In [3]:
```
# Importing important libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime as dt
import xverse
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from dmba import classificationSummary, regressionSummary
from dmba import classificationSummary, gainsChart, liftChart
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score, recall_score, precision_scor
e, f1_score, classification_report
%matplotlib inline
```

```
no display found. Using non-interactive Agg backend
```

In [4]:
```
org=pd.read_csv('org.csv', parse_dates=["date_of_joining","last_working_
date", "cutoff_date", "date_of_birth"])
org.head(5)
```

Out[4]:

	emp_id	status	turnover	location	level	date_of_joining	date_of_birth	last_working_date
0	E11061	Inactive	1	New York	Analyst	2012-03-22	1992-03-22	2014-11-09
1	E1031	Inactive	1	New York	Analyst	2012-09-03	1992-10-01	2014-05-06
2	E6213	Inactive	1	New York	Analyst	2012-06-01	1992-06-02	2014-04-30
3	E5900	Inactive	1	New York	Analyst	2012-03-22	1991-12-19	2014-09-04
4	E3044	Inactive	1	Florida	Analyst	2012-03-29	1991-10-12	2014-01-23

In [5]:
```
org.shape
```

Out[5]:
```
(2291, 14)
```

In [6]:
```
org.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2291 entries, 0 to 2290
Data columns (total 14 columns):
emp_id               2291 non-null object
status               2291 non-null object
turnover             2291 non-null int64
location             2291 non-null object
level                2291 non-null object
date_of_joining      2291 non-null datetime64[ns]
date_of_birth        2291 non-null datetime64[ns]
last_working_date    410 non-null datetime64[ns]
gender               2291 non-null object
department           2291 non-null object
mgr_id               2291 non-null object
cutoff_date          2291 non-null datetime64[ns]
generation           2291 non-null object
emp_age              2291 non-null float64
dtypes: datetime64[ns](4), float64(1), int64(1), object(8)
memory usage: 250.7+ KB
```

Data cleaning

Changing data types of some columns **Filling NaN values with 0

In [7]:
```
#print(today_date)
org["last_working_date"]= org["last_working_date"].fillna(pd.to_datetime
("2021-03-12"))
org.head(10)
```

Out[7]:

	emp_id	status	turnover	location	level	date_of_joining	date_of_birth	last_working_date
0	E11061	Inactive	1	New York	Analyst	2012-03-22	1992-03-22	2014-11-09
1	E1031	Inactive	1	New York	Analyst	2012-09-03	1992-10-01	2014-05-06
2	E6213	Inactive	1	New York	Analyst	2012-06-01	1992-06-02	2014-04-30
3	E5900	Inactive	1	New York	Analyst	2012-03-22	1991-12-19	2014-09-04
4	E3044	Inactive	1	Florida	Analyst	2012-03-29	1991-10-12	2014-01-23
5	E4008	Active	0	Florida	Assistant Manager	2013-11-27	1992-06-05	2021-03-12
6	E6636	Active	0	New York	Specialist	2012-02-17	1992-01-23	2021-03-12
7	E13796	Inactive	1	New York	Analyst	2012-03-30	1990-12-19	2014-11-05
8	E13549	Active	0	New York	Analyst	2012-09-03	1991-12-22	2021-03-12
9	E13430	Inactive	1	New York	Analyst	2012-09-03	1991-08-19	2014-10-16

In [8]:
```
org.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2291 entries, 0 to 2290
Data columns (total 14 columns):
emp_id               2291 non-null object
status               2291 non-null object
turnover             2291 non-null int64
location             2291 non-null object
level                2291 non-null object
date_of_joining      2291 non-null datetime64[ns]
date_of_birth        2291 non-null datetime64[ns]
last_working_date    2291 non-null datetime64[ns]
gender               2291 non-null object
department           2291 non-null object
mgr_id               2291 non-null object
cutoff_date          2291 non-null datetime64[ns]
generation           2291 non-null object
emp_age              2291 non-null float64
dtypes: datetime64[ns](4), float64(1), int64(1), object(8)
memory usage: 250.7+ KB
```

Exploratory Data Analysis

Time frame of data

In [9]:
```
time_max=org["cutoff_date"].max()
time_min=org["date_of_joining"].min()
print("End time for data collection", time_max)
print("Starting time for data collection", time_min)
```

```
End time for data collection 2014-12-31 00:00:00
Starting time for data collection 1994-01-21 00:00:00
```

In [10]:
```
# Number of employees at the start of the 20 year time period- active an
d inactive
org["status"].value_counts()
```

Out[10]:
```
Active      1881
Inactive     410
Name: status, dtype: int64
```

Turnover rate= Total number of inactive employees / (Active employees at beginning of time period+Active employees at end of time period)/2

In [11]:
```
count_2004_active=org[(org["date_of_joining"]<="2004-12-31")&
                      (org["last_working_date"]>"2004-12-31")]["emp_id"]
.count()
count_2004_inactive=org[(org["date_of_joining"]<="2004-12-31")
                       &(org["last_working_date"]<"2004-12-31")]["emp_i
d"].count()
print("Number of active employees in 2004: ",count_2004_active)
print("Number of inactive employees in 2004: ",count_2004_inactive)
print("\n")

count_2005_active = org[(org["date_of_joining"]<="2005-12-31") &
                      (org["last_working_date"]>="2005-12-31")]["emp_id"
].count()
count_2005_inactive = org[(org["date_of_joining"]<="2005-12-31") &
                        (org["last_working_date"]<= "2005-12-31")]["emp_
id"].count()
print("Number of active employees in 2005: ",count_2005_active)
print("Number of inactive employees in 2005: ",count_2005_inactive)
print("\n")

count_2006_active=org[(org["date_of_joining"]<="2006-12-31") &
                      (org["last_working_date"]>="2006-12-31")]["emp_id"
].count()
count_2006_inactive=org[(org["date_of_joining"]<="2006-12-31") &
                        (org["last_working_date"]<="2006-12-31")]["emp_i
d"].count()
print("Number of active employees in 2006: ",count_2006_active)
print("Number of inactive employees in 2006: ",count_2006_inactive)
print("\n")

count_2013_active=org[(org["date_of_joining"]<="2013-12-31") &
                      (org["last_working_date"]>="2013-12-31")]["emp_id"
].count()
count_2013_inactive=org[(org["date_of_joining"]<="2013-12-31") &
                        (org["last_working_date"]<="2013-12-31")]["emp_i
d"].count()
print("Number of active employees in 2013: ",count_2013_active)
print("Number of inactive employees in 2013: ",count_2013_inactive)
print("\n")


count_2014_active=org[(org["date_of_joining"]<="2014-12-31") &
                      (org["last_working_date"]>="2014-12-31")]["emp_id"
].count()
count_2014_inactive=org[(org["date_of_joining"]<="2014-12-31") &
                        (org["last_working_date"]<="2014-12-31")]["emp_i
d"].count()
print("Number of active employees in 2014: ",count_2014_active)
print("Number of inactive employees in 2014: ",count_2014_inactive)
```

```
Number of active employees in 2004:  148
Number of inactive employees in 2004:  0


Number of active employees in 2005:  206
Number of inactive employees in 2005:  0


Number of active employees in 2006:  329
Number of inactive employees in 2006:  0


Number of active employees in 2013:  2291
Number of inactive employees in 2013:  0


Number of active employees in 2014:  1881
Number of inactive employees in 2014:  410
```

In [12]:
```
average1=(2291+1881)/2
turnover_rate_13_14= 410/average1
turnover_rate_13_14
```

Out[12]:
```
0.1965484180249281
```

In [13]:
```
turnover_year=org.groupby("cutoff_date")["turnover"].mean()
print(turnover_year)
```

```
cutoff_date
2014-12-31    0.178961
Name: turnover, dtype: float64
```

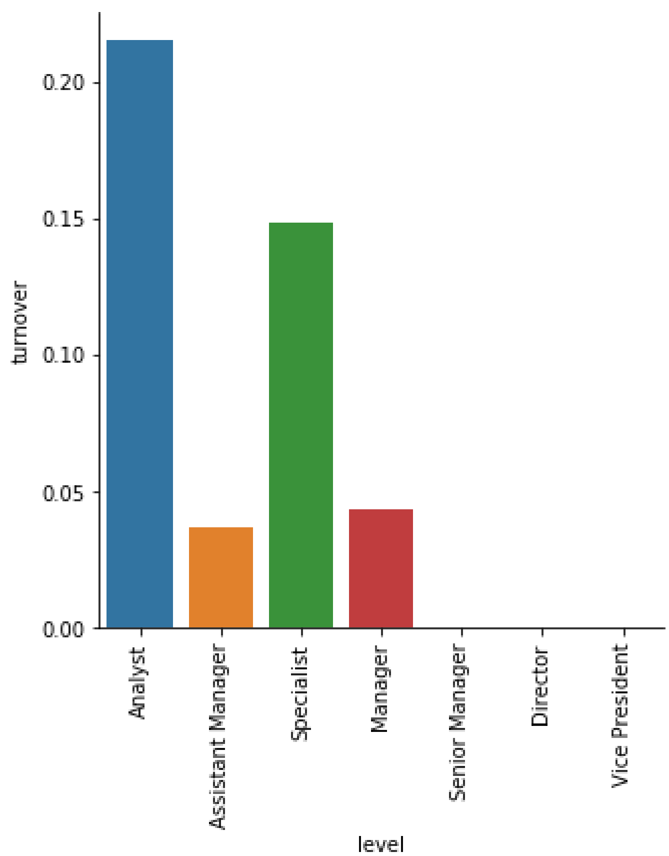
In [14]:
```
# Number of new joinees every 3 years
```

In [15]:
```
joining_1994_1997 = org[(org["date_of_joining"]>="1994-01-01") &
                               (org["date_of_joining"]<="1997-12-31")]

joining_1997_2000 = org[(org["date_of_joining"]>="1997-01-01") &
                               (org["date_of_joining"]<="2000-12-31")]

joining_2000_2003 = org[(org["date_of_joining"]>="2000-01-01") &
                               (org["date_of_joining"]<="2003-12-31")]

joining_2003_2006= org[(org["date_of_joining"]>="2003-01-01") &
                               (org["date_of_joining"]<="2006-12-31")]

joining_2006_2009 = org[(org["date_of_joining"]>="2006-01-01") &
                               (org["date_of_joining"]<="2009-12-31")]

joining_2009_2012 = org[(org["date_of_joining"]>="2009-01-01") &
                               (org["date_of_joining"]<="2012-12-31")]

joining_2012_2015 = org[(org["date_of_joining"]>="2012-01-01") &
                               (org["date_of_joining"]<="2015-12-31")]
```

