Introduction

While we have some understanding of how individuals with post-stroke aphasia relearn language, why some patients respond to treatment while others do not remains a looming question in the field of aphasia rehabilitation (Best & Nickels, 2000; Kelly & Armstrong, 2009). While research has demonstrated that patients with aphasia are capable of new verbal learning (Kelly & Armstrong, 2009; Tuomiranta et al., 2011), we suggest that learning in general presents an underexplored avenue through which individual variability following treatments might be better understood and explained.

In a recent study exploring non-linguistic category learning in aphasia and in age-matched controls (Vallila & Kiran, 2011; Vallila & Kiran, 2012), researchers found that only five out of ten patients with aphasia demonstrated the ability to successfully learn non-linguistic categories in contrast to controls, all of whom showed successful category learning. Results suggested that differences arise between non-linguistic learning in aphasia and in healthy individuals.

The current study further extends this research, probing some of the aspects of training and stimulus characteristics that might contribute to successful learning in patients with aphasia. The goal of this study is to determine whether patients with demonstrated difficulty learning non-linguistic categories can benefit from instruction limited to a set of stimuli with salient category features. Additionally, this study compares results when instruction is feedback-based or paired associate in nature.

Methods

Stimuli

Stimuli for the experiment are two sets of 1024 cartoon animals developed by Zeithamova et al. (2008) that vary on ten binary dimensions (e.g., shape, feet). For each set, one stimulus was selected as prototype A, with each other animal identified in terms of the number of features by which it differed from this prototype. This difference is described as the animal's *distance* from prototype A. Only one animal differed from prototype A by all ten features (distance 10) and was selected as prototype B

Animals at distances 1 to 4 share 90% to 60% of their features with prototype A and are considered members of category A. Consequently, these animals share 10% to 40% of their features with prototype B. Animals at distances 6 to 9 share a majority of their features with prototype B and are therefore considered members of category B. In this manner, two categories are established along a continuum, each with an internal structure related to the percentage of features shared with each of the two prototypes. For the current study, animals that share between 80% and 90% of their features with each prototype are considered high overlap animals, or *typical* category members. Animals that share between 60% and 70% of their features with each prototype have a low overlap of features and are considered *atypical* category members (see Figure 1).

Design and Procedures

Each participant completed four category learning paradigms comprised of training and testing phases. Two were feedback-based (FB) and two were paired associate (PA). In FB learning, animals were presented one at a time and participants were required to guess each animal's affiliation. Participants received feedback telling them the correct category and whether their guess was correct or incorrect. In PA learning, animals were presented along with a label denoting their category affiliation and participants pressed the button that matched the category affiliation.

In addition, there were two training set conditions: typical (80-90% shared features with the prototype) and atypical (60-70% shared features with the prototype). In the typical condition, participants were trained to recognize categories through exposure to items with a high percentage of shared features to prototypes alone. Participants saw each feature associated 24 – 30 times with one category and only 3 – 6 times with the opposite category. It is hypothesized that the high correspondence of features across training items increases the saliency of feature-category associations.

In the atypical condition, participants were trained to recognize categories through exposure to animals with a low feature overlap with prototypes (distances 3, 4, 6 and 7). In this condition, participants saw features associated 15 to 21 times with one category and 9 to 15 times with the opposite category. Successful learning is hypothesized to more heavily rely on gradual probabilistic learning in which participants must process varying frequencies of feature-category associations (Knowlton et al., 1994). These conditions differ from the Vallila & Kiran (2011) study in which participants were trained on a full range of animals that varied from prototypes by 60% to 90%.

All training paradigms were followed by a 72-trial testing phase. Participants were tested on their categorization of prototypes, typical, atypical items and animals seen in training. Training phases were identically structured following all conditions. Data were collected on accuracy and reaction time.

Participants

Thus far data have been collected from nine patients with aphasia and six age-matched controls. Patient aphasia severity quotients range from 25 – 83 AQ as characterized by the Western Aphasia Battery (Kertesz, 1982). All of these participants previously completed non-linguistic category learning in which training was comprised of a full range of animals. Based on these experiments, participants were classified as learners or non-learners; all controls and four patients were learners. Five patients tested were non-learners.

