LAB03 - TABULAR DATA MANIPULATION

Loading in Data

The first step in any ML problem is identifying what format your data is in, and then loading it into whatever framework you're using. For Kaggle compeitions, a lot of data can be found in CSV files, so that's the example we're going to use.

Since I'm a huge sports fan, we're going to be looking at a sports dataset that shows the results from NCAA basketball games from 1985 to 2016. This dataset is in a CSV file, and the function we're going to use to read in the file is called **pd.read_csv()**. This function returns a **dataframe** variable. The dataframe is the golden jewel data structure for Pandas. It is defined as "a two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns)".

Just think of it as a table for now.

In [1]:

```
import pandas as pd
df = pd.read_csv('data/RegularSeasonCompactResults.csv')
display(df.head())
```

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0
3	1985	25	1165	70	1432	54	H	0
4	1985	25	1192	86	1447	74	H	0

The Basics

Now that we have our dataframe in our variable df, let's look at what it contains. We can use the function **head()** to see the first couple rows of the dataframe (or the function **tail()** to see the last few rows).

In [2]:

```
display(df.head(10))
```

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0
3	1985	25	1165	70	1432	54	H	0
4	1985	25	1192	86	1447	74	H	0
5	1985	25	1218	79	1337	78	H	0
6	1985	25	1228	64	1226	44	N	0
7	1985	25	1242	58	1268	56	N	0
8	1985	25	1260	98	1133	80	H	0
9	1985	25	1305	97	1424	89	H	0

```
In [3]: df.tail(10)
```

Out[3]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
145279	2016	131	1392	80	1436	74	H	0
145280	2016	131	1401	71	1261	38	N	0
145281	2016	131	1419	82	1426	71	N	0
145282	2016	131	1433	76	1172	54	N	0
145283	2016	131	1451	62	1285	59	N	0
145284	2016	132	1114	70	1419	50	N	0
145285	2016	132	1163	72	1272	58	N	0
145286	2016	132	1246	82	1401	77	N	1
145287	2016	132	1277	66	1345	62	N	0
145288	2016	132	1386	87	1433	74	N	0

We can see the dimensions of the dataframe using the the **shape** attribute

```
In [4]: df.shape

Out[4]: (145289, 8)
```

We can also extract all the column names as a list, by using the **columns** attribute and can extract the rows with the **index** attribute

```
In [5]: df.columns.tolist()

Out[5]: ['Season', 'Daynum', 'Wteam', 'Wscore', 'Lteam', 'Lscore', 'Wloc', 'Numot']
```

In order to get a better idea of the type of data that we are dealing with, we can call the **describe()** function to see statistics like mean, min, etc about each column of the dataset.

In [6]:

```
df.describe()
```

Out[6]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Numot
count	145289.000000	145289.000000	145289.000000	145289.000000	145289.000000	145289.000000	145289.000000
mean	2001.574834	75.223816	1286.720646	76.600321	1282.864064	64.497009	0.044387
std	9.233342	33.287418	104.570275	12.173033	104.829234	11.380625	0.247819
min	1985.000000	0.000000	1101.000000	34.000000	1101.000000	20.000000	0.000000
25%	1994.000000	47.000000	1198.000000	68.000000	1191.000000	57.000000	0.000000
50%	2002.000000	78.000000	1284.000000	76.000000	1280.000000	64.000000	0.000000
75%	2010.000000	103.000000	1379.000000	84.000000	1375.000000	72.000000	0.000000
max	2016.000000	132.000000	1464.000000	186.000000	1464.000000	150.000000	6.000000

Okay, so now let's looking at information that we want to extract from the dataframe. Let's say I wanted to know the max value of a certain column. The function **max()** will show you the maximum values of all columns

In [7]:

```
df.max()
```

Out[7]:

```
Season    2016
Daynum     132
Wteam     1464
Wscore     186
Lteam     1464
Lscore     150
Wloc         N
Numot        6
dtype: object
```

Then, if you'd like to specifically get the max value for a particular column, you pass in the name of the column using the bracket indexing operator

In [8]:

```
df['Wscore'].max()
```

Out[8]:

```
186
```

If you'd like to find the mean of the Losing teams' score.

```
In [9]: df['Lscore'].mean()
```

```
Out[9]: 64.49700940883343
```