Showing turnover rate level-wise

In [16]:
```
turnover_level=org.groupby("level")["turnover"].mean()
print(turnover_level)
sns.catplot(kind="bar",
            x="level",
            y="turnover",
            data=org,
            ci=None)
plt.xticks(rotation=90)
plt.show()

"""Turnover rate is highest at Analyst and Specialist level"""
```

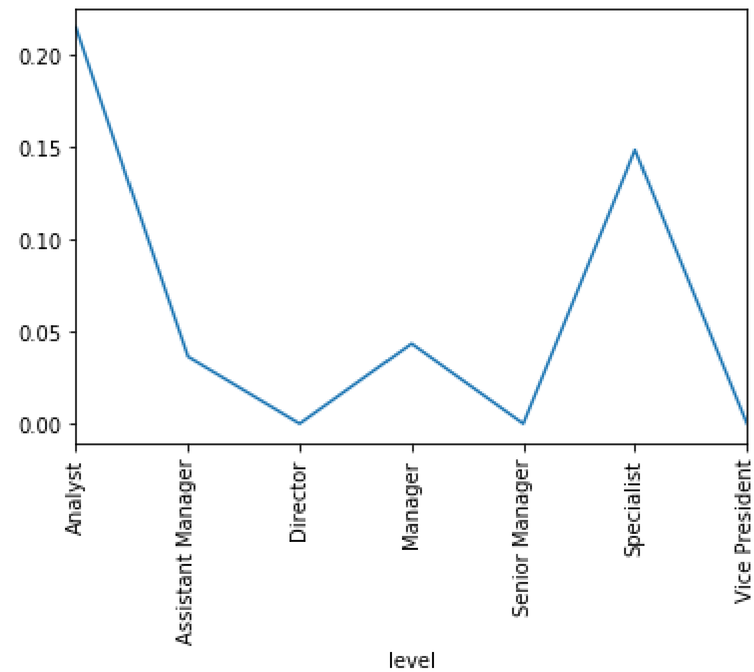
```
level
Analyst              0.215087
Assistant Manager    0.036458
Director             0.000000
Manager              0.043478
Senior Manager       0.000000
Specialist           0.148571
Vice President       0.000000
Name: turnover, dtype: float64
```



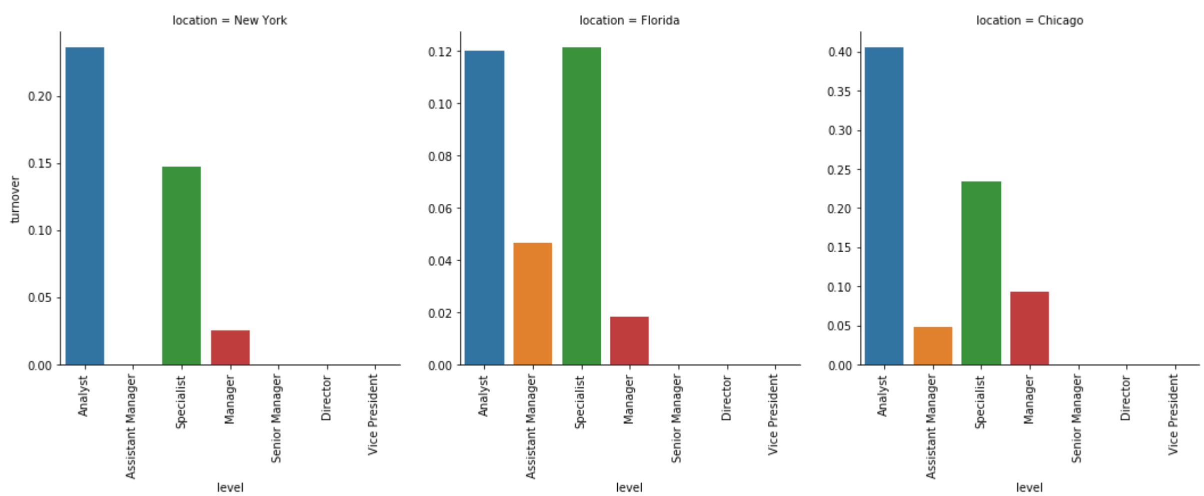
Out[16]: 'Turnover rate is highest at Analyst and Specialist level'

In [17]:
```
turnover_level.plot()
plt.xticks(rotation=90)
```

Out[17]:
```
(array([0., 1., 2., 3., 4., 5., 6.]), <a list of 7 Text xticklabel obje
cts>)
```



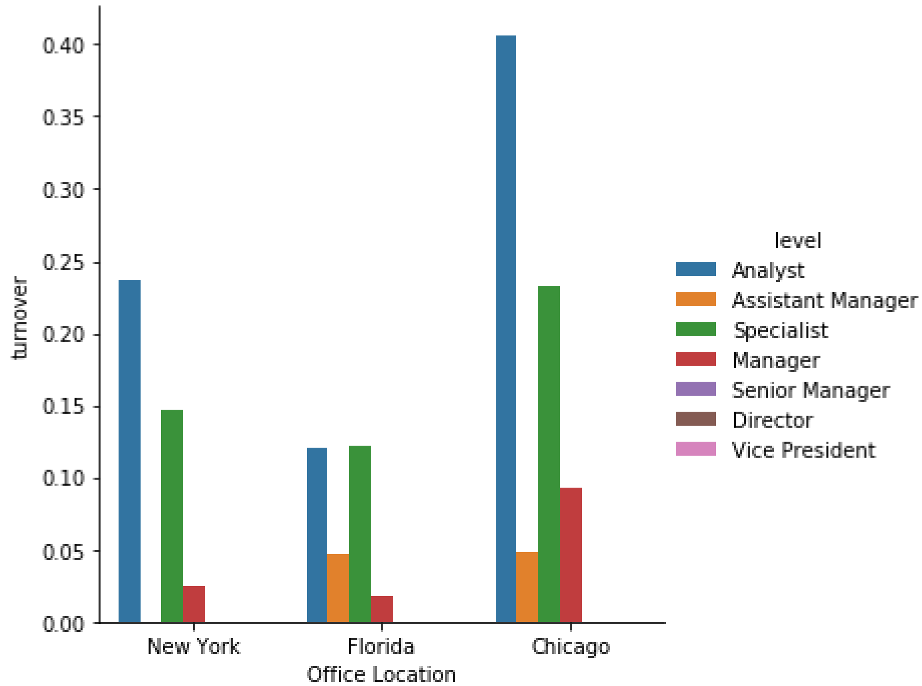
In [18]:
```
g=sns.catplot(data=org,
            kind="bar",
            x="level",
            y="turnover",
            col="location",
            col_wrap=3,
            ci=None,
            sharey=False)
for ax in g.axes:
    plt.setp(ax.get_xticklabels(), visible= True, rotation=90)
#plt.xticks(rotation=90)
plt.show()

"""Turnover rate is highest at Analyst and Specialist level at all locat
ions."""
```



Out[18]:
```
'Turnover rate is highest at Analyst and Specialist level at all locati
ons.'
```

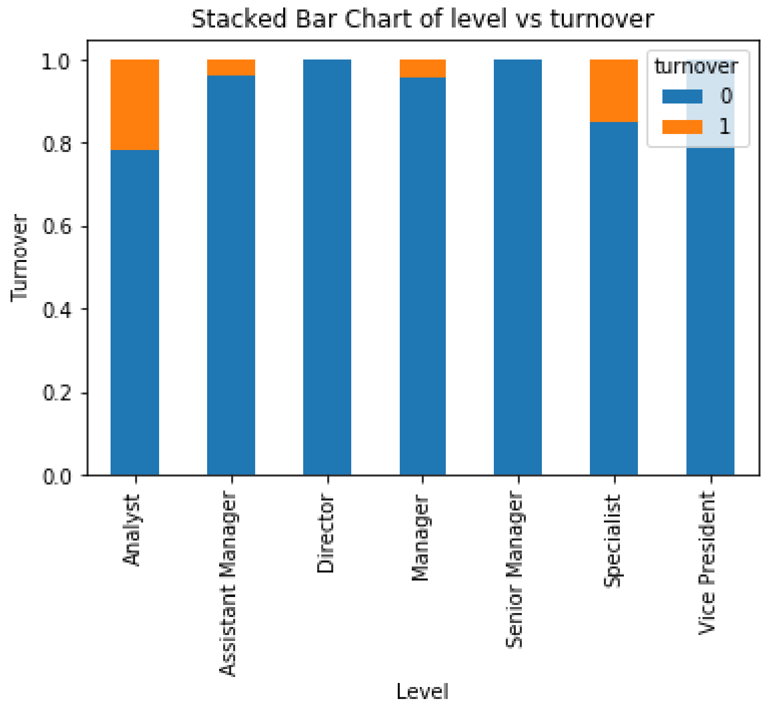
In [19]:
```
ans= org.groupby("location")["turnover"].agg(np.mean)
print(ans)
sns.catplot(kind="bar", x="location",y ="turnover", hue="level", data=or
g, ci=None)
plt.xlabel("Office Location")
plt.show()
"""Turnover rate is high in Chicago as compared to other locations"""
```

```
location
Chicago     0.325641
Florida     0.105513
New York    0.202591
Name: turnover, dtype: float64
```



Out[19]: 'Turnover rate is high in Chicago as compared to other locations'

In [20]:
```
table=pd.crosstab(org.level,org.turnover)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of level vs turnover')
plt.xlabel('Level')
plt.ylabel('Turnover')
plt.savefig('Level vs Turnover')
```



We can calculate categorical means for other categorical variables such as education and marital status to get a more detailed sense of our data.

