Lab 8: Sampling and Distributions - Sampling Basketball Data

Welcome to Lab 8! In this lab we will go over the topic of sampling and distributions.

The data used in this lab will contain salary data and other statistics for basketball players from the 2014-2015 NBA season. This data was collected from the following sports analytic sites: Basketball Reference and Spotrac.

First, set up the tests and imports by running the cell below.

In [1]:
```
# Run this cell, but please don't change it.

# These lines import the Numpy and Datascience modules.
import numpy as np
from datascience import *

# These lines do some fancy plotting magic
import matplotlib
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
```

Run the cell below to load player and salary data that we will use for our sampling.

In [2]:
```
player_data = Table().read_table("player_data.csv")
salary_data = Table().read_table("salary_data.csv")
full_data = salary_data.join("PlayerName", player_data, "Name")

# The show method immediately displays the contents of a table.
# This way, we can display the top of two tables using a single cell.
player_data.show(3)
salary_data.show(3)
full_data.show(3)
```

Name	Age	Team	Games	Rebounds	Assists	Steals	Blocks	Turnovers	Points
James Harden	25	HOU	81	459	565	154	60	321	2217
Chris Paul	29	LAC	82	376	838	156	15	190	1564
Stephen Curry	26	GSW	80	341	619	163	16	249	1900

... (489 rows omitted)

PlayerName	Salary
Kobe Bryant	23500000
Amar'e Stoudemire	23410988
Joe Johnson	23180790

... (489 rows omitted)

PlayerName	Salary	Age	Team	Games	Rebounds	Assists	Steals	Blocks	Turnovers	Poir
A.J. Price	62552	28	TOT	26	32	46	7	0	14	1
Aaron Brooks	1145685	30	CHI	82	166	261	54	15	157	9
Aaron Gordon	3992040	19	ORL	47	169	33	21	22	38	2

... (489 rows omitted)

Rather than getting data on every player (as in the tables loaded above), imagine that we had gotten data on only a smaller subset of the players. For 492 players, it's not so unreasonable to expect to see all the data, but usually we aren't so lucky.

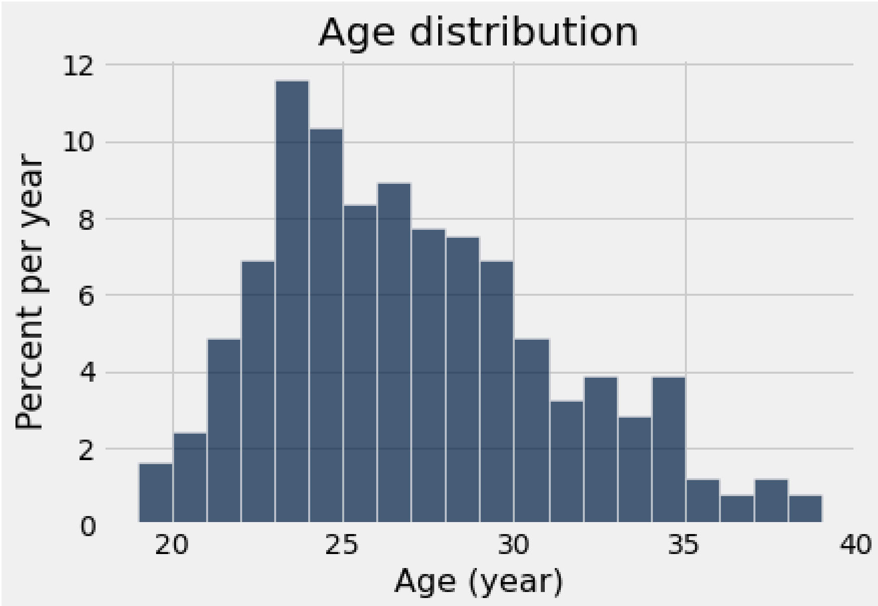
If we want to make estimates about a certain numerical property of the population (known as a statistic, e.g. the mean or median), we may have to come up with these estimates based only on a smaller sample. Whether these estimates are useful or not often depends on how the sample was gathered. We have prepared some example sample datasets to see how they compare to the full NBA dataset. Later we'll ask you to create your own samples to see how they behave.

