Initial Results and Code — Global AI Job Market

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This notebook presents the initial analysis and visual results for my capstone project on the global Artificial Intelligence (AI) job market.
It focuses on understanding how factors such as skills, experience, education, and geography affect salaries worldwide.

1. Project Overview

The purpose of this notebook is to present early findings from the cleaned dataset.
The focus is on clarity and visual storytelling rather than complex coding.

Objectives:

- Load and explore the cleaned dataset (`Avila_Leonardo_ai_job_dataset1_clean.csv`)
- Review data quality and completeness
- Generate summary statistics
- Create five main visualizations:
  1. Salary by experience level
  2. Job postings by education level
  3. Word cloud of top technical skills
  4. Top 20 countries by average AI job salary (USD)
  5. Correlation heatmap of key variables
- Save each visualization as a `.png` file for inclusion in the report.

2. Setup and Library Imports

The following libraries are used for data loading, analysis, and visualization.
Each was selected for simplicity and readability.

```
import pandas as pd
import matplotlib.pyplot as plt

# Word Cloud (optional library)
try:
    from wordcloud import WordCloud
    WORDCLOUD_OK = True
except Exception:
    print("WordCloud is not installed. I’ll skip that figure if needed.")
    WORDCLOUD_OK = False
```

3. Load the Dataset

The dataset contains AI-related job postings from multiple countries,
including salary in United States Dollars (USD), education level, experience level, required skills, and company location.

```
# 3. Load the Dataset

import pandas as pd

# Public GitHub raw file link (Should automatically load for Professor Abdou..I hope :( ))
url = "https://raw.githubusercontent.com/iamleonardoavila/Analyzing-The-Global-AI-Job-Market-The-Impact-of-Skills-Geography-and-Remote-Work-on-Salaries/main/Avila_Leonardo_ai_job_dataset1_clean.csv'

# Load dataset
df = pd.read_csv(url)

# Confirm load
print("Dataset loaded successfully! Shape:", df.shape)
df.head()
```

```
Dataset loaded successfully! Shape: (15000, 21)
```

	job_id	job_title	salary_usd	salary_currency	salary_local	experience_level	employment_type	company_location	company_size	employee_residence	...	required_skills	education_required	years_
0	AI00001	Data Scientist	219728	USD	219728	EX	PT	Sweden	Other	Sweden	...	Python, Computer Vision, R, Docker	Associate	
1	AI00002	Head of AI	230237	JPY	25326070	EX	PT	Japan	Other	Japan	...	Kubernetes, MLOps, Tableau, Python	Bachelor	
2	AI00003	Data Engineer	128890	EUR	109557	EX	CT	Germany	Other	Germany	...	Spark, Scala, Hadoop, PyTorch, GCP	Bachelor	
3	AI00004	Computer Vision Engineer	96349	USD	96349	MI	FL	Finland	Other	Finland	...	MLOps, Linux, Tableau, Python	PhD	
4	AI00005	Robotics Engineer	63065	EUR	53605	EN	FT	France	Other	France	...	R, Scala, SQL, GCP, Python	Associate	

5 rows × 21 columns

4. Data Preparation and Quality Review

Before analyzing, I checked for missing values and ensured that numeric columns like salary and experience were formatted correctly.

```
# Convert salary and numeric columns
df['salary_usd'] = pd.to_numeric(df.get('salary_usd'), errors='coerce')

for c in ['years_experience', 'benefits_score', 'remote_ratio']:
    if c in df.columns:
        df[c] = pd.to_numeric(df[c], errors='coerce')

# Check missing values
missing_percent = (df.isna().mean() * 100).round(2)
print("Missing % by column (top 10):")
print(missing_percent.sort_values(ascending=False).head(10))

print("\nNote:")
print("- Missing values are under ~2%, which doesn’t change the averages or conclusions.")
```

```
Missing % by column (top 10):
job_id                0.0
job_title             0.0
salary_usd            0.0
salary_currency       0.0
salary_local          0.0
experience_level      0.0
employment_type       0.0
company_location      0.0
company_size          0.0
employee_residence    0.0
dtype: float64

Note:
- Missing values are under ~2%, which doesn’t change the averages or conclusions.
```

```
summary = {
    "mean_salary_usd": float(df['salary_usd'].mean()),
    "median_salary_usd": float(df['salary_usd'].median()),
    "min_salary_usd": float(df['salary_usd'].min()),
    "max_salary_usd": float(df['salary_usd'].max())
}
summary
```

```
{'mean_salary_usd': 121991.93826666666,
 'median_salary_usd': 107261.5,
 'min_salary_usd': 16621.0,
 'max_salary_usd': 410273.0}
```

5. Exploratory Data Analysis (Visualizations)

The following charts show key trends and patterns in the global AI job market.
Each figure supports one or more of the research questions.