In [21]:
```
org.groupby("location").mean()
```

Out[21]:

	turnover	emp_age
location		
Chicago	0.325641	31.247436
Florida	0.105513	31.011692
New York	0.202591	27.915548

In [22]:
```
org.groupby("level").mean()
# the following gives same output too
#org.pivot_table(values=["turnover","emp_age"], index="level", aggfunc
="mean")
```

Out[22]:

level	turnover	emp_age
Analyst	0.215087	28.480611
Assistant Manager	0.036458	34.354167
Director	0.000000	39.000000
Manager	0.043478	36.166667
Senior Manager	0.000000	39.600000
Specialist	0.148571	31.326286
Vice President	0.000000	40.000000

In [23]:
```
org.groupby("gender").mean()
```

Out[23]:

gender	turnover	emp_age
Female	0.175389	29.091231
Male	0.180556	30.267424

BINS CREATION

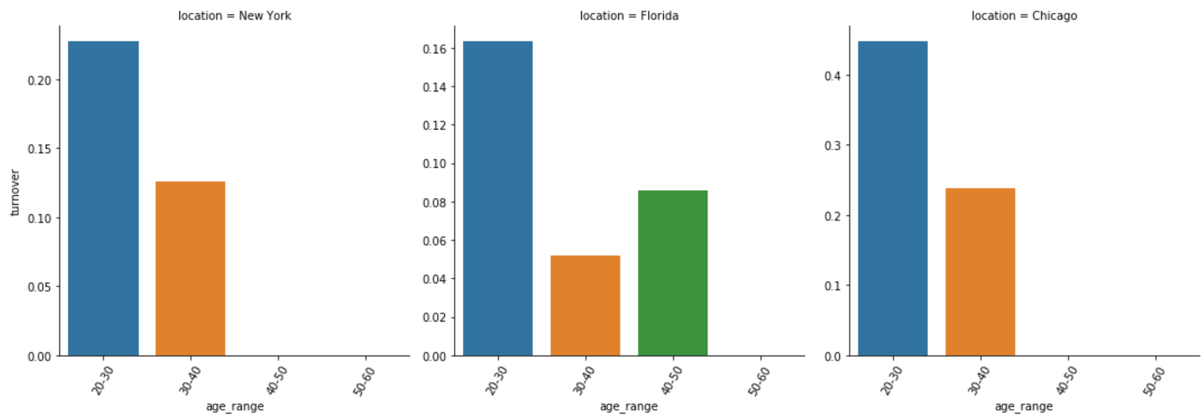
In [24]:
```
# making bins of Employee age
#org["emp_age"].min()---22
#org["emp_age"].max()---58
bins=[20,30,40,50,60]
bin_labels=["20-30","30-40","40-50","50-60"]
org["age_range"]=pd.cut(org["emp_age"],bins=bins,right=True, labels=bin_
labels)
org
```

Out[24]:

	emp_id	status	turnover	location	level	date_of_joining	date_of_birth	last_working_d
0	E11061	Inactive	1	New York	Analyst	2012-03-22	1992-03-22	2014-11
1	E1031	Inactive	1	New York	Analyst	2012-09-03	1992-10-01	2014-05
2	E6213	Inactive	1	New York	Analyst	2012-06-01	1992-06-02	2014-04
3	E5900	Inactive	1	New York	Analyst	2012-03-22	1991-12-19	2014-09
4	E3044	Inactive	1	Florida	Analyst	2012-03-29	1991-10-12	2014-01
...	...	...	...	...	...	...	...	
2286	E8787	Inactive	1	Florida	Assistant Manager	2013-06-03	1965-07-20	2014-02
2287	E12351	Active	0	Florida	Assistant Manager	1996-09-10	1965-12-06	2021-03
2288	E6282	Active	0	New York	Manager	2012-08-23	1960-05-18	2021-03
2289	E5195	Active	0	Florida	Analyst	2002-07-01	1972-07-01	2021-03
2290	E11037	Active	0	Florida	Manager	1994-01-21	1956-10-15	2021-03

2291 rows × 15 columns

In [25]:
```
g=sns.catplot(data=org,
            kind="bar",
            x="age_range",
            y="turnover",
            col="location",
            col_wrap=3,
            ci=None,
            sharey=False)
for ax in g.axes:
    plt.setp(ax.get_xticklabels(), visible= True, rotation=60)

plt.show()

"""Turnover is highest among 20-30 years of age range.
However, in Florida, about 8% of turnover is among employees between 40-
50 years of age. """
```



Out[25]:
```
'Turnover is highest among 20-30 years of age range.\nHowever, in Flori
da, about 8% of turnover is among employees between 40-50 years of age.
'
```

Observations

Approximately 18% of employees left the organization from 2013-2014 year.

The turnover is highest at Analyst and Specialist level.

Turnover rate is high in Chicago as compared to other locations.

The mean age of employees at Analyst and Specialist level is about 29 and 31 respectively.

There is not much difference in turnover rate across male and female employees. The gender does not seem a strong predictor for the turnover.

In [26]:
```
org.groupby("level")["location"].value_counts()
```

Out[26]:
```
level              location
Analyst            Florida     682
                   New York    656
                   Chicago     266
Assistant Manager  Florida     129
                   New York     42
                   Chicago      21
Director           Florida       1
Manager            Florida      55
                   Chicago      43
                   New York     40
Senior Manager     Florida       3
                   New York      2
Specialist         Florida     181
                   New York    109
                   Chicago      60
Vice President     Florida       1
Name: location, dtype: int64
```

Talent segments We will exclude top level management and middle mangement from analysis. We will focus our analysis on Analysts and Specialists as they form majority of the workforce. See the count below:

In [27]:
```
org["level"].value_counts()
```

Out[27]:
```
Analyst              1604
Specialist            350
Assistant Manager     192
Manager               138
Senior Manager          5
Vice President          1
Director                1
Name: level, dtype: int64
```

In [28]:
```
entry_level=["Analyst", "Specialist"]
org2 =org[org.level.isin(entry_level)]
```

In [29]:
```
#org1=org[(org["level"]=="Analyst") | (org["level"]=="Specialist")]
#org1
```

In [30]:
```
turnover_level=org.groupby("generation")["turnover"].mean()
print(turnover_level)
```

```
generation
Baby Boomers    0.000000
Generation X    0.086047
Millennials     0.200646
Name: turnover, dtype: float64
```

Exploratory Data Analysis results:

Combining data from different HR sources

In [31]:
```
survey=pd.read_csv("survey.csv")
survey.head()
```

Out[31]:

	mgr_id	mgr_effectiveness	career_satisfaction	perf_satisfaction	work_satisfaction
0	E1003	0.76	0.76	0.71	0.82
1	E10072	0.65	0.67	0.56	0.84
2	E10081	0.80	0.82	0.73	0.84
3	E10234	0.65	0.63	0.75	0.70
4	E1026	0.70	1.00	1.00	0.92

In [32]:
```
survey.shape
```

Out[32]: (350, 5)

In [33]:
```
#left_df.merge(right_df, on='user_id', how='left', indicator=True)
org_2=org.merge(survey,on="mgr_id", how='left', indicator= False)
org_2.head()
```

Out[33]:

	emp_id	status	turnover	location	level	date_of_joining	date_of_birth	last_working_date
0	E11061	Inactive	1	New York	Analyst	2012-03-22	1992-03-22	2014-11-09
1	E1031	Inactive	1	New York	Analyst	2012-09-03	1992-10-01	2014-05-06
2	E6213	Inactive	1	New York	Analyst	2012-06-01	1992-06-02	2014-04-30
3	E5900	Inactive	1	New York	Analyst	2012-03-22	1991-12-19	2014-09-04
4	E3044	Inactive	1	Florida	Analyst	2012-03-29	1991-10-12	2014-01-23

In [34]:
```
org_2.shape
```

Out[34]: (2291, 19)

In [35]:
```
rating=pd.read_csv("rating.csv")
rating.head()
```

Out[35]:

	emp_id	rating
0	E8	Acceptable
1	E9	Acceptable
2	E12	Acceptable
3	E15	Acceptable
4	E34	Acceptable

In [36]:
```
org_3=org_2.merge(rating, on="emp_id", how='left', indicator=False)
org_3.head()
```

Out[36]:

	emp_id	status	turnover	location	level	date_of_joining	date_of_birth	last_working_date
0	E11061	Inactive	1	New York	Analyst	2012-03-22	1992-03-22	2014-11-09
1	E1031	Inactive	1	New York	Analyst	2012-09-03	1992-10-01	2014-05-06
2	E6213	Inactive	1	New York	Analyst	2012-06-01	1992-06-02	2014-04-30
3	E5900	Inactive	1	New York	Analyst	2012-03-22	1991-12-19	2014-09-04
4	E3044	Inactive	1	Florida	Analyst	2012-03-29	1991-10-12	2014-01-23

In [37]:
```
org_3.shape
```

Out[37]: (2291, 20)

In [38]:
```
#org_3.info()
```

Feature Engineering---using a different dataset

Process of using domain knowledge to create new variables which help you discover new insights. Crucial step before building a predictive model.

New features added:

Age difference= manager age- employee age Views, handling pressure, Expectation, Work ethics Younger employees feel Older employees cannot deal with changing work pace.

JOB hopper- Job hopper is a person who switches job frequently for financial or career advancement opportunities. Recruiters and hiring managers views job hoppers in a negative light. There is a high chance they would quit soon. Job hop index = Total work experience/Number of companies worked.

Employee Tenure

Inactive employees: date_of_joining & last_working_date

Active employee : date_joining & cutoff_date(study period end date)

The more the number of years an employee works in the organization, it is less likely that he/she will quit.

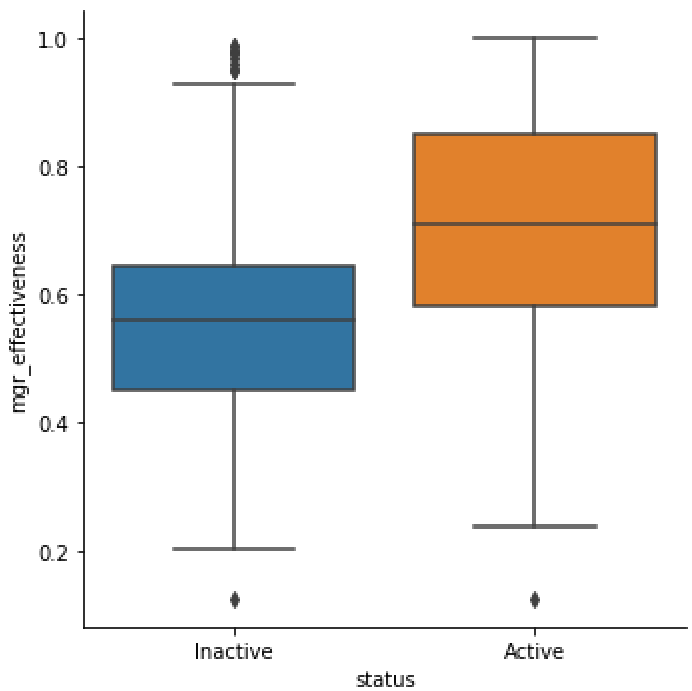
In [39]:
```
org_final=pd.read_csv("org_final.csv", parse_dates=["date_of_joining","last_working_date","cutoff_date"])
org_final.shape
```

Out[39]:
```
(1954, 34)
```

In [40]:
```
#org_final.info()
```

In [41]:
```
mgr_eff=org_final.groupby("status")["mgr_effectiveness"].agg(np.mean)
print(mgr_eff)
sns.catplot(kind="box",
            data=org_3,
            x="status",
            y="mgr_effectiveness")
plt.show()
```

```
status
Active      0.708169
Inactive    0.568516
Name: mgr_effectiveness, dtype: float64
```



Observations:

Mean manager effectivess seemed to be higher in active employees as compared to inactive employees.

