

Language Explorer: Adaptive Language Learning Using Commonsense Knowledge

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ABSTRACT

Adaptability is the key functionality a language learning system should have so that it can provide the most assistance to users. Existing language learning systems only present limited adaptability, e.g. location or student's knowledge. We argue that commonsense knowledge is a good resource for language learning systems to provide various adaptation. We present *Language Explorer*, a mobile application that adapts to a learner's context and capability by leveraging the crowd-sourced commonsense knowledge base ConceptNet, the location based service Foursquare, and dialogues in online courses to automatically arrange materials and generate dialogues that fit the learner's current situation. The state-of-the-art commonsense reasoning techniques also demonstrated its ability to help the system to go beyond ngram co-occurrence based analysis.

ACM Classification Keywords

H.5.m Information interfaces and presentation (e.g. HCI):
Miscellaneous

General Terms

Design, Experimentation, and Human Factors.

Author Keywords

Language Learning, Commonsense Reasoning, Commonsense, Mobile, Context-Aware, Adaptive Learning

INTRODUCTION

Language is a foundation of our daily interaction. With more and more interaction between countries, people start to learn a second language in the hope to communicate with people from other countries fluently. There are already many applications, courses, and resources online for people to easily get access to them. For example, Rossetta Stone¹ uses an audio-visual approach to help learners infer the mapping between concepts and photos; Popup Chinese² provides podcasts of dialogues to help learners understand a situation.

Most current language learning applications today are based on a sequential, lesson-by-lesson format, or use a flashcard-based system to teach concepts/phrases. They provide static content to every learner instead of adapting to the learner's capability and interest. With the demands from family, work, and friends, it is hard for language learners to maintain their

executive motivation [11]. So, it is impractical to encourage most language learners to spend all their free time to spend at least one year to follow online curriculums.

In order to provide most assistance to a user's learning process, *adaptability* is the key functionality a language learning application should be equipped with. With *adaptive language learning* [16, 26], the application would not only present the same vocabularies and sentences to learners, but also introduce new content to the learners according to their learning goals and current interactions with the system. The rationale of adaptive learning reflects on two folds of design in second language learning applications.

- Adapt to learner's context: Since most people learn a second language with a specific goal in their communication to accomplish, it is necessary to provide meaningful contexts for second language learning [3]. For example, when a learner is going to order a drink in coffee shop, it is better to teach him/her the vocabulary of drinks and the dialogue of ordering food. Contextualized communication also helps learners reduce the gaps between language comprehension and production by reinforcing "noticing and focused output" process [22, 14]. Learners would better notice concepts embedded in the contexts they developed [4]. These noticed concepts can then be carefully structured and managed into output dialogues for learners to acquire new language.
- Adapt to learner's capability: Since there is a wide span of language output complexity, it is essential to present materials that accord with learner's current knowledge while providing sufficient challenges to the learner [17]. The language learning application should serve as a guide to bring learners step by step into exploring the language space. By incrementally presenting new or more complex words and phrases to learners, it also helps complexify the learners' productive linguistic repertoire [22] to improve their communication.

Although it seems intuitive for an application to provide adaptive language learning, there are only a few systems that adapt to either learners' contexts or capability. For most context-aware language learning applications, their models of context are simply based on location [12]. We hypothesize that the time it takes to build a richer context model and arrange materials to learners of different levels is too high for developers to automatically build up these models. In the conventional intelligent tutoring system [9], developers need to hand-craft

¹<http://www.rosettastone.com>

²<http://popupchinese.com>

the associations between contexts and learning content, and find an expert to give a difficulty ranking of materials so that the system can match the suitable materials to a learner.

Since humans use lots of commonsense knowledge in daily communication. The commonsense knowledge base offers us many clues to present language learning materials to learners. In this paper, we present *Language Explorer*, a mobile language learning application that utilizes commonsense knowledge to achieve *adaptive language learning*. Language Explorer uses (1) the activities that take place in a location to infer the possible goals a learner may have in that location, (2) the ad-hoc categories of a concept to update the learning dialogue dynamically, and (3) the strength of associations between concepts to decide the difficulty of content. Combining commonsense reasoning and ordinary language learning materials, Language Explorer helps learners to discover the learning path that is most suitable for them toward using a language.