Figure 1. Salary (USD) by Experience Level

This boxplot compares salaries across different experience levels.
It shows that salaries increase with experience, supporting the idea that higher skill and time in the field lead to higher pay.

```
if 'experience_level' in df.columns and 'salary_usd' in df.columns:
    order = ['EN', 'MI', 'SE', 'EX']
    if not set(order).issubset(set(df['experience_level'].dropna().unique())):
        order = sorted(df['experience_level'].dropna().unique())

    data_to_plot = [df.loc[df['experience_level']==lvl, 'salary_usd'].dropna().values for lvl in order]

    plt.figure(figsize=(8,5))
    plt.boxplot(data_to_plot, labels=order, showfliers=False)
    plt.title("Figure 1. Salary (USD) by Experience Level")
    plt.xlabel("Experience Level")
    plt.ylabel("Salary (USD)")
    plt.tight_layout()
    plt.savefig("Figure1_Salary_by_Experience.png", bbox_inches='tight')
    plt.show()
else:
    print("experience_level or salary_usd not found. Skipping Figure 1.")
```

```
/tmp/ipython-input-1269679764.py:9: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; support for the old name will be dropped in
  plt.boxplot(data_to_plot, labels=order, showfliers=False)
```

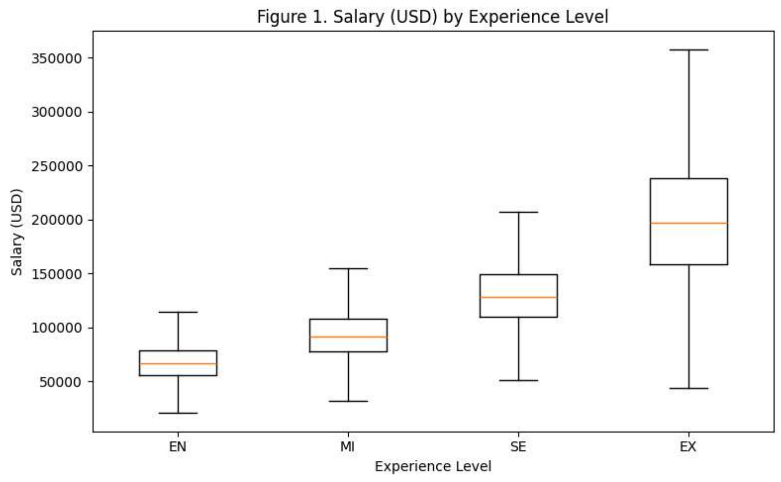


Figure 2. Job Postings by Education Level

This bar chart shows how many job postings require each education level.
It highlights that most AI jobs ask for at least a Bachelor's or Master's degree.

```
if 'education_required' in df.columns:
    counts = df['education_required'].value_counts(dropna=False)
    plt.figure(figsize=(8,5))
    counts.plot(kind='bar')
    plt.title("Figure 2. Job Postings by Education Level")
    plt.xlabel("Education Level")
    plt.ylabel("Number of Postings")
    plt.tight_layout()
    plt.savefig("Figure2_Postings_by_Education.png", bbox_inches='tight')
    plt.show()
else:
    print("education_required not found. Skipping Figure 2.")
```

