Data Wrangling - Obtaining the Data and Checking for Issues

October 1, 2017

0.1 Data Wrangling

Data wrangling is the process of collecting data and transforming it into a usable form. For this project on drafting NFL running backs, we were able to find our data available on various web sites. In order to properly "wrangle" this data, we would need to find a way of taking it from a web site and transforming into a CSV file. Having our data in CSV files would allow us to run data analysis later.

We were interested in three different subjects of data: college football statistics, NFL statistics for the rookie running backs of each year, and NFL statistics for all running backs of each year. The web sites that we specifically accessed have been mentioned in the 'Project Proposal' portion of this project.

0.1.1 College Football and NFL Rookie Statistics

When data collecting began, we were not yet aware of how to utilize the process of web scraping in order to obtain our data. Thus, we manually copied the college football statistics and the NFL rookie statistics into Excel spreadsheets, which we were then able to save as a CSV file. While we were certain that we would not be missing any information by doing this, we wanted to check anyway. Below is the code for checking for missing values in one year of both the college statistics and the NFL rookie statistics. Note that we separated each set of statistics into a different CSV file for each year so that we could more easily determine when the data was coming from.

```
In [7]: # Import the pandas module so that we may use data frames, and the numpy module so that
        import pandas as pd
        import numpy as np
        # Import these packages so that we may plot our missing values.
        %matplotlib inline
        import matplotlib.pyplot as plt
        import seaborn as sns

        # Imports the data from our CSV file into a data frame, which we can perform data analys
        cf_09 = pd.DataFrame.from_csv('data/College_FB_2009.csv', index_col=None, encoding='utf-
        # The source of this data represents missing values with '--', so we need to transform t
        cf_09 = cf_09.replace('--', np.nan)
        cf_09.head()
```

```
Out[7]:          Player  Team    Att    Gain  Loss     Yds   Avg  Lg    TD
        0   Toby Gerhart  STAN  343.0  1913.0  42.0  1871.0  5.45 NaN  28.0
```

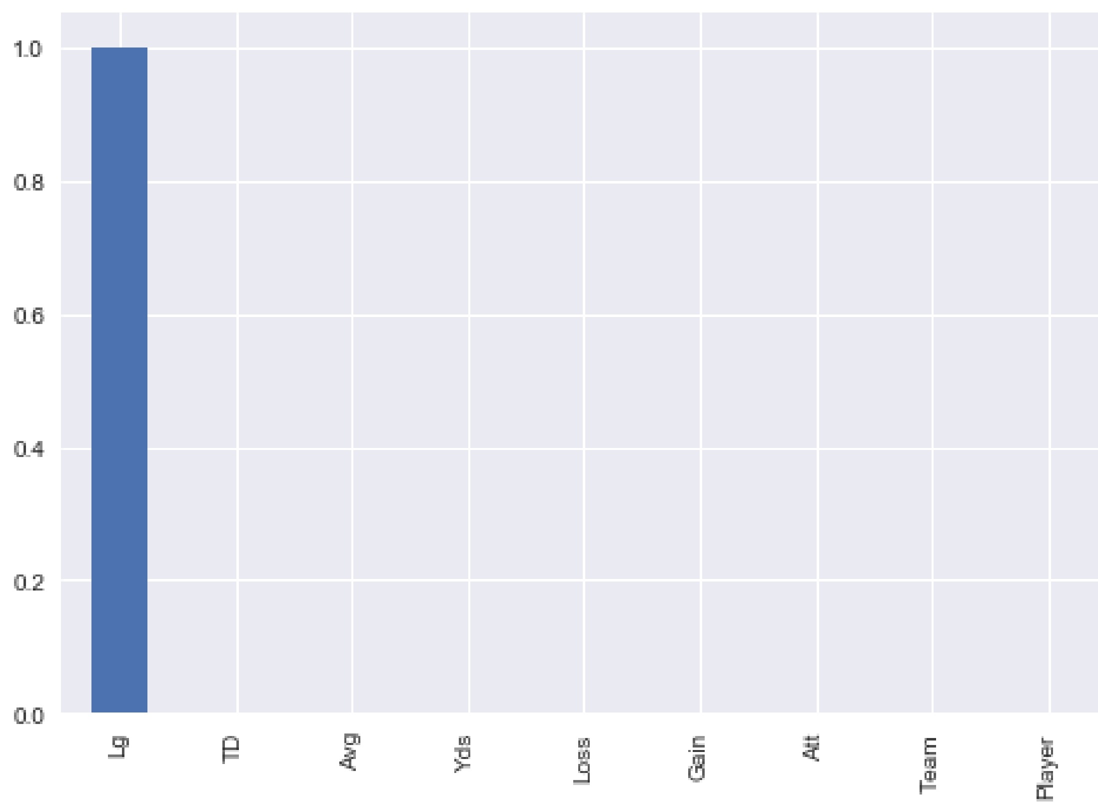
```
1   Ryan Mathews  FRES  276.0  1850.0  42.0  1808.0  6.55 NaN  19.0
2     Dion Lewis  PITT  325.0  1862.0  63.0  1799.0  5.54 NaN  17.0
3    Mark Ingram   ALA  271.0  1678.0  20.0  1658.0  6.12 NaN  17.0
4  Ryan Williams    VT  293.0  1720.0  65.0  1655.0  5.65 NaN  21.0
```

