In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
from scipy.stats import norm
from IPython.display import Markdown, display

from IPython.display import display, HTML, Latex
display(HTML("<style>.container { width:85% !important; }</style>"))

%matplotlib inline
```

Get Some Data!

- Where to get data
- What to look for in data
- Is it important?

In [2]:
```
def get_data():
    df = pd.read_csv("survey_results_slim.csv")
    df = df.dropna(subset=["Salary"]).copy()
    return df

df = get_data()
```

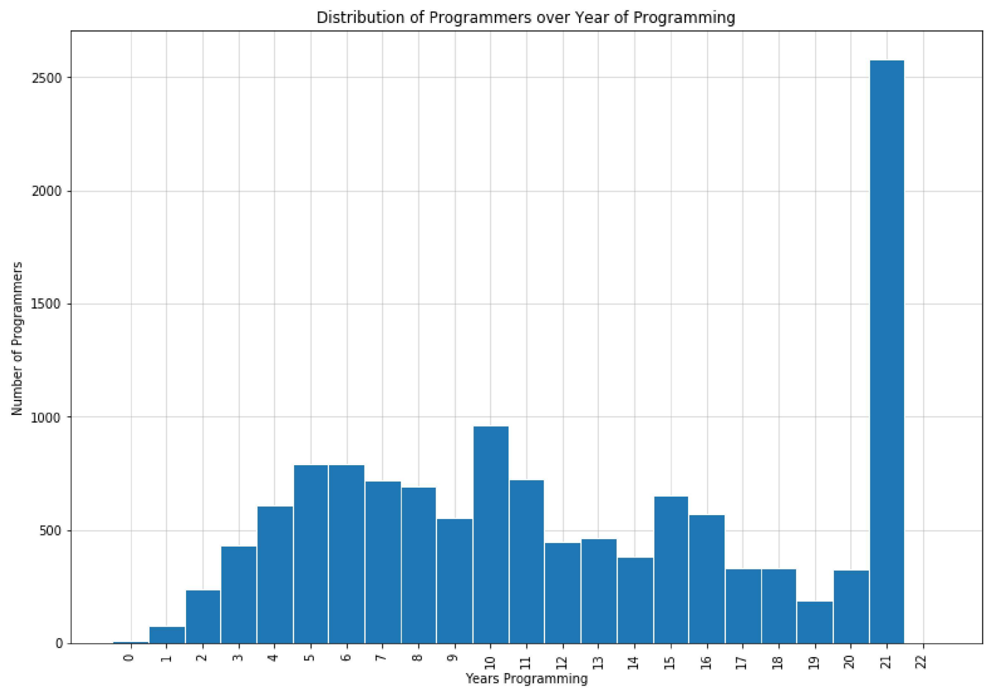
Dataset Info

- Columns
- Size
- Start Getting *Ideas*

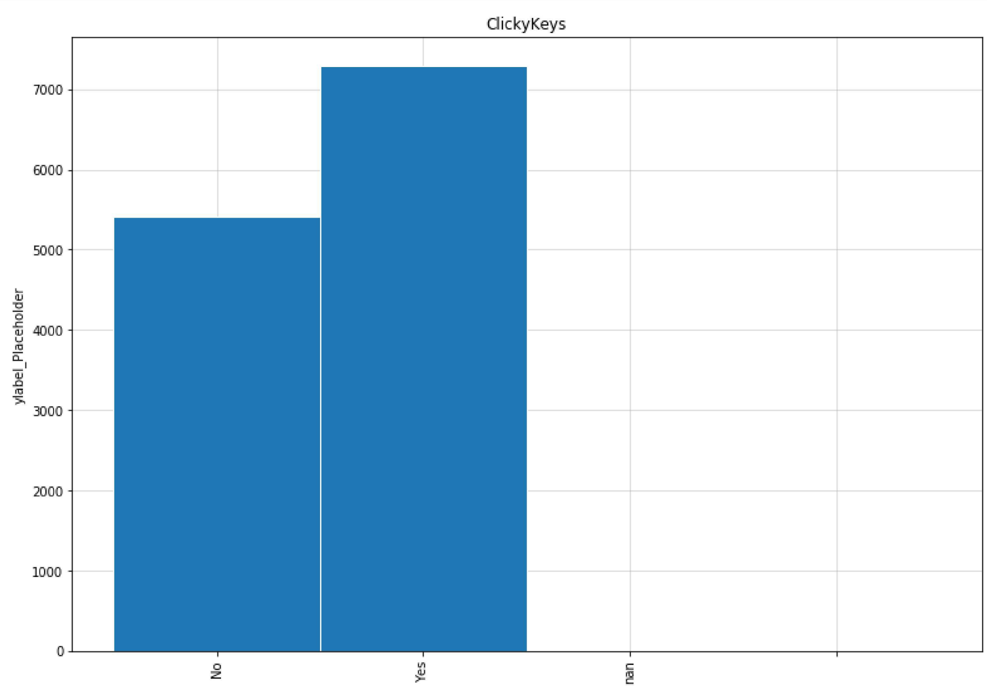
In [3]:
```
columns = list(df)
print(columns[0:5])
length = len(df)
print(df["Salary"][0:5])
```

