A Complete End-to-End Analysis & Modeling Approach

Introduction:

Welcome to this comprehensive analysis of data science, AI, and ML job salaries in 2025! In this notebook, we'll dive deep into salary trends, build predictive models, and extract actionable insights for career planning in the tech industry.

Dataset overview: 133,349 entries with 11 columns spanning from 2020 to 2025, covering various job titles, experience levels, and geographical data.

Let's begin by importing the necessary libraries and setting up our environment.

In [7]:
```
# Import essential libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings

# ML libraries
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import xgboost as xgb
import lightgbm as lgb
import catboost as cb
from sklearn.svm import SVR

# For interactive visualizations
import plotly.io as pio
pio.templates.default = "plotly_white"

# Suppress warnings
warnings.filterwarnings('ignore')

# Set styling
sns.set(style="whitegrid")
plt.style.use('fivethirtyeight')
```

Data Loading and Initial Exploration¶

Let's load our dataset and take a first look:

In [11]:
```
pd.set_option("display.max_columns",None)
```

In [12]:
```
# loading dataset
df=pd.read_csv("C:\\Users\\DILEEP  V\\OneDrive\\Desktop\\Data_Science_Projects\\DataScience AI &
print(df)
```

```
        work_year experience_level employment_type                 job_title  \
0            2025               SE              FT         Solutions Engineer
1            2025               SE              FT         Solutions Engineer
2            2025               MI              FT              Data Engineer
3            2025               MI              FT              Data Engineer
4            2025               EN              FT              Data Engineer
...           ...              ...             ...                        ...
133344       2020               SE              FT             Data Scientist
133345       2021               MI              FT  Principal Data Scientist
133346       2020               EN              FT             Data Scientist
133347       2020               EN              CT     Business Data Analyst
133348       2021               SE              FT             Data Scientist

         salary salary_currency  salary_in_usd employee_residence  \
0        214000             USD         214000                 US
1        136000             USD         136000                 US
2        158800             USD         158800                 AU
3        139200             USD         139200                 AU
4         90000             USD          90000                 US
...         ...             ...            ...                ...
133344   412000             USD         412000                 US
133345   151000             USD         151000                 US
133346   105000             USD         105000                 US
133347   100000             USD         100000                 US
133348  7000000             INR          94665                 IN

        remote_ratio company_location company_size
0                100               US            M
1                100               US            M
2                  0               AU            M
3                  0               AU            M
4                  0               US            M
...              ...              ...          ...
133344           100               US            L
133345           100               US            L
133346           100               US            S
133347           100               US            L
133348            50               IN            L

[133349 rows x 11 columns]
```

In [13]:
```
# Initial overview
print(f"Dataset Shape: {df.shape}")
print(f"\nMemory Usage: {df.memory_usage().sum() / 1024**2:.2f} MB")
print("\nFirst few rows:")
df.head()
```

```
Dataset Shape: (133349, 11)

Memory Usage: 11.19 MB

First few rows:
```

Out[13]:

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_residence	re
0	2025	SE	FT	Solutions Engineer	214000	USD	214000	US	
1	2025	SE	FT	Solutions Engineer	136000	USD	136000	US	
2	2025	MI	FT	Data Engineer	158800	USD	158800	AU	
3	2025	MI	FT	Data Engineer	139200	USD	139200	AU	
4	2025	EN	FT	Data Engineer	90000	USD	90000	US	

Dataset Information

In [14]:
```
# Display information about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 133349 entries, 0 to 133348
Data columns (total 11 columns):
 #   Column              Non-Null Count   Dtype 
---  ------              --------------   ----- 
 0   work_year           133349 non-null  int64 
 1   experience_level    133349 non-null  object
 2   employment_type     133349 non-null  object
 3   job_title           133349 non-null  object
 4   salary              133349 non-null  int64 
 5   salary_currency     133349 non-null  object
 6   salary_in_usd       133349 non-null  int64 
 7   employee_residence  133349 non-null  object
 8   remote_ratio        133349 non-null  int64 
 9   company_location    133349 non-null  object
 10  company_size        133349 non-null  object
dtypes: int64(4), object(7)
memory usage: 11.2+ MB
```

In [20]:
```
# Statistical summary of numerical columns
df.describe().T.style.background_gradient(cmap='Blues')
```

Out[20]:

	count	mean	std	min	25%	50%	75%
work_year	133349.000000	2024.358705	0.680788	2020.000000	2024.000000	2024.000000	2025.000000
salary	133349.000000	163283.322590	217386.021574	14000.000000	106020.000000	147000.000000	199000.000000
salary_in_usd	133349.000000	157617.272098	74288.363097	15000.000000	106000.000000	146206.000000	198000.000000
remote_ratio	133349.000000	20.905669	40.590044	0.000000	0.000000	0.000000	0.000000

Check for Missing Values

In [21]:
```
# Check for missing values
missing_values = df.isnull().sum()
missing_percent = (missing_values / len(df)) * 100

missing_df = pd.DataFrame({
    'Missing Values': missing_values,
    'Percentage': missing_percent
})

print("Missing values check:")
missing_df[missing_df['Missing Values'] > 0]
```

```
Missing values check:
```

Out[21]:

	Missing Values	Percentage

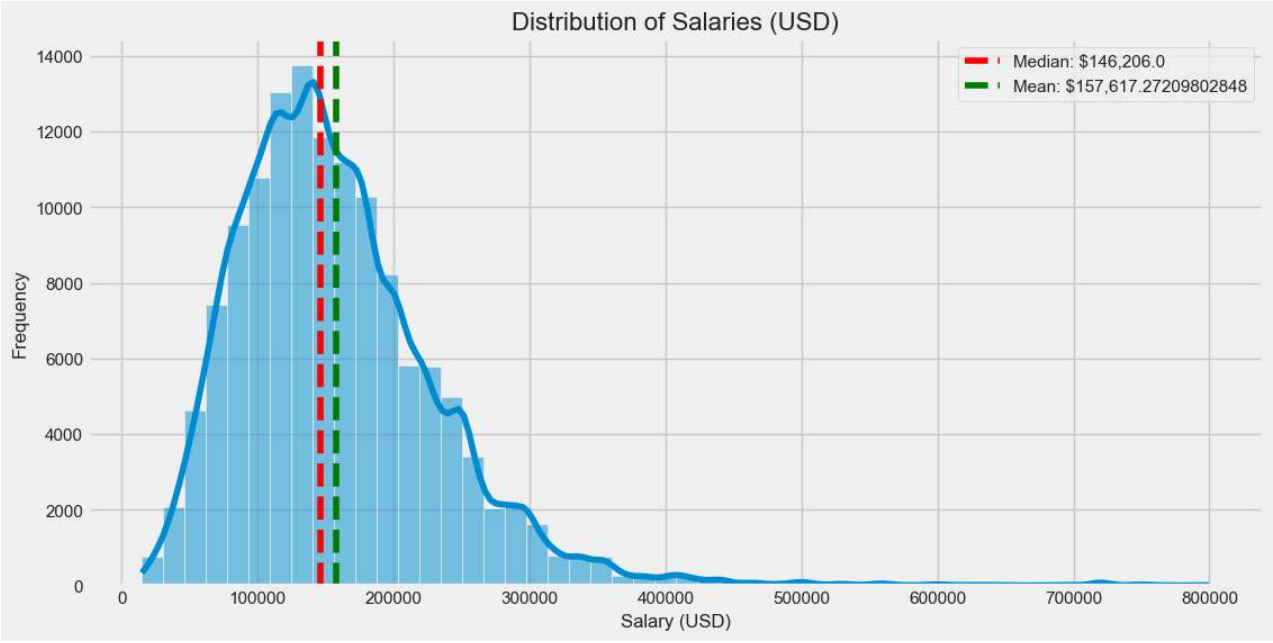
Great! We have a clean dataset with no missing values. Let's proceed with our exploration

