



**RIPE NCC**

RIPE NETWORK COORDINATION CENTRE

# CLOUD ATLAS

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# Introduction

Hadoop at the NCC



# Lots of data

- RIPE Atlas generates a lot of measurement data
- In totality, consumes ~66TB (compressed)
- Stored on the NCC's Hadoop cluster(s)



# Lots of data

- We need tools that make exploration and analysis of this data easy
- Apache Spark on Hadoop gets us part way there



# Running an in-house Hadoop cluster is not easy

- Expenditure: hardware, rack space
- Expenditure: system engineering, maintenance, uptime, patching, user requests, support
- Expenditure: research engineering time



# Data Analysis is Exploratory

- Iterative development of an analysis is critical
- Want this to be as tight a loop as possible



# Atlas → Cloud

A prototype

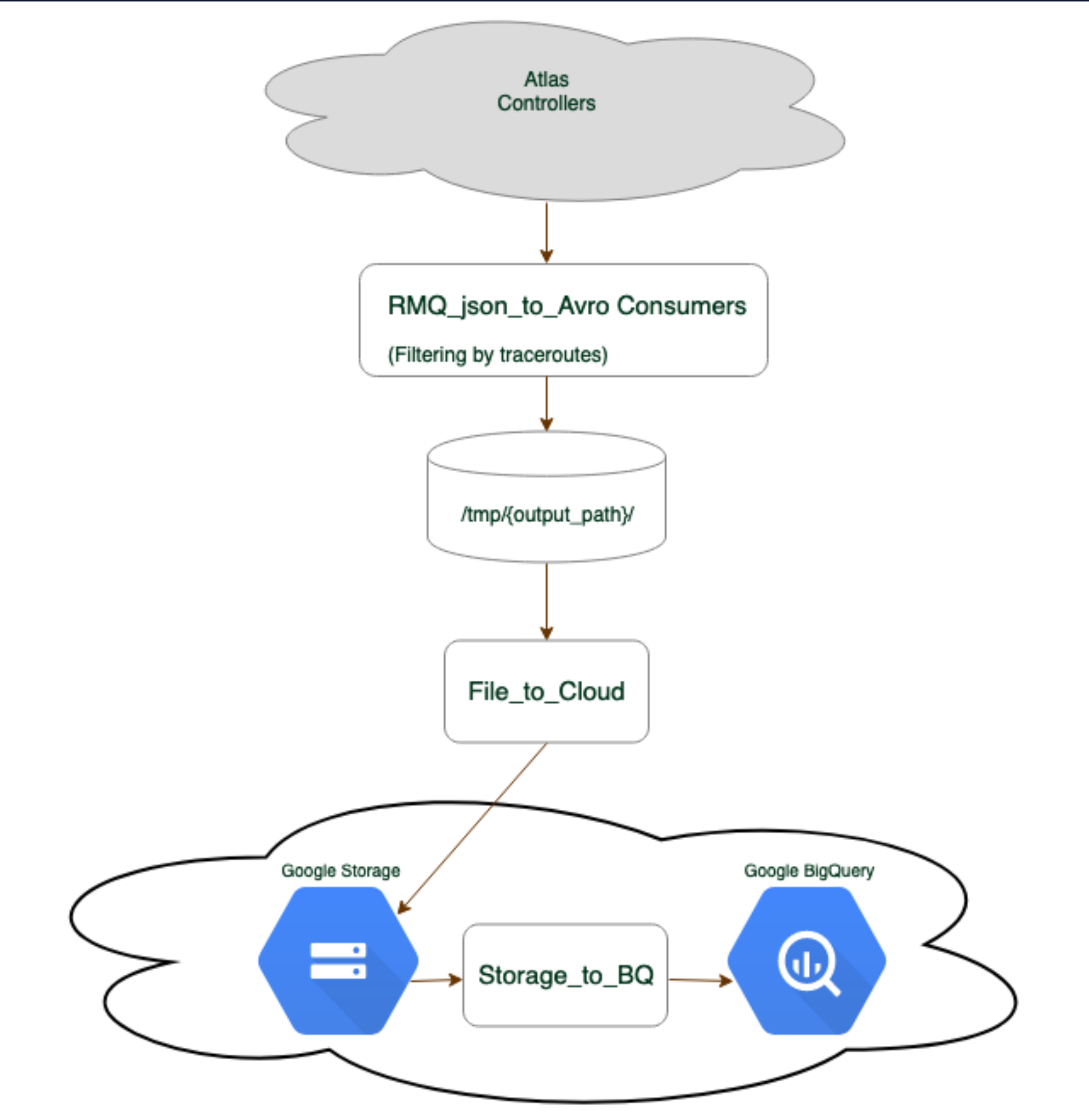


# Why the cloud?

- The big three cloud platforms are many years old
  - they reduce expenditure on hardware and time
  - they have SLAs that help keep things running
  - they have all sorts of tooling ready to use (or not use, as we wish)
- We've been prototyping against Google Cloud Platform



# Prototyping data ingress





# Google Cloud Platform

- **Cloud Storage**

- Avro files dropped in here, to be accessed by BigQuery

- **BigQuery**

- Data warehouse to store and query massive datasets enabling super-fast SQL queries using the Google infrastructure
- BigQuery abstracts most everything away



# Traceroute data includes nested results



```
{
  "dst_addr": "193.0.19.59",
  "type": "traceroute",
  "dst_name": "193.0.19.59",
  "msm_name": "Traceroute",
  "timestamp": 1551700827,
  "msm_id": 5030,
  "src_addr": "193.0.10.36",
  "prb_id": 6003,
  "from": "193.0.10.36",
  "endtime": 1551700831,
