Human Sources analysis

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Background

“Turnover” : turnover is that churn refers to the gradual loss of employees over a period of time. In a company, the employee turnover is the biggest issue facing HR and high costs Therefore, analysis the employee turnover is the way to prevent the damange and save mony to company. Usually, the comon reasons employee turnover is better opportunity, healh, rolocation, eaducation, and personal reasons etc.In addition, some hidden reasons of employees turnover includes percent salary hike, overtime, travel distance, career satisfaction, tenure, and supervisor’s personality etc.

Data

emp_id: employees id

status: working status, Active and Inactive

location: location of working city

level: Job level in Company

gender: Male and Female

emp_age: employees age

rating: Internal work evaluation level

mar_rating: employees’ manager internal work evaluation level

mgr_reportees: employees’ manager report

mgr_age: employees’ manager age

mgr_tenure: employees’ manager tenure

compensation: salary

percent_hike: precentage of increase salary

hiring_score: hire interview score

hiring_sourece: platform for job

no_previous_companies_worked: number of previous work rompaneies

distance_from_homne: distance between home and work place

total_dependets: number of dependets

marital_status: status of marry

education: education level

promotion_last_2_years: the promotion of employee within last 2 years

no_leaves_taken: number of leaves have been taken

total_experience: total of work experience

monthly_overtime_hrs: total number of monthly overtime hours

date_of_joining: date of join the companey

```
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

## -- Attaching packages --------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.2     v purrr   0.3.4
## v tibble  3.0.4     v stringr 1.4.0
## v tidyr   1.1.2     v forcats 0.5.0

## -- Conflicts ------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## [1] 1954   34

## [1] 1954   34
```

Fomular for turnover rate

Turnover rate = Number of employees who left / Total number of employees

counting the status from data frame. we know the active employee is 1557, and 397 employees left the company.

```
##     status    n
## 1   Active 1557
## 2 Inactive  397
```

calculate a mean of turnover_rate. the rate is approximation 18% for employees left

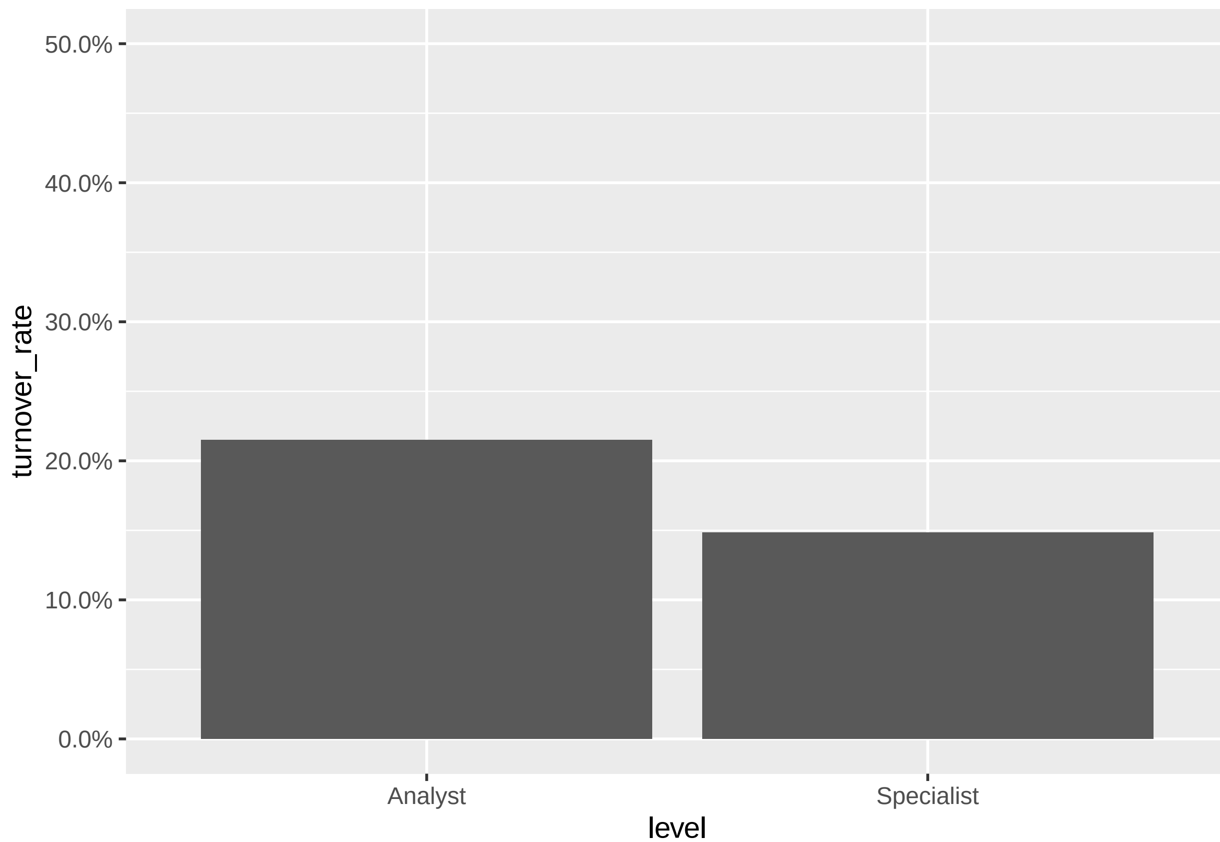
```
##   turnover_rate
## 1      0.203173
```

Approximation 22% of Analyst job level leaving and 15% of Specialist level leaving end of 12/31/2014 in the company.

```
## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 2 x 2
##   level      turnover_rate
##   <fct>              <dbl>
## 1 Analyst            0.215
## 2 Specialist         0.149
```

use graph for data visulization. the graph is showing the rate value between the analyst level and spcialist level.

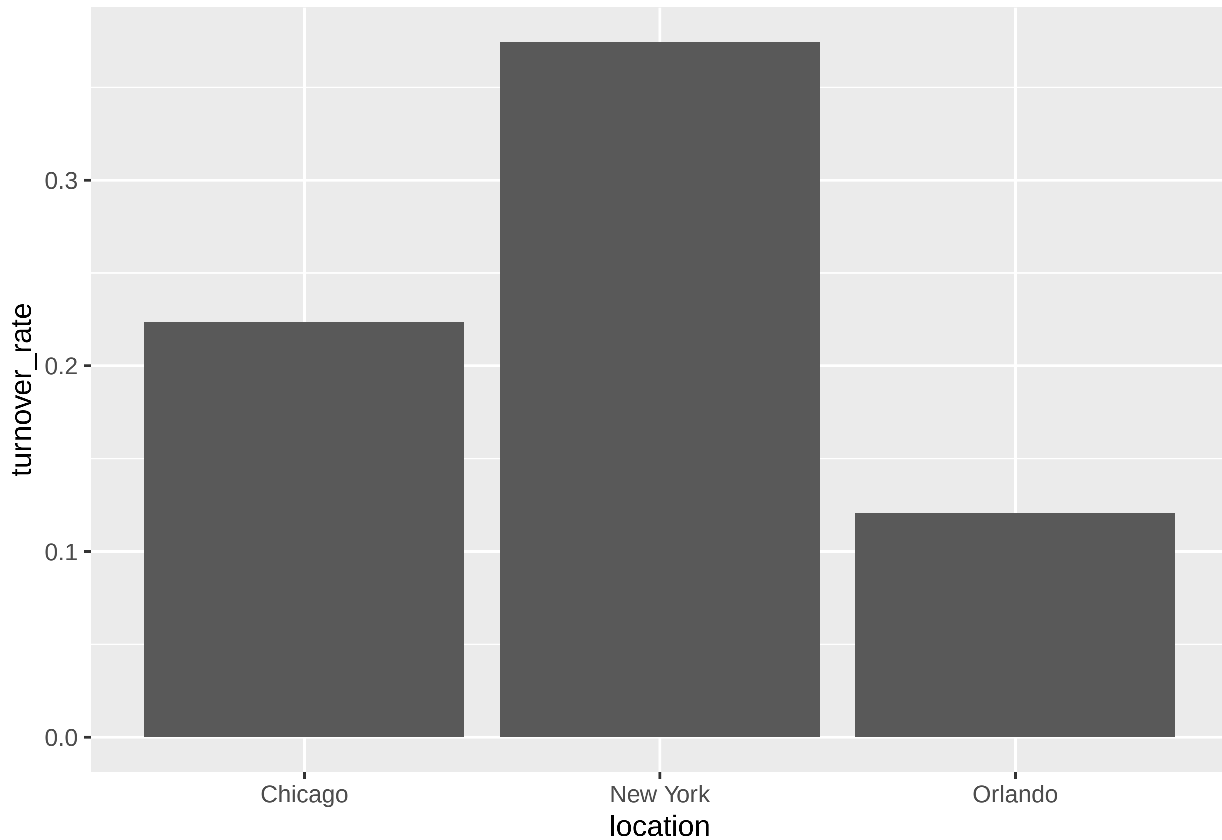
```
##
## Attaching package: 'scales'

## The following object is masked from 'package:purrr':
##
##     discard

## The following object is masked from 'package:readr':
##
##     col_factor
```



