Big Data Lab

April 24, 2017

Start an EMR cluster

- Launch an EMR cluster from the AWS console

- Select the "Spark" radio button under Applications
- You can use just 1 EC2 instance (1 master only)
- You *must* select the public/private key pair you created! (this is needed to SSH into the master node)

Spark’s MLlib

- MLlib is Spark’s machine learning library
- Goal is to make practical machine learning scalable and easy
- Includes common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, lower-level optimization primitives and higher-level pipeline APIs

FP-Growth

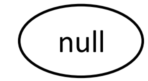
- “FP”=“frequent pattern”
- Like apriori-like algorithms, the first step of FP-growth is to calculate item frequencies and identify frequent items
- Unlike apriori-like algorithms, the second step of FP-growth uses a suffix tree (FP-tree) structure to encode transactions without generating candidate sets explicitly
- Based on the paper Han, Pei, and Yin, “Mining frequent patterns without candidate generation”, SIGMOD, 2000.

FP-Growth

- After the second step, the frequent itemsets can be extracted from the FP-tree.
- spark.mllib implements a parallel version of FP-growth called PFP, as described in Li et al., PFP: Parallel FP-growth for query recommendation
- PFP distributes the work of growing FP-trees based on the suffices of transactions, and hence more scalable than a single-machine implementation
- Spark’s FP-Growth implementation takes the following parameters:
  - minSupport: the minimum support for an itemset to be identified as frequent. For example, if an item appears 3 out of 5 transactions, it has a support of 3/5=0.6.
  - numPartitions: the number of partitions used to distribute the work

Han, Pei, and Yin, “Mining frequent patterns without candidate generation”, SIGMOD, 2000

Example



TID	Items Bought	(Ordered) Frequent Items
100	f, a, c, d, g, i, m, p	f, c, a, m, p
200	a, b, c, f, l, m, o	f, c, a, b, m
300	b, f, h, j, o	f, b
400	b, c, k, s, p	c, b, p
500	a, f, c, e, l, p, m, n	f, c, a, m, p

- Create root of the tree, labeled “null”

Han, Pei, and Yin, “Mining frequent patterns without candidate generation”, SIGMOD, 2000

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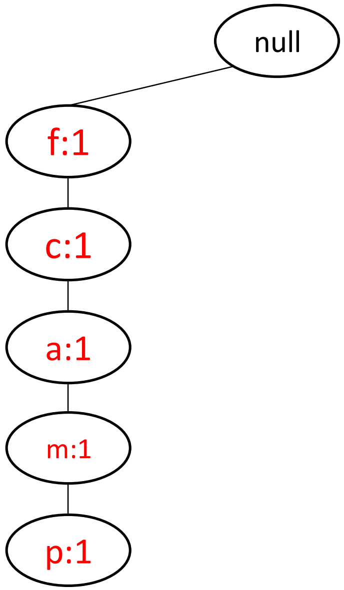

- Create root of the tree, labeled “null”
- Second scan of the DB:
- Scan of first transaction leads to first branch of the tree: <(f:1), (c:1), (a:1), (m:1), (p:1)>

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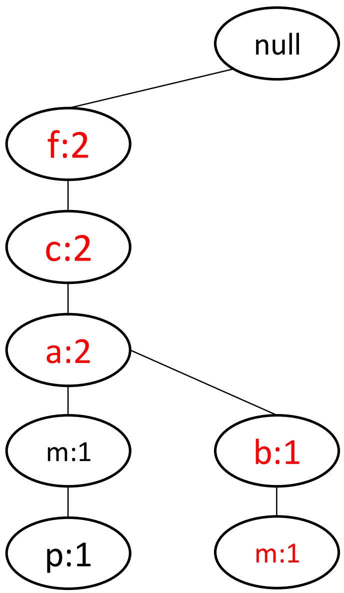

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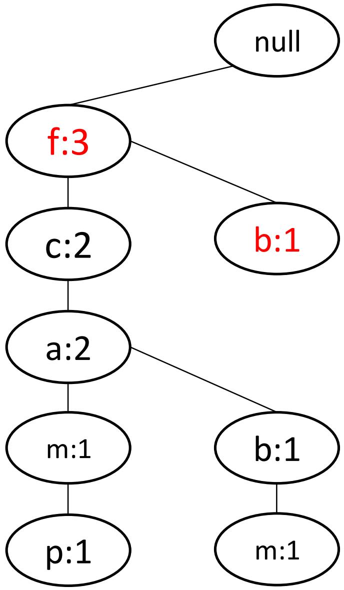