Data Analysis

In order to analyze data, responses were converted from percent accuracy score at each distance into a percent B response score (%BResp). Successful learning was determined relative to the internal category structure, with accurate %BResp predicted to increase by a factor of 10% with each incremental distance increase from prototype A. For each individual, we examined the correlation between %BResp and distance, with a significant positive correlation representing successful learning. In addition, we fit subject regression lines of %BResp as a factor of distance for each individual's performance on each task and examined the slope of these lines.

Results

All six control participants demonstrated successful category learning when trained on typical category animals following both FB and PA instruction. Five controls also demonstrated the ability to learn categories following both methods of instruction when training was limited to atypical stimuli. All patient participants who had demonstrated successful category learning when trained on a full range of animals showed successful category learning in the FB typical condition. Three of these patients were also able to learn following FB and PA atypical training.

Most importantly, four out of five patients who were unable to learn categories when trained on a full range of animals demonstrated successful learning in the PA typical condition and three learned in the FB typical condition (See figure 2).

Discussion

Preliminary results further support the hypothesis that general learning ability varies among individuals with aphasia. In addition, results suggest that many patients who have difficulty learning novel category information benefit from training on a limited set of stimuli that saliently emphasize characteristic features. In contrast, some patients were observed to learn even in complex training conditions in which training items had low feature overlap with prototypes. These patients were able to process and generalize information accrued from atypical animals, successfully categorizing novel typical and atypical stimuli. We suggest that learning ability contributes to differential success with therapy and should be considered in the diagnostic characterization of patients with aphasia to tailor treatment to individuals. We hope to report data from 15 patients and controls at the conference.

References

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Figures

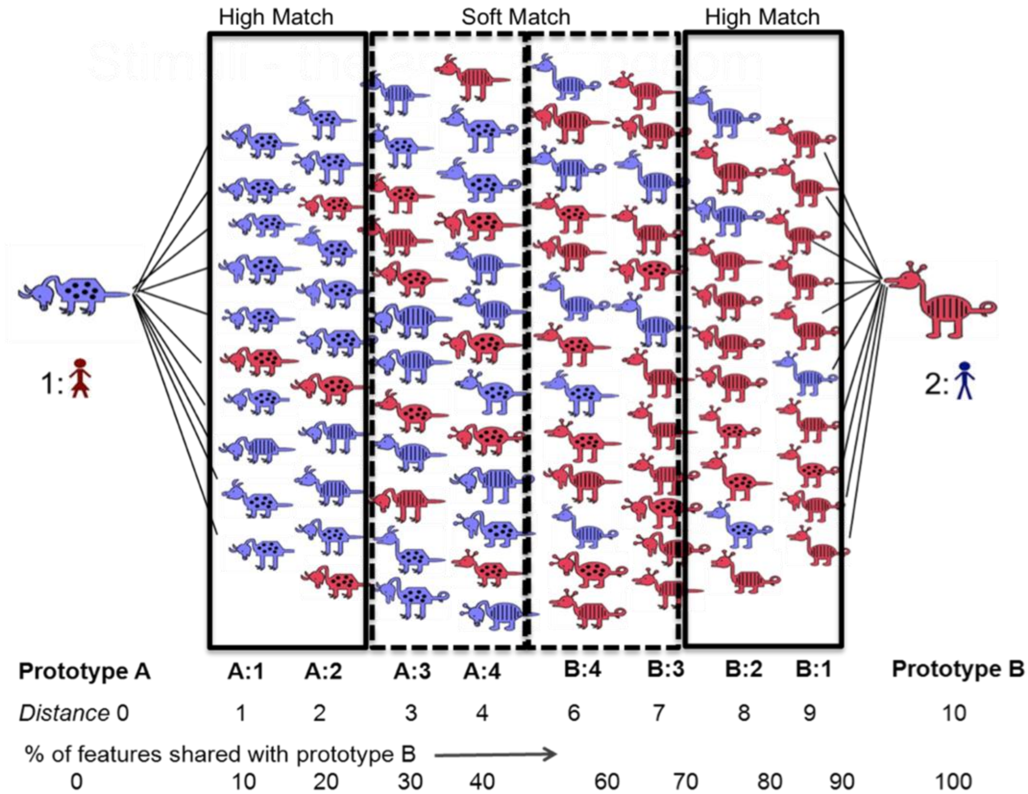

Figure 1. Sample animal stimuli contributed by Zeithamova et al. (2008). Animals are arranged according to the number of features with which they differ from each prototypical animal. The number of features by which an animal differs from each prototype is referred to as its *distance* from the prototype. High match animals share 80% to 90% of their features with prototypes. Soft match animals share 60% to 70% of their features with prototypes.

