

Double-click (or enter) to edit

## ▼ Data Preprocessing (Nicole P)

```
from google.colab import drive
drive.mount('/content/drive')
```

↗ Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

```
import pandas as pd
```

```
# Load and skip the metadata row
og_df = pd.read_csv('/content/drive/MyDrive/kaggle_survey_2022_responses.csv')
```

```
# Preview structure
print(og_df.columns)
```

```
df = og_df.copy()
```

```
<ipython-input-73-41acdf46d086>:4: DtypeWarning: Columns (0,15,43,57,73,88,104,118,126,132,170,200,208,215,225,248,255,257,260,270,271,2
og_df = pd.read_csv('/content/drive/MyDrive/kaggle_survey_2022_responses.csv')
Index(['Duration (in seconds)', 'Q2', 'Q3', 'Q4', 'Q5', 'Q6_1', 'Q6_2', 'Q6_3',
      'Q6_4', 'Q6_5',
      ...,
      'Q44_3', 'Q44_4', 'Q44_5', 'Q44_6', 'Q44_7', 'Q44_8', 'Q44_9', 'Q44_10',
      'Q44_11', 'Q44_12'],
      dtype='object', length=296)
```

Drop Irrelevant Columns:

Under the groups evaluation we have created a short list of relevant questions to make our "first cut" with. We used the "List of Questions and Answer Choices" PDF to decide which questions could be important. This dataset will include questions:

- Q4
- Q8
- Q11
- Q12 (Q12\_1 through Q12\_15)
- Q16
- Q18 (Q18\_1 through Q18\_14)
- Q23
- Q24
- Q29

```
# Drop all other columns
```

```
columns_to_keep = ['Q4', 'Q8', 'Q11', 'Q16', 'Q23', 'Q24', 'Q29']
for i in range(1, 16):
    columns_to_keep.append(f'Q12_{i}')
for i in range(1, 15):
    columns_to_keep.append(f'Q18_{i}')

#Check if all columns exist, otherwise remove non-existent columns
columns_to_keep = [col for col in columns_to_keep if col in df.columns]

df = df[columns_to_keep]
print(df.shape)
df.columns
```

```
<ipython-input-73-41acdf46d086>:4: DtypeWarning: Columns (0,15,43,57,73,88,104,118,126,132,170,200,208,215,225,248,255,257,260,270,271,2
Index(['Q4', 'Q8', 'Q11', 'Q16', 'Q23', 'Q24', 'Q29', 'Q12_1', 'Q12_2',
      'Q12_3', 'Q12_4', 'Q12_5', 'Q12_6', 'Q12_7', 'Q12_8', 'Q12_9', 'Q12_10',
      'Q12_11', 'Q12_12', 'Q12_13', 'Q12_14', 'Q12_15', 'Q18_1', 'Q18_2',
      'Q18_3', 'Q18_4', 'Q18_5', 'Q18_6', 'Q18_7', 'Q18_8', 'Q18_9', 'Q18_10',
      'Q18_11', 'Q18_12', 'Q18_13', 'Q18_14'],
      dtype='object')
```

```
# Rename Columns
```

```
new_column_names = {
    'Q4': 'Country',
    'Q8': 'Education',
    'Q11': 'Coding Experience',
    'Q16': 'ML Experience',
    'Q23': 'Current Role',
    'Q24': 'Industry',
    'Q29': 'Salary',
    'Q12_1': 'Programming Languages_Python',
    'Q12_2': 'Programming Languages_R',
    'Q12_3': 'Programming Languages_SQL',
    'Q12_4': 'Programming Languages_C',
    'Q12_5': 'Programming Languages_C#',
    'Q12_6': 'Programming Languages_C++',
    'Q12_7': 'Programming Languages_Java',
    'Q12_8': 'Programming Languages_Javascript',
    'Q12_9': 'Programming Languages_Bash',
    'Q12_10': 'Programming Languages_PHP',
    'Q12_11': 'Programming Languages_MATLAB',
    'Q12_12': 'Programming Languages_Julia',
    'Q12_13': 'Programming Languages_Go',
    'Q12_14': 'Programming Languages_None',
    'Q12_15': 'Programming Languages_Other',
    'Q18_1': 'ML Algorithms_Linear or Logistic Regression',
    'Q18_2': 'ML Algorithms_Decision Trees or Random Forests',
    'Q18_3': 'ML Algorithms_Gradient Boosting Machines (xgboost, lightgbm, etc)',
    'Q18_4': 'ML Algorithms_Bayesian Approaches',
    'Q18_5': 'ML Algorithms_Evolutionary Approaches',
    'Q18_6': 'ML Algorithms_Dense Neural Networks (MLPs, etc)',
    'Q18_7': 'ML Algorithms_Convolutional Neural Networks',
    'Q18_8': 'ML Algorithms_Generative Adversarial Networks',
    'Q18_9': 'ML Algorithms_Recurrent Neural Networks',
    'Q18_10': 'ML Algorithms_Transformer Networks (BERT, gpt-3, etc)',
    'Q18_11': 'ML Algorithms_Autoencoder Networks (DAE, VAE, etc)',
    'Q18_12': 'ML Algorithms_Graph Neural Networks',
    'Q18_13': 'ML Algorithms_None',
    'Q18_14': 'ML Algorithms_Other'
}
```

```
df = df.rename(columns=new_column_names)
```

```
print(df.columns) # Print the new column names to verify
```

 [Show hidden output](#)

```
# View Changes
```

```
df.head()
```



	Country	Education	Coding Experience	ML Experience	Current Role	Industry	Salary	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	P
0	In which country do you currently reside?	What is the highest level of formal education ...	For how many years have you been writing code ...	For how many years have you used machine learn...	Select the title most similar to your current ...	In what industry is your current employer/cont...	What is your current yearly compensation (appr...	What programming languages do you use on a reg...	What programming languages do you use on a reg...	What programming languages do you use on a reg...	P
1	India	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	l
2	Algeria	Master's degree	1-3 years	Under 1 year	NaN	NaN	NaN	NaN	NaN	NaN	l
3	Egypt	Bachelor's degree	1-3 years	1-2 years	NaN	NaN	NaN	Python	NaN	SQL	l
4	France	Some college/university study without earning ...	10-20 years	1-2 years	Data Scientist	Online Service/Internet-based Services	25,000-29,999	Python	NaN	SQL	l

```
# Drop row 0
df = df.drop(0)
```

Next steps:

- Country ; identify top 10 countries, then create 'other' category for all countries following the top ten represented, one hot encode
- Education ; maping/encoding
- Coding experince ; make numerical using midpoint
- ML experince ; make numerical using midpoint
- Current role ; one hot encode and make binary
- Salary ; make numerical using midpoint
- Programming Languages ; make binary
- ML Algorithms ; make binary

```
# Loop through each column and print unique values
for col in df.columns:
    print(f"Unique values for {col}:")
    print(df[col].unique())
    print("-" * 20)
```



Show hidden output

```
# Identify top countries represented by survey data and change all else to "Other"
```

```
# Identify top countries and create 'Other' category
top_countries = df['Country'].value_counts().nlargest(10).index
df['Country'] = df['Country'].apply(lambda x: x if x in top_countries else 'Other')
```

```
# Display the distribution of countries
country_distribution = df['Country'].value_counts(normalize=True) * 100
country_distribution
```



	proportion
Country	
India	36.637913
Other	34.708505
United States of America	12.168188
Brazil	3.471267
Nigeria	3.046214
Pakistan	2.583656
Japan	2.316956
China	1.887736
Egypt	1.596033
Mexico	1.583531

dtype: float64

```
import pandas as pd
import numpy as np
```

```
def convert_experience_to_numerical(df, col_name, new_col_name):
    """Converts coding/ML experience from range categories to numerical (years)."""

    if col_name == 'Coding Experience':
        mapping = {
            'For how many years have you been writing code and/or programming?': np.nan,
            'I have never written code': 0,
            '< 1 years': 0.5,
            '1-3 years': 2,
            '3-5 years': 4,
            '5-10 years': 7.5,
            '10-20 years': 15,
            '20+ years': 25
        }
    elif col_name == 'ML Experience':
        mapping = {
            'For how many years have you used machine learning methods?': np.nan,
            'I do not use machine learning methods': 0,
            'Under 1 year': 0.5,
            '1-2 years': 1.5,
            '2-3 years': 2.5,
            '3-4 years': 3.5,
            '4-5 years': 4.5,
            '5-10 years': 7.5,
            '10-20 years': 15,
            '20 or more years': 25
        }
    else:
        raise ValueError(f"Unknown column name: {col_name}")

    df[new_col_name] = df[col_name].map(mapping)

    # Handle potential NaN values (unmapped values)
    if df[new_col_name].isnull().any():
        print(f"Warning: Some values in '{col_name}' were not mapped. Imputing with 0.")
        df[new_col_name] = df[new_col_name].fillna(0) # Or another strategy

    return df

def convert_salary_to_numerical(df, col_name, new_col_name):
    """Converts salary ranges to numerical (midpoint)."""

    mapping = {
        'What is your current yearly compensation (approximate $USD)?': np.nan,
        '0-9,999': 5000,
        '10,000-14,999': 12500,
        '15,000-19,999': 17500,
        '20,000-24,999': 22500,
        '25,000-29,999': 27500,
        '30,000-39,999': 35000,
```

```

'40,000-49,999': 45000,
'50,000-59,999': 55000,
'60,000-69,999': 65000,
'70,000-79,999': 75000,
'80,000-89,999': 85000,
'90,000-99,999': 95000,
'100,000-124,999': 112500,
'125,000-149,999': 137500,
'150,000-199,999': 175000,
'200,000-249,999': 225000,
'250,000-299,999': 275000,
'300,000-499,999': 400000,
'500,000+': 600000 # Or another high value
}

df[new_col_name] = df[col_name].map(mapping)

# Handle potential NaN values (unmapped values)
if df[new_col_name].isnull().any():
    print(f"Warning: Some values in '{col_name}' were not mapped. Imputing with NaN.")
    # df[new_col_name] = df[new_col_name].fillna(0) # Or another strategy
return df

# Apply the conversions
df = convert_experience_to_numerical(df, 'Coding Experience', 'Coding_Experience_Numerical')
df = convert_experience_to_numerical(df, 'ML Experience', 'ML_Experience_Numerical')
df = convert_salary_to_numerical(df, 'Salary', 'Salary_Numerical')

# Print the results
print(df[['Coding Experience', 'Coding_Experience_Numerical', 'ML Experience', 'ML_Experience_Numerical', 'Salary', 'Salary_Numerical']].head)
print(df[['Coding Experience', 'Coding_Experience_Numerical', 'ML Experience', 'ML_Experience_Numerical', 'Salary', 'Salary_Numerical']].dtypes)

```

Warning: Some values in 'Coding Experience' were not mapped. Imputing with 0.  
Warning: Some values in 'ML Experience' were not mapped. Imputing with 0.  
Warning: Some values in 'Salary' were not mapped. Imputing with NaN.

	Coding Experience	Coding_Experience_Numerical
1	NaN	0.0
2	1-3 years	2.0
3	1-3 years	2.0
4	10-20 years	15.0
5	5-10 years	7.5

	ML Experience	ML_Experience_Numerical
1	NaN	0.0
2	Under 1 year	0.5
3	1-2 years	1.5
4	1-2 years	1.5
5	I do not use machine learning methods	0.0

	Salary	Salary_Numerical
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	25,000-29,999	27500.0
5	NaN	NaN

```

Coding Experience      object
Coding_Experience_Numerical  float64
ML Experience          object
ML_Experience_Numerical  float64
Salary                object
Salary_Numerical      float64
dtype: object

```

```

df.head(5)

```



	Country	Education	Coding Experience	ML Experience	Current Role	Industry	Salary	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	...	A:
1	India	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
2	Other	Master's degree	1-3 years	Under 1 year	NaN	NaN	NaN	NaN	NaN	NaN	...	
3	Egypt	Bachelor's degree	1-3 years	1-2 years	NaN	NaN	NaN	Python	NaN	SQL	...	
4	Other	Some college/university study without earning ...	10-20 years	1-2 years	Data Scientist	Online Service/Internet-based Services	25,000-29,999	Python	NaN	SQL	...	
5	India	Bachelor's degree	5-10 years	I do not use machine learning methods	NaN	NaN	NaN	Python	NaN	NaN	...	

