Conditional Random Fields Applied to Punctuation Tagging

CSE250B, Winter 2014, Project 2

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March 14, 2014

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1 Abstract

Nowadays, most smart-phones are moving towards a full touch interface, with a keypad popping up at the time of user interaction. Users want to quickly respond to email messages, create documents and send text messages, but screen real-estate limits the keypad to only alphanumeric characters, often requiring users to switch to a different keypad to add the punctuations. We aim to solve this problem by training a conditional random field (CRF) to predict the required punctuation tags for a given sentence in the English language.
We experiment with two different optimization techniques - Stochastic gradient ascent (SGA) and Collins perceptron (CP), on a set of feature function templates and analyze their results. The former provides word-level accuracy of 89.36%, and the latter 92.31%. The application requires quick prediction, thus we also focus on an efficient and further speed up through preprocessing, achieving average prediction time of 3ms.

2 Introduction

Our task is to train an unsupervised learning model to discover hidden topics in a given corpus of documents. We use a latent Dirichlet allocation (LDA) model to learn the hidden topics for each word instance in the given set of documents. Using word instances allows us to assign different topics for each occurrence of word in the document, enabling us to achieve the notion of multiple topics per document.
We evaluate the effectiveness of LDA on two datasets, Classic400 and BBC Sports dataset. We perform LDA using different values for the hyper parameters number of topics K, α and β. We run collapsed Gibbs sampling for 500 epochs and manually examine the top 10 words for each topic. We see meaningful topics such as general science terminology, biology and aerospace for the Classic400 dataset and topics such as football, cricket, rugby, tennis and athletics for the BBC sports dataset. Varying the number of topics shows us interesting results such as splitting of topics such as football Given the set of true labels for each document we test the quality of clustering of the LDA model on the datasets, using VI distance and clustering accuracy. We also discuss issues associated with Gibbs sampling such as goodness of fit and overfitting.

Section 3 talks about LDA and the collapsed Gibbs sampling technique used to train such a model. Section 4 then explains the design of our experiments followed by Section 5 which depicts our results, observations and lessons learnt through the course of the project.

3 Model analysis

3.1 Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is an unsupervised learning technique to discover latent semantic topics amongst a collection of documents . LDA is based on the intuition that each document consists of words from different topics, where the proportion of each topic varies but the topics themselves are the same for each document. LDA achieves this notion of multiple topics per document by assigning each word instance to its appropriate topic. Learning in this model is unsupervised because the input data is incomplete: the corpus provides only the words within documents; there is no training set with topic or subject annotations.

3.2 Representation of Data

Ideally we would like to represent data in a form that retains the ordering of words, however this representation would lead to each document having varying lengths. Instead it is sufficient to use a simple bag-of-words representation that only retains the count of the words in the document. We need to identify the set of all words that occur in the corpus, we define this set of words as our vocabulary V. Further optimizations can be made, such as including only words that occur at least twice and removing "stop" words - words that are common in most documents. After the vocabulary is fixed, each document is represented as a vector with integer entries of length m where m is the size of the vocabulary. x_j represents the number of occurrence of word j in the document. The length of the document is $n=\sum_{j=1}^{m} x_j$. The collection of documents is represented as a two-dimensional matrix where each row describes a document and each column corresponds to a word.

3.3 Generation Process

Unsupervised learning is often done by assuming that the data were generated by some probabilistic process, and then tries to learn the parameters of this process. The generative process assumed by LDA is as follows. First, draw a topic weight vector θ according to a Dirichlet distribution β that determines which topics are most likely to appear in a document. For each word that is to appear in the document, choose a single topic from the topic weight distribution ϕ according to a Dirichlet distribution α. To actually generate the word, draw from the probability distribution conditioned on the chosen topic. In this procedure each word in a document is generated by a different, randomly chosen topic. The process is defined more formally below.

