Salaries of San Francisco

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Contents

Abstract

The objective of this project is to perform a descriptive analysis of the San Francisco's salaries dataset in order to find if there exists links betweeen the variables of this dataset and give answers to different questions by utilizing the following discriminant analysis methods, *Principal Component Analysis*, *Correspondence Analysis*, and *Factorial Discriminant Analysis.* R Studio was utilized for exploring and cleaning the data, while SPAD was used for the analysis.

Intro

In order for San Francisco to become a more transparent city, they decided to release a sample dataset of the Salaries of the city from the years 2010-2014. We chose this dataset in order to answer the following questions:

1. Are there any links or correlation between the Salaries of the residents of San Francisco?
2. Is there a link between Job Title and the working Status (Full-Time, Part-Time)?
3. Can we use Salary to explain the Job Title or the working Status?

In order to pursue this study, the methods of discriminant analysis *PCA*, *CA*, and *FDA* were applied.

Dataset

The dataset was loaded, and its dimensions explored. The dataset contains 13 variables and 148654 observations. Which we knew in advance that it is more than what could be read by SPAD. For this reason the data would be futher explored in order to determine what are the important variables for the study.

Description

The dataset has the following variables:

Name	Class	Description
Id	Int	Id of the dataframe
EmployeeName	Factor	Name of the employee
JobTitle	Factor	Title of the job position
BasePay	Factor	Base anual salary
OvertimePay	Factor	Total Overtime payment
OtherPay	Factor	Other payments
Benefits	Factor	Anual extra benefits received
TotalPay	Numerical	Total salariy without Benefits
TotalPayBenefits	Numerical	Total Payment including Benefits
Year	Int	Year (2010-2014)
Notes	Logical	Notes are Empty
Agency	Factor	Place (San Francisco for all the observations)
Status	Factor	Status of the Employee (Full Time, Part Time)

An exploration of the *structure* and a *summary* of the data was made in order to gain insights from the data. These provided us enough information to decide which variables have to be filtered, reduced or even removed.

Preprocessing the dataset:

1. Columns droped: `Id, EmployeeName, Notes , Agency` will not be useful for the analysis, so they can be removed.
2. Filter the year: The dataset contains 3 years of data. For the purpose of our study, we will only analyse the year 2014.
3. Filter variable `TotalPayBenefits`: The values below zero are errors, hence filtered out.
4. Filterd values: The empty values for “Status” will be filtred out.
5. Classes: `BasePay, Overtime Pay, Other Pay`and `Benefits` are turn to numerical values.

At this point, the dataframe was reduced to: 9 variables, out of which 7 are numerical and 2 categorical, and 19000 observations.

Since the variable `JobTitle` (categorical), was hard to analyse as it had 2159 levels, or modalities. SPAD’s student license could not handle such a huge dataset, hence a decision was made to filter the data by top 10 popular `Job Titles` in San Francisco.

Finally the dataset ends up with the following structure and summary:

The dataframe was reduced to: 9 variables and 5282 observations.

Data Structure

```
## 'data.frame':    5282 obs. of  9 variables:
##  $ JobTitle        : Factor w/ 2159 levels "Account Clerk",..: 2038 2038 2038 2038 2038 2038 2038 203
##  $ BasePay         : num  83997 84651 83101 82222 81838 ...
##  $ OvertimePay     : num  59452 57451 52025 49521 47731 ...
##  $ OtherPay        : num  68826 69563 76318 73639 74802 ...
##  $ Benefits        : num  72037 73204 72029 70263 70017 ...
##  $ TotalPay        : num  155765 151286 138509 131865 128545 ...
##  $ TotalPayBenefits: num  194247 190147 176989 169765 166361 ...
##  $ Year            : int  2014 2014 2014 2014 2014 2014 2014 2014 2014 2014 ...
##  $ Status          : Factor w/ 3 levels "","FT","PT": 2 2 2 2 2 2 2 2 2 2 ...
```

