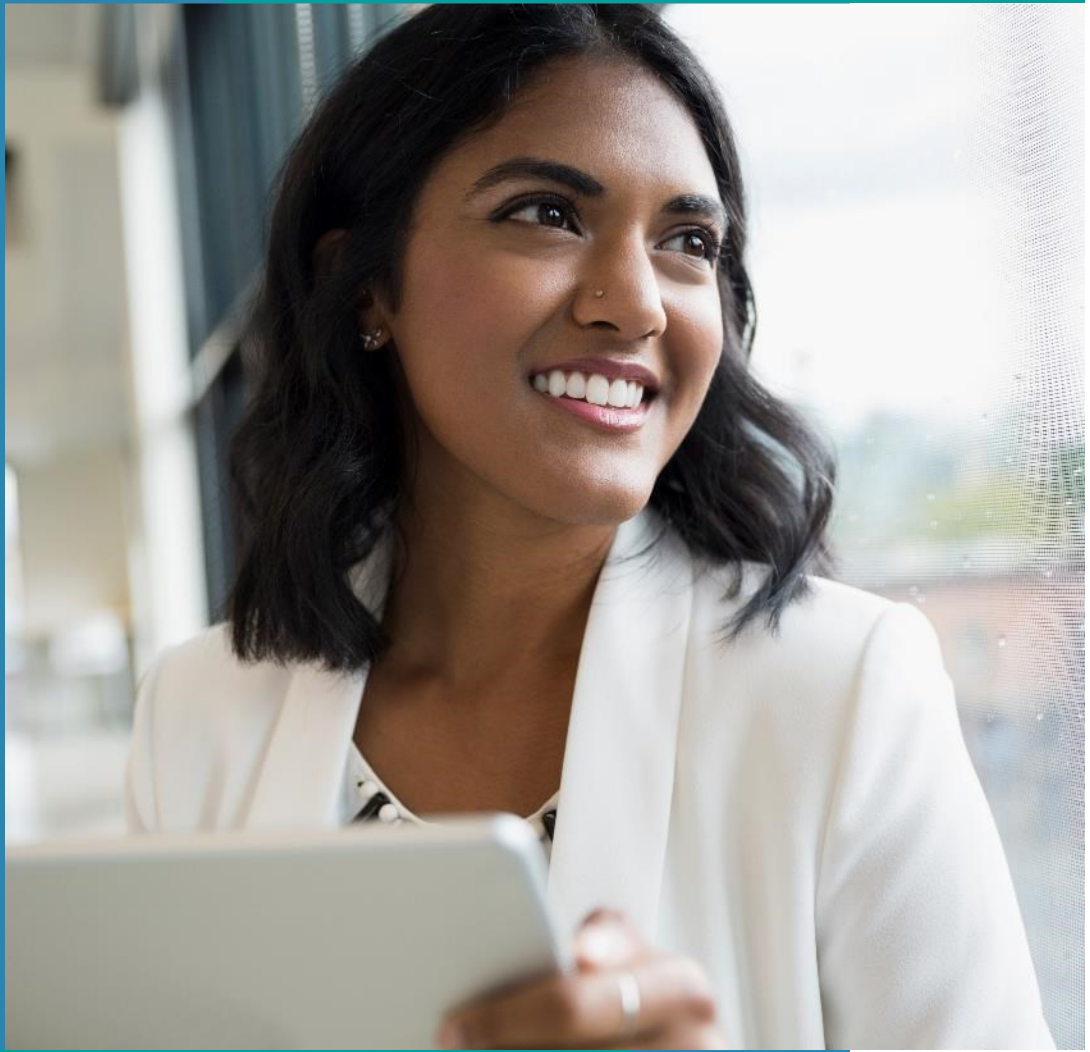
Coders Wanted 2022 Hackathon

Category 4: Open



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Introduction & Objective

- This is a challenge by Coders Wanted 2022 Hackathon
- I will be doing Category 4: Open.
- The dataset provided seems to be information of users particularly on their occupation level as majority of the columns describe job related info.
- **Objective**: I will try to uncover valuable insights from the dataset which may provide potential impactful changes to the data owner.

