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無所不在的數位式語言學習：設計與實用之融合--無所不在的數位式語言學習：設計與實用之融合(1/3)

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無所不在的數位式語言學習：設計與實用之融合(1/3)

計畫類別：□ 個別型計畫　　■ 整合型計畫

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1. Introduction

In this midterm project report we present two aspects of research related to multiword expressions (MWEs). In the first section, we propose a probabilistic model for suggesting corrections to multiword expression errors that utilizes certain word-association features such as mutual information and semantic similarity. Specifically, we focus on how to automatically extract correct collocation suggestions from a standard corpus for specific lexical miscollocations made by English L2 learners. In the second section, we report data collected from an eye-tracking experiment which explores how MWEs are processed and stored in the human mind. Our data confirm several previous researchers' assumption that MWEs have a processing advantage and tend to be processed as "wholes" rather than individual words by native speakers.

2. Automatic Computation of MWEs

2.1 Introduction

Error detection and correction in the writing of second language learners has become an important topic in NLP research. Many projects have been analyzing learner errors through the use of learner corpora, such as NICT Japanese Learners of English (JLE), The Chinese Learners of English Corpus (CLEC) (Gamon, 2008) and English Taiwan Learner Corpus (or TLC) (Wible et al., 2003). In these projects, several typical ESL errors are categorized and most of the automatic correction research focuses on a single error type, such as spelling correction (Golding and Roth, 1999), article presence (Han et al., 2004) and preposition usage (Chodorow et al., 2007). To our knowledge, few studies in this literature address lexical miscollocations. Pearce (2001) proposes how to apply synonym relations in WordNet to extract collocations and applies the same knowledge source to miscollocation identification. However, he does not describe details of the approaches.

Collocation errors are a sub-type of lexical choice errors, specifically where the correct word is determined by convention and governed by the presence of some co-occurring word. For example, the error *eat medicine* is corrected by replacing *eat* with *take*, where this choice is governed by the noun *medicine*, and is determined not by grammatical or semantic rules but by convention.

2.1.1 Collocation in language learning

Corpora have been applied to assist language learners with a variety of aspects of language learning. One example is in the creation of learner dictionaries, such as Collins Cobuild English Dictionary, where definitions and examples are informed by corpus findings concerning the contextual features of the head words. Another common use of corpora is in language learning classrooms where standard corpora play a role is the use of concordancing (Chambers, 2005; Horst, Cobb and Nicolae, 2005). Several researchers have recognized the harm that large corpora might do to learners and suggest the use of small corpora tailored to the learners' needs (Aston, 1997; Roe, 2000).

Kita and Ogata (1996) design a bilingual collocation concordancer which extracts a collocation in one language on the basis of a given collocation in another language. The collocations extracted are mostly formulaic phrases like 'I would like to', 'I got it' and 'the other day', etc. Unlike Kita and Ogata's method that retrieves juxtaposed chunks, we deal with restricted lexical collocations in this paper. What can computers and language corpora cast collocation in the role of language learning, however, remain unclear and needs to be redefined.

Studies that compare the language of L1 speakers and L2 learners have suggested that the amount of collocations that learners are capable of employing are not only fewer than L1 speakers but also are limited to a small set. Although the underlying causes of learners' miscollocations are believed to be chaotic, ranging from L1 interference, the confusion of synonymous words to learners' creative use, collocation has been widely considered as one of the criteria in gauging the language proficiency of L2 learners.

A paradoxical issue arises in a language classroom in that, unlike idioms that are introduced to learners as a whole and are frequently highlighted, collocation, though significant, is commonly ignored or seen as marginal in pedagogy; yet when assessing proficiency, particularly in writing, collocations/miscollocations use are considered a deciding factor. For instance, Howarth (1996) compares the academic writing of advanced L2 learners and native speakers by exploring the collocational density and use of each. Although there is no correlation between the general proficiency of a learner and the number of collocations used as Howarth points out, the fact that collocation remains an unresolved issue even for advanced learners is worthy noticing.