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- Third transaction: f’s count is incremented by 1, (b:1) is created as a child of (f:3)

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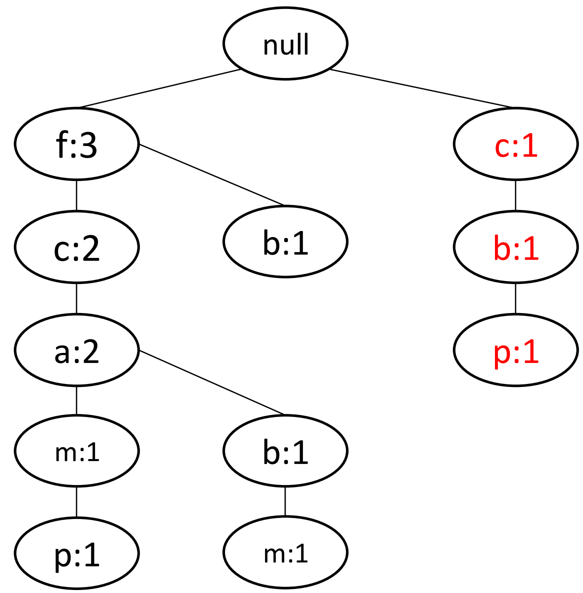

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- Fourth transaction: Since no prefix in common, create the second branch of the tree <(c:1), (b:1), (p:1)>

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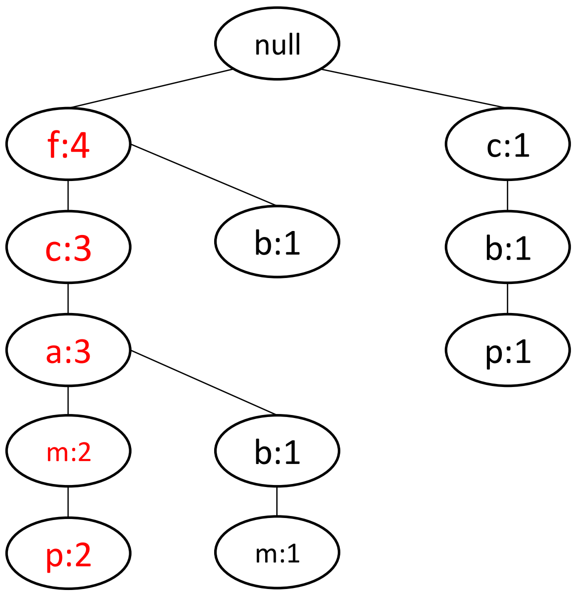

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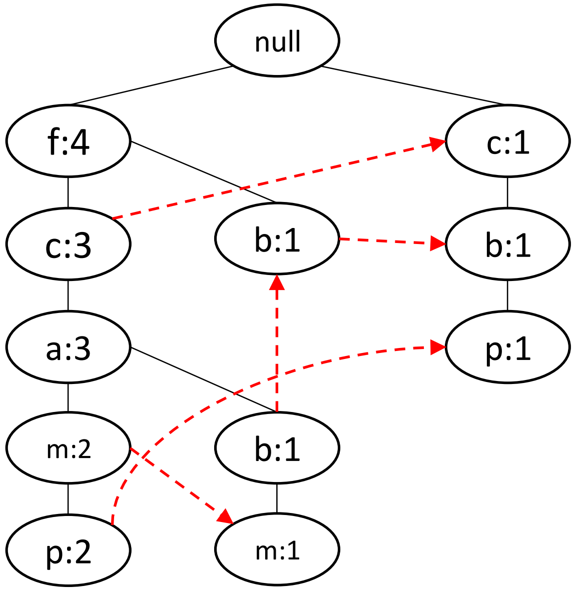

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- Nodes with the same item name are linked via “node-links”