```
['Professional', 'ProgramHobby', 'Country', 'University', 'EmploymentStatu
s']
2     113750.0
14    100000.0
17    130000.0
18     82500.0
22    100764.0
Name: Salary, dtype: float64
```

In [4]:
```
def make_hist(data, title="Title_Placeholder", xlabel="xlabel_Placeholder",
 ylabel="ylabel_Placeholder"):
    bins = len(set(data))+1
    fig, ax = plt.subplots(figsize=(13,9))
    ax.hist(data, bins=bins, align='left', range=(0,bins), edgecolor="whit
e")
    ax.grid(alpha=0.5)
    ax.set_axisbelow(True)
    plt.xticks(rotation=90)
    ax.set_xticks(range(0, bins))
    ax.set_title(title)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)
    plt.show()

make_hist(df['YearsProgram'], "Distribution of Programmers over Year of Pro
gramming", "Years Programming", "Number of Programmers")
```



In [5]:
```
column = "ClickyKeys"
make_hist(df[column], title=column, xlabel="")
```



In [6]:
```
print("Clicky keys salary:", df.loc[df["ClickyKeys"] == "Yes"]["Salary"].me
an())
print("No clicky keys salary:", df.loc[df["ClickyKeys"] == "No"]["Salary"].
mean())
```

```
Clicky keys salary: 56595.78196684976
No clicky keys salary: 56239.59610183224
```

In [7]:
```
print("The right way salary:", df.loc[df["PronounceGIF"] == 'With a hard
 "g," like "gift"']["Salary"].mean())
print("The wrong way salary:", df.loc[df["PronounceGIF"] == 'With a soft
 "g," like "jiff"']["Salary"].mean())
```

```
The right way salary: 57578.96229224571
The wrong way salary: 57056.27510153962
```

In [8]:
```
print(set(df["TabsSpaces"]))
```

```
{nan, 'Spaces', 'Tabs', 'Both'}
```

In [9]:
```
print("Tabs salary:", df.loc[df["TabsSpaces"] == 'Tabs']["Salary"].mean())
print("Spaces salary:", df.loc[df["TabsSpaces"] == 'Spaces']["Salary"].mean
())
print("Both salary:", df.loc[df["TabsSpaces"] == 'Both']["Salary"].mean())
```