But what if that's not enough? Let's say we want to actually see the game(row) where this max score happened. We can call the **idmax()** function to identify the row index

```
In [10]: df['Wscore'].idxmax()
```

```
Out[10]: 24970
```

One of the most useful functions that you can call on certain columns in a dataframe is the **value_counts()** function. It shows how many times each item appears in the column. This particular command shows the number of games in each season

```
In [11]: df['Season'].value_counts()
```

```
Out[11]: 2016    5369
         2014    5362
         2015    5354
         2013    5320
         2010    5263
         2012    5253
         2009    5249
         2011    5246
         2008    5163
         2007    5043
         2006    4757
         2005    4675
         2003    4616
         2004    4571
         2002    4555
         2000    4519
         2001    4467
         1999    4222
         1998    4167
         1997    4155
         1992    4127
         1991    4123
         1996    4122
         1995    4077
         1994    4060
         1990    4045
         1989    4037
         1993    3982
         1988    3955
         1987    3915
         1986    3783
         1985    3737
         Name: Season, dtype: int64
```

Acessing Values

Then, in order to get attributes about the game, we need to use the **iloc[]** function. Iloc is definitely one of the more important functions. The main idea is that you want to use it whenever you have the integer index of a certain row that you want to access. As per Pandas documentation, iloc is an "integer-location based indexing for selection by position."

In [12]:
```
df.iloc[[df['Wscore'].idxmax()]]
```

Out[12]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
24970	1991	68	1258	186	1109	140	H	0

Let's take this a step further. Let's say you want to know the game with the highest scoring winning team (this is what we just calculated), but you then want to know how many points the losing team scored.

In [13]:
```
df.iloc[[df['Wscore'].idxmax()]]['Lscore']
```

Out[13]:
```
24970    140
Name: Lscore, dtype: int64
```

When you see data displayed in the above format, you're dealing with a Pandas **Series** object, not a dataframe object.

In [14]:
```
type(df.iloc[[df['Wscore'].idxmax()]]['Lscore'])
```

Out[14]:
```
pandas.core.series.Series
```

In [15]:
```
type(df.iloc[[df['Wscore'].idxmax()]])
```

Out[15]:
```
pandas.core.frame.DataFrame
```

The following is a summary of the 3 data structures in Pandas (Haven't ever really used Panels yet)

When you want to access values in a Series, you'll want to just treat the Series like a Python dictionary, so you'd access the value according to its key (which is normally an integer index)

In [16]:
```
df.iloc[[df['Wscore'].idxmax()]]['Lscore'][24970]
```

Out[16]:
```
140
```

The other really important function in Pandas is the **loc** function. Contrary to iloc, which is an integer based indexing, loc is a "Purely label-location based indexer for selection by label". Since all the games are ordered from 0 to 145288, iloc and loc are going to be pretty interchangable in this type of dataset

In [17]:
```
df.iloc[:3]
```

Out[17]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0

In [18]:
```
df.loc[:3]
```

Out[18]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0
3	1985	25	1165	70	1432	54	H	0

Notice the slight difference in that iloc is exclusive of the second number, while loc is inclusive.

Below is an example of how you can use loc to acheive the same task as we did previously with iloc

In [19]:
```
df.loc[df['Wscore'].idxmax(), 'Lscore']
```

Out[19]:
```
140
```

A faster version uses the **at()** function. At() is really useful wheneever you know the row label and the column label of the particular value that you want to get.

In [20]:
```
df.at[df['Wscore'].idxmax(), 'Lscore']
```

Out[20]:
```
140
```

If you'd like to see more discussion on how loc and iloc are different, check out this great Stack Overflow post: http://stackoverflow.com/questions/31593201/pandas-iloc-vs-ix-vs-loc-explanation (http://stackoverflow.com/questions/31593201/pandas-iloc-vs-ix-vs-loc-explanation). Just remember that **iloc looks at position** and **loc looks at labels**. Loc becomes very important when your row labels aren't integers.

