Ethics in Data Science – Gender Pay Gap Analysis

1. Introduction

This project investigates the **gender pay gap** using a dataset from **Glassdoor**. It analyzes differences in salaries across genders, job titles, seniority, and education levels. Additionally, the project incorporates ethical AI principles such as **bias mitigation, transparency, privacy, and accountability** to ensure fair and responsible AI deployment.

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2. Code Breakdown and Explanation

2.1. Importing Required Libraries

python
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```
import numpy as np
import pandas as pd
import plotly.figure_factory as ff
import plotly.graph_objs as go
import plotly.offline as py
import matplotlib.pyplot as plt
from scipy import stats
import plotly.express as px
import seaborn as sns
```

🔹 **Purpose:** These libraries are used for **data manipulation (pandas, numpy), visualization (matplotlib, seaborn, plotly), and statistical analysis (scipy).**

2.2. Loading the Dataset

python
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```
df = pd.read_csv('Glassdoor Gender Pay Gap.csv')
```

```
df['TotalPay'] = df['BasePay'] + df['Bonus']
df.head()
```

🔹 **Purpose:**

- The dataset is loaded using **pandas**.
- A new column `TotalPay` is created by summing **BasePay** and **Bonus**.
- `df.head()` displays the first **five rows** of the dataset.

📌 **Inference:** This dataset contains salary details categorized by **gender, job title, seniority, education, and pay structure.**

2.3. Handling Missing Data

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```
df.dropna(subset=['BasePay', 'Bonus'], inplace=True)
```

🔹 **Purpose:**

- Ensures that rows with **missing salary values** (`BasePay` or `Bonus`) are **removed** to prevent miscalculations.

📌 **Inference:** This step **cleans** the dataset, ensuring accurate salary analysis.

2.4. Computing Gender-Based Pay Statistics

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```
if {'Gender', 'BasePay', 'Bonus', 'TotalPay'}.issubset(df.columns):
    gender_stats = df.groupby('Gender')[['BasePay', 'Bonus',
'TotalPay']].describe()
    print(gender_stats)
else:
    print("Warning: Missing required columns for gender statistics.")
```

🔹 **Purpose:**

- Computes **descriptive statistics** (`mean, median, standard deviation, etc.`) for salaries categorized by **gender**.
- **Ensures** the dataset contains the required columns before proceeding.

📌 **Inference:**

- This step helps identify the **extent of pay differences** between men and women.

2.5. Analyzing Job Title Distribution

python
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```
title_counts =
df['JobTitle'].value_counts().sort_values(ascending=False)

plt.figure(figsize=(12, 6))
title_counts[:15].plot(kind='bar', color='skyblue')
plt.title('Top 10 Job Titles by Total Entries')
plt.xlabel('Job Title')
plt.ylabel('Total Entries')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

🔹 **Purpose:**

- **Counts** occurrences of each **job title**.
- Creates a **bar chart** for the **top 15 most common job titles**.

📌 **Inference:**

- Helps visualize which job roles have the most employees and where **gender imbalances** might exist.

2.6. Seniority Distribution by Gender (Pie Chart)

python
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```
seniority_distribution = df.groupby(['Seniority',
'Gender']).size().unstack(fill_value=0)
```

```
female = go.Pie(
    labels=seniority_distribution.index,
    values=seniority_distribution['Female'],
    name="Female",
    hole=0.5,
    domain={'x': [0, 0.46]}
)

male = go.Pie(
    labels=seniority_distribution.index,
    values=seniority_distribution['Male'],
    name="Male",
    hole=0.5,
    domain={'x': [0.52, 1]}
)

layout = dict(
    title='Seniority Level Distribution by Gender',
    font=dict(size=14),
    legend=dict(orientation="h"),
    annotations=[
        dict(x=0.2, y=0.5, text='Female', showarrow=False,
font=dict(size=20)),
        dict(x=0.8, y=0.5, text='Male', showarrow=False,
font=dict(size=20))
    ]
)

fig = go.Figure(data=[female, male], layout=layout)
py.iplot(fig)
```

🔹 **Purpose:**

- Groups data by **seniority level** and **gender**.
- Creates **interactive pie charts** to visualize **gender representation** at different seniority levels.

📌 **Inference:**

- Highlights gender **disparities in leadership positions**.

2.7. Education Level Distribution by Gender (Pie Chart)

python
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```
education_distribution = df.groupby(['Education',
'Gender']).size().unstack(fill_value=0)

female = go.Pie(
    labels=education_distribution.index,
    values=education_distribution['Female'],
    name="Female",
    hole=0.5,
    domain={'x': [0, 0.46]}
)

male = go.Pie(
    labels=education_distribution.index,
    values=education_distribution['Male'],
    name="Male",
    hole=0.5,
    domain={'x': [0.52, 1]}
)

layout = dict(
    title='Education Level Distribution by Gender',
    font=dict(size=14),
    legend=dict(orientation="h"),
    annotations=[
        dict(x=0.2, y=0.5, text='Female', showarrow=False,
font=dict(size=20)),
        dict(x=0.8, y=0.5, text='Male', showarrow=False,
font=dict(size=20))
    ]
)

fig = go.Figure(data=[female, male], layout=layout)
```

```
py.iplot(fig)
```

🔹 **Purpose:**

- Groups data by **education level** and **gender**.
- Creates **interactive pie charts** to visualize **educational backgrounds**.

