Google Advanced Data Analytics Capstone

Salifort Motors

Project

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Github

PACE Framework

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PACE: Plan

Background, The goal, Initial EDA and Data Cleaning

About the company

Salifort Motors is a fictional French-based alternative energy vehicle manufacturer. Its global workforce of over 100,000 employees research, design, construct, validate, and distribute electric, solar, algae, and hydrogen-based vehicles. Salifort's end-to-end vertical integration model has made it a global leader at the intersection of alternative energy and automobiles.

Project scenario overview: Salifort Motors

Background

The HR department at Salifort Motors wants to take some initiatives to improve employee satisfaction levels at the company. They collected data from employees, and ask me to provide data-driven suggestions based on my understanding of the data.

The Goal

Analyze the data collected by the HR department and to build a model that predicts whether or not an employee will leave the company.

HR Dataset

contains 15,000 rows and 10 columns

Variable	Description
satisfaction_level	Employee-reported job satisfaction level [0–1]
last_evaluation	Score of employee's last performance review [0–1]
number_project	Number of projects employee contributes to
average_monthly_hours	Average number of hours employee worked per month
time_spend_company	How long the employee has been with the company (years)
Work_accident	Whether or not the employee experienced an accident while at work
left	Whether or not the employee left the company
promotion_last_5years	Whether or not the employee was promoted in the last 5 years
Department	The employee's department
salary	The employee's salary (U.S. dollars)

Step 1. Import Packages and Load Dataset

Import Packages

```
In [1]: # Import packages
        # For data manipulation
        import numpy as np
        import pandas as pd

        # For data visualization
        import matplotlib.pyplot as plt
        import seaborn as sns

        # For displaying all of the columns in dataframes
        pd.set_option('display.max_columns', None)

        # For data modeling
        from xgboost import XGBClassifier
        from xgboost import XGBRegressor
        from xgboost import plot_importance

        from sklearn.linear_model import LogisticRegression
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.ensemble import RandomForestClassifier

        # For metrics and helpful functions
        from sklearn.model_selection import GridSearchCV, train_test_split
        from sklearn.metrics import accuracy_score, precision_score, recall_score,\
        f1_score, confusion_matrix, ConfusionMatrixDisplay, classification_report
        from sklearn.metrics import roc_auc_score, roc_curve
        from sklearn.tree import plot_tree

        # For saving models
        import pickle
```

Load dataset

Pandas is used to read a dataset called HR_capstone_data.csv

```
In [2]: # Load dataset into a dataframe
        df0 = pd.read_csv("HR_capstone_dataset.csv")

        # Display first few rows of the dataframe
        df0.head()
```

Out[2]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left
0	0.38	0.53	2	157	3	0	1
1	0.80	0.86	5	262	6	0	1
2	0.11	0.88	7	272	4	0	1
3	0.72	0.87	5	223	5	0	1
4	0.37	0.52	2	159	3	0	1

Step 2. Data Exploration (Initial EDA and Data Cleaning)

Gather basic information about the data

```
In [3]: # Gather basic information about the data
        df0.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   Department             14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

Rename columns

As a data cleaning step, rename the columns as needed. Standardize the column names so that they are all in snake_case, correct any column names that are misspelled, and make column names more concise as needed.

```
In [5]: # Display all column names
        df0.columns

Out[5]: Index(['satisfaction_level', 'last_evaluation', 'number_project',
               'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
               'promotion_last_5years', 'Department', 'salary'],
              dtype='object')
```

```
In [6]: # Rename columns as needed
        df0 = df0.rename(columns={'Work_accident': 'work_accident',
                                  'average_montly_hours': 'average_monthly_hours',
                                  'time_spend_company': 'tenure',
                                  'Department': 'department'})

        # Display all column names after the update
        df0.columns

Out[6]: Index(['satisfaction_level', 'last_evaluation', 'number_project',
               'average_monthly_hours', 'tenure', 'work_accident', 'left',
               'promotion_last_5years', 'department', 'salary'],
              dtype='object')
```

PACE: Plan

Step 2. Data Exploration (Initial EDA and Data Cleaning)

Check missing values

In [7]:
```
# Check for missing values
df0.isna().sum()
```

Out[7]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_monthly_hours    0
tenure                   0
work_accident            0
left                     0
promotion_last_5years    0
department               0
salary                   0
dtype: int64
```

There are no missing values in the data.

Check duplicates

In [8]:
```
# Check for duplicates
df0.duplicated().sum()
```

Out[8]:
```
3008
```

3,008 rows contain duplicates. That is 20% of the data.

In [9]:
```
# Inspect some rows containing duplicates as needed
df0[df0.duplicated()].head()
```

Out[9]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left	promotion_last_5years	department	salary
396	0.46	0.57	2	139	3	0	1	0	sales	low
866	0.41	0.46	2	128	3	0	1	0	accounting	low
1317	0.37	0.51	2	127	3	0	1	0	sales	medium
1368	0.41	0.52	2	132	3	0	1	0	RandD	low
1461	0.42	0.53	2	142	3	0	1	0	sales	low

The above output shows the first five occurences of rows that are duplicated farther down in the dataframe. How likely is it that these are legitimate entries? In other words, how plausible is it that two employees self-reported the exact same response for every column?

I could perform a likelihood analysis by essentially applying Bayes' theorem and multiplying the probabilities of finding each value in each column, but this does not seem necessary. With several continuous variables across 10 columns, it seems very unlikely that these observations are legitimate. I can proceed by dropping them.

Step 2. Data Exploration (Initial EDA and Data Cleaning)

Drop duplicates

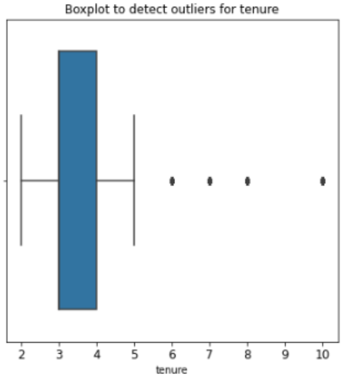
In [10]:
```
# Drop duplicates and save resulting dataframe in a new variable as needed
df1 = df0.drop_duplicates(keep='first')

# Display first few rows of new dataframe as needed
df1.head()
```

Out[10]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left
0	0.38	0.53	2	157	3	0	1
1	0.80	0.86	5	262	6	0	1
2	0.11	0.88	7	272	4	0	1
3	0.72	0.87	5	223	5	0	1
4	0.37	0.52	2	159	3	0	1

Check outliers

In [11]:
```
# Create a boxplot to visualize distribution of `tenure` and detect any outliers
plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for tenure', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df1['tenure'])
plt.show()
```



The boxplot above shows that there are outliers in the 'tenure' variable.

PACE: Plan

Step 2. Data Exploration (Initial EDA and Data Cleaning)

Investigate how many rows in the data contain outliers in the ‘tenure’ column.

In [12]:
```
# Determine the number of rows containing outliers
# Compute the 25th percentile value in `tenure`
percentile25 = df1['tenure'].quantile(0.25)

# Compute the 75th percentile value in `tenure`
percentile75 = df1['tenure'].quantile(0.75)

# Compute the interquartile range in `tenure`
iqr = percentile75 - percentile25

# Define the upper limit and lower limit for non-outlier values in `tenure`
upper_limit = percentile75 + 1.5 * iqr
lower_limit = percentile25 - 1.5 * iqr
print("Lower limit:", lower_limit)
print("Upper limit:", upper_limit)

# Identify subset of data containing outliers in `tenure`
outliers = df1[(df1['tenure'] > upper_limit) | (df1['tenure'] < lower_limit)]

# Count how many rows in the data contain outliers in `tenure`
print("Number of rows in the data containing outliers in `tenure`:", len(outliers))
```

```
Lower limit: 1.5
Upper limit: 5.5
Number of rows in the data containing outliers in `tenure`: 824
```

02

PACE: Analyze

Data Exploration, Data Visualizations,
Correlations between variables, Insight

Step 2. Data Exploration (Continue EDA)

```
In [13]: # Get numbers of people who left vs. stayed
         print(df1['left'].value_counts())
         print()

         # Get percentages of people who left vs. stayed
         print(df1['left'].value_counts(normalize=True))

0    10000
1     1991
Name: left, dtype: int64

0    0.833959
1    0.166041
Name: left, dtype: float64
```

Begin by understanding how many employees left and what percentage of all employees this figure represents.

