

Predictive Modeling for Employee Terminations

Tom Rice

Goal

This analysis will attempt to predict when an employee will terminate, which will help the HR department with employee turnover by developing strategies to fill upcoming vacant roles. This analysis is divided into three parts: descriptive analysis, diagnosis analysis, and predictive analysis. This analysis will use binary classification, as there can only be two outcomes determining whether an employee is active or terminated. The concepts covered in this project include data munging, splitting the dataset into test, validation and training sets, descriptive analytics, diagnostic analytics, and predictive analytics, supervised learning, feature selection, logistic regression, and supervised neural networks.

Data Munging

The data must be cleaned and prepared for the machine learning analysis before it can be performed. This researcher took the following steps to prepare the data for analysis.

1. For privacy, the name and employee columns were replaced with Row ID columns.
2. The effective date row was removed as it was not needed for analysis.
3. Location and Department IDs are numerical values that needed to be combined so that the data in all locations and departments was uniform.
4. The location description column was munged, so all the location descriptions were uniform and correct.
5. Normalized the Pay group column so all pay groups are numerical values. Daisy Elementary had an experimental all-year-round program that changed their pay group designations to include alpha numeric characters.
6. The building column had missing values. The building column is tied to the location column, so the missing values were filled in based on the populated values of the location.
7. The building column was divided into eight categories. Program schools are also considered high schools, so their values change to 10. The following tables illustrate the numerical codes given to building descriptions.

Building_Code	Description
10	High Schools
20	Middle Schools
30	Elementary Schools
50	Other Schools
60	Transporation
70	Multi-School
80	Other Locations
90	To be Determined

8. The date fields were corrupted, so this researcher had to update the fields to show the correct date. The following image shows the corrupted fields and data missing from the BUILDING column.

M	N	O	P	Q
POSITION	BUILDING	HIRE_DT	BIRTHDAT	HCS_Pi
3225		1/0/1900	1/0/1900	S
3249		1/0/1900	1/0/1900	P
1790		1/0/1900	1/0/1900	S
3110		1/0/1900	1/0/1900	S
3490		1/0/1900	1/0/1900	P
3491		1/0/1900	1/0/1900	S
1131		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
2738		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
3069		1/0/1900	1/0/1900	P
1023		1/0/1900	1/0/1900	P
4502	40	1/0/1900	1/0/1900	S
3224	40	1/0/1900	1/0/1900	S
2109		1/0/1900	1/0/1900	S
3664	40	1/0/1900	1/0/1900	S
6053	40	1/0/1900	1/0/1900	S
4470	40	1/0/1900	1/0/1900	P

9. The Termination Date was missing from the original dataset and was added for analysis.
10. Hire Date and Termination date were subtracted based on year to determine Years of Service
11. Age was determined by subtracting their Termination date or today's day if still active by their birthday.
12. Adjust NULL Date rows to show blank, but in the calculations, use the current date to get years of service
13. Create an age column by subtracting today's date from the employees' age.
14. Categorized the Positions into ten broad categories. The following tables illustrate the numerical codes given to employee positions.

POS_CAT	Description
1	Teachers
2	Principals
3	Assistant Principals
4	Custodians
5	Food Service
6	District Admins
7	Non-Teaching Prof
8	Support Staff
9	Bus Drivers
10	Board Members

15. Termination reasons were given numerical categories. The following tables illustrate the numerical codes given to employee termination reasons.

Code	Termination Description
1	Active
2	Death
3	Retire
4	Unknown
5	Leaving Profession
6	Another Position in Education
7	Family Reasons
8	Temporary Agreements
9	Declined Position
10	Health Issues
11	Dismissal
12	Moving
13	Cert Issues

16. Adjusted employee pay grades are to be numerical, and normalized pay grades are to match the current HCS salary scale.

17. The employee's steps were normalized to reflect the proper years of service. The district uses different numbers for ROTC instructors (Step 97) and new teachers (Step 99).
18. This researcher adjusted the binary employee status field to represent 0 for terminated and 1 for active employees.
19. Removed 5 Duplicate Rows

Importing Python Packages

After the data was cleaned and prepared for analysis, the environment for this analysis was prepared in Python by importing the required packages. The following image shows the packages needed for this analysis.

```
##Employee Termination Analysis
## By: Tom Rice
## IST 679 - Big Data Analytics

##Libraries to start with
#####
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import scipy
from scipy import stats
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OrdinalEncoder, OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.pipeline import make_pipeline
from pycaret.classification import *
#####
```

Descriptive Analysis

With the environment ready, the data was imported into a Python data frame using Pandas. The data was munged by applying numerical designations to all numerical fields in the data frame. This researcher created a function to run a series of descriptive functions to help understand how this researcher shaped the data frame and provide summary statistics for each field. The following images show how the descriptive functions run successfully, summarizing the data frame.

```
File Edit View Navigate Code VCS Help Final_Project.py
Python library root, C:\Users\...
External Libraries
Scratches and Consoles

2024-04-30 14:01:33.989610: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; d
2024-04-30 14:01:33.990255: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on
This dataframe has 14237 rows
This dataframe has 25 columns
RangeIndex(start=0, stop=14237, step=1)

--DF HEADERS--
ROWID HCS_POS_POSITION HCS_POS_GRADE_SUB ... ANNUAL_RT DAILY_RT EMPL_STATUS
0 1 AIDE INTERVENT ... 17968.125 97.125000 0
1 2 ASSTPRIN II ... 65229.225 343.311711 0
2 3 CAFETERIA WRKR ... 4095.540 22.380000 0
3 4 CAFETERIA WRKR ... 23731.440 129.680000 0
4 5 CARADVIS NaN ... 41868.400 220.360000 0

[5 rows x 25 columns]

--DF Summary--
count ROWID POS_CAT ... DAILY_RT EMPL_STATUS
mean 14237.000000 4.216689 ... 239.879426 0.453326
std 4110.612226 3.245388 ... 114.796264 0.497834
min 1.000000 1.000000 ... 0.000000 0.000000
25% 3560.000000 1.000000 ... 135.525000 0.000000
50% 7119.000000 4.000000 ... 229.250000 0.000000
75% 10678.000000 8.000000 ... 327.200000 1.000000
max 14237.000000 10.000000 ... 1162.400000 1.000000

[8 rows x 10 columns]
```

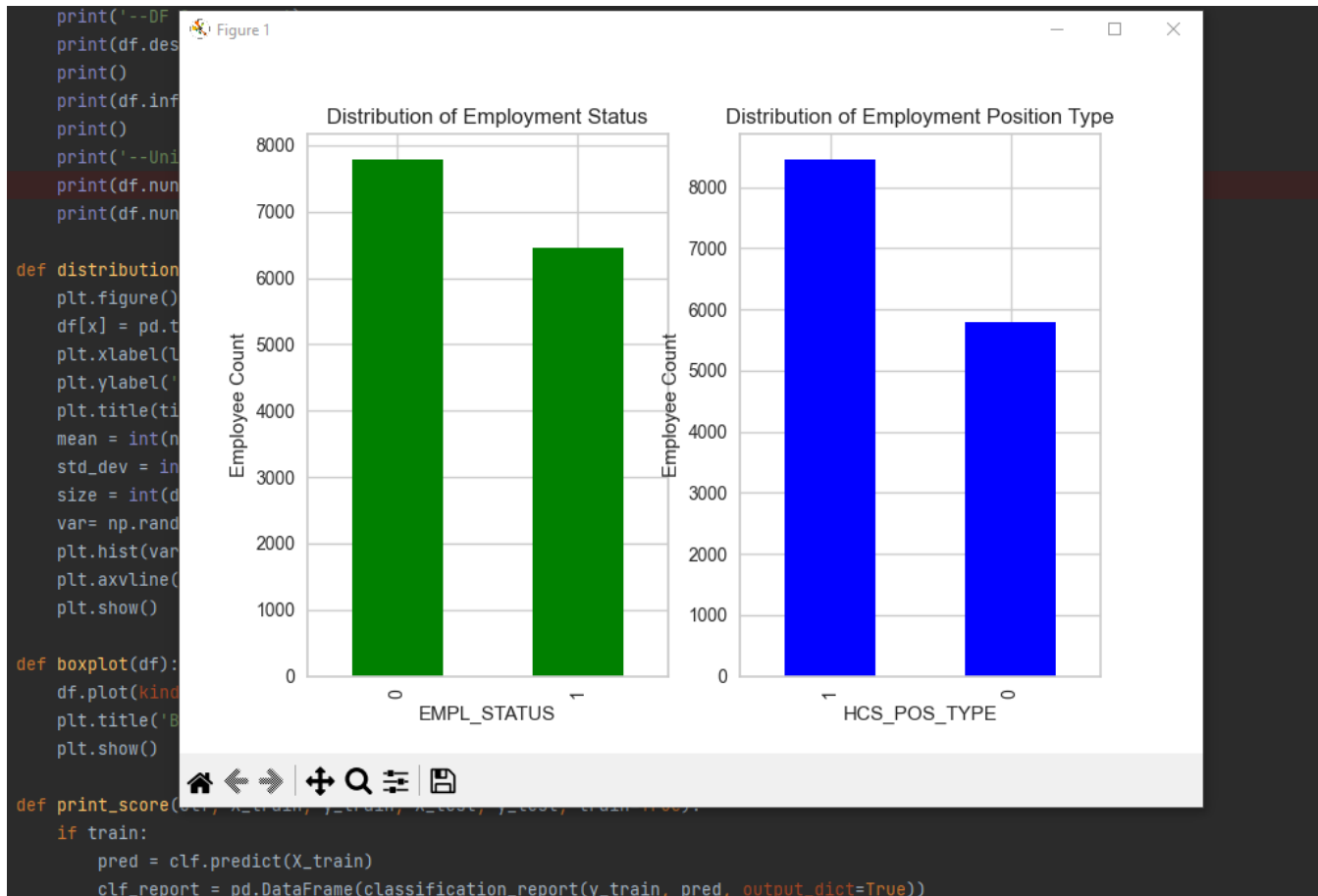
```
File Edit View Navigate Code VCS Help Final_Project.py
Python library root, C:\Users\...
External Libraries
Scratches and Consoles

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14237 entries, 0 to 14236
Data columns (total 25 columns):
# Column Non-Null Count Dtype
---
0 ROWID 14237 non-null int64
1 HCS_POS_POSITION 14237 non-null object
2 HCS_POS_GRADE_SUB 13088 non-null object
3 POS_CAT_DESCR 14237 non-null object
4 POS_CAT 14237 non-null int64
5 LOCATION 14237 non-null int64
6 DESCR 14237 non-null object
7 DEPTID 14237 non-null int64
8 Department 14237 non-null object
9 PAYGROUP 14237 non-null int64
10 POSITION_NBR 14237 non-null int64
11 BUILDING 14237 non-null int64
12 HIRE_DT 14233 non-null object
13 TERMINATION_DT 14237 non-null object
14 YOS 14237 non-null int64
15 BIRTHDATE 14236 non-null object
16 AGE 14237 non-null int64
17 HCS_POS_TYPE 14237 non-null int64
18 REASON_LEAVE 14237 non-null object
19 ACTION_REASON 14237 non-null int64
20 GRADE 14237 non-null int64
21 STEP 14237 non-null int64
22 ANNUAL_RT 14237 non-null float64
23 DAILY_RT 14237 non-null float64
24 EMPL_STATUS 14237 non-null int64
dtypes: float64(2), int64(14), object(9)
memory usage: 2.7+ MB
None
```

