CSCM10 Project Specification: Implementing Vague and Sarcastic Language Recognition for a Python Based Chatbot

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Abstract—This specification will outline the aims and motivations of this project, background research, and a multiphase plan to achieve this projects goals. The goals of which include implementing a model for sarcasm and vague language in a python based chatbot. This chatbot will use machine learning techniques such as convolutional neural networks to identify instances of sarcasm and vague language. This document will also outline the potential risks and issues within this project as well as ways of reducing the probability of these issues occurring.

1 INTRODUCTION

Interaction between us humans and computers has never been as fluent as the interaction we have between ourselves, we are able to convey a large amount of information with the many tools we have at our disposal, including tone, gestures and an understanding of context. Computer programs do not have the same innate luxuries, often there are specific commands and messages programmed into the system with specific responses and actions as a reply. This, along with the frequent lack of ability to read the aforementioned tools us humans use, leads to slow and inefficient communication with the machines we use on a daily basis (and arguably rely on). The area just briefly outlined here is the area of Human-Computer Interaction (HCI), in particular, we have touched upon some of the problems faced when improving interaction between humans and agents. These are programs that carry out jobs for the user, much like a virtual assistant and in recent years often incorporate human like qualities such as speech. These jobs are casually requested in day to day life hence a good flow for the interaction is highly valued.

So if these are some of the problems in Human-Agent Interaction (HAI), then what is the solution? Natural language processing (NLP) is the area of computer science tasked with understanding and decoding natural language, the informal and fluent communication that we use when talking to other humans. This type of language is able to impart quick and efficient sentiments, but only to something that can read the subtleties behind it. Allowing a program, something that is likely faster with internet searches, computations and calculations than a user, to understand the users will without the need for rigorous syntax, but rather casual everyday language, would massively improve the experience and flow of the interaction. If done correctly, it may even improve the result.

So why is the improvement of conversational agent interaction important enough for a dedicated project, such as the one this document will outline? The simple answer is the sheer range of applications both in industry, hospitals [1] and most generally, the everyday lives of the ever increasing number of users across the world. The most recognisable modern form of these agents is the Intelligent Personal Assistant (IPA), these may be programs on smartphones such as siri, or as a dedicated agent device, such as smart speakers (e.g. Amazon Alexa and Google Home). And with the usage and interest of IPAs increasing at a rapid rate with the market for IPA technology being predicted to exceed $9 billion by 2023 [2], understanding NLP is more relevant than ever.

The project that we will outline here will aim to improve the ideas behind NLP by implementing a strong natural language model, including the analysis of vague language (VL) and sarcasm. If possible we will implement other such natural language components that we may find when creating our natural language model. Of course the overall aim will be to improve the flow and quality of HAI, thus this project will examine and implement other properties of conversational language where time constraints will allow. Currently, the inclusion of a conversational log that the program uses to recall contextual details is one such possible extra system. Secondly this project will aim to showcase such improvements with a basic chatbot program, the level of sophistication will revolve around the time constraints of this project, but the program should be able to understand and respond with language exhibiting natural language properties. The final aim of this project will be to test the value of including such abilities in an agent with a brief questionnaire about the performance of the chatbot.

By the end of this project, we should have the improvements needed to advance HAI, improvements that could aid the efficiency and efficacy of tools in industry, the medical scene, and for the everyday user, hopefully making the world a productive place.

2 Background Research

Before we begin to outline the plan for this project we will need to understand the current status of the field of NLP, in this section we will as such, firstly reviewing the literature, then the current tools available to us and the techniques typically used within NLP.

2.1 What Is Natural Language?

The first step is to investigate the concept of natural language and some of the properties/aspects included within it. The preliminary report for this project looked specifically at the area of VL, which was shown to be an important and useful aspect of natural language. The reader is advised to consult the CSCM10 report linked with this project for the full discussion and development of a VL model. Here we will only focus on the highlights from the research done in that report, hopefully limiting repetition, and leaving more room for other aspects of natural language.

2.1.1 Pragmatic Competence: The Case of Hedging, B. Fraser, 2010

Fraser provides one of the major sources used to build a model for VL in the linked report. In this book he speaks of the ability of pragmatic competence, which he defines as "the ability to communicate your intended message with all its nuances in any socio-cultural context and to interpret the message of your interlocutor as it was intended." [3]. This is the skill we wish to implement in our agent as Fraser goes on to state it importance in recognising hedging (synonymously VL). Specifically he outlines three core classifications of hedging, those being propositional and speech act hedging, and reinforcement. The latter being eventually classified as being, in essence, a negative form of hedging, but equally valuable when creating our model. The first two categories however are the most essential and fundamental forms of hedging. The first true case here is propositional hedging, this is where the semantic meaning of a phrase is purposely weakened such that only the gist of the sentiment remains, and although this may sound like a detriment it actually raises the efficiency of a phrase. This is due to it being employed in situations where only the gist is required or to imply quick hidden meanings. Fraser highlights this with insertable words and phrases that add to the fuzziness of a phrase, e.g. "*hes **sort of** nice*" or "*there are **around** 20 birds*". Speech-act hedging on the other hand is somewhat more subtle, Fraser describes it as signalling a lack of commitment to the full force of the speech act being conveyed, giving the example "*Come over here, **can you**?*". Here, although it is phrased like a question, it conveys a request that is clearly defined. In a way it is the opposite of propositional hedging in that it is used to deliver a well defined pragmatic meaning through its use of vagueness rather than the gist of the sentiment. This ultimately leads it to be the more complex form of the two.

Frasers investigation into VL yields a strong linguistic model for the rules of multiple categories of hedging, including discussions on vocalizations and their role in hedging. In fact Fraser provides a deep enough dive to be the major source on this particular section of natural language for the project.

2.1.2 Sarcasm, Pretence and The Semantics/Pragmatics Distinction, E. Camp

Now we briefly look at a source for the subject of sarcasm, a significant component of natural language. This will hopefully help us later when attempting to implement sarcasm. Camp delivers a valuable discussion on the nature of the subject by evaluating the common definition of sarcasm, that being that it is the case of a speaker meaning the opposite of what they say, and develops it further. Camp looks into typical Gricean theory, which states that that in speaking sarcastically, a speaker exploits a mutually shared assumption that he could not plausibly have meant what he said [4][5]. Immediately this adds an element logical evaluation to the recognition of sarcasm, where the evaluation of how plausible the raw semantic sentiment is reveals the existence of sarcasm. Joshi et al expands on this idea, describing how one may evaluate how similar two sides of a comparative simile are, giving the example of "*A women needs a man like a fish needs a bicycle*"[6]. The components of the phrase can be analysed using word vector similarity scores, revealing (through its lack of similarity) that the chance is, a fish does not need a bicycle, hence we may now conclude that the sentiment behind the first relation was a sarcastic one. With a better understanding of the theory of sarcasm we can begin to compile a robust model for it, Camp creates her own model by outlining five core types of sarcasm:

2.1.2.1 ***Sarcasm and Verbal Irony***: Firstly Camp looks into the relationship between sarcasm and verbal irony, particularly where they overlap. She states the best characterization of the broad genus of verbal irony derives from Kumon-Nakamura et als (1995) allusional pretense theory [7]. Their view consists of two claims, firstly, ironic utterances are allusive, in the sense of "call[ing] the listeners attention to some expectation that has been violated in some way"; where this violation of expectation itself entails "a discrepancy between what is expected (what should be) and what actually is". Typically, a speaker draws attention to this discrepancy in order to communicate a negative evaluation of the actual circumstances; but as Kumon-Nakamura et al note, the expressed attitude may also be positive. Secondly, ironic utterances involve pretense, in the sense that the speech act is presented as not being straightforwardly genuine or sincere [5].

2.1.2.2 ***Propositional Sarcasm***: Camp describes how the most straightforward cases of sarcasm are those in which the sarcasms scope is directed toward some proposition to which a sincere utterance would have committed the speaker. Camp goes on to say that this proposition evokes a situation at one extreme of an evaluative scale, typically the positive end, and by pretending to assert this proposition, the user implicates the contrary. An example of this form: "James must be a real hit with the ladies".

2.1.2.3 ***Lexical Sarcasm***: This form of sarcasm is described to be a more extreme version of propositional sarcasm through having a tighter connection to an evoked evaluative scale. Where propositional sarcasm may be pragmatically evoked, lexical sarcasm is evoked through the inclusion of the extreme end of a conventionally associated scale, again often being positive in nature, e.g. "genius" and "brilliant".

2.1.2.4 ***Like-prefixed Sarcasm***: As the name suggest, this form of sarcasm occurs when the phrase begins with the term "like" or even "as if", Camp describes how these terms are used to target a proposition, again much like propositional sarcasm, but are specifically applicable to declarative sentences. An example is "Like Alan has any money". Users of this form of sarcasm cannot pretend to have intended to fully claim the content of their proposition, and thus this becomes one of the easier forms of sarcasm to diagnose.

2.1.2.5 ***Illocutionary Sarcasm***: Finally we have illocutionary sarcasm, Camp describes this form of sarcasm as targeting speech acts with an illocutionary force other than the assertion, a key example of this form is "thanks for holding the door". Camp goes on to describe how "it can also include the full range of implicatures, including especially implicatures that express evaluative attitudes such as pity, admiration, or surprise"[5].

This source is a particularly rich one, with a level of detail that matches the evident subtleties of the topic of sarcasm, but now we must move on to dissect sources that will inform us of the current state of how natural language is implemented. This will include the general area of NLP and then more specifically, a dive into how phrases are labelled.

2.2 Implementing NLP

2.2.1 Natural Language Processing with TensorFlow, T.Ganegedara

Ganegedara provides a full guide to the current practises for NLP in python using the TensorFlow library [8], starting from the installation of python, to deep neural networks, through to word and topic embedding mechanics in NLP and finally on to applying NLP to chatbots and social media. Before looking into the coding techniques, we must first look to the task of NLP, Ganegedara list 8 distinct tasks:

- **Tokenization** separating a text corpus into atomic units, e.g. words.
- **Word-sense Disambiguation (WSD)** identifying the correct meaning for a word.
- **Named Entity Recognition (NER)** extracting entities (person, location, etc.)
- **Part-of-Speech (PoS) tagging** assigning words their respective parts of speech.
- **Sentence/Synopsis classification** categorizing content, e.g. political, technology.
- **Language generation** training machine learning (ML) model
- **Question Answering (QA)**
- **Machine Translation (MT)** language translation (this will not be needed for this project).

The most important of these is the PoS tagging and sentence classification, here we will be able to expand the categories for analysis to include the natural language tools we have previously mentioned and hopefully achieve this projects aim. Ganegedara discusses the method of Convolutional Neural networks (CNN) as the optimal tool for sentence classification. CNN is a stack of layers, such as convolutional layers, pooling layers and fully connected layers, all of which are discussed in great technical detail in this book, as well as ways to implement them for sentence classification. While CNNs are typically used for pictures, they can be used with word embedding systems such as Global Vectors (GloVe) to allow for sentence classification and basic sentiment analysis. This classification is typically the identification of positive and negative sentiments but using the same system, we should be able to classify vague and non-vague, sarcastic and non sarcastic phrases and hopefully more.

From here Ganegedara provides a highly detailed description on many of the techniques we will need for the majority of components in the chatbot infrastructure, this will allow us to dedicate more time to achieving our primary aim. This source will no doubt be the most valuable resource for the technical side of this project.

3 The Project

This project is all about improving the naturalness of the language used in HAI, hopefully improving the flow of interaction, the effectiveness of an agents interpretation and the overall satisfaction for users. More specifically it is about implementing a model for natural language aspects such as VL and sarcasm into a CNN system for sentence classification. The final product of this report will be a trained basic python based chatbot that is able to showcase these implementations in action.

The tools being used in this project mostly revolve around the core tool, python, this includes python libraries such as TensorFlow, numpy and sklearn. Much of this project will be accomplishable on standard personal computers, but one tool available to help with the computationally expensive neural network training is the Swansea University Computer Society (SUCS) Virtual Machines (VM). This outsourcing of tasks will speed up the development of the chatbot as repeated runs of training code will cost valuable time.

3.1 The Plan

Figure 1 shows the layout of the project, showing the time distribution, milestones (labelled M) and a basic difficulty indicator with a traffic light system (with green being easy). The difficulties are based of previous experience and research done within the preparation period, but it is entirely possible that tasks may prove to be easier or harder than expected. The timings are again based of previous experience and again may be subject to change. Any breaks have not been included but instead will be planned at the beginning of each phase. The phases are marked by the milestones (solid black lines) and signify four key segments in this project:

3.1.1 Phase 1: The Preparation

This stage includes the inception of the project idea, as a result of discussions with the project advisor Dr. Leigh Clark, it also includes the CSCM10 report on a relevant topic (VL), and of course, this document, the project specification. After the completion of this document we will have a firm plan for the rest of the project, including foundation building knowledge, risk awareness and a time table for all the key points of the project. We shall then be ready for phase 2.

3.1.2 Phase 2: The Theory

This phase is all about discovering what improvements from natural language tools can actually be implemented and the theory of why they should be implemented. We shall also look to understand the core methods used in NLP within TensorFlow, this shall be a long but rewarding task hopefully making the next phase smoother. Finally we need to locate the most ideal word corpora to do our analysis on, the exact specifications of which will be known after a study of TensorFlow NLP logistics.

3.1.3 Phase 3: The Coding/Implementation

This phase is likely to be the hardest, this is where we have to implement all the knowledge and theory we have learned, into python. We need to import and optimise the data for analysis, build and optimise our classification model and finally design a chatbot. Despite the amount of work just outlined, more time has been allocated to the previous phase, this is due to the importance of fully learning the methods such that the actual implementation becomes easier. By the end of this phase we should have completed the primary objective of having constructed a chatbot adapted to understand a wide range of natural language constructs.

3.1.4 Phase 4: The Evaluation and Write-up

This is the final stage, and despite only having two tasks, it has the longest time dedicated to it after phase 1. The first task is to evaluate and analyse the performance of the chatbot, this will include internal evaluation, such as confusion matrices for the classification model, and it will include a basic survey. The time dedicated to task 1 is due to this survey, the exact details of how or what participants will answer has yet to be determined as the current COVID-19 pandemic provides a difficult barrier to typical survey techniques. If possible, participants will be obtained through word of mouth, including virtually on social media and will not be required to give any personal information. The objective of the survey will be to determine how well participants feel an interaction flowed, and to rate an interaction, possible in comparison with another chatbot.

Finally we have the writing of the final documentation, and while notes and general documenting will take place over the entirety of the project, this will be where all the information acquired will be compiled into one document.

3.2 Risk Analysis

3.2.1 Personal Risks

As this project takes place entirely within code and research there are little physical risks outside of the expected danger to the eyes and possibly wrists after long exposure to computers. These are trivial issues and easily remedied with regular breaks. These issues are low in probability and low in consequence but there is no reason to not be mindful of them.

3.2.2 Hardware and Software Risks

The more pressing issues relate to the safety of the work completed, including documentation and code. One highly consequential risk is that the main laptop used in this project breaks in a way that limits the access, or outright destroys any documentation saved on it at the time. If this occurs and the documentation has not been backed up correctly, there will be a huge time cost added to the project and it may be likely that the project will not be completed on time. The solution is to backup all progress on a regular basis, this is possible both with hard backups with flash drives and on the cloud, most likely google drive. These backup solutions come with there own potential issues, corruption or loss of data is still possible. However if the documents have been backed up on all three devices/systems then the chance of a total loss of documents is negligible. This issue has a low probability of occurring but with a huge consequence, if the documents are backed up on multiple devices as regularly as possible then this issue is perfectly manageable.

3.2.3 The Ideal Word Corpora

Now we move on to an issue whos nature is less predictable. This potential issue is with the content of the dataset of the phrases to be analysed. Neural networks are a type of supervised learning, meaning they require labels in the data. There is a potential risk that a labelled data set can not be located that perfectly suits our needs. Solutions include adapting our ML model by possibly using a unsupervised classification model or even labelling a percentage of the dataset manually (this will likely be a last resort). This issue will be easier to tackle after the TensorFlow source has been fully reviewed but ultimately the consequence of this issue is a small time cost and will not halt the project.