Step 2. Data Exploration (Data Visualizations)

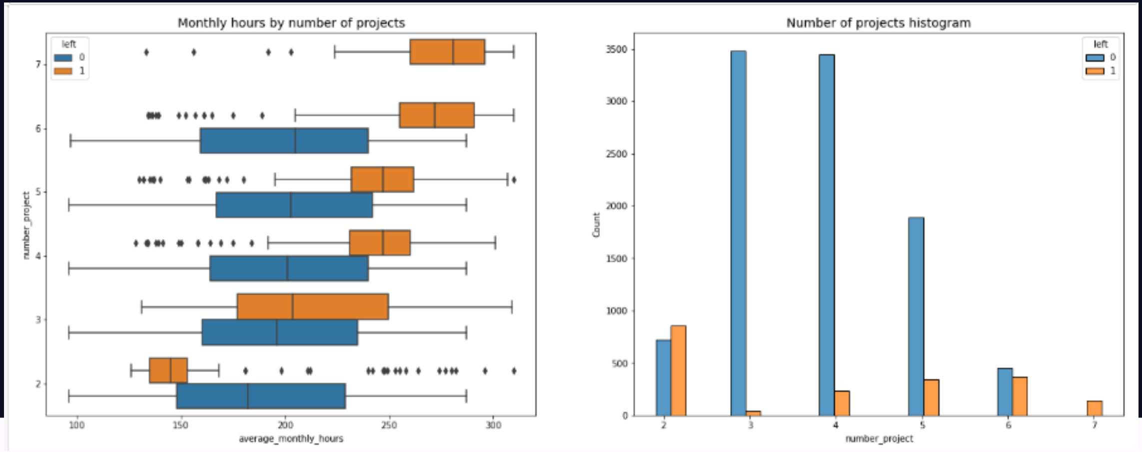
Start by creating a stacked boxplot showing average_monthly_hours distributions for number_project, comparing the distributions of employees who stayed versus those who left.

Box plots are very useful in visualizing distributions within data, but they can be deceiving without the context of how big the sample sizes that they represent are. So, I could also plot a stacked histogram to visualize the distribution of number_project for those who stayed and those who left.

In [14]:

```
# Create a plot as needed
# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (22,8))

# Create boxplot showing `average_monthly_hours` distributions for `number_project`, comparing employees who stayed versus those
sns.boxplot(data=df1, x='average_monthly_hours', y='number_project', hue='left', orient="h", ax=ax[0])
ax[0].invert_yaxis()
ax[0].set_title('Monthly hours by number of projects', fontsize='14')

# Create histogram showing distribution of `number_project`, comparing employees who stayed versus those who left
tenure_stay = df1[df1['left']==0]['number_project']
tenure_left = df1[df1['left']==1]['number_project']
sns.histplot(data=df1, x='number_project', hue='left', multiple='dodge', shrink=2, ax=ax[1])
ax[1].set_title('Number of projects histogram', fontsize='14')

# Display the plots
plt.show()
```

Step 2. Data Exploration (Data Visualizations)



It might be natural that people who work on more projects would also work longer hours. This appears to be the case here, with the mean hours of each group (**stayed** and **left**) increasing with number of projects worked. However, a few things stand out from this plot.

1. There are two groups of employees who left the company: (A) those who worked considerably less than their peers with the same number of projects, and (B) those who worked much more. Of those in group A, it's possible that they were fired. It's also possible that this group includes employees who had already given their notice and were assigned fewer hours because they were already on their way out the door. For those in group B, it's reasonable to infer that they probably quit. The folks in group B likely contributed a lot to the projects they worked in; they might have been the largest contributors to their projects.
2. Everyone with seven projects left the company, and the interquartile ranges of this group and those who left with six projects was ~255–295 hours/month—much more than any other group.
3. The optimal number of projects for employees to work on seems to be 3–4. The ratio of left/stayed is very small for these cohorts.
4. If I assume a work week of 40 hours and two weeks of vacation per year, then the average number of working hours per month of employees working Monday–Friday = 50 weeks * 40 hours per week / 12 months = 166.67 hours per month. This means that, aside from the employees who worked on two projects, every group—even those who didn't leave the company—worked considerably more hours than this. **It seems that employees here are overworked.**

Step 2. Data Exploration (Data Visualizations)

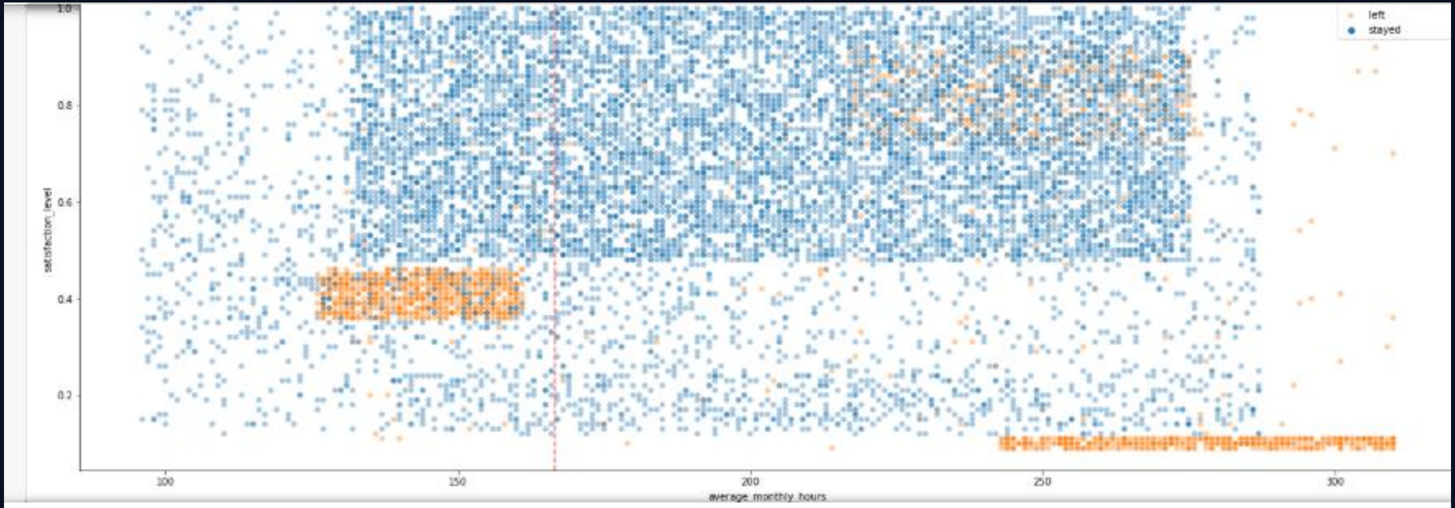
As the next step, I could confirm that all employees with seven projects left.

```
In [15]: # Get value counts of stayed/left for employees with 7 projects
         df1[df1['number_project']==7]['left'].value_counts()

Out[15]: 1    145
         Name: left, dtype: int64
```

Examine the average monthly hours versus the satisfaction levels.

```
In [16]: # Create scatterplot of `average_monthly_hours` versus `satisfaction_level`, comparing employees who stayed v
         plt.figure(figsize=(16, 9))
         sns.scatterplot(data=df1, x='average_monthly_hours', y='satisfaction_level', hue='left', alpha=0.4)
         plt.axvline(x=166.67, color='#ff6361', label='166.67 hrs./mo.', ls='--')
         plt.legend(labels=['166.67 hrs./mo.', 'left', 'stayed'])
         plt.title('Monthly hours by last evaluation score', fontsize='14');
```

Step 2. Data Exploration (Data Visualizations)