  "result": [
    {
      "hop": 1,
      "result": [
        {
          "rtt": 2.728,
          "ttl": 255,
          "from": "193.0.10.2",
          "size": 28
        },
        {
          "rtt": 2.011,
          "ttl": 255,
          "from": "193.0.10.2",
          "size": 28
        },
        {
          "rtt": 1.628,
          "ttl": 255,
          "from": "193.0.10.2",
          "size": 28
        }
      ]
    },
    {
      "hop": 2,
      "result": [
        {
          "rtt": 107.264,
          "ttl": 62,
          "from": "193.0.19.59",
          "size": 68
        },
        {
          "rtt": 2.122,
          "ttl": 62,
          "from": "193.0.19.59",
          "size": 68
        },
        {
          "rtt": 1.952,
          "ttl": 62,
          "from": "193.0.19.59",
          "size": 68
        }
      ]
    }
  ]
}
```

# BigQuery table schema



FIELD	TYPE
IpFrom	STRING
dstAddress	STRING
startTime	TIMESTAMP
endTime	TIMESTAMP
msmId	INTEGER
prbId	INTEGER
groupId	INTEGER
hops	RECORD - REPEATED
hops.hop	INTEGER
hops.resultHops	RECORD - REPEATED
hops.resultHops.rtt	FLOAT
hops.resultHops.from	STRING



# BigQuery table schema: example data



IpFrom	dstAddress	startTime	endTime	msmld	prbld	groupid	hop	IpAddHop	rtt
79.127.124.186	193.0.19.109	2019-02-27 04:12:00 UTC	2019-02-27 04:12:14 UTC	2067456	6314	2067456	1	79.127.124.185	1.02
								79.127.124.185	0.785
								79.127.124.185	0.774
							2	172.19.17.65	0.413
								172.19.17.65	0.364
								172.19.17.65	0.385
							3	172.19.17.194	3.765
								172.19.17.194	2.901
								172.19.17.194	2.767



# Comparisons





# Comparisons

- apples vs. oranges
  - Python with Apache Spark, running on a private Hadoop cluster, vs
  - bigquery running on Google's own public platform

