

Graph Analytics in Spark

2015-06-08 • Scala Days • Amsterdam

Paco Nathan, [@pacoid](#)



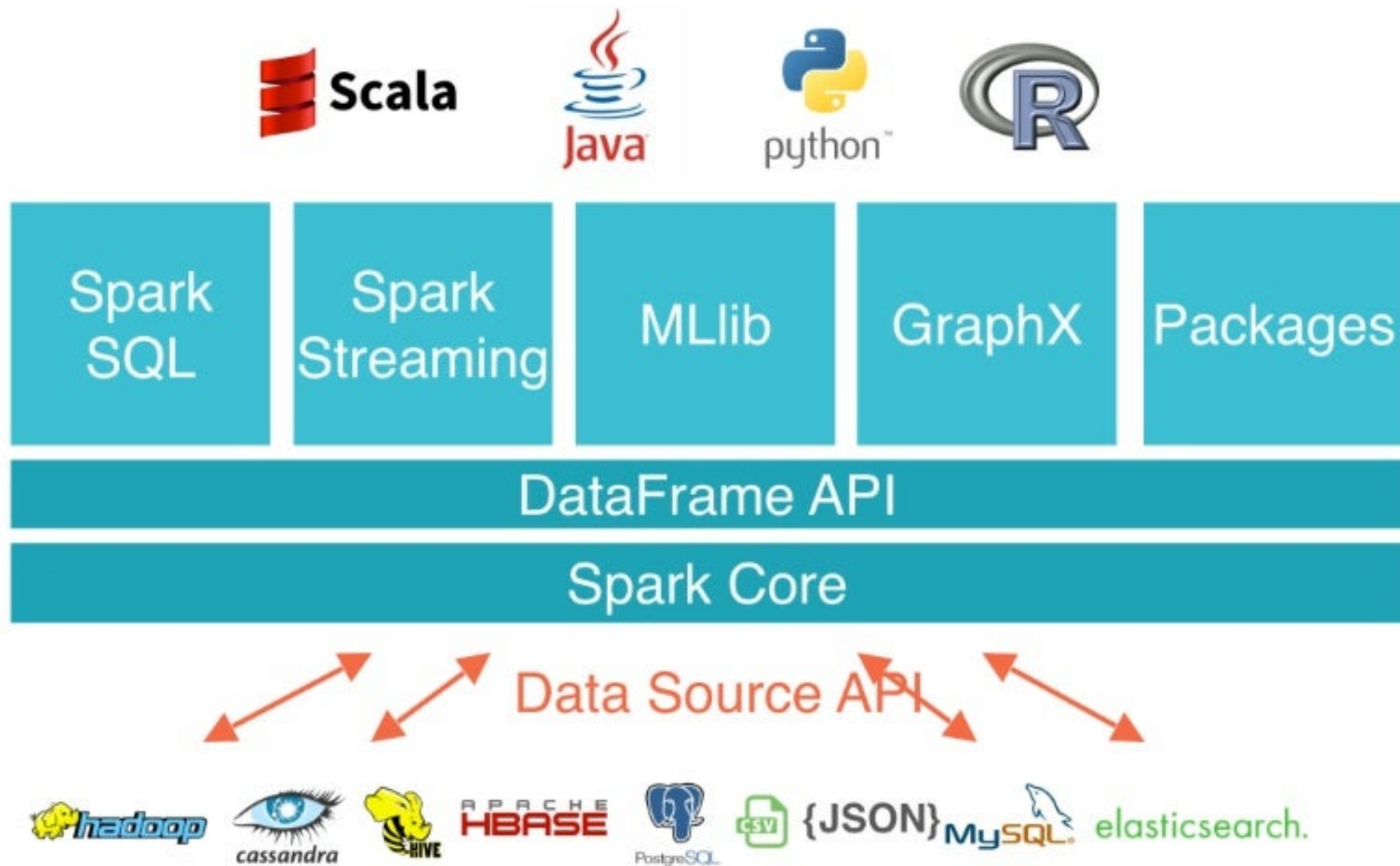
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Spark Overview

	Hadoop MR Record	Spark Record	Spark 1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network	virtualized (EC2) 10Gbps network
Sort rate	1.42 TB/min	4.27 TB/min	4.27 TB/min
Sort rate/node	0.67 GB/min	20.7 GB/min	22.5 GB/min

Spark Overview: Components



Spark

Spark Overview: *Key Distinctions vs. MapReduce*

- generalized patterns
⇒ unified engine for many use cases
- lazy evaluation of the lineage graph
⇒ reduces wait states, better pipelining
- generational differences in hardware
⇒ off-heap use of large memory spaces
- functional programming / ease of use
⇒ reduction in cost to maintain large apps
- lower overhead for starting jobs
- less expensive shuffles



TL;DR: *Smashing The Previous Petabyte Sort Record*

databricks.com/blog/2014/11/05/spark-officially-sets-a-new-record-in-large-scale-sorting.html

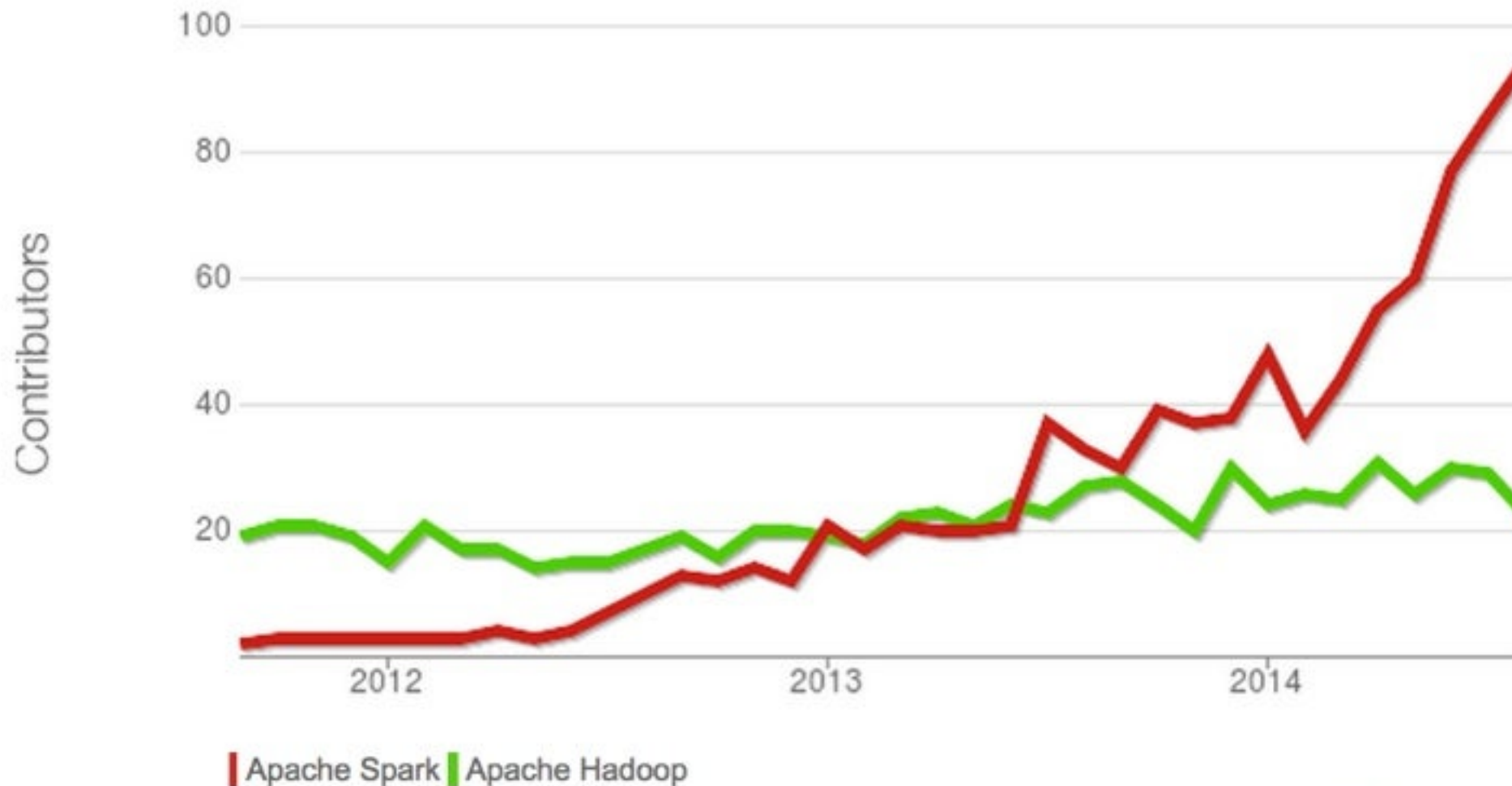
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TL;DR: *Sustained Exponential Growth*

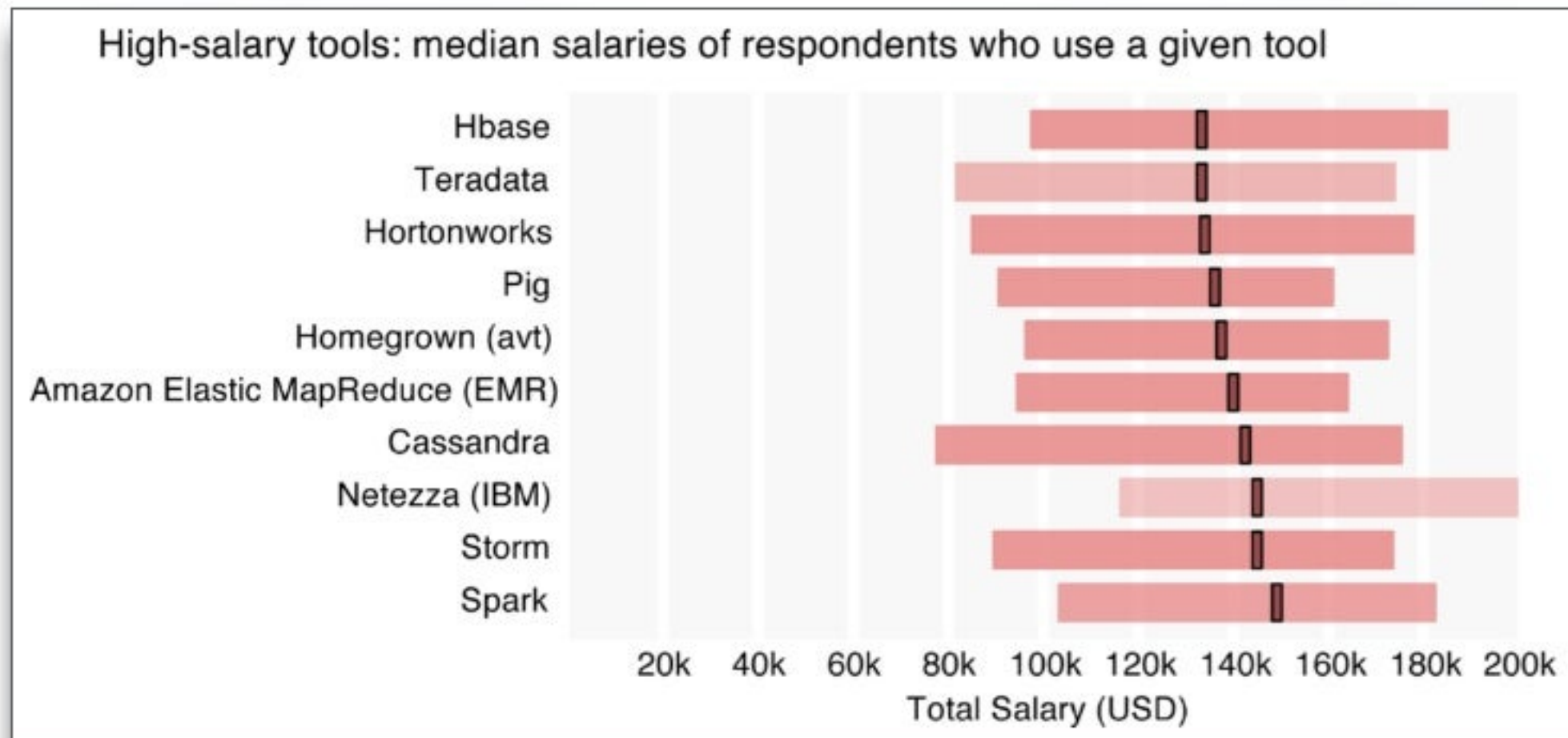
Spark is one of the most active Apache projects
ohloh.net/orgs/apache

Number of contributors who made changes to the project source code each month.



