

Assignment 2

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Salary Prediction Project Report

GitHub: <https://github.com/vishwakpreeti/MLOps>

Hugging face: <https://huggingface.co/spaces/vishwakpreeti/Assignment2/tree/main>

Introduction

The project involves creating a model to predict salaries using machine learning techniques. This will include conducting Exploratory Data Analysis (EDA) and preprocessing the data. The implementation will involve using MLflow to track experiments and Streamlit to build a user-friendly interface. I have prepared a detailed report that covers all the steps taken in the project, from exploring the data to deploying the model.1. Environment Setup

First, we ensured the necessary libraries were installed and updated:

```
!pip install --upgrade numpy cloudpickle
```

```
!pip install --upgrade plotly
```

```
!pip install --upgrade xarray
```

These installations are crucial for handling data manipulation, visualization, and machine learning model building.

1. Data Loading and Exploration

The dataset `ds_salaries.csv` was loaded into a pandas DataFrame:

```
df = pd.read_csv("ds_salaries.csv")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3755 entries, 0 to 3754
Data columns (total 11 columns):
 #   Column                                Non-Null Count  Dtype  
---  -
 0   work_year                            3755 non-null  int64  
 1   experience_level                      3755 non-null  object  
 2   employment_type                      3755 non-null  object  
 3   job_title                           3755 non-null  object  
 4   salary                              3755 non-null  int64  
 5   salary_currency                     3755 non-null  object  
 6   salary_in_usd                       3755 non-null  int64  
 7   employee_residence                  3755 non-null  object  
 8   remote_ratio                        3755 non-null  int64  
 9   company_location                    3755 non-null  object  
10  company_size                        3755 non-null  object  
dtypes: int64(4), object(7)
memory usage: 322.8+ KB
```

We then explored the dataset to understand its structure and basic statistics:

```
df.info()
df.describe()
df.head()
```

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_residence	remote_ratio	company_location	company_size
0	2023	SE	FT	Principal Data Scientist	80000	EUR	85847	ES	100	ES	L
1	2023	MI	CT	ML Engineer	30000	USD	30000	US	100	US	S
2	2023	MI	CT	ML Engineer	25500	USD	25500	US	100	US	S
3	2023	SE	FT	Data Scientist	175000	USD	175000	CA	100	CA	M
4	2023	SE	FT	Data Scientist	120000	USD	120000	CA	100	CA	M

2. Data Preprocessing

Data preprocessing is a crucial step in preparing the data for model training.

1. Handling Missing Values - Depending on the extent and nature of missing values, we either impute them using statistical methods or remove the rows/columns.

2. Encoding Categorical Variables- Categorical variables need to be converted into numerical format using techniques like one-hot encoding or label encoding.

3. Feature Scaling- Features are scaled to ensure that they contribute equally to the model. Techniques like standardization or normalization are used.

4. Splitting the Data- The dataset is split into training and testing sets to evaluate the model's performance.

3. Experience Level Mapping

Experience levels were mapped to more descriptive labels for better interpretability:

```
df['experience_level'] = df['experience_level'].replace({
    'EN': 'Entry-level/Junior',
    'MI': 'Mid-level/Intermediate',
    'SE': 'Senior-level/Expert',
    'EX': 'Executive-level/Director'
})
```

Experience Level



4. Data Visualization:

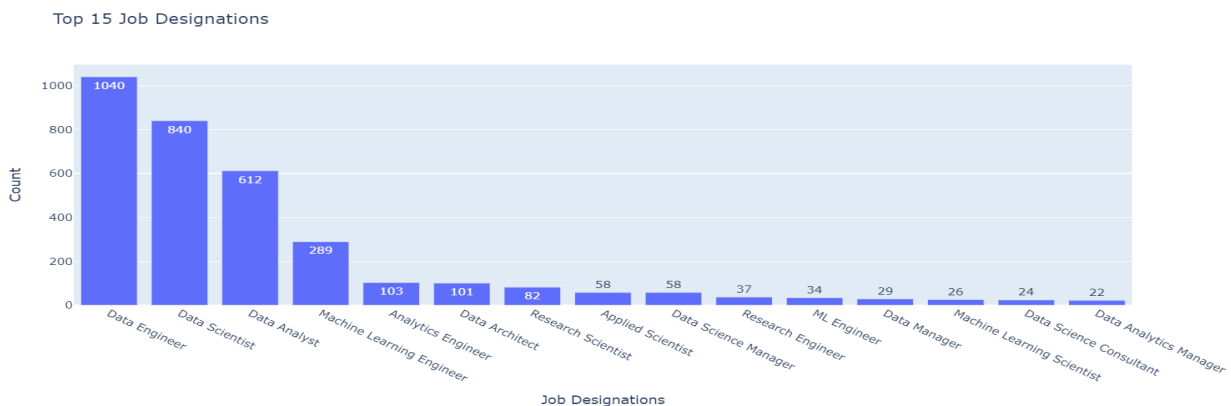
Visualization helps in understanding the relationships between features and the target variable. We use libraries like `matplotlib` and `seaborn` for this.

