



# **COMP9321 Data Services Engineering**

**Term1, 2020**

**Week 3: Data Pre-processing**

# Removing Unnecessary Data

- Some times you don't need all the data in the tables so it might help you achieve better performance if you remove the irrelevant data.
- Some columns or rows might be useless for you in the analysis due to having many missing values and replacing them with default values would produce wrong insights.
- Sometimes you are restricted from storage capacity perspective and hence you need to keep what is relevant to the job and drop the others.
- Python has a very good function `Drop()` to help you with this

# Dropping Columns/Raws with NaN values

- Dropping Columns with all NaN values

Example:

				data.dropna(axis=1, how='all')		
ohio Colorado Utah				Colorado Utah		
0	NaN	12	11	0	12	11
1	NaN	33	7	1	33	7
2	NaN	44	4	2	44	4
3	NaN	32	22	3	32	22

# Dropping Columns/Raws with NaN values

- Dropping Raws with all NaN values

```
data2.dropna(axis=0, how='all')
```

Example:

	ohio	Colorado	Utah
0	NaN	NaN	NaN
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

	ohio	Colorado	Utah
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

# Dropping Columns that are not needed

Example:

	ohio	Colorado	Utah
0	NaN	NaN	NaN
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

```
to_drop = ['ohio', 'Utah']
```

```
data2.drop(to_drop, inplace=True,  
axis=1)
```

Colorado

1	33.0
2	44.0
3	32.0

# Dropping Rows on a Condition

- To drop a row based on a condition you use  
`df = df.drop(df[<some boolean condition>].index)`

Example:

	ohio	Colorado	Utah
0	32	0	10.0
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

```
df.drop(df[df.Colorado == 0].index,  
inplace=True)
```

	ohio	Colorado	Utah
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

# Dropping Duplicate Rows

- To drop duplicate rows we use `drop_duplicates` function

Example:

	ohio	Colorado	Utah
0	32	0	10.0
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0
4	12.0	33.0	7.0

`df.drop_duplicates()`

	ohio	Colorado	Utah
0	32	0	10.0
1	12.0	33.0	7.0
2	23.0	44.0	4.0
3	34.0	32.0	22.0

# Formatting data

- Data read from source may not have the correct format (e.g., reading integer as a string)
- Some strings in the data have spacing which might not play well with your analysis at some point.
- The date/time format may not appropriate for your analysis
- Some times the data is generated by a computer program, so it probably has some computer-generated column names, too. Those can be hard to read and understand while working.



# Formatting data Examples

- Example1 (change data type on read):

```
df = pd.read_csv('mydata.csv', dtype={'Integer_Column': int})
```

- Example2 (change data type in dataframe)

```
df['column'] = df['column'].to_numeric()
```

```
df['column'] = df['column'].astype(str)
```

- Example3 (Spacing within the values):

```
data['Column_with_spacing'].str.strip()
```

# Formatting data Examples

- Example4 (unnecessary time item in the date field):

```
df['MonthYear'] = pd.to_datetime(df['MonthYear'])
```

```
df['MonthYear'] = df['MonthYear'].apply(lambda x: x.date())
```

- Example5 (rename columns)

```
data = data.rename(columns = {'Bad_Name1':Better_Name1',  
'Bad_Name2':Better_name2'})
```

# Manipulating the data

- Merging Data
- Applying a function to data
- Pivot tables
- Change the index of a dataframe
- Groupby

# Merging Data

- Sometimes in order to have complete dataset you need to Concatenate two datasets when reading from source.

Example:

```
Dataset1=pd.read_csv('datasets/project1/dataset1.csv')
```

```
Dataset2=pd.read_csv('datasets/project1/dataset2.csv')
```

```
Full_data=pd.concat[Dataset1, Dataset2] axis=0, ignore_index=True)
```

# Merging Data (Cont'd)

- Sometimes in order to have complete dataset you need to merge two Dataframes

	state	population_2016
0	California	39250017
1	Texas	27862596
2	Florida	20612439
3	New York	19745289

	name	ANSI
0	California	CA
1	Florida	FL
2	New York	NY
3	Texas	TX

# Merging Data (Cont'd)

```
In [1]: pd.merge(left=state_populations, right=state_codes,  
...:             on=None, left_on='state', right_on='name')
```

```
Out[1]:
```

	state	population_2016	name	ANSI
0	California	39250017	California	CA
1	Texas	27862596	Texas	TX
2	Florida	20612439	Florida	FL
3	New York	19745289	New York	NY

