

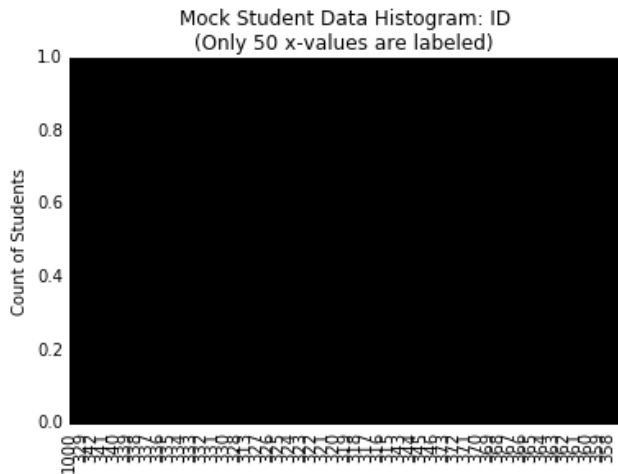
```
In [1]: # Machine Learning for Public Policy  
        # Assignment 1: Prepping Student Data  
        # Name: Vi Nguyen
```

```
In [1]: %matplotlib inline
```

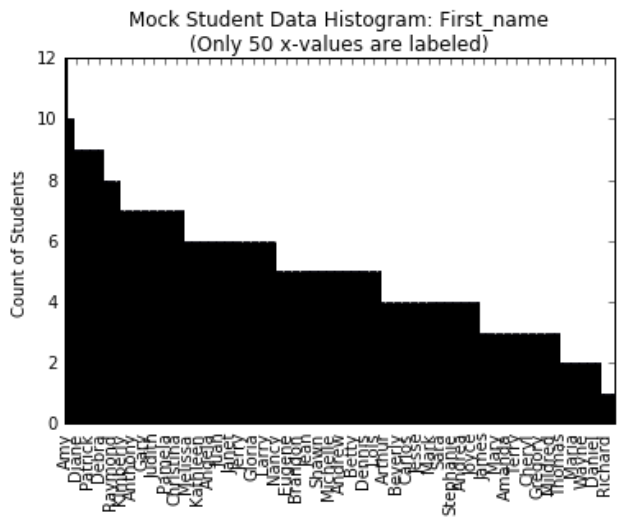
```
In [ ]: # Problem A #
```

In [2]: `import prep_data`

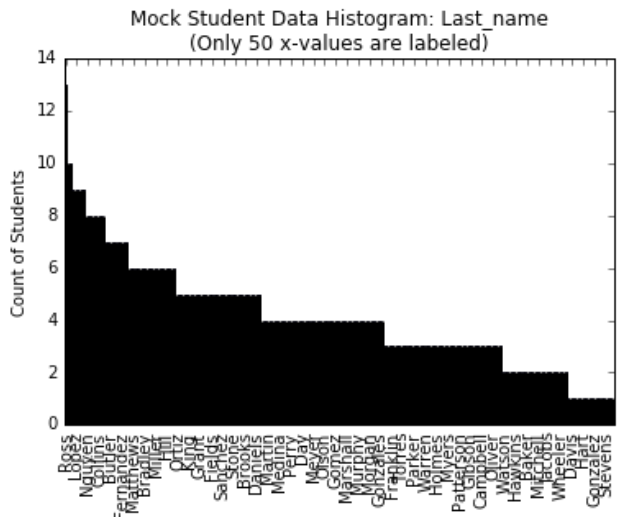
hist_ID.png created



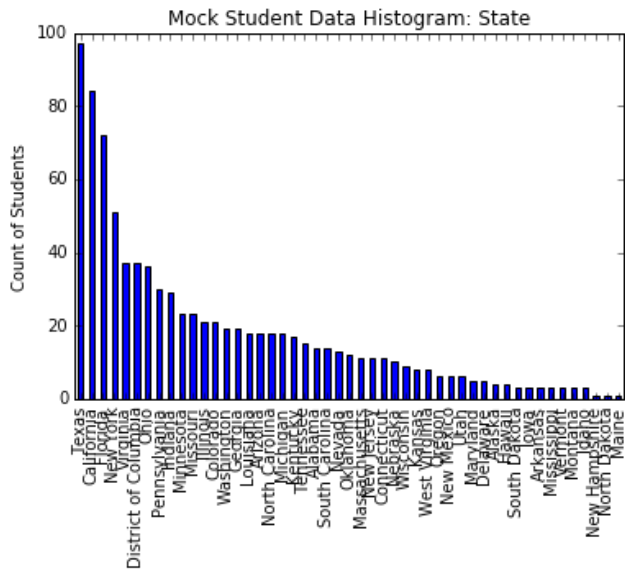
hist_First_name.png created



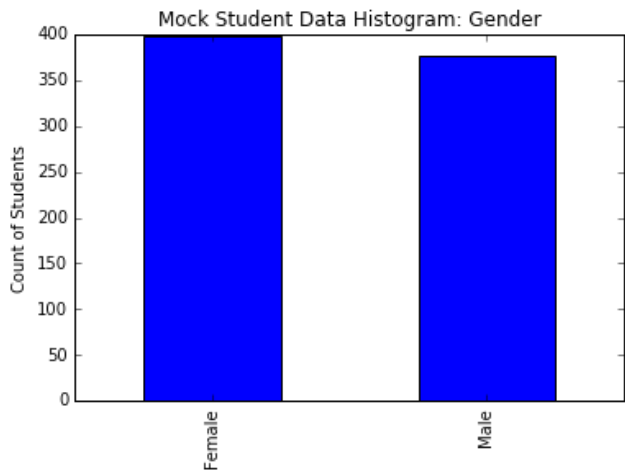
hist_Last_name.png created



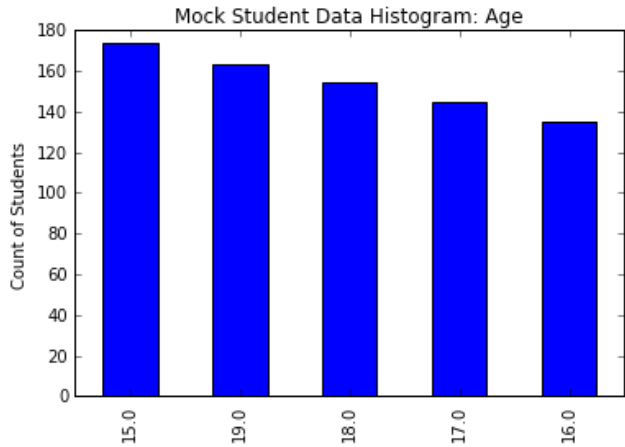
hist_State.png created



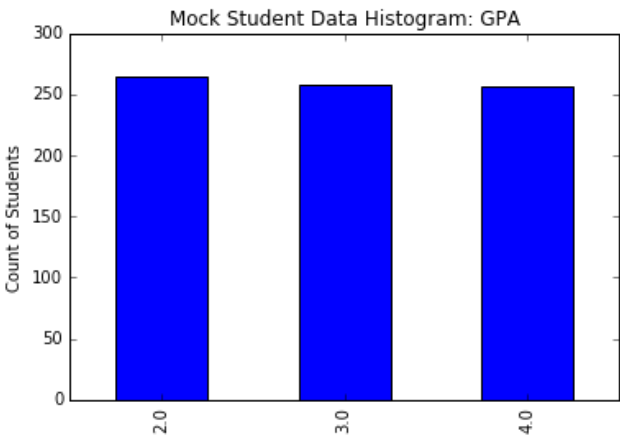
hist_Gender.png created



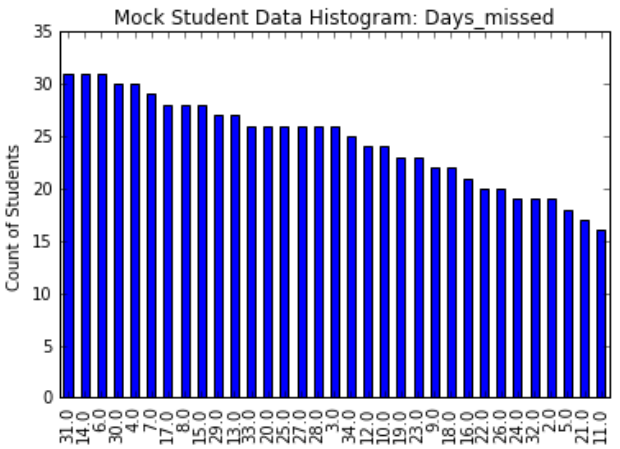
hist_Age.png created



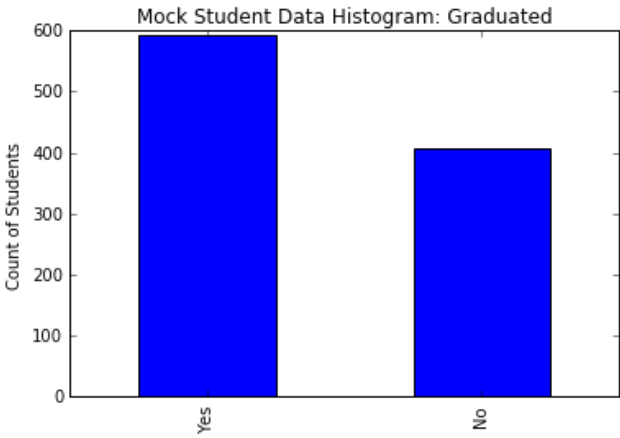
hist_GPA.png created



hist_Days_missed.png created



hist_Graduated.png created



summary_stats.csv created
mock_student_data_gender_inferred.csv created
Number of records with missing gender after inference: 0
mock_student_data_gend_inf_fillna_mean.csv created
mock_student_data_gend_inf_fillna_cond_mean.csv created
mock_student_data_gend_inf_fillna_cond_mean2.csv created

```
In [6]: # Problem A (continued) #  
