```
Python                  72.228844
```

```
SQL                     55.899881
R                       30.393325
Bash/Shell/PowerShell   26.340882
HTML/CSS                25.148987
JavaScript              24.076281
Java                    21.573302
C++                     15.613826
C                       14.302741
VBA                     13.706794
C#                      10.369487
Scala                    8.104887
PHP                      6.793802
Go                       4.052443
Assembly                 3.218117
TypeScript               2.622169
Perl                     2.383790
Julia                    2.264601
Ruby                     2.264601
Haskell                  2.026222
Swift                    1.907032
Kotlin                   1.787843
Rust                     1.311085
Objective-C              1.072706
Dart                     1.072706
dtype: float64
```

People related to data science use mostly python

Most common language for people other than front end developers

```
most_used_language_nonwebdeveloper_df = survey_df[survey_df.DevType != "Developer, fron
```

```
most_used_language_nonwebdeveloper_df1 = split_multicolumn(most_used_language_nonwebdev
```

```
most_used_language_nonwebdeveloper_df1.mean().sort_values(ascending=False) * 100
```

```
JavaScript              59.328311
HTML/CSS                55.305487
SQL                     49.071778
Python                  39.589294
Java                    36.125946
Bash/Shell/PowerShell   29.615678
C#                      28.199504
PHP                     23.215080
TypeScript              22.121559
C++                     21.461949
C                       19.535571
Go                       7.872401
Kotlin                   7.001399
```

```
Ruby                    6.255960
Assembly                5.551847
VBA                     5.485091
Swift                   5.305487
R                       5.154492
Rust                    4.580711
Objective-C             3.657257
Dart                    3.568250
Scala                   3.213809
Perl                    2.811685
Haskell                 1.885053
Julia                   0.797889
dtype: float64
```

People other than front end developers use mostly javascript

Developers use mostly python who are related to data science

Q: Which languages are the most people interested to learn over the next year?

