

HR Maze Analytics

Job Change of Data Scientists



Data Science and Big Data Course

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**Imagine you're navigating through a maze of
career opportunities....!!!**

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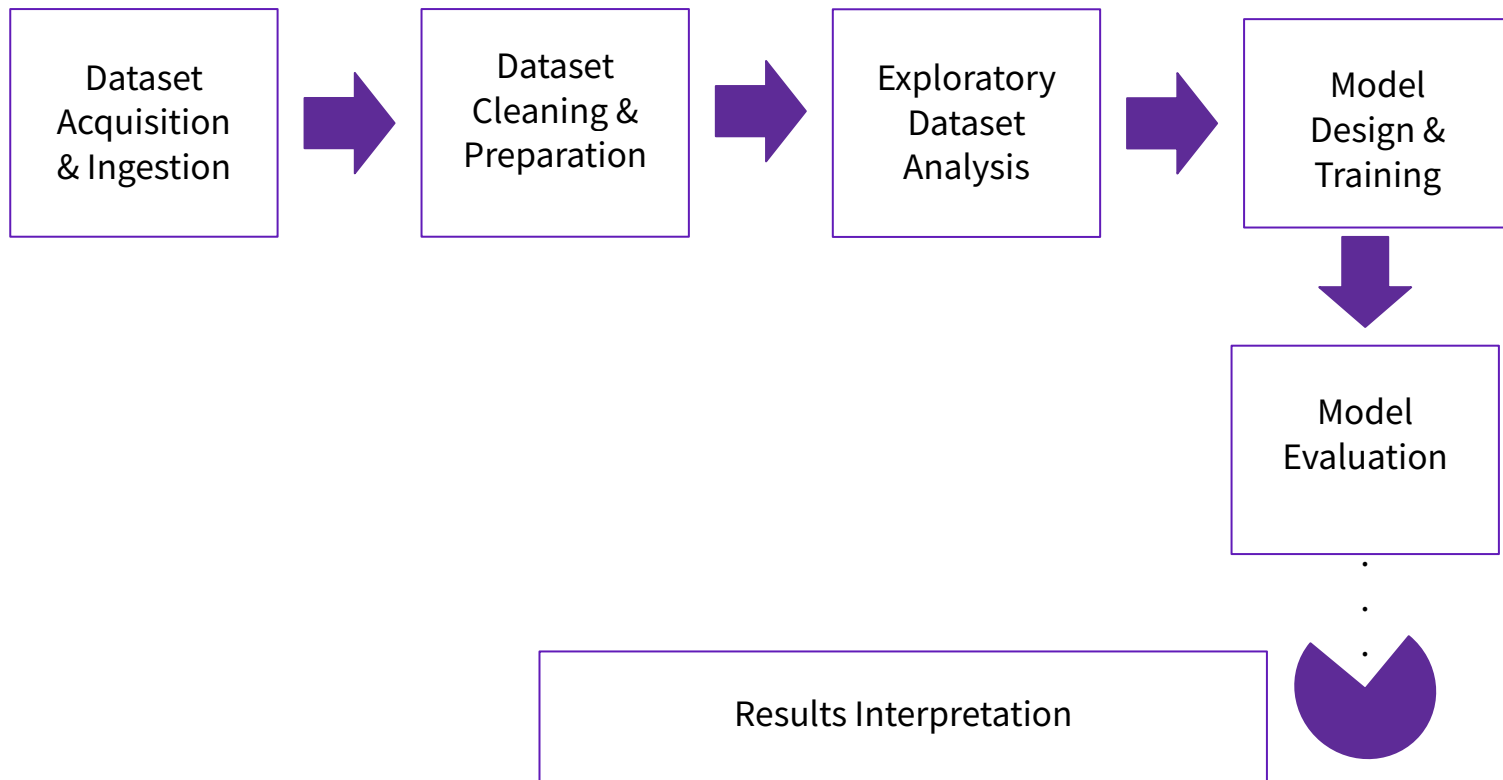
Introduction

This project rapidly evolving landscape of Big Data and Data Science, titled "**HR Maze Analytics**" delves into predicting job change intentions among candidates who have completed specialized training in data science. By leveraging machine learning algorithms and advanced analytics, the aim is to unravel the intricate interplay between educational background, professional experience, and career aspirations within the context of data science careers.

Project Objectives

1. Optimize the Influence of Education/Experience on Job Change Decisions,
2. Leverage Big Data Tools for Scalable Data Processing,
3. Investigate Key Hypotheses on Job-Seeking Behavior,
4. Build and Evaluate Predictive Models.

Project Workflow



Methodology & Architecture

Dataset Overview

HR Analytics: Job Change of Data Scientists

- Rows 2124
- Columns 13
- Usability 10
- Target predicting job changing

Data collection purpose:

A Big Data and Data Science company wants to identify which candidates from their training courses intend to work for the company versus those seeking new employment.

- To optimize training costs and quality.
- The dataset includes demographics, education, experience information, and ...

Goal

To use this data to predict candidates' job-seeking intentions and understand the factors influencing these decisions

Tool and Techniques

- Virtual MachineBox Enviroment
- Hadoop (Mapper & Reducer)
- Spark
- Python Language
 - Pandas, Seaborn Libraries Python Language to Visualization
- Mongodb/PyMongoDb
- Machine Learning Models

Initial Hypotheses

#H1:

Candidates with **longer experience** are **less** likely to seek new job opportunities.

#H2:

Candidates **enrolled in university courses** are **more** likely to seek new job opportunities.

