Data 603 – Big Data Platforms

Lecture 11
Graph Analytics

Graph Analytics

Graphs

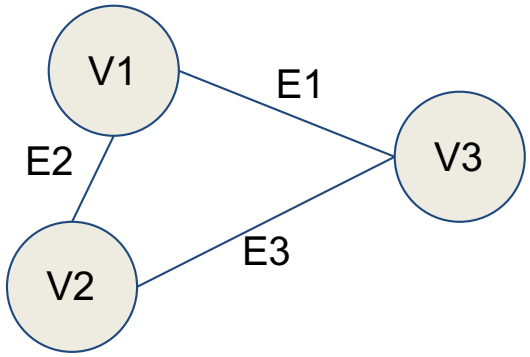
- A representation of the relationships between pairs objects.
  - A graph models “things” and relationships between “things.”
  - A representation of a set of objects (e.g. people) and the pairwise relationships between them (e.g. friendships)
- Data structures composed of nodes (vertices) and edges that define relationships between the nodes.
- Vertices are arbitrary objects (people, objects, places, concepts, etc.).
- Graph analytics is the process of analyzing the relationships between verticies.
  - A node represents a person, place, or thing
  - Edge represents a relationship

Graph Analytics Intro

Graph Terminology

Vertex (or Node)

- The object being represented.
- Represented by ***V***.



Edges

- Representation of pairwise relationships between nodes.
- Represented by ***E***.

G = (V,E)

- Graph ***G*** with vertices ***V*** and edges ***E***.

Note: Edges and vertices in graphs can have data associated with them.

Graph Terminology

Directed vs. Undirected Graphs

- Directed Graph
  - Each edge is an ordered pair, with the edge traveling from the first vertex to the second.
  - The relationship is from a source (or head) vertex to a destination (or tail) vertex.
  - Edges do not have specified “start” and “end” vertices.
  - The two ends of the edge play different roles (e.g. parent-child relationship)
  - Examples:
    - A link from on the web from page A to page B
    - A path on the route from Baltimore to Disney World

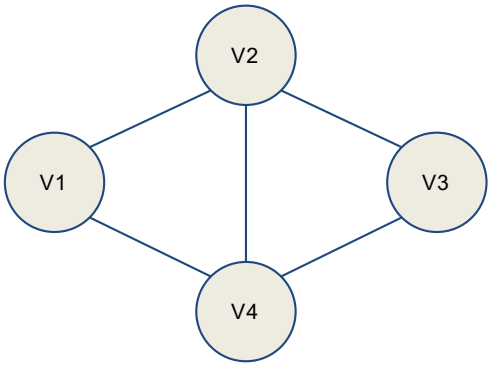
Graph Terminology

Directed vs. Undirected Graphs

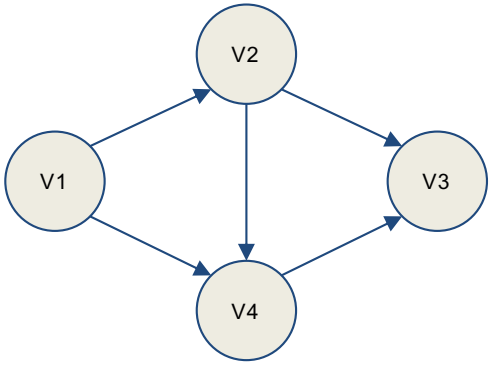
- Undirected graph, each edge corresponds to an unordered pair of vertices.
- Edges have no arrow; the relationship is symmetrical
  - A is a friend of B
  - B is a friend of A

