San Diego Salary Comparisions

April 20, 2023

[1]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os

pd.set_option('display.max_rows', 7)
```

0.1 San Diego City Salaries

The dataset at hand includes a list of all San Diego city employee salaries for a particular year. This includes employee names and job titles, as well as the components of their total pay during the year 2017.

Dataset link : https://transparentcalifornia.com/salaries/san-diego/

[2]:
```
salary_path = os.path.join('data', 'san-diego-2017.csv')
salaries = pd.read_csv(salary_path)
salaries.reset_index(drop=True)
```

[2]:
```
          Employee Name                Job Title  Base Pay  Overtime Pay  \
0       David P Gerboth      Fire Battalion Chief   81917.0      172590.0
1      Scott C Chadwick  Chief Operating Officer  255000.0           0.0
2      Glen A Bartolome             Fire Captain   85904.0      120682.0
…                   …                       …        …            …
12490    Stephen J Hill          Council Rep 2 A       0.0           0.0
12491      Tania  Serhan           Sr Mgmt Anlyst       0.0           0.0
12492    Brian D Cassels          Police Officer       0.0           0.0

      Other Pay  Benefits  Total Pay  Pension Debt  Total Pay & Benefits  \
0      68870.00   21784.0   323377.0           NaN              345161.0
1      31164.00   49921.0   286164.0           NaN              336085.0
2      99408.00   26470.0   305994.0           NaN              332464.0
…           …         …         …            …                    …
12490      8.00       0.0        8.0           NaN                   8.0
12491      8.00       0.0        8.0           NaN                   8.0
12492      3.00       0.0        3.0           NaN                   3.0
```

```
       Year  Notes     Agency Status
0      2017    NaN  San Diego     FT
1      2017    NaN  San Diego     FT
2      2017    NaN  San Diego     FT
…       …    …          …     …
12490  2017    NaN  San Diego     PT
12491  2017    NaN  San Diego     PT
12492  2017    NaN  San Diego     PT

[12493 rows x 13 columns]
```

0.1.1 Basic description of employee pay

The table below contains a basic of description of employee pay. What does typical pay look like?

[3]:
```
salaries.describe().T
```

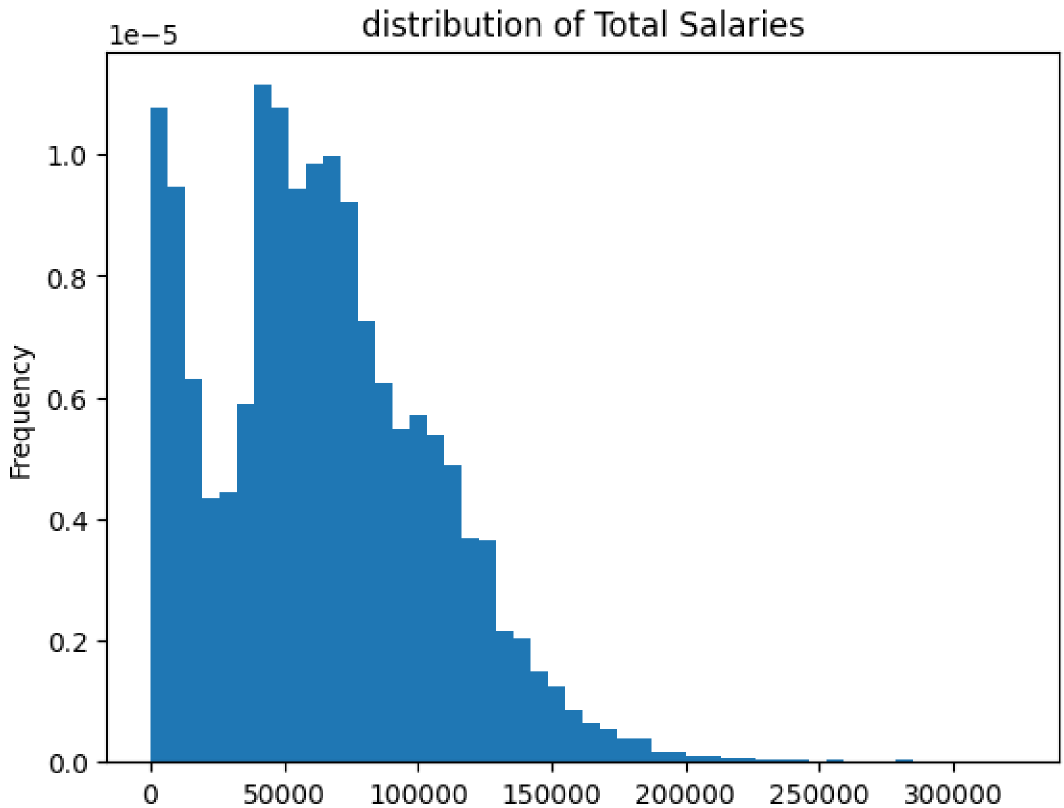
[3]:
```
                      count          mean           std     min      25%  \
Base Pay            12493.0  48843.853918  29377.449188     0.0  28888.0
Overtime Pay        12493.0   6573.031858  15308.455700  -623.0      0.0
Benefits            12493.0  12853.013207   9199.780447   -29.0   5262.0
…                       …           …            …      …       …
Total Pay & Benefits  12493.0  77837.984231  49224.288964     3.0  46218.0
Year                12493.0   2017.000000      0.000000  2017.0   2017.0
Notes                   0.0           NaN           NaN     NaN      NaN