Question: calculate the turnover rate in different cites ### Company has 3 controlled company in Chicago, New York, Orlando. After calculating the trunover_rate, we can see the highest proportion is in New York city, and the lowest is Orlando.

```
## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 3 x 2
##   location turnover_rate
##   <fct>            <dbl>
## 1 Chicago          0.224
## 2 New York         0.374
## 3 Orlando          0.121
```

```r
location%>%  #histogram to data visulization
  ggplot(aes(location,turnover_rate))+ geom_col()
```



chekcing rating relationship for turnover_rate

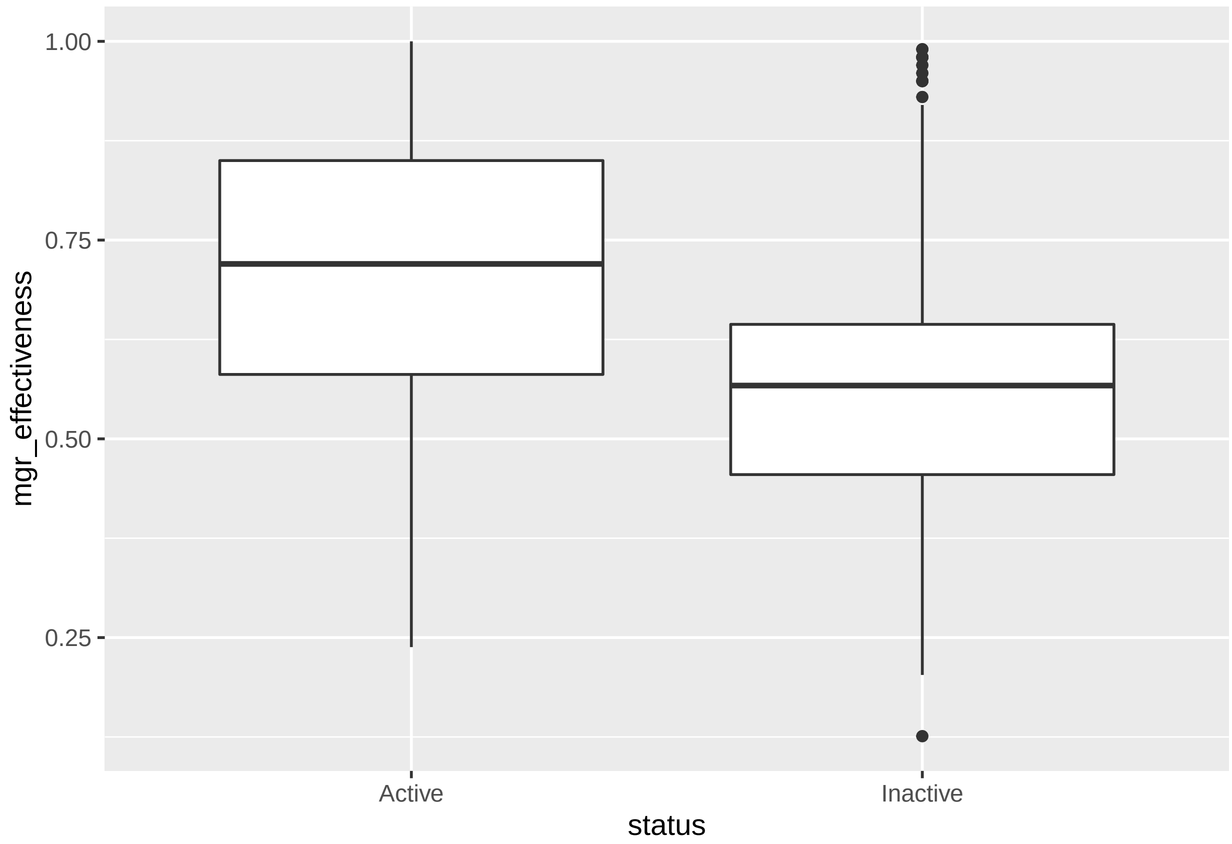
from the data calculating, the internal work evulation rate are showing that the unacceptable is 63% highest proportion of turnover_rate. The number 2 higher proportion is below average rating. On the contraction, the acceptable is 22%, above average 13% and excellent only 3%

