

Graph-based!

Recommenders 101

Caroline Harbitz

This workshop is...

- A basic overview of traditional recommendation algorithms
- A hands-on introduction to graph-powered recommendations

This workshop is not about...

- In-depth analyses of recommendation algorithms
- Graph theory
- Implementing a graph database application
- Bashing RDBMS and aggregate stores
- nordstrom.com's recommendations

Before we get started: some useful links

- Clone (or download) this workshop's github repository

<https://github.com/cterp/rec101-workshop>

- Neo4j documentation

<http://neo4j.com/docs/stable/>

- Intro to Cypher

<http://neo4j.com/developer/cypher-query-language/>

- Neo4j ref card

<http://neo4j.com/docs/stable/cypher-refcard/>

Workshop outline

Part 1: Recommendation algorithms

Part 2: Graph database basics and queries

Part 3: Build your own simple recommender

Customers also considered



\$12.57

Tide HE Turbo Powder
Laundry Detergent

★★★★★ 33



\$12.57



HEC Simply Clean
& Fresh...

★★★★★ 95

Walmart

Recently Viewed Items and Featured Recommendations

Viewing history



Holiday Wonderland 300-
Count Clear Christmas Mini
Light Set

★★★★★ 293

\$21.99 ✓ Prime



Resin

28.5-Inch

★★★★★ 293

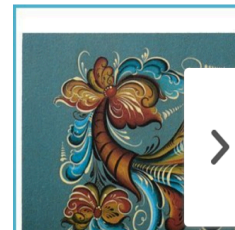
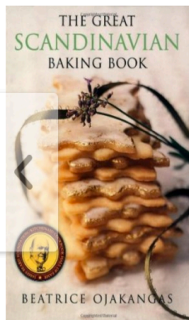
\$22.45 ✓ Prime



Popular on eBay

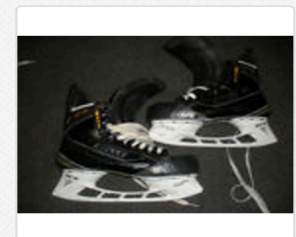
You might also like...

Recommendations for You in Books



ebay

Free shipping



Used Bauer Supreme
TotalOne MX3 Pro...

\$79.99

1 bid



NORDSTROM

Bestsellers



(Women)
Was: \$169.95
Now: \$149.90 10% OFF
★★★★★ (1598)



Bootie (Women) (Nordstrom
Exclusive)
Was: \$149.95
Now: \$99.90 33% OFF
★★★★★ (289)



Was: \$99.95
Now: \$79.90 20% OFF
★★★★★ (1864)