# Example 1



Count IPv6 addrs each probe  
ran traceroutes to in 1 day

# Example 1: pyspark

- Execution time:
  - 16-20 minutes (adhoc queue)
  - 5-6 minutes with a higher priority queue and the cluster isn't loaded

```
1 from pyspark import SparkContext
2 import json
3
4 def get_prb_ips( iterator ):
5     out = {}
6     for d in iterator:
7         if d['af'] != 6:
8             continue
9         if 'dst_addr' not in d:
10            continue
11
12            prb_id = d['prb_id']
13            ip     = d['dst_addr']
14
15            out.setdefault( prb_id, set() )
16            out[prb_id].add( ip )
17
18            return out.iteritems()
19
20 def collect_sets( a, b ):
21     out = a
22     for prb_id in b:
23         foo = out[prb_id]
24         foo = foo.union(b[prb_id])
25         out[prb_id] = foo
26     return out
27
28 def count_ips( a, b ):
29     out = a
30     for prb_id in b:
31         out[prb_id] = len(b[prb_id])
32     return out
33
34 sc = SparkContext()
35 reader = sc.sequenceFile("/raw/atlas/day/type=traceroute/2019-04-10.seq/*")
36
37 z = reader.map(lambda v: json.loads(v[1]) )
38 a = z.mapPartitions( get_prb_ips )
39 b = a.reduceByKey(lambda x,y: x.union(y))
40
41 c = b.collect()
42 d = map( lambda x: (x[0], len(x[1])), c )
43
44 for x in d:
45     print x
```





# Example 1: bigquery

```
1  select prbId, count(distinct dstAddress)
2  from    prod.traceroute_atlas_prod_previous_day
3  where   af = 6
4  group by prbId
5
```

- Execution time:
  - 4-5 seconds

# Example 2



Find lowest RTT between  
source and each hop

# Example 2: pyspark



- Execution time:
  - ~30 minutes

```
def mp_as_rtts( iterator ):
    """
    input: raw atlas traceroutes
    """
    out = {}
    for d in iterator:
        ## array: 0: hops with responses 1: hops without responses
        if 'result' in d:
            if not 'prb_id' in d or not 'dst_addr' in d:
                continue
            for hr in d['result']:
                if 'result' in hr:
                    for h in hr['result']:
                        if 'edst' in h:
                            # doesn't belong in this trace
                            continue
                        if 'from' in h and 'rtt' in h:
                            ip = h['from']
                            key = (d['prb_id'],ip)
                            if (not key in out or out[key] > h['rtt']) and h['rtt'] > 0 and 'late' not in h:
                                out[ key ] = h['rtt']

    return out.iteritems()

trace_path="/raw/atlas/day/type=traceroute/%s.seq" % ( DAY )

# load traceroute
t1 = sc.hadoopFile(trace_path, file_format, key_class, value_class)
t2 = t1.map( lambda v: json.loads(v[1]) )

# finds all RTTs for (src,dst) combinations in a partition
t3 = t2.mapPartitions( mp_as_rtts )
t4 = t3.reduceByKey( min )

t5 = t4.map( lambda x: json.dumps( x ) ).saveAsTextFile('/user/edominguez/output-ips3')
```



## Example 2: bigquery



```
SELECT result.from AS IpAddress, prbld, MIN(result.rtt) AS minRtt
FROM `data-test-194508.prod.traceroute_atlas_prod`, unnest (hops) AS hop, unnest
(resultHops) AS result
WHERE startTime >= TIMESTAMP("2019-02-15") and startTime < TIMESTAMP("2019-02-16")
GROUP BY result.from, prbld
```

