Homework 4

October 23, 2015

1 Homework 4

1.1 Alex Pine, akp258

1.1.1 Question 1: Topic modeling code

```
In [ ]: # Hack to get python to look for the pip modules before the OS X versions.
        # This ensures the newest version of the 'six' library is used, which gensim requires.
        import sys
        sys.path.insert(0, '/Library/Python/2.7/site-packages')
        import gensim
```

1.a: Prepare document corpus Using the UC Irvine's "Daily Kos" weblog corpus.

```
In [65]: from gensim import corpora, models

         corpus = corpora.UciCorpus('docword.kos.txt', fname_vocab='vocab.kos.txt')
```

1.b Prepare Document Corpus Train LDA models with default parameters. gensim's LDA module defaults to 100 topics.

```
In [66]: # Defaults to num_topics=100
         default_model = models.LdaMulticore(corpus, id2word=corpus.create_dictionary(), workers=4)
```

```
WARNING:gensim.models.ldamulticore:too few updates, training might not converge; consider increasing the
```

```
In [70]: def print_top_topics(model, num_topics):
             print 'Number of topics:', model.num_topics
             for i, topic in enumerate(default_model.print_topics(num_topics=num_topics, num_words=6)):
                 print 'Topic', str(i+1), ':', topic

         print_top_topics(default_model, 100)
```

```
Number of topics: 100
Topic 1 : 0.013*bush + 0.011*campaign + 0.007*kerry + 0.007*democratic + 0.006*senate + 0.005*time
Topic 2 : 0.016*november + 0.011*bush + 0.008*republicans + 0.008*poll + 0.007*senate + 0.007*house
Topic 3 : 0.014*iraq + 0.011*kerry + 0.010*bush + 0.008*war + 0.005*news + 0.005*campaign
Topic 4 : 0.027*bush + 0.010*kerry + 0.007*war + 0.007*general + 0.006*campaign + 0.005*people
Topic 5 : 0.007*bush + 0.006*iraq + 0.005*campaign + 0.005*democrats + 0.005*senate + 0.004*news
Topic 6 : 0.012*dean + 0.008*iowa + 0.008*kerry + 0.007*campaign + 0.007*bush + 0.007*general
Topic 7 : 0.008*bush + 0.008*democratic + 0.007*war + 0.007*iraq + 0.005*november + 0.005*kerry
Topic 8 : 0.017*bush + 0.013*kerry + 0.008*million + 0.007*republicans + 0.006*administration + 0.005*se
Topic 9 : 0.008*bush + 0.007*primary + 0.006*states + 0.006*iraq + 0.006*democratic + 0.006*house
Topic 10 : 0.016*bush + 0.009*kerry + 0.007*iraq + 0.007*state + 0.006*war + 0.005*house
```

```
Topic 11 : 0.013*bush + 0.008*poll + 0.007*kerry + 0.007*november + 0.007*house + 0.007*president
Topic 12 : 0.018*bush + 0.012*kerry + 0.007*iraq + 0.007*war + 0.006*dean + 0.005*poll
Topic 13 : 0.025*bush + 0.009*kerry + 0.007*administration + 0.006*people + 0.006*general + 0.005*presi
Topic 14 : 0.015*kerry + 0.012*edwards + 0.012*dean + 0.010*democratic + 0.008*primary + 0.008*bush
Topic 15 : 0.013*party + 0.012*bush + 0.011*democratic + 0.006*state + 0.006*kerry + 0.006*war
Topic 16 : 0.023*november + 0.011*bush + 0.007*media + 0.007*senate + 0.007*poll + 0.006*democratic
Topic 17 : 0.016*bush + 0.010*kerry + 0.007*administration + 0.005*war + 0.005*time + 0.005*vote
Topic 18 : 0.007*bush + 0.006*house + 0.006*people + 0.005*national + 0.005*democratic + 0.005*party
Topic 19 : 0.020*bush + 0.019*kerry + 0.010*democratic + 0.008*percent + 0.008*house + 0.007*poll
Topic 20 : 0.010*war + 0.010*bush + 0.009*iraq + 0.007*cheney + 0.007*campaign + 0.006*president
Topic 21 : 0.014*bush + 0.009*kerry + 0.008*house + 0.008*november + 0.007*general + 0.006*democratic
Topic 22 : 0.007*iraq + 0.007*bush + 0.006*republicans + 0.006*state + 0.005*party + 0.005*war
Topic 23 : 0.025*bush + 0.016*kerry + 0.012*percent + 0.009*poll + 0.008*president + 0.006*war
Topic 24 : 0.018*bush + 0.015*kerry + 0.009*iraq + 0.007*war + 0.007*november + 0.007*poll
Topic 25 : 0.016*kerry + 0.008*edwards + 0.007*dean + 0.007*clark + 0.006*war + 0.006*poll
