Some Reminders for a Seamless Online Class…

- Please turn on your video
- Mute yourself (press and hold spacebar when you'd like to talk)
- Don't do anything you wouldn't do in an in-person class
- I will occasionally check the chat for messages if you'd like to share there instead
- Please say your name before you speak

Recap

- Data-savviness is the future!
- "Classical" relational databases
  - Notion of a DBMS
  - The relational data model and algebra: bags and sets
  - SQL Queries, Modifications, DDL
  - Database Design
  - Views, constraints, triggers, and indexes
  - Query processing & optimization
  - Transactions
- Non-classical data systems
  - Data preparation:
    - Semi-structured data and document stores
    - Unstructured data and search engines
  - Data Exploration:
    - Cell-structured data and spreadsheets
    - Dataframes and dataframe systems
    - OLAP, summarization, and visual analytics
  - Batch Analytics:
    - Compression and column stores
    - Parallel data processing and map-reduce
    - Streaming, sketching, approximation
  - Special Topics:
    - **Graph processing systems**

Today's Lecture

- Let's talk about graphs!

A lot of real-world datasets can be modeled as graphs…

- Social network datasets
  - A follows B, A is a friend of B
- Internet dataset
  - Page A links to Page B
- Road network datasets
  - Road A is connected to road B
- Scientific literature datasets
  - Paper is written by author, cites another paper
- Scientific interaction datasets
  - Disease treated by drug, drug A and drug B have interactions

So how do we manage and process graphs?

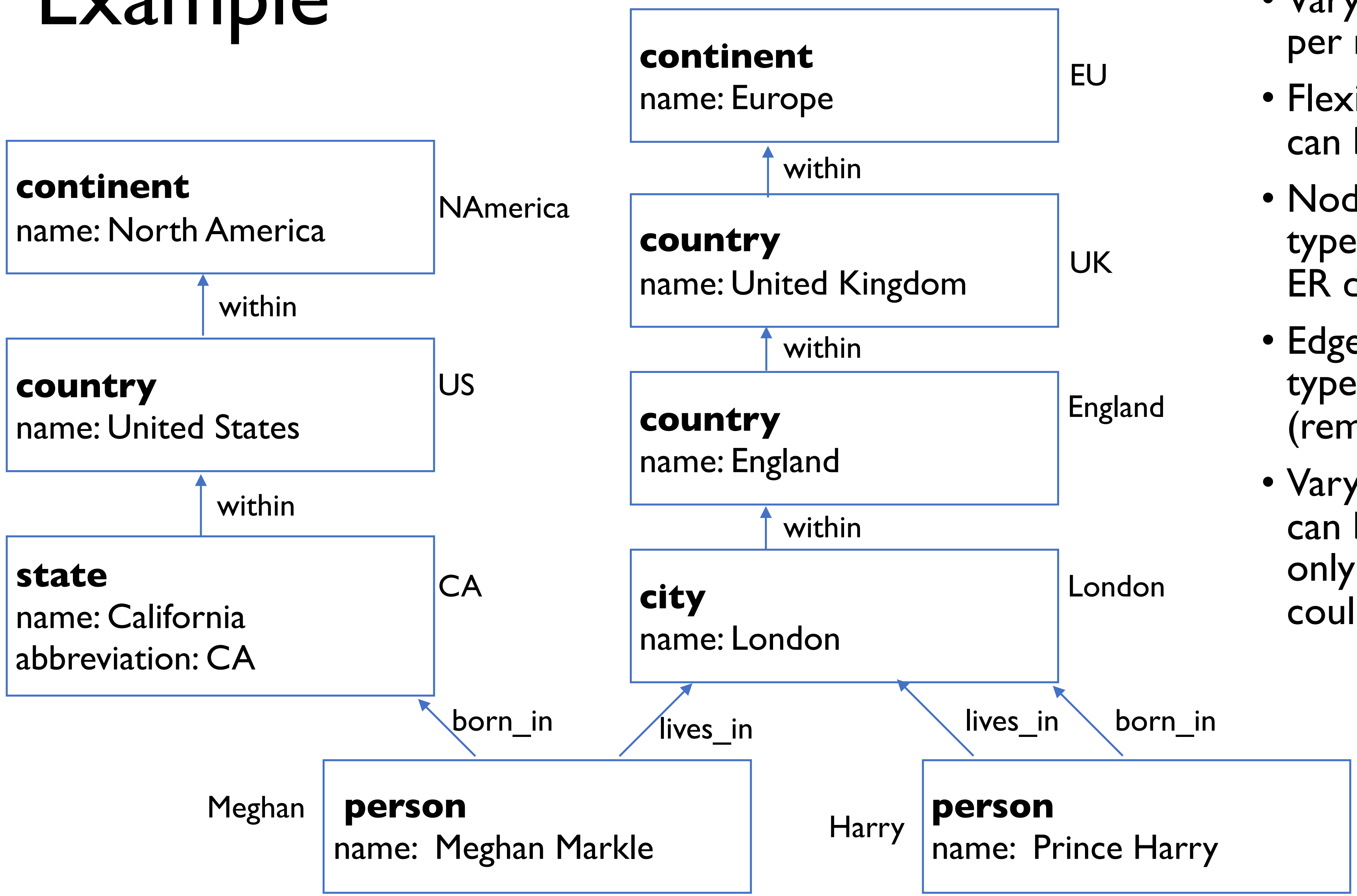
- Graph databases:
  - We'll briefly describe two different types of models for representing graphs
    - Property graph model
      - Systems like Neo4J, Titan, InfiniteGraph
    - Triple-store
      - Systems like Datomic, AllegroGraph, …
    - Contrast with RDBMS representation
  - Talk about querying languages: Cypher and SQL for RDBMS representations
- Graph processing systems:
  - Graphlab and Pregel (briefly)