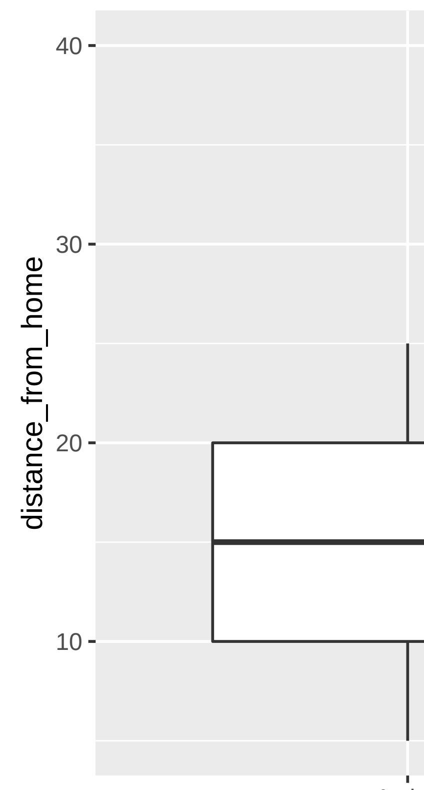
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 2
##   rating        turnover_rate
##   <fct>                 <dbl>
## 1 Above Average        0.131
## 2 Acceptable           0.221
## 3 Below Average        0.385
## 4 Excellent            0.0305
## 5 Unacceptable         0.633
```

Question: is the work evulation as main factor for employee turnover? the employee was fire by company?

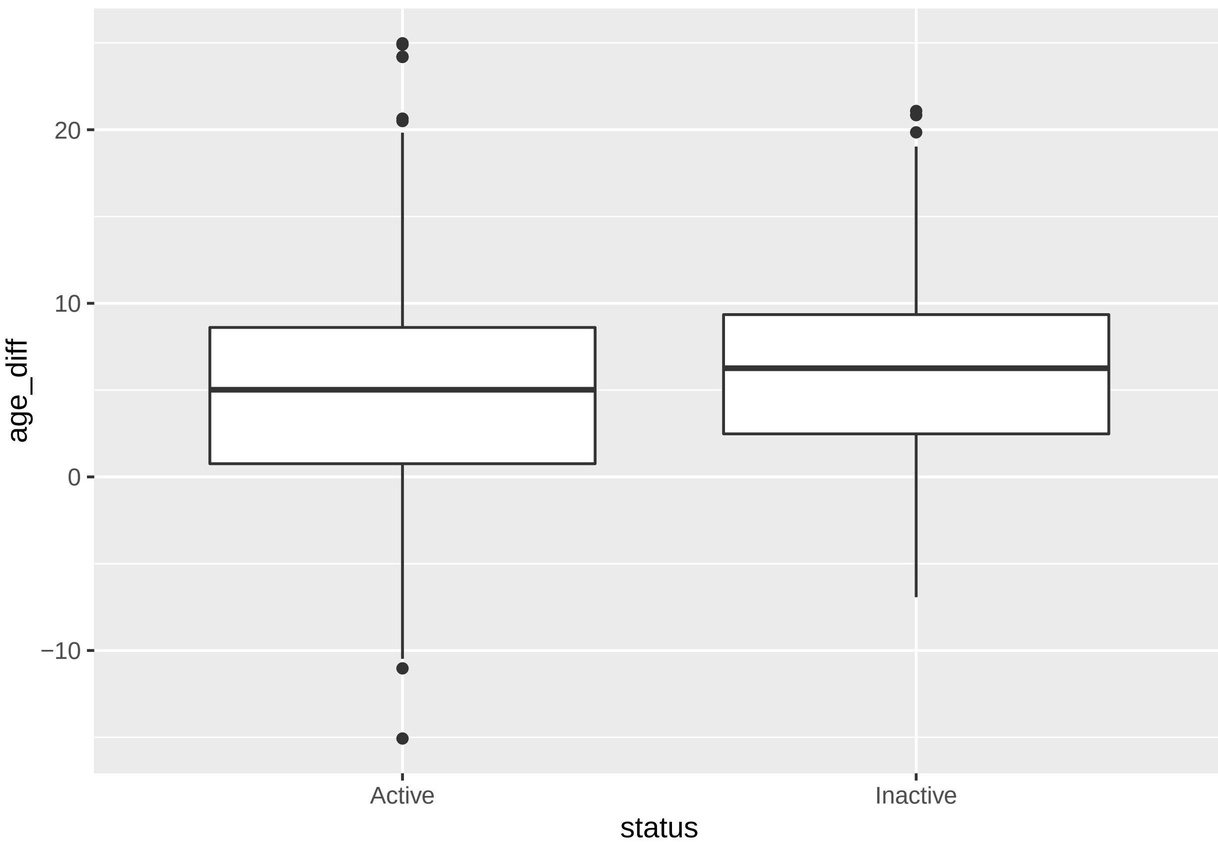
the grph showing manager effectiveness also affct the employee turnover. the box-plot shows the outliers of inactive. however, overall shows that the mean of manger effectiveness of active is higher than inactive. according to box-plot, we know the manger effectiveness also affect turnover of employees.





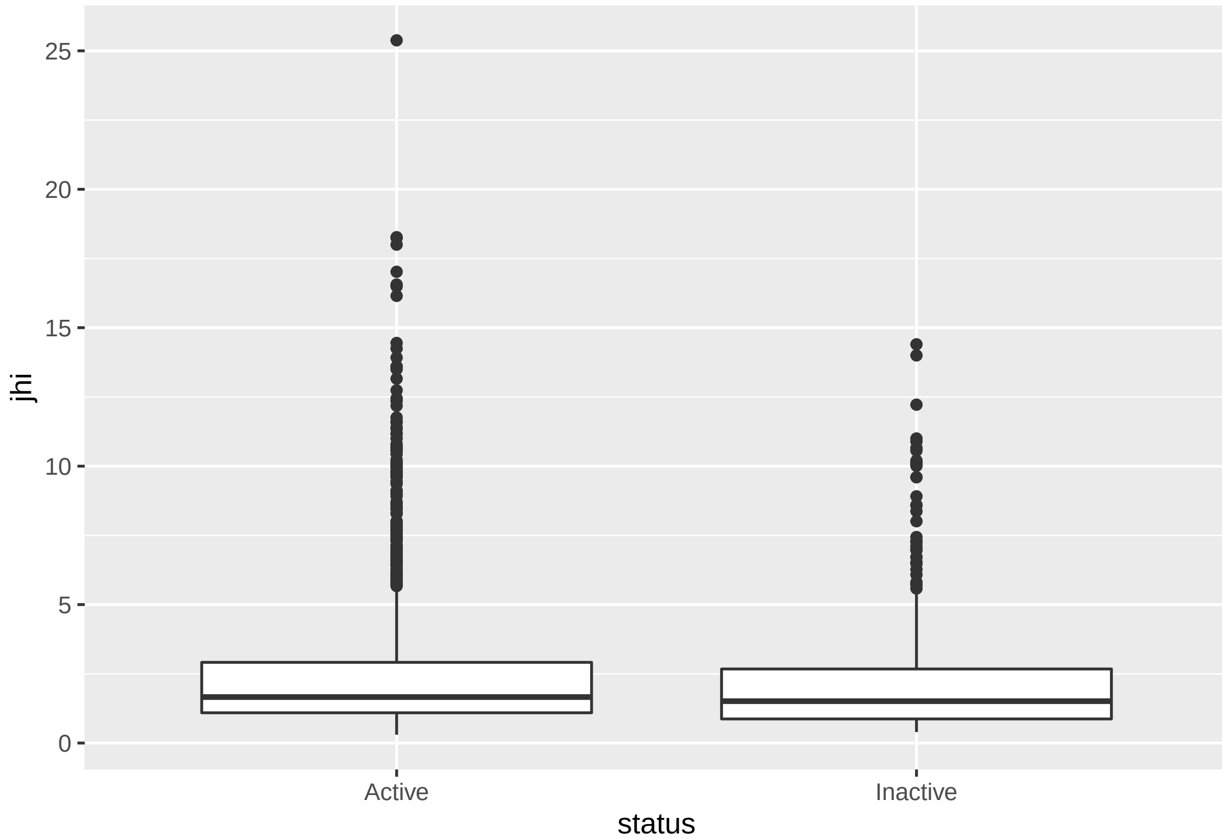
Due to figure out more significant factors which are affecting the employee turnover. ### Question: How does our company provide the hope to our employee? is data showing the relationship between the age and experience? ### We want to calculate some Job-Hop to our company. Differece of age between the employees and their supervisor, also improve the data to display the age and experiences. Provide a Job-Hop into data frame for reducing employee turnover. ### extra a data for difference of employe age and manager age. Why calculate that? It's a reason that age difference will provide the hope for the Junior employee. They can know how long or what experience would supoort them move on next level.

Box-plot below, shows some outliers for status. it notice us, the mean of age difference of Inactive higher than actvie.This leads to the next idea of whether there is a big gap in age or experience between employees leaving and job expectations. Should we improve the system or shrink the age stage of the working layer.



###When Box-plot shows huge outliers, even the experience and number of previous worked experience might affect the Job-Hop, they were not consider in our concern.

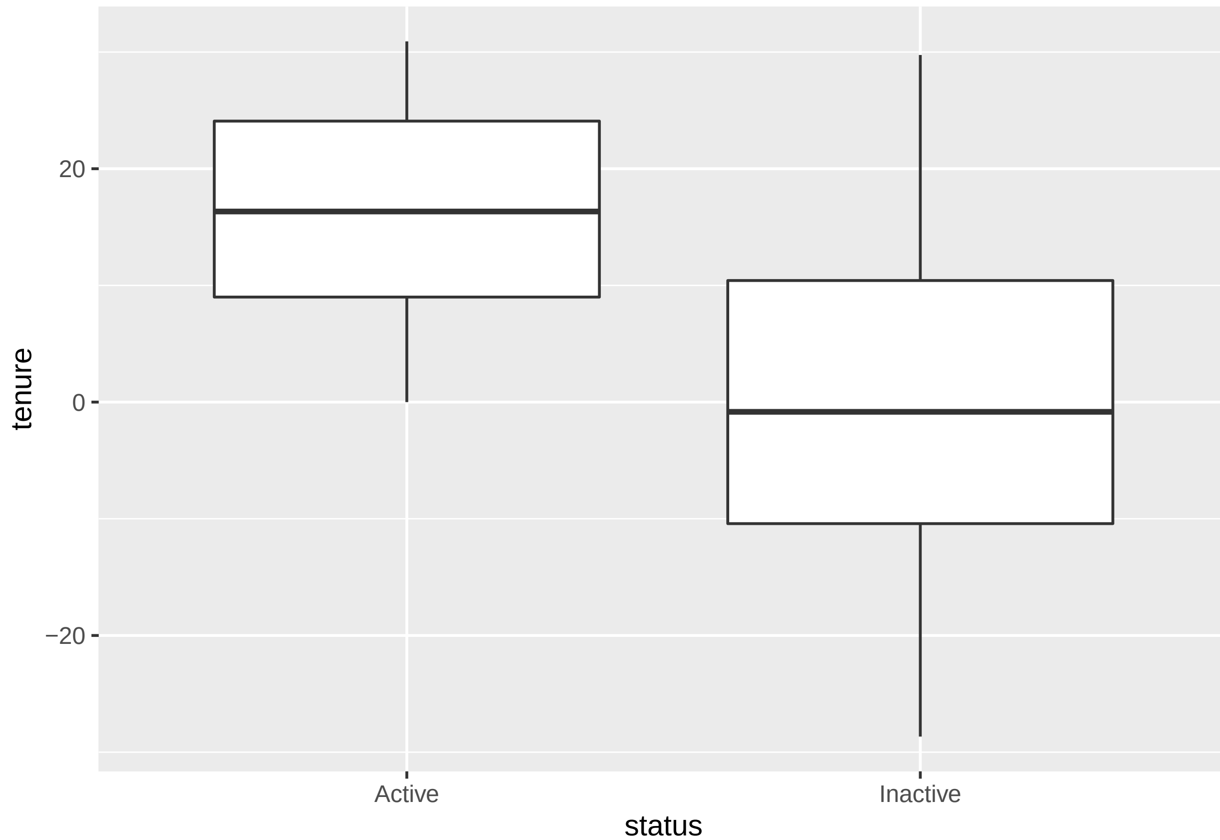
```
## Warning: Removed 186 rows containing non-finite values (stat_boxplot).
```




