Resume Screening

Group 2: Ruiyuan Luan, Sandhya Nallarkkiniyan, Shuang Peng, Chenyi Zhang

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OVERVIEW

Why Important?

Resume is the first impression

What are the Goals?

- What job category fits your resume?
- How your resume matches your desired job?

What are the Tools?

TextHero
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Lexical diversity
Summarization
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ML Models
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02

EXPLORATORY DATA ANALYSIS

ABOUT OUR DATASET

2 Columns

Category and Resume

25 Categories

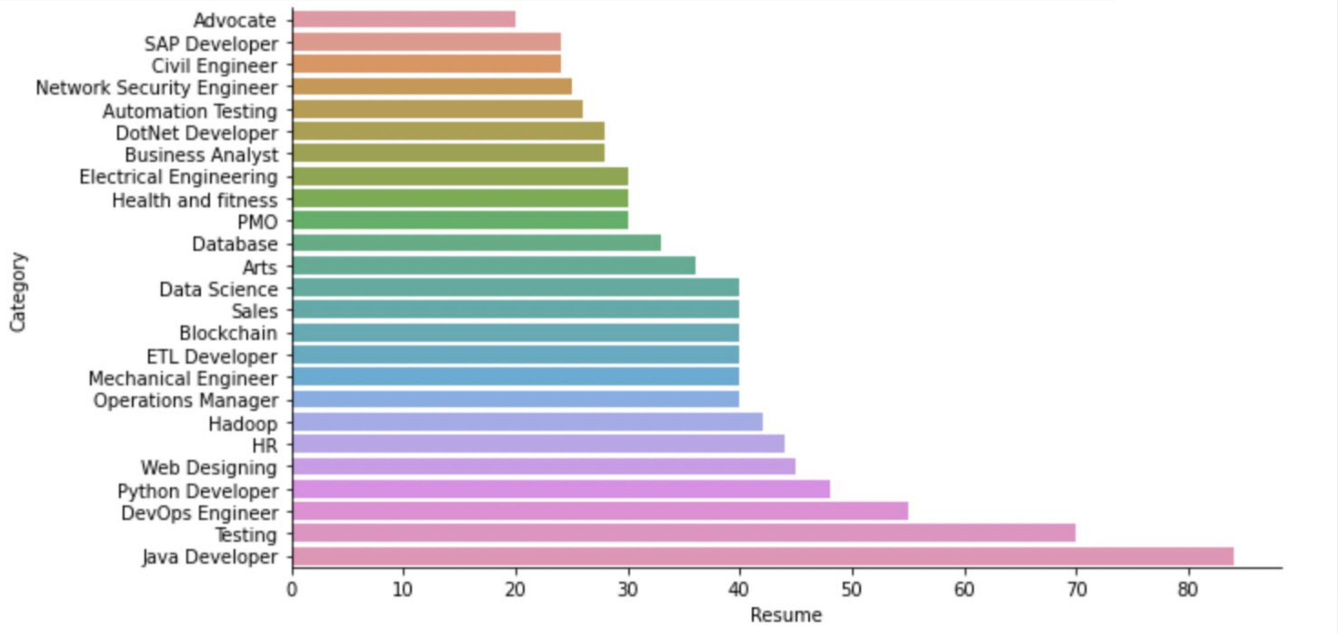
'Data Science', 'HR', 'Web Designing', 'Mechanical Engineer', 'Civil Engineer', 'Java Developer', 'Business Analyst', 'Operations Manager', 'Python Developer'.......