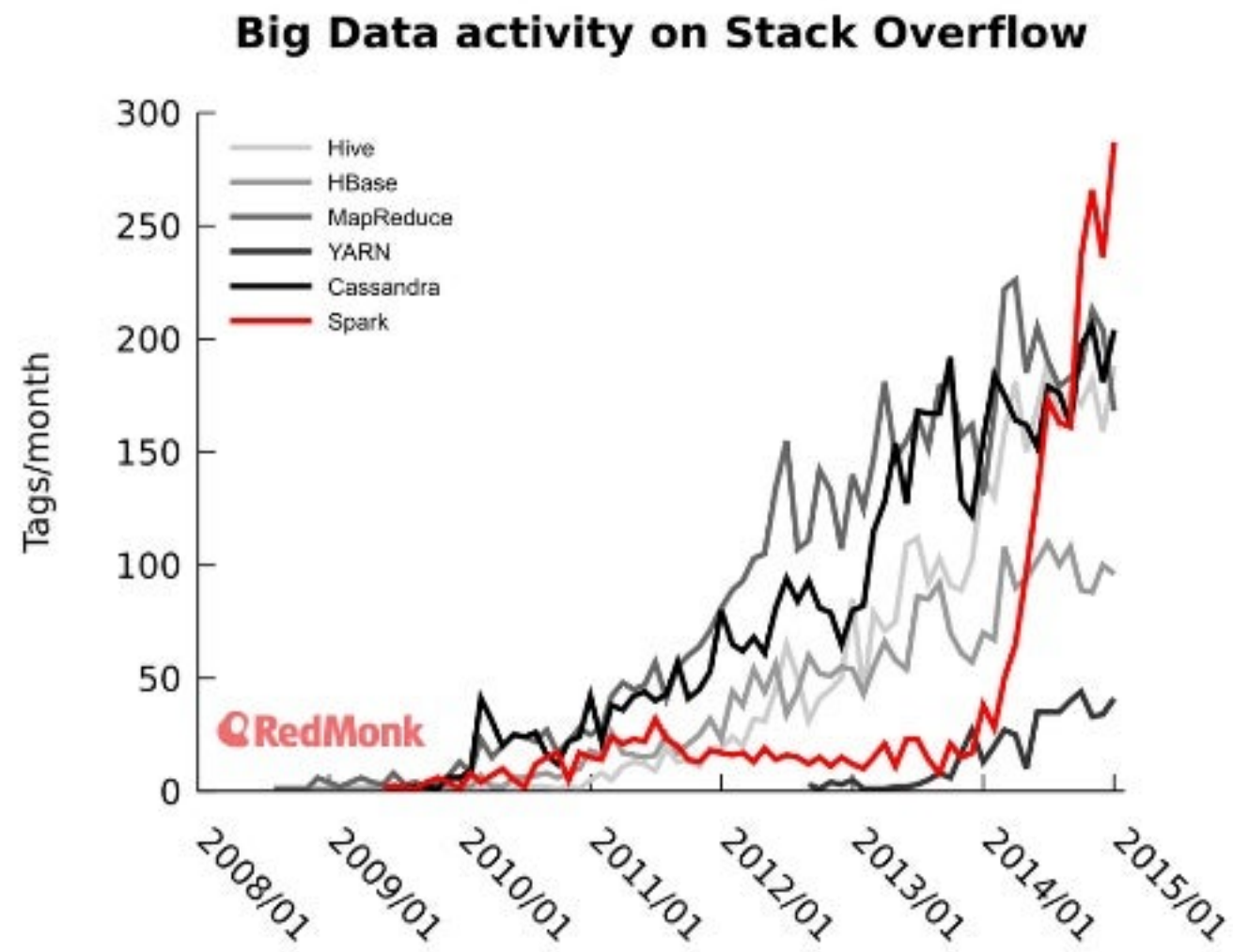
TL;DR: *Spark Expertise Tops Median Salaries within Big Data*

oreilly.com/data/free/2014-data-science-salary-survey.csp



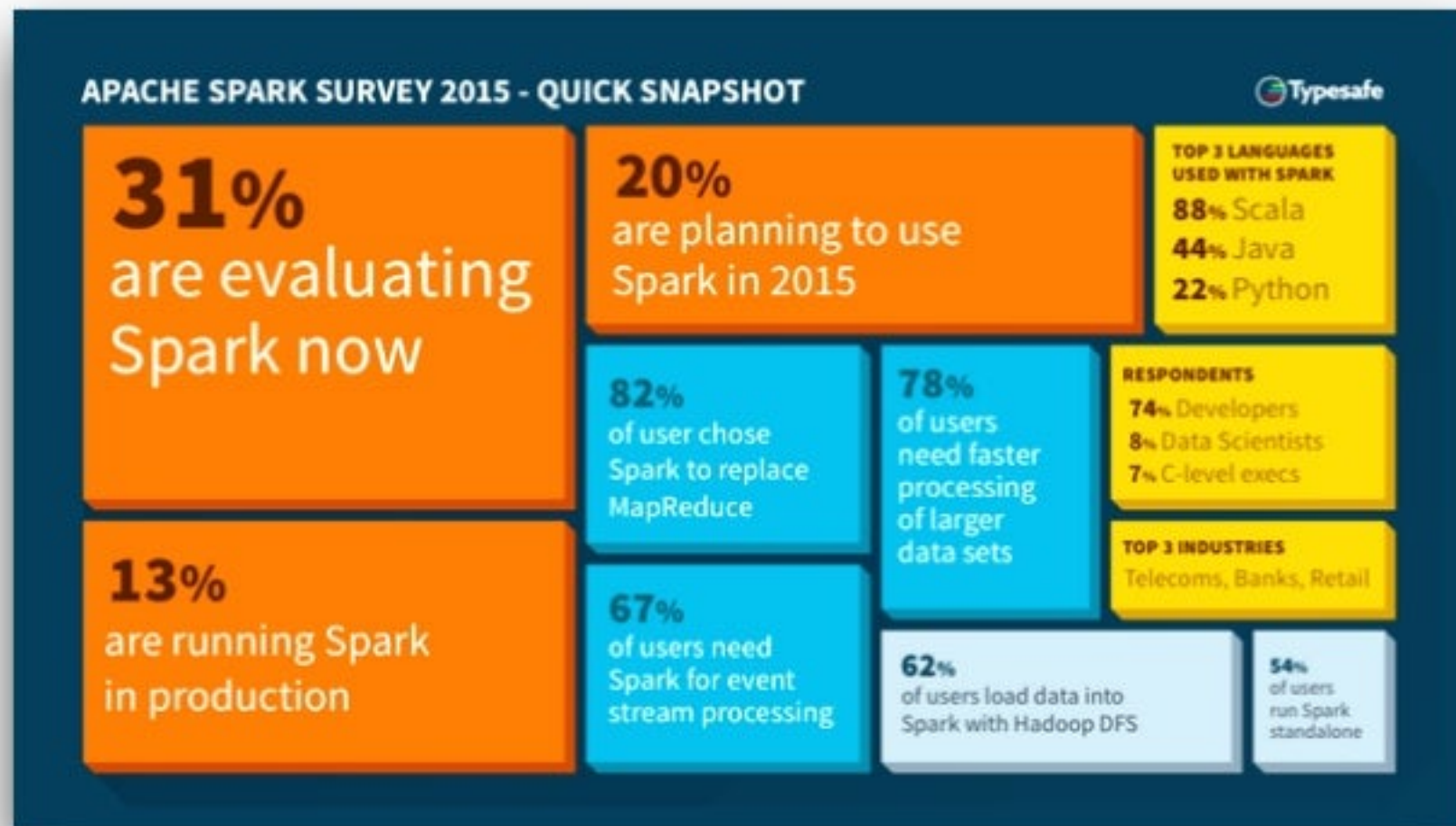
TL;DR: *Spark on StackOverflow*

twitter.com/dberkholz/status/568561792751771648



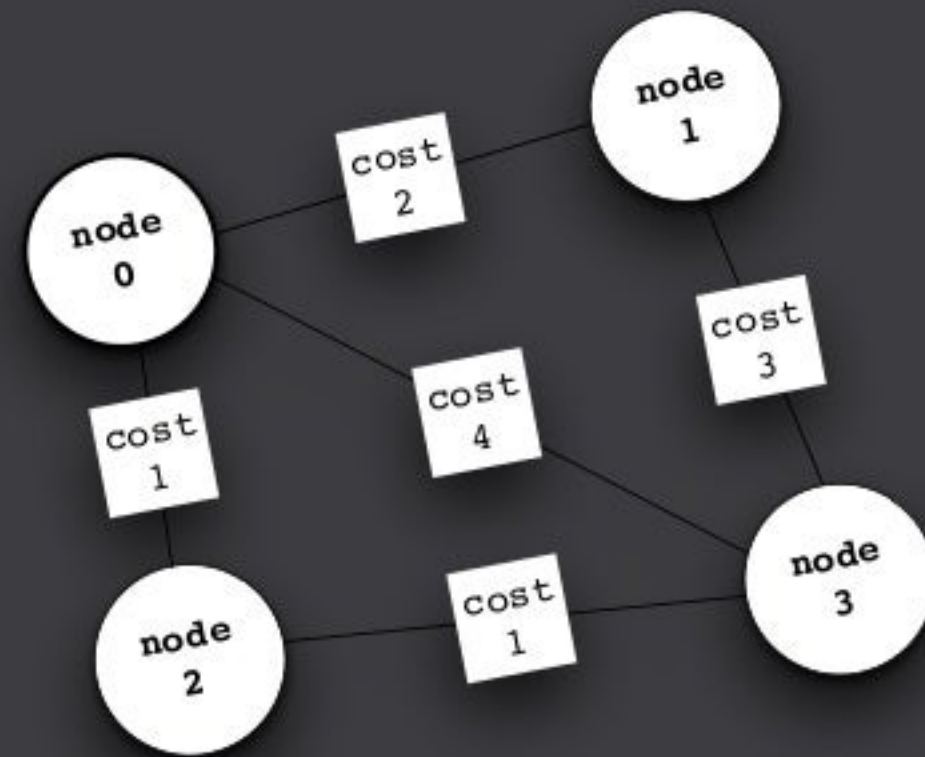
TL;DR: Spark Survey 2015 by Databricks + Typesafe

databricks.com/blog/2015/01/27/big-data-projects-are-hungry-for-simpler-and-more-powerful-tools-survey-validates-apache-spark-is-gaining-developer-traction.html



Spark

GraphX examples



GraphX:

spark.apache.org/docs/latest/graphx-programming-guide.html

Key Points:

- graph-parallel systems
- emphasis on integrated workflows
- optimizations

GraphX: *Further Reading...*

PowerGraph: Distributed Graph-Parallel Computation on Natural Graphs

J. Gonzalez, Y. Low, H. Gu, D. Bickson, C. Guestrin

graphlab.org/files/osdi2012-gonzalez-low-gu-bickson-guestrin.pdf

Pregel: Large-scale graph computing at Google

Grzegorz Czajkowski, et al.

googleresearch.blogspot.com/2009/06/large-scale-graph-computing-at-google.html

GraphX: Graph Analytics in Spark

Ankur Dave, Databricks

spark-summit.org/east-2015/talk/graphx-graph-analytics-in-spark

Topic modeling with LDA: MLib meets GraphX

Joseph Bradley, Databricks

databricks.com/blog/2015/03/25/topic-modeling-with-lda-mlib-meets-graphx.html

GraphX: *Compose Node + Edge RDDs into a Graph*

```
val nodeRDD: RDD[(Long, ND)] = sc.parallelize(...)
val edgeRDD: RDD[Edge[ED]] = sc.parallelize(...)

val g: Graph[ND, ED] = Graph(nodeRDD, edgeRDD)
```

GraphX: Example – simple traversals

// <http://spark.apache.org/docs/latest/graphx-programming-guide.html>

```
import org.apache.spark.graphx._
import org.apache.spark.rdd.RDD

case class Peep(name: String, age: Int)

val nodeArray = Array(
  (1L, Peep("Kim", 23)), (2L, Peep("Pat", 31)),
  (3L, Peep("Chris", 52)), (4L, Peep("Kelly", 39)),
  (5L, Peep("Leslie", 45))
)
val edgeArray = Array(
  Edge(2L, 1L, 7), Edge(2L, 4L, 2),
  Edge(3L, 2L, 4), Edge(3L, 5L, 3),
  Edge(4L, 1L, 1), Edge(5L, 3L, 9)
)

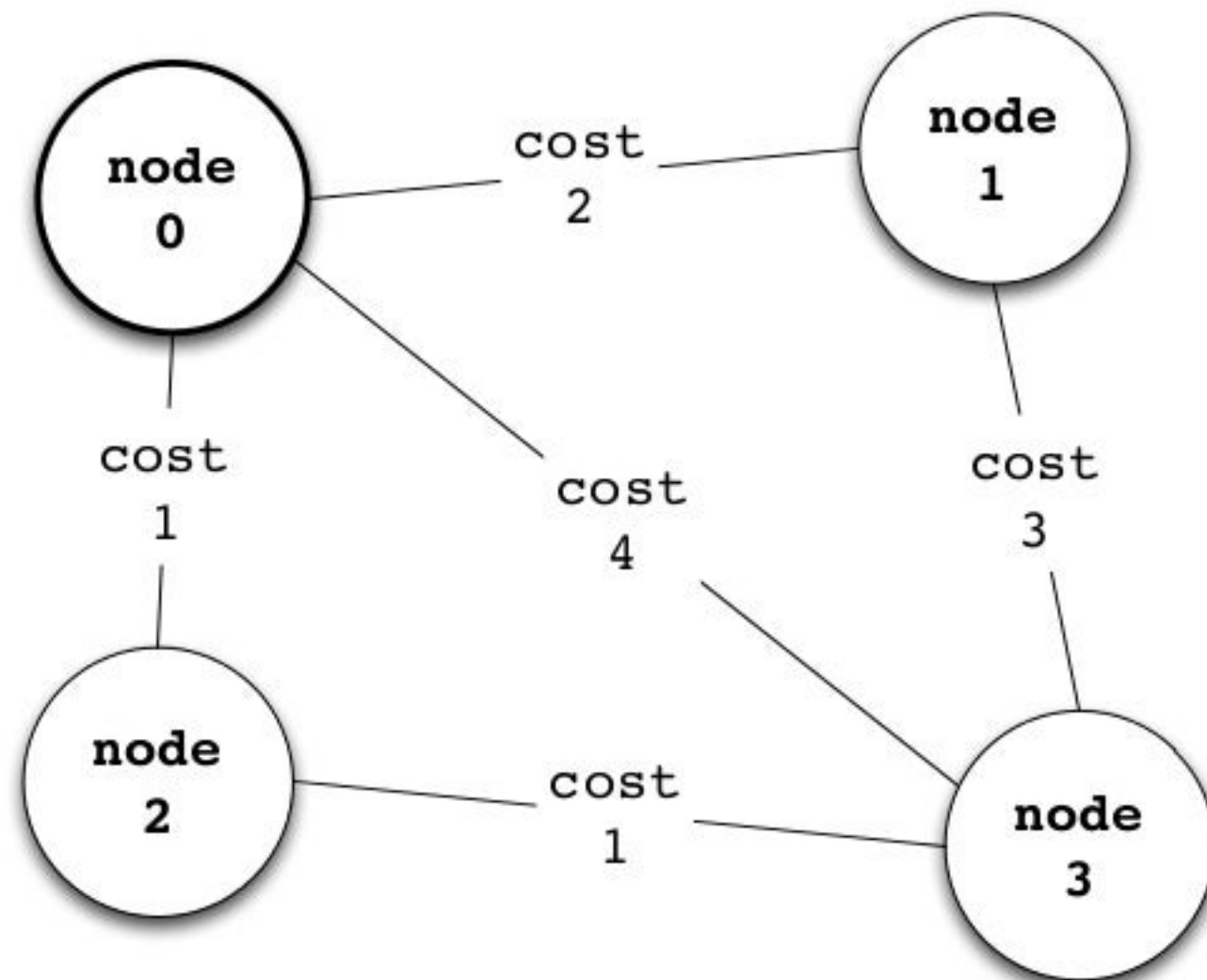
val nodeRDD: RDD[(Long, Peep)] = sc.parallelize(nodeArray)
val edgeRDD: RDD[Edge[Int]] = sc.parallelize(edgeArray)
val g: Graph[Peep, Int] = Graph(nodeRDD, edgeRDD)

val results = g.triplets.filter(t => t.attr > 7)

for (triplet <- results.collect) {
  println(s"${triplet.srcAttr.name} loves ${triplet.dstAttr.name}")
}
```