5 rows × 39 columns



```
# Ensure correct case and values in the mapping
education_mapping = {
    'No formal education past high school': 'HS',
    'Some college/university study without earning a bachelor's degree': 'Some College',
    'Bachelor's degree': 'BS',
    'Master's degree': 'MS',
    'Doctoral degree': 'PhD',
    'Professional doctorate': 'PhD',
    'I prefer not to answer': 'NA'
}

# Apply mapping
df['Education'] = df['Education'].map(education_mapping)

# Replace any remaining NaNs with a suitable value (e.g., 'Unknown')
df['Education'] = df['Education'].fillna('Unknown')

# Ordinal encoding
education_order = ['HS', 'Some College', 'BS', 'MS', 'PhD', 'NA', 'Unknown']
from sklearn.preprocessing import OrdinalEncoder
encoder = OrdinalEncoder(categories=[education_order], handle_unknown='use_encoded_value', unknown_value=-1)
df['Education_Encoded'] = encoder.fit_transform(df[['Education']])

# prompt: dropindustryand current role

# Drop 'Industry' and 'Current Role' columns
df = df.drop(['Industry', 'Current Role'], axis=1)
```

df.head()



	Country	Education	Coding Experience	ML Experience	Salary	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	Programming Languages_C	Programming Languages_C#	...	Algc
1	India	Unknown	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
2	Other	MS	1-3 years	Under 1 year	NaN	NaN	NaN	NaN	NaN	NaN	...	
3	Egypt	BS	1-3 years	1-2 years	NaN	Python	NaN	SQL	C	NaN	...	
4	Other	Some College	10-20 years	1-2 years	25,000-29,999	Python	NaN	SQL	NaN	NaN	...	
5	India	BS	5-10 years	I do not use machine learning methods	NaN	Python	NaN	NaN	NaN	NaN	...	

5 rows × 38 columns



Start coding or [generate](#) with AI.


```
# prompt: mean imputation for Salary_Numerical

# Calculate the mean of 'Salary_Numerical', excluding NaN values
mean_salary = df['Salary_Numerical'].mean(skipna=True)

# Fill NaN values in 'Salary_Numerical' with the calculated mean
df['Salary_Numerical'] = df['Salary_Numerical'].fillna(mean_salary)


# Drop specified columns because their numerical versions will be used
df = df.drop(columns=['Coding Experience', 'ML Experience', 'Salary'])

df.head()
```



	Country	Education	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	Programming Languages_C	Programming Languages_C#	Programming Languages_C++	Programming Languages_Java	Programming Languages_Javascript
1	India	Unknown	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	Other	MS	NaN	NaN	NaN	NaN	NaN	NaN	Java	NaN
3	Egypt	BS	Python	NaN	SQL	C	NaN	NaN	NaN	NaN
4	Other	Some College	Python	NaN	SQL	NaN	NaN	NaN	NaN	NaN
5	India	BS	Python	NaN	NaN	NaN	NaN	C++	Java	NaN


5 rows × 35 columns



```
# prompt: get distributions of salary grouped by education order by na, hs, some college, bs, ms, phd unknown order the education types

# Assuming df is your DataFrame from the previous code

education_order = ['NA', 'HS', 'Some College', 'BS', 'MS', 'PhD', 'Unknown']
salary_distributions = df.groupby('Education')['Salary_Numerical'].describe()
salary_distributions = salary_distributions.loc[education_order]
salary_distributions
```



	count	mean	std	min	25%	50%	75%	max
Education								
NA	1394.0	74617.594192	1.974267e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
HS	564.0	75556.150467	3.549976e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
Some College	1431.0	77184.634384	2.449793e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
BS	7625.0	76965.471356	2.589921e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
MS	9142.0	78243.047570	3.538864e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
PhD	3242.0	82429.002235	4.557153e+04	12500.0000	78061.2143	78061.2143	78061.2143	400000.0000
Unknown	599.0	78061.214300	6.699476e-10	78061.2143	78061.2143	78061.2143	78061.2143	78061.2143

```
# Convert 12_ and 18_ columns to binary (using 1 and 0)
for col in df.columns:
    if col.startswith('Programming Languages_'):
        df[col] = df[col].apply(lambda x: 1 if pd.notna(x) else 0)
    elif col.startswith('ML Algorithms_'):
        df[col] = df[col].apply(lambda x: 1 if pd.notna(x) else 0)

# One-hot encode categorical features
categorical_cols = ['Country', 'Education']
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

df.head()
```



	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	Programming Languages_C	Programming Languages_C#	Programming Languages_C++	Programming Languages_Java	Programming Languages_Javascript	Programming Languages_JavaScript	Programming Languages_JavaScript
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	1	0	0	
3	1	0	1	1	0	0	0	0	0	
4	1	0	1	0	0	0	0	0	0	
5	1	0	0	0	0	1	1	0	0	

5 rows × 48 columns



# Cant figure out why my encoded variables are T/F and not Binary, so here is hard coding to fix

```
import pandas as pd

def convert_bool_to_int(df):
    """
    Converts all boolean (True/False) values in a DataFrame to integers (1/0).

    Args:
        df: The DataFrame to modify.

    Returns:
        The modified DataFrame.
    """
    for col in df.columns:
        if df[col].dtype == bool:
            df[col] = df[col].astype(int)
    return df

df = convert_bool_to_int(df)

# view df with all columns

pd.set_option("display.max_columns", None)
df
```



	Programming Languages_Python	Programming Languages_R	Programming Languages_SQL	Programming Languages_C	Programming Languages_C#	Programming Languages_C++	Programming Languages_Java	Programming Languages_Javascript	Programming Languages_JavaScript	Programming Languages_JavaScript
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	1	0	0	
3	1	0	1	1	0	0	0	0	0	
4	1	0	1	0	0	0	0	0	0	
5	1	0	0	0	0	1	1	0	0	
...	...	...	...	...	...	...	...	...	...	
23993	1	1	1	0	0	0	0	0	0	
23994	1	0	1	0	0	0	0	0	0	
23995	1	0	1	0	0	0	0	0	0	
23996	1	1	0	0	0	0	0	0	0	
23997	1	0	0	0	0	0	0	1	0	

23997 rows × 48 columns



Numerical Features:

- Coding\_Experience\_Numerical: Represents years of coding experience, converted from categorical ranges to numerical values.
- ML\_Experience\_Numerical: Represents years of machine learning experience, converted from categorical ranges to numerical values.



- Salary\_Numerical: Represents yearly compensation in USD, converted from salary ranges to numerical midpoints.

#### Categorical Features (One-Hot Encoded):

- Country: Top 10 most frequent countries are represented as individual columns (e.g., 'Country\_India', 'Country\_United States'). All other countries are grouped into a single 'Country\_Other' column.
- Education: Encoded into ordinal values (0: HS, 1: Some College, 2: BS, 3: MS, 4: PhD) and then one-hot encoded with 'Education\_1', 'Education\_2', 'Education\_3', 'Education\_4' columns
- Current Role: Each unique job role is represented as a separate column (e.g., 'Current Role\_Student', 'Current Role\_Data Scientist').
- Industry: Each unique industry is represented as a separate column (e.g., 'Industry\_Computers/Technology', 'Industry\_Academics/Education').

