02_DataFrame

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0.1 Structure of Data Frames

We have seen that pandas data frames have a spreadsheet like structure with the following characteristics:

- **columns** correspond to different variables and have a single type, either numerical (integer, floating point, complex) or categorical (character strings or boolean).
- **rows** are labeled by an **index** that identifies individual elements, which may be subjects, different time points, subject visits at different time points, products, or any other basic unit under study.

This basic spreadsheet structure is made abundently clear by how we can use the pandas .read_csv function to read an Excel-style comma separated file directly into a pandas data frame.

We have also seen that there are other functions that operate on data frames either to extract their attributes (e.g. the pandas .head() function) or perform other operations like summing, averaging or graphing.

In this section we delve further into the data frame structure, investigating:

- How to build up data frames from simpler objects;
- How to import and export data files;
- How to extract subsets of the data and refer to individual elements in a data frame;
- How to add new data;
- How to combine data from multiple sources;
- How to sort data by specific variables in the data frame.
- How missing data are represented, and how we can process them.

0.1.1 Building a data frame from scratch

[1]:
```
import pandas as pd
```

[2]:
```
courses = ['cs105', 'stat107', 'stat207', 'adv307', 'hist407']
enrollment = [345, 197, 53, 38, 26]
print(courses, enrollment)
```

```
['cs105', 'stat107', 'stat207', 'adv307', 'hist407'] [345, 197, 53, 38, 26]
```

We can bundle these arrays into a data frame as in the example below. Pay close attention to the different types of brackets.

- '( )' enclose function arguments
- '[ ]' enclose elements in a *list* or *array*
- '{ }' enclose elements in a *dictionary* {'key1': value1, 'key2': value2, ...}

[3]:
```
littledf = pd.DataFrame({'course': courses, 'enrolled': enrollment})
littledf
```

[3]:
```
    course  enrolled
0    cs105       345
1  stat107       197
2  stat207        53
3   adv307        38
4  hist407        26
```

[4]:
```
littledf['college'] = ['ENGR', 'LAS', 'LAS', 'MEDIA', 'LAS']
littledf
```

[4]:
```
    course  enrolled college
0    cs105       345    ENGR
1  stat107       197     LAS
2  stat207        53     LAS
3   adv307        38   MEDIA
4  hist407        26     LAS
```

0.1.2 Reading external files into data frames

Often data reside in a structured file such as a comma separated variables (.csv) file, tab separated file, or Excel spreadsheet, and we wish to read the data into Python for data processing and analytics. For example, in the same folder as this notebook, the file 'USmelanoma.csv' contains state level summary data on male melanoma mortality rates (per million) from 1950-1967. The first few lines of the file look like this:

```
"state","mortality","latitude","longitude","ocean"
"Alabama",219,33,87,"yes"
"Arizona",160,34.5,112,"no"
"Arkansas",170,35,92.5,"no"
"California",182,37.5,119.5,"yes"
"Colorado",149,39,105.5,"no"
...
```

Using the pandas read_csv command we can read this into a data frame as follows, assuming we previously imported the pandas library as 'pd':

[5]:
```
df = pd.read_csv('USmelanoma.csv')
```

Here are the first few lines of the imported data:

[6]:
```
df.head(6)
```

[6]:
```
         state  mortality  latitude  longitude ocean
0      Alabama        219      33.0       87.0   yes
1      Arizona        160      34.5      112.0    no
2     Arkansas        170      35.0       92.5    no
3   California        182      37.5      119.5   yes
4     Colorado        149      39.0      105.5    no
5  Connecticut        159      41.8       72.8   yes
```

Note the .function(arguments) syntax, which is characteristic of many operations on pandas data objects.

0.1.3 Exporting data frames to external files

The reverse operation is to write an internal data frame to an external file, perhaps after some data processing to merge data from multiple sources. Here we export the 'littledf' data to an external csv file using the pandas.DataFrame.to_csv function.

[7]:
```
littledf.to_csv('courses.csv')
```

0.1.4 Conditional extraction of data subsets

How can we extract data for LAS courses only? First, observe how we can check each course for whether or not it is an LAS course with an array operation:

[8]:
```
littledf['college']=='LAS'
```

[8]:
```
0    False
1     True
2     True
3    False
4     True
Name: college, dtype: bool
```

The data frame can take this boolean array as a condition for selecting rows:

[9]:
```
littledf[littledf['college']=='LAS']
```

[9]:
```
    course  enrolled college
1  stat107       197     LAS
2  stat207        53     LAS
4  hist407        26     LAS
```

What if we only want the enrollments of the LAS courses?

