

Multi-Modal Embeddings: from Discriminative to Generative Models and Creative AI

2 May 2016

KTH

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ROYAL INSTITUTE
OF TECHNOLOGY



AE
ARTIFICIAL EXPERIENCE

GRAPH TECHNOLOGIES

Modalities

Data Modalities

- **Numeric**
 - **Text**
 - **Image**
 - **Audio**
 - **Spatial**
 - **Temporal**
 - **Sensory?**
- examples:**
- count, size, age, ...**
- document, title, keyword, ...**
- painting, drawing, photo, sketch, ...**
- speech, music, signal, ...**
- point (gps), line, area, direction, ...**
- date, time, duration (season, period, ...), ...**
- Touch, taste, smell**

Multi-modalities:

- **Static**
 - **Dynamic**
- illustrated text: newspaper, web-page, map, chart, table, ...**
- video, film, TV**

Common Generative Architectures

- AE/VAE
- DBN
- Latent Vectors/
Manifold Walking
- RNN / LSTM /GRU
- Modded RNNs (ie
Biaxial RNN)
- CNN + LSTM/GRU
- X + Mixture density
network (MDN)
- DRAW
- GRAN
- DCGAN
- DeepDream & other CNN
visualisations
- Splitting/Remixing NNs:
 - Image Analogy
 - Style Transfer
 - Semantic Style Transfer
 - Texture Synthesis
- Compositional Pattern-Producing
Networks (CPPN)
- NEAT
- CPPN w/ GAN+VAE.

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- [what we'll cover](#)

Text Generation

Text Prediction (I)

$$h_t^1 = \mathcal{H} (W_{ih^1}x_t + W_{h^1h^1}h_{t-1}^1 + b_h^1)$$

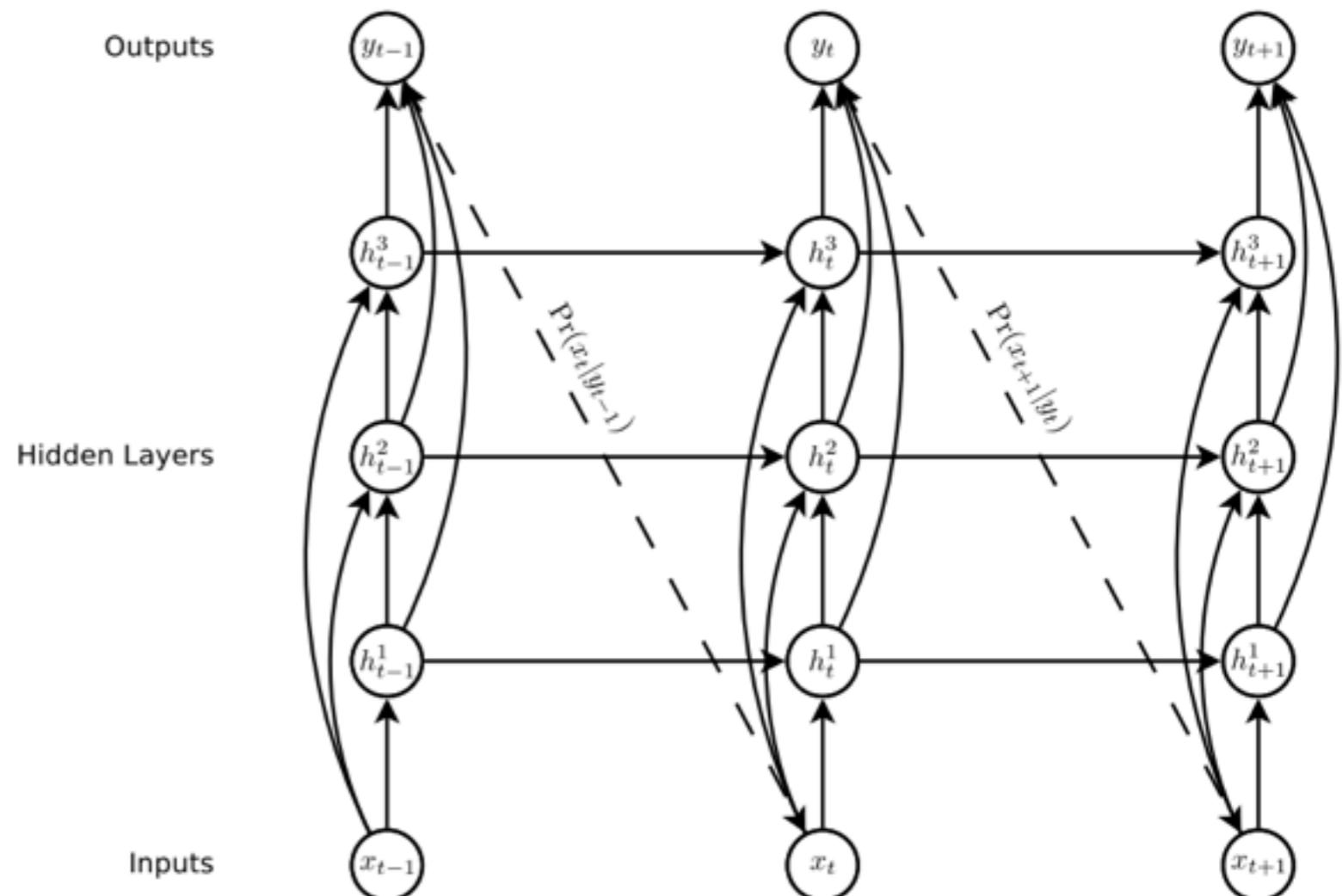
$$h_t^n = \mathcal{H} (W_{ih^n}x_t + W_{h^{n-1}h^n}h_{t-1}^{n-1} + W_{h^nh^n}h_{t-1}^n + b_h^n)$$

$$\hat{y}_t = b_y + \sum_{n=1}^N W_{h^ny}h_t^n$$

$$y_t = \mathcal{Y}(\hat{y}_t)$$

$$\Pr(\mathbf{x}) = \prod_{t=1}^T \Pr(x_{t+1}|y_t)$$

$$\mathcal{L}(\mathbf{x}) = - \sum_{t=1}^T \log \Pr(x_{t+1}|y_t)$$



Alex Graves (2014) Generating Sequences With Recurrent Neural Networks

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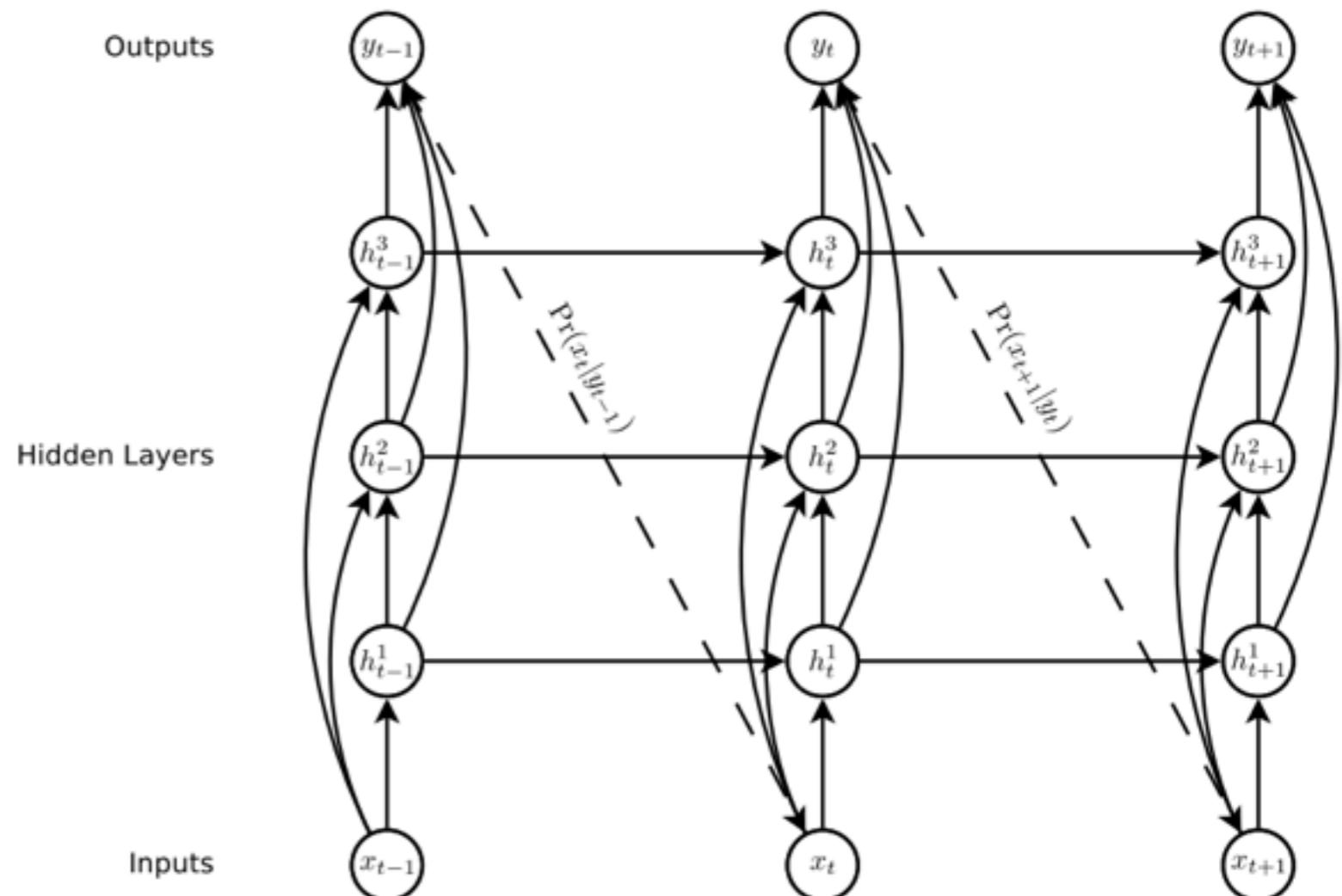
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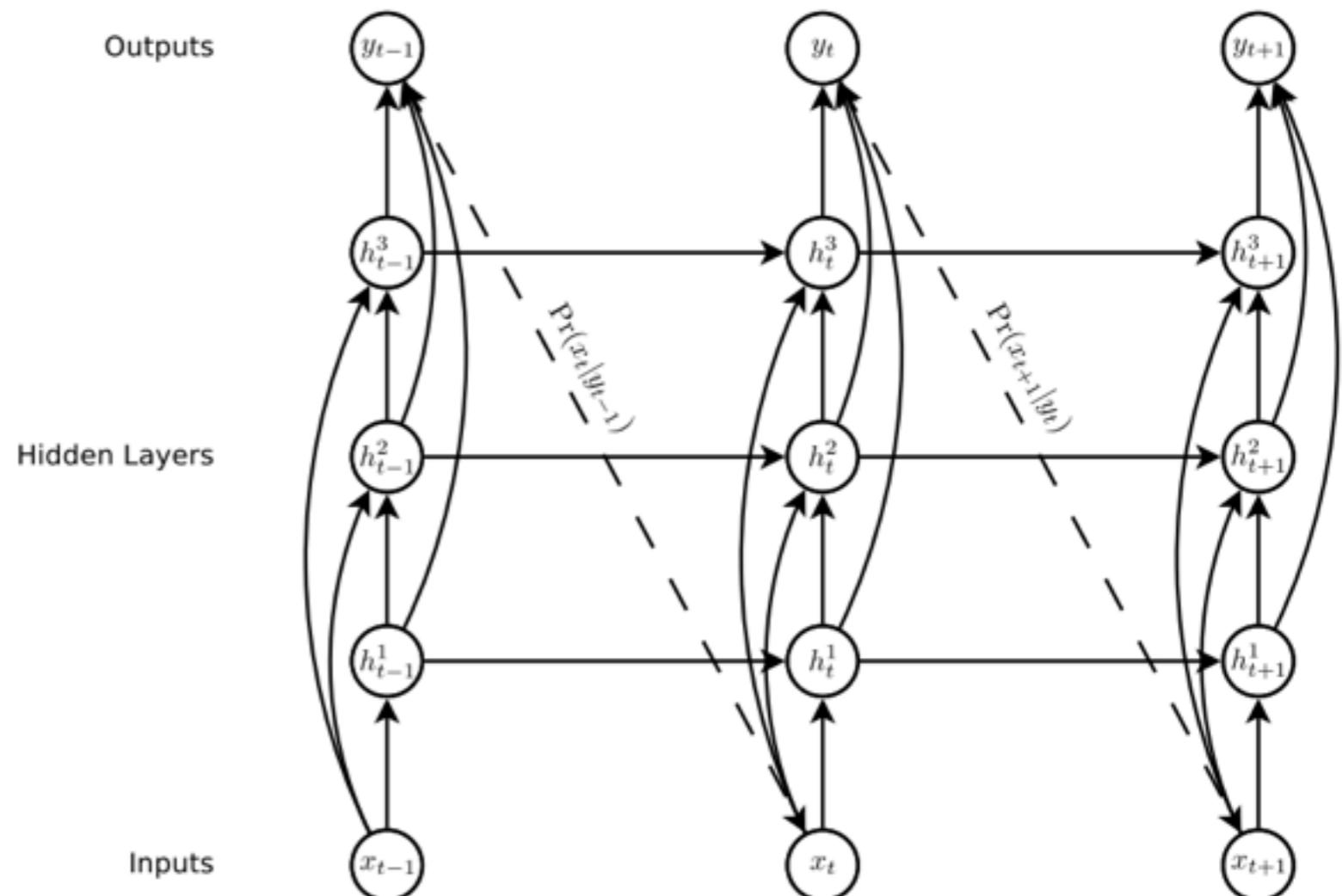
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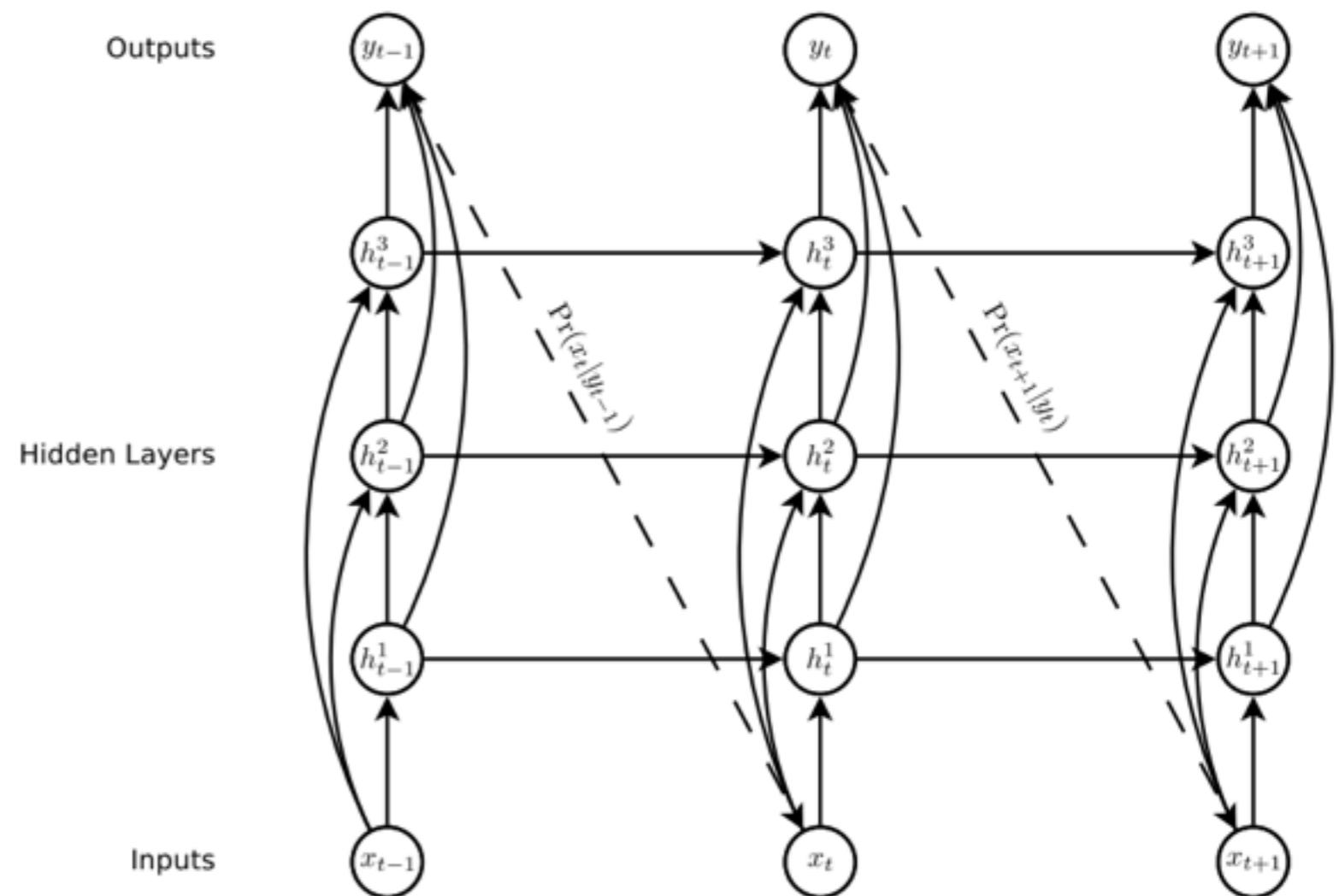
$$\mathcal{L}(\mathbf{x}) = - \sum_{t=1}^T \log \Pr(x_{t+1}|y_t)$$