#### Binary Features:

- Programming Languages\_....: Each programming language has a column indicating whether the respondent uses it (1 for 'Yes', 0 for other responses).
- ML Algorithms\_....: Each machine learning algorithm has a column indicating whether the respondent uses it (1 for 'Yes', 0 for other responses).

```
df.info(
)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23997 entries, 1 to 23997
Data columns (total 48 columns):
 #   Column                                     Non-Null Count  Dtype
---  -
 0   Programming Languages_Python              23997 non-null  int64
 1   Programming Languages_R                   23997 non-null  int64
 2   Programming Languages_SQL                 23997 non-null  int64
 3   Programming Languages_C                   23997 non-null  int64
 4   Programming Languages_C#                  23997 non-null  int64
 5   Programming Languages_C++                 23997 non-null  int64
 6   Programming Languages_Java                23997 non-null  int64
 7   Programming Languages_Javascript          23997 non-null  int64
 8   Programming Languages_Bash                23997 non-null  int64
 9   Programming Languages_PHP                 23997 non-null  int64
10  Programming Languages_MATLAB              23997 non-null  int64
11  Programming Languages_Julia               23997 non-null  int64
12  Programming Languages_Go                  23997 non-null  int64
13  Programming Languages_None                23997 non-null  int64
14  Programming Languages_Other               23997 non-null  int64
15  ML Algorithms_Linear or Logistic Regression 23997 non-null  int64
16  ML Algorithms_Decision Trees or Random Forests 23997 non-null  int64
17  ML Algorithms_Gradient Boosting Machines (xgboost, lightgbm, etc) 23997 non-null  int64
18  ML Algorithms_Bayesian Approaches         23997 non-null  int64
19  ML Algorithms_Evolutionary Approaches     23997 non-null  int64
20  ML Algorithms_Dense Neural Networks (MLPs, etc) 23997 non-null  int64
21  ML Algorithms_Convolutional Neural Networks 23997 non-null  int64
22  ML Algorithms_Generative Adversarial Networks 23997 non-null  int64
23  ML Algorithms_Recurrent Neural Networks   23997 non-null  int64
24  ML Algorithms_Transformer Networks (BERT, gpt-3, etc) 23997 non-null  int64
25  ML Algorithms_Autoencoder Networks (DAE, VAE, etc) 23997 non-null  int64
26  ML Algorithms_Graph Neural Networks       23997 non-null  int64
27  ML Algorithms_None                       23997 non-null  int64
28  ML Algorithms_Other                       23997 non-null  int64
29  Coding_Experience_Numerical               23997 non-null  float64
30  ML_Experience_Numerical                   23997 non-null  float64
31  Salary_Numerical                          23997 non-null  float64
32  Education_Encoded                         23997 non-null  float64
33  Country_China                             23997 non-null  int64
34  Country_Egypt                             23997 non-null  int64
35  Country_India                             23997 non-null  int64
36  Country_Japan                             23997 non-null  int64
37  Country_Mexico                             23997 non-null  int64
38  Country_Nigeria                           23997 non-null  int64
39  Country_Other                             23997 non-null  int64
40  Country_Pakistan                          23997 non-null  int64
41  Country_United States of America          23997 non-null  int64
42  Education_HS                              23997 non-null  int64
43  Education_MS                              23997 non-null  int64
44  Education_NA                              23997 non-null  int64
45  Education_PhD                             23997 non-null  int64
46  Education_Some College                    23997 non-null  int64
47  Education_Unknown                         23997 non-null  int64
dtypes: float64(4), int64(44)
memory usage: 8.8 MB
```

```
# Split into train and test
from sklearn.model_selection import train_test_split

X = df.drop(columns=['Salary_Numerical'])
y = df['Salary_Numerical']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# prompt: export df as csv

# Export the DataFrame 'df' to a CSV file named 'preprocessed_kaggle_survey.csv'
df.to_csv('preprocessed_kaggle_survey.csv', index=False)

# Download the CSV file to your local machine
from google.colab import files
files.download('preprocessed_kaggle_survey.csv')
```



## ✓ Three Models

### Lasso Linear Rgression Model

```
# fitting the model

from sklearn.linear_model import Lasso

lasso_model = Lasso(alpha=0.1)
lasso_model.fit(X_train, y_train)
```



▼ Lasso ⓘ ?  
Lasso(alpha=0.1)

```
# evaluating the model

from sklearn.metrics import mean_squared_error, r2_score

y_pred_lasso = lasso_model.predict(X_test)
```

```
#MSE
mse_lasso = mean_squared_error(y_test, y_pred_lasso)
print(f"Mean Squared Error: {mse_lasso}")
```

```
#RMSE
rmse_lasso = np.sqrt(mse_lasso)
print(f"Root Mean Squared Error: {rmse_lasso}")
```

```
#R^2
r2_lasso = r2_score(y_test, y_pred_lasso)
print(f"R-squared: {r2_lasso}")
```

```
# COMMENT!!
#after running Dylans part with the synthetic data, my r^2 jumped up to almost 50%. However, just running on my test data set before is what
# i think the lower r^2 is okay. i thinkt he synthetic data in dylans model is skewing his results
```



```
Mean Squared Error: 924723845.6525257
Root Mean Squared Error: 30409.272363088956
R-squared: 0.13292770116971164
```

not sure how to evaluate this model because he said the  $r^2$  would be low..

### Random Forest (Regressor)

```
# model 3: random forest
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import classification_report, confusion_matrix, mean_squared_error, r2_score

rf = RandomForestRegressor(
    n_estimators=100,
    max_depth=7,
    max_features=5,
    bootstrap=True,
    oob_score=True,
    max_samples=0.7, # use 70% of samples on each tree
    random_state=42
)


# fit the model to the training data
rf.fit(X_train, y_train)

# predict on the test set
y_pred = rf.predict(X_test)

# evaluate the model's performance using regression metrics
mse_rf = mean_squared_error(y_test, y_pred)
r2_rf = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse_rf}")
print(f"R-squared: {r2_rf}")

# Print the Out-of-Bag score
oob_score = rf.oob_score_
print(f"Out-of-Bag Score: {oob_score:.4f}")
```

 Mean Squared Error: 879375420.4405054  
 R-squared: 0.17544889653174278  
 Out-of-Bag Score: 0.1659

