Interactive Second Language Learning from News Websites

Abstract

We propose a web browser extension that allows readers to learn a second language vocabulary while reading news online. Injected tooltips allow readers to look up selected vocabulary and give interactive tests to assess vocabulary mastery.

We discover that two key system components needed improvement, both which stem from the need to model context. These two issues are in practical word sense disambigution (WSD) to aid translation quality and constructing the interactive tests. We start with Microsoft's Bing translation API but employ additional dictionary based heuristics that significantly improve translation quality over a baseline in both coverage and accuracy. We also propose techniques for generating appropriate distractors for multiple-choice word mastery tests. Our preliminary user survey confirms the need and viability of such a language learning platform.

1 Introduction

Learning a new language from language learning websites is time consuming. Research shows that regular practice, guessing, memorization (Rubin, 1975) as well as immersion into real scenarios (Naiman, 1978) hastens language learning process. To make second language learning attractive and efficient, we seek to interleave language learning with a popular daily activity: online news reading.

Most existing language learning software are either instruction-driven or user-driven. Duolingo[1] is a popular instruction-driven system that teaches through structured lessons. Instruction driven systems demand dedicated learner time on a daily basis and are limited by learning materials as lesson curation is often labor-intensive.

In contrast, many people informally use Google Translate[2] to learn vocabulary, making it a prominent example of a user-driven system. Translate, however, lacks the rigor of a learning platform as it lacks tests to allow learners to demonstrate mastery. In our work, we merge learning and assessment within the single activity of news reading. Our system also adapts to the learner's skill during assessment.

We propose a system to enable online news readers to efficiently learn a new language. Our prototype targets Chinese language learning while reading English language news. Learners are provided translations of open-domain words for learning from an English news page. In the same environment – for words that the system deems mastered by the learner – learners are assessed by replacing the original English text in the article with their Chinese translations and asked to translate them back given a choice of possible translations. The system, deployed as a Chrome web browser extension, is triggered when readers visit a preconfigured list of news websites.

A key design property of our language learning extension is only active on certain news websites. This is important as news articles typically are classified with respect to a news category, such as *finance*, *world news*, and *sports*. If we know which category of news the learner is viewing, we can leverage this contextual knowledge to improve the learning experience.

In the development of the system, we discov-

[1] `https://www.duolingo.com/`

[2] `https://translate.google.com/`

ered two key components that can be affected by this context modeling. We report on these developments here. In specific, we propose algorithms: **(i)** for translating English words to Chinese from news articles, **(ii)** for generating distractor translations for learner assessment.

2 The SystemA Chrome Extension

We give a running scenario to illustrate the use of our language learning platform, SystemA. When a learner browses to an English webpage on a news website, our extension selectively replaces certain original English words with their Chinese translation (Figure 1, middle). While the meaning of the Chinese word is often apparent in context, the learner can choose to learn more about the replaced word, by mousing over the translation to reveal a definition tooltip (Figure 1, left) to aid mastery of the Chinese word. Once the learner has encountered the replaced word a few times, SystemA will assess the learner's mastery by generating a multiple choice translation test on the target word (Figure 1, right). Our learning platform thus can be viewed as three logical components: *translating*, *learning* and *testing*.

Translating. We pass the main content of the webpage from the extension client to our server for candidate selection and translation. As certain words are polysemous, the server must select the most appropriate translation among all possible meanings. Our initial selection method replaces any instance of words stored in our dictionary. For translation, we check the word's stored meanings against the machine translation of each sentence obtained from the Microsoft Bing Translation API (hereafter, "Bing"). Matches are deemed as correct translations and are pushed back to the Chrome client for rendering.

Learning. Hovering the mouse over the replacement Chinese word causes a tooltip to appear, which gives the translation, pronunciation, simplified and traditional written form, and a More link that loads additional contextual example sentences (that were previously translated by the backend) for the learner to study. The more link must be clicked for activation, as we find this two-click architecture helps to minimize latency and the loading of unnecessary data. The server keeps record of the learning tooltip activations, logging the enclosing webpage URL, the target word and the user identity.

Testing. After the learner encounters the same word a pre-defined number $t = 3$ times, SystemA generates a MCQ test to assess mastery. When the learner hovers over the replaced word, the test is shown for the learner to select the correct answer. When an option is clicked, the server logs the selection, and the correct answer is revealed by the client extension. Statistics on the user's test history are also updated.

