DATASCI W261: Machine Learning at Scale

W261-2 Spring 2016
Week 12: Criteo CTR Project
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Click-Through Rate Prediction Lab

This lab covers the steps for creating a click-through rate (CTR) prediction pipeline. You will work with the Criteo Labs (http://labs.criteo.com/) dataset that was used for a recent Kaggle competition (https://www.kaggle.com/c/criteo-display-ad-challenge).

This lab will cover:

- *Part 1:* Featurize categorical data using one-hot-encoding (OHE)
- *Part 2:* Construct an OHE dictionary
- *Part 3:* Parse CTR data and generate OHE features
  - *Visualization 1:* Feature frequency
- *Part 4:* CTR prediction and logloss evaluation
  - *Visualization 2:* ROC curve
- *Part 5:* Reduce feature dimension via feature hashing
  - *Visualization 3:* Hyperparameter heat map

Note that, for reference, you can look up the details of the relevant Spark methods in Spark's Python API (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD) and the relevant NumPy methods in the NumPy Reference (http://docs.scipy.org/doc/numpy/reference/index.html)

In [1]:
```
labVersion = 'MIDS_MLS_week12_v_0_9'
```

In [2]:
```
# We will need these so we can reload modules as we modify them
%load_ext autoreload
%autoreload 2
```

In [3]:
```
import os
import sys
spark_home = os.environ.get('SPARK_HOME', None)

if not spark_home:
    raise ValueError('SPARK_HOME enviroment variable is not s
et')
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 1.5.0-cdh5.5.0
      /_/

Using Python version 2.7.11 (default, Dec  6 2015 18:08:32)
SparkContext available as sc, HiveContext available as sqlCon
text.
```

Part 1: Featurize categorical data using one-hot-encoding

(1a) One-hot-encoding

We would like to develop code to convert categorical features to numerical ones, and to build intuition, we will work with a sample unlabeled dataset with three data points, with each data point representing an animal. The first feature indicates the type of animal (bear, cat, mouse); the second feature describes the animal's color (black, tabby); and the third (optional) feature describes what the animal eats (mouse, salmon).

In a one-hot-encoding (OHE) scheme, we want to represent each tuple of `(featureID, category)` via its own binary feature. We can do this in Python by creating a dictionary that maps each tuple to a distinct integer, where the integer corresponds to a binary feature. To start, manually enter the entries in the OHE dictionary associated with the sample dataset by mapping the tuples to consecutive integers starting from zero, ordering the tuples first by featureID and next by category.

Later in this lab, we'll use OHE dictionaries to transform data points into compact lists of features that can be used in machine learning algorithms.

In [4]:
```
# Data for manual OHE
# Note: the first data point does not include any value for t
he optional third feature
sampleOne = [(0, 'mouse'), (1, 'black')]
sampleTwo = [(0, 'cat'), (1, 'tabby'), (2, 'mouse')]
sampleThree =  [(0, 'bear'), (1, 'black'), (2, 'salmon')]
sampleDataRDD = sc.parallelize([sampleOne, sampleTwo, sampleT
hree])
```

In [5]:
```
# TODO: Replace <FILL IN> with appropriate code
sampleOHEDictManual = {}
sampleOHEDictManual[(0,'bear')] = 0
sampleOHEDictManual[(0,'cat')] = 1
sampleOHEDictManual[(0,'mouse')] = 2
sampleOHEDictManual[(1, 'black')] = 3
sampleOHEDictManual[(1, 'tabby')] = 4
sampleOHEDictManual[(2, 'mouse')] = 5
sampleOHEDictManual[(2, 'salmon')] = 6
```

In [6]:
```
%%writefile test_helper.py
# A testing helper
#https://pypi.python.org/pypi/test_helper/0.2
import hashlib

class TestFailure(Exception):
  pass
class PrivateTestFailure(Exception):
  pass

class Test(object):
  passed = 0
  numTests = 0
  failFast = False
  private = False

  @classmethod
  def setFailFast(cls):
    cls.failFast = True

  @classmethod
  def setPrivateMode(cls):
    cls.private = True

  @classmethod
  def assertTrue(cls, result, msg=""):
    cls.numTests += 1
    if result == True:
      cls.passed += 1
      print "1 test passed."
    else:
      print "1 test failed. " + msg
      if cls.failFast:
        if cls.private:
          raise PrivateTestFailure(msg)
        else:
          raise TestFailure(msg)

  @classmethod
  def assertEquals(cls, var, val, msg=""):
    cls.assertTrue(var == val, msg)

  @classmethod
  def assertEqualsHashed(cls, var, hashed_val, msg=""):
    cls.assertEquals(cls._hash(var), hashed_val, msg)

  @classmethod
  def printStats(cls):
    print "{0} / {1} test(s) passed.".format(cls.passed, cls.
numTests)
```

```
Overwriting test_helper.py
```

In [7]:
```
# TEST One-hot-encoding (1a)
from test_helper import Test

Test.assertEqualsHashed(sampleOHEDictManual[(0,'bear')],
                        'b6589fc6ab0dc82cf12099d1c2d40ab994e8
410c',
                        "incorrect value for sampleOHEDictMan
ual[(0,'bear')]")
Test.assertEqualsHashed(sampleOHEDictManual[(0,'cat')],
                        '356a192b7913b04c54574d18c28d46e63954
28ab',
                        "incorrect value for sampleOHEDictMan
ual[(0,'cat')]")
Test.assertEqualsHashed(sampleOHEDictManual[(0,'mouse')],
                        'da4b9237bacccdf19c0760cab7aec4a83590
10b0',
                        "incorrect value for sampleOHEDictMan
ual[(0,'mouse')]")
Test.assertEqualsHashed(sampleOHEDictManual[(1,'black')],
                        '77de68daecd823babbb58edb1c8e14d7106e
83bb',
                        "incorrect value for sampleOHEDictMan
ual[(1,'black')]")
Test.assertEqualsHashed(sampleOHEDictManual[(1,'tabby')],
                        '1b6453892473a467d07372d45eb05abc2031
647a',
                        "incorrect value for sampleOHEDictMan
ual[(1,'tabby')]")
Test.assertEqualsHashed(sampleOHEDictManual[(2,'mouse')],
                        'ac3478d69a3c81fa62e60f5c3696165a4e5e
6ac4',
                        "incorrect value for sampleOHEDictMan
ual[(2,'mouse')]")
Test.assertEqualsHashed(sampleOHEDictManual[(2,'salmon')],
                        'c1dfd96eea8cc2b62785275bca38ac261256
e278',
                        "incorrect value for sampleOHEDictMan
ual[(2,'salmon')]")
Test.assertEquals(len(sampleOHEDictManual.keys()), 7,
                  'incorrect number of keys in sampleOHEDictM
anual')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

(1b) Sparse vectors

Data points can typically be represented with a small number of non-zero OHE features relative to the total number of features that occur in the dataset. By leveraging this sparsity and using sparse vector representations of OHE data, we can reduce storage and computational burdens. Below are a few sample vectors represented as dense numpy arrays. Use [SparseVector (https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.linalg.SparseVector)](https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.linalg.SparseVector) to represent them in a sparse fashion, and verify that both the sparse and dense representations yield the same results when computing [dot products (http://en.wikipedia.org/wiki/Dot_product)](http://en.wikipedia.org/wiki/Dot_product) (we will later use MLlib to train classifiers via gradient descent, and MLlib will need to compute dot products between SparseVectors and dense parameter vectors).

Use `SparseVector(size, *args)` to create a new sparse vector where size is the length of the vector and args is either a dictionary, a list of (index, value) pairs, or two separate arrays of indices and values (sorted by index). You'll need to create a sparse vector representation of each dense vector `aDense` and `bDense`.

In [8]:
```
import numpy as np
from pyspark.mllib.linalg import SparseVector
```

In [9]:
```
# TODO: Replace <FILL IN> with appropriate code
aDense = np.array([0., 3., 0., 4.])
aSparse = SparseVector(4, {1: 3., 3: 4.})

bDense = np.array([0., 0., 0., 1.])
bSparse = SparseVector(4, {3: 1.})

w = np.array([0.4, 3.1, -1.4, -.5])
print aDense.dot(w)
print aSparse.dot(w)
print bDense.dot(w)
print bSparse.dot(w)
```

```
7.3
7.3
-0.5
-0.5
```

In [10]:
```
# TEST Sparse Vectors (1b)
Test.assertTrue(isinstance(aSparse, SparseVector), 'aSparse n
eeds to be an instance of SparseVector')
Test.assertTrue(isinstance(bSparse, SparseVector), 'aSparse n
eeds to be an instance of SparseVector')
Test.assertTrue(aDense.dot(w) == aSparse.dot(w),
                'dot product of aDense and w should equal dot
 product of aSparse and w')
Test.assertTrue(bDense.dot(w) == bSparse.dot(w),
                'dot product of bDense and w should equal dot
 product of bSparse and w')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

(1c) OHE features as sparse vectors

Now let's see how we can represent the OHE features for points in our sample dataset. Using the mapping defined by the OHE dictionary from Part (1a), manually define OHE features for the three sample data points using SparseVector format. Any feature that occurs in a point should have the value 1.0. For example, the `DenseVector` for a point with features 2 and 4 would be `[0.0, 0.0, 1.0, 0.0, 1.0, 0.0, 0.0]`.