In the following sections, we start by presenting a scenario to introduce the usage of Language Explorer. We then compare commonsense knowledge and statistical collocation to see what commonsense offers for language learning problem along with the algorithm that is used for presenting and generating content with commonsense reasoning. The plan of evaluation is also proposed as a follow-up for this project. The paper concludes with a survey of related language learning system and a summary of our contribution.

LEARNING WITH LANGUAGE EXPLORER

Language Explorer is a mobile application for Chinese learning. Since most people's goal for learning a second language is to have a fluent conversation in that language, Language Explorer focuses on helping users learn the required concepts and dialogues in a user-select situation. By carrying on an simulated conversation in a context and prepping for such a conversation ahead of time, learners are able to acquire more successful oral communication [8].

Identifying context

Consider the scenario in which a learner stays in a office and starts to use Language Explorer to learn Chinese. Figure 1 shows the initial interface Language Explorer presents to the learner. Language Explorer detects learner's longitude and latitude to find out the nearest locations to populate the first dropdown box for the learner to identify his location. In Figure 1a, the learner chooses "office" as his location. The second dropdown box is then populated with the actions that may take place in an "office" for learner to identify his intended situation (see Figure 1b). Through this step, the learner provides the context he is interested in to Language Explorer so that the Language Explorer can narrow down the materials to those that is helpful for the learner.

Concept learning

In order to facilitate the learners to have a sense of what is the knowledge he needs to know to carry on a conversation

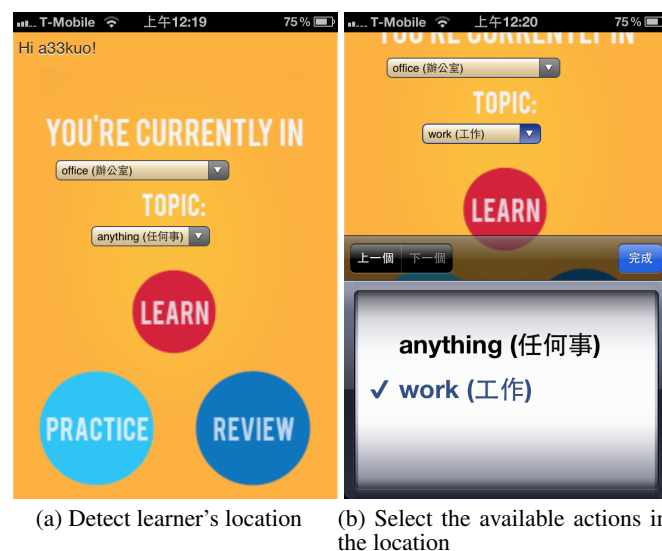


Figure 1: Identify learner's context

in the selected context, Language Explorer presents a concept overview to the learner if they choose to learn in a context. The concept overview is consisted of concepts that the learner need to know at his current knowledge level but not yet to know so that they cannot use them in conversation. Figure 2a is the screen a learner sees when he is in the context "working in a office" for the first time. At first, Language Explorer shows the basic concepts such as 老闆(boss), 工作(work), and 休息(rest). The different font colors represent the different categories of concepts. The usage of concepts in different categories is totally different in dialogues. For example, we will say "I need to work today" and "Boss is not here" but we will not use them reversely. With concept categories, the learner can learn and use the concept by making analogy within a group of concepts.

When the learner want to learn the concept "老闆(boss)", he can click the concept in the overview page. It leads the learner to the detailed information of the concept. Figure 2b shows the interface to present the materials for learners to understand the concept. It is a multi-modal presentation of concepts. The materials includes Chinese characters, Pinyin (i.e. the pronunciation), image, English translation, and audio clips of the concept. The learner can interact with the concept by choosing the learning dimensions that are easier for him to make association between the meaning of a concept and its Chinese.

