DATASCI W261, Machine Learning at Scale

Assignement: week #13

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Due: 2016-04-29, 8AM PST

Start Spark

In [1]:
```
import os
import sys
spark_home = os.environ['SPARK_HOME'] = '/Users/leiyang/Downloads/spark-1.6.1-bin-hadoop2.6/'
if not spark_home:
    raise ValueError('SPARK_HOME enviroment variable is not set')
sys.path.insert(0,os.path.join(spark_home,'python'))
sys.path.insert(0,os.path.join(spark_home,'python/lib/py4j-0.8.2.1-src.zip'))
execfile(os.path.join(spark_home,'python/pyspark/shell.py'))
```

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.6.1
      /_/

Using Python version 2.7.9 (default, Dec 15 2014 10:37:34)
SparkContext available as sc, HiveContext available as sqlContext.
```

HW 13.1: Spark implementation of basic PageRank

Write a basic Spark implementation of the iterative PageRank algorithm that takes sparse adjacency lists as input. Make sure that your implementation utilizes teleportation (1-damping/the number of nodes in the network), and further, distributes the mass of dangling nodes with each iteration so that the output of each iteration is correctly normalized (sums to 1). [NOTE: The PageRank algorithm assumes that a random surfer (walker), starting from a random web page, chooses the next page to which it will move by clicking at random, with probability d, one of the hyperlinks in the current page. This probability is represented by a so-called 'damping factor' d, where d ∈ (0, 1). Otherwise, with probability (1 − d), the surfer jumps to any web page in the network. If a page is a dangling end, meaning it has no outgoing hyperlinks, the random surfer selects an arbitrary web page from a uniform distribution and "teleports" to that page]

In your Spark solution, please use broadcast variables and caching to make sure your code is as efficient as possible.

As you build your code, use the test data

s3://ucb-mids-mls-networks/PageRank-test.txt Or under the Data Subfolder for HW7 on Dropbox with the same file name. (On Dropbox https://www.dropbox.com/sh/2c0k5adwz36lkcw/AAAAKsjQfF9uHfv-X9mCqr9wa?dl=0 (https://www.dropbox.com/sh/2c0k5adwz36lkcw/AAAAKsjQfF9uHfv-X9mCqr9wa?dl=0))

with teleportation parameter set to 0.15 (1-d, where d, the damping factor is set to 0.85), and crosscheck your work with the true result, displayed in the first image in the Wikipedia article:

https://en.wikipedia.org/wiki/PageRank (https://en.wikipedia.org/wiki/PageRank)

and here for reference are the corresponding PageRank probabilities:

A,0.033 B,0.384 C,0.343 D,0.039 E,0.081 F,0.039 G,0.016 H,0.016 I,0.016 J,0.016 K,0.016

Run this experiment locally first. Report the local configuration that you used and how long in minutes and seconds it takes to complete your job.

Repeat this experiment on AWS. Report the AWS cluster configuration that you used and how long in minutes and seconds it takes to complete your job. (in your notebook, cat the cluster config file)

PageRank

In [10]:
```
from time import time
from datetime import datetime
```

```
def initialize(line):
    # parse line
    nid, adj = line.strip().split('\t', 1)
    exec 'adj = %s' %adj
    # initialize node struct
    node = {'a':adj.keys(), 'p':0}
    rankMass = 1.0/len(adj)
    # emit pageRank mass and node
    return [(m, rankMass) for m in node['a']] + [(nid.strip('"'), node)]

def accumulateMass(a, b):
    if isinstance(a, float) and isinstance(b, float):
        return a+b
    if isinstance(a, float) and not isinstance(b, float):
        b['p'] += a
        return b
    else:
        a['p'] += b
        return a

def getDangling(node):
    global nDangling
    if isinstance(node[1], float):
        nDangling += 1
        return (node[0], {'a':[], 'p':node[1]})
    else:
        return node

def redistributeMass(node):
    node[1]['p'] = (p_dangling.value+node[1]['p'])*damping + alpha
    return node

def distributeMass(node):
    global lossMass
    mass, adj = node[1]['p'], node[1]['a']
    node[1]['p'] = 0
    if len(adj) == 0:
        lossMass += mass
        return [node]
    else:
        rankMass = mass/len(adj)
        return [(x, rankMass) for x in adj]+[node]

def getIndex(line):
    elem = line.strip().split('\t')
    return (elem[1], elem[0])

def logTime():
    return str(datetime.now())
```

Driver

In [4]:

```
from operator import add

# Load the graph
graph_file = sc.textFile('hdfs://localhost:9000/user/leiyang/PageRank-test.txt')
index_file = sc.textFile('file:///Users/leiyang/Downloads/toy_index.txt')

# initialize variables
nDangling = sc.accumulator(0)
lossMass = sc.accumulator(0.0)
damping = 0.85
alpha = 1 - damping
nTop, nIter = 100, 10
start = time()
print '%s: start PageRank initialization ...' %(logTime())
graph = graph_file.flatMap(initialize).reduceByKey(accumulateMass).map(getDangling).cache()
# get graph size
G = graph.count()
# broadcast dangling mass for redistribution
p_dangling = sc.broadcast(1.0*nDangling.value/G)
graph = graph.map(redistributeMass)
print '%s: initialization completed, dangling node(s): %d, total nodes: %d' %(logTime(), nDangling.value, G)

for i in range(nIter-1):
    print '%s: running iteration %d ...' %(logTime(), i+2)
    lossMass.value = 0.0
```

```
    lossMass.value = 0.0
    graph = graph.flatMap(distributeMass).reduceByKey(accumulateMass).cache() #checkpoint()?
    # need to call an action here in order to have loss mass
    graph.count()
    print '%s: redistributing loss mass: %.4f' %(logTime(), lossMass.value)
    p_dangling = sc.broadcast(lossMass.value/G)
    graph = graph.map(redistributeMass)

totalMass = graph.aggregate(0, (lambda x, y: y[1]['p'] + x), (lambda x, y: x+y))
print '%s: normalized weight of the graph: %.4f' %(logTime(), totalMass/G)
print '%s: PageRanking completed in %.2f minutes.' %(logTime(), (time()-start)/60.0)
# get the page name by join
topPages = graph.map(lambda n:(n[0],n[1]['p']/G)).sortBy(lambda n: n[1], ascending=False).take(nTop)
rankList = index_file.map(getIndex).join(sc.parallelize(topPages)).map(lambda l: l[1])
# save final rank list
rankList.sortBy(lambda n: n[1], ascending=False).saveAsTextFile('pageRank')
print '%s: results saved, job completed!' %logTime()
```

```
2016-04-15 22:52:21.595538: start PageRank initialization ...
2016-04-15 22:52:22.789142: initialization completed, dangling node(s): 1, total nodes: 11
2016-04-15 22:52:22.789784: running iteration 2 ...
2016-04-15 22:52:22.893942: redistributing loss mass: 0.6523
2016-04-15 22:52:22.900249: running iteration 3 ...
2016-04-15 22:52:23.016227: redistributing loss mass: 0.4174
2016-04-15 22:52:23.021943: running iteration 4 ...
2016-04-15 22:52:23.103576: redistributing loss mass: 0.7042
2016-04-15 22:52:23.108007: running iteration 5 ...
2016-04-15 22:52:23.193200: redistributing loss mass: 0.4136
2016-04-15 22:52:23.197213: running iteration 6 ...
2016-04-15 22:52:23.274630: redistributing loss mass: 0.4254
2016-04-15 22:52:23.278632: running iteration 7 ...
2016-04-15 22:52:23.352806: redistributing loss mass: 0.3753
2016-04-15 22:52:23.356641: running iteration 8 ...
2016-04-15 22:52:23.430620: redistributing loss mass: 0.3812
2016-04-15 22:52:23.434674: running iteration 9 ...
2016-04-15 22:52:23.531019: redistributing loss mass: 0.3659
2016-04-15 22:52:23.536714: running iteration 10 ...
2016-04-15 22:52:23.635844: redistributing loss mass: 0.3660
2016-04-15 22:52:23.679582: normalized weight of the graph: 1.0000
2016-04-15 22:52:23.679781: PageRanking completed in 0.03 minutes.
2016-04-15 22:52:24.634718: results saved, job completed!
```

In [5]:

```
!cat pageRank/part*
```

```
(u"'Node_b", 0.3632359489889102)
(u"'Node_c", 0.36288372803871793)
(u"'Node_e", 0.08114525762548769)
(u"'Node_d", 0.03938466342002967)
(u"'Node_f", 0.03938466342002967)
(u"'Node_a", 0.03293010178620472)
(u"'Node_h", 0.016207127344124005)
(u"'Node_j", 0.016207127344124005)
(u"'Node_g", 0.016207127344124005)
(u"'Node_i", 0.016207127344124005)
(u"'Node_k", 0.016207127344124005)
```

HW 13.2: Applying PageRank to the Wikipedia hyperlinks network

Run your Spark PageRank implementation on the Wikipedia dataset for 10 iterations, and display the top 100 ranked nodes (with alpha = 0.85).

Run your PageRank implementation on the Wikipedia dataset for 50 iterations, and display the top 100 ranked nodes (with teleportation factor of 0.15). Plot the pagerank values for the top 100 pages resulting from the 50 iterations run. Then plot the pagerank values for the same 100 pages that resulted from the 10 iterations run. Comment on your findings. Have the top 100 ranked pages changed? Have the pagerank values changed? Explain.

Report the AWS cluster configuration that you used and how long in minutes and seconds it takes to complete your job.

NOTE: ==== English Wikipedia hyperlink network.data ==== The dataset is available via Dropbox at:

[https://www.dropbox.com/sh/2c0k5adwz36lkcw/AAAAKsjQfF9uHfv-X9mCqr9wa?dl=0 (https://www.dropbox.com/sh/2c0k5adwz36lkcw/AAAAKsjQfF9uHfv-X9mCqr9wa?dl=0)](https://www.dropbox.com/sh/2c0k5adwz36lkcw/AAAAKsjQfF9uHfv-X9mCqr9wa?dl=0)

on S3 at s3://ucb-mids-mls-networks/wikipedia/ -- s3://ucb-mids-mls-networks/wikipedia/all-pages-indexed-out.txt # Graph -- s3://ucb-mids-mls-networks/wikipedia/indices.txt # Page titles and page Ids

The dataset is built from the Sept. 2015 XML snapshot of English Wikipedia. For this directed network, a link between articles:

A -> B

is defined by the existence of a hyperlink in A pointing to B. This network also exists in the indexed format:

Data: s3://ucb-mids-mls-networks/wikipedia/all-pages-indexed-out.txt Data: s3://ucb-mids-mls-networks/wikipedia/all-pages-indexed-in.txt Data: s3://ucb-mids-mls-networks/wikipedia/indices.txt

but has an index with more detailed data:

(article name) \t (index) \t (in degree) \t (out degree)

In the dictionary, target nodes are keys, link weights are values . Here, a weight indicates the number of time a page links to another. However, for the sake of this assignment, treat this an unweighted network, and set all weights to 1 upon data input.

Submit job to the cluster

- ssh i the master node of EMR cluster
- do data preparation
- submit job to spark
- **Note: summary of time, and discussion are presented after the GraphX results in next problem**

Cluster configuration: 1 m1.large master node + 9 m1.large task nodes

In [ ]:
```
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--name LeiPageRankToy \
--py-files PageRank.py \
--executor-memory '4600m' \
--executor-cores 2 \
--driver-memory '4600m' \
--num-executors 11 \
PageRankDriver.py > wiki_10_log
```

10 Iterations log (https://raw.githubusercontent.com/leiyang-mids/MIDS/master/W261/HW13-Questions/spark_log_10_iterations)

- execution time: 29.62 minutes

In [1]:
```
!cat pageRank_time_10_iterations
```