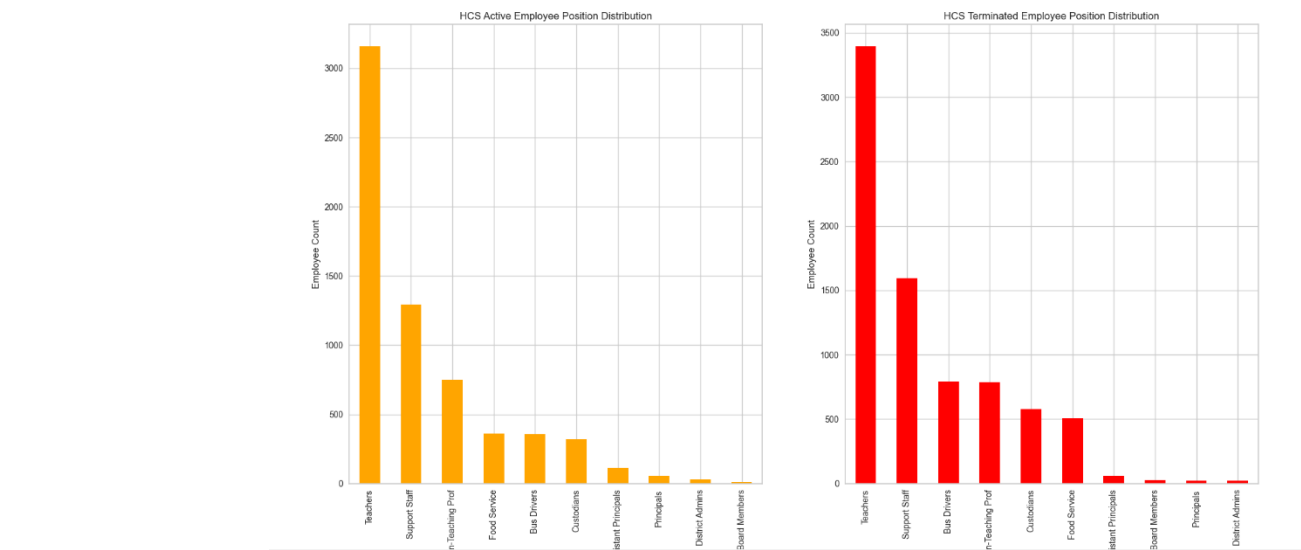
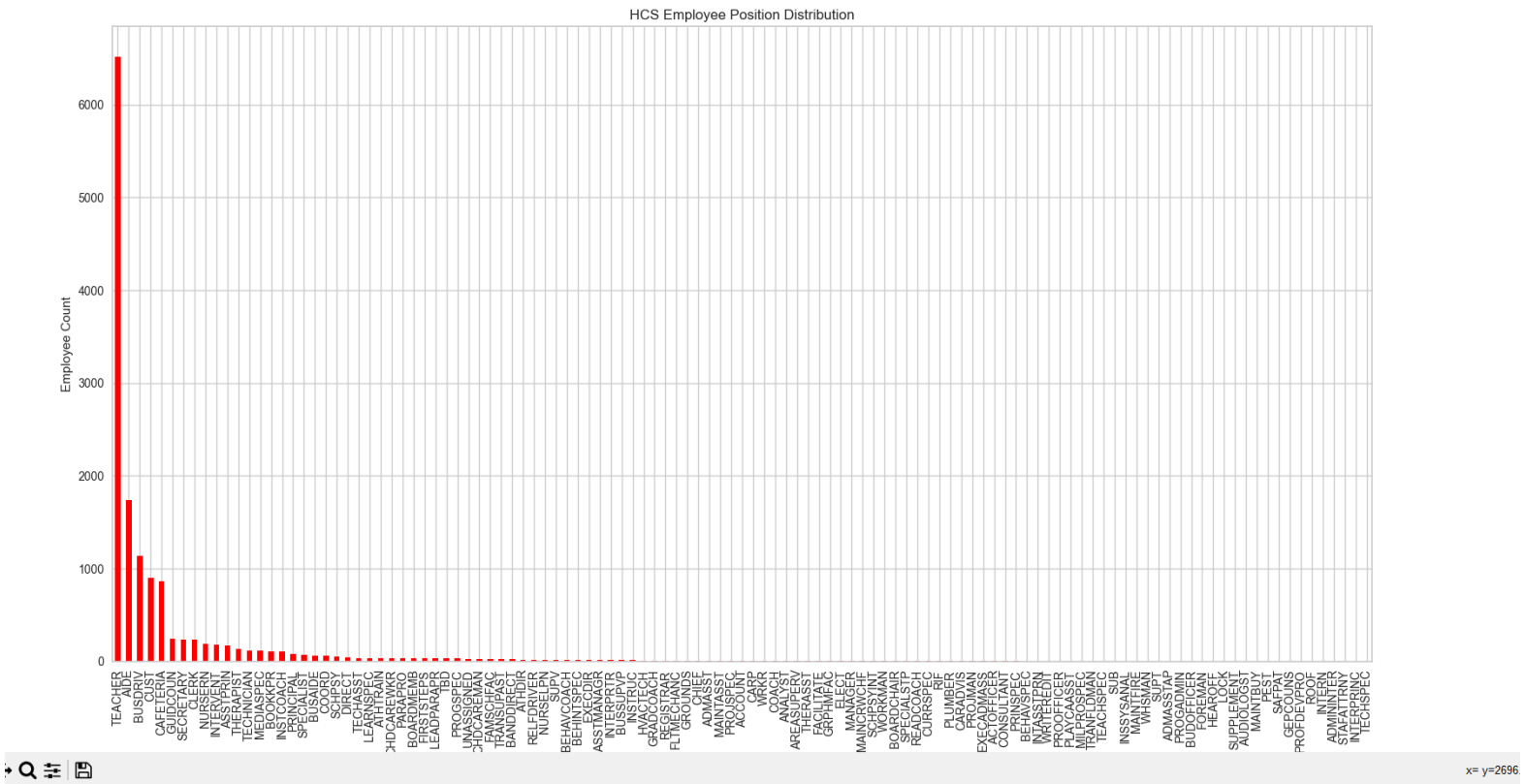
```
File Edit View Navigate Code VCS Help Final_Project.py
Python library root, C:\Users\...
External Libraries
Scratches and Consoles

--Unique Values Vs Nulls--
ROWID 14237
HCS_POS_POSITION 115
HCS_POS_GRADE_SUB 189
POS_CAT_DESCR 10
POS_CAT 10
LOCATION 87
DESCR 91
DEPTID 176
Department 182
PAYGROUP 13
POSITION_NBR 3877
BUILDING 8
HIRE_DT 3406
TERMINATION_DT 2508
YOS 52
BIRTHDATE 10071
AGE 78
HCS_POS_TYPE 2
REASON_LEAVE 13
ACTION_REASON 13
GRADE 62
STEP 38
ANNUAL_RT 4627
DAILY_RT 3776
EMPL_STATUS 2
dtype: int64
ROWID 14237
HCS_POS_POSITION 115
HCS_POS_GRADE_SUB 190
POS_CAT_DESCR 10
POS_CAT 10
LOCATION 87
DESCR 91
DEPTID 176
```

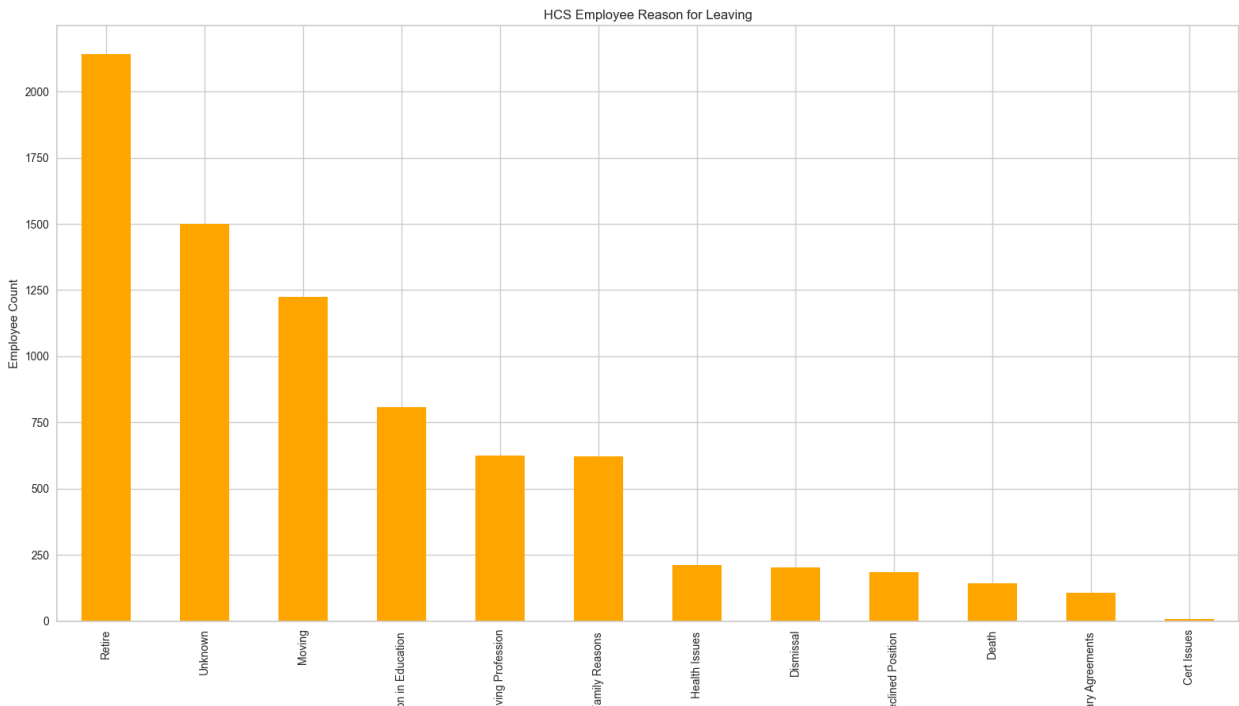
After the program lists the data frame's summary statistics, the program did not reveal any noticeable outliers. The analysis continued by looking at a distribution of the number of terminated employees compared to those still active and the number of professional and support staff. While there is a slight imbalance in the number of terminated employees compared to active employees, this researcher chose not to remove any records. If this researcher determines there needs to be a balance between the number of active (1) and terminated (0) employees, this researcher would remove the older termination records, keeping the more recent records for analysis. The following image also shows an imbalance between professional (1) and support (0) employees.



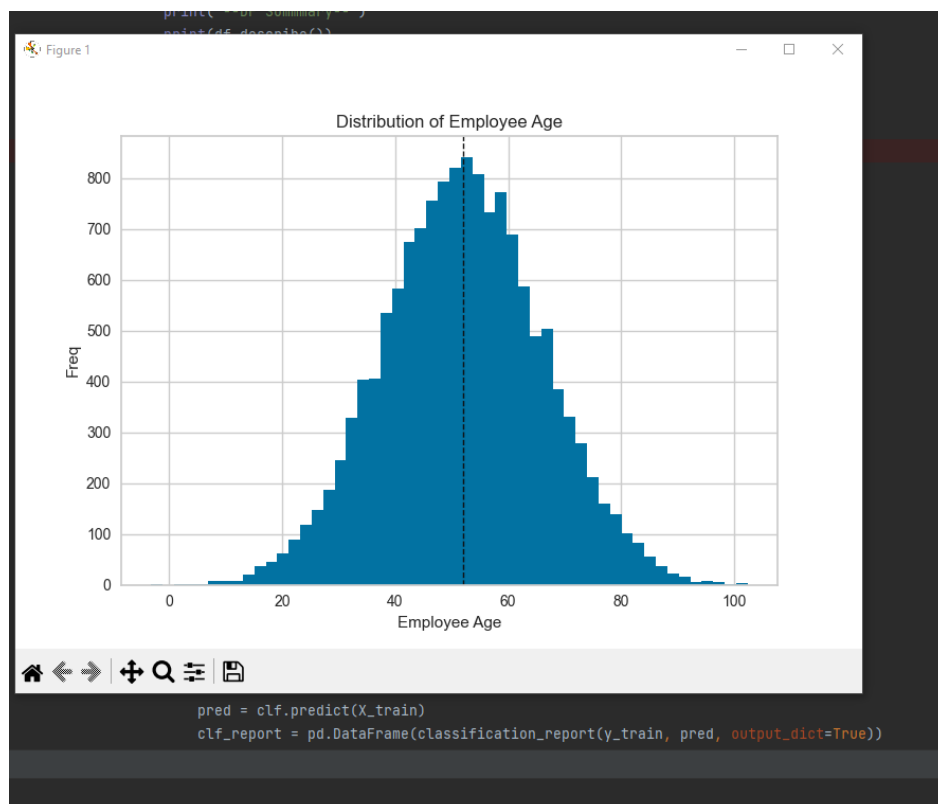
The following images show the distribution of employees based on their position type and position category. The chart shows a large imbalance in the number of teacher records compared to other employee types. The top four employee types after Teachers are aides, bus drivers, custodians, and cafeteria staff. This researcher added the option to focus specific position types if needed.



