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Assessment of Classifiers for Potential Voice-Enabled Transportation Apps

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ASSESSMENT OF CLASSIFIERS FOR POTENTIAL VOICE-ENABLED TRANSPORTATION APPS

by

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DEDICATION

I dedicate this work to my parents, Gias Uddin and Farida Begum, who have always believed in me and who helped me in my early learning to work hard and to think critically.

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ABSTRACT

Transportation apps are playing a positive role for today's technology-driven users. They provide users with a convenient and flexible tool to access transportation data and services, as well as collect and manage data. In many of these apps, such as Google Maps, their operations rely on the effectiveness of the voice recognition system. For the existing and new apps to be truly effective, the built-in voice recognition system needs to be robust (i.e., being able to recognize words spoken in different pitch and tone). The goal of this study is to assess three post-processing classifiers (i.e., bag-of-sentences, support vector machine, and maximum entropy) to enhance the commonly used Google's voice recognition system. The experiments investigated three factors (original phrasing, reduced phrasing, and personalized phrasing) at three levels (zero training repetition, 5 training repetitions, and 10 training repetitions). Results indicated that personal phrasing yielded the highest correctness and that training the device to recognize an individual's voice improved correctness as well. Although simplistic, the bag-of-sentences classifier significantly improved voice recognition correctness. The classification efficiency of the maximum entropy and support vector machine algorithms was found to be nearly identical. These results suggest that post-processing techniques could significantly enhance Google's voice recognition system.

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CHAPTER 1

INTRODUCTION

1.1 Background

The rapid growth of the Internet, mobile communications, and technology-enabled transportation services has the great potential to empower the traveling public. The existing and emerging apps provide travelers with a convenient and flexible tool to access transportation data and services, as well as collect and manage data. Travelers can efficiently choose when and where to drive, when to share ride, and when to use public transportation. Travelers can even determine when it is advantageous to use the bicycle or walk mode (Dutzik et al., 2013). To truly realize the benefits of transportation apps, a smart-device (e.g., smartphone, mobile tablet) is a must. As of 2014, 64% of adults in the U.S. own a smartphone of some kind, and 67% of the smartphone owners used their phones on an occasional basis for turn-by-turn navigation while driving (Smith, 2015).

Programs in smart-devices are known as apps. With the increased user adoption of smart-devices, so does the growth of mobile apps. As of July 2015, the Google Play Store (provider of Android-based mobile apps) has over 1.6 million mobile apps available (Statista, 2015); a number of these apps pertain to transportation. For instance, there are apps that allow transit users to find an optimal route based on their origin and destination and time of departure, and there are apps that allow users to track the movement of a bus or train in real time (Dutzik et al., 2013). The currently available transportation apps cover a wide variety of transportation needs, such as taxi-calling, transit routing, parking, navigation, route information, carsharing, and shipment management. In the near foreseeable future, travelers will be able to use their smartphones as transit passes given that users are now able to use their smartphones as credit cards. Figure 1.1 shows the logos of a few popular transportation apps.

(a)

(b)

(c)

(d)

Figure 1.1 A few popular transportation apps: (a) Uber[1], (b) Waze[2], (c) SFpark[3], and (d) uShip[4]

A number of the existing transportation apps offer voice recognition capability and it is expected that in the future more apps will offer this capability given the current trend to allow users to perform everyday functions using voice (e.g., searching the Internet using voice, writing an email or document using voice, and searching for a movie on TV using voice). In voice-enabled apps, their operations rely on the effectiveness of the voice recognition system. Studies have indicated that the current voice recognition

[1] https://www.uber.com/
[2] https://www.waze.com/
[3] http://sfpark.org/
[4] http://www.uship.com/about/mobileapplications.aspx

accuracy rate is about 53% (Uddin et al., 2015); thus, there is a need for additional research to improve voice recognition accuracy. The goal is to enhance the voice recognition capability in transportation apps, and the challenge is to make the app understands users with different speech patterns and accents.

1.2 Research Overview

This study examines how to improve voice recognition system in mobile computing technology so that the accuracy of recognition could be increased. To accomplish this, three different post-processing algorithms, also known as classifiers, are investigated to improve the performance of Google's voice recognition system: bag-of-sentences, support vector machine, and maximum entropy. Bag-of-sentences is a many-to-few mapping between phrases returned by the speech recognizer and phrases need to be recognized. Support vector machine is a supervised machine learning technique, which is based on training, testing, and performance evaluation. Maximum entropy, a probability distribution estimation technique, is used for text classification by estimating the conditional distribution of the class variable given the document.

The three aforementioned algorithms are applied on a smart-app named Perioperative Services Mobile Learning System (POS-MLS). Although POS-MLS is a health care app, its functionality and application is similar to that of most transportation apps, and therefore, was selected for this study. POS-MLS is an Android-based app. Its voice recognition capability is enabled by the Android built-in speech recognizer. The Android speech recognizer gathers a sound sample from the user and sends it to Google's cloud-based voice recognition service, which then returns a plain text reply, as string.

1.3 Organization of the Thesis

The thesis is organized into 5 chapters. Chapter 1 provides the background and motivation for the study and an overview of the thesis.

Chapter 2 presents the literature review of existing transportation apps, followed by a discussion of voice recognition system (VRS) and the current application of VRS in health care setting. The chapter concludes with the limitations and outlook of VRS.

Chapter 3 presents the methodology used in this research. Details regarding the classifiers (algorithms) and how they are used to classify texts are provided.

Chapter 4 provides a case study for the application of the methodology in pre-operative service operation management. It describes the experimental set-up, data collection procedure, and findings from the analyses.

Chapter 5 presents the conclusions of the study and recommendations for future research directions.

CHAPTER 2

LITERATURE REVIEW

This chapter provides a review of existing transportation apps, followed by a discussion of voice recognition system and the current application of voice recognition system in health care setting. The limitations and outlook of voice recognition system are also provided.

2.1 Existing Transportation Apps

There are a wide variety of transportation apps that are designed to facilitate travel, such as transit apps that help users to find the optimal route, navigation apps that provide turn-by-turn instructions, travel apps that provide real-time arrival and departure information, and parking apps that help users to find available parking space. The following provides a brief review of the functionalities of some of the transportation apps.

Google Maps is one of the most popular and widely used apps for trip planning and navigation (Google Maps, 2015). It provides users with the shortest route(s) based on the prevailing travel time between the indicated origin and destination. Google Maps will automatically reroute users in the event of an accident, such those reported by users of Waze. Waze is an app based on crowdsourcing; it provides driving directions, gas price information, and the reported locations of highway patrol vehicles (Waze, 2015). In addition, users can report locations of accidents and congestion.

NextBus is an app that provides arrival time of a bus or shuttle at a designated stop in real-time (Next Bus, 2015); through the use of GPS technology and an algorithm that uses historical travel time data and current location and speed. To date, 135 agencies use the NextBus app and service, including the University of South Carolina. Another innovative app related to transit is called NexTime (NexTime, 2015). It integrates real-time bus locations with riders' locations (via smartphone GPS) and notifies the riders when they should leave to catch a bus at the nearest stop on time. The NexTime app and service is currently being used by six major transit agencies in North America. Another bus-related app is OneBusAway, which uses data from local transit agencies to provide bus users with real-time arrival and departure information (One Bus Away, 2015). The app also allows users to view bus stops and routes as well as search for a nearby stop using their current locations (provide by the smart-device built-in GPS). Lastly, the Roadify app helps commuters find bus and train information in real-time and notifies users when there is a delay (Roadify, 2015). It also provides information about carsharing and bikeshare stations.

Taxi hailing has become more convenient with the inception of mobile app-based use. Uber is making strides in recent years, which is a peer-to-peer taxi ride sharing service (Uber, 2015). It allows the users to call a taxi using the app in both desired location and time. The app can also notify the users about the taxi in real-time. Hailo is another popular taxi hailing app, slightly different in geographic area of operation (Hailo, 2015). However, its operating strategies are almost similar to Uber.

A greater number of commuters have elected the ridesharing mode due to the emergence of ridesharing, though their use is limited to major metropolitan areas. The

Lyft (Lyft, 2015), SideCar (Side Car, 2015), and Carma (Carma, 2015) apps help riders to get rides in real-time. These apps pair up riders by matching up their origins and destinations. A unique phenomenon about these apps is that ordinary people are sharing their rides in exchange for money. Participants (i.e., drivers) are required to have good driving records. In a nutshell, these ridesharing apps help to connect drivers and riders, and to ensure safe and secure fare payment transactions.

The SFpark app provides available parking space information to the drivers at San Francisco, CA in real-time (SFpark, 2015). It maintains balance between parking prices and demands in a way so that price will increase if it is difficult to find parking space and vice versa. Another parking related app is ParkingPanda, which can find all available parking options and prices in real-time for 40 U.S. cities (Parking Panda, 2015). One of the useful features of the app is the provision of reserving parking space in advance for a special event. Taking the input of arrival and departure times, "Best Parking" app provides free, metered, and prohibited parking information in an interactive map with color coding (Best Parking, 2015). Currently, the app covers 105 cities and 115 airports in North America.

