UNIVERSITI PUTRA MALAYSIA

DYNAMIC BAYESIAN NETWORKS AND VARIABLE LENGTH GENETIC ALGORITHM FOR DIALOGUE ACT RECOGNITION

ANWAR ALI YAHYA

FSKTM 2007 17

DYNAMIC BAYESIAN NETWORKS AND VARIABLE LENGTH GENETIC ALGORITHM FOR DIALOGUE ACT RECOGNITION

By

ANWAR ALI YAHYA

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirement for the Degree of Doctor of Philosophy

August 2007

DEDICATION

This thesis is dedicated to the memory of my late father, my beloved mother, my wonderful wife, my lovely son, my sisters, and my brothers.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

DYNAMIC BAYESIAN NETWORKS AND VARIABLE LENGTH GENETIC ALGORITHM FOR DIALOGUE ACT RECOGNITION

By

ANWAR ALI YAHYA

August 2007

Chairman: **Associate Professor Ramlan Mahmod, PhD**

Faculty: **Computer Science and Information Technology**

The recognition of dialogue act is a task of crucial importance for the processing of natural language in many applications such as dialogue system. However, it is one of the most challenging problems. The current dialogue act recognition models, namely cue-based models, are based on machine learning techniques, particularly statistical ones. Despite the success of the cue-based models, they still have serious drawbacks. Among them are, inadequate representation of dialogue context, intra-utterance and inter-utterances independencies assumptions, inaccurate estimation of the recognition accuracy and suboptimality of the lexical cues selection approaches.

Motivating by these drawbacks, this research proposes a new model of dialogue act recognition in which dynamic Bayesian machine learning is applied to induce dynamic Bayesian networks models from task-oriented dialogue corpus using sets of lexical cues selected automatically by means of new variable length genetic algorithm. In achieving

this, the research is planned in three main stages. In the initial stage, the dynamic Bayesian networks models are constructed based on a set of lexical cues selected tentatively from the dialogue corpus. The results are compared with the results of static Bayesian networks and naïve bayes. The results confirm the merits of using dynamic Bayesian networks for dialogue act recognition.

In the second stage, the previous ranking approaches are investigated for the selection of lexical cues. The main drawbacks of these approaches are highlighted, and based on that an alternative approach is proposed. The proposed approach consists of preparation phase and selection phase. The preparation phase transforms the original dialogue corpus into phrases space. In the selection phase, a new variable length genetic algorithm is applied to select the lexical cues. The results of the proposed approach are compared with the results of the ranking approaches. The results provide experimental evidences on the ability of the proposed approach to avoid the drawbacks of the ranking approaches.

In the final stage; the dynamic Bayesian networks models are redesigned using the lexical cues generated from the proposed lexical cues selection approaches. The results confirm the effectiveness of proposed approaches for the design of dialogue act recognition model.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

RANGKAIAN BAYESIAN DINAMIK DAN ALGORITMA GENETIK PANJANG BOLEHUBAH BAGI PENGECAMAN AKSI DIALOG

Oleh

ANWAR ALI YAHYA

Ogos 2007

Pengerusi: **Profesor Madya Ramlan Mahmod, PhD**

Fakulti: **Sains Komputer dan Teknologi Maklumat**

Pengecaman aksi dialog adalah sebuah tugas penting bagi pemprosesan bahasa tabii dalam pelbagai aplikasi seperti sistem dialog. Ia juga merupakan satu permasalahan yang sangat sukar. Model-model pengecaman aksi dialog terkini, contohnya model pengecaman berasaskan isyarat, adalah bersandarkan teknik-teknik pembelajaran mesin terutamanya statistik. Di sebalik kejayaan model statistik berasaskan isyarat, model-model ini mempunyai kelemahan yang serius. Antaranya adalah kekurangan dalam perwakilan konteks dialog, andaian terhadap keterbergantungan antara intra-tuturan dan inter-tuturan, anggaran ketepatan pengecaman yang tidak tepat, serta kaedah pemilihan isyarat leksikal yang tidak optima.

