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Design of meta-semantic analysis for automatic detection of Alzheimer's disease

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An abstract of

a thesis submitted to the Faculty of Emory College of Arts and Sciences

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Abstract

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Nowadays, manual diagnosis of early stages of neurodegenerative disorders such as Alzheimer’s disease (AD) has been a challenge. While current neuropsychological examinations often fail to provide satisfactory result in detecting Mild Cognitive Impairment (MC) and linguistic ability has shown to be a good indication of symptoms of AD, in this thesis I examine the semantic linguistic features resulting from verbal utterances of potential patients to distinguish healthy people and people with the disease. For this purpose, I perform statistical and machine learning analysis on a specific language transcript dataset, consisting of 50 healthy people and 50 probable MCIs. Experimental and statistical evaluations suggest that certain patterns and semantic features are effective in helping the clinical diagnosis of MCI.

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Chapter 1

Introduction

1.1 Manual Diagnosis of AD

It is challenging to manually diagnose AD and other types of dementia has a challenging nature [1-4]. Current diagnosis tools include Montreal Cognitive Assessment (MoCA) screening tools which are composed of a series of questions and cognitive tests that assess different cognitive abilities [5]. Evans & Mitchell [6,7] demonstrate that it takes two years to use the cognitive tests to distinguish between the sub-types of dementia: Mild Cognitive Impairment (MCI) and AD. It is challenging for the cognitive tests to manually distinguish effectively between sub-types of dementia over a large population [7].

1.2 Related Works

Various Alzheimer's Disease screening methods using Natural Language Processing techniques have been proposed to date. Well-known studies were those conducted by Roark [8,9] which analyzed the lexical features and syntactic feature from transcripts of spoken narrative such as neuropsychological approaches [10] and automatic speech analysis approaches [11]. Some of them used automatic speech recognition [12]. Aramaki [13] specifically examined vocabulary size in speech transcription. Tanaka [14] proposed a novel approach using computer avatars. In addition, Orimaye [15] used machine learning algorithms to build diagnostic models using syntactic and lexical features, and Jarrold [16] used Linguistic Inquiry and Word Count (LIWC) for aided diagnosis of Dementia. Shibata [17] examined the usage of LIWC classified words in detecting AD. The values of <Social> in AD group were significantly lower than those in Healthy Control (HC) group. The values <Ipron>, <Verbs> and <Present> in AD group were also significantly larger than those in HC group. de Alba [18] enhanced the protocol of semantic features employed in that study by using Natural Language Processing systems such as FunGramKB [19,20,21,22,23]. This lexical-conceptual knowledge base incorporated a series of feature descriptors for the definition of semantic knowledge with the inheritance and inference relations established among concepts in the ontology. It enriched the collection of semantic features used in the test of semantic attribute's production for the detection of semantic memory impairment [24]. Orimaye [25] combined n -grams with a reliable ML algorithm that learns several low-level linguistic features and identifies the probable AD group from the healthy elderly group. Hernndez [26] compared the computed performance and language functions of patients during standardized picture description tasks against a population with similar socio-demographic characteristics. They trained machine learning algorithms to evaluate the informativeness and pertinence of the descriptions of patients, as well as their lexical richness.

In terms of deep learning approaches, Guerrero [27] have developed a Bayesian networks (BN) for Cognitive Impairment (CI) diagnosis in mild and moderate AD patients by analyzing the oral production of semantic features. The BN causal model represents Lexical-semantic- conceptual deficit (LSCD) in certain semantic categories, both of living things (dog, pine, and apple) and non-living things (chair, car, and trousers), as symptoms of CI. Ramirez [28] proposed another Bayesian algorithm that classifies the sentimental polarity of the conversational phrases.

1.3 Why Meta-Semantics

Semantics sets out to specify the meanings of linguistic expressions. Meta-semantics inquires into the nature of certain properties investigated by natural language semantics. It seeks a certain fundamental characterization of these properties. It asks whether and how these semantic properties might admit to some illuminating reduction to, or unification with, non-semantic properties [29]. Differences between semantics and meta-semantics can be illustrated by the following questions :

1. What is the content (semantic value) of s?
2. In virtue of what does s have the content(semantic value) that it has?

The first we would call a descriptive semantic question; the second one we would call a foundational question about semantic value.

In my thesis, I examine the meta-semantic features besides semantic features because meta-semantics tells about not only semantic values of words, but also how the words communicate with each other and their properties. For example, in the sentence “This is a sad elephant,” in our meta-semantic annotation, we are able to retrieve much more information about “sad” than the fact that it is a noun modifier by its semantic role. “Sad” is also an attribute of the mention of “elephant. ” In addition, “sad” as a noun modifier has an attribute of “emotion” itself. In this way, we can obtain much richer information from the averagely 15-sentence transcripts and generate a more valuable training data set.

1.4 Motivation and Objectives

To automate the process of AD detection using semantic features of human language, I designed an Annotation Guideline that aims to extract valuable features which can distinguish MCI group and healthy controls in their description of a picture called “Circus Procession.” I performed observational, statistical and machine learning analysis in extracting significant semantic features in distinguishing the two groups.

Chapter 2

Background

2.1 Significance of Linguistic Ability in Detecting AD

[30,31] shows that linguistic ability captured from verbal utterances could indicate symptoms of AD. Neurodegenerative disorders (ND) deteriorate nerve cells that control cognitive, speech and language processes [31]. Language impairment in Alzheimer's disease initially affects verbal fluency and naming ,which require integrity of semantic concepts, before breaking down in other facets of the brain[32]. In particular, performance is impaired on tasks that require relatively complete, elaborate semantic representations but is preserved when the task requires only partial semantic representations consisting largely of shared features [33].

[34] investigated the significance of lexical and syntactic features from the verbal narratives of AD patients by performing several statistical tests based on 121 elderly participants comprising 60 subjects with AD and 61 healthy subjects. In their paper, immediate word repetitions, word revisions, and coordinated sentences could be used to distinguish those patients with AD from the healthy elderly group.

More recently, in [35] mAD (mild Alzheimer's disease) shows worse overall performance compared to the healthy controlss: less informative discourse, greater impairment in global coherence, greater modulization, and inferior narrative structure.

2.2 Picture Description and Linguistic Ability

[36] shows that picture description tasks are useful tools for detecting differences in a wide variety of language and communicative measures, because picture description is a constrained task that relies less on episodic memory and more on semantic knowledge and retrieval, within the cognitive demands of a communication context.