- Execution time:
  - ~25 seconds

# Example 3



## Emile's probe similarity work

# Example 3: pyspark

- Execution time:
  - ~2 hours

```
1  ## find similarities between probes, based on the traceroute results
2  ## compare jaccard index per similar measurement, and take 25th,50th,75th percentile
3
4  ## number of users per day and related
5  import sys
6  import numpy
7  import os
8  from pyspark.sql import SQLContext, Row
9  from pyspark.sql import functions as F
10 import ujson as json
11 from pyspark.context import SparkContext
12 from operator import add
13 import bz2
14 import radix
15 import subprocess
16
17 sc = SparkContext()
18 sqlContext = SQLContext(sc)
19
20 ## http://stackoverflow.com/questions/25193488/how-to-turn-off-info-logging-in-pyspark
21 def quiet_logs( sc ):
22     logger = sc._jvm.org.apache.log4j
23     logger.LogManager.getLogger("org").setLevel( logger.Level.ERROR )
24     logger.LogManager.getLogger("akka").setLevel( logger.Level.ERROR )
25     quiet_logs( sc )
26
27 ## find all the measurements, and split out the 'system' based ones
28 DAY=sys.argv[1]
29 TYPE='traceroute'
30 ## address family
31 AF=int(sys.argv[2])
32
33 r = radix.Radix()
34 ## unconsidered addresses
35 r.add('10.0.0.0/8')
36 r.add('172.16.0.0/12')
37 r.add('192.168.0.0/16')
38 r.add('100.64.0.0/10')
39 r.add('fe80::/64')
40
41 rtreeBroadcast = sc.broadcast( r )
42 afBroadcast = sc.broadcast( AF )
43
44 def mp_extract_ips( iterator ):
45     out = {}
46     rtree = rtreeBroadcast.value
47     af = afBroadcast.value
48     for d in iterator:
49         if d['af'] != af:
50             continue
51         #key = (row['prb_id'],row['dst_addr'])
52         #key = "%s%s" % (row['prb_id'], row['dst_addr'])
53         ## array: 0: hops with responses 1: hops without responses
54         ips = set()
55         if 'result' in d:
56             for hr in d['result']:
57                 if 'hop' in hr:
58                     this_hop = hr['hop']
59                 else:
60                     continue
61                 if 'result' in hr:
62                     for h in hr['result']:
63                         if 'edst' in h:
64                             continue # doesn't belong in this trace!
65                         if 'from' in h:
66                             ip = h['from']
67                             # don't consider dst address and rfc1918 etc.
68                             if 'dst_addr' in d and d['dst_addr'] == ip:
69                                 continue
70                             if rtree.search_best( ip ):
71                                 continue
72                             ips.add(ip)
73
74         for ip in ips:
75             out.setdefault( d['prb_id'], {} )
76             out[ d['prb_id'] ].setdefault( d['msm_id'], set() )
77             out[ d['prb_id'] ][ d['msm_id'] ].add( ip )
78         return out.iteritems()
79
80 ## load traces (non cleaned-up)
81 file_format="org.apache.hadoop.mapred.SequenceFileInputFormat"
82 key_class="org.apache.hadoop.io.Text"
