

# Query Languages for Unrestricted Graph Data

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# The Age of the Graph Is Upon Us (Again)

- Early-mid-90s: semi- or un-structured data research was all the rage
  - data logically viewed as graph
  - initially motivated by modeling WWW (page=vertex, link=edge)
  - query languages expressing constrained reachability in graph
- Late 90s: special case XML (graph restricted to tree shape)
- 2000s: JSON and friends (also tree shaped)
- ~2010 to present: back to unrestricted graphs
  - Initially motivated by analytic tasks in social networks,
  - Now universal use (data is linked in all scenarios)

# The Unrestricted Graph Data Model

- Nodes correspond to entities
- Edges are binary, correspond to relationships
- Edges may be directed or undirected
- Nodes and edges may carry labels
- Nodes and edges annotated with data
  - both have sets of attributes (key-value pairs)
- A schema is not required to formulate queries

# Example Graph

Vertex types:

- Product (name, category, price)
- Customer (ssn, name, address)

Edge types:

- Bought (discount, quantity)
- Customer c bought 100 units of product p at discount 5%:

modeled by edge

$c \text{ -- (Bought \{discount=5\%, quantity=100\})} \rightarrow p$

# Expressing Graph Analytics

- Two Different Approaches
  - High-level query languages à la SQL
  - Low-level programming abstractions
    - Programs written in C++, Java, Scala, Groovy...
- Initially adopted by disjoint communities (recall NoSQL debates)
- Recent trend towards unification

# High-Level Query Languages

# Some Modern Graph QLs We Will Discuss

There is a host of them! Spectrum includes

- Datalog with aggregation (LogicBlox)
- Cypher (neo4j)
  - declarative, highly similar to StruQL (and hence CRPQs)
- Gremlin (Apache and commercial projects)
  - dataflow programming model: graph annotated with tokens (“traversers”) that flow through it according to user program
- New arrival: GSQL (TigerGraph)
  - Inspired by SQL + BSP, extended for more flexible grouping/aggregation

# Key Ingredients for High-Level Query Languages

- Pioneered by academic work on Conjunctive Query (CQ) extensions for graphs (since '87)
  - Path expressions (PEs) for navigation
  - Variables for manipulating data found during navigation
  - Stitching multiple PEs into complex navigation patterns  
→ conjunctive regular path queries (CRPQs)
- Beyond CRPQs, needed in modern applications:
  - Aggregation of data encountered during navigation  
→ support for bag semantics as prerequisite
  - Intermediate results assigned to nodes/edges
  - Control flow support for class of iterative algorithms that converge to result in multiple steps
    - (e.g. PageRank-class, recommender systems, shortest paths, etc.)



# Path Expressions

# Path Expressions

- Express reachability via constrained paths
- Early graph-specific extension over conjunctive queries
- Introduced initially in academic prototypes in early 90s
  - StruQL (AT&T Research, Fernandez, Halevy, Suciu)
  - WebSQL (Mendelzon, Mihaila, Milo)
  - Lorel (Widom et al)
- Today supported by languages of commercial systems
  - Cypher, SparQL, Gremlin, GSQL

# Path Expression Syntax

Notations vary. Adopting here that of SparQL W3C Recommendation.

path  $\rightarrow$  edge label

	_	// wildcard, any edge label
	^ edge label	// inverse edge
	path . path	// concatenation
	path   path	// alternation
	path*	// 0 or more reps
	path*(min,max)	// at least min, at most max
	(path)	

# Path Expression Examples (1)

- Pairs of customer and product they bought:

***Bought***

- Pairs of customer and product they were involved with (bought or reviewed)

***Bought/Reviewed***

- Pairs of customers who bought same product (lists customers with themselves)

***Bought.^Bought***

# Path Expression Examples (2)

- Pairs of customers involved with same product (like-minded)

***(Bought/Reviewed).^(^Bought/^Reviewed)***

- Pairs of customers connected via a chain of like-minded customer pairs

***((Bought/Reviewed).^(^Bought/^Reviewed))\****

# Path Expression Semantics

- In most academic research, the semantics are defined in terms of *sets of node pairs*
- Traditionally specified in two ways:
  - Declaratively, based on satisfaction of formulae/patterns
  - Procedurally, based on algebraic operations over relations
- These are equivalent