962 Resume

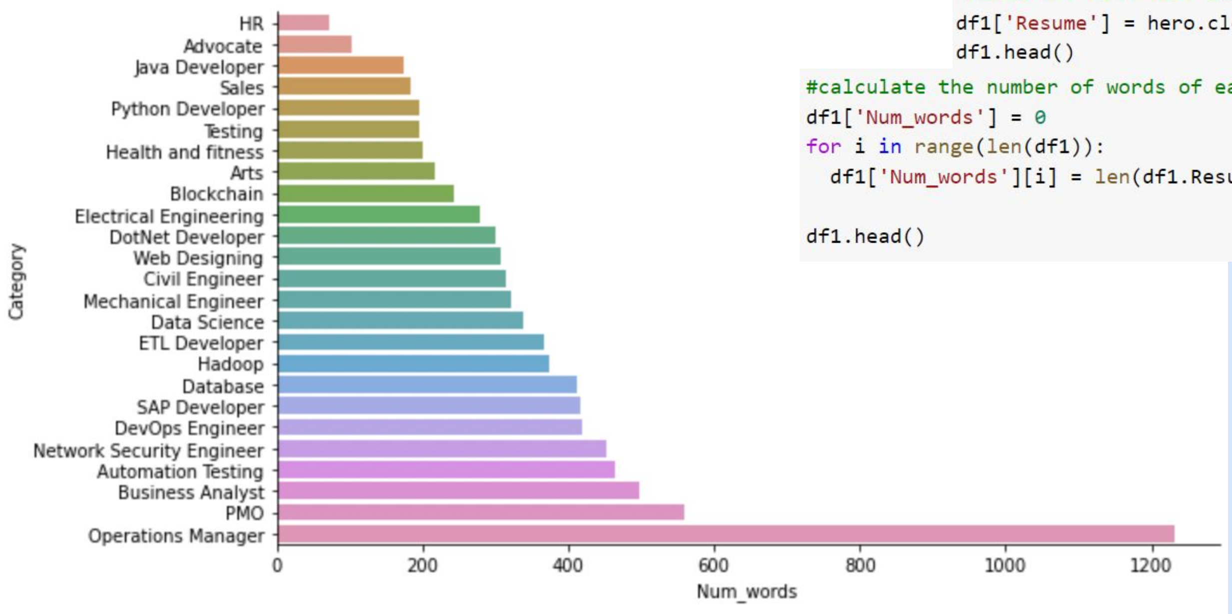
Source: https://www.kaggle.com/code/jillanisofttech/resume-screening-with-knn-ml-99

Category vs. Resume

```
sns.catplot(x='Resume',y='Category',data=df_group,aspect=2, kind = 'bar')
```



Category vs. No. of Words (TextHero)

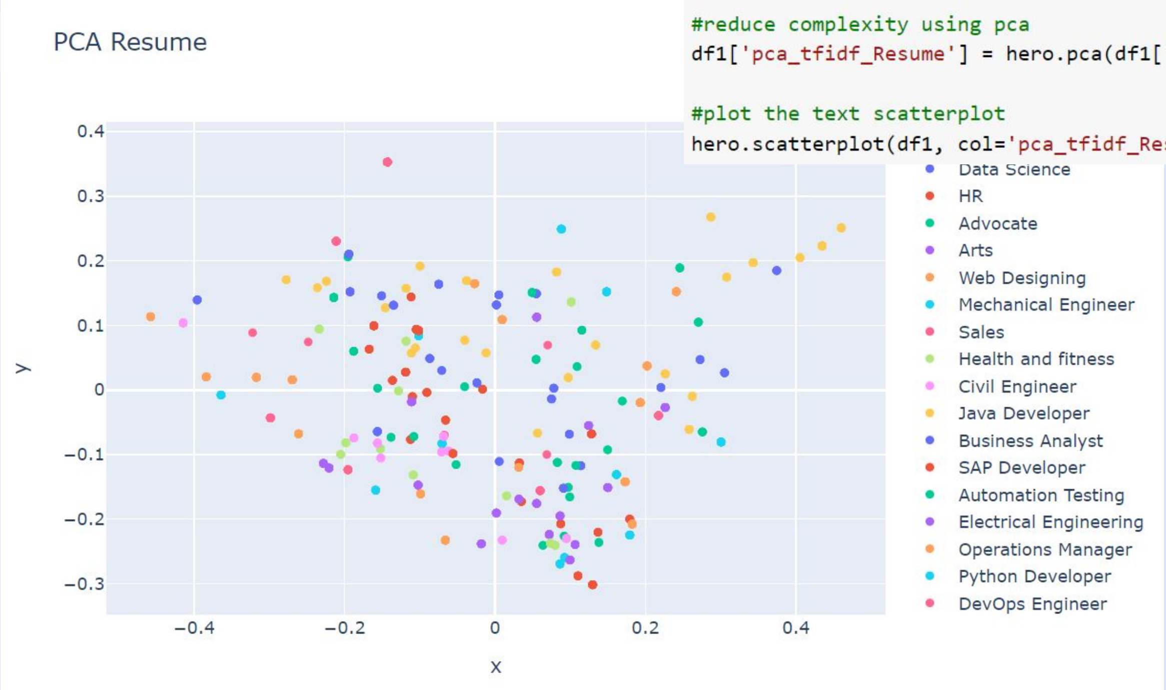



```
#clean the text file using texthero
df1['Resume'] = hero.clean(df1['Resume'])
df1.head()
```

```
#calculate the number of words of each resume
df1['Num_words'] = 0
for i in range(len(df1)):
  df1['Num_words'][i] = len(df1.Resume[i].split(" "))

df1.head()
```

