# Resume Screening using NLP+Different ML Algorithms

#### A summary of resume screening:

- 1. Definition: Resume screening is the process of determining whether a candidate is qualified for a role based his or her education, experience, and other information captured on their resume.
- 2. How to screen resumes: First, screen resumes based on the job's minimum qualifications. Second, screen resumes based on the job's preferred qualifications. Third, screen resumes based on the shortlist of candidates you want to move onto the interview phase.
- 3. The challenges recruiters face while screening resumes: The high volume of resumes received up to 88% of them are unqualified greatly increases time to fill. Recruiters face increased pressure to show quality of hire but lack tools to link their resume screening to post-hire metrics.
- 4. Tech innovations in resume screening: Intelligent resume screening by using AI to learn from historical hiring decisions to improve quality of hire and reduce employee turnover.

#### Source

In this project, machine learning models is developed for the Resume Screening task.

### **Notebook Content**

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## Importing Basic Libraries and Loading Dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

df= pd.read_csv('UpdatedResumeDataSet.csv')
df.head()
```

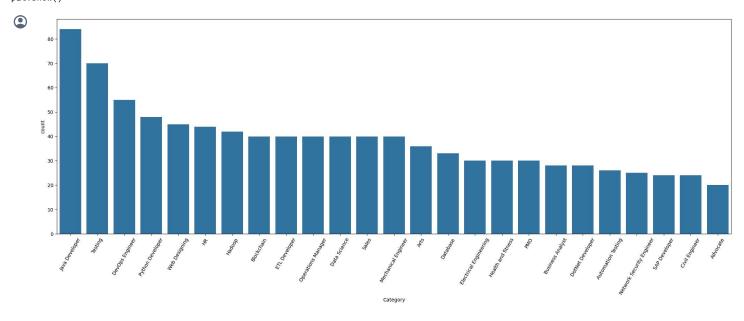
	Category	Resume
0	Data Science	Skills * Programming Languages: Python (pandas
1	Data Science	Education Details \r\nMay 2013 to May 2017 B.E
2	Data Science	Areas of Interest Deep Learning, Control Syste
3	Data Science	Skills â¼¢ R â¼¢ Python â¼¢ SAP HANA â¼¢ Table
4	Data Science	Education Details \r\n MCA YMCAUST, Faridab

# **Understanding Dataset**

	Category	count
0	Java Developer	84
1	Testing	70
2	DevOps Engineer	55
3	Python Developer	48
4	Web Designing	45
5	HR	44
6	Hadoop	42
7	Blockchain	40
8	ETL Developer	40
9	Operations Manager	40
10	Data Science	40
11	Sales	40
12	Mechanical Engineer	40
13	Arts	36
14	Database	33
15	Electrical Engineering	30
16	Health and fitness	30
17	РМО	30
18	Business Analyst	28
19	DotNet Developer	28
20	Automation Testing	26
21	Network Security Engineer	25
22	SAP Developer	24
23	Civil Engineer	24
24	Advocate	20

```
plt.figure(figsize=(25,8))
plt.xticks(rotation=60)
# count plot on single categorical variable
sns.countplot(x ='Category', data= df, order= df['Category'].value_counts().index)
# Show the plot
```

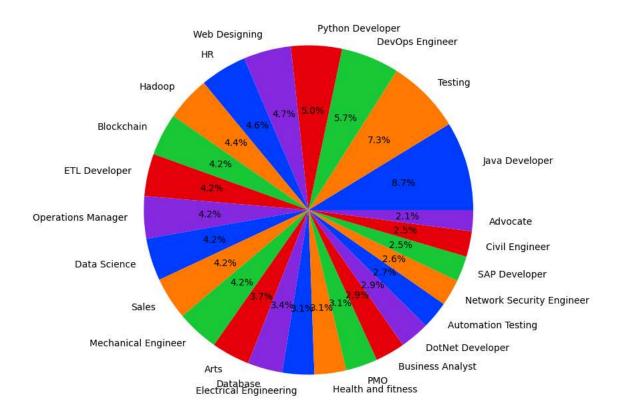
# Show the plot
plt.show()



```
plt.figure(figsize=(25,8))