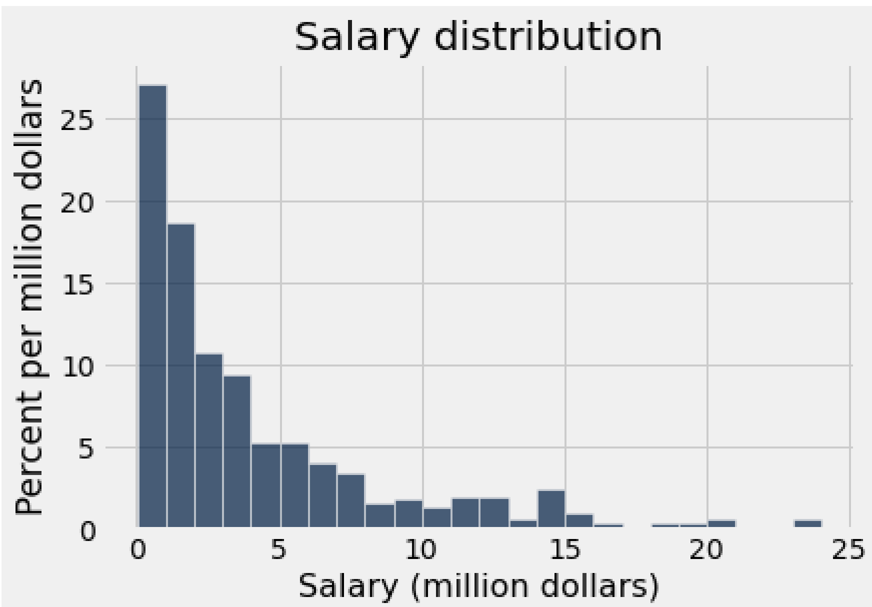
To save typing and increase the clarity of your code, we will package the analysis code into a few functions. This will be useful in the rest of the lab as we will repeatedly need to create histograms and collect summary statistics from that data.

We've defined the `histograms` function below, which takes a table with columns `Age` and `Salary` and draws a histogram for each one. It uses bin widths of 1 year for `Age` and $1,000,000 for `Salary`.

In [3]:
```
def histograms(t):
    ages = t.column('Age')
    salaries = t.column('Salary')/1000000
    t1 = t.drop('Salary').with_column('Salary', salaries)
    age_bins = np.arange(min(ages), max(ages) + 2, 1)
    salary_bins = np.arange(min(salaries), max(salaries) + 1, 1)
    t1.hist('Age', bins=age_bins, unit='year')
    plt.title('Age distribution')
    t1.hist('Salary', bins=salary_bins, unit='million dollars')
    plt.title('Salary distribution')

histograms(full_data)
print('Two histograms should be displayed below')
```

```
Two histograms should be displayed below
```





Question 1.. Create a function called `compute_statistics` that takes a table containing ages and salaries and:

- Draws a histogram of ages
- Draws a histogram of salaries
- Returns a two-element array containing the average age and average salary (in that order)

You can call the `histograms` function to draw the histograms!