In [ ]:
```
# Reminder of the sample features
# sampleOne = [(0, 'mouse'), (1, 'black')]
# sampleTwo = [(0, 'cat'), (1, 'tabby'), (2, 'mouse')]
# sampleThree =  [(0, 'bear'), (1, 'black'), (2, 'salmon')]
```

In [11]:
```
# TODO: Replace <FILL IN> with appropriate code
sampleOneOHEFeatManual = SparseVector(7, {2: 1., 3: 1.})
sampleTwoOHEFeatManual = SparseVector(7, {1: 1., 4: 1., 5:1.}
)
sampleThreeOHEFeatManual = SparseVector(7, {0: 1., 3: 1., 6:
1.,})
```

In [12]:
```
# TEST OHE Features as sparse vectors (1c)
Test.assertTrue(isinstance(sampleOneOHEFeatManual, SparseVect
or),
                'sampleOneOHEFeatManual needs to be a SparseV
ector')
Test.assertTrue(isinstance(sampleTwoOHEFeatManual, SparseVect
or),
                'sampleTwoOHEFeatManual needs to be a SparseV
ector')
Test.assertTrue(isinstance(sampleThreeOHEFeatManual, SparseVe
ctor),
                'sampleThreeOHEFeatManual needs to be a Spars
eVector')
Test.assertEqualsHashed(sampleOneOHEFeatManual,
                        'ecc00223d141b7bd0913d52377cee2cf5783
abd6',
                        'incorrect value for sampleOneOHEFeat
Manual')
Test.assertEqualsHashed(sampleTwoOHEFeatManual,
                        '26b023f4109e3b8ab32241938e2e9b9e9d62
720a',
                        'incorrect value for sampleTwoOHEFeat
Manual')
Test.assertEqualsHashed(sampleThreeOHEFeatManual,
                        'c04134fd603ae115395b29dcabe9d0c66fbd
c8a7',
                        'incorrect value for sampleThreeOHEFe
atManual')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

(1d) Define a OHE function

Next we will use the OHE dictionary from Part (1a) to programatically generate OHE features from the original categorical data. First write a function called `oneHotEncoding` that creates OHE feature vectors in `SparseVector` format. Then use this function to create OHE features for the first sample data point and verify that the result matches the result from Part (1c).

In [13]:
```
# TODO: Replace <FILL IN> with appropriate code
def oneHotEncoding(rawFeats, OHEDict, numOHEFeats):
    """Produce a one-hot-encoding from a list of features and
 an OHE dictionary.

    Note:
        You should ensure that the indices used to create a S
parseVector are sorted.

    Args:
        rawFeats (list of (int, str)): The features correspon
ding to a single observation.  Each
            feature consists of a tuple of featureID and the
feature's value. (e.g. sampleOne)
        OHEDict (dict): A mapping of (featureID, value) to un
ique integer.
        numOHEFeats (int): The total number of unique OHE fea
tures (combinations of featureID and
            value).

    Returns:
        SparseVector: A SparseVector of length numOHEFeats wi
th indicies equal to the unique
            identifiers for the (featureID, value) combinatio
ns that occur in the observation and
            with values equal to 1.0.
    """
    sparseVecDict = {}

    for i in rawFeats:
        featureID = OHEDict[i]
        sparseVecDict[featureID] = 1.

    return SparseVector(numOHEFeats, sparseVecDict)


# Calculate the number of features in sampleOHEDictManual
numSampleOHEFeats = len(sampleOHEDictManual)

# Run oneHotEnoding on sampleOne
sampleOneOHEFeat = oneHotEncoding(sampleOne, sampleOHEDictMan
ual, numSampleOHEFeats)

print sampleOneOHEFeat
```

```
(7,[2,3],[1.0,1.0])
```

In [14]:
```
# TEST Define an OHE Function (1d)
Test.assertTrue(sampleOneOHEFeat == sampleOneOHEFeatManual,
                'sampleOneOHEFeat should equal sampleOneOHEFe
atManual')
Test.assertEquals(sampleOneOHEFeat, SparseVector(7, [2,3], [1
.0,1.0]),
                  'incorrect value for sampleOneOHEFeat')
Test.assertEquals(oneHotEncoding([(1, 'black'), (0, 'mouse')]
, sampleOHEDictManual,
                                 numSampleOHEFeats), SparseVe
ctor(7, [2,3], [1.0,1.0]),
                  'incorrect definition for oneHotEncoding')
```

```
1 test passed.
1 test passed.
1 test passed.
```

(1e) Apply OHE to a dataset

Finally, use the function from Part (1d) to create OHE features for all 3 data points in the sample dataset.

In [15]:
```
# TODO: Replace <FILL IN> with appropriate code
sampleOHEData = sampleDataRDD.map(lambda x: oneHotEncoding(x,
 sampleOHEDictManual, numSampleOHEFeats))
print sampleOHEData.collect()
```

```
[SparseVector(7, {2: 1.0, 3: 1.0}), SparseVector(7, {1: 1.0,
4: 1.0, 5: 1.0}), SparseVector(7, {0: 1.0, 3: 1.0, 6: 1.0})]
```

In [16]:
```
# TEST Apply OHE to a dataset (1e)
sampleOHEDataValues = sampleOHEData.collect()
Test.assertTrue(len(sampleOHEDataValues) == 3, 'sampleOHEData
 should have three elements')
Test.assertEquals(sampleOHEDataValues[0], SparseVector(7, {2:
 1.0, 3: 1.0}),
                  'incorrect OHE for first sample')
Test.assertEquals(sampleOHEDataValues[1], SparseVector(7, {1:
 1.0, 4: 1.0, 5: 1.0}),
                  'incorrect OHE for second sample')
Test.assertEquals(sampleOHEDataValues[2], SparseVector(7, {0:
 1.0, 3: 1.0, 6: 1.0}),
                  'incorrect OHE for third sample')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

Part 2: Construct an OHE dictionary

(2a) Pair RDD of `(featureID, category)`

To start, create an RDD of distinct `(featureID, category)` tuples. In our sample dataset, the 7 items in the resulting RDD are `(0, 'bear')`, `(0, 'cat')`, `(0, 'mouse')`, `(1, 'black')`, `(1, 'tabby')`, `(2, 'mouse')`, `(2, 'salmon')`. Notably `'black'` appears twice in the dataset but only contributes one item to the RDD: `(1, 'black')`, while `'mouse'` also appears twice and contributes two items: `(0, 'mouse')` and `(2, 'mouse')`. Use [flatMap (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.flatMap)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.flatMap) and [distinct (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.distinct)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.distinct).

In [17]:
```
# TODO: Replace <FILL IN> with appropriate code
sampleDistinctFeats = sampleDataRDD.flatMap(lambda x: x).dist
inct()
```

In [18]:
```
# TEST Pair RDD of (featureID, category) (2a)
Test.assertEquals(sorted(sampleDistinctFeats.collect()),
                  [(0, 'bear'), (0, 'cat'), (0, 'mouse'), (1,
 'black'),
                   (1, 'tabby'), (2, 'mouse'), (2, 'salmon')]
,
                  'incorrect value for sampleDistinctFeats')
```

```
1 test passed.
```

(2b) OHE Dictionary from distinct features

Next, create an RDD of key-value tuples, where each `(featureID, category)` tuple in `sampleDistinctFeats` is a key and the values are distinct integers ranging from 0 to (number of keys - 1). Then convert this RDD into a dictionary, which can be done using the `collectAsMap` action. Note that there is no unique mapping from keys to values, as all we require is that each `(featureID, category)` key be mapped to a unique integer between 0 and the number of keys. In this exercise, any valid mapping is acceptable. Use [zipWithIndex (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.zipWithIndex)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.zipWithIndex) followed by [collectAsMap (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.collectAsMap)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.collectAsMap).