In [8]:
```python
# We want to count the number of null values in the cf_09 data frame.
cf_09_c = cf_09.copy()
c = cf_09_c.isnull().sum().sort_values(ascending = False)/len(cf_09_c.index)
c
```

Out[8]:
```
Lg        1.0
TD        0.0
Avg       0.0
Yds       0.0
Loss      0.0
Gain      0.0
Att       0.0
Team      0.0
Player    0.0
dtype: float64
```

In [9]:
```python
# Plots the percentage of missing values for each column.
c.plot(kind='bar');
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x231c4cc3780>



As we can see, the college football statistics for 2009 is missing all of the information on longest run. However, it does not have any other missing information. We will consider this to be acceptable because all of the data has the same column of information missing.

```
In [10]: # Typically we would have the same import statements here as before. However, since we
         # modules earlier, we can leave the import statements out of this code block.

         nr_10 = pd.DataFrame.from_csv('data/NFL_Rookies_2010.csv', index_col=None, encoding='ut
         nr_10 = nr_10.replace('--', np.nan)
         nr_10.head()
```

```
Out[10]:    Rk             Player Team Pos  Att  Att/G   Yds  Avg  Yds/G  TD  Lng  1st  \
         0   1  LeGarrette Blount   TB  RB  201   15.5  1007  5.0   77.5   6   53   38
         1   2        Chris Ivory   NO  RB  137   11.4   716  5.2   59.7   5  55T   44
         2   3       Ryan Mathews   SD  RB  158   13.2   678  4.3   56.5   7  31T   25
         3   4        Jahvid Best  DET  RB  171   10.7   555  3.2   34.7   4   45   25
         4   5       James Starks   GB  RB   29    9.7   101  3.5   33.7   0   16    5

            1st%  20+  40+  FUM
         0  18.9   10    3    3
         1  32.1    5    1    4
         2  15.8    4    0    4
         3  14.6    3    1    1
         4  17.2    0    0    0
```

```
In [11]: nr_10_c = nr_10.copy()
         nr = nr_10_c.isnull().sum().sort_values(ascending = False)/len(nr_10_c.index)
         nr
```

```
Out[11]: FUM       0.0
         40+       0.0
         20+       0.0
         1st%      0.0
         1st       0.0
         Lng       0.0
         TD        0.0
         Yds/G     0.0
         Avg       0.0
         Yds       0.0
         Att/G     0.0
         Att       0.0
         Pos       0.0
         Team      0.0
         Player    0.0
         Rk        0.0
         dtype: float64
```

Without even plotting, we can see that this data is not missing any information. Note that we started our NFL data collection with the year 2010 because the earliest year of college statistics we could obtain was in 2009.

0.1.2 NFL Running Back Statistics and Web Scraping

By the time we were ready to obtain statistics on the entire pool of NFL running backs (regardless of whether or not they were rookies), we had learned how to do web scraping. In short, web scraping is the act of writing code that will access web sites and perform data collection for us. While we needed to make minor modifications to the code for each year, here is the code used to obtain the 2010 NFL running back statistics.