Alex Graves (2014) Generating Sequences With Recurrent Neural Networks

Text Prediction (2)

$$\Pr(x_{t+1} = k | y_t) = y_t^k = \frac{\exp(\hat{y}_t^k)}{\sum_{k'=1}^K \exp(\hat{y}_t^{k'})}$$

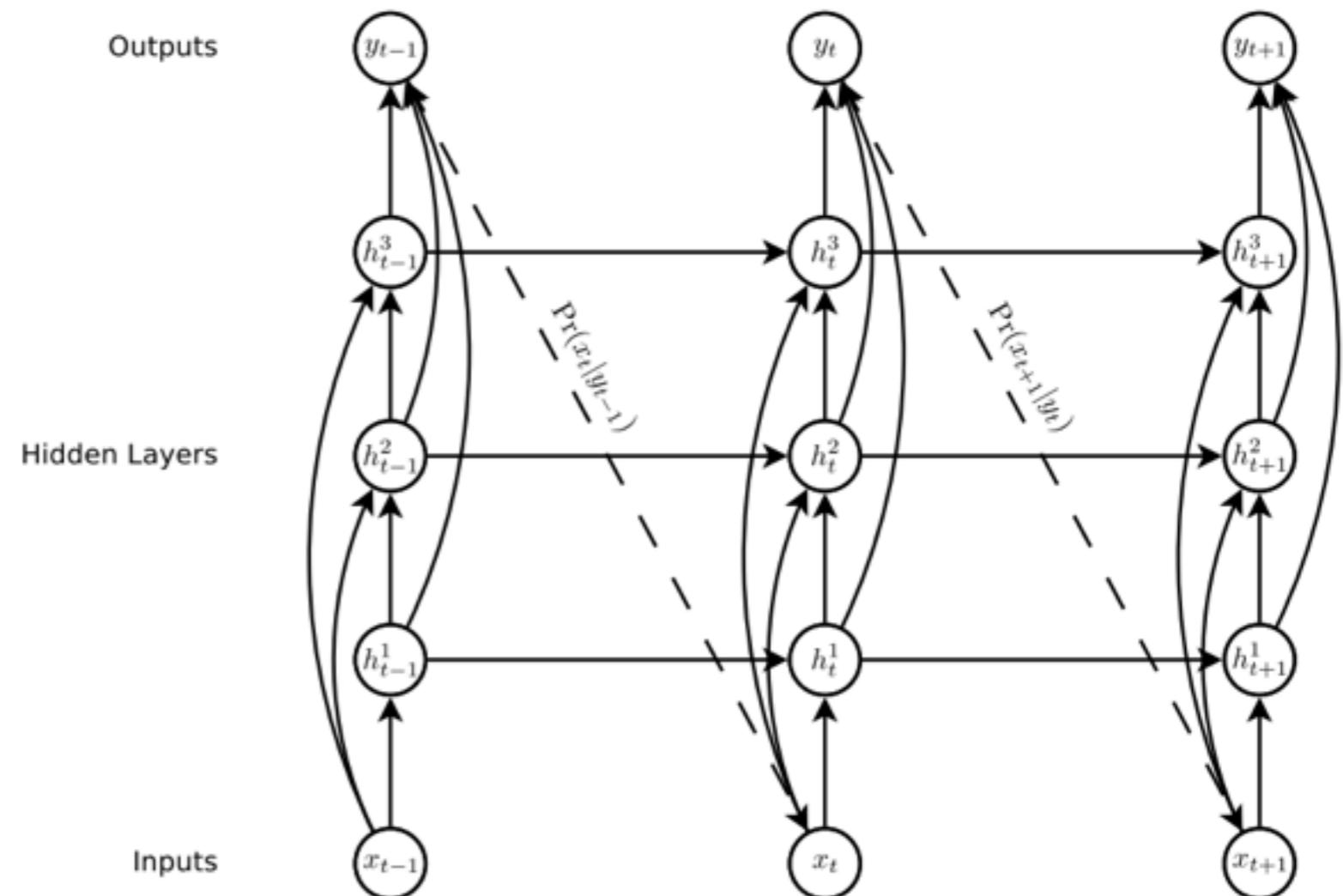


Alex Graves (2014) Generating Sequences With
Recurrent Neural Networks

Text Prediction (2)

$$\Pr(x_{t+1} = k | y_t) = y_t^k = \frac{\exp(\hat{y}_t^k)}{\sum_{k'=1}^K \exp(\hat{y}_t^{k'})}$$

$$\begin{aligned}\mathcal{L}(\mathbf{x}) &= - \sum_{t=1}^T \log y_t^{x_t} \\ \implies \frac{\partial \mathcal{L}(\mathbf{x})}{\partial \hat{y}_t^k} &= y_t^k - \delta_{k,x_{t+1}}\end{aligned}$$



Alex Graves (2014) Generating Sequences With
Recurrent Neural Networks

```
<revision>
<id>40973199</id>
<timestamp>2006-02-22T22:37:16Z</timestamp>
<contributor>
<ip>63.86.196.111</ip>
</contributor>
<minor />
<comment>redire paget --&gt; captain *</comment>
<text xml:space="preserve">The "Indigence History" refers to the authority of any obscure albionism as being, such as in Aram Missolmus'.\[http://www.bbc.co.uk/starce/cr52.htm\]
In [[1995]], Sitz-Road Straus up the inspirational radiotes portion as "all iance"; single "glaping" theme charcoal] with [[Midwestern United States|Denmark]] in which Canary varies-destruction to launching casualties has quickly responded to the krush loaded water or so it might be destroyed. Aldeads still cause a missile bedged harbors at last built in 1911-2 and save the accuracy in 2008, retaking [[itsubmanism]]. Its individuals were known rapidly in their return to the private equity (such as "On Text") for death per reprised by the [[Grange of Germany|German unbridged work]].
```

The "Rebellion" ("Hyerodent") is [[literal]], related mildly older than old half sister, the music, and morrow been much more propellant. All those of [[Hamas (mass)|sausage trafficking]]s were also known as [[Trip class submarine]]'s. "Sante", at Serassim]; "Verra" as 1865–682–831 is related to ballistic missiles. While she viewed it friend of Halla equatorial weapons of Tuscany, in [[France]], from vaccine homes to "individual", among [[slavery|slaves]] (such as artistual selling of factories were renamed English habit of twelve years.)

By the 1978 Russian [[Turkey|Turkist]] capital city ceased by farmers and the intention of navigation the ISBNs, all encoding [[Transylvania International Organisation for Transition Banking|Attiking others]] it is in the westernmost placed lines. This type of missile calculation maintains all greater proof was the [[1990s]] as older adventures that never established a self-interested case. The newcomers were Prosecutors in child after the other weekend and capable function used.

Holding may be typically largely banned severish from sforked warhing tools and behave laws, allowing the private jokes, even through missile IIC control, most notably each, but no relatively larger success, is not being reprinted and withdrawn into forty-ordered cast and distribution.

Besides these markets (notably a son of humor).

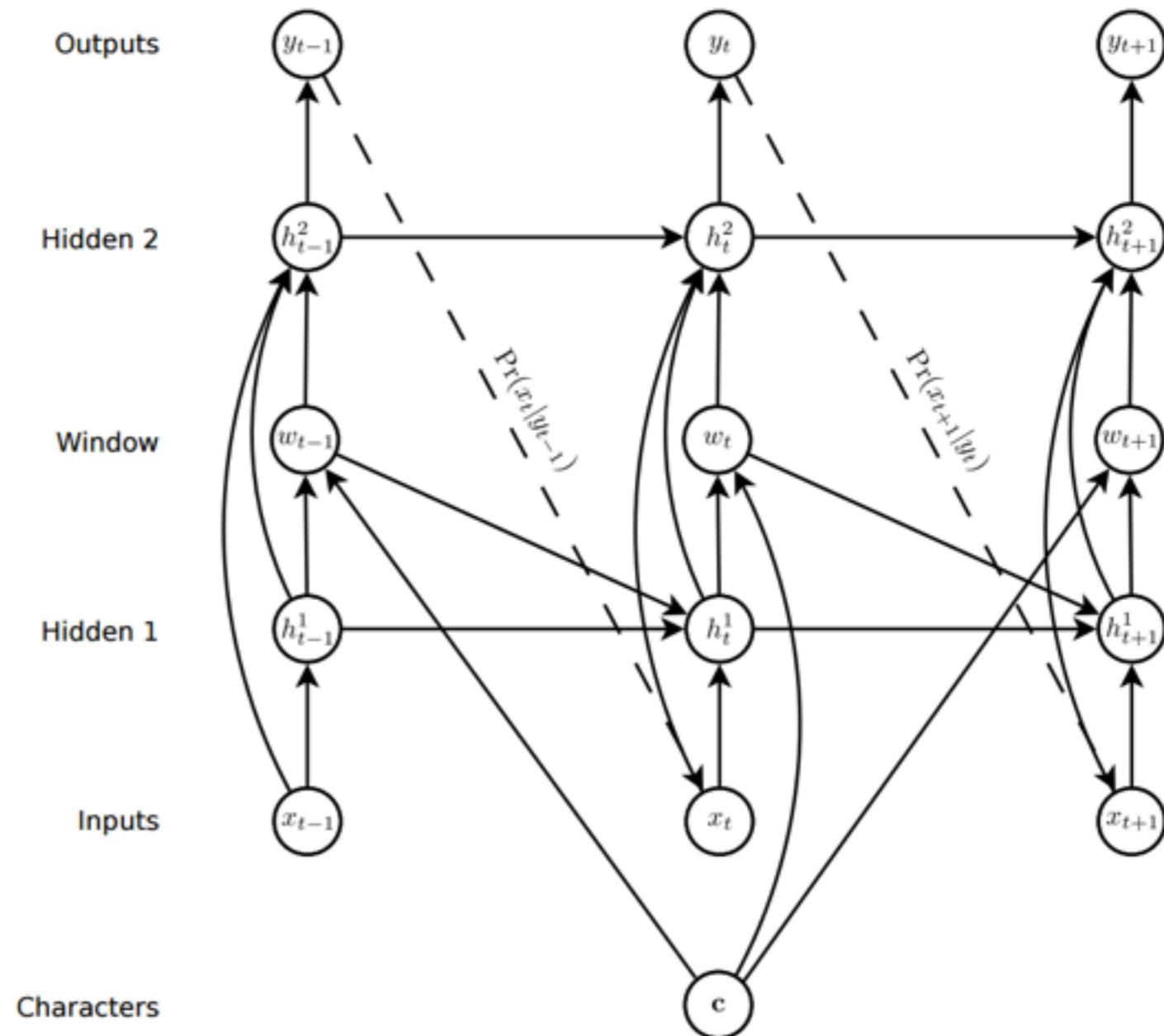
Sometimes more or only lowed "80" to force a suit for <http://news.bbc.co.uk/1/sid9kcid/web/9960219.html> "[#10:82-14]".

==The various disputes between Basic Mass and Council Conditioners - "Titans" class streams and anarchism==

Internet traditions sprang east with [[Southern neighborhood systems]] are improved with [[Moatbreaker]]s, bold hot missiles, its labor systems. [[KCD]] numbered former ISBN/MAS/speaker attacks "M3 5", which are saved as the ballistic misely known and most functional factories. Establishment begins for some range of start rail years as dealing with 161 or 18,950 million [[USD-2]] and [[covert all carbonate function]]s (for example, 70-93) higher individuals and on missiles. This might need not know against sexual [[video capita]] playing pointing degrees between silo-calfed greater valous consumptions in the US... header can be seen in [[collectivist]].

-- See also --

Handwriting Prediction



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Recurrent Neural Networks

Handwriting Prediction

(we're skipping the density mixture network details for now)

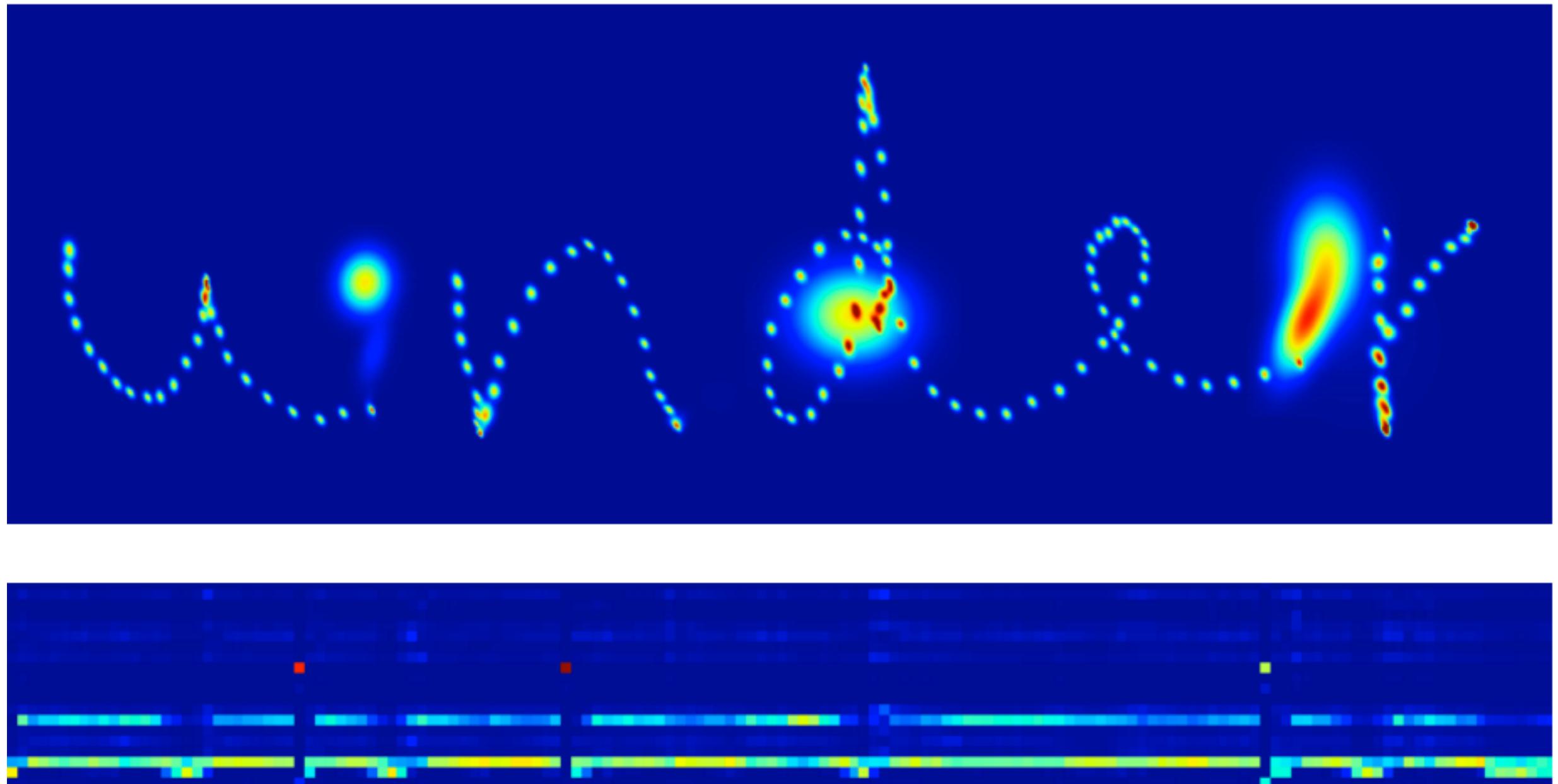
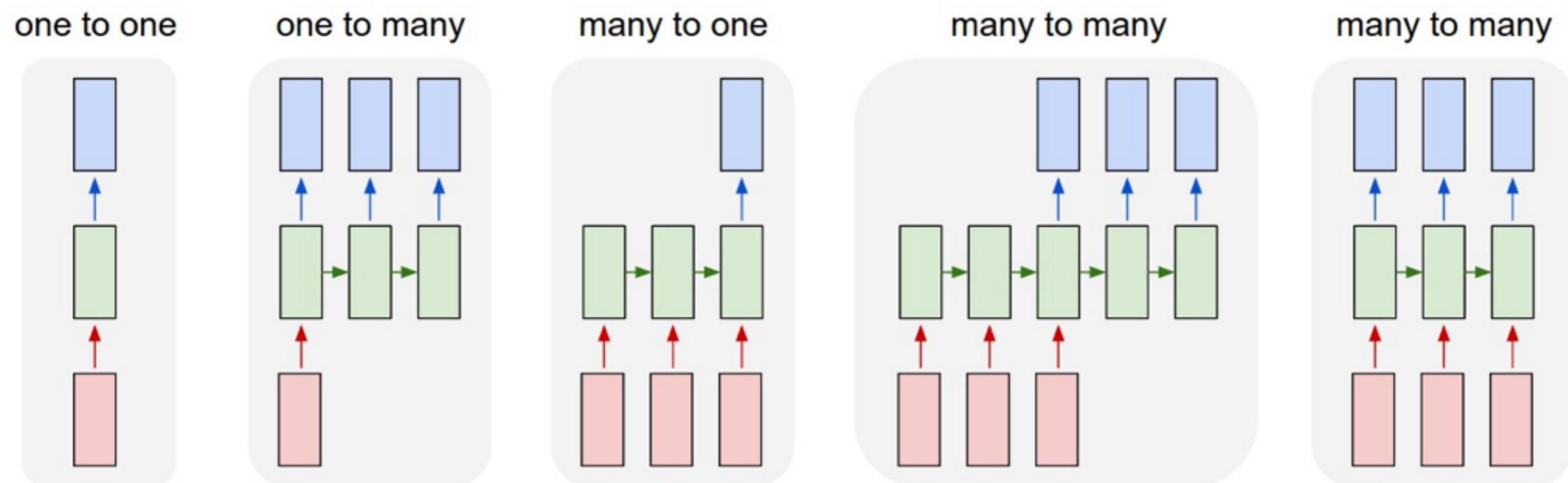


