**To what extent neural network models reveal L2 constructs? Relationship between text similarity and learner proficiency**

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With the recent development of NLP techniques, a number of second language (L2) studies utilise these techniques to automatically analyse learner corpora (Meurers, 2015). One area in learner corpus research is text quality, which concerns semantic–pragmatic aspects of language use to influence overall text quality (e.g., Crossley et al., 2019). Despite increasing interests in employing various NLP techniques (e.g., Dascalu et al., 2017), little attention has been paid to how similarly/differently each technique reveals L2 constructs such as learner proficiency. In addition, NLP-based L2 research is heavily biased towards L2-English, which does not ensure the generalisability of its implications. Against this background, we investigate the relationship between learner proficiency and text similarity of L2-Korean learners’ written production (relative to native speakers’ writing) measured through neural network models.

**Method** (Table 1). Thirty-six L1-Chinese L2-Korean learners (age: mean = 24.2; *SD* = 3.11) were asked to write argumentative essays on two topics: *preservation vs. exploitation of the nature; competition vs. cooperation*. Learner proficiency was measured separately, using the Korean C-test (Lee-Ellis, 2009; ranging from 0 to 188; mean = 135.98; *SD* = 32.23). Essays from 10 native Korean speakers were collected as a reference text. After extracting content words from the essays, we computed cosine similarity scores between individual learner writing and the reference text by employing two neural network models—Word2Vec (Mikolov et al., 2013; bag-of-words; context-independent) and BERT (Devlin et al., 2018; transformer; context-dependent). The similarity scores (predictor) and proficiency scores (outcome) were then submitted to linear regression models.

**Results** (Figure 1 & Table 2). The Word2Vec model showed a significant relationship between the two variables for both topics: *F*(1, 34) = 3.405, *p* = .074, *R*2 = .064, *B* = 113.86 for Topic 1 (albeit marginal); *F*(1, 34) = 8.748, *p* = .006, *R*2 = .181, *B* = 172.59 for Topic 2. For the BERT model, the slope of the regression line for Topic 1 was nearly horizontal whereas that for Topic 2 was positively oblique. This was reflected in the linear regression analysis, with marginal significance only for Topic 2: *F*(1, 34) = 3.79, *p* = .060, *R*2 = .074, *B* = 32.296. To further examine how each neural network model classified the participants into the same group uniformly, we created two proficiency groups (highest; lowest) with seven essays by topic. These models demonstrated distinctive classification patterns, yielding weak congruency across the topics/models.

Together, these results indicate that (i) the degree that neural network models explain L2 constructs (learner proficiency in this study) was asymmetric and (ii) these models’ performance was sensitive to essay topics (and particularly to word use such as repetitions of keywords), manifesting some limits on addressing individual variability of L2 writing as well. Given the recent trend that NLP techniques are widely used in learner corpus research, our findings suggest the need for researchers to be aware of NN models’ algorithmic characteristics, together with possible influences of topic variations, in conducting automatic L2 text analysis research in pursuit of addressing L2 constructs.

**Table 1**. Information about data by topic (numeric values = number of words)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Topic | L2 learner | | | Native speaker | | |
| Mean (SD) | Minimum | Maximum | Mean (SD) | Minimum | Maximum |
| 1 | 107 (36.36) | 62 | 201 | 158 (21.27) | 131 | 194 |
| 2 | 113 (38.48) | 57 | 203 | 166 (33.89) | 110 | 211 |

|  |  |  |  |
| --- | --- | --- | --- |
| Word2Vec | | BERT | |
| Chart, scatter chart  Description automatically generated | Chart, scatter chart  Description automatically generated | A picture containing text, white  Description automatically generated | Chart, scatter chart  Description automatically generated |

**Figure 1**. Scatterplot: Similarity scores (X-axis) and proficiency scores (Y-axis).

**Table 2**. Seven highest/lowest similarity scores and their proficiency scores

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Word2Vec | | | | | | BERT | | | | | |
|  | Topic 1 | | | Topic 2 | | | Topic 1 | | | Topic 2 | | |
|  | PPT | SIM | PRF | PPT | SIM | PRF | PPT | SIM | PRF | PPT | SIM | PRF |
| Highest | 13 | 0.848 | 156 | 32 | 0.805 | 181 | 19 | 1.000 | 171 | 13 | 1.000 | 156 |
| 11 | 0.812 | 102 | 12 | 0.786 | 154 | 2 | 0.997 | 122 | 19 | 0.997 | 171 |
| 34 | 0.807 | 119 | 13 | 0.774 | 156 | 35 | 0.993 | 144 | 25 | 0.989 | 165 |
| 33 | 0.807 | 156 | 11 | 0.773 | 102 | 11 | 0.993 | 102 | 35 | 0.985 | 144 |
| 7 | 0.803 | 167 | 19 | 0.761 | 171 | 26 | 0.991 | 176 | 9 | 0.983 | 132 |
| 32 | 0.796 | 181 | 18 | 0.733 | 172 | 18 | 0.979 | 172 | 12 | 0.953 | 154 |
| 10 | 0.785 | 138 | 21 | 0.731 | 186 | 20 | 0.977 | 125 | 16 | 0.593 | 99 |
| Lowest | 23 | 0.625 | 128 | 36 | 0.605 | 92 | 34 | 0.085 | 119 | 15 | 0.096 | 91 |
| 35 | 0.616 | 144 | 6 | 0.575 | 92 | 28 | 0.063 | 148 | 11 | 0.073 | 102 |
| 5 | 0.597 | 138 | 4 | 0.573 | 153 | 14 | 0.057 | 167 | 6 | 0.069 | 92 |
| 4 | 0.595 | 153 | 2 | 0.547 | 122 | 9 | 0.051 | 132 | 32 | 0.064 | 181 |
| 9 | 0.590 | 132 | 3 | 0.544 | 121 | 4 | 0.034 | 153 | 23 | 0.029 | 128 |
| 14 | 0.543 | 167 | 22 | 0.539 | 49 | 27 | 0.017 | 120 | 5 | 0.016 | 138 |
| 22 | 0.482 | 49 | 27 | 0.373 | 120 | 7 | 0.000 | 167 | 22 | 0.000 | 49 |

*Note*. PPT = participant; PRF = proficiency score; SIM = similarity score

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