```
In [12]: # Imports webdriver from the selenium module. This will allow our code to access the in
         from selenium import webdriver
         # It is important to note that we would normally need to import both pandas and numpy h
         # in an earlier code block, so we do not need to do it again now.

         # Open up the first page for the year we are working on.
         browser = webdriver.Chrome()
         browser.get('http://www.nfl.com/stats/categorystats?archive=true&conference=null&statis

         # Create an empty data frame and create column headers.
         df = pd.DataFrame()
         column_headers = ['Rk', 'Player', 'Team', 'Pos', 'Att', 'Att/G', 'Yds', 'Avg', 'Yds/G',

         # This loop will find all of the elements in the table, put them into a list and then a
         # to the next page.
         while(True):
             # The 'td' was selected because this is the html tag that specifies all table entri
             elems = browser.find_elements_by_tag_name('td')
             # Creates an empty list to put all found elements in.
             myList = list()
             i = 0
             while (i < len(elems)):
                 myList.append(elems[i].text)
                 i = i + 1
             # We create rows this way so that we have the correct number of rows (the last page
             # the other pages). There are 16 columns, which is why we use 16. Then we create a
             # our final data frame.
             rows = int(len(myList)/16)
             dftemp = pd.DataFrame(np.array(myList).reshape(rows,16), columns = column_headers)
             df = pd.concat([df, dftemp])
             # Every page except the last one has a button labeled 'next' that navigates to the
             # know we have finished with the last page, and so the loop breaks.
             try:
                 linkElem = browser.find_element_by_link_text('next')
                 linkElem.click()
             except:
```