Electronic ticketing has emerged as a convenient tool in recent years for the payment of transit fares. "TriMet Tickets" allows a transit rider to purchase ticket directly from the app (TriMet Tickets, 2015). It has the flexibility of storing tickets for future use. This paperless ticketing technology will be introduced by the Chicago metropolitan commuter railroad, Metra, very soon (Hilkevitch & Wronski, 2015). The prospect of this app-based ticketing is very promising.

Mobile apps can also be used for multi-modal trip planning; combining transit, taxi, carsharing, ridesharing, and bikesharing services. The Resrobot app helps to choose sustainable modes in Sweden (Resrobot, 2015). It provides alternative routes with different modes and allows users to make a knowledgeable decision. The RideScount app shows available transportation options in real-time considering multiple modes (Ride Scout, 2015). Users can compare available mode options on the basis of cost and type. The app requires only destination information as input and outputs with a list of mode options.

Freight related mobile apps can improve supply chain efficiency to a great extent. The uShip app keeps shipping customers updated on all their shipments (uShip, 2015). In a study by Santoso and Noche (2015), it is found that mobile app-based tracking system and supply chain monitoring are more beneficial than conventional method for biodiesel distribution.

2.2 Voice Recognition System (VRS)

Voice recognition is the process of creating texts from speech or voice using software. The system records the speech signal, processes the signal and compares the analyzed speech patterns with a collection of possible words and finally, generates the written text (O'Shaughnessy, 2003). Voice recognition technology is not a new concept, though the use of mobile devices using voice recognition is increasing day-by-day. Today's systems have the flexibility to be used in both user dependent and independent domains. User independent systems can be employed by all users without the need to train the system for each individual user, while user dependent systems require training for individual speech patterns (Durling & Lumsden, 2008). Voice recognition technology has matured and advanced significantly in recent years and its potential for health care applications is growing (Zhao, 2009).

Advances in computing power allow current systems to process a large amount of speech data, so that voice recognition technology now has a high of level of accuracy (Zhao, 2009). Moreover, voice recognition has a natural place in the next generation of "smart" environments and has great potential for widespread application (Pentland & Choudhury, 2000). However, there remain challenges, including different speech styles, speech rates, and voice characteristics (Furui, 2005).

Voice recognition technology could potentially simplify many management tasks. For example, health care generates a large amount of text and documentation, which needs to be accessed quickly (Al-Aynati & Chorneyko, 2003). Health care's traditional documentation method, handwritten records, is time consuming, and dictated records have the added expense of transcription services. Voice recognition is free from these problems as it can immediately transfer spoken words into text (Korn, 1998). Using a voice recognition system, the physician can dictate, edit and create electronic reports instantly; these reports can be made available to other physicians immediately and can be added to the patient record. As a result, the total patient care process can take less time and may lead to better service at a lower cost.

2.3 Applications of VRS in Health Care

Voice recognition is already being applied in some health care settings. A computer-automated telephone system, known as an Interactive Voice Response System (IVRS), responds when a patient dials a number and selects from a menu of options by pressing the appropriate numbers on the telephone keypad. The IVRS system leads the patient to a computer network system, which records and documents the voice of the patient and allows the patient to converse with a talking computer. This interaction includes reminders to refill medication, schedule a clinic visit, check blood pressure, take medication, etc. The IVRS is an effective data management and reporting system. However, a common issue is that the system often drops patients during a call. Nonetheless, IVRSs can be a very handy tool for health care services because IVRSs provide live communication (Lee et al., 2003).

The Vocera communication system uses a wearable badge device, which offers a push-to-call button, a small text message screen, and versatile voice-dialing capabilities based on voice recognition. It also offers hands-free conversation, such as hands-free call and voice message when the recipient is unavailable. In an experiment in St. Vincent's Hospital, Birmingham, AL, the utility of this system was verified. Another advantage of this system is biometric security, as only the proper user can initiate the call. The Vocera system can also dial by role or team according to the account information stored on the server (Stanford, 2003).

Alapetite (2008) found that the traditional touch-screen and keyboard interface imposed a steadily increasing mental workload (in terms of items to keep in memory). In contrast, a speech input interface allowed anesthesiologists to enter medications and observations almost simultaneously. During time-constrained situations, speech input reduced mental workload related to the memorization of events to be registered because it imposed shorter delays between event occurrence and event registration. However, existing voice recognition technology and speech interfaces require training to be used successfully.

Voice recognition decreased report turnaround time compared to conventional dictation. However, it performed better when English was the user's first language (Bhan et al., 2008; Mehta et al., 1998; Akhtar et al., 2011). Another viewpoint is that improvement in report turnaround time is correlated with work habits rather than workload (Krishnaraj et al., 2010). Furthermore, radiology reports prepared using VRS had significantly more errors than other methods. Typically, increased errors occurred in noisy areas with high workload and with radiologists whose first language was not English (McGurk et al., 2008).

Rana et al. (2005) found that for long reports voice recognition was advantageous over traditional tape dictation-transcription in total reporting time. Voice recognition methods incorporate dictation and transcription into one stage, whereas dictation-transcription method requires several stages and individuals in the process. Several issues with voice recognition in the radiology department included: (1) inadequate training, (2) insufficient attention to operational issues, (3) an increase in the dictation cost, and (4) an increase in the workload of the radiologist.

Voice recognition has been used in many other hospital departments. Computer-based transcription is a relatively inexpensive alternative to traditional human transcription in pathology where numerous reports must be regularly transcribed (Al-Aynati & Chorneyko, 2003). Voice recognition technology improved the efficiency of workflow, minimized transcription delays and costs, and contributed to improved turnaround time in surgical pathology (Henricks et al., 2002). Emergency departments have used voice recognition systems as a tool for physician charting and have been found to be nearly as accurate as traditional transcription, with shorter turnaround times and lower costs (Zick & Olsen, 2001). Voice recognition technology has been used for nurse dictation (Carter-Wesley, 2009) and has improved workflow in many clinical processes. However, Issenman and Jaffer (2004) found that computer dictation and correction time was greater using voice recognition than using electronic signatures for letters typed by an experienced transcriptionist in a pediatric gastroenterology unit.

Nuance's Dragon NaturallySpeaking is used with the Apple iPhone. Parente et al. (2004) found this technology to be very cost effective and acceptable to physicians for filling out different types of forms, as well as in creating an electronic health record (EHR). Dragon NaturallySpeaking has been used by radiologists to create reports, significantly reducing turnaround times and decreasing transcription costs (Donnelly, 2013).

2.4 Limitations of VRS

Currently, there are multiple problems with voice recognition software. Devine et al. (2000) found that Dragon Systems NaturallySpeaking Medical Suite, version 3.0 had the highest error rate among three commercially available continuous voice recognition software packages: (1) IBM ViaVoice 98, (2) Dragon Systems NaturallySpeaking Medical Suite, and (3) L&H Voice Xpress for Medicine. Murchie and Kenny (1988) found that voice recognition resulted in significantly more errors than keyboard entry. Moreover, Grasso (1995) found that a voice recognition system had some limitations in terms of vocabulary size, continuity of speech and speaker dependency. The system needed *a priori* training to verify the capability of the device to act on various conditions. When the vocabulary size became bigger it needed more time for training. It could not distinguish multiple word boundaries—as in “youth in Asia” and “euthanasia”. Increasing the size of the vocabulary also adversely affected the accuracy of the system.

2.5 VRS Outlook

The use of voice recognition is becoming more popular than traditional transcription with the increase in computing power and the decrease in the price of technology. In addition, the accuracy of voice recognition is also increasing because of dramatic improvement in voice recognition technology. Voice recognition has come a long way. Major barriers to the implementation of voice recognition technology in health care have been removed with the advancement and widespread adoption of mobile technology (i.e., smart phones and tablets are ubiquitous in the work place). To apply this technology more efficiently in the future, voice-aware user and application interfaces should be developed.

CHAPTER 3

METHODOLOGY

A variety of supervised learning algorithms (classifiers) have been using for text classification: naïve Bayes (Lewis, 1998), support vector machine (Dumais et al., 1998), maximum entropy (Nigam et al., 1999) and k-nearest neighbor (Yang, 1999). For this study, we investigated support vector machine (SVM) and maximum entropy (MAXENT), in addition to the simple “bag-of-sentences” approach. A comparison between SVM and MAXENT classifiers can be found in the work by Du and Wang (2012). The simplest algorithm, “bag-of-sentences”, is described next.

3.1 Bag-of-Sentences

During a training round we matched each of the returned phrases to the desired phrase. For example, if we said “administer medications” but the speech recognizer returned “Minister medications” we then added the fact that “Minister medications” should always match “administer medications” to the learning table. If some other spoken phrase returned “Minister medications” then that phrase would always be matched. That is, new matches overwrote old matches during the training phase. In this manner, we created a many-to-few mapping between phrases returned by the speech recognizer and phrases we needed to recognize. Once the training was done, the app uses the table to translate text phrases returned by the speech recognizer into one of the target phrases.

