Compsci 101
Recommender

```
ratings = \
          {"Sarah Lee"   : [3, 3, 3, 3,  0,-3, 5, 0,-3],
           "Melanie"     : [5, 0, 3, 0,  1, 3, 3, 3, 1],
            "J J"        : [0, 1, 0,-1,  1, 1, 3, 0, 1],
            "Sly one"    : [5, 0, 1, 3,  0, 0, 3, 3, 3],
            "Sung-Hoon"  : [0,-1,-1, 5,  1, 3,-3, 1,-3],
            "Nana Grace" : [5, 0, 3,-5, -1, 0, 1, 3, 0],
            "Harry"      : [5, 3, 0,-1, -3,-5, 0, 5, 1],
            "Wei"        : [1, 1, 0, 3, -1, 0, 5, 3, 0]
          }
```

Susan Rodger

April 13, 2023

V is for …

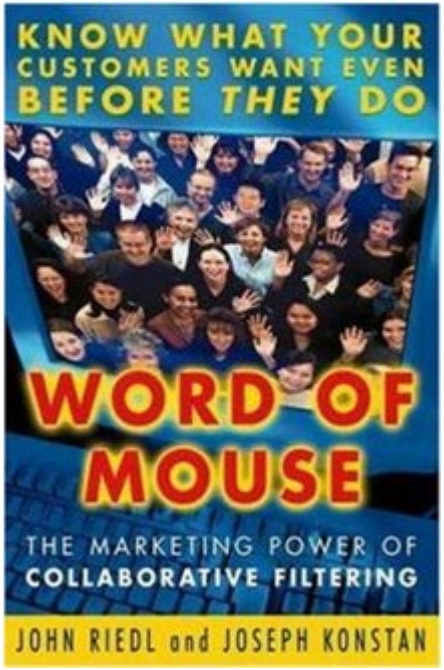
- **Viral Video**
  - Husky Dog sings with iPAD – 18 million views
  - https://www.youtube.com/watch?v=Mk4bmK-acEM
- **Virtual Memory**
  - It is and is not there!
- **Virtual Reality**
  - Augmenting IRL
  - http://bit.ly/vr-playlist

John Riedl

- **Co-Inventor of Recommender systems**
- **PhD at Purdue University**
- **Professor at Univ. of Minnesota**
- **ACM Software System Award – GroupLens System**
- **Died of cancer in 2013**

- **Quote from his son about John:**

"He once looked into how likely people are to follow your book recommendations based on how many books you recommend. We went to his talk at the AH Conference in which he described the answer. It turns out that if you recommend too many books to people, they get overwhelmed and are less likely to follow your suggestions. As he told us in his talk, the optimal number of books to recommend turns out to be about two. Then he proceeded to recommend eight books during the talk."



Announcements

- **APT-6 due Tonight, April 13**

- **Assign 6 – Recommender, due Thursday, 4/20**
- **APT-7 out today, due Tuesday, 4/25**
- **Assign 7 – out today, due Wed. 4/26**
  - But can be turned in by Sunday 4/30 with no penalty

- **Lab 10 this week is different!**
  - No pre-lab this week

Lab 10 is required, cannot drop it

- **Do Lab 10 on your own all in one session**
- **It is about 60 minutes. It is not timed**
- **You will receive an email from me today with instructions for completing Lab 10**
- **Do lab 10 anytime between 4/13 and Monday 4/17**
- **Lab 10 is a lesson on a new topic and includes practice with the topic, an assessment, and a survey**
- **Your grade is based on a good attempt and completing each part**

Extra Credit for Exam 3

- **Go to Sakai quiz: Exam 3 Bonus (opens later today)**
- **Answer the survey question from Prof. Kristin Stephens-Martinez's (only one question!)**

- **If 65% of class answer the question**
  - 1 extra point on Exam 3 for everyone
- **If 75% of class answer the question**
  - An additional extra point on Exam 3 for everyone

Assignment 7: Create, Due April 26

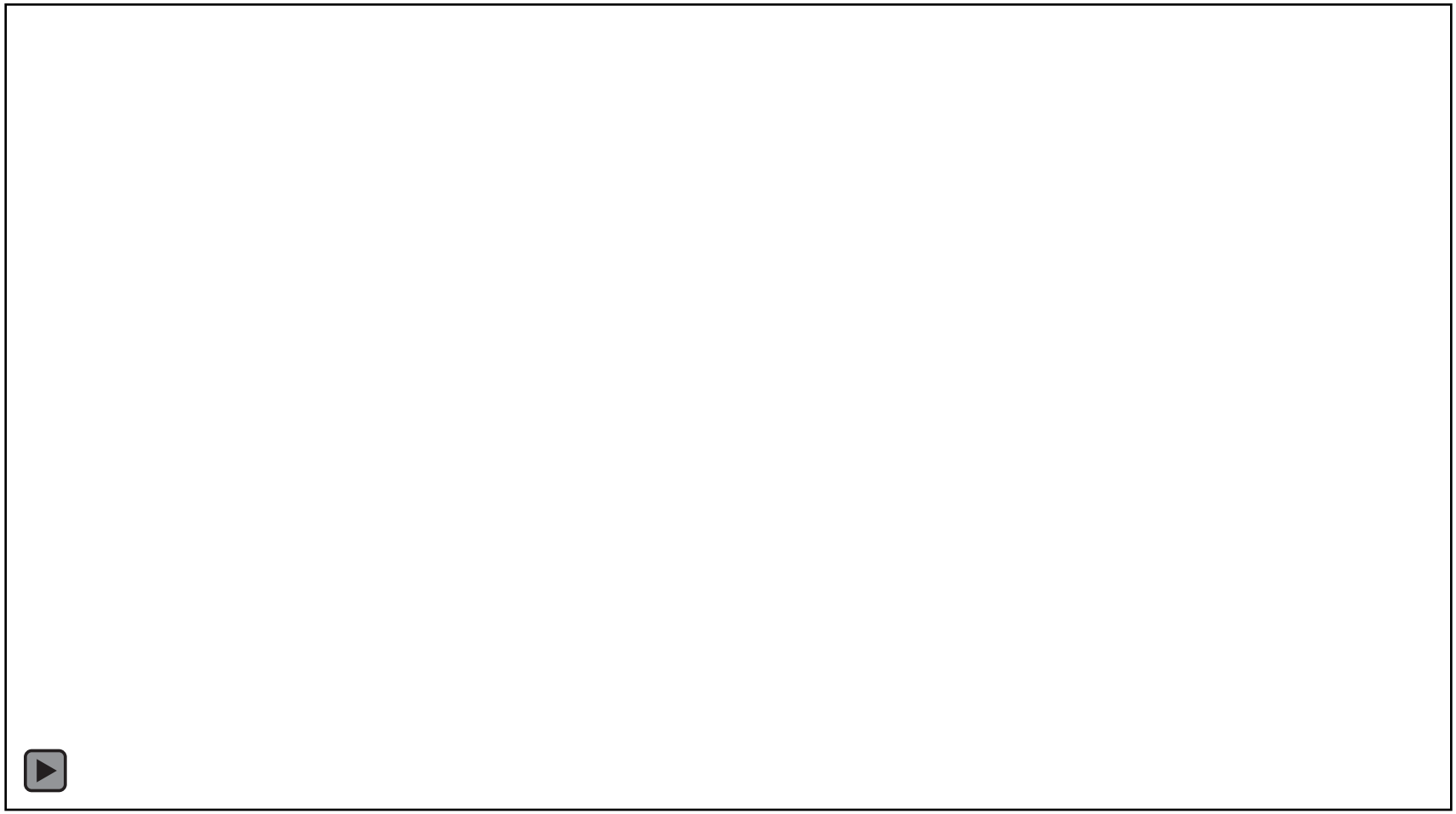
Can turn in no penalty by April 30,
No turnin after April 30!
This assignment is **required**!