```python
            break

    # This prints out the data frame so that we may manually check that we received the cor
    df
```

Out[12]:

```
    Rk                 Player Team Pos  Att Att/G    Yds  Avg  Yds/G  TD  \
0    1           Arian Foster  HOU  RB  327  20.4  1,616  4.9  101.0  16
1    2    Maurice Jones-Drew  JAC  RB  299  21.4  1,324  4.4   94.6   5
2    3        Jamaal Charles   KC  RB  230  14.4  1,467  6.4   91.7   5
3    4        Darren McFadden  OAK  RB  223  17.2  1,157  5.2   89.0   7
4    5       Adrian Peterson  MIN  RB  283  18.9  1,298  4.6   86.5  12
5    6        Michael Turner  ATL  RB  334  20.9  1,371  4.1   85.7  12
6    7         Chris Johnson  TEN  RB  316  19.8  1,364  4.3   85.2  11
7    8    Rashard Mendenhall  PIT  RB  324  20.2  1,273  3.9   79.6  13
8    9        Steven Jackson  STL  RB  330  20.6  1,241  3.8   77.6   6
9   10            Frank Gore   SF  RB  203  18.5    853  4.2   77.5   3
10  11     LeGarrette Blount   TB  RB  201  15.5  1,007  5.0   77.5   6
11  12        Ahmad Bradshaw  NYG  RB  276  17.2  1,235  4.5   77.2   8
12  13              Ray Rice  BAL  RB  307  19.2  1,220  4.0   76.2   5
13  14           Ryan Torain  WAS  RB  164  16.4    742  4.5   74.2   4
14  15         Peyton Hillis  CLE  RB  270  16.9  1,177  4.4   73.6  11
15  16          LeSean McCoy  PHI  RB  207  13.8  1,080  5.2   72.0   7
16  17         Cedric Benson  CIN  RB  321  20.1  1,111  3.5   69.4   7
17  18            Matt Forte  CHI  RB  237  14.8  1,069  4.5   66.8   6
18  19 BenJarvus Green-Ellis   NE  RB  229  14.3  1,008  4.4   63.0  13
19  20          Joseph Addai  IND  RB  116  14.5    495  4.3   61.9   4
20  21   LaDainian Tomlinson  NYJ  RB  219  14.6    914  4.2   60.9   6
21  22     DeAngelo Williams  CAR  RB   87  14.5    361  4.1   60.2   1
22  23       Knowshon Moreno  DEN  RB  182  14.0    779  4.3   59.9   5
23  24           Chris Ivory   NO  RB  137  11.4    716  5.2   59.7   5
24  25          Fred Jackson  BUF  RB  222  13.9    927  4.2   57.9   5
25  26        Dominic Rhodes  IND  RB   37  12.3    172  4.6   57.3   0
26  27          Ryan Mathews   SD  RB  158  13.2    678  4.3   56.5   7
27  28          Thomas Jones   KC  RB  245  15.3    896  3.7   56.0   6
28  29      Jonathan Stewart  CAR  RB  178  12.7    770  4.3   55.0   2
29  30        Brandon Jacobs  NYG  RB  147   9.2    823  5.6   51.4   9
..  ...                   ...  ...  ..  ...   ...    ...  ...    ...  ..
13  114          Josh Vaughan  CAR  RB    3   1.0      7  2.3    2.3   1
14  115       Quinton Ganther  BUF  RB    9   1.1     18  2.0    2.2   0
15  115        Ovie Mughelli  ATL  FB   13   0.8     36  2.8    2.2   0
16  117          Jason Wright  ARI  RB    6   0.4     28  4.7    1.9   0
17  118        Spencer Larsen  DEN  FB    3   0.3     18  6.0    1.6   0
18  119       Michael Bennett  OAK  RB    2   0.3     11  5.5    1.6   0
19  119        Tony Fiammetta  CAR  FB    7   0.5     22  3.1    1.6   0
20  121       Rock Cartwright  OAK  RB    9   0.6     22  2.4    1.4   0
21  122      Chris Gronkowski  DAL  FB    5   0.4     17  3.4    1.2   0
22  123       Jehuu Caulcrick  BUF  RB    1   0.5      2  2.0    1.0   0
23  123         Larry Johnson  WAS  RB    5   2.5      2  0.4    1.0   0
```

24	123	Mike Karney	STL	FB	6	0.5	12	2.0	1.0	0
25	126	Tony Richardson	NYJ	FB	5	0.3	13	2.6	0.8	0
26	127	Lawrence Vickers	CLE	FB	5	0.3	11	2.2	0.7	0
27	128	Garrett Wolfe	CHI	RB	4	0.2	8	2.0	0.5	0
28	129	Corey McIntyre	BUF	FB	4	0.2	5	1.3	0.3	1
29	130	Tim Castille	KC	FB	5	0.5	3	0.6	0.3	0
30	131	Greg Jones	JAC	FB	2	0.1	4	2.0	0.2	0
31	132	Cedric Peerman	CIN	RB	2	0.3	1	0.5	0.1	0
32	133	Heath Evans	NO	FB	2	0.1	2	1.0	0.1	0
33	133	Mike Sellers	WAS	FB	4	0.2	2	0.5	0.1	0
34	135	Naufahu Tahi	MIN	FB	1	0.1	1	1.0	0.1	0
35	136	Ahmard Hall	TEN	FB	1	0.1	1	1.0	0.1	0
36	137	Patrick Cobbs	MIA	RB	4	0.2	0	0.0	0.0	0
37	137	Kregg Lumpkin	TB	RB	1	0.1	0	0.0	0.0	0
38	137	Moran Norris	SF	FB	3	0.2	0	0.0	0.0	0
39	137	Chris Pressley	CIN	RB	1	0.2	0	0.0	0.0	0
40	137	Leonard Weaver	PHI	FB	1	1.0	0	0.0	0.0	0
41	142	Antone Smith	ATL	RB	1	0.1	-3	-3.0	-0.3	0
42	143	Devin Moore	IND	RB	2	0.5	-2	-1.0	-0.5	0

	Long	1st Downs	1st Down %	20+	40+	FUM
0	74T	89	27.2	12	3	3
1	37	75	25.1	8	0	2
2	80	70	30.4	10	3	2
3	57T	45	20.2	14	4	3
4	80T	70	24.7	9	2	1
5	55	71	21.3	9	1	2
6	76T	55	17.4	13	4	2
7	50T	61	18.8	11	1	2
8	42T	60	18.2	7	1	1
9	64	42	20.7	6	1	3
10	53	38	18.9	10	3	3
11	48T	61	22.1	13	2	7
12	50	51	16.6	4	1	0
13	54	35	21.3	7	1	2
14	48	57	21.1	5	1	8
15	62	48	23.2	7	5	1
16	26	59	18.4	2	0	7
17	68T	42	17.7	9	2	0
18	33T	62	27.1	4	0	0
19	46	31	26.7	1	1	2
20	31	42	19.2	5	0	2
21	39T	12	13.8	4	0	1
22	35	34	18.7	3	0	3
23	55T	44	32.1	5	1	4
24	39	42	18.9	6	0	4
25	15	8	21.6	0	0	1
26	31T	25	15.8	4	0	4