```
##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date
```

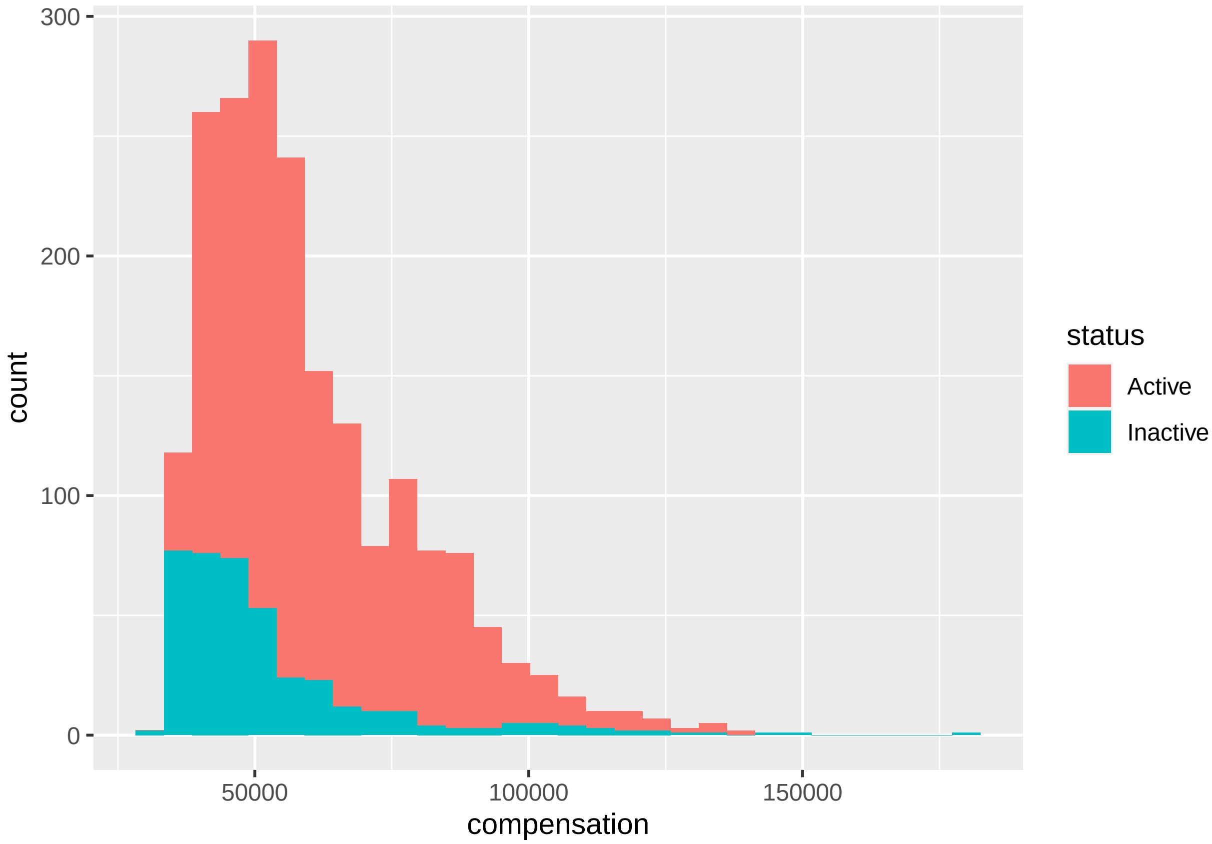
Question: Any suggestion to improve a employee turnover?

Calulate the empolyee tenure. According to below box-plot, we can see the Q1 percentile of active is almost equal the Q3 percentile of Inactive employee. In inactive employee, only 50% work like a year in the company. However, active empolyees are working for a long time than inactive employee. As a result. we can assume that the inactive employee domain percentage is new employee. According that, we have to improve the Junior employees in their first year.

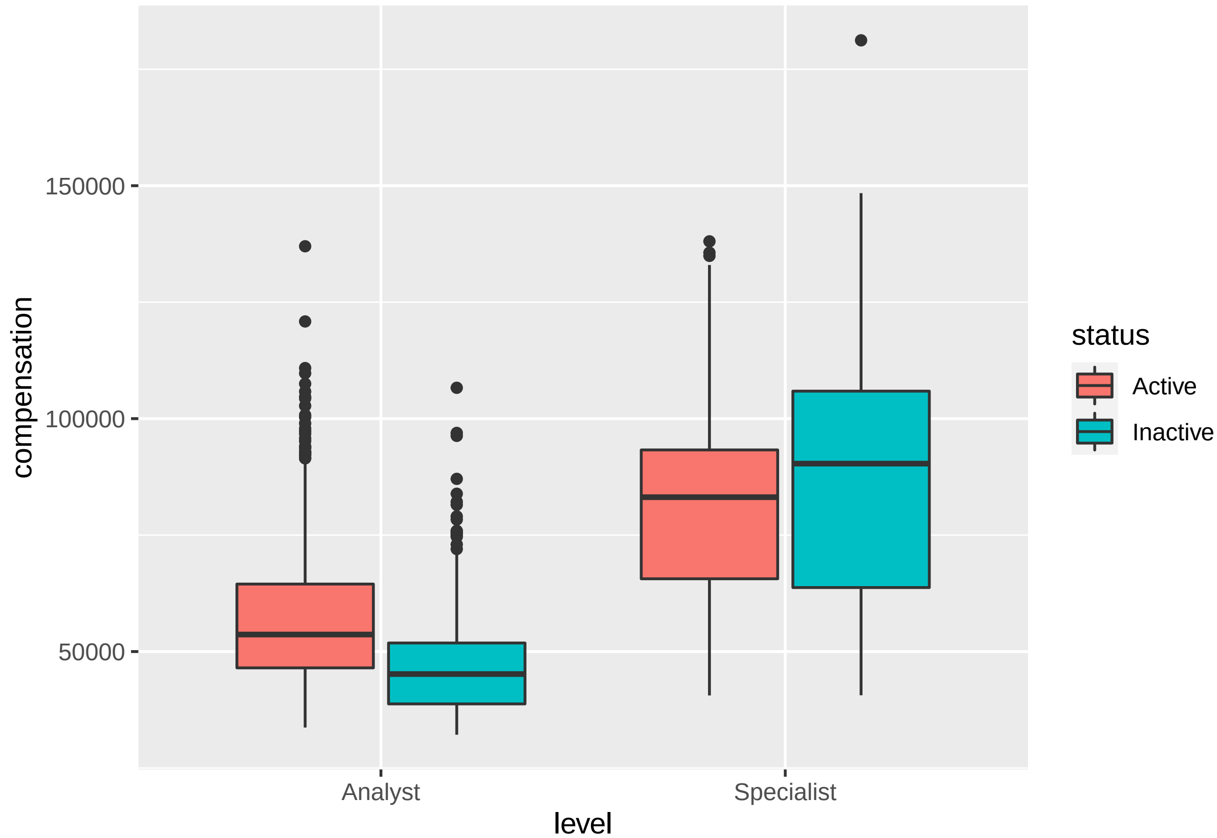


The inactive employees' salary are lower than active employees.

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



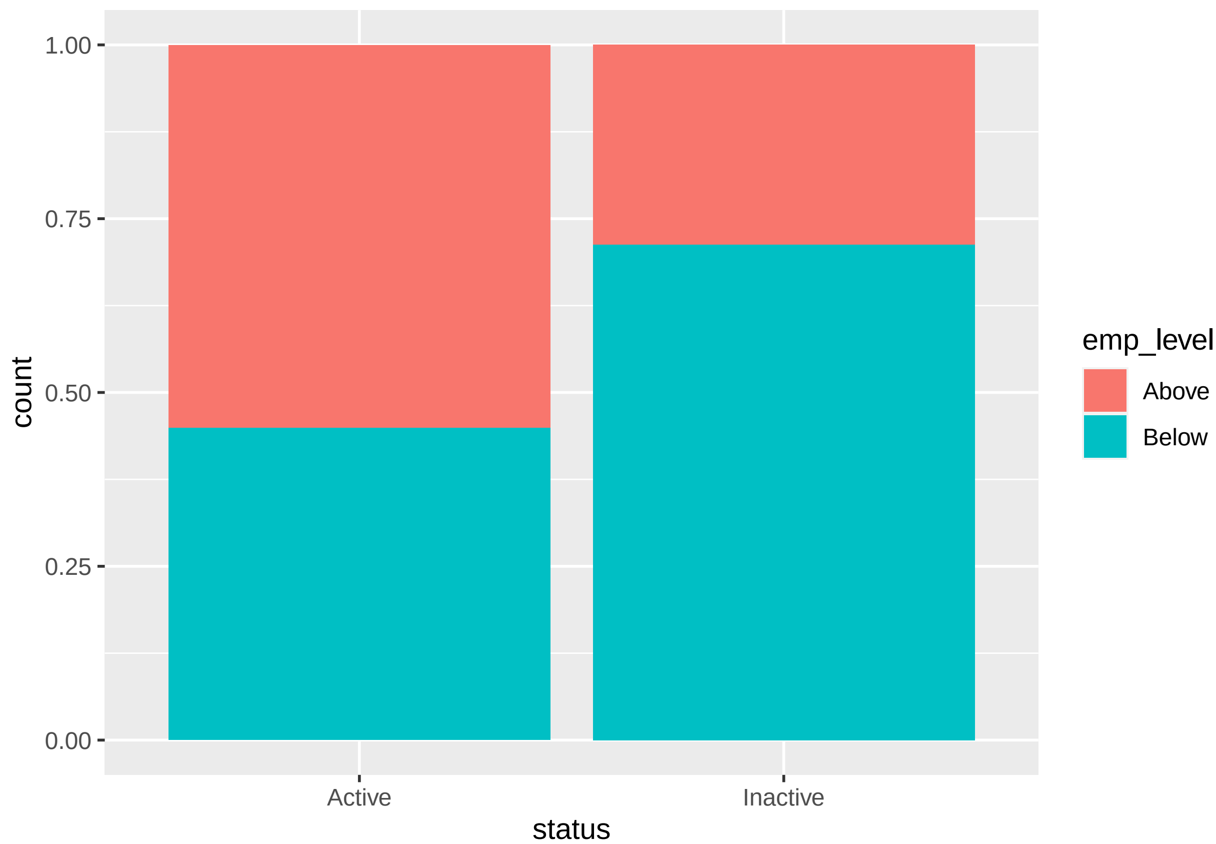
Graph shows the relationship between level, compensation and status. In Analyst level, active employees compensation higher than inactive. However, in Specialist level, the inactive employess higher than active



employees.
Compa Ratio is estimation to evaluate the employee wage percentage to median pay. ##Compa Ratio = Actual Compensation / Median Compensation