Reading Data

```
import findspark
```

```
findspark.init()
```

```
import pyspark
```

```
from pyspark.sql import SparkSession
```

```
spark = SparkSession.builder \
    .master("local[1]") \
    .appName("PySpark  
Read CSV and Convert to JSON") \
    .getOrCreate()
```

```
csv_file = '/home/ubuntu/aug_test.csv'
```

```
df = spark.read.csv(csv_file,  
inferSchema=True, header=False)
```

```
df.show()
```

Results

_c0	_c1	_c2	_c3	_c4	_c5	_c6	_c7	_c8	_c9	_c10	_c11	_c12
10021	city_16	0.91	Female	Has relevent expe...	no_enrollment	Graduate	STEM	5	10000+	Pvt Ltd	1	22\t
10049	city_160	0.92	Male	Has relevent expe...	no_enrollment	Graduate	STEM	>20	100-500	Pvt Ltd	1	20\t
10050	city_103	0.92	Male	Has relevent expe...	no_enrollment	Masters	STEM	10	10000+	Pvt Ltd	>4	20\t
10162	city_160	0.92	Female	Has relevent expe...	no_enrollment	Graduate	STEM	15	500-999	Pvt Ltd	3	29\t
10167	city_103	0.92	Female	No relevent exper...	Part time course	Graduate	STEM	2	50-99	Funded Startup	1	35\t
10171	city_61	0.9129999999999999	Male	Has relevent expe...	no_enrollment	Masters	STEM	>20	10/49	Pvt Ltd	>4	40\t
10198	city_105	0.794	Male	Has relevent expe...	Full time course	Graduate	STEM	11	100-500	Pvt Ltd	>4	3\t
10217	city_159	0.843	Male	Has relevent expe...	no_enrollment	Graduate	STEM	8	50-99	Pvt Ltd	1	33\t
10230	city_103	0.92	Male	Has relevent expe...	no_enrollment	Masters	STEM	>20	500-999	Funded Startup	1	60\t
10246	city_160	0.92	Male	Has relevent expe...	no_enrollment	Masters	STEM	17	null	null	1	9\t
1026	city_162	0.767	null	Has relevent expe...	no_enrollment	Masters	STEM	11	1000-4999	Pvt Ltd	3	62\t
10260	city_21	0.624	null	No relevent exper...	Part time course	Masters	STEM	2	null	null	2	32\t
10279	city_71	0.884	null	No relevent exper...	Full time course	Graduate	STEM	6	null	null	never	45\t
10287	city_160	0.92	Male	Has relevent expe...	no_enrollment	Graduate	STEM	13	500-999	Pvt Ltd	1	20\t
10304	city_103	0.92	Male	Has relevent expe...	no_enrollment	Masters	STEM	10	null	Public Sector	1	31\t
10308	city_160	0.92	Female	No relevent exper...	no_enrollment	Graduate	STEM	1	100-500	NGO	1	8\t
10311	city_67	0.855	Male	Has relevent expe...	Full time course	Graduate	STEM	11	10/49	null	1	106\t
10324	city_16	0.91	Male	Has relevent expe...	Part time course	Graduate	STEM	>20	10000+	Pvt Ltd	2	12\t
10348	city_103	0.92	Male	No relevent exper...	no_enrollment	Graduate	STEM	18	50-99	Pvt Ltd	>4	28\t
10394	city_103	0.92	Male	Has relevent expe...	no_enrollment	Graduate	Other	15	50-99	Funded Startup	1	10\t

only showing top 20 rows

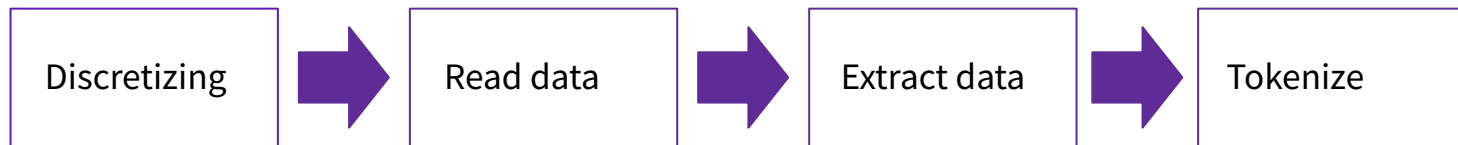
```
from pyspark.sql.functions import  
round,when,regexp_replace,col
```

```
df_cleaned = df1.fillna("Others")
```

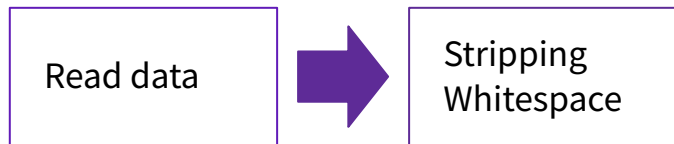
```
df_cleaned = df_cleaned.withColumn("last_new_job",  
  when(col("last_new_job") == ">4", "5")  
  .otherwise(col("last_new_job")))
```

