

# EasyVisa - Problem Statement

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PGP - Data Science & Business Analytics  
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# Executive Summary

- Businesses face growing challenges in attracting qualified talent domestically and internationally, leading to the need of effective solutions to meet workforce demands while complying with labor regulations
- The Immigration and Nationality Act (INA) allows foreign workers to fill workforce shortages while monitoring US labor market conditions through oversight by the Office of Foreign Labor Certification (OFLC)
- EasyVisa has been hired to streamline visa approval processes by identifying key factors influencing case outcomes
- EasyVisa will be using a machine learning-based classification model
- The model will allow for a more efficient process by predicting visa approval likelihood, aiding decision-making, and recommending profiles for certification or denial to support OFLC's mission effectively

# Business Problem Overview

- The OFLC faces a surge in labor certification applications, processing nearly 776,000 in FY 2016, with demand increasing annually.
- The manual review of applications has become time consuming, impacting efficiency and decision-making speed.
- Ensuring that the case follow all the rules while still getting through the workload is difficult
- Identifying key factors influencing visa approvals is critical to make the decision-making process more efficient and allocate resources effectively.
- A data-driven machine learning model is required to assist in automating the applicant shortlisting process and improve outcomes.

# Solution Approach

The following describe the solution approach:

- Analyze historical data from past applications to discover patterns and identify the key factors that influence visa approval outcomes.
- Build a machine learning classification model to accurately predict the likelihood of visa approval for each applicant based on relevant factors.
- Implement an automated system to prioritize applications with higher chances of approval, lowering manual effort and speeding up the process.
- Provide the OFLC with detailed insights and recommendations to help them efficiently certify or deny applications while maintaining compliance.
- Design a flexible framework that can adapt to increasing application volumes and evolving needs over time.

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25480 entries, 0 to 25479
Data columns (total 12 columns):
 #   Column                                Non-Null Count  Dtype
---  -
 0   case_id                              25480 non-null  object
 1   continent                            25480 non-null  object
 2   education_of_employee                25480 non-null  object
 3   has_job_experience                   25480 non-null  object
 4   requires_job_training                25480 non-null  object
 5   no_of_employees                     25480 non-null  int64
 6   yr_of_estab                         25480 non-null  int64
 7   region_of_employment                25480 non-null  object
 8   prevailing_wage                     25480 non-null  float64
 9   unit_of_wage                        25480 non-null  object
10   full_time_position                  25480 non-null  object
11   case_status                         25480 non-null  object
dtypes: float64(1), int64(2), object(9)
memory usage: 2.3+ MB

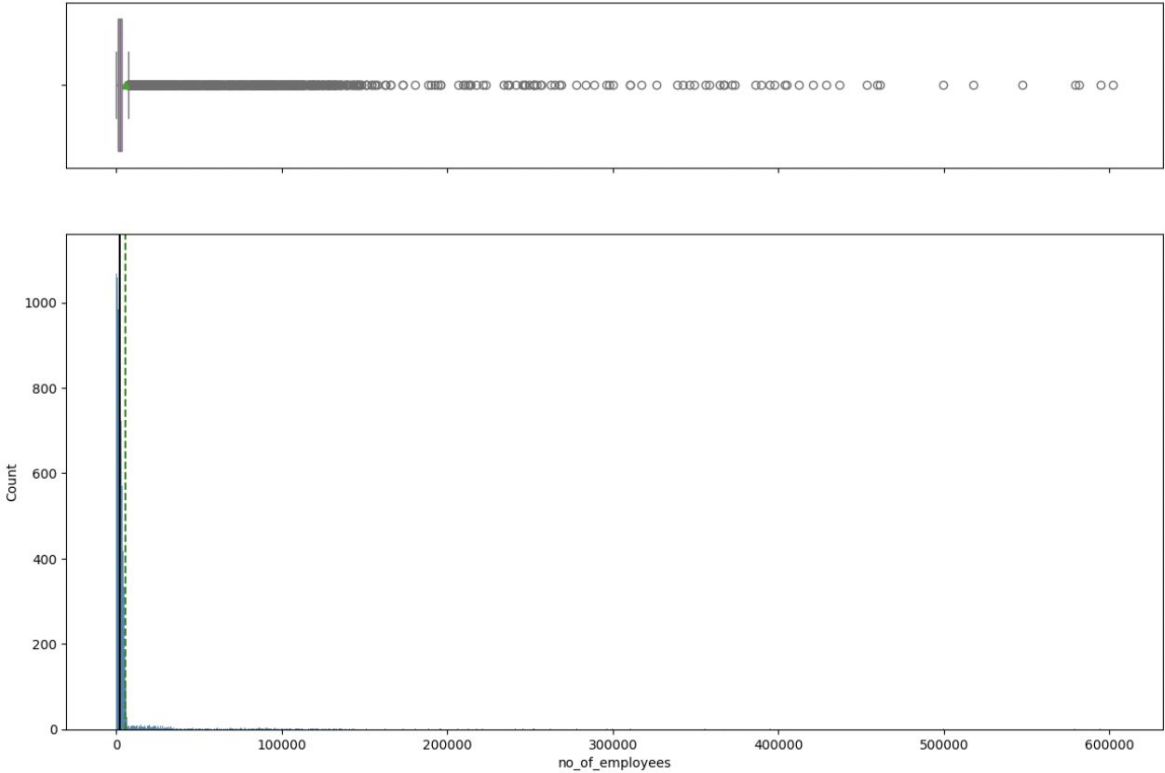
```

- There are 9 columns of the dtype object, 1 column of the dtype float64, and 2 columns of the dtype int64.
- There are no missing values nor any duplicates in the data.

# EDA Results - Univariate Analysis

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# Observations on number of employees



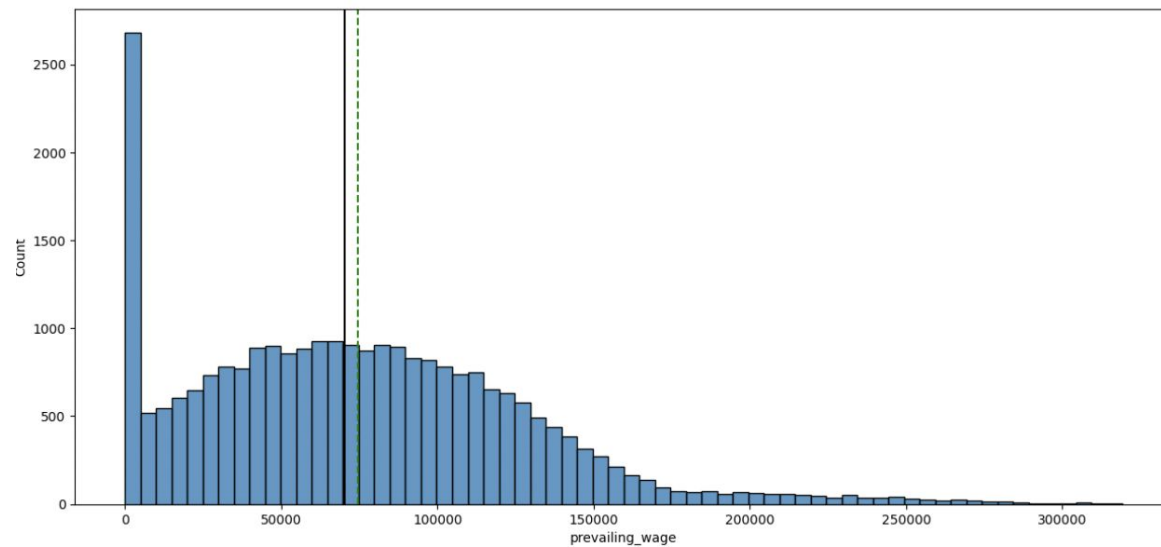
The data and graphs above, indicate the distribution of companies by number of employee is heavily right skewed.