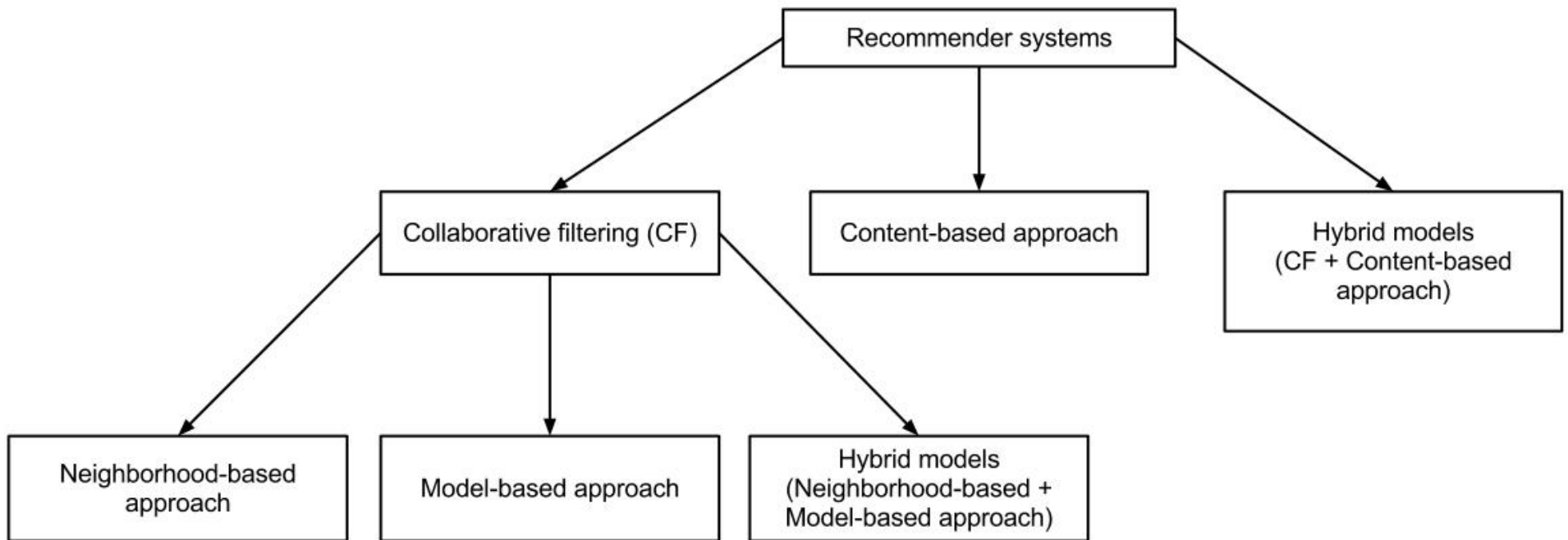


Converse Chuck Taylor®
'Shoreline' Sneaker (Women)
(Regular Retail Price: \$49.95)
Add to cart to see price
★★★★★ (258)



Dolce Vita 'Garim' Wedge
Bootie (Women) (Nordstrom
Exclusive)
Was: \$109.95
Now: \$79.90 25% OFF
★★★★★ (7)

Part 1: Recommenders



https://en.wikipedia.org/wiki/Collaborative_filtering

Recommendation process

Purpose: personalize each customer's online store.

1. Find potential recommendations
2. Narrow down potential recommendations
3. Hide irrelevant recommendations
4. Measure the quality of the recommendations

Collaborative filtering

Predict a person's affinity for something by connecting that person to other people with similar tastes.