```
## # A tibble: 2 x 2
## # Groups:   level [2]
##   level      median_compensation
##   <fct>                    <dbl>
## 1 Analyst                  51840
## 2 Specialist               83496
```

```
emp_final<- emp_ratio%>%
  mutate(emp_level = ifelse( compa_ratio > 1, "Above", "Below")) # add compa level , if compa_ration ge
emp_final%>%
  ggplot(aes(status, fill = emp_level))+geom_bar(position = "fill") #compare compa level between active
```



Unstanding information value : measure of predictive power of independent variable to accurately predict the dependent variable

Information value = sima(% of non-events-% of events))* log(% of non-events/% of events)

information value : less than 0.15 meaning predictive power is poor, if 0.15 < IV < 0.4 id moderate, else greater than 0.4 meaning strong.

```
## [1] "Variable emp_id was removed because it is a non-numeric variable with >1000 categories"
## [1] "Variable department was removed because it has only 1 unique value"
## [1] "Variable cutoff_date was removed because it has only 1 unique value"

##                       Variable           IV
## 12                percent_hike 1.144784e+00
## 17            total_dependents 1.088645e+00
## 21             no_leaves_taken 9.404533e-01
## 33                      tenure 7.636901e-01
## 27           mgr_effectiveness 6.830020e-01
## 11                compensation 6.074885e-01
## 35                 compa_ratio 4.768892e-01
## 24             date_of_joining 4.330804e-01
## 6                       rating 3.869373e-01
```

```
## 23        monthly_overtime_hrs 3.786644e-01
## 8                mgr_reportees 3.620543e-01
## 2                     location 2.963023e-01
## 36                   emp_level 2.940446e-01
## 26                      mgr_id 2.820235e-01
## 5                      emp_age 2.275477e-01
## 16          distance_from_home 1.470549e-01
## 30           work_satisfaction 1.378953e-01
## 22            total_experience 1.345781e-01
## 19                   education 1.253865e-01
## 20       promotion_last_2_years 9.979915e-02
## 9                      mgr_age 9.816205e-02
## 29           perf_satisfaction 7.099511e-02
## 13                hiring_score 6.684727e-02
## 31                    age_diff 6.634065e-02
## 32                         jhi 6.586588e-02
## 10                  mgr_tenure 5.918048e-02
## 28         career_satisfaction 3.539857e-02
## 3                        level 2.726491e-02
## 34         median_compensation 2.726491e-02
## 18              marital_status 2.588063e-02
## 7                   mgr_rating 2.172222e-02
## 15 no_previous_companies_worked 1.729893e-02
## 14               hiring_source 8.773529e-03
## 4                       gender 3.959968e-05
## 1                       status 0.000000e+00
## 25           last_working_date 0.000000e+00
```

logistic regression

As a summary showing the overall for the multiple linear regression, we can see the p-value to design which is significant factors. Compensation, career_satisfaction, rating, work_satification and promotion_last_2_years are not significant to this regression.

```
## 
## Call:
## glm(formula = turnover ~ emp_age + percent_hike + hiring_score + 
##     compensation + distance_from_home + total_dependents + total_experience + 
##     monthly_overtime_hrs + career_satisfaction + perf_satisfaction + 
##     work_satisfaction + location + rating + marital_status + 
##     education + promotion_last_2_years, family = "binomial", 
##     data = org)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -2.3728  -0.2997  -0.1162  -0.0249   3.3442  
## 
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)    
## (Intercept)              -2.184e+00  2.733e+00  -0.799 0.424291    
## emp_age                  -2.738e-01  5.781e-02  -4.737 2.17e-06 ***
## percent_hike             -4.669e-01  4.891e-02  -9.545  < 2e-16 ***
## hiring_score              6.108e-02  3.086e-02   1.980 0.047760 *  
```

```
## compensation             -5.404e-06  6.901e-06  -0.783 0.433585
## distance_from_home        2.013e-01  1.491e-02  13.496  < 2e-16 ***
## total_dependents          7.443e-01  7.223e-02  10.304  < 2e-16 ***
## total_experience          1.170e-01  5.737e-02   2.040 0.041316 *
## monthly_overtime_hrs      1.723e-01  2.533e-02   6.804 1.02e-11 ***
## career_satisfaction       4.193e-01  9.003e-01   0.466 0.641378
## perf_satisfaction        -2.455e+00  7.882e-01  -3.115 0.001841 **
## work_satisfaction        -2.979e-01  9.881e-01  -0.302 0.763024
## locationNew York          1.396e+00  2.764e-01   5.051 4.39e-07 ***
## locationOrlando          -8.959e-01  2.417e-01  -3.706 0.000210 ***
## ratingAcceptable         -1.681e-01  2.391e-01  -0.703 0.481963
## ratingBelow Average      -1.531e+00  4.318e-01  -3.546 0.000391 ***
## ratingExcellent          -3.753e-01  6.233e-01  -0.602 0.547124
## ratingUnacceptable       -2.634e+00  7.617e-01  -3.458 0.000544 ***
## marital_statusSingle      1.684e+00  3.366e-01   5.002 5.67e-07 ***
## educationMasters          1.751e+00  3.843e-01   4.558 5.18e-06 ***
## promotion_last_2_yearsYes -4.267e-02  2.748e-01  -0.155 0.876607
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1972.64  on 1953  degrees of freedom
## Residual deviance:  800.29  on 1933  degrees of freedom
## AIC: 842.29
##
## Number of Fisher Scoring iterations: 7
```

```
##
## Call:
## glm(formula = turnover ~ emp_age + percent_hike + hiring_score +
##     distance_from_home + total_dependents + total_experience +
##     monthly_overtime_hrs + perf_satisfaction + work_satisfaction +
##     location + marital_status + education, family = "binomial",
##     data = org)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4686  -0.3170  -0.1320  -0.0318   3.0960
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -2.20596    2.63514  -0.837  0.40252
## emp_age              -0.28830    0.05351  -5.388 7.14e-08 ***
## percent_hike         -0.32873    0.03007 -10.930  < 2e-16 ***
## hiring_score          0.04918    0.03016   1.630  0.10300
## distance_from_home    0.19869    0.01459  13.617  < 2e-16 ***
## total_dependents      0.73606    0.07098  10.370  < 2e-16 ***
## total_experience      0.10135    0.05626   1.801  0.07163 .
## monthly_overtime_hrs  0.16180    0.02452   6.600 4.12e-11 ***
## perf_satisfaction    -2.37872    0.58944  -4.036 5.45e-05 ***
## work_satisfaction    -0.34245    0.95838  -0.357  0.72085
## locationNew York      1.40716    0.26298   5.351 8.76e-08 ***
## locationOrlando      -0.85796    0.23221  -3.695  0.00022 ***
```

```
## marital_statusSingle  1.62941    0.33074   4.927 8.37e-07 ***
## educationMasters      1.78722    0.37628   4.750 2.04e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1972.64  on 1953  degrees of freedom
## Residual deviance:  822.69  on 1940  degrees of freedom
## AIC: 850.69
##
## Number of Fisher Scoring iterations: 7
```

In the catogrical variables, 1 is yes, and 0 is baseline. For example, Marital_status summary only show Single, the married as baseline. we could state that when employee is single, it is associate 1.63 increase turnover with employee is single.

turnover= -2.21x-0.288emp__age-0.329percent__hike+0.049hiring__sore+0.199distance__from__homw+0.736to
2.379per__satisfaction-0.342work__satisfaction+1.41New york or -0.858 Orlando+1.63Sigale+1.787
Masters.

```
##          (Intercept)              emp_age         percent_hike
##          -2.20595505          -0.28829617          -0.32872906
##         hiring_score   distance_from_home     total_dependents
##           0.04917649           0.19869275           0.73606333
##     total_experience monthly_overtime_hrs    perf_satisfaction
##           0.10135401           0.16180301          -2.37872259
##    work_satisfaction     locationNew York      locationOrlando
##          -0.34245419           1.40716345          -0.85796263
## marital_statusSingle     educationMasters
##           1.62941476           1.78722459
```

after we assume a realtionship to employees' self, we can add the manager information in the model.