Berpandukan kelemahan-kelemahan tersebut, penyelidikan ini mencadangkan satu model pengecaman aksi dialog yang baru melalui penggunaan pembelajaran mesin bagi membentuk sebuah rangkaian Bayesian dinamik daripada korpus dialog berasaskan tugasan dengan menggunakan sebuah set isyarat leksikal yang dipilih secara automatik

melalui algoritma genetik panjang bolehubah. Bagi mencapai tujuan tersebut, penyelidikan ini dirancang dalam tiga tahap. Pada tahap permulaan, model rangkaian Bayesian dinamik dibentuk berdasarkan set isyarat leksikal yang dipilih daripada korpus dialog. Keputusan eksperimen kemudiannya dibandingkan dengan keputusan daripada rangkaian Bayesian statik dan Naïve Bayes. Keputusan yang didapati mengesahkan hasil rangkaian Bayesian dinamik bagi pengecaman aksi dialog.

Pada tahap kedua, pendekatan susunan untuk pemilihan isyarat-isyarat leksikal diselidik. Kekurangan utama pendekatan ini ditekankan melalui perbandingan dengan pendekatan alternatif yang dicadangkan. Pendekatan yang dicadangkan terdiri daripada fasa persediaan dan fasa pemilihan. Fasa persediaan mengubah korpus dialog yang asal kepada ruangan frasa-frasa. Dalam fasa pemilihan, algoritma genetik panjang bolehubah digunakan bagi memilih isyarat-isyarat leksikal tersebut. Keputusan daripada pendekatan yang dicadangkan kemudiannya dibandingkan dengan keputusan pendekatan berasaskan susunan. Hasil keputusan memberikan bukti ekperimental bahawa pendekatan yang dicadangkan berupaya mengelak daripada kelemahan-kelemahan dalam pendekatan berasaskan susunan.

Dalam fasa terakhir, model rangkaian Bayesian dinamik diolah bagi menggunakan isyarat-isyarat leksikal yang dihasilkan melalui pendekatan isyarat leksikal yang dicadang. Hasil keputusan mengesahkan bahawa pendekatan yang dicadangkan adalah berguna dan efektif bagi rekabentuk model pengecaman aksi dialog.

ACKNOWLEDGEMENTS

I would like to take this opportunity and thank my supervisor, Assoc. Prof. Dr. Ramlan Mahmod, for his support, guidance, and understanding. Through the course of my study I have had the great fortune to get to know and interact with him. His comments and suggestions for further development as well as his assistance during writing this thesis are invaluable to me. His talent, diverse background, interest, teaching and research style have provided me an exceptional opportunity to learn and made me a better student.

I would also like to thank the committee member, Assoc.Prof.Dr. Md. Nasir Suliman and Assoc.Prof.Dr. Fatimah Dato Ahmad for their help and valuable suggestions.

Special thanks and gratitude to Simon Keizer and prof. Anton Nigholt from Parlivnk research group, University of Twente, The Netherlands, for their generous sharing of dialogue corpus, dissertations, and ideas.

A sincere thanks to my family and friends, without whose support I would never have managed to complete this work.

A final word of thanks goes to Thamar Umiversity for their financial support during my study.

I certify that an Examination Committee met on 21 / 8 / 2007 to conduct the final examination of Anwar Ali Yahya on his Doctor of Philosophy thesis entitled " Dynamic Bayesian Networks and Variable Length Genetic Algorithm for Dialogue Act Recognition" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

Hamidah Ibrahim, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

Azmi Jaafar, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Rahmita Wirza O.K Rahmat, PhD
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Y.Bhg. Tengku Mohd Tengku Sembok, PhD
Professor
National Defense University of Malaysia
(External Examiner)

_____
HASANAH MOHD. GHAZALI, Ph.D.
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 27 September 2007

This thesis submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Ramlan Mahmod, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

Md. Nasir Sulaiman, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Fatimah Dato Ahmad, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

_____

AINI IDERIS, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 15th November 2007

DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations, which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UPM or other institutions.