## Observations on prevailing wage

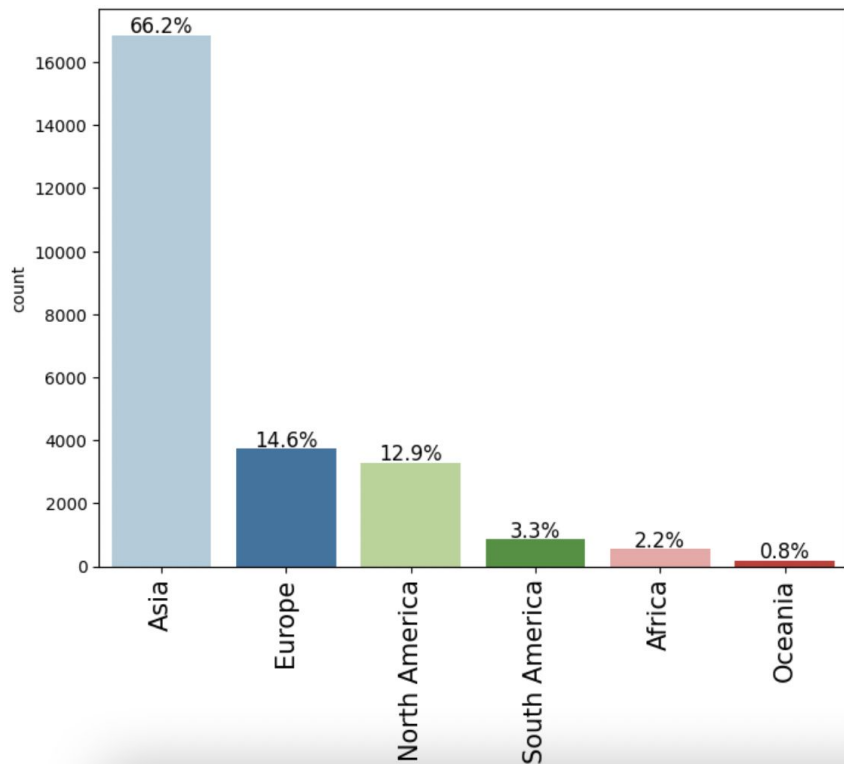


- Outliers
- median is the 50th percentile
- 



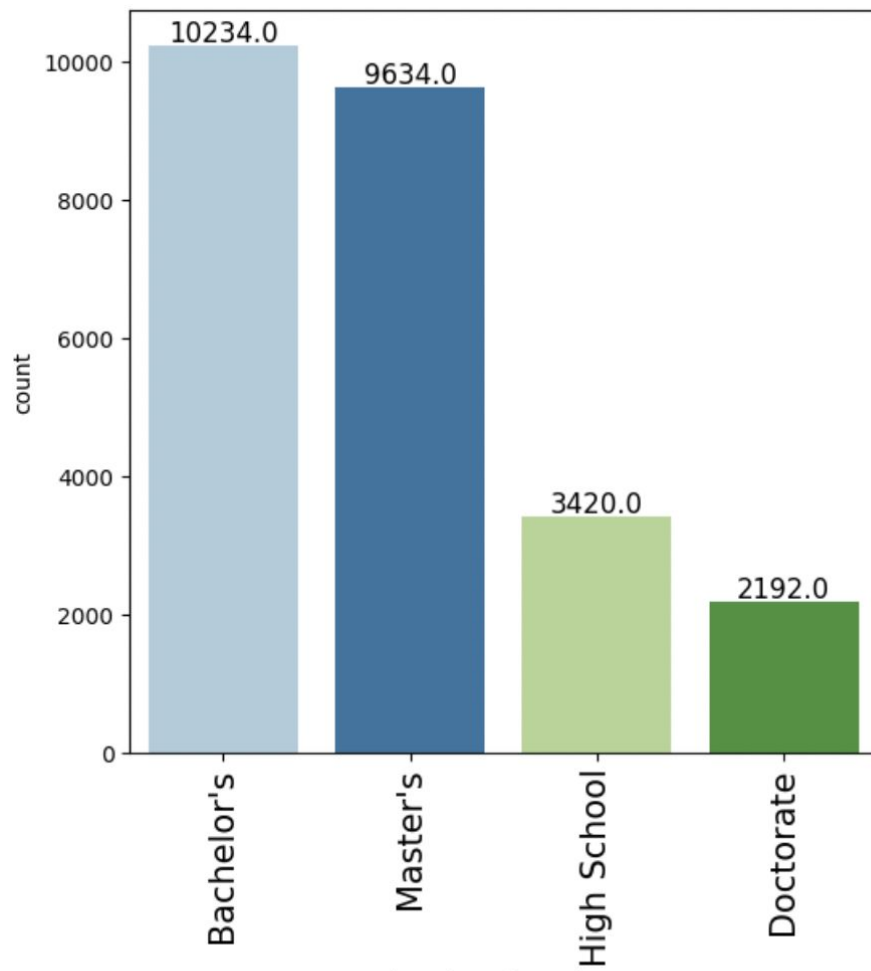
## Observations on continent

- most of the applicants are from asia (more than half)

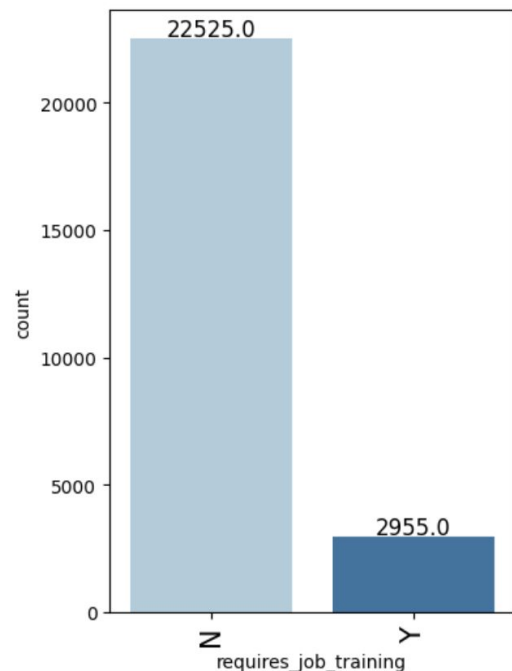


Observations on education of employee

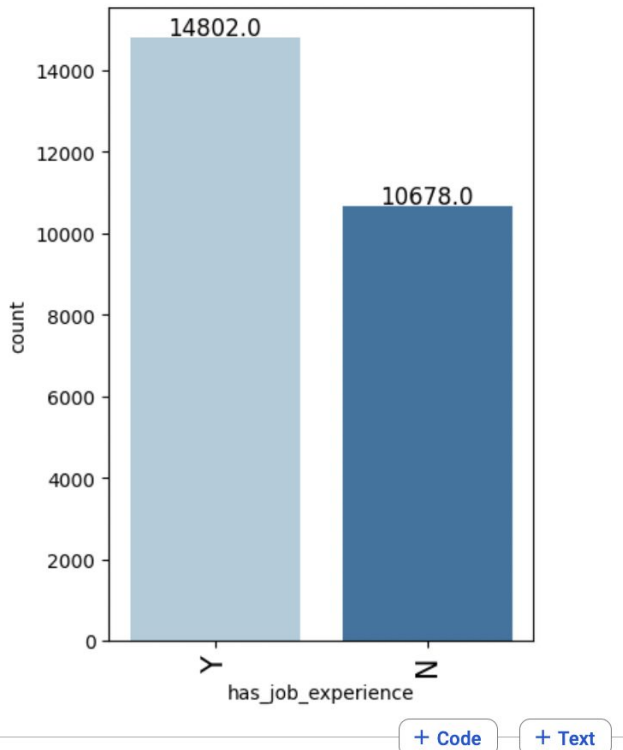
- Most visa applicants in the dataset have a Bachelor's degree. A substantial amount have Master's.