Sorting

Let's say that we want to sort the dataframe in increasing order for the scores of the losing team

In [21]:
```
df.sort_values('Lscore').head()
```

Out[21]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
100027	2008	66	1203	49	1387	20	H	0
49310	1997	66	1157	61	1204	21	H	0
89021	2006	44	1284	41	1343	21	A	0
85042	2005	66	1131	73	1216	22	H	0
103660	2009	26	1326	59	1359	22	H	0

In [22]:
```
df.groupby('Lscore')
```

Out[22]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x000002163D273C18>
```

Filtering Rows Conditionally

Now, let's say we want to find all of the rows that satisy a particular condition. For example, I want to find all of the games where the winning team scored more than 150 points. The idea behind this command is you want to access the column 'Wscore' of the dataframe df (df['Wscore']), find which entries are above 150 (df['Wscore'] > 150), and then returns only those specific rows in a dataframe format (df[df['Wscore'] > 150]).

```
In [23]: df[df['Wscore'] > 150]
```

Out[23]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
5269	1986	75	1258	151	1109	107	H	0
12046	1988	40	1328	152	1147	84	H	0
12355	1988	52	1328	151	1173	99	N	0
16040	1989	40	1328	152	1331	122	H	0
16853	1989	68	1258	162	1109	144	A	0
17867	1989	92	1258	181	1109	150	H	0
19653	1990	30	1328	173	1109	101	H	0
19971	1990	38	1258	152	1109	137	A	0
20022	1990	40	1116	166	1109	101	H	0
22145	1990	97	1258	157	1362	115	H	0
23582	1991	26	1318	152	1258	123	N	0
24341	1991	47	1328	172	1258	112	H	0
24970	1991	68	1258	186	1109	140	H	0
25656	1991	84	1106	151	1212	97	H	0
28687	1992	54	1261	159	1319	86	H	0
35023	1993	112	1380	155	1341	91	A	0
40060	1995	32	1375	156	1341	114	H	0
52600	1998	33	1395	153	1410	87	H	0

This also works if you have multiple conditions. Let's say we want to find out when the winning team scores more than 150 points and when the losing team scores below 100.

In [24]:

```
df[(df['Wscore'] > 150) & (df['Lscore'] < 100)]
```

Out[24]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
12046	1988	40	1328	152	1147	84	H	0
12355	1988	52	1328	151	1173	99	N	0
25656	1991	84	1106	151	1212	97	H	0
28687	1992	54	1261	159	1319	86	H	0
35023	1993	112	1380	155	1341	91	A	0
52600	1998	33	1395	153	1410	87	H	0

Grouping

Another important function in Pandas is **groupby()**. This is a function that allows you to group entries by certain attributes (e.g Grouping entries by Wteam number) and then perform operations on them. The following function groups all the entries (games) with the same Wteam number and finds the mean for each group.

In [25]:

```
df.groupby('Wteam')['Wscore'].mean().head()
```

Out[25]:

```
Wteam
1101    78.111111
1102    69.893204
1103    75.839768
1104    75.825944
1105    74.960894
Name: Wscore, dtype: float64
```

This next command groups all the games with the same Wteam number and finds where how many times that specific team won at home, on the road, or at a neutral site

```
In [26]: df.groupby('Wteam')['Wloc'].value_counts().head(9)
```

```
Out[26]: Wteam  Wloc
         1101   H        12
                A         3
                N         3
         1102   H       204
                A        73
                N        32
         1103   H       324
                A       153
                N        41
         Name: Wloc, dtype: int64
```

Each dataframe has a **values** attribute which is useful because it basically displays your dataframe in a numpy array style format

```
In [27]: df.values
```

```
Out[27]: array([[1985, 20, 1228, ..., 64, 'N', 0],
                [1985, 25, 1106, ..., 70, 'H', 0],
                [1985, 25, 1112, ..., 56, 'H', 0],
                ...,
                [2016, 132, 1246, ..., 77, 'N', 1],
                [2016, 132, 1277, ..., 62, 'N', 0],
                [2016, 132, 1386, ..., 74, 'N', 0]], dtype=object)
```

Now, you can simply just access elements like you would in an array.

```
In [28]: df.values[0][0]
```

```
Out[28]: 1985
```

Dataframe Iteration

In order to iterate through dataframes, we can use the **iterrows()** function. Below is an example of what the first two rows look like. Each row in iterrows is a Series object

In [29]:
```
for index, row in df.iterrows():
    print(row)
    if index == 1:
        break
```

```
Season    1985
Daynum      20
Wteam     1228
Wscore      81
Lteam     1328
Lscore      64
Wloc         N
Numot        0
Name: 0, dtype: object
Season    1985
Daynum      25
Wteam     1106
Wscore      77
Lteam     1354
Lscore      70
Wloc         H
Numot        0
Name: 1, dtype: object
```

Extracting Rows and Columns

The bracket indexing operator is one way to extract certain columns from a dataframe.

