ON-LINE NEW EVENT DETECTION AND CLUSTERING USING THE CONCEPTS OF THE COVER COEFFICIENT-BASED CLUSTERING METHODOLOGY

A THESIS
SUBMITTED TO THE DEPARTMENT OF COMPUTER ENGINEERING
AND THE INSTITUTE OF ENGINEERING AND SCIENCE
OF BILKENT UNIVERSITY
IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
MASTER OF SCIENCE

by

Ahmet Vural

August, 2002

ABSTRACT

ONLINE NEW EVENT DETECTION AND CLUSTERING USING THE CONCEPTS OF THE COVER COEFFICIENT-BASED CLUSTERING METHODOLOGY

Ahmet Vural
M.S. in Computer Engineering
Supervisor: Prof. Dr. Fazlı Can
August, 2002

In this study, we use the concepts of the cover coefficient-based clustering methodology (C^3M) for on-line new event detection and event clustering. The main idea of the study is to use the seed selection process of the C^3M algorithm for the purpose of detecting new events. Since C^3M works in a retrospective manner, we modify the algorithm to work in an on-line environment. Furthermore, in order to prevent producing oversized event clusters, and to give equal chance to all documents to be the seed of a new event, we employ the window size concept. Since we desire to control the number of seed documents, we introduce a threshold concept to the event clustering algorithm. We also use the threshold concept, with a little modification, in the on-line event detection. In the experiments we use TDT1 corpus, which is also used in the original topic detection and tracking study. In event clustering and event detection, we use both binary and weighted versions of TDT1 corpus. With the binary implementation, we obtain better results. When we compare our on-line event detection results to the results of UMASS approach, we obtain better performance in terms of false alarm rates.

Keywords: Clustering, on-line event clustering, on-line event detection.

ÖZET

KAPLAMA KATSAYISI TABANLI KÜME OLUŞTURMA METODOLOJİSİ KULLANARAK ANINDA YENİ OLAY BELİRLEME VE KÜME OLUŞTURMA

Ahmet Vural
Bilgisayar Mühendisliği, Yüksek Lisans
Tez Yöneticisi: Prof. Dr. Fazlı Can
Ağustos, 2002

Bu çalışmada, anında yeni olay belirlemek ve olay kümeleri oluşturmak amacıyla, kaplama katsayısı tabanlı küme oluşturma metodolojisi (C^3M) kavramları kullanıldı. Çalışmanın ana teması, yeni olay belirlemek için C^3M algoritmasının tohum seçme işlemini kullanmaktır. C^3M'in çalışma prensibi anında kümelemeye uygun olmadığından, algoritmada değişiklikler yapıldı. Ayrıca, çok büyük olay kümelerinin oluşumunu önlemek ve bütün dokümanlara, tohum olabilmeleri için eşit şans tanımak amacıyla, pencere yöntemi kullanıldı. Tohum dokümanlarının miktarını kontrol etmek maksadıyla, olay kümeleme işi için bir eşik kavramı ortaya çıkarıldı. Bu kavramı, çok küçük değişikliklerle, yeni olay belirlemede de kullanıldı. Deneyler esnasında, orjinal konu belirleme ve takip çalışmasında da kullanılan TDT1 yığınından yararlanılmıştır. Yeni olay belirleme ve olay kümeleme işlemlerinde TDT1 yığınının ağırlıklı ve düz uyarlamaları kullanıldı. Düz uygulamalar için daha iyi sonuçlar elde edildi. Anında olay belirleme alanındaki sonuçlar UMASS yaklaşımınınkilerle karşılaştırıldığında, yanlış alarm oranları açısından daha iyi performans elde edilmiştir.

Anahtar Sözcükler: Kümeleme, anında olay kümelemesi, anında olay belirleme.

ACKNOWLEDGEMENTS

I would like to express my special thanks and gratitude to Prof. Dr. Fazlı Can, from whom I have learned a lot, due to his supervision, suggestions, and support during this research.

I am also indebted to Assoc. Prof. Dr. Özgür Ulusoy and Assist. Prof. Dr. Uğur Güdükbay for showing keen interest to the subject matter and accepting to read and review this thesis.

I would like to thank to Turkish Armed Forces for giving this great opportunity.

I would like to thank all my colleagues and dear friends for their help and support.

Anneme ve Ablalarıma.

Contents

List of Figures

List of Tables

List of Symbols and Abbreviations

α_i	: Alpha, reverse of row sum of D matrix.
β_k	: Beta, reverse of column sum of D matrix.
δ_i	: Decoupling coefficient.
ψ_i	: Coupling coefficient.
P_i	: Cluster seed power of document $d_{i.}$
P	: Average seed power value.
C	: Document-by-document ($m \times m$) cover coefficient matrix whose entries, c_{ij} values, indicate the probability of selecting any term of document (d_i) from document (d_j), where d_i and d_j are the members of D matrix.
C'	: Term-by-term ($n \times n$) cover coefficient matrix.
C^3M	: Cover Coefficient based Clustering Methodology .
CBR	: Cluster-Based Retrieval.
CC	: Cover Coefficient.
c_{ij}	: The probability of selecting any term of d_i from $d_{j..}$
CMU	: Carnegie Mellon University.
D	: Document–by-term matrix, contains document vectors.
$d_{i\text{Date}}$	: The date of new coming document.
$d_{j\text{Date}}$	: The date of the oldest document in the current window.
DRAGON	: Dragon Systems.
FS	: Full Search.
JGI	: Journal of Graphics Institute.

KNN	: k Nearest Neighbour Algorithm.
LDC	: Linguistic Data Consortium.
m	: The number of documents in the database.
MUC	: Message Understanding Conferences.
TDT	: Topic Detection and Tracking.
tf×idf	: Term Frequency times Inverse Document Frequency.
t_{gs}	: The average number of seed documents per term.
Tr	: Threshold value.
UMASS	: University of Massachusetts at Amherst.
WS	: Window Size.
x_d	: The average number of distinct terms per document.

Chapter 1
Introduction

1.1 Definitions

We live in a quickly changing world. We do not have time to stop and rest for a moment, if we do not want to miss the developments in the changing world. How much can human being resist this stress? There should be a way to save our time and our life. The computer can help, but it is not enough. In addition to computer, an intelligent assistant system is desirable. This system should be able to follow the current news, form of a content summary of a corpus for a quick review, provide a temporal evolution of past events of interest, or detect new events that demonstrate a significant content from any previously known events.

In order to find a solution to this problem, a study called Topic Detection and Tracking (TDT) Pilot Study project [2], which is the primary motivation of this thesis, was initiated in 1997. The aim of TDT study was to explore the modern way of finding and following new events in a stream of broadcast news stories. At first, the study grouped the streaming news into related topic. During evolution, the notion of "topic" improved and specified to "event." In the TDT study, "event" is defined as some unique thing that happens at some point in time. The time property distinguishes event from the meaning of "topic," which is identified as: a seminal event along with all related events. Story, news and document are the elements of event, and in this thesis, they are used in turn in place of each other.

In TDT study, there are three tasks. *The segmentation task* aims to segment a continuous stream of text into its element stories. The boundaries of the news are identified. *The detection task* identifies stories that discuss new events, which have not been previously reported. *The tracking task* links incoming stories to the events known to the system. The user initially identifies the classifier of a particular event. The diagram in Figure 1.1 depicts how these tasks are accomplished.

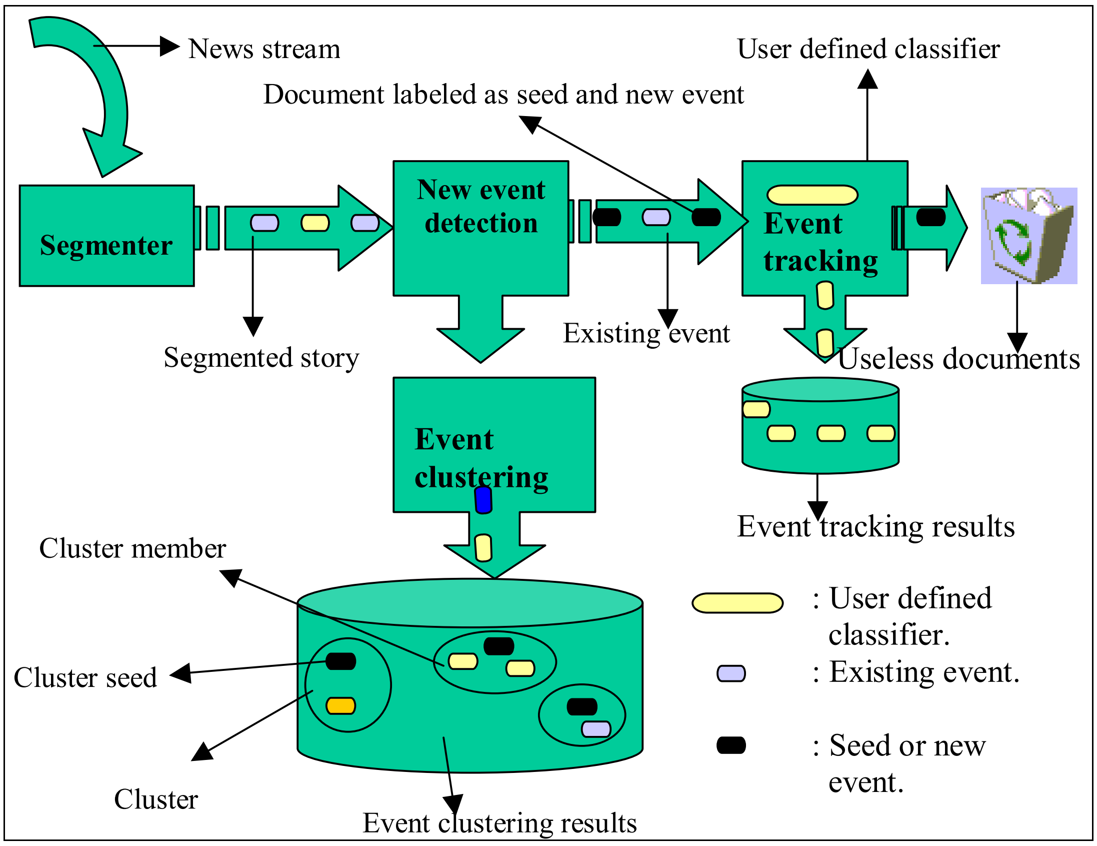


Figure 1.1: On-line new event detection, event tracking, event clustering and segmentation process.

Figure 1.1 is a model to visualize the processes. There are four processes depicted in the figure. Segmentation process identifies the boundaries of each story in the streaming news. After this process is over, the stories are labeled by the new event detection process, as discussing new event or not. The dark ovals in the diagram represent the new events in the data. We can apply one of the two processes, the event tracking or the event clustering. The event tracking process begins with the identification of a classifier, which is created from the contents of the document specified by the user. The classifier is then used to make on-line decisions about subsequent documents on the news stream. If the documents are related to the classifier, they are labeled as relevant. Otherwise, they are useless. The last process depicted in the figure is event clustering. Event clustering is an unsupervised problem solving process where the goal is to automatically group documents by events that may exist in the data. The significant difference from event tracking method is that the latter needs training documents about each event to formulate a classifier, while the former operates without training documents. On the other hand, new event detection problem is also unsupervised because no training documents are required for processing the data. However, different from event clustering, the goal of new event detection is to separate documents that discuss new events from documents discussing existing events.

1.2 Research Contributions

The previous works that most influenced our approach, to new event detection and event clustering, are based on single-pass clustering [33] and Cover Coefficient based Clustering Methodology (C^3M) [8]. We use the concepts of the cover coefficient-based clustering methodology (C^3M) for on-line new event detection and event clustering.

The C^3M algorithm is seed based. We use the idea of using seed selection process of C^3M algorithm for event clustering and detecting new events. We aim to select the initial stories of the events as seed documents, and group the follower stories around selected seeds. Documents, which are selected as seed, are also accepted by the system as the new events.

Since C^{3}M works in retrospective environment, we modified the algorithm to work in on-line manner by processing the documents sequentially, and one at a time.

We introduce a window size concept to the algorithm. This prevents oversized clusters, and gives equal chance to all documents to be a cluster seed.

We introduce a threshold concept for the seed selection process of event clustering. With the help of threshold, we obtain acceptable performance. A modified version of the threshold concept is also used for the task of on-line new event detection.

We apply the algorithm to both binary and weighted version of the TDT1 corpus. We obtain better performance with binary implementation than weighted implementation.

1.3 Thesis Overview

In the next chapter, we provide a brief overview of on-line event clustering and on-line event detection. This chapter also covers the approaches of the participants of TDT study and previous literature related to these topics. Chapter3 describes the C^{3}M algorithm. We give the necessary information about this algorithm, which are related to our approach. In Chapter 4, we describe the TDT1 corpus and the evaluation methodologies we used to explore our approach. We present our solutions and results for the on-line event clustering and on-line new event detection, in Chapters 5 and 6, respectively. Conclusion and possible future extensions are presented in Chapter 7.