Graph Analytics

Directed vs. Undirected Graphs



Undirected Graph

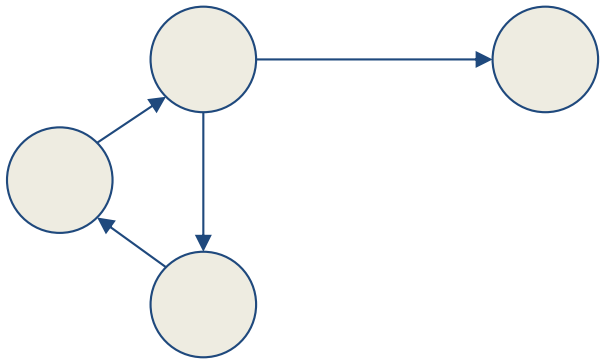


Directed Graph

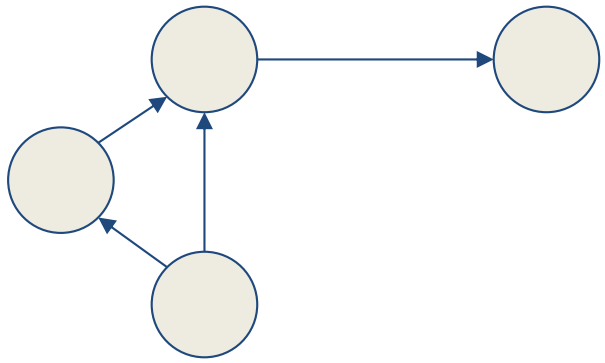
Graph Terminology

Cyclic vs. Acyclic Graphs

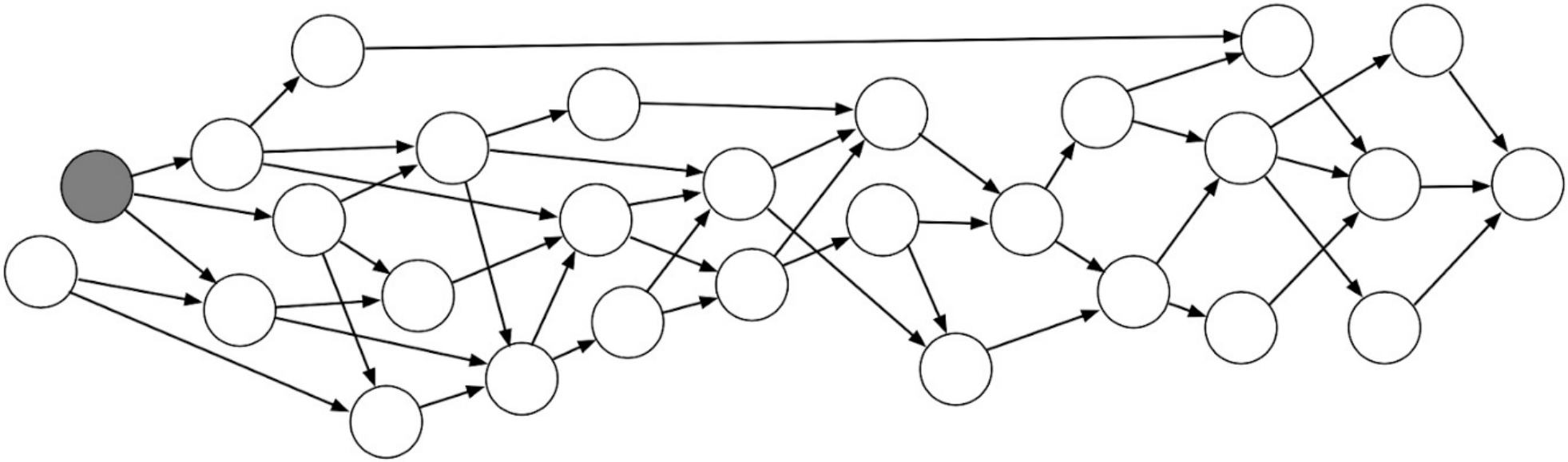
- A cyclic graph contains cycles
  - A series of vertices connected in a loop.
  - Poses the risk that traversing of such graph can follow edges in an infinite-loop.
- An acyclic graph contains no cycles.



Cyclic Graph



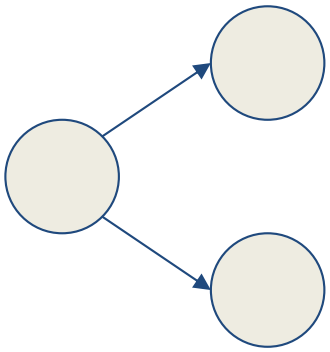
Acyclic Graph



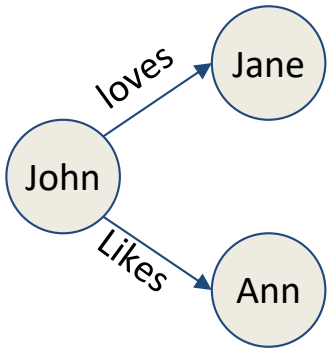
Graph Terminology

Unlabeled vs. Labeled Graphs

- In a labeled graph, vertices and/or edges have data (labels) associated with them other than their unique identifier
  - Vertex-labeled graphs: graphs with labeled vertices
  - Edge-labeled graphs: graphs with labeled edges
- A completely unlabeled graph is not useful.
  - Normally at least the vertices are labeled.



