The artificial synesthete: Image-melody translations with variational autoencoders

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This project presents a system of neural networks to translate between images and melodies. Autoencoders compress the information in samples to abstract representation. A translation network learns a set of correspondences between musical and visual concepts from repeated joint exposure. The resulting “artificial synesthete” generates simple melodies inspired by images, and images from music. These are novel interpretation (not transposed data), expressing the machine’s perception and understanding. Observing the work, one explores the machine’s perception and thus, by contrast, one’s own.

Translating between visual arts and music using computers has always woven together science, technology, and art. Technologists started performing the first pioneering experiments with automated generation of image and music in the 1950s and 60s [21, 31], which evolved into an assistance to human artists Berg [4], Daudrich [12], Taylor [12], Xenakis [40]. Recent advances in hardware and algorithms made neural-networks-based generation widely accessible for both research and art Alvarez-Melis and Amores [2], Briot et al. [3], Broad and Grierson [6], Carnovalini and Rodá [7], Diaz-Jerez [13], Fernandez and Vico [16], Goodfellow et al. [17], Larsen et al. [20], Roberts et al. [37], Roche et al. [39].

Scientific and artistic interests also meet in bridging between the expressions: music visualization—an idea rooted in early 20th century art Corra [10], Kandinsky [23], Moritz [29]—is mostly the purview of artists Ox and Keefer [32], while much of the image-to-music transformation is based on sonification, often with a scientific-technological focus Barrass and Kramer [3], Dubus and Bresin [14], Kramer et al. [22], Walker and Nees [43].

One-to-one mappings between elements (for example pixels and notes) are a simple, immediate, and common way to translate between image and music. Since the transformation is bijective, simple algorithms can use it to visualize music as well as play images. Pablo Samuel Castro’s jidiji experiment Castro [8] and Wolfgang M. Heckl’s installation Atomare Klangwelte Heckl [19] are but two examples. However, the musical results often sound random, because these algorithms blindly transpose data. Neural networks, thanks to their considerable autonomy, offer more generative power and potential for artificial creativity Colton [9], Jordanous [22], Saunders [41]. A recent work Müller-Eberstein and van Noord [30], for example, used variational autoencoder networks to generate novel (i.e. not transposed) melodies from artworks, based on idiosyncratic audiovisual correspondences. We present a system of neural networks, sketched in Figure 1 constituting an “artificial synesthete” able to translate between simple melodies and pictures. The translation uses a core of cross-modal correspondences to link musical and visual concepts. This allow us to better comprehend how the machine understands information and how it applies, reinterprets, or breaks the rules.

![Figure 1. Sketch of the encoding/decoding/conversion.](image-url)
Autoencoders are neural networks with two constituent parts (Figure 1). An encoder recognizes important information in the input, and compresses it in an internal representation. A decoder reconstructs the most likely original input from a given compressed representation. Encoder and decoder are trained together, with the goal of compressing and reconstructing the training inputs. Variational Autoencoders (VAEs) Higgins et al. [20], Kingma and Welling [24] further assume a continuous representation space, with a Gaussian prior. Therefore, VAEs can also generate new samples, by remixing features they encountered in training samples. This generative power makes VAEs particularly useful for both image and music generation Broad and Grierson [6], Roberts et al. [37], Roche et al. [39].

The image VAE was trained on a set comprising over 4000 abstract artworks from several abstract styles in the WikiArt database WikiArt [45], plus 10000 images generated algorithmically from music samples (see Online Supplement Wienand and Heckl [44]). All images were downsampled to 64×64 pixels for computational manageability. To represent and generate music, we use Google’s pre-trained MusicVAE Roberts et al. [37, 38]. Particularly, the models trained on 2- and 16-bar-long, single-voice MIDI melodies. Though MIDI is musically limiting, it allows us to work with melodies and build on clearer, existing translation processes (see below), which would be harder with natural sound.

Learning Synesthetic Associations

The translation between images and music has at its core a set of synesthetic associations between visual and musical information. Instead of leaving this key component entirely to the idiosyncrasies of the neural networks (as in Müller-Eberstein and van Noord [30]), we decided to ground it in a simple algorithmic conversion, based on Atomare Klangwelte Heckl [19]. Inspired by scanning microscopes, the algorithm reads the image row by row, turning each pixel into a note. Conversely, it also reads music note by note and renders it in pixel sequences, with longer notes becoming longer strings of pixels.