# 3c. I'm using conditional mean on Graduation and Gender to infer the  
# missing values for Age, GPA, and Days_missed. We could have used padding  
# methods in pandas if we thought there was some mathematical relationship  
# between one missing value and the next. We could also have used linear  
# regression to infer the missing values but there were a lot of missing  
# values.
```

```
In [7]: # Problem B #
```

```
In [9]: # Problem B, Initial Question A #  
# David and Chris would be expected to have the same probability of  
# of graduation. Since Chris and Adam differ only on income, Chris's  
# probability will be  $-0.109 * \ln(10,000)$  relative to Adam's (where the  
# 10,000 is the difference in income between the two). Similarly, David's  
# probability will also be  $-0.109 * \ln(10,000)$ , relative to Bob's. Because  
# Bob and Adam have the same probability, and Chris and David differ by  
# the same amount relative to Bob's and Adam's probability--Chris and David  
# have the same probability of graduation, as predicted by the model.
```

```
In [10]: # Problem B, Second Question A  
# The negative coefficient on AfAm_Male indicates that relative to  
# non-African American Males, African American Males are less likely to  
# graduate. Since the coefficients on Female, and AfAm are -2.11, and  
# 2.07 respectively--the negative coefficient on AfAm_Male indicates that  
# relative to African American Females, African American Males are also  
# less likely to graduate.
```

```
In [13]: # Problem B, Question B  
# Although the z-scores on Age and Age_Sq are not high enough in absolute  
# value to be significant, the coefficients indicate that different ages  
# may be correlated differently with the probability of graduation. The  
# model variables estimate that the incremental probability of  
# graduation changes to positive beyond age 65.  
#  $0 = -0.013 + .0001 * 2 * \text{Age}$   
# Age = 65
```

```
In [12]: # Problem B, Question C  
# I would drop either the Male or Female variable since having both of them  
# is redundant. Having a coefficient on Male also gives us a sense of the  
# correlation between being a Female (when Male = 0) and the probability of  
# graduating. I would also potentially look into removing the Age variables  
# since the z-scores are not significant. However, I would need to know how  
# that would affect the model (Would run F-tests), and understand  
# what is the reason for our model. If we are trying to understand how Age  
# is correlated with probability of graduation, then removing Age and Age_sq  
# would not make sense even if it did not affect our model.
```