In our sample dataset, one valid list of key-value tuples is: `[((0, 'bear'), 0), ((2, 'salmon'), 1), ((1, 'tabby'), 2), ((2, 'mouse'), 3), ((0, 'mouse'), 4), ((0, 'cat'), 5), ((1, 'black'), 6)]`. The dictionary defined in Part (1a) illustrates another valid mapping between keys and integers.

In [19]:
```
# TODO: Replace <FILL IN> with appropriate code
sampleOHEDict = sampleDistinctFeats.zipWithIndex().collectAsM
ap()
print sampleOHEDict
```

```
{(2, 'mouse'): 3, (0, 'cat'): 5, (0, 'bear'): 0, (2, 'salmon'
): 1, (1, 'tabby'): 2, (1, 'black'): 6, (0, 'mouse'): 4}
```

In [20]:
```
# TEST OHE Dictionary from distinct features (2b)
Test.assertEquals(sorted(sampleOHEDict.keys()),
                  [(0, 'bear'), (0, 'cat'), (0, 'mouse'), (1,
 'black'),
                   (1, 'tabby'), (2, 'mouse'), (2, 'salmon')]
,
                  'sampleOHEDict has unexpected keys')
Test.assertEquals(sorted(sampleOHEDict.values()), range(7), '
sampleOHEDict has unexpected values')
```

```
1 test passed.
1 test passed.
```

(2c) Automated creation of an OHE dictionary

Now use the code from Parts (2a) and (2b) to write a function that takes an input dataset and outputs an OHE dictionary. Then use this function to create an OHE dictionary for the sample dataset, and verify that it matches the dictionary from Part (2b).

In [21]:
```
# TODO: Replace <FILL IN> with appropriate code
def createOneHotDict(inputData):
    """Creates a one-hot-encoder dictionary based on the inpu
t data.

    Args:
        inputData (RDD of lists of (int, str)): An RDD of obs
ervations where each observation is
            made up of a list of (featureID, value) tuples.

    Returns:
        dict: A dictionary where the keys are (featureID, val
ue) tuples and map to values that are
            unique integers.
    """
    return inputData.flatMap(lambda x: x).distinct().zipWithI
ndex().collectAsMap()

sampleOHEDictAuto = createOneHotDict(sampleDataRDD)
print sampleOHEDictAuto
```

```
{(2, 'mouse'): 3, (0, 'cat'): 5, (0, 'bear'): 0, (2, 'salmon'
): 1, (1, 'tabby'): 2, (1, 'black'): 6, (0, 'mouse'): 4}
```

In [22]:
```
# TEST Automated creation of an OHE dictionary (2c)
Test.assertEquals(sorted(sampleOHEDictAuto.keys()),
                  [(0, 'bear'), (0, 'cat'), (0, 'mouse'), (1,
 'black'),
                   (1, 'tabby'), (2, 'mouse'), (2, 'salmon')]
,
                  'sampleOHEDictAuto has unexpected keys')
Test.assertEquals(sorted(sampleOHEDictAuto.values()), range(7
),
                  'sampleOHEDictAuto has unexpected values')
```

```
1 test passed.
1 test passed.
```

Part 3: Parse CTR data and generate OHE features

Before we can proceed, you'll first need to obtain the data from Criteo. If you have already completed this step in the setup lab, just run the cells below and the data will be loaded into the `rawData` variable.

Below is Criteo's data sharing agreement. After you accept the agreement, you can obtain the download URL by right-clicking on the "Download Sample" button and clicking "Copy link address" or "Copy Link Location", depending on your browser. Paste the URL into the `# TODO` cell below. The file is 8.4 MB compressed. The script below will download the file to the virtual machine (VM) and then extract the data.

If running the cell below does not render a webpage, open the [Criteo agreement (http://labs.criteo.com/downloads/2014-kaggle-display-advertising-challenge-dataset/)](http://labs.criteo.com/downloads/2014-kaggle-display-advertising-challenge-dataset/) in a separate browser tab. After you accept the agreement, you can obtain the download URL by right-clicking on the "Download Sample" button and clicking "Copy link address" or "Copy Link Location", depending on your browser. Paste the URL into the `# TODO` cell below.

Note that the download could take a few minutes, depending upon your connection speed.

The Criteo CTR data is for HW12.1 is available here (24.3 Meg, 100,000 Rows):

```
https://www.dropbox.com/s/m4jlnv6rdbqzzhu/dac_sample.txt?dl=0
```

Alternatively you can download the sample data directly by following the instructions contained in the cell below (8M compressed).

In [23]:
```
# Run this code to view Criteo's agreement
# from IPython.lib.display import IFrame

# IFrame("http://labs.criteo.com/downloads/2014-kaggle-displa
y-advertising-challenge-dataset/",
#        600, 350)
```

In [24]:
```
# TODO: Replace <FILL IN> with appropriate code
# Just replace <FILL IN> with the url for dac_sample.tar.gz
import glob
import os.path
import tarfile
import urllib
import urlparse

# Paste url, url should end with: dac_sample.tar.gz
url = 'http://labs.criteo.com/wp-content/uploads/2015/04/dac_
sample.tar.gz'

url = url.strip()
baseDir = os.path.join('data')
inputPath = os.path.join('w261', 'dac_sample.txt')
fileName = os.path.join(baseDir, inputPath)
inputDir = os.path.split(fileName)[0]

def extractTar(check = False):
    # Find the zipped archive and extract the dataset
    tars = glob.glob('dac_sample*.tar.gz*')
    if check and len(tars) == 0:
      return False

    if len(tars) > 0:
        try:
            tarFile = tarfile.open(tars[0])
        except tarfile.ReadError:
            if not check:
                print 'Unable to open tar.gz file.  Check you
r URL.'
            return False

        tarFile.extract('dac_sample.txt', path=inputDir)
        print 'Successfully extracted: dac_sample.txt'
        return True
    else:
        print 'You need to retry the download with the correc
t url.'
        print ('Alternatively, you can upload the dac_sample.
tar.gz file to your Jupyter root ' +
              'directory')
        return False


if os.path.isfile(fileName):
    print 'File is already available. Nothing to do.'
elif extractTar(check = True):
    print 'tar.gz file was already available.'
elif not url.endswith('dac_sample.tar.gz'):
    print 'Check your download url.  Are you downloading the
```

```
File is already available. Nothing to do.
```

In [25]:
```
import os.path
baseDir = os.path.join('data')
inputPath = os.path.join('w261', 'dac_sample.txt')
fileName = os.path.join(baseDir, inputPath)
hdfsFileName = '/user/miki/week12/dac_sample.txt'

!hdfs dfs -copyFromLocal {fileName} {hdfsFileName}

rawData = (sc
           .textFile(hdfsFileName, 2)
           .map(lambda x: x.replace('\t', ',')))  # work with
 either ',' or '\t' separated data
print rawData.take(1)
```

```
copyFromLocal: `/user/miki/week12/dac_sample.txt': File exist
s
[u'0,1,1,5,0,1382,4,15,2,181,1,2,,2,68fd1e64,80e26c9b,fb93613
6,7b4723c4,25c83c98,7e0ccccf,de7995b8,1f89b562,a73ee510,a8cd5
504,b2cb9c98,37c9c164,2824a5f6,1adce6ef,8ba8b39a,891b62e7,e5b
a7672,f54016b9,21ddcdc9,b1252a9d,07b5194c,,3a171ecb,c5c50484,
e8b83407,9727dd16']
```

(3a) Loading and splitting the data

We are now ready to start working with the actual CTR data, and our first task involves splitting it into training, validation, and test sets. Use the [randomSplit method (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.randomSplit)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.randomSplit) with the specified weights and seed to create RDDs storing each of these datasets, and then [cache (https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.cache)](https://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD.cache) each of these RDDs, as we will be accessing them multiple times in the remainder of this lab. Finally, compute the size of each dataset.