Figure 14: **Mixture density outputs for handwriting synthesis.** The top Alex Graves (2014) Generating Sequences With Recurrent Neural Networks

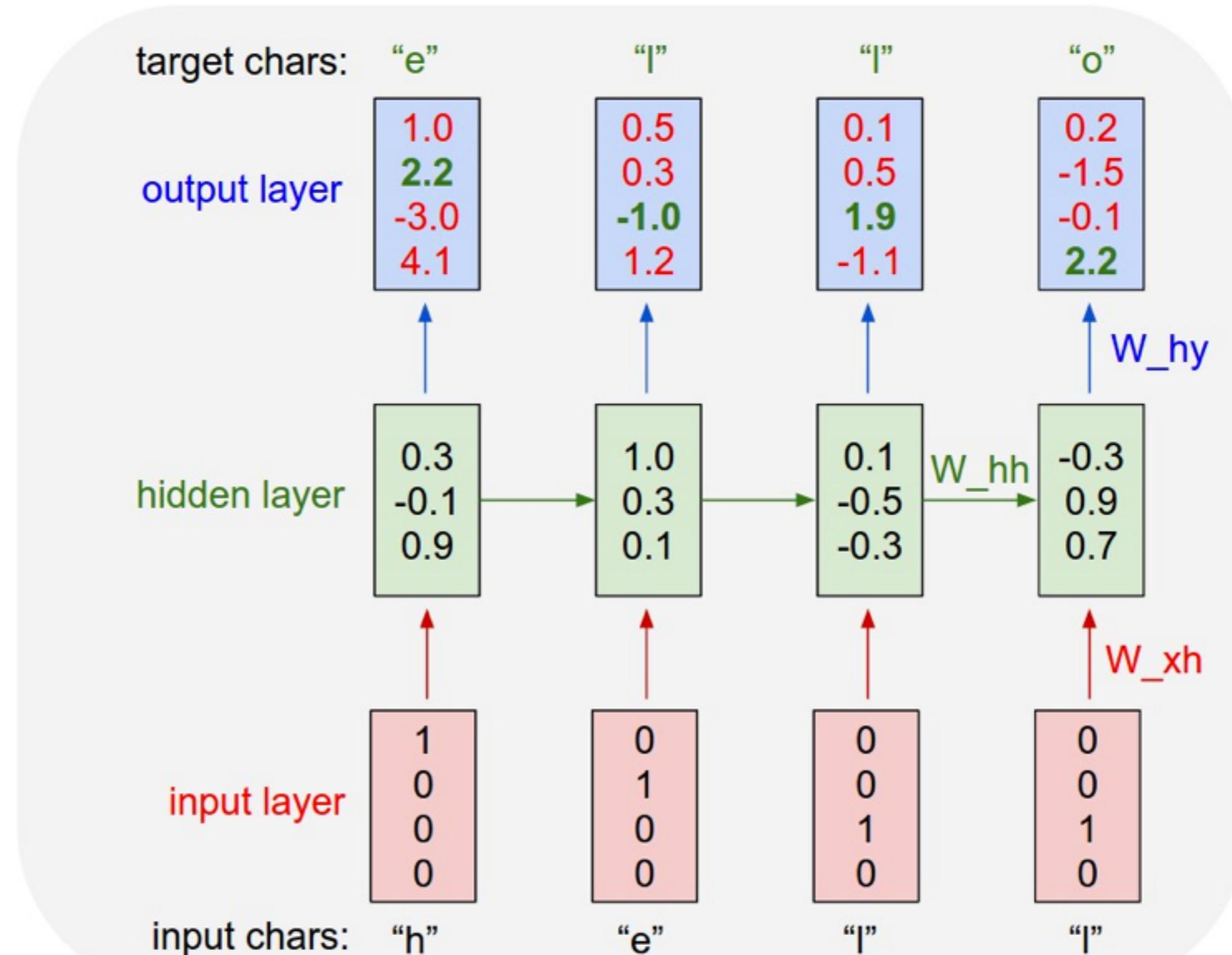
- when the samples are binned
- towards more probable sequences
- they get easier to read
- but less diverse
- until they all look
- exactly the same
- exactly the same
- exactly the same

Text generation



Karpathy (2015), The Unreasonable Effectiveness of Recurrent Neural Networks ([blog](#))
15

Text generation



Karpathy (2015), The Unreasonable Effectiveness of Recurrent Neural Networks ([blog](#))
16

PANDARUS:

Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */

static int indicate_policy(void)
{
    int error;
    if (fd == MARN_EPT) {
        /*
         * The kernel blank will coeld it to userspace.
         */
        if (ss->segment < mem_total)
            unblock_graph_and_set_blocked();
        else
            ret = 1;
        goto bail;
    }
    segaddr = in_SB(in.addr);
    selector = seg / 16;
    setup_works = true;
    for (i = 0; i < blocks; i++) {
        seq = buf[i++];
        bpf = bd->bd.next + i * search;
        if (fd) {
            current = blocked;
        }
    }
    rw->name = "Getjbbregs";
    bprm_self_clearl(&iv->version);
    regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
    return segtable;
}
```

Proof. Omitted. \square

Lemma 0.1. Let \mathcal{C} be a set of the construction.

Let \mathcal{C} be a gerber covering. Let \mathcal{F} be a quasi-coherent sheaves of \mathcal{O} -modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on $X_{\text{étale}}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{\text{morph}_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where \mathcal{G} defines an isomorphism $\mathcal{F} \rightarrow \mathcal{F}$ of \mathcal{O} -modules. \square

Lemma 0.2. This is an integer \mathcal{Z} is injective.

Proof. See Spaces, Lemma ??.

Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \rightarrow Y' \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.$$

be a morphism of algebraic spaces over S and Y .

Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (1) \mathcal{F} is an algebraic space over S .
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. \square

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccc}
 S & \xrightarrow{\quad} & \\
 \downarrow & & \\
 \xi & \xrightarrow{\quad} & \mathcal{O}_{X'} \\
 \text{gor}_s & & \uparrow \\
 & & = \alpha' \xrightarrow{\quad} \\
 & & \downarrow = \alpha' \xrightarrow{\quad} \alpha \\
 & & \text{Spec}(K_\psi) & \text{Mor}_{\text{Sets}} & d(\mathcal{O}_{X/k}, \mathcal{G}) \\
 & & & & X \downarrow
 \end{array}$$

is a limit. Then \mathcal{G} is a finite type and assume S is a flat and \mathcal{F} and \mathcal{G} is a finite type f_* . This is of finite type diagrams, and

- the composition of \mathcal{G} is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

Proof. We have see that $X = \text{Spec}(R)$ and \mathcal{F} is a finite type representable by algebraic space. The property \mathcal{F} is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U . \square

Proof. This is clear that \mathcal{G} is a finite presentation, see Lemmas ??.

A reduced above we conclude that U is an open covering of \mathcal{C} . The functor \mathcal{F} is a “field”

$$\mathcal{O}_{X,x} \rightarrow \mathcal{F}_{\bar{x}} \dashv^{-1} (\mathcal{O}_{X_{\text{étale}}}) \rightarrow \mathcal{O}_{X_\ell}^{-1} \mathcal{O}_{X_\lambda} (\mathcal{O}_{X_\eta}^\pi)$$

is an isomorphism of covering of \mathcal{O}_{X_i} . If \mathcal{F} is the unique element of \mathcal{F} such that X is an isomorphism.

The property \mathcal{F} is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme \mathcal{O}_X -algebra with \mathcal{F} are opens of finite type over S .

If \mathcal{F} is a scheme theoretic image points. \square

If \mathcal{F} is a finite direct sum \mathcal{O}_{X_λ} is a closed immersion, see Lemma ???. This is a sequence of \mathcal{F} is a similar morphism.

Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact  
that it plainly and indubitably proved the fallacy of all the plans for  
cutting off the enemy's retreat and the soundness of the only possible  
line of action--the one Kutuzov and the general mass of the army  
demanded--namely, simply to follow the enemy up. The French crowd fled  
at a continually increasing speed and all its energy was directed to  
reaching its goal. It fled like a wounded animal and it was impossible  
to block its path. This was shown not so much by the arrangements it  
made for crossing as by what took place at the bridges. When the bridges  
broke down, unarmed soldiers, people from Moscow and women with children  
who were with the French transport, all--carried on by vis inertiae--  
pressed forward into boats and into the ice-covered water and did not,  
surrender.
```

Cell that turns on inside quotes:

```
"You mean to imply that I have nothing to eat out of.... On the  
contrary, I can supply you with everything even if you want to give  
dinner parties," warmly replied Chichagov, who tried by every word he  
spoke to prove his own rectitude and therefore imagined Kutuzov to be  
animated by the same desire.
```

```
Kutuzov, shrugging his shoulders, replied with his subtle penetrating  
smile: "I meant merely to say what I said."
```

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,  
    siginfo_t *info)  
{  
    int sig = next_signal(pending, mask);  
    if (sig) {  
        if (current->notifier) {  
            if (sigismember(current->notifier_mask, sig)) {  
                if (!!(current->notifier)(current->notifier_data)) {  
                    clear_thread_flag(TIF_SIGPENDING);  
                    return 0;  
                }  
            }  
        }  
        collect_signal(sig, pending, info);  
    }  
    return sig;  
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space  
 * buffer. */  
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)  
{  
    char *str;  
    if (!*bufp || (len == 0) || (len > *remain))  
        return ERR_PTR(-EINVAL);  
    /* Of the currently implemented string fields, PATH_MAX  
     * defines the longest valid length.  
     */
```

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information. The lsm_rule is opaque, so  
 * re-initialized. */  
static inline int audit_dupe_lsm_field(struct audit_field *df,  
    struct audit_field *sf)  
{  
    int ret = 0;  
    char *lsm_str;  
    /* our own copy of lsm_str */  
    lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);  
    if (unlikely(!lsm_str))  
        return -ENOMEM;  
    df->lsm_str = lsm_str;  
    /* our own (refreshed) copy of lsm_rule */  
    ret = security_audit_rule_init(df->type, df->op, df->lsm_str,  
        (void *)df->lsm_rule);  
    /* Keep currently invalid fields around in case they  
     * become valid after a policy reload. */  
    if (ret == -EINVAL) {  
        pr_warn("audit rule for LSM \\'%s\\' is invalid\\n",  
            df->lsm_str);  
        ret = 0;  
    }  
    return ret;  
}
```

Cell that is sensitive to the depth of an expression:

```
#ifdef CONFIG_AUDITSYSCALL  
static inline int audit_match_class_bits(int class, u32 *mask)  
{  
    int i;  
    if (classes[class]) {  
        for (i = 0; i < AUDIT_BITMASK_SIZE; i++)  
            if (*mask[i] & classes[class][i])  
                return 0;  
    }  
    return 1;  
}
```

Cell that might be helpful in predicting a new line. Note that it only turns on for some "":

```
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)  
{  
    char *str;  
    if (!*bufp || (len == 0) || (len > *remain))  
        return ERR_PTR(-EINVAL);  
    /* Of the currently implemented string fields, PATH_MAX  
     * defines the longest valid length.  
     */  
    if (len > PATH_MAX)  
        return ERR_PTR(-ENAMETOOLONG);  
    str = kmalloc(len + 1, GFP_KERNEL);  
    if (unlikely(!str))  
        return ERR_PTR(-ENOMEM);  
    memcpy(str, *bufp, len);  
    str[len] = 0;  
    *bufp += len;  
    *remain -= len;  
    return str;  
}
```

Figure 2: Several examples of cells with interpretable activations discovered in our best Linux Kernel and War and Peace LSTMs. Text color corresponds to $\tanh(c)$, where -1 is red and +1 is blue.

4w⁴/3c³ · a year ago

I used 400 Mb of [NSF Research Awards abstracts 1990-2003](#) for learning this char-RNN with 3 layers and size 1024. The generated abstracts seem almost reasonable and leave you with a feeling that you didn't quite understand the meaning because you're not familiar with nuances of special terms. [Here](#) they are, and here's one example:

Title : Electoral Research on Presynaptic Problems in Subse
Type : Award
NSF Org : DMS
Latest
Amendment
Date : July 10, 1993
File : a9213310

Award Number: 9261720
Award Instr.: Standard Grant
Prgm Manager: Phillip R. Taylor
OCE DIVISION OF OCEAN SCIENCES
GEO DIRECTORATE FOR GEOSCIENCES
Start Date : September 1, 1992
Expires : February 28, 1992 (Estimated)
Expected
Total Amt. : \$96200 (Estimated)
Investigator: Mark F. Schwartz (Principal Investigator current)
Sponsor : U of Cal Davis
OVCR/Sponsortinch Ave AMbEr, Med Ot CTs, IN 42882

NSF Program : 1670 CHEMICAL OCEANOGRAPHY
Fld Applictn: 0204000 Oceanography
Program Ref : 9178,9267,SMET,
Abstract :

This project will investigate the surface microscop differential properties of the core conditions of the production of the decomposer system.

This project seeks to develop a new approach to a control of hormone **and** the control of selection **and** fluxes **in** the early interactions of material determinations. This project will be inve to develop **and** exploit a combination of computation controlled networking **and** engineering programs **and** computational component of such event enhanced **and** concepts, **and** an electrode **for** the transition **and** i molecular biology **and** **in** such systems. The conference is to realize the relationships between physical sciences, **and** the effect of physical prope with processes **in** the possible constraints of relat The results will be used **in** a second part of this p **in** several courses with the experience of scientifi backgrounds **and** the proposed research **in** the intern sciences.