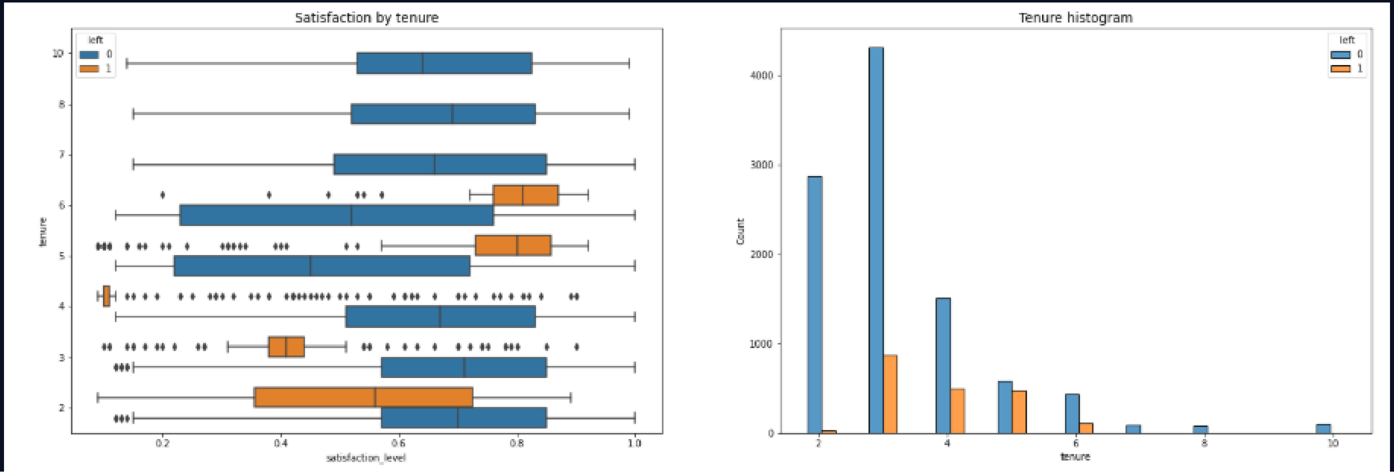
- The scatterplot above shows that there was a sizeable group of employees who worked **~240–315 hours per month**. 315 hours per month is over 75 hours per week for a whole year. It's likely this is related to their **satisfaction levels being close to zero.**
- The plot also shows another group of people who left, those who **had more normal working hours**. Even so, their **satisfaction was only around 0.4**. It's difficult to speculate about why they might have left. It's possible they felt pressured to work more, considering so many of their peers worked more. And that pressure could have lowered their satisfaction levels.
- Finally, there is a group who **worked ~210–280 hours per month**, and they had **satisfaction levels ranging ~0.7–0.9**.

Step 2. Data Exploration (Data Visualizations)

Note the strange shape of the distributions here. This is indicative of data manipulation or synthetic data.

```
#For the next visualization, it might be interesting to visualize satisfaction levels by tenure.
# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (25,8))

# Create boxplot showing distributions of `satisfaction_level` by tenure, comparing employees who stayed versus those who left
sns.boxplot(data=df1, x='satisfaction_level', y='tenure', hue='left', orient="h", ax=ax[0])
ax[0].invert_yaxis()
ax[0].set_title('Satisfaction by tenure', fontsize='14')

# Create histogram showing distribution of `tenure`, comparing employees who stayed versus those who left
tenure_stay = df1[df1['left']==0]['tenure']
tenure_left = df1[df1['left']==1]['tenure']
sns.histplot(data=df1, x='tenure', hue='left', multiple='dodge', shrink=5, ax=ax[1])
ax[1].set_title('Tenure histogram', fontsize='14')

plt.show();
```

Step 2. Data Exploration (Data Visualizations)



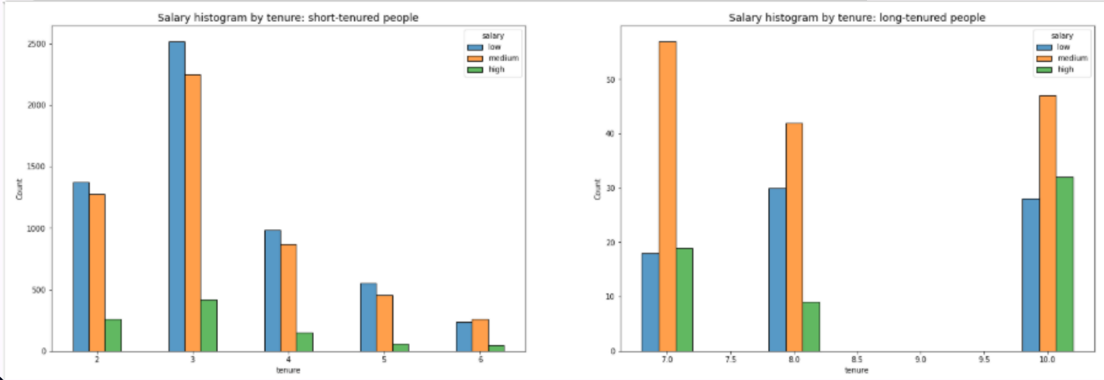
There are many observations you could make from this plot.

- **Employees who left fall into two general categories**: **dissatisfied** employees with shorter tenures and **very satisfied** employees with medium-length tenures.
- **Four-year employees who left** seem to have an **unusually low satisfaction level**. It's worth investigating changes to company policy that might have affected people specifically at the four-year mark, if possible.
- **The longest-tenured** employees **didn't leave**. Their satisfaction levels aligned with those of newer employees who stayed.
- The histogram shows that there are relatively few longer-tenured employees. It's possible that they're the **higher-ranking, higher-paid employees.**

Step 2. Data Exploration (Data Visualizations)

Calculate the mean and median satisfaction scores of employees who left and those who didn't.

```
# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (25,8))

# Define short-tenured employees
tenure_short = df1[df1['tenure'] < 7]

# Define long-tenured employees
tenure_long = df1[df1['tenure'] > 6]

# Plot short-tenured histogram
sns.histplot(data=tenure_short, x='tenure', hue='salary', discrete=1,
             hue_order=['low', 'medium', 'high'], multiple='dodge', shrink=.5, ax=ax[0])
ax[0].set_title('Salary histogram by tenure: short-tenured people', fontsize='14')

# Plot long-tenured histogram
sns.histplot(data=tenure_long, x='tenure', hue='salary', discrete=1,
             hue_order=['low', 'medium', 'high'], multiple='dodge', shrink=.4, ax=ax[1])
ax[1].set_title('Salary histogram by tenure: long-tenured people', fontsize='14');
```

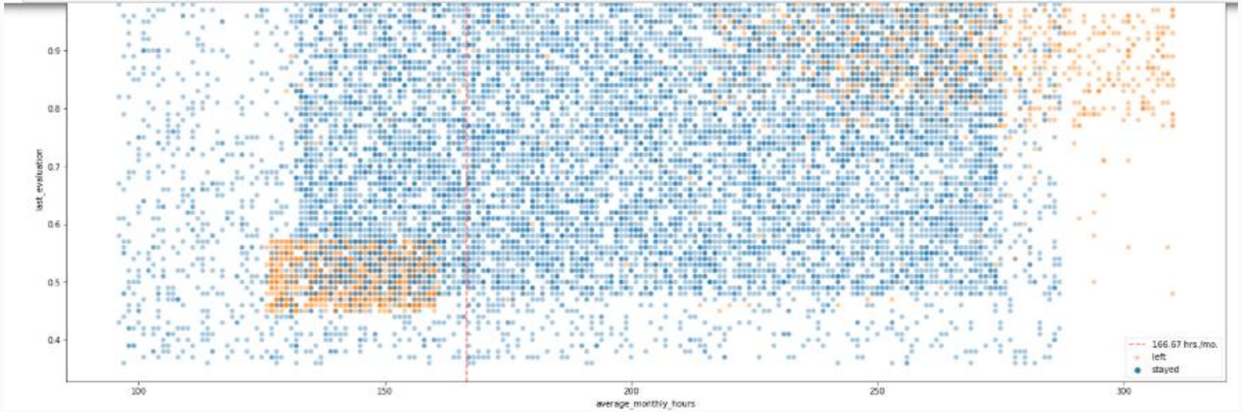


The plots show that long-tenured employees were not disproportionately comprised of higher-paid employees.

Step 2. Data Exploration (Data Visualizations)

Explore whether there's a correlation between working long hours and receiving high evaluation scores. You could create a scatterplot of average_monthly_hours versus last_evaluation.

```
# Create scatterplot of `average_monthly_hours` versus `last_evaluation`
plt.figure(figsize=(25, 9))
sns.scatterplot(data=df1, x='average_monthly_hours', y='last_evaluation', hue='left', alpha=0.4)
plt.axvline(x=166.67, color='#ff6361', label='166.67 hrs./mo.', ls='--')
plt.legend(labels=['166.67 hrs./mo.', 'left', 'stayed'])
plt.title('Monthly hours by last evaluation score', fontsize='14');
```

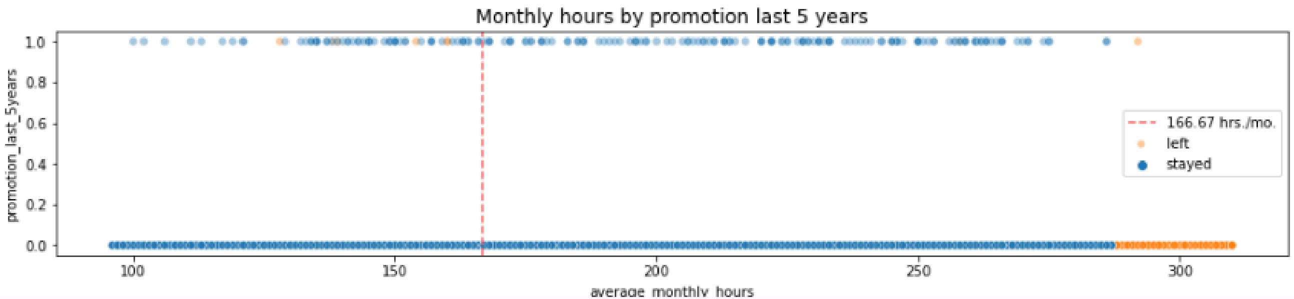


- **The scatterplot indicates two groups of employees who left**: overworked employees who performed very well and employees who worked slightly under the nominal monthly average of 166.67 hours with lower evaluation scores.
- There seems to be a **correlation between hours worked and evaluation score**.
- There isn't a high percentage of employees in the upper left quadrant of this plot; but **working long hours doesn't guarantee a good evaluation score**.
- Most of the employees in this company **work well over 167 hours per month**.