```
2016-04-22 21:47:50.407410: start PageRank initialization ...
2016-04-22 21:51:14.131401: initialization completed, dangling node(s): 9410987, total nodes: 15192277
2016-04-22 21:51:14.131474: running iteration 2 ...
2016-04-22 21:54:16.556416: redistributing loss mass: 7608969.0130
2016-04-22 21:54:16.564424: running iteration 3 ...
2016-04-22 21:57:10.348773: redistributing loss mass: 7103036.3037
2016-04-22 21:57:10.356219: running iteration 4 ...
2016-04-22 21:59:57.663450: redistributing loss mass: 6940792.1449
2016-04-22 21:59:57.720320: running iteration 5 ...
2016-04-22 22:02:49.159656: redistributing loss mass: 6884560.5231
2016-04-22 22:02:49.166445: running iteration 6 ...
2016-04-22 22:05:39.179975: redistributing loss mass: 6863177.9617
2016-04-22 22:05:39.186458: running iteration 7 ...
2016-04-22 22:08:22.604490: redistributing loss mass: 6854533.8830
2016-04-22 22:08:22.610610: running iteration 8 ...
2016-04-22 22:11:08.030830: redistributing loss mass: 6850834.1086
2016-04-22 22:11:08.037460: running iteration 9 ...
2016-04-22 22:13:54.898048: redistributing loss mass: 6849174.4055
2016-04-22 22:13:54.904239: running iteration 10 ...
2016-04-22 22:16:43.731913: redistributing loss mass: 6848394.4811
2016-04-22 22:17:27.460246: normalized weight of the graph: 1.0000
2016-04-22 22:17:27.460319: PageRanking completed in 29.62 minutes.
2016-04-22 22:22:26.496599: results saved, job completed!
```

50 Iterations log (https://raw.githubusercontent.com/leiyang-mids/MIDS/master/W261/HW13-Questions/spark_log_50_iterations)

- execution time: 141.40 minutes

In [2]:
```
!cat pageRank_time_50_iterations
```

```
[hadoop@ip-172-31-9-186 lei]$ cat wiki_50_log
2016-04-22 22:27:22.269262: start PageRank initialization ...
2016-04-22 22:30:40.932047: initialization completed, dangling node(s): 9410987, total nodes: 15192277
```

```
2016-04-22 22:30:40.932248: running iteration 2 ...
2016-04-22 22:33:38.183716: redistributing loss mass: 7608969.0130
2016-04-22 22:33:38.191269: running iteration 3 ...
2016-04-22 22:36:25.688220: redistributing loss mass: 7103036.3037
2016-04-22 22:36:25.695027: running iteration 4 ...
2016-04-22 22:39:13.888332: redistributing loss mass: 6940792.1449
2016-04-22 22:39:13.895518: running iteration 5 ...
2016-04-22 22:42:05.660363: redistributing loss mass: 6884560.5231
2016-04-22 22:42:05.667313: running iteration 6 ...
2016-04-22 22:44:48.044150: redistributing loss mass: 6863177.9617
2016-04-22 22:44:48.050751: running iteration 7 ...
2016-04-22 22:47:42.365782: redistributing loss mass: 6854533.8830
2016-04-22 22:47:42.372406: running iteration 8 ...
2016-04-22 22:50:25.247508: redistributing loss mass: 6850834.1086
2016-04-22 22:50:25.255316: running iteration 9 ...
2016-04-22 22:53:09.848617: redistributing loss mass: 6849174.4055
2016-04-22 22:53:09.854675: running iteration 10 ...
2016-04-22 22:55:57.404165: redistributing loss mass: 6848394.4811
2016-04-22 22:55:57.411764: running iteration 11 ...
2016-04-22 22:58:41.922640: redistributing loss mass: 6848013.2672
2016-04-22 22:58:41.928333: running iteration 12 ...
2016-04-22 23:01:32.333966: redistributing loss mass: 6847819.5157
2016-04-22 23:01:32.340206: running iteration 13 ...
2016-04-22 23:04:18.220337: redistributing loss mass: 6847717.6750
2016-04-22 23:04:18.226064: running iteration 14 ...
2016-04-22 23:07:08.545158: redistributing loss mass: 6847662.3248
2016-04-22 23:07:08.551160: running iteration 15 ...
2016-04-22 23:09:57.948047: redistributing loss mass: 6847631.4424
2016-04-22 23:09:57.953785: running iteration 16 ...
2016-04-22 23:12:41.704867: redistributing loss mass: 6847613.7325
2016-04-22 23:12:41.711388: running iteration 17 ...
2016-04-22 23:15:23.701817: redistributing loss mass: 6847603.3743
2016-04-22 23:15:23.707803: running iteration 18 ...
2016-04-22 23:18:11.871462: redistributing loss mass: 6847597.1814
2016-04-22 23:18:11.877195: running iteration 19 ...
2016-04-22 23:20:58.774307: redistributing loss mass: 6847593.4216
2016-04-22 23:20:58.781808: running iteration 20 ...
2016-04-22 23:23:42.773786: redistributing loss mass: 6847591.0941
2016-04-22 23:23:42.779676: running iteration 21 ...
2016-04-22 23:26:31.514418: redistributing loss mass: 6847589.6330
2016-04-22 23:26:31.520147: running iteration 22 ...
2016-04-22 23:29:15.093137: redistributing loss mass: 6847588.6974
2016-04-22 23:29:15.099334: running iteration 23 ...
2016-04-22 23:32:04.386726: redistributing loss mass: 6847588.0890
2016-04-22 23:32:04.394860: running iteration 24 ...
2016-04-22 23:34:56.203852: redistributing loss mass: 6847587.6843
2016-04-22 23:34:56.209404: running iteration 25 ...
2016-04-22 23:37:45.932104: redistributing loss mass: 6847587.4101
2016-04-22 23:37:45.937876: running iteration 26 ...
2016-04-22 23:40:33.264800: redistributing loss mass: 6847587.2194
2016-04-22 23:40:33.270828: running iteration 27 ...
2016-04-22 23:43:20.503157: redistributing loss mass: 6847587.0841
2016-04-22 23:43:20.508909: running iteration 28 ...
2016-04-22 23:46:05.315308: redistributing loss mass: 6847586.9854
2016-04-22 23:46:05.361283: running iteration 29 ...
2016-04-22 23:48:51.634831: redistributing loss mass: 6847586.9119
2016-04-22 23:48:51.641059: running iteration 30 ...
2016-04-22 23:51:37.549179: redistributing loss mass: 6847586.8559
2016-04-22 23:51:37.555017: running iteration 31 ...
2016-04-22 23:54:25.350505: redistributing loss mass: 6847586.8124
2016-04-22 23:54:25.356260: running iteration 32 ...
2016-04-22 23:57:13.681911: redistributing loss mass: 6847586.7780
2016-04-22 23:57:13.688034: running iteration 33 ...
2016-04-23 00:00:00.771290: redistributing loss mass: 6847586.7505
2016-04-23 00:00:00.777150: running iteration 34 ...
2016-04-23 00:02:55.747675: redistributing loss mass: 6847586.7281
2016-04-23 00:02:55.753448: running iteration 35 ...
2016-04-23 00:05:50.139292: redistributing loss mass: 6847586.7098
2016-04-23 00:05:50.145276: running iteration 36 ...
2016-04-23 00:08:46.292962: redistributing loss mass: 6847586.6947
2016-04-23 00:08:46.298539: running iteration 37 ...
2016-04-23 00:11:32.824491: redistributing loss mass: 6847586.6821
2016-04-23 00:11:32.830260: running iteration 38 ...
2016-04-23 00:14:17.957812: redistributing loss mass: 6847586.6716
2016-04-23 00:14:17.963311: running iteration 39 ...
2016-04-23 00:17:15.913726: redistributing loss mass: 6847586.6628
2016-04-23 00:17:15.919166: running iteration 40 ...
2016-04-23 00:20:01.584078: redistributing loss mass: 6847586.6555
2016-04-23 00:20:01.590802: running iteration 41 ...
```

