Exploratory Data Analysis of StackOverFlow Survery on Salaries of Various Coding Background Professions

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import altair as alt
from sklearn.model_selection import train_test_split

alt.data_transformers.enable('data_server')
alt.renderers.enable('mimetype')
```

Out[1]:
```
RendererRegistry.enable('mimetype')
```

Functions used

In [2]:
```
# Returns True if 'data' in a string , else returns False
def data_in_text(x):
    if type(x) is str:
        return 'data' in x
    else:
        return False


# Returns float values for different string inputs
def convert2float(x):
    if  x == 'More than 50 years' :
        return float(50)
    elif x == 'Less than 1 year':
        return float(0)
    else:
        return float(x)
```

Summary of the dataset

The goal of the project is to create a machine learning model by busing the job related information from the collected dataset, to predict the target `ConvertedCompYearly`, which is the converted yearly compensation for the Data scientist/analysis related jobs in the US and Canada.
The final model will be a regression model as the target will be a continuous variable.

In [3]:
```
survey_df = pd.read_csv("data/survey_results_public.csv")
```

In [4]:
```
survey_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73268 entries, 0 to 73267
Data columns (total 79 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
```

```
 0   ResponseId                      73268 non-null  int64
 1   MainBranch                      73268 non-null  object
 2   Employment                      71709 non-null  object
 3   RemoteWork                      58958 non-null  object
 4   CodingActivities                58899 non-null  object
 5   EdLevel                         71571 non-null  object
 6   LearnCode                       71580 non-null  object
 7   LearnCodeOnline                 50685 non-null  object
 8   LearnCodeCoursesCert            29389 non-null  object
 9   YearsCode                       71331 non-null  object
 10  YearsCodePro                    51833 non-null  object