Chapter 2

Related Work

Whole story is initiated by Topic Detection and Tracking (TDT) Pilot Study project [2]. TDT study is a DARPA-supported program to explore the modern way of finding and following new events in a stream of broadcast news stories. The TDT problem consists of three major tasks:

- *The Segmentation Task:* The segmentation task is defined to be the task of segmenting a continuous stream of text into its element stories. It locates the boundaries between neighboring stories, for all stories in the corpus. In this thesis, we do not focus on this task, since the data used in experiments are already segmented.
- *The Detection Task*: The goal of the task is to identify stories that discuss new events, which have not been previously reported. For example, a good new event detection system should aware the user to the first story about a specific event such as a political crisis, or an earthquake in a particular time and place. In addition, we introduce a method, which clusters the stories in an on-line manner.
- *The Tracking Task:* The tracking task is defined to be the task of linking incoming stories with events known to the system. An event is defined

("known") by its relationship with stories that discuss the event. In the tracking task a target event is given, and each successive story must be classified as to whether or not it discusses the target event [32]. This task is not covered in the scope of this study.

The TDT Pilot Study ran from September 1996 through October 1997 [2]. The primary participants were DARPA, Carnegie Mellon University (CMU), Dragon Systems (DRAGON), and the University of Massachusetts (UMASS) at Amherst. The approaches of the first participants and other researches are covered in the next section.

The TDT study is proposed to explore techniques for detecting the emergence of new topics and for tracking the re-emergence and evolution of them. During the first portion of TDT study, the notion of a "topic" was modified to be an "event," meaning some unique thing that happens at some point in time. The notion of an event differs from a broader category of event's specificity. For example, "Turkish Economic crisis in February, 2001" is an event, whereas "crisis" in general is considered a class of events. Events might be unexpected, such as the eruption of a volcano, or expected, such as a political election.

2.1 New Event Detection Approaches

New event detection is an unsupervised learning task consists of two subtasks: retrospective detection and on-line detection. The former is about the discovery of previously collected and unidentified events in a static data and the latter attempts to identify the beginning of new events from live news streaming in real-time. Both forms of detection do not have any previous knowledge of novel events, but have permission to use historical data for training purposes [36].

The on-line new event detection has two modes of operation: immediate and delayed. In immediate mode, system is a strict real-time application and it identifies whether the current document contains a new event or not before processing the next document. In delayed mode, decisions deferred for a pre-specified time interval. For example, the system may collect news throughout the day and presents the results of detection task at the end of the day [24].

Since our detection system works in immediate mode, some approaches to immediate mode of on-line new event detection are considered below.

2.1.1 CMU Approach

The CMU (Carnegie Mellon University) approach used conventional vector space model to represent the documents and traditional clustering techniques in information retrieval to represent the events [25]. A story is presented as a vector whose dimensions are the stemmed unique terms in the corpus, and whose elements are the term (word or phrase) weights in the story. In choosing a term weighting system, low weights should be assigned to high-frequency words that occur in many documents of a collection, and high weights to terms that are important in particular documents but unimportant in the remainder of the collection. They used the well-known term weighting system [25] tf×idf (Term Frequency times Inverse Document Frequency) to assign weights to terms. As a clustering algorithm, an incremental (single-pass) clustering algorithm with a time window is used. The algorithm is given in Figure 2.1.

A cluster is represented using a prototype vector (or centroid), which is the normalized sum of story vectors in the cluster. The SMART [27] retrieval engine is embedded in the system. They used a clustering strategy with a detection threshold that managed the minimum document cluster similarity score required for the system to label the current document as containing a new event. They also used a combining threshold to decide whether adding a document to an existing cluster or not. By using a constant window size, they aimed to limit the number of comparisons.

1. Documents are processed sequentially.
2. The first document becomes the cluster representative of the first cluster.
3. Each subsequent document is matched against all cluster representatives.
4. A given document is assigned to a cluster according to some similarity measure.When a document is assigned to a cluster, the representative for that cluster is recomputed.
6. If a document fails a similarity test, it becomes a cluster representative of a new cluster.

Figure 2.1: Single-pass clustering algorithm.

2.1.2 The UMass Approach

UMASS solution to new event detection is related to the problem of on-line document clustering. By clustering the streaming documents, and returning the earliest document in each cluster to the user, UMASS aimed to find a solution to new event detection problem. In this approach [22], they reevaluated some of the well-known approaches to retrospective clustering and analyzed their effectiveness in an on-line manner. For this purpose, a modified version of the single-pass clustering algorithm is used for new event detection. As shown before in Figure 2.1, this algorithm processes each new document on the stream sequentially. In addition to this implementation, the new-event detection algorithm was implemented by combining the ranked-retrieval mechanisms of Inquery [17], a feature extraction and selection process based on relevance feedback [1], and the routing architecture of InRoute [4]. The algorithm is presented in Figure 2.2.

1. Use feature extraction and selection techniques to build a query representation to define the document's content.
2. Determine the query's initial threshold by evaluating the new document with the query.
3. Compare the new document against previous queries in memory.
4. If the document does not trigger any previous query by exceeding its threshold, the document contains a new event.
5. If the document triggers an existing query, the document is not containing a new event.
6. (Optional) Add the document to the agglomeration list of queries it triggered.
7. (Optional) Rebuild existing queries using the document.
8. Add new query to memory.

Figure 2.2: UMASS new event detection algorithm.

2.1.3 Dragon System Approach

The Dragon system used a language modeling approach of single word (unigram) frequencies for cluster and document representations: their document representation did not use tf×idf scores, as used in the UMASS system and the CMU system. Dragon's cluster comparison methodology is based on the KullbackLeibler distance measure [2]. They used a preprocessing step in which an iterative k-means clustering algorithm was used to build 100 background models (clusters) from an auxiliary corpus. Initially, the first story in the corpus is defined as an initial cluster [2]. The remaining stories in the corpus are processed sequentially; for each one, the "distance" to each of the existing clusters is computed. In their decision process, a document is considered to contain a new event when it is closer to a background model than to an existing story cluster.

As a modification, they introduced "decay term" to cause clusters to have a limited existence in time. By adjusting the decay parameter and the overall threshold the on-line detection system can be tuned.

2.1.4 UPenn Approach

The UPenn approach used the single-link (nearest neighbor) clustering method to characterize each event. This method begins with all stories in their own singleton clusters. Two clusters are merged if the similarity between any story of the first cluster and any story of the second cluster exceeds a threshold. As a system parameter, a deferral period is defined to be the number of files (each containing multiple stories) the system is allowed to process before it relates an event with the stories contained in the files. To implement the clustering, the UPenn approach takes the stories of each deferral period and creates an inverted index. Then each story, in turn, is compared with all preceding stories (including those from previous deferral periods). When the similarity metric for two stories exceeds a threshold, their clusters are merged. The clusters of earlier deferral periods cannot merge since they have already been reported. If a story cannot be merged with an existing cluster, it becomes a new cluster, which means a new event.

2.1.5 BBN Technologies' Approach

The BBN approach uses an incremental k-means algorithm in order to cluster the stories. Although it is similar, the clustering algorithm they used is not precisely a k-means algorithm, because the number of cluster, k is not given beforehand. For every newcomer document, the algorithm tries to make appropriate changes and modifications on the clusters, until no more change can be applied.

There are two types of metrics that are useful for the clustering algorithm: "selection metric," which is the maximum probability value of the BBN topic spotting metric and "thresholding metric," which is the binary decision metric to add a story to a cluster. A score normalization method is used to produce improved scores [35]. The algorithm, which is derived from Bayes' Rule, is shown in Figure 2.3.

1. Use the incremental clustering algorithm to process stories up to the end of the current modifiable window.
2. Compare each story in the modifiable window with the old clusters to determine whether each story should be merged with that cluster or used as a seed for a new cluster.
3. Modify all the clusters at once according to the new assignments.
4. Iterate steps (2)-(3) until the clustering does not change.

Figure 2.3: BBN new event detection algorithm.

2.1.6 On-Line New Event Detection in a Multi-Resource Environment

Kurt[20] used traditional vector space model to represent documents. In his MS Thesis, the system assigns weights to terms by using tf×idf method. In order to limit the similarity calculations between documents, time-penalty functionality was added to the system [2, 36, 37]. In addition to novel threshold, which is very similar with the one, used by Papka [22], another threshold, called “support threshold,” is introduced in order to decrease the number of new event alarms. By the help of this threshold, the number of false alarms can be decremented enormously. The hypothesis was: If a new event is worth for alarming, it should be supported by up-coming news in a short time. The algorithm is depicted in Figure 2.4.

1. Prepare a vector space model of the document.
2. Remove the old documents that exceed the time window.
3. Calculate the similarities between the new document and existing documents in the time window.
4. Calculate the decision score for the new document.
5. If the decision score is positive, then the document contains a new event. Calculate support value.
6. If the decision score is negative, the document does not contain a new event. Then, start event tracking process to find the similar stories.
7. If the support value of any event exceeds the support threshold, perform alarm process.
8. Add the new document to the time window.

Figure 2.4: New event detection and tracking algorithm.

The system works on k-Nearest Neighbor (kNN) Algorithm and it detects new events on-line, and at the same time, it performs event-tracking process.

A summary of on-line new event detection approaches is given in Table 2.1.

	CMU	**UMass**	**Dragon**	**UPenn**	**BBN**	**Kurt**
Term weight	Ltc version of tf-idf	tf-idf	N/A	tf-idf	Probabil-istic	tf-idf
Document represent-ation	Vector-space model	Query representation	N/A	Vector space model	Vector space model	Vector space model
Event represent-ation	Single-pass clustering	single-pass clustering	k-means clustering	Nearest neighbor clustering	Incremental k-means clustering	No clustering
Similarity	Cosine similarity	Previous queries run on new document	Distance between document to clusters	Cosine similarity	Probabilistic similarity	Cosine similarity
Time window	Used	Used	Used	N/A	N/A	Used

Table 2.1: The summary of on-line new event detection approaches (N/A means no information is available).

2.2 Event Clustering Approaches

Event clustering is an unsupervised problem where the goal is to automatically group documents by events that may exist in the data. The significant difference from supervised methods is that the supervised clustering needs training documents about each event to formulate a classifier, while the unsupervised setting operates without training documents. On the other hand, new event detection problem is also unsupervised because no training documents are required for processing the data, however, different from event clustering, the goal of new event detection is to separate documents that discuss new events from documents discussing existing events.

Most of the news classification research prior to Topic Detection and Tracking (TDT) deals with classification problems using topics instead of events. For example, Hayes et al. [16] describe a news organization system in which a rule-based approach was used to group 500 news stories into six topics. The filtering problem analyzed at the Text Retrieval Conferences [18], is another example of topic-based news classification. However, some event-based research has been reported prior to the first TDT workshop [24].

A data structure for news classification, called "Frames," is introduced in 1975 by R. Schank. [29]. The frames are constructed manually and are coded for a semantic organization of text extracted by a natural language parser. Frames contain slots for structured text that can be organized at different semantic levels. For example, frames can be coded to understand entire stories [15], or for understanding the parts of a person's name [11].

A frame-based system that attempted to detect events on a newswire was constructed by DeJong in 1979 [14]. He used pre-specified software objects called sketchy scripts. Frames and scripts for general news events such as "Vehicular Accidents"' and "Disasters" were constructed by hand. The goal of his system was to predict which frame needed to be populated. This system was working mainly as a natural language parser, but as a side effect, it decided whether a document contains an event. However, it did not detect new events.

In 1997, Carrick and Watters introduced an application that matched news stories to photo captions using a frame-based approach modeling proper nouns [11]. They claimed that, when the extracted lexical features are used, their frame-based approach was nearly as effective as using the same features in a word matching approach. Another research related to frame-based representations on news data are discussed at Message Understanding Conferences (MUC) [23].

In order to represent different aspects of the natural language parse, frames can be used helpfully; however, as new types of events appear and existing events grow in a news environment, it is difficult to maintain the number of frames and the details of their contents.

In general, the previous approaches to clustering were used in a retrospective environment where all the documents were available to the process before clustering begins. In his dissertation [22], Papka tested previous approaches to document clustering and he evaluated their effectiveness for online event clustering. He applied retrospective approaches to an online environment. He reevaluated single-link, average-link, and complete-link hierarchical agglomerative clustering strategies, but use them in a single-pass (incremental) clustering context, in which a cluster is determined for the current document before looking at the next document.

2.3 Document Clustering Approaches

Document clustering is an unsupervised process that groups documents similar to each other. Since the clustering algorithm does not need any training instance or any information describing the group, the problem of clustering is often known as automatic document classification. Clustering has been studied extensively in the literature [19], and the common element among clustering methods is a model of word co-occurrence that is applicable to text classification problems in general. By using this model, constructed clusters contain documents consist of words common to most of the documents into that cluster. A historical account of clustering research is given by van Rijsbergen [33], who also discusses cluster similarity coefficients applied to simple word matching techniques. In another research, Salton [25] discusses clustering approaches that use tf×idf representations for text. In addition, Croft [12] introduced a probabilistically based clustering algorithm, and several works have been presented, including by TDT participants in the context of event clustering [2, 35].

