SPOONS: NETFLIX OUTAGE DETECTION USING MICROTEXT CLASSIFICATION

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Abstract

SPOONS: Netflix Outage Detection Using Microtext Classification

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Every week there are over a billion new posts to Twitter services and many of those messages contain feedback to companies about their services. One company that has recognizes this unused source of information is Netflix. That is why Netflix initiated the development of a system that lets them respond to the millions of Twitter and Netflix users that are acting as sensors and reporting all types of user visible outages. This system enhances the feedback loop between Netflix and its customers by increasing the amount of customer feedback that Netflix receives and reducing the time it takes for Netflix to receive the reports and respond to them.

The goal of the SPOONS (Swift Perceptions of Online Negative Situations) system is to use Twitter posts to determine when Netflix users are reporting a problem with any of the Netflix services. This work covers the architecture SPOONS system and framework as well as outage detection using tweet classification.

Acknowledgements

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Part 1

Introduction

Chapter 1

Problem: Swift Perception Of Online Negative Situations

Twitter is an immensely popular micro-blogging service. According to Twitter, as of March 14^{th} 2011, approximately one billion micro-posts, *tweets*, were being posted per week[29]. Because of the low time and effort cost of tweeting, only a few seconds from a smart phone, Twitter users post tweets about almost every aspect of their daily lives. Because of this large stream of information, Twitter makes an excellent source of information for data miners interested in real-time events. Already, researchers have been using Twitter to attempt to track and model disease outbreaks[5], earthquakes[16], and the stock market[11].

Netflix is the one of the largest online Internet subscription service for streaming movies and television shows. Netflix has over 25 million subscribers watching media streamed to over 450 different platforms. Even a short disruption of their streaming service can affect millions of users. Therefore, quickly detecting service outages is essential to keep customers happy. However, service outage detection is no trivial matter in Netflix's environment. In addition to constantly streaming thousands of different videos to hundreds of different platforms, Netflix also has to deal with problems caused by most of their infrastructure being hosted in the cloud with Amazon Web Services (AWS).

Netflix saw the power in Twitter as a potential data source for detecting service outages that is orthogonal to their current, more traditional outage detection methods. Currently, Netflix utilizes four different methods for detecting outages:

Internal Monitoring Systems. Like any sizable service providing company, Netflix utilizes many different internal monitoring systems to detect service outages. However, there are some classes of problems that are difficult to solve with internal monitoring. These problems include corrupt video files or a problem on a third-party delivery platform such as Roku or AppleTV. These problems are obvious to the end user, but very difficult to detect internally. In addition, the internal monitoring systems share the same infrastructure as the service providing system. Therefore, a problem in the infrastructure can cause both systems to go down at the same time.

External Monitoring Systems. Netflix contracts with external services that can periodically probe its systems to try and detect problems. However, this model too has problems. There are many problems that cannot be seen from an external probe. Also, if this system probes too often then it is taking compute time away from the servers that are trying to deliver content to end users.

Customer Service. Calls to customer service are a very straight-forward way to detect outages. Unfortunately, this method is very slow and inconsistent. It

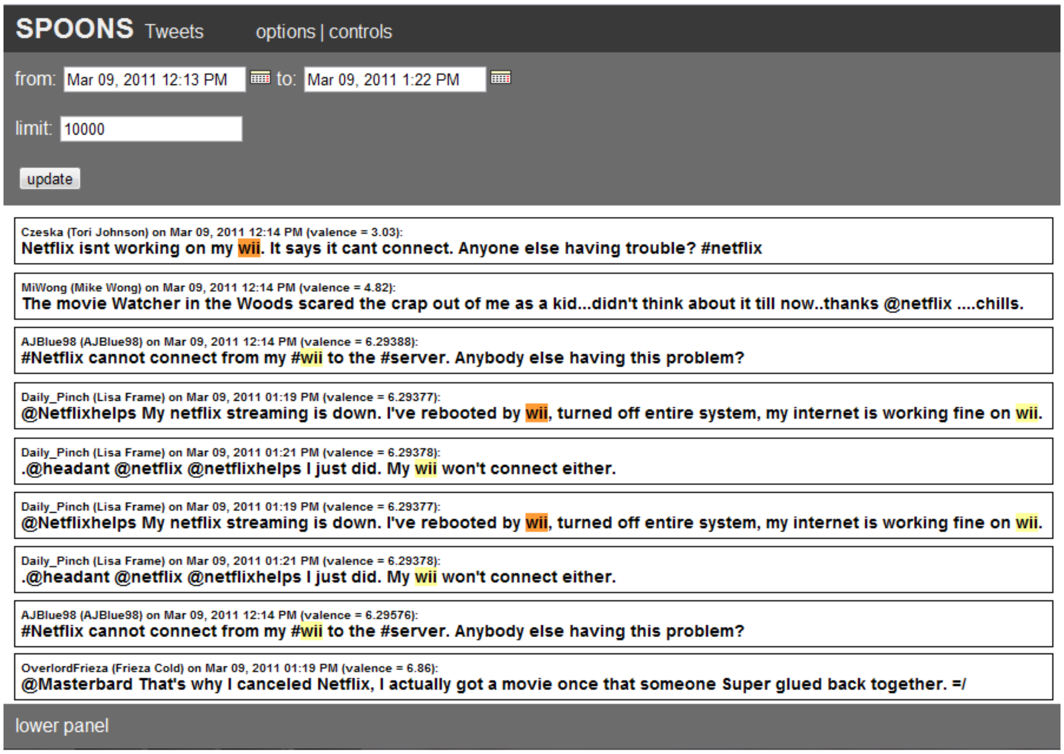


Figure 1.1: Tweets posted on March 9, 2011 during a disruption of Netflix streaming to the Nintendo Wii console.

takes a lot of frustration to get a user to lookup a phone number and complain.

Manual Twitter Observation. Manual observation shows that there is usually a response on Twitter when Netflix suffers a service outage. Figure 1.1 shows some tweets that occurred during a disruption of Netflix's service to the Nintendo Wii. However without any infrastructure, Twitter observation is slow and inconsistent. It is also very time consuming to have someone constantly watching Twitter for signs of an outage.

Given all these deficiencies Netflix wanted a monitoring system that is separate from their infrastructure, fast, and does not require any human intervention[17].

Chapter 2

Solution Overview

SPOONS (Swift Perception Of Online Negative Situations) is a system that is designed to use tweets to detect outages in Netflix content delivery systems. At present, the system supports a wide variety of detection methods that use some combination of time series analysis, classification, natural language processing, sentiment analysis, and filtering.

Figure 2.1 shows how the SPOONS system can be divided into three main parts: input; analysis pipelines; and output. The inputs are tweets gathered from Twitter. Then the analysis pipelines use a combination of sentiment estimation, classification, and traffic volume analysis to detect when an outage is occurring. The outputs of the system are: email alerts to Netflix engineers, and a web UI that displays information about the outage.

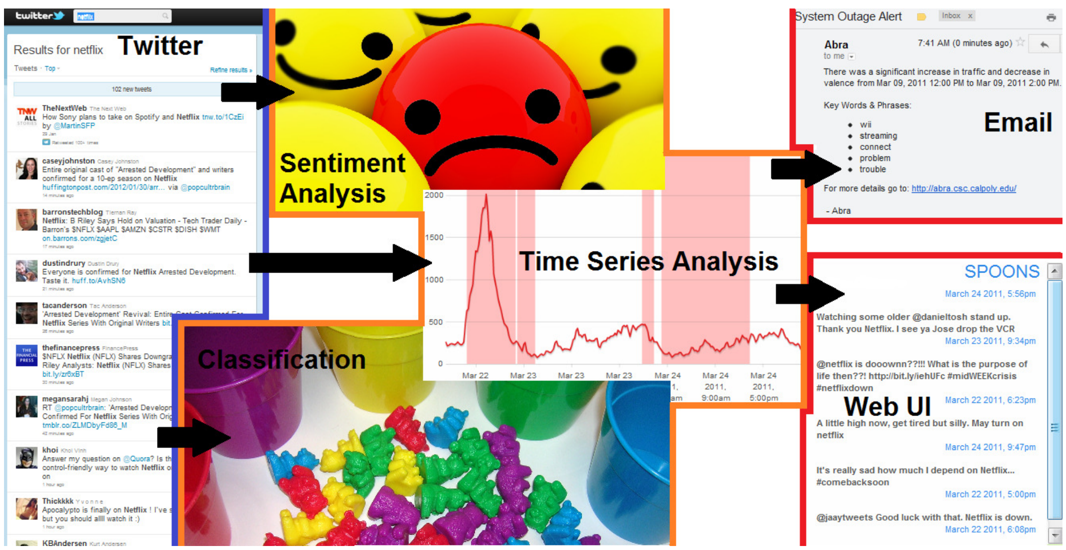


Figure 2.1: This system concept diagram shows the general flow of processing done in the SPOONS system.

Chapter 3

Ethics of Twitter Observation

The work in this project uses content that users post on Twitter without their knowledge. This monitoring system isn't being announced to the public because widespread knowledge of it would increase the likelihood of a malicious attack. This practice may lead to concerns about the level of privacy or ownership being provided to Twitter users regarding the content they post through the Twitter services. The goal of this section is to address these concerns by providing more information about the Twitter services and how the SPOONS system and this work uses the tweets.

3.1 Twitter Terms of Service

According to Twitter Terms of Service[30] agreement that everyone accepts automatically by accessing or using Twitter services:

"You retain your rights to any Content you submit, post or display on or through the Services. By submitting, posting or displaying Content on or through

the Services, you grant us a worldwide, non-exclusive, royalty-free license (with the right to sublicense) to use, copy, reproduce, process, adapt, modify, publish, transmit, display and distribute such Content in any and all media or distribution methods (now known or later developed)."

"This license is you authorizing us to make your Tweets available to the rest of the world and to let others do the same."

"You agree that this license includes the right for Twitter to make such Content available to other companies, organizations or individuals who partner with Twitter for the syndication, broadcast, distribution or publication of such Content on other media and services, subject to our terms and conditions for such Content use."

"We encourage and permit broad reuse of Content. The Twitter API exists to enable this."

"Such additional uses by Twitter, or other companies, organizations or individuals who partner with Twitter, may be made with no compensation paid to you with respect to the Content that you submit, post, transmit or otherwise make available through the Services."

In short, Twitter takes ownership of user tweets as soon as they are posted on Twitter. Using the Twitter API allows SPOONS to obtain the tweets with the consent of Twitter. Therefore, the collection and analysis of Twitter data by SPOONS is well withing the Twitter Terms of Service.

Chapter 4

SPOONS Requirements

Netflix has provided the following set of key requirements to be met by the SPOONS system:

Structural Independence. The outage detection system shall be structurally independent of both the software and the hardware infrastructure used by Netflix. It shall rely only on information that is publicly available and free for use. This ensures that the outage detection system stays up even when any or all Netflix servers are experiencing downtime.

Use of Amazon Web Services. Netflix is one of the largest customers of Amazon.com's cloud computing service, Amazon Web Services (AWS). AWS allows users to create new cloud machines (instances) in many regions throughout the world. The outage detection system shall be deployed on one or more AWS servers that are operationally independent of other AWS servers used by Netflix. Using a cloud solution allows the outage detection and alert system to be deployable on a global scale.

Real-Time. Netflix's streaming services run in real-time and any downtime has an immediate impact on customers. To minimize that impact, the outage detection system shall notify Netflix of detected outages as soon as possible.

Precise Outage Detection. The number of non-outage situations that raise an alert shall be minimized. While a small number of false positives detected in real-time may be acceptable, the outage detection system shall detect outages and generate alerts with as high precision as possible.

Comprehensive Outage Detection. Not all Netflix service outages generate a signal on Twitter. Those that don't may be allowed to go unnoticed by the outage detection system (as the system has no basis for detecting them), but any outage that causes a signal on Twitter shall be detected.

User-Friendly Online UI. The outage detection and alert system shall have an easy-to-use, informative, online UI which shall provide Netflix employees with real-time information and historic data about the state of Netflix according to Twitter. The information provided shall include:

- times of outages;
- times of other anomalous events;
- current and recent Netflix-related Twitter traffic trends;
- and samples of Netflix-related tweets.

Chapter 5

Contributions and Organization

SPOONS is a continual team effort and has been touched and improved by many different people. The idea originated at Netflix and was passed to the ABRA team at Cal Poly. The ABRA team has published a paper on SPOONS [2]. In addition, Cailin Cushing defended a thesis on a part of SPOONS devoted to outage detection through sentiment analysis[6].

The main contributions of this work are as follows:

- Design and implementation of the SPOONS system.
- Design and implementation of the SPOONS framework.
- Design and implementation of the SPOONS server architecture.
- Design and implementation of the SPOONS distributed computation model.
- Design of the SPOONS database structure and all table schemas.
- Design and implementation of all SPOONS classification based outage detection methods.

The rest of the paper is organized as follows. Chapter 6 covers background and related work. Part 2 discusses the architecture of SPOONS. Part 3 discuss the work done by the spoons system to detect outages. With Chapter 12 focusing on the details of the classifiers used in SPOONS, and Chapter 13 extending the problem of classification to full outage detection. Part 4 wraps up the paper.

Chapter 6

Background & Related Work

6.1 Twitter Traffic Analysis

Twitter proves to be a great resource for data mining because of the large number of real-time, posts from millions of users. However, tweets can be very difficult to work with because they suffer from three large drawbacks:

Length. Tweets can only be 140 characters long. This limit severely restricts the possible information content of a tweet. Compared to more traditional media sources, e.g. news articles, the text of tweets contain almost no information. Although this makes it very difficult to do naive text classification on tweets, Twitter users have found ways to increase their information density. Links to news stories, slang, and Twitter symbols (see Section 12.6.1) help Twitter users express more with fewer characters.

Informal Language. Informal language, e.g. slang, jargon, and abbreviations, is common place on Twitter. The use of informal language can be partially attributed to the strict character limit. Informal language can be difficult to deal with because it it less likely to appear in well established Natural Language Processing corpora. Not having a corpus forces researchers to either only use unsupervised methods, or build their own corpus.

Typos. The nature of Twitter is very informal for most users whose tweets are only read by their friends. This informal environment and the large amount of tweets coming from hand-held devices without a traditional keyboard leads to many tweets containing typos. Typos make text analysis difficult because it obfuscates words and increases the number of unique words.

6.1.1 Twitter Classification

There has been much work in using classifiers on both tweets and Twitter users. Most of the classification efforts has gone into trying to determine the sentiment, the general feeling, of a tweet [12][18][28][32]. Raz et al. tackle the task of classifying humorous tweets as a specific type of humor such as irony, observational, or wordplay[27]. The traditional text classification task of topic modeling has also been attempted various times[10][34]. Instead of trying to classify tweets, Pennacchiotti et al. try to classify user associations from their tweets[21].

6.1.2 Twitter Anomaly Detection

Levchenko et al.[15] created a system that uses tweets to detect outages in several widely used Web services such as Amazon, Gmail, Google, PayPal, Netflix, Youtube, Facebook, Wikipedia, and Flickr. They describe Twitter users as acting as millions of sensors who have a large breadth and flexibility of in the definition of failure. The detection mechanism employed in this work is fairly straightforward. A collection of tweets that either contain the phrase "`X is down`" or a "`#Xfail`" hashtag, where "X" is the name of a service (e.g., "`#netflixfail`") is gathered. The traffic is compared against expected traffic to determine if there is an outage.

Levchenko et al. were only able to validate a subset of their detected events because a full validation would require a list of all outages during 2009 for every service that they were monitoring. So while the events they were able to verify indicate that the system can detect outages, the full effectiveness of their method is still largely unknown.

6.2 Classifiers

SPOONS uses a variety of different classifiers for text classification. This section gives an overview of each different type of classifier used.

Formal Definition

The classification problem that the classifiers are trying to solve can be defined as follows:

Given a set of documents D

$$D = \{d | d \in D\}$$

where each document d is a vector of n features

$$d = (\mathrm{f}_1, \mathrm{f}_2, ..., \mathrm{f}_n)$$

and a set of classes C where

$$C = \{c|c \in C\}$$

We want to associate each document with a class based off the patterns observed in a training set T of already classified documents.

$$T = \{(d, c)|c \in C\}$$

6.2.1 Naive Bayes

Naive Bayes classifier works by applying the Bayes' theorem with the assumption that the probability of each feature in a document is independent from the probability of any other feature appearing in the same document.[13][8]

The Bayes' theorem states that the probability of observing class c given document d, $Pr(c|d)$, can be represented as:

$$Pr(c|d) = \frac{Pr(c) \cdot Pr(d|c)}{Pr(d)} \tag{6.1}$$

$Pr(c)$ is the prior probability of class c, that is, the probability of observing c regardless of the document attached to it. When training the classifier, this is just the percentage of times that the class appeared in the training set.

$Pr(d)$ is the prior probability of document d. Like $Pr(c)$, it is just the probability of observing the collection of features d regardless of the class associated with it. Note that for classification, it is not necessary to compute $Pr(d)$ because it is constant among all documents and classes. A classifier can just choose the class with the largest $Pr(c) \cdot Pr(d|c)$ term.

$Pr(d|c)$ is the probability of observing document d given that d is already recognized as belonging to class c. Remember that document d is really just a vector of n features, $(\mathrm{f}_1, \mathrm{f}_2, ..., \mathrm{f}_n)$. Assuming **conditional independence** (the naive part in Naive Bayes), $Pr(d|c)$ can be constructed as a product of the probability of observing each feature in d:

$$Pr(d|c) = Pr(\mathrm{f}_1|c) \cdot Pr(\mathrm{f}_2|c) \cdot ... \cdot Pr(\mathrm{f}_n|c) = \prod_{i=1}^{n} Pr(\mathrm{f}_i|c) \tag{6.2}$$

Now the last step is to estimate the conditional probabilities of the n features. When dealing with discrete features, then estimating $Pr(\mathrm{f}_m|c)$ $(1 \leq m \leq n)$ can be done by finding the percentage of training documents that contain feature f_m and have class c.

6.2.2 Bayes Net

A Bayesian Network is a probabilistic, directed acyclic graphs that represents a set of random variables and their conditional probabilities. In a Bayesian Network, the collection of incoming edges represent the conditional probability distribution between two random variables. Each node represents a variable and a probability function that takes as input the state of the node's parents.[20][19]

Figure 6.1 shows a simple Bayesian Network that models the chance of going on a picnic. Note that whether or not it is Spring affects the chance of it raining; and both the season and weather affect the chance of going on a picnic.

Figure 6.2 shows the probability distributions for the network. The chance of the season being Spring if fully independent, and therefore takes no parameters into its probability function. However, the weather and picnic decision takes one and two input parameters respectively.

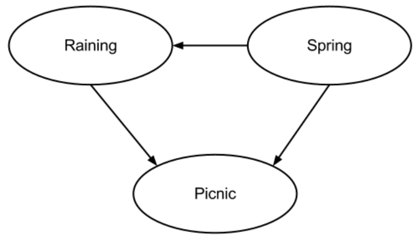
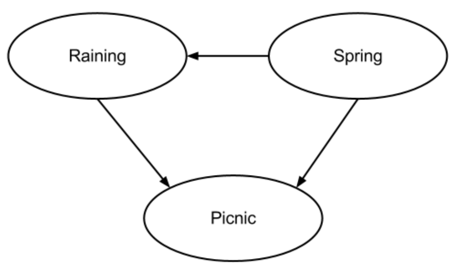


Figure 6.1: A simple Bayesian Network modeling the chance of going on a picnic given the season and weather. The season affects the weather and both the season and weather affect the chance of going on a picnic.

	Raining	
Spring	T	F
T	0.30	0.70
F	0.05	0.95

Spring	
T	F
0.25	0.75



		Picnic	
Raining	Spring	T	F
T	T	0.01	0.99
T	F	0	1
F	T	**0.50**	0.50
F	F	0.05	0.95

Figure 6.2: The simple Bayesian Network augmented with the probability functions for each node.

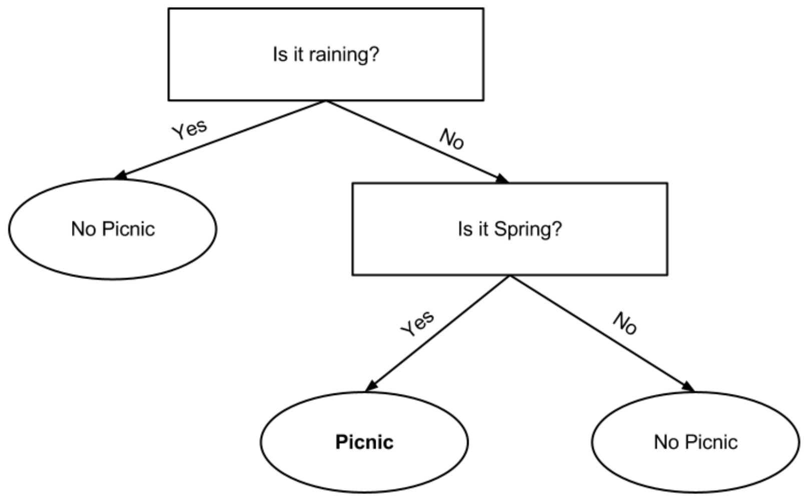


Figure 6.3: A simple decision tree trying to answer the question of whether or not to go on a picnic.

6.2.3 J48

J48 is a specific implementation of the C4.5 algorithm. C4.5 is an algorithm that is used to generate a decision tree given a training set.

Decision Trees

A decision tree is a simple data structure used to come to come conclusion based off of a number of observations. At each non-terminal node, a question is asked. The answers to the question are represented by the node's outgoing edges. The tree is traversed in this fashion until a terminal node is reached. The terminal node contains the final conclusion. In a classification context, each non-terminal node is labeled with an attribute, each edge is the value (or range of values) for that attribute, and each terminal node is a class. Each attribute can only appear once in the tree.

Figure 6.3 shows a decision tree that may be generated for the picnic example discussed in Section 6.2.2. Note that once the decision tree is built, reaching a terminal node is fairly trivial.

C4.5 — Decision Tree Induction Algorithm

C4.5 recursively builds a decision tree by continually splitting the dataset on a single attribute[25]. The splitting attribute is determined by the normalized information gain (Kullback-Leibler divergence) and becomes a node in the tree and the possible values for the attribute become edges. Each subtree is then recursively built using only the data where the splitting attribute takes the value given by the incoming edge. The algorithm has two stopping conditions. First, when all the data has the same class. In which case a single node tree is constructed that contains the class. Secondly, when there are no more attributes or when the information gain from splitting on each attribute is below a threshold. In this case, a single node tree is constructed which contains the plurality class.

6.2.4 K-Nearest Neighbors

k-Nearest Neighbors (KNN) is simple and effective classification technique[7]. While training, the classifier remembers the entire training set. During the classification phase, the classifier finds the k nearest neighbors to the query point. The predicted class is simply the plurality of the k nearest neighbors. Figure 6.4 shows an example of k-Nearest Neighbors with a simple search space.

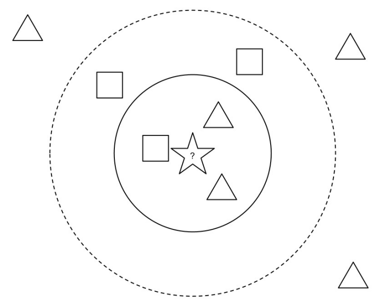


Figure 6.4: A simple example of KNN. If $k = 3$, then the query point (the star) will be classified as a triangle. However, if $k = 5$ then the query point will be classified as a square.

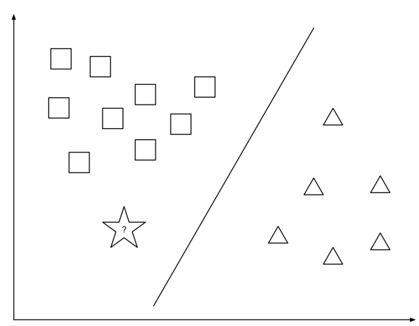


Figure 6.5: A simple example of a support vector machine. The SVM chose a partition that maximizes the margin between the squares and triangles.

6.2.5 Support Vector Machines

Support Vector Machines (SVMs) are considered one of the best off-the-shelf classification techniques[4]. When training, SVMs use hyperplanes to partition the data into surfaces based off of the different classes of the training examples. When classifying, the SVM finds which surface the query point falls on and give that class to the point. SVMs try and choose the partitioning hyperplane to maximize the margin between the two groups of data. Depending on the implementation, the SVM may choose the optimal partition or just an approximation.

Figure 6.5 shows a simple example of a linear binary SVM. Note that the partition line is chosen to maximize the distance between the triangles and squares. The query point (the star) falls into the squares' partition and is therefore classified as a square.

Sequential Minimal Optimization

Sequential Minimal Optimization (SMO) is an efficient algorithm for solving SVMs invented by John Platt in 1998[22].

6.2.6 BPNB

BPNB is a method developed by Chu[3]. It is based off of Naive Bayes, except the relative probability of each feature is accounted for.

BPNB states that the probability of observing class c given document d, $Pr(c|d)$, can be represented as:

$$Pr(c|d) = Pr(c) \cdot \prod_{i=1}^{n} g(\mathrm{f}_i, c) \tag{6.3}$$

Where $g(\mathrm{f}_m, c)$ is the weight of feature f_m in class c.

$$g(\mathrm{f}_m, c) = \beta^{1-\frac{Pr(\mathrm{f}_m|c)}{Ave(\mathrm{f}_m)}}, 0 < \beta < 1 \tag{6.4}$$

$$Ave(\mathrm{f}_m) = \frac{\sum_{i=1}^{|C|} Pr(\mathrm{f}_m|c_i)}{|C|}, c_i \in C \tag{6.5}$$

6.2.7 WEKA

SPOONS utilizes several classifiers provided in the *WEKA Machine Learning Package*. WEKA is an open source package written under the GNU General Public License[9].