 11  DevType                         61302 non-null  object
 12  OrgSize                         51039 non-null  object
 13  PurchaseInfluence               50969 non-null  object
 14  BuyNewTool                      67963 non-null  object
 15  Country                         71771 non-null  object
 16  Currency                        51264 non-null  object
 17  CompTotal                       38422 non-null  float64
 18  CompFreq                        44425 non-null  object
 19  LanguageHaveWorkedWith          70975 non-null  object
 20  LanguageWantToWorkWith          67027 non-null  object
 21  DatabaseHaveWorkedWith          60121 non-null  object
 22  DatabaseWantToWorkWith          51014 non-null  object
 23  PlatformHaveWorkedWith          49924 non-null  object
 24  PlatformWantToWorkWith          40415 non-null  object
 25  WebframeHaveWorkedWith          53544 non-null  object
 26  WebframeWantToWorkWith          46122 non-null  object
 27  MiscTechHaveWorkedWith          44992 non-null  object
 28  MiscTechWantToWorkWith          36810 non-null  object
 29  ToolsTechHaveWorkedWith         54171 non-null  object
 30  ToolsTechWantToWorkWith         46566 non-null  object
 31  NEWCollabToolsHaveWorkedWith    70347 non-null  object
 32  NEWCollabToolsWantToWorkWith    64108 non-null  object
 33  OpSysProfessional use           65503 non-null  object
 34  OpSysPersonal use               70963 non-null  object
 35  VersionControlSystem            71379 non-null  object
 36  VCInteraction                   68156 non-null  object
 37  VCHostingPersonal use           0 non-null      float64
 38  VCHostingProfessional use       0 non-null      float64
 39  OfficeStackAsyncHaveWorkedWith  46223 non-null  object
 40  OfficeStackAsyncWantToWorkWith  32072 non-null  object
 41  OfficeStackSyncHaveWorkedWith   62128 non-null  object
 42  OfficeStackSyncWantToWorkWith   47688 non-null  object
 43  Blockchain                      71071 non-null  object
 44  NEWSOSites                      71365 non-null  object