Step 2. Data Exploration (Data Visualizations)

Examine whether employees who worked very long hours were promoted in the last five years

```
In [20]: # Create plot to examine relationship between `average_monthly_hours` and `promotion_last_5years`
plt.figure(figsize=(16, 3))
sns.scatterplot(data=df1, x='average_monthly_hours', y='promotion_last_5years', hue='left', alpha=0.4)
plt.axvline(x=166.67, color='#ff6361', ls='--')
plt.legend(labels=['166.67 hrs./mo.', 'left', 'stayed'])
plt.title('Monthly hours by promotion last 5 years', fontsize='14');
```



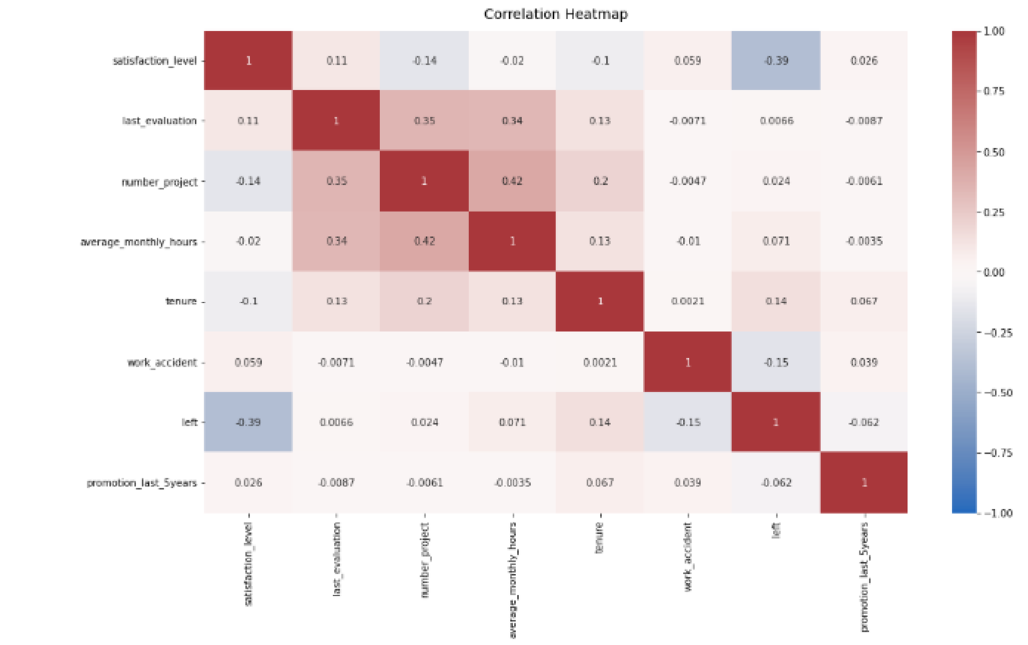
The plot above shows the following:

- very few employees who were promoted in the last five years left
- very few employees who worked the most hours were promoted
- all of the employees who left were working the longest hours

Step 2. Data Exploration (Data Visualizations)

Check for strong correlations between variables in the data.

In [23]:
```
# Plot a correlation heatmap
plt.figure(figsize=(16, 9))
heatmap = sns.heatmap(df0.corr(), vmin=-1, vmax=1, annot=True, cmap=sns.color_palette("vlag", as_cmap=True))
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':14}, pad=12);
```



The correlation heatmap confirms that the number of projects, monthly hours, and evaluation scores all have some **positive correlation with each other**, and whether an employee leaves is negatively correlated with their satisfaction level.

Insight

It appears that employees are leaving the company as a result of **poor management**.

- Leaving is tied to longer working hours, many projects, and generally lower satisfaction levels.
- It can be ungratifying to work long hours and not receive promotions or good evaluation scores.
- There's a sizeable group of employees at this company who are probably burned out.
- It also appears that if an employee has spent more than six years at the company, they tend not to leave.

03

PACE: Construct

Model Building

PACE: Construct Stage

Determine which models are most appropriate

Construct the model

Confirm model assumptions

Evaluate the model

Identify the type of prediction

My goal is to predict whether an employee leaves the company, which is a **categorical** outcome variable. So this stage involves classification. More specifically, this involves binary classification, since the outcome variable left can be either 1 (indicating employee left) or 0 (indicating employee didn't leave).

Identify the types of models

Since the variable you want to predict (whether an employee leaves the company) is categorical, so I will build a **Logistic Regression model and Tree-based Machine Learning model**, then compare them

Logistic Regression Model Assumptions

- Outcome variable is categorical
- Observations are independent of each other
- No severe multicollinearity among X variables
- No extreme outliers
- Linear relationship between each X variable and the logit of the outcome variable
- Sufficiently large sample size

Logistic Regression Model Assumptions

Binomial logistic regression suits this project because it involves binary classification. Before splitting the data, encode the non-numeric variables. There are two: department and salary.

- department is a categorical variable, which means you can dummy it for modeling.
- salary is categorical too, but it's ordinal. There's a hierarchy to the categories, so it's better not to dummy this column, but rather to convert the levels to numbers, 0–2.

In [24]:

```
# Copy the dataframe
df_enc = df1.copy()

# Encode the `salary` column as an ordinal numeric category
df_enc['salary'] = (
    df_enc['salary'].astype('category')
    .cat.set_categories(['low', 'medium', 'high'])
    .cat.codes
)

# Dummy encode the `department` column
df_enc = pd.get_dummies(df_enc, drop_first=False)

# Display the new dataframe
df_enc.head()
```

Out[24]:

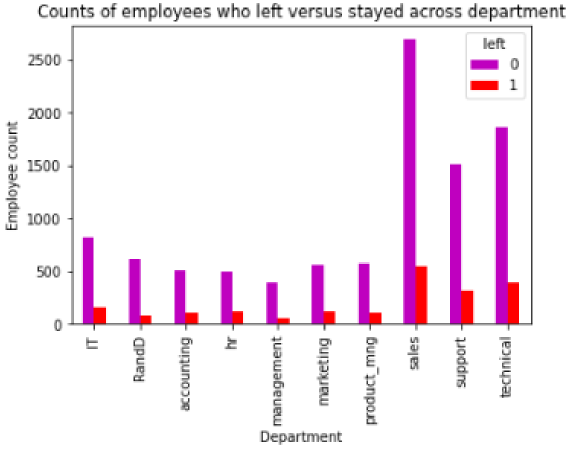
	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left	promotion_last_5years	salary	department_IT	departn
0	0.38	0.53	2	157	3	0	1	0	0	0	
1	0.80	0.86	5	262	6	0	1	0	1	0	
2	0.11	0.88	7	272	4	0	1	0	1	0	
3	0.72	0.87	5	223	5	0	1	0	0	0	
4	0.37	0.52	2	159	3	0	1	0	0	0	

Logistic Regression Model Assumptions

In [25]:
```
# Create a heatmap to visualize how correlated variables are
plt.figure(figsize=(8, 6))
sns.heatmap(df_enc[['satisfaction_level', 'last_evaluation', 'number_project', 'average_monthly_hours', 'tenure']]
            .corr(), annot=True, cmap="crest")
plt.title('Heatmap of the dataset')
plt.show()
```

Logistic Regression Model Assumptions

In [26]:
```
# Create a stacked bart plot to visualize number of employees across department, comparing those who left with those who didn't
# In the legend, 0 (purple color) represents employees who did not leave, 1 (red color) represents employees who left
pd.crosstab(df1['department'], df1['left']).plot(kind ='bar',color='mr')
plt.title('Counts of employees who left versus stayed across department')
plt.ylabel('Employee count')
plt.xlabel('Department')
plt.show()
```



Logistic Regression Model Assumptions

Since logistic regression is quite sensitive to outliers, it would be a good idea at this stage to remove the outliers in the tenure column that were identified earlier.