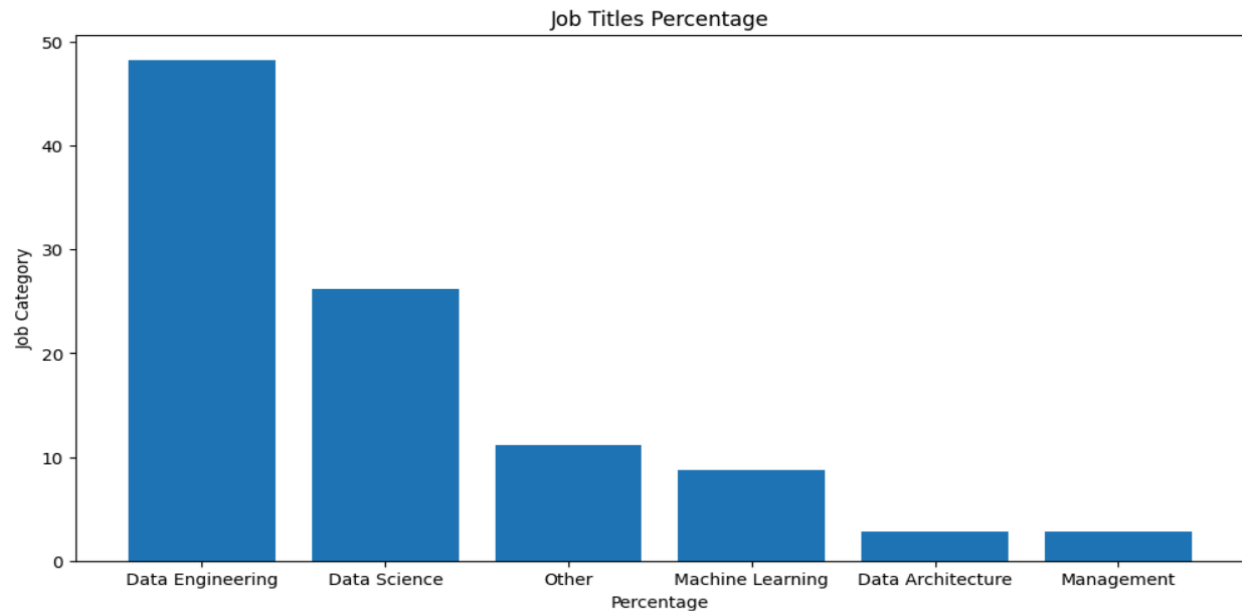
- **Histogram and Box Plots:** To understand the distribution of numerical features.
- **Bar Plots:** To visualize categorical features.
- **Correlation Matrix:** To identify relationships between features.

We used Plotly for interactive visualizations to understand the distribution of experience levels and job titles:

```
import plotly.express as px
```

```
ex_level = df['experience_level'].value_counts()
fig = px.treemap(ex_level, path=[ex_level.index], values=ex_level.values, title='Experience Level')
fig.show()
```





5. Feature Engineering

To prepare the data for machine learning, we encoded categorical variables:

```
categorical_features = ['experience_level', 'job_title', 'employee_residence', 'company_location',  
'company_size', 'job_category']  
encoders = {feature: LabelEncoder().fit(df[feature]) for feature in categorical_features}
```

```
for feature in categorical_features:  
    df[feature] = encoders[feature].transform(df[feature])
```