Document clustering is also used for information retrieval purposes. The goal of information retrieval system is to retrieve documents, which are relevant to the query of a user. One of well-known query processing approach is cluster-based retrieval (CBR), which is a method for improving document retrieval in terms of speed and effectiveness [27, 25]. There are many researches about CBR [25, 28, 15, 33]. These approaches are based on the "cluster hypothesis," which states, "closely associated documents tend to be relevant to the same request," [33]. However, some databases do not obey this hypothesis, whereas some do [34]. The results presented by Voorhees [34] as well as Croft [13] imply that some collections and requests benefit from pre-clustering, while others do not. Furthermore, according to Can [6], no CBR approach is better than full search (FS), one of the well-known query processing approach, in terms of space and time.

The previous work, which most influenced our approach to new event detection and clustering, is based on single-pass clustering [33] and Cover Coefficient based Clustering Methodology (C^3M) [8]. In the remainder of this section, a brief description of these methods is provided.

2.3.2 Single-Pass Clustering

Single-pass clustering or incremental clustering is an approach for creating clusters on-line. The algorithm is discussed by van Rijsbergen [33] and depicted before in Figure 2.1.

The single-pass algorithm sequentially processes documents using a pre-specified order. The current document is compared to all existing clusters, and it is merged with the most similar cluster if the similarity exceeds a certain threshold, otherwise it starts its own cluster. The single-pass algorithm results in faster processing than the agglomerative hierarchical clustering algorithm, even though both approaches have an $O(n^2)$ asymptotic running time. The main disadvantage of the single-pass method is that the effectiveness of the algorithm is dependent on the order in which documents are processed. This is not a problem in event clustering, because the order is fixed.

2.3.3 Cover Coefficient-based Clustering Methodology

The C^3M algorithm is a partitioning-type clustering algorithm, which means that clusters cannot have common documents, and the algorithm operates in a single-pass approach. The algorithm consists of three main parts:

- Select the cluster seeds; C^3M is one of the nonhierarchical clustering algorithms, and it is seed-based. The chosen seed must attract relevant documents onto itself. To perform this issue, it must be calculated in a multidimensional space that, how much seed document covers non-seeds and what the amount of similarity is.
- Construct clusters; group the non-seed documents around the selected seeds.
- Group documents into a ragbag cluster, which are not fit to any cluster.

C^3M is covered in more details in the next chapter.

Chapter 3

Cover Coefficient-based Clustering Methodology: C^3M

As mentioned in the second chapter, one of the previous work that most influences our approach to new event detection and clustering is based on Cover Coefficient based Clustering Methodology (C^3M) [8]. In the remainder of this chapter, we explain this clustering method in more details.

The C^3M algorithm is a single-pass partitioning-type clustering algorithm, which means that clusters cannot have common documents. The algorithm has three parts, the first part determines the number of clusters and the cluster seeds, the second part groups the non-seed documents around the selected seeds, and the last part gathers the documents that are not fit to other clusters, into a ragbag cluster. A brief description of the algorithm is shown in Figure 3.1.

The complexity of the algorithm is $O(m \times x_d \times t_{gs})$. In this expression, x_d is the average number of distinct terms per document, t_{gs} is the average number of seed documents per term, and m is the number of documents in the database [8].

```
C³M:
1. Determine number of clusters and cluster seeds.
2. Construct the clusters:
        i = 1;
        repeat;
          if d_i is not a cluster seed
            then
                begin;
                  Find the cluster seed (if any) that maximally covers d_i; if there is
                  more  than one cluster seed that meets this condition, assign
                  d_i to cluster whose seed power value is the greatest among
                  the candidates;
                end;
          i = i+1;
        until i>m.
3. If there remain unclustered documents, group them into a ragbag cluster (some
   nonseed documents may not have any covering seed document).
```

Figure 3.1: C^{3}M Algorithm.

C^{3}M is seed-based. The chosen seed must attract relevant documents onto itself. To perform this complete operation, seed value must be calculated in a multidimensional space with respect to the coverage of non-seed documents and the amount of similarity. Using the cover coefficient (CC) concept, these relationships are reflected in the C matrix. The algorithm constructs a C matrix by using a D matrix that contains whole data before clustering begins, and it is a document by term (m × n) matrix. A sample D matrix is shown below:

$$\begin{array}{cccccc|c} t_1 & t_2 & t_3 & t_4 & t_5 & t_6 & \\ 1 & 0 & 0 & 1 & 0 & 1 & d_1 \\ 1 & 1 & 1 & 1 & 0 & 0 & d_2 \\ 1 & 0 & 0 & 0 & 1 & 1 & d_3 \\ 0 & 0 & 0 & 0 & 1 & 1 & d_4 \\ 1 & 0 & 1 & 0 & 0 & 0 & d_5 \end{array}$$

Figure3.2: Sample D Matrix.

By definition of Can and Özkarahan [8]: “A D matrix that represents the document database {d_1, d_2, ...d_m} described by the index terms T={t_1, t_2, ...t_n} is given. The CC matrix, C, is a document-by-document matrix whose entries c_{ij} ($1 \leq i, j \leq m$) indicate the probability of selecting any term of d_i from d_j.”

In the Figure 3.2, each row indicates one document, and each column indicates one individual term. To able to represent a document in D matrix, each document must have at least one term and each term must appear at least in one document. D matrix can be generated manually or automatically. On the other hand C matrix is a document-by-document matrix whose entries, c_{ij} values, indicate the probability of selecting any term of document (d_i) from document (d_j), where d_i and d_j are the members of D matrix.

Two-phase experiment must be processed to generate C matrix. The C matrix summarizes the results of two-phase experiment. At first phase the algorithm chooses a term randomly from the terms of d_i, from the selected term then it tries to draw d_j. The sum of the probability values to select d_j from d_i forms c_{ij}, which is the member of C matrix. The best way to explain this issue is using an analogy. It would be helpful to repeat the same analogy that is used by Can and Özkarahan [8] about two-phase experiment: “Suppose we have many urns and each urn contains balls of different colors. Then what is the probability of selecting a ball of a particular color? To find this probability experimentally, notice that first we have to choose an urn at random, and then we have to choose a ball at random. In terms of the D matrix, what we have is the following: From the terms (urns) of d_i, choose one at random. Each term appears in many documents, or each urn contains many balls. From the selected term, try to draw a ball of a particular color. What is the probability of getting d_j, or what is the probability of selecting a ball of a particular color? This is precisely the probability of selecting any term of d_i from d_j, since we are trying to draw the selected term of d_i from d_j at the second stage.”

If we consider s_{ik} is the event of first stage, and s'_{ik} is the event of second stage, then the probability P(s_{ik}, s'_{ik}) can be represented as P(s_{ik})$\times$ P(s'_{ik}) [17].

By using s_{ik} and D matrix, we can construct S probability matrix. Multiplying S matrix with the transpose of S' (S'^T) forms the *m*-by-*m* C matrix. For example, by using D matrix in Figure 3.2, constructed S and S'^T matrixes are shown in Figure 3.3.

$$\mathrm{S} = \begin{bmatrix} 1/3 & 0 & 0 & 1/3 & 0 & 1/3 \\ 1/4 & 1/4 & 1/4 & 1/4 & 0 & 0 \\ 1/3 & 0 & 0 & 0 & 1/3 & 1/3 \\ 0 & 0 & 0 & 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 & 0 \end{bmatrix}, \quad S'^T = \begin{bmatrix} 1/4 & 0 & 0 & 1/2 & 0 & 1/3 \\ 1/4 & 1 & 1/2 & 1/2 & 0 & 0 \\ 1/4 & 0 & 0 & 0 & 1/2 & 1/3 \\ 0 & 0 & 0 & 0 & 1/2 & 1/3 \\ 1/4 & 0 & 1/2 & 0 & 0 & 0 \end{bmatrix}$$

Figure 3.3: S and S'^T matrixes derived from the D matrix of Figure 3.2.

By multiplying the two matrixes in Figure 3.3, the C matrix, in Figure 3.4, is constructed.

$$\begin{bmatrix} 0.361 & 0.250 & 0.194 & 0.111 & 0.083 \\ 0.188 & 0.563 & 0.063 & 0.0 & 0.188 \\ 0.194 & 0.083 & 0.361 & 0.277 & 0.083 \\ 0.167 & 0.0 & 0.417 & 0.417 & 0.0 \\ 0.125 & 0.375 & 0.125 & 0.0 & 0.375 \end{bmatrix}$$

Figure 3.4: Sample C matrix.

Calculation of one element of the C matrix is shown below:

$$c_{12} = \sum_{k=1}^{6} s_{1k} * s'_{2k}$$

$$c_{12} = \frac{1}{3}\times\frac{1}{4} + 0\times 1 + 0\times\frac{1}{2} + \frac{1}{3}\times\frac{1}{2} + 0\times 0 + \frac{1}{3}\times 0 = 0.250$$

The entries of the C matrix can be defined as follows:

$$c_{ij} = \sum_{k=1}^{n} s_{ik} \times s'^{T}{}_{kj} \qquad \text{where} \qquad s'^{T}{}_{kj} = s'_{jk}$$

This equation can be rewritten as:

$$c_{ij} = \alpha_i \times \sum_{k=1}^{n} d_{ik} \times \beta_k \times d_{jk},\ 1 \le\ i, j \le m \tag{3.1}$$

Where; α_i and β_k are the reciprocals of the i^{th} row sum and the k^{th} column sum, respectively, as shown below:

$$\alpha_i = \left[\sum_{j=1}^{n} d_{ij}\right]^{-1}, \qquad 1 \le\ i \le m, \tag{3.2}$$

$$\beta_k = \left[\sum_{j=1}^{m} d_{jk}\right]^{-1}, \qquad 1 \le\ k \le n, \tag{3.3}$$

Some properties [7] of the C matrix are depicted in Figure 3.5. The proofs of properties 1-4 are given in [7] and [10]. The proof of property 5 is given in [9].

1. For $i \neq j, 0 \leq c_{ij} \leq c_{ii}, c_{ii} > 0$ ($c_{ij} > c_{ii}$ is possible for weighted D matrix).
2. $c_{i1} + c_{i2} + ... + c_{im} = 1$ (Sum of row *i* is equal to 1 for $1 \leq i \leq m$).
3. If non of the terms of d_i is used by the other documents, then c_{ii}=1; otherwise, c_{ii}<1.
4. If c_{ij} = 0, then c_{ji} = 0, and similarly, if c_{ij} > 0, then c_{ji} > 0; but in general, $c_{ij} \neq c_{ji}$.
5. $c_{ii} = c_{ii} = c_{ij} = c_{ji}$ iff d_i and d_j are identical.

Figure 3.5: Some properties of the C matrix.

The diagonal values of the C matrix (c_{ii}) is called decoupling coefficient, and is denoted with the symbol δ_i. This measure shows how much the documents is not related to the other documents. On the contrary, coupling coefficient is calculated by using i^{th} row off-diagonal entries sum, it is denoted with the symbol ψ_i. This coefficient indicates the extent of coupling of d_i with the other documents of the database. The concepts of decoupling and coupling coefficients, δ_i' and ψ_i', are the counterparts of the same concepts defined for documents.

$\delta_i = c_{ii}$: Decoupling coefficient of d_i.

$\psi_i = 1 - \delta_i$: Coupling coefficient of d_i.

By following a methodology similar to the construction of the C matrix, a term-by-term ($n \times n$) C' matrix of size *n* by *n* can be formed for index terms. C' has the same properties with C matrix. As with the C matrix, the C' matrix summarizes the results of a two-stage experiment in a term-wise manner. C' matrix can be defined as follows:

$$c'_{ij} = \beta_i \times \sum_{k=1}^{m} d_{ki} \times \alpha_k \times d_{kj} \quad 1 \leq i, j \leq n \tag{3.4}$$

As mentioned before, the C^3M Algorithm is seed based. In order to select seed documents, cluster seed power for all documents is calculated, by using the following formula:

$$P_i = \delta_i \times \psi_i \times \sum_{j=1}^{n} d_{ij} \tag{3.5}$$

This equation is used for binary D matrix, which means that; if the term occurs in the document, the term frequency is taken as 1, it is taken as 0 otherwise. δ_i provides the separation of clusters, ψ_i provides the connection among the documents within a cluster, and summation provides normalization. For weighted matrix, a modified version of cluster seed power formula is used:

$$P_i = \delta_i \times \psi_i \times \sum_{j=1}^{n} (d_{ij} \times \delta'_j \times \psi'_j) \tag{3.6}$$

After cluster seed power applied to the documents, the document that has highest seed power is selected as candidate. Because this procedure can produce identical seeds, to eliminate these false seeds, a threshold value is used. All documents are sorted by their seed power values, so that identical documents are grouped into the sorted list. If the value, which is obtained by comparing their C matrix values is smaller than threshold value then it means that we have a false seed. For each false seed, another document from the sorted list is considered.

This process can be applied on-line with some modifications. In the on-line clustering environment, each document is analyzed sequentially and is either placed into an existing cluster or initiates a new cluster and thus becomes a cluster seed. In our approach we do not have falsified seeds, thus we do not apply false seed elimination process. How the concepts of C^3M algorithm applied to on-line clustering and on-line event detection is the subject of Chapters 5 and 6, respectively.