_____

ANWAR ALI YAHYA

Date : 5th September 2007

TABLE OF CONTENTS

	Page
DEDICATION	ii
ABSTRACT	iii
ABSTRAK	v
ACKNOWLEDGEMENTS	vii
DECLARATION	x
LIST OF TABLES	xv
LIST OF FIGURES	xvii
LIST OF ABBREVIATIONS/NOTATIONS/GLOSSARY OF TERMS	xxi

CHAPTER

1 INTRODUCTION	
1.1 Introduction	1.1
1.2 Problem Statement	1.4
1.3 Research Objective	1.8
1.4 Scope of the Study	1.9
1.5 Research Methodology	1.9
1.6 Organization of the Thesis	1.13
2 DIALOGUE ACT	
2.1 Introduction	2.1
2.2 Natural Language Dialogue : Pragmatics Perspective	2.1
2.3 Linguistics Theories of Meaning	2.7
2.3.1 Use Theories of Meaning	2.8
2.3.2 Speech Act theory	2.10
2.4 Dialogue Act : Extensions of Speech Acts Theories	2.14
2.4.1 Communicative Acts: Communicative Activity Analysis	2.14
2.4.2 Dialogue Act: Dynamic Interpretation Theory	2.18
2.4.3 Conversation Acts theory	2.26
2.5 Dialogue Acts Coding Schemes	2.30
2.5.1 DAMSL Coding Scheme	2.32
2.5.2 SWBD-DAMSL	2.34
2.5.3 VerbMobil	2.34

3 LITERATURE REVIEW

3.1 Introduction 3.1
3.2 Dialogue Act Recognition 3.1
3.3 Plan-base Models 3.4
3.3.1 Intuition 3.4
3.3.2 Basic Model 3.5
3.3.3 Extensions 3.10
3.3.4 Pros and Cons 3.13
3.4 Cue-based Models 3.15
3.4.1 Intuition 3.15
3.4.2 Statistical Cue-based Models 3.17
3.4.3 Symbolic Cue-based Models 3.30
3.4.4 Subsymbolic Cue-based Models 3.33
3.4.5 Lexical Cues Selection Approaches 3.37
3.5 Drawbacks of Cue-based Models 3.42
3.5.1 Inadequate Representation of Dialogue Context 3.42
3.5.2 Intra-utterance and Inter-utterances Independency Assumptions 3.43
3.5.3 Inaccurate Estimation of the Recognition Accuracy 3.44
3.5.4 Suboptimal Lexical Cues Selection Approaches 3.44

4 DYNAMIC BAYESIAN NETWORKS FOR DIALOGUE ACTS RECOGNITION

4.1 Introduction 4.1
4.2 Bayesian Networks 4.1
4.2.1 Network Structure 4.4
4.2.2 Conditional Probabilities Distributions 4.5
4.2.3 Conditional independencies 4.6
4.2.4 Joint Probability Distribution 4.8
4.3 Dynamic Bayesian Networks 4.8
4.3.1 Inference 4.10
4.3.2 Learning 4.15
4.3.3 DBNs Software Packages 4.19
4.4 DBNs for Modeling 4.22
4.5 DBNs for Modeling DAR 4.24
4.5.1 Why DBNs ? 4.24
4.5.2 Specification of DBNs Random Variables 4.27
4.5.3 Learning DBN Structure 4.28

