### **Assignment Presentation**

### Probabilistic Graphical Models

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M. Tech. in Machine learning and intelligent systems

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**Module Name:** Probabilistic Graphical Models

Module Code: MIS503



### **Marking Scheme**

Head	Maximum	Score
Technical Content	5	
Grasp and Explanation	5	
Quality of Slides and Delivery	5	
Q & A	5	
Total	20	



### **Presentation Outline**

- Discriminative model is better than generative model in structured classification problems.
- Development of an algorithm to extract syntactic cues and semantic labels from a narrative text such that they form an input to knowledge representation module.
- Development of an algorithm for action description of a narrative text using Bayesian network.



# Generative model is better than discriminative model in structured classification problems

 Application: Structured Classification Problem in Natural Language Processing.

#### Need:

- Probability estimates can be smoothed to accommodate unseen events
- Redundancy in language supports effective statistical inference procedures \ the stimulus is richer than it might seem.
- Statistical learning theory: generalization ability of a model class can be measured independently of model representation.



# Advantages and disadvantages of Generative and Discriminative models

- Discriminative models do not offer clear representations of relations between features and classes in the dataset.
- Generative models often outperform discriminative models on smaller datasets because their generative assumptions place some structure on your model that prevent overfitting.
- **Stance:** Discriminative models are more powerful than the generative models and hence work better for larger datasets than smaller datasets. The only problem is of Overfitting in smaller Datasets.



# Develop an algorithm to extract syntactic cues and semantic labels from a narrative text such that they form an input to knowledge representation module.

- Tokenization of the narrative text.
  - The narrative text is tokenised into two forms word and sentences.

#### Sentence tokenization output:

['One day Buddha was walking through a village.', 'A very angry and rude young man came up and began insulting him.', '"You have no right teaching others," he shouted.', '"You are as stupid as everyone else.']

#### Word tokenization output:

['One', 'day', 'Buddha', 'was', 'walking', 'through', 'a', 'village', '.', 'A', 'very', 'angry', 'and', 'rude', 'young', 'man', 'came', 'up', 'and', 'began', 'insulting', 'him', '.', '"', 'You', 'have', 'no', 'right', 'teaching', 'others', ',', '"', 'he', 'shouted', '.', '"', 'You', 'are', 'as', 'stupid', 'as', 'everyone', 'else']



# Develop an algorithm to extract the syntactic cues from the text

- Read text.
- Identify the Special Characters and flag them(Not included for POS tagging)
- Creation of the dictionary the only picks the required words
  - Words that starts with the Noun=>Adjective=>Noun
  - Words ending (Leaf Ending) which has a conjunction as parent.
- Perform tokenisation eliminating the special characters.
- Run through parts of speech tagger.
- With the help of the dictionary only select the words that fit into and print.



# Develop an algorithm to extract the syntactic cues from the text

### Output:

Sentence 1	Sentence 4	Sentence 6	Sentence 7
day		young	
buddha	everyone	man	gift
village	Sentence 5	tell	P., C
Sentence 2	Semence 3	gift	
rude	nothing	someone	buddha
young		person	
man	fake	gift	anger
Sentence 3		belong	
right	buddha	man	
teach	insult	strange	anger
other		question	



### Formation of a semantic label table

• Semantics is the meaning of words in sentences. it refers to meaning that does not depend on the context where it appears. Semantic table consists of [Context1, Intent1, Dependencies, Dep]. Context has the words in the sentence, Intent represents to the Action that is performed in the sentence, Dependencies represents the dependence of other words in the same sent to the word in the context, Dep is the semantic role label.

•	0	One	day		nummod
•	1	day	walking	[One]	npadvmod
•	2	Buddha	walking		nsubj
•	3	was	walking		aux
•	4	walking	walking	[day, Buddha, was, through, .]	ROOT
•	5	through	walking	[village]	prep
•	6	a village		[]	det
•	7	village	through	[a]	pobj
•	8 .	walking		[]	punct



# Development of an algorithm to extract the semantic labels

### Algorithm:

- Read text.
- Tokenize the paragraph into sentences.
- Identify the 'and' and 'also' words in the input and combine if wrongly tokenised in tokenisation.
- Links between the words are identified.
- The word with maximum links is the word that contains the action(Meaning) of the sentences.
- The root word is extracted from the whole sentence.