```
Tabs salary: 49680.68101741523
Spaces salary: 65540.3040558787
Both salary: 50240.20998933888
```

[30 points] Problem 2: Gender Balance in Movements Between Academic Disciplines

Every year, the online academic resume service, ORCID, dumps the data from all of the professors who have their privacy settings set to “public” so that the research community can learn about the makeup of the academic workforce. In this real-data problem, we’re going to study the flows of professors between different academic fields to learn about gender differences. We’ll use a pre-processed dataset used by actual researchers studying gender imbalance across fields.

First, some information about the data. For each of the 1.6 million professors in the public ORCID data dump, the researchers determined (a) what field they are currently in, (b) what field they did their PhD in, and (c) their gender. Here, because the goal of the study was originally to learn about disparities between men and women, gender was coded by the researchers as male or female, as indicated by the professors. Those who chose not to mark their gender as public were not included in the processed dataset.

The researchers have provided CSCI 3022 with two files: **totals.csv** and **switch_edgelist.csv**. The first file enumerates the total numbers of men and women in each of 30 different fields. The second file enumerates the total numbers of men and women who switched from one field to another field during their career.

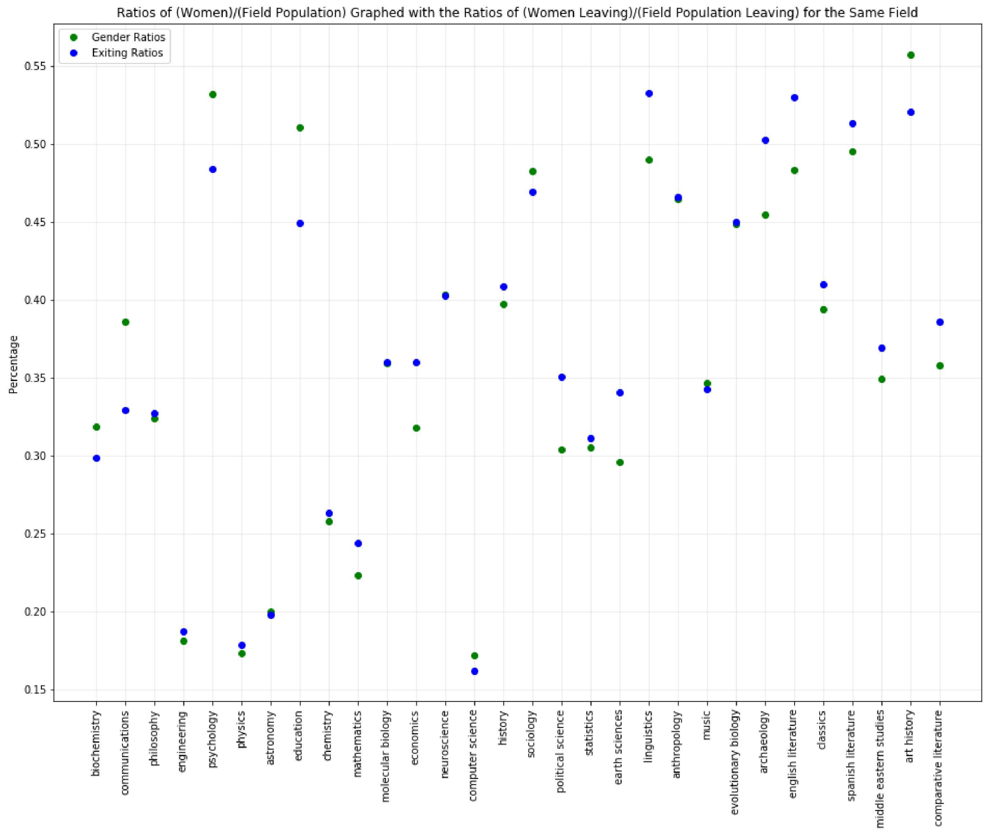
The null hypothesis about the data is that the gender balance of people leaving field X is the same as the gender balance in field X. For example, if Anthropology is 50% women and 50% men, we expect people who have moved from Anthropology to another field to reflect this $50/50$ balance. On the other hand, if Physics is only 15% women and 85% men, we expect people who have moved from Physics to another field to reflect a $15/85$ balance.

In symbolic form, we might write this as follows. Let the proportion of professors in field i who are women be given by p_i, and let the proportion of women who move from field i to some other field be given by q_i. Then the expected result is that p_i = q_i. The researchers are interested to know if there is statistical evidence that $p_i \neq q_i$ for any of the fields i.

Part A: Wrangle those data files. Then, make a plot of p_i for all $i = 1, 2, \ldots, 30$ fields using a green color, and on the same axes, plot q_i using a blue color.

In [10]:
```
def two_a(ret, graph):
    totals = pd.read_csv("totals.csv")
    edge_list = pd.read_csv("switch_edgelist.csv")