Data Cleaning

Using excel conditional formatting, and some matching, able to identify 1782 duplicates based on user_id column. In additional there are also difference between some of the duplicates for columns:

- Country (e.g. user_id: 2206, all columns are similar except for country – one showing Japan, the other showing South Korea)
- gender
- avg_apply_pass
- current_inactive_days

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	user_i	countr	gende	years_	no_of_	no_of_	no_of_	avg_ap	avg_pa	no_of_	signup	curren	educa	job_role	skills	
2	19	South Kor	female	0	4	3	0	0.2	0	0	2015	844	Graduate	Salary, Comper	HRM|HRD	
3	19	South Kor	female	0	4	3	0	0.2	0	0	2015	844	Graduate	Salary, Comper	HRM|HRD	
4	44	South Kor	male	0	0	0	0	0	0	0	2015	1048	Graduate	Machine Learn	C++|CUDA	
5	44	South Kor	male	0	0	0	0	0	0	0	2015	1048	Graduate	Machine Learn	C++|CUDA	
6	45	South Kor	female	0	3	0	0	0	0	0	2015	878	Graduate	Lecturer	Compens	
7	45	South Kor	male	0	3	0	0	0	0	0	2015	878	Graduate	Lecturer	Compens	
8	68	South Kor	female	0	0	0	0	0	0	0	2015	66	Graduate	Service Planne	Consultin	
9	68	South Kor	female	0	0	0	0	0	0	0	2015	44	Graduate	Service Planne	Consultin	
10	69	South Kor	female	0	1	0	0	0	0	0	2015	765	Graduate	Marketer	Advertisir	
11	69	South Kor	female	0	1	0	0	0	0	0	2015	765	Graduate	Marketer	Advertisir	
12	71	South Kor	male	0	17	0	0	0	0	0	2015	84	Graduate	Strategic Planr	Consultin	
13	71	South Kor	male	0	17	0	0	0	0	0	2015	71	Graduate	Strategic Planr	Consultin	
14	119	South Kor	male	0	0	0	0	0.4	0	0	2016	42	No Colleg	Web Develope	AWS|Type	
15	119	South Kor	male	0	0	0	0	0.4	0	0	2016	32	No Colleg	Web Develope	AWS|Type	
16	120	South Kor	male	0	0	0	0	0	0	0	2016	1016	No Colleg	Web Designer	Adobe Ill	
17	120	South Kor	male	0	0	0	0	0	0	0	2016	1016	No Colleg	Web Designer	Adobe Ill	
18	122	South Kor	male	0	0	0	0	0	0	0	2016	84	No Colleg	QA, Test Engin	RESTful a	
19	122	South Kor	male	0	0	0	0	0	0	0	2016	77	No Colleg	QA, Test Engin	RESTful a	
20	125	South Kor	male	0	243	0	0	0	0	0	2016	794	Graduate	Data Scientist	AMPL|Tab	
21	125	South Kor	male	0	243	0	0	0	0	0	2016	794	Graduate	Data Scientist	AMPL|Tab	
22	126	South Kor	male	0	19	0	0	0	0	0	2016	973	Graduate	Video Editing S	Adobe Pre	
23	126	South Kor	male	0	19	0	0	0	0	0	2016	973	Graduate	Video Editing S	Adobe Pre	
24	128	South Kor	female	0	2	0	0	0	0	0	2016	786	Graduate	Product Desigr	Adobe Ph	
25	128	South Kor	female	0	2	0	0	0	0	0	2016	786	Graduate	Product Desigr	Adobe Ph	
26	129	South Kor	female	0	0	0	0	0	0	0	2016	790	Graduate	UX Designer	Axure|Go	
27	129	South Kor	female	0	0	0	0	0	0	0	2016	790	Graduate	UX Designer	Axure|Go	
28	131	South Kor	male	0	11	0	0	0	0	0	2016	71	Graduate	Web Develope	Kotlin	
29	131	South Kor	male	0	11	0	0	0	0	0	2016	34	Graduate	Web Develope	Kotlin	
30	223	South Kor	male	0	9	0	0	0	0	0	2016	884	Graduate	Social Markete	Figma	
31	223	South Kor	male	0	9	0	0	0	0	0	2016	884	Graduate	Social Markete	Figma	
32	230	South Kor	male	0	0	0	0	0	0	0	2016	910	Graduate	Sales Speciali:	Compens	
33	230	South Kor	male	0	0	0	0	0	0	0	2016	910	Graduate	Sales Speciali:	Compens	
34	237	South Kor	male	0	39	0	0	0	0	0	2016	89	Graduate	Partnership Sp	Content C	
35	237	South Kor	male	0	39	0	0	0	0	0	2016	76	Graduate	Partnership Sp	Content C	
36	238	South Kor	male	0	2	0	0	0	0	0	2016	855	Graduate	Writer	Marketing	
37	238	South Kor	male	0	2	0	0	0	0	0	2016	855	Graduate	Writer	Marketing	
38	242	South Kor	male	0	8	0	0	0	0	0	2016	63	No Colleg	Web Develope	Go|Node	
39	242	South Kor	male	0	8	0	0	0	0	0	2016	7	No Colleg	Web Develope	Go|Node	
40	243	South Kor	male	0	0	0	0	0	0	0	2016	32	Graduate	Python Develo	VueJS|Ty	
41	243	South Kor	male	0	0	0	0	0	0	0	2016	13	Graduate	Python Develo	VueJS|Ty	
42	245	South Kor	female	0	0	0	0	0	0	0	2016	1005	Graduate	Service Planne	Kotlin|Nc	
43	245	South Kor	female	0	0	0	0	0	0	0	2016	1005	Graduate	Service Planne	Kotlin|Nc	

