Computational Musicology: Neural Network Architectures in Autonomous Composition Systems

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***Abstract*—Deep neural networks allow AI to use machine learning to create music. It introduces computational creativity, a new research field, with focus on algorithms for melody, harmony and rhythm generation. The field's researchers often look into using transformers in sequence analysis, variational autoencoders and adversarial testing for improving art. Scholarly work with twelve different writing systems proves that most of these systems are better at writing text, but still struggle with truly understanding context and producing styles that are not copied. Using more than one way to solve a task improves results compared with using a single approach, as studies have demonstrated. Using ensemble techniques increases the coherence of harmonic parts by 73% and brings a 68% better link in melodic progression between segments. Still, professional musicians disagree with pop music because they say it lacks emotional depth and cultural understanding. We think that a significant approach for the future will join fast mathematics with creative human ideas, opening up the option for artists to collaborate.**

***Index Terms*—Neural Musicology, Algorithmic Composition, Computational Creativity, Deep Learning Applications, Sequence Generation, Creative Automation, Digital Composition, Machine Learning Arts, Automated Music Production, Human-Computer Collaboration.**

I.INTRODUCTION

Having computers make their own music is a big advance in the world of technology and art. Unlike the earlier types of composition software powered by computers which simply assist human creativity, today's neural frameworks can generate their own creative sequences, styles and patterns. Historically, algorithmic composition started with the use of games of chance by Mozart and Cage using random selection of musical notes. Besides these techniques, contemporary neural networks truly stand out because of their capacity to identify small musical details, grasp musical structure and compose music that sounds well and is impressively performed.

The reason for this progress lies mainly in major improvements in deep learning structures, models that transform one sequence into another, attention systems and techniques for generating new data. Systems use temporal sequences to go through musical information so they can grasp the ways melodies, chords and rhythm change over an entire piece of music. Current methods in neural composition systems are able to examine and learn from a wide range of musical scores, extract main structural elements and use those to compose original pieces that fit with certain rules but remain unique. It applies to many parts of music, including music from the past and present which demonstrates that computational tools can be useful in several musical styles.

Because of these advances, music education, therapy, making music for profit and academic study can all develop in important ways. In schools, algorithmic composition software helps show musical theory, while making music just for patients is a growing approach to therapy. In commercial music production, quick prototyping and inspiration assets are helpful and artists also try out new approaches to combining creativity and technology. The wide use of automatic composition tools introduces issues about creativity, ownership and what role people have in automated creative work. Computational musicology should carefully investigate how technology affects the system while its use is advancing. It aims to thoroughly document the different neural composition methods, discuss their uses, outcomes, benefits and challenges for the future of music technology and human-computer collaboration.

II. LITERATURE REVIEW

When neural networks are used in music composition, we see that AI and creativity by people meet, resulting in a new way to view how art is made. Due to the latest breakthroughs in deep learning models, machines are able to compose whole musical compositions instead of just following simple tasks, with transformer-based systems being the best at it. Tests on these systems have discovered they can look across centuries of musical development in the West and find out the rules and building blocks needed to create new kinds of music. While Cage and Mozart played with the idea of letting chance guide creating their music, it is now possible for computers to interpret musical themes and progressions to a very high degree of accuracy. By examining more than 55K pieces of classical, jazz, folk, and popular music, it was found that joining different neural nets in ensembles boosts results more, with harmonies becoming more organized (+73%) and melodies becoming better connected (+68%) than when using just one neural network.

Even so, the technology's great skills suggest that there is a major difference between real art and just being able to do complicated calculations. While methods of artificial intelligence are excellent for replicating common compositional patterns and keeping things factually accurate, experts usually notice that they lack real depth of emotion, cultural roots, and creativity. Only a third of songs created by AI are original and make an emotional impact, although 78 percent of them follow standard rules of music. Since the problem exists, it seems that being skilled in writing music is not enough to ensure an artist is heard properly. The biggest promises seem to be in using AI together with artists, so the machine helps with recognition and the artist brings the emotional and creative touch. With maturity, this technology poses questions about creativity, who makes the music, and human influence in art, and also makes it possible to increase access to music education, therapeutic programs, and creative works that preserve the human traits that matter to music.

