Data Bootcamp Midterm Project

April 1, 2021

0.1 Spring 2021 Data Bootcamp Midterm Project

0.1.1 Daniel Abboudi

0.1.2 Carlisle Catacutan

0.1.3 Garima Chaudhary

0.2 To start our project we imported packages and read-in the csv file. To better understand the data we read it in as a dataframe.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
path = 'DB_MidtermSampleData_Mar21.csv'
```

In [2]:
```
df = pd.read_csv(path)
```

0.3 We then cleaned up the data by replacing the empty fields.

In [3]:
```
# Treat 'empty' fields as NaN
df = df.replace('empty',np.NaN)
```

0.4 We were interested in the companies listed in the dataframe so we listed them out.

In [4]:
```
df['company'].value_counts().index
```

Out[4]:
```
Index(['Johnson & Johnson', 'Procter & Gamble Co', 'Omnicom Group Inc',
       'International Business Machines Corporation', 'Walmart Inc',
       'Verizon Communications Inc.', 'Coca-Cola Company', 'JPMorgan Chase',
       'MICROSOFT CORPORATION', 'Amazon.com, Inc.', 'General Electric Company',
       'PepsiCo, Inc.', 'Intel Corporation', 'Alphabet Inc.',
       'Hewlett Packard Enterprise Company', 'Siemens AG',
       'Honeywell International Inc', 'Orange SA', 'Tata Group', 'Apple, Inc.',
       'Walt Disney Company', 'Facebook Inc', 'AT&T', 'Dell Technologies Inc',
       'Vodafone Group PLC', 'GENERAL MOTORS COMPANY', 'Ford Motor Company',
       'Oracle Corporation', 'Unilever NV', 'CVS Health Corporation',
       'Barclays PLC', 'Accenture PLC', 'Nestle SA', 'Volkswagen AG',
```

```
 'Novartis AG', 'Morgan Stanley', 'ABB Ltd', 'Pfizer Inc',
 'Staples Inc.', 'WPP PLC', 'Bank of America Corporation',
 'United Technologies Corporation', 'Citigroup Inc', 'Roche Holding AG',
 'Infosys Ltd', 'Cisco Systems, Inc.', 'Abbott Laboratories', 'Aon PLC',
 'IQVIA', 'Comcast Corporation', 'SAP SE', 'Capgemini SE',
 'Medtronic PLC', 'Blackstone Group L.P.', 'Bayer AG',
 'Merck & Co., Inc.', 'Starbucks Corporation', 'HP Inc',
 'Lockheed Martin Corporation', 'UnitedHealth Group Inc',
 'DXC Technology Co', 'Caterpillar Inc', 'Toyota Motor Corp',
 'FedEx Corporation', 'The Boeing Company', 'HSBC Holdings PLC',
 'GlaxoSmithKline PLC', 'Atos SE', 'Wells Fargo & Company',
 'Target Corporation', 'Wipro Ltd', 'Northrop Grumman Corporation',
 'American Airlines Group, Inc.', 'Delta Air Lines, Inc.',
 'HCA Healthcare, Inc.', 'HCL Technologies Ltd', 'Banco Santander SA'],
dtype='object')
```

0.5 Then we checked each column of data to see what type of data we were working with.

In [5]:
```
df.dtypes
```

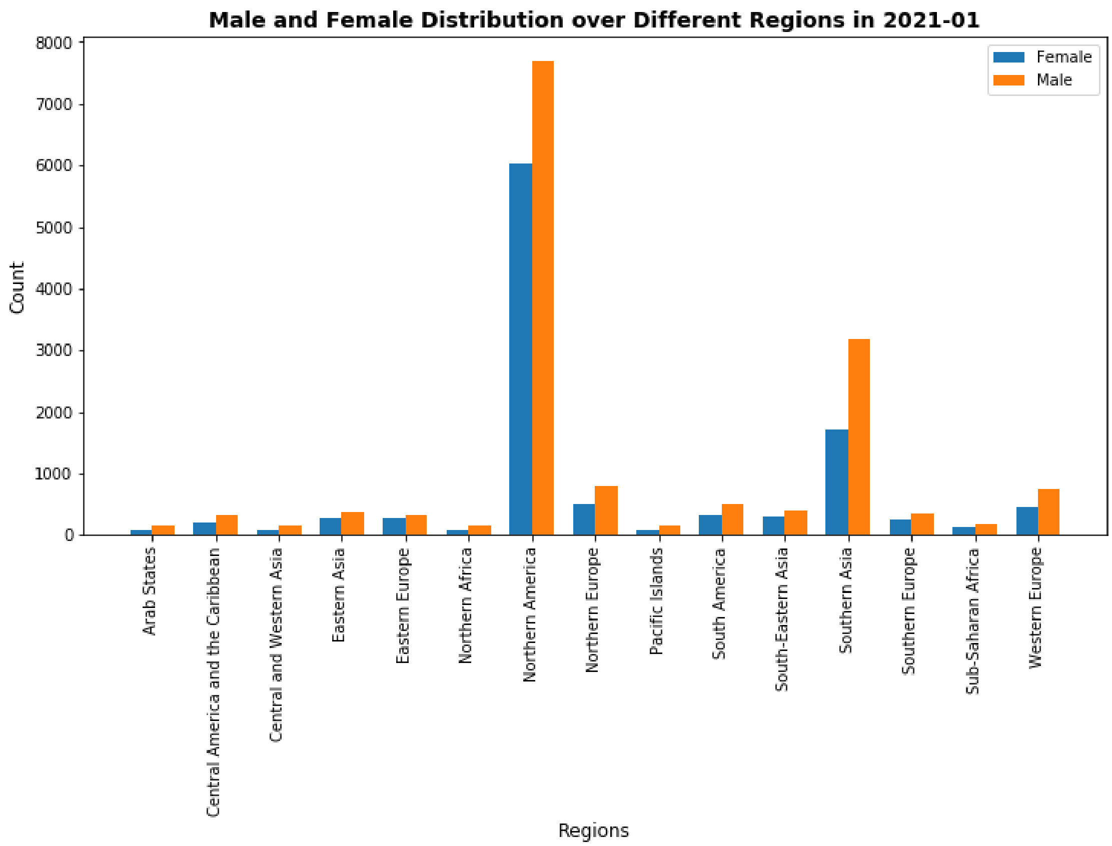
Out[5]:
```
company          object
sector           object
month            object
job_category     object
region           object
gender           object
count           float64
inflow          float64
outflow         float64
dtype: object
```

0.6 We first looked at the geographical breakdown for each gender.

In [6]:
```
# Q. What is the distribution of males and females in different regions for the
#    most recent month?

# Getting most recent month
recent_month = df['month'].max()
recent_month

# Filtering out females
df_female = df.loc[(df['gender'] == 'female') &
                   (df['month'] == recent_month), :]

# Filtering out males
df_male = df.loc[(df['gender'] == 'male') &
                 (df['month'] == recent_month), :]
```

```python
# Distribution of females in different regions
region_female = df_female.groupby('region', as_index=False).agg({'count': 'mean'}).sor

# Distribution of males in different regions
region_male = df_male.groupby('region', as_index=False).agg({'count': 'mean'}).sort_val

# Graph:

n = np.arange(len(region_female['region'])) # the label locations
width = 0.35  # the width of the bars
upper_limit = max(region_female['count'].max(), region_male['count'].max())+1000 # max
label = list(region_female['region'])

female = list(region_female['count'])
male = list(region_male['count'])


fig, ax = plt.subplots(figsize=(12,6))

rects1 = ax.bar(n - width/2, female, width, label='Female')
rects2 = ax.bar(n + width/2, male, width, label='Male')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Count', size= 12)
ax.set_xlabel('Regions', size= 12)
ax.set_title('Male and Female Distribution over Different Regions in '+ recent_month, s
ax.set_xticks(n)
ax.set_xticklabels(label)
plt.xticks(rotation=90)

ax.legend()
```

Out[6]: <matplotlib.legend.Legend at 0x7f69f42a1ac8>



0.7 Interesting! It seems that most of our data is concentrated in North America. It is also noteworthy that there are more male employees than female employees in every region.ű

0.8 With this in mind, we wanted to pick a company that would could look in to, but our approach to developing a set of code was to build in a way that enabled us to change the company name and sector.

In [7]:
```
# Define Company
company = 'MICROSOFT CORPORATION'