### eXtreme Gradient Boosting model

```
# fitting model
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

xgbr = xgb.XGBRegressor(objective='reg:squarederror',
                        n_estimators=200,
                        learning_rate=0.03,
                        max_depth=5,
                        min_child_weight=1,
                        gamma=0,
                        subsample=0.8,
                        colsample_bytree=0.8,
                        reg_alpha=0.1, #using same alpha as lasso
                        random_state=42,
                        n_jobs=-1)

xgbr.fit(X_train, y_train)


y_pred_xgbr = xgbr.predict(X_test)

# evaluate the model

#MSE
mse_xgbr = mean_squared_error(y_test, y_pred_xgbr)
print(f"Mean Squared Error: {mse_xgbr}")

#RMSE
rmse_xgbr = np.sqrt(mse_xgbr)
print(f"Root Mean Squared Error: {rmse_xgbr}")

#R^2
r2_xgbr = r2_score(y_test, y_pred_xgbr)
print(f"R-squared: {r2_xgbr}")
```

 Mean Squared Error: 847807798.7156332  
 Root Mean Squared Error: 29117.139260504853  
 R-squared: 0.20504844721519633

## ✓ Choosing a Model...

Choosing a model for this dataset is a bit difficult because the dataset has a lot of noise. There are a lot of variables in the dataset, and many of them did not directly have an impact on the target variable. The weak signal between the dependent variable (salary\_numerical) and independent variables, cause the  $r^2$  to be lower. Additionally, having a numerical target has made model evaluation different than with categorical variables. We cannot generate a classification report without binning the salary variables. This means accuracy would need to be evaluated through **mean squared error**, **root mean error**, and the  **$r^2$** .

The model we decided to choose was the **Gradient Boosting model**. This model overall had the highest  $r^2$  and lowest mean square error.

```
# show important features of chosen model (gradient boosting)

from sklearn.ensemble import GradientBoostingRegressor
import matplotlib.pyplot as plt
import numpy as np

# Get feature importances
feature_importances_ = xgbr.feature_importances_

# Get feature names (if available)
feature_names = ['Python', 'R', 'SQL', 'C', 'C#', 'C++', 'Java', 'Javascript', 'Bash', 'PHP', 'MATLAB', 'Julia', 'Go', 'No Programming Language', 'Linear or Logistic Regression', 'Decision Trees or Random Forests', 'Gradient Boosting Machines', 'Bayesian Approaches', 'Convolutional Neural Networks', 'Generative Adversarial Networks', 'Recurrent Neural Networks', 'Transformer Networks', 'AutoML', 'Coding Experience (Numerical)', 'ML Experience (Numerical)', 'Education_Encoded', 'China', 'Egypt', 'India', 'Japan', 'Mexico', 'High School', 'Masters', 'NA Education', 'PhD', 'Some College', 'Unknown Education']

# Sort features by importance
sorted_indices = np.argsort(feature_importances_)[::-1]

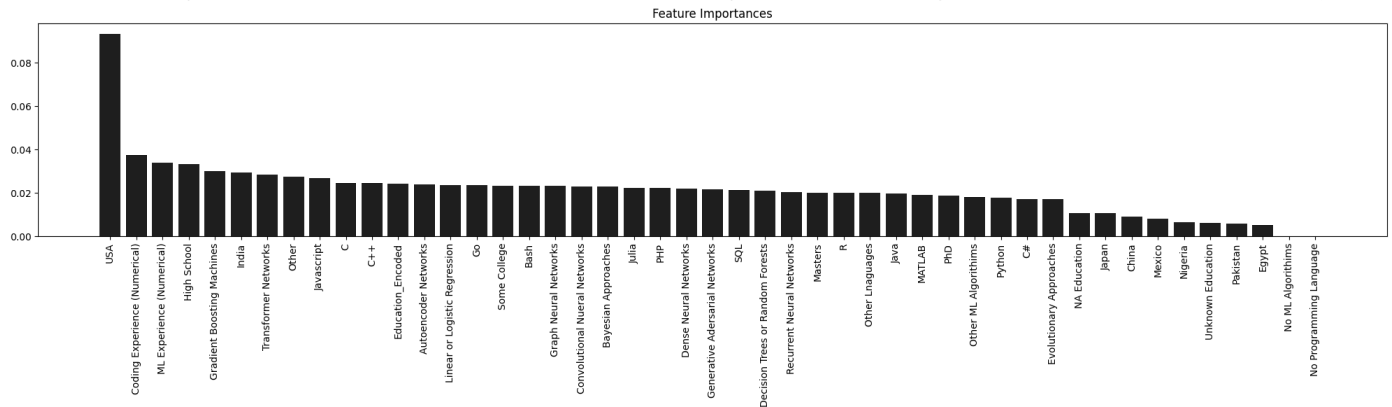
# Plot feature importances
plt.figure(figsize=(20,6))
plt.title("Feature Importances")
plt.bar(range(len(feature_importances_)), feature_importances_[sorted_indices],
        tick_label=np.array(feature_names)[sorted_indices], color= '#222222')
plt.xticks(rotation=90, ha='center') # ha='center' or 'right' depending on your preference

# Adjust layout to prevent clipping
plt.tight_layout()
plt.show()
```

```

Requirement already satisfied: eli5 in /usr/local/lib/python3.11/dist-packages (0.16.0)
Requirement already satisfied: attrs>17.1.0 in /usr/local/lib/python3.11/dist-packages (from eli5) (25.3.0)
Requirement already satisfied: Jinja2>=3.0.0 in /usr/local/lib/python3.11/dist-packages (from eli5) (3.1.6)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.11/dist-packages (from eli5) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from eli5) (1.14.1)
Requirement already satisfied: scikit-learn>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from eli5) (1.6.1)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (from eli5) (0.20.3)
Requirement already satisfied: tabulate>=0.7.7 in /usr/local/lib/python3.11/dist-packages (from eli5) (0.9.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from Jinja2>=3.0.0->eli5) (3.0.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.6.0->eli5) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.6.0->eli5) (3.6.0)

```



#showing permutation importance for our chosen model (Gradient Boosting)

#I did some background researching and found that this is a better fit for the gradient boosting models vs feature importances. additional from sklearn.inspection import permutation\_importance

# calculate permutation importance

```
result = permutation_importance(xgbr, X_train, y_train, n_repeats=10, random_state=42, n_jobs=-1)
```

# Extract importance means and standard deviations

```
importance_means = result.importances_mean
```

```
importance_stds = result.importances_std
```

