Responsible Data Science Course Project

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1 Introduction

The purpose of this project is to build an interpretability tool for an Automated Decision System (ADS) which we have chosen to audit.

Automated Decision Systems are in widespread use in government and industry, and a number of efforts are currently underway to regulate them. New York City recently passed a law (Local Law 49 of 2018) that compels the development of procedures and recommendations that City agencies should follow when explaining the operation of an ADS to the public, and demonstrating that an ADS does not discriminate against individuals based on membership in protected groups.

In this project, we attempt to help NYC and other municipalities by designing a"nutritional label" (similar to a label used to evaluate food products) for an algorithmic system of our choice.

2 Background

In recent years, the growing demands for jobs in data science have driven the creation of a myriad of degree programs, massive online open courses, online certification programs, and boot camps. While the abundance of those learning resources has made data science accessible to a wide range of people looking to enter the field, the variety of credentials has also made it difficult for companies to evaluate the qualifications of job seekers. The process of hiring data scientists is often both expensive and time-consuming. Therefore, companies have incentives to hire qualified data scientists and keep them from leaving.

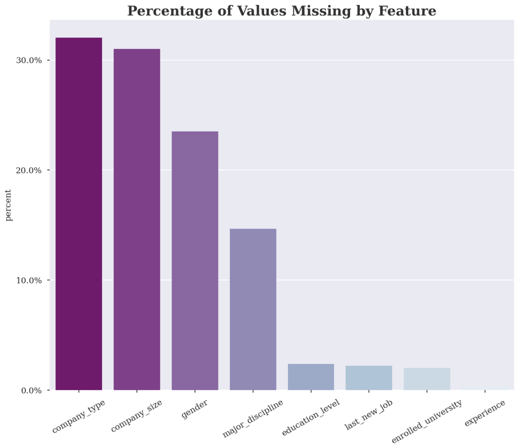
As as a result of this trend, the Automated Decision System (ADS) that we chose to examine is from the Human Resources and hiring space. In particular, we wish to examine a top entry from an HR Analytics Kaggle competition published here. The source of these data come from a company active in the big data and data science industries that is looking to hire data scientists amongst a group of candidates who have taken training courses hosted by the company. Many candidates sign up for training and the firm would like to know which trainees would be interested in working for the company and which are currently looking for new employment. Targeting these candidates reduces costs and time associated with hiring data scientists. In addition, a model of this kind would also help improve the quality of these trainings and the planning of courses that might further help categorize candidates in the future. The desired outcome of this model is to accurately predict the probability that a given trainee is on the job market and is actively looking for a new position. The ultimate action taken as a result of this ADS is determining which trainees should be invited to interview for data science positions at the company.

In the course of our analysis, we will examine these data, the cleaning process, and the system itself in order to evaluate whether the ADS discriminates on the basis of gender or socioeconomic status. If present, such discrimination could result in certain groups of employees receiving less rigorous training, fewer promotions and denied access to other benefits. Our aim is to design a “nutritional label” for the ADS that examines the bias in the data, the processing, and one machine learning model used in this decisionmaking process.

3 Input and Output

These data, made available by the company, are designed to understand the factors that lead a data scientist to search for a new job. Important information pertaining to demographics, education and prior experience is made available (on an anonymized basis) from registered and enrolled candidates. There is little information available about the geography of the candidate population in question or even the time during which these data were collected however we can discern from that they represent job candidates from 123 different cities of varying levels of development. The development of a candidate's city is expressed by the city development index. The index is calculated based on five sub indices: infrastructure, waste, health, education and city product. The total data set for the ADS comprises 19,158 candidates with the following 14 features describing each:

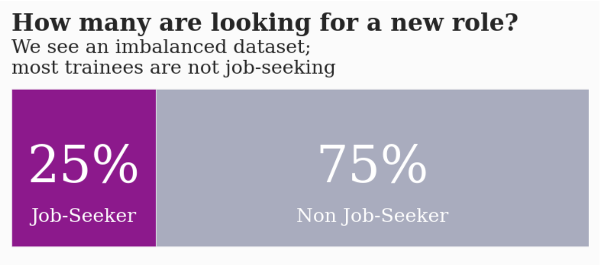
Feature	Description
enrollee_id	Unique ID for candidate
city	Code given for candidate's city
city_development_index	Development index of the city (scaled)
gender	Gender of candidate
relevant_experience	Relevant experience of candidate
enrolled_university	Type of University course enrolled if any
education_level	Education level of candidate
major_discipline	Education major discipline of candidate
experience	Candidate total experience in years
company_size	Number of employees in current employer's company
company_type	Type of current employer
last_new_job	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



The majority of these features are categorical(Nominal, Ordinal, Binary), some with high cardinality. The exceptions are *city_development_index* and *training hours* both of which are numeric. Some features have large proportions of missing values, particularly *company_type*, *company_size* and *gender*.

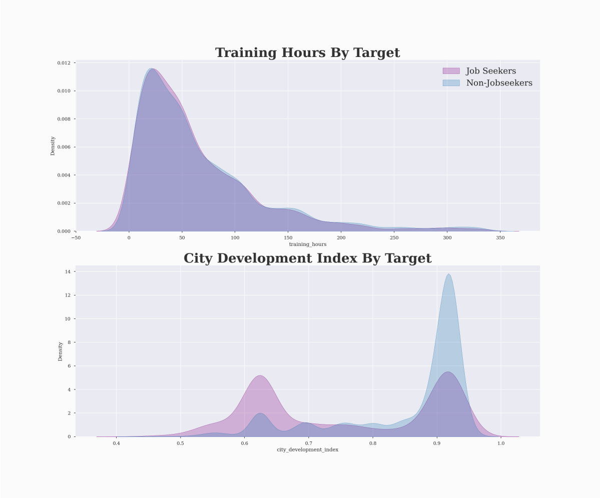
Feature	Data Type	Distinct Values	% Null
enrollee_id	int64	19,158	0.0 %
city	object	123	0.0 %
city_development_index	float64	93	0.0 %
gender	object	4	23.5 %
relevant_experience	object	2	0.0 %
enrolled_university	object	4	2.0 %
education_level	object	6	2.4 %
major_discipline	object	7	14.7 %
experience	object	23	0.7 %
company_size	object	9	31.0 %
company_type	object	7	32.0 %
last_new_job	object	7	2.2 %
training_hours	int64	241	0.0 %
target	int64	2	0.0 %

In terms of relative distributions, this dataset is largely imbalanced on our target variable with 75% of candidates not seeking a new job and only 25% actively on the job market. This imbalance is significant in that it will impact the choice of modeling and necessary data preparation steps of the decision system.