2.1 News Categories

As our learning platform is active only on certain news websites, we model the news category of both individual words and webpages. Of particular importance to SystemA is the association of words to a news category, which is used downstream in both word sense disambiguation (Section 3) and the generation of distractors in the interactive tests (Section 4). Here, our goal is to automatically find highly relevant words to a particular news category – e.g., "what are typical *finance* words?".

We first obtain a large sample of categorized English news webpages, by creating custom crawlers for specific news websites. We use a seed list of words that are matched against a target webpage's URL. If any match, the webpage is deemed to be of that category. For example, a webpage that has the seed word "football" in its URL is deemed of category "Sports". After a survey of a number of news websites, we decided on seven categories: namely, "World", "Technology", "Sports", "Entertainment", "Finance", "Health" and "Travel".

We tokenize and part-of-speech tag the main body text of the categorized articles, discarding punctuation and stopwords. The remaining words are classified to a news category based on document frequency. A word w is classified to a category c if it appears a tunable threshold $\delta = 10$ more often than its average category document frequency. Note that a word can be categorized to multiple categories under this scheme.

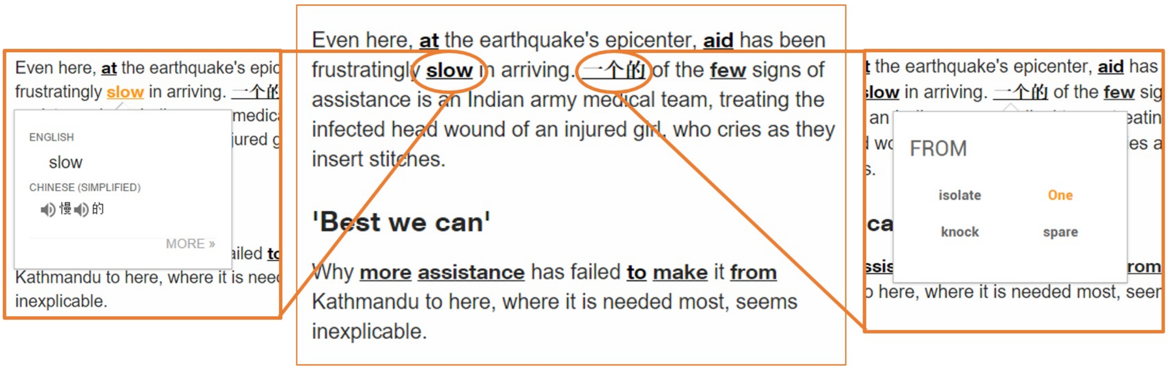


Figure 1: Merged screenshots of our Chrome extension on the CNN English article *Treacherous journey to epicenter of deadly Nepal earthquake*. Underlined components are clickable to yield tooltips of two different forms: (l) a definition for learning, (r) a multiple-choice interactive test.

Table 1: Experimental results.

Chinese Category	English Category	Example Words
Entertainment	Entertainment	design
Military	World	attacks
Finance	Finance	accounts
Sports	Sports	score
International	World	attacks
Social	World	attacks
Technology	Tech	phone
Lady	Fashion	—
Auto	Travel	natural
Game	—	—
Education	—	—
—	Health	stress

3 Word Sense Disambiguation System

It is common knowledge that a word in one language can often have multiple translations in another language. Our extension is expected to show the most appropriate one based on the context. We call such translation selection as cross-lingual word sense disambiguation (c-WSD). WSD is an open task in natural language processing, aiming at identifying the proper sense (*i.e.*, meaning) of a word in a context, when the word has multiple meanings (Navigli, 2009). Traditionally, WSD systems identify the right sense in the same language. Here, we find the proper sense in the target language for a given word in the source language.

Context information is the key to disambiguate word sense. We, therefore, make use of context at different granularities, *i.e.*, the category of the news, the word class, and the sentence, to select proper translations from our bilingual dictionary.

3.1 News Category

Topic information has been shown to be useful in WSD (Boyd-Graber et al., 2007). as For example, consider the English word *interest*. In finance related articles, "interest" is more likely to be "a share, right, or title in the ownership of property" ("利息" in Chinese), than 'the feeling of a person whose attention, concern, or curiosity is particularly engaged by something" ("兴趣"). Therefore, analysing the topic of the original article and selecting the translation with the same topic label might help disambiguate the word sense. We use the algorithm described in Section 2.1 to obtain the category for news and candidate Chinese translations.