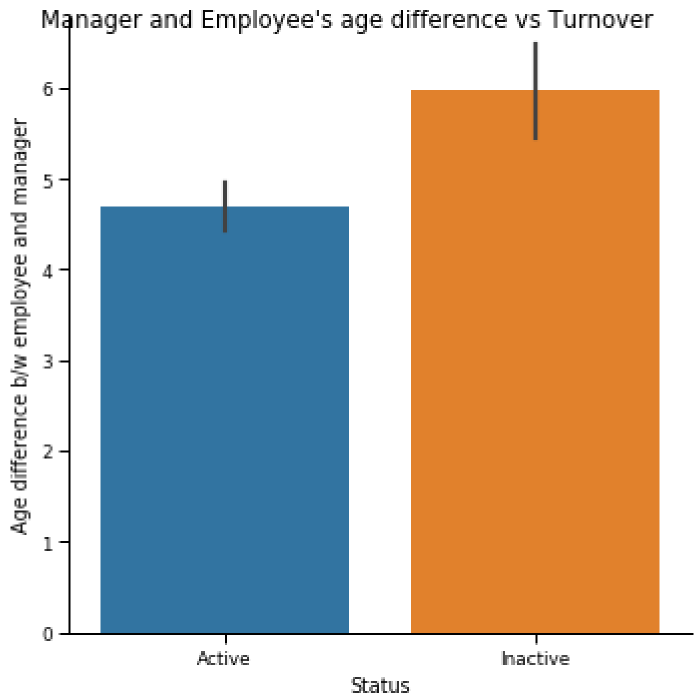
Age difference between manager and employee seem to be higher in inactive employees than active. Therefore coluld be a predictor for turnover.

Median job hop index for active and inactive employee are similar.

Age difference between manager and employee

In [42]:
```
sns.set_context("paper")
org_final["age_diff"]=org_final["mgr_age"]-org_final["emp_age"]
age_2=org_final.groupby("status")["age_diff"].mean()
print(age_2)
g=sns.catplot(kind="bar",
           x="status",
           y="age_diff",
           data=org_final)
g.fig.suptitle("Manager and Employee's age difference vs Turnover ")
g.set(xlabel="Status", ylabel="Age difference b/w employee and manager")
plt.show()
```

```
status
Active      4.691946
Inactive    5.982393
Name: age_diff, dtype: float64
```



Job- Hop Index

If its high means person didnt switch much. If its low, means employee switched a lot.

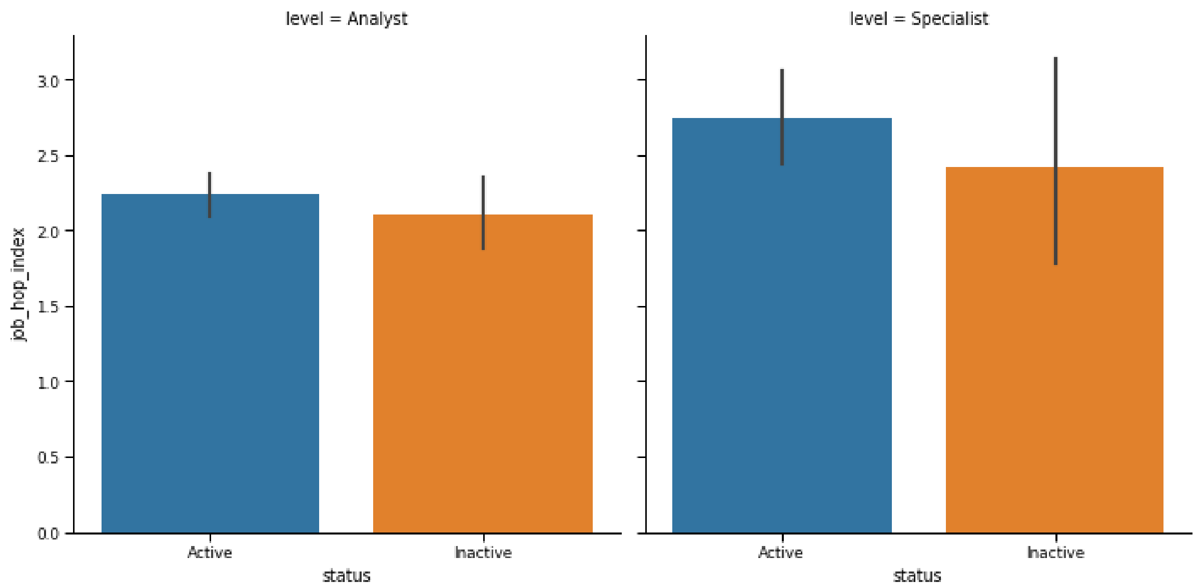
In [43]:
```
# replacing infinite values(inf) with zero
org_final["job_hop_index"]= org_final["total_experience"].div(org_final[
"no_previous_companies_worked"]).replace(np.inf, 0)
org_final[["job_hop_index"]]
```

Out[43]:

	job_hop_index
0	0.000000
1	0.542222
2	2.850000
3	0.952000
4	0.000000
...	...
1949	4.050000
1950	2.600000
1951	2.425000
1952	1.428571
1953	0.920000

1954 rows × 1 columns

In [44]:
```
sns.catplot(kind="bar",
            y="job_hop_index",
            x="status",
            data=org_final,
            col="level")
plt.show()

"""Analysts have a lower mean job hop index- means they are more likely
 to leave than Specialists"""
```



Out[44]: 'Analysts have a lower mean job hop index- means they are more likely to leave than Specialists'

In [45]:
```
org_final["date_of_joining"].fillna(0)
org_final["last_working_date"].fillna(0)
org_final["date_of_joining"]=pd.to_datetime(org_final["date_of_joining"
])
org_final["last_working_date"]=pd.to_datetime(org_final["last_working_da
te"])
org_final["cutoff_date"]=pd.to_datetime(org_final["cutoff_date"])
#org_final.info()
```

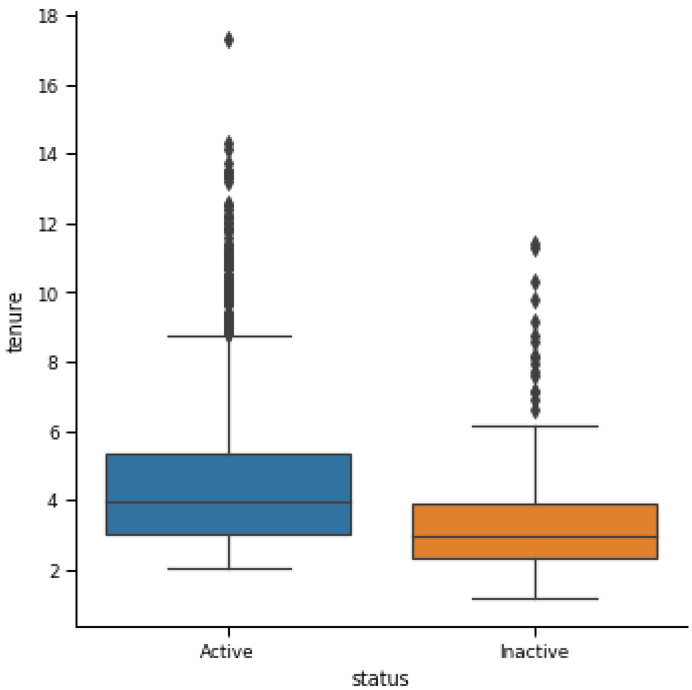
Calculating tenure in years

In [46]:
```
# Different calculations for 'Active' and "Inactive" employees
org_final.loc[org_final["status"]=="Inactive", "tenure"] = (org_final["l
ast_working_date"]-org_final["date_of_joining"])/np.timedelta64(1, 'Y')
org_final.loc[org_final["status"]=="Active", "tenure"] = (org_final["cut
off_date"]-org_final["date_of_joining"])/np.timedelta64(1, 'Y')
#org_final
```

In [47]:
```
ten_lev= org_final.groupby("level")["tenure"].agg(np.median)
print(ten_lev)
```

```
level
Analyst       3.438811
Specialist    5.411473
Name: tenure, dtype: float64
```

In [48]:
```
sns.catplot(data=org_final, x="status", y="tenure", kind="box")
plt.show()

"""The median tenure of inactive employees is less than the tenure of ac
tive employees."""
```

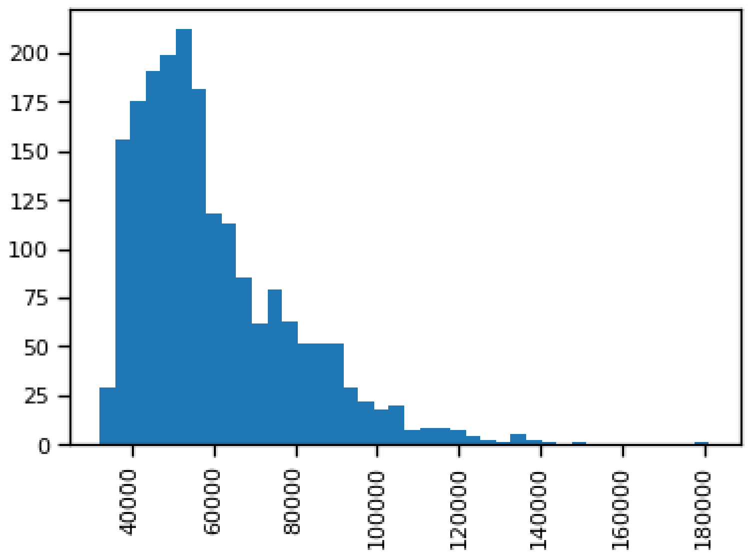


Out[48]:
```
'The median tenure of inactive employees is less than the tenure of act
ive employees.'
```

Viewing distribution of compensation among all employees

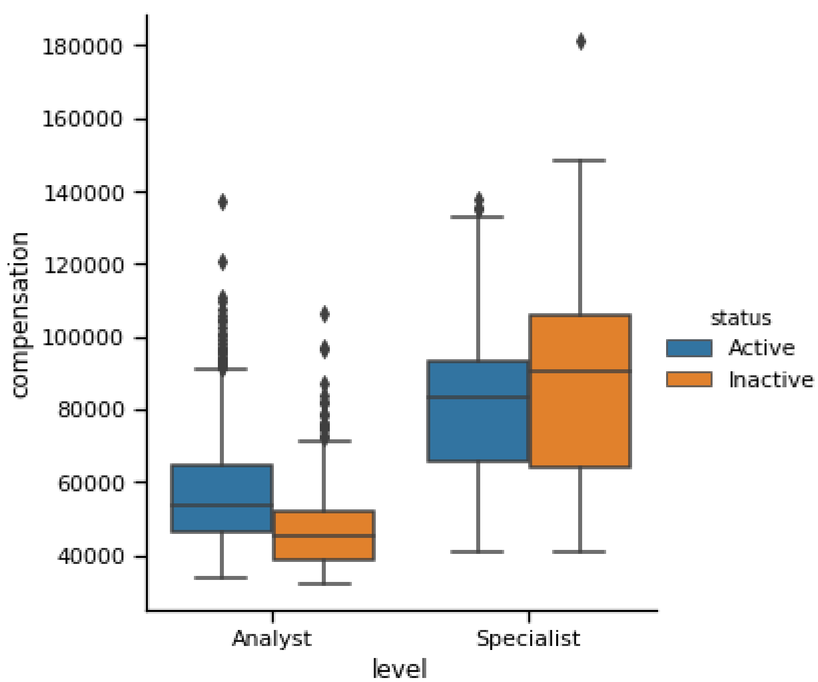
In [49]:
```
sns.set_context("notebook")
plt.hist(x="compensation", data=org_final, bins=40)
plt.xticks(rotation=90)
plt.plot()
```

Out[49]: []



The distribution is right skewed.