learning_mumr3	city	age	gender	work	edu	stsch	inc	inc2	inc3	inc4	inc5	inc6	inc7	inc8	inc9	inc10	inc11	inc12	inc13	inc14	inc15	inc16	inc17	inc18	inc19	inc20	inc21	inc22	inc23	inc24	inc25	inc26	inc27	inc28	inc29	inc30	inc31	inc32	inc33	inc34	inc35	inc36	inc37	inc38	inc39	inc40	inc41	inc42	inc43	inc44	inc45	inc46	inc47	inc48	inc49	inc50	inc51	inc52	inc53	inc54	inc55	inc56	inc57	inc58	inc59	inc60	inc61	inc62	inc63	inc64	inc65	inc66	inc67	inc68	inc69	inc70	inc71	inc72	inc73	inc74	inc75	inc76	inc77	inc78	inc79	inc80	inc81	inc82	inc83	inc84	inc85	inc86	inc87	inc88	inc89	inc90	inc91	inc92	inc93	inc94	inc95	inc96	inc97	inc98	inc99	inc100	inc101	inc102	inc103	inc104	inc105	inc106	inc107	inc108	inc109	inc110	inc111	inc112	inc113	inc114	inc115	inc116	inc117	inc118	inc119	inc120	inc121	inc122	inc123	inc124	inc125	inc126	inc127	inc128	inc129	inc130	inc131	inc132	inc133	inc134	inc135	inc136	inc137	inc138	inc139	inc140	inc141	inc142	inc143	inc144	inc145	inc146	inc147	inc148	inc149	inc150	inc151	inc152	inc153	inc154	inc155	inc156	inc157	inc158	inc159	inc160	inc161	inc162	inc163	inc164	inc165	inc166	inc167	inc168	inc169	inc170	inc171	inc172	inc173	inc174	inc175	inc176	inc177	inc178	inc179	inc180	inc181	inc182	inc183	inc184	inc185	inc186	inc187	inc188	inc189	inc190	inc191	inc192	inc193	inc194	inc195	inc196	inc197	inc198	inc199	inc200	inc201	inc202	inc203	inc204	inc205	inc206	inc207	inc208	inc209	inc210	inc211	inc212	inc213	inc214	inc215	inc216	inc217	inc218	inc219	inc220	inc221	inc222	inc223	inc224	inc225	inc226	inc227	inc228	inc229	inc230	inc231	inc232	inc233	inc234	inc235	inc236	inc237	inc238	inc239	inc240	inc241	inc242	inc243	inc244	inc245	inc246	inc247	inc248	inc249	inc250	inc251	inc252	inc253	inc254	inc255	inc256	inc257	inc258	inc259	inc260	inc261	inc262	inc263	inc264	inc265	inc266	inc267	inc268	inc269	inc270	inc271	inc272	inc273	inc274	inc275	inc276	inc277	inc278	inc279	inc280	inc281	inc282	inc283	inc284	inc285	inc286	inc287	inc288	inc289	inc290	inc291	inc292	inc293	inc294	inc295	inc296	inc297	inc298	inc299	inc300	inc301	inc302	inc303	inc304	inc305	inc306	inc307	inc308	inc309	inc310	inc311	inc312	inc313	inc314	inc315	inc316	inc317	inc318	inc319	inc320	inc321	inc322	inc323	inc324	inc325	inc326	inc327	inc328	inc329	inc330	inc331	inc332	inc333	inc334	inc335	inc336	inc337	inc338	inc339	inc340	inc341	inc342	inc343	inc344	inc345	inc346	inc347	inc348	inc349	inc350	inc351	inc352	inc353	inc354	inc355	inc356	inc357	inc358	inc359	inc360	inc361	inc362	inc363	inc364	inc365	inc366	inc367	inc368	inc369	inc370	inc371	inc372	inc373	inc374	inc375	inc376	inc377	inc378	inc379	inc380	inc381	inc382	inc383	inc384	inc385	inc386	inc387	inc388	inc389	inc390	inc391	inc392	inc393	inc394	inc395	inc396	inc397	inc398	inc399	inc400	inc401	inc402	inc403	inc404	inc405	inc406	inc407	inc408	inc409	inc410	inc411	inc412	inc413	inc414	inc415	inc416	inc417	inc418	inc419	inc420	inc421	inc422	inc423	inc424	inc425	inc426	inc427	inc428	inc429	inc430	inc431	inc432	inc433	inc434	inc435	inc436	inc437	inc438	inc439	inc440	inc441	inc442	inc443	inc444	inc445	inc446	inc447	inc448	inc449	inc450	inc451	inc452	inc453	inc454	inc455	inc456	inc457	inc458	inc459	inc460	inc461
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Mapper



Reducer



Read data

```
for line in sys.stdin:
```

Stripping Whitespace

```
line.strip()
```

Mapper

Discretizing

```
Def
discretize_experience(
experience):
    try:
        if experience ==
'>20':
            return 21
        elif experience ==
'<1':
            return 0
        else:
            return
int(experience)
    except ValueError:
        return experience
```

Read and extract data

```
header = True

for line in sys.stdin:
    if header:

        print(line.strip())
        header = False
        continue
```

Tokenize

```
columns =
line.strip().split(',')

discrete_experience =
discretize_experience(
columns[0])
```