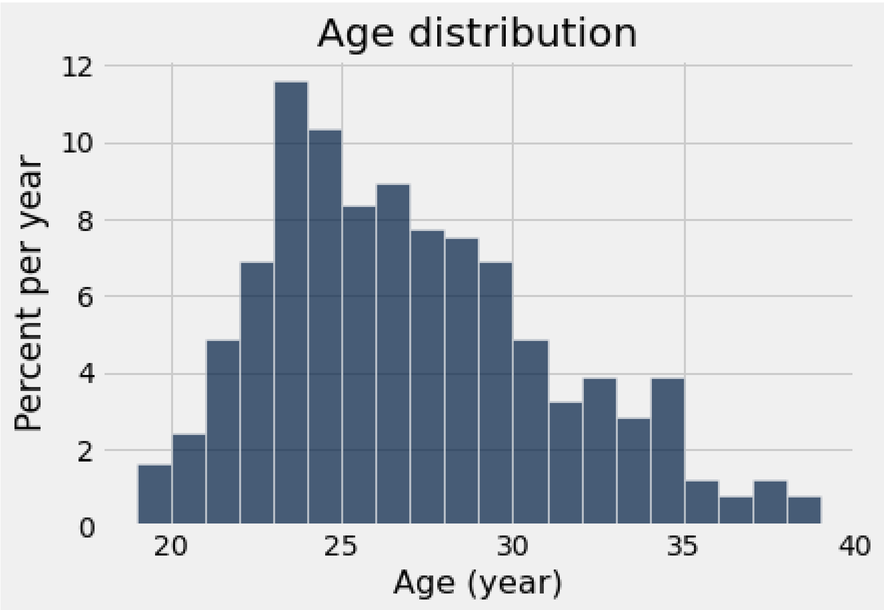
Note: More charts will be displayed when running the test cell. Please feel free to ignore the charts.

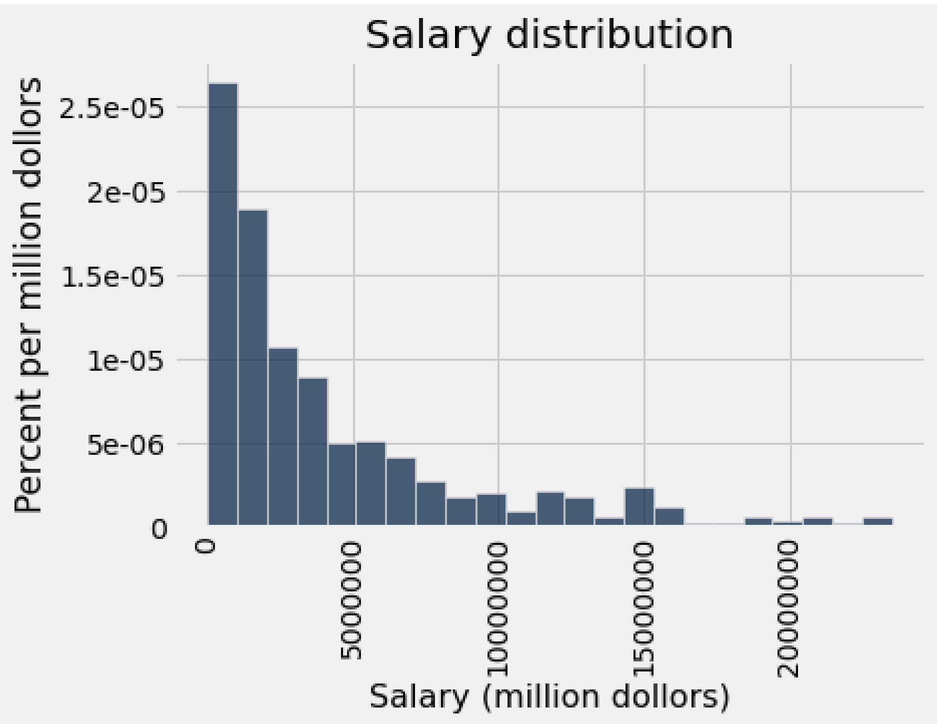
In [4]:
```
def compute_statistics(age_and_salary_data):
    a = []
    age = age_and_salary_data.column('Age')
    sal = age_and_salary_data.column('Salary') / 1000000
```

```
    age_bin = np.arange(min(age), max(age) + 2, 1)
    sal_bin = int(max(sal) - min(sal) / 1000)
    age_and_salary_data.hist('Age', bins = age_bin, unit = 'year')
    plt.title('Age distribution')
    age_and_salary_data.hist('Salary', bins = sal_bin, unit = 'million dollors'
    plt.title('Salary distribution')
    a = ([sum(age) / len(age), sum(sal) / len(sal) * 1000000])

    return a

full_stats = compute_statistics(full_data)
full_stats
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-package
s/datascience/tables.py:5800: UserWarning: FixedFormatter should only be used
together with FixedLocator
  axis.set_xticklabels(ticks, rotation='vertical')
```

