Final_Project-Team3

December 8, 2024

[348]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree
import statsmodels.api as sm
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score
from sklearn.naive_bayes import MultinomialNB
from sklearn import metrics
```

Data Importing and Pre-processing

[349]:
```python
# Load the dataset
data = pd.read_csv('data_science_salaries.csv')
data.head()
```

[349]:
```
         job_title experience_level employment_type work_models  work_year  \
0   Data Engineer        Mid-level       Full-time      Remote       2024
1   Data Engineer        Mid-level       Full-time      Remote       2024
2  Data Scientist     Senior-level       Full-time      Remote       2024
3  Data Scientist     Senior-level       Full-time      Remote       2024
4    BI Developer        Mid-level       Full-time     On-site       2024

  employee_residence  salary salary_currency  salary_in_usd company_location  \
0      United States  148100             USD         148100    United States
1      United States   98700             USD          98700    United States
2      United States  140032             USD         140032    United States
3      United States  100022             USD         100022    United States
4      United States  120000             USD         120000    United States

  company_size
0       Medium
1       Medium
2       Medium
```

```
3       Medium
4       Medium
```

[350]:
```python
# Find missing data
data.isnull().sum()
```

[350]:
```
job_title             0
experience_level      0
employment_type       0
work_models           0
work_year             0
employee_residence    0
salary                0
salary_currency       0
salary_in_usd         0
company_location      0
company_size          0
dtype: int64
```

[351]:
```python
# Check for duplicates and remove if any
data.duplicated().sum()
```

[351]: 0

[352]:
```python
# Remove irrelevant columns
data = data[data['employee_residence'].str.contains("United States")]
data = data.drop(columns=["salary_currency", 'employee_residence'])
```

[353]:
```python
data.dtypes
```

[353]:
```
job_title           object
experience_level    object
employment_type     object
work_models         object
work_year            int64
salary               int64
salary_in_usd        int64
company_location    object
company_size        object
dtype: object
```

[354]:
```python
# Encode categorical variables
categorical_cols = ['job_title', 'experience_level', 'employment_type',
                    'work_models', 'company_location', 'company_size']

data_encoded = pd.get_dummies(data, columns=categorical_cols, drop_first=False)

# Check for outliers in salary_in_usd using the IQR method
```

```
q1, q3 = data['salary_in_usd'].quantile([0.25, 0.75])
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# Remove rows with outliers in salary_in_usd
data_cleaned = data[(data['salary_in_usd'] >= lower_bound) &
                    (data['salary_in_usd'] <= upper_bound)]
```

[355]:
```
# Display summary of cleaned data
print(data_cleaned.info())
print(data_cleaned.head())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5204 entries, 0 to 6556
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   job_title         5204 non-null   object
 1   experience_level  5204 non-null   object
 2   employment_type   5204 non-null   object
 3   work_models       5204 non-null   object
 4   work_year         5204 non-null   int64
 5   salary            5204 non-null   int64
 6   salary_in_usd     5204 non-null   int64
 7   company_location  5204 non-null   object
 8   company_size      5204 non-null   object
dtypes: int64(3), object(6)
memory usage: 406.6+ KB
None
        job_title experience_level employment_type work_models  work_year  \
0   Data Engineer        Mid-level       Full-time      Remote       2024
1   Data Engineer        Mid-level       Full-time      Remote       2024
2  Data Scientist     Senior-level       Full-time      Remote       2024
3  Data Scientist     Senior-level       Full-time      Remote       2024
4    BI Developer        Mid-level       Full-time     On-site       2024

   salary  salary_in_usd company_location company_size
0  148100         148100    United States       Medium
1   98700          98700    United States       Medium
2  140032         140032    United States       Medium
3  100022         100022    United States       Medium
4  120000         120000    United States       Medium
```

[356]:
```
data_cleaned.describe()
```

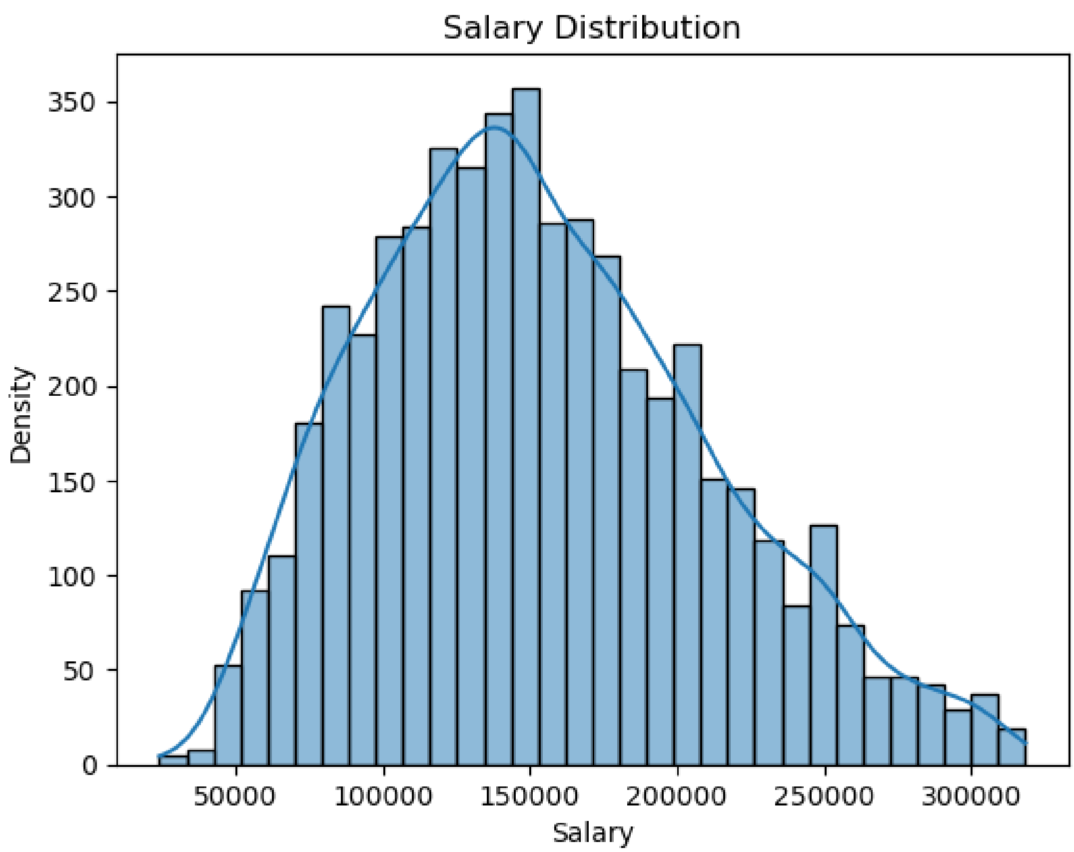
[356]:

	work_year	salary	salary_in_usd
count	5204.000000	5204.000000	5204.000000
mean	2022.888163	153211.435050	153220.955419
std	0.590284	57568.049715	57552.569690
min	2020.000000	24000.000000	24000.000000
25%	2023.000000	110000.000000	110000.000000
50%	2023.000000	147000.000000	147000.000000
75%	2023.000000	190000.000000	190000.000000
max	2024.000000	318300.000000	318300.000000

Data Analysis and Visualization

[357]:

```
sns.histplot(data_cleaned['salary_in_usd'], kde=True)
plt.xlabel('Salary')
plt.ylabel('Density')
plt.title('Salary Distribution')
plt.show()
```

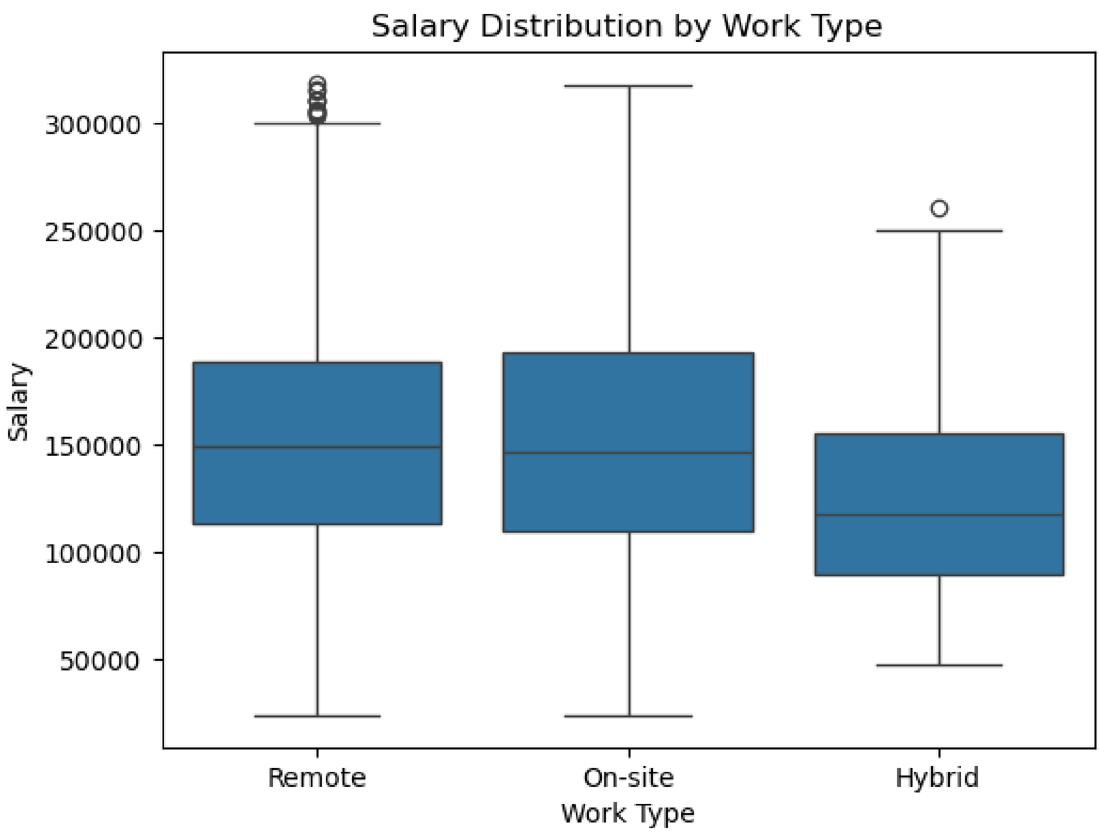


[358]:

```
# Salary distribution across experience level
sns.boxplot(x='experience_level', y='salary_in_usd', data=data_cleaned)
```