GraphX: Example – routing problems

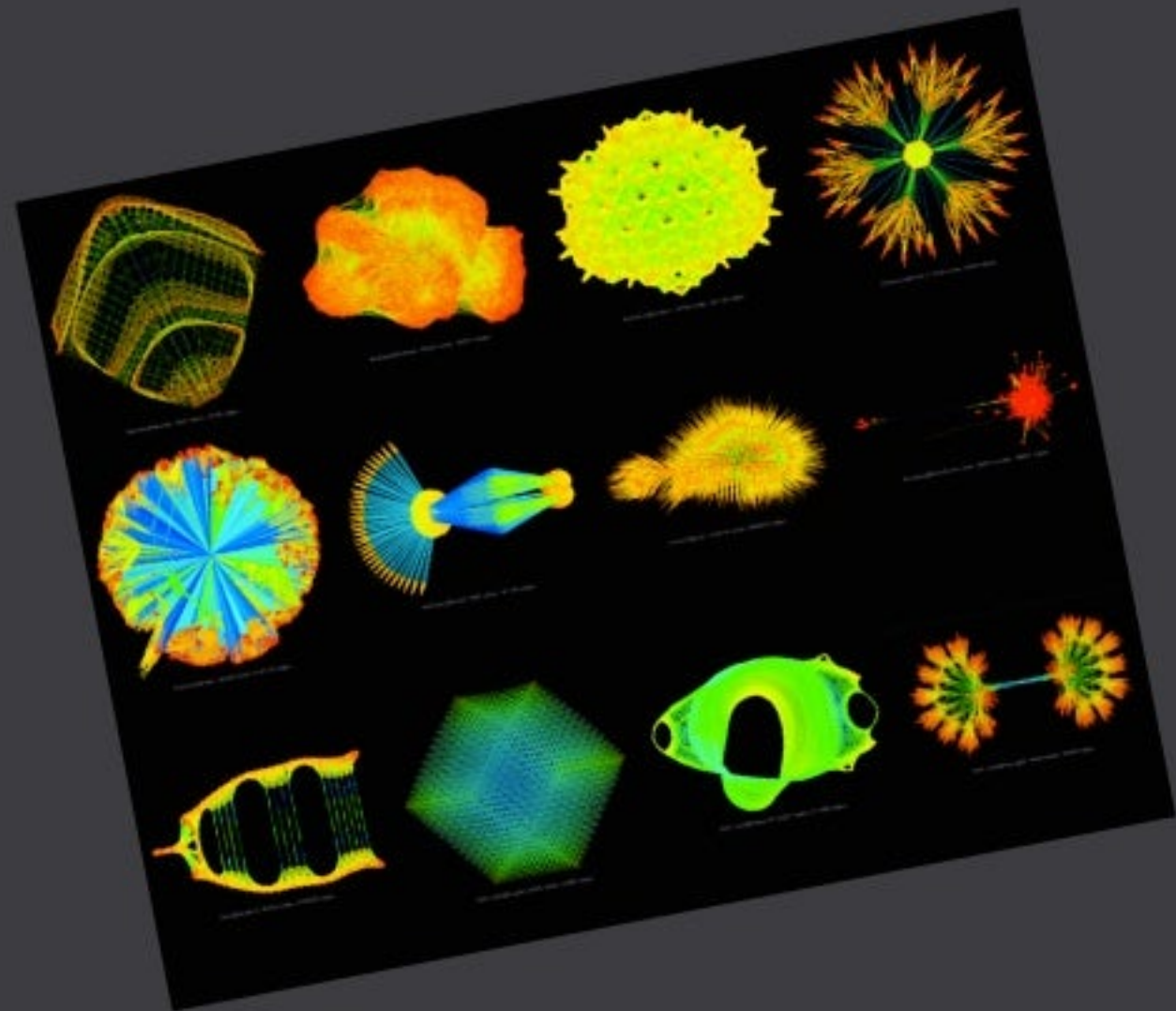
What is the cost to reach **node 0** from any other node in the graph? This is a common use case for graph algorithms, e.g., **Dijkstra**



GraphX: *code examples...*

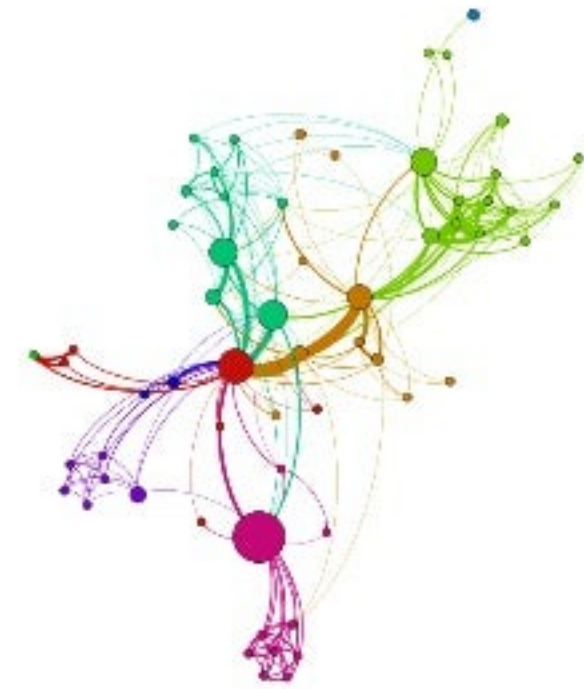
Let's check
some code!

Graph Analytics



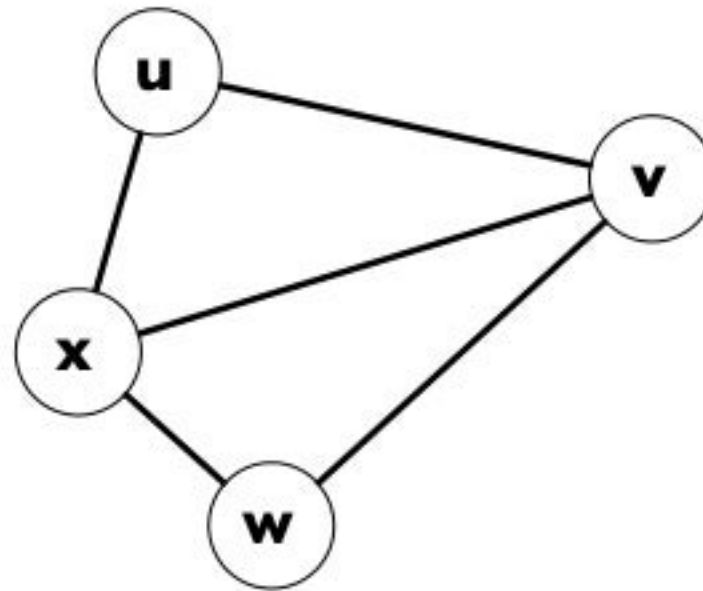
Graph Analytics: *terminology*

- many real-world problems are often represented as *graphs*
- graphs can generally be converted into *sparse matrices* (bridge to linear algebra)
- *eigenvectors* find the stable points in a system defined by matrices – which may be more efficient to compute
- beyond simpler graphs, complex data may require work with *tensors*



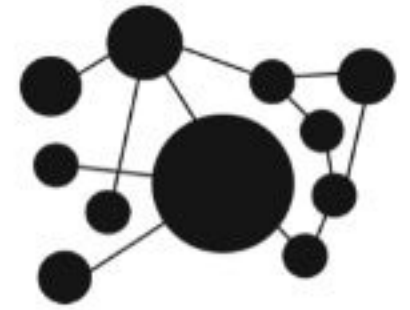
Graph Analytics: *example*

Suppose we have a graph as shown below:

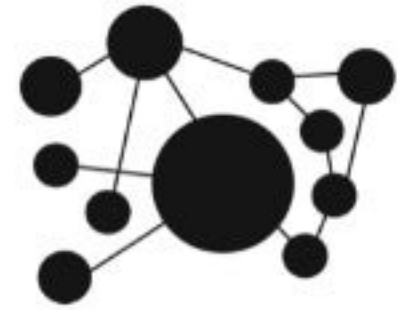


We call **x** a *vertex* (sometimes called a *node*)

An *edge* (sometimes called an *arc*) is any line connecting two vertices

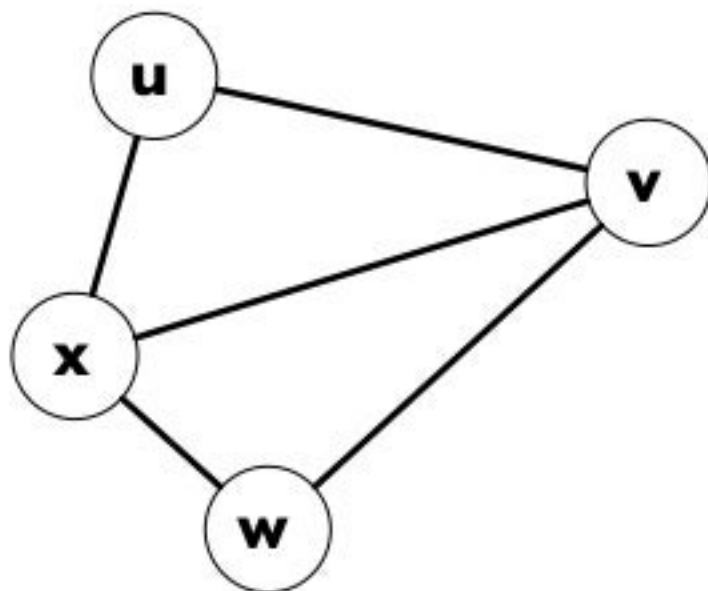


Graph Analytics: *representation*



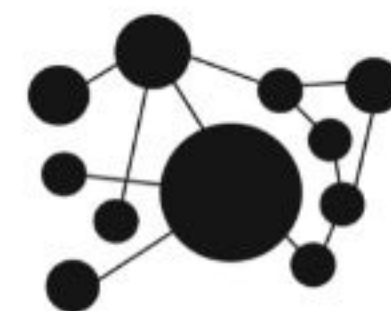
We can represent this kind of graph as an *adjacency matrix*:

- label the rows and columns based on the vertices
- entries get a 1 if an edge connects the corresponding vertices, or 0 otherwise



	u	v	w	x
u	0	1	0	1
v	1	0	1	1
w	0	1	0	1
x	1	1	1	0

Graph Analytics: *algebraic graph theory*



An *adjacency matrix* always has certain properties:

- it is *symmetric*, i.e., $\mathbf{A} = \mathbf{A}^T$
- it has real eigenvalues

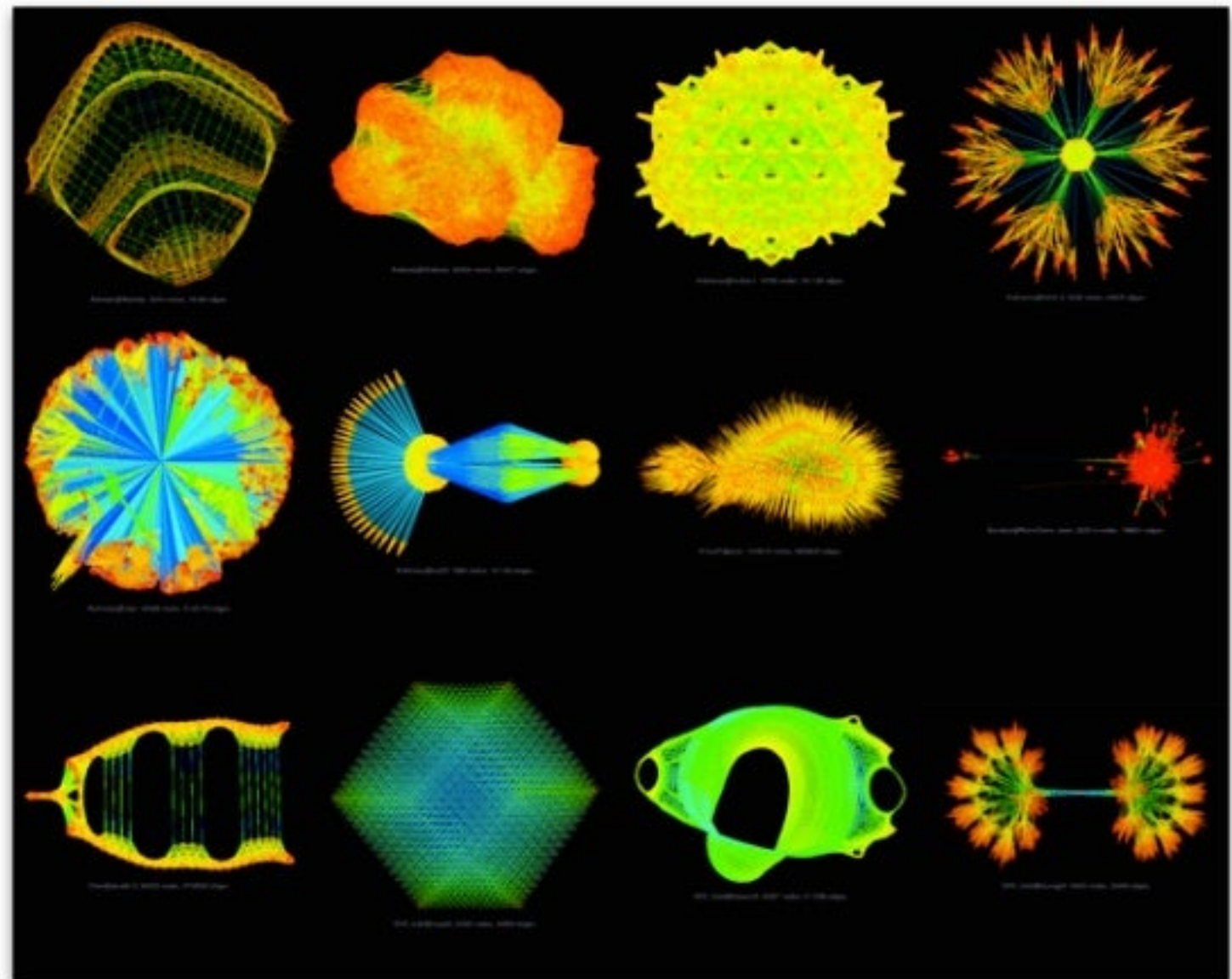
$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