After the learner interact with a concept, he may choose to see how the concept used in a dialogue by clicking the triangle on the corner or go back to the overview page to explore other concepts. If he go back to overview, he will find an updated page as shown in Figure 3a. The concept "老闆(boss)" he just browsed becomes smaller and bring up a new concept "書(book)" into the overview. When the learner looks at the concept more times or answer the practice question regarding the concept correctly, the concept would become smaller and



(a) Concept overview for “work-ing” in a “office” (b) Learn concept “boss”

Figure 2: Concepts learning



(a) Overview after learning one concept (b) Overview after learning multiple concepts

Figure 3: Overview for “office” after learning some concepts

leaves the room for more concepts to show up. Figure 3 is an example after the learner browses more concepts and looks at “老闆(boss)” for many times.

Language Explorer uses font size to highlight target concepts. The larger the concept is, it indicates the learner may not know well about it and should learn the concept first. This is a way of increasing the learner’s noticing of those concepts, which has been shown to be very important in second language learning [23]. If Language Explorer considers the learner already be able to handle the concept well (i.e. the font size of the concept is very small), it will remove the concept from the overview. Through the dynamic update of font sizes, Language Explorer also tells the learners that they are making progress in this context.

Dialog learning

If the learner chooses to flip the concept page to see the usage of the concept in a dialogue, it leads the learner to the dialogue examples of the concept (see Figure 4). Language Explorer shows simple dialogue, e.g. “你[老闆]在嗎? (Is your [boss] here?)” in Figure 4a, to the learner if he did not learn any dialogue of this concept category before. Similar to the update of concept overview, when the learner looks at the dialogue more times or answer the practice question regarding the dialogue correctly, Language Explorer will replace the current dialogue with a more complex dialogue. A more complex dialogue can be the following types.

- The extension of the current dialogue. It contains more sentences in a dialogue. For example, Figure 4b includes the response of the question in Figure 4.
- The longer sentences. For example, “[筆]在哪裡? (Where is the pen?)” is replaced by “可以借我[筆]嗎? (Could you lend me a [pen]?)”.
- The dialogue involving more concepts. This kind of dialogue requires the learner to know more concepts to understand its meaning, e.g. “你需要[筆]和[紙]嗎? (Do you need a [pen] and [paper]?)”.

The concept categories also contribute to the learning of dialogues. Because the concepts in the same category shares some attributes in the same context, they are able to fit in the same set of dialogues. Language Explorer can draw the connection between the concepts in the same category and apply the same dialogue on them. For example, “書(book)” and “筆(pen)” are in the same concept category, and both of them can put into the sentence “可以借我___嗎? (Could you lend me a ___?)” (see Figure 5). Therefore, the dialogue learn from one concept or context can be extend to other concepts. The learner would learn more variety of dialogue usage through this kind of analogy.

In addition to concept and dialogue learning, Language Explorer presents audio concept association and sentence selection exercise in practice section. After taking an exercise, the learning content will also be updated. The learner would be able to freely explore in the context they want to learn while being guided by Language Explorer to learn concepts and dialogues based on his knowledge level.



Figure 4: Dialogues for “boss”

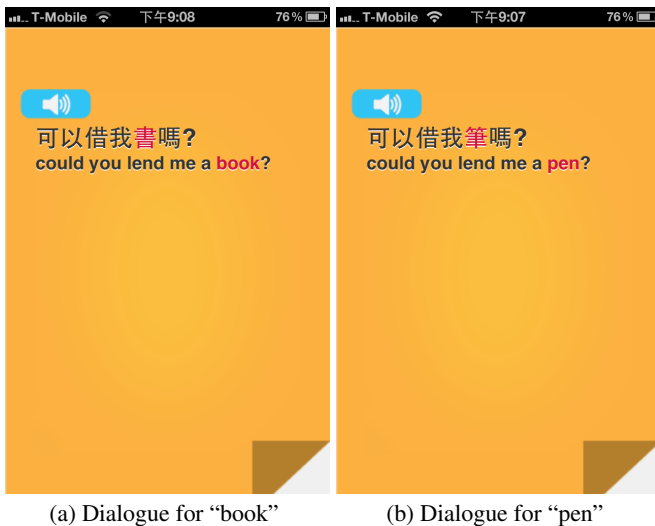


Figure 5: Dialogues for concepts in the same category

COMMONSENSE FOR LANGUAGE LEARNING

Because commonsense knowledge is knowledge of a language [7], people tend to learn a language based on their existing commonsense knowledge. Language Explorer leverages commonsense knowledge, which is a set of shared knowledge people use in our everyday communication, to generate the content that is suitable for learners to learn in their current stage. For example, “You may use fork when you eat”, “Latte is a kind of coffee”, and “You can find food in a cafe” are the defaults people should know in a cafeteria. In this section, we also compare this knowledge and statistical measure of word co-occurrence, which is another approach people often use to harvest correlation of concepts in intelligent tutoring system [17], to see what commonsense knowledge offers for second language learning application like Language Explorer.