In [26]:
```
# TODO: Replace <FILL IN> with appropriate code
weights = [.8, .1, .1]
seed = 42
# Use randomSplit with weights and seed
rawTrainData, rawValidationData, rawTestData = rawData.random
Split(weights, seed)
# Cache the data
rawTrainData.cache()
rawValidationData.cache()
rawTestData.cache()

nTrain = rawTrainData.count()
nVal = rawValidationData.count()
nTest = rawTestData.count()
print nTrain, nVal, nTest, nTrain + nVal + nTest
print rawData.take(1)
```

```
79911 10075 10014 100000
[u'0,1,1,5,0,1382,4,15,2,181,1,2,,2,68fd1e64,80e26c9b,fb93613
6,7b4723c4,25c83c98,7e0ccccf,de7995b8,1f89b562,a73ee510,a8cd5
504,b2cb9c98,37c9c164,2824a5f6,1adce6ef,8ba8b39a,891b62e7,e5b
a7672,f54016b9,21ddcdc9,b1252a9d,07b5194c,,3a171ecb,c5c50484,
e8b83407,9727dd16']
```

In [27]:
```
# TEST Loading and splitting the data (3a)
Test.assertTrue(all([rawTrainData.is_cached, rawValidationDat
a.is_cached, rawTestData.is_cached]),
                'you must cache the split data')
Test.assertEquals(nTrain, 79911, 'incorrect value for nTrain'
)
Test.assertEquals(nVal, 10075, 'incorrect value for nVal')
Test.assertEquals(nTest, 10014, 'incorrect value for nTest')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

(3b) Extract features

We will now parse the raw training data to create an RDD that we can subsequently use to create an OHE dictionary. Note from the `take()` command in Part (3a) that each raw data point is a string containing several fields separated by some delimiter. For now, we will ignore the first field (which is the 0-1 label), and parse the remaining fields (or raw features). To do this, complete the implemention of the `parsePoint` function.

In [28]:
```
# TODO: Replace <FILL IN> with appropriate code
def parsePoint(point):
    """Converts a comma separated string into a list of (feat
ureID, value) tuples.

    Note:
        featureIDs should start at 0 and increase to the numb
er of features - 1.

    Args:
        point (str): A comma separated string where the first
 value is the label and the rest
            are features.

    Returns:
        list: A list of (featureID, value) tuples.
    """
    fields = point.split(',')[1:]
    features = zip(range(len(fields)), fields)
    return features

parsedTrainFeat = rawTrainData.map(parsePoint)

numCategories = (parsedTrainFeat
                 .flatMap(lambda x: x)
                 .distinct()
                 .map(lambda x: (x[0], 1))
                 .reduceByKey(lambda x, y: x + y)
                 .sortByKey()
                 .collect())

print numCategories[2][1]
```

```
855
```

In [29]:
```
# TEST Extract features (3b)
Test.assertEquals(numCategories[2][1], 855, 'incorrect implem
entation of parsePoint')
Test.assertEquals(numCategories[32][1], 4, 'incorrect impleme
ntation of parsePoint')
```

```
1 test passed.
1 test passed.
```

(3c) Create an OHE dictionary from the dataset

Note that parsePoint returns a data point as a list of `(featureID, category)` tuples, which is the same format as the sample dataset studied in Parts 1 and 2 of this lab. Using this observation, create an OHE dictionary using the function implemented in Part (2c). Note that we will assume for simplicity that all features in our CTR dataset are categorical.

In [30]:
```
# TODO: Replace <FILL IN> with appropriate code
ctrOHEDict = createOneHotDict(parsedTrainFeat)
numCtrOHEFeats = len(ctrOHEDict.keys())
print numCtrOHEFeats
print ctrOHEDict[(0, '')]
```

```
233286
36164
```

In [31]:
```
# TEST Create an OHE dictionary from the dataset (3c)
Test.assertEquals(numCtrOHEFeats, 233286, 'incorrect number o
f features in ctrOHEDict')
Test.assertTrue((0, '') in ctrOHEDict, 'incorrect features in
 ctrOHEDict')
```

```
1 test passed.
1 test passed.
```

(3d) Apply OHE to the dataset

Now let's use this OHE dictionary by starting with the raw training data and creating an RDD of [LabeledPoint (http://spark.apache.org/docs/1.3.1/api/python/pyspark.mllib.html#pyspark.mllib.regression.LabeledPoint)](http://spark.apache.org/docs/1.3.1/api/python/pyspark.mllib.html#pyspark.mllib.regression.LabeledPoint) objects using OHE features. To do this, complete the implementation of the `parseOHEPoint` function. Hint: `parseOHEPoint` is an extension of the `parsePoint` function from Part (3b) and it uses the `oneHotEncoding` function from Part (1d).

In [32]:
```
from pyspark.mllib.regression import LabeledPoint
```

In [33]:
```
# TODO: Replace <FILL IN> with appropriate code
def parseOHEPoint(point, OHEDict, numOHEFeats):
    """Obtain the label and feature vector for this raw obser
vation.

    Note:
        You must use the function `oneHotEncoding` in this im
plementation or later portions
        of this lab may not function as expected.

    Args:
        point (str): A comma separated string where the first
 value is the label and the rest
            are features.
        OHEDict (dict of (int, str) to int): Mapping of (feat
ureID, value) to unique integer.
        numOHEFeats (int): The number of unique features in t
he training dataset.

    Returns:
        LabeledPoint: Contains the label for the observation
and the one-hot-encoding of the
            raw features based on the provided OHE dictionary
.
    """
    fields = point.split(',')
    label = fields[0]
    features = zip(range(len(fields[1:])), fields[1:])
    return LabeledPoint(label, oneHotEncoding(features, OHEDi
ct, numOHEFeats))


OHETrainData = rawTrainData.map(lambda point: parseOHEPoint(p
oint, ctrOHEDict, numCtrOHEFeats))
OHETrainData.cache()
print OHETrainData.take(1)

# Check that oneHotEncoding function was used in parseOHEPoin
t
backupOneHot = oneHotEncoding
oneHotEncoding = None
withOneHot = False
try: parseOHEPoint(rawTrainData.take(1)[0], ctrOHEDict, numCt
rOHEFeats)
except TypeError: withOneHot = True
oneHotEncoding = backupOneHot
```

```
[LabeledPoint(0.0, (233286,[386,3077,6799,8264,8862,11800,128
02,16125,17551,18566,29331,33132,39525,55794,61786,81396,8265
9,93573,96929,100677,109699,110646,112132,120260,128596,13239
7,132803,140620,160675,185498,190370,191146,195925,202664,204
273,206055,222737,225958,229942],[1.0,1.0,1.0,1.0,1.0,1.0,1.0
,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,
1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1
.0,1.0]))]
```

In [34]:

```
# TEST Apply OHE to the dataset (3d)
numNZ = sum(parsedTrainFeat.map(lambda x: len(x)).take(5))
numNZAlt = sum(OHETrainData.map(lambda lp: len(lp.features.in
dices)).take(5))
Test.assertEquals(numNZ, numNZAlt, 'incorrect implementation
of parseOHEPoint')
Test.assertTrue(withOneHot, 'oneHotEncoding not present in pa
rseOHEPoint')
```

```
1 test passed.
1 test passed.
```

Visualization 1: Feature frequency

We will now visualize the number of times each of the 233,286 OHE features appears in the training data. We first compute the number of times each feature appears, then bucket the features by these counts. The buckets are sized by powers of 2, so the first bucket corresponds to features that appear exactly once (2^0), the second to features that appear twice (2^1), the third to features that occur between three and four (2^2) times, the fifth bucket is five to eight (2^3) times and so on. The scatter plot below shows the logarithm of the bucket thresholds versus the logarithm of the number of features that have counts that fall in the buckets.

In [35]:
```
def bucketFeatByCount(featCount):
    """Bucket the counts by powers of two."""
    for i in range(11):
        size = 2 ** i
        if featCount <= size:
            return size
    return -1

featCounts = (OHETrainData
              .flatMap(lambda lp: lp.features.indices)
              .map(lambda x: (x, 1))
              .reduceByKey(lambda x, y: x + y))
featCountsBuckets = (featCounts
                     .map(lambda x: (bucketFeatByCount(x[1]),
 1))
                     .filter(lambda (k, v): k != -1)
                     .reduceByKey(lambda x, y: x + y)
                     .collect())
print featCountsBuckets
```

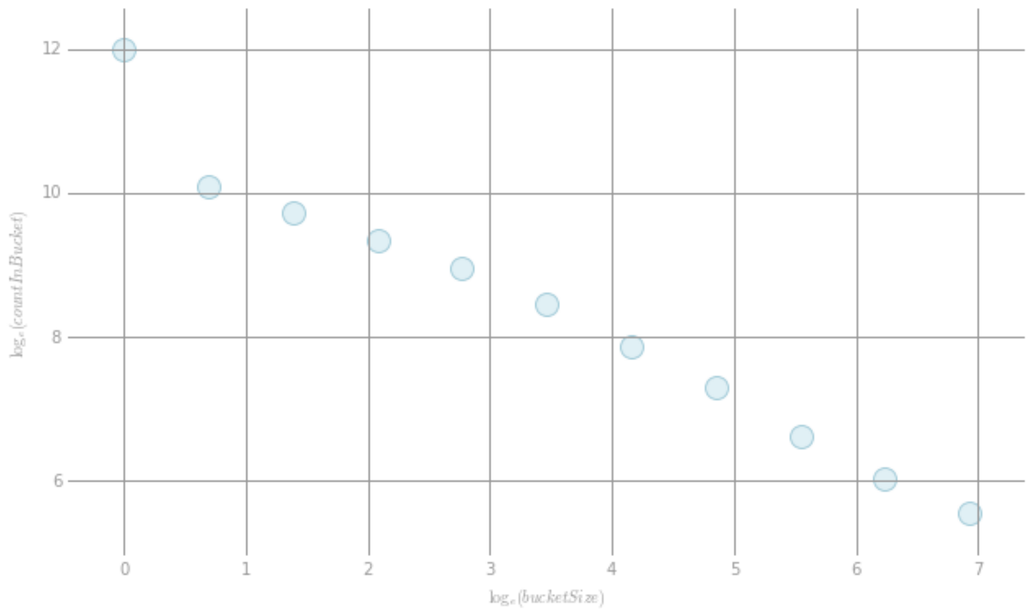
```
[(256, 748), (1024, 255), (2, 24076), (4, 16639), (32, 4755),
 (8, 11440), (64, 2627), (128, 1476), (16, 7752), (512, 414),
 (1, 162813)]
```

In [36]:
```
%matplotlib inline
import matplotlib.pyplot as plt

