# **Tech Salaries Mini Project: Python Implementation**

### 1. Project Overview

#### 1.1 Project Title

Tech Salaries Analysis: US and International Salary & Experience Landscape

#### 1.2 Objective

- Analyze and compare tech salaries across the US and international markets.
- Explore the relationship between salaries, experience, education, and skills.
- Provide actionable insights for job seekers, employers, and policymakers.

#### 1.3 Key Questions

- How do tech salaries in the US compared to international markets?
- What is the impact of experience, education, and skills on salaries?
- Which countries or cities offer the highest salaries for tech roles?
- How do remote work trends affect salary structures?

### 2. Python Tools and Libraries

#### 2.1 Core Libraries

- Programming Languages: Python,
- Data Manipulation: Pandas, NumPy
- Visualization: Matplotlib, Seaborn, Plotly
- Geospatial Analysis: Folium

### 3. Data Collection

```
#Load the dataset

df = pd.read_csv("salaries_clean.csv")

print(df.head())
```

### 4. Data Cleaning

#### 4.1 Handling Missing Values

```
missing_values = df.isnull().sum()
print("Missing values per column:\n", missing_values)
```

```
#Imputation for critical columns
df['annual_base_pay'].fillna(df['annual_base_pay'].median(), inplace=True)

# Imputation for `total_experience_years` and `employer_experience_years` with
median
df['total_experience_years'].fillna(df['total_experience_years'].median(),
inplace=True)
df['employer_experience_years'].fillna(df['employer_experience_years'].median(),
inplace=True)

# Imputation for `employer_name`
df['employer_name'].fillna('A stranger', inplace=True)
```

```
#Imputation for `employer_name`
df['employer_name'].fillna('A stranger', inplace=True)

# Imputation for categorical columns with fashion
df['location_state'].fillna(df['location_state'].mode()[0], inplace=True)
df['location_country'].fillna(df['location_country'].mode()[0], inplace=True)
df['location_latitude'].fillna(df['location_latitude'].mode()[0], inplace=True)
df['location_longitude'].fillna(df['location_longitude'].mode()[0], inplace=True)
df['job_title_rank'].fillna(df['job_title_rank'].mode()[0], inplace=True)
```

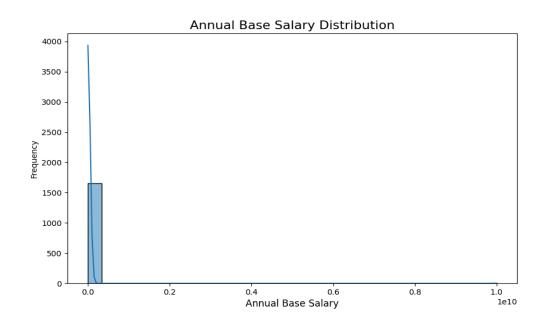
## 5. Exploratory Data Analysis (EDA)

#### 5.1 Exploratory Data Analysis (EDA)

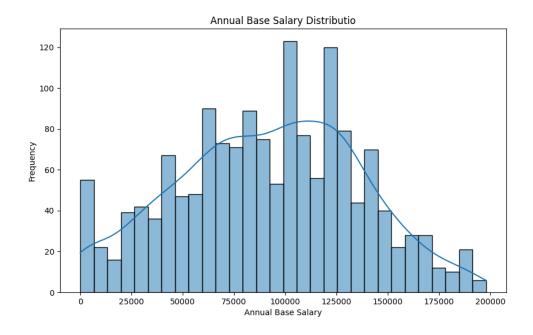
- Summary statistics (mean, median, standard deviation).
- Distribution of salaries by role, location, and experience.
- Heatmaps and correlation matrices.

#### 5.1 Visualization

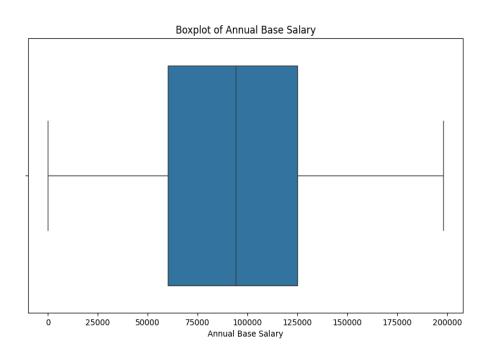
Annual Base Salary Distribution



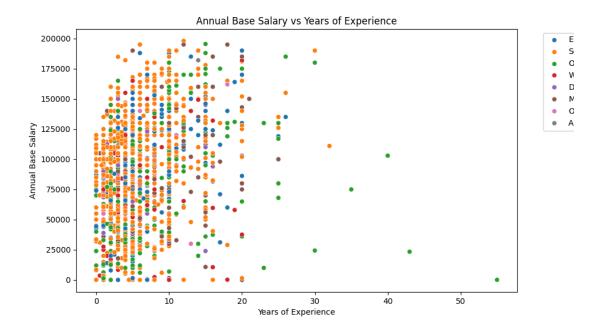
#### Annual Base Salary Distribution



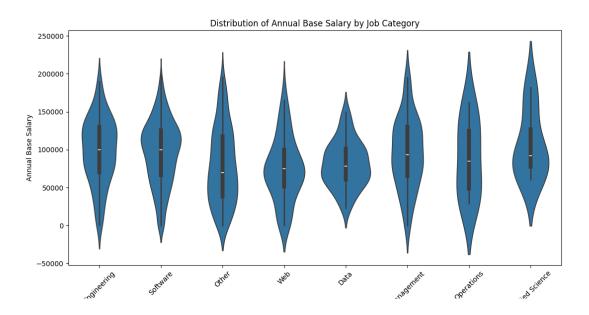
### • Boxplot of Annual Base Salary



### Annual Base Salary vs Year of Experience



### Distribution of Annual Base by job category



#### **5.2 Summary Statistics**

```
print(df['salary'].describe())
```

#### 5.3 Uni Variate Visualization #1: Salary Histogram

```
plt.figure(figsize=(10, 6))
sns.histplot(df['annual_base_pay'], bins=30, kde=True)
plt.title('Annual Base Salary Distribution',fontsize=16)
plt.xlabel('Annual Base Salary',fontsize=12)
plt.ylabel('Frequency')
plt.show()
```

```
Uni variate Visualization #1: Salary Histogram

plt.figure(figsize=(10, 6))

sns.histplot(df2['annual_base_pay'], bins=30, kde=True)

plt.title('Annual Base Salary Distributio')

plt.xlabel('Annual Base Salary')

plt.ylabel('Frequency')

plt.show()
```

#### 6. Visualization

#### 6.1 Interactive Salary Map

## 7. Deliverables

- Cleaned Dataset: cleaned\_tech\_salaries.csv
- 2. Visualizations: Interactive dashboards and charts.
- 3. Final Report: Insights and recommendations.

### 8. Deliverables

- 1. Cleaned Dataset: salaries\_clean.csv
- 2. Visualizations: Interactive dashboards and charts.
- 3. Final Report: Insights and recommendations

# 9. Project Timeline

Task	Timeline
Data Collection	Day's1-2
Data Cleaning	Day's 2
EDA and Visualization	Day's 3
Final Report	Day's 2