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On developing adaptive vocabulary learning game for children with an early language delay

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***Abstract*—Vocabulary replenishment is an ordinary child development process. Deviations in this process can significantly affect the further progress and perception of the educational material in the school. A hypothesis was proposed that the similarity of words on various factors can influence the child's understanding. To test this hypothesis in this work, we propose the development of AdapTalk game for children. This game is concentrated on learning words, in the context of animals. The game will create the basis for further testing the influence of the semantic similarity of words for the child. This work describes the development background, the basic principles of calculating the semantic similarity of words, as well as the main game processes, such as filtering, training, and testing. The proposed functionality is a good base for introducing other factors of similarity of words, further testing and introduction of an adaptive mechanism for improving the vocabulary of children.**

Keywords-adaptive learning, semantic distance, learning game, late talkers.

I. INTRODUCTION

Late talkers are children who start learning words and forming sentences later than their typically developing peers who start putting words together before the age of 2 [1]. While many of these children later catch up with their peers, the delay in the early development of the reading skill has been connected with later difficulties with language learning, such as dyslexia [2], [3], [4]. A recent finding in [4] confirmed earlier observation [3] revealing that if the delay considers receptive language, i.e. comprehension of spoken language during early years, such children will face serious difficulties in becoming fully literate.

A lot of attention has been given to providing interventions for these children to avoid the difficulties in the future. For example, in [5] authors reviewed 67 studies on young children's oral language development. Positive general effects on the impact of vocabulary interventions in the early years were reported, but their efficiency was suggested to be improved to succeed in closing the gap in preschool-aged children. Continuation meta-analysis by the same authors in [5] concluded similarly emphasizing the need of creating powerful enough interventions, especially for children with low socio-economical status.

Games have been widely recognized to generate a positive effect on learning with motivating and engaging, which they do most successfully when they succeed in facilitating a flow experience [6]. Flow is a state of mind where surroundings and track of time is lost while being fully occupied with doing tasks that are of optimal difficulty level - not difficult which could cause anxiety and not too easy either since that could lead to boredom [7]. Learning with mobile devices is recognized to be motivational as well as sufficient in keeping children's attention [8]. Facilitation with this technology provides a cost-efficient basis for developing learning environments that can adapt tasks to the optimal difficulty for each learner individually.

In our previous work, we described the general idea of an adaptive gamified word-learning application for late talkers (AdapTalk), whose adaptivity is based on the similarity distance mapping [9]. The software is to be used by children of age one and up, and teaching of words is done with simple multiple-choice tasks. These tasks include a sound heard from headphones and an array of pictures on a screen of a mobile device of which the learner then tries to choose the correct one. The role of the adaptivity algorithm, in this case, is to choose an appropriate array of pictures. In our previous work, we stated a hypothesis that the tasks would be easier if the array of other pictures than the correct one would be different according to a chosen similarity mapping, and vice versa, that the tasks would be harder if the array were chosen to include the most similar ones. Testing this hypothesis provides its challenge for both developing the software and experiment design, and in this paper, we concentrate on describing these aspects.

This paper consists of description of adaptive learning for late talkers (Chapter 2); proposed system description (Chapter 3); semantic similarity calculation methods and method that was used in particular work (Chapter 4); game process description itself, which include filtering, learning and testing (Chapter 5); and conclusions with description of future work (Chapter 6).

II. ADAPTIVE LEARNING FOR LATE TALKERS

A. Late Talkers

Diagnosis of late talkers can be done through estimating the child's vocabulary size and ability to form word pairs while ruling out other developmental deficits. Many late talkers catch

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up with their typically developed peers sooner or later, but some do not achieve age-appropriate language skills even as adults [10]. In later years these children can be diagnosed with Dyslexia [11] and Specific Language Impairment (SLI). SLI can be diagnosed during the pre-school years (age three to five) and means a deficit specific to language that is not related to hearing loss, neurological damage, and nonverbal intelligence, and it is expected to persist [10].