Data Summary

```
##                          JobTitle       BasePay        OvertimePay
##  Transit Operator            :1266   Min.   :    14   Min.   :    3
##  Special Nurse               : 753   1st Qu.: 17184   1st Qu.:    3
##  Registered Nurse            : 589   Median : 47800   Median :15834
##  Public Svc Aide-Public Works: 449   Mean   : 48420   Mean   :21567
##  Firefighter                 : 424   3rd Qu.: 74658   3rd Qu.:40316
##  Custodian                   : 401   Max.   :109713   Max.   :66127
##  (Other)                     :1400
##     OtherPay        Benefits         TotalPay       TotalPayBenefits
##  Min.   :    7   Min.   :    7   Min.   :     0   Min.   :     0
##  1st Qu.:14924   1st Qu.:22134   1st Qu.: 14859   1st Qu.: 16835
##  Median :37138   Median :59250   Median : 64044   Median : 88554
##  Mean   :37888   Mean   :51692   Mean   : 69099   Mean   : 90208
##  3rd Qu.:59660   3rd Qu.:78564   3rd Qu.:114865   3rd Qu.:148326
##  Max.   :84216   Max.   :98639   Max.   :287480   Max.   :325718
```

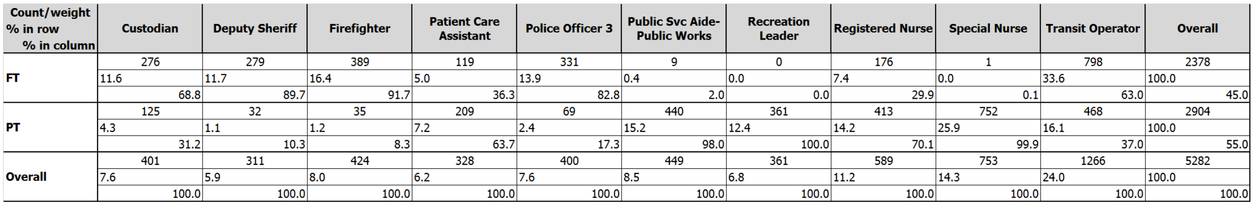
```
##
##        Year       Status
##  Min.   :2014      :   0
##  1st Qu.:2014    FT:2378
##  Median :2014    PT:2904
##  Mean   :2014
##  3rd Qu.:2014
##  Max.   :2014
##
```

Now this is the dataset which will be uploaded to SPAD in order to be analyzed.

Discriminant Analysis

After importing the data to SPAD, the first step is to generate statistics and explore our values. The continuous variables do not appear to have any anomalies, it is only important to be aware for further analysis that `TotalPay` and `TotalBenefitsPay` are the linear combination of the other continuous variables.

Then, it is important to evaluate the behaviour of the categorical variables by creating a cross table, which will be later needed for a Correspondance Analysis.



Count/weight % in row % in column	Custodian	Deputy Sheriff	Firefighter	Patient Care Assistant	Police Officer 3	Public Svc Aide-Public Works	Recreation Leader	Registered Nurse	Special Nurse	Transit Operator	Overall
FT	276	279	389	119	331	9	0	176	1	798	2378
	11.6	11.7	16.4	5.0	13.9	0.4	0.0	7.4	0.0	33.6	100.0
	68.8	89.7	91.7	36.3	82.8	2.0	0.0	29.9	0.1	63.0	45.0
PT	125	32	35	209	69	440	361	413	752	468	2904
	4.3	1.1	1.2	7.2	2.4	15.2	12.4	14.2	25.9	16.1	100.0
	31.2	10.3	8.3	63.7	17.3	98.0	100.0	70.1	99.9	37.0	55.0
Overall	401	311	424	328	400	449	361	589	753	1266	5282
	7.6	5.9	8.0	6.2	7.6	8.5	6.8	11.2	14.3	24.0	100.0
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