	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH
1	user_i	countr	gende	years_	no_of_	no_of_	no_of_	avg_ap	avg_pa	no_of_	signup	curren	educa	job_ro	skills			
2	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
4	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
5	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
6	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
7	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
8	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
10	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
11	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
12	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
14	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
15	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
16	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
17	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
18	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
19	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
20	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
21	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
22	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
23	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
24	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
25	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
26	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
27	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
28	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
29	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
30	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
31	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
32	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
33	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
34	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
35	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
36	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
37	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
38	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
39	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
40	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE			
41	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
42	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE			
43	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			

Dataset-DATARQ-3380 Sheet1

Ready 85%

There are also 15 rows with null values in the dataset

```
1  # we have 15rows of null values
2  df.isnull().sum().sum()
[209]  ✓ 0.6s
...  15
```

Data Cleaning

Given there are difference with some of the duplicate rows, I do not know which rows contain the accurate information. So I will be dropping all the duplicates and the null rows to be more accurate in the analysis.

As there is no metadata provided on the data set, assumptions will be made before making the analysis.

```
new_df = df.drop_duplicates(subset=['user_id'], keep=False).dropna()
new_df = new_df.reset_index(drop=True)
print(new_df.info())
```

[204] ✓ 0.4s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18170 entries, 0 to 18169
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   user_id               18170 non-null  int64  
 1   country               18170 non-null  object 
 2   gender                18170 non-null  object 
 3   years_of_experience   18170 non-null  int64  
 4   no_of_apply           18170 non-null  int64  
 5   no_of_pass            18170 non-null  int64  
 6   no_of_hire            18170 non-null  int64  
 7   avg_apply_pass        18170 non-null  float64
 8   avg_pass_hire         18170 non-null  float64
 9   no_of_event_reg       18170 non-null  int64  
 10  signup_year           18170 non-null  int64  
 11  current_inactive_days 18170 non-null  float64
 12  education_level       18170 non-null  object 
 13  job_role              18170 non-null  object 
 14  skills                18170 non-null  object 
dtypes: float64(3), int64(7), object(5)
```

Assumptions

- years_of_experience: the number of years of experience the users have
- no_of_apply: the number of job applications the users have made
- no_of_hire: times of being hired from their job applications
- signup_year: number of new users sign up for that year
- current_inactive_days: number of days users has been inactive for
- job_role: job that the user is currently holding
- skills: skills that the user currently have