Some research suggests that LT's word learning strategies are rather a-typical than delayed. Beckage, Smith and Hills in [12] analyzed LT's and typically developing children vocabularies semantic connections. Authors' method included retrieving the vocabularies with Bates-MacArthur word form [13] and making the connections to the collected words from co-occurrences from CHILDES, a dictionary of child-directed speech. Both studies concluded that LT's network structures were less connected – containing words with less frequent connections. Authors presented an explanation that they called the 'odd-ball-model' where the child would rather learn a word that is less connected to other words as if that would be more interesting. This model is in line with Borovsky, Schafer and Fahey's [14] eye-tracking study's results where authors found that toddlers would answer multiple-choice questions incorrectly more likely when the distracting item was previously unknown. Both results suggest that LT's would be picking their interest from rather unknown than known words on the contrary to word-learning studies of adults and typical learners where, as Borovsky in [14] summarizes, the results commonly suggest that a word is more likely to enter the vocabulary if it shares connections to other previously known words. Borovsky et. al. in [14] however did not find differences in network structures when vocabulary size was controlled, while Beckage et. al. did [15].

If LT's learning strategies are indeed more a-typical than just delayed, developing an adaptive learning environment is a relevant approach to address the need for developing more effective interventions.

B. Adaptive word learning

It is a well-known fact that personalized approach is beneficial for any learning process [16]. This knowledge and background from educational theories should be used while creating technologically improved learning environments that adjust to the student's needs. These learning environments are often referred to as "adaptive" or "intelligent" studying systems.

Adaptive learning is a system of methods focused on "creating a unique learning experience for each person through the introduction of computer software [17]." Adaptive learning systems allow organizing content, recognizing the method to learn based on student's knowledge, and use individual estimation results to ensure personalized feedback for each learner [18].

Adaptive learning systems have a lot of attributes and functions in [19] brought together to produce appropriate content, assistance and to lead the learner through the adaptive learning tasks or units: pre-test, pacing and control, feedback and estimation, progress tracking and reports, motivation and reward.

These systems can be uncomplicated or algorithm-based [20]. The more basic ones are based on rules, established with the usage of if-then-statements. Algorithm-based systems apply advanced mathematical formulas and machine learning ideas to adjust to individual learners more specifically. Earlier research by [21] divides these systems into Adaptive Hypermedia Systems and Intelligent Tutoring Systems. These technologies can be used for adding adaptive or intelligent functions into learning systems.

Adaptive Hypermedia Systems involve adaptive presentation and adaptive navigation assistance, and also adaptive information filtering, which includes collaborative filtering and content-based filtering. Intelligent Tutoring Systems consist of intelligent solution research, curriculum sequencing, problem-solving guidance and intelligent collaborative learning, which includes adaptive group formation and adaptive collaborative assistance.

Discovering an optimum way to introduce the notions to the children during their first years of life might benefit in reducing their risk to have troubles in language learning in after years. That is the reason for us to have an adaptive content presentation in learning system for late talkers. We should use the adaptive presentation technology to make it accessible. The goal is to adjust the content of a hypermedia page to the user's aims with knowledge stored in the user model [22]. In an adaptive presentation system, the pages are dynamically generated or built from the pieces for every user [23]. The content presented to the kids should not be predetermined but should have the power to adapt by user's responses.

We suppose that recognizing some special notion among several other similar ones is a more difficult task. Every child can embrace pictures and sounds corresponding to them in different ways. For one child, it is difficult to differentiate between words, which sound alike. For another child, it could be difficult to differentiate between words that have a similar pattern, whether they could have a similar shape or similar color. Another child may have difficulty with distinguishing words, which are semantically close to each other.