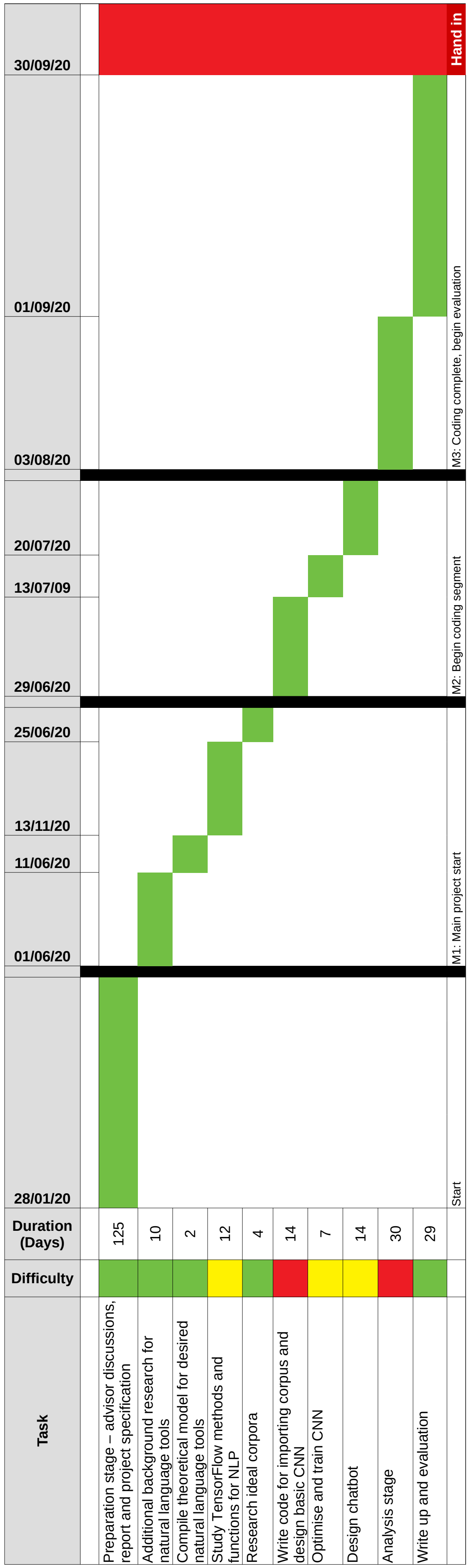
4 Conclusion

This specification has begun to form a rigorous model for VL, sarcasm and an understanding of the modern methods of NLP implementation in python. This is done using three highly detailed documents, but there is room for additional research during the second phase of this project. Gaining additional knowledge from different sources may reveal new methods or information that would have not been found otherwise. Also outlined here is a four phase plan for achieving the goal of this project, the goal of implementing a developed language model into a basic chatbot. This chatbot will be designed to exhibit a more natural flow of interaction with us humans. All of which will be designed with the improvement of agents in mind. There are a number of issues and challenges that need to be kept in mind during this project. The most important challenge is to learn the ins and outs of the TensorFlow library, as understanding this will help us tackle the problem of an unideal word corpus. Furthermore a deeper understanding of TensorFlow will give more power to use when implementing the language model, and will allow for a speedier development cycle.

The development of this chatbot will mean little to nothing if it can not be evaluated properly and any conclusions we wish to draw will have little validity as well. Testing the effectiveness of this chatbot with participants will help in this regard, allowing us to see if the improvements are indeed improvements. The survey remains a bit of a question mark in the face of the current pandemic, hopefully the situation improves from the time of writing this document and we are fully able to evaluate our product.

This project will no doubt be difficult. Formulating this language model, finding or creating an ideal word corpus and forming a convolutional word based neural network are all daunting tasks. But with the right time management, and a heavy focus on mastering the theories behind TensorFlow, achieving these aims is not only possible, it is probable.

Fig. 1. The Gantt chart.



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