3.2 Support Vector Machine

Support Vector Machine (Cortes & Vapnik, 1995), a supervised machine learning technique, is gaining much attention due to its superior data classification and regression performance (Pham et al., 2011). SVM has been applied to many fields for classification problems (Tong & Koller, 2002; Melgani & Bruzzone, 2004; Maglogiannis & Zafiropoulos, 2004; Yu et al., 2010; Zhang et al., 2011). The SVM algorithm is based on training, testing and performance evaluation because it is a learning machine. In training, a convex cost function is optimized. In testing the model is evaluated using support vectors to classify a test data set, and performance evaluation is based on error rate determination.

For this text classification study an ε-SVM was adopted—similar to Pham et al. (2011). A text classification problem with N inputs $\{x(i)\}_{i=1}^{N}$, $x(i) \in R^{In}$ and outputs $\{y(i)\}_{i=1}^{N}$, $y(i) \in R^{1}$ is assumed. The set of real numbers is denoted by R^1, and the set of real numbers in Infinite-dimensional space is denoted by R^{In}. Using a function $\Phi(x(i))$, the ε-SVM model maps the inputs from the Infinite-dimensional space into a higher h-dimensional space. The estimation function of output $y(i)$ has the form specified in Equation (1). The parameter w is a weight vector in the higher h-dimensional space, and b is the bias.

$$\hat{y}(i) = f(x(i)) = w^T \Phi(x(i)) + b \tag{1}$$

The coefficients, b and w, are estimated using Equation (2) – (5).

$$\text{Minimize} \qquad \frac{1}{2} w^T w + \frac{C}{N} \sum_{i=1}^{N} \left(\xi_i + \xi_i^* \right) \tag{2}$$

Subject to $\quad w^T \Phi(x(i)) + b - y(i) \le \varepsilon + \xi_i \quad (3)$

$$y(i) - w^T \Phi(x(i)) - b \le \varepsilon + \xi_i^* \quad (4)$$

$$\xi_i, \xi_i^* \ge 0, \qquad i = 1, \ldots\ldots, N \quad (5)$$

Here ξ_i and ξ_i^* = slack variables,

C = a regularization parameter,

T = transpose, and

ε = soft margin loss parameter.

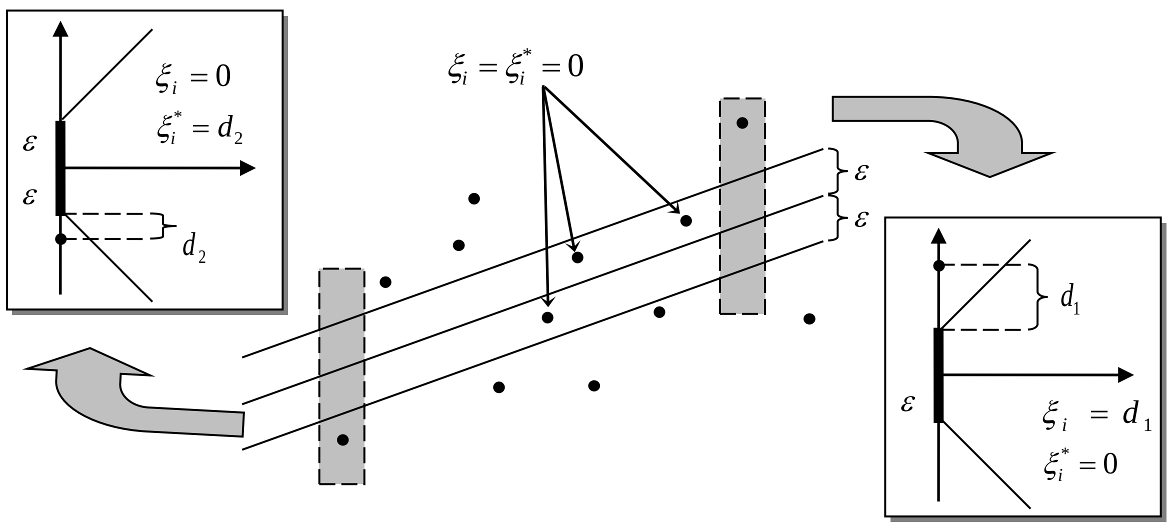

Figure 3.1 Soft margin loss parameter in ε-SVM (Pham et al., 2011)

If the difference between $\hat{y}(i)$ and $y(i)$ is larger than ε, ξ_i or ξ_i^* can only be greater than zero (Figure 3.1).

3.3 Maximum Entropy

Maximum entropy classification has been shown to be an effective technique in a number of natural language processing applications (Berger et al., 1996). Its application for text classification was proposed by Nigam et al. (1999). The following provides a brief review of the maximum entropy algorithm and explains how it classifies texts (refer to Nigam et al. (1999) for additional details).

Training data is used to set constraints on the conditional distribution. When any real-valued function of the document and class is a feature, $f_i(d,c)$, the model distribution will have the same expected value for this feature similar to the training data, D. Then, the learned conditional distribution, $P(c \mid d)$, must have the property specified in Equation (6). The document distribution is denoted by $P(d)$.

$$\frac{1}{D}\sum_{d\in D} f_i(d,c(d)) = \sum_{d} P(d)\sum_{c} P(c \mid d) f_i(d,c) \tag{6}$$

And, the distribution of $P(c \mid d)$ has an exponential form (Della Pietra et al., 1997), where each $f_i(d,c)$ is a feature/class function for feature f_i, $Z(d)$ is a normalization factor to ensure proper probability and λ_i is a parameter.

$$P(c \mid d) = \frac{1}{Z(d)}\exp\left(\sum_{i} \lambda_i f_i(d,c)\right) \tag{7}$$

Word counting is a feature of text classification with maximum entropy, since applying maximum entropy to a domain requires the selection of a set of features to use for setting the constraints. For each word-class combination the feature is considered as:

$$f_{w,c'}(d,c) = \begin{cases} 0 & \text{if } c \neq c' \\ \dfrac{N(d,w)}{N(d)} & \text{Otherwise} \end{cases} \tag{8}$$

where $N(d,w)$ is the number of times word w occurs in document d, and $N(d)$ is the number of words in d.

It is expected that features accounting for the number of times a word occurs should improve classification in text. This implies that the weight for the word-class pair would be higher than for the word paired with other classes if a word occurs often in one class.

3.4 RTextTools

RTextTools is a supervised learning package for text classification (Jurka et al., 2013). It provides a comprehensive approach to text classification and also accelerates the classification process. The statistical software R is essential for using this text classification package. The classification process starts with loading data from a CSV, Access or Excel file by calling a function in R. Then a matrix is generated from the data. Then a container object is created that contains all the objects for further analysis. After that, the data are trained by algorithms. Data classification is done next. Finally, the classification is summarized to find the correct classification, which will give the percentage of correct classifications.

RTextTools can work with nine algorithms for training of data. In our study, we used the support vector machine and maximum entropy algorithms to train our data. RTextTools uses support vector machine from the 'e1071' package (Meyer et al., 2012) and maximum entropy from the 'maxent' package (Jurka, 2012) of R. SVM is used to train a support vector machine, and can be used for general regression and classification. MAXENT is used for low-memory, multinomial logistic regression.

CHAPTER 4

CASE STUDY[1]

A smart-app named Perioperative Services Mobile Learning System (POS-MLS)—developed using the latest Android API (Level 19)—was utilized to test the classifiers. Basically, the purpose of the app is to improve coordination between different Perioperative Services (POS) units via mobile computing technology. This app enables POS staff to: (1) dictate task completion milestones, which require the smart-app to understand spoken information and to store the data; (2) query for information by speaking, which would require the smart-app to understand the context of the question and provide a precise answer; and (3) obtain feedback and guidance about task decisions. A particular challenge that arose during the development of the smart-app is the accuracy of Google's voice recognition system. This challenge motivates the assessment of post-process learning algorithms or classifiers so that the performance of voice recognition system could be improved.

POS services are performed in three phases: *preoperative* (Pre-op), *intraoperative* and *postoperative*. In the Pre-op phase the POS first schedules the procedure in an operating room (OR) and then prepares supplies, equipment and OR for the surgeon to perform the procedure. The second Pre-op step is to assess and physically prepare the patient on the day-of-surgery. This is led by a registered nurse (RN) in Pre-op. Figure

[1] This chapter has been adapted from "Uddin, M. M., Huynh, N., Vidal, J. M., Taaffe, K. M., Fredendall, L. D., & Greenstein, J. S. (2015). Evaluation of Google's voice recognition and sentence classification for health care applications. *Engineering Management Journal*, *27*(3), 152–162". Reprinted here with permission of publisher.