[10]:
```
littledf[littledf['college']=='LAS']['enrolled']
```

[10]:
```
1    197
2     53
4     26
Name: enrolled, dtype: int64
```

Why does this work? Extracting the three row data frame for LAS courses only gives us a shorter three-column data frame. We can refer to the 'enrolled' column of this short data frame in the same way as for the taller original.

By similar logic, we could have gotten to the same result by a different path as follows:

[11]:
```
littledf['enrolled'][littledf['college']=='LAS']
```

[11]:
```
1    197
2     53
4     26
Name: enrolled, dtype: int64
```

How about a different type of condition, like extracting all the courses with enrollments of at least 50?

[12]:
```
littledf[littledf['enrolled']>=50]
```

[12]:

	course	enrolled	college
0	cs105	345	ENGR
1	stat107	197	LAS
2	stat207	53	LAS

Or extracting the courses with enrollments less than 50?

[13]:
```
littledf[littledf['enrolled']<50]
```

[13]:

	course	enrolled	college
3	adv307	38	MEDIA
4	hist407	26	LAS

We can extract the record corresponding to a particular course:

[14]:
```
littledf[littledf['course']=='adv307']
```

[14]:

	course	enrolled	college
3	adv307	38	MEDIA

0.1.5 Pandas functions and data subsets

The subsetted data inherits data frame features. Therefore in many cases we can apply pandas functions to the extracted data. For example, suppose we want the total enrollment in the LAS classes. Below is one way to get it, using the .sum() function. It is good practice to label results, so we use a print statement do do that here.

[15]:
```
print("Enrollment = ",
      littledf[littledf['college']=='LAS']['enrolled'].sum()
     )
```

```
Enrollment =  276
```

We can also use pandas functions to define subsets. Let's find the maximum course enrollment.

[16]:
```
print("Maximum Enrollment = ", littledf['enrolled'].max())
```

```
Maximum Enrollment =  345
```

Which course(s) had the maximum enrollment?

[17]:
```python
littledf[littledf['enrolled']==littledf['enrolled'].max()]
```

[17]:
```
  course  enrolled college
0  cs105       345    ENGR
```

0.1.6 Data subset slicing by index and column number

Using the **.iloc** (index location) attribute, we can refer to specific elements or "slices" of elements in the data frame.

Here, again, is our sample data frame in full:

[18]:
```python
littledf
```

[18]:
```
    course  enrolled college
0    cs105       345    ENGR
1  stat107       197     LAS
2  stat207        53     LAS
3   adv307        38   MEDIA
4  hist407        26     LAS
```

In this 5 x 3 array the rows are numbered 0, 1, . . . , 4 and the columns are numbered 0,1,2. We can extract the upper left element using .iloc:

[19]:
```python
littledf.iloc[0,0]
```

[19]:
```
'cs105'
```

We extract the element in row 3, column 2 as:

[20]:
```python
littledf.iloc[3,2]
```

[20]:
```
'MEDIA'
```

We can extract a slice of more than one element using the sequence notation i:j:k to refer to indices running from i to j-k using step-size k. If we leave out the step it is assumed k=1. If we leave out the range elements the sequence covers the whole range.

Here's an example where we can extract the middle three rows of the data frame. Note that "1:4" results in the inclusion of rows 1, 2 and 3 but not 4!

[21]:
```python
littledf.iloc[1:4,:]
```

[21]:
```
    course  enrolled college
1  stat107       197     LAS
2  stat207        53     LAS
3   adv307        38   MEDIA
```

If we wanted to include rows 0-3 we can use the sequence ":4", which includes all rows before the row with index=4.

[22]:
```python
littledf.iloc[:4,:]
```

[22]:
```
    course  enrolled college
0    cs105       345    ENGR
1  stat107       197     LAS
2  stat207        53     LAS
3   adv307        38   MEDIA
```

If, on the other hand, we wished to include all rows after rows 0 and 1 the sequence "2:" will do this.