Chapter 4

Experimental Data and Evaluation Methods

4.1 TDT Corpus

In our experiments, we used TDT1 corpus, which is also used by the participants of TDT pilot study. In order to support the TDT study effort, Linguistic Data Consortium (LDC) has developed this corpus using text and transcribed speech. TDT1 covers the documents containing news from July 1, 1994 to June 30, 1995 and includes 15,863 stories. About half of the data is taken from Reuter's newswire and half from CNN broadcast news transcripts. The transcripts were produced by the Journal of Graphics Institute (JGI). The stories in this corpus are arranged in chronological order, are structured in SGML format that has a size of 53,563 KB, and are available on the LDC web page (http://www.ldc.upenn.edu/).

A set of 25 target events has been chosen from TDT1 to support the TDT study effort. These events include both expected and unexpected events. They are described in some detail in documents provided as part of the TDT Corpus. The TDT corpus was completely interpreted with respect to these events, so that each story in the corpus is appropriately flagged for each of the target events discussed in it. There are three possible flag values: YES (the story discusses the event), NO (the story does not discuss the event), and BRIEF (the story mentions the event only briefly, or merely references the event without discussion; less than 10% of the story is about the event in question). Flag values for all events are available in the file "tdt-corpus judgments" with stories.

The average document contains 460 (210 unique) single-word features after stemming and removing stop-words. The names of all 25 events chosen from the TDT1 Corpus are listed in Figure 4.1.

1. Aldrich Ames spy case
2. The arrest of 'Carlos the Jackal'
3. Carter in Bosnia
4. Cessna crash on White House lawn
5. Salvi clinic murders
6. Comet collision with Jupiter
7. Cuban refugees riot in Panama
8. Death of Kim Jong II
9. DNA evidence in OJ trial
10. Haiti ousts human rights observers
11. Hall's helicopter down in N. Korea
12. Flooding in Humble, Texas
13. Breyer's Supreme Court nomination
14. Nancy Kerrigan assault
15. Kobe Japan earthquake
16. Detained U.S. citizens in Iraq
17. New York City subway bombing
18. Oklahoma City bombing

Figure 4.1: Judged 25 events in TDT corpus.

The judgments were obtained by two independent groups of assessors and then reconciled to form a set of final judgments. Documents were judged on a ternary scale to be irrelevant, to have content relevant to the event, or to contain only a brief mention of the event in a generally irrelevant document. We use 1124 relevant documents in the experiments after eliminating briefs and overlaps.

4.2 Evaluation

4.2.1 Effectiveness Measures

It is desirable to have one measure of effectiveness for cross system comparisons. Unfortunately, no measure uniquely determines the overall effectiveness characteristics of a classification system. Several definitions for single valued measures have emerged, and are reviewed by van Rijsbergen [33]. One widespread approach is to evaluate text classification using F1 Measure [21], which is a combination of recall and precision and it is defined later.

Since there does not exist an agreed upon single valued metric that uniquely captures the accuracy of a system, it is often the case that two or more measures are needed, and efforts to define combination measures do not necessarily lead to an applicable measure of usefulness. In what follows, we assume usefulness is a function of user satisfaction with the classification effectiveness of a system. In practice, usefulness is constantly changing; one system can be useful for some particular purpose, while it would be useless for others. For example, consider two systems: a car alarm and a radar system for an aircraft guiding a missile. Car alarm system may sound occasionally, especially when it is set to oversensitive. It may be acceptable to sound occasionally when no theft event exists, but if an alarm does not sound during an actual theft, this means that the system is useless. In other words, the owner of the car has a low tolerance for false alarms and no tolerance for misses. On the other hand, radar system has a different usefulness function. It may be tolerable for the system to miss a target, but a false targeting may cause a disaster. With these requirements in mind, without inventing another measure, we report several effectiveness measures, which have been previously used for the analysis of text classification experiments.

Text classification effectiveness is often based on two measures. It is common for information retrieval experiments to be evaluated in terms of recall and precision, where recall measures how well the system retrieves relevant documents and classify them correctly, and precision measures how well the system distinguishes relevant documents from irrelevant ones in the set of retrieved group. In addition, F1 measure [21] is used, which is the combination of recall and precision. In TDT, and the work described here, system error rates are used to evaluate text classification. These errors are system misses and false alarms. The accuracy of a system improves when both types of errors approaches to zero. In new event detection, misses occur when the system does not detect a new event, and false alarms occur when the system indicates a document contains a new event when in truth it does not. In addition to system error rates, we report performance (pfr), which is based on the Euclidean distance average miss rate and false alarm rate from the origin.

The methods for calculating the effectiveness measures for on-line event clustering, and on-line new event detection are summarized below using modified version of Swets's [31] two-by-two contingency table (Tables 4.1 and 4.2):

	Relevant	Non-Relevant
Retrieved	a	b
Not Retrieved	c	d

Table 4.1: Two-by-two contingency table for event clustering.

Where the retrieved documents in the table are those that have been classified by the system as positive instances of an event, and the relevant documents are those that have been manually judged relevant to an event.

	New is True	Old is True
System Predicted New	a	b
System Predicted Old	c	d

Table 4.2: Two-by-two contingency table for event detection.

Assuming S represents the set of retrieved documents, and S' represents the set of not retrieved documents, then:

a = number of documents in S discussing new events,

b = number of documents in S not discussing new events,

c = number of documents in S' discussing new events,

d = number of documents in S' not discussing new events;

By using the two-by-two contingency table, we can derive the effectiveness measures as follows:

$$\text{Recall} = R = \frac{a}{a+c}, \tag{4.1}$$

$$\text{Precision} = P = \frac{a}{a+b}, \tag{4.2}$$

$$\text{F1 Measure} = \frac{2PR}{P+R}, \tag{4.3}$$

$$\text{Miss Rate} = M = \frac{c}{c+a}, \tag{4.4}$$

$$\text{False Alarm Rate} = FA = \frac{b}{b+d}, \tag{4.5}$$

$$\text{Distance from Origin} = \sqrt{M^2 + F^2}, \tag{4.6}$$

$$\text{Performance (pfr)} = 100 - \text{Distance from Origin.} \tag{4.7}$$

The difference between event clustering and new event detection about effectiveness calculations is that; for the former, two-by-two contingency table is formed for each cluster that is selected as the best cluster for that event, and the overall system effectiveness is calculated by taking the averages of each measure. For the later, there is only one contingency table formed, and the effectiveness measures are computed by using Table 4.2.

In the experiment results, effectiveness measures are given as rates, except the performance (pfr).

4.2.1 Experimental Methodology

The experiments of both event detection and event clustering are executed on a personal computer, which has Intel Pentium 550 Mhz. Central Processor Unit (CPU) and has 128 MB of main memory.

It is considered that a time gap between bursts of topically similar stories is often an indication of different events. It is also experienced that events are typically reported in a brief time window (e.g., 1-4 weeks) [22]. These determinations in mind, we applied a time windowing in days to limit the size of comparisons. We see that time windowing influenced the CPU time. In other words, evaluating more days results with more CPU time.

4.2.2 Preprocessing

In the preprocessing phase, we eliminate stop words from the corpus by the help of a pre-constructed stop word list. This list consists of terms like (a, an, and, the) that are fatal importance to the structure of English grammar (stop word list is attached to the appendix part). In order to able to find the terms, which have the same root, we apply Porter's stemming algorithm [30] to the corpus. We get stemmed word list consists of 72,034 terms and phrases. At the same time, we construct the document vectors in the format of <docno, termno, termfrequency> as shown in Figure 4.2. We get 15,863 document vectors containing this format.

```
DOC1: 1:1:2:1:3:1:4:1:5:1:6:1:7:1:8:1

DOC2: 9:1:10:1:11:1:12:1:13:1

DOC3: 3:1:6:1:15:1:16:1:17:1

DOC4: 6:1:16:1:17:1

DOC5: 2:1:3:1:4:1:5:1:7:1:8:1:17:1

.

.

DOCn: . . . . . . . . . . .
```

Figure 4.2: An example document vector.

This structure is used during both on-line event clustering and on-line event detection experiments.

Chapter 5

On-Line Event Clustering

In this chapter, we focus on the problem of on-line mode of event clustering. We introduce a new algorithm as a solution to the problem, with the help of C^3M algorithm.

5.1 Window Size

In our experiments, we add window size concept to the algorithm. This prevents producing oversized clusters, and gives equal chance to all documents to be a cluster seed. When we analyze the distribution of documents for a particular event, we determine that the most of the documents for an event ends in a few days from the first occurrence of that event. There are exceptions for some events, which lasts for the most days of the year. For example, events 9, 22, 25, listed in Table 5.1, do not follow this tendency. The details are shown in Table 5.1.

In Table 5.1, number of documents are counted for the first 10, 20, 30, 40 days of each event, and for the whole life of that particular event, that is; from the first occurrence to the last story about that event. The table summarizes that, stories about most of the events appear in first 30 or 40 days. At the end of the table, total number of documents shows a trend that the most significant window sizes are these two day-periods.

Events	**Event Life in Days**	**No. of Documents in Window**				
		Life	**40**	**30**	**20**	**10**
1. Aldrich Ames spy case	96	8	6	5	3	2
2. The arrest of "Carlos the Jackal"	30	10	10	10	9	7
3. Carter in Bosnia	49	30	29	29	27	25
4. Cessna crash on White House lawn	2	14	2	2	2	2
5. Salvi clinic murders	60	41	34	34	33	33
6. Comet collision with Jupiter	121	45	44	44	44	6
7. Cuban refugees riot in Panama	3	2	2	2	2	2
8. Death of Kim Jong II	317	56	45	44	41	36
9. DNA evidence in OJ trial	376	114	29	12	7	4
10. Haiti ousts human rights observers	3	12	12	12	12	12
11. Hall's helicopter down in N. Korea	20	97	97	97	97	50
12. Flooding in Humble, Texas	8	22	22	22	22	22
13. Breyer's Supreme Court nomination	80	7	6	6	6	5
14. Nancy Kerrigan assault	180	2	1	1	1	1
15. Kobe Japan earthquake	127	84	82	81	81	74
16. Detained U.S. citizens in Iraq	54	44	33	32	29	11
17. New York City subway bombing	8	24	24	24	24	24
18. Oklahoma City bombing	45	273	261	249	226	215
19. Pentium chip flaw	9	4	4	4	4	4
20. Quayle's lung clot	9	12	12	12	12	12
21. Serbians down F16	10	65	65	65	65	65
22. Serb's violation of Bihac safe area	130	90	1	1	1	1
23. Faulkner's admission into the Citadel	180	7	4	4	3	3
24. Crash of US Air flight 427	140	39	37	37	36	35
25. World Trade Center bombing	360	22	1	1	1	1
Total number of documents:	-	1124	863	832	790	654

Table 5.1: Distribution of the documents in time (window size in days).

This distribution of documents is depicted in more details for a specific event (event number 18). It has the maximum number of related stories (273) among 25 events. Figure 5.1, is borrowed from Papka [22], illustrates the window size concept. In this figure, we see that the most of the news about "Oklahoma city bombing" appeared between the days of 293 and 305 (in the fist ten days). After the second week of first occurrence of the event, it is observed that the amount of streaming news is reduced. Most of the events in TDT1 corpus behave as the event seen in this figure.

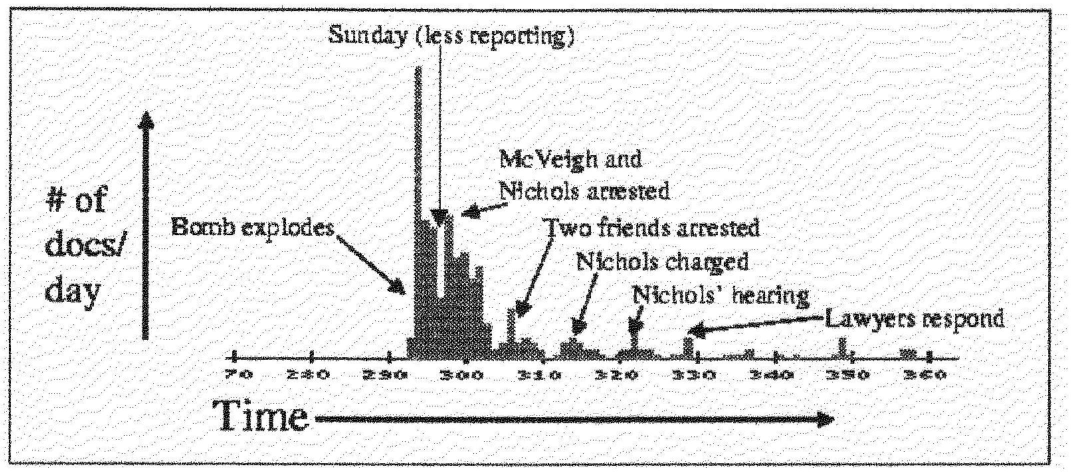


Figure 5.1: Event evolution; Oklahoma city bombing (adapted from Papka[22])

This tendency in mind, we use a window size concept, in order to improve the performance of the system. The hypothesis is that; limiting the number of documents, by processing only the documents in predetermined window size would help to improve the effectiveness of the system. This hypothesis is verified for events following the same tendency. However, as a disadvantage, the miss rate of the system is increased dramatically for the events, which do not follow the common trend.

