Massive Data Analysis Instructor: Dr.Gholampour

Fall 2024

HW 1

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1 Research & Theory

1.1 Join example

Assume we want to analyze the join problem as follows:

```
R(A,B) S(B,C) T(C,D) U(D,E)
```

In this problem R,S,T,U are tables of size r,s,t,u, respectively. The probability that R&S agree on B, S&T agree on C, and T&U agree on D are all p.

- Using the Map-Reduce model and the **Single Step approach**, design an algorithm for solving this join problem.
- Evaluate the solution of this algorithm in terms of Replication rate, Communication cost, Reducer size, and the number of Map and Reduce nodes.

1.1.1 Map

We use the appropriate hash function. The hash function we use is the remainder of the division. Suppose the number of reducers is k. Keys are (i, j, k).

Let x, y, and z be three numbers such that M = xyz.

Map operation on the data:

```
1 For each row in R:
2 For j in range(y):
3 For k in range(z):
4 emit < key = (mod(b, x), j, k), value = (a, b, 'R')>
5 For each row in S:
6 For k in range(z):
7 emit < key = (mod(b, x), mod(c, y), k), value = (b, c, 'S')>
8 For each row in T:
9 For i range(x):
10 emit < key = (i, mod(c, y), mod(d, z), value = (c, d, 'T'))>
11 For each row in U:
12 For i in range(x):
13 For j in range(y):
14 emit < key = (i, j, mod(d, z), value(d, e, 'U'))>
```

1.1.2 Reduce

- All elements that have the same key are directed to a reducer.
- Consider the value of the elements in each reducer.

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• Starting with the elements of table R and b: match them with b elements of table S, and likewise for c and d of tables T and U.

• Multiply all the a and e that are matched by Cartesian.

Calculate Cartesian product of:
$$(a_1, a_2, \ldots, a_n) \times (e_1, e_2, \ldots, e_m)$$

1.1.3 Cost

$$Cost = r + s + t + u + ryz + sz + tx + uxy$$

 $Such that: xyz = M ; M: number of reducer$

We should find z,x,y such that the cost is lowest:

$$Min \ r + s + t + u + ryz + sz + tx + uxy$$

 $Subject \ to \ xyz = M$

Which is equivalent to the optimization problem:

Minimize
$$ryz + sz + tx + uxy$$

Subject to: $xyz = M$

Using *Lagrange*, we have:

$$\mathcal{L}(x, y, z, \lambda) = ryz + sz + tx + uxy + \lambda(xyz - M)$$

$$\frac{\partial \mathcal{L}}{\partial x} = t + uy + \lambda yz = 0$$

$$\frac{\partial \mathcal{L}}{\partial y} = rz + ux + \lambda xz = 0$$

$$\frac{\partial \mathcal{L}}{\partial z} = ry + s + \lambda xy = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = xyz - M = 0$$

For simplicity, let:

$$u = t = s = r$$

Which leads to:

$$\begin{split} \frac{\partial \mathcal{L}}{\partial x} &= r + ry + \lambda yz = 0 \\ \frac{\partial \mathcal{L}}{\partial y} &= rz + rx + \lambda xz = 0 \\ \frac{\partial \mathcal{L}}{\partial z} &= ry + r + \lambda xy = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= xyz - M = 0 \end{split}$$

Resulting:

$$x = \sqrt{M}, \quad z = \sqrt{M}, \quad y = 1$$

Final cost is:

