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# Nonword-to-Image Generation Considering Perceptual Association of Phonetically Similar Words

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### Text-to-Image (T2I) generation

- Recent innovation in **Text-to-Image (T2I) generation** models
  - Stable Diffusion<sup>[1]</sup> is one such example

#### Example of T2I generation using Stable Diffusion



a hamburger floating in the sky an astronaut swimming under the sea

[1] Rombach et al., "High-resolution image synthesis with latent diffusion models", CVPR 2022.

#### How Stable Diffusion works

- Stable Diffusion<sup>[1]</sup>: Open-source text-to-image generation model
  - Generates images from embeddings of the CLIP text encoder
  - CLIP<sup>[2]</sup>: Vision & language foundation model
    - > Consists of text and image encoders co-trained via contrastive learning
    - Subword tokenization: Tokenizes each word in a text into subwords



[2] Radford et al., "Learning transferable visual models from natural language supervision", ICML 2021.

#### Problem of T2I Generation Models: Nonword Input

- They generate unintuitive images when input contains **nonwords** 
  - Nonwords := "Nonsense words that have no definition within a language"



[3] Köhler, "Gestalt Psychology", H. Liveright, 1929.

[4] Goldinger et al., "Form-based priming in spoken word recognition: The roles of competition and bias", J. Exp. Psychol. Learn. Mem. Cogn., 1992.

#### Problem of T2I Generation Models: Tokenization

- Subword tokenization does not work for nonwords
  - It splits nonwords into unmeaningful subwords
    > "fouse" → 'f' + 'ouse' (two subword tokens)
    > Cf. "house" → 'house' (one token)
- Making nonword-to-image generation unintuitive



#### Research Goal

- More intuitive nonword-to-image generation
- Approach
  - Replace CLIP text encoder with our new pronunciation encoder
    - Discard the use of subword tokenization

> Our **phoneme-level tokenization** considers **phonetic similarity** of an input



#### Proposed Method: Pronunciation-to-Image Generation

- Our framework consists of two modules:
  - Pronunciation Encoder: Pronunciation -> CLIP embedding
  - Image Generator (Stable Diffusion): CLIP embedding\* -> Images



### IPA-based Phoneme Embedding (1/2)

- IPA: "International Phonetic Alphabet"
- IPA chart<sup>[5]</sup> is used as a source of phonetic relationships
  - Defines phonetic properties of each phoneme/phone in any language

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Magnitude Vector

- Enables computing phonetic similarity
- Compute a **magnitude vector** for each phoneme



**IPA** Chart for Consonants

International Phonetic Association, Handbook of the International Phonetic Association: A guide to the use of the [5] International Phonetic Alphabet, Cambridge University Press, 1999.

## IPA-based Phoneme Embedding (2/2)

Aim to assign a **phonetically continuous** token for each phoneme

- 1. Prepare magnitude vector based on phonetic property
- 2. Multiply it with a trainable weight matrix
- 3. Obtain a phoneme embedding reflecting the phonetic property



### Distillation of CLIP Text Encoder

- Distill the CLIP text encoder with text-pronunciation pairs
  - 1. Prepare pronunciation for each text in training data<sup>[6]</sup>
    - Use existing pronunciation dictionaries
  - 2. Train a student encoder (**IPA-CLIP**) to output the identical embedding to the teacher encoder with the corresponding pronunciation input



[6] Carlsson et al., "Cross-lingual and multilingual CLIP", LREC 2022.

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#### CLIP Text Encoder Explained in Detail



#### Pronunciation-to-Image Generation

- 1. Reconstruct  $L \times D_{hidden}$ -dim. embedding from the  $D_{CLIP}$ -dim. one
  - Train a multilayer perceptron
- 2. Insert it into a pretrained Stable Diffusion model



### **Qualitative Evaluations**

- Asked English speakers on **Amazon Mechanical Turk** 
  - Two trials with different instructions

by either

(Comparative)

- Trial 1: Choose which images depict similar-sounding words?
- Trial 2: Choose which images are more intuitive?
- Prepared 270 questions/nonwords from an English nonword dataset<sup>[7]</sup>



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Sabbatino et al., ""splink" is happy and "phrouth" is scary: Emotion intensity analysis for nonsense words.", WASSA 2022.

#### Results

- Proposed method wins over the comparative method
  - Generated images of the proposed method:
    - $\checkmark$  Depict the concepts of their phonetically similar words more accurately
    - ✓ Match human expectations more closely
- Proposed method has a larger gain in Trial 1 than Trial 2
  - Intuitiveness involves more factors other than phonetic similarity





#### Image Generation Example

#### What kind of imagery does "Flike" evoke in your mind?



### Conclusion

- Pronunciation-to-Image generation robust against nonwords
  - Motivation: More intuitive nonword-to-image generation
  - Approach: Associate nonwords with their phonetically similar words
- Evaluation showed effectiveness of our method over Stable Diffusion
  Depict phonetically similar (similar-sounding) words more accurately
  Generate images more intuitive to humans



- Future Work
  - Extend to other languages and perform cross-lingual comparison
    E.g., German, Japanese, and Chinese