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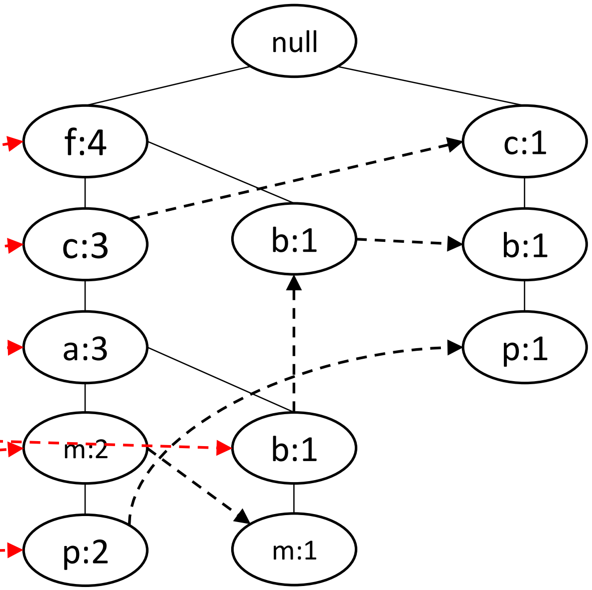
Example

Header Table

Item	Head of node-links
f	
c	
a	
b	
m	
p	



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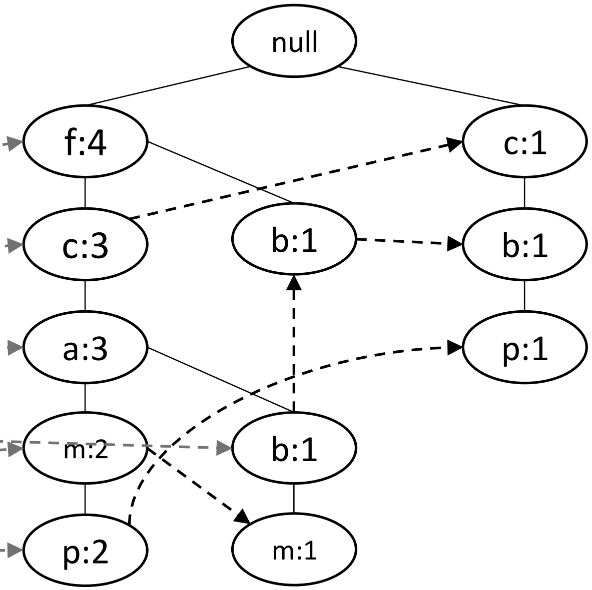

- Mining frequent patterns
- Collect all patterns that a node x participates in by starting from x’s head (in the header table) and following x’s node-links

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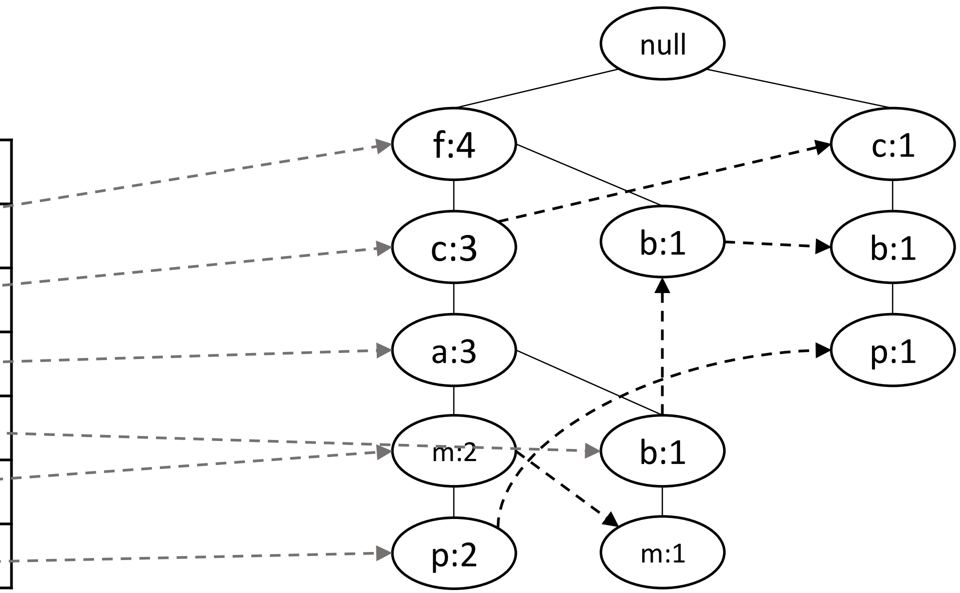