4.1 illustrates the process flow in Pre-op. During the intraoperative phase, the POS provides staff (i.e., anesthesiologist, surgical technician, circulating nurse, and certified registered nurse anesthetist or CRNA) to assist the surgeon in the actual surgical procedure. In the postoperative phase, POS provides the recovery rooms (i.e., post anesthesia care unit, or PACU, sometimes followed by a Phase 2 recovery) and the appropriate level of nursing care until patient discharge or transfer.

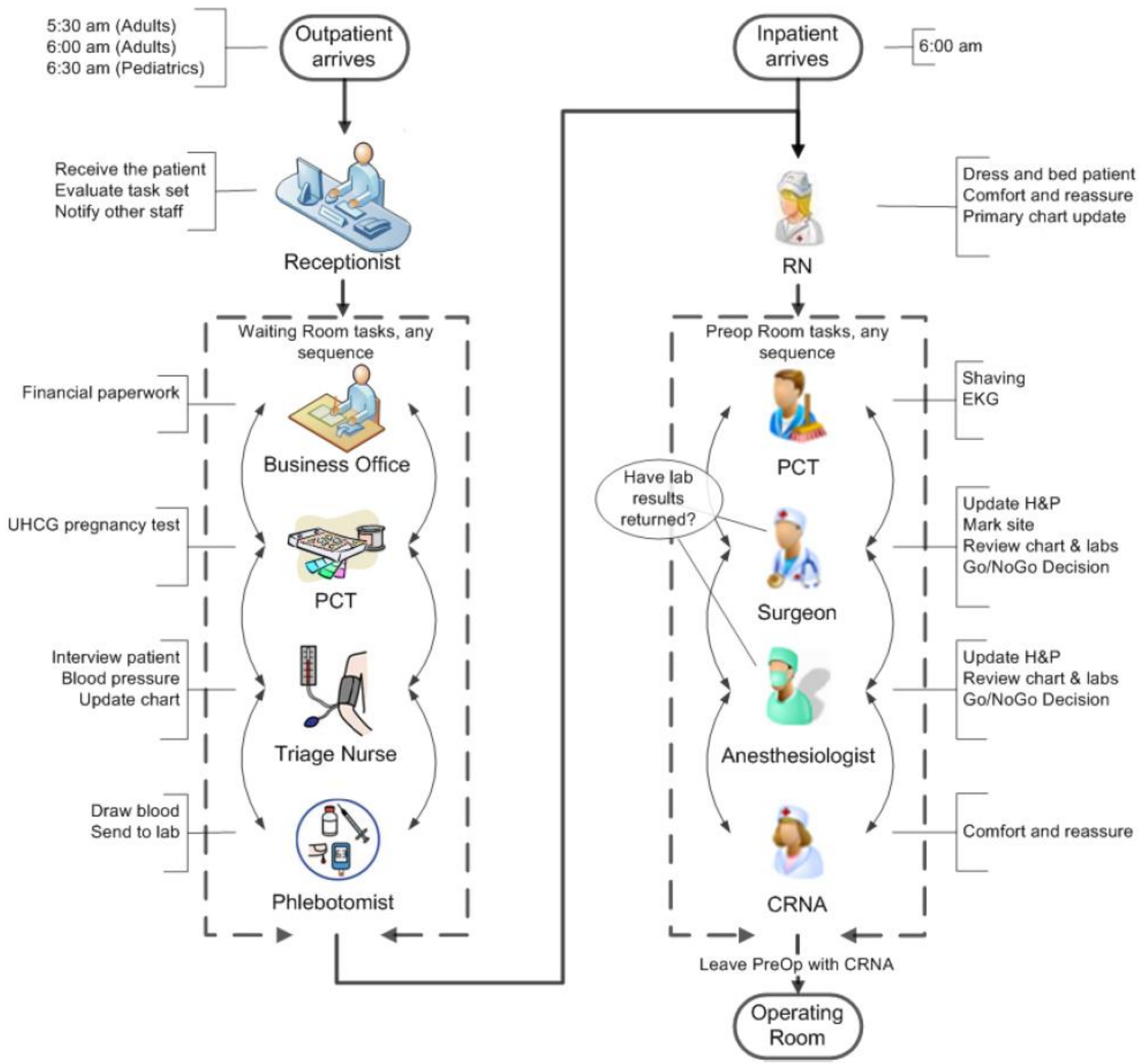

Figure 4.1 Pre-op process flow map (Pearce et al., 2010)

4.1 Data Collection Device

One portion of the app (POS-MLS) includes a screen with 16 Pre-op checklist items that could be marked complete using touch or voice. The voice recognition is enabled by the Android platform with its built-in speech recognizer. The Android speech recognizer gathers a sound sample from the user and sends it to Google's cloud-based voice recognition service, which then returns a plain text reply, as a string. The speech recognizer performs a best effort to find the most likely set of words to match the sound sample. We set the language to U.S. English, indicating to the recognizer our choice of spoken language for testing. The data collected for this paper were based on version 0.7 of the smart-app. Figure 4.2 shows a screenshot of the checklist items.

4.2 Data Collection Procedure

The smart-app was installed on Google Nexus 4, 7, and 10 mobile devices for the experiments. The experiments investigated three factors, with each factor having three levels. The three factors were: as-is phrase (from the Pre-op checklist items), reduced phrase (developed by the research team), and personalized phrase (selected by the individual participant; see Table 4.1). Each factor had three levels in the experiment: Google-only (zero training repetition), Train-5 (5 training repetitions), and Train-10 (10 training repetitions). In the Google-only case, the app is not 'learning' from prior data. When training is allowed in the Train-5 and Train-10 levels, the app can learn from past mistakes and recognize phrases based on those mistakes. The results collected from the experiments were classified as either correct or incorrect in terms of recognition of the spoken phrase. Note that the phrases consist of distinct words; hence, there is no chance of recognizing one phrase by saying another phrase, or recognizing more than one phrases by saying a single phrase to the app.

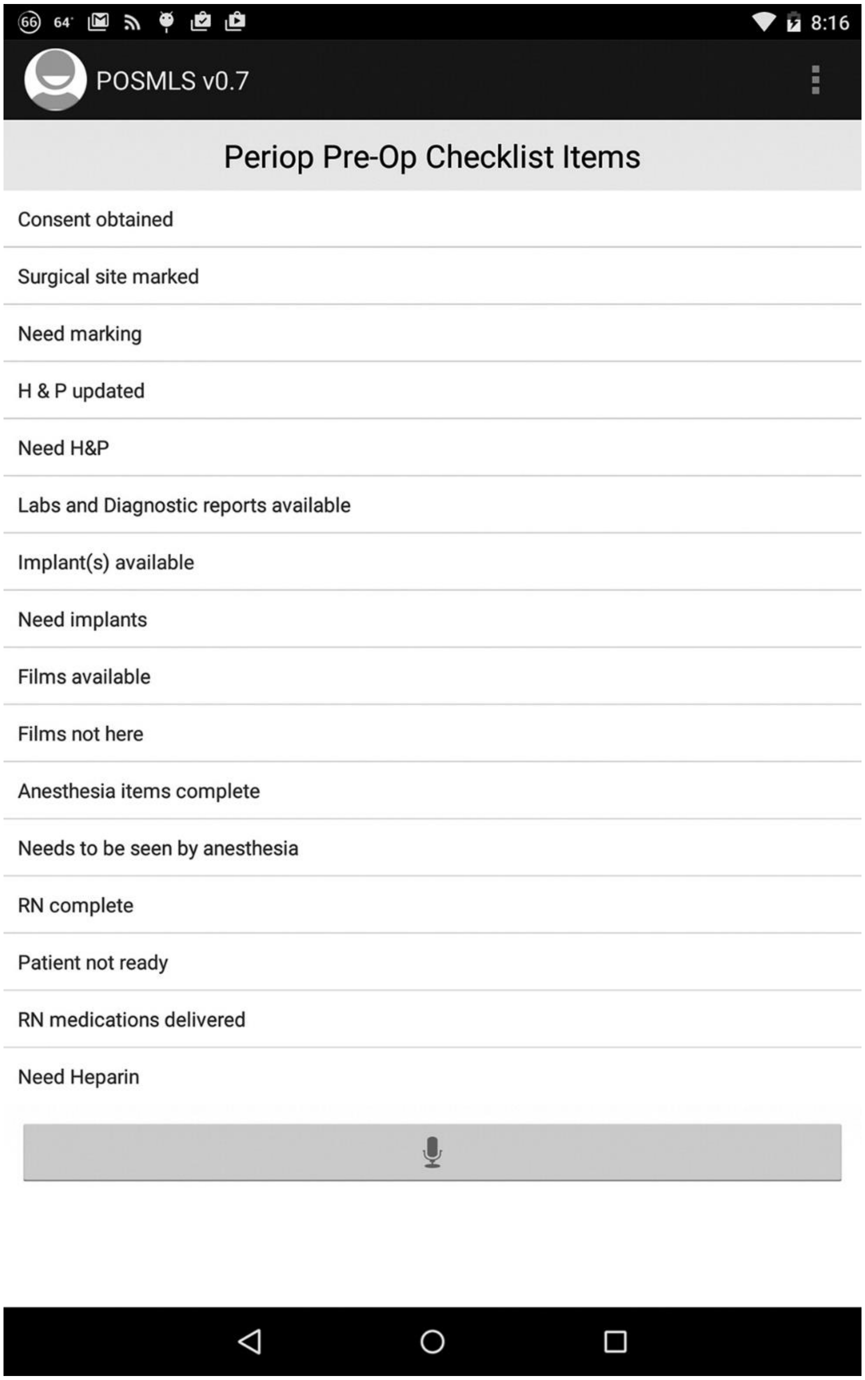

Figure 4.2 Screenshot of the smart-app (POS-MLS)