                        50%       75%       max
Base Pay            49254.0   68952.0  255000.0
Overtime Pay          393.0    5408.0  196978.0
Benefits            12483.0   18633.0   81633.0
…                       …        …        …
Total Pay & Benefits  74289.0  109483.0  345161.0
Year                 2017.0    2017.0    2017.0
Notes                   NaN       NaN       NaN

[8 rows x 8 columns]
```

Observations: * What are the negative payments? Near zero salaries? * Other pay column is not present * Are the salaries in the 'max' column real?

0.1.2 Empirical Distribution of Salaries

. Plotting the empirical distribution of salaries raises two observations: * The distribution is 'bimodal' and is likely comprised of two distributions. * The salaries have a skew to the right, which is typical for a quantity that can only be non-negative.

[4]:
```
salaries['Total Pay'].plot(kind='hist', bins=50, density=True,␣
 ↪title='distribution of Total Salaries');
```



A reasonable guess for the bimodal nature of the distribution of salaries is the employment status. One would expect salaries to vary significantly based on whether an employee works Part-time versus Full-time. Splitting the population up by job status reveals two distributions: * The part-time jobs tend to have lower salaries, closer to 0, * The full-time jobs tends to have salaries centered around 80,000 USD.

[5]:
```
bystatus = salaries.groupby('Status')
bystatus['Total Pay'].plot(kind='kde', alpha=0.5, title='Salary by Full-time/
 ↪Part-time')
plt.legend(bystatus.groups);
```

[6]:
```python
salaries = salaries[['Employee Name', 'Job Title', 'Total Pay', 'Status']].
 ↪copy()
```

0.1.3 Do women earn similar pay to their contemporaries?

One problem : this dataset doesn't contain information on the gender of employees. The dataset does have the first names of employees, which contains imperfect information about gender. A reasonable approach is to find a dataset that contains information about correspondences between names and gender, the Social Security Administration publishes a "baby names" dataset that does exactly this.

0.1.4 SSA names dataset

The Social Security Administration compiles a list of all names on social security applications in a given year, whether the applicant identified as Male or Female. This list can then be used to label the most likely gender of the employees using their first names.

Dataset link : https://www.ssa.gov/oact/babynames/limits.html

[7]:
```python
from glob import glob
import os
```

```
names_path = os.path.join('data', 'names.csv')
names = pd.read_csv(names_path)
names.head()
```

[7]:

	firstname	gender	count	year
0	Emily	F	25956	2000
1	Hannah	F	23082	2000
2	Madison	F	19968	2000
3	Ashley	F	17997	2000
4	Sarah	F	17702	2000

0.1.5 Basic check of names:

There are a number of details to attend to in SSA dataset: * Many names identify to both genders (gender-neutral names). * Most names occur only a few times per year (most names are rare). * A few names make up most the applications.

Notice, the name "Madison" is mostly identified as female, though there are consistently a few males with that name as well:

[8]:
```
# look at a single name
names[names['firstname'] == 'Madison'].sort_values(by='year', ascending=False)
```

[8]:

	firstname	gender	count	year
1887827	Madison	M	36	2018
1866629	Madison	F	7036	2018
161087	Madison	F	7875	2017
…	…	…	…	…
1932167	Madison	M	27	1882
1843222	Madison	M	28	1881
1841285	Madison	M	22	1880

[178 rows x 4 columns]

0.1.6 Approach to joining gender:

- Create a table of distinct names with the proportion of applications on which that name identifies as female.
- That is, for each name N, compute:

$$P(\text{person is female} \mid \text{person has first name } N)$$

- Join this table to the salaries dataset.

[9]:
```
# Counts by gender
cnts_by_gender = names.pivot_table(
    index='firstname',
    columns=['gender'],
```