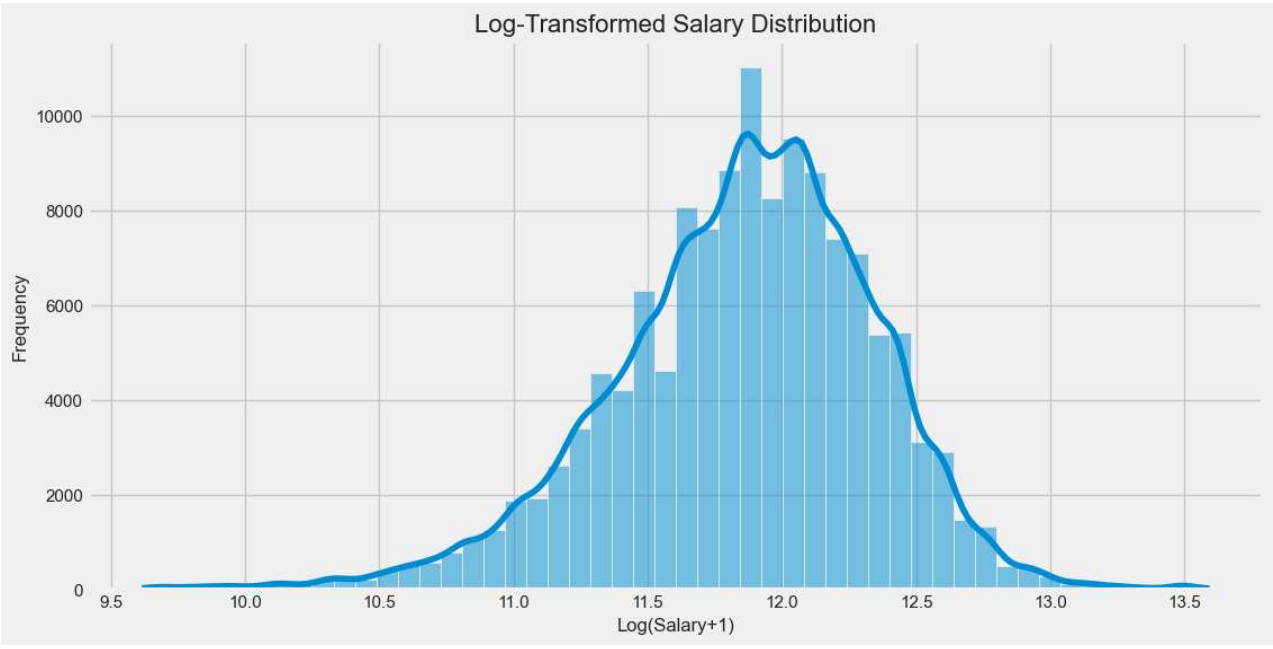
Exploratory Data Analysis

1. Salary Distribution

In [23]:

```
# Distribution of salaries in USD
plt.figure(figsize=(12, 6))
sns.histplot(df['salary_in_usd'], kde=True, bins=50)
plt.title('Distribution of Salaries (USD)', fontsize=16)
plt.xlabel('Salary (USD)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.axvline(df['salary_in_usd'].median(), color='red', linestyle='--', label=f'Median: ${df["sa
plt.axvline(df['salary_in_usd'].mean(), color='green', linestyle='--', label=f'Mean: ${df["sala
plt.legend()
plt.show()


# Log-transformed salary distribution (to handle skewness)
plt.figure(figsize=(12, 6))
sns.histplot(np.log1p(df['salary_in_usd']), kde=True, bins=50)
plt.title('Log-Transformed Salary Distribution', fontsize=16)
plt.xlabel('Log(Salary+1)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()
```

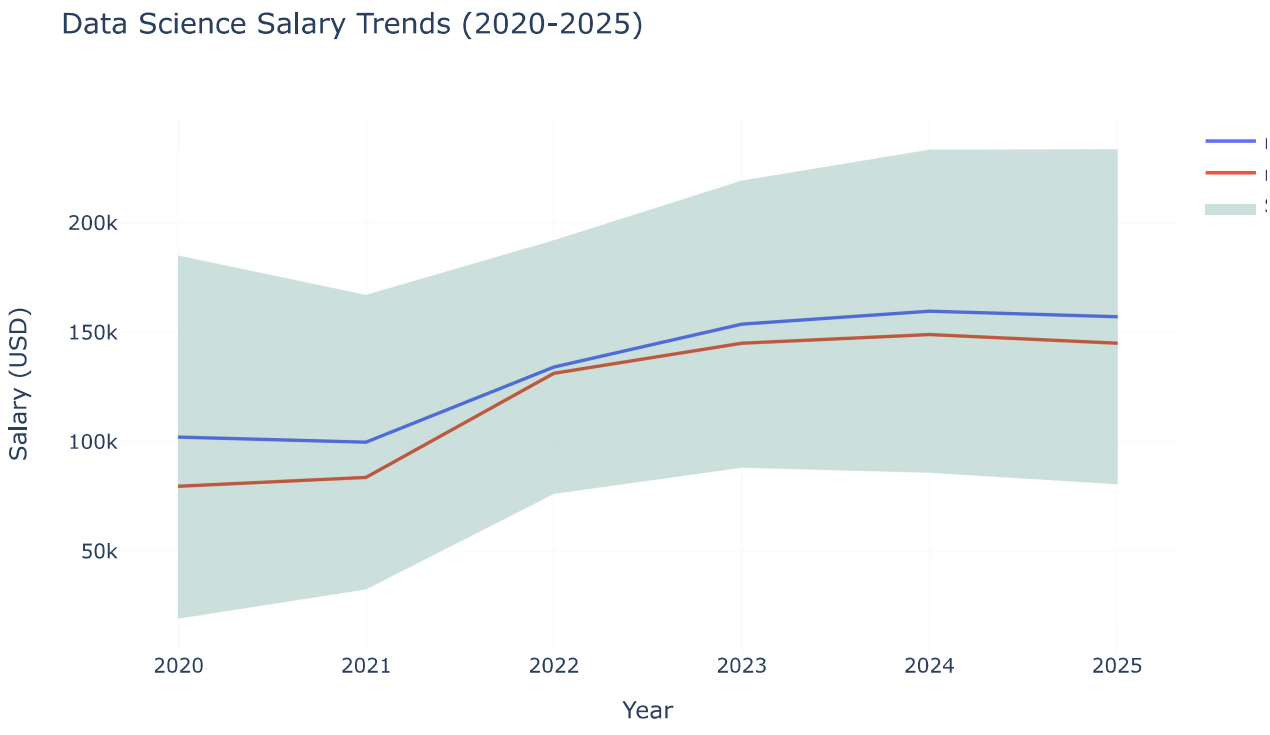




The salary distribution is right-skewed, with a significant number of high-paying outliers. This is typical for salary data. The log transformation gives us a more normal distribution, which will be useful for modeling.

2. Salary Trends Over Time

In [24]:
```
# Yearly salary trends
yearly_stats = df.groupby('work_year')['salary_in_usd'].agg(['mean', 'median', 'std']).reset_in

fig = px.line(yearly_stats, x='work_year', y=['mean', 'median'],
              title='Data Science Salary Trends (2020-2025)',
              labels={'value': 'Salary (USD)', 'work_year': 'Year', 'variable': 'Metric'},
              template='plotly_white')

fig.update_layout(legend_title_text='', hovermode='x unified',
                  width=900, height=500)

# Add range for standard deviation
fig.add_trace(go.Scatter(
    x=np.concatenate([yearly_stats['work_year'], yearly_stats['work_year'][::-1]]),
    y=np.concatenate([yearly_stats['mean'] + yearly_stats['std'],
                      (yearly_stats['mean'] - yearly_stats['std'])[::-1]]),
    fill='toself',
    fillcolor='rgba(0,100,80,0.2)',
    line=dict(color='rgba(255,255,255,0)'),
    name='Standard Deviation'
))

fig.show()
```