Single Step Cost =
$$4r + 4r\sqrt{M}$$

1.2 RDD vs DataFrame

Feature	RDD	DataFrame
Abstraction	Low-level abstraction	High-level abstraction
Level		
Type Safety	Supports compile-time type safety	Limited type safety; more schema-
		based
Data Represen-	Distributed collection of objects	Distributed collection of data organized
tation		into named columns, similar to a table
		in a relational database
Optimization	No built-in optimization	Optimized through Catalyst query op-
		timizer and Tungsten execution engine
API	Provides transformations and actions	Provides domain-specific language
	using a more functional programming	(DSL) and SQL-like query capabilities
	style (e.g., map, filter, reduce)	
Serialization	Requires manual serialization and de-	Built-in optimized serializers for faster
	serialization	processing
Schema	No inherent schema support; can hold	Enforces schema, making it easier to
	any type of data	manipulate structured data
Performance	Typically less efficient for complex	Generally more efficient due to opti-
	queries	mizations
Ease of Use	Requires more complex code to achieve	Simplifies code with higher-level ab-
	certain tasks	stractions and SQL-like syntax
Use Cases	Suitable for unstructured data and	Ideal for structured data and SQL-like
	complex transformations	operations

1.3 Boosting PySpark

1. Use DataFrame/Dataset over RDD:

DataFrames and Datasets provide a higher-level abstraction and benefit from optimizations like Project Tungsten and the Catalyst optimizer. They are generally more efficient than RDDs.

2. Optimize Data Serialization:

Use efficient data formats like Parquet or ORC for data storage and processing. These formats are optimized for both storage and speed.

3. Cache Data:

Use caching to store frequently accessed data in memory. This can significantly reduce the time taken for repeated data access. You can cache DataFrames using the 'cache()' method.

4. Minimize Shuffling:

Shuffling is an expensive operation that involves redistributing data across the cluster. Minimize shuffling by using operations like 'coalesce()' instead of 'repartition()' when reducing the number of partitions.

5. Tune Spark Configurations:

Adjust Spark configurations such as the number of executors, executor memory, and core usage to match your cluster's resources. This ensures that Spark utilizes the available resources efficiently.

6. Avoid UDFs (User Defined Functions):

UDFs can be slow because they are executed in Python and not optimized by Spark. Try to use built-in functions and DataFrame operations whenever possible.

7. Reduce Logging Levels:

Disable unnecessary logging levels like DEBUG and INFO to reduce overhead.

8. Use Efficient Data Structures:

Use appropriate data structures and algorithms that are optimized for your specific use case.

9. Partition Data Properly:

Ensure that your data is partitioned correctly to balance the load across the cluster. This can help in parallelizing the processing and improving performance

10. Profile and Monitor:

Use Spark's built-in tools like the web UI and event logs to monitor and profile your application. This can help identify performance bottlenecks and areas for improvement.

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2 Practical

2.1 Reading the data

2.1.1 parse the json string

After mounting drive files, using .textFile and $.map(lambda\ line:\ json.loads(line))$ functions:

```
['{"id":"0704.0001", "submitter":"Pavel Nadolsky", "authors":"C. Bal\\\\\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuam", "fitle":"Calculation of prompt diphoton production cross sections at Tevatron and\\n IHC energies", "comments": "37 pages, 15 figures; published version", "journal: ref": "Phys. Rev. D/6:033009, 2007", "doi:"10.1103/PhysRevD.76.013009", "report-no:"ANL-HPP-RR-07-12", "categories":"her-ph", "license":null, "abstract": A fully differential calculation in perturbative quantum chromodynamics is\\presented for the production of massive photon pairs at hadron colliders. All\\nnext-to-leading order perturbative contributions from quark-antiquark, and gluon-gluon subprocesses are included, as well as\\nall-orders resummation of initial-state gluon radiation valid at\\nnext-to-leading logarithmic accuracy. The region of phase space is\\nspecified in which the calculation is most reliable. Good agreement is\'ndemonstrated with data from the Fermib Tevatron, and predictions are made for\\mnore detailed tests with CDF and DO data. Predictions are shown for\\ndistributions of diphoton pairs produced at the energy of the Large Hadron\\ncollider (LHC). Distributions of the diphoton pairs from the decay of a Higgs\\nhoson are contrasted with those produce from QCD processes at the LHC, showing\\natlambda the LHC, showing
```

Figure 1: Raw json(sample)

```
[('50' '8706.0031', 'Paral Nadolsy', 'amandary 'Samandary 'Sama
```

Figure 2: Parsed json(sample)

2.1.2 Create a function that extracts and lists all fields (e.g., title, abstract, etc.) from the parsed RDD.

Here we us function FieldExtractor to impute missing values: (Note: It does'nt make categories field N/A for sake of reducing run-time of later steps)

2.2 Preprocessing

In this section, we will clean the dataset by removing stop words and irrelevant characters to ensure the data is well-prepared for analysis.