# Define Sector
sector = 'Information Technology'
```

0.9 So we started by filtering the dataframe for the company and sector we were interested in exploring.

In [8]:
```
# Pull company
com = df.loc[df['company']==company,:]
```

0.10 Then we looked into some simple questions about the company makeup.

In [9]:
```
# How many employees does the company have?
com.loc[com['month']==com['month'].max(),'count'].sum()
```

Out[9]: 439855.08444770006

In [10]:
```
# How many males?
com.loc[(com['month']==com['month'].max()) & (com['gender']=='male'),'count'].sum()
```

Out[10]: 281009.58535538713

In [11]:
```
# How many females?
com.loc[(com['month']==com['month'].max()) & (com['gender']=='female'),'count'].sum()
```

Out[11]: 158845.49909231294

0.11 Then we created another dataframe to look deeping into the types of roles that each gender had within the company.

In [12]:
```
# What positions do com employees fulfill? Need to sum by 'job_category'
com2 = com.loc[com['month']==com['month'].max(),:]
com2 = com2.groupby(['job_category','gender']).agg({'count':'sum'})
com2 = com2.reset_index()

# Split the data into two groups by gender
male = com2.loc[com2['gender']=='male',:].set_index('job_category')
female = com2.loc[com2['gender']=='female',:].set_index('job_category')
female
```

Out[12]:

job_category	gender	count
administrative	female	4919.452199
engineer	female	56931.897171
finance	female	8290.367964
management	female	37982.177935
marketing	female	9642.722500
sales	female	20223.363519
scientist	female	4762.938735
technician	female	5902.232550

In [13]:
```
male
```

Out[13]:

job_category	gender	count
administrative	male	4475.086883
engineer	male	127441.503137
finance	male	6281.660796
management	male	66348.732761
marketing	male	11675.654514
sales	male	31940.603128
scientist	male	5880.197481
technician	male	10573.823638

0.12 With this data in hand, we wanted to see how the company compared to other companies in the same sector. So we refiltered the original data.

In [14]:
```
# Pull Sector data and Remove company from this data to compare rest of sector
# to company

sector_df = df.loc[(df['sector']==sector) & (df['company']!=company) & (df['month']==
sector_df[:10]
```

Out[14]:
```
                    company                  sector    month    job_category  \
570187          Apple, Inc.  Information Technology  2021-01      management
570188        Accenture PLC  Information Technology  2021-01           sales
570197   DXC Technology Co  Information Technology  2021-01  administrative
570200           Wipro Ltd  Information Technology  2021-01         finance
570203         Infosys Ltd  Information Technology  2021-01       marketing
570204   Intel Corporation  Information Technology  2021-01       marketing
570206             Atos SE  Information Technology  2021-01         finance
570214             Atos SE  Information Technology  2021-01       scientist
570216           Wipro Ltd  Information Technology  2021-01       scientist
576067               IQVIA  Information Technology  2021-01  administrative

                                   region  gender         count        inflow  \
570187                    Northern Africa  female  2.060316e+02  1.948740e+00
570188                    Southern Europe    male  4.210479e+02  7.184832e+00
570197                   Northern America  female  2.364157e+02  7.113997e+00
570200                        Arab States  female  2.547437e+01  2.854053e-01
570203                 Sub-Saharan Africa    male  1.517675e+01  1.538913e-01
570204                     Western Europe    male  7.746985e+01  1.721060e+00
570206                      South America    male  6.209916e+01  1.649090e+00
570214           Central and Western Asia    male  5.879089e-19  5.879089e-19
570216                     Western Europe  female  9.313484e-01  5.143460e-03
576067  Central America and the Caribbean    male  1.285085e+01  2.733745e-01

             outflow
570187  6.192986e-01
570188  4.669169e+00
570197  4.296831e+00
570200  9.172009e-02
570203  6.263603e-02
570204  1.988730e+00
570206  1.407529e+00
570214  4.322669e-19
570216  4.368691e-03
576067  2.797548e-01
```

In [15]:
```
sector_df2 = sector_df.groupby(['job_category','gender']).agg({'count':'sum'})
sector_df2 = sector_df2.reset_index()

# Split the data into two groups by gender
```

```
male_sector = sector_df2.loc[sector_df2['gender']=='male',:].set_index('job_category'
female_sector = sector_df2.loc[sector_df2['gender']=='female',:].set_index('job_catego
female_sector
```

Out[15]:

	gender	count
job_category		
administrative	female	4.901621e+04
engineer	female	1.010572e+06
finance	female	8.304000e+04
management	female	4.429822e+05
marketing	female	4.132721e+04
sales	female	1.363506e+05
scientist	female	3.152170e+04
technician	female	3.239551e+04

In [16]:
```
male_sector
```

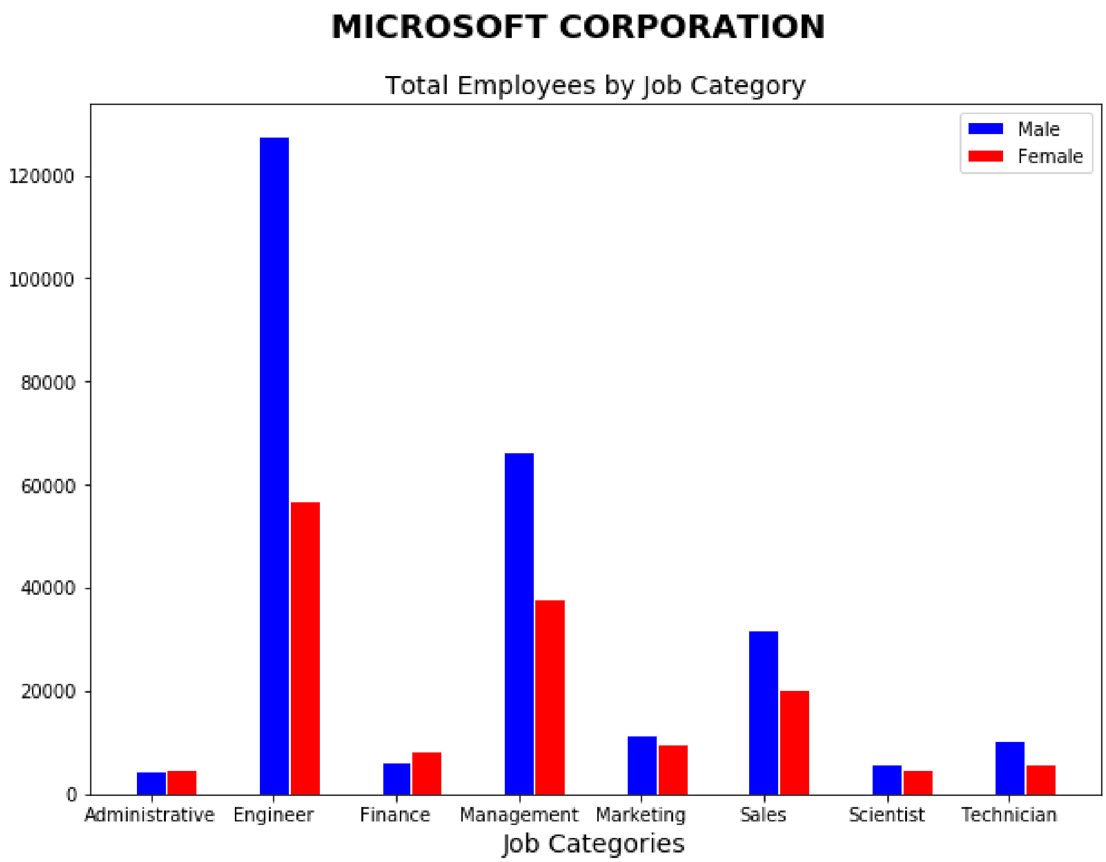
Out[16]:

	gender	count
job_category		
administrative	male	4.111243e+04
engineer	male	1.956867e+06
finance	male	9.163431e+04
management	male	7.924661e+05
marketing	male	5.059552e+04
sales	male	2.523236e+05
scientist	male	2.791048e+04
technician	male	8.164888e+04

0.13 We used the data to build charts that reflected the company job breakdown by gender, and then did the same for the sector.

In [17]:
```
fig,ax = plt.subplots(nrows=1,ncols=1,sharex=True,figsize=(10,7))