x, y = zip(*featCountsBuckets)
x, y = np.log(x), np.log(y)

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_yax
is(), 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(Fals
e), ['bottom', 'top', 'left', 'right'])
    return fig, ax

# generate layout and plot data
fig, ax = preparePlot(np.arange(0, 10, 1), np.arange(4, 14, 2
))
ax.set_xlabel(r'$\log_e(bucketSize)$'), ax.set_ylabel(r'$\log
_e(countInBucket)$')
plt.scatter(x, y, s=14**2, c='#d6ebf2', edgecolors='#8cbfd0',
 alpha=0.75)
pass
```



(3e) Handling unseen features

We naturally would like to repeat the process from Part (3d), e.g., to compute OHE features for the validation and test datasets. However, we must be careful, as some categorical values will likely appear in new data that did not exist in the training data. To deal with this situation, update the `oneHotEncoding()` function from Part (1d) to ignore previously unseen categories, and then compute OHE features for the validation data.

In [37]:

```
# TODO: Replace <FILL IN> with appropriate code
def oneHotEncoding(rawFeats, OHEDict, numOHEFeats):
    """Produce a one-hot-encoding from a list of features and
 an OHE dictionary.

    Note:
        If a (featureID, value) tuple doesn't have a correspo
nding key in OHEDict it should be
        ignored.

    Args:
        rawFeats (list of (int, str)): The features correspon
ding to a single observation.  Each
            feature consists of a tuple of featureID and the
feature's value. (e.g. sampleOne)
        OHEDict (dict): A mapping of (featureID, value) to un
ique integer.
        numOHEFeats (int): The total number of unique OHE fea
tures (combinations of featureID and
            value).

    Returns:
        SparseVector: A SparseVector of length numOHEFeats wi
th indicies equal to the unique
            identifiers for the (featureID, value) combinatio
ns that occur in the observation and
            with values equal to 1.0.
    """
    sparseVecDict = {}

    for i in rawFeats:
        if i in OHEDict:
            featureID = OHEDict[i]
            sparseVecDict[featureID] = 1.

    return SparseVector(numOHEFeats, sparseVecDict)

OHEValidationData = rawValidationData.map(lambda point: parse
OHEPoint(point, ctrOHEDict, numCtrOHEFeats))
OHEValidationData.cache()
print OHEValidationData.take(1)
```

```
[LabeledPoint(0.0, (233286,[7576,9187,15510,21585,31213,36164
,39525,49198,61786,66603,67218,68211,68311,73035,76672,81329,
81396,91981,96929,98450,109699,110946,117015,121552,141711,14
6496,147649,171128,184132,184687,185498,194763,198537,201039,
210717,213588,222162,222626,227709],[1.0,1.0,1.0,1.0,1.0,1.0,
1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1
.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.
0,1.0,1.0]))]
```

In [38]:
```
# TEST Handling unseen features (3e)
numNZVal = (OHEValidationData
            .map(lambda lp: len(lp.features.indices))
            .sum())
Test.assertEquals(numNZVal, 372080, 'incorrect number of feat
ures')
```

```
1 test passed.
```

Part 4: CTR prediction and logloss evaluation

(4a) Logistic regression

We are now ready to train our first CTR classifier. A natural classifier to use in this setting is logistic regression, since it models the probability of a click-through event rather than returning a binary response, and when working with rare events, probabilistic predictions are useful. First use [LogisticRegressionWithSGD (https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.classification.LogisticRegressionWithSGD)](https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.classification.LogisticRegressionWithSGD) to train a model using `OHETrainData` with the given hyperparameter configuration. `LogisticRegressionWithSGD` returns a [LogisticRegressionModel (https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.regression.LogisticRegressionModel)](https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.regression.LogisticRegressionModel). Next, use the `LogisticRegressionModel.weights` and `LogisticRegressionModel.intercept` attributes to print out the model's parameters. Note that these are the names of the object's attributes and should be called using a syntax like `model.weights` for a given `model`.

In [39]:
```
from pyspark.mllib.classification import LogisticRegressionWi
thSGD

# fixed hyperparameters
numIters = 50
stepSize = 10.
regParam = 1e-6
regType = 'l2'
includeIntercept = True
```

In [40]:
```
# TODO: Replace <FILL IN> with appropriate code
model0 = LogisticRegressionWithSGD.train(OHETrainData,
                                         iterations=numIters,

                                         step=stepSize,
                                         regParam=regParam,
                                         regType=regType,
                                         intercept=includeInt
ercept)
sortedWeights = sorted(model0.weights)
print sortedWeights[:5], model0.intercept
```

```
[-0.45899236853575609, -0.37973707648623956, -0.3699655826675
3304, -0.36934962879928263, -0.32697945415010637] 0.564550840
25
```

In [41]:
```
# TEST Logistic regression (4a)
Test.assertTrue(np.allclose(model0.intercept,  0.56455084025)
, 'incorrect value for model0.intercept')
Test.assertTrue(np.allclose(sortedWeights[0:5],
                [-0.45899236853575609, -0.37973707648623956,
-0.36996558266753304,
                 -0.36934962879928263, -0.32697945415010637])
, 'incorrect value for model0.weights')
```

```
1 test passed.
1 test passed.
```

(4b) Log loss

Throughout this lab, we will use log loss to evaluate the quality of models. Log loss is defined as:

$$\ell_{log}(p, y) = \begin{cases} -\log(p) & \text{if } y = 1 \\ -\log(1-p) & \text{if } y = 0 \end{cases}$$

where p is a probability between 0 and 1 and y is a label of either 0 or 1. Log loss is a standard evaluation criterion when predicting rare-events such as click-through rate prediction (it is also the criterion used in the [Criteo Kaggle competition (https://www.kaggle.com/c/criteo-display-ad-challenge)](https://www.kaggle.com/c/criteo-display-ad-challenge)). Write a function to compute log loss, and evaluate it on some sample inputs.

In [42]:
```
# TODO: Replace <FILL IN> with appropriate code
from math import log

def computeLogLoss(p, y):
    """Calculates the value of log loss for a given probabilt
y 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 (ep
silon) 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
    if p == 0:
        prob = epsilon
    elif p == 1:
        prob = 1 - epsilon
    else:
        prob = p * 1.
    return -(y * log(prob) + (1 - y) * log(1 - prob))

print computeLogLoss(.5, 1)
print computeLogLoss(.5, 0)
print computeLogLoss(.99, 1)
print computeLogLoss(.99, 0)
print computeLogLoss(.01, 1)
print computeLogLoss(.01, 0)
print computeLogLoss(0, 1)
print computeLogLoss(1, 1)
print computeLogLoss(1, 0)
```

```
0.69314718056
0.69314718056
0.0100503358535
4.60517018599
4.60517018599
0.0100503358535
25.3284360229
1.00000008275e-11
25.3284359402
```

In [43]:
```
# TEST Log loss (4b)
Test.assertTrue(np.allclose([computeLogLoss(.5, 1), computeLo
gLoss(.01, 0), computeLogLoss(.01, 1)],
                            [0.69314718056, 0.0100503358535,
4.60517018599]),
                'computeLogLoss is not correct')
Test.assertTrue(np.allclose([computeLogLoss(0, 1), computeLog
Loss(1, 1), computeLogLoss(1, 0)],
                            [25.3284360229, 1.00000008275e-11
, 25.3284360229]),
                'computeLogLoss needs to bound p away from 0
and 1 by epsilon')
```

