

Music Generation with Variational Recurrent Autoencoder Supported by History

Alexey Tikhonov¹ and Ivan P. Yamshchikov²

¹ Yandex, Berlin altsoph@gmail.com

² Max Planck Institute for Mathematics in the Sciences, Leipzig
ivan@yamshchikov.info

Abstract. A serious problem for automated music generation is to propose the model that could reproduce complex temporal and melodic patterns that would correspond to the style of the training input. We propose a new architecture of an artificial neural network that helps to deal with such tasks. We discuss the proposed approach and compare it with a long short-term memory language model and with variational recurrent autoencoder. The proposed architecture comprises a number of advantages of language model and variational autoencoder when dealing with temporally rich inputs and helps to generate results of higher complexity and diversity.

Keywords: Artificial Intelligence, Variational Recurrent Autoencoder, Language Model

1 Introduction

A rapid progress in artificial intelligence in general and artificial neural networks in particular is gradually erasing the border between the arts and the sciences. The areas that were previously regarded as entirely human due to the creative or intuitive character of the tasks transform and give space for the algorithmic approaches. This particular paper addresses automated music generation, but one can find projects on poetry generation [14], [24], classical painting generation [2] or even generation of Chinese calligraphy [22]. In fact, there was a number of attempts to automate the process of music composition long before the artificial intelligence era. A well developed theory of music inspired a number of heuristic approaches to this task some of them dating as far back as 19th century see [13]. In the middle of the twentieth century a Markov-chain approach for music composition was developed in [8]. Yet recently a significant number of advances in automated music generation were made with the help of artificial neural networks [16], [19]. These results as well as a number of other works dealing with music or text generation have demonstrated an exceptional capability of artificial neural networks to deal with datasets of a nontrivial multidimensional structure.

Music can be represented as a series of specific events. Corresponding conditional probabilities of these events could be used to model the resulting track. One can come up with a number of model set-ups starting from a prediction

of a next note based on one or several previous notes, predicting a phrase or a chord based of a longer time-window or sampling the note or a melody from a previously learned distribution. There are several artificial neural network architectures suggested for music generation. A variety of recurrent neural networks (RNNs) used, for example, in [4], [5], [10] or [21] has proven to give interesting and promising result. Long short-term memory (LSTM) neural networks, being a particular type of RNNs, seem to be even more interesting for the music generation. A crucial feature of LSTM network that makes it extremely attractive in this context is that LSTM shows significantly better results when dealing with time lags of unknown size between important events [5]. This comparable insensitivity to gap length gives a unique advantage to LSTMs over hidden Markov models, alternative recurrent neural networks and other sequence learning methods when algorithm works with music. Music patterns can be temporally complex and LSTMs seem to be apt to capture this complexity to a high extent [20]. For an example of LSTM applied to the music automation we address the reader to [3]. There is a number of other architectures that try to advance this features even further such as multilayered LSTM used in [21] or highway network cell introduced in [25] that we work with in this particular paper.

The second powerful tool proved to be particularly effective for text generation is a variational autoencoder (VAE) [1], [17]. VAE is a variational approach for latent representation learning based on several assumptions on the distribution of latent variables. This method uses an additional loss component and a specific training algorithm called Stochastic Gradient Variational Bayes (SGVB) [15], [11]. VAE-based generative models can generate realistic examples as if they are drawn from the input data distribution. Since music could also have a discrete representation as in [3] it is only natural to expect that some of the methods successfully used for text generation could be applicable to the generation of music. It is also important to note that VAE-architecture gives a significant control over the parameters of the generated output. In context of image generation that property of VAE was shown in [12], [23]. One would like to see if this property is preserved during music generation.

In this paper we suggest a new architecture for algorithmic composition of monotonic music and also discuss possible further developments of this architecture. We compare several possible approaches based on Language model (LM), LSTM and sequence-to-sequence learning introduced in [20]. We describe the resulting structure and discuss its advantages for music generation.

