Artistic Style Transfer

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MLRG Fall 2016

Outline

Introduction

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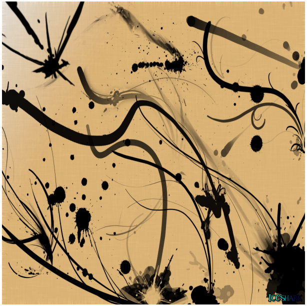

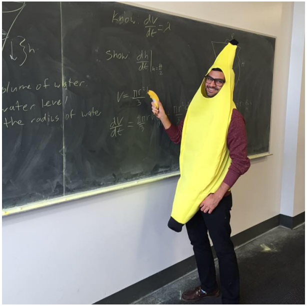

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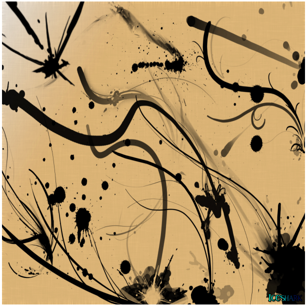

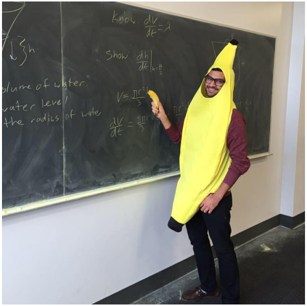

This is a very difficult task for humans, even talented ones.

Our goal is to teach a computer to do exactly this.

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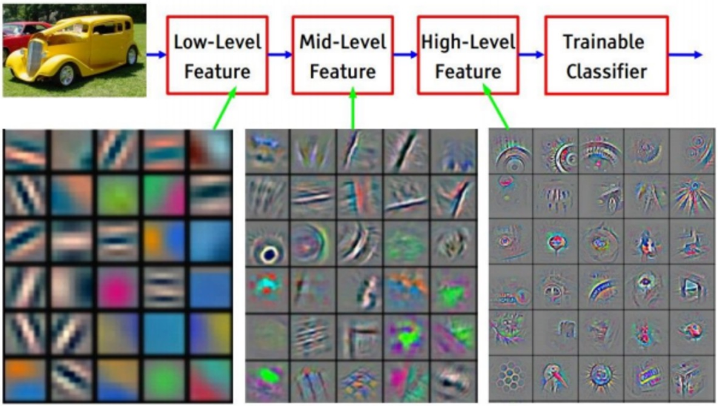
Typically the deeper we go in the network, high level content is identified as opposed to just pixel values.

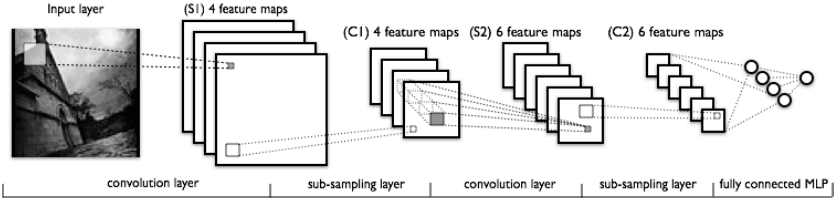
CNN Overview



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Feature Maps

Suppose layer l of the network has N_l filters, we will refer the collection of filtered images the **feature maps** at layer l.



VGG Network

The content generated in this talk was done using the VGG-19 network without the fully connected layer. Implementations in Lenet and Resnet also exist.

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Properties of VGG.

- Won ImageNet with a 7.3% top 5 error rate.
- Only 3x3 Conv stride 1, pad 1
- 2x2 MAX POOL stride 2
- 140 Million parameters

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We will make precise what we mean by style and content, but first, let us set up the problem formally.

Notation

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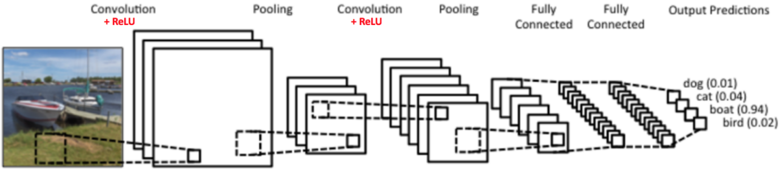
Our aim to is to construct an image $\mathbf{x}$ with the content of image $\mathbf{p}$ in the style of image $\mathbf{a}$.

We suppose that in our network, layer l has N_l filters, each with spatial dimension M_l (the product of its width and height).