6.3 Singletons

The SPOONS architecture makes heavy use of singletons to guarantee certain assumptions. A **singleton** is an object-oriented class that may have at most one instance of itself instantiated at a time. SPOONS uses two types of singletons: singletons that are relative to the base class and singletons that are relative to the child classes.

Base Relative Singletons. Base relative singletons are singletons that only allow one instance of to base class in the inheritance hierarchy to be instantiated at a time. This means that there can only be one instance allowed for the entire inheritance hierarchy. Figure 6.6 shows an inheritance diagram of a hierarchy that uses a base relative singleton. Note that because one of the children have been instantiated, no other class in the hierarchy can be instantiated.

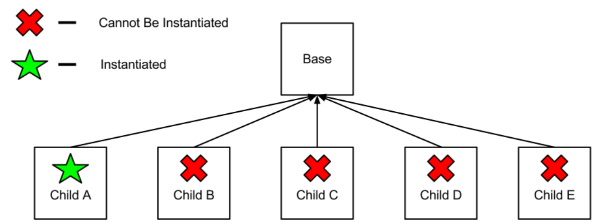


Figure 6.6: An example base relative singleton inheritance hierarchy. Note that instantiating any child removes the ability to instantiate any other part of the hierarchy.

Child Relative Singletons. Child relative singletons are singletons that allows only one instance of each leaf child in the inheritance hierarchy to be instantiated at a time. This allows the inheritance hierarchy to have as many instance as leaf children. Figure 6.7 shows an inheritance diagram of a hierarchy that uses child relative singletons. Note that all the children can be instantiated once.

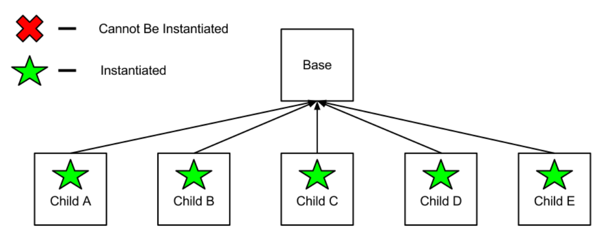


Figure 6.7: An example child relative singleton inheritance hierarchy. Note that any child can be instantiated, but only once.

6.4 Accuracy Measures

The accuracy of classification is primarily determined using three metrics: Recall, Precision, and F Score.

Consider the situation of trying to classify documents into class A with A and

B being the two possible classes. The following definitions are used to calculate the accuracy metrics:

- tp — True Positive. A document with the true class A was correctly classified as A.
- fp — False Positive. A document with the true class B was incorrectly classified as A.
- fn — False Negative. A document with the true class A was incorrectly classified as B.
- tn — True Negative. A document with the true class B was correctly classified as B.

6.4.1 Recall

The percent of the documents that were correctly classified.

$$Recall = \frac{tp}{tp+fn}$$

6.4.2 Precision

The percent of correct classifications of all documents classified as A.

$$Precision = \frac{tp}{tp+fp}$$

6.4.3 F Score

A harmonic mean between recall and precision. The standard F_1 score evenly weighs precision and recall. SPOONS uses the $F_{0.5}$ score. $F_{0.5}$ weighs precision more than recall. Precision is being weighed more heavily than recall because every alert that SPOONS generates would require the intervention of a Netflix engineer. Generating too many false positives would just cause SPOONS to be ignored.

$$F_\beta = (1+\beta^2) \cdot \frac{precision \cdot recall}{\beta^2 \cdot precision + recall}$$

$$F_{0.5} = 1.25 \cdot \frac{precision \cdot recall}{.25 \cdot precision + recall}$$

6.4.4 Coverage

In the context of outage detection, $F_{0.5}$ score cannot completely capture the effectiveness of an outage detection method. A flaw in solely relying on the $F_{0.5}$ score is that an outage detection method can produce an unjustly high F score by generating long alerts. Taken to the extreme, an outage detection method can generate just one alert an have it span the entire evaluation period. This one alert will capture every service outage, and therefore have a recall of 1. Also, the single alert it generates will intersect with a real outage which will produce a precision of 1. No matter the type of F score used, a precision and recall of 1 will result in the highest possible F score of 1. Figure 6.8 shows a graphical representation of this problem.

To counteract this, an outage detection's coverage is also taken into account. Coverage is the percentage of frames in the evaluation period that are during alerts.

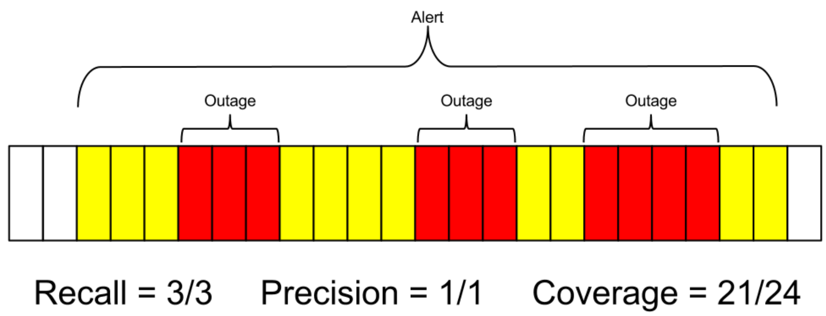


Figure 6.8: A long alert producing an unjustly high precision and recall.

Chapter 7

Twitter API

All of the data data that SPOONS uses is obtained in real time using the Twitter Search REST API[31].

7.1 Rate Limiting

Twitter imposes a limit on the number of queries to the Search API. Twitter does not publish the official limit. However, our experiments suggest that SPOONS can query the API for all new Tweets once every two minutes without suffering from rate limiting.

7.2 Pagination

Twitter paginates the results from its search API. The maximum results you can get per page is 100, and each query can return at most 15 pages. Therefore when there are more than 1500 tweets generated per minute, SPOONS must do multiple search queries.

7.3 Query Anatomy

The typical structure of a Twitter API query is shown in Figure 7.1.

http://search.twitter.com/search.**json**?**q**=⟨query⟩&**rpp**=100& **result_type**=recent&**since_id**=⟨tweet id⟩&**max_id**=⟨tweet id⟩

Figure 7.1: The structure of a typical query to the Twitter API.

The parameters are:

json: Twitter can supply the result data in either ATOM or JSON format. Testing with both have shown that the ATOM results are less consistent and provide less data. Because of the more accurate information returned from the JSON API, we are able to write more efficient queries. Using the ATOM API, we could query Twitter only once every five minutes; as opposed to every two minutes with the JSON API.

q: The search query. Twitter supports some advanced search features such as conjunction and negation.

rpp: "Results Per Page". Twitter paginates the responses from the Search API. SPOONS always uses the maximum pagination value to decrease the number of requests per hour and lessen the chance of being rate limited.

result_type: Twitter allows users to get results ordered by either relevance or time. Since we want to gather all tweets about our query, we choose to get the results ordered by time. In addition, the "since_id" and "max_id" parameters do not work when results are sorted by relevance.

since_id: The id of the oldest tweet that should be returned. This is not a hard limit, but provides a nice starting point.

max_id: The id of the most recent tweet that should be returned. It may seem counter-intuitive to provide a cap on the most recent tweet, when one wants to query for all of the most recent tweets. However when a query's results spans across more than 15 pages, it needs to be broken into a new query restarting at the first page. In this situation, not providing an upper limit includes new tweets outside of the original search scope. This can result in tweets that are forever lost to us.

7.4 Result Anatomy

Figure 7.2 shows the result from the query "eriq netflix". Notice that some fields, like the `geo` field, can be null. Also note that the API incorrectly guessed the language of the tweet as Danish.

```
{
    completed_in: 0.012,
    max_id: 298199940868489200,
    max_id_str: "298199940868489216",
    page: 1,
    query: "netflix+eriq",
    refresh_url: "?since_id=298199940868489216&q=netflix%20eriq&result_type=recent",
  - results: [
      - {
            created_at: "Sun, 03 Feb 2013 22:43:00 +0000",
            from_user: "eriq_augustine",
            from_user_id: 238374031,
            from_user_id_str: "238374031",
            from_user_name: "eriq",
            geo: null,
            id: 298199940868489200,
            id_str: "298199940868489216",
            iso_language_code: "da",
          - metadata: {
                result_type: "recent"
            },
            profile_image_url: "http://a0.twimg.com/sticky/default_profile_images/
                                default_profile_0_normal.png",
            profile_image_url_https: "https://si0.twimg.com/sticky/default_profile_images/
                                      default_profile_0_normal.png",
            source: "&lt;a href=&quot;http://twitter.com/&quot;&gt;web&lt;/a&gt;",
            text: "eriq love netflix",
            to_user: null,
            to_user_id: 0,
            to_user_id_str: "0",
            to_user_name: null
        },
    ],
    results_per_page: 100,
    since_id: 0,
    since_id_str: "0"
}
```


Figure 7.2: A JSON result from the Twitter Search API

Part 2

SPOONS Architecture

Chapter 8

Architecture Breakdown

There are multiple levels of architecture within SPOONS that need to be discussed. Chapter 9 describes the framework architecture (Figure 8.1). The framework architecture describes the relations between the different pieces of the SPOONS framework. Chapter 10 describes both the layout of the different servers involved in the SPOONS system and the Distribution Model which describes how pieces of work are distributed between the different servers Finally, Chapter 11 discusses the architecture of the database that backs SPOONS.

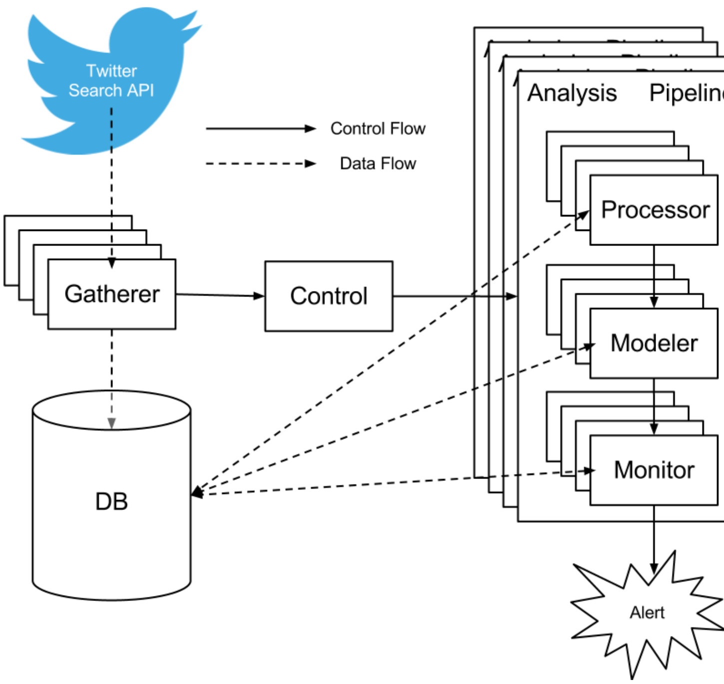


Figure 8.1: The flow of control and data through the SPOONS framework system.

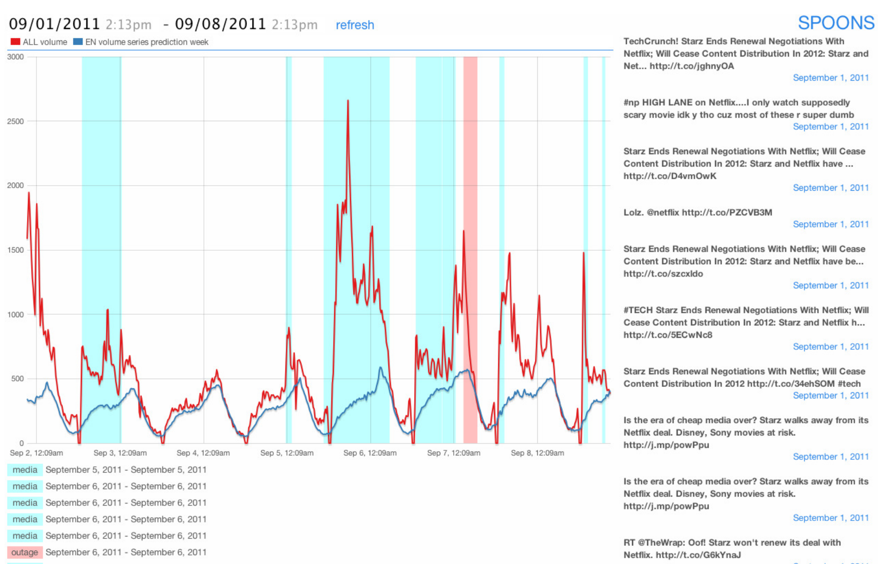


Figure 8.2: The web UI for SPOONS.

Chapter 9

Framework Architecture

This chapter describes the architecture of the SPOONS framework. The SPOONS framework includes all pieces of SPOONS that take the data from gathering all the way through to final analysis.

9.1 High Level Solution

The general solution taken by SPOONS consists of four main steps:

Collect: Collect tweets from Twitter.

Process: Convert the tweets from plain text to some form of information that can be analyzed.

Model: Use the information generated from the previous step to build a mathematical model of the information. Use past information to predict what the current model of the data should look like.

Compare: Compare the two models generated in the previous step. A significant divergence means that there is anomalous traffic.

9.1.1 Framework Overview

Figure 8.1 shows the flow of control and data through the SPOONS framework. Data comes into SPOONS in the form of Tweets collected by the Gatherers, and leave SPOONS in the form of alerts generated by the Monitors.

Gatherer. Gatherers are responsible for collecting documents from a specified data source such as the Twitter Search API.

Database. After the tweets are gathered, they are placed in the database. In addition to storing just tweets, the database also stores configuration data, intermediate calculations, and the results of the Analysis Pipelines.

Control. The Control is responsible for controlling the SPOONS server. It maintains data structures with all of the Gatherers and Analysis Pipelines. It is also responsible for communication with other servers in the SPOONS cluster.

Processor. Processors are data transformation utilities that take raw data and puts it in a form that other components can use.

Modeler. Modelers are responsible for building a mathematical model of the data and can be split into two groups: **Predictors** and **Counters**. Predictors build a predictive model of the data. Counters build a model of the data that was actually gathered by the system.

Monitor. Monitors take the models produced by the Predictors and Counters and compares them. The Monitors are responsible for making the final decision on about a period of time being anomalous.

9.2 Gatherers

The data enters SPOONS at the Gatherers. The Gatherers run periodically (for Twitter, every two minutes). Gatherers are asynchronous and not dependent on any other part of the framework. There may be multiple different Gatherers running on the same machine. Gatherers are abstracted to be able to gather data from any source. Once the Gatherers obtain their data, they place the data in the database and notify the Control that there is new data available to the system.

9.2.1 Twitter Holes

It is worth noting that sometimes the Twitter Search API fails to return any data. We have not discovered the cause of this, but Twitter does not report any errors. For unspecified amounts of time the Twitter API reports zero new tweets. We call these dead zones “holes”. We have found that a query from a different IP usually does not experience the same hole. To counteract holes, we run Gatherers on multiple servers and resolve duplicate tweets upon insertion into the database.

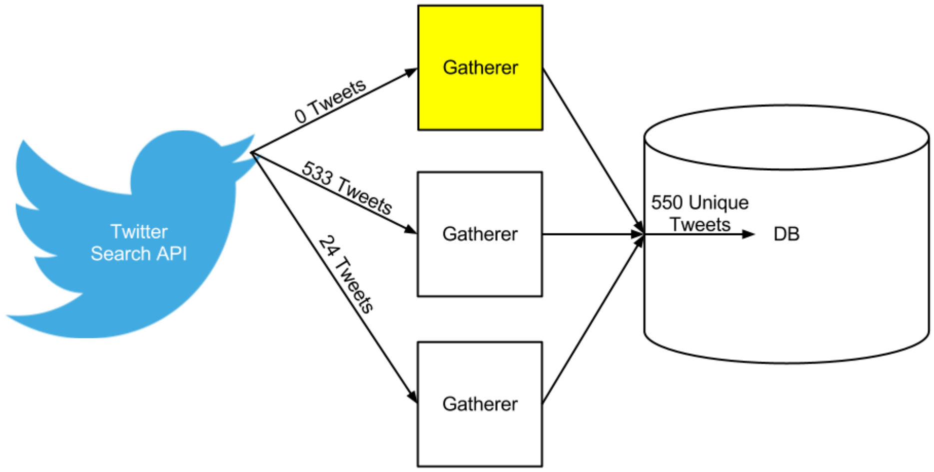


Figure 9.1: One server in a hole is covered by two other gathering servers.

9.3 Processors

Processors are responsible for processing or transforming data before it goes into the analysis pipelines.

- Classifier Processors: There exists a Processor for every tweet classifier used in SPOONS (see Chapter 12). Because of the high number of classifiers used, these constitute the majority of Processors and form the largest unit of work in SPOONS. These Processors classify every tweet into one of the nine tweet categories discussed in Section 12.3.

- Author Processors: The Author Processors extract the author of tweets and try to establish which authors are credible. These Processors are outside the scope of this work and are discussed in other work[6].

- Valence Processors: The Valence Processors assign a numeric “happiness” score to every tweet. How that score is produced is outside the scope of this work (see Section 16.2).

- Document Frequency Processors: The Document Frequency Processors maintain term frequencies and inverse document frequencies for the collection of tweets in SPOONS.

Implementation Notes: Unlike most parts of the analysis pipeline, Processors are a shared resource. That is, multiple analysis pipelines invoke the same Processors. However, it does not make sense to restart the processing once it is started, or to start another instance of the same Processor for the same data. Processors have a finite amount of data to process and may be cumulative. To make sure that no redundant work is done, Processors are singleton. When multiple threads call into a Processor to do work, the Processor blocks all incoming threads until the work is complete. Then, the Processor releases all of the threads that requested the work. This model allows all the analysis pipelines to share the same Processor without any redundancies.

9.4 Analysis Pipelines

An Analysis Pipeline (also called Analysis Method) is the analytical center of the SPOONS framework. Pipelines are split into Tasks (see Section 9.5) which are chunked units of work. The exact number and types of Tasks used are different for each pipeline.

The run of an Analysis Pipeline is typically as follows:

1. Pre-process incoming traffic.

2. Model the existing traffic.

3. Predict what the current traffic should be.
4. Raise an alert if the existing traffic varies significantly from the predicted traffic.

Every Analysis Pipeline gets its own thread, and there is no interdependence between the different pipelines. Currently, SPOONS usually runs more than 20 Analysis Pipelines at a time.

9.5 Tasks

Tasks are the core unit of computation in SPOONS. Almost everything that can be “run” is a Task. Every Task gets its own thread, and callers into the Task may request that the Task block the calling thread until the Task is complete.

Implementation Notes: Tasks are singleton with respect to the leaf child class. This ensures that although there there are many different Tasks, every Task can be uniquely referenced. This singleton behavior is enforced by checking the fully-qualified class name in the Task base class upon construction. The uniqueness of tasks is very important to SPOONS distribution model discussed in Chapter 10.

9.6 Modelers

Modelers are Tasks that are responsible for building a mathematical representation for the data.

9.6.1 Predictors

Predictors build a predictive model of the data. For example, we have noticed that tweet volume tends to be periodic day-to-day and week-to-week. Therefore, a Predictor may model that prediction by guessing that the volume in the future will be the same as it was the previous week or day.

9.6.2 Counters

Counters attempt to build a model of data that was actually gathered by the system. Going with the previous example, the Counter for modeling tweet volume would simply count the number of tweets gathered for a period.

9.7 Monitors

Monitors take the models produced by the Predictors and Counters and compares them one point at a time. If the two models differ significantly, then an alert is raised. The different types of Monitors are described in detail in Section 13.3. The Monitors are responsible for making the final decision about a period of time being anomalous.

9.7.1 Auto-Tuning

Monitors are the most configurable part of the Analysis Pipeline taking anywhere from two to six configurable parameters. To find the best set of parameters, the Monitors can automatically run themselves on a training set and search the space of all possible parameters. They then keep the parameters that result in the best score. This process is called “auto-tuning”.

9.7.2 Resistance

At any given time, a Monitor is either in a normal, non-alerting, state or an alerting state. A Monitor’s “resistance” is its tendency not to move into or out of an alerting state. The resistance is the number of normal or abnormal observations it needs to be trigger a state change. Monitors are given resistance because otherwise an outliers could cause a Monitor to rapidly switch between alerting and normal states. There currently are three different methods of observing resistance. The method of resistance as well as the resistance thresholds can also be auto-tuned.

Fighting Resistance

Parameter	Description	Restrictions
A	The number the counter must reach to enter an alerting state.	$A > 0$
R	The number the counter must reach to enter a normal state.	$R > 0$

Fighting resistance counts every time that there is a normal period as a +1, and every time there is an anomalous period as a -1. If the counter reaches $-A$, then the Monitor is put into an alerting state. If the counter reaches R, then the Monitor is put into a normal state.

Continuous Resistance

Parameter	Description	Restrictions
A	The number the counter must reach to enter an alerting state.	$A > 0$
R	The number the counter must reach to enter a normal state.	$R > 0$

Continuous resistance must get A continuous anomalous observations to enter an alerting state, and R continuous normal observations to enter a normal state.

Window Resistance

Parameter	Description	Restrictions
W	The window size.	$W > 0$
C	The number of anomalous observations necessary for an alerting state.	$0 < C <= W$

Window resistance remembers W previous observations as being normal or anomalous. If the number of anomalous observations is or exceeds C, then an alerting state is declared. Otherwise, the Monitor stays in a normal state.

9.7.3 Smoothers

The Monitors have a chance to smooth the data before it gets analyzed. Smoothers take in a stream of data. As with resistance methods, different smoothers and smoothing parameters can be auto-tuned.

No Smoother

Do not smooth. If this smoother is put into the parameter search space, then the effects of no smoothing can be seen.

Moving Mean Smoother

Parameter	Description	Restrictions
W	The window size.	$W > 0$

The Moving Mean Smoother works by taking the mean in a sliding window of size W. This Smoother tolerates a smaller window if there is not enough data available. Therefore, this Smoother always outputs a number for every number in the input stream.

9.8 Control

The Control is the center of a SPOONS instance. It handles the flow of all control and has the ability to start and stop any Task or Analysis Pipeline on demand. It holds references to all the threads for the Gatherers and Analysis Pipelines. The Control handles all the setup and tear down in the system.

There are different types of Controls that decide the behavior of SPOONS on each respective server. There are three types of Controls: **Master Control**, **Worker Control**, and **Single Control**. The Control is singleton with respects to the base class. Therefore, only one instance of any type of Control can be active on a server at any given time.

Implementation Notes: The Control is very careful to never allow anyone to own a reference to the currently running Control. All requests to the Control are made statically to the "Control" base class. The base class then forwards the request onto the specific instance of Control currently active on the server. This is done so that the rest of the SPOONS system never knows what kind of Control is currently active. Because of that, a server can be switched between different roles without restarting the system or notifying any other components of the SPOONS system.

9.8.1 Master Control

The Master Control is the Control that is responsible for the controlling SPOONS when it is in distributed mode. The Master Control maintains information on all the active worker servers including what Tasks are currently assigned to them.

Implementation Notes: The Master Control maintains "shallow execution" of every pipeline in the system. This means that this control runs each pipeline, but then distributes work for each pipeline as the work is generated.

9.8.2 Worker Control

Worker Controls do not take any initiative to run any tasks. Instead, they just wait for a Master Control to tell them what to do.

9.8.3 Single Control

The Single Control is for a SPOONS instance that wants to run on a single server.

Chapter 10

Distributed Computation Model

As discussed before, SPOONS is a multi-server system (Fig 10.1). The SPOONS system uses the master/worker paradigm with a single master and N workers.

All of the servers share two resources: the primary database and a NoSQL property store. When a master or worker comes online, it inserts an entry for itself into the shared property store. If the new server is a worker, it alerts the current master about its existence, and visa-versa, if the new server is a master. In addition, all workers are required to heartbeat to the master every 15 seconds and the master heartbeats to the workers every 15 seconds. Using this system, the master always knowns about all of the workers and the worker always knows about the current master. When a server misses three heartbeats, the server expecting that heartbeat assumes that the server has gone down.

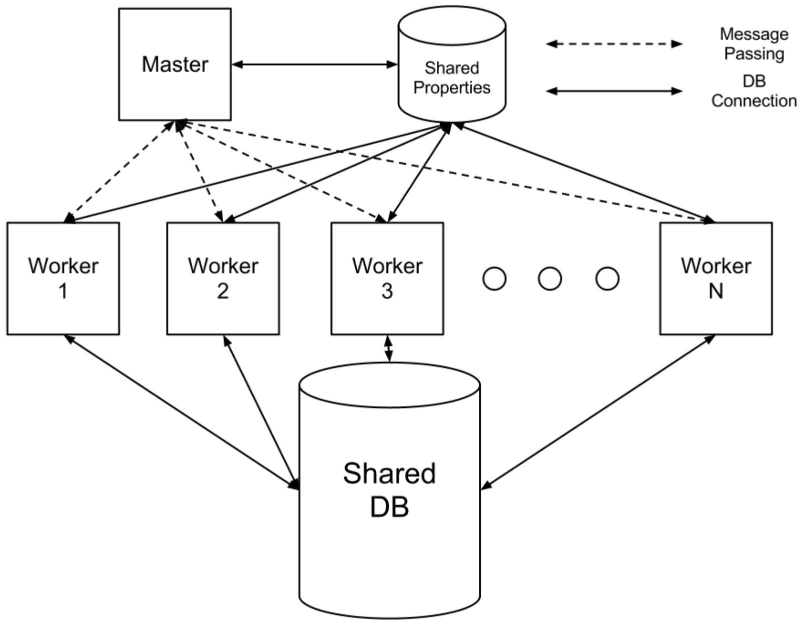


Figure 10.1: The server architecture of the SPOONS system.