 45  SOVisitFreq                     70961 non-null  object
 46  SOAccount                       71572 non-null  object
 47  SOPartFreq                      58229 non-null  object
 48  SOComm                          71408 non-null  object
 49  Age                             70946 non-null  object
 50  Gender                          70853 non-null  object
 51  Trans                           70315 non-null  object
 52  Sexuality                       66565 non-null  object
 53  Ethnicity                       69474 non-null  object
 54  Accessibility                   67244 non-null  object
 55  MentalHealth                    66447 non-null  object
 56  TBranch                         52670 non-null  object
 57  ICorPM                          36283 non-null  object
 58  WorkExp                         36769 non-null  float64
 59  Knowledge_1                     35804 non-null  object
 60  Knowledge_2                     34973 non-null  object
 61  Knowledge_3                     35133 non-null  object
 62  Knowledge_4                     35097 non-null  object
 63  Knowledge_5                     35014 non-null  object
 64  Knowledge_6                     34991 non-null  object
 65  Knowledge_7                     34977 non-null  object
```

```
 66   Frequency_1                      35371 non-null   object
 67   Frequency_2                      35344 non-null   object
 68   Frequency_3                      34515 non-null   object
 69   TimeSearching                    36198 non-null   object
 70   TimeAnswering                    36022 non-null   object
 71   Onboarding                       35679 non-null   object
 72   ProfessionalTech                 34906 non-null   object
 73   TrueFalse_1                      35819 non-null   object
 74   TrueFalse_2                      35715 non-null   object
 75   TrueFalse_3                      35749 non-null   object
 76   SurveyLength                     70444 non-null   object
 77   SurveyEase                       70508 non-null   object
 78   ConvertedCompYearly              38071 non-null   float64