Topic 26 : 0.016*november + 0.008*bush + 0.007*house + 0.006*governor + 0.006*state + 0.006*poll
Topic 27 : 0.012*bush + 0.009*november + 0.009*party + 0.008*house + 0.007*war + 0.007*republicans
Topic 28 : 0.019*bush + 0.009*iraq + 0.008*kerry + 0.007*president + 0.006*people + 0.006*war
Topic 29 : 0.020*bush + 0.014*kerry + 0.007*poll + 0.006*president + 0.006*democratic + 0.006*dean
Topic 30 : 0.016*bush + 0.014*kerry + 0.007*war + 0.006*iraq + 0.006*million + 0.005*administration
Topic 31 : 0.019*kerry + 0.013*bush + 0.008*democratic + 0.008*poll + 0.008*dean + 0.007*edwards
Topic 32 : 0.007*state + 0.007*kerry + 0.006*election + 0.006*vote + 0.006*senate + 0.005*republican
Topic 33 : 0.010*bush + 0.010*republican + 0.007*states + 0.007*republicans + 0.007*senate + 0.006*state
Topic 34 : 0.020*bush + 0.009*administration + 0.007*dean + 0.005*party + 0.004*media + 0.004*democrats
Topic 35 : 0.010*bush + 0.006*president + 0.006*campaign + 0.005*voters + 0.005*iraq + 0.004*states
Topic 36 : 0.016*iraq + 0.011*bush + 0.010*war + 0.007*president + 0.006*kerry + 0.005*states
Topic 37 : 0.017*bush + 0.016*kerry + 0.007*democratic + 0.007*house + 0.006*president + 0.006*democrats
Topic 38 : 0.012*kerry + 0.010*campaign + 0.009*dean + 0.007*bush + 0.006*democratic + 0.005*people
Topic 39 : 0.022*bush + 0.010*kerry + 0.008*administration + 0.007*campaign + 0.006*president + 0.006*el
Topic 40 : 0.009*dean + 0.006*bush + 0.006*media + 0.005*campaign + 0.005*senate + 0.005*democratic
Topic 41 : 0.021*bush + 0.016*november + 0.009*house + 0.008*democrats + 0.008*republicans + 0.007*poll
Topic 42 : 0.017*kerry + 0.014*bush + 0.007*dean + 0.007*poll + 0.006*democratic + 0.006*general
Topic 43 : 0.019*bush + 0.017*kerry + 0.008*campaign + 0.006*people + 0.006*general + 0.006*war
Topic 44 : 0.007*kerry + 0.007*poll + 0.006*dean + 0.006*senate + 0.006*race + 0.006*democratic
Topic 45 : 0.019*kerry + 0.017*bush + 0.012*poll + 0.011*november + 0.008*dean + 0.007*democratic
Topic 46 : 0.024*bush + 0.008*iraq + 0.008*president + 0.007*war + 0.006*bin + 0.006*laden
Topic 47 : 0.018*november + 0.009*house + 0.008*bush + 0.007*party + 0.007*democratic + 0.006*poll
Topic 48 : 0.012*bush + 0.008*republicans + 0.008*house + 0.007*democrats + 0.006*iraq + 0.005*republica
Topic 49 : 0.018*kerry + 0.014*bush + 0.010*dean + 0.009*edwards + 0.008*poll + 0.006*cheney
Topic 50 : 0.007*november + 0.007*bush + 0.007*war + 0.005*house + 0.005*senate + 0.005*political
Topic 51 : 0.007*campaign + 0.007*gotv + 0.007*democratic + 0.006*saudi + 0.005*media + 0.005*bush
Topic 52 : 0.011*bush + 0.010*kerry + 0.006*iraq + 0.005*campaign + 0.005*court + 0.004*dean
Topic 53 : 0.013*bush + 0.009*war + 0.008*iraq + 0.008*november + 0.006*president + 0.005*senate
Topic 54 : 0.009*kerry + 0.008*house + 0.008*campaign + 0.008*bush + 0.007*state + 0.005*states
Topic 55 : 0.012*kerry + 0.009*poll + 0.009*bush + 0.007*percent + 0.007*edwards + 0.006*polls
Topic 56 : 0.023*november + 0.018*bush + 0.013*kerry + 0.008*general + 0.007*senate + 0.007*polls
Topic 57 : 0.009*state + 0.008*states + 0.007*house + 0.007*senate + 0.007*poll + 0.007*democratic
Topic 58 : 0.013*november + 0.010*bush + 0.006*house + 0.005*election + 0.005*poll + 0.005*democratic
Topic 59 : 0.008*bush + 0.007*democratic + 0.007*party + 0.006*november + 0.006*democrats + 0.006*campai
Topic 60 : 0.023*bush + 0.011*kerry + 0.008*administration + 0.006*general + 0.006*war + 0.005*iraq
Topic 61 : 0.013*iraq + 0.011*war + 0.010*bush + 0.006*poll + 0.005*people + 0.004*nader
Topic 62 : 0.015*bush + 0.010*kerry + 0.008*war + 0.007*iraq + 0.006*republican + 0.006*general