In [50]:
```
sns.set_context("notebook")
sns.catplot(kind="box",
            y="compensation",
            x="level",
            data=org_final,
            hue="status")
plt.show()
```



Compensation varies acrooss jobs and levels. At Analyst level, median compensation of Inactive employees is low when compared to Active employees.(Compensation could be a reason for leaving).

At specialist level, the median compensation of inactive employees was higher than active employees(some other reason for leaving).

Employees always expect that they are paid fairly compared to their co-workers, and hence, maintaining internal pay parity is important.

Competitiveness of each employee's pay can be assessed by Compa-ratio. In this exercise, you'll derive compa-ratio as:

Compa-ratio= Actual compensation/Median compensation

Median compensation is used by organizations to estimate the typical pay for any role/level. This metric helps the organization to correct the compensation of employees who are way below the median compensation.

Remember, median is also known as the 50th percentile. Exactly 50 percent of people make less than the median and 50 percent make more.

In [51]:
```
median_comp=org_final.groupby("level")["compensation"].agg(np.median)
median_comp
```

Out[51]:
```
level
Analyst       51840
Specialist    83496
Name: compensation, dtype: int64
```

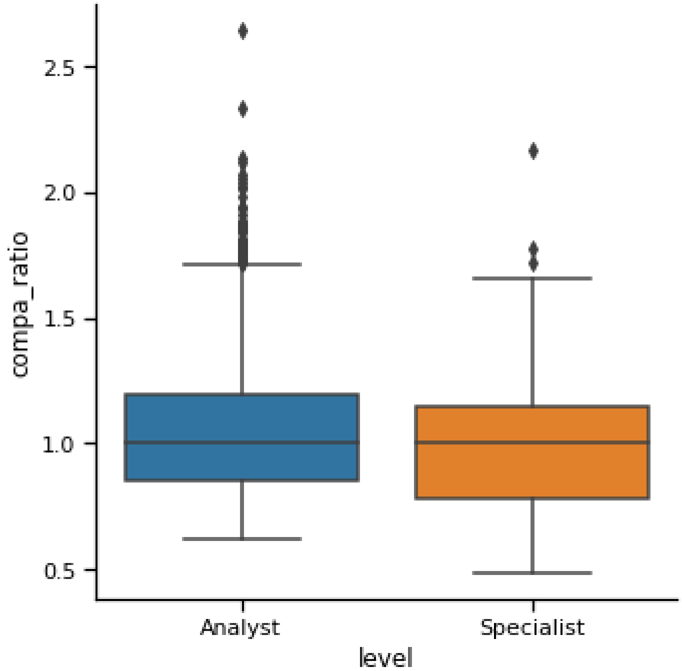
In [52]:
```
org_final.loc[org_final["level"]=="Analyst", "compa_ratio"]=org_final["c
ompensation"]/51840
org_final.loc[org_final["level"]=="Specialist", "compa_ratio"]=org_final
["compensation"]/83496
org_final
```

Out[52]:

	emp_id	status	location	level	gender	emp_age	rating	mgr_rating	mgr_reporte
0	E10012	Active	New York	Analyst	Female	25.09	Above Average	Acceptable	
1	E10025	Active	Chicago	Analyst	Female	25.98	Acceptable	Excellent	
2	E10027	Active	Orlando	Specialist	Female	33.40	Acceptable	Above Average	
3	E10048	Active	Chicago	Specialist	Male	24.55	Acceptable	Acceptable	
4	E10060	Active	Orlando	Analyst	Male	31.23	Acceptable	Acceptable	
...	...	...	...	...	...	...	...	...	
1949	E9960	Active	Orlando	Analyst	Male	27.81	Excellent	Acceptable	
1950	E9977	Active	Orlando	Analyst	Male	27.64	Above Average	Above Average	
1951	E9980	Active	New York	Specialist	Male	27.63	Acceptable	Acceptable	
1952	E9992	Active	Chicago	Specialist	Male	28.34	Acceptable	Acceptable	
1953	E9993	Active	Orlando	Analyst	Female	26.25	Acceptable	Acceptable	

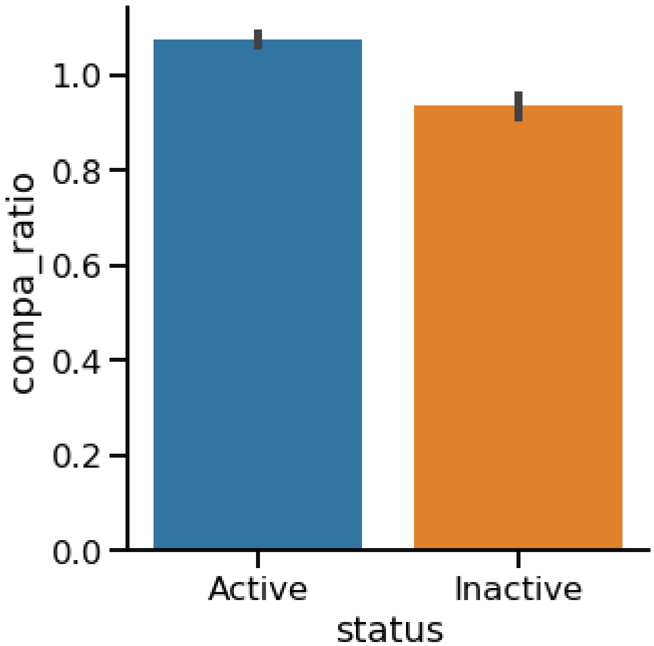
1954 rows × 38 columns

In [53]:
```
sns.catplot(kind="box",
            x="level",
            y="compa_ratio",
            data=org_final)
plt.show()
```



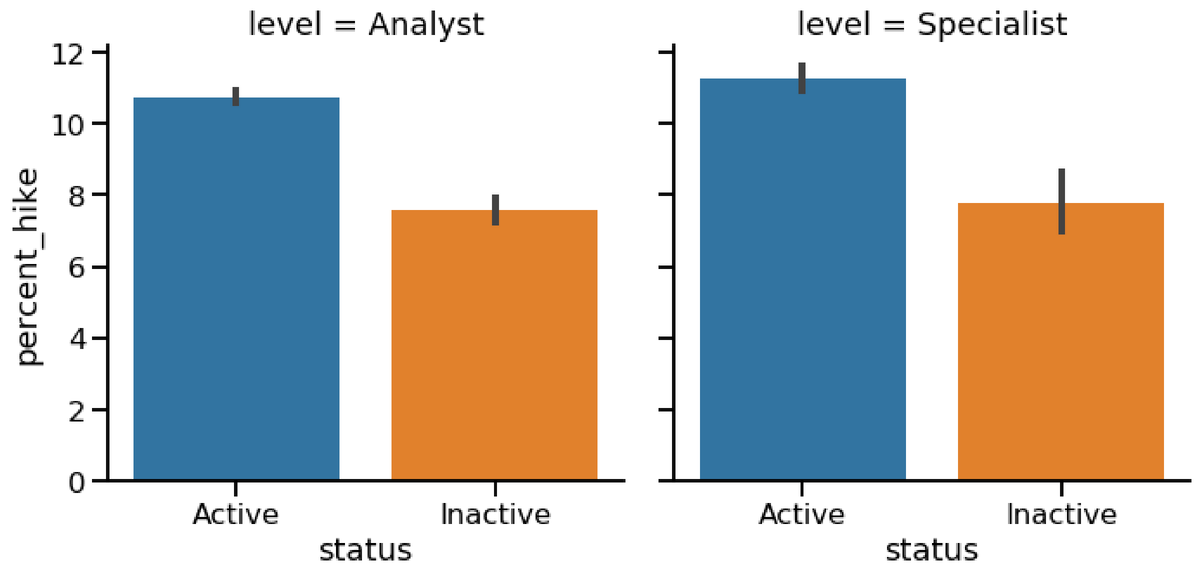
Median compa-ratio is same in both analysts and Specialists. At specialist level, median is closer to 75th percentile, more number of employees have compa-ratio less than the median.

In [54]:
```
sns.set_context("talk")
sns.catplot(data=org_final,
            x="status",
            y="compa_ratio",
            kind="bar")

plt.show()

"""A greater proportion of inactive employees were paid less than median
compensation."""
```



Out[54]: 'A greater proportion of inactive employees were paid less than median compensation.'

