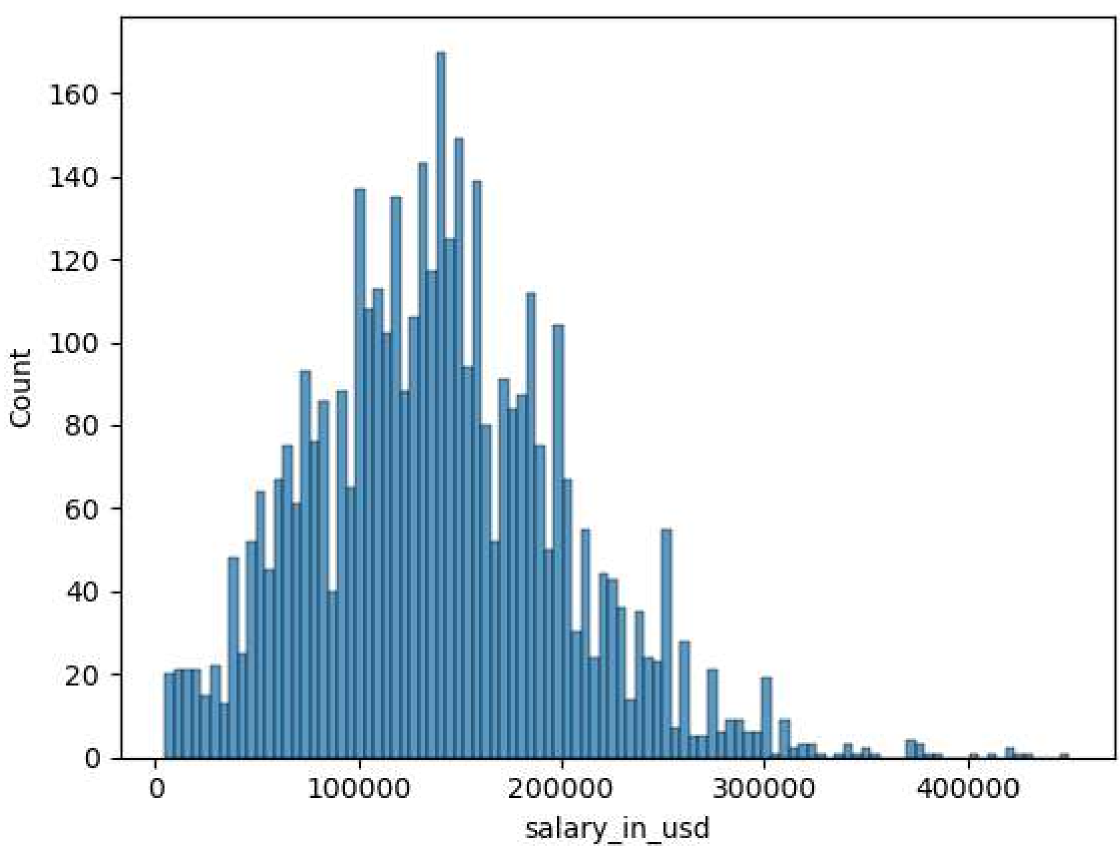
In [1]:
```
import pandas as pd
import  numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
from scipy.stats import pearsonr
from scipy.stats import norm
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
```

In [2]:
```
#imports the dataset and deletes unneeded columns/rows.
salaries_df = pd.read_csv('C:/Users/predi/Documents/GitHub/DSC530 Assignments/salaries
salaries_df.drop(salaries_df.query(" `employment_type`!='FT' ").index, inplace=True)
salaries_df.drop (columns = ['salary', 'salary_currency', 'employee_residence','employ
#salaries_df.drop(salaries_df.query(" `company_location`!='US' ").index, inplace=True)
```

In [3]:
```
#Creates a histogram for each variable. Uncomment other lines to see histogram for dif
sns.histplot(salaries_df['salary_in_usd'], bins=100)
#sns.histplot(salaries_df['work_year'], bins=4)
#sns.histplot(salaries_df['remote_ratio'], bins=3)
#sns.histplot(salaries_df['experience_level'], bins=4)
#sns.histplot(salaries_df['company_size'], bins =3)
#sns.histplot(salaries_df['company_location'])
#sns.histplot(salaries_df['job_title'])
```