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The feature maps extracted by the network from the original image $\mathbf{p}$, the style image $\mathbf{a}$ and the stylized image $\mathbf{x}$ we denote by $\mathbf{P}^l$, $\mathbf{S}^l$, and $\mathbf{F}^l$ respectively.

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The dimensionality of these feature maps is $N_l \times M_l$.

Content Representation

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We will say $\mathbf{x}$ matches the content of $\mathbf{p}$ at layer l, if their feature responses at layer l of the network are the same.

Content Loss

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We define the content loss at layer l to be,

$$\begin{aligned}\mathcal{L}^l_c(\mathbf{x}, \mathbf{p}) &= \frac{1}{2N_l M_l} \|\Phi^l(\mathbf{x}) - \Phi^l(\mathbf{p})\|_2^2 \\ &= \frac{1}{2N_l M_l} \sum_{i,j} |F^l_{ij} - P^l_{ij}|^2\end{aligned}$$

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We define our content reconstruction $\mathbf{x}^l_c$ to be

$$\mathbf{x}^l_c = \mathrm{argmin}_{\mathbf{x}} \mathcal{L}^l_c(\mathbf{x}, \mathbf{p})$$

Content Loss

We have $\mathcal{L}_c^l$ satisfies

$$\frac{\partial \mathcal{L}_c^l}{\partial F_{ij}^l} = \begin{cases} (\mathbf{F}^l - \mathbf{P}^l)_{ij} & F_{ij}^l > 0 \\ 0 & F_{ij}^l < 0 \end{cases}$$

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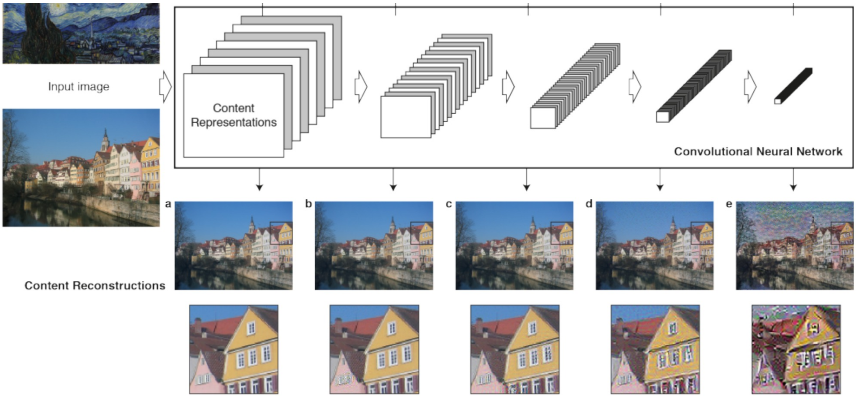
Normally $\mathbf{x}$ is initialized as a Gaussian white noise.

Content Reconstruction



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The feature responses in higher layers better encode the content of the image.

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The feature responses of an image **a** at layer l encode the content, however to determine style we are less interested in any individual feature of our image but rather how they all relate to each other.

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This was the main insight of Gatys, et al.

Style Representation

We will encode the correlations of the feature maps into the Graham Matrices,

$$A_{ij}^{l} = \mathbf{S}_{i\bullet}^{l} \cdot \mathbf{S}_{j\bullet}^{l} = \sum_{k=1}^{M_l} S_{ik}^{l} S_{jk}^{l}$$

$$G_{ij}^{l} = \mathbf{F}_{i\bullet}^{l} \cdot \mathbf{F}_{j\bullet}^{l} = \sum_{k=1}^{M_l} F_{ik}^{l} F_{jk}^{l}$$

$\mathbf{A}^l$ and $\mathbf{G}^l$ define a $N_l \times N_l$ dimension matrix, where N_l is the number of filters in layer l.

Style Loss

We define the style loss at layer l to be,

$$\begin{aligned}\mathcal{L}_s^l(\mathbf{x}, \mathbf{a}) &= \frac{1}{4N_l^2 M_l^2} \|\mathbf{G}^l - \mathbf{A}^l\|_F^2 \\ &= \frac{1}{4N_l^2 M_l^2} \sum_{i,j} |G_{ij}^l - A_{ij}^l|^2\end{aligned}$$

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$$\mathbf{x}_s^l = \mathrm{argmin}_{\mathbf{x}} \mathcal{L}_s^l(\mathbf{x}, \mathbf{a})$$