4.5.4 Learning DBN Parameters 4.30
4.5.5 Inference 4.31

5 VARIABLE LENGTH GENETIC ALGORITHM FOR LEXICAL CUES SELECTION
5.1 Introduction 5.1
5.2 Feature Selection 5.1
5.2.1 Wrapper Approaches 5.3
5.2.2 Filter Approaches 5.4
5.3 Feature Selection for High Dimensional Domain 5.5
5.4 Feature Selection using Ranking Approaches 5.7
5.4.1 Mutual Information 5.9
5.4.2 Information Gain 5.10
5.4.3 Chi Square 5.11
5.4.4 Correlation Coefficient 5.12
5.4.5 Simplified Chi Square 5.12
5.4.6 Odds Ratio 5.13
5.4.7 Balanced Metric 5.14
5.5 Drawbacks of Ranking Approaches 5.15
5.6 Lexical Cues Selection for DBNs Models of DAR 5.16
5.7 The Proposed VLGA-based Approach for Lexical Cues Selection 5.19
5.7.1 Preparation Stage 5.20
5.7.2 Selection Stage 5.25
5.8 VLGA for Lexical Cues Selection 5.26
5.8.1 Conventional GA 5.26
5.8.2 VLGA: Adapting VLGA for Lexical Cues Selection 5.29

6 RESULTS AND DISCUSSIONS
6.1 Introduction 6.1
6.2 Settings of Experiments 6.1
6.2.1 Dialogue Corpus 6.2
6.2.2 Dialogue Corpus Translation 6.2
6.2.3 Dialogue Corpus Annotation 6.5
6.2.4 Dialogue Acts Selection 6.7
6.2.5 Dataset Preparation 6.9
6.2.6 Dataset Partitioning 6.10
6.3 Results and Discussions 6.13
6.3.1 Baseline Approaches 6.13

6.3.2 Initial DBNs Model 6.16
6.3.3 Lexical Cues Selection 6.25
6.3.4 Enhanced DBNs Model 6.57

7 CONCLUSIONS AND FUTURE WORKS
7.1 Introduction 7.1
7.2 Conclusions 7.3
7.2.1 Baseline Approaches 7.3
7.2.2 Initial DBNs Model 7.3
7.2.3 Lexical Cues Selection 7.4
7.2.4 Enhanced DBNs Model 7.6
7.3 Future Works 7.7

REFERENCES R.1
APPENDICES A.1
BIODATA OF THE AUTHOR B.1

LIST OF TABLES

Table		Page
2.1	Examples of the Difference between Literal and Intended Meaning	2.6
2.2	Analysis of the Expressive and Evocative Dimensions of Four Communicative Acts (Allwood, 1995)	2.18
6.1	Selected Flf and Blf DAs	6.7
6.2	Flf DAs Distribution within the Corpus	6.8
6.3	Blf DAs Distribution within the Corpus	6.9
6.4	Flf Cross-validation Partitioning	6.12
6.5	Flf Cross-validation Partitioning	6.12
6.6	Results of NB DAR Models	6.14
6.7	Results of SBNs DAR Models	6.14
6.8	DBNs Random Variables	6.17
6.9	Results of Initial DBNs Model of Flf DAR	6.18
6.10	Results of Initial DBNs Model of Blf DAR	6.19
6.11	Average Recognition Accuracies for NB, SBN, and DBNs	6.20
6.12	Confusion Matrix of Initial DBNs Model for Flf DAR	6.23
6.13	Confusion Matrix of Initial DBNs Model for Blf DAR	6.24
6.14	Results of Lexical Cues Selection for Flf DAs using Ranking Approaches	6.27
6.15	Results of Lexical Cues Selection for Blf DAs using Ranking Approaches	6.28
6.16	Results of VLGA Case1 Experiments (Flf DAs)	6.34
6.17	Results of VLGA Case1 Experiments (Blf DAs)	6.34
6.18	Results of VLGA Case2 Experiments (Flf DAs)	6.39

