Google Wachine Learning

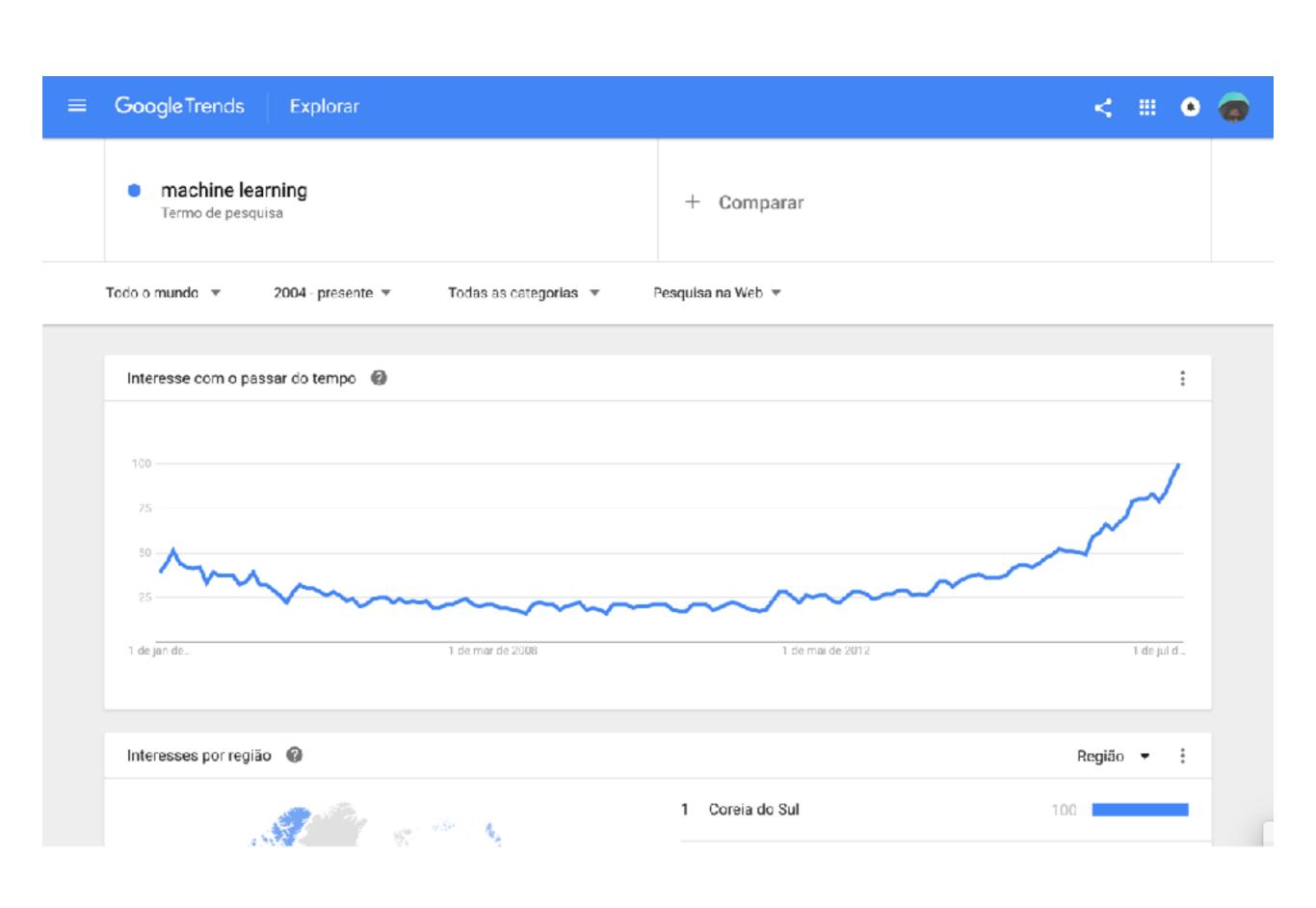
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Maria Clara



- Embaixadora Auth0;
- Women Techmakers Lead;
- Entusiasta de Machine Learning;



Bringing Impressionism to Life with Neural Style Transfer in Come Swim

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Figure 1: Usage of Neural Style Transfer in Come Swim; left: content image, middle: style image, right: upsampled result. Images used with permission, (c) 2017 Starlight Studios LLC & Kristen Stewart.