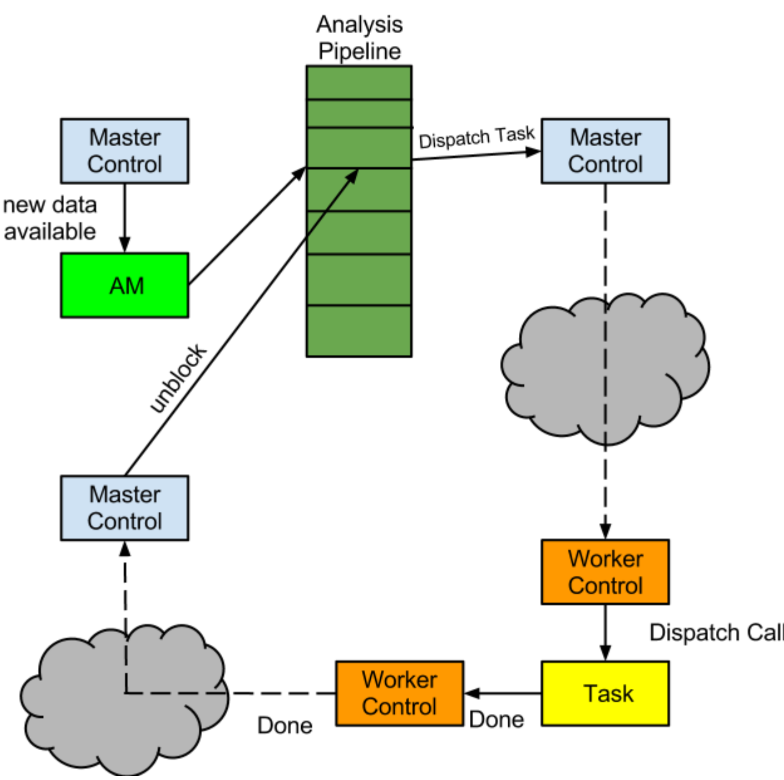


Figure 10.2: The control flow for distributable tasks.

10.1 Distribution Requirements

The design of the SPOONS distribution model was dominated by two main concerns: performance and usability.

Performance. SPOONS is a real-time system. Any attempt at distribution cannot compromise the response time of the system. In addition, SPOONS has to be able to survive a server dying. These two concerns led to three requirements:

- Efficiency: A distributed SPOONS should have comparable response time to a single server SPOONS.
- Fault Tolerance: SPOONS should be able to survive any non-database server failing.
- Scalability: Scaling a SPOONS cluster should be straightforward.

Usability. SPOONS is meant to be a general real-time analysis system that many different types of people can use. The average developer using SPOONS should be concerned only with the framework level. Server, network, and distribution semantics should remain transparent to a user of the framework. To make a distributed SPOONS easy to use for a developer working with the framework, three requirements are stipulated:

- DB: There should be one database, and a framework developer should not have to do anything that is not required on a simple single-server system.
- Framework Complexity: All distribution specifics should be hidden from the framework developer.

- Single Mode: SPOONS should be able to run on a single server.

10.2 Distribution Assumptions

The SPOONS distribution model relies on two assumptions about the system: every server contains exactly the same data in memory and every Task can be uniquely referenced.

10.2.1 Same Data

SPOONS assumes that every server has the same data in memory on every server. This means that not only does every server need to have the same data structures in memory, but also that every server needs to have the same classes instantiated. The only exception to this assumption is the Control. Depending on the role of the server, a different Control is instantiated. Because of this assumption, we do not have to worry about active replication between servers or a worker being asked to do work that requires a class that is not instantiated.

10.2.2 Uniquely Referenced Tasks

As stated in Section 9.5, Tasks are the basic unit of work inside SPOONS. When a worker is told to execute some work, it is being asked to execute a specific Task with specified parameters. Therefore, Tasks need to be able to be referenced by a key that can be serialized and sent over the wire from the master to the worker.

10.3 Distributable Tasks

Distributable Task is a subclass of Task that provides the distribution mechanism for Tasks. When a Task is to be distributed, the Distributable Task calls into the Control and requests that the Control distributes it. The next step varies depending on the type of Control that is active:

10.3.1 Master Control

The Task distributing control flow is described in Figure 10.2. A Master Control blocks the calling thread and send a message to a selected worker[1] telling it to run the Task with given parameters. The message that goes to the worker just contains the Task's unique identifier and the parameters to the Task's run. When the Task is complete, the Worker Control sends the Task's return status back to the Master Control. When the master receives a message from the worker that the requested Task has completed its run, it resumes the original calling thread and have it return with the return status given by the worker.

10.3.2 Worker Control

Worker Controls do not distribute Tasks. Because Tasks are atomic units of work, Tasks are not supposed to call other Tasks. If Task A calls upon a Worker Control to distribute a Task B, then that means that Task A has violated its own atomicity. This is considered a violation of the framework and causes the Worker Control to throw an error.

[1]The current scheduling algorithm chooses the worker that has the fewest Tasks currently assigned to it.

10.3.3 Single Control

Instead of blocking the calling thread like in the Master Control, a Single Control just uses the calling thread to run the Task. When the Task is complete, the Single Control returns control to the caller.

10.4 Shared Properties

As previously stated, all servers must maintain a consistent in-memory view of the system. This can be troublesome if a Task needs to maintain cumulative settings or member datum. Not only will this data need to be consistent on all the servers, but it also needs to maintain this data between starts and stop of the system. An Analysis Pipeline should be able to be interrupted at any moment, and then restarted later without losing data or its place.

To enforce these restrictions, SPOONS uses a shared property store. The shared property store is a MongoDB server. Whenever a Task needs to store member datum, it places the data in the shared store, making the data available to any server in the cluster. A Task can first be run to completion on Server A and then, when new data is available, run on Server B. Because the Task stores the necessary information in the shared property store, Server B can have all the information gained from the run on Server A and not lose any positional information.

In addition to storing shared properties, the shared property store houses information on every active server. When a server comes online, it queries the property store to find all the other active servers and inserts itself into the store. If a server fails to heartbeat, then the rest of the cluster that is still active removes the entry for that server from the property store.

Chapter 11

Database

SPOONS is backed by a MySQL database. SPOONS currently uses 225 tables and 35 stored procedures. The 225 tables are further divided into six different categories that are used in different stages of the analysis pipeline. In addition to tweets, configuration data, intermediate calculations, analysis results, and final alerting decisions are stored in the database. Keeping all of this data allows the users to look back at any point in time for reference or debugging.

The database uses naming and schema conventions to maintain organization on its tables. The naming and schema conventions allow different components of the Analysis Pipeline to be interchanged without any need to change/reprocess the data. In addition the conventions allows the UI to represent new tables without the need for specifying them.

11.1 Tables and Schemas

Each stage in an analysis pipeline generally stores some information in the database. Because each stage generally deals with similar types of data, these tables are considered to be in the same group. We enforce group membership using hints in the table names. For example, the table name "`RESULT_EN_class_heuristic_bayes_net`" gives five hints as to the type of the table.

1. `RESULT` - Marks this table as a result table. This means that it is guaranteed to be shown in the UI.
2. `EN` - The language of the tweets that were input into this method.
3. `class` - Indicates that this these results are output from a tweet classifier.
4. `heuristic` - States that the type of classifier used was a heuristic classifier.
5. `bayes_net` - The name of the classifier used.

Using all of these hints, the UI can then ask for data for specific types of tables (eg. all result tables that are for English tweets).

The six different top level categories that SPOONS recognizes are:

1. CALC - These tables store intermediate results in analysis pipelines. CALC tables are typically only used when large sets of past data are needed for cumulative models. They are never shown to the UI.
2. CONFIG - Contains information that analysis methods used to configure themselves before runs. These tables have been mostly replaced with the shared property store (see Section 10.4).

3. DATA - Raw input data. These tables are generally the output from the Gatherers.
4. META - Contains information that is not analyzed, but required by the system. For example, the different classes that the classifiers use along with descriptions of each class.
5. RESULT - These tables are output from some analysis pipeline. They are guaranteed to be shown in the UI. These tables typically contain time series of some analytical signal.
6. TEST - These tables are used for debugging and development. They are never shown in a user-facing UI, however may be shown in development UIs.

The full schemas for select tables are described in Appendix A.

11.1.1 Data Flow

The flow of data through the different types of tables is described in Figure 11.1. The data originates from the Gatherers and is moved into DATA tables. Information from DATA, CONFIG, and META tables are analyzed and placed in either CALC, RESULT, or TEST tables. At a later time the data from CALC tables is further analyzed and the results are placed in a RESULT table.

11.1.2 Tweets Table

As the most used and important table in the database, the table that houses all of our tweets, "DATA_tweets", gets special attention.

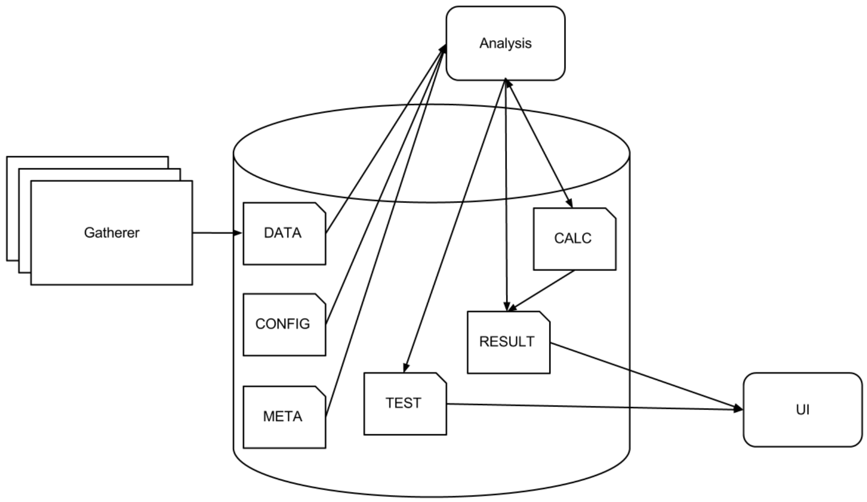


Figure 11.1: The flow of data through the different types of tables in SPOONS.

The tweets table contains ten attributes which are described in Table 11.1.

Frames

Inside SPOONS, we use a "frame" as the atomic unit of time. Currently, a frame corresponds to a minute. Bucketing the tweets into frames allows us to gain a natural aggregation and smoothing. It also provides a natural index. Maintaining an index on *frame_id* allows quick retrieval of time series data which is the primary task of SPOONS. Because insertions are generally chronological, insertions are also quick and do not require a rebuild of the B-Tree index[1].

11.2 UI Stored Procedures

In addition to utility procedures, the database holds many stored procedures used by the UI. This keeps the UI fairly stable in the face of database changes.

Data_tweets Schema

Name	Description
id	An auto-incremented primary key.
twitter_id	The unique id Twitter gives to a tweet.
published	The epoch time that the tweet was posted according to Twitter.
content	The raw content of the tweet.
source	Information on where the tweet was posted from (eg. from a third party app).
lang	The suggested language of the tweet.
author	The author of the tweet.
frame_id	The frame that this tweet falls into, has an index on it.
place	Information on where the tweet was posted from. This is a JSON structure and may contain fields such as "city" and "state".
geo	Geographical coordinates of place.

Table 11.1: The database attributes used to describe tweets.

Schema Name	Required Columns
Volume	start_frame, value
Volume Prediction	start_frame, prediction
Valence	start_frame, value
Valence	start_frame, prediction
Class	start_frame, undecided, media, neutral, snafu, watching, response, complaint, refuse_to_rate, happy
Group	start_frame, media, bad, other

Table 11.2: The different types of schemas that the UI looks for in RESULT tables.

11.2.1 Expected Schemas

The UI Stored Procedures look for 6 distinct name/schema combinations all of which are required to have the "RESULT" prefix. The different schema requirements are shown in Table 11.2, and described below:

Volume. This schema is for tables that contain time series information about tweet volumes. This includes tables that hold the time series for the total Netflix-related Twitter traffic.

Volume Prediction. These tables contain time series that are predictive models of Netflix-related Twitter traffic.

Valence. These tables contain time series for estimates of the current sentiment about Netflix.

Valence Prediction. These tables contain time series that are predictive models of the sentiment about Netflix.

Class. These tables contain time series for the volume of tweets that were classified into each of the nine categories described in Section 12.3.

Group. These tables contain time series for the volume of tweets that were classified into each of the thee different groupings described in Section 12.3.1.

The stored procedures further divides the tables by language. The currently recognized languages are English, Spanish, and Portuguese.

Part 3

Analysis

Chapter 12

Classifiers

12.1 Why Classification?

Classification helps discover Netflix service outages by differentiating between different types of Twitter traffic.

Figure 12.1 shows the normal pattern of Netflix-related Twitter traffic over the course of a single week. The peaks appear at around 7pm PST and the valleys are around 2am PST. This kind of pattern is very regular and repeats weekly during normal times. However, where there is some sort of event, the traffic develops spikes. Figure 12.2 shows a period with two anomalous spikes. However, sampling tweets from the different spikes hints that the causes for the two spikes are very different. Figure 12.3 shows tweets sampled from each spike. The left spike is composed mostly of tweets indicating that Netflix is experiencing a service outage. The right spike however, is composed mainly of tweets linking to a news article about Netflix. Therefore, we see that not only service outages generate spikes in Netflix-related Twitter traffic.

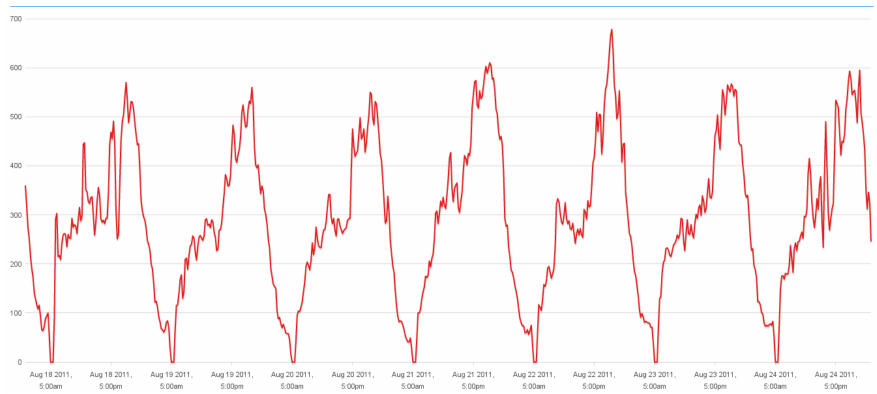


Figure 12.1: A week's worth of Netflix-related Twitter traffic. Notice the daily periodicity.

Figure 12.2: Netflix-related Twitter traffic with two different anomalies.

This is where classifiers become useful. If tweets can be placed into different classes according to their type, then the different types of traffic can be differentiated. Figure 12.4 shows the result of classifying the tweets and then building time series of the classes respective traffic. It becomes obvious that the spike on the left is caused by outage related traffic and that the spike on the right is caused by media related traffic.

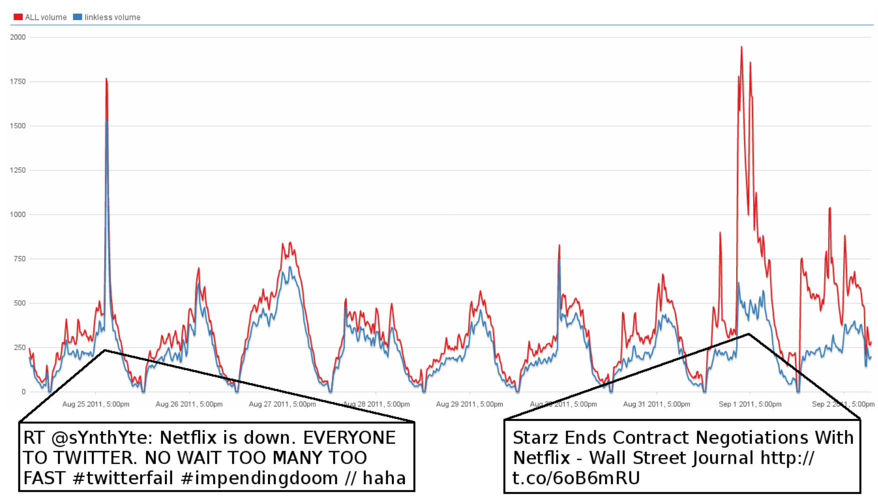


Figure 12.3: The same traffic shown in Figure 12.2, with an additional line showing Netflix-related Twitter traffic that does not contain a URL.

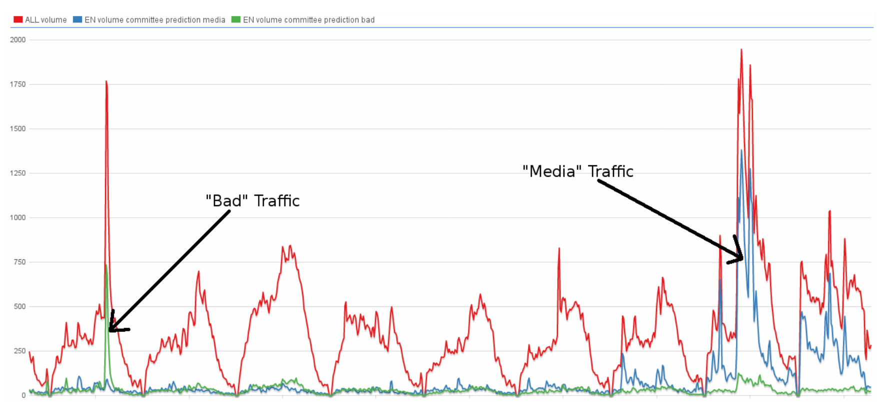


Figure 12.4: The same traffic shown in Figure 12.2, with two addition lines: the volume of tweets classified as "Bad" and the volume of tweets classified as "Media".

12.2 Classification Roadmap

The steps that SPOONS takes to use classification to detect service outages can be divided into two categories: prep work and online.

The prep work includes:

1. Observe Netflix-related Twitter traffic and observe the different classes that the tweets fall into.
2. Build a training set biasing anomalous traffic.
3. Classify incoming tweets.
4. Group classified tweets according to the type of traffic that class produces.
5. Establish the best classifiers.

After the off-line prep work is complete, the online analysis can begin:

1. Use the best classifiers in an Analysis Pipeline.
2. Observe the differences between the total traffic and the traffic classified as anomalous.
3. Declare an outage when the two traffics diverge significantly.

12.3 Tweet Classes

After observing Netflix-related Twitter traffic, we decided tweets fall into at least one of nine different categories.

- `Media` – Tweets relating to a media story about Netflix. Typically a link to a news article.
- `Snafu` – Tweets that talk about a Netflix outage.
- `Complaint` – Tweets where people are complaining about Netflix.
- `Happy` – Tweets that expresses the user's joy about Netflix.
- `Neutral` – Tweets that are just a neutral observation or comment about Netflix.
- `Watching` – Tweets that gives updates about what the user is currently watching.
- `Response` – Tweets that are a neutral response to another user in a Netflix-related conversation.
- `Refuse To Rate` – Tweets that we we refuse to rate entirely (usually tweets that are in a different language than the training set).
- `Undetermined` – This class does not exist in the wild. It is used during classification as default for all tweets that don't match any other class.

Examples of tweets with their corresponding classes are shown in Table 12.1.

12.3.1 Tweet Groups

Because the goal of SPOONS is to detect anomalous traffic, it is useful to collapse the nine classes into three different groups that account for the different types of Netflix-related traffic.

Class	Tweet Example
Media	Netflix Now Available Through Facebook - http://bit.ly/ffpBHH - [Geeky Gadgets]
Snafu	And netflix is broken. Why is this happening to me.
Complaint	netflix keeps taking little things i like about the site away...Why?
Happy	Netflix :)
Neutral	about to download this netflix free trial
Watching	Watching Family Guy on Netflix
Response	@BeehiveBlog Both good movies. I think I'll put on the netflix list.
Refuse To Rate	en serio, QUIERO pagar por algo como Netflix, DEJARME pagar

Table 12.1: Examples of the types of tweets that go with each class.

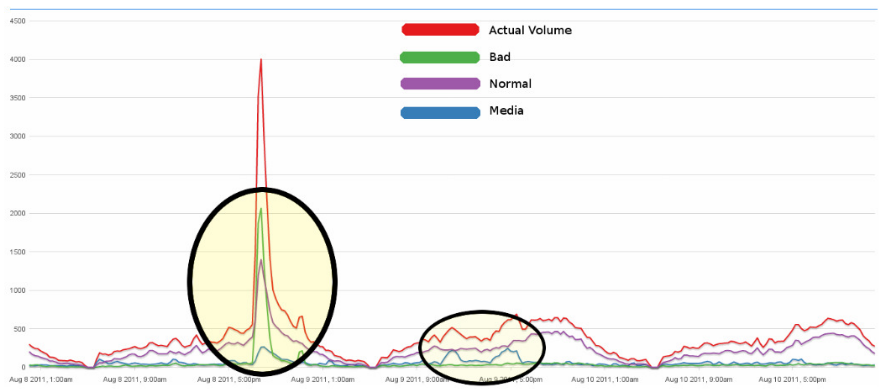


Figure 12.5: The different volumes for different tweet classes during an outage (left) and media event (right).

- `Media`: Contains only the `media` class.
- `Bad`: Contains both the `snafu` and `complaint` classes.
- `Other/Normal`: Contains all other classes.

Figure 12.5 shows the amount of Netflix-related tweets during a Netflix outage and media event. During normal times, the `normal` traffic is responsible for the majority of the overall traffic. However during outage and media events, we see that the `bad` and `media` dominate the respective periods.

12.4 WEKA Classifiers

SPOONS uses several classifiers from the WEKA machine learning package[9]. All of these classifiers have been discussed in Section 6.2. The WEKA classifiers used are:

- Naive Bayes
- Bayes Net

- J48 (a method of generating a C4.5 decision tree[26])
- K-Nearest Neighbors
- SMO (Support Vector Machine trained with Sequential Minimal Optimization[23])

12.5 Non-WEKA Classifiers

In addition to the WEKA classifiers, SPOONS uses two classifiers implemented from scratch. Because of low performance and inflexible API, the WEKA classifiers are being reimplemented. As of now, only Naive Bayes has been reimplemented. The other classifier implemented from scratch is a BPNB classifier which is discussed in Section 6.2.6.

12.6 Text Pre-Processing

Before the tweets are classified, they are pre-processed. During processing, the text is transformed to make classification of the text easier. Standard text operations like stemming, stopword removal, and case normalization; as well as Twitter and Netflix specific operations like hashtag and movie title recognition are preformed. After the text is processed, it is split into unigrams to be used as features in the classifiers.

12.6.1 Text Filtering

Before the input text is split into features, it goes through heavy pre-processing. The text filtering involves normalizing the case, remove extra characters, and replacing special features.

Link Replacement

The first step in processing the text is to replace links. Following a link may provide information about a tweet, however the link text of the link itself provides no information. The presence of a link, however, can provide information about a tweet.

Twitter-Specific Symbols

Tweets often contain several special symbols specific to tweets.

RT. "RT" stands for "re-tweet". It means that the posted tweet is a repost of a tweet made by another user. This symbol contains no reference to the original post. "RT" usually appears at the beginning of the tweet. For example, after the comedian Conan O'Brien posted the following tweet:

```
If I'm ever a ghost, I hope the person I haunt has Netflix.
```

There were hundreds of identical tweets that said:

```
RT: If I'm ever a ghost, I hope the person I haunt has Netflix.
```

#. A "#" (pronounced "hashtag") is used to mark keywords or topics. Users can search for tweets by hashtag and see the collection of tweets supposedly about the same topic. A hashtag does not have to reference a pre-existing topic.

@. An “@” in Twitter, simply pronounced “at”, is a reference to another Twitter user. A reference to a user alerts that user about the posted tweet. For example, the following tweet references my Twitter account.

`Hi there, @eriqaugustine`

Emoticon Parsing

Emoticons are parsed out and replaced with meta words. SPOONS emoticon parser was written by Ryan Hanarkis and Allen Dunlea as part of a project for Graduate Artificial Intelligence course. Emoticons provide a plethora of information about a tweet. Sarcasm aside, an emoticon can surmise the sentiment of an entire tweet.

Title Replacement

Because our tweets are always about Netflix, a television show and movie streaming service, titles are a common occurrence. However, movie and show titles often contain words that can be detrimental to our analysis. For example, “Death At A Funeral” is the title of a movie, but contains two words that have very negative connotations: “death” and “funeral”.