# Classical Declarative Semantics

- Given:
  - graph  $G$
  - path expression  $PE$
- the meaning of  $PE$  on  $G$ , denoted  $PE(G)$  is

the set of node pairs  $(src, tgt)$

s.t. there exists a path in  $G$  from  $src$  to  $tgt$

whose concatenated labels spell out a word in  $L(PE)$

$L(PE)$  = language accepted by  $PE$  when seen as regular expression over alphabet of edge labels

# Classical Procedural Semantics

$PE(G)$  is a binary relation over nodes, defined inductively as:

- $E(G)$  = set of s-t node pairs of E edges in G
- $\_ (G)$  = set of s-t node pairs of any edges in G
- $\wedge E(G)$  = set of t-s node pairs of E edges in G
- $P1.P2(G) = P1(G) \circ P2(G)$
- $P1|P2(G) = \text{set union } (P1(G), P2(G))$
- $P^*(G) = \text{reflexive transitive closure of } P(G)$

relational  
composition

finite due to  
saturation



# Conjunctive Regular Path Queries

- Replace relational atoms appearing in CQs with path expressions.
- Explicitly introduce variables binding to source and target nodes of path expressions.
- Allow multiple path expression atoms in query body.
- Variables can be used to stitch multiple path expression atoms into complex patterns.

# CRPQ Examples

- Pairs of customers who have bought same product (do not list a customer with herself):

**$Q1(c1,c2) :- c1 \text{ --Bought.}^{\wedge}\text{Bought--} \rightarrow c2, c1 \neq c2$**

- Customers who have bought and also reviewed a product:

**$Q2(c) :- c \text{ --Bought--} \rightarrow p, c \text{ --Reviewed--} \rightarrow p$**

# CRPQ Semantics

- Naturally extended from single path expressions, following model of CQs
- Declarative
  - lifting the notion of satisfaction of a path expression atom by a source-target node pair to the notion of satisfaction of a conjunction of atoms by a tuple
- Procedural
  - based on SPRJ manipulation of the binary relations yielded by the individual path expression atoms

# Limitation of Set Semantics

- Common graph analytics need to aggregate data
  - e.g. count the number of products two customers have in common
- Set semantics does not suffice
  - baked-in duplicate elimination affects the aggregation
- As in SQL, practical systems resort to bag semantics

# Path Expressions Under Bag Semantics

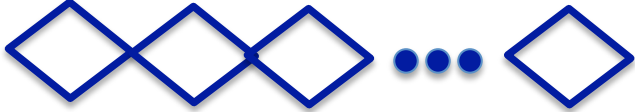
PE(G) is a bag of node pairs, defined inductively as:

- $E(G) = \text{set } \mathbf{bag}$  of s-t node pairs of E edges in G
- $\_ (G) = \text{set } \mathbf{bag}$  of s-t node pairs of any edges in G
- $\wedge E(G) = \text{set } \mathbf{bag}$  of t-s node pairs of E edges in G
- $P1.P2(G) = P1(G) \circ P2(G)$
- $P1|P2(G) = \text{set } \mathbf{bag}$  union  $(P1(G), P2(G))$
- $P^*(G) = \text{reflexive transitive closure of } P(G)$

relational  
composition for  
*bags*

Not necessarily  
finite under bag  
semantics!

# Issues with Bag Semantics

- Performance and semantic issues due to number of distinct paths
- Multiplicity of s-t pair in query output reflects number of distinct paths connecting s with t
  - Even in DAGs, these can be exponentially many.  
Chain of diamonds example: 
  - More serious: in cyclic graphs, can be infinitely many

# Solutions In Practice: Bound Traversal Length

- Upper-bound the length of the traversed path
  - Recall bounded Kleene construct  $*(min,max)$
  - Bounds length and hence number of distinct paths considered
  - Supported by Gremlin, Cypher, SparQL, GSQL, very common in tutorial examples and in industrial practice

# Solutions In Practice: Restrict Cycle Traversal

- No repeating vertices (simple paths)
  - Rules out paths that go around cycles
  - Recommended in Gremlin style guides, tutorials, formal semantics paper
  - Gremlin's `simplePath()` predicate supports this semantics
  - Problem: membership of s-t pair in result is NP-hard
- No repeating edges
  - Allows cyclic paths
  - Rules out paths that go around same cycle more than once
  - This is the Cypher semantics