6.19	Results of VLGA Case2 Experiments (Blf DAs)	6.40
6.20	Results of VLGA Case3 Experiments (Flf DAs)	6.44
6.21	Results of VLGA Case3 Experiments (Blf DAs)	6.45
6.22	Results of VLGA Case4 Experiments (Flf DAs)	6.50
6.23	Results of VLGA Case4 Experiments (Blf DAs)	6.50
6.24	Results of Enhanced DBNs Model with MI Lexical Cues	6.59
6.25	Results of Enhanced DBNs Model with VLGA Case2 Lexical Cues	6.59
6.26	Results of Enhanced DBNs Model with VLGA Case3 Lexical Cues	6.59
6.27	Results of Enhanced DBNs Model with VLGA Case4 Lexical Cues	6.59
6.28	Confusion Matrix of Enhanced DBNs Model for Flf DAR	6.63
6.29	Confusion Matrix of Enhanced DBNs Model of Blf DAR	6.64
B.1	Baseline Approaches Random Variables Definition	A.13
C.1	Selected Lexical Cues for Flf DAs using MI	A.15
C.2	Selected Lexical Cues for Blf DAs using MI	A.18
C.3	Selected Lexical Cues for Flf DAs using VLGA Case1	A.21
C.4	Selected Lexical Cues for Blf DAs using VLGA Case1	A.22
C.5	Selected Lexical Cues for Flf DAs using VLGA Case2	A.23
C.6	Selected Lexical Cues for Blf DAs using VLGA Case2	A.24
C.7	Selected Lexical Cues for Flf DAs using VLGA Case3	A.25
C.8	Selected Lexical Cues for Blf DAs using VLGA Case3	A.27
C.9	Selected Lexical Cues for Flf DAs using VLGA Case4	A.29
C.10	Selected Lexical Cues for Flf DAs using VLGA Case4	A.31

LIST OF FIGURES

Figure		Page
1.1	Dialogue from the AT&T HMIHY System.	1.2
1.2	Dialogue Example from Theater Domain	1.2
1.3	Typical Dialogue System Architecture	1.2
1.4	NLU Linguistic Analysis Example	1.3
1.5	Research Methodology	1.12
2.1	DIT DAs Taxonomy	2.24
2.2	Task-oriented DAs	2.24
2.3	Dialogue Control Act	2.26
2.4	Forward-looking function DAs	2.33
2.5	Backward-looking function DAs	2.33
3.1	Dialogue Act Recognition	3.2
3.2	Information-state Dialogue System Architecture	3.3
3.3	Plan-based DAR Model	3.4
3.4	Definition of `request` DA	3.6
3.5	Definition of `inform` DA	3.8
3.6	Definition of `request` DA	3.9
3.7	Definition of S.REQUEST	3.9
3.8	Cue-based DAR Model	3.17
4.1	A BN for Lung Cancer Problem	4.4
4.2	Types of Connection in Causal Networks	4.6

4.3	DBNs Structure	4.9
4.4	DBN as a Prior and Transition Networks	4.10
4.5	Inference in DBNs	4.11
4.6	The Main Types of Inference in DBNs	4.12
4.7	DBNs Inference Algorithms	4.14
4.8	Hill-climbing Algorithm for DBNs Structure Learning	4.29
4.9	Initialization Step of the Interface Algorithm	4.32
4.10	Example of Initialization Step	4.33
4.11	Junction Trees for Time Slice *t-1* and *t* after Initialization Step	4.34
4.12	Forward Pass of the Interface Inference Algorithm	4.34
4.13	Backward pass of the Interface Inference Algorithm	4.35
5.1	Wrapper Approaches for Feature Selection	5.4
5.2	Filter Approaches for Feature Selection	5.5
5.3	Contingency Table	5.9
5.4	Preparation Stage of the Proposed Approach	5.21
5.5	Tokenization	5.22
5.6	Removing Morphological Variations	5.23
5.7	Semantic Clustering	5.24
5.8	*N*-gram Phrases Generation	5.24
5.9	Conventional GA	5.29
5.10	Fixed Length Chromosome GA for Feature Selection	5.29
5.11	Variable Length Chromosome for Lexical Cue Selection	5.31

