

Proposal for predicting a candidate looking for a new job

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Overview

1. This dataset designed to understand the factors that lead a person will work for the company (leaving current job), and the goal of this task is building model(s) that uses the current credentials,demographics,experience to predict the probability of a candidate looking for a new job or will work for the company.
2. The whole data divided to train and test . Target isn't included in test but the test target values data file is in hands for related tasks. A sample submission correspond to enrollee_id of test set provided too with columns : enrollee_id , target.

Note:

- The dataset is imbalanced.
- Most features are categorical (Nominal, Ordinal, Binary), some with high cardinality.

Dataset description

	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_size
0	8949	city_103	0.920	Male	Has relevent experience	no_enrollment	Graduate	STEM	>20	NaN
1	29725	city_40	0.776	Male	No relevent experience	no_enrollment	Graduate	STEM	15	50-99
2	11561	city_21	0.624	NaN	No relevent experience	Full time course	Graduate	STEM	5	NaN
3	33241	city_115	0.789	NaN	No relevent experience	NaN	Graduate	Business Degree	<1	NaN
4	666	city_162	0.767	Male	Has relevent experience	no_enrollment	Masters	STEM	>20	50-99

❑ Data sources:

- ❑ The datasets are sourced from the website kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners that allows users to find and publish datasets, explore and build models in a web-based data-science environment.
- ❑ The dataset aug_train.csv used in this project was collected in August, 2020. This data set contains **19,158 observations**, 14 columns. i.e 13 features + 1 label.

- ❑ 10 categorical variables: city, gender, relevent_experience, enrolled_university, education_level, major_discipline, experience, company_size,last_new_job,company_type

3 numerical variables: enrollee_id, city_development_index,training_hours

1 label variable - target

❑ Features

- **enrollee_id** : Unique ID for candidate
- **city**: City code
- **city_development_index** : Development index of the city (scaled)
- **gender**: Gender of candidate
- **relevent_experience**: Relevant experience of candidate
- **enrolled_university**: Type of University course enrolled if any
- **education_level**: Education level of candidate
- **major_discipline** : Education major discipline of candidate
- **experience**: Candidate total experience in years
- **company_size**: No of employees in current employer's company
- **company_type** : Type of current employer
- **lastnewjob**: Difference in years between previous job and current job
- **training_hours**: training hours completed
- **target**: 0 – Not looking for job change, 1 – Looking for a job change

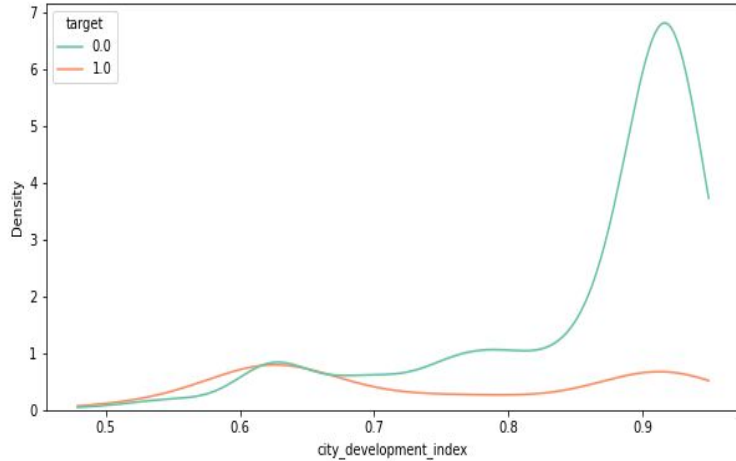
Key Findings

❏ 8 Columns have missing values.