Commonsense knowledge base: ConceptNet

In order to have computers understand the commonsense knowledge required in human communication, we need to encode this kind of knowledge into computer readable forms. The Open Mind Common Sense (OMCS) project at MIT took the Web 2.0 approach and appeal for contributions from on-line users to collect commonsense assertions. Over a million sentences in multiple languages have been collected and are encoded as semantic networks called ConceptNet [15]. The ConceptNet represents all collected sentences as a directed graph. The nodes of this graph are *concepts*, and its labeled edges are *relations* of commonsense knowledge connecting two concepts. There are over 20 relation types defined in ConceptNet. For example,

- UsedFor (*a*, *b*), e.g. [Spoon] is used for [eating].
- IsA (*a*, *b*), e.g. [Latte] is a kind of [coffee].

Top concepts

Since ConceptNet is a crowdsourced commonsense knowledge base, we think the number of assertions connecting to a concept in ConceptNet represents how common the concept are used in people’s life. In order to verify this hypothesis, we analyzed the top 100K words released from Microsoft Web N-Gram Service³ and the concepts in ConceptNet. After removing stop words and html schemas, we sorted the concepts in web corpus and ConceptNet according to their number of occurrence and the number of assertions respectively. The top 30 concepts are listed in Table 1.

From these top concepts, we can find that the popular words in web corpus, e.g. search, news, page, site, etc, are news articles or the legend in the webpages. We rarely use these concepts to understand the situation in our daily life. The top concepts in ConceptNet, on the other hand, are common entities or actions in our daily life. All of them are also the words taught in the class as basic words. This property suggests us that the degree of a concept may be a good indicator to measure how basic a concept is. Once learners learned the basics concepts, we can then build up more specific or difficult concepts on them.

³<http://web-ngram.research.microsoft.com/>

Table 1: Top 30 concepts in web corpus and ConceptNet

Microsoft Web N-Gram	ConceptNet
home, search, information, news, time, view, use, page, site, business, free, get, see, pm, help, first, services, name, online, like, data, service, people, here, year, web, add, state, email, top	person, human, child, fun, water, book, man, dog, money, paint, music, horse, car, house, write, dance, food, cat, exercise, animal, eat, drink, party, home, fish, computer, paper, plant, city, plate

Concepts in contexts

There are over 20 relation types in ConceptNet. From the previous research, we know that ConceptNet provides various contextual information for applications to use [19]. We may call for different relations to get different types of knowledge, such as location, action, object, goal, etc, for applications to use. We think this kind of contextual information is suitable for the “overview” page of Language Explorer. In order to verify that the contextual information retrieved from ConceptNet is better to represent the context in real life, we compare the associated concepts of “restaurant” in bigram of different corpus and ConceptNet to illustrate their differences. We used NYU n-gram search engine⁴ [24] to search for “* restaurant” and “restaurant *”, i.e. the words that attach to restaurant, and sorted them by frequency to filter out the most popular words in two corpus: 86 year news paper and Open American National Corpus⁵. The contextual concepts are retrieved by using all the relations to find the concepts that connect to restaurant and then sorted them by the frequency of assertions we filtered these concepts. For example, we use `AtLocation(x, restaurant)` and `AtLocation(restaurant, y)` to filter out that x may be “table” and y may be “city”; the assertion `AtLocation(table, restaurant)` is mentioned 8 times and `AtLocation(restaurant, city)` is mentioned 5 times in ConceptNet. So, table is ranked higher than city in the context restaurant. The result is listed in Table 2.