Without title replacement, the following tweet would be very difficult to classify:

`Death at a Funeral is hilarious! #netflix`

However after title replacement, the tweet becomes very easy to classify:

`⟨$title$⟩ is hilarious! #netflix`

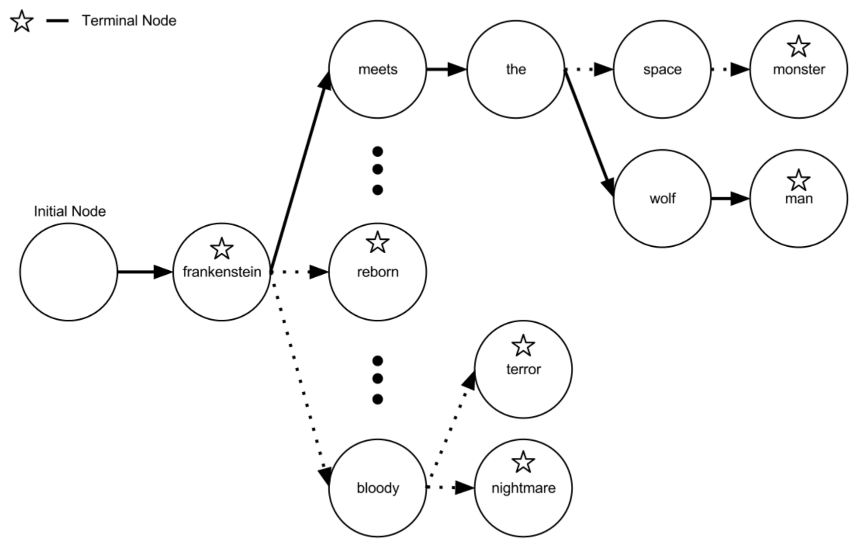


Figure 12.6: A sample trie of Frankenstein movie titles. The solid lines show what nodes the search for "Frankenstein Meets The Wolf Man" would traverse.

SPOONS contains a table that has over 50,000 movie and show titles on Netflix. The titles were gathered using the Netflix API. On startup, SPOONS builds a trie (prefix tree)[33] of all of the titles. In this trie titles can only be split on a word level, not on a character level. Therefore, moving to the next node consumes a single word. Searching for a title becomes a simple walk down the trie. If the walk of the trie ends on a terminal node, then a title is found. If not, then the trie is walked again from the beginning starting at the next word in the tweet. Figure 12.6 shows a sample walk in the title trie.

Stemming

Stemming finds the root of a word. This allows words to be categorized by their roots which decreases the number of unique words being evaluated and emphasizes linguistic patterns. This preprocessor uses Porter's stemmer for the

English language [24].

Stop Word Removal

Stopwords, or words that carry little or no semantic information, are identified based on a static table of words mapped to levels. Stopwords are assigned levels which allow processes to use different sets of stop words. All words less than 3 character are also automatically considered stop words.

Punctuation/Non-English Character Removal

Removes all punctuation and characters not in the English alphabet. This simplifies word extraction and comparison.

Meta Words

Below is an overview of meta words that SPOONS recognizes:

⟨**$title$**⟩ Indicates the presence of a movie or show title.

⟨**$link$**⟩ Indicates the presence of a URL.

⟨**$emote:*$**⟩ Replaces an emoticon.

⟨**RT**⟩ Indicates that a tweet is a “retweet” (a repeat of another tweet).

⟨**$#$**⟩ Inserted when a “hashtag” is found in a tweet. The original subject of the hashtag is separated off into another word. E.g. “#Netflix” becomes “⟨$#$⟩ Netflix”.

⟨**$@$**⟩ Inserted when a reference to another Twitter user is made. The user that is the subject of the reference is separated off into another word.

Class	# Tweets	Class	# Tweets
`Media`	103	`Neutral`	66
`Outage`	158	`Watching`	135
`Complaint`	146	`Response`	30
`Happy`	147	`Undetermined`	48

Table 12.2: Overview of the Netflix-related Twitter post training set used to train classifiers in SPOONS.

12.7 Training Set

The classifiers were trained on a small set of **759** tweets which were pulled from from periods of both normal and anomalous traffic. Each tweet in the training set was manually classified by multiple researchers until consensus about the classification was reached. Because the goal is anomalous traffic detection, the training set over-samples the tweets from `media`, `snafu`, and `complaint`: categories. Table 12.2 documents the structure of the training set and shows the number of tweets classified into each of the eight categories. Tweets were allowed to belong to multiple classes because of posts like, "`I love netflix! Watching Law and Order online!`", which could be classified as both `happy` and `watching`.

See Appendix D for the full training set.

12.8 Evaluation

Each classifier is individually evaluated just on its ability to classify tweets against the training set. Each classifier varies the type of filtering it uses between no filtering and full filtering (every method discussed in Section 12.6.1). Table 12.3 shows the combinations of classifiers and filters used for the classifier evaluation. There will be 24 classifier/filtering combinations.

Classifiers
BayesNetClassifier
BinaryBayesNetClassifier
BinaryJ48Classifier
BinaryKNNClassifier
BinaryNaiveBayesClassifier
BinarySMOClassifier
J48Classifier
KNNClassifier
NaiveBayesClassifier
Non-Weka BPNBClassifier
Non-Weka NaiveBayesClassifier
SMOClassifier

$\times$

Filtering
None
Full

Table 12.3: The cross product of the classifier and filtering will be used to evaluate the classifiers.

12.8.1 Confusion Matrices

The results of the classification evaluation are shown in confusion matrices. Table 12.4 shows the confusion matrix of the Naive Bayes classifier using full filtering as an example. Down the vertical are the actual classes of the tweets, and across the horizontal are the predicted classes that the classifiers output. Note that the example shows that this classifier incorrectly classified eight `media` tweets as another class (seen by looking down the `media` column), and misclassified 22 non-media tweets as `media` (seen by looking across the `row`).

Overall accuracy for the classifier can be calculated by taking the number of correctly classified tweets (down the diagonal) over the total number of tweets. Accuracy for a specific classification can be considered two ways: accuracy of classifying tweets **from** that class and accuracy of classifying **into** that class. The accuracy of classifying tweets **from** a class can be seen by looking down a column. The number correctly classified tweets (**bold**) over the total number of tweets in that column. The accuracy of classifying tweets **info** a class can be seen using the same method as before, except looking across the class's row instead of its column.

Actual / Classified	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
media	**81**	3	0	1	3	0	14	1
neutral	0	**23**	3	14	11	11	1	3
snafu	0	7	**81**	8	4	55	2	1
watching	0	26	0	**82**	5	12	0	10
response	2	12	3	6	**3**	1	0	3
complaint	1	9	36	9	8	**77**	3	3
refuse to rate	5	4	1	2	4	9	**21**	2
happy	0	18	5	22	5	31	1	**65**

Table 12.4: An example confusion matrix for a classifier. The `undecided` class was removed because there were no tweets in that class.

12.8.2 Results

Table 12.7 shows a summary of the results of the evaluation. The SMO classifier took the top two spots with a top accuracy of **.5750**. This is a decent accuracy, but much of the misclassification occurs between classes that don't matter as much when trying to identify the different types of classes. For example, it does not matter if a `watching` tweet is misclassified as a `happy` tweet. Both of those classes contribute to normal background traffic. Table 12.5 shows the confusion matrix for the top ranked classifier (SMO with no filtering). All of the misclassification of the `other` group that would become correct classification if the nine classes were compressed to the three groups are **bold**. Because of this, the classifiers will be evaluated again, but the different classes will be compressed into their respective groups before the results are evaluated.

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	0	0	0	0	0	0	0	0	0
media	0	98	0	0	2	2	0	0	1
neutral	0	3	11	2	**16**	**7**	7	0	**20**
snafu	0	0	1	87	4	4	41	0	21
watching	0	2	**12**	3	88	**5**	4	0	**21**
response	0	2	**5**	4	**7**	0	3	**1**	**8**
complaint	0	2	5	40	4	1	68	1	25
refuse to rate	0	9	**1**	1	**1**	**1**	0	18	**17**
happy	0	1	**9**	3	**13**	**6**	8	0	107

Table 12.5: The SMO results with no filtering. Every misclassification that would map to the `other` group is bold.

12.8.3 Compressed Results

Table 12.8 shows a summary of the compressed results. After the classes have been compressed, the SMO classifier is still on top but now with a best accuracy of **.8583**. Compressing the classes into groups greatly increases the accuracy of the classifiers.

It is important to note that not only is overall accuracy important, but also the precision for the `snafu` group. If SPOONS is stable capturing and classifying anomalous traffic, then when there is a spike then it will be visible. However if there are too many false positives, then a spike cannot be trusted. Recall affects the size of a spike, but precision affects the shape of the spike.

Table 12.6 shows an example of a compressed classification confusion matrix. The **bold** cells shows `snafu` tweets that were misclassified as other groups. Our number one priority is to minimize these cells. These cells represent the precision of the classifier for the `snafu` group (lower numbers generate higher precision). The *italics* cells shows tweets that were incorrectly classified as `snafu`. Although we also want to minimize these cells, they are not as important as the **bold** cells.

Classified \ Actual	media	snafu	other
media	95	**0**	8
snafu	*1*	252	*51*
other	13	**77**	336

Table 12.6: A sample compressed classification confusion matrix showing misclassified `snafu` tweets.

Full results for both the uncompressed and compressed evaluation can be found in Appendix B.

Classifier	Text Filter	Accuracy
SMOClassifier	**None**	**0.5726**
SMOClassifier	Full	0.5618
BinaryNaiveBayesClassifier	None	0.5606
NaiveBayesClassifier	None	0.5462
J48Classifier	Full	0.5414
BinaryNaiveBayesClassifier	Full	0.5414

Classifier	Text Filter	Accuracy
J48Classifier	None	0.5294
Non-Weka BPNBClassifier	Full	0.5210
NaiveBayesClassifier	Full	0.5198
BinarySMOClassifier	Full	0.5174
BinarySMOClassifier	None	0.5126
BinaryBayesNetClassifier	Full	0.4982
BayesNetClassifier	None	0.4970
Non-Weka BPNBClassifier	None	0.4958
BinaryBayesNetClassifier	None	0.4958
BayesNetClassifier	Full	0.4646
BinaryJ48Classifier	Full	0.4622
BinaryJ48Classifier	None	0.4514
BinaryKNNClassifier	None	0.4406
KNNClassifier	None	0.4382
Non-Weka NaiveBayesClassifier	Full	0.4082
KNNClassifier	Full	0.3854
BinaryKNNClassifier	Full	0.3830
Non-Weka NaiveBayesClassifier	None	0.3553

Table 12.7: Uncompressed Classification Results Summary

Classifier	Text Filter	Accuracy
SMOClassifier	**Full**	**0.8583**
SMOClassifier	None	0.8499

Classifier	Text Filter	Accuracy
Non-Weka BPNBClassifier	Full	0.8271
BinarySMOClassifier	None	0.8259
BinarySMOClassifier	Full	0.8235
BinaryNaiveBayesClassifier	None	0.8235
BinaryNaiveBayesClassifier	Full	0.8199
NaiveBayesClassifier	None	0.8175
Non-Weka BPNBClassifier	None	0.8151
J48Classifier	Full	0.8091
NaiveBayesClassifier	Full	0.8079
BinaryKNNClassifier	None	0.7899
J48Classifier	None	0.7887
KNNClassifier	None	0.7863
KNNClassifier	Full	0.7623
Non-Weka NaiveBayesClassifier	Full	0.7611
BinaryKNNClassifier	Full	0.7575
Non-Weka NaiveBayesClassifier	None	0.7263
BayesNetClassifier	None	0.7263
BinaryJ48Classifier	None	0.6879
BinaryBayesNetClassifier	Full	0.6855
BinaryBayesNetClassifier	None	0.6819
BinaryJ48Classifier	Full	0.6759
BayesNetClassifier	Full	0.6603

Table 12.8: Compressed Classification Results Summary

Chapter 13

Outage Detection

13.1 Ground Truth

Netflix has provided us with a list of outages that occurred between March 14, 2011 and January 30, 2012. This list is not comprehensive and some of the times are questionable. Some of the outages contained in the list are internal outages that did not affect their streaming service. These outages generated no signal on Twitter. Therefore, errors of omission could fall into one of two categories: true failures to recognize outages, and uncatchable outages. Regardless, we use this as our ground truth about all of the Netflix outages in that time period.

13.2 Success Metrics

Recall from Section 6.4, the definition of **True Positive**, **False Positive**, and **False Negative**. In the context of outage detection, these metrics have more specific definitions:

- True Positive — Any intersection between a reported outage range and a detected outage range.
- False Positive — Any detected outage that has no intersection in the events reported by Netflix.
- False Negative — An alert that has no intersection on an event reported by Netflix is a false negative.

Precision. Netlfix has specified an acceptable precision of 0.5. This means that SPOONS is allowed to generate an incorrect alert for ever correct alert. Any precision lower than 0.5 will cause SPOONS to be too noisy and consume too much engineer time.

Coverage. The list of outages that Netflix supplied has a coverage of 0.3341. SPOONS tries to minimize the coverage to supply directed outages with low noise.

13.2.1 Adjusted Score

Because of the coverage problem, outage detection methods cannot be compared using just their $F_{0.5}$ scores. Therefore, they will be compared using an adjusted score that rewards a high $F_{0.5}$ score and punishes a high coverage.

$$AdjustedScore = F_{0.5} \times (1 - coverage) \tag{13.1}$$

13.3 Monitors

SPOONS uses a number of Monitors that use different methods to try and detect anomalies in the traffic. This section describes each Monitor used. Each Monitor described has two tables describing the parameters that can tune this Monitor and the inputs that the Monitor takes. In addition, each Monitor will have a text description along with it.

13.3.1 Baseline Monitor

Parameter	Description	Restrictions
B	Baseline	$B > 0$

Input	Description	Restrictions
X	Any time series	-

The Baseline Monitor looks for any value above B, and counts that as anomalous. Ironically, because of its naïveté it also provides a decent baseline for the Monitors.

For example, the Baseline Monitor can be used to monitor the number of tweets classified as `bad`. The Monitor can be assigned a baseline of 200. Therefore whenever there are more than 200 `bad` tweets in a period, the Baseline Monitor will alert.

13.3.2 Windowed Standard Deviation Monitor

Parameter	Description	Restrictions
W	Window Size	$W > 0$
L	Lower Threshold	$L > 0$
U	Upper Threshold	$U >= L$

Input	Description	Restrictions
X	Any time series	-

The Windowed Standard Deviation Monitor is one of the simplest Monitors. This Monitor takes a W sized window worth of data and uses the standard deviation of the window to find outliers. Any outliers more than L standard deviations away are considered anomalies and counts towards an alert, but are still included in the windowed standard deviation calculation. Any value more than U standard deviations away is considered an anomaly, but not included in the standard deviation calculation. The reason for this is that values above U are extreme outliers.

The calculation for the standard deviation is based off of an iterative approach described in Knuth's "The Art of Computer Programming"[14]. Because Knuth's approach is iterative, it can be modified it to calculate for a range of values in an on-line fashion.

Adding the kth value, x, to the window:

$$Mean(k) = \frac{Mean(k-1) * (k-1) - Mean(k-W) + x}{k}$$

$$V(k) = (x - Mean(k)) * (x - Mean(k-1))$$

$$T(k) = T(k-1) - V(k-W) + V(k)$$

$$WindowStdDev(k) = \sqrt{\frac{T(K))}{k-1}}$$

For example, the Windowed Standard Deviation Monitor can be used to monitor the number of tweets classified as `bad` with a lower threshold of 2, an upper threshold of 3, and a window size of 3. Table 13.1 shows the process of the Windowed Standard Deviation Monitor at each iteration. Note that iterations 1 - 3 are filling the window and will never alert. Iteration 5 observed a value that was over the lower threshold, so generated an alert. However it as under the upper threshold, so was included in the window. Iteration 6 observed a value that was greater than the upper threshold. Therefore, that value produced an alert and was not included in the window.

Iteration	Window	Mean	Standard Deviation	Observed Point	Alert?
1	-	-	-	5	No
2	5	5	0	6	No
3	5, 6	5.5	0.7071	3	No
4	5, 6, 2	4.3333	2.0817	6	No
5	6, 2, 6	4.6667	2.3094	10	Yes
6	2, 6, 10	6	4	20	Yes
6	2, 6, 10	6	4	6	No

Table 13.1: An example of how the Windowed Standard Deviation Monitor determines when to alert.

13.3.3 Weekly Offset Windowed Standard Deviation Monitor

Parameter	Description	Restrictions
W	Window Size	$W > 0$
L	Lower Threshold	$L > 0$
U	Upper Threshold	$U >= L$

Input	Description	Restrictions
X	Any time series	-

The Weekly Offset Window Standard Deviation Monitor leverages the periodicity of tweet volume. Not only is there a daily pattern in traffic, but there is also an even stronger weekly pattern. The stronger weekly pattern makes sense if one views Netflix-related Twitter traffic as a representative for the number of people currently watching Netflix. People tend to have pattern that they follow, and people are more available on different days of the week (especially Friday).

This Monitor holds a windowed standard deviation for every 30 minute time period with 15 minute offsets for every week. Therefore, values are not compared to the other values around it, but to expected values from previous weeks. This Monitor uses the same tactics as the Windows Standard Deviation Monitor for counting anomalies.

For example, the Weekly Offset Windowed Standard Deviation Monitor can be used to monitor the number of tweets classified as `bad`. Unlike the Baseline Monitor, this Monitor allows for both weekly trends and daily variance. Therefore a period of 200 `bad` tweets may be acceptable on a Friday evening when traffic is typically high, but considered anomalous on a Tuesday morning when traffic is typically low.

13.3.4 Mean Squared Error Monitor

Parameter	Description	Restrictions
W	Window Size	$W > 0$
T	Threshold	$T > 0$

Input	Description	Restrictions
X	The expected time series	-
Y	The actual time series	$Y(k) \leq X(k)$

The Mean Square Error Monitor keeps a windowed mean squared error (MSE). This Monitor requires two sets of input, a set of expected values and a set of actual values. Any value that causes the MSE to go above a certain threshold, T, counts towards an anomaly.

Adding the kth value to a full window:

$$V(k) = (X(k) - Y(k))^2$$

$$MSE(k) = \frac{MSE(k-1) * W - V(k-W) + V(k)}{W}$$

For example, the Mean Square Error Monitor can be used to monitor the number of tweets classified as `bad` by letting X be the actual volume of tweets and Y be the number of total tweets **not** classified as `bad`. Table 13.2 shows the process of a Mean Square Error Monitor with a window size of 3 and a threshold of 100 at each iteration. Iteration 5 produces an alert because an MSE over the threshold was observed. An MSE over the threshold means that the number of tweets excluding tweets classified as `bad` became a poor predictor for the actual traffic of all tweets. This indicates that the traffic of `bad` tweets is becoming a significant factor to the overall Netflix-related Twitter traffic, which signifies an outage.

Iteration	Window (Errors)	Old MSE	Observed X	Observed Y	New MSE	Alert?
1	-	-	100	95	25	No
2	5	25	105	95	62.5	No
3	5, 10	62.5	100	98	43	No
4	5, 10, 2	43	95	88	51	No
5	10, 2, 7	51	100	80	151	Yes

Table 13.2: An example of how the MSE Monitor determines when to alert.

13.3.5 Ratio Monitor

Parameter	Description	Restrictions
T	Threshold	$0 < T < 1$

Input	Description	Restrictions
X	The expected time series	-
Y	The actual time series	$Y(k) < X(k)$

The Ratio Monitor takes the ratio of the actual value over the expected value for every time period. Whenever the ratio dips under the threshold T, then that period counts towards an anomaly. This Monitor may seem simple, but the real challenge lies in picking a proper X and Y. If a good approximating time series can be chosen, then the Monitor can be very successful.

For example, the Ratio Monitor can be used with X being the actual volume of tweets and Y being the number of total tweets **not** classified as `bad`. Therefore, any divergence in X and Y would be caused by the traffic of tweets classified as `bad`.

13.3.6 Class Correlation Monitor

Parameter	Description	Restrictions
W	Window Size	$W > 0$
T	Threshold	$-1 < T < 1$

Input	Description	Restrictions
X	The expected time series	-
Y	The actual time series	$Y(k) < X(k)$

The Correlation Monitor takes the Pearson Correlation between X and Y for a running window of size W. Pearson Correlation is used because of its ability to catch the linear correlation between two time series within a normalized range.

For performance reasons SPOONS uses an approximation of Pearson Correlation which uses the windowed standard deviation approach described in Section 13.3.2.

Adding the kth value, to the window:

$$\text{Let } \bar{X} \text{ be the windowed mean of } X.$$

$$\text{Let } \bar{Y} \text{ be the windowed mean of } Y.$$

$$T(k) =$$
$$T(k-1) + (X(k) * Y(k)) - (X(k-W) * Y(k-W))$$

$$Pearson(k) =$$
$$\frac{T(k) - (W * \bar{X} * \bar{Y})}{(W-1) * WindowStdDev(X) * WindowStdDev(Y)}$$

For example, the Correlation Monitor can use the same tactic described by the MSE and Ratio Monitors, By letting X be the actual volume of tweets and Y be the number of total tweets **not** classified as `bad`, the Correlation Monitor can view the effects of tweets classified as `bad`.

13.4 Evaluation

The classifiers chosen to be used in the outage detection evaluation are the top ten classifiers from the classifier evaluation (see Section 12.8.2). Each of the ten classifiers are paired with one of the monitors six monitors discussed in Section 13.3 making 60 different combinations as shown in Table 13.3.

Classifiers	**Filtering**
SMO	Full
SMO	None
BPNB	Full
BinarySMO	None
BinarySMO	None
BinaryNaiveBayes	None
BinaryNaiveBayes	Full
NaiveBayes	None
BPNB	None
J48	Full

$\times$

Monitor
Baseline
Windowed Standard Deviation
Weekly Offset Windowed Standard Deviation
Mean Squared Error
Ratio
Class Correlation

Table 13.3: The cross product of the classifier and Monitor will be used to evaluate the outage detection methods.

After the combination is chosen, the classifier will be fun on all of the tweets in the evaluation period. The Monitor will then use the classified data to auto-tune (Section 9.7.1). The output will be a set of optimal parameters and a confusion matrix with the actual results. Table 13.4 shows an example of the J48 classifier paired with the Weekly Window Standard Deviation Monitor. Note that the confusion matrix is much more simple than the classification confusion matrix. The "True" label indicates an outage. It does not make sense to fill the true negative (false/false) cell because the confusion matrix is dealing in outages and that cell represents the number of non-outages that were correctly classified as non-outages. Since neither precision nor recall uses this cell, it can be left undefined.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	6
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	6.0
Window Size	10

Actual / Predicted	True	False
True	84	4
False	120	X

Table 13.4: An example of the output for an outage detection method.

13.5 Results

Table 13.5 shows a summary of the outage detection evaluation results. The full outage detection results are in Appendix C.

The best outage detection method was the SMO classifier using full filtering and the Weekly Window Standard Deviation Monitor. This method achieved a precision of 0.9583, a recall of 0.4510, a $F_{0.5}$ score of 0.6970, a coverage 0.2890, and an adjusted score of 0.4956. The very high precision means that this method will almost never give an erroneous alert. The recall of this method is only 0.4510, however this is fairly good considering that not all reported outages produce signals Twitter.

All of the top ten methods use the Weekly Window Standard Deviation Monitor. This shows that the weekly trends in Twitter are very strong. The Monitor that took best advantage of the natural trends in the data did the best.

Full filtering was used in five of the top ten methods, which all have a very close adjusted score. This indicates that the type of filtering is not actually significant.

All of the top 35 methods were able to achieve Netflix's requirement of a precision greater than 0.5. Only 40 of all 50 methods failed to meet this requirement.