## Observations on job experience and job training

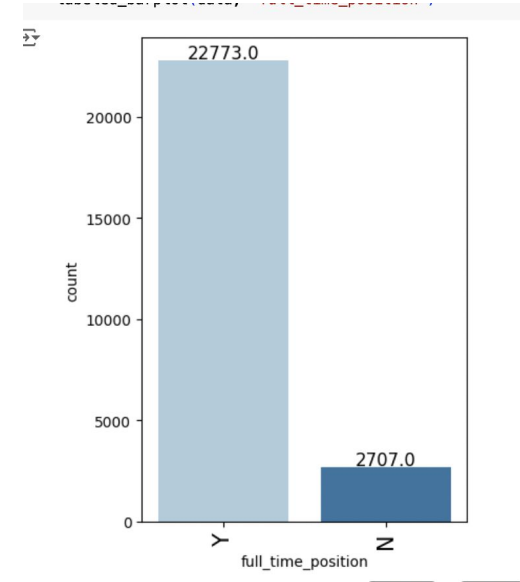
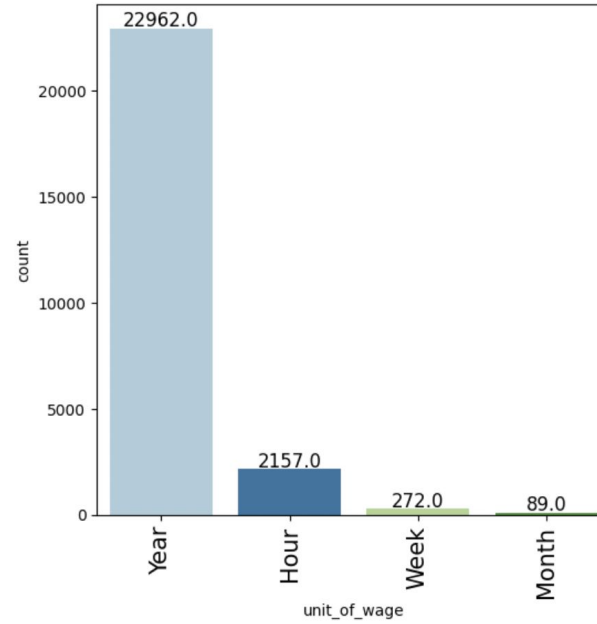
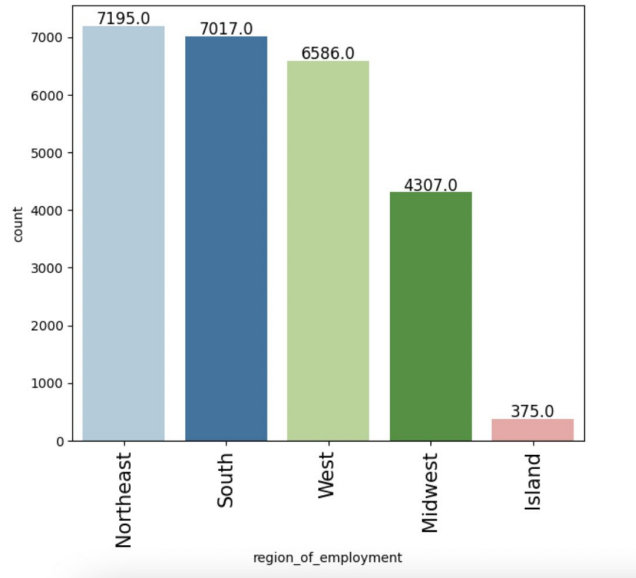


Majority of the applicants do not require job training, meaning they are well equipped for a job.



More Visa applicants do have job experience, but a good amount still do not have experience.

## Observations on region of employment, unit of wage & full time position



Most are paid in yearly wage

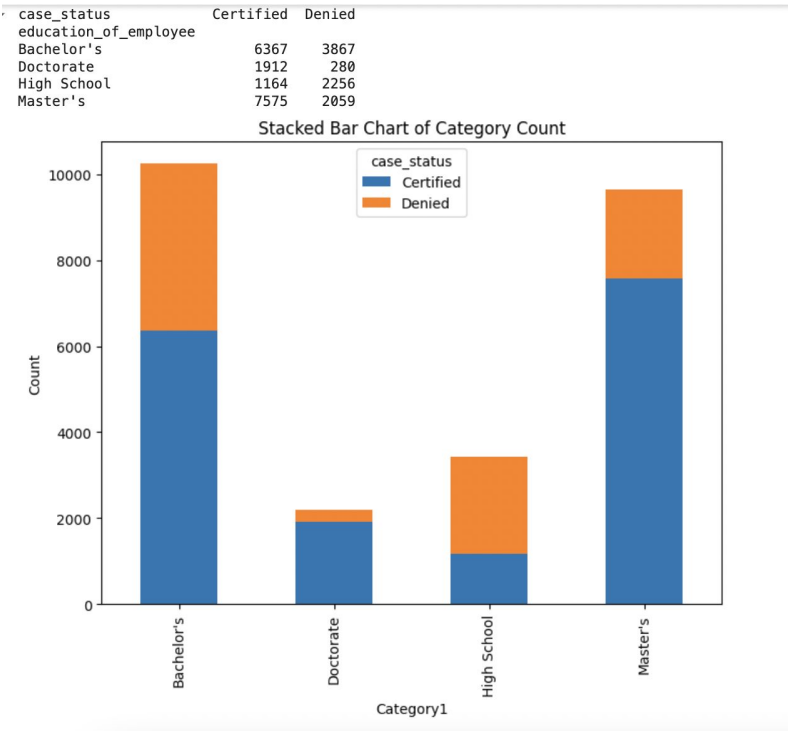
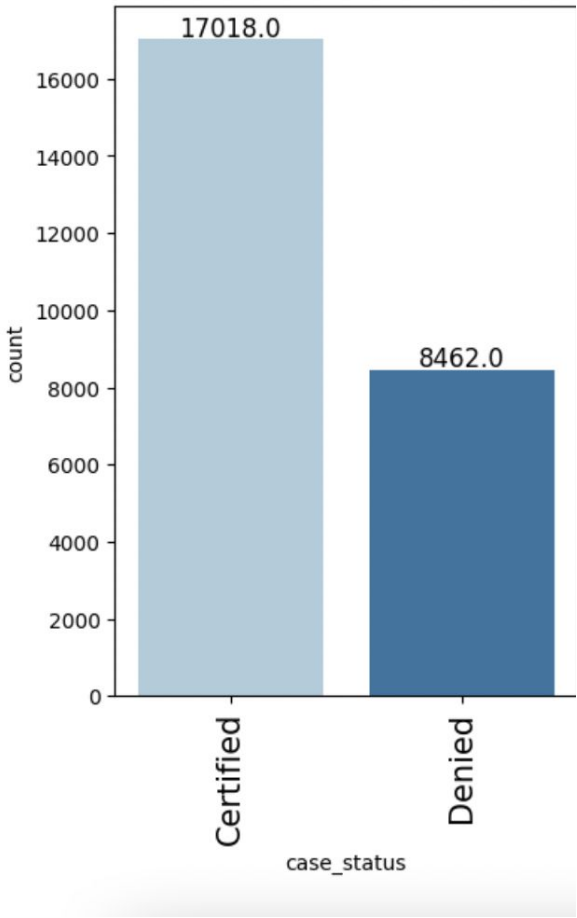
Most are full time positions

Northeast, South, and West have almost equal percentages of applicants. The Island region

Might be an outlier

# Observations on case status

It does not seem that guests who require a parking space have a substantial effect on cancellations.