Table 2: Top 15 concepts related to “restaurant” in web corpus and ConceptNet

Bigram of 86 year news paper	Bigram of Open American National Corpus	ConceptNet
chain, owner, business, industry, company, manager, workers, concern, group, operations, employees, sales, food, scene	serving, offers, business, provided, review, overlooking, chain, terraces, table, owners, complex, waitstaff, char-broilers, features	place, eat out, potato, eat, butter, bill, wine list, buffet, restaurant table, city, restaurant storage area, chef special, cook, town, hotel

⁴<http://nlp.cs.nyu.edu/nsearch/>

⁵<http://americannationalcorpus.org/OANC/>

From Table 2, we find that the concepts harvest from bigrams are very corpus dependent. The concepts extracted from newspaper corpus are business related such as industry, company, manager, etc, which are topics we would easily found in newspaper. The concepts extracted from Open American National Corpus shows more variety than concepts from newspaper because it contains data from government, journal, travel guides, face to face, and telephone conversation. However, there are still more written knowledge than the spoken knowledge in these corpus. It is more suitable for us to use the correlation to do writing correction in a particular domain, but hard for us to use these concepts to get a comprehensive understanding of a situation in everyday interaction with other people and the environment.

The top concepts associated with restaurant, on the other hand are intuitive for us to identify how to use it in a dialogue. These concepts implicitly shows the categories of concepts in a context. For example, “potato” and “butter” are in food category, we may use these concepts to ask if a restaurant provides certain food; “wine list” and “chef special” are part of a menu, we may use these concepts to ask for the menu or suggestions in a food ordering situation in a restaurant.

For an adaptive language learning application like Language Explorer, the knowledge it adapts to implies its ability to facilitate learners to achieve their communication goals. From the above comparison, we know that the commonsense associations are more useful for learners to build up their understanding in a situation and use their common sense in their first language to apply the concepts in a new dialogue.

Commonsense reasoning

In addition to the large commonsense knowledge base, we are also using commonsense reasoning techniques to reason beyond the simple associations between concepts. Language Explorer uses subevent chaining and analogical reasoning to find the possible actions in a location and the ad-hoc categories of concepts to help learners make sense of the learning materials.

Find possible actions

Given a location, we would like to find all the actions that is related to the location for learners to select from so that we can specify learner’s context. *Subevent chaining* is a forward-chaining style inference. It starts from the specified location concept and recursively includes all the actions connected by the “HasSubevent” relation into the possible actions of the location. For example, we use assertion `HasSubevent`(see a movie, movie theater) to get “see a movie” as one of the possible actions in a movie theater. And then, starting from “see a movie” we can get “buy movie ticket” and “buy popcorn” from assertions `HasSubevent`(buy movie ticket, see a movie) and `HasSubevent`(buy popcorn, see a movie). So, “buy movie ticket” and “buy popcorn” are also the possible actions of movie theater. In order to guarantee the relevance of the concepts, we only consider chaining for two layers.

Find ad-hoc categories

In order to get the implicit categories of concepts in a context, e.g. hamburger, fries, and fried chicken are the food we can order in a fast food restaurant, we need a method to retrieve these analogous concepts. *AnalogySpace* [25] is a reasoning tools that provides analogical reasoning in the commonsense semantic network. It generalizes the reasoning method called cumulative analogy [6]. Unlike first-order logic approaches for finding analogy, it is computationally efficient, and tolerant of noises. The assertions in ConceptNet are divided into *concepts* and *features*, i.e. descriptions of concepts such as “UsedFor eating” or “latte IsA”. The knowledge in ConceptNet is represented as a sparse matrix, whose rows are concept, and whose columns are features. The most prominent features of concepts can be identified by using singular value decomposition (SVD). After applying SVD on the matrix, every concept is described by a vector of the most prominent features. These prominent features help us measure the concepts by vector calculation. For instance, we can use the cosine similarity to measure the similarity of any two concepts. Given a set of concept vectors, we can then use cosine similarity as a distance measure to cluster the concepts into different ad-hoc categories, e.g. “watermelon”, “corn”, and “tomato” fall into the same category in the context “farm”.

