A Phoneme-Based Student Model for Adaptive Spelling Training

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Abstract. We present a novel phoneme-based student model for spelling training. Our model is data driven, adapts to the user and provides information for, e.g., optimal word selection. We describe spelling errors using a set of features accounting for phonemic, capitalization, typo, and other error categories. We compute the influence of individual features on the error expectation values based on previous input data using Poisson regression. This enables us to predict error expectation values and to classify errors probabilistically. Our model is generic and can be utilized within any intelligent language learning environment.

Keywords. spelling, student model, phoneme, adaptivity, error classification

Introduction

Intelligent, computer-based language training environments are gaining increasing importance. A key ingredient of such systems is an individualized student model [1], a representation that accounts for student behavior based on background knowledge of the student and the domain. To allow for a student adjusted training, the model has to provide the spelling software with global information about user strengths and weaknesses as well as local information about erroneous inputs. A core challenge when building such a model is to identify patterns and similarities in spelling errors across the entire word data base and to represent them using as few parameters as possible.

Our new model is data driven and the result of an extensive analysis of a user study [2] that has been carried out to evaluate the Dybuster training software [3]. The software includes a multi-modal German spelling training for dyslexic children. In our setting words are prompted orally and have to be typed in by the student on a keyboard. A signal tone responds to erroneous input so as to encourage the student to correct the error letter immediately. This immediate correction is paramount to effective training, however, it restricts the error analysis of the input string to the actual error symbol making unambiguous error classification more difficult. We illustrate this with the following example: *Unmut* /ʊnmuːt/ - `Unn` The confusion of the letter *'m'* and *'n'* could be due to a doubelling of the *'n'*, due to a confusion of similar phonemes /m/ and /n/, or due to the small key distance of *'m'* and *'n'*, (typo).

This example shows that some errors are not unambiguously classifiable, even manually. For this reason, we introduce a set of features to characterize errors. Analyzing the available input data using these features enables us to estimate the student's error characteristics and to provide a probabilistic error classification. This requested global and

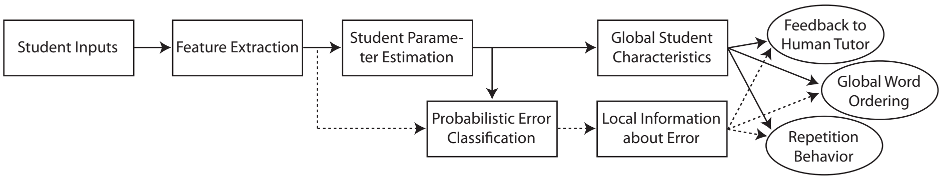

Figure 1. Work flow of the presented student model.

local information about the student allows for an user-adaptation in word ordering and repetition behavior, and is valuable as feedback for human tutors supervising the spelling training. The described work flow is shown in Figure 1.

1. Error Model

Spelling errors of the categories typo and capitalization as well as parts of the letter confusion (see also Table 1) can be modeled by comparing correct and false letters directly. However, our analysis of all misspellings in the user study clearly revealed that most of the errors can be traced back to difficulties on the phonological level. As an example, the error *Spiel* /*ʃpi:l*/ - `Spil` (see Figure 2.c)) is caused by the diversity of grapheme representations (*'i'*, *'ie'*, *'ih'* and *'ieh'*) of the phoneme /iː/. In order to model such phoneme-grapheme based errors we introduce language specific, phoneme-based features.

Table 1 presents a taxonomy of errors a student can make during word spelling training as well as the corresponding features to detect them. In the following we only

Table 1. Error taxonomy and the corresponding features as implemented by our model

Category	Features	
Typo: Error committed due to typing difficulties. Strongly dependent on the input device used.	**Key distance** (categorical): *Left/Right*, *Top/Bottom*, *Distant*	**letter level**
	Technical (binary): Input device specific confusion between umlaut and corresponding vowel.	
Capitalization (Cap): Error due to upper and lower case confusion.	**Capitalization** (categorical): *ToLowerCase*, *ToUpperCase*, *CorrectCase*.	
Letter Confusion (LetC): Confusion of letters can be caused by visual similarity of letters (e.g. *'d'-'b'*) or by auditory similarity of corresponding sounds (/n/-/m/). Both are typical difficulties for dyslexic children.	**Visual Similarity (VS)** (numerical): Based on normalized cross-correlation between images of letters. Computed on actual and horizontally mirrored image for lower, upper and the combination of lower and upper case representations.	
	Auditory Similarity (AS) (categorical): Based on a hierarchical phoneme structure.	**phoneme level**
Phoneme Omission (PhoO): Error of leaving out an entire phoneme representation.	**Phoneme Omission** (binary): Phoneme alignment	
Phoneme-Grapheme Matching (PGM): Entering wrong representation of correct phoneme. These errors are caused by the non-bijectivity of the phoneme-grapheme correspondence.	**Phoneme Matching (PM)** (categorical): Phoneme alignment (PhoA)	
	Elongation (El) (categorical): PhoA	
	Sharpening (Sh) (categorical): PhoA	
Phoneme Insertion & Phoneme Transposition: Insertion of an entire phoneme and transposition of two phonemes in a word.	The detection of both categories require information about the complete user input. Therefore, these categories can not reliably be detected.	

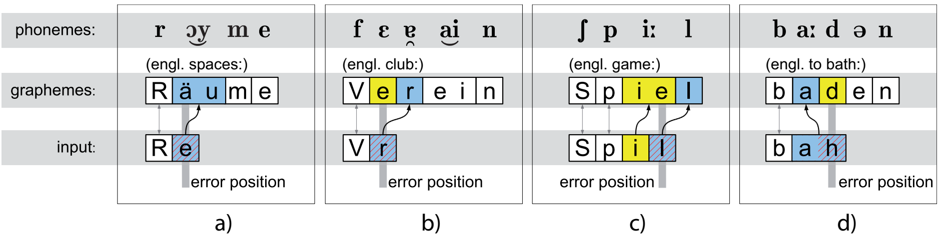

Figure 2. Alignment of correct and input phonemes and resulting error categories: a) Phoneme matching b) Phoneme omission c) Letter omission d) Letter addition

give a detailed description of the phoneme-based features for phoneme omission (PhoO) and phoneme-grapheme matching (PGM):

Phoneme Alignment To detect the PhoO and PGM errors, we locally align the user input and the phonological structure of the correct word. We then test the false letter against the current, the following, and the previous phoneme (see Figure 2). The error categories *LetterOmission* and *LetterAddition* are both subdivided into *Elongation* and *Sharpening* based on the type of phoneme the error occurred in (*Vowel*/*Consonant*).

2. Student Model

A vector containing all presented features characterizes an isolated error. By analyzing the available input data of a student, we obtain empirical error probabilities for all possible error feature vectors. However, the large number of different feature vectors and their uneven frequency distribution leads to a very slow convergence to the true, underlying error probabilities of a student. Therefore, our model estimates the particular difficulties a student has on the types of error described by each feature, using a Poisson regression [4]. Using these parameters we can analyze unprompted words and predict the difficulties a student will have spelling them. Additionally, the gained information allows to compute the probabilities of each error category being the cause of a committed error. A more detailed description of the student model can be found in [5].

This difficulty prediction and error classification enables a spelling software to adapt the training to the student's needs. It allows for a word selection based on the students strengths and weaknesses, to adapt the repetition of words to the cause of an error and holds valuable information for tutors supervising the spelling training.

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