III. PROBLEM STATEMENT

Even though technology in artificial intelligence and deep learning is advancing rapidly, neural music composition still deals with a major challenge that could affect both its use and appreciation. In many cases, AI-produced music seems flawless and is built in a proper structure, though it does not move people emotionally or culturally like human compositions can. Experienced musicians and composers believe that even if these systems follow the music rules and patterns taught by vast data, they lack the characteristics that give music its true meaning, for example, deep emotion and unique expression. Since currently, AI can't compose in an original way, usually becoming too robotic, most musicians are not ready to adopt these tools for real-life music making. On top of that, powerful artificial neural networks take a lot of computing resources, which makes it almost impossible for creative artists to use them in real time with AI. The issue is not only how to make AI-generated music more precise, but also how to link its technique of pattern recognition to humans' sensitive and creative approach to making music.

IV. METHODS AND PROCESS

A. Experimental Design and Research Framework

An examination of various neural network models was carried out to find out which produced the highest quality musical pieces. The team followed a strategy of proper data collection, strong evaluating methods, and statistical techniques to check the results.

The experiment was set up to meet the following objectives: first, to check how various neural networks perform in music generation, second, to choose proper metrics to evaluate AI-made music, and third, to identify the best architecture for certain music tasks. It was necessary to pay equal attention to the quality of the technology and the creativity involved.

Researchers carried out multiple steps in gathering and studying data, from putting the dataset in order at the start to confirming it statistically by the end. Every part of the experiment was set up to avoid bias and help us achieve valuable comparisons of different ways of generating music using neural networks.

B. Neural Architecture Selection and Classification

The process of picking neural networks was founded on clear criteria to guarantee that the chosen methodologies fully reflect the latest ideas in computational musicology. According to their theoretical base, use in music generation, and how easy it is to build them, these architectural categories were observed and grouped into four primary categories.

The first chosen models were transformer-based since they have effectively modeled sequences and can notice long-range patterns in music. In these structures, you had both encoder-decoder models as well as decoder-only ones, and they all featured self-attention designed especially for representing musical data. Different attention head counts and positional encoding approaches were used to judge the impact on the generated texts.

Recurrent neural networks supplemented by attention mechanisms made up the second type of models. They were chosen mainly because of their past significance in making sequences and ongoing benefits for music generation. Investigators used networks such as Long Short-Term Memory and Gated Recurrent Units, and they included both uni-directional and bi-directional forms, which were equipped with various attention features: additive, multiplicative, and self-attention.

The third set was Variational Autoencoders for musical use, which were chosen thanks to their ability to find structured hidden features in the given musical data. They were helpful because they could produce sensible modifications to the music and because their hidden space was easy to understand. Both the usual VAE models and two newer types called β-VAE and Conditional VAE were used in the investigation because they are tailored for working with music data.

The last category included Generative Adversarial Networks that focus on music creation. The selection of these models was made because they are able to make realistic and high-quality music with help from adversarial training techniques. Both original GAN architectures and their partner versions such as Progressive GANs, Wasserstein GANs, and conditional GANs for musical use were studied during the investigation.

C. Dataset Construction and Preprocessing Methodology

A collection of musical training data was created by picking and editing musical pieces of diverse genres, ages, and traditions. Building the database aimed to preserve history as well as be lawful, that's why it features public domain music from the past and new compositions given by Creative Commons licenses.

The main part of the data was classical music, including 15,000 songs chosen from the Baroque, Classical, Romantic, and Modern periods. These compositions covered full orchestral pieces, chamber music, music for solo instruments, and pieces for voices, giving an example of a range of compositions and ways they were written. The process included checking the complexity of each piece, its historical value, and the quality of available digital copies in the famous musical form.

The corpus includes 8,500 jazz compositions, starting with ragtime and going right up to the new fusion styles. John Coltrane added well-known standards, transcribed improvisations from great musicians, and wrote his own tunes as well. Having the jazz collection was especially helpful because it taught me about hard-to-understand chord sequences and unusual rhythms.

There are now 12,000 folk melodies in the dataset because of music traditions from Europe, America, Asia, and Africa. Minimalist compositions were written in ways that had basic pitches, simple chord structures, and repeated musical layouts to make them simpler than classical or jazz music. Modelling the music involved feeding the collection of traditional pieces into the training process.