Some content drawn from "Designing Data Intensive Applications"

Graph Databases: The Property-Graph Model

- Only two different types of entities:
  - Node and Edges
- Each Node consists of:
  - A unique identifier
  - A type for the node
  - A collection of properties (key, value pairs, like in JSON)
- Each edge consists of
  - A unique identifier
  - A head and a tail node id
  - A type for the relationship
  - A collection of properties (key, value pairs, like in JSON)

Example



- Varying number of properties per node
- Flexibility in edges: a country can be within a country
- Nodes encompass a variety of types of entities (remember ER diagrams!)
- Edges encompass a variety of types of relationships (remember ER diagrams!)
- Varying granularities: born_in can be a state if that is the only information known, or could be a city if that is known

Why is this powerful?

- At a high level, there are only two "relations" — nodes and edges, as opposed to the relational schema where you may have many different entities and relationships, each encoded into its own relations
  - Can easily evolve by adding new nodes, edges, or adding properties to existing nodes or edges
- Unlike pure json which nests everything making it hard to operate on/query, the property graph data model surfaces the graph itself as an important structure to "traverse" and walk across forward or backward

- To see this, we'll look at some examples of queries
- But before that, how do we represent this data model in an RDBMS?

Supporting Property Graphs in RDBMSs

```
CREATE TABLE Nodes
   (node_id STRING PRIMARY KEY,  type STRING, properties JSON)
CREATE TABLE Edges
   (edge_id STRING PRIMARY KEY,
    head_id INTEGER REFERENCES Nodes (node_id),
    tail_id INTEGER REFERENCES Nodes (node_id),
    type STRING, properties JSON)
```

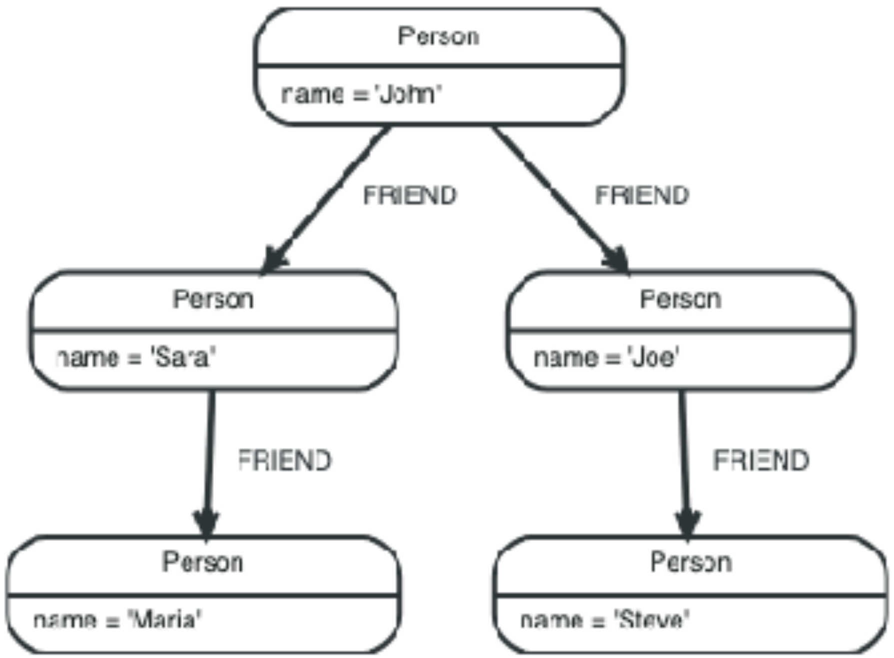
Property graphs allow rapid traversal on both head and tail nodes, so

```
CREATE INDEX edge_tails ON Edges (tail_id);
CREATE INDEX edge_heads ON Edges (head_id);
```