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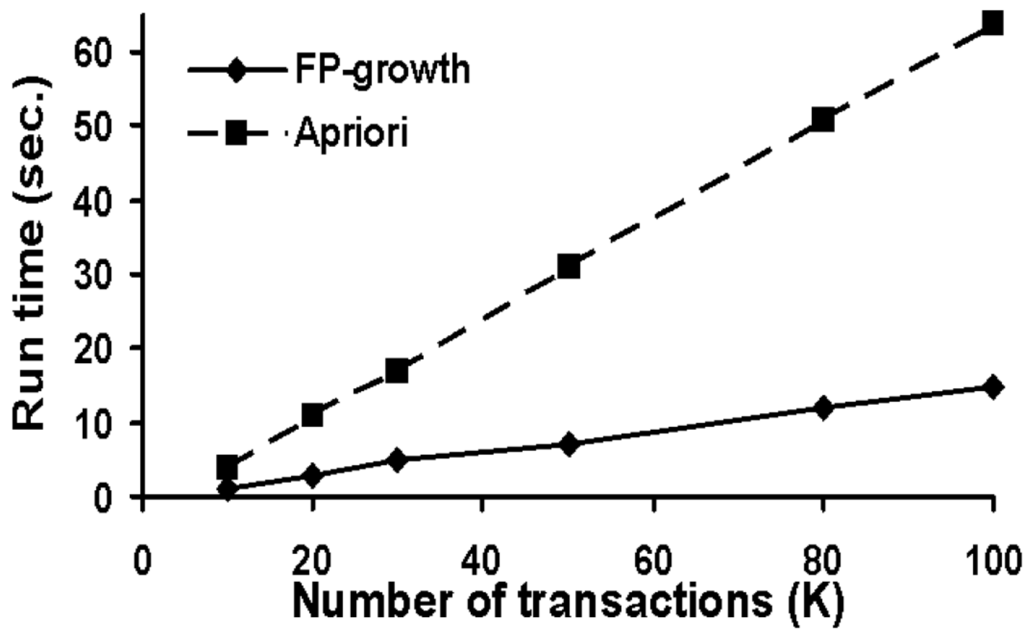
- Example: item p
- Node p derives a frequent pattern (p:3) and two paths in the FP tree: <f:4, c:3, a:3, m:2, p:2> and <c:1, b:1, p:1>
  - The first path indicates that the string (f,c,a,m,p) appears twice in the DB
  - Second path indicates that (c,b,p) appears once in the DB
- Since both paths contain (c,p), this is a frequent pattern, (cp:3)

Benefits

- Apriori-like algorithms can generate an exponential number of candidates in the worst case, but size of an FP-tree is bounded by the size of its database
- Can lead to faster runtime