Chapter 3

Approach

I developed an Annotation Guideline that aims to extract valuable features which can distinguish MCI group and healthy controls in their description of a picture called 'Circus Procession'.

3.1 Dataset and Tools

Similar to Sylvester [25] which shows that the BDAE Cookie-Theft picture has been shown to be clinically relevant in identifying linguistic deficits in both Alzheimers disease and Aphasia patients, the Circus Procession picture (See figure 3.1.) has also been proved to have the same usage. Our dataset consists of audio recording of 50 MCI people and 50 healthy control people's response to several tasks including depiction of the picture circus procession and other language tasks (Natural Speech and Fluency Tasks)(See figure 3.2) These 100 individuals have similar MoCA scores, which means that normal cognitive tests can not distinguish them. We use the tool TEMI[38] to automate the process of transforming audio to texts and annotators manually check and fix to ensure the final quality of the transcripts. Texts are pre-processed in preparation for annotation. The tool BRAT[39] helps with visualization and enhance efficiency when we do the annotation.

Figure 3.1: Circus Procession

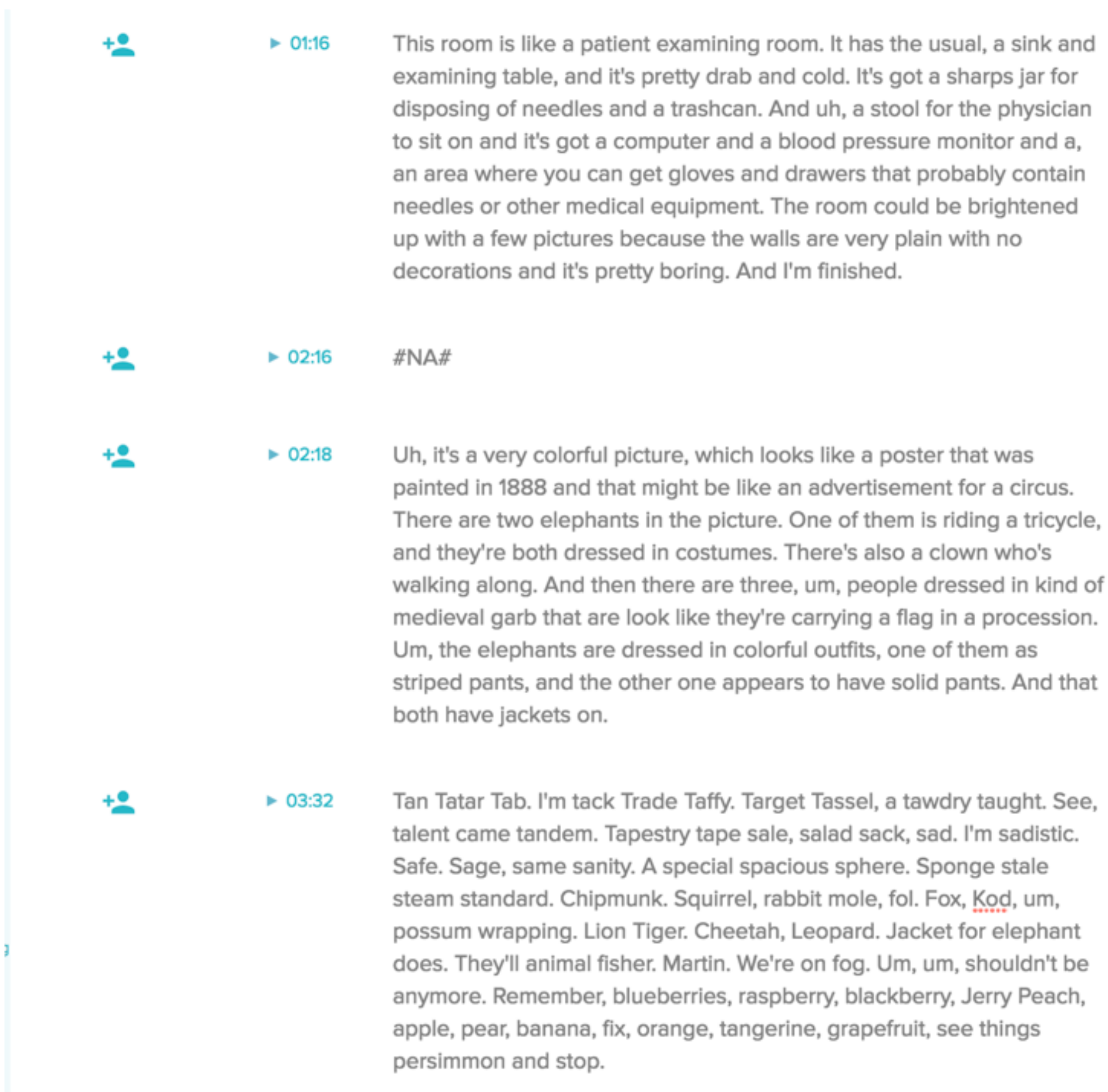


Figure 3.2: Recording tasks

3.2 Annotation Guideline

An annotation guideline is essential in the task of effectively generating significant semantic features for training data. Existed annotation guidelines such as PropBank [40] and Penn TreeBank [41] are heavily studied and referenced in making my annotation guideline. However, given the task is different, this annotation guideline is highly picture-oriented and I revised the guideline numerous times through the process of observation when doing the annotation and also statistical computation to add or eliminate features. Differences are big between the first version and the final version.See figure 3.3.

Figure 3.3: difference between versions

Annotation Guideline Contents

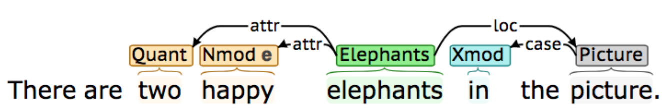
3.2.1 Introduction

3.2.1.1 Annotation Goals

The annotation of the transcripts creates a valuable corpus, which can be used as training data for natural language processing research on diagnosis of the early stage of the disease. Training data, essentially, is what computer scientists and computational linguists can use to 'teach the computer' about different aspects of human language. In our annotation, a sentence is annotated to identify mentions of some real-world entities (objects) and their types, and a relation between two. Named entity recognition and information extraction tasks are accomplished. The main tasks of this annotation are: entity type labeling, entity attribute labeling and relation labeling.

For example, given the sentence '*There are two elephants in the picture.*'

In BRAT tool we will see



In raw form we will get the following tables. The three types of information (Entity, Entity Attribute if it has any, Relation) are mixed together in reality, the tables are shown for clearer visualization.