LANGUAGE EXPLORER DESIGN

We designed the system to utilize commonsense knowledge to arrange the learning materials. Language Explorer’s system structure is composed of the following components:

- A *learning repository* of concepts and dialogues.
- A *material matching module* that returns the concepts and dialogues to the learner given the learner’s learning history and context selection.
- A *dialogue generation module* that creates the suitable dialogue for the learner based on the selected concept and the learning history/context of the learner.

Learning repository

Since ConceptNet is a multilingual commonsense knowledge base, it enables us to easily use the commonsense knowledge in languages other than English. In Language Explorer, we choose Chinese ConceptNet as our base knowledge. The up-to-date knowledge in the Chinese ConceptNet was successfully collected and verified via question-answering between players in social games [18]. Using the network structure, almost every concept in the ConceptNet is either associated with a location or an action that are included in the contexts. The dialogues used in Language Explorer are scraped from online language learning courses. We preprocessed these materials by associating them with contexts, difficulty level, and categories so that the Language Explorer can easily present them in the phone interface.

Context association

The context we used can be divided into two parts: the locations and the actions. All the concepts and dialogues presented in the Language Explorer are related to the specified location or action. First, we applied subevent chaining on

Chinese ConceptNet to get the possible actions of a list of predefined locations. An action may take place in multiple locations. Then, we used the locations and actions as labels to annotate their neighbor concepts in ConceptNet. The dialogues from online courses are already classified into different contexts such as “buying shoes in a department store” or “ordering food in a restaurant”. We only need to re-label them using the location and action list. When a learner select a location and an action, only the concepts and dialogues with the selected labels are retrieved for concept overview and dialogue examples.

Difficulty ranking

However, not all the related concepts of a context are suitable for the learner’s current language capability to learn. In order to know the relative difficulty of different concepts, we built two partial orders on the concepts/dialogues respectively to capture the sense of difficulty we think in memorize the concepts/dialogues. The partial order of concepts is based on how commonly a concept is used in our life, which is determined by:

- Number of assertions associated with the concept. The concepts of higher degree is related to most concepts. So, it is a basic concept learner should learn first.
- Length of concept in Chinese. Because most people is not good at remembering long words, the longer concept is more difficult.

For example, in our partial order, “老闆(boss)” is easier than “總經理(general manager)” because (1) there is 784 assertions containing “老闆(boss)” but only 28 assertions containing “總經理(general manager)” and (2) “老闆(boss)” is a two-character word but “總經理(general manager)” is a three-character word.

The difficulty of dialogue follows our sense of complex dialogues as described in “Learning with Language Explorer” section. The partial order of dialogues is decided by the following factors:

- Number of sentences in a dialogue. The dialogue involves more sentences (i.e. interaction) are more difficult for non-native speakers to master.
- Number of tokens in a dialogue. For example, “老闆在嗎?(Is your boss here?)” is tokenized to “老闆”, “在”, and “嗎”; “我要咖啡和蛋糕(I want coffee and cake)” is tokenized to “我”, “要”, “咖啡”, “和”, and “蛋糕”. So, it is easy to observe that the sentences with fewer tokens tends to be simpler.
- Number of concepts that can be substituted in a dialogue. For instance, there is only one concept “老闆(boss)” that can be substituted in “老闆在嗎?(Is your boss here?)”, but two concepts “咖啡(coffee)” and “蛋糕(cake)” that can be substituted in “我要咖啡和蛋糕(I want coffee and cake)”. The latter sentence requires the learners to have more knowledge to understand.

Concept categories

After related concepts of a location or actions are identified, we need to find their categories so that they can be presented in a group for learners to make analogy between concepts in the same category. The categories a concept belong to are calculated for every location and action respectively, which means the usage of a concept may be different in different contexts. In order to find the categories, we get AnalogySpace vectors of all the related of the given location or action and use affinity propagation to cluster these concepts [13].