PCA

```
#vectorize the resume column
df1['tfidf_Resume'] = hero.tfidf(df1['Resume'])

#reduce complexity using pca
df1['pca_tfidf_Resume'] = hero.pca(df1['tfidf_Resume'])

#plot the text scatterplot
hero.scatterplot(df1, col='pca_tfidf_Resume', color='Category', title="PCA Resume")
```



Top Words

```python
#most common words of wach category
NUM_TOP_WORDS = 6
df1.groupby('Category')['Resume'].apply(lambda x: hero.top_words(x)[:NUM_TOP_WORDS])
```

```
Data Science          data           396
                      exprience      248
                      months         240
                      aC             236
                      learning       204
                      python         176
```

```
Business Analyst      aC             482
                      business       252
                      test           214
                      description    168
                      company        168
                      |              134
```

```
Java Developer        java           636
                      exprience      408
                      months         372
                      developer      288
                      details        276
                      aC             270
```

```
DevOps Engineer       aC             784
                      exprience      424
                      project        420
                      months         386
                      shell          257
                      team           215
```

Top Words

```
common_words = ['aC/','university','+-','bo','|','test']

for i in range(len(df1)):
  df1['Resume'][i] = df1['Resume'][i].replace('exprience', 'experience')
  for j in common_words:
    df1['Resume'][i] = df1['Resume'][i].replace(j, '')
```

```
DevOps Engineer        experience    444
                       project       420
                       months        386
                       shell         257
                       team          215
                       company       213
```

```
Business Analyst       business      252
                       description   168
                       company       168
                       management    128
                       ing           128
                       project       124
```

```
Data Science           data          396
                       experience    300
                       months        240
                       learning      204
                       python        176
                       year          168
```

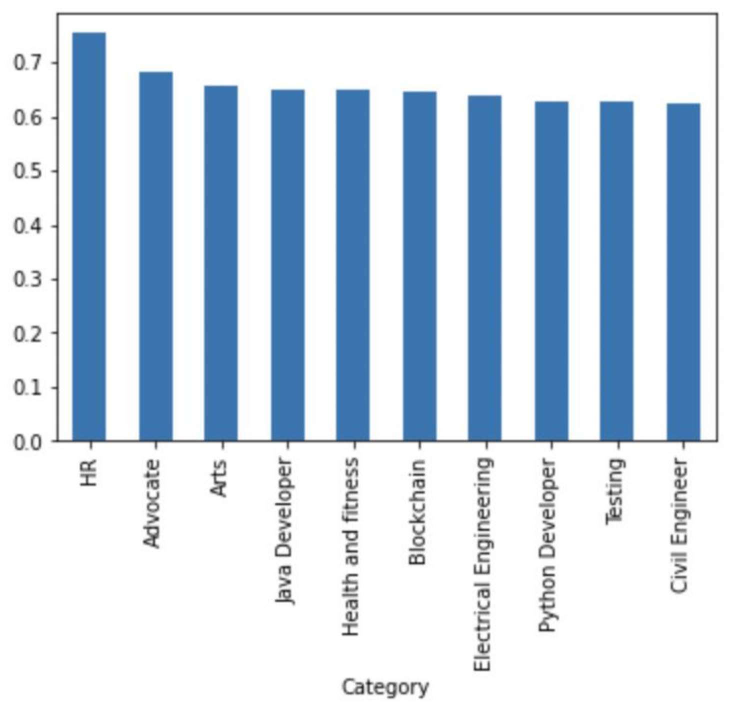
```
Java Developer         java          636
                       experience    426
                       months        372
                       developer     288
                       details       276
                       description   198
```

Word Cloud

```python
text = ''
for i in range(len(df1)):
    text = text + ' ' + df1['Resume'][i]
#number of words in total
len(text.split())
```


```python
from wordcloud import WordCloud
wordcloud = WordCloud().generate(text)

#Use pyplot from matplotlib
figure(figsize=(20,10))
pyplot.imshow(wordcloud, interpolation='bilinear')
pyplot.axis("off")
```