In [27]:
```
# Select rows without outliers in `tenure` and save resulting dataframe in a new variable
df_logreg = df_enc[(df_enc['tenure'] >= lower_limit) & (df_enc['tenure'] <= upper_limit)]

# Display first few rows of new dataframe
df_logreg.head()
```

Out[27]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left	promotion_last_5years	salary	department_IT	departn
0	0.38	0.53	2	157	3	0	1	0	0	0	
2	0.11	0.88	7	272	4	0	1	0	1	0	
3	0.72	0.87	5	223	5	0	1	0	0	0	
4	0.37	0.52	2	159	3	0	1	0	0	0	
5	0.41	0.50	2	153	3	0	1	0	0	0	

In [28]:
```
# Isolate the outcome variable, which is the variable that I want my model to predict.
y = df_logreg['left']

# Display first few rows of the outcome variable
y.head()
```

Out[28]:
```
0    1
2    1
3    1
4    1
5    1
Name: left, dtype: int64
```

Logistic Regression Model Assumptions

Since logistic regression is quite sensitive to outliers, it would be a good idea at this stage to remove the outliers in the tenure column that were identified earlier.

In [27]:
```python
# Select rows without outliers in `tenure` and save resulting dataframe in a new variable
df_logreg = df_enc[(df_enc['tenure'] >= lower_limit) & (df_enc['tenure'] <= upper_limit)]

# Display first few rows of new dataframe
df_logreg.head()
```

Out[27]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left	promotion_last_5years	salary	department_IT	departn
0	0.38	0.53	2	157	3	0	1	0	0	0	
2	0.11	0.88	7	272	4	0	1	0	1	0	
3	0.72	0.87	5	223	5	0	1	0	0	0	
4	0.37	0.52	2	159	3	0	1	0	0	0	
5	0.41	0.50	2	153	3	0	1	0	0	0	

In [28]:
```python
# Isolate the outcome variable, which is the variable that I want my model to predict.
y = df_logreg['left']

# Display first few rows of the outcome variable
y.head()
```

Out[28]:
```
0    1
2    1
3    1
4    1
5    1
Name: left, dtype: int64
```

Logistic Regression Model Assumptions

In [29]:
```
# Select the features you want to use in your model
X = df_logreg.drop('left', axis=1)

# Display the first few rows of the selected features
X.head()
```

Out[29]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	promotion_last_5years	salary	department_IT	department_
0	0.38	0.53	2	157	3	0	0	0	0	
2	0.11	0.88	7	272	4	0	0	1	0	
3	0.72	0.87	5	223	5	0	0	0	0	
4	0.37	0.52	2	159	3	0	0	0	0	
5	0.41	0.50	2	153	3	0	0	0	0	

In [30]:
```
# Split the data into training set and testing set.
#Don't forget to stratify based on the values in y, since the classes are unbalanced.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, stratify=y, random_state=42)
```

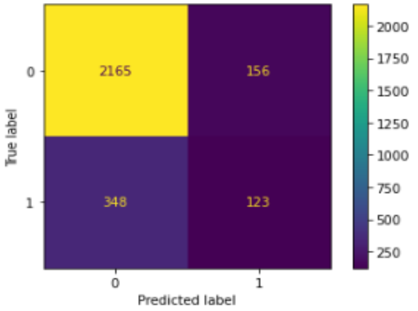
In [31]:
```
#Construct a logistic regression model and fit it to the training dataset
log_clf = LogisticRegression(random_state=42, max_iter=500).fit(X_train, y_train)
```

In [32]:
```
#Test the logistic regression model: use the model to make predictions on the test set.
# Use the logistic regression model to get predictions on the test set
y_pred = log_clf.predict(X_test)
```

Logistic Regression Model Assumptions

Create a confusion matrix to visualize the results of the logistic regression model.

```
In [33]: # Compute values for confusion matrix
         log_cm = confusion_matrix(y_test, y_pred, labels=log_clf.classes_)

         # Create display of confusion matrix
         log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm,
                                           display_labels=log_clf.classes_)

         # Plot confusion matrix
         log_disp.plot(values_format='')

         # Display plot
         plt.show()
```



The upper-left quadrant displays the number of **true negatives**. The upper-right quadrant displays the number of **false positives**. The bottom-left quadrant displays the number of **false negatives**. The bottom-right quadrant displays the number of **true positives**.

- *True negatives*: The number of people who did not leave that the model accurately predicted did not leave
- *False positives*: The number of people who did not leave the model inaccurately predicted as leaving
- *False negatives*: The number of people who left that the model inaccurately predicted did not leave
- *True positives*: The number of people who left the model accurately predicted as leaving

Logistic Regression Model Assumptions

Create a classification report that includes precision, recall, f1-score, and accuracy metrics to evaluate the performance of the logistic regression model.

Check the class balance in the data. In other words, check the value counts in the left column. Since this is a binary classification task, the class balance informs the way you interpret accuracy metrics.

```
In [34]: df_logreg['left'].value_counts(normalize=True)

Out[34]: 0    0.831468
         1    0.168532
         Name: left, dtype: float64
```

There is an approximately 83%-17% split. So the data is not perfectly balanced, but it is not too imbalanced. In this case, I can use this data without modifying the class balance and continue evaluating the model.

```
In [35]: # Create classification report for logistic regression model
         target_names = ['Predicted would not leave', 'Predicted would leave']
         print(classification_report(y_test, y_pred, target_names=target_names))

                            precision    recall  f1-score   support

Predicted would not leave       0.86      0.93      0.90      2321
    Predicted would leave       0.44      0.26      0.33       471

                 accuracy                           0.82      2792
                macro avg       0.65      0.60      0.61      2792
             weighted avg       0.79      0.82      0.80      2792
```

The classification report shows that the logistic regression model achieved a **precision of 79%, recall of 82%, f1-score of 80% (all weighted averages),** and **accuracy of 82%**. However, if it's most important to predict employees who leave, then the scores are significantly lower.

Tree-based Model

This approach covers implementation of Decision Tree and Random Forest.

```
In [36]: # Isolate the outcome variable
         y = df_enc['left']

         # Display the first few rows of `y`
         y.head()

Out[36]: 0    1
         1    1
         2    1
         3    1
         4    1
         Name: left, dtype: int64
```

```
In [37]: # Select the features
         X = df_enc.drop('left', axis=1)

         # Display the first few rows of `X`
         X.head()
```

Out[37]:

	satisfaction_level	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	promotion_last_5years	salary	department_IT	department_
0	0.38	0.53	2	157	3	0	0	0	0	
1	0.80	0.86	5	262	6	0	0	1	0	
2	0.11	0.88	7	272	4	0	0	1	0	
3	0.72	0.87	5	223	5	0	0	0	0	
4	0.37	0.52	2	159	3	0	0	0	0	

```
In [38]: #Split the data into training, validating, and testing sets.
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, stratify=y, random_state=0)
```

Decision Tree - Round 1

Construct a decision tree model and set up cross-validated grid-search to exhaustively search for the best model parameters.

In [39]:
```
# Instantiate model
tree = DecisionTreeClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth':[4, 6, 8, None],
             'min_samples_leaf': [2, 5, 1],
             'min_samples_split': [2, 4, 6]
             }

# Assign a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}

# Instantiate GridSearch
tree1 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

Decision Tree - Round 1

Fit the decision tree model to the training data.

```
In [40]: %%time
         tree1.fit(X_train, y_train)

         CPU times: user 2.92 s, sys: 172 ms, total: 3.09 s
         Wall time: 3.09 s

Out[40]: GridSearchCV(cv=4, error_score=nan,
                      estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                                       criterion='gini', max_depth=None,
                                                       max_features=None,
                                                       max_leaf_nodes=None,
                                                       min_impurity_decrease=0.0,
                                                       min_impurity_split=None,
                                                       min_samples_leaf=1,
                                                       min_samples_split=2,
                                                       min_weight_fraction_leaf=0.0,
                                                       presort='deprecated',
                                                       random_state=0, splitter='best'),
                      iid='deprecated', n_jobs=None,
                      param_grid={'max_depth': [4, 6, 8, None],
                                  'min_samples_leaf': [2, 5, 1],
                                  'min_samples_split': [2, 4, 6]},
                      pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
                      scoring={'accuracy', 'roc_auc', 'precision', 'recall', 'f1'},
                      verbose=0)
```

Identify the optimal values for the decision tree parameters.