```
    values='count',
    aggfunc='sum',
    fill_value=0
)

names_idx = ['Aaron', 'Maria', 'Dakota', 'Ashley', 'Avery', 'Paris']
cnts_by_gender.loc[names_idx, :]
```

[9]:

```
gender          F       M
firstname
Aaron        4307  581330
Maria      546026    4237
Dakota      33204   86089
Ashley     846120   15668
Avery      125883   55646
Paris       28841    8812
```

From the total counts in the above table, calculate the proportion of a given name that's identified as female. If this number is greater than 0.5, then the name is likely associated to female; otherwise the name mostly associates to male.

[10]:

```
# proportion of a given name that's identified female
prop_female = (cnts_by_gender['F'] / cnts_by_gender.sum(axis=1))
genders = (
    prop_female.rename('proportion of a given name that\'s identified as␣
 ↪female').to_frame()
    .assign(**{'gender':
               prop_female.apply(lambda x:'F' if x > 0.5 else 'M').
 ↪rename('prop_female').to_frame()
              }))

genders.loc[names_idx]
```

[10]:

```
           proportion of a given name that's identified as female gender
firstname
Aaron                                               0.007354          M
Maria                                               0.992300          F
Dakota                                              0.278340          M
Ashley                                              0.981819          F
Avery                                               0.693459          F
Paris                                               0.765968          F
```

0.1.7 Add a given name column to salaries and join names

This table of names and their most likely gender attaches a 'most likely gender' to the employees in the salaries dataset. This identification is approximate and doesn't reflect the actual gender with which the employees identify.

[11]:
```python
# Add firstname column
salaries.loc[:, 'firstname'] = salaries['Employee Name'].str.split().
 ↪apply(lambda x:x[0])

# join gender
salaries_with_gender = salaries.merge(genders.reset_index(), on='firstname',␣
 ↪how='left')
salaries_with_gender.sample(5).reset_index(drop=True)
```

[11]:
```
          Employee Name                   Job Title  Total Pay Status  \
0        James L Gaboury           Deputy Fire Chief   185560.0     FT
1   Francisco  Lizarraga  Seven-Gang Mower Operator    47954.0     FT
2       Hanna K Johnston                Lifeguard 1    11415.0     PT
3      Thien-Long Q Tran           Jr Engineer-Civil    67858.0     FT
4         Rebecca S Vela        Court Support Clrk 1    25943.0     PT

    firstname  proportion of a given name that's identified as female gender
0       James                                           0.004510            M
1   Francisco                                           0.007064            M
2       Hanna                                           0.996534            F
3  Thien-Long                                                NaN          NaN
4     Rebecca                                           0.997186            F
```

0.1.8 Do women earn similar pay to their contemporaries?

With a most likely gender attached to the salaries dataset, the salaries can now be described by gender:

[12]:
```python
pd.concat([
    salaries_with_gender.groupby('gender')['Total Pay'].describe().T,
    salaries_with_gender['Total Pay'].describe().rename('All')
], axis=1)
```

[12]:
```
                  F              M            All
count   4153.000000    7895.000000   12493.000000
mean   53946.543703   71239.687017   64984.971024
std    36254.857386   43430.325681   41812.990357
…               …              …              …
50%    50787.000000   67920.000000   61452.000000
75%    75127.000000  100729.000000   91400.000000
max   237512.000000  323377.000000  323377.000000