2.1.2 The Study

We focus on how to provide correct collocation suggestions for specific lexical miscollocation. Three features are employed to predict the correct collocation for specific miscollocation: word association measurement, semantic similarity between correct and misused words, and the concept of clustering collocation proposed by Cowie and Howarth (1995). We will first describe the challenge of miscollocation in NLP and language learning in section 2. In section 3, we discuss the basic concepts and the underlying rationale of bringing in the above three features in predicting correct collocation. A probabilistic model is then presented to combine the three features for prediction. We present the experimental results of the suggestions found by various models in Section 4. Some discussion and application as well as future direction in language learning and NLP will be presented in Section 5.

2.2 The Challenge of Miscollocation

Miscollocation refers to the unconventional use of collocations found in learners' language production. Two main challenges arise in examining learners' miscollocation via NLP. The first challenge lies in the detection whereas the second is the correction of it. Whereas detecting collocation in a standard corpus can be achieved via, for example, t-test, chi-square, MI and log-likelihood, etc. (Pecina and Schlesinger, 2006), the detection of miscollocation in a learner corpus poses greater difficulty since the language to be processed is a mixture of standard and non-standard language. Liu (2002) examines miscollocations marked by English teachers through an online writing platform[1] and identifies the source of errors. The access to learner's miscollocations is made possible through the action of teachers' marking archived in English Taiwan Learners' Corpus. That is, the detection is made by humans rather than by computers. Nevertheless, how to achieve the automated detection of miscollocation is not the thesis of this paper.

The difficulty in correcting miscollocation requires the intelligence of not only 'knowing' it is wrong but 'knowing' what is wrong and then to offer the correct correspondent one. Without the mediation of human intelligence, a successful miscollocation correction will need to process the semantics as well as the syntactic structure of the sentence where a miscollocation is imbedded. A fallacy occurs if we apply the traditional collocation extraction approach in finding suggestions for a miscollocation because there is not a solid ground to argue that an unfound collocation is not a collocation. To solve this, we bring in three features in the process of finding suggestions.

2.3 Methodologies

Before we present the probabilistic model that utilizes word association, semantic similarity and cluster collocation, we will consider the concepts and performance of these three features individually.

2.3.1 Word Association Measurement

Most of the researches use some kind of association measurement to extract collocation from corpora and most of the measurements are statistical-based methods. A threshold is usually set to identify whether or not a word combination is a collocation. The roles of word association in miscollocation detection are twofold: 1. all suggested correct collocations have to be identified as collocations, at least, thus we assume candidate replacements for the miscollocate verb must exceed a threshold word association strength with the focal noun; 2. more than simply meeting a threshold word association strength, we examine the possibility that the higher the word association score the more likely it is to be a correct substitute for the wrong collocate. Figure 1 shows the trend. The data will be explained in Section 4. We adopt Mutual Information (Pecina and Schlesinger, 2006) as our association measurement. Only when the MI value of a collocation is higher than three will be identified as a candidate collocation. The X axis presents normalized association strength and the Y-axis presents the probability of the strength range. Normalized association strength of one candidate is defined as follow:

$$normalized\ association\ strength = \frac{MI(C)}{\max MI(C)}$$

,where C means the function *MI()* means Mutual Information value of candidate collocation for specific miscollocation and *maxMI() is the maximum value of MI in all candidates.*

The black bar presents the probability of the correct collocation for specific miscollocation: *P(association strength/correct collocation for specific miscollocation)* and the white bar presents the

[1] Intelligent Web-based Interactive Language Learning. http://www.iwillnow.org/iwill

probability of all collocation *P(association strength)*. The histogram shows that association strength did provide good prior knowledge for predicting correct collocation for specific miscollocation.