Cypher Query Language (from Neo4j)

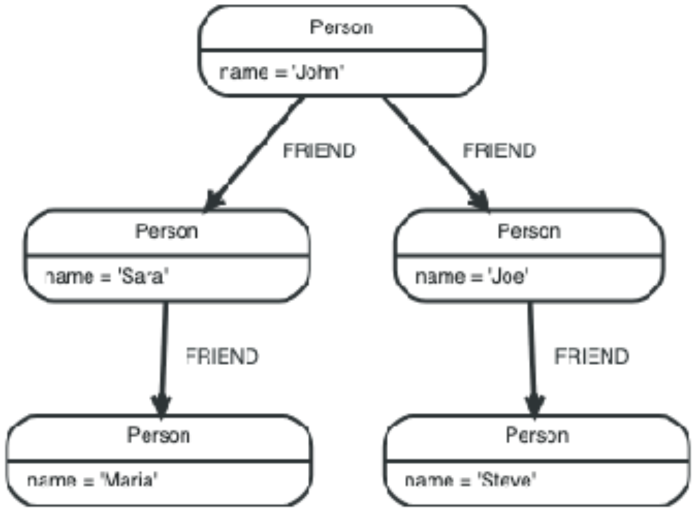
- A declarative query language for property graphs
- First let's consider a simple example that we construct…

```
CREATE (john:Person {name: 'John'})
CREATE (joe:Person {name: 'Joe'})
CREATE (steve:Person {name: 'Steve'})
CREATE (sara:Person {name: 'Sara'})
CREATE (maria:Person {name: 'Maria'})
CREATE (john)-[:FRIEND]->(joe)-[:FRIEND]->(steve)
CREATE (john)-[:FRIEND]->(sara)-[:FRIEND]->(maria)
```



Cypher Query Language (from Neo4j)

```
MATCH (john {name: 'John'})-[:FRIEND]->()-[:FRIEND]->(fof)
RETURN john.name, fof.name
```



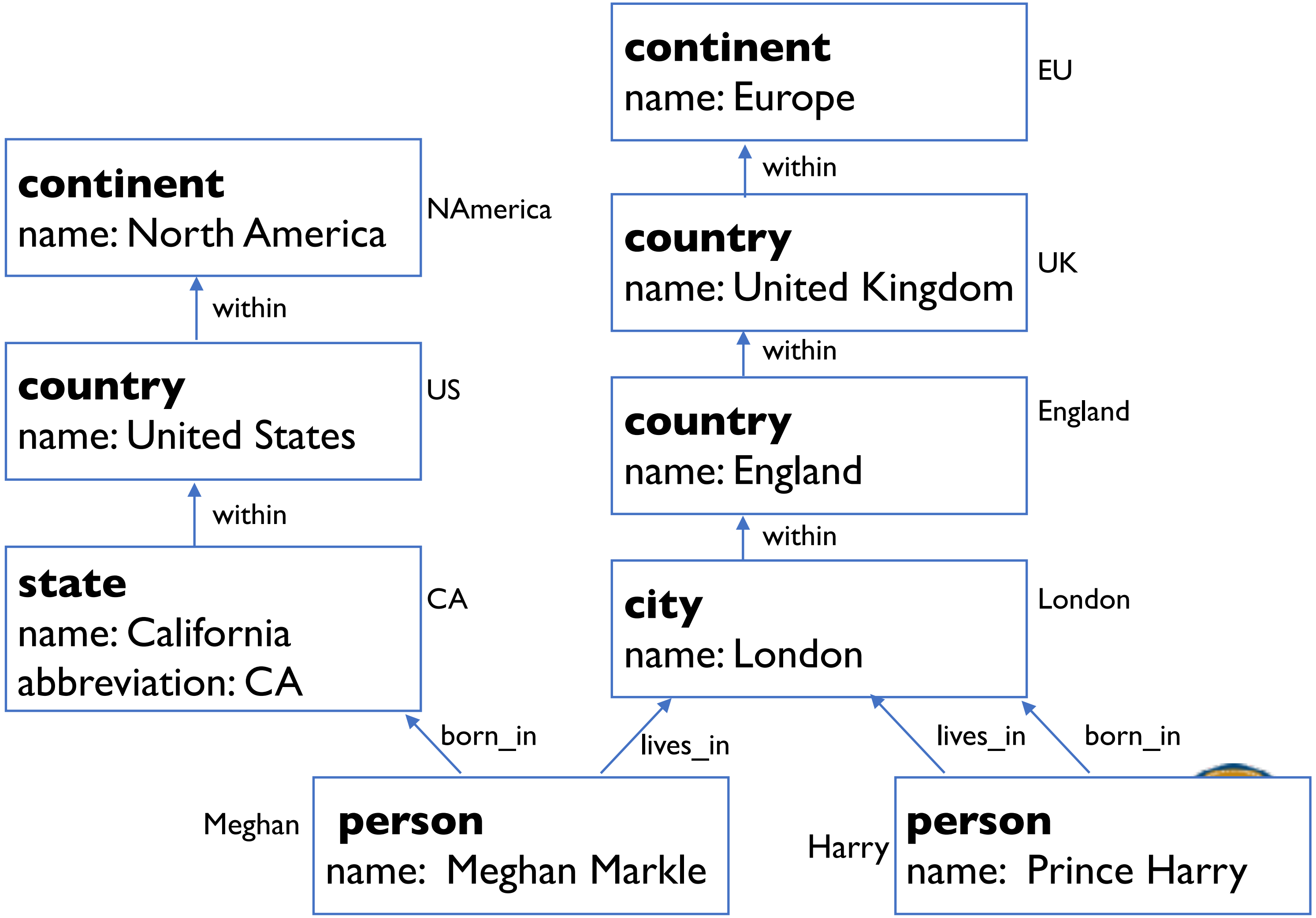
- What do we think this query returns?

```
MATCH (user)-[:FRIEND]->(follower)
WHERE user.name IN ['Joe', 'John', 'Sara', 'Maria',
'Steve'] AND follower.name =~ 'S.*'
RETURN user.name, follower.name
```