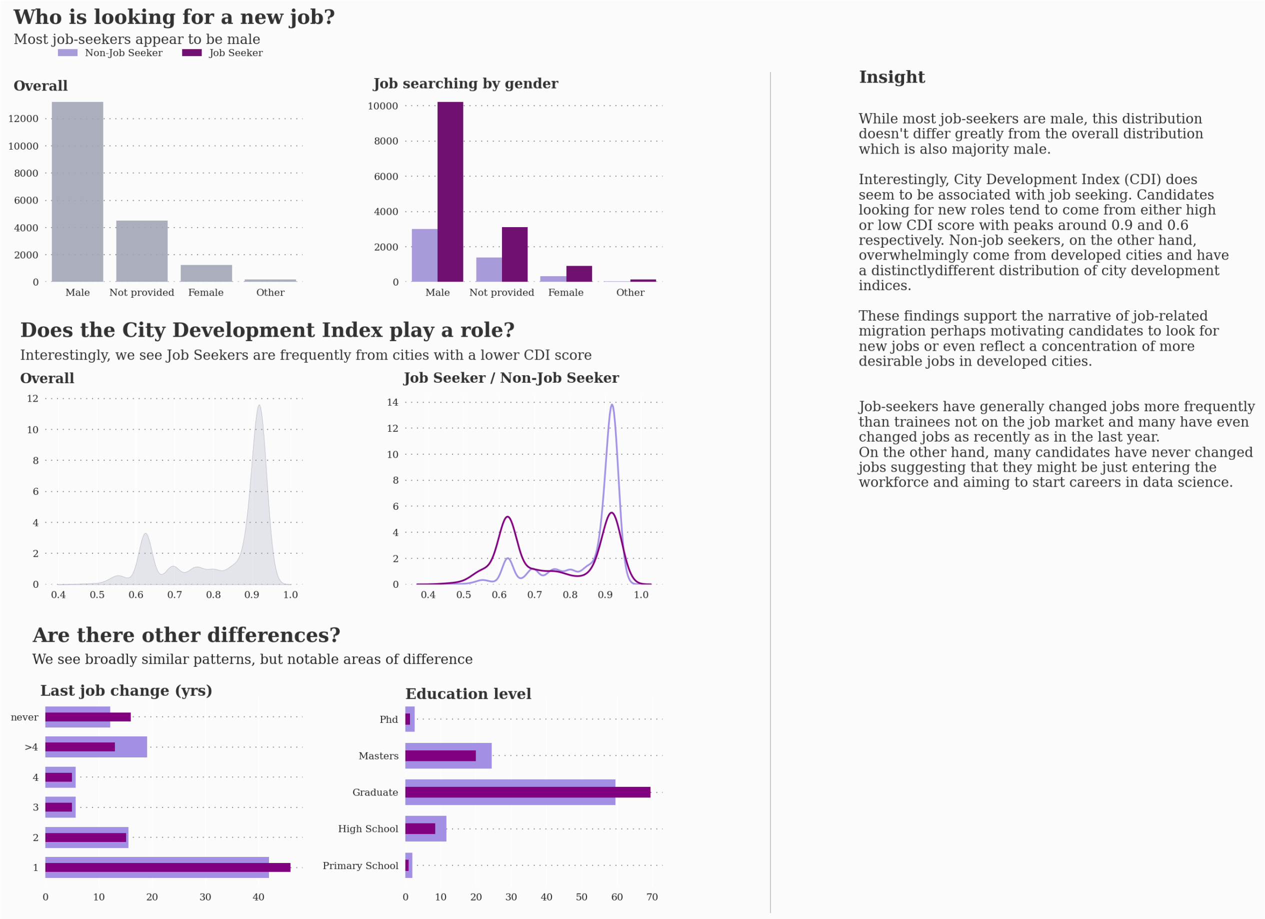
The overwhelming majority of candidates in the dataset are male, representing nearly 70% of the total population. Similarly the majority of trainees have prior data science experience and at least an undergraduate degree in a STEM field. The candidate pool is also largely experienced in the workforce with 60% having 10 or more years of experience. The majority of candidates competed 47 hours of training or less with a long right tail. While a large portion of candidates come from cities with high development indices, there is another pool of candidates that comes from cities with an index just above 0.6. The full set of distribution plots and exploratory data analysis of each feature in the dataset can be found on our accompanying jupyter notebook here.

While job seekers and non-job seekers share similar distributions on many features, there are several key differences that might provide some insight on factors that motivate candidates to search for new roles. In particular, a smaller proportion of job seekers seem to have relevant data science experience, indicating that professionals outside of the field might be motivated to switch to careers in the growing data science industry. Similarly, job seekers are much more likely to be full-time students looking for positions after graduation. This might also explain why many job-seekers do not supply information about their current company since they may not be currently employed. The gender distribution be-



tween candidates actively searching and those who are not appear roughly the same, with a slighter larger share of applicants not reporting their gender. In general, job seekers are also less experienced than their peers not on the job market and if employed, have been in the current role for 4 years or longer.

Interestingly, job seekers are much more likely to come from cities with lower development indices. In addition, experienced trainees overwhelmingly live in developed cities, much more so than their peers staring out in the workforce. This supports the narrative that experienced candidates migrate to more developed centers and that job seekers might be motivated to do the same through a change of employment.


Who is looking for a new job?

Most job-seekers appear to be male

Does the City Development Index play a role?

Interestingly, we see Job Seekers are frequently from cities with a lower CDI score

Are there other differences?

We see broadly similar patterns, but notable areas of difference

Insight

While most job-seekers are male, this distribution doesn't differ greatly from the overall distribution which is also majority male.

Interestingly, City Development Index (CDI) does seem to be associated with job seeking. Candidates looking for new roles tend to come from either high or low CDI score with peaks around 0.9 and 0.6 respectively. Non-job seekers, on the other hand, overwhelmingly come from developed cities and have a distinctlydifferent distribution of city development indices.

These findings support the narrative of job-related migration perhaps motivating candidates to look for new jobs or even reflect a concentration of more desirable jobs in developed cities.

