
Question Answering in Cooking Recipes

*A dissertation submitted in partial fulfillment
of the requirements for the degree of*

Master of Engineering

in

Computer Science & Engineering

by

Sreela Das

Examination Roll No.: M4CSE19027

Class Roll No.: 001710502025

Registration No.: 140764 of 2017-18

Under the Guidance of

Prof. Sivaji Bandyopadhyay

Dr. Dipankar Das

Department of Computer Science and Engineering

JADAVPUR UNIVERSITY

Kolkata - 700032.

Declaration of Authorship

I, Sreela Das, declare that this thesis titled, "Question Answering on Cooking Recipes" and the work presented in it are my own. I confirm that this work was done wholly or mainly while in candidature for a Master degree in Computer Science and Engineering at this University

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Examination Roll Number: M4CSE19027

Class Roll Number: 01710502025

Registration Number: 140764 of 2017-18

Signature :

Date :

Faculty Council of Engineering and Technology

JADAVPUR UNIVERSITY, KOLKATA 700032

Certificate of Recommendation

This is to certify that the thesis entitled “**Question Answering on Cooking Recipes**” is a bona-fide record of work carried out by Sreela Das, Examination Roll No.: M4CSE19027, University Registration No.: 140764 of 2017-2018 in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Computer Science and Engineering from the Department of Computer Science and Engineering, Jadavpur University for the academic session 2017-2019. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

Dr. Sivaaji Bandyopadhyay
Professor (Thesis Supervisor)
Dept of Computer Science and Engineering
Jadavpur University
Kolkata - 700 032

Dr. Dipankar Das
Professor (Thesis Supervisor)
Dept of Computer Science and Engineering
Jadavpur University
Kolkata - 700 032

Prof.(Dr.) Mahantapas Kundu(HOD)
Dept. of Computer Science and Engineering,
Jadavpur University,
Kolkata – 700 032

Prof.(Dr.) Chiranjib Bhattacharjee(Dean)
Faculty Council of Engineering and Technology,
Jadavpur University,
Kolkata – 700 032

Abstract

This Thesis is all about **Question Answering in Cooking Domain**. Question Answering (QA) is a fast-growing research area that brings together research from Information Retrieval, Information Extraction and Natural Language Processing. It is not only an interesting and challenging application, but also the techniques and methods developed from question answering inspire new ideas in many closely related areas such as document retrieval, time and named-entity expression recognition, etc. Cooking domain of question answering is another challenging new domain. In this thesis we are using machine learning algorithm to classify Cooking question and then extract ranked list of answer of a test question. So, System is able to give answer list whenever a question is initiated.

Acknowledgements

I express my deep sense of gratitude to **Prof. Sivaji Bandyopadhyay** for encouraging me to take project under Natural Language Processing (NLP). Also, I am very much thankful to **Dr. Dipankar Das** for his valuable guidance, keen interest and encouragements at various stages in the completion of my term paper. I am thankful for giving me an opportunity to work on this project and helped me gain knowledge. At last, I would like to express my deep and sincere gratitude to my family members for the constant support that they gave me. Without them, it would have been impossible for me to be in this position.

Contents

Declaration of Authorship	i
Certificate of Recommendation	ii
Abstract	iv
Acknowledgements	v
List of Figures	viii
1 Introduction	1
1.1 Natural Language Processing and Information Retrieval	1
1.2 Question-Answering(QA)	2
1.2.1 Question type Classification	2
1.2.2 Answer type detection	3
1.3 Applications	4
1.4 Motivation :Cooking Question Answering	5
1.5 Challenges	6
1.6 Hypothesis	7
1.7 Objectives of the thesis	8
1.8 Thesis Outline	8
2 Related Work	10
2.1 QA systems for various domains	10
2.2 QA systems on cooking domain	13
3 Data-set Preparation	15
3.1 QA Taxonomy for Cooking Domain	15
3.2 Cooking data-set-1	16
3.2.1 Annotation Process	16
3.2.2 Corpus Details	22
3.3 Cooking dataset-2(Yahoo qs-ans)	22
3.3.1 Corpus Details	23

4	Question-type Classification:	25
4.0.1	Lexical-Features	26
4.0.2	Syntactic Feature:	27
4.1	Feature Engineering	28
4.1.1	Features	29
4.2	Classification	32
5	ANSWER SELECTION	35
5.1	Answer Pool Detection	36
5.2	Answer Retrieval	37
5.3	Answer-Ranking	39
6	Experimental Results and Discussion	40
6.1	Evaluation on Question Classification	40
6.1.1	Machine Learning Experiments	40
6.1.2	Deep Neural Network	40
6.1.3	Error Analysis :	41
6.2	Answer Type Detection :	42
6.3	Results :	43
7	Conclusion and Future Work	46
7.1	Conclusion	46
7.2	Future-Work	47

List of Figures

1.1	Question answering module	4
2.1	The QA components covered by QA research	11
2.2	The QA components covered by QA research	12
2.3	The publication of papers on QA System	13
3.1	Cooking Ontology	18
4.1	Neural Network	33
4.2	Convolution Neural Network	34

*The fear of the Lord is the beginning of wisdom . . .
Dedicated to My Family.*

Chapter 1

Introduction

1.1 Natural Language Processing and Information Retrieval

Natural language processing (NLP) is the ability of a computer program to understand human language as it is spoken. Natural Language Processing is an area that combines of Artificial Intelligence and linguistics. It involves intelligent analysis understand, manipulate of human language. Challenges in natural language processing frequently involve speech recognition, natural language understanding, and natural language generation[1].

Uses of natural language processing: Most of the research being done on natural language processing revolves around search, especially enterprise search. This involves allowing users to query data sets in the form of a question that they might pose to another person[2]. The machine interprets the important elements of the human language sentence, such as those that might correspond to specific features in a data set, and returns an answer. Other applications are:

- Information Retrieval(Google finds relevant and similar results).
- Information Extraction(Mail structures events from emails).
- Question Answering(IBM Watson's answers to a query).
- Natural Language Generation(Generation of text from image or video data.)
- Text Simplification(Rewording simplifies the meaning of sentences).
- Sentiment Analysis(Hater News gives us the sentiment of the user).
- Text Summarization(Summary or Reddit's autotldr gives a summary of sentences).

- Spam Filter(Email filters spam emails separately).

Information retrieval (IR) is the activity of obtaining information resources relevant to an information need from a collection of information resources. The process begins when an user enters a query into the system. Queries are formal statements of information needs. User queries are matched against the database information. Most IR systems compute a numeric score on how well each object in the database matches the query, and ranks the objects according to this value. The top ranking objects are then shown to the user[3]. Automated information retrieval systems are used to reduce what has been called information overload. An IR system is a software that provide access to books, journals and other documents, stores them and manages the document. Web search engines are the most visible IR applications[4].

1.2 Question-Answering(QA)

Question answering (QA) is a computer science discipline within the fields of information retrieval and natural language processing (NLP), which is concerned with building systems that automatically answer questions posed by humans in a natural language[6].A QA implementation, usually a computer program, may construct its answers by querying a structured database of knowledge or information, usually a knowledge base. More commonly, QA systems can pull answers from an unstructured collection of natural language documents[5].

Question answering (QA) is a well-researched problem in NLP. In spite of being one of the new research areas, QA has application in a wide variety of tasks, such as information retrieval and entity extraction. Recently, QA has also been used to develop dialog systems[36] and chatbots[34] designed to simulate human conversation. Traditionally, most of the research in this domain used a pipeline of conventional linguistically-based NLP techniques, such as parsing, part-of-speech tagging and co reference resolution.

1.2.1 Question type Classification

Factoid Question:

Factoid questions is about providing cosine facts[7].

Example 1: Who wrote “The Universal Declaration of Human Rights”?

Example 2: How many calories are there in two slices of apple pie?

YesNo Question: This is about to provide one word answer either yes or no.

Example 1: Is there any hospital with in 5km of your home?

Complex Questions: This is the narrative questions.

Example 1: In children with an acute febrile illness, what is the efficacy of acetaminophen in reducing fever?

Example 2: What do scholars think about Jefferson's position on dealing with pirates?

1.2.2 Answer type detection

Several Rules are there to detect answers,

Hand-written rules

- For answer type detection Regular Expression based rules are more productive to find an answer of a question[8].

Example 1: Who is—was—are—were PERSON

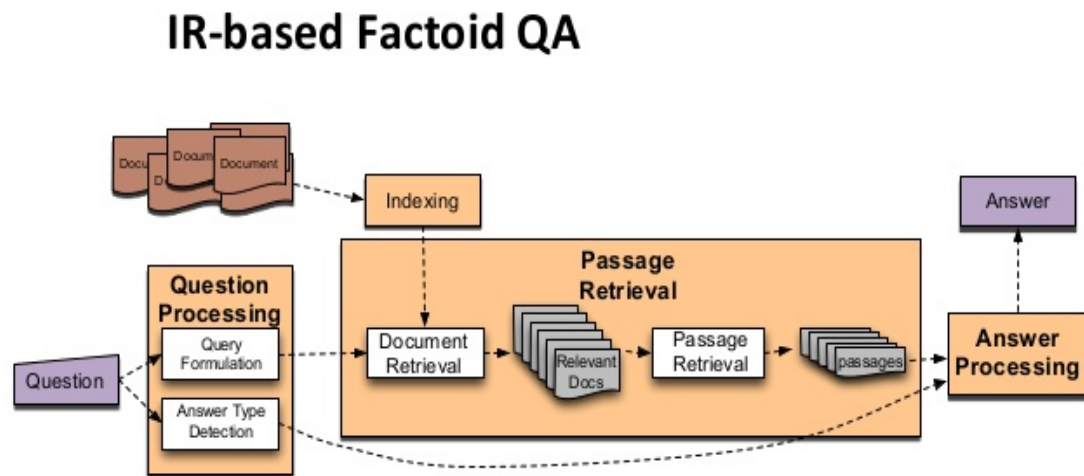
- Head-word detection in the question in another way to find suitable answer.(the headword of the first noun phrase after the wh-word).

Machine Learning based rules

Most often, problems are treated as machine learning classification. Define a taxonomy of question types. Then annotate training data for each question type. Train classifiers for each question class using a rich set of features. Features include those hand-written rules. Other than hand-written rules there are several machine learning algorithms are available to detect the answer type such as SVM, Naive Bayes, Logistic regression etc[9].

Features for Answer Type Detection Features for answer type detection are

1. Question words and phrases
2. Part-of-speech tags
3. Parse features (headwords)
4. Named Entities
5. Semantically related words



35

FIGURE 1.1: Question answering module

1.3 Applications

Question Answering is a first growing research area. QA systems have been extended in recent years to encompass additional domains of knowledge. For example, systems have been developed to automatically answer temporal and geo spatial questions, questions of definition and terminology, biographical questions, multilingual questions, and questions about the content of audio, images, and video [10][11].

