DYNAMIC SERVING OF CUSTOM STYLED CONTENT REPRESENTATION USING STYLE TRANSFER IN CONVOLUTIONAL NEURAL NETWORKS

V Sathya, Siddharth Singh, Anirudh Agarwal, Anirudha Deb, Pranab Kumar Shukla Department of Computer Science and Engineering, SRM Institute of Science and Technology,Chennai,India

ABSTRACT

User Interaction is increased in Digital Content providers by utilizing custom visual representation to aid recommend-er systems. Previously this was either done with systems that had a large amount of static media store. The proposed model utilizes convolutional neural networks to create a self generating media store which is then served as a micro- service endpoint to the end developer. We aim to propose a fully fledged L2 cache augmented service to aid the problem of custom styled content representation media distribution to increase user interaction.

KEYWORDS: Convolutional Neural Networks, Software as a Service

INTRODUCTION

Large Scale Digital content providers utilize artwork person- alization to tailor content representation media that increases the likelihood of user interaction.Such Systems have been used by Digital Distribution platforms like Netflix for a considerable amount of time. This has proven to not only increase user interaction but also help users stay with the digital content longer than originally possible since it removes the presuppositions that content usually have attached with themselves.[1][2] Large scale emergence of SAAS products have seen emergence in the market due to the advent of reasonably priced cloud infrastructure providers like Amazon Web Services and Microsoft Azure. Such emergence has also augmented these services to incorporate in them some preset Machine Learning Algorithms like those present in Amazon Sage Maker. This Paper plans to provide one such service endpoint mechanism for visual representation media and utilizes style transfer from convolutional neural networks for the same.

BACKGROUND

A. Convolutional Neural Networks

Convolutional Neural Network (ConvNet or CNN) is a special kind of neural system used effectively for image recognition and classification. They are highly proficient in areas like identification of objects, faces, and traffic signs apart from generating vision in selfdriving cars and robots too.Convolutional Neural Networks are a subclass of Deep Neural Networks that aid in automatic feature extraction with the help of trainable convolution filters. They are highly utilized in the field of visual imagery. A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a cnn commonly comprises of convolutional layers relu layer such as activation function, pooling layers, fully connected layers and normalization layers.

B. Cloud Computing

Cloud computing makes PC framework assets particularly capacity and computing power accessible on interest without direct dynamic administration by the client. The term is commonly used to depict data centers accessible to numerous clients over the web. Massive clouds, leading today, frequently have functions dispersed over different areas from central servers. In the event that the association with the client is moderately close it might be assigned an edge server.

Clouds may be restricted to only one organization, be available to numerous organizations or a mix of both. Cloud computing relies upon the sharing of assets to achieve level- headedness. Supporters of public endured clouds note that cloud computing permits companies to avoid or reduce up- front IT foundation costs. Advocates also guarantee that cloud computing enables ventures to get their applications going quicker, with improved manageabil-ity and less upkeep, and that it empowers IT teams to more quickly modify assets to fulfill fluctuating and eccentric demand. Cloud suppliers commonly use a pay-as-you-gomodel, which prompt to unexpected operating costs if can administrators are not acclimated with cloud-estimating models. The accessibility of high-limit networks, minimal effort computers and storage gadgets in addition to the across the board acceptance of hardware virtualization, service-oriented architecture, and self regulating and utility computing has bulged to development in cloud computing.

C. Software as a Service

Software as a service is used as a delivery and software authorizing model. Here, the software is authorized on basis of a subscription and is hosted centrally. It was originally called "on-demand software" or "software plus services". It is normally accessed by its users using a web browser. For some business applications it has become a delivery model, including messaging software, management software, develop- ment software, CAD software, gamification, talent acquisition, virtualization, accounting, collaboration, enterprise resource planning, invoicing, customer relationship management, human resource Geographic Information management, Systems, learning management systems, content management (CM) and service desk management.SaaS has been consolidated into the planning of almost all the leading software companies.

SaaS functions are also termed as Web-based software, hosted software and on-demand software. The term SaaS (Software as a Service) is viewed as a major aspect of the classification of distributed computing, alongside Desktop as Service, Platform as Service, [9] managed software as service, mobile backend as service, Infrastructure as Service.

PROPOSED WORK

A. System Architecture

The Convolutional Neural Network resides in a separate module that fetches all uploaded digital media from a central store. Which then periodically performs style transfer for every image in the store to generate a specific image for every sentimental demographic this is then supplied in a single transaction to the NOSQL Store, the NOSQL store can be utilized as a L2 Cache to allow faster retrieval for the endpoint. Subsequently permitting quicker access times for the service. This provides a PUSH CDN mechanism for the service. A push CDN relieves the developer from the responsibility of developing a efficient delivery mechanism for digital media content. This however assumes that such a mechanism is both affordable and already in place for the organisation providing a service that complies with our model. Since providing a CDN is essentially a financially non-trivial task it poses a major financial hurdle for the implementaion of our model.

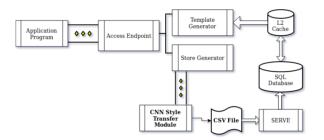


Fig. 1: System Architecture for the Service

We utilise the VGG19 model as discussed in the paper by Karen Simonyan[4]. One Interesting feature of the VGG19 model is that the depth of Convolutional Layer at every layer increases from left to right. Every last one of these filters are then used to calculate the loss function regarding the equation to be illustrated next.

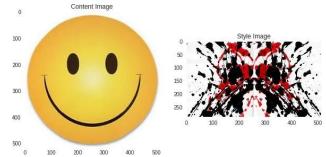
B. Neural Network

We utilise the VGG19 model as discussed in the paper by Karen Simonyan[4]. One Interesting feature of the VGG19 model is that the depth of Convolutional Layer at every layer increases from left to right. Every last one of these filters are then used to calculate the loss function regarding the equation to be illustrated next.