Out[3]: <Axes: xlabel='salary_in_usd', ylabel='Count'>



In [4]:
```
#caculates the Mean, Mode, Spread, and Tails of the various variables.
#Uncomment other lines to see summaries for different variables.
salaries_df['salary_in_usd'].describe()
#salaries_df['work_year'].describe()
#salaries_df['experience_level'].describe()
#salaries_df['remote_ratio'].describe()
#salaries_df['company_size'].describe()
#salaries_df['company_location'].describe()
```

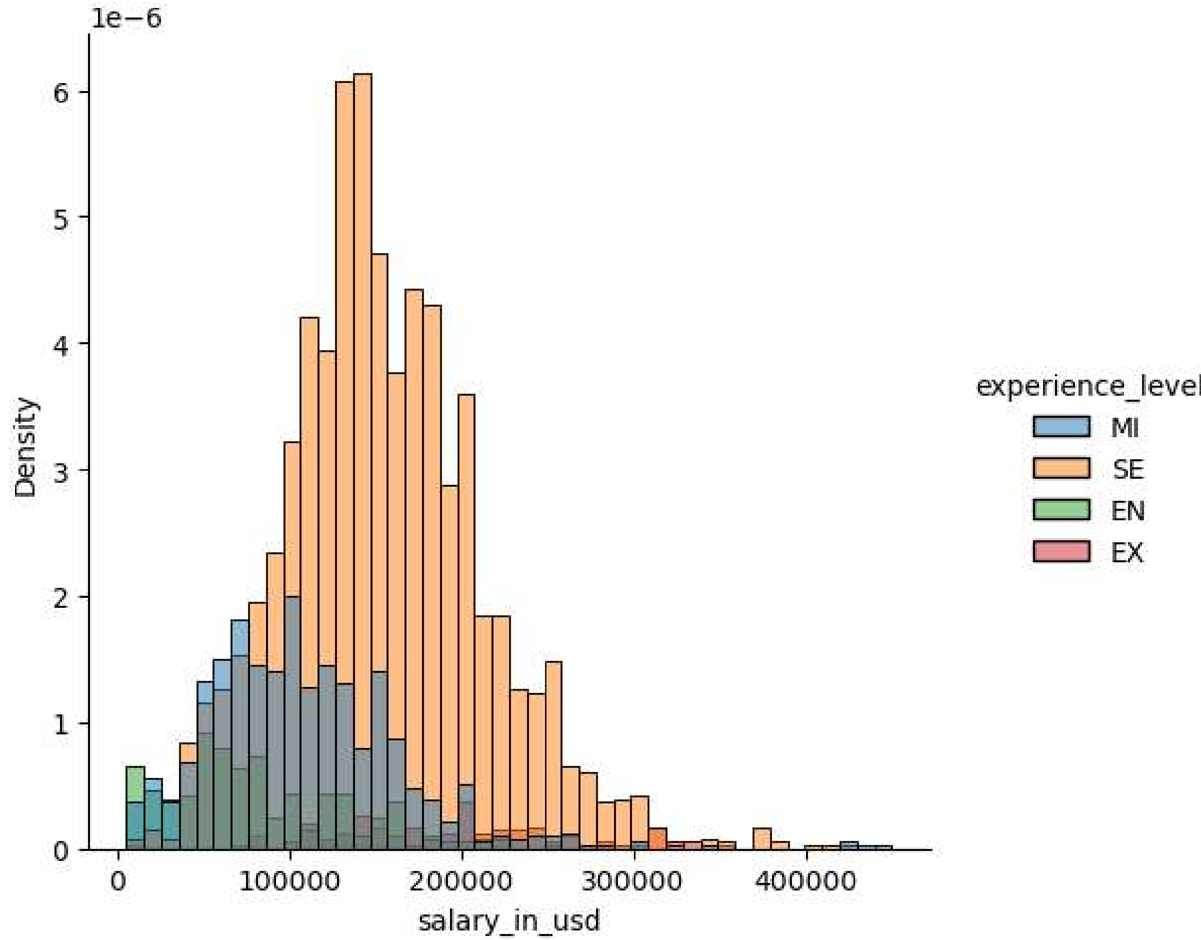
Out[4]:
```
count      4093.000000
mean     140116.351332
std       62983.078569
min        5132.000000
25%       99050.000000
50%      136000.000000
75%      180000.000000
max      450000.000000
Name: salary_in_usd, dtype: float64
```