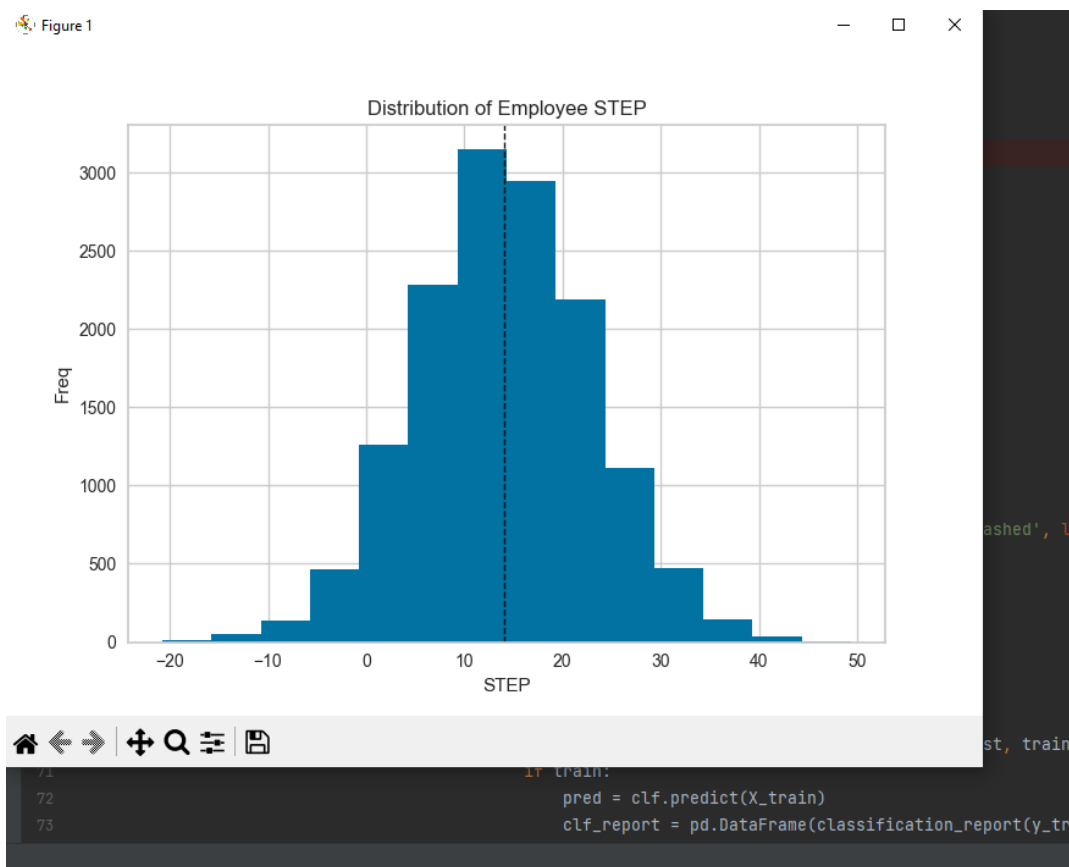
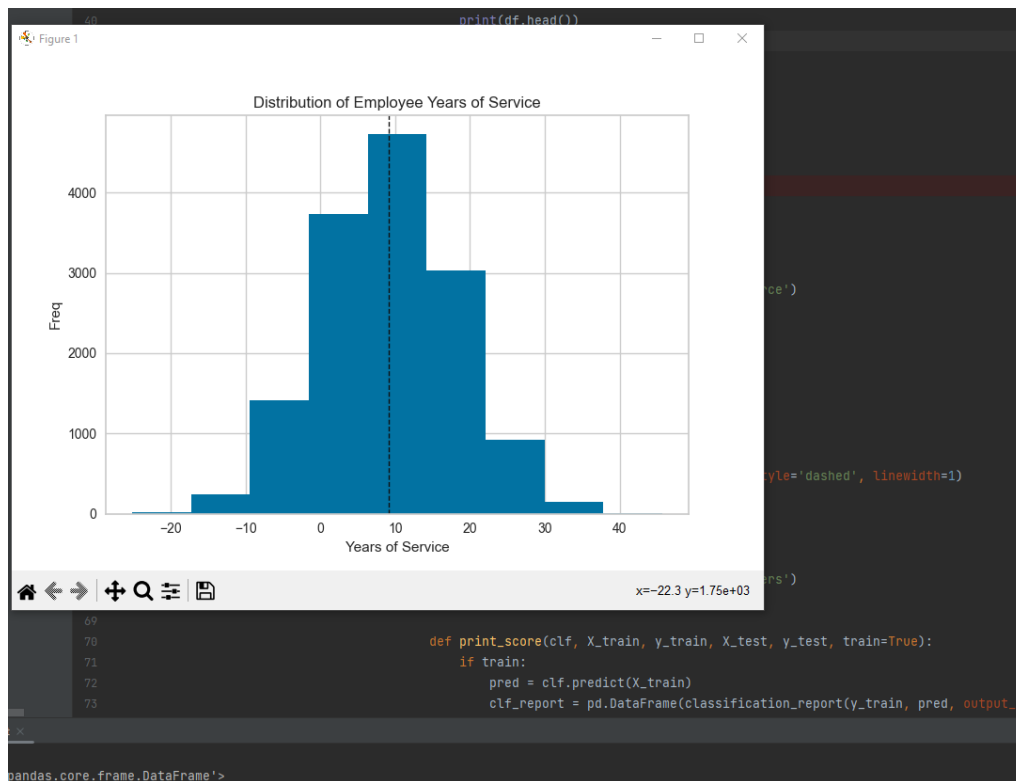
The following images show the distribution of employees based on their position type and position category. The chart shows a significant imbalance in teacher records compared to other employee types. The top four employee types after Teachers are aides, bus drivers, custodians, and cafeteria staff. This researcher added the option to focus on specific position types if needed.



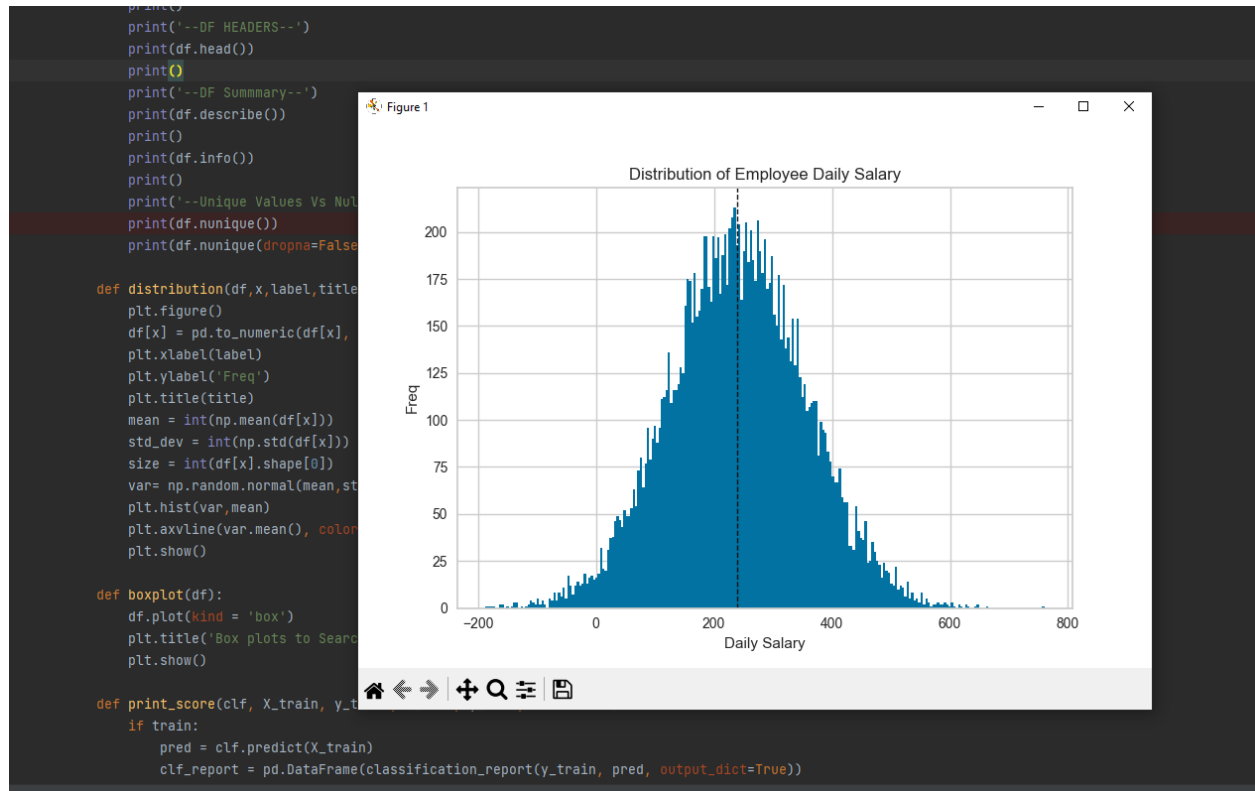
The following image shows employee distribution by age. The distribution shows that the average age for employees is 51, indicating an older workforce.



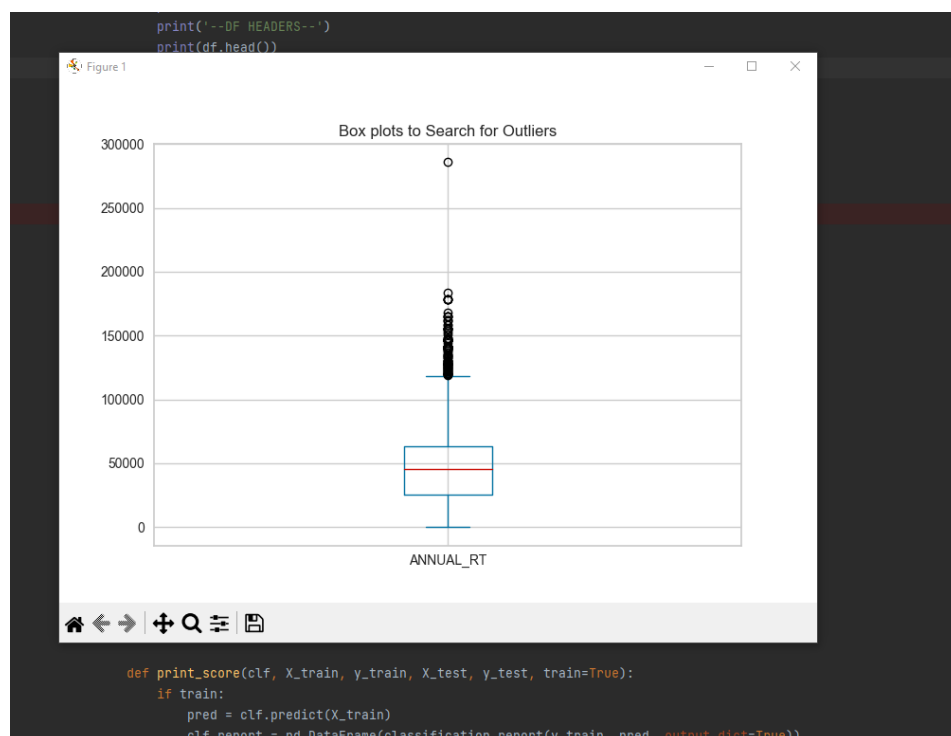
The following images show employee distribution by years of service and steps. Steps are similar designations to years of service, so these charts are expected to show identical results. If these charts were not comparable, an error would be flagged somewhere in the data.