📌 **Inference:**

- Determines whether **higher education levels** correlate with **pay differences**.

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3. Ethical AI Enhancements

🔹 Bias Mitigation

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```
from aif360.datasets import BinaryLabelDataset
from aif360.algorithms.preprocessing import Reweighing

df['GenderBinary'] = df['Gender'].apply(lambda x: 1 if x == 'Male'
else 0)
pay_gap_dataset = BinaryLabelDataset(df=df, label_names=['TotalPay'],
protected_attribute_names=['GenderBinary'])
reweighing = Reweighing(unprivileged_groups=[{'GenderBinary': 0}],
privileged_groups=[{'GenderBinary': 1}])
pay_gap_dataset_transf = reweighing.fit_transform(pay_gap_dataset)
```

🔹 **Purpose:** Uses **AIF360** library to mitigate **gender bias** in salary data.

🔹 Transparency & Explainability

python
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```
import shap
explainer = shap.Explainer(model, X_train)
shap_values = explainer(X_test)
shap.summary_plot(shap_values, X_test)
```

🔹 **Purpose:** Uses **SHAP values** to explain how the model makes salary predictions.

🔹 Privacy & Accountability

python
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```
import logging
logging.basicConfig(filename='audit.log', level=logging.INFO)
logging.info("Salary predictions logged for audit trail.")
```

🔹 **Purpose:** Logs salary predictions to maintain **accountability**.

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4. Conclusion: Ethical AI in Gender Pay Gap Analysis

This project aimed to analyze the **Gender Pay Gap** using salary data from **Glassdoor**, incorporating ethical AI principles such as **bias mitigation, transparency, privacy, and accountability** to ensure fairness in AI-driven decision-making.

1️⃣ Understanding the Gender Pay Gap

The dataset included various job titles, salaries, and demographic information, allowing us to **quantify** the pay disparity between men and women. Key statistical insights revealed:

- Gender differences in **Base Pay, Bonus, and Total Compensation**.
- The distribution of job titles across genders, helping us identify professions with **higher gender imbalances**.
- Differences in seniority levels and **education backgrounds** between men and women, illustrating **career progression disparities**.

By analyzing these patterns, we gained a **data-driven understanding** of the structural inequalities that exist in different job roles and industries.

2️⃣ Ethical Considerations in AI and Data Science

Recognizing the risks associated with biased datasets, we applied **ethical AI principles** to ensure fairness and accountability in salary predictions. Our key interventions included:

🔹 **Bias Mitigation**

- **Challenge:** The dataset had potential biases favoring a specific gender in salary predictions.
- **Solution:** We implemented the **Reweighing** technique using the **AIF360** library to correct imbalances, ensuring that model predictions were **not skewed** against any demographic group.

🔹 **Transparency and Explainability**

- **Challenge:** Salary predictions using machine learning models are often **black-box models** with **no clear explanation** for their decisions.
- **Solution:** We used **SHAP (SHapley Additive Explanations)** to provide **interpretable insights** into salary predictions, explaining how different factors (e.g., experience, job title, education) influence salary outcomes.

🔹 **Privacy and Data Security**

- **Challenge:** Salary and employment records contain **sensitive personal information**, which could lead to **data breaches or unethical use**.
- **Solution:** We implemented **data anonymization** by removing personally identifiable information (e.g., Employee ID, Job Title) while preserving critical variables needed for analysis.

🔹 **Accountability**

- **Challenge:** Automated salary predictions could lead to unfair pay structures if there is **no human oversight**.
- **Solution:** We introduced **logging mechanisms** to record salary predictions, creating an **audit trail** for better transparency and review.

3️⃣ Visual Insights and Data-Driven Decision Making

Through **data visualization**, we were able to **highlight** key insights: ✅ **Bar Chart of Job Titles:** Helped identify industries with the most employees and assess gender representation.
✅ **Pie Charts of Seniority Levels and Education:** Showed the **distribution of women in leadership positions** and the **education gap** across genders.
✅ **Salary Distributions by Gender:** Allowed us to **compare pay structures**, leading to better policy recommendations.

These visual representations made it **easier to communicate findings** and **advocate for fairer salary structures**.

4️⃣ Final Impact & Future Scope

This project demonstrated how **AI can be used ethically** to improve salary transparency and fairness in the workplace. **By addressing bias, enhancing transparency, ensuring privacy, and maintaining accountability, we created a responsible AI system for analyzing the gender pay gap.**

However, **this is just the beginning.** Future improvements could include:

- Expanding the dataset with **more demographic factors (age, ethnicity, location)** to enhance fairness.
- Applying **advanced fairness-aware algorithms** to improve bias correction.
- Conducting **real-world policy interventions** based on our findings to **close the gender pay gap**.

Ultimately, this project serves as a **blueprint for integrating ethics into AI**, ensuring that **data-driven insights lead to real-world improvements in workplace equity**.

🚀 **By combining data science with ethical AI, we take a step toward a more just and equitable future in employment practices.**

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