In order to improve the performance, Papka [22] used time windowing in his system. The main motivation of his approach is that documents closer together on the stream are more likely to discuss similar events than documents further apart on the stream. As depicted in Figure 5.1, when a significant new event occurs there are usually several related documents in the initial days. Over time, coverage of old events is displaced by events that are more recent. Different from our approach, Papka integrated time in the thresholding model.

5.2 Threshold Model

In the seed selection process, we apply a threshold model, which varies from document to document. For on-line clustering subject, we aimed to find a way of putting a threshold in front of the documents, to make the decision of flagging as seed. Without thresholding all the documents in the corpus would be a seed, and this would produce number of clusters equals to the number of documents in the corpus. This is not a desired situation for event clustering. On the other hand, when a greater value is used as a threshold, the system would give unproductive results; in other words, the miss rate of the system would be unacceptable. Thus, we want an appropriate number of clusters for each individual event. It is acceptable for the system to produce at least one representative cluster for each event; while doing this the system must classify the related stories into that clusters. In other words, we don't desire weak or empty clusters (without member except the seed). As a solution, we use a threshold concept, by computing the average P value for documents in the scope of predetermined window size, and compare this value to the P_i value of new coming document. The expression of threshold Tr is given below:

$$Tr = \sum_{d_i \in window} P_i \;/\; (\text{No. of documents in window}) \tag{5.1}$$

The idea behind this approach is that; P_i value is a sign for a document how the document is different from the others, if this value can exceed the average P value, this means that the particular document reviews a different story, and it deserves to be a seed of a new cluster.

5.3 The Algorithm

The on-line event-clustering algorithm constructs the cluster structure by processing document vectors sequentially in a sing-pass manner; a simple example of the document vector structure is given in Figure 4.2. The algorithm is shown in Figure 5.2.

When a document (say d_i) arrives, the update process begins if the difference between the dates of the oldest document and the youngest one exceeds the pre-determined window size. In the update process, system deletes the old documents until the date difference falls under the value of window size. If the deleted document is a seed of a cluster, the whole cluster is deleted after computing its effectiveness. However, the members of the deleted cluster, which do not exceed the window size, remain in the system and they are used in the

```
For each new coming document $d_i$;
1.  let $d_j$= oldest document
2.  **if** $d_{i\text{Date}} - d_{j\text{Date}^*} \geq$ predetermined window size (WS)
        **repeat;**
            delete $d_j$
            **if** $d_j$ is seed
                delete cluster started by $d_j$
            $d_j$= oldest document in WS
        **until** $d_{i\text{Date}} - d_{j\text{Date}} <$ WS
3.  calculate the seed power value $P_i$
4.  determine the threshold ($Tr$)
5.  **if** $P_i \geq Tr$
        label the document as seed and initiate a new cluster
    **else**
        **if** there exists any cluster
            calculate $c_{ij}$ value to decide which cluster it is attached
        **else**
            put the document in a ragbag cluster
(*) $d_{j\text{Date}}$ = 0 if there is no previous document in the window.
```

Figure 5.2: On-line event clustering algorithm.

computation of β values. For the next step, the seed power (P_i) of the document d_i, and then the threshold for the same document are calculated. If seed power value of the document, exceeds the threshold, then it is labeled as a new seed, and a new cluster is initiated. Otherwise, the similarity calculations are done. That is; the similarities between the document and the previous seed documents are computed, and the document is classified as a member of the cluster of the seed document, which constitutes the maximum similarity with the current document d_i. If there is no cluster formed, or all clusters are deleted during the update process, the document is put in a ragbag cluster.

In Figure 5.2, $d_{i\text{Date}}$ and $d_{j\text{Date}}$ demonstrate the date of new coming document and the date of the oldest document in the window size respectively. Ragbag cluster is a cluster that gathers the non-seed documents, which have no common terms with current seeds, or there is no cluster introduced in the window size.

Different from C^3M algorithm, in on-line event clustering algorithm, once a document is determined as a seed, it stays as seed until it leaves the system. Recall that in C^3M algorithm, when a document joins to a cluster it may influence the centroid of that cluster. This is not the point in our clustering strategy. Because the idea is that when a document is selected as a seed document, then the only information to pull the other documents is the seed document itself. When a document is selected as a seed, it always remains the same and it is used as the cluster centroid.

5.3.1 An Operational Example

Generation of Clusters

To make the algorithm more understandable, we give an example using the sample D matrix of Chapter 3. Assume that the system receives the documents one at a time, and d_1, d_2 and d_5 discuss the same event while d_3 and d_4 discusses a different event (actually we have two events).

When d_1 arrives:

$$\delta_1 = 1 \Rightarrow \psi_1 = 0 \Rightarrow P_1 = 1 \times 0 \times 3 = 0$$

$$Tr = \frac{0}{1} = 0$$

$P_1 = Tr \Rightarrow d_1$ is flagged as seed and it forms Cluster-1.

When d_2 arrives:

$$\delta_2 = 0.75 \Rightarrow \psi_2 = 0.25 \Rightarrow P_2 = 0.75 \times 0.25 \times 4 = 0.75$$

$$Tr = \frac{0 + 0.75}{2} = 0.38$$

$P_2 > Tr \Rightarrow d_2$ is flagged as seed and it forms Cluster-2.

When d_3 arrives:

$$\delta_3 = 0.61 \Rightarrow \psi_3 = 0.39 \Rightarrow P_3 = 0.61 \times 0.39 \times 3 = 0.71$$

$$Tr = \frac{0 + 0.75 + 0.71}{3} = 0.49$$

$P_3 > Tr \Rightarrow d_3$ is flagged as seed and it forms Cluster-3.

When d_4 arrives:

$$\delta_4 = 0.41 \Rightarrow \psi_4 = 0.59 \Rightarrow P_4 = 0.41 \times 0.59 \times 2 = 0.48$$

$$Tr = \frac{0 + 0.75 + 0.71 + 0.48}{4} = 0.49$$

$P_4 < Tr \Rightarrow c_{ij}$ values must be calculated for d_4 as illustrated before in Chapter 3, and classified with the seed document that has the highest similarity with c_{ij}.

By using Equations 3.1, 3.2, and 3.3:

$\alpha_4 = \frac{1}{2}$ and $\beta_5 = \frac{1}{2}, \beta_6 = \frac{1}{3}$ => then;

$$\left.\begin{aligned} c_{41} &= \frac{1}{2} \times \left(0+0+0+0+0+1\times\frac{1}{3}\times 1\right) = \frac{1}{6} = 0.17 \\ c_{42} &= \frac{1}{2} \times (0+0+0+0+0+0) = 0 \\ c_{43} &= \frac{1}{2} \times \left(0+0+0+0+1\times\frac{1}{2}\times 1 + 1\times\frac{1}{3}\times 1\right) = \frac{5}{12} = 0.42 \end{aligned}\right\} d_4 \text{ goes to Cluster-3,}$$

since the similarity value between d_4 and d_3 is more than the others.

When d_5 arrives:

$$\delta_5 = 0.38 \Rightarrow \psi_5 = 0.62 \Rightarrow P_5 = 0.38 \times 0.62 \times 2 = 0.47$$

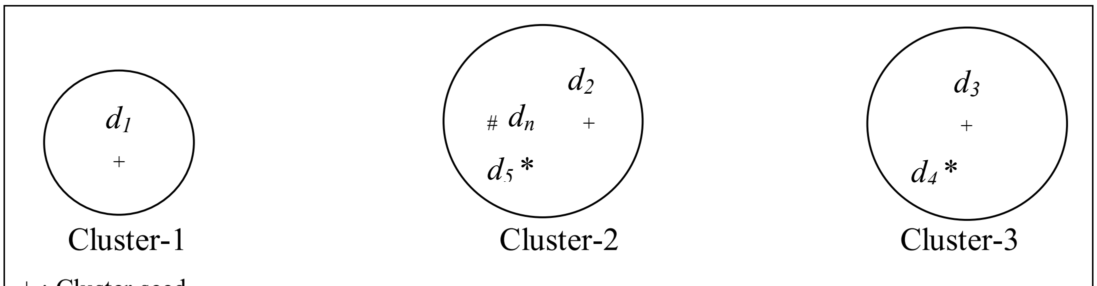
$$Tr = \frac{0 + 0.75 + 0.71 + 0.48 + 0.49}{5} = 0.48$$

$P_5 < Tr \Rightarrow c_{ij}$ values must be calculated for d_5.

By following the same procedure:

$$\left.\begin{aligned} c_{51} &= 0.12 \\ c_{52} &= 0.38 \\ c_{53} &= 0.12 \end{aligned}\right\} d_5 \text{ goes to Cluster-2.}$$

The clusters are shown in Figure 5.3.



+ : Cluster seed.

* : Member document relevant to the event started by the cluster seed.

# : Member document not related to the event started by the cluster seed.

Figure 5.3: Final event clusters.

In Figure 5.3, the seed documents, the relevant members, and non-relevant members are represented by the symbols (+, *, and #) respectively. In order to show false alarm measure, an extra document d_n is added to Cluster-2 intentionally.

Calculation of Effectiveness Measures

In the effectiveness process, for each event, we choose the best cluster from the clusters related to the same event, note that the cluster seed determines the related event of the corresponding cluster. The best cluster is the one that contains the maximum number of the stories of the related event. For example, consider that clusters 1 and 2 contain the documents discussing the same event; Cluster-2 is chosen as the best cluster, because it contains more number of relevant elements. Cluster 3 is the only cluster related to the next event; therefore, we include it in our computations. Performance is computed with the help of measures covered in Chapter 4. The results are given in Figure 5.4. Window size notion is not applied to this sample data, because it is very small when compared to the data used in our experiments.

	Relevant	Non-Relevant
Retrieved	2	1
Not Retrieved	1	2

Two-by-two contingency table for Cluster-2

	Relevant	Non-Relevant
Retrieved	2	0
Not Retrieved	0	4

Two-by-two contingency table for Cluster-3

With the help of effectiveness measures that covered in Chapter 4:

	Recall	Precision	F1	Miss	False Alarm
Cluster-2	0.67	0.67	0.67	0.33	0.33
Cluster-3	1	1	1	0	0
Pooled Avg.	0.84	0.84	0.84	0.17	0.17

System performance.

Figure 5.4: Effectiveness measure results for the example data.

5.4 Experimental Results

We obtain two sets of experimental results, one set for binary D matrix and one set for weighted. For the first set, the system takes the term frequencies of document vectors as binary, in other words if a particular term exists in the vector the system takes its term frequency as 1, it is taken as 0 otherwise. In order to calculate the P_i value, equation (3.5) is used. For the second set, the system incorporates the actual term frequencies into equation (3.6). For example, if a term appears in a document 10 times, term frequency (d_{ij}) is taken as 10.

5.4.1 Results of Binary Implementation

For obtaining binary implementation results, we execute the algorithm six times for six different window sizes. The idea behind this execution method is that; we aim to see the impact of different window sizes to the effectiveness results. For each window size, the best clusters are chosen, and pooled average of effectiveness results, containing all 25 events, is computed. These results are depicted in Table 5.2.

EVENT CLUSTERING (BINARY)						
W-Size	**Recall %**	**Precision %**	**F1 %**	**Miss %**	**F-Alarm %**	**Performance(pfr)**
15	25	75	35	75	0.8	25
20	27	77	37	73	0.8	27
25	28	75	38	72	0.6	28
30	30	73	39	70	0.7	30
35	31	73	39	69	0.8	31
40	29	70	37	71	0.7	29

Table 5.2: Event clustering results according to six window sizes (binary).

In Table 5.2, we observe that; while window size expands, the probability of retrieving relevant documents improves, in other words recall improves, until a peak point of this improvement, which is the window size of 35. The experiments, after this point for windows 40, 45 and 50, show that the performance (prf) suffers. On the contrary, general trend of precision is negative, since the number of retrieved documents increases with the increase of window size. The performance(pfr) measure has the same trend with recall, and it shows that the best performance(pfr) is obtained with the window size 35. Change of effectiveness measures and change of performances (pfr) in terms of different window sizes are illustrated in Figures 5.5 and 5.6.

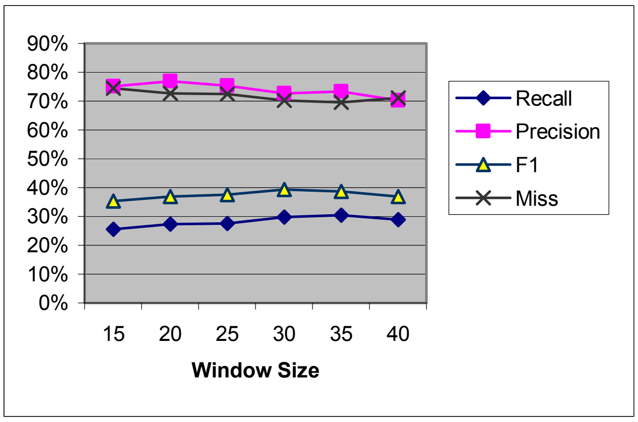


Figure 5.5: Change of effectiveness measures vs. window size (binary).

