Illinois Data Science Club

Basics of Python

Application of Data Science

Business & Finance:

- Customer Analytics: Businesses use data science to analyze customer behavior, preferences, and purchasing patterns to optimize marketing strategies and improve customer experiences.
- Risk Assessment: Data science models evaluate credit risk, fraud detection, and market trends to inform investment decisions.

Healthcare:

- Predictive Analytics: Data science is used to predict disease outbreaks, patient admissions, and trends in patient health, improving resource allocation and planning.

Application of Data Science

Computer Science:

- Natural Language Processing (NLP): Data science techniques power language understanding, sentiment analysis, and chatbots.
- Machine Learning: Computer science employs data science to develop algorithms for tasks like image recognition, recommendation systems, and fraud detection.

Psychology:

- Behavioral Analysis: Data science helps analyze human behavior patterns from experiments, surveys, and digital interactions.

Application of Data Science

Statistics and Mathematics:

- Statistical Analysis: Data science extends traditional statistical methods to analyze large and complex datasets for insights.
- Regression Analysis: Statistical modeling is used to understand relationships between variables, making predictions and inferences.

Autonomous Vehicles:

- Data science plays a critical role in self-driving cars by processing data from sensors such as cameras and radar to make real-time decisions.
- Machine learning models analyze road conditions, predict the behavior of other vehicles, and control the vehicle's movements.

Application of Data Science

Netflix's Recommendation System:

- Netflix uses data science to analyze users' viewing history, preferences, and ratings to recommend movies and TV shows tailored to individual tastes.
- Collaborative filtering and machine learning algorithms suggest content similar to what users have watched or liked.

Amazon's Shopping Recommendation:

- Amazon's recommendation system employs data science to analyze users' browsing and purchasing behavior to suggest products they might be interested in.
- This system uses techniques like collaborative filtering, item-based filtering, and deep learning models to improve product recommendations.

PYTHON

Data Wrangling with pandas Cheat Sheet

http://pandas.pydata.org

Pandas API Reference Pandas User Guide

Creating DataFrames

	a	b	c
1	4	7	10
2	5	8	11
3	6	9	12

```
df = pd.DataFrame(
        {"a" : [4, 5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
      index = [1, 2, 3])
```
Specify values for each column.

```
df = pd.DataFrame(
     [[4, 7, 10],
      [5, 8, 11],
      [6, 9, 12]],
     index=[1, 2, 3],
     columns=['a', 'b', 'c'])
```
Specify values for each row.

		a	b	c
N	v			
D	1	4	7	10
	2	5	8	11
e	2	6	9	12

```
df = pd.DataFrame(
        {"a" : [4 ,5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
      [('d', 1), ('d', 2),
       ('e', 2)], names=['n', 'v']))
```
Create DataFrame with a MultiIndex

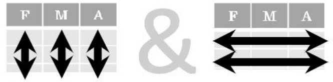
Method Chaining

Most pandas methods return a DataFrame so that another pandas method can be applied to the result. This improves readability of code.

```
df = (pd.melt(df)
      .rename(columns={
              'variable':'var',
              'value':'val'})
      .query('val >= 200')
     )
```

Tidy Data – A foundation for wrangling in pandas

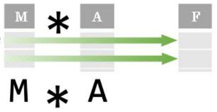
In a tidy data set:



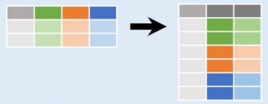
Each **variable** is saved in its own **column**

Each **observation** is saved in its own **row**

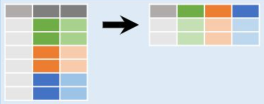
Tidy data complements pandas's **vectorized operations**. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas.



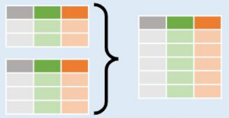
Reshaping Data – Change layout, sorting, reindexing, renaming



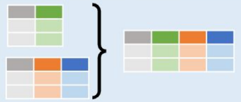
`pd.melt(df)`
Gather columns into rows.



`df.pivot(columns='var', values='val')`
Spread rows into columns.



