Class 8: Spark Algorithms

New York University

Summer 2017

Agenda

1. Common Spark Use Cases
2. Iterative Algorithms in Spark
3. Graph Processing and Analysis
4. Machine Learning

- **Spark is especially useful when working with any combination of:**
  - Large amounts of data
    - Distributed storage
  - Intensive computations
    - Distributed computing
  - Iterative algorithms
    - In-memory processing and pipelining

- **Examples**
  - Risk analysis
    - "How likely is this borrower to pay back a loan?"
  - Recommendations
    - "Which products will this customer enjoy?"
  - Predictions
    - "How can we prevent service outages instead of simply reacting to them?"
  - Classification
    - "How can we tell which mail is spam and which is legitimate?"

- **Spark includes many example programs that demonstrate some common Spark programming patterns and algorithms**
  - k-means
  - Logistic regression
  - Calculate pi
  - Alternating least squares (ALS)
  - Querying Apache web logs
  - Processing Twitter feeds
- **Examples**
  - **`$SPARK_HOME/examples/lib`**
    - **`spark-examples-`*`version`*`.jar` - Java and Scala examples**
    - **`python.tar.gz` - Pyspark examples**

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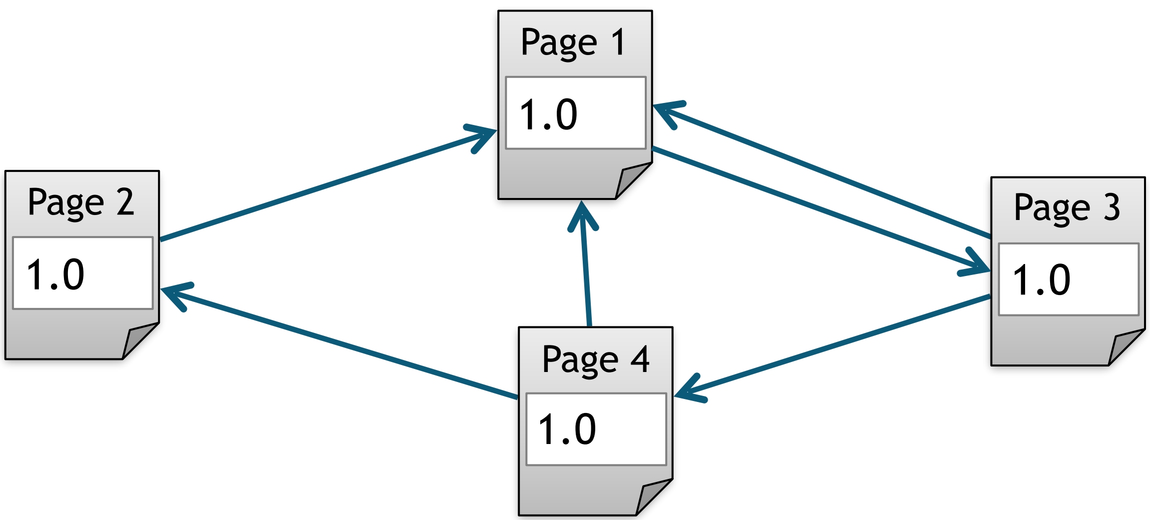
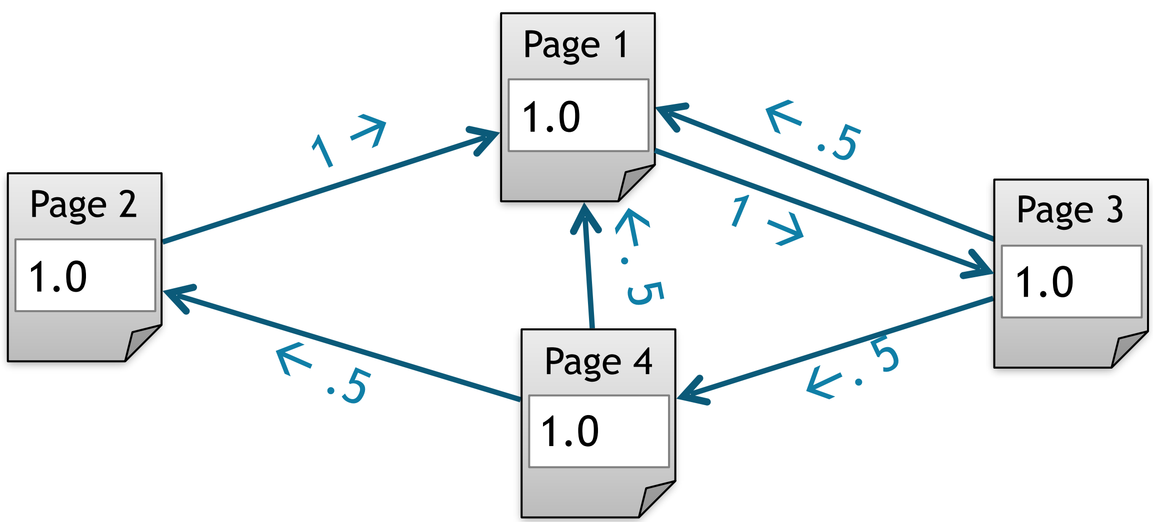
- **PageRank gives web pages a ranking score based on links from other pages**
  - Higher scores given for more links, and links from other high ranking pages
- **Why do we care?**
  - PageRank is a classic example of big data analysis (like WordCount)
    - Lots of data – needs an algorithm that is distributable and scalable
    - Iterative – the more iterations, the better the answer