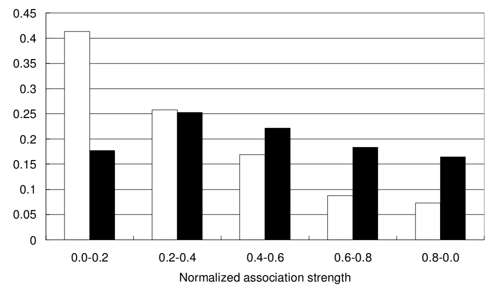

Figure 1

2.3.2 Semantic Similarity

Liu (2002) proposes in her study of miscollocations that a miscollocate is not arbitrary word choice error but stand in some semantic relation to the correct collocate counterpart. This finding corresponds to the results in Gitsaki et al. (2000). We follow this assumption that the misused word in a miscollocation has similar meaning to the correct collocate in a correct collocation in searching for the suggestion. For example, *say* in an attested learner miscollocation "say story" is found to be a synonym of the correct verb *tell* in WordNet. Based on this assumption, words that share semantic similarity to a certain level are possible candidates for replacing the misused words. Figure 2 shows this trend.

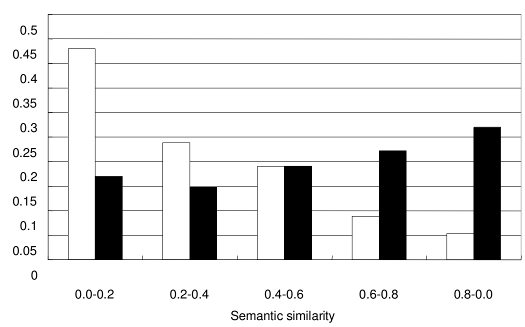

Figure 2

Y-axis presents the same meaning in Figure 1 and X-axis presents semantic similarity between misused word and correct one while MI of these collocation are all greater than 3. We adopt WordNet as our knowledge for similarity measurement. The similarity function is as follow (Tsao et al., 2003):

$$Sim(w_1, w_2) = \max_{s_i \in synset(w_1), s_j \in synset(w_2)} \left(1 - \frac{dis(s_i, s_j)}{2 \times \max(L_{s_i}, L_{s_j})}\right)$$

, where $dis(s_i, s_j)$ means the node path length between the synset s_i and s_j in WordNet hyper/hypo tree. L_s means the level number of s in hyper/hypo tree so the level of top node is1. Multiply $2\times\max(L_{s_i}, L_{s_j})$ by 2 insures the similarity is less than 1. If s_i and s_j are synonymous, the similarity will be 1. The black bar presents the probability of similarity between misused word(for example, say) and correct one(for example, tell) and the white bar presents the probability of similarity between misused word and all candidate words(for example, write). The histogram also shows promising prior knowledge for predicting correct collocation for specific miscollocation.

2.3.3 Clustering Collocation

Cowie and Howarth (1995) and Howarth (1996) propose the concept of overlapping cluster to describe collocations that carry similar meaning and shared collocates. Figure 3 represents, for example, a cluster of collocations that express the notion of 'bringing something into actuality.' The key here is that not all V N combinations in Figure 3 are acceptable. While *fulfill* and *achieve* collocate with the four nouns on the right, *realize* does not collocate with *purpose* as is indicated by the dotted line; neither *dream* nor *ambition* or *purpose* combine with the fourth verb, *reach*. Cowie and Howarth's point is that collocations that can be clustered via shared collocates, like the one shown in Figure 3, can be the source of collocation errors for language learners through a sort of overgeneralization. From the similarity that both *fulfill* and *reach* collocate with the noun *goal* and the further collocability of *fulfill* with the nouns *ambition* and *purpose,* learners easily assume that *reach* shares this collocability as well, leading by overgeneralization to the miscollocations *reach an ambition* or *reach a purpose*.

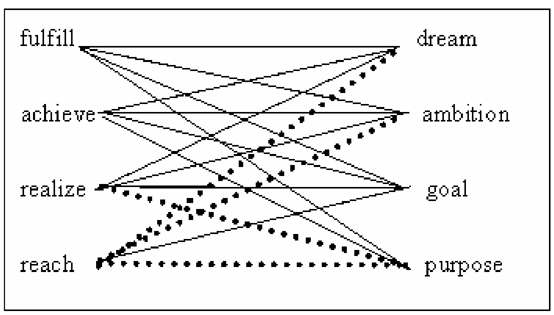

Figure 3. Overlapping Cluster.