In [55]:
```
sns.set_context("talk")
sns.catplot(data=org_final,
            x="status",
            y="percent_hike",
            kind="bar",
            col="level")
plt.show()
```



In [56]:
```
sns.set_context("talk")
sns.catplot(data=org_final,
            x="turnover",
            y="percent_hike",
            kind="bar",
            hue="level",
            col="location",
            ci=None)
plt.xticks(rotation=90)
plt.show()
```

Predictor variable's contribution

In [57]:
```
# only for quantitative variables
corr_matrix_f = org_final.corr().round(2)
corr_matrix_f
```

Out[57]:

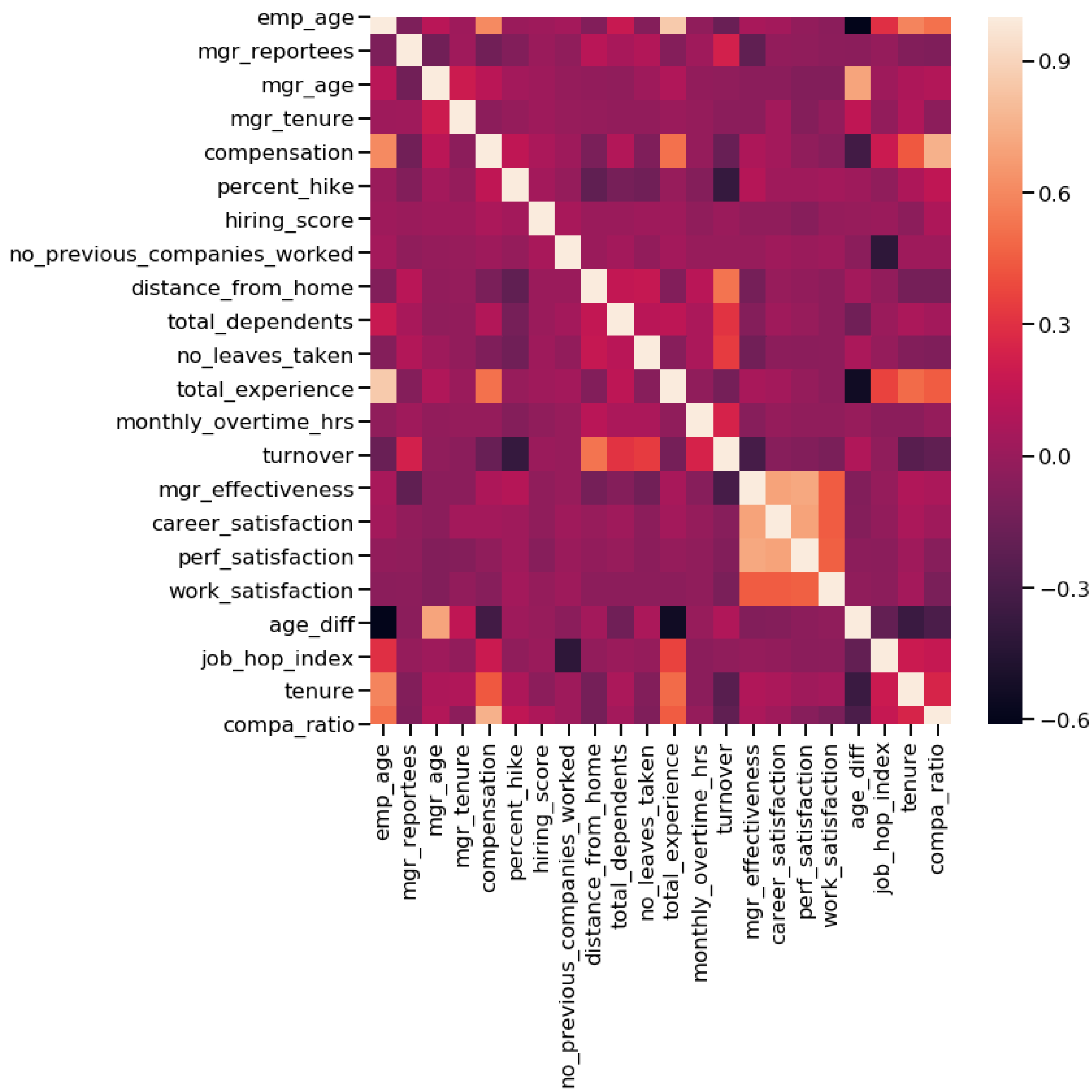
	emp_age	mgr_reportees	mgr_age	mgr_tenure	compensation	per
emp_age	1.00	-0.10	0.12	0.02	0.61	
mgr_reportees	-0.10	1.00	-0.14	0.03	-0.14	
mgr_age	0.12	-0.14	1.00	0.20	0.13	
mgr_tenure	0.02	0.03	0.20	1.00	-0.04	
compensation	0.61	-0.14	0.13	-0.04	1.00	
percent_hike	0.01	-0.08	0.04	-0.01	0.15	
hiring_score	0.02	0.01	0.02	0.02	0.07	
no_previous_companies_worked	0.05	-0.03	-0.01	-0.00	0.02	
distance_from_home	-0.08	0.12	-0.02	-0.01	-0.11	
total_dependents	0.18	0.06	-0.03	-0.02	0.10	
no_leaves_taken	-0.07	0.10	0.02	-0.02	-0.09	
total_experience	0.86	-0.07	0.09	0.01	0.52	
monthly_overtime_hrs	-0.03	0.03	-0.02	-0.01	-0.01	
turnover	-0.17	0.23	-0.03	-0.05	-0.18	
mgr_effectiveness	0.06	-0.21	-0.05	-0.05	0.08	
career_satisfaction	0.04	-0.02	-0.05	0.04	0.04	
perf_satisfaction	-0.02	-0.03	-0.08	-0.07	-0.03	
work_satisfaction	-0.05	-0.04	-0.08	-0.02	-0.06	
age_diff	-0.61	-0.05	0.71	0.15	-0.33	
job_hop_index	0.30	-0.01	0.02	-0.02	0.19	
tenure	0.59	-0.08	0.08	0.09	0.44	
compa_ratio	0.52	-0.09	0.10	-0.04	0.76	

22 rows × 22 columns

In [58]:
```
# distance_from_home, compensation, mgr_effectiveness, perf_satisfactio
n, age_diff, tenure,
```

In [59]:
```
plt.figure(figsize=(10,10))
sns.heatmap(corr_matrix_f)
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa725bd45d0>



Weight of evidence (WOE) and Information value (IV) are simple, yet powerful techniques to perform variable transformation and selection. These concepts have huge connection with the logistic regression modeling technique. It is widely used in credit scoring to measure the separation of good vs bad customers.

In [60]:
```
# removing variables which have no predictive power

# emp_id, mgr_id ----are id columns
# date_of_joining, last_working_date, cutoff_date ----tenure is a linear
combination of these columns.
# mgr_age, emp_age-----age_diff is a linear combination of these column
s.
# department-----
# status ---is same as turnover
```

In [61]:
```
from xverse.transformer import MonotonicBinning
independent_var=['location', 'level', 'gender', 'emp_age', 'rating','mgr
_rating', 'mgr_reportees', 'mgr_age',
                  'mgr_tenure', 'compensation','percent_hike', 'hiring_sc
ore', 'hiring_source',
                  'no_previous_companies_worked','distance_from_home','to
tal_dependents', 'marital_status', 'education',
                  'promotion_last_2_years', 'no_leaves_taken', 'total_exp
erience',
                  'monthly_overtime_hrs','department','turnover', 'mgr_ef
fectiveness',
                  'career_satisfaction', 'perf_satisfaction', 'work_satis
faction','age_diff', 'job_hop_index', 'tenure', 'compa_ratio']
x_check=org_final[independent_var]
y_check=org_final["turnover"]
clf = MonotonicBinning()
clf.fit(x_check, y_check)

#print(clf.bins)
```

Out[61]:
```
MonotonicBinning(cardinality_cutoff=5, custom_binning=None, feature_nam
es='all',
                  force_bins=4, max_bins=20, prefix=None)
```

In [62]:
```
from xverse.transformer import WOE

clf = WOE()
clf.fit(x_check, y_check)

print(clf.woe_df.head()) #Weight of Evidence transformation dataset
```

```
         Variable_Name         Category  Count  Event  Non_Event  Event
_Rate  \
0             age_diff  (-15.071, 2.48]    652    100        552    0.1
53374
1             age_diff     (2.48, 7.59]    651    144        507    0.2
21198
2             age_diff    (7.59, 24.98]    651    153        498    0.2
35023
3  career_satisfaction   (-0.001, 0.75]    689    151        538    0.2
19158
4  career_satisfaction     (0.75, 0.87]    631    128        503    0.2
02853

   Non_Event_Rate  Event_Distribution  Non_Event_Distribution       WOE
\
0        0.846626            0.251889                0.354528 -0.341798
1        0.778802            0.362720                0.325626  0.107882
2        0.764977            0.385390                0.319846  0.186418
3        0.780842            0.380353                0.345536  0.096001
4        0.797147            0.322418                0.323057 -0.001980

   Information_Value
0           0.051302
1           0.051302
2           0.051302
3           0.007064
4           0.007064

/opt/anaconda3/lib/python3.7/site-packages/pandas/core/series.py:853: R
untimeWarning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [63]:
```
print(clf.iv_df) #Information value dataset

# Less than 0.02 - Not useful for prediction
# 0.02 - 0.1 - Weak predictive power
# 0.1 - 0.3  - Medium predictive power
# 0.3 - 0.5  - Strong predictive power
# >0.5       - Suspicious predictive power.
```

```
                 Variable_Name  Information_Value
28            total_dependents           1.081841
5           distance_from_home           0.878127
23                percent_hike           0.769505
16           mgr_effectiveness           0.586315
27                      tenure           0.472047
3                 compensation           0.413557
21             no_leaves_taken           0.392402
26                      rating           0.386937
13                    location           0.296302
18               mgr_reportees           0.287404
2                  compa_ratio           0.285904
20         monthly_overtime_hrs           0.181906
7                      emp_age           0.174745
6                    education           0.125387
29            total_experience           0.110376
25       promotion_last_2_years           0.099799
31           work_satisfaction           0.063526
0                     age_diff           0.051302
11               job_hop_index           0.044011
19                  mgr_tenure           0.039950
24           perf_satisfaction           0.032243
15                     mgr_age           0.030725
12                       level           0.027265
9                 hiring_score           0.026808
14              marital_status           0.025881
17                  mgr_rating           0.021722
10               hiring_source           0.008774
1          career_satisfaction           0.007064
22  no_previous_companies_worked           0.001342
8                       gender           0.000040
4                   department           0.000000
30                    turnover           0.000000
```

Predictive Analysis

Logistic Regression

Its a classification problem where we are trying to predict whether turnover will occur or not. Our dependent variable(turnover) is categorical.