# Solutions In Practice: Mix Bag and Set Semantics

- Bag semantics for star-free fragments of PE
- Set semantics for Kleene-starred fragments of PE
- Combine them using (bag-aware) joins

- Example:

**$p1.p2*.p3(G)$**

treated as

**$p1(G) \circ (\text{distinct } (p2*(G))) \circ p3(G)$**

- This is the SparQL semantics (in W3C Recommendation)

# Solutions In Practice: Leave it to User

- User explicitly programs desired semantics
- Path is first-class citizen, can be mentioned in query
- Can simulate each of the above semantics, e.g. by checking the path for repeated nodes/edges
- Could lead to infinite traversals for buggy programs
- Supported by Gremlin, GSQL
  - also partially by Cypher (modulo restriction that only edge non-repeating paths are visible)

# One Semantics I Would Prefer

- Allow paths to go around cycles, even multiple times
- Achieve finiteness by restriction to *pumping-minimal* paths
  - in the sense of Pumping Lemma for Finite State Automata (FSA)
  - PE are regular expressions, they have an equivalent FSA representation (unique up to minimization)
  - As path is traversed, FSA state changes at every step
  - Rule out paths in which a vertex is repeatedly reached in the same FSA state
- Can be programmed by user in Gremlin and GSQL (costly!)

# A Tractable Semantics: Shortest Paths

- For pattern

$x \text{ -Pattern-} \rightarrow y,$

vertex pair  $(s,t)$  is an answer iff there is a path  $p$  from  $s$  to  $t$  s.t.

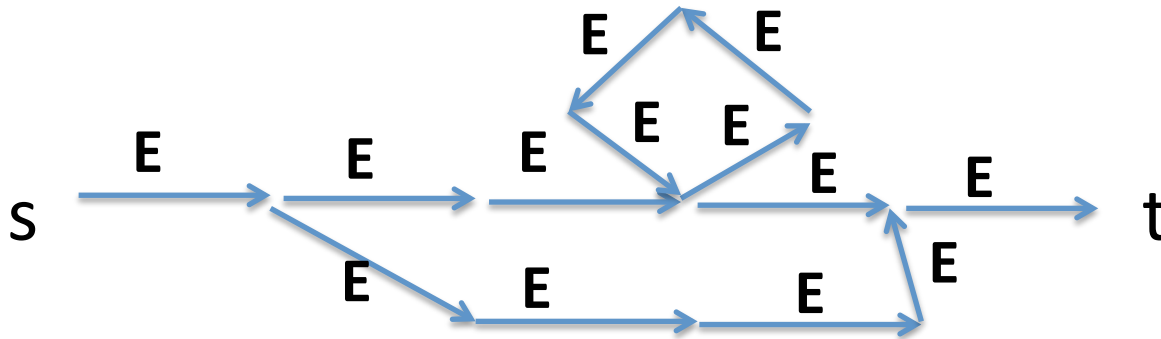
– word spelled by edge labels of  $p$  is in  $L(\text{Pattern})$

–  $p$  is *shortest* among all such paths from  $s$  to  $t$

- Multiplicity of  $(s,t)$  in answer is the count of such shortest paths

# Contrasting Semantics

- pattern  $E^*$  over graph:



- $s$ - $t$  is an answer under all semantics, but
  - Simple-path:  $s$ - $t$  has multiplicity 2
  - Unique-edge:  $s$ - $t$  has multiplicity 3
  - Shortest-path:  $s$ - $t$  has multiplicity 1

# Aggregation

# Let's See it First as CQ Extension

- Count toys bought in common per customer pair

**$Q(c1, c2, count(p)) :- c1 \text{ -Bought-} \rightarrow p, c2 \text{ -Bought-} \rightarrow p,$   
 $p.category = \text{"toys"}, c1 < c2$**

- $c1, c2$ : composite group key - no explicit group-by clause
- Standard syntax for aggregation-extended CQs and Datalog
- Rich literature on semantics
  - (tricky for Datalog when aggregation and recursion interleave).