Instead of merely identifying the source of an attested learner miscollocation '**reach* their *purposes'* as explained above, we assume that the concept of 'overlapping collocation cluster' and 'shared collocates' can also contribute to identifying the correct counterpart to these miscollocations. In this case of '**reach* their *purposes*,' we believe that finding the verbs that collocate with *purpose* as well as with other nouns that *reach* collocates with can yield the correct verb collocate.

According to this line of thinking, we identify candidate substitutes for the incorrect verb *reach* in the miscollocation *reach purpose* by finding the verbs that collocate with purpose and also share the most other collocating nouns with the wrong verb *reach*. Figure 4 shows the performance of this method. X axis presents normalized overlapping collocates number. The equation is as follows:

$$\mathit{normalized\ shared\ collocates\ number} = \frac{N(SC)}{\max N(SC)}$$

where N(SC) means number of shared collocateds between specific candidate and misused. maxN(SC) is the max number in all N(SC).

Y-axis presents the probability of the number range. The black bar presents the probability of shared collocates number between misused word (reach) and correct one (fulfill) and the white bar presents the probability of shared collocates number between misused word and all candidate words, for example, *set*, *serve*, *defeat* and *suit*, etc. The histogram also shows promising prior knowledge for predicting correct collocation for specific miscollocation.

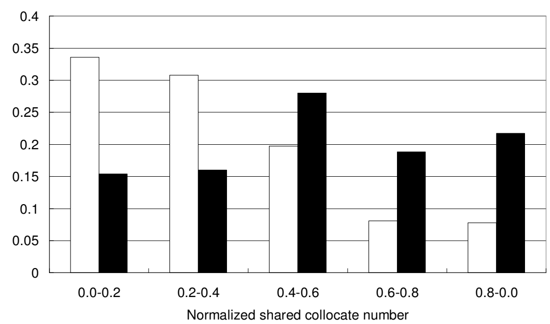

Figure 4

2.3.4 Hybrid Model

The three features we described above are weak orthogonal, which means they can provide quite different results for each miscollocation. For instance, we use each feature to look up the correct collocation suggestion for miscollocation "**make damage*". A possible suggestion "*cause damage*" is shown in 5th answer by using MI, in second answer by semantic similarity and 14^{th} by using shared collocates. Therefore we propose a probabilistic model to combine these features. Based on the probabilistic model, "*cause damage*" is ranked the first answer.

The probability of each candidate can be presented as:

$$P\left(C/F\right)$$

, where C means the candidate is correct one for specific miscollocation and F means the features of this candidate. According to Bayes theorem and Bayes assumption, which assumes that these features are independent, the probability can be computed by:

$$P\left(C/F\right)=\frac{P\left(F/C\right)P(C)}{P(F)}\approx\frac{\prod_{f\in F}P\left(f/C\right)P(C)}{\prod_{f\in F}P(f)}$$

Since P(C) are the same to each candidate, we can compare these probability by following equation:

$$\prod_{f\in F}\frac{P\left(f/C\right)}{P(f)}$$

2.4 Experimental Results

We use Liu's (2002) list of miscollocations as the training and the testing data. 84 miscollocations from the list are used in the experiments. We randomly choose half of them to be the training data and the other half to be the testing data. Two experienced English teachers (one native and one non-native English speaker) manually examine the suggestions to judge the adequacy of suggestions for the tested 84 miscollocations. Table 1 shows some examples of miscollocations and the correspondent correct collocations labeled by the two human experts.

Miscollocation	Correct Collocations
pay time	spend time, devote time
make damage	cause damage,
pay effort	spend effort make effort
get knowledge	gain knowledge, acquire knowledge
make conclusion	draw conclusion

Table 1

A discrete probability distribution is produced for each feature. Table 2 shows the precision of k-best suggestions for only considering single feature, where MI means Mutual Information, SS means Semantic Similarity and SC means Shared Collocates. The k-best results for each hybrid model are put to be compared in Table3.