In the experiments of binary implementation, one of the events, "Cuban refugees riot in Panama," which has the event number of 7, cannot be clustered, because the documents of this event cannot be chosen as seed. For this reason, while computing the pooled averages, the effect of this event to the results reflects in a negative way. If we execute the same experiments neglecting that particular event, we observe an improvement of 7% and 4% in terms of recall and precision respectively.

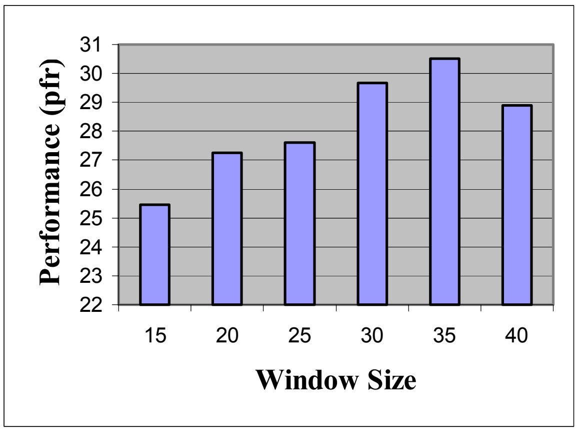


Figure 5.6: Change of performance (pfr) vs. window size.

In Figure 5.6, it is shown that the performance (pfr) improves with the growing size of window. We obtain the best performance (pfr) with window size 35. After this point, since the number of seed documents appeared in the same window increases, the previous seeds and the current seeds are presented in the same window. In other words, the seed documents from the previous event interfere with the seed documents of the current event. This gives an alternative to non-seed documents to join different clusters. For this reason, 35-day window size is selected as the optimum window size for the system.

5.4.2 Results of Weighted Implementation

We follow the same procedure with the binary implementation to obtain the results of weighted version. Different from binary, we use actual term frequencies while computing seed power values and similarities.

In Table 5.3, we observe usually the similar results with binary implementation. The window size 35 is again detected as the best choice for the system in terms of miss rate and Performance (pfr).

EVENT CLUSTERING (WEIGHTED)						
W-Size	Recall %	Precision %	F1 %	Miss %	F-Alarm %	Performance(pfr)
15	26	81	36	74	0.6	26
20	27	82	39	73	0.5	27
25	27	85	39	73	0.4	27
30	28	87	40	72	0.3	28
35	29	76	38	71	0.3	29
40	28	73	36	72	0.5	28

Table 5.3: Event clustering results according to six window sizes (weighted).

Change of measures (recall, precision, F1 and miss) and change of performance(pfr)s in terms of different window sizes are illustrated in Figure 5.7 and Figure 5.8.

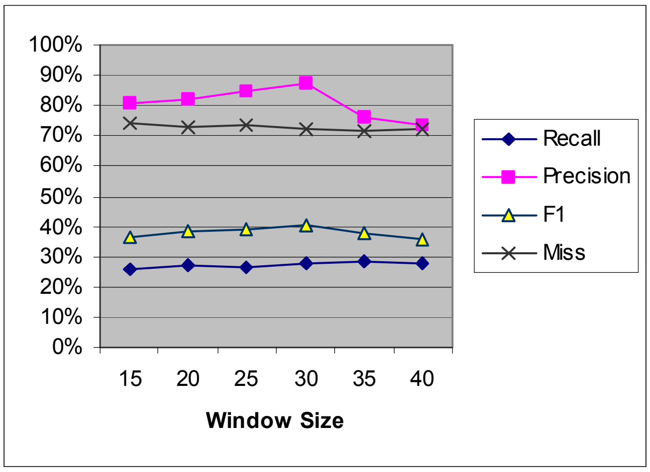


Figure 5.7: Change of effectiveness measures vs. window size (weighted).

In the experiments of binary implementation, recall that one of the events, "Cuban refugees riot in Panama," which has the event number of 7, cannot be clustered, because the documents of this event cannot be chosen as seed. In the situation of weighted implementation, because of the effect of actual term frequencies, the system selects one of its two documents as seed. The reason is that; the number of term used in the document is more than the average number of term frequencies in that particular window size. Therefore, the seed power of the document (TDT007817) exceeds the threshold value. With this progress, all the events have a representative cluster, which is a desired situation. However, as a side affect, the number of clusters is grown by 10% according to the binary version. For this reason, the weaker clusters are produced by the system when comparing to the clusters of the binary implementation, and this decreases the effectiveness.

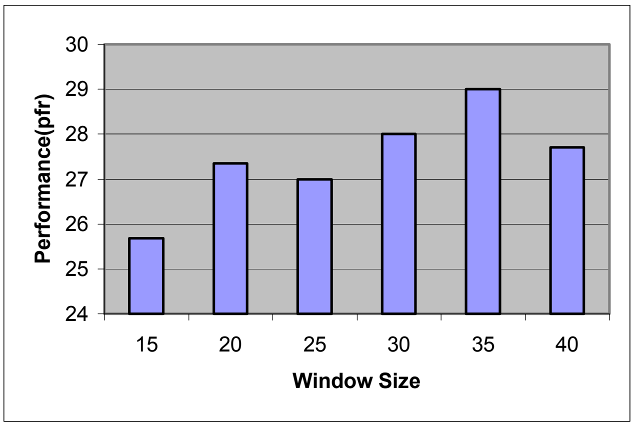


Figure 5.8: Change of effectiveness measures vs. window size.

In Figure 5.8, results are generally similar to the binary version of the implementations. The best Performance(pfr) is once more obtained with window size 35.

Comparisons of binary and weighted versions of the implementation of the algorithm are depicted in Figures 5.9 and 5.10.

Improvement in F1 measure is the effect of precision, because extra clusters retrieve irrelevant documents, from the other cluster point of view, as well as retrieving relevant ones. This reduces the number of members in the clusters, and the amount of recall, nevertheless it increases precision value.

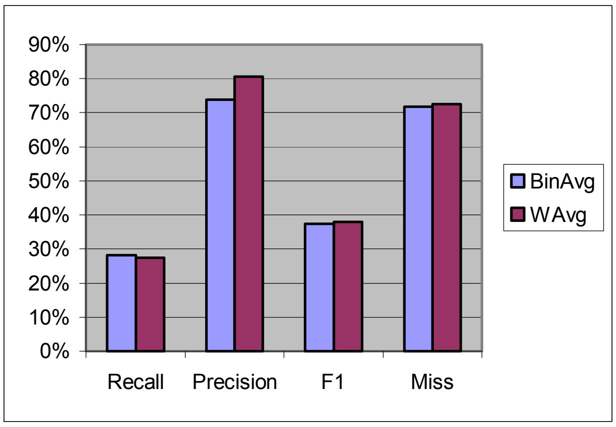


Figure 5.9: Comparison of effectiveness measures (recall, precision, F1, miss).

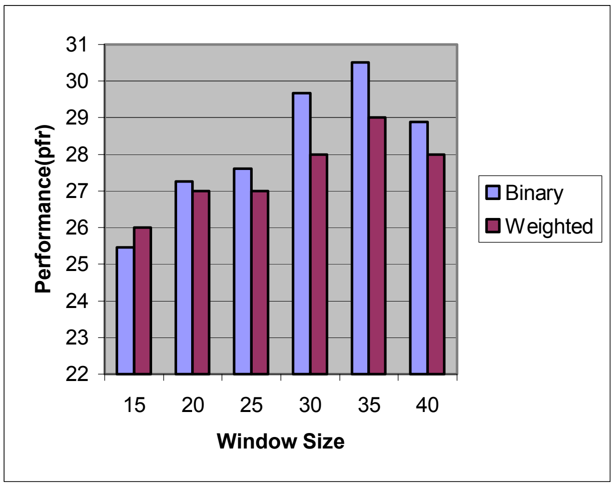


Figure 5.10: Comparison of implementation performances (pfr).

In Figure 5.10, the average values of performance (pfr) with respect to six window sizes is shown for both binary and weighted implementations of the system. Weighted version has an advantage of producing clusters for all the events that are identified before. In spite of this advantage over binary one, producing weak clusters decreases the overall performance (pfr) of the system.

Chapter 6

On-Line New Event Detection

In this chapter, we focus on the problem of on-line new event detection. We use the same algorithm, which is used before for the problem of on-line event clustering, with some modifications.

6.1 Window Size

To support the on-line new event detection task, we again use the window size concept. We aim to prevent the effects of previously detected events. That is, recall from the previous chapter that each cluster is the representative of a different event; it means that each seed document is the sign of new event detection process indirectly. Therefore, we want to find a way to detect the first story of each event as a cluster seed, without constructing any clusters. By adjusting the window size, the chance of the documents to be seed can be changed, since each document in window has an effect on the decision of selecting the current processed document as a seed.

Different from on-line event clustering, in this task, when a narrower window is chosen, the performance improves because of the usage of a different threshold model, which is covered in the next section.

6.2 Threshold Model

In the desired on-line new event detection system, the number of seed documents should be equal to the number of events, and in addition, each event should be represented with a seed. Within the context of new event detection, our previous threshold model yields huge number of seeds. This situation is unacceptable, since it causes a dramatic decrease in terms of precision. To provide an acceptable precision value while increasing recall, we modify the previous threshold model. In the threshold concept, which is used for on-line event clustering, initially we compute the average P value for documents in the scope of predetermined window, and then we compare this value to the P_i value of new coming document. Different from this method, in the initial step, the average P value is computed for only the current seed documents, the seeds in the scope of window (in order to not miss the very first document and to prevent errors, we take the number of seed documents as 1 if there is no seed in the system). Then we use this value as the threshold for the document that processed at that time.

$$Tr = \sum_{d_i \in window} P_i \, / \, (\text{No. of seed documents in window}) \tag{6.1}$$

When a document exceeds this threshold, it is flagged as a seed document, and it becomes a candidate new event. Because, the seed power value of the new event should be greater than the average seed power value of the seed documents in the window. This means that, the particular document reviews a different story, and it deserves to be a seed, in other words a new event.

6.3 The Algorithm

Different from the on-line event clustering algorithm, the task of on-line new event detection algorithm is to flag the current document in the stream as new or old event. For this purpose, we modify the previous algorithm. Since we do not need the clusters at the end, we exclude the clustering phase. That is, if a document cannot exceed the threshold, the similarity computations for classification of the document are excluded in the on-line new event detection algorithm. With the modification in thesholding model, we aim to produce an acceptable number of seeds, in which each event has only one representative seed document. The algorithm is shown in Figure 6.1 and is explained with an example in the next section.

```
For each new coming document $d_i$;
1. Let $d_j$ = the oldest document in window,
2. if $d_{i\text{Date}} - d_{j\text{Date}^*} \geq$ predetermined window size (WS)
       repeat
               delete $d_j$
               $d_j$ = the oldest document in window
       until $d_{i\text{Date}} - d_{j\text{Date}} <$ (WS)
3. calculate the seed power value $P_i$
4. calculate threshold $Tr$ (let $Tr$=0 if there is no previous seed)
5. if $P_i \geq Tr$
       label the document as seed and as a new event
   else
       label the document as an old event


(*) $d_{j\text{Date}}$ = 0 if there is no previous document in the window.
```

Figure 6.1: On-line new event detection algorithm.

6.3.1 An Operational Example

Selection of new events

We use the same sample D matrix of Chapter 3. Assume that, the system receives the documents one at a time, and d_1 and d_3 discuss the new event while d_2, d_4 and d_5 discusses old events (actually we have two events).

When d_1 arrives:

$$\delta_1 = 1 \Rightarrow \psi_1 = 0 \Rightarrow P_1 = 1 \times 0 \times 3 = 0$$

$$Tr = \frac{0}{1} = 0$$

$P_1 = Tr \Rightarrow d_1$ is flagged as seed and new event.

When d_2 arrives:

$$\delta_2 = 0.75 \Rightarrow \psi_2 = 0.25 \Rightarrow P_2 = 0.75 \times 0.25 \times 4 = 0.75$$

$$Tr = \frac{0.75}{1} = 0.75$$

$P_2 = Tr \Rightarrow d_2$ is flagged as seed and new event.

When d_3 arrives:

$$\delta_3 = 0.61 \Rightarrow \psi_3 = 0.39 \Rightarrow P_3 = 0.61 \times 0.39 \times 3 = 0.71$$

$$Tr = \frac{0 + 0.75}{2} = 0.38$$

$P_3 > Tr \Rightarrow d_3$ is flagged as seed and new event.

When d_4 arrives:

$$\delta_4 = 0.41 \Rightarrow \psi_4 = 0.59 \Rightarrow P_4 = 0.41 \times 0.59 \times 2 = 0.48$$

$$Tr = \frac{0 + 0.75 + 0.71}{3} = \frac{1.46}{3} = 0.49$$

$P_4 < Tr \Rightarrow$ Label the document as old.

When d_5 arrives:

$$\delta_5 = 0.38 \Rightarrow \psi_5 = 0.62 \Rightarrow P_5 = 0.38 \times 0.62 \times 2 = 0.47$$

$$Tr = \frac{0 + 0.75 + 0.71}{3} = 0.49$$

$P_5 < Tr \Rightarrow$ Label the document as old.

The results of prediction of the system, obtained at the end of the whole process, are shown in Table 6.1.

System Prediction	
New	**Old**
d_1	d_4
d_2	d_5
d_3	-

Table 6.1: Final Document Labels.