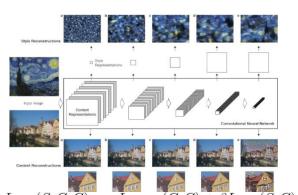
Fig. 2: Convolutional Filters of the Neural Network utilised[3]

C. The Loss Function

At every stage of the iteration all the three images i.e The Style Image, The Content Image and the Generated Image are passed to the network. The α and β parameters are used to curb the amount of the original picture and also the amount of style is to be preserved.



One almost always has to employ heuristics to decide



 $L_{total}(S, C, G) = \alpha L_{content}(C, G) + \beta L_{style}(S, G)$ on that since visually determining the most appeasing configuration is a non-trivial task.

Fig. 3: Loss function of the CNN

RESULT ANALYSIS

The Sample set consisted of 72 Images of Digital Art and 19 Rorschach Test styled Ink Blots. The



Emotionally Light arts were generated by using the style images from the very same pool of Images as the Digital Art while to generate Emotionally Dark Images the Rorschach Test Style Pool was used. The Following section analyses the results from both the visual aesthetic viewpoint and the quantitative viewpoint for web servers.

A. Visual Results

The Neural Network was able to perform well with images that contain abstract digital aesthetic when style is concerned like the inkblots for style references on cartoon-ish images like the Smileys. One such result is discussed below.

Fig. 4: Smiley on the Left and Ink Blot for Style Reference The generation of digital representation media is a computationally intensive task and for this very specific reason the system architecture had the network as a separate module rather than including it in the server endpoint. The gener- ated images are fetched from the CSV file after particular intervals, we choose this period to be 4 minutes since we were conducting controlled tests in a simulated quantitative lab environment. But in practical world one could increase or decrease the period depending on how often they serve new content. Image 5 was generated by the network.

Another test for dark aesthetic was to see if the module could handle real world objects (Fig 6) and preserve their visual authenticity.

The Neural Transfer was although able to create an aesthetically valid image (Fig 7) for the purpose but it wasn't able to completely preserve the visual features of real world entities.

Fig. 5: The Aesthetically Dark Representation of the Smiley

Fig. 6: A Manhattan Skyline and A Dark Sea for Style Transfer

Fig. 7: The Aesthetically Dark Representation of the City

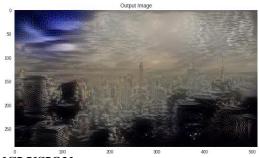
B. Server Semantics

Fig. 8: Response Time Statistics

The Response time for User Page Template Generation is illustrated by the above statistic.

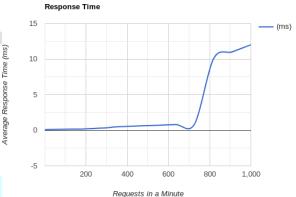
We've tested the module from 1 to 1000 requests. It took the web server 0.1 ms for a single request the web server times started to increase rapidly as the number of requests go high. The implementation of L2 Cache and distribution of the requests however affects performance can its effect can be seen from the graph.

There are some cases even when high traffic still shows significant performance boost.



CONCLUSION

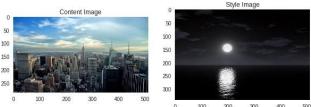
The proposed model is an effort to improve the performance times of the Digital Representation Media



Serving while providing a backdrop for a real time implementation which can be utilized to provide a software solution capable of producing accurate, meaningful fast interactive results.

ACKNOWLEDGEMENT

The Authors would like to thank Mrs. V Sathya and the Department of Computer Science and Engineering at the SRM Institute of Science and Technology for their valuable guidance and gracious support throughout the whole process of the project.



And also acknowledge their further involvement in the future development of the project.

REFERENCES

 Leidy Esperanza Molina Fernndez, "Recommendation System For Netflix", Biomed. Opt. Express 1, 658-675 (2010)

[2] L. Li, W. Chu, J. Langford, And X. Wang, Unbiased Offline Evaluation Of Contextual-Bandit-Based News Article Recommendation Algorithms, In Proceedings Of The Fourth Acm International Conference On Web Search And Data Mining, New York, Ny, Usa, 2011, Pp. 297306.

[3] A Neural Algorithm Of Artistic Style Leon A.Gatys Arxiv:1508.06576

[4] Very Deep Convolutional Networks For Large-Scale Image Recognition - Karen Simonyan AndrewZisserman

[5] Paolo Cremonesi, Yehuda Koren, Roberto Turrin"Performance Of Recom- Mender Algorithms On Top-N Recommendation Tasks," September 26-30, 2010, Barcelona, Spain [Doi 10.1145/1864708.1864721]

[6] Paolo Massa, Paolo Avesani "Trust-Aware
Recommender Systems, "Min-Neapolis, Mn, Usa
October 19 - 20, 2007 Acm New York, Ny, Usa 2007
[Doi 10.1145/1297231.1297235]

[7] Mohsen Jamali, Martin Ester"A Matrix Factorization Technique With Trust Propagation For Recommendation In Social Networks, "Barcelona, Spain September 26 - 30, 2010 Acm New York, Ny, Usa 2010 [Doi 10.1145/1864708.1864736]

[8] Alexandros Karatzoglou, Xavier Amatriain,
Linas Baltrunas, Nuria Oliver"Multiverse
Recommendation: N-Dimensional Tensor FactorizaTion For Context-Aware Collaborative Filtering,"
Barcelona, Spain September 26 - 30, 2010 Acm New
York, Ny, Usa 2010 [Doi 10.1145/1864708.1864727]