dtypes: float64(5), int64(1), object(73)
memory usage: 44.2+ MB
```

As we can see there are 79 columns and 73268 rows.

In [5]:
```
survey_df['Country'].value_counts()[:10].to_frame().style.set_caption('Table 1. Counts o
```

Out[5]:

Table 1. Counts of observation for top ten countries

	Country
United States of America	13543
India	6639
Germany	5395
United Kingdom of Great Britain and Northern Ireland	4190
Canada	2490
France	2328
Brazil	2109
Poland	1732
Netherlands	1555
Spain	1521

Since we want to focus on the data points for US and Canada, data scientist/analysis related jobs, we filter the dataset by `United States of America` and `Canada`.

In [6]:
```
north_america_data = survey_df.query("Country == 'United States of America' or Country =
```

In [7]:
```
north_america_data.shape
```

Out[7]:
```
(16033, 79)
```

Since we don't need all the features from the dataset, thus we will only keep the remaining ones for the prediction purpose:

- MainBranch
- Employment
- RemoteWork
- EdLevel
- YearCode
- YearCodePro
- DevType

- OrgSize
- Country
- LanguageHaveWorkedWith
- DatabaseHaveWorkedWith
- PlatformHaveWorkedWith
- WebframeHaveWorkedWith
- MiscTechHaveWorkedWith
- ToolTechHaveWorkedWith
- NEWCollabToolsHaveWorkedWith
- OpSysProfessional use
- VersionControlSystem
- VCInteraction
- OfficeStackAsyncHaveWorkedWith
- Age
- WorkExp
- Icorpm

In [8]:
```
cols_to_choose = ['MainBranch',
'Employment',
'RemoteWork',
'EdLevel',
'YearsCode',
'YearsCodePro',
'DevType',
'OrgSize',
'Country',
'LanguageHaveWorkedWith',
'DatabaseHaveWorkedWith',
'PlatformHaveWorkedWith',
'WebframeHaveWorkedWith',
'MiscTechHaveWorkedWith',
'ToolsTechHaveWorkedWith',
'NEWCollabToolsHaveWorkedWith',
'OpSysProfessional use',
'VersionControlSystem',
'VCInteraction',
'OfficeStackAsyncHaveWorkedWith',
'Age',
'WorkExp',
'ICorPM',
'ConvertedCompYearly']
```

In [9]:
```
north_america_data = north_america_data[cols_to_choose]
```

In [10]:
```
multianswerq_cols = [
'DevType',
'LanguageHaveWorkedWith',
'DatabaseHaveWorkedWith',
'PlatformHaveWorkedWith',
'WebframeHaveWorkedWith',