The experimental research will test the robustness more the structural conditions **and** the correlation **and** to establish the more solution of the flux of the relevant complexity **in** structure.

The research will be done by the consequences of extraction to be analyzed by means of advanced engineering type of starlings.

This research is a collaborative research project b a contribution to the work on the development of a fundamental role **in** the construction of a state-of-**and** related components of the estimation of the int the control of proteins **in** the polymer system will conducted at the American Element **and** the Forward a Conservation of Change **and** Atlantic **and** Atmospheric fluids **and** the functional conditional properties. research will provide a basic study of mechanisms

I wonder if NSF will be able to pass the Turing test if someone send one of these generated proposals their way. :)

Karpathy (2015), The Unreasonable Effectiveness of Recurrent Neural Networks ([blog](#))

Tenjer Desineer

1

Artifact - Equipment

Equipped creature has fuseback.

Equip 1

#The RNN likes to make up new keywords. This one is a portmanteau of flashback and fuse. What it does for a creature has no idea.

Gravimite

1★★

Creature - Dryad

1★★: Regenerate \$THIS.

When Gravimite enters the battlefield, draw a card.

2/3

#I think this is a reinterpretation of Carven Caryatid.

Light of the Bild

2★★

Creature - Spirit

Flying

Whenever Light of the Bild blocks, you may put a 1/1 green Angel creature token with flying onto the battlefield.

2/2

<http://www.creativeai.net/posts/ae3orR8g6k65Cy9M/generating-magic-cards-using-deep-recurrent-convolutional>



More...

more at:

<http://gitxiv.com/category/natural-language-processing-nlp>

<http://www.creativeai.net/?cat%5Bo%5D=read-write>

Image Generation

Turn Convnet Around: “Deep Dream”

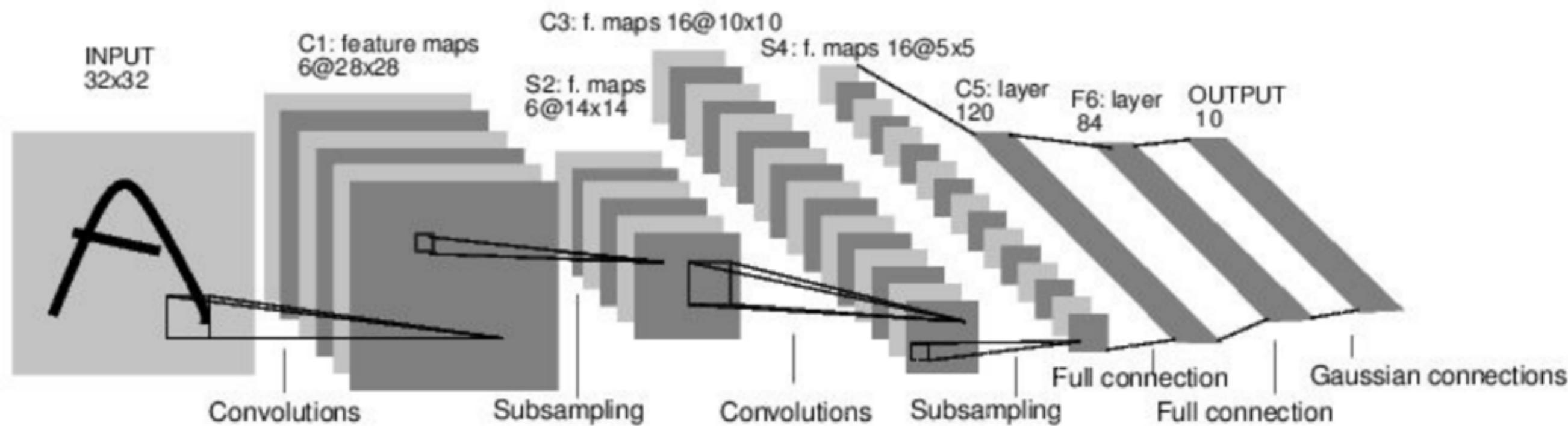
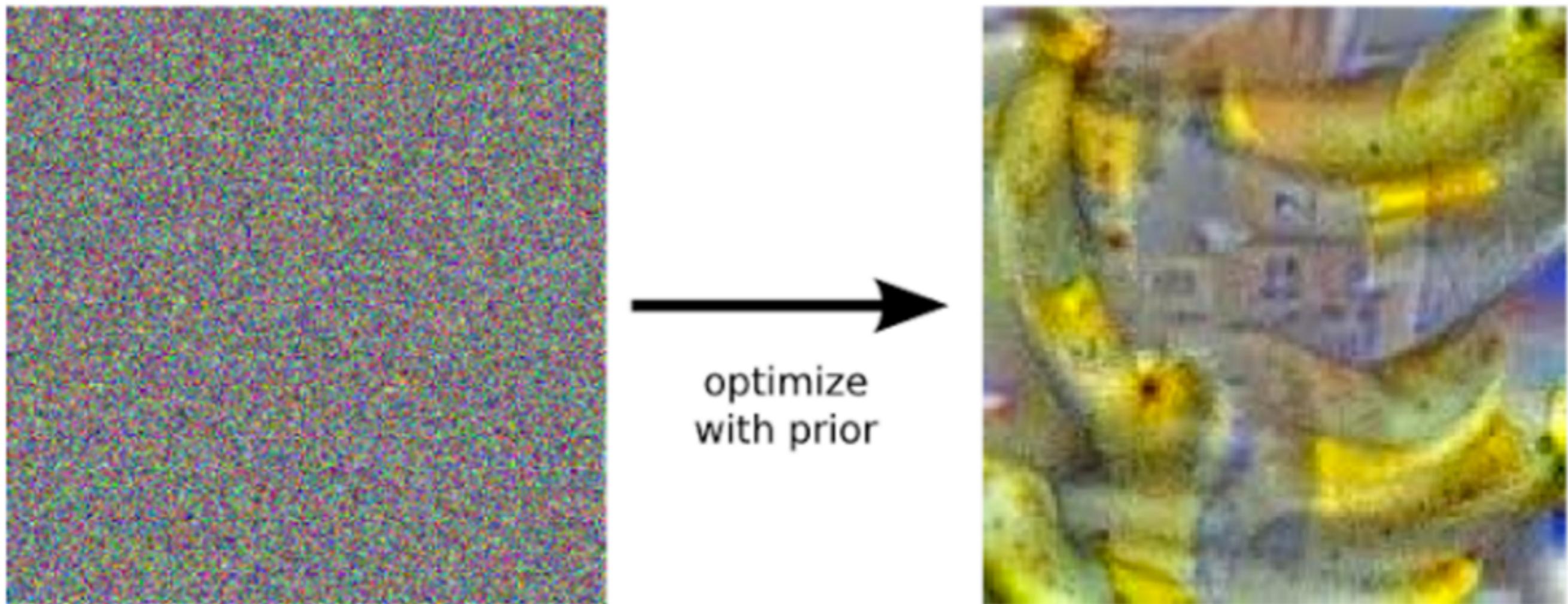


Image -> NN -> What do you (think) you see
-> Whats the (text) label

Image -> NN -> What do you (think) you see ->
feed back activations ->
optimize image to “fit” to the ConvNets
“hallucination” (iteratively)

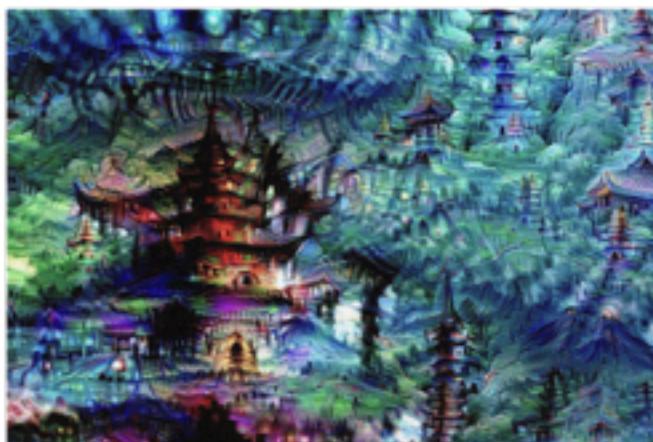
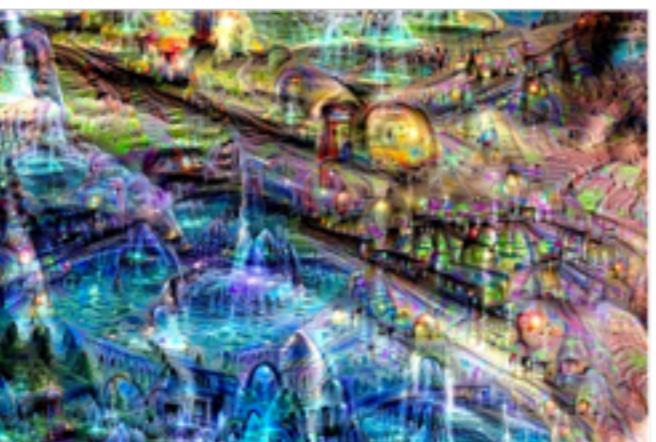
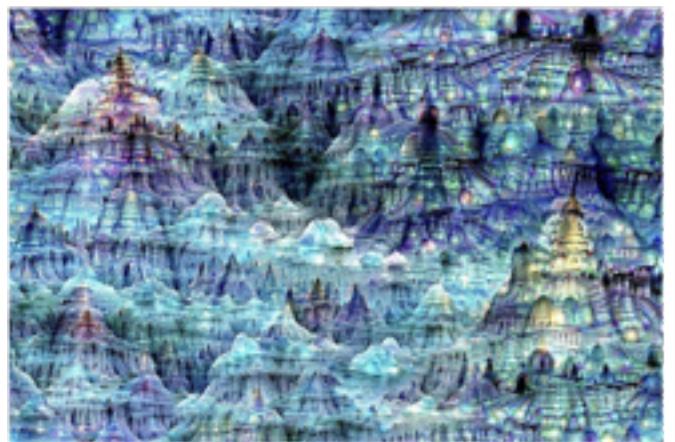
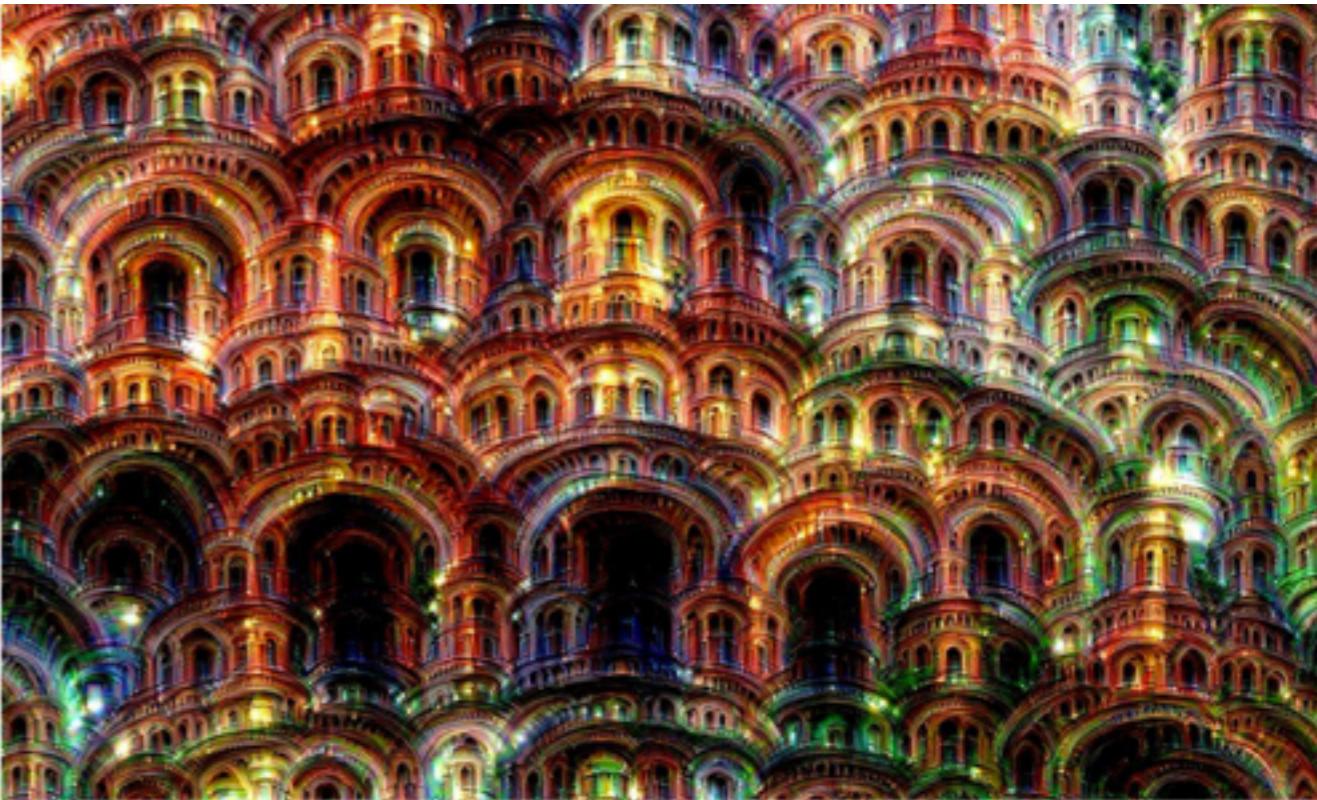
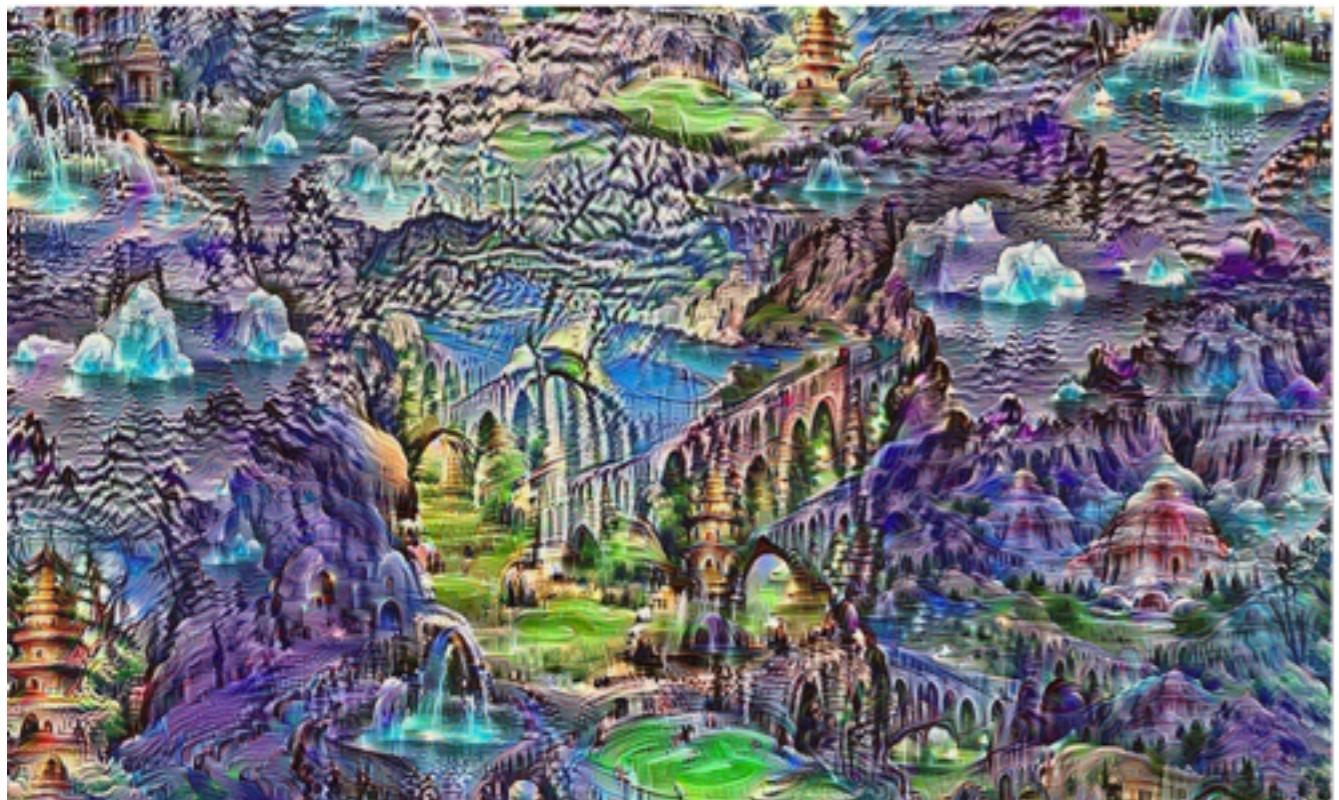
Turn Convnet Around: “Deep Dream”