ENTITY TAG	ENTITY	SPAN	WORD
T1	Quantity	146 149	two
T2	Elephants	157 166	elephants
T3	Xmod	167 169	in
T4	Picture	174 181	picture
T5	Nmod	149 156	happy

RELATION TAG	RELATION	SOURCE	TARGET
R1	attr	Arg1:T2	Arg2:T1
R2	loc	Arg1:T2	Arg2:T4
R3	case	Arg1:T4	Arg2:T3
R4	attr	Arg1:T2	Arg2:T5

ATTRIBUTION TAG	ATTRIBUTION	SUBJECT
A1	Emotion	T5

3.2.2 Entity Type Annotation

Instructions

Entities are word or chunk of words that have semantic roles within a text. Function words, auxiliary verbs and conjunction words are not annotated as entities. We have four classes of entities in our annotation---Mentions, Predicates, Noun modifiers and Adverbial-modifiers. We do not annotate entities that are unrelated to the picture itself. Subjective deviations, imaginations made by the narrator from the mentions in the pictures are not annotated as well. e.g.: *The three men in the middle remind me of the three musketeers.* Here *'the three musketeer'* are not annotated.

3.2.2.1 Mentions

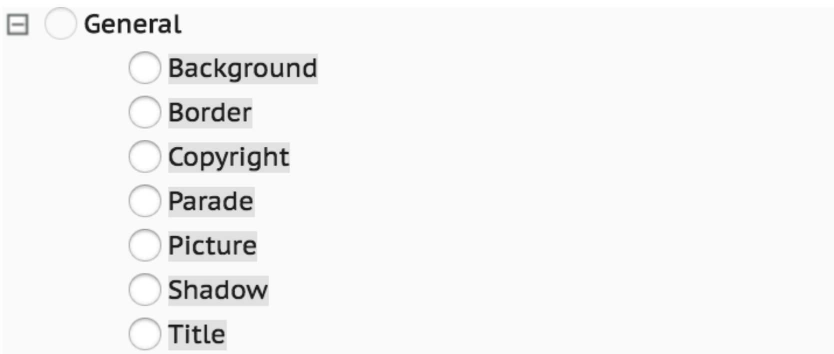
Mentions are real life objects appeared in the picture, commonly noun phrases. We omit articles in our annotation. Mentions are classified into two general types---common and other.

3.2.2.1.1 Common Mentions

Common mentions are objects that constantly appear in each transcript. We came up with a list of common mentions based on our observation of the transcripts.

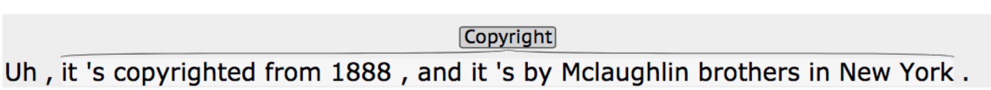
Descriptions of the picture in general:

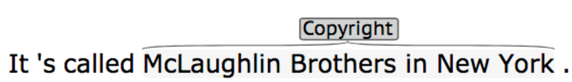
- *Picture, Background, Border, Copyright, Parade, Picture, Shadow, Title*

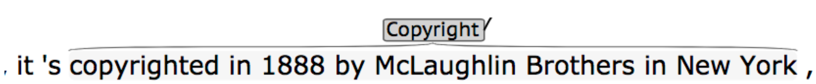


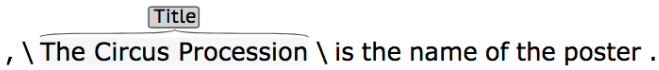
The way of annotating 'Copyright' and 'Title' : They do not refer to exactly the word '*copyright*' or 'Title' in the text. Instead, a whole sentence, a clause, or a couple of words can all be annotated as 'copyright'or 'Title'.

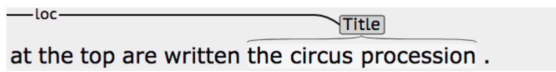
Below are different examples of 'copyright' or 'Title'











Mentions related to both elephants:

- *Elephants, Costume, Hats*

Mentions related to the left elephant:

- *Elephant_left, Tricycle, Jacket, Beanie, Collar, Head, Tie, Pants, Trunk*

Mentions related to the right elephant:

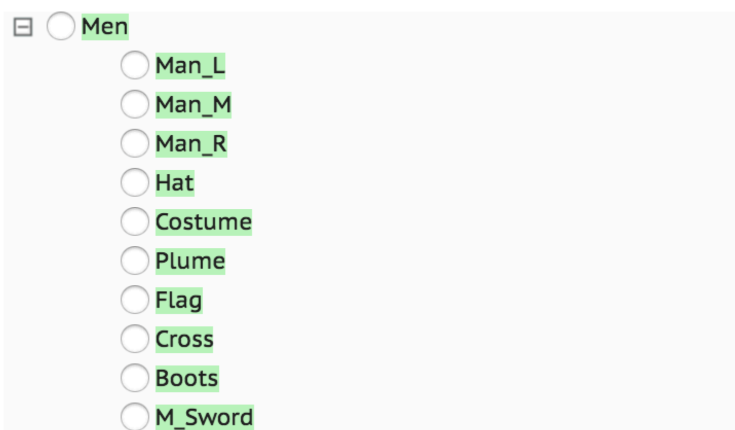
- *Elephant_right, Fedora, Coat, Vest, Cane, Fan, Glasses, Head, Collar,*

Pants, Tie, Hand, Feet, Trunk

Mentions related to men:

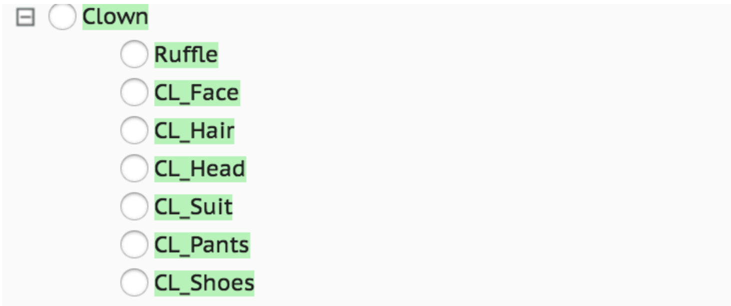
- *Men, Man in the left, Man in the middle, Man in the right, Hat, Costume,*

Plume, Flag, Cross, Boots, Sword



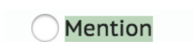
Mentions related to the clown:

- *Clown, Ruffle, Face, Hair, Head, Suit, Pants, Shoes*



3.2.2.1.2 Other Mentions

Mentions that are not categorized into the above classes are annotated as ‘Mention’.