Checking multicollinearity

Inappproppriate use of dummies causes multilinearity too. I removed the categorical data to check for multicollinearity

In [64]:
```
non_cat= {"tenure", "compensation", "no_leaves_taken","compa_ratio", "hi
ring_score","percent_hike",
              "emp_age", "distance_from_home" ,"mgr_reportees", "monthly_
overtime_hrs",
             "total_experience"}
x_df=pd.get_dummies(org_final[non_cat])
```

In [65]:
```
from statsmodels.stats.outliers_influence import variance_inflation_fact
or
# For each X, calculate VIF and save in dataframe
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_df.values, i) for i in
range(x_df.shape[1])]
vif["features"] = x_df.columns
vif.round(1)
```

Out[65]:

	VIF Factor	features
0	8.0	tenure
1	127.5	hiring_score
2	10.8	percent_hike
3	6.4	distance_from_home
4	228.2	emp_age
5	31.3	compensation
6	39.2	compa_ratio
7	7.6	mgr_reportees
8	3.4	monthly_overtime_hrs
9	23.5	total_experience
10	4.1	no_leaves_taken

Removing employee age

In [66]:
```
x_df=x_df.drop(columns="emp_age")
```

In [67]:
```
from statsmodels.stats.outliers_influence import variance_inflation_fact
or
# For each X, calculate VIF and save in dataframe
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_df.values, i) for i in
range(x_df.shape[1])]
vif["features"] = x_df.columns
vif.round(1)
```

Out[67]:

	VIF Factor	features
0	7.1	tenure
1	44.8	hiring_score
2	10.8	percent_hike
3	6.4	distance_from_home
4	30.8	compensation
5	38.4	compa_ratio
6	7.6	mgr_reportees
7	3.4	monthly_overtime_hrs
8	11.3	total_experience
9	4.1	no_leaves_taken

Removing compa ratio

In [68]:
```
x_df=x_df.drop(columns="compa_ratio")
```

In [69]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_df.values, i) for i in
range(x_df.shape[1])]
vif["features"] = x_df.columns
vif.round(1)
```

Out[69]:

	VIF Factor	features
0	6.8	tenure
1	40.3	hiring_score
2	10.8	percent_hike
3	6.3	distance_from_home
4	16.3	compensation
5	7.6	mgr_reportees
6	3.4	monthly_overtime_hrs
7	10.9	total_experience
8	4.1	no_leaves_taken

Removing hiring score

In [70]:
```
x_df=x_df.drop(columns="hiring_score")
```

In [71]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_df.values, i) for i in
range(x_df.shape[1])]
vif["features"] = x_df.columns
vif.round(1)
```

Out[71]:

	VIF Factor	features
0	6.8	tenure
1	7.6	percent_hike
2	5.5	distance_from_home
3	14.7	compensation
4	6.3	mgr_reportees
5	3.3	monthly_overtime_hrs
6	10.6	total_experience
7	3.8	no_leaves_taken

Removing compensation

In [72]:
```
x_df=x_df.drop(columns="compensation")
```

In [73]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_df.values, i) for i in
range(x_df.shape[1])]
vif["features"] = x_df.columns
vif.round(1)
```

Out[73]:

	VIF Factor	features
0	6.3	tenure
1	6.5	percent_hike
2	5.4	distance_from_home
3	6.3	mgr_reportees
4	3.3	monthly_overtime_hrs
5	8.3	total_experience
6	3.8	no_leaves_taken

CHOSEN PREDICTORS AND DUMMY CODING

In [74]:
```
# predictors chosen with very little multicollinearity and categorical v
ariables added back
predictors={"mgr_effectiveness","tenure", "no_leaves_taken","rating","em
p_age", "location", "distance_from_home" ,"mgr_reportees", "monthly_over
time_hrs", "promotion_last_2_years",
            "total_experience","percent_hike"}
target="turnover"
x=pd.get_dummies(org_final[predictors], drop_first=True)
y=org_final[target]
#x.head()
```

Using statsmodels to display summary

In [75]:
```
import statsmodels.api as sm
logit_model=sm.Logit(y, x)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.184229
         Iterations 9
                           Logit Regression Results
=======================================================================
=======
Dep. Variable:                turnover   No. Observations:
1954
Model:                           Logit   Df Residuals:
1938
Method:                            MLE   Df Model:
15
Date:                 Thu, 15 Apr 2021   Pseudo R-squ.:
0.6350
Time:                         00:27:41   Log-Likelihood:
-359.98
converged:                        True   LL-Null:
-986.32
Covariance Type:             nonrobust   LLR p-value:                 7.8
86e-258
=======================================================================
=======================
                                 coef    std err          z      P>|z|
[0.025      0.975]
-----------------------------------------------------------------------
-----------------------
tenure                        -0.3937      0.075     -5.266      0.000
-0.540      -0.247
mgr_effectiveness             -4.4025      0.561     -7.848      0.000
-5.502      -3.303
percent_hike                  -0.4570      0.047     -9.634      0.000
-0.550      -0.364
distance_from_home             0.2192      0.016     13.417      0.000
0.187       0.251
emp_age                       -0.0632      0.034     -1.843      0.065
-0.130       0.004
mgr_reportees                  0.1104      0.019      5.914      0.000
0.074       0.147
monthly_overtime_hrs           0.2015      0.027      7.481      0.000
0.149       0.254
total_experience               0.0070      0.050      0.140      0.889
-0.092       0.106
no_leaves_taken                0.1233      0.013      9.332      0.000
0.097       0.149
location_New York              1.3033      0.277      4.699      0.000
0.760       1.847
location_Orlando              -0.4246      0.230     -1.843      0.065
-0.876       0.027
rating_Acceptable             -0.1233      0.242     -0.509      0.611
-0.598       0.352
rating_Below Average          -1.5228      0.436     -3.490      0.000
-2.378      -0.668
rating_Excellent              -0.6544      0.630     -1.038      0.299
-1.890       0.581
rating_Unacceptable           -2.6284      0.766     -3.430      0.001
-4.130      -1.127
promotion_last_2_years_Yes    -0.0173      0.286     -0.061      0.952
```

```
-0.577       0.542
==============================================================================
=======================
```

**I noticed several variables are insignificant. In multiple regression models, this can happen due to multicollinearity.

In [76]:
```
x_train, x_test, y_train,y_test=train_test_split(x,y,test_size=0.3, rand
om_state=1)
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(1367, 16)
(1367,)
(587, 16)
(587,)
```

Logistic Regression

In [77]:
```
# Regress all variables in the dataframe on target variable 'turnover'
model=LogisticRegression(solver='liblinear', random_state=1)
model.fit(x_train,y_train)
```

Out[77]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=1, solver='liblinear', tol=0.0001, verb
ose=0,
                   warm_start=False)
```

Predicting

In [78]:
```
y_pred=model.predict(x_test)
y_pred_proba=model.predict_proba(x_test)

result=pd.DataFrame({"Observed": y_test,
                     "Predicted": y_pred,
                    "p(0)":[p[0] for p in y_pred_proba],
                    "p(1)":[p[1] for p in y_pred_proba]})
print(result)
print(y_pred.shape)
```

```
      Observed  Predicted      p(0)      p(1)
1812         0          0  0.992061  0.007939
1576         0          0  0.989677  0.010323
1926         0          0  0.986105  0.013895
1378         0          0  0.996522  0.003478
1446         0          0  0.990683  0.009317
...        ...        ...       ...       ...
110          0          0  0.998302  0.001698
1105         0          0  0.938261  0.061739
1481         0          0  0.982100  0.017900
1247         0          0  0.996325  0.003675
955          0          1  0.480526  0.519474

[587 rows x 4 columns]
(587,)
```

Model Evaluation

In [79]:
```
prediction_train = model.predict(x_train)
prediction_valid = model.predict(x_test)
print("Accuracy of model on training set is:",accuracy_score(y_train,pre
diction_train))
print("Accuracy of model on test set is:",accuracy_score(y_test,predicti
on_valid))
```

```
Accuracy of model on training set is: 0.9180687637161667
Accuracy of model on test set is: 0.9369676320272572
```

In [80]:
```
#Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[470  11]
 [ 26  80]]
```

The result is telling us that we have 467+72 correct predictions and 14+34 incorrect predictions.

In [81]:
```
# Classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.98      0.96       481
           1       0.88      0.75      0.81       106

    accuracy                           0.94       587
   macro avg       0.91      0.87      0.89       587
weighted avg       0.94      0.94      0.94       587
```

In [82]:
```
score_ = accuracy_score(y_test, y_pred)
prec_score = precision_score(y_test, y_pred)
f1=f1_score(y_test,y_pred)

print("The accuracy score for the test is:", score_, "\n")
print(f1)
print(regressionSummary(y_test,y_pred))
print(model.score(x_test,y_test))
```

```
The accuracy score for the test is: 0.9369676320272572

0.8121827411167513

Regression statistics

               Mean Error (ME) : 0.0256
Root Mean Squared Error (RMSE) : 0.2511
     Mean Absolute Error (MAE) : 0.0630
None
0.9369676320272572
```

The precision is the ratio tp / (tp + fp) where tp is the number of true positives and fp the number of false positives. The precision is intuitively the ability of the classifier to not label a sample as positive if it is negative.

The recall is the ratio tp / (tp + fn) where tp is the number of true positives and fn the number of false negatives. The recall is intuitively the ability of the classifier to find all the positive samples.

The F-beta score can be interpreted as a weighted harmonic mean of the precision and recall, where an F-beta score reaches its best value at 1 and worst score at 0.**

The F-beta score weights the recall more than the precision by a factor of beta. beta = 1.0 means recall and precision are equally important.

The support is the number of occurrences of each class in y_test.