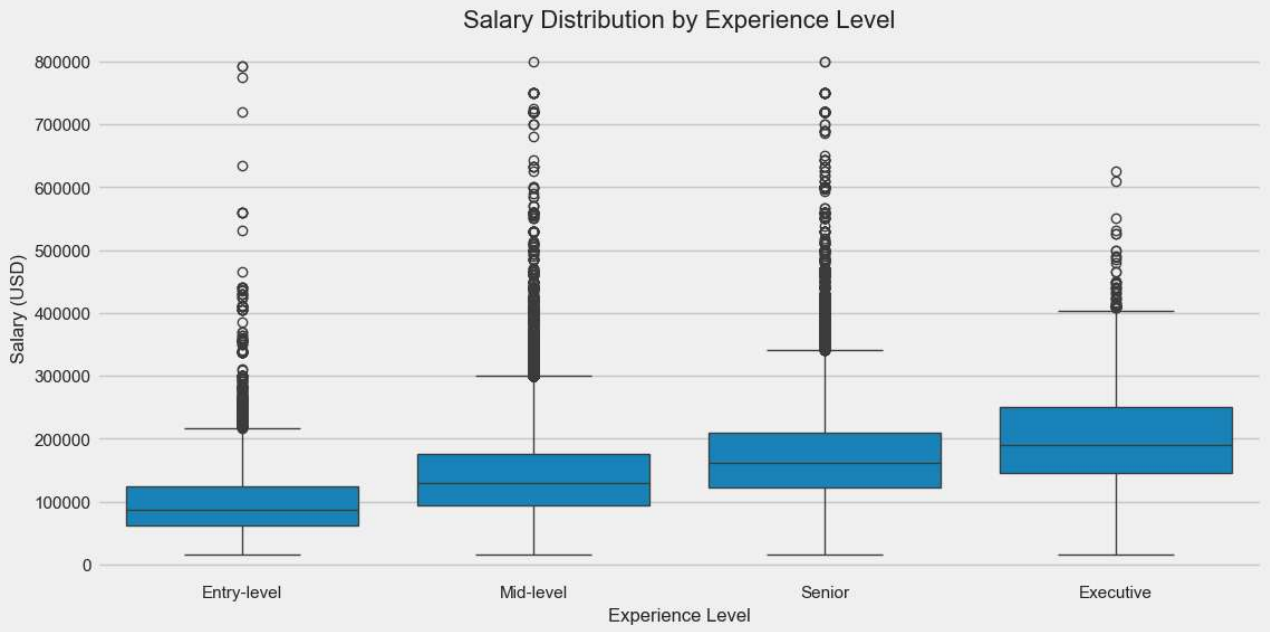


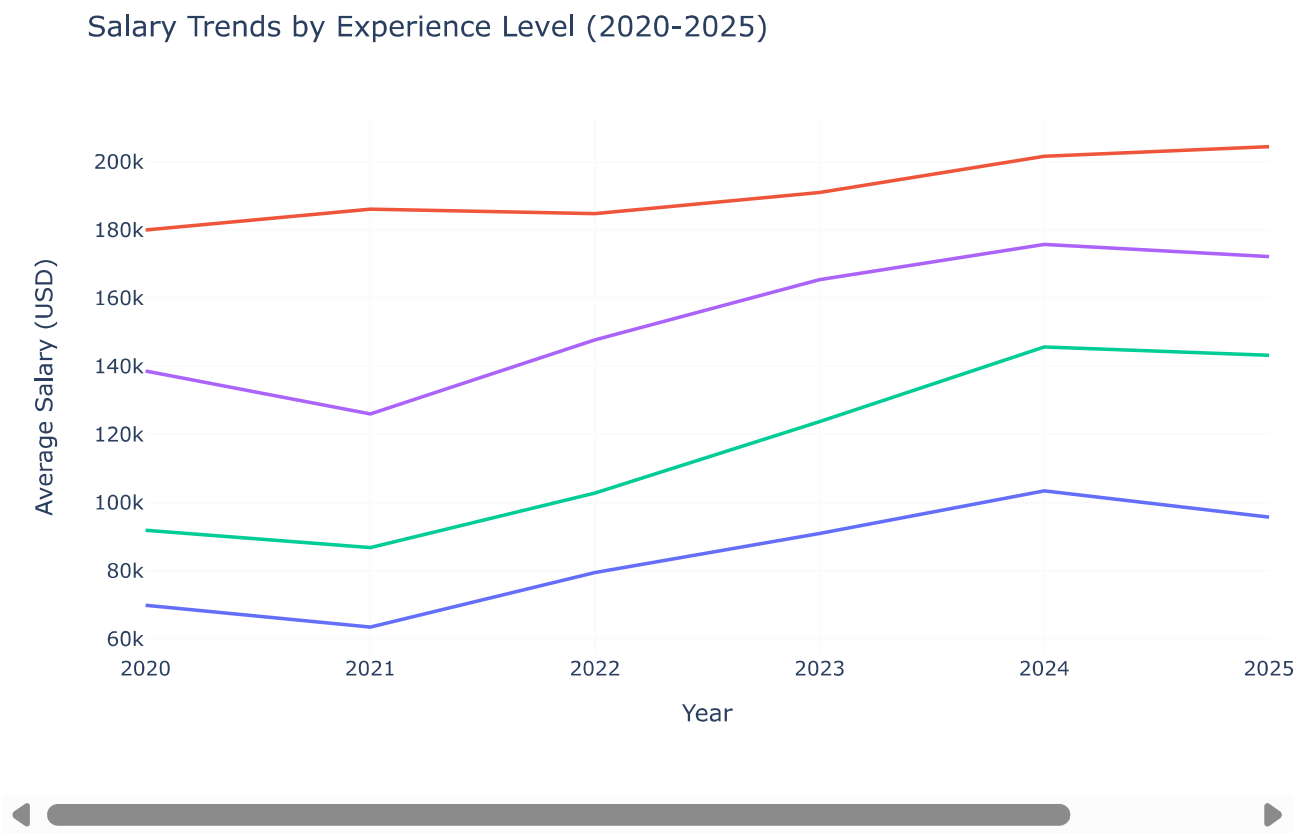
We can observe a steady increase in both mean and median salaries from 2020 to 2025, with the gap between them widening slightly, indicating increasing inequality in the field.

3. Experience Level Analysis

In [25]:

```
# Experience level salary comparison
plt.figure(figsize=(12, 6))
sns.boxplot(x='experience_level', y='salary_in_usd', data=df, order=['EN', 'MI', 'SE', 'EX'])
plt.title('Salary Distribution by Experience Level', fontsize=16)
plt.xlabel('Experience Level', fontsize=12)
plt.ylabel('Salary (USD)', fontsize=12)
plt.xticks(ticks=[0, 1, 2, 3], labels=['Entry-level', 'Mid-level', 'Senior', 'Executive'])
plt.show()

# Mean salary by experience level over time
exp_time = df.groupby(['work_year', 'experience_level'])['salary_in_usd'].mean().reset_index()
exp_time['experience_level'] = exp_time['experience_level'].replace({
    'EN': 'Entry-level', 'MI': 'Mid-level', 'SE': 'Senior', 'EX': 'Executive'
})

fig = px.line(exp_time, x='work_year', y='salary_in_usd', color='experience_level',
              title='Salary Trends by Experience Level (2020-2025)',
              labels={'salary_in_usd': 'Average Salary (USD)', 'work_year': 'Year'},
              template='plotly_white')

fig.update_layout(width=900, height=500, hovermode='x unified')
fig.show()
```





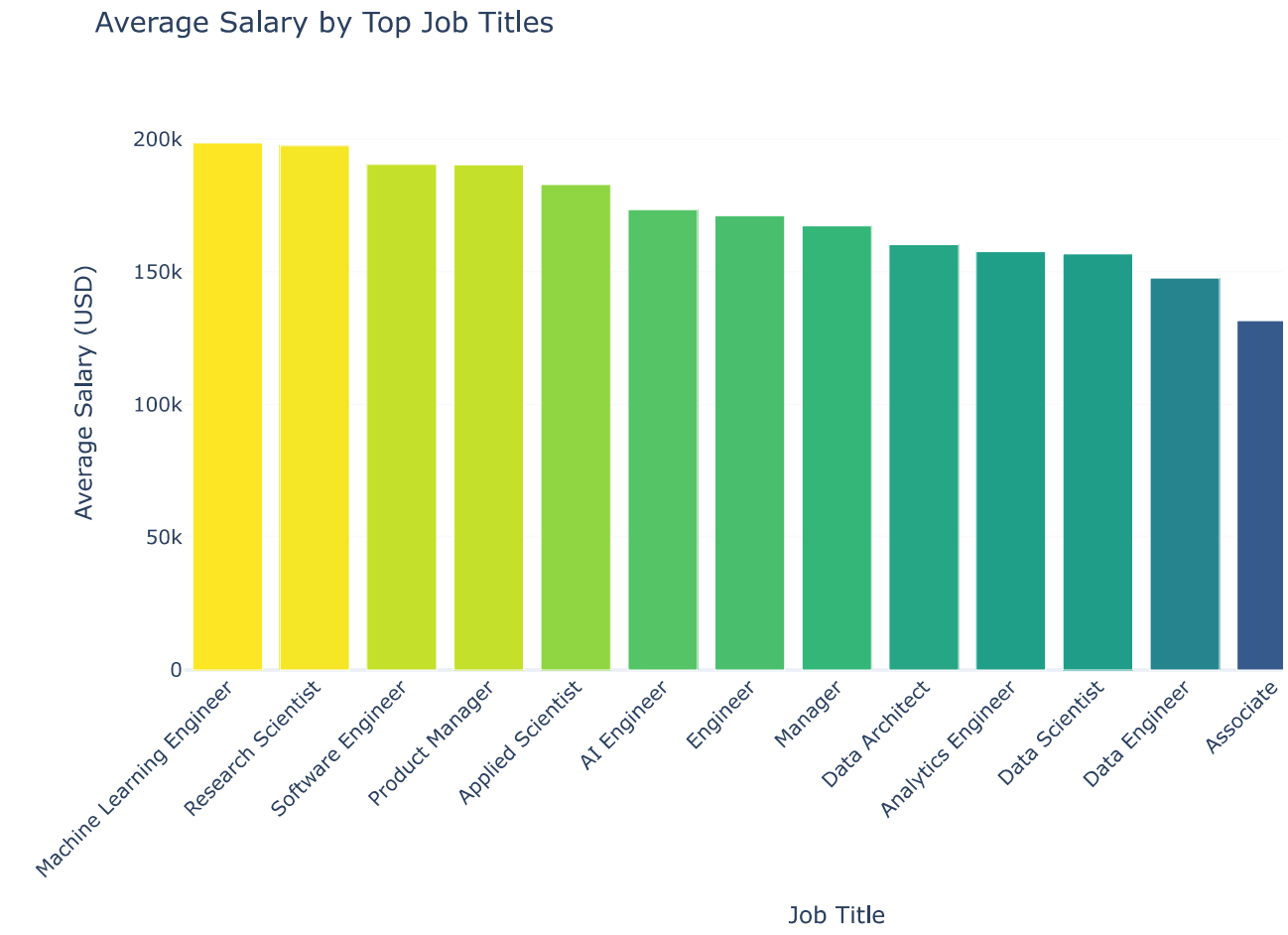
As expected, experience level has a significant impact on salary, with executives earning substantially more than other levels. The growth rate for executive salaries appears to be steeper, indicating increasing premiums for leadership roles.