Given: Dirichlet distribution with parameter vector α of length K
Given: Direchlet distribution with parameter vector β of length V
for topic number 1 to topic number K
draw a multinomial with parameter vector ϕ_k according to β
for document number 1 to document number M
draw a topic distribution, i.e. a multinomial θ according to α
for each word in the document
draw a topic z according to θ
draw a word w according to ϕ_z

3.4 Training the model

We assume the prior distributions α and β fixed and known, as are the number of topics K, the number of documents M, the length of each document N_m and the size of vocabulary V. Our goal is to infer (i) the document-topic distribution *theta* for each document m and (ii) topic-word distribution *phi* for each topic k.
We use collapsed Gibbs sampling to infer the hidden value z for each word occurrence in each document. We use the term word occurrence as in Gibbs sampling different appearances of the same word, in the same or different document, may be assigned to different topics; thus every word has its own z value.
Let $\bar{w}$ be the sequence of words making up the entire corpus, and let $\bar{z}$ be a corresponding sequence of z values. Pick a random word occurrence w_i. Suppose we know the value of z for every word occurrence in the corpus except for word w_i. The idea of Gibbs sampling is to draw a z_i for i randomly according to its current distribution, then assign this topic z_i for the word i and then repeat this process for next random word occurrence w_i. It can be proved that eventually this process converges to a correct distribution of z values for all the words in the corpus. We perform Gibbs sampling using the following equation:

$$p(z_i = j|\bar{z}', \bar{w}) \propto \frac{q'_{jw_i} + \beta_{w_i}}{\Sigma_t q'_{jt} + \beta_t} \frac{n'_{mj} + \alpha_j}{\Sigma_k n'_{mk} + \alpha_k} \tag{1}$$

where n_{mk} is the number of times $z_i = k$ within document m and q_{kt} is the number of times that word t occurs with topic k in the while corpus.

4 Design of experiments

4.1 Datasets

We conduct experiments on two datasets to evaluate performance of LDA in topic modeling. First one is the Classic400 dataset which has 400 documents with a 6205 word vocabulary. The data has been provided as a

sparse matrix where each row corresponds to the count of non-zero words in a document.

Second dataset is the BBC dataset which consists of documents from the BBC Sport website corresponding to sports news articles in five topical areas: athletics, cricket, football, rugby, tennis. This dataset has 737 documents over a vocabulary of 4613 words. The preprocessing steps included removal of stop-words, applying Porter's stemmer on the wordlist and then converting document-word counts into a sparse matrix format

4.2 Goodness-of-fit measurement

Evaluating goodness-of-fit of topic models is a tricky task. If topics ϕ_1 to ϕ_k are given, then goodness-of-fit can be modeled as $p(\mathbf{w}|\phi, \alpha)$ which is the probability of data or likelihood of the model. It is defined as:

$$p(\mathbf{w}|\phi, \alpha) = \int_\theta p(\mathbf{w}|\theta, \phi)p(\theta|\alpha) = \int_\theta \int_z p(\mathbf{w}|\mathbf{z}, \phi)p(\mathbf{z}|\theta) \tag{2}$$

If the topic ϕ are not given, the goodness-of-fit can be modeled as $p(w|\alpha, \beta)$. This is defined as:

$$p(\mathbf{w}|\alpha, \beta) = \int_\phi p(\mathbf{w}|\phi, \alpha)p(\phi|\beta) \tag{3}$$

This is difficult to calculate and several approximations exists for this.[2]

4.3 Analysis of clustering

The document-topic distributions produced by LDA are a soft clustering. (i.e. we have the probabilities for topics in a document).
One naive approach can be to assign each document the topic with highest probability. When number of topics K is equal to the natural classes given, then a clustering accuracy can be computed. But, we do not know the correspondence between LDA topics and natural classes, we did not use this approach. Instead, we trained a KNN (K nearest neighbour) classifier by giving feature vector for a document as the probabilities of topics associated with it. The prediction accuracy obtained by the classifier is treated as a measure for measuring clustering quality.
Another approach is to treat the given categorization as a deterministic topic distribution for each document, and then compute distance between this distribution and LDA topic distribution. We use the Variation of Information distance (VI-distance)[...ref..] as the distance measure.