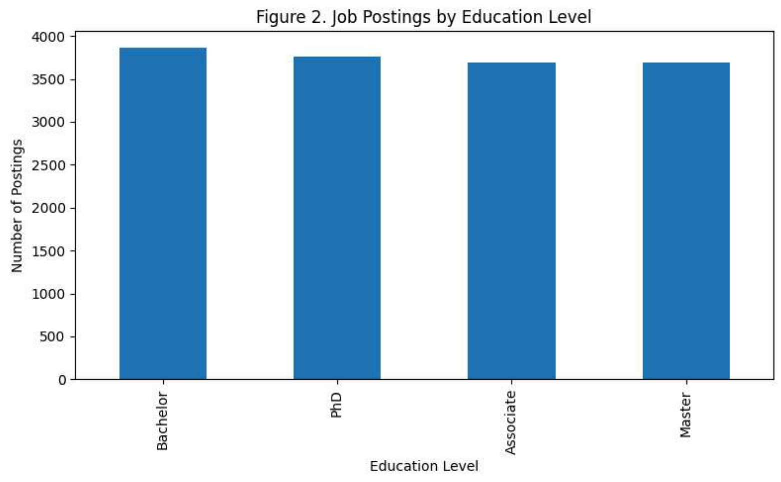


Figure 3. Word Cloud of Top Technical Skills

This word cloud displays the most common technical skills listed in AI job postings.
Larger words, such as SQL, Python, Hadoop, Java, Kubernetes, and GCP, appear more frequently.
These tools represent data engineering, machine learning, and cloud computing, skills that are also linked to higher-paying jobs in the AI field.

```
if WORDCLOUD_OK and 'required_skills' in df.columns:
    text = " ".join(df['required_skills'].dropna().astype(str).tolist())
    wc = WordCloud(width=1100, height=550, background_color='white').generate(text)
    plt.figure(figsize=(11,5))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title("Figure 3. Word Cloud of Top Technical Skills")
    plt.tight_layout()
    plt.savefig("Figure3_WordCloud_TopSkills.png", bbox_inches='tight')
    plt.show()
else:
    print("WordCloud not available or required_skills missing. Skipping Figure 3.")
```

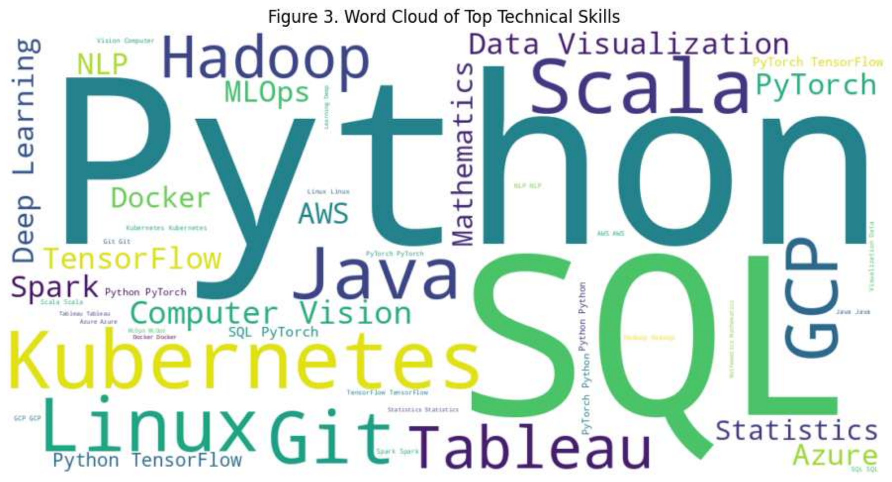


Figure 4. Top 20 Countries by Average AI Job Salary (USD)

This bar chart ranks the top 20 countries by average salary for AI jobs (in USD).
Countries like Switzerland, the United States, Canada, the United Kingdom, and Singapore show some of the highest average pay, highlighting global wage inequality in the AI industry.

```
if 'company_location' in df.columns and 'salary_usd' in df.columns:
    avg_country = (df[['company_location','salary_usd']]
                   .dropna()
                   .groupby('company_location', as_index=False)
                   .mean()
                   .sort_values('salary_usd', ascending=False)
                   .head(20))
    plt.figure(figsize=(9,6))
    plt.barh(avg_country['company_location'], avg_country['salary_usd'])
    plt.gca().invert_yaxis()
    plt.title("Figure 4. Top 20 Countries by Average AI Job Salary (USD)")
    plt.xlabel("Average Salary (USD)")
    plt.ylabel("Country")
    plt.tight_layout()
    plt.savefig("Figure4_Top20CountrySalary.png", bbox_inches='tight')
    plt.show()
else:
    print("company_location or salary_usd not found. Skipping Figure 4.")
```