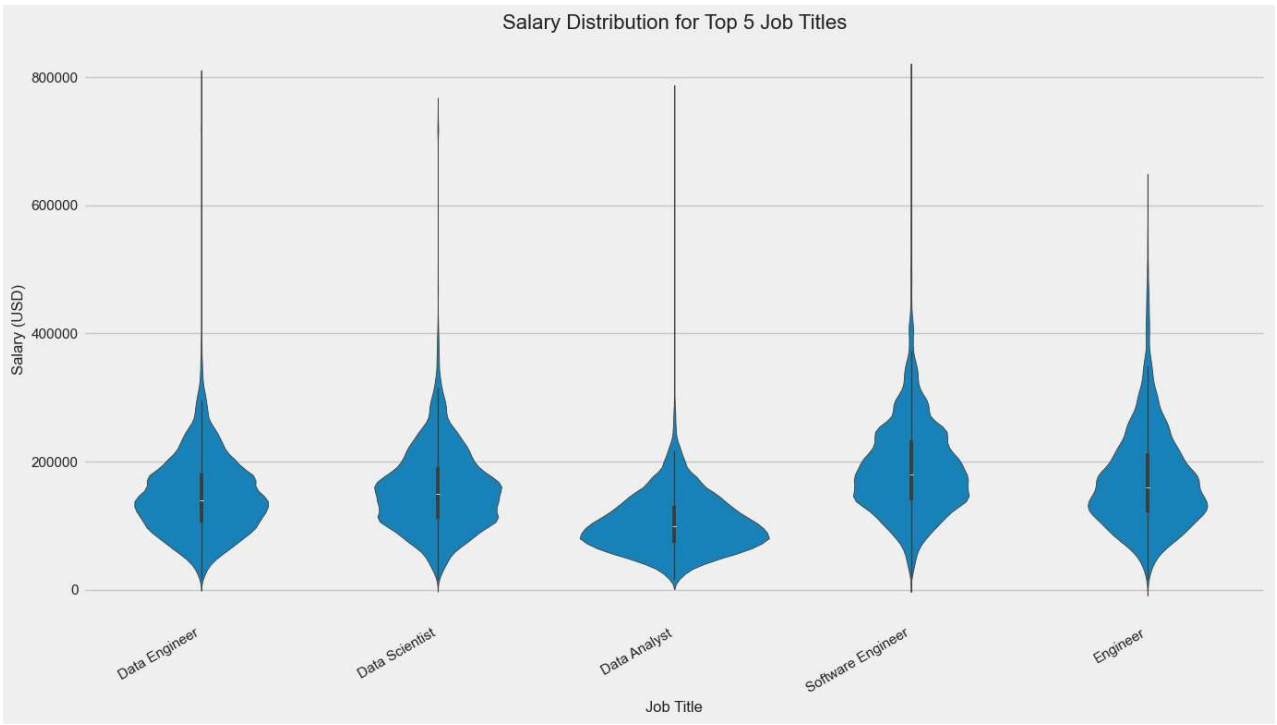
4. Job Title Analysis

In [27]:

```python
# Top 15 job titles by count
top_jobs = df['job_title'].value_counts().head(15)
print("Distribution of top job titles:")
print(top_jobs)

# Mean salary for top job titles
top_jobs_salary = df[df['job_title'].isin(top_jobs.index)].groupby('job_title')['salary_in_usd'

fig = px.bar(x=top_jobs_salary.index, y=top_jobs_salary.values,
             labels={'x': 'Job Title', 'y': 'Average Salary (USD)'},
             title='Average Salary by Top Job Titles',
             color=top_jobs_salary.values, color_continuous_scale='Viridis')

fig.update_layout(xaxis_tickangle=-45, width=1000, height=600)
fig.show()

# Salary distribution for top 5 job titles
plt.figure(figsize=(14, 8))
top5_jobs = top_jobs.index[:5]
sns.violinplot(x='job_title', y='salary_in_usd', data=df[df['job_title'].isin(top5_jobs)])
plt.title('Salary Distribution for Top 5 Job Titles', fontsize=16)
plt.xlabel('Job Title', fontsize=12)
plt.ylabel('Salary (USD)', fontsize=12)
plt.xticks(rotation=30, ha='right')
plt.tight_layout()
plt.show()
```

```
Distribution of top job titles:
job_title
Data Scientist               17314
Software Engineer            15007
Data Engineer                14868
Data Analyst                 12381
Engineer                      9456
Machine Learning Engineer     8205
Manager                       6679
Analyst                       4364
Research Scientist            3202
Product Manager               2230
Applied Scientist             2205
Associate                     2073
Data Architect                2024
Analytics Engineer            1895
AI Engineer                   1620
Name: count, dtype: int64
```