Topic 63 : 0.011*kerry + 0.009*bush + 0.007*dean + 0.007*people + 0.006*democratic + 0.006*general
Topic 64 : 0.013*bush + 0.007*war + 0.006*state + 0.006*iraq + 0.006*house + 0.006*senate
```

```
Topic 65 : 0.020*kerry + 0.016*november + 0.011*dean + 0.011*bush + 0.007*war + 0.006*primary
Topic 66 : 0.008*bush + 0.007*kerry + 0.006*general + 0.006*senate + 0.006*iraq + 0.004*time
Topic 67 : 0.016*bush + 0.009*kerry + 0.007*percent + 0.007*democratic + 0.006*party + 0.006*democrats
Topic 68 : 0.009*gotv + 0.008*republicans + 0.008*democratic + 0.008*kerry + 0.008*party + 0.007*dean
Topic 69 : 0.025*bush + 0.016*kerry + 0.009*poll + 0.007*democratic + 0.007*time + 0.007*republicans
Topic 70 : 0.010*percent + 0.009*bush + 0.009*general + 0.009*november + 0.007*senate + 0.007*nader
Topic 71 : 0.011*house + 0.010*bush + 0.010*november + 0.007*kerry + 0.005*republicans + 0.005*democrats
Topic 72 : 0.027*november + 0.009*senate + 0.008*house + 0.007*bush + 0.007*democratic + 0.007*poll
Topic 73 : 0.014*bush + 0.010*kerry + 0.009*democratic + 0.008*iraq + 0.007*million + 0.006*campaign
Topic 74 : 0.009*kerry + 0.009*bush + 0.008*democratic + 0.007*people + 0.006*democrats + 0.005*party
Topic 75 : 0.019*bush + 0.018*kerry + 0.008*president + 0.007*dean + 0.006*poll + 0.006*general
Topic 76 : 0.026*bush + 0.008*campaign + 0.008*november + 0.007*democratic + 0.006*kerry + 0.006*poll
Topic 77 : 0.010*bush + 0.010*kerry + 0.009*war + 0.007*iraq + 0.006*campaign + 0.006*democratic
Topic 78 : 0.014*bush + 0.012*kerry + 0.012*campaign + 0.007*general + 0.006*john + 0.005*iraq
Topic 79 : 0.015*bush + 0.009*edwards + 0.006*john + 0.006*war + 0.006*kerry + 0.005*attacks
Topic 80 : 0.011*bush + 0.011*november + 0.010*poll + 0.010*kerry + 0.006*news + 0.006*vote
Topic 81 : 0.010*november + 0.008*iraq + 0.008*war + 0.008*bush + 0.005*democratic + 0.004*percent
Topic 82 : 0.017*bush + 0.013*november + 0.012*kerry + 0.006*poll + 0.005*iraq + 0.005*general
Topic 83 : 0.009*bush + 0.006*bunning + 0.005*people + 0.005*war + 0.004*poll + 0.004*campaign
Topic 84 : 0.016*november + 0.012*bush + 0.006*war + 0.006*polls + 0.006*general + 0.006*republicans
Topic 85 : 0.018*november + 0.015*bush + 0.012*kerry + 0.009*house + 0.006*general + 0.006*democrats
Topic 86 : 0.013*bush + 0.007*republican + 0.006*general + 0.006*kerry + 0.006*war + 0.005*democratic
Topic 87 : 0.035*november + 0.011*republicans + 0.011*poll + 0.009*bush + 0.007*governor + 0.007*electo
Topic 88 : 0.021*dean + 0.013*kerry + 0.009*campaign + 0.008*people + 0.007*bush + 0.006*president
Topic 89 : 0.015*bush + 0.014*kerry + 0.008*percent + 0.007*iraq + 0.007*democratic + 0.006*poll
Topic 90 : 0.009*war + 0.009*democrats + 0.008*iraq + 0.007*democratic + 0.006*house + 0.006*bush
Topic 91 : 0.025*bush + 0.017*november + 0.008*kerry + 0.008*house + 0.007*republicans + 0.006*poll
Topic 92 : 0.023*bush + 0.011*kerry + 0.008*war + 0.008*president + 0.007*iraq + 0.007*general
Topic 93 : 0.022*november + 0.013*bush + 0.009*house + 0.008*kerry + 0.007*republicans + 0.007*war
Topic 94 : 0.026*bush + 0.014*kerry + 0.012*percent + 0.008*poll + 0.006*voters + 0.006*iraq
Topic 95 : 0.011*bush + 0.007*specter + 0.007*poll + 0.006*toomey + 0.005*campaign + 0.005*democratic
Topic 96 : 0.006*delay + 0.006*republicans + 0.006*democratic + 0.006*house + 0.006*party + 0.006*novem
Topic 97 : 0.009*bush + 0.007*democratic + 0.007*poll + 0.006*percent + 0.006*kerry + 0.006*party
Topic 98 : 0.025*kerry + 0.016*dean + 0.014*edwards + 0.010*democratic + 0.010*november + 0.009*clark
Topic 99 : 0.012*iraq + 0.012*bush + 0.009*war + 0.007*november + 0.006*administration + 0.006*percent
Topic 100 : 0.016*november + 0.010*poll + 0.009*kerry + 0.008*senate + 0.007*house + 0.006*democratic
```