```
##
## Call:
## glm(formula = turnover ~ emp_age + percent_hike + hiring_score +
##     distance_from_home + total_dependents + total_experience +
##     monthly_overtime_hrs + perf_satisfaction + work_satisfaction +
##     location + marital_status + education + mgr_rating + mgr_reportees +
##     mgr_age + mgr_tenure, family = "binomial", data = org)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.77652  -0.30516  -0.12154  -0.02717   3.04969
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -4.35211    2.85720  -1.523  0.12771
## emp_age                -0.29176    0.05636  -5.177 2.26e-07 ***
```

```
## percent_hike            -0.33470    0.03131 -10.690  < 2e-16 ***
## hiring_score             0.04341    0.03148   1.379  0.16790
## distance_from_home       0.19817    0.01516  13.074  < 2e-16 ***
## total_dependents         0.72643    0.07467   9.728  < 2e-16 ***
## total_experience         0.09618    0.05881   1.635  0.10199
## monthly_overtime_hrs     0.16441    0.02591   6.344 2.23e-10 ***
## perf_satisfaction       -2.54492    0.64147  -3.967 7.27e-05 ***
## work_satisfaction       -0.52446    1.07491  -0.488  0.62562
## locationNew York         1.51056    0.28523   5.296 1.18e-07 ***
## locationOrlando         -0.64191    0.24213  -2.651  0.00802 **
## marital_statusSingle     1.65180    0.35593   4.641 3.47e-06 ***
## educationMasters         1.75622    0.39708   4.423 9.74e-06 ***
## mgr_ratingAcceptable     0.21178    0.23285   0.910  0.36308
## mgr_ratingBelow Average -0.36585    0.40655  -0.900  0.36817
## mgr_ratingExcellent      0.39011    0.33076   1.179  0.23823
## mgr_ratingUnacceptable   0.35634    0.85852   0.415  0.67809
## mgr_reportees            0.12535    0.01918   6.536 6.32e-11 ***
## mgr_age                  0.03771    0.02362   1.597  0.11034
## mgr_tenure              -0.03958    0.02673  -1.481  0.13862
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1972.64  on 1953  degrees of freedom
## Residual deviance:  768.39  on 1933  degrees of freedom
## AIC: 810.39
##
## Number of Fisher Scoring iterations: 7
```

```
##
## Call:
## glm(formula = turnover ~ emp_age + percent_hike + distance_from_home +
##     total_dependents + monthly_overtime_hrs + perf_satisfaction +
##     location + marital_status + education + mgr_reportees, family = "binomial",
##     data = org)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.73695  -0.30182  -0.11947  -0.02871   3.12217
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -2.10268    1.27825  -1.645  0.09998 .
## emp_age              -0.21065    0.03360  -6.270 3.61e-10 ***
## percent_hike         -0.33307    0.03097 -10.754  < 2e-16 ***
## distance_from_home    0.19458    0.01475  13.192  < 2e-16 ***
## total_dependents      0.72930    0.07310   9.976  < 2e-16 ***
## monthly_overtime_hrs  0.15724    0.02513   6.256 3.95e-10 ***
## perf_satisfaction    -2.41213    0.51329  -4.699 2.61e-06 ***
## locationNew York      1.64616    0.26924   6.114 9.71e-10 ***
## locationOrlando      -0.63414    0.23525  -2.696  0.00703 **
## marital_statusSingle  1.71471    0.34570   4.960 7.04e-07 ***
## educationMasters      1.72941    0.39196   4.412 1.02e-05 ***
```

```
## mgr_reportees         0.12310    0.01872   6.577 4.80e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1972.6  on 1953  degrees of freedom
## Residual deviance:  781.5  on 1942  degrees of freedom
## AIC: 805.5
##
## Number of Fisher Scoring iterations: 7
```

split the data 70% into train and 30% into test

```
library(ISLR)
smp_siz <- floor(0.7 * nrow(emp_final) )
smp_siz
```

```
## [1] 1367
```

```
set.seed(1234)
train_ind<-sample(seq_len(nrow(emp_final)), size = smp_siz)
train <- emp_final [train_ind,]
test<- emp_final [-train_ind,]
```

```
train%>%
  count(status)%>%
  mutate(prop=n/sum(n)) #calculate the proportion in train for level and status
```

```
## # A tibble: 4 x 4
## # Groups:   level [2]
##   level      status       n  prop
##   <fct>      <fct>    <int> <dbl>
## 1 Analyst    Active     874 0.780
## 2 Analyst    Inactive   246 0.220
## 3 Specialist Active     212 0.858
## 4 Specialist Inactive    35 0.142
```

```
test%>%
  count(status)%>%
  mutate(prop=n/sum(n)) # calculate the proportion in test for level and status
```

```
## # A tibble: 4 x 4
## # Groups:   level [2]
##   level      status       n  prop
##   <fct>      <fct>    <int> <dbl>
## 1 Analyst    Active     385 0.795
## 2 Analyst    Inactive    99 0.205
## 3 Specialist Active      86 0.835
## 4 Specialist Inactive    17 0.165
```

```r
log<- glm(turnover ~ percent_hike,
          family= "binomial",
          data=train) # build a logistic regression using percent_hike to predict turnover
summary(log)
```

```
##
## Call:
## glm(formula = turnover ~ percent_hike, family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9286  -0.7093  -0.4514  -0.2808   2.6717
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.69046    0.23039   7.337 2.18e-13 ***
## percent_hike -0.32692    0.02521 -12.967  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1388.9  on 1366  degrees of freedom
## Residual deviance: 1167.1  on 1365  degrees of freedom
## AIC: 1171.1
##
## Number of Fisher Scoring iterations: 5
```

```r
mul_log<- glm(turnover~ level+gender+mgr_rating+compensation+hiring_score+marital_status+distance_from_h
              family="binomial",
              data=train) #bulid a multiple regression model for couple independent variables to predic
summary(mul_log)
```

```
##
## Call:
## glm(formula = turnover ~ level + gender + mgr_rating + compensation +
##     hiring_score + marital_status + distance_from_home + monthly_overtime_hrs +
##     work_satisfaction, family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7460  -0.5310  -0.2587  -0.1051   2.9871
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -4.140e+00  2.296e+00  -1.803 0.071379 .
## levelSpecialist         7.524e-01  2.889e-01   2.605 0.009196 **
## genderMale              3.537e-01  1.948e-01   1.816 0.069360 .
## mgr_ratingAcceptable    3.352e-01  2.110e-01   1.588 0.112280
## mgr_ratingBelow Average -2.210e-01  3.808e-01  -0.580 0.561713
## mgr_ratingExcellent     2.069e-01  3.089e-01   0.670 0.502907
## mgr_ratingUnacceptable  -1.212e+00  9.908e-01  -1.223 0.221234
```

```
## compensation           -4.466e-05  6.780e-06  -6.587 4.48e-11 ***
## hiring_score            2.765e-02  2.925e-02   0.945 0.344466
## marital_statusSingle   -1.007e-01  2.409e-01  -0.418 0.676056
## distance_from_home      2.141e-01  1.458e-02  14.677  < 2e-16 ***
## monthly_overtime_hrs    1.767e-01  2.491e-02   7.096 1.28e-12 ***
## work_satisfaction      -2.923e+00  8.538e-01  -3.424 0.000617 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1388.91  on 1366  degrees of freedom
## Residual deviance:  848.93  on 1354  degrees of freedom
## AIC: 874.93
##
## Number of Fisher Scoring iterations: 6
```

```r
mul_log1<- glm(turnover~ level+compensation+distance_from_home+monthly_overtime_hrs+work_satisfaction,
               family="binomial",
               data=train)
summary(mul_log1)
```

```
##
## Call:
## glm(formula = turnover ~ level + compensation + distance_from_home +
##     monthly_overtime_hrs + work_satisfaction, family = "binomial",
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6147  -0.5487  -0.2623  -0.1091   2.9730
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.601e+00  8.249e-01  -1.940   0.0523 .
## levelSpecialist       7.406e-01  2.900e-01   2.554   0.0107 *
## compensation         -4.230e-05  6.456e-06  -6.551 5.70e-11 ***
## distance_from_home    2.121e-01  1.444e-02  14.691  < 2e-16 ***
## monthly_overtime_hrs  1.691e-01  2.454e-02   6.891 5.55e-12 ***
## work_satisfaction    -3.247e+00  8.143e-01  -3.987 6.68e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1388.91  on 1366  degrees of freedom
## Residual deviance:  859.92  on 1361  degrees of freedom
## AIC: 871.92
##
## Number of Fisher Scoring iterations: 6
```

Variance Inflation Factor