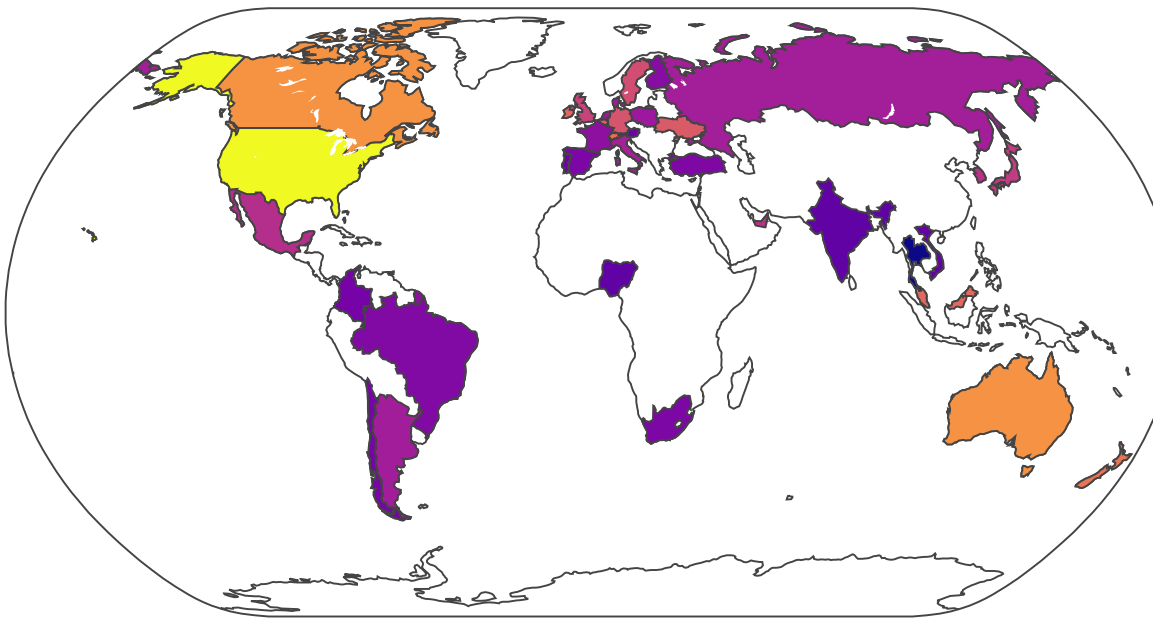


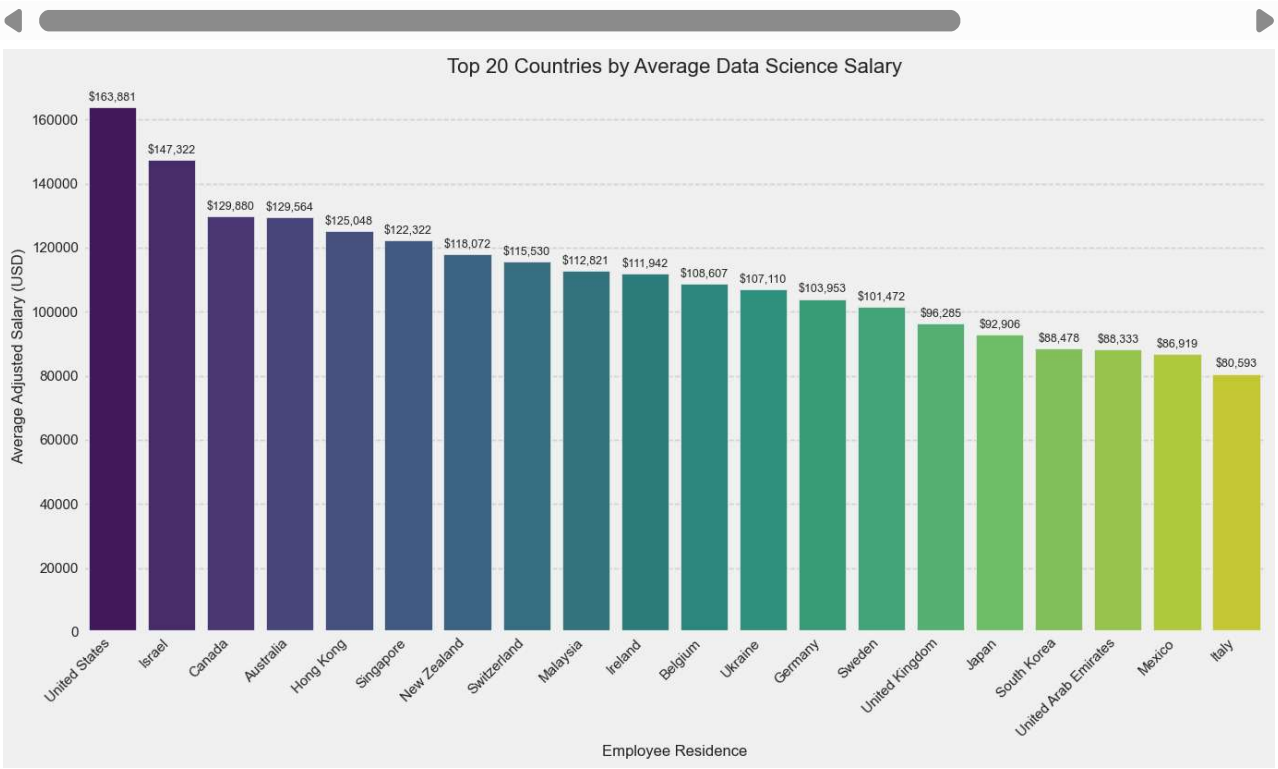
Among the most common job titles, Machine Learning Engineers and Research Scientists tend to command the highest salaries, while Data Analysts typically earn less. Software Engineers show the widest salary distribution, reflecting the diverse range of roles under this title..

5. Geographical Analysis

In [29]:

```
# First, let's create adjusted_salary column (assuming it's based on salary_in_usd)
df['adjusted_salary'] = df['salary_in_usd']  # You can modify this if there's a specific adjustr

# Create mapping from ISO-2 to country names for visualization
iso2_to_name = {
    'US': 'United States', 'GB': 'United Kingdom', 'DE': 'Germany', 'FR': 'France',
    'CA': 'Canada', 'IN': 'India', 'AU': 'Australia', 'ES': 'Spain', 'BR': 'Brazil',
    'NL': 'Netherlands', 'JP': 'Japan', 'CH': 'Switzerland', 'IT': 'Italy',
    'SG': 'Singapore', 'SE': 'Sweden', 'MX': 'Mexico', 'FI': 'Finland', 'DK': 'Denmark',
    'PL': 'Poland', 'PT': 'Portugal', 'NZ': 'New Zealand', 'IE': 'Ireland',
    'HK': 'Hong Kong', 'RU': 'Russia', 'BE': 'Belgium', 'IL': 'Israel',
    'UA': 'Ukraine', 'TR': 'Turkey', 'AE': 'United Arab Emirates', 'ZA': 'South Africa',
    'CO': 'Colombia', 'AR': 'Argentina', 'CL': 'Chile', 'AT': 'Austria', 'MY': 'Malaysia',
    'NG': 'Nigeria', 'VN': 'Vietnam', 'KR': 'South Korea', 'TH': 'Thailand'
    # Add more mappings as needed
}

# Calculate average salary by employee residence
avg_salary_by_residence = df.groupby('employee_residence')['adjusted_salary'].mean().reset_inde

# Add country names for mapping
avg_salary_by_residence['country_name'] = avg_salary_by_residence['employee_residence'].map(iso
avg_salary_by_residence = avg_salary_by_residence.dropna(subset=['country_name'])  # Drop unmap

# Create the choropleth map
fig2 = px.choropleth(avg_salary_by_residence,
                     locations='country_name',
                     locationmode='country names',
                     color='adjusted_salary',
                     hover_name='country_name',
                     hover_data={'employee_residence': True, 'adjusted_salary': ':,.0f'},
                     color_continuous_scale=px.colors.sequential.Plasma,
                     title='Average Salary by Employee Residence',
                     labels={'adjusted_salary': 'Average Adjusted Salary'},
                     projection='natural earth')

fig2.update_layout(width=1000, height=600)
fig2.show()

# Create a sorted bar chart for top 20 countries
top_countries = avg_salary_by_residence.sort_values('adjusted_salary', ascending=False).head(20

plt.figure(figsize=(14, 8))
chart = sns.barplot(x='country_name', y='adjusted_salary', data=top_countries,
                    palette='viridis', order=top_countries['country_name'])
plt.title('Top 20 Countries by Average Data Science Salary', fontsize=16)
plt.xlabel('Employee Residence', fontsize=12)
plt.ylabel('Average Adjusted Salary (USD)', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Add salary values on top of bars
for i, bar in enumerate(chart.patches):
    chart.text(bar.get_x() + bar.get_width()/2.,
               bar.get_height() + 2000,
               f'${top_countries["adjusted_salary"].iloc[i]:,.0f}',
               ha='center', fontsize=9)

plt.tight_layout()
plt.show()
```