```
2016-04-23 00:22:51.051490: redistributing loss mass: 6847586.6493
2016-04-23 00:22:51.057546: running iteration 42 ...
2016-04-23 00:25:39.505687: redistributing loss mass: 6847586.6440
2016-04-23 00:25:39.511355: running iteration 43 ...
2016-04-23 00:28:27.865999: redistributing loss mass: 6847586.6396
2016-04-23 00:28:27.871538: running iteration 44 ...
2016-04-23 00:31:23.585961: redistributing loss mass: 6847586.6358
2016-04-23 00:31:23.591691: running iteration 45 ...
2016-04-23 00:34:09.044370: redistributing loss mass: 6847586.6327
2016-04-23 00:34:09.049998: running iteration 46 ...
2016-04-23 00:36:57.104713: redistributing loss mass: 6847586.6300
2016-04-23 00:36:57.112818: running iteration 47 ...
2016-04-23 00:39:42.006896: redistributing loss mass: 6847586.6277
2016-04-23 00:39:42.012373: running iteration 48 ...
2016-04-23 00:42:25.421774: redistributing loss mass: 6847586.6258
2016-04-23 00:42:25.427903: running iteration 49 ...
2016-04-23 00:45:16.739738: redistributing loss mass: 6847586.6242
2016-04-23 00:45:16.745799: running iteration 50 ...
2016-04-23 00:48:06.250673: redistributing loss mass: 6847586.6228
2016-04-23 00:48:46.169341: normalized weight of the graph: 1.0000
2016-04-23 00:48:46.169409: PageRanking completed in 141.40 minutes.
2016-04-23 00:53:36.124725: results saved, job completed!
```

Top 100 nodes and rank

- 98% pages are in the same order except two has swapped place, but the difference of ranking score is small
- the procedure is actually converging pretty well after 10 iteratins, more iterations won not improve ranking much
- and the plot below show ranking from both execution are very close

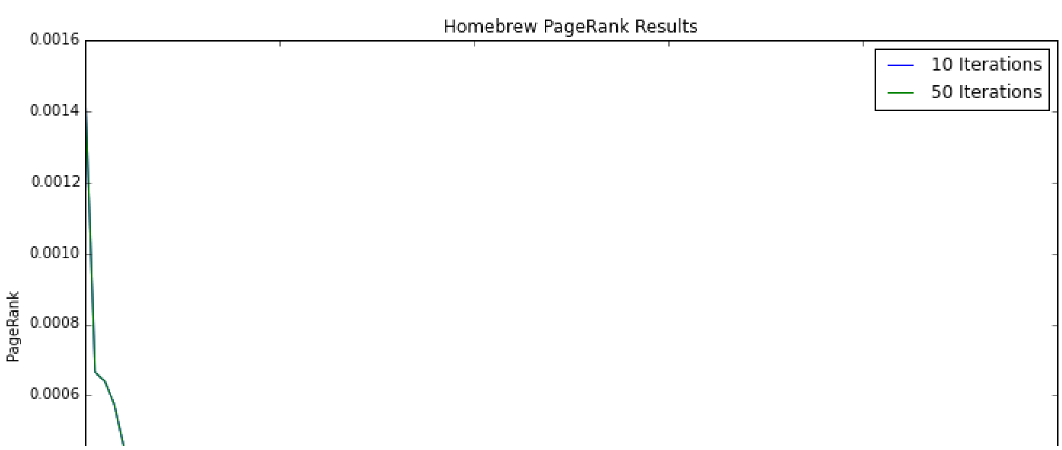
Order	Name	Rank (Iter=10)	Name	Rank (Iter=50)	*Equal?*
1	United States	0.001461	United States	0.001462	Y
2	Animal	0.000666	Animal	0.000666	Y
3	France	0.000640	France	0.000640	Y
4	Germany	0.000575	Germany	0.000575	Y
5	Arthropod	0.000450	Arthropod	0.000450	Y
6	Canada	0.000447	Canada	0.000447	Y
7	Insect	0.000445	Insect	0.000445	Y
8	List of sovereign states	0.000444	List of sovereign states	0.000444	Y
9	United Kingdom	0.000433	United Kingdom	0.000433	Y
10	India	0.000428	India	0.000428	Y
11	England	0.000423	England	0.000423	Y
12	Iran	0.000398	Iran	0.000398	Y
13	World War II	0.000385	World War II	0.000385	Y
14	Poland	0.000363	Poland	0.000363	Y
15	village	0.000344	village	0.000344	Y
16	Countries of the world	0.000338	Countries of the world	0.000338	Y
17	Japan	0.000329	Japan	0.000329	Y
18	Italy	0.000329	Italy	0.000329	Y
19	List of countries	0.000326	List of countries	0.000326	Y
20	Australia	0.000325	Australia	0.000325	Y
21	Voivodeships of Poland	0.000313	Voivodeships of Poland	0.000313	Y
22	National Register of Historic Places	0.000310	National Register of Historic Places	0.000310	Y
23	Lepidoptera	0.000308	Lepidoptera	0.000308	Y
24	Powiat	0.000304	Powiat	0.000303	Y
25	Gmina	0.000298	Gmina	0.000298	Y
26	The New York Times	0.000286	The New York Times	0.000286	Y
27	London	0.000283	London	0.000284	Y

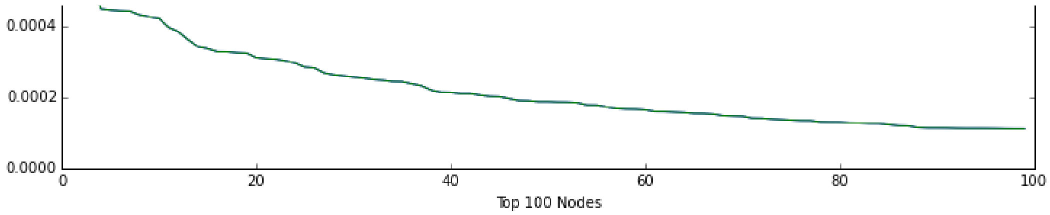
28	English language	0.000269	English language	0.000269	Y
29	China	0.000264	China	0.000264	Y
30	Russia	0.000261	Russia	0.000261	Y
31	New York City	0.000258	New York City	0.000258	Y
32	Departments of France	0.000255	Departments of France	0.000255	Y
33	Spain	0.000251	Spain	0.000251	Y
34	Communes of France	0.000249	Communes of France	0.000249	Y
35	moth	0.000245	moth	0.000245	Y
36	Brazil	0.000245	Brazil	0.000245	Y
37	Association football	0.000239	Association football	0.000239	Y
38	association football	0.000233	association football	0.000233	Y
39	California	0.000221	California	0.000221	Y
40	Counties of Iran	0.000215	Counties of Iran	0.000215	Y
41	Provinces of Iran	0.000215	Provinces of Iran	0.000215	Y
42	Central European Time	0.000211	Central European Time	0.000211	Y
43	Romania	0.000211	Romania	0.000211	Y
44	Bakhsh	0.000207	Bakhsh	0.000207	Y
45	Sweden	0.000203	Sweden	0.000203	Y
46	Rural Districts of Iran	0.000203	Rural Districts of Iran	0.000203	Y
47	Netherlands	0.000197	Netherlands	0.000197	Y
48	Private Use Areas	0.000191	Private Use Areas	0.000191	Y
49	World War I	0.000191	World War I	0.000191	Y
50	Central European Summer Time	0.000188	New York	0.000188	**N**
51	New York	0.000188	Central European Summer Time	0.000188	**N**
52	Mexico	0.000187	Mexico	0.000187	Y
53	Iran Standard Time	0.000187	Iran Standard Time	0.000187	Y
54	AllMusic	0.000185	AllMusic	0.000185	Y
55	Iran Daylight Time	0.000179	Iran Daylight Time	0.000179	Y
56	Hangul	0.000178	Hangul	0.000178	Y
57	Scotland	0.000173	Scotland	0.000173	Y
58	gene	0.000170	gene	0.000169	Y
59	Soviet Union	0.000168	Soviet Union	0.000168	Y
60	Norway	0.000167	Norway	0.000167	Y
61	Allmusic	0.000165	Allmusic	0.000165	Y
62	Paris	0.000161	Paris	0.000161	Y
63	New Zealand	0.000161	New Zealand	0.000161	Y
64	Turkey	0.000159	Turkey	0.000159	Y
65	Plant	0.000158	Plant	0.000158	Y
66	Geographic Names Information System	0.000155	Geographic Names Information System	0.000155	Y
67	Switzerland	0.000155	Switzerland	0.000155	Y
68	Los Angeles	0.000153	Los Angeles	0.000153	Y
69	Romanize	0.000149	Romanize	0.000149	Y
70	United States Census Bureau	0.000148	United States Census Bureau	0.000148	Y
71	Europe	0.000147	Europe	0.000147	Y
72	Angiosperms	0.000142	Angiosperms	0.000142	Y
73	South Africa	0.000141	South Africa	0.000141	Y
74	census	0.000139	census	0.000139	Y

75	Flowering plant	0.000138	Flowering plant	0.000138	Y
76	Austria	0.000136	Austria	0.000136	Y
77	protein	0.000135	protein	0.000135	Y
78	U.S. state	0.000135	U.S. state	0.000135	Y
79	Argentina	0.000131	Argentina	0.000131	Y
80	Political divisions of the United States	0.000130	Political divisions of the United States	0.000130	Y
81	population density	0.000130	population density	0.000130	Y
82	Catholic Church	0.000128	Catholic Church	0.000128	Y
83	Chordate	0.000128	Chordate	0.000128	Y
84	BBC	0.000127	BBC	0.000127	Y
85	Belgium	0.000127	Belgium	0.000127	Y
86	Chicago	0.000124	Chicago	0.000124	Y
87	Washington D.C.	0.000121	Washington D.C.	0.000121	Y
88	Pakistan	0.000120	Pakistan	0.000120	Y
89	Finland	0.000116	Finland	0.000116	Y
90	The Guardian	0.000114	The Guardian	0.000115	Y
91	Latin	0.000114	Latin	0.000114	Y
92	Ontario	0.000114	Ontario	0.000114	Y
93	Czech Republic	0.000114	Czech Republic	0.000114	Y
94	Philippines	0.000113	Philippines	0.000113	Y
95	Denmark	0.000113	Denmark	0.000113	Y
96	Greece	0.000113	Greece	0.000113	Y
97	genus	0.000113	genus	0.000113	Y
98	football (soccer)	0.000112	football (soccer)	0.000112	Y
99	Hungary	0.000112	Hungary	0.000112	Y
100	Eastern European Time	0.000112	Eastern European Time	0.000112	Y

In [25]:

```
%matplotlib inline
import matplotlib.pyplot as plt

with open('PlotPageRank0', 'r') as f:
    header = f.readline()
    ranks = [map(float, l.strip().split('\t')) for l in f.readlines()]

plt.figure(figsize=(12,7))
p = plt.plot(ranks)

plt.legend(['10 Iterations', '50 Iterations'])
plt.xlabel('Top 100 Nodes')
plt.ylabel('PageRank')
plt.title('Homebrew PageRank Results')
plt.show()
```





HW 13.3: Spark GraphX versus your implementation of PageRank

Run the Spark GraphX PageRank implementation on the Wikipedia dataset for 10 iterations, and display the top 100 ranked nodes (with alpha = 0.85).

Run your PageRank implementation on the Wikipedia dataset for 50 iterations, and display the top 100 ranked nodes (with teleportation factor of 0.15). Have the top 100 ranked pages changed? Comment on your findings. Plot both 100 curves.

Report the AWS cluster configuration that you used and how long in minutes and seconds it takes to complete this job.

Put the runtime results of HW13.2 and HW13.3 in a tabular format (with rows corresponding to implemention and columns corresponding to experiment setup (10 iterations, 50 iterations)). Discuss the run times and explaing the differences.

Plot the pagerank values for the top 100 pages resulting from the 50 iterations run (using GraphX). Then plot the pagerank values for the same 100 pages that resulted from the 50 iterations run of your homegrown pagerank implemnentation. Comment on your findings. Have the top 100 ranked pages changed? Have the pagerank values changed? Explain.

Scala code

In [ ]:
```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark.SparkConf
import org.apache.spark.graphx._
import org.apache.spark.graphx.lib._


object WikiPageRank {

  def main(args: Array[String]) {
    val t0 = System.nanoTime()
    val conf = new SparkConf().setAppName("WikiPageRank")
    val sc = new SparkContext(conf)
    var nIter = args(0).toInt