Given two class distributions for a document: $p(c = j|d_m)$ and $p(z = k|d_m)$ with true labels $j = 1...J$ and $m = 1....M$. We evaluate class probabilities $p(c = j = \frac{1}{M}\Sigma_m p(c = j|d_m))$ and $p(z = k) = \frac{1}{M}\Sigma_m p(z = k|d_m)$ as well the probabilities of co-occurrence of pairs of classes $p(c = j, z = k) = \frac{1}{M}\sum_{m=1}^{M} p(c = j|d_m)p(z = k|d_m)$
VI-distance between two distributions is defined as:

$$D_{VI}(C, Z) = H(C) + H(Z) - 2I(C, Z) \tag{4}$$

where $H(Z) = -\sum_{k=1}^{K} p(z = k)log_2 p(z = k)$ and $H(C) = -\sum_{j=1}^{J} p(c = j)log_2 p(c = j)$ $H(Z)$ and $H(C)$ are the entropies of corresponding distributions Mutual information $I(C, Z)$ is defined as:

$$I(C, Z) = \sum_{j=1}^{J}\sum_{k=1}^{K} p(c = j, z = k)[log_2 p(c = j, z = k) - log_2 p(c = j)p(z = k)] \tag{5}$$

We also report results of VI-distance between distribution of true labels and LDA topic model distribution.

4.4 Convergence and overfitting

We are checking for convergence by monitoring the values of VI-distance and classifier accuracy on the training set. We can check for overfitting by computing the test set classifier accuracy and compare it with that on training set. For no overfitting, difference between two should be less.

4.5 Effect of hyperparameters

Hyperparameter α represents the strength of topics in a document and β represents the strength of words in a topic. Since LDA model treats all the topics and the words in the same way, we have chosen same α for all topics and same β for all words. If the values of α and β are high, that means our prior beliefs are strong and more iterations of Gibbs sampling will be needed to revise the beliefs. α and β also have a smoothing effect on document-topic and topic-word distribution as well. Lower the value, less will be the smoothing and distributions will be well separated.

In our experiments, we have used $\alpha\epsilon\{1/K, 5/K\}$ and $\beta\epsilon\{0.1, 1\}$.

4.6 Number of Topics

An obvious choice for K or number of topics is to take them equal to number of natural classes given. If K is smaller that number of natural classes, then it is possible that some of the topics may merge. Similarly, for K larger than number of given categories, we might discover sub-topics from the corpus or we may discover the noise as a topic. In our experiments, we choose $K = 3, 4$ for Classic400 dataset with 3 natural categories and $K = 4, 5, 6$ for BBC dataset with 5 natural categories.

5 Results and discussion

Firstly, we show the 3D scatter plot of documents in topic space in Figure 1. Each document is represented as a point with probabilities of each topic in the document is taken as its coordinates. The color of the point represents the truelabel associated with it. For small α, documents are well separated and located towards the corners but for larger α, they are clustered close to each other and topic mixing is more as compared to small α. For a higher value of β i.e. for $\beta = 1$, we are obtaining good clustering as compared to $\beta = 0.1$

For $K = 3$, the documents reside on a 3-simplex. For $K = 4$, we first used principal component analysis (PCA) to project the data on a 3D space and then plotted them.

We display the top ten words for each LDA topic in Table1. We have identified three categories from Classic400 dataset - Dynamics, Medicine and Science according to documents given. When $K = 3$, top ten words in each LDA topic are suggestive of the categories identified. For $K = 4$, we observer that a topic Dynamics splits into two sub-topics - one related to Aerodynamics and other to Fluid-dynamics. It's important to note here that counts of words assigned to Dynamics topic for $K = 3$ is almost two times that of other two topics.

Higher classification accuracy that our model fits the true labels well. Smaller VI-distance suggests that learned document-topic distribution has higher similarity to distribution of true labels. In Figure 2, results also support our observation in Figure1 that smaller α leads to better clustering. Similarly, a larger value of β is preferred but effect of α seems to dominate effect of β. A stability in the value of both classification accuracy and VI-distance suggests that our topic models have achieved convergence. For all combination of hyperparameters, we achieve more than 85% accuracy

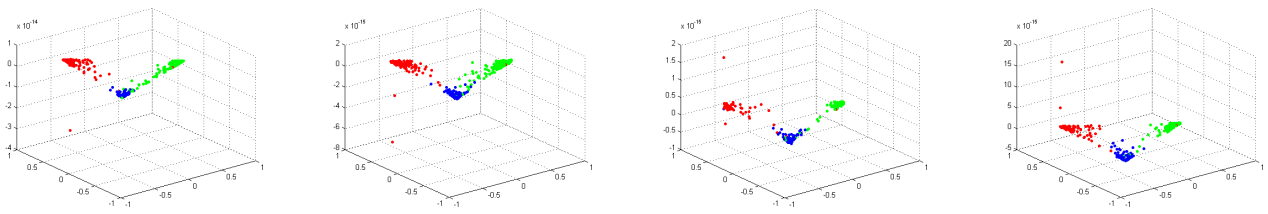
For same value of α and β, we can see in Figure 3 that when K is equal to number of given categories, then a better quality model is obtained. This difference is more prominent for VI-distance as shown in Figure 3(b).