Therefore *algebraic graph theory* bridges between *linear algebra* and *graph theory*

Graph Analytics: *beauty in sparsity*

Sparse Matrix Collection... for when you **really** need a wide variety of sparse matrix examples, e.g., to evaluate new ML algorithms

University of Florida
Sparse Matrix Collection
[cise.ufl.edu/
research/sparse/
matrices/](http://cise.ufl.edu/research/sparse/matrices/)



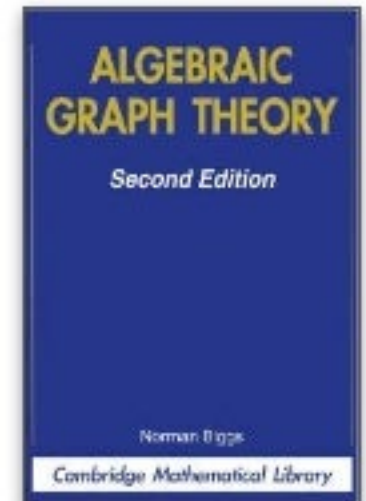
Graph Analytics: *resources*

Algebraic Graph Theory

Norman Biggs

Cambridge (1974)

[amazon.com/dp/0521458978](https://www.amazon.com/dp/0521458978)

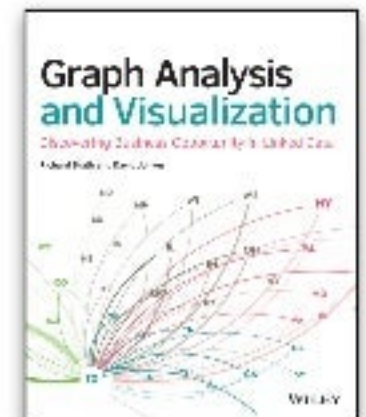


Graph Analysis and Visualization

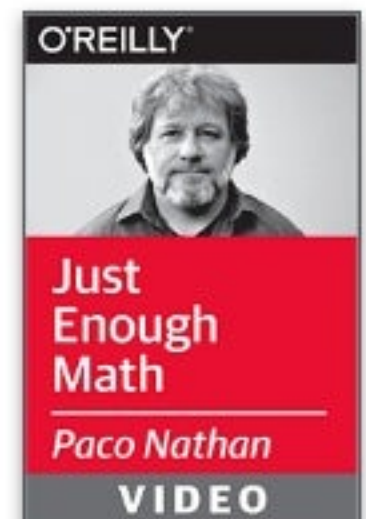
Richard Brath, David Jonker

Wiley (2015)

shop.oreilly.com/product/9781118845844.do



See also examples in: **Just Enough Math**



Graph Analytics: *tensor solutions emerging*

Although tensor factorization is considered problematic, it may provide more general case solutions, and some work leverages Spark:

The Tensor Renaissance in Data Science

Anima Anandkumar @UC Irvine

radar.oreilly.com/2015/05/the-tensor-renaissance-in-data-science.html



Spacey Random Walks and Higher Order Markov Chains

David Gleich @Purdue

slideshare.net/dgleich/spacey-random-walks-and-higher-order-markov-chains



Data Preparation



Data Prep: *Exsto Project Overview*

- insights about dev communities, via data mining their email forums
- works with any Apache project email archive
- applies NLP and ML techniques to analyze message threads
- graph analytics surface themes and interactions
- results provide feedback for communities, e.g., leaderboards

Data Prep: *Exsto Project Overview – four links*

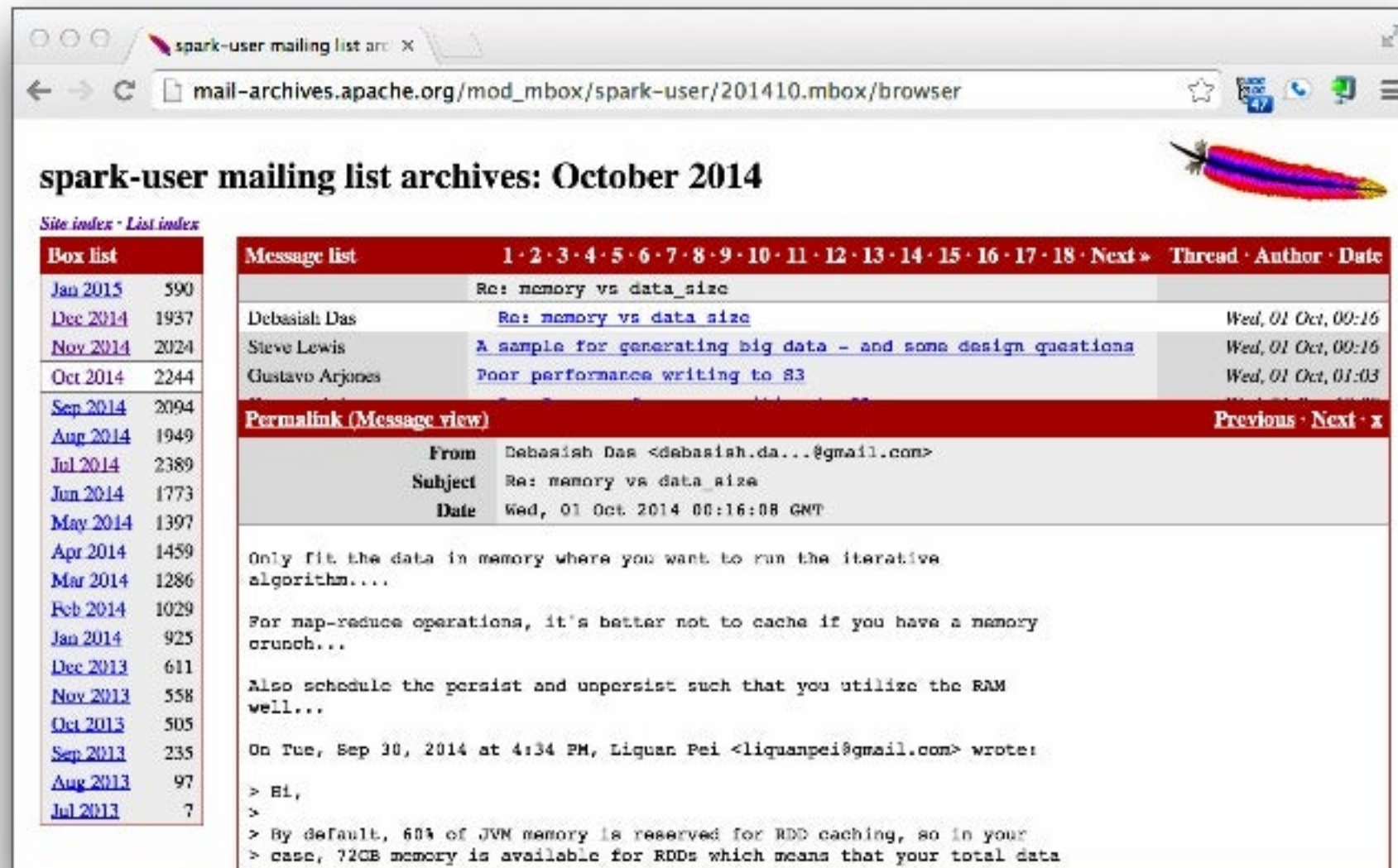
<https://github.com/ceteri/spark-exercises/tree/master/exsto/dbc>

<http://web.eecs.umich.edu/~mihalcea/papers/mihalcea.emnlp04.pdf>

http://mail-archives.apache.org/mod_mbox/spark-user/

<https://class01.cloud.databricks.com/#notebook/67011>

Data Prep: *Scraper pipeline*



spark-user mailing list archives: October 2014

Site index · List index

Box list	Message list
Jan 2015 590	1 · 2 · 3 · 4 · 5 · 6 · 7 · 8 · 9 · 10 · 11 · 12 · 13 · 14 · 15 · 16 · 17 · 18 · Next »
Dec 2014 1937	Thread · Author · Date
Nov 2014 2024	Re: memory vs data_size
Oct 2014 2244	Debasish Das Re: memory vs data_size Wed, 01 Oct, 09:16
Sep 2014 2094	Steve Lewis A sample for generating big data - and some design questions Wed, 01 Oct, 09:16
Aug 2014 1949	Gustavo Arjones Poor performance writing to S3 Wed, 01 Oct, 01:03
Jul 2014 2389	Permalink (Message view) Previous · Next · x
Jun 2014 1773	From Debasish Das <debasish.da...@gmail.com>
May 2014 1397	Subject Re: memory vs data_size
Apr 2014 1459	Date Wed, 01 Oct 2014 00:16:08 GMT
Mar 2014 1286	Only fit the data in memory where you want to run the iterative algorithm....
Feb 2014 1029	For map-reduce operations, it's better not to cache if you have a memory crunch...
Jan 2014 925	Also schedule the persist and unpersist such that you utilize the RAM well...
Dec 2013 611	On Tue, Sep 30, 2014 at 4:34 PM, Liguang Pei <liquanpei@gmail.com> wrote:
Nov 2013 558	> Hi,
Oct 2013 505	>
Sep 2013 235	> By default, 60% of JVM memory is reserved for RDD caching, so in your
Aug 2013 97	> case, 72GB memory is available for RDDs which means that your total data
Jul 2013 7	

+

github.com/ceteri/spark-exercises/tree/master/exsto/dbc

Data Prep: *Scraper pipeline*

Typical data rates, e.g., for dev@spark.apache.org:

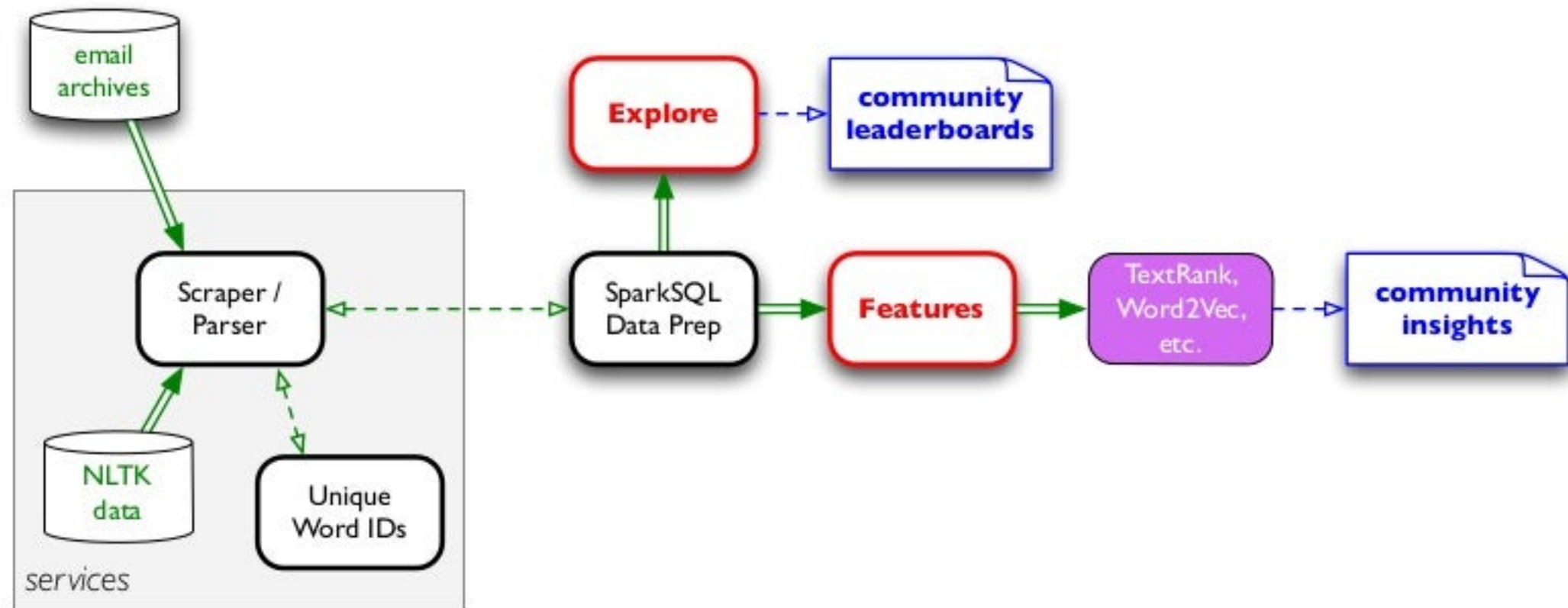
- ~2K msgs/month
- ~18 MB/month parsed in JSON