Job-seekers have generally changed jobs more frequently than trainees not on the job market and many have even changed jobs as recently as in the last year.
On the other hand, many candidates have never changed jobs suggesting that they might be just entering the workforce and aiming to start careers in data science.

The output of this ADS comes from a logistic regression model that was trained on a synthetically upsampled data set to correct for imbalance in the target variable. While the output of the machine learning model is a probability of the candidate being on the job market, the output of this ADS is a class label (either ‘Job Seeking’ or ‘Not Job Seeking’) that assumes that candidates with predicted probabilities above a threshold of 0.5 are looking for a job.

4 Implementation and Validation

The ultimate model used for this ADS is a logistic regression trained on a dataset that was augmented using the Synthetic Minority Oversampling Technique (SMOTE). Prior to training the model however, the creator made several choices pertaining to the preparation and pre-processing that ultimately impacted the algorithm's results.

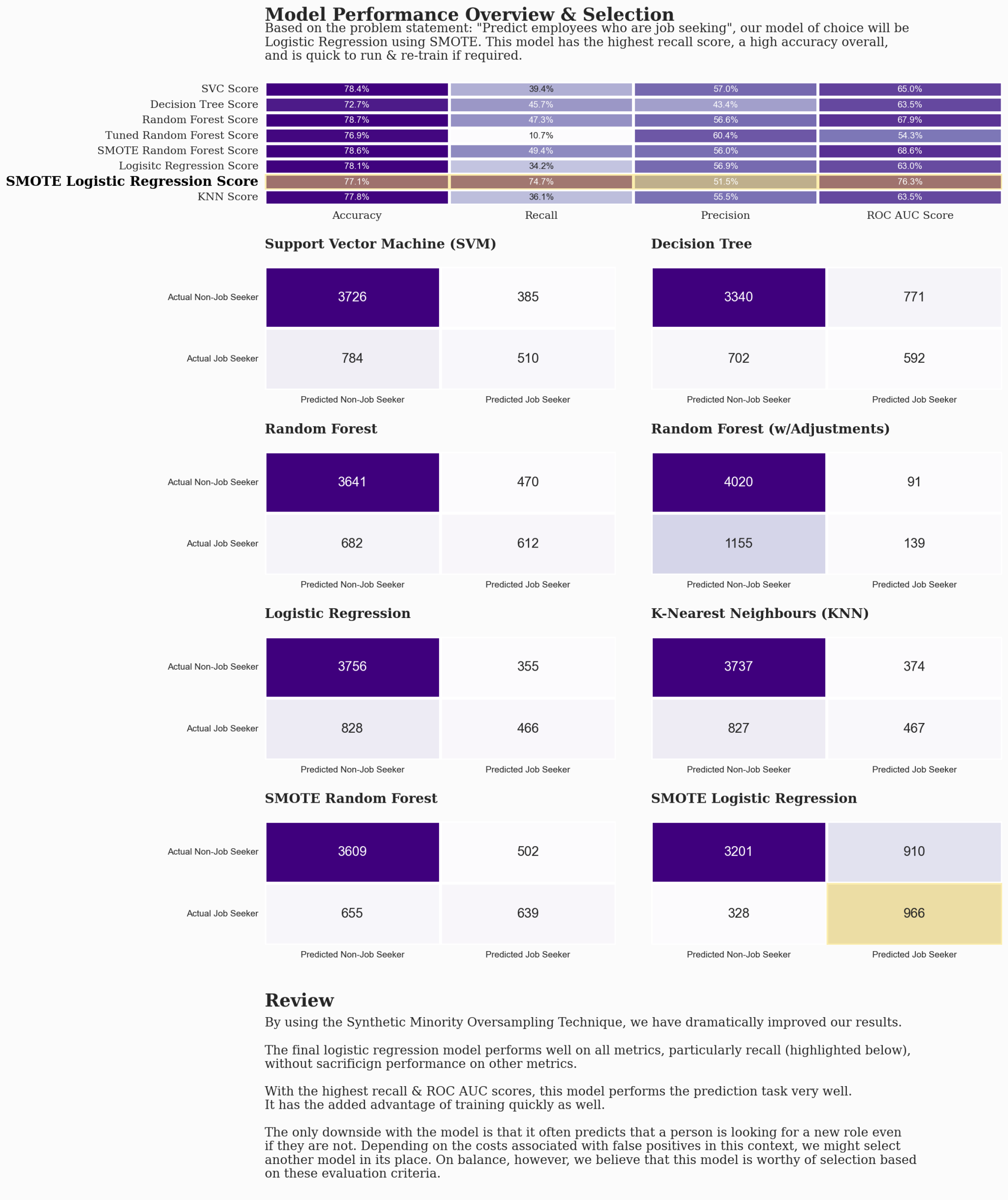
Given the prevalence of missing values in the dataset, the imputation technique used might significantly change the distribution of our training set. In this instance, the creator choose to handle missing values for 'company_type', 'major_discipline', and 'gender' by treating them as a separate class altogether, labeled 'Unknown' or 'Not Provided', while missing values for 'company_size' were unilaterally imputed as 0. Any observations that had missing values outside of these features were then dropped, bringing our population down to 18,014 candidates. Given that our final model is a logistic regression, and therefore sensitive to null values, it is usually appropriate to handle imputations this way.

In addition to imputing null values, the creator took several steps to prepare features before training any models. This involved creating dummy variables for each of our many categorical variables and removing the target and unique identifier. This expands our dataset to 190 features. For the purposes of future validation, the population is then split into test and train datasets at a 30/70 ratio. No validation set was held out for hyper-parameter tuning. Finally, in nearly all model pipelines, the creator scaled features through Z-score normalization, an important pre-processing step for many classification algorithms especially logistic regression. From our analysis of distributions above, we see that the continuous variables in this dataset are rarely normally distributed although we make the assumption that they are in z-standard normalization.

Given the large imbalance of job seekers to non-job seekers in this data set (25% to 75% respectively), the creator employs Synthetic Minority Oversampling Technique (SMOTE) to solve for this problem and improves model performance. SMOTE is one of the most commonly used oversampling methods that aims to balance by randomly increasing minority class examples by replicating them. The technique synthetically generates new instances of the minority class from existing instances of the class by linear interpolation. These synthetic training records are generated by randomly selecting one or more of the knearest neighbors for each example in the minority class. A randomly selected neighbor is chosen and a synthetic example is created a random point between the two existing examples in feature space. We can replicate this procedure as many times as necessary to create class balance. In the case of our human resources dataset, we generated over 6,000 new samples and increased the training dataset by roughly 50%. This approach is generally effective since it ensures that the new synthetic examples are plausible and relatively close, in feature space, to the existing observations of the minority class.