Figure 4 shows the plots of documents in topic space for BBC dataset. For $K >= 4$, we use PCA to reduce dimensionality of data to 3 dimensions. Clustering follows the same pattern as for Classic400 dataset i.e. for smaller α and comparatively larger β, clusters are more separated from each other.

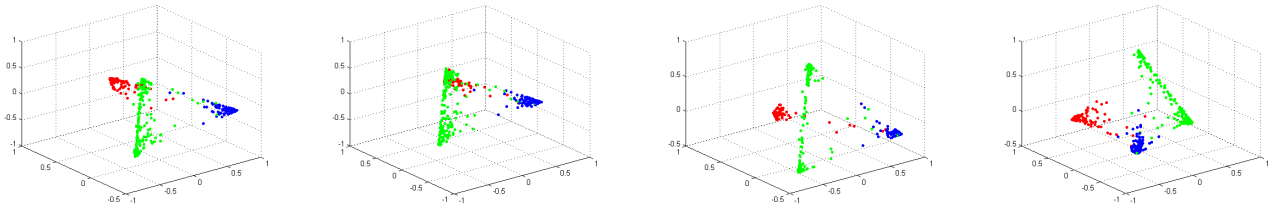
Table 2 shows the top frequency words for $K = 4, 5, 6$. For $K = 4$, we observe that the topics Tennis and Athletics have merged together. This can be due to the reason that both of them are individual sports and are clustered together. For $K = 5$, we see top words in LDA topics resemble the natural classes given. For $K = 6$, we see that words from topic football split to two sub-topics. For K=5, count of words assigned topic as Football is almost double than that the count for other topics. This agrees with similar observation on Classic400 dataset as well that topics from bigger cluster divide into two subtopics.

Figure 5 shows model quality measures for BBC dataset. All choices of hyperparamters obtain more than 85% accuracy. Small α and large β performs better both in classification accuracy and VI-distance.

In Figure 6, better clustering performance is achieved when $K = 5$ i.e. number of LDA topics match the number of natural classes.



(a) $\alpha = 0.66, \beta = 0.1, K = 3$ (b) $\alpha = 1.66, \beta = 0.1, K = 3$ (c) $\alpha = 0.66, \beta = 1, K = 3$ (d) $\alpha = 1.66, \beta = 1, K = 3$



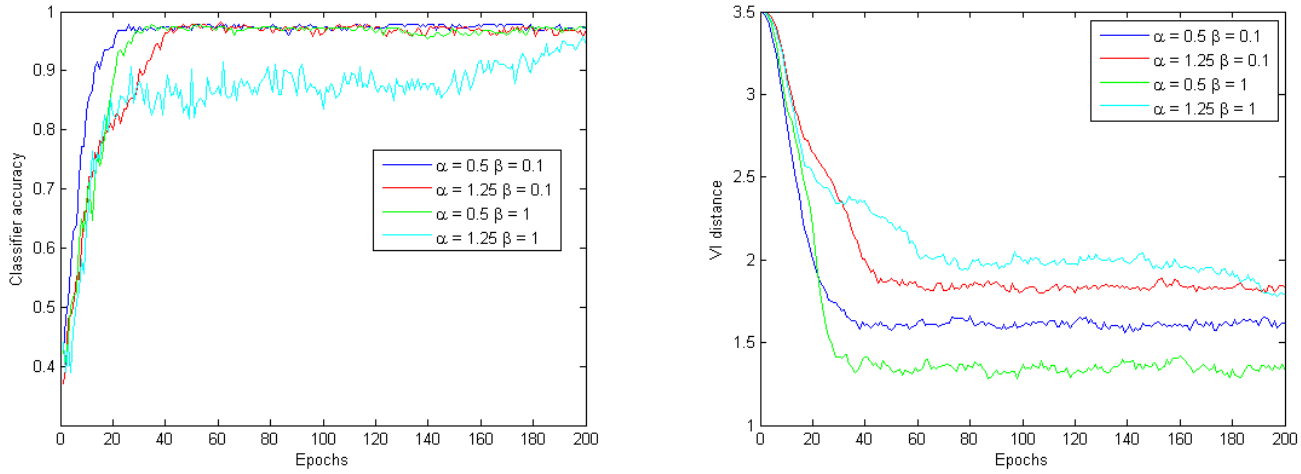
(e) $\alpha = 0.5, \beta = 0.1, K = 4$ (f) $\alpha = 1.25, \beta = 0.1, K = 4$ (g) $\alpha = 0.5, \beta = 1, K = 4$ (h) $\alpha = 1.25, \beta = 1, K = 4$