Pick one:

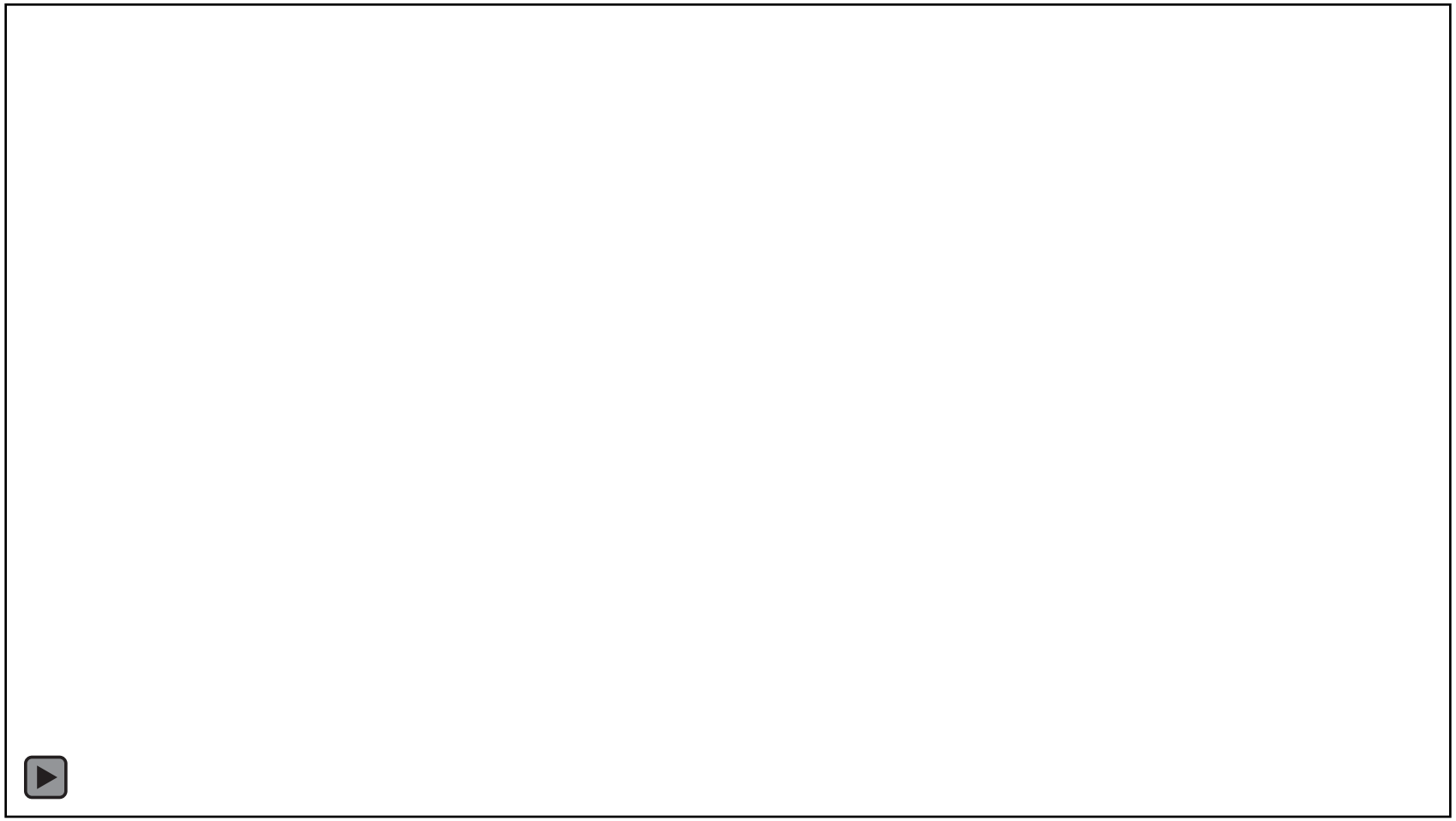
- **Video: Green dance, advertisement for 101, song, other**
- **Poem or Multiple Haikus**
- **Story**
- **Comic**
- **One-pager**
- **Feedback**