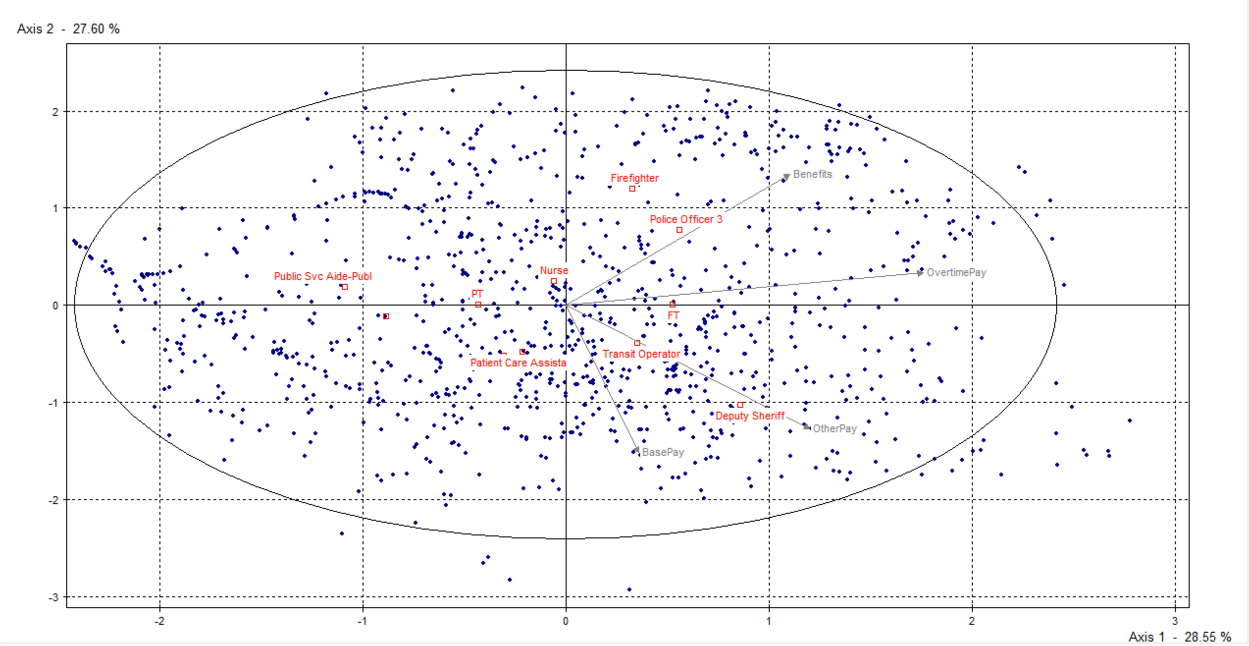
Because Special Nurse and Recreation Leader have a frequency lower than five for one of the modalities of Status, then *Yates correction* is applied. Special Nurse and Registered Nurse will now become the new category `Nurse`, while, `Recreational Leader` will be discarded, providing with these changes another variable called `New_JobTitle`.

Principal Component Analysis

The four continuous variables selected for PCA were `BasePay`, `OvertimePay`, `OtherPay`, and `Benefits`. `New_JobTitle` and `Status` were chosen as supplementary categorical variables. The other two continuous variables `TotalPay` and `TotalPayBenefits` were removed from the analysis as we previously said, they are linear combinations of the variables selected for PCA.

Are there any links or correlation between the Salaries of the residents of San Francisco?

The first two principle axis capture 56% of the variation in data. The significant active variables on the first factorial plane are `OvertimePay` and `OtherPay`, and the significant active variables on the second factorial plane are `BasePay`, `Benefits` and `OtherPay`.
There is a link between `OvertimePay` and `OtherPay` on the first factorial plane where as `Benefits` and `BasePay` are in opposition on the second factorial plane. We see that Transit Operator and Deputy Sheriff have similar profile just as Firefighter and Police Officer have similar profiles, they both tend to be `FullTime`, different from Public Service Aid, which tends to be `PartTime`.