Figure 1: Plots of Classic400 dataset in LDA topic space

Aero	Science	Fluid	Medicine
wing	system	boundary	patients
mach	scientific	solution	ventricular
supersonic	research	plate	left
wings	retrieval	laminar	fatty
ratio	science	layer	cases
shock	language	transfer	acids
lift	methods	temperature	aortic
aerodynamic	systems	field	blood
layer	problems	fluid	normal
boundary	journals	problem	glucose

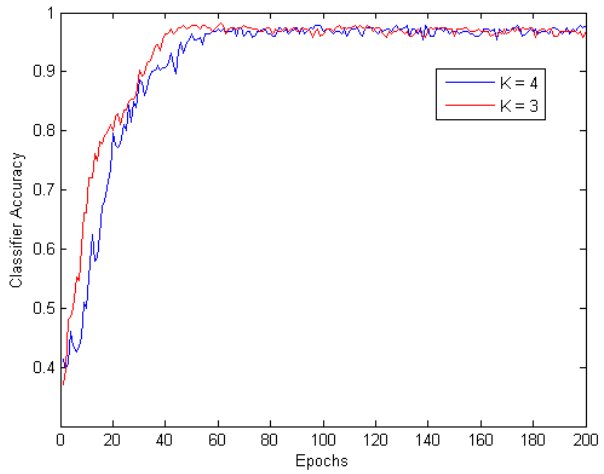
Dynamics	Science	Medicine
boundary	patients	system
layer	ventricular	scientific
wing	fatty	research
mach	left	retrieval
supersonic	nickel	science
ratio	cases	language
wings	acids	subject
velocity	aortic	methods
shock	blood	systems
effects	normal	journals

Table 1: Top 10 words for each LDA topic for K=3 and K=4 in Classic400 dataset

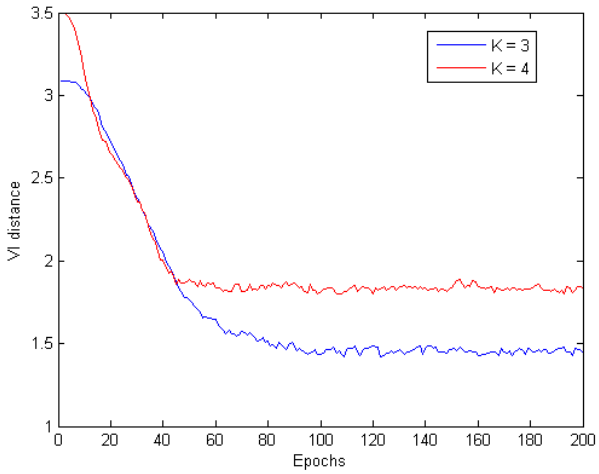


(a) classification accuracy for $K = 4$ (b) VI distance for $K = 4$

Figure 2: Plot of clustering quality measures for Classic400 dataset

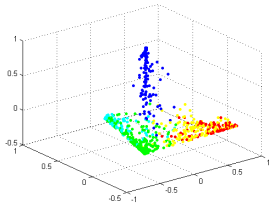


(a) $\alpha = 1.25, \beta = 0.1$

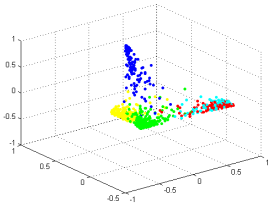


(b) $\alpha = 1.25, \beta = 0.1$

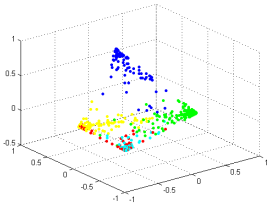
Figure 3: Plots of Classic400 dataset in LDA topic space