# Aggregation in Modern Graph QLs

- Cypher's RETURN clause uses similar syntax as aggregation-extended CQs
- Gremlin and SparQL use an SQL-style GROUP BY clause
- GSQL uses aggregating containers called "accumulators"



# Flavor of Representative Languages

# Running Example in CRPQ Form

- Recall:

count toys bought in common per customer pair

**$Q(c1, c2, count(p)) :- c1 \text{ -Bought-} \rightarrow p, c2 \text{ -Bought-} \rightarrow p,$   
 $p.category = \text{"toys"}, c1 < c2$**

# SparQL

- Query language for the semantic web
  - graphs corresponding to RDF data are directed, labeled graphs
- W3C Standard Recommendation

# Running Example in SparQL

```
SELECT ?c1, ?c2, count (?p)
```

```
WHERE { ?c1 bought ?p.  
        ?c2 bought ?p.  
        ?p category ?cat.
```

```
        FILTER (?cat == "toys" && ?c1 < ?c2) }
```

```
GROUP BY ?c1, ?c2
```

# SparQL Semantics by Example

- Coincides with CRPQ version

**$Q(c1, c2, count(p)) :- c1 \text{ -Bought-} \rightarrow p, c2 \text{ -Bought-} \rightarrow p,$**   
 **$p.category = \text{“toys”}, c1 < c2$**

# Cypher

- The query language of the neo4j commercial native graph db system
- Essentially StruQL with some bells and whistles
- Also supported in a variety of other systems:
  - SAP HANA Graph, Agens Graph, Redis Graph, Memgraph, CAPS (Cypher for Apache Spark), ingraph, Gradoop, Ruruki, Graphflow

# Running Example in Cypher

**MATCH** (c1:Customer) -[:Bought]-> (p:Product)  
          <-[:Bought]- (c2:Customer)

**WHERE** p.category = "Toys" **AND** c1.name < c2.name

**RETURN** c1.name **AS** cust1,  
          c2.name **AS** cust2,  
          **COUNT** (p) **AS** inCommon

c1.name, c2.name are composite group key  
– no explicit group-by clause, just like CQ

# Cypher Semantics by Example

- Coincides with CRPQ version

**$Q(c1, c2, count(p)) :- c1 \text{ -Bought-} \rightarrow p, c2 \text{ -Bought-} \rightarrow p, c1 < c2$**

- Modulo non-repeating edge restriction
  - no effect here since repeated-edge paths satisfying the two PE atoms would necessarily have  $c1 = c2$



# Gremlin

- Supported by major Apache projects
  - TinkerPop and JanusGraph
- Also by commercial systems including
  - TitanGraph (DataStax)
  - Neptune (Amazon),
  - Azure (Microsoft),
  - IBM Graph

# Gremlin Semantics

- Based on *traversers*, i.e. tokens that flow through graph binding variables along the way
- A Gremlin program adorns the graph with a set of traversers that co-exist simultaneously
- A program is a pipeline of steps, each step works on the set of traversers whose state corresponds to this step
- Steps can be
  - map steps (work in parallel on individual traversers)
  - reduce steps (aggregate set of traversers into a single traverser)