Out[4]: [26.536585365853657, 4269775.766260159]





In [5]:
```
# TEST
stats = compute_statistics(full_data)
plt.close()
plt.close()
round(float(stats[0]), 2) == 26.54
```

Out[5]: True

In [6]:
```
# TEST
stats = compute_statistics(full_data)
plt.close()
plt.close()
round(float(stats[1]), 2) == 4269775.77
```

Out[6]: True

Convenience sampling

One sampling methodology, which is **generally a bad idea**, is to choose players who are somehow convenient to sample. For example, you might choose players from one team who are near your house, since it's easier to survey them. This is called, somewhat pejoratively, *convenience sampling*.

Suppose you survey only *relatively new* players with ages less than 22. (The more experienced players didn't bother to answer your surveys about their salaries.)

Question 2. Assign `convenience_sample` to a subset of `full_data` that contains only the rows for players under the age of 22.

In [7]:
```
convenience_sample = full_data.where(full_data.column('Age') < 22)
convenience_sample
```

Out[7]:

PlayerName	Salary	Age	Team	Games	Rebounds	Assists	Steals	Blocks	Turnovers	Poir
Aaron Gordon	3992040	19	ORL	47	169	33	21	22	38	2
Alex Len	3649920	21	PHO	69	454	32	34	105	74	4
Andre Drummond	2568360	21	DET	82	1104	55	73	153	120	11
Andrew Wiggins	5510640	19	MIN	82	374	170	86	50	177	13
Anthony Bennett	5563920	21	MIN	57	216	48	27	16	36	2
Anthony Davis	5607240	21	NOP	68	696	149	100	200	95	16
Archie Goodwin	1112280	20	PHO	41	74	44	18	9	48	2
Ben McLemore	3026280	21	SAC	82	241	140	77	19	138	9
Bradley Beal	4505280	21	WAS	63	241	194	76	18	123	9
Bruno Caboclo	1458360	19	TOR	8	2	0	0	1	4	

... (34 rows omitted)

In [8]:
```
# TEST
convenience_sample.num_columns == 11
```
Out[8]:
```
True
```

In [9]:
```
# TEST
convenience_sample.num_rows == 44
```
Out[9]:
```
True
```

Question 3. Assign `convenience_stats` to an array of the average age and average salary of your convenience sample, using the `compute_statistics` function. Since they're computed on a sample, these are called *sample averages*.

In [10]:
```
age = convenience_sample.column('Age')
sal = convenience_sample.column('Salary')
convenience_stats = ([sum(age) / len(age), sum(sal) / len(sal)])
convenience_stats
```
Out[10]:
```
[20.363636363636363, 2383533.8181818184]
```