1. Start each page with a rank of 1.0



1. **Start each page with a rank of 1.0**
2. **On each iteration:**
   1. each page contributes to its neighbors its own rank divided by the number of its neighbors: $contrib_p = rank_p \,/\, neighbors_p$



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2. **On each iteration:**
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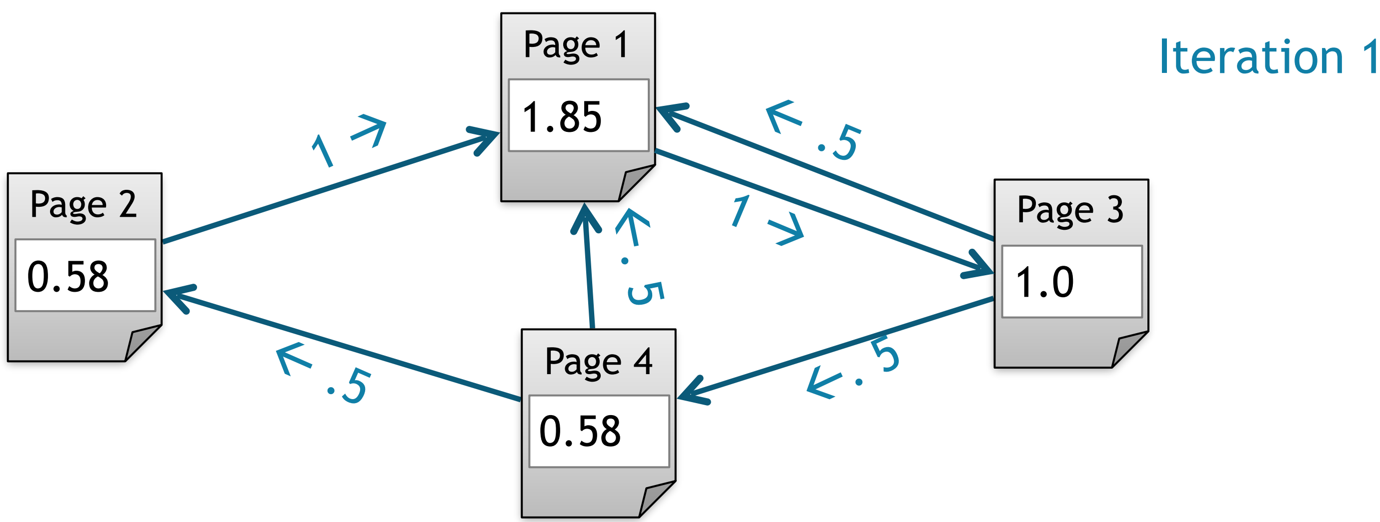