`pd.concat([df1,df2])`
Append rows of DataFrames



`pd.concat([df1,df2], axis=1)`
Append columns of DataFrames

`df.sort_values('mpg')`
Order rows by values of a column (low to high).

`df.sort_values('mpg', ascending=False)`
Order rows by values of a column (high to low).

`df.rename(columns = {'y':'year'})`
Rename the columns of a DataFrame

`df.sort_index()`
Sort the index of a DataFrame

`df.reset_index()`
Reset index of DataFrame to row numbers, moving index to columns.

`df.drop(columns=['Length', 'Height'])`
Drop columns from DataFrame

Subset Observations - rows

`df[df.Length > 7]`
Extract rows that meet logical criteria.

`df.drop_duplicates()`
Remove duplicate rows (only considers columns).

`df.sample(frac=0.5)`
Randomly select fraction of rows.

`df.sample(n=10)` Randomly select n rows.

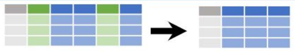
`df.nlargest(n, 'value')`
Select and order top n entries.

`df.nsmallest(n, 'value')`
Select and order bottom n entries.

`df.head(n)`
Select first n rows.

`df.tail(n)`
Select last n rows.

Subset Variables - columns



`df[['width', 'length', 'species']]`
Select multiple columns with specific names.

`df['width']` *or* `df.width`
Select single column with specific name.

`df.filter(regex='regex')`
Select columns whose name matches regular expression *regex*.

Using query

query() allows Boolean expressions for filtering rows.

```
df.query('Length > 7')
df.query('Length > 7 and Width < 8')
df.query('Name.str.startswith("abc")',
                 engine="python")
```

Subsets - rows and columns

Use **df.loc[]** and **df.iloc[]** to select only rows, only columns or both.
Use **df.at[]** and **df.iat[]** to access a single value by row and column.
First index selects rows, second index columns.

`df.iloc[10:20]`
Select rows 10-20.

`df.iloc[:, [1, 2, 5]]`
Select columns in positions 1, 2 and 5 (first column is 0).

`df.loc[:, 'x2':'x4']`
Select all columns between x2 and x4 (inclusive).

`df.loc[df['a'] > 10, ['a', 'c']]`
Select rows meeting logical condition, and only the specific columns .

`df.iat[1, 2]` Access single value by index

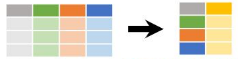
`df.at[4, 'A']` Access single value by label

Logic in Python (and pandas)			
`<`	Less than	`!=`	Not equal to
`>`	Greater than	`df.column.isin(values)`	Group membership
`==`	Equals	`pd.isnull(obj)`	Is NaN
`<=`	Less than or equals	`pd.notnull(obj)`	Is not NaN
`>=`	Greater than or equals	`&,|,~,^,df.any(),df.all()`	Logical and, or, not, xor, any, all

regex (Regular Expressions) Examples	
`'\.'`	Matches strings containing a period '.'
`'Length$'`	Matches strings ending with word 'Length'
`'^Sepal'`	Matches strings beginning with the word 'Sepal'
`'^x[1-5]$'`	Matches strings beginning with 'x' and ending with 1,2,3,4,5
`'^(?!Species$).*'`	Matches strings except the string 'Species'

Summarize Data

```
df['w'].value_counts()
```
Count number of rows with each unique value of variable
```
len(df)
```
# of rows in DataFrame.
```
df.shape
```
Tuple of # of rows, # of columns in DataFrame.
```
df['w'].nunique()
```
# of distinct values in a column.
```
df.describe()
```
Basic descriptive and statistics for each column (or GroupBy).



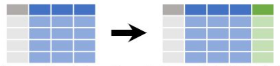
pandas provides a large set of summary functions that operate on different kinds of pandas objects (DataFrame columns, Series, GroupBy, Expanding and Rolling (see below)) and produce single values for each of the groups. When applied to a DataFrame, the result is returned as a pandas Series for each column. Examples:

`sum()` Sum values of each object.	`min()` Minimum value in each object.
`count()` Count non-NA/null values of each object.	`max()` Maximum value in each object.
`median()` Median value of each object.	`mean()` Mean value of each object.
`quantile([0.25,0.75])` Quantiles of each object.	`var()` Variance of each object.
`apply(function)` Apply function to each object.	`std()` Standard deviation of each object.