# set width of bars
barWidth = 0.25

# set heights of bars
bars1 = male['count']
bars2 = female['count']

# Set position of bar on X axis
r1 = np.arange(len(bars1))
r2 = [x + barWidth for x in r1]

# Make the plot
plt.bar(r1, bars1, color='b', width=barWidth, edgecolor='white', label='Male')
plt.bar(r2, bars2, color='r', width=barWidth, edgecolor='white', label='Female')

plt.suptitle(company,size=18,fontweight='bold')
```

```
plt.title('Total Employees by Job Category',size=14)
plt.xlabel('Job Categories',size=14)
plt.xticks(male.reset_index().index,male.index.str.capitalize(),size=10)

# Create legend & Show graphic
plt.legend()
plt.show()
```

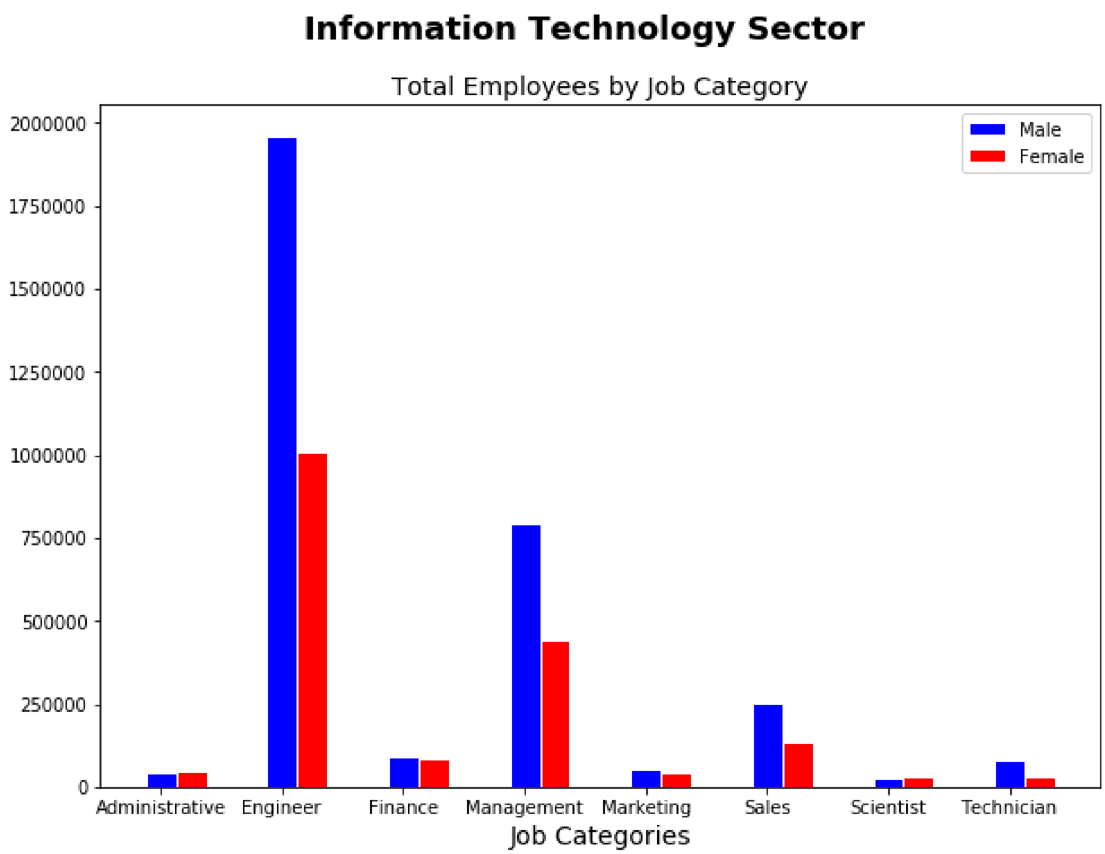


0.14 We see that for Microsoft, the most popular job is Engineer and that males outnumber females by a large margin. In marketing, there are much fewer employees, but this job seems to be more evenly split between males and females.

0.15 So what does the rest of the sector look like? Let's see!

```
In [18]: fig,ax = plt.subplots(nrows=1,ncols=1,sharex=True,figsize=(10,7))

         # set width of bars
         barWidth = 0.25

         # set heights of bars
```

```
bars1 = male_sector['count']
bars2 = female_sector['count']

# Set position of bar on X axis
r1 = np.arange(len(bars1))
r2 = [x + barWidth for x in r1]

# Make the plot
plt.bar(r1, bars1, color='b', width=barWidth, edgecolor='white', label='Male')
plt.bar(r2, bars2, color='r', width=barWidth, edgecolor='white', label='Female')

plt.suptitle((sector+' Sector'),size=18,fontweight='bold')
plt.title('Total Employees by Job Category',size=14)
plt.xlabel('Job Categories',size=14)
plt.xticks(male_sector.reset_index().index,male_sector.index.str.capitalize(),size=10)

# Create legend & Show graphic
plt.legend()
plt.show()
```



0.16 **The graphs look fairly similar! Once again, Engineer is the most popular job, and the males outnumber females in this role. Management, marketing and sales for the sector look proportionally similar to Microsoft. This suggests the job breakdown for Microsoft is similar to the industry as a whole.**

0.17 **The next thing we wanted to explore was the spread in the percentage of male and female employees, for both the company and the sector as a whole. So we took a similar approach as above, creating dataframes for the company and then sector.**

```
In [19]: # Company Hiring Over Time
         com_month = com.groupby(['month','gender'])[['count']].sum().reset_index()
         com_month

         # Find spread between % of employees as male vs female
         com_month['percentage'] = 0

         # Difference between % male and % female (spread = 0 if split is 50/50)
         com_month['spread'] = 0
         for i in range(len(com_month)):
             com_month.loc[i,'percentage'] = (com_month.loc[i,'count']/com_month
                                              .loc[com_month['month']==com_month
                                                   .loc[i,'month'],'count'].sum())
             com_month.loc[i,'spread'] = com_month.loc[i,'percentage']-(1-com_month.loc[i,'perc
         com_month[:10]
```

Out[19]:

	month	gender	count	percentage	spread
0	2012-01	female	102376.380712	0.341496	-0.317009
1	2012-01	male	197411.944975	0.658504	0.317009
2	2012-02	female	101114.763900	0.341446	-0.317109
3	2012-02	male	195022.479654	0.658554	0.317109
4	2012-03	female	101656.914626	0.341432	-0.317136
5	2012-03	male	196080.147403	0.658568	0.317136
6	2012-04	female	101906.983898	0.341423	-0.317153
7	2012-04	male	196569.864725	0.658577	0.317153
8	2012-05	female	102754.733276	0.341234	-0.317532
9	2012-05	male	198372.106035	0.658766	0.317532

0.18 **Note that we are exploring the spread over time. Good news is we have almost a decade of data!**

```
In [20]: male = com_month.loc[com_month['gender']=='male',:]
         female = com_month.loc[com_month['gender']=='female',:]
         female[:10]
```

Out[20]:

	month	gender	count	percentage	spread
0	2012-01	female	102376.380712	0.341496	-0.317009
2	2012-02	female	101114.763900	0.341446	-0.317109
4	2012-03	female	101656.914626	0.341432	-0.317136