Technical limitations restrict our choice of translation rules. MusicVAE, for one, works within strictly limited music parameters: it requires single-voice MIDI samples, all with the same tempo and length, and notes of constant velocity (i.e., volume). Therefore, notes are reduced to pitch and duration. To augment the data in notes, we express each pitch as octave and note on the chromatic scale. For pixels, we limit information loss by working in color (instead of grayscale as in Heckl [19]). We express each pixel’s color in the Hue-Chroma-Value space (Figure 2(a)) with Chroma (similar to saturation) fixed. The note-color mapping combines physics-inspired and shared human synesthetic correspondences Parise and Spence [35]. Specifically, we associate the color’s Hue with a note on the chromatic scale based on wave frequencies (Figure 2(b)).
from a red C (lowest sound frequency on the chromatic scale and lowest frequency of visible light), to a violet B (highest sound and visible light frequency). Though not immediate for humans, we imagine this numerical link can be an intuitive audiovisual correspondence for the machine. We also map the color’s Value (essentially, the luminosity) to the note’s octave (between C2 and B5, Figure 2(c)), following the correspondence between low pitches and darkness, common to humans too. Parise and Spence \cite{28}. This map (incidentally similar to Castro \cite{8}, Corra \cite{10}) forms the basis of the perceptual associations of our networks, learned through repeated exposure and ingrained in the translation network.

**Translation network training**

We use the note-color map to turn 10000 MusicVAE-generated melodies into images (Figure 2(d), which were also added to the training of the image VAE). The respective encoders compress each melody and image to their representations. These music-image pairs in representation space serve as ground truth to train simple multilayer perceptron networks connecting the two representation spaces (Figures 1 and 2(e)). Thus the translation networks learn the synesthetic correspondences implicitly—connecting representation features, not pixels and notes. Furthermore, the correspondences originate from connections between neural networks and repeated joint exposure, reflecting some hypotheses on the origin of human synesthesia Parise and Spence \cite{28}, Ramachandran and Hubbard \cite{36}.

To reinforce the correspondences, we use simplified images to further train the translation network. From each of WikiArt’s “Color Field Painting” and “Hard-Edge Painting” styles, 50 works were selected at random and broken into 64x64 tiles (for a total of almost 10000 tiles). Each tile is a segment of its original, unmodified picture. Therefore, putting all tiles from the same picture side by side would reconstruct the original picture. These tiles are thus reduced-information versions of real-world examples (instead of the synthetic images used previously). The translation network converts them to melodies. Encoding tiles and melodies produces new music-image pairs, serving as ground truth to train the translation network again, Figure 2(f). This reinforces the correspondences and expands the range of representations for which the translation network learned definite associations. The entire training process was carried out twice: once based using the 16-bar MusicVAE, once using the 2-bar version.

From this process emerges an “artificial synesthete” that is inspired from the color-note associations instead of bound to them.

**PLAYING IMAGES, PAINTING MUSIC**

Figure 3 shows some examples of the artificial synesthete’s work. Since MusicVAE only generates single-voice MIDI, the music samples focus entirely on the central melodic motif. Image generation is the opposite. In its pictures, the synesthete conveys blurry impressions, with little details to focus on.

We made the synesthete generate 16-bar melodies from the images in the top row of Figure 3(a) (MIDI samples and sheet music in the Online Supplement). The samples clearly show that the synesthete bends the MusicVAE generator to fit its experience: melodies are more dissonant, have fewer rests, and less rhythmic variation than the typical MusicVAE samples (see Online Supplement). The melody composed from the first sketch on the left obsessively repeats the same few notes, reflecting the few colors in the image. However, these are very short notes (mostly 16th), so the networks seem to recognize the elementary composition of the sketch, but see small chunks of different shades instead of a large, flat field. Indeed, neural networks are known to perceive structures and patterns in the pixels that are invisible to humans. \cite{18}. The second sketch has a clearer structure (two equal rectangles), which translates to a rhythmic structure (roughly every third bar is entirely quarter notes). Similarly, the third sketch inspires a melody clearly divided in three parts: beginning with short notes gradually slowing to all quarter notes. Translating the fourth, darker sketch, the synesthete clearly perceives lower shades and pitches, and even rests. Finally, consider Lipide. Much of the detail is lost to the networks (see the autoencoder’s reconstruction in the middle row), which see a grey-blue haze with few details emerging. Accordingly, the synesthete generates a melody anchored to an A (blue in the map). Small musical figures briefly appear before melting back like objects in the fog—or the details in the reconstructed picture. The inverse process—translating these melodies back to images—produces the pictures at the bottom of Figure 3(a). These are visually similar to those obtained from a simple pass through the image autoencoder (middle row), despite some information loss. In other words, the translation is consistently reversible.