Six months' list activity represents a graph of:

- 1882 senders
- 1,762,113 nodes
- 3,232,174 edges

A large graph?! In any case, it satisfies definition of a *graph-parallel system* – lots of data locality to leverage

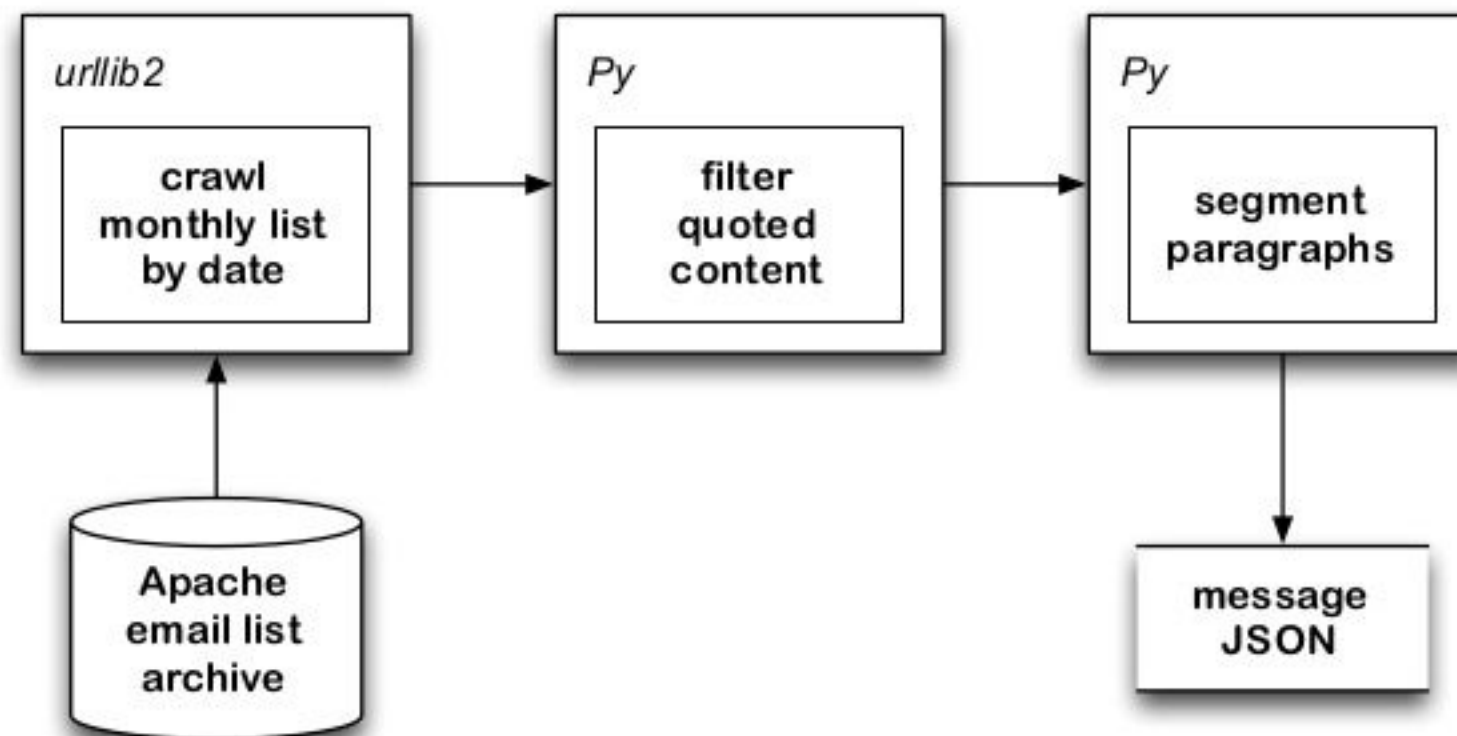
Data Prep: Microservices meet Parallel Processing



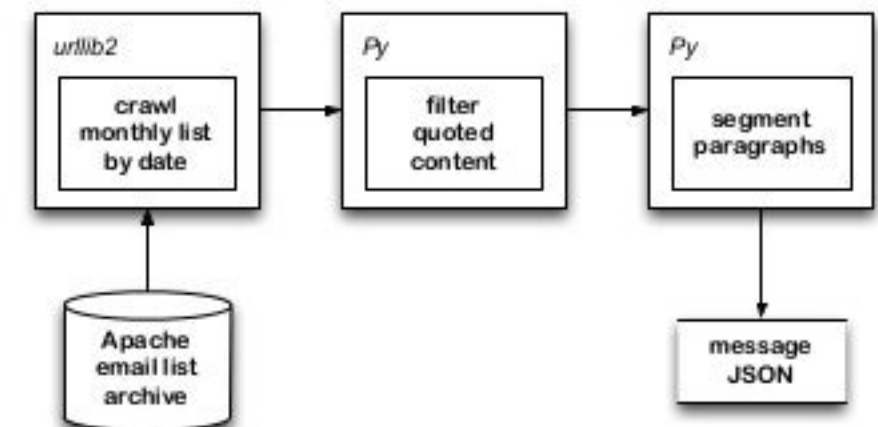
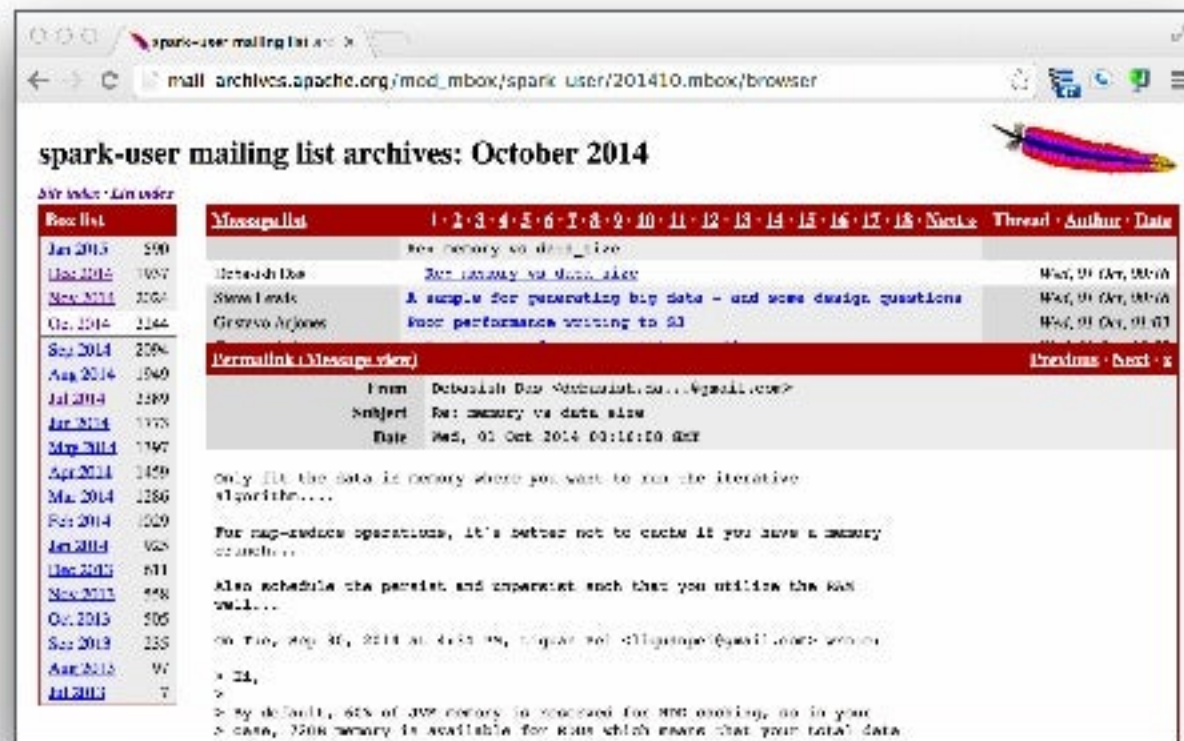
not so big data...

relatively big compute...

Data Prep: *Scraper pipeline*

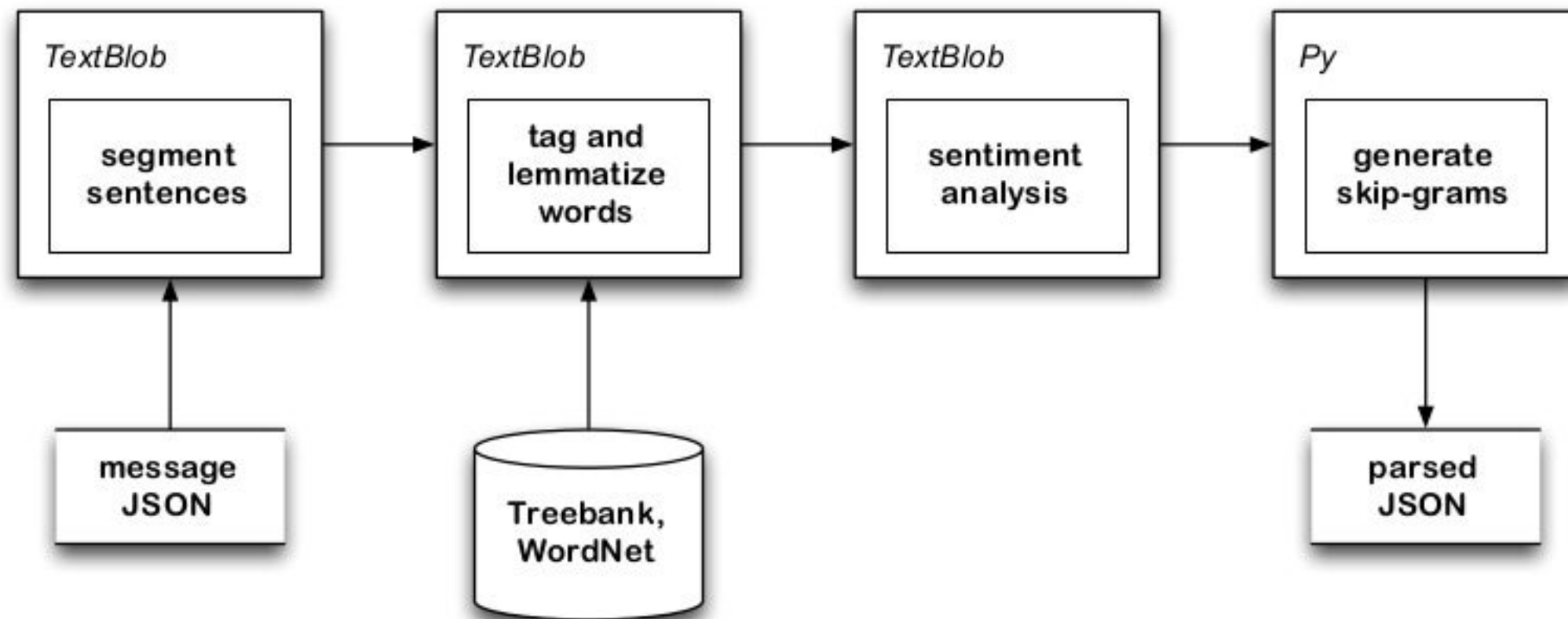


Data Prep: *Scraper pipeline*



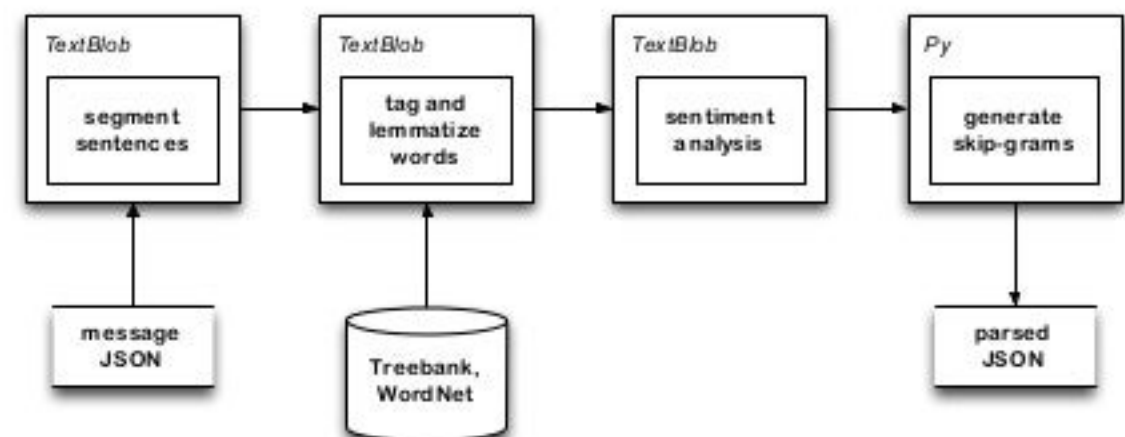
```
{
  "date": "2014-10-01T00:16:08+00:00",
  "id": "CA+B-+fyrBUlyGZAYJM_u=gnBVtzB=sXoBHkhmS-6Lln8K5Hhbw",
  "next_thread": "CALEj8eP5hpQDM=p2xryL-JT-x_VhkRcD59Q+9Qr9LJ9sYLeLVg",
  "next_url": "http://mail-archives.apache.org/mod_mbox/spark-user/201410 mbox/%3cCALEj8eP5hpQ",
  "prev_thread": "",
  "sender": "Debasish Das <debasish.da...@gmail.com>",
  "subject": "Re: memory vs data_size",
  "text": "\nOnly fit the data in memory where you want to run the iterative\nalgorithm....\n\n"
}
```