Here is the clustering example for related concepts of the location concept “早餐店 (breakfast joint)”:

- 鹽巴(salt)
- 飲料(drinks), 豆漿(soy bean milk), and 奶茶(milk tea)
- 漢堡(hamburger) and 三明治(sandwich)

We can easily identify that the categories are seasoning, drinks, and sandwich. These categories are the basic idea a learner should have in this location. Most concept categories found by clustering location related concepts tend to be the items/actions in that location. Unlike categories for location related concepts, the clustering results for related concepts of an action concept are related to the items used for accomplishing the action or the location/action that related to the action. For example, the categories found for “野餐 (have a picnic)” is as follows:

- 食物(food), 水果(fruit), and 三明治(sandwich)
- 汽車(car) and 休旅車(SUV)
- 郊遊(excursion) and 遠足(excursion)
- 餐具(tableware), 紙杯(paper cup), and 桌巾(tablecloths)
- 草地(meadow), 草原(grassland), and 郊外(outskirts)

“Food, fruit, and sandwich” are items people eat in a picnic. “Car and SUV” are vehicles that takes people to a picnic. From the examples for “breakfast joint” and “have a picnic”, we can also learn that sandwich is in different categories of usage in the two contexts. This kind of categorization helps learners to have a better idea to use a concept.

Dialogue generation

Since there are lots of combination of concepts and dialogues, it is hard for us to handcraft all the dialogues by the human. We use the dialogues scraped from online courses as templates and utilized the concept categories of found for the context to modify the original dialogue template. When the learner clicks a concept in a context, the system will retrieve all the dialogues that are annotated in that context. Then, the system goes over the retrieved dialogues and modify the dialogue list in two ways:

- If the category of the clicked concept does not contain any concept in the dialogue, remove the dialogue from the list.
- Otherwise, the system replace the matched concept by the clicked concept. For example, if the dialogue template is

“我們有帶[餐具]嗎? Do we bring [tableware]?” and the learner click “紙杯(paper cup)”, the system will replace “tableware” by “paper cup” and update the the dialogue to “我們有帶[紙杯]嗎? Do we bring [paper cup]?”

After this match-replace procedure, we can get a list of dialogues that contain the clicked concept. The list of dialogues are the candidates for our system to display.

Material matching and diaplay

With all the processed materials, material matching module is design to find the best material for presentation. It is consisted of two parts. The first part is to return the concepts for overview based on the learner’s context and his concept learning history. The second part is to find the example dialogue given the learner’s clicked concept, context, and dialogue learning history.

In order to find the concepts for overview, we have a learner’s ability evaluation for the concepts. Initially, the learner’s ability scores for all the concepts related to the given location and action are set to zero. This score is updated by the learner’s learning history of the concept. The concept learning history contains viewing frequency of a concept v , counts of correct answers $a_{correct}$, and counts of incorrect answers $a_{incorrect}$ to the questions containing the concept. The learner’s ability score of a concept is the weighted sum of the history counts: $\alpha \times v + \beta \times (a_{correct} - a_{incorrect})$, the importance of learning and practicing section is determined by α and β . Here, we introduce two threshold, (1) learning threshold $\theta_{learning}$, which indicates the learner is learning the concept but hasn’t learned it very well, and (2) learned threshold $\theta_{learned}$, which indicates the learner look at the concept many times and perform well in the practice section. In our definition, $\theta_{learning} < \theta_{learned}$, the number of concepts the learner learning is $n_{learning}$. Every time when the learner enters the overview of a context, our system will remove the concepts whose ability score $> \theta_{learned}$ from the related concepts of the input context, and return $(n_{learning} + 1)$ simplest concepts for display. This process guarantees we provide learners concepts from simpler to more difficult and present from fewer concepts to more concepts so that the learner can have a feel of progress in using Language Explorer.

Similar to finding concepts for overview, the learner’s ability scores for all the dialogue templates found from dialogue generation are set to zero. This score is updated by the learner’s dialogue learning history, which contains viewing frequency of a dialogue template v , counts of correct answers $d_{correct}$, and counts of incorrect answers $d_{incorrect}$ to the questions about the dialogue template. Therefore, the learner’s ability score of a dialogue is: $\alpha \times v + \beta \times (d_{correct} - d_{incorrect})$. We also have $\theta_{learned}$ for dialogue to decide if the learner already know a dialogue very well. Every time when the learner flip to the dialogue example of a concept in a given context, the system will remove the dialogues whose ability score $> \theta_{learned}$ from the generated dialogues, and then display the simplest dialogue in the list to the learner. Through the combination of concepts and dialogues, it implies the progress of learning starts from simple concept with simple dialogue,

difficult concept with simple dialogue, simple concept with complex dialogue, and finally reaches difficult concept with complex dialogue.