In [11]:
```
# TEST
len(convenience_stats) == 2
```
Out[11]:
```
True
```

In [12]:
```
# TEST
round(float(convenience_stats[0]), 2) == 20.36
```

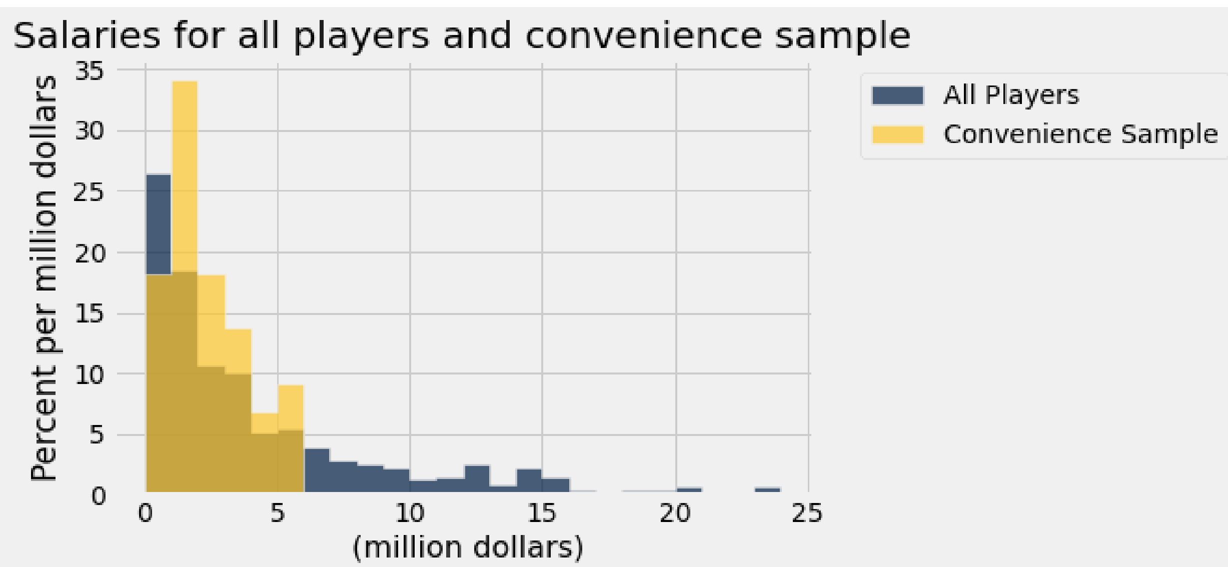
Out[12]: True

In [13]:
```
# TEST
round(float(convenience_stats[1]), 2) == 2383533.82
```

Out[13]: True

Next, we'll compare the convenience sample salaries with the full data salaries in a single histogram. To do that, we'll need to use the `bin_column` option of the `hist` method, which indicates that all columns are counts of the bins in a particular column. The following cell does not require any changes; **just run it**.

In [14]:
```
def compare_salaries(first, second, first_title, second_title):
    """Compare the salaries in two tables."""
    first_salary_in_millions = first.column('Salary')/1000000
    second_salary_in_millions = second.column('Salary')/1000000
    first_tbl_millions = first.drop('Salary').with_column('Salary', first_salar
    second_tbl_millions = second.drop('Salary').with_column('Salary', second_sa
    max_salary = max(np.append(first_tbl_millions.column('Salary'), second_tbl_
    bins = np.arange(0, max_salary+1, 1)
    first_binned = first_tbl_millions.bin('Salary', bins=bins).relabeled(1, fir
    second_binned = second_tbl_millions.bin('Salary', bins=bins).relabeled(1, s
    first_binned.join('bin', second_binned).hist(bin_column='bin', unit='millic
    plt.title('Salaries for all players and convenience sample')

compare_salaries(full_data, convenience_sample, 'All Players', 'Convenience San
```



Question 4. Does the convenience sample give us an accurate picture of the salary of the full population? Would you expect it to, in general? Before you move on, write a short answer in English below. You can refer to the statistics calculated above or perform your own analysis.

No, the convenience sample do not give us an accurate picture of the salary of the full population. The graph would be more accuaret if we differentiate the colrs. We believe that this would be accurate if we make changes to the graph combination.

Simple random sampling

A more justifiable approach is to sample uniformly at random from the players. In a **simple random sample (SRS) without replacement**, we ensure that each player is selected at most once. Imagine writing down each player's name on a card, putting the cards in an box, and shuffling the box. Then, pull out cards one by one and set them aside, stopping when the specified sample size is reached.

Producing simple random samples

Sometimes, it’s useful to take random samples even when we have the data for the whole population. It helps us understand sampling accuracy.

`sample`

The table method `sample` produces a random sample from the table. By default, it draws at random **with replacement** from the rows of a table. It takes in the sample size as its argument and returns a **table** with only the rows that were selected.

Run the cell below to see an example call to `sample()` with a sample size of 5, with replacement.

In [15]:
```
# Just run this cell

salary_data.sample(5)
```

Out[15]:

PlayerName	Salary
Stephen Curry	10629213
Rajon Rondo	12909091
Alec Burks	3034356
Joel Anthony	3800000
Andre Dawkins	29843

The optional argument `with_replacement=False` can be passed through `sample()` to specify that the sample should be drawn without replacement.