    # First we want to get the unique fields
    unique_fields = totals.field.unique()

    # Set up information containers
    gender_ratios = []
    retention_ratios = []
    gender_populations = []
    retention_populations = []

    for field in unique_fields:
        # Select the male count in the given field
        males_in_field = totals[totals["field"] == field].loc[totals["gend_
cat"] == "male"]["N"].item()
        # Select the female count in the given field
        females_in_field = totals[totals["field"] == field].loc[totals["gen
d_cat"] == "female"]["N"].item()
        # Get the sum of the counts
        total = males_in_field + females_in_field
        # Log the total of the population
        gender_populations.append(total)
        # Log the ratio of females to population
        gender_ratios.append(females_in_field/total)

    for field in unique_fields:
        females_left = 0
        males_left = 0
        # Since there can be more than one link from the given field, we ne
ed to iterate through all of them
        for entry in edge_list[edge_list["from"] == field].loc[edge_list["g
end_cat"] == "female"]["N"].items():
            # Get the running sum of females who left from that field (does
n't matter which field they went to)
            females_left += entry[1]
        # Since there can be more than one link from the given field, we ne
ed to iterate through all of them
        for entry in edge_list[edge_list["from"] == field].loc[edge_list["g
end_cat"] == "male"]["N"].items():
            # Get the running sum of males who left from that field (does
n't matter which field they went to)
            males_left += entry[1]
        # Get the sum of populations
        total = males_left + females_left
        # Log the total of the population
        retention_populations.append(total)
        # Log the ratio of females to population
        retention_ratios.append(females_left/total)

    if graph:
        # Do Graph Stuff
        fig, ax = plt.subplots(figsize=(16,12))
        ax.plot(range(1,31), gender_ratios, 'o', label="Gender Ratios", col
or="green")
        ax.plot(range(1,31), retention_ratios, 'o', label="Exiting Ratios",
 color="blue")

        ax.grid(alpha=0.25)
        plt.xticks(range(1,31), unique_fields, rotation='vertical')
        ax.set_axisbelow(True)
        ax.legend()
        ax.set_title("Ratios of (Women)/(Field Population) Graphed with the
 Ratios of (Women Leaving)/(Field Population Leaving) for the Same Field")
        ax.set_ylabel("Percentage")
        plt.show()