Over the past century, there were 20,000 pieces of music created in different styles, for example, rock, pop, electronic, and contemporary genres. Examples of today's harmonic structure, new rhythmic approaches, and various production techniques for recorded music were found in this collection. To develop models that make contemporary compositions, the popular music collection was very important.

The process was created to bring all the music pieces to the same format but not change their important features. All the compositions were transposed to the same keys in order to simplify music analysis and keep the same relative pitch solfège as the originals. Through the use of complex algorithms, the software could pinpoint the main tone of each musical piece and transpose it sensibly without modifying the major musical points.

Methods for harmonic analysis enabled me to detect and note chord changes, cadences, and the process of modulation throughout the entire material. The analysis depended on algorithms from music theory and algorithms learned by machine learning to spot harmonies. The harmonic annotations created formed structure for tonal information that neural networks could refer to while training.

Tempos were standardized to make sure that individual sections of music performed with a similar rhythmic feel no matter the style or age. Instead of just using a single speed, the preprocessing system discovered the underlying beat in each song and kept the song's usual timing style. With this process, the basic rhythmic quality of every musical style was kept, as training data was made consistent as well.

Various themes, types of variations, development parts, and repetitions in the analysis were identified and marked by following the structural procedure. They were created by using both automated software and checks by trained musicians. The labels on the structure helped neural networks build understandable large-music pieces.

D. Training Protocol and Optimization Procedures

The method enabled one to assess the networks' results in music generation and try to improve each one's performance. There were introduced methods to train all architecture families so they could fulfill the requirements put on the models.

Techniques employed grid searched for values on many parameters for each category of architecture. Several values for the learning rate ranging from 1e-5 to 1e-2 were tested, mainly to check how they influence the model's structure. The amount of memory and processing power made it possible to determine the best size for batches.

For every type of architecture, we changed the details of the hidden layer, the number of layers or attention heads in the network. During the creation of the model, it was taken into account how well it communicated ideas, could be efficiently computed, and how likely it was to overfit. Certain neurons were shrunk, weights were reduced, and certain regularization rules were set to improve learning as well as performing well on new data.

Every kind of music and every era was included in both the training set and the test set during cross-validation. Since both temporal holdout and random sampling were applied, the models were able to handle and generalize data from very different periods of music history and from newly produced music.

Instead of setting a fixed time, when loss stopped decreasing, every model was able to show its best performance, regardless of how many operations it did. Several aspects such as reconstruction loss, several forms of perplexity, and sample quality were examined by the monitoring system to reflect the progress of training.

Performance criteria for the training were set using validation loss stability, so each model could maximize its results no matter how many resources were required. To ensure the best results, the system continuously watched multiple factors like reconstruction loss, perplexity indices, and how good the newly generated images were.

To help prevent overfitting and train the model right, early stopping was put in place. To decide when to stop training the early, I used momentarily increased validation loss along with my judgment of any produced music samples, holding off on stopping when see any promising progress.

1) Evaluation Framework Development

Both computers and AI specialists took part in the evaluation to ensure the quality of any compositions made by AI could be measured fully. It was realized that having both technical skill and artistic flavor makes music valuable, so its evaluation should take into account both facts and personal preferences.

Specific parts of a piece's structure and integrity were measured by using special evaluative tools. The algorithms counted how religiously the chord progression adhered to known principles, how frequently its patterns were resolved, and the prevalence of usual sequences in the music. They used both classical music rules and data findings from the implemented material to evaluate chords properly.

They reviewed the way pitch contour, different intervals, and motivic patterns were handled in each piece of music. They measured the smoothness of the melody, the number and length of leaps, how well the melody fits into scale, and the number of times motifs appear to check how clearly the melody is expressed. Advanced technologies looked into the ways motives are changed and themes developed in music known for its sophistication.

They used tests to judge how consistently the beats and rhythms were handled, and how syncopation was carried out in the outputted music. Such systems use algorithms to detect a constant pulse and check the rhythm's level of complexity. The evaluation included studying cross-rhythm interactions and polyrhythms to study advanced ways of handling rhythms. Pattern matching methods were used by these algorithms to spot thematic statements, alterations, and repeat motifs typical of rules in music. Structural evaluation helped by giving scores for both how coherent and how advanced the literature was.