'MiscTechHaveWorkedWith',
'ToolsTechHaveWorkedWith',
'NEWCollabToolsHaveWorkedWith',
'OpSysProfessional use',
'VCInteraction',
'VersionControlSystem',
'OfficeStackAsyncHaveWorkedWith',
'Employment']
```

Split data set into training and test splits

In [11]:
```
train_df, test_df = train_test_split(north_america_data, test_size=0.2, random_state=123


train_df = train_df.dropna(subset=['ConvertedCompYearly'])
```

Data Wranging

In [12]:
```
train_df['YearsCode'] = train_df['YearsCode'].apply(lambda x: convert2float(x))

train_df['YearsCodePro'] = train_df['YearsCodePro'].apply(lambda x: convert2float(x))
```

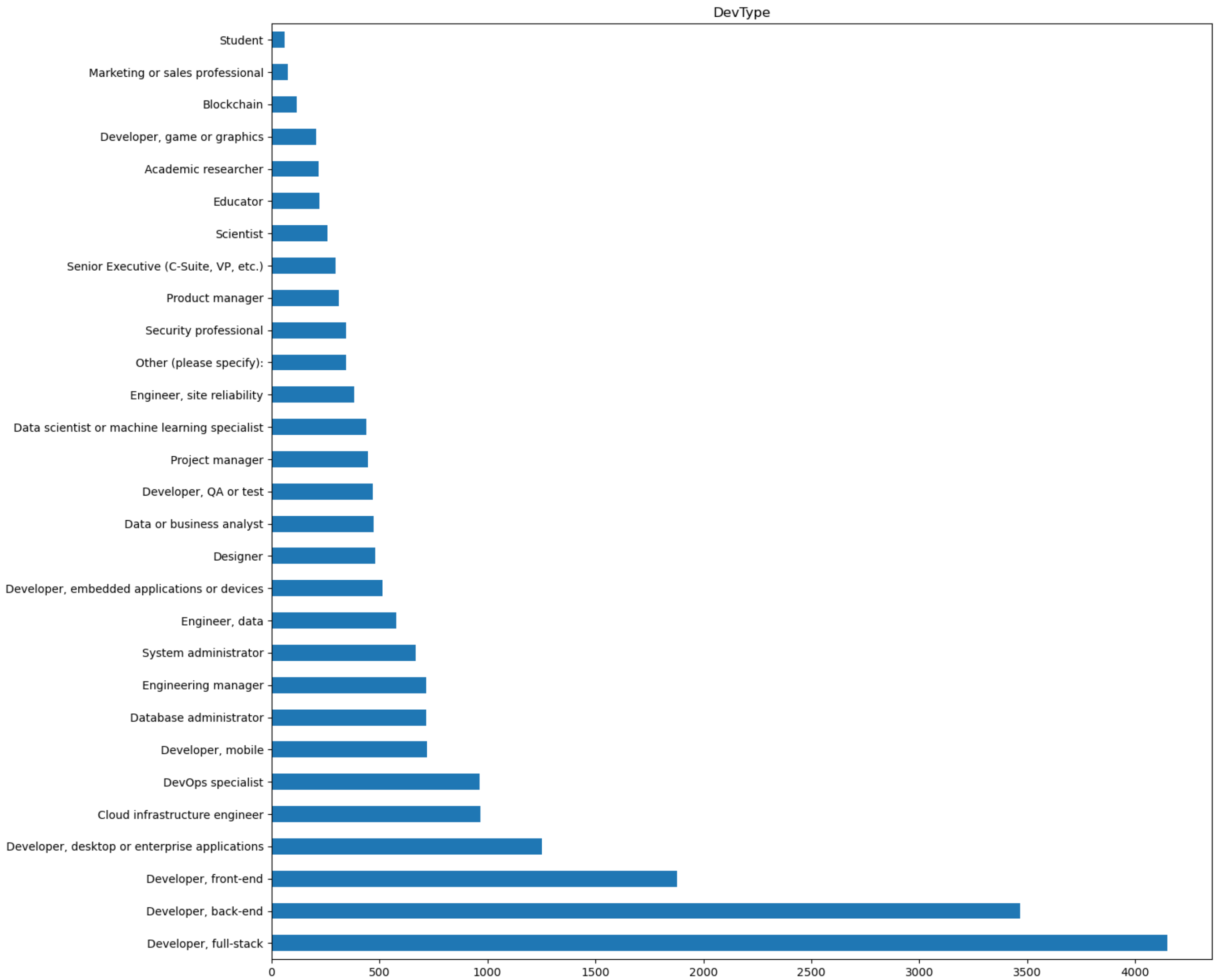
EDA on the Training Dataset

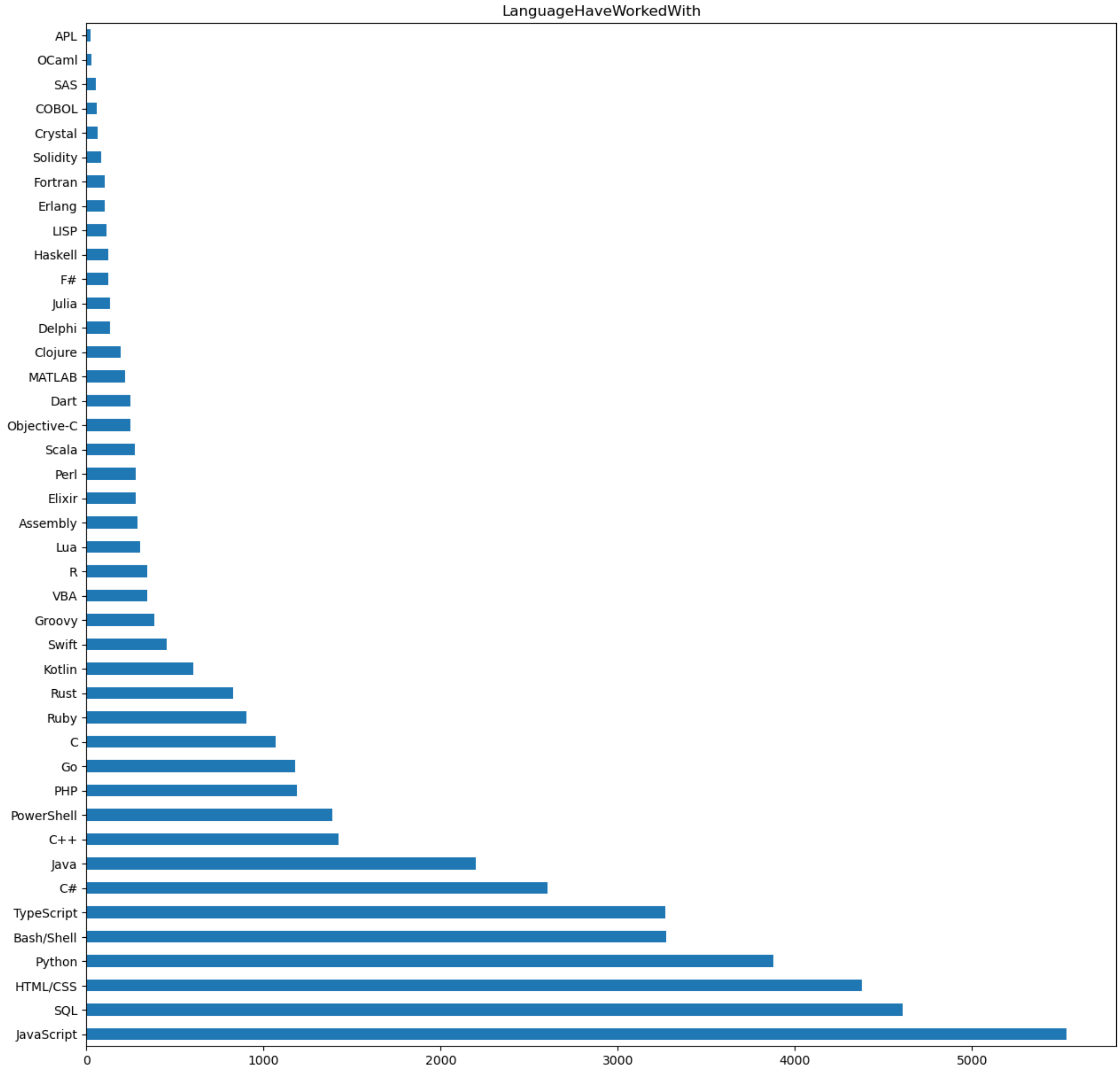
Coding for all the charts

In [13]:
```
converted_comp_hist = alt.Chart(train_df).mark_bar().encode(
    x=alt.X('ConvertedCompYearly', bin=alt.Bin(maxbins=30)),
    y='count()'
)

years_code = alt.Chart(train_df).mark_rect().encode(
    alt.X('YearsCode', bin=alt.Bin(maxbins=40)),
    alt.Y('ConvertedCompYearly', bin=alt.Bin(maxbins=40)),
    alt.Color('count()'))

years_code_pro = alt.Chart(train_df).mark_rect().encode(
    alt.X('YearsCodePro', bin=alt.Bin(maxbins=40)),
    alt.Y('ConvertedCompYearly', bin=alt.Bin(maxbins=40)),
    alt.Color('count()')
)


work_exp = alt.Chart(train_df).mark_rect().encode(
    alt.X('WorkExp', bin=alt.Bin(maxbins=40)),
    alt.Y('ConvertedCompYearly', bin=alt.Bin(maxbins=40)),
    alt.Color('count()'))

columns = ['Country', 'ICorPM', 'RemoteWork', 'OrgSize', 'EdLevel']

multi_bar_plot = alt.Chart(train_df).mark_bar().encode(
    y=alt.Y(alt.repeat(), sort='x'),
    x='median(ConvertedCompYearly)'
).repeat(columns, columns=2)

corr_table = train_df.corr().style.background_gradient().set_caption('Table 2. Correlati
```

In [14]:
```
# only for plotting
plotting_dataset  = train_df.copy()
for col in multianswerq_cols:
    plotting_dataset = plotting_dataset.dropna(subset=[col])
```

```
    plotting_dataset[col] = plotting_dataset[col].apply(lambda x: x.split(';'))