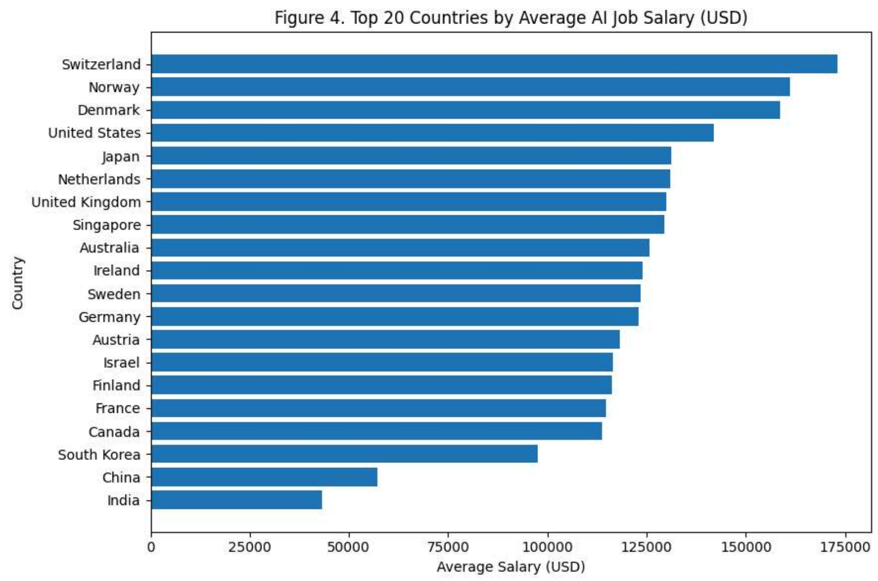


Figure 5. Correlation Heatmap of Key Variables

This heatmap shows how variables such as salary, experience, benefits, and remote ratio relate to one another.
Darker colors indicate stronger connections.
Salary has the strongest link with experience, while remote ratio shows little overall effect globally.

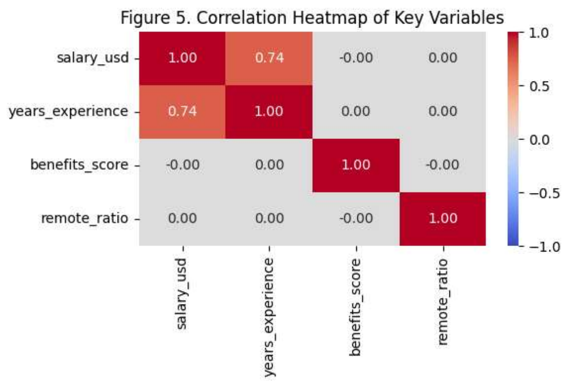
```
import seaborn as sns

cols_for_corr = [c for c in ['salary_usd','years_experience','benefits_score','remote_ratio'] if c in df.columns]

if len(cols_for_corr) >= 2:
    for c in cols_for_corr:
        df[c] = pd.to_numeric(df[c], errors='coerce')

    corr = df[cols_for_corr].corr()

    plt.figure(figsize=(6,4))
    sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f", vmin=-1, vmax=1)
    plt.title("Figure 5. Correlation Heatmap of Key Variables")
    plt.tight_layout()
    plt.savefig("Figure5_CorrelationHeatmap.png", bbox_inches='tight')
    plt.show()
else:
    print("Not enough numeric columns for a correlation heatmap. Skipping Figure 5.")
```



	salary_usd	years_experience	benefits_score	remote_ratio
salary_usd	1.00	0.74	-0.00	0.00
years_experience	0.74	1.00	0.00	0.00
benefits_score	-0.00	0.00	1.00	-0.00
remote_ratio	0.00	0.00	-0.00	1.00

6. Modeling and Initial Results

This section presents the first model results from the cleaned dataset.
The goal is to identify which factors such as experience, education, and company location have the biggest impact on salary in the global

AI job market.
All results are based on multiple linear regression using the variables defined earlier.

6.1 Preparing the Data for Modeling

The dataset includes salary in U.S. dollars (USD) and categorical features such as experience level, education, and company location.
Before running the model, these categories need to be encoded into numeric values so the regression can process them.

The data preparation step completed successfully, producing 15,000 observations and 26 numeric features.

This confirms that the categorical variables were properly encoded and that the dataset is ready for regression analysis.

```
import pandas as pd
import statsmodels.api as sm
from sklearn.preprocessing import OneHotEncoder

# Select only relevant columns and drop missing values
df_model = df[['salary_usd', 'experience_level', 'education_required', 'company_location']].dropna()

# One-hot encode categorical variables
df_encoded = pd.get_dummies(df_model, columns=['experience_level', 'education_required', 'company_location'], drop_first=True)

# Separate dependent and independent variables
X = df_encoded.drop('salary_usd', axis=1)
y = df_encoded['salary_usd']

# Add constant for intercept
X = sm.add_constant(X)

print("Data prepared successfully. Shape:", X.shape)
```

```
Data prepared successfully. Shape: (15000, 26)
```