83 value_class="org.apache.hadoop.io.Text"
84 trace_path="/raw/atlas/day/type=traceroute/%s.seq" % ( DAY )
85
86 t1 = sc.hadoopFile(trace_path, file_format, key_class, value_class)
87 t2 = t1.map( lambda v: json.loads(v[1]) )
88
89 rdd1 = t2.mapPartitions( mp_extract_ips )
90
91 def reduce_nestedset( a, b ):
92     out = a
93     for msm_id in b:
94         out.setdefault( msm_id, set() )
95         for ip in b[ msm_id ]:
96             out[ msm_id ].add( ip )
97     return out
98
99 ips_unfilt_rdd = rdd1.reduceByKey( reduce_nestedset )
```

```
100 def fm_weed_out( row ):
101     """
102     weed out measurements with less than 2 ips
103     weed out probes that only have measurements with less than 2 ips
104     """
105     out = {}
106     for msm_id,ipset in row[1].iteritems():
107         if len( ipset ) > 1:
108             out[ msm_id ] = ipset
109     if len( out.keys() ) > 0:
110         return [ ( row[0], out ) ]
111     else:
112         return []
113
114 ## weed out cases where no useful ipset was created
115 ips_rdd = ips_unfilt_rdd.flatMap( fm_weed_out )
116
117 # multinested structure: keys are prb_ids, inside are msm_id: ip_sets
118 collect = ips_rdd.collectAsMap()
119
120 prb_ids = collect.keys()
121 idx1=0
122
123 def compare(data,id1,id2):
124     #find the common set of measurements
125     msm1 = set( data[id1].keys() )
126     msm2 = set( data[id2].keys() )
127     msm_set = msm1 & msm2
128     metric_per_msm = []
129     usable_set_size = 0
130     for msm in msm_set:
131         ipset1 = data[id1][msm]
132         ipset2 = data[id2][msm]
133         if len( ipset1 ) < 2 or len( ipset2 ) < 2: # threshold
134             continue
135         usable_set_size += 1
136         ipset_incommon = ipset1 & ipset2
137         ipset1_size = len(ipset1)
138         ipset2_size = len(ipset2)
139         ipset_both_size = len(ipset_incommon)
140         ipset1_uniq = ipset1_size - ipset_both_size
141         ipset2_uniq = ipset2_size - ipset_both_size
142         total_size = ipset1_uniq + ipset2_uniq + ipset_both_size
143         if total_size > 0:
144             metric_per_msm.append( ipset_both_size * 1.0 / total_size )
145     if usable_set_size < 17: # don't output a value if we don't have enough measurements in common
146         return
147     metric_per_msm = sorted( metric_per_msm )
148     metric25 = -1
149     metric50 = -1
150     metric75 = -1
151     (metric25,metric50,metric75) = numpy.percentile( metric_per_msm, [25,50,75] )
152     print "%s %s %s %s %s %s %.3f %.3f %.3f" % (
153         id1,
154         id2,
155         len(msm1),
156         len(msm2),
157         len(msm_set),
158         usable_set_size,
159         metric25,
160         metric50,
161         metric75
162     )
163
164 print "#prb_id1 prb_id2 msm_set_size1 msm_set_size2 msm_set_size_overlap msm_set_size_overlap_usable metric_q1 metric_q2 metric_q3"
165 for idx1, prb_id1 in enumerate(prb_ids):
166     for prb_id2 in prb_ids[idx1+1:]:
167         compare(collect,prb_id1,prb_id2)
```