Collaborative filtering: user-user

- Compute “distance” between all users
- Neighborhoods
- Pitfalls:
 - Neighborhood quality
 - Online calculations

Collaborative filtering: item-item

- Example: amazon.com
- Find items that customers tend to purchase together
- Calculate the similarity between a single product and all related products

Collaborative filtering: item-item



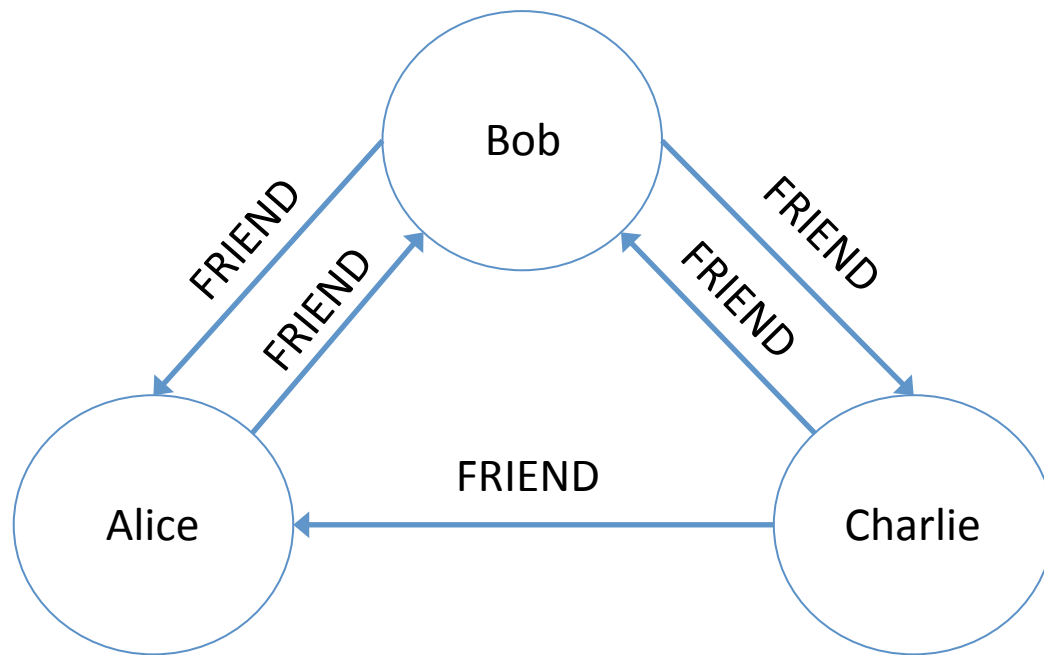
```
For each item in product catalog  $I_1$ 
  For each customer  $C$  who purchased  $I_1$ 
    For each item  $I_2$  purchased by customer  $C$ 
      Record that a customer purchased  $I_1$  and  $I_2$ 
For each item  $I_2$ 
  Compute the similarity between  $I_1$  and  $I_2$ 
```