Let's see some examples

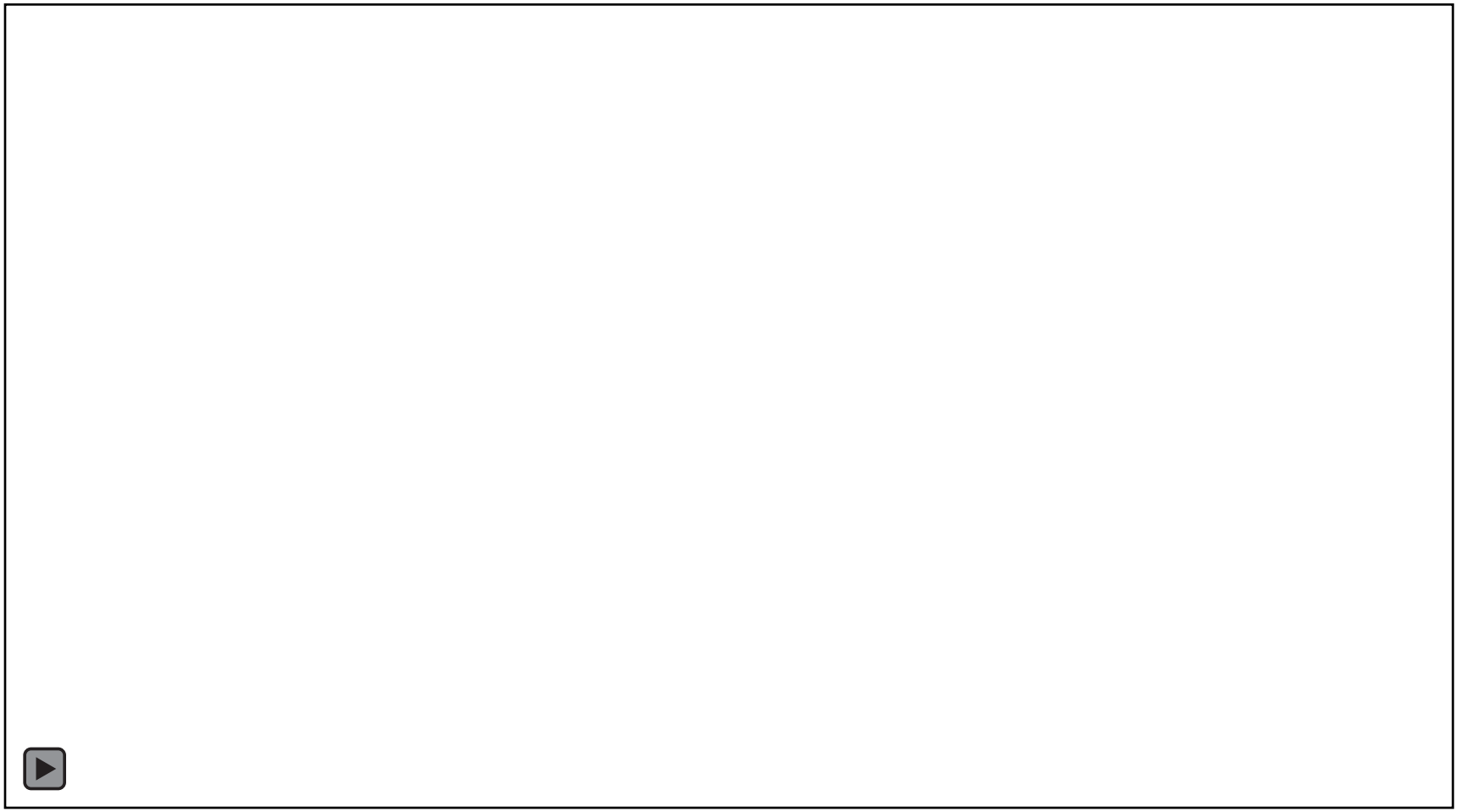
Video Advertisement for CompSci 101



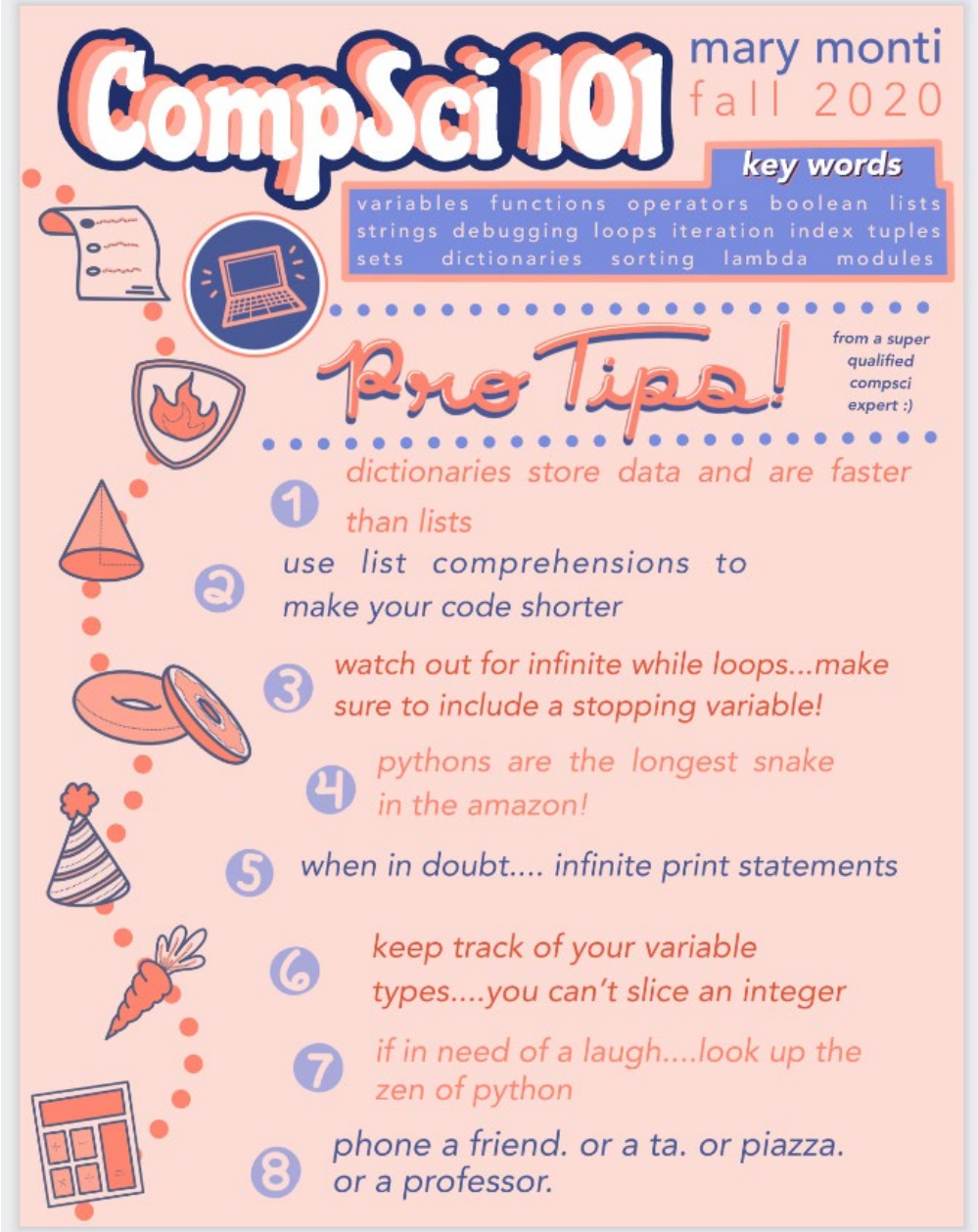
Green Dance Video



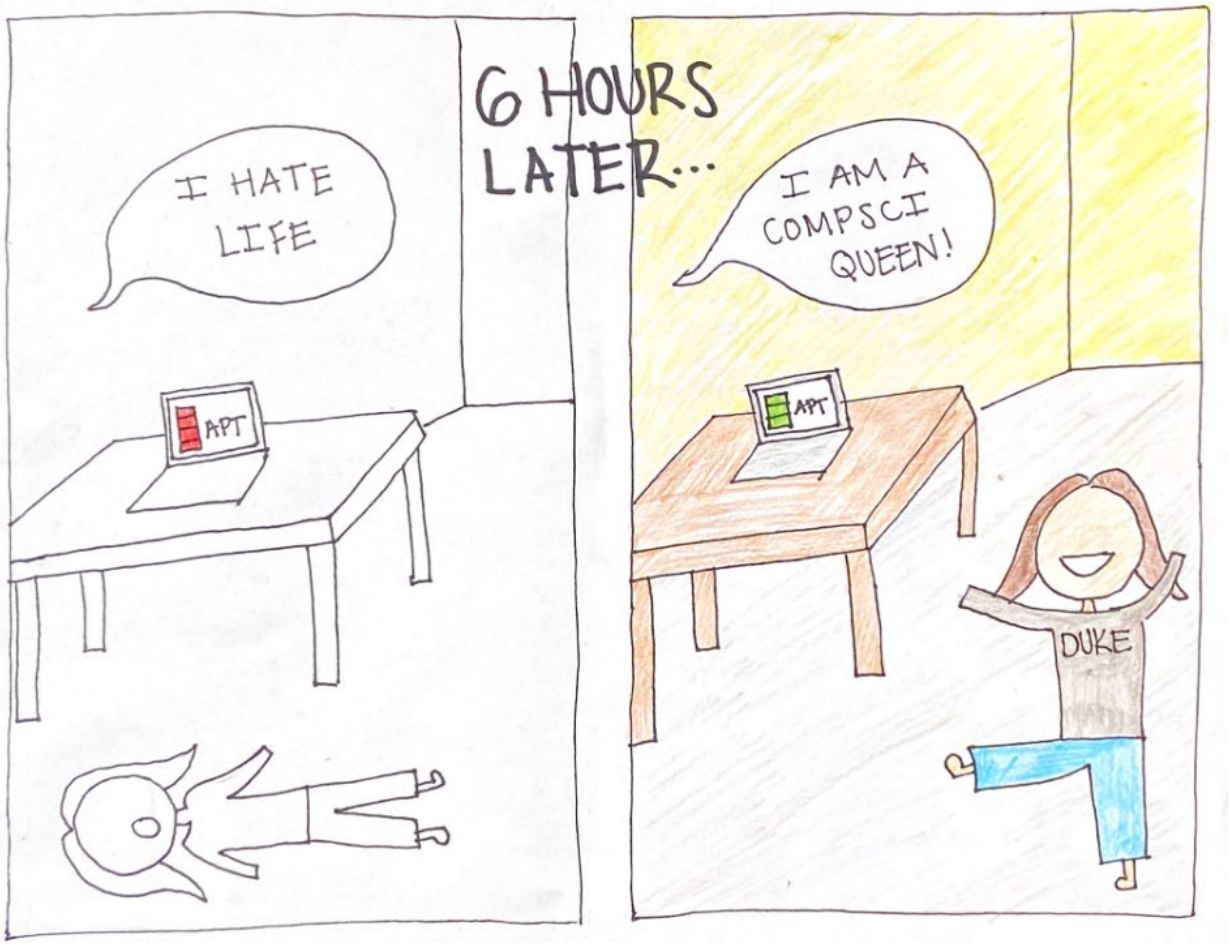
Video Simple Green Dance



One Pager


CompSci 101
mary monti
fall 2020
key words
variables functions operators boolean lists
strings debugging loops iteration index tuples
sets dictionaries sorting lambda modules
Pro Tips!
from a super qualified compsci expert :)
1 dictionaries store data and are faster than lists
2 use list comprehensions to make your code shorter
3 watch out for infinite while loops...make sure to include a stopping variable!
4 pythons are the longest snake in the amazon!
5 when in doubt.... infinite print statements
6 keep track of your variable types....you can't slice an integer
7 if in need of a laugh....look up the zen of python
8 phone a friend. or a ta. or piazza. or a professor.