Analysis The top five topics have a great deal of overlap. All of them are about the 2004 US presidential election. The first topic refers contains topics words related to electoral politics in general, and a few words specific to that election, such as “marriage” (as in “gay marriage”, I assume). The second topic is similar, and the third topic is about presidential challengers “Kerry”, “Edwards”, and “Dean. All the other topics seem to be minor variations on these themes.

1.c Try different values for num_topics Trying out the same model with 5, 10, and 20 different topics.

```
In [293]: num_topics_list = [5, 10, 20]
          for num_topics in num_topics_list:
              model = models.LdaMulticore(corpus, num_topics=num_topics, id2word=corpus.create_dictiona
              print_top_topics(model, num_topics)
```

```
WARNING:gensim.models.ldamulticore:too few updates, training might not converge; consider increasing th
WARNING:gensim.models.ldamulticore:too few updates, training might not converge; consider increasing th

Number of topics: 5
Topic 1 : 0.010*bush + 0.010*republican + 0.007*states + 0.007*republicans + 0.007*senate + 0.006*state
```

```
Topic 2 : 0.013*november + 0.010*bush + 0.006*house + 0.005*election + 0.005*poll + 0.005*democratic
Topic 3 : 0.009*war + 0.009*democrats + 0.008*iraq + 0.007*democratic + 0.006*house + 0.006*bush
Topic 4 : 0.012*dean + 0.008*iowa + 0.008*kerry + 0.007*campaign + 0.007*bush + 0.007*general
Topic 5 : 0.019*bush + 0.009*iraq + 0.008*kerry + 0.007*president + 0.006*people + 0.006*war

WARNING:gensim.models.ldamulticore:too few updates, training might not converge; consider increasing the

Number of topics: 10
Topic 1 : 0.009*gotv + 0.008*republicans + 0.008*democratic + 0.008*kerry + 0.008*party + 0.007*dean
Topic 2 : 0.009*kerry + 0.009*bush + 0.008*democratic + 0.007*people + 0.006*democrats + 0.005*party
Topic 3 : 0.009*bush + 0.006*bunning + 0.005*people + 0.005*war + 0.004*poll + 0.004*campaign
Topic 4 : 0.017*bush + 0.013*november + 0.012*kerry + 0.006*poll + 0.005*iraq + 0.005*general
Topic 5 : 0.020*kerry + 0.016*november + 0.011*dean + 0.011*bush + 0.007*war + 0.006*primary
Topic 6 : 0.018*bush + 0.012*kerry + 0.007*iraq + 0.007*war + 0.006*dean + 0.005*poll
Topic 7 : 0.019*kerry + 0.013*bush + 0.008*democratic + 0.008*poll + 0.008*dean + 0.007*edwards
Topic 8 : 0.016*bush + 0.009*kerry + 0.007*percent + 0.007*democratic + 0.006*party + 0.006*democrats
Topic 9 : 0.015*kerry + 0.012*edwards + 0.012*dean + 0.010*democratic + 0.008*primary + 0.008*bush
Topic 10 : 0.018*bush + 0.015*kerry + 0.009*iraq + 0.007*war + 0.007*november + 0.007*poll
Number of topics: 20
Topic 1 : 0.012*bush + 0.008*republicans + 0.008*house + 0.007*democrats + 0.006*iraq + 0.005*republican
Topic 2 : 0.013*bush + 0.007*republican + 0.006*general + 0.006*kerry + 0.006*war + 0.005*democratic
Topic 3 : 0.019*kerry + 0.013*bush + 0.008*democratic + 0.008*poll + 0.008*dean + 0.007*edwards
Topic 4 : 0.020*bush + 0.009*administration + 0.007*dean + 0.005*party + 0.004*media + 0.004*democrats
Topic 5 : 0.011*bush + 0.007*specter + 0.007*poll + 0.006*toomey + 0.005*campaign + 0.005*democratic
Topic 6 : 0.015*kerry + 0.012*edwards + 0.012*dean + 0.010*democratic + 0.008*primary + 0.008*bush
Topic 7 : 0.014*bush + 0.009*kerry + 0.008*house + 0.008*november + 0.007*general + 0.006*democratic
Topic 8 : 0.016*november + 0.010*poll + 0.009*kerry + 0.008*senate + 0.007*house + 0.006*democratic
Topic 9 : 0.025*bush + 0.016*kerry + 0.012*percent + 0.009*poll + 0.008*president + 0.006*war
Topic 10 : 0.017*bush + 0.013*kerry + 0.008*million + 0.007*republicans + 0.006*administration + 0.005*s
Topic 11 : 0.009*bush + 0.007*democratic + 0.007*poll + 0.006*percent + 0.006*kerry + 0.006*party
Topic 12 : 0.008*bush + 0.007*kerry + 0.006*general + 0.006*senate + 0.006*iraq + 0.004*time
Topic 13 : 0.020*bush + 0.019*kerry + 0.010*democratic + 0.008*percent + 0.008*house + 0.007*poll
Topic 14 : 0.009*war + 0.009*democrats + 0.008*iraq + 0.007*democratic + 0.006*house + 0.006*bush
Topic 15 : 0.017*bush + 0.013*november + 0.012*kerry + 0.006*poll + 0.005*iraq + 0.005*general
Topic 16 : 0.015*bush + 0.014*kerry + 0.008*percent + 0.007*iraq + 0.007*democratic + 0.006*poll
Topic 17 : 0.007*campaign + 0.007*gotv + 0.007*democratic + 0.006*saudi + 0.005*media + 0.005*bush
Topic 18 : 0.011*bush + 0.011*november + 0.010*poll + 0.010*kerry + 0.006*news + 0.006*vote
Topic 19 : 0.013*bush + 0.007*war + 0.006*state + 0.006*iraq + 0.006*house + 0.006*senate
Topic 20 : 0.019*bush + 0.018*kerry + 0.008*president + 0.007*dean + 0.006*poll + 0.006*general
```