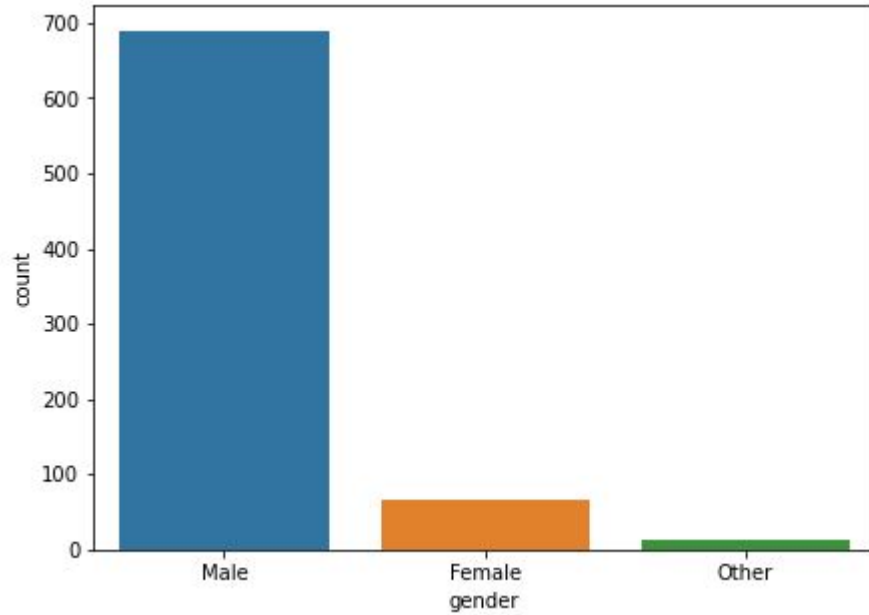
	null_numm	null_percent
gender	4508	0.240000
enrolled_university	386	0.020000
education_level	460	0.020000
major_discipline	2813	0.150000
experience	65	0.000000
company_size	5938	0.310000
company_type	6140	0.320000
last_new_job	423	0.020000

1. The company type has the largest missing value, with a missing percentage of 32%.
2. The company size has the largest missing value, with a missing ratio of 31%.

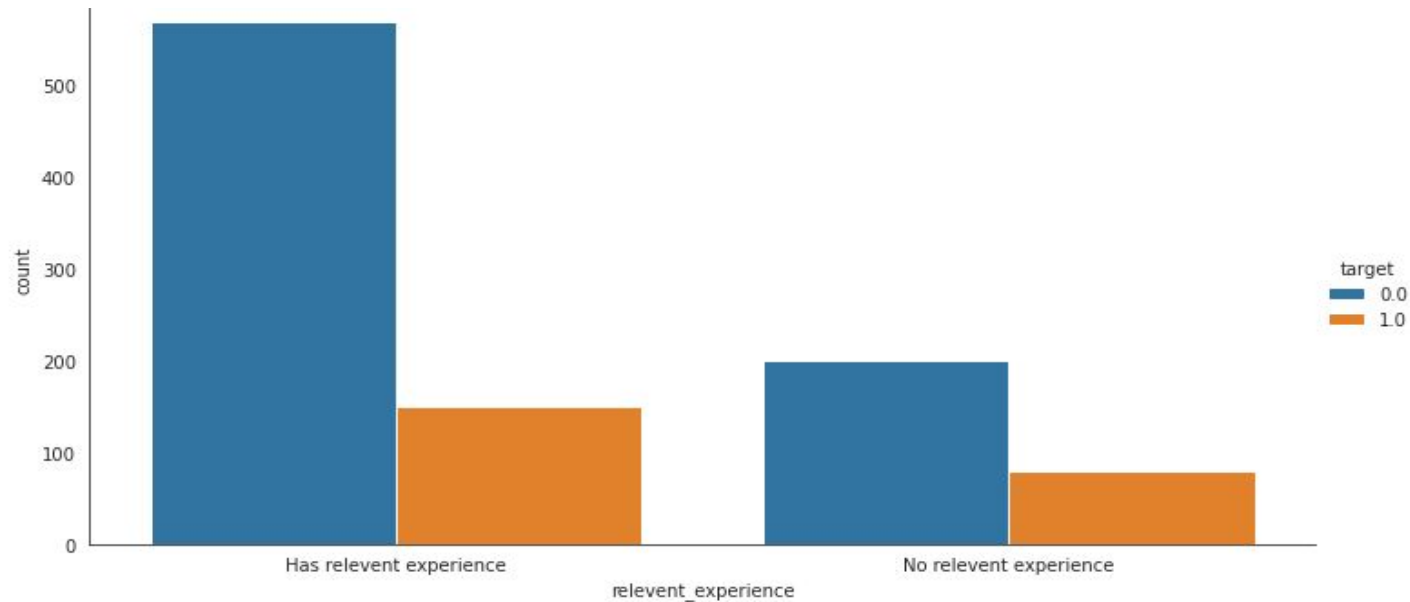
Visualisation and Missing Values Treatment