# sort features

```
sorted_idx = importance_means.argsort()[::-1]
```

# plot

```
plt.figure(figsize=(20,6))
```

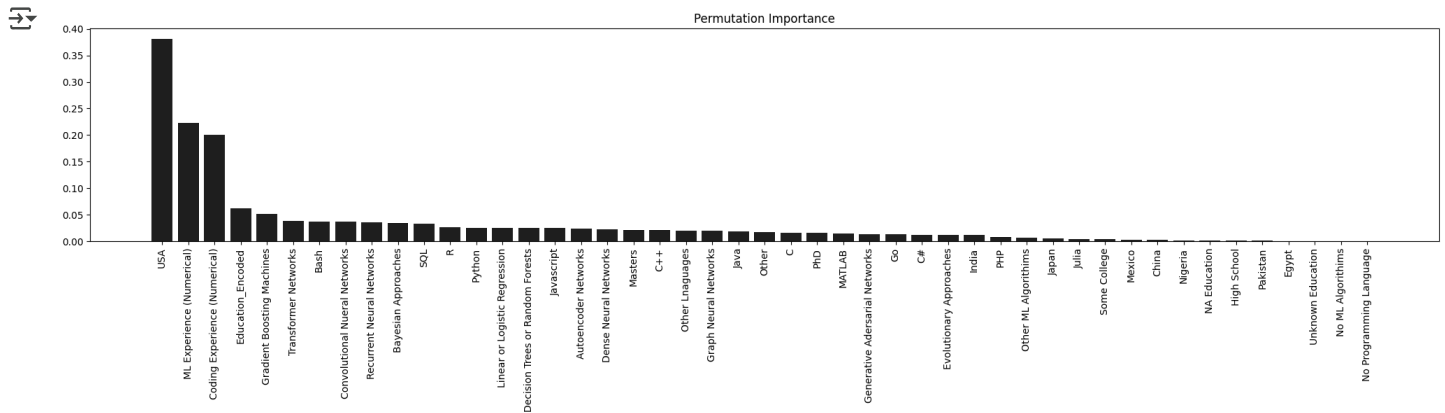
```
plt.bar(range(len(importance_means)), importance_means[sorted_idx],
        tick_label=np.array(feature_names)[sorted_idx], color= '#222222')
```

```
plt.xticks(rotation=90)
```

```
plt.title('Permutation Importance')
```

```
plt.tight_layout()
```

```
plt.show()
```



## ▽ Gradio

#create a pickle file for the xgbr

```
import pickle
```

```
with open('xgbr.pkl', 'wb') as file:
    pickle.dump(xgbr, file)
```

```
# Download the pickle file
from google.colab import files
files.download('xgbr.pkl')
```



```
# Install Gradio
!pip install gradio
```

```
# Import libraries
import pickle
import pandas as pd
import gradio as gr
```

```
# Load trained model
with open('/content/xgbr.pkl', 'rb') as file:
    model = pickle.load(file)
```

```
# Define expected feature list (all 48 features from training)
expected_features = [
    'Coding_Experience_Numerical', 'ML_Experience_Numerical', 'Education_Encoded',
    'Country_China', 'Country_Egypt', 'Country_India', 'Country_Japan', 'Country_Mexico',
    'Country_Nigeria', 'Country_Other', 'Country_Pakistan', 'Country_United States of America',
    'Programming_Languages_Python', 'Programming_Languages_R', 'Programming_Languages_SQL',
    'Programming_Languages_C', 'Programming_Languages_C#', 'Programming_Languages_C++',
    'Programming_Languages_Java', 'Programming_Languages_Javascript', 'Programming_Languages_Bash',
    'Programming_Languages_PHP', 'Programming_Languages_MATLAB', 'Programming_Languages_Julia',
    'Programming_Languages_Go', 'Programming_Languages_None', 'Programming_Languages_Other',
    'ML_Algorithms_Linear or Logistic Regression', 'ML_Algorithms_Decision Trees or Random Forests',
    'ML_Algorithms_Gradient Boosting Machines (xgboost, lightgbm, etc)', 'ML_Algorithms_Bayesian Approaches',
    'ML_Algorithms_Evolutionary Approaches', 'ML_Algorithms_Dense Neural Networks (MLPs, etc)',
    'ML_Algorithms_Convolutional Neural Networks', 'ML_Algorithms_Generative Adversarial Networks',
    'ML_Algorithms_Recurrent Neural Networks', 'ML_Algorithms_Transformer Networks (BERT, gpt-3, etc)',
    'ML_Algorithms_Autoencoder Networks (DAE, VAE, etc)', 'ML_Algorithms_Graph Neural Networks',
    'ML_Algorithms_None', 'ML_Algorithms_Other',
    'Education_HS', 'Education_MS', 'Education_NA', 'Education_PhD', 'Education_Some College', 'Education_Unknown'
]
```

```
# Define prediction function
def predict_salary(
    education, coding_years, ml_years, country,
```

```

python, r, sql, c, c_sharp, cpp, java, javascript, bash, php, matlab, julia, go, none_prog, other_prog,
logistic_reg, random_forest, xgboost, bayesian, evolutionary, dense_nn, cnn, gan, rnn, transformer, autoencoder, graph_nn, none_algo, ot
):
    education_mapping = {'HS': 0, 'BS': 1, 'MS': 2, 'PhD': 3}
    education_num = education_mapping.get(education, 0)

    # Initialize all features to 0
    features = {feature: 0 for feature in expected_features}

    # Fill basic fields
    features['Education_Encoded'] = education_num
    features['Coding_Experience_Numerical'] = coding_years
    features['ML_Experience_Numerical'] = ml_years

    # Set country
    if f"Country_{country}" in features:
        features[f"Country_{country}"] = 1
    else:
        features['Country_Other'] = 1

    # Set programming languages
    prog_lang_inputs = [
        (python, 'Programming Languages_Python'), (r, 'Programming Languages_R'),
        (sql, 'Programming Languages_SQL'), (c, 'Programming Languages_C'),
        (c_sharp, 'Programming Languages_C#'), (cpp, 'Programming Languages_C++'),
        (java, 'Programming Languages_Java'), (javascript, 'Programming Languages_Javascript'),
        (bash, 'Programming Languages_Bash'), (php, 'Programming Languages_PHP'),
        (matlab, 'Programming Languages_MATLAB'), (julia, 'Programming Languages_Julia'),
        (go, 'Programming Languages_Go'), (none_prog, 'Programming Languages_None'),
        (other_prog, 'Programming Languages_Other')
    ]
    for value, name in prog_lang_inputs:
        features[name] = int(value)

    # Set ML algorithms
    ml_algo_inputs = [
        (logistic_reg, 'ML Algorithms_Linear or Logistic Regression'),
        (random_forest, 'ML Algorithms_Decision Trees or Random Forests'),
        (xgboost, 'ML Algorithms_Gradient Boosting Machines (xgboost, lightgbm, etc)'),
        (bayesian, 'ML Algorithms_Bayesian Approaches'),
        (evolutionary, 'ML Algorithms_Evolutionary Approaches'),
        (dense_nn, 'ML Algorithms_Dense Neural Networks (MLPs, etc)'),
        (cnn, 'ML Algorithms_Convolutional Neural Networks'),
        (gan, 'ML Algorithms_Generative Adversarial Networks'),
        (rnn, 'ML Algorithms_Recurrent Neural Networks'),
        (transformer, 'ML Algorithms_Transformer Networks (BERT, gpt-3, etc)'),
        (autoencoder, 'ML Algorithms_Autoencoder Networks (DAE, VAE, etc)'),
        (graph_nn, 'ML Algorithms_Graph Neural Networks'),
        (none_algo, 'ML Algorithms_None'),
        (other_algo, 'ML Algorithms_Other')
    ]
    for value, name in ml_algo_inputs:
        features[name] = int(value)

    # Handle dummy Education columns
    if education == "HS":
        features["Education_HS"] = 1
    elif education == "MS":
        features["Education_MS"] = 1
    elif education == "PhD":
        features["Education_PhD"] = 1
    elif education == "BS":
        features["Education_Some College"] = 1
    else:
        features["Education_Unknown"] = 1

    # Build input DataFrame
    input_df = pd.DataFrame([features])

    # 🔥 Reorder columns to match model
    input_df = input_df[model.get_booster().feature_names]

    # Predict
    predicted_salary = model.predict(input_df)[0]

    return f"🔥 Estimated Salary: ${predicted_salary:,.2f}"