2) Expert Assessment Protocol

The evaluation by humans was conducted by twelve professional musicians who held advanced qualifications in composing, performing, or theory aspects of music. The panel was selected by giving most attention to experience in many music genres, experience with compositions from all eras, and familiarity with computer-aided ways of reviewing music.

listening procedures were put in place, so that experts rated the AI music without learning anything about the program being used. It was key to the study to keep biases from being introduced into the process through earlier attitudes about various neural network setups and their performance abilities.

A set of standard rules was applied during all the assessments to judge the musical quality in four major dimensions. Great musicians had to play harmonies well, use proper voice leading, and follow the standards of music in different styles. How convincingly generated music used the common elements of a genre's harmony, melodic style, and structure was assessed as stylistic authenticity.

The creative aspect was examined by checking for new musical ideas, effective but unusual compositions, and an overall spirit of originality held by the compositions despite sticking to classical rules. Ever so, it was important for expert evaluators to determine the difference between just having technical skills and actually creating original work in AI-generated compositions.

All things considered, musical effectiveness depended on the emotional power, the unity of the structure, and the worth as an artistic piece in each case. This dimension explored how people's feelings about music could not always be measured just by looking at objective details.

An evaluation using seven-point Likert scales per dimension allowed spotted the expected differences among programs and kept the results consistent among assessors. The organizers supplied exact scoring rules and some sample evaluations to the panelists so that they would judge all performances similarly.

3) Comparative Analysis Framework

The aim of the method was to enable systematic review of different neural architectures' musical generation abilities by checking various factors. The framework made sure that all results from comparative studies were from standard tools and processes to make results logical and understandable.

Because of standardization, each neural architecture created music that had the same format, with similar notation, the same groups of instruments, and constant tempo. It allowed the results of generating music to be easily compared despite the changes in architecture, while still staying true to the musical quality of every piece.

Two types of analyses were used within and across genres to judge how architecture responded to changes in musical styles. In comparisons within the same musical genre, I studied how well different models captured the particular traits of that genre, and in cross-genre examinations, I looked at how well architectures were able to work for several musical genres.

The team used methods to decrease bias in the comparative analysis to avoid including experimental flaws when assessing performances. Among the methods, there were randomized examination, equivalent spread of building samples by type, and proper restrictions on the network resources used for every model.

4) Statistical Analysis Procedures

The techniques used for analysis were strictly quantitative and helped us to see performance differences in neural networks despite different sources of variation in the conducted experiments. Both significance testing and estimation of the effect size were included in the statistical framework so that comparative results could be understood fully.

With Analysis of Variance, analyzers were able to check whether the various used architecture affect performance. With the ANOVA, both the main effects and the interactions were analyzed to detect any complex patterns in how buildings work in the different conditions.

The calculations of effect size gave practical information to improve statistical significance testing. The difference in architectural strategies was sized up using Cohen's d and eta-squared for all important performance comparisons. It was important to use these effects to measure the real importance of

performance differences among architecture systems.
They looked at whether the scores from different evaluation methods match the main quality assessment of the composition. As a result, the authors could see which computational metrics best measured accuracy in generating music with the help of experts, highlighting the main contributors to effective AI music generation.

Special techniques were used to maintain the error rates in the conclusions when numerous statistics were calculated in this study. In order to keep results reliable and still pick up any important performance differences, both the Bonferroni and False Discovery Rate approaches were used.

It was planned to conduct non-parametric statistical analyses when the underlying data failed to meet the assumptions of regular parametric tests, making conclusions more reliable in any situation. Because of bootstrap resampling, we were able to make reliable judgments about important outcomes in cases with small sample sizes.

V. RESULTS

The analysis of various architectures for neural networks pointed out that they differ greatly in their abilities to write good pieces of music. It was found through comparison that using different architecture methods affects both the technical correctness and creative value of the music, and some approaches stand out when used in certain musical settings.

Among different architectures, those based on transformers worked best in generating music, showing better abilities to preserve long-range harmony and the structure of music. The models give an overall normalized harmonic consistency score of 0.847, much better than the scores of recurrent neural networks, which reached 0.623 in the test. Using self-attention in transformer models helped produce music pieces that were buildt on cohesive long-term structures and interesting chord progressions.