```
plt.xlabel('Experience Level')
plt.ylabel('Salary')
plt.title('Salary Distribution by Experience Level')
plt.show()
```

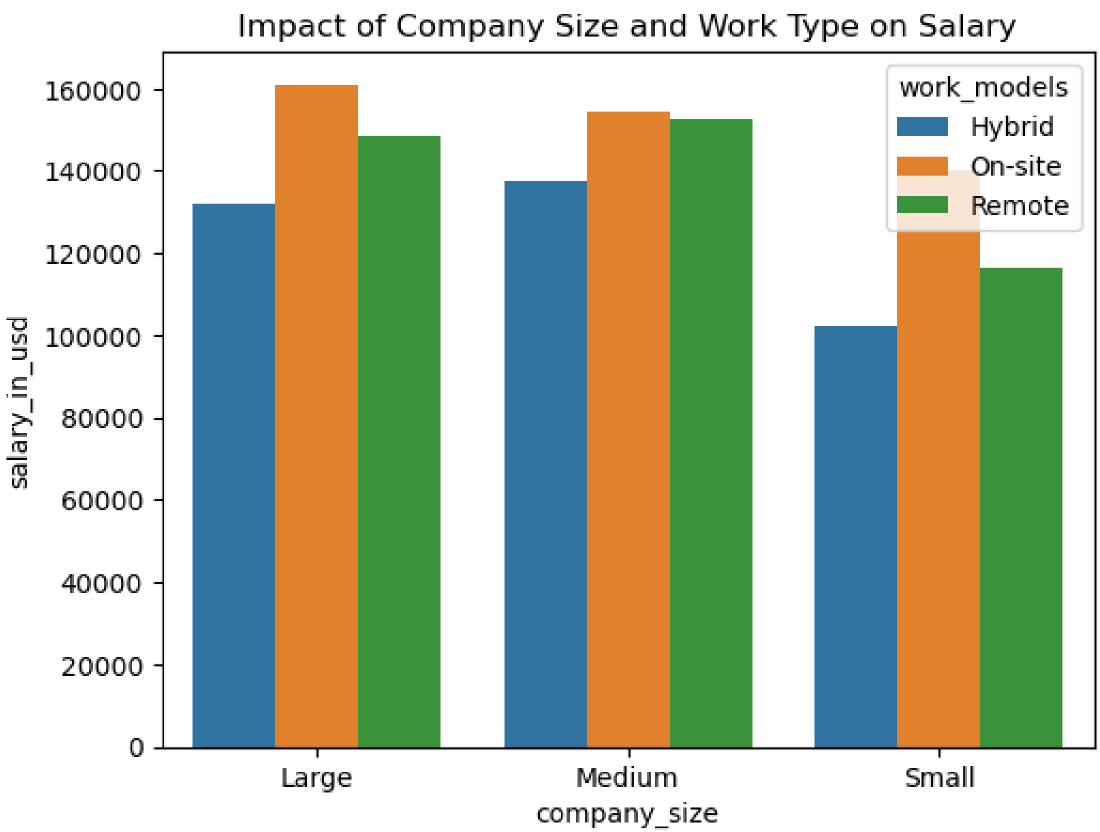
[359]:
```
# Salary distribution across work type
sns.boxplot(x='work_models', y='salary_in_usd', data=data_cleaned)
plt.xlabel('Work Type')
plt.ylabel('Salary')
plt.title('Salary Distribution by Work Type')
plt.show()
```



[360]:
```
# Salary distribution across company size
sns.boxplot(x='company_size', y='salary_in_usd', data=data_cleaned)
plt.xlabel('Company Size')
plt.ylabel('Salary')
plt.title('Salary Distribution by Company Size')
plt.show()
```

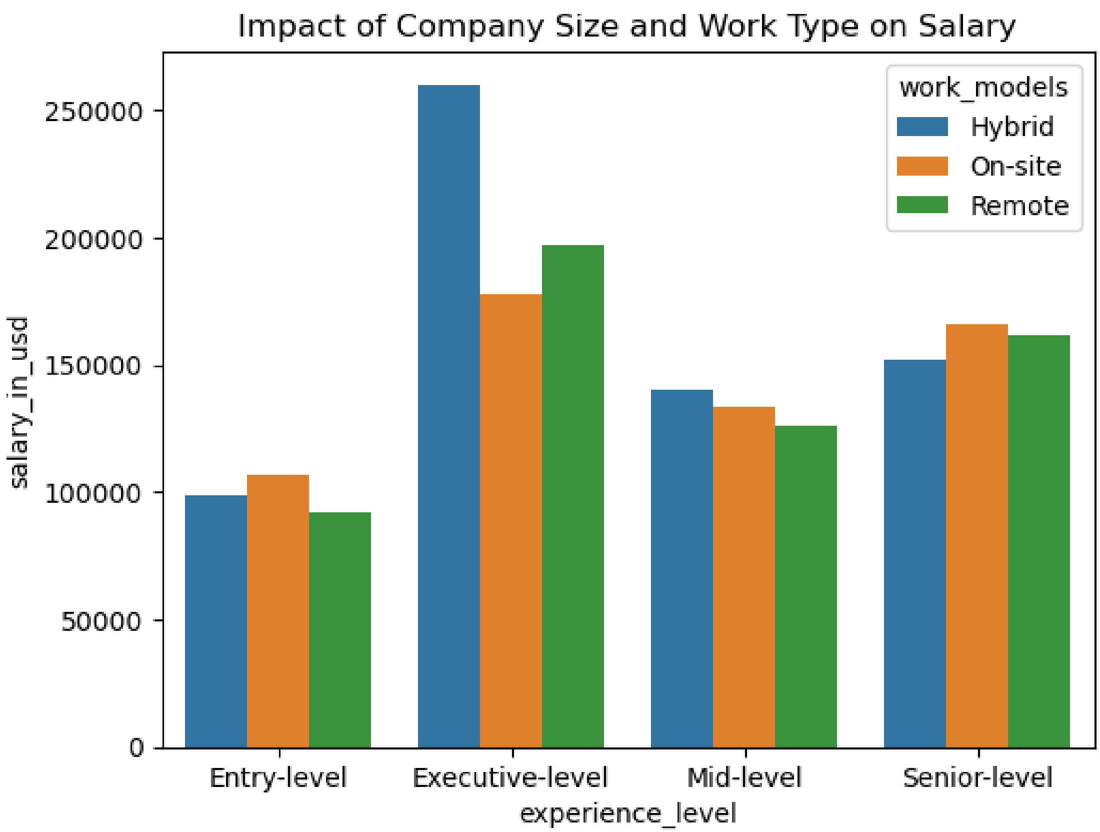
[361]:
```
interaction_effects = data_cleaned.groupby(['work_models',
    'company_size'])['salary_in_usd'].mean().reset_index()
```

[362]:
```
# Bar plot to visualize company size and work type on salary
sns.barplot(data=interaction_effects, x='company_size', y='salary_in_usd',
    hue='work_models')
plt.title("Impact of Company Size and Work Type on Salary")
plt.show()
```



[363]:
```
interaction_effects2 = data_cleaned.groupby(['work_models',
    'experience_level'])['salary_in_usd'].mean().reset_index()
```

[364]:
```
# Bar plot to visualize experience level and work type on salary
sns.barplot(data=interaction_effects2, x='experience_level', y='salary_in_usd',
    hue='work_models')
plt.title("Impact of Company Size and Work Type on Salary")
plt.show()
```



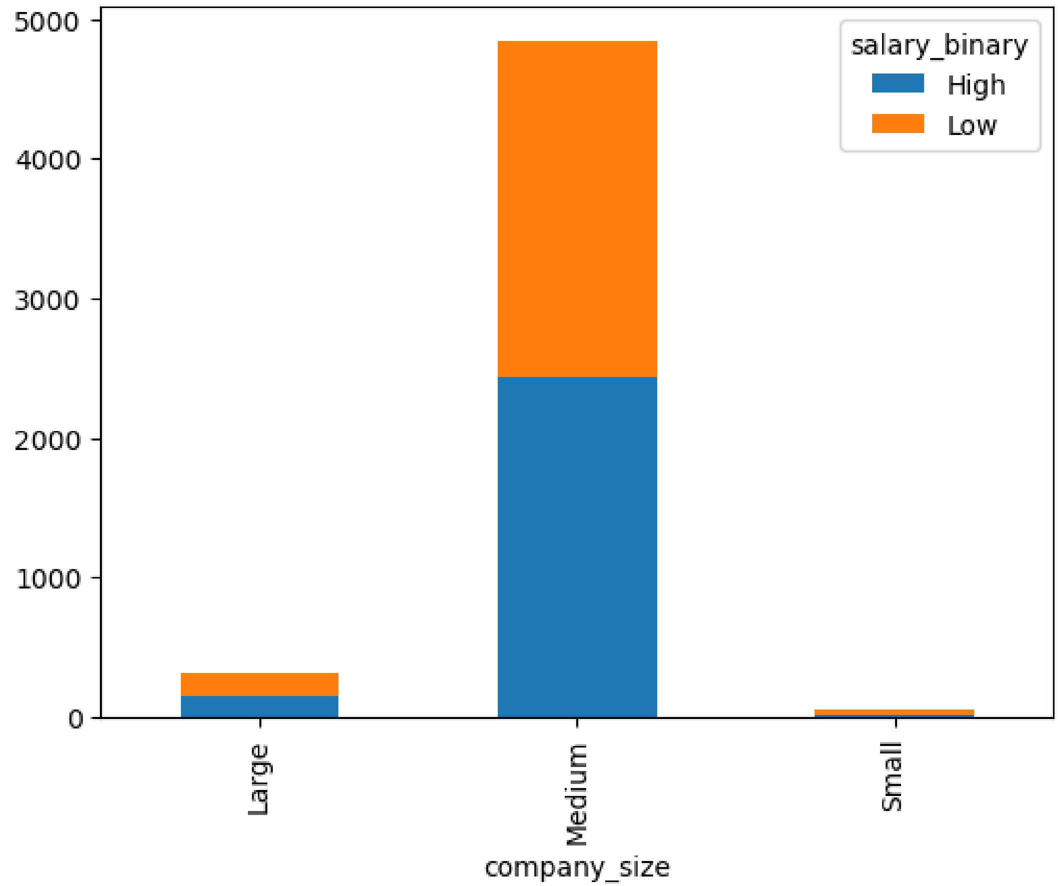
[365]:
```
# Median of salary
salary_median = data_cleaned['salary_in_usd'].median()
```

[366]:
```