3.2 Part-of-Speech Tagger

The word class, *i.e.*, the Part-of-Speech (POS) tag is believed to be beneficial for WSD (Wilks and Stevenson, 1998) and Machine Translation (Toutanova et al., 2002; Ueffing and Ney, 2003). For example, the English word "book" has two major classes, verb and noun, meaning "reserve" ("预定" in Chinese) and "printed work" ("书"), respectively. The two Chinese translations have the same POS tag as their corresponding English counterpart. Therefore, knowledge of the word's POS tag English cold be used to pick

Table 2: Example translations of WSD approaches. The target words are italicized and the proper translations are bolded. We omit the results for Category-based method, due to its poor performance.

English Sentence	Dictionary	Baseline	POST	Bing	Bing+	Bing++
... a very *close* friend of ...	verb: 关闭, 合, 关 ... adj: 密切, 紧密, 闭合 ... 亲密 ...	关闭	密切	**亲密**	**亲密**	**亲密**
... kids cant *stop* singing ...	verb: 停止, 站, 阻止, 停 ...	**停止**	阻止	**停止**	**停止**	**停止**
... it was about elsa being happy and *free* ...	adj: 免费, 自由, 游离, 畅, 空闲的...	免费	免费	**自由**	**自由**	**自由**
... why obama's *trip* to my homeland is meaningful ...	noun: 旅, 旅程 ... 旅游 ...	旅	旅	旅	**旅行**	**旅行**
... winning more points in the *match* ...	noun: 匹配, 比赛, 赛, 敌手, 对手, 火柴 ...	匹配	匹配	**比赛**	**比赛**	**比赛**
... *state* department spokeswoman jen psaki said that the allies had a long history of cooperation ...	noun: 态, 国, 州, 状况 ... verb: 声明, 陈述, 述, 申明 ... 发言 ... adj: 国家的 ...	态	态	发言	发言人	**国家**

Chinese translation with the same POS tag from the dictionary. In our system, we employ Standford Log-linear Part-of-Speech tagger (Toutanova et al., 2003) to obtain the POS tag for the English word. POS tag for Chinese words are contained in our dictionary. In some cases, after applying this rule, there are still multiple candidate Chinese translations. In such cases, we select the most frequently used candidate.

3.3 Machine Translation

Neighbouring words provide a richer context. In our work, we consider the sentence in which the target word appears as our context. We then acquire its translation from Microsoft Bing Translator[3], an online machine translation system. The Chinese translation, however, does not have explicit word alignment to the original English sentence. Therefore, we need to align the Chinese and English sentences to find the Chinese word that is aligned to the English target.

Bing. As potential Chinese translations are available in our dictionary, the most intuitive processing is to perform a substring match, *i.e.*, check whether the candidate Chinese translation is a substring of the Bing translation. If more than one candidate match, we pick the one with longest match as the final output. If none match, the system does not output a translation for the word.

Bing+. The previous method is limited by the coverage of our dictionary. As language is flexible, it is likely that our dictionary does not capture all the possible Chinese translations. To alleviate this, we relax the substring restriction, allowing the Bing translation to be a super-string of a candidate translation in our dictionary. To this end, we first segment the Bing translation with Stanford Chinese Word Segmenter (Chang et al., 2008), and then use the matching rule to find the proper Chinese word.

Bing++. The previous method may match the Chinese candidate translation in our dictionary with multiple words in the Bing translation. However, we do not know which Chinese word corresponds to the target English word. This suggests that word alignment information would be useful to resolve this issue. To obtain the alignment, we send the original English sentence and Chinese translation to Bing Word Alignment API[4],

[3] https://www.bing.com/translator/

[4] https://msdn.microsoft.com/en-us/library/dn198370.aspx

and then apply the same matching rule as Bing+.

3.4 Evaluation

To evaluate the effectiveness of our proposed methods, we randomly sampled 707 words and their sentences from recent CNN[5] news articles, and manually annotated the ground truth translation for each target English word. We report both the **coverage** (*i.e.*, the ability of the system is to return a translation) and **accuracy** (*i.e.*, the accuracy of the translation). For comparison purpose, we also report the performance for the baseline method – selecting the most frequently used Chinese translation.