- What do we think this query returns?

More complicated query

```
MATCH
  (person)-[:BORN_IN]->()-[:WITHIN*0..]->(us:Country {name: 'United States'})
  (person)-[:LIVES_IN]->()-[:WITHIN*0..]->(eu:Continent {name: 'Europe'})
RETURN person.name
```



How would we issue the same query in SQL?

- Query: find people who were born in the US and live in Europe.
  - Let's focus on a subquery: we just want to find all the locations within the US.
  - Nodes (node_id, type, properties)
  - Edges (edge_id, head_id, tail_id, type, properties)
- We use *recursive common table expressions*
  - WITH defines a CTE; WITH RECURSIVE defines a CTE where the relation can refer to itself.

```
WITH RECURSIVE in_usa (node_id)
AS (
   SELECT node_id FROM Nodes WHERE properties->>'name' = 'United States'
   UNION
   SELECT tail_id FROM Edges JOIN in_usa ON Edges.head_id = in_usa.node_id
   WHERE Edges.type = 'WITHIN'
   )
SELECT * FROM in_usa;
```

How would we issue the same query in SQL?

- We use *recursive common table expressions*
- WITH defines a CTE; WITH RECURSIVE defines a CTE where the relation can refer to itself.
- Semantics:
  - Start by adding the contents from the first subquery
  - Then, in each round, we "add" new content using the second subquery
  - We stop when we have no more to add

```
WITH RECURSIVE in_usa (node_id)
AS (
   SELECT node_id FROM Nodes WHERE properties->>'name' = 'United States'
   UNION
   SELECT tail_id FROM Edges JOIN in_usa ON Edges.head_id = in_usa.node_id
   WHERE Edges.type = 'WITHIN'
   )
SELECT * FROM in_usa;
```

Constructing the query in SQL

- The full query is even more complicated: this was just one of four query fragments

- In general, really hard to do graph traversal type queries via SQL

Triple-Stores

- A different model to represent the same information as property graphs
- Everything is a triple
  - (subject, predicate, object)
- For example:

(Meghan, type, person)

(Meghan, name, Meghan Markle)