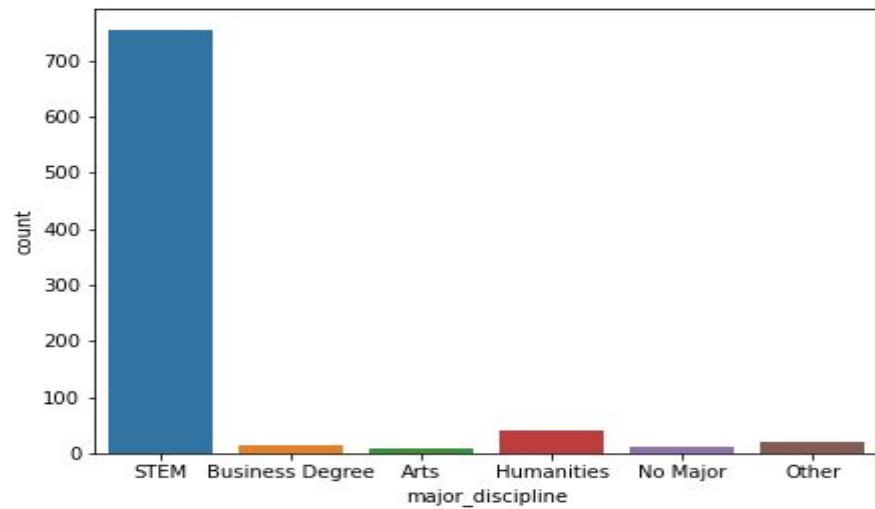
From this graph, we can observe that people who live in developed cities have a lower likelihood of changing occupations.



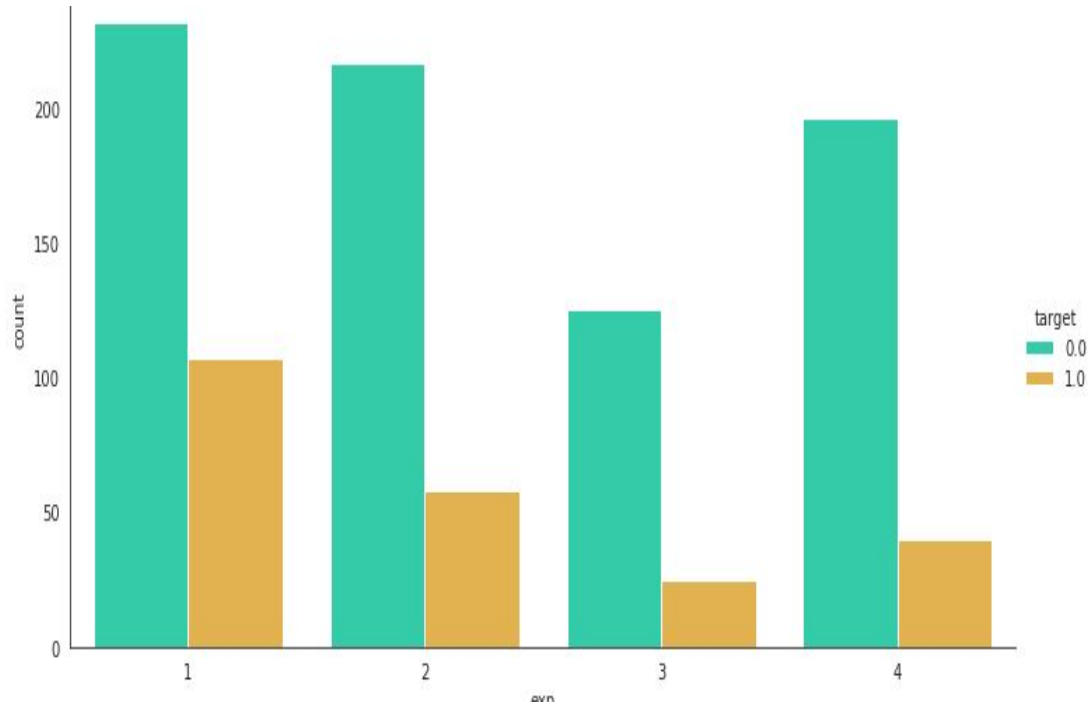
The number of male candidates who applied for the job is the highest.