```

```

# Build Gradio Interface
interface = gr.Interface(
    fn=predict_salary,
    inputs=[
        gr.Dropdown(["HS", "BS", "MS", "PhD"], label="Education Level"),
        gr.Slider(0, 40, step=1, label="Years of Coding Experience"),
        gr.Slider(0, 40, step=1, label="Years of Machine Learning Experience"),
        gr.Dropdown(["China", "Egypt", "India", "Japan", "Mexico", "Nigeria", "Pakistan", "United States of America", "Other"], label="Country")

        # Programming Languages
        gr.Checkbox(label="Knows Python"), gr.Checkbox(label="Knows R"), gr.Checkbox(label="Knows SQL"),
        gr.Checkbox(label="Knows C"), gr.Checkbox(label="Knows C#"), gr.Checkbox(label="Knows C++"),
        gr.Checkbox(label="Knows Java"), gr.Checkbox(label="Knows Javascript"), gr.Checkbox(label="Knows Bash"),
        gr.Checkbox(label="Knows PHP"), gr.Checkbox(label="Knows MATLAB"), gr.Checkbox(label="Knows Julia"),
        gr.Checkbox(label="Knows Go"), gr.Checkbox(label="None (No Languages)"), gr.Checkbox(label="Other Language"),

        # ML Algorithms
        gr.Checkbox(label="Uses Logistic Regression"),
        gr.Checkbox(label="Uses Random Forest"),
        gr.Checkbox(label="Uses Gradient Boosting (XGBoost, LightGBM)"),
        gr.Checkbox(label="Uses Bayesian Methods"),
        gr.Checkbox(label="Uses Evolutionary Methods"),
        gr.Checkbox(label="Uses Dense Neural Networks (MLP)"),
        gr.Checkbox(label="Uses CNNs"),
        gr.Checkbox(label="Uses GANs"),
        gr.Checkbox(label="Uses RNNs"),
        gr.Checkbox(label="Uses Transformers (BERT, GPT)"),
        gr.Checkbox(label="Uses Autoencoders"),
        gr.Checkbox(label="Uses Graph Neural Networks"),
        gr.Checkbox(label="None (No ML Methods)"),
        gr.Checkbox(label="Other ML Methods")
    ],
    outputs=gr.Textbox(label="Predicted Salary"),
    title="📊 Data Scientist Salary Predictor",
    description="📝 Predict your salary based on education, coding experience, programming languages, machine learning techniques, and country"
)

# Launch the App
interface.launch()