Comic



PFTD

- **Recommender**
- **Some APTs**

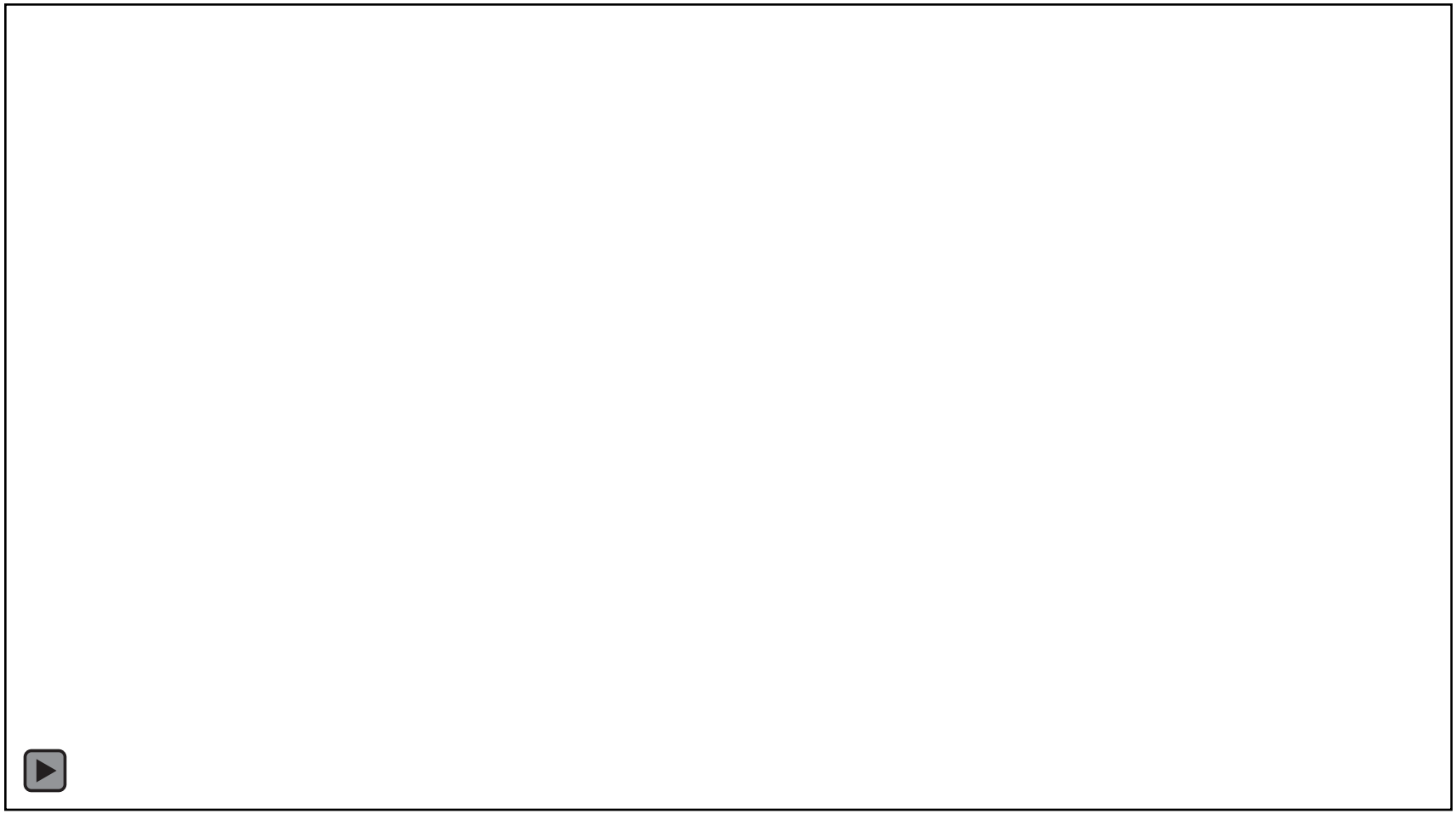
Recommendation Systems: Yelp

- **Are all users created equal?**
- **Weighting reviews**

- **What is a recommendation?**

Recommendation Systems: Yelp

https://www.youtube.com/watch?v=PniMEnM89iY



Recommendation Systems: Yelp

https://www.youtube.com/watch?v=PniMEnM89iY

Recommender Systems: Amazon

- **How does Amazon create recommendations?**

Recommendation Systems: Netflix

- **Netflix offered a prize in 2009**
  - Beat their system? Win a million $$
  - http://nyti.ms/sPvR

Compsci 101 Recommender

- **Doesn't work at the scale of these systems, uses publicly accessible data, but ...**
  - Movie data, food data, book data

- **Make recommendations**
  - Based on ratings, how many stars there are
  - Based on weighting ratings by users like you!

- **Collaborative Filtering: math, stats, compsci**

Compsci 101 Recommender

- **Doesn't work at the scale of these systems, uses publicly accessible data, but ...**
  - Movie data, food data, book data

- **Make recommendations**
  - Based on ratings, how many stars there are
  - Based on weighting ratings by users like you!

- **Collaborative Filtering: math, stats, compsci**

Machine learning!

Where to eat? Simple Example

Tandoor	IlForno	McDon	Loop	Panda	Twin
0	3	5	0	-3	5
1	1	0	3	0	-3
-3	3	3	5	1	-1

- Rate restaurants on a scale of (low) -5 to 5 (high)
  - Each row is one user's ratings
  - But a zero/0 means no rating, not ambivalent
- What restaurant should I choose to go to?
  - What do the ratings say? Let's take the average!

Calculating Averages

- **What is average rating of eateries?**

Tandoor	IlForno	McDon	Loop	Panda	Twin
0	3	5	0	-3	5
1	1	0	3	0	-3
-3	3	3	5	1	-1

- **Tandoor:**

Calculating Averages

- **What is average rating of eateries?**

Tandoor	IlForno	McDon	Loop	Panda	Twin
0	3	5	0	-3	5
1	1	0	3	0	-3
-3	3	3	5	1	-1

- **Tandoor:** `(1 + -3)/2 = -1.00`
  - Don't count rating if not rated

Calculating Averages

- **What is average rating of eateries?**

Tandoor	IlForno	McDon	Loop	Panda	Twin
0	3	5	0	-3	5
1	1	0	3	0	-3
-3	3	3	5	1	-1

- **Tandoor:** `(1 + -3)/2 = -1.00`
  - Don't count rating if not rated
- **Il Forno:** `(3 + 1 + 3)/3 = 2.33`
- **Where should we eat? What's the best average**
- **Highest: 8/2 = 4 for McDonalds and The Loop**

Python Specification

- **Items: list of strings (header in table shown)**

```
items = ["DivinityCafe", "FarmStead", "IlForno", "LoopPizzaGrill",
         "McDonalds", "PandaExpress", "Tandoor", "TheCommons",
         "TheSkillet"]
```

- **Values in dictionary are ratings: int list**
  - **`len(ratings[i]) == len(items)`**

```
ratings = \
          {"Sarah Lee"  : [3, 3, 3, 3,  0,-3, 5, 0,-3],
           "Melanie"    : [5, 0, 3, 0,  1, 3, 3, 3, 1],
           "J J"        : [0, 1, 0,-1,  1, 1, 3, 0, 1],
           "Sly one"    : [5, 0, 1, 3,  0, 0, 3, 3, 3],
           "Sung-Hoon"  : [0,-1,-1, 5,  1, 3,-3, 1,-3],
           "Nana Grace" : [5, 0, 3,-5, -1, 0, 1, 3, 0],
           "Harry"      : [5, 3, 0,-1, -3,-5, 0, 5, 1],
           "Wei"        : [1, 1, 0, 3, -1, 0, 5, 3, 0]
          }
```