    // Create an RDD for the edges and vertices
    val links = sc.textFile("hdfs:///user/leiyang/all-pages-indexed-out.txt", 80).flatMap(getLinks);
    val pages = sc.textFile("hdfs:///user/leiyang/indices.txt", 16).map(getPages);

    // Build the initial Graph
    val graph = Graph(pages, links);
    // Run pageRank
    val rank = PageRank.run(graph, numIter=nIter).vertices.cache()
    // Normalize the rank score
    val total = rank.map(l=>l._2).sum()
    val tops = rank.sortBy(l=>l._2, ascending=false).take(200).map(l => (l._1, l._2/total))
    val ret = sc.parallelize(tops).join(pages).map(l => (l._2._2._1, l._2._1)).sortBy(l=>l._2, ascending=f
alse).take(200)
    val elapse = (System.nanoTime()-t0)/1000000000.0/60.0
    // Show results
    println("PageRanking finishes in " + elapse + " minutes!")
    println(ret.mkString("\n"))
  }

  def getLinks(line: String): Array[Edge[String]] = {
      val elem = line.split("\t", 2)
      for {n <-  elem(1).stripPrefix("{").split(",")
          // get Edge between id
      }yield Edge(elem(0).toLong, n.split(":")(0).trim().stripPrefix("'").stripSuffix("'").toLong, "")
  }

  def getPages(line: String): (VertexId, (String, String)) = {
      val elem = line.split("\t")
      return (elem(1).toLong, (elem(0), ""))
  }
}
```

Submit Job to Spark - 1 m1.xlarge master node + 9 m1.xlarge task nodes

- package job to build jar with sbt
- 10 iteration log (https://raw.githubusercontent.com/leiyang-mids/MIDS/master/W261/HW13-Questions/spark_log_10_iterations_graphX)
- 50 iteration log (https://raw.githubusercontent.com/leiyang-mids/MIDS/master/W261/HW13-Questions/spark_log_50_iterations_graphX)

In [3]:
```
# 10 iterations
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--class WikiPageRank \
--name "WikiPageRank" \
--executor-memory '4600m' \
--num-executors 11 \
--driver-memory '4600m' \
target/scala-2.10/pagerank-project_2.10-1.0.jar \
10 > wiki_10_log_GraphX

# 50 iterations
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--class WikiPageRank \
--name "WikiPageRank" \
--executor-memory '4600m' \
--num-executors 11 \
--driver-memory '4600m' \
target/scala-2.10/pagerank-project_2.10-1.0.jar \
50 > wiki_50_log_GraphX
```

Results

- **E10?** indicates if the name is the same between homebrew code and GraphX after *10* iteration
- **E50?** indicates if the name is the same between homebrew code and GraphX after *50* iteration
- **Equal?** indicate if the name is the same between *10* and *50* iterations of GraphX results

Order	Name	Rank (Iter=10)	E10?		Name	Rank (Iter=50)	E50?		*Equal?*
1	United States	0.001456	Y		United States	0.001462	Y		Y
2	Animal	0.000669	Y		Animal	0.000666	Y		Y
3	France	0.000638	Y		France	0.000640	Y		Y
4	Germany	0.000573	Y		Germany	0.000575	Y		Y
5	Arthropod	0.000452	Y		Arthropod	0.000450	Y		Y
6	Insect	0.000447	**N**		Canada	0.000447	Y		**N**
7	Canada	0.000445	**N**		Insect	0.000445	Y		**N**
8	List of sovereign states	0.000444	Y		List of sovereign states	0.000444	Y		Y
9	United Kingdom	0.000430	Y		United Kingdom	0.000433	Y		Y
10	India	0.000427	Y		India	0.000428	Y		Y
11	England	0.000422	Y		England	0.000423	Y		Y
12	Iran	0.000399	Y		Iran	0.000398	Y		Y
13	World War II	0.000383	Y		World War II	0.000385	Y		Y
14	Poland	0.000362	Y		Poland	0.000363	Y		Y
15	village	0.000345	Y		village	0.000344	Y		Y
16	Countries of the world	0.000339	Y		Countries of the world	0.000338	Y		Y
17	Japan	0.000329	Y		Japan	0.000329	Y		Y
18	Italy	0.000328	Y		Italy	0.000329	Y		Y
19	List of countries	0.000327	Y		List of countries	0.000326	Y		Y
20	Australia	0.000324	Y		Australia	0.000325	Y		Y
21	Voivodeships of Poland	0.000314	Y		Voivodeships of Poland	0.000313	Y		Y

22	National Register of Historic Places	0.000310	Y		National Register of Historic Places	0.000310	Y		Y
23	Lepidoptera	0.000309	Y		Lepidoptera	0.000308	Y		Y
24	Powiat	0.000304	Y		Powiat	0.000303	Y		Y
25	Gmina	0.000298	Y		Gmina	0.000298	Y		Y
26	The New York Times	0.000282	Y		The New York Times	0.000286	Y		Y
27	London	0.000282	Y		London	0.000284	Y		Y
28	English language	0.000267	Y		English language	0.000269	Y		Y
29	China	0.000263	Y		China	0.000264	Y		Y
30	Russia	0.000260	Y		Russia	0.000261	Y		Y
31	New York City	0.000255	Y		New York City	0.000258	Y		Y
32	Departments of France	0.000255	Y		Departments of France	0.000255	Y		Y
33	Spain	0.000250	Y		Spain	0.000251	Y		Y
34	Communes of France	0.000249	Y		Communes of France	0.000249	Y		Y
35	moth	0.000247	Y		moth	0.000245	Y		Y
36	Brazil	0.000245	Y		Brazil	0.000245	Y		Y
37	Association football	0.000238	Y		Association football	0.000239	Y		Y
38	association football	0.000233	Y		association football	0.000233	Y		Y
39	California	0.000220	Y		California	0.000221	Y		Y
40	Counties of Iran	0.000216	Y		Counties of Iran	0.000215	Y		Y
41	Provinces of Iran	0.000216	Y		Provinces of Iran	0.000215	Y		Y
42	Romania	0.000211	**N**		Central European Time	0.000211	Y		**N**
43	Central European Time	0.000211	**N**		Romania	0.000211	Y		**N**
44	Bakhsh	0.000208	Y		Bakhsh	0.000207	Y		Y
45	Rural Districts of Iran	0.000204	**N**		Sweden	0.000203	Y		**N**
46	Sweden	0.000203	**N**		Rural Districts of Iran	0.000203	Y		**N**
47	Netherlands	0.000196	Y		Netherlands	0.000197	Y		Y
48	Private Use Areas	0.000192	Y		Private Use Areas	0.000191	Y		Y
49	World War I	0.000189	Y		World War I	0.000191	Y		Y
50	Central European Summer Time	0.000188	Y		New York	0.000188	Y		**N**
51	Iran Standard Time	0.000188	**N**		Central European Summer Time	0.000188	Y		**N**
52	New York	0.000187	**N**		Mexico	0.000187	Y		**N**
53	Mexico	0.000187	**N**		Iran Standard Time	0.000187	Y		**N**
54	AllMusic	0.000185	Y		AllMusic	0.000185	Y		Y
55	Iran Daylight Time	0.000180	Y		Iran Daylight Time	0.000179	Y		Y
56	Hangul	0.000179	Y		Hangul	0.000178	Y		Y
57	Scotland	0.000172	Y		Scotland	0.000173	Y		Y
58	gene	0.000170	Y		gene	0.000169	Y		Y
59	Norway	0.000167	**N**		Soviet Union	0.000168	Y		**N**
60	Soviet Union	0.000166	**N**		Norway	0.000167	Y		**N**
61	Allmusic	0.000166	Y		Allmusic	0.000165	Y		Y
62	New Zealand	0.000160	**N**		Paris	0.000161	Y		**N**
63	Paris	0.000160	**N**		New Zealand	0.000161	Y		**N**
64	Turkey	0.000159	Y		Turkey	0.000159	Y		Y
65	Plant	0.000158	Y		Plant	0.000158	Y		Y
66	Geographic Names Information System	0.000155	Y		Geographic Names Information System	0.000155	Y		Y
67	Switzerland	0.000154	Y		Switzerland	0.000155	Y		Y

68	Los Angeles	0.000152	Y	Los Angeles	0.000153	Y	Y
69	Romanize	0.000150	Y	Romanize	0.000149	Y	Y
70	United States Census Bureau	0.000147	Y	United States Census Bureau	0.000148	Y	Y
71	Europe	0.000146	Y	Europe	0.000147	Y	Y
72	Angiosperms	0.000142	Y	Angiosperms	0.000142	Y	Y
73	South Africa	0.000141	Y	South Africa	0.000141	Y	Y
74	census	0.000139	Y	census	0.000139	Y	Y
75	Flowering plant	0.000138	Y	Flowering plant	0.000138	Y	Y
76	Austria	0.000136	Y	Austria	0.000136	Y	Y
77	protein	0.000136	Y	protein	0.000135	Y	Y
78	U.S. state	0.000134	Y	U.S. state	0.000135	Y	Y
79	Argentina	0.000130	Y	Argentina	0.000131	Y	Y
80	Political divisions of the United States	0.000130	Y	Political divisions of the United States	0.000130	Y	Y
81	population density	0.000130	Y	population density	0.000130	Y	Y
82	Chordate	0.000129	**N**	Catholic Church	0.000128	Y	**N**
83	Catholic Church	0.000127	**N**	Chordate	0.000128	Y	**N**
84	Belgium	0.000126	**N**	BBC	0.000127	Y	**N**
85	BBC	0.000126	**N**	Belgium	0.000127	Y	**N**
86	Chicago	0.000123	Y	Chicago	0.000124	Y	Y
87	Pakistan	0.000120	**N**	Washington D.C.	0.000121	Y	**N**
88	Washington D.C.	0.000119	**N**	Pakistan	0.000120	Y	**N**
89	Finland	0.000115	Y	Finland	0.000116	Y	Y
90	Ontario	0.000114	**N**	The Guardian	0.000115	Y	**N**
91	genus	0.000113	**N**	Latin	0.000114	Y	**N**
92	Czech Republic	0.000113	**N**	Ontario	0.000114	Y	**N**
93	The Guardian	0.000113	**N**	Czech Republic	0.000114	Y	**N**
94	Latin	0.000113	**N**	Philippines	0.000113	Y	**N**
95	Philippines	0.000113	**N**	Denmark	0.000113	Y	**N**
96	Denmark	0.000113	**N**	Greece	0.000113	Y	**N**
97	Greece	0.000113	**N**	genus	0.000113	Y	**N**
98	Eastern European Time	0.000112	**N**	football (soccer)	0.000112	Y	**N**
99	football (soccer)	0.000112	**N**	Hungary	0.000112	Y	**N**
100	species	0.000112	**N**	Eastern European Time	0.000112	Y	**N**

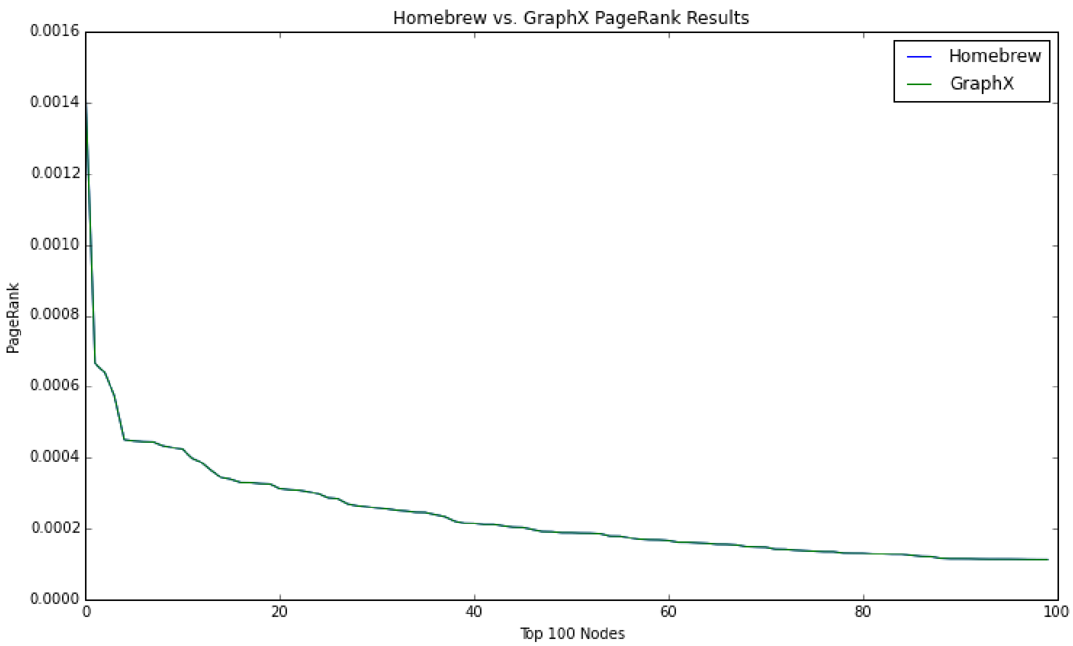
Execution Time and Discussion

- the homebrew code is able to execute on m1.large instance smoothly, however GraphX constantly running out of memory with m1.large, so we have to beef up the hardware to m1.xlarge
- execution time in minutes:

Iterations	GraphX	Homebrew	X
10	6.76	29.62	4.4
50	24.35	141.40	5.8

- results of 10 iterations between homebrew code and GraphX have some discrepancies, but they are mainly between neighbor pages, in addition the difference between the page ranking score is small
- results (order) of 50 iteratios between homebrew code and GraphX are identical. Since our homebrew code has reached this order with just 10 iterations, the convergence is quite satisfying. Given that it's running on an inferior EC2 tier, the homebrew code performance is not too shabby.
- Finally, let's plot the ranking value for the top 100 pages:

In [24]:
```
%matplotlib inline
import matplotlib.pyplot as plt