Example for not common mentions:

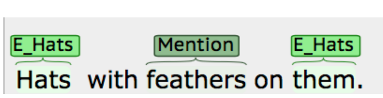
stripe, umbrella

3.2.2.1.3 Handling coreference

Coreference occurs when two or more expressions in the text refer to the same person or thing. Example: *hats with feathers on them*

> Here 'hats' and 'them' are co-referenced.

Correct way of annotating this is



3.2.2.1.4 Handling misspelling and wrong expression

We still annotate the misspelling words or wrong expressions as long as we can identify what the narrator is trying to refer from the context.

e.g. These are all annotated as ‘Title’.

circus profession
the circus profession
procession
The Circus Procession
the circus procession

If the mention in the text refer to the same thing in the common mentions list above and only uses a different word expression, we annotate them as common mention.

minstrels, soldiers > men

bicycle > tricycle

balloon > fan

Some rare examples include big ‘slip of the tongue’ of the narrator. For example, the narrator describes the left elephant for two sentences and suddenly the subjects of the rest of the passage all change to ‘the left monkey’. In this case we annotate monkey as ‘elephant_l’.

3.2.2.3 Predicate

Predicate is the part of a sentence that tells what the subject does. We only annotate one word which is usually the verb. We omit the auxiliary verbs (am, is, are). One type of predicates we pay special attention to is **Motion**, which usually conveys the mention is performing some actions rather than a static state of itself.

Examples of motion predicates:

hold, carry, stand, march, ride, walk, go, wave, peddle, operate, drive, follow, dance

Examples of other predicates:

wear, dressed

Light verb usage (e.g. *take a shower, have a drink*) where predicates appear as a clause is treated as a whole.

3.2.2.3.1 Annotating ‘have’ and ‘get;

We do not annotate 'have' and ‘get’ in the cases where it refers that a mention is wearing/dressed in something or own some decorations.

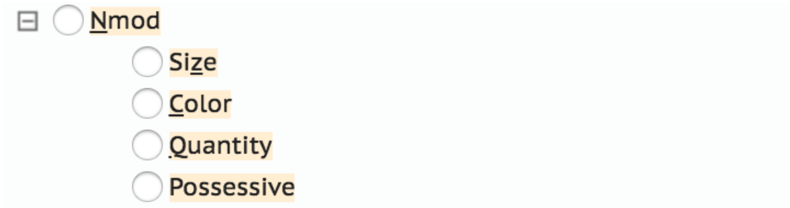
Example where we annotate 'have':

have a hard time, have the tricycle move

I originally annotated ‘have’ as a common predicate, however, I observed that most ‘have’ and ‘get’ appeared in a context when it referred to wearing something or own some ornaments, and ‘have’ actually had the most appearance among the predicates in both control group and group with AD. This caused confusion when I did statistical computation of the predicates. So I decided to separate ‘have’ and other predicates which give specific information on what the object is doing. See 4.3.1 ‘With’ relation.

3.2.2.4 Nmod

a modifier is an optional element in phrase structure or clause structure [21]. It modifies another entity in the sentence and can be removed without affecting the grammar of the sentence. Nmod is the group of adjective noun modifiers. Most common types of Nmod appeared in the transcripts are **Color / Size / Quantity / Possessive**.



Color :

red, yellow

Size:

large, small

Quantity :

one, two, a bouquet of, a group of, a great deal of

Possessive:

Used with nouns referring to mentions, and shows a relationship of belonging.

his

Sometimes compound nouns can function as modifier as well.

e.g. *a polka dot dress*

> Here 'polka dot' is Nmod.

Nmods that do not belong to any of these four categories are annotated as 'Nmod'

e.g. *striped pant, a variety of characters, diamond shape pattern, side leg*

> Here 'striped', 'a variety of', 'diamond shape', 'side' are Nmods.

3.2.2.5 Xmod

Xmod is the class of any other types of modifiers including adverbials. Xmod modifies verbs and also nouns. In addition, all of the prepositions are considered as Xmod. We have four special classes of adverbials that we are interested in : **Fuzzy/ Certain/Emphasis/Negation/IMO**

Fuzzy:

probably, likely, ,possibly, it could be, believable, credible

Certain:

Must, doubtlessly, surely, certainly, indubitably, decisively

Emphasis:

Actually, exactly, very, clearly, really, definitely, absolutely, pretty

Negation :

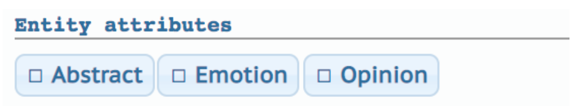
don't, not

IMO (In my opinion.):

I guess, i am assuming, i think, what i would like, is supposed to

3.2.3 Entity Attribute Annotation Instruction

Entity attributes are attributes which we assign to the entities in Chapter 2. There can be a lot of attributes, however, in our annotation we only define the following attribute types: Abstract, Emotion, Opinion.



3.2.3.1 Abstract

Different from what abstract nouns typically imply in linguistics, the 'abstract' attribute here conveys a sense of unclear and ambiguous. Examples are:

something, one, those type of

If we got information about this abstract mention from its context, we do not attach the 'abstract' attribute, for example,

One elephant is riding the tricycle and the other one is walking behind him.

> Here 'one elephant' is annotated as the known mention 'Elephant_R', without attribute 'abstract'.

If we don't get any information about the mention from the context, for example

The clown is holding something in the hand.

> Here 'something' is annotated as an unknown mention, with attribute ‘abstract’.

Colors can also have abstract attribute when it refers to the clothes, for instance

the elephant with blue on

> Here 'blue' has attribute 'Abstract'.

3.2.3.2 Emotion

Emotion attributes generally describes modifiers that are highly subjective and express emotional feelings of the narrator on the object he describes. Examples: *sad, cruel, painful, happy*

3.2.3.3 Opinion

Opinions are a more generalized class than emotion words.

1. subjective adjectives or nouns

Examples of adjectives: *fancy, nice, bored, beautiful, normal looking, different*

Examples of nouns: *the baby elephant, the father elephant*

> Here 'baby' and 'father' are 'Opinion' Nmods.

2. descriptive clauses that contain the word "like"

dressed up in a human, dressed up like a millionaire

> Here human (millionaire) is opinion.