Unlabeled Graph

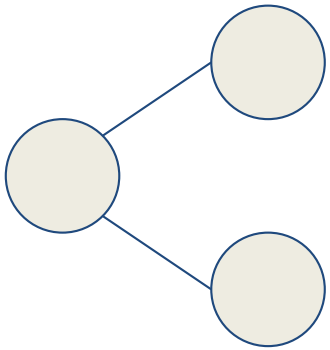


Labeled Graph

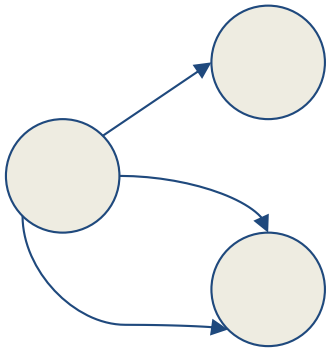
Graph Terminology

Parallel Edges and Loops

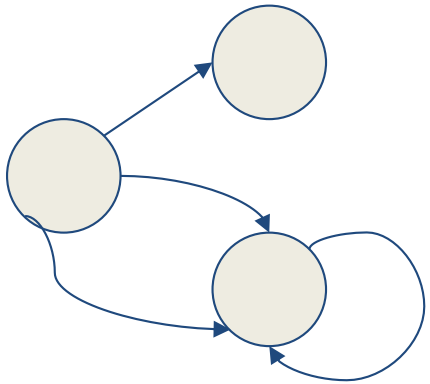
- Multigraph: Allowing multiple edges between the same pair of vertices
- Pseudograph: An edge that starts and ends with the same vertex.



Simple Graph



Multigraph

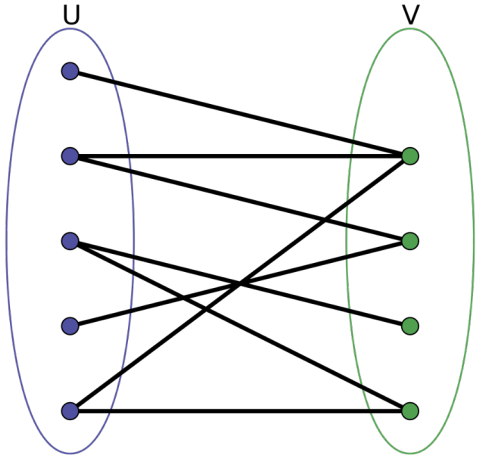


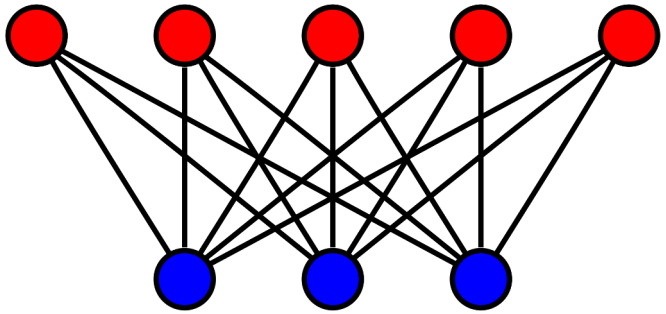
Pseudograph

Graph Terminology

Bipartite Graph

- A bipartite graph (or bigraph) is a graph whose vertices can be divided into two disjoint and independent sets *U* and *V* such that every edge connects a vertex in *U* to one *V*.
- Vertex sets *U* and *V* are usually called the parts of the graph.
- A bipartite graph is a graph that does not contain any odd-length cycles.