with open('PlotPageRank', 'r') as f:
    header = f.readline()
    ranks = [map(float, l.strip().split('\t')) for l in f.readlines()]

plt.figure(figsize=(12,7))
p = plt.plot(ranks)

plt.legend(['Homebrew', 'GraphX'])
plt.xlabel('Top 100 Nodes')
plt.ylabel('PageRank')
plt.title('Homebrew vs. GraphX PageRank Results')
plt.show()
```



HW 13.4: Criteo Phase 2 baseline

SPECIAL NOTE: Please share your findings as they become available with class via the Google Group. You will get brownie points for this. Once results are shared please use them and build on them.

The Criteo data for this challenge is located in the following S3/Dropbox buckets:

- On Dropbox see: https://www.dropbox.com/sh/dnevke9vsk6yj3p/AABoP-Kv2SRxuK8j3TtJsSv5a?dl=0 (https://www.dropbox.com/sh/dnevke9vsk6yj3p/AABoP-Kv2SRxuK8j3TtJsSv5a?dl=0)
- Raw Data: (Training, Validation and Test data) https://console.aws.amazon.com/s3/home?region=us-west-1#&bucket=criteo-dataset&prefix=rawdata/ (https://console.aws.amazon.com/s3/home?region=us-west-1#&bucket=criteo-dataset&prefix=rawdata/)
- Hashed Data: Training, Validation and Test data in hash encoded (10,000 buckets) and sparse representation https://console.aws.amazon.com/s3/home?region=us-west-1#&bucket=criteo-dataset&prefix=processeddata/ (https://console.aws.amazon.com/s3/home?region=us-west-1#&bucket=criteo-dataset&prefix=processeddata/)
- source: https://s3-eu-west-1.amazonaws.com/criteo-labs/dac.tar.gz (https://s3-eu-west-1.amazonaws.com/criteo-labs/dac.tar.gz)

Using the training dataset, validation dataset and testing dataset in the Criteo bucket perform the following experiment:

- write spark code (borrow from Phase 1 of this project) to train a logistic regression model with the following hyperparamters:
  - Number of buckets for hashing: 1,000
  - Logistic Regression: no regularization term
  - Logistic Regression: step size = 10
- Report the AWS cluster configuration that you used and how long in minutes and seconds it takes to complete this job.
- Report in tabular form the AUC (https://en.wikipedia.org/wiki/Receiver_operating_characteristic) value for the Training, Validation, and Testing datasets.
- Report in tabular form the logLossTest for the Training, Validation, and Testing datasets.
- Don't forget to put a caption on your tables (above each table).

Supporting Functions

In [2]:
```
%%writefile CriteoHelper2.py
```

```
from pyspark.mllib.classification import LogisticRegressionWithSGD
from pyspark.mllib.regression import LabeledPoint
from pyspark.mllib.linalg import SparseVector
from collections import defaultdict
from datetime import datetime
from sklearn import metrics
from math import log, exp
import numpy as np
import hashlib

# hash function
def hashFunction(numBuckets, rawFeats, printMapping=False):
    """Calculate a feature dictionary for an observation's features based on hashing.

    Note:
        Use printMapping=True for debug purposes and to better understand how the hashing works.

    Args:
        numBuckets (int): Number of buckets to use as features.
        rawFeats (list of (int, str)): A list of features for an observation.  Represented as
            (featureID, value) tuples.
        printMapping (bool, optional): If true, the mappings of featureString to index will be
            printed.

    Returns:
        dict of int to float:  The keys will be integers which represent the buckets that the
            features have been hashed to.  The value for a given key will contain the count of the
            (featureID, value) tuples that have hashed to that key.
    """
    mapping = {}
    for ind, category in rawFeats:
        featureString = category + str(ind)
        mapping[featureString] = int(int(hashlib.md5(featureString).hexdigest(), 16) % numBuckets)
    if(printMapping): print mapping
    sparseFeatures = defaultdict(float)
    for bucket in mapping.values():
        sparseFeatures[bucket] += 1.0
    return dict(sparseFeatures)

# feature hash
def parseHashPoint(point, numBuckets):
    """Create a LabeledPoint for this observation using hashing.

    Args:
        point (str): A comma separated string where the first value is the label and the rest are
            features.
        numBuckets: The number of buckets to hash to.

    Returns:
        LabeledPoint: A LabeledPoint with a label (0.0 or 1.0) and a SparseVector of hashed
            features.
    """
    elem = point.strip().split(',')
    rawFea = [(i, elem[i+1]) for i in range(len(elem) - 1)]
    index = np.sort(hashFunction(numBuckets, rawFea, False).keys())
    return LabeledPoint(elem[0], SparseVector(numBuckets, index, [1]*len(index)))

# Logistic Regression Modeling & Evaluation
def getP(x, w, intercept):
    """Calculate the probability for an observation given a set of weights and intercept.

    Note:
        We'll bound our raw prediction between 20 and -20 for numerical purposes.

    Args:
        x (SparseVector): A vector with values of 1.0 for features that exist in this
            observation and 0.0 otherwise.
        w (DenseVector): A vector of weights (betas) for the model.
        intercept (float): The model's intercept.

    Returns:
        float: A probability between 0 and 1.
    """
    rawPrediction = x.dot(w) + intercept
    # Bound the raw prediction value
    rawPrediction = min(rawPrediction, 20)
    rawPrediction = max(rawPrediction, -20)
    return 1/(1+exp(-rawPrediction))
```

```
def computeLogLoss(p, y):
    """Calculates the value of log loss for a given probabilty and label.

    Note:
        log(0) is undefined, so when p is 0 we need to add a small value (epsilon) to it
        and when p is 1 we need to subtract a small value (epsilon) from it.

    Args:
        p (float): A probabilty between 0 and 1.
        y (int): A label.  Takes on the values 0 and 1.

    Returns:
        float: The log loss value.
    """
    epsilon = 10e-12
    return -log(p+epsilon) if y==1 else -log(1-p+epsilon)

def evaluateResults(lrModel, data):
    """Calculates the log loss for the data given the model.

    Args:
        model (LogisticRegressionModel): A trained logistic regression model.
        data (RDD of LabeledPoint): Labels and features for each observation.

    Returns:
        float: Log loss for the data.
    """
    return data.map(lambda p: computeLogLoss(getP(p.features, lrModel.weights, lrModel.intercept), p.labe
l)).mean()

# misc
def logTime(): return str(datetime.now())
def getFP(index): yield max(index)
def getTP(label): yield sum(label)

# calculate AUC score
def getAUCfromRdd(rddData, lrModel):
    labelsAndScores = rddData.map(lambda lp: (lp.label, getP(lp.features, lrModel.weights, lrModel.interce
pt)))
    if labelsAndScores.getNumPartitions() < 100:
        labelAndIndex = labelsAndScores.repartition(100).sortBy(lambda (k,v): v, ascending=False).zipWithI
ndex()
    else:
        labelAndIndex = labelsAndScores.sortBy(lambda (k,v): v, ascending=False).zipWithIndex()
    labelAndIndex.cache()

    truePositives = np.cumsum(labelAndIndex.map(lambda l: l[0][0]).mapPartitions(getTP).collect())
    falsePositives = labelAndIndex.map(lambda l: l[1]+1).mapPartitions(getFP).collect() - truePositives
    numPositive = truePositives[-1]
    length = labelAndIndex.count()

    truePositiveRate = truePositives / numPositive
    falsePositiveRate = falsePositives / (length - numPositive)
    return metrics.auc(falsePositiveRate, truePositiveRate)

def encodeData(sc, numBuckets):
    rawTrainData = sc.textFile('s3://criteo-dataset/rawdata/train/part*', 180).map(lambda x: x.replace
('\t', ','))
    rawValidationData = sc.textFile('s3://criteo-dataset/rawdata/validation/part*', 180).map(lambda x: x.r
eplace('\t', ','))
    rawTestData = sc.textFile('s3://criteo-dataset/rawdata/test/part*', 180).map(lambda x: x.replace('\t',
','))