III. System Description

Empirical evidence in the learning game environment for language development and disorders, as documented, e.g., in [24], emphasizes the role of perceptual differentiation of acoustically close phonemes, i.e., acoustic dissimilarity. Here we generalize this starting point by hypothesizing that concept learning and identification depend on personal comprehension of multiple parameters, such as sound and optical representations, as well as their semantics. Our method is based on processing the complexity level of concept identification induced by these factors. Taking accuracy of user's' replies into consideration, the proposed system will automatically increase or reduce the level of complexity, adjust it to the personal learning abilities of the users, and in such a way will improve the learning process.

The functionality of the approach, presented in the previous paper [9] takes into account differences between visual and auditory stimuli. Visual similarity for different concepts could be measured using Euclidean distance because of its simplicity [25], or with Tangent distance [26], etc. The phonetic similarity could be measured using string-based techniques like Edit Distance, Jaro-Winkler measure [27], N-gram similarity function [28], Soundex Mokotoff [29]. More detailed information about visual and phonetic similarity measures are given in [9].

Assuming that sets of more alike ideas cause more difficulties for their identification (recognition), we should automate the process of picture selection using multidimensional concept resemblance metric, measured as a collection of similarity values of the three mentioned factors. After, it is possible to personalize proposed learning instrument via modifying the delta (Δ) of motion similarity and "fiddling" with various levels of impact of the three factors on collective resemblance.

$$ConceptSim\left(c_i, c_j\right) = F(Sim_V, Sim_P, Sim_S) \quad (1)$$

ontological nodes through the 'is-a' –links [30]. Identically remote pairs of ideas on the upper level of taxonomy are computed less similar to the ones, which refer to a lower level [32]. Frequently the depth of ontology is united with the shortest path length in a nonlinear function in [33], sometimes with the overlap between the nodes [34]. In [35] authors applied cluster-based measure on top of a minimum length path and taxonomical depth. The taxonomical edge-counting technique was extended by involving non-taxonomic semantic links to the idea in the path [36].

b) Feature-based measures: utilize taxonomical features retrieved from the ontology. The resemblance between two notions can be determined as a function of their general and differential attributes (assessing the similarity between ideas as a function of their attributes) [30]. Such facet-based classification could be united with the similarity of common properties' values.

c) Combined measures: Combined measures which involve the edge-calculation based on information content (IC)-based measures with edge weight [37].

A. Semantic Classification

$$ConceptSim\left(c_i, c_j\right) = w_V * \sum_{k_V=0}^{n_V} w_{k_V} * Sim_{V_{k_V}} + w_P * \sum_{k_P=0}^{n_P} w_{k_P} * Sim_{P_{k_P}} + w_S * \sum_{k_S=0}^{n_S} w_{k_S} * Sim_{S_{k_S}} \quad (2)$$

where w_V, w_P, w_S are coefficients of weighted influence of visual, phonetical and semantic factors on concept similarity; n_V, n_P, n_S are number of different similarity measuring techniques used to calculate visual (Sim_V), phonetical (Sim_P) and semantic (Sim_S) similarity with corresponding weights of their influence ($w_{k_V}, w_{k_P}, w_{k_S}$).

Since all of our concept similarity factors (visual, phonetic and semantic) could be represented as weighted functions of various similarity measuring techniques, we defined a general formula to calculate the similarity between the concepts in [9].

The general architecture of adaptive vocabulary learning was also presented in [9]. It was concentrated on the functionality that if the learners improve, then the system should be able to provide them with more challenging tasks.

In this particular work, we concentrate more on semantic similarity, not on other ones, for future testing of our hypothesis that semantic similarity may influence learner's speed of learning, as well as their ability to differ words.

IV. Semantic Similarity

Determination of semantic similarity between ideas, i.e., comparable objects like different words or texts, has a central role in semantic sense comprehension. To measure similarity is not a straightforward task. The most widespread method is to measure semantic resemblance based on domain ontology; a theoretical model that depicts the appropriate domain.