```
In [41]: # Check best parameters
         tree1.best_params_

Out[41]: {'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 2}

In [42]: #Identify the best AUC score achieved by the decision tree model on the training set.
         # Check best AUC score on CV
         tree1.best_score_

Out[42]: 0.969819392792457
```

This is a strong AUC score, which shows that this model can predict employees who will leave very well.

Decision Tree - Round 1

A function that will help to extract all the scores from the grid search.

```
In [43]: def make_results(model_name:str, model_object, metric:str):
             # Create dictionary that maps input metric to actual metric name in GridSearchCV
             metric_dict = {'auc': 'mean_test_roc_auc',
                            'precision': 'mean_test_precision',
                            'recall': 'mean_test_recall',
                            'f1': 'mean_test_f1',
                            'accuracy': 'mean_test_accuracy'
                           }

             # Get all the results from the CV and put them in a df
             cv_results = pd.DataFrame(model_object.cv_results_)

             # Isolate the row of the df with the max(metric) score
             best_estimator_results = cv_results.iloc[cv_results[metric_dict[metric]].idxmax(), :]

             # Extract Accuracy, precision, recall, and f1 score from that row
             auc = best_estimator_results.mean_test_roc_auc
             f1 = best_estimator_results.mean_test_f1
             recall = best_estimator_results.mean_test_recall
             precision = best_estimator_results.mean_test_precision
             accuracy = best_estimator_results.mean_test_accuracy

             # Create table of results
             table = pd.DataFrame()
             table = pd.DataFrame({'model': [model_name],
                                   'precision': [precision],
                                   'recall': [recall],
                                   'F1': [f1],
                                   'accuracy': [accuracy],
                                   'auc': [auc]
                                  })

             return table
```

Identify the optimal values for the decision tree parameters.

```
In [44]: # Get all CV scores
         tree1_cv_results = make_results('decision tree cv', tree1, 'auc')
         tree1_cv_results
```

Out[44]:

	model	precision	recall	F1	accuracy	auc
0	decision tree cv	0.914552	0.916949	0.915707	0.971978	0.969819

All of these scores from the decision tree model are strong indicators of good model performance.

Note that decision trees can be vulnerable to overfitting, and **random forests** avoid overfitting by incorporating multiple trees to make predictions. Next, I construct a random forest model.

Random Forest - Round 1

Construct a random forest model and set up cross-validated grid-search to exhaustively search for the best model parameters.

In [45]:
```
# Instantiate model
rf = RandomForestClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth': [3,5, None],
             'max_features': [1.0],
             'max_samples': [0.7, 1.0],
             'min_samples_leaf': [1,2,3],
             'min_samples_split': [2,3,4],
             'n_estimators': [300, 500],
             }

# Assign a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}

# Instantiate GridSearch
rf1 = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

Random Forest - Round 1

Fit the random forest model to the training data.

```
In [46]: %%time
         rf1.fit(X_train, y_train) # --> Wall time: ~10min

         CPU times: user 9min 44s, sys: 8.16 s, total: 9min 53s
         Wall time: 9min 53s

Out[46]: GridSearchCV(cv=4, error_score=nan,
                      estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                                       class_weight=None,
                                                       criterion='gini', max_depth=None,
                                                       max_features='auto',
                                                       max_leaf_nodes=None,
                                                       max_samples=None,
                                                       min_impurity_decrease=0.0,
                                                       min_impurity_split=None,
                                                       min_samples_leaf=1,
                                                       min_samples_split=2,
                                                       min_weight_fraction_leaf=0.0,
                                                       n_estimators=100, n_jobs=None,...
                                                       verbose=0, warm_start=False),
                      iid='deprecated', n_jobs=None,
                      param_grid={'max_depth': [3, 5, None], 'max_features': [1.0],
                                  'max_samples': [0.7, 1.0],
                                  'min_samples_leaf': [1, 2, 3],
                                  'min_samples_split': [2, 3, 4],
                                  'n_estimators': [300, 500]},
                      pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
                      scoring={'accuracy', 'roc_auc', 'precision', 'recall', 'f1'},
                      verbose=0)
```

Random Forest - Round 1

Define functions to pickle the model and read in the model.

```
In [48]: def write_pickle(path, model_object, save_as:str):
             '''
             In:
                 path:         path of folder where you want to save the pickle
                 model_object: a model you want to pickle
                 save_as:      filename for how you want to save the model

             Out: A call to pickle the model in the folder indicated
             '''

             with open(path + save_as + '.pickle', 'wb') as to_write:
                 pickle.dump(model_object, to_write)
```

```
In [49]: def read_pickle(path, saved_model_name:str):
             '''
             In:
                 path:             path to folder where you want to read from
                 saved_model_name: filename of pickled model you want to read in

             Out:
                 model: the pickled model
             '''
             with open(path + saved_model_name + '.pickle', 'rb') as to_read:
                 model = pickle.load(to_read)

             return model
```

Use the functions to save the model in a pickle file and then read it in

```
In [50]: # Write pickle
         write_pickle(path, rf1, 'hr_rf1')
```

```
In [51]: # Read pickle
         rf1 = read_pickle(path, 'hr_rf1')
```

Identify the best AUC score achieved by the random forest model on the training set.

```
In [52]: # Check best AUC score on CV
         rf1.best_score_

Out[52]: 0.9804250949807172
```

Identify the optimal values for the parameters of the random forest model.

```
In [53]: # Check best params
         rf1.best_params_

Out[53]: {'max_depth': 5,
          'max_features': 1.0,
          'max_samples': 0.7,
          'min_samples_leaf': 1,
          'min_samples_split': 4,
          'n_estimators': 500}
```

Random Forest - Round 1

Collect the evaluation scores on the training set for the decision tree and random forest models.

```
In [54]: # Get all CV scores
         rf1_cv_results = make_results('random forest cv', rf1, 'auc')
         print(tree1_cv_results)
         print(rf1_cv_results)

              model  precision    recall        F1  accuracy       auc
0  decision tree cv   0.914552  0.916949  0.915707  0.971978  0.969819
              model  precision    recall        F1  accuracy       auc
0  random forest cv   0.950023  0.915614  0.932467  0.977983  0.980425
```

The evaluation scores of the random forest model are better than those of the decision tree model, with the exception of recall (the recall score of the random forest model is approximately 0.001 lower, which is a negligible amount). This indicates that the random forest model mostly outperforms the decision tree model.

Next, I can evaluate the final model on the test set.

Define a function that gets all the scores from a model's predictions.

```
In [55]: def get_scores(model_name:str, model, X_test_data, y_test_data):
             '''
             Generate a table of test scores.

             In:
                 model_name (string):  How you want your model to be named in the output table
                 model:                A fit GridSearchCV object
                 X_test_data:          numpy array of X_test data
                 y_test_data:          numpy array of y_test data

             Out: pandas df of precision, recall, f1, accuracy, and AUC scores for your model
             '''

             preds = model.best_estimator_.predict(X_test_data)

             auc = roc_auc_score(y_test_data, preds)
             accuracy = accuracy_score(y_test_data, preds)
             precision = precision_score(y_test_data, preds)
             recall = recall_score(y_test_data, preds)
             f1 = f1_score(y_test_data, preds)

             table = pd.DataFrame({'model': [model_name],
                                   'precision': [precision],
                                   'recall': [recall],
                                   'f1': [f1],
                                   'accuracy': [accuracy],
                                   'AUC': [auc]
                                  })

             return table
```

Random Forest - Round 1

Use the best performing model to predict on the test set.

```
In [56]: # Get predictions on test data
         rf1_test_scores = get_scores('random forest1 test', rf1, X_test, y_test)
         rf1_test_scores
```

Out[56]:

	model	precision	recall	f1	accuracy	AUC
0	random forest1 test	0.964211	0.919679	0.941418	0.980987	0.956439

The test scores are very similar to the validation scores, which is good. This appears to be a strong model. Since this test set was only used for this model, I can be more confident that my model's performance on this data is representative of how it will perform on new, unseen data.

Feature Engineering

RF Evaluation Score

Out[56]:

	model	precision	recall	f1	accuracy	AUC
0	random forest1 test	0.964211	0.919679	0.941418	0.980987	0.956439

In this case, it's likely that the company won't have satisfaction levels reported for all of its employees. It's also possible that the average_monthly_hours column is a source of some data leakage. If employees have already decided upon quitting, or have already been identified by management as people to be fired, they may be working fewer hours.

There is a chance that there is some **data leakage** when the evaluation score is significantly high. **Data leakage is** when you use data to train your model that should not be used during training, either because it appears in the test data or because it's not data that you'd expect to have when the model is actually deployed. Training a model with leaked data can give **an unrealistic score** that is not replicated in production.