512	Phrases Space Mask	5.32
5.13	Pseudocode of the Uniform Crossover for VLGA	5.35
5.14	Example of Uniform Crossover for VLGA	5.35
5.15	Pseudocode of Mutation Operator	5.36
5.16	Example of VLGA Mutation Operator	5.37
5.17	Pseudocode of VLGA AlertLength Operator	5.38
5.18	Example of VLGA AlertLength Operator	5.38
6.1	Fragment of the Translated SCHISMA Dialogue Corpus	6.5
6.2	Decision Tree for `influencing_addressee_future_action`	6.6
6.3	Dataset Interface	6.10
6.4	K-fold cross-validation procedure	6.11
6.5	2T-DBNs model of Flf DAR	6.19
6.6	2T-DBNs model of Blf DAR	6.19
6.7	Ranking Approaches Lexical Cues Selection for *Statement*	6.29
6.8	Ranking Approaches Lexical Cues Selection for *Positive_Answer*	6.29
6.9	VLGA Case1 Evolution of Lexical cues Selection for *Statement*	6.35
6.10	VLGA Case1 Evolution of Lexical Cues Selection for *Query_ref*	6.35
6.11	VLGA Case1 Evolution of Lexical Cues Selection for *No_blf*	6.36
6.12	VLGA Case1 Evolution of Lexical Cues Selection for *Positive_answer*	6.36
6.13	VLGA Case2 Evolution of Lexical Cues Selection for *Statement*	6.40
6.14	VLGA Case2 Evolution of Lexical Cues Selection for *Query_ref*	6.41
6.15	VLGA Case2 Evolution of Lexical Cues Selection for *No_blf*	6.41

6.16	VLGA Case2 Evolution of Lexical Cues Selection for *Positive_answer*	6.41
6.17	VLGA Case3 Evolution of Lexical Cues Selection for *Statement*	6.45
6.18	VLGA Case3 Evolution of Lexical Cues Selection for *Query_ref*	6.46
6.19	VLGA Case3 Evolution of Lexical Cues Selection for *No_blf*	6.46
6.20	VLGA Case3 Evolution of Lexical Cues Selection for *Positive_answer*	6.46
6.21	VLGA Case4 Evolution of Lexical Cues Selection for *Statement*	6.51
6.22	VLGA Case4 Evolution of Lexical Cues Selection for *Query_ref*	6.51
6.23	VLGA Case4 Evolution of Lexical Cues Selection for *No_blf*	6.51
6.24	VLGA Case4 Evolution of Lexical Cues Selection for *Positive_answer*	6.52
6.25	Lexical Cues Selection for Flf DAs (Maximum Predictivity)	6.54
6.26	Lexical Cues Selection for Blf DAs (Maximum Predictivity)	6.54
6.27	Lexical Cues Selection for Flf DAs (Maximum Aggressivity)	6.55
6.28	Lexical Cues Selection for Blf DAs (Maximum Aggressivity)	6.55
6.29	Enhanced 2T-DBNs Model of Flf DAR	6.60
6.30	Enhanced 2T-DBNs Model of Blf DAR	6.60
B.1	NB model for Flf DAR	A.14
B.2	SBNs model for Flf DA	A.14

LIST OF ABBREVIATIONS/NOTATIONS/GLOSSARY OF TERMS

2TBN	Two-slice Temporal BN
AI	Artificial Intelligence
ANNs	Artificial Neural Nets
BDe	Bayesian Dirichlet equivalent
BIC	Bayesian Information Criterion
Blf	Backward looking function
BM	Balanced Metric
BNT	Bayes Net Toolbox
CAA	Communicative Activity Analysis
CART	Classification And Regression Trees
CAT	Conversational Analysis Theory
CC	Correlation Coefficient
CPD	Conditional Probabilities Distributions
CPT	Conditional Probabilities Table
DA	Dialogue Act
DAG	Directed Acyclic Graph
DAMSL	Dialogue Act Markup in Several Layers
DAR	Dialogue Act Recognition
DBNs	Dynamic Bayesian Networks
DIT	Dynamic Interpretation theory
DNF	Disjunctive Normal Form