Analysis I would have expected the topic to become more specific as the number of topics increased, but that doesn't seem to be the case here. The "Daily KOS" is a political blog that focuses on US presidential elections nearly exclusively. As a result, varying the number of topics to search for doesn't have much of an effect–the topics overlap so much as to be nearly identical. They are still all related to the 2004 presidential election.

1.2 Question 2 and Question 3

Question 2 and question 3 can be found in a seperate PDF file that was submitted alongside this PDF.

1.3 Question 4

I collaborated with Israel Malkin, Maya Rotmensch, Charlie Guthrie, Peter Li, and Justin Mao-Jones on this problem.

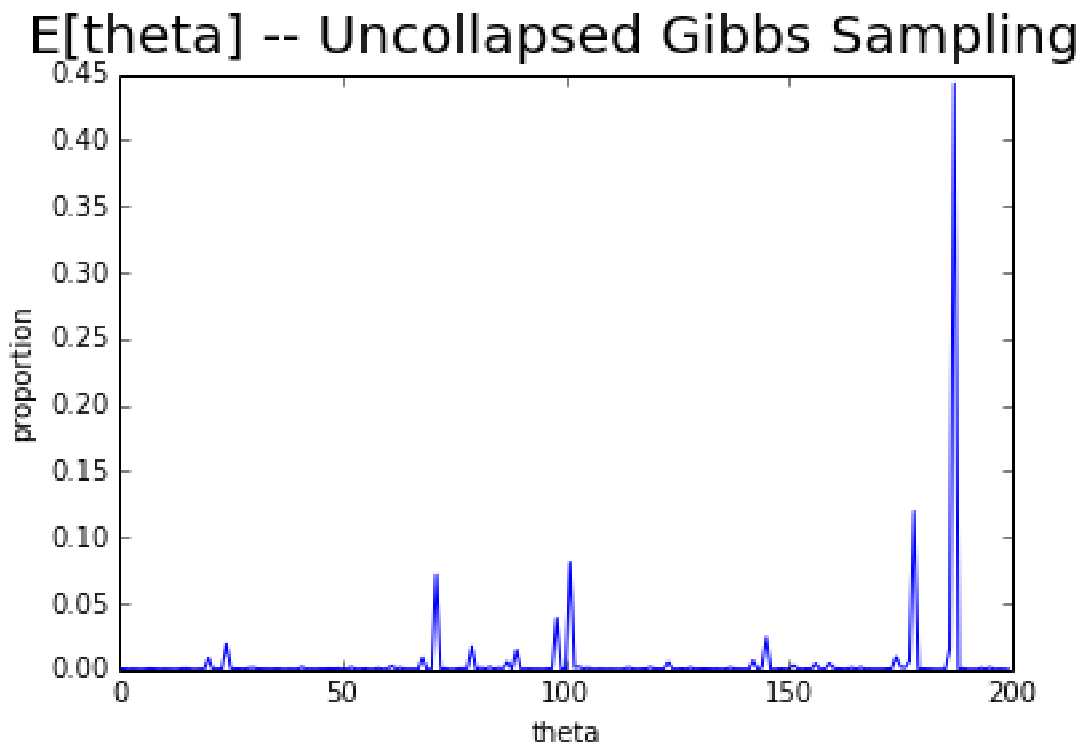
In [224]:
```
# Code that reads in data files for question 4

import os

class Doc:
    def __init__(self, num_topics, topic_priors, word_priors):
        self.num_topics = num_topics
        self.topic_priors = topic_priors  # alpha.
        self.word_priors = word_priors  # beta


def parse_input_file(filename):
    num_topics = 0
    # Dirichlet hyperparams, aka alphas
    topic_priors = []
    # Beta prior for this document, words are rows, topic probabilities are columns
    word_priors = {}

    with open(filename, 'r') as f:
        lines = [line for line in f]
        num_topics = int(lines[0])
        assert(num_topics > 0)
        topic_priors = [float(tok.strip()) for tok in lines[1].split()]
        assert(len(topic_priors) == num_topics)
        for word_index, line in enumerate(lines[2:]):
            tokens = line.split()
            word = tokens[0].strip()  # not used
            word_probs = [float(tok.strip()) for tok in tokens[1:]]
            assert(len(word_probs) == num_topics)
            word_priors[word_index] = word_probs
    return num_topics, topic_priors, word_priors


doc = Doc(*parse_input_file('ps4_data/abstract_nips21_NIPS2008_0517.txt.ready'))
```

In [225]:
```
%matplotlib inline

import matplotlib
import matplotlib.pyplot as plt
import numpy as np
from numpy.random import mtrand

# Sample a topic probability (theta) for the uncollapsed sampler.
def sample_topic_dist(topic_priors, topics):
    topic_counts = np.bincount(topics, minlength=len(topic_priors))
    posterior_topic_priors = [prior + count
                              for prior, count in zip(topic_priors, topic_counts)]