[8 rows x 3 columns]
```

There is clearly a large difference in salaries between the males and females! Some points to think before giving out any conclusions! * Is this difference the result of some sort of true unfairness, or perhaps the difference is just due to chance? * If the difference isn't due to chance, why does it exist?

Can women's median pay be explained as a random subset of the population of city of SD salaries?

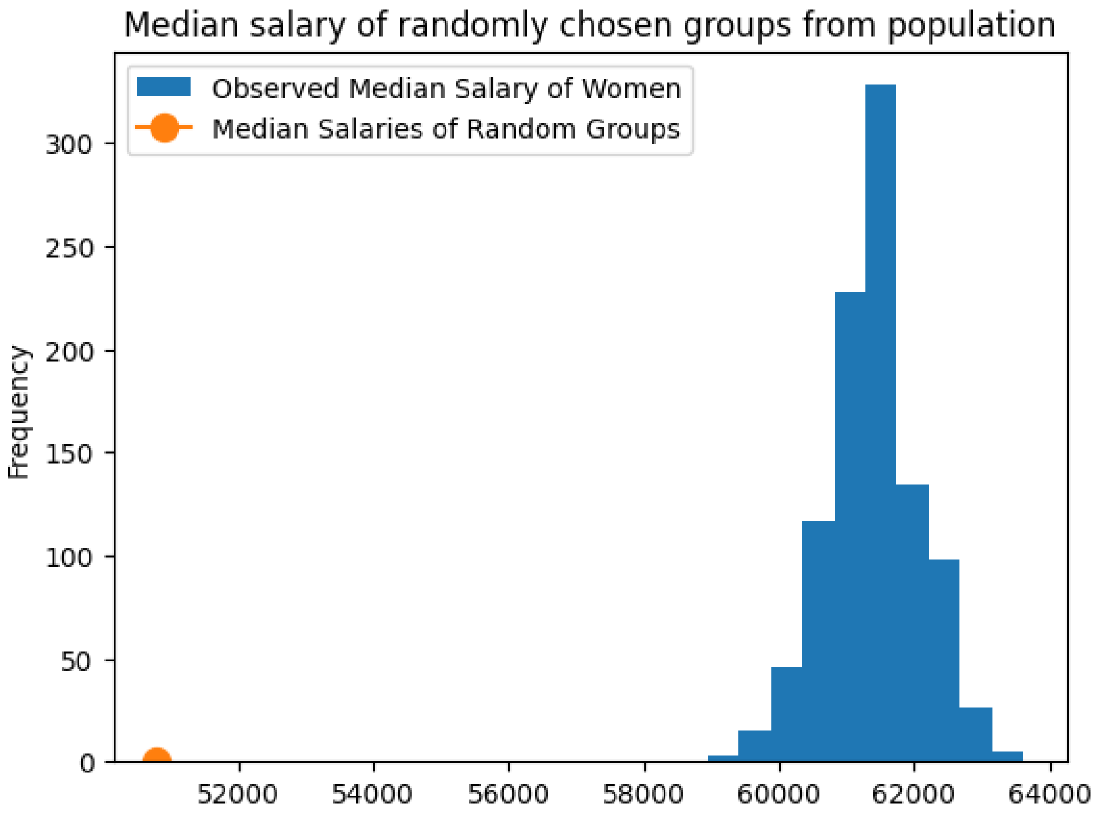
If so, the salary of women doesn't significantly differ from the population; otherwise, some other explanation is needed to explain the difference!

We can perform a hypothesis test to answer this question. * Random subsets of employees are drawn from the dataset, of the same size as the number of female employees, * The median salary of each of these random groups is calculated, * The observed salary of female employees is compared to the simulated 'randomly drawn' median salaries. Finally, one asks if the observed, real-life salary was just as likely drawn from a random subset of employees. If so, then the observed difference may have occurred due to chance; otherwise, something else is going on!

The plot below illustrates the results of this simulation: * The blue distribution represents the median salaries of these 'randomly formed groups'. * The orange dot represents the real-life median female salary.

It seems unlikely this difference is due to chance!

[13]:
```
# size of sample is number of women:
n_female = (salaries_with_gender['gender'] == 'F').sum()


# calculate observed
female_median = salaries_with_gender.loc[salaries_with_gender['gender'] ==␣
↪'F']['Total Pay'].median()