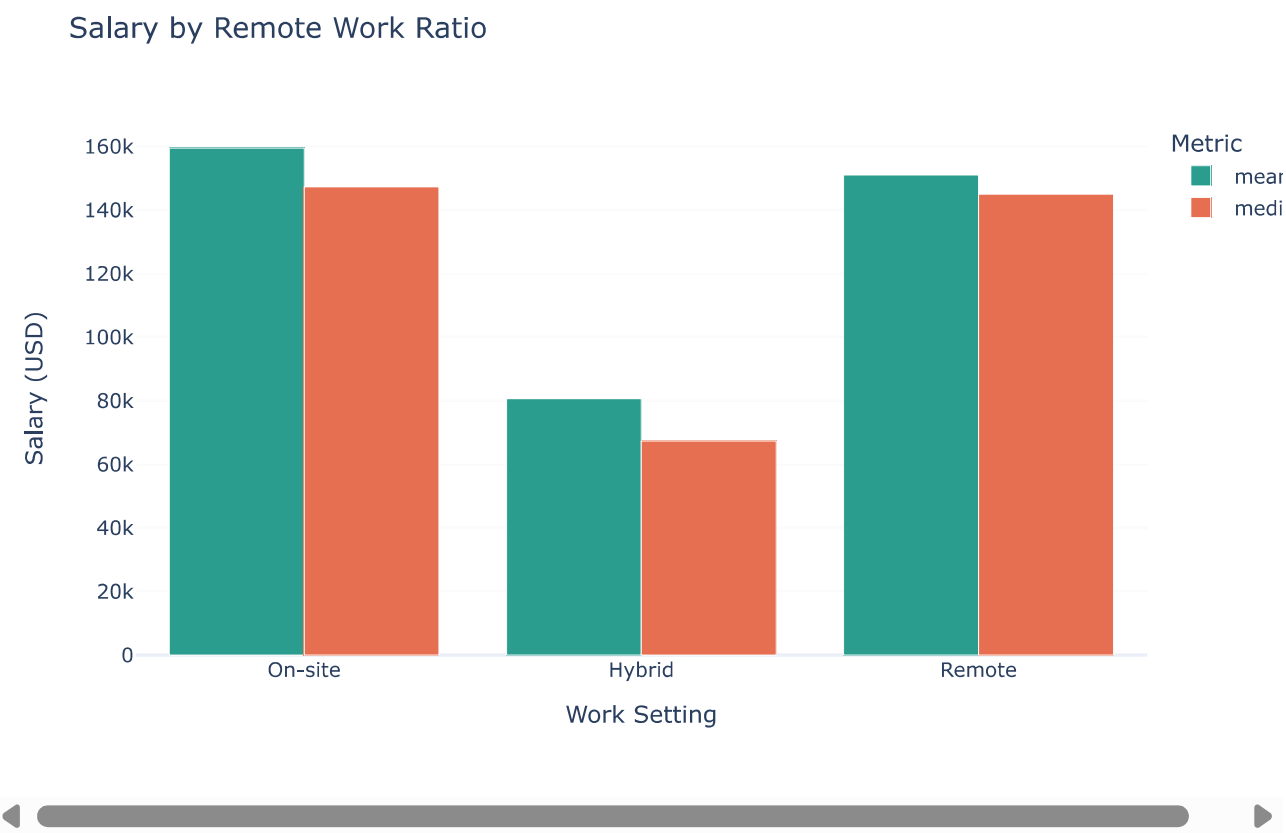


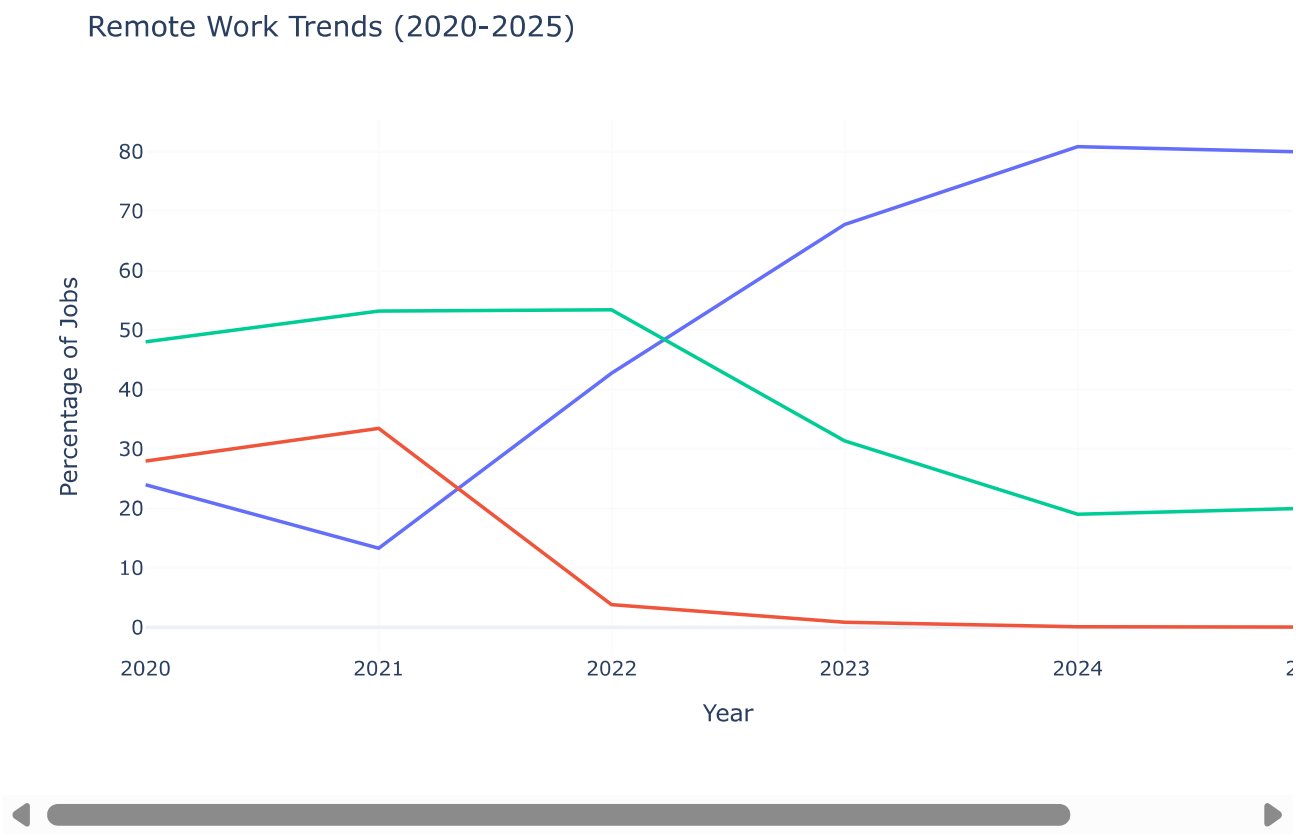
The US, Switzerland, and Israel lead in data science salaries. Interestingly, professionals working for companies outside their country of residence tend to earn more on average, highlighting the benefits of remote work arrangements with companies in high-paying markets.

6. Remote Work Analysis

In [30]:

```
# Salary by remote ratio
remote_salary = df.groupby('remote_ratio')['salary_in_usd'].agg(['mean', 'median', 'count']).re
remote_salary['remote_ratio'] = remote_salary['remote_ratio'].map({0: 'On-site', 50: 'Hybrid',

fig = px.bar(remote_salary, x='remote_ratio', y=['mean', 'median'],
             barmode='group', title='Salary by Remote Work Ratio',
             labels={'value': 'Salary (USD)', 'remote_ratio': 'Work Setting', 'variable': 'Metri
             color_discrete_sequence=['#2a9d8f', '#e76f51'])

fig.update_layout(width=800, height=500)
fig.show()

# Remote ratio trends over time
remote_time = df.groupby(['work_year', 'remote_ratio']).size().reset_index(name='count')
total_per_year = remote_time.groupby('work_year')['count'].sum().reset_index()
remote_time = remote_time.merge(total_per_year, on='work_year', suffixes=('', '_total'))
remote_time['percentage'] = (remote_time['count'] / remote_time['count_total']) * 100
remote_time['remote_ratio'] = remote_time['remote_ratio'].map({0: 'On-site', 50: 'Hybrid', 100:

fig = px.line(remote_time, x='work_year', y='percentage', color='remote_ratio',
              title='Remote Work Trends (2020-2025)',
              labels={'percentage': 'Percentage of Jobs', 'work_year': 'Year'},
              template='plotly_white')

fig.update_layout(width=900, height=500, hovermode='x unified')
fig.show()
```