2.2.1 Identify and remove or impute any null values, especially in critical fields Already taken care of in previous section-part2:

FieldExtractor Function

2.2.2 Find and remove stopwords

we filer out stop-words via StopWordsRemover library which contains 150 stop-words.thereafter, Using function $process_stopwords$:

```
[[id: '9704.0801',
'subthter': 'PaveN Madolsky',
'subthter': 'PaveN Madolsky',
'subthter': 'PaveN Madolsky',
'subthter': 'C. Sail\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuan',
'itlle': 'Calculation prompt diphoton production cross sections Tevatron and\n LHC energies',
'comments': '37 pages, 15 figures; published version',
'journal-ref: 'Phys.Rev.D76:031009, 2007',
'doi: '10.103/PhysRevD.76.031009',
'report-no': 'All-HEP-Per-Per-Til',
'report-no': 'All-HEP-Per-Per-Til',
'report-no': 'All-HEP-Per-Per-Til',
'abstract': 'fully differential calculation perturbative quantum chromodynamics is\npresented production massive photon pairs hadron colliders.
All\nnext-to-leading order perturbative contributions quark-mutiquark,\ngluon-(ant)quark, gluon-gluon subprocesses included, well as\nall-orders
'all\nnext-to-leading order perturbative contributions quark-mutiquark,\ngluon-(ant)quark, gluon-gluon subprocesses included, well as\nall-orders
'all\nnext-to-leading order perturbative contributions quark-mutiquark,\ngluon-(ant)quark, gluon-gluon subprocesses included, well as\nall-orders
'all\nnext-to-leading order perturbative contributions quark-mutiquark,\ngluon-(ant)quark, gluon-gluon subprocesses included, well as\nall-orders
'all\nnext-to-leading order perturbative contribution squark-mutiquark,\ngluon-(ant)quark, gluon-gluon subprocesses included, well as\nall-orders
'reliable. Good agreement is\ndemonstrated data fermilab Tevatron, predictions entitle fasts CDF OD data. Predictions shown
'calculation of pairs produced energy large Haddenmon(Colliders (HC). Distributions diphoton pairs decay Higgs\nboson contrasted those produced
'versions': ('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'('version': 'v'', 'created': 'Mon, 2 Apr 2009 19:18:22 GMT'),
'(
```

Figure 3: Filtering stop-words and None values

2.2.3 Find and remove useless characters

Using *cleaner* function we replace meaningless characters with space:

Note that only title & abstract fields contain these characters

'abstract': 'fully differential calculation perturbative quantum chromodynamics is presented production massive photon pairs hadron colliders All n ', 'abstract': ' fully differential calculation perturbative quantum chromodynamics is\npresented production massive photon pairs hadron colliders