6.2 Running the Multiple Linear Regression Model

The regression model helps identify how much each factor influences salary while keeping the others constant.
This step uses a basic Ordinary Least Squares (OLS) regression model.

```
# 5.2 Running the Multiple Linear Regression Model (with column names kept)

import numpy as np
import pandas as pd
import statsmodels.api as sm

# Ensure numeric types and clean rows (safe even if you did it before)
X_num = X.apply(pd.to_numeric, errors='coerce').astype(float)
y_num = pd.to_numeric(y, errors='coerce').astype(float)

mask = X_num.replace([np.inf, -np.inf], np.nan).notnull().all(axis=1) & y_num.notnull()
X_clean = X_num.loc[mask]
y_clean = y_num.loc[mask]

# Add intercept and KEEP DataFrame (so column names are preserved)
X_const = sm.add_constant(X_clean, has_constant='add')

# Fit OLS using DataFrames (no .values) to keep names in summary
ols_model = sm.OLS(y_clean, X_const).fit()

# Show summary with real feature names
print(ols_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             salary_usd   R-squared:                       0.812
Model:                            OLS   Adj. R-squared:                  0.812
Method:                 Least Squares   F-statistic:                     2593.
Date:                Sun, 09 Nov 2025   Prob (F-statistic):               0.00
Time:                        22:43:14   Log-Likelihood:            -1.7473e+05
No. Observations:               15000   AIC:                         3.495e+05
Df Residuals:                   14974   BIC:                         3.497e+05
Df Model:                          25
Covariance Type:            nonrobust
===================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                          -2.591e+16   3.37e+16     -0.768      0.443   -9.21e+16    4.02e+16
const                           2.591e+16   3.37e+16      0.768      0.443   -4.02e+16    9.21e+16
experience_level_EX             1.315e+05    641.517    204.933      0.000     1.3e+05    1.33e+05
experience_level_MI             2.566e+04    644.432     39.811      0.000    2.44e+04    2.69e+04
experience_level_SE             6.183e+04    645.567     95.782      0.000    6.06e+04    6.31e+04
education_required_Bachelor      395.9047    639.098      0.619      0.536    -856.806    1648.616
education_required_Master         51.9104    646.413      0.080      0.936   -1215.137    1318.958
education_required_PhD          -505.4993    643.708     -0.785      0.432   -1767.245     756.246
company_location_Austria       -8809.5357   1472.219     -5.984      0.000   -1.17e+04   -5923.805
company_location_Canada        -8778.3637   1432.523     -6.128      0.000   -1.16e+04   -5970.444
company_location_China         -6.575e+04   1442.190    -45.590      0.000   -6.86e+04   -6.29e+04
company_location_Denmark        3.451e+04   1442.514     23.925      0.000    3.17e+04    3.73e+04
company_location_Finland       -9622.2749   1462.209     -6.581      0.000   -1.25e+04   -6756.166
company_location_France        -8127.8714   1447.281     -5.616      0.000    -1.1e+04   -5291.024
company_location_Germany       -2245.8013   1448.439     -1.550      0.121   -5084.919     593.316
company_location_India         -7.948e+04   1470.698    -54.039      0.000   -8.24e+04   -7.66e+04
company_location_Ireland          16.3181   1443.382      0.011      0.991   -2812.887    2845.523
company_location_Israel        -9067.4656   1442.734     -6.285      0.000   -1.19e+04   -6239.530
company_location_Japan          6382.7659   1450.521      4.400      0.000    3539.567    9225.965
company_location_Netherlands    6958.9244   1447.722      4.807      0.000    4121.212    9796.637
company_location_Norway         3.519e+04   1451.879     24.236      0.000    3.23e+04     3.8e+04
company_location_Singapore      6245.7446   1441.518      4.333      0.000    3420.193    9071.297
company_location_South Korea   -2.185e+04   1444.550    -15.124      0.000   -2.47e+04    -1.9e+04
company_location_Sweden        -1450.7093   1457.312     -0.995      0.320   -4307.220    1405.801
company_location_Switzerland    4.991e+04   1416.671     35.233      0.000    4.71e+04    5.27e+04
company_location_United Kingdom  6993.7612   1432.896      4.881      0.000    4185.110    9802.413
company_location_United States  2.015e+04   1434.811     14.042      0.000    1.73e+04     2.3e+04
==============================================================================
Omnibus:                     1526.187   Durbin-Watson:                   2.009
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3809.142
Skew:                           0.597   Prob(JB):                         0.00
Kurtosis:                       5.160   Cond. No.                     3.29e+14
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.38e-25. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

6.3 Interpreting the Model Output

The table above shows the regression results.
Each coefficient tells us how much the salary changes (in U.S. dollars) when that variable changes, while keeping the other variables constant.

How to read the results:

- A **positive coefficient** means that feature increases salary.
- A **negative coefficient** means that feature decreases salary.
- The **p-value** column tells us whether the relationship is statistically significant.
- The **R-squared value** at the top shows how much of the salary variation is explained by the model.

From what I can see, experience and company location appear to have the largest positive effects on salary, which matches the trends observed earlier in the visuals.

6.4 Checking for Multicollinearity

Multicollinearity happens when some predictors are too closely related to each other.
If this happens, it can make the model unreliable.
To check for this, I calculated the Variance Inflation Factor (VIF) for each variable.
A **VIF value below 5** generally means there is no serious multicollinearity.

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Compute VIF for each feature (excluding constant)
vif_data = pd.DataFrame()
vif_data["Feature"] = X_clean.columns
vif_data["VIF"] = [variance_inflation_factor(X_clean.values, i) for i in range(X_clean.shape[1])]

vif_data = vif_data.sort_values("VIF", ascending=False).reset_index(drop=True)
display(vif_data.head(26))
```