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In PySpark

```
from pyspark.mllib.fpm import FPGrowth

data = sc.textFile("data/mllib/sample_fpgrowth.txt")

transactions = data.map(lambda line: line.strip().split(' '))

model = FPGrowth.train(transactions, minSupport=0.2, numPartitions=10)



result = model.freqItemsets().collect()

for fi in result:
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takes an RDD of transactions, where each transaction is an List of items of a generic type

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Could access item list by fi.items, frequency by fi.freq

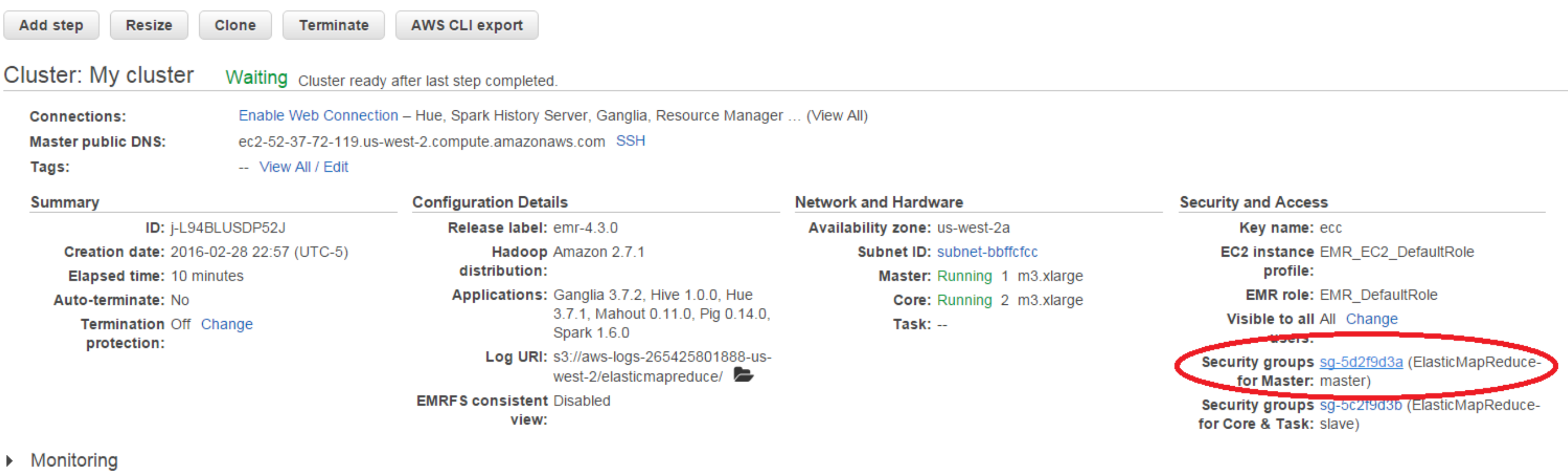
Resources

- https://spark.apache.org/docs/latest/mllib-frequent-pattern-mining.html

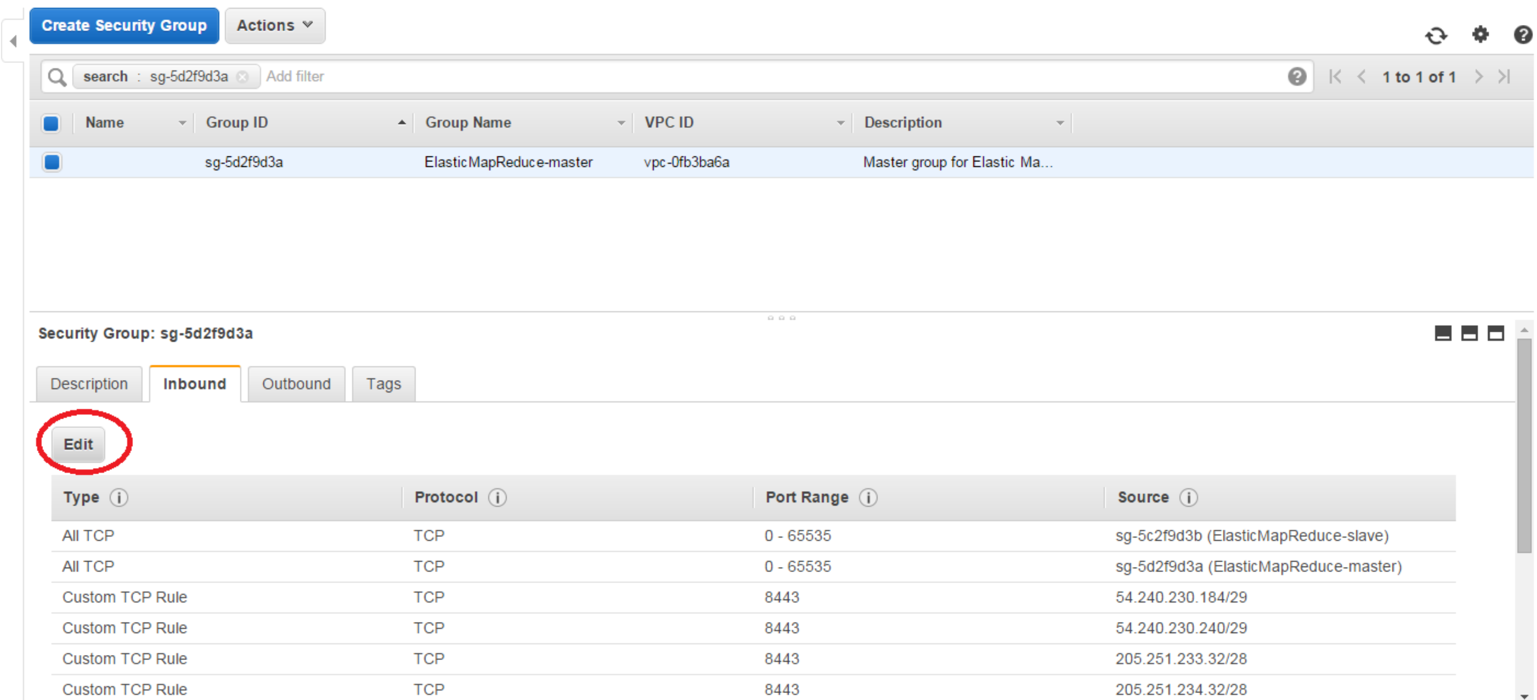
- https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.fpm.FPGrowth

Set Security Group Settings

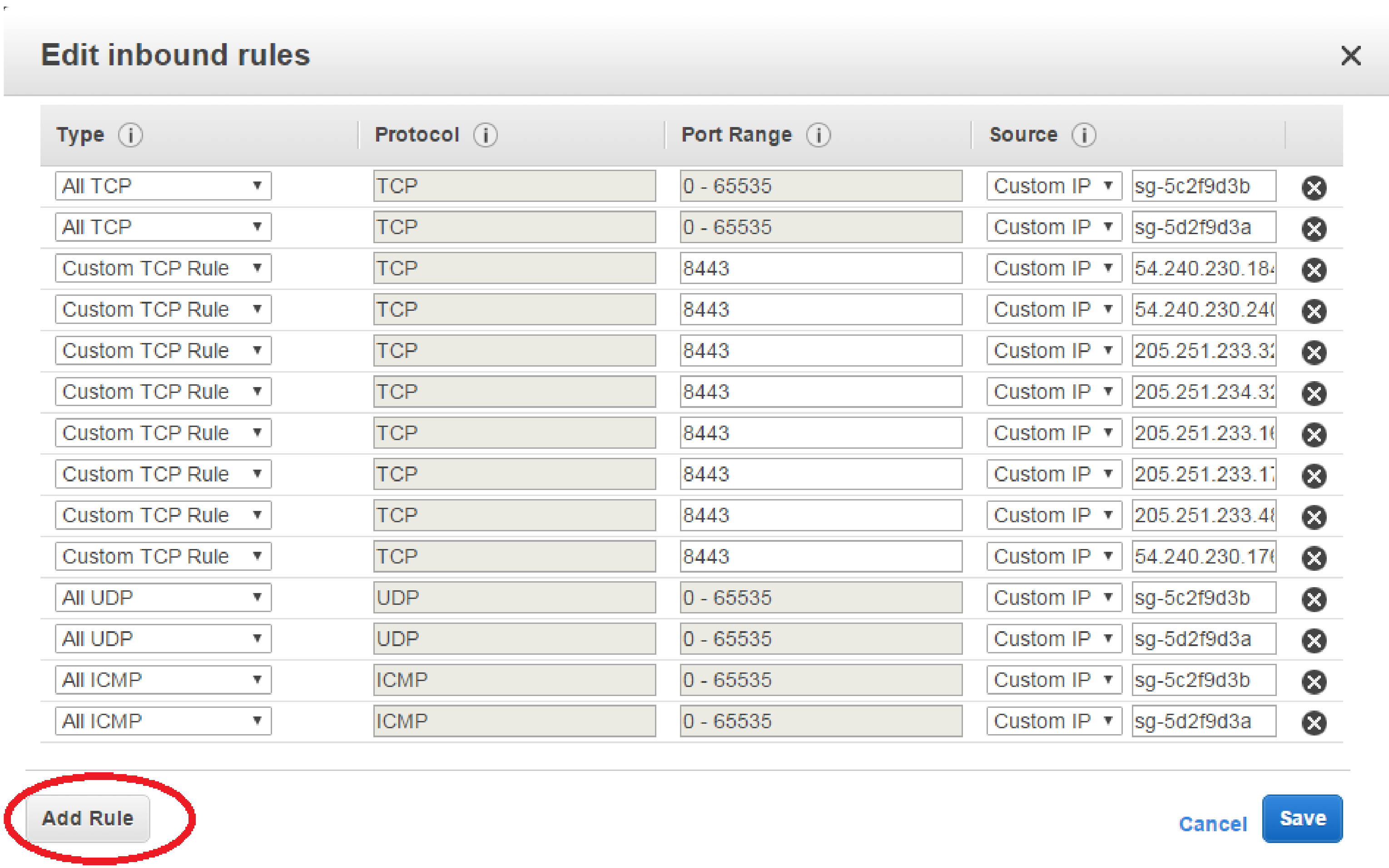
- In order to connect to your master node via SSH, you will need to first modify your security group.