EM	Expectation Maximization
Flf	Forward looking function
GAs	Genetic Algorithms
GMTK	Graphical Models ToolKit
H	Hearer
HMM	Hidden Markov Model
HMM	Hidden Markov Model
IG	Information Gain
ME	Maximum Entropy
MI	Mutual Information
ML	Machine Learning
MLE	Maximum Likelihood Estimation
NB	Naïve Bayes
NLP	Natural Language Processing
NLU	Natural Language Understanding
OR	Odd Ratio
PGMs	Probabilistic Graphical Models
PNL	Probabilistic networks library
S	Speaker
SBNs	Static Bayesian Networks
SCHISMA	SCHouwburg Informatie Systeem
VLGA	Variable Length Genetic Algorithm
XML	eXtensible Markup Language

CHAPTER 1

INTRODUCTION

1.1 Introduction

Emulation of human conversation ability is one of the earliest goals of Artificial Intelligence (AI). In 1950, in an article published in the scientific journal Mind, British mathematician, Alan Turing, asked the question *"Can a machine think?*" He answered in the affirmative, but he went on to ask another question: "*If a computer could think, how could we tell?*" Turing's suggestion was that if the responses from the computer are indistinguishable from that of a human, the computer could be said to be thinking. This is known as *Turing Test*, and it is the main motivation for the researches in the area of Natural Language Processing (NLP) in general and dialogue system in particular.

Fifteen years after Turing proposed his test, Weizenbaum (1966) designed his first dialogue system, named *ELIZA*, which attempted to engage a human in a conversation. Since then, dialogue systems have witnessed substantial developments, and as a result of this, many commercial domains that demand human-machine interaction have adopted dialogue system technology. Travel planning domain has been the key concern of dialogue systems for quite a long time. Automatic call routing is another interesting domain of dialogue systems. In this domain, the call routing dialogue system directs incoming call in a telephone call centre, transferring the call to the appropriate human. Figure 1.1 shows an example of a dialogue from the AT&T system between the system and the user, denoted by S and U respectively (Gorin *et al*., 1997).

S: How may I help you?
U: Can you tell me how much it is to Tokyo?
S: You want to know the cost of a call?
U: Yes, that's right.
S: Please hold on for rate information.

Figure 1.1: Dialogue from the AT&T System (Gorin *et al.*, 1997).

A somewhat different domain is information exchange and transaction in virtual environments such as theatre. The dialogue system provides information to its users about theatre performances and can also make reservations if necessary. Figure 1.2 shows part of a dialogue from the theatre domain.

U: What will be on in the theater next week (19 March)?
S: There is no show on that date.
U: And on 18 March?
S: on 18 March you can go to Deelder Denkt and Indonesian Tales.
U: At what time does Deelder start?
S: The show starts at 20:00.
U: How much does it cost? …

Figure 1.2: Dialogue Example from Theater Domain

Technically speaking, dialogue system is an advanced NLP application that provides a relatively natural interaction between users and computer-based applications. In so doing, the dialogue system subsumes the major fields of NLP including speech recognition and synthesis, language understanding, dialogue management, and language generation. Figure 1.3 shows how the typical architecture of the dialogue system combines the major fields of NLP.

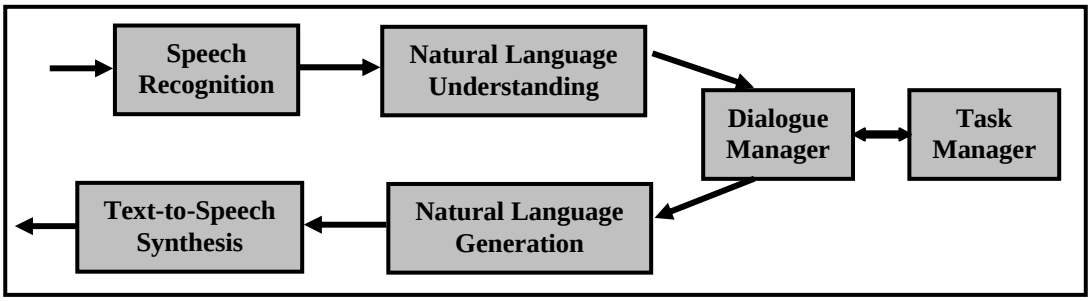

Figure 1.3: Typical Dialogue System Architecture (Jurafsky and Martin, 2000)