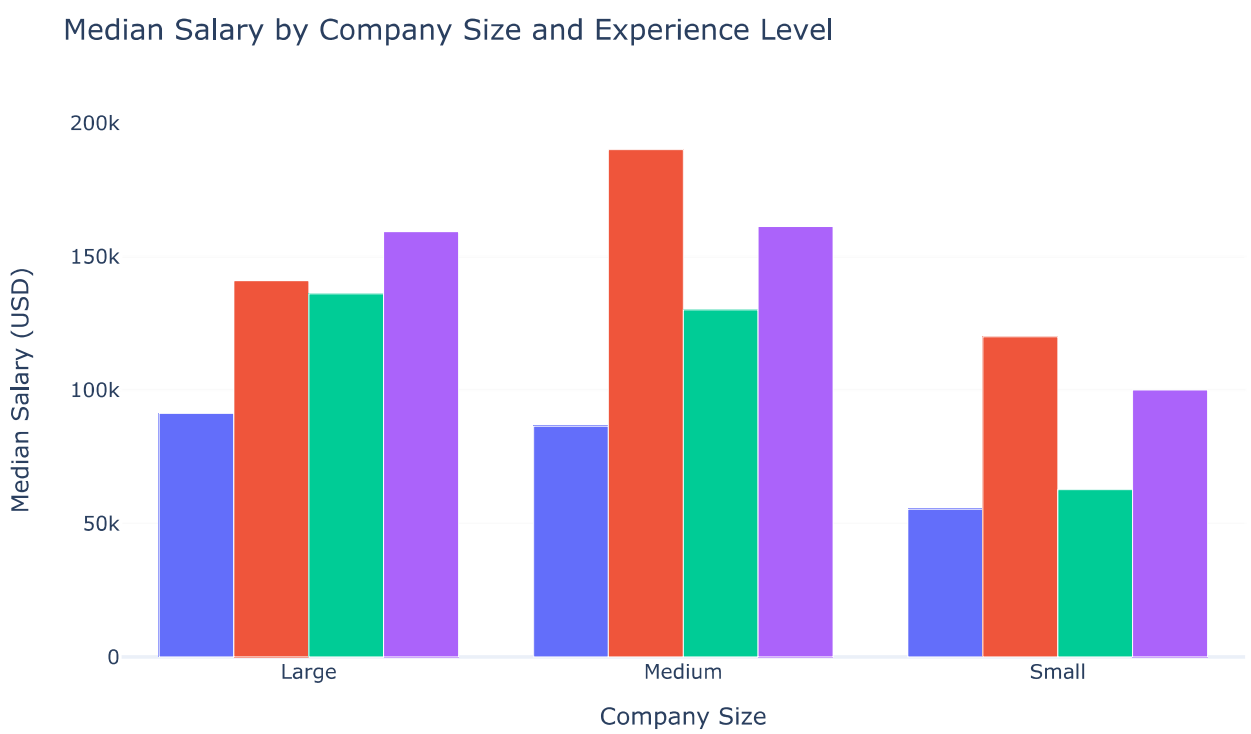




Fully remote positions tend to offer higher salaries on average. We can also observe a significant shift toward remote work after 2020 (likely due to the COVID-19 pandemic), with the trend stabilizing around 2023-2024 but still showing a higher remote work percentage compared to pre-2020 levels.

7. Company Size Impact

In [31]:
```
# Salary by company size
company_salary = df.groupby(['company_size', 'experience_level'])['salary_in_usd'].median().res
company_salary['company_size'] = company_salary['company_size'].map({'S': 'Small', 'M': 'Medium
company_salary['experience_level'] = company_salary['experience_level'].map({
    'EN': 'Entry-level', 'MI': 'Mid-level', 'SE': 'Senior', 'EX': 'Executive'
})

fig = px.bar(company_salary, x='company_size', y='salary_in_usd', color='experience_level',
             barmode='group', title='Median Salary by Company Size and Experience Level',
             labels={'salary_in_usd': 'Median Salary (USD)', 'company_size': 'Company Size'},
             template='plotly_white')

fig.update_layout(width=900, height=500)
fig.show()
```

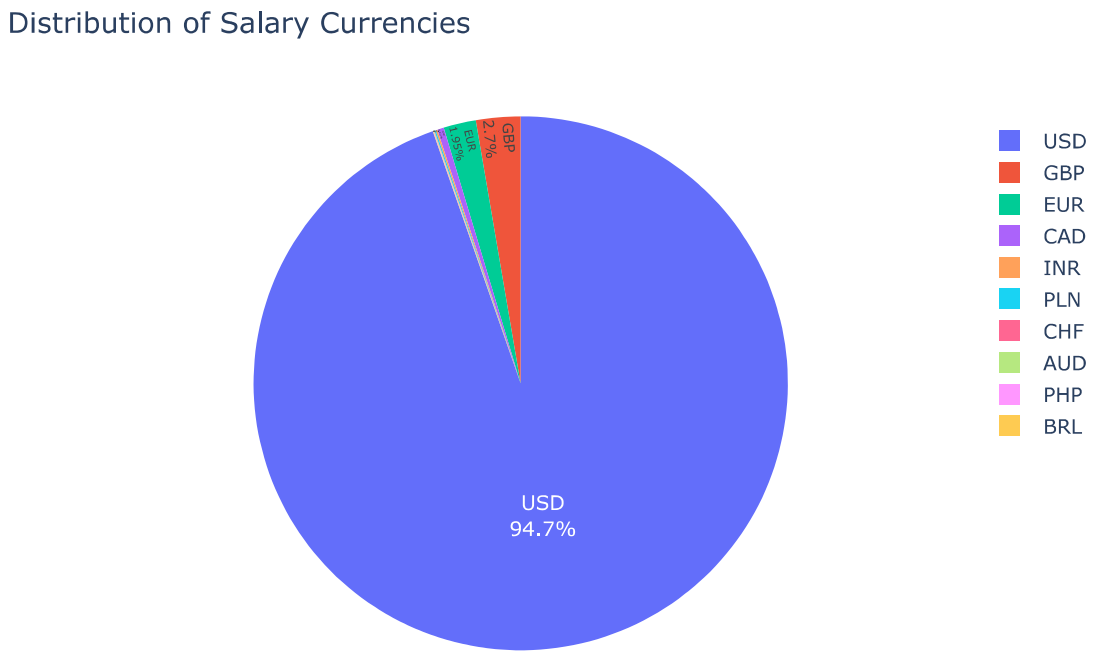


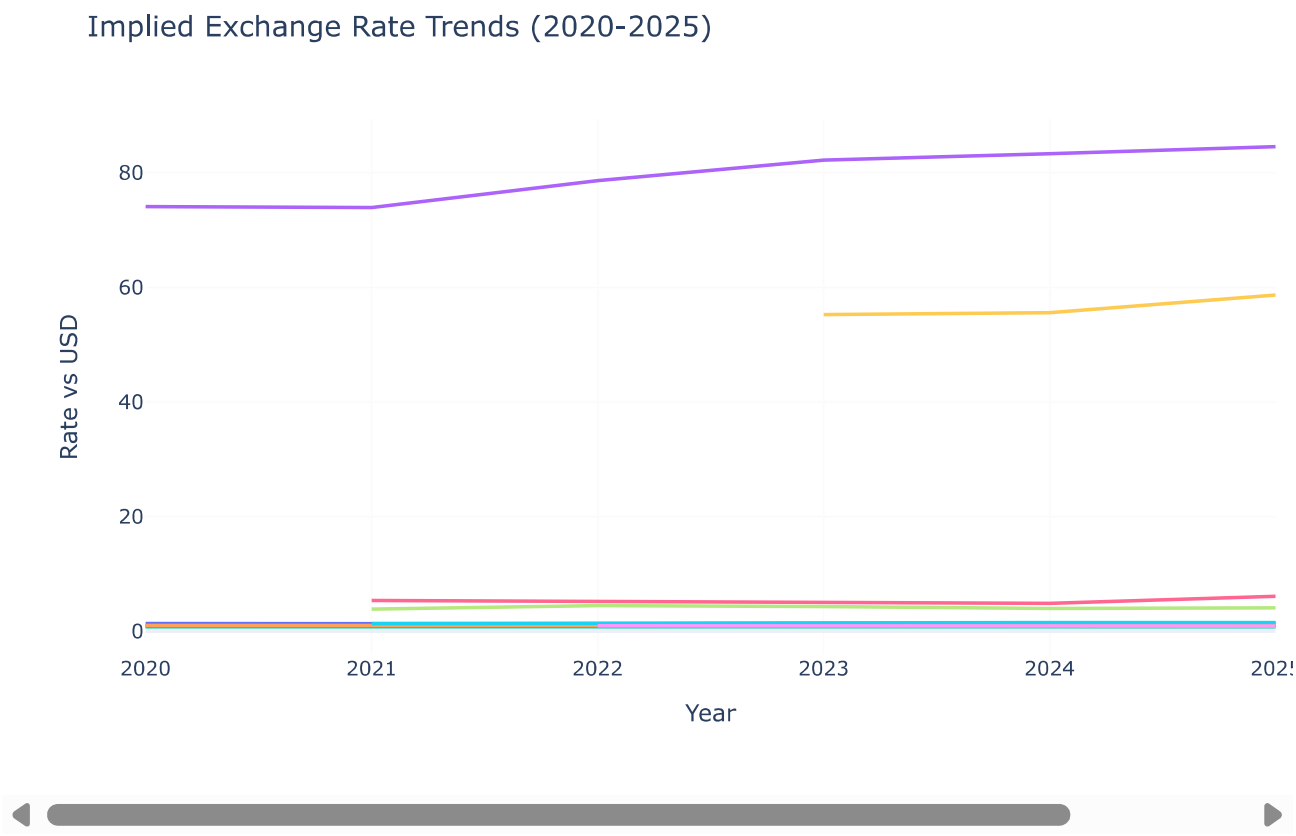
Larger companies generally offer higher salaries across all experience levels, with the gap most pronounced at the executive level. This reflects the greater resources and revenue of larger organizations