Decision trees

In [83]:
```
# i had to remove all categorical variables from predictors
```

In [84]:
```
# predictors chosen with very little multicollinearity and categorical v
ariables added back
predictors_tree={"mgr_effectiveness","tenure", "no_leaves_taken","emp_ag
e", "distance_from_home" ,"mgr_reportees", "monthly_overtime_hrs",
                 "total_experience","percent_hike"}
target="turnover"
x=pd.get_dummies(org_final[predictors_tree], drop_first=True)
y=org_final[target]
#x.head()
x_train, x_test, y_train,y_test=train_test_split(x,y,test_size=0.3, rand
om_state=1)
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

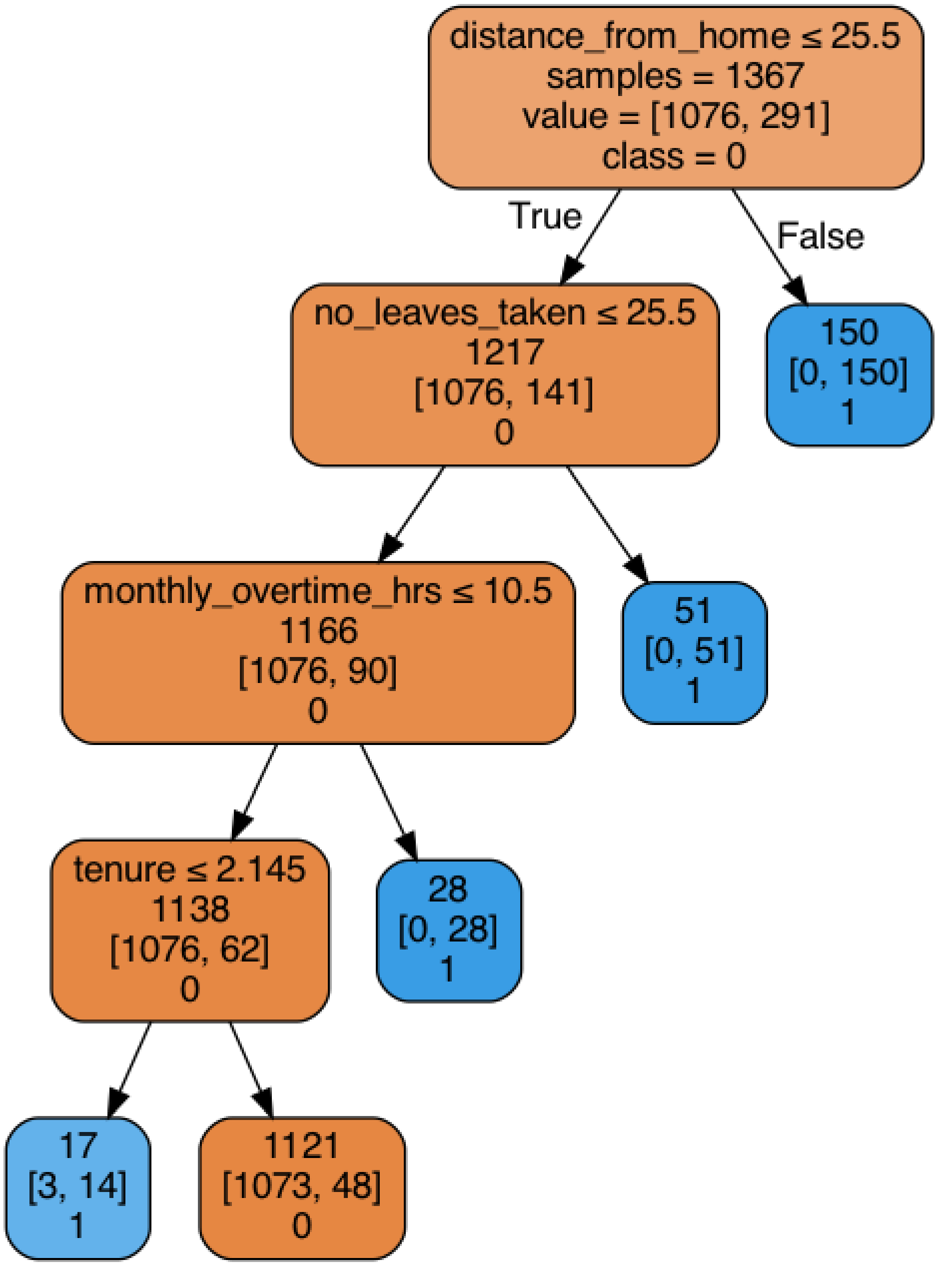
```
(1367, 9)
(1367,)
(587, 9)
(587,)
```

In [85]:
```
#Build decision tree
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(max_depth = 4)
dt.fit(x_train, y_train)
```

Out[85]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=
4,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

In [86]:
```
from dmba import plotDecisionTree, gainsChart, liftChart
from dmba import classificationSummary, regressionSummary

plotDecisionTree(dt,feature_names=org_final[predictors_tree].columns, cl
ass_names=dt.classes_)
```

Out[86]:



In [87]:
```
importances = dt.feature_importances_
imp_features = pd.DataFrame({'feature': x_train.columns, 'importance': i
mportances})
imp_features = imp_features.sort_values('importance', ascending = False)
print(imp_features)
```

```
              feature  importance
3   distance_from_home    0.577893
8      no_leaves_taken    0.230354
6  monthly_overtime_hrs    0.135248
0               tenure    0.056504
1     mgr_effectiveness    0.000000
2         percent_hike    0.000000
4              emp_age    0.000000
5        mgr_reportees    0.000000
7     total_experience    0.000000
```

In [88]:
```
#get the accuracy score
from sklearn.metrics import accuracy_score
# Get the prediction for both train and test
prediction_train = dt.predict(x_train)
prediction_valid = dt.predict(x_test)

# Measure the accuracy of the model for both train and test sets
print("Accuracy on train is:",accuracy_score(y_train,prediction_train))
print("Accuracy on test is:",accuracy_score(y_test,prediction_valid ))
```

```
Accuracy on train is: 0.9626920263350403
Accuracy on test is: 0.9761499148211243
```

Retention Strategy

In [89]:
```
# filter data for only active employees

org_final_active=org_final[org_final["status"]=="Active"]
org_final_active
```

Out[89]:

	emp_id	status	location	level	gender	emp_age	rating	mgr_rating	mgr_reporte
0	E10012	Active	New York	Analyst	Female	25.09	Above Average	Acceptable	
1	E10025	Active	Chicago	Analyst	Female	25.98	Acceptable	Excellent	
2	E10027	Active	Orlando	Specialist	Female	33.40	Acceptable	Above Average	
3	E10048	Active	Chicago	Specialist	Male	24.55	Acceptable	Acceptable	
4	E10060	Active	Orlando	Analyst	Male	31.23	Acceptable	Acceptable	
...	...	...	...	...	...	...	...	...	
1949	E9960	Active	Orlando	Analyst	Male	27.81	Excellent	Acceptable	
1950	E9977	Active	Orlando	Analyst	Male	27.64	Above Average	Above Average	
1951	E9980	Active	New York	Specialist	Male	27.63	Acceptable	Acceptable	
1952	E9992	Active	Chicago	Specialist	Male	28.34	Acceptable	Acceptable	
1953	E9993	Active	Orlando	Analyst	Female	26.25	Acceptable	Acceptable	

1557 rows × 38 columns

In [90]:
```
# predictors chosen with very little multicollinearity and categorical v
ariables added back
predictors=["mgr_effectiveness","tenure", "no_leaves_taken","rating","em
p_age", "location", "distance_from_home" ,"mgr_reportees", "monthly_over
time_hrs", "promotion_last_2_years",
             "total_experience","percent_hike"]
target="turnover"
x_active=pd.get_dummies(org_final_active[predictors], drop_first=True)
y_active=org_final_active[target]
```

In [91]:
```
# Directly asking the model to predict for all employees who are active
# No test and training sets
y_pred=model.predict(x_active)
y_pred_proba=model.predict_proba(x_active)

result=pd.DataFrame({"Predicted": y_pred,
                     "p(0)":[p[0] for p in y_pred_proba],
                     "p(1)":[p[1] for p in y_pred_proba]})
print(result)
```

```
      Predicted      p(0)          p(1)
0             0  0.996922  3.077946e-03
1             0  0.999999  1.131291e-06
2             0  1.000000  1.155836e-13
3             0  0.999916  8.384654e-05
4             0  0.999997  2.971293e-06
...         ...       ...           ...
1552          0  0.999556  4.442536e-04
1553          0  1.000000  1.976737e-07
1554          0  1.000000  1.723229e-07
1555          0  0.999544  4.559267e-04
1556          0  0.995317  4.683232e-03

[1557 rows x 3 columns]
```

In [92]:
```
org_final_active["risk_probability"]=result["p(1)"]
org_final_active["risk_probability"]=org_final_active["risk_probability"
].fillna(0)
#org_final_active
```

0 < Employees with turnover probability < 0.5 --- NO risk bucket

0.5 < Employees with turnover probability < 0.6 ---- Low risk

0.6 < Employees with turnover probability < 0.8 --- High risk bucket

Employees with turnover probability > 0.8 --- High risk bucket

In [93]:
```
df=org_final_active.copy()
```

In [94]:
```
# Finding high risk employees(employee ids) most likely to leave

high_risk_df= df[df["risk_probability"]>=0.8]
medium_risk_df=df[(df["risk_probability"]<0.8)&(df["risk_probability"]>=
0.6)]
low_risk_df= df[(df["risk_probability"]>=0.5)& (df["risk_probability"]<
0.6)]
no_risk_df= df[df["risk_probability"]<0.5]

high_risk_df["risk_probability"].count()
```

Out[94]: 3

In [95]:
```
medium_risk_df["risk_probability"].count()
```
Out[95]: 5

In [96]:
```
low_risk_df["risk_probability"].count()
```
Out[96]: 5

In [97]:
```
no_risk_df["risk_probability"].count()
```
Out[97]: 1544

Retention Strategy

High risk

If a high risk emploee is a high performer and has high potential,immidiate action planning needed.

A. Engage in a conversation with this employee to generally understand the perspective about work and future plans.

B. Ask the employee's manager to have a conversation and explore the engagement levels and concerns, if any.

Medium risk

A. Medium term action planning.

B. Have one-on-one or open house discussion.

C. Keep tracking of any behavioral change.

Low risk

A. Long-term action planning

B. Keep tracking for any behavioral change.

C. Have open house discussion.

No risk

No action required.

Cost of employee turnover:

Costs to off-board employee

Cost-per-hire for replacement

Transition costs, including opportunity costs

The most important predictor- percent_hike. Consider giving a better percentage hike.

In [98]:
```
org_fin=pd.read_csv("org_final.csv")
org_fin.fillna(0)
```

Out[98]:

	emp_id	status	location	level	gender	emp_age	rating	mgr_rating	mgr_reporte
0	E10012	Active	New York	Analyst	Female	25.09	Above Average	Acceptable	
1	E10025	Active	Chicago	Analyst	Female	25.98	Acceptable	Excellent	
2	E10027	Active	Orlando	Specialist	Female	33.40	Acceptable	Above Average	
3	E10048	Active	Chicago	Specialist	Male	24.55	Acceptable	Acceptable	
4	E10060	Active	Orlando	Analyst	Male	31.23	Acceptable	Acceptable	
...	...	...	...	...	...	...	...	...	
1949	E9960	Active	Orlando	Analyst	Male	27.81	Excellent	Acceptable	
1950	E9977	Active	Orlando	Analyst	Male	27.64	Above Average	Above Average	
1951	E9980	Active	New York	Specialist	Male	27.63	Acceptable	Acceptable	
1952	E9992	Active	Chicago	Specialist	Male	28.34	Acceptable	Acceptable	
1953	E9993	Active	Orlando	Analyst	Female	26.25	Acceptable	Acceptable	

1954 rows × 34 columns

In [99]:
```
org_hike_count=org_fin["percent_hike"].value_counts()
org_hike_count
```

Out[99]:
```
9     229
10    220
11    214
12    198
14    181
13    180
7     180
8     170
15    100
6      67
5      49
3      41
4      30
0      30
16     16
19     16
17     15
18     12
2       6
Name: percent_hike, dtype: int64
```

In [100]:
```
#org_final["percent_hike"] = org_final["percent_hike"].astype('categor
y')

cat_1=org_fin.loc[(org_fin["percent_hike"] >=0 ) & (org_fin["percent_hik
e"] < 5 ),"percent_hike"]
cat_2=org_fin.loc[(org_fin["percent_hike"] >=5 ) & (org_fin["percent_hik
e"] < 10 ),"percent_hike"]
cat_3=org_fin.loc[(org_fin["percent_hike"] >=10 ) & (org_fin["percent_hi
ke"] < 15 ),"percent_hike"]
print(cat_2)
```

```
1       8
3       8
5       8
7       9
8       9
       ..
1943    9
1944    9
1945    8
1952    7
1953    8
Name: percent_hike, Length: 695, dtype: int64
```