In [33]:
```
salaries_df['salary_in_usd'].var()
#salaries_df['work_year'].var()
#salaries_df['experience_level'].var()
#salaries_df['remote_ratio'].var()
#salaries_df['company_size'].var()
#salaries_df['company_location'].var()
```

Out[33]:
```
3966868186.05594
```

In [5]:
```
#Plots the PMFs for salery usings the experience level and the remote work percentage.
sns.displot(data=salaries_df, x='salary_in_usd',hue='experience_level',stat="density")
#sns.displot(data=salaries_df, x='salary_in_usd',hue='remote_ratio',stat="density")
```

Out[5]:
```
<seaborn.axisgrid.FacetGrid at 0x277bbdb6950>
```

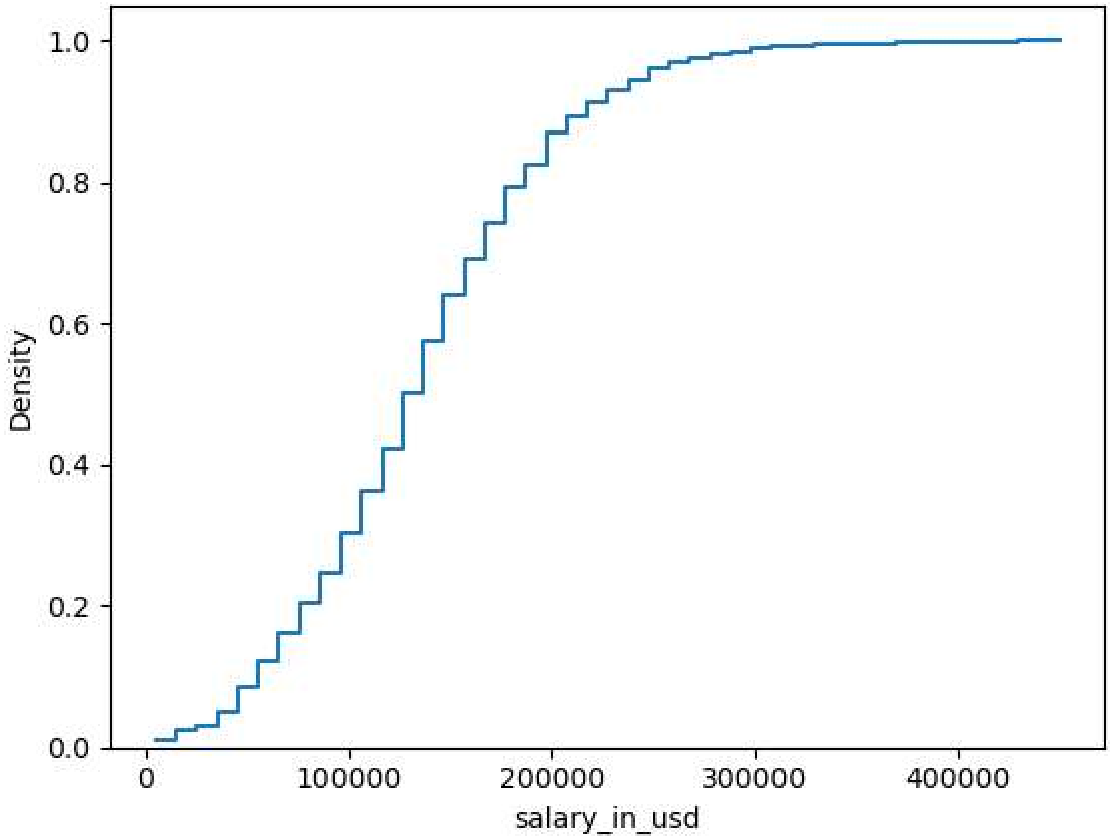


In [6]:
```
#calculates teh mean salary for each expereince level
salaries_df.groupby(['experience_level'])['salary_in_usd'].mean()
```

Out[6]:
```
experience_level
EN     80192.331250
EX    193833.709677
MI    107652.774566
SE    154698.150144
Name: salary_in_usd, dtype: float64
```