The Applications of QA-System are:

- interactivity—clarification of questions or answers
- answer reuse or caching
- answer presentation
- knowledge representation and reasoning
- social media analysis with QA systems
- sentiment analysis
- utilization of thematic roles

IBM's question answering system, Watson, defeated the two greatest Jeopardy! champions, Brad Rutter and Ken Jennings, by a significant margin. Facebook Research has

made their DrQA system available under an open source license[12]. This system has been used for open domain question answering using Wikipedia as knowledge source.

1.4 Motivation :Cooking Question Answering

The main aim of Question Answering is to find the exact answers to natural language question from a large collection of documents[13]. In general Question-answering systems that combine the Information Retrieval (IR) with extraction techniques to detect a set of candidates and then use some selection strategy to generate the final answers. The most popular classes of technique for QA are open-domain and restricted-domain. These two domains use thesauri and lexicons in classifying documents and categorizing the questions. Open domain question answering (ODQA) (Yang et al., 2003) deals with questions about nearly everything and can only rely on general ontology[17].

To answer unrestricted questions, a general ontology or commonsense knowledge would be useful. Restricted-domain question answering (RDQA) (Diekema et al., 2004) deals with questions under a specific domain like tourism, medicine, etc. Yet another way of classifying the field of QA deals with language. In monolingual QA both the questions and the corpus are in the same language. In cross-language QA the language of the questions (source language) is different from the language of the documents (target language). The question has to be translated in order to be able to perform the search. Multilingual systems deal with multiple target languages, i.e., the corpus contains documents written in different languages. In multilingual QA, translation issues are thus central as well[14].

Over the years, many question answering systems have been developed, for a variety of purposes: Some systems are intended to provide database access in very specific domains, while others are more open-domain oriented, aiming to answer general trivia-like questions. The context in which a QA system is used, i.e., the anticipated user, the type of questions, the type of expected answers, and the format in which the available information is stored, determines the design of the system. Two basic types of question answering systems can be distinguished: systems that try to answer a question by accessing structured information contained in a database, and systems that try to answer a question by analyzing unstructured information such as plain texts. Since 1992, the annual Text REtrieval Conference (TREC) (<http://trec.nist.gov/>) organized by the National Institute of Standards and Technology (NIST) provides a forum for researchers to compare the effectiveness of their systems in information retrieval related tasks. In 2002, total 34 research groups (Voorhees, 2004) participated in the question-answering track of TREC, each group having implemented their own system. These systems cover a wide

spectrum of different techniques and architectures, and it is impossible to capture all variations within a single architecture. Nevertheless, most systems also have a number of features in common, which allows us to give a general architecture of a prototypical question answering system[15].

Cooking is a dynamic, challenging, multi-modal domain of Question-Answering system. To explore the cooking field in QA domain has started few years back. Some work has been done depending on recipes images, some work has been done depending on different recipes only etc. There is a huge chance to explore this cooking domain. As this is a restricted field of question answering the profession like Chef, bakers, food server manager, house wife etc are going to be very much benefited using this cooking QA-System. Understanding and reasoning about cooking recipes and related questions about Cooking is a fruitful research direction towards enabling machines to interpret procedural text[16].

New direction, challenging domain, dynamic field of NLP that is QA system, motivate us to work and explore this field. More over using Machine -Learning algorithms and NLP tools to make something new in Cooking QA-System domain inspire us to work in Cooking QA-System [8].

1.5 Challenges

Question-Answering are computer-based systems that aim to provide information that more exactly meets user needs than the lists of often irrelevant results given by search engines[17]. This is done through natural language processing. Question answering with knowledge base aims to answer natural language questions using real-world facts stored in an existing, large-scale database.

We proposed QA system, which is intended for cooking domain. In cooking recipe domain, the textual data contains a set of queries that show how to prepare dishes, what is the preparation time, what are the ingredients used, what advise should follow to make it etc.

The main challenges here are-

1. Generally a QA-system needs a huge amount of data. To give a answer of a question properly, a huge amount of data is needed, so data-set preparation and picking up exact data related to cooking domain and gathering or collecting huge amount of data are a challenging task for us.

2. From the fixed domain type point of view, closed domain question answering systems accept questions only from a specific domain while open domain question answering systems do not have this limitation. The question answering systems that are most popular and are being given more attention to are closed domain question answering systems. This is justified by the need of modern systems to be extensive and inclusive of specific areas of information and knowledge.

3. The questions are being given more attention are factoid question answering. Factoid questions are questions that can be answered with simple facts expressed in short text answers. However, the researchers noticed a growing number of contributions, especially in 2016, on non-factoid question answering systems. This fact suggests a growing interest in the research community for this kind of question answering systems and a possible trend towards systems that are more intelligent and closer to humans, making an intelligent system challenging. This Question-Answering System is a factoid question-answering system, so extracting accurate answers is challenging.

1.6 Hypothesis

We define the following hypothesis for our thesis

- Quality and quantity of the data-set plays a vital role in any Question-Answering system. As it is a Cooking domain question-answering system, the role of the data set plays a more crucial role. The answers class is not defined or can say there is a huge amount of answers available and for a particular question has a variety of answers, it is difficult to give a class to answers. So we make a hypothesis that for dataset questions have a class and the answers belong to the same class. More specifically, we can say that the questions have multiple answers belong to the same class. We keep a hypothesis that all the answers are of the same class which is assigned to the question.
- The dataset has multiple answers for a single question. And no ranking of the answers are given. So which answer is more relevant for the question is not present in the dataset. For the ranking of the answers module, we give equal importance to all the answers. Initially, we assume all the answers in the gold standard dataset have a rank of 1. All the answers have equal relevancy.

1.7 Objectives of the thesis

Cooking QA-System contain different type of questions, and unstructured answers are related to cooking. The main objective of the thesis is Classify the cooking questions in different class like time,direction,preparation etc.and then classify the answers in different classes depending on the question type, the overall system is able to identify the a new question and give a perfect answer or able to give a list of answers of the questions, which are more suitable ordered list or ranked list.When ever a question is initiated the system is able to find out the class of the question and then extract answer of the question from that particular answer class, and fetch the answers, if more than one answer is possible then it gives a ranked list of answers.

- Classify the cooking related question set in different classes. There are several types of questions are possible for cooking domain such as preparation time,ingredients name, cooking direction etc.Depending on the type of questions the question set need to be classify among different classes.
- Answer set is need to classify in different classes same as question set.All the cooking related answer exist in a pool. Then answers are fetched and classified among different classes. The class name same as the question class.
- When a new question is initiated, the system is able to extract answers.The question is transferred to the query then we need to determine the class of the question, and going to the same class we are extracting the answer of the question.
- More than one answer is possible for cooking question.If the system is able to fetch a multiple related answer to the question,then System provides a rank list of answers for the question.

1.8 Thesis Outline

The outline of the thesis is as followed

- Chapter 2 describes the related work. All the past work done in question answering system. Then we describe the work done in cooking system till date.
- Chapter 3 describes brief description of dataset.How and why dataset is prepared and detailed description and statistic of dataset.

- Chapter 4 describes the module Question Classification. Here detailed description of feature extraction and feature selection and classification model is given.
- Chapter 5 describes the module of Answer section and answer classification, answer pool detection and answer ranking.
- Chapter 6 gives experimental results, classification accuracy is given here.
- Chapter 7 describes conclusion and Future work.

Chapter 2

Related Work

In this chapter we will discuss about the detailed survey of voluminous work done so far on natural language processing to question-answering. We will also discuss the work so far done on cooking domain with a detailed description of algorithm and techniques.

2.1 QA systems for various domains

The main objective of The Question Answering system is to find the exact answers to natural language question from a large collection of documents, passages or text[19].

In general Question Answering systems that combine the IR with extraction techniques to detect a set of candidates answer and then use some selection strategy to generate the final answers. In general, a ‘procedure’ is a specified series of actions or operations or a set of commands which have to be executed in order to obtain a goal. Less precisely speaking, the word ‘procedure’ can indicate a sequence of activities, task, steps, decisions, calculations and processes, that when undertaken in the sequence laid down produces the described results, product or outcome. Therefore, procedural texts compose of a sequence of instructions in order to reach a goal and range from apparently simple cooking recipes to large maintenance manuals. It also include documents as diverse as teaching texts, medical notices, social behaviour recommendations, directions for use, assembly notices, do-it-yourself notices, itinerary guides, advice texts, savoir-faire guides etc.

So, the questions of procedural text are as diverse as its range of diversity. In our perspective, procedural questions will be of much growing interest to the non-technical as well as technical staff. Statistics also showed that procedural questions is the second largest set of queries formed to web search engines after factoid questions. This is confirmed by another detailed study carried out by the paper[20].

Question Answering Systems present a fascinating way for querying unstructured and structured information. This makes Question-Answering a versatile and research-oriented topic. Many researchers are highly motivated to build new things in Question-Answering which will be a more advanced system. This is why a large number of QA systems have been developed to various languages. Some languages, such as Latin, English, Arabic etc. English language question answering system can better serve than other question answering systems. This might be related to the language features and the maturity of research [21].

Next we present a survey of QA, with different sources: structured databases, unstructured free text.

QA Components		Question Processing			Document Processing			Answer Processing		
		Question Analysis	Question Classification	Question Reformulation	Information Retrieval	Paragraph Filtering	Paragraph Ordering	Answer Identification	Answer Extraction	Answer Validation
QA Research										
	✓									
		✓								
			✓							
	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	✓	✓		✓			✓	✓		
		✓					✓			
	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
		✓					✓	✓		
		✓					✓	✓		
	✓	✓	✓	✓			✓	✓		
		✓		✓			✓	✓		
		✓		✓			✓	✓		

FIGURE 2.1: The QA components covered by QA research

Historically, the best-known early question answering system was BASEBALL, a program developed by Green et al. in 1961 for answering questions about baseball games played in the American league over one season. Also, the most well-remembered other early work in this field is the LUNAR system, which was designed in 1971 as a result of the Apollo moon mission, to enable lunar geologists to conveniently access, compare and evaluate the chemical analysis data on lunar rock and soil composition that was accumulating [22].

Many other early QA systems such as SYNTH EX, LIFER, and PLANES aimed to achieve the same objective of getting an answer for a question asked in natural language. However, QA systems have developed over the past few decades until they reached

the structure that we have nowadays. QA systems, as mentioned before, have a backbone composed of three main parts: question classification, information retrieval, and answer extraction. Therefore, each of these three components attracted the attention of QA researchers[23].