Monitor	Classifier	Filtering	Precision	Recall	$F_{0.5}$ Score	Coverage	Adjusted Score
WeeklyWindowStdDev	**SMO**	**Full**	**0.9583**	**0.4510**	**0.6970**	**0.2890**	**0.4956**
WeeklyWindowStdDev	BinaryNaiveBayes	Full	0.8846	0.4510	0.6699	0.2618	0.4945
WeeklyWindowStdDev	J48	Full	0.9545	0.4118	0.6632	0.2583	0.4919
WeeklyWindowStdDev	BPNB	None	0.9667	0.4265	0.6797	0.2894	0.4830
WeeklyWindowStdDev	BinarySMO	None	0.9588	0.4559	0.7010	0.3116	0.4825
WeeklyWindowStdDev	SMO	None	0.9659	0.4167	0.6711	0.2837	0.4807
WeeklyWindowStdDev	BinaryNaiveBayes	None	0.9625	0.3775	0.6346	0.2462	0.4784
WeeklyWindowStdDev	NaiveBayes	None	0.9205	0.3971	0.6395	0.2529	0.4777
WeeklyWindowStdDev	BinarySMO	Full	0.8481	0.3284	0.5552	0.1542	0.4697
WeeklyWindowStdDev	BPNB	Full	0.9266	0.4951	0.7180	0.3509	0.4661
Baseline	BinarySMO	Full	0.8947	0.3333	0.5730	0.2019	0.4573
Ratio	J48	Full	0.9438	0.4118	0.6597	0.3201	0.4485
MSE	BinaryNaiveBayes	None	0.9722	0.3431	0.6034	0.2579	0.4478
MSE	NaiveBayes	None	0.8646	0.4069	0.6288	0.2949	0.4434
Baseline	J48	Full	0.9508	0.2843	0.5337	0.1727	0.4416
Baseline	SMO	None	0.8767	0.3137	0.5486	0.2056	0.4358
Baseline	BinaryNaiveBayes	Full	0.9067	0.3333	0.5763	0.2448	0.4352
Baseline	NaiveBayes	None	0.8447	0.4265	0.6366	0.3213	0.4321
Baseline	BinaryNaiveBayes	None	0.9000	0.3971	0.6328	0.3184	0.4313
MSE	BinarySMO	None	0.7982	0.4461	0.6319	0.3193	0.4302
MSE	BinarySMO	Full	0.8367	0.4020	0.6150	0.3032	0.4286
Baseline	BinarySMO	None	0.7524	0.3873	0.5725	0.2526	0.4279
MSE	SMO	None	0.8800	0.4314	0.6535	0.3482	0.4259
Baseline	BPNB	Full	0.9041	0.3235	0.5657	0.2486	0.4251
Ratio	BPNB	Full	0.8947	0.3333	0.5730	0.2607	0.4237
Baseline	SMO	Full	0.8526	0.3971	0.6168	0.3166	0.4215

Monitor	Classifier	Filtering	Precision	Recall	$F_{0.5}$ Score	Coverage	Adjusted Score
Ratio	SMO	Full	0.6600	0.3235	0.4901	0.1430	0.4200
Baseline	BPNB	None	0.8989	0.3922	0.6283	0.3345	0.4181
Ratio	SMO	None	0.7250	0.2843	0.4780	0.1420	0.4101
Ratio	BinaryNaiveBayes	None	0.5922	0.2990	0.4463	0.0912	0.4056
Ratio	NaiveBayes	None	0.7931	0.2255	0.4313	0.0627	0.4042
Ratio	BinarySMO	Full	0.5980	0.2990	0.4485	0.1081	0.4001
Correlation	SMO	Full	0.5636	0.3039	0.4387	0.1097	0.3906
Ratio	BinarySMO	None	0.7333	0.2157	0.4074	0.0533	0.3857
Ratio	BPNB	None	0.5124	0.3039	0.4170	0.1134	0.3697
Correlation	BPNB	Full	0.5500	0.2696	0.4084	0.0978	0.3685
Ratio	BinaryNaiveBayes	Full	0.8660	0.4118	0.6332	0.4423	0.3531
Correlation	BPNB	None	0.5732	0.2304	0.3832	0.0828	0.3514
Correlation	BinaryNaiveBayes	Full	0.5312	0.2500	0.3864	0.0921	0.3508
Correlation	J48	Full	0.6129	0.1863	0.3476	0.0553	0.3284
Correlation	SMO	None	0.6275	0.1569	0.3137	0.0480	0.2987
MSE	J48	Full	0.4444	0.6471	0.4962	0.4363	0.2798
MSE	BPNB	None	0.4518	0.6667	0.5062	0.4683	0.2691
Correlation	BinaryNaiveBayes	None	0.5273	0.1422	0.2771	0.0518	0.2627
Correlation	BinarySMO	Full	0.4507	0.1569	0.2775	0.0650	0.2594
Correlation	BinarySMO	None	0.4384	0.1569	0.2743	0.0661	0.2562
Correlation	NaiveBayes	None	0.6471	0.1078	0.2426	0.0234	0.2370
MSE	SMO	Full	0.5260	0.7941	0.5927	0.5986	0.2379
MSE	BinaryNaiveBayes	Full	0.5000	0.7500	0.5625	0.5779	0.2374
MSE	BPNB	Full	0.5327	0.7990	0.5993	0.6247	0.2249
WindowStdDev	BinarySMO	None	0.7029	0.9510	0.7698	0.8537	0.1126
WindowStdDev	NaiveBayes	None	0.7029	0.9510	0.7698	0.8576	0.1096
WindowStdDev	BinaryNaiveBayes	None	0.7055	0.9510	0.7719	0.8582	0.1094
WindowStdDev	BinarySMO	Full	0.7029	0.9510	0.7698	0.8591	0.1084
WindowStdDev	SMO	None	0.7055	0.9510	0.7719	0.8610	0.1073
WindowStdDev	J48	Full	0.7106	0.9510	0.7760	0.8622	0.1069

Monitor	Classifier	Filtering	Precision	Recall	$F_{0.5}$ Score	Coverage	Adjusted Score
WindowStdDev	BPNB	None	0.7055	0.9510	0.7719	0.8616	0.1068
WindowStdDev	BPNB	Full	0.7091	0.9559	0.7759	0.8670	0.1032
WindowStdDev	BinaryNaiveBayes	Full	0.7159	0.9510	0.7802	0.8691	0.1021
WindowStdDev	SMO	Full	0.7132	0.9510	0.7781	0.8689	0.1020

Table 13.5: Outage Detection Results Summary

Part 4

Conclusions

Chapter 14

Conclusions

SPOONS has proven to be a system that is capable of Netflix outage detection using only tweets. This work has proven that all of the contributions stated in Chapter 5 have been fulfilled. Chapters 8, 9, and 10 discuss the design and implementation of the SPOONS system, framework, server architecture, and distributed computation model. Chapter 11 discusses the design of the SPOONS database. Chapters 12 and 13 discuss the design and implementation of the classification based outage detection methods.

14.1 Tweet Classification

Tweet classification has proven to be a difficult problem (see Section 6.1.1). However, SPOONS has shown that it is possible to classify tweets with high accuracy (0.8583). With knowledge about the domain of the tweets and a tight restriction on the classes, tweets can be classified with high accuracy. Section 12.8.2 highlights the success of the classifiers.

14.2 Outage Detection

SPOONS has shown the ability to detect Netflix service outages with very high precision (0.9583), good recall (0.4510), and with an acceptable coverage (0.2890). This proves that it is possible to use social media to precisely detect Netflix service outages. Section 13.5 highlights the success of the outage detection methods.

14.3 Fulfilled Requirements

Netflix provided six requirement that SPOONS was to fulfil (see Chapter 4):

1. Structural Independence
2. Use of Amazon Web Services
3. Real-Time Detection
4. Precise Outage Detection
5. Comprehensive Outage Detection
6. User-Friendly UI

The scope of this work covers the first four of these requirements. And the sixth was covered in a senior project by Matthew Tognetti.

Structural Independence. SPOONS was build from scratch and uses no infrastructure from Netflix.

Use of Amazon Web Services. SPOONS is deployed on Amazon Web Services.

Real-Time Detection. SPOONS is a real-time system that continuously runs and provides results within minutes.

Precise Outage Detection. Section 13.5 shows that the top 35 outage detection methods provide the precision required by Netflix. The top method provides almost perfect precision.

Comprehensive Outage Detection. Although the best outage detection methods provide a recall greater than 0.4, the true comprehension of a method is beyond the scope of this work. Accurately determining how comprehensive the outage detection methods are would require an omniscient way of determining when Twitter generates an outage signal. A more accurate list of Netflix outages can also serve as a way to test if the outage detection methods are comprehensive.

Chapter 15

Current Limitations of SPOONS

Real Time Tuning. All the results generated were the result of auto-tuning on the entire set of data. This assumes that the traffic that occurs in the future will be similar to the traffic that occurred in the past. Ideally, SPOONS would continually re-tune itself every time new outage data is acquired.

Severity. SPOONS does not try to determine how severe an outage it. Severity can be measures in two different ways: breadth and depth. The breath measure would be how many different platforms or regions are affected. Both of these pieces of information could be available through tweets. The depth measure would be how many users are affected. This measure is much more simple, it would be relative to the size of the outage spike.

Malicious Tweet Attack. SPOONS is currently susceptible to a type of attack where a user generates many fake tweets. SPOONS currently makes no attempt to verify the validity of a tweet, or the credibility of its author. Therefore, an attacker can just generate hundreds of simple tweets like:

```
Netflix is down.
```

This will be probably be enough to cause SPOONS to report an outage when there is none.

Nature of an Outage. Currently, SPOONS cannot detect the root cause of an outage. Even though during an outage there are many tweets like:

```
Damn NetFlix via Xbox 360 DOWN! (Bbm Sad Face)
```

SPOONS does not yet try to determine the cause of an outage.

Chapter 16

Current and Future Work

16.1 WEKA Classifier Reimplementation

The WEKA machine learning package offers a wide variety of classifiers. However, their implementation and API has some room for improvement. Because of this, SPOONS already uses two classifiers implemented from scratch. I plan on continuing this to make a classification package centered around performance and ease of use.

16.2 Advanced Sentiment Analysis

Kim Paterson, a member of the SPOONS team, is currently working on improving the sentiment analysis work from Cailin Cushing[6]. If completed, then SPOONS can use both text classification and sentiment analysis to determine when there is an outage. Because of their orthogonal natures, having both would allow SPOONS to recognize even more outages.

16.3 SPOONS Scaling

Another member of the SPOONS team, Brett Armstrong, is working to improve the scalability of SPOONS. Because of its distributed architecture (see Chapter 10), SPOONS already has the potential to scale horizontally. If there is too much traffic/work, then another server can just be added to the cluster. However, that currently requires manual intervention. Since there are spikes when outages occur, we may not know when there is going to be a lot of traffic. To solve this problem, Brett will use SPOONS to monitor itself. The end result of an Analysis Pipeline will not be an email alert, rather it will be the creation of a new AWS instance.

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Appendix A

SPOONS Database Schema Highlights

A.1 DATA_tweets

```
CREATE TABLE DATA_tweets (
    twitter_id varchar(32) COLLATE utf8_unicode_ci NOT NULL,
    published int(11) NOT NULL,
    content text COLLATE utf8_unicode_ci NOT NULL,
    source text COLLATE utf8_unicode_ci,
    lang varchar(3) COLLATE utf8_unicode_ci NOT NULL,
    author varchar(50) COLLATE utf8_unicode_ci
       NOT NULL DEFAULT 'Jon Doe',
    frame_id int(11) DEFAULT NULL,
    id int(11) NOT NULL AUTO_INCREMENT,
    place text COLLATE utf8_unicode_ci,
```

```
    geo text COLLATE utf8_unicode_ci,
    PRIMARY KEY (id),
    UNIQUE KEY tweet_id (twitter_id),
    UNIQUE KEY twitter_id (twitter_id),
    KEY frame_index (frame_id),
    KEY published_index (published),
    KEY lang (lang)
);

CREATE TABLE DATA_EN_class_training (
    tweet_id int(11) DEFAULT NULL,
    class int(11) NOT NULL DEFAULT '1',
    user_id int(11) DEFAULT NULL,
    UNIQUE KEY double_rating (tweet_id,class),
    KEY class (class)
);

CREATE TABLE DATA_netflix_titles (
    id int(11) NOT NULL AUTO_INCREMENT,
    title varchar(100) COLLATE utf8_unicode_ci NOT NULL,
    expire int(11) DEFAULT NULL,
    PRIMARY KEY (id),
    KEY title (title),
    KEY title_index (title)
);

CREATE TABLE DATA_reported_events (
    id int(11) NOT NULL AUTO_INCREMENT,
```

```
    start_frame int(11) NOT NULL,
    end_frame int(11) NOT NULL,
    severity varchar(32) COLLATE utf8_unicode_ci
        NOT NULL DEFAULT 'unknown',
    type enum('outage','hole','media','poutage','meme spkie')
        COLLATE utf8_unicode_ci NOT NULL DEFAULT 'outage',
    source varchar(64) COLLATE utf8_unicode_ci NOT NULL
        DEFAULT 'unknown',
    description varchar(256) COLLATE utf8_unicode_ci DEFAULT '',
    PRIMARY KEY (id)
);

CREATE TABLE META_logs (
    id int(11) NOT NULL AUTO_INCREMENT,
    timestamp bigint(20) NOT NULL,
    level enum('info','debug','warn','error','fatal')
        COLLATE utf8_unicode_ci NOT NULL DEFAULT 'info',
    entry text COLLATE utf8_unicode_ci NOT NULL,
    PRIMARY KEY (id)
);

CREATE TABLE META_tweet_classes (
    id int(11) NOT NULL AUTO_INCREMENT,
    class varchar(20) COLLATE utf8_unicode_ci NOT NULL,
    description text COLLATE utf8_unicode_ci,
    PRIMARY KEY (id),
    UNIQUE KEY class (class)
```

```
);

CREATE TABLE RESULT_ALL_volume (
    start_frame int(11) NOT NULL,
    end_frame int(11) NOT NULL,
    value float DEFAULT NULL,
   PRIMARY KEY (start_frame),
   UNIQUE KEY end_frame (end_frame),
   KEY start_frame (start_frame),
   KEY end_frame_2 (end_frame)
)

CREATE TABLE RESULT_EN_class_smo (
    tweet_id int(11) NOT NULL DEFAULT '0',
    class int(11) NOT NULL,
   PRIMARY KEY (tweet_id,class),
   KEY tweet_id (tweet_id),
   KEY class (class)
);

CREATE TABLE RESULT_EN_volume_smo (
    start_frame int(11) NOT NULL,
    end_frame int(11) NOT NULL,
    undecided float NOT NULL DEFAULT '0',
    media float NOT NULL DEFAULT '0',
    neutral float NOT NULL DEFAULT '0',
    snafu float NOT NULL DEFAULT '0',
    watching float NOT NULL DEFAULT '0',
```

```
    response float NOT NULL DEFAULT '0',
    complaint float NOT NULL DEFAULT '0',
    refuse_to_rate float NOT NULL DEFAULT '0',
    happy float NOT NULL DEFAULT '0',
    PRIMARY KEY (start_frame),
    UNIQUE KEY end_frame (end_frame),
    KEY start_frame (start_frame),
    KEY end_frame_2 (end_frame)
);

CREATE TABLE RESULT_EN_volume_weighted_series_prediction_week (
    start_frame int(11) NOT NULL,
    prediction float DEFAULT NULL,
    PRIMARY KEY (start_frame)
);
```

Appendix B

Full Classifier Evaluation Results

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**48**	50	0	1	2	2	0	0
neutral	0	1	**40**	3	8	8	2	0	4
snafu	0	0	48	**69**	3	6	32	0	0
watching	0	2	65	3	**46**	6	3	1	9
response	0	2	11	4	6	**1**	0	1	5
complaint	0	0	41	53	4	1	**44**	0	3
refuse to rate	0	2	24	0	2	2	0	**18**	0
happy	0	2	40	36	22	8	7	2	**30**

(a) Non-Weka NaiveBayesClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**93**	1	1	1	3	3	1	0
neutral	0	9	**12**	5	16	13	4	0	7
snafu	0	0	2	**104**	10	5	34	1	2
watching	0	4	23	5	**83**	7	2	1	10
response	0	3	7	4	9	**0**	0	1	6
complaint	0	6	3	66	6	3	**57**	0	5
refuse to rate	0	9	2	0	2	2	1	**29**	3
happy	0	4	17	41	32	6	10	2	**35**

(b) Non-Weka BPNBClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**85**	4	1	2	4	0	6	1
neutral	0	0	**25**	3	11	13	3	0	11
snafu	0	0	6	**94**	7	7	25	1	18
watching	0	0	26	2	**82**	9	1	0	15
response	0	2	14	3	6	**3**	0	0	2
complaint	0	1	12	42	8	10	**54**	0	19
refuse to rate	0	6	4	0	1	2	2	**30**	3
happy	0	1	22	15	14	6	7	0	**82**

(c) NaiveBayesClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**87**	4	0	2	0	1	8	1
neutral	0	1	**1**	9	20	0	1	2	32
snafu	0	0	0	**77**	9	0	21	0	51
watching	0	0	0	6	**105**	1	1	0	22
response	0	2	0	4	9	**0**	1	0	14
complaint	0	2	0	36	10	0	**24**	0	74
refuse to rate	0	9	1	2	0	0	1	**23**	12
happy	0	1	0	26	21	0	2	0	**97**

(d) BayesNetClassifier

Table B.1: Uncompressed, None Filter Classification Confusion Matricies

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**95**	1	0	2	0	1	3	1
neutral	0	4	**9**	5	13	1	7	3	24
snafu	0	0	5	**84**	3	0	36	2	28
watching	0	2	6	2	**84**	5	7	0	29
response	0	2	6	5	5	**0**	1	0	11
complaint	0	2	4	37	5	1	**54**	4	39
refuse to rate	0	11	2	4	0	1	6	**14**	10
happy	0	1	5	9	17	5	9	0	**101**

(e) J48Classifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**56**	0	0	1	2	0	0	44
neutral	0	0	**3**	2	7	4	5	0	45
snafu	0	0	0	**45**	0	4	59	0	50
watching	0	1	10	0	**73**	4	5	0	42
response	0	2	4	4	5	**0**	1	1	13
complaint	0	0	4	36	2	0	**61**	0	43
refuse to rate	0	2	0	0	1	1	0	**4**	40
happy	0	0	3	1	10	5	5	0	**123**

(f) KNNClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**98**	0	0	2	2	0	0	1
neutral	0	3	**11**	2	16	7	7	0	20
snafu	0	0	1	**87**	4	4	41	0	21
watching	0	2	12	3	**88**	5	4	0	21
response	0	2	5	4	7	**0**	3	1	8
complaint	0	2	5	40	4	1	**68**	1	25
refuse to rate	0	9	1	1	1	1	0	**18**	17
happy	0	1	9	3	13	6	8	0	**107**

(g) SMOClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**98**	1	0	2	2	0	0	0
neutral	0	1	**23**	2	12	13	4	0	11
snafu	0	0	6	**97**	7	7	25	1	15
watching	0	0	21	2	**92**	5	2	0	13
response	0	2	14	3	6	**3**	0	0	2
complaint	0	1	11	45	10	8	**53**	0	18
refuse to rate	0	13	4	1	0	3	1	**23**	3
happy	0	1	17	17	19	6	9	0	**78**

(h) BinaryNaiveBayesClassifier

Table B.1: Uncompressed, None Filter Classification Confusion Matricies Cont.

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**97**	0	2	0	0	1	2	1
neutral	0	2	**4**	10	10	0	3	1	36
snafu	0	0	0	**61**	6	0	26	0	65
watching	0	1	4	6	**80**	0	13	0	31
response	0	2	2	4	4	**0**	1	0	17
complaint	0	2	1	30	5	0	**41**	0	67
refuse to rate	0	14	0	2	1	0	5	**5**	21
happy	0	1	3	20	11	0	24	0	**88**

(i) BinaryJ48Classifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**90**	10	0	2	0	0	1	0
neutral	0	2	**2**	9	18	0	32	0	3
snafu	0	0	1	**85**	6	0	64	2	0
watching	0	0	1	4	**107**	0	20	0	3
response	0	2	1	4	9	**0**	14	0	0
complaint	0	1	2	33	10	0	**99**	0	1
refuse to rate	0	10	2	2	0	0	12	**22**	0
happy	0	1	2	26	19	0	91	0	**8**

(j) BinaryBayesNetClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**57**	0	0	1	2	0	0	43
neutral	0	0	**3**	1	8	4	5	0	45
snafu	0	0	0	**45**	0	4	59	0	50
watching	0	1	10	0	**74**	4	5	0	41
response	0	2	5	4	5	**0**	0	1	13
complaint	0	0	4	36	2	0	**61**	0	43
refuse to rate	0	2	0	0	1	1	0	**4**	40
happy	0	0	3	1	10	5	5	0	**123**

(k) BinaryKNNClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**92**	7	0	1	2	1	0	0
neutral	0	1	**33**	3	10	4	3	0	12
snafu	0	0	32	**69**	2	4	43	0	8
watching	0	2	28	2	**84**	4	2	0	13
response	0	2	11	4	5	**0**	0	1	7
complaint	0	1	38	37	3	0	**55**	0	12
refuse to rate	0	9	13	1	0	1	1	**19**	4
happy	0	1	50	1	13	5	2	0	**75**

(l) BinarySMOClassifier

Table B.1: Uncompressed, None Filter Classification Confusion Matricies Cont.

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**59**	36	0	2	3	3	0	0
neutral	0	1	**39**	4	9	6	3	0	4
snafu	0	0	42	**69**	5	5	36	0	1
watching	0	2	64	5	**45**	5	4	0	10
response	0	2	11	4	5	**1**	1	1	5
complaint	0	1	39	51	4	1	**47**	0	3
refuse to rate	0	2	17	4	2	2	0	**21**	0
happy	0	2	39	13	21	5	7	1	**59**

(a) Non-Weka NaiveBayesClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**88**	2	4	2	3	3	1	0
neutral	0	9	**9**	5	19	7	8	0	9
snafu	0	1	2	**100**	9	5	39	0	2
watching	0	3	19	8	**82**	5	2	1	15
response	0	3	5	4	9	**1**	1	1	6
complaint	0	7	4	66	5	2	**57**	0	5
refuse to rate	0	7	1	4	5	2	1	**26**	2
happy	0	4	11	18	27	5	10	1	**71**

(b) Non-Weka BPNBClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**81**	3	0	1	3	0	14	1
neutral	0	0	**23**	3	14	11	11	1	3
snafu	0	0	7	**81**	8	4	55	2	1
watching	0	0	26	0	**82**	5	12	0	10
response	0	2	12	3	6	**3**	1	0	3
complaint	0	1	9	36	9	8	**77**	3	3
refuse to rate	0	5	4	1	2	4	9	**21**	2
happy	0	0	18	5	22	5	31	1	**65**

(c) NaiveBayesClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**94**	1	0	0	0	1	5	2
neutral	0	3	**0**	8	3	1	49	0	2
snafu	0	0	0	**48**	1	2	103	0	4
watching	0	0	3	5	**79**	2	39	0	7
response	0	2	0	8	4	**2**	9	1	4
complaint	0	2	0	20	2	4	**112**	0	6
refuse to rate	0	14	0	5	0	0	20	**8**	1
happy	0	1	0	11	10	2	79	0	**44**

(d) BayesNetClassifier

Table B.2: Uncompressed, Full Filter Classification Confusion Matricies

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**99**	0	0	0	0	2	1	1
neutral	0	4	**10**	2	8	3	13	1	25
snafu	0	0	5	**71**	4	3	50	0	25
watching	0	1	7	2	**90**	2	11	1	21
response	0	2	5	2	8	**0**	2	0	11
complaint	0	2	7	35	4	1	**72**	0	25
refuse to rate	0	13	2	1	3	1	6	**10**	12
happy	0	1	11	4	14	3	15	0	**99**

(e) J48Classifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**58**	17	9	1	2	7	0	9
neutral	0	0	**21**	13	8	4	10	0	10
snafu	0	0	20	**57**	0	4	72	0	5
watching	0	1	39	12	**40**	4	11	0	28
response	0	2	5	5	4	**0**	2	1	11
complaint	0	0	18	53	2	0	**66**	0	7
refuse to rate	0	0	13	9	2	1	7	**4**	12
happy	0	0	36	16	6	5	9	0	**75**

(f) KNNClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**98**	1	0	1	2	0	1	0
neutral	0	4	**7**	3	15	5	6	0	26
snafu	0	0	3	**86**	2	4	50	0	13
watching	0	2	13	2	**92**	5	8	0	13
response	0	2	6	4	5	**1**	1	1	10
complaint	0	2	4	48	5	3	**74**	0	10
refuse to rate	0	11	0	1	2	2	6	**8**	18
happy	0	1	7	6	16	5	10	0	**102**

(g) SMOClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**95**	2	0	1	2	0	2	1
neutral	0	2	**23**	4	14	9	11	0	3
snafu	0	0	7	**85**	8	4	52	1	1
watching	0	0	21	0	**87**	5	12	0	10
response	0	2	12	3	6	**3**	1	0	3
complaint	0	1	10	42	9	7	**73**	2	2
refuse to rate	0	9	4	1	2	4	9	**17**	2
happy	0	0	16	6	21	5	30	1	**68**

(h) BinaryNaiveBayesClassifier

Table B.2: Uncompressed, Full Filter Classification Confusion Matricies Cont.

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**99**	0	2	0	0	0	0	2
neutral	0	4	**0**	25	13	0	22	0	2
snafu	0	0	0	**97**	6	0	55	0	0
watching	0	1	0	28	**78**	0	23	0	5
response	0	2	1	2	5	**0**	18	1	1
complaint	0	2	0	80	2	0	**59**	0	3
refuse to rate	0	14	0	14	3	0	12	**4**	1
happy	0	0	1	58	10	0	30	0	**48**

(i) BinaryJ48Classifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**95**	0	0	0	4	1	1	2
neutral	0	5	**1**	19	3	0	34	0	4
snafu	0	0	1	**73**	1	0	79	0	4
watching	0	0	1	10	**75**	0	32	0	17
response	0	2	1	6	4	**0**	11	0	6
complaint	0	2	1	27	2	0	**107**	0	7
refuse to rate	0	13	0	6	0	2	17	**9**	1
happy	0	0	2	18	9	0	63	0	**55**

(j) BinaryBayesNetClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**57**	19	11	1	2	7	0	6
neutral	0	0	**23**	14	8	4	10	0	7
snafu	0	0	22	**57**	0	4	72	0	3
watching	0	1	41	12	**42**	4	11	0	24
response	0	2	7	7	4	**0**	1	1	8
complaint	0	0	18	57	3	0	**66**	0	2
refuse to rate	0	0	16	13	2	1	7	**4**	5
happy	0	0	40	17	6	5	9	0	**70**

(k) BinaryKNNClassifier

Classified \ Actual	undecided	media	neutral	snafu	watching	response	complaint	refuse to rate	happy
undecided	**0**	0	0	0	0	0	0	0	0
media	0	**96**	4	0	1	2	0	0	0
neutral	0	4	**37**	2	8	4	3	0	8
snafu	0	0	44	**70**	2	4	37	0	1
watching	0	2	32	1	**84**	5	4	0	7
response	0	2	11	4	6	**0**	0	1	6
complaint	0	2	43	38	4	0	**57**	0	2
refuse to rate	0	10	24	0	1	1	1	**9**	2
happy	0	1	46	1	13	5	3	0	**78**

(l) BinarySMOClassifier

Table B.2: Uncompressed, Full Filter Classification Confusion Matricies Cont.