3. sentences with hint words at the front

In my experience, as far as i can see, it is obvious that

3.2.4 Relation Annotation Instructions

An relation takes place between two entities when one entity has an semantic role over the other. We annotate every possible relation within a sentence. We do not annotate relations across the sentences.

3.2.4.0 Choosing Source and Target Arguments

Similar to PropBank Annotation Guideline[19], source arguments are the subjects of transitive verbs and a class of intransitive verbs called unergatives. Semantically, external arguments have what Dowty (1991) called Proto-Agent properties, such as:

1. Volitional involvement in the event or state
2. Causing an event or change of state in another participant
3. Movement relative to the position of another participant (Dowty, 1991)

Target arguments are the objects of transitive verbs and the subjects of intransitive verbs called unaccusatives. These arguments have Proto-Patient properties, which means that these arguments:

1. Undergo change of state
2. Are causally affected by another participant
3. Are stationary relative to movement of another participant (Dowty, 1991)

3.2.4.1 Core Argument

An argument is an expression that helps complete the meaning of a predicate [22]. Subject and object arguments are known as core arguments. This relation usually takes place between Mention – Predicate – Mention (- Mention)

By [23], In languages that have morphological case, the arguments of a predicate must appear with the correct case markings (e.g. nominative, accusative, dative, genitive, etc.) imposed on them by their predicate. The semantic arguments of the predicate, in contrast, remain consistent, e.g. In our annotation, we treat all of the arguments as semantic argument.

Jack is liked by Jill.

Jill's liking Jack

Jack's being liked by Jill

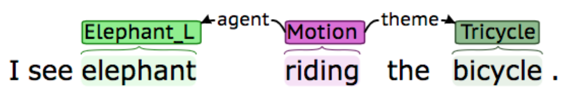
the liking of Jack by Jill

Jill's like for Jack

3.2.4.1.1 Agent and Theme Relation

Agents are usually the subject of a transitive, ditransitive, or unergative verb. Themes are mostly the direct object of a transitive or ditransitive verb.

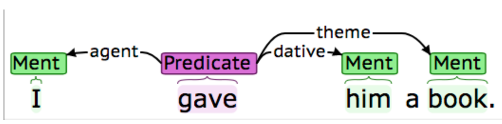
e.g. *I see the elephant riding the bike.*



3.2.4.1.2 Dative Relation

Besides normal agent and theme, the verb has another indirect object.

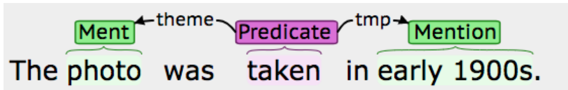
e.g. *I gave him a book.*



3.2.4.1.3 Handling sentences in passive voice

Because our annotation emphasizes on semantic features rather than syntax features, the choices of voices should not change the way of annotation. We still keep the same source and target based on its semantic meaning.

e.g. *The photo was taken in early 1900s.*



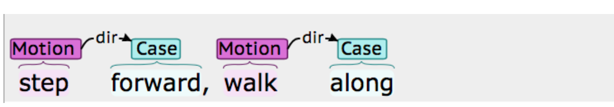
3.2.4.2 Thematic Roles

Thematic relations, also known as semantic roles, are the various roles that a noun phrase may play with respect to the action or state described by a governing verb, commonly the sentence's main verb. A list of the major thematic relations can be found at [24]. In our annotation, we select some thematic relations from the list.

3.2.4.2.1 (DIR)Directional

Directional relations show motion along some path, where the action is directed towards

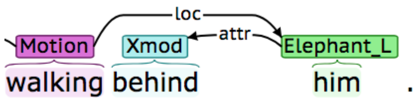
e.g. step forward, walk along



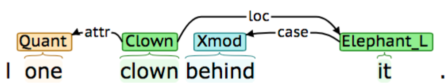
3.2.4.2.2 (LOC)Locative

Locative relations indicate where some action takes place. Both physical location and abstract locations are marked as locative.

e.g. walking behind him



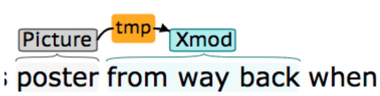
e.g. One clown behind it



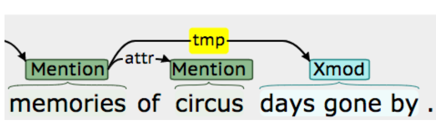
3.2.4.2.3 (TMP)Temporal

Temporal words show when an action takes place. Also included in this category are adverbs of frequency: *always, often*, adverbs of duration: *for a year*.

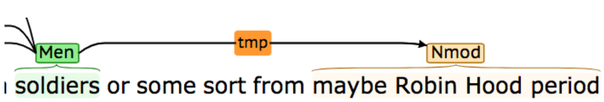
e.g. poster from the way back then



e.g. memories of circus days gone back



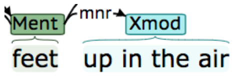
e.g. soldiers from maybe Robin Hood period



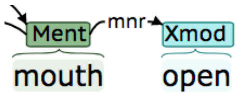
3.2.4.2.4 (MNR)Manner

Manner relations indicate how an action is performed.

e.g. feet up in the air



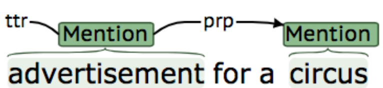
e.g. mouth open



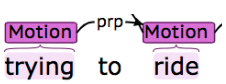
3.2.4.2.5 (PRP)Purpose

Explains the motivation for some action. Clauses beginning with ‘for', ‘in order to' and 'so that' are common purpose clause.

e.g. advertisement for a circus



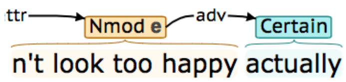
e.g. trying to ride



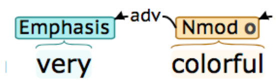
3.2.4.2.6 (ADV)Adverbial

Usually found between ‘Xmod and predicates’ or ‘Xmod and Nmod’ or ‘Xmod and Mention’ to complete the modify relation

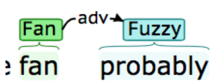
e.g. *not look too happy actually*



e.g. *very colorful*



e.g. *the fan probably*



3.2.4.2.7 Omitted Thematic Roles

Some thematic roles that we included in our early versions of the guideline contain GOL(Goal), CAU (Causal), MOD (Modal). Either they can be replaced with other thematic role relations or they don't contribute much in the statistical analysis. In the circumstances that some of them appear too few times, it will cause bias in performing linear regression.