QA Approaches		Question Classification				Information Retrieval		Answer Extraction	
		Flat Taxonomy	Hierarchical Taxonomy	Rule-based Classifier	Machine Learning	Web Corpus	Knowledge-base Corpus	Text Patterns	Named Entity
QA Research									
	Gaizauskas & Humphreys (QA-LaSIE) [20]	✓		✓		✓			✓
	Harabagiu <i>et al.</i> (FALCON) [16]		✓	✓		✓			✓
	Hermjakob <i>et al.</i> [18]		✓		✓				✓
	Kangavari <i>et al.</i> [21]		✓	✓		✓	✓	✓	
	Lee <i>et al.</i> (ASQA) [25]		✓	✓	✓	✓			✓
	Li & Roth [17]		✓		✓				
	Moldovan <i>et al.</i> (LASSO) [8]		✓	✓		✓			✓
	Peng <i>et al.</i> [24]			✓	✓	✓		✓	✓
	Radev <i>et al.</i> (NSIR) [15]	✓		✓	✓	✓		✓	
	Ravichandran & Hovy [22]							✓	
	Stoyanchev <i>et al.</i> (StoQA) [6]					✓	✓	✓	✓
	Xu <i>et al.</i> [23]	✓		✓		✓		✓	
	Zhang & Lee [19]		✓		✓				✓

FIGURE 2.2: The QA components covered by QA research

Tables 2.1 and 2.2 show a comparative summary between the the researches with respect to the QA components and the QA approaches, respectively. (Table 2.1) shows the different QA system components that were covered QA -system, while (Table 2.2) shows the approaches that were utilized by each research within every component[24].

AND TOPIC BASED ANALYSIS OF QUESTION ANSWERING SYSTEM

We first make a quantitative analysis of the collected research. We had divided the papers into two categories: new systems and existing system improvement.shows the total number of publications for each year, as well as the number of publications for each category.

These data suggest that QA System are gaining popularity and interest from the research community. We also notice that the majority of contributions are new QA System. This suggests that QA System is a rapidly growing and evolving field of research where new ideas are being implemented continuously with success. This also justifies the fact that a considerate amount of research is being done on improving and implementing new ideas to existing state of the art QA System and incremental results are being achieved. As

regards we can say that there is a growing trend in publications indicating an increased interest in this area from the research community.

Year	Total number of publications	New systems/ Improvements	New systems/ Improvements (%)
2016	57	39 / 18	68.5 / 31.5
2015	37	24 / 13	64.9 / 35.1
2014	35	25 / 10	71.5 / 28.5
Total	129	88 / 41	68.3 / 31.7

FIGURE 2.3: The publication of papers on QA System

2.2 QA systems on cooking domain

A paper[33] introduce an ontology based cooking system which was developed to integrate among different question answering system. The paper gives details on the steps performed for the building process, which mainly consisted in: specification, knowledge acquisition,conceptualization, implementation and evaluation. The ontology comprehends four main modules covering the key concepts of the cooking domain – actions, food,recipes, and utensils – and three auxiliary modules – units and measures,equivalencies and plate types. The knowledge model was then formalized using open-source ontology editor and framework for building intelligent systems.

A Food-Oriented Ontology-Driven system was presented for food or menu planning in a restaurant, clinic/hospital, or at home. The ontology contains specifications of ingredients, substances, nutrition facts, recommended daily intakes for different regions, dishes, and menus. An Ontology Design Pattern for Cooking Recipes present a detailed description and result of an ontology modelling. The aim of the model is to bridge heterogeneity across representational choices by developing a content ontology design pattern which is general enough to allow for the integration of information from different web sites[26].

In proposed a model for the instructional structure and criteria to identify its contents such as: titles, instructions, warnings and prerequisites. The main aim of this research, besides a contribution to text processing, was to be able to answer procedural questions (How-to? questions), where the answer was a well-formed portion of a text, not a small set of words as for factoid questions[27].

In this paper addressed the parsing and analysing argumentative structures in procedural texts[28].

The pattern matching based query classification for procedural QA has proposed in this paper[29].

In this paper what they are doing is explores the question recommendation and answer extraction is in question answering system. The system uses the statistical language model to find out user interest distribution, and develop the user list of question recommendation. This paper also analyses the candidate answers, calculates the similarity between the question and the answer with the help of multiple syntactic and semantic features, and then gets the probable answer list, so the user can more easily choose the best required answer[30].

This paper[31] described an IR based question answering system is developed which analyses user questions, retrieves service documents from an inverted index and ranks them with a customized scoring function. The QA system is designed to generate direct answers to questions in German concerning governmental services. The system successfully maintains ambiguous questions with the help of retrieval methods, task trees and a rule-based approach.

This paper [32]follows a machine learning approach is described to develop some components of a question answering system i.e., POS tagger, a shallow parser, a named entity recognition module, and a module for finding the aim of the question. These modules are used for analysing the questions and also for analysing the selected passages which may contain the exact answer. Question analyser extracts the syntactic and semantic features using these three components and save it in question –analysis records, Passage retriever uses this information to extract relevant passages. Answer selector compare the question – analysis record and retrieved passages and generate the final answer with the help of these three learning components.

Chapter 3

Data-set Preparation

3.1 QA Taxonomy for Cooking Domain

The main aim of Question Answering is to find the exact answers to natural language question from a large collection of documents. In general Question-answering systems that combine the Information Retrieval(IR) with extraction techniques to detect a set of candidates and then use some selection strategy to generate the final answers. The most popular classes of technique for QA are open-domain and restricted domain. Open domain question answering (ODQA) deals with questions about nearly everything and can only rely on general ontology. In contrast, restricted-domain question answering (RDQA) deals with questions under a specific domain like railways, jobs, agriculture, automobiles, medicine or cooking[34].

We proposed a cooking system based on cooking domain. the textual data contains a set of queries that show how to make a specific dishes, how much time it will take, what are the ingredients it required, what advise to follow to make this dishes and etc. This cooking domain data consist of huge amount of data which is very helpfully in real life world. This Cooking QA-System becomes essential to the people in general band to the people in specific such as chefs, house-wives, nutritionists etc.

All the cooking data-set consist data depending on the real life, real situations. As this QA-System is restricted to the Cooking domain, all the data fallback belongs to cooking field. As this data-set based on real life and multi modal ,preparing this data-set is very challenging.

Under QA-Domain Cooking recipes is all most new ,dynamic and challenging domain. Most of the work till date done on cooking domain used data-set which contain only image, or

only recipes, or based on ontology etc. Our data-set consist data which not only about recipes but also on different recipes, time, advise, utilities etc.

3.2 Cooking data-set-1

To our knowledge, there is no standard corpora for specific cooking related questions are available for research. So, we had no choice to use any standard data and we had to prepare experimental data for our own.

There are some website over Cooking, which contains information of Cooking. For example- Several recipes, ingredients, the precaution one should take to make any recipes, the time taken to cook anything etc. There are some other websites where viewer can ask questions related to cooking. Stack-overflow, Facebook etc, this are some website where people can ask questions when they have a doubt, and people who know the answer can give answer. Like that some website also available in cooking domain where people can ask there doubts, and some other people can answer that questions. Among those website, top viewed website is Punjabi-recipes.com, Where people can ask question. So we choose this website to collect questions. We use Crawler to collect data.

Crawler: A web crawler is a relatively simple automated program, or script that methodically scans or "crawls" through Internet pages to create an index of the data it's looking for. Alternative names for a web crawler include web spider, web robot, crawler, and automatic indexer. A focused crawler or topical crawler is a web crawler that attempts to download only web pages that are relevant to a pre-defined topic or set of topics. Topical crawling generally assumes that only the topic is given, while focused crawling also assumes that some labelled examples of relevant and not relevant pages are available. The importance of a page for a crawler can also be expressed as a function of the similarity of a page to a given query. Focused crawlers or topical crawlers attempt to download pages that are similar to each other. The system uses the crawler in two cases, such as case 1: crawler will search and save all the relevant web pages in the web and case 2: when the system encounters an unknown recipe requested by the user, it will search through Google, Alta Vista and only ten top ranked links will be considered for crawling[38][37].

3.2.1 Annotation Process

The data is collected from Punjabi-recipes.com. Here We have used Nutch Crawler which is an open source tool that crawls cooking data from different websites. After that we

clean that collected data using some basic NLP cleaning process. Depending on the question type we divide the total question data-set in 13 classes. We used ontology to describe the class definition.

The ontology[40] is based on the requirement analysis of cooking domain. The concepts there in provide a schematic view of the particulars involved in the domain. The relationships between the concepts or classes comprehend the real world interaction among various modules of ontology.

This model describes the following process:

1. identification of concepts or classes
2. classification of groups of concepts in classification trees;
3. description of properties or attributes of classes. relationships between the classes.

Concepts within these hierarchies were associated through IS-A relations. Attribute based relations were used to associate concepts from the several hierarchies. The scope of the ontology is described through some basic questions that are called competency questions. The ontology building process will start through finding the answers to these competency questions.

CQ1: Method-oriented

- CQ1.1: How to make the dish x?
- CQ1.2: Help me to cook the dish x?
- CQ1.3: What are the tips to cook x?

CQ2: Time-oriented

- CQ2.1: What is the preparation time to cook X?
- CQ2.2: What is the cooking time of X?
- CQ2.3: What is the total time make the dish X?

CQ3: Ingredient-oriented

- CQ3.1: What are the ingredients to make X?
- CQ3.2: What is the quantity of a particular ingredient to make x?
- CQ3.3: What are the quantities to use when making recipe X for 4 persons?

CQ4: Utensil-oriented

- CQ4.1: Which utensils can we use to make the recipe X?
- CQ4.2: Which recipes can be made using the oven?

The ontology has been designed on the basis of the answers to these questions. However, more implicit questions will be answered as the development of cooking ontology will

take into complete structure. The proposed cooking ontology has shown in the following Figure

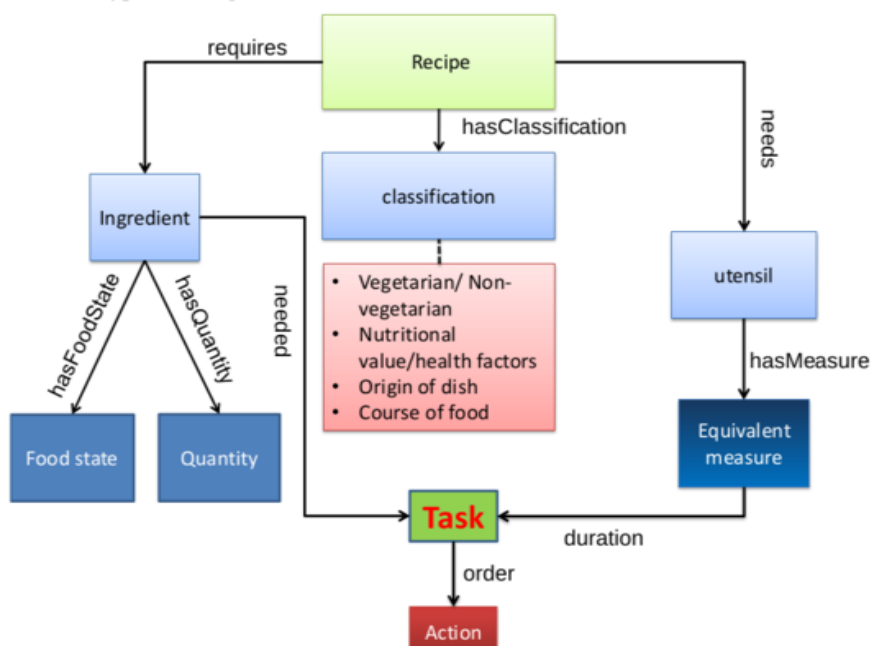


FIGURE 3.1: Cooking Ontology

The definition of the classes are-

1.DIR: DIR stands for DIRECTION. All the question Which are asking for direction to prepare some recipes are falls under direction class.