output

```
columns[0] =
str(discrete_experience)

print(",".join(columns))
```

HDFS

Result of mapp and reducer on HDFS

```
start-dfs.sh
start-yarn.sh
```

```
hdfs dfs -put
/path/to/local/cleandata.csv
/input_path/cleandata.csv
```

```
hdfs dfs -rm -r /new_output_path2
hadoop jar
/usr/local/hadoop/share/hadoop/to
ols/lib/hadoop-streaming-*.jar \
-input /input_path/cleandata.csv \
-output /new_output_path2 \
-mapper
/home/ubuntu/mapper2.py \
-reducer
/home/ubuntu/reducer2.py

hdfs dfs -cat
/new_output_path2/part-00000
```

```
9106,city_104,0.92,Male,yes,NO,Graduate,STEM,21,50-99,Pvt Ltd,5,95
9134,city_21,0.62,Others,yes,NO,Graduate,STEM,7,50-99,Pvt Ltd,2,85
9149,city_23,0.9,Others,yes,NO,Masters,STEM,18,50-99,Pvt Ltd,3,60
915,city_103,0.92,Others,yes,NO,Masters,Humanities,16,1000-4999,Pvt Ltd,1,11
9163,city_21,0.62,Male,yes,NO,Graduate,Other,4,100-500,Pvt Ltd,1,24
9184,city_136,0.9,Male,yes,Parttime,Masters,STEM,3,10000+,Pvt Ltd,1,34
9195,city_21,0.62,Male,yes,NO,Graduate,STEM,10,100-500,Pvt Ltd,2,129
9205,city_143,0.74,Others,yes,NO,Graduate,STEM,13,others,Others,5,37
9207,city_114,0.93,Male,yes,NO,High School,Others,8,9,Pvt Ltd,never,39
9208,city_21,0.62,Others,No,Parttime,Graduate,STEM,2,10-49,Pvt Ltd,1,58
9209,city_121,0.78,Other,yes,NO,Graduate,STEM,0,50-99,Funded Startup,1,62
923,city_103,0.92,Male,yes,NO,Graduate,Humanities,21,50-99,Funded Startup,1,102
9234,city_61,0.91,Others,yes,NO,Graduate,STEM,21,9,Pvt Ltd,3,220
9237,city_65,0.8,Others,yes,NO,Phd,STEM,17,50-99,Pvt Ltd,5,41
9268,city_160,0.92,Male,yes,NO,Others,Others,21,9,Pvt Ltd,2,26
9270,city_162,0.77,Male,yes,Parttime,Graduate,STEM,6,10-49,NGO,4,31
9272,city_90,0.7,Male,yes,NO,Graduate,STEM,20,10-49,Pvt Ltd,2,51
9275,city_158,0.77,Male,yes,Parttime,Graduate,STEM,13,others,Others,5,324
9291,city_16,0.91,Male,yes,NO,Masters,STEM,15,10-49,Pvt Ltd,2,15
9302,city_149,0.69,Others,yes,NO,Graduate,STEM,0,others,Others,2,152
9335,city_103,0.92,Male,No,Phd,STEM,18,100-500,NGO,1,25
9345,city_16,0.91,Other,yes,NO,High School,Others,8,50-99,Pvt Ltd,1,18
9462,city_21,0.62,Others,No,Parttime,Others,Others,1,others,Others,never,204
9487,city_21,0.62,Male,No,Fulltime,Graduate,STEM,5,others,Others,never,141
9501,city_71,0.88,Male,yes,NO,Graduate,STEM,5,100-500,Others,1,20
9514,city_160,0.92,Male,yes,Fulltime,High School,Others,12,100-500,Pvt Ltd,1,9
952,city_103,0.92,Male,yes,NO,Graduate,STEM,7,10000+,Pvt Ltd,1,96
9544,city_21,0.62,Male,No,NO,Graduate,STEM,4,others,Others,never,190
9548,city_114,0.93,Male,yes,NO,Masters,STEM,21,50-99,Pvt Ltd,5,65
9556,city_49,0.78,Others,yes,NO,Graduate,STEM,20,others,Others,1,23
9561,city_28,0.94,Others,yes,NO,Masters,STEM,19,others,Others,2,72
9562,city_73,0.75,Male,yes,NO,Graduate,STEM,21,others,Others,1,167
9564,city_103,0.92,Others,yes,NO,Graduate,STEM,9,1000-4999,Pvt Ltd,3,72
9586,city_103,0.92,Female,yes,NO,Masters,STEM,4,5000-9999,Public Sector,1,20
9618,city_103,0.92,Female,yes,NO,Graduate,Humanities,21,others,Others,5,22
9630,city_103,0.92,Male,yes,NO,Graduate,STEM,21,1000-4999,Pvt Ltd,5,43
9649,city_103,0.92,Male,yes,NO,Graduate,Business Degree,16,50-99,Pvt Ltd,1,33
9664,city_41,0.83,Male,yes,Parttime,Graduate,STEM,8,9,Pvt Ltd,2,86
9700,city_71,0.88,Female,No,NO,Graduate,Humanities,4,10000+,Pvt Ltd,2,34
9706,city_136,0.9,Male,No,NO,Masters,STEM,10,100-500,NGO,5,26
9707,city_103,0.92,Male,No,Fulltime,Graduate,STEM,8,others,Others,2,96
9726,city_160,0.92,Male,yes,NO,Graduate,STEM,16,others,Others,5,42
9740,city_103,0.92,Male,No,NO,Graduate,STEM,21,10000+,Pvt Ltd,5,21
9752,city_21,0.62,Others,yes,Fulltime,Graduate,STEM,6,others,Others,4,32
9753,city_37,0.79,Female,No,Fulltime,Graduate,STEM,4,others,Others,never,86
976,city_67,0.86,Male,yes,NO,Graduate,STEM,7,100-500,Pvt Ltd,2,57
9766,city_83,0.92,Male,yes,NO,Graduate,STEM,5,1000-4999,Pvt Ltd,2,14
9772,city_114,0.93,Male,No,NO,High School,Others,5,others,Others,never,32
9789,city_160,0.92,Male,yes,NO,Graduate,STEM,21,10000+,Pvt Ltd,5,4
9800,city_103,0.92,Others,No,NO,Masters,STEM,21,10000+,Pvt Ltd,3,59
9806,city_65,0.8,Male,yes,NO,Masters,STEM,15,10000+,Pvt Ltd,5,27
9827,city_138,0.84,Male,No,Fulltime,High School,Others,2,others,Others,never,112
9837,city_61,0.91,Male,yes,NO,Graduate,STEM,21,others,Others,1,42
9840,city_114,0.93,Male,No,Fulltime,High School,Others,8,others,Public Sector,1,81
9852,city_103,0.92,Male,yes,NO,Graduate,STEM,21,others,Others,3,23
```


Converting to Json

Listing Files in Directory

```
for filename in
os.listdir(input_directory):

if filename.startswith('part-'):

    file_path =
os.path.join(input_directory,
filename) data = []
```