2 Music Representation and Data

In this particular work we have decided to concentrate on the monotonic music generation. First of all, a monotonic melody could be represented as a sequence of characters which allows us to apply a number of approaches and algorithms that proved to be successful for automated text generation. Second, one can expect that these algorithms would perform even better in the task of monotonic melody generation. Indeed, the text generation models could be roughly

split into two approaches: a word-based generation and a char-based generation of texts. A word based approach for text generation suffers from an extensive multidimensionality. A dataset typically contains millions of words that relate to each other semantically and morphologically yet an algorithm has to determine these relations in the process of learning. A char-based approach in which an algorithm generates texts letter by letter is closer to the case of monotone music generation. However, when dealing with a monotonic melody recorded as a sequence of notes and octaves one has a very low dimensional space of elementary sounds that is enhanced with a well documented structure given to us by the theory of music and the design of this state space. Such structure on the character-level is rarely found in natural languages, and allows to train a model on a very dense set of possible inputs that are concentrated in a specific region of the state space.

For the training we have used 4 Gb of midi files that included songs of different epochs and genres. The dataset was preprocessed in the following ways before it was used. Since one midi file can contain several tracks with meaningful information yet can have some tracks of little importance one has to split the files into tracks and use an heuristics that would filter the tracks. Each note in midi file is defined with several parameters such as pitch, length, strength plus the parameters of the track (e.g. the instrument that is playing the note) and the parameters of the file (such as tempo). Despite the fact that nuancing is playing an important role in musical compositions we omitted the strengths of the notes, focusing on the melodic patterns determined by the pitches and temporal parameters of the notes and pauses in between. In order to make the learning state space denser we have centered the pitches throughout the dataset transposing median pitch of every track to the 4th octave. We also normalized the pauses throughout the dataset in the following manner. For each track we have calculated a median pause. It is only to be expected that absolute majority of the pauses in the track were equal to the median pause multiplied with a rational coefficient (naturally $1/2$ and $3/2$ were especially popular in the majority of the tracks). We counted all possible pauses in every track and left only the tracks that had 11 different values of the pauses or less (the median + most popular pauses on each side of it). The tracks with higher variety of pauses were not included in the final dataset. Generally, temporal normalization of the midi files might be rather challenging but the pause filtering trick described above allowed us to normalize the obtained tracks using the value of the median pause. Finally to make the input diverse enough we have filtered the tracks with exceedingly small entropy. In Figure 1 one can see the distribution of entropy across the dataset.

Since the LM predicts the track on a note-by-note basis an exceeding amount of tracks with low pitch entropy (say, house bass-line with the same note repeating itself throughout the whole track) would drastically decrease the quality of the output. Finally, we have obtained a dataset that consisted of 15+ thousand normalized tracks which was used for training.

