SmallSEOTools

PLAGIARISM SCAN REPORT

Words	915	Date	April 22,2021
Characters	5961	Excluded URL	

2% Plagiarism	98% Unique	1 Plagiarized Sentences	55 Unique Sentences

Content Checked For Plagiarism

2.2 MAJOR CONSTRAINTS
• The astronomical image data required for training purposes is mostly raw. There exists no structured dataset that is already cleaned. The unavailability of a dataset is a major constraint for the project
• Scraped data from the archives is noisy and requires heavy processing and cleaning in order to be usable by the model
• The images available for download are of low resolution, which sets an upper bound on the maximal upscale factor
• The image data is large and needs high computation power to process
• The data needs to be cleaned manually as there exist no methods to automatically do this particular task
• The model involves neural networks which heavily rely on computation power for its training. The hardware required for training is not readily available because of absence of a workstation supporting heavy computations
• The training part requires large amount of memory
• Absence of an NVIDIA workstation GPU will slow down the training further
2.3 METHODOLOGIES OF PROBLEM SOLVING AND EFFICIENCY ISSUES
• Data gathering and processing
– Data Scraping
* Owing to unavailability of a dataset, raw data can be acquired by the means of web scraping
* Images from the snapshots of entire night sky can be obtained in such a way from the Hubble Legacy Archive
– Data Cleaning
* The scraped data consists of snapshots of the entire night sky with 1 degree deviation of the telescope
* This results in large amount of noisy, overexposed, irregular data images
* This data needs to be cleaned manually before it can be used for any kind of study
• Image colorization
– The problem of image colorization has been solved using multiple methodologies
– [10] used convolutional neural networks with residual encoders using the VGG16 architecture
– Though the system performs extremely well in realistically colorizing various images, it consisted of L2 loss which was a function of the Euclidean distance between the pixel’s blurred color channel value in the target and predicted image
L2loss =

nå
i=1
(ytrue□ypredicted)2 (2.1)
– This is a regression based approach and the pixel-wise L2 loss will impose
an averaging effect over all possible candidates and will result in
dimmer and patchy colorization
– Generative Adversarial Networks introduced by [13] use a minimax loss
which is different than the L2 loss as it will choose a color to fill an area
rather than averaging. This is similar to a classification based approach
• Image Upscaling
– One of the most popular approach to image upscaling was sparse-coding.
This approach assumes that images can be sparsely represented by a dictionary
of atoms in some transformed domain [21]. The dictionary is
learned during the training process.
– The main drawback for this was that the optimization algorithm was
computationally expensive
– Dong et. al explored super-resolution using convolutional neural network
and calling it SRCNN [22]. They explained how CNN had many similarities to the sparse-coding-based super-resolution.
– Kim et. al improved upon SRCNN's results using their very own model
inspired from the VGG-net architecture[23].
– After the introduction of GANs, Ledig et. al applied them to superresolution
(SRGAN) using a network inspired by the ResNets [20][12].
– SR-GAN works well with for single image super-resolution as it also
uses an intelligent content loss function that uses pre-trained VGG-net
layers. However, Ledig et. al noted that further information could be
used if this network were to be adapted to a video, such as temporal
information.
• A generative network, G, is meant to learn the underlying distribution of a data
set, Y. For e.g. we can train a GAN over face images to generate images similar
to those faces. With just a generative network however, we must visually
assess the quality of network outputs and judge how we can adapt the network
to produce more convincing results.
• With a discriminative network D, we can incorporate this tweaking directly
into training. The discriminative network takes in both fabricated inputs generated
by G and the real inputs from Y. It's sole purpose is to classify if the
input has come from G or Y.
• The key idea is back propagation of the gradients from the results of D's classification
to G so that G gets better at producing images and in turn fooling
D.
• For the project, we split the data into two categories: X that serves as the data
for the Y, which are its corresponding labels.
• G1 takes in a low resolution x 2 X which is black & white and produces ˆ y,
a colorized version of x. The descriminator D, in turn takes in a colorized
image and outputs the probability that the image comes from Y, instead of as
outputs from G, G(x). As such, if the discriminator is fooled by out generator, it should output a probability greater than 0.5 for the set of inputs coming from
G(x) and a probability less than 0.5 for images coming from Y.
• The same is the process for generator G2 with the only difference being that
the X is the set of colorized images but having low resolution and Y is the
set of high resolution images that serve as the labels for underlying mapping
of X. G2 takes in the low resolution image x 2 X and produces ˆ y and the
discriminator outputs a probability determining whether the image is superresolved
by G2 or the ground truth images from Y.

Sources	Similarity
Super-Resolution on Image and Video must then visually assess the quality of network outputs and judge how we can adapt the network to produce more con-vincing results. With a discriminative network, D, we can incorporate this tweaking directly into training. The discriminative net-work takes in both fabricated inputs generated by G and inputs coming from the "real" dataset, Y. Its purpose is to http://cs231n.stanford.edu/reports/2017/pdfs/312.pdf	3%