Example

Help me to cook Amazing Chocolate Chip Cookie Recipe.	DIR
Guide me in cooking Mashroom Chilli.	DIR
How to prepare raw mango chutney?	DIR

2.ADV: ADV stands for ADVICE.The questions which are asking for advice or per-
cussion to make any recipes are comes under this domain.

Example:

What are the tips to prepare Dahi or Yo-ghurt quickly ?	ADV
What are the tips used in the preparation of Chicken Tikka Masala?	ADV
Suggest one tip for making garlic dip.	ADV

TIME:Time stands for TIME. The questions are asking for what time is needed to prepare any recipes ,We marked that questions as Time class.

Example

What is the cooking time for the preparation of Eggless Punjabi Atta Biscuits?	TIME
Total time required for making paneer tikka?	TIME
What is the preparation time for Chat Masala demistified?	TIME

PREP:Prep stands for PREPARATION.The questions which is about how to prepare or make some food or what is the procedure to make some food are tagged as PREPARATION.

Example

How do you prepare indian kulfi	PREP
What is the method for making jal jeera?	PREP
How do you prepare chapati?	PREP

QTY: QTY stands for QUANTITY.The questions which are asking for some quantity of food or some indigence of a recipes are tagged as QTY class.

Example

In how many ways can we prepare dal?	QTY
How many glasses of water should be added to the one cup of dal?	QTY
How long we have to cut the Drum Sticks?	QTY

WRN:WRN stands for WARNING.The questions, which are asking about some warning or some message or some sentences are defining some moral are given class to warning.

Example

How often should I wash my hands in order to remove germs ?	WRN
What are the precautions for preparing onion tomato rava dosa?	WRN
What are some safe measures for pineapple sheera?	WRN

NAME NAME stands for NAME Class.The sentences which are describing about some name of a recipes or name of any inferences are tagged as NAME class.

Example:

What is potato halwa called in hindi?	NAME
Turmeric is also called?	NAME
What is the other name of haldi?	NAME

YESNO: YESNO stands for YESNO CLASS. The cooking related questions answers are either yes or no these questions are named as YESNO class

Example:

Is cooking time is more than preparation time?	YESNO
Can Boiled Chickpeas be converted into a nice tasting starters?	YESNO
Do we need mutton for preparing Punjabi Chole Masala?	YESNO

SPLINFO SPLINFO stands for SPECIAL INFORMATION. The sentences or the questions are asked for some some special information or special data or special statistics are named as SPLINFO

Example:

How do I know when my wine is properly reduced ?	SPLINFO
In a tomato sauce recipe, how can I cut the acidity ?	SPLINFO

OBJ:OBJ stands for OBJECTIVE: The sentences described some objective or ask to define some objective of a recipes are comes under OBJTIVE class

Example:

What is Jal Jeera?	OBJ
What is milk badam?	OBJ

JUST:JUST stands for JUSTIFICATION. The questions asked for any justification or the sentences described any justification are tagged as JUST class.

Example

why the yolk of eggs are different in colour?	JUST
Why rasmalai is kept freezed?	JUST

DIFF:DIFF stands for DIFFERENCE. The questions asking for describing some difference are tagged as DIFF class.

Example:

What is the difference between Naan and tandoori Roti?	DIFF
What is the difference between dips and chutney?	DIFF

3.2.2 Corpus Details

Here is a table below gives the detailed statistic of Total number of classes, Total data in each classes present in Cooking Dataset-1.

CLASS	STATISTIC
DIR	250
ADV	160
TIME	200
PRER	100
QTY	200
WRN	99
SPLINFO	413
NAME	219
YESNO	382
OBJ	376
JUST	200
DIFF	235
EQUIP	93

3.3 Cooking dataset-2(Yahoo qs-ans)

To our knowledge, there is no standard corpora for specific cooking related questions are available for research. So, we had no choice to use any standard data and we had to prepare experimental data for our own. Due to broad coverage and authenticity, we have selected Yahoo Answers(<http://answers.yahoo.com>) and for data collection. More

than seven hundred questions of cooking domains Yahoo Answers have been collected and approximately six hundred eighty two recipe data have been identified under human supervision.

We have used Nutch Crawler which is an open source tool that crawls cooking data from different websites. The importance of a page for a crawler can also be expressed as a function of the similarity of a page to a given query. Focused crawlers or topical crawlers attempt to download pages that are similar to each other. The system uses the crawler in two cases, such as case 1: crawler will search and save all the relevant web pages in the web and case 2: when the system encounters an unknown recipe requested by the user, it will search through Google, Alta Vista and only ten top ranked links will be considered for crawling.

The collected corpus will in HTML format. All the HTML data will extract first using by HTML Parser. The HTML Parser extracts the sentences from the document. After parsing the documents, it will index by using Lucene2, an open source full text search tool.

After indexing has been done, the queries have to be processed to retrieve relevant sentences from the associated documents. Each query is processed to identify the query words for submission to Lucene. Each hypothesis has been submitted to Lucene after removing stop words (using the stop word list). The remaining words are identified as the query words. Query words may appear in inflected forms in the question.

3.3.1 Corpus Details

This 18mb data consist of questions and corresponding answer. one question has multiple answers. Some question has 7 to answers some questions has 2 to 3 answers. But most of the questions- and answers are irrelevant. They are not belongs to cooking domain. Some Question-answer belongs to cooking domain. So we collect question and answer which are belongs to cooking domain. we find out 1k question and nearly 2k answers which are belong to cooking background. This is our data-set2.

QUESTION	ANSWER
POLL: Which is better; cakes or pies?	Cakes
POLL: Which is better; cakes or pies?	coke
POLL: Which is better; cakes or pies?	PIE
What should I make with mince meat?	bobotie - a spicy, fruity minced beef dish topped with a savoury custard.
What should I make with mince meat?	Spag bol, Chili, Kebabs, Meatballs, Pasta bake, Cottage pie, Meatloaf.
What should I make with mince meat?	Chilli Kabobs Hamburger patties for future use (freeze) or salad/ chips Topping Nachos
What should I make with mince meat?	Cottage pie or spag bol.
Who likes greek food? I do!?	Oh, god, yes! Roasted honey chicken and all that spectacular variety. Good, clean, delicious cuisine.
Who likes greek food? I do!?	YUM! We had corn mousakka last night. I love it.
Who likes greek food? I do!?	yes i love shish kebabs and falafel sandwiches.

Chapter 4

Question-type Classification:

Question Answering (QA) is a Natural Language Processing (NLP) task that requires the system to provide concise answers to Natural Language questions. This field of NLP has grown dramatically over the past couple of years, in part due to advances in Information retrieval, information extraction and Machine Learning, that have allowed for significant improvements in QA systems. Apple Siri, IBM Watson, Google Now has developed based on Advanced Question-answering.

Question classification plays an important role in question answering. The task of QS-Classifier is to classify a question to find expected and more accurate answers. As an example, the question “Who is the prime minister of India?” could be assigned the class “person”, whereas the question “Where is the prime minister of India?” could belong to the class “location”. Since the task involves identifying the type of Question, it is sometimes referred to as Question Type Classification. To segregate the question in different classes, actually narrow down the answer space. For example a question of Definition type can find its answer in definition type answer search space. Question of location type can find its answers in ‘Location’ answer space and so on.

Features are most important and play a vital role for Question-Classification. Different features identification for different type of question is a challenging task. Few algorithms are designed to extract basic features. Feature extraction algorithms are designed for extracting different features depending on the questions or type of questions.

Tokenization

Given a character sequence and a defined document unit, tokenization is the task of chopping it up into pieces, called tokens, perhaps at the same time throwing away

certain characters, such as punctuation. Tokens are the independent and small textual components that have some define semantics and syntax.

Example 1: Input: Friends, Romans, Countrymen, lend me your ears; Output: Friends,Romans,Country

Example 2: “Where is the famous house?” Output: Where,is,famous,house

Feature Selection:

Feature selection is the process of selecting a subset of the terms occurring in the training set and using only this subset as features in text classification. Feature selection serves two main purposes.It makes training and applying a classifier more efficient by decreasing the size of the effective vocabulary.Each question is represented by a bag of features. After that this features are feed-ed into classifier for classify the group of the sentences in the training stage.All the basic features that includes lexical features and semantic features are added in the feature space[32].

4.0.1 Lexical-Features

NgramsThese are usually selected based on the words presented in the question.An n-gram is a contiguous sequence of n items from a given sample of text or speech. The items can be phonemes, syllables, letters, words or base pairs according to the application. The n-grams typically are collected from a text or speech corpus. Unigram is a particular case of the n-gram features. To extract n-gram features, a sequence of n-words in a question is counted as a feature.

1. Unigram: If we consider the single word as features is called unigram,N=1.

Example:-Input: “ wireless speakers for tv”

Output: “wireless” , “speakers”, “for” , “tv”

2. Bigram: Contiguous two words is called bigram feature,Where N=2.

Example:-Input: “ wireless speakers for tv”

Output “wireless speakers”, “speakers for” , “for tv”

3. Trigram:-Contiguous three words as a feature is called trigram ,Where N=3.

Example:-Input: “ wireless speakers for tv” .

Output- “wireless speakers for” , “speakers for tv”

WH-Words: Other than YesNo question, most of the factoid questions starts with WH-Words. The wh-words, namely which, how, where, what, why, when, who and remaining. For example, 'Which is the Tallest building of the world?' is 'which'. Considering the wh-words as a separate feature improves the performance of QA according to the experimental studies.

Question-Length: Question length plays another vital role in question classification. Number of the words presents in the sentence can use to classify a sentence is a definition type or other.

QS-Length=(Total no of words in the question)

WordNet: WordNet is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. The main relation among words in WordNet is synonyms, as between the words shut and close or car and automobile. Synonyms words that denote the same concept and are interchangeable in many contexts are grouped into unordered sets (synsets). WordNet's structure makes it a useful tool for computational linguistics and natural language processing. We use NLTK for using WordNet[34].

Example: Input

Synonyms of "good" are

Output: ('beneficial', 'just', 'upright', 'thoroughly', 'well', 'skilful', 'skillful', 'sound', 'unspoiled', 'expert', 'proficient', 'honorable', 'adept', 'secure', 'commodity', 'estimable', 'soundly', 'right', 'respectable', 'good', 'serious', 'ripe', 'salutary', 'dear', 'practiced', 'goodness', 'safe', 'effective', 'dependable', 'honest', 'full', 'near')

Input: anonymous of "good" are:

Output: ('evil', 'evilness', 'bad', 'badness', 'ill')

4.0.2 Syntactic Feature:

The most basic syntactical features are Part of Speech (POS) tags and headwords. POS tags indicate such as NP (Noun Phrase), JJ (adjective), etc. Example Sentence- "Which sportson was made the brand ambassador of newly fro med state of Telangana". The above mentioned the pos tags: Which/WDT sportsperson/NN was/VBD made/VBN the/DT brand/NN am- bassador/NN of/IN newly/RB formed/VBN state/NN of/IN Telangana/NNP. A POS tagger obtains the pos tags of a question. In QA, all the pos tags of a question in feature vector can be added applied as bag-of-pos tags[37][36].