# Define Seaborn color palette to use
colors = sns.color_palette('bright')[0:5]

# Create pie chart
plt.pie(categories['count'], labels=categories['Category'], colors=colors, autopct='%.1f%%')
plt.show()
```



# Preprocessing

Let's create a helper function to remove URLs, hashtags, mentions, special letters and punctuation Firstly, Let's add a new column for this:

	Category	Resume	cleaned_resume	
0	Data Science	Skills * Programming Languages: Python (pandas		
1	Data Science	Education Details \r\nMay 2013 to May 2017 B.E		
2	Data Science	Areas of Interest Deep Learning, Control Syste		
3	Data Science	Skills â¼¢ R â¼¢ Python â¼¢ SAP HANA â¼¢ Table		
4	Data Science	Education Details \r\n MCA YMCAUST, Faridab		
957	Testing	Computer Skills: âll¢ Proficient in MS office (		
958	Testing	â $\ensuremath{\mathtt{M}}$ Willingness to accept the challenges. â $\ensuremath{\mathtt{M}}$		
959	Testing	PERSONAL SKILLS â\& Quick learner, â\& Eagerne		
960	Testing	COMPUTER SKILLS & SOFTWARE KNOWLEDGE MS-Power $\dots$		
961	Testing	Skill Set OS Windows XP/7/8/8.1/10 Database MY		
962 rows × 3 columns				

Function:

```
import re
def clean_function(resumeText):
    resumeText = re.sub('http\S+\s*', ' ', resumeText) # remove URLs
    resumeText = re.sub('RT|cc', ' ', resumeText) # remove RT and cc
    resumeText = re.sub('#\S+', '', resumeText) # remove hashtags
    resumeText = re.sub('@\S+', ' ', resumeText) # remove mentions
    resumeText = re.sub('[%s]' % re.escape("""!"#$%&'()*+,-./:;<=>?@[\]^_\{|}~"""), ' ', resumeText) # remove punctuations
    resumeText = re.sub(r'[^\x00-\x7f]',r' ', resumeText)
    resumeText = re.sub('\s+', ' ', resumeText) # remove extra whitespace
    return resumeText
```

#### Let's apply to columns:

	Category	Resume	cleaned_resume
0	Data Science	Skills * Programming Languages: Python (pandas	Skills Programming Languages Python pandas num
1	Data Science	Education Details \r\nMay 2013 to May 2017 B.E	Education Details May 2013 to May 2017 B E UIT
2	Data Science	Areas of Interest Deep Learning, Control Syste	Areas of Interest Deep Learning Control System
3	Data Science	Skills â¼¢ R â¼¢ Python â¼¢ SAP HANA â¼¢ Table	Skills R Python SAP HANA Tableau SAP HANA SQL
4	Data Science	Education Details \r\n MCA YMCAUST, Faridab	Education Details MCA YMCAUST Faridabad Haryan

### Let's encode the Category column:

```
from sklearn.preprocessing import LabelEncoder
df2= df1.copy()
df2['Category']= LabelEncoder().fit_transform(df2['Category'])
df2.head()
```

Cat	tegory	Resume	cleaned_resume
0	6	Skills * Programming Languages: Python (pandas	Skills Programming Languages Python pandas num
1	6	Education Details \r\nMay 2013 to May 2017 B.E	Education Details May 2013 to May 2017 B E UIT
2	6	Areas of Interest Deep Learning, Control Syste	Areas of Interest Deep Learning Control System
3	6	Skills â¼¢ R â¼¢ Python â¼¢ SAP HANA â¾¢ Table	Skills R Python SAP HANA Tableau SAP HANA SQL
4	6	Education Details \r\n MCA YMCAUST, Faridab	Education Details MCA YMCAUST Faridabad Haryan

### Let's create wordcloud:

```
import nltk
from nltk.corpus import stopwords
import string
from wordcloud import WordCloud
nltk.download('stopwords')
nltk.download('punkt')
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk data] Unzipping corpora/stopwords.zip.
     [nltk_data] Downloading package punkt to /root/nltk_data...
     [nltk_data] Unzipping tokenizers/punkt.zip.
#Stop words are generally the most common words in a language.
#English stop words from nltk:
SetOfStopWords= set(stopwords.words('english')+['``',"''"])
totalWords= []
Sentences= df2['Resume'].values
cleanedSentences= ""
```