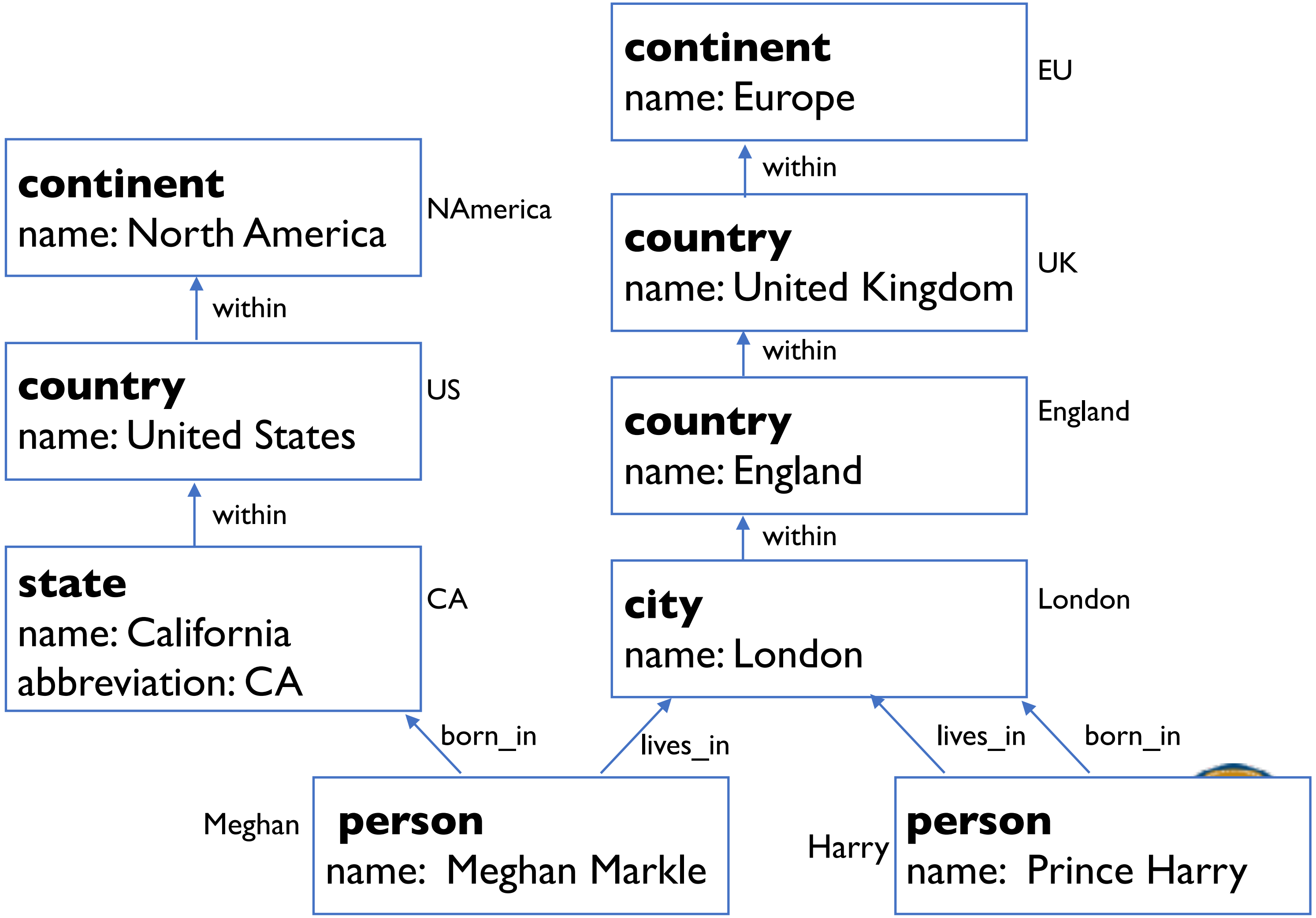
(Meghan, born_in, CA)

(Meghan, lives_in, London)

(CA, type, state)

(CA, name, California)

…



Triple-Stores

- A different model to represent the same information as property graphs
- Everything is a triple
  - (subject, predicate, object)

- RDF: Resource Description Format: is a mechanism for encoding data in triple stores
- SPARQL: Query language, like Cypher, that operates on RDF

Graph Processing Systems

- Another type of systems for graphs focus on analytics on graphs as opposed to management of graph data
- For example:
  - Computing connected components of a graph
  - Computing pagerank of nodes

- Also many ML algorithms!

Some slides courtesy Joey Gonzalez

Large Scale ML

Data-Parallel

Graph-Parallel

Map Reduce

Feature Extraction

Cross Validation

Computing Sufficient Statistics

Graphical Models
Gibbs Sampling
Belief Propagation
Variational Opt.