Lexical diversity




```
df1['lex_div'] = 0

for i in range(len(df1)):
  df1['lex_div'][i] = df['Resume'][i].split()
  df1['lex_div'][i] = len(set(df1['lex_div'][i])) / len(df1['lex_div'][i])
```

```
df2 = df1.groupby('Category')['lex_div'].mean()
df2.nlargest(10).plot(kind='bar')
```

Summarization

```
from transformers import pipeline
summarizer = pipeline("summarization")
```

'summary_text': ' Python pandas numpy scipy scikit and matplotlib are programming languages . Java jquery machine learning regression svm naa-ve bayes knn random forest decision trees osting techniques cluster analysis.'

```
txt = df2['Resume'][0]
```

```
if len(txt)>1024:
  txt = txt[:1024]
print(summarizer(txt, max_length=int(len(txt)/4), min_length=25))
```

03

Job Category Recommendations

Auto Gluon Text Classification Models

MODEL 1

Input feature: ***"Resume"***

Train test split

Train Set: 70%

Test Set: 30%

MODEL 2

Additional features:

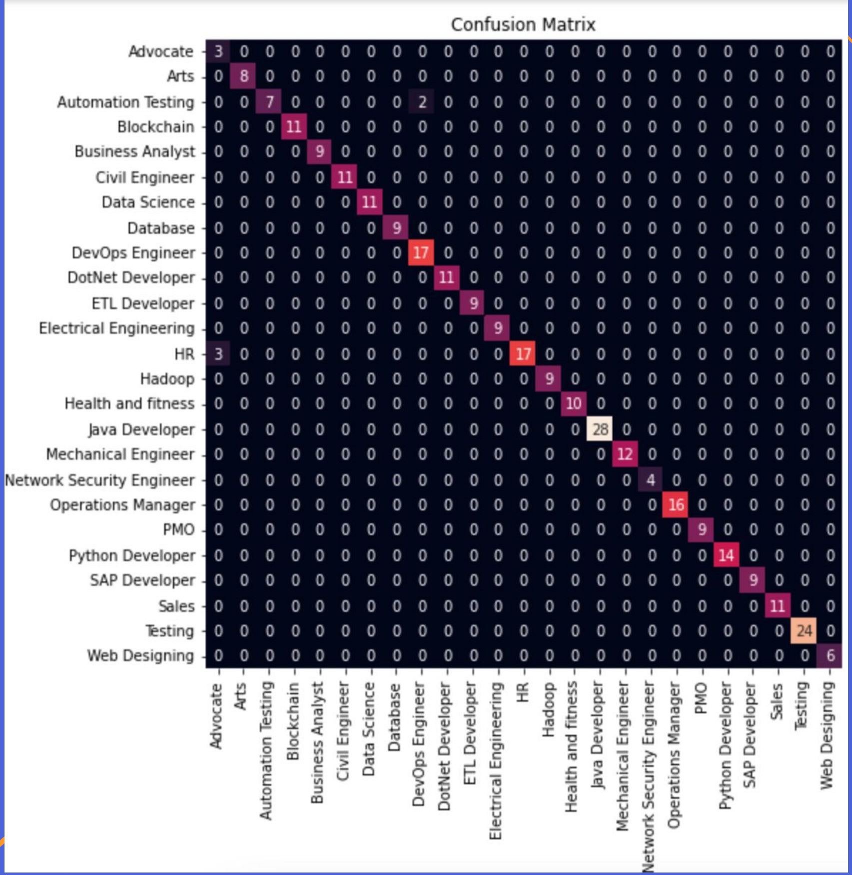
"Num_words", 'lex_div'

Category	Resume
Data Science	skills programming languages python pandas num...
Data Science	education details may may b e uit rgpv data sc...
Data Science	areas interest deep learning control system de...
Data Science	skills aC/ r aC/ python aC/ sap hana aC/ table...
Data Science	education details mca ymcaust faridabad haryan...