Implementation

We implemented Language Explorer as an HTML5 mobile application. The location tag and canvas are used to get geo location and draw overview concept cloud. The client uses JSON to communicate with our Python-based web service. We exploited the Foursquare venue API to derive the venue types. The content display in the concept information page is from Microsoft image search, text-to-speech, and translator results. All dialogues are tokenized by existing Chinese word segmentation⁶ library before doing dialogue generation and difficulty ranking. We also recorded user logs to keep track of users status.

EVALUATION

Since the application involves material arrangement/generation and user learning, we have decided to evaluate it from the two parts. For the first part, we will check the accuracy of concept clusters and generated dialogues. In our case, we can guarantee the quality of our content if we have good concept clusters and dialogues. The errors we find in the concept clusters can also help us during knowledge base debugging for Chinese ConceptNet to improve the overall commonsense knowledge base. For the second part, we would like to find real users from Chinese learning class to evaluate our application. We plan to log their every click to analyze what is the most used functions and facilitate a cognitive walkthrough. Questions we would like to ask our learners include:

- Are the concepts and dialogue too hard, too easy?
- Are there too many concepts/phrases in the overview?
- Do the words and phrases actually pertain to what they want to use in real life?

Finally, we would also analyze learners' practice results to see if they're actually learning by using the materials provided by Language Explorer.

RELATED WORK

Several established systems have been used for language learning. However, most of them are lesson-by-lesson style or vocabulary-based flashcards. Current research on language learning system focus on finding other dimensions of learning. For example, Duolingo⁷ extends the translation dimension to design lessons that make people learn a language while translating the web.

Adapting to learner's context and capability is another dimension for language learning applications to enhance. Previous research has been proposed to provide Chinese learning content based on the learner's level and location, but they did not implement it [1]. TenseITS is another system that attempts to adapt to learner's location, concentration level, interruption

frequency, and available time, but it only focused on the usage of learning English tenses [10].

Other context-based mobile language learning applications only considered location as their context. MicroMandarin provides city-wide location-based flashcards for microlearning [12]. In the ubiquitous computing field, systems have been designed to learn from the learner's interactions with the objects in an environment [2, 21]. The learner uses a RFID reader to learn from the tagged objects. This approach helps learners to associate items with the language, but it is always in a static setting that does not adapt to the learner's level.

Most adaptive language learning systems are intelligent tutoring systems (ITS) [17, 16]. They model students' knowledge from their learning history so that they can provide content that is suitable for the students, but most of them only focus on reading comprehension or writing. It is hard for learners to improve their conversation abilities using the current ITS.

Common sense provides a resource for language-based application to enhance different dimensions of learning. SIFU [5] uses Chinese ConceptNet to analyze Chinese news articles and present the similar/related concepts of a specified concept to learners so that they can better understand the usage of a concept. However, it focuses on news reading. It is only suitable for more advanced learners to use. GloBuddy [20] is another system that uses commonsense to provide phrases in a travel context. It only acts as a phrase book assistant and does not help users learn a language.

Although we find a number of interesting systems for language learning, none of them implement comprehensive adaptation to the learners or utilizing commonsense reasoning in language learning. A dynamic and adaptive language learning system is still required to fit into the everyday life of learners.

CONCLUSION

This paper presents *Language Explorer*, a system that utilizes existing language learning materials and commonsense knowledge to provide adaptive language learning. Language Explorer is the first system that utilizes commonsense knowledge to provide various adaptation to the learners. We suggest the usage of commonsense inference techniques to (1) extend context from location to actions, (2) associate materials with context, (3) build natural difficulty ranking of concepts/dialogues, and (4) learn concepts/dialogues by analogy within the concept in the same category. The process of building up the system can be applied on any pair of languages. With more multilingual commonsense knowledge, we anticipate to have a language learning system for any source and target languages.

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⁶<https://github.com/a33kuo/postagger.zh>

⁷<http://duolingo.com>

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