Calculation of effectiveness measures

In the effectiveness process, we use the information given in Table 6.1. Two-by-two contingency table in Table 4.2 is used for effectiveness calculations. Performance is computed with the help of measures covered in Chapter 4. The results are given in Figure 6.2. Window size notion is not applied to this sample data, because it is very small when compared to the data used in real experiments.

	New is True	Old is True
System Predicted New	2	1
System Predicted Old	0	2

Two-by-two contingency table for Cluster-2

With the help of effectiveness measures that covered in Chapter 4:

	Recall	Precision	F1	Miss	False Alarm
Performance	1	0.67	0.80	0	0.33

System performance.

Figure 6.2: Effectiveness measure results for the example data.

6.4 Experimental Results

We apply two sets of experiments for on-line event detection as we do for event detection before. The way we follow is similar to one that explained at the beginning of Section 5.4.

6.4.1 Results of Binary Implementation

For obtaining binary implementation results, we execute the new event detection algorithm for four different window sizes. The idea behind this execution method is that; we aim to see the impact of different window sizes to the effectiveness results. For each window size, we compute the effectiveness measures as explained in Section 6.3. The results are obtained without any deletion or skipping of any event. These results are depicted in Table 6.2.

EVENT DETECTION (BINARY)						
W-Size	Recall %	Precision %	F1 %	Miss %	F-Alarm %	Performance(pfr)
5	56	50	53	44	1.27	56
10	44	65	52	56	0.5	44
15	36	75	49	64	0.3	36
20	24	75	36	76	0.2	24

Table 6.2: On-line event detection results according to four windows (binary).

Different from the event clustering results, we observe that narrowing the window increases the performance of the system. There are some reasons: a number of first coming documents have high seed power values, these values reduce the chance of later document to be selected as seed. In wider windows, the effects of these first seeds reach documents, which are quite faraway from these seeds in terms of time. In addition narrowing the window size decreases the probability of occurrence of documents, which are outside of the determined 25 events. This gives more chance to new events to be selected as seed, at the same time, to be detected as new events.

In Table 6.2, in brief; using narrower window affects the performance in a positive way. On the contrary, precision improves with wide windows, since the number of documents, labeled as new, decreases with the increase of window size. This also decreases the number of false alarms. The performance (pfr) measure has the same trend with recall, and it shows that the best performance (pfr) is obtained with the narrowest window, which is 5. Change of measures (recall, precision, F1, miss) and change of performances (pfr) in terms of different window sizes are illustrated in Figures 6.3 and 6.4.

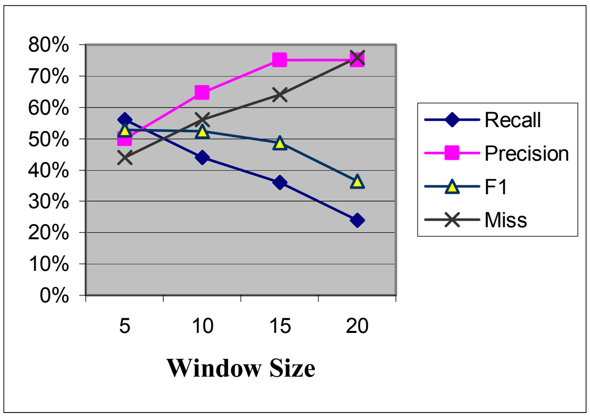


Figure 6.3: Change of effectiveness measures vs. window size.

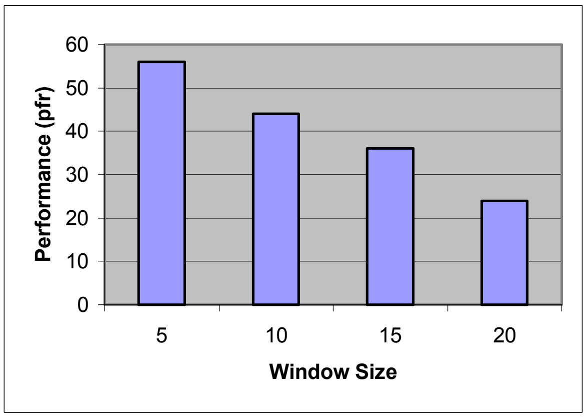


Figure 6.4: Change of performance (pfr) vs. window size.

In Figure 6.4, it is shown that the performance decreases with wide windows. We obtain the best performance with window size 5. For this reason, 5-day window size is selected as the optimum window size for on-line new event detection.

6.4.2 Results of Weighted Implementation

We follow the same procedure with the binary implementation to obtain the results of weighted version. Different from binary, we use actual term frequencies while computing seed power values and similarities. The results of weighted implementation are shown in Table 6.3.

EVENT DETECTION (WEIGHTED)						
W-Size	**Recall %**	**Precision %**	**F1 %**	**Miss %**	**F-Alarm %**	**Performance(pfr)**
5	48	63	55	52	0.6	48
10	36	75	49	64	0.2	36
15	28	78	41	72	0.4	28
20	16	100	28	84	0.0	16

Table 6.3: On-line new event detection results according to four windows.

In Table 6.3, we observe usually the similar results with weighted implementation. The significant point is that, precision and false alarm values are better than the binary implementation, while the recall values are lower. This is because, for the case of binary implementation, system selects more number of seeds than the number of seeds for weighted case. This increases the probability of false alarms; the system determines more candidate documents. Less number of documents decreases the probability of false labels, for example, system labels a document contains a new event, when in truth it does not. This reduction improves the precision while recall suffers. Furthermore, the system gives less false alarm reaction. The window size 5 is again detected as the best choice for the system in terms of miss rate and performance. Change of effectiveness measures and change of performances in terms of different window sizes are illustrated in Figures 6.5 and 6.6.

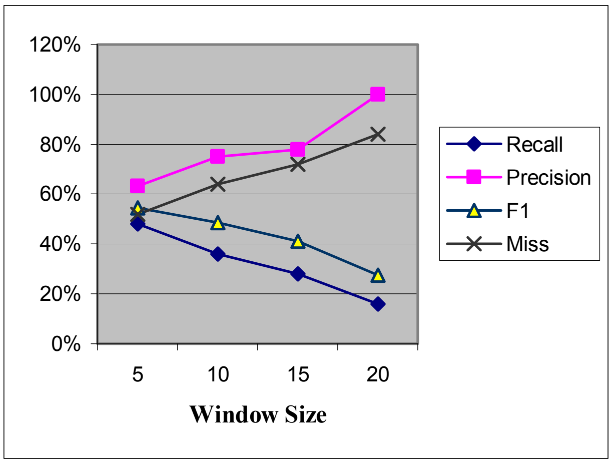


Figure 6.5: Change of effectiveness measures vs. window size.

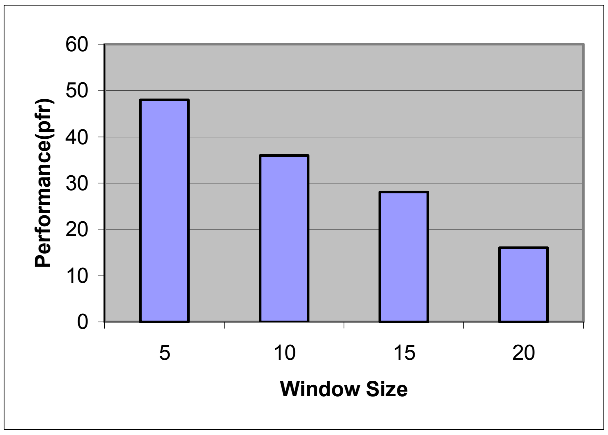


Figure 6.6: Change of performance vs. window size.

In Figure 6.6, results are generally similar to the binary version of the implementations. The best performance is once more obtained with window 5.

Comparisons of binary and weighted versions of the implementation of the algorithm are depicted in Figures 6.7 and 6.8. The binary implementation results are better than weighted implementation, except the precision and the false alarm values. As mentioned before, when the on-line new event detection system uses weighted values, it selects less number of seeds as candidate new events, and this reduction in the number of documents, also decreases the probability of false alarms.

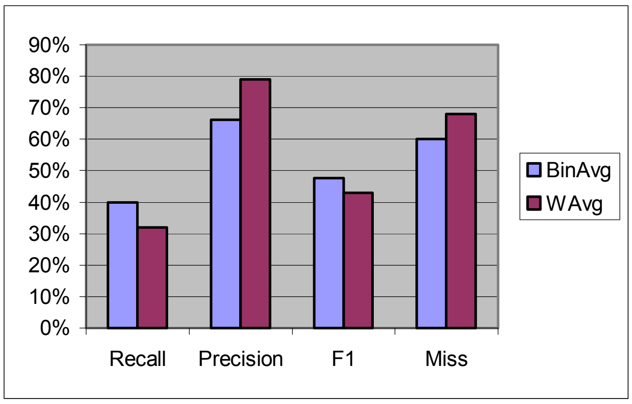


Figure 6.7: Comparison of effectiveness measures (recall, precision, F1, miss).

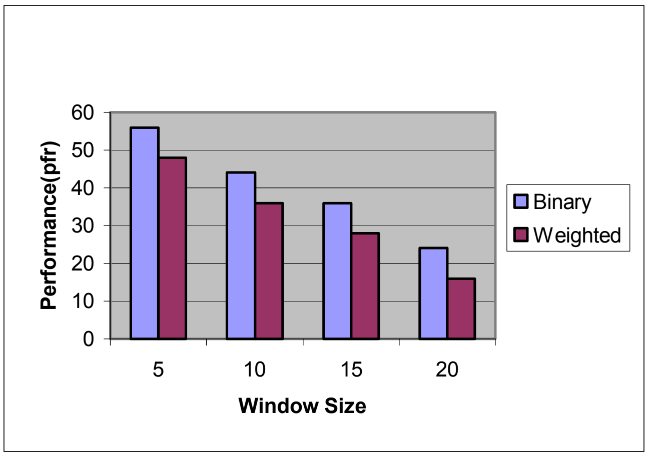


Figure 6.8: Comparison of implementation performances.

In Figure 6.8, the values of performance(pfr) with respect to four window sizes is shown for both binary and weighted implementations of the system.

The comparison of binary and weighted implementation to the UMASS approach is shown in Table 6.4. The values of UMASS are barrowed from Papka [22]. These values are the best performances of the UMASS approach and we compare them to our best results of both binary and weighted implementation.

System	**Corpus**	**Miss %**	**False Alarm %**	**Recall %**	**Precision %**	**F1**
UMASS	TDT1	40	1.27	60	52	0.56
Binary	TDT1	44	1.27	56	50	0.53
Weighted	TDT1	52	0.6	48	63	0.55

Table 6.4: Comparison of on-line new event detection approaches.

In Table 6.4, the UMASS approach has better performance results than our system, but the UMASS approach gives twice false alarms than our system, when compared to weighted implementation.

The results of on-line new event detection approaches in TDT study are shown in Table 6.5. These are the pooled average of 11-pass methodology. Since only 25 events were judged, this evaluation method is introduced by TDT study in order to expand the number of trials. But the actual effectiveness values are the reflection of the task without using 11-pass method. In other words, the actual system performance is the performance that determined in the 0-pass, without skiping any document of any event.

System	**Miss %**	**False Alarm %**	**Recall %**	**Precision %**	**F1**
UMASS	50	1.34	50	45	0.45
CMU	59	1.43	41	38	0.39
DRAGON	58	3.47	42	21	0.28

Table 6.5: Comparison of systems presented at the first TDT workshop.

In Table 6.5, the UMASS approach has the best results among the other approaches. Since we do not have the 0-pass values of CMU and DRAGON approaches, we just compare our system performance to the UMASS approach values.

Chapter 7

Conclusion and Future Work

In this thesis, we implement and evaluate alternative solutions to on-line new event clustering and on-line event detection problems. The results presented in this work are based on problem definitions, evaluation methodologies, and data developed by the topic detection and tracking (TDT) project.

The previous approaches to clustering are usually based on retrospective solutions, where all the data are available before clustering begins. In order to find a way to on-line classification, we use the concepts of the C^3M algorithm in an online environment, in which a cluster is determined for the current document before looking at the next document. For this reason, we introduce an algorithm that works in a single-pass manner, where the documents are processed sequentially, one at a time. We use the seed selection process of C^3M for detecting new events. A document detected as new, is also used as the seed of a cluster. In order to obtain the best performance, we aim to select the initial stories of the events as seed documents, and group the following stories around the selected seeds. Furthermore, to prevent producing oversized event clusters, and to give equal chance to all documents to be the seed of a new event, we employ the window size concept. The main motivation of this approach is that; documents closer together on the stream are more likely to discuss similar events than documents further apart on the stream. In our experiments, we aim to see the impact of different window sizes to the effectiveness results. For this purpose, we execute the event clustering and on-line new event detection algorithms for each window. In event clustering experiments, we observe that, the performance improves with the growing size of window until a point, which is the window size of 35 (days) in our case. After this point, since the number of documents increases with the wider window size, the old seeds and the new seeds co-exist in the same window. Accordingly, the seed documents of the previous events interfere with the seed documents of the new events. This provides many different clusters to non-seed documents to join and decreases the system performance. In event detection experiments, the best window size observed 5. Different from the event clustering results, we detect that, narrowing the window increases the performance of the event detection system.