```
for records in Sentences:
    cleanedText= clean function(records)
    cleanedSentences += cleanedText
    requiredWords = nltk.word_tokenize(cleanedText)
     for word in requiredWords:
         if word not in SetOfStopWords and word not in string.punctuation:
              totalWords.append(word)
wordfreqdist = nltk.FreqDist(totalWords)
wordfregdist
     FreqDist({'Exprience': 3829, 'months': 3233, 'company': 3130, 'Details': 2967, 'description': 2634, '1': 2134, 'Project': 1808, 'project': 1579, '6': 1499, 'data': 1438, ...})
mostcommon = wordfreqdist.most_common(30)
mostcommon
      [('Exprience', 3829),
       ('months', 3233),
       ('company', 3130), ('Details', 2967),
       ('description', 2634),
       ('1', 2134),
       ('Project', 1808),
       ('project', 1579),
       ('6', 1499),
       ('data', 1438),
       ('team', 1424),
('Maharashtra', 1385),
       ('year', 1244),
('Less', 1137),
       ('January', 1086),
       ('using', 1041),
('Skill', 1018),
('Pune', 1016),
       ('Management', 1010),
       ('SQL', 990),
('Ltd', 934),
       ('management', 927),
       ('C', 896),
       ('Engineering', 855),
       ('Education', 833),
('Developer', 806),
       ('Java', 773),
       ('2', 754),
       ('development', 752),
       ('monthsCompany', 746)]
WordCloud= WordCloud().generate(cleanedSentences)
plt.figure(figsize=(10,10))
plt.imshow(WordCloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



# **Building Models**

```
from \ sklearn.model\_selection \ import \ train\_test\_split
from sklearn.feature_extraction.text import TfidfVectorizer
from scipy.sparse import hstack
Text= df2['cleaned_resume'].values
Target= df2['Category'].values
Here we will preprocess and convert the 'cleaned_resume' column into vectors. We will be using the 'Tf-Idf' method to get the vectors:
word_vectorizer = TfidfVectorizer(sublinear_tf=True, stop_words='english')
word_vectorizer.fit(Text)
WordFeatures= word_vectorizer.transform(Text)
We have 'WordFeatures' as vectors and 'Target' and target after this step.
WordFeatures.shape
     (962, 7351)
Let's split the data into training and test set:
X\_train, X\_test, y\_train, y\_test = train\_test\_split(WordFeatures, Target, random\_state = 42)
print(X_train.shape)
print(X_test.shape)
     (721, 7351)
     (241, 7351)
```

We have trained and tested the data and now let's build the models:

from sklearn.multiclass import OneVsRestClassifier

```
from \ sklearn.neighbors \ import \ KNeighbors Classifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
models = {
    'K-Nearest Neighbors' : KNeighborsClassifier(),
    'Logistic Regression' : LogisticRegression(),
    'Support Vector Machine' : SVC(),
    'Random Forest' : RandomForestClassifier()
}
model_list=[]
for model in models.values():
    model_list.append(OneVsRestClassifier(model))
model list
for i in model_list:
    i.fit(X_train, y_train)
    print(f'{i} trained')
print("*"*60)
print("all models trained")
for count, value in enumerate(model list):
    print(f"Accuracy of {value} on training set :", model_list[count].score(X_train, y_train))
    print(f"Accuracy of {value} on test set :", model_list[count].score(X_test, y_test))
    print("*"*100)
print("all scores calculated")
from sklearn.metrics import confusion_matrix as CM
from sklearn.metrics import classification_report
from sklearn.metrics import roc curve
from sklearn.metrics import roc_auc_score
for count, value in enumerate(model_list):
    print(f'{value} classification report')
    print("-"*80)
    print(classification_report(y_test, model_list[count].predict(X_test)))
    print("*"*100)
    print(" ")
     OneVsRestClassifier(estimator=KNeighborsClassifier()) trained
     {\tt OneVsRestClassifier} ({\tt estimator=LogisticRegression()}) \ {\tt trained}
     OneVsRestClassifier(estimator=SVC()) trained
     OneVsRestClassifier(estimator=RandomForestClassifier()) trained
     all models trained
     Accuracy of OneVsRestClassifier(estimator=KNeighborsClassifier()) on training set : 0.9805825242718447
     Accuracy of OneVsRestClassifier(estimator=KNeighborsClassifier()) on test set : 0.966804979253112
     Accuracy of OneVsRestClassifier(estimator=LogisticRegression()) on training set : 1.0
     Accuracy of OneVsRestClassifier(estimator=LogisticRegression()) on test set: 0.991701244813278
     Accuracy of OneVsRestClassifier(estimator=SVC()) on training set : 1.0
     Accuracy of OneVsRestClassifier(estimator=SVC()) on test set: 0.991701244813278
     Accuracy of OneVsRestClassifier(estimator=RandomForestClassifier()) on training set : 1.0
     Accuracy of OneVsRestClassifier(estimator=RandomForestClassifier()) on test set : 0.983402489626556
     all scores calculated
     OneVsRestClassifier(estimator=KNeighborsClassifier()) classification report
                   precision recall f1-score support
                0
                        1.00
                                 1.00
                                            1.00
                        1.00
                                  1.00
                                            1.00
                1
                                                          8
                2
                        1.00
                                  1.00
                                            1.00
                                                          6
                        1.00
                                  1.00
                3
                                            1.00
                                                         10
                4
                        1.00
                                  1.00
                                            1.00
                                                          5
                        1.00
                                  1.00
                                            1.00
                6
                        0.88
                                  0.78
                                            0.82
                                                          9
                        1.00
                                  0.89
                                            0.94
                8
                        1.00
                                  0.88
                                            0.94
                                                         17
                9
                        1.00
                                  1.00
                                            1.00
                                                         10
               10
                        1.00
                                  1.00
                                            1.00
                        1.00
                                  1.00
                                            1.00
                                                         7
               11
               12
                        1.00
                                  1.00
                                            1.00
                                                         15
                                  1.00
               13
                        1.00
                                            1.00
                                                          6
                        1.00
                                  0.70
                                            0.82
                                                         10
```

```
15
                 1.00
                          1.00
                                    1.00
                                               21
                 1.00
                          1.00
                                   1.00
                                               10
         16
         17
                 1.00
                         1.00
                                   1.00
                                                3
                 1.00
                          1.00
                                   1.00
                        1.00
         19
                 0.80
                                 0.89
                                 1.00
         20
                 1.00 1.00
                                               11
         21
                 0.78
                          1.00
                                    0.88
         22
                 0.75
                         1.00
                                   0.86
                         1.00
                                 1.00
                 1.00
         23
                                               19
         24
                 1.00
                          1.00
                                    1.00
                                              241
                                    0.97
   accuracy
                 0.97
  macro avg
                          0.97
                                    0.97
                                              241
weighted avg
                 0.97
                          0.97
                                    0.97
{\tt OneVsRestClassifier} ({\tt estimator=LogisticRegression()}) \ {\tt classification} \ {\tt report}
```