    boom_data = plotting_dataset.explode(col)
    boom_data[col].value_counts().plot.barh(title = col, figsize  = [15, 15])
    plt.show()
```





LanguageHaveWorkedWith
APL
OCaml
SAS
COBOL
Crystal
Solidity
Fortran
Erlang
LISP
Haskell
F#
Julia
Delphi
Clojure
MATLAB
Dart
Objective-C
Scala
Perl
Elixir
Assembly
Lua
R
VBA
Groovy
Swift
Kotlin
Rust
Ruby
C
Go
PHP
PowerShell
C++
Java
C#
TypeScript
Bash/Shell
Python
HTML/CSS
SQL
JavaScript
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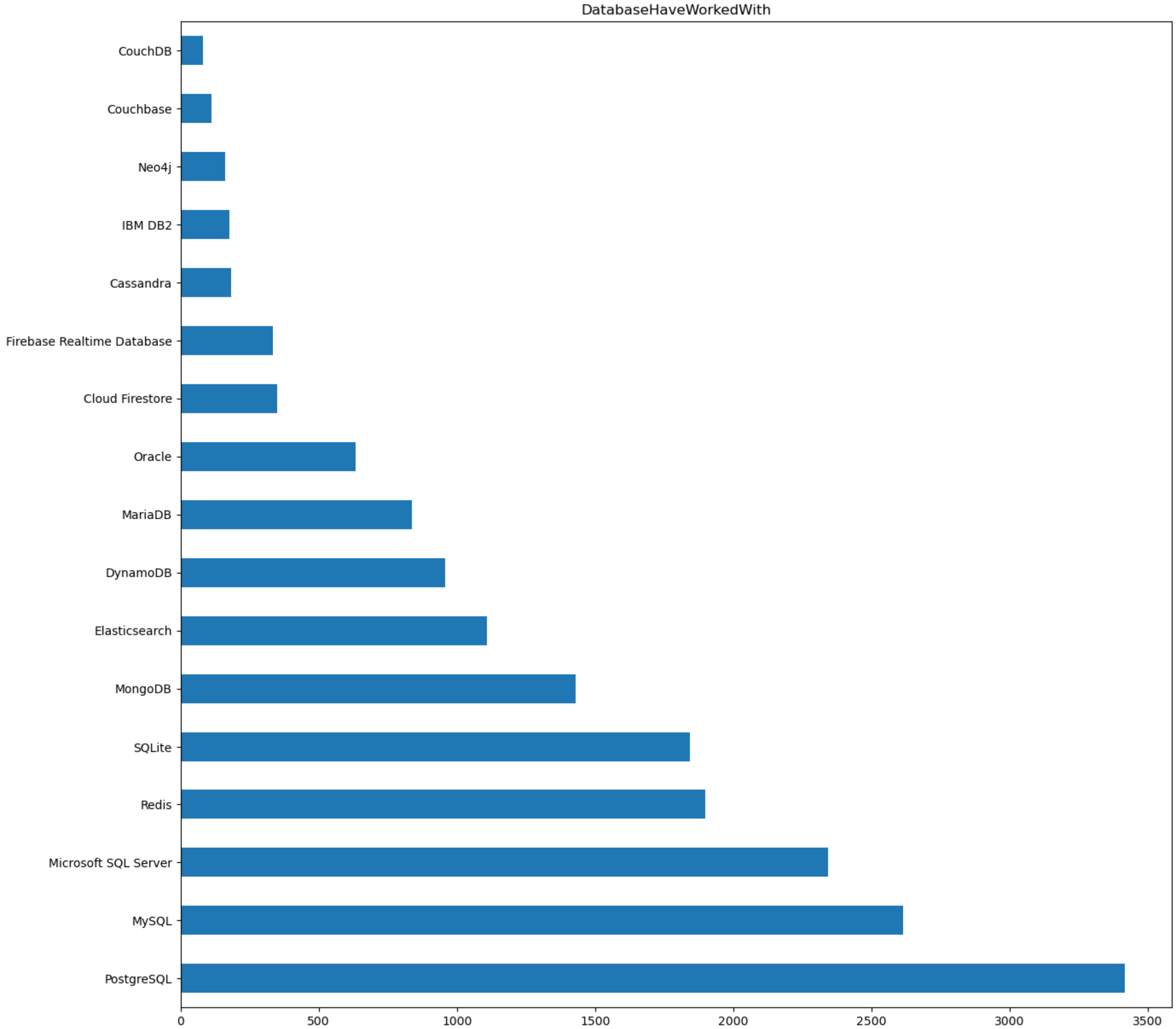
DatabaseHaveWorkedWith
CouchDB
Couchbase
Neo4j
IBM DB2
Cassandra
Firebase Realtime Database
Cloud Firestore
Oracle
MariaDB
DynamoDB
Elasticsearch
MongoDB
SQLite
Redis
Microsoft SQL Server
MySQL
PostgreSQL
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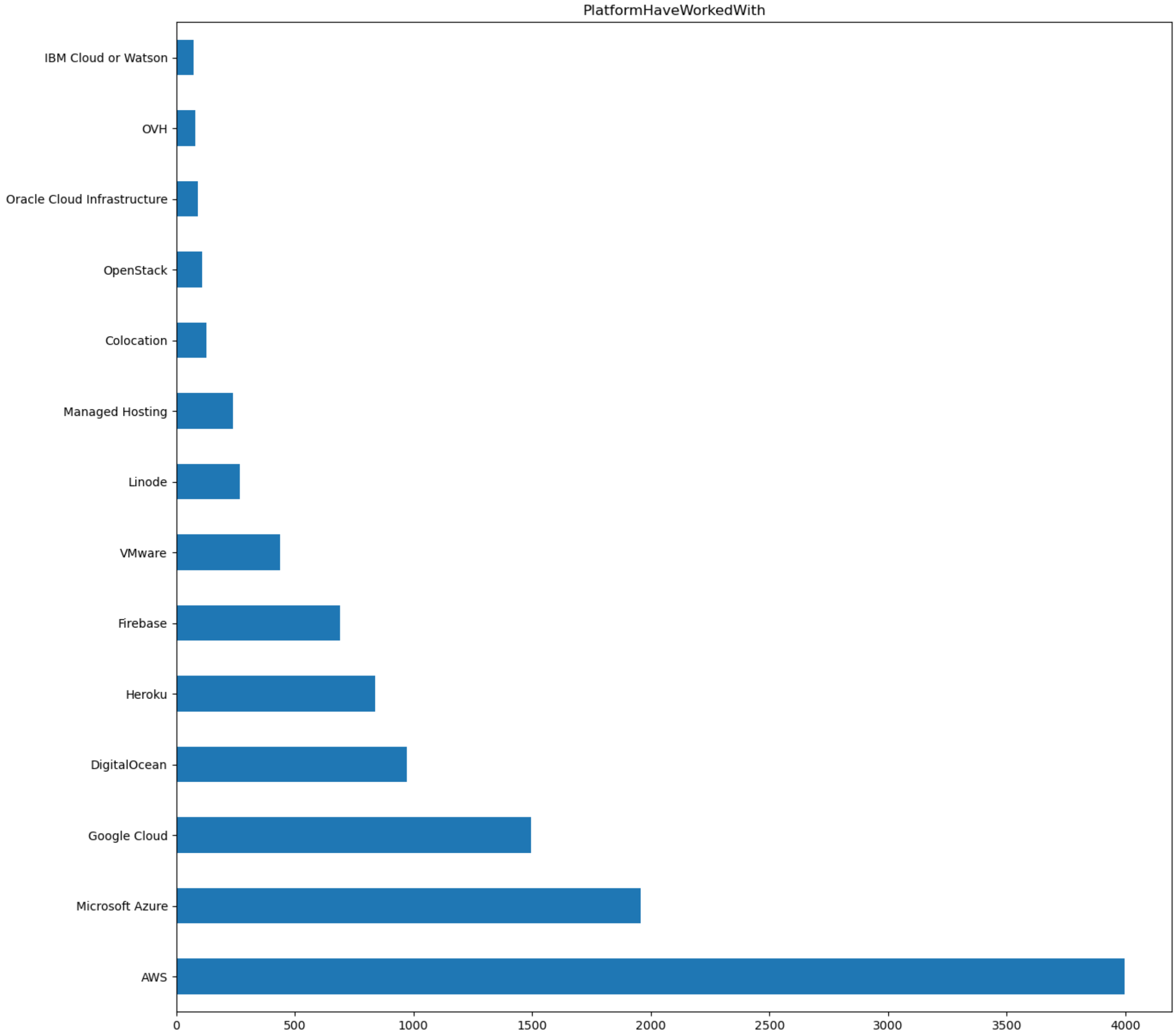
PlatformHaveWorkedWith
IBM Cloud or Watson
OVH
Oracle Cloud Infrastructure
OpenStack
Colocation
Managed Hosting
Linode
VMware
Firebase
Heroku
DigitalOcean
Google Cloud
Microsoft Azure
AWS
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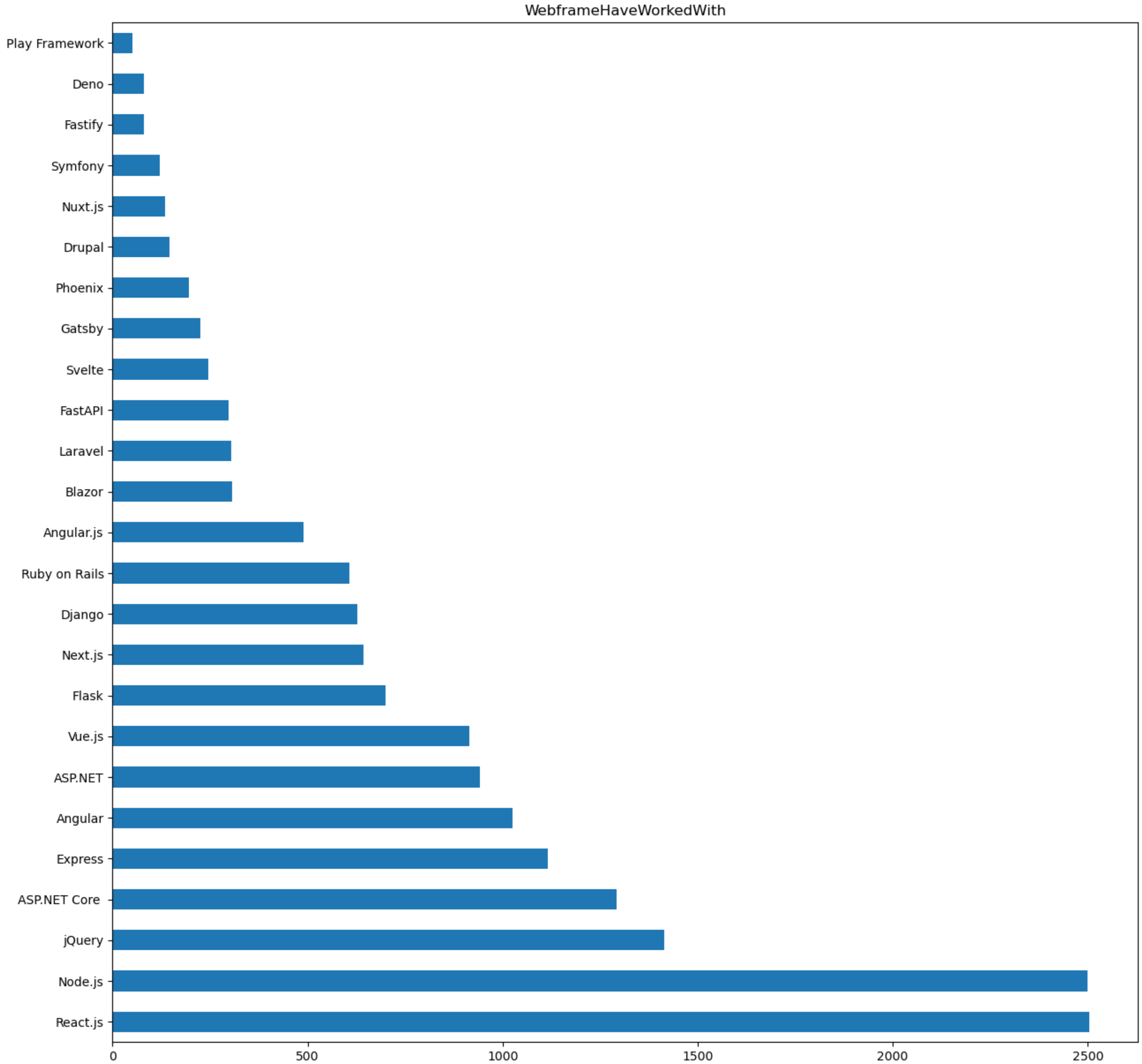
WebframeHaveWorkedWith
Play Framework
Deno
Fastify
Symfony
Nuxt.js
Drupal
Phoenix
Gatsby
Svelte
FastAPI
Laravel
Blazor
Angular.js
Ruby on Rails
Django
Next.js
Flask
Vue.js
ASP.NET
Angular
Express
ASP.NET Core
jQuery
Node.js
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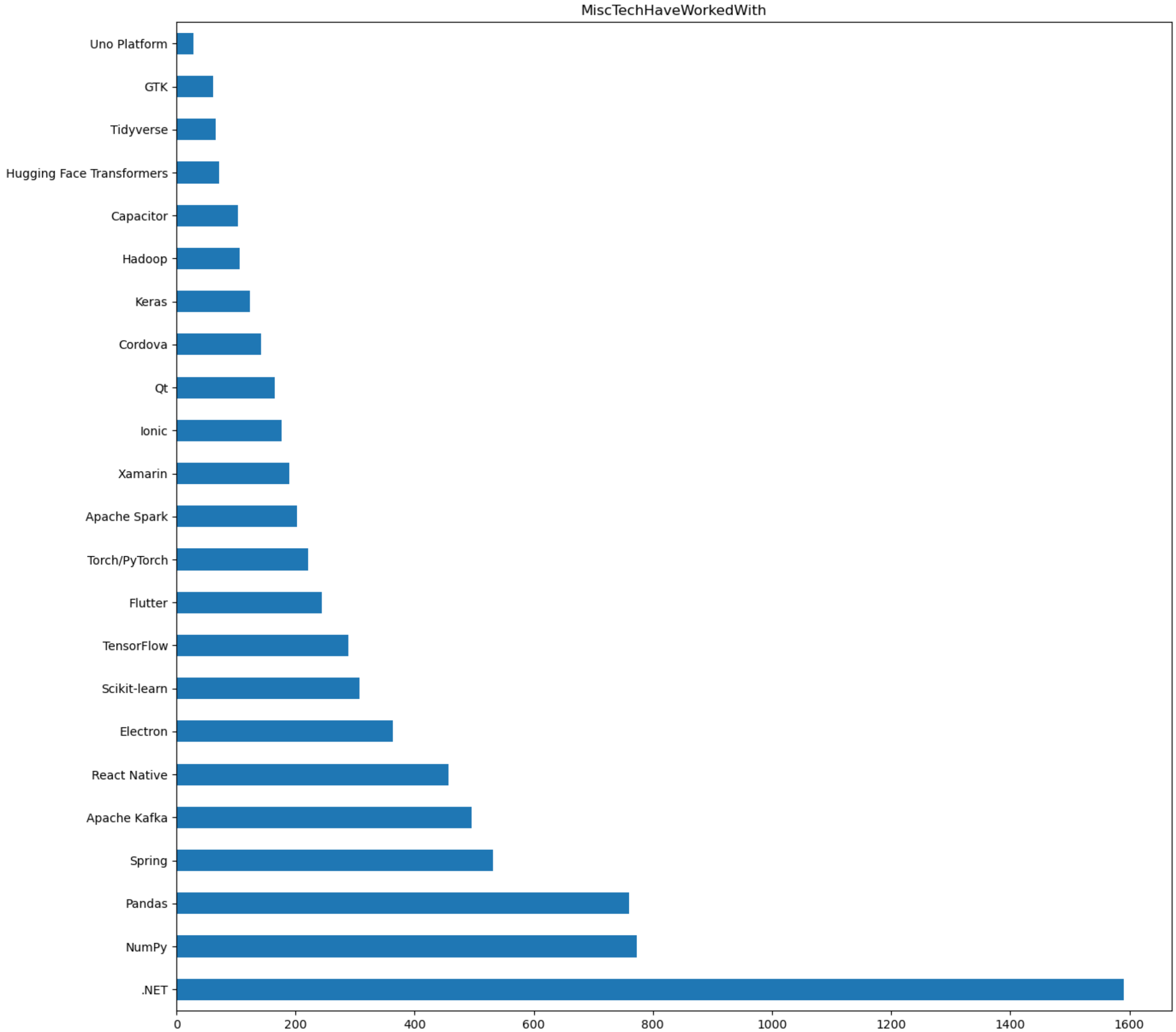
MiscTechHaveWorkedWith
Uno Platform
GTK
Tidyverse
Hugging Face Transformers
Capacitor
Hadoop
Keras
Cordova
Qt
Ionic
Xamarin
Apache Spark
Torch/PyTorch
Flutter
TensorFlow
Scikit-learn
Electron
React Native
Apache Kafka
Spring
Pandas
NumPy
.NET
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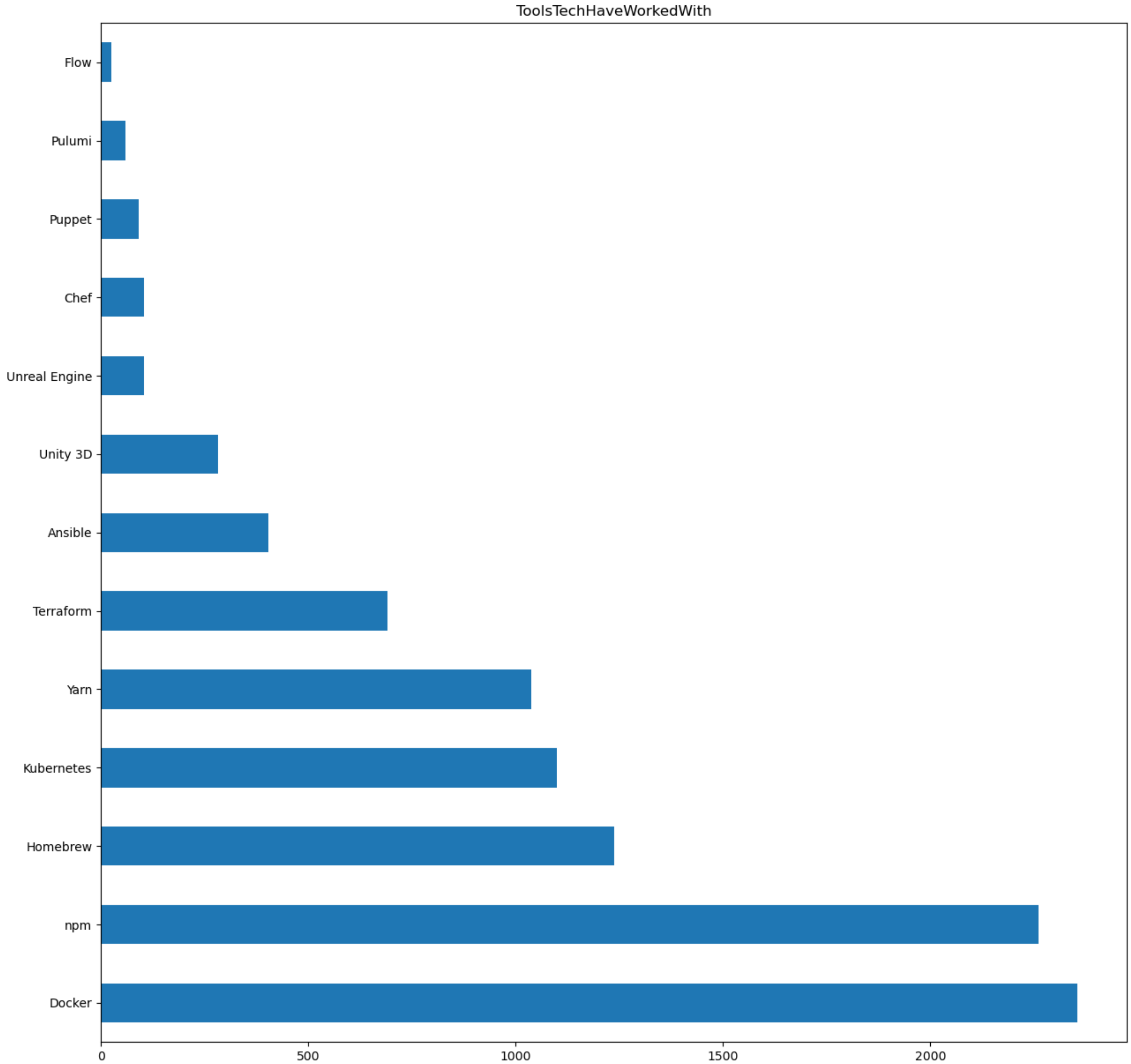
ToolsTechHaveWorkedWith
Flow
Pulumi
Puppet
Chef
Unreal Engine
Unity 3D
Ansible
Terraform
Yarn
Kubernetes
Homebrew
npm
Docker
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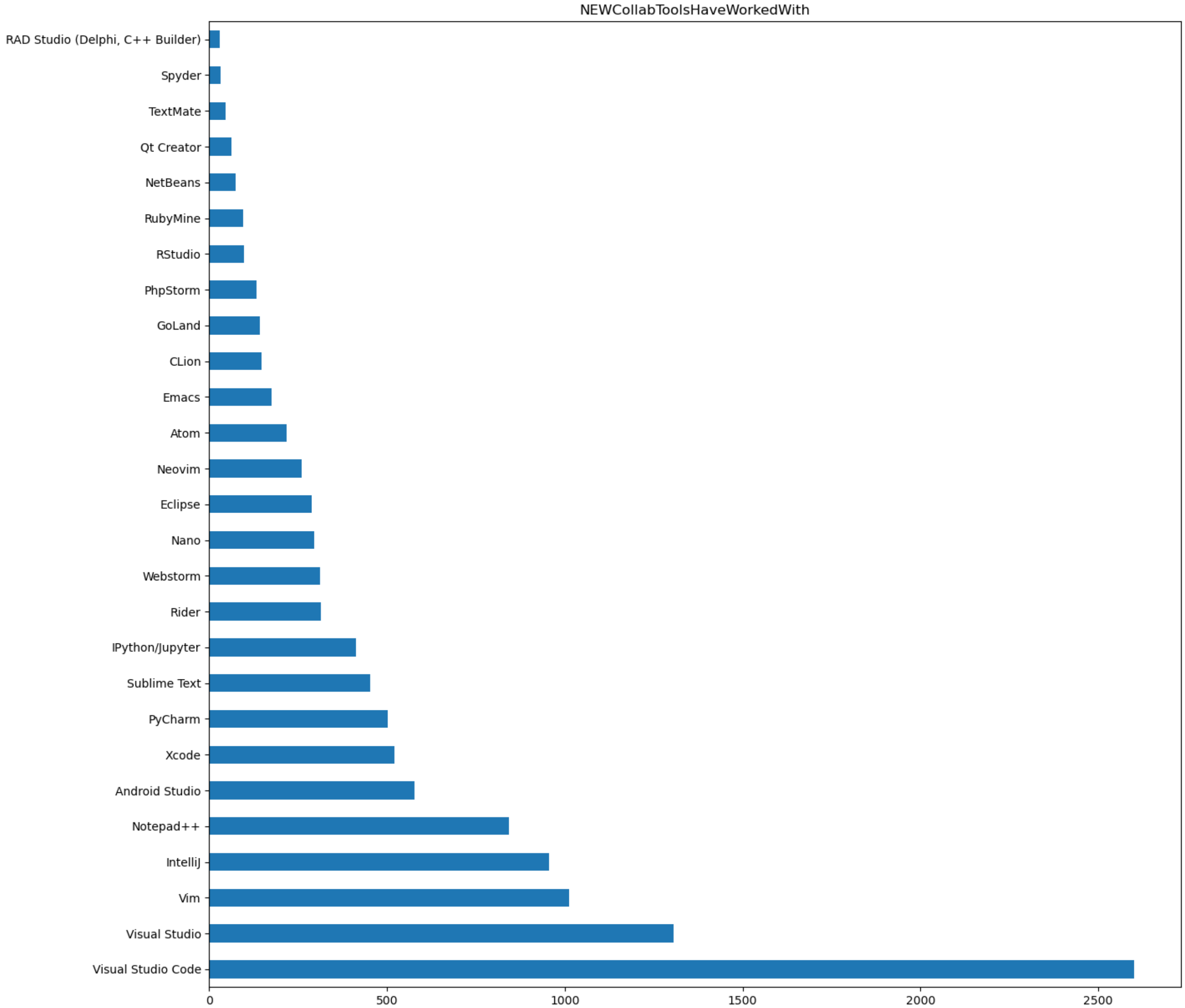
NEWCollabToolsHaveWorkedWith
RAD Studio (Delphi, C++ Builder)
Spyder
TextMate
Qt Creator
NetBeans
RubyMine