```
In [30]: df[['Wscore', 'Lscore']].head()
```

Out[30]:

	Wscore	Lscore
0	81	64
1	77	70
2	63	56
3	70	54
4	86	74

Notice that you can acheive the same result by using the loc function. Loc is a veryyyy versatile function that can help you in a lot of accessing and extracting tasks.

```
In [31]: df.loc[:, ['Wscore', 'Lscore']].head()
```

Out[31]:

	Wscore	Lscore
0	81	64
1	77	70
2	63	56
3	70	54
4	86	74

Note the difference is the return types when you use brackets and when you use double brackets.

```
In [32]: type(df['Wscore'])

Out[32]: pandas.core.series.Series
```

```
In [33]: type(df[['Wscore']])

Out[33]: pandas.core.frame.DataFrame
```

You've seen before that you can access columns through df['col name']. You can access rows by using slicing operations.

In [34]:

```
df[0:3]
```

Out[34]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0

Here's an equivalent using iloc

In [35]:

```
df.iloc[0:3,:]
```

Out[35]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
2	1985	25	1112	63	1223	56	H	0

In [36]:

```
# Extract Data by condition
df[df["Wscore"] > 70].head()
```

Out[36]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1106	77	1354	70	H	0
4	1985	25	1192	86	1447	74	H	0
5	1985	25	1218	79	1337	78	H	0
8	1985	25	1260	98	1133	80	H	0

In [37]:

```
# Extract Data by condition
df[(df["Wscore"] > 70) & (df["Wloc"] == "N")].head()
```

Out[37]:

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
11	1985	25	1344	75	1438	71	N	0
53	1985	27	1228	75	1332	72	N	3
55	1985	27	1268	72	1397	49	N	0
56	1985	27	1314	81	1200	65	N	0

In [38]:

```
# Reset Index of condition data
conditiondf = df[(df["Wscore"] > 70) & (df["Wloc"] == "N")]
print("Original DataFrame")
display(conditiondf.head())

print("Reset Index DataFrame but still keep the original index")
conditiondf01 = conditiondf.reset_index()
display(conditiondf01.head())

print("Reset Index DataFrame but remove original index")
conditiondf02 = conditiondf.reset_index(drop = True)
display(conditiondf02.head())
```

```
Original DataFrame
```

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
11	1985	25	1344	75	1438	71	N	0
53	1985	27	1228	75	1332	72	N	3
55	1985	27	1268	72	1397	49	N	0
56	1985	27	1314	81	1200	65	N	0

```
Reset Index DataFrame but still keep the original index
```

	index	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	0	1985	20	1228	81	1328	64	N	0
1	11	1985	25	1344	75	1438	71	N	0
2	53	1985	27	1228	75	1332	72	N	3
3	55	1985	27	1268	72	1397	49	N	0
4	56	1985	27	1314	81	1200	65	N	0

```
Reset Index DataFrame but remove original index
```

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot
0	1985	20	1228	81	1328	64	N	0
1	1985	25	1344	75	1438	71	N	0
2	1985	27	1228	75	1332	72	N	3
3	1985	27	1268	72	1397	49	N	0
4	1985	27	1314	81	1200	65	N	0

Data Cleaning

One of the big jobs of doing well in Kaggle competitions is that of data cleaning. A lot of times, the CSV file you're given (especially like in the Titanic dataset), you'll have a lot of missing values in the dataset, which you have to identify. The following **isnull** function will figure out if there are any missing values in the dataframe, and will then sum up the total for each column. In this case, we have a pretty clean dataset.