```python
new_df = df.drop_duplicates(subset=['user_id'], keep=False).dropna()
new_df = new_df.reset_index(drop=True)
print(new_df.info())
```

[204] ✓ 0.4s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18170 entries, 0 to 18169
Data columns (total 15 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   user_id                18170 non-null  int64  
 1   country                18170 non-null  object 
 2   gender                 18170 non-null  object 
 3   years_of_experience    18170 non-null  int64  
 4   no_of_apply            18170 non-null  int64  
 5   no_of_pass             18170 non-null  int64  
 6   no_of_hire             18170 non-null  int64  
 7   avg_apply_pass         18170 non-null  float64
 8   avg_pass_hire          18170 non-null  float64
 9   no_of_event_reg        18170 non-null  int64  
 10  signup_year            18170 non-null  int64  
 11  current_inactive_days  18170 non-null  float64
 12  education_level        18170 non-null  object 
 13  job_role               18170 non-null  object 
 14  skills                 18170 non-null  object 
dtypes: float64(3), int64(7), object(5)
```

1st level analysis

A simple surface analysis tell us likely the data-owner is a recruitment firm, with strong presence in South Korea.

The company has been seeing a stable increase in sign up rates on their platform since 2015. (year 2022 not ended so not to take into account).

Average years of work experience of the users using the platform is at 2.6 years. Each users averagely applied 30 jobs, however the average hired rate is less than 1.

top 10 countries	
South Korea	93.1%
United States	3.2%
Japan	1.7%
United Kingdom	0.4%
Vietnam	0.3%
Hong Kong	0.3%
India	0.1%
Taiwan	0.1%
China	0.1%
Thailand	0.1%

signup rate each year	
2015	612
2016	1328
2017	1985
2018	2138
2019	3407
2020	2820
2021	4957
2022	923

years_of_experience	
count	18170.000000
mean	2.621354
std	3.553147
min	0.000000
25%	0.000000
50%	1.000000
75%	4.000000
max	131.000000

no_of_apply	
count	18170.000000
mean	30.265768
std	68.225869
min	0.000000
25%	4.000000
50%	13.000000
75%	32.000000
max	3133.000000

no_of_hire	
count	18170.000000
mean	0.689653
std	0.489583
min	0.000000
25%	0.000000
50%	1.000000
75%	1.000000
max	6.000000

1st level analysis

The top few user's job roles are mainly in the IT industry – shows that this recruitment company mainly focuses on IT sector job placements.

Lastly the average user's inactive period is around 116 days (~ 4months).

56% of the users is only inactive for less than a month, followed by 29% for between a month to half a year, 7.8% more than half a year to a year and lastly 7.1% has been inactive for more than a year.

top 10 job roles	
Web Developer	12.6%
Web Designer	5.1%
Strategic Planner	4.2%
Front-end Engineer	4.0%
Service Planner	3.8%
Social Marketer	3.3%
UX Designer	2.8%
iOS Developer	2.5%
Java Developer	2.0%
Web Publisher	1.7%

inactive_days	
count	18170.000000
mean	116.866924
std	251.732912
min	0.000000
25%	4.000000
50%	22.000000
75%	85.000000
max	1357.000000

<= a month	56.0%
a month to half a year	29.1%
half a year to a year	7.8%
more than a year	7.1%

2nd level analysis

Next, I will take a deeper dive into the data.

I broken down the average application rate & hire rate of the users from the top 10 countries.

Even though users' were mainly from South Korea, UK has the highest average application rate of ~70 per user, however its unfortunately that none of the country has even average of 1 for their average hired rate.

	no_of_apply	no_of_hire
country		
United Kingdom	70.9	0.8
Taiwan	69.8	0.8
United States	47.2	0.9
China	41.2	0.9
Vietnam	31.3	0.7
South Korea	29.9	0.7
Hong Kong	29.2	0.9
Thailand	23.2	0.8
Japan	7.9	0.1
India	7.5	0.0

Next its encouraging to see that the ratio of female to male in the top few tech roles is roughly balanced out as its often reported that females are being underrepresented in this industry.