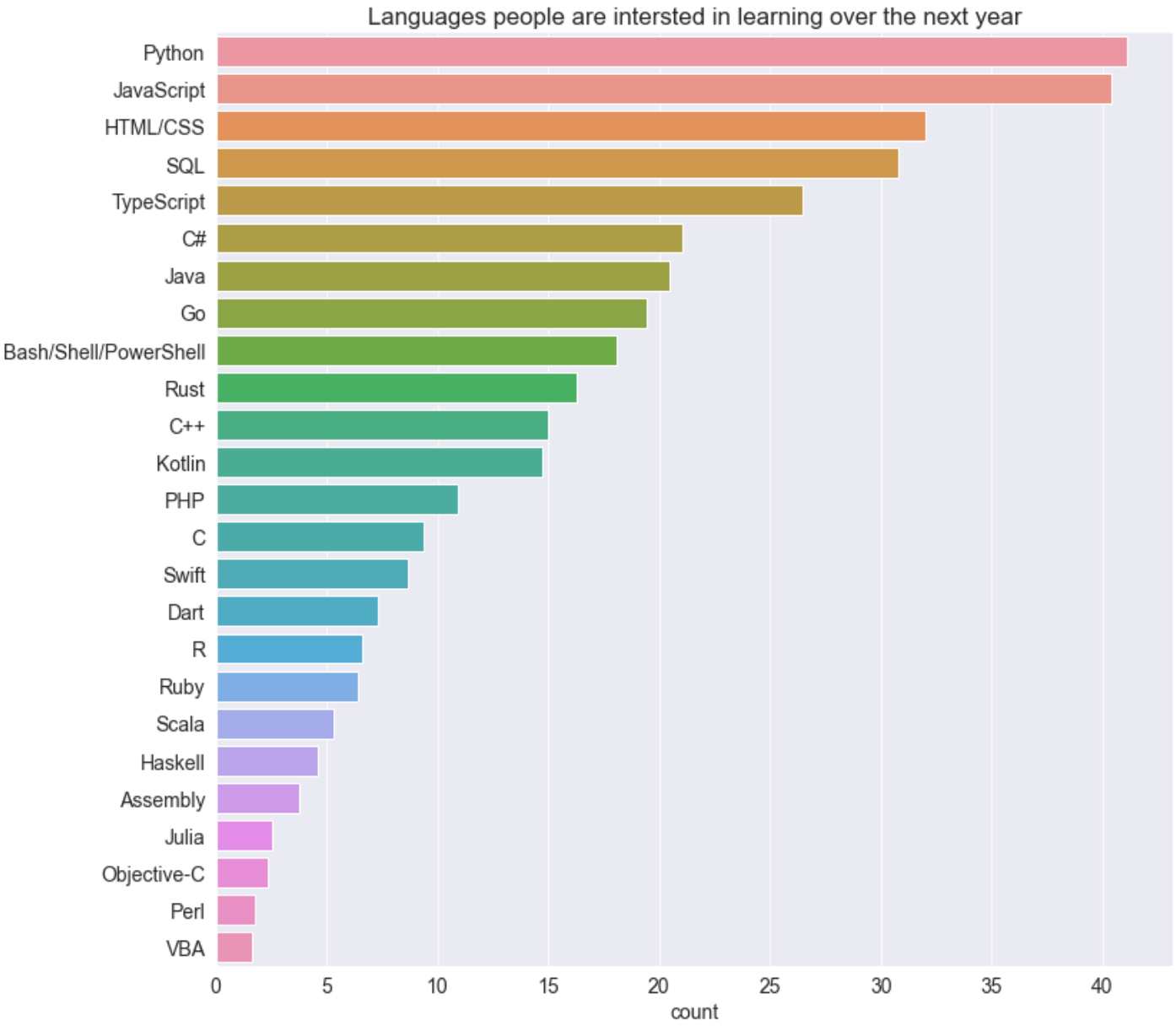
For this, we can use the `LanguageDesireNextYear` column, with similar processing as the previous one.

```
languages_interested_df = split_multicolumn(survey_df.LanguageDesireNextYear)
languages_interested_percentages = languages_interested_df.mean().sort_values(ascending
languages_interested_percentages
```

```
Python                  41.143906
JavaScript              40.425466
HTML/CSS                32.028116
SQL                     30.799614
TypeScript              26.451653
C#                      21.058688
Java                    20.464653
Go                      19.432090
Bash/Shell/PowerShell   18.057413
Rust                    16.270643
C++                     15.014151
Kotlin                  14.760676
PHP                     10.947657
C                        9.359935
Swift                    8.692812
Dart                     7.308805
R                        6.571704
Ruby                     6.425528
Scala                    5.326097
Haskell                  4.593662
Assembly                 3.766367
Julia                    2.540976
Objective-C              2.338818
Perl                     1.761888
```

```
VBA                             1.611047
dtype: float64
```

```
plt.figure(figsize=(12, 12))
sns.barplot(x=languages_interested_percentages, y=languages_interested_percentages.inde
plt.title("Languages people are intersted in learning over the next year");
plt.xlabel('count');
```



Once again, it's not surprising that Python is the language most people are interested in learning - since it is an easy-to-learn general-purpose programming language well suited for a variety of domains: application development, numerical computing, data analysis, machine learning, big data, cloud automation, web scraping, scripting, etc. We're using Python for this very analysis, so we're in good company!

Exercises: Repeat the exercises from the previous question, replacing "most common languages" with "languages people are interested in learning/using."

Q: Which are the most loved languages, i.e., a high percentage of people who have used the language want to continue learning & using it over the next year?