RStudio
PhpStorm
GoLand
CLion
Emacs
Atom
Neovim
Eclipse
Nano
Webstorm
Rider
IPython/Jupyter
Sublime Text
PyCharm
Xcode
Android Studio
Notepad++
IntelliJ
Vim
Visual Studio
Visual Studio Code
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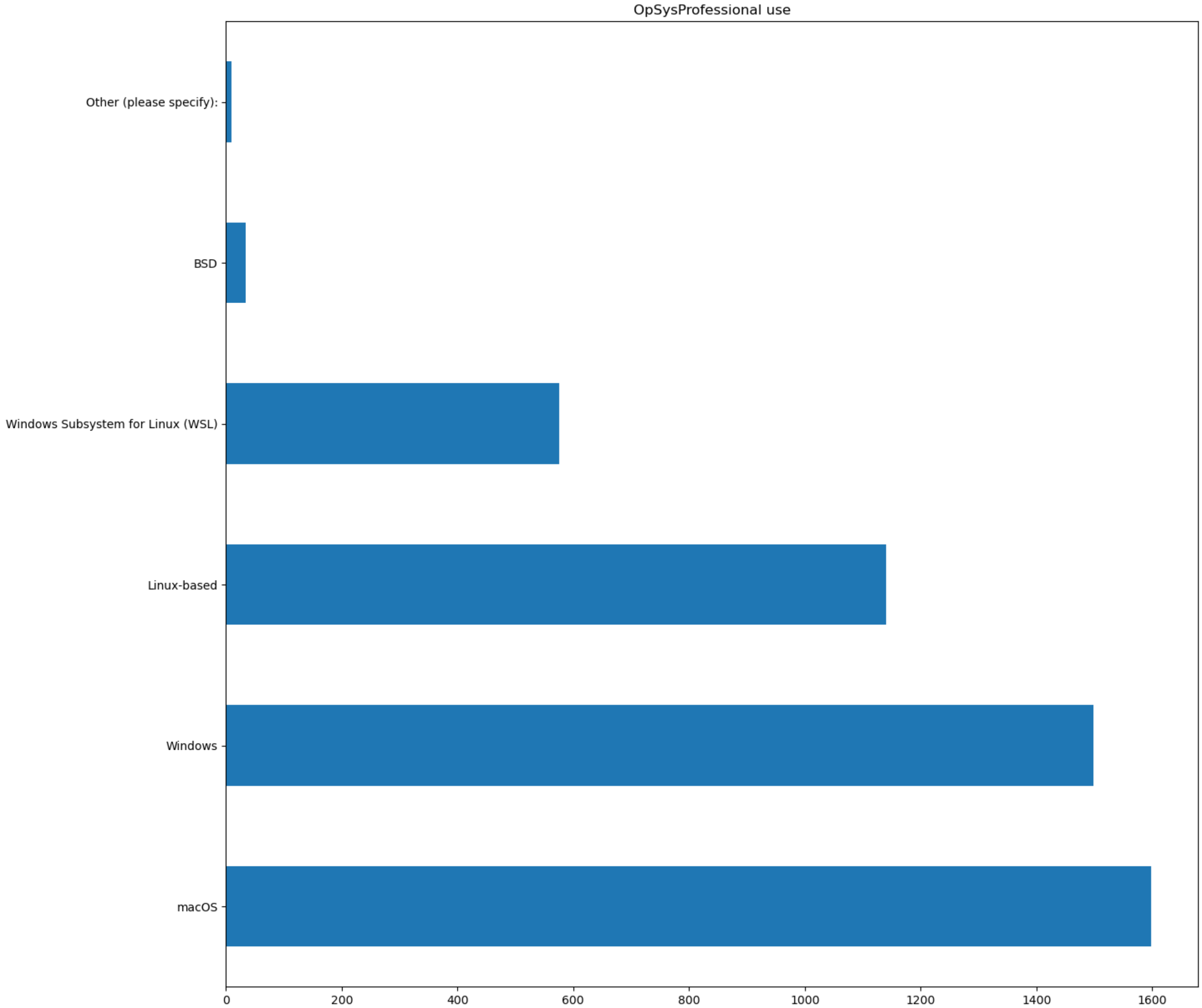
OpSysProfessional use
Other (please specify):
BSD
Windows Subsystem for Linux (WSL)
Linux-based
Windows
macOS
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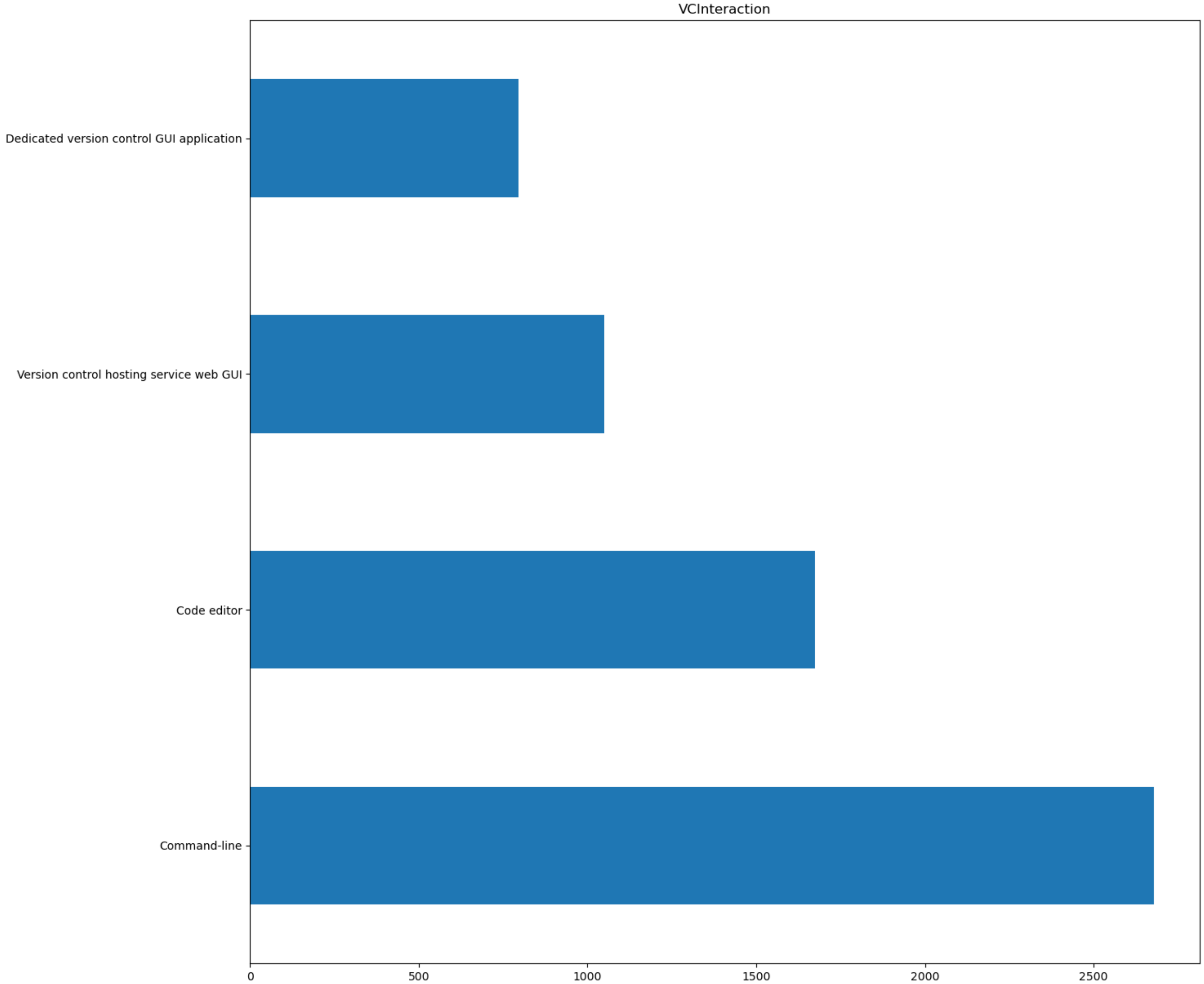

VCInteraction
Dedicated version control GUI application
Version control hosting service web GUI
Code editor
Command-line
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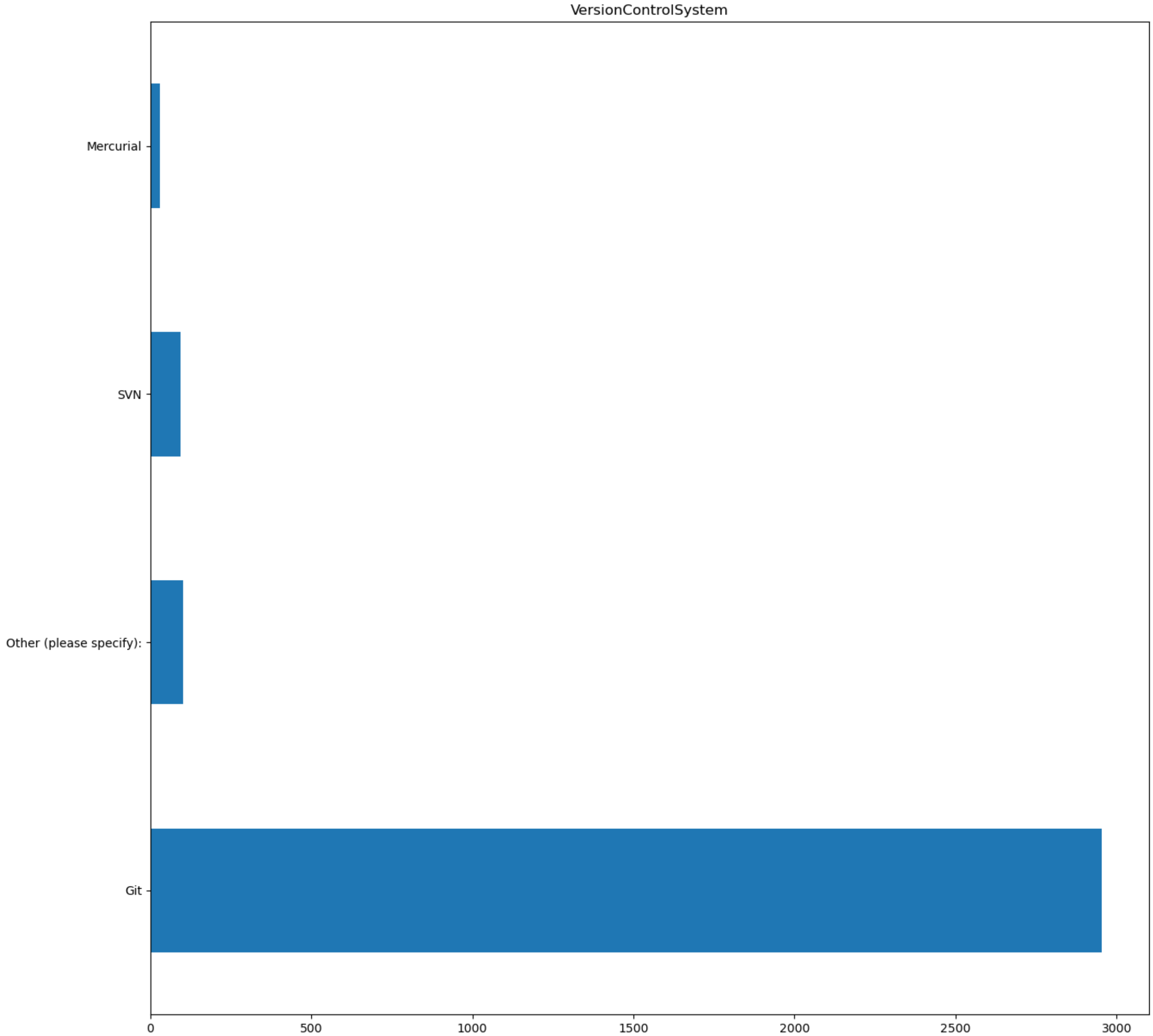
VersionControlSystem
Mercurial
SVN
Other (please specify):
Git
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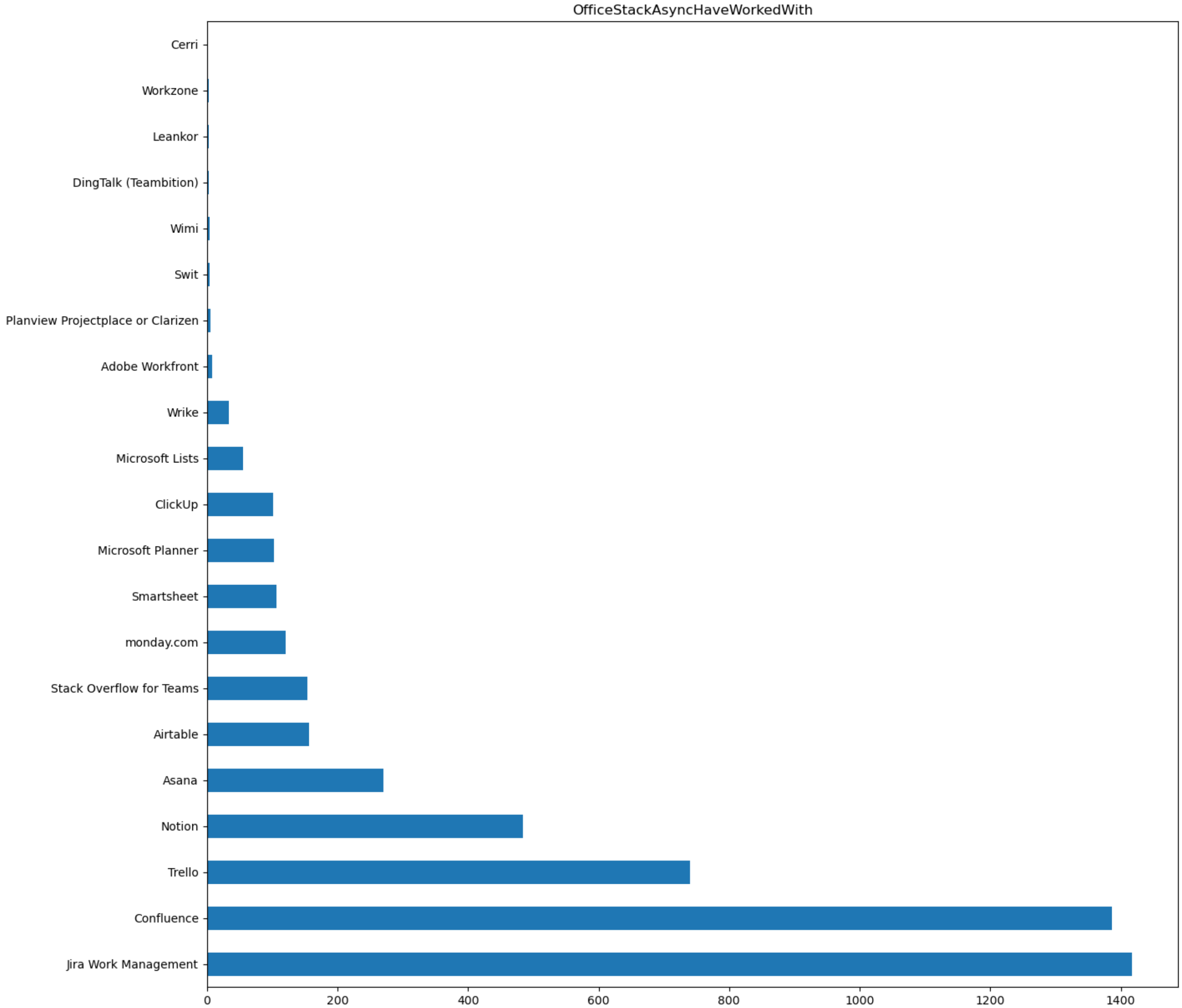
OfficeStackAsyncHaveWorkedWith
Cerri
Workzone
Leankor
DingTalk (Teambition)
Wimi
Swit
Planview Projectplace or Clarizen
Adobe Workfront
Wrike
Microsoft Lists
ClickUp
Microsoft Planner
Smartsheet
monday.com
Stack Overflow for Teams
Airtable
Asana
Notion
Trello
Confluence
Jira Work Management
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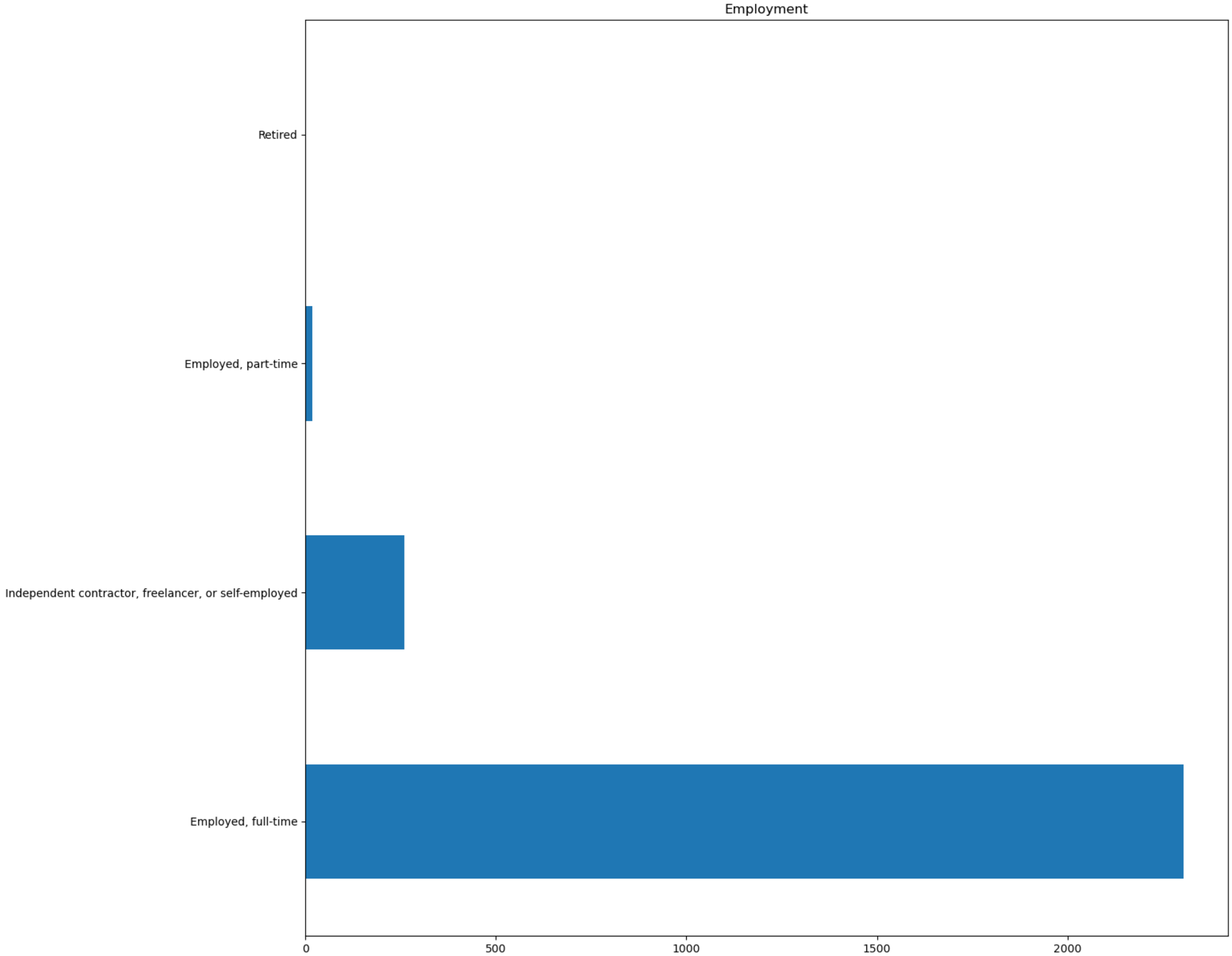
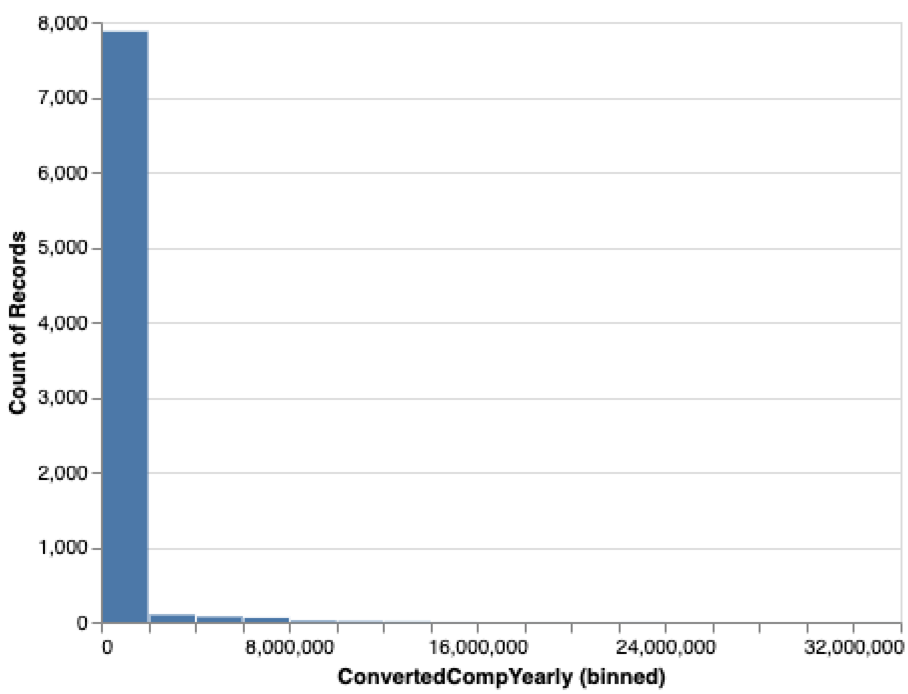


Taking the look at the distribution in our plots, all these features can be used in our model by one hot encoding them. There are a lot of missing values, we will try various imputation techniques to deal with this issue. For class imbalance issues, we will try to club classes having very few counts or make use undersampling/oversampling techniques

In [15]:
```
converted_comp_hist
```

Out[15]:



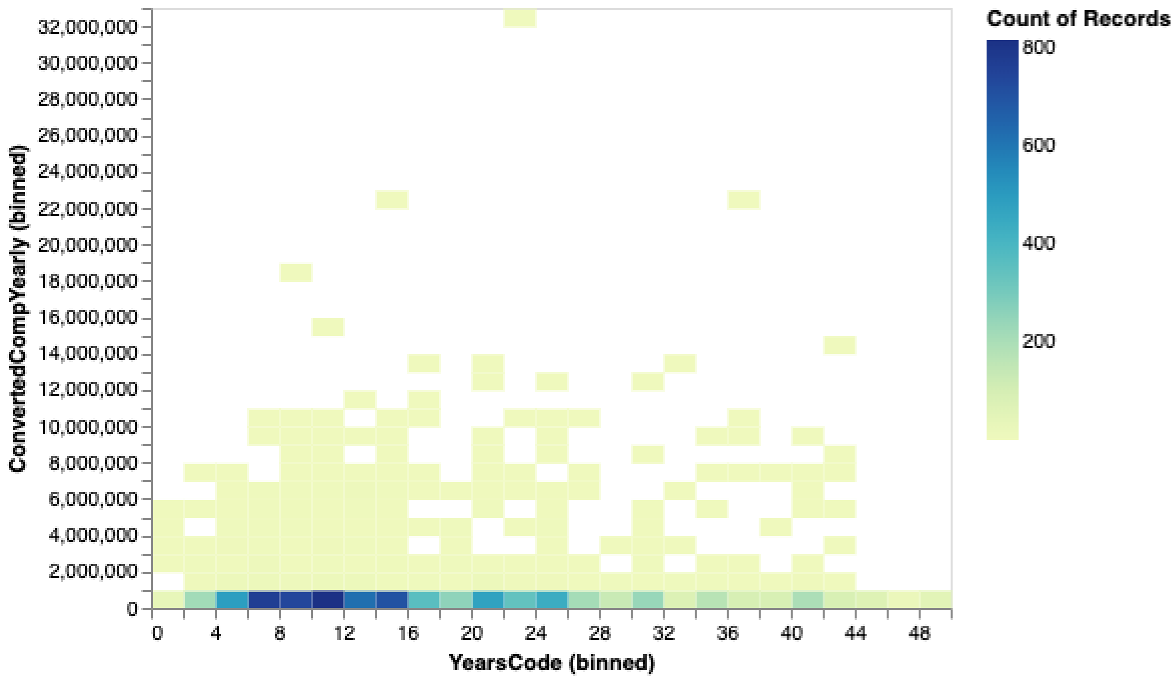
This shows that the salary data is highly skewed therefore it is better if we take median as a measure since it is better against the outliers

2D Histogram for YearsCode and ConvertedCompYearly

There appear to be very less outliers in the above chart and also most of the data lies between 6-12 years

In [16]:
```
years_code
```

Out[16]:

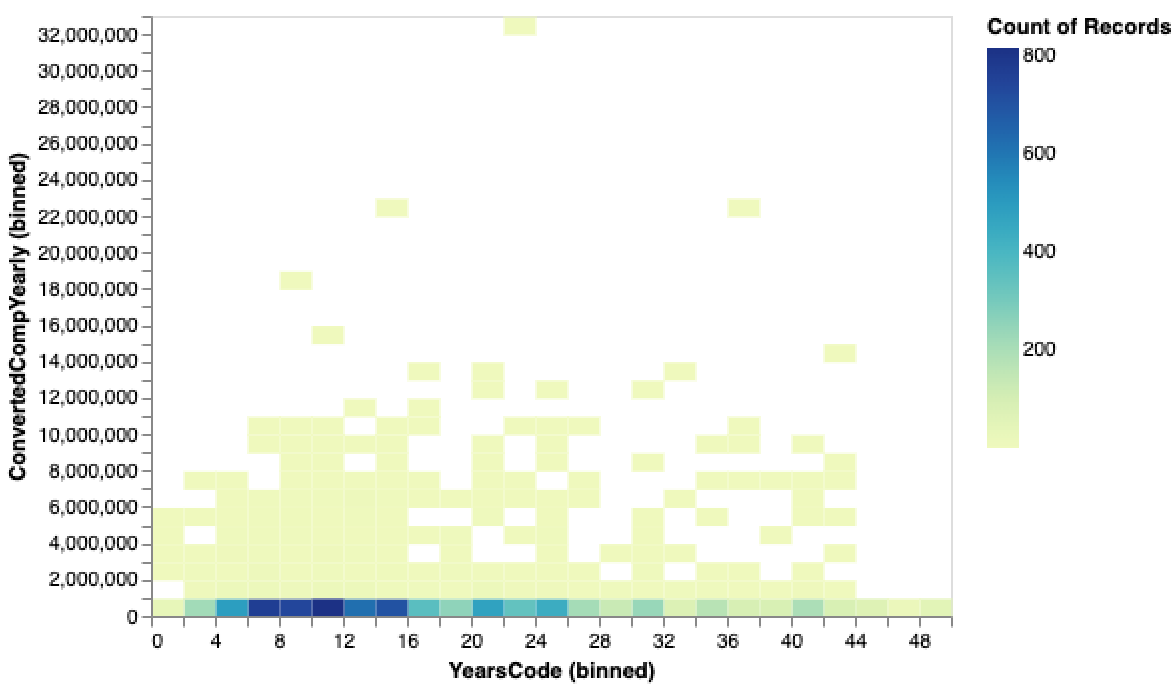


2D Histogram for YearsCodePro and ConvertedCompYearly

There appear to be very less outliers in the above chart and also most of the data lies between 2-8 years

In [17]:
```
years_code
```

Out[17]:

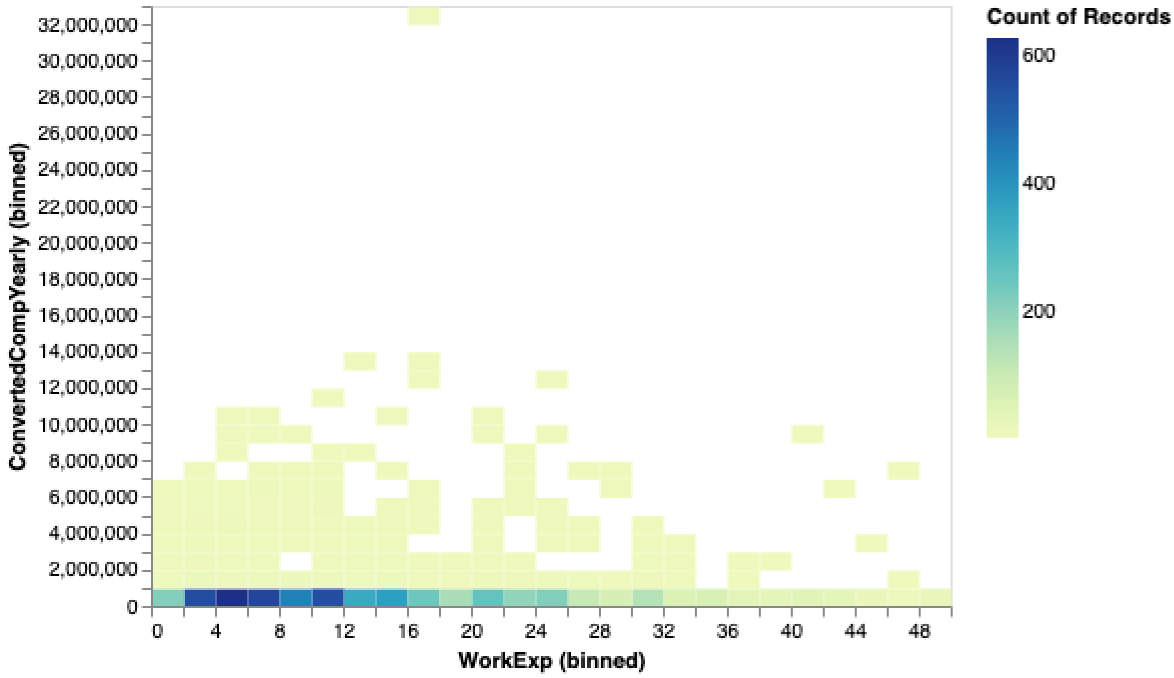


2D Histogram for WorkExp and ConvertedCompYearly

There appear to be barely any outliers in the above chart and also most of the data lies between 2-6 years

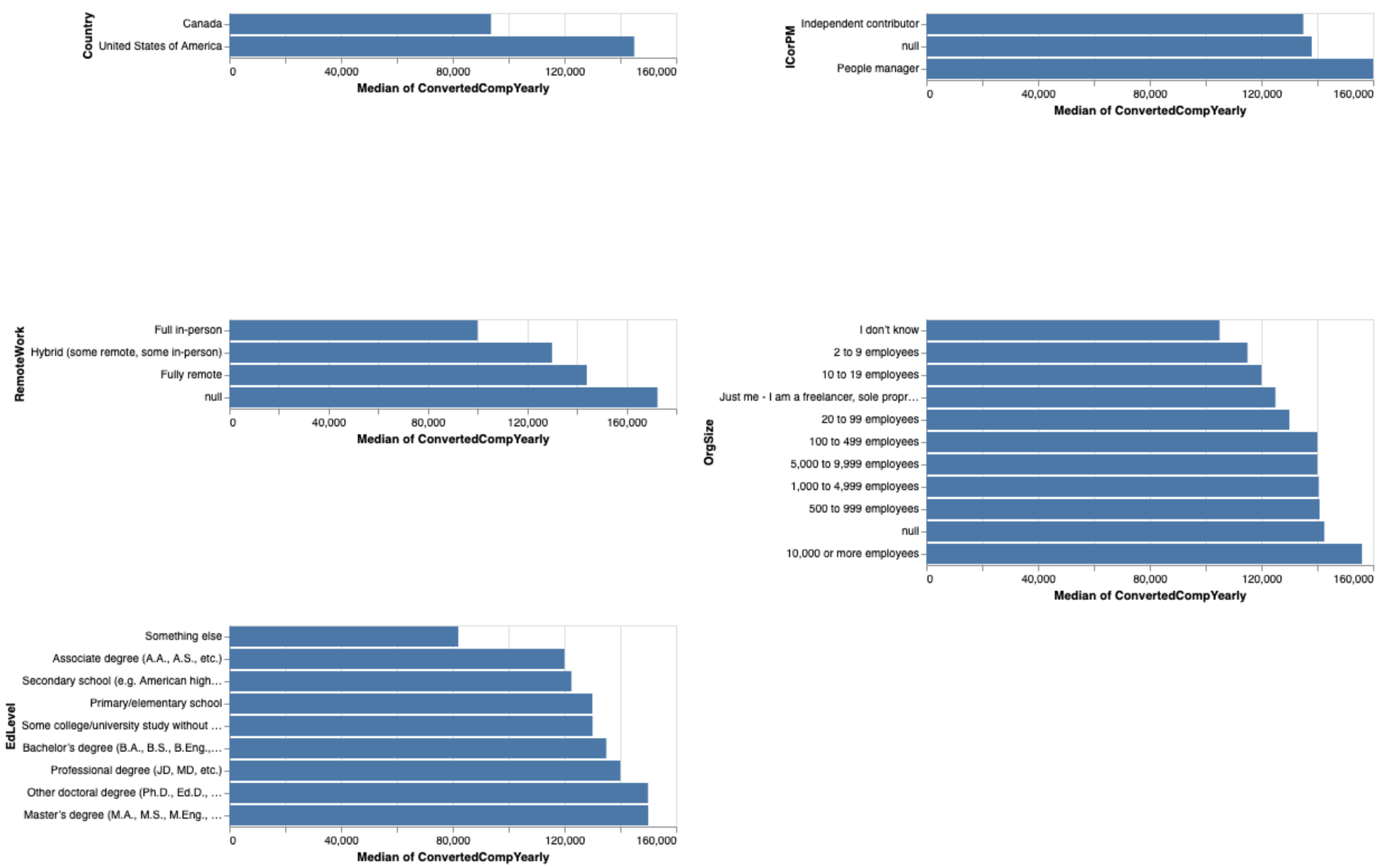
In [18]:
```
work_exp
```

Out[18]:



In [19]:
```
multi_bar_plot
```

Out[19]:



1. The bar chart for Country and ConvertedCompYearly shows that median salary for US is about 130K and 95K for Canada

2. The bar chart for ICorPM and ConvertedCompYearly shows that highest median salary are for people manager
3. The bar chart for RemoteWork and ConvertedCompYearly shows that median salary for is highest for those working fully remote
4. The bar chart for Orgsize and ConvertedCompYearly shows that median salary is highest for companies having 10,000 employees or more
5. The bar chart for Edlevel and ConvertedCompYearly shows that highest median salary are having a masters degree

Overall here there is less class imbalance for these features

In [20]:
```
corr_table
```

Out[20]:

Table 2. Correlation Plot between numeric data

	YearsCode	YearsCodePro	WorkExp	ConvertedCompYearly
YearsCode	1.000000	0.915677	0.844152	0.018527
YearsCodePro	0.915677	1.000000	0.902687	0.019431
WorkExp	0.844152	0.902687	1.000000	0.007428
ConvertedCompYearly	0.018527	0.019431	0.007428	1.000000

It is seen that there is very high correlation between the three numeric features so they can be used to predict the ConvertedCompYearly

References

1. Analyst-2 (analyst-2.ai) / Inspirient GmbH (inspirient.com) (2021). 'Salary and more-Data Scientist, Analyst, Engineer' analyzed by Analyst-2 [Dataset]. https://info.stackoverflowsolutions.com/rs/719-EMH-566/images/stack-overflow-developer-survey-2022.zip

2. https://www.kaggle.com/datasets/phuchuynguyen/salary-and-moredata-scientist-analyst-engineer