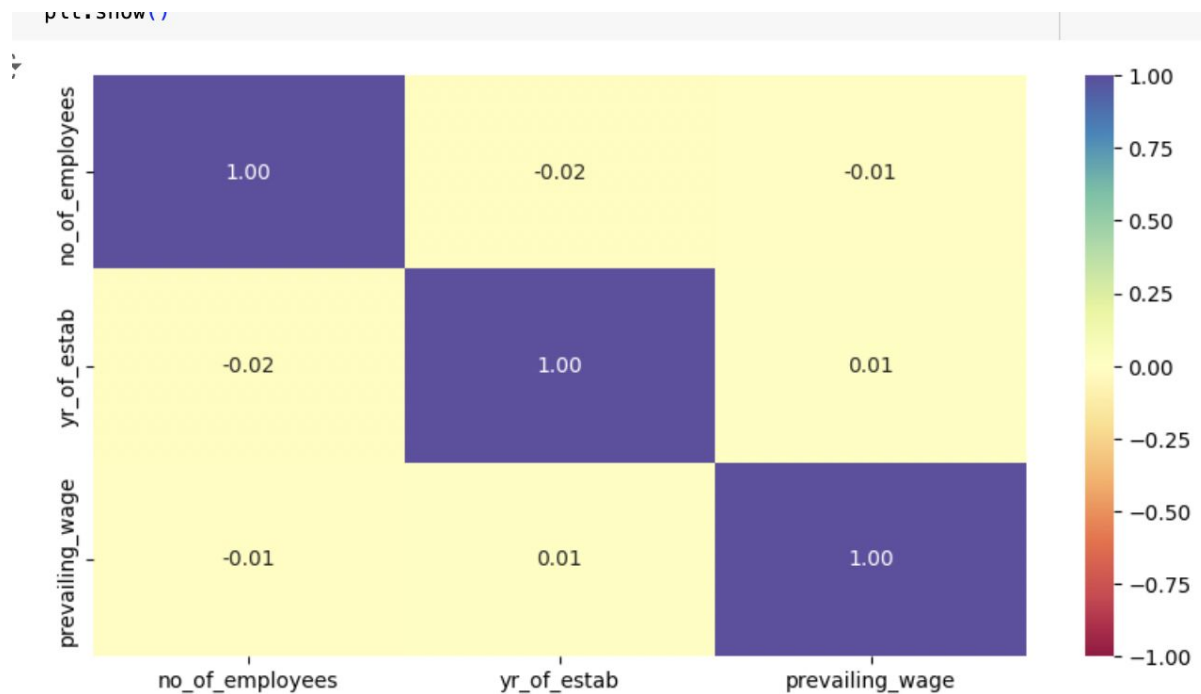
# EDA Results - Bivariate Analysis

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# Heat Map

The correlation coefficient between these variables is very close to zero

This indicates a weak correlation or almost no linear relationship

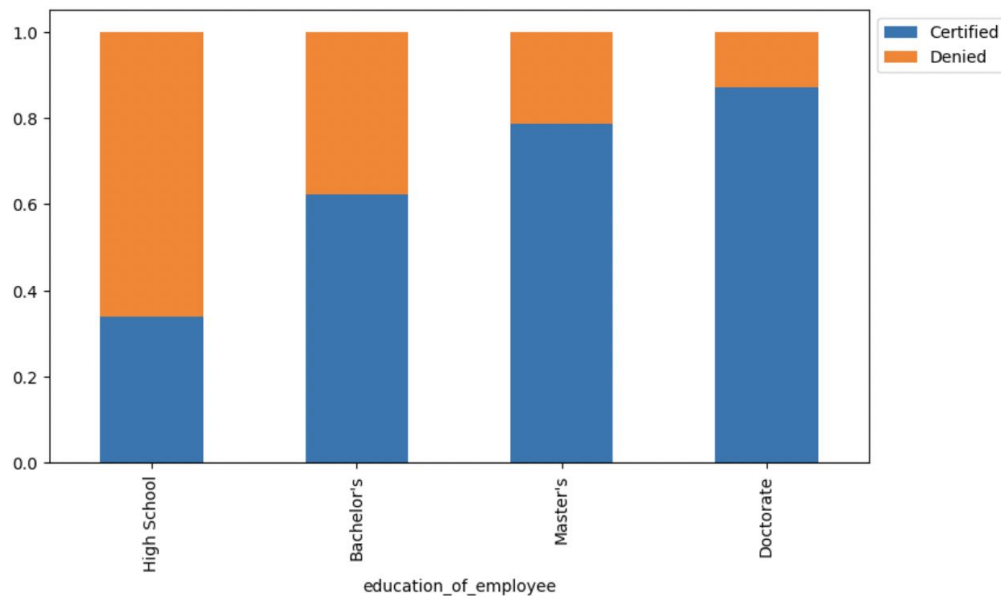




Higher education may want to travel abroad for a well-paid job.

The higher the degree  
one has, the more likely  
your visa will be  
accepted

case_status education_of_employee	Certified	Denied	All
All	17018	8462	25480
Bachelor's	6367	3867	10234
High School	1164	2256	3420
Master's	7575	2059	9634
Doctorate	1912	280	2192



# Regions and special requirements

Requirement for applicants who have passed high school is most in the South region, followed by Northeast region.

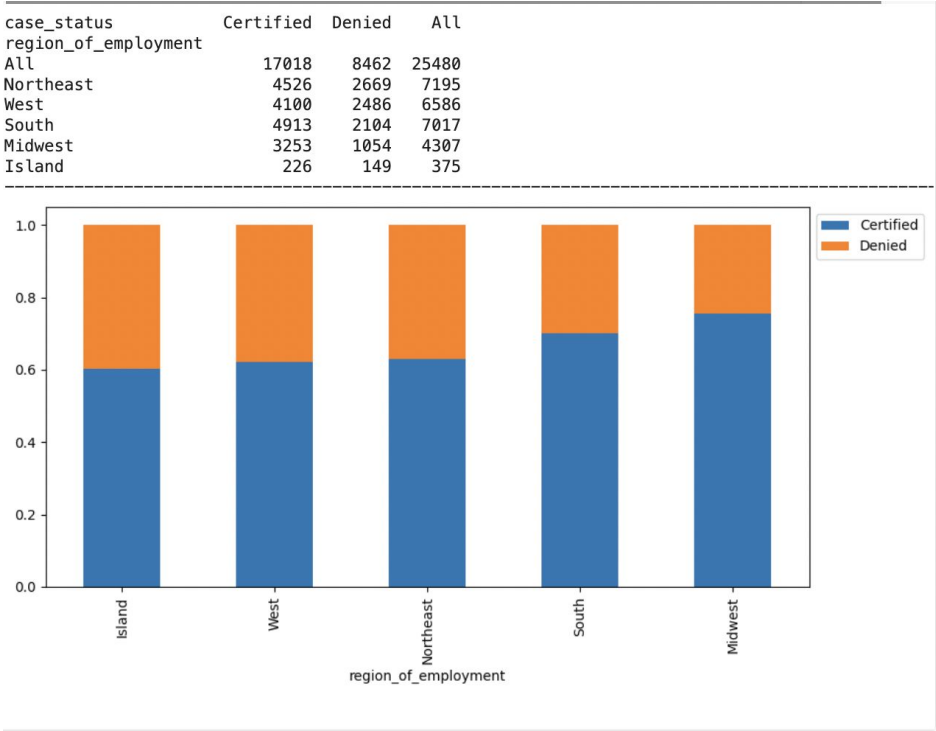
Requirement for Bachelor's is mostly in South region, followed by West region.

For Master's is most in Northeast region, followed by South region. The requirement for Doctorate's is mostly in West region, followed by Northeast region.



percentage of visa certifications across each region

Midwest has highest number of visa certifications but its not the most picked from any level of education



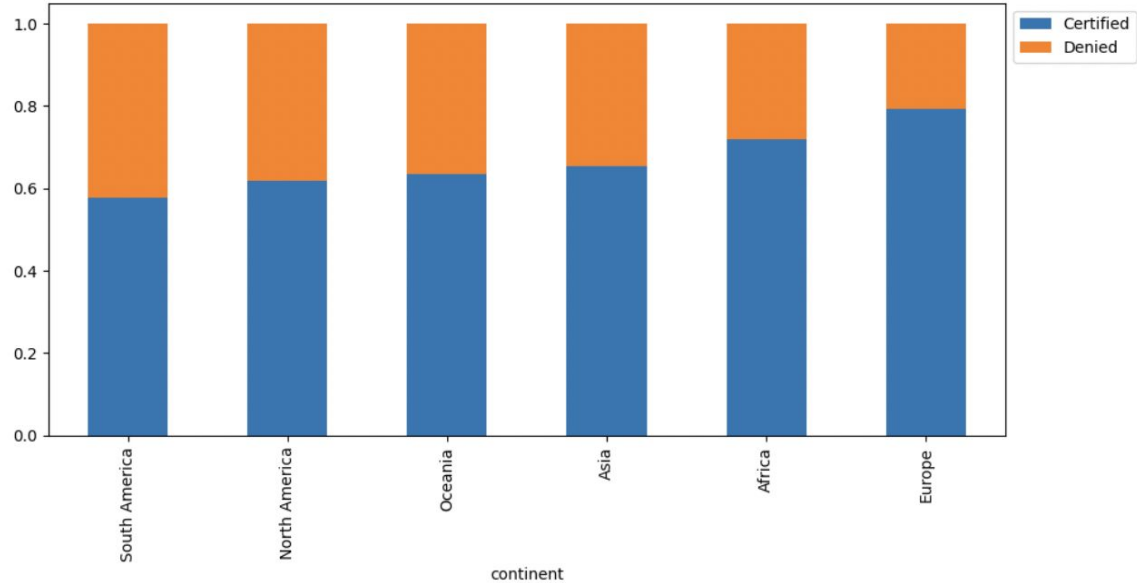
how the visa status vary across different continents.