Source: https://en.wikipedia.org/wiki/Bipartite_graph

Graph Query Language

SPARQL

- A SQL-like language promoted by W3C for querying Resource Description Framework (RDF) graphs

Cypher

- A query language used in Neo4j, an open source database

Tinkerpop Gremlin

- An attempt to create a standard interface to graph databases and processing systems.

GraphX + GraphFrame

Refer to https://en.wikipedia.org/wiki/GQL_(Graph_Query_Language)

Other Graph Processing Tools

- JanusGraph (Distributed, open source, graph database)
- **Neo4j** (open source, graph database)
- ArangoDB (Distributed, open source, multi-model database)
- Dgraph (Distributed, open source, graph database)
- OrientDB (Distributed, open source, multi-model database)
- TigerGraph (Proprietary graph database)
- **NetworkX** (Python package for complex network analytics)
- Azure CosmosDB (Cloud-native, multi-model database)
- AWS Neptune (Cloud-native, graph database)

Why Graph Processing on Spark?

- Relational databases are often not suited for graph analytics.
  - SQL is not built to present graph notions such as following a trail of connections.
- Traditional methods of data processing fail to scale as the size of the data to be analyzed increase.
- Graph processing systems (including Apache Spark GraphFrames) provide the means to create graph structures from raw data sources.
- GraphX (RDD) and GraphFrames (DataFrame) are graph processing layers on top of Spark that bring the power of distributed and scalable Big Data processing to graphs.

Where is Graph used?

- Fraud Detection & Analysis
- Network and Database Infrastructure Monitoring for IT Operations
- Recommended Engine & Product Recommendation Systems
- Master Data Management
- Identity and Access Management
- Knowledge Graphs
- Google Maps

Refer to https://neo4j.com/use-cases/

Where is Graph used?

- Motif finding
- Determining importance of papers in bibliographic networks (which papers are most referenced)
- Ranking web pages (Google's PageRank algorithm)
- Other important things such as Six Degrees of Kevin Bacon (Social Media and Social Network Graphs)

Refer to https://neo4j.com/use-cases/

Spark Graph Analytics

Spark Graph Analytics

- GraphX (kind of like spark.mllib)
  - RDD-based library
  - Provides low-level interface
  - Powerful, but not easy to use or optimize
- GraphFrames (kind of like spark.ml)
  - Extends GraphX to provide a DataFrame API and support for Spark's different language bindings so that users of Python can take advantage of the scalability of the tool.
  - Available as an external package.
  - Improved user experience with small penalty in performance due to some overhead .

Building a Graph

Users can create GraphFrames from vertex and edge DataFrames.

- Define vertices and edges using DataFrames with special named columns.
- Both DataFrames can have arbitrary other columns which can represent vertex and edge attributes.
- A GraphFrame can also be constructed from a single DataFrame containing edge information.
  - The vertices will be inferred from the sources and destinations of the edges.

Building a Graph

- Vertex DataFrame
  - Should contain a special column named “id” which specifies unique IDs for each vertex in the graph.

- Edge DataFrame
  - Should contain two special columns:
    - “src” (source vertex ID of edge)
    - “dst” (destination vertex ID of edge)

Building a Graph

```
# Vertex DataFrame
v = sqlContext.createDataFrame([
  ("a", "Alice", 34),
  ("b", "Bob", 36),
  ("c", "Charlie", 30),
  ("d", "David", 29),
  ("e", "Esther", 32),
  ("f", "Fanny", 36),
  ("g", "Gabby", 60)
], ["id", "name", "age"])

# Edge DataFrame
e = sqlContext.createDataFrame([
  ("a", "b", "friend"),
  ("b", "c", "follow"),
  ("c", "b", "follow"),
  ("f", "c", "follow"),
  ("e", "f", "follow"),
  ("e", "d", "friend"),
  ("d", "a", "friend"),
  ("a", "e", "friend")
], ["src", "dst", "relationship"])
# Create a GraphFrame
g = GraphFrame(v, e)
```

Building a Graph

- Define vertices and edges using DataFrames with special named columns.
- To define a graph, use the naming conventions for columns presented in the GraphFrames library.
  - In the vertices table, define the identifier as *id*
  - In the edges tables, label each edge's source vertex ID as *src* and destination ID as *dst* (for directed graph)

```
stationVertices =
bikeStations.withColumnRenamed("name","id").distinct()
tripEdges = tripData \
       .withColumnRenamed("Start Station", "src")\
       .withColumnRenamed("End Station", "dst")
from graphFrames import GraphFrame
stationGraph = GraphFrame(stationVertices, tripEdges)
stationGraph.cache()
```