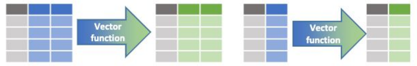
Handling Missing Data

```
df.dropna()
```
Drop rows with any column having NA/null data.
```
df.fillna(value)
```
Replace all NA/null data with value.

Make New Columns



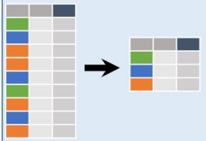
```
df.assign(Area=lambda df: df.Length*df.Height)
```
Compute and append one or more new columns.
```
df['Volume'] = df.Length*df.Height*df.Depth
```
Add single column.
```
pd.qcut(df.col, n, labels=False)
```
Bin column into n buckets.



pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

`max(axis=1)` Element-wise max.	`min(axis=1)` Element-wise min.
`clip(lower=-10,upper=10)` Trim values at input thresholds	`abs()` Absolute value.

Group Data



```
df.groupby(by="col")
```
Return a GroupBy object, grouped by values in column named "col".
```
df.groupby(level="ind")
```
Return a GroupBy object, grouped by values in index level named "ind".

All of the summary functions listed above can be applied to a group. Additional GroupBy functions:

`size()` Size of each group.	`agg(function)` Aggregate group using function.

The examples below can also be applied to groups. In this case, the function is applied on a per-group basis, and the returned vectors are of the length of the original DataFrame.

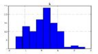
`shift(1)` Copy with values shifted by 1.	`shift(-1)` Copy with values lagged by 1.
`rank(method='dense')` Ranks with no gaps.	`cumsum()` Cumulative sum.
`rank(method='min')` Ranks. Ties get min rank.	`cummax()` Cumulative max.
`rank(pct=True)` Ranks rescaled to interval [0, 1].	`cummin()` Cumulative min.
`rank(method='first')` Ranks. Ties go to first value.	`cumprod()` Cumulative product.

Windows

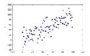
```
df.expanding()
```
Return an Expanding object allowing summary functions to be applied cumulatively.
```
df.rolling(n)
```
Return a Rolling object allowing summary functions to be applied to windows of length n.

Plotting

```
df.plot.hist()
```
Histogram for each column



```
df.plot.scatter(x='w',y='h')
```
Scatter chart using pairs of points



Combine Data Sets

adf

x1	x2
A	1
B	2
C	3

+

bdf

x1	x3
A	T
B	F
D	T

=

Standard Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NaN

```
pd.merge(adf, bdf,
         how='left', on='x1')
```
Join matching rows from bdf to adf.

x1	x2	x3
A	1.0	T
B	2.0	F
D	NaN	T

```
pd.merge(adf, bdf,
         how='right', on='x1')
```
Join matching rows from adf to bdf.

x1	x2	x3
A	1	T
B	2	F

```
pd.merge(adf, bdf,
         how='inner', on='x1')
```
Join data. Retain only rows in both sets.

x1	x2	x3
A	1	T
B	2	F
C	3	NaN
D	NaN	T

```
pd.merge(adf, bdf,
         how='outer', on='x1')
```
Join data. Retain all values, all rows.

Filtering Joins

x1	x2
A	1
B	2

```
adf[adf.x1.isin(bdf.x1)]
```
All rows in adf that have a match in bdf.

x1	x2
C	3

```
adf[~adf.x1.isin(bdf.x1)]
```
All rows in adf that do not have a match in bdf.

ydf

x1	x2
A	1
B	2
C	3

+

zdf

x1	x2
B	2
C	3
D	4

=

Set-like Operations

x1	x2
B	2
C	3

```
pd.merge(ydf, zdf)
```
Rows that appear in both ydf and zdf (Intersection).