The synesthete was also made to translate samples of well-known classical music to images, generating series with clearly different flavors for different pieces, depicted in Figure 3(b) (MIDI samples and sheet music in the Online Supplement). Altogether, lighter images mirror higher-pitched samples, and one can recognize some composition elements. Bach’s Prelude No.1 in C Maj BWV 846 (top row) has mostly yellow-orange tints with
green features, structurally quite similar to each other. Correspondingly, the music samples all present the same repeating structure. Beethoven’s *Waldstein Sonata* Op. 53 (bottom row), skews blue. Brown or reddish features and diversified structures mirror the diverse melodies (in particular the second and fourth sample).

Figure 3(c) quantifies the diversity of music and image (calculation details in the Online Supplement). The bars indicate the average normalized distance in representation space between the samples in Figure 3(b) and the average of the corresponding series (orange for Bach’s *Prelude*, blue for Beethoven’s *Waldstein*). The *Waldstein* samples have higher heterogeneity than those from the *Prelude* (which have, for example, a strict rhythmic structure), and so are the translated picture series. This means that MusicVAE sees the *Prelude* samples as more similar to each other than the *Waldstein* ones. Therefore, it encodes them to a smaller region in the representation space. Analogously, according to the image VAE, the pictures series obtained from the *Prelude* is less heterogeneous than that from the *Waldstein*.

**Interpolation videos**

Variational autoencoders (VAEs) can also interpolate between samples, generating intermediate image and music Roberts et al. [38], Wienand and Heckl [44]. We leverage this capability to produce suggestive video sequences. After picking two images, we had the synesthete translate each to a 2-bar melody. Using a spherical interpolation between the encoded representations of the melody extremes, we generated 7 interpolating music samples (enough to perceive a gradual change, but keeping a limited cumulative duration). The concatenation of these melodies gives the audio track. Analogously, we obtain the video track from the series of images (24 samples per second of music) obtained interpolating between the starting and ending pictures. Figure 4 shows a sketch of the process, as well as example bars and frames from the video in the Online Supplement Wienand and Heckl [44]. Visually, the top and bottom of Nassos Daphnis’ *11-68* slowly morph into two separate circles. Simultaneously, we hear the rapid 16th notes become longer and more staccato. Gradually, the pitch shifts down, until the last two bars, which represent a detail from Heckl’s *Coronen Molke*, *vale.*
CONCLUSION: TOWARDS A MORE CREATIVE SYNESTHETE

We developed an “artificial synesthete” that translates between pictures and music. Using variational autoencoders (VAEs)—a type of neural network—the machine learns to read and organize visual and musical information. Its synesthetic ability is rooted in a set of learned correspondences between images and melodies. These correspondences are the synesthete’s interpretation of an underlying note-color map. Similar learning experience are thought to be the base of some widely shared cross-modal correspondences in humans Maurer et al. [27], Parise and Spence [35], Ramachandran and Hubbard [36]. The resulting translations are novel works, instead of transposed data.

The learned correspondences set our artificial synesthete apart from algorithmic data transposition Castro [8], Heckl [19] and idiosyncratic translation networks Müller-Eberstein and van Noord [30], as they allow us insight to comprehend what the synesthete sees. Moreover, they increase the creativity of the machine, at least in the framework of Colton’s simple “creativity tripod” Colton [9] (made of appreciation, imagination, and skill). In fact, these correspondences give the machine better appreciation. Based on these guidelines, the synesthete decides what is more or less important to translate, and what are better or worse translation choices. The weakest leg of the tripod for our synesthete is certainly imagination. By construction, VAEs remix features they have seen: they cannot generate fully novel works. Training the image VAE on a larger and more diverse set of images would give the synesthete a broader representation space. This would at least increased the perception of imagination, although the network would remain a remixer. Finally, our system still has limited generation skill: the images are still very blurry, the music feels flat. Larger training samples could improve this aspect as well. Alternatively, generative adversarial networks have shown integration potential with VAEs for improved image generation Broad and Grierson [6], Larsen et al. [26]. Music skill could be improved similarly, layering further networks that articulate from the MusicVAE-generated samples, e.g. varying tempo and intensity, adding voices or harmony.

Finally, emotions play an important role in color-music correspondences for humans (synesthete and not Curwen [11], Palmer et al. [33, 34]) but not in our neural networks. Affective tagging, already in us to analyze and generate images and music Alameda-Pineda et al. [1], Alvarez-Melis and Amores [2], Ehrlich et al. [15], Mohammad and Kiritchenko [28], You et al. [47], could bridge this gap. However, the unemotional experience of the artificial synesthete can, by contrast, highlight our own emotions, as well as elicit new ones when it presents translations we find unexpected or discordant. This also spotlights the deeply personal nature of all perception, synesthetic and not. Comparing and contrasting with the machine’s synthetic perception helps us explore our own, organic experience of music, image,
and their pairing.

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