Table 4.1 Types of phrases

As-is Phrase	Reduced Phrase	Personalized Phrase*
Consent obtained	Have consent	Consent good
Surgical site marked	Site marked	Site marked
Need marking	Need site marked	Need marking
H&P updated	History Physical updated	HP good
Need H&P	Need History Physical	Need HP
Labs and diagnostic reports available	Reports ready	Reports ready
Implant(s) available	Implants ready	Implants ready
Need implants	Need implants	Get implants
Films available	Films here	Films here
Films not here	Need films	Need films
Anesthesia items complete	Anesthesia complete	Anesthesia done
Need to be seen by anesthesia	Need anesthesia	Need anesthesia
RN complete	Nurse done	Nurse done
Patient not ready	Patient not done	Patient not done
RN medications delivered	Medications delivered	Meds given
Need heparin	Need heparin	Need hep

* Each participant created his/her own personalized phrase

4.3 Experimental Set-Up

We conducted 16 experiments that were designed to test the ability of the app to recognize the Pre-op checklist items correctly using voice. The participants were from various age groups, both genders, native and non-native speakers, various ethnic groups, and had different occupations. All of the participants were provided with a Nexus device with the voice-recognition app (version 0.7) installed on it. In the case of as-is phrases, every phrase was spoken five times for all three levels (i.e., Google-only, Train-5, and Train-10). Thus, we have a total of 80 (16×5) observations for each phrase at all three levels. In the Train-5 and Train-10 levels for the as-is phrases, we have an additional 5 and 10 training repetitions of phrases, respectively. Data for the reduced and personalized phrases were collected using a similar procedure, with each having 80 observations at all three levels. Table 4.2 summarizes the phrases, levels, and corresponding post-processing methods. As noted by the check marks, the Google-only level does not involve any training repetition.

Table 4.2 Summary of experimental set-up

Phrases	Training Repetitions	Testing Repetitions	Google-only	Post-Processing Methods: Bag-of-sentences	Post-Processing Methods: Support Vector Machine	Post-Processing Methods: Maximum Entropy
As-is	0	5	✓			
	5	5		✓	✓	✓
	10	5		✓	✓	✓
Reduced	0	5	✓			
	5	5		✓	✓	✓
	10	5		✓	✓	✓
Personalized	0	5	✓			
	5	5		✓	✓	✓
	10	5		✓	✓	✓

4.4 Correctness by Level

Table 4.3 summarizes the app's ability to correctly recognize as-is phrases over 80 observations. On its own (Google-only), the app correctly identified the phrases from under 4% to 86% with a median of 34%. In the Google-only level, most of the phrases were identified correctly at a very low rate. The four phrases identified correctly less than 15% of the time, included words not frequently used in daily life (e.g., RN, H&P, and heparin). At the Train-5 level, recognition correctness increased to approximately 63% (median) but ranged from 38% to 91%. Two phrases ("need implants" and "implant(s) available") were not recognized at a high percentage. Similarly, recognition correctness increased further with Train-10. Most of the phrases were correctly identified with a median of 69%, but ranged from 44% to 79%. Recognition correctness of three phrases—"patient not ready", "RN complete", and "need marking"—decreased in Train-10. Statistically significant differences in recognition correctness between training levels were identified for 11 of the 16 phrases using a Chi-Squared test. Closer examination of these phrases revealed that phrases relying more heavily on medical terminology, such as 'anesthesia', 'heparin', 'RN', and 'H&P'. This suggests that training contributes significantly to the correct classification of these phrases. Phrases consisting of commonly used words (e.g., "consent obtained", "need implants") have large *p*-values. They tended to have high correct classification scores regardless of training level.

The second factor replaced the as-is 16 phrases with shorter phrases using less medical-based terminology. Results are summarized in Table 4.4. On its own (Google-only level), the app correctly recognized 53% (median) of the phrases, with a range from 5% to 76%. Seven of the phrases were identified correctly less often than their counterparts in Table 4.3. The phrases "site marked", "need site marked", "reports ready", "implants ready", "films here", "need films", "need heparin", and "need anesthesia" have *p*-values less than 0.05, indicating statistically significant differences in recognition correctness among Google-only, Train-5, and Train-10.

Table 4.3 Comparison of percent correct and number of correct classifications at different training levels for as-is phrases

As-is Phrase	% Correct Classification (Number of Correct Classification)			*p*-Value
	Google-only	Train-5	Train-10	
Consent obtained	66.3 (53)	73.8 (59)	75.0 (60)	0.414
Surgical site marked	28.8 (23)	53.8 (43)	57.5 (46)	<0.001
Need marking	31.3 (25)	65.0 (52)	63.8 (51)	<0.001
H&P updated	40.0 (32)	62.5 (50)	70.0 (56)	<0.001
Need H&P	11.3 (9)	50.0 (40)	53.8 (43)	<0.001
Labs and diagnostic reports available	18.8 (15)	41.3 (33)	43.8 (35)	0.001
Implant(s) available	65.0 (52)	65.0 (52)	75.0 (60)	0.292
Need implants	75.0 (60)	75.0 (60)	76.3 (61)	0.978
Films available	57.5 (46)	66.3 (53)	70.0 (56)	0.237
Films not here	40.0 (32)	61.3 (49)	73.8 (59)	0.005
Anesthesia items complete	28.8 (23)	37.5 (30)	53.8 (43)	0.001
Need to be seen by anesthesia	37.5 (30)	62.5 (50)	65.0 (52)	<0.001
RN complete	8.8 (7)	81.3 (65)	76.3 (61)	<0.001
Patient not ready	86.3 (69)	91.3 (73)	78.8 (63)	0.079
RN medications delivered	3.8 (3)	50.0 (40)	67.5 (54)	<0.001
Need heparin	5.0 (4)	46.3 (37)	60.0 (48)	<0.001

In reviewing the results presented in Table 4.3 and 4.4, for every phrase, when the Google-only approach did not recognize an as-is or reduced phrase at least half the time, both training levels (Train-5 and Train-10) improved recognition correctness.

Table 4.4 Comparison of percent correct and number of correct classifications at different training levels for reduced phrases

Reduced Phrase	% Correct Classification (Number of Correct Classification)			*p*-Value
	Google-only	Train-5	Train-10	
Have consent	63.8 (51)	72.5 (58)	77.5 (62)	0.151
Site marked	7.5 (6)	57.5 (46)	70.0 (56)	<0.001
Need site marked	12.5 (10)	36.3 (29)	52.5 (42)	<0.001
History Physical updated	50.0 (40)	47.5 (38)	53.8 (43)	0.729
Need History Physical	37.5 (30)	41.3 (33)	47.5 (38)	0.433
Reports ready	67.5 (54)	76.3 (61)	91.3 (73)	0.001
Implants ready	53.3 (43)	70.0 (56)	72.5 (58)	0.026
Need implants	75.0 (60)	76.3 (61)	77.5 (62)	0.933
Films here	28.8 (23)	75.0 (60)	77.5 (62)	<0.001
Need films	30.0 (24)	68.8 (55)	72.5 (58)	<0.001
Anesthesia complete	51.3 (41)	61.3 (49)	67.5 (54)	0.107
Need anesthesia	53.8 (43)	53.8 (43)	75.0 (60)	0.006
Nurse done	56.3 (45)	65.0 (52)	68.8 (55)	0.242
Patient not done	76.3 (61)	75.0 (60)	77.5 (62)	0.933
Medications delivered	75.0 (60)	83.8 (67)	83.8 (67)	0.268
Need heparin	5.0 (4)	42.5 (34)	57.5 (46)	<0.001

We did not perform statistical comparisons for the personalized phrases across levels because each participant chose their own unique phrases, and thus, the Chi-Squared test could not be performed.