Collaborative filtering: Limitations

- Rigid
- Scaling
- Recommendation quality
- Data sparsity

Part 2: Neo4j graphs

- A graph: a collection of *nodes* and *edges*

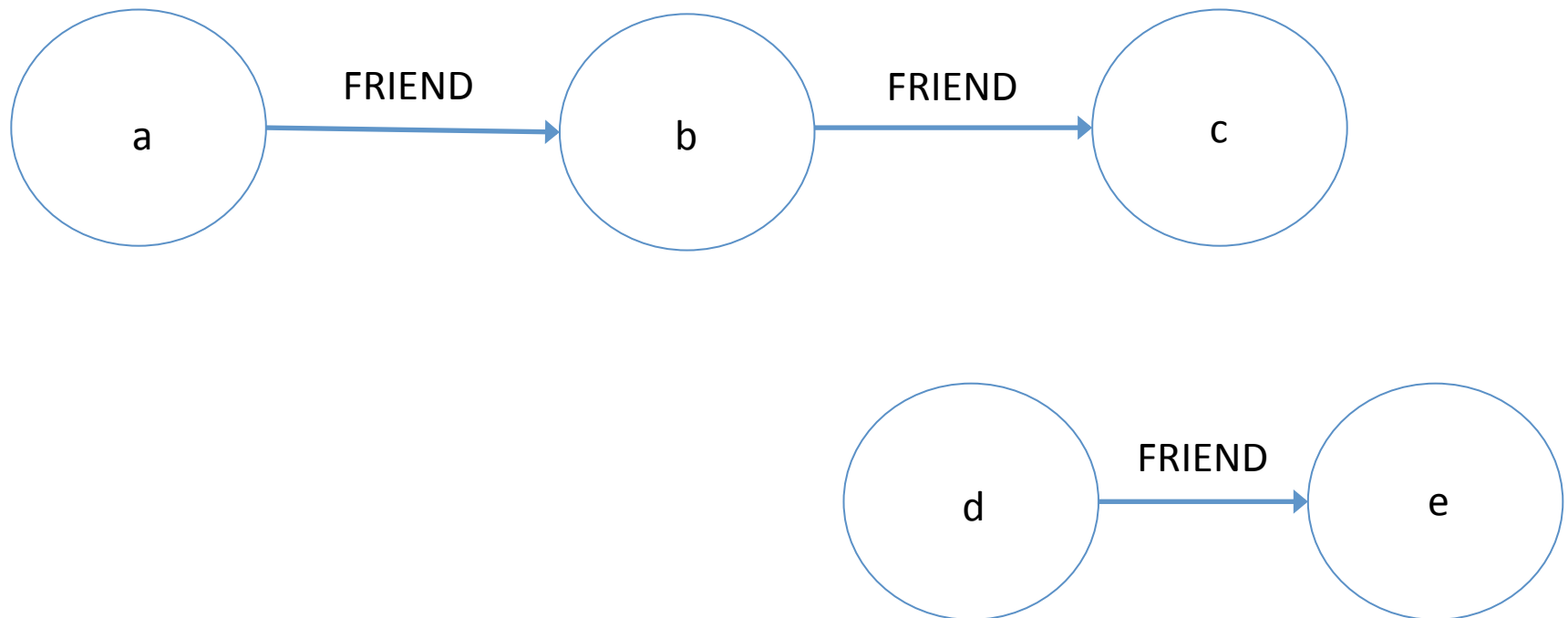


A simple property graph.

4 building blocks of a Neo4j graph

1. Nodes: entities
2. Relationships: connect nodes
3. Properties: entity attributes, relationship qualities, and metadata
4. Labels: group nodes by role

What is a traversal?



Ok, so what?

- Graphs let you forget about:
 - Primary and foreign key constraints
 - Expensive joins
 - Expensive reciprocal queries
 - Sparse tables with nullable columns
- Graphs are all about connectedness:
 - Store direct references to neighboring nodes
 - Relationships are first-class citizens of graph data model
 - Connect your data as the domain dictates rather than a schema imposed upfront

Limitations of this approach

- Your graph is only as good as your data model
- Neo4j's implementation optimizes traversals (OLTP) at the expense of non-traversal queries (OLAP)
- Not a standard industry tool

Why neo4j?

- Large user community
- Easy to use
- Documentation

Cypher

- Neo4j's graph query language
 - DSL to query a Neo4j graph database
- In a nutshell: describe paths in the graph by using ASCII art

Cypher examples

- Nodes: ()
- Relationships: []
- Directions: -> and <-
- Graph pattern examples:

`()-[]-()`

`()-[]->()`

`()<-[]-()`

ASCII art describes the graph pattern of a Cypher query.

Frequently used statements

MATCH

- Draws the query pattern
- MATCH (node1:Label1)-[rel:REL_TYPE]->(node2:Label2)

RETURN

- Equivalent to SQL SELECT

WHERE

- Filter your pattern matching results

WITH

- Chain query parts; similar to Unix pipe. RETURN.

Start your Neo4j servers

From your Neo4j directory, run:

```
$ ./bin/neo4j start
```

Then, in your browser go to:

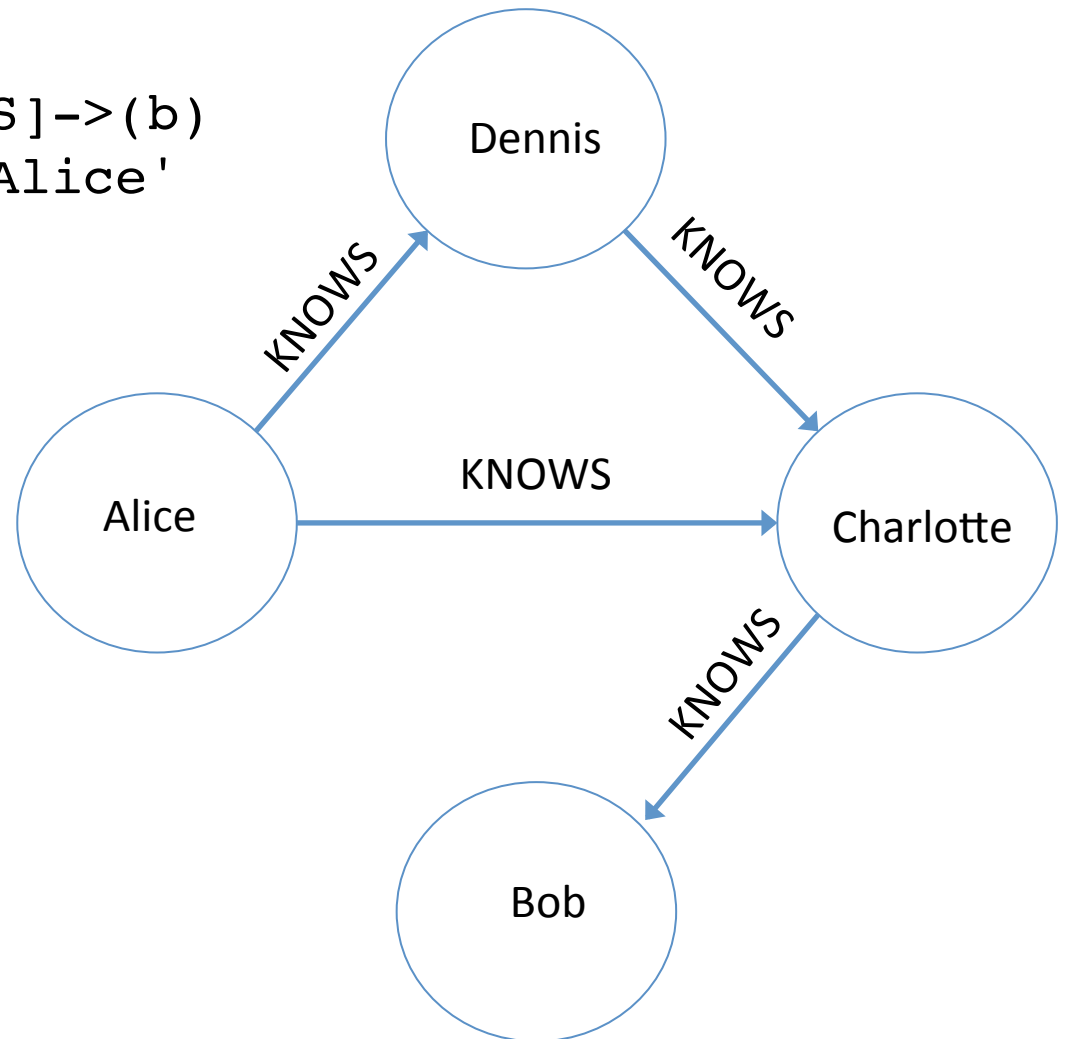
<http://localhost:7474/browser/>

Run 'part_2.cypher' in the browser

Example 1: find Alice's friends

```
MATCH (a:Person)-[:KNOWS]->(b)
WHERE a.person_name = 'Alice'
RETURN b.person_name;
```

What happens when you return just 'b'?



Equivalent queries

```
MATCH (a:Person)-[:KNOWS]->(b)
WHERE a.person_name = 'Alice'
RETURN b.person_name;
```