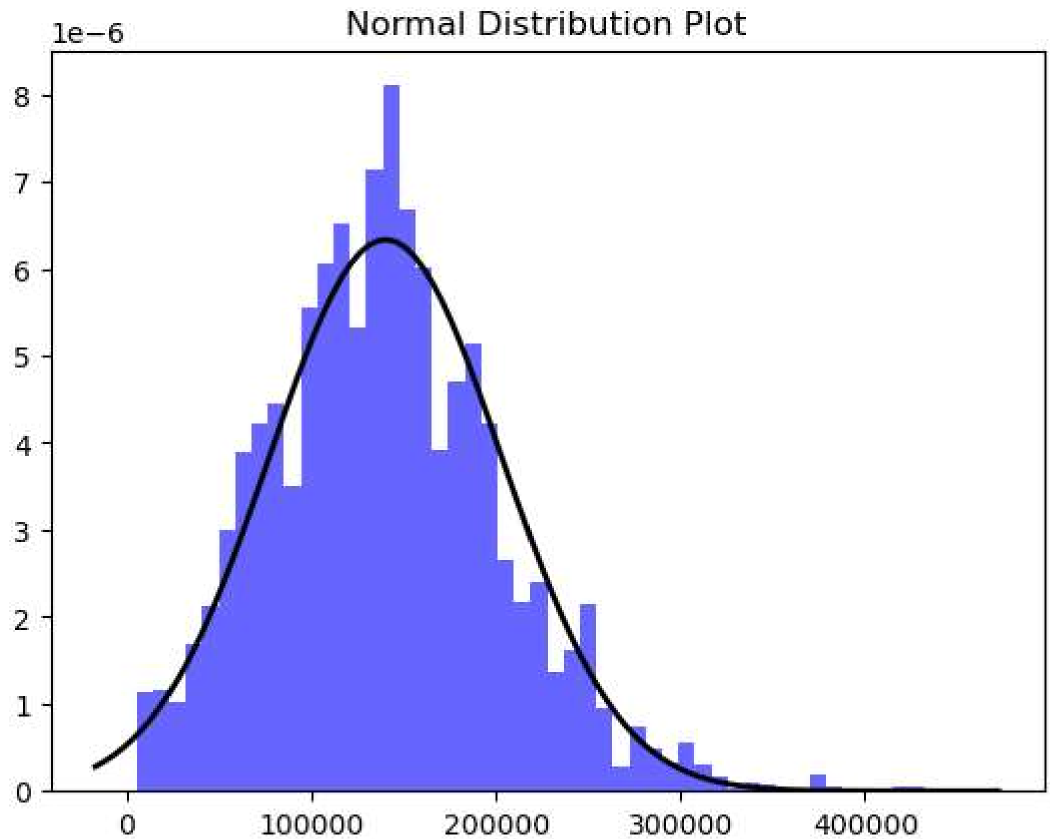
In [7]:
```
#Creates the CDF for the reported salaries.
sns.histplot(data=salaries_df, x="salary_in_usd", element="step",
             fill=False,cumulative=True, stat="density", common_norm=False,)
```