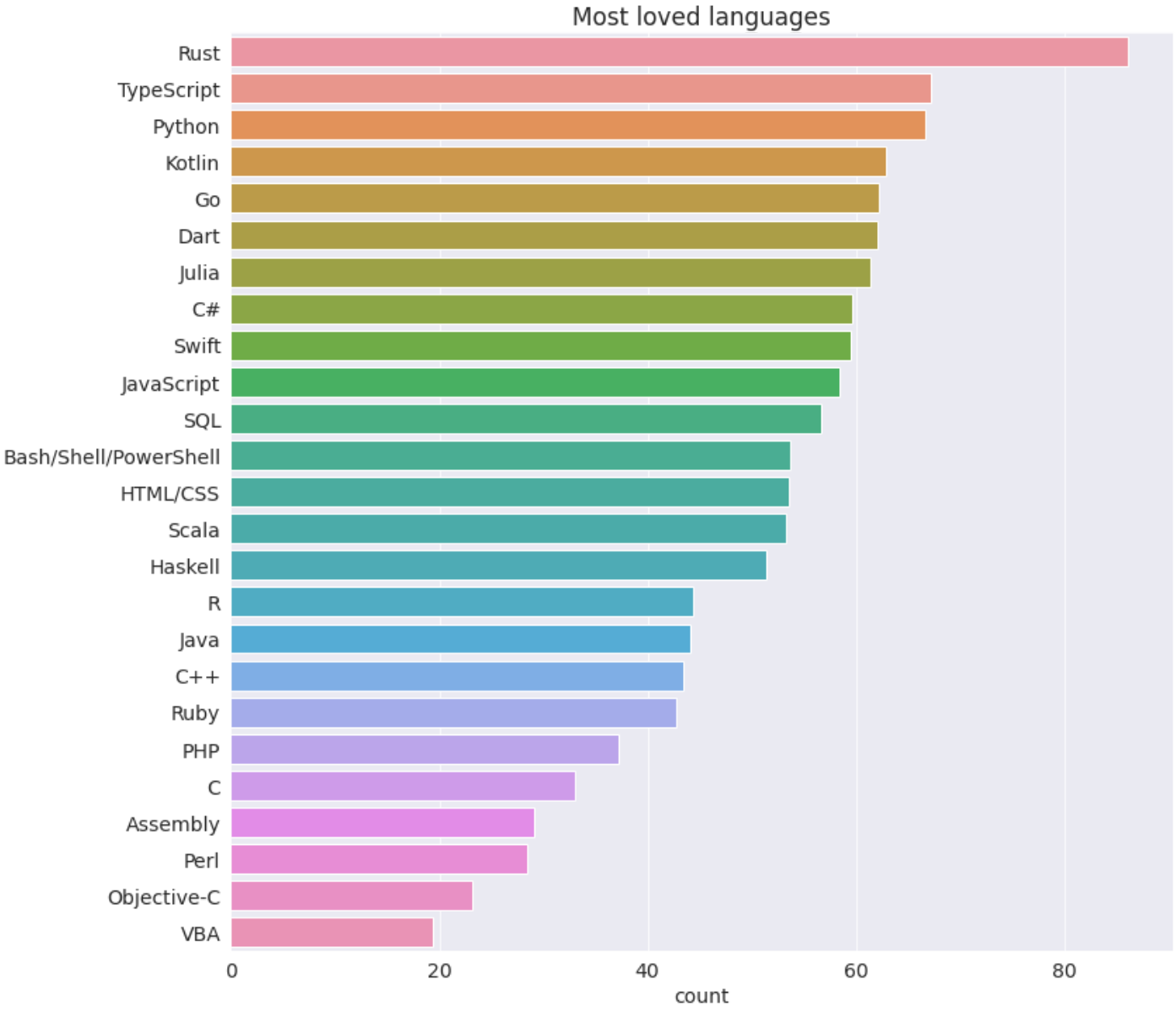
While this question may seem tricky at first, it's straightforward to solve using Pandas array operations. Here's what we can do:

- Create a new data frame `languages_loved_df` that contains a `True` value for a language only if the corresponding values in `languages_worked_df` and `languages_interested_df` are both `True`
- Take the column-wise sum of `languages_loved_df` and divide it by the column-wise sum of `languages_worked_df` to get the percentage of respondents who "love" the language
- Sort the results in decreasing order and plot a horizontal bar graph

```
languages_loved_df = languages_worked_df & languages_interested_df
```

```
languages_loved_percentages = (languages_loved_df.sum() * 100/ languages_worked_df.sum(
```

```
plt.figure(figsize=(12, 12))
sns.barplot(x=languages_loved_percentages, y=languages_loved_percentages.index)
plt.title("Most loved languages");
plt.xlabel('count');
```



Rust has been StackOverflow's most-loved language for four years in a row. The second most-loved language is TypeScript, a popular alternative to JavaScript for web development.

Python features at number 3, despite already being one of the most widely-used languages in the world. Python has a solid foundation, is easy to learn & use, has a large ecosystem of domain-specific libraries, and a massive worldwide community.

Exercises: What are the most dreaded languages, i.e., languages which people have used in the past year but do not want to learn/use over the next year. Hint: `~languages_interested_df` .

```
languages_dreaded_df = split_multicolumn(survey_df.LanguageDesireNextYear)
languages_dreaded_percentages = languages_interested_df.mean().sort_values(ascending=Tr
languages_dreaded_percentages
```

```
VBA                        1.611047
Perl                       1.761888
Objective-C                2.338818
Julia                      2.540976
Assembly                   3.766367
Haskell                    4.593662
Scala                      5.326097
Ruby                       6.425528
R                          6.571704
Dart                       7.308805
Swift                      8.692812
C                          9.359935
PHP                       10.947657
Kotlin                    14.760676
C++                       15.014151
Rust                      16.270643
Bash/Shell/PowerShell     18.057413
Go                        19.432090
Java                      20.464653
C#                        21.058688
TypeScript                26.451653
SQL                       30.799614
HTML/CSS                  32.028116
JavaScript                40.425466
Python                    41.143906
dtype: float64
```

Five most dreaded languages :

VBA,

Perl,

Objective-C,

Julia,

Assembly

Q: In which countries do developers work the highest number of hours per week? Consider countries with more than 250 responses only.