```
6   2012-04  female  101906.983898    0.341423 -0.317153
8   2012-05  female  102754.733276    0.341234 -0.317532
10  2012-06  female  103735.444477    0.341256 -0.317487
12  2012-07  female  104582.636440    0.341280 -0.317441
14  2012-08  female  104606.598807    0.340878 -0.318244
16  2012-09  female  104666.018523    0.340638 -0.318724
18  2012-10  female  104793.183663    0.340842 -0.318316
```

In [21]:
```
male[:10]
```

Out[21]:
```
      month gender          count  percentage    spread
1   2012-01   male  197411.944975    0.658504  0.317009
3   2012-02   male  195022.479654    0.658554  0.317109
5   2012-03   male  196080.147403    0.658568  0.317136
7   2012-04   male  196569.864725    0.658577  0.317153
9   2012-05   male  198372.106035    0.658766  0.317532
11  2012-06   male  200245.527688    0.658744  0.317487
13  2012-07   male  201860.032029    0.658720  0.317441
15  2012-08   male  202267.555418    0.659122  0.318244
17  2012-09   male  202598.565554    0.659362  0.318724
19  2012-10   male  202660.831728    0.659158  0.318316
```

0.19 Now that we have company dataframes, we do the same for the sector.

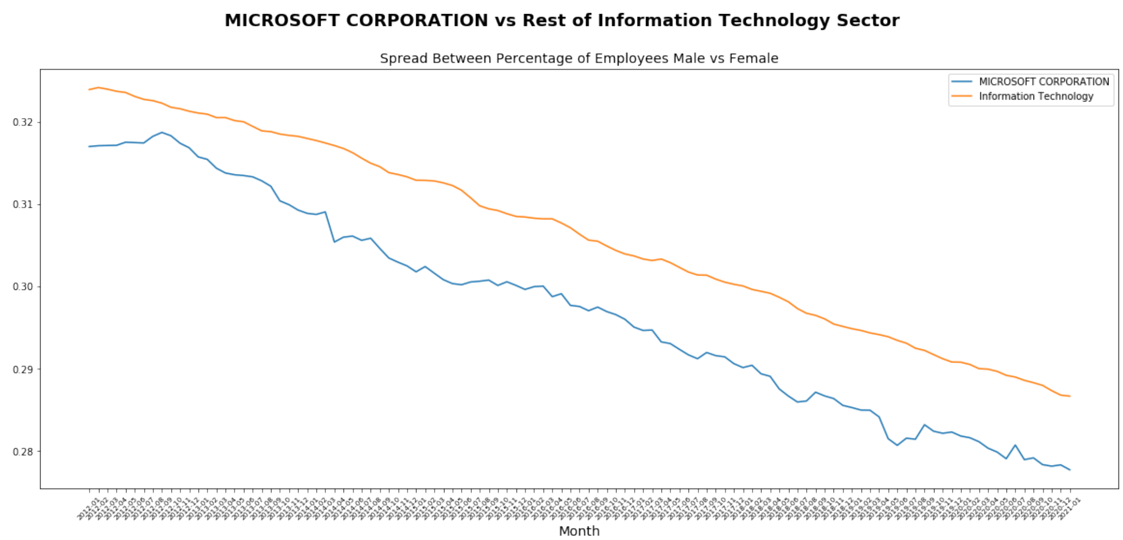
In [22]:
```
# Sector Hiring Over Time
sector_df3 = df.loc[(df['sector']==sector) & (df['company']!=company),:]
sector_month = sector_df3.groupby(['month','gender'])[['count']].sum().reset_index()
sector_month

# sectord spread between % of employees as male vs female
sector_month['percentage'] = 0

# Difference between % male and % female (spread = 0 if split is 50/50)
sector_month['spread'] = 0
for i in range(len(sector_month)):
    sector_month.loc[i,'percentage'] = (sector_month.loc[i,'count']/sector_month
                                        .loc[sector_month['month']==sector_month
                                             .loc[i,'month'],'count'].sum())
    sector_month.loc[i,'spread'] = sector_month.loc[i,'percentage']-(1-sector_month.lo
sector_month[:10]
```

Out[22]:
```
     month  gender         count  percentage    spread
0  2012-01  female  1.411999e+06    0.338035 -0.323930
1  2012-01    male  2.765083e+06    0.661965  0.323930
2  2012-02  female  1.399580e+06    0.337913 -0.324174
3  2012-02    male  2.742255e+06    0.662087  0.324174
4  2012-03  female  1.406512e+06    0.338010 -0.323980
5  2012-03    male  2.754641e+06    0.661990  0.323980
6  2012-04  female  1.411519e+06    0.338139 -0.323722
```

```
7   2012-04     male  2.762858e+06     0.661861  0.323722
8   2012-05   female  1.418344e+06     0.338212 -0.323575
9   2012-05     male  2.775303e+06     0.661788  0.323575
```

0.20 Now we build the graph to see how the company compares to the sector.

```
In [23]: fig,ax = plt.subplots(figsize=(20,8))
         x=com_month.loc[com_month['gender']=='male','spread']
         z=sector_month.loc[sector_month['gender']=='male','spread']
         x.plot.line(ax=ax,label=company)
         z.plot.line(ax=ax,label=sector)

         plt.suptitle(company+' vs Rest of '+sector+' Sector',size=18,fontweight='bold')
         plt.title('Spread Between Percentage of Employees Male vs Female',size=14)
         plt.xlabel('Month',size=14)

         plt.xticks(com_month.loc[com_month['gender']=='male']
                    .index,com_month
                    .loc[com_month['gender']=='male','month'],
                    size=7.5,rotation=45)

         plt.legend()
         plt.show()
```



0.21 Interesting! We see that Microsoft does better than the sector in terms of having a lower spread. And overall, the company and the Information Technology sector are trending in the right direction towards equiality between the genders.

0.22 The next question we wanted to explore is “What is the job makeup of the spread?”. We know that the overall trend is that the spread is lowering so another way to ask the question is, “Which jobs have added more males than females?” And again, we started by filtering the data for the company, and then doing the same for the sector.

In [24]:
```
# Company Hiring Over Time
com_all = df.loc[df['company']==company,:]
com_split = (com_all.groupby(['month','gender','job_category'])[['count']]
             .sum()
             .reset_index())
com_split

com_split['percentage'] = 0

# Percentage change in employee count for each gender from beginning to end of data
com_split['end'] = 0
for i in range(len(com_split)):
    com_split.loc[i,'percentage'] = (com_split
                                     .loc[i,'count']/com_split
                                     .loc[(com_split['month']==com_split
                                           .loc[i,'month']) &
                                          (com_split['job_category']==com_split
                                           .loc[i,'job_category']),'count']
                                     .sum())
    com_split.loc[i,'end'] = float(com_split
                                   .loc[(com_split['month']==com_split['month'].max()
                                        (com_split['job_category']==com_split
                                         .loc[i,'job_category']) &
                                        (com_split['gender']==com_split
                                         .loc[i,'gender']),
                                        'count'])/float(com_split
                                                        .loc[(com_split['month']==com_
                                                              .min()) &
                                                             (com_split['job_category
                                                              .loc[i,'job_category'])
                                                             (com_split['gender']==co
                                                              .loc[i,'gender']),'coun

com_split[:10]
```

Out[24]:

	month	gender	job_category	count	percentage	end
0	2012-01	female	administrative	3684.005177	0.531910	0.335354
1	2012-01	female	engineer	32001.730989	0.283336	0.779026
2	2012-01	female	finance	6173.481920	0.558494	0.342900