Read csv file

```
with open(file_path, mode='r',
encoding='utf-8') as file: csv_reader =
csv.DictReader(file,fieldnames=fieldn
ames)

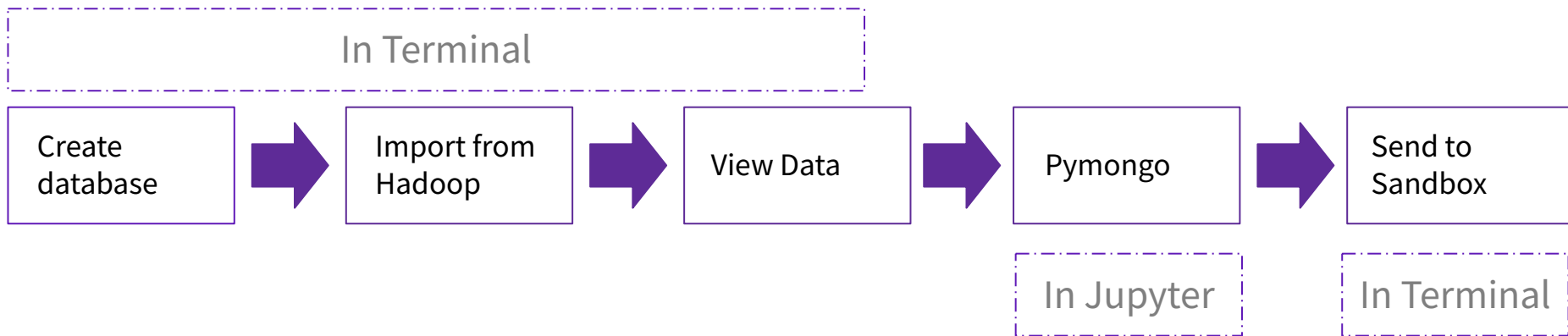
for row in csv_reader:
data.append(row)
```

Writing Data to JSON Files

```
json_filename =
os.path.join(output_directory,
f"{filename}.json") with
open(json_filename, mode='w',
encoding='utf-8') as json_file:

json.dump(data, json_file, indent=4,
ensure_ascii=False) print(f"Converted
{file_path} to {json_filename}")
```

MongoDB



Mongodb

Create database

use your_database

Importing from Hadoop

```
for file in *.json; do
  mongoimport --uri
  mongodb://localhost:27017/your_database \
    --collection your_collection \
    --file "$file" \
    --jsonArray
done
```

View Data

```
mongo --host localhost --port
27017
```

use your_database

```
db.your_collection.find().pretty()
```

All in Terminal

Results

```
{
  "_id" : ObjectId("66782a3171c97f29dcf53a7a"),
  "enrollee_id" : 10348,
  "city" : "city_103",
  "city_development_index" : 0.92,
  "gender" : "Male",
  "relevant_experience" : "No",
  "enrolled_university" : 1,
  "education_level" : "Graduate",
  "major_discipline" : "STEM",
  "experience" : 18,
  "company_size" : "50-99",
  "company_type" : "Pvt Ltd",
  "last_new_job" : "5",
  "training_hours" : "28",
  "target" : 0
}

{
  "_id" : ObjectId("66782a3171c97f29dcf53a7b"),
  "enrollee_id" : 10394,
  "city" : "city_103",
  "city_development_index" : 0.92,
  "gender" : "Male",
  "relevant_experience" : "yes",
  "enrolled_university" : 1,
  "education_level" : "Graduate",
  "major_discipline" : "Other",
  "experience" : 15,
  "company_size" : "50-99",
  "company_type" : "Funded Startup",
  "last_new_job" : "1",
  "training_hours" : "10",
  "target" : 1
}
Type "it" for more
> █
```

Work with data in PyMongo

Connect to mongodb

```
from pymongo import  
MongoClient  
import pandas as pd  
  
client =  
MongoClient('mongo  
db://localhost:27017  
/')  
db =  
client.your_database  
collection =  
db.your_collection
```

Fetch data from MongoDB

```
data = list(collection.find())
```

Convert to Pandas DataFrame

```
df = pd.DataFrame(data)
```

Send to sandbox

```
scp /path/to/sandbox/data.parquet  
user@your-sandbox-ip:/desired/path
```

Results

	_id	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_size	company_ty
0	66782a3171c97f29dcf53a68	10021.0	city_16	0.91	Female	yes	1	Graduate	STEM	5.0	10000+	Pvt
1	66782a3171c97f29dcf53a69	10049.0	city_160	0.92	Male	yes	1	Graduate	STEM	21.0	100-500	Pvt
2	66782a3171c97f29dcf53a6a	10050.0	city_103	0.92	Male	yes	1	Masters	STEM	10.0	10000+	Pvt
3	66782a3171c97f29dcf53a6b	10162.0	city_160	0.92	Female	yes	1	Graduate	STEM	15.0	500-999	Pvt
4	66782a3171c97f29dcf53a6c	10167.0	city_103	0.92	Female	No	2	Graduate	STEM	2.0	50-99	Funded Star
5	66782a3171c97f29dcf53a6d	10171.0	city_61	0.91	Male	yes	1	Masters	STEM	21.0	10-49	Pvt
6	66782a3171c97f29dcf53a6e	10198.0	city_105	0.79	Male	yes	0	Graduate	STEM	11.0	100-500	Pvt
7	66782a3171c97f29dcf53a6f	10217.0	city_159	0.84	Male	yes	1	Graduate	STEM	8.0	50-99	Pvt
8	66782a3171c97f29dcf53a70	10230.0	city_103	0.92	Male	yes	1	Masters	STEM	21.0	500-999	Funded Star
9	66782a3171c97f29dcf53a71	10246.0	city_160	0.92	Male	yes	1	Masters	STEM	17.0	others	Oth

Analysis & Testing

Steps

1. Loading Data
2. Data Preprocessing
3. Selecting Features and Target
4. Visualization the distribution of categorical feature (Bar and Histogram plot)
5. Train-Test Split
6. Classification ML Model for prediction
7. Evaluate ML models
8. Analysis