Europe has the highest visa acceptance followed by africa

asia has the 3rd highest visa certification but has the highest no of application

```
stacked_barplot(data, 'continent', 'case_status') ## Complete the code to plot stacked barplot
```

case_status	Certified	Denied	All
continent			
All	17018	8462	25480
Asia	11012	5849	16861
North America	2037	1255	3292
Europe	2957	775	3732
South America	493	359	852
Africa	397	154	551
Oceania	122	70	192



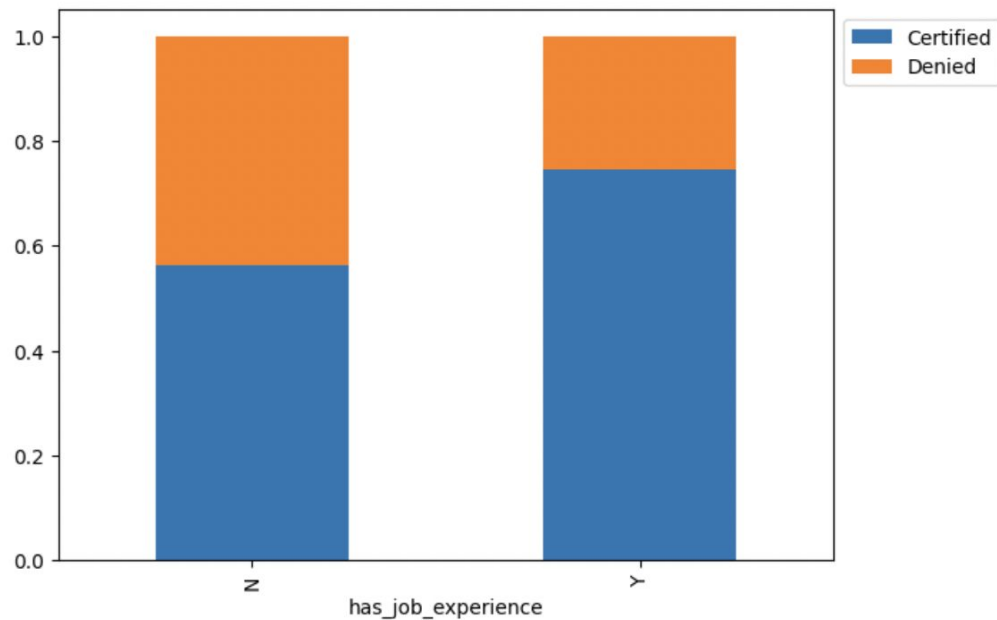
Europe has the highest visa acceptance followed by africa

## Work experience and visa certification

People with job experience have a higher chance of their visa being certified.

but a good amount of people without have a job experience also got their visa certified

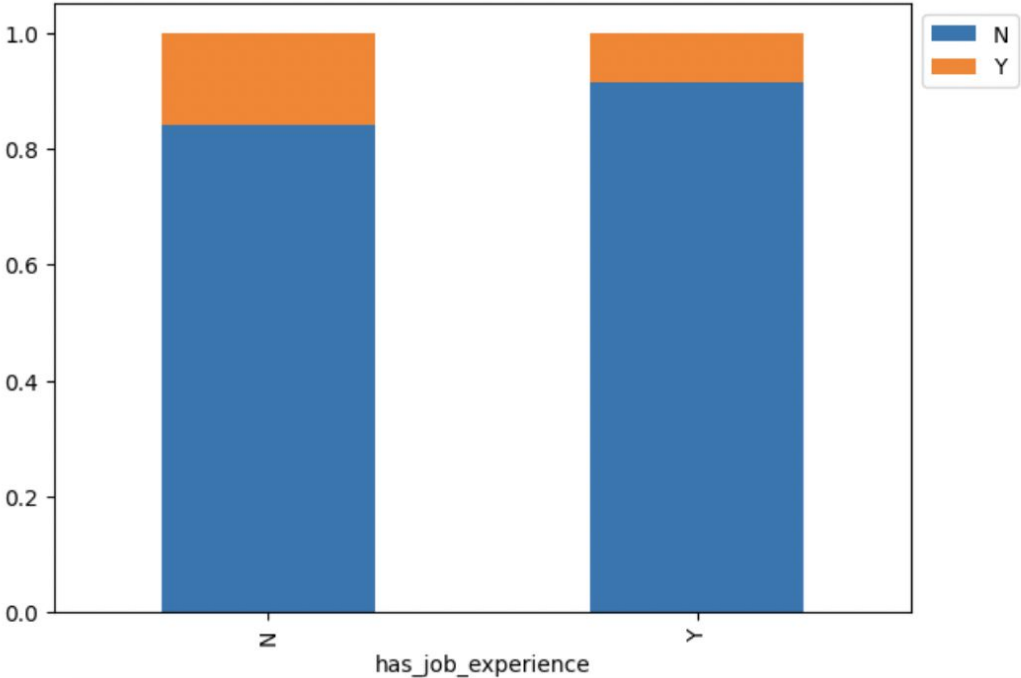
case_status	Certified	Denied	All
has_job_experience			
All	17018	8462	25480
N	5994	4684	10678
Y	11024	3778	14802



Prior work experience and job training?

requires_job_training	N	Y	All
has_job_experience			
All	22525	2955	25480
N	8988	1690	10678
Y	13537	1265	14802

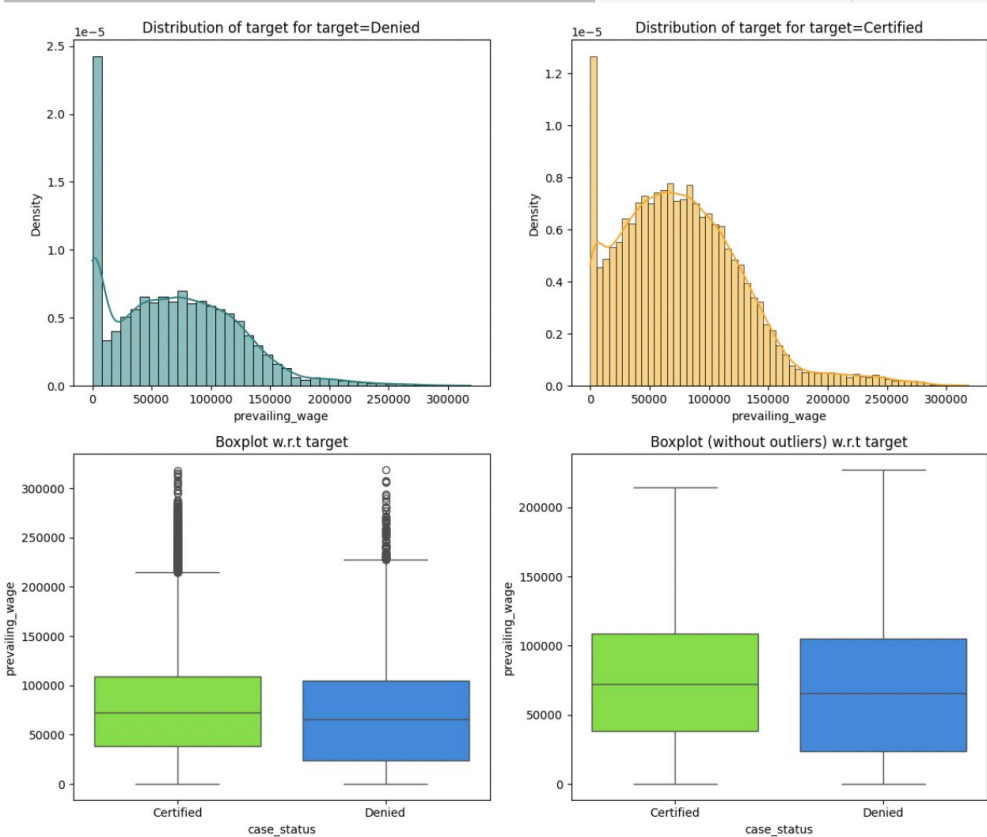
minimum percentage of applicants  
dont require job training  
but less if they have job experience



visa status and the prevailing wage

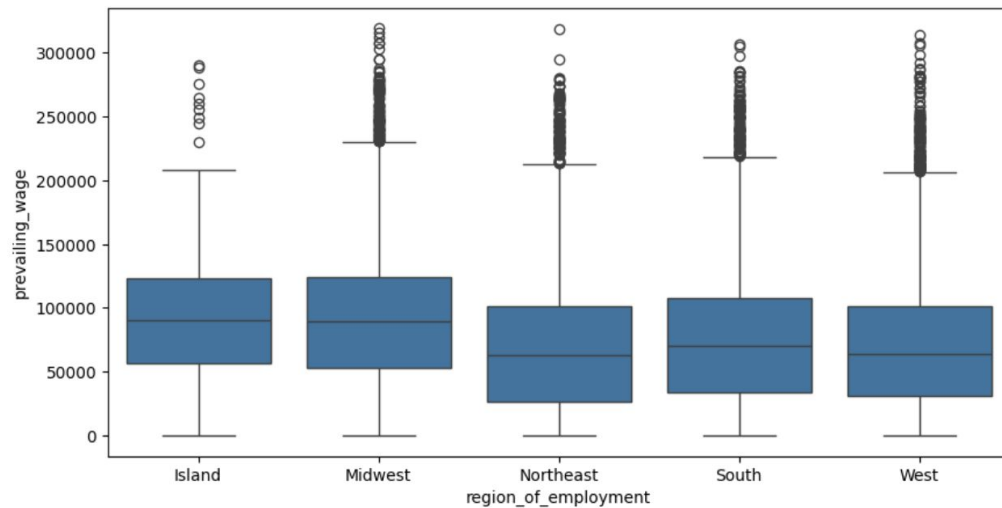
the median wage for the certified applications is slightly higher than the denied application

but is the prevailing wage similar across all region



## Prevailing wage across regions of the US

midwest and inland have slightly higher median wages compared to other regions



West and inland have slightly higher median wages compared to other regions

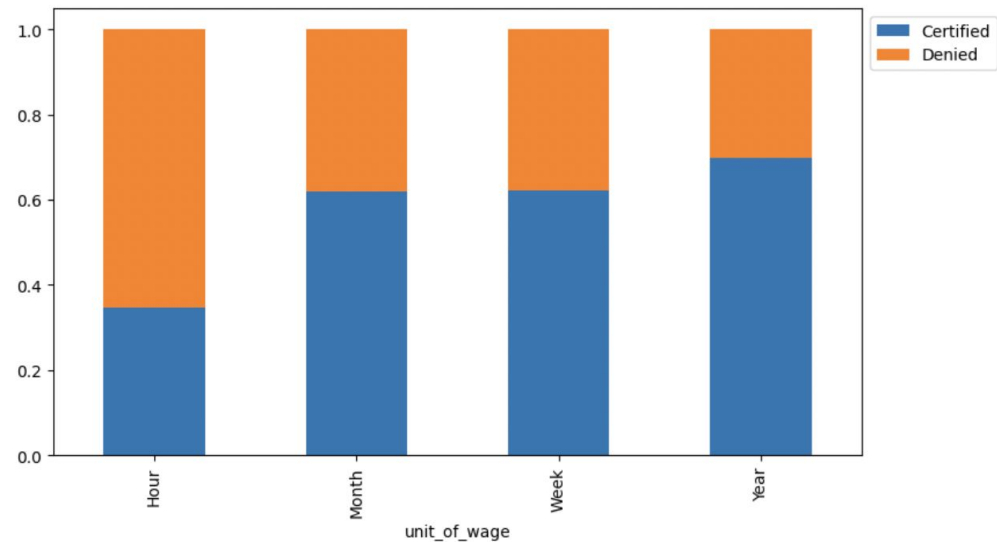


# Unit of wage impact on visa applications getting certified

yearly is most likely to be certified.