[23]:
```
littledf.iloc[2:,:]
```

[23]:

	course	enrolled	college
2	stat207	53	LAS
3	adv307	38	MEDIA
4	hist407	26	LAS

[24]:
```
littledf.iloc[[0,1,2,4],:]
```

[24]:

	course	enrolled	college
0	cs105	345	ENGR
1	stat107	197	LAS
2	stat207	53	LAS
4	hist407	26	LAS

0.1.7 Adding data: concatenation

Suppose we had more enrollment data to add to the data frame, for additional courses. We can use the pandas **concat** funtion to combine the original data frame with a new data frame containing the additional records. Here we create a new data frame with the hypothetical new data.

[25]:
```
moredf = pd.DataFrame({'course': ['math277', 'is417'],
                       'enrolled': [41, 43],
                       'college': ['LAS', 'IS']})
```

Here are the original data frame and the data we wish to add:

[26]:
```
display(littledf, moredf)
```

	course	enrolled	college
0	cs105	345	ENGR
1	stat107	197	LAS
2	stat207	53	LAS
3	adv307	38	MEDIA
4	hist407	26	LAS

	course	enrolled	college
0	math277	41	LAS
1	is417	43	IS

Next we combine them, and specify to ignore the original index values and create a new index for the combined data.

[27]:
```
fulldf = pd.concat([littledf, moredf], ignore_index=True)
#fulldf = pd.concat([littledf, moredf])  # uncomment to see the difference
fulldf
```

[27]:
```
     course  enrolled college
0     cs105       345     ENGR
1   stat107       197      LAS
2   stat207        53      LAS
3    adv307        38    MEDIA
4   hist407        26      LAS
5   math277        41      LAS
6     is417        43       IS
```

A quick way to add new records is using the **append()** function.

[28]:
```
newdf = pd.DataFrame({'course': ['badm210'],
                      'enrolled': [215],
                      'college': ['BUSN']})
updateddf = fulldf.append(newdf, ignore_index=True)
display(newdf, updateddf)
```

```
    course  enrolled college
0  badm210       215    BUSN
```

```
    course  enrolled college
0    cs105       345    ENGR
1  stat107       197     LAS
2  stat207        53     LAS
3   adv307        38   MEDIA
4  hist407        26     LAS
5  math277        41     LAS
6    is417        43      IS
7  badm210       215    BUSN
```

0.1.8 Merging data frames

Another common scenario is to have more than one source of data on different variables, and we wish to combine data sets for further analysis. As an example, suppose in the previous course list example we had another source with the credit hours for each class. We'd like to add this information.

[29]:
```
creditdf = pd.DataFrame({'course': ['adv307', 'cs105', 'stat107', 'stat207',
                                    'hist407', 'math277', 'is417', 'badm210'],
                         'credit': [3.0, 3.0, 4.0, 3.0, 4.0, 5.0, 3.0, 3.0]})
creditdf
```

[29]:
```
    course  credit
0   adv307     3.0
1    cs105     3.0
2  stat107     4.0
3  stat207     3.0
4  hist407     4.0
5  math277     5.0
```

```
6    is417     3.0
7  badm210     3.0
```

In this case, we can do a one-to-one join between the two data frames using the pandas **merge()** function. Notice that the order of the courses does not need to be the same; the records are matched based on the shared course name.

[30]:
```
fullerdf = pd.merge(updateddf, creditdf)
fullerdf
```

[30]:
```
    course  enrolled college  credit
0    cs105       345    ENGR     3.0
1  stat107       197     LAS     4.0
2  stat207        53     LAS     3.0
3   adv307        38   MEDIA     3.0
4  hist407        26     LAS     4.0
5  math277        41     LAS     5.0
6    is417        43      IS     3.0
7  badm210       215    BUSN     3.0
```

Often the two data sources will not be in one-to-one correspondence between their records. Then we might need to perform and "many-to-one" merge.

Example: In one data source we have courses and section enrollments. In the other data source we have courses and credit hours. Let's combine them. First we'll create a data frame with the section information.

