Mutual Context Based Word Prediction

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Declaration of Authorship

We, A.S.M. Towfique Hasan and Mubin Mohammad, declare that this thesis titled, 'Mutual Context Based Word Prediction' and the work presented in it are our own. We confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
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Abstract

Word prediction systems can reduce the number of keystrokes required to form a message. In our daily life we use lots of messengers online to communicate with friends and others. In our daily life chatting is almost inevitable. In recent years the keyboards that we use have a built in structure for predicting and suggesting our next word. These suggestions are helpful in most of the cases. There already has been lots of works done in this regard and researches are still ongoing. One of the mechanisms of next word prediction is the contextual word prediction. Context is defined as, "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." Our hypothesis is that word prediction models can be more enhanced if we use mutual context between the users as a paramater in word prediction. We also hypothesize that that mutual context based word prediction has great potential in enhancing word prediction increasing communication rate, but the amount is dependent on the accuracy of detecting the mutual context. We show that in a conversation mutual context based word predition model can do better word prediction than traditional word prediction models.

Keywords: Context, Mutual Context, Contextual Information, Local Dcitionary, Context Awareness, Word Prediction

Contents

Chapter 1

Introduction

While communcating in Internet Messengers we always use predicted words that are provided by almost all the key boards i.e. G-Board, Flesky etc. All these key boards provide us word predictions based on the words that we already used in our day to day life. They keep a log of used words and provide predictions based on the keyborad log that it creates automatically. The main reason we write less and use the prediction to help us releaase to a less amount of typing. As a result we do less typing or otherwise entering information into a computing device can be cumbersome and time consuming where each individual word must be typed in its entirety or handwritten in its entirety in the case of electronic handwriting input methods or spoken accurately in the case of speech recognition input methods. Typing information on small mobile devices can be particularly difficult due to the decreased size or form factor of the mobile device and associated keyboard[11]. Input methods have been developed that provide word prediction or word suggestions as a user types in order to reduce the number of keys that must be pressed[10]. Prior solutions often make use of static dictionaries containing language dictionaries and lists of words that the user had previously entered using the input method. While these solutions may help the user in general text input, the word that are predicted are not always in the context of the current task the user is trying to complete or the current situation the user is going through, especially the person he is having a chat with. For example, according to current data input solutions, a word prediction user interface that changes after each key press may be provided, but if a user wants to type a word i.e. a phrase, ' hey doc! i'm not feeling well, need an appointment with you" and the same person is trying to have a conversation with his boss, he would give input like, 'hi sir, how's it going?'. In both the cases the person that the first user is chatting with mostly defines the words he is going to use. Current used systems will provide te prediction after the word 'hi' is either 'doc' or 'sir' which mostly depends on the probability or the classification that was used to classify these inputs. [3] Again suppose if the user has a long chat hsitory with lots people and they are all professionally different then the addressings will never be the same. As the current prediction models don't consider any of these they are not able to predic the next words according to the user is having a chat with.

1.1 Motivation

The realization that communication between two persons depend on their correlation came to us when we were studying about natural language processing and its implementation in Human Computer Interaction. Word prediction systems can in fact speed communication rate, and that a more accurate word prediction system can raise communication rate higher than is explained by the additional accuracy of the system alone [13].

Word completion and word prediction were originally developed for individuals with physical disabilities to decrease the number of keystrokes required to type words and sentences (MacArthur,1996). Word completion provides the user with one or more predictive suggestions after the user has typed the initial letters of a word (Hunnicutt & Carlberger, 2001). Word prediction is a feature of some word completion programs that, after a selection has been made for the current word , attempts to predict the next word in the sentence[14].

We found in our research that most word prediction tools are based on single context of the user and that too even totally dependent on the classification and probability. In some of the researches we also found context based word prediction where they stated that predictive text systems in place use the frequency-based disambiguation method and predict the most commonly used word above other possible words[15]. Classification and Probability are two very powerful tools to allow us predict the next word, there is no doubt on that. So the problem with not getting more accurate prediction lies where we are searching for the next word. We hypothesize that communication is based on the mutual environment of participants. We found from our studies that most of the work done in prediction is based on frequency of used words and by creating a local dictionary for a particular user. Considering the relationship between the persons participating in an IM chat can provide more accuracy in word prediction. We found that current word prediction models fail in this regard. So we introduce a new term in this regard 'Mutual Context'. Mutual context is baically the mutualization of the contexts' of both users who are having a chat.It can be useful in a sense that it is a new scheme that considers the correlation between users and then predicts the next words, while the existing works predict on a singular context and are mostly dependent on frequency of words, their classification and the probability of one word after another. Here we would like to state that mutual context has a new scope to determine the context in a better manner and help us predict the next word in a better accurate manner.

1.2 Context

Context is any information that can be used to characterize the situation of an entity[1]. Here entity is a new term. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves[1]. Context is the perspective that we talk to each other about. Basically it is the subject that we talk about or the topic that we chat with each other about. When we have a conversation with someone, independent of the platform, may be in face to face or in internet messenger, we always talk on a particular topic. This is the context. Not necessarily it is always the same with the same person, we talk with different persons in a vast field, with the same person we may have lots of conversations with lots of types. That changes the context every time we change the topic. A question may arrive if the context is not fixed then how can the mutual context cope up with the change of context. We want to set the persons that we are having a conversation with in a differentiated order, not the topic. We define the context as an entity or topic or simply as it is, but the Mutual Context in a new way.