Week and month's percentage of employees certified is almost the same

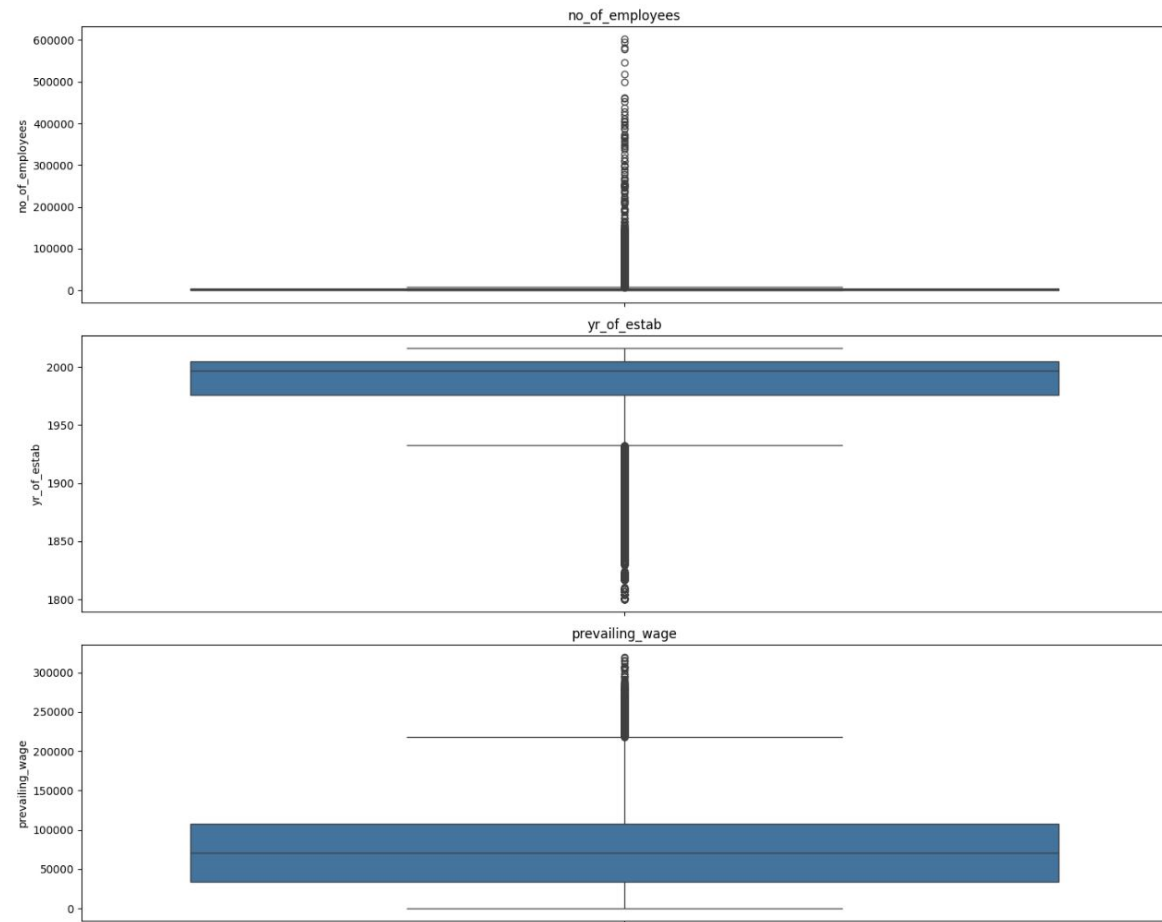
case_status	Certified	Denied	All
unit_of_wage			
All	17018	8462	25480
Year	16047	6915	22962
Hour	747	1410	2157
Week	169	103	272
Month	55	34	89



# Data Preprocessing

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# Outlier Detection



# Model Building

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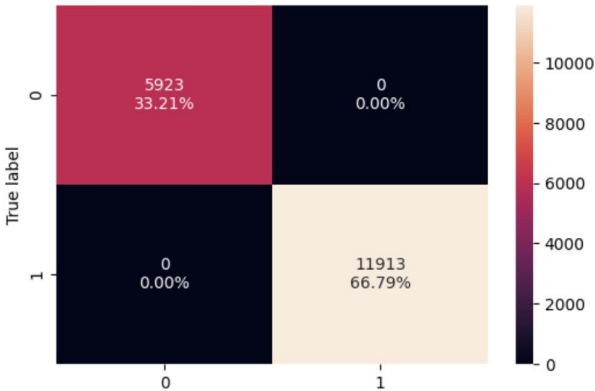
# Decision Tree - Model Building and Hyperparameter Tuning

Relatively higher accuracy and F1-score for class 1,

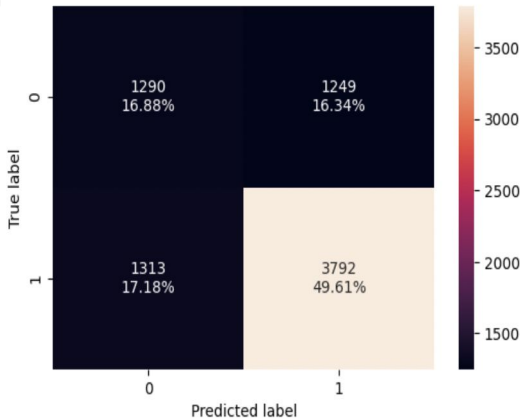
Performance on class 0 is lower, as evident from the lower recall and F1-score for class 0.