Querying the Graph

- GraphFrames provide simple access to both vertices and edges as DataFrames.

```
From pyspark.sql.functions import desc
stationGraph.edges.groupBy("src", "dst"). \
       count().orderBy(desc("count")).show(10)
```

- Filter by any valid DataFrame expression

```
stationGraph.edges
       .where("src='Townsend at 7th' OR dst = 'Townsend at
7th'")
       .groupBy("src", "dst").count()
       .orderBy(desc("count"))
       .show(10)
```

Subgraphs

- Subgraphs are smaller graphs within the larger one

```
townAnd7thEdges = stationGraph.edges \
        .where("src = 'Townsend at 7th' OR dst = 'Townsend at
7th'")
subgraph = GraphFrame(stationGraph.vertices, townAnd7thEdges)
```

Motif Finding

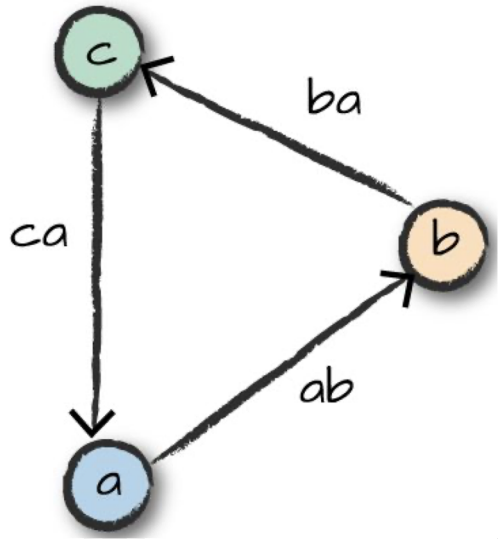
- *Motifs* are a way of expressing structural patterns in a graph.
- When a motif is specified, patterns are queried instead of actual data.
- In GraphFrames, a query is specified in a domain-specific language similar to Neo4J's Cypher language.
  - Allows specifying of combinations of vertices and edges and assign them names.
  - Specify that a given vertex connects to another vertex b through an edge ab: (a)-[ab]->(b)
  - The names inside parentheses or brackets do not signify values but instead what the columns for matching vertices and edges should be named in the resulting DataFrame.
  - The names can be omitted if the resulting values don't need to be queried. (e.g. (a)-[]->())

Motif Finding

- *Find all the rides that form a ”triangle” pattern between three stations.*

motifs = stationGraph.find(“(a)-[ab]->(b);(b)-[bc]->(c);(c)-[ca]->(a)”)

- (a) signifies the starting station
- [ab] represents an edge from (a) to the next station (b)
- This is repeated for stations (b) to (c), and then from (c) to (a)
- The resulting DataFrame from the query contains nested fields for vertices a, b, and c, as well as respective edges.
- The resulting query can be queried just like any other DataFrames.



Graph Algorithms

- A graph is a logical representation of data
- Graph theory provides numerous algorithms for analyzing graph data.
- GraphFrames provides a number of algorithms out of the box.
  - http://graphframes.github.io/graphframes/docs/_site/user-guide.html#graph-algorithms

Types of Graph Algorithms

Pathfinding

- Finding shortest path from vertex A to vertex B.
- e.g. Google Map.

Centrality

- Understanding which nodes are important within the network.
- e.g. Who is the central figure in the class? Who is most popular important person? Web search ranking.