4.5 Correctness by Phrase Type

Table 4.5 compares the average recognition correctness percentages in terms of phrase type (i.e., as-is, reduced, and personalized). All differences in recognition correctness as a function of training are significant ($p < 0.05$) with the exception of the difference between Train-5 and Train-10 for the as-is phrase ($p = 0.129$). This suggests that training improved recognition correctness. The average recognition correctness for the as-is phrase was 61% when the app was trained with 5 repetitions compared to zero repetition. This increasing trend was also seen between Train-5 and Train-10. The average correctness in Train-10 was increased by about 5% relative to Train-5. These results suggest that training repetitions improved the correctness of classification for the as-is phrases in comparison to Google-only. In the case of reduced phrases, a similar improvement was observed. Moreover, the correctness percentages, for all three levels, was always greater than that of the as-is phrases (38% vs 47%, 61% vs 63% etc.). However, these improvements of correctness over as-is phrases is significant only for Google-only level ($p = 0.025$). For the personalized phrase, the average correctness percentages, for all the three levels, were the highest. Average correctness also increased with training levels. It is clear that training repetitions improve the app performance, and increasing the number of training repetitions from 5 to 10 continued to increase recognition correctness with the exception of as-is phrases. In addition, personalized phrases are more suitable than as-is and reduced phrases for pre-op checklist items within a voice recognition application.

Table 4.5 Comparison of average correctness percentages for different phrase types

(a)

	Google-only		Train-5		Train-10		*p*-Value[a]	*p*-Value[b]	*p*-Value[c]
	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.			
As-is	37.7	11.2	61.4	17.9	66.3	18.7	<0.001	<0.001	0.129
Reduced	46.5	22.3	62.7	14.5	70.2	15.9	0.003	<0.001	<0.001
Personalized	53.8	22.7	72.3	16.2	78.7	12.7	<0.001	<0.001	0.002

[a] Test between Google-only and Train-5.
[b] Test between Google-only and Train-10.
[c] Test between Train-5 and Train-10.

(b)

Test Variable	*p*-Value		
	Google-only	Train-5	Train-10
As-is and Reduced	0.025	0.382	0.127
As-is and Personalized	<0.001	0.007	0.006
Reduced and Personalized	0.022	<0.001	0.003

4.6 Correctness by Classifier

For classification using supervised algorithms, training data is required to classify the text. For that reason we do not have correctness values for the Google-only level. Table 4.6 compares the average correctness percentages between the support vector machine (SVM) algorithm and the maximum entropy (MAXENT) algorithm. It is clear from Table 4.5(a) and 4.6 that classification using SVM and MAXENT algorithms improved classification correctness significantly more than the bag-of-sentences approach in most cases (5 out of 6). Train-5 with as-is phrases yields the maximum average correctness for SVM of 82% and for MAXENT of 84%. However, those values for Train-10 are within 1% of the Train-5 value. Unlike the bag-of-sentences approach, increasing training repetitions does not lead to further correctness of classification. Average correctness results using the reduced phrases show the same decreasing pattern. Average correctness of SVM decreases from 79% to 77% and MAXENT from 80% to 79% for reduced phrase. The average correctness for Train-10 is less than Train-5 for both algorithms. For the personalized phrases, the average correctness value for SVM with Train-10 (77%) is less than the bag-of-sentences (79%); however, the average correctness value for MAXENT (81%) is greater than the bag-of-sentences. In case of personalized phrase, *p*-values suggest that with higher levels of training there is no difference between SVM and MAXENT. The biggest differences in average correctness occurred between bag-of-sentences and supervised algorithms and were 21% for SVM and 23% for MAXENT. The MAXENT algorithm outperformed SVM for three different cases (as-is, using both Train-5 and Train-10, and personalized using train-5 only). There was no difference between SVM and MAXENT for the other three cases.

Table 4.6 Comparison of average correctness percentages among the classifiers

	SVM		MAXENT		*p*-Value[a]	*p*-Value[b]	*p*-Value[c]
	Average	Std. dev.	Average	Std. dev.			
As-is							
Train-5	81.9	11.8	84.0	9.4	<0.001	<0.001	0.018
Train-10	80.9	8.7	83.8	7.7	<0.001	<0.001	0.022
Reduced							
Train-5	78.6	14.1	80.2	9.9	<0.001	<0.001	0.166
Train-10	77.4	15.5	79.1	13.1	0.004	<0.001	0.114
Personalized							
Train-5	79.0	13.0	81.3	13.5	0.001	<0.001	0.015
Train-10	76.7	14.5	80.6	11.6	0.292	0.222	0.052

[a] Test between Bag-of-sentences and SVM.
[b] Test between Bag-of-sentences and MAXENT.
[c] Test between SVM and MAXENT.

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

This study sought to identify a suitable algorithm to classify phrases in order to improve the performance of Google's voice recognition system. It also sought to examine whether training improve system performance. Three sets of phrases were tested. The as-is phrases were actual word-for-word phrases from an existing hospital checklist. The reduced phrases were developed by the researchers to reduce the number of words and to avoid words that users are likely to have trouble pronouncing. The personalized phrases were selected by each, individual user.

As expected, using the as-is phrases and the Google-only speech recognizer without any classifier had the lowest phrase recognition correctness in their respective settings. The use of reduced phrases or personalized phrases improved recognition correctness compared to the as-is phrases. The use of post-processing learning algorithms (support vector machine and maximum entropy) enhanced voice recognition correctness compared to the bag-of-sentences approach. Training (i.e., repetitions of phrases) significantly increased voice recognition correctness for all levels of post-processing. Overall, Google's voice recognition system was significantly enhanced by the use of post-processing techniques.

Although this study used a non-transportation app to test the effectiveness of different post-processing algorithms, the findings from this study are generalizable to transportation applications. Specifically, the results indicated that training improved recognition correctness, and thus, a transportation app should consider having users say selected phrases prior to its use to develop a voice profile to better recognize the user's voice and spoken commands. Furthermore, users may consider saying phrases of commonly used words and short in length to a voice-enabled transportation app for better performance. Lastly, the incorporation of classifiers with the existing and new apps would result in improved voice recognition accuracy.

Future research is needed to examine other voice recognition engines, such as those developed for iOS and Windows platforms, as well as other types of classifiers (e.g., random forest, boosting, and bagging). Most importantly, the evaluation needs to be done using apps designed for transportation application. Traffic safety is a big concern with the use of mobile devices during driving these days. Voice-based commands for operating mobile apps could alleviate this to some extent. However, a fundamental issue that needs to be researched is how voice-enabled apps should be designed and used in vehicles without distracting drivers. For example, a parking app would not only be ineffective but dangerous to use if it requires drivers to provide multitude of details. Similarly, the 511 Traveler Information System would be ineffective if it does not provide drivers with an easy method to request verbally traffic information.

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APPENDIX A

SAMPLE EXPERIMENTAL DATA

A.1 GOOGLE-ONLY DATA

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:15:22 EDT 2013	obtain		
Wed Sep 18 16:17:41 EDT 2013	content of pain		
Wed Sep 18 16:17:49 EDT 2013	consent obtained		
Wed Sep 18 16:17:57 EDT 2013	consent obtain		
Wed Sep 18 16:18:08 EDT 2013	content of pain		
Wed Sep 18 16:18:18 EDT 2013	physical fight mark		
Wed Sep 18 16:18:24 EDT 2013	surgical fight mark		
Wed Sep 18 16:18:31 EDT 2013	surgical fight mark		
Wed Sep 18 16:18:37 EDT 2013	surgical fight mark		
Wed Sep 18 16:18:45 EDT 2013	surgical fight mark		
Wed Sep 18 16:18:56 EDT 2013	need parking		
Wed Sep 18 16:19:05 EDT 2013	need mark		
Wed Sep 18 16:19:11 EDT 2013	need marking		
Wed Sep 18 16:19:18 EDT 2013	need mark		
Wed Sep 18 16:19:23 EDT 2013	need more thing		
Wed Sep 18 16:19:31 EDT 2013	a_t_&_t again		
Wed Sep 18 16:19:38 EDT 2013	h and p of days		
Wed Sep 18 16:19:46 EDT 2013	h and p a kid		
Wed Sep 18 16:19:52 EDT 2013	a_t_&_t a bit		
Wed Sep 18 16:19:58 EDT 2013	a_t_&_t often		
Wed Sep 18 16:20:07 EDT 2013	need a champion		
Wed Sep 18 16:20:13 EDT 2013	need a tempe		
Wed Sep 18 16:20:19 EDT 2013	need a tempe		
Wed Sep 18 16:20:24 EDT 2013	need a champion		
Wed Sep 18 16:20:30 EDT 2013	need a tempe		
Wed Sep 18 16:20:38 EDT 2013	lassen diagnostic for the bill		
Wed Sep 18 16:20:46 EDT 2013	lab and I to report available		
Wed Sep 18 16:20:54 EDT 2013	lab and I know the airport available		
Wed Sep 18 16:21:01 EDT 2013	labs and I know reports ville		
Wed Sep 18 16:21:09 EDT 2013	lab and I not to report avail		
Wed Sep 18 16:21:16 EDT 2013	implant available		
Wed Sep 18 16:21:22 EDT 2013	implant available		
Wed Sep 18 16:21:27 EDT 2013	implant avail		
Wed Sep 18 16:21:31 EDT 2013	implant available		
Wed Sep 18 16:21:36 EDT 2013	implant available		
Wed Sep 18 16:21:42 EDT 2013	need implants		
Wed Sep 18 16:21:47 EDT 2013	need implants		
Wed Sep 18 16:21:52 EDT 2013	need implants		
Wed Sep 18 16:22:00 EDT 2013	need in place		
Wed Sep 18 16:22:05 EDT 2013	need implants		