Data Prep: *Parser pipeline*



Data Prep: Parser pipeline

```
{
  "date": "2014-10-01T00:16:08+00:00",
  "id": "CA+B-+fyrBUlyGZAYJM_u=gnBVtzB=sXoBHkhmS-6L1n8K5Hhbw",
  "next_thread": "CALEj8eP5hpQDM=p2xryL-JT-x_VhkRcD59Q+9Qr9LJ9sYLeLVg",
  "next_url": "http://mail-archives.apache.org/mod_mbox/spark-user/201410.mbox/%3cCALEj8eP5hpQDM=p2xryL-JT-x_VhkRcD59Q+9Qr9LJ9sYLeLVg%3e",
  "prev_thread": "",
  "sender": "Debasish Das <debasish.da...@gmail.com>",
  "subject": "Re: memory vs data_size",
  "text": "\nOnly fit the data in memory where you want to run the iterative\nalgorithm....\n\nFor"
}
```

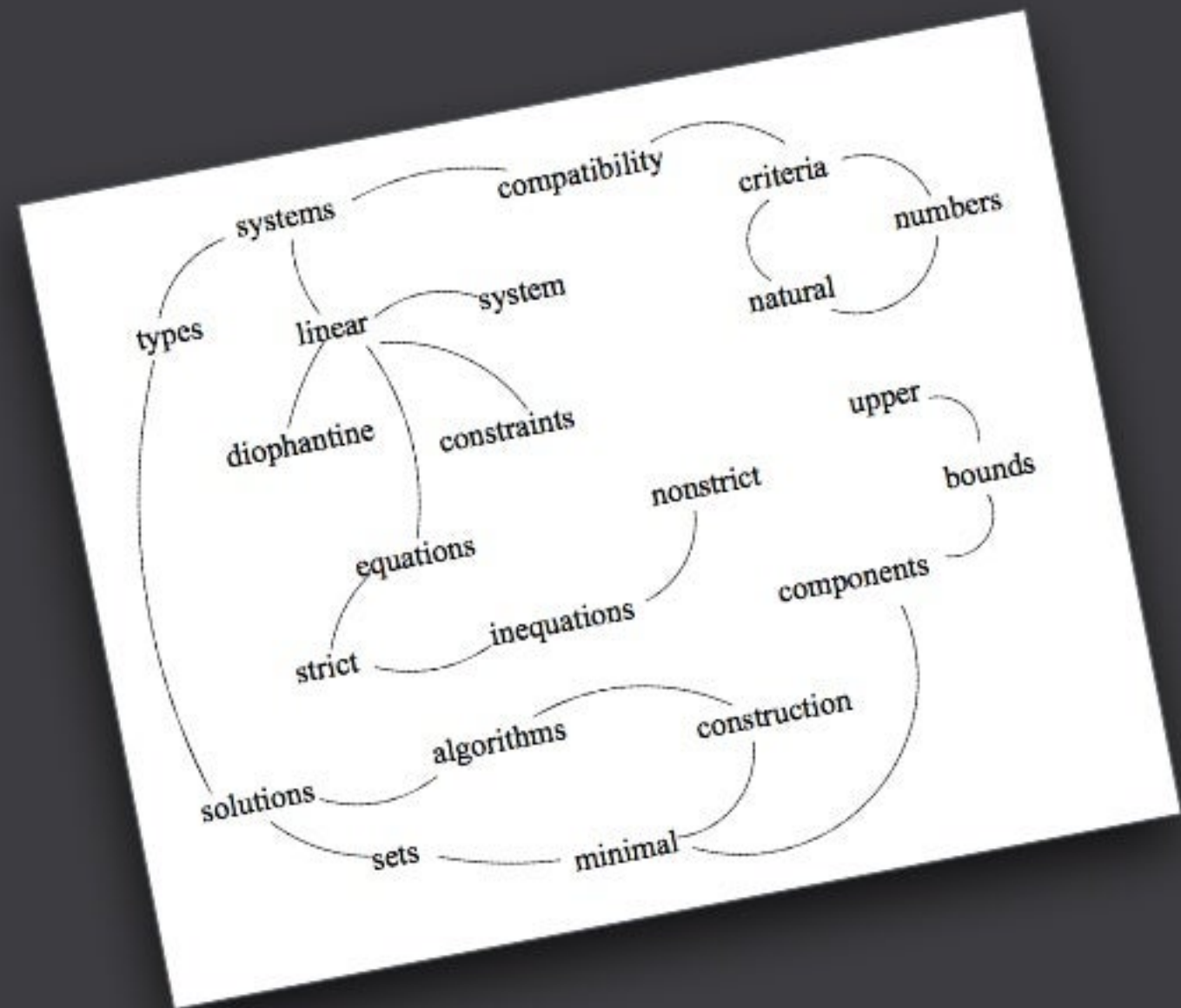


```
{
  "graf": [ [1, "Only", "only", "RB", 1, 0], [2, "fit", "fit", "VBP", 1, 1] ... ],
  "id": "CA+B-+fyrBUlyGZAYJM_u=gnBVtzB=sXoBHkhmS-6L1n8K5Hhbw",
  "polr": 0.2,
  "shal": "178b7a57ec6168f20a8a4f705fb8b0b04e59eeb7",
  "size": 14,
  "subj": 0.7,
  "tile": [ [1, 2], [2, 3], [3, 4] ... ]
}
```

Data Prep: *code examples...*

Let's check
some code!

TextRank in Spark



TextRank: *original paper*

TextRank: Bringing Order into Texts

Rada Mihalcea, Paul Tarau

Conference on Empirical Methods in Natural
Language Processing (July 2004)

<https://goo.gl/AJnA76>

<http://web.eecs.umich.edu/~mihalcea/papers.html>

<http://www.cse.unt.edu/~tarau/>



TextRank: *other implementations*

Jeff Kubina (Perl / English):

<http://search.cpan.org/~kubina/Text-Categorize-Textrank-0.51/lib/Text/Categorize/Textrank/En.pm>

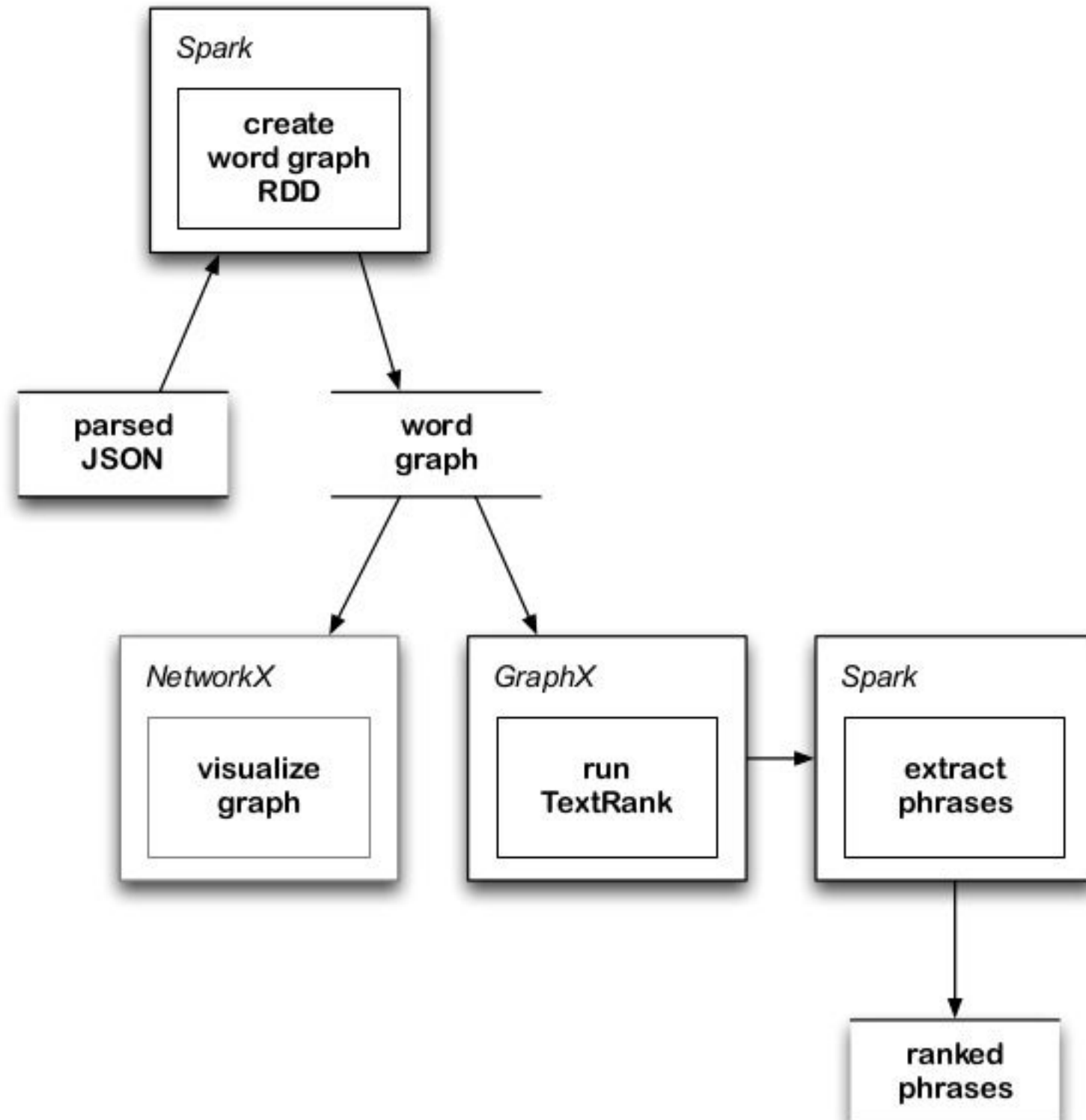
Paco Nathan (Hadoop / English+Spanish):

<https://github.com/ceteri/textrank/>

Karin Christiasen (Java / Icelandic):

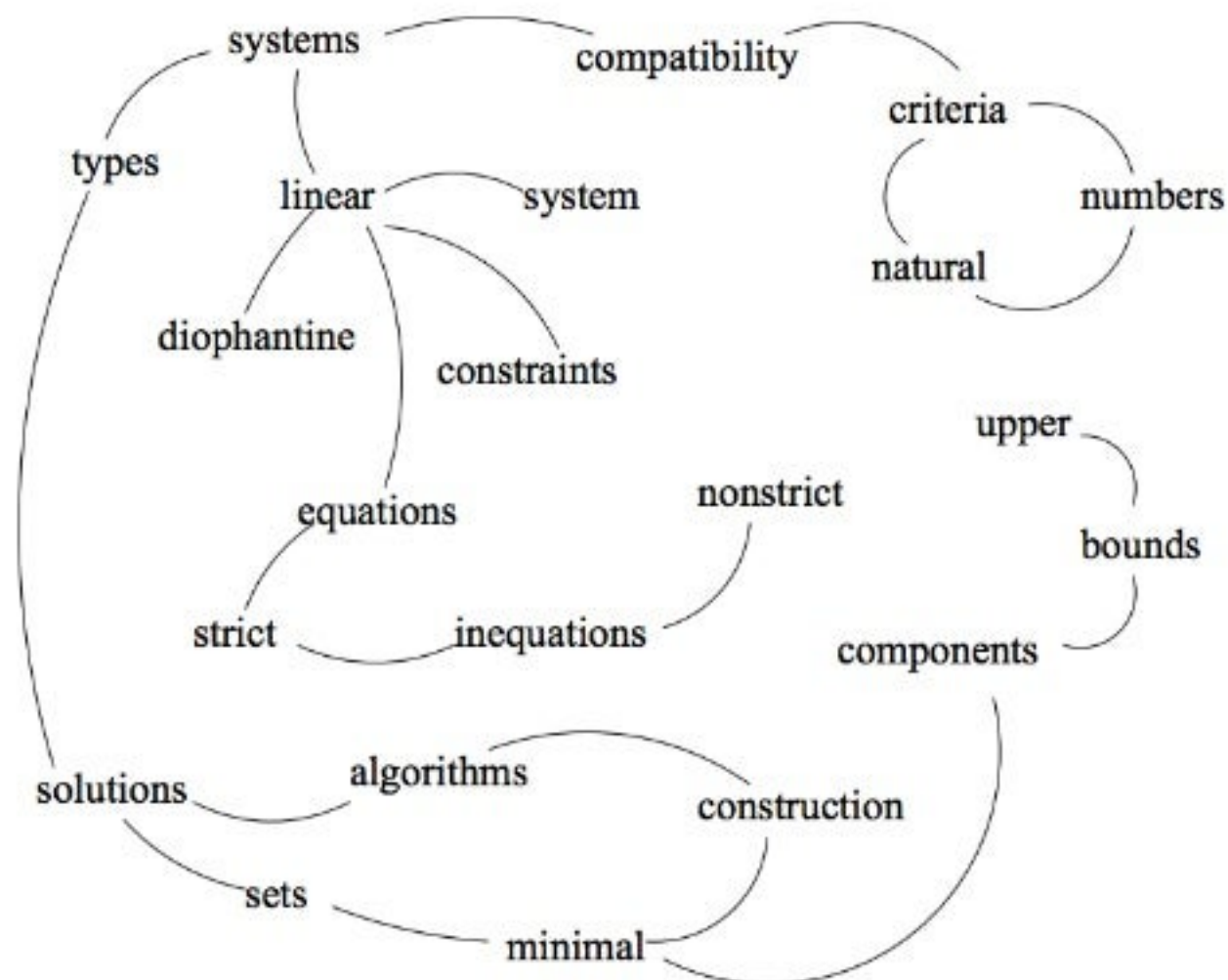
<https://github.com/karchr/icetextsum>

TextRank: *Spark-based pipeline*



TextRank: *raw text input*

Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequations, and nonstrict inequations are considered. Upper bounds for components of a minimal set of solutions and algorithms of construction of minimal generating sets of solutions for all types of systems are given. These criteria and the corresponding algorithms for constructing a minimal supporting set of solutions can be used in solving all the considered types systems and systems of mixed types.