Category	Resume	Num_words	lex_div
Data Science	skills programming languages python pandas num...	503	0.637313
Data Science	education details may may b e uit rgpv data sc...	129	0.619632
Data Science	areas interest deep learning control system de...	190	0.641509
Data Science	skills aC/ r aC/ python aC/ sap hana aC/ table...	763	0.476334
Data Science	education details mca ymcaust faridabad haryan...	49	0.42029

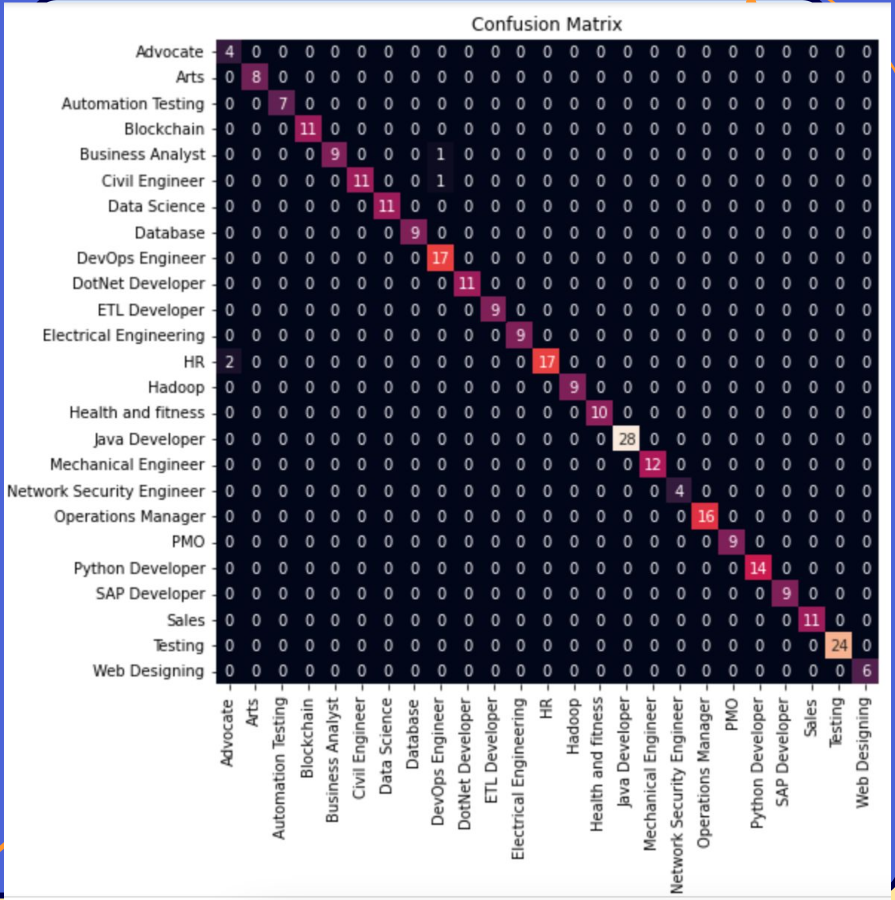
MODEL 1

	precision	recall	f1-score	support
Advocate	1.00	0.50	0.67	6
Arts	1.00	1.00	1.00	8
Automation Testing	0.78	1.00	0.88	7
Blockchain	1.00	1.00	1.00	11
Business Analyst	1.00	1.00	1.00	9
Civil Engineer	1.00	1.00	1.00	11
Data Science	1.00	1.00	1.00	11
Database	1.00	1.00	1.00	9
DevOps Engineer	1.00	0.89	0.94	19
DotNet Developer	1.00	1.00	1.00	11
ETL Developer	1.00	1.00	1.00	9
Electrical Engineering	1.00	1.00	1.00	9
HR	0.85	1.00	0.92	17
Hadoop	1.00	1.00	1.00	9
Health and fitness	1.00	1.00	1.00	10
Java Developer	1.00	1.00	1.00	28
Mechanical Engineer	1.00	1.00	1.00	12
Network Security Engineer	1.00	1.00	1.00	4
Operations Manager	1.00	1.00	1.00	16
PMO	1.00	1.00	1.00	9
Python Developer	1.00	1.00	1.00	14
SAP Developer	1.00	1.00	1.00	9
Sales	1.00	1.00	1.00	11
Testing	1.00	1.00	1.00	24
Web Designing	1.00	1.00	1.00	6
accuracy			0.98	289
macro avg	0.99	0.98	0.98	289
weighted avg	0.99	0.98	0.98	289