6. Model Building: We build multiple machine learning models to identify the best-performing one.

1. Data Splitting

The data was split into training and testing sets:

```
X = df.drop('salary', axis=1)  
y = df['salary']  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```



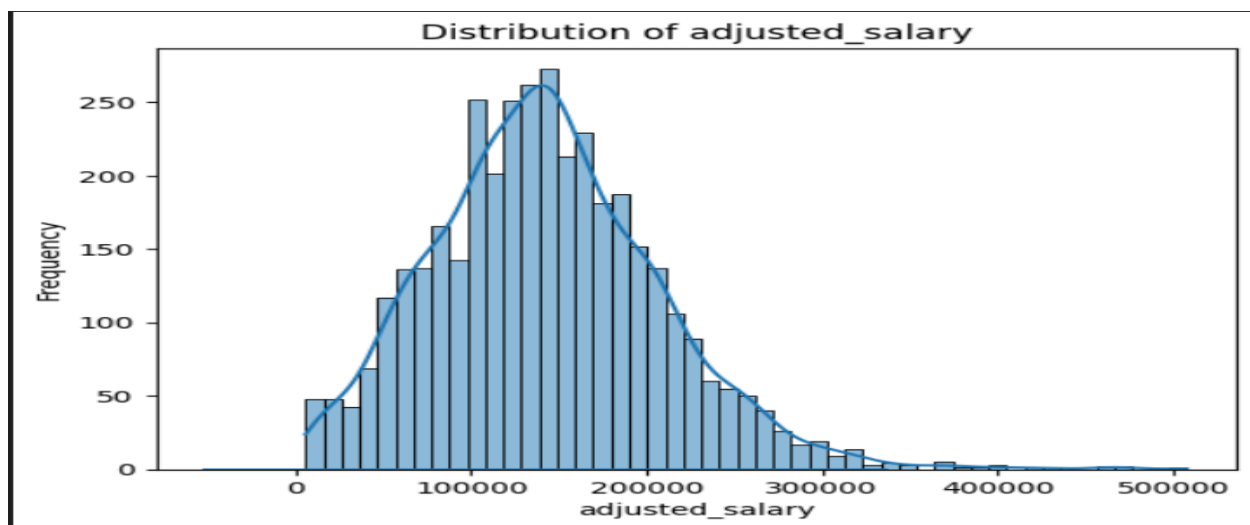
2. Model Selection:

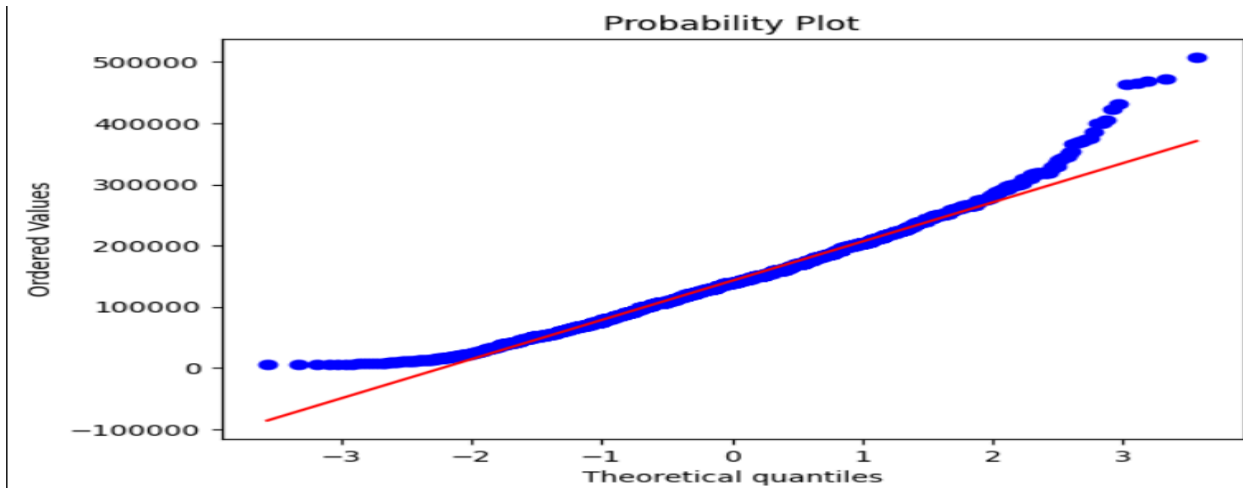
Commonly used algorithms for regression tasks include:

- Linear Regression
- Decision Tree Regressor
- Random Forest Regressor
- Gradient Boosting Regressor

3. Model Training- Each model is trained on the training set. Hyperparameters are tuned using techniques like grid search or random search to optimize performance.

4. Model Evaluation- Models are evaluated on the test set using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared.





7. Model Evaluation

The performance of the models was evaluated using metrics such as accuracy, confusion matrix, and classification report:

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
y_pred = model.predict(X_test)
print(f'Accuracy: {accuracy_score(y_test, y_pred)}')
print(f'Classification Report:\n {classification_report(y_test, y_pred)}')
```