    return mtrand.dirichlet(posterior_topic_priors)


# Create the posterior probabilities for topics (z) for the uncollapsed sampler.
def sample_posterior_topic(word_index, word_priors, topic_dist):
    posterior_topic_probs = []
    denominator = 0.0
```

```
        word_prior_list = word_priors[word_index]
        for topic_index in range(len(topic_dist)):
            numerator = word_prior_list[topic_index] * topic_dist[topic_index]
            posterior_topic_probs.append(numerator)
            denominator += numerator
        posterior_topic_probs = [prob/denominator for prob in posterior_topic_probs]
        topic_counts = mtrand.multinomial(1, posterior_topic_probs)
        for topic_index, sample_value in enumerate(topic_counts):
            if sample_value == 1:
                return topic_index
        raise Exception('Error occured while sampling topic')


    # Returns an array of topic distribution samples
    def uncollapsed_gibbs_sampler(doc, num_iterations):
        # Initialize the topic_dist and topics to dummy values to start.
        initial_topic_dist = [1.0/doc.num_topics]*num_topics
        initial_topics = [1]*len(doc.word_priors)
        topic_dist_samples = [initial_topic_dist]
        topic_samples = [initial_topics]

        for iteration in range(num_iterations):
            prev_topics = topic_samples[-1]
            # Sample topic distribution (theta)
            topic_dist_sample = sample_topic_dist(doc.topic_priors, prev_topics)
            # Initialize the topic sample to be the sample as the last one
            topics_sample = list(prev_topics)
            for i in range(len(topics_sample)):
                # Sample each topic instantiation (z_{mn})
                topics_sample[i] = sample_posterior_topic(i, doc.word_priors,
                                                          topic_dist_sample)
            topic_dist_samples.append(topic_dist_sample)
            topic_samples.append(topics_sample)
        # Remove the 'burn' samples
        topic_dist_samples = topic_dist_samples[50:]
        return np.array(topic_dist_samples)


    def uncollapsed_expected_value(samples):
        return np.mean(samples, axis=0)
```

In [290]:
```
# Uncollapsed topic distribution samples
u_topic_dist_samples = uncollapsed_gibbs_sampler(doc, 10000)
```