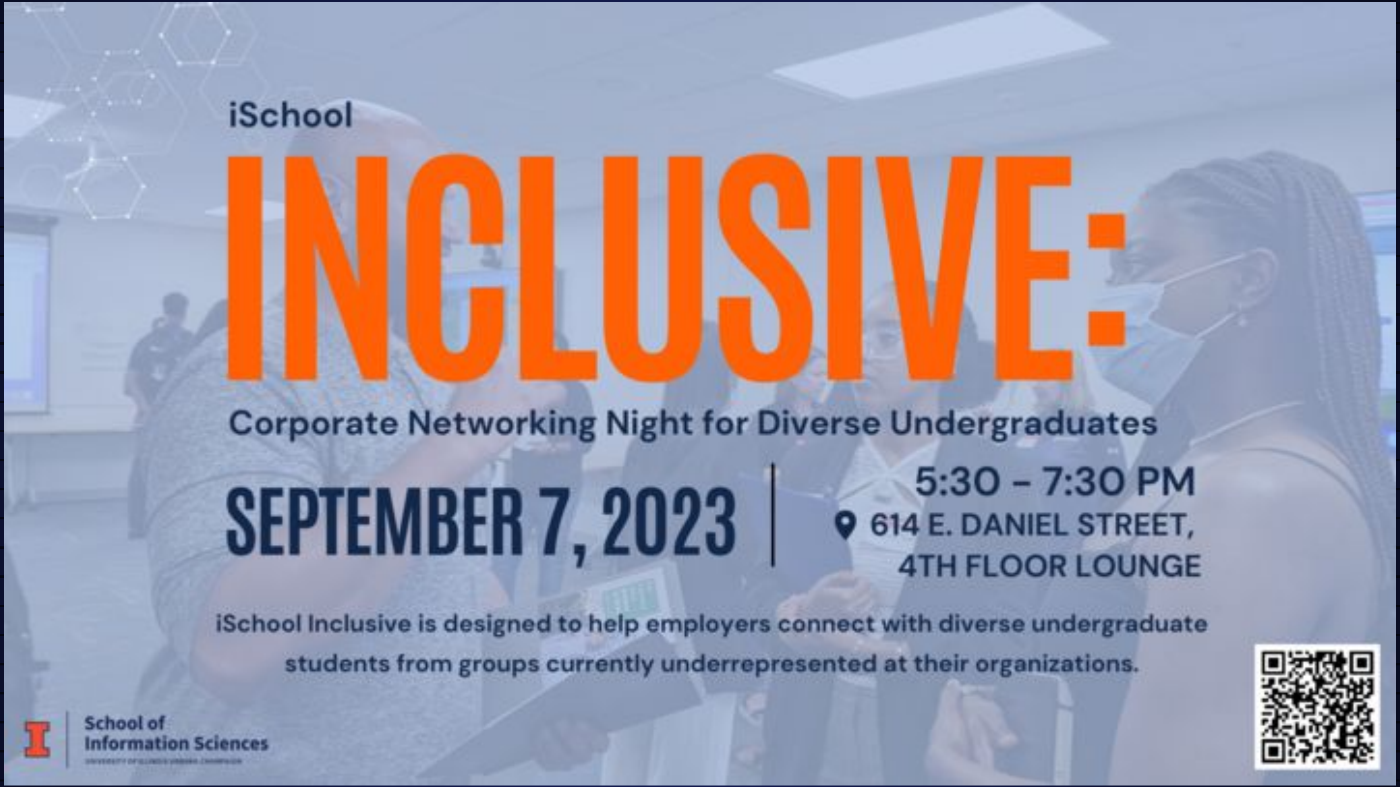
x1	x2
A	1
B	2
C	3
D	4

```
pd.merge(ydf, zdf, how='outer')
```
Rows that appear in either or both ydf and zdf (Union).

x1	x2
A	1

```
pd.merge(ydf, zdf, how='outer',
         indicator=True)
.query('_merge == "left_only"')
.drop(columns=['_merge'])
```
Rows that appear in ydf but not zdf (Setdiff).

It’s Time For Some Trivia!!



iSchool

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Corporate Networking Night for Diverse Undergraduates

SEPTEMBER 7, 2023

5:30 - 7:30 PM

614 E. DANIEL STREET, 4TH FLOOR LOUNGE

iSchool Inclusive is designed to help employers connect with diverse undergraduate students from groups currently underrepresented at their organizations.

School of Information Sciences

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

Thanks for coming!
See you on Thursday