### Cross Validation for Models

```
from sklearn.model_selection import cross_val_score, KFold
results = {}
kf = KFold(n_splits= 10)
for count, value in enumerate(model_list):
   result = cross_val_score(model_list[count], X_train, y_train, scoring= 'accuracy', cv= kf)
   results[value] = result
print("r2 scores")
for name, result in results.items():
    print(f'{name} : {round(np.mean(result),3)}')
    print("----")
     r2 scores
     ***********
     OneVsRestClassifier(estimator=KNeighborsClassifier()) : 0.958
     {\tt OneVsRestClassifier} ({\tt estimator=LogisticRegression()}) \; : \; {\tt 0.99}
     OneVsRestClassifier(estimator=SVC()) : 0.997
     {\tt OneVsRestClassifier} (estimator = {\tt RandomForestClassifier}()) \; : \; {\tt 0.994}
```

```
import matplotlib.pyplot as plt
# Bar plot for accuracy scores
train_accuracy = [model_list[i].score(X_train, y_train) for i in range(len(model_list))]
test_accuracy = [model_list[i].score(X_test, y_test) for i in range(len(model_list))]
plt.figure(figsize=(10, 6))
plt.barh(list(models.keys()), train_accuracy, color='skyblue', label='Training Accuracy')
plt.barh(list(models.keys()), test_accuracy, color='orange', label='Test Accuracy')
plt.xlabel('Accuracy')
plt.title('Accuracy of Different Models on Training and Test Sets')
plt.legend()
plt.show()
# Line plot for cross-validation scores
cv_scores = [np.mean(results[model]) for model in model_list]
plt.figure(figsize=(10, 6))
plt.plot(list(models.keys()), cv_scores, marker='o', color='green')
plt.xlabel('Models')
plt.ylabel('Cross-Validation Score')
plt.title('Cross-Validation Scores of Different Models')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

```
from sklearn.metrics import confusion_matrix
for count, value in enumerate(model_list):
print(f'{value} confusion matrix')
print("-" * 40)
print(confusion_matrix(y_test, model_list[count].predict(X_test)))
print("*" * 100)
print(" ")
 OneVsRestClassifier(estimator=RandomForestClassifier()) confusion matrix
 0]
 01
 0]
 0]
 [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0
           0
            0 0 0 0 0 0 0 0 0
 0]
 0]
 0]
 0]
 0]
 0]
 0]
 0]
 0 0 0 0 0 0 0 0 0
 01
 0]
 0]
 0]
```