To answer this question, we'll need to use the `groupby` data frame method to aggregate the rows for each country. We'll also need to filter the results to only include the countries with more than 250 respondents.

```
countries_df = survey_df.groupby('Country')[['WorkWeekHrs']].mean().sort_values('WorkWe
```

```
high_response_countries_df = countries_df.loc[survey_df.Country.value_counts() > 250].h
```

```
high_response_countries_df
```

Country	WorkWeekHrs
Iran	44.337748
Israel	43.915094
China	42.150000
United States	41.802982
Greece	41.402724
Viet Nam	41.391667
South Africa	41.023460
Turkey	40.982143
Sri Lanka	40.612245
New Zealand	40.457551
Belgium	40.444444
Canada	40.208837
Hungary	40.194340
Bangladesh	40.097458
India	40.090603

The Asian countries like Iran, China, and Israel have the highest working hours, followed by the United States. However, there isn't too much variation overall, and the average working hours seem to be around 40 hours per week.

Exercises:

- How do the average work hours compare across continents? You may find this list of countries in each continent useful.
- Which role has the highest average number of hours worked per week? Which one has the lowest?
- How do the hours worked compare between freelancers and developers working full-time?

This part is left empty as the link is not working

Q: How important is it to start young to build a career in programming?

Let's create a scatter plot of `Age` vs. `YearsCodePro` (i.e., years of coding experience) to answer this question.

```
schema.YearsCodePro
```

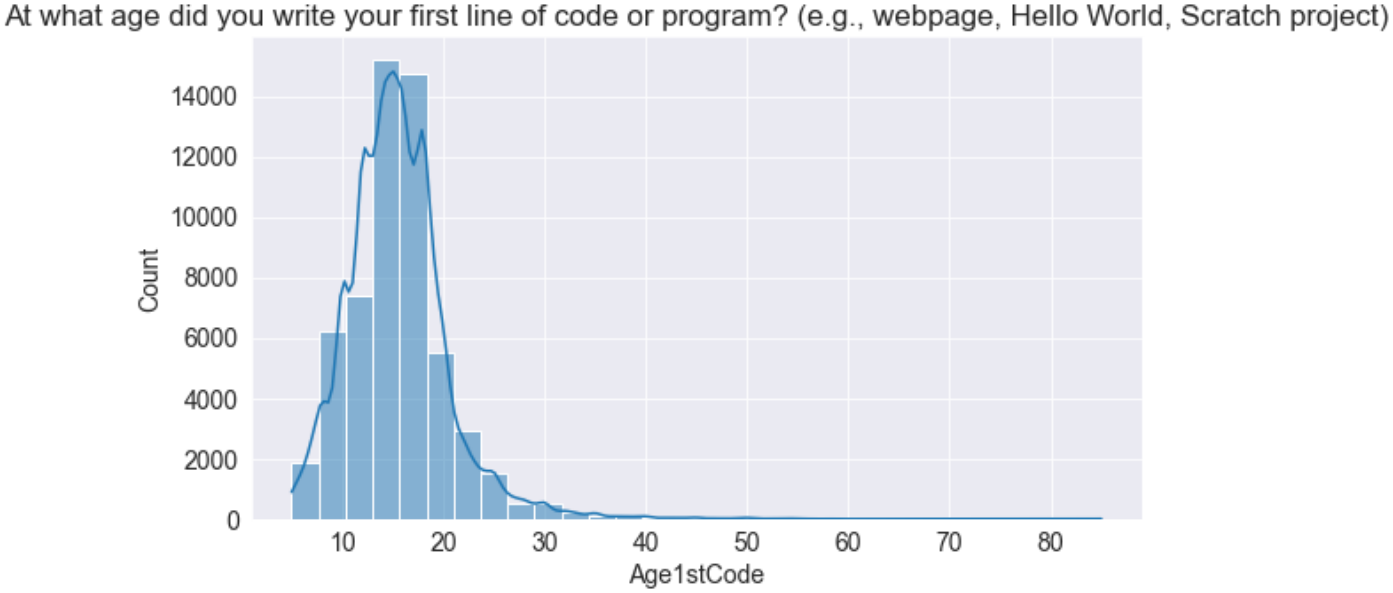
```
'NOT including education, how many years have you coded professionally (as a part of your work)?'
```

```
sns.scatterplot(x='Age', y='YearsCodePro', hue='Hobbyist', data=survey_df)
plt.xlabel("Age")
plt.ylabel("Years of professional coding experience");
```