Despite its widespread use and broad adoption of the technique for class balancing, the effect of such strategies on model fairness is largely unknown and is an undergoing area of research. In their 2020 CIKM presentation, Yan et al. demonstrated that popular balancing techniques contribute to greater differences of statistical parity, equal opportunity and equalized odds when applied to the COMPAS decision system. SMOTE, in particular, created the greatest disparity in fair outcomes of any other technique tested. By only balancing on the target variables, they argue, traditional class balancing techniques do not consider the distribution of sensitive attributes when creating synthetic samples and therefore have the potential to exacerbate unfairness towards underrepresented groups. In the context of our job seeking algorithm, for example, we could imagine seeing an overrepresentation of candidates in the upsampled dataset who do not have relevant experience given the difference in distributions of experienced candidates between target classes. Similarly, we might observe an over-representation of candidates who did not provide their gender and conversely an under-representation of candidates who identify as male. New techniques have been introduced such as fair class balancing and FAIR-SMOTE that begin to address some of these inequalities however they were not applied in the creation of this ADS.

After preparing a training dataset, the author ran a series of classification machine learning models (Support Vector Classification, a Decision Tree, Random Forrest, Logistic Regression and a KNN-algorithm) and evaluated the performance of each prior to deciding on a final model. The performance measures that were evaluated included Accuracy, Recall, Precision and ROC Area under the curve. All of the classification models performed significantly better when trained on the SMOTE upsampled training data set. While the author did not specify which they were optimizing for specifically, one could imagine favoring models with higher precision or recall depending on the time and investment associated with inviting a candidate to interview. In the end, the logistic regression was chosen for its dramatically higher recall score and high overall accuracy.



Model Performance Overview & Selection

Based on the problem statement: "Predict employees who are job seeking", our model of choice will be
Logistic Regression using SMOTE. This model has the highest recall score, a high accuracy overall,
and is quick to run & re-train if required.

	Accuracy	Recall	Precision	ROC AUC Score
SVC Score	78.4%	39.4%	57.0%	65.0%
Decision Tree Score	72.7%	45.7%	43.4%	63.5%
Random Forest Score	78.7%	47.3%	56.6%	67.9%
Tuned Random Forest Score	76.9%	10.7%	60.4%	54.3%
SMOTE Random Forest Score	78.6%	49.4%	56.0%	68.6%
Logisitc Regression Score	78.1%	34.2%	56.9%	63.0%
SMOTE Logistic Regression Score	77.1%	74.7%	51.5%	76.3%
KNN Score	77.8%	36.1%	55.5%	63.5%

Support Vector Machine (SVM)

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3726	385
Actual Job Seeker	784	510

Decision Tree

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3340	771
Actual Job Seeker	702	592

Random Forest

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3641	470
Actual Job Seeker	682	612

Random Forest (w/Adjustments)

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	4020	91
Actual Job Seeker	1155	139

Logistic Regression

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3756	355
Actual Job Seeker	828	466

K-Nearest Neighbours (KNN)

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3737	374
Actual Job Seeker	827	467

SMOTE Random Forest

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3609	502
Actual Job Seeker	655	639

SMOTE Logistic Regression

	Predicted Non-Job Seeker	Predicted Job Seeker
Actual Non-Job Seeker	3201	910
Actual Job Seeker	328	966

Review

By using the Synthetic Minority Oversampling Technique, we have dramatically improved our results.

The final logistic regression model performs well on all metrics, particularly recall (highlighted below), without sacrificign performance on other metrics.

With the highest recall & ROC AUC scores, this model performs the prediction task very well.
It has the added advantage of training quickly as well.

The only downside with the model is that it often predicts that a person is looking for a new role even if they are not. Depending on the costs associated with false positives in this context, we might select another model in its place. On balance, however, we believe that this model is worthy of selection based on these evaluation criteria.

5 Outcomes

Now, we will examine the bias and fairness of the ADS by evaluating its performance across subpopulations. In particular, we examine five attributes: gender, education level, relevant experience, general experience, and city development. Given the context of our task, we consider the following metrics:

- Sample size, which we use to measure the balance of the dataset.
- Selection rate, which is the portion of predicted labels matching the ‘good’ outcome. In this case, the ’good’ outcome is being a ”job seeker”. This is because companies will often provide extra benefit to those of their employees seeking new jobs in attempts to keep them from leaving. The job seekers will also receive more job opportunities if other companies were to obtain this information. We choose this measure to whether one group receive disproportionately more ”good” outcomes than others.
- Accuracy, which is defined as $\frac{TP+TN}{P+N}$. We choose accuracy as a standard measure of the model’s performance in subgroups.
- False Negative Rate (FNR), which in this context is the percentage of job-seekers that are predicted to be not job-seeking. We care about FNR because the false negative cases represent a lost benefit: those who could have gotten job opportunities or higher chance of promotion did not get them. The term is defined as $\frac{FN}{FN+TP}$.
- False Positive Rate (FPR), which is the percentage among non-job-seekers that were predicted to be job-seeking. This means those who are not seeking new jobs receive potential promotion, which is a plus, and job opportunities, which might or might not be an annoyance. The companies, on the other hand, waste resources in trying to keep people who don’t want to leave in the first place, hence t would be in the interest of the companies using the ADS to reduce FPR. The term is defined as $\frac{FP}{FP+TN}$.
- Average Precision, which summarizes a precision-recall curve as the weighted mean of precision achieved at each threshold, with the increase in recall from the previous threshold used as the weight.
- ROC AUC score, which computes the Area Under the Receiver Operating Characteristic Curve (ROC AUC) from prediction scores. We choose both Average precision and ROC score as additional measures of the accuracy.

The baseline values for these data are as follows:

Measure	Baseline Value
sample size	5405
selection rate	0.348566
FNR	0.256569
FPR	0.224276
accuracy	0.767993
average precision	0.441032
ROC score	0.759577

The first protected attribute we examine is gender, which is a categorical variable with values "Female", "Male", "Others", and "Not provided". For the sake of readability, we leave all the diagrams in the appendix. As mentioned in previous section, there are disproportionately many more in the dataset. Nevertheless, the model doesn't have a significant gender bias. All measures demonstrate reasonable parity across gender groups.