Classified \ Actual	media	snafu	other
media	**48**	2	53
snafu	0	**198**	106
other	9	58	**359**

(a) Non-Weka NaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**93**	4	6
snafu	6	**261**	37
other	29	72	**325**

(b) Non-Weka BPNBClassifier

Classified \ Actual	media	snafu	other
media	**85**	1	17
snafu	1	**215**	88
other	9	36	**381**

(c) NaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**87**	1	15
snafu	2	**158**	144
other	13	53	**360**

(d) BayesNetClassifier

Classified \ Actual	media	snafu	other
media	**95**	1	7
snafu	2	**211**	91
other	20	55	**351**

(e) J48Classifier

Classified \ Actual	media	snafu	other
media	**56**	0	47
snafu	0	**201**	103
other	5	23	**398**

(f) KNNClassifier

Classified \ Actual	media	snafu	other
media	**98**	0	5
snafu	2	**236**	66
other	17	35	**374**

(g) SMOClassifier

Classified \ Actual	media	snafu	other
media	**98**	0	5
snafu	1	**220**	83
other	17	41	**368**

(h) BinaryNaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**97**	3	3
snafu	2	**158**	144
other	20	88	**318**

(i) BinaryJ48Classifier

Classified \ Actual	media	snafu	other
media	**90**	0	13
snafu	1	**281**	22
other	15	214	**197**

(j) BinaryBayesNetClassifier

Classified \ Actual	media	snafu	other
media	**57**	0	46
snafu	0	**201**	103
other	5	21	**400**

(k) BinaryKNNClassifier

Classified \ Actual	media	snafu	other
media	**92**	1	10
snafu	1	**204**	99
other	15	19	**392**

(l) BinarySMOClassifier

Table B.3: Compressed, None Filter Classification Confusion Matricies

Classified \ Actual	media	snafu	other
media	**59**	3	41
snafu	1	**203**	100
other	9	45	**372**

(a) Non-Weka NaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**88**	7	8
snafu	8	**262**	34
other	26	61	**339**

(b) Non-Weka BPNBClassifier

Classified \ Actual	media	snafu	other
media	**81**	0	22
snafu	1	**249**	54
other	7	76	**343**

(c) NaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**94**	1	8
snafu	2	**283**	19
other	20	233	**173**

(d) BayesNetClassifier

Classified \ Actual	media	snafu	other
media	**99**	2	2
snafu	2	**228**	74
other	21	58	**347**

(e) J48Classifier

Classified \ Actual	media	snafu	other
media	**58**	16	29
snafu	0	**248**	56
other	3	94	**329**

(f) KNNClassifier

Classified \ Actual	media	snafu	other
media	**98**	0	5
snafu	2	**258**	44
other	20	47	**359**

(g) SMOClassifier

Classified \ Actual	media	snafu	other
media	**95**	0	8
snafu	1	**252**	51
other	13	77	**336**

(h) BinaryNaiveBayesClassifier

Classified \ Actual	media	snafu	other
media	**99**	2	2
snafu	2	**291**	11
other	21	232	**173**

(i) BinaryJ48Classifier

Classified \ Actual	media	snafu	other
media	**95**	1	7
snafu	2	**286**	16
other	20	216	**190**

(j) BinaryBayesNetClassifier

Classified \ Actual	media	snafu	other
media	**57**	18	28
snafu	0	**252**	52
other	3	101	**322**

(k) BinaryKNNClassifier

Classified \ Actual	media	snafu	other
media	**96**	0	7
snafu	2	**202**	100
other	19	19	**388**

(l) BinarySMOClassifier

Table B.4: Compressed, Full Filter Classification Confusion Matricies

Appendix C

Full Outage Detection Evaluation Results

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	9
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	6.0
Window Size	10

Predicted \ Actual	True	False
True	92	4
False	112	X

Table C.1: The parameters and confusion matrix for SMO (full filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	9
Recovery Resistance	9
Smoothing Method	Moving Mean
Smoothing Window Size	90
Lower Tolerance	2.0
Upper Tolerance	4.0
Window Size	10

Predicted \ Actual	True	False
True	92	12
False	112	X

Table C.2: The parameters and confusion matrix for BinaryNaiveBayes (full filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	6
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	6.0
Window Size	10

Predicted \ Actual	True	False
True	84	4
False	120	X

Table C.3: The parameters and confusion matrix for J48 (full filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	7
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	5.0
Window Size	20

Predicted \ Actual	True	False
True	87	3
False	117	X

Table C.4: The parameters and confusion matrix for BPNB (no filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	8
Recovery Resistance	8
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	4.0
Window Size	10

Predicted \ Actual	True	False
True	93	4
False	111	X

Table C.5: The parameters and confusion matrix for BinarySMO (no filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	10
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	5.0
Window Size	10

Predicted \ Actual	True	False
True	85	3
False	119	X

Table C.6: The parameters and confusion matrix for SMO (no filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	8
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	6.0
Window Size	20

Predicted \ Actual	True	False
True	77	3
False	127	X

Table C.7: The parameters and confusion matrix for BinaryNaiveBayes (no filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	5
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	9.0
Window Size	10

Predicted \ Actual	True	False
True	81	7
False	123	X

Table C.8: The parameters and confusion matrix for NaiveBayes (no filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	6
Recovery Resistance	10
Smoothing Method	Moving Mean
Smoothing Window Size	80
Lower Tolerance	3.0
Upper Tolerance	4.0
Window Size	15

Predicted \ Actual	True	False
True	67	12
False	137	X

Table C.9: The parameters and confusion matrix for BinarySMO (full filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	5
Smoothing Method	None
Lower Tolerance	1.0
Upper Tolerance	6.0
Window Size	10

Predicted \ Actual	True	False
True	101	8
False	103	X

Table C.10: The parameters and confusion matrix for BPNB (full filtering) using the WeeklyWindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	2
Recovery Resistance	8
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	50.0

Predicted \ Actual	True	False
True	68	8
False	136	X

Table C.11: The parameters and confusion matrix for BinarySMO (full filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	None

Predicted \ Actual	True	False
True	84	5
False	120	X

Table C.12: The parameters and confusion matrix for J48 (full filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	9
Tolerance	1900.0000
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	40

Predicted \ Actual	True	False
True	70	2
False	134	X

Table C.13: The parameters and confusion matrix for BinaryNaive-Bayes (no filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	8
Recovery Resistance	10
Tolerance	1800.0000
Smoothing Method	Moving Mean
Smoothing Window Size	30
Window Size	20

Predicted \ Actual	True	False
True	83	13
False	121	X

Table C.14: The parameters and confusion matrix for NaiveBayes (no filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	2
Recovery Resistance	1
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	80.0

Predicted \ Actual	True	False
True	58	3
False	146	X

Table C.15: The parameters and confusion matrix for J48 (full filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continiuous
Alert Resistance	1
Recovery Resistance	3
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	60.0

Predicted \ Actual	True	False
True	64	9
False	140	X

Table C.16: The parameters and confusion matrix for SMO (no filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continiuous
Alert Resistance	2
Recovery Resistance	8
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	90.0

Predicted \ Actual	True	False
True	68	7
False	136	X

Table C.17: The parameters and confusion matrix for BinaryNaiveBayes (full filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	7
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	40.0

Predicted \ Actual	True	False
True	87	16
False	117	X

Table C.18: The parameters and confusion matrix for NaiveBayes (no filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	1
Recovery Resistance	6
Smoothing Method	Moving Mean
Smoothing Window Size	100
Baseline	40.0

Predicted \ Actual	True	False
True	81	9
False	123	X

Table C.19: The parameters and confusion matrix for BinaryNaive-Bayes (no filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Window
Window Size	6
Control	2
Tolerance	1900.0000
Smoothing Method	None
Window Size	40

Predicted \ Actual	True	False
True	91	23
False	113	X

Table C.20: The parameters and confusion matrix for BinarySMO (no filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	10
Tolerance	1800.0000
Smoothing Method	Moving Mean
Smoothing Window Size	10
Window Size	30

Predicted \ Actual	True	False
True	82	16
False	122	X

Table C.21: The parameters and confusion matrix for BinarySMO (full filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	1
Smoothing Method	Moving Mean
Smoothing Window Size	60
Baseline	40.0

Predicted \ Actual	True	False
True	79	26
False	125	X

Table C.22: The parameters and confusion matrix for BinarySMO (no filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	9
Recovery Resistance	10
Tolerance	1900.0000
Smoothing Method	Moving Mean
Smoothing Window Size	40
Window Size	10

Predicted \ Actual	True	False
True	88	12
False	116	X

Table C.23: The parameters and confusion matrix for SMO (no filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	8
Smoothing Method	Moving Mean
Smoothing Window Size	100
Baseline	100.0

Predicted \ Actual	True	False
True	66	7
False	138	X

Table C.24: The parameters and confusion matrix for BPNB (full filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Window
Window Size	15
Control	2
Tolerance	0.7500
Smoothing Method	Moving Mean
Smoothing Window Size	100

Predicted \ Actual	True	False
True	68	8
False	136	X

Table C.25: The parameters and confusion matrix for BPNB (full filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	2
Recovery Resistance	2
Smoothing Method	Moving Mean
Smoothing Window Size	50
Baseline	80.0

Predicted \ Actual	True	False
True	81	14
False	123	X

Table C.26: The parameters and confusion matrix for SMO (full filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	3
Recovery Resistance	9
Tolerance	0.7500
Smoothing Method	None

Predicted \ Actual	True	False
True	66	34
False	138	X

Table C.27: The parameters and confusion matrix for SMO (full filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	9
Recovery Resistance	9
Smoothing Method	Moving Mean
Smoothing Window Size	40
Baseline	60.0

Predicted \ Actual	True	False
True	80	9
False	124	X

Table C.28: The parameters and confusion matrix for BPNB (no filtering) using the Baseline Monitor.

Parameter	Value
Resistance Method	Continiuous
Alert Resistance	3
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	None

Predicted \ Actual	True	False
True	58	22
False	146	X

Table C.29: The parameters and confusion matrix for SMO (no filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continiuous
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8000
Smoothing Method	None

Predicted \ Actual	True	False
True	61	42
False	143	X

Table C.30: The parameters and confusion matrix for BinaryNaiveBayes (no filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	3
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	None

Predicted \ Actual	True	False
True	46	12
False	158	X

Table C.31: The parameters and confusion matrix for NaiveBayes (no filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Window
Window Size	15
Control	2
Tolerance	0.8500
Smoothing Method	None

Predicted \ Actual	True	False
True	61	41
False	143	X

Table C.32: The parameters and confusion matrix for BinarySMO (full filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	62	48
False	142	X

Table C.33: The parameters and confusion matrix for SMO (full filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	2
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	None

Predicted \ Actual	True	False
True	44	16
False	160	X

Table C.34: The parameters and confusion matrix for BinarySMO (no filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.7500
Smoothing Method	None

Predicted \ Actual	True	False
True	62	59
False	142	X

Table C.35: The parameters and confusion matrix for BPNB (no filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8000
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	55	45
False	149	X

Table C.36: The parameters and confusion matrix for BPNB (full filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Fighting
Alert Resistance	10
Recovery Resistance	9
Tolerance	0.8000
Smoothing Method	None

Predicted \ Actual	True	False
True	84	13
False	120	X

Table C.37: The parameters and confusion matrix for BinaryNaive-Bayes (full filtering) using the Ratio Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	47	35
False	157	X

Table C.38: The parameters and confusion matrix for BPNB (no filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	80
Window Size	10

Predicted \ Actual	True	False
True	51	45
False	153	X

Table C.39: The parameters and confusion matrix for BinaryNaive-Bayes (full filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	9
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	38	24
False	166	X

Table C.40: The parameters and confusion matrix for J48 (full filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	9
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	32	19
False	172	X

Table C.41: The parameters and confusion matrix for SMO (no filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Tolerance	1900.0000
Smoothing Method	None
Window Size	10

Predicted \ Actual	True	False
True	132	165
False	72	X

Table C.42: The parameters and confusion matrix for J48 (full filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	9
Recovery Resistance	1
Tolerance	1900.0000
Smoothing Method	None
Window Size	10

Predicted \ Actual	True	False
True	136	165
False	68	X

Table C.43: The parameters and confusion matrix for BPNB (no filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	90
Window Size	10

Predicted \ Actual	True	False
True	29	26
False	175	X

Table C.44: The parameters and confusion matrix for BinaryNaiveBayes (no filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	50
Window Size	10

Predicted \ Actual	True	False
True	32	39
False	172	X

Table C.45: The parameters and confusion matrix for BinarySMO (full filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	10
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	50
Window Size	10

Predicted \ Actual	True	False
True	32	41
False	172	X

Table C.46: The parameters and confusion matrix for BinarySMO (no filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	1
Recovery Resistance	8
Tolerance	0.8500
Smoothing Method	Moving Mean
Smoothing Window Size	10
Window Size	10

Predicted \ Actual	True	False
True	22	12
False	182	X

Table C.47: The parameters and confusion matrix for NaiveBayes (no filtering) using the Correlation Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Tolerance	1900.0000
Smoothing Method	None
Window Size	10

Predicted \ Actual	True	False
True	162	146
False	42	X

Table C.48: The parameters and confusion matrix for SMO (full filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Tolerance	1900.0000
Smoothing Method	None
Window Size	10

Actual / Predicted	True	False
True	153	153
False	51	X

Table C.49: The parameters and confusion matrix for BinaryNaive-Bayes (full filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Tolerance	1900.0000
Smoothing Method	None
Window Size	10

Actual / Predicted	True	False
True	163	143
False	41	X

Table C.50: The parameters and confusion matrix for BPNB (full filtering) using the MSE Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	82
False	10	X

Table C.51: The parameters and confusion matrix for BinarySMO (no filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	82
False	10	X

Table C.52: The parameters and confusion matrix for NaiveBayes (no filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	81
False	10	X

Table C.53: The parameters and confusion matrix for BinaryNaive-Bayes (no filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	82
False	10	X

Table C.54: The parameters and confusion matrix for BinarySMO (full filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	81
False	10	X

Table C.55: The parameters and confusion matrix for SMO (no filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	79
False	10	X

Table C.56: The parameters and confusion matrix for J48 (full filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	81
False	10	X

Table C.57: The parameters and confusion matrix for BPNB (no filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	195	80
False	9	X

Table C.58: The parameters and confusion matrix for BPNB (full filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	77
False	10	X

Table C.59: The parameters and confusion matrix for BinaryNaive-Bayes (full filtering) using the WindowStdDev Monitor.

Parameter	Value
Resistance Method	Continuious
Alert Resistance	10
Recovery Resistance	1
Smoothing Method	None
Lower Tolerance	3.0
Upper Tolerance	3.0
Window Size	20

Predicted \ Actual	True	False
True	194	78
False	10	X

Table C.60: The parameters and confusion matrix for SMO (full filtering) using the WindowStdDev Monitor.

Appendix D

Full Training Set

complaint	I hate netflix sometimes
complaint	Fuck netflix
complaint	Wat the fuck is a fuck n netflix ?
watching	Netflix movies all dayyy
neutral	!!!!! THEY HAVE AAAHH! REAL MONSTERS ON NETFLIX! FUCK YEAH.
complaint	NETFLIX Y U HATE ME?
complaint	Netflix is so trash wtf.
neutral	Netflix stoped messing up #hypetweet
complaint	ugh...netflix is THEE worse
complaint	I hate when netflix fucks up!
snafu	I hate when netflix fucks up!
snafu	Netflix is down. EVERYBODY PANIC
snafu	Netflix and Xbox not getting along.
response	RT @Nat3Th3Gr3at: myy netflix isn't workin.. : (
snafu	RT @Nat3Th3Gr3at: myy netflix isn't workin.. : (
snafu	Netflix isn't working!o:¡
snafu	Netflix... can access movie but can't play.... what an evil game they r playing. Anyone else having this problem? #netflix

snafu	Dear @netflix and @Xbox and @XboxSupport please fix yoru Netflix crap.... I was in the middle of finishing up season 4 of My Name is Earl!
snafu	Netflix, Y U NO WORK?
complaint	@sh33k360 Yeah. I can access my queue, but when I hit play, it goes back to the list after about 10 seconds of loading. #netflix
snafu	@sh33k360 Yeah. I can access my queue, but when I hit play, it goes back to the list after about 10 seconds of loading. #netflix
snafu	Netflix won't stream WTF Mavs dont play for another 40 mins
snafu	@xboxsupport please fix netflix ASAP! K, thnks!
snafu	@VballChickPMS I've got a few pings via Xbox Xperts asking the same thing. Seems Netflix is having problems.
snafu	@XboxSupport any reports of Netflix issues tonight in Canada?I try to start a movie, get 4 "quality" bars, then back to menu screen.
snafu	Anybody else having trouble with Netflix right now?
snafu	Is anyone else having issues with Netflix via Xbox? iPhone & PC work fine.
snafu	Why the Eff is my Netflix acting stupid
snafu	Damn NetFlix via Xbox 360 DOWN! (Bbm Sad Face)
snafu	@netflix not loading vids on xbox
response	@thornlordslady apparently it's just xbox 360 and netflix is working on a fix.saw the tweet from them about 5 mins ago.
snafu	@thornlordslady apparently it's just xbox 360 and netflix is working on a fix.saw the tweet from them about 5 mins ago.
snafu	Hmm...been having issues myself lately.Just blamed TWC for it :-/RT @TheSocialGamer: Is something going on with #Netflix for #Xbox360?
snafu	Grrr xbox is not playing nice with netflix right now, yet my ps3 works just fine. Buuuhh
snafu	Is Netflix on 360 not working for anyone else right now?
complaint	netflix is screwing up...#fml
snafu	netflix is screwing up...#fml
snafu	Looks like it is not just me, Netflix is not working on my Xbox.
snafu	Why isn't my netflix working?

snafu	#netflix fix your shit!
snafu	Netflix isn't working =(
snafu	Is #netflix on Xbox down for anyone else?
snafu	@XboxSupportWhere is netflix on the dashboard??
snafu	Y Netflix actn all dumb nd shit!
snafu	Dear @netflix, I've been using the service on my Xbox for a few hours now. All of a sudden I can't play anything. Please fix. Thank you.
snafu	@xboxsupport i cant get my netflix to work. When i start a movie it starts normal like its loadibg then goes back to the main screen
snafu	Anyone else having trouble getting netflix work on the xbox? Mine kicks out after determining my picture quality to be HD.
snafu	why isn't my netflix working :(
snafu	NO NETFLIX UGH NOW HOW ARE WE GOIN TO WATCH MOVIES.....jacked up stuff yo gosh smh **folds arms and pouts**
snafu	@XboxSupportYo where can i find netflix?
snafu	@Netflix I can't watch anything on my 360 says it can't contact, my friend are having the same problem, what's up?
snafu	I'm really mad Netflix on xbox isn't working ¿:O
snafu	myy netflix isn't workin.. : (
snafu	Netflix on Xbox Live having issues streaming tonight. Boo!
snafu	OMFG FUCK YOU NETFLIX! Being hella laggy and shit. ugh!!
complaint	Holy fucking slow #netflix
snafu	Holy fucking slow #netflix
snafu	What's wrong with #Netflix
snafu	need help my netflix is not working on my xbox 360
snafu	Dammit #Xbox and/or @netflix! Why did you suddenly decide to stop working?!?!
response	@evilly_innocent i am going to figure out what the heck happened to my netflix ¿.¡
snafu	@evilly_innocent i am going to figure out what the heck happened to my netflix ¿.¡
watching	#netflix chainsaw massacre
watching	Kangaroo Jack on Netflix - sick daughter's choice

watching	First day of dead week– watching Criminal Minds... :) Yay for netflix!
complaint	Bumass netflix -__-
watching	Death at a funeral #netflix #ps3
response	RT @SamuelDeLaGetto: Watchu watchin? Im watchin ”Donnie Darko” RT @MarcusGdaCeleb: #Netflix
watching	RT @SamuelDeLaGetto: Watchu watchin? Im watchin ”Donnie Darko” RT @MarcusGdaCeleb: #Netflix
snafu	???Netflix???????????????????????????????
watching	Coughing up hairballs (not literally) and watching netflix on XBL *sighs* I hate being sick!
happy	Netflix¡3
watching	Watching #aaahhrealmonsters on #netflix! Hell yessss
complaint	Stupid fucking PS3 and stupid fucking Netflix. #mallorieproofed
snafu	Stupid fucking PS3 and stupid fucking Netflix. #mallorieproofed
complaint	Fuck netflix
complaint	Stupid, stupid Netflix.
watching	Watchin netflix
complaint	Netflix suxs
complaint	NetFlix Bitch!
complaint	Ugh, fucking Netflix fucking up.
snafu	Ugh, fucking Netflix fucking up.
complaint	ughh stupid netflix
complaint	#stupid netflix
complaint	sorry, i hate netflix.
complaint	#netflix wtf
complaint	WTF #netflix!?
complaint	Ugh I hate netflix.
complaint	WTF Netflix
complaint	OMFG WTF NETFLIX
refuse to rate	en serio, QUIERO pagar por algo como Netflix, DEJARME pagar
refuse to rate	Contratar Netflix o no contratar Netflix, ese es el dilema...
complaint	Ughh wtf netflix!!!!

response	Also @cbye is it you or one of your other Netflix friends watching Party Down? If it isn't you I suggest you start immediately!
watching	Also @cbye is it you or one of your other Netflix friends watching Party Down? If it isn't you I suggest you start immediately!
media	http://bit.ly/92a4un ¡– Online Petition to STOP Internet Bandwidth Overage Charges in Shaw's response to Netflix vs Video On Demand
happy	off to bed netflix to lull me to sleep ¡3
neutral	Chillin at home with Netflix and a home cooked meal!
neutral	"The Wild and Wonderful Whites of West Virginia" kept Karly up well past 11 on a weeknight. Netflix it to see life lived without a tomorrow.
response	@DrumMajorsATL What it do my nigga i'm just cooling it watching netflix,lol what u up too
watching	@DrumMajorsATL What it do my nigga i'm just cooling it watching netflix,lol what u up too
refuse to rate	No es jevy eso?RT @BackHand29: @BaBy_FrEsH103 oye chekeate SPARTICUS en Netflix pa k te cure
media	The Mobile Tsunami is Near: Blame Netflix and Apple: Cisco anticipates that mobile network-connected tablets wil... http://bit.ly/i8Fvmv
complaint	@enriqueztwb the real question is when is CSI getting to Netflix Streaming? that is the REAL question.
neutral	@enriqueztwb the real question is when is CSI getting to Netflix Streaming? that is the REAL question.
response	@enriqueztwb the real question is when is CSI getting to Netflix Streaming? that is the REAL question.
neutral	@friedgreenhalos yep. netflix instant streaming. I love Christopher Lloyd and Michael Jeter (RIP Michael Jeter).
response	@friedgreenhalos yep. netflix instant streaming. I love Christopher Lloyd and Michael Jeter (RIP Michael Jeter).
refuse to rate	#nw waterworld with kev cosner....ill shit #netflix
complaint	netflix keeps taking little things i like about the site away...Why?
complaint	And netflix is broken. Why is this happening to me.
snafu	And netflix is broken. Why is this happening to me.
media	it's like the netflix challenge but with lives instead of movies!RT @timoreilly: $3 Million Prize Offered... http://bit.ly/hyRzHn
response	it's like the netflix challenge but with lives instead of movies!RT @timoreilly: $3 Million Prize Offered... http://bit.ly/hyRzHn

media	The Mobile Tsunami Is Near: Blame Netflix and Apple http://feeds.nytimes.com/click.phdo?i=c959df9634be496
media	The Mobile Tsunami Is Near: Blame Netflix and Apple http://feeds.nytimes.com/click.phdo?i=c959df9634be496
watching	Bouts to browse through my #Netflix on my 360 see wht I wanna watch
neutral	@sarahsteinmeier I got an email from netflix alerting me that it will be arriving tomorrow! I am excite.
response	@sarahsteinmeier I got an email from netflix alerting me that it will be arriving tomorrow! I am excite.
media	Thanks to the recommendation of @superbetch I watch Netflix on my phone almost every day :)
watching	Thanks to the recommendation of @superbetch I watch Netflix on my phone almost every day :)
neutral	Boondocks Saints 2. Netflix #chillmode
watching	Boondocks Saints 2. Netflix #chillmode
media	Last minute again RT @boxee: Netflix App works, but is still ”coming soon” due to strict security requirements - http://bit.ly/dRIoJv
response	Last minute again RT @boxee: Netflix App works, but is still ”coming soon” due to strict security requirements - http://bit.ly/dRIoJv
neutral	What you missed on Netflix Movie Night: http://www.youtube.com/watch?v=X7UQyerHXB0
response	@DstEeZNLikeWOAH netflix just sent me that shit!
neutral	@DirectTV - yes RED was great. I got it from @Netflix. So STOP blasting out the AD at such a high vol my NEIGHBORS know U have it! #juststop
refuse to rate	Netflix. Nigga.((:
watching	Let’s see what’s on Netflix ..
neutral	Perusing Netflix titles on Apple TV sucks unless you have perfect vision or sit 2 inches from the TV. Roku gets it right.
neutral	Netflix streaming a history of the Monarchy, a nice whiskey glow and still, I have writers block...
neutral	How do you get Netflix ??
complaint	Netflix is being so slow #hurryup
happy	@zachgalifianakis ur comedy on netflix is #bomb
response	@zachgalifianakis ur comedy on netflix is #bomb
neutral	What did I watch to make Netflix think I like foreign buddy flicks?
media	The Mobile Tsunami Is Near: Blame Netflix and Apple http://nyti.ms/i3Wgv3
happy	Netflix might be the best invention
watching	multitaskin lol doin work n watchin Exam on netflix

neutral	anyone know of a really good, really happy fluffy movie that might be on netflix... ? at all? or anything at all? i'm so boowooored!
watching	I'm not watching Secret Life of American Teenager on netflix o_O #lies
happy	UK Skins on Netflix. Yes.
happy	I need NetFlix in my life asap
media	Amazon Prime members to get unlimited video streaming, a la Netflix? http://t.co/Ox2NZtn via @digitaltrends
media	So excited! RT @boxee: Netflix App works, but is still "coming soon" due to strict security requirements - http://bit.ly/dRIoJv
complaint	NETFLIX pisses me off when it doesnt work correctly
snafu	NETFLIX pisses me off when it doesnt work correctly
neutral	Its Netflix tiiiiiime! What film should I watch? I need some suggestions. . .
complaint	@Morena485 I'm not terribly impressed with Netflix and their selection of movies. :/
complaint	man, this Shit sucks on tha computer. #netflix
watching	watchinggg avatar, the last air bender withh my sleeping brother on netflix! haha soo muchh for watching tv together #sleepyhead
complaint	Why is netflix online mad limited though?
happy	thank goodness for netflix... bones marathon by maseff!
response	@joshuabier Netflix queue: Day After Tomorrow, 2012, The Shining, Alive, Fargo, and Snow White and the 7 Dwarfs.
neutral	I don't think I'd ever leave the house if I got Netflix.
watching	Everyone's sleep. Just wanted to watch @netflix & its down...so now im officially bored.
happy	Damn 2mor is a PERFECT day 4 layin up & watch netflix smh
neutral	@PaprChasNMahni lol I'm watching it now on netflix
watching	@PaprChasNMahni lol I'm watching it now on netflix
response	@riskyrae get netflix for free for a month. That's how I got Josh addicted.
watching	Watching Gamer on Netflix.
neutral	If you haven't watched Spartacus on @netflix you're LOSING majorly.
happy	So @netflix is amazing

media	Netflix shares jolted: In addition to streaming movies, Amazon may look to strike a partnership with Coinstar, w... http://bit.ly/fW12pq
watching	Going to watch a movie on netflix, "Julie & Julia". Can't sleep now after that fat nap.
watching	i need to watch something semi-boring instead of party movies on netflix, party related anything makes me wanna stay up all night!
watching	Just tried out Netflix and watched Broken Embraces by Pedro Almodovar, Loved it!
neutral	This history paper is going a lot slower than I first imagined, thanks to discovering Desperate Housewives on Netflix stream-on-demand.
response	RT @Lupintheone2011@RonGreco it can snow all it wants as long as it don't mess with my netflix streaming
neutral	found harry and the hendersons on netflix
watching	I haven't watched a movie on #Netflix in awhile now... think i will check it out right now n find something to watch.
neutral	Thinkin bout gettin a xbox just so I could get Netflix on my tv lol
neutral	netflix changed their instant playing set up.
media	Safeway Inc : Option Skews - Relatively Heavy Put Activity on Netflix Inc., Costco Wholesale ... - Schaeffers http://uxp.in/27814953
happy	@netflix the craft. Girlfriend loves the crap out of that movie
neutral	@netflix the craft. Girlfriend loves the crap out of that movie
neutral	I imagine Netflix streaming is getting a workout these days...
neutral	I need to get netflix again! Idk what happened in bones, dexter, weeds, and nip/tuck!
complaint	So wanted to watch wizards of waverly place the movie So I turned it on on Netflix and Wendy wu homecoming warrior came on. What the heck?!
neutral	@BeehiveBlogBoth good movies.I think I'll put on the netflix list.
response	@BeehiveBlogBoth good movies.I think I'll put on the netflix list.
response	I've been watching a lot of @ABCFgreek on Netflix, and the more I do, the more I realize I need a @scottmfoster (Cappie) for myself! Haha.
complaint	Hey Netflix! Just mail me my dang movie already! Geeesh!
neutral	There'll be time enough for all the movies in my NetFlix queue, right now I want keep Fringe-ing by starting season 2.