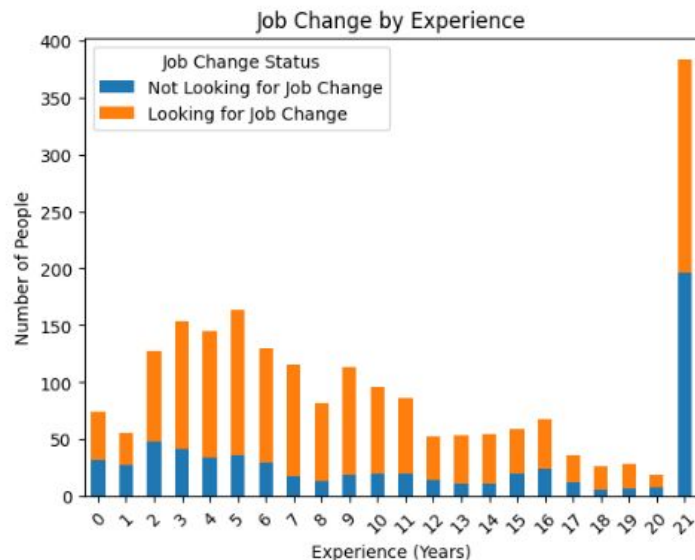
H1: Candidates with longer experience are less likely to seek new job opportunities.

Data Preprocessing

- The `experience` column is converted to numerical values using the `convert_experience` function.

Features and Target (showing in bar plot)

- The feature (X) includes **only** the `experience_category`,
- The target (y) includes the `changing_job`



H1: Candidates with longer experience are less likely to seek new job opportunities.

Decision tree for Model Prediction

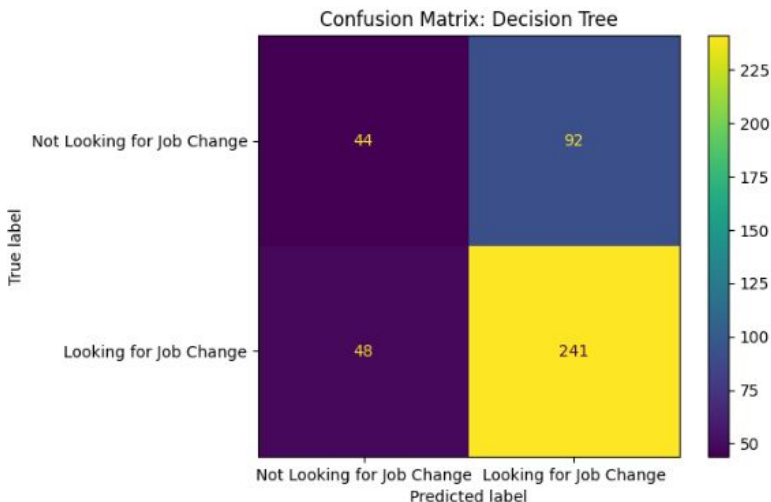
- **Precision**: when the model predicts a candidate is looking for a job change, it is correct **72%** of the time.
- **Recall**: The model correctly identifies **83%** of the candidates who are looking for a job change.
- The **F1-score** is the harmonic mean of precision and recall.

Decision Tree Model Performance:					
		precision	recall	f1-score	support
NL	0.0	0.48	0.32	0.39	136
L	1.0	0.72	0.83	0.77	289
accuracy				0.67	425
macro avg		0.60	0.58	0.58	425
weighted avg		0.65	0.67	0.65	425

Confusion Matrix (Evaluation)

0	(TN): 44	(FP): 92
1	(FN): 48	(TP): 241

- Positive/ Negative: NL/L for job
- True/ False: Identified correctly/ incorrectly by model



H1: Candidates with longer experience are less likely to seek new job opportunities.

- Random forest for Model Prediction

Changing the algorithm and considering more variables and re-examining their effect on the target.

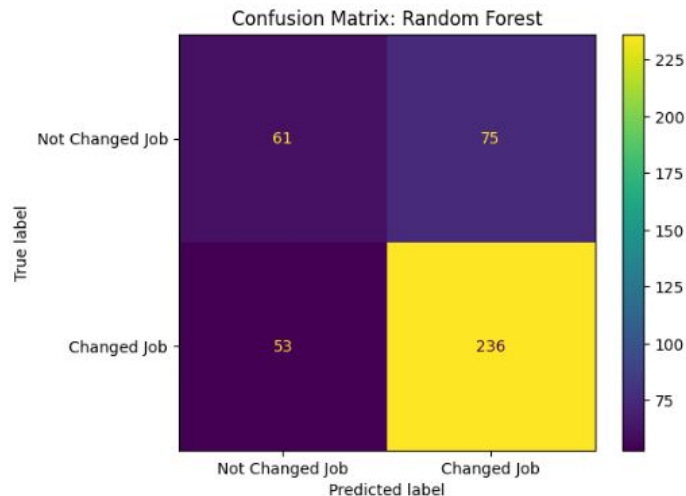
- Education_level, relevant_experience
- Overall accuracy: 0.70

Given that the "experience" feature is the most important feature in the model:

- Individuals with less experience (class 0) are more likely to change jobs.
- Individuals with more experience (class 1) are less likely to change jobs.

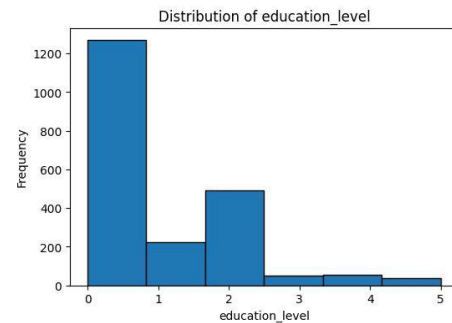
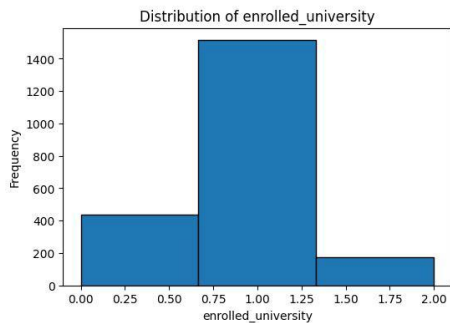
Random Forest Model Performance:

		precision	recall	f1-score	support
NL	0.0	0.54	0.45	0.49	136
L	1.0	0.76	0.82	0.79	289
accuracy				0.70	425
macro avg		0.65	0.63	0.64	425
weighted avg		0.69	0.70	0.69	425