1.3 Mutual Context

Mutual informations are very useful to recognize a persons current state and scenario[16]. We define mutual context of two entities participating in an interaction by their correlation of individual context with one another. We divided the correlation factors into physical and psychological cues. The physical and psychological cues are mostly depend on the participants' nature and their correlation with each another.
The Mutual Context scenario can be expained like, suppose we talk about a lot of things, and among all those we consider two people are talking together, they can be talking about their context and also in their own way they will talk. For example lets say there are several contexts to talk about and they are in a set or collection

$$C_i = \{c_1, c_2, ...c_n\}$$

Here $\mathrm{C_i}$ can be any context from user_i. Any context means any contextual value. We enumerate the contexts in a fashion so that we can store that in our database in a numeric order and then retrieve them more efficiently. So $\mathrm{C_i}$ basically means the contextual value of one side. We consider the context as a set and the mutual context is a pair of collection of them. So the collection goes like the following for the Mutual Context

$$M^i_{ij} = \{C^p_i, C^p_j\} \tag{1.1}$$

Here the

$$M_{ij}^{i}$$

has a significance as, the 'M' stands for the Mutual Context identity, i is the first user or the user side who is considered to start the conversation or simply who is having conversation with User_2 and j stands for the context of User_2.

The difference between traditional context based word prediction and mutual context is that here the prediction is generated by calculating the correlation of two individuals. These correlations are defined by some psychological and physiological cues.

When the context is derived then we share the context from one user to the other. In this process the context gets mutualized. For this mutualization we do the following:

- Derive context from both the users
- Send context information from one user to the other.
- Generate the mutual context.
- Check if the derived contexts match with any other existing one.
- If there is a match we use that particular context match, we use the existing table from the datavase to predict the next words.
- Otherwise a new table is generated in the database for saving the input words based on the new mutual context.

Chapter 2

Current Scenario

In android OS the most used keyboard and word prediction mechanism used is the Google Gboard keyboard where Google already implemented a prediction model that predicts the next word based on context. They developed a software application which utilizes words contained in an application document to provide context-based word prediction in the same or a related document. The Software application creates an application defined data source and populates the data source with field of classification search for words occurring in a document. When the same or a related document is edited via an input method, for example, typing, speech recognition, electronic handwriting, etc. A prediction engine presents candidate words from the application defined data source that match current text input, and the user may choose from the presented candidate words for automatic population into the document being edited. Information from the application defined data source mey be transferred between computing devices, for example, between a mobile computing device and a desktop (non-mobile) computing device [17]. For a small overview and a glance at the current prediction system we show the following figure where a user is having a conversation with his doctor. The user types 'hey', the prediction doesn't even predict the next word near enough to make a guess. Again after exchanging a few sentences when he types 'having some' the next predicted word makes sense this time, but again nothing almost close to the actual word. It is admitted that in some cases the next word is not predictable by the system. But in most cases the words are predictable. The existing systems fail in this regard, suppose if the user in the first case got the perfect prediction, or simply the prediction he got is 'doc', what if the next person he will have a conversation is not a doctor. The current mechanisms will not be able differentiate between the two situations or circumstances. In the following figures the situation is shown in actual conversation with the doctor, that we stated above.

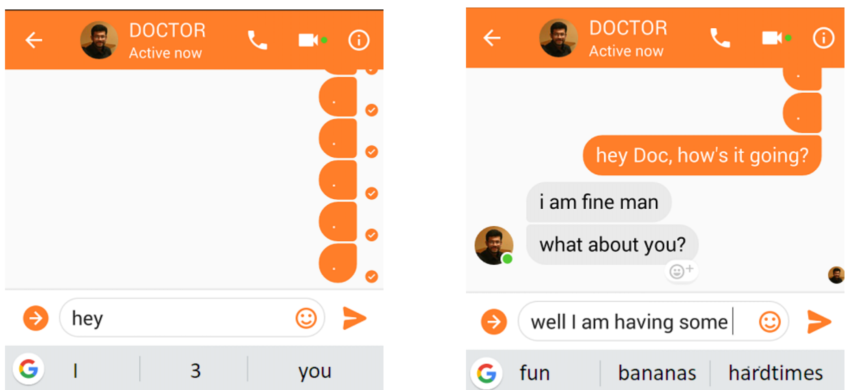

Figure 2.1: Current Scenario of Word Prediction

Chapter 3

Related Works

There have been lots of works done in this regard for the past decade. According to our study we found the following researches that are similar:

3.1 Automatic derivation of context description from sensor data and correlation

In this particular research we found a process to characterize contexts. They correlated raw contextual information with user activities to determine accurate context descriptions. In a case study they showed that different statistical methods can be used to determine correlations, and analyze their applicability [2]. In order to implement contextawareness, one key challenge is the inference of contexts based on a variety of information sources. Mobile devices, for instance, are equipped with a variety of physical sensors (e.g., light intensity, acceleration, WiFi connectivity, cell tower information, geolocation) and information can also be retrieved from non-physical sources, e.g., email, calendar or the address book.

3.2 Classification Based Approach

In this paper they showed an approach to word prediction that is based on learning a representation for each word as a function of words and linguistics predicates in its context. In order to learn good word representations it is necessary to use an expressive representation of the context. They said that the number of words "competing" for each prediction is large, there is a need to "focus the attention" on a smaller subset of these. They exhibited the contribution of a "focus of attention" mechanism to the performance of the word predictor. They also described a large scale experimental study in which the approach they presented was shown to yield significant improvements in word prediction tasks [3].

3.3 Domain specific word prediction for augmentative communication

As many augmentative communication systems employ word prediction to help minimize the number of user actions needed to construct messages and statistical prediction techniques rely upon a database (model) of word frequencies and inter-word correlations derived from a large text corpus. Again one potential means to improve prediction is to create a set of models derived from domain-specific corpora, dynamically switching to the model most appropriate for the current conversation. By using telephone transcripts to generate prediction models for 20 different topic domains, they observed a clear benefit to including domain-specific models in an overall prediction scheme. The text used to train a word prediction system should match as closely as possible the kind of messages produced by the augmented communicator[4]. Although core vocabulary stays fairly constant, fringe vocabulary may change substantially through the course of a day as different topics and settings are encountered [4].

3.4 Context Aware Mobile Computing REsearches

In this research where the researchers focused on context awareness based computing they found that context-aware computing is a mobile computing paradigm. Applications can discover and take advantage of contextual information [5]. They also found that context-aware computing:

- Brings us one step closer to the Pervasive Computing vision
- Enables computer systems to anticipate users' needs and to act in advance
- An emerging paradigm to free everyday users from manually configuring and instructing computer systems

3.5 A Learning-Classification Based Approach for Word Prediction

In this research they stated the problem as an important NLP problem. They wanted to predict the correct word in a given context. The paper shows word completion utilities, predictive text entry systems, writing aids, and language translation that are some of common word prediction applications. This paper presents a new word prediction approach based on context features and machine learning. The proposed method casts the problem as a learning-classification task by training word predictors with highly discriminating features selected by various feature selection techniques. The contribution of this work lies in the new way of presenting this problem, and the unique combination of a top performer in machine learning, svm, with various feature selection techniques MI, X^2 and more. The method was implemented and evaluated using several datasets [9].

Chapter 4

Proposed Approach

We propose a system where we define the mutual context as the mutual subject between the two persons in a communication. In relation to the above stated example we want to state a scenario where the following predictions will be made. With different users the predictions will be different. In the following diagram such scenario is explained.

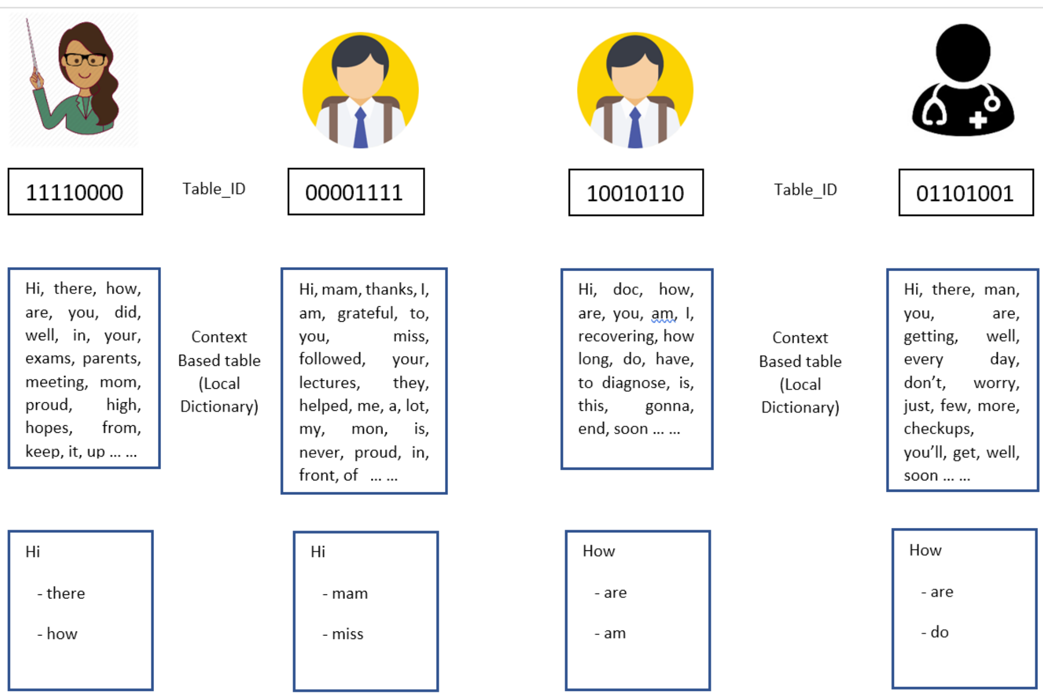

Figure 4.1: Proposed Word Prediction

We hypothesize that the factors that affect a mutual context are basically some psychological and physical cues. Here we have stated the cues that affect a conversation in brief. But for our proposed system we use the one that affect the system the most. The overall cues are:

4.1 Physical Attributes

In the physical attributes we consider the data that we collect from each of the users. They are described in the following. The factors that we state are hypothetically impactful on the context of a discussion. As we found results in the end, so we can say that these are the factors that count most in a conversation.

- **Sensor data:**

  The GPS and indoor or outdoor condition has a good impact on detecting the mood of an operator. Indoor and outdoor conditions basically select a persons mood. This sensor data can also help detect a person's mood and there is already research works done in this regard.

- **GPS:**

  GPS allows us to know the position of the user which can be used to find out the current location providing the knowledge to figure out if the user is in his workplace or at home, (preferably GPS will provide two locations, home and workplace, for simpler calculation). When the user is at home he will most probably use the words that are used for communicating with his family. There is a catch, if he is talking with his colleague then the context will most probably be based on their work status or something related to their work. Again, when the user will be at office he might talk to his wife or simply communicate to his home. In both these cases the context will have to be derived by the mutual relationship between the two users. For instance, suppose one is at home and the other person he is communicating is at office, then their communication will most probably be about their work. The GPS value from both the devices will allow to know the context as work.

- **Outdoor / Indoor:**

  In the outdoor and indoor communication, we consider outdoor for outside home and not office, and indoor is taken as home. Therefore, these values will help the context to depend on 3 cases. Home, work place and outdoor.

- **Weather:**

  Weather basically helps the context derivation to find the context related to the weather. For instance, the weather helps to determine that if the communication is about the weather or what ever the users are talking about depends on the weather. As it will not have that much of an impact on the context the impact is at most 5% on the context(estimated).

- **Temperature:**

  The temperature also changes the mood of a user. Most of the conversation between users depend on the users' mood. But though not that much of mood depend on the temperature. So we consider 8% to 10% dependency on the temperature.

4.2 Psychological Attributes

There are many psychological attributes that make up the conversation, for example the most important psychological fact is the emotion. So in our model we put more emphasis on the emotion detection part. We will use sensor data and user input section or user text to find out the emotion of the user. These along with the other factors are described below:

- **Emotion:**

  Emotion recognition technology plays the essential role of enhancement in Human-

Computer Interaction (HCI) [12]. The initial step of analyzing an emotional scenario is to define the emotions relevant to the application scenario. Six (basic) emotions from Ekman's research [6] happiness, sadness, anger, fear, surprise and disgust.

It is found that Texts from IM are divided into Affective words. We employ WordNet-Affect Database [7] of ITS-irst (The Center for Scientific and Technological Research of Autonomous Province of Trento, Italy) with WordNet 1.6 [4] to first find synonyms sets of affective words. We select the emotion "seed" words according to these six emotion categories, i.e., "happy", "sad", "angry", "surprise", "fear", "disgusted", then use key words recognition and synonyms to choose related words from WordNet based on the affective words set. The emotional weight of these words is given based on their sense that represents a meaning of a word in WordNet database. Normally, a word has several meanings, but not all the meanings of it are emotional. For example, the verb "beat" has 5 emotional senses among 23 senses in WordNet. Emotion detection[8].

- **Social Status:**

  User's social status has an impact on his messages. We would like to propose a model where this status can be used as a context for WP. For example- A diplomat or a politician will always use words which doesn't fall into general WP. We want to use their social status for predicting the words.

- **Profession:**

  For different professions their word predictions should be different. We propose a model where mutual profession between IM users will be considered as context variables.

- **Relationship Status:**

  Relationship status among users places a huge impact on their conversation. We want to use this information as context variable and predict words based on their relation.

- **Recent events:**

  Recent events play a huge impact when messaging. We want to use these recent events as context variables for WP.

4.3 Proposed System Architecture

At first we need to extract the context from the users where we take the inputs from the users about four basic mutual context attributes. We defined the mutual context into some psychological and physical cues, where we focus on two psychological and two physical attributes which have the most impact in a mutual condition. We focus on the GPS and the Timestamp as a physical cue or attribute and the Emotion and the professional relation, profession and relational status (referred as profession and relational status). We enumerate these four in the backend and take input from the user as prompt input by keyboard entry. When the user enters the value then they are enumerated in the background and saved in the database creating a Table_ID. Before generating the Table_ID we take the information from the other end as well, this sharing is what makes it a mutual context. After sharing the context attribute values a concatenated Table_ID is generated and this Table_ID is unique in a sense if the same type of Table_ID is again generated then the context is same, otherwise the context is different. This tableID is what makes it unique in contribution. The total flow of the whole system is defined step by step in the following diagram with a description to follow:

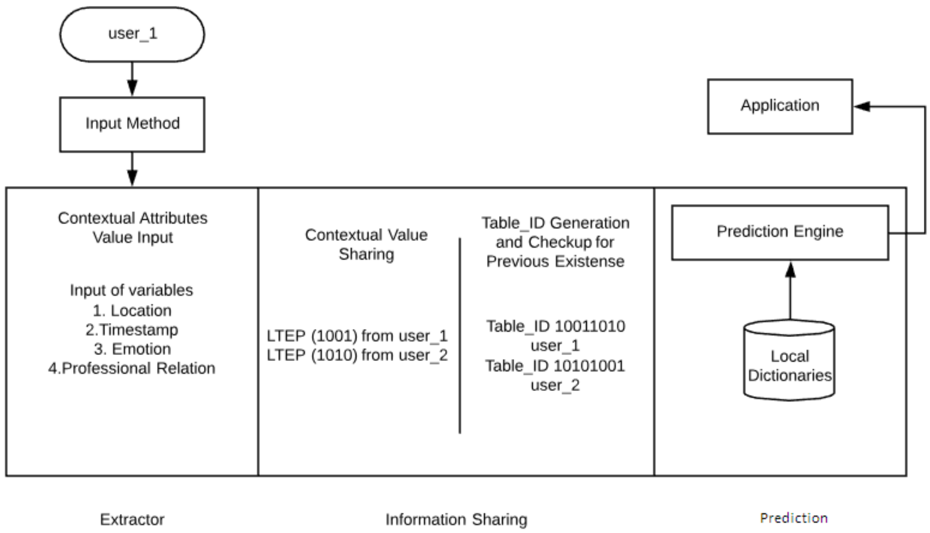

Figure 4.2: Proposed Model

4.3.1 Proposed Data Flow

We breakdown the whole process into 3 blocks. The blocks are:

- Context Extraction
- Information Sharing
- Predcition

The flow of these blocks are shown by a block diagram below. The block diagram reflect the flow of data in our proposed system. It basically shows step by step process in both the sides of the conversation. When users start chatting their context features are collected first. As context features we take four inputs location, timestamp, emotion, and professional_relationship. For our context extraction we first take the inputs from users in boths sides. We take the inputs as prompts and create a Table_ID after taking the inputs from the other user as well.

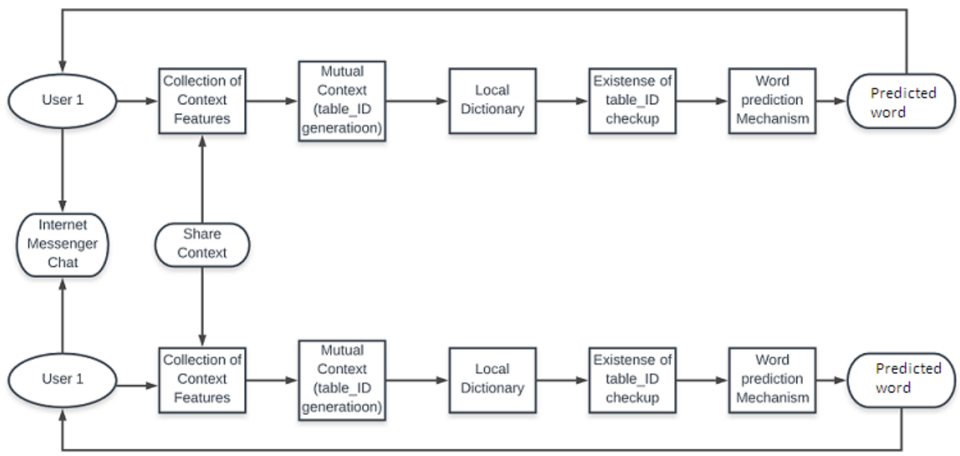

Figure 4.3: Proposed Approach Flow Diagram

4.3.2 Local Dicationary

Again for the local dictionary concept we divide the total dictionary into different local dictionaries. Where these local dictionaries are basically tables. These tables sum upto the total dictionary. These parts are basically the parts that are underneath each context (stated as Table_ID). Here these context's are the conditions and situations that we are in and the that is what the conversation is about. The local dictionary concept goes like the following, we consider the tables as Contex1, Context2, etc. All the contexts together make up the total dictionary.

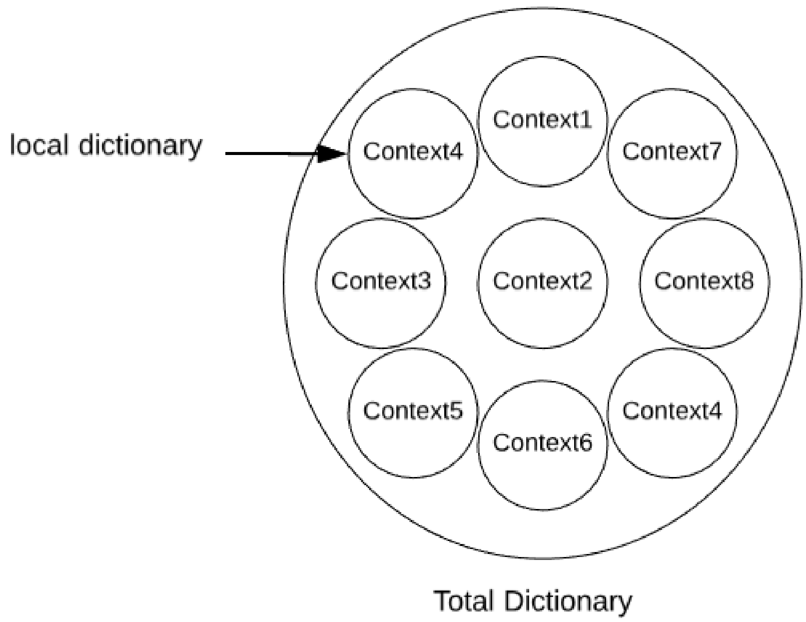

Figure 4.4: Proposed Model For Local Dictionary

4.3.3 TableID Generation

For generating the value of the context or simply generating the context number we follow or use a numerical approach. The approach basically enumerates all the possible contexts coming up. And in future if the same situation arrives, then the database is mapped to the previous saved or created network. The context value generation mechanism goes like the following:

There will be multiple tables for defining the contexts. The contexts are defined as the values of timeStamp, GPS (Location), Emotion, ProfessionalRelation. The value of these will basically derive the context number. We derive a context number as follows:

Context = {T, L, E, P}

Here T is Timestamp, G is the GPS, E stands for Emotion and P stands for Professional Relationship. We enumerate these values as the following:

TimeStamp = {Day (1), Night (2) }

Location = {Loc1 (1), Loc2 (2), Loc3 (3)}

Emotion = {Happy (1), Sad(2), Angry (3)}

Professional_Relation = {Relation1 (1), Relation2 (2), Relation3 (3)}

After enumerating we generate the ContextID as follows:

$$C\_ID = T * 1000 + L * 100 + E * 10 + P \tag{4.1}$$

For example, if the context is

$$T = \{Day\}, L = \{Loc1\}, E = \{Happy\}, P = \{Relation1\} \tag{4.2}$$

For this type of context, the Context_Id will be:

$$C\_ID = 1 * 1000 + 1 * 100 + 1 * 10 + 1 \tag{4.3}$$

And if the context is

$$T = \{Night\}, L = \{Loc3\}, E = \{Angry\}, P = \{Relation2\} \tag{4.4}$$

The corresponding Context_ID will be

$$C\_ID = 2 * 1000 + 3 * 100 + 3 * 10 + 3 = 2333 \tag{4.5}$$

In this way there will be always unique generation of contextID based on the values of the context status. And the database will have one table containing all the information about the contextIDs of the whole database and there will be other tables with the names of the contextIDs to track them. This way all the words matching to an existing table name (existing contextID) will simply be retrieved and the new ones will be created and will store new words and retrieve accordingly.

The database will hold a table for keeping track of all the generated tables. The previously generated tables are just saved in a table. The schema diagram for the database goes like the following:

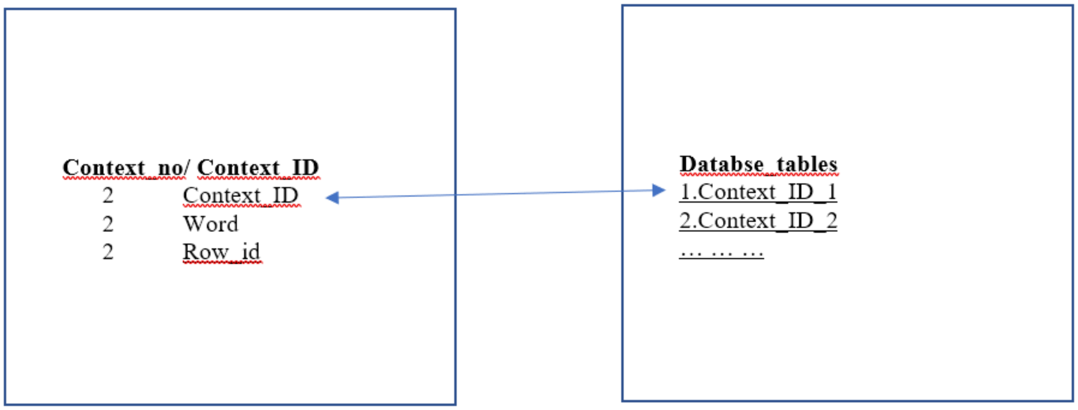

Figure 4.5: Database Schema

One table will hold all the values of the context's for figuring out if there is any existing table, then the dictionary for the conversation will be the existing table. So as a whole the Context_ID generation criteria for one user will be as follows:

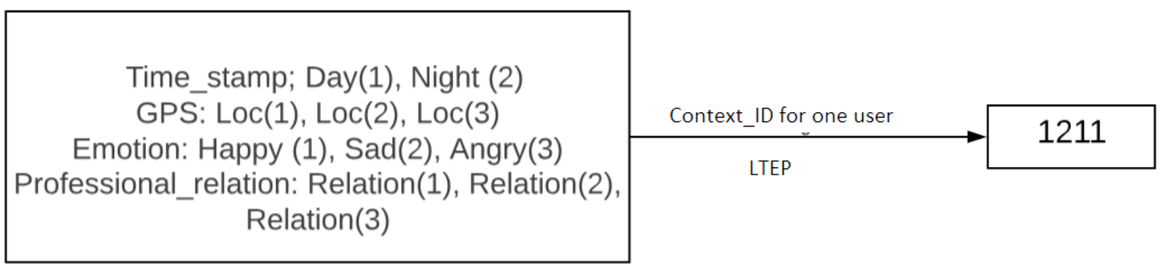

Figure 4.6: TableID Generation Mechanism

After generating the context value, we need to share one Context_ID of a singe user to the other for generating the mutualized Context_ID, sharing the table id across the network to the other person who is on the other side of the IM chat. Considering this mutualization we generate the mutual context and the use a particular table to save and retrieve used words of a user. The mutualization process we stated before was a small novice introductory one, the actual mutualization is described below with a image of the concept and the sharing criteria as well. In the table mapping part we map the table by their Table_ID, we just look through the table that holds all the Table_IDs, If there is a match, then we go to that table, all the tables that are over there are already generated ones. So there wont be any chance of duplicity. So formally the steps are:

- When the Context_ID is generated this new context's local dictionary will save the newly used words under this particular Table_ID.
- When the new context arrives, or simply, a situation arrives we just need to find out the context and exchange to see if the new situation is already there or not.
- If the situation (context) is already there then there is no need to create a new dictionary, just simply use it.
- Otherwise create a new dictionary (a new table)!

A diagram showing this Table_ID match is showed below:

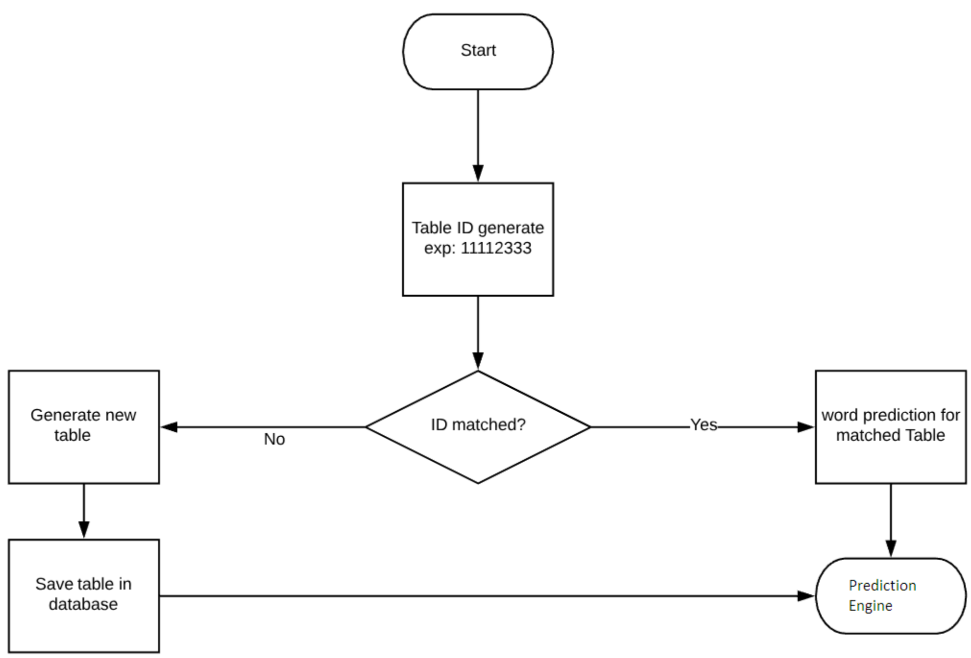

Figure 4.7: Existing TableID checkup

There can be a question about the pre-existing words and their suggestions. We are not in a situation to keep any words in the dictionary from previous situation, we are more likely to give the users their own freedom to save words from their own. Now here arrives another question, what about the general English Dictionary? We are keeping the general Dictionary apart, it will be there for corrections and showing mistakes, for any kind of spell-check as well. Basically, we are saying that if a context is already no need to use another one or create another one, just use a previously generated one. As a result, for native English users that won't be of too much help other than using some short words and differentiating words in the basis of professional relationship.

Chapter 5

Results and Evaluation

For generating results we developed a simple simulation tool based on the perspectives that we mentioned earlier. Where the main fact lies is the word choosing section. So did not apply any perful word prediction mechanism. The results were good enough to bring competition with any existing prediction based key board. So we first set the enumerated parameters as simple user inputs and then start typing. When the context variables are given the context is derived. When the context is derived we can easily predict words for the conversation. The suggested words are derived based on their ranking. The ranking of these words are done by the following criteria-

- Existing or built in dictionary words' frequency.
- Local dictionary words frequency.
- In current mutual context the probability of a word from the list from local dictionary to be typed next.

As we would use the frequency mechanism for word prediction. Which gives a good enough accuracy in a small scale conversation. We deveopled the simulation program which follows the criteria that we stated above to save and predict words. Following is a snippet of the results that we achieved.

```
USER 1:
Time: 1
Location: 0
emotion: 0
Professional relation: 0
USER 2:
Time : 1
Location: 0
emotion: 0
Professional relation: 0
Start typing words:
hi doc
hows it going
long since we had a conversation
hi
predicted word: doc   frequency: 1
long
predicted word: since   frequency: 1
recently I am having a headache. Dont know whats wrong
```

Figure 5.1: Simulation of a scenario

As we stated earlier that we don't keep any initial words in our dictionary so when we give the ipnuts of the context variables. We set the values of our defined values for User_1 as

Time = 1 Location = 0 Emotion = 0 and Professional Relation = 0

And for User_2 we set

Time = 1 Location = 0 Emotion = 0 and Professional Relation = 1

Now we start typing a conversation. As long as there is no repition of a word there is no prediction as the dictionary is total empty. Again when a same word input is encountered we find a prediction. Here when we encounter the same word 'hi' second time the model gives us a predicion 'doc'. Basically the scenario is a conversation between a doctor and a patient. So when again the word 'hi' is given as input the prediction is 'doc' as like the previous time.

Now lets consider another situation when we give the same input of the Contex variables and evaluate the output. In the following figure the same input of the context variables is given for the user1 and user2.

When we give the same input 'hi' as previous, normally the same prediction should be given according to the proposed approach. And the predicted word is 'doc' and that's what was expected. Then we give another input 'hows' the next predicted word is 'it' and the prediction from our approach is also same. Then we give another input the previously predicted one 'it' the next prediction is 'going' and for this case the next predicted word was the same. Some scenario can be there when we will not obviously use the same words one after another but the proposed approach is not able to predict such cases, so basically expecting a prediction in this sort of scenario is not viable.

```
#
USER 1:
Time: 1
Location: 0
emotion: 0
Professional relation: 0
USER 2:
Time : 1
Location: 0
emotion: 0
Professional relation: 0
Start typing words:
hi
predicted word: doc   frequency: 2
hows
predicted word: it   frequency: 2
it
predicted word: going   frequency: 2
recently
predicted word: I   frequency: 2
```

Figure 5.2: Simulation of a scenario

Now we consider a scenario, the main focus or contribution of the proposed approach, what if we have a conversation with a different person and type some same words but the sentences of the conversation are not totally the same. Such a scenario is stated below in a snippet.

In this scenario user1 is the same person from the previous conversation but the user2 is a teacher not doctor. Obviously the conversation between a doctor and a teacher will not be the same with the same person. Here the main difference is the contextual value. When the contextual values are different (the context variables values are different) the dictionary is located to a different table resulting from a new context.The context is different and as there was no previous conversation in this context there will be no

```
USER 1:
Time: 0
Location: 1
emotion: 1
Professional relation: 1
USER 2:
Time : 0
Location: 1
emotion: 1
Professional relation: 1
Start typing words:
hi
miss
how are you
i didnt understand some part of todays lecture
can you help me
hi
predicted word: miss   frequency: 1
```

Figure 5.3: Simulation of a scenario

predictions from the beginning. So we first enter a few lines to save some words to the local dictionary. The conversations starts with 'hi miss, how are you' and then we input 'hi' again, here the predicted word should be 'miss' as we gave input earlier in this context. And our developed simulation according to our propsed approach predicts the same. Which is the main focus of our proposal and it has been achieved!

5.1 Evaluation by Performance

Evaluation of word prediction systems is a tough one. And another problem is there is no benchmark data to compare to. The existing benchmarks are basically there to run an algorithm and check its accuracy. But the main problem with this kind of checkup is these benchmarks are focused on random data that is no part of communication between two users in an Internet Messenger Chat. So typical evaluation schemes are not viable in this case. What we can do is check the accuracy by implementing the proposed approach in an android keyboard and some users to use the keyboard and find out his satisfaction in relative to the previously used keyboard. Our developed simulation scheme was run for checking the satisfaction and then the results were tremendous in a small case scenario. The users were five students who used the same input for the google keyboard and in our simulation and the simulation was able to predict more accurate in percentage reaching over 80%. The table showing the number of accurtae predictions are given below.

The simulation was based on a very simple implementation of mixed version of fre-

User_ID	No. of Words Used for Dataset	Accurate Words Predicted by G-Board	Correct Prediction by Simulation
User_1	120	67	82
User_2	167	83	117
User_3	85	56	66
User_4	185	114	138
User_5	56	35	44

quency and probabilty. The results were tremendous. But the result of the actual implementation in any android keyboard would have given the best evaluation. For the results above the contexts were user given inputs. The parameter scenarion for giving inputs to the contextual information is as follows: Context = {T, L, E, P}

Here T is Timestamp, G is the GPS, E stands for Emotion and P stands for Professional Relationship. We enumerate these values as the following:

TimeStamp = {Day (1), Night (2) }

Location = {Loc1 (1), Loc2 (2), Loc3 (3)}

Emotion = {Happy (1), Sad(2), Angry (3)}

Professional_Relation = {Relation1 (1), Relation2 (2), Relation3 (3)}

While considering these values for User_1's perspective, his contextual value was 2111 and for the other user, User_2 the contextual value was 2121. So, the mutual context for our User_1 is 21112121. Similarly for User_2 that was 21212111. And for User_3 it was 11111211, for User_4 it was 12111111. User_5 had conversation with User_1 where User_5's contextual value was 1322 and his mutual context while in conversation with USer_1 was 13222112. That is how the experiment was set up and we achieved the above mentioned result.

5.2 Evaluation by User Study

This is another evaluation technique, where we take the same users form the previous evaluationa and give them some options to clarify their satisfaction. The options they were provided are, satisfied, unsatisfied, both are same or simply same as GBoard some what satisfied or kinda satisfied. We take the satisfation because we need to check if the users are satisfied with the performance of the keyboard. We developed a prototype based on an existing keyboard that was given to the previous five users and they replied as in terms of the satisfaction in respect to the existing keyboard of Google. Their opinions are given in the following table:

User_ID	Review of G-Board	Review of the provided keyboard
User_1	satisfied	better than G-Board
User_2	not satisfied	kinda satisfied
User_3	satisfied	same as G-Board
User_4	satisfied	better than G-board
User_5	satisfied	kinda satisfied

Chapter 6

Conclusion and Future Works

We are highly motivated to see that our proposed approach provides the exact type of output that we proposed. So we should implement it in full flex. For full flex output we will implement the proposed approach in IM applications. After the implementation we should check how satisfiable the new keyboard is to the users. After checking the satisfaction level of the users we have to find out the accuracy by checking the number of words correctly predicted by the proposed approach. Then we can go for publishing the keyboard in app stores. As a final touch we can add emoji suggestions and gif suggestions for even better user experience.

The Mutual Context Based Word Prediction system should performs better than the traditional frequency based method. The context that traditional word predictions use can do better with the mutual context parameters. Context awareness is a key factor for new applications in the area of ubiquitous computing. We want to develop a interaction model between IM users based on our mutual context concept. We believe that our model will be more accurate in helping the users for better word prediction. Our interaction model should support any platform. We believe that our interaction method will give is better accuracy and speed. It should be more faster and comfortable to use as the dictionary that will be used to predict is narrowed through our concept. It should take away the human cognition load and enable us to choose words more freely according to our own choice in particular situations.

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