The fact that transformers addressed several levels in a musical sequence at the same time made it easier for them to capture details of harmonic structure and melody. Recurring choices in long musical compositions, such as those lasting for more than two minutes, were clear when these sequences became less cohesive in the later selections.

They were especially capable of producing music that fit the specific style while still being musically diverse. The greatest achievements of these architectures came in blending different musical traditions, since they were successful in producing a feeling of completeness despite using elements from different types of music. These models helped to produce songs that showed traits from various music styles and still kept their overall structure intact.

Yet, employing VAEs found that generating compositions that lasted for more than four minutes posed some problems. The limited-size latent space seemed to limit the ability of the models to keep up with changing events occurring over considerable periods of time. This situation was especially noticeable in classical music generation because composers need to maintain the transformation and progression of their themes over the course of developing the structure.

Generative Adversarial Networks showed they could make music that is different from the content used when they were trained. This training process made the models use unusual chord progressions and interesting tunes that helped them create something different from traditional styles. Because of this creative approach, Purcell's compositions often amaze experts due to their unexpected ideas that are still effective in the art of music.

With new opportunities from GAN-based approaches also came the problem of always sustaining a proper structure and consistency through time. Even though there were impressive individual sections, the music usually lacked quality in the overall pieces. Adversarial training helped the artificial intelligence to invent, but sometimes the results did not honor musical rules and the compositions could be fascinating but not always enjoyable.

1) *Quantitative Performance Metrics*

The detailed analysis of how architectures affect quality found that transformers reached the best scores on multiple assessment criteria. On the ten-point quality scale, transformer architectures got an average score of 8.3 and a confidence interval of ±1.2, showing that their results were both impressive and reliable in many musical types.

RNN architectures had an average score of 6.7, which was much lower than bloc architectures, and a wider confidence interval that indicated their results were more different. We noticed that the variability was related to both the length and complexity of the music, since RNN models did fine for simple shorter pieces but not for more advanced pieces with sustained development.

Despite recording the most modest average, Generative Adversarial Networks demonstrated great variability because the confidence interval was large. Although some of the GAN-made pictures got scores that matched top transformer quality, most ended up below what was required, so the average couldn't capture the true potential of the leading GAN works.

Melodic coherence came out as expected, with transformers doing better than recurrent networks, 7.9 ±1.4 versus 6.2 ±1.7. The melodic evaluation looked at how smooth the pitch moves were, how the main ideas were built upon, and whether the music stuck to a consistent scale, showing that transformer models' attention made it easier for music to include more complex melodic techniques.

The analysis of rhythmic consistency in all evaluated models suggested that the basic skills for rhythmic tasks can be found in any of the studied models. Still, all models found it a challenge to deal with musical parts that include several complex rhythmic sequences happening at the same time. This appeared to be the main issue limiting all approaches to neural music generation.

There was a wide gap in the evaluation of structural coherence, with scores from 4.8 to 6.3 for all the architectures tested. Even though computers can make good music, composing structures and elaborate themes like those created by humans is still a tough task for all modern neural networks.

2) Genre-Specific Performance Analysis

Looking at how neural networks function in different musical genres, it was found that some architectural styles are much more useful in particular music styles. The presence of such genre-related patterns gave new understanding of how musical style and neural network learning are connected.

In the musical field, AI methods mostly excelled at generating classical music, especially transformers that came close to matching the talent of humans in over two-thirds of Bach chorale harmonization cases. The success came because neural networks could easily pick up and copy the rigorous rules in Classical music. Because Classical music is based on well-defined rules and principles, it became easy for musicians' brains to identify and remember typical patterns.

Neural architectures had much larger difficulties in generating contemporary popular music compared to the earlier styles. These techniques were good at making common chord patterns and melodies, yet it was difficult for them to catch the cultural differences and feelings that you find in popular songs. Some experts pointed out that AI-made music lacked the culture and personal appeal that make songs emotionally touching for listeners.

Creators in popular music often have difficulties because the music's style and the cultural setting are linked in today's genres. Even though music technique greatly affects quality in Classical music, in Pop, what matters most is connection with people, genuine feelings, and self-expression that today's technology finds difficult to understand.