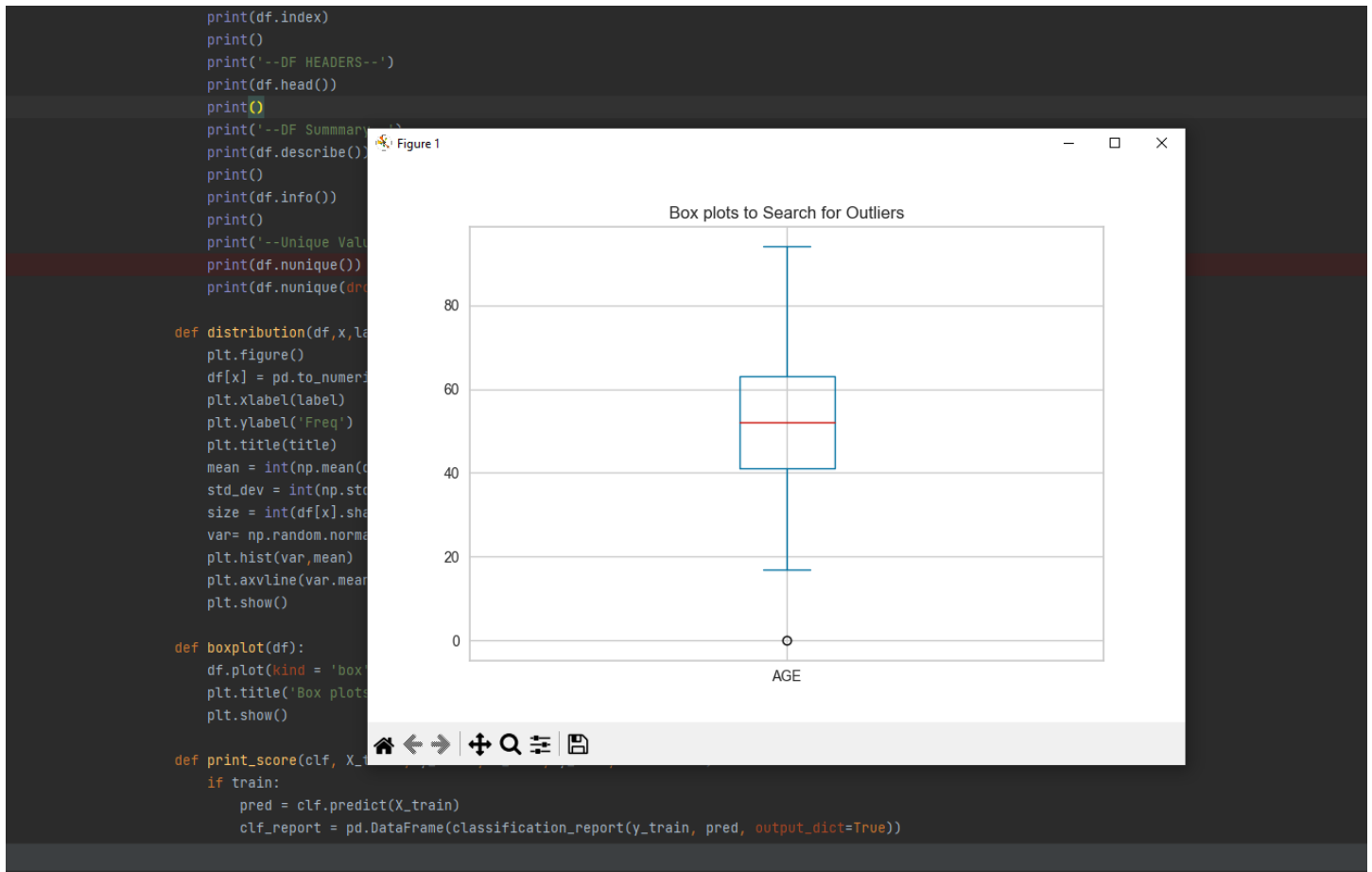
The following image shows the distribution of the employees' daily salaries. Some outliers can be seen at the extremities of the distribution. While these can be removed, this researcher has included them in this analysis.



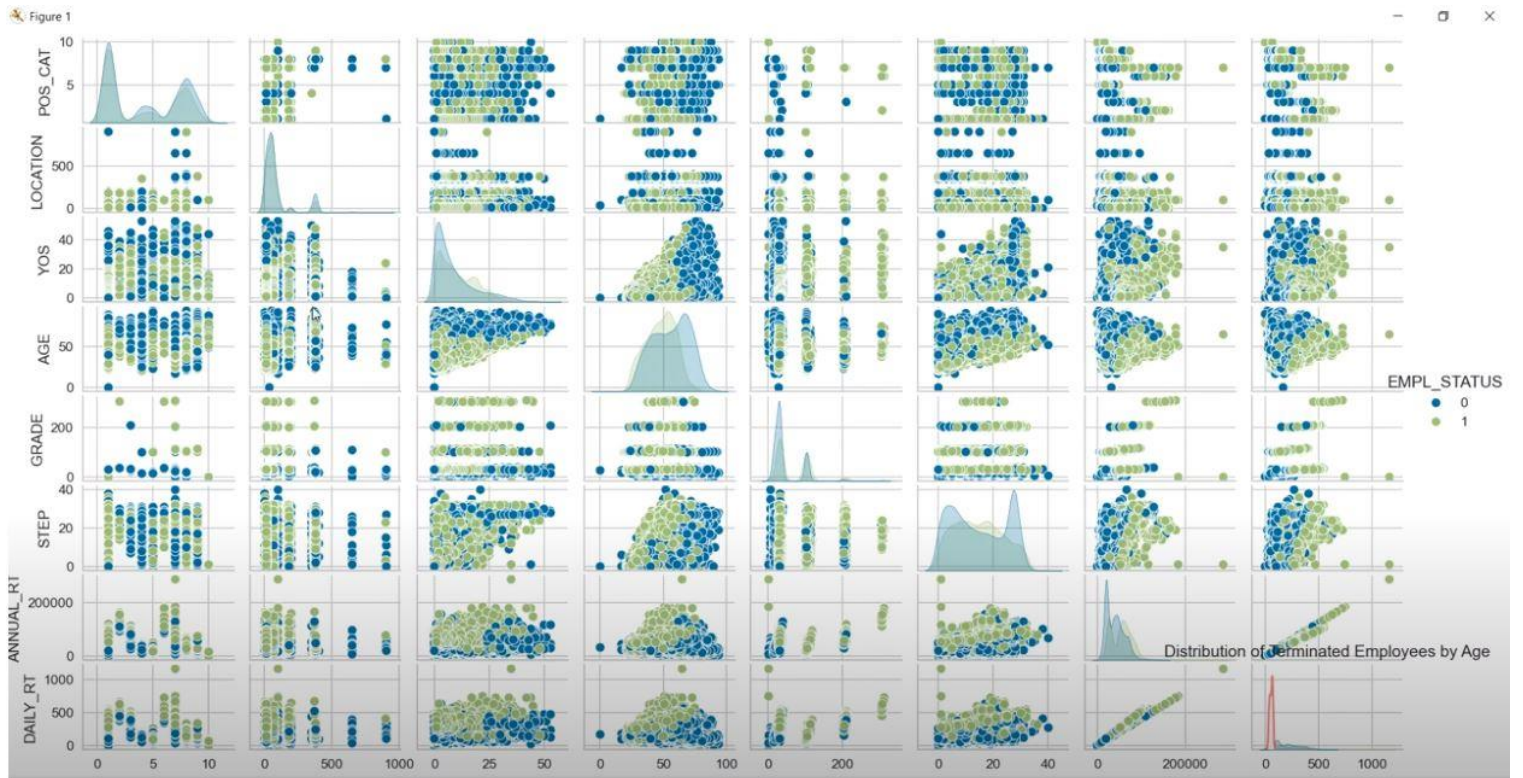
The following image shows outlier salaries for employees, indicating a severe imbalance in the district's pay practices. The outlier salaries are for the principal, district administrators, and superintendent.



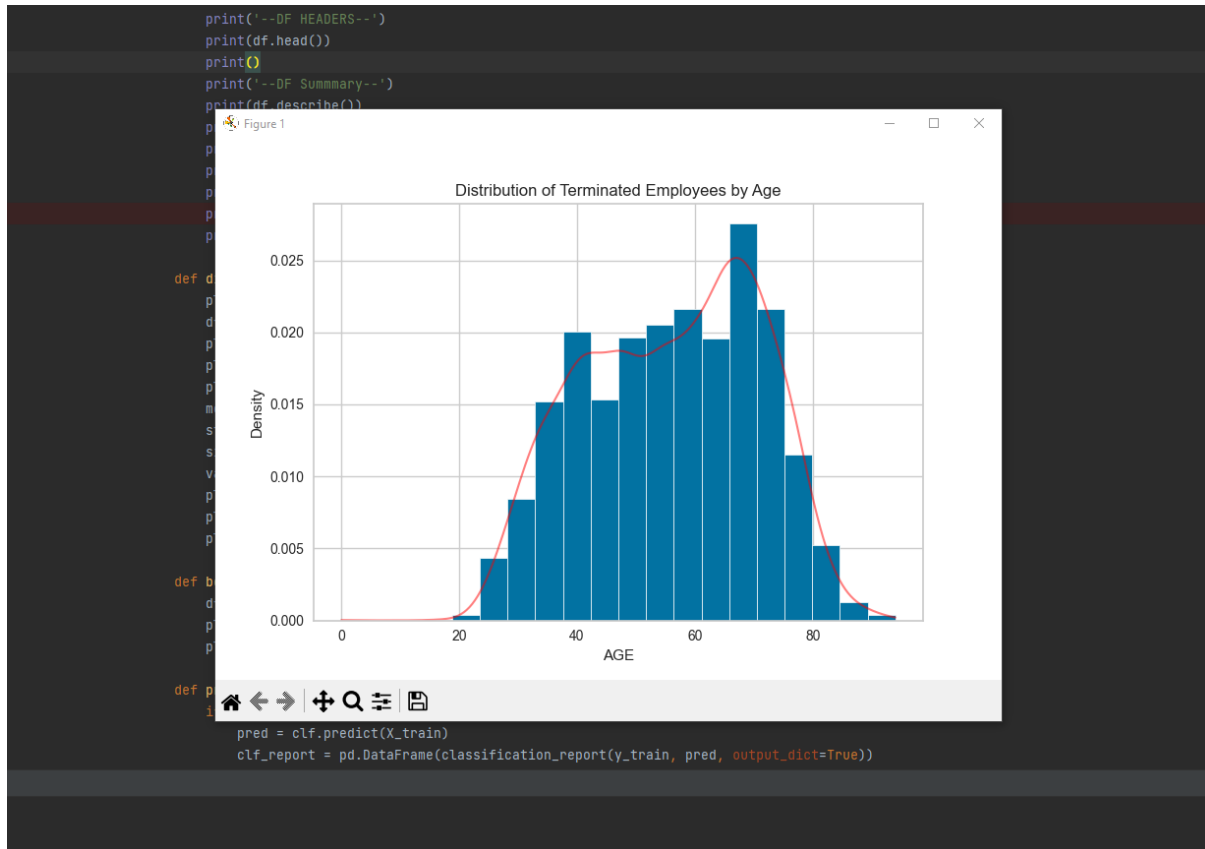
When looking for outliers for employee age, the program found an outlier for an employee who was 0 years old. Upon further research, this researcher discovered that the employee needed to provide Horry County with information, as the district terminated the employee before beginning work. This record will be an outlier but included in this analysis as issues with filling out new hire paperwork could indicate terminations..