# Convert 'salary_in_usd' to binary
data_cleaned['salary_binary'] = data_cleaned['salary_in_usd'].apply(lambda x:␣
↪'High' if x > salary_median else 'Low')
```

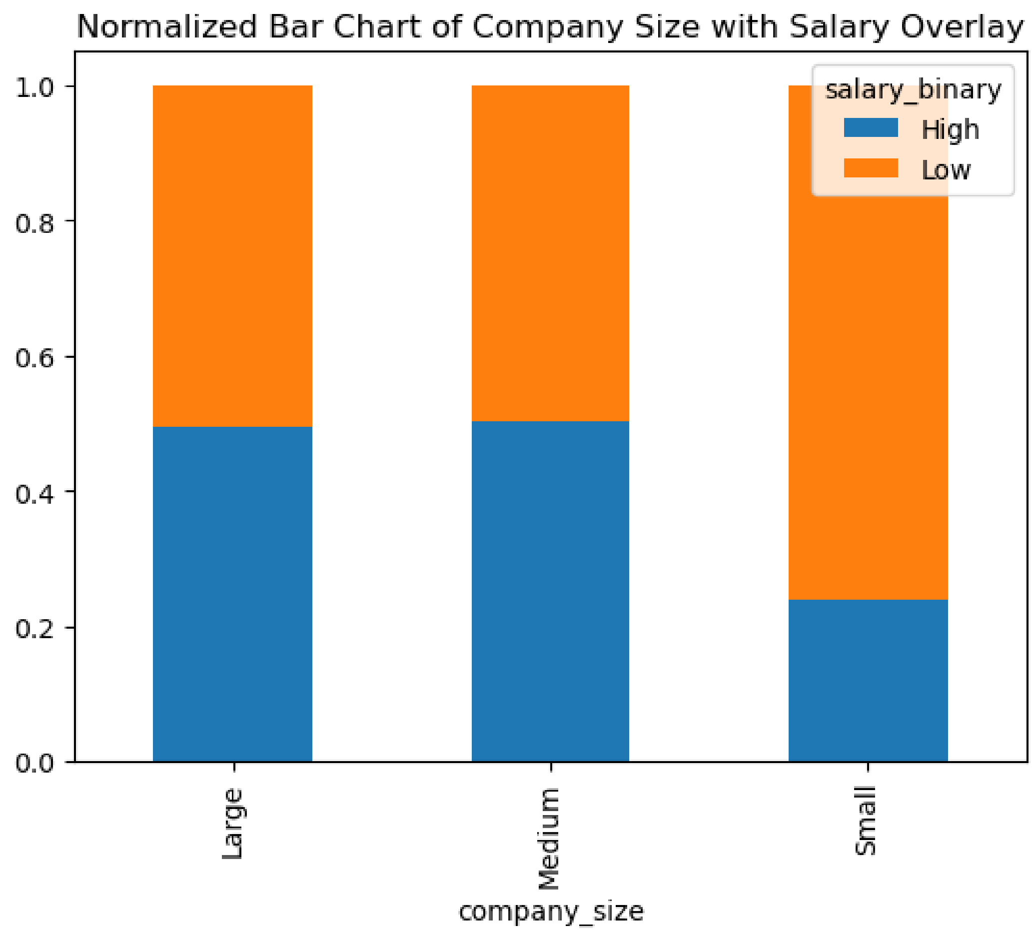
```
/var/folders/6j/qtnqw_nn0bj948l89lgcc38m0000gn/T/ipykernel_9252/884209481.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data_cleaned['salary_binary'] = data_cleaned['salary_in_usd'].apply(lambda x:
'High' if x > salary_median else 'Low')
```

[367]:
```
# Bar graph of company_size by salary
company_salary = pd.crosstab(data_cleaned['company_size'],␣
↪data_cleaned['salary_binary'])
company_salary.plot(kind='bar', stacked=True)
```

[367]: <Axes: xlabel='company_size'>

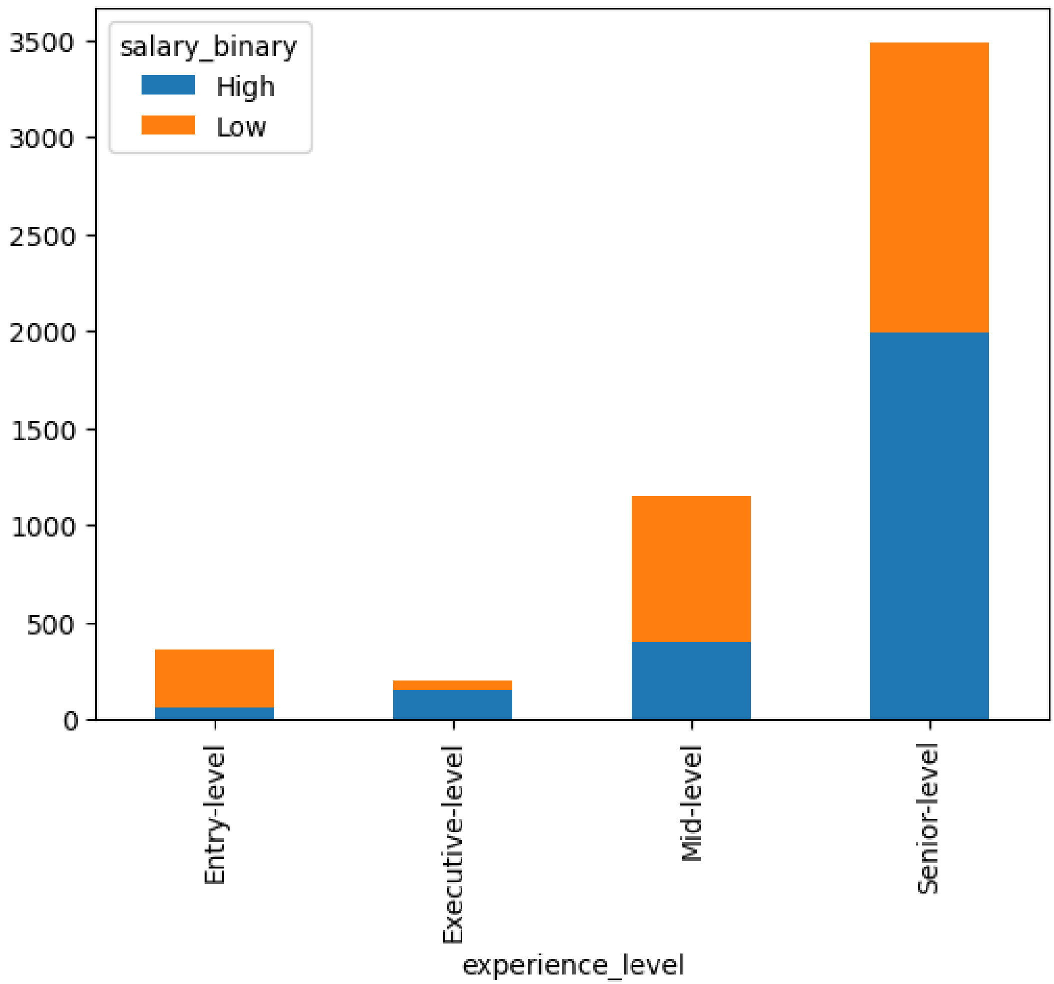


[368]:
```
# Normalized
company_salary_norm = company_salary.div(company_salary.sum(1), axis = 0)
company_salary_norm.plot(kind='bar', stacked=True)
plt.title('Normalized Bar Chart of Company Size with Salary Overlay')
plt.show()
```

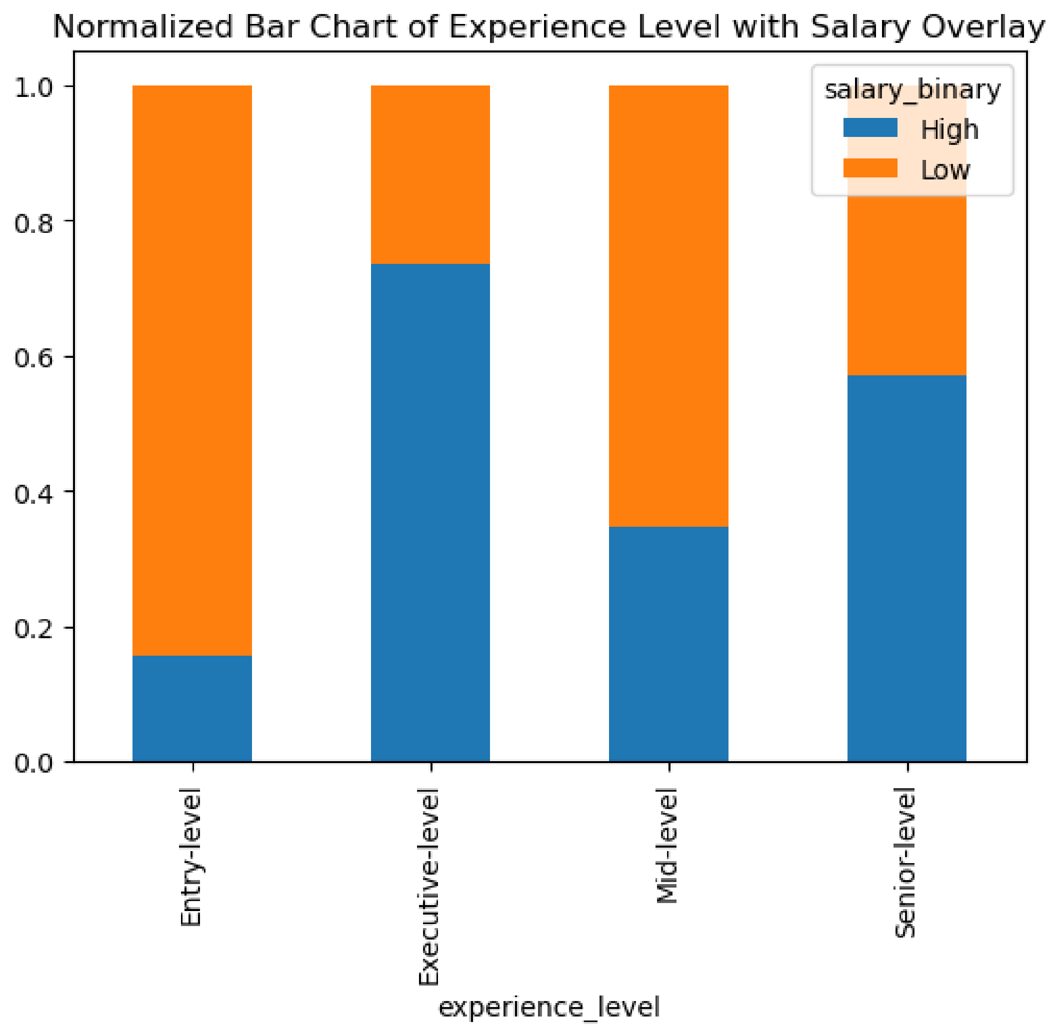


[369]:
```
# Bar graph of experience_level by salary
experience_salary = pd.crosstab(data_cleaned['experience_level'],␣
↪data_cleaned['salary_binary'])
experience_salary.plot(kind='bar', stacked=True)
```

[369]: <Axes: xlabel='experience_level'>

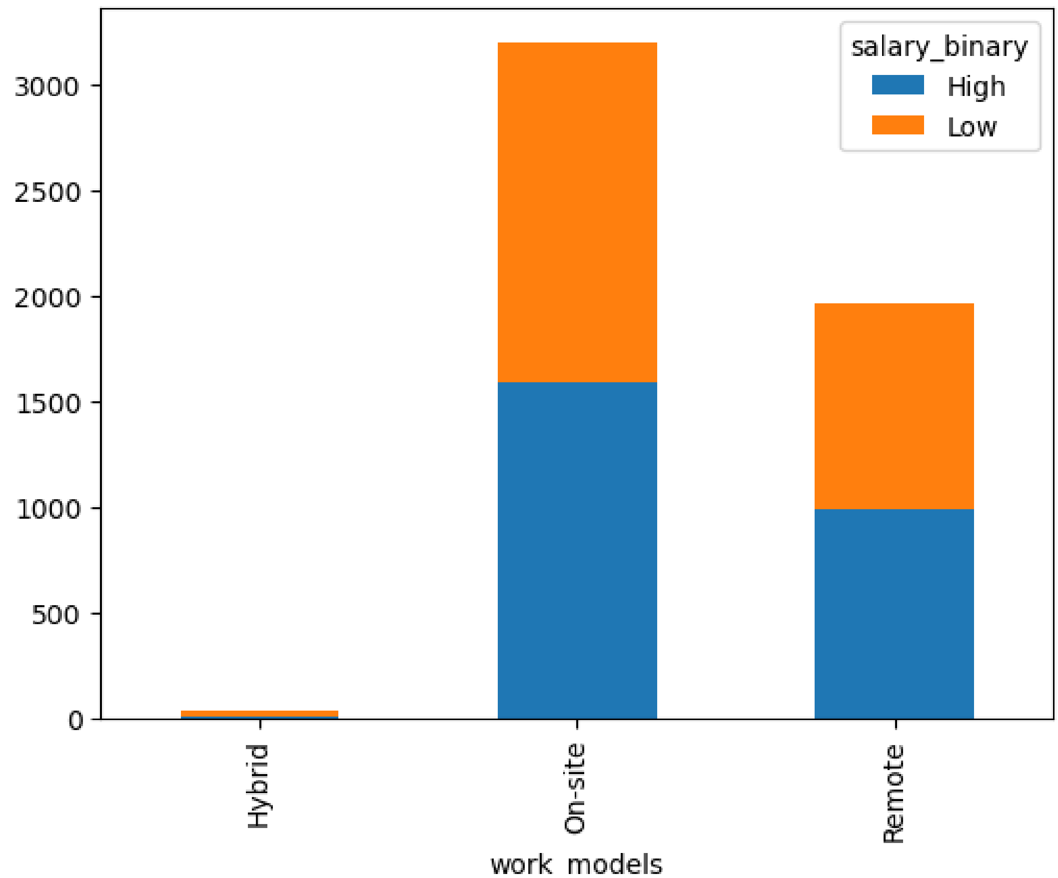


[370]:
```
# Normalized
experience_salary_norm = experience_salary.div(experience_salary.sum(1), axis =␣
↪0)
experience_salary_norm.plot(kind='bar', stacked=True)
plt.title('Normalized Bar Chart of Experience Level with Salary Overlay')
plt.show()
```

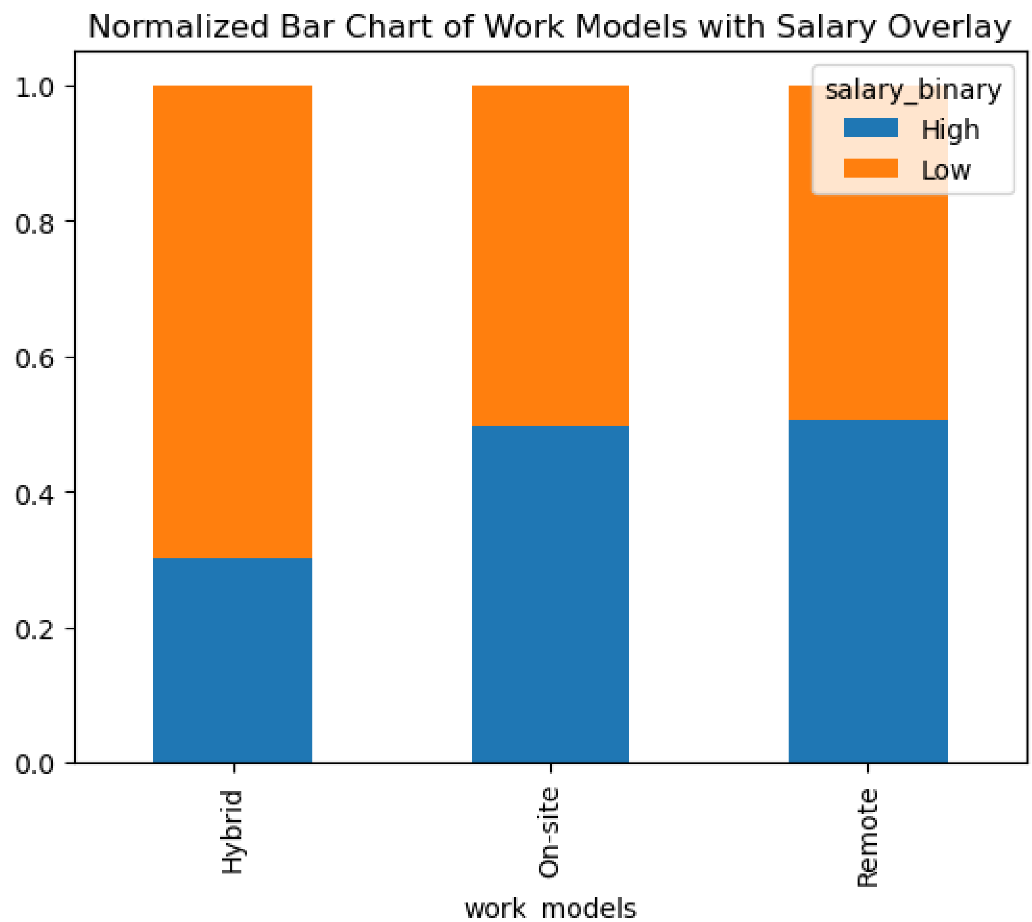