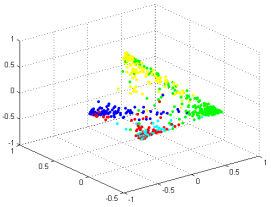
(a) $\alpha = 0.66, \beta = 0.1, K = 3$



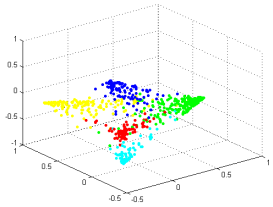
(b) $\alpha = 1.66, \beta = 0.1, K = 3$



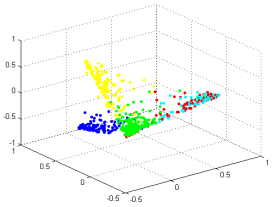
(c) $\alpha = 0.66, \beta = 1, K = 3$



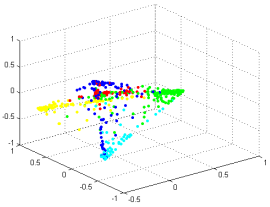
(d) $\alpha = 1.66, \beta = 1, K = 3$



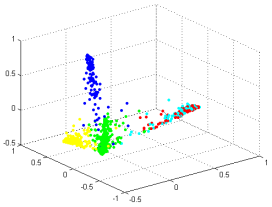
(e) $\alpha = 0.66, \beta = 0.1, K = 3$



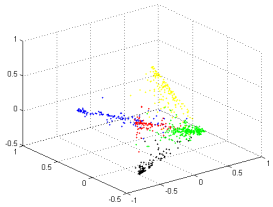
(f) $\alpha = 1.66, \beta = 0.1, K = 3$



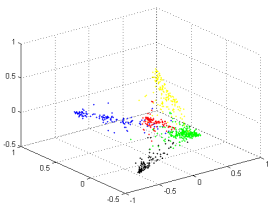
(g) $\alpha = 0.66, \beta = 1, K = 3$



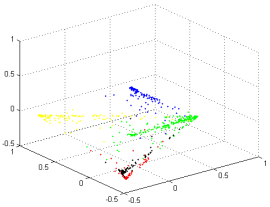
(h) $\alpha = 1.66, \beta = 1, K = 3$



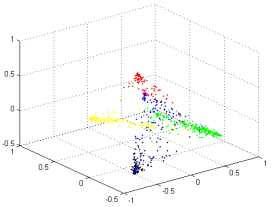
(i) $\alpha = 0.5, \beta = 0.1, K = 4$



(j) $\alpha = 1.25, \beta = 0.1, K = 4$



(k) $\alpha = 0.5, \beta = 1, K = 4$



(l) $\alpha = 1.25, \beta = 1, K = 4$

Figure 4: Plots of BBC sports dataset in LDA topic space

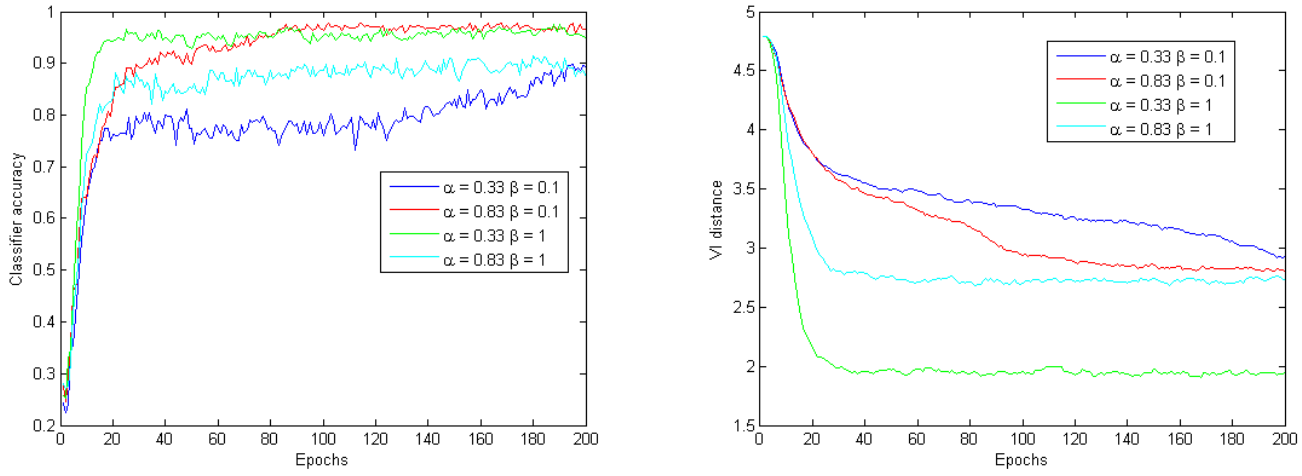
Rugb	Olym	Cric	Tennis	Foot
england	second	test	plai	player
ireland	world	cricket	win	game
wale	minut	australia	first	plai
game	race	seri	open	club
against	olymp	pakistan	match	go
rugbi	win	plai	set	leagu
nation	european	first	england	chelsea
six	goal	india	two	want
plai	indoor	match	south	footbal
franc	athlet	tour	year	team