Community Detection

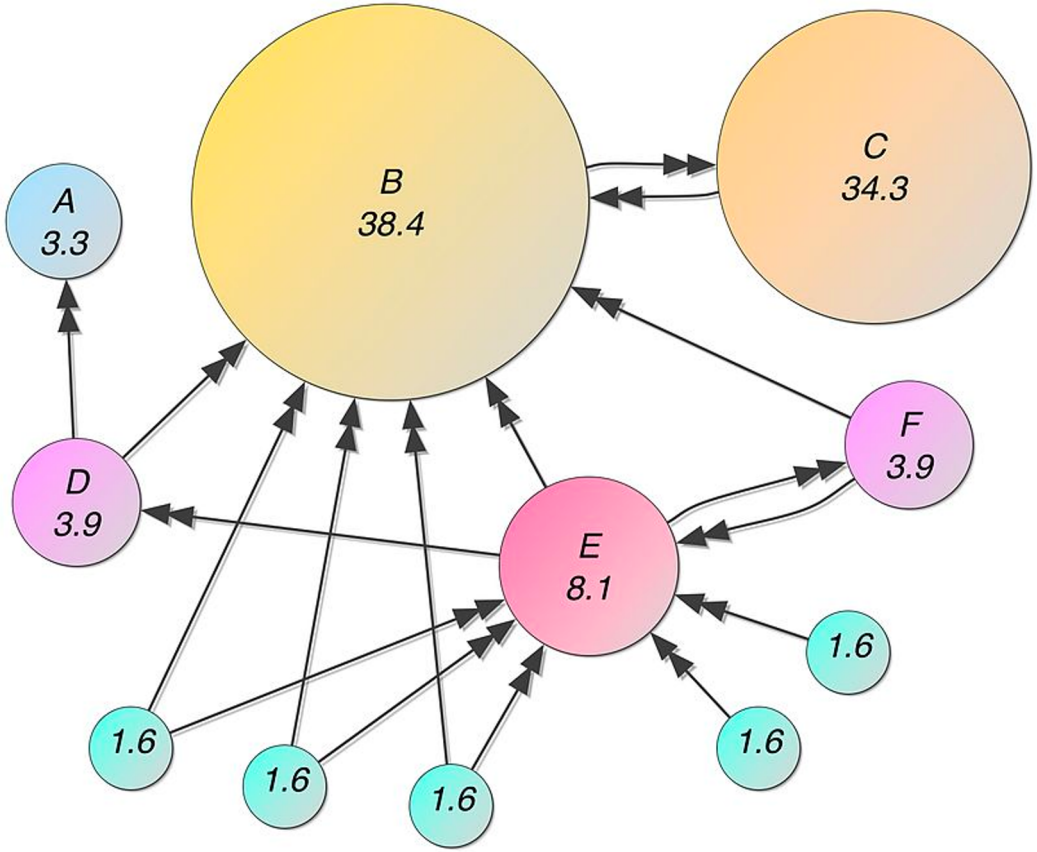
- Used to find communities (sub-structures/graphs) and quantify the quality of groupings.

Reference: Graph Algorithms - Practical Examples in Apache Spark & Neo4j, O'reilly 2019

Graph Algorithms - PageRank

- Created by Larry Page (cofounder of Google) as a research project for how to rank web pages.
- A way to measure the "authority" or centrality of vertices in a graph
- It measures the transitive (directional) influence of nodes.
- PageRank considers the influence of a node's neighbors, and their neighbors.
- It is not based on the number of vertices that have edges pointing to the vertex in question, but on the PageRanks of those vertices.
- Measures the number and quality of incoming relationships to a vertex to determine an estimation of how important the vertex is.