```
[371]: # Bar graph of work_models by salary
work_salary = pd.crosstab(data_cleaned['work_models'],
 ↪data_cleaned['salary_binary'])
work_salary.plot(kind='bar', stacked=True)
```

```
[371]: <Axes: xlabel='work_models'>
```



[372]:
```
# Normalized
work_salary_norm = work_salary.div(work_salary.sum(1), axis = 0)
work_salary_norm.plot(kind='bar', stacked=True)
plt.title('Normalized Bar Chart of Work Models with Salary Overlay')
plt.show()
```



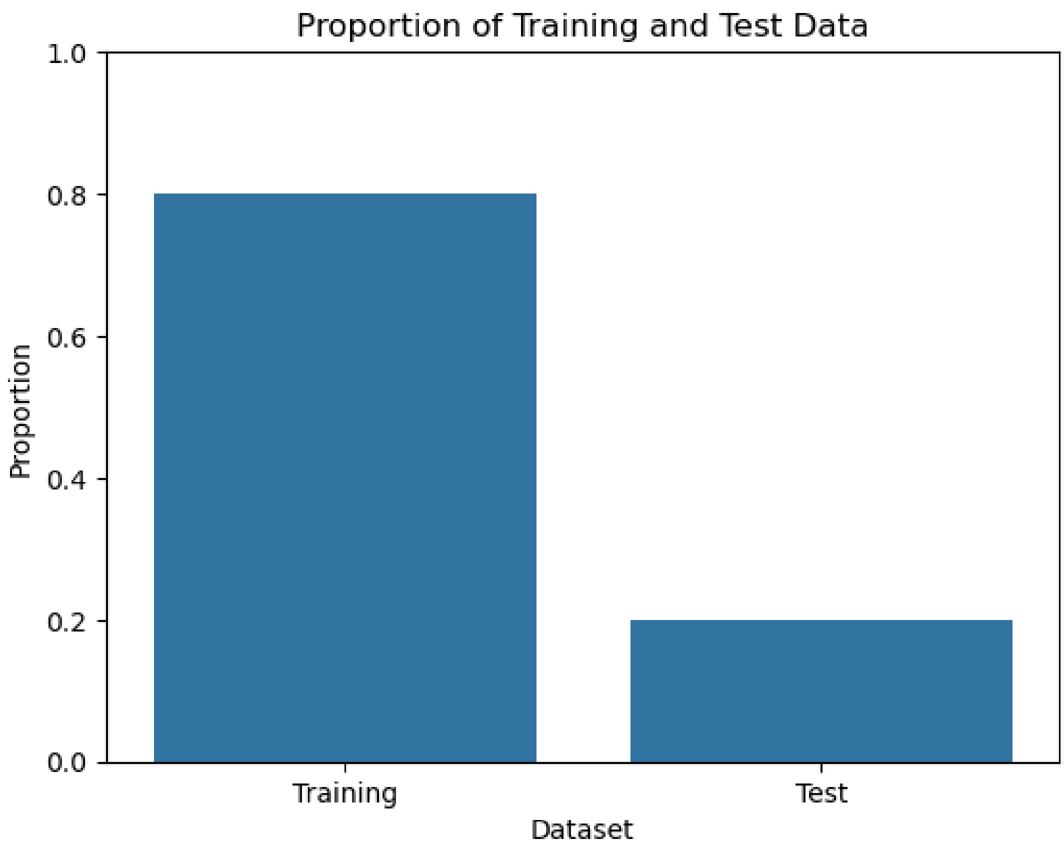
Split dataset to training and test

[373]:
```
# Partition dataset
data_train, data_test = train_test_split(data_cleaned, test_size = 0.2,␣
↪random_state = 7)
```

[374]:
```
# Confirm split proportions
split_proportions = pd.DataFrame({'Dataset': ['Training', 'Test'],
                                  'Proportion': [len(data_train) /␣
↪len(data_cleaned), len(data_test) / len(data_cleaned)]
})
```

[375]:
```
sns.barplot(x='Dataset', y='Proportion', data=split_proportions)

plt.title('Proportion of Training and Test Data')
plt.ylabel('Proportion')
plt.xlabel('Dataset')
plt.ylim(0, 1)
```