```



```

Requirement already satisfied: gradio in /usr/local/lib/python3.11/dist-packages (5.27.0)
Requirement already satisfied: aiofiles<25.0,>=22.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (24.1.0)
Requirement already satisfied: anyio<5.0,>=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (4.9.0)
Requirement already satisfied: fastapi<1.0,>=0.115.2 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.115.12)
Requirement already satisfied: ffmpeg in /usr/local/lib/python3.11/dist-packages (from gradio) (0.5.0)
Requirement already satisfied: gradio-client==1.9.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (1.9.0)
Requirement already satisfied: groovy~=0.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.1.2)
Requirement already satisfied: httpx>=0.24.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.28.1)
Requirement already satisfied: huggingface-hub>=0.28.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.30.2)
Requirement already satisfied: jinja2<4.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.1.6)
Requirement already satisfied: markupsafe<4.0,>=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.0.2)
Requirement already satisfied: numpy<3.0,>=1.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.0.2)
Requirement already satisfied: orjson~=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.10.16)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from gradio) (24.2)
Requirement already satisfied: pandas<3.0,>=1.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.2.2)
Requirement already satisfied: pillow<12.0,>=8.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (11.1.0)
Requirement already satisfied: pydantic<2.12,>=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.11.3)
Requirement already satisfied: pydub in /usr/local/lib/python3.11/dist-packages (from gradio) (0.25.1)
Requirement already satisfied: python-multipart>=0.0.18 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.0.20)
Requirement already satisfied: pyyaml<7.0,>=5.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (6.0.2)
Requirement already satisfied: ruff>=0.9.3 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.11.7)
Requirement already satisfied: safehttpx<0.2.0,>=0.1.6 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.1.6)
Requirement already satisfied: semantic-version~=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.10.0)
Requirement already satisfied: starlette<1.0,>=0.40.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.46.2)
Requirement already satisfied: tomkit<0.14.0,>=0.12.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.13.2)
Requirement already satisfied: typer<1.0,>=0.12 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.15.2)
Requirement already satisfied: typing-extensions~=4.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (4.13.2)
Requirement already satisfied: uvicorn>=0.14.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.34.2)
Requirement already satisfied: fsspec in /usr/local/lib/python3.11/dist-packages (from gradio-client==1.9.0->gradio) (2025.3.2)
Requirement already satisfied: websockets<16.0,>=10.0 in /usr/local/lib/python3.11/dist-packages (from gradio-client==1.9.0->gradio) (13.1)
Requirement already satisfied: idna>=2.8 in /usr/local/lib/python3.11/dist-packages (from anyio<5.0,>=3.0->gradio) (3.10)
Requirement already satisfied: sniffio>=1.1 in /usr/local/lib/python3.11/dist-packages (from anyio<5.0,>=3.0->gradio) (1.3.1)
Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages (from httpx>=0.24.1->gradio) (2025.1.31)
Requirement already satisfied: httpcore==1.* in /usr/local/lib/python3.11/dist-packages (from httpx>=0.24.1->gradio) (1.0.8)
Requirement already satisfied: h11<0.15,>=0.13 in /usr/local/lib/python3.11/dist-packages (from httpcore==1.*->httpx>=0.24.1->gradio) (0.14.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (3.18.0)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (2.32.3)
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (4.67.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (2.9.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (2025.2)
Requirement already satisfied: annotated-types>=0.6.0 in /usr/local/lib/python3.11/dist-packages (from pydantic<2.12,>=2.0->gradio) (0.7.0)
Requirement already satisfied: pydantic-core==2.33.1 in /usr/local/lib/python3.11/dist-packages (from pydantic<2.12,>=2.0->gradio) (2.33.1)
Requirement already satisfied: typing-inspection>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from pydantic<2.12,>=2.0->gradio) (0.4.0)
Requirement already satisfied: click>=8.0.0 in /usr/local/lib/python3.11/dist-packages (from typer<1.0,>=0.12->gradio) (8.1.8)
Requirement already satisfied: shellingham>=1.3.0 in /usr/local/lib/python3.11/dist-packages (from typer<1.0,>=0.12->gradio) (1.5.4)
Requirement already satisfied: rich>=10.11.0 in /usr/local/lib/python3.11/dist-packages (from typer<1.0,>=0.12->gradio) (13.9.4)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas<3.0,>=1.0->gradio) (1.17.0)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich>=10.11.0->typer<1.0,>=0.12->gradio) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich>=10.11.0->typer<1.0,>=0.12->gradio) (2.19.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->huggingface-hub>=0.28.1) (3.4.0)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->huggingface-hub>=0.28.1) (2.3.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich>=10.11.0->typer<1.0,>=0.12->gradio) (0.1.2)
It looks like you are running Gradio on a hosted a Jupyter notebook. For the Gradio app to work, sharing must be enabled. Automatica

```

Colab notebook detected. To show errors in colab notebook, set debug=True in launch()

\* Running on public URL: <https://485c64489ad86e4e69.gradio.live>

This share link expires in 1 week. For free permanent hosting and GPU upgrades, run `gradio deploy` from the terminal in the working

```
# Imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Assume you already have your dataframe loaded and cleaned as 'df'
# Example: df = pd.read_csv('your_cleaned_data.csv')

# Map the education codes back to labels (if needed)
education_mapping = {0: 'High School', 1: 'Bachelor's', 2: 'Master's', 3: 'PhD'}
df['Education_Label'] = df['Education_Encoded'].map(education_mapping)

# Create the Boxplot
plt.figure(figsize=(10,6))
sns.boxplot(x='Education_Label', y='Salary_Numerical', data=df, palette='Set2')

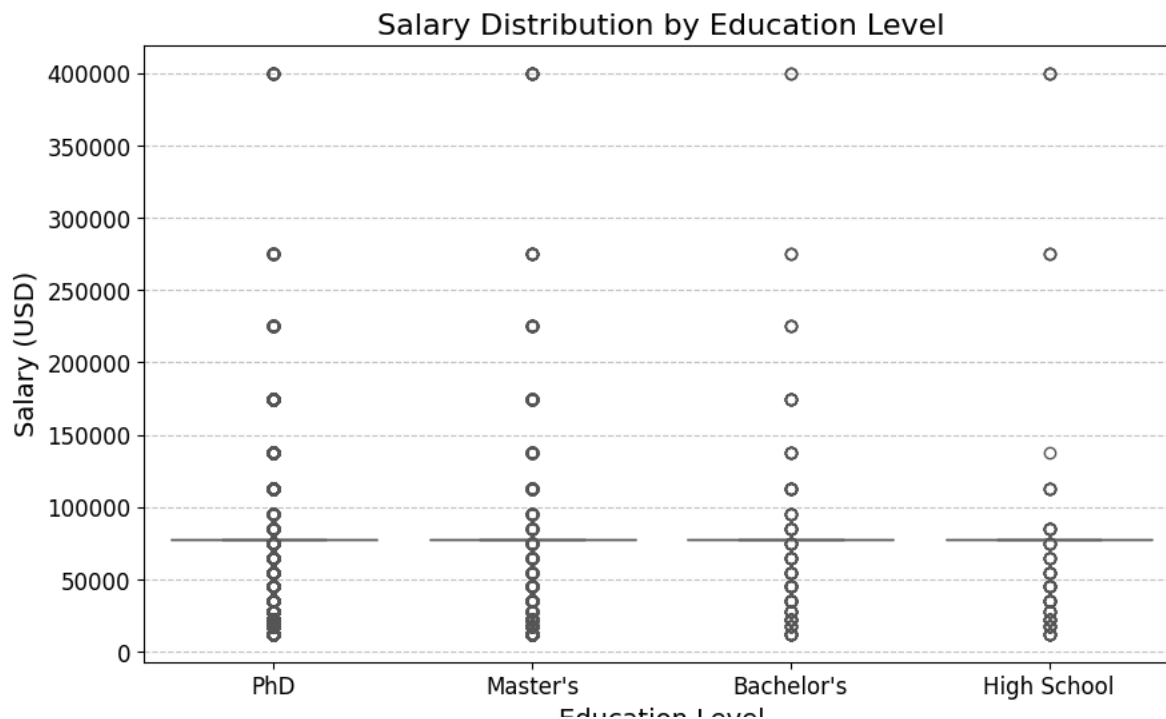
# Customize
plt.title('Salary Distribution by Education Level', fontsize=16)
plt.xlabel('Education Level', fontsize=14)
plt.ylabel('Salary (USD)', fontsize=14)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)

# Show the plot
plt.show()
```

 <ipython-input-53-0ad5315411a4>:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend`

```
sns.boxplot(x='Education_Label', y='Salary_Numerical', data=df, palette='Set2')
```



```
# Imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Assume you already have your dataframe loaded and cleaned as 'df'
```