POS tag:The Natural Language Toolkit (NLTK) is a platform used for building programs for text analysis. One of the most powerful aspects of the NLTK module is the Part of Speech tagging. In corpus linguistics, part-of-speech tagging (POS tagging or PoS tagging or POST), also called grammatical tagging or word-category disambiguation.

Example:

Input: Everything is all about money.

Output: [('Everything', 'NN'), ('is', 'VBZ'), ('all', 'DT'), ('about', 'IN'), ('money', 'NN'), ('.', '.')]]

Head-Words: The head is the most important word in a phrase. All the other words in a phrase depend on the head. Words which are part of the phrase and which come before the head are called the pre-head. Words which are part of the phrase and which come after the head are called the post-head. In syntactic features, headword is the most edifying word in a question or a word that represents the object that question attempts. Identifying a headword can improve the efficiency of a QA system. For example for the question ‘Which is the newly formed state of India?’, ‘state’ is the headword. The word ‘state’ majorly contribute to classifier to tag LOC:state. Extracting questions headword is challenging. The headword of a question frequently selected based on the syntax tree of the question. To extract the headword, it is required to parse the question to form the syntax tree. The syntax (parse) tree is a tree that represents the syntactical structure of a sentence base on some grammar rules[38].

Focused Pattern: Focused pattern is also another syntactic feature for classification text. some sentence follow some pattern which is able to determine the type or the class of sentences. so pattern matching plays a vital role in question classification[39].

4.1 Feature Engineering

Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work. Feature engineering is fundamental to the application of machine learning, and is both difficult and expensive. Here we used manual feature engineering. We extract features to classify the the sentences by using machine learning algorithm[41][9].

In our Methodology We first extract features from Question set(Cooking Data-set 1).The extracted features are:

4.1.1 Features

1. **POS-TAG:** We run NLTK pos tagger over the Cooking detest-1 to get the pos tag of each word of the question set. Among all the words we took only NOUN, VERB, ADJECTIVE word. We used this Noun, verb, adjective as a feature-set.
2. **WORDS:-** We extract rare words or meaning full words from each of the sentences of the Cooking data-set1. After removing stopwords, we make each of the words to its root form by Lemmatization. We choose the rare words and cut down rest of the words of each sentence.
3. **TF-IDF: Term-Frequency** gives us the frequency of the word in each document in the corpus. It is the ratio of number of times the word appears in a document compared to the total number of words in that document. It increases as the number of occurrences of that word within the document increases. Each document has its own tf.

$$tft = \log(1 + tf_{t,d})$$

Document-Frequency used to calculate the weight of rare words across all documents in the corpus. The words that occur rarely in the corpus have a high IDF score. It is given by the equation below.

$$idf_t = \log_{10}(N/df_t)$$

TF-IDF-

$$W_{t,d} = \log(1 + tf_{t,d}) \times \log_{10}(N/df_t)$$

We found TF-IDF for each of the sentences. It gives a numeric score. we used it as a feature.

4. **WordNet:** We find the synonyms of adjective, verb and noun. We used WordNet to to make a list of adjective ,verb etc. We used this as a feature.
5. **WH-words:** We find out Head-word of each sentences, and if it is a WH-word ,we made a list and used it as a feature.
6. **Question-length:** We find out length of each sentence, that basically the total number of Use full words in the sentences.
7. **2GMS-**For each of the class we make a dictionary of most important and frequent occurring 2-gms. For each of the sentences in training data we first make a list of

two grams of the sentence, then matched with the Pool of the important 2-grams of each class. Depending on that matched pattern We give a Score to each of the Sentence of the training data-set.

8. 4-GMS-For each of the class we make a dictionary of most important and frequent occurring 2-gms. For each of the sentences in training data we first make a list of two grams of the sentence, then matched with the Pool of the important 4-grams of each class. Depending on that matched pattern We give a Score to each of the Sentence of the training data-set.

We use total 12 features for classify the Cooking data set.

Methodology Description of the features are,

- **Noun:** We run pos tagger on each of the sentences of Cooking dataset-1, It gives all the tags of each sentences, using NLTK tool. Among them we fetched only nouns for each of the sentences.

For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**

Noun: time, for, Imli, Ki, Chatni, Tamarind, Chutney.

Every question has some noun tag. Average noun tag per question is 5.

- **Adjective:** We run pos tagger on each of the sentences of Cooking dataset-1, It gives all the tags of each sentences, using NLTK tool. Among them we fetched only adjective for each of the sentences.

For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**

Adjective: cooking

Some questions have adjective some do not have adjective. Average Adjective tag per question is 2.

- **Verb:** We run pos tagger on each of the sentences of Cooking dataset-1, It gives all the tags of each sentences, using NLTK tool. Among them we fetched only verbs for each of the sentences.

For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**

Verb: is

Every question has verb. Average verb tag per question is 2.

- **Noun Synset:** We find the synonyms of each noun tag using WordNet ,tool of nltk.
 For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**
Noun Synset:'chi', 'Tamarindus', 'indica', 'ki', 'clock', 'time', 'qi', 'chutney', 'metre', "ch'i", 'clip', 't
 Average Noun Synset tag per question is 10.
- **Verb Synset:** We find the synonyms of each verb tag using WordNet ,tool of nltk.
 For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**
Verb Synset:'be', 'constitute', 'embody', 'exist', 'personify', 'follow', 'cost', 'comprise', 'make', 'up', 'equal', 'live', 'represent'
 Average verb Synset tag per question is 6.
- **Adjective Synset:** We find the synonyms of each adjective tag using WordNet ,tool of nltk.
 For example Input Sentence **What is the cooking time for Imli Ki Chatni or Tamarind Chutney ?**
Adjective Synset:'fudge', 'fix', 'preparation', 'make', 'wangle', 'cooking', 'ready', 'manipulate', 'fake', 'misrepresent', 'falsify', 'prepare', 'cooking', 'cook'
 Average adjective Synset tag per question is 8.
- **WH-words:** Some question has WH words some are yes/no questions starting with is, can, does etc, and rest are sentences want description or help etc. Among 2177 question more than 2000 are WH questions.
- **Word-Count:** Word Count represent total number of words in each sentences. Average word count for each sentence is 9.
- **Tf-Idf:** We found Tf-Idf of each questions, which gives a good accuracy improvement in classification results. We do Tf-Idf vectorization for each sentence and then calculate a summation score of Tf-Idf of each sentence. Average Tf-idf score for each sentence is 0.92245.
- **2Grams:** 2-grams plays an important role in classification. Based on 2 grams pattern we can differentiate between sentences in different class. Example
 Direction: (how, to), (how do), (Help me) 2-gms are most frequent.
 Quantity: (how, many), (how, much) 2gms are most frequent

- **4Grams:** 4-grams plays another important role in classification. Based on 4 grams pattern we can differentiate between sentences in different class.
Example Difference class:(what,is the difference) pattern is more frequent.

4.2 Classification

Text Classification assigns one or more classes to a sentence or text according to their content. Classes are selected from a previously established taxonomy (a hierarchy of categorize or classes). The Text Classification API takes care of all preprocessing tasks (extracting text, tokenization, stopword removal and lemmatization) required for classification.

There are several supervised and unsupervised machine learning algorithms, which are used for text classification. Some popular machine learning algorithms for text classification are naive Bayes, support vector machine, linear classifier, bagging model, boosting model, deep neural network etc. We have used deep neural network to classify Cooking questions among 13 classes.

We run several machine learning algorithms for text classification among them Naive Bayes, Support Vector machine and deep learning gives good accuracy results.

Naive Bayes

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other. Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

In the statistics and computer science literature, naive Bayes models are known under a variety of names, including simple Bayes and independence Bayes. All these names reference the use of Bayes' theorem in the classifier's decision rule, but naive Bayes is not (necessarily) a Bayesian method.

Support vector machine

Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in

classification problems. In this algorithm, we plot each data item as a point in n -dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well (look at the below snapshot).

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

Neural Network

A neural network[42] is a network or circuit of neurons, or in a modern sense, an artificial neural network, composed of artificial neurons or nodes.[1] Thus a neural network is either a biological neural network, made up of real biological neurons, or an artificial neural network, for solving artificial intelligence (AI) problems. The connections of the biological neuron are modeled as weights. A positive weight reflects an excitatory connection, while negative values mean inhibitory connections. All inputs are modified by a weight and summed. This activity is referred as a linear combination. Finally, an activation function controls the amplitude of the output. For example, an acceptable range of output is usually between 0 and 1, or it could be 1 and 1. Neural network consist of 3 layers input layer, hidden layer, output layer. A deep neural network has more number of hidden layers.

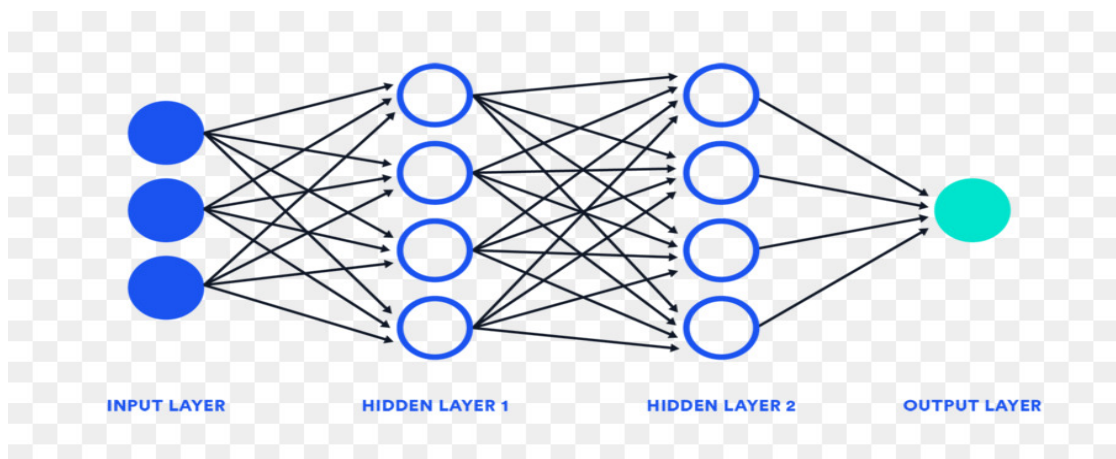


FIGURE 4.1: Neural Network

Deep L-Layer Neural Network

Shallow vs depth is a matter of degree of neural network. A logistic regression is a very shallow model as it has only one layer. A deeper neural network has more number of hidden layers. Here is some of the notations related to deep neural networks[44]:

L is the number of layers in the neural network

$n[l]$ is the number of units in layer l

$a[l]$ is the activations in layer l

$w[l]$ is the weights for $z[l]$

Forward Propagation in a Deep Neural Network For a single training example, the forward propagation steps can be written as:

$$z[l] = w^l a^{(l-1)} + b^l$$

$$a[l] = g^{(l)}(z^l)$$

In Convolutional[43] neural networks, convolutions over the input layer are used to compute the output. This results in local connections, where each region of the input is connected to a neuron in the output. Each layer applies different filters and combines their results.