```
1 test passed.
1 test passed.
```

(4c) Baseline log loss

Next we will use the function we wrote in Part (4b) to compute the baseline log loss on the training data. A very simple yet natural baseline model is one where we always make the same prediction independent of the given datapoint, setting the predicted value equal to the fraction of training points that correspond to click-through events (i.e., where the label is one). Compute this value (which is simply the mean of the training labels), and then use it to compute the training log loss for the baseline model. The log loss for multiple observations is the mean of the individual log loss values.

In [44]:
```
# TODO: Replace <FILL IN> with appropriate code
# Note that our dataset has a very high click-through rate by
 design
# In practice click-through rate can be one to two orders of
magnitude lower
classOneFracTrain = OHETrainData.map(lambda x: x.label).reduc
e(lambda x, y: x + y)/OHETrainData.count()
print classOneFracTrain

logLossTrBase = (OHETrainData
                 .map(lambda x: computeLogLoss(classOneFracTr
ain, x.label))
                 .reduce(lambda x, y: x + y)) / OHETrainData.
count()
print 'Baseline Train Logloss = {0:.3f}\n'.format(logLossTrBa
se)
```

```
0.22717773523
Baseline Train Logloss = 0.536
```

In [45]:
```
# TEST Baseline log loss (4c)
Test.assertTrue(np.allclose(classOneFracTrain, 0.22717773523)
, 'incorrect value for classOneFracTrain')
Test.assertTrue(np.allclose(logLossTrBase, 0.535844), 'incorr
ect value for logLossTrBase')
```

```
1 test passed.
1 test passed.
```

(4d) Predicted probability

In order to compute the log loss for the model we trained in Part (4a), we need to write code to generate predictions from this model. Write a function that computes the raw linear prediction from this logistic regression model and then passes it through a sigmoid function (http://en.wikipedia.org/wiki/Sigmoid_function) $\sigma(t) = (1 + e^{-t})^{-1}$ to return the model's probabilistic prediction. Then compute probabilistic predictions on the training data.

Note that when incorporating an intercept into our predictions, we simply add the intercept to the value of the prediction obtained from the weights and features. Alternatively, if the intercept was included as the first weight, we would need to add a corresponding feature to our data where the feature has the value one. This is not the case here.

In [46]:
```
# TODO: Replace <FILL IN> with appropriate code
from math import exp #  exp(-t) = e^-t

def getP(x, w, intercept):
    """Calculate the probability for an observation given a s
et 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 fea
tures 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))

trainingPredictions = OHETrainData.map(lambda x: getP(x.featu
res, model0.weights, model0.intercept))

print trainingPredictions.take(5)
```

```
[0.3026288202391113, 0.10362661997434078, 0.2836342478387561,
 0.17846102057880123, 0.5389775379218853]
```

In [47]:
```
# TEST Predicted probability (4d)
Test.assertTrue(np.allclose(trainingPredictions.sum(), 18135.
4834348),
                'incorrect value for trainingPredictions')
```

```
1 test passed.
```

(4e) Evaluate the model

We are now ready to evaluate the quality of the model we trained in Part (4a). To do this, first write a general function that takes as input a model and data, and outputs the log loss. Then run this function on the OHE training data, and compare the result with the baseline log loss.

In [48]:
```
# TODO: Replace <FILL IN> with appropriate code
def evaluateResults(model, data):
    """Calculates the log loss for the data given the model.

    Args:
        model (LogisticRegressionModel): A trained logistic r
egression model.
        data (RDD of LabeledPoint): Labels and features for e
ach observation.

    Returns:
        float: Log loss for the data.
    """
    return (data
            .map(lambda x: computeLogLoss(getP(x.features, mo
del.weights, model.intercept), x.label))
            .reduce(lambda x, y: x + y)) / data.count()


logLossTrLR0 = evaluateResults(model0, OHETrainData)
print ('OHE Features Train Logloss:\n\tBaseline = {0:.3f}\n\t
LogReg = {1:.3f}'
       .format(logLossTrBase, logLossTrLR0))
```

```
OHE Features Train Logloss:
	Baseline = 0.536
	LogReg = 0.457
```

In [49]:
```
# TEST Evaluate the model (4e)
Test.assertTrue(np.allclose(logLossTrLR0, 0.456903), 'incorre
ct value for logLossTrLR0')
```

```
1 test passed.
```

(4f) Validation log loss

Next, following the same logic as in Parts (4c) and 4(e), compute the validation log loss for both the baseline and logistic regression models. Notably, the baseline model for the validation data should still be based on the label fraction from the training dataset.

In [50]:
```
# TODO: Replace <FILL IN> with appropriate code
logLossValBase = (OHEValidationData
                  .map(lambda x: computeLogLoss(classOneFracTr
ain, x.label))
                  .reduce(lambda x, y: x + y)) / OHEValidation
Data.count()

logLossValLR0 = evaluateResults(model0, OHEValidationData)
print ('OHE Features Validation Logloss:\n\tBaseline = {0:.3f
}\n\tLogReg = {1:.3f}'
       .format(logLossValBase, logLossValLR0))
```

```
OHE Features Validation Logloss:
        Baseline = 0.528
        LogReg = 0.457
```

In [51]:
```
# TEST Validation log loss (4f)
Test.assertTrue(np.allclose(logLossValBase, 0.527603), 'incor
rect value for logLossValBase')
Test.assertTrue(np.allclose(logLossValLR0, 0.456957), 'incorr
ect value for logLossValLR0')
```

```
1 test passed.
1 test passed.
```

Visualization 2: ROC curve

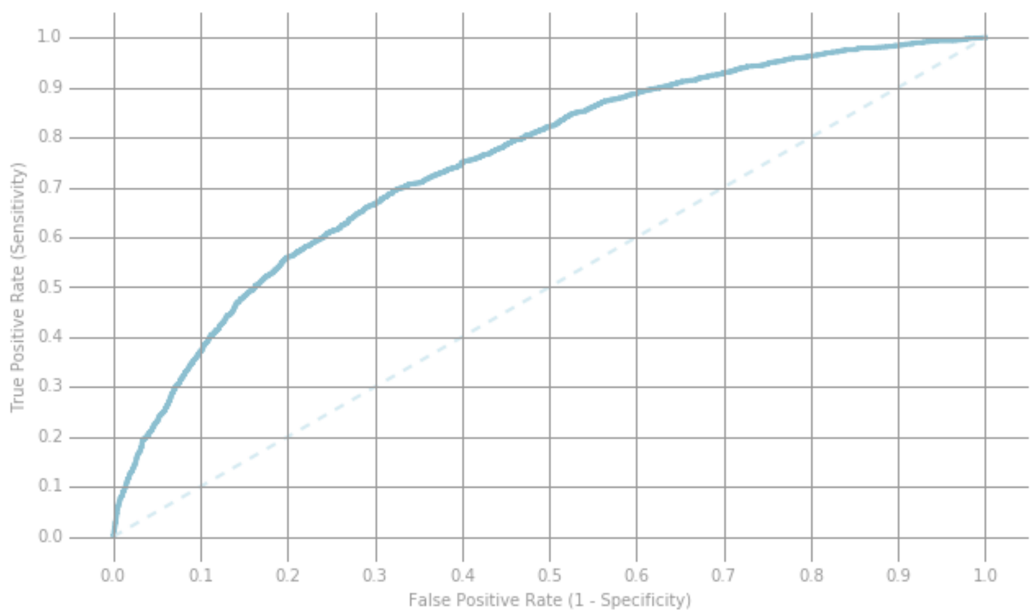
We will now visualize how well the model predicts our target. To do this we generate a plot of the ROC curve. The ROC curve shows us the trade-off between the false positive rate and true positive rate, as we liberalize the threshold required to predict a positive outcome. A random model is represented by the dashed line.

In [52]:
```
labelsAndScores = OHEValidationData.map(lambda lp:
                                            (lp.label, getP(l
p.features, model0.weights, model0.intercept)))
labelsAndWeights = labelsAndScores.collect()
labelsAndWeights.sort(key=lambda (k, v): v, reverse=True)
labelsByWeight = np.array([k for (k, v) in labelsAndWeights])

length = labelsByWeight.size
truePositives = labelsByWeight.cumsum()
numPositive = truePositives[-1]
falsePositives = np.arange(1.0, length + 1, 1.) - truePositiv
es

truePositiveRate = truePositives / numPositive
falsePositiveRate = falsePositives / (length - numPositive)