## Decision Tree Model

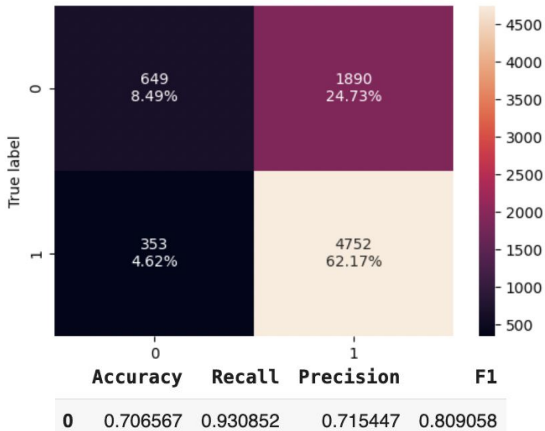
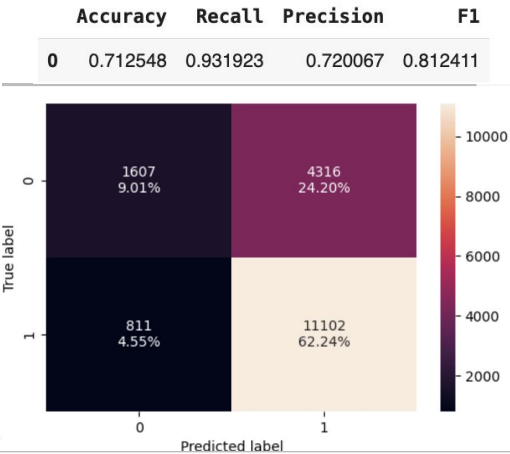
	Accuracy	Recall	Precision	F1
0	1.0	1.0	1.0	1.0



	Accuracy	Recall	Precision	F1
0	0.664835	0.742801	0.752232	0.747487

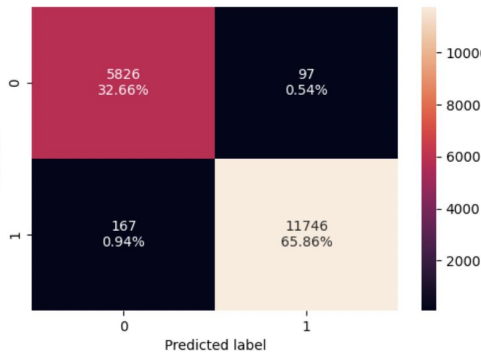


# Hyperparameter Tuning

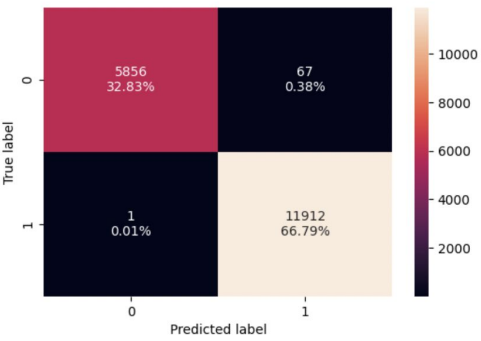


# Bagging - Model Building and Hyperparameter

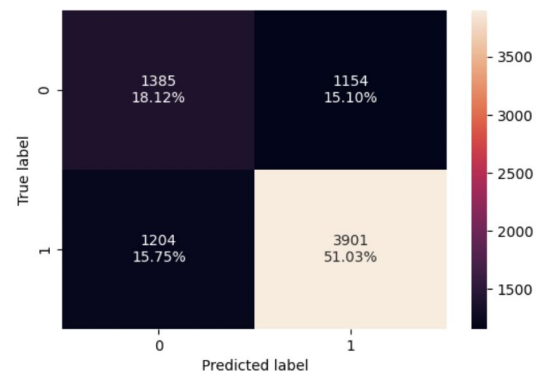
## Tuning



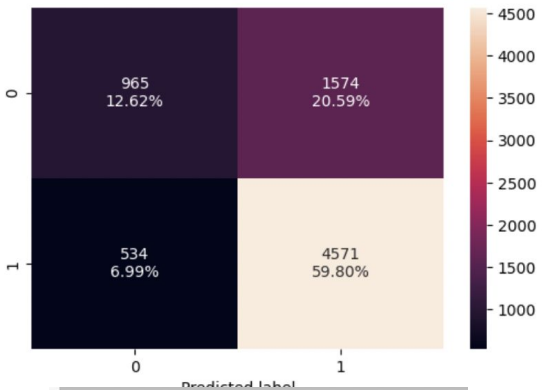
	Accuracy	Recall	Precision	F1
0	0.985367	0.986317	0.991729	0.989016



	Accuracy	Recall	Precision	F1
0	0.996187	0.999916	0.994407	0.997154



	Accuracy	Recall	Precision	F1
0	0.691523	0.764153	0.771711	0.767913



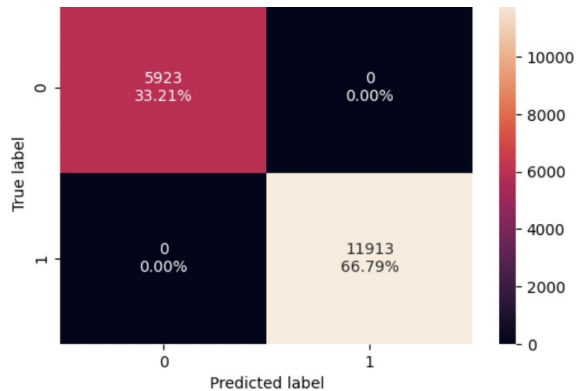
	Accuracy	Recall	Precision	F1
0	0.724228	0.895397	0.743857	0.812622

## Bagging Classifier

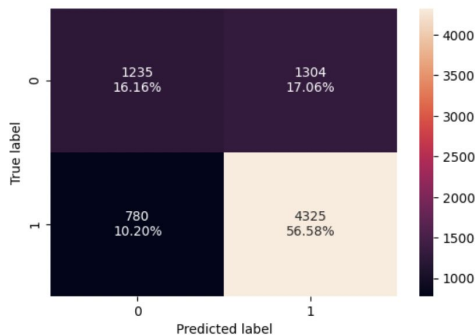
The tuned bagging classifier model shows good performance with the test set showing an F1 score of .81. The first class is still good.

## Tuned

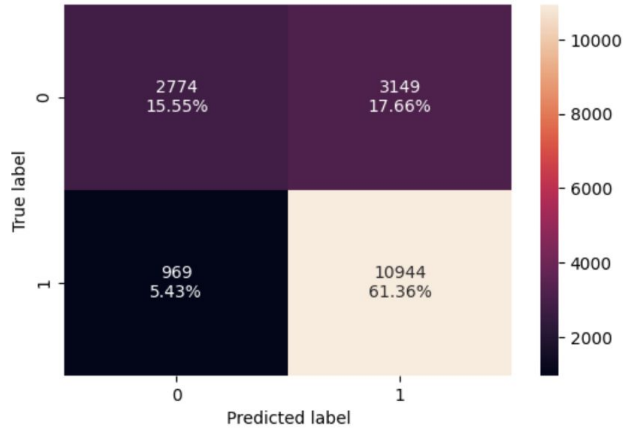
Rf



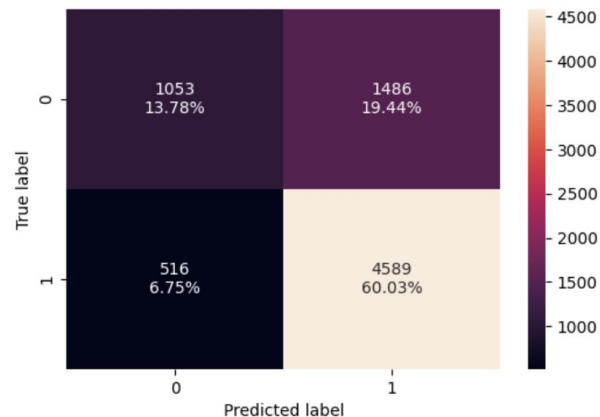
	Accuracy	Recall	Precision	F1
0	1.0	1.0	1.0	1.0



	Accuracy	Recall	Precision	F1
0	0.727368	0.847209	0.768343	0.805851



	Accuracy	Recall	Precision	F1
0	0.769119	0.91866	0.776556	0.841652

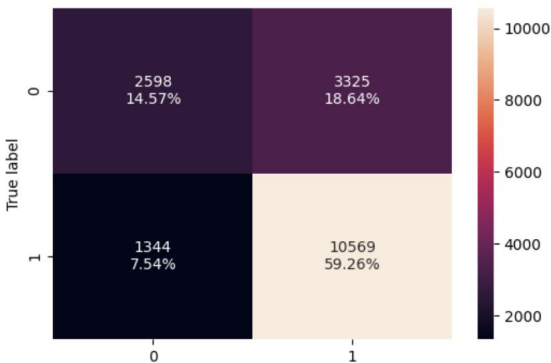


	Accuracy	Recall	Precision	F1
0	0.738095	0.898923	0.755391	0.82093

Rf  
tuned

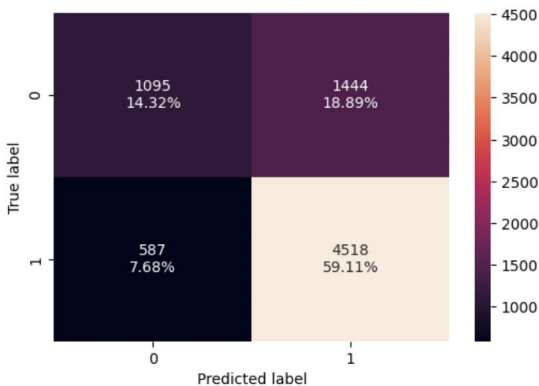
The rf tuned F1 score sits at .82 vs the rf F1 score of .80. Based on these F1 scores, the rf tuned model will be more accurate.