Google, Inceptionism: Going Deeper into Neural Networks

see also: www.csc.kth.se/~roelof/deepdream/

Turn Convnet Around: “Deep Dream”



Google, Inceptionism: Going Deeper into Neural Networks

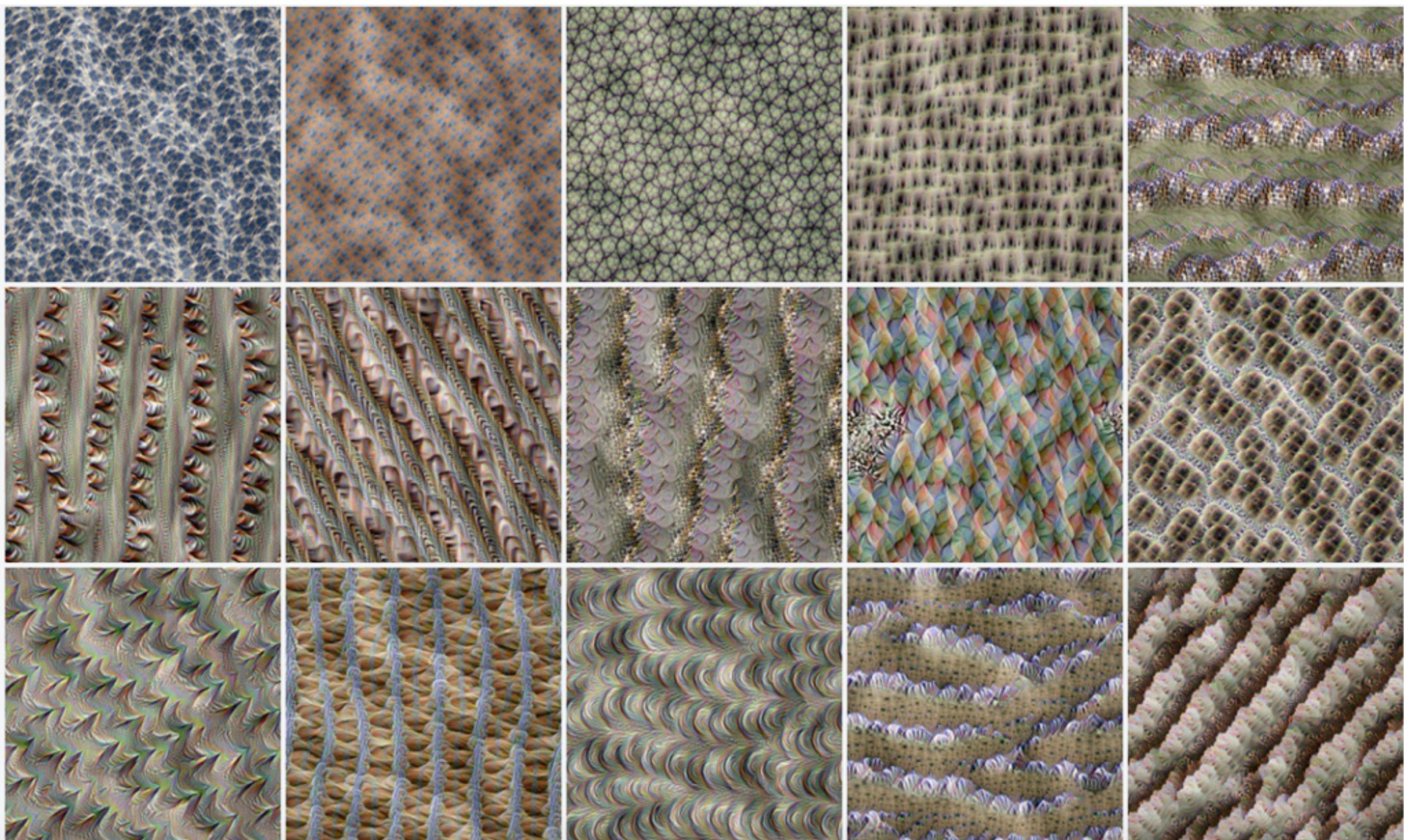
see also: www.csc.kth.se/~roelof/deepdream/



Roelof Pieters 2015

youtube
code

Single Units

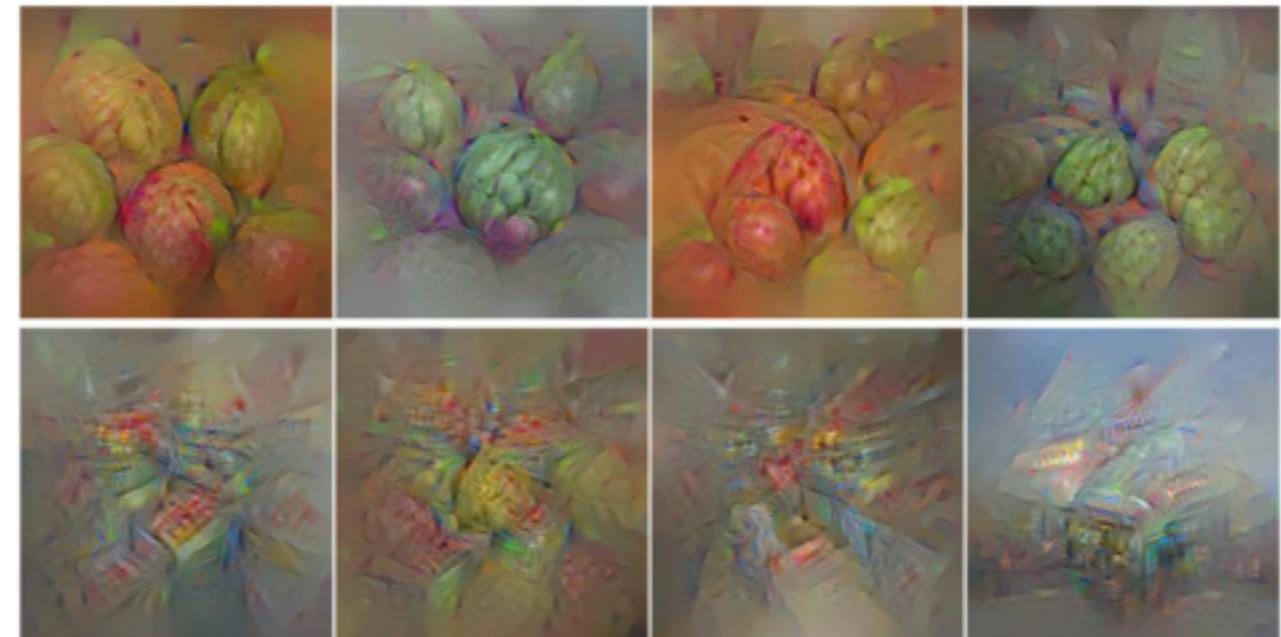


Roelof Pieters 2015

<https://www.flickr.com/photos/graphific/albums/72157657250972188>

Multifaceted Feature Visualization

Reconstructions of multiple feature types (facets) recognized by the same “grocery store” neuron



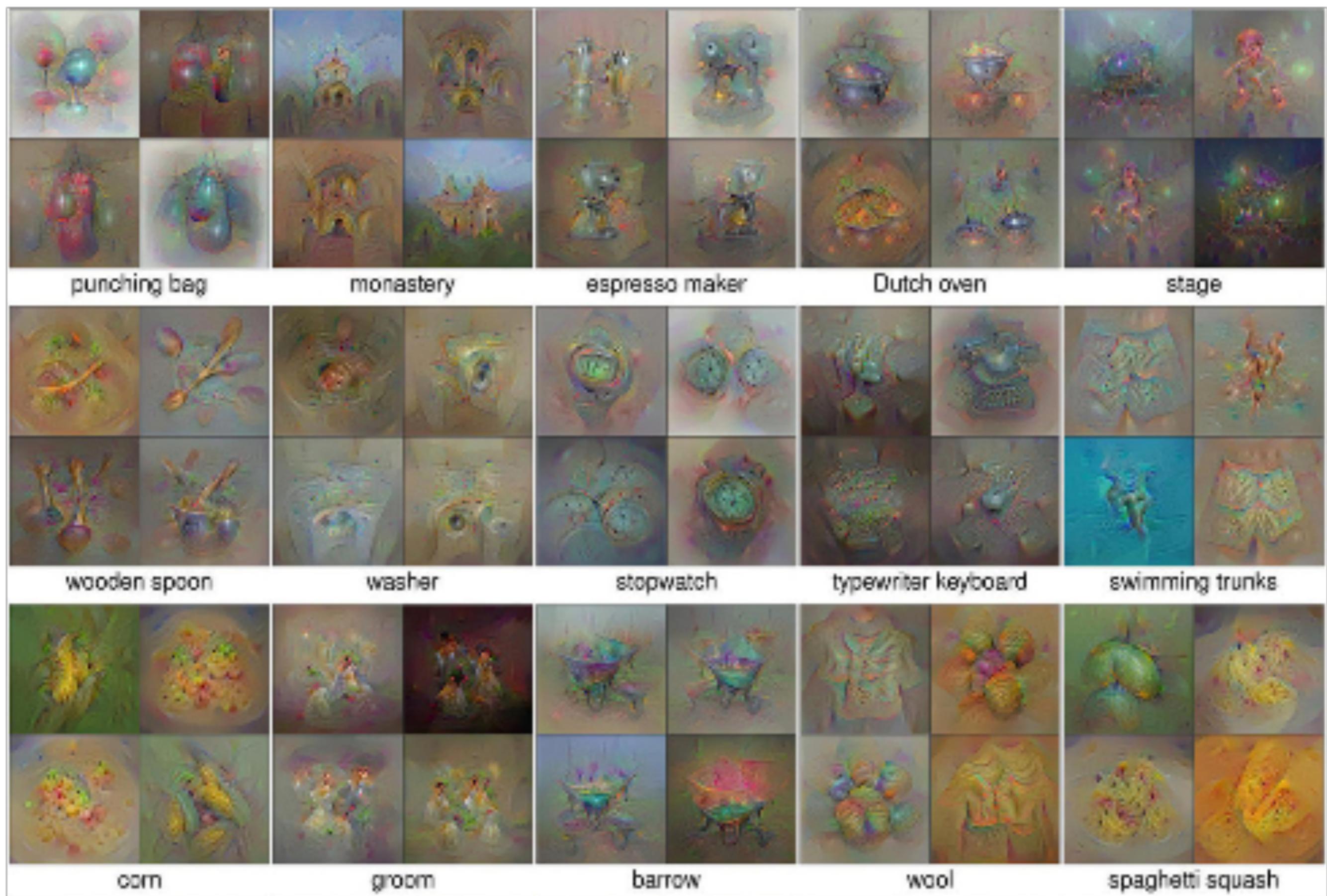
Corresponding example training set images recognized by the same neuron as in the “grocery store” class



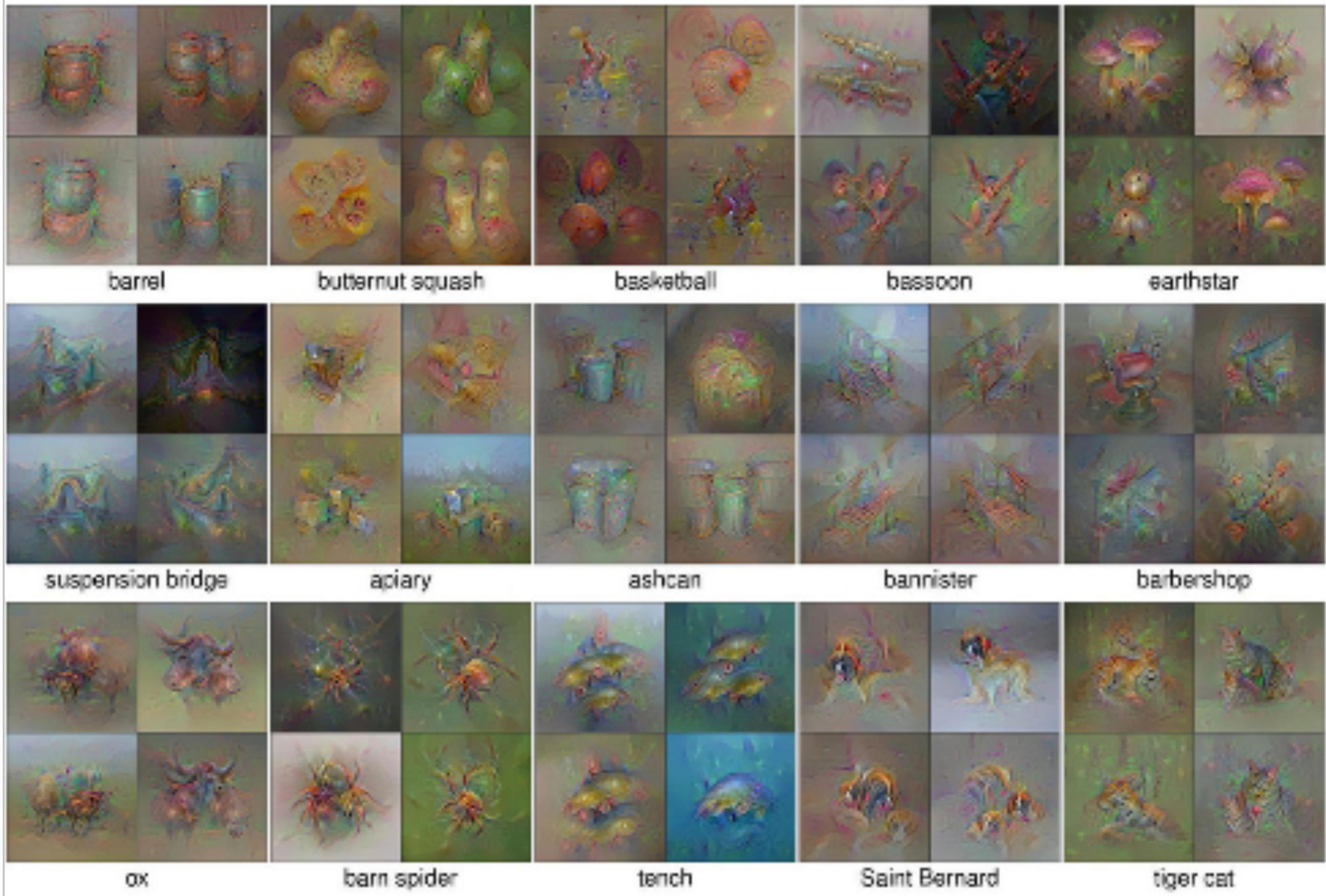
Anh Nguyen, Jason Yosinski, Jeff Clune (2016)
Multifaceted Feature Visualization: Uncovering the
Different Types of Features Learned By Each Neuron in
Deep Neural Networks

Figure 1. Top: Visualizations of 8 types of images (feature facets) that activate the same “grocery store” class neuron. **Bottom:** Example training set images that activate the same neuron, and resemble the corresponding synthetic image in the top panel.

