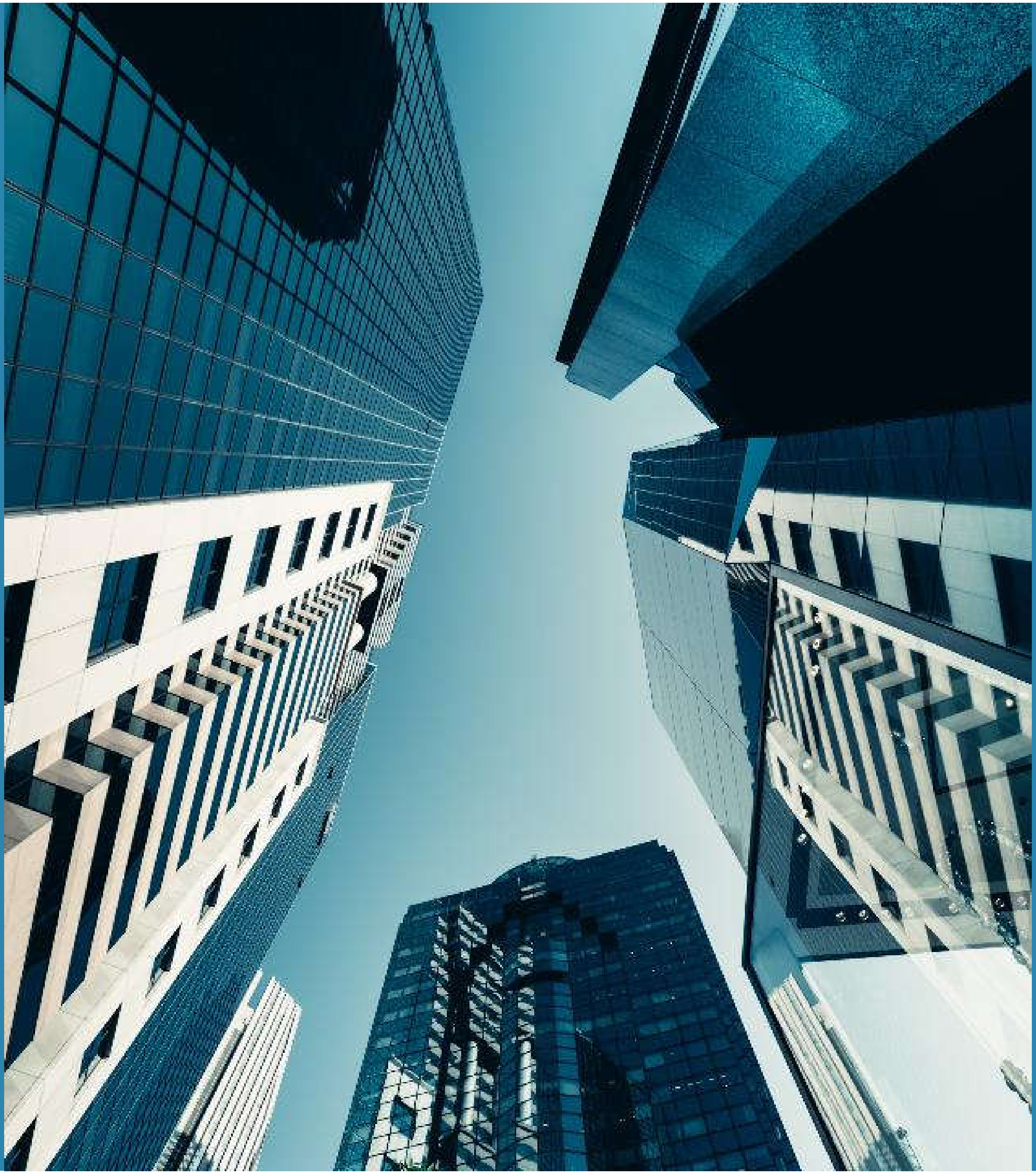
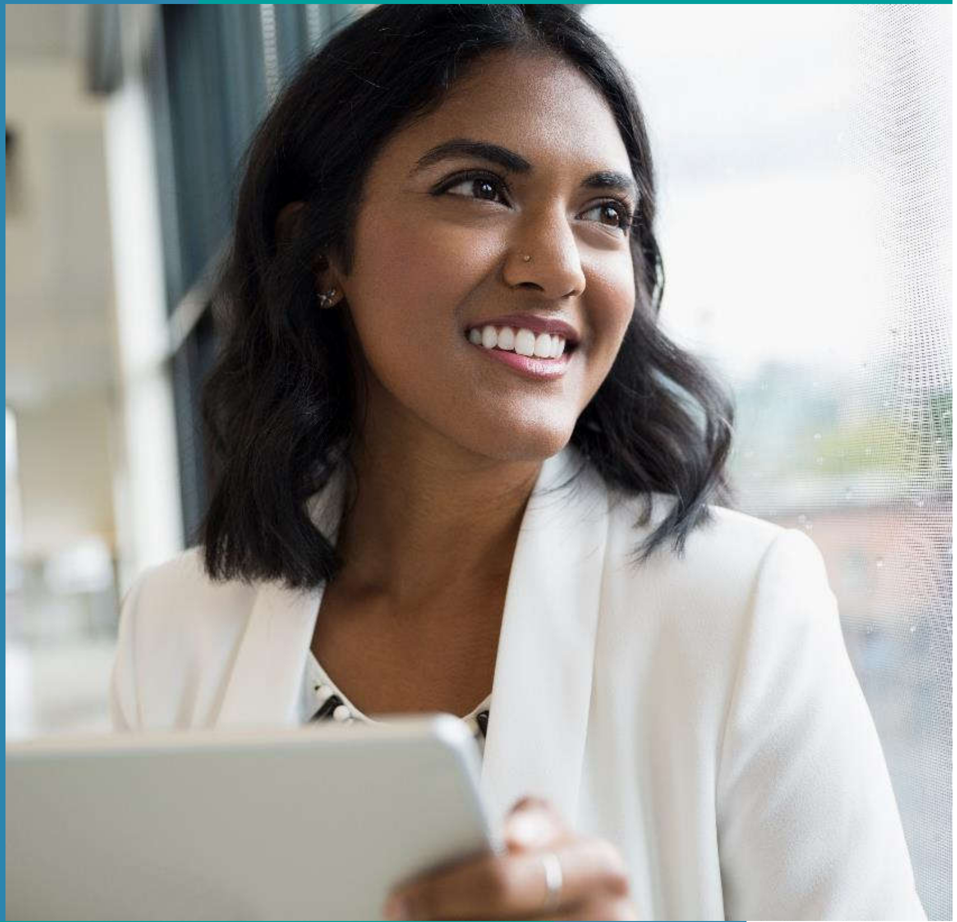