In [292]:
```
u_topic_dist = uncollapsed_expected_value(u_topic_dist_samples)
fig = plt.figure()
fig.suptitle('E[theta] -- Uncollapsed Gibbs Sampling', fontsize=20)
plt.xlabel('theta')
plt.ylabel('proportion')
plt.plot(range(len(u_topic_dist)), u_topic_dist)
plt.show()
```

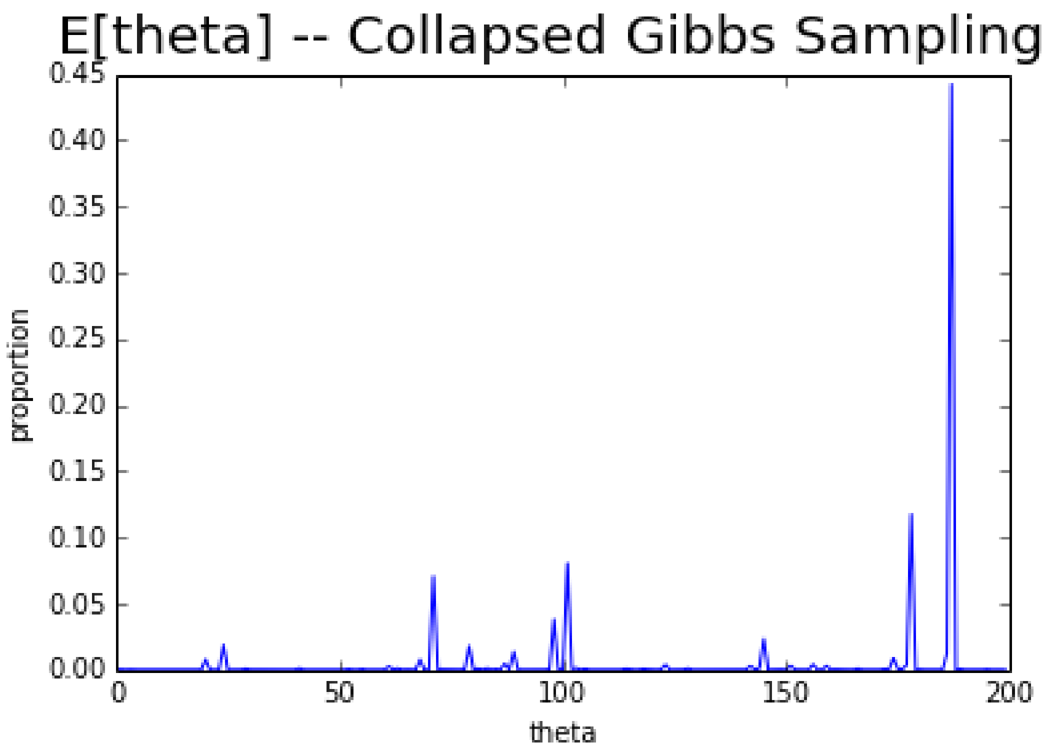



```
In [254]: # Collapsed Gibbs Sampling

          # Conditional probability of
          def sample_posterior_topic_collapsed(word_index, topic_sample, word_priors, topic_priors):
              # Bucket topic samples, excluding the current topic sample
              topic_counts = [0]*len(topic_priors)
              for i, topic in enumerate(topic_sample):
                  if i != word_index:
                      topic_counts[topic] += 1
              # Compute each posterior topic probability
              posterior_topic_probs = []
              for topic_index in range(len(topic_priors)):
                  word_prior = word_priors[word_index][topic_index]
                  topic_prior = topic_priors[topic_index]
                  topic_count = topic_counts[topic_index]
                  prob = word_prior * (topic_prior + topic_count)
                  posterior_topic_probs.append(prob)
              normalizer = sum(posterior_topic_probs)
              posterior_topic_probs = [prob/normalizer for prob in posterior_topic_probs]
              # Sample from the distribution
              sample = mtrand.multinomial(1, posterior_topic_probs)
              for topic_index, sample_value in enumerate(sample):
                  if sample_value == 1:
                      return topic_index
              raise Exception('Error occured while sampling topic')
```