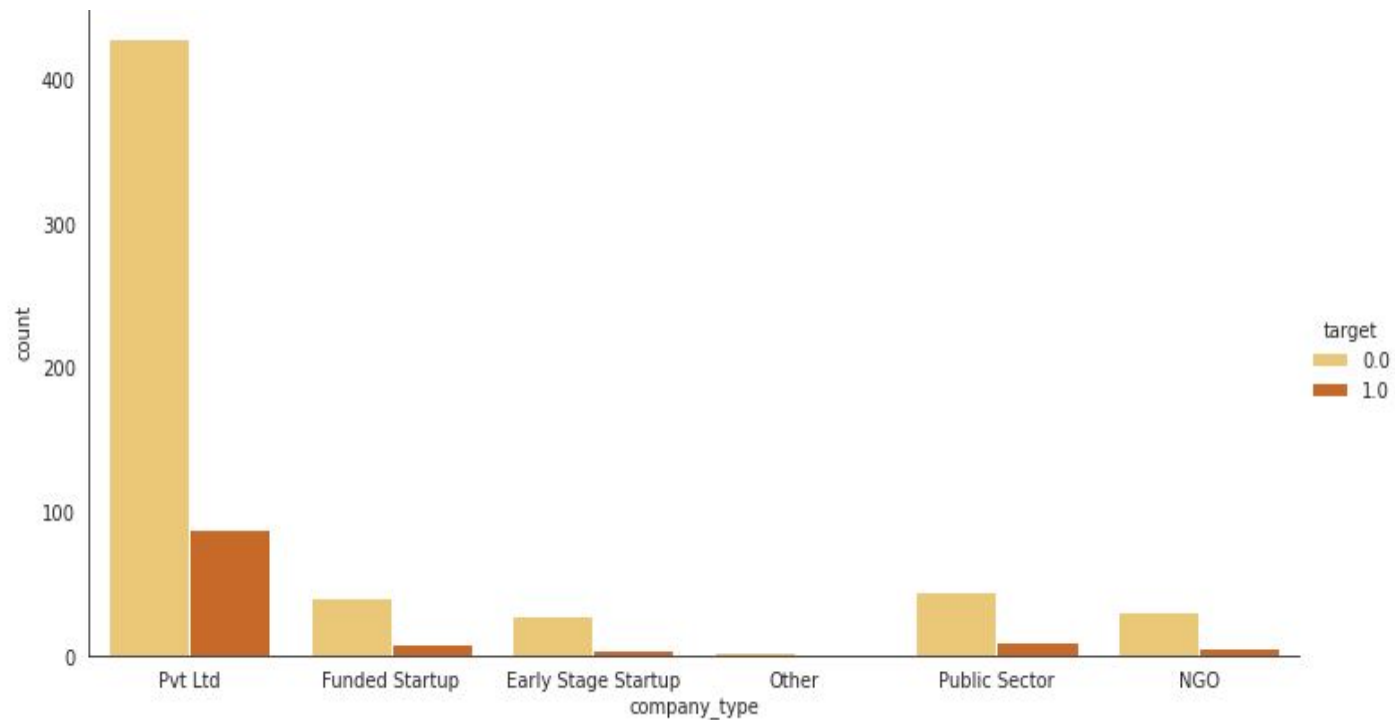
Here, from this chart, we can analyse that candidates who are having relevant experience in the concerned field are less likely to switch their job in comparison to the others who have no relevant experience.