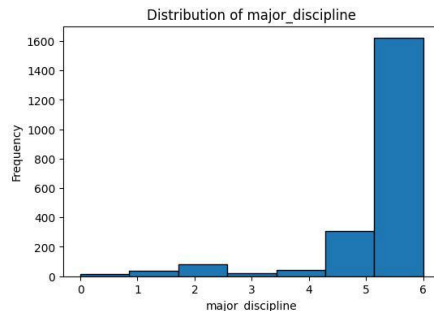
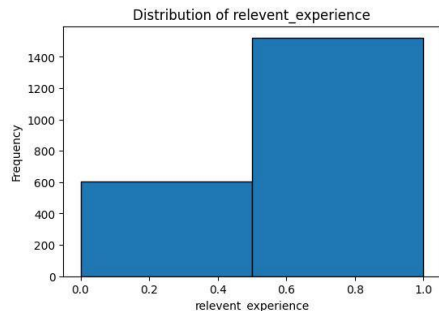


H2 Candidates enrolled in university courses are more likely to look for new job opportunities.

Firstly, we made histogram plots in our sample code visualize the distribution of categorical features (`enrolled_university`, `education_level`, `relevent_experience`, `major_discipline`).



Here's what each part does:



H2: Candidates enrolled in university courses are more likely to look for new job opportunities.

Neural Network Model based on the figure results, the neural network (NN) model achieves an accuracy of **0.61**, with a **precision** of **0.57**, recall of **0.35**, and **F1-score** of **0.43** for candidates likely to seek new job opportunities (**class 1**).

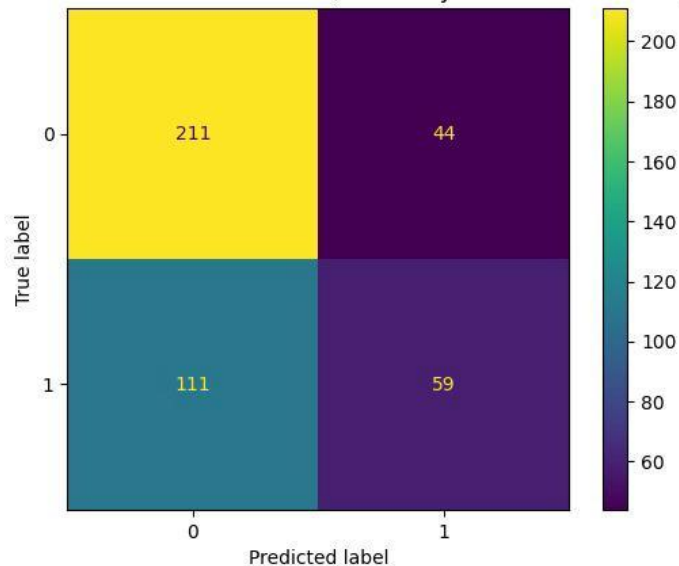
These metrics indicate that NN effectively identifies a substantial number of candidates who are actually looking for new job opportunities while maintaining a balanced performance in terms of precision and recall.

Therefore, NN is recommended for predicting candidates' likelihood to seek new job opportunities based on their experience.

Neural Network Model Performance (University Enrolled Candidates):

	precision	recall	f1-score	support
0	0.66	0.83	0.73	255
1	0.57	0.35	0.43	170
accuracy			0.64	425
macro avg	0.61	0.59	0.58	425
weighted avg	0.62	0.64	0.61	425

Confusion Matrix: Neural Network (University Enrolled Candidates)



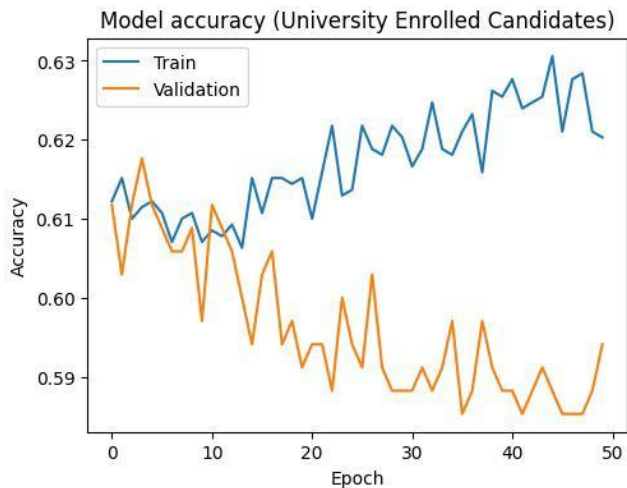
H2 Candidates enrolled in university courses are more likely to look for new job opportunities.

```
# Evaluate the model on university enrolled candidates
```

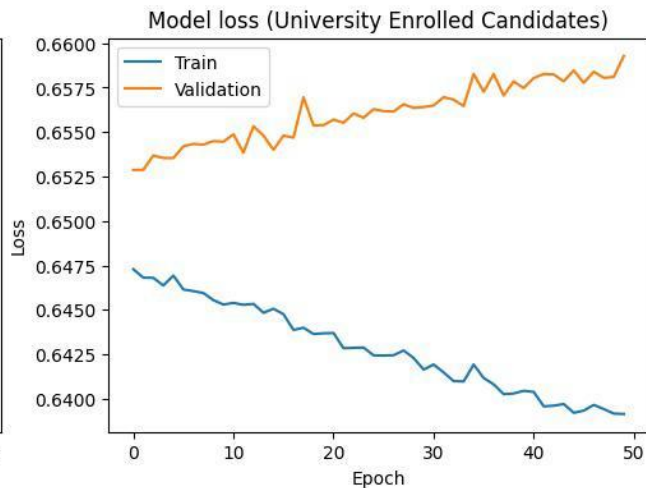
```
y_pred_prob_univ = model.predict(X_test_univ)
```

```
y_pred_univ = (y_pred_prob_univ > 0.5).astype(int)
```

Training & validation accuracy values for
university enrolled candidates



Training & validation loss values for
university enrolled candidates



H2 Candidates enrolled in university courses are more likely to look for new job opportunities.