```python
plt.show()
```



[376]:
```python
# Check if rebalance is needed
data_train['salary_binary'].value_counts()
```

[376]:
```
salary_binary
High    2085
Low     2078
Name: count, dtype: int64
```

[377]:
```python
# Prep data for modeling
y_train = data_train[['salary_binary']]
y_test = data_test[['salary_binary']]
data_train = pd.get_dummies(data_train, prefix=None, columns=['company_size',
 ↪'experience_level','work_models'], drop_first=False)
data_test = pd.get_dummies(data_test, prefix=None, columns=['company_size',
 ↪'experience_level','work_models'], drop_first=False)
```

[378]:
```python
data_train.columns
```

[378]: Index(['job_title', 'employment_type', 'work_year', 'salary', 'salary_in_usd',
       'company_location', 'salary_binary', 'company_size_Large',
       'company_size_Medium', 'company_size_Small',
       'experience_level_Entry-level', 'experience_level_Executive-level',
       'experience_level_Mid-level', 'experience_level_Senior-level',
       'work_models_Hybrid', 'work_models_On-site', 'work_models_Remote'],
      dtype='object')

[379]:
```
X_train = data_train[['company_size_Large', 'company_size_Medium',␣
↪'company_size_Small', 'experience_level_Entry-level',␣
↪'experience_level_Executive-level', 'experience_level_Mid-level',␣
↪'experience_level_Senior-level', 'work_models_Hybrid',␣
↪'work_models_On-site', 'work_models_Remote']]
X_test = data_test[['company_size_Large', 'company_size_Medium',␣
↪'company_size_Small', 'experience_level_Entry-level',␣
↪'experience_level_Executive-level', 'experience_level_Mid-level',␣
↪'experience_level_Senior-level', 'work_models_Hybrid',␣
↪'work_models_On-site', 'work_models_Remote']]
```

[380]:
```
X_names = ["company_size_Large", "company_size_Medium", "company_size_Small",␣
↪"experience_level_Entry-level", "experience_level_Executive-level",␣
↪"experience_level_Mid-level", "experience_level_Senior-level",␣
↪"work_models_Hybrid", "work_models_On-site", "work_models_Remote"]
y_names = ["High", "Low"]
```

Random Forest

[381]:
```
rf = RandomForestClassifier(random_state=42, n_estimators=100).fit(X_train,␣
↪y_train)
```

```
/var/folders/6j/qtnqw_nn0bj9481891gcc38m0000gn/T/ipykernel_9252/2484856752.py:1:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example using
ravel().
  rf = RandomForestClassifier(random_state=42, n_estimators=100).fit(X_train,
y_train)
```

[382]:
```
y_pred_rf = rf.predict(X_test)
```

[383]:
```
cm = confusion_matrix(y_test, y_pred_rf)
cm
```

[383]:
```
array([[421,  91],
       [323, 206]])
```

[384]:
```
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.6023054755043228
```

```
Classification Report:
              precision    recall  f1-score   support

        High       0.57      0.82      0.67       512
         Low       0.69      0.39      0.50       529

    accuracy                           0.60      1041
   macro avg       0.63      0.61      0.58      1041
weighted avg       0.63      0.60      0.58      1041
```

[385]:
```
TN = cm[1][1]
FP = cm[1][0]
FN = cm[0][1]
TP = cm[0][0]
TAN = TN + FP
TAP = FN + TP
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[386]:
```
print("Random Forest Accuracy:", Accuracy)
print("Random Forest Error Rate:", ErrorRate)
print("Random Forest Sensitivity:", Recall)
print("Random Forest Specificity:", Specificity)
print("Random Forest Precision:", Precision)
print("Random Forest F1:", F1)
print("Random Forest F2:", F2)
print("Random Forest F0.5:", F0_5)
```

```
Random Forest Accuracy: 0.6023054755043228
Random Forest Error Rate: 0.3976945244956772
Random Forest Sensitivity: 0.822265625
Random Forest Specificity: 0.389413988657845
Random Forest Precision: 0.5658602150537635
Random Forest F1: 0.6703821656050956
Random Forest F2: 0.7539398280802293
Random Forest F0.5: 0.6034977064220185
```

Logistic Regression

[387]:
```python
log_reg = LogisticRegression().fit(X_train, y_train.values.ravel())
```

[388]:
```python
y_pred_logreg = log_reg.predict(X_test)
```

[389]:
```python
cm_logreg = confusion_matrix(y_test, y_pred_logreg)
cm_logreg
```

[389]:
```
array([[421,  91],
       [319, 210]])
```

[390]:
```python
print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_logreg))
print("Classification Report:\n", classification_report(y_test, y_pred_logreg))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_logreg))
```

```
Logistic Regression Accuracy: 0.6061479346781941
Classification Report:
               precision    recall  f1-score   support

        High       0.57      0.82      0.67       512
         Low       0.70      0.40      0.51       529

    accuracy                           0.61      1041
   macro avg       0.63      0.61      0.59      1041
weighted avg       0.63      0.61      0.59      1041

Confusion Matrix:
 [[421  91]
 [319 210]]
```

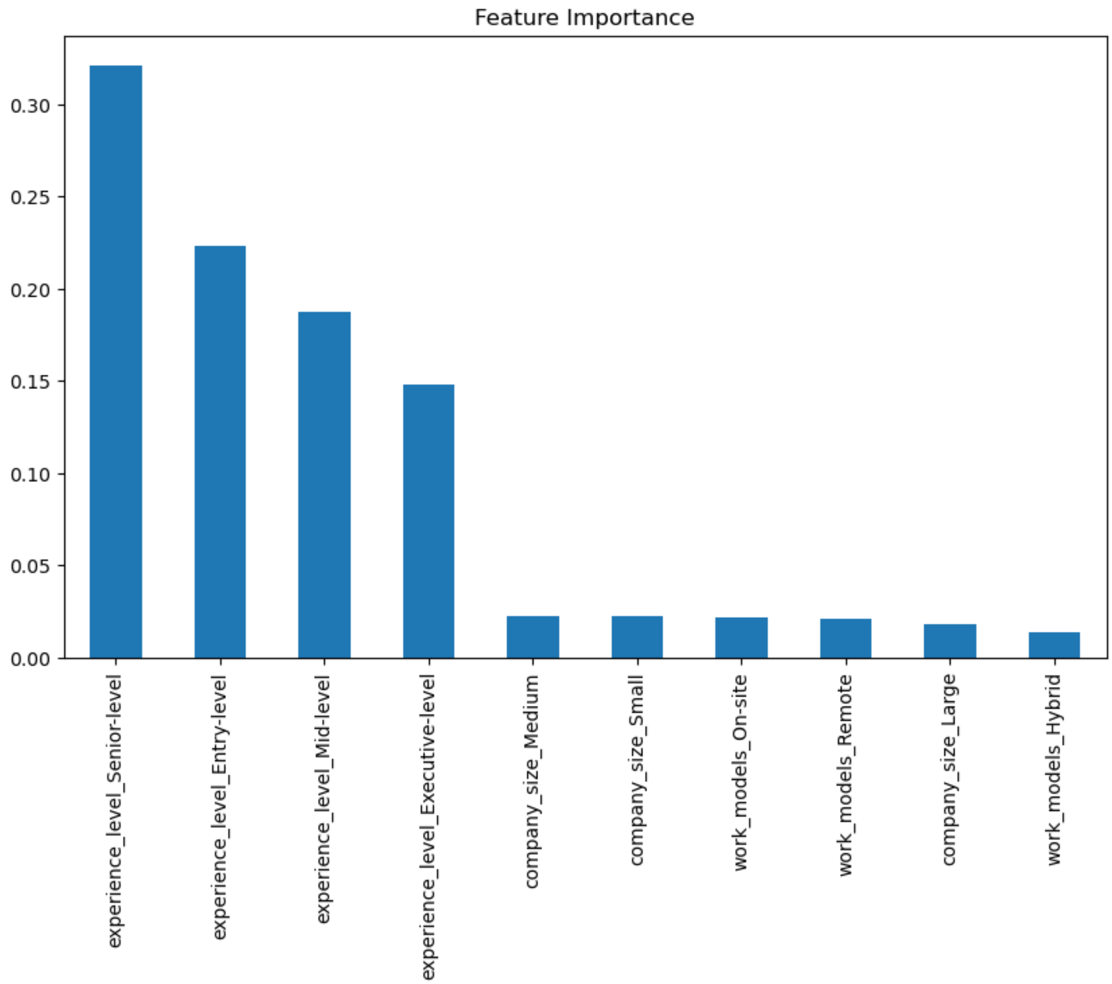
[391]:
```python
TN = cm_logreg[1][1]
FP = cm_logreg[1][0]
FN = cm_logreg[0][1]
TP = cm_logreg[0][0]
TAN = TN + FP
TAP = FN + TP
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
```

```
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[392]:
```
print("Logistic Regression Accuracy:", Accuracy)
print("Logistic Regression Error Rate:", ErrorRate)
print("Logistic Regression Sensitivity:", Recall)
print("Logistic Regression Specificity:", Specificity)
print("Logistic Regression Precision:", Precision)
print("Logistic Regression F1:", F1)
print("Logistic Regression F2:", F2)
print("Logistic Regression F0.5:", F0_5)
```