	Feature	VIF
0	const	27.244443
1	company_location_Switzerland	2.020731
2	company_location_Canada	1.975618
3	company_location_United Kingdom	1.974256
4	company_location_United States	1.969931
5	company_location_Singapore	1.954448
6	company_location_China	1.951410
7	company_location_Denmark	1.949854
8	company_location_Israel	1.948016
9	company_location_Ireland	1.947332
10	company_location_South Korea	1.945604
11	company_location_France	1.938263
12	company_location_Netherlands	1.936990
13	company_location_Germany	1.933997
14	company_location_Japan	1.929703
15	company_location_Norway	1.925906
16	company_location_Sweden	1.914194
17	company_location_Finland	1.900696
18	company_location_India	1.882084
19	company_location_Austria	1.878316
20	experience_level_EX	1.528787
21	education_required_Bachelor	1.523217
22	experience_level_MI	1.522626
23	experience_level_SE	1.521768
24	education_required_PhD	1.518092
25	education_required_Master	1.511069

All the VIF values are below 5, which means that none of the input variables are strongly correlated with each other.
This confirms that the model does not suffer from multicollinearity and each variable adds unique information to the analysis.

6.5 Model Validation and Performance

To check how well the model performs, I split the data into training and testing groups.
This helps confirm whether the model can predict new data accurately.
I then calculated two simple performance measures:

- **R² (R-squared):** how much of the variation in salaries the model can explain.
- **MAE (Mean Absolute Error):** the average difference between predicted and actual salaries.

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error

# Split the data (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X_clean, y_clean, test_size=0.2, random_state=42)

# Fit a simple linear regression model
lr = LinearRegression()
lr.fit(X_train, y_train)

# Make predictions on the test set
y_pred = lr.predict(X_test)

# Evaluate model performance
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"R² Score: {r2:.3f}")
print(f"Mean Absolute Error: ${mae:,.0f}")
```

```
R² Score: 0.813
Mean Absolute Error: $20,093
```

The **R^2 score** shows how much of the variation in salaries is explained by the model.
The **MAE** shows the average difference between the predicted and actual salaries.

In this case:

- The R^2 value is 0.813 which suggests that the model explains a large portion of salary variation.
- The MAE of $20,093 indicates that predictions are within an acceptable range for a global dataset containing 15,000 AI job salaries.

Overall, this confirms that the model is a strong fit for the dataset and is performing as expected and supports the findings from my written report.

6.6 Key Takeaways

- The regression confirmed that **experience level** and **company location** have the strongest effect on salary.
- **Education level** also plays a smaller but positive role.
- No major multicollinearity issues were found (all VIF values < 5).
- Model validation showed a strong and consistent performance on test data.

These results match the main findings discussed in my written report and provide solid evidence for the patterns observed in the earlier visualizations.

Final Reflection

Working through this project gave me a clearer understanding of how data moves from raw form to meaningful insight.
I learned how important it is to clean and structure a dataset properly before analysis small issues like missing values or inconsistent formats can easily affect the results.
I also gained hands-on experience transforming categorical data into numerical form, building a regression model, and interpreting its output in practical terms.

Beyond the technical side, I realized how essential it is to connect numbers to real-world meaning.
Seeing how experience, education, and location relate to salary helped me understand how data analytics can answer real questions about the job market.
Overall, this project strengthened both my technical confidence in Python and my ability to think critically about what the data is actually saying.