You can see points all over the graph, which indicates that you can **start programming professionally at any age**. Many people who have been coding for several decades professionally also seem to enjoy it as a hobby.

We can also view the distribution of the `Age1stCode` column to see when the respondents tried programming for the first time.

```
plt.title(schema.Age1stCode)
sns.histplot(x=survey_df.Age1stCode, bins=30, kde=True);
```



As you might expect, most people seem to have had some exposure to programming before the age of 40. However, but there are people of all ages and walks of life learning to code.

Exercises:

- How does programming experience change opinions & preferences? Repeat the entire analysis while comparing the responses of people who have more than ten years of professional programming experience vs. those who don't. Do you see any interesting trends?
- Compare the years of professional coding experience across different genders.

```
pro_coder = survey_df[survey_df.YearsCode >= 10]
```

```
language_preffered_by_pro_df = split_multicolumn(pro_coder.LanguageDesireNextYear)
languages_by_pro_percentages = language_preffered_by_pro_df.mean().sort_values(ascendir
languages_by_pro_percentages
```

```
JavaScript               41.437597
Python                   40.375773
SQL                      34.315769
HTML/CSS                 33.994906
TypeScript               29.271278
C#                       24.640270
Bash/Shell/PowerShell    22.629089
Go                       21.527571
Rust                     20.161424
Java                     19.202143
Kotlin                   15.381562
C++                      14.065033
PHP                      10.330455
C                         9.348020
Swift                     8.616983
R                         6.503258
Ruby                      6.215474
Scala                     6.060005
Dart                      6.056697
Haskell                   5.190037
Assembly                  3.436869
Julia                     2.642982
Objective-C               2.335351
Perl                      2.017796
VBA                       1.617545
dtype: float64
```

```
not_pro_coder = survey_df[survey_df.YearsCode < 10]
```

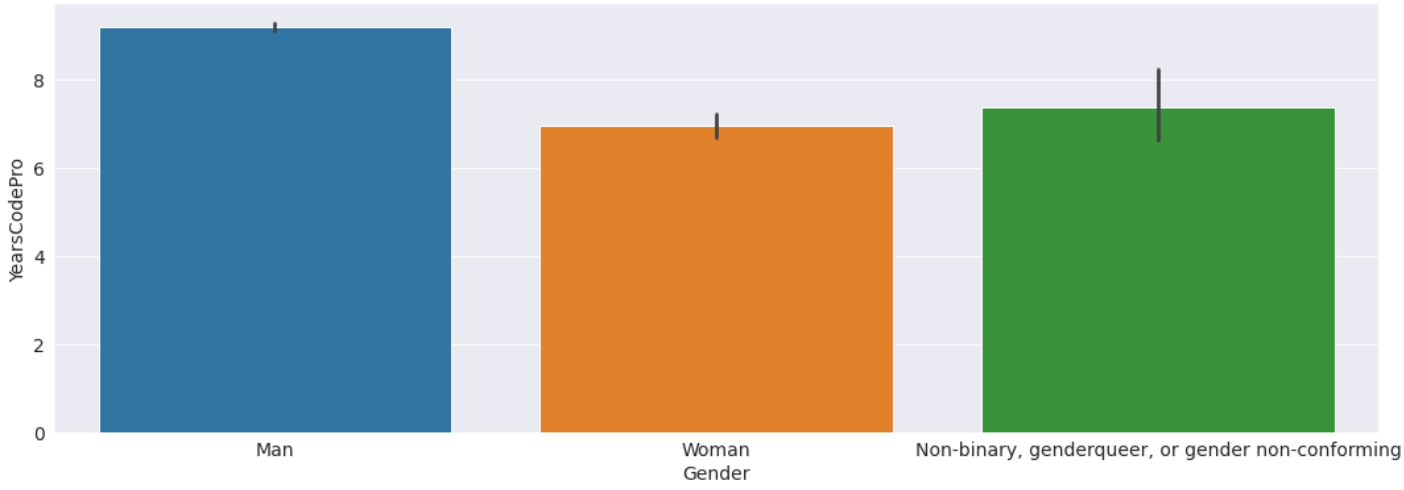
```
language_preffered_by_not_a_pro_df = split_multicolumn(not_pro_coder.LanguageDesireNext
languages_by_not_a_pro_percentages = language_preffered_by_pro_df.mean().sort_values(as
languages_by_not_a_pro_percentages
```

```
JavaScript                41.437597
Python                    40.375773
SQL                       34.315769
HTML/CSS                  33.994906
TypeScript                29.271278
C#                        24.640270
Bash/Shell/PowerShell     22.629089
Go                        21.527571
Rust                      20.161424
Java                      19.202143
Kotlin                    15.381562
C++                       14.065033
PHP                       10.330455
C                          9.348020
Swift                      8.616983
R                          6.503258
Ruby                       6.215474
Scala                      6.060005
Dart                       6.056697
Haskell                    5.190037
Assembly                   3.436869
Julia                      2.642982
Objective-C                2.335351
Perl                       2.017796
VBA                        1.617545
dtype: float64
```