As Table 3 shows, hybrid model 4, which combines the three features (MI + SS+ SC), provides the highest proportion of true positives at every value of k except k = 1. Considering the results for each feature run separately, however, the feature semantic similarity outperforms the other two. Comparing semantic similarity with hybrid model 4, it is clear that our probabilistic model that considers MI, semantic similarity and shared collocates outperforms it. In other words, when dealing with miscollocations, we believe that considering one single feature seems insufficient. The best results are achieved when both statistical and semantic features are taken into consideration.

K-Best	MI	SS	SC
K=1	16.67	40.48	22.62
K=2	36.9	53.57	38.1
K=3	47.62	64.29	50
K=4	52.38	67.86	63.1
K=5	64.29	75	72.62
K=6	65.48	77.38	75
K=7	67.86	80.95	77.38
K=8	70.24	83.33	82.14
K=9	72.62	86.9	85.71
K=10	76.19	86.9	88.1

Table 2

	Hybrid models			
K-Best	1	2	3	4
	MI+SS	MI+SC	SS+SC	MI+SS +SC
K=1	48.81	29.76	55.95	53.57
K=2	60.71	44.05	63.1	67.86
K=3	71.43	59.52	77.38	78.57
K=4	77.38	72.62	80.95	82.14
K=5	83.33	78.57	83.33	85.71
K=6	85.71	83.33	84.52	88.1
K=7	86.9	86.9	86.9	89.29
K=8	86.9	89.29	88.1	91.67
K=9	88.1	92.86	90.48	92.86
K=10	88.1	94.05	90.48	94.05

Table 3

Tables 4, 5, and 6 each show the k-best suggestions provided by three feature combinations for k=5 for three specific miscollocations, specifically for *reach purpose*, *make damage* and *pay time,* respectively. The asterisks (*) indicate the true positives in the tables.

Miscollocation: reach purpose			
K-Best	SS	SS + SC	MI+SS +SC
K=1	*achieve purpose	*achieve purpose	*achieve purpose
K=2	teach purpose	account purpose	account purpose
K=3	explain purpose	trade purpose	trade purpose
K=4	account purpose	treat purpose	*fulfill purpose
K=5	trade purpose	allocate purpose	serve purpose

Table 4. The K-Best suggestions of different models for *reach purpose*

Miscollocation: get knowledge			
K-Best	SS	SS + SC	MI+SS +SC
K=1	aim knowledg e	*obtain knowledge	*acquire knowledge
K=2	generate knowledg e	share knowledge	share knowledge
K=3	draw knowledge	*develop knowledge	*obtain knowledge
K=4	*obtain knowledge	generate knowledge	*develop knowledge
K=5	*develop knowledge	*acquire knowledge	*gain knowledge

Table 5. The K-Best suggestions of different models for *get knowledge*.

Miscollocation: pay time			
K-Best	SS	SS + SC	MI+SS +SC
K=1	*devote time	*spend time	*spend time
K=2	*spend time	*invest time	waste time
K=3	expend time	*devote time	*devote time
K=4	spare time	date time	*invest time
K=5	*invest time	waste time	date time

Table 6. The K-Best suggestions of different models for *pay time*

2.5 Conclusions

We have presented a hybrid probabilistic model that adapts word association measurement, semantic similarity and shared collocates in looking for proper suggestions for learners' miscollocations. Unlike traditional collocation extraction, what we tackle with is miscollocations in which the causes could be various from learners' creative production, L1 interference to the confusion of two similar words. By bringing in semantic considerations, semantic similarity and shared collocates, we have shown that the automated suggestions is feasible because the results have indicated that the proposed model is not only applicable but it is also promising.

Although only verb-noun miscollocations are examined, the system is designed to be applicable to other types of miscollocations. Correction of miscollocations requires the understanding of what the problem is and the supports from the context. We have proved that the task is not impossible through the implementation of NLP and semantic consideration. The proposed model enables computers to play a significant role in language learning. It is hoped that such model will not only assist language teachers in marking compositions but will also help learners in fostering the acquisition of collocations.