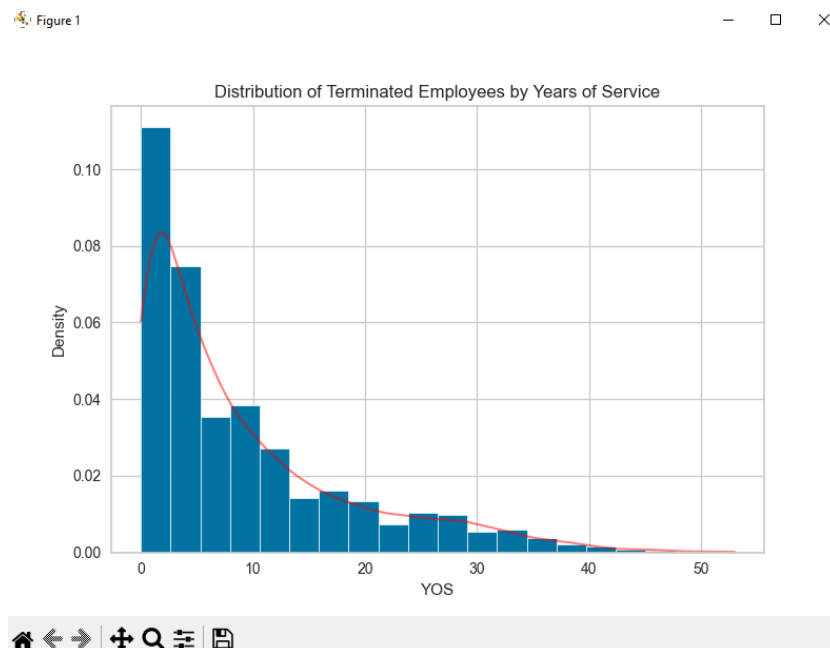
The following image displays a pair plot created by the program to help this researcher visualize any hidden trends when comparing the different variables in the dataset. This technique helps determine what type of machine learning algorithm should be used as this researcher can see logistic, linear, and other types of nonlinear relationships among the variables. This researcher can use these charts to validate any hypothesis regarding the variables' relationships and check for data inconsistencies. Pair plotting is a valuable technique for visualizing and describing the relationships of many variables at one time.



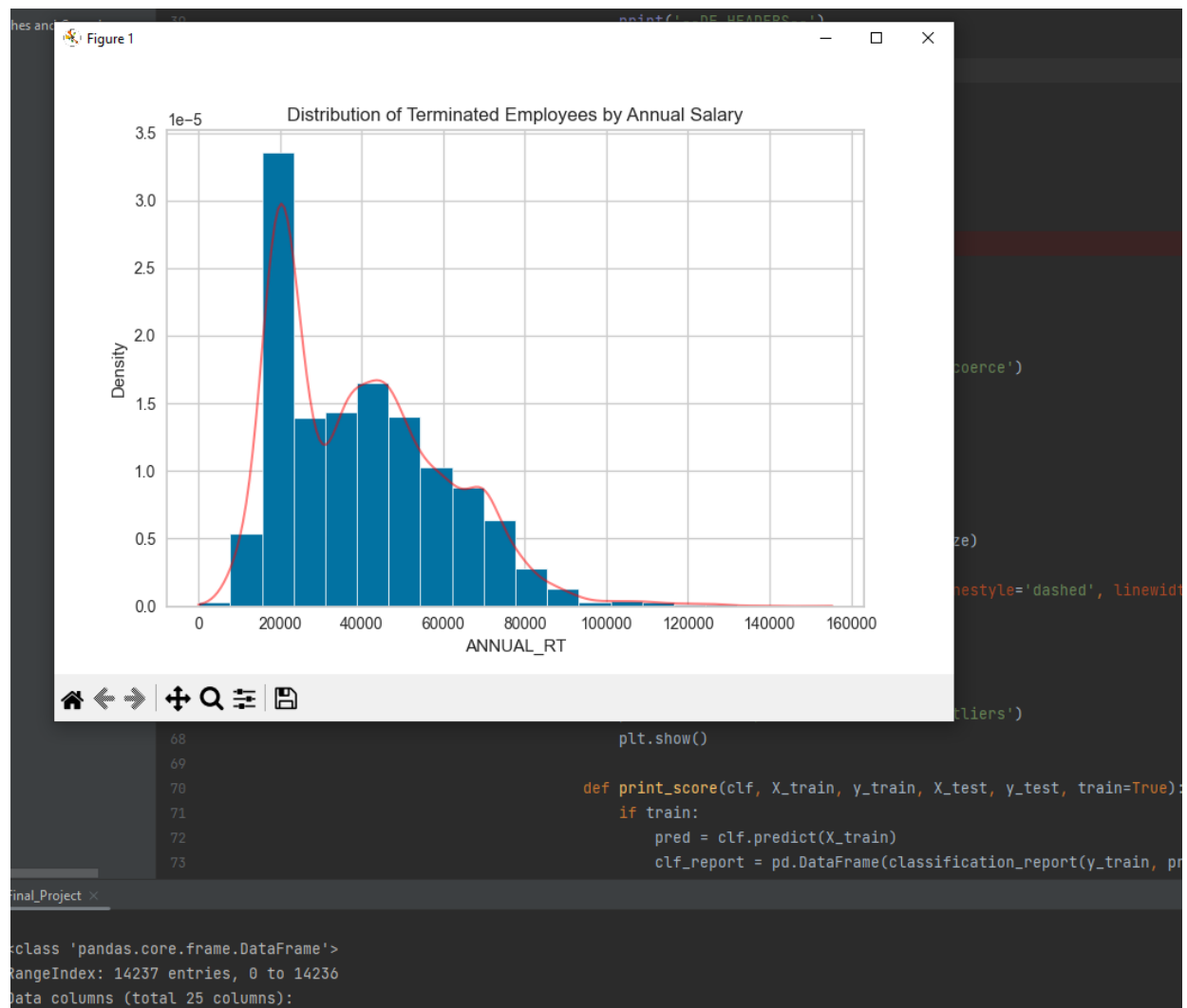
The following image shows the distribution of the employees who have been terminated by age. There is a large spike in terminations among employees between the ages of 35 and 40 and when they are over 60.



The following image shows the distribution of terminated employees' years of service. There is a significant spike in terminations with employees who have served less than five years. While retirement is the more frequent cause of termination, this is interesting as this chart indicates most employees who terminate leave within five years of working for the district. This researcher also developed the hypothesis that retirement is the dominating reason for employees' termination when they have over ten years of service.



The following image shows the distribution of employees terminated by their annual salary. There is a significant spike in terminations for employees who earn less than \$30,000 annually. The chart is interesting as it can relate to the outlier chart when looking at the wide variance in employee salaries.

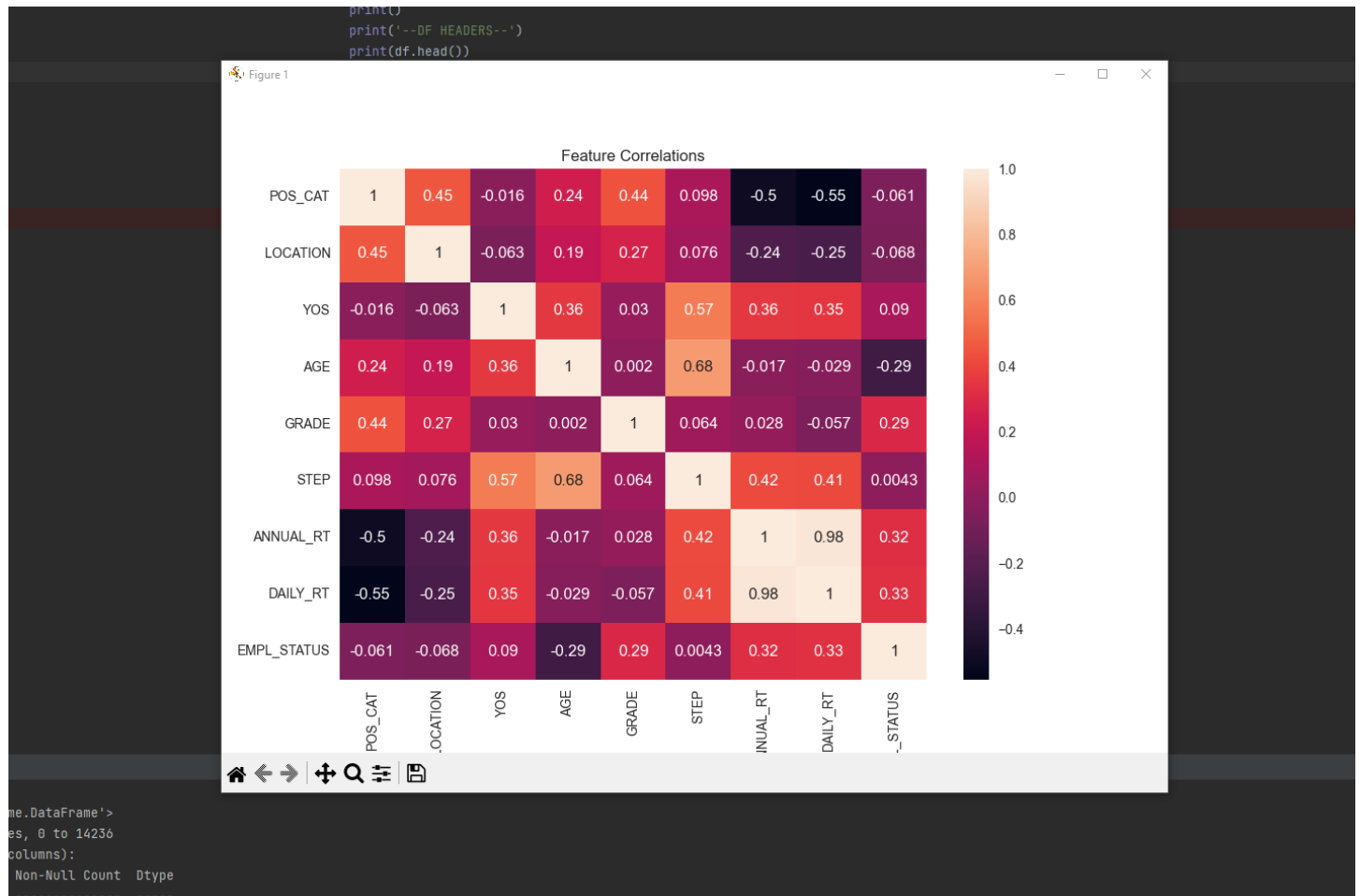


Descriptive Analysis Summary

Based on the historical data provided, the descriptive analysis described what factors lead to employee terminations. The study showed that an employee's age may significantly affect terminations. As employees age, they retire, and younger employees are more likely to shift jobs and careers. There is a significant spike in employees who leave before five years of service, indicating there may be a lack of support for new employees. The analysis also described that unknown causes are the second leading cause for terminations, which could suggest that employees are disgruntled. The absence of data indicates many terminated employees do not want to fill out the resignation paperwork as they leave the district. Custodial, cafeteria, and bus drivers have higher turnover than professional employees, indicating low pay and job difficulties could be leading causes for employees leaving before retirement. There is also a significant variation in employee salaries, which may be a component that leads to employees terminating before retirement.

Diagnostic Analysis

The next stage of this analysis is to build on the previous descriptive analysis and identify key variables that would affect employee terminations. The following images show feature correlations, creating the basis for the diagnostic analysis. Daily rate, annual salary, and employee pay grade all have stronger positive correlations to employment status, while age has a significant negative correlation to employee status. The position category has a strong negative correlation to daily and annual rates.