# Patching your Data

`combine_first` can do some sort of “patching” missing data in the calling object with data from the object you pass

```
In [91]: df1 = DataFrame({'a': [1., np.nan, 5., np.nan],  
.....:                  'b': [np.nan, 2., np.nan, 6.],  
.....:                  'c': range(2, 18, 4)})
```

```
In [92]: df2 = DataFrame({'a': [5., 4., np.nan, 3., 7.],  
.....:                  'b': [np.nan, 3., 4., 6., 8.]})
```

```
In [93]: df1.combine_first(df2)
```

```
Out[93]:
```

	a	b	c
0	1	NaN	2
1	4	2	6
2	5	4	10
3	3	6	14
4	7	8	NaN

# Applying a function to the entire dataset

- Sometimes You need to apply a function on the level of the entire dataset (e.g., removing, adding, averaging)

```
def cleaning_function(row_data):  
    # Computation steps  
    # Computation steps  
df.apply(cleaning_function, axis=1)
```



# Applying a Function to Columns

- Sometimes You need to apply a function on the level of Columns

Example:

```
1 Original Dataframe
2   x y z
3 a 22 34 23
4 b 33 31 11
5 c 44 16 21
6 d 55 32 22
7 e 66 33 27
8 f 77 35 11
```

```
1 # Apply a function to one column and assign it back to
2 the column in dataframe
   df['z'] = df['z'].apply(np.square, axis=1)
```

```
1   x y z
2 a 22 34 529
3 b 33 31 121
4 c 44 16 441
5 d 55 32 484
6 e 66 33 729
7 f 77 35 121
8
```

# Pivot Tables

- Summary tables
- Introduce new columns from calculations
- Table can have multiple Indexes
- Excel is famous for it

# Pivot Table Example

```
>>> df = pd.DataFrame({"A": ["foo", "foo", "foo", "foo", "foo",  
...                          "bar", "bar", "bar", "bar"],  
...                    "B": ["one", "one", "one", "two", "two",  
...                          "one", "one", "two", "two"],  
...                    "C": ["small", "large", "large", "small", "small",  
...                          "small", "large", "small", "small",  
...                          "large"],  
...                    "D": [1, 2, 2, 3, 3, 4, 5, 6, 7]})  
>>> df
```

	A	B	C	D
0	foo	one	small	1
1	foo	one	large	2
2	foo	one	large	2
3	foo	two	small	3
4	foo	two	small	3
5	bar	one	large	4
6	bar	one	small	5
7	bar	two	small	6
8	bar	two	large	7

# Pivot Table Example

```
>>> table = pivot_table(df, values='D', index=['A', 'B'],  
...                      columns=['C'], aggfunc=np.sum)  
>>> table
```

		large	small
A	B		
bar	one	4.0	5.0
	two	7.0	6.0
foo	one	4.0	1.0
	two	NaN	6.0

# Groupby

- Groupby splits the data into different groups depending on a variable of your choice.
- The output from a groupby and aggregation operation is it a Pandas Series or a Pandas Dataframes?
  - As a rule of thumb, if you calculate more than one column of results, your result will be a Dataframe. For a single column of results, the agg function, by default, will produce a Series.

# Groupby Example

- If our dataset is tweets extracted from Twitter and we want to group all the tweets by the username and count the number of tweets each user has

```
Our_grouped_tweets= df.groupby('username') ['tweets'].count()
```

# Indexing the Dataframe

- Sometimes it is helpful to use a uniquely valued identifying field of the data as its index
  - How to check uniqueness? (`df['Unique_column'].is_unique`)
  - How to set the index? (`df = df.set_index(' Unique_column')`)
  - Is it necessary to have unique vales in column? No, but it will affect the performance
- Pandas supports three types of Multi-axes indexing:
  - `.loc()`      Label based
  - `.iloc()`      Integer based
  - `.ix()`      Both Label and Integer based

# Sorting Data

- Sometimes it is required to sort the data according to one or multiple columns.
- Pandas allow this using the function `.sort_values()`

Example:

```
df = pd.DataFrame({'col1' : ['A', 'A', 'B', np.nan, 'D', 'C'], 'col2' : [2, 1, 9, 8, 7, 4], 'col3': [0, 1, 9, 4, 2, 3]})
```

```
df.sort_values(by=['col1'])
```

	col1	col2	col3
0	A	2	0
1	A	1	1
2	B	9	9
5	C	4	3
4	D	7	2
3	NaN	8	4



# Questions?

# Useful Read

- Python for Data Analysis, Wes McKinney
- <https://www.altexsoft.com/blog/datascience/preparing-your-dataset-for-machine-learning-8-basic-techniques-that-make-your-data-better/>
- <https://pandas.pydata.org/pandas-docs/stable/tutorials.html>
- <https://www.analyticsvidhya.com/blog/2016/01/12-pandas-techniques-python-data-manipulation/>
- <https://www.dataquest.io/blog/machine-learning-preparing-data/>
- <https://thispointer.com/pandas-apply-a-function-to-single-or-selected-columns-or-rows-in-dataframe/>
- <https://datacarpentry.org/python-ecology-lesson/05-merging-data/index.html>