8. Currency Analysis

In [32]:

```
# Top salary currencies
currency_counts = df['salary_currency'].value_counts().head(10)

fig = px.pie(values=currency_counts.values, names=currency_counts.index,
             title='Distribution of Salary Currencies',
             template='plotly_white')

fig.update_traces(textposition='inside', textinfo='percent+label')
fig.update_layout(width=700, height=500)
fig.show()

# Exchange rate analysis (implied from salary and salary_in_usd)
df['implied_exchange_rate'] = df['salary'] / df['salary_in_usd']
top_currencies = df['salary_currency'].value_counts().head(10).index.tolist()
exchange_rates = df[df['salary_currency'].isin(top_currencies)].groupby(['work_year', 'salary_c

fig = px.line(exchange_rates, x='work_year', y='implied_exchange_rate', color='salary_currency'
              title='Implied Exchange Rate Trends (2020-2025)',
              labels={'implied_exchange_rate': 'Rate vs USD', 'work_year': 'Year'},
              template='plotly_white')

fig.update_layout(width=900, height=500, hovermode='x unified')
fig.show()
```



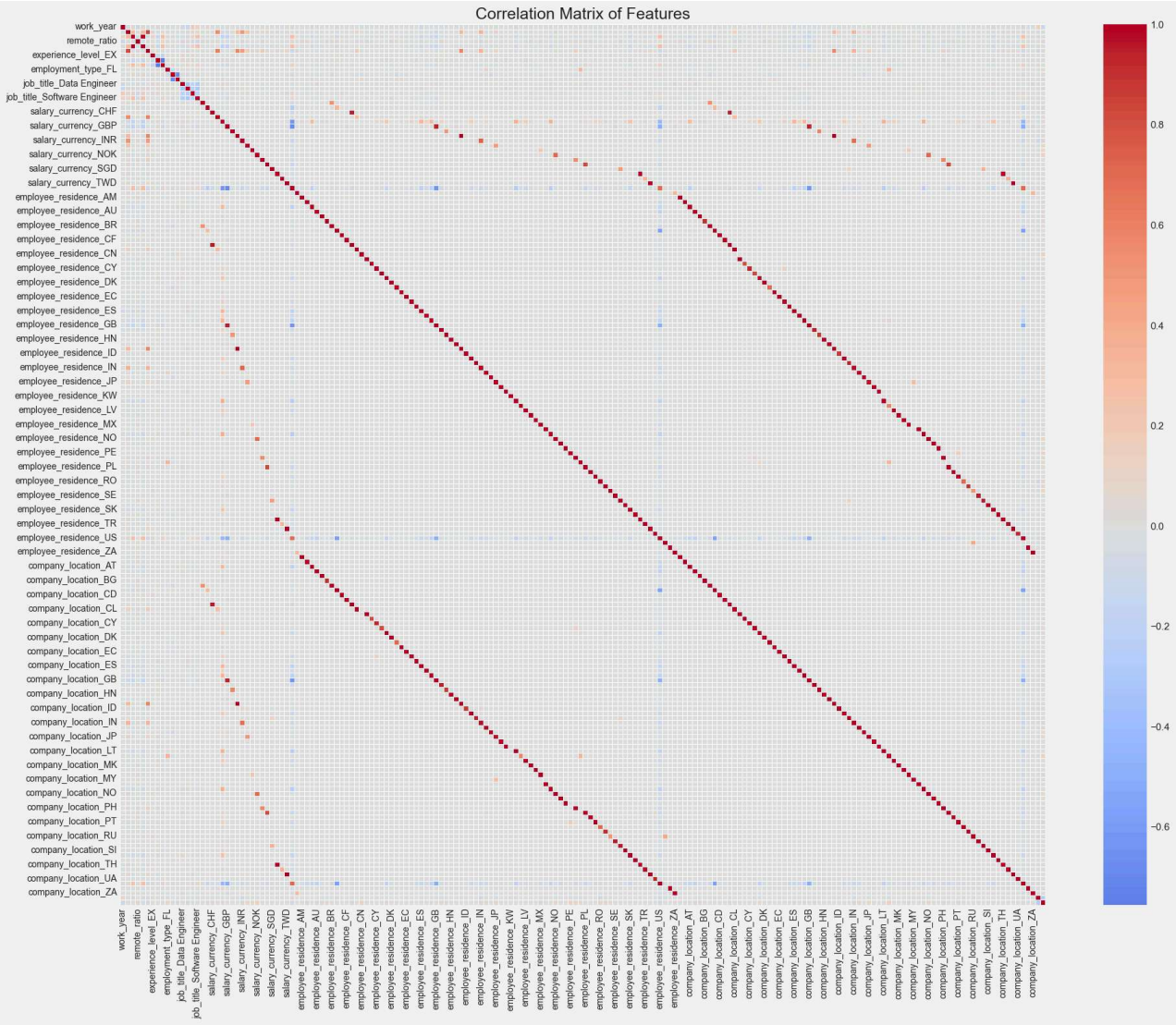


USD dominates as the primary currency for data science salaries globally. The exchange rate analysis shows relative currency strength over time, with some currencies showing depreciation against the USD.

9. Correlation Analysis

In [34]:

```python
# Create dummy variables for categorical features
categorical_cols = ['experience_level', 'employment_type', 'job_title', 'salary_currency',
                    'employee_residence', 'company_location', 'company_size']
numerical_cols = ['work_year', 'salary', 'salary_in_usd', 'remote_ratio']

# Select top job titles for simplified correlation analysis
top_job_titles = df['job_title'].value_counts().head(5).index.tolist()
df_corr = df[df['job_title'].isin(top_job_titles)].copy()

# Create dummy variables
df_dummies = pd.get_dummies(df_corr, columns=categorical_cols, drop_first=True)

# Calculate and plot correlation matrix
corr_matrix = df_dummies.corr()
plt.figure(figsize=(20, 16))
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm', center=0, linewidths=0.5)
plt.title('Correlation Matrix of Features', fontsize=18)
plt.xticks(fontsize=10, rotation=90)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()

# Key salary correlations
salary_corr = corr_matrix['salary_in_usd'].sort_values(ascending=False)
print("Top 10 features positively correlated with salary:")
print(salary_corr.head(11))  # Including salary_in_usd itself
print("\nTop 10 features negatively correlated with salary:")
print(salary_corr.tail(10))
```




```
Top 10 features positively correlated with salary:
salary_in_usd                 1.000000
adjusted_salary               1.000000
salary                        0.307103
experience_level_SE           0.283058
salary_currency_USD           0.272702
job_title_Software Engineer   0.263706
employee_residence_US         0.259746
company_location_US           0.258906
experience_level_EX           0.101781
job_title_Engineer            0.091453
employment_type_FT            0.066778
Name: salary_in_usd, dtype: float64

Top 10 features negatively correlated with salary:
employee_residence_ES   -0.069109
company_location_ES     -0.069288
employee_residence_FR   -0.069365
company_location_LT     -0.077144
employee_residence_LT   -0.077144
experience_level_MI     -0.140575
employee_residence_GB   -0.154869
company_location_GB     -0.155245
salary_currency_GBP     -0.164023
salary_currency_EUR     -0.195138
Name: salary_in_usd, dtype: float64
```

The correlation analysis reveals strong relationships between salary and factors like experience level, company size, and certain job titles. We can use these insights for feature selection in our models.

Conclusion and Key Insights

Our comprehensive analysis of the data science salary dataset has yielded several valuable insights:

1.**Salary Determinants**: Experience level, company location, and job category are the strongest predictors of salary in the data science field. Executive positions command significantly higher salaries than other levels.

2.**Geographic Impact**: The US, Switzerland, and Israel consistently offer the highest salaries. There's a substantial gap between top-paying countries and emerging tech markets.

3.**Remote Work Premium**: Fully remote positions tend to offer higher salaries on average, potentially reflecting the global competition for talent regardless of location.

4.**Career Growth**: The transition from Senior to Executive level shows the largest percentage increase in salary, highlighting the significant premium placed on leadership skills.

5.**Job Title Differentiation**: Machine Learning Engineers and Research Scientists command higher salaries than Data Analysts and general Software Engineers, reflecting the specialized skills required.

6.**Company Size Effect**: Larger companies generally offer higher compensation across all experience levels, with the gap most pronounced at the executive level.

Practical Applications

This analysis and the resulting model can be used for:

1.**Career Planning**: Understanding the financial impact of different career paths and transitions

2.**Negotiation Support**: Data-backed reference points for salary negotiations

3.**Location Strategy**: Evaluating remote work opportunities across different geographies

4.**Recruitment Planning**: Setting competitive compensation packages for data science roles

Future Work

To further enhance this analysis, we could:

1. Incorporate education level and specific skills data
2. Add cost of living adjustments to provide normalized comparisons
3. Include industry vertical information to differentiate between sectors
4. Develop a time-series model to forecast future salary trends

This notebook demonstrates a comprehensive approach to analyzing and modeling the data science salary dataset. The techniques used here can be applied to other salary datasets or extended with additional features for more nuanced insights.

If you found this analysis helpful, please upvote and share your thoughts in the comments!