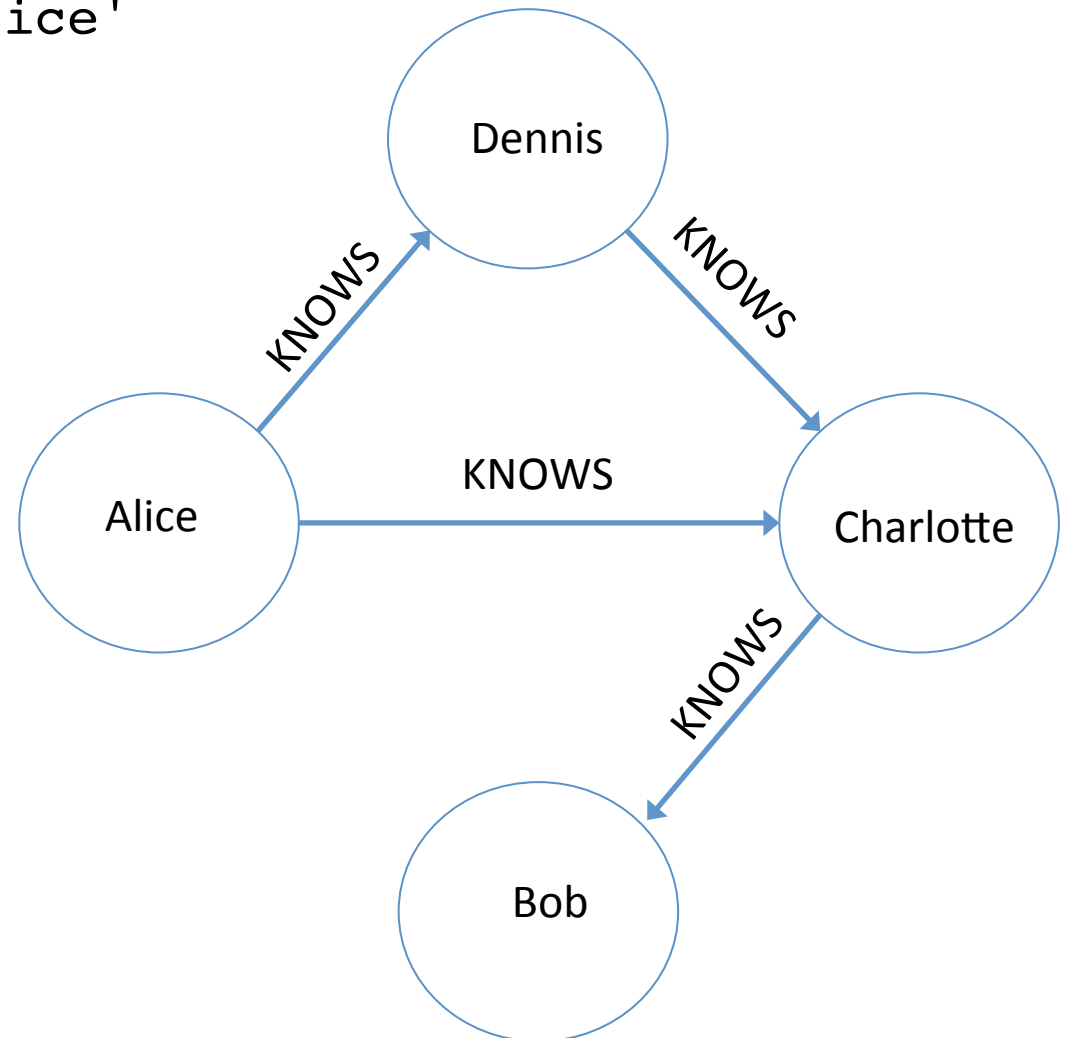
```
MATCH (a:Person)-[:KNOWS]->(b:Person)
WHERE a.person_name = 'Alice'
RETURN b.person_name;
```

```
MATCH (a)-[:KNOWS]->(b)
WHERE a.person_name = 'Alice'
RETURN b.person_name;
```

```
MATCH (a:Person {person_name: 'Alice'})-[:KNOWS]
      ->(b:Person)
RETURN b.person_name;
```

