Artistic style transfer for videos

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Introduction

Figure: Prisma, the App for AI Powered Art Styles

Introduction

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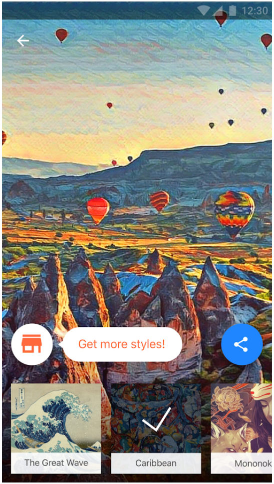

Outline

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Biological vision for Neural Networks

We use Convolutional Neural Networks

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- Many layers of processing units

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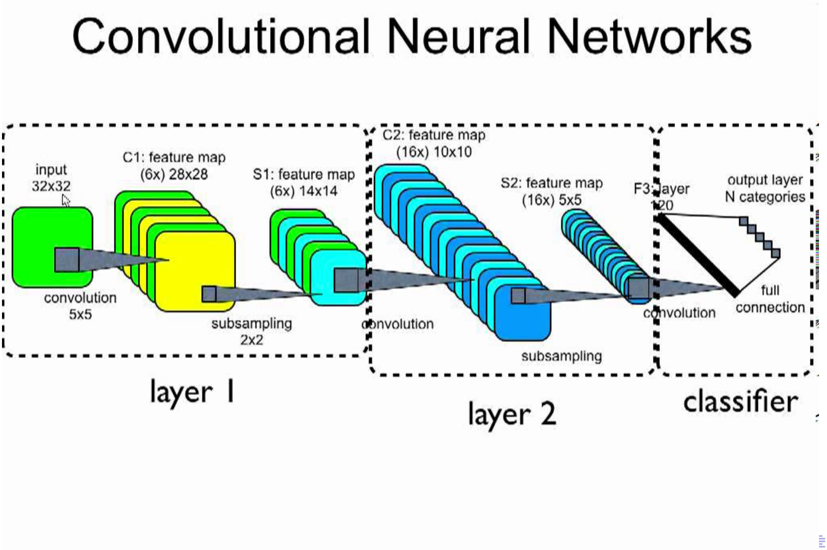
- Each unit applies image filters

Biological vision for Neural Networks

We use Convolutional Neural Networks

- Many layers of processing units
- Each unit applies image filters
- Output: Feature map

Biological vision for Neural Networks



Biological vision for Neural Networks

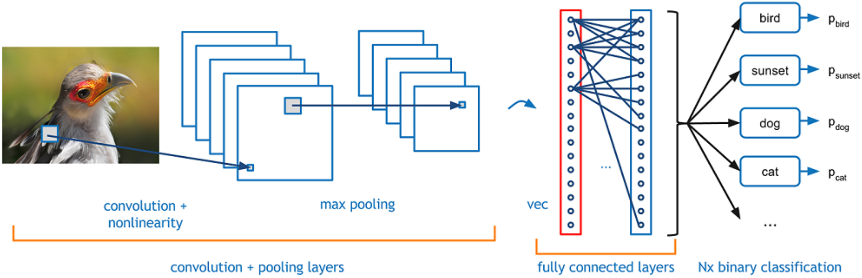


Figure: Work of a CNN

Content and Style

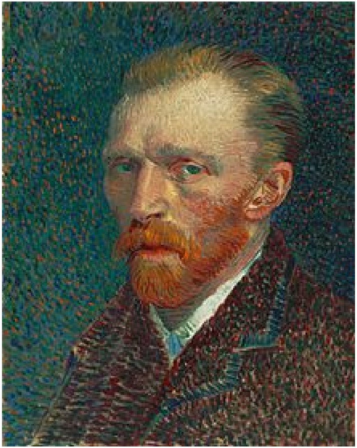


Figure: Van Gogh self-portrait

Difference between content and style?

Content and Style

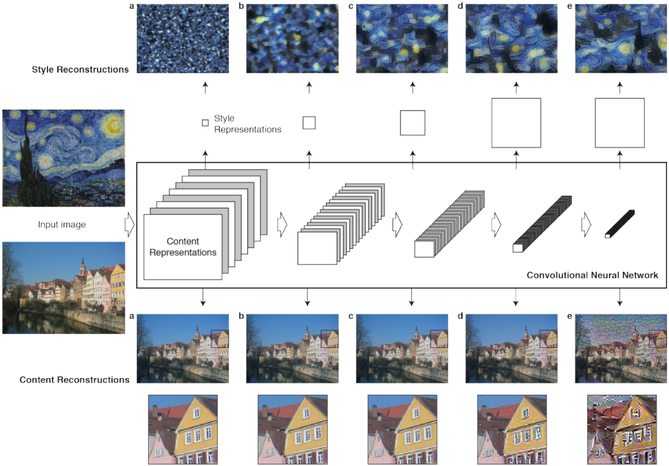


Figure: Model for the network [1]

Content and Style

Result:

- Representations of content and style in CNNs are separable

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Result:

- Representations of content and style in CNNs are separable
- Both representations can be changed independently.
- $\longrightarrow$ Mix style and content of two source images

Content and Style

Content reconstruction

Notation:

- $\vec{p}$ = Original Picture, $\vec{x}$ = initial random image
- P^l and F^l feature representation in layer l

Content reconstruction: Encode $\vec{x}$ until it generates the same response in some layers of the CNN as $\vec{p}$

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- Set $\vec{x}$ to a white noise image

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- $\overrightarrow{p}$ = Original Picture, $\overrightarrow{x}$ = initial random image
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- Set $\overrightarrow{x}$ to a white noise image
- Perform gradient descent on the image
- $\longrightarrow$ find $\overrightarrow{x}$ that matches feature responses of $\overrightarrow{p}$

Style reconstruction

- For style reconstruction we basically do the same
- Perform gradient descent on the image
- find $\vec{x}$ that matches style representation of original image

Content and style

In total: When $\vec{p}$ is the photograph and $\vec{a}$ is the artwork, we try to minimise the loss function:

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

Encoding of one image

Outline

Differences in video recognition

- First approach: Process each frame individually

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- $\rightarrow$ flickering and false continuities

Differences in video recognition

Specific Problems

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- Every frame is initialized with an independent white noise picture
  $\longrightarrow$ every frame converges differently
- Idea: Initialize the optimization for the frame $i+1$ with the stylized frame i
- Result: Problem with movement of objects

Short-term consistency

- Estimate optical flow
- $\longrightarrow$ Warp previous frame: $x'^{(i+1)} = \omega_i^{i+1}(x^{(i)})$

Temporal consistency

- Stronger consistency between frames needed
- In some areas we can estimate optical flow with high confidence
- $\longrightarrow$ extra Loss-function
- Calculate flow forward and backward $\rightarrow$ should be approximately the same in areas without occlusion

Long-term consistency

Temporally occluded ares should get the same style as before they got occluded.

$\longrightarrow$ Punish deviations from older frames

Multi-pass algorithm

Problem: low contrast, image boundaries less diverse

$\longrightarrow$ Process sequence multiple times and with different directions

Examples

Outline

Conclusion

Style transfer in Videos:

- suitable initialization
- shortterm consistency
- longterm consistency
- $\longrightarrow$ Production of stable and stylized videos possible

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References

- L. A. G. et al., "A neural algorithm of artistic style."
- [Online]. Available: https://en.wikipedia.org/wiki/Vincent_van_Gogh#/media/File:Vincent_van_Gogh_-_Self-Portrait_-_Google_Art_Project_(454045).jpg
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