Rugb	Olym	Cric	Tennis	Foot	Foot
goal	england	player	plai	olymp	test
minut	ireland	game	open	world	cricket
unit	wale	club	win	athlet	england
arsen	game	plai	first	race	first
score	rugbi	go	match	test	plai
ball	against	want	set	indoor	seri
chelsea	nation	think	final	year	south
second	six	team	roddick	champion	australia
chanc	franc	footbal	year	athen	ball
refere	win	leagu	world	european	run

Table 2: Foo

Rugb	Olym	Cric	Tennis
win	test	england	game
world	cricket	ireland	player
year	england	wale	plai
set	plai	game	club
final	first	against	chelsea
open	seri	nation	arsen
olymp	south	rugbi	leagu
plai	australia	six	goal
second	ball	coach	unit
champion	run	franc	footbal

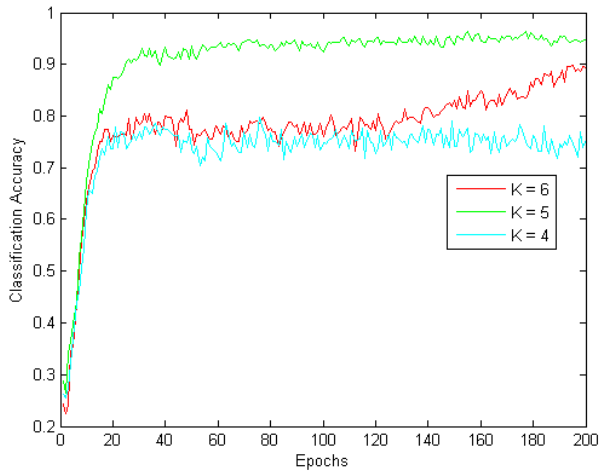
Table 3: Foo



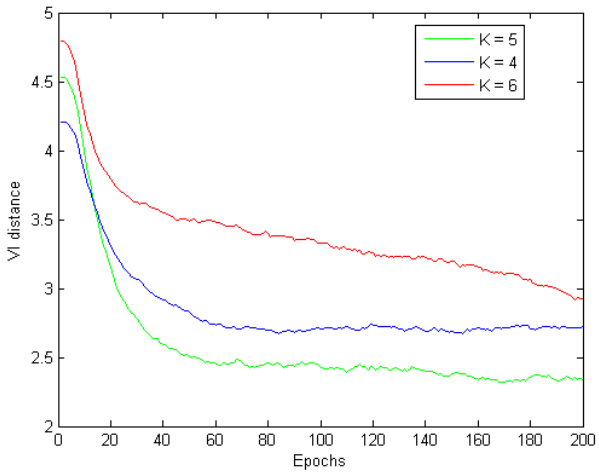
(a) classification accuracy for $K = 4$

(b) VI distance for $K = 4$

Figure 5: Plot of clustering quality measures for BBC sports dataset



(a) $\alpha = 0.33, \beta = 0.1$



(b) $\alpha = 0.33, \beta = 0.1$

Figure 6: Plots of BBC sports dataset in LDA topic space

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