Since we desire to control the number of seed documents, we introduce a threshold concept to the event clustering algorithm. We also use the threshold concept, with a little modification, in the on-line new event detection.

We use both binary and weighted versions of TDT1 corpus, and compare the results of both cases to each other. For the binary case, the system takes the term frequencies of document vectors (document vectors are created from TDT1, and they are stemmed and cleaned of stop-words), as binary, in other words if a particular term exists in the vector, the system takes its term frequency as 1, it is taken as 0 otherwise. On the contrary, for the weighted implementation, if a term appears in a document 10 times; its term frequency is taken as 10. Our results indicate that, for the case of binary event clustering, between 25%-30% of the documents of the predetermined events are classified by the system correctly. We obtain better results for binary implementation for event clustering over weighted case. As an advantage of weighted implementation, the system produces at least one cluster for each event, which is a desired situation. However, as a side affect, the number of clusters increases by 10% with respect to the binary version.

For the case of on-line new event detection, we use the same concepts that are used for the event clustering. According to our experimental results for binary case, we detect between 24%-56% of the documents discussing new events at relatively low false alarm rates of 0.2%-1.3%. Again, we obtain better results for the binary implementation, except the precision and false alarm rate. The false alarm rate of weighted implementation is 54% better than the binary case. This is because, for the case of binary implementation, system labels more documents as new. More documents increase the probability of false labels, for example, system labels a document as new event, when in truth it is not a new event. Selecting more documents as new, improves the recall value but produces a weaker false alarm rate.

Different from the event clustering results, in the on-line event detection case, we observe that narrowing the window size improves the performance of the system. Using narrower window limits the influence of old seeds to the new coming events. Since the first seeds have higher seed power values, this affects the threshold *Tr*. Accordingly, this high *Tr* value reduces the chance of new documents to be selected as a seed. When we use a wider window size, the effects of these first seeds reach documents, which are quite far away from these seeds in terms of time. Narrowing the window size decreases the probability of co-existence of relevant documents with non-relevant ones. This gives more possibility to new events to be selected as seed.

When we don't use the window size concept, in the case of event clustering, the system uses 40% more CPU time, since the number of documents, processed in a particular window size, is smaller than the whole corpus. We obtain less number of clusters (33% of the binary implementation with the window 35) without using window concept. This means that, the first coming documents, which have higher seed power values, enhance the average seed power value (P_{avg}). This reflects directly to the threshold value (*Tr*). Since the system could not eliminate these kinds of documents without determining a window size, they attract most of the stories in the corpus and construct fat and ineffective clusters. By the help of window size concept, we give equal chance to each document to be selected as seed. In the case of new event detection, without using window size concept, we obtain the worst results, which have the performance (prf) of 8. This is because, without eliminating powerful seed documents (documents that have high seed power value) from the system, desired documents cannot exceed the threshold, so that they are not labeled as seed.

Our results are relatively close to the results of TDT study, however, the accuracy of our approach, even at optimal parameter settings, is far from perfect. One of the reasons is that, our system is based on the word co-occurrences, which means that document similarities are computed based on the term similarities. However, this approach is insufficient for some events. As the event progresses, many of its properties are either not initially known, or are assumed to be known by the user, and therefore they are not necessarily clear in news text. For example, for the event 15, about the earthquake in Kobe, Japan, this referred to the event as “the worst disaster in Japan’s history,’’ with no explicit mention of Kobe or the fact that the story was about an earthquake. These kinds of stories reduce the effectiveness of the system. In order to prevent this, lexical chaining can be incorporated with our system.

In order to obtain better event clustering and new event detection accuracy, the same work can be repeated in the retrospective environment, for this purpose the original C^3M algorithm can be used.

Bibliography

[1] Allan, J., Incremental Relevance Feedback for Information Filtering, *In Proceedings of ACM SIGIR*, 270-278, 1996.

[2] Allan, J., Carbonell, J., Doddington, G., Yamron, J. and Yang, Y., Topic Detection and Tracking Pilot Study Final Report, *In Proceedings of the DARPA Broadcast News Transcription and Understanding Workshop,* February, 1998.

[3] Allan, J., Ballesteros, L., Callan, J. and Croft, W., Recent Experiments with Inquery, *In Proceedings of TREC-4*, pages 49-63, 1995.

[4] Callan, J. Document ltering with Inference Networks, *In Proceedings of the 19th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 262-269, 1996.

[5] Callan, J., Croft, W. and Broglio, J., TREC and TIPSTER Experiments with INQUERY. *Information Processing & Management*, 31(3):327-343, 1994.

[6] Can, F., On the Efficiency of Best Match Cluster Searches, *Information Processing & Management*, Vol.30, No.3, pp. 343-361, 1994.

[7] Can, F. A New Clustering Schema and It's Use in an Information Retrieval System Incorporating the Support of a Database Machine, *Ph. D. dissertation*, Dept. of Computer Engineering, Middle East Technical Univ., Ankara, Turkey, 1985.

[8] Can, F. and Ozkarahan, E.A., Concepts and Effectiveness of the Cover Coefficient-based Clustering Methodology for Text Databases, *ACM Transactions on Database Systems*, 15(4): 483-517, 1990.

[9] Can, F. and Ozkarahan, E. A., Effectiveness Assessment of The Cover Coefficient-based Clustering Methodology, *working paper* 89-002, Dept. of System Analysis, Miami Univ., Oxford, Ohio, Oct. 1989.

[10] Can, F. and Ozkarahan, E. A., A Clustering Scheme, *In the Proceedings of the 16 th Annual International ACM-SIGIR Conference*. ACM, New York, 1983, pp, 115 – 121.

[11] Carrick, C. and Watters, C., Automatic Association of News Items, *Information Processing & Management*, 33(5): 615-632, 1997.

[12] Croft, W.B., A Model of Cluster Searching Based on Classification, *Information Systems*, 5(3): 189-195, 1980.

[13] Croft, W.B., and Harper, D. J., Using Probabilistic Models of Document Retrieval without Relevance Information, *Journal of Documentation*, 5(3): 285-295, 1979.

[14] DeJong, G., Prediction and Substantiation: A New Approach to Natural Language Processing, *Cognitive Science*, 3: 251-273, 1979.

[15] Goldman, R. P., A Probabilistic Approach to Language Understanding, *Ph.D. Thesis*, Brown University, 1990.

[16] Hayes, P.J., Knecht, L.E. and Cellio, M.J., A News Story Categorization System, *In Proceedings of the 2nd Conference on Applied Natural Language Process* (1988), reprinted *in Readings in Information Retrieval, K. Sparck Jones and P. Willet editors, Morgan Kaufmann Publishing*, San Francisco, CA, pp. 518- 526, 1997.

[17] Hodges, J. L. and Lehmann, E. L., Basic Concepts of Probability and Statistics, *Holden Day in San Francisco*, CA., 1964.

[18] Hull, D., *In Proceedings of Text Retrieval Conferences (TREC6)*, NIST Special Publication, pp. 45-67, 1998.

[19] Jain, A. K., Dubes, R. C., Algorithms for Clustering Data, *Prentice Hall*, Upper Saddle River, NJ, 1988.

[20] Kurt, H., On-Line New Event Detection and Tracking in A Multi-Resource Environment, *MS. Thesis*, Bilkent University, 2001.

[21] Lewis, D. and Gale, W., A Sequential Algorithm for Training Text Classifiers, *In Proceedings of ACM SIGIR*, 313, 1994.

[22] Papka, R., On-line New Event Detection, Clustering, and Tracking, *Ph. D. Thesis*, University of Massachusetts at Amherst, September 1999.

[23] Proceedings of Message Understanding Conferences, *Morgan Kaufmann,* 1988.

[24] *Proceedings of the TDT Workshop*, University of Maryland, College Park, MD, October 1997 (Unpublished).

[25] Salton, G., Automatic Text Processing: The Transformation, Analysis and Retrieval of Information by Computer, *Reading, MA: Addison-Wesley*, 1989.

[26] Salton, G., Dynamic Information and Library Processing, Englewood Cliffs, *NJ: Prentice-Hall*, 1975.

[27] Salton, G., Relevance Feedback and Optimization of Retrieval Effectiveness, in The Smart System - Experiments in Automatic Document Processing, *Prentice -Hall*, Englewood Cliffs, N.J., pp. 324-336, 1971.

[28] Salton, G. and McGill, M.J., Introduction to Modern Information Retrieval, New York, *McGraw-Hill*, 1983.

[29] Schank, R., Conceptual Information Processing, *Elsevier,* North Holland, New York, 1975.

[30] Sparck, Jones, Karen, and Peter Willet, 1997, Readings in Information Retrieval, San Francisco: *Morgan Kaufmann*.

[31] Swets, J., Measuring the Accuracy of Diagnostic Systems, *Science*, 240:1285-1293, 1988.

[32] The Topic Detection and Tracking (TDT) Pilot Study Evaluation Plan, Version 2.8, October 97.

[33] van Rijsbergen, C. J., Information retrieval, 2nd ed., London: Butterworths, 1979.

[34] Voorhees, E. M., The Effectiveness and Efficiency of Agglomerative Hierarchical Clustering in Document Retrieval, *Ph. D. Thesis*, Cornell University, Ithaca, NY, 1986.

[35] Walls, F., Jin, H. Sista, S. and Schwartz, R., Topic Detection in Broadcast News, *In Proceedings of the DARPA Broadcast News Workshop*, pp. 193-198, 1999.

[36] Yang, Y., Carbonell, J., Brown, R., Pierce, T., Archibald, B. and Liu, X., Learning Approaches for Detecting and Tracking News Events, *IEEE Intelligent Systems*, 14(4):32-43, 1999.

[37] Yang, Y., Pierce, T. and Carbonell, J., A Study on Retrospective and On-Line Event Detection, *In Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 28-36, 1998.

Appendix

The stop-word list that used for cleaning the TDT1 corpus is given in the sequel.

a	anywhere	cf	everywhere	hast
about	apart	choose	except	hath
above	are	contrariwise	excepted	have
according	around	cos	excepting	he
across	as	could	exception	hence
added	at	cu	exclude	henceforth
adding	av	d	excluding	her
after	b	day	exclusive	here
afterwards	be	do	f	hereabouts
again	became	does	far	hereafter
against	because	doesn	farther	hereby
albeit	become	doing	farthest	herein
all	becomes	dost	few	hereto
almost	becoming	doth	ff	hereupon
alone	been	double	first	hers
along	before	down	for	herself
already	beforehand	dual	formerly	him
also	behind	during	forth	himself
although	being	e	forward	hindmost
always	below	each	from	his
am	beside	either	front	hither
among	besides	else	further	hitherto
amongst	between	elsewhere	furthermore	how
an	beyond	enough	furthest	however
and	both	et	g	howsoever
another	but	etc	get	i
any	by	even	go	ie
anybody	c	ever	h	if
anyhow	can	every	had	in
anyone	cannot	everybody	halves	inasmuch
anything	canst	everyone	hardly	inc
anyway	certain	everything	has	

include	nevertheless	save	thenceforth	week
included	next	saw	there	well
including	no	see	thereabout	were
indeed	nobody	seeing	thereabouts	what
indoors	none	seem	thereafter	whatever
inside	nonetheless	seemed	thereby	whatsoever
insomuch	noone	seeming	therefore	when
instead	nope	seems	therein	whence
into	nor	seen	thereof	whenever
inward	not	seldom	thereon	whensoever
inwards	nothing	selves	thereto	where
is	notwithstanding	sent	thereupon	whereabouts
it	now	several	these	whereafter
its	nowadays	shalt	they	whereas
itself	nowhere	she	this	whereat
j	o	should	those	whereby
just	of	shown	thou	wherefore
k	off	sideways	though	wherefrom
kg	often	since	thrice	wherein
kind	ok	slept	through	whereinto
km	on	slew	throughout	whereof
l	once	slung	thru	whereon
last	one	slunk	thus	wheresoever
latter	only	smote	thy	whereto
latterly	onto	so	thyself	whereunto
less	or	some	till	whereupon
lest	other	somebody	to	wherever
let	others	somehow	together	wherewith
like	otherwise	someone	too	whether
little	ought	something	toward	whew
ltd	our	sometime	towards	which
m	ours	sometimes	u	whichever
many	ourselves	somewhat	ugh	whichsoever
may	out	somewhere	unable	while
maybe	outside	spake	under	whilst
me	over	spat	underneath	whither
meantime	own	spoke	unless	who
meanwhile	p	spoken	unlike	whoa
might	per	sprang	until	whoever
more	perhaps	sprung	up	whole
moreover	plenty	stave	upon	whom
most	provide	staves	upward	whomever
mostly	q	still	upwards	whomsoever
mr	quite	such	us	whose
mrs	r	supposing	use	whosoever
ms	rather	t	used	why
much	really	than	using	will
must	reuter	that	v	wilt
my	reuters	the	very	with
myself	round	thee	via	within
n	s	their	vs	without
namely	said	them	w	worse
need	sake	themselves	want	worst
neither	same	then	was	would
never	sang	thence	we	wow

x y ye year yet yippee you your yours yourself yourselves z				