The first round of decision tree and random forest models **included all variables as features**. This next round will incorporate feature engineering to build improved models.

Feature Engineering

First, proceed by dropping satisfaction_level and creating a new feature that roughly captures whether an employee is overworked. Call this new feature overworked. It will be a binary variable.

In [57]:
```
# Drop `satisfaction_level` and save resulting dataframe in new variable
df2 = df_enc.drop('satisfaction_level', axis=1)

# Display first few rows of new dataframe
df2.head()
```

Out[57]:

	last_evaluation	number_project	average_monthly_hours	tenure	work_accident	left	promotion_last_5years	salary	department_IT	department_RandD	depar
0	0.53	2	157	3	0	1	0	0	0	0	
1	0.86	5	262	6	0	1	0	1	0	0	
2	0.88	7	272	4	0	1	0	1	0	0	
3	0.87	5	223	5	0	1	0	0	0	0	
4	0.52	2	159	3	0	1	0	0	0	0	

In [58]:
```
# Create `overworked` column. For now, it's identical to average monthly hours.
df2['overworked'] = df2['average_monthly_hours']

# Inspect max and min average monthly hours values
print('Max hours:', df2['overworked'].max())
print('Min hours:', df2['overworked'].min())
```

```
Max hours: 310
Min hours: 96
```

Feature Engineering

166.67 is approximately the **average** number of monthly hours for someone who works 50 weeks per year, 5 days per week, 8 hours per day. I could define being **overworked as working more than 175 hours per month** on average. To make the overworked column binary, reassign the column using a Boolean mask.

- df3['overworked'] > 175 creates a series of Booleans, consisting of True for every value > 175 and False for every values ≤ 175
- .astype(int) converts all True to 1 and all False to 0

In [59]:
```
# Define `overworked` as working > 175 hrs/week
df2['overworked'] = (df2['overworked'] > 175).astype(int)

# Display first few rows of new column
df2['overworked'].head()
```

Out[59]:
```
0    0
1    1
2    1
3    1
4    0
Name: overworked, dtype: int64
```

In [60]:
```
# Drop the `average_monthly_hours` column
df2 = df2.drop('average_monthly_hours', axis=1)

# Display first few rows of resulting dataframe
df2.head()
```

Out[60]:

	last_evaluation	number_project	tenure	work_accident	left	promotion_last_5years	salary
0	0.53	2	3	0	1	0	0
1	0.86	5	6	0	1	0	1
2	0.88	7	4	0	1	0	1
3	0.87	5	5	0	1	0	0

In [61]:
```
# Again, isolate the features and target variables
# Isolate the outcome variable
y = df2['left']

# Select the features
X = df2.drop('left', axis=1)
```

Split the data into training and testing sets.

In [62]:
```
# Create test data
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.25, stratify=y, random_state=0)
```

Decision Tree - Round 2

```
In [63]: # Instantiate model
         tree = DecisionTreeClassifier(random_state=0)

         # Assign a dictionary of hyperparameters to search over
         cv_params = {'max_depth':[4, 6, 8, None],
                      'min_samples_leaf': [2, 5, 1],
                      'min_samples_split': [2, 4, 6]
                      }

         # Assign a dictionary of scoring metrics to capture
         scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}

         # Instantiate GridSearch
         tree2 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

```
In [64]: %%time
         tree2.fit(X_train, y_train)

         CPU times: user 2.51 s, sys: 6.61 ms, total: 2.52 s
         Wall time: 2.52 s

Out[64]: GridSearchCV(cv=4, error_score=nan,
                      estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                                       criterion='gini', max_depth=None,
                                                       max_features=None,
                                                       max_leaf_nodes=None,
                                                       min_impurity_decrease=0.0,
                                                       min_impurity_split=None,
                                                       min_samples_leaf=1,
                                                       min_samples_split=2,
                                                       min_weight_fraction_leaf=0.0,
                                                       presort='deprecated',
                                                       random_state=0, splitter='best'),
                      iid='deprecated', n_jobs=None,
                      param_grid={'max_depth': [4, 6, 8, None],
                                  'min_samples_leaf': [2, 5, 1],
                                  'min_samples_split': [2, 4, 6]},
                      pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
                      scoring={'accuracy', 'roc_auc', 'precision', 'recall', 'f1'},
                      verbose=0)
```

Decision Tree - Round 2

In [63]:
```
# Instantiate model
tree = DecisionTreeClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth':[4, 6, 8, None],
             'min_samples_leaf': [2, 5, 1],
             'min_samples_split': [2, 4, 6]
             }

# Assign a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}

# Instantiate GridSearch
tree2 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

In [64]:
```
%%time
tree2.fit(X_train, y_train)
```

```
CPU times: user 2.51 s, sys: 6.61 ms, total: 2.52 s
Wall time: 2.52 s
```

Out[64]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=0, splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': [4, 6, 8, None],
                         'min_samples_leaf': [2, 5, 1],
                         'min_samples_split': [2, 4, 6]},
             pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
             scoring={'accuracy', 'roc_auc', 'precision', 'recall', 'f1'},
             verbose=0)
```

Decision Tree - Round 2

```
In [65]: # Check best params
         tree2.best_params_
```

```
Out[65]: {'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 6}
```

```
In [66]: # Check best AUC score on CV
         tree2.best_score_
```

```
Out[66]: 0.9586752505340426
```

This model performs very well, even without satisfaction levels and detailed hours worked data.

Next, check the other scores.

```
In [67]: # Get all CV scores
         tree2_cv_results = make_results('decision tree2 cv', tree2, 'auc')
         print(tree1_cv_results)
         print(tree2_cv_results)
```

```
               model  precision    recall        F1  accuracy       auc
0   decision tree cv   0.914552  0.916949  0.915707  0.971978  0.969819
                model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.856693  0.903553  0.878882  0.958523  0.958675
```

Some of the other scores fell. That's to be expected given fewer features were taken into account in this round of the model. Still, the scores are very good.

Random Forest - Round 2

```
In [68]: # Instantiate model
rf = RandomForestClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth': [3,5, None],
             'max_features': [1.0],
             'max_samples': [0.7, 1.0],
             'min_samples_leaf': [1,2,3],
             'min_samples_split': [2,3,4],
             'n_estimators': [300, 500],
             }

# Assign a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}

# Instantiate GridSearch
rf2 = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

```
In [69]: %%time
rf2.fit(X_train, y_train) # --> Wall time: 7min 5s

CPU times: user 7min 25s, sys: 1.89 s, total: 7min 27s
Wall time: 7min 27s

Out[69]: GridSearchCV(cv=4, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,...
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': [3, 5, None], 'max_features': [1.0],
                         'max_samples': [0.7, 1.0],
                         'min_samples_leaf': [1, 2, 3],
                         'min_samples_split': [2, 3, 4],
                         'n_estimators': [300, 500]},
             pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
             scoring={'accuracy', 'roc_auc', 'precision', 'recall', 'f1'},
             verbose=0)
```

Random Forest - Round 2

In [70]:
```
# Write pickle
write_pickle(path, rf2, 'hr_rf2')
```

In [71]:
```
# Read in pickle
rf2 = read_pickle(path, 'hr_rf2')
```

In [72]:
```
# Check best params
rf2.best_params_
```

Out[72]:
```
{'max_depth': 5,
 'max_features': 1.0,
 'max_samples': 0.7,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 300}
```

In [73]:
```
# Check best AUC score on CV
rf2.best_score_
```

Out[73]:
```
0.9648100662833985
```

In [74]:
```
# Get all CV scores
rf2_cv_results = make_results('random forest2 cv', rf2, 'auc')
print(tree2_cv_results)
print(rf2_cv_results)
```

```
              model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.856693  0.903553  0.878882  0.958523  0.958675
              model  precision    recall        F1  accuracy       auc
0  random forest2 cv   0.866758  0.878754  0.872407  0.957411  0.96481
```

Again, the scores dropped slightly, but the random forest performs better than the decision tree if using AUC as the deciding metric. Score the champion model on the test set now.