Semi-Supervised Learning
Label Propagation
CoEM

Collaborative Filtering
Tensor Factorization

Graph Analysis
PageRank
Triangle Counting

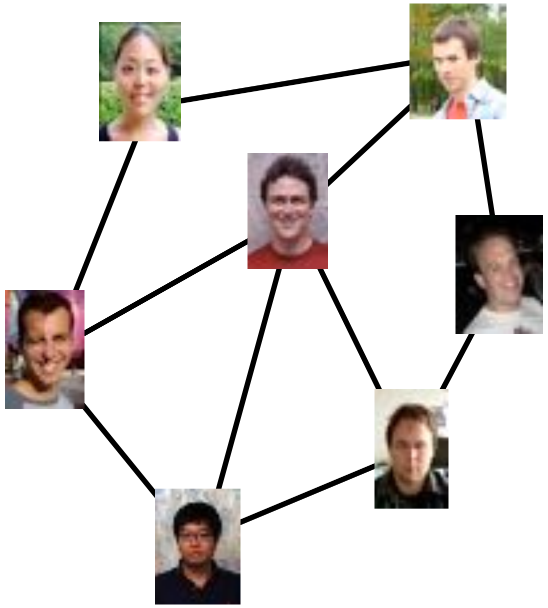
Label Propagation for Content Recommendation

- Recurrence Algorithm:

$$Likes[i] = f\left(\sum_{j \in Friends[i]} g(w_{ij}, Likes[j])\right)$$

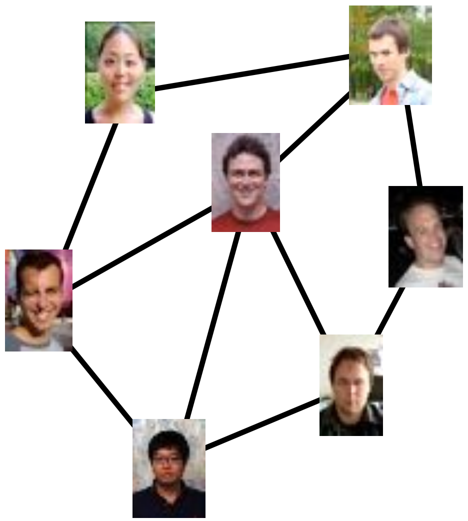
  – iterate until convergence

- Parallelism:
  – Compute all *Likes[i]* in parallel

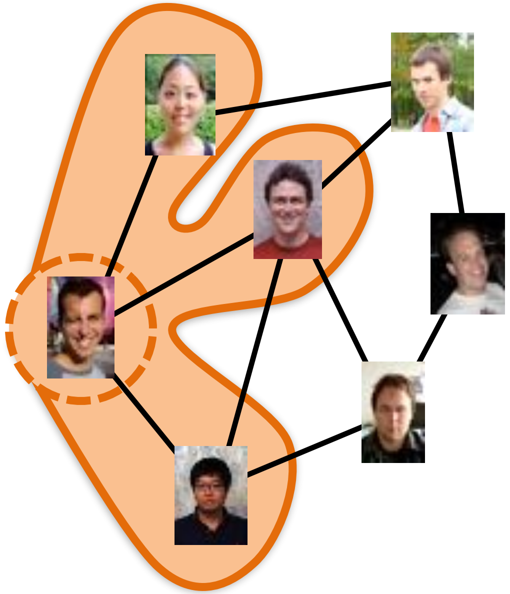


Properties of Graph-Parallel Algorithms

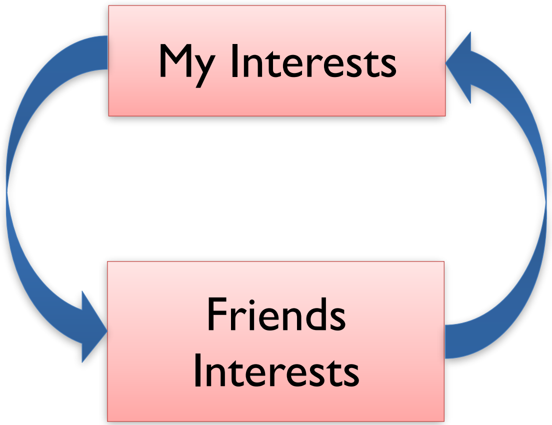
Dependency Graph



Local Updates



Iterative Computation



Large Scale ML

Data-Parallel | Graph-Parallel

Map Reduce

Feature Extraction

Cross Validation

Computing Sufficient Statistics

Graph Proc. Systems

Graphical Models
Gibbs Sampling
Belief Propagation
Variational Opt.