# Gremlin Semantics by Example

**v()**



place one traverser on each vertex

# Gremlin Semantics by Example

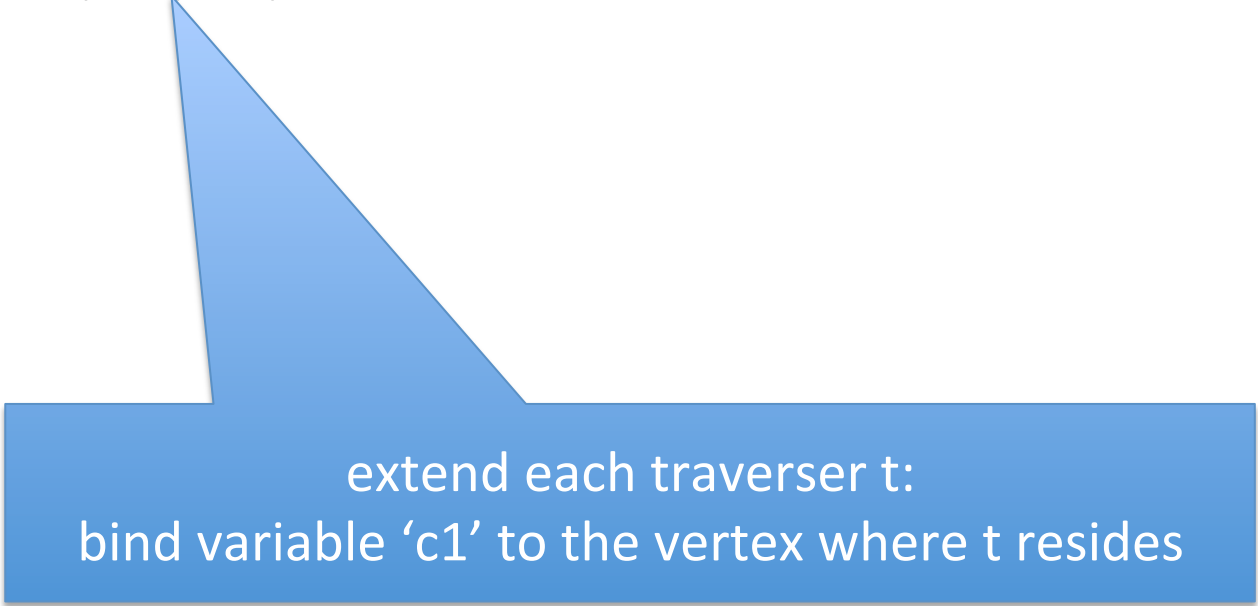
`V().hasLabel('Customer')`



filter traversers by label

# Gremlin Semantics by Example

**V().hasLabel('Customer').as('c1')**



extend each traverser t:  
bind variable 'c1' to the vertex where t resides

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought')
```



Traversers flow along out-edges of type 'Bought'.

If multiple such edges emanate from a Customer vertex  $v$ , the traverser at  $v$  *splits* into one copy per edge, placed at edge destination.

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys')
```



filter traversers at destination of 'Bought' edges:  
vertex label must be 'Product' and they must have a  
property named 'category' of value 'Toys'

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys').as('p')
```

extend surviving traversers with binding of variable 'p' to their location vertex.

now each surviving traverser has two variable bindings:  
c1, p



# Gremlin Semantics by Example

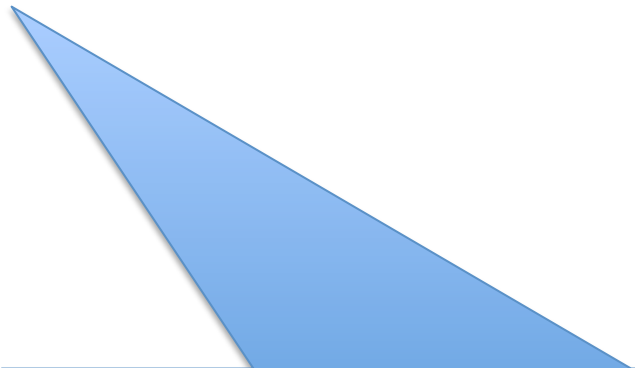
```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys').as('p')  
  .in('Bought')
```



Surviving traversers cross incoming edges of type 'Bought'. Multiple in-edges result in further splits.

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys').as('p')  
  .in('Bought').hasLabel('Customer').as('c2')  
  
.select ('c1', 'c2','p').by('name')
```



for each traverser extract the tuple of bindings for variables c1,c2,p, return its projection on 'name' property.

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys').as('p')  
  .in('Bought').hasLabel('Customer').as('c2')  
  
.select ('c1', 'c2', 'p').by('name')  
.where ('c1', lt('c2'))
```



filter these tuples according to where condition

# Gremlin Semantics by Example

```
V().hasLabel('Customer').as('c1')  
  .out('Bought').hasLabel('Product').has('category','Toys').as('p')  
  .in('Bought').hasLabel('Customer').as('c2')
```

```
.select ('c1', 'c2', 'p').by('name')  
.where ('c1', lt('c2'))
```

group tuples

```
.group().by(select('c1','c2')).by(count())
```

first by() specifies group key

second by() specifies group aggregation

# GSQL

- The query language of TigerGraph, a native parallel graph db system
- A recent start-up founded by UCSD DB lab's PhD alum Yu Xu
- Full disclosure: I have been involved in design

# GSQL Accumulators

- GSQL traversals collect and aggregate data by writing it into *accumulators*
- Accumulators are containers (data types) that
  - hold a data value
  - accept inputs
  - aggregate inputs into the data value using a binary operation
- May be built-in (sum, max, min, etc.) or user-defined
- May be
  - global (a single container accessible from all traversal steps)
  - local (one per node, accessible only when reached by traversal)

# Running Example in GSQL