Abstract

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Neural Style Transfer is a striking, recently-developed technique that uses neural networks to artistically redraw an image in the style of a source style image. This paper explores the use of this technique in a production setting, applying Neural Style Transfer to redraw key scenes in Come Swim in the style of the impressionistic painting that inspired the film. We document how the technique can be driven within the framework of an iterative creative process to achieve a desired look, and propose a mapping of the broad parameter space to a key set of creative controls. We hope that this mapping can provide insights into priorities for future research.

Keywords: style transfer, rendering, applied computer graphics

Concepts: •Computing methodologies → Computer graphics; Image-based rendering; •Applied computing → Media arts;

1 Introduction

In Image Style Transfer Using Convolutional Neural Networks, Gatys et al [Gatys et al. 2015] outline a novel technique using convolutional neural networks to re-draw a centent image in the broad artistic style of a single style image. A wide range of implementations have been made freely available [Liu 2016; Johnson 2015; Athalye 2015], based varyingly on different neural network evaluators such as Caffe [Jia et al. 2014] and Tensorflow [Abadi and et al. 2016] and wrappers such as Torch and PyCaffe [Bahrampour et al. 2015]. There has been a strong focus on automatic techniques, even with extensions to otherently process video [Ruder et al. 2016].

execute efficiently and predictably. In a production setting, however, a great deal of creative control is needed to tune the result, and a rigid set of algorithmic constraints run counter to the need for this creative exploration. While early investigations to better map the low-level neural net evaluations to stylistic effects are underway [Li et al. 2017], in our paper we focused on examining the higher-level parameter space for Neural Style Transfer and found a set of working shortcuts to map them to a reduced but meaningful set of creative controls.

2 Realizing Directorial Intent

Come Swim is a poetic, impressionistic portrait of a heartbroken man underwater. The film itself is grounded in a painting (figure 2 by coauthor Kristen Stewart) of man rousing from sleep. We take a novel artistic step by applying Neural Style Transfer to redraw key scenes in the movie in the style of the painting, realizing them almost literally pointing that underpins the film.

The painting itself evokes the thoughts an individual has in the first moments of waking (fading in-between dreams and reality), and this theme is explored in the introductory and final scenes where this technique is applied. This directly drove the look of the shot, leading us to map the emotions we wanted to evoke to parameters in the algorithm as well as making use of more conventional techniques in the 2D compositing stage.



Google Cloud APIs

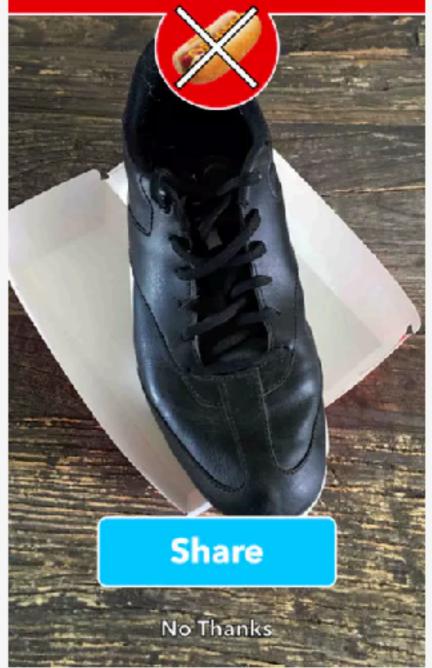
Vision API



- · Detecção de faces;
- Detecção de logomarcas;
- Detecção de labels;
- · Detecção de texto;
- · etc...

Hotdog! Share No Thanks

Not hotdog!



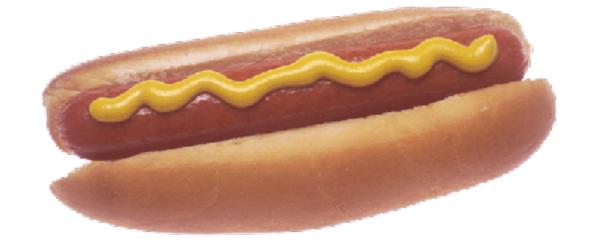
```
from google.cloud import vision
vision_client = vision.Client()

def detect_labels_uri(uri):
   image = vision_client.image(source_uri=uri)

labels = image.detect_labels()
```

python vision-api.py labels-uri imageuri





Output:

Labels: frankfurter würstchen, hot dog, bockwurst, knackwurst, sausage, kielbasa, cervelat, german food, hot dog bun, chilidog

```
def detect_faces_uri(uri):
    image = vision_client.image(source_uri=uri)
    faces = image.detect_faces()
def detect_text_uri(uri):
    image = vision_client.image(source_uri=uri)
    texts = image.detect_text()
def detect_logos_uri(uri):
    image = vision_client.image(source_uri=uri)
    logos = image.detect_logos()
```

python vision-api.py faces-uri imageuri





Output:

Faces:

anger: Likelihood.VERY_UNLIKELY

joy: Likelihood.VERY_LIKELY

surprise: Likelihood.VERY_UNLIKELY

face bounds: (794,98),(992,98),(992,328),

(794, 328)





Natural Language API



- · Análise de sentimento;
- · Análise de entidades;
- · Análise de sintaxe;

python natural-language-api.py
sentiment sample.txt



sample.txt > "My hope is that the
 sequels are actual attempts at
movies. The world doesn't need any
 more toothless cinema."

Output:

Overall Sentiment: score of 0.2 with magnitude of 0.4

python natural-language-api.py entities
sample.txt



sample.txt > "My hope is that the
 sequels are actual attempts at
movies. The world doesn't need any
 more toothless cinema."

Output:

```
Entity: 0, name: hope, salience: 0.4828899
Entity: 1, name: sequels, salience: 0.17383586
Entity: 2, name: movies, salience: 0.13395432
Entity: 3, name: attempts, salience: 0.123159915
Entity: 4, name: world, salience: 0.05997689
Entity: 5, name: cinema, salience: 0.026183115
```

Speech API



- Reconhecimento síncrono;
- Reconhecimento assíncrono;
- Reconhecimento via streaming;

```
def transcribe_speech_sync(speech_file):
    with io.open(speech_file, 'rb') as audio_file:
        content = audio file.read()
        audio_sample = speech_client.sample(
            content=content,
            source_uri=None,
            encoding='LINEAR16',
            sample rate hertz=16000)
    alternatives = audio_sample.recognize('en-US')
```

```
python speech-api.py resources/
speech_sync_sample.raw
```



speech_sync_sample.raw > "how old
 is the Brooklyn Bridge"

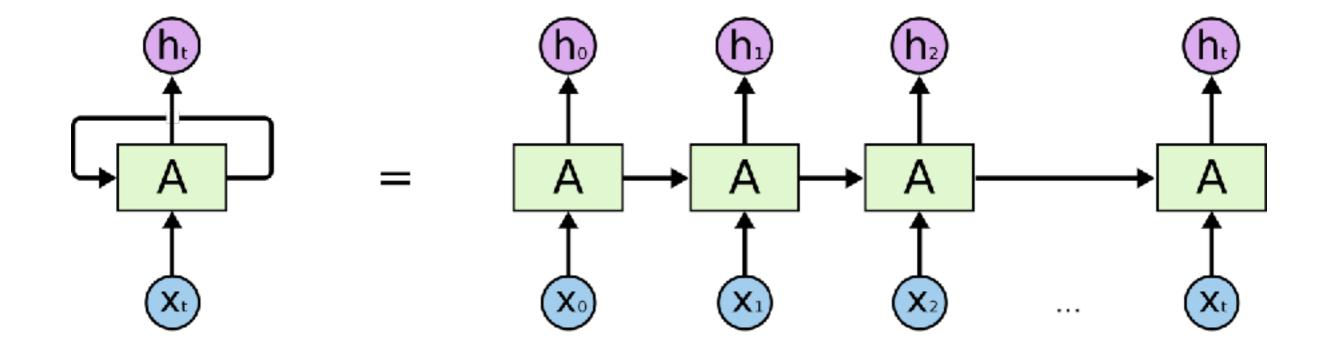
Output:

Transcript: how old is the Brooklyn Bridge,

Confidence: 0.987628996372

Comprimindo imagens com Redes Neurais Recorrentes

Redes Neurais Recorrentes



Vamos comprimir imagens!