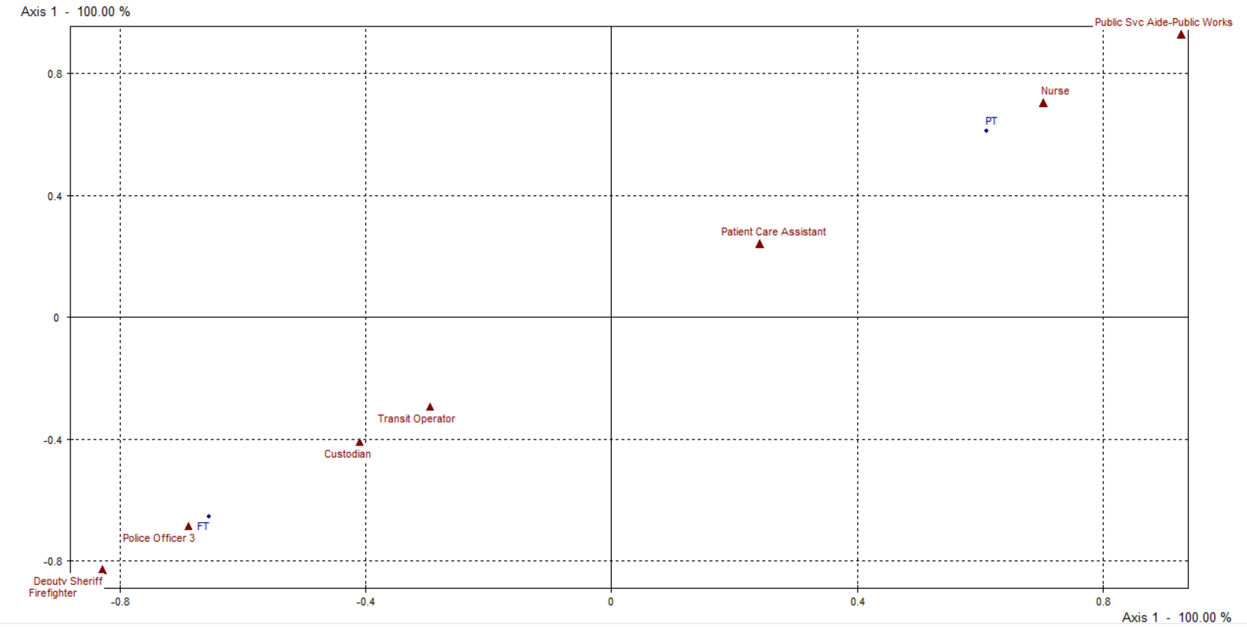
Hereby is the Table of Contributions.

Correspondence Analysis

In order to pursue a Correspondence Analysis (CA), the first step is to check if there exists dependence between the two categorical variables. The variables selected for the CA are `JobTitle` and `Status`. A Cross Table was built and its Chi-square value is equal to 1969 and P-value is less than .001. These previous numbers confirm a strong dependence between the variables `Job Title` and `Status`, hence a it is possible to do a Correspondence Analysis in order to answer this question.

Is there a link between Job Title and the working Status (Full-Time, Part-Time)?

All the variation in our data is well captured by the first principle component since one of our variables has two modalities. For the variable `JobTitle`: Nurse, Public Service Aide and Fire Fighter have high contribution on the first factorial plane compared to other modalities. There exist a strong link between Full time jobs and Deputy Sheriff, Fire Fighter and Police Officer. In contrast there is also a strong link between Part time jobs and Public Service Aide and Nurse.



Hereby is the Table of Contributions.

Factorial Discriminant Analysis

Given the fact that in order to do a Factorial Discriminant Analysis (FDA), is necessary to have an explain categorical variable and several explanatory continuous variables, two FDAs will be executed, one with the variable to explain being, `JobTitle` and the other being, `Status`.

Can we use Salary to explain the Job Title or the working Status?

Factorial Discriminant Analysis on JobTitle

Normally a Factorial Discriminant Analysis would be capable of analysing an explain categorical variable with multiple modalities. Since the SPAD student version used for this study can not support more than two modalities, hence they were merged. This new variable was called `Job Category` and its modalities are the following:

- `Defense`: By merging `Custodian`, `Deputy Sheriff`, `Firefighters`, `Police Officer 3`, and `Transit Operator`.
- `Healthcare`: `Patient Care Assistant`, `Public Svc Aide-Public Works`, `Recreation Leader`, `Registered Nurse`, and 'Special Nurse'.

The explanatory variables are `BasePay`, `OvertimePay`, `OtherPay` and `Benefits` to explain the variable `JobCategory`. Modalities of the variable `JobCategory` are Defense and Healthcare. The model obtained is significant as P-value is less than 5%. All the explanatory variables are significant as their absolute ratios are higher than 1.96. The model shows that 68% of the data points are well classified. Overtime pay has the highest function of Fisher, hence the highest contribution.

Hereby is the Classification Table.