MODEL 2

	precision	recall	f1-score	support
Advocate	1.00	0.67	0.80	6
Arts	1.00	1.00	1.00	8
Automation Testing	1.00	1.00	1.00	7
Blockchain	1.00	1.00	1.00	11
Business Analyst	0.90	1.00	0.95	9
Civil Engineer	0.92	1.00	0.96	11
Data Science	1.00	1.00	1.00	11
Database	1.00	1.00	1.00	9
DevOps Engineer	1.00	0.89	0.94	19
DotNet Developer	1.00	1.00	1.00	11
ETL Developer	1.00	1.00	1.00	9
Electrical Engineering	1.00	1.00	1.00	9
HR	0.89	1.00	0.94	17
Hadoop	1.00	1.00	1.00	9
Health and fitness	1.00	1.00	1.00	10
Java Developer	1.00	1.00	1.00	28
Mechanical Engineer	1.00	1.00	1.00	12
Network Security Engineer	1.00	1.00	1.00	4
Operations Manager	1.00	1.00	1.00	16
PMO	1.00	1.00	1.00	9
Python Developer	1.00	1.00	1.00	14
SAP Developer	1.00	1.00	1.00	9
Sales	1.00	1.00	1.00	11
Testing	1.00	1.00	1.00	24
Web Designing	1.00	1.00	1.00	6
accuracy			0.99	289
macro avg	0.99	0.98	0.98	289
weighted avg	0.99	0.99	0.99	289



04

Job Description Matching

Using Text Similarity

MODELING PROCESS

Import Real Job Description for **7 Roles: Data Scientist, Business Analyst, Python Developer, Software Engineer, DevOps Engineer, and ETL Developer**

2 Documents: Job Description and Resume

Import Data — **Clean Data** — **Vectorization** — **Similarity**

Use TextHero

Use **Cosine Similarity** and **Jaccard Similarity**

Working Code

```
job =  df1['Job_Description']
resume = df2['Resume']

columns = list(df_similarity)
data = []

resume_job = []

for r in resume:
    resume_job = []
    resume_job.append(r)
    similarity = []
    for j in job:
        corpus = [r,j]   #Creating corpus of the resume and job to be compared
        trsfm = vectorizer.fit_transform(corpus)  #Vectorizing the text
        cosine = cosine_similarity(trsfm[0:1], trsfm) #Finding Cosine Similarity
        cosine_prcnt = cosine[0,1]*100
        similarity.append(cosine_prcnt)
    resume_job.extend(similarity)
    zipped = zip(columns, resume_job)
    a_dictionary = dict(zipped)
    data.append(a_dictionary)

#Creating the similarity matrix
df_similarity = df_similarity.append(data, True)
#Finding Max Match
df_similarity['Max_Match_Prcnt'] = df_similarity.drop(['Resume'],axis=1).max(axis=1)
df_similarity['Max_Match_Job'] = df_similarity.drop(['Resume'],axis=1).idxmax(axis=1)
```

Output - Cosine Similarity

	Resume	Data Scientist-Google	Data Scientist-Meta	Business Analyst-Amazon	Python Developer-Microsoft	Software Engineer-Apple	DevOps Engineer-Amazon	ETL Developer-Amazon	Max_Match_Prcnt	Max_Match_Job
0	skills programming languages python pandas num...	19.115197	14.651894	12.564862	14.832144	7.887163	5.032347	12.953251	19.115197	Data Scientist-Google
1	education details may may b e uit rgpv data sc...	4.206203	5.376500	4.992131	3.710819	1.329258	1.143470	3.703753	5.376500	Data Scientist-Meta
2	areas interest deep learning control system de...	8.016517	8.978215	7.097594	10.097543	5.893798	3.391123	7.409766	10.097543	Python Developer-Microsoft
3	skills aC/ r aC/ python aC/ sap hana aC/ table...	12.688287	11.118550	14.245513	11.615033	8.014396	5.644845	9.641717	14.245513	Business Analyst-Amazon
4	education details mca ymcaust faridabad haryan...	7.009412	4.833435	5.485900	5.089924	2.928431	0.376121	4.476053	7.009412	Data Scientist-Google

- >15% match makes the resume a very good fit for the job description (61/962 resumes - Top 6%)
- The best resumes in our database had 28% match

05

END USER INTERFACE: DASHBOARD

06

RECOMMENDATIONS & LIMITATIONS

Recommendations

- Perfect tool when finding a specific job title/role
- Useful if you want to know how to edit your resume
- SCU Practicum Program should consider to use this tool
- Can coordinate with employment websites (Indeed/LinkedIn)

Limitations

- Limited dataset
  - Add more publicly available job descriptions and resumes
- Limited advice on resume
- Please share your resumes and the jobs you are interested in to help us improve the model. :-)

Thank You!
Good luck!