    if ret:
        return gender_ratios, retention_ratios, gender_populations, retenti
on_populations, unique_fields
```

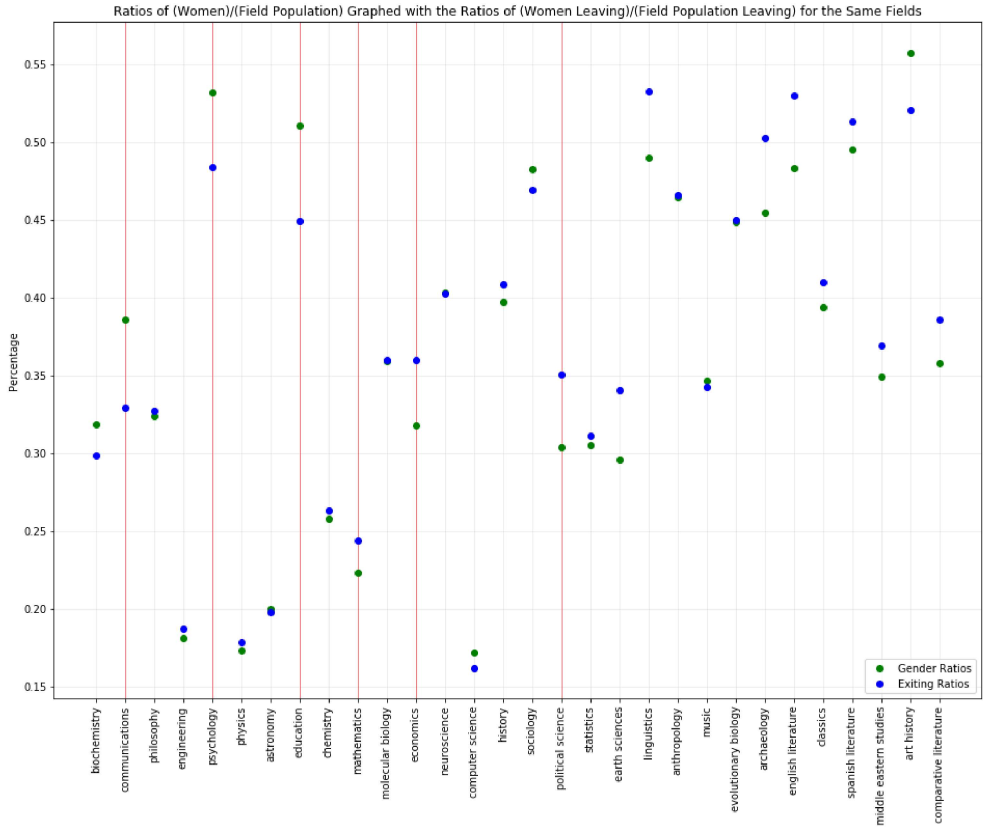
```
two_a(ret=False, graph=True)
```



Part B: At the $\alpha = 0.05$ significance level, use the method of your choice to determine whether there is sufficient evidence that $p_i \neq q_i$. Be sure to explain why you are justified in using the method that you used, and report the numbers that helped you make your decision for each of the fields. Please use only methods we have discussed in class. Then, replicate your plot from **Part A** and add a red symbol to those fields, if any, where p_i and q_i are statistically different at the given significance level. Comment on any significant findings.

In [11]:

```
def two_b(z_alpha):
    gender_ratios, retention_ratios, gender_populations, retention_popula
tions, fields = two_a(True, False)

    # Create Information Variables
    gender_variances = []
    retention_variances = []
    different = []
    good_bad = []

    # Calculate Z val once because it won't change from test to test
    z = norm.ppf(1-z_alpha/2)

    for i in range(len(fields)):

        # Pull information from arrays
        gender_mean = gender_ratios[i]
        gender_population = gender_populations[i]
        retention_mean = retention_ratios[i]
        retention_population = retention_populations[i]

        # Calculate Difference of Means for Comparison of Population Prop
ortions
        difference_of_means = gender_mean-retention_mean

        # Calculate Standard Deviation for Comparison of Population Propo
rtions
        std_deviation = np.sqrt(gender_mean*(1-gender_mean)/gender_popula
tion + retention_mean*(1-retention_mean)/retention_population)

        # Get lower bound of confidence interval
        lower_bound = difference_of_means - z*std_deviation

        # Get upper bound of confidence interval
        upper_bound = difference_of_means + z*std_deviation

        # Check to see if our confidence interval really matters (if it c
ontains 0 they're not sufficiently different)
        if lower_bound <= 0 and upper_bound >= 0:
            different.append(0)
        else:
            different.append(1)

    # Do Graph Stuff
    fig, ax = plt.subplots(figsize=(16,12))

    for x in range(len(different)):
        if different[x] == 1:
            ax.axvline(x+1, color="red", linewidth=0.5)

    ax.plot(range(1,31), gender_ratios, 'o', label="Gender Ratios", color
="green")
    ax.plot(range(1,31), retention_ratios, 'o', label="Exiting Ratios", c
olor="blue")

    ax.grid(alpha=0.25)
    plt.xticks(range(1,31), fields, rotation='vertical') # Change it so t
hat labels are colored, not dots
    ax.set_axisbelow(True)
    ax.legend()
    ax.set_title("Ratios of (Women)/(Field Population) Graphed with the R
atios of (Women Leaving)/(Field Population Leaving) for the Same Fields")
    ax.set_ylabel("Percentage")
    plt.show()

two_b(.05)
```



Part C: Repeat the procedure from **Part B** at the $\alpha = 0.01$ level.

```
In [12]: two_b(.01)
```