3. Cognitive Aspects of MWEs

To achieve a high level of proficiency of a language, a learner not only has to know the linguistic rules underlying his/her target language, but needs to process a great quantity of lexical chunks (e.g. *from the point of view* and *as a matter of fact*) holistically in their memory (Pawley & Syder, 1983). These "fixed" and "formulaic" lexical chunks have been assumed to overcome the limitation of working memory capacity (only seven bits of information can be processed simultaneously in it, according to Miller, 1956) and enable language users to speak fluently in daily conversation. Based on this claim, to be proficient in a second language, grammatical knowledge and knowledge of fixed lexical chunks are both crucial and necessary.

Although the significance of lexical chunks in language learning has been comprehensively recognized, there are some important research topics which have not been addressed. One of them is how lexical chunks are represented in our cognitive system. Most researchers only assume that lexical chunks are stored and processed in our mind as single units while such an assumption has not been approved by enough empirical evidence. The only studies which have investigated this issue were Schmitt & Underwood (2004), Underwood, Schmitt, and Galpin (2004), Conklin & Schmitt (2007), and Jiang & Nekrasova (2007), and their findings did not provide a definite answer as to whether lexical chunks were indeed processed as wholes or not. Specifically, the findings of these experiments were rather diverse; while some of them showed both natives and non-native speakers processed chunks as wholes (Conklin & Schmitt, 2007; Jiang & Nekrasova, 2007), others did not show this holistic processing in non-natives (Underwood et al., 2004) or in both natives and non-natives (Schmitt & Underwood, 2004). In this project, we have tried to address this question by using an eye-tracking research technique to understand how human beings process lexical chunks. We have collected sixteen English native speakers' eye-movement data which clearly demonstrate this holistic processing of lexical chunks. A detailed description of the materials we used and the research findings is offered below.

3.1 Materials

The materials used include three types of sentences which contain either chunks or non-chunks. The lexical chunks were extracted from the British National Corpus (BNC) with a computational chunking tool developed by Wible, Kuo, and Tsao (2004) which takes a computational approach to extract recurrent word strings from corpora. In this experiment, for instance, the word *money* has been used to look for words which frequently co-occur with this target word. Once certain word pairs have been collected, these pairs were taken as input into the next process. This process was repeated several times until no other word could be found. The final results of this process were a list of lexical strings containing the target word (*e.g. a large sum of money*). For the present research, totally, we collected 25 chunks which have been checked by six English native speakers for their formulaicity. These chunks were then put into sentences as well as two other groups of comparison sentences. Example sentences of the chunk "*a large sum of money*" are presented below:

1a. *Someone just put* ***a large sum of money*** *into my bank account and I have no idea who it was.*

1b. *I was hoping that I would have the* ***money*** *for six weeks in Europe but I wasn't very confident.*

1c. *He reluctantly accepted* ***a large sum of books*** *as payment for the money owed to him by the publishing company.*

If the subjects processed this chunk holistically in their mind, they were expected to have shorter fixation duration on the word *money* in sentence 1a than in 1 b and process the whole chunk *a large sum of money* much faster than its control string *a lar sum of books*.

3.2 Results and Data Analysis

In the data analysis, we focused on a variety of eye movement measures with regard to the target words and chunks, including: (1) first-fixation duration, (2) gaze duration, and (3) fixation probability. First-fixation duration refers to the initial stay on a word in the first-pass reading. Gaze duration is the sum of all fixations on a single word before the eyes make a saccade to another word. In fixation probability we calculated the subjects' probability of fixating the target words.

First, we examine the same words occurring in both chunk and non-chunk contexts, with the data shown in Table 1. As the data demonstrate, the subjects had a lower probability of fixating the target words appearing in chunk contexts. When the words were actually fixated, the ones in the chunk contexts took both shorter first-fixation durations and shorter gaze durations. An analysis of variance (ANOVA) was used to assess the effect of the contexts. For first-fixation duration, the ANOVA displayed that the distance was significant by both items [($F(1,48) = 10.944$, $p=.002$] and subjects [$F(1, 15) = 10.739$, $p=.005$]. For the gaze duration data, the effect of the chunk context was marginally significant by items [$F(1,48) = 3.728$, $p=.059$] and significant by subjects [$F(1,15) = 8.497$, $p=.011$]. These figures confirmed the strong effect of the chunk context and suggested that lexical chunks did facilitate the recognition of their internal words.