[31]:
```
courses = ['cs105', 'cs105', 'stat107', 'badm210', 'badm210']
sections = ['A', 'B', 'A', 'A', 'B']
enrollments = [345, 201, 197, 215, 197]
sectdf = pd.DataFrame({'course': courses,
                       'section': sections,
                       'enrolled': enrollments})
sectdf
```

[31]:
```
    course section  enrolled
0    cs105       A       345
1    cs105       B       201
2  stat107       A       197
3  badm210       A       215
4  badm210       B       197
```

We'd like to merge this with the credit information:

[32]:
```
creditdf
```

[32]:
```
    course  credit
0   adv307     3.0
1    cs105     3.0
2  stat107     4.0
3  stat207     3.0
4  hist407     4.0
5  math277     5.0
6    is417     3.0
```

```
7  badm210     3.0
```

We can try a "default" merge and see what we get:

[33]:
```
pd.merge(sectdf, creditdf)
```

[33]:
```
    course section  enrolled  credit
0    cs105       A       345     3.0
1    cs105       B       201     3.0
2  stat107       A       197     4.0
3  badm210       A       215     3.0
4  badm210       B       197     3.0
```

Did it work? Yes, in the sense that all course sections in the first data frame have now been assigned credit hours. Any course that appears in both data sources gets matched. The courses missing from one or the other we not included.

In some cases we need to specify which variable to use as the matching **key** using the **on=** option:

[34]:
```
pd.merge(sectdf, creditdf, on='course')
```

[34]:
```
    course section  enrolled  credit
0    cs105       A       345     3.0
1    cs105       B       201     3.0
2  stat107       A       197     4.0
3  badm210       A       215     3.0
4  badm210       B       197     3.0
```

0.1.9 Sorting data by specific columns in the Data Frame

In the examples we've been considering, the course names are in no particular order. What if we want the courses to be in alphanumeric order? pandas has a function for that: **.sort_values**. For the syntax see: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.sort_values.html

To select a specific column on which to sort we use the **by=** option as in the following example:

[35]:
```
creditdf
```

[35]:
```
    course  credit
0   adv307     3.0
1    cs105     3.0
2  stat107     4.0
3  stat207     3.0
4  hist407     4.0
5  math277     5.0
6    is417     3.0
7  badm210     3.0
```

[36]:
```
creditdf.sort_values(by='course')
```

[36]:
```
    course  credit
0   adv307     3.0
7  badm210     3.0
```

```
1    cs105     3.0
4  hist407     4.0
6    is417     3.0
5  math277     5.0
2  stat107     4.0
3  stat207     3.0
```

Remarks:

1. We can specify more than one variable for sorting, and we can also select various other options such as "ascending=False" (default is "ascending=True"), where to put NaNs in the ordering ("na_position='last'), and whether to sort in-place (overwriting the original object).
2. This operation did **not** replace the original data with sorted data, it merely displayed the sorted data. If we wanted to save this we assign to a new pandas object, or we can sort "in place" as illustrated below.

Here we see the effect of in-place sorting.

[37]:
```
creditdf.sort_values(by='course', inplace=True)  # sorting in place and␣
↪replacing original
```

[38]:
```
creditdf   # now the original is in sorted order
```

[38]:
```
    course  credit
0   adv307     3.0
7  badm210     3.0
1    cs105     3.0
4  hist407     4.0
6    is417     3.0
5  math277     5.0
2  stat107     4.0
3  stat207     3.0
```

As a different application, here we sort class sections by enrollment, from highest to lowest.

[39]:
```
sectdf.sort_values(by='enrolled', ascending=False)
```

[39]:
```
    course section  enrolled
0    cs105       A       345
3  badm210       A       215
1    cs105       B       201
2  stat107       A       197
4  badm210       B       197
```

0.1.10 Application: compare melanoma mortality rates across different states

Earlier we imported 'USmelanoma.csv' into the data frame 'df'.