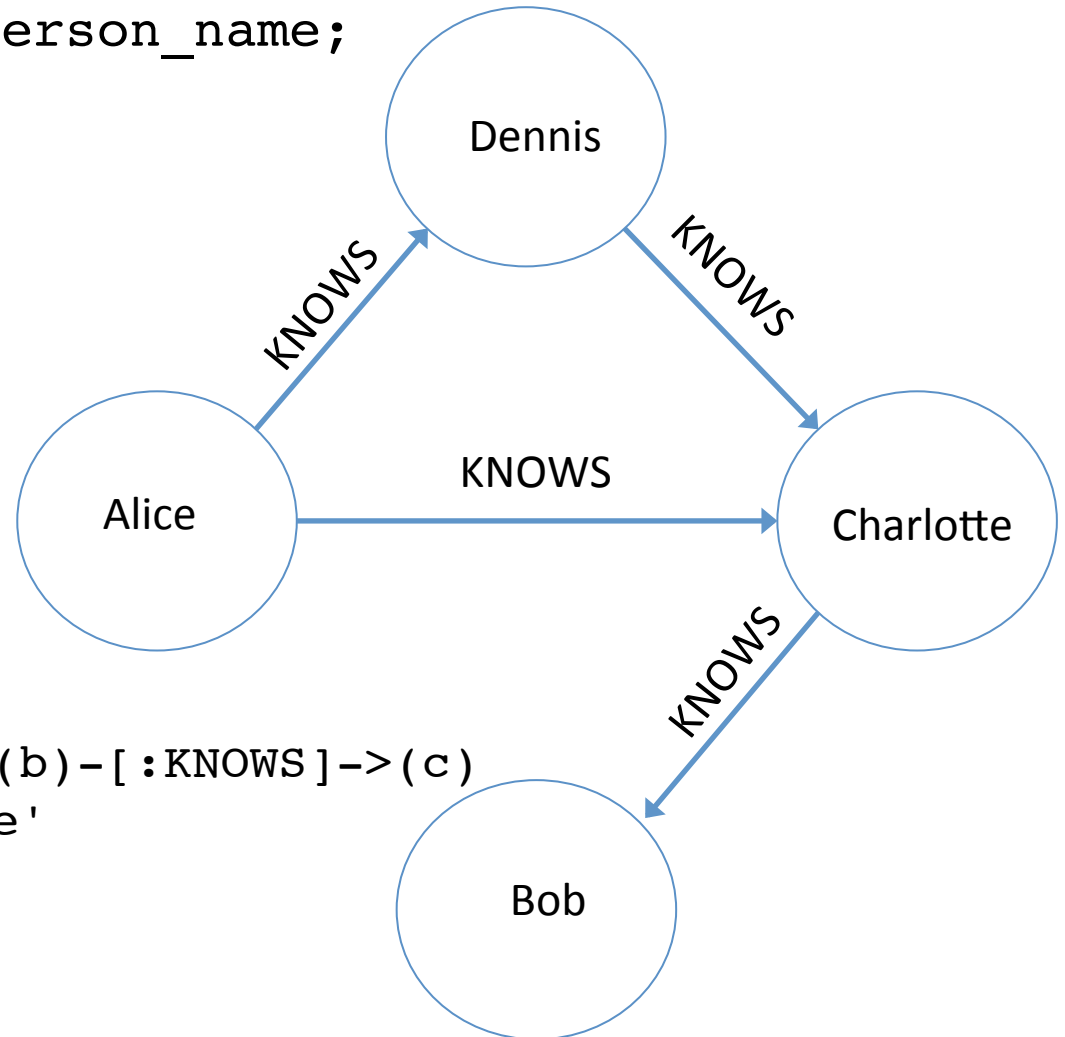
Example 2: find Alice's mutual friend

```
MATCH (a:Person)-[:KNOWS]->(b)-[:KNOWS]->(c),  
      (a)-[:KNOWS]->(c)  
WHERE a.person_name = 'Alice'  
RETURN b.person_name;
```