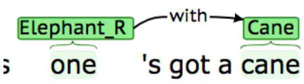
3.2.4.3 Noun

The Noun Relation takes place between Mention - Mention / Nmod.

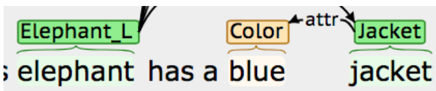
3.2.4.3.1 'With' relation

Describe the relationship between a mention and clothes he wears or ornaments he owns.

e.g. *one's got a cane*



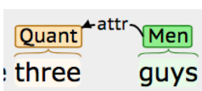
e.g. *elephant has a blue jacket*



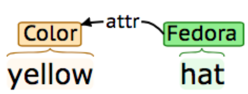
3.2.4.3.2 'Attribute' relation

Describe the relationship between a mention and his modifiers.

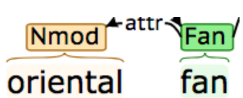
e.g. *three guys*



e.g. *yellow hat*



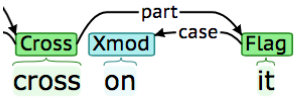
e.g. *oriental fan*



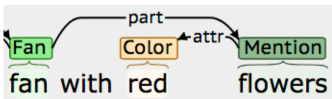
3.2.4.3.3 'Part' relation

Describe the relationship between two mentions when one mention adheres to, grows on, is part of the other.

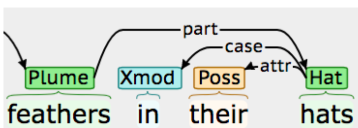
e.g. *cross on the flag*



e.g. *fan with flowers*



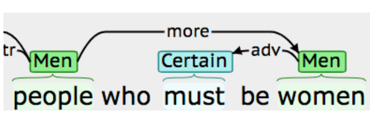
e.g. *feathers in hats*



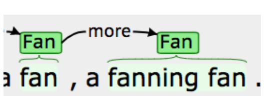
3.2.4.3.4 'More' relation

We say there is a 'more' relation when a mention repeatedly occurs in one sentence, usually adding more information or serving as a correction to the mention.

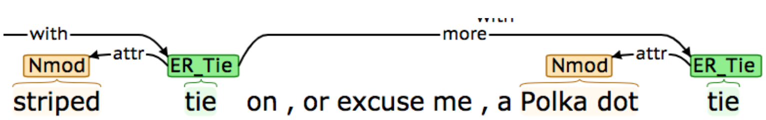
e.g. people who must be women



e.g. a fan, a fanning fan



e.g. a striped tie, excuse me, a Polka dot tie

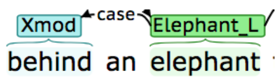


3.2.4.4 Others

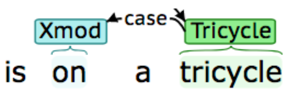
3.2.4.4.1 Case

Describe the relationship of the Xmod and mention.

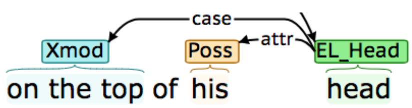
e.g. *behind an elephant*



e.g. *on a bicycle*



e.g. *on the top of his head*



3.2.5 Special Cases Handling

1. Treat compound nouns as a whole mention

polka dot, straw hat, face makeup

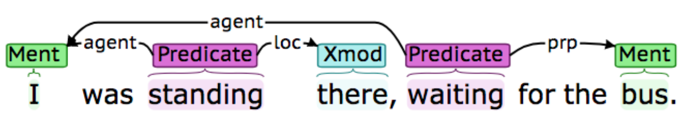
2. We do not annotate anything that is not related to the picture.

3. When a sentence appears as incomplete, we only annotate the 'Mention' in the sentence.

4. Way of handling relative clauses, adverbial clauses:

We disregard the connection words (which, that), treat the clause as a separate sentence with the same object, and annotate the relations as usual.

e.g. I was standing there, waiting for the bus.



5. Disregard anything after 'I don't know..', 'I cannot describe...'

Chapter 4

Analysis

After finishing the annotation task of 100 transcripts (50 healthy controls and 50 MCI), I was eager to find out if there were any valuable meta-semantic features that could effectively distinguish the two groups. My analysis was done in two steps; first, I did observational analysis on the annotation and then statistical analysis including count, linear regression and density analysis to validate my observational conjectures and obtain a systematical overview of the data.

4.1 Observational Analysis

- Number of sentences uttered in the one-minute limit: the MCI group on average speaks fewer sentences than that of the healthy control group.

gives out more than 20 sentences, which means that their speech is disjointed and they like to use more pronouns.