neutral	Watching a random movie on netflix and eating some food(:
watching	Watching a random movie on netflix and eating some food(:
happy	Finally watching Ponyo. So happy to have netflix again.
watching	Finally watching Ponyo. So happy to have netflix again.
happy	Netflix in class best class ever
media	Confirmed: Netflix App Available Exclusively On Future Qualcomm Smartphones, Starting With The LG Revolution http://bit.ly/i4tKyO
watching	Watchin the A-Team....shit is hilarious #Netflix
happy	Awesome! @netflix finally got my Valentine's Day gift from @netflix. They started streaming all 9 seasons of #Scrubs
happy	so happy i spent my day watching documentaries on Netflix
media	Qualcomm promises Netflix streaming support on 'future Android d... [Engadget Mobile] http://bzbx.us/PAs #Netflix #Qualcomm via buzzbox.com
media	Confirmed: Netflix App Available Exclusively On Future Qualcomm Smartphones ... http://f.ast.ly/VyuxF
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://goo.gl/fb/6vAol
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://goo.gl/fb/1Ii3g
happy	I #love my #netflix for the #wii :) its perfect for lazy ppl like me who hate getting up to change my #familyguy dvd
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video]: ... http://bit.ly/fsmPsN
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://dlvr.it/Gk8jh
media	#Tech #News: Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://dlvr.it/Gk8X3 (via Gizmodo)
neutral	@Karlemilymr nothin home relaxinb, eatin & about 2 watch a movie on netflix hbu?
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://goo.gl/fb/J5eXR
neutral	I got half a mind to take another vacation say stay home and watch netflix all day
watching	Still up watching "The Decent 2" on Netflix. I don't mind this rain though cause my stupid car needed a washing.
media	R11 Boxee Box gains Netflix support http://nxy.in/tqhav #techworld
happy	Online netflix brings me so much happiness.

media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video]: [GIZ]Those upcoming Snap... http://tinyurl.com/4vnrw5u
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] (Gizmodo) http://goo.gl/fb/sESlM
media	Apple will take 30%http://tonight.newestheadlines.com/apple-will-take-30-of-subscription-fees-from-content-based-apps-like-hulu-netflix-2/
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://sns.ly/kdbEy1
media	Netflix Now Available Through Facebook - http://bit.ly/ffpBHH - [Geeky Gadgets]
media	Netflix Now Available Through Facebook http://goo.gl/fb/gXSiQ
media	Netflix Now Available Through Facebook http://bit.ly/eoobW1 #tech #apple #web
media	Netflix was established in 1997, and they offer the ability to rent DVDs online via the Internet. I initially joined... http://dlvr.it/GkCrb
media	Morgan Stanley Downgraded Netflix To EW From OW, Maintained $245 PT (NFLX): Feb 15, 2011 (SmarTrend News Watch v... http://bit.ly/hZQyE6
media	Netflix the most engaging online video destination in US: Last month saw the arrival of newcomers to the top ten... http://bit.ly/dUW4vY
media	Netflix arrives on the Boxee Box: Boxee's Avner Ronen has announced that TV shows and movies streaming instantly... http://bit.ly/getN8z
happy	Netflix :)
media	Video: The Next Snapdragons Can Stream Netflix on Android Phones [Video] http://dld.bz/NhT6
complaint	Y these netflix movies keep stopin an sayin retrieving #ntheway
snafu	Y these netflix movies keep stopin an sayin retrieving #ntheway
happy	NETFLIX¡3
happy	@SUGARHEEL Hell Yea!! Shit I'm in Flint!! Andddd I got Netflix! Lmao!
watching	@alLOVEson_ im watchn it on netflix loll
complaint	Ugh Fuck you Netflix.
happy	netflix works yay!!!
watching	layin down watchin movies on netflix, bored ass hell
snafu	.....is netflix fuckin up?
media	Is Facebook Sounding the Netflix Death Knell? http://bit.ly/fsm7ZV

happy	Damn I luv Netflix
happy	Netflix gettin hip
watching	Watching this documentary about war in Afganistan on Netflix. Scary & sad... :/
complaint	Tryna get dis netflix on my damn ps3
complaint	netflix always fucks me in the ass
happy	#netflix Yeah!
happy	Netflix rules.
happy	NetFlix FTW
watching	Watchin kevin hart on netflix...shit never gets old haha
happy	Netflix =)
watching	watching heroes on netflix.....#addicted
complaint	@netflix #netflix :(
snafu	Netflix is fucking up WTF ?
watching	@nicoleka8701 just watchin netflix and being bored lol
complaint	Netflix wtf
complaint	Netflix is Soooo stupid
watching	watchin more hey arnold on netflix lmao
watching	Watching anger management on netflix cause I need dis shit lol
snafu	yooooo netflix is playing games right now ughhh
complaint	@BrentButt Netflix sux!
watching	arrested development streaming netflix. yah.
happy	netflix¡3
happy	@netflix YAYYYY
happy	Netflix is my bestfriend!!!!! Lol
happy	#Netflix :)
happy	OHHHHHHHHH!!!!!!! BLUESTREAK IS ON NETFLIX!!!!!!!!! HELL YEAH!!!
happy	Netflix!¡3
complaint	Netflix is honestly PISSING me off.
happy	Netflix FTW
watching	I'm watching Monsters on NetFlix , so pumped #aliens #monsters #scifi #horror

happy	OMFG, Netflix has Invader Zim!
watching	#NowWatching Black Snake Moan #Netflix
happy	Wooooo we got netflix!!
happy	Addicted to Netflix! #lol
snafu	smh sad as hel...l netflixnot working
snafu	Tryna fix dis netflix is pissin me off
snafu	ugh. NETFLIX WHY ARE YOU FUCKING UP.
watching	Watching ”Death at a Funeral”. #Netflix
complaint	okay netflix kinda sucks
complaint	Netflix instant queue movies suck...
happy	Netflix is a hell of a drug
happy	Netflix ... WOO!
complaint	Netflix sucks
happy	Wheeee Downton Abbey on Netflix!
watching	Watchin Death At A Funeral on Netflix lmfao.
happy	Netflix da shit
happy	@netflix is the shizz!!
snafu	slow azz internet, cant even watch netflix
snafu	#netflix wont work!!! UGH!!!!!!
happy	I’m addicted to netflix.
happy	Netflix is bomb
happy	@danieltosh haha dude is cracking me up watching his shit on netflix I’m like pissing my pants about to run outa underwear
watching	#Watchin #Reaper on NetFlix
complaint	this Netflix shit suck
happy	Netflix is fucking awesome.
happy	netflix timee!
happy	I loveeeee Netflix.
happy	Hell yeahhh got connection again ! #Netflix ¡ 33
snafu	maaaan ma netflix is effin up

happy	AWWWWWWWW SHIT LATE NIGHT RAGE AGAINST THE MACHINE =)AND THE NETFLIX HAS DEXTER PLAYING!!!!!!!!! MOSH PIT N E ONE???
happy	addicted to netflix...
happy	Just got netflix :) hell yeaaaa
complaint	Netflix sucks
watching	Watching Prison Break in school on #Netflix? #addicted? I think not
complaint	Damnit! Season 2 of Californication isn't on Netflix instant :(
complaint	RT @EXOTIC1988: Netflix kinda suxx's
complaint	Netflix kinda suxx's
happy	Sesame street on netflix.Yay... something different to watch.I've had my fill of Bob the Builder.;)
happy	Omg "Dorian Gray" is on instant on Netflix. Yesssss! Ben Barnes is so, so very attractive.
happy	Just discovered Netflix has added CLEOPATRA to its library. SOOOOO excited!!! How FURIOUS LOVE all began....
watching	Watchin netflix
snafu	Streaming Netflix is being stupid again
snafu	widespread panic!Netflix streaming is down!#Netflix #Panic
complaint	RT @joemsf: widespread panic!Netflix streaming is down!#Netflix #Panic
complaint	No,Netflix is not working for me on Android.
complaint	Netflix turned the app off. Assholes.
snafu	Damn Netflix is acting stupid right now #Pissed
snafu	Netflix is down. WUT!? :[
snafu	fucking netflix is taking forever to load. i just wanna watch dexter. darn.
snafu	Y is Netflix tripping? Grrrr!
complaint	Dude. Seriously, what happened to the @Netflix app. It freakin' blows now. @instant_netflix @netflix-helps
complaint	is anybody else's netflix being really slow?
snafu	is anybody else's netflix being really slow?
response	@geezymcgee naw just Netflix.
snafu	@geezymcgee naw just Netflix.
snafu	WTF? Netflix just crapper out on me?

complaint	Fucking netflix!!!
snafu	Pissed my fucking #netflix not working
snafu	@Netflix seems to be having trouble loading tonight.
complaint	Netflix is giving me a fucking headache
snafu	So netflix isnt workin?
snafu	Why is Netflix on xbox fucked up?
snafu	Having problems getting on @netflix sigh
snafu	ahhh i hate you crack whore Netflix, once again ur down for the count
complaint	#netflix is buggin'
snafu	#netflix is buggin'
snafu	Wth my netflix just broke
complaint	Wtf my netflix is malfunctioning
snafu	Wtf my netflix is malfunctioning
snafu	@jujukoo NETFLIX??!?!?
snafu	Damn Netflix. work!!!
snafu	Netflix is down...smh...
snafu	Netflix isn't working #firstworldproblems
snafu	Problems with Netflix instant on wii. So slow tonight.
complaint	Dammit netflix
snafu	Is #Netflix down?
snafu	about to get super #pissed at fuckin Netflix
complaint	@netflix @Netflixhelps Useless CUNTS!
snafu	#netflix is down :-(
snafu	Fucking netflix isn't working
snafu	NETFLIX WHAT THE FUCK IS YOUR MAJOR MALFUNCTION? HUH??
happy	netflix is tha shittt
complaint	Wtf #Netflix, down again ??
snafu	Wtf #Netflix, down again ??
snafu	Is @Netflix down?
complaint	Sigh @netflix

snafu	is anyone elses netflix actin up?
snafu	Wtf y isn't netflix working
snafu	NetFlix down on playstation BUST
complaint	Man y the fuck aint my netflix workin smdh
snafu	Man y the fuck aint my netflix workin smdh
complaint	Netflix is pissin me off tonight
complaint	Netflix down.......bummer
snafu	Netflix down.......bummer
complaint	Is #Netflix broken?
snafu	Is #Netflix broken?
complaint	#NETFLIX WII FAIL!!!
snafu	#NETFLIX WII FAIL!!!
complaint	Got damn netflix is fuckin up smh
snafu	Got damn netflix is fuckin up smh
complaint	Right! fucking pieces of shit, did this happen last sunday same time too @Goddard23 Fuck you netflix
snafu	Right! fucking pieces of shit, did this happen last sunday same time too @Goddard23 Fuck you netflix
snafu	@pitaman @netflix Yep. Netflix is messing up.
complaint	@mommywantsvodka We're having probs too. Boo you Netflix. Boo.
snafu	@mommywantsvodka We're having probs too. Boo you Netflix. Boo.
snafu	Meh, come on, apparently #netflix is having instant streaming outages.
snafu	Netflix is fucking up tryna watch god damn prison break
snafu	Fucking Netflix, fucking work!!!!!
snafu	Damn it......Netflix Streaming is down AGAIN!!!!
snafu	Hey netflix quit fucking around I wanna watch a movie
snafu	Sad thing though, @netflix is having troubles connecting.
snafu	This fuckin netflix actin up
complaint	WTF Netflix #smh
snafu	@L4Lyfe yeah.. netflix is just being gay
snafu	Netflix is down. I'm hella pissed
complaint	Grrrr @Netflix you're broken AGAIN! Wtf??

snafu	Grrrr @Netflix you're broken AGAIN! Wtf??
happy	Netflix + me = happiness ¡3
snafu	Grumble. Netflix on the xbox is down. Boo cloud :(
snafu	This weather fucking up my netflix
complaint	WTF, Netflix? AGAIN?
snafu	WTF, Netflix? AGAIN?
complaint	FUCK WHERE'D NETFLIX GO
snafu	FUCK WHERE'D NETFLIX GO
snafu	Netflix won't open. #WhatTheFuck #IMightAsWellBeDead
complaint	Our neighbors WIFI is fuckin up. Im gettin pissed off. Niggas tryin to watch Netflix -_-
complaint	Netflix is down. Dang.
snafu	Netflix is down. Dang.
complaint	Why netflix why
snafu	Why netflix why
snafu	@Netflix is down on my xbox smh.
snafu	@netflix is dead on the roku, works on the laptop...
snafu	Ugh, @Netflix is turning into such a fail.
snafu	Netflix is acting stupid there goes my night -__-
snafu	"Netflix is currently unavailable. try again later." #NetFlix #FML #DrWho #WhyMe #Sad @Netflix
snafu	Netflix ROKU #FAIL
snafu	RT @Vann_Rich: Netflix temporarily down WTH :(/ WTF?!
complaint	noting pisses me off like slow internet connections messing up my netflix experience
complaint	Netflix fuck
complaint	These stupid ass netflix dvds don't let u skip past the previews smdh #bullshit
watching	This week on the #Netflix line-up: Fair Game and I Love You Phillip Morris.
happy	#Netflix you've been gone for too long ! #welcome back
neutral	shitty part about this last breakup: i got the cat, she got the netflix account. #whattodonow..
watching	Watching Fullmetal Alchemist: Brotherhood on Netflix while we wait to get into the production set space
happy	Uh oh #glee is on #netflix now
neutral	Uh oh #glee is on #netflix now

happy	RT @robert3t: @silug @DirecTV_TiVoHave you tried Roku with Netflix/Amazon/Crackle/Hulu Plus - it's like letting someone else TiVo for you.
neutral	RT @robert3t: @silug @DirecTV_TiVoHave you tried Roku with Netflix/Amazon/Crackle/Hulu Plus - it's like letting someone else TiVo for you.
watching	Watching 3rd Rock from the Sun marathon on Netflix.
media	ok @MissGinaDarling... u need to bring your kinect back to my house now =P http://aol.it/fKVBe9
happy	Dear Netflix, I love you a lot.
watching	Watching @ToddGlass on Netflix. Had to follow him ASAP, never laughed so hard alone in the dark, stoned, eating cake at 5am... This week...
happy	now time for some netflix ¡3
watching	#Watching 3rd Rock from the Sun marathon on Netflix, suck it BlockBuster... yeah I said it.
watching	Watching Angus on Netflix instant. Huge h/t to @TedDouglass. Angus!! Love it or quit being my friend.
happy	Thank god for netflix! Makes this 12 hour shift go by alot faster...
watching	SMH @ me taking this long to re-activate Netflix on my Xbox. was up all night watching foreign gangster flicks/anime
happy	@YoungMykewut game r u playin ? & . im watchin season 2 of jersey shore on netflix lol
watching	5am and #nowwatching Stephen King's The Langoliers on netflix
watching	I should be sleeping- not tweeting- but I'm watching Cheers on Netflix and it's addictive. #ILoveSitcoms
watching	I 100% should go to bed RIGHT NOW. But, I'm up watching even more netflix! oh boy, oh boy.
watching	Watching Glee on netflix music is dope story ia gay but chicks are dope
happy	So I'm about to hit up netflix while I'm eating pudding out of a cup with merely my tongue ;D
watching	So I'm about to hit up netflix while I'm eating pudding out of a cup with merely my tongue ;D
happy	Just found the original twilight zone on Netflix. Awesome.
watching	Guess I'll watch some Netflix
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7HZ
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7HT
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7HG

media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7HF
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7GM
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7GL
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7GG
media	Stock Investing — Can Netflix Push Forward By Benefiting From Online Streaming Video? http://dlvr.it/Nh7GH
media	http://bit.ly/hZHbzl Is the tax man after Netflix?
neutral	@mootbooxle o fosho man! keep at it! its all good here just watching some netflix wishing work would end sooner haha
watching	@mootbooxle o fosho man! keep at it! its all good here just watching some netflix wishing work would end sooner haha
media	Kinect for Xbox 360 Now Adds Support For Netflix http://bit.ly/eoVg6o
happy	I love netflix
happy	@hoopz79 it's streaming on netflix! You can watch it whenever you want :)
complaint	Fuck you netflix i cant watch goodfellas anymore.
happy	Netflix is the greatest thing ever
neutral	This weather got me wanting to curl up in bed with some good netflix joints!
complaint	#iwish the Americans with Disabilities Act applied to @netflix streaming. CAPTIONS! SUBTITLES! Please?
media	In case you didn't know, they are putting the bond movies on netflix
complaint	@ThatBuddha @netflix RE: closed captions.You still wouldn't b able to hear it if there were cc's! ;)But seriously sucks there isn't #WTF
happy	Finally...Kinect support for Netflix! Hooray!
media	Netflix Coupon Codes! Try Netflix For FREE! http://t.co/L1DZLOt
media	8 Strategies for Winning the Upcoming Super Bowl 4 Talent http://t.co/LfIkkwz via @ERE_net by @loua...nice compliment 4 our customer Netflix

response	@JBoyd4 Yeah. Cause then Netflix will suggest some terribly similar movies. #crap
neutral	I need to remember to buy batteries for my wiimote. I haven't watched a Netflix movie in weeks.
watching	Type bored watching netflix on my couch.
watching	thank you #netflix !! now watching #heyarnold :) takes me back to better days lol
complaint	damn you @netflix . why cant you support @linux ? @hulu can. silverlight is garbage and there is no work around. get with the times!!!
watching	Just started watching the devil may cry series on netflix, mad as fuk that I slept on this. You see it? @Dreadhead1914
watching	I've watched almost every documentary on netflix
neutral	so today will consist of Dominos pizza & netflix, while icing this ankle of mine .. ehh : complaint,RT @FreshPres: Netflix is disrespectful for not having Coneheads On their site.
happy	Netflix *thumbs up*
watching	Watching Capitalism: A Love Story on Netflix.....this movie is sooo relevant right now. Check it out if you haven't seen it.
complaint	@netflix has every old james bond flick but goldfinger, from russian with love and dr. no. ill take that as a big "fuck you."
watching	RT @PornStarPaul: netflix type of day* I'm watching nexflix now -_-
happy	omg...all seasons of ghost whisperer& scrubs on netflix...love it!
complaint	My sister must have put a Tyler Perry movie in my Netflix Queue.. Someone done lost they mind I see... Fuck Tyler Perry
watching	My sister must have put a Tyler Perry movie in my Netflix Queue.. Someone done lost they mind I see... Fuck Tyler Perry
happy	Netflix to my rescue. ¡3 http://t.co/hrv4sS7
media	Netflix Kinect: Control Movies With Your Hands http://t.co/ILePgA5 Welcome to the future.
happy	Still watching #glee on #netflix :D
watching	Still watching #glee on #netflix :D
neutral	I like that they made the netflix trial commercials look like a match.com commercial. #fillyourloneli-nesswithmovies
media	Panasonic DMP-BD85K : Enjoy The Netflix Feature http://is.gd/QQaOp3

complaint	Fuck you netflix! You fucken piece of shit! I can't even fucking sign up for my free month because I'm " http://tl.gd/9sr2ps
media	Xbox 360 Update Adds Kinect Support for Netflix - Maximum PC http://sns.mx/Jvc8y8 #Xbox
happy	God I love #Netflix. Not only do I get new movies to go with today's perfect movie-watching weather, I get the bonus of mail presents, too.
watching	Watching Inheritance on Netflix.. damn
watching	Watching the other guys on netflix
watching	Watching Family Guy on Netflix
watching	Watching marmaduke on netflix
watching	Watching the Cosby Show on Netflix with the kids. So funny!
watching	watching naruto in japanese with Manik on Netflix. it's like I'm 10 again. with Junior & Cindy.
happy	The twilight zone is on Netflix my life is complete.
complaint	Hey @netflix - streaming is great, but would closed captions for the hearing impaired kill you? Give us access to the subtitle options?
complaint	Someone at Netflix is fucking up, who put All About the Benjamins under Suspenseful Movies?
complaint	@FENTONFALLON I like netflix but am sad that not EVERYTHING on there is instant. Sometimes I don't want to wait for it to come in the mail!
happy	Cosby Show on @netflix... FTW!!!
happy	I love watching Netflix in my living room TV!!!
happy	RT @AlexGoral: Netflix is the greatest thing ever
happy	i love netflix's romance section
happy	RT @AlexGoral: Netflix is the greatest thing ever
watching	Watching The Last Song, on Netflix. :)
watching	Watching #stargate atlantis on netflix.
watching	is watching The Other Guys#My6http://vapr.me/2vf7
complaint	They say in 5 years we'll b able 2 replace our own organs w our own cells, but why can't I instant netflixThe Hand That Rocks the Cradle?
complaint	Why doesn't #Netflix have more social aspects? Isn't going to/watching movies primarily a social activity?
media	#netflix stream from PC http://bit.ly/cAjJ99 @GetGlue #BizarreFoods

complaint	Netflix sucks!
neutral	contemplating what I should do till Portal 2 drops... 1. a short game 2. work on music 3. catch up on netflix... maybe all three
neutral	@spookypastor this is going to be a wallet-draining summer at the movies. Thankfully, there's a 42" TV with surround at home...and Netflix.
response	@spookypastor this is going to be a wallet-draining summer at the movies. Thankfully, there's a 42" TV with surround at home...and Netflix.
watching	Such an ugly day. Perfect for a Sons Of Anarchy marathon on Netflix ¿:)
watching	Watching The Office on Netflix, doing Laundry, and slowly cleaning the house.
response	@Br0wn_Suga it's on Netflix. It's called city island. It's so funny. Fat girls cookin butt naked in the kitchen live on the web cam. Lol
neutral	@natheist Ok, I have a working silverlight install from http://go-mono.com/moonlight/ Can't test it against netflix, mind trying it?
happy	Thank God for Netflix! :D
neutral	Got an email from Netflix. Dvd which never arrived and I reported lost has been returned to them. Odd, that.
happy	Netflix biotxhh!???
watching	Gone to watch me some Netflix...
response	@DarkEyeSocket I saw it on Netflix "Instant Watch." It's never been officially released on DVD but you may be able to find a bootleg on ebay
watching	@DarkEyeSocket I saw it on Netflix "Instant Watch." It's never been officially released on DVD but you may be able to find a bootleg on ebay
complaint	#Netflix is more like net flicker lately. Pretty sure it's been down at least half the time I've tried to use it this month.
snafu	#Netflix is more like net flicker lately. Pretty sure it's been down at least half the time I've tried to use it this month.
neutral	Wwe has recently just posted over 7 new doucumentaries and wwe studios movies in netflix including "the john cena experince" watch them now!
watching	Wwe has recently just posted over 7 new doucumentaries and wwe studios movies in netflix including "the john cena experince" watch them now!