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:22:12 EDT 2013	film avail		
Wed Sep 18 16:22:20 EDT 2013	film avail		
Wed Sep 18 16:22:25 EDT 2013	film avail		
Wed Sep 18 16:22:30 EDT 2013	film avail		
Wed Sep 18 16:22:36 EDT 2013	jones avail		
Wed Sep 18 16:22:43 EDT 2013	film not here		
Wed Sep 18 16:22:52 EDT 2013	film not here		
Wed Sep 18 16:22:58 EDT 2013	don't not here		
Wed Sep 18 16:23:05 EDT 2013	film not here		
Wed Sep 18 16:23:10 EDT 2013	film not here		
Wed Sep 18 16:23:18 EDT 2013	anesthesia items complete		
Wed Sep 18 16:23:25 EDT 2013	anesthesia items be		
Wed Sep 18 16:23:31 EDT 2013	anesthesia items complete		
Wed Sep 18 16:23:37 EDT 2013	anesthesia island complete		
Wed Sep 18 16:23:43 EDT 2013	anesthesia I didn't complete		
Wed Sep 18 16:23:51 EDT 2013	need to be seen by anna seizure		
Wed Sep 18 16:23:58 EDT 2013	need to be seen by anesthesia		
Wed Sep 18 16:24:04 EDT 2013	need to be seen by anesthesia		
Wed Sep 18 16:24:14 EDT 2013	need to be seen by anesthesia		
Wed Sep 18 16:24:20 EDT 2013	need to be seen by anesthesia		
Wed Sep 18 16:24:28 EDT 2013	are in complete		
Wed Sep 18 16:24:34 EDT 2013	r_n complete		
Wed Sep 18 16:24:41 EDT 2013	are in complete		
Wed Sep 18 16:24:55 EDT 2013	are in complete		
Wed Sep 18 16:25:01 EDT 2013	r_n complete		
Wed Sep 18 16:25:18 EDT 2013	patient not ready		
Wed Sep 18 16:25:24 EDT 2013	patient not ready		
Wed Sep 18 16:25:29 EDT 2013	patient not ready		
Wed Sep 18 16:25:34 EDT 2013	patient not ready		
Wed Sep 18 16:25:40 EDT 2013	patient not ready		
Wed Sep 18 16:25:53 EDT 2013	r_n medication delivered		
Wed Sep 18 16:26:01 EDT 2013	r_n medication delivered		
Wed Sep 18 16:26:08 EDT 2013	r_n medication delivered		
Wed Sep 18 16:26:14 EDT 2013	r_n medication delivered		
Wed Sep 18 16:26:20 EDT 2013	r_n medication delivered		
Wed Sep 18 16:26:27 EDT 2013	need ever		
Wed Sep 18 16:26:32 EDT 2013	need a friend		
Wed Sep 18 16:26:38 EDT 2013	need heparin		
Wed Sep 18 16:26:44 EDT 2013	need ever		
Wed Sep 18 16:26:49 EDT 2013	need to print		

A.2 TRAINING DATA

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:28:28 EDT 2013	content obtain		Consent obtained
Wed Sep 18 16:28:32 EDT 2013	content of pain		Consent obtained
Wed Sep 18 16:28:37 EDT 2013	consent obtained	Consent obtained	Consent obtained
Wed Sep 18 16:28:41 EDT 2013	consent of pain		Consent obtained
Wed Sep 18 16:28:45 EDT 2013	consent obtain		Consent obtained
Wed Sep 18 16:28:53 EDT 2013	circle fight mark		Surgical site marked
Wed Sep 18 16:28:57 EDT 2013	circle fight mark	Surgical site marked	Surgical site marked
Wed Sep 18 16:29:01 EDT 2013	circle fight mark	Surgical site marked	Surgical site marked
Wed Sep 18 16:29:05 EDT 2013	circle fight mark	Surgical site marked	Surgical site marked
Wed Sep 18 16:29:08 EDT 2013	turtle flight mark		Surgical site marked
Wed Sep 18 16:29:13 EDT 2013	need marking	Need marking	Need marking
Wed Sep 18 16:29:17 EDT 2013	need mark		Need marking
Wed Sep 18 16:29:20 EDT 2013	need parking		Need marking
Wed Sep 18 16:29:24 EDT 2013	need marking	Need marking	Need marking
Wed Sep 18 16:29:27 EDT 2013	need mark	Need marking	Need marking
Wed Sep 18 16:29:33 EDT 2013	a_t_&_t often		H & P updated
Wed Sep 18 16:29:36 EDT 2013	a_t_&_t often	H & P updated	H & P updated
Wed Sep 18 16:29:41 EDT 2013	a_t_&_t of days		H & P updated
Wed Sep 18 16:29:44 EDT 2013	a_t_&_t of days	H & P updated	H & P updated
Wed Sep 18 16:29:48 EDT 2013	a_t_&_t of it		H & P updated
Wed Sep 18 16:29:53 EDT 2013	need a tempe		Need H&P
Wed Sep 18 16:29:57 EDT 2013	need a tempe	Need H&P	Need H&P
Wed Sep 18 16:30:01 EDT 2013	need a champion		Need H&P
Wed Sep 18 16:30:04 EDT 2013	need at&t		Need H&P
Wed Sep 18 16:30:08 EDT 2013	need at&t	Need H&P	Need H&P
Wed Sep 18 16:30:14 EDT 2013	laugh and I nothing for porterville		Labs and Diagnostic reports available
Wed Sep 18 16:30:20 EDT 2013	laugh and I not to report		Labs and Diagnostic reports available
Wed Sep 18 16:30:25 EDT 2013	laugh and I cannot afford the field		Labs and Diagnostic reports available
Wed Sep 18 16:30:30 EDT 2013	lab in diagnostic report mobile		Labs and Diagnostic reports available

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:30:35 EDT 2013	lab and I cannot afford available		Labs and Diagnostic reports available
Wed Sep 18 16:30:41 EDT 2013	implant avail		Implant(s) available
Wed Sep 18 16:30:46 EDT 2013	implant avail	Implant(s) available	Implant(s) available
Wed Sep 18 16:30:50 EDT 2013	implant avail	Implant(s) available	Implant(s) available
Wed Sep 18 16:30:53 EDT 2013	implant available		Implant(s) available
Wed Sep 18 16:30:57 EDT 2013	implant available	Implant(s) available	Implant(s) available
Wed Sep 18 16:31:02 EDT 2013	need implants	Need implants	Need implants
Wed Sep 18 16:31:06 EDT 2013	need implants	Need implants	Need implants
Wed Sep 18 16:31:09 EDT 2013	need and play		Need implants
Wed Sep 18 16:31:12 EDT 2013	need implant		Need implants
Wed Sep 18 16:31:16 EDT 2013	need them point		Need implants
Wed Sep 18 16:31:21 EDT 2013	don't available		Films available
Wed Sep 18 16:31:24 EDT 2013	jonesville		Films available
Wed Sep 18 16:31:29 EDT 2013	don't avail		Films available
Wed Sep 18 16:31:33 EDT 2013	don't avail	Films available	Films available
Wed Sep 18 16:31:36 EDT 2013	film available		Films available
Wed Sep 18 16:31:45 EDT 2013	don't not here	Films not here	Films not here
Wed Sep 18 16:31:49 EDT 2013	don't not here	Films not here	Films not here
Wed Sep 18 16:31:53 EDT 2013	dillons not here		Films not here
Wed Sep 18 16:31:59 EDT 2013	don't not here	Films not here	Films not here
Wed Sep 18 16:32:02 EDT 2013	stone not here		Films not here
Wed Sep 18 16:32:08 EDT 2013	anesthesia island complete		Anesthesia items complete
Wed Sep 18 16:32:13 EDT 2013	anesthesia items complete	Anesthesia items complete	Anesthesia items complete
Wed Sep 18 16:32:17 EDT 2013	anthony's island complete		Anesthesia items complete
Wed Sep 18 16:32:20 EDT 2013	anesthesia island complete	Anesthesia items complete	Anesthesia items complete
Wed Sep 18 16:32:24 EDT 2013	anesthesia island complete	Anesthesia items complete	Anesthesia items complete
Wed Sep 18 16:32:30 EDT 2013	need to be seen by in a season		Needs to be seen by anesthesia
Wed Sep 18 16:32:34 EDT 2013	needs to be seen by anesthesia	Needs to be seen by anesthesia	Needs to be seen by anesthesia
Wed Sep 18 16:32:39 EDT 2013	needs to be seen by anesthesia	Needs to be seen by anesthesia	Needs to be seen by anesthesia
Wed Sep 18 16:32:45 EDT 2013	need to be seen by anesthesia		Needs to be seen by anesthesia