Table 3: Experimental results.

	Coverage	Accuracy
Baseline	**100%**	57.3%
News Category	2.0%	7.1%
POSTagger	94.5%	55.2%
Bing	78.5%	79.8%
Bing+	75.7%	80.9%
Bing++	76.9%	**97.4%**

Table 3 shows the experimental results for the six methods. As expected, frequency-based baseline achieves 100% coverage, but a low accuracy (57.3%). POS tagger method performs similarly. News category based method performs the worst, suggesting that category by itself is insufficient for WSD. This is could be because news category only provides a high-level context and not all of word senses have a strong topic tendency. The three Bing methods improve the accuracy iteratively and all have a reasonable coverage. Among all the methods, Bing++ is the best in terms of accuracy (97.4%), significantly betters others. This shows that sentence-level context is the most beneficial for our WSD task.

4 Distractors Generation Algorithm

Assesing mastery over vocabulary is a key functionality in our extension. In this section, we investigate a way to automatically generate suitable distractors (in English form) for a target word. We postulate "a set of suitable distractors" as: 1) having the same form as the target word, 2) fitting the reading context, and 3) having proper difficulty level according to user's level of mastery. We obtain the POS tag for the target word and restrict the candidate distractors to the same word class. To make the distractors fit the context, we identify the target word's news category (approach is detailed in Section 2.1), and select the distractors from the same category.

The difficulty of a distractor is measured by its **semantic distance** to the target word: the closer it is to the target word, the more difficult the distractor is. To quantify the semantic distance, we employ Lin's Distance (Lin, 1998) to measure the distance between two words in WordNet (Miller, 1995) and define distractors to be difficult if the Lin's Distance score is below some threshold. We empirically set 0.1 as the threshold.

4.1 User knowledge Aware Approach

As previously mentioned, our extension logs user's detailed learning history. We categorize a user's knowledge on a certain word into three levels, based on the number of times that he / she has encountered the word. Then we adopt different strategies to generate distractors for users in different knowledge levels.

Knowledge Level 1 (K1): This is the default knowledge level assigned to a user on a new word. Users aren't tested on words where their knowledge level is K1.

Knowledge Level 2 (K2): This indicates that the user has known this word for three times. Therefore, the testing is expected to be harder. The first two distractors are randomly selected from those words that share the same news category. For the third distractor, its semantic distance to the target word is checked in addition, making it a more difficult distractor.

Knowledge Level 3 (K3): At this level the user is expected to have a good understanding of the word since she has *i.e.*, passed the test six times. Therefore, we make the test even harder, and choose all three distractors from the same news category along with the semantic distance criteria.

4.2 Evaluation

To compare with our proposed method, we reimplemented an existing distractor generation

[5]Cable News network accessible at `http://edition.cnn.com/`

method used in WordGap system (Knoop and Wilske, 2013). WordGap adopts a knowledge-based approach: selecting the synonyms of synonyms (computed in WordNet) as distractors. That is, they select the most frequently used word, w1, from the target word's synonym set. Then they select the synonyms of w1 and call this set as s1. Synset s1 contains all the words that are synonyms of synonyms of the target word. Finally they select three most frequently used words from s1 as distractors. This we use is as our baseline approach for comparison.

Our proposed method adopts three different strategies to generate distractors according to user's knowledge level. In our evaluation, we study distractors generated for the two extreme cases, *i.e.*, knowledge level 1, and knowledge level 3. Therefore, we conduct a pairwise comparison – K1 vs. Baseline, and K3 vs. Baseline, using the same test dataset.

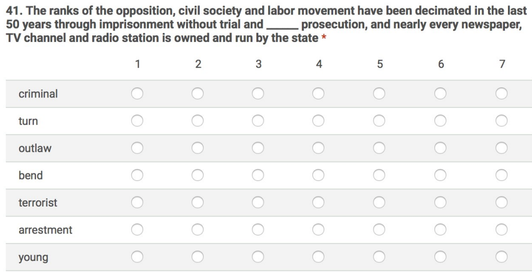
4.2.1 User Study

To compare the two approaches in generating distractors, we ask users to compare the plausibility of distractors. We randomly selected 50 sentences from recent news articles and then chose a noun or adjective from the sentence as the target word. In our survey, each question looks like a real MCQ quiz: we show the original sentence (leaving the target word as blank) as the context, and randomly display the six distractors and the target word as choices. Users are required to read the sentence and select the correct answer (that they think) as rating 1, and rank the other choices from 2 (most plausible) to 7 (least plausible) based on their plausibility. Figure 2 shows an example survey question.