neutral	Yay my first Netflix film is on its way; predicted arrival time is Monday. Woot.
neutral	about to download this netflix free trial
neutral	Just bought one month of Netflix. God help me.
watching	I need recommendations for good movies to watch on Netflix!?
media	Netflix is looking for: Senior Software Engineer - Recommendation A... http://jobvite.com/m?3Mny3fwu #job
neutral	Groundbreaking news: I have netflix!!
response	@_shalyn its hilarious i didnt even know what it was til my friend told me to check it out.. netflix has it so that rocks. i was dying when
neutral	Friday night: got to cook 3 pizzas (food allergies!), figure out what movie to watch on Netflix, and do some tatting and knitting.
neutral	I love those random moments of netflix when you get hd for like ten seconds
watching	Just turned on Netflix, watching Poetic Justice. I'm on Janet mode right now.
neutral	#fe3 [Shelton] Big data means algorithms will find the patterns (so humans don't have to).Amazon rec and Netflix suggest everywhere.
complaint	Watching material girls on youtube since ournetflix acting stupid
snafu	Watching material girls on youtube since ournetflix acting stupid
watching	Watching Anastasia on @Netflix while baking blueberry oatmeal cookies. It's been a glorious Saturday morning.
neutral	@JackkiJack I haven't watched buffy, but I'm always down for suggestions! I love love love netflix instant cue!
complaint	I was told that all of Star Trek was coming to Netflix Instant. I have yet to see it. Someone needs to answer some questions. #khan!!
complaint	It looks like Netflix took season one of Doctor Who off instant streaming, which is sad :(
happy	Where would I be without my netflix!?
watching	Watchin the old V miniseries on netflix, love it
complaint	Yo Netflix! That's a real bitch move having season 1-2 and none of the rest of it. Fuck is up?!
media	Netflix is looking for: Driver 3 - Lansing http://jobvite.com/m?3vny3fwd #job
happy	i have been watching invador zim im sooo excited i llove netflix i love it im start to watch every episode
watching	i have been watching invador zim im sooo excited i llove netflix i love it im start to watch every episode

watching	i think im just going to watch netflix movies all day...
neutral	Finished ssn1 of Glee...Season two isn't on Netflix...so im prolly screwed for a while since my mom just bought my the first ssn last night.
happy	Pizza + Netflix + Photoshop = Saturday fun.
watching	let me see what I can find on Netflix today...
watching	Yes! Thank God for Netflix now I can watch movies on my iPod.
neutral	Toy Story 3 is available on Netflix today. Our kids HAD to watch it, even though they've been 100% uninterested our DVD copy since day 1.
neutral	i find the strangest movies to watch on Netflix.
watching	i find the strangest movies to watch on Netflix.
watching	Watching Glee season 1, the season I missed. Thank gosh Netflix!! (:
media	"Rivals target Netflix"http://bit.ly/dRjwsZ
complaint	damn theres nothing to watch on netflix
watching	On a scale of 1-10, if The Wire was a 10, then Sons of Anarchy is a 9.5.Just finished the first season on Netflix.Holy shit.
watching	Twin Peaks on Netflix Instant.... Holy shit yes
watching	Black Dynamite is on Netflix Instant.For the love of all that is holy, watch it. Thank me later!
happy	#Netflix :)
happy	SPRING BREAAKK !! i celebrate by getting a free month of netflix MOVIES!!
neutral	#Netflix ?20 more people please I need 20 more people whoever didn't take this survey please do it http://www.surveymonkey.com/s/MLKZ2BZ
watching	perhaps it's time to stop watching 'my so called life' on netflix and be productive today.
happy	Netflix!! ¡33
media	Samsung 3D Wi-Fi Blu-ray Disc Player + 3 Month Netflix Membership! RV $280! #Win @savvycoupon-mom http://bit.ly/fBBNBc #GIVEAWAY
watching	Holy crap!! Netflix instant queue has MS3TK!!!
watching	Dead Alive is on Netflix Instant? it's the Lord of the Rings of ridiculous zombie movies!
complaint	@justinswife40 I Love Lucy is on Netflix, but not for streaming. =(I love I Love Lucy!
watching	Trying to get on the treadmill while the littlest one sleeps and the other 2 watch #iCarly.So glad it is streaming on #Netflix.

media	Wii 2 Details, Netflix Gets Kinect, Gears of War 3 Beta Live Stream Video - IGN http://go.ign.com/hLL4AR via @IGN
happy	netflix :)
happy	Netflix¡3
complaint	Nightmare on Elm Street...oh wait, netflix sux
complaint	Damn netflix
complaint	Wow Netflix! I hate you.
complaint	I hate netflix.
happy	NETFLIX #love #love #love
complaint	aye fuck netflix right now!!!
complaint	I'm disappointed with Netflix Canada's Matt Damon selection... So Mr Wahlberg will be saving the night!
complaint	*fucks wit Netflix*
neutral	*fucks wit Netflix*
neutral	Netflix + ? = ?
complaint	Bummed no new episodes till 2012, but at least "Mad Men Will Be on Netflix Instant in July" http://t.co/a3r0Rve
complaint	Netflix's iPhone app won't show you disc only movie details - what kind of idiot UX is that?!
complaint	Aughhhh, alright Netflix, you win tonight. I GIVE UPPPP.
happy	Netflix :D
watching	Watching "the creature from the black lagoon" on Netflix, holllaaa
neutral	Jeff teased me with Arthur on netflix yesterday... He put it on, got me all excited then turned it off. Basically I need netflix.
response	@dermhurl I don't have netflix :(
neutral	And on that note I'm going to watch Netflix
happy	Netflix Saved My Night
happy	Netflix is on point !....where have this been all my life
watching	Watching Toy Story 3 on instant netflix. One of my faves! :D
neutral	Netflix on PS3
watching	Watching Cheers on Netflix.¡3

happy	Netflix saves Lives
media	Control Netflix Movies Using Gestures or Voice With Kinect http://yhoo.it/eTy7rB
complaint	I swear netflix be weak as f*ck sometimes
happy	I love Netflix
watching	Just watched @thewaywegetby on Netflix. Such a moving and inspiring documentary. The best I have seen in a while. PLEASE WATCH IT!
complaint	I'm going to resuspend my Netflix account nothing is on here
media	Video killed the radio star, but will streaming TV online lead to death of the big media players? http://bit.ly/gliaAX (via @guardiantech)
happy	I just convinced my brother to drop his DirectTV and get a wireless router, a roku HD and a netflix subscription.
happy	I wanna spend like 3 weeks of my life sitting on the couch watching netflix and eating hot pockets. #Ginaboothe
happy	So they have Arthur on Netflix now! When I get off work, its a done deal!
refuse to rate	Forgot my headphones at home today. That rules out @netflix or my iPod for nap time. #bummer
refuse to rate	@rannahshell But you watch netflix all the time. You need something fun that you don't normally get to do.
response	@rannahshell But you watch netflix all the time. You need something fun that you don't normally get to do.
media	Daily SV News: Earnings train: First stop, Netflix http://om.ly/BSOVA
media	Netflix posts 'buy' button but still no transactions http://cnet.co/hlF1GO
neutral	Wat movie should I watch on netflix
happy	@JuliaBlueEyes :(Don't feel that way, friend. Btw I just found happy tree friends on Netflix and it reminded me of senior year! Lol
response	@JuliaBlueEyes :(Don't feel that way, friend. Btw I just found happy tree friends on Netflix and it reminded me of senior year! Lol
media	Updated: Netflix earns coming out next week. RT @GMSV: Earnings train: First stop, Netflix http://bit.ly/hmxTQ1 #tech #siliconvalley
happy	The Pixar Story is streaming on netflix :)
media	# Xbox 360 Online — Kinect-controlled Netflix Available Today On Xbox 360 http://bit.ly/hK1gxi

happy	And my Netflix obsession begins...
happy	@kdhnews. Blockbuster Video...Do you go there.... I have Netflix and Vudu,wit those 2 I'm afraid I don't go to Blockbuster stores.
response	@kdhnews. Blockbuster Video...Do you go there.... I have Netflix and Vudu,wit those 2 I'm afraid I don't go to Blockbuster stores.
complaint	@netflix idea for the website, make rated movies searchable by genre and rating, for seeking friend recommends among thousands of ratings
happy	Why im in class watching netflix hahaha the life #teamiphone4
watching	Why im in class watching netflix hahaha the life #teamiphone4
neutral	About to watch a movie on netflix
neutral	Netflix
refuse to rate	@Str8_No_Chas3r lol true. I say hulu plus for the TV shows. Netflix for the movies
happy	Netflix Instant has added all of the Larry Sanders Show- GOOD!
happy	Rocko's Modern Life is but one awesome show I remember growing up and I love how netflix has it to stream.
happy	I realize I'm super late on this, but LOST is the shit! Thank you Netflix.
happy	I purposely look for the grossest movies on netflix just to get a good laugh
happy	@RussianDollFace oh I watched so many of those the other day on netflix!
response	@RussianDollFace oh I watched so many of those the other day on netflix!
complaint	HOW SAD. REBA ISN'T ON INSTANT NETFLIX. THIS IS A SAD DAY IN BASEBALL.
watching	watching a scrubs marathon on Netflix. @zachbraff and @donald_faison you guys are fricken hilarious!
neutral	Watching my Netflix til my bae hit me bck - finta ignore #2mof dumb a** . lol
watching	Watching my Netflix til my bae hit me bck - finta ignore #2mof dumb a** . lol
media	Top News- Netflix posts 'buy' button but still no transactions http://adf.ly/1FTkk
happy	@kdhnews We haven't rented DVDs in years.Netflix all the way.
response	@kdhnews We haven't rented DVDs in years.Netflix all the way.
media	mSpot streams brand-new movies to iOS devices: A video-streaming service is aiming to beat Netflix and Hulu at t... http://bit.ly/dR22nU
watching	Watching 'Sneakers' on #Netflix. This could be a great re-make.

watching	My room is a shit-show so while I'm cleaning I'm watching Clean House on @netflix which means I'm just watching other people clean...
watching	Hey Arnold on Netflix...Oh yeah!
watching	Wild Thornberry's S1:E2, "Dinner with Darwin" on Netflix. :)
watching	Watching Buffy and not feeling too well. Thank god it's on netflix.
media	MSpot Streams Brand-new Movies to IOS Devices: A video-streaming service is aiming to beat Netflix and Hulu at t... http://bit.ly/dEzgeS
media	MSpot Streams Brand-new Movies to IOS Devices: A video-streaming service is aiming to beat Netflix a... http://bit.ly/ftU9fs #technology
complaint	Biggest bogey in (recent) Television history: Cancelling Life on Mars (US). Thank you Netflix!
watching	Biggest bogey in (recent) Television history: Cancelling Life on Mars (US). Thank you Netflix!
refuse to rate	RT @jpyun: ?? App Store? ??????? "?????" ???? "????+??"?? ??. ?? app?? 10-20? ????? ???? ?? 1??, Netflix, ??? ?? ?? ???. http://goo.gl/htwtS
happy	Luckily, have Netflix & video games. That'll be nice.
happy	Watched the first episode of #TwinPeaks last night with hubby.He was not impressed.But I loved it.Loving #Netflix.
watching	Watched the first episode of #TwinPeaks last night with hubby.He was not impressed.But I loved it.Loving #Netflix.
snafu	Netflix shawty
happy	Netflix is the fucking BOMB!!!!
complaint	Damn netflix
media	Netflix to Become Largest Subscription Entertainment Business in U.S. http://j.mp/hdN3IA
media	Netflix to Become Largest Subscription Entertainment Business in U.S. http://j.mp/hdN3IA ????? ???? ??? ???? ?? ??. ?? ??? 1?? ?? ??!
complaint	Damn netflix. -.-
snafu	Bored and Netflix is being stupid.
complaint	OMG I HATE NETFLIX!!!
complaint	Netflix #wtf
snafu	Netflix pissin me off!!!
snafu	My fucken netflix fucken up. I'm tryna watch #avatar:thelastairbender

complaint	Fuck Netflix ¿:[
complaint	@reishka stupid netflix!
snafu	whyy netflix actin so slowww!
complaint	Netflix suck ass
snafu	@krisfluck my stupid netflix instand keeps freezing on my tv....grrrrrrrrr
snafu	Fukn Netflix just cut off. Lol
snafu	Netflix pissin me off
complaint	wtf #netflix ??????
snafu	RIP Netflix..
complaint	Damn Netflix
watching	Watching terrible netflix movies with brad. Hahahahahaha.
snafu	yo wtf netflix?!
snafu	Netflix?????????????????????
snafu	Netflix?????????????????????????????
watching	Watching Prison Break on Netflix.
happy	HELL YES. netflix works again :)
complaint	I hate you netflix
snafu	NETFLIX WONT FUCKIN WORK .
snafu	I'm mad my Netflix is being slow -_-
complaint	Netflix=gay
snafu	Netflix is being stupid, again
snafu	SHIT netflix acting funny
snafu	Netflix is #lame
complaint	I want dubbed, Netflix... fucking assholes.
snafu	Netflix was being stupid today. Ugh
snafu	Grrrrrr stupid PS3 won't let me stream Netflix.
happy	¡3 netflix #addicted
watching	watchin Netflix
snafu	I hate when netflix fucks up shit is annoying
media	TechCrunch? Netflix?30????????????????????????? http://dlvr.it/PhxTm

snafu	Got my netflix fucked up
snafu	Fuck netflix this bullshit
complaint	smh, netflix ruins lives.
complaint	Fuck #NetFlix
media	How Netflix Stole My Eyepatch & I Stopped Stealing Movies http://tinyurl.com/3rgoqes
refuse to rate	Netflix (ya tienen casi 23 millones de usuarios) sube y el uso de Bittorrent baja en EEUU. Pasar lo mismo por aqu? #lodudo
refuse to rate	Subieron la primera temporadade Glee a Netflix pero no me atrevo a verla
refuse to rate	@burritosound estaba chebere, graciosa. Pero no pagues por verla maximo NETFLIX
watching	#Nowwatching: Black Snake Moan #netflix
refuse to rate	@fernanhugo tal vez por eso Netflix vaya a abrir en Latinoamrica donde las derechos de cine se venden para toda la region
refuse to rate	Interesante artculo sobre #Netflix. Muy interesante. http://www.asinorum.com/netflix/2699/
refuse to rate	@manuxcristobal @fernanhugo existe la posibilidad de adquirir derechos no territorialmente y hacerlo por lengua. Latinoamerica Netflix?
refuse to rate	OMGGGGG Entrar a hulu, netflix y tal solo cambiando una DNS y funcionando sin proxis ni nada!
complaint	i hate netflix
refuse to rate	Cuando el servicio merece la pena se paga y Netflix es un ejemplo:
refuse to rate	@Tavoteg nunca he usado netflix...
happy	Netflix :)
complaint	Fugg I hate how Netflix rewinds!!
happy	Netflix :)
refuse to rate	Alguien llego a conocer el sitio argentino DVDinamic.com? Era el mismo modelo de negocio que netflix.com
happy	Netflix ¡3
happy	Netflix ¡3
refuse to rate	uff, ahora xbox live tiene Hulu, sera mejor que Netflix, vamo a ver....
complaint	Netflix is being stupid right
snafu	Netflix is being stupid right
happy	Netflix :)

refuse to rate	En momentos como este echo en falta Netflix.
refuse to rate	Estan llegando buenas pelculas mexicanas a netflix
happy	netflix¡3
refuse to rate	"@tavoluna: Alguna buena pagina para ver pelis online?, sugieran" / netflix
refuse to rate	Esta movie se ve interesante se llama MILF esta en netflix me fui
complaint	Netflix movies REALLY fucking suck.
happy	Netflix :)
happy	#Netflix :)
happy	Netflix ¡3(:
happy	Yay Netflix (:
happy	Seriously loveee netflix! (:
happy	netflix :)
happy	Netflix :)
watching	Watching prison break on netflix
happy	Netflix
watching	watchin netflix
watching	Watchin Netflix
snafu	#netflix is broken :(
snafu	Netflix broken on TiVo?
complaint	Huuhhh Netflix so fuckin slow
refuse to rate	@karito_villamar estoy viendo una en mi cuarto ya me conoces (netflix boy) jajaja la proxima vez si veremos RIO jajaja
watching	Watching lost on #netflix
refuse to rate	@jimenabauer / cual es?? dimela y la pido manana por netflix....
happy	Netflix is The Bomb (;
refuse to rate	A pesar de no tener sueo me voy...buscare una pelicula mala en el netflix... #SomniferoDeEmergencia
watching	Watching Hey Aronald on Netflix
complaint	Pissed netflix is down ... #iCare
snafu	Pissed netflix is down ... #iCare
happy	Netflix timeeee.!

watching	Netflix timeeee.!
happy	Netflix timeeee.!
watching	Netflix timeeee.!
happy	dear @netflix , i love you. i want to make sweet, sweet love to you. shhh, shhh it's ok..it's ok
refuse to rate	Woot Deals: End Of Month Sale! Insignia 1080p HD Blu-Ray Player WiFi Networking for Netflix/CinemaNow/Pandora... f... http://bit.ly/lfPGbT
watching	Watching Zach Galiafianakis standup on Netflix. Hilarious shit!
happy	netflix is amazinggg(:
happy	@lopedope yeeeeeee netflix!
happy	Netflix , I love you , even tho I hardly use you .
happy	netflix is awesomeness...#NW Friday
happy	netflix is the shiiiiiiiit
refuse to rate	#Netflix - Isso vai ser a minha salvao e por 12 dolares ao mes...
happy	Man Netflix is awesome.
happy	I love netflix..
refuse to rate	Watch Hulu, Netflix, Comedy Central and More on Your Android Phone.: PlayOn can now stream... http://goo.gl/fb/8XHG5
refuse to rate	Guy and Madeline on a Park Bench: Black-and-white verit meets the charm of the classic Hollywood musical in wri... http://bit.ly/ilCSTV
watching	Watching Easy A on netflix :D
refuse to rate	@phroc Comparto 100% tu punto de vista con Spotify, y si sale el rumor de que pondrn pelculas y sale antes que Netflix, tambin caer.
watching	Just watched Joneses on Netflix. Awesome movie.
watching	now im watching degrassi on #netflix
complaint	@VIIXXIVXCI Hmmmm I hate NetFlix
refuse to rate	"@YungBDaInfamous: About To Watch Some Netflix!! Later #TweetHeads" me too
refuse to rate	FYI: Netflix Knocks Comcast Off Its Throne - By: Brittney Wilson (Senior Editor)Over 7% of... http://tinyurl.com/6b5pm5x #MRT
refuse to rate	Y sorprendido al leer que stos mismos que se quejan del cambio en Spotify han bendecido en algn momento el modelo de Netflix... #spotify

watching	watching this Anime called "Claymore" on Netflix - its really good lol
watching	Watching the Pixar Story on Netflix
refuse to rate	What the Music Business Can Learn From Netflix's Success http://bit.ly/grqcpL
watching	Guess ill watch netflix
refuse to rate	@lalai e a tv da sala netflix ready, mas quem diz que eu acho o modem?
media	Terrestrial Radio Needs to Embrace Its Online Future: Just as Netflix has admitted that TV Everywhere provides a... http://bit.ly/mydSh1
media	"we want engineering teams to be used to a constant level of failure in the cloud" ¿¿ http://bit.ly/mQGZkx
media	Lessons Netflix Learned from the AWS Outage http://zite.to/k8ABGX via @Ziteapp
media	Netflix reflects on the AWS outage — http://tinyurl.com/3fl2566 (they are hosted on Amazon but were not affected) http://bit.ly/k3sc7c
media	Terrestrial Radio Needs to Embrace Its Online Future: Just as Netflix has admitted that TV Everywhere provides a... http://bit.ly/mAnsRS
media	Terrestrial Radio Needs to Embrace Its Online Future: Just as Netflix has admitted that TV Everywhere provides a... http://bit.ly/mAnsRS
media	Netflix, I love you, but you're big enough to make an iPad app that doesn't suck: http://t.co/sIKwZdT
refuse to rate	RT @mrgelk: ACTUALIZADO: Spotify NO se mete en el negocio de Streaming de Video - Talfin.net http://t.co/umGks7M via @talfin
media	Netflix Said to Spend $1 Billion in 2011 on Streaming Content http://t.co/tyDcuss via @technobuffalo #TechnoBuffalo
watching	Watching Flashpoint on @netflix. Pretty much chilling out all day. Don't have anything to do! :D
happy	Yes Netflix thank you for having this. #deadalive
media	Lessons Netflix Learned from the AWS Outage http://j.mp/mQGZkx
refuse to rate	RT @myrealitytech: FYI: Netflix Knocks Comcast Off Its Throne - By: Brittney Wilson (Senior Editor)Over 7% of... http://tinyurl.com/6b5pm5x #MRT
media	The discussion on the closed caption class action lawsuit against Netflix is still going strong at Roku forum http://bit.ly/hiMKIy
media	Can Netflix Kill Illegal Downloads?: Analysis: TorrentFreak suggests legal movie streaming will reduce the illeg... http://bit.ly/luY8s1

media	Music Downloads: Can Netflix Kill Illegal Downloads?: You still can't get good PC games free on Netflix, or anyw... http://bit.ly/itg7mC
complaint	RT @GreysonsGirl: I'm SO MAD A NETFLIX! I HOPE IT GOES BANKRUPT!
complaint	I'm SO MAD A NETFLIX! I HOPE IT GOES BANKRUPT!
watching	Gonna watch more netflix x)
media	Pretty interesting read - Lessons Netflix Learned from the AWS Outage http://zite.to/k8ABGX
media	Can Netflix Kill Illegal Downloads? http://goo.gl/fb/pO1j0
media	Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
complaint	RT @Lexandrahorn- Dear Netflix Instant Watch, Could you for once work on the weekend?
snafu	RT @Lexandrahorn- Dear Netflix Instant Watch, Could you for once work on the weekend?
refuse to rate	this show is SICK! You gotta #Netflix it and watch season one if you haven't, season two tonight!"@NoReservations: TREME tonight!"
media	Can Netflix Kill Illegal Downloads? - PCWorld http://bit.ly/jMeQxK
refuse to rate	Verizon document suggests LG Revolution will have Netflix pre-installed: We didn't exactly need any more evidenc... http://bit.ly/mvZgXV
snafu	NETFLIX WTF IS YOUR PROBLEM. STOP RETRIEVING.
media	RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
refuse to rate	RT @ConanObrien: If I'm ever a ghost, I hope the person I haunt has Netflix.
media	Can Netflix Kill Illegal Downloads? http://bit.ly/luY8s1
refuse to rate	roku dlna-Viewsonic NexTV VMP75 1080p Network Media Player – Stream Netflix, Internet radios/videos & access to ... http://bit.ly/moPiVn
refuse to rate	roku dlna-Viewsonic NexTV VMP75 1080p Network Media Player – Stream Netflix, Internet radios/videos & access to ... http://bit.ly/moPiVn
snafu	my Netflix acct is down... *stabs self in stomach* #dead
media	How to Trade Apple, Baidu, Netflix–and Win Big http://goo.gl/fb/ePPxj
media	RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
media	Lotsa nothing...zzzz..RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy

watching	Watchin this big foot show on netflix.big foot is real
media	Syndication is dead. NETFLIX is the ultimate re-run channel. Newest additions to Instant View here - http://fb.me/QdMat6iy (via @ProgGrrl)
media	NETFLIX MANAGEMENT SECRETS: CEO Reed Hasting's Presentation On A Culture Of Freedom And Responsibility http://read.bi/g9yj6D
happy	netflix netflix netflix netflix ¡3 ;D
happy	I absolutely love @netflix ... where else can I find so many bad zombie movies to watch? :)
media	RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
happy	@lauramv23 netflix saved the day
media	RT @MarkRaganCEO: How successful companies like @Ford and @Netflix reframe difficult situations http://bit.ly/mTWQ7e
happy	@GHFans Netflix! :)
refuse to rate	Photo: The Funhouse, dir. Tobe Hooper (1981) Now Streaming on Netflix..... http://tumblr.com/xzl2cdnrgi
refuse to rate	Netflix demuestra la rentabilidad del alquiler de vdeos en Internet http://awe.sm/5IcC8
watching	We're watching it now RT @TheBuie HIGHLANDER ON NETFLIX....! CHEA!!
media	Lots of good stuff! RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
media	RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
complaint	@evilcrash9 @axnollouse Can't see it, Netflix hates my phone/can't remember my account info
refuse to rate	@settern So that's 2 Sorkin series (also Studio 60). If only West Wing would come to Netflix Instant.
media	www.ArcaVir.asia Can Netflix Kill Illegal Downloads?: Analysis: TorrentFreak suggests legal... http://bit.ly/j6qLm2 #security #antivirus
media	RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://fb.me/QdMat6iy
media	Yes! RT @feedfliks: Netflix releases a ton of fine titles to Instant today. Happy Streaming! http://bit.ly/mEvOlH
media	Netflix's chief: No plan to create Armageddon with pay TV providers http://bit.ly/loArMh #netflix

`neutral`	Netflix till work
`snafu`	Netflix on my phone isn't working.... guess I'm napping in the library 'til 3 "/
`watching`	Watchibg dragon tiger gate on netflixM
`happy`	Oh and btw I am really diggin' Netflix....love streaming those movies!!
`complaint`	I HATE YOU AGAIN NETFLIX!!
`refuse to rate`	@parra Bueno... es gratis en algunos casso con publicidad. En otros son suscripcion. Similar a Netflix (aunque yo prefiero Netflix XD)
`happy`	Netflix? :)