Out[7]:
```
<Axes: xlabel='salary_in_usd', ylabel='Density'>
```



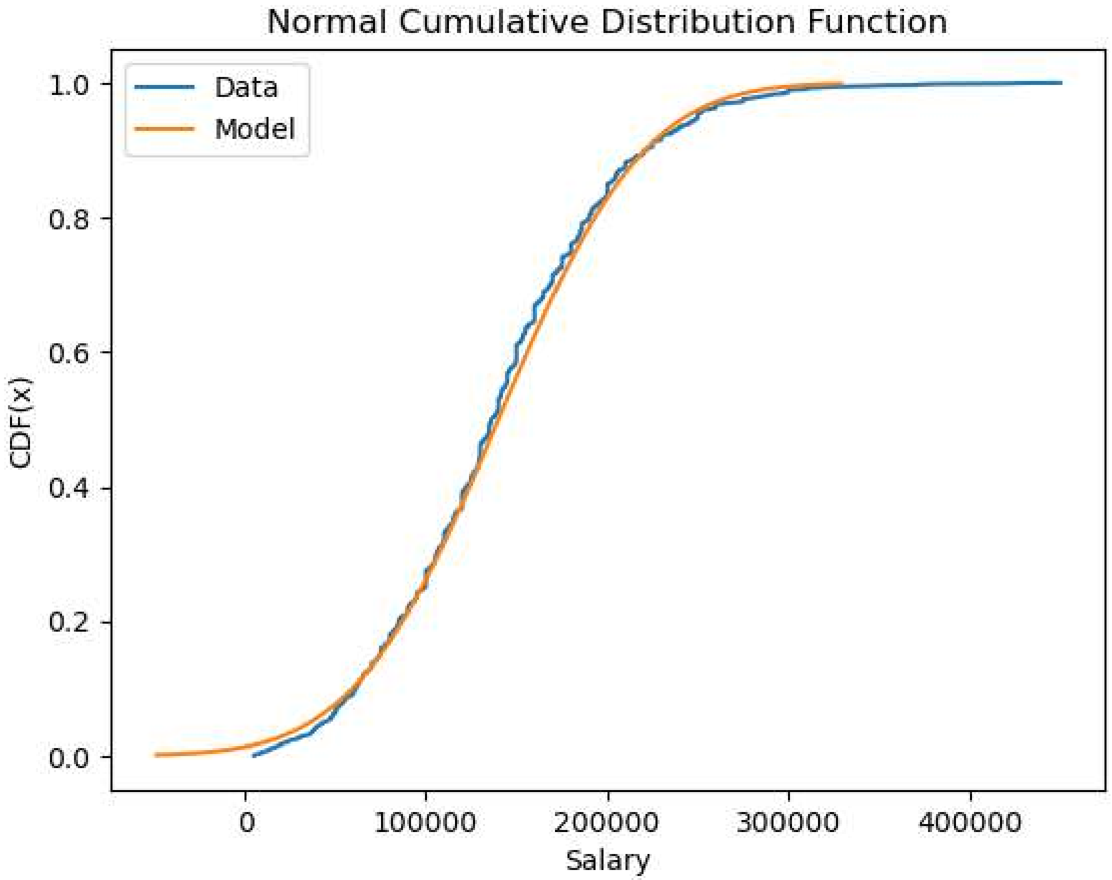
In [8]:
```
#Plots the salary data with a normal distribution model.
#calculates mean and standard deviation.
data =salaries_df['salary_in_usd']
mu = salaries_df['salary_in_usd'].mean()
std=salaries_df['salary_in_usd'].std()

#plots the salary distribution and creates a model for expected distribution absed on
plt.hist(data, bins=50, density=True, alpha=0.6, color='b')

xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
p = norm.pdf(x, mu, std)

plt.plot(x, p, 'k', linewidth=2)