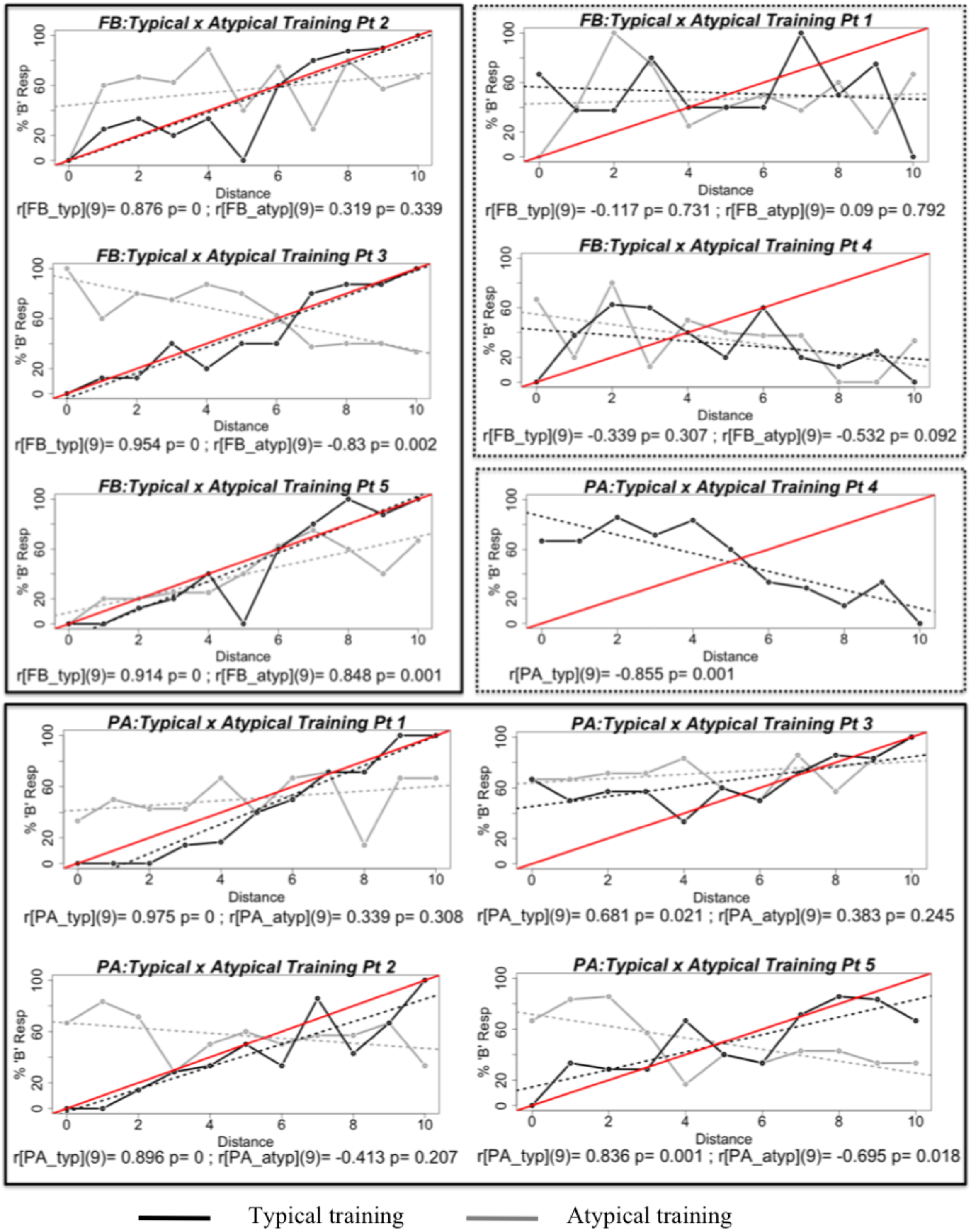

Figure 2. FB and PA result plots for patients unable to learn categories when trained on a full range of animals. Red lines represent ideal learning. Results grouped by solid lines (left and bottom) indicate patients who learned following typical training. Results grouped by dotted lines indicate patients who did not show learning.