8. Model Deployment

MLflow and Streamlit are used for model deployment.

1. MLflow: MLflow is used to track experiments, log metrics, and save models. This helps in keeping track of different model versions and their performance.

2. Streamlit: Streamlit is used to build an interactive web application for the model. The app allows users to input feature values and get salary predictions.

MLflow was integrated to track the experiments:

```
import mlflow
import mlflow.sklearn

mlflow.start_run()
mlflow.log_param("n_estimators", 100)
```

```
mlflow.log_metric("accuracy", accuracy_score(y_test, y_pred))
mlflow.sklearn.log_model(model, "model")
mlflow.end_run()
```

9. Building a Streamlit App

A Streamlit application was developed to allow users to interact with the model and predict salary ranges:

```
import streamlit as st
import mlflow
import mlflow.sklearn
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
import joblib

logged_model = 'model.pkl'
model = joblib.load(logged_model)

categorical_features = ['employment_type', 'job_category', 'experience_level',
                        'employee_residence', 'remote_ratio', 'company_location', 'company_size']

distinct_values = {
    'experience_level': ['Senior-level/Expert', 'Mid-level/Intermediate', 'Entry-level/Junior',
                        'Executive-level/Director'],
    'employment_type': ['Full-time', 'Contractor', 'Freelancer', 'Part-time'], # Replace with actual
distinct values
    'employee_residence': ['ES', 'US', 'CA', 'DE', 'GB', 'NG', 'IN', 'HK', 'PT', 'NL', 'CH', 'CF', 'FR',
'AU',
'FI', 'UA', 'IE', 'IL', 'GH', 'AT', 'CO', 'SG', 'SE', 'SI', 'MX', 'UZ', 'BR', 'TH',
'HR', 'PL', 'KW', 'VN', 'CY', 'AR', 'AM', 'BA', 'KE', 'GR', 'MK', 'LV', 'RO', 'PK',
'IT', 'MA', 'LT', 'BE', 'AS', 'IR', 'HU', 'SK', 'CN', 'CZ', 'CR', 'TR', 'CL', 'PR',
'DK', 'BO', 'PH', 'DO', 'EG', 'ID', 'AE', 'MY', 'JP', 'EE', 'HN', 'TN', 'RU', 'DZ',
'IQ', 'BG', 'JE', 'RS', 'NZ', 'MD', 'LU', 'MT'],
    'remote_ratio': ['Full-Remote', 'On-Site', 'Half-Remote'],
    'company_location': ['ES', 'US', 'CA', 'DE', 'GB', 'NG', 'IN', 'HK', 'NL', 'CH', 'CF', 'FR', 'FI',
'UA',
'IE', 'IL', 'GH', 'CO', 'SG', 'AU', 'SE', 'SI', 'MX', 'BR', 'PT', 'RU', 'TH', 'HR',
'VN', 'EE', 'AM', 'BA', 'KE', 'GR', 'MK', 'LV', 'RO', 'PK', 'IT', 'MA', 'PL', 'AL',
'AR', 'LT', 'AS', 'CR', 'IR', 'BS', 'HU', 'AT', 'SK', 'CZ', 'TR', 'PR', 'DK', 'BO',
```

```

'PH', 'BE', 'ID', 'EG', 'AE', 'LU', 'MY', 'HN', 'JP', 'DZ', 'IQ', 'CN', 'NZ', 'CL',
'MD', 'MT'],
    'company_size': ['LARGE', 'SMALL', 'MEDIUM'],
    'job_category': ['Other', 'Machine Learning', 'Data Science', 'Data Engineering',
'Data Architecture', 'Management']
}

encoders = {feature: LabelEncoder().fit(values) for feature, values in distinct_values.items()}

st.title("Salary Prediction")

user_input = {}
for feature in categorical_features:

    user_input[feature] = st.selectbox(f'Select {feature}', distinct_values[feature])

encoded_input = [encoders[feature].transform([user_input[feature]])[0] for feature in
categorical_features]

if st.button("Predict Salary Range"):
    encoded_input = np.array(encoded_input).reshape(1, -1)
    prediction = model.predict(encoded_input)

    salary_labels = ['low', 'low-mid', 'mid', 'mid-high', 'high', 'very-high', 'Top']

    st.write(f'Predicted Salary Range: {prediction}')