    # data encoding
    hashTrainData = rawTrainData.map(lambda p: parseHashPoint(p, numBuckets))
    hashTrainData.cache()
    hashValidationData = rawValidationData.map(lambda p: parseHashPoint(p, numBuckets))
    hashValidationData.cache()
    hashTestData = rawTestData.map(lambda p: parseHashPoint(p, numBuckets))
    hashTestData.cache()

    return hashTrainData, hashValidationData, hashTestData
```

```
Overwriting CriteoHelper2.py
```

Driver

In [27]:
```
%%writefile Criteo_Driver_1.py

from time import time, gmtime, strftime

execfile('CriteoHelper2.py')

# define parameters
print '%s: start logistic regression job ...' %(logTime())
numBucketsCTR = 5000
lrStep = 10
start = time()
sc = SparkContext()

# data preparaion
print '%s: preparing data ...' %(logTime())
dTrain, dValidation, dTest = encodeData(numBucketsCTR)

# build model
print '%s: building logistic regression model ...' %(logTime())
model = LogisticRegressionWithSGD.train(dTrain, iterations=500, step=lrStep, regType=None, intercept=True)

# get log loss
print '%s: evaluating log loss ...' %(logTime())
logLossVa = evaluateResults(model, dValidation)
logLossTest = evaluateResults(model, dTest)
logLossTrain = evaluateResults(model, dTrain)

# get AUC
print '%s: evaluating AUC ...' %(logTime())
aucTrain = getAUCfromRdd(dTrain, model)
aucVal = getAUCfromRdd(dValidation, model)
aucTest = getAUCfromRdd(dTest, model)
print '\n%s: job completes in %.2f minutes!' %(logTime(), (time()-start)/60.0)

# show results
print '\n\t\t log loss \t\t\t AUC'
print 'Training:\t %.4f\t\t %.4f' %(logLossTrain, aucTrain)
print 'Validation:\t %.4f\t\t %.4f' %(logLossVa, aucVal)
print 'Test:\t %.4f\t %.4f' %(logLossTest, aucTest)
```

```
Overwriting Criteo_Driver_1.py
```

Spark Job Results

- cluster: 1 m1.large master node + 9 m1.large task nodes
- execution time: 18.22 minutes
- LogLoss and AUC:

Data	Log Loss	AUC
Training	0.5042	0.7266
Validation	0.5045	0.7264
Test	0.5044	0.7268

In [29]:
```
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--name LeiCriteoJob \
--py-files CriteoHelper2.py \
--num-executors 21 \
--executor-memory '4600m' \
--executor-cores 2 \
--driver-memory '4600m' \
Criteo_Driver_1.py > Criteo_log1
```

```
2016-04-24 19:16:52.044625: start logistic regression job ...
2016-04-24 19:17:28.296266: preparing data ...
2016-04-24 19:17:29.625300: building logistic regression model ...
2016-04-24 19:34:36.063671: evaluating log loss ...
2016-04-24 19:41:06.268458: evaluating AUC ...

2016-04-24 19:47:16.500257: job completes in 30.41 minutes!

                 log loss                        AUC
Training:        0.5042         0.7266
Validation:      0.5045         0.7264
```

```
Test:    0.5044  0.7268
```

HW 13.5: Criteo Phase 2 hyperparameter tuning

SPECIAL NOTE: Please share your findings as they become available with class via the Google Group. You will get brownie points for this. Once results are shared please used them and build on them.

NOTE: please do HW 13.5 in groups of 3

Using the training dataset, validation dataset and testing dataset in the Criteo bucket perform the following experiments:

- write spark code (borrow from Phase 1 of this project) to train a logistic regression model with various hyperparamters. Do a gridsearch of the hyperparameter space and determine optimal settings using the validation set.
  - Number of buckets for hashing: 1,000, 10,000, ... explore different values here
  - Logistic Regression: regularization term: [1e-6, 1e-3] explore other values here also
  - Logistic Regression: step size: explore different step sizes. Focus on a stepsize of 1 initially.
- Report the AWS cluster configuration that you used and how long in minutes and seconds it takes to complete this job.
- Report in tabular form and using heatmaps the AUC values (https://en.wikipedia.org/wiki/Receiver_operating_characteristic (https://en.wikipedia.org/wiki/Receiver_operating_characteristic)) for the Training, Validation, and Testing datasets.
- Report in tabular form and using heatmaps the logLossTest for the Training, Validation, and Testing datasets.
- Don't forget to put a caption on your tables (above the table) and on your heatmap figures (put caption below figures) detailing the experiment associated with each table or figure (data, algorithm used, parameters and settings explored.
- Discuss the optimal setting to solve this problem in terms of the following:
  - Features
  - Learning algortihm
  - Spark cluster

Justiy your recommendations based on your experimental results and cross reference with table numbers and figure numbers. Also highlight key results with annotations, both textual and line and box based, on your tables and graphs.

In [6]:
```
%%writefile Criteo_Driver_2.py

from time import time, gmtime, strftime
from subprocess import call
from pyspark import SparkContext

execfile('CriteoHelper2.py')

# define parameter space
print '%s: start logistic regression job ...' %(logTime())
numBucketsCTR = [1000, 5000, 10000, 20000, 40000]
lrStep = [20, 10, 5, 1]
regParams = [1e-7, 1e-5, 1e-3, 1e-1]
nSteps = len(numBucketsCTR)*len(lrStep)*len(regParams)
print '%s: bucket sizes: %s' %(logTime(), str(numBucketsCTR))
print '%s: LR steps: %s' %(logTime(), str(lrStep))
print '%s: regularization: %s' %(logTime(), str(regParams))
print '%s: total steps: %d' %(logTime(), nSteps)

# initialize
start = time()
bestModel, bestLogLoss, bestAUC = None, 1e10, 0
sc = SparkContext()

iStep = 1
# grid search
for nBucket in numBucketsCTR:
    # data preparaion
    dTrain, dValidation, dTest = encodeData(sc, nBucket)
    for stp in lrStep:
        for reg in regParams:
            # build model
            print '%s: step %d/%d starts with bucket-%d, step-%d, reg-%.9f, modeling ...' %(logTime(), iSt
ep, nSteps,
                                                                                                   nBucket, stp,
reg)
            model = LogisticRegressionWithSGD.train(dTrain, iterations=500, step=stp,
                                                    regParam=reg, regType='l2', intercept=True)
            # get log loss
            print '%s: evaluating log loss ...' %(logTime())
            logLossVa = evaluateResults(model, dValidation)
            # get AUC
            print '%s: evaluating AUC ...' %(logTime())
            aucVal = getAUCfromRdd(dValidation, model)
            # compare model
```

```
            print '%s: step %d/%d completed, logLoss-%.4f, AUC-%.4f' %(logTime(), iStep, nSteps, logLossV
a, aucVal)
            if logLossVa < bestLogLoss:
                bestLogLoss, bestModel, bestAUC = logLossVa, model, aucVal
            # save all results to s3, in case job crashes - aws s3 cp toy_index.txt s3://w261.data/HW13/to
y.txt
            logName = 's3://w261.data/HW13/criteo_search_log_' + strftime("%d%b%Y_%H%M%S", gmtime())
            call(['aws', 's3', 'cp', '/home/hadoop/lei/criteo_search_log.txt', logName, '--region', 'us-we
st-2'])
            iStep += 1

# use best model to evaluate
print '%s: grid search completed in %.2f minutes!' %(logTime(), (time()-start)/60.0)
print '%s: our best model has log loss %.4f and AUC %.4f' %(logTime(), bestLogLoss, bestAUC)

# show results
print '%s: checking log loss for test data ...' %logTime()
logLoss = evaluateResults(bestModel, dTest)
print '%s: checking AUC for test data ...' %logTime()
aucTest = getAUCfromRdd(dTest, bestModel)
print '%s: our best model has log loss %.4f and AUC %.4f on test data.' %(logTime(), logLoss, aucTest)

# save log to s3
print '\n%s: job completes in %.2f minutes!' %(logTime(), (time()-start)/60.0)
logName = 's3://w261.data/HW13/criteo_search_log_' + strftime("%d%b%Y_%H%M%S", gmtime())
call(['aws', 's3', 'cp', '/home/hadoop/lei/criteo_search_log.txt', logName, '--region', 'us-west-2'])
```

```
Overwriting Criteo_Driver_2.py
```

Spark Job Results for Parameter Tuning

- cluster: **1 m3.xlarge master node + 10 m3.xlarge task nodes**
- parameter space:
  - bucket size = [1000, 5000, 10000, 20000, 40000]
  - step = [20, 10, 5, 1]
  - regularization params = [1e-7, 1e-5, 1e-3, 1e-1]
  - total: 4x4x4=64
- job log (https://raw.githubusercontent.com/leiyang-mids/MIDS/master/W261/HW13-Questions/Criteo_grid_search)
- execution time: **300.52** minutes
- best model obtained with **20,000 bucket, 20 steps, and 0.0000001 regularization**
- with best model: test data **log loss: 0.4879, AUC: 0.7527**

In [ ]:

```
# DO NOT change log file name at the end
# m3.xlarge
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--name LeiCriteoJob \
--py-files CriteoHelper2.py \
--num-executors 20 \
--executor-memory '10280m' \
--executor-cores 4 \
--driver-memory '10280m' \
Criteo_Driver_2.py > criteo_search_log.txt