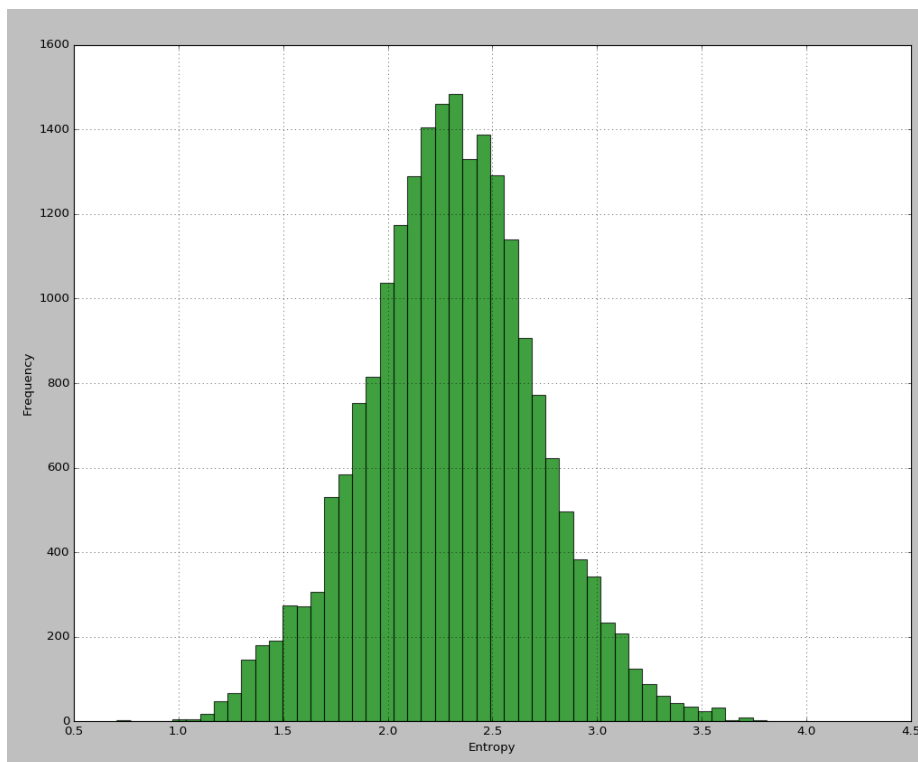


Fig. 1. *The distribution of tack entropy across the dataset before filtering.*

For each note we were building a note embedding that corresponded to the pitch of the note, an octave embedding that corresponded to the octave of the note and a delay embedding that corresponded to the length of the note. We were using this three embeddings and meta-information of a given MIDI track to build a concatenated note representation that was used as an input for training throughout this paper.

3 Architecture

The applications of LSTMs to language modeling are relatively well described. In [18] the authors state several basic principles that could be applied to a variety of LSTMs developed for language modeling:

- The input words are encoded by 1-of-K coding where K is the number of words in the vocabulary,
- At the output layer, a softmax activation function is used to produce correctly normalized probability values,
- The cross entropy error which is equivalent to maximum likelihood is used as a training criterion.

In our case these principles were used not in the context of words in a document but in the context of notes in a track. On Figure 2 the reader can see a general structure of the model. The network was to read the input that consisted of MIDI meta-information and concatenated note representations and to predict the n_{k+1} note basing on n_1, \dots, n_k previous inputs. The principle structure of that model is shown in Figure 2.

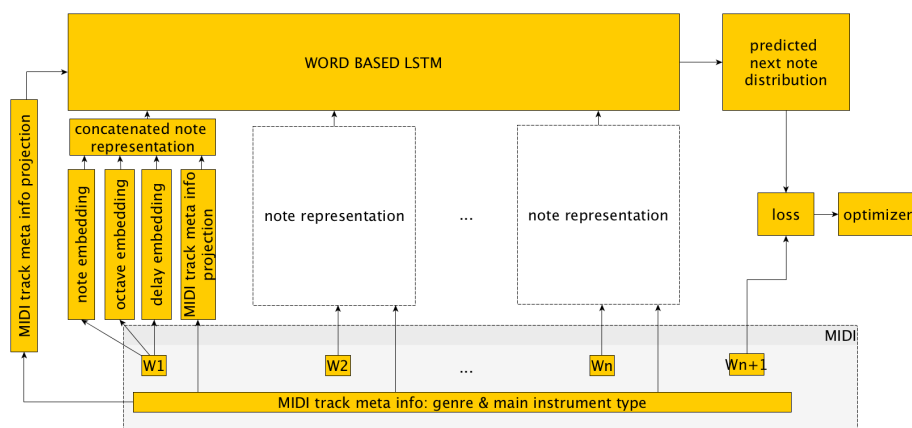


Fig. 2. *LSTM language model in the context of music generation.*

A weakness of LM is that it does not capture global features in an interpretable way [1]. One can think of a number of approaches to the music generation that would deal with this problem paying more attention to the macro structure of the track, for example, VAE or Recurrent Highway Networks that we have already mentioned above. Recurrent Highway Networks extend the LSTM architecture to allow step-to-step transition depths larger than one. Several experiments demonstrated that RHN is an efficient model, that can outperform LSTM [25]. So we reorganized the LSTM language model that is described in Figure 2 and proposed the architecture shown in Figure 3 that is a version of VAE called variational recurrent autoencoder. Here the first network (encoder) compresses the given track into a latent vector that works as a bottleneck. The second network (decoder) learns to reconstruct the melody out of a latent representation. This approach stimulates the network to work with a macrostructure of the track due to the low dimensionality of the latent vector.