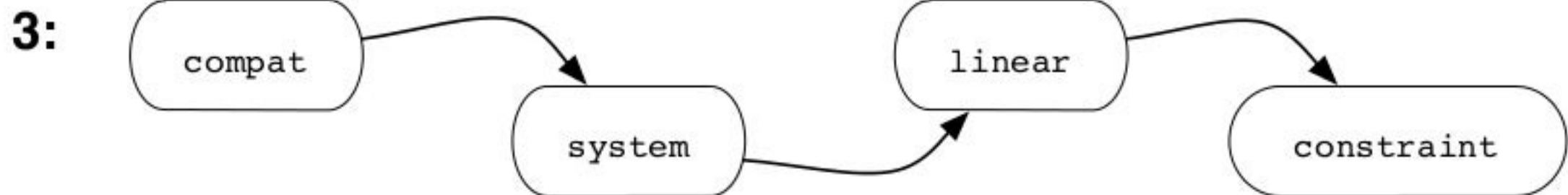


TextRank: *data results*

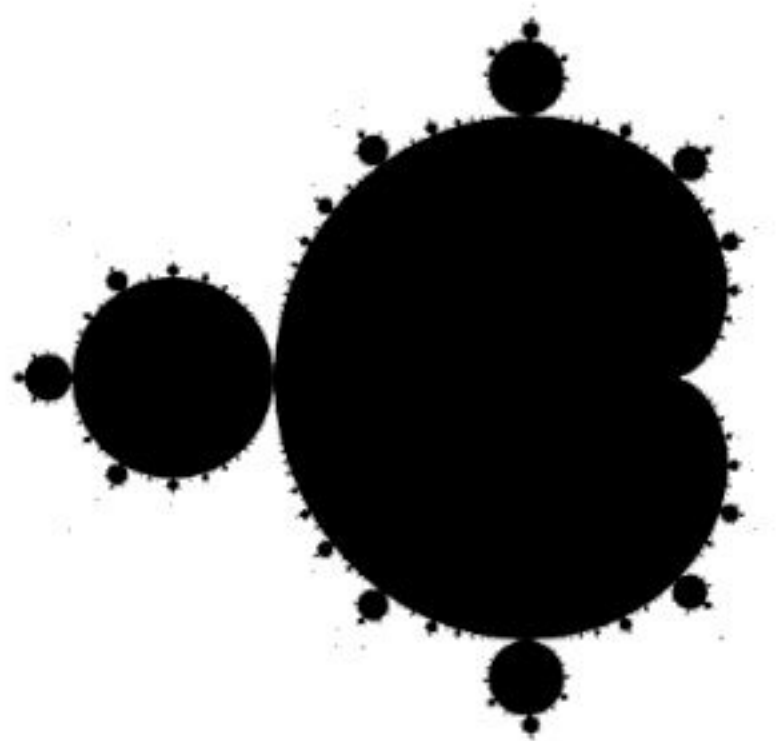
1: "Compatibility of systems of linear constraints"

2:

```
[{'index': 0, 'stem': 'compat', 'tag': 'NNP', 'word': 'compatibility'},  
 {'index': 1, 'stem': 'of', 'tag': 'IN', 'word': 'of'},  
 {'index': 2, 'stem': 'system', 'tag': 'NNS', 'word': 'systems'},  
 {'index': 3, 'stem': 'of', 'tag': 'IN', 'word': 'of'},  
 {'index': 4, 'stem': 'linear', 'tag': 'JJ', 'word': 'linear'},  
 {'index': 5, 'stem': 'constraint', 'tag': 'NNS', 'word': 'constraints'}]
```



TextRank: *dependencies*

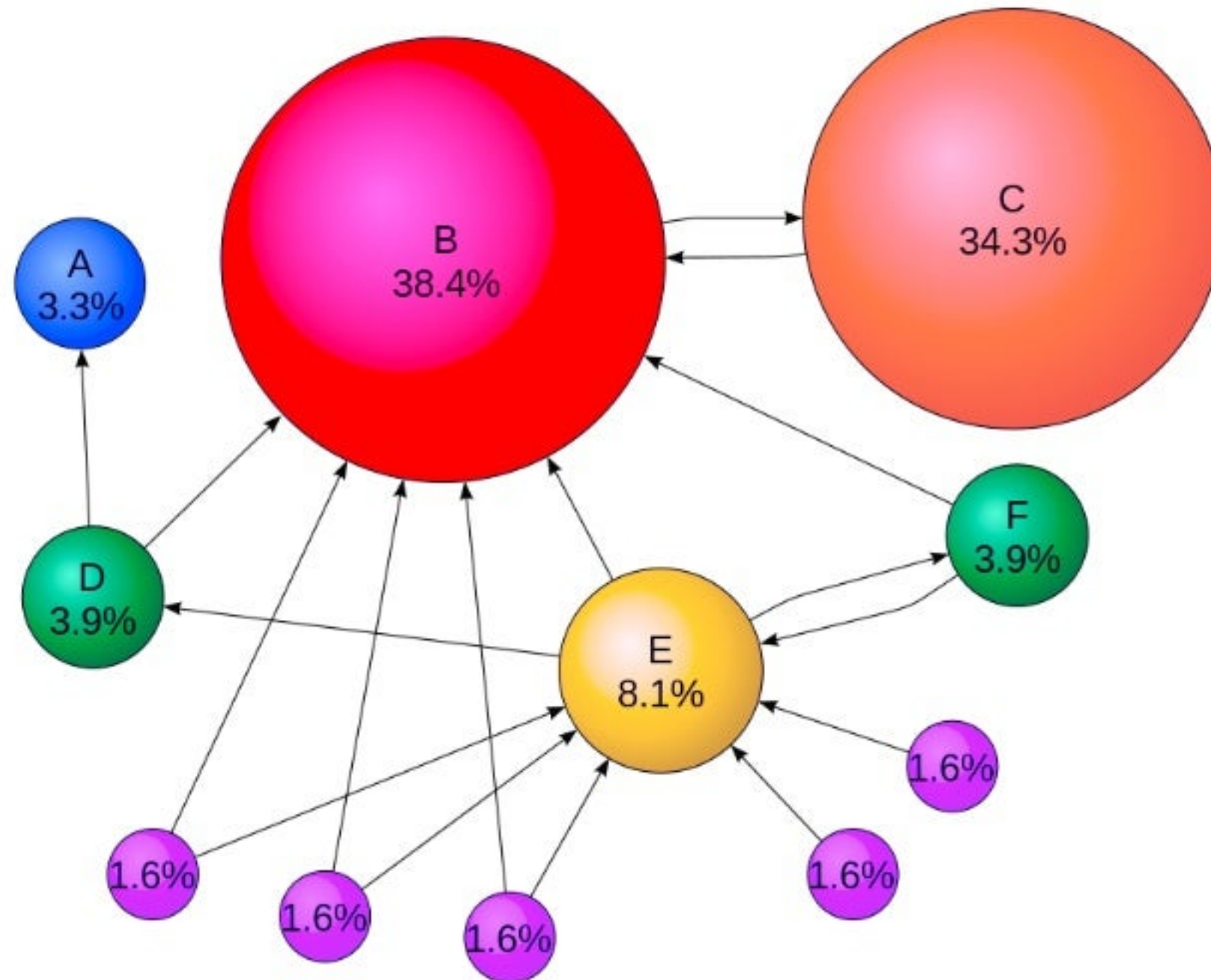


TextBlob



TextRank: *how it works*

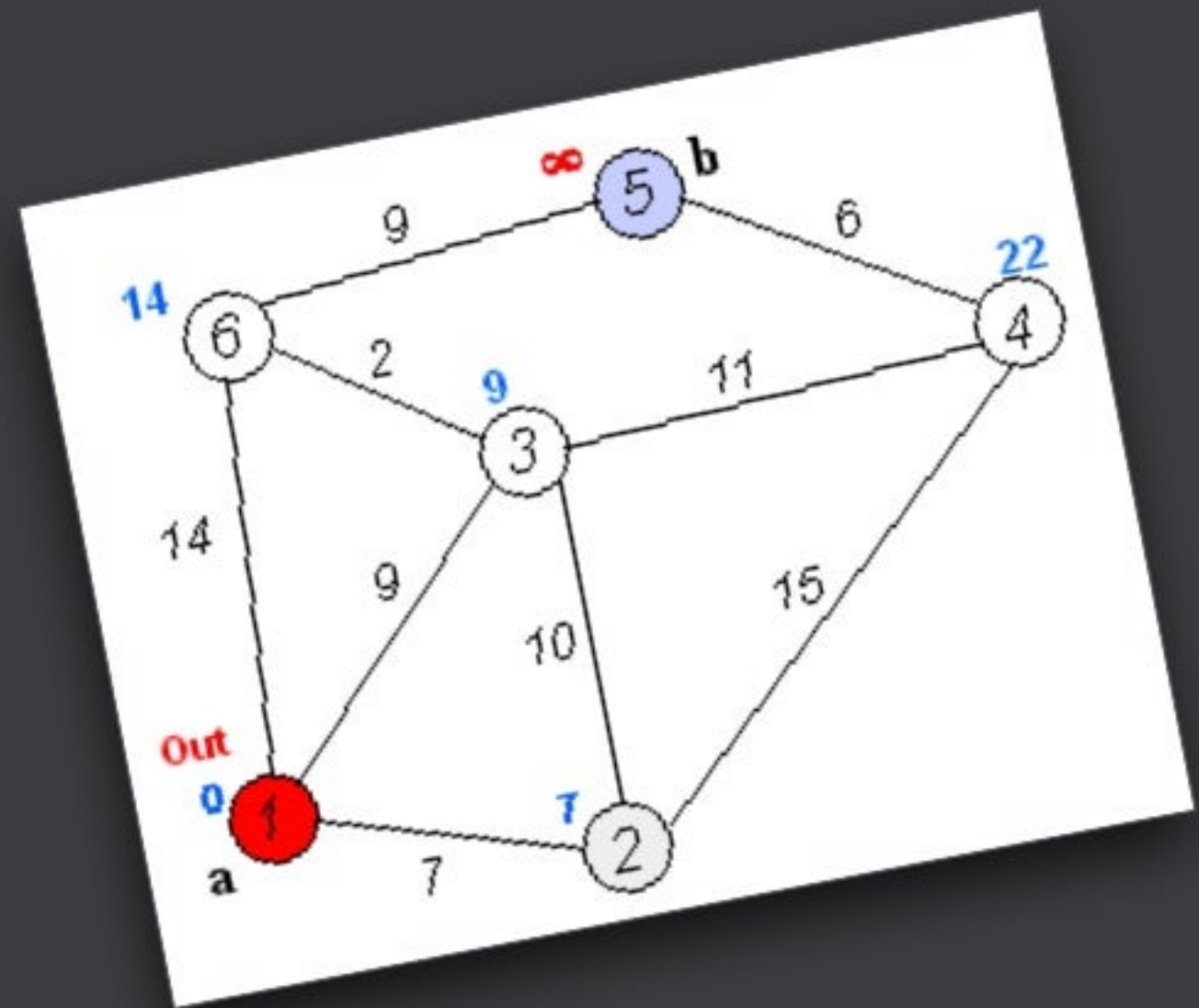
<https://en.wikipedia.org/wiki/PageRank>



TextRank: *code examples...*

Let's check
some code!

Social Graph



Social Graph: *use GraphX to run graph analytics*

```
// run graph analytics
val g: Graph[String, Int] = Graph(nodes, edges)
val r = g.pageRank(0.0001).vertices
r.join(nodes).sortBy(_._2._1, ascending=false).foreach(println)

// define a reduce operation to compute the highest degree vertex
def max(a: (VertexId, Int), b: (VertexId, Int)): (VertexId, Int) = {
  if (a._2 > b._2) a else b
}

// compute the max degrees
val maxInDegree: (VertexId, Int) = g.inDegrees.reduce(max)
val maxOutDegree: (VertexId, Int) = g.outDegrees.reduce(max)
val maxDegrees: (VertexId, Int) = g.degrees.reduce(max)

// connected components
val scc = g.stronglyConnectedComponents(10).vertices
node.join(scc).foreach(println)
```

Social Graph: PageRank of top dev@spark email, 4Q2014

```
(389,(22.690229478710016,Sean Owen <so...@cloudera.com>))
(857,(20.832469059298248,Akhil Das <ak...@sigmoidanalytics.com>))
(652,(13.281821379806798,Michael Armbrust <mich...@databricks.com>))
(101,(9.963167550803664,Tobias Pfeiffer <...@preferred.jp>))
(471,(9.614436778460558,Steve Lewis <lordjoe2...@gmail.com>))
(931,(8.217073486575732,shahab <shahab.mok...@gmail.com>))
(48,(7.653814912512137,ll <duy.huynh...@gmail.com>))
(1011,(7.602002681952157,Ashic Mahtab <as...@live.com>))
(1055,(7.572376489758199,Cheng Lian <lian.cs...@gmail.com>))
(122,(6.87247388819558,Gerard Maas <gerard.m...@gmail.com>))
(904,(6.252657820614504,Xiangrui Meng <men...@gmail.com>))
(827,(6.0941062762076115,Jianshi Huang <jianshi.hu...@gmail.com>))
(887,(5.835053915864531,Davies Liu <dav...@databricks.com>))
(303,(5.724235650446037,Ted Yu <yuzhih...@gmail.com>))
(206,(5.430238461114108,Deep Pradhan <pradhandeep1...@gmail.com>))
(483,(5.332452537151523,Akshat Aranya <aara...@gmail.com>))
(185,(5.259438927615685,SK <skrishna...@gmail.com>))
(636,(5.235941228955769,Matei Zaharia <matei.zaha...@gmail.com>))
```

```
// seaaaaaaaaaan!
```

```
maxInDegree: (org.apache.spark.graphx.VertexId, Int) = (389,126)
maxOutDegree: (org.apache.spark.graphx.VertexId, Int) = (389,170)
maxDegrees: (org.apache.spark.graphx.VertexId, Int) = (389,296)
```