[40]:
```
df.head()
```

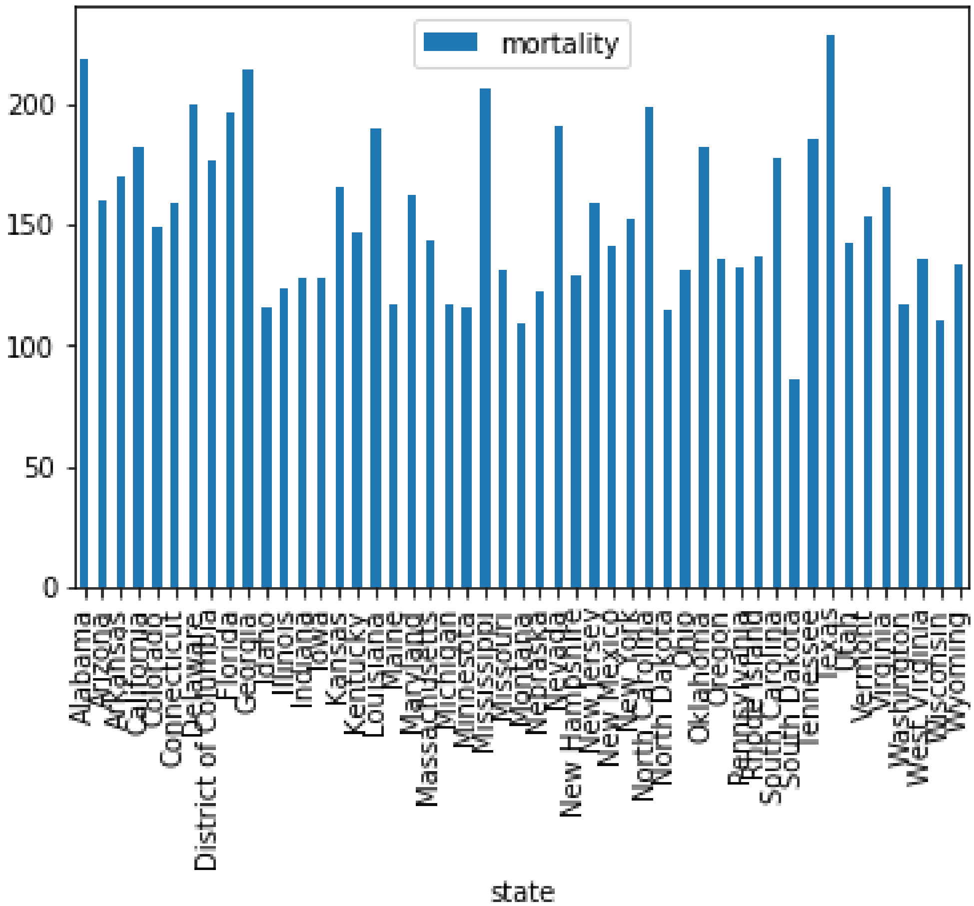
[40]:
```
         state  mortality  latitude  longitude ocean
0      Alabama        219      33.0       87.0   yes
1      Arizona        160      34.5      112.0    no
```

```
2    Arkansas        170      35.0       92.5    no
3  California        182      37.5      119.5   yes
4    Colorado        149      39.0      105.5    no
```

Let's plot mortality rates across different states, in alphabetical order.