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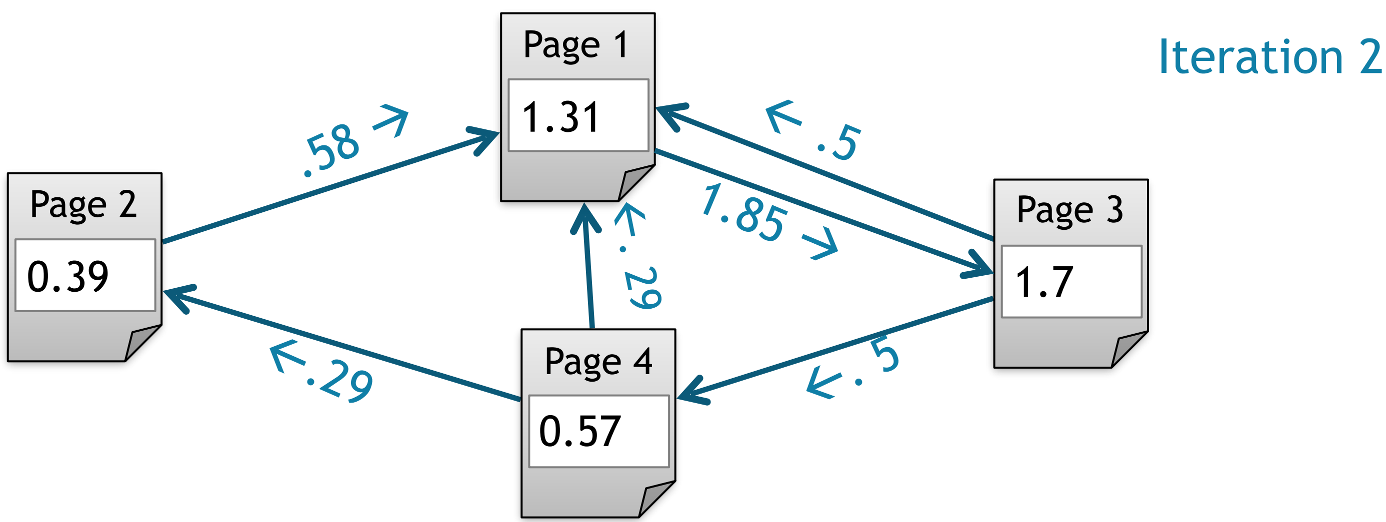
3. **Each iteration incrementally improves the page ranking**