```
3  2012-01  female      management  26864.420199    0.338418  0.413847
4  2012-01  female       marketing   7310.310015    0.437954  0.319058
5  2012-01  female           sales  12852.050639    0.347372  0.573551
6  2012-01  female       scientist   3447.204368    0.448394  0.381682
7  2012-01  female      technician   5060.875939    0.367242  0.166247
8  2012-01    male  administrative   3241.990324    0.468090  0.380352
9  2012-01    male        engineer  80944.315629    0.716664  0.574434
```

In [25]:
```python
end = com_split.loc[com_split['month']==com_split['month'].max(),:]
end['job_category'] = end['job_category'].str.capitalize()
end = end.set_index('job_category')

end
```

Out[25]:

job_category	month	gender	count	percentage	end
Administrative	2021-01	female	4919.452199	0.523650	0.335354
Engineer	2021-01	female	56931.897171	0.308786	0.779026
Finance	2021-01	female	8290.367964	0.568923	0.342900
Management	2021-01	female	37982.177935	0.364055	0.413847
Marketing	2021-01	female	9642.722500	0.452320	0.319058
Sales	2021-01	female	20223.363519	0.387688	0.573551
Scientist	2021-01	female	4762.938735	0.447513	0.381682
Technician	2021-01	female	5902.232550	0.358231	0.166247
Administrative	2021-01	male	4475.086883	0.476350	0.380352
Engineer	2021-01	male	127441.503137	0.691214	0.574434
Finance	2021-01	male	6281.660796	0.431077	0.287143
Management	2021-01	male	66348.732761	0.635945	0.263354
Marketing	2021-01	male	11675.654514	0.547680	0.244521
Sales	2021-01	male	31940.603128	0.612312	0.322820
Scientist	2021-01	male	5880.197481	0.552487	0.386616
Technician	2021-01	male	10573.823638	0.641769	0.212610

0.23 Now for the sector.

In [26]:
```python
# Sector Hiring Over Time
sector_split = (sector_df3.groupby(['month','gender','job_category'])[['count']]
                .sum()
                .reset_index())
sector_split

sector_split['percentage'] = 0

# Percentage change in employee count for each gender from beginning to end of data
sector_split['end'] = 0
for i in range(len(sector_split)):
    sector_split.loc[i,'percentage'] = (sector_split.loc[i,'count']/sector_split
                                        .loc[(sector_split['month']==sector_split
```

```
                                                    .loc[i,'month']) &
                                                   (sector_split['job_category']==sector_spl
                                                    .loc[i,'job_category']),'count'].sum())

    sector_split.loc[i,'end'] = float(
        sector_split.loc[(sector_split['month']==sector_split['month']
                          .max()) &
                         (sector_split['job_category']==sector_split
                          .loc[i,'job_category']) &
                         (sector_split['gender']==sector_split
                          .loc[i,'gender']),
                         'count'])/float(sector_split
                                         .loc[(sector_split['month']==sector_split['mo
                                               .min()) &
                                              (sector_split['job_category']==sector_sp
                                               .loc[i,'job_category']) &
                                              (sector_split['gender']==sector_split
                                               .loc[i,'gender']),'count'])-1

sector_split[:10]
```

Out[26]:

	month	gender	job_category	count	percentage	end
0	2012-01	female	administrative	3.979177e+04	0.531047	0.231818
1	2012-01	female	engineer	7.341031e+05	0.322552	0.376607
2	2012-01	female	finance	7.187587e+04	0.487891	0.155325
3	2012-01	female	management	3.256730e+05	0.336166	0.360205
4	2012-01	female	marketing	3.098397e+04	0.425261	0.333826
5	2012-01	female	sales	1.128452e+05	0.323720	0.208297
6	2012-01	female	scientist	2.208161e+04	0.506068	0.427509
7	2012-01	female	technician	2.725999e+04	0.269746	0.188390
8	2012-01	male	administrative	3.513898e+04	0.468953	0.169995
9	2012-01	male	engineer	1.541818e+06	0.677448	0.269195

In [27]:

```
sector_end = sector_split.loc[sector_split['month']==sector_split['month'].max(),:]
sector_end['job_category'] = sector_end['job_category'].str.capitalize()
sector_end = sector_end.set_index('job_category')
sector_end
```

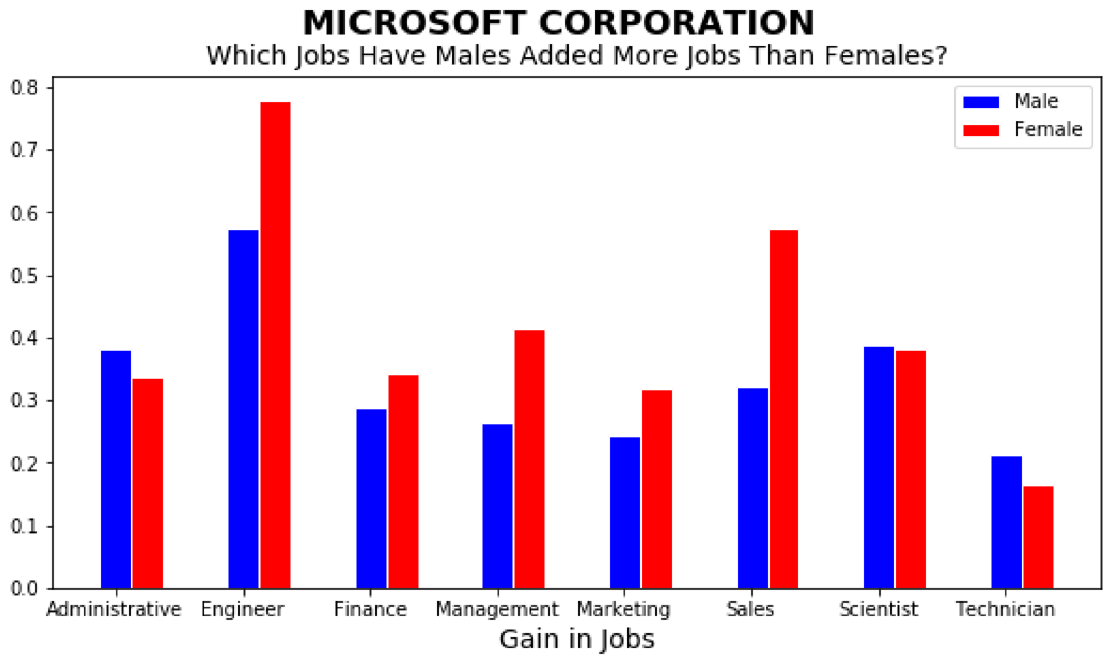
Out[27]:

job_category	month	gender	count	percentage	end
Administrative	2021-01	female	4.901621e+04	0.543847	0.231818
Engineer	2021-01	female	1.010572e+06	0.340553	0.376607
Finance	2021-01	female	8.304000e+04	0.475399	0.155325
Management	2021-01	female	4.429822e+05	0.358560	0.360205
Marketing	2021-01	female	4.132721e+04	0.449586	0.333826
Sales	2021-01	female	1.363506e+05	0.350809	0.208297
Scientist	2021-01	female	3.152170e+04	0.530381	0.427509
Technician	2021-01	female	3.239551e+04	0.284061	0.188390

```
Administrative  2021-01    male  4.111243e+04    0.456153  0.169995
Engineer        2021-01    male  1.956867e+06    0.659447  0.269195
Finance         2021-01    male  9.163431e+04    0.524601  0.214604
Management      2021-01    male  7.924661e+05    0.641440  0.232235
Marketing       2021-01    male  5.059552e+04    0.550414  0.208259
Sales           2021-01    male  2.523236e+05    0.649191  0.070329
Scientist       2021-01    male  2.791048e+04    0.469619  0.295023
Technician      2021-01    male  8.164888e+04    0.715939  0.106386
```

0.24 And now we build the graphs for the company.

In [28]:
```
# Company Data

fig,ax = plt.subplots(figsize=(10,5))