Run the cell below to see an example call to `sample()` with a sample size of 5, without replacement.

In [16]:
```
# Just run this cell

salary_data.sample(5, with_replacement=False)
```

Out[16]:

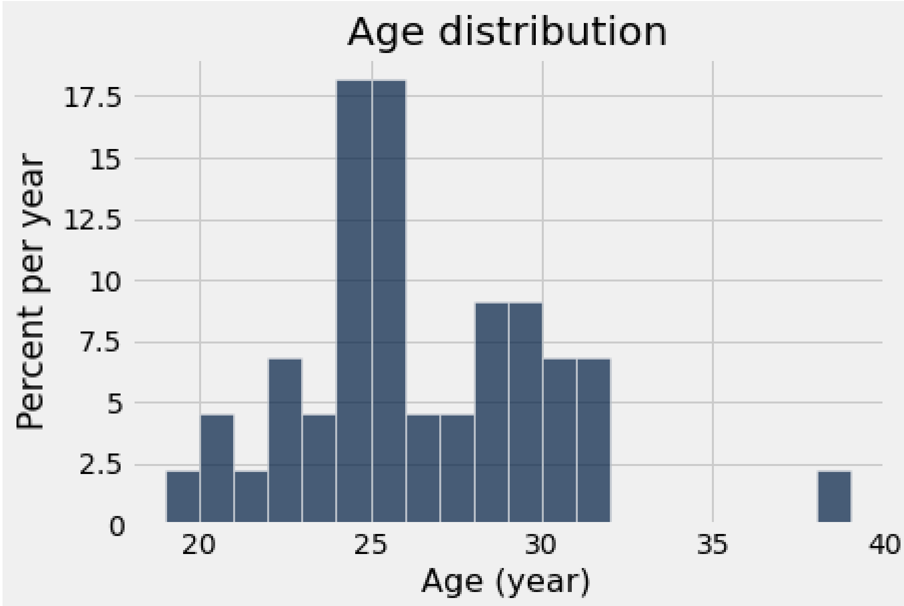
PlayerName	Salary
Vince Carter	3911981
DeAndre Jordan	11440124
Darius Morris	702756
Brandan Wright	5000000
Reggie Bullock	1200720

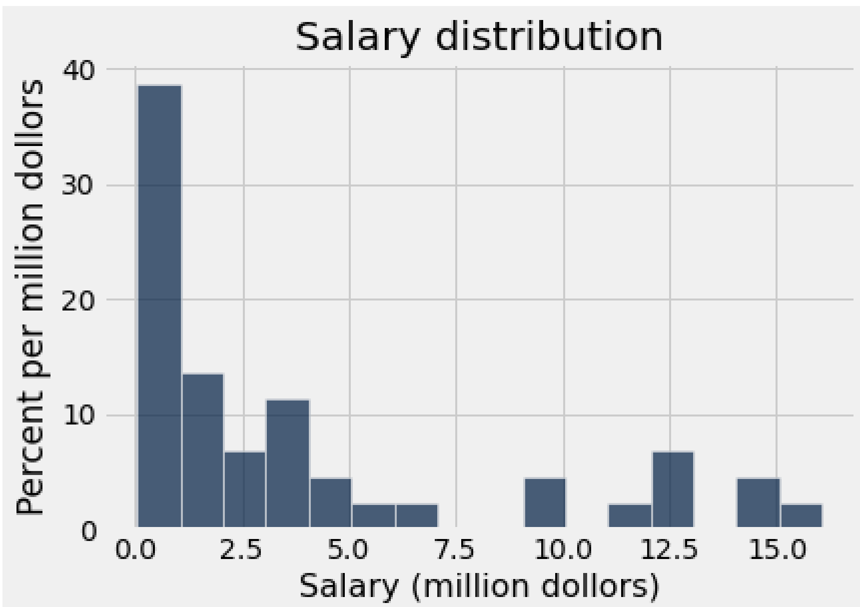
Question 5. Produce a simple random sample of size 44 from `full_data`. Run your analysis on it again. Run the cell a few times to see how the histograms and statistics change across different samples.