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:32:49 EDT 2013	are incomplete		RN complete
Wed Sep 18 16:32:52 EDT 2013	are incomplete	RN complete	RN complete
Wed Sep 18 16:32:56 EDT 2013	are incomplete	RN complete	RN complete
Wed Sep 18 16:32:59 EDT 2013	r and complete		RN complete
Wed Sep 18 16:33:03 EDT 2013	r and complete	RN complete	RN complete
Wed Sep 18 16:33:07 EDT 2013	patient not ready	Patient not ready	Patient not ready
Wed Sep 18 16:33:10 EDT 2013	patient not ready	Patient not ready	Patient not ready
Wed Sep 18 16:33:13 EDT 2013	patient not ready	Patient not ready	Patient not ready
Wed Sep 18 16:33:16 EDT 2013	patient not ready	Patient not ready	Patient not ready
Wed Sep 18 16:33:19 EDT 2013	patient not ready	Patient not ready	Patient not ready
Wed Sep 18 16:33:24 EDT 2013	r_n medications live		RN medications delivered
Wed Sep 18 16:33:28 EDT 2013	r_n medication delivered		RN medications delivered
Wed Sep 18 16:33:31 EDT 2013	r_n medications delivered		RN medications delivered
Wed Sep 18 16:33:36 EDT 2013	r and medication delivered		RN medications delivered
Wed Sep 18 16:33:41 EDT 2013	r_n medication delivered	RN medications delivered	RN medications delivered
Wed Sep 18 16:33:46 EDT 2013	need to print		Need Heparin
Wed Sep 18 16:33:49 EDT 2013	need heparin	Need Heparin	Need Heparin
Wed Sep 18 16:33:52 EDT 2013	need to print	Need Heparin	Need Heparin
Wed Sep 18 16:33:55 EDT 2013	need ever		Need Heparin
Wed Sep 18 16:33:58 EDT 2013	need habra		Need Heparin

A.3 TESTING DATA

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:34:13 EDT 2013	consent attend		
Wed Sep 18 16:34:20 EDT 2013	content of pain	Consent obtained	
Wed Sep 18 16:34:26 EDT 2013	content obtain	Consent obtained	
Wed Sep 18 16:34:35 EDT 2013	content of pain	Consent obtained	
Wed Sep 18 16:34:40 EDT 2013	content of 10		
Wed Sep 18 16:34:48 EDT 2013	circle fight mark	Surgical site marked	
Wed Sep 18 16:34:53 EDT 2013	30 flight mark		
Wed Sep 18 16:34:58 EDT 2013	circle fight mark	Surgical site marked	
Wed Sep 18 16:35:03 EDT 2013	certified mark		
Wed Sep 18 16:35:07 EDT 2013	surgical fight mark		
Wed Sep 18 16:35:13 EDT 2013	need market		
Wed Sep 18 16:35:18 EDT 2013	need mark	Need marking	
Wed Sep 18 16:35:22 EDT 2013	need mark	Need marking	
Wed Sep 18 16:35:26 EDT 2013	need mark	Need marking	
Wed Sep 18 16:35:31 EDT 2013	need mark	Need marking	
Wed Sep 18 16:35:37 EDT 2013	a_t_&_t often	H & P updated	
Wed Sep 18 16:35:42 EDT 2013	a_t_&_t update		
Wed Sep 18 16:35:48 EDT 2013	a_t_&_t a bit		
Wed Sep 18 16:35:53 EDT 2013	a_t_&_t often	H & P updated	
Wed Sep 18 16:35:58 EDT 2013	a_t_&_t a bit		
Wed Sep 18 16:36:05 EDT 2013	need a tempe	Need H&P	
Wed Sep 18 16:36:09 EDT 2013	need agency		
Wed Sep 18 16:36:15 EDT 2013	need at&t	Need H&P	
Wed Sep 18 16:36:19 EDT 2013	need a 20		
Wed Sep 18 16:36:25 EDT 2013	need a t a p		
Wed Sep 18 16:36:34 EDT 2013	laugh and I cannot afford to do		
Wed Sep 18 16:36:41 EDT 2013	laugh and I cannot afford ville		
Wed Sep 18 16:36:48 EDT 2013	lassen diagnostic report available		
Wed Sep 18 16:36:55 EDT 2013	lab and I report ville		
Wed Sep 18 16:37:01 EDT 2013	laugh and I know support ville		
Wed Sep 18 16:37:08 EDT 2013	and plantsville		
Wed Sep 18 16:37:17 EDT 2013	implant ville		
Wed Sep 18 16:37:22 EDT 2013	in plainville		
Wed Sep 18 16:37:26 EDT 2013	implant avail	Implant(s) available	
Wed Sep 18 16:37:31 EDT 2013	implant avail	Implant(s) available	
Wed Sep 18 16:37:43 EDT 2013	need anything		
Wed Sep 18 16:37:48 EDT 2013	need implants	Need implants	
Wed Sep 18 16:37:53 EDT 2013	need implants	Need implants	
Wed Sep 18 16:38:00 EDT 2013	the template		

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:38:05 EDT 2013	need implant	Need implants	
Wed Sep 18 16:38:11 EDT 2013	don't avail	Films available	
Wed Sep 18 16:38:15 EDT 2013	still avail		
Wed Sep 18 16:38:20 EDT 2013	film avail		
Wed Sep 18 16:38:25 EDT 2013	don't avail	Films available	
Wed Sep 18 16:38:30 EDT 2013	hillsville		
Wed Sep 18 16:38:37 EDT 2013	don't not here	Films not here	
Wed Sep 18 16:38:44 EDT 2013	dillons not here	Films not here	
Wed Sep 18 16:38:49 EDT 2013	don't not here	Films not here	
Wed Sep 18 16:38:54 EDT 2013	don't not here	Films not here	
Wed Sep 18 16:38:58 EDT 2013	does not here		
Wed Sep 18 16:39:06 EDT 2013	anesthesia I don't sleep		
Wed Sep 18 16:39:11 EDT 2013	anesthesia islands complete		
Wed Sep 18 16:39:16 EDT 2013	anesthesia items complete	Anesthesia items complete	
Wed Sep 18 16:39:21 EDT 2013	anesthesia I don't complain		
Wed Sep 18 16:39:26 EDT 2013	anesthesia island complete	Anesthesia items complete	
Wed Sep 18 16:39:34 EDT 2013	need to be seen by anesthesia	Needs to be seen by anesthesia	
Wed Sep 18 16:39:41 EDT 2013	need to be seen by anesthesia	Needs to be seen by anesthesia	
Wed Sep 18 16:39:48 EDT 2013	need to be seen by and see		
Wed Sep 18 16:39:53 EDT 2013	needs to be seen by anesthesia	Needs to be seen by anesthesia	
Wed Sep 18 16:39:59 EDT 2013	need to be seen by anesthesia	Needs to be seen by anesthesia	
Wed Sep 18 16:40:06 EDT 2013	are incomplete	RN complete	
Wed Sep 18 16:40:11 EDT 2013	are incomplete	RN complete	
Wed Sep 18 16:40:16 EDT 2013	are incomplete	RN complete	
Wed Sep 18 16:40:20 EDT 2013	are incomplete	RN complete	
Wed Sep 18 16:40:26 EDT 2013	are incomplete	RN complete	
Wed Sep 18 16:40:31 EDT 2013	patient not ready	Patient not ready	
Wed Sep 18 16:40:36 EDT 2013	patient not ready	Patient not ready	
Wed Sep 18 16:40:40 EDT 2013	patient not ready	Patient not ready	
Wed Sep 18 16:40:44 EDT 2013	patient not ready	Patient not ready	
Wed Sep 18 16:40:49 EDT 2013	patient not ready	Patient not ready	
Wed Sep 18 16:40:55 EDT 2013	r_n medications later		
Wed Sep 18 16:41:01 EDT 2013	r and medications to look		
Wed Sep 18 16:41:07 EDT 2013	are in medication delivered		
Wed Sep 18 16:41:13 EDT 2013	r_n medication delivered	RN medications delivered	
Wed Sep 18 16:41:19 EDT 2013	r_n medication to look		

Time	Text-to-Speech Result	Translation	User Clicked-on Phrase
Wed Sep 18 16:41:25 EDT 2013	need ever	Need Heparin	
Wed Sep 18 16:41:29 EDT 2013	need ever	Need Heparin	
Wed Sep 18 16:41:35 EDT 2013	need ever	Need Heparin	
Wed Sep 18 16:41:39 EDT 2013	need ever	Need Heparin	
Wed Sep 18 16:41:43 EDT 2013	need ever	Need Heparin	

APPENDIX B

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