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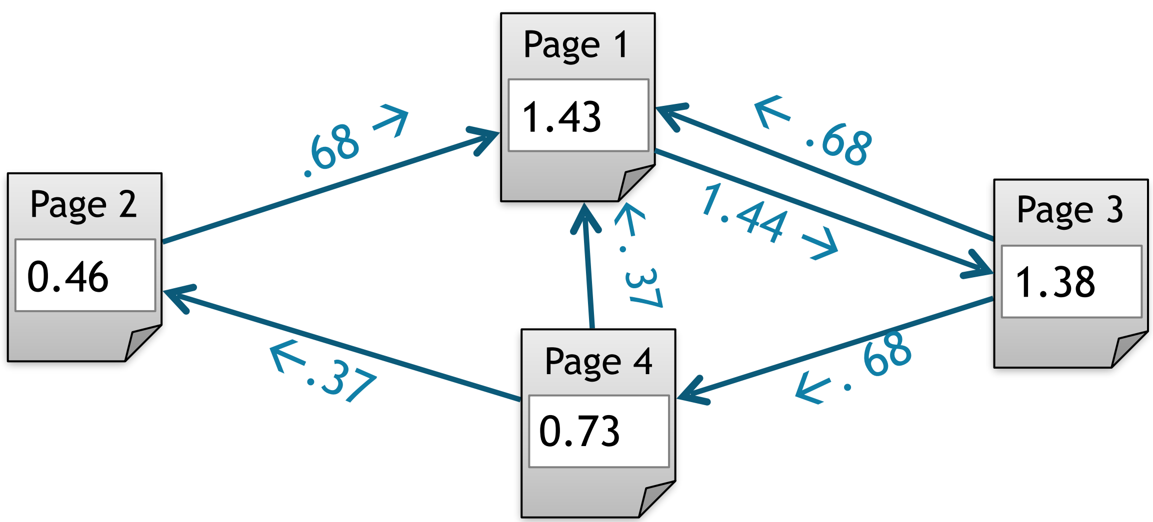
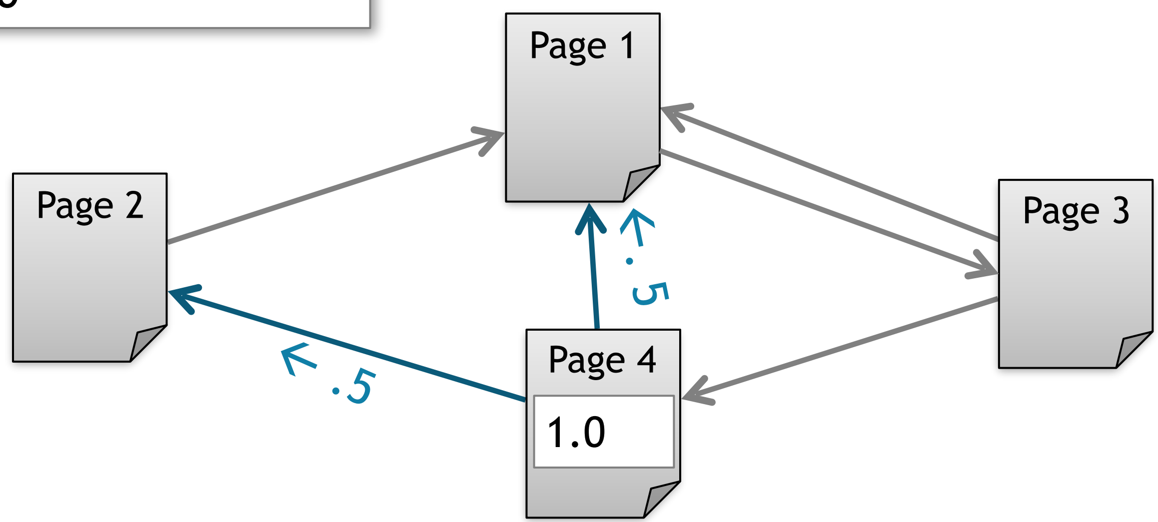


Iteration 10
(Final)

```
Define a function, computeContribs(neighbors, rank)
    For each neighbor, output: (neighbor, rank/len(neighbors))
```