Next, we examine education level, which is correlated with socioeconomic status. The categorical values comprise 'Primary School', 'High School', 'Graduate', 'Masters', and 'PhD', where we assume "Graduate" to indicate a college graduate. These data is, again, imbalanced, with significantly more "Graduate" and "Masters" than any other education level. We observe that "graduate" have both the highest selection rate and the highest FPR, indicating that the ADS is highly likely to label "Graduate" as job-seekers. On the other hand, those with "High School" education level have the lowest selection and FPR rate, meaning the ADS is highly likely to label them as non-job seekers. The accuracy for the two groups are similar, meaning that there is some truth to "Graduate" having a higher likelihood to be seeking jobs and the same for those with high school diplomas. Nevertheless, this means those with high school diplomas will potentially receive less job opportunities (if the ADS is used by other companies) and chance of promotion (if the ADS is used by the current company).

Then, we examine relevant experience, which is a binary variable containing either "yes" or "no". We observe that the selection rate and FPR for those with no job experience are about twice as much as that of those with job experience, indicating that the ADS has the tendency to label those with no relevant job experience as "job seekers". This hurts job seekers with relevant experience because they are less likely to be viewed as job-seeking, and therefore may receive fewer opportunities as a result.

Furthermore, we examine experience in general, which correlates with age. Recall that in the previous section, we changed the years in experience of everyone with more than 20 years of experience to 20. We observe that the more experience a person has, the less likely the ADS will think they are job-seeking. The Selection rate and the FPR for those with no experience is almost three times higher than the values for those with 20 or more years of experience. This bias put older candidates at a disadvantage since they are less likely to be viewed as job-seeking and they will miss out on job opportunities and potential promotion as a result.

Lastly, we examine the development index of the city that the data scientist currently resides. Recall that the index is calculated based on five sub indices: infrastructure, waste, health, education and city product. We observe that the selection rate and FPR for cities with development index less than 0.6 is almost 1, meaning that being in such a city make the ADS automatically label one as a "job-seeker". The lower accuracy for those cities help us discern that this is more likely a bias than a fact. Such a bias will bring benefits to those living in those relatively less developed cities. On the other hand, companies will waste resources as a result and potentially lose employees in more developed cities due to the high FNR.

Besides the previously mentioned measure, we also calculated the demographic parity ratio and the equalized odds ratio to further evaluate the fairness of the ADS. The demographic parity ratio is defined as the ratio between the smallest and the largest group-level selection rate, across all values of the sensitive feature(s). The demographic parity ratio of 1 means that all groups have the same selection rate. Equalized Odds Ratio is the smaller of two metrics: true positive rate ratio and false positive rate ratio. The equalized odds ratio of 1 means that all groups have the same true positive, true negative, false positive, and false negative rates.The results are the follow:

Sensitive Attributes	Demographic Parity Ratio	Equalized Odds Ratio
gender	0.80	0.69
education level	0.12	0.00
relevant experience	0.57	0.48
experience	0.18	0.18
city development	0.19	0.13

6 Conclusion & Summary

This automated decision system in the data science hiring space provided multiple insights in terms of bias and fairness of such a system. Despite the limited amount of information available on the source of these data, we have no reason to believe that they are inappropriate for the purposes of identifying candidates or that the target variable is not a adequate representation of which trainees are interested in new data science jobs.

The implementation itself utilizes many best practices in model development, however model performance and fairness could be improved by taking some additional measures. In terms of data preparation, the ADS might benefit from a more robust treatment of missing values, particularly in reference to dropping candidates who did not provide information for a small set of attributes from the dataset entirely. By either requiring values for these features at data collection or imputing with values derived from the associations in the dataset, the system could avoid dropping these candidates unnecessarily. More importantly, however, the model is very likely to exacerbate pre-existing bias in the candidate population in using SMOTE to upsample the target class. By not taking into account interactions between sensitive attributes in the dataset, SMOTE most likely contributed to greater unfairness in the model's predictions. In an area as sensitive in hiring, we strongly suggest the use of FAIR-SMOTE or fair class balancing to correct for this. Model development could further be improved by using a holdout validation set, a best practice in model development, and a more rigorous approach to hyper-parameter tuning which this ADS largely ignored.

The resulting model, while very accurate, suffers from some bias in several sensitive attributes, namely *education level*, *age* and *city development*. Those with high school diplomas are disproportionately viewed as non-job-seeking, a discrimination that robs them of potential job and promotion opportunities. Those with more experience, with correlates with age, are disproportionately viewed as non-job-seeking, reinforcing an age bias already deep-rooted in hiring. Lastly, those living in relatively less developed cities are disproportionately labeled as job-seekers. Though it might not bring disadvantage to the candidates, the companies using the model may waste resources and lose employees from more developed cities to competing firms if the companies were to focus their hiring on less-developed cities.

In its current state, we do not feel comfortable using this decision system to make decisions in hiring. As a result of bias in the attributes mentioned above, the ADS fails to identify a workforce that is representative of the overall trainee population. While this obviously causes harm to candidates with these attributes, this unfairness can also have several adverse affects to the company who deploys such a system. First, they may miss the opportunity of hiring good candidates from protected classes thereby losing potentially great talent to their competition. If deployed over time, such a system would create a less diverse company workforce and in addition, to lowering the innovation and cultural gains from having diverse candidates, the system could potentially make the company liable for discrimination in hiring on the basis of sensitive attributes.

For further reference on our auditing process and analysis, all accompanying code and plots can be found here.