The Python Package PyCaret validated essential variables for the following diagnostic analysis. As this analysis will use logistic regression and random forest decision trees, PyCaret created two models to determine significant variables using logistic regression and random forests. The package also provided summary statistics identifying 14 numeric features, seven categorical features, and 8.1% of the rows in the dataset that were missing data. The created models indicated that age, pay grade, years of service, step, daily rate, and annual salary are significant variables, which supports the correlation analysis above.

```

Python library root, C:\Users\
External Libraries
Scratches and Consoles

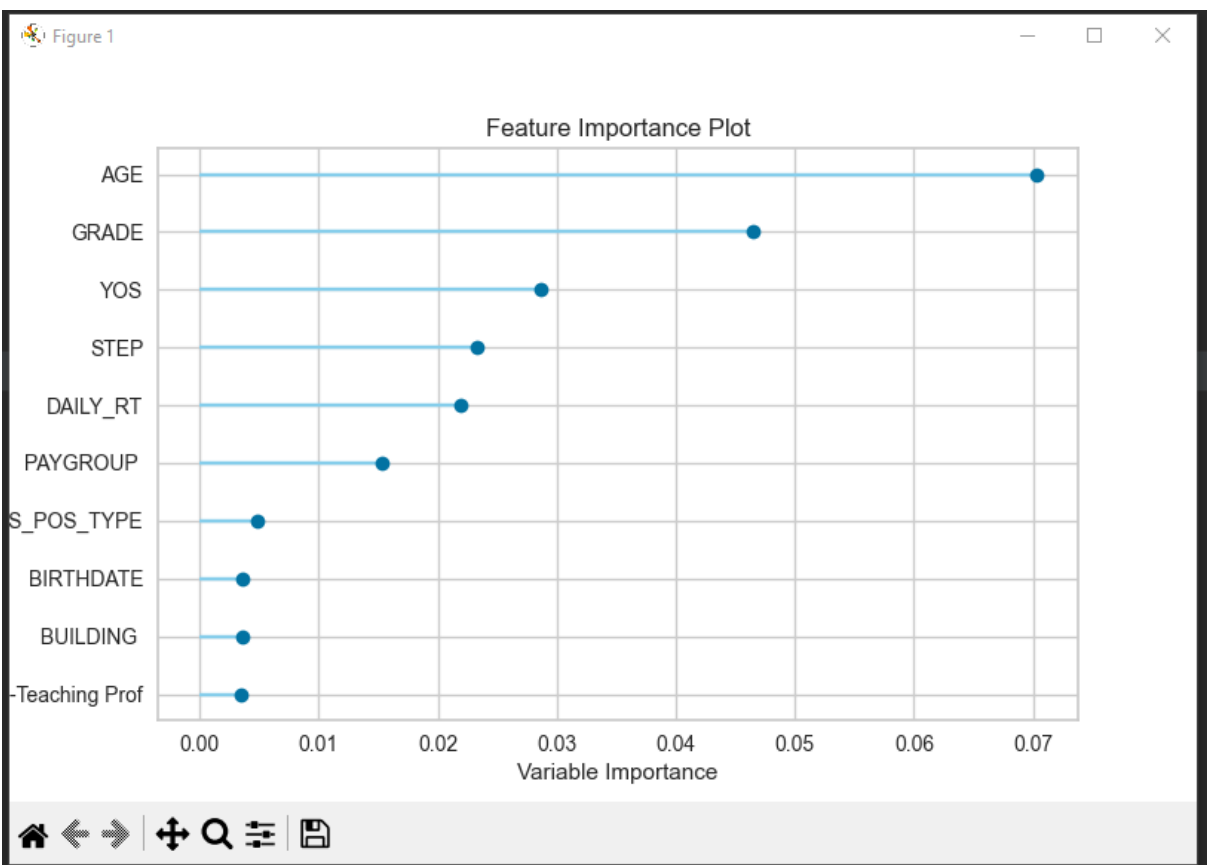
12 from scipy import stats
13 import tensorflow as tf
14 from tensorflow import keras
15 from tensorflow.keras import layers
16 from sklearn.metrics import roc_auc_score
17 from sklearn.preprocessing import StandardScaler
18 from sklearn.compose import ColumnTransformer
19 from sklearn.model_selection import train_test_split
20 from sklearn.linear_model import LogisticRegression
21 from sklearn.ensemble import RandomForestClassifier
22 from sklearn.impute import SimpleImputer
23 from sklearn.pipeline import Pipeline
24 from pycaret.classification import setup
25 #####
26
27 ##Descriptive Analysis##
28 ##Brining the Data in##

```

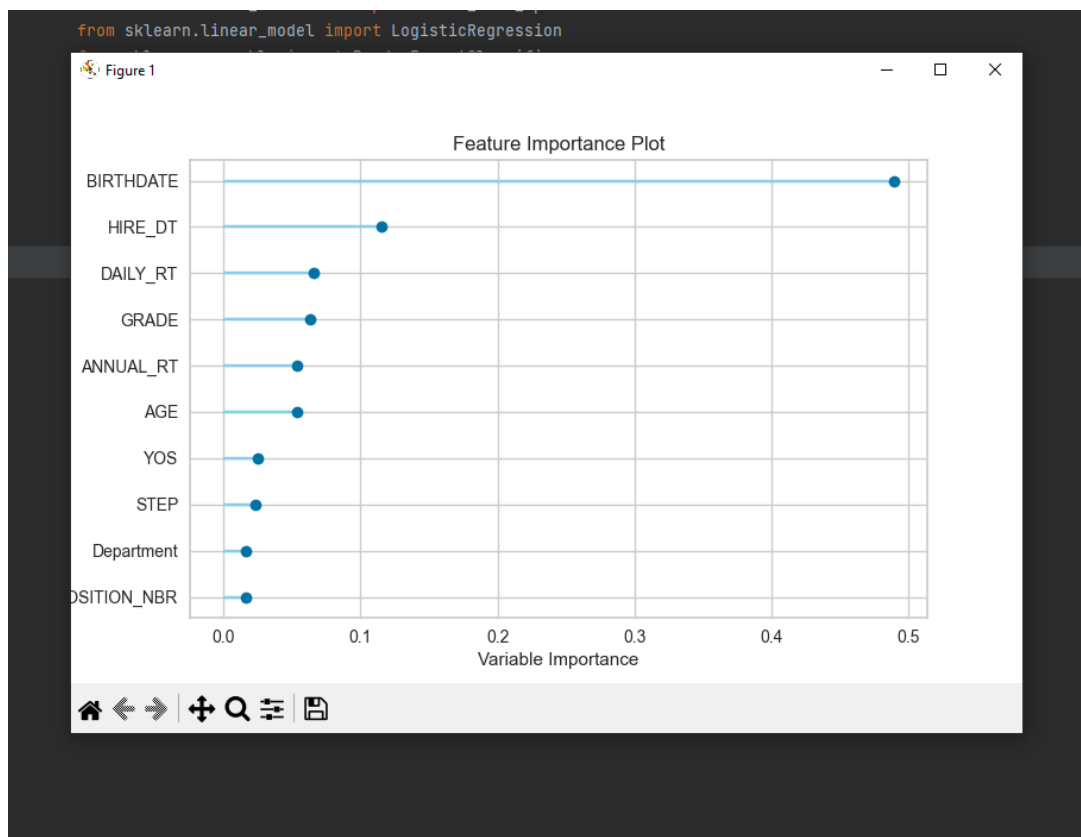
Run: Final_Project x
7/83

	Description	Value
0	Session id	123
1	Target	EMPL_STATUS
2	Target type	Binary
3	Original data shape	(14237, 22)
4	Transformed data shape	(14237, 31)
5	Transformed train set shape	(9965, 31)
6	Transformed test set shape	(4272, 31)
7	Numeric features	14
8	Categorical features	7
9	Rows with missing values	8.1%
10	Preprocess	True
11	Imputation type	simple
12	Numeric imputation	mean
13	Categorical imputation	mode
14	Maximum one-hot encoding	25
15	Encoding method	None
16	Fold Generator	StratifiedKfold
17	Fold Number	10
18	CPU Jobs	-1
19	Use GPU	False
20	Log Experiment	False
21	Experiment Name	clf-default-name
22	USI	089d
	Accuracy	AUC Recall Prec. F1 Kappa MCC

Feature Significance for using Logistic Regression



Feature Significance for using Random Forest



Diagnostic Analysis Summary

The diagnostic analysis showed that employee age is the most significant variable in determining when an employee will be terminated followed by employee grade and step, years of service and their daily rate. The random forest model was identical to the logistic regression model showing employee birthday, hire date, daily rate, and employee grade as significant variables. Both models support age, years of service, employee grade and step, and salary as important features to determine if an employee will terminate. Employee grade is related to position category as each position is assigned a pay grade. These features will be used in the following predictive analysis.

Predictive Analysis

After this researcher identified significant variables, this researcher used the machine learning algorithms logistic regression, random forest model, and supervised neural network to compare employee termination predictions based on selected variables.

The data was split into training and test sets using a 90% to 10% split and was normalized using a standard scaler. The following image shows the data being split into training and test data before running the model.

```
#SETTING UP THE ANALYSIS
X = df_corr.drop(['EMPL_STATUS'],axis = 1) #Features chosen from our Descriptive Analysis
y = df['EMPL_STATUS']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=15)

num_columns = ['POS_CAT','LOCATION','YOS','AGE','GRADE','STEP','ANNUAL_RT','DAILY_RT']

scale = make_column_transformer(
    (MinMaxScaler(), num_columns),
    (StandardScaler(), num_columns),
    remainder='passthrough'
)

X_train = scale.fit_transform(X_train)
X_test = scale.transform(X_test)
```

Logistic Regression Results with Training Data using a Standard Scaler

```
Results Logistic Regression With Training Data
Training Result:
=====

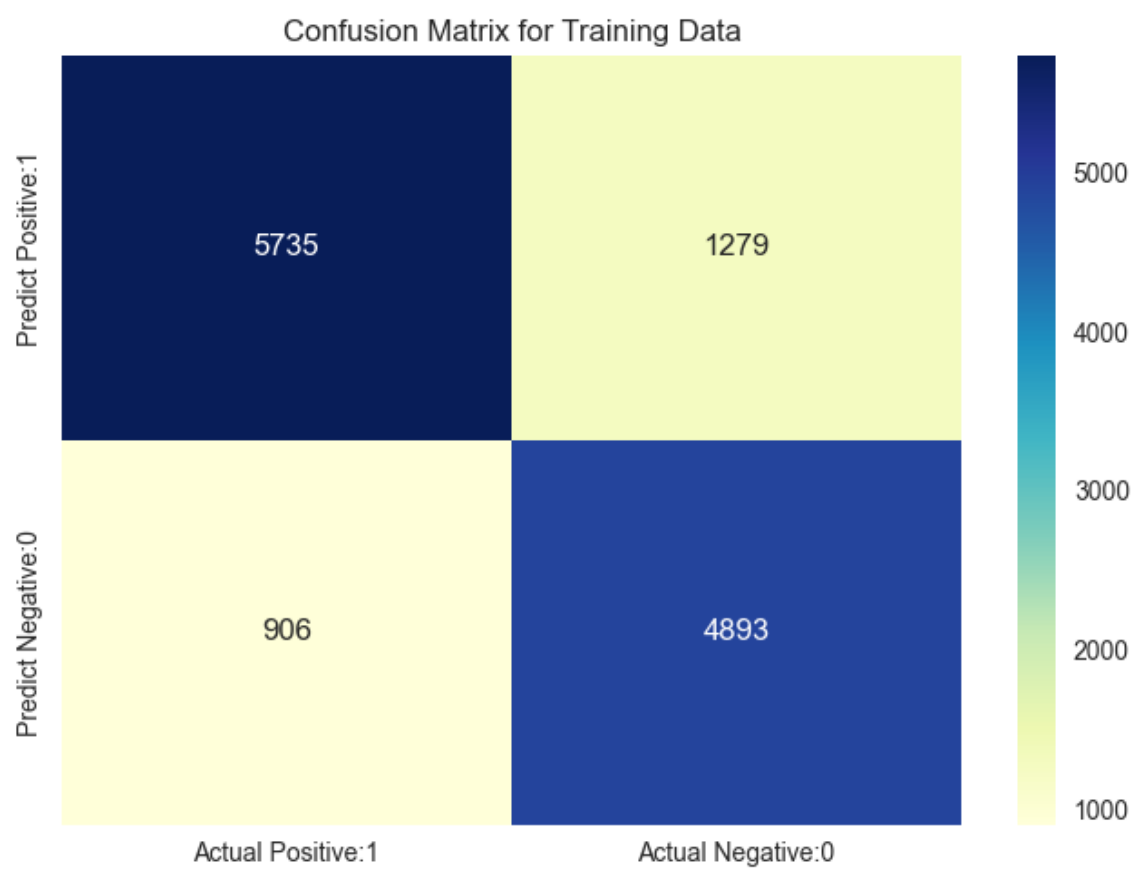
-----
CLASSIFICATION SUMMARY:

```

	0	1	accuracy	macro avg	weighted avg
precision	0.863575	0.792774	0.82947	0.828174	0.831531
recall	0.817650	0.843766	0.82947	0.830708	0.829470
f1-score	0.839985	0.817476	0.82947	0.828730	0.829798
support	7014.000000	5799.000000	0.82947	12813.000000	12813.000000

```
Accuracy Score: 82.95%
```

Figure 1

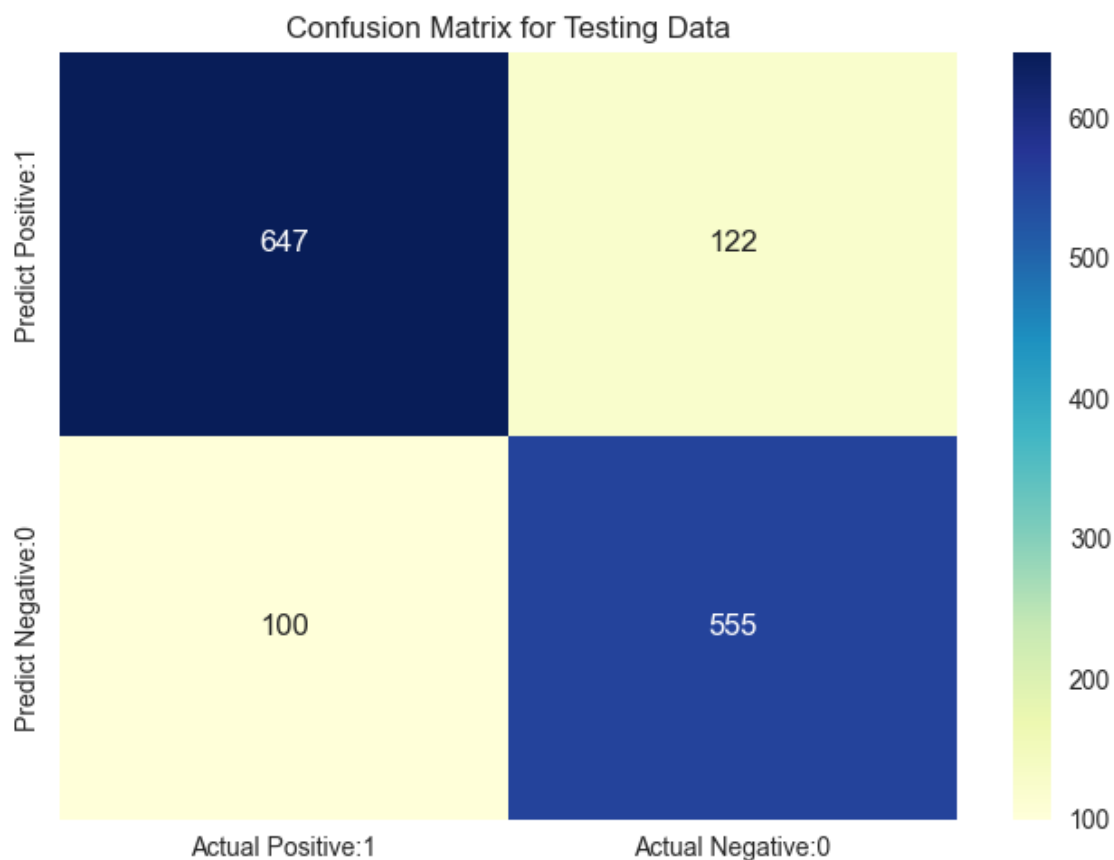


L Logistic Regression Results with Testing Data using a Standard Scaler

```
Results Logistic Regression With Testing Data
Testing Results:
=====
CLASSIFICATION SUMMARY:
          0          1  accuracy  macro avg  weighted avg
precision  0.866131  0.819793  0.844101   0.842962   0.844817
recall    0.841352  0.847328  0.844101   0.844340   0.844101
f1-score   0.853562  0.833333  0.844101   0.843448   0.844257
support   769.000000  655.000000  0.844101  1424.000000  1424.000000

-----
Accuracy Score: 84.41%
```

Figure 1



Random Forest Classifier Results with Training Data based on 1000 estimates

Results Random Forest Classifier with Training Data

Training Result:

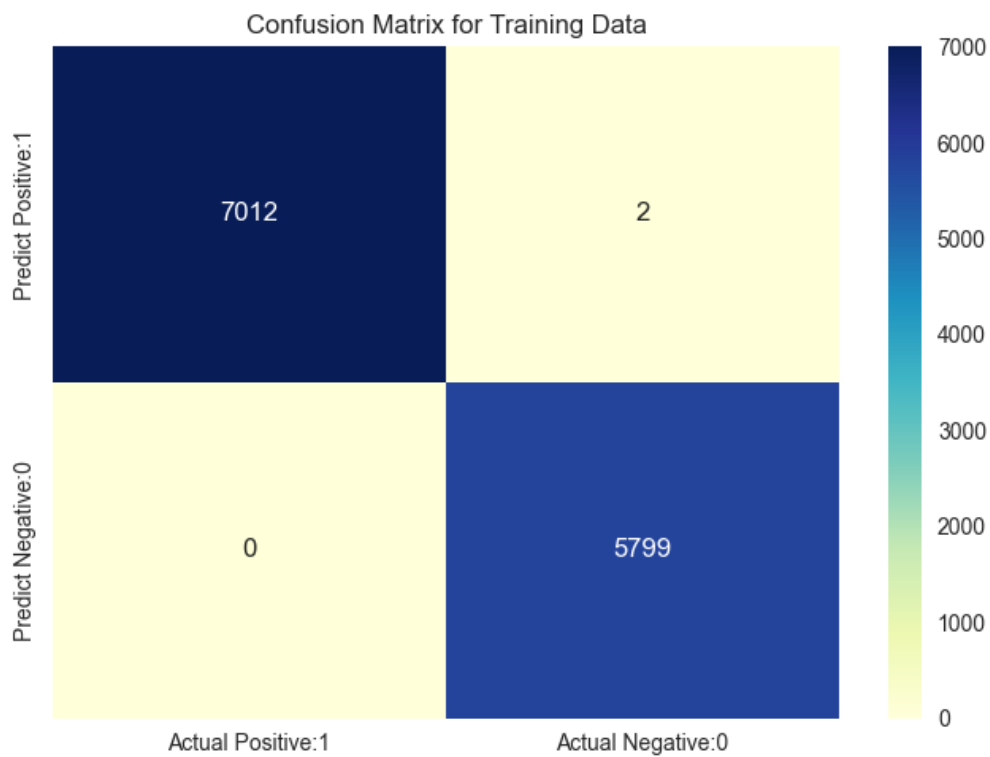
=====

CLASSIFICATION SUMMARY:

	0	1	accuracy	macro avg	weighted avg
precision	1.000000	0.999655	0.999844	0.999828	0.999844
recall	0.999715	1.000000	0.999844	0.999857	0.999844
f1-score	0.999857	0.999828	0.999844	0.999842	0.999844
support	7014.000000	5799.000000	0.999844	12813.000000	12813.000000

Accuracy Score: 99.98%

Figure 1



Random Forest Classifier Results with Testing Data based on 1000 estimates

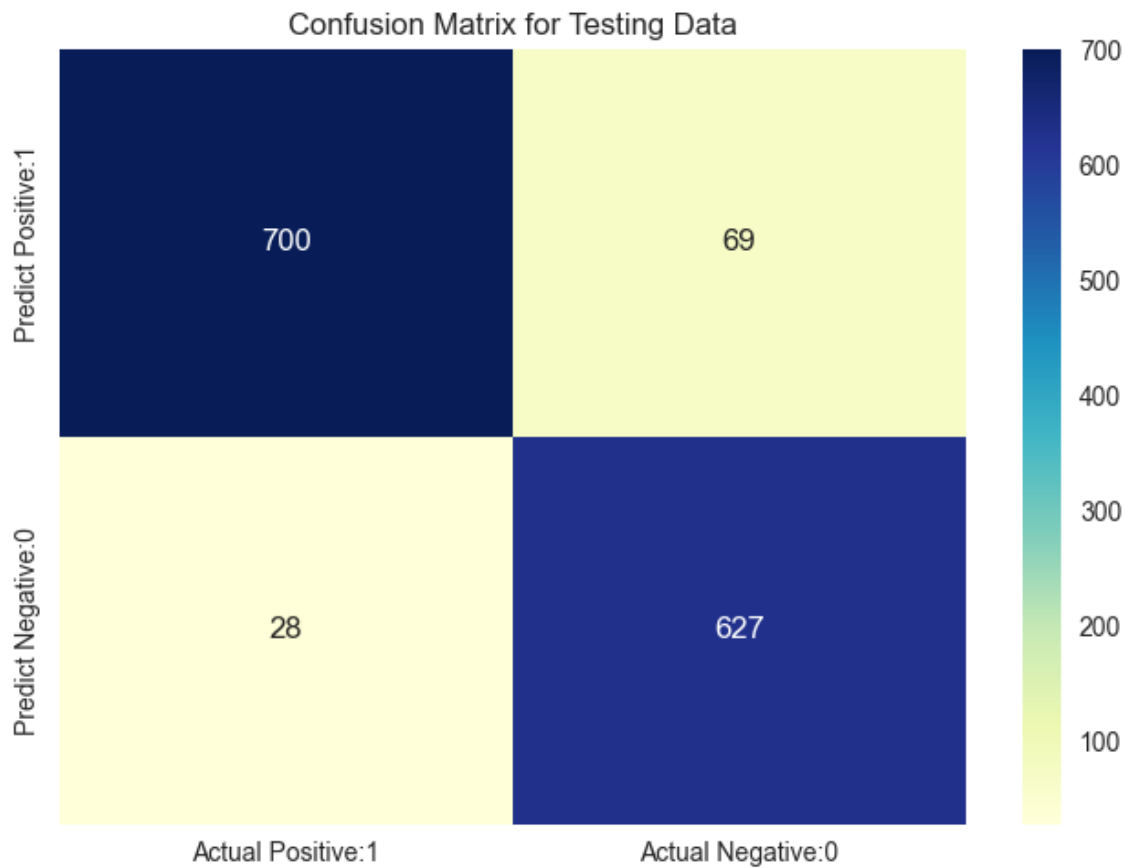
```
Results Random Forest Classifier with Testing Data
Testing Results:
=====
CLASSIFICATION SUMMARY:

```

	0	1	accuracy	macro avg	weighted avg
precision	0.961538	0.900862	0.931882	0.931200	0.933629
recall	0.910273	0.957252	0.931882	0.933762	0.931882
f1-score	0.935204	0.928201	0.931882	0.931703	0.931983
support	769.000000	655.000000	0.931882	1424.000000	1424.000000

```
-----
Accuracy Score: 93.19%
```

Figure 1



Supervised Neural Network

This researcher created a supervised Neural Network using binary cross-entropy to validate the logistic regression and random forest classifier results. This researcher split the dataset using 90% for training data and 10% for testing data. Of the 90% training data, 10% was used for validation data when training the model. The images below show the structure of the neural network, the format for the training, testing, and validation data, and the successful completion of training the network.

```
##From our X features in the Diagnostic Analyticis
X1_train, X1_test, y1_train, y1_test = train_test_split(X,y,stratify=y, test_size=0.1, random_state=15)
X1_train = scale.fit_transform(X1_train)
X1_test = scale.transform(X1_test)

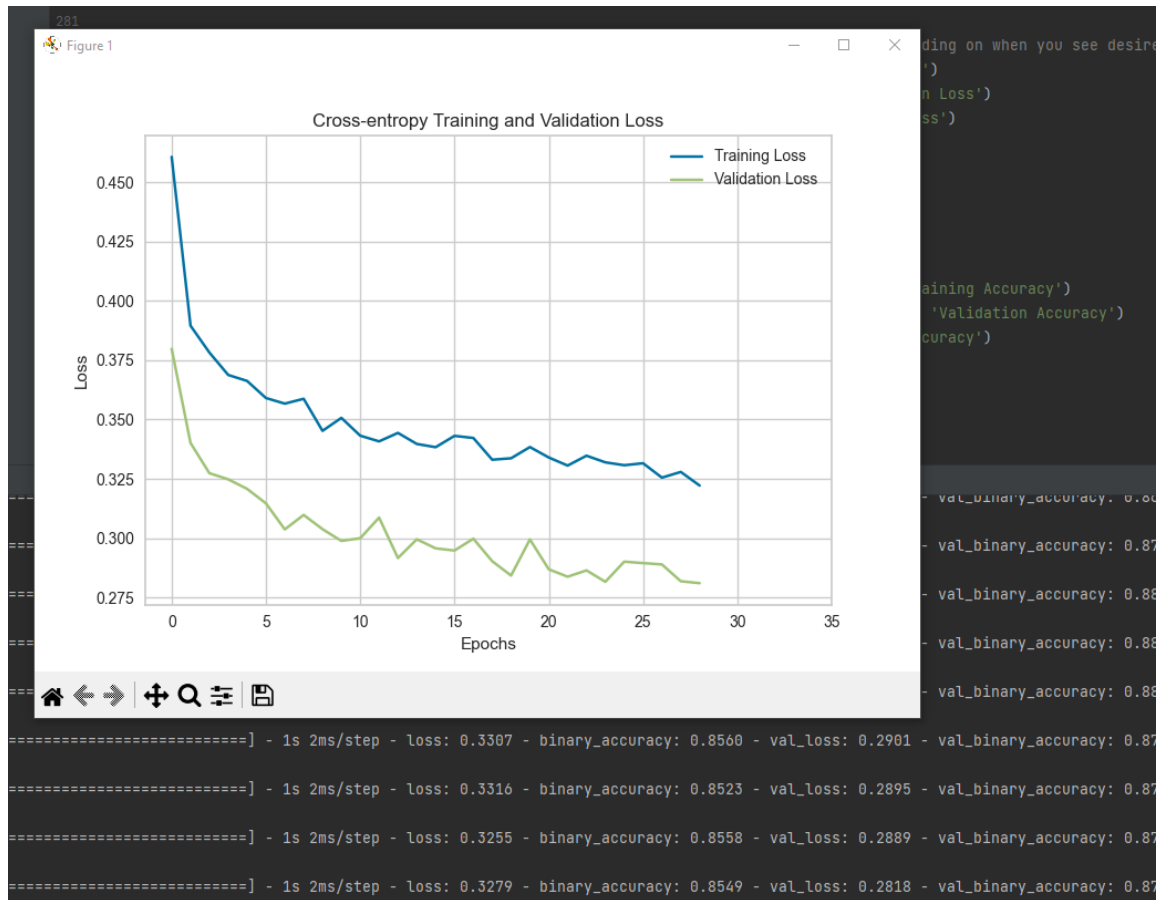
input_shape = [X1_train.shape[1]]

model = keras.Sequential([
    layers.BatchNormalization(input_shape=input_shape),
    layers.Dense(32,activation='relu'),
    layers.Dense(32,activation='relu'),
    layers.Dense(1,activation='sigmoid')])

model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['binary_accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    patience=5,
    min_delta=0.001,
    restore_best_weights=True,
)
history = model.fit(
    X1_train, y1_train,
    batch_size=30,
    epochs=50,
    validation_split=0.1,|
    callbacks=[early_stopping],
)
```

When analyzing the loss function the final loss value mimics that of the logistic regression but it appears to be under fitting with its high loss value. This is an indication more data is needed to use this model.

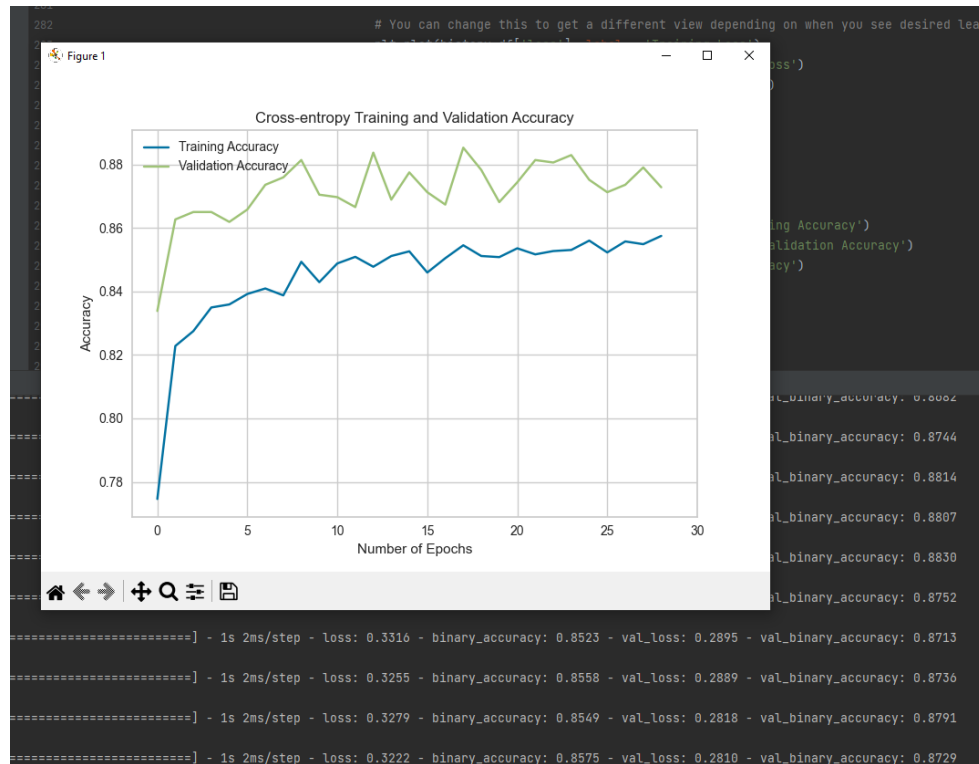


```

276         validation_split=0.1,
277         callbacks=[early_stopping],
278     )
279
280     history_df = pd.DataFrame(history.history)
281
282     # You can change this to get a different view depending on when you see desired learning loss at an
283     plt.plot(history_df['loss'], label = 'Training Loss')
284     plt.plot(history_df['val_loss'], label = 'Validation Loss')
285     plt.title('Cross-entropy Training and Validation Loss')
286     plt.legend(loc="upper right")
287     plt.xlabel('Epochs')
288     plt.ylabel('Loss')
289     plt.xticks(range(0, 40, 5))
290     plt.show()
291
292     #
293     plt.plot(history_df['binary_accuracy'], label = 'Training Accuracy')
294     plt.plot(history_df['val_binary_accuracy'], label = 'Validation Accuracy')
295     plt.title('Cross-entropy Training and Validation Accuracy')
296     plt.xlabel('Number of Epochs')
297     plt.legend(loc="upper left")
298     plt.ylabel('Accuracy')
299     plt.xticks(range(0, 35, 5))
300     plt.show()

```

The model's accuracy mimics that of the logistic regression used earlier.



After comparing all three machine learning algorithms, this researcher recommends using a logistic regression for this dataset. While the random forest classifier appears to be the most accurate, this researcher needs to scrutinize its high accuracy to verify that it accurately predicts employee terminations or if some noise affects the results. The supervised neural network would be ideal if this dataset were significant. Still, the loss function indicates it is under-fitting and needs more data or complex data to perform optimally. The following image displays the test data output from the data set combined with the logistic regression predictions. Creating an output like this allows researchers to scrutinize the model's results. Without using a standard scaler, the logistic regression model could predict employee terminations with 79.49% accuracy.

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Data Types

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Clear

Reapply

Advanced

Sort & Filter

Text to Columns

Data Tools

What-If Analysis

Forecast Sheet

Forecast

Group

Ungroup

Subtotal

Outline

Data Analysis

Solver

Analyze

P5

fx

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1		POS_CAT	LOCATION_YOS	AGE	GRADE	STEP		ANNUAL_F	DAILY_RT	EMPL_STA	y_pred												
2	0	9	100	6	54	103	8	21961.8	122.01	0	0	TRUE			TRUE	1132							
3	1	7	71	5	32	32	5	59538.4	313.36	1	1	TRUE			FALSE	292							
4	2	8	16	3	54	18	6	19119.75	103.35	0	0	TRUE				0.7949438							
5	3	8	25	38	72	17	27	23361.8	126.28	0	0	TRUE											
6	4	1	29	3	52	31	24	78538.4	413.36	1	1	TRUE											
7	5	4	100	12	63	15	28	23484	123.6	0	0	TRUE											
8	6	8	45	24	68	103	14	22118.6	119.56	0	0	TRUE											
9	7	1	33	5	27	31	4	54993.6	289.44	1	1	TRUE											
10	8	1	51	2	53	29	23	69251.2	364.48	0	1	FALSE											
11	9	8	61	29	54	103	23	29421	163.45	1	1	TRUE											
12	10	1	54	1	29	28	0	36010.7	189.53	0	0	TRUE											
13	11	1	11	2	31	29	8	54993.6	289.44	1	1	TRUE											
14	12	4	49	1	64	15	27	22392.65	117.856	0	0	TRUE											
15	13	7	10	19	52	32	27	90807.6	465.68	1	1	TRUE											
16	14	8	52	3	74	17	19	19391.4	107.73	0	0	TRUE											
17	15	5	47	2	50	101	6	18015.3	97.38	1	0	FALSE											
18	16	8	379	1	73	16	21	20952	116.4	0	0	TRUE											
19	17	1	10	13	50	31	18	70467.2	370.88	1	1	TRUE											
20	18	1	65	2	28	28	1	38586.02	203.0843	0	1	FALSE											
21	19	8	10	13	74	18	22	24905.63	134.625	0	0	TRUE											
22	20	1	25	13	44	28	9	54020.8	284.32	1	1	TRUE											
23	21	1	73	10	54	31	13	51045.4	268.66	0	0	TRUE											
24	22	1	70	3	55	32	7	61681.6	324.64	1	0	FALSE											
25	23	8	23	5	50	106	6	25061.4	139.23	1	1	TRUE											
26	24	9	373	2	63	103	11	19885.5	110.475	0	0	TRUE											
27	25	8	50	31	66	19	30	31464	165.6	0	0	TRUE											
28	26	8	49	7	47	104	7	22196.3	119.98	0	1	FALSE											

lr_test_output