In [75]:
```
# Get predictions on test data
rf2_test_scores = get_scores('random forest2 test', rf2, X_test, y_test)
rf2_test_scores
```

Out[75]:

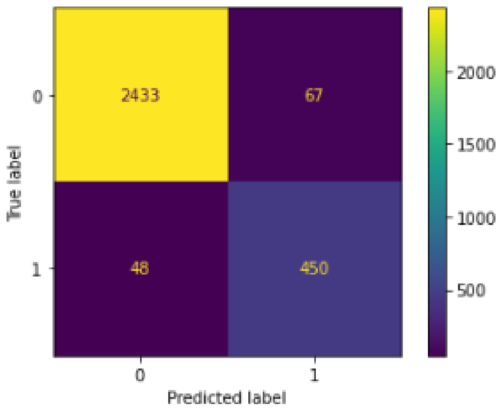
	model	precision	recall	f1	accuracy	AUC
0	random forest2 test	0.870406	0.903614	0.8867	0.961641	0.938407

This seems to be a stable, well-performing final model.

Random Forest - Round 2

Plot a confusion matrix to visualize how well it predicts on the test set.

```
In [76]: # Generate array of values for confusion matrix
preds = rf2.best_estimator_.predict(X_test)
cm = confusion_matrix(y_test, preds, labels=rf2.classes_)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=rf2.classes_)
disp.plot(values_format='');
```

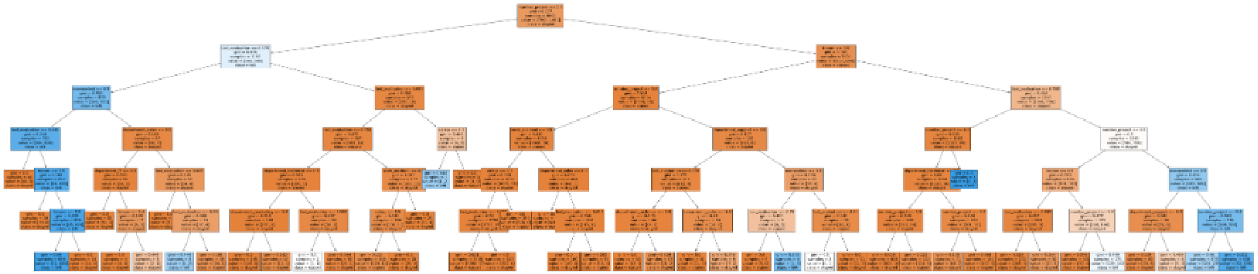


The model **predicts more false positives** than false negatives, which means that some **employees may be identified as at risk of quitting or getting fired,** when that's actually not the case. But this is still a strong model.

For exploratory purpose, I will inspect the splits of the decision tree model and the most important features in the random forest model.

Decision Tree splits

```
In [79]: # Plot the tree
         plt.figure(figsize=(85,20))
         plot_tree(tree2.best_estimator_, max_depth=6, fontsize=14, feature_names=X.columns,
                   class_names={0:'stayed', 1:'left'}, filled=True);
         plt.show()
```



Decision Tree Feature Importance

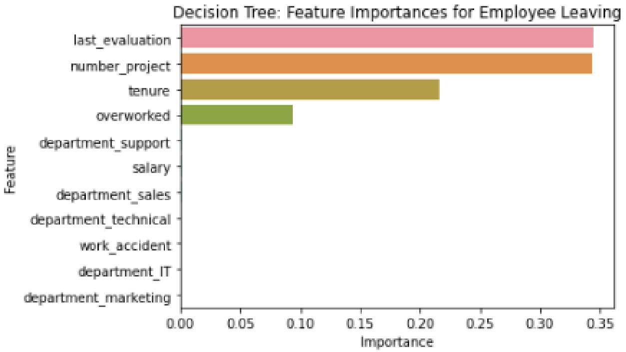
In [80]:
```
#tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_, columns=X.columns)
tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,
                                 columns=['gini_importance'],
                                 index=X.columns
                                )
tree2_importances = tree2_importances.sort_values(by='gini_importance', ascending=False)

# Only extract the features with importances > 0
tree2_importances = tree2_importances[tree2_importances['gini_importance'] != 0]
tree2_importances
```

Out[80]:

	gini_importance
last_evaluation	0.343958
number_project	0.343385
tenure	0.215681
overworked	0.093498
department_support	0.001142
salary	0.000910
department_sales	0.000607
department_technical	0.000418
work_accident	0.000183
department_IT	0.000139
department_marketing	0.000078

Decision Tree Feature Importance

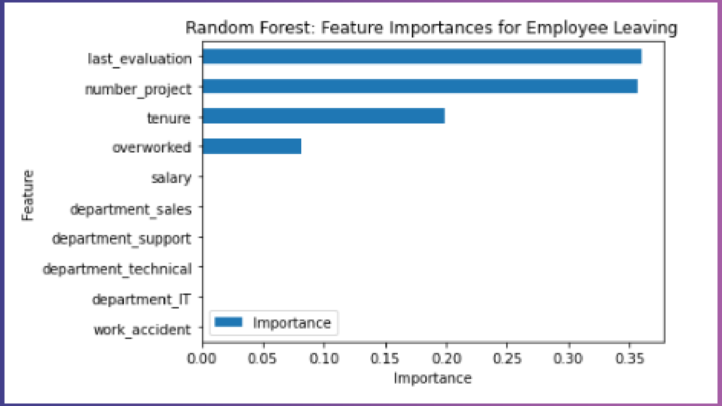
```
In [81]: #  Create a barplot to visualize the decision tree feature importances
sns.barplot(data=tree2_importances, x="gini_importance", y=tree2_importances.index, orient='h')
plt.title("Decision Tree: Feature Importances for Employee Leaving", fontsize=12)
plt.ylabel("Feature")
plt.xlabel("Importance")
plt.show()
```



The barplot shows that in this decision tree model, last_evaluation, number_project, tenure, and overworked have the highest importance, in that order. These variables are most helpful in predicting the outcome variable, left.

Random Forest Feature Importance

```
In [82]: # Get feature importances
         feat_impt = rf2.best_estimator_.feature_importances_

         # Get indices of top 10 features
         ind = np.argpartition(rf2.best_estimator_.feature_importances_, -10)[-10:]

         # Get column labels of top 10 features
         feat = X.columns[ind]

         # Filter `feat_impt` to consist of top 10 feature importances
         feat_impt = feat_impt[ind]

         y_df = pd.DataFrame({"Feature":feat,"Importance":feat_impt})
         y_sort_df = y_df.sort_values("Importance")
         fig = plt.figure()
         ax1 = fig.add_subplot(111)

         y_sort_df.plot(kind='barh',ax=ax1,x="Feature",y="Importance")

         ax1.set_title("Random Forest: Feature Importances for Employee Leaving", fontsize=12)
         ax1.set_ylabel("Feature")
         ax1.set_xlabel("Importance")

         plt.show()
```



The plot shows that in this random forest model, last_evaluation, number_project, tenure, and overworked have the highest importance, in that order. These variables are most helpful in predicting the outcome variable, left, and they are the same as the ones used by the decision tree model.

04

PACE: Execute

Interpret model performance and results, Share actionable steps with stakeholders

Step 4. Results and Evaluation

1. Interpret model
2. Evaluate model performance using metrics
3. Prepare results, visualizations, and actionable steps to share with stakeholders

Summary of Model Results

Summary

Logistic Regression

The logistic regression model achieved precision of 80%, recall of 83%, f1-score of 80% (all weighted averages), and accuracy of 83%, on the test set.

Tree-based Machine Learning

After conducting feature engineering, the decision tree model achieved AUC of 93.8%, precision of 87.0%, recall of 90.4%, f1-score of 88.7%, and accuracy of 96.2%, on the test set..

The random forest modestly outperformed the decision tree model.

Conclusion & Recommendations

The models and the feature importance's extracted from the models confirm that employees at the company are overworked.
The following recommendations could be:

Cap the number of projects that employees can work on.

Consider promoting employees who have been with the company for at least four years, or conduct further investigation about why four-year tenured employees are so dissatisfied.

Either reward employees for working longer hours, or don't require them to do so.

If employees aren't familiar with the company's overtime pay policies, inform them about this. If the expectations around workload and time off aren't explicit, make them clear.

Hold company-wide and within-team discussions to understand and address the company work culture, across the board and in specific contexts.

High evaluation scores should not be reserved for employees who work 200+ hours per month. Consider a proportionate scale for rewarding employees who contribute more/put in more effort.

Next Step

- It may be justified to still have some concern about data leakage. It could be prudent to consider how predictions change when last_evaluation is removed from the data. It's possible that evaluations aren't performed very frequently, in which case it would be useful to be able to predict employee retention without this feature. It's also possible that the evaluation score determines whether an employee leaves or stays, in which case it could be useful to pivot and try to predict performance score. The same could be said for satisfaction score.
- For another project, you could try building a K-means model on this data and analyzing the clusters. This may yield valuable insight.

Thank You

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Google Advanced Data Analytics Certification