```
GroupByAccum <string cust1, string cust2,  
SumAccum<int> inCommon> @@res;
```

cust1, cust2 form  
composite group key

inCommon is group value  
(a sum aggregation)

Global accum

```
SELECT _  
FROM Customer:c1 -(Bought>)- Product:p -(<Bought)- Customer:c2  
WHERE p.category == "Toys" AND c1.name < c2.name  
ACCUM @@res += (c1.name, c2.name -> 1);
```

aggregate this input into  
accumulator

create input associating value 1 to key  
(c1.name, c2.name)

# GSQL Semantics by Example

```
GroupByAccum <string cust1, string cust2,  
                SumAccum<int> inCommon> @@res;
```

For every distinct path satisfying FROM  
pattern and WHERE condition...

```
SELECT _  
FROM Customer:c1 -(Bought>)- Product:p -(<Bought)- Customer:c2  
WHERE p.category == "Toys" AND c1.name < c2.name  
ACCUM @@res += (c1.name, c2.name -> 1);
```

...execute ACCUM clause



# Why Aggregate in Accumulators Instead of Select-Group By Clauses?

revenue per customer

```
GroupByAccum <string cust, SumAccum<float> total> @@cSales;  
GroupByAccum <string prod, SumAccum<float> total> @@pSales;
```

revenue per product

```
SELECT _  
FROM Customer:c -(Bought>:b)- Product:p  
ACCUM float thisSalesRevenue = b.quantity*(1-b.discount)*p.price,  
@@cSales += (c.name -> thisSalesRevenue),  
@@pSales += (p.name -> thisSalesRevenue);
```

local variable, this is a let clause

multiple aggregations in one pass,  
even on different group keys

# Local Accumulators

- Minimize bottlenecks due to shared global accums, maximize opportunities for parallel evaluation

```
SumAccum<float> @cSales, @pSales;
```

local accums, one instance per node

```
SELECT _
```

```
FROM Customer:c -(Bought>:b)- Product:p
```

```
ACCUM float thisSalesRevenue = b.quantity*(1-b.discount)*p.price,  
c.@cSales += thisSalesRevenue,  
p.@pSales += thisSalesRevenue;
```

groups are distributed, each node accumulates its own group

# Role of SELECT Clause? Compositionality

- queries can output set of nodes, stored in variables
- used by subsequent queries as traversal starting point:

**S1 = SELECT t**  
**FROM S0:s – pattern1 – T1:t**  
**WHERE ... ACCUM ...**

Variable S1 stores set of nodes  
reached in traversal

**S2 = SELECT t**  
**FROM S1:s – pattern2 – T2:t ...**  
**WHERE ... ACCUM ...**

S1 used in subsequent traversals  
(query chaining)

**S3 = SELECT t**  
**FROM S1:s – pattern3 – T3:t ...**  
**WHERE ... ACCUM ...**

# Recommended Toys Ranked by Log-Cosine Similarity

```
SumAccum<float> @rank, @lc;  
SumAccum<int> @inCommon;
```

```
I = {Customer. 1};
```

```
ToysILike, OthersWhoLikeThem =
```

```
  SELECT      p, o  
  FROM        I:c -(Likes>)- Product:p -(<Likes)- Customer:o  
  WHERE       p.category == "Toys" and o != c  
  ACCUM       o.@inCommon += 1  
  POST-ACCUM  o.@lc = log (1 + o.@inCommon);
```

```
ToysTheyLike =  SELECT      t  
                 FROM        OthersWhoLikeThem:o -(Likes>)- Product:t  
                 WHERE       t.category == "toy"  
                 ACCUM       t.@rank += o.@lc;
```

```
RecommendedToys = ToysTheyLike - ToysILike;
```

# Control Flow Primitives

# Loops Are Essential

- Loops (until condition is satisfied)
  - Explicitly supported in Gremlin and GSQL
  - Necessary to program iterative algorithms like PageRank, recommender systems, shortest-path, etc.
  - Can be used to program match of Kleene-starred path expressions under various semantics
- If-then-else, case constructs
  - Supported by all QLs in some way

# PageRank in GSQL

```
CREATE QUERY pageRank (float maxChange, int maxIteration, float dampingFactor) {  
  
  MaxAccum<float> @@maxDifference = 9999; // max score change in an iteration  
  SumAccum<float> @received_score = 0;    // sum of scores received from neighbors  
  SumAccum<float> @score = 1;            // initial score for every vertex is 1.  
  