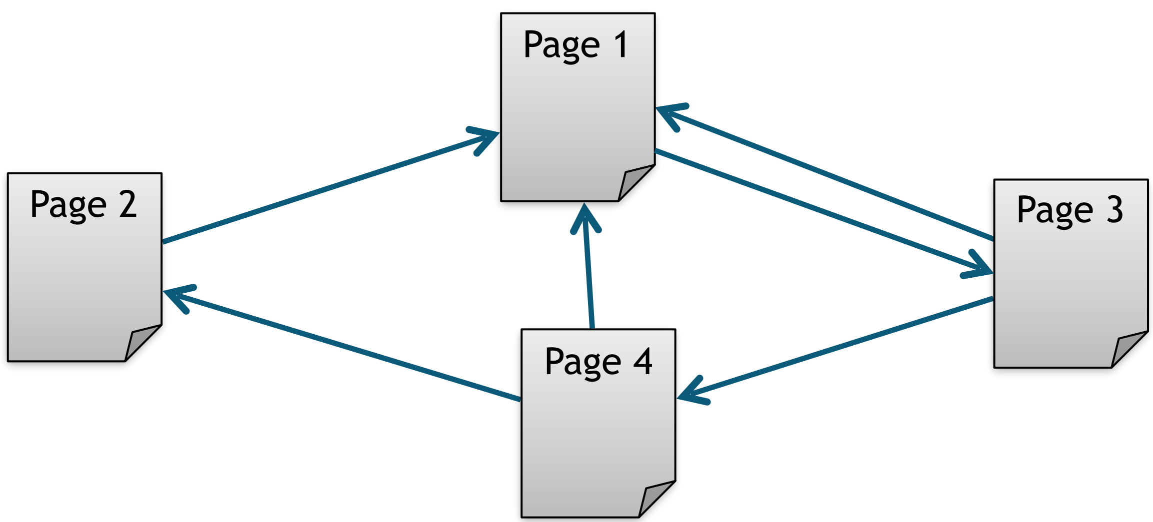
neighbors:
[page1,page2]
rank: 1.0

(page1,.5)
(page2,.5)



Data Format:
source-page destination-page
...

```
page1 page3
page2 page1
page4 page1
page3 page1
page4 page2
page3 page4
```



```
Define a function, computeContribs(neighbors, rank)
    For each neighbor, output: (neighbor, rank/len(neighbors)

Read in the file and use map and distinct to generate tuples.
```

```
page1 page3
page2 page1
page4 page1
page3 page1
page4 page2
page3 page4
```

(page1,page3)
(page2,page1)
(page4,page1)
(page3,page1)
(page4,page2)
(page3,page4)

```
page1 page3
page2 page1
page4 page1
page3 page1
page4 page2
page3 page4
```

Define a function, computeContribs(neighbors, rank)
    For each neighbor, output: (neighbor, rank/len(neighbors)

```
(page1,page3)
(page2,page1)
(page4,page1)
(page3,page1)
(page4,page2)
(page3,page4)
```

Read in the file and use map and distinct to generate tuples.

Use groupByKey to group pages related to a given page.

links

```
(page4, [page2,page1])
(page2, [page1])
(page3, [page1,page4])
(page1, [page3])
```

```
Define a function, computeContribs(neighbors, rank)
    For each neighbor, output: (neighbor, rank/len(neighbors)

Read in the file and use map and distinct to generate tuples.

Use groupByKey() to group pages related to a given page.

Use persist() to persist the cache the links information.
```

```
page1 page3
page2 page1
page4 page1
page3 page1
page4 page2
page3 page4
```

(page1,page3)
(page2,page1)
(page4,page1)
(page3,page1)
(page4,page2)
(page3,page4)

links

(page4, [page2,page1])
(page2, [page1])
(page3, [page1,page4])
(page1, [page3])

```
Define a function, computeContribs(neighbors, rank)
    For each neighbor, output: (neighbor, rank/len(neighbors))

Read in the file and use map and distinct to generate tuples.

Use groupByKey() to group pages related to a given page.

Use persist() to persist the cache the links information.

Create an RDD, ranks, that initializes rank to 1.0 for each page.
```

links
(page4, [page2,page1])
(page2, [page1])
(page3, [page1,page4])
(page1, [page3])

ranks
(page4, 1.0)
(page2, 1.0)
(page3, 1.0)
(page1, 1.0)