# set width of bars
barWidth = 0.25

# set heights of bars
bars1 = end.loc[end['gender']=='male','end']
bars2 = end.loc[end['gender']=='female','end']

# Set position of bar on X axis
r1 = np.arange(len(bars1))
r2 = [x + barWidth for x in r1]

# Make the plot
plt.bar(r1, bars1, color='b', width=barWidth, edgecolor='white', label='Male')
plt.bar(r2, bars2, color='r', width=barWidth, edgecolor='white', label='Female')

plt.suptitle(company,size=18,fontweight='bold')
plt.title('Which Jobs Have Males Added More Jobs Than Females?',size=14)
plt.xlabel('Gain in Jobs',size=14)
plt.xticks(end.loc[end['gender']=='male',:].reset_index().index,
           end.loc[end['gender']=='male'].index,
           size=10)
plt.ylabel('')

# Create legend & Show graphic
plt.legend()
plt.show()
```

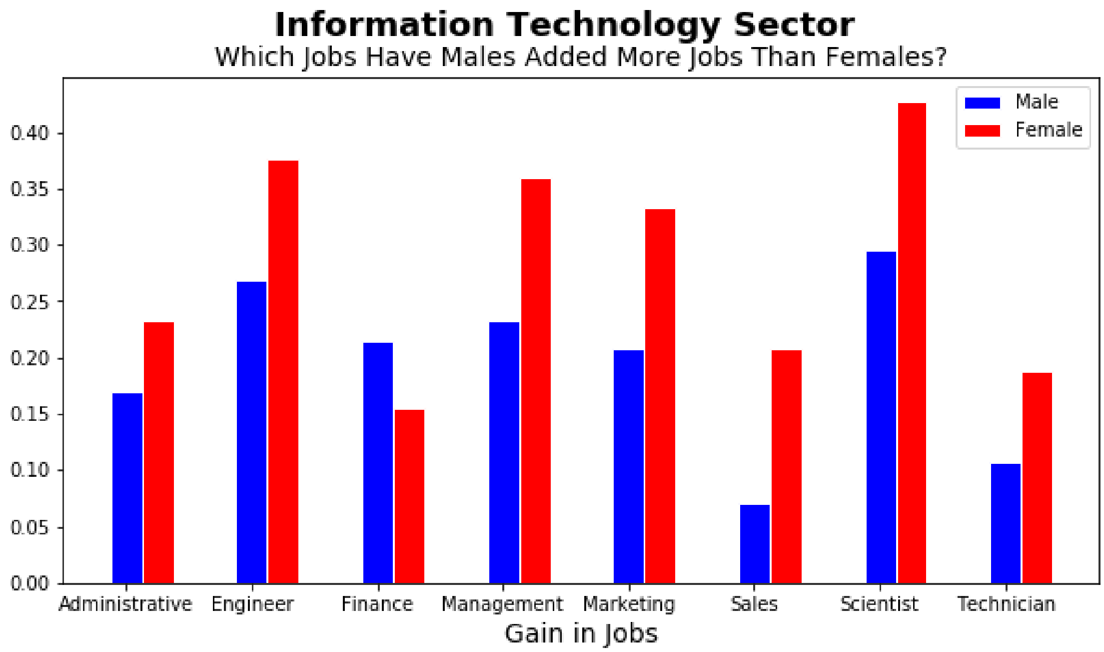


0.25 Interesting! We see that Females were hired more in every job, with the exception of administrative and scientist.

0.26 What does the sector look like? Lets's build the graph and take a look!

In [29]:
```
# Rest of Sector Data

fig,ax = plt.subplots(figsize=(10,5))

# set width of bars
barWidth = 0.25

# set heights of bars
bars1 = sector_end.loc[sector_end['gender']=='male','end']
bars2 = sector_end.loc[sector_end['gender']=='female','end']

# Set position of bar on X axis
r1 = np.arange(len(bars1))
r2 = [x + barWidth for x in r1]

# Make the plot
plt.bar(r1, bars1, color='b', width=barWidth, edgecolor='white', label='Male')
plt.bar(r2, bars2, color='r', width=barWidth, edgecolor='white', label='Female')

plt.suptitle(sector+' Sector',size=18,fontweight='bold')
plt.title('Which Jobs Have Males Added More Jobs Than Females?',size=14)
```

```python
plt.xlabel('Gain in Jobs',size=14)
plt.xticks(sector_end.loc[sector_end['gender']=='male',:].reset_index().index,
           sector_end.loc[sector_end['gender']=='male'].index,
           size=10)
plt.ylabel('')

# Create legend & Show graphic
plt.legend()
plt.show()
```



0.27 We see that Finance is where Males have added more jobs than Females.

0.28 Next, we looked at inflow of female changes over time, for Information Technology companies in North America with job category as Engineer, assuming inflow represents a firm acquiring new talents. To do this, we had to make changes to the dataset.

In [30]:
```python
# remove empty
df = df.loc[df['region'] != 'empty']
```

In [31]:
```python
# Extracting year
df['year'] = pd.DatetimeIndex(df['month']).year

# Extracting month
df['month_in_year'] = pd.DatetimeIndex(df['month']).month
```

In [32]:
```
# Set Values
sector = 'Information Technology'
region = 'Northern America'
job = 'engineer'
```

In [33]:
```
# Females
females = df.loc[(df['sector'] == sector) &
                 (df['region'] == region) &
                 (df['gender'] == 'female') &
                 (df['job_category'] == job),
                 ['company','month', 'count', 'inflow',
                  'outflow', 'year', 'month_in_year']]

# Males
males = df.loc[(df['sector'] == sector) &
                 (df['region'] == region) &
                 (df['gender'] == 'male') &
                 (df['job_category'] == job),
                 ['company','month', 'count', 'inflow',
                  'outflow', 'year', 'month_in_year']]
```

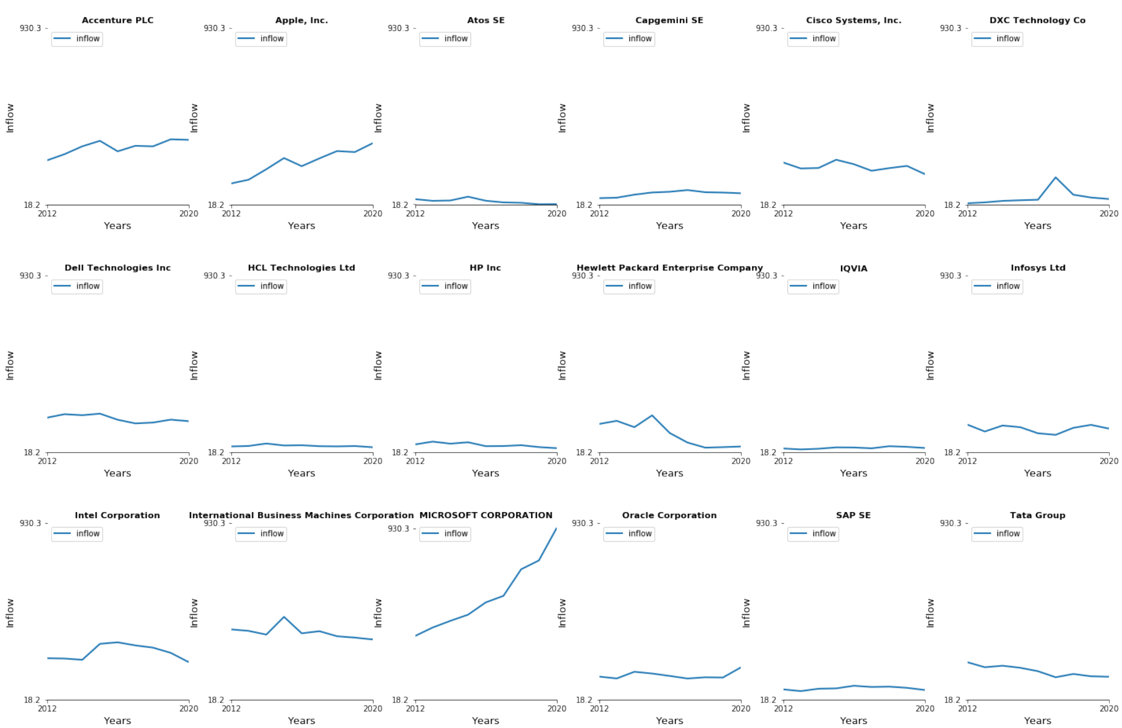
In [34]:
```
# Females flow
female_flow = (females.groupby(['company','year'], as_index=False)
                 .agg({'inflow':'mean', 'outflow':'mean'})
                 .sort_values(['company','year']))

# Males flow
male_flow = (males.groupby(['company','year'], as_index=False)
                 .agg({'inflow':'mean','outflow':'mean'})
                 .sort_values(['company','year']))
```

In [35]:
```
# Companies List
female_company = female_flow['company'].unique()
```

In [36]:
```
# maximum and minimum inflow values
max_inflow = female_flow['inflow'].max()
min_inflow = female_flow['inflow'].min()
```

In [37]:
```
# How inflow for females changes over time for different companies in Information
# Technology Sector in North American in Engineering job category?