```
library(car)
```

```
## Loading required package: carData
```

```
##
## Attaching package: 'car'
```

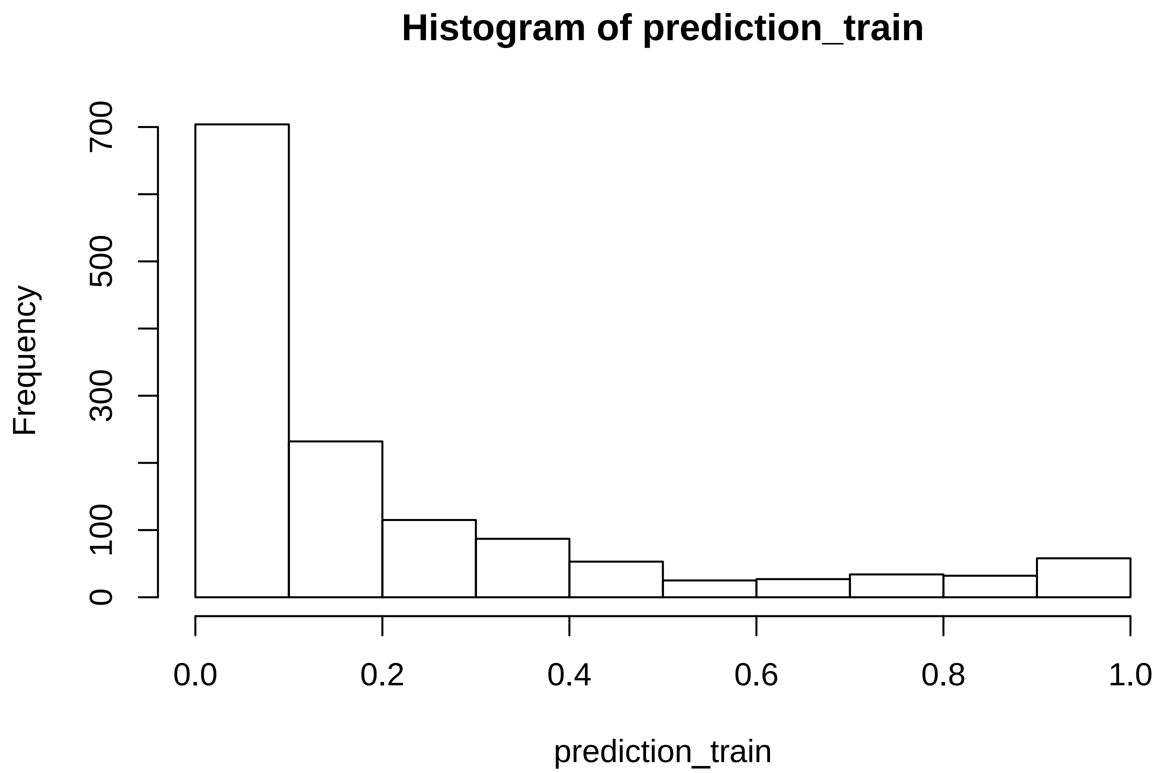
```
## The following object is masked from 'package:purrr':
##
##     some
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

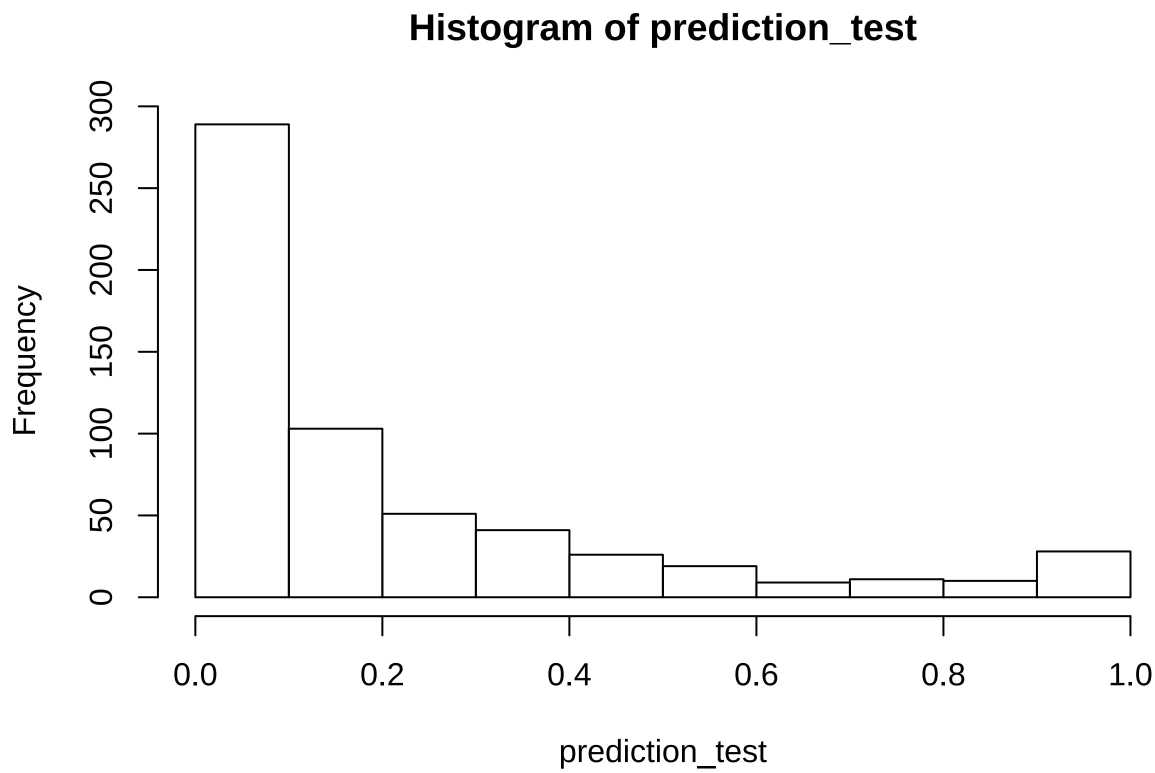
```
vif(mul_log1) #check a multicollinearity, the vif for each variables is greater than 1 but less than 2.
```

```
##                level         compensation   distance_from_home
##             1.483949             1.529480             1.050157
## monthly_overtime_hrs    work_satisfaction
##             1.027776             1.035387
```

```
prediction_train<- predict(mul_log1, newdata= train,
                           type = "response")
hist(prediction_train) # distribution skewed left, and histogram shown the probability to the employees
```




```r
prediction_test<-predict(mul_log1 , newdata = test,
                          type = "response")
hist(prediction_test) # check a train data into test data
```



Turn probabilities in categories by using a cut-off

```
pre_cut <- ifelse(prediction_test >0.5 , 1 ,0) #classify predictions using a cut-off of 0.5
conf_matrix<- table(pre_cut , test$turnover)
conf_matrix # 1 means inactive while 0 is active
```

```
##
## pre_cut   0   1
##       0 456  54
##       1  15  62
```

```
n<-sum(conf_matrix) #number of instances
nc<- nrow(conf_matrix) # number of classes
diag <- diag(conf_matrix) # number of correctly classified instances per class
rowsums <- apply(conf_matrix, 1, sum) # number of instances per class
colsums <- apply(conf_matrix, 2, sum) # number of predictions per class
p <- rowsums / n # distribution of instances over the actual classes
q <- colsums / n # distribution of instances over the predicted classes
```

```
accuracy <- sum(diag) / n ; accuracy # the model's accuracy is 0.88
```

```
## [1] 0.8824532
```

```
precision <- diag/colsums;precision # the model's precision to active is 0.97 and inactive 0.53
```

```
##         0         1
## 0.9681529 0.5344828
```

create retension strategy

```
library(tidypredict)
emp_risk<- emp_final %>%
  filter (status == "Active")%>%
  tidypredict_to_column(mul_log1) # calculate probability of turnover and add predictions using the mul
```

```
emp_risk %>%
  select(emp_id , fit)%>%
  group_by(level)%>%
  top_n(5, wt = fit)%>%
  arrange(desc(fit))  # look at the employee's probability of turnover from high to low
```

```
## Adding missing grouping variables: `level`
```

```
## # A tibble: 10 x 3
## # Groups:   level [2]
##    level      emp_id   fit
##    <fct>      <fct>  <dbl>
##  1 Analyst    E277   0.728
##  2 Analyst    E7328  0.716
##  3 Specialist E10412 0.715
##  4 Analyst    E1800  0.706
##  5 Analyst    E5942  0.704
##  6 Analyst    E6249  0.683
##  7 Specialist E440   0.611
##  8 Specialist E13662 0.569
##  9 Specialist E13617 0.548
## 10 Specialist E10462 0.526
```

```
emp_risk_bucket <- emp_risk%>%
  mutate(risk_bucket =cut(fit, breaks =c(0,0.3,0.5,0.7,1),
                          labels = c("no-risk", "low-risk", "medium-risk", "high-risk")))
emp_risk_bucket%>%
  count(risk_bucket)%>% #calculate the risk of turnover to the active employee
  group_by(risk_bucket)
```