Python Specification

- **Items: list of strings (header in table shown)**

```
items = ["DivinityCafe", "FarmStead", "IlForno", "LoopPizzaGrill",
         "McDonalds", "PandaExpress", "Tandoor", "TheCommons",
         "TheSkillet"]
```

- **Values in dictionary are ratings: int list**
  - **`len(ratings[i]) == len(items)`**

index = 4

index = 4

```
ratings = \
        {"Sarah Lee"  : [3, 3, 3, 3,  0,-3, 5, 0,-3],
         "Melanie"    : [5, 0, 3, 0,  1, 3, 3, 3, 1],
          "J J"       : [0, 1, 0,-1,  1, 1, 3, 0, 1],
          "Sly one"   : [5, 0, 1, 3,  0, 0, 3, 3, 3],
          "Sung-Hoon" : [0,-1,-1, 5,  1, 3,-3, 1,-3],
          "Nana Grace": [5, 0, 3,-5, -1, 0, 1, 3, 0],
          "Harry"     : [5, 3, 0,-1, -3,-5, 0, 5, 1],
          "Wei"       : [1, 1, 0, 3, -1, 0, 5, 3, 0]
        }
```

Recommender averages

- **`def averages(items,ratings):`**

- ***Input: items -- list of restaurants/strings***
- ***Input: dictionary of rater-name to ratings***
  - ratings: list of ints, **`[1,0,-1, ... 1]`** -- parallel list to list of restaurants
    - k^{th} rating maps to k^{th} restaurant
- ***Output: recommendations***
  - List of tuples (name, avg rating) or (str, float)
    - Sort by rating from high to low

WOTO-1 Averages
http://bit.ly/101-s23-0413-1

Drawbacks of Averaging, Instead …

- **Are all user's ratings the same to me?**
  - Weight/value ratings of people most similar to me
- **Collaborative Filtering**
  - https://en.wikipedia.org/wiki/Collaborative_filtering
  - How do we determine who is similar to/"near" me?
- **Mathematically: treat ratings as vectors in an N-dimensional space, N = # of items that are rated**
  - a.k.a. weight has higher value → closer to me

Determining "closeness"

- **Calculate a number measuring closeness to me**
  - The higher the number, the closer to me
  - I’m also a rater, "me" is parameter to function

- **Function:**
  - `similarities("rodger", ratings)`

Determining "closeness"

- **Calculate a number measuring closeness to me**
  - The higher the number, the closer to me
  - I'm also a rater, "me" is parameter to function

- **Function:**
  - `similarities("rodger", ratings)`

Same as before, dictionary of rater to ratings

Determining "closeness"

- **Calculate a number measuring closeness to me**
  - The higher the number, the closer to me
  - I'm also a rater, "me" is parameter to function

Same as before, dictionary of rater to ratings

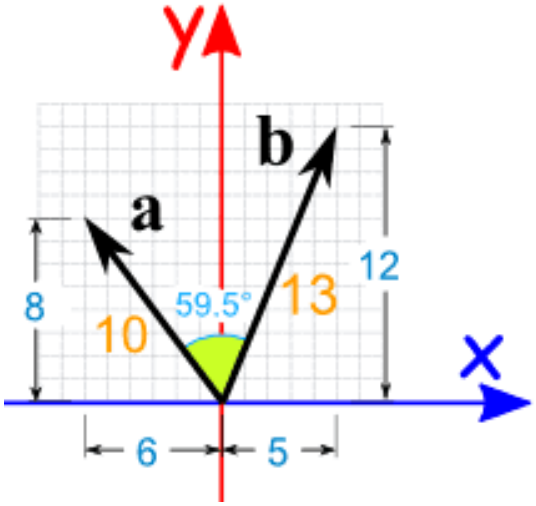
- **Function:**
  - `similarities("rodger", ratings)`

- **Return `[("rater1", #), ("rater2", #), ...]`**
  - List of tuples based on closeness to me
  - sorted high-to-low by similarity
  - "rodger" should not be in that list!

What's close? Dot Product

- https://en.wikipedia.org/wiki/Dot_product
  - For [3,4,2] and [2,1,7]
    - `3*2 + 4*1 + 2*7 = 6+4+14 = 24`

- **How close am I to each rater?**
- **What happens if the ratings are**
  - Same sign? Me: 3, -2 Other: 2, -5
  - Different signs? Me: -4 Other: 5
  - One is zero? Me: 0 Other: 4
- **What does it mean when # is…**
  - Big? Small? Negative?



What's close? Dot Product

- https://en.wikipedia.org/wiki/Dot_product
  - For [3,4,2] and [2,1,7]
    - `3*2 + 4*1 + 2*7 = 6+4+14 = 24`
- **How close am I to each rater?**
- **What happens if the ratings are**
  - Same sign? Me: 3, -2 Other: 2, -5
  - Different signs? Me: -4 Other: 5
  - One is zero? Me: 0 Other: 4
- **What does it mean when # is…**
  - Big? Small? Negative?

We agree!

We disagree!

One not rated, don't count! These cancel out!

Writing similarities

- **Given a name and a dictionary, return list of tuples**

```
def similarities(name, ratings):
    return [('name0', #), ...('nameN', #)]
```

- **What is the # here?**
  - Dot product of two lists
  - One list is fixed (name)
  - Other list varies (loop)

- **Think: How many tuples are returned?**

food.json

```
{"Sarah Lee":
   [3, 3, 3, 3, 0, -3, 5, 0, -3],
 "Melanie":
   [5, 0, 3, 0, 1, 3, 3, 3, 1],
  "J J":
   [0, 1, 0, -1, 1, 1, 3, 0, 1],
  "Sly one":
   [5, 0, 1, 3, 0, 0, 3, 3, 3],
  "Sung-Hoon":
   [0, -1, -1, 5, 1, 3, -3, 1, -3],
  "Nana Grace":
   [5, 0, 3, -5, -1, 0, 1, 3, 0],
  "Harry":
   [5, 3, 0, -1, -3, -5, 0, 5, 1],
  "Wei":
   [1, 1, 0, 3, -1, 0, 5, 3, 0]
}
```