# simulate 1000 draws from the population of size n_female
medians = []
for _ in np.arange(1000):
    median = salaries_with_gender.sample(n_female)['Total Pay'].median()
    medians.append(median)


title='Median salary of randomly chosen groups from population'
pd.Series(medians).plot(kind='hist', title=title);
plt.plot([female_median], [0], marker='o', markersize=10)
plt.legend(['Observed Median Salary of Women', 'Median Salaries of Random␣
↪Groups']);
```



Now that the question of differences in the salaries of genders is answered, however there are still some more questions.

First, are the results correct? * Is the name-to-gender assignment correct (enough)? * What biases might have been introduced when joining the dataset of names to salaries? * Are the results applicable outside of 2017? outside of San Diego?

Second, why are the results what they are? * Is the disparity correlated to pay-type? job status? job type? * What is the cause of the disparity?

The sections below approach each of these questions, giving a feel for what's involved in answering them.

0.1.9 Is the name-to-gender assignment correct?

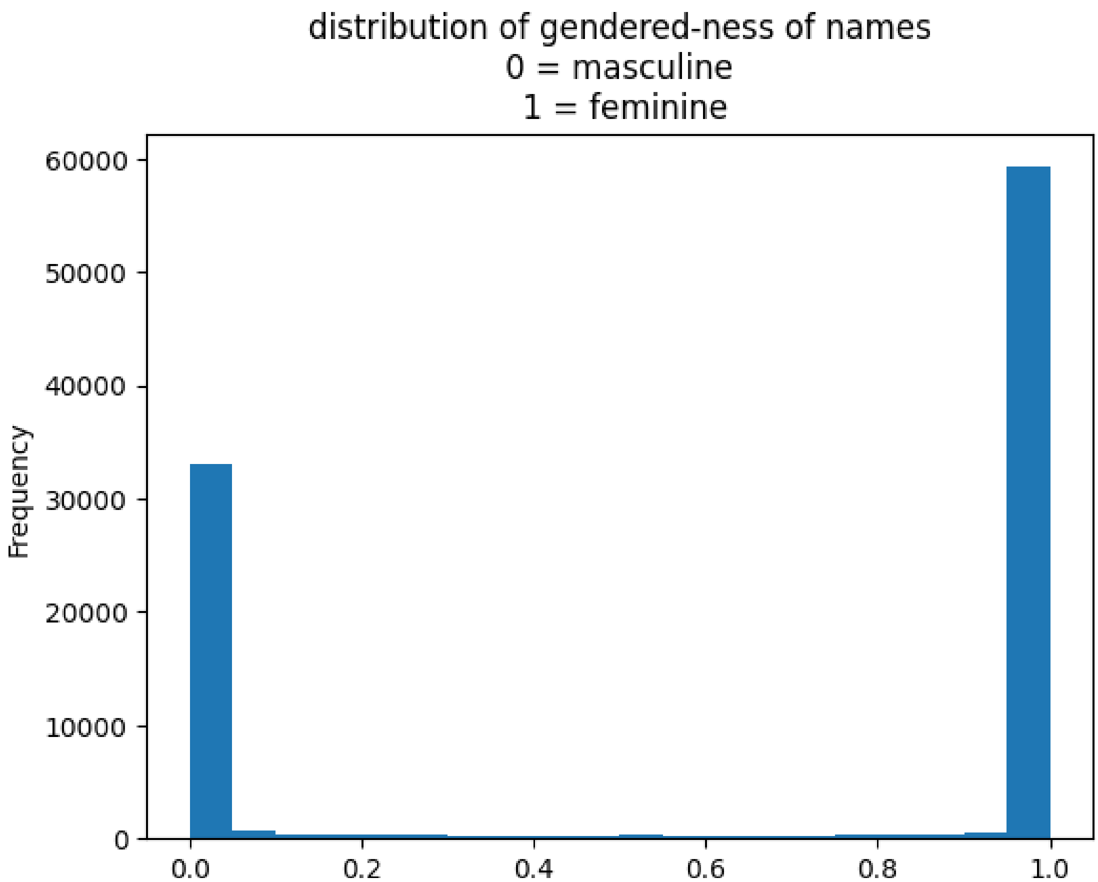
- How many names are borderline male/female?
- Does it make sense to incorporate name usage from all years in the dataset? (1880-2017?)

The plot below shows the distribution of 'proportions of names being female.' * The bar near 0 are counts of names that are almost entirely male. * The bar near 1 are counts of names that are almost entirely female. * There are very few names in the middle that are gender-neutral.