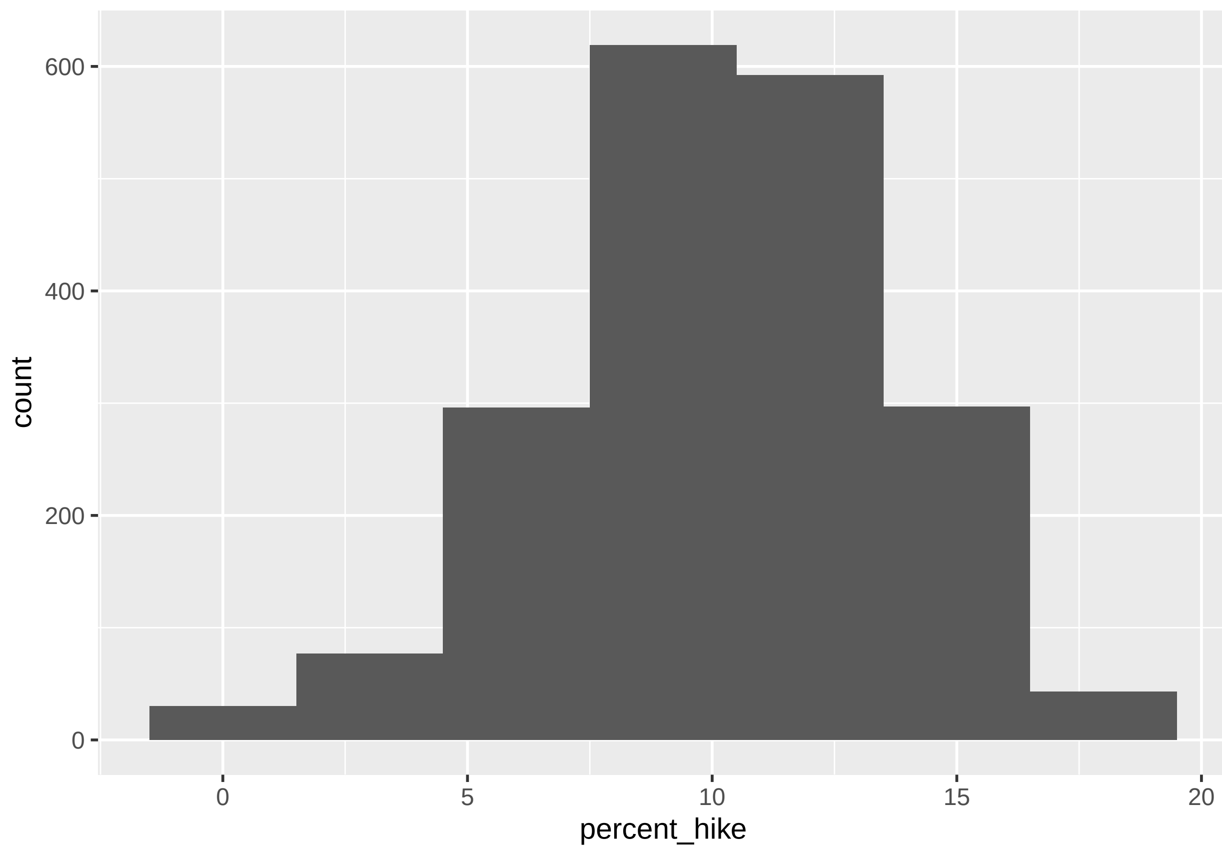
```
## # A tibble: 8 x 3
## # Groups:   risk_bucket [4]
##   level      risk_bucket     n
##   <fct>      <fct>       <int>
## 1 Analyst    no-risk      1089
## 2 Analyst    low-risk      134
```

```
## 3 Analyst    medium-risk    32
## 4 Analyst    high-risk       4
## 5 Specialist no-risk       272
## 6 Specialist low-risk       21
## 7 Specialist medium-risk     4
## 8 Specialist high-risk       1
```

ROI: retun on investment

ROI = Program Benifits / Program Cost

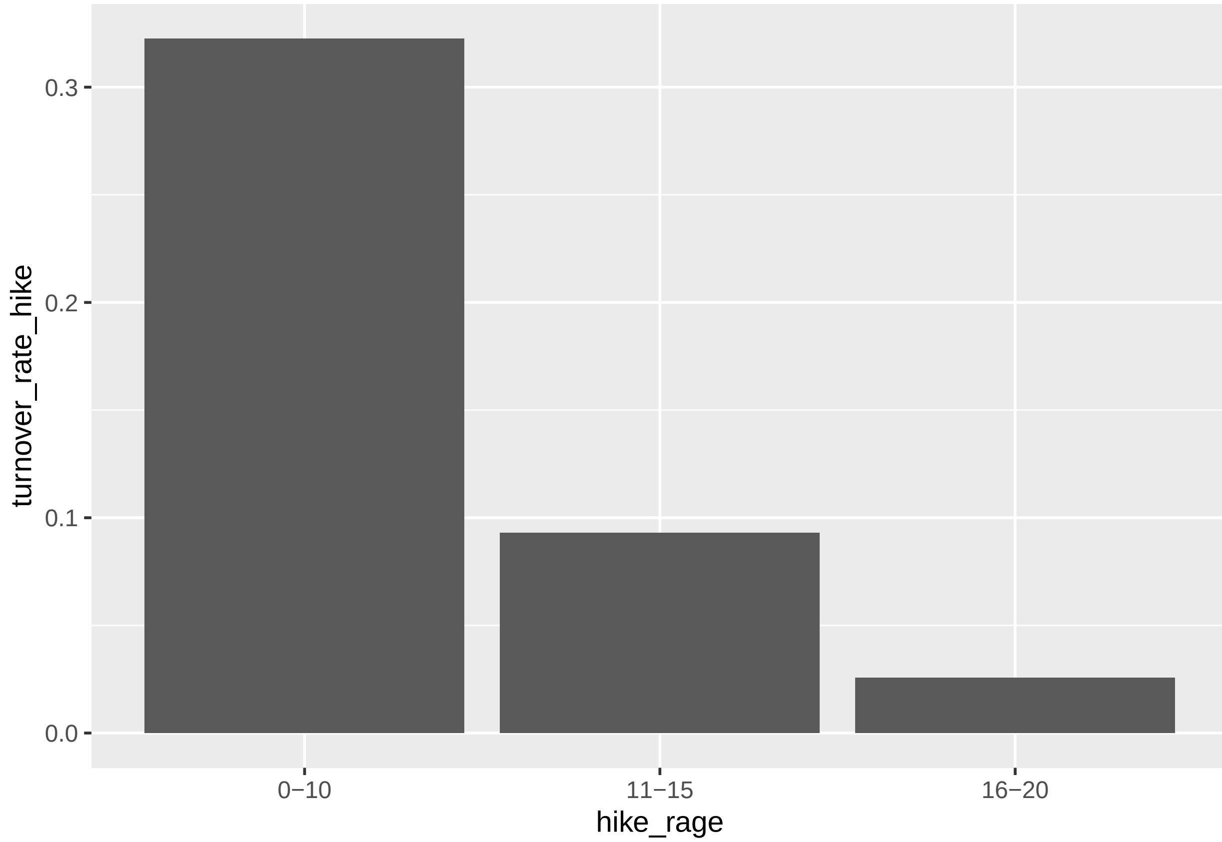
```
emp_final%>%
  ggplot(aes(percent_hike))+geom_histogram(binwidth = 3) #plot histogram of percent hike
```




```
emp_hike_range<- emp_final%>%
  filter(level == "Analyst")%>%
  mutate(hike_rage = cut(percent_hike, breaks = c(0,10,15,20),
                         include.lowest = TRUE,
                         labels = c("0-10","11-15","16-20"))) #create salary hike_rage of analyst level
df_hike<-emp_hike_range%>%
  group_by(hike_rage)%>%
  summarise(turnover_rate_hike = mean(turnover)) # calculate the turnover rate for each salary hike rag
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```r
df_hike%>%
  ggplot(aes(hike_rage, turnover_rate_hike))+geom_col()
```




```r
emp_final%>%
  filter(level == "Analyst")%>%
  count(median_compensation) # after filter we know median_compensation of analyst is 51840
```

```
## # A tibble: 1 x 3
## # Groups:   level [1]
##   level   median_compensation     n
##   <fct>                 <dbl> <int>
## 1 Analyst               51840  1604
```

```r
emp_final%>%
  filter(level=="Analyst")%>%
  select(compensation)%>%
  arrange(compensation)%>%
  head()#calculate the minium salary to analyst
```

```
## Adding missing grouping variables: `level`
```

```
## # A tibble: 6 x 2
```

```
## # Groups:   level [1]
##   level   compensation
##   <fct>          <int>
## 1 Analyst        32148
## 2 Analyst        32304
## 3 Analyst        33696
## 4 Analyst        33768
## 5 Analyst        33768
## 6 Analyst        33900
```

```r
extra_cost<- 51840 * 0.05 ; extra_cost #increase the salary 5%
```

```
## [1] 2592
```

```r
savings <- 40000*0.17 ; savings #assuming the analyst left then hire other one and traning cost
```

```
## [1] 6800
```

```r
ROI<-(savings / extra_cost)*100
cat(paste0("The return on investment is ", round(ROI), "%!"))
```

```
## The return on investment is 262%!
```