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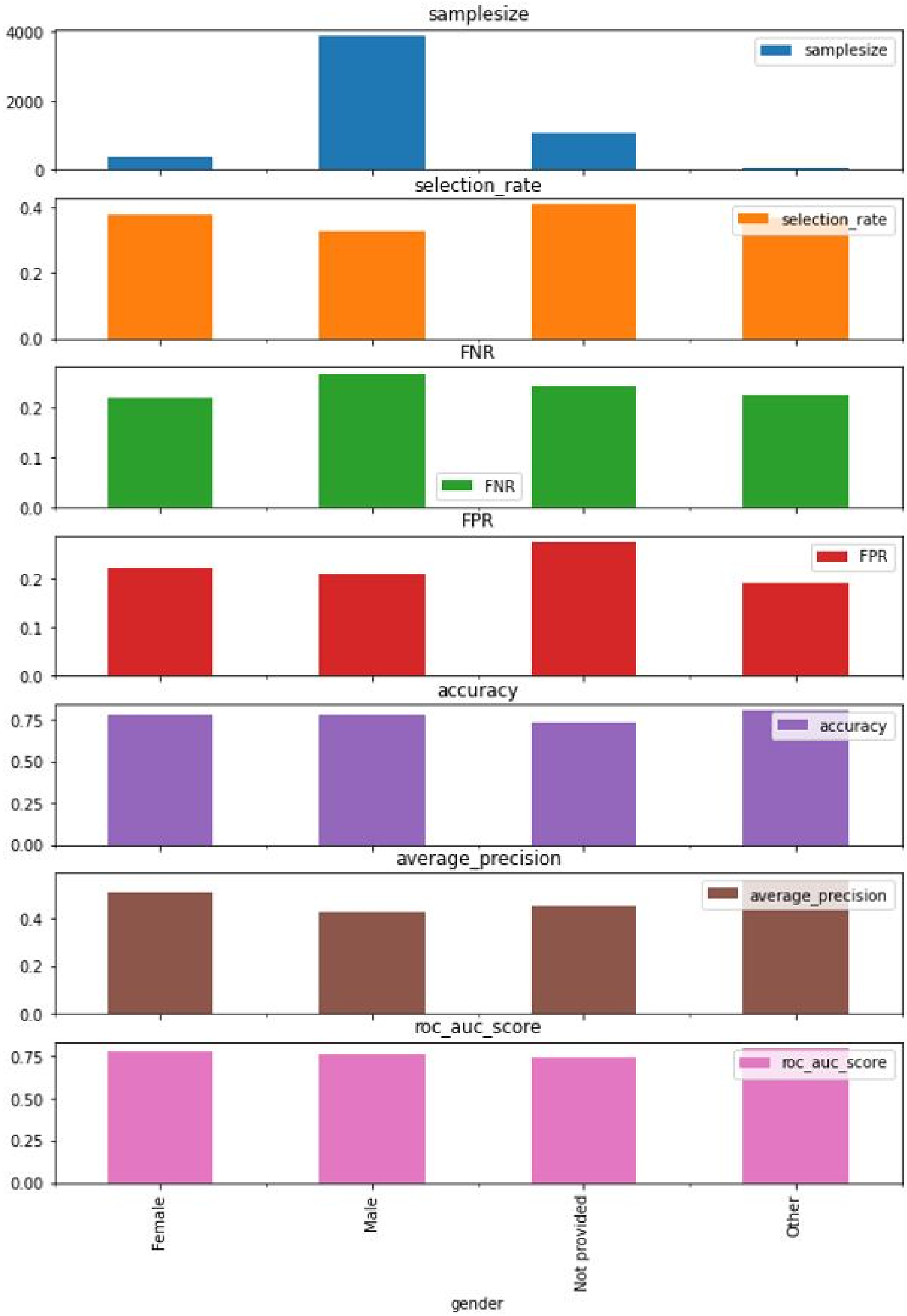
7 Appendix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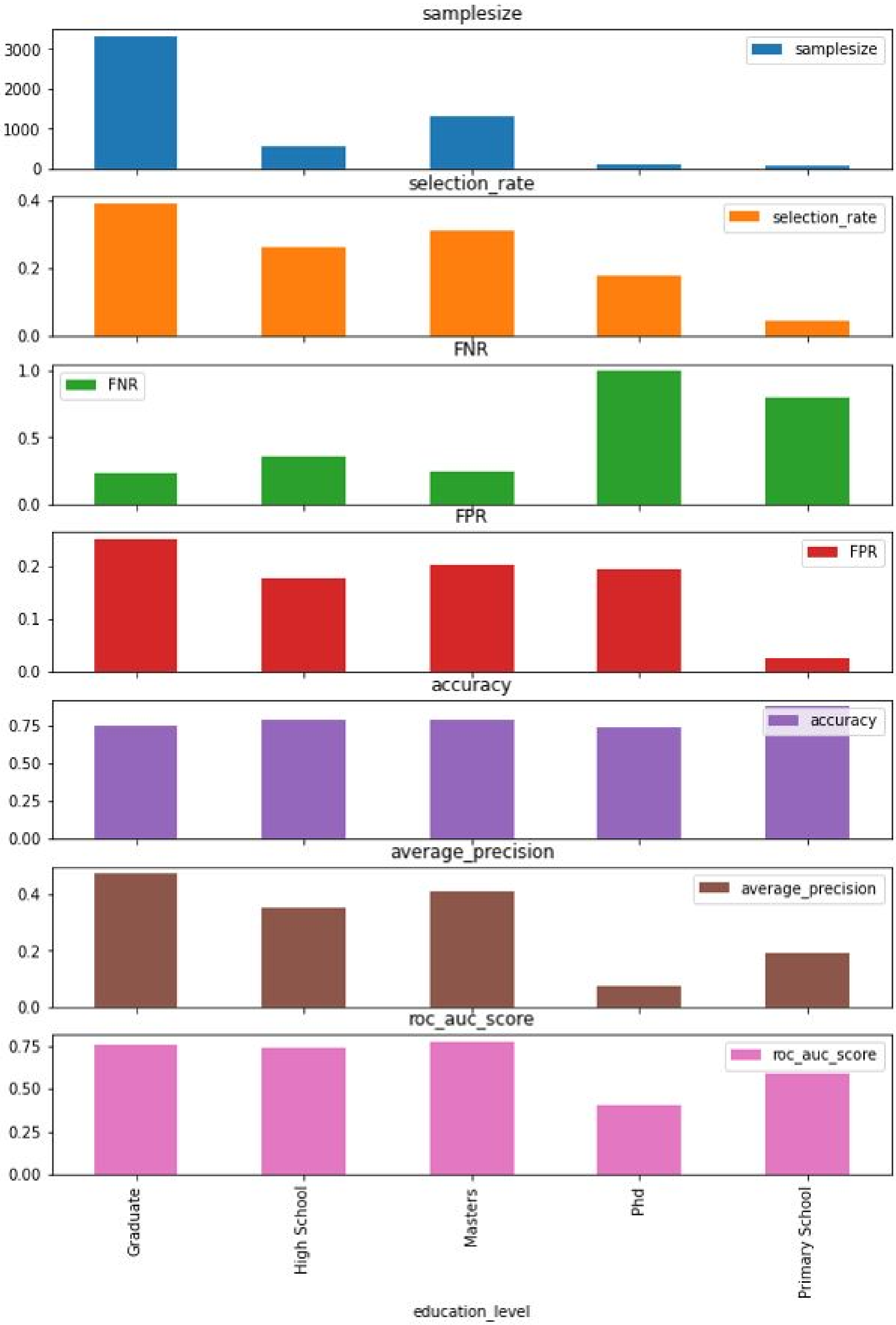
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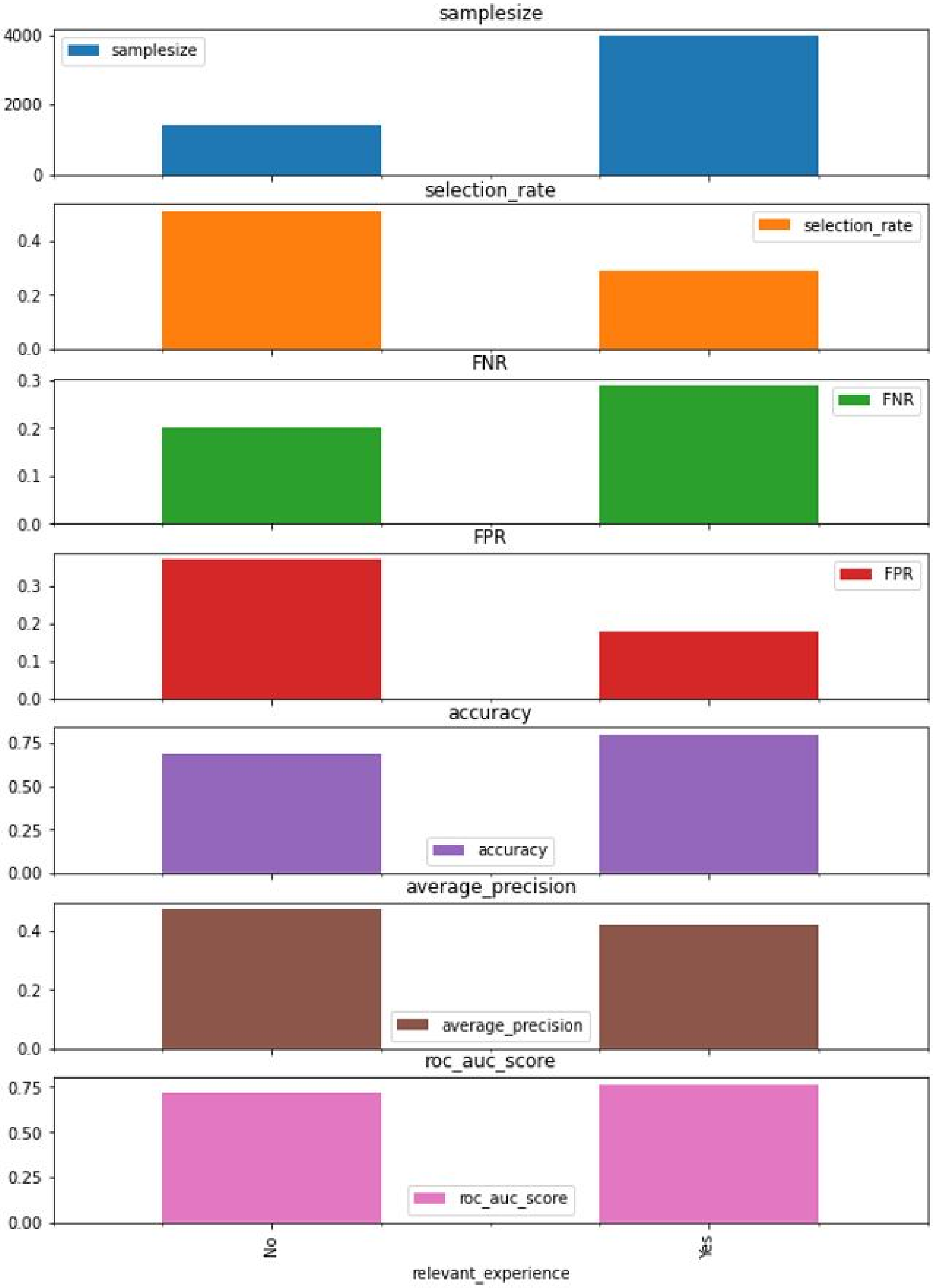