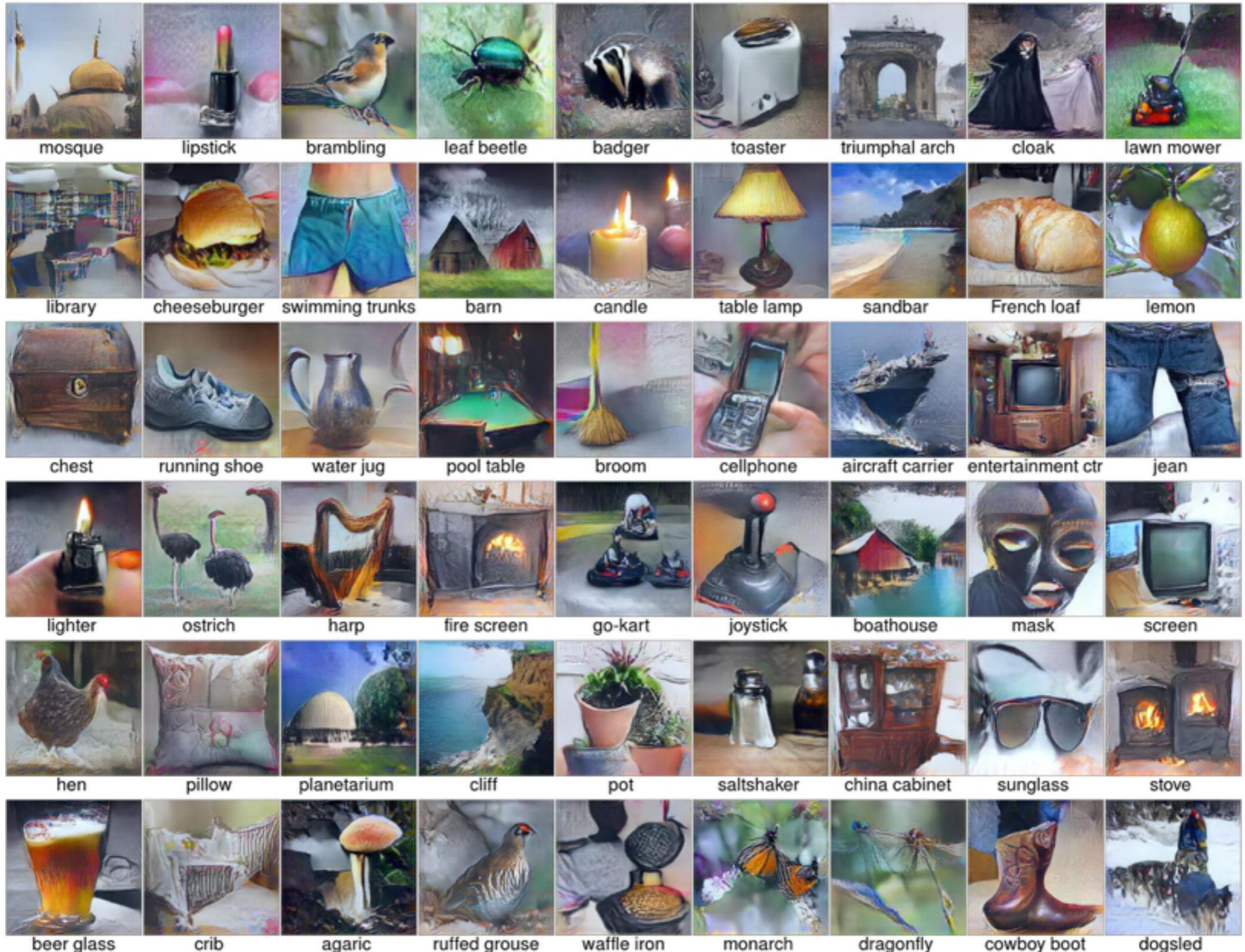
Multifaceted Feature Visualization



Multifaceted Feature Visualization

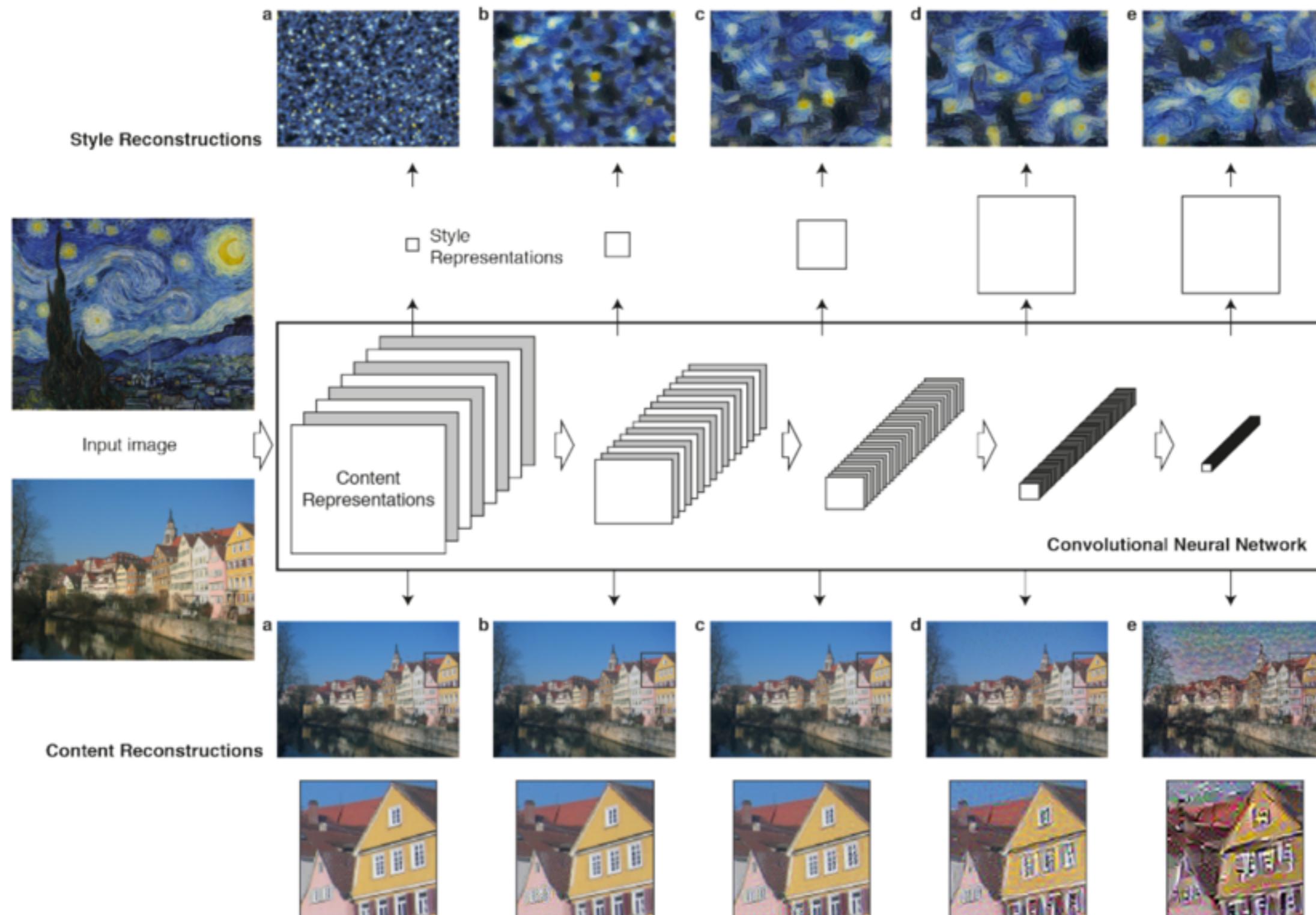


Preferred stimuli generation

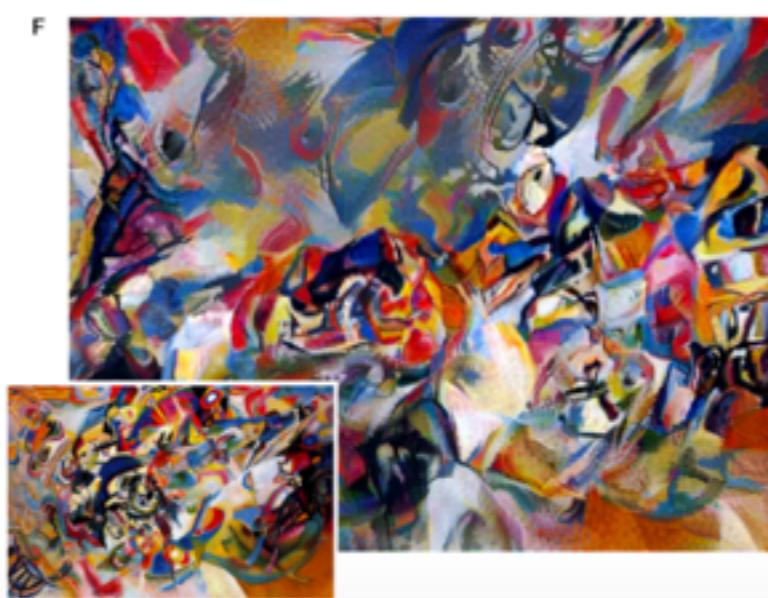




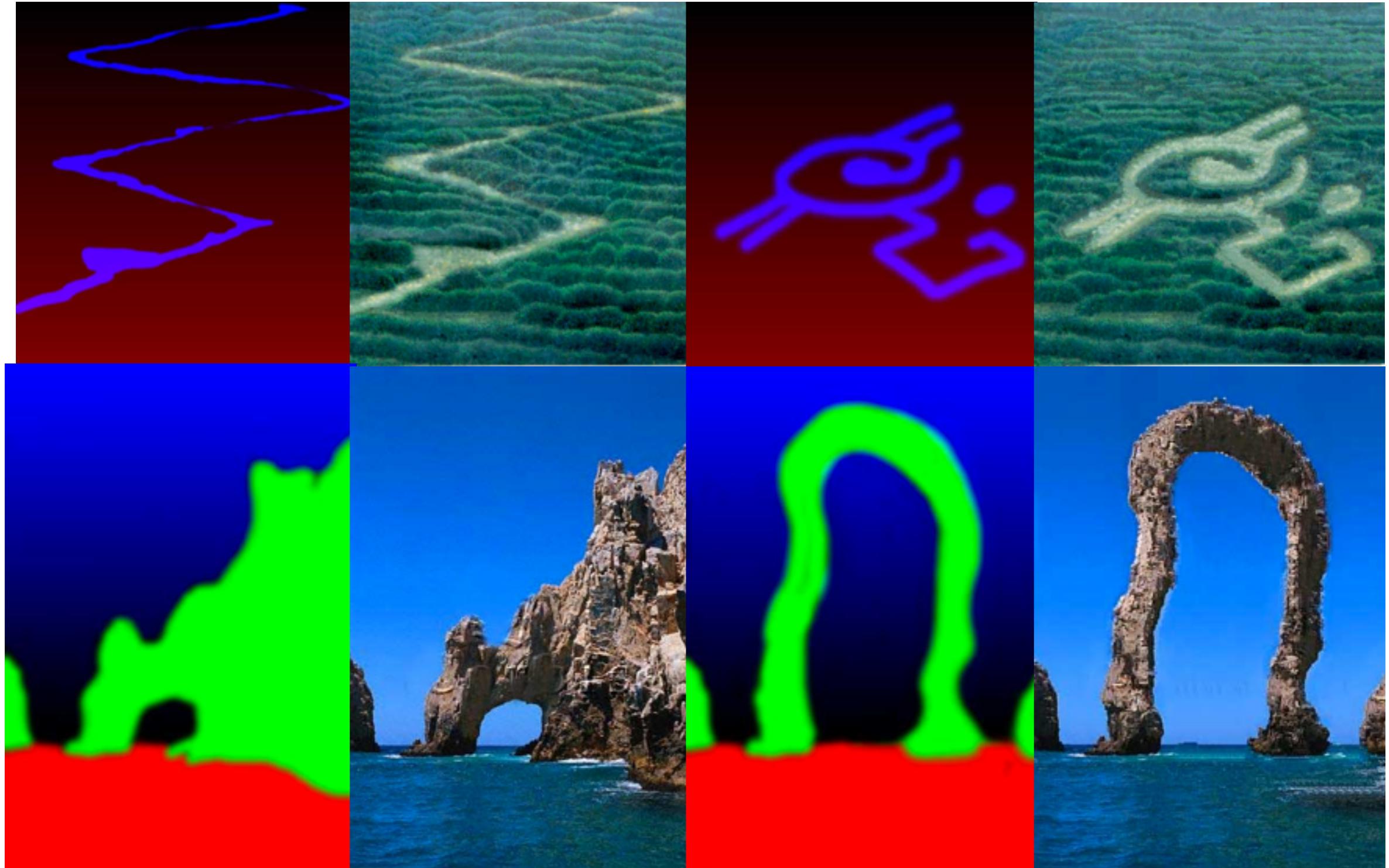
Inter-modal: Style Transfer (“Style Net” 2015)



Leon A. Gatys, Alexander S. Ecker, Matthias Bethge , 2015.
A Neural Algorithm of Artistic Style ([GitXiv](#))



Inter-modal: Image Analogies (2001)



A. Hertzmann, C. Jacobs, N. Oliver, B. Curless, D. Salesin.
(2001) Image Analogies, SIGGRAPH 2001 Conference Proceedings.
A. Hertzmann (2001) Algorithms for Rendering in Artistic Styles
Ph.D thesis. New York University. May, 2001.