However, each unit plotted is a distinct name; the proportions hide the number of people with each name. What if the most popular name in the country is gender-neutral?

What's more appropriate is to look at this distribution of confidence among the dataset of employees.

[14]:
```
title = 'distribution of gendered-ness of names\n 0 = masculine \n 1 = feminine'
prop_female.plot(kind='hist', bins=20, title=title);
```



0.1.10 Assessment of the join?

- Are there names in the salary dataset that aren't in the SSA dataset?
  - Who might not be in the SSA dataset?
  - Might these names be biased toward certain salaries?
- Does the salary dataset have a disproportionately large portion of gender-neutral names.
- Is it better to use a subset of the SSA dataset (e.g. by state? by year?)
  - Do the gender of names typically vary by geography or over time?

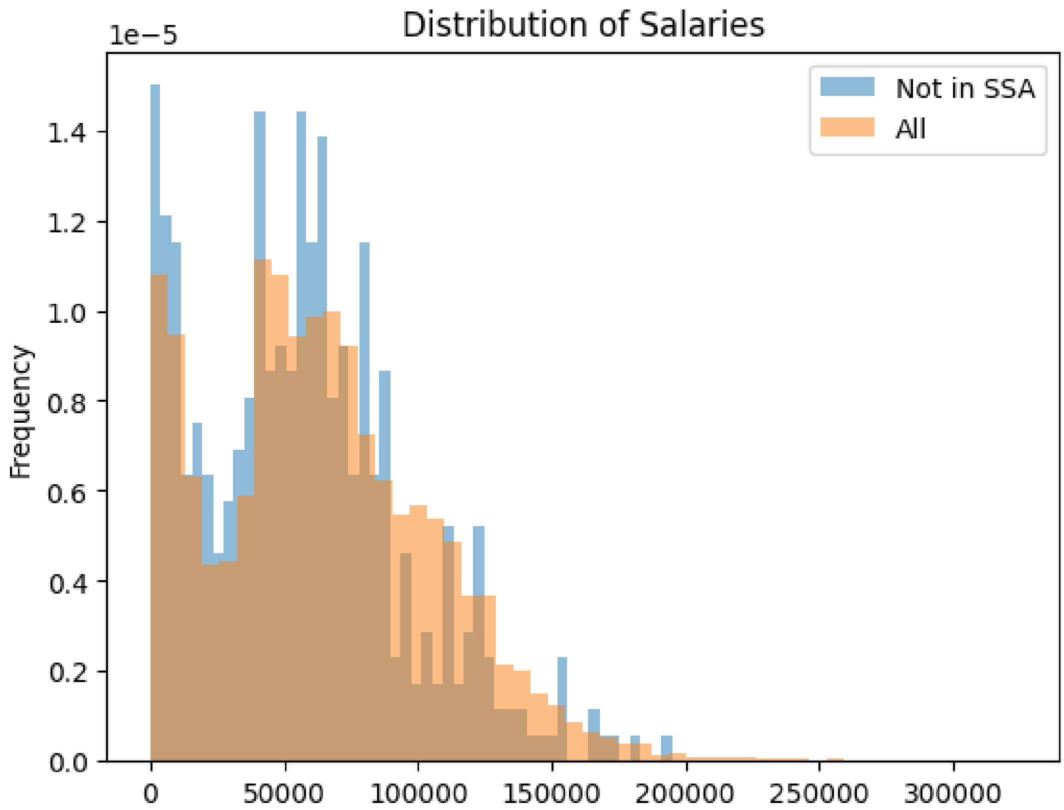
The proportion of employees not in the SSA data is 3.5%, which is fairly small, but may affect the results. These individuals should be investigated more closely; a look at the employees with a gender assigned versus those that didn't appear in the SSA names dataset reveals some bias (see table below).

Perhaps those that didn't appear in the names dataset have lower salaries because they belong to an uncommon ethnic group (e.g. an immigrant group)? Such populations would likely work in jobs that earn lower salaries. One could further clean up these missing genders by incorporating the demographic information from immigration data.

[15]:
```
# proportion of employees not in SSA dataset
# salaries_with_gender['gender'].isnull().mean()