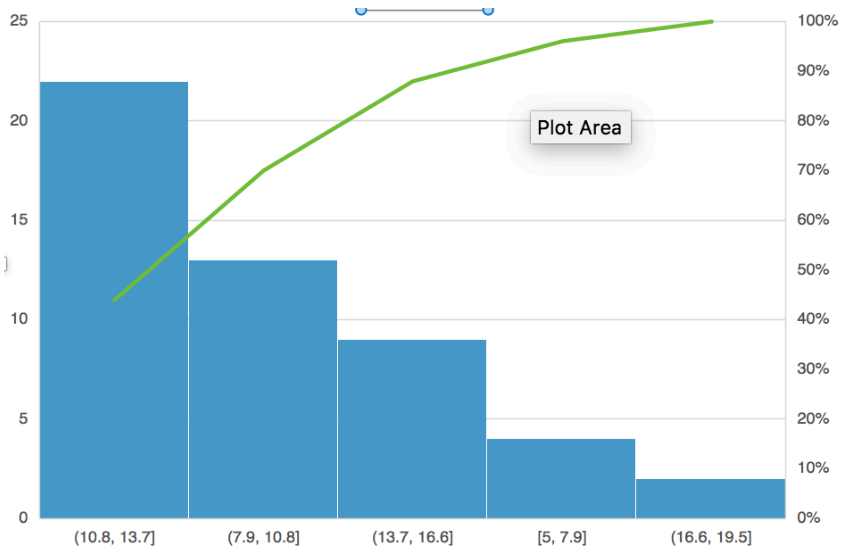


Figure 4.1 Control Group Number of Sentences

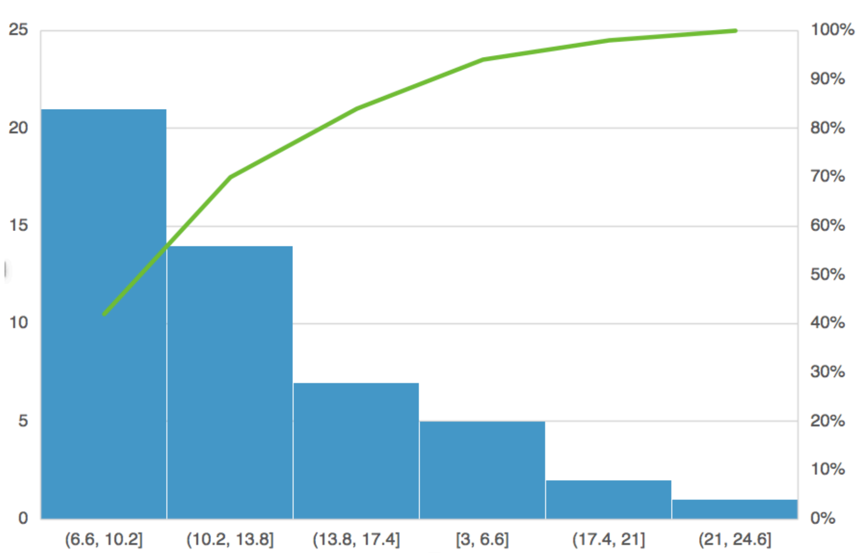


Figure 4.2 MCI Group Number of Sentences

4.2.2 Mention Weight

A linear regression analysis is performed on all the entities to find which entities are significantly mentioned more by the control group or the MCI group. Figure 4.3 and 4.4 shows the respective entities that are mentioned more by the control group and MCI group.

Proportional Difference (PD) is calculated by (CTR-MCI)/max(CTR,MCI)

Entity	**CTR**	**MCI**	**PD**
er__fan	0.62	0.52	0.16
el__jacket	0.52	0.40	0.23
er__vest	0.42	0.32	0.24
el__pants	0.54	0.40	0.26
m__flag	0.42	0.30	0.29
er__trunk	0.32	0.22	0.31
el__collar	0.30	0.20	0.33
er__glasses	0.40	0.20	0.50
e__custume	0.26	0.12	0.54
m__boots	0.26	0.04	0.85
cl__pants	0.12	0.00	1.00

Table 4.1 Entities that Control Group mention more

Entity	**CTR**	**MCI**	**PRE**
background	0.06	0.20	-0.70
el_tie	0.14	0.26	-0.46
el_hat	0.30	0.40	-0.25
man_l	0.00	0.02	-1.00

Table 4.2 Entities that MCI Group mention more

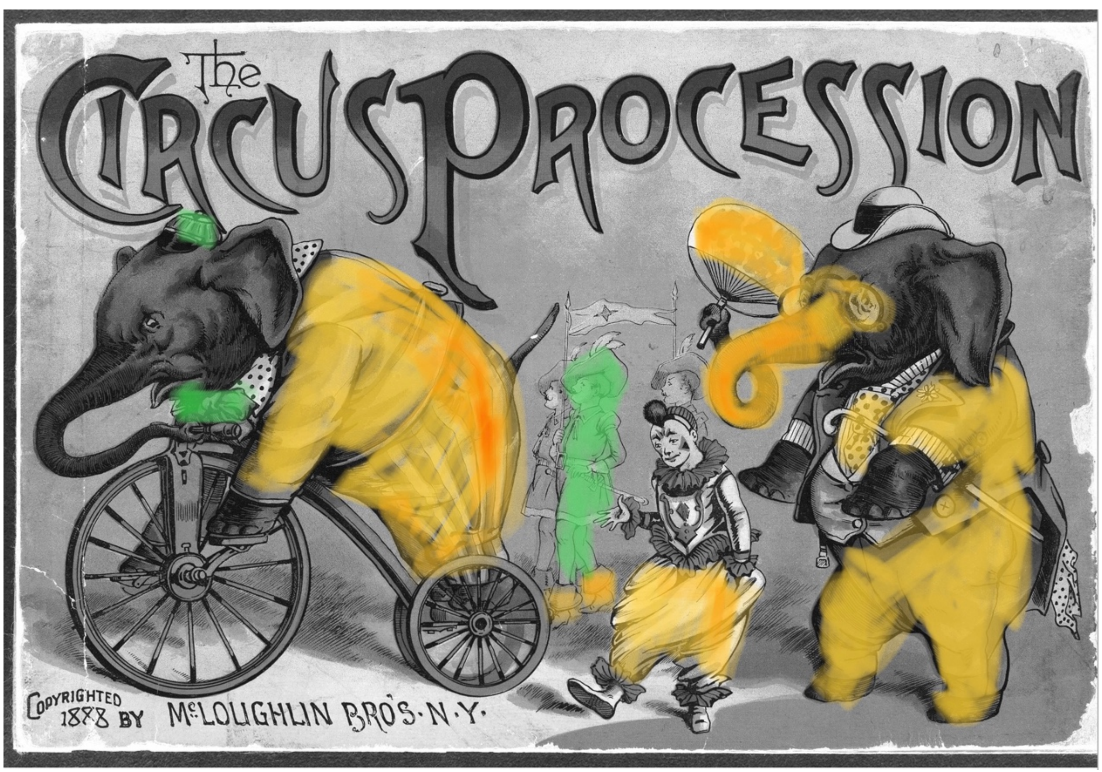


Figure 4.3 Visualization

In Figure 4.3, portion highlighted in yellow is mentioned more by healthy control while the green colored portion is mentioned more by the MCI group.

4.2.3. Mention Density

To obtain information on mention coverage as well as on the amount of details the mentions are described in, I examine the density of mentions. Each meta-semantic transcript consists of clusters where mentions are directly or indirectly connected by relations within a cluster and every cluster is mutually inclusive. We calculate the size of cluster (density) by counting these relations. In figure 4.6, the x-axis represents clusters in each transcript ranked from biggest to smallest, and the y-axis is the size of the cluster.