```
Logistic Regression Accuracy: 0.6061479346781941
Logistic Regression Error Rate: 0.39385206532180594
Logistic Regression Sensitivity: 0.822265625
Logistic Regression Specificity: 0.39697542533081287
Logistic Regression Precision: 0.5689189189189189
Logistic Regression F1: 0.6725239616613419
Logistic Regression F2: 0.7550215208034432
Logistic Regression F0.5: 0.606278801843318
```

[393]:
```
# Analyze feature importance
importance = pd.Series(rf.feature_importances_, index=X_train.columns)
importance.sort_values(ascending=False).plot(kind='bar', figsize=(10, 6))
plt.title('Feature Importance')
plt.show()
```



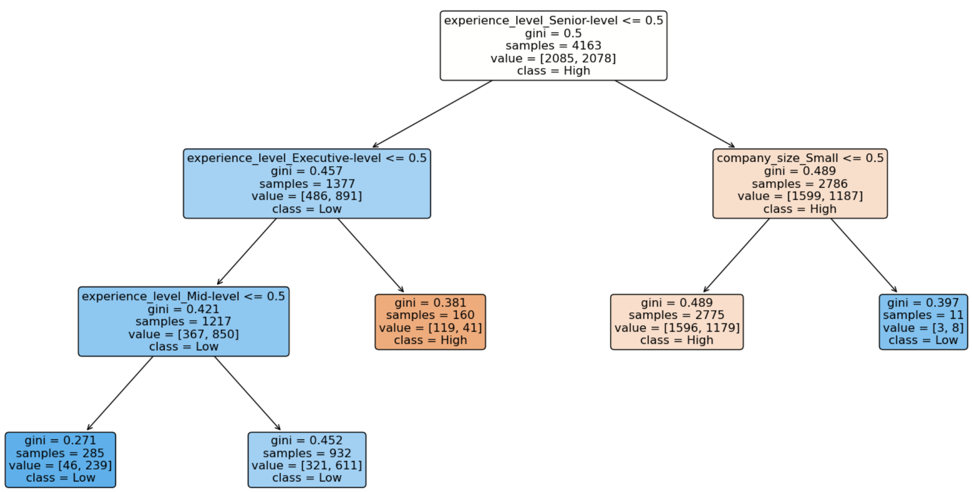
CART

[394]:
```
cart = DecisionTreeClassifier(criterion = "gini", max_leaf_nodes=5).
 ↪fit(X_train, y_train)
```

[395]:
```
plt.figure()
plt.figure(figsize=(20,10))
plot_tree(cart,
          feature_names= X_names,
          class_names = y_names,
          filled=True,
          rounded = True)
```

[395]:
```
[Text(0.5555555555555556, 0.875, 'experience_level_Senior-level <= 0.5\ngini =
0.5\nsamples = 4163\nvalue = [2085, 2078]\nclass = High'),
 Text(0.3333333333333333, 0.625, 'experience_level_Executive-level <= 0.5\ngini
= 0.457\nsamples = 1377\nvalue = [486, 891]\nclass = Low'),
```

```
 Text(0.2222222222222222, 0.375, 'experience_level_Mid-level <= 0.5\ngini =
0.421\nsamples = 1217\nvalue = [367, 850]\nclass = Low'),
 Text(0.1111111111111111, 0.125, 'gini = 0.271\nsamples = 285\nvalue = [46,
239]\nclass = Low'),
 Text(0.3333333333333333, 0.125, 'gini = 0.452\nsamples = 932\nvalue = [321,
611]\nclass = Low'),
 Text(0.4444444444444444, 0.375, 'gini = 0.381\nsamples = 160\nvalue = [119,
41]\nclass = High'),
 Text(0.7777777777777778, 0.625, 'company_size_Small <= 0.5\ngini =
0.489\nsamples = 2786\nvalue = [1599, 1187]\nclass = High'),
 Text(0.6666666666666666, 0.375, 'gini = 0.489\nsamples = 2775\nvalue = [1596,
1179]\nclass = High'),
 Text(0.8888888888888888, 0.375, 'gini = 0.397\nsamples = 11\nvalue = [3,
8]\nclass = Low')]

<Figure size 640x480 with 0 Axes>
```



[396]:
```
y_pred_cart = cart.predict(X_test)
y_pred_cart
```

[396]:
```
array(['High', 'High', 'Low', …, 'High', 'High', 'High'], dtype=object)
```

[397]:
```
cm_cart = confusion_matrix(y_test, y_pred_cart)
cm_cart
```

[397]:
```
array([[421,  91],
       [319, 210]])
```

[398]:
```
print("CART Accuracy:", accuracy_score(y_test, y_pred_cart))
print("Classification Report:\n", classification_report(y_test, y_pred_cart))
```

```
CART Accuracy: 0.6061479346781941
Classification Report:
               precision    recall  f1-score   support

        High       0.57      0.82      0.67       512
         Low       0.70      0.40      0.51       529

    accuracy                           0.61      1041
   macro avg       0.63      0.61      0.59      1041
weighted avg       0.63      0.61      0.59      1041
```

[399]:
```
TN = cm_cart[1][1]
FP = cm_cart[1][0]
FN = cm_cart[0][1]
TP = cm_cart[0][0]
TAN = TN + FP
TAP = FN + TP
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[400]:
```
print("CART Accuracy:", Accuracy)
print("CART Error Rate:", ErrorRate)
print("CART Sensitivity:", Recall)
print("CART Specificity:", Specificity)
print("CART Precision:", Precision)
print("CART F1:", F1)
print("CART F2:", F2)
print("CART F0.5:", F0_5)
```

```
CART Accuracy: 0.6061479346781941
CART Error Rate: 0.39385206532180594
CART Sensitivity: 0.822265625
CART Specificity: 0.39697542533081287
```

```
CART Precision: 0.5689189189189189
CART F1: 0.6725239616613419
CART F2: 0.7550215208034432
CART F0.5: 0.606278801843318
```