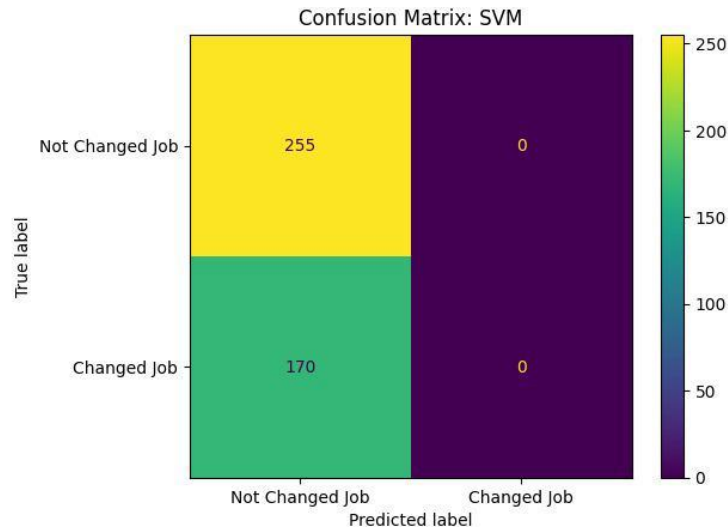
SVM Support Vector Machine show a precision, recall, and F1-score of 0.00 for candidates seeking new job opportunities (class 1), this means the model fails to correctly identify any of these candidates.

As a result, SVM does not effectively capture the relationship between candidates' experience and their likelihood to seek new job opportunities.

Therefore, SVM's performance in this regard is inadequate for drawing conclusions about this hypothesis

Support Vector Machine (SVM) Model Performance:

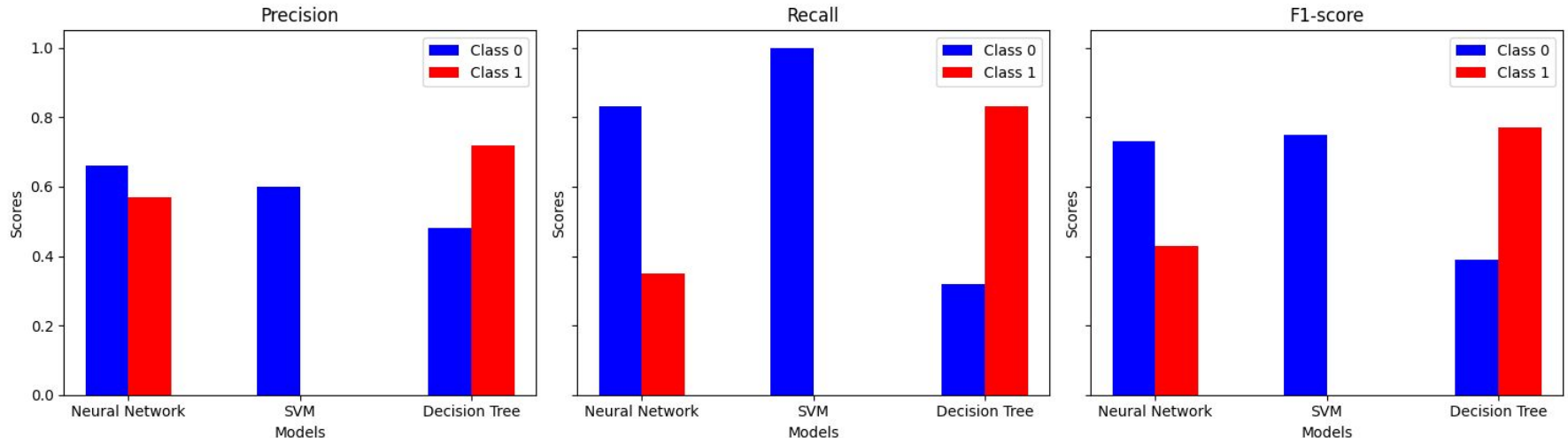
	precision	recall	f1-score	support
0	0.60	1.00	0.75	255
1	0.00	0.00	0.00	170
accuracy			0.60	425
macro avg	0.30	0.50	0.37	425
weighted avg	0.36	0.60	0.45	425



Conclusion

This comparison helps evaluate the models' capabilities in validating hypotheses related to candidate job change behavior, such as the influence of university enrollment and work experience length.

Model Performance Comparison



Challenge & Limitation

- HDFs restrict connectivity in our devices, causing problems with VMs connecting effectively to intensive processes.
- The sandbox environment struggles to establish a reliable connection between MongoDB data storage and machine learning code files, leading to operational issues.
- In hypothesis 1, there are limitations in working with only one values, so we improved the problem in the second hypothesis.
- Attempts to use machine learning models for prediction were unsuccessful, even after switching models, as results remained inaccurate. Further efforts to categorize data into two columns did not yield useful outcomes.

References

DataSet Source :

<https://www.kaggle.com/datasets/arashnic/hr-analytics-job-change-of-data-scientists>

DS&BD Course Notes:

<https://elearning.unipv.it/course/view.php?id=6951>

VM Environment Configuration :

https://drive.google.com/file/d/1KxCrpDNotz2kuo-G8O5VvRp_YFNRNDdX/view

Any Questions?

Thank you
شكرًا - Moteshakeram

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