B. Ontology-based Semantic Similarity

II. Ontology-based semantic similarity can be estimated with various methods [30], [31]:

a) Edge-counting method (graph-based method): computes the minimum path length connecting the appropriate

In our current solution, we have limited our focus to a domain of animals. Each domain brings certain specifics to the metric measuring semantic similarity. Semantic similarity can be measured differently depending on the context. The context-dependent similarities could be calculated separately and be further aggregated using different weights for different contexts. Thus, for the chosen domain, we may highlight several classifications:

- Geolocation-based classification: here we distinguished animals by geographical regions they live in. It is a complex metric that integrates continent-based, latitude- and climate zone based clustering. Similarity between the clusters is calculated based on climate groups' hierarchy and similarity of different continents.
- Domestication-based classification: animals could be also divided to those who are fully domesticated by human and live at their homes and farms, those whom we may meet in a zoo, and those who live only in wild nature and most probably are only seen via video records and photos. In this case, distances between the classes could be predefined. Also, other metrics that define semantic similarity in other contexts may exist. Therefore, analogically to other similarity factors, final semantic similarity measure could be aggregated by weighted products/sum.

- Biological species-based classification: this metric is based on subclass hierarchy of animals classified by biological families of animals. In this case, the most suitable approaches to measure similarity are graph-based techniques (e.g. Jaccard metric, Scaled shortest path, Depth of the subsumer and closeness to the concepts, etc.) [38], [39], [40], [41]. Thus, we calculate semantic similarity of concepts based on locations of corresponding nodes in the graph, using taxonomy-based ontology that represents class hierarchy of animals.

B. *Semantic Similarity for Particular Case*

The semantic similarity is calculated as the distance between the nodes in a semantic network. Our network is, in fact, a biological species-based classification. The network was created with webprotege (http://webprotege.stanford.edu/) from a basis found from the same platform. The ontology was then modified by deleting classes, which do not have an instance in our collection of words and further by stabilizing classes and their child nodes so that each animal would be equally far from the center node. Fig.1 presents the visualization of the ontology of animals. On Fig.2 part of Coldblooded animals are presented. On Fig.3 sub taxonomy of Warmblood animals is depicted. The categorizations nature has the advantage of mapping more similar *looking* animals closer to each other. For example, dog and bear which are both mammals will be counted as more similar, while a semantic map formed from ,e.g., co-occurrences from children's books (e.g., fish and chicken are both frequently served dishes) might have disadvantages of mapping similarities between visual forms.

V. PROCESS DESCRIPTION

The aim of this work is to test the hypothesis, that semantic distance influences children's' learning, as well as to see how children behave using this system. The system is a game-based learning environment for mobile phones and tablets, which presents tasks to a learner where one should point a referent from an array of pictures according to a sound (the object's name) which is heard from headphones.

The main goal is to determine which distractors affect learning more, choosing the pictures from the ones that are more similar versus less similar to the target. More precisely, whether choosing the right referent item is easier if the distractors are not similar to the target item.

To determine this, we chose to provide two main settings for the application. One that provides trials with most similar items and one with most distant items. To minimize the effect of previously known words and to determine results, we divided the game into three phases: filtering, learning, and testing.

The filtering phase provides two trials per each item until the learner has answered incorrectly to target amount of items. Two trials per item were chosen because answering twice correctly by chance is less likely than doing it once.