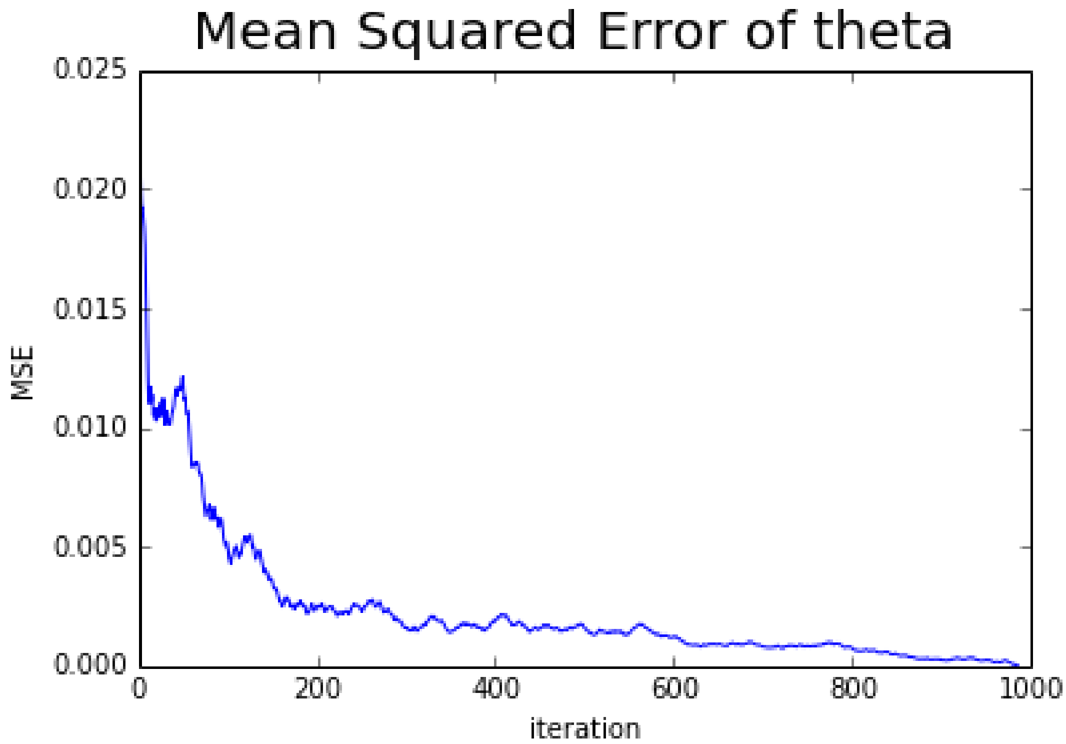
```
# Returns an array of topic samples
def collapsed_gibbs_sampler(doc, num_iterations):
    # Initialize the topics to dummy values to start.
    initial_topics = [1]*len(doc.word_priors)
    topic_samples = [initial_topics]
    for iteration in range(num_iterations):
        topic_sample = list(topic_samples[-1])
        for i in range(len(topic_sample)):
            # Sample each topic instantiation (z_{mn})
            topic_sample[i] = sample_posterior_topic_collapsed(
                i, topic_sample, doc.word_priors, doc.topic_priors)
        topic_samples.append(topic_sample)
    # Remove the 'burn' samples
    topic_samples = topic_samples[50:]
    return np.array(topic_samples)


# Returns the expected value of the topic distribution (theta).
def collapsed_expected_topic_dist(topic_samples, topic_priors):
    T = len(topic_samples)
    topic_dist = np.zeros(len(topic_priors))
    for topic_sample in topic_samples:
        topic_dist += np.bincount(topic_sample, minlength=len(topic_priors))
    N = len(topic_samples[0])
    topic_dist += np.array([N*topic_prior for topic_prior in topic_priors])
    topic_dist /= T * (sum(topic_priors) + N)
    return topic_dist
```

In [260]:
```
# Collapsed topic distribution samples
c_topic_samples = collapsed_gibbs_sampler(doc, 10000)
```

In [288]:
```
c_topic_dist = collapsed_expected_topic_dist(c_topic_samples, doc.topic_priors)
fig = plt.figure()
fig.suptitle('E[theta] -- Collapsed Gibbs Sampling', fontsize=20)
plt.xlabel('theta')
plt.ylabel('proportion')
plt.plot(range(len(c_topic_dist)), c_topic_dist)
plt.show()
```



In [285]:
```
import math

def plot_error(samples, start_num_iterations, topic_priors):
    assert(start_num_iterations < len(samples))
    gt_topic_dist = collapsed_expected_topic_dist(samples, topic_priors)
    errors = []
    for i in range(start_num_iterations, len(samples), 10):
        tmp_topic_dist = collapsed_expected_topic_dist(samples[:i], topic_priors)
        error = math.sqrt(sum((gt_topic_dist - tmp_topic_dist)**2))
        errors.append(error)
    fig = plt.figure()
    fig.suptitle('Mean Squared Error of theta', fontsize=20)
    plt.xlabel('iteration')
    plt.ylabel('MSE')
    plt.plot(range(len(errors)), errors)
    plt.show()

plot_error(c_topic_samples, 100, doc.topic_priors)
```


Mean Squared Error of theta
MSE
iteration
0.025
0.020
0.015
0.010
0.005
0.000
0
200
400
600
800
1000