Example 3: find Alice's friend-of-friends

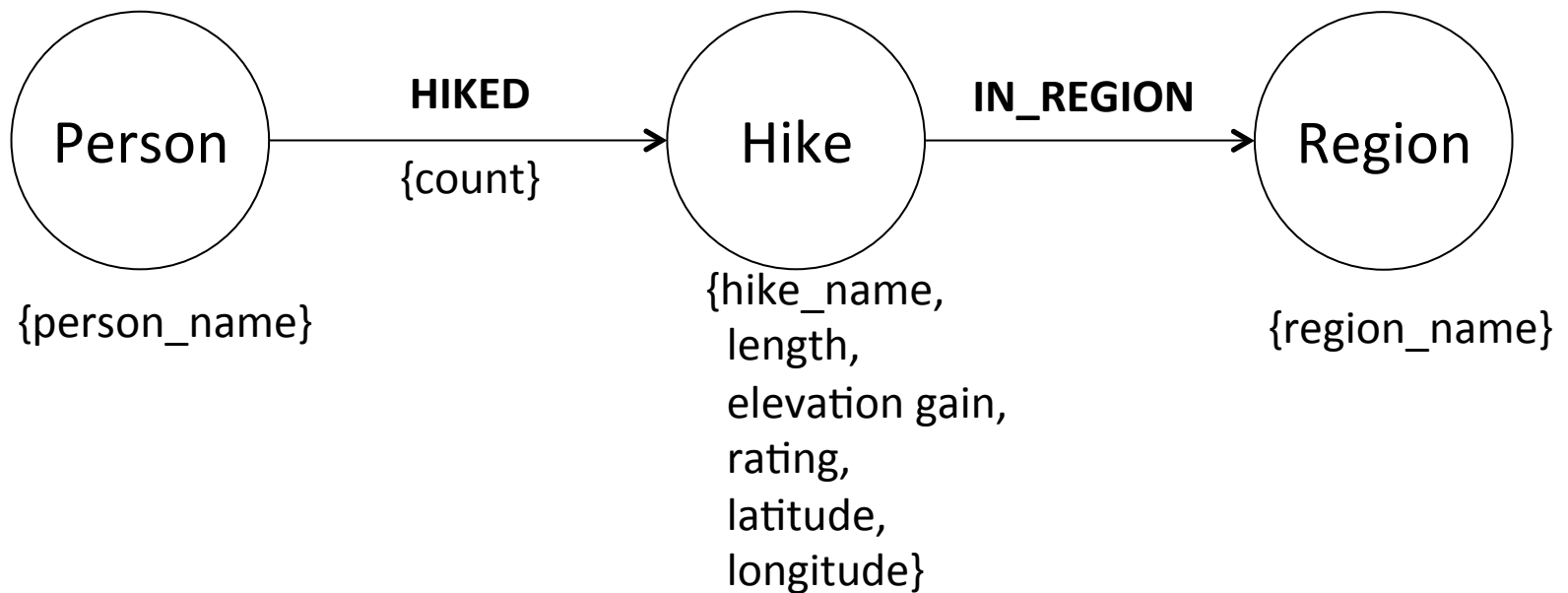
```
MATCH (p:Person {person_name: 'Alice'})-  
      [:KNOWS*..2]->(friend_of_friend)  
WHERE NOT (p)-[:KNOWS]-(friend_of_friend)  
RETURN friend_of_friend.person_name;
```



```
// Equivalent query  
MATCH (a:Person)-[:KNOWS]->(b)-[:KNOWS]->(c)  
WHERE a.person_name = 'Alice'  
AND NOT (a)-[:KNOWS]->(c)  
RETURN c.person_name;
```

Part 3: Build your own recommender

Data model



Let's gradually build up our recommender

1. Universally popular hikes
2. A person's favorite hikes
3. Hikes that similar people liked

Take a moment to run these in the browser:

1. `'clean_database.cypher'`
2. `'import_hikes.cypher'`

Warm-up queries

Find...

- All the hikes on the Olympic Peninsula
- All the hikes with more than 4000 feet of elevation gain (**hint**: use `toInt()`)

1. Universally popular hikes

Let's define "popular" as the hikes that our hikers hiked most often.

Write a query that finds the most popular hikes.

2. A robot's favorite* hikes

Write a query that lists Bender's top 5 favorite (most hiked) hikes.

3. Suggest new* hikes to Bender

Write a query that:

1. takes Bender's 5 favorite hikes,
2. finds other people that liked those hikes, and
3. returns the favorite hikes of those other people.

Hint: WITH will be useful.

3. Suggest hikes to Bender

- Take the favorite hikes,
- And find other hikers who hiked Bender's favorite hikes:
- We need to take Bender out of his recommendations:
- Now find those hikers' favorite hikes that are not Bender's favorite hikes:
- Now take out Bender's favorite hikes and return some recommendations:

Improvements

- Score recommendations and boost/penalize some scores
- Remove irrelevant or lowly rated recommendations
 - Blacklist, filter
- Measure the quality of recommendations
- Different graph implementation

What I hope you've gained

- Appreciation for a new data structure
- Insight into the complicated world of recommendations

Non-technical concerns

- \$\$\$
- Computers are not creative:
 - Apple and Spotify hire DJs to compile some of their playlists
- Machines make educated guesses but can't understand music or appreciate the utility of an item