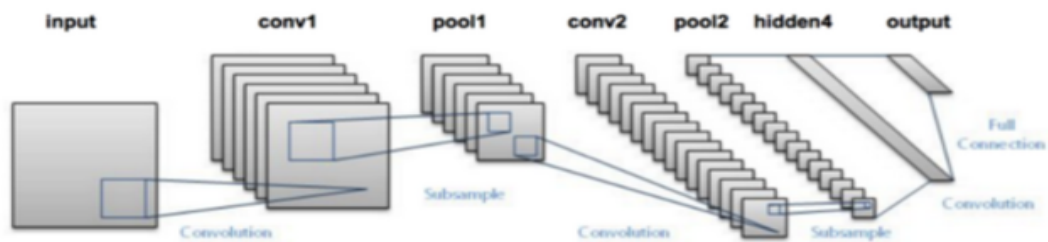


FIGURE 4.2: Convolution Neural Network

Methodology of Question Classification

We use Convolution Neural Network for classify 2177 questions among 13 different classes. We use this feature file of 12 features for classification. We extract 12 features from each of the questions. Then we feed ed this feature file to convolution neural network. We distribute the data-set in 60:40 data set. so 60% for training data and 40% test data. For training data-set we get an accuracy of 96% and for test data-set we get an accuracy of 70%.

Cooking dataset 1 was manually annotated for classification, After classification classifier gives a class to each questions. Now We have two tables one for manual classification another is automation classification most of the cases both class is same but some questions are there where manual class and model annotated class are different. This knowledge we used for answer classification. Creating the answer pools we use both manual and machine annotated class.

Chapter 5

ANSWER SELECTION

Question-Answering is a dynamic topic in today's world. Generally a QA system consists of three modules, 1. Question Analysis 2. Document retrieval 3. answer extraction. A QA system follows a pipeline architecture that chains together three main modules. Since the Answer Extraction component should be able to deal with unstructured text, it needs an efficient, and some methods that can deal with ambiguities, a module that can even have the ability to analyze the text structures (syntactical analysis) and extract the tokens [52][51].

QA system usually employs a pipeline architecture that chains together three modules.

Question analysis module: This module processes the question, analyzes the question type, and produces a set of keywords for retrieval. Depending on the retrieval and answer extraction strategies, some question analysis modules also perform syntactic and semantic analysis of the questions, such as dependency parsing and semantic role labeling [50].

Document or passage retrieval module: This module takes the keywords produced by the question analysis module, and uses some search engine to perform document or passage retrieval. Two of the most popular search engines used by many QA systems are Indri (Metzler and Croft 2004) and Lucene 1.

Answer extraction module: given the top N relevant documents or passages from the retrieval module, the answer extraction module performs detailed analysis and pinpoints the answer to the question. Usually answer extraction module produces a list of answer candidates and ranks them according to some scoring function

Methodology for Answer Extraction

Answer type classification is a subsequent and related component to question classification. It is based on a mapping of the question classification. Once a question has been

classified, a simple rule based mapping would be used to determine the potential answer types. Again, because question classification can be ambiguous, the system should allow for multiple answer types

5.1 Answer Pool Detection

Nearly all question answering system use a huge unstructured text for give a proper answer to a question. Every question answering system need a rich document collection to give proper answer or at-least nearest answer.

This is a special field of question-answering system, where the domain of the question answering system is cooking. As the domain is fixed the question are analyzed and classified on that particular domain. So The answer set belongs to that particular domain which is cooking. The COOKING DATASET 2(Yahoo-Answer) Contains a huge amount of data, all data are not belongs to the cooking field. so we extract that data from COOKING DATASET-2(Yahoo-Answer). We extract only those data which are related to cooking field.

The extract dataset contains the data of the bellow classes: 1. NAME 2. YESNO, 3. TIME, 4. DIRECTION, 5. JUSTIFICATION, 6. DIFFERENCE, 7. PREPARATION, 8. QUANTITY. Now We divide the total data-set in to sub-pools. For example Some answers are belongs to NAME class, some answers is belongs to TIME class and so on. So that unstructured data is classified into these classes. It can be said that the extracted data from DATASET-2 is itself a pool of all candidate answers. So now the classes are given the answer candidates are belongs to different classes. They are the sub-pools of answers.

The answer is in unstructured form so we structured the answer. first we find clean the text using RegEx function. A RegEx, or Regular Expression, is a sequence of characters that forms a search pattern. RegEx can be used to check if a string contains the specified search pattern. Python has a built-in package called re, which can be used to work with Regular Expressions. Then we built a dictionary.

Steps to build dictionary Answer-Set

1. **Lower Case:** All the uppercase letter are transfer into lowercase letter. This avoids having multiple copies of the same words. For example, while calculating the word count, 'Analytic' and 'analytic' will be taken as different words.

2. **Removing Punctuation:** The next work is to remove punctuation, as it doesn't add any extra information while treating text data. Therefore removing all instances of it will help us reduce the size of the training data.
3. **Removing stop-words** stop words (or commonly occurring words) should be removed from the text data. For this purpose, we can either create a list of stop-words ourselves or we can use predefined libraries.
4. **Tokenization:** Tokenization refers to dividing the text into a sequence of words or sentences. We used NLTK for tokenization.
5. **Stemming:** Stemming refers to the removal of suffices, like "ing", "ly", "s", etc. by a simple rule-based approach. For this purpose, we will use PorterStemmer from the NLTK library.
6. **Lemmatization:** Lemmatization is a more effective option than stemming because it converts the word into its root word, rather than just stripping the suffices. It makes use of the vocabulary and does a morphological analysis to obtain the root word

The Dictionary has two columns 1. The answer 2. The words of the questions which are extracted by following the above steps. For example this is a answer sub-pool of direction type question-answer dictionary.

5.2 Answer Retrieval

The document processing module in QA systems is also commonly referred to as paragraph indexing module, where the reformulated question is submitted to the information retrieval system, which in turn retrieves a ranked list of relevant documents[47]. The document processing module usually relies on one or more information retrieval systems to gather information from a collection of document corpora. The documents returned by the information retrieval system is then filtered and ordered. Therefore, the main goal of the document processing module is to create a set of candidate ordered paragraphs that contain the answer(s), and in order to achieve this goal, the document processing module is required to:

1. Retrieve a set of ranked documents that are relevant to the submitted question[48].

2. Filter the documents returned by the retrieval system, in order to reduce the number of candidate documents, as well as the amount of candidate text in each document.

3. Order the candidate paragraphs contains the correct answer.

The use ability for shortening documents into paragraphs is making a faster system. The response time of a QA system is very important due to the interactive nature of question answering. This ensures that a reasonable number of paragraphs are passed on to the answer processing module. retrieval system is to retrieve accurate results in response to a query submitted by the user, and to rank these results according to their relevancy.

One thing to be considered is that it is not desirable in QA systems to rely on IR systems which use the cosine vector space model for measuring similarity between documents and queries. This is mainly because a QA system usually wants documents to be retrieved only when all keywords are present in the document. This is because the keywords have been carefully selected and reformulated by the Question Processing module. IR systems based on cosine similarity often return documents even if not all keywords are present.

Information retrieval systems are usually evaluated based on two metrics – precision and recall. Precision refers to the ratio of relevant documents returned to the total number of documents returned. Recall refers to the number of relevant documents returned out of the total number of relevant documents available in the document collection being searched. In general, the aim for information retrieval systems is to optimize both precision and recall.

In our system the answer retrieval process based on pattern matching or keyword matching. Here the patterns and keyword are matched against the answer set. The steps that are followed in the answer retrieval process are.

1. The sample question is classified in the particular class using question classifier module.
2. The the sample question is tokenized and stop-words from the questions are removed. the question is transferred in query which contains meaning-full important words.
3. For answer extraction process, the model tries to find the answer in the pool of the particular class given by the question classifier.
4. We are matching the query words with the answer keywords, or patterns of the answer in that pool of answers.
5. Then a set of answered are retrieved from the pool based on query keyword matching.

5.3 Answer-Ranking

The aim of answer ordering is to rank the answer according to a plausibility degree of containing the correct answer[45]. answer ordering is performed using sorting algorithm. The sorting algorithm involves two different characteristic.

The scores to order paragraphs:

- i. Same word sequence score: the number of words from the question that are recognized in the same sequence within the current answer window.
- ii. Missing keyword score: the number of unmatched keywords in the current paragraph window[46].

Chapter 6

Experimental Results and Discussion

6.1 Evaluation on Question Classification

We have 2177 questions on cooking domain. We classify it in 13 classes. Several machine learning algorithms are available for classification. For small dataset Support vector machine usually gives better result. For text classification Naive Bayes gives better result. So we checked the classification task with top 5 machine learning algorithm. Among them Naive Bayes, SVM and Deep neural network give better result.

6.1.1 Machine Learning Experiments

As we discussed among top machine learning algorithms Naive Bayes, SVM, Deep learning give better results

Approach 1: We run Naive Bayes algorithm over 2177 questions. It gives around 95% accuracy. It can segregate the questions in 13 classes with 95% accuracy.

Approach 2: We also run SVM classifier over 2177 questions. It gives around 90% accuracy. It can segregate the questions in 13 classes with 90% accuracy.

6.1.2 Deep Neural Network

Table 6.2 shows the confusion matrix for Deep Learning classifier. There are 2177 training data available. They are classified between 13 classes. Deep learning shows 97% accuracy in classification. With 3% error it classifies sentences in different classes.