In [17]:

```
my_small_srswor_data = full_data.sample(44)
print(my_small_srswor_data)
def histogram(table):
    age = table.column('Age')
    sal = table.column('Salary') / 1000000
    tbl = table.drop('Salary').with_column('Salary', sal)
    age_bin = np.arange(min(age), max(age) + 2, 1)
    sal_bin = np.arange(min(sal), max(sal) + 1, 1)
    tbl.hist('Age', bins = age_bin, unit = 'year')
    plt.title('Age distribution')
    tbl.hist('Salary', bins = sal_bin, unit = 'million dollors')
    plt.title('Salary distribution')
    plt.show()

histogram(my_small_srswor_data)
my_small_stats = ([sum(my_small_srswor_data.column('Age')) / len(my_small_srswo
                  sum(my_small_srswor_data.column('Salary')) / sum(my_small_srs
my_small_stats
```

```
PlayerName        | Salary   | Age  | Team | Games | Rebounds | Assists | Steal
s | Blocks | Turnovers | Points
Rodney Stuckey    | 1227985  | 28   | IND  | 71    | 248      | 219     | 56
| 10      | 118         | 896
Jeffery Taylor    | 915243   | 25   | CHO  | 29    | 53       | 22      | 12
| 1       | 19          | 127
Brook Lopez       | 15719063 | 26   | BRK  | 72    | 535      | 50      | 43
| 126     | 104         | 1236
Mirza Teletovic   | 3368100  | 29   | BRK  | 40    | 194      | 46      | 14
| 16      | 53          | 339
Hassan Whiteside  | 769881   | 25   | MIA  | 48    | 482      | 6       | 27
| 123     | 58          | 564
Noah Vonleh       | 2524200  | 19   | CHO  | 25    | 86       | 4       | 4
| 9       | 11          | 83
Evan Fournier     | 1483920  | 22   | ORL  | 58    | 153      | 120     | 40
| 2       | 82          | 698
Kyle O'Quinn      | 915243   | 24   | ORL  | 51    | 199      | 59      | 31
| 39      | 55          | 294
Nick Johnson      | 507336   | 22   | HOU  | 28    | 39       | 11      | 7
| 3       | 19          | 74
Joe Ingles        | 507336   | 27   | UTA  | 79    | 175      | 182     | 72
| 10      | 98          | 396
... (34 rows omitted)
```





Out[17]:
```
[25.886363636363637, 1000000.0]
```

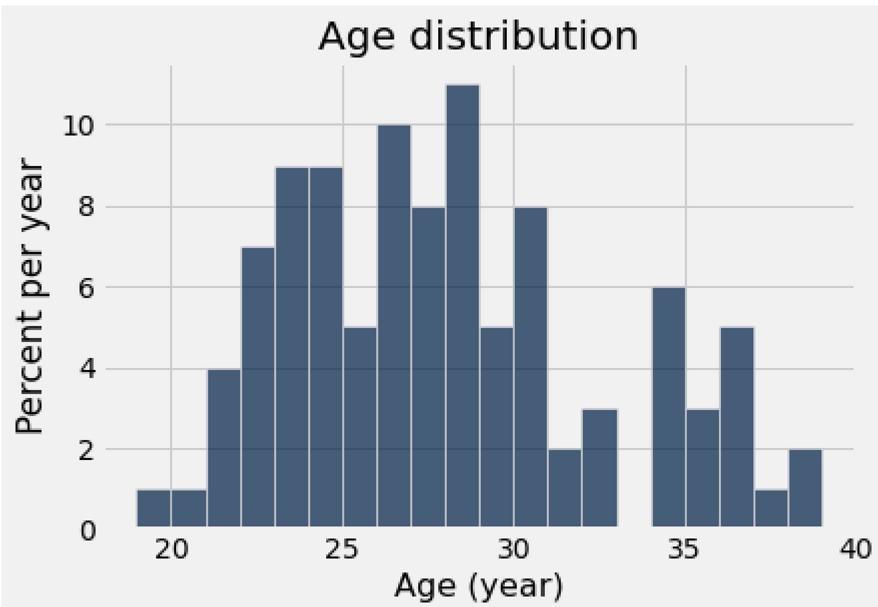
Before you move on, write a short answer for the following questions in English:

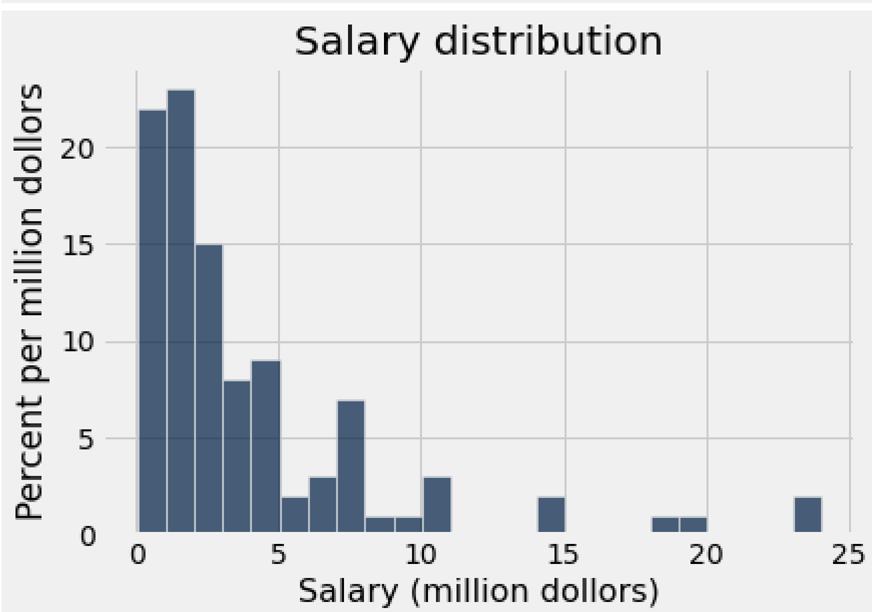
- How much does the average age change across samples?
- What about average salary?

1. The average could be calaulated by using mean of ages. Since, we have different age group people with different percentages. The highest percentage lies between age group 25 and 28, hence the average must be around 26.5.
2. The salary disctribution is decreasing if the mllion dollor increases, the average salary lies between 2 to 4 per the histogram.

Question 6. As in the previous question, analyze several simple random samples of size 100 from `full_data`.

In [18]:
```
my_large_srswor_data = full_data.sample(100)
def histogram(table):
    age = table.column('Age')
    sal = table.column('Salary') / 1000000
    tbl = table.drop('Salary').with_column('Salary', sal)
    age_bin = np.arange(min(age), max(age) + 2, 1)
    sal_bin = np.arange(min(sal), max(sal) + 1, 1)
    tbl.hist('Age', bins = age_bin, unit = 'year')
    plt.title('Age distribution')
    tbl.hist('Salary', bins = sal_bin, unit = 'million dollors')
    plt.title('Salary distribution')
    plt.show()

histogram(my_large_srswor_data)
age1 = my_large_srswor_data.column('Age')
sal1 = my_large_srswor_data.column('Salary')
my_large_stats = ([sum(age1) / len(age1), sum(sal1) / len(sal1) * 1000000])
my_large_stats
```





Out[18]:
```
[27.54, 3965641040000.0]
```

Answer the following questions in English:

- Do the histogram shapes seem to change more or less across samples of 100 than across samples of size 44?
- Are the sample averages and histograms closer to their true values/shape for age or for salary? What did you expect to see?

1. Yes, histogram shapes seemed to be changed more for the samples of 100 than 44. As the sample increase the more number of bins involvement makes hostogram changes.
2. Yes, the sample averages and histograms are closer to their shapes for age and salary.

Congratulations, you're done with Lab 8! Be sure to...

- run all the tests,
- print the notebook as a PDF,
- and submit both the notebook and the PDF to Canvas.

In [ ]: