Formalizing the "zone of proximal development" in early reading development: Reaching further into the zone is associated with greater gains

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Background

An essential aspect of learning and teaching is the identification of learning experiences that push the individual's knowledge towards some positive (or optimal) objective.

Educational theories lean on Vygotsky's notion of the zone of proximal development to understand these learning dynamics – a construct that posits that learning progresses towards objectives as the result of the student's independent performance aided by the actions (usually construed broadly) of a knowledgeable other (Vygotsky, 1978).

While application of this concept in the context of early reading instruction is difficult due to abstract nature of the formulation, the idea is nonetheless important from a developmental standpoint. Educational experiences ought to be oriented towards the identification and provision of learning experiences that are well-tuned to the individual child's reading abilities.

This is furthermore difficult in early reading instruction in orthographies like English given the semi-systematic nature of the mappings between print and speech. This complexity makes it difficult to map from child performance on word reading tasks to the structure of the writing system and back again in service of designing learning experiences that are well-suited to the individual child's progress towards optimal word reading skills (e.g., the ability to read all common words in the language).

Questions

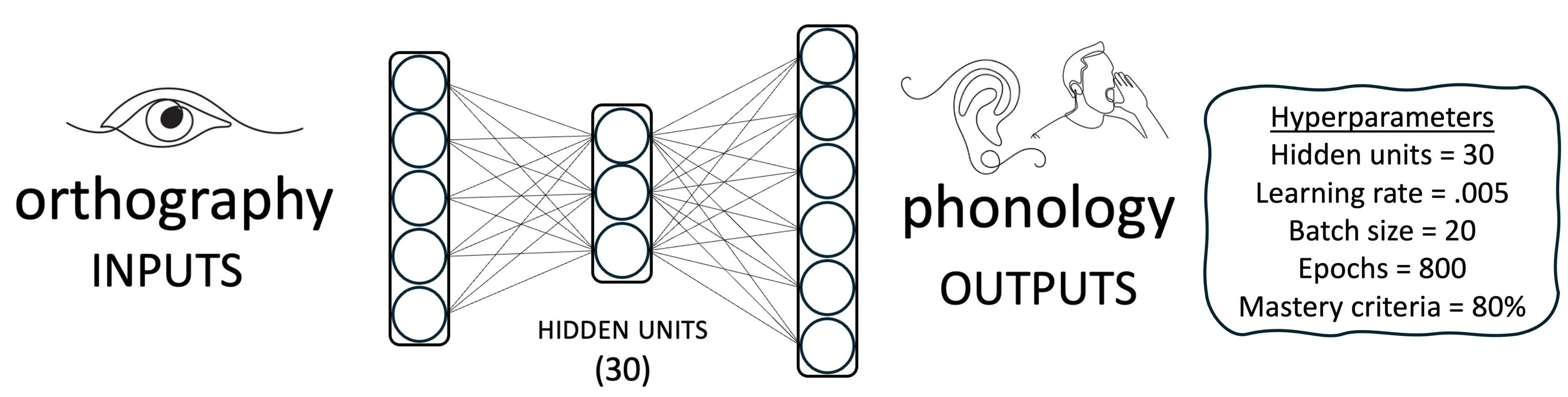
Question 1: Does defining the zone of proximal development in different ways based on word difficulty yield different outcomes (levels of mastery) for learners?

Question 2: Do outcomes differ when both word difficulty and similarity are considered when identifying words for learning?

Question 3: Are effects different when defining outcomes as words directly taught versus generalization items?

Methods

Architecture: Learning was simulated using a connectionist model that maps print to speech, like those used in other simulation work (Cox et al., 2018; Seidenberg & McClelland, 1989; Harm & Seidenberg, 1999).



Learning environment: Models learned 500 of the most frequent words in English. Learning progressed across 800 learning trials (epochs) and were all tested on the untrained items from training pool at each training point. Monosyllabic words were collected from children's books, with learning weighted by frequency.

20 words were selected for learning at each training point (batch size) in one of five difficulty conditions ("condition") and learned in one of two methods for sampling training words ("sampling method"). Words ensured to be learned to 80% accuracy prior to resampling.

Conditions: Five learning conditions were implemented based on the difficulty of the words selected for training at each training point (one condition was a random sample).

Condition	Description	Color
25th %ile	Words at the 25th percentile of difficulty (easiest)	red
50th %ile	Words around average for difficulty	blue
75th %ile	Words at the 75th %ile of difficulty	green
Maximum	The most difficult 20 words (hardest)	purple
Random	A set of 20 words sampled randomly from pool (control)	orange

Sampling methods: Two methods were used: (1) difficulty only and (2) difficulty + similarity. In (1) the 20 words for training were selected only based on their difficulty (in one of five difficulty conditions above). In (2) a target word is identified based on its difficulty level (e.g., 75th %ile of difficulty across item pool) and the nearest 19 (batch size - 1) items based on orthographic-phonological similarity (e.g., "rust", "bust", and "must") are selected (determined by hidden layer activations from a model that has learned all training pool words to a high level of expertise).

Results

Figure 1

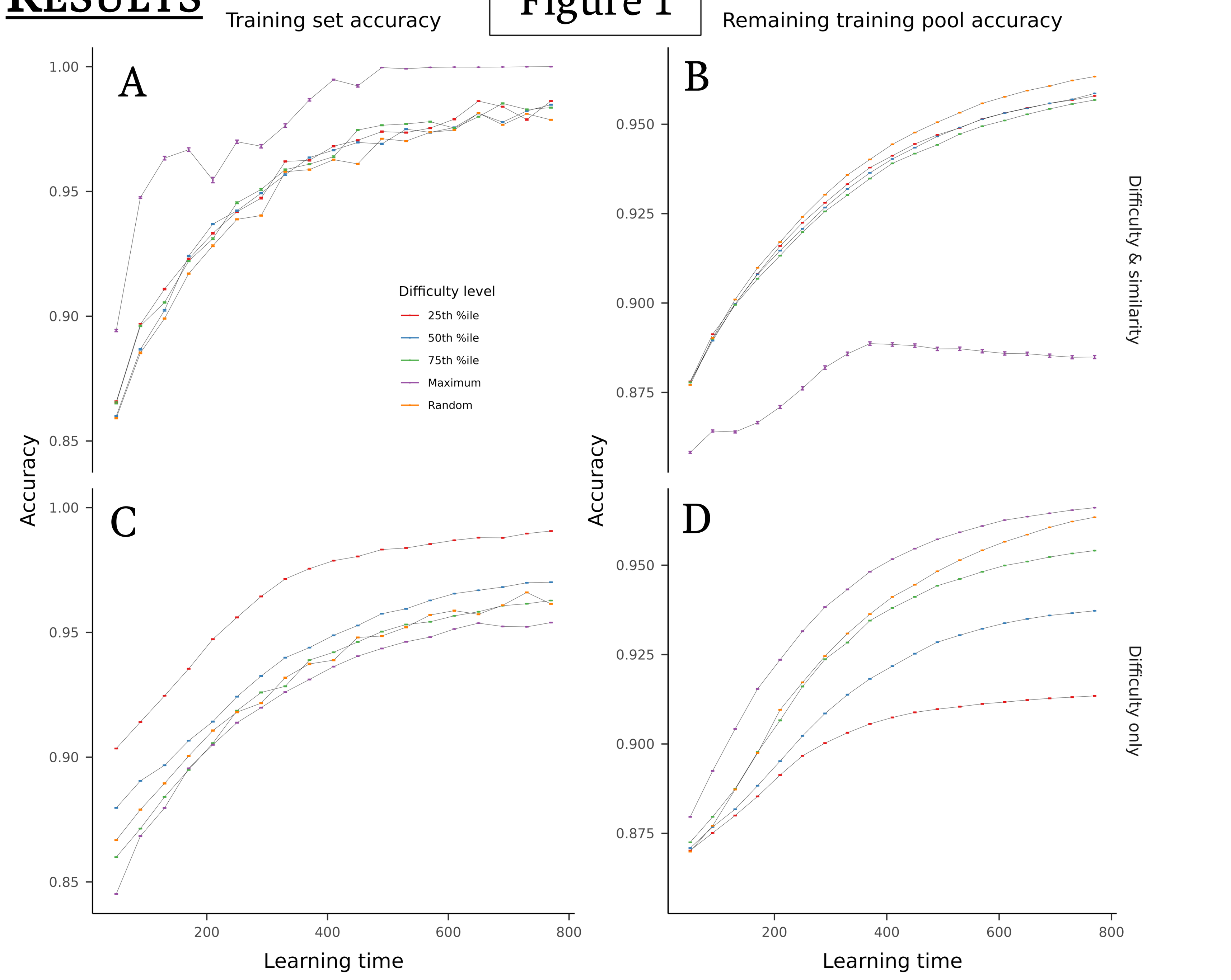


Figure 1: Learning curves for the training items (left column; A and C) and test items (right column; B and D) are shown for the five difficulty level conditions (see legend) and two training methods (rows). Curves demonstrate discrepancy between identifying a ZPD and associated outcomes on training (A and C) versus test items (B and D). Optimal methods require considering test accuracy and selecting training words that are difficult to learn or randomly sampled depending on the teaching method. Bars are standard error of the mean (SEM; barely visible).

Figure 2

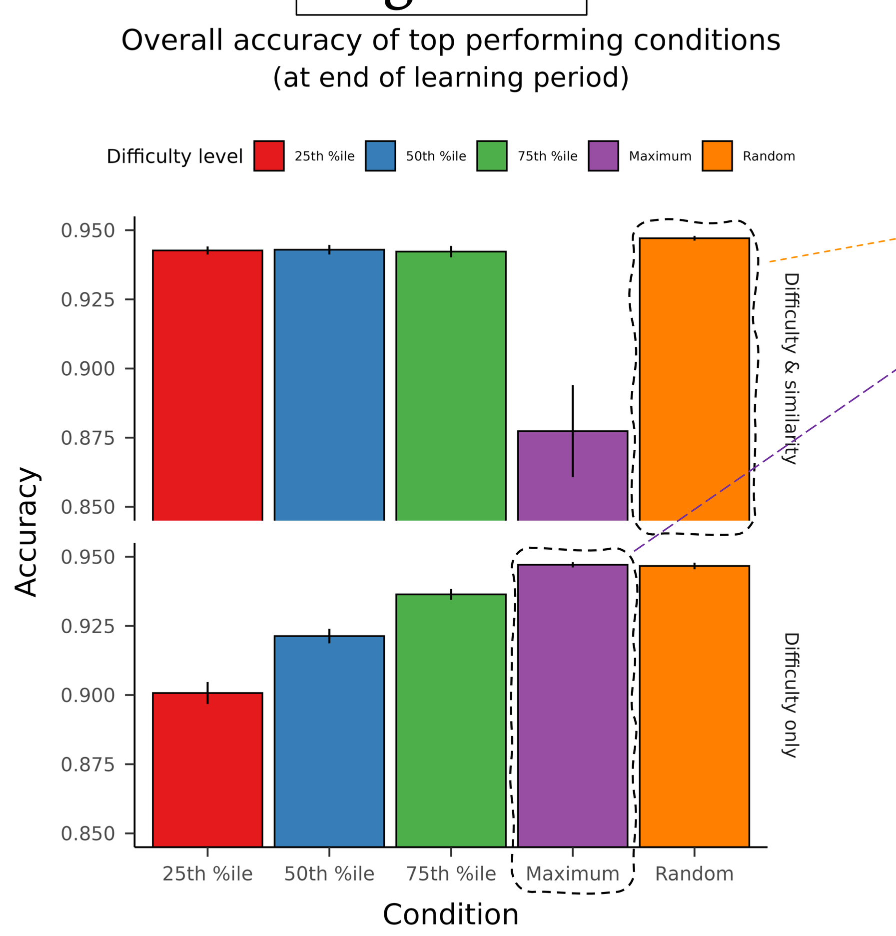


Figure 2: Learning outcomes for five conditions across two sampling methods at the end of learning. The two best conditions numerically are identified (see also Fig. 3). Bars are calculated as standard error of the mean.

Figure 3

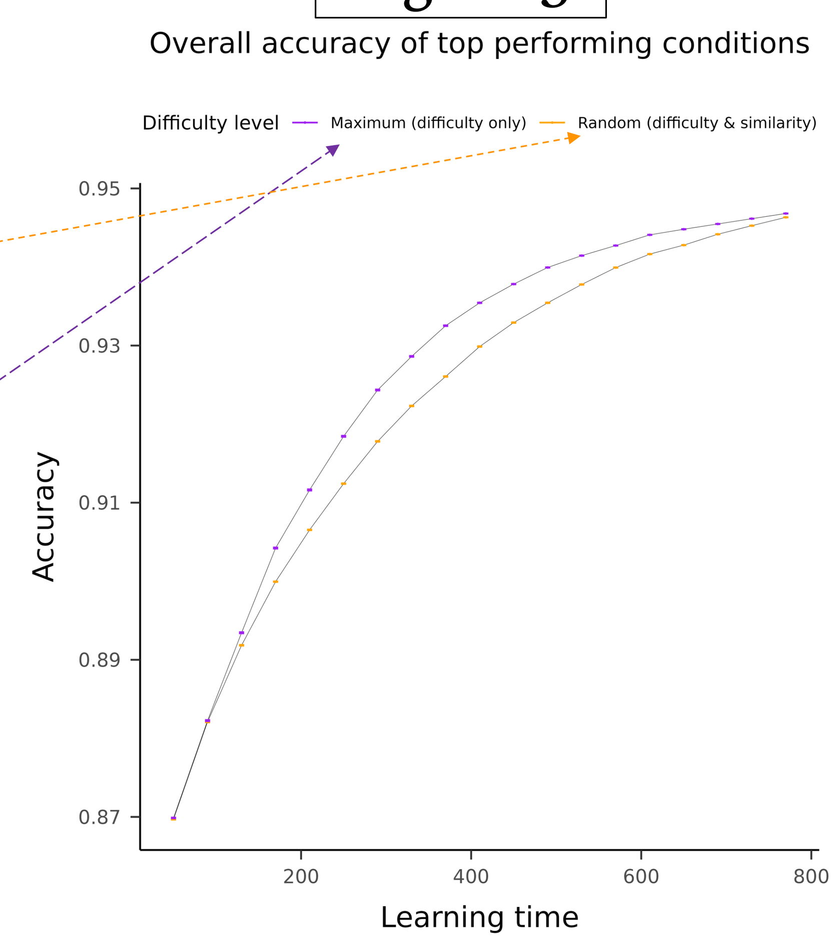


Figure 3: The learning curves of the two superior conditions. Top performer (purple) achieves the highest level of performance and does so consistently throughout training. Bars also SEM.

Discussion

Sampling methods show different learning patterns across conditions. Sampling words too similar (Fig. 1A, purple) leads to poor generalization (Fig. 1B, purple).

Better methods involve training on harder words to gain higher test accuracy at the expense of superior learning of training items.

Best methods of sampling (identifying the "zone of proximal development") involve either sampling randomly based on difficulty alone, or sampling the most difficult items based jointly on accuracy and similarity.

Conclusions

Findings are consistent with research showing that practice involving interleaved items during inductive learning lead to more robust gains across patterns (Wegener et al., 2023; Carvalho et al., 2017).

Findings should be interpreted being mindful of the costs associated with the identification of words that are related structurally and tuned to the needs of specific learners. Random methods of sampling words are much less time intensive for teachers.

Next steps: Additional manipulation of the learning parameters used here would allow more general inference about aspects of the learning environment that would extend these findings (e.g., batch size and training pool). These should be investigated across levels of learner skill.

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