—	TIME	ING	DIR	YESNO	PRER	ADV	SPLINFO	NAME	WRN	EQUIP	OBJ	QTY	DIFF	JUST	CLASS PRECISION (in %)
pred. TIME	187	0	0	0	1	1	0	0	1	0	0	1	0	1	97.40%
pred. ING	0	127	0	0	1	0	0	0	0	0	0	0	0	0	99.22%
pred. DIR	0	0	203	0	0	0	1	0	0	0	0	0	0	0	99.51%
pred. YESNO	0	2	0	281	0	0	1	1	2	0	1	0	0	0	97.57%
pred. PRER	0	0	4	0	137	0	0	0	0	0	0	0	0	0	97.16%
pred. ADV	0	0	1	0	0	121	0	0	0	0	0	0	0	1	98.37%
pred. SPLINFO	0	8	3	1	1	6	311	0	2	3	5	0	0	1	91.20%
pred. NAME	0	0	0	0	2	0	0	117	0	0	0	0	0	0	98.32%
pred. WRN	0	0	0	0	0	0	0	0	51	0	0	0	0	0	100.00%
pred. EQUIP	0	0	0	0	0	0	0	0	0	41	0	0	0	0	100.00%
pred. OBJ	0	2	1	0	0	1	0	1	0	0	270	0	0	0	98.18%
pred. QTY	0	0	0	0	0	2	0	0	3	0	0	94	0	1	94.00%
pred. DIFF	0	0	0	0	0	0	0	0	0	0	0	0	75	0	100.00%
pred. JUST	0	0	0	0	0	1	0	0	0	0	0	0	0	96	98.97%
CLASS RECALL (in %)	100.00%	91.37%	95.75%	99.65%	96.48%	91.67%	99.36%	98.32%	86.44%	93.18%	97.83%	98.95%	100.00%	96.00%	

TABLE 6.1: Confusion matrix in Deep Learning

Table 6.2 shows the confusion matrix for Deep Learning classifier over test data. There are 2177 training data available. As deep learning gives the maximum accuracy on train data we used deep learning model for test data. We use 800 cooking questions as test data. we get an accuracy on 70% on test data. The model can classify overall 70% questions correctly. Other models like Naive Bayes classify 68% of the questions correctly among 13 different class. SVM classify 60% of the questions correctly among 13 different class. As Deep learning approach shows better result than other classifier so we choose deep learning here.

—	TIME	ING	DIR	YESNO	PRER	ADV	SPLINFO	NAME	WRN	EQUIP	OBJ	QTY	DIFF	JUST	CLASS PRECISION (in %)
TIME	151	0	1	1	1	2	0	0	2	0	0	3	0	0	93.79
ING	0	115	2	0	2	3	5	0	2	5	4	0	1	1	82.14
DIR	8	1	119	1	20	8	12	0	2	0	2	1	1	4	66.48
YESNO	2	4	18	256	6	15	22	17	2	1	9	0	3	3	71.51
PRER	1	1	25	2	97	0	3	1	0	0	0	2	0	0	73.48
ADV	1	3	12	2	1	68	15	5	2	0	11	1	2	4	53.5
SPLINFO	5	7	24	7	7	17	161	23	7	3	34	4	5	13	50.79
NAME	0	0	0	3	3	0	15	55	0	2	5	0	0	0	66.27
WRN	0	0	1	1	2	4	4	0	41	0	3	0	0	1	71.93
EQUIP	0	4	1	1	1	0	0	0	0	31	2	1	0	0	75.61
OBJ	1	3	3	2	2	6	41	13	1	2	196	8	0	1	70.25
QTY	17	0	4	1	0	5	10	3	0	0	4	75	1	1	61.9
DIFF	1	1	2	4	0	1	4	2	0	0	1	0	62	0	79.49
JUST	0	0	0	1	0	3	21	0	0	0	5	0	0	72	70.59
CLASS RECALL (in %)	80.75	82.73	56.13	90.78	68.31	51.52	51.44	46.22	69.49	70.45	71.01	78.95	82.67	72.00	

TABLE 6.2: Comparison Matrix on Test Data

6.1.3 Error Analysis :

We classify the questions depending on 12 features in 13 classes. For test dataset Deep learning gives 30% of error. 30% Questions are miss classified, for example Preparation class miss classified to Time class, Direction class miss classified to Justification class and so on. Naive Bayes gives around 40% of error and SVM gives about 45% of error. They miss classified the sentences as around 40% of rate.

- Naive Bayes error rate 40%.
- Support Vector machine error rate 45%.
- Deep learning error rate 30%

6.2 Answer Type Detection :

This is a Cooking question answering system. A set of cooking question is chosen for test data. The total system is divided into 3 modules.

- Question classification Module: This test question set is classified into 13 different classes. Here the classifier gives an accuracy of 70%.
- According to the classified class the answers of the questions are extracted from the corresponding answer pools. We first search the corresponding class answer pool and then using some methodology we extract one or multiple answers from that answer pool.
- If multiple answer is extracted then we are giving a ranked list of answers. We ranked the answers such as most relevant answer of the question comes first and least relevant of the answers comes last. A question can have at most 5 answers. This 5 answers are ranked according to their relevancy. Here we define a **Modified MRR** which shows how much the ranking is correct. This Modified MRR of 8 different classes shows in Table 6.3. Here is a hypothesis that in the gold standard dataset no answer is ranked so we make a hypothesis that all the answers of the question have rank 1. All the answers are equally relevant. Then we calculate this Modified MRR.

Mean Reciprocal Rank

The mean reciprocal rank is a statistical measure for evaluating any process that produces a list of possible responses to a sample of queries, ordered by probability of correctness. The reciprocal rank of a query response is the multiplicative inverse of the rank of the first correct answer: 1 for first place, half for second place, one third for third place and so on. The mean reciprocal rank is the average of the reciprocal ranks of results for a sample of queries Q .

Modified MRR: Concept is same as MRR only the denominator part of the MRR is changed, here we divide with 3 because we are showing top 3 results of answers of a question. So Modified MRR is more strict than MRR.

CLASS	Modified MRR
DIR	0.458
ADV	0.270
TIME	0.37
PRER	0.39
QTY	0.458
NAME	0.2916
YESNO	0.270
JUST	0.58
DIFF	0.315

TABLE 6.3: Modified MRR

6.3 Results :

The following Table gives the comparison between two class given to the sentences of test question data. One class is given manually and another class is our system generated.

SENTENCE	CLASS	prediction (CLASS)
Are hotdogs considered sandwiches?	YESNO	YESNO
What do yall like to eat with Hot cheetos? If you dont like them dont comment.?	ADV	NAME
Is italian food good?	YESNO	YESNO
What is your favourite flavour of tea/ coffee and how does it make you feel?	NAME	NAME
Can anyone give me a cheap grocery list to feed two people for a month?	YESNO	YESNO
Does anybody else hate hot chips ?	YESNO	YESNO
Why does Mexican food taste so awful?	JUST	JUST
Do vegan consume enough cholesterol?	YESNO	YESNO
I Need a Very Very Small Caramel Sauce Recipe?	PRER	NAME
What mexican food originated in texas?	NAME	NAME
Do you like lentil lunches?	YESNO	YESNO
Can I die from eating too much Cream of Tartar?	YESNO	YESNO
What is your favorite way to eat cheese?	NAME	NAME
What is a cheap food dish that I can make for 3 houses?	NAME	NAME
How do i make the coconut shrimp that they make at red lobster?	DIR	DIR
Which is tastier, apple pie or blueberry pie?	NAME	NAME

Table 6.4 continued from previous page

SENTENCE	CLASS	prediction (CLASS)
Canadians, what are some must try American restaurants/- food?	NAME	NAME
Is being an alcoholic any fun?	YESNO	YESNO
What is something different for a Thanksgiving dessert?	NAME	NAME
What are the best brands of Canadian Whiskey?	NAME	NAME
What are your favorite desserts?	NAME	NAME
What is your favorite flavor of hot tea?	NAME	NAME
How long do I bake a 10 deep dish pumpkin pie?	TIME	DIR
Is shark fin soup a terrible act of violence?	YESNO	YESNO
How do I get rid of a hangover please quick?	DIR	DIR
How to make a treasure map birthday cake?	DIR	DIR
Why would anyone be AGAINST veganism?	JUST	JUST
Whats your favorite food?	NAME	NAME
How to get rid of a hangover?	DIR	DIR
How do I make my meatballs juicy and tender?	DIR	DIR
What is it the best dipping sauce for French fries?	NAME	NAME
Why is juice tart?	JUST	JUST
Why is dried fruit more sugary than fresh?	JUST	JUST
How is whole grain white flour made?	DIR	DIR
Is coconut oil vegan?	YESNO	YESNO
Is it safe to eat raw steak?	YESNO	YESNO
Whats your favorite canadian cuisine?	NAME	NAME
How do I become drunk without drinking?	DIR	DIR
Does honey freeze at room temperature?	YESNO	YESNO
When was the last time you ate baby food?	TIME	NAME
What should I make with mince meat?	NAME	NAME
What are the best brands of Canadian Whiskey?	NAME	NAME
Is there any peanut butter out there made with no oil?	YESNO	YESNO
What are some of your favorite easy to make crockpot recipes?	NAME	NAME
How to make cookies or other treats if you dont have a bake feature on your oven?	DIR	DIR
How many servings of cranberry juice can you get out of a single large bottle?	QTY	QTY

Table 6.4 continued from previous page

SENTENCE	CLASS	prediction (CLASS)
How do I cook Japanese soba noodles?	DIR	DIR
How much would you sell brownies for?	QTY	QTY
How to make white cheese sauce like at a mexican restraurant?	DIR	DIR
How much is a beer in canada ?	QTY	QTY
Is a Hotdog a sandwich?	YESNO	YESNO
Is this sauce okay to eat?	YESNO	YESNO
How much caffeine is in a Cadburys Crunchie bar UK?	QTY	QTY
Why do i feel like this when i drink coffee?	JUST	JUST
Is this weird?	YESNO	YESNO
Why do vegetarians become vegetarians? Are ethical reason really justified?	JUST	JUST
Why is underage drinking bad?	JUST	JUST

Chapter 7

Conclusion and Future Work

7.1 Conclusion

The main objective of this thesis is to build a strong classifier which is able to classify sentences more correctly among different classes and give the precised answer list or more accurate answer to any Cooking related question.

Question Answering is a fast growing research area that brings together research from information retrieval, Information Extraction and Natural language processing. It is not only an interesting and challenging application, but also the techniques and methods developed from question answering inspire new ideas in many closely related areas such as document retrieval, time and named-entity expression recognition, etc. This is a dynamic field and growing day by day. QA systems have been extended in recent years to encompass additional domains of knowledge. For example, systems have been developed to automatically answer temporal and geo spatial questions, questions of definition and terminology, biographical questions, multilingual questions, and questions about the content of audio, images, and video. Current QA research topics include interactivity—clarification of questions or answers, answer reuse or caching, answer presentation, knowledge representation and reasoning, social media analysis with QA systems.

- Cooking is a new domain of question-answering system. Cooking question answering is a very new topic. Few works has done in this field. As this is a new field very few proper dataset are available. This is the main disadvantage of cooking QA-System. Our thesis gives a approach to classify sentences in different class, classify the answers depending on the questions, make different pools of answer. For a test question it is able to give proper answer or a nearest answers.

- From the question type point of view, the QA System that are most popular and are being given more attention to are factoid question answering. However, we noticed a growing number of contributions, especially in 2016, on non-factoid QA System. This fact suggests a growing interest in the research community for this kind of QA System and a possible trend towards systems that are more intelligent and closer to humans. Our work is on factoid question answering system, so it can be improved in human intelligent perspective.

7.2 Future-Work

In this thesis we presented a Question-Answering System over Cooking domain. Cooking Question answering system is a new topic of Question-answering System. Research work on this field has been started. So there is a lack of proper format data on Cooking System.