Figure 4: Sample with and without redundant characters

2.2.4 Even more purity!

Since after removing extra charachters, stopwords apear again, we need to remove the new stopwords which is done by running part 2.2.2

```
[('id': '0704.0001',
    'submitter': 'Pavel Nadolsky',
    'suthors': "C. Bal\\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuan",
    'title': 'Calculation prompt diphoton production cross sections Tevatron LHC energies',
    'comments': '37 pages, 15 figures; published version',
    'journal-ref': 'Phys.Rev.D76.013009,2007',
    'doi: '10.1103/PhysRev.D76.013009,2007',
    'doi: '10.1103/PhysRev.D7.6.013009',
    'report-no: 'ANL-HEP-PR-07-12',
    'categories': 'hep-ph',
    'license': 'N/A',
    'abstract': 'fully differential calculation perturbative quantum chromodynamics presented production massive photon pairs hadron colliders All next
leading order perturbative contributions quark antiquark gluon anti quark gluon gluon subprocesses included well all orders resummation initial state gluon
radiation valid next next leading logarithmic accuracy region phase space specified which calculation most reliable Good agreement demonstrated data
fermilab Tevatron predictions made more detailed tests CDF DO data Predictions shown distributions diphoton pairs produced energy Large Hadron Collider LHC
Distributions diphoton pairs decay Higgs boson contrasted those produced QCD processes LHC showing enhanced sensitivity signal can obtained judicious
selection events',
    'versions': [{'version': 'v1', 'created': 'Mon, 2 Apr 2007 19:18:42 GMT'},
    {'versions': 'v2', 'created': 'Tue, 24 Jul 2007 20:10:27 GMT'}],
    'update_date': '2008-11-26',
    'undors_parsed': [['Balázs', 'C.', ''],
    ['Berger', 'E. L.', ''],
    ['Nadolsky', 'P. M.', ''],
    ['Yuan', 'C. -P.', '']],
    ['Nadolsky', 'P. M.', ''],
    ['Yuan', 'C. -P.', '']],
```

Figure 5: Sample preprocessed element

2.3 Dataset Analysis

2.3.1 How many articles exist in each category (e.g., hep-ph, math.co)?

This snippet code will take care of the task:

```
# Create (category, 1) pairs
fields_rdd.map(lambda record: (record['categories'], 1))
# Aggregate counts
.reduceByKey(lambda a, b: a + b)
```

```
('math.NT math.AC', 119), ('math.AC math.GM math.NT math.RA', 1), ('math-ph cond-mat.str-el math.MP', 57), ('physics.acc-ph physics.optics', 145)
```

Figure 6: Sample categories count

2.3.2 Which category has the most articles?

Using $.map(lambda \ a: (a[1], \ a[0])).sortByKey()$:

```
[(86911, 'astro-ph'),

(81999, 'hep-ph'),

(71007, 'quant-ph'),

(63257, 'cs.CV'),

(59401, 'hep-th'),

(40266, 'cond-mat.mtrl-sci'),

(35492, 'cond-mat.mes-hall'),

(35333, 'math.AP'),

(31712, 'astro-ph.GA'),

(31068, 'gr-qc')]
```

Figure 7: Highest rated categories

2.3.3 What is the distribution of the number of authors per article? (e.g., what percentage of articles have 1 author, more than 3 authors?)

Using comprehensive run of $.map(lambda\ x:\ len(x['authors'].split(','))).countByValue()\ we get:$

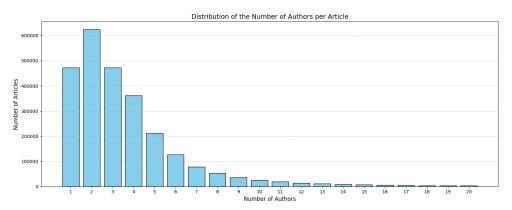


Figure 8: Highest # of authors

2.3.4 Filter out the articles that have more than 3 authors and generate a list of their titles and authors. Display the first 10 results.

• Filter(>3 collaborators):

.filter(lambda paper: len(paper['authors'].split(',')) > 3)

• map:

.map(lambda paper: (paper['title'], paper['authors']))

```
1. Title: Calculation prompt diphoton production cross sections Tevatron LHC energies, Authors: C. Bal\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuan
2. Title: The Spitzer c d Survey Large Nearby Insterstellar Clouds IX Serpens YSO Population Observed IRAC MIPS, Authors: Paul Harvey, Bruno Merin, Tracy L. h. Chapman, Neal J. Evans II, Philip C. Myers
3. Title: Lifetime doubly charmed baryons, Authors: Chao-Hsi Chang, Nong Li, Xue-Qian Li, Yu-Ming Mang
4. Title: Spectroscopic Observations Intermediate Polar EX Hydrae Quiescence, Authors: Nceba Mhlahlo, David H. Buckley, Vikram S. Dhillon, Steven B. Potter, Brian Narner, Patric A. Woudt
5. Title: Formation quasi solitons transverse confined ferromagnetic film media, Authors: A. A. Sergs, M. Kostylev, JB. Hillebrands
6. Title: Spectroscopic Properties Polarons Strongly Correlated Systems Exact Diagrammatic Monte Carlo Method, Authors: A. S. Mishchenko (1,2), N. Nagaosa (1,2 Science, Technology Agency, (2) Russian Research Centre 'Kurchatov
1. Title: Filling Factor Dependent Magnetophonon Resonance Graphene, Authors: M. O. Goerbig, J.-N. Fuchs, K. Kechedzhi, Vladimir I. Fal'ko
8. Title: Astrophysical gyrokinetics kinetic fluid turbulent cascades magnetized weakly collisional plasmas, Authors: A. A. Schekochihin (Oxford), S. C. Cowle (Maryland), G. W. Hammett (Princeton), G. G. Howes (Towa), E. Quataert (Berkeley), T. Tatsuno (Maryland)
9. Title: Inference white dwarf binary systems using first round Mock LTSA Data Challenges data sets, Authors: Alexander Stroeer, John Veitch, Christian Roeve Clark, Melson Christensen, Martin Hendry, Chris Messenger, Renate Meyer, Matthew Pitkin, Jennifer Toher, Richard Umstaetter, Alberto Vecchio and Graham Woan
10. Title: Potassium intercalation graphite van der Waals density functional study, Authors: Eleni Ziambaras, Jesper Kleis, Elsebeth Schroder, Per Hyldgaard
```

Figure 9: Articles with >3 authors

2.3.5 Plot a time series of the number of articles submitted per year.

Yet another comprehensive run by $.map(lambda\ x:\ (x['update_date'][:4],\ 1)).filter(lambda\ x:\ x[0]\ is\ not\ None).reduceByKey(lambda\ a,\ b:\ a+b).collect()\ results:$

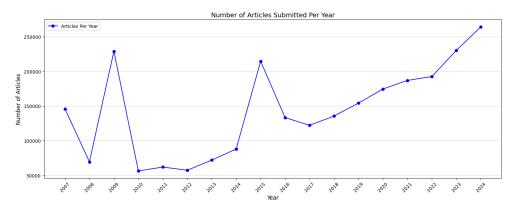


Figure 10: Number of articles per year

2.3.6 What are the 20 most frequent words in abstract? + 2.3.7: WordCloud

Using .flatMap(process) & $.map(lambda\ word:\ (word,\ 1)).reduceByKey(lambda\ a,\ b:\ a\ +\ b)$ functions where

- def process(record):
- words = record['abstract'].lower().split()
- cleaned_words = [re.sub(r"[^a-zA-Z0-9]", "", word) for word in words]
- return [word for word in cleaned_words if word and word not in stopwords]
 we get:

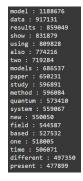


Figure 11: Most frequent words in abstract



Figure 12: WordCloud

2.4 Advanced Data Exploration

• Due to comprehensive runtime of first 2 parts, we retrieved output only once in 3rd part. Using:

- .filter(lambda x: 'algorithm' in x['abstract'].re.IGNORECASE())
- .map(lambda x: (x['title'], len(x['abstract'].split())))
- $.sortBy(lambda\ x:\ x/1),\ ascending=False).take(5)$

we get:

```
Title: The Nonlinearity Coefficient - A Practical Guide to Neural Architecture
Design, Word Count: 498
Title: Generating a Generic Fluent API in Java, Word Count: 488
Title: Boxicity and Poset Dimension, Word Count: 484
Title: An Anytime Algorithm for Optimal Coalition Structure Generation, Word Count: 484
Title: McMini: A Programmable DPOR-Based Model Checker for Multithreaded
Programs, Word Count: 475
```

Figure 13: Top 5 articles with the highest word counts in their abstract (containing 'algorithm')