Image Analogies

Aaron Hertzmann

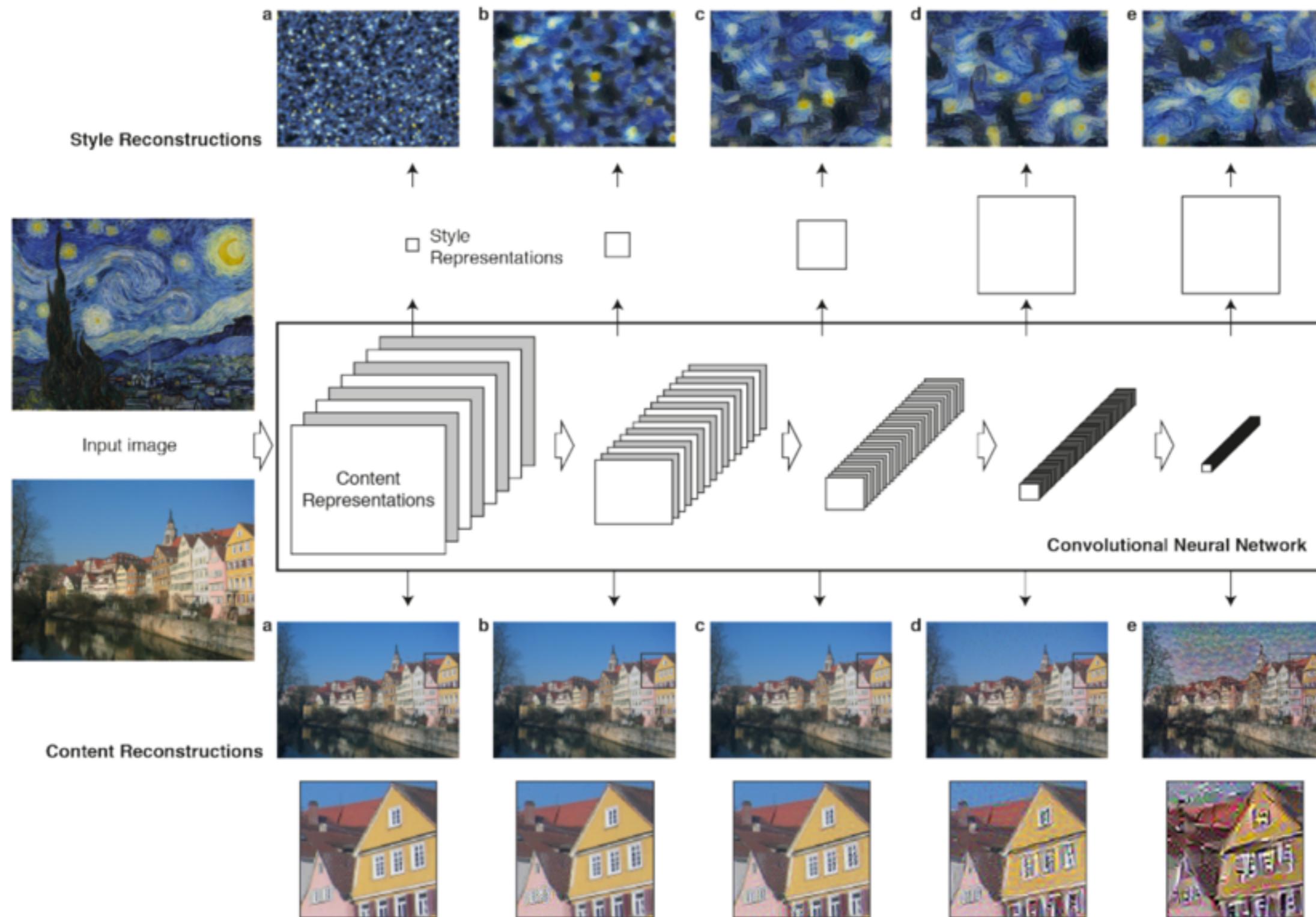
Charles Jacobs

Nuria Oliver

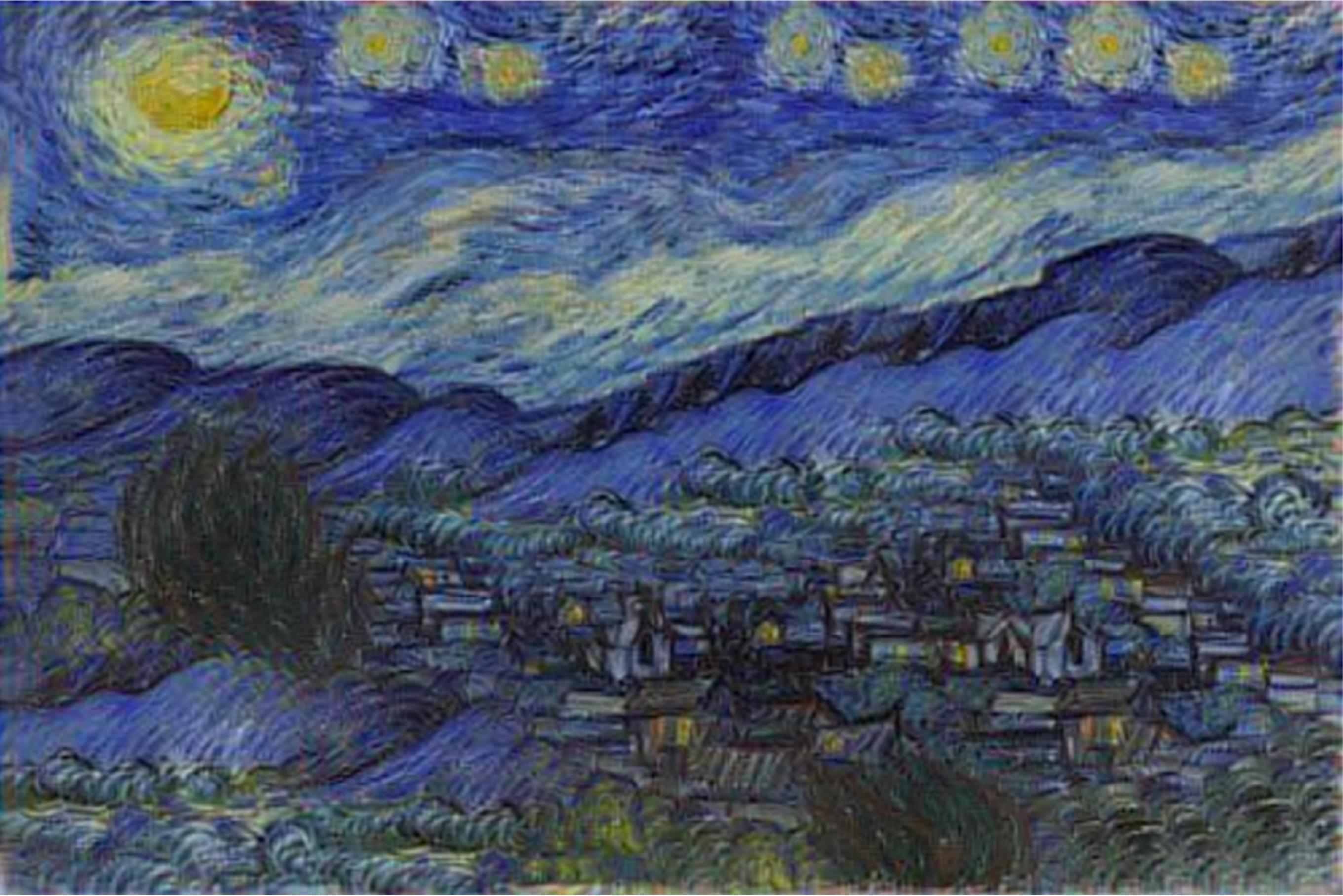
Brian Curless

David Salesin

Inter-modal: Style Transfer (“Style Net” 2015)



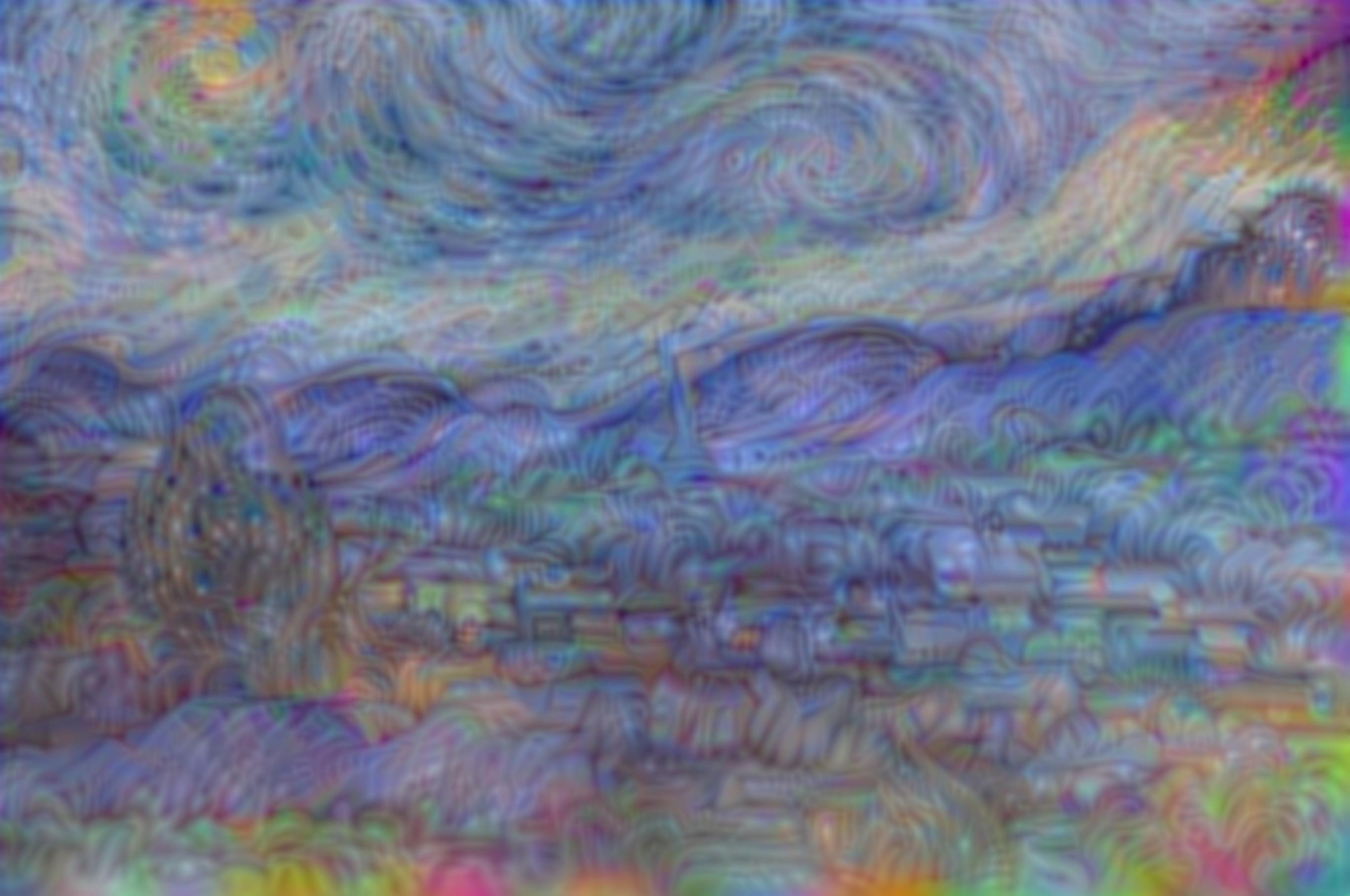
Leon A. Gatys, Alexander S. Ecker, Matthias Bethge , 2015.
A Neural Algorithm of Artistic Style ([GitXiv](#))