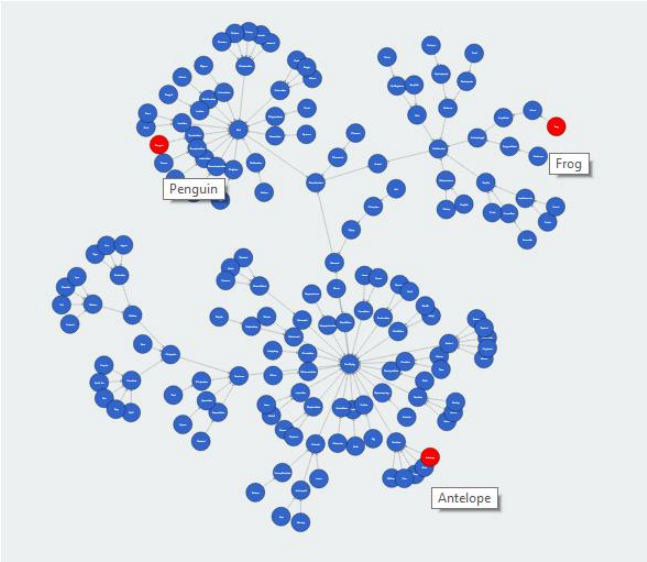

Fig. 1. Visualisation of ontology from Webvowl (*http://visualdataweb.de/webvowl/*)

Once enough previously unknown items are collected, these items are then included in the learning phase, which provides four trials for each item. The first trial of learning phase presents the item alone and expects the learner to choose it. This is immediately followed by two trials with different distractors.

When all the learning items have been presented in four trials, the system proceeds to the testing phase. In this phase, all target items are presented once more with the same distractors as in the filtering phases for the first trial.

The distractors are chosen as follows: the semantic distance matrix is sorted for each concept starting from the most semantically distant (means that distant between words is minimal) to more semantically close (means that distance between words is minimal). Then we will be showing the most semantically distant distractor concepts for avoiding semantical influence on the process of filtration, learning, and testing.

The amount of trials, which should be presented, in one level, is calculated from approximates as follows. One trial consists of (1) presenting the trial and the sound, (2) waiting for the answer from the player and (3) the feedback animations, each taking approximately two seconds. In sum, this would be six seconds per trial, which means that we can fit approximately ten trials in one minute. In this case, we chose to fit the levels with ten trials in filtering, nine in learning and ten in filtering. Like this, one filtering level will contain five different items, a testing level contains ten, and a single learning level fits handling three items. This means that ten-minute exposure time for trials is enough for 90 trials. The time between levels is not controlled, and not calculated as stimulation time.

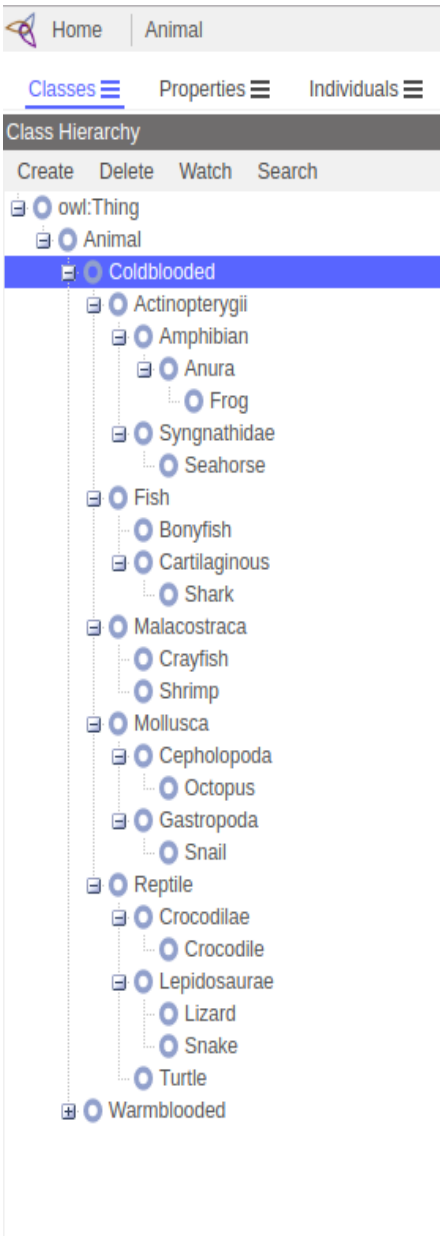

Fig. 2. Classes pf coldblood animals

C. Filtering Process

In the first phase, the aim is to filter out the words which Filtering Process the learner already knows, so that we will not include them as words which the child should learn during playing. Preliminary test at the beginning of the game checks if the the child knows any concepts from the predefined pool of the concepts. For example, child receives 20 pictures of concepts and the system checks each of the concept. If the child answers correctly about some particular concept few times, then system reduce this concept from the pool of presented concepts and until there will be only set of "unknown" concepts for that specific child.