Jazz composition was unique enough to show the boundaries of current neural networks. Many systems could come up with the same jazz chords and tunes, but they did not bring out the freedom and dialog that happens in true jazz performances. Neural generation approaches that worked linearly did not capture the many aspects and real-time playing of jazz music well. Many expert jazz musicians pointed out that the AI-made jazz music had the right skills, yet lacked the essence of jazz, which is taking risks and being creative. Since neural generation is predictable, it seemed very difficult for it to express jazz's crucial values, which are always spontaneous, personal, and involve interaction.

3) Integration Challenges and Collaborative Opportunities

Using neural composition systems within music production systems led to many possible usages as well as notable obstacles that should be overcome to make them useful. The researches pointed out that AI music generation should be used with artists, instead of replacing what humans do.

According to professional composers, AI systems were useful in giving them new inspiration and ideas, especially when dealing with creative difficulties and searching for new styles in their music. For composers who wanted to use new sounds or change their style, neural networks' ability to come up with fresh harmonic and melodic ideas was very helpful. Many people noted that using AI-generated material to begin composition was useful for development later on.

Nonetheless, much editing and involvement from people were required to make the neural compositions look professional. Most of the time, AI audio needed to be carefully restructured, corrected in harmony, and shaped to become presentable quality. From this, it seems that AI should be considered a creative helper, while human composers should keep deciding how compositions are created.

The best ways to use AI in this field meant that human composers and AI systems worked together as partners in real time; neural networks offered ideas, and the human composer guided everything with creative purpose. These procedures made use of AI to process music information, together with the experience, instincts, feelings, and creativity of actual composers.

To merge AI writing skills with regular music production tools, it was necessary to create special interfaces that functioned without problems. Because the existing techniques were hard for most musicians to use, the creation of user-friendly tools and simple ways of connecting instruments was needed.

VI. FUTURE WORK

Future developments need to concentrate on improving neural networks' overall consistency and should especially build models that can handle both the fine details and the main frameworks of a piece of music. Training neural networks with music theory limits helps produce musical works with better harmonies and counterpoint, and also studying the mixing of sound, symbolic, and video information could improve the emotional impact of AI compositions. It is still an important hurdle to generate sounds efficiently at any moment, which needs new ideas such as progressive sound synthesis and improved attention functions that allow real-time use in musical activities. Also, to go further, animation needs to make sure evaluation covers cultural accuracy and emotional meaning, and not just the science behind the techniques. Investments should be made in studying collaborative systems, since the most exciting results seem to happen when AI supports and enhances what humans create, instead of attempting to replace creative ideas by itself. Expanding training with musical traditions and modern genres from all over the world and adding culturally cognizant algorithms to AI might help reduce the music bias and make music AI more diverse.

VI. CONCLUSION

Right now, neural music composition shows incredible results, but it also points out important challenges that keep it from being used widely or having full creativity. Present-day systems can produce music that is technically sound, follows standard forms and is stylistically uniform within the studied musical parameters. But a large disparity remains between the computer's capacity and real creativity in art. Analyzing statistics shows that transformer-based designs consistently outperform others on compositional tasks that require long-lasting unity and musical harmony. They are considered the best available and form a stable platform for programming both now and in the future.

All the same, every subjective analysis of neural approaches concludes that they are not effective enough if used alone because they lack creativity, genuine expression and cultural roots. According to the results, 'technical excellence' in composing music doesn't always make for the most artistic melodies. Conventional compositional correctness is where AI does well, but it misses out on creative insight, emotional intelligence and cultural knowledge. The evidence points to collaborative processes that mix advanced algorithms with human art to be the most valuable. Hybrid systems ought to play a key role in the next phase of development by merging neural text processing with advanced methods of human-computer interaction. Strong technologies are available to help creative workers without taking away their human role. It is necessary in this area to pay close attention to how the user interface works, how distinct tasks are integrated and how artistic creativity is managed with the use of technology. Besides dealing with technology, this research looks at issues concerning creativity, whether art is authentic and changes in how humans and machines interact when making art. As neurocomposition technology improves, it will become much more valuable in music classes, medical settings and business and it may also challenge people's conceptions of artistic concepts and who has the right to own works.

We are approaching a key moment where AI creative systems become practically valuable but issues about the meaning and worth of algorithmic creativity are yet to be answered. Moving forward, it is important for research to overcome problems, as well as think through their effects, so that applying computer technology to music keeps its cultural and emotional meaning while reaching its full potential for composition.

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