Table 7
First-Fixation Duration, Gaze Duration, & Fixation Probability on Target Words in Chunk & Non-Chunk Contexts

Context	Fixation Probability	First-Fixation Duration	Gaze Duration
Chunk	73%	200.16	211.85
Non-Chunk	77%	212.88	222.56

Then, we treated the two types of strings (e.g. *a large sum of money* vs. *a large sum of books*) as areas of interest and computed the gaze duration and total reading time (the sum of all fixations on an area including regressions) on them. According to the data in Table 2, the subjects did have longer gaze duration on the control strings and regress to them more often. A T-test, using items as the random factor, confirmed that the chunks were processed significantly faster in terms of gaze duration [t(34) = 2.273, p=.029] and total reading time [t(34) = 3.698, p=.001]. These figures suggest that lexical chunks be represented in the human mind as fixed word strings and any word that replaces words in chunks will result in a certain level of processing difficulty.

Table 8

Gaze Duration & Total Reading Time on Chunk & Non-Chunk Strings

Context	Gaze Duration	Total Reading Time
Chunk	592.21	677.95
Non-Chunk String	690.11	908.44

In sum, the data presented above displayed the strong processing advantage imposed by lexical chunks on linguistic processing. A word which appeared at the end of a chunk was highly predictable and required shorter time to be identified. Additionally, the lexical chunks were processed as single units and took significantly shorter gaze duration and total reading time than the control word strings. These findings confirmed our hypothesis that native speakers tend to process a chunk as a single unit in their cognitive system rather than separate words.

In addition to observing how chunks are processed by native speakers, a more important and interesting question to ask is how this holistic processing is formed in language acquisition process. We plan to investigate this issue by examining Taiwan English learners' acquisition of lexical chunks. We have prepared different types of input materials and trying to see which kind of input will help second language learners treat chunks as wholes unconsciously when they process their target language. With the findings of the planned study, we can expect that a better understanding of how second language learners acquire, process, and store lexical chunks in their inner world will be gained.

References

Aston, G. 1997. Small and Large Corpora in Language Learning. In B. Lewandowska-Tomaszczyk & J. P. Melia (Eds.), *Practical Applications in Language Corpora,* 51-62. Lodz, Poland: Lodz University Press.

Chamber, A. 2005. Integrating Corpus Consultation in Language Studies, *Language Learning & Technology*, Vol. 9, No. 2, May 2005, 111-125.

Chodorow, M., Joel R. Tetreault and Na-Rae Han. 2007. Detection of Grammatical Errors Involving Prepositions, *Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, Special Interest Group on Semantics*, Workshop on Prepositions, 25-30.

Conklin, K. & Schmitt, N. (2003). Formulaic Sequences: Are They Processed More Quickly than Nonformulaic Language by Native and Nonnative Speakers? Applied Linguistics Advance Access published on July 17, 2007, doi:10.1093/applin/amm022.

Cowie, A.P. & Peter Howarth. (1995). Phraseological Competence and Written Proficiency, Paper Presented at the *British Association of Applied Linguistics Conference* (BAAL), Southampton, England, September.

Gamon, M., J. Jianfeng Gao, Chris Brockett, Alexandre Klementiev, William B. Dolan, Dmitriy Belenko, Lucy Vanderwende. 2008. Using Contextual Speller Techniques and Language Modeling for ESL Error Correction, *Proceedings of The Third International Joint Conference on Natural Language Processing,* Hyderabad, India.

George A. Miller. 1990. WordNet: An On-line Lexical Database, *International Journal of Lexicography.*

Gitsaki, C., Nagoya Shoka Daigaku, and Richard P. Taylor. 2000. English Collocations and Their Place in the EFL Classroom, Available at: http://www.hum.nagoya-cu.ac.jp/ ~taylor/publications/collocations.html.

Golding, Andrew R. and Dan Roth. 1999. A Winnow-Based Approach to Context-Sensitive Spelling Correction, *Machine Learning*, Vol 34, Issue 1-3, 107-130.