Years of experiece varying across gender

```
plt.figure(figsize=(18, 6))
sns.barplot(data = survey_df , x= 'Gender', y= 'YearsCodePro')
```

```
<AxesSubplot:xlabel='Gender', ylabel='YearsCodePro'>
```



Hopefully, you are already thinking of many more questions you'd like to answer using this data. Use the empty cells below to ask and answer more questions.

Let's save and commit our work before continuing

```
import jovian
```

```
jovian.commit()
```

Inferences and Conclusions

We've drawn many inferences from the survey. Here's a summary of a few of them:

- Based on the survey respondents' demographics, we can infer that the survey is somewhat representative of the overall programming community. However, it has fewer responses from programmers in non-English-speaking countries and women & non-binary genders.
- The programming community is not as diverse as it can be. Although things are improving, we should make more efforts to support & encourage underrepresented communities, whether in terms of age, country, race, gender, or otherwise.
- Although most programmers hold a college degree, a reasonably large percentage did not have computer science as their college major. Hence, a computer science degree isn't compulsory for learning to code or building a career in programming.
- A significant percentage of programmers either work part-time or as freelancers, which can be a great way to break into the field, especially when you're just getting started.
- Javascript & HTML/CSS are the most used programming languages in 2020, closely followed by SQL & Python.
- Python is the language most people are interested in learning - since it is an easy-to-learn general-purpose programming language well suited for various domains.
- Rust and TypeScript are the most "loved" languages in 2020, both of which have small but fast-growing communities. Python is a close third, despite already being a widely used language.
- Programmers worldwide seem to be working for around 40 hours a week on average, with slight variations by country.
- You can learn and start programming professionally at any age. You're likely to have a long and fulfilling career if you also enjoy programming as a hobby.

Exercises

There's a wealth of information to be discovered using the survey, and we've barely scratched the surface. Here are some ideas for further exploration:

- Repeat the analysis for different age groups & genders, and compare the results
- Pick a different set of columns (we chose 20 out of 65) to analyze other facets of the data
- Prepare an analysis focusing on diversity - and identify areas where underrepresented communities are at par with the majority (e.g., education) and where they aren't (e.g., salaries)
- Compare the results of this year's survey with the previous years and identify interesting trends

References and Future Work

Check out the following resources to learn more about the dataset and tools used in this notebook:

- Stack Overflow Developer Survey: https://insights.stackoverflow.com/survey
- Pandas user guide: https://pandas.pydata.org/docs/user_guide/index.html
- Matplotlib user guide: https://matplotlib.org/3.3.1/users/index.html
- Seaborn user guide & tutorial: https://seaborn.pydata.org/tutorial.html
- `opendatasets` Python library: https://github.com/JovianML/opendatasets

As a next step, you can try out a project on another dataset of your choice: https://jovian.ml/aakashns/zerotopandas-course-project-starter .

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "tarif9351/python-eda-stackoverflow-survey" on https://jovian.com
[jovian] Committed successfully! https://jovian.com/tarif9351/python-eda-stackoverflow-survey
```

```
'https://jovian.com/tarif9351/python-eda-stackoverflow-survey'
```

```

```