# Description of total pay by joined vs not joined
(
    salaries_with_gender
    .assign(joined=salaries_with_gender['gender'].notnull())
    .groupby('joined')['Total Pay']
    .describe()
    .T
)
```

[15]:
```
joined          False          True
count      445.000000  12048.000000
mean     57033.523596  65278.662434
std      38261.845670  41910.973914
…                 …             …
50%      55282.000000  61650.500000
75%      78970.000000  91895.000000
max     194920.000000 323377.000000

[8 rows x 2 columns]
```

[16]:
```
nonjoins = salaries_with_gender.loc[salaries_with_gender['gender'].isnull()]

title = 'Distribution of Salaries'
nonjoins['Total Pay'].plot(kind='hist', bins=50, alpha=0.5, density=True,␣
 ↪sharex=True)
salaries_with_gender['Total Pay'].plot(kind='hist', bins=50, alpha=0.5,␣
 ↪density=True, sharex=True, title=title)
plt.legend(['Not in SSA','All']);
```



0.1.11 Why does pay disparity exist?

Is the pay disparity correlated to another field? job status? job type? Is the proportion of women in a job type correlated to pay? One approach might ask if women earn similar salaries as men for a given job type.

Below, a few job types are isolated for investigation. For example, those who work in 'Fire' related fields tend to be male and make high salaries:

[17]:
```
# select jobs with word 'fire' in them
firejobs = salaries_with_gender.loc[salaries_with_gender['Job Title'].str.
↪contains('Fire')]
firejobs.sample(5)
```

[17]:

	Employee Name	Job Title	Total Pay	Status	firstname	\
9839	Alan M Cummings	Fire Fighter 2	30470.0	PT	Alan	
5882	Marco A Romero Valdez	Fire Fighter 1	66152.0	PT	Marco	
2256	Dylan E Chiu	Fire Engineer	106768.0	FT	Dylan	
1288	Skip Reed	Fire Captain	112946.0	FT	Skip	
1422	David K Conde	Fire Captain	136443.0	PT	David	

```
      proportion of a given name that's identified as female gender
9839                                               0.003077          M
5882                                               0.004758          M
2256                                               0.033090          M
1288                                               0.000000          M
1422                                               0.003552          M
```

The proportion of fire-related jobs held by women is only 8.8%, yet fire-related jobs make significantly more than the overall median pay of 61,000USD per year:

[18]:
```python
# Proportion of fire-related jobs held by women
#(firejobs['gender'] == 'F').mean()

# Pay Statistics for fire-related jobs
firejobs['Total Pay'].describe()
```

[18]:
```
count      1017.000000
mean     110967.646018
std       49678.113970
              …
50%      112568.000000
75%      141502.000000
max      323377.000000
Name: Total Pay, Length: 8, dtype: float64
```

On the other hand, those with library-related jobs tend to be female and make lower-than-average salaries:

[19]:
```python
# select jobs with library related jobs
libjobs = salaries_with_gender.loc[salaries_with_gender['Job Title'].str.
 ↪contains('Librar')]
libjobs.sample(5)
```

[19]:
```
             Employee Name      Job Title  Total Pay Status firstname  \
11795       Beatriz  Rovira   Library Aide     5268.0     PT   Beatriz
9965      Darryle  Williams  Library Clerk    24326.0     PT   Darryle
12181     Heolbare  Reynoso   Library Aide     2467.0     PT  Heolbare
11811     Romulo P Belarmino   Library Aide     5124.0     PT    Romulo
11653   Elissa R Livingstone   Library Aide     6393.0     PT    Elissa

       proportion of a given name that's identified as female gender
11795                                               0.996994          F
9965                                                0.000000          M
12181                                                    NaN        NaN
11811                                               0.000000          M
11653                                               1.000000          F
```

The proportion of library-related jobs held by women is 64%, yet library related jobs make significantly less than the overall median salary:

[20]:
```
# Proportion of library-related jobs held by women
#(libjobs['gender'] == 'F').mean()

# Pay Statistics for fire-related jobs
libjobs['Total Pay'].describe()
```

[20]:
```
count       651.000000
mean      30383.377880
std       23236.318495
              …
50%       26952.000000
75%       43566.000000
max      167269.000000
Name: Total Pay, Length: 8, dtype: float64
```

We see that there can be other factors for pay inequality as well like women working more in low paying jobs (i.e as a librarian) in our case while men working in high paying jobs (fireman), however it's not white and black and further analysis definately needs to be done for such complicated topics