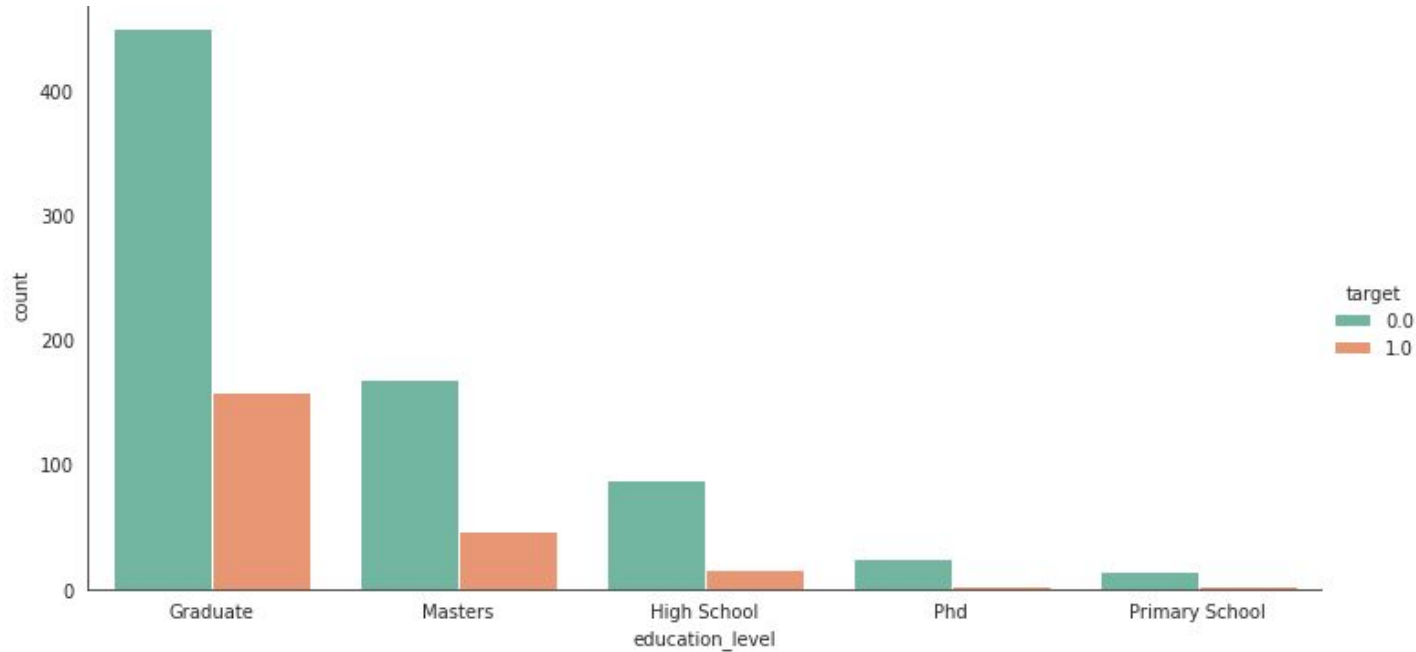
Majority of the candidates are from STEM.