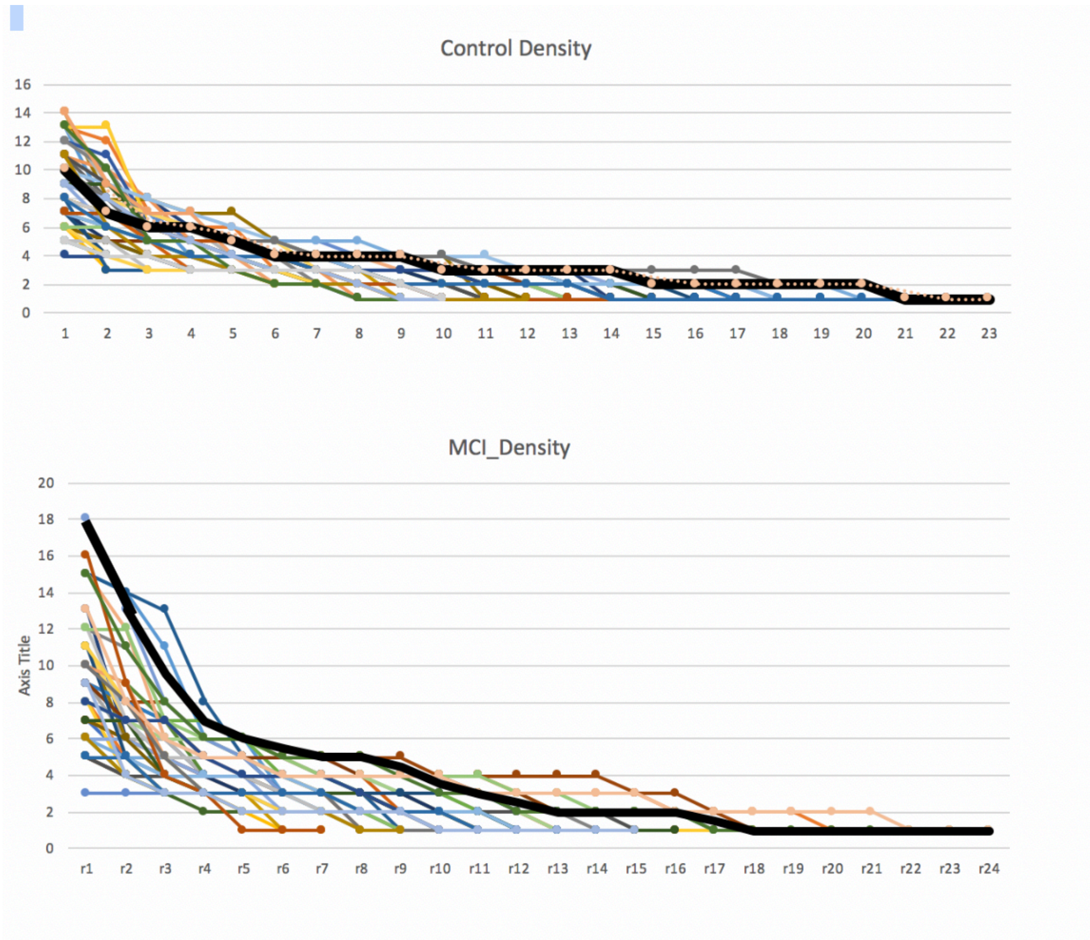


Figure 4.4 Mention Density of the two groups

The thick black lines are the average trend line. From the graphs we can observe that the control group has a more linear density function. The healthy control group distributes time fairly to describe the mentions. In the contrary, the MCI group spends much more time to describe the top two mentions.

4.2.4 Predicate Analysis

Next we look at predicates (See Annotation Guideline 2.3). Because motion predicates specifically are not statistically important in the linear regression computation, we merge all of the predicates. We sum up the number of distinct predicates that appear in each transcripts. We perform the same computation on the relations are associated with predicates.

Label	**CTR**	**MCI**	**PD**
Predicate	273	220	0.19
Agent	259	200	0.23
Theme	155	126	0.19
Adv	12	5	0.58
Mnr	40	30	0.25
Dir	9	5	0.44
Loc	23	24	-0.04
Tmp	2	1	0.50
Prp	4	0	1.00

Table 4.3 Predicate Analysis

The result shows that Predicate is a useful semantic feature in distinguishing the two groups. Among the relations related to Predicate : agent, theme, adv, mnr, dir, prp are important.

4.2.5 Attribute Analysis

We perform the same computation as in 4.2.4 in analyzing entity attribute. (See Annotation Guideline chapter 3).

Label	**CTR**	**MCI**	**PRE**
Abstract	33	74	-0.55
Emotion	15	17	-0.12
Opinion	69	54	0.22

Table 4.4 Attribute Analysis

‘Abstract’ is significantly different. MCI group use much more ‘Abstract’ descriptions in their descriptions of mentions than the healthy control. This conveys that MCI’s speech has high occurrence of ambiguity. We cannot tell what they would like to refer to even with the presence of context. ‘Abstract’ is actually the most important feature that can distinguish the two groups in our annotation.

4.2.6 Xmod Analysis

We perform similar computation on Xmod (See Annotation Guideline 2.5)

Label	**CTR**	**MCI**	**PRE**
Xmod	251	244	0.03
Certain	7	5	0.29
Emphasis	28	16	0.43
Fuzzy	30	38	-0.21
Negation	1	3	-0.67

Table 4.5 Xmod Analysis

The result shows that Emphasis (2.5.3) is used much more in healthy control group's speech. This also demonstrates that the healthy control people are very clear and assured about their descriptions or opinions. In contrast, the MCI group shows sense of vague in their expressions.

4.2.7 Nmod Analysis

At last, we look at the last class of mentions --- noun modifiers. Possesive and Size show small differences, but not as important as Abstract, Certain and Predicates. This indicates that the two groups are similar in usage of noun modifiers.

Label	**CTR**	**MCI**	**PRE**
Nmod	158	143	0.09
Color	221	227	-0.03
Possessive	49	56	-0.13
Size	35	48	-0.27
Quantity	82	90	-0.09

Table 4.6 Nmod Analysis

Chapter 5

Limitations and Future Works

Up until now only 100 annotated transcripts from this dataset are available for training. In the future with more annotations being finished, deep learning models can be performed, and better results can be expected. We have seen from our analysis result that the 'abstract' entity attribute plays an important role in distinguish the two groups. However, our transcripts were obtained from mere audio recording. If visual recording can be incorporated, gestures may play a part in clarifying the ambiguity, which provides explanation for the 'abstract'. In addition, Emery 2000 shows that Semantic errors reportedly are the most common and distinct language deficit because dementia patients tend to substitute target names with superordinate category names or demonstrate circumlocutory speech with impaired naming . Other reports have also described unrelated errors (Moreaud 2001). If this aspect of semantic errors are also considered, our annotation of some mentions are not accurate enough. For example, there may exist a shared habit of depicting the 'fan' as a 'balloon' among MCI group or control group.

Future works can include combining the results we conclude from this picture description task with the results of other tasks in the transcripts to get a more comprehensive understanding of the differences that distinguish the two groups.

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