Writing similarities

- **Given a name and a dictionary, return list of tuples**

```
def similarities(name, ratings):
    return [('name0', #), ...('nameN', #)]
```

- **What is the # here?**
  - Dot product of two lists
  - One list is fixed (name)
  - Other list varies (loop)

- **Think: How many tuples are returned?**

7

food.json

```
{"Sarah Lee":
   [3, 3, 3, 3, 0, -3, 5, 0, -3],
 "Melanie":
   [5, 0, 3, 0, 1, 3, 3, 3, 1],
  "J J":
   [0, 1, 0, -1, 1, 1, 3, 0, 1],
  "Sly one":
   [5, 0, 1, 3, 0, 0, 3, 3, 3],
  "Sung-Hoon":
   [0, -1, -1, 5, 1, 3, -3, 1, -3],
  "Nana Grace":
   [5, 0, 3, -5, -1, 0, 1, 3, 0],
  "Harry":
   [5, 3, 0, -1, -3, -5, 0, 5, 1],
  "Wei":
   [1, 1, 0, 3, -1, 0, 5, 3, 0]
}
```

Collaborative Filtering

- **Once we know raters "near" me? Weight them!**
  - How many raters to consider? 1? 10?
  - Suppose Fran is `[2, 4, 0, 1, 3, 2]`
- **What is Sam's similarity to Fran?**

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1

Collaborative Filtering

- **Once we know raters "near" me? Weight them!**
  - How many raters to consider? 1? 10?
  - Suppose Fran is `[2, 4, 0, 1, 3, 2]`
- **What is Sam's similarity to Fran?**
  - 2*0 + 4*3 + 0*5 + 1*0 + 3*-3 + 2*5 = **13**
  - **Sam's ratings** `[0, 3, 5, 0, -3, 5] * 13`
  - **Sam's weighted**: `[0, 39, 65, 0, -39, 65]`

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1

Think: What is Chris's similarity?

What is Chris's similarity and weights?

- **Suppose Fran is `[2, 4, 0, 1, 3, 2]`**
- **Chris's similarity is:**

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1

What is Chris's similarity and weights?

- **Suppose Fran is `[2, 4, 0, 1, 3, 2]`** 
- **Chris's similarity is:**
  - 2*1 + 4*1 + 0*0 + 1*3 + 3*0 + 2*(-3) = 3
- **Chris' weighted ratings:**
  - 3 * [1, 1, 0, 3, 0, -3]
  - `[3, 3, 0, 9, 0, -9]`

Sam is more similar to Fran than Chris
Sam's weightings will count more than Chris'

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1

Steps for Recommendations

- **Start with you, a rater/user and all the ratings**
  - Get similarity "weights" for users: dot product
- **Calculate new weighted ratings for all users**
  - `[weight * r for r in ratings]`
- **Based on these new ratings, find average**
  - Don't use zero-ratings
- **Check recommendations by … (not required)**
  - Things I like are recommended? If so, look at things I haven't tried!

Recommendations

- **Get new weighted averages for each eatery**
  - Then find the best eatery I've never been to

```
def recommendations(name,items,ratings,numUsers)
   return [('eatery0', #), ...('eateryN', #)]
```

Fran gets
a recommendation
(considering numUsers raters)


```
rc = recommendations("Fran",items,ratings,3)
#use this to provide evals to Fran
```

Recommendations

Number of "nearby" raters

- **Get new weighted averages for each eatery**
  - Then find the best eatery I've never been to

```
def recommendations(name,items,ratings,numUsers)
   return [('eatery0', #), ...('eateryN', #)]
```

Fran gets a recommendation (considering numUsers raters)


```
rc = recommendations("Fran",items,ratings,3)
#use this to provide evals to Fran
```

Similarities Summarized

- **How do we get weighted ratings?**

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1
Fran	2	4	0	1	3	2

```
def similarities(name,ratings):
    return [('name', #), ...('name', #)]

weights = similarities("Fran", ratings)
```

Making Recommendations

- **How do we get weighted ratings? Call average?**

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	3	5	0	-3	5
Chris	1	1	0	3	0	-3
Nat	-3	3	3	5	1	-1
Fran	2	4	0	1	3	2

```
weights = similarities("Fran", ratings)
weights = #slice based on numUsers
weightedRatings = {}. # new dictionary
for person, weight in weights:
    weightedRatings[?] = ?
```

Calculating Weighted Average

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	39	65	0	-39	65
~~Chris~~	~~3~~	~~3~~	~~0~~	~~9~~	~~0~~	~~-9~~
Nat	-36	36	36	60	12	-12
Total	-36	75	101	60	-27	53
Avg	-36	37.5	50.5	60	-13.5	26.5

`recommendations("Fran",items,ratings,2)`

- Make recommendation for Fran? Best? Worst?
- Fran should eat at Loop! Even though only using Nat's rating
- But? Fran has been to Loop! Gave it a 1, … McDonalds!!!! ??

Calculating Weighted Average

	Tandoor	IlForno	McDon	Loop	Panda	Twin
Sam	0	39	65	0	-39	65
~~Chris~~	~~3~~	~~3~~	~~0~~	~~9~~	~~0~~	~~-9~~
Nat	-36	36	36	60	12	-12
Total	-36	75	101	60	-27	53
Avg	-36	37.5	50.5	60	-13.5	26.5

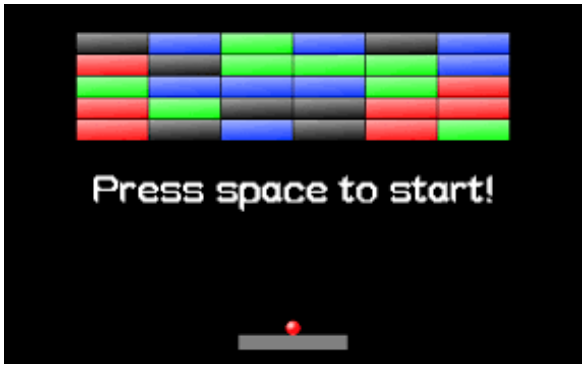
`recommendations("Fran",items,ratings,2)`

- Make recommendation for Fran? Best? Worst?
- Fran should eat at Loop! Even though only using Nat's rating
- But? Fran has been to Loop! Gave it a 1, … McDonalds!!!! ??