Imagem original

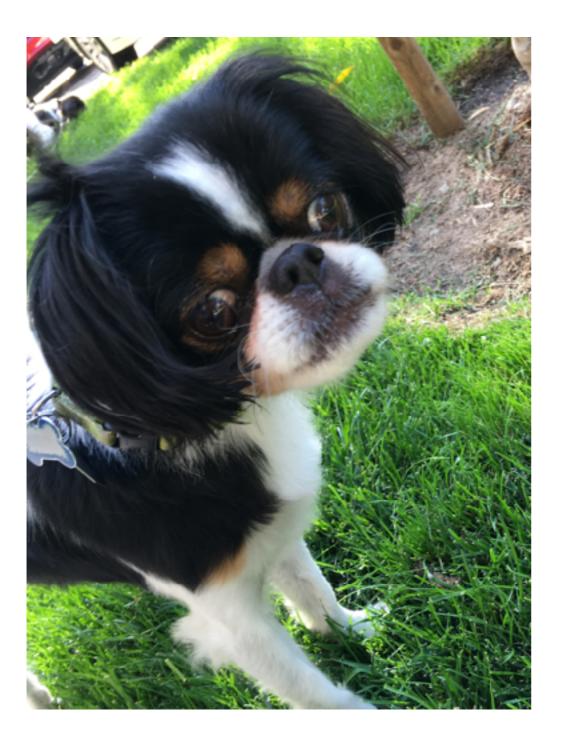


Imagem comprimida

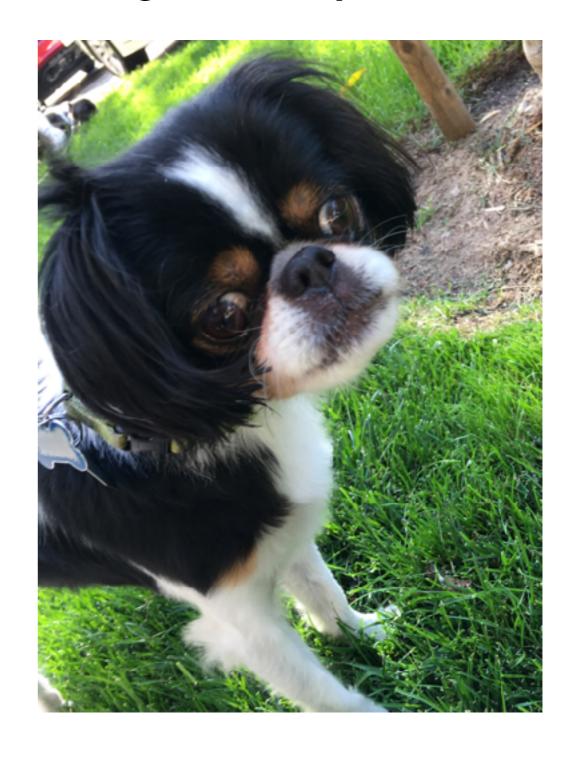


Imagem original

Imagem comprimida

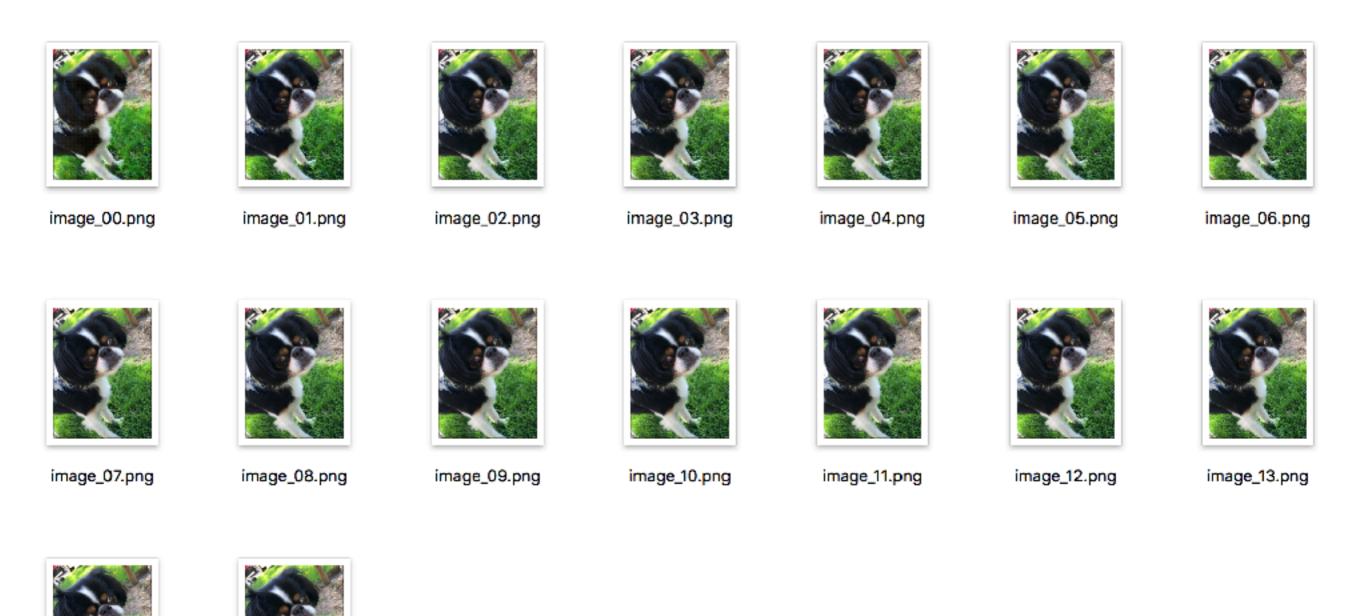
Kind: Portable Network Graphics image Size: 3.155.141 bytes (3,2 MB on disk) Where: iCloud Drive • Documents • gdg- compression • image_encoder Created: Today 00:36 Modified: Today 00:36 Stationery pad Locked	Kind: Portable Network Graphics image Size: 1.357.267 bytes (1,4 MB on disk) Where: iCloud Drive ➤ Desktop Created: Today 01:16 Modified: Today 01:16 Stationery pad Locked
▼ More Info: Last opened: Today 01:42	▼ More Info: Dimensions: 768 × 1024
Dimensions: 768 × 1024	Color space: RGB