Filtering process steps are as follows (Fig. 4):

1. We are building a matrix of distances (semantic distances). This matrix will show how particular concepts are distant (how they are not similar) to other concepts.

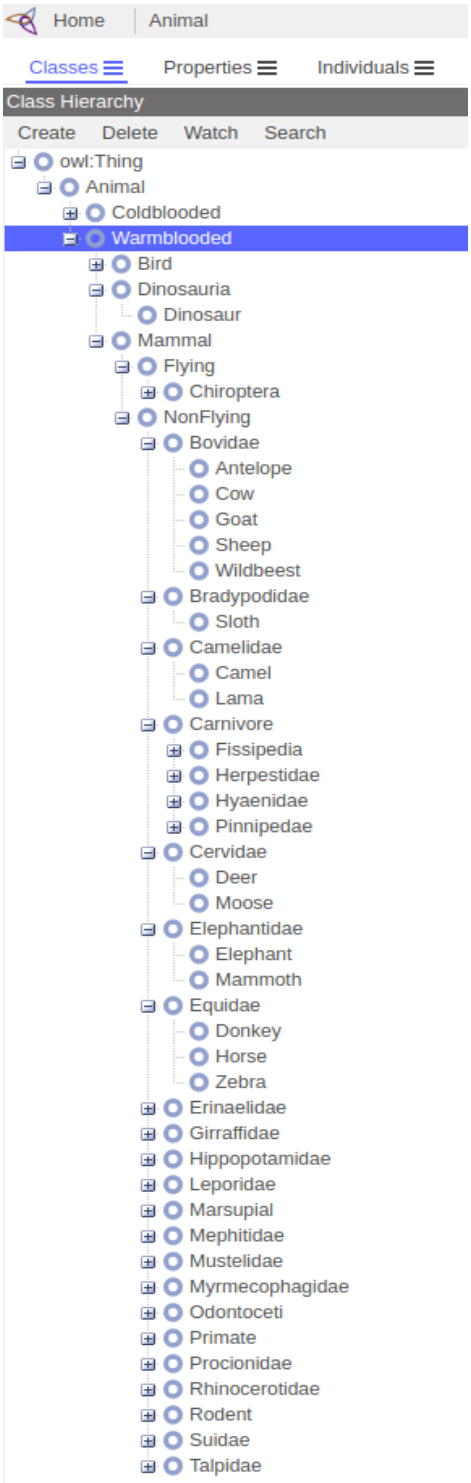

Fig. 3. Classes of warmblood animals

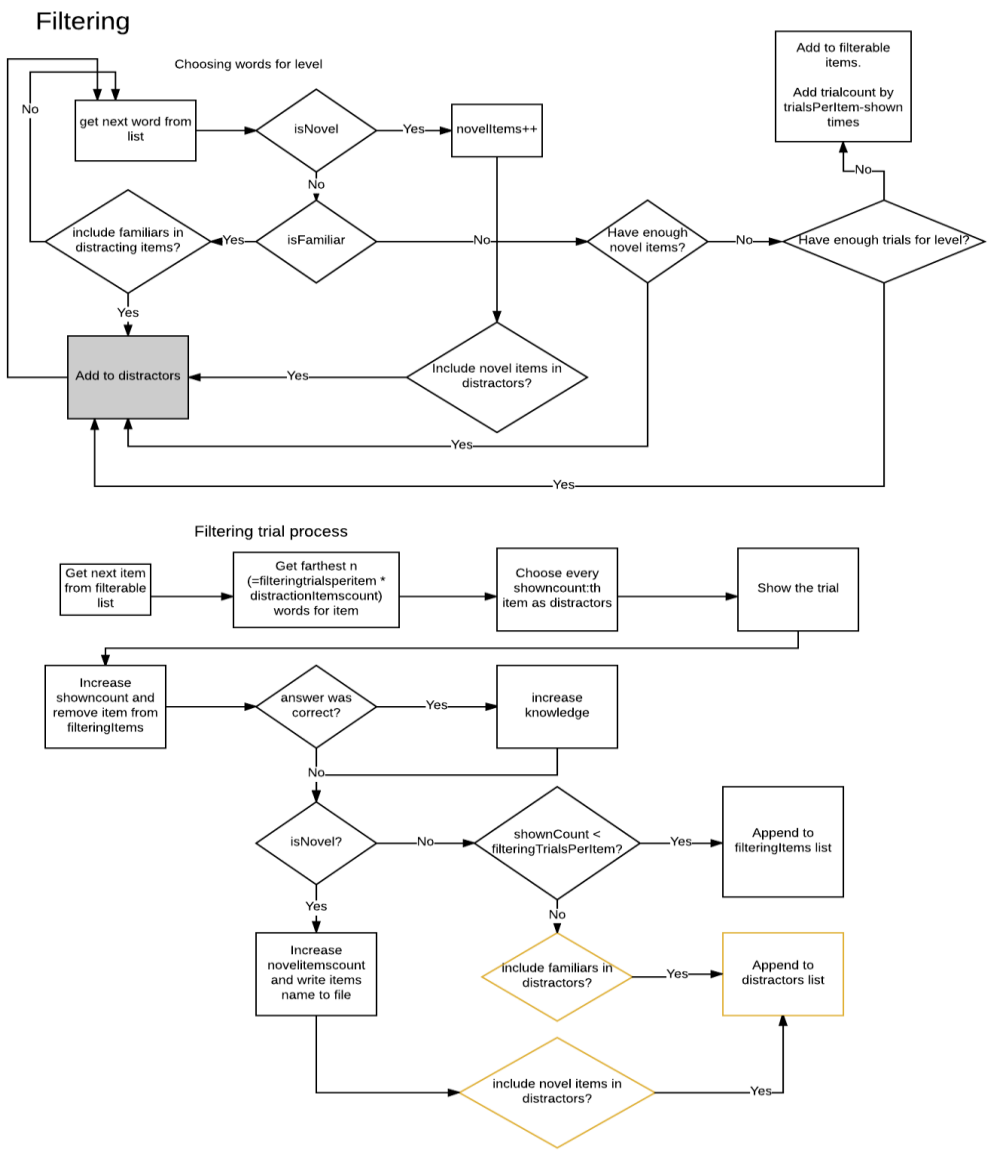

Fig. 4. Filtering process

2. We are sorting matrix for each concept from the most semantically distant (means that distance is minimum) to more semantically close (means that distance is high). Like from 0 to 10. Also, we are showing the most semantically distant distraction concepts just to avoid semantic influence on the process of the filtration.
3. The system contains **x** number of words which are all presented in referent recognition tasks. The distractors in these tasks are selected from the most distant distractors as possible. Each item is presented two times with two different sets of distractors. The selection is done by choosing first the required number of nodes from the furthest nodes for two trials, twelve in our case since each trial requires six distractors and then every other of these is chosen to the trial. The formula for the number of concepts that we are taking as a distraction ones = N showing times * N distraction concepts.
4. The order of the filtering trials is the same for each learner and familiarity is not considered in choosing the objects. The trials proceed in previously determined order so that none is presented twice in a row. The position of the correct object is randomized. If the learner answers incorrectly to both trials for one word, this word is then considered novel and added to a list of words which would be exposed to in the learning phase. In filtering phase, the learners do not get feedback to their answers.