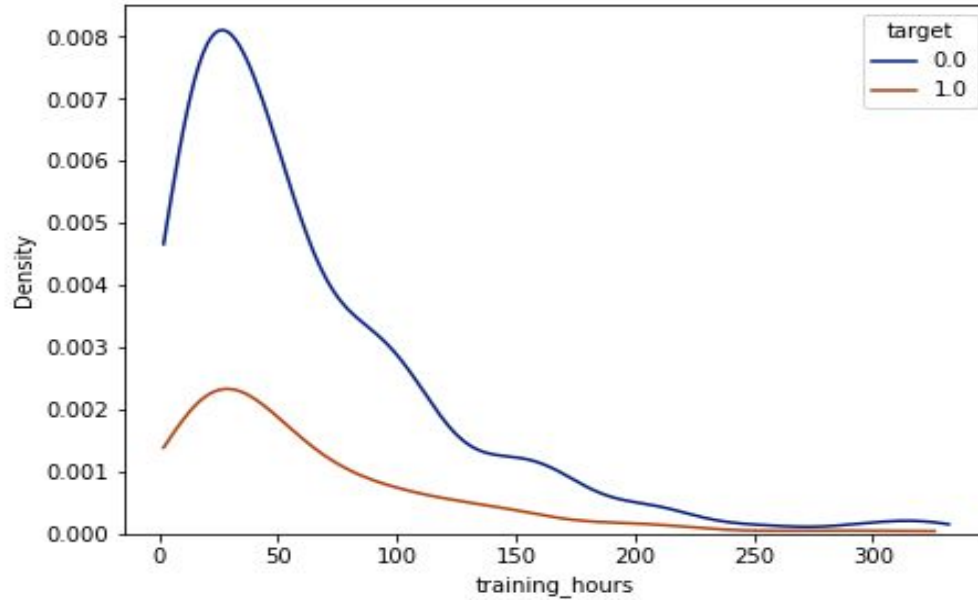
According to the analysis, those who are having less experience are more vulnerable to switch their job, rather than those who are having more experience.



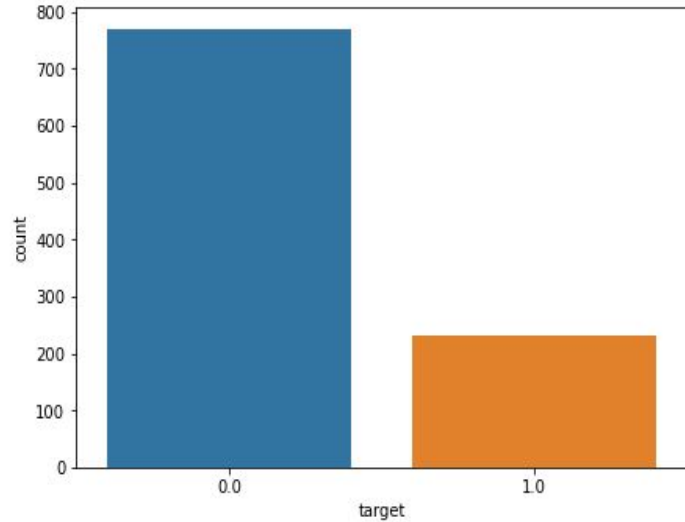
People who are working in private companies have lesser possibility of changing their job.



Most of the candidates are having graduation as their highest qualification followed by masters, and very few candidates are having Phd as their qualification.



From this graph, we can observe that employees with less training hours had a decreased likelihood of changing employment.



Here it is clearly visible that the data is highly imbalanced. In order to train the model properly, we need to balance and for the same we use SMOTE (Synthetic Minority Oversampling Technique) to balance the data.

Modeling and Analysis

Model Selection

We studied the performance of 5 classification models: Logistic Regression, Gaussian Naïve Bayes, k-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, BernoulliNB.

Final Model Selection and Hyperparameters Tuning

	Models	Accuracy Score
3	SVC	0.835
4	RandomForestClassifier	0.830
5	KNeighborsClassifier	0.805
0	LogisticRegression	0.800
2	BernoulliNB	0.775
1	GaussianNB	0.280

- Random Forest Classifier and SCV though comparatively time consuming, were the most accurate with the least number of misclassifications followed by Logistic Regression and KNeighborsClassifier.