Composição do Sistema

- Encoder (E);
- Binarizer (B);
- Decoder (D);

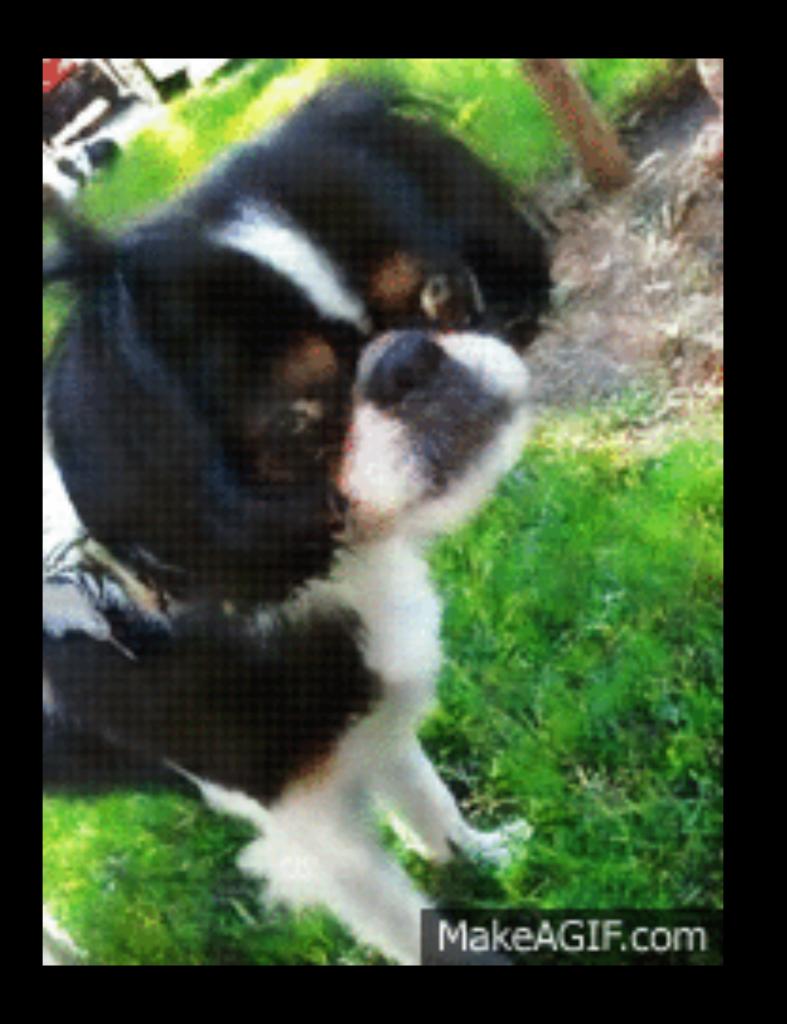
Residual Gated Recurrent Unit

Iteration	ВРР	Compression Ratio
0	0.125	192:1
1	0.250	96:1
2	0.375	64:1
3	0.500	48:1
4	0.625	38.4:1
5	0.750	32:1
6	0.875	27.4:1
7	1.000	24:1
8	1.125	21.3:1
9	1.250	19.2:1
10	1.375	17.4:1
11	1.500	16:1
12	1.625	14.7:1
13	1.750	13.7:1
14	1.875	12.8:1
15	2.000	12:1



image_14.png

image_15.png



Verificando a similaridade entre as imagens:

• MM-SSIM (multi-space structural similarity)
rate = 0.990523568071;

Obrigada.



https://olarclara.github.io