[41]:
```python
import matplotlib.pyplot as plt
```

[42]:
```python
df.plot.bar(x='state', y='mortality')
plt.show()
```



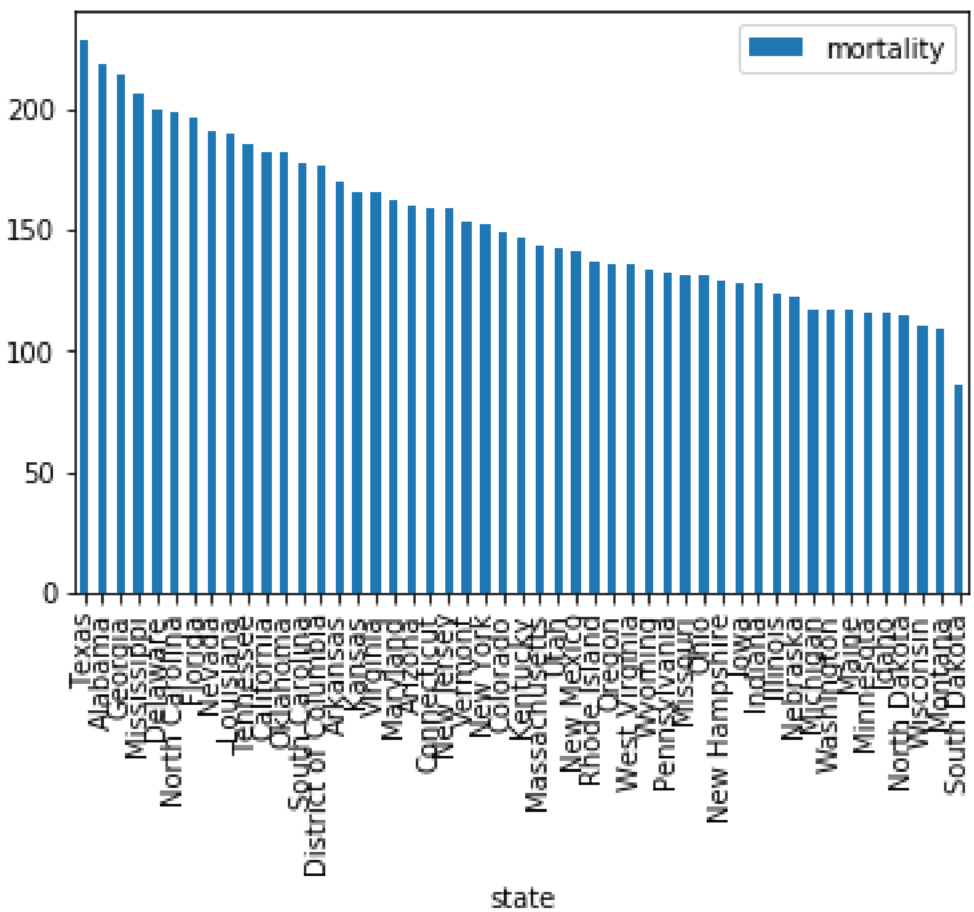
It will be easier to compare if we sort by mortality rates.

[43]:
```python
dfsorted = df.sort_values(by='mortality', ascending=False)
dfsorted.head()
```

[43]:
```
          state  mortality  latitude  longitude ocean
41        Texas        229      31.5       98.0   yes
0       Alabama        219      33.0       87.0   yes
9       Georgia        214      33.0       83.5   yes
22  Mississippi        207      32.8       90.0   yes
```

```
6      Delaware        200      39.0        75.5    yes
```

[44]:
```python
dfsorted.plot.bar(x='state', y='mortality')
plt.show()
```



0.1.11 Handling missing data

Missing data are very common in real data applications. How can we handle them at a basic level? To illustrate, consider the hypothetical section enrollment data. We'll make one element go missing.

[45]:
```python
tmp = sectdf  # copy of data frame
tmp
```

[45]:

	course	section	enrolled
0	cs105	A	345
1	cs105	B	201
2	stat107	A	197
3	badm210	A	215

```
4  badm210        B       197
```

```
[46]: tmp['enrolled'][4]   # Access the enrollment for badm210 section B
```

```
[46]: 197
```

```
[47]: tmp.iloc[4,2] # another way to access
```

```
[47]: 197
```

```
[48]: tmp.iloc[4,2] = None    # coding this element as missing
      tmp
```

```
[48]:     course section  enrolled
      0    cs105       A     345.0
      1    cs105       B     201.0
      2  stat107       A     197.0
      3  badm210       A     215.0
      4  badm210       B       NaN
```

We see that the missing value is encoded as NaN (not a number).

What if we wanted to sort by enrollment? We need to specify whether missing values go first or last on the list.

```
[49]: tmp.sort_values(by='enrolled', na_position='first')
```

```
[49]:     course section  enrolled
      4  badm210       B       NaN
      2  stat107       A     197.0
      1    cs105       B     201.0
      3  badm210       A     215.0
      0    cs105       A     345.0
```

By default, many functions will skip data with missing values. Often this makes sense, but not always!

```
[50]: tmp['enrolled'].sum()
```

```
[50]: 958.0
```

The 'DataFrame.isna' function can scan a data frame for missing values. 'DataFrame.notna' scans for non-missing values.

```
[51]: tmp.isna()
```

```
[51]:   course  section  enrolled
      0  False    False     False
      1  False    False     False
      2  False    False     False
      3  False    False     False
      4  False    False      True
```

If we want to analyze only the data with complete information the 'DataFrame.dropna' function can extract the complete data for us.

```
[52]: tmp.dropna()
```

[52]:

	course	section	enrolled
0	cs105	A	345.0
1	cs105	B	201.0
2	stat107	A	197.0
3	badm210	A	215.0

STAT 207, Douglas Simpson, University of Illinois at Urbana-Champaign