So if we get high volume of data then more research can be done in this field. As we know answer extraction needed a rich structured text data so that possibility of accurate answer extraction is increased. One work can be done on answer classification part, but due to lack of data that part of work gives a low level of accuracy so that answer classification is not possible. So in this thesis what we did is we make a hypothesis that questions have an answer belongs to the same class of the questions. In future we can try to make a proper dataset of answer with answer class, and feed that dataset in a machine learning classifier to classify the answers to different classes. If it is possible with an high accuracy then we can say that extracted answer of a cooking test question is more accurate and reliable.

Cooking question-answering system is a vast field. It has many real life examples. This system can be attached to a recommendation system related to cooking so that people get answers of their query and also the system can recommend dishes, restaurants etc. Hence we can say that there is vast knowledge and research work can be done on Cooking question answering system so that this system can do a lot more using other methods and approaches or algorithms.

Bibliography

- [1] Authors: Alisa Kongthon, Chatchawal Sangkeettrakarn, Sarawoot Kongyoung and Choochart Haruechaiyasak. Published by ACM 2009 Article, Bibliometrics Data Bibliometrics. Published in: Proceeding, MEDES '09 Proceedings of the International Conference on Management of Emergent Digital EcoSystems, ACM New York, NY, USA. ISBN 978-1-60558-829-2, doi:10.1145/1643823.1643908
- [2] Roger C. Schank and Robert P. Abelson (1977). Scripts, plans, goals, and understanding: An inquiry into human knowledge structures
- [3] Jansen, B. J. and Rieh, S. (2010) The Seventeen Theoretical Constructs of Information Searching and Information Retrieval. *Journal of the American Society for Information Sciences and Technology*. 61(8), 1517-1534
- [4] Foote, Jonathan (1999). "An overview of audio information retrieval". *Multimedia Systems*. 7: 2–10. CiteSeerX 10.1.1.39.6339. doi:10.1007/s005300050106.
- [5] irschman, L. Gaizauskas, R. (2001) Natural Language Question Answering. The View from Here. *Natural Language Engineering* (2001), 7:4:275-300 Cambridge University Press.
- [6] Lin, J. (2002). The Web as a Resource for Question Answering: Perspectives and Challenges. In *Proceedings of the Third International Conference on Language Resources and Evaluation (LREC 2002)*.
- [7] Moritz Schubotz; Philipp Scharpf; et al. (12 September 2018). "Introducing MathQA: a Math-Aware question answering system". *Information Discovery and Delivery*.
- [8] Chen, Danqi; Fisch, Adam; Weston, Jason; Bordes, Antoine (2017). "Reading Wikipedia to Answer Open-Domain Questions".
- [9] Bahadorreza Ofoghi; John Yearwood Liping Ma (2009). "The impact of frame semantic annotation levels, frame-alignment techniques, and fusion methods on factoid answer processing". *Journal of the American Society for Information Science and Technology*. 60 (2): 247–263.

-
- [10] B. F. Green, A. K. Wolf, C. Chomsky and K. Laughery, "BASEBALL: An automatic question answerer," in Proceedings of Western Joint IRE-AIEE-ACM Computing Conference, Los Angeles, 1961
- [11] C. Paris, "Towards More Graceful Interaction: A Survey of Question-Answering Programs," Columbia University Computer Science Technical Reports, 1985.
- [12] D. Radev, W. Fan, H. Qi, H. Wu and A. Grewal, "Probabilistic Question Answering on the Web," Journal of the American Society for Information Science and Technology, vol. 56, no. 6, pp. 571-583, 2005.
- [13] Gruber, T. 1993. A translation approach to portable ontology specifications. Knowledge acquisition 5, 2, 199-220.
- [14] Delpech, E. (2008, May). Investigating the structure of procedural texts for answering how- to questions. In Language Resources and Evaluation Conference (LREC 2008) (pp. p-544).
- [15] Serhatli, M., Alpaslan, F. N. (2009). An ontology based question answering system on software test document domain. World Academy of Science, Engineering and Technology, 54(09)
- [16] Zhang, D., Lee, W. S. (2003, July). Question classification using support vector machines. In Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval (pp. 26-32). ACM.
- [17] S. Harabagiu, D. Moldovan, M. Pasca, R. Mihalcea, M. Surdeanu, R. Bunescu, R. Girju, V. Rus and P. Morarescu, "FALCON: Boosting Knowledge for Answer Engines," in Proceedings of the Ninth Text Retrieval Conference.
- [18] Aouladomar, F. Saint-Dizier, P. (2005). An exploration of the diversity of natural argumentation in instructional Texts. In 5th International Workshop on Computational Models of Natural Argument, IJCAI, Edinburgh.
- [19] L. Hirschman and R. Gaizauskas, "Natural language question answering: the view from here," Natural Language Engineering, vol. 7, no. 4, pp. 275-300, 2001.
- [20] D. Zhang and W. Lee, "A Web-based Question Answering System," Massachusetts Institute of Technology (DSpace@MIT), 2003.
- [21] M. M. Sakre, M. M. Kouta and A. M. N. Allam, "Automated Construction of Arabic-English Parallel Corpus," Journal of the Advances in Computer Science, vol. 3, 2009.

-
- [22] M. Ramprasath and S. Hariharan, "A Survey on Question Answering System," *International Journal of Research and Reviews in Information Sciences (IJRRIS)*, pp. 171-179, 2012.
- [23] S. Harabagiu, D. Moldovan, M. Pasca, R. Mihalcea, M. Surdeanu, R. Bunescu, R. Girju, V. Rus and P. Morarescu, "FALCON: Boosting Knowledge for Answer Engines," in *Proceedings of the Ninth Text Retrieval Conference (TREC9)*, 2000.
- [24] X. Li and D. Roth, "Learning question classifiers," in *Proceedings of the 19th International Conference on Computational Linguistics (COLING 2002)*, 2002.
- [25] D. Zhang and W. Lee, "Question Classification using Support Vector Machines," in *Proceedings of the 26th Annual International ACM SIGIR Conference*, 2003.
- [26] S. Harabagiu, D. Moldovan, M. Pasca, R. Mihalcea, M. Surdeanu, R. Bunescu, R. Girju, V. Rus and P. Morarescu, "FALCON: Boosting Knowledge for Answer Engines," in *Proceedings of the Ninth Text Retrieval Conference (TREC9)*, 2000.
- [27] Yang Xianfeng (2016) Question Recommendation and Answer Extraction in Question Answering Community.
- [28] Schwarzer, Malte, et al. "An Interactive e-Government Question Answering System." (2016).
- [29] Batista, F., Pardal, J. P., Mamede, P. V. N., Ribeiro, R. (2006). Ontology construction: cooking domain. *Artificial Intelligence: Methodology, Systems, and Applications*, 41, 1-30.
- [30] Snae, C., Bruckner, M. (2008, February). FOODS: a food-oriented ontology-driven system. In *Digital Ecosystems and Technologies, 2008. DEST 2008. 2nd IEEE International Conference on* (pp. 168-176). IEEE.
- [31] De Rijke, M. (2005). Question Answering: What's Next?, In *Sixth International Workshop on Computational Semantics*, Tilburg.
- [32] Yin, L. (2004). Topic Analysis and Answering Procedural Questions, *Information Technology Research Institute Technical Report Series, ITRI-04-14*, University of Brighton, UK.
- [33] Aouladomar, F. Saint-Dizier, P. (2005). An exploration of the diversity of natural argumentation in instructional Texts. In *5th International Workshop on Computational Models of Natural Argument, IJCAI*, Edinburgh.
- [34] Walke, P. P., and S. Karale. "Implementation approaches for various categories of question answering system." *Information Communication Technologies (ICT), 2013 IEEE Conference on*. IEEE, 2013.

-
- [35] Silvia Quarteroni. 2007. A Chatbot-based Interactive Question Answering System. 11th Workshop on the Semantics and Pragmatics of Dialogue: 8390
- [36] Christopher Manning. Text-based Question Answering systems. <http://web.stanford.edu/class/cs224n/handouts/cs224n-QA-2013.pdf>, p. 7.
- [37] Van Dijk, David Tsagkias, Manos de Rijke, Maarten (2015) —Early Detection of Topical Expertise in Community Question Answering SIGIR
- [38] Viet Hung, Nguyen Quoc Chi Tang, Duong Weidlich, Matthias Aberer, Karl (2015) —ERICA: Expert Guidance in Validating Crowd Answers SIGIR
- [39] Keikha, Mostafa Hyun Park, Jae Croft, W. Bruce (2014) —Evaluating answer passages using summarization measures, SIGIR
- [40] Bast, Hannah Haussmann, Elmar (2015) —More Accurate Question Answering on Freebase, CIKM
- [41] Sondhi, Parikshit Zhai, ChengXiang (2014) —Mining Semi-Structured Online Knowledge Bases to Answer Natural Language Questions on Community QA Websites, CIKM
- [42] Pang, Liang Lan, Yanyan Guo, Jiafeng Xu, Jun Cheng, Xueqi (2016) —SPAN: Understanding a Question with Its Support Answers, AAAI
- [43] Shen, Yikang Rong, Wenge Sun, Zhiwei Ouyang, Yuanxin Xiong, Zhang (2015) —Question/Answer Matching for CQA System via Combining Lexical and Sequential Information, AAAI
- [44] Omari, Adi Carmel, David Rokhlenko, Oleg Szpektor (2016) —Idan: Novelty based Ranking of Human Answers for Community Questions, SIGIR
- [45] Petersil, Boaz Mejer, Avihai Szpektor, Idan Crammer, Koby (2016) —That’s Not My Question: Learning to Weight Unmatched Terms in CQA Vertical Search, SIGIR
- [46] Savenkov, David Agichtein, Eugene (2016) —When a Knowledge Base Is Not Enough: Question Answering over Knowledge Bases with External Text Data, SIGIR
- [47] Ture, Ferhan Jojic, Oliver (2016) —Ask Your TV: Real-Time Question Answering with Recurrent Neural Networks, SIGIR

-
- [48] Boguraev, Branimir Patwardhan, Siddhath Kalyanpur, Jennifer Chu-Carroll Lally, Adam (2014) —Parallel and nested decomposition for factoid questions, *Natural Language Engineering*
- [49] Oh, Jong-Hoon Torisawa, Kentaro Hashimoto, Chikara Iida, Ryu Tanaka, Masahiro Kloetzer, Julien (2016) —A Semi-Supervised Learning Approach to Why-Question Answering, *AAAI*
- [50] Feng, Guangyu Xiong, Kun Tang, Yang Cui, Anqi Li, Hang Yang, Qiang Li, Ming (2015) —Question Classification by Approximating Semantics
- [51] C. Raghavi, Khyathi Chinnakotla, Manoj Shrivastava, Manish (2015) —”Answer ka type kya he?”: Learning to Classify Questions in Code-Mixed Language,
- [52] Pudipeddi, Jagat Akoglu, Leman Tong, Hanghang (2014) —User churn in focused question answering sites: characterizations and prediction,