Use 2 raters who are closest: Sam and Nat

WOTO-2 Sims to Recs
http://bit.ly/101s23-0413-2

- **From Similarities to Recommendations**



Assignment Modules

RecommenderEngine
1.averages(…)
2.similaries(…)
3.recommendations(…)

MovieReader
1.getdata(…)

BookReader
1.getdata(…)

RecommenderMaker
1.makerecs(…)

TestRecommender

Assignment Modules

Implement functions in this order

RecommenderEngine
1. averages(…)
2. similaries(…)
3. recommendations(…)

Can be implemented before Recommender stuff or after

MovieReader
1. getdata(…)

BookReader
1. getdata(…)

RecommenderMaker
1. makerecs(…)

TestRecommender

RecommenderEngine before RecommenderMaker and use TestRecommender

Function Call Ordering

- **Some_Reader_Module.getdata(…)**
- **RecommenderMaker.makerecs(…)**
  - RecommenderEngine.recommendations(…)
    - RecommenderEngine.similarities(…)
    - RecommenderEngine.averages(…)

Function Call Ordering

- **Some_Reader_Module.getdata(…)**
- **RecommenderMaker.makerecs(…)**
  - RecommenderEngine.recommendations(…)
    - RecommenderEngine.similarities(…)
    - RecommenderEngine.averages(…)

Start with inner most call and work outwards

Test on your computer and on Gradescope as you go!

When and What's in CompSci 101

- **Problem to solve**
  - Use 7 steps
  - Step 5: How do you translate algorithm to code?
    - What do you use to solve it?
    - When do you use it?

What are the “what’s”?

- **Data Structures: list, set, dictionary, tuple**
  - Combined: list of lists, dictionary of key to list
- **Loops : from for to while, index loop**
- **Other:**
  - List comprehensions
  - Parallel lists
  - Lambda
  - If…if…if
  - If…elif…else

Quick When's and What's for 101

- **Whichever makes more sense to you:**
  - Parallel lists vs dictionaries
  - If…if…if vs if…elif…else
  - List comprehension vs for loop
  - Tuples vs Lists
    - If you want to prevent mutation -> tuples
  - Need single line function
    - Lambda vs create normal helper function

APT – Sorted Freqs

APT SortedFreqs

Problem Statement

Specification

```
filename: SortedFreqs.py

def freqs(data):
    """
    return list of int values corresponding
    to frequencies of strings in data, a list
    of strings
    """
```

The frequency with which data occurs is sometimes an important statistic. In this problem you'll determine how frequently strings occur and return a list representing the frequencies of each different/unique string. The list returned contains as many frequencies as there are unique strings. The returned frequencies represent an alphabetic/lexicographic ordering of the unique words, so the first frequency is how many times the alphabetically first word occurs and the last frequency is the number of times the alphabetically last word occurs.

Consider these strings (quotes for clarity, they're not part of the strings).

```
["apple", "pear", "cherry", "apple", "cherry", "pear", "apple", "banana"]
```

The list returned is `[3,1,2,2]` since the alphabetically first word is `"apple"` which occurs 3 times; the second word alphabetically is `"banana"` which occurs once, and the other words each occur twice.

What's the best way to …

- **SortedFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortedfreqs.html

- **Count how many times each string occurs**
  - Create d = {}, iterate over list updating values
- **OR**
  - Use data.count(w) for each w

What's the best way to …

- **SortedFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortedfreqs.html

- **Count how many times each string occurs**
  - Create d = {}, iterate over list updating values
- **OR**
  - Use data.count(w) for each w
    - Wait, that looks like …

```
6   def freqs(data):
7       return [data.count(d) for d in sorted(set(data))]
```

APT: SortByFreqs

APT SortByFreqs

Problem Statement

Specification

```
filename: SortByFreqs.py

def sort(data):
    """
    return list of strings based on
    the list of strings in parameter data
    """
```

The frequency with which data occurs is sometimes an important statistic. In this problem you are given a list of strings and must determine how frequently the strings occur. Return a list of strings that is sorted (ordered) by frequency. The first element of the returned list is the most frequently occurring string, the last element is the least frequently occurring. Ties are broken by listing strings in lexicographic/alphabetical order. The returned list contains one occurrence of each unique string from the list parameter.

Consider these strings (quotes for clarity, they're not part of the strings).

```
["apple", "pear", "cherry", "apple", "pear", "apple", "banana"]
```

The list returned is:

```
[ "apple", "pear", "banana", "cherry" ]
```

since the most frequently occurring string is `"apple"` which occurs 3 times; the string `"pear"` occurs twice and the other strings each occur once so they are returned in alphabetical order.

Wait, wait, but what's …

- **SortByFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortbyfreqs.html

- **Sort by # occurrences high to low**
  - Tuples with count/lambda and reverse=True?
  - Break ties in alphabetical order: two passes

Wait, wait, but what's …

- **SortByFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortbyfreqs.html

- **Sort by # occurrences high to low**
  - Tuples with count/lambda and reverse=True?
  - Break ties in alphabetical order: two passes

```
6   def sort(data):
7       tups = [(data.count(t),t) for t in sorted(set(data))]
8       result = [t[1] for t in sorted(tups,key=lambda x : x[0],reverse=True)]
9       return result
```

SortByFreqs Example

- **SortByFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortbyfreqs.html

```
6   def sort(data):
7       tups = [(data.count(t),t) for t in sorted(set(data))]
8       result = [t[1] for t in sorted(tups,key=lambda x : x[0],reverse=True)]
9       return result
```

SortByFreqs Example

- **SortByFreqs**
  - https://www2.cs.duke.edu/csed/pythonapt/sortbyfreqs.html

```
6   def sort(data):
7       tups = [(data.count(t),t) for t in sorted(set(data))]
8       result = [t[1] for t in sorted(tups,key=lambda x : x[0],reverse=True)]
9       return result
```

data = ["apple", "pear", "cherry", "apple", "pear", "apple", "banana“]

tups = [(3, "apple"),(1, "banana"),(1,"cherry"),(2,"pear")]

sorted(…) line 8 = [(3,"apple"),(2,"pear"),(1, "banana"),(1,"cherry")]

result = ["apple", "pear", "banana", "cherry"]

PRINT A LOT!

WOTO-3 (DIDN'T DO)
http://bit.ly/101s23-0413-3