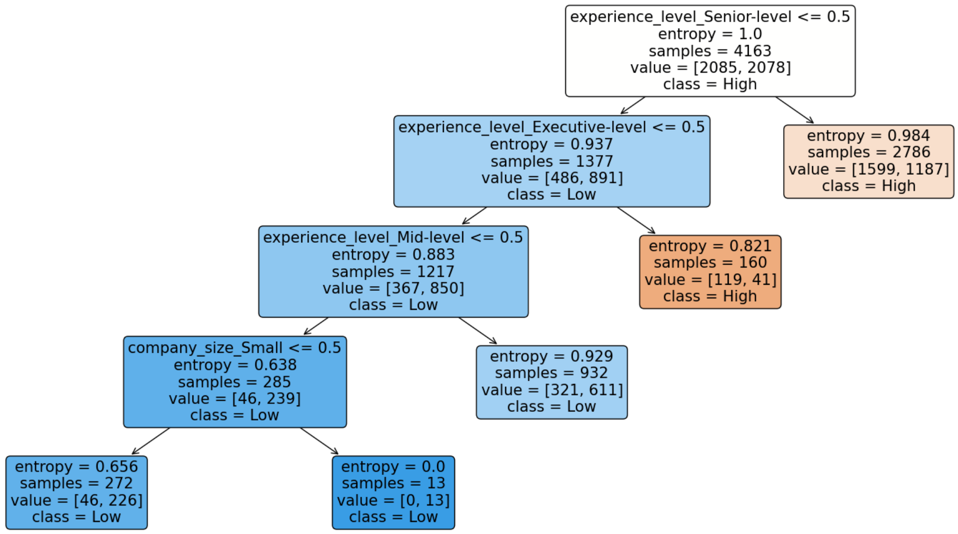
C5.0 Model

[401]:
```
c50 = DecisionTreeClassifier(criterion="entropy", max_leaf_nodes=5).
 ↪fit(X_train, y_train)
```

[402]:
```
plt.figure()
plt.figure(figsize=(20,10))
plot_tree(c50,
          feature_names = X_names,
          class_names = y_names,
          filled=True,
          rounded = True)
```

[402]:
```
[Text(0.7142857142857143, 0.9, 'experience_level_Senior-level <= 0.5\nentropy =
1.0\nsamples = 4163\nvalue = [2085, 2078]\nclass = High'),
 Text(0.5714285714285714, 0.7, 'experience_level_Executive-level <= 0.5\nentropy
= 0.937\nsamples = 1377\nvalue = [486, 891]\nclass = Low'),
 Text(0.42857142857142855, 0.5, 'experience_level_Mid-level <= 0.5\nentropy =
0.883\nsamples = 1217\nvalue = [367, 850]\nclass = Low'),
 Text(0.2857142857142857, 0.3, 'company_size_Small <= 0.5\nentropy =
0.638\nsamples = 285\nvalue = [46, 239]\nclass = Low'),
 Text(0.14285714285714285, 0.1, 'entropy = 0.656\nsamples = 272\nvalue = [46,
226]\nclass = Low'),
 Text(0.42857142857142855, 0.1, 'entropy = 0.0\nsamples = 13\nvalue = [0,
13]\nclass = Low'),
 Text(0.5714285714285714, 0.3, 'entropy = 0.929\nsamples = 932\nvalue = [321,
611]\nclass = Low'),
 Text(0.7142857142857143, 0.5, 'entropy = 0.821\nsamples = 160\nvalue = [119,
41]\nclass = High'),
 Text(0.8571428571428571, 0.7, 'entropy = 0.984\nsamples = 2786\nvalue = [1599,
1187]\nclass = High')]
```

```
<Figure size 640x480 with 0 Axes>
```



[403]:
```python
y_pred_c50 = c50.predict(X_test)
```

[404]:
```python
cm_c50 = confusion_matrix(y_test, y_pred_c50)
cm_c50
```

[404]:
```
array([[423,  89],
       [321, 208]])
```

[405]:
```python
print("C5.0 Accuracy:", accuracy_score(y_test, y_pred_c50))
print("Classification Report:\n", classification_report(y_test, y_pred_c50))
```

```
C5.0 Accuracy: 0.6061479346781941
Classification Report:
               precision    recall  f1-score   support

        High       0.57      0.83      0.67       512
         Low       0.70      0.39      0.50       529

    accuracy                           0.61      1041
   macro avg       0.63      0.61      0.59      1041
weighted avg       0.64      0.61      0.59      1041
```

[406]:
```python
TN = cm_c50[1][1]
FP = cm_c50[1][0]
FN = cm_c50[0][1]
TP = cm_c50[0][0]
TAN = TN + FP
TAP = FN + TP
```

```
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[407]:
```
print("C5.0 Accuracy:", Accuracy)
print("C5.0 Error Rate:", ErrorRate)
print("C5.0 Sensitivity:", Recall)
print("C5.0 Specificity:", Specificity)
print("C5.0 Precision:", Precision)
print("C5.0 F1:", F1)
print("C5.0 F2:", F2)
print("C5.0 F0.5:", F0_5)
```

```
C5.0 Accuracy: 0.6061479346781941
C5.0 Error Rate: 0.39385206532180594
C5.0 Sensitivity: 0.826171875
C5.0 Specificity: 0.3931947069943289
C5.0 Precision: 0.5685483870967742
C5.0 F1: 0.6735668789808917
C5.0 F2: 0.7575214899713466
C5.0 F0.5: 0.6063646788990825
```

Naive Bayes

[408]:
```
nb = MultinomialNB().fit(X_train, y_train.values.ravel())
```

[409]:
```
y_pred_nb = nb.predict(X_test)
```

[410]:
```
cm_nb = confusion_matrix(y_test, y_pred_nb)
cm_nb
```

[410]:
```
array([[418,  94],
       [318, 211]])
```

[411]:
```
print("Naive Bayes Accuracy:", accuracy_score(y_test, y_pred_nb))
print("Classification Report:\n", classification_report(y_test, y_pred_nb))
```

```
Naive Bayes Accuracy: 0.6042267050912584
Classification Report:
```

```
              precision    recall  f1-score   support

        High       0.57      0.82      0.67       512
         Low       0.69      0.40      0.51       529

    accuracy                           0.60      1041
   macro avg       0.63      0.61      0.59      1041
weighted avg       0.63      0.60      0.59      1041
```

[412]:
```python
TN = cm_nb[1][1]
FP = cm_nb[1][0]
FN = cm_nb[0][1]
TP = cm_nb[0][0]
TAN = TN + FP
TAP = FN + TP
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[413]:
```python
print("NB Accuracy:", Accuracy)
print("NB Error Rate:", ErrorRate)
print("NB Sensitivity:", Recall)
print("NB Specificity:", Specificity)
print("NB Precision:", Precision)
print("NB F1:", F1)
print("NB F2:", F2)
print("NB F0.5:", F0_5)
```

```
NB Accuracy: 0.6042267050912584
NB Error Rate: 0.3957732949087416
NB Sensitivity: 0.81640625
NB Specificity: 0.3988657844990548
NB Precision: 0.5679347826086957
NB F1: 0.6698717948717948
NB F2: 0.7507183908045977
NB F0.5: 0.6047453703703703
```

Baseline Model

[414]:
```python
from sklearn.dummy import DummyClassifier

baseline = DummyClassifier(strategy='uniform', random_state = 7).fit(X_train,␣
↪y_train.values.ravel())
```

[415]:
```python
y_pred_baseline = baseline.predict(X_test)
```

[416]:
```python
cm_baseline = confusion_matrix(y_test, y_pred_baseline)
cm_baseline
```

[416]:
```
array([[250, 262],
       [276, 253]])
```

[417]:
```python
TN = cm_baseline[1][1]
FP = cm_baseline[1][0]
FN = cm_baseline[0][1]
TP = cm_baseline[0][0]
TAN = TN + FP
TAP = FN + TP
TPN = TN + FN
TPP = FP + TP
GT = TN + FP + FN + TP

Accuracy = (TN + TP)/GT
ErrorRate = 1 - Accuracy
Sensitivity = TP/TAP
Recall = Sensitivity
Specificity = TN/TAN
Precision = TP/TPP
F1 = (2*Precision*Recall)/(Precision + Recall)
F2 = (5*Precision*Recall)/((4*Precision) + Recall)
F0_5 = (1.25*Precision*Recall)/((.25*Precision)+Recall)
```

[418]:
```python
print("Baseline Accuracy:", Accuracy)
print("Baseline Error Rate:", ErrorRate)
print("Baseline Sensitivity:", Recall)
print("Baseline Specificity:", Specificity)
print("Baseline Precision:", Precision)
print("Baseline F1:", F1)
print("Baseline F2:", F2)
print("Baseline F0.5:", F0_5)
```

```
Baseline Accuracy: 0.48318924111431316
Baseline Error Rate: 0.5168107588856868
Baseline Sensitivity: 0.48828125
Baseline Specificity: 0.4782608695652174
Baseline Precision: 0.4752851711026616
Baseline F1: 0.4816955684007707
```

```
Baseline F2: 0.48562548562548563
Baseline F0.5: 0.47782874617737
```