Han, N-R., Martin Chodorow and Claudia Leacock. 2004. Detecting Errors in English Article Usage with a Maximum Entropy Classifier Trained on a Large, Diverse Corpus, *Proceedings of the 4th International Conference on Language Resources and Evaluation*, Lisbon, Portugal.

Horst, M., Tom Cobb & Ioana Nicolae. 2005. Expanding Academic Vocabulary with an Interactive On-line Database. *Language Learning and Technology, 9*(2), 90-110.

Howarth, P. 1998. Phraseology and Second Language Acquisition. *Applied Linguistics*. 19/1, 24-44.

Jiang, N. & Nekrasova, T. (2007). The processing of formulaic sequence by second language speakers. *Modern Language Journal, 91,* 433-445.

Kita, K. and Hiroaki Ogata. 1997. Collocations in Language Learning: Corpus-based Automatic compilation of Collocations and Bilingual Collocation Concordancer, *Computer Assisted Language Learning*. Vol.10, No. 3, 229-238.

Leacock, C., and Martin Chodorow. 2003. Automated Grammatical Error Detection, In MD Shermis & JC Burstein (Eds.), *Automated Essay Scoring: A Cross-disciplinary*, Mahwah, NJ: Lawrence Erlbaum Associates.

Liu, L. E. 2002. *A Corpus-based Lexical Semantic Investigation of Verb-Noun Miscollocations in Taiwan Learners' English*. Master Thesis, Tamkang University, Taiwan.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63*, 81-97.

Pawley, A. & Syder, F. H. (1983). Two puzzles for linguistic theory: Nativelike selection and nativelike fluency. In J. C. Richards & R. W. Schmidt (Eds.), *Language and Communication* (pp. 192-226). London: Longman.

Pecina, P. & Pavel Schlesinger. 2006. Combining Association Measures for Collocation Extraction, *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, Main Conference Poster Sessions. 651–658.

Pearce, D. 2001. Synonymy in Collocation Extraction. In WordNet and Other Lexical Resources: Applications, Extensions and Customizations, Workshop in *Second Meeting of the North American Chapter of the Association for Computational Linguistics,* 41-46.

Roe, P. 2000. The ASTCOVEA German Grammar in conText Project. In B. Dodd (Ed.), *Working With German Corpora*. Birmingham, England: University of Birmingham Press. 199-216.

Schmitt, N. & Underwood, G. (2004). Exploring the processing of formulaic sequences through a self-paced reading task. In N. Schmitt (Ed.), *Formulaic Sequences: Acquisition, processing, and use* (pp. 173-189). Netherlands: John Benjamins.

Tsao, N.-L., David Wible and Chin-Hwa Kuo. 2003. Feature Expansion for Word Sense Disambiguation, *Proceedings of the International Conference on Natural Language Processing and Knowledge Engineering*, 126-131.

Underwood, G., Schmitt, N., and Galpin, A. (2004). The eyes have it: An eye-movement study into the processing of formulaic sequences. In N. Schmitt (Ed.), *Formulaic Sequences: Acquisition, processing, and use* (pp. 153-172). Netherlands: John Benjamins.

Wible, D., Chin-Hwa Kuo, Nai-Lung Tsao, Anne Liu, and Hsiu-Lin Lin. 2003. Bootstrapping in a Language Learning Environment. *Journal of Computer Assisted Learning*, 19, 90-102.

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出國人員姓名 服務機關及職稱	碩士級專任助理劉麗娥 (中央大學)
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Abstract

Collocational knowledge has drawn considerable attention of researchers and teachers in gauging learners' vocabulary knowledge. It is widely recognized that a native-like usage of collocations of learners suggests a more thorough understanding of the target language. With an increase of exposure alone does not improve learners' collocations (Nesselhauf, 2004). By implementing a novel learning tool, UWiLL Collocator, this presentation aims to address the issue of how the collocational awareness of learners might be promoted via an online reading task. The result indicates that learners' perception of collocation can indeed be changed which, in turn, implies that learners can identify a collocation rather than seeing the two words of a pair as two separated units. Further, learners' receptive knowledge on collocations is explored in light of the theoretical proposals presented in the paper.