# Graph: For this we used Sparkline Charts which is typically drawn without axes
# or coordinates

fig, ax = plt.subplots(nrows = 3, ncols= 6, figsize=(10,5))
fig.subplots_adjust(right=2, top=2.5, wspace = 0.3, hspace = 0.4)

c = 0
for i in range(0, 3):
```

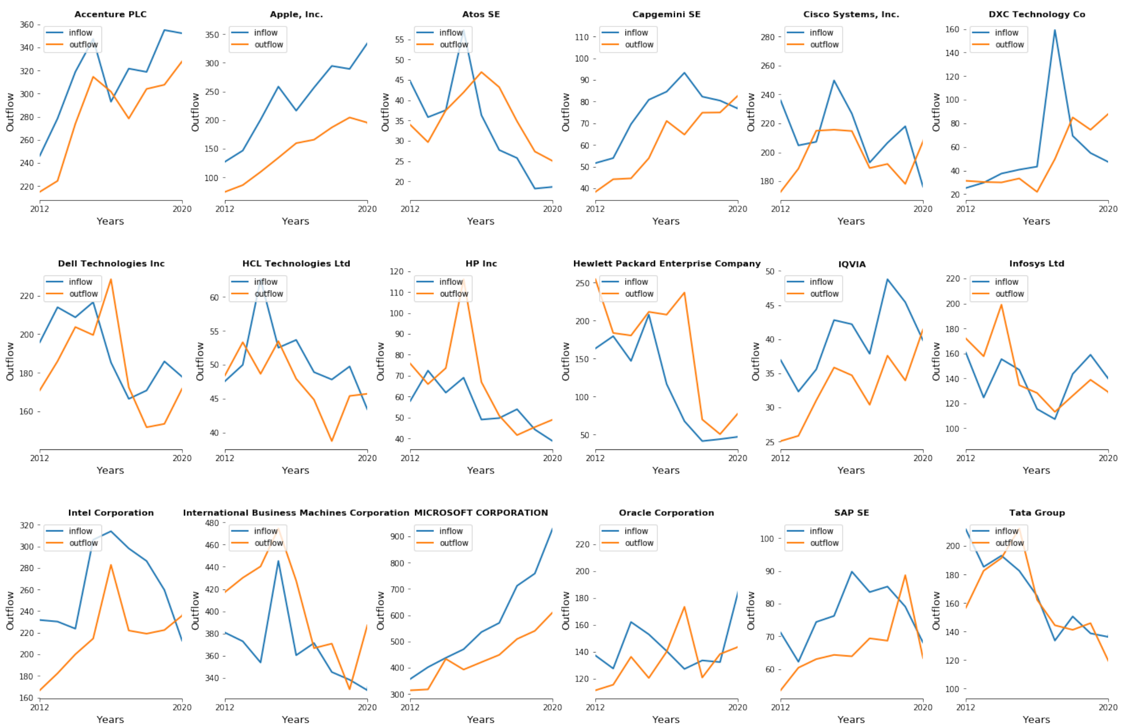
```python
    for j in range(0,6):
        df_female_inflow = female_flow.loc[female_flow['company'] == female_company[c]]
                                          [['year', 'inflow']].sort_values('year')

        df_female_inflow.plot(ax=ax[i][j], x = 'year', y = 'inflow', linewidth=2)

        ax[i][j].set_title(female_company[c], size=11.2, fontweight="bold")

        ax[i][j].spines['top'].set_visible(False)
        ax[i][j].spines['right'].set_visible(False)
        ax[i][j].spines['left'].set_visible(False)

        # Only considering data till 2020 because for year 2021, only 1 month
        # data is available
        ax[i][j].set_xlim(2012, 2020)

        # To remove the unnecessary information because our aim here is to
        # observe the trend of females between different companies, not
        # to find the precise value at a particular time.
        ax[i][j].set_xticks([2012,2020])

        # Same range for y axis for easy comparison between companies
        ax[i][j].set_yticks([min_inflow, max_inflow])
        ax[i][j].legend(loc="upper left")
        ax[i][j].set_xlabel('Years', size=13)
        ax[i][j].set_ylabel('Inflow', size=13)
        c+=1
```



0.29 Interesting, we see here Mircosoft has a high uptrend.

0.30 Now we do the same for outflow, assuming that means a firms ability to retain talent.

In [38]:
```
# How Inflow and Outflow of Female changes over time for Northern America region
# in Information Technology Sector in Engineer Job Category?

fig, ax = plt.subplots(nrows = 3, ncols= 6, figsize=(10,5))
fig.subplots_adjust(right=2, top=2.5, wspace = 0.3, hspace = 0.4)

c = 0
for i in range(0, 3):
    for j in range(0,6):
        # Inflow
        df_female_inflow = female_flow.loc[female_flow['company'] == female_company[c]
                                  ['year', 'inflow']].sort_values('year')

        df_female_inflow.plot(ax=ax[i][j], x = 'year', y = 'inflow', linewidth=2)

        # Outflow
        df_female_outflow = female_flow.loc[female_flow['company'] == female_company[c
                                  ['year', 'outflow']].sort_values('year')

        df_female_outflow.plot(ax=ax[i][j], x = 'year', y = 'outflow', linewidth=2)

        ax[i][j].set_title(female_company[c], size=11.2, fontweight="bold")
        ax[i][j].spines['top'].set_visible(False)
        ax[i][j].spines['right'].set_visible(False)
        ax[i][j].spines['left'].set_visible(False)

        # Only considering data till 2020 because for year 2021, only 1 month
        # data is available
        ax[i][j].set_xlim(2012, 2020)