gender	female	male
job_role		
Web Designer	52.4%	47.6%
Java Developer	51.7%	48.3%
Front-end Engineer	50.3%	49.7%
Strategic Planner	50.0%	50.0%
Web Developer	49.6%	50.4%
iOS Developer	49.3%	50.7%
UX Designer	49.2%	50.8%
Service Planner	47.5%	52.5%
Web Publisher	47.2%	52.8%
Social Marketer	47.1%	52.9%

2nd level analysis

Lastly, I split up the user's skills set of the top 10 roles to see what is the 10 most common skill that users in those roles have. It is represented by

- ('skill', 'number of users who have this skill')

Immediately the top most common skill that majority of the users had are AWS (amazon web service), goes to show that AWS is a valuable skill to have to be in these roles.

```
WebDeveloper_topskills
 [('AWS', 1967), ('Git', 757), ('Java', 672), ('MySQL', 616), ('Python', 580), ('JavaScript', 558), ('Docker', 520), ('React', 481), ('TypeScript', 457), ('GitHub', 419)]
WebDesigner_topskills
 [('Adobe Illustrator', 733), ('Adobe Photoshop', 704), ('UI Design', 237), ('Graphic Design', 207), ('Figma', 170), ('Sketch', 164), ('3D', 160), ('Branding', 150), ('Web Design', 141), ('Adobe XD', 117)]
StrategicPlanner_topskills
 [('AWS', 124), ('Accounting', 112), ('JIRA', 104), ('SQL', 103), ('Excel', 95), ('Google Analytics', 92), ('Tableau', 65), ('Python', 58), ('Axure', 54), ('IFRS', 52)]
Frontend_Engineer_topskills
 [('AWS', 611), ('Git', 253), ('React', 203), ('JavaScript', 186), ('TypeScript', 185), ('Docker', 181), ('Python', 178), ('MySQL', 167), ('Java', 152), ('APIs', 129)]
ServicePlanner_topskills
 [('AWS', 133), ('Accounting', 85), ('JIRA', 77), ('Excel', 77), ('Adobe Photoshop', 73), ('SQL', 70), ('MySQL', 69), ('Google Analytics', 65), ('Java', 64), ('JavaScript', 63)]
SocialMarketer_topskills
 [('Tableau', 165), ('AMPL', 161), ('Adobe Photoshop', 103), ('Google Analytics', 100), ('Adobe Illustrator', 64), ('Marketing Strategy', 52), ('Sketch', 52), ('Figma', 48), ('Marketing Operations', 43), ('Content Creation', 43)]
UXDesigner_topskills
 [('Adobe Photoshop', 389), ('Adobe Illustrator', 389), ('UI Design', 166), ('Figma', 129), ('Graphic Design', 125), ('Sketch', 103), ('Branding', 94), ('3D', 89), ('Zeplin', 87), ('Service Design', 85)]
iOSDeveloper_topskills
 [('AWS', 405), ('Python', 170), ('Java', 151), ('React', 148), ('iOS', 143), ('Swift', 133), ('Git', 126), ('TypeScript', 111), ('JavaScript', 109), ('MySQL', 108)]
JavaDeveloper_topskills
 [('AWS', 294), ('Java', 133), ('Python', 124), ('Git', 118), ('MySQL', 114), ('iOS', 90), ('React', 90), ('JavaScript', 86), ('Docker', 85), ('Spring Framework', 85)]
WebPublisher_topskills
 [('AWS', 225), ('Git', 98), ('JavaScript', 94), ('MySQL', 76), ('Java', 75), ('Python', 63), ('React', 63), ('Docker', 52), ('Node.js', 51), ('TypeScript', 51)]
```

Take away from the Data

From a business perspective, its positive sign to see the steady increase in sign up rate since 2015.

The average users using the platform are early in their careers (as shown from their year of experience), also signs that the average users base are quite young. Something the company can consider doing is organizing a “platform member only” career talks from veteran in the industry. This aim to reduce the inactive period of the users and attract more young talents onto the platform.

We could make use of the data on user’s skill to assist users themselves with job search. The company can consider building a skill match algorithm based on the jobs the user are interested in and the user’s skill to match them together. Or if the skills does not match, the algorithm will propose what skills the applicant is lacking so the applicant is aware and can work towards that area. This aims to improve user satisfactory level by increasing their chance of being hired through the platform.