Coders Wanted 2022 Hackathon

Category 4: Open



Content

- Introduction & Objective
- Data Cleaning
  - Assumptions made on the data
- 1st level analysis
- 2nd level analysis
- Take away from the Data

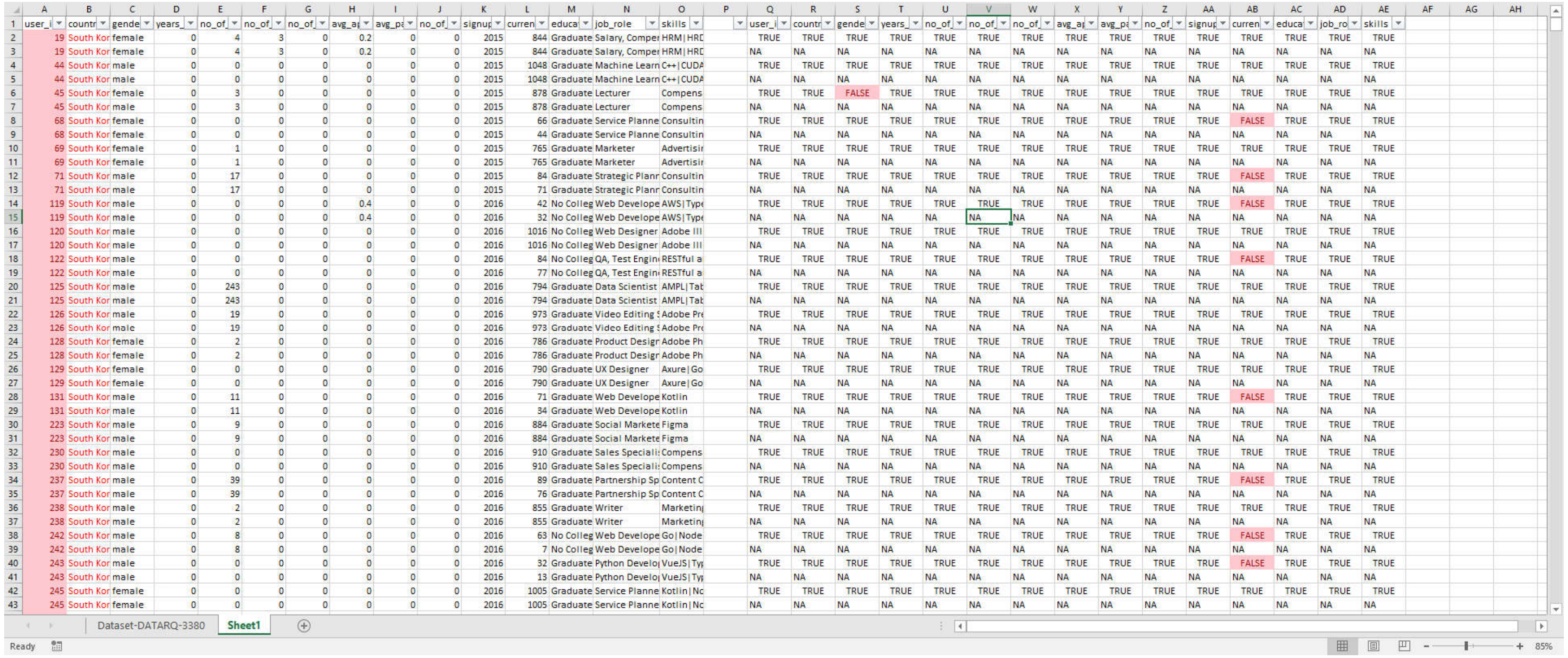
Introduction & Objective

- 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.

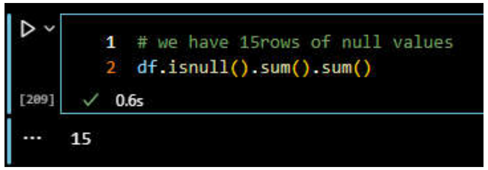
Data Cleaning

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



There are also 15 rows with null values in the dataset



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

```
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.