```
27   70         39        15.9   3   1   3
28   48         32        18.0   5   2   4
29   73         39        26.5  10   1   2
..  ...        ...         ...  ..  ..  ..
13    6          1        33.3   0   0   0
14   11          1        11.1   0   0   0
15    6          7        53.8   0   0   0
16   10          3        50.0   0   0   0
17   14          3       100.0   0   0   0
18    6          0         0.0   0   0   0
19   11          4        57.1   0   0   0
20   10          1        11.1   0   0   0
21    8          2        40.0   0   0   0
22    2          1       100.0   0   0   0
23    7          0         0.0   0   0   0
24    4          3        50.0   0   0   0
25    4          3        60.0   0   0   0
26    3          2        40.0   0   0   0
27    7          0         0.0   0   0   0
28    2          3        75.0   0   0   0
29    3          0         0.0   0   0   0
30    3          0         0.0   0   0   0
31    1          0         0.0   0   0   0
32    2          0         0.0   0   0   0
33    1          1        25.0   0   0   0
34    1          1       100.0   0   0   0
35    1          1       100.0   0   0   0
36    4          0         0.0   0   0   0
37    0          0         0.0   0   0   0
38    1          0         0.0   0   0   0
39    0          0         0.0   0   0   0
40    0          0         0.0   0   0   0
41   -3          0         0.0   0   0   0
42    1          0         0.0   0   0   1

[143 rows x 16 columns]
```

In [14]:
```
# This converts our data frame into a csv file.
df.to_csv('data/NFL_Pro_2010.csv', index = False)
```

Now that we have obtained our CSV file, we should make sure that we can load it into a data frame and once again check for missing values.

In [15]:
```
# Typically we would have the same import statements here as our previous attempts at c
# have already imported our necessary modules earlier, we can leave the import statemen

np_10 = pd.DataFrame.from_csv('data/NFL_Pro_2010.csv', index_col=None, encoding='utf-8'
np_10 = np_10.replace('--', np.nan)
np_10.head()
```

```
Out[15]:    Rk              Player Team Pos  Att  Att/G    Yds  Avg  Yds/G  TD Long  \
        0   1        Arian Foster  HOU  RB  327   20.4  1,616  4.9  101.0  16  74T
        1   2  Maurice Jones-Drew  JAC  RB  299   21.4  1,324  4.4   94.6   5   37
        2   3      Jamaal Charles   KC  RB  230   14.4  1,467  6.4   91.7   5   80
        3   4     Darren McFadden  OAK  RB  223   17.2  1,157  5.2   89.0   7  57T
        4   5     Adrian Peterson  MIN  RB  283   18.9  1,298  4.6   86.5  12  80T

           1st Downs  1st Down %  20+  40+  FUM
        0         89        27.2   12    3    3
        1         75        25.1    8    0    2
        2         70        30.4   10    3    2
        3         45        20.2   14    4    3
        4         70        24.7    9    2    1
```

```
In [18]: np_10_c = np_10.copy()
         np = np_10_c.isnull().sum().sort_values(ascending = False)/len(np_10_c.index)
         np
```

```
Out[18]: FUM           0.0
         40+           0.0
         20+           0.0
         1st Down %    0.0
         1st Downs     0.0
         Long          0.0
         TD            0.0
         Yds/G         0.0
         Avg           0.0
         Yds           0.0
         Att/G         0.0
         Att           0.0
         Pos           0.0
         Team          0.0
         Player        0.0
         Rk            0.0
         dtype: float64
```

Once again, we can see that this data is not missing any information. Thus, our data wrangling is complete, and we can move on to the next section of our project.