```
In [39]: df.isnull().sum()
```

```
Out[39]: Season    0
         Daynum    0
         Wteam     0
         Wscore    0
         Lteam     0
         Lscore    0
         Wloc      0
         Numot     0
         dtype: int64
```

If you do end up having missing values in your datasets, be sure to get familiar with these two functions.

- **dropna()** - This function allows you to drop all(or some) of the rows that have missing values.
- **fillna()** - This function allows you replace the rows that have missing values with the value that you pass in.

In [41]:

```
# Change the categorical to numeric columns
# Import label encoder
from sklearn import preprocessing
# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()
# Encode labels in column 'species'.
df['Wloc_Number']= label_encoder.fit_transform(df['Wloc'])

print("Wloc distinct values : ",df['Wloc'].unique())
print("Wloc_Number distinct values : ", df['Wloc_Number'].unique())

display(df.head())
```

```
Wloc distinct values :  ['N' 'H' 'A']
Wloc_Number distinct values :  [2 1 0]
```

	Season	Daynum	Wteam	Wscore	Lteam	Lscore	Wloc	Numot	Wloc_Number
0	1985	20	1228	81	1328	64	N	0	2
1	1985	25	1106	77	1354	70	H	0	1
2	1985	25	1112	63	1223	56	H	0	1
3	1985	25	1165	70	1432	54	H	0	1
4	1985	25	1192	86	1447	74	H	0	1

Visualizing Data

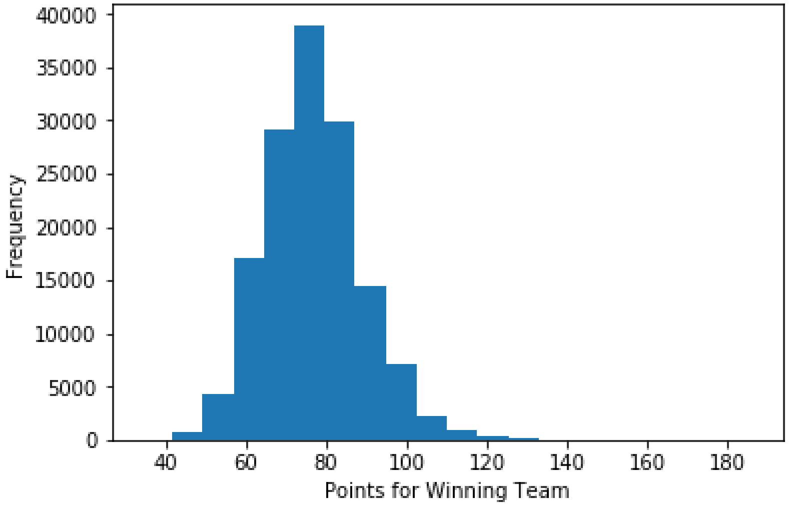
An interesting way of displaying Dataframes is through matplotlib.

In [42]:

```
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [43]: ax = df['Wscore'].plot.hist(bins=20)
         ax.set_xlabel('Points for Winning Team')
```

```
Out[43]: Text(0.5, 0, 'Points for Winning Team')
```



Other Useful Functions

- **drop()** - This function removes the column or row that you pass in (You also have the specify the axis).
- **agg()** - The aggregate function lets you compute summary statistics about each group
- **apply()** - Lets you apply a specific function to any/all elements in a Dataframe or Series
- **get_dummies()** - Helpful for turning categorical data into one hot vectors.
- **drop_duplicates()** - Lets you remove identical rows

Lots of Other Great Resources

Pandas has been around for a while and there are a lot of other good resources if you're still interested on getting the most out of this library.

- http://pandas.pydata.org/pandas-docs/stable/10min.html (http://pandas.pydata.org/pandas-docs/stable/10min.html)
- https://www.datacamp.com/community/tutorials/pandas-tutorial-dataframe-python (https://www.datacamp.com/community/tutorials/pandas-tutorial-dataframe-python)
- http://www.gregreda.com/2013/10/26/intro-to-pandas-data-structures/ (http://www.gregreda.com/2013/10/26/intro-to-pandas-data-structures/)
- https://www.dataquest.io/blog/pandas-python-tutorial/ (https://www.dataquest.io/blog/pandas-python-tutorial/)
- https://drive.google.com/file/d/0ByIrJAE4KMTtTUtiVExiUGVkRkE/view (https://drive.google.com/file/d/0ByIrJAE4KMTtTUtiVExiUGVkRkE/view)
- https://www.youtube.com/playlist?list=PL5-da3qGB5ICCsgW1MxlZ0Hq8LL5U3u9y (https://www.youtube.com/playlist?list=PL5-da3qGB5ICCsgW1MxlZ0Hq8LL5U3u9y)