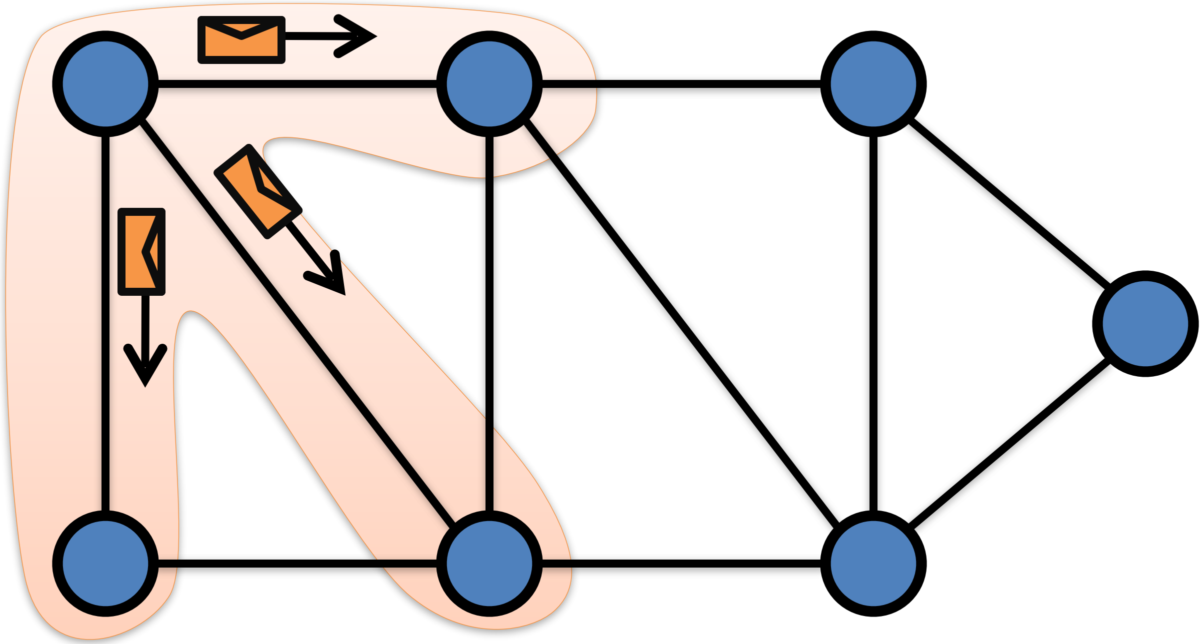
Semi-Supervised Learning
Label Propagation
CoEM

Collaborative Filtering
Tensor Factorization

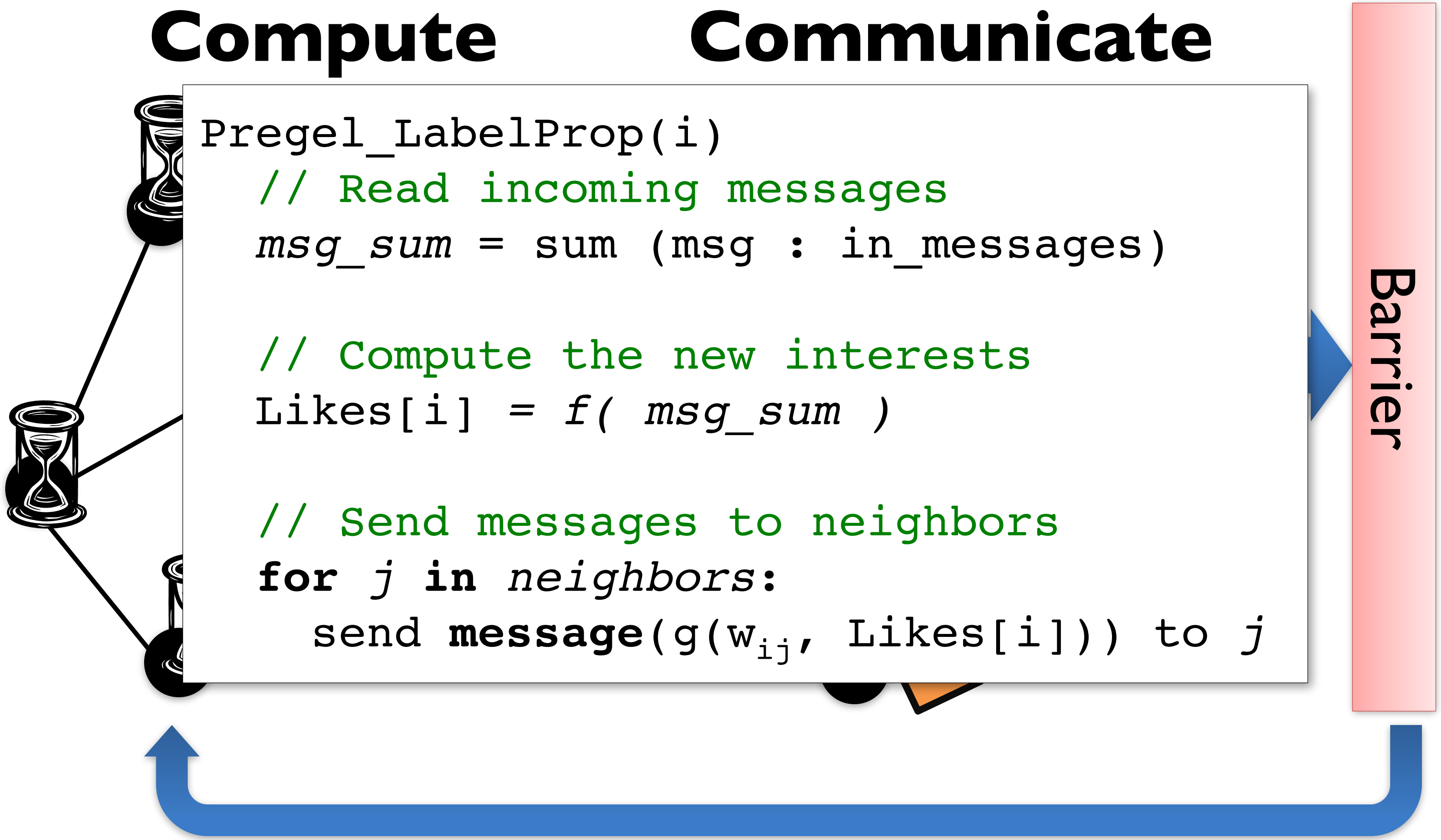
Graph Analysis
PageRank
Triangle Counting