Fig. 5 shows a typical task in filtering phase where the correct item is 'Baboon'. As exemplified, the other items are selected from the most distant nodes; none of them are mammals like the baboon.

Fig. 5. Filtering process in the game

D. Learning Process

The learning phase proceeds similarly as the filtering, yet learners are exposed only to the novel words. Before starting the learning phase, the same amount of words is chosen to every learner, so that the amount of trials and exposure time is the same for all players. In practice, this amount is the same as the amount of novel items of the learner that knew most of the words in advance, yet the maximum of 20 words to control the total time of the experiment. These novel words are then presented in trials as follows. The experiment group's distractors are chosen from the most similar nodes in the network and the control groups in contrast, from the most distant items. These distractors are chosen in practice similarly as in filtering phase — twelve nodes for each word (six for both trials with distractors), choosing every other for the trials so that the same distractors are not shown with the same item. If familiar items are amongst these words, they are left out, and another is chosen instead. Note that it is possible though, that some of the distractors are repeated amongst trials with different target items. Each word is presented first without distractors, immediately followed by two trials with six distractors. If the answer is incorrect, the correct answer is shown, and the incorrectness is indicated by a sound and an avatar-animation (frowning, shaking head). If the answer is correct, this is indicated by a sound and an animation with the avatar (smiling, nodding). After all, words are gone through, the game proceeds to the testing phase. Fig. 6 shows learning process.

E. Testing Process

In the testing phase, all words, in the same order as learning, are presented in the trials with most different or least different words depending on whether the learner is in the control or experiment group. The distractors are then the same ones as in learning phase's first trial. Feedback on correct and incorrect answers is given similarly as in learning phase.

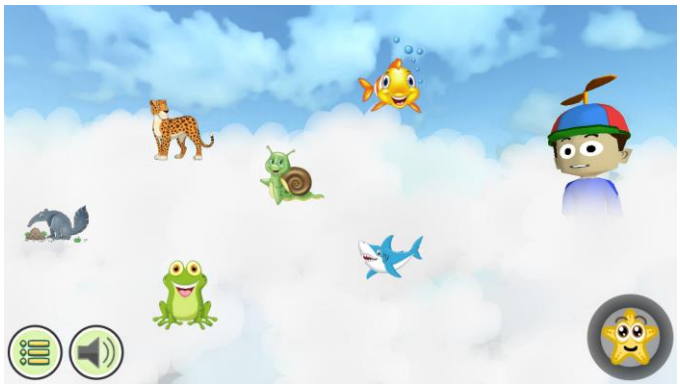

Fig. 6. Learning process in the game

VI. Conclusions and Future Work

We presented here a design of a learning game for late talkers, whose prototype is also available. The main ingredient of the proposed system is its adaptivity based on the semantic similarity. The overall game play was divided into filtering, learning, and testing phases.

The goal of this work was a prototype developing of AdapTalk learning game for children for future improvement of their vocabulary. According to our hypothesis that semantic distance between words could influence learning process, we developed learning game, which takes into account those distances.

In the future work, the proposed system will be tested with the children from kindergarten. We plan to compare control and experiment groups of children to study the efficiency of the game design. Especially, we can study the times a child is spending on filtering, learning, and testing phases. Also, the results of the filtration and testing (i.e., correct and incorrect answers) will be analyzed. After analyzing the corresponding log files, one can make rigor conclusions on the role of semantic similarity in vocabulary learning for young children.

First, testing of AdapTalk should be made with normal children to see if they recognize distances. After that to test this learning game with slow learners to see if they have the same learning capabilities as normal children and if the semantic distance of the words also influence them. According to the analyzed log files, it will be possible to make conclusions and based on them make adaptation process where semantic distance will be regulated according to learners' progress in extending vocabulary.

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