Naturally, there is a trade-off between the potential of the network to capture the macro-structure and its possibility to generate locally diverse melodies. One would like to propose an architecture that could combine both these features and would balance local diversity with global structure. We believe that the Variational Recurrent Autoencoder Supported by History (that we would further

refer to as VRASH) proposed in [1], where it was applied to the text generation, might address these issues.

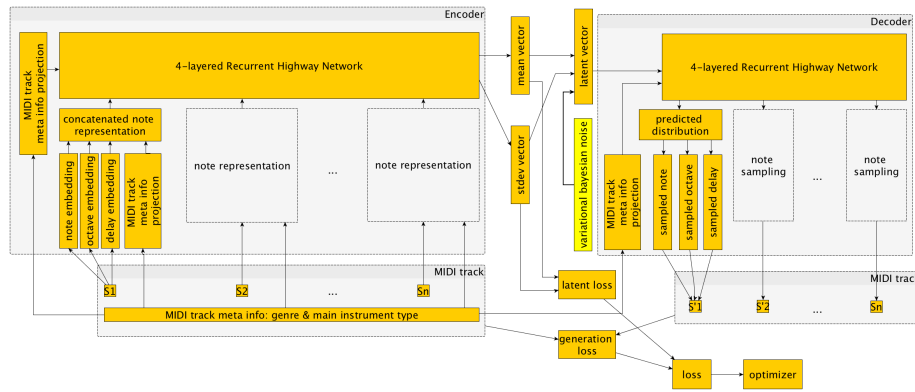


Fig. 3. Variational autoencoder scheme for music generation.

VRASH in a sense combines a language model and variational recurrent autoencoder in order to increase the performance on the data with varying input length. VRASH architecture is principally described in Figure 4. Here analogously to the scheme on Figure 3 the decoder tries to reconstruct the track out of the latent vector, but this vector is distorted with a variational bayesian noise. The decoder also uses the previous outputs as additional inputs. It "listens" to the notes that it has composed already and uses them as additional "historic" inputs.

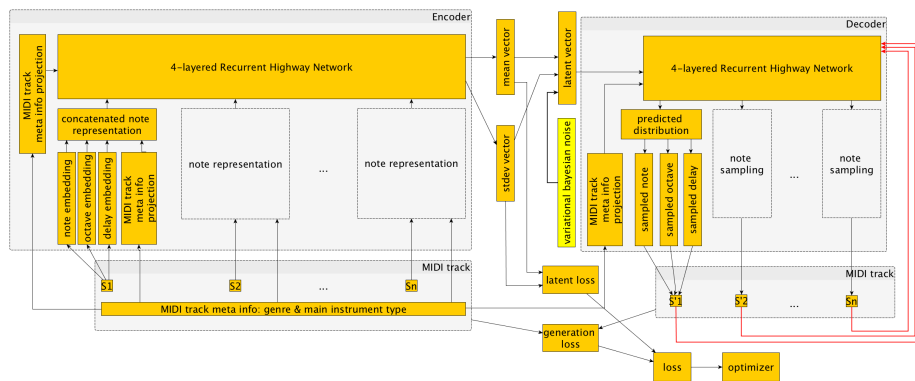


Fig. 4. Variational Recurrent Autoencoder Supported by History (VRASH) scheme for music generation.

In the next section we compare the proposed architectures.

4 Experiments

Before we start with the comparison of the proposed architectures we need to make the following remark. It is still not clear how one could compare the results of generative algorithms that work in the area of arts. Indeed, since music, literature, cinema etc. are intrinsically subjective it is rather hard to compare them according to a certain rigorous metric. Majority of approaches are usually based on the peer-review systems where the amount of human peers can significantly vary depending on the research. For example, in [9] the authors refer to 26 peers subjective opinions, whereas in [7] more than 12 hundred peers responses are analyzed. Such collaborative approach based on individual subjective assessments could be used to characterize the quality of the output but is rather ineffective and hardly can produce quantitative results. The amount of peers needed to compare several different architectures and obtain rigorous quantitative differences between them drastically exceeds the ambition of this particular research. Generally speaking, with an ever growing interest of computer scientists to art-generating algorithms one would expect the development of some rigorous art metrics to become a specific task within the interdisciplinary focus of arts and sciences. Keeping this remarks in mind we would rather compare the proposed architectures with respect to the cross-entropy that is commonly used as a loss-term in such tasks and share our personal subjective opinion on the output produced by different architectures.