# Example 3: bigquery

- Execution time:
  - ~25 minutes

```
1 SELECT msmId, prbId, result.from as ipAdd
2 FROM `prod.traceroute_atlas_prod`, UNNEST(hops) as hop, UNNEST(resultHops) as result
3 WHERE startTime >= TIMESTAMP('{{ds}}') and startTime < TIMESTAMP('{{macros.ds_add(ds,1)}}')
4 AND LENGTH(result.fromBytes) = 4
5 AND NET.IP_FROM_STRING(dstAddress) <> NET.IP_FROM_STRING(result.from)
6 AND result.edst = ''
7 -- unconsidered addresses ('10.0.0.0/8') ('172.16.0.0/12') ('192.168.0.0/16') ('100.64.0.0/10') ('fe80::/64')
8 AND NET.IP_FROM_STRING(result.from) not between NET.IP_FROM_STRING("10.0.0.1") and NET.IP_FROM_STRING("10.255.255.254")
9 AND NET.IP_FROM_STRING(result.from) not between NET.IP_FROM_STRING("172.16.0.1") and NET.IP_FROM_STRING("172.31.255.254")
10 AND NET.IP_FROM_STRING(result.from) not between NET.IP_FROM_STRING("192.168.0.1") and NET.IP_FROM_STRING("192.168.255.254")
11 AND NET.IP_FROM_STRING(result.from) not between NET.IP_FROM_STRING("100.64.0.1") and NET.IP_FROM_STRING("100.127.255.254")
12 GROUP BY msmId, prbId, ipAdd
13
14
15 WITH
16 F1 AS (
17 SELECT msmId AS MSM1, prbId AS PRB1, count(IpAdd) AS COUNTIPS1
18 FROM `prod_tmp.task1_pair_probes_temporary_table_ipv4` GROUP BY msmid, prbid
19 ),
20 F2 AS (
21 SELECT msmId as MSM2, prbId as PRB2, count(ipAdd) as COUNTIPS2
22 FROM `prod_tmp.task1_pair_probes_temporary_table_ipv4` group by msmid, prbid
23 )
24 SELECT MSM1 as msmId, PRB1 as prbId1, prb2 as prbId2, countips1+countips2 as totalIps
25 FROM F1, F2
26 WHERE MSM1 = msm2 and prb1 < prb2 and countips1 > 1 and countips2 > 1
27
28
29 WITH
30 F1 AS (
31 SELECT msmId AS MSM, prbId AS PRB, IpAdd AS IP
32 FROM `prod_tmp.task1_pair_probes_temporary_table_ipv4`
33 ),
34 F2 AS (
35 SELECT MSM, PRB as PRB1, prbId AS PRB2, IP
36 FROM F1, `prod_tmp.task1_pair_probes_temporary_table_ipv4`
37 WHERE PRB <> prbId and MSM = msmId and IP = IpAdd and PRB < prbId
38 )
39 SELECT MSM as msmId, PRB1 as prbId1, PRB2 as prbId2, count(IP) as commonIps
40 FROM F2
41 WHERE PRB1 < PRB2 group by MSM, PRB1, PRB2
42
43 SELECT a.prbId1 as prbId1, a.prbId2 as prbId2, ARRAY_AGG(coalesce(commonIps, 0)/(totalIps - coalesce(commonIps, 0))) as distance
44 FROM `prod_tmp.task2_pair_probes_count_ips_temporary_table_ipv4` as a
45 LEFT JOIN `prod_tmp.task3_pair_probes_common_ips_ipv4` as b
46 ON a.msmId = b.msmId AND a.prbId1 = b.prbId1 AND a.prbId2 = b.prbId2
47 GROUP BY a.prbId1, a.prbId2
48
49 select prbId1, prbId2, median25, median5, median75
50 FROM (
51 SELECT prbId1, prbId2,
52 percentile_cont(dist, 0.25) over (partition by prbId1, prbId2) as median25,
53 percentile_cont(dist, 0.5) over (partition by prbId1, prbId2) as median5,
54 percentile_cont(dist, 0.75) over (partition by prbId1, prbId2) as median75
55 FROM `prod_tmp.task4_pair_probes_distance_by_msm_ipv4`, unnest(distance) as dist)
56 GROUP BY prbId1, prbId2, median25, median5, median75
57
```

# Takeaways



- But the point is that the abstractions are hidden well by the language *and* processing time is faster
- The end result: **more rapid data analysis**



# The Future





# The Future

- This is prototype, exploratory work
  - putting other datasets in here, e.g., IPmap data, ping data, peeringdb data
- Project not costed, etc, etc
- But, it looks promising



# General Access to Data *and* Tooling?

- Most Atlas data is public, if not always easy to aggregate
- If data is in a commodity cloud system, maybe it can be made more generally accessible
- Give people access to all the data, **and the platform's tooling to operate over that data, easily**
- Get to the science faster?



# General Access to Data *and* Tooling?

- Charging models: the NCC provides the data, and researchers pay for compute cycles/network transit they use
- Big vendors support open data initiatives with free storage:
  - <https://aws.amazon.com/opendata/>
  - <https://cloud.google.com/bigquery/public-data/>
- This doesn't have to be hosted on Google, but any commodity platform that people are familiar with opens up the measurement data



# Questions?

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