- To do this, go to the cluster you just created, and click on the blue link following "Security groups for Master".



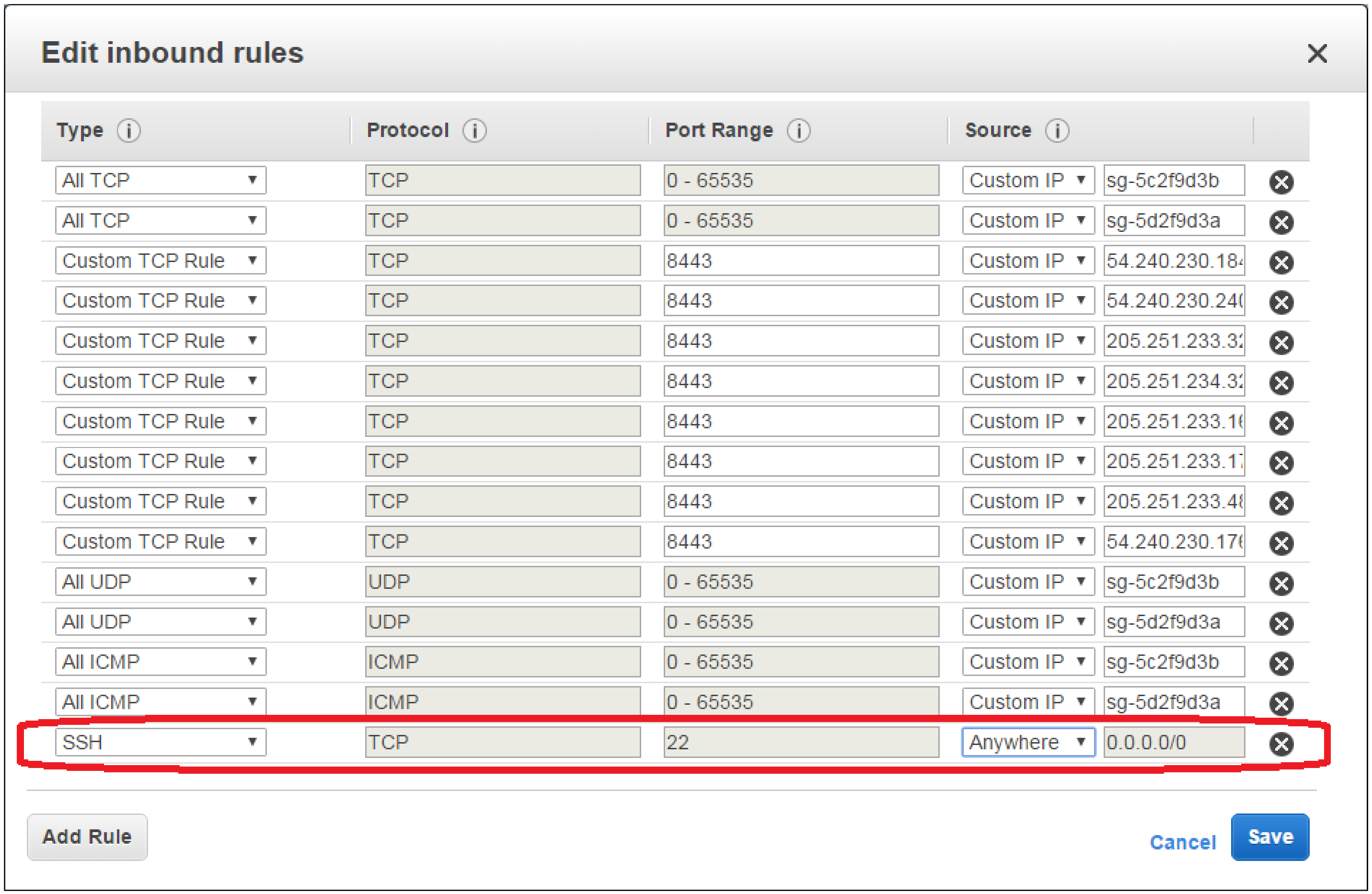
- In the bottom pane, select the Inbound tab and click the Edit button.



- Click Add Rule

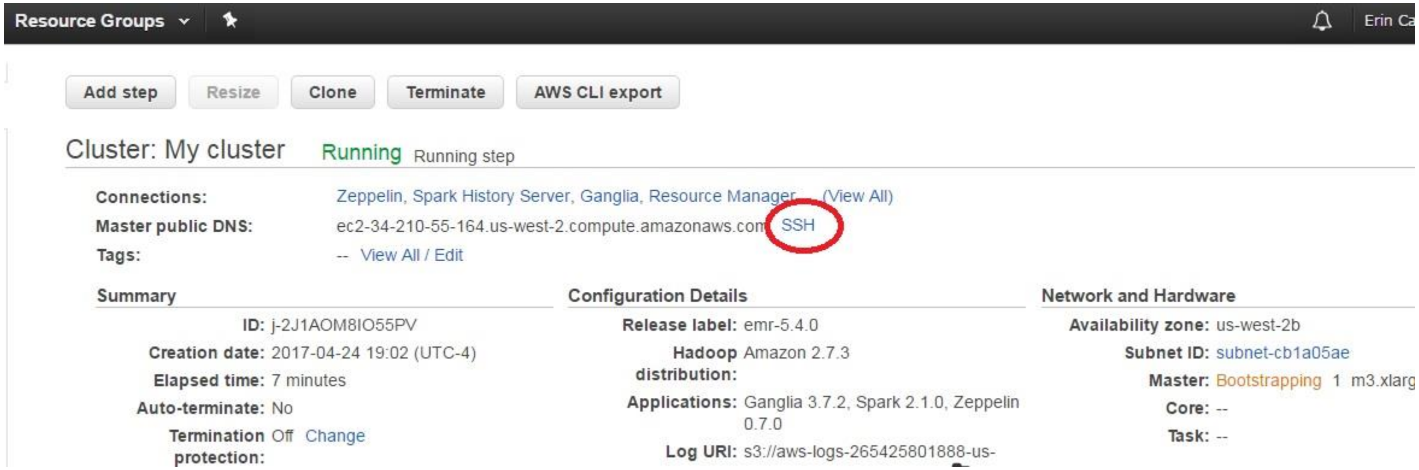


- select SSH for Type and Anywhere for the Source. Click Save.



SSH into the EMR master node

- From the EMR console, click "SSH" for instructions on how to SSH into the master node



Get the files

Once SSHed into the master node, get the files for the lab by typing:

```
hadoop fs -get s3://bigdataclassecc/Lab11/freqitems.py
hadoop fs -get s3://bigdataclassecc/Lab11/groceries.csv
hadoop fs -copyFromLocal groceries.csv
```

Run the Sample Program

1. Type

```
cat freqitems.py
```

to view the program

2. To run the job, use the command

```
spark-submit freqitems.py groceries.csv > freqitemsoutput.txt
```

3. Type

```
cat freqitemsoutput.txt
```

to view the output file

Getting the output from EMR

- To get the output from the program onto your local machine, you can use scp. From a terminal on your local machine, type, for example:

scp -i ~/private-key.pem hadoop@ec2-35-161-42-105.us-west-2.compute.amazonaws.com:/home/hadoop/modifiedoutput.txt .

on Windows, from command line:

pscp -scp -i C:\Users\ecc\Desktop\private-key.ppk hadoop@ec2-35-161-42-105.us-west-2.compute.amazonaws.com:/home/hadoop/modifiedoutput.txt .

(red text should be replaced with your path to private key, EMR master address, and file localtion)

Deliverable

Due Wednesday, April 26, 2017, 6pm

Suppose you are deciding which items to place next to each other at the grocery store, so you only care about frequent itemsets of size 2 or greater which appear in at least 2% of the transactions.

1. Modify the freqitems.py file to meet these constraints. Your code should print itemsets of size 2 or larger that appear in at least 2% of transactions, **sorted by decreasing frequency**. (This involves both setting an appropriate minSupport and modifying the code to prune itemsets of size 1 and sort).
2. Run the job with your modified freqitems.py file using spark-submit, saving the output to the file modifiedoutput.txt
3. Submit the modifiedoutput.txt file to NYU Classes.