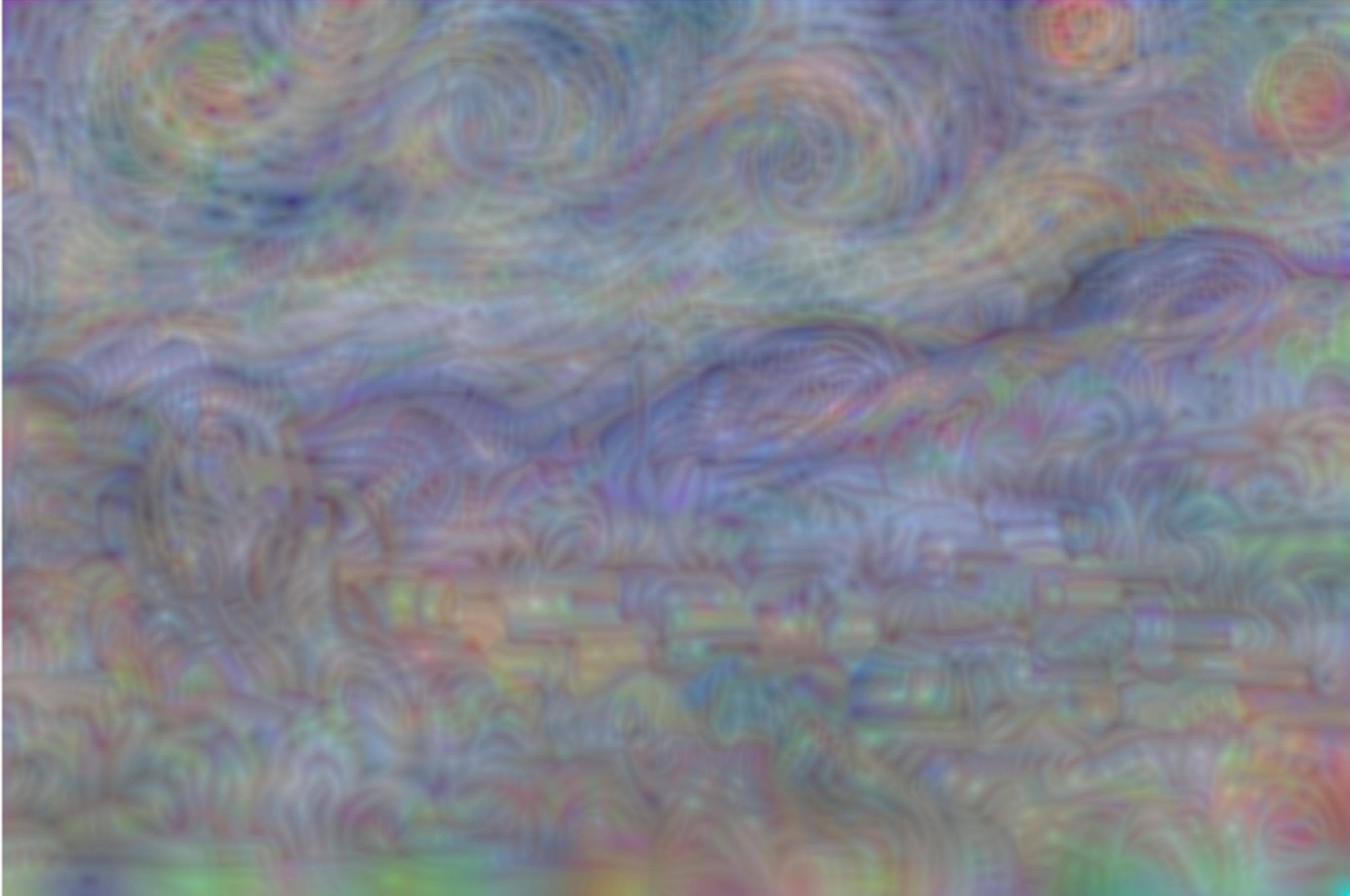
style layers: 3_1,4_1,5_1



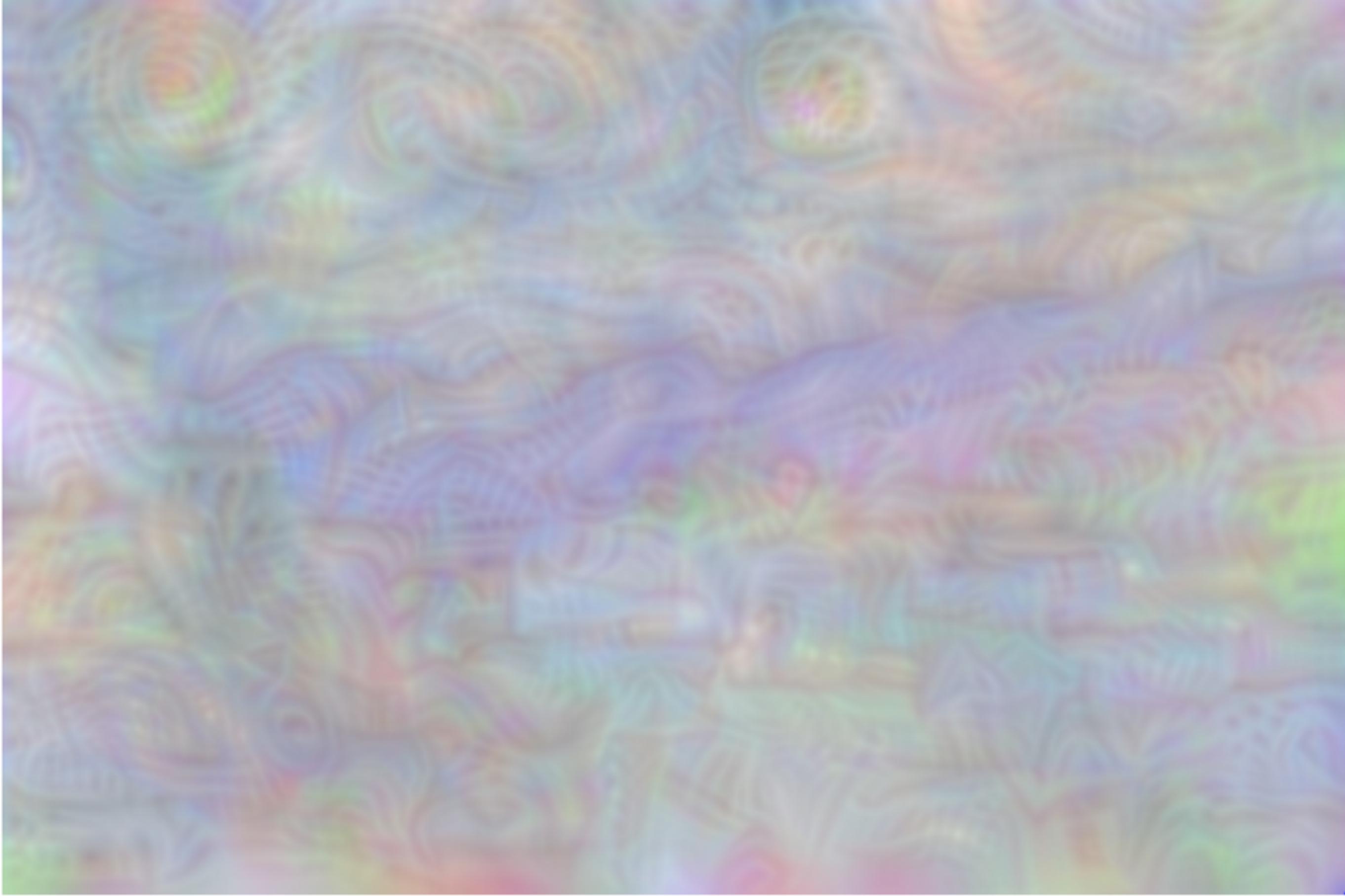
style layers: 3_2



style layers: 5_1

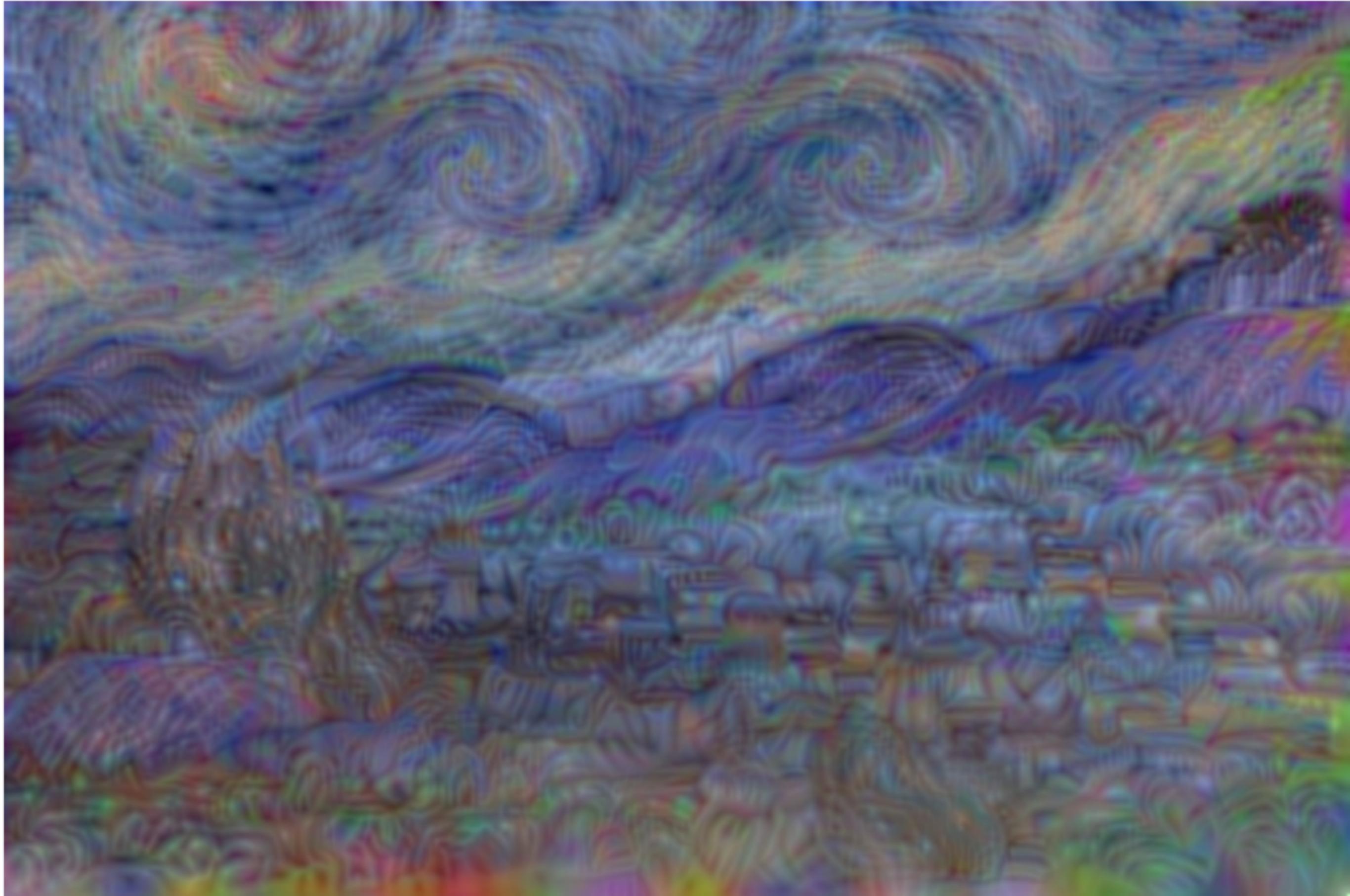


style layers: 5_2



style layers: 5_3

style layers: 5–4



style layers: 5_1 + 5_2 + 5_3 + 5_4



Pablo Picasso



Gene Kogan, 2015. Why is a Raven Like a Writing Desk? ([vimeo](#))

Inter-modal: Style Transfer+MRF (2016)

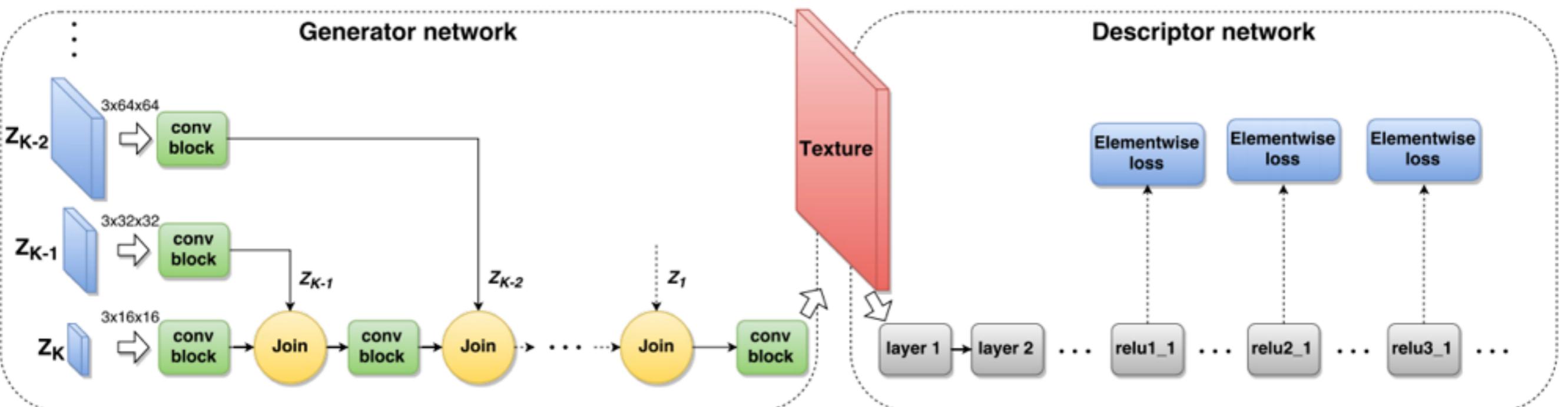
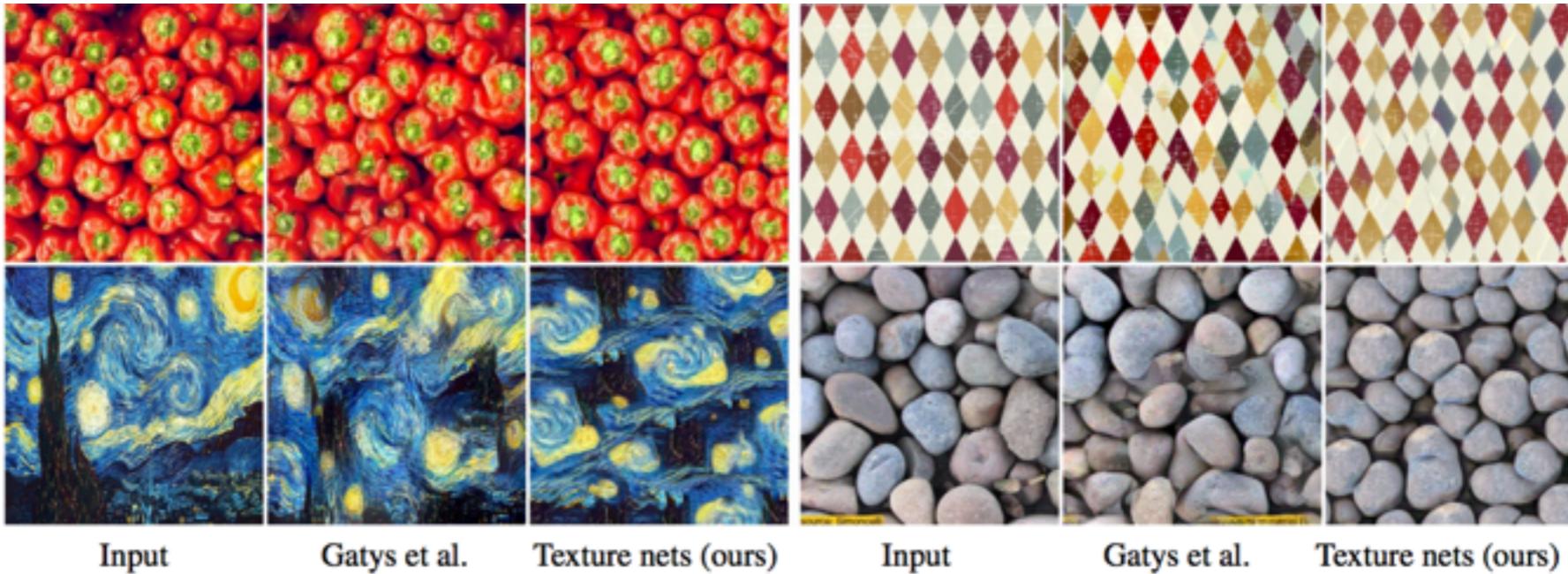


Figure 6: Comparison with Gatys et al. [8] for artistic synthesis. Content images credited to flickr users *Christopher Michel* (top) and *Peter Dahlgren* (bottom).

Inter-modal: Style Transfer+MRF (2016)



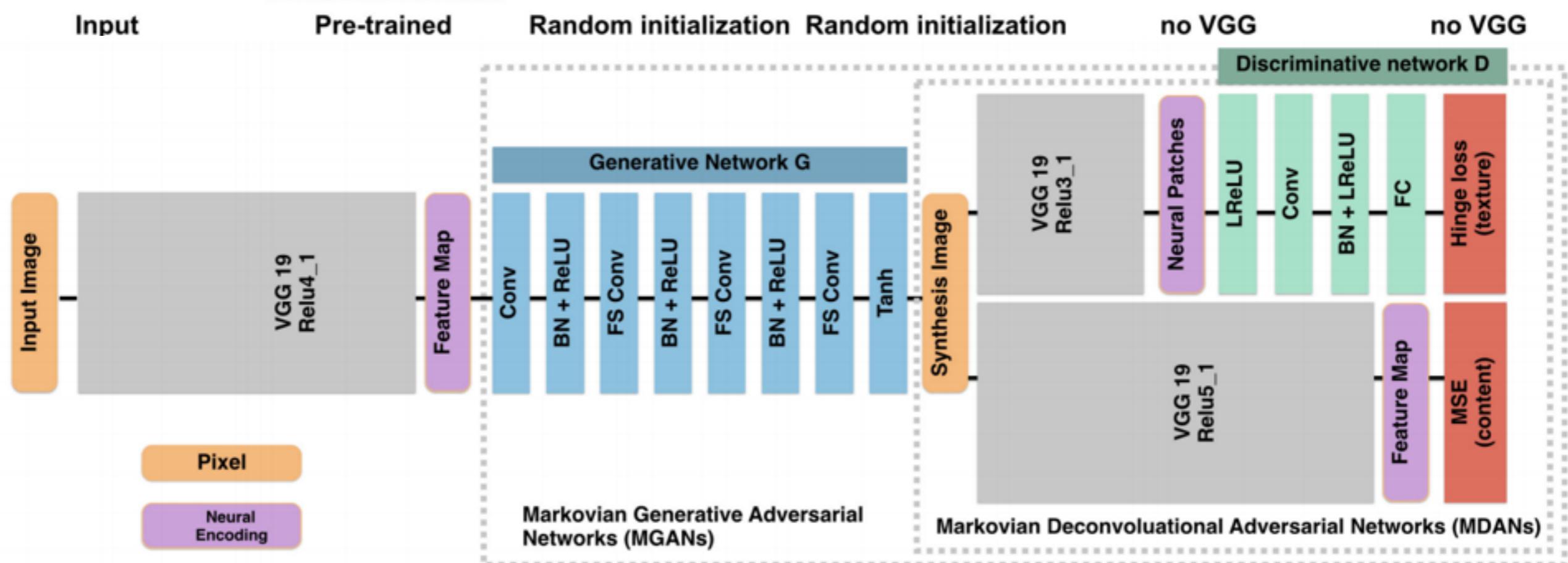
Inter-modal: Pretrained Style Transfer (2016)



500x speedup! (avg min loss from 10s to 20ms)

Texture Networks: Feed-forward Synthesis of Textures and Stylized Images, 2016, Dmitry Ulyanov, Vadim Lebedev, Andrea Vedaldi, Victor Lempitsky

Inter-modal: Pretrained Style Transfer #2 (2016)



similarly 500x speedup

Inter-modal: Perceptual Loss ST (2016)

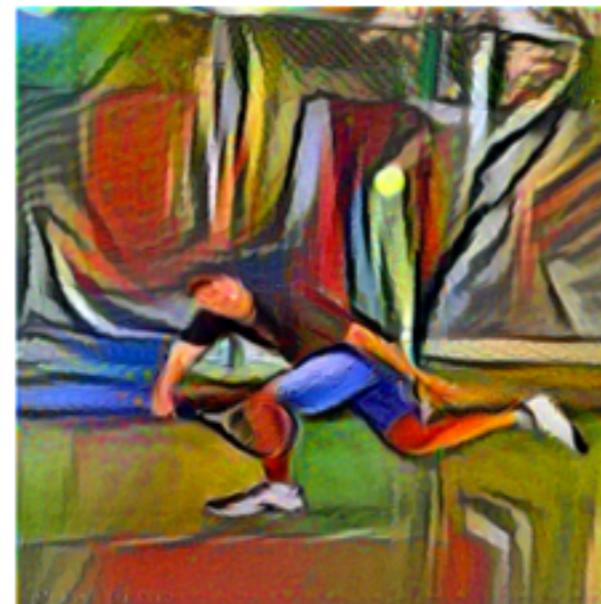
Style



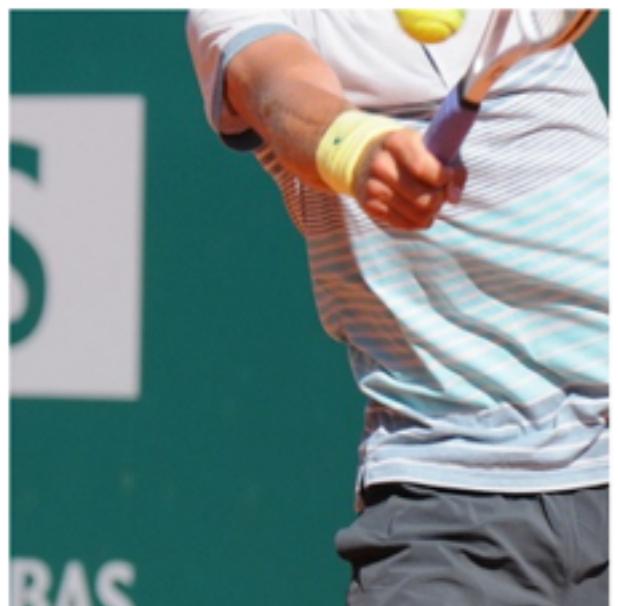
Content



Gatys *et al* [10]



Ours



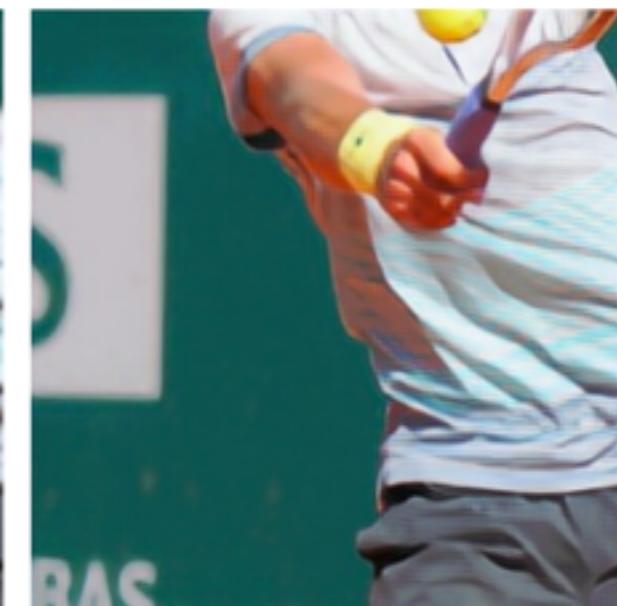
Ground Truth



Bicubic