ab



Accuracy Recall Precision F1

0 0.738226 0.887182 0.760688 0.81908



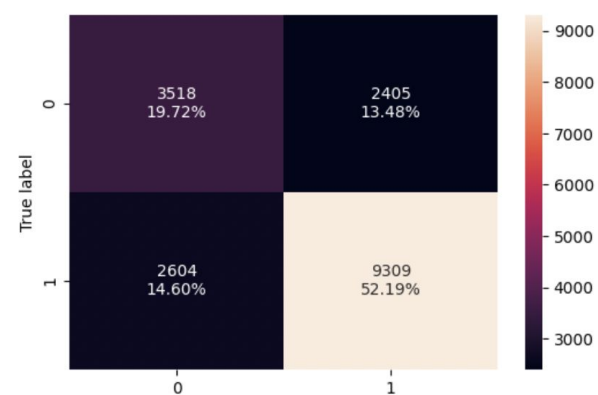
Accuracy Recall Precision F1

0 0.734301 0.885015 0.757799 0.816481

## Boosting - Model Building and Hyperparameter Tuning

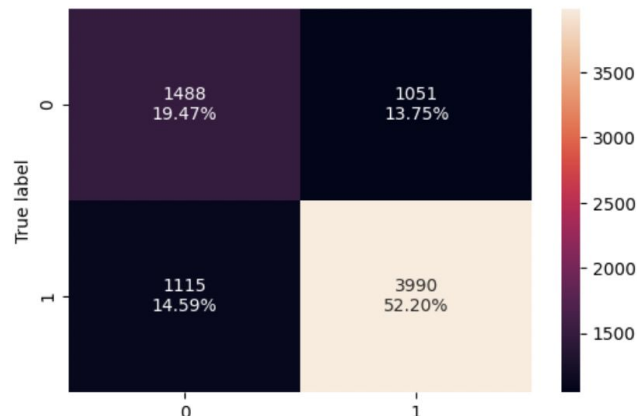
An F1 score of 0.81 for the AdaBoost Classifier means the model is relatively effective vs the F1 score of 0.78 for the tuned version.

tuned



Accuracy Recall Precision F1

0 0.719163 0.781415 0.79469 0.787997



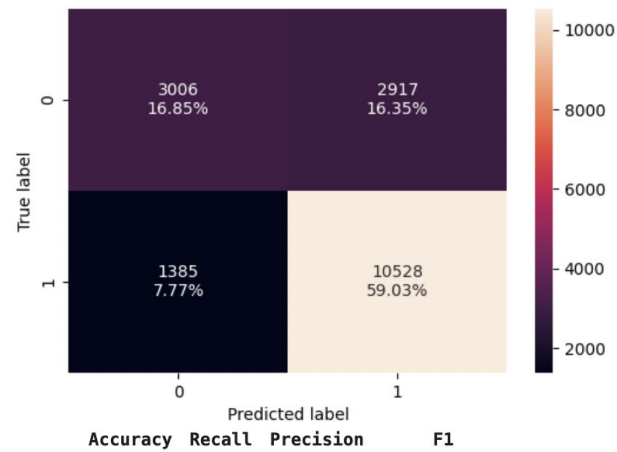
Accuracy Recall Precision F1

0 0.716641 0.781587 0.79151 0.786517

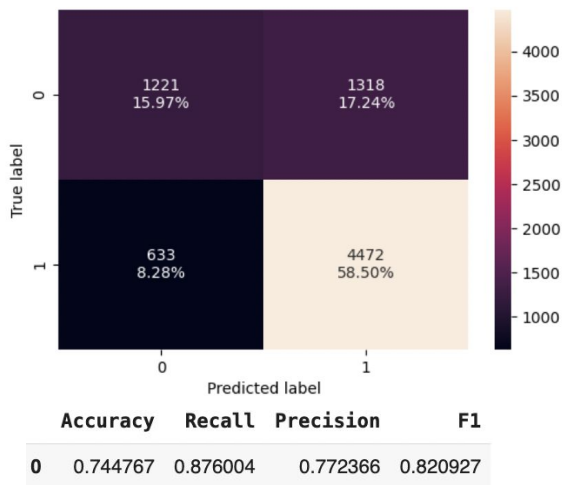


gb

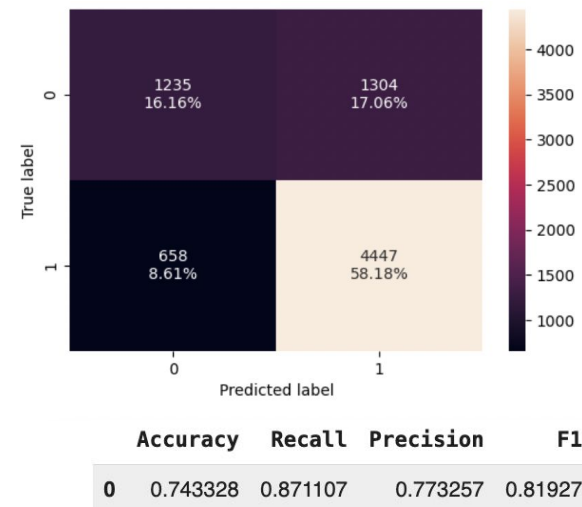
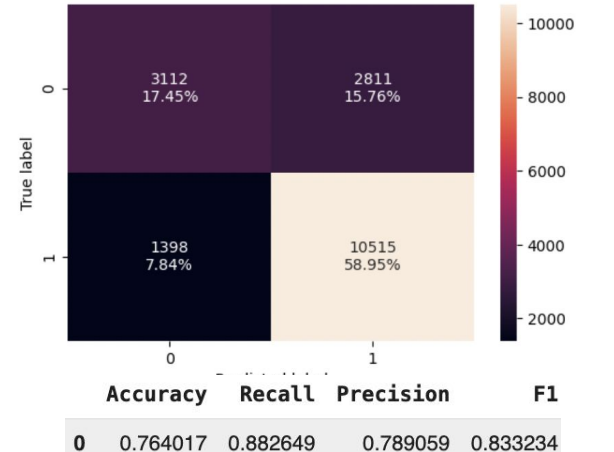
Gradient Boosting Classifier



Gb model F1 score of .82 vs the tuned version F1 score of .81 suggests that the original model performed slightly better. Shows that tuning doesn't always guarantee performance improvements.



Tuned



# Model Performance Comparison and Final Model Selection

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# Model performance Summary

Training performance comparison:

	Decision Tree	Random Forest	Tuned Random Forest	Adaboost Classifier	Tuned Adaboost Classifier	Gradient Boost Classifier	Tuned Gradient Boost Classifier
Accuracy	1.0	1.0	0.769119	0.738226	0.719163	0.758802	0.764017
Recall	1.0	1.0	0.918660	0.887182	0.781415	0.883740	0.882649
Precision	1.0	1.0	0.776556	0.760688	0.794690	0.783042	0.789059
F1	1.0	1.0	0.841652	0.819080	0.787997	0.830349	0.833234

Based on the training performance summary, it would be best to go with the decision tree or random forest model. These models have perfect scores for precision, recall, and accuracy.

# Insights & Recommendations

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## Recommendations

- The analysis shows that education level, job experience, and prevailing wage are key factors in predicting application approvals.
- OFLC should use these insights to streamline its pre-screening process. The simplicity of the Decision-Tree model also hints at potential biases against less skilled or entry-level applicants, which should be addressed to ensure fairness and transparency.

To efficiently allocate resources for screening applications likely to be approved, the OFLC should:

- Prioritize applications by education level, reviewing those with higher qualifications first.
- Sort by job experience, reviewing applicants with relevant experience first.
- Separate applications by wage type (hourly vs. annual), rank each group by prevailing wage, and prioritize salaried jobs from highest to lowest wage.