We have two tests (K1 vs. Baseline, and K3 vs. Baseline) and each contains 50 questions. We further group 25 questions as one session, and give users the freedom to participate one or more sessions. Each question will be answered by at least five different users. Finally, we recruited 15 users from our university, and half of them are native English speakers. In average, each user participate two sessions.

4.2.2 Results and Analysis

As each question is answered by five different users, we compute the average rating for each


41. The ranks of the opposition, civil society and labor movement have been decimated in the last 50 years through imprisonment without trial and _____ prosecution, and nearly every newspaper, TV channel and radio station is owned and run by the state *

	1	2	3	4	5	6	7
criminal							
turn							
outlaw							
bend							
terrorist							
arrestment							
young							

Figure 2: A sample survey question

choice. A lower rating means a more plausible (harder) distractor. Unsurprisingly, the rating for all the target words is low (1.1 in average), as they are the ground truth. This implies that the users answered the survey questions seriously, and the evaluation quality is controlled. For each question, we determine a algorithm to be the winner if its three distractors as a whole (the sum of three average ratings) are more plausible than the distractors by another algorithm. We calculate the number of winning questions for each algorithm and compute the average score across the 50 questions. Winning more questions, and obtaining a lower average score denotes a better performance for an algorithm.

Table 4: Baseline vs. Knowledge Level 1

	Number of winning questions	Average score
Baseline	27	3.84
K1	23	4.10

Table 5: Baseline vs. Knowledge Level 3

	Number of winning questions	Average score
Baseline	21	4.16
K3	29	3.49

We display the results for Baseline vs. K1 and Baseline vs. K3, in Table 4 and Table 5, respectively. We see baseline outperforms the K1 algorithm by four more winning questions and 0.26 average score. Recall that, K1 algorithm is solely relied on category information, without taking word semantic relatedness into account. When a target word does not have a strong category tendency, *e.g.*, "venue" and "week", it is hard for K1 algorithm to select plausible distractors. On the other hand, we see context information (*i.e.*, new category) do play a key role, as K1 wins for 23 times.

In Table 5, we see our K3 algorithm significantly betters the baseline for both winning questions (8 more) and average score (0.67 lower). This further confirms that context and semantic information are complementary for distractor generation. As we mentioned before, a good distractor should fit the reading context and have a certain level of difficulty.

5 Platform Viability and Usability Survey

We have thus far described and evaluated two critical components that can benefit from capturing the learner's news article context. In the larger context, we also need to check the viability of second language learning intertwined with news reading. In a requirements survey prior to the prototype development, two-thirds of the respondents indicated that although they have used language learning software, they use it infrequently (less than once per week), giving us motivation for our development.

Post-prototype, we conducted a summative survey to assess whether our prototype product satisfied the target niche, in terms of interest, usability and possible interference with normal reading activities. We gathered 16 respondents, 15 of which were between the ages of 18–24. 11 (the majority) also claimed native Chinese language proficiency.

The respondents felt that the extension platform was a viable language learning platform (3.4 of 5; on a scale of 1 "disagreement" to 5 "agreement") and that they would like to try it when available for their language pair (3 of 5).

In our original prototype, we replaced the original English word with the Chinese translation. While most felt that replacing the original English with the Chinese translation would not hamper their reading, they still felt a bit uncomfortable (3.7 of 5). This finding prompted us to review and change the default setting of the learning tooltip to simply add an underline to hint at the tooltip presence.

6 Conclusion

We have described `SystemA`, a software extension and server backend to transform the web browser into a second language learning platform. Leveraging web-based machine translation APIs and a static dictionary, it offers a viable user-driven language learning experience by pairing an improved, context-sensitive tooltip definition capability with the generation of context-sensitive multiple choice questions.

`SystemA` is potentially not confined to use in news websites; one respondent noted that they would like to use it on arbitrary websites, but currently we feel usable word sense disambiguation is difficult enough even in the restricted domain. We also note that respondents are more willing to use a mobile client for news reading, such that our future development work may be geared towards an independent mobile application, rather than a browser extension.

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