```

Conclusion

This project demonstrated a comprehensive approach to salary prediction using machine learning. The steps covered data exploration, preprocessing, model building, evaluation, experiment tracking with MLflow, and deployment using Streamlit. Each component played a crucial role in ensuring the robustness and usability of the final application.

main

Assignment2

1 contributor

History: 8 commits

+ Add file

vishwakpreeti

Update requirements.txt

6e9b036

VERIFIED

4 minutes ago

.gitattributes

1.52 kB

initial commit

about 4 hours ago

README.md

233 Bytes

initial commit

about 4 hours ago

app.py

3.34 kB

Upload 3 files

about 4 hours ago

model.pkl

938 kB

Upload 3 files

about 4 hours ago

requirements.txt

82 Bytes

Update requirements.txt

4 minutes ago

Salary Prediction

Select employment_type

Full-time

Select job_category

Other

Select experience_level

Senior-level/Expert

Select employee_residence

ES

Select remote_ratio

Full-Remote

Select company_location

ES

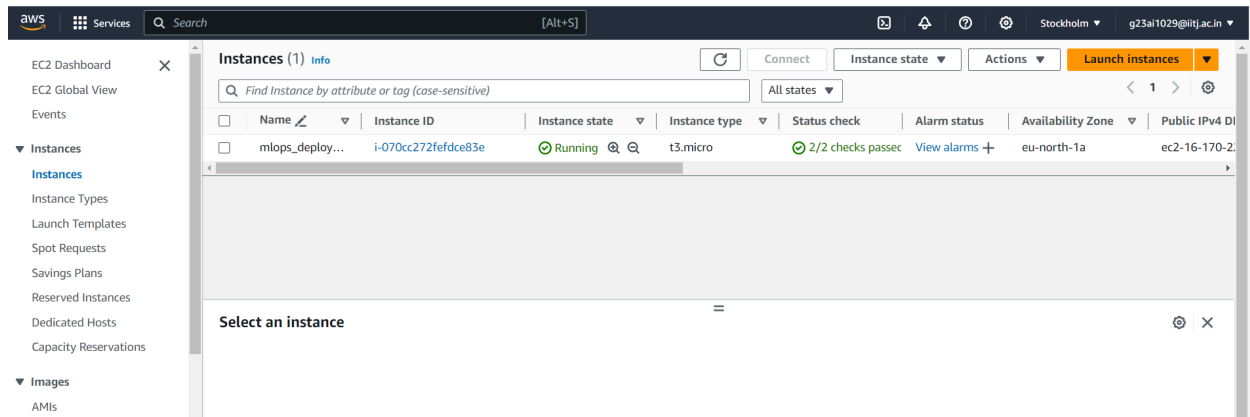
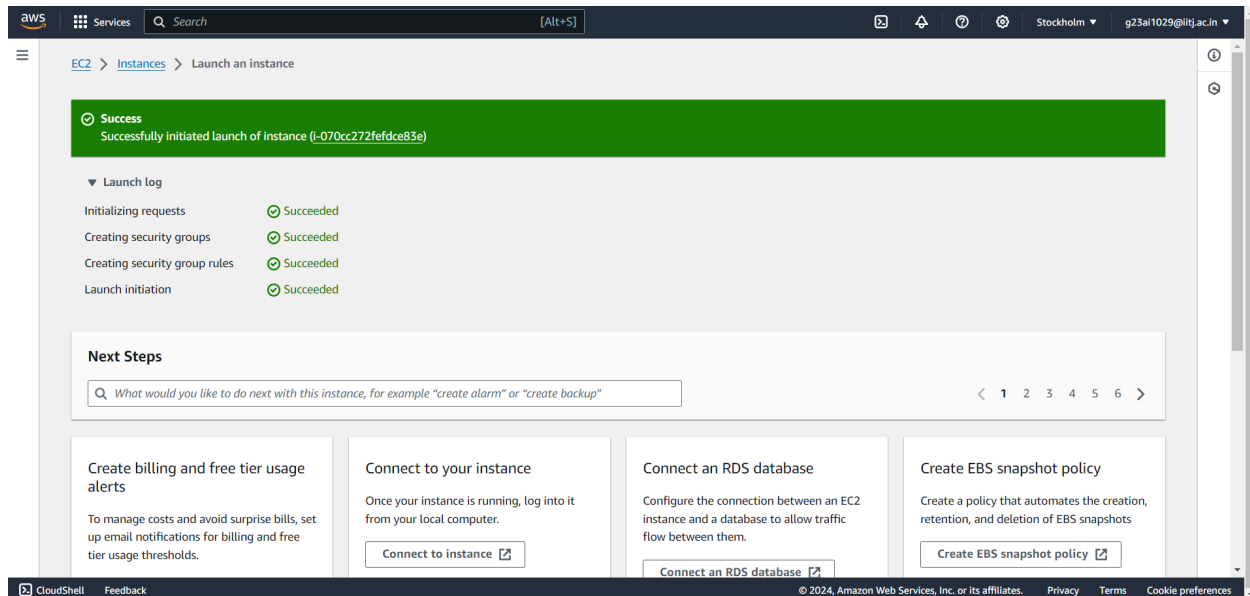
Select company_size