# Generate layout and plot data
fig, ax = preparePlot(np.arange(0., 1.1, 0.1), np.arange(0.,
1.1, 0.1))
ax.set_xlim(-.05, 1.05), ax.set_ylim(-.05, 1.05)
ax.set_ylabel('True Positive Rate (Sensitivity)')
ax.set_xlabel('False Positive Rate (1 - Specificity)')
plt.plot(falsePositiveRate, truePositiveRate, color='#8cbfd0'
, linestyle='-', linewidth=3.)
plt.plot((0., 1.), (0., 1.), linestyle='--', color='#d6ebf2',
 linewidth=2.)  # Baseline model
pass
```



Part 5: Reduce feature dimension via feature hashing

(5a) Hash function

As we just saw, using a one-hot-encoding featurization can yield a model with good statistical accuracy. However, the number of distinct categories across all features is quite large -- recall that we observed 233K categories in the training data in Part (3c). Moreover, the full Kaggle training dataset includes more than 33M distinct categories, and the Kaggle dataset itself is just a small subset of Criteo's labeled data. Hence, featurizing via a one-hot-encoding representation would lead to a very large feature vector. To reduce the dimensionality of the feature space, we will use feature hashing.

Below is the hash function that we will use for this part of the lab. We will first use this hash function with the three sample data points from Part (1a) to gain some intuition. Specifically, run code to hash the three sample points using two different values for `numBuckets` and observe the resulting hashed feature dictionaries.

In [53]:
```
from collections import defaultdict
import hashlib

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

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

    Args:
        numBuckets (int): Number of buckets to use as feature
s.
        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 whic
h represent the buckets that the
            features have been hashed to.  The value for a gi
ven key will contain the count of the
            (featureID, value) tuples that have hashed to tha
t key.
    """
    mapping = {}
    for ind, category in rawFeats:
        featureString = category + str(ind)
        mapping[featureString] = int(int(hashlib.md5(featureS
tring).hexdigest(), 16) % numBuckets)
    if(printMapping): print mapping
    sparseFeatures = defaultdict(float)
    for bucket in mapping.values():
        sparseFeatures[bucket] += 1.0
    return dict(sparseFeatures)

# Reminder of the sample values:
# sampleOne = [(0, 'mouse'), (1, 'black')]
# sampleTwo = [(0, 'cat'), (1, 'tabby'), (2, 'mouse')]
# sampleThree =  [(0, 'bear'), (1, 'black'), (2, 'salmon')]
```

In [54]:
```
# TODO: Replace <FILL IN> with appropriate code
# Use four buckets
sampOneFourBuckets = hashFunction(4, sampleOne, True)
sampTwoFourBuckets = hashFunction(4, sampleTwo, True)
sampThreeFourBuckets = hashFunction(4, sampleThree, True)

# Use one hundred buckets
sampOneHundredBuckets = hashFunction(100, sampleOne, True)
sampTwoHundredBuckets = hashFunction(100, sampleTwo, True)
sampThreeHundredBuckets = hashFunction(100, sampleThree, True
)

print '\t\t 4 Buckets \t\t\t 100 Buckets'
print 'SampleOne:\t {0}\t\t {1}'.format(sampOneFourBuckets, s
ampOneHundredBuckets)
print 'SampleTwo:\t {0}\t\t {1}'.format(sampTwoFourBuckets, s
ampTwoHundredBuckets)
print 'SampleThree:\t {0}\t {1}'.format(sampThreeFourBuckets,
 sampThreeHundredBuckets)
```

```
{'black1': 2, 'mouse0': 3}
{'cat0': 0, 'tabby1': 0, 'mouse2': 2}
{'bear0': 0, 'black1': 2, 'salmon2': 1}
{'black1': 14, 'mouse0': 31}
{'cat0': 40, 'tabby1': 16, 'mouse2': 62}
{'bear0': 72, 'black1': 14, 'salmon2': 5}
                 4 Buckets                       100 Buckets
SampleOne:       {2: 1.0, 3: 1.0}                {14: 1.0, 31
: 1.0}
SampleTwo:       {0: 2.0, 2: 1.0}                {40: 1.0, 16
: 1.0, 62: 1.0}
SampleThree:     {0: 1.0, 1: 1.0, 2: 1.0}        {72: 1.0, 5:
 1.0, 14: 1.0}
```

In [55]:
```
# TEST Hash function (5a)
Test.assertEquals(sampOneFourBuckets, {2: 1.0, 3: 1.0}, 'inco
rrect value for sampOneFourBuckets')
Test.assertEquals(sampThreeHundredBuckets, {72: 1.0, 5: 1.0,
14: 1.0},
                  'incorrect value for sampThreeHundredBucket
s')
```

```
1 test passed.
1 test passed.
```

(5b) Creating hashed features

Next we will use this hash function to create hashed features for our CTR datasets. First write a function that uses the hash function from Part (5a) with numBuckets = $2^{15} \approx 33K$ to create a `LabeledPoint` with hashed features stored as a `SparseVector`. Then use this function to create new training, validation and test datasets with hashed features. Hint: `parseHashPoint` is similar to `parseOHEPoint` from Part (3d).

In [56]:
```
# TODO: Replace <FILL IN> with appropriate code
def parseHashPoint(point, numBuckets):
    """Create a LabeledPoint for this observation using hashi
ng.

    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.
    """

    fields = point.split(',')
    label = fields[0]
    features = zip(range(len(fields[1:])), fields[1:])

    return LabeledPoint(label, SparseVector(numBuckets, hashF
unction(numBuckets, features)))

numBucketsCTR = 2 ** 15
hashTrainData = rawTrainData.map(lambda x: parseHashPoint(x,
numBucketsCTR))
hashTrainData.cache()
hashValidationData = rawValidationData.map(lambda x: parseHas
hPoint(x, numBucketsCTR))
hashValidationData.cache()
hashTestData = rawTestData.map(lambda x: parseHashPoint(x, nu
mBucketsCTR))
hashTestData.cache()

print hashTrainData.take(1)
```

```
[LabeledPoint(0.0, (32768,[1305,2883,3807,4814,4866,4913,6952
,7117,9985,10316,11512,11722,12365,13893,14735,15816,16198,17
761,19274,21604,22256,22563,22785,24855,25202,25533,25721,264
87,26656,27668,28211,29152,29402,29873,30039,31484,32493,3270
8],[1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1
.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.
0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0]))]
```

In [57]:
```
# TEST Creating hashed features (5b)
hashTrainDataFeatureSum = sum(hashTrainData
                              .map(lambda lp: len(lp.features
.indices))
                              .take(20))
hashTrainDataLabelSum = sum(hashTrainData
                            .map(lambda lp: lp.label)
                            .take(100))
hashValidationDataFeatureSum = sum(hashValidationData
                                   .map(lambda lp: len(lp.fea
tures.indices))
                                   .take(20))
hashValidationDataLabelSum = sum(hashValidationData
                                 .map(lambda lp: lp.label)
                                 .take(100))
hashTestDataFeatureSum = sum(hashTestData
                             .map(lambda lp: len(lp.features.
indices))
                             .take(20))
hashTestDataLabelSum = sum(hashTestData
                           .map(lambda lp: lp.label)
                           .take(100))

Test.assertEquals(hashTrainDataFeatureSum, 772, 'incorrect nu
mber of features in hashTrainData')
Test.assertEquals(hashTrainDataLabelSum, 24.0, 'incorrect lab
els in hashTrainData')
Test.assertEquals(hashValidationDataFeatureSum, 776,
                  'incorrect number of features in hashValida
tionData')
Test.assertEquals(hashValidationDataLabelSum, 16.0, 'incorrec
t labels in hashValidationData')
Test.assertEquals(hashTestDataFeatureSum, 774, 'incorrect num
ber of features in hashTestData')
Test.assertEquals(hashTestDataLabelSum, 23.0, 'incorrect labe
ls in hashTestData')
```

```
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
1 test passed.
```

(5c) Sparsity

Since we have 33K hashed features versus 233K OHE features, we should expect OHE features to be sparser. Verify this hypothesis by computing the average sparsity of the OHE and the hashed training datasets.

Note that if you have a `SparseVector` named `sparse`, calling `len(sparse)` returns the total number of features, not the number features with entries. `SparseVector` objects have the attributes `indices` and `values` that contain information about which features are nonzero. Continuing with our example, these can be accessed using `sparse.indices` and `sparse.values`, respectively.

In [58]:

```
# TODO: Replace <FILL IN> with appropriate code
def computeSparsity(data, d, n):
    """Calculates the average sparsity for the features in an
 RDD of LabeledPoints.