title = "Normal Distribution Plot"
plt.title(title)
```

Out[8]:
```
Text(0.5, 1.0, 'Normal Distribution Plot')
```



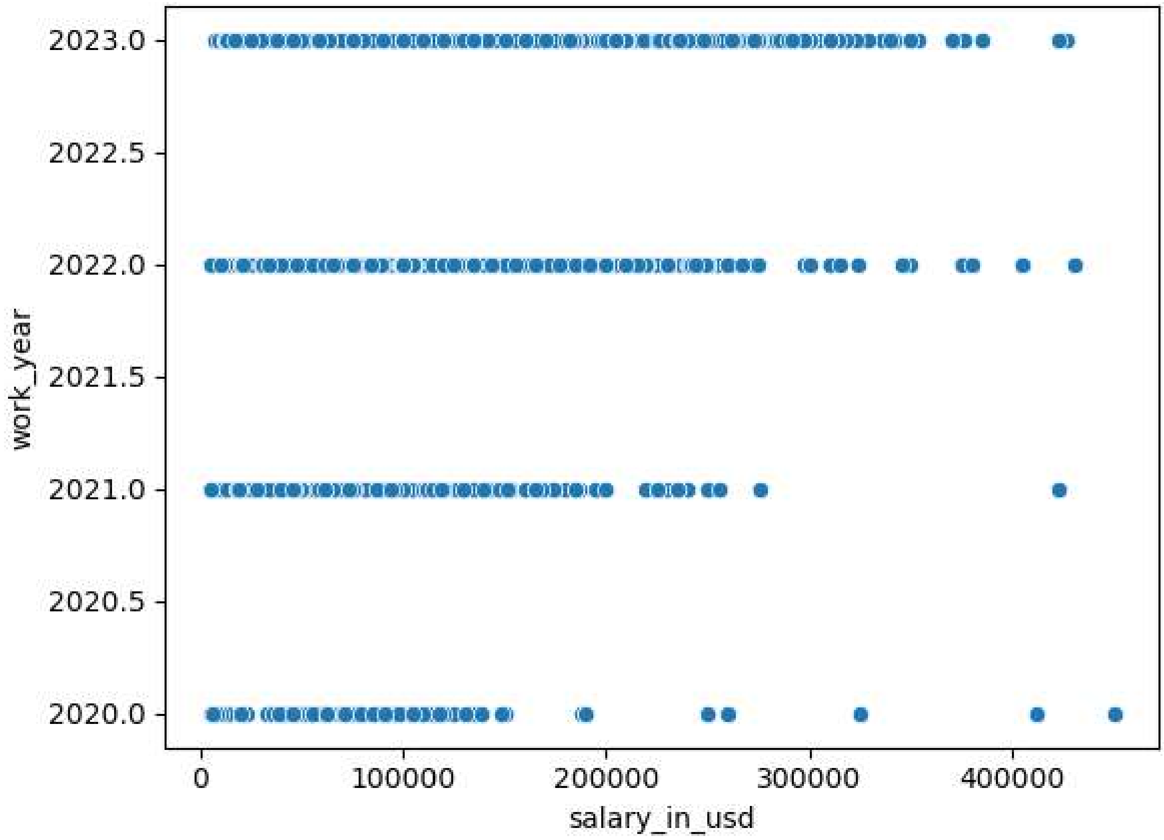
In [9]:
```
#Plots the analytical distribution for the salary data.
data=salaries_df['salary_in_usd']
x = np.sort(data)
y = 1. * np.arange(len(data)) / (len(data) - 1)
x2 = np.linspace(mu - 3*std, mu + 3*std, 100)
y2 = norm.cdf(x2, mu, std)

plt.plot(x, y, label="Data")
plt.plot(x2, y2, label="Model")
plt.legend(loc="upper left")
plt.plot()
plt.title('Normal Cumulative Distribution Function')
plt.xlabel('Salary')
plt.ylabel('CDF(x)')
```