Graph Algorithms - PageRank



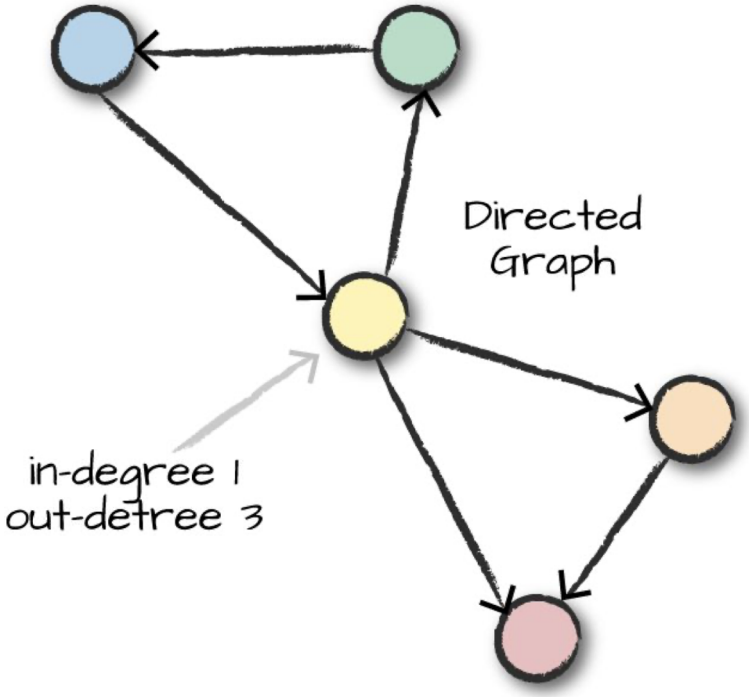
https://en.wikipedia.org/wiki/PageRank

Graph Algorithms - PageRank

- The results of the algorithm are stored as one or more columns in the GraphFrame's vertices and/or edges or the DataFrame
- For PageRank, the algorithm returns a GraphFrame. Estimated PageRank values for each vertex can be extracted from the new *pagerank* column.

```
from pyspark.sql.functions import desc
ranks = stationGraph.pageRank(resetProbability=0.15, maxIter=10)
ranks.vertices.orderBy(desc("pagerank")).select("id","pagerank")
.show(10)
```

In-Degree and Out-Degree Metrics



- One of the common task is to count the number of edges that are inbound and outbound in relation to a vertex.
- Applicable in the context of social networking.

In-Degree and Out-Degree Metrics

- The results of the algorithm are stored as one or more columns in the GraphFrame's vertices and/or edges or the DataFrame

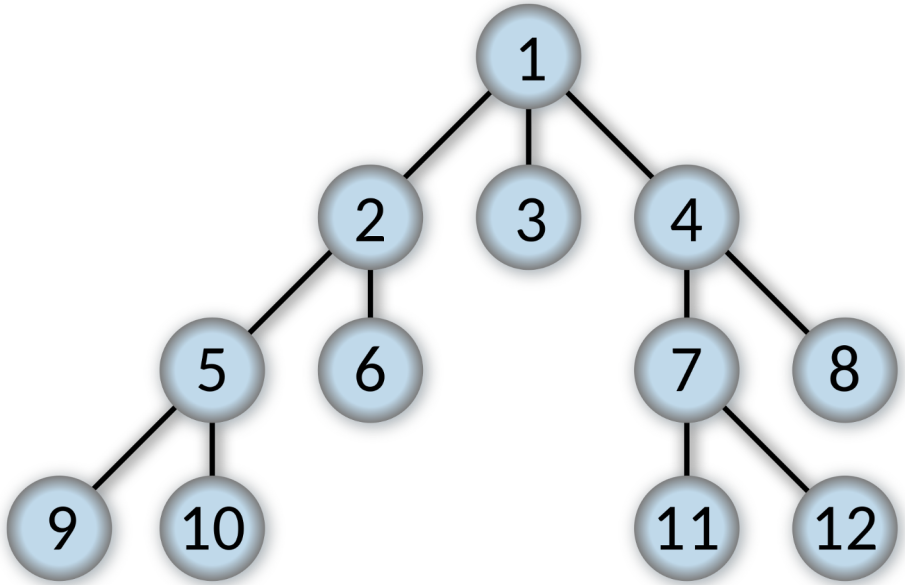
- High ratio: where large number of trips end. Lower ratio: where the trips start

```
outDeg = stationGraph.outDegrees
outDeg.orderBy(desc("outdegree")).show(5, False)


degreeRatio = inDeg.join(outDeg, "id")\
        .selectExpr("id", "double(indegree)/double(outDegree) as
degreeRatio")
degreeRatio.orderBy(desc("degreeRatio")).show(10, False)
degreeRatio.orderBy("degreeRatio").show(10, False)
```

Breadth-First Search

- Breadth-first search searches a graph for how to connect two sets of nodes based on the edges in the graph. E.g. Find shortest paths to different bike stations.
- Explores the vertices of a graph in layers in order of increasing distance from the starting vertex.