Graph-Parallel Abstractions

- Vertex-Program associated with each vertex
- Graph constrains the interaction along edges
  - Pregel: Programs interact through Messages: synchronous, exact
  - GraphLab: Programs can read each-others state: asynchronous, approximate



The Pregel Abstraction




```
Pregel_LabelProp(i)
   // Read incoming messages
   msg_sum = sum (msg : in_messages)

   // Compute the new interests
   Likes[i] = f( msg_sum )

   // Send messages to neighbors
   for j in neighbors:
      send message(g(w_ij, Likes[i])) to j
```

The Pregel Abstraction

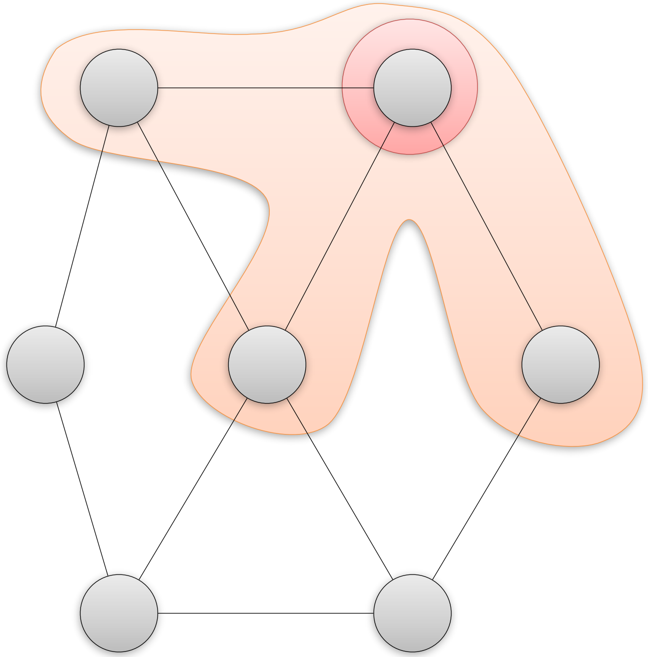
- "Thinking like a vertex"
- *Bulk Synchronous Parallel* (BSP) of parallel programming
- Each vertex maintains its own state and logic, and exchanges messages with neighboring vertexes in each round
    - After a point, if no vertexes receive any new messages, they can opt to terminate

- Q: Let's say I want to compute connected components using pregel, how would I do it?

The GraphLab Abstraction

Vertex-Programs are executed asynchronously and directly read the neighboring vertex-program state. So Approximate BSP

```
GraphLab_LblProp(i, neighbors
Likes)
  // Compute sum over neighbors
  sum = 0
  for j in neighbors of i:
    sum = g(wij, Likes[j])
  // Update my interests
  Likes[i] = f( sum )
  // Activate Neighbors if needed
  if Like[i] changes then
    activate_neighbors();
```



Activated vertex-programs are executed *eventually* and can read the new state of their neighbors

Graph Processing Systems Today

- Apache Giraph, GraphX within Spark, Naiad (but also supports streaming applications), GPS, …

- More recently, ML systems have become more tensor centric thanks to deep learning
  - TensorFlow, PyTorch, … support distributed tensor manipulation in a semi-declarative interface
  - A lot to say here but we don't have time

Takeaways