Out[9]:
```
Text(0, 0.5, 'CDF(x)')
```



In [10]:
```
#creates a scatter plot of "salary_in_usd" vs ""
sns.scatterplot(data=salaries_df,x="salary_in_usd", y="work_year")
```

Out[10]:
```
<Axes: xlabel='salary_in_usd', ylabel='work_year'>
```

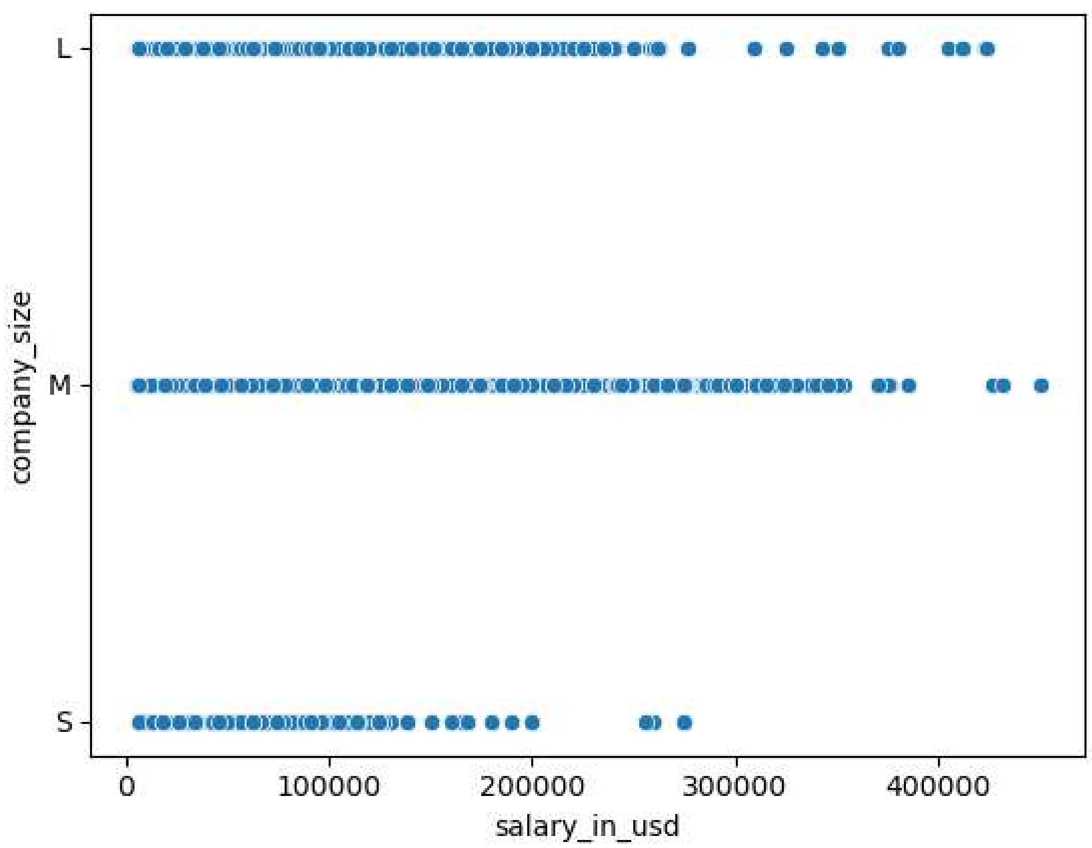


In [11]:

```
#creates a scatter plot of "salary_in_usd" vs "company_size"
sns.scatterplot(data=salaries_df, x="salary_in_usd", y="company_size")
```

Out[11]:

```
<Axes: xlabel='salary_in_usd', ylabel='company_size'>
```



In [12]:
```
#encodes the various categorical columns for the regression model
salaries_df['experience_level'] = salaries_df['experience_level'].replace({'EN':1, 'MI
salaries_df['remote_ratio'] = salaries_df['remote_ratio'].replace({0:0, 50:0.5, 100:1}
salaries_df['company_size'] = salaries_df['company_size'].replace({'S':1, 'M':2, 'L':3
le = preprocessing.LabelEncoder()
salaries_df['job_title'] = le.fit_transform(salaries_df['job_title'])
salaries_df['company_location'] = le.fit_transform(salaries_df['company_location'])
```

In [13]:
```
salaries_df.corr()
```

Out[13]:

	work_year	experience_level	job_title	salary_in_usd	remote_ratio	company_locati
work_year	1.000000	0.181717	-0.023719	0.229923	-0.220775	0.2138
experience_level	0.181717	1.000000	-0.000026	0.427251	-0.032196	0.2618
job_title	-0.023719	-0.000026	1.000000	0.124641	-0.035764	-0.0603
salary_in_usd	0.229923	0.427251	0.124641	1.000000	-0.063465	0.3863
remote_ratio	-0.220775	-0.032196	-0.035764	-0.063465	1.000000	-0.0675
company_location	0.213858	0.261841	-0.060368	0.386305	-0.067564	1.0000
company_size	-0.142282	-0.071258	-0.013052	-0.005463	0.030887	-0.0326

In [14]:
```
#hypothesis test - Pearson’s correlation test for salary vs remote ratio
corr=[]
pvalue=[]
for x in range(1000):
    sampled_df = salaries_df.sample(n=2000, random_state=x)
    cr, pv = pearsonr(sampled_df.salary_in_usd, sampled_df.remote_ratio)
    corr.append(cr)
    pvalue.append(pv)

min(corr), max(corr), max(pvalue)
```

Out[14]:
```
(-0.12074993902861468, -0.008932860775154792, 0.6897105587956726)
```

In [15]:
```
#hypothesis test - Pearson’s correlation test for salary vs experience_level
corr=[]
pvalue=[]
for x in range(1000):
    sampled_df = salaries_df.sample(n=2000, random_state=x)
    cr, pv = pearsonr(sampled_df.salary_in_usd, sampled_df.experience_level)
    corr.append(cr)
    pvalue.append(pv)

min(corr), max(corr), max(pvalue)
```

Out[15]:
```
(0.38586088030572036, 0.4700912819633741, 5.252138788446747e-72)
```

In [18]:
```
#splits the data fram into X and y dataframes,then splits them for validating of the m
y=salaries_df['salary_in_usd']
X = salaries_df.loc[:, salaries_df.columns != 'salary_in_usd']
```

```
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state = 0)
X
```

Out[18]:

	work_year	experience_level	job_title	remote_ratio	company_location	company_size
0	2023	2	4	1.0	67	3
1	2023	3	50	0.0	67	2
2	2023	3	50	0.0	67	2
3	2023	3	35	1.0	67	2
4	2023	3	35	1.0	67	2
...	...	...	...	...	...	...
4128	2021	3	52	1.0	67	3
4129	2020	3	50	1.0	67	3
4130	2021	2	89	1.0	67	3
4131	2020	1	50	1.0	67	1
4133	2021	3	48	0.5	35	3