In Figure 5 one can see cross-entropy of the proposed architectures near the saturation point. The first untrained random network is used as a reference baseline. For the three other architectures shown in Figure 2, Figure 3, and Figure 4 the columns show the cross-entropy of the model near the point of saturation. LM and VRASH models demonstrate comparable cross-entropy with the values of 2.34 and 2.11 respectively.

Despite the fact that formally VRASH demonstrates only marginally better performance in comparison with the language model we claim that the results produced by VRASH are more interesting subjectively and further development of this architecture in context of music generation looks promising. One can compare the examples of the output generated by LM¹, VAE² and VRASH³. Our subjective judgement is that autoencoder based architectures do demonstrate a better grasp of macro structure and therefore are interesting for further automated arrangements.

¹ <https://soundcloud.com/creaited-labs/pianola-lm-example-1>

<https://soundcloud.com/creaited-labs/pianola-lm-example-2>

² <https://soundcloud.com/creaited-labs/pianola-vae-example-1>

<https://soundcloud.com/creaited-labs/pianola-vae-example-2>

³ <https://soundcloud.com/creaited-labs/pianola-vrash-example-1>

<https://soundcloud.com/creaited-labs/pianola-vrash-example-2>

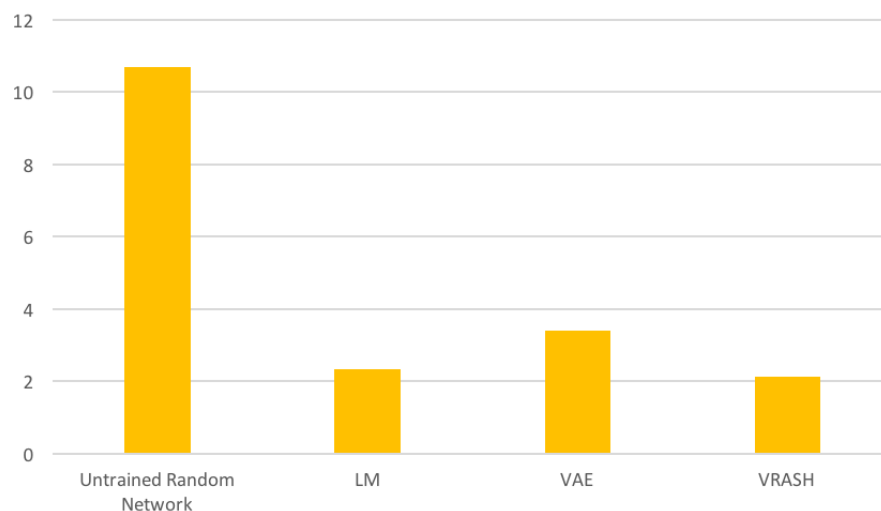


Fig. 5. *Cross-entropy of the proposed architectures near the saturation point.*

5 Discussion

As we have told in the previous section the estimation of the quality of the music is entirely subjective. This is a serious problem that can hardly be ignored and demands some separate attention. However, we can discuss our personal assessments of the results of different models. Subjectively assessing the tracks produced by different algorithms we claim that the percentage of tracks with more interesting temporal and melodic structures is the highest for VRASH.

All three proposed architectures work relatively well and generate music that is diverse and interesting enough if the dataset for training is big and has high quality, however, they have certain important differences. The first general problem that occurs in many generative models is the tendency to repeat a certain note. This difficulty is more prominent for Language Model whereas VAE and, specifically, VRASH tend to deal with this challenge better. Another issue is the macro structure of the track. Throughout the history of music a number of standard music structures were developed starting with a relatively simple structure of a song (characterized with a repetitive chorus that is divided with verses) and finishing with symphonies that comprise a number of different music forms. Despite the fact that VAE and VRASH specifically are developed to capture macrostructures of the track they do not always provide distinct structural dynamics that characterizes a number of human-written musical tracks. However, VRASH seems to be the right way to go. In Figure 6 one can see a t-sne visualization of 16-dimensional latent vectors learned by VRASH in correspondence with different music authors, genres or classes. The distinctively visible clustering of the certain tracks might correspond to the relative resemblance of

music structures used in these tracks. Indeed, additional attention should be given to the macro-structure of the tracks in future. One could either work on a better structure classification that could be used within a meta-information input for every track or develop other architectures that would be capable to capture repetitive melodic structures that are placed on varying distances within a given track.

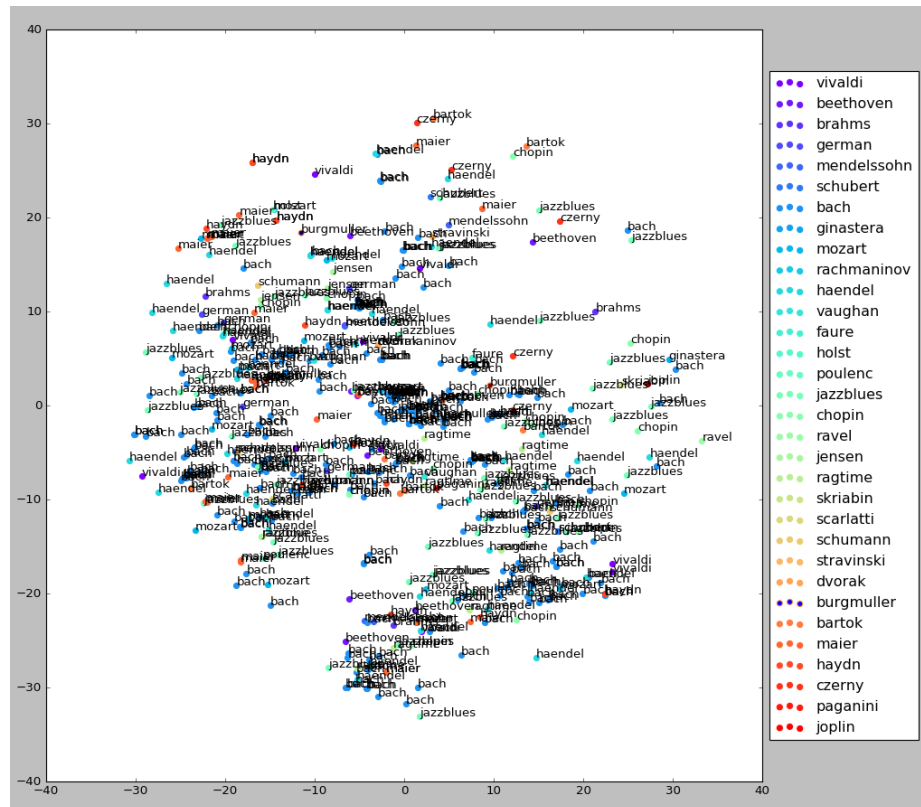


Fig. 6. *t*-SNE visualization of the learned music classes.

6 Conclusion

In this paper we have described several architectures for monotonic music generation. We have compared Language Model, Variational Recurrent Autoencoder and Variational Recurrent Autoencoder Supported by History (VRASH). This is the first application of VRASH to music generation that we know. There are several strong advantages of this model that make it especially interesting in

context of the automated music generation. First of all, it provides a good balance between global and local structures of a track. VAE allows to focus on the macrostructure but advancing it in the way described above enables a network to generate more locally diverse and interesting patterns. Second, the proposed structure is relatively easy to implement and train. The last, but not the least, it allows to control the style of the output (through the latent representation of the input vector) and generate tracks corresponding to the given parameters.

References

1. Bowman, S. R., Vilnis, L., Vinyals, O., Dai, A. M., Jozefowicz, R., and Bengio, S. (2015). Generating sentences from a continuous space. arXiv preprint arXiv:1511.06349.
2. Brown, M. (2016). 'New Rembrandt' to be unveiled in Amsterdam. <https://www.theguardian.com/artanddesign/2016/apr/05/new-rembrandt-to-be-unveiled-in-amsterdam>
3. Choi, K., Fazekas, G., and Sandler, M. (2016). Text-based LSTM networks for automatic music composition. arXiv preprint arXiv:1604.05358.
4. Chu, H., Urtasun, R., and Fidler, S. (2016). Song From PI: A Musically Plausible Network for Pop Music Generation. arXiv preprint arXiv:1611.03477.
5. Colombo, F., Muscinelli, S. P., Seeholzer, A., Brea, J., and Gerstner, W. (2016). Algorithmic Composition of Melodies with Deep Recurrent Neural Networks. arXiv preprint arXiv:1606.07251.
6. Colombo, F., Seeholzer, A., and Gerstner, W. (2017). Deep Artificial Composer: A Creative Neural Network Model for Automated Melody Generation. In *International Conference on Evolutionary and Biologically Inspired Music and Art* (pp. 81-96). Springer, Cham.
7. Hadjeres, G., and Pachet, F. (2016). DeepBach: a Steerable Model for Bach chorales generation. arXiv preprint arXiv:1612.01010.
8. Hiller, L., and Isaacson, L.M. (1959). *Experimental Music. Composition with an Electronic Computer*. McGraw-Gill Company.
9. Huang, A., and Wu, R. (2016). Deep learning for music. arXiv preprint arXiv:1606.04930.
10. Johnson, D. D. (2017) Generating Polyphonic Music Using Tied Parallel Networks. *International Conference on Evolutionary and Biologically Inspired Music and Art* (pp. 128-143). Springer, Cham.
11. Kingma, D. P., and Welling, M. (2013). Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.
12. Larsen, A. B. L., Sønderby, S. K., and Winther, O.. (2015). Autoencoding beyond pixels using a learned similarity metric. CoRR abs/1512.09300. <http://arxiv.org/abs/1512.09300>
13. Lovelace, A. (1843) Notes on L Menabrea's sketch of the analytical engine.
14. Oliveira, H. G., Hervs, R., Daz, A., and Gervs, P. (2014, June). Adapting a Generic Platform for Poetry Generation to Produce Spanish Poems. In *ICCC* (pp. 63-71).
15. Rezende, D. J., Mohamed, S., and Wierstra, D. (2014). Stochastic backpropagation and approximate inference in deep generative models. *ICML* (pp. 1278 - 1286)
16. Roberts, A., Engel, J., Hawthorne, C., Simon, I., Waite, E., Oore, S., Jaques, N., Resnick, C., and Eck, D. Interactive musical improvisation with Magenta. <https://nips.cc/Conferences/2016/Awards>

17. Semeniuta, S., Severyn, A., and Barth, E. (2017). A Hybrid Convolutional Variational Autoencoder for Text Generation. arXiv preprint arXiv:1702.02390.
18. Sundermeyer, M., Schlter, R., and Ney, H. (2012). LSTM Neural Networks for Language Modeling. *Interspeech* (pp. 194-197).
19. Sigtia, S., Benetos, E., and Dixon, S. (2016). An end-to-end neural network for polyphonic piano music transcription. *IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP)*, 24(5), 927-939.
20. Sutskever, I., Vinyals, O., and Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems* (pp. 3104-3112).
21. Waite, E., Eck, D., Roberts, A., and Abolafia, D. Project magenta. <https://magenta.tensorflow.org/>
22. Xu, S., Lau, F. C., Cheung, W. K., and Pan, Y. (2005). Automatic generation of artistic Chinese calligraphy. *IEEE Intelligent Systems*, 20(3), 32-39.
23. Yan, X., Yang, J., Sohn, K., and Lee, H. (2015). Attribute2image: Conditional image generation from visual attributes. *CoRR* abs/1512.00570. <http://arxiv.org/abs/1512.00570>.
24. Zhang, X., and Lapata, M. (2014). Chinese Poetry Generation with Recurrent Neural Networks. In *EMNLP* (pp. 670-680).
25. Zilly, J. G., Srivastava, R. K., Koutnik, J., and Schmidhuber, J. (2016). Recurrent highway networks. arXiv preprint arXiv:1607.03474.