  AllV = {Page.*};                       // start with all vertices of type Page  
  WHILE @@maxDifference > maxChange LIMIT maxIteration DO  
    @@maxDifference = 0;  
  
    S= SELECT          s  
      FROM            AllV:s -(Linkto)-> :t  
      ACCUM          t.@received_score += s.@score/s.outdegree()  
      POST-ACCUM    s.@score = 1-dampingFactor + dampingFactor * s.@received_score,  
                    s.@received_score = 0,  
                    @@maxDifference += abs(s.@score - s.@score');  
  
  END;  
}
```

# Low-level, NoSQL-style Programming for Parallel Graph Analytics



# Think-Like-a-Vertex (TLAV) aka Vertex-Centric

- Parallel computing abstraction
- Conceptually, each vertex is a processor
- Vertices execute a vertex program in parallel
- Instances of vertex programs communicate via messages to neighbors
- Vertices typically execute in lockstep (via synchronization barriers)

# Pregel: A TLAV Programming Abstraction

- Bulk-synchronous parallel computing abstraction
- Introduced by Pregel System (Google)
- Supported in open-source systems
  - e.g. Giraph (Apache), GraphX (Apache Spark)
- Pregel program executes in lockstep a series of supersteps
- During each superstep, vertices (in parallel)
  - receive inbound messages sent in previous superstep,
  - compute a new value for the vertex data
  - send messages to neighboring vertices (received in next superstep)

# Gather-Apply-Scatter (GAS)

- Isomorphic with Pregel when vertices evaluate in lockstep
- Also supports asynchronous evaluation
- Introduced by GraphLab system (an open-source project)
- Each vertex program step is organized in three phases:
  - **Gather**: may directly access information from its one-hop neighborhood, aggregating it with user-defined function
  - **Apply**: vertex value is updated by incorporating this sum
  - **Scatter**: neighborhood values updated using result of apply phase
- Communication abstraction: shared memory, not messaging

# PowerGraph

- Refinement of GAS abstraction to process *edges* in parallel
  - for load balancing in presence of high-degree vertices
- Gather phase executes a function that maps over edges
- Results of edge map are reduced by a user-defined Sum function
- Apply phase uses the reduced result
- Only edges incident on *active vertices* work.
  - Vertices can be explicitly activated during scatter phase.

# GSQL's Edge-Map/Vertex-Reduce (EM/VR)

- Extends PowerGraph for flexibility
  - user can define *multiple* independent reducers via accumulators
  - accums can *be local or global*
  - accums are *first-class citizens*
    - persist across steps, can be mentioned by future steps
  - parallel map over edges generates accum inputs
  - reduce phase updates each accum value by aggregating all inputs into it

# GSQL As High-level EM/VR Program

```
SumAccum<float> @cSales, @pSales;
```

SELECT clause specifies vertex to activate next

local accums implement two independent reducers

```
SELECT p
FROM Customer:c -(Bought>:b)- Product:p
ACCUM float thisSalesRevenue = b.quantity*(1-b.discount)*p.price,
c.@cSales += thisSalesRevenue,
p.@pSales += thisSalesRevenue;
```

FROM clause filters edges undergoing map

ACCUM clause executes per edge, generates accum inputs

# Summary

- We discussed representative high-level graph QLs
  - from point of view of expressive power and semantics
  - de-emphasizing syntax
- We have seen NoSQL-style low-level parallel graph programming abstractions
- No need to choose between high-level and low-level (false choice claimed by prior NoSQL-related debates)
  - abstraction levels can be harmonized (as shown for GSQL)

# Topics Not Covered Here

- Creating/modifying vertices and edges
  - As opposed to just returning tables of variable bindings
- Non-scalar vertex and edge properties (these can be lists/arrays and other containers)
- Behavior when a vertex/edge property does not exist (options are comprehensively laid out in Part A on hierarchical graph model)
- Graph schemas