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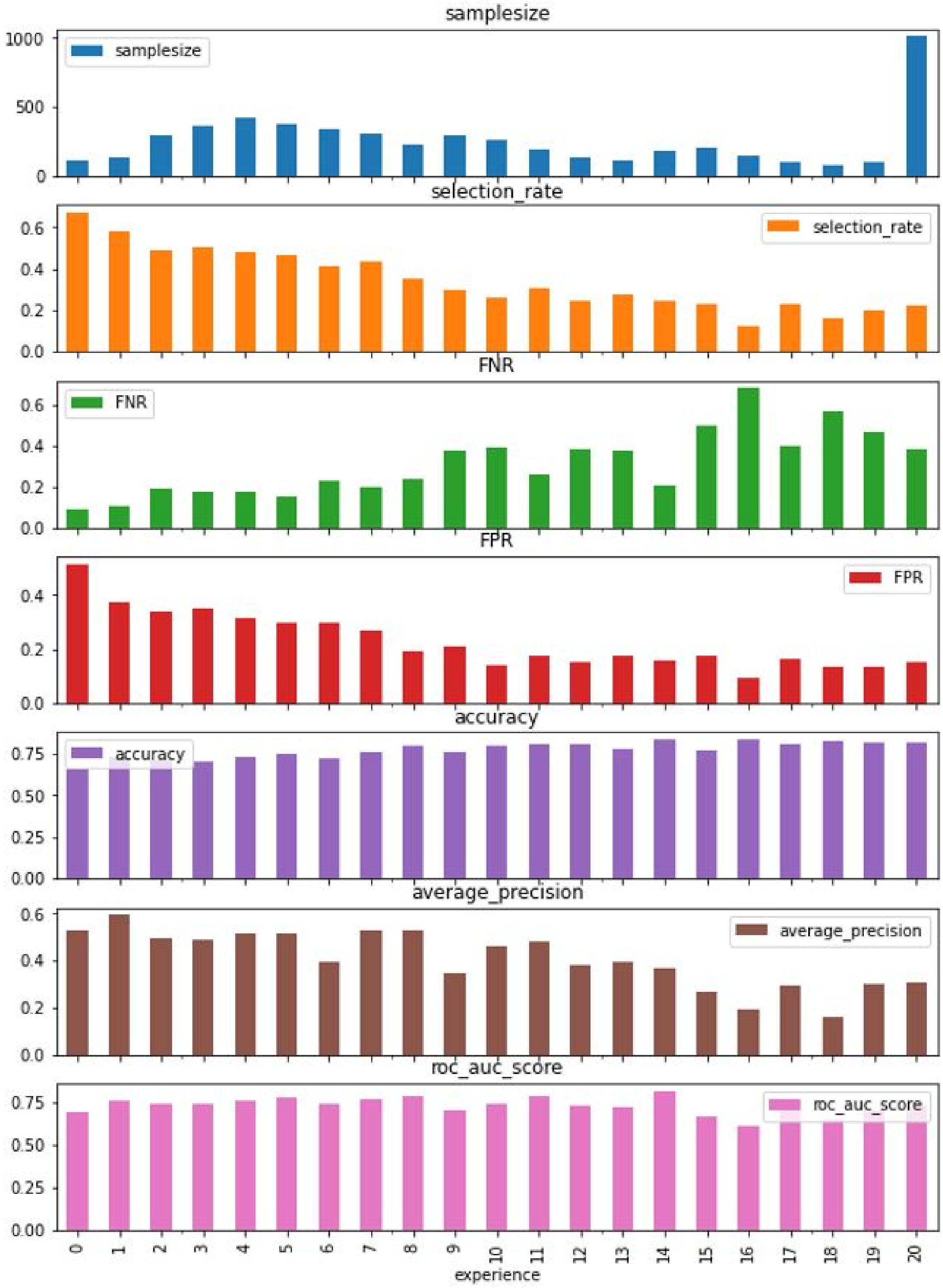
relevant_experience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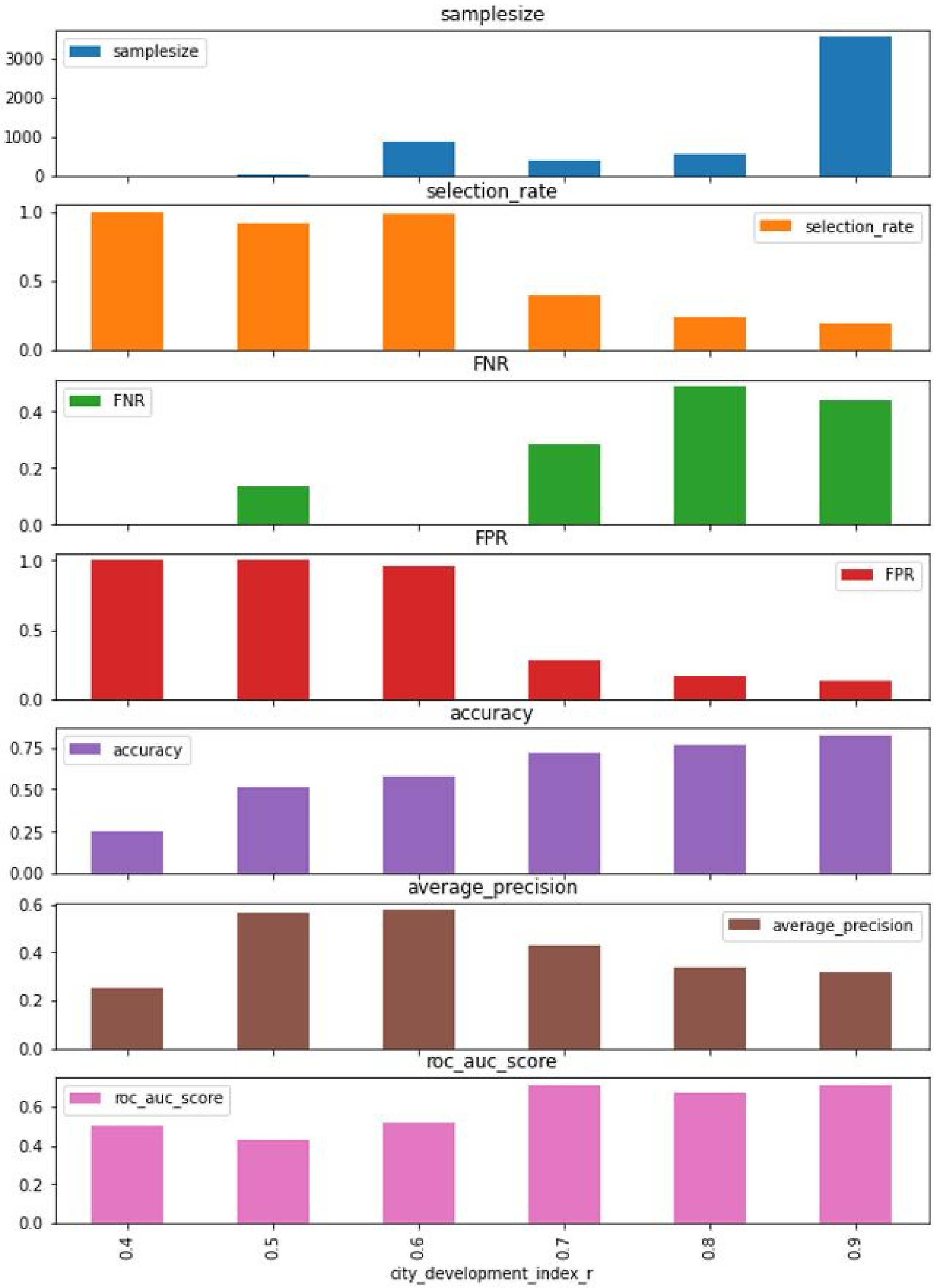
20
experience


samplesize
samplesize
3000
2000
1000
0
selection_rate
selection_rate
1.0
0.5
0.0
FNR
FNR
0.4
0.2
0.0
FPR
FPR
1.0
0.5
0.0
accuracy
accuracy
0.75
0.50
0.25
0.00
average_precision
average_precision
0.6
0.4
0.2
0.0
roc_auc_score
roc_auc_score
0.6
0.4
0.2
0.0
0.4
0.5
0.6
0.7
0.8
0.9
city_development_index_r