# r3.xlarge
/usr/bin/spark-submit \
--master yarn \
--deploy-mode client \
--name LeiCriteoJob \
--py-files CriteoHelper2.py \
--num-executors 20 \
--executor-memory '20000m' \
--executor-cores 4 \
--driver-memory '20000m' \
Criteo_Driver_2.py > criteo_search_log.txt
```

Grid Search Summary

Time	Bucket	Step	Reg	Log Loss	AUC
2016-04-25 03:16:01	1000	20	0.0000001	0.5031	0.7280
2016-04-25 03:31:14	1000	20	0.00001	0.5031	0.7280

2016-04-25 03:35:59	1000	20	0.001	0.5031	0.7280
2016-04-25 03:40:49	1000	20	0.1	0.5364	0.6930
2016-04-25 03:47:17	1000	10	0.0000001	0.5045	0.7260
2016-04-25 03:50:54	1000	10	0.00001	0.5045	0.7260
2016-04-25 03:54:28	1000	10	0.001	0.5051	0.7250
2016-04-25 03:57:49	1000	10	0.1	0.5364	0.6930
2016-04-25 04:00:29	1000	5	0.0000001	0.5070	0.7220
2016-04-25 04:04:24	1000	5	0.00001	0.5070	0.7220
2016-04-25 04:08:21	1000	5	0.001	0.5075	0.7210
2016-04-25 04:12:12	1000	5	0.1	0.5363	0.6930
2016-04-25 04:13:51	1000	1	0.0000001	0.5192	0.7040
2016-04-25 04:17:51	1000	1	0.00001	0.5192	0.7040
2016-04-25 04:21:52	1000	1	0.001	0.5194	0.7040
2016-04-25 04:25:49	1000	1	0.1	0.5372	0.6900
2016-04-25 22:18:46	5000	20	0.0000001	0.4913	0.7470
2016-04-25 22:34:38	5000	20	0.00001	0.4914	0.7470
2016-04-25 22:39:36	5000	20	0.001	0.4931	0.7440
2016-04-25 22:44:14	5000	20	0.1	0.5353	0.6950
2016-04-25 22:50:29	5000	10	0.0000001	0.4956	0.7400
2016-04-25 22:55:23	5000	10	0.00001	0.4956	0.7400
2016-04-25 23:00:17	5000	10	0.001	0.4972	0.7380
2016-04-25 23:04:49	5000	10	0.1	0.5354	0.6950
2016-04-25 23:07:32	5000	5	0.0000001	0.5006	0.7330
2016-04-25 23:12:29	5000	5	0.00001	0.5006	0.7330
2016-04-25 23:17:28	5000	5	0.001	0.5016	0.7320
2016-04-25 23:22:07	5000	5	0.1	0.5353	0.6950
2016-04-25 23:23:46	5000	1	0.0000001	0.5168	0.7080
2016-04-25 23:28:26	5000	1	0.00001	0.5168	0.7080
2016-04-25 23:32:55	5000	1	0.001	0.5170	0.7080
2016-04-25 23:37:26	5000	1	0.1	0.5362	0.6920
2016-04-25 23:40:34	10000	20	0.0000001	0.4889	0.7500
2016-04-25 23:56:11	10000	20	0.00001	0.4889	0.7500
2016-04-26 00:01:38	10000	20	0.001	0.4913	0.7470
2016-04-26 00:06:38	10000	20	0.1	0.5351	0.6960
2016-04-26 00:13:19	10000	10	0.0000001	0.4940	0.7430
2016-04-26 00:18:42	10000	10	0.00001	0.4940	0.7430
2016-04-26 00:24:11	10000	10	0.001	0.4958	0.7410
2016-04-26 00:28:50	10000	10	0.1	0.5352	0.6960
2016-04-26 03:41:33	10000	5	0.0000001	0.4995	0.7350
2016-04-26 03:57:35	10000	5	0.00001	0.4995	0.7350
2016-04-26 04:03:00	10000	5	0.001	0.5006	0.7330
2016-04-26 04:08:07	10000	5	0.1	0.5351	0.6960
2016-04-26 04:09:49	10000	1	0.0000001	0.5163	0.7090
2016-04-26 04:14:38	10000	1	0.00001	0.5163	0.7090
2016-04-26 04:19:32	10000	1	0.001	0.5166	0.7090
2016-04-26 04:24:23	10000	1	0.1	0.5360	0.6930
2016-04-26 02:00:30	20000	20	0.0000001	**0.4879**	**0.752**

2016-04-26 02:17:10	20000	20	0.00001	0.4879	0.7520
2016-04-26 02:23:14	20000	20	0.001	0.4906	0.7490
2016-04-26 02:28:33	20000	20	0.1	0.5352	0.6960
2016-04-26 02:35:39	20000	10	0.0000001	0.4934	0.7440
2016-04-26 02:41:32	20000	10	0.00001	0.4934	0.7440
2016-04-26 02:47:23	20000	10	0.001	0.4953	0.7420
2016-04-26 02:52:34	20000	10	0.1	0.5352	0.6960
2016-04-26 02:55:27	20000	5	0.0000001	0.4992	0.7350
2016-04-26 03:01:13	20000	5	0.00001	0.4992	0.7350
2016-04-26 03:06:59	20000	5	0.001	0.5003	0.7340
2016-04-26 03:12:20	20000	5	0.1	0.5351	0.6960
2016-04-26 03:14:03	20000	1	0.0000001	0.5163	0.7090
2016-04-26 03:19:12	20000	1	0.00001	0.5163	0.7090
2016-04-26 03:24:32	20000	1	0.001	0.5165	0.7090
2016-04-26 03:29:37	20000	1	0.1	0.5361	0.6930

Discussion

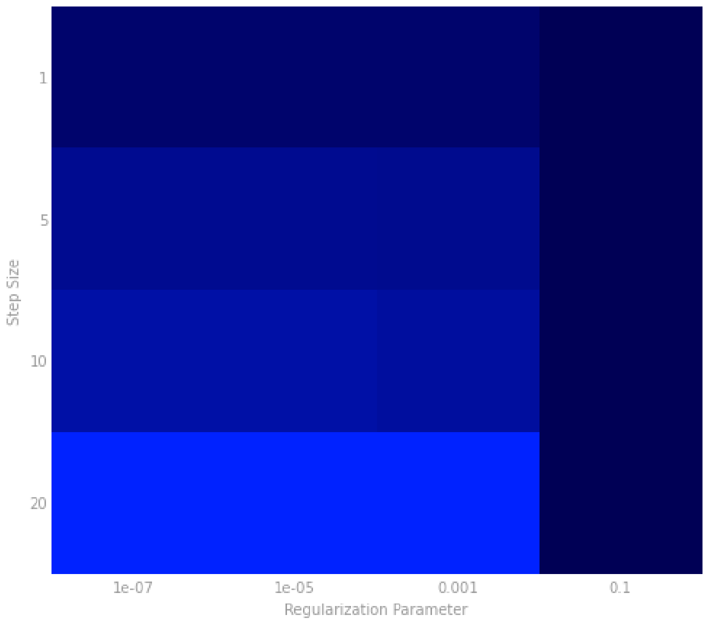
- we can see larger bucket size yields better results, this indicates that hashing with **small** bucket size will not provide optimal feature. The grid search should continue with bigger bucket size in order to obtain better results.
- as bucket size increases, input dimension also increase, but due to sparcity, the training time of logistic regression doesn't change too much.
- smaller regularization parameter also give better results, this indicates the convergence process is not so smooth, we need to take baby step in order to avoid slippery slope.
- finally, larger step is better than smaller step, which gives better stochastic gradient descent performance.
- below we show the heatmap of LogLoss for each bucket size:

In [5]:
```python
from matplotlib.colors import LinearSegmentedColormap
import matplotlib.pyplot as plt

def preparePlot(xticks, yticks, figsize=(10.5, 6), hideLabels=False, gridColor='#999999',
                gridWidth=1.0):
    """Template for generating the plot layout."""
    plt.close()
    fig, ax = plt.subplots(figsize=figsize, facecolor='white', edgecolor='white')
    ax.axes.tick_params(labelcolor='#999999', labelsize='10')
    for axis, ticks in [(ax.get_xaxis(), xticks), (ax.get_yaxis(), yticks)]:
        axis.set_ticks_position('none')
        axis.set_ticks(ticks)
        axis.label.set_color('#999999')
        if hideLabels: axis.set_ticklabels([])
    plt.grid(color=gridColor, linewidth=gridWidth, linestyle='-')
    map(lambda position: ax.spines[position].set_visible(False), ['bottom', 'top', 'left', 'right'])
    return fig, ax

def showHeatMap(stepSizes, regParams, logLoss):
    numRows, numCols = len(stepSizes), len(regParams)
    logLoss = np.array(logLoss)
    logLoss.shape = (numRows, numCols)

    fig, ax = preparePlot(np.arange(0, numCols, 1), np.arange(0, numRows, 1), figsize=(8, 7),
                          hideLabels=True, gridWidth=0.)
    ax.set_xticklabels(regParams), ax.set_yticklabels(stepSizes)
    ax.set_xlabel('Regularization Parameter'), ax.set_ylabel('Step Size')

    colors = LinearSegmentedColormap.from_list('blue', ['#0022ff', '#000055'], gamma=.2)
    image = plt.imshow(logLoss,interpolation='nearest', aspect='auto', cmap = colors)
    #pass
    plt.show()
```

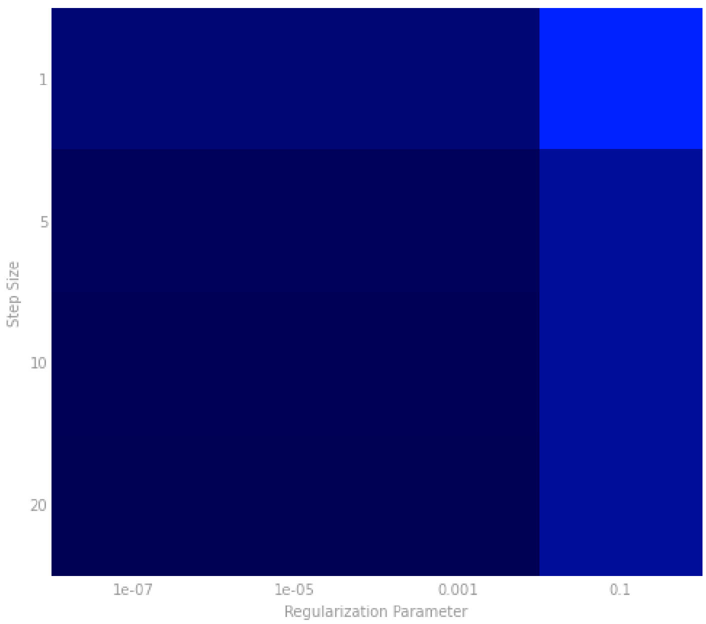
In [8]:
```python
%matplotlib inline
import numpy as np

buckets = [1000, 5000, 10000, 20000]
steps = [1, 5, 10, 20]
regParam = [1e-7, 1e-5, 1e-3, 1e-1]
```

