Assignment 6, Literature Review, Academic English 1

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The relation between word forms and their meanings in natural language is commonly referred to as sound symbolism. A well studied phenomenon of sound symbolism is the bouba-kiki effect, in which participants label abstract shapes with non-word names. Rounded shapes are systematically labelled bouba over kiki, this effect is often ascribed to cross-sensory mappings between acoustic properties of sound and shape. Cuskley et al.[4] suggest that this phenomenon is also heavily mediated by the symbolic, culturally acquired shapes of letters. This similarity between orthography and abstract shapes forms the basis of this research, in which the aim is to find if this relation can also be found between graphemes and phonemes. Graphemes represent the smallest individual characters of a writing system and phonemes relate to the sound of particular graphemes[6]. Phonemes represent a standardized collection of spoken language and are collected in the International Phonetic Alphabet (IPA)[1]. How these IPA symbols represent the exact pronunciation of a phoneme can be found in a phonological encoding scheme. By using machine learning to classify graphemes to phonemes, previously hidden relations may be discovered, aswell as a wide variety of writing systems (Alphabets, Abjads and Abugidas) can be explored. Convolutional neural networks (CNN) are among the most suitable architectures for handwritten digit and character recognition[3]. Neural networks learn intermediate representations of their inputs, which can be useful for subsequent classification tasks. The structure of CNNs, mimicking receptive fields, followed by pooling and activation operations is particularly useful for handling data that can be represented as two- or higher-dimensional input, such as images[5]. Deep CNNs also incorporate many layers and thus many intermediate representations, while keeping the number of free parameters small[2]. Recent work with CNNs on computer vision was applied to recognition of natural images and 3D objects, image denoising and image segmentation. CNNs seem to work well for supervised and unsupervised learning tasks and can be succesfull using relatively small datasets[3].

References

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