Factorial Discriminant Analysis on Status

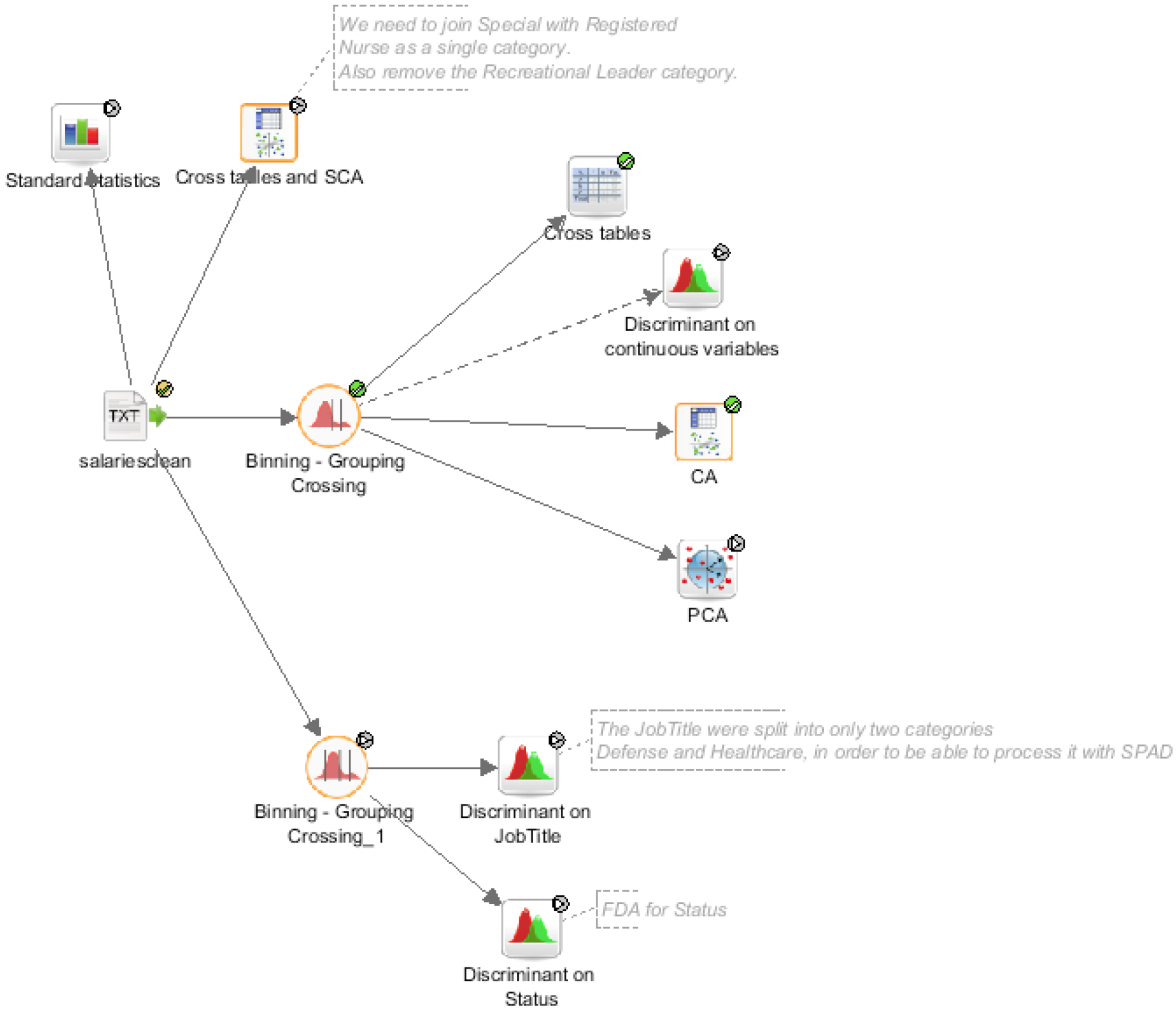
For the Discriminant Analysis on `Status` in SPAD, since it only has two categories, it is not necesary to do any merge.

The explanatory variables are `BasePay`, `OvertimePay`, `OtherPay`, and `Benefits` to explain the variable `Status`. Modalities of the variable `Status` are Full Time and Part Time. The model obtained is significant as P-value is less than 5%. All the explanatory variables are significant as their absolute ratios are higher than 1.96. The model shows that 70% of the data points are well classified. Overtime pay has the highest function of Fisher, hence a highest contribution.

Hereby is the Classification Table.

Appendix

SPAD MODEL:


We need to join Special with Registered
Nurse as a single category.
Also remove the Recreational Leader category.
Standard statistics
Cross tables and SCA
Cross tables
Discriminant on
continuous variables
salariesclean
Binning - Grouping
Crossing
CA
PCA
The JobTitle were split into only two categories
Defense and Healthcare, in order to be able to process it with SPAD
Binning - Grouping
Crossing_1
Discriminant on
JobTitle
FDA for Status
Discriminant on
Status