        # To remove the unnecessary information because our aim here is to
        # observe the trend of females between different companies, not
        # to find the precise value at a particular time.
        ax[i][j].set_xticks([2012,2020])
        ax[i][j].legend(loc="upper left")
        ax[i][j].set_xlabel('Years', size=13)
        ax[i][j].set_ylabel('Outflow', size=13)
        c+=1
```

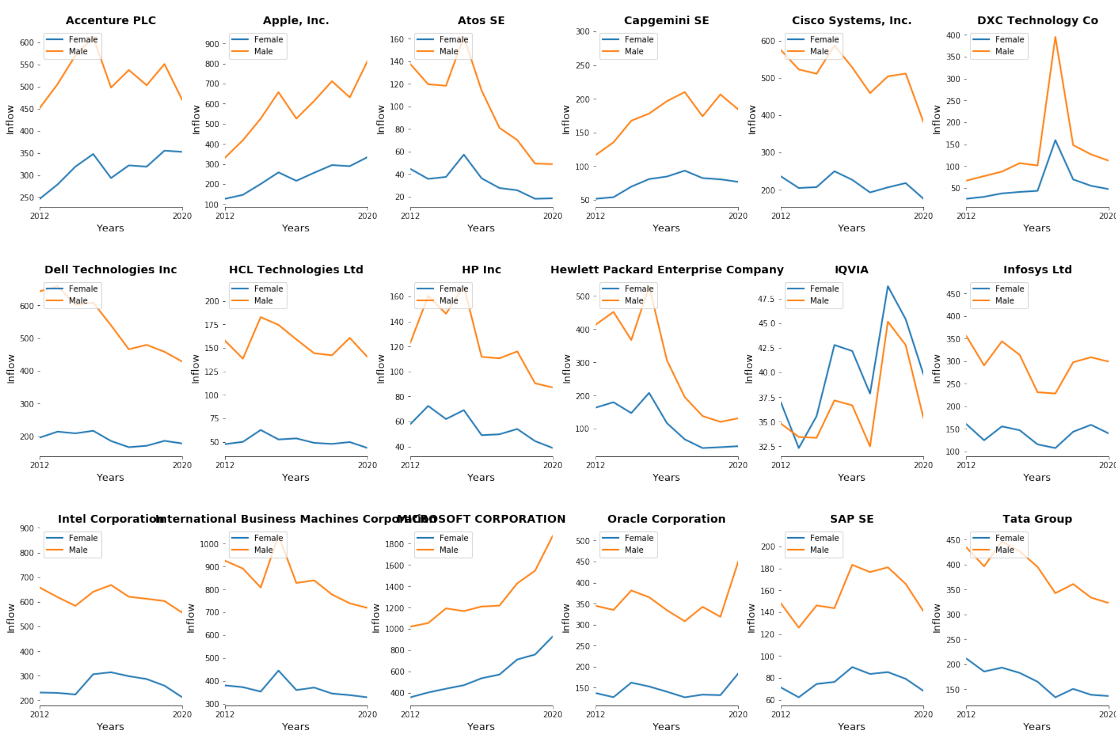


0.31 Spikes in the inflow might represent a company expanding or developing R&D while a spike in outflow might mean a company struggling to retain its talent, restructuring or showing itself to be more competitive to shareholders

0.32 The last thing we wanted to plot was the Male vs Female outflows and inflows. First we started with inflow.

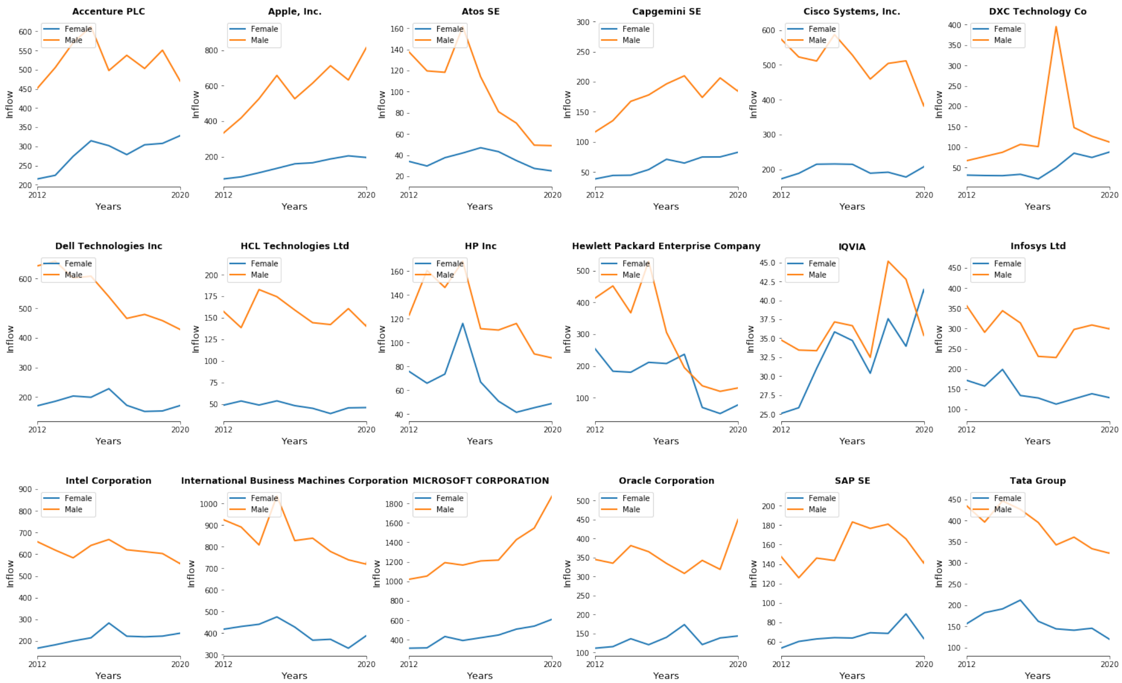
In [39]:
```
# How Inflow of Male and Female changes over time for Northern America region
# in Information Technology Sector in Engineer Job Category?

fig, ax = plt.subplots(nrows = 3, ncols= 6, figsize=(10,5))
fig.subplots_adjust(right=2, top=2.5, wspace = 0.3, hspace = 0.4)

c = 0
for i in range(0, 3):
    for j in range(0,6):

        # Female Inflow
        df_female_inflow = female_flow.loc[female_flow['company'] == female_company[c
                                      ['year', 'inflow']].sort_values('year')

        df_female_inflow.plot(ax=ax[i][j], x = 'year', y = 'inflow', linewidth=2)

        # Male Inflow
```

```
df_male_inflow = male_flow.loc[male_flow['company'] == female_company[c],
                               ['year', 'inflow']].sort_values('year')

df_male_inflow.plot(ax=ax[i][j], x = 'year', y = 'inflow', linewidth=2)


ax[i][j].set_title(female_company[c], size=14, fontweight="bold")
ax[i][j].spines['top'].set_visible(False)
ax[i][j].spines['right'].set_visible(False)
ax[i][j].spines['left'].set_visible(False)
ax[i][j].set_xlim(2012, 2020)

# To remove the unnecessary information because our aim here is to
# observe the trend of females between different companies, not
# to find the precise value at a particular time.
ax[i][j].set_xticks([2012,2020])

ax[i][j].legend(['Female', 'Male'], loc="upper left")
ax[i][j].set_xlabel('Years', size=13)
ax[i][j].set_ylabel('Inflow', size=13)
c+=1
```



0.33 Then we did the same for outflow.

In [40]:
```
# How Outflow of Male and Female changes over time for Northern America region
# in Information Technology Sector in Engineer Job Category?

fig, ax = plt.subplots(nrows = 3, ncols= 6, figsize=(10,5))
fig.subplots_adjust(left = 0, right=2, top=2.5, wspace = 0.3, hspace = 0.4)

c = 0
for i in range(0, 3):
    for j in range(0,6):

        # Female Outflow
        df_female_outflow = female_flow.loc[female_flow['company'] == female_company[c
                                        ['year', 'outflow']].sort_values('year')

        df_female_outflow.plot(ax=ax[i][j], x = 'year', y = 'outflow', linewidth=2)

        # Male Outflow
        df_male_outflow = male_flow.loc[male_flow['company'] == female_company[c],
                                        ['year', 'inflow']].sort_values('year')

        df_male_outflow.plot(ax=ax[i][j], x = 'year', y = 'inflow', linewidth=2)


        ax[i][j].set_title(female_company[c], size=12, fontweight="bold")
        ax[i][j].spines['top'].set_visible(False)
        ax[i][j].spines['right'].set_visible(False)
        ax[i][j].spines['left'].set_visible(False)
        ax[i][j].set_xlim(2012, 2020)

        # To remove the unnecessary information because our aim here is to
        # observe the trend of females between different companies, not
        # to find the precise value at a particular time.
        ax[i][j].set_xticks([2012,2020])
        ax[i][j].legend(['Female', 'Male'], loc="upper left")
        ax[i][j].set_xlabel('Years', size=13)
        ax[i][j].set_ylabel('Inflow', size=13)
        c+=1
```



0.34 We can see that females are less likely to leave the firm as compared to males - However, IQVIA is interesting as Females are leaving more.

0.35 And that's our project! Hope you had as much fun as we did exploring the data!