Learning to Simplify: Fully Convolutional Networks for Rough Sketch Cleanup

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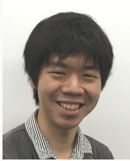
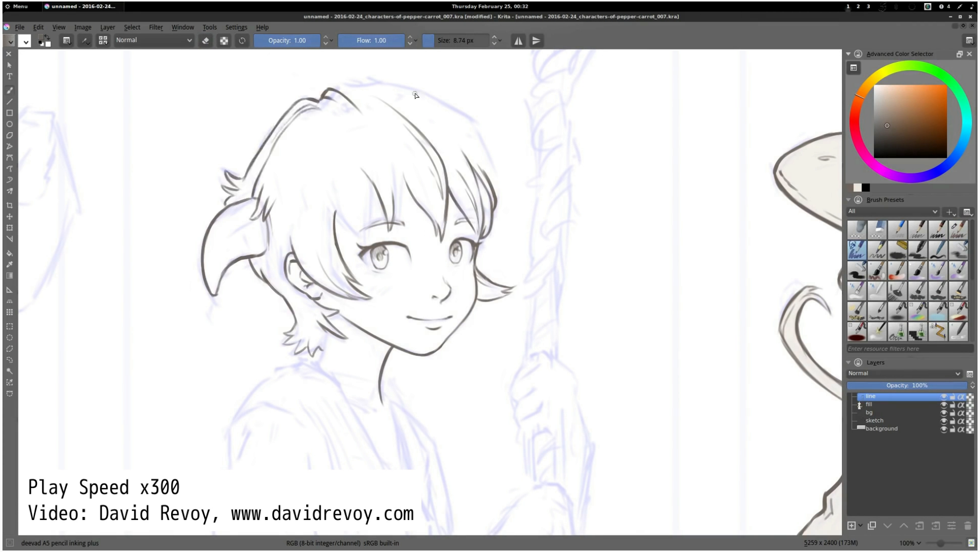
Waseda University



Sketch Simplification



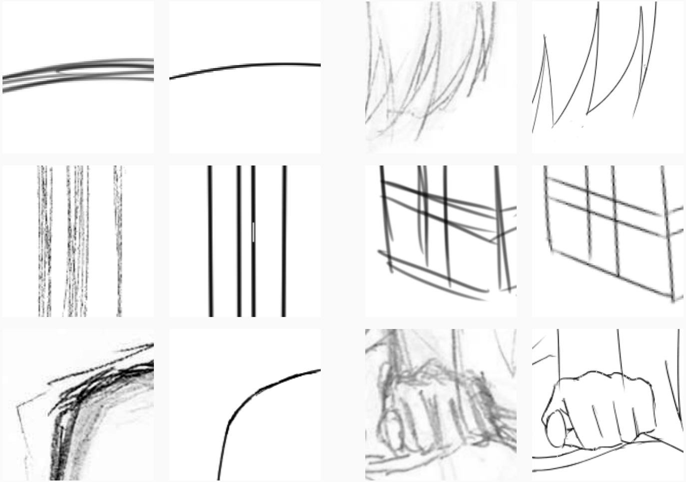
Sketch Simplification

Input: Rough Sketch

Output: Line Art

Sketch Simplification

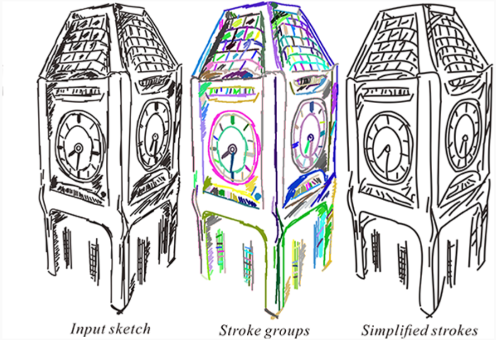
Rough Target Rough Target



Related Work

Related Work

1. Sketch Simplification
   1.1 Progressive Online Modification
   1.2 Stroke Reduction
   1.3 Stroke Grouping



Liu et al. 2015

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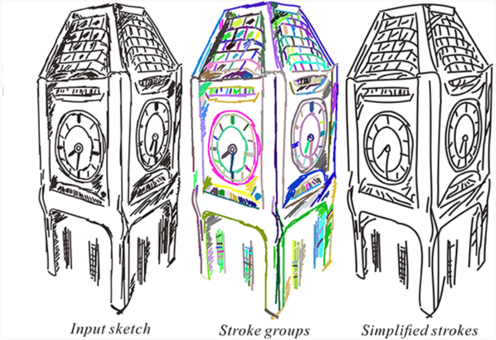

Liu et al. 2015

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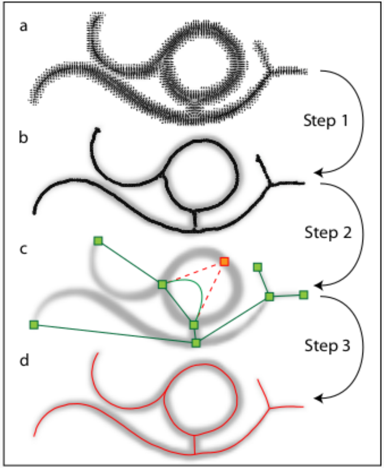
2. Vectorization
   2.1 Model Fitting (Bezier, ...)
   2.2 Gradient-based approaches



Noris et al. 2013

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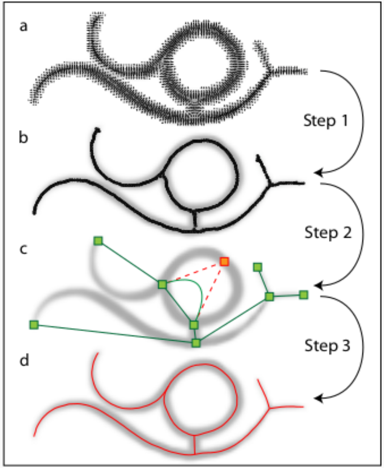

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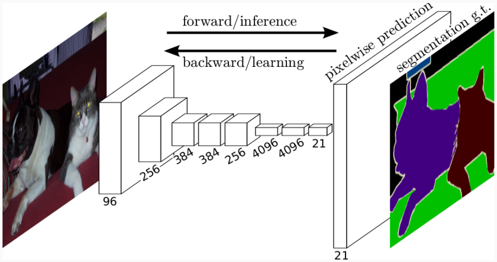
3. Deep Learning
    3.1 Fully Convolutional Network

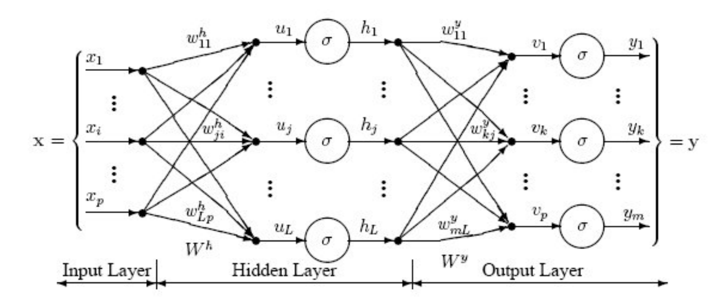


Long et al. 2015

Proposed Approach

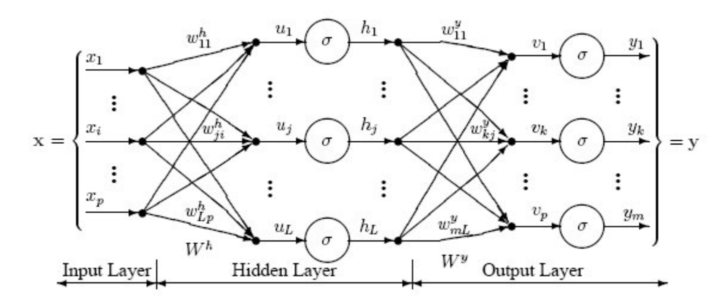
Deep Learning

- Modern Neural Networks
  - Computational efficiency with GPU
  - Large scale datasets



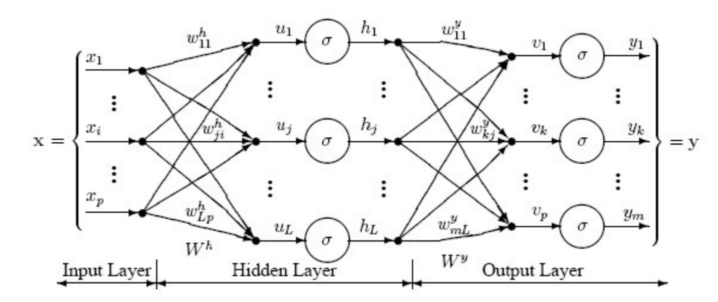
Deep Learning

- Modern Neural Networks
  - Computational efficiency with GPU
  - Large scale datasets
- Learns input to output mapping
- Basic building block layer: $f(x) = \sigma(Wx)$



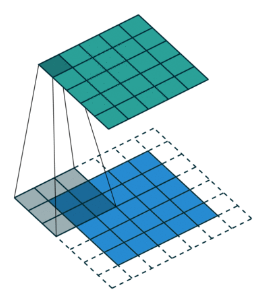
Deep Learning

- Modern Neural Networks
  - Computational efficiency with GPU
  - Large scale datasets
- Learns input to output mapping
- Basic building block layer: $f(x) = \sigma(Wx)$
- Parameters $(W \ldots)$ are learnt
- Hyper-parameters are set by hand



Fully Convolutional Network

- Uses only convolutional layers
- Each layer convolves many filters
- Layer hyperparameters: kernel, padding, and stride
  - Weights expressed with kernels
  - Padding conserves the image size
  - Stride can change the output resolution



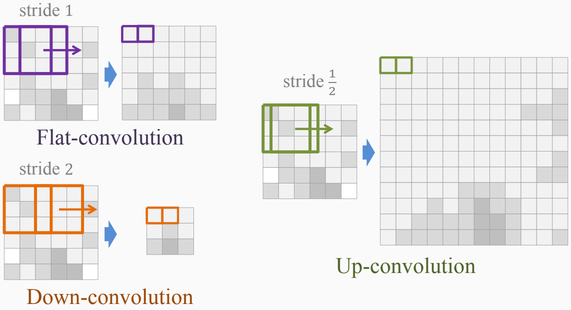
Output

Input

Fully Convolutional Network

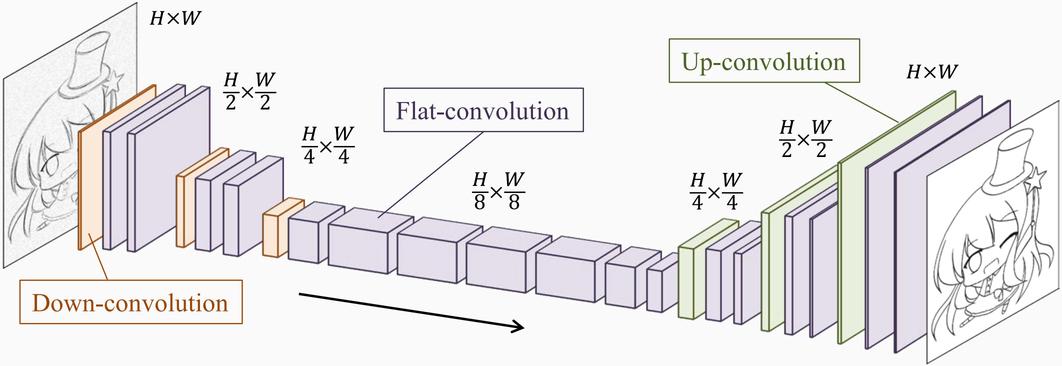
We create three building blocks by modifying the stride:

1. Flat-convolution
    1.1 3×3px kernel, 1×1px padding, 1px stride
2. Down-convolution
    2.1 3×3px kernel, 1×1px padding, 2px stride
3. Up-convolution
    3.1 4×4px kernel, 1×1px padding, $^1/_2$px stride



Model

- 23 convolutional layers
- Output has the same resolution as the input
- Encoder-Decoder architecture
    - Reduces memory usage
    - Increases spatial resolution

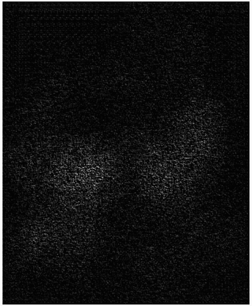


Learning

- Trained from scratch
- Using 424×424px patches
- Weighted Mean Square Error loss
- Batch Normalization [Ioffe and Szegedy 2015] is critical
- Optimized with ADADELTA [Zeiler 2012]

Input

Output

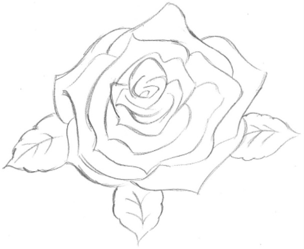


Target

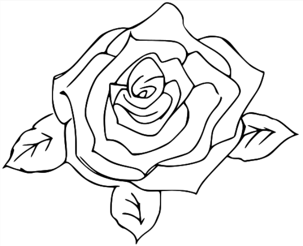
Vectorization and Simplification

- Vectorization with potrace
  - Open source software
  - High pass filter and binarization

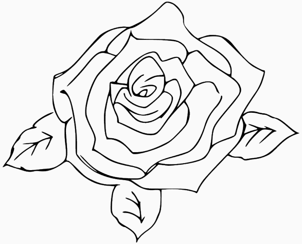
Input



Output



Vector



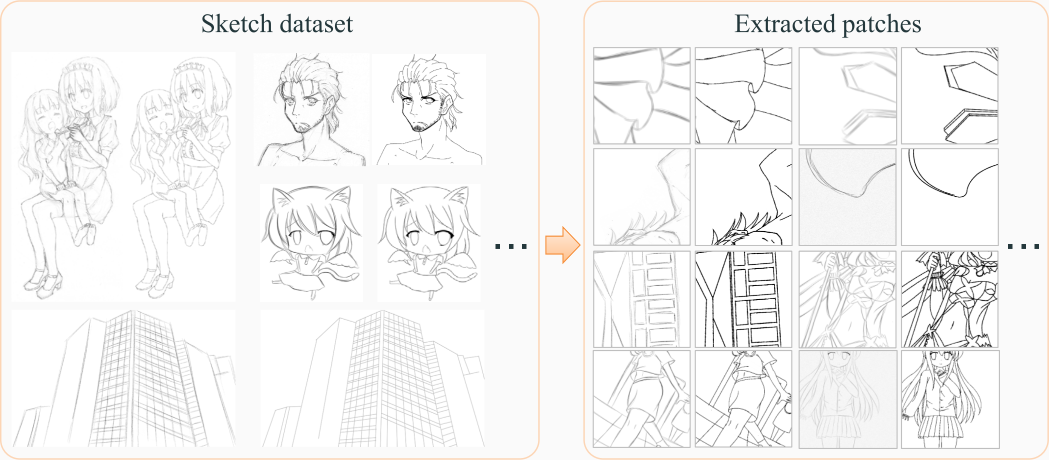
Vectorization and Simplification

- Vectorization with potrace
  - Open source software
  - High pass filter and binarization
- Scaling input changes simplification degree

Sketch Dataset

Sketch dataset

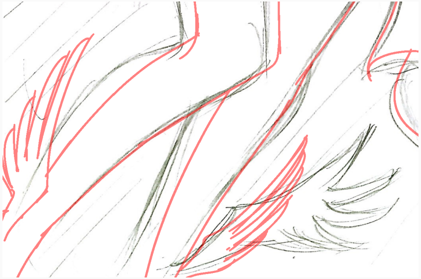
- 68 pairs of rough and target sketches
- 5 illustrators



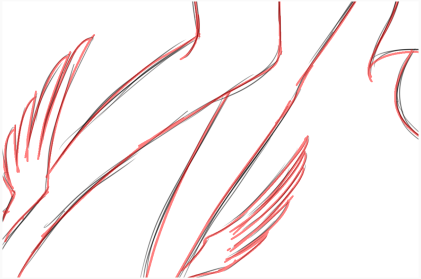
Inverse Dataset Creation

- Data quality is critical
- Creating target sketches from rough sketches has misalignments
- Creating rough sketches from target sketches properly aligns

Standard

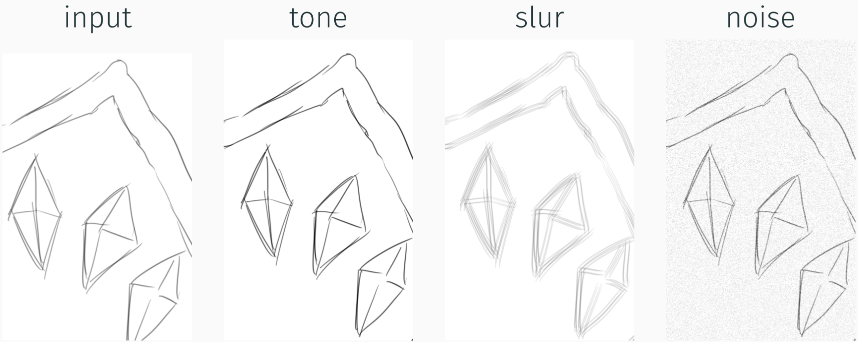


Inverse Creation



Data Augmentation

- 68 pairs is insufficient
- Scaling training data
- Random cropping, flipping and rotation
- Additional augmentation: tone, slur, and noise



Results and Comparisons

Results

- Intel Core i7-5960X CPU (3.00GHz)
- NVIDIA GeForce TITAN X GPU
- 3 weeks training time

Image Size	Pixels	CPU (s)	GPU (s)	Speedup
320×320	102,400	2.014	0.047	$42.9\times$
640×640	409,600	7.533	0.159	$47.4\times$
1024×1024	1,048,576	19.463	0.397	$49.0\times$

Comparison

Input

Potrace

Adobe Live Trace

Ours

Comparison

Input

Potrace

Adobe Live Trace

Ours

User Study

- Comparison with 15 images
- 19 users participated (10 with illustration experience)
- Absolute rating (1 to 5 scale)
- Relative evaluation (best of two)

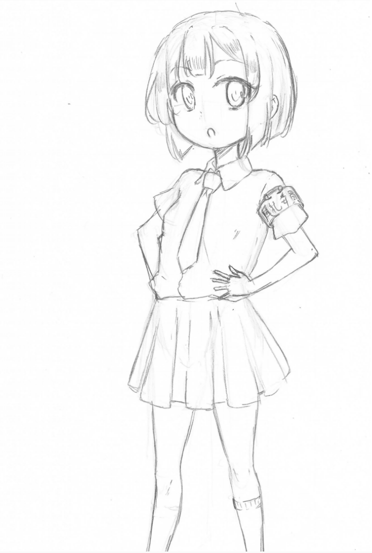
	Ours	Live Trace	Potrace
Score	4.53	2.94	2.80
vs Ours	-	2.5%	2.8%
vs Live Trace	97.5%	-	30.3%
vs Potrace	97.2%	69.7%	-

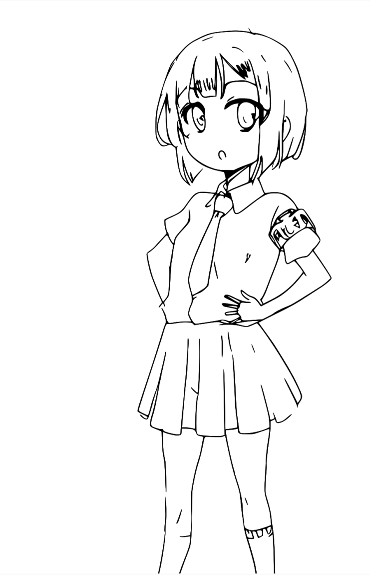
Comparison

Results

Results

Results





Results

Conclusions

- Automatic Sketch Simplification Approach
- Convolutional networks are suited to image processing
- Proper data is crucial for training

Conclusions

- Automatic Sketch Simplification Approach
- Convolutional networks are suited to image processing
- Proper data is crucial for training

Try Online: http://hi.cs.waseda.ac.jp:8081/

Model

type	kernel size	stride	output size
input	-	-	$1 \times H \times W$
down-convolution	5×5	2×2	$48 \times H/2 \times W/2$
flat-convolution	3×3	1×1	$128 \times H/2 \times W/2$
flat-convolution	3×3	1×1	$128 \times H/2 \times W/2$
down-convolution	3×3	2×2	$256 \times H/4 \times W/4$
flat-convolution	3×3	1×1	$256 \times H/4 \times W/4$
flat-convolution	3×3	1×1	$256 \times H/4 \times W/4$
down-convolution	3×3	2×2	$256 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$512 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$1024 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$1024 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$1024 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$1024 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$512 \times H/8 \times W/8$
flat-convolution	3×3	1×1	$256 \times H/8 \times W/8$
up-convolution	4×4	$1/2 \times 1/2$	$256 \times H/4 \times W/4$
flat-convolution	3×3	1×1	$256 \times H/4 \times W/4$
flat-convolution	3×3	1×1	$128 \times H/4 \times W/4$
up-convolution	4×4	$1/2 \times 1/2$	$128 \times H/2 \times W/2$
flat-convolution	3×3	1×1	$128 \times H/2 \times W/2$
flat-convolution	3×3	1×1	$48 \times H/2 \times W/2$
up-convolution	4×4	$1/2 \times 1/2$	$48 \times H \times W$
flat-convolution	3×3	1×1	$24 \times H \times W$
flat-convolution	3×3	1×1	$1 \times H \times W$