`Use join() to join links and rank data.`

links

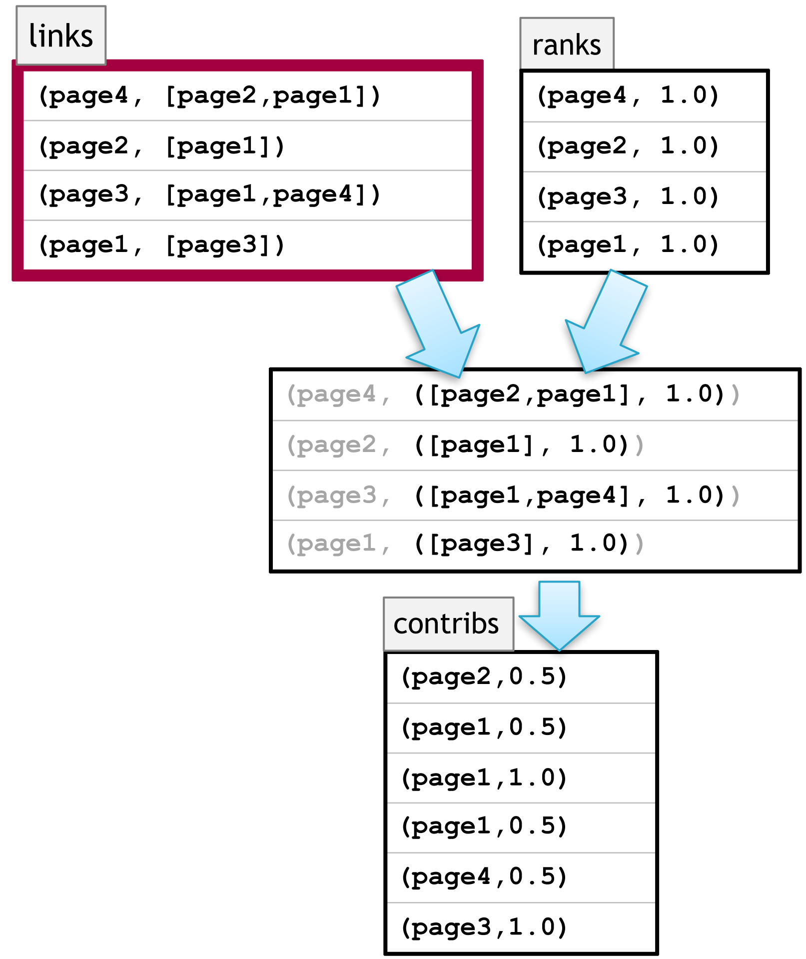
```
(page4, [page2,page1])
(page2, [page1])
(page3, [page1,page4])
(page1, [page3])
```

ranks

```
(page4, 1.0)
(page2, 1.0)
(page3, 1.0)
(page1, 1.0)
```

```
(page4, ([page2,page1], 1.0))
(page2, ([page1], 1.0))
(page3, ([page1,page4], 1.0))
(page1, ([page3], 1.0))
```

`After join(), use flatMap and call computeContribs to compute the contributions.`



Use reduceByKey to produce the results by summing partial ranks.

contribs

(page2,0.5)
(page1,0.5)
(page1,1.0)
(page1,0.5)
(page4,0.5)
(page3,1.0)

(page4,0.5)
(page2,0.5)
(page3,1.0)
(page1,2.0)

`After reduceByKey, compute the rank by multiplying by .85 and adding .15`

contribs

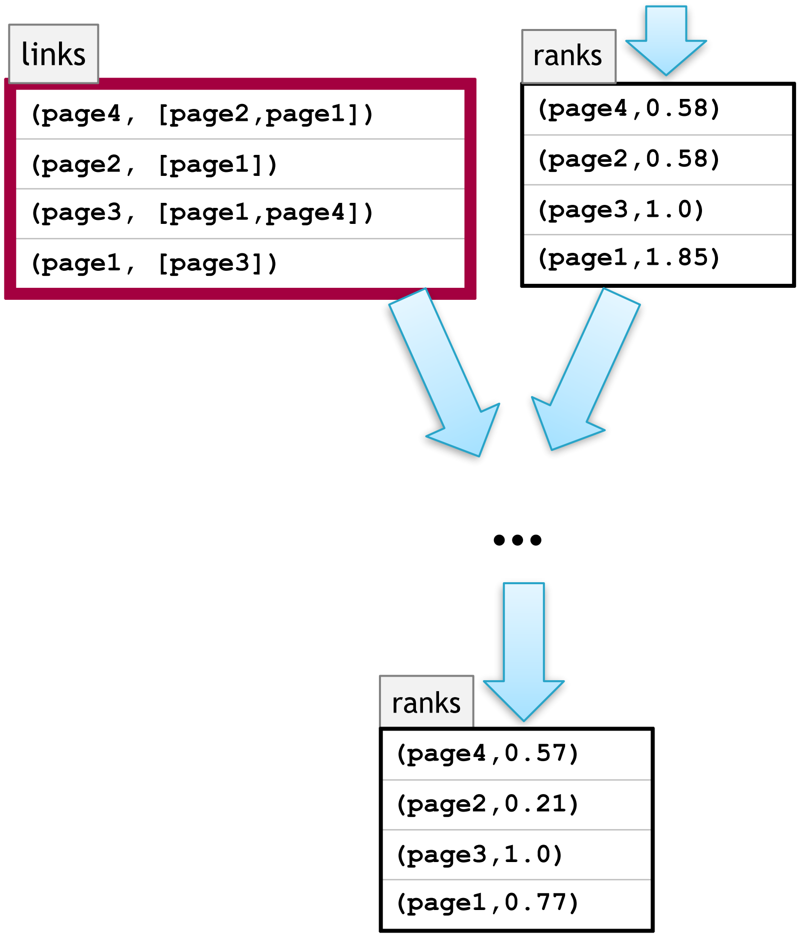
(page2,0.5)
(page1,0.5)
(page1,1.0)
(page1,0.5)
(page4,0.5)
(page3,1.0)