SMALL

Predict Salary Range

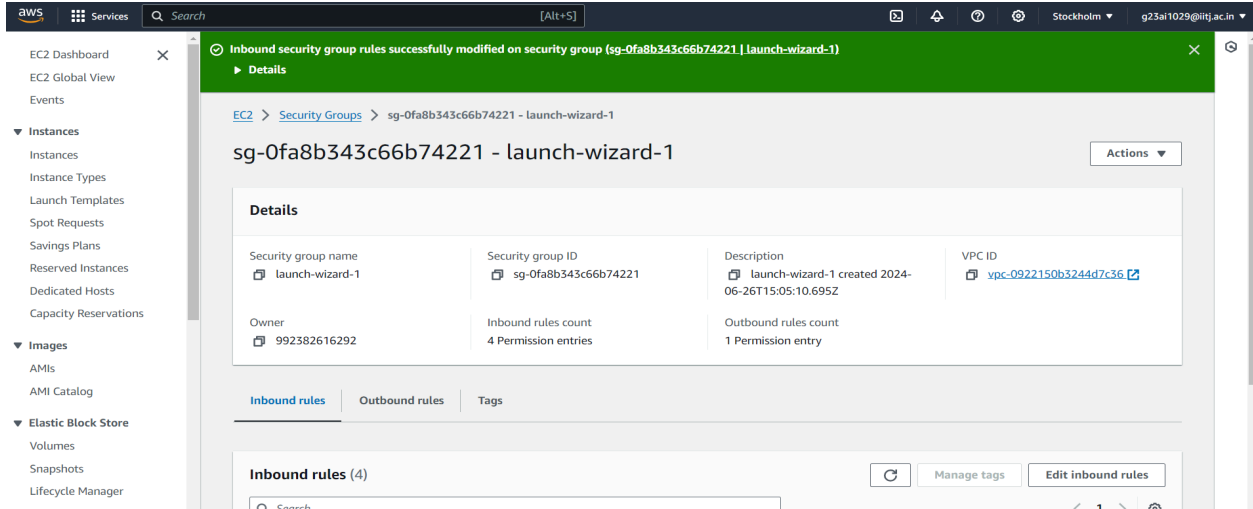
Predicted Salary Range: [Low]

EC2 Configuration:



Instance ARN: arn:aws:ec2:eu-north-1:992382616292:instance/i-070cc272fe9dce83e

AWS Credential: ec2-16-170-227-52.eu-north-1.compute.amazonaws.com



IP: 16.170.227.52