    Args:
        data (RDD of LabeledPoint): The LabeledPoints to use
in the sparsity calculation.
        d (int): The total number of features.
        n (int): The number of observations in the RDD.

    Returns:
        float: The average of the ratio of features in a poin
t to total features.
    """
    return (data
            .map(lambda x: len(x.features.indices) / float(d)
)
            .reduce(lambda x, y: x + y)) / n

averageSparsityHash = computeSparsity(hashTrainData, numBucke
tsCTR, nTrain)
averageSparsityOHE = computeSparsity(OHETrainData, numCtrOHEF
eats, nTrain)

print 'Average OHE Sparsity: {0:.7e}'.format(averageSparsityO
HE)
print 'Average Hash Sparsity: {0:.7e}'.format(averageSparsity
Hash)
```

```
Average OHE Sparsity: 1.6717677e-04
Average Hash Sparsity: 1.1805561e-03
```

In [59]:
```
# TEST Sparsity (5c)
Test.assertTrue(np.allclose(averageSparsityOHE, 1.6717677e-04
),
                'incorrect value for averageSparsityOHE')
Test.assertTrue(np.allclose(averageSparsityHash, 1.1805561e-0
3),
                'incorrect value for averageSparsityHash')
```

```
1 test passed.
1 test passed.
```

(5d) Logistic model with hashed features

Now let's train a logistic regression model using the hashed features. Run a grid search to find suitable hyperparameters for the hashed features, evaluating via log loss on the validation data. Note: This may take a few minutes to run. Use `1` and `10` for `stepSizes` and `1e-6` and `1e-3` for `regParams`.

In [60]:
```
numIters = 500
regType = 'l2'
includeIntercept = True

# Initialize variables using values from initial model traini
ng
bestModel = None
bestLogLoss = 1e10
```

In [61]:
```
# TODO: Replace <FILL IN> with appropriate code
stepSizes = [1, 10]
regParams = [1e-3, 1e-6]
for stepSize in stepSizes:
    for regParam in regParams:
        model = (LogisticRegressionWithSGD
                 .train(hashTrainData, numIters, stepSize, re
gParam=regParam, regType=regType,
                        intercept=includeIntercept))
        logLossVa = evaluateResults(model, hashValidationData
)
        print ('\tstepSize = {0:.1f}, regParam = {1:.0e}: log
loss = {2:.3f}'
               .format(stepSize, regParam, logLossVa))
        if (logLossVa < bestLogLoss):
            bestModel = model
            bestLogLoss = logLossVa

print ('Hashed Features Validation Logloss:\n\tBaseline = {0:
.3f}\n\tLogReg = {1:.7f}'
       .format(logLossValBase, bestLogLoss))
```

```
        stepSize = 1.0, regParam = 1e-03: logloss = 0.475
        stepSize = 1.0, regParam = 1e-06: logloss = 0.475
        stepSize = 10.0, regParam = 1e-03: logloss = 0.452
        stepSize = 10.0, regParam = 1e-06: logloss = 0.450
Hashed Features Validation Logloss:
        Baseline = 0.528
        LogReg = 0.4497401
```

In [62]:
```
# TEST Logistic model with hashed features (5d)
Test.assertTrue(np.allclose(bestLogLoss, 0.4497401), 'incorre
ct value for bestLogLoss')
```

```
1 test passed.
```

Visualization 3: Hyperparameter heat map

We will now perform a visualization of an extensive hyperparameter search. Specifically, we will create a heat map where the brighter colors correspond to lower values of `logLoss`.

The search was run using six step sizes and six values for regularization, which required the training of thirty-six separate models. We have included the results below, but omitted the actual search to save time.

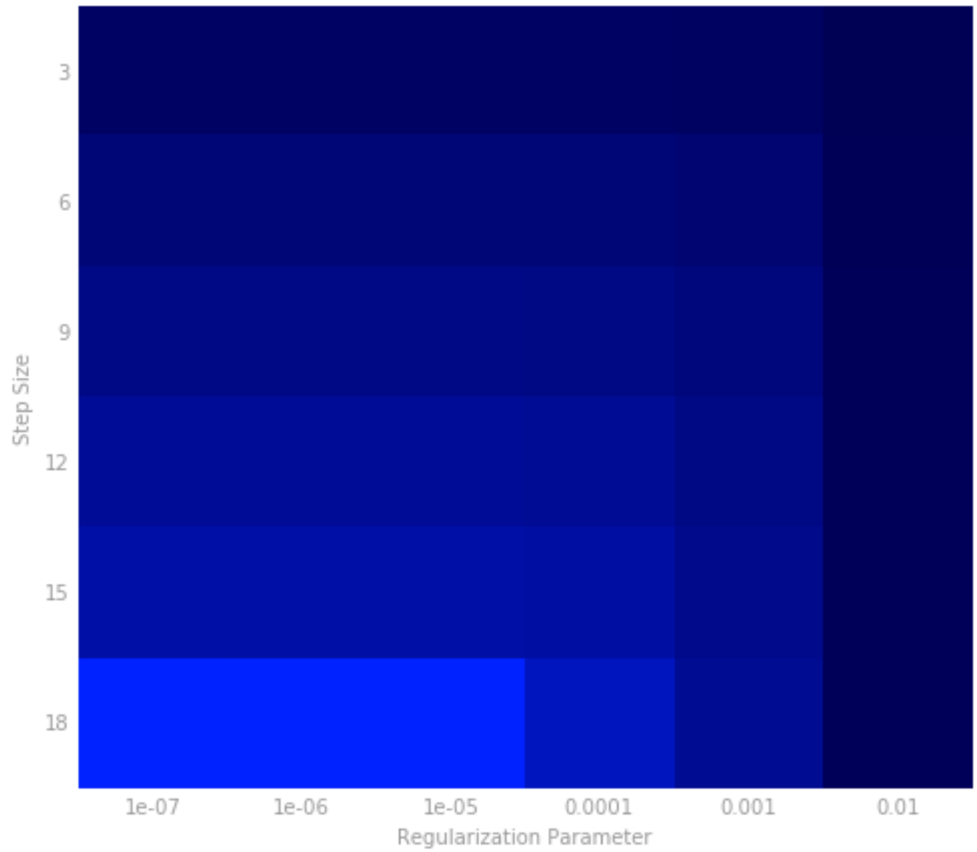
In [63]:
```
from matplotlib.colors import LinearSegmentedColormap

# Saved parameters and results.  Eliminate the time required
to run 36 models
stepSizes = [3, 6, 9, 12, 15, 18]
regParams = [1e-7, 1e-6, 1e-5, 1e-4, 1e-3, 1e-2]
logLoss = np.array([[ 0.45808431,  0.45808493,  0.45809113,
0.45815333,  0.45879221,  0.46556321],
                    [ 0.45188196,  0.45188306,  0.4518941,
0.4520051,   0.45316284,  0.46396068],
                    [ 0.44886478,  0.44886613,  0.44887974,
0.44902096,  0.4505614,   0.46371153],
                    [ 0.44706645,  0.4470698,   0.44708102,
0.44724251,  0.44905525,  0.46366507],
                    [ 0.44588848,  0.44589365,  0.44590568,
0.44606631,  0.44807106,  0.46365589],
                    [ 0.44508948,  0.44509474,  0.44510274,
0.44525007,  0.44738317,  0.46365405]])

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('Ste
p Size')

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



(5e) Evaluate on the test set

Finally, evaluate the best model from Part (5d) on the test set. Compare the resulting log loss with the baseline log loss on the test set, which can be computed in the same way that the validation log loss was computed in Part (4f).

In [64]:
```
# TODO: Replace <FILL IN> with appropriate code
# Log loss for the best model from (5d)
logLossTest = evaluateResults(bestModel, hashTestData)

# Log loss for the baseline model
logLossTestBaseline = (hashTestData
                       .map(lambda x: computeLogLoss(classOne
FracTrain, x.label))
                       .reduce(lambda x, y: x + y)) / hashTes
tData.count()

print ('Hashed Features Test Log Loss:\n\tBaseline = {0:.3f}\
n\tLogReg = {1:.3f}'
       .format(logLossTestBaseline, logLossTest))
```

```
Hashed Features Test Log Loss:
        Baseline = 0.537
        LogReg = 0.457
```

In [65]:
```
# TEST Evaluate on the test set (5e)
Test.assertTrue(np.allclose(logLossTestBaseline, 0.537438),
                'incorrect value for logLossTestBaseline')
Test.assertTrue(np.allclose(logLossTest, 0.4572551687), 'inco
rrect value for logLossTest')
```

```
1 test passed.
1 test passed.
```