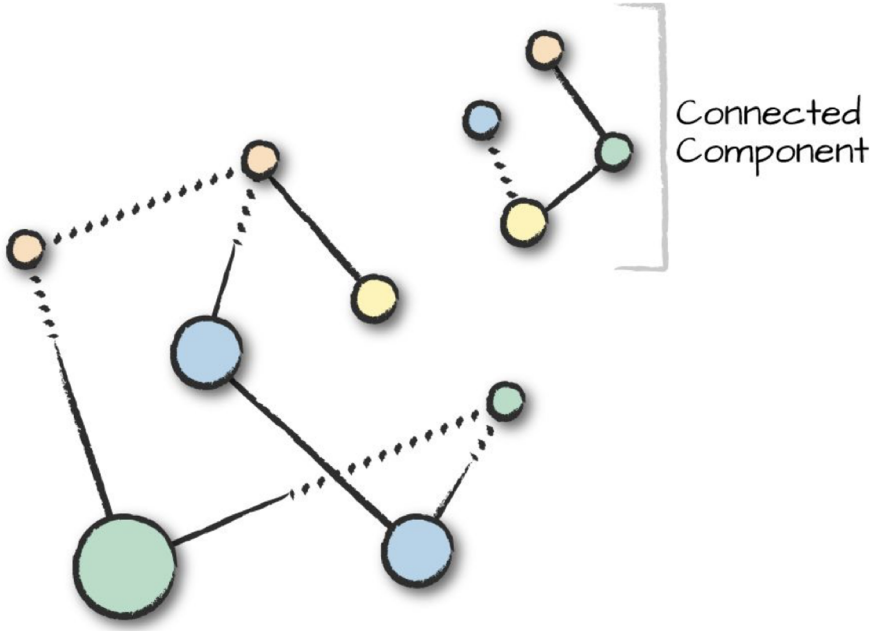
Breadth-First Search

```
stationGraph.bfs(fromExpr="id='Townsend at 7th'",
        toExpr = "id='Spear at Folsom'"), maxPathLength = 2).
show(10)
```

- maxLengthPath: maximum edges to follow
- Possible to specify an edgeFilter to filter out edges that do not meet a requirement

Connected Components

- A connected component defines an (undirected) subgraph that has connections to itself but does not connect to the greater graph.
- Connected component assumes an undirected graph.
- One of the most expensive algorithms in GraphFrames.



Connected Components

```
spark.sparkContext.setCheckpointDir("/tmp/checkpoints")
minGraph = GraphFrame(stationVertices,
        tripEdges.sample(False, 0.1))
Cc = minGraph.connectedComponents()
cc.where("components != 0").show()
```

Strongly Connected Components

- Strongly connected components takes directionality into account.
- Strongly connected component is a subgraph that has paths between all pairs of vertices inside it.

```
scc = minGraph.stronglyConnectedComponents(maxIter = 3)
scc.groupBy("component").count().show()
```

Saving and Loading

Saving and Loading

- Since GraphFrames are built around DataFrames, they automatically support saving and loading to and from the same set of datasources.

```
from graphframes.examples import Graphs
g = Graphs(sqlContext).friends()  # Get example graph

# Save vertices and edges as Parquet to some location.
g.vertices.write.parquet("hdfs://myLocation/vertices")
g.edges.write.parquet("hdfs://myLocation/edges")

# Load the vertices and edges back.
sameV = sqlContext.read.parquet("hdfs://myLocation/vertices")
sameE = sqlContext.read.parquet("hdfs://myLocation/edges")

# Create an identical GraphFrame.
sameG = GraphFrame(sameV, sameE)
```

Useful Links

- GraphFrames user guide:
  - https://graphframes.github.io/graphframes/docs/_site/user-guide.html
  - https://docs.databricks.com/spark/latest/graph-analysis/graphframes/user-guide-python.html
- Graph Algorithm e-Book (free):
  - https://neo4j.com/lp/book-graph-algorithms/
  - https://resources.oreilly.com/examples/0636920233145
  - https://github.com/neo4j-graph-analytics/book/blob/master/data/188591317_T_ONTIME.csv.gz
- PageRank
  - PageRank Beyond the Web: https://arxiv.org/abs/1407.5107
  - https://graphframes.github.io/graphframes/docs/_site/user-guide.html#pagerank
  - PageRank Convergence: https://stackoverflow.com/a/29321153

Questions