(page4,0.5)
(page2,0.5)
(page3,1.0)
(page1,2.0)

ranks

(page4,.58)
(page2,.58)
(page3,1.0)
(page1,1.85)

Finally, collect() the results.



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- **Many data analytics problems work with "data parallel" algorithms**
  - Records can be processed independently of each other
  - Very well suited to parallelizing
- **Some problems focus on the relationships between the individual data items. For example:**
  - Social networks
  - Web page hyperlinks
  - Roadmaps
- **These relationships can be represented by graphs**
  - Requires "graph parallel" algorithms

- **Graph Creation**
  - Extracting relationship information from a data source
    - For example, extracting links from web pages
- **Graph Representation**
  - e.g., adjacency lists in a table
- **Graph Analysis**
  - Inherently iterative, hard to parallelize
- **Post-analysis processing**
  - e.g., incorporating product recommendations into a retail site

- **Spark is very well suited to graph parallel algorithms**
- **Apache GraphX**
  - UC Berkeley AMPLab project on top of Spark
  - Unifies optimized graph computation with Spark's fast data parallelism and interactive abilities
  - Supersedes predecessor Bagel (Pregel on Spark)

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- **Most programs tell computers exactly what to do**
  - Database transactions and queries
  - Controllers
    - Phone systems, manufacturing processes, transport, weaponry, etc.
  - Media delivery
  - Simple search
  - Social systems
    - Chat, blogs, email, etc.
- **An alternative technique is to have computers *learn* what to do**
- **Machine Learning programs leverage collected data to drive future program behavior**

- **Machine Learning is an active area of research and new applications**
- **There are three well-established categories of techniques for exploiting data**
  - Collaborative filtering (recommendations)
  - Clustering
  - Classification
- **Highly computation intensive and iterative**

- **Collaborative Filtering is a technique for recommendations**
- **Example application: given people who each like certain books, learn to suggest what someone may like in the future based on what they already like**
- **Helps users navigate data by expanding to topics that have affinity with their established interests**
- **Collaborative Filtering algorithms are agnostic to the different types of data items involved**
  - Useful in many different domains

- **Clustering algorithms discover structure in collections of data**
  - Where no formal structure previously existed
- **They discover what clusters, or groupings, naturally occur in data**
- **Examples**
  - Finding related news articles
  - Computer vision

- **The previous two techniques are considered *unsupervised* learning**
  - The algorithm discovers groups or recommendations itself
- **Classification is a form of *supervised* learning**
- **A classification system accepts as input a set of records with labels**
  - Learns how to label new records based on that information
- **Examples**
  - Given a set of e-mails identified as spam/not spam, label new e-mails as spam/not spam
  - Given tumors identified as benign or malignant, classify new tumors

- **MLlib is part of Apache Spark**
- **Includes many common ML functions**
  - ALS (alternating least squares)
  - k-means
  - Logistic Regression
  - Linear Regression
  - Gradient Descent

Homework

See the homework packet for details.