Social Graph: *code examples...*

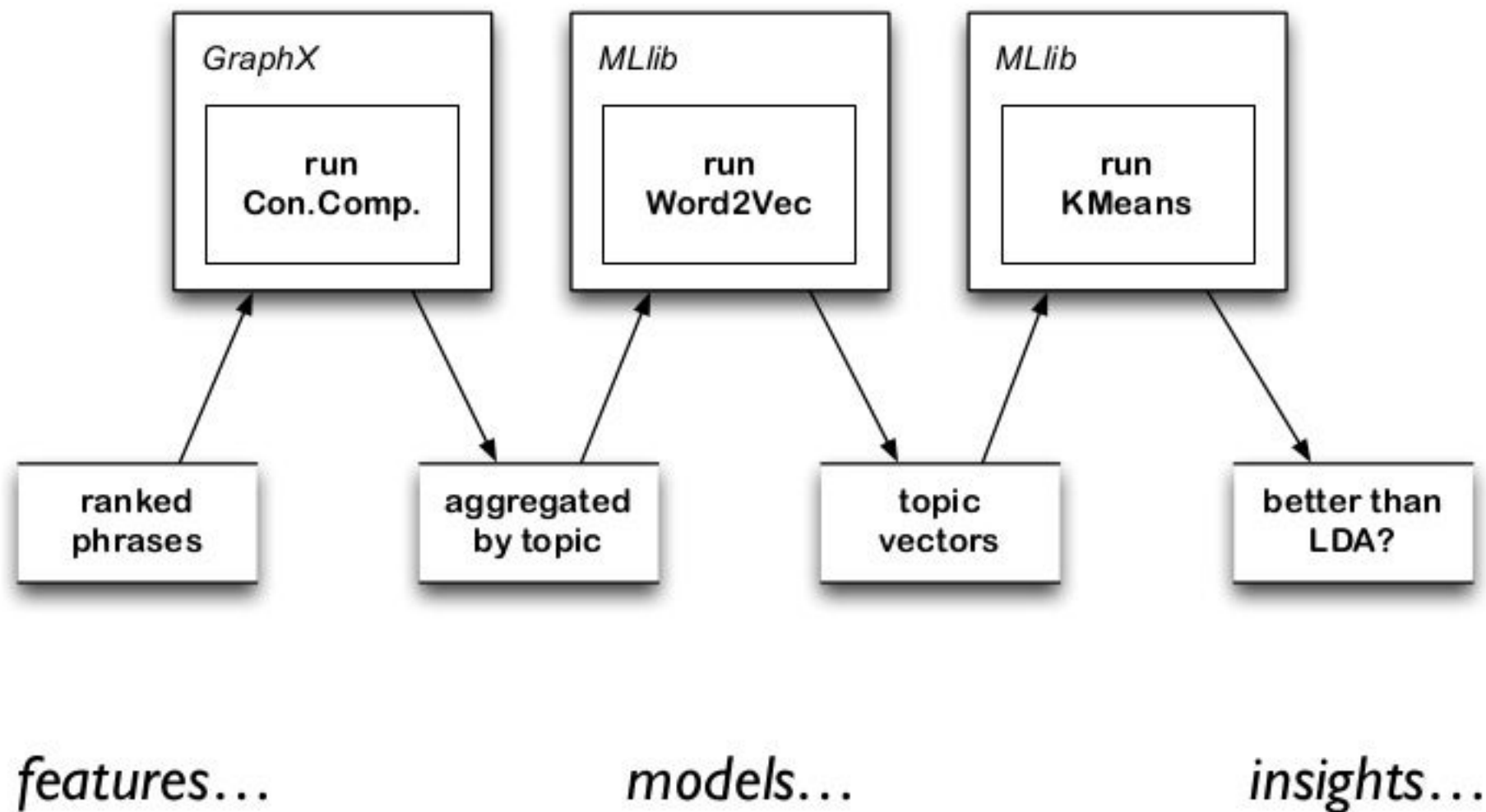
Let's check
some code!

Misc., Etc., Maybe:

Feature learning with Word2Vec

Matt Krzus

www.yseam.com/blog/WV.html



Resources

Spark Developer Certification

- go.databricks.com/spark-certified-developer
- defined by Spark experts @Databricks
- assessed by O'Reilly Media
- establishes the bar for Spark expertise



Developer Certification: *Overview*

- 40 multiple-choice questions, 90 minutes
- mostly structured as choices among code blocks
- expect some Python, Java, Scala, SQL
- understand theory of operation
- identify best practices
- recognize code that is more parallel, less memory constrained

Overall, you need to write Spark apps in practice

community:

spark.apache.org/community.html

events worldwide: goo.gl/2YqJZK

YouTube channel: goo.gl/N5Hx3h

video+preso archives: spark-summit.org

resources: databricks.com/spark/developer-resources

workshops: databricks.com/spark/training

MOOCs:

Anthony Joseph

UC Berkeley

early June 2015

edx.org/course/uc-berkeleyx/uc-berkeleyx-cs100-1x-introduction-big-6181



Introduction to Big Data with Apache Spark

Learn how to apply data science techniques using parallel programming in Apache Spark to explore big (and small) data.



Scalable Machine Learning

Learn the underlying principles required to develop scalable machine learning pipelines and gain hands-on experience using Apache Spark.

Ameet Talwalkar

UCLA

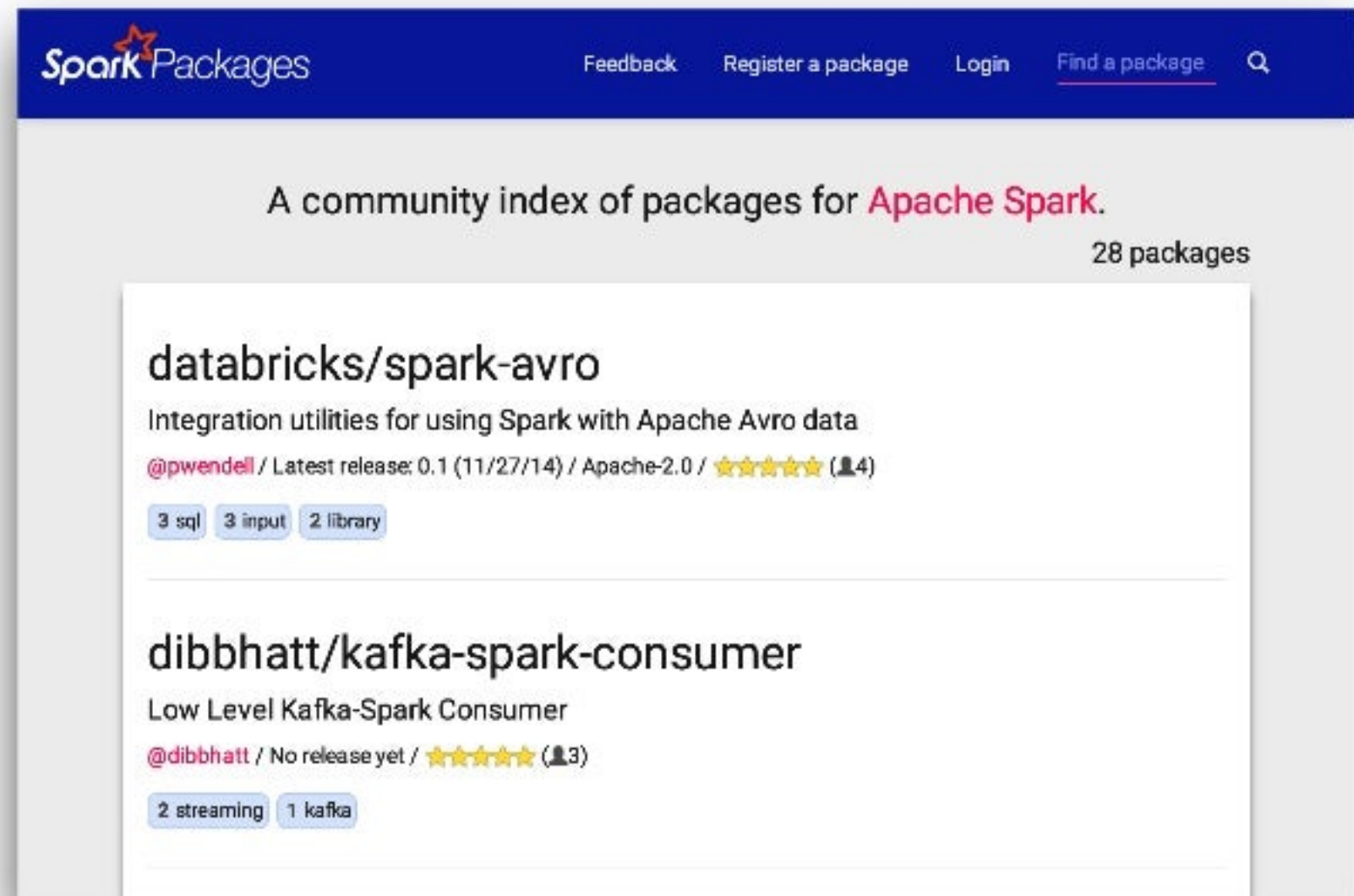
late June 2015

edx.org/course/uc-berkeleyx/uc-berkeleyx-cs190-1x-scalable-machine-6066

Resources: *Spark Packages*

Looking for other libraries and features? There are a variety of third-party packages available at:

<http://spark-packages.org/>



Resources: *Spark Summit conferences*



Spark Summit 2015

Spark Spot

Past Events

Subscribe to the Newsletter



<http://spark-summit.org/>

discount code **datamining15** for 15% off registration

Resources: *Strata + Hadoop World* conferences

Strata+
Hadoop
WORLD



New York, NY | Sept 29–Oct 1, 2015



Singapore | December 1–3, 2015



San Jose, CA | March 29–31, 2016
Visit the Strata + Hadoop World San Jose 2015 website

SAVE THE
DATE



London, UK | June 1–3, 2016
Visit the Strata + Hadoop World in London 2015 website

SAVE THE
DATE

<http://strataconf.com/>

Resources: *O'Reilly Podcast*

O'REILLY®

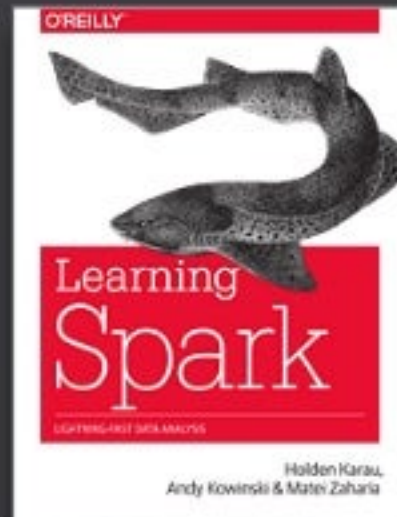
The Data Show

New Ideas. True Stories. Blistering Insights.

<https://itunes.apple.com/podcast/id944929220>

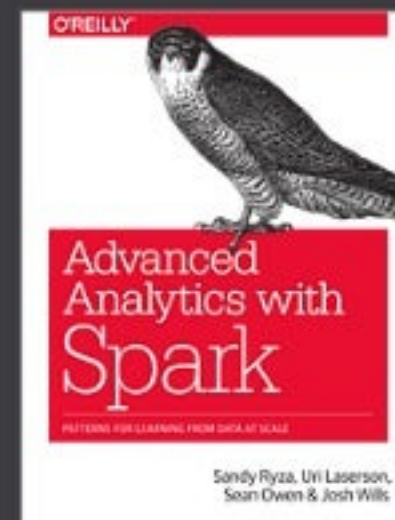
books+videos:

Learning Spark
**Holden Karau,
Andy Konwinski,
Parick Wendell,
Matei Zaharia**
O'Reilly (2015)
[shop.oreilly.com/
product/
0636920028512.do](http://shop.oreilly.com/product/0636920028512.do)



Intro to Apache Spark
Paco Nathan
O'Reilly (2015)
[shop.oreilly.com/
product/
0636920036807.do](http://shop.oreilly.com/product/0636920036807.do)

Advanced Analytics with Spark
**Sandy Ryza,
Uri Laserson,
Sean Owen,
Josh Wills**
O'Reilly (2015)
[shop.oreilly.com/
product/
0636920035091.do](http://shop.oreilly.com/product/0636920035091.do)

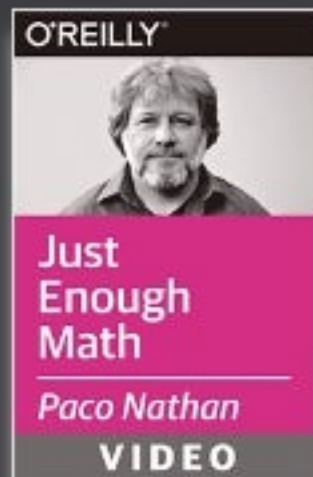


Data Algorithms
**Mahmoud
Parsian**
O'Reilly (2014)
[shop.oreilly.com/
product/
0636920033950.do](http://shop.oreilly.com/product/0636920033950.do)

presenter:

monthly newsletter for updates,
events, conf summaries, etc.:

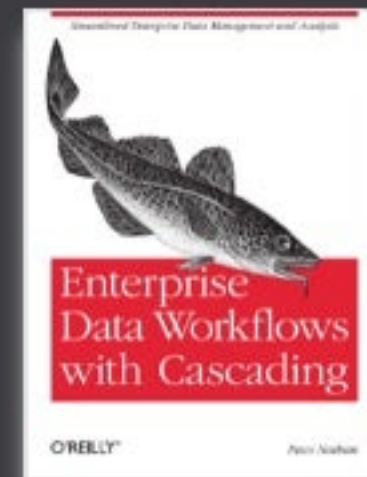
liber118.com/pxn/



Just Enough Math
O'Reilly (2014)

justenoughmath.com

preview: youtu.be/TQ58cWgdCpA



*Enterprise Data Workflows
with Cascading*
O'Reilly (2013)

[shop.oreilly.com/product/
0636920028536.do](http://shop.oreilly.com/product/0636920028536.do)