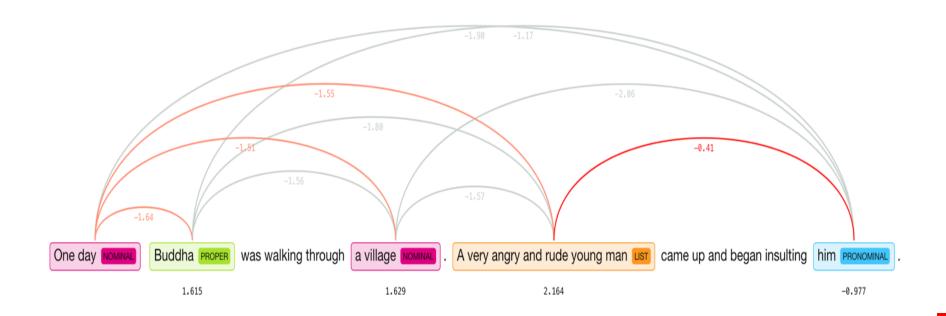
# Development of an algorithm to extract the semantic labels

Sentence 1	Walking
Sentence 2	Angry, Came, Began
Sentence 3	Shouted
Sentence 4	Are Stupid
Sentence 5	Are Fake
Sentence 6	Take, gift, Buy, Belong
Sentence 7	Falls, Anger



# Development of an algorithm for coreference resolution for the extracted syntactic and semantic information

 Coreference resolution is the task of determining linguistic expressions that refer to the same realworld entity in natural language.





# Feature identification by integrating syntactic, semantic, and coreference information.

- Each every step that is achieved until now has given some important information for further processing to be precise with the information contributed by the individuals are as follows.
- Syntactic Extractor: Base words that form the story.
- Semantic Extractor: Main Theme of the sentence.
- Coreference resolution: Relationship between linguistic expression and real world word.



# Develop an algorithm for action description of a narrative text using Bayesian network.

- Development of a knowledge representation algorithm using the features identified in Part-B.
- The actual story the main context of the story lies in the conversation of Buddha and the young Man.
- The part before the conversation tells the thinking of the young man about Buddha.
- The Conversation refers to the Intent call gift but ultimately it is referred to the anger and the hurt.
- The complete reference to gift has to be taken to the Anger and Hurt.



# Identification of threshold patterns for joint probability distribution

Accepting	notaccepting	accepting
buyer	0.9	0.2
otherperson	0.1	0.8

Accepting notaccepting	accepting	
buyer 0.9	0.2	
otherperson 0.1	0.8	

.1 .				
notbuying	0.5	notfake	0.1	notstu
la constanta	0.5	Hottake	0.1	
buying	0.5	fake	0.9	stupid
		Take	0.5	

Buying A gift	notbuying	buying
notgiving	1.0	0.1
giving	0.0	0.9

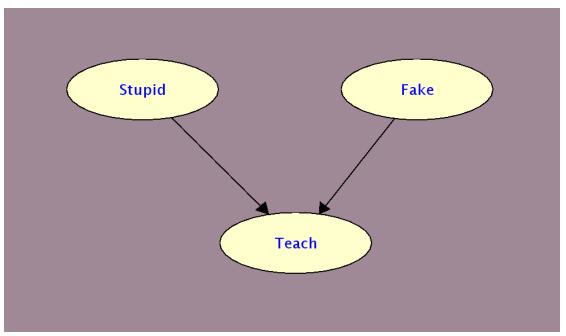
Stupid	notst	upid	stu	pid
Fake	notfake	fake	notfake	fake
capableto	0.8	0.5	0.5	0.25
notcapabl	0.2	0.5	0.5	0.75

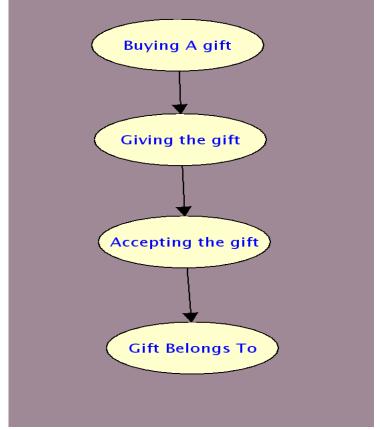


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### Development of a Bayesian network model

- As the story is seen in perspective of two parts I.e.
  - Before conversation
  - While conversation







# Development of a reasoning scheme for inferring action description

 Reasoning scheme for inferring the action is done using the python library for probabilistic graphical model pgmpy.

### OUTPUT

 $\label{eq:query} q = storybeforeconv\_model.query(variables=['Teach'], evidence=\{'Stupid': 0\}) \\ \textbf{print}(q['Teach'])$ 

+	+
: .	phi(Stupid)
Teach_0   Teach_1 +	0.3000
т	· T



## Analysis of results and comment on the influence of representation, inference, and learning algorithm

Computing the probability of teaching given stupid.

+	++
•	phi(Stupid)   -+
Teach_0	•
Teach_1	-
+	++

- Looking at the above result it clearly made an inference of if the person is stupid there is no point of him teaching.
- In this model the inference of the anger and is directly obtained it is from the Knowledge representation only.
- Similarly as given all the inference can be made from the above graphical models.



### References

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