```
llMap = {b:np.eye(len(steps)) for b in buckets}
aucMap = {b:np.eye(len(steps)) for b in buckets}

with open('PlotGridSearch', 'r') as f:
    header = f.readline()
    for l in f.readlines():
        ts, bucket, step, reg, ll, auc = l.strip().split('\t')
        llMap[int(bucket)][steps.index(int(step))][regParam.index(float(reg))] = float(ll)
        aucMap[int(bucket)][steps.index(int(step))][regParam.index(float(reg))] = float(auc)

for b in buckets:
    print 'Log Loss, bucket size: %d' %b
    showHeatMap(steps, regParam, llMap[b])
    print 'AUC, bucket size: %d' %b
    showHeatMap(steps, regParam, aucMap[b])
```

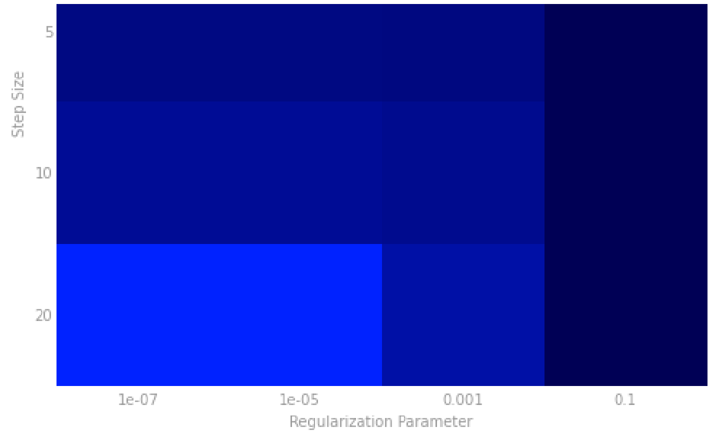
```
Log Loss, bucket size: 1000
```



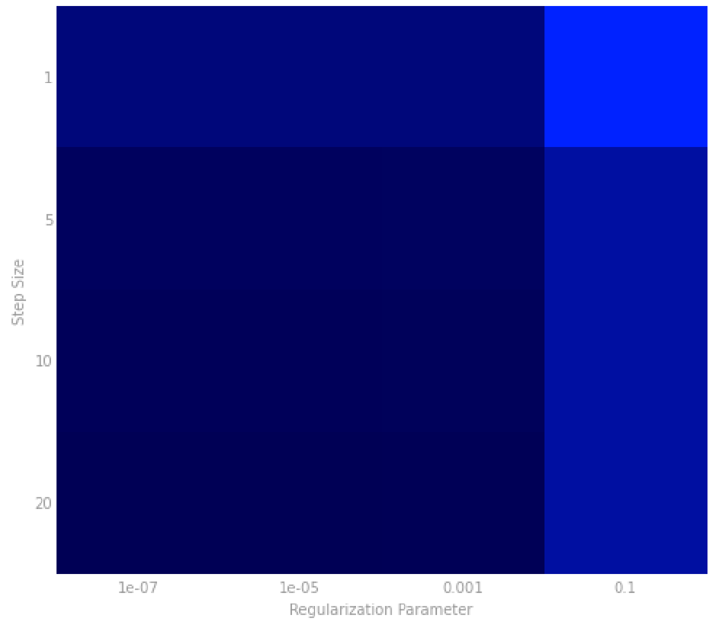

```
AUC, bucket size: 1000
```



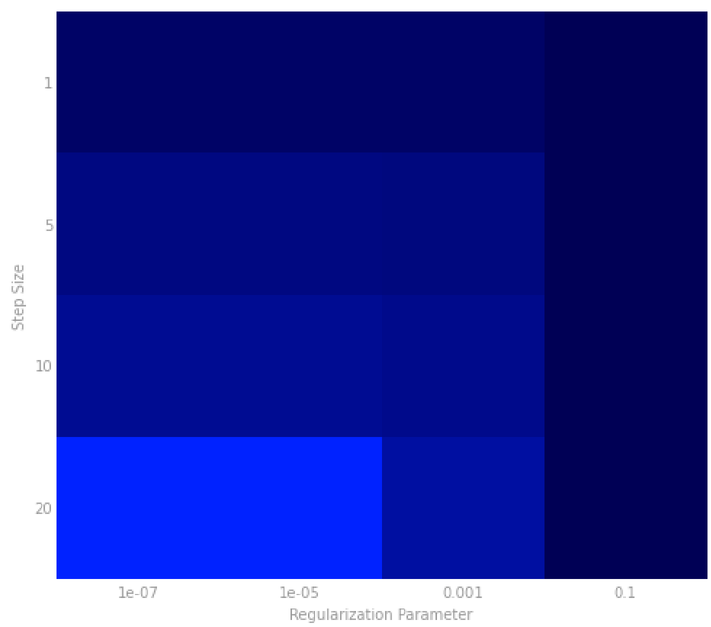

```
Log Loss, bucket size: 5000
```



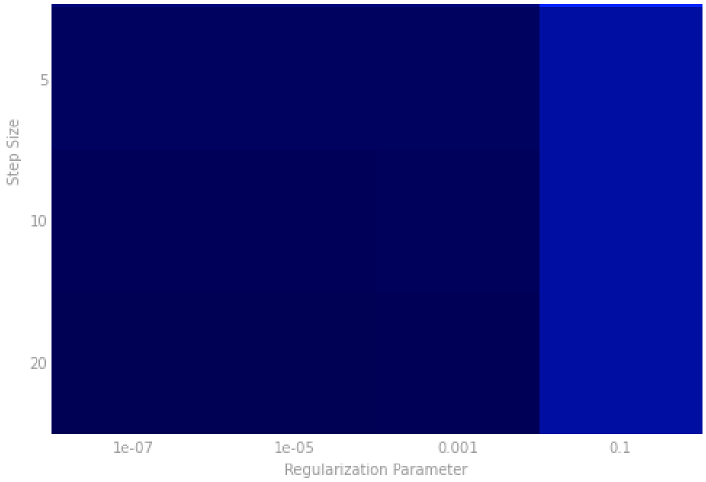
AUC, bucket size: 5000



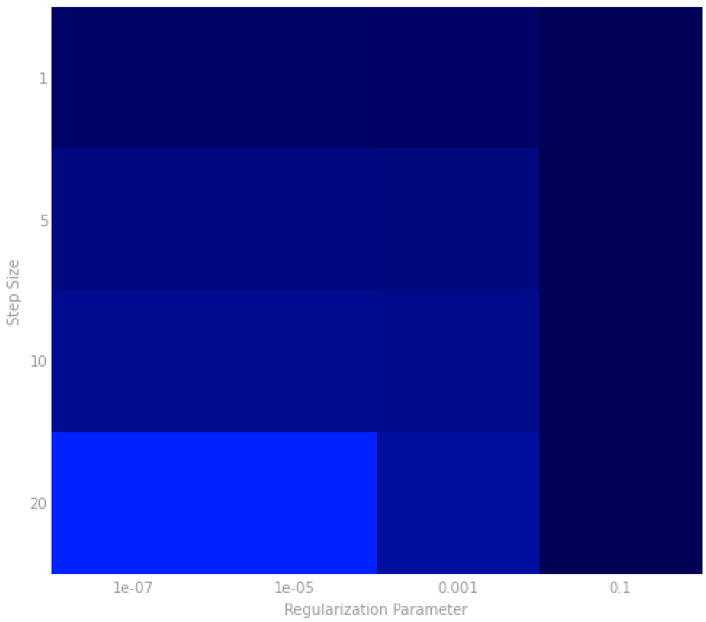
Log Loss, bucket size: 10000



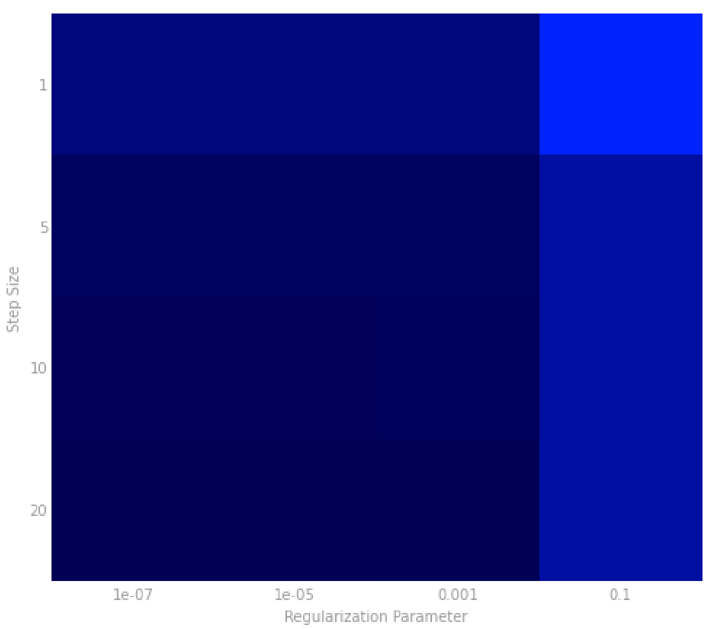
AUC, bucket size: 10000




```
Log Loss, bucket size: 20000
```




```
AUC, bucket size: 20000
```



HW13.6 Heritage Healthcare Prize (OPTIONAL)

The slides for Week 13 Live session contain background information for the HHH competition to predict the number of days a patient will spend in hospital. Please review the sldies. All the data, RCode, documentation, and slides for HHH problem are located at:

https://www.dropbox.com/sh/upt0j2q44ncrn1m/AAApdpXNYaEFy8KbMoE90-KSa?dl=0 (https://www.dropbox.com/sh/upt0j2q44ncrn1m/AAApdpXNYaEFy8KbMoE90-KSa?dl=0)

In particular have a look at the following R Code:

https://www.dropbox.com/s/jltk9z7jkc1o856/mainDriver.R?dl=0 (https://www.dropbox.com/s/jltk9z7jkc1o856/mainDriver.R?dl=0)

This code runs and will produce a baseline submission file for HHH.

Challenge:

Rewrite this code in Spark (all steps) and produce a submission file. Report your experimental setup and experimental times.

Improve the predictive quality of your system through activities such as:

-- new features -- feature transformations -- data sampling/deletion -- third party data -- learning algorithms -- hyperparameter tuning -- etc.

State your assumptions (Training data, validation data, held out test data). Report your experimental setup and experimental times, and evaluation metrics versus the baseline submission code provided above and discuss.

In [ ]:

Start HDFS

In [8]:

```
!/usr/local/Cellar/hadoop/2*/sbin/start-yarn.sh
!/usr/local/Cellar/hadoop/2*/sbin/start-dfs.sh
!/usr/local/Cellar/hadoop/2*/sbin/mr-jobhistory-daemon.sh --config /usr/local/Cellar/hadoop/2*/libexec/et
c/hadoop/ start historyserver
```

```
starting yarn daemons
resourcemanager running as process 17585. Stop it first.
localhost: nodemanager running as process 17686. Stop it first.
Starting namenodes on [localhost]
localhost: starting namenode, logging to /usr/local/Cellar/hadoop/2.7.1/libexec/logs/hadoop-leiyang-nameno
de-Leis-MacBook-Pro.local.out
localhost: starting datanode, logging to /usr/local/Cellar/hadoop/2.7.1/libexec/logs/hadoop-leiyang-datano
de-Leis-MacBook-Pro.local.out
Starting secondary namenodes [0.0.0.0]
0.0.0.0: starting secondarynamenode, logging to /usr/local/Cellar/hadoop/2.7.1/libexec/logs/hadoop-leiyang
-secondarynamenode-Leis-MacBook-Pro.local.out
historyserver running as process 18148. Stop it first.
```

Stop HDFS

In [6]:

```
!/usr/local/Cellar/hadoop/2*/sbin/stop-yarn.sh
```