4093 rows × 6 columns

In [19]:

```
#Creates a linear regression model and calculates the mean absolute error.
lr_model = LinearRegression().fit(train_X, train_y)
lr_predictions = lr_model.predict(val_X)
print('MAE:', mean_absolute_error(val_y, lr_predictions))
print('R-Squared:', lr_model.score(train_X, train_y))
```

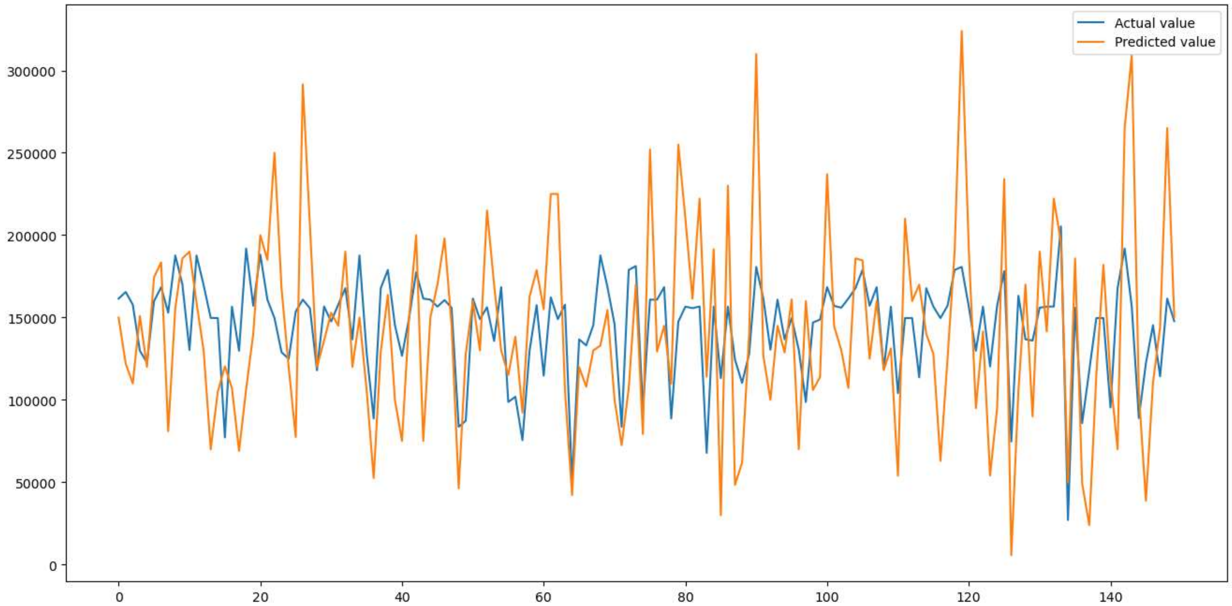
```
MAE: 40962.34112890344
R-Squared: 0.297174844696634
```

In [20]:

```
#creates a plot comparing predictions versus actuals.
test = pd.DataFrame({'Predicted value':lr_predictions, 'Actual value':val_y})
fig= plt.figure(figsize=(16,8))
test = test.reset_index()
test = test.drop(['index'],axis=1)
plt.plot(test[:150])
plt.legend(['Actual value','Predicted value'])
```

Out[20]:

```
<matplotlib.legend.Legend at 0x277c42765c0>
```



In [21]:
```
#Creates a random forest regression model and calculates the mean absolute error.
forest_model = RandomForestRegressor(random_state=1)
forest_model.fit(train_X, train_y)
fm_predictions = forest_model.predict(val_X)
print('MAE:', mean_absolute_error(val_y, fm_predictions))
print('R-Squared:', forest_model.score(train_X, train_y))
```

```
MAE: 36727.55598628675
R-Squared: 0.5601203668852214
```

In [22]:
```
#creates a plot comparing predictions versus actuals.
test = pd.DataFrame({'Predicted value':fm_predictions, 'Actual value':val_y})
fig= plt.figure(figsize=(16,8))
test = test.reset_index()
test = test.drop(['index'],axis=1)
plt.plot(test[:150])
plt.legend(['Actual value','Predicted value'])
```

Out[22]: <matplotlib.legend.Legend at 0x277c4277400>