Style Loss

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$$\frac{\partial \mathcal{L}_s^l}{\partial F_{ij}^l} = \begin{cases} \frac{1}{N_l^2 M_l^2}((\mathbf{F}^l)^T(\mathbf{G}^l - \mathbf{A}^l))_{ij} & \mathbf{F}_{ij}^l > 0 \\ 0 & \mathbf{F}_{ij}^l < 0 \end{cases}$$

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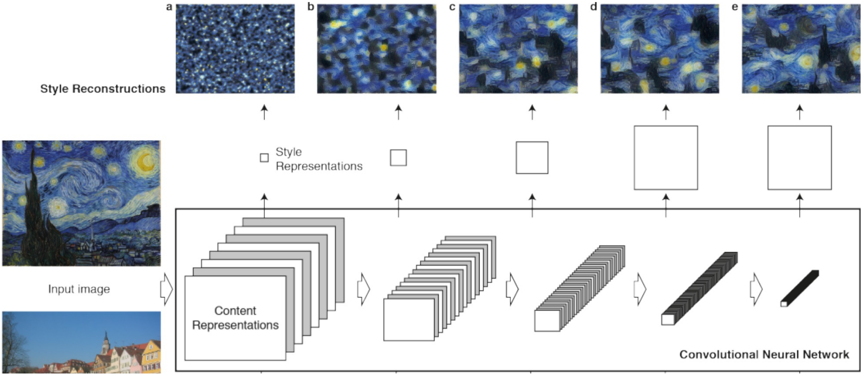
We can use back propagation and descent methods to iteratively minimize $\mathcal{L}_s^l$ and learn $\mathbf{x}_s^l$

Style Reconstruction



Style Reconstruction

Note the size and complexity of local image structures from the input image increases along the hierarchy.

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Heuristically, the higher layers learn more complex features than lower layers, and produce a more detailed style representation.

Image Construction

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We will define our content (style) loss as the weighted average of the style (content) loss at each layer.

$$\mathcal{L}_c(\mathbf{x}, \mathbf{p}) = \sum_l \alpha^l \mathcal{L}_c^l(\mathbf{x}, \mathbf{p})$$

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Often we take the $\alpha^l = 0$ for low l, and $\beta^l = 1$.

Image Construction

To match the content we need to minimize $\mathcal{L}_c$ and to match the style we need to minimize $\mathcal{L}_s$. Therefore we will minimize both simultaneously by minimizing

$$\mathcal{L}(\mathbf{x}, \mathbf{p}, \mathbf{a}) = \alpha \mathcal{L}_c(\mathbf{x}, \mathbf{p}) + \beta \mathcal{L}_s(\mathbf{x}, \mathbf{a}).$$

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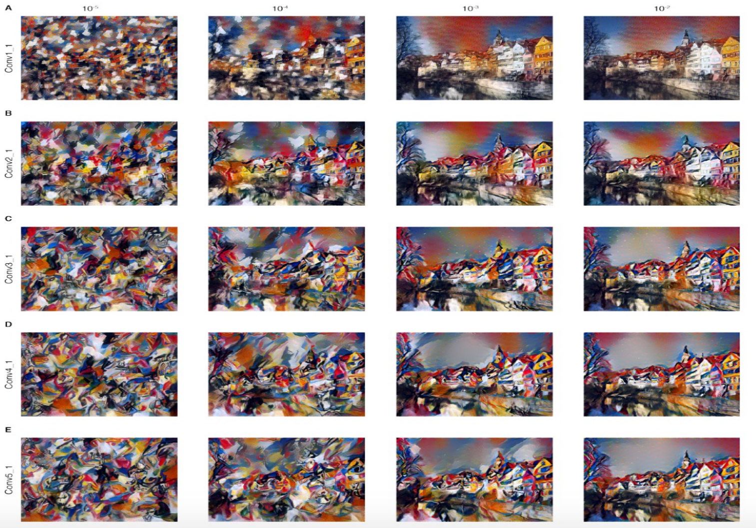

Figure: Columns: $\frac{\alpha}{\beta}$. Row: Layer of network

Examples

B

Figure: **Left:** Neckarfront in Tubingen, Germany, **B:** *The Shipwreck of the Minotaur* by J.M.W. Turner, 1805

Examples

c

Figure: **Left:** Neckarfront in Tubingen, Germany, **C:** *The Starry Night* by Vincent van Gogh, 1889

Examples

D

Figure: **Left:** Neckarfront in Tubingen, Germany, **D:** *Der Schrei* by Edvard Munch, 1893

Examples

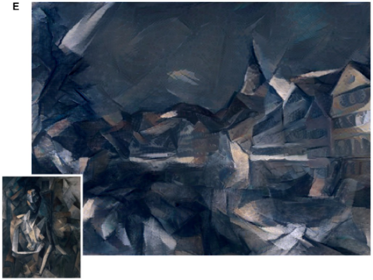

Figure: **Left:** Neckarfront in Tubingen, Germany, **E:** *Femme nue assise* by Pablo Picasso, 1910

Examples

F

Figure: **Left:** Neckarfront in Tubingen, Germany, **F:** *Composition VII* by Wassily Kandinsky, 1913

Examples

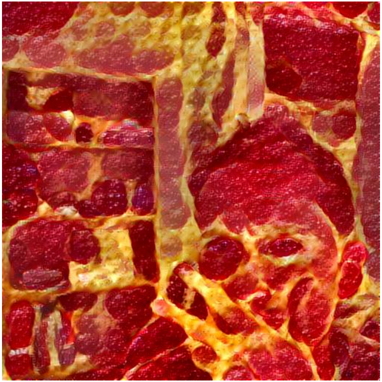

Figure: **Left:** My friend Grant, **Right:** Grant as a pizza

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Some examples include:

- “Combining Markov Random Fields and Convolutional Neural Networks for Image Synthesis” (Li and Wand, Jan 2016)
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Following Gatys, et al. Li and Wand, tried to match the content and style simultaneously by trying to minimize a linear combination of content and style loss function in addition to a regularizer.

$$\mathcal{L}^{MRF}(\mathbf{x}, \mathbf{p}, \mathbf{a}) = \alpha \mathcal{L}_c(\mathbf{x}, \mathbf{p}) + \beta \tilde{\mathcal{L}}_s(\mathbf{x}, \mathbf{a}) + \lambda R(\mathbf{x})$$

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Where $\mathcal{L}_c$ is the same content loss function used in the Gatys construction.

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The patches are of dimension $k \times k \times N_l$, where k is the width and height of the patch (typically k is small) and N_l is the number of filters in layer l.

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The patches are of dimension $k \times k \times N_l$, where k is the width and height of the patch (typically k is small) and N_l is the number of filters in layer l.

Our goal will be to match patches of $\Phi^l(\mathbf{x})$ to $\Phi^l(\mathbf{a})$ in some layer l.

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Given i, we define $NN(i)$ to be the position of the patch in $\Psi(\Phi^l(\mathbf{a}))$ that deviates the most from from $\Psi_i(\Phi^l(\mathbf{x}))$. I.e.

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$$NN(i) = \mathrm{argmin}_j \frac{\Psi_i(\Phi^l(\mathbf{x})) \cdot \Psi_j(\Phi^l(\mathbf{a}))}{|\Psi_i(\Phi^l(\mathbf{x}))| \cdot |\Psi_j(\Phi^l(\mathbf{a}))|}$$

So we define $\tilde{\mathcal{L}}_s$ to be

$$\tilde{\mathcal{L}}_s(\mathbf{x}, \mathbf{a}) = \sum_{i=1}^{m_l} \|\Psi_i(\Phi^l(\mathbf{x})) - \Psi_{NN(i)}(\Phi^l(\mathbf{a}))\|^2$$

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There is smoothness in the image when $\|\Delta \mathbf{x}\|_2^2$ is small, so we let

$$R(\mathbf{x}) = \|\Delta \mathbf{x}\|_2^2 = \sum_{i,j} (x_{i+1,j} - x_{i,j})^2 + (x_{i,j+1} - x_{i,j})^2$$

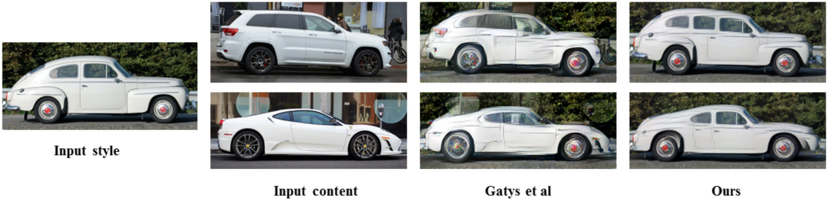
Examples

Input A   Input B   Content A + Style B   Content B + Style A

Examples

Content Image Gatys et al Ours

Examples



Input style — Input content — Gatys et al — Ours

Examples

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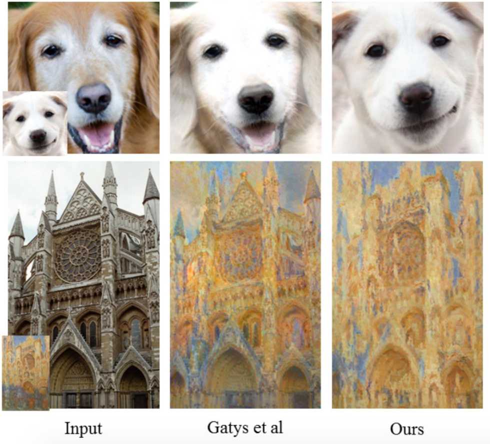

Figure: Example of Gatys, et al performing better

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Artistic Style Transfer for Video

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The two main issues we will have to deal with is the initialization of the optimization procedure and the temporal consistency between frames.

Notation

We use the following notation: Let $\mathbf{p}$ be the content video with frames $\mathbf{p}^i$, and $\mathbf{a}$ be the style image. We want to create a video $\mathbf{x}$ such that each frame $\mathbf{x}^i$ has the content of $\mathbf{p}^i$ and style $\mathbf{a}$.

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Our goal will be to determine $\mathbf{x}^i$ in chronological order. We will also denote $\mathbf{x}_0^i$ to be the initialization of in the optimization procedure to determine $\mathbf{x}^i$.

Naive Method

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The next natural step would be to initialize the optimization procedure by $\mathbf{x}_0^i = \mathbf{x}^{i-1}$.

If there is motion in the scene, this simple approach does not perform well since moving objects are initialized incorrectly.

Optical Flow to the rescue

The **optical flow** in a the content video $\mathbf{p}$ between frame j to i (denoted by w_j^i) is a function that warps a given image $\mathbf{p}^j$ using the optical flow field that was estimated between frame $\mathbf{p}^j$ and $\mathbf{p}^i$.

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Given the optical flow of w_{i-1}^i between frame $\mathbf{p}^{i-1}$ and $\mathbf{p}^i$ of the content video, we can initialize $\mathbf{x}_0^i$ via

$$\mathbf{x}_0^i = w_{i-1}^i(\mathbf{x}^{i-1}).$$

Temporal consistency

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We define the temporal loss to be

$$\mathcal{L}_{temp}(\mathbf{x}, \mathbf{w}, \mathbf{c}) = \frac{1}{D} \sum_{k=1}^{D} c_k (x_k - w_k)^2$$

Where D is the dimension of the image. And $c_k = 0$ if the motion at pixel w_k is a boundary point, and 1 otherwise. $\mathbf{c}^i$ can be approximated using optical flow. For details of this procedure see Arxiv 1604.08610.

Temporal Consistency

To force some consistency between consecutive frames, we can minimize

$$\begin{aligned}\mathcal{L}_{short}(\mathbf{x}^i, \mathbf{p}^i, \mathbf{a}) = \; & \alpha \mathcal{L}_c(\mathbf{x}^i, \mathbf{p}^i) + \beta \mathcal{L}_s(\mathbf{x}^i, \mathbf{a}) \\ & + \gamma \mathcal{L}_{temp}(\mathbf{x}^i, w_{i-1}^i(\mathbf{x}^{i-1}), \mathbf{c}^i)\end{aligned}$$

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& + \gamma \mathcal{L}_{temp}(\mathbf{x}^i, w_{i-1}^i(\mathbf{x}^{i-1}), \mathbf{c}^i)
\end{aligned}
$$

To get a smoother result, it is better to achieve some long term cosistency between not just the previous frame, but rather the previous J frames (typically $J = 1, 2, 4$).

$$
\begin{aligned}
\mathcal{L}_{long}(\mathbf{x}^i, \mathbf{p}^i, \mathbf{a}) = \ & \alpha \mathcal{L}_c(\mathbf{x}^i, \mathbf{p}^i) + \beta \mathcal{L}_s(\mathbf{x}^i, \mathbf{a}) \\
& + \gamma \sum_{j=1}^{J} \mathcal{L}_{temp}(\mathbf{x}^i, w_{i-j}^i(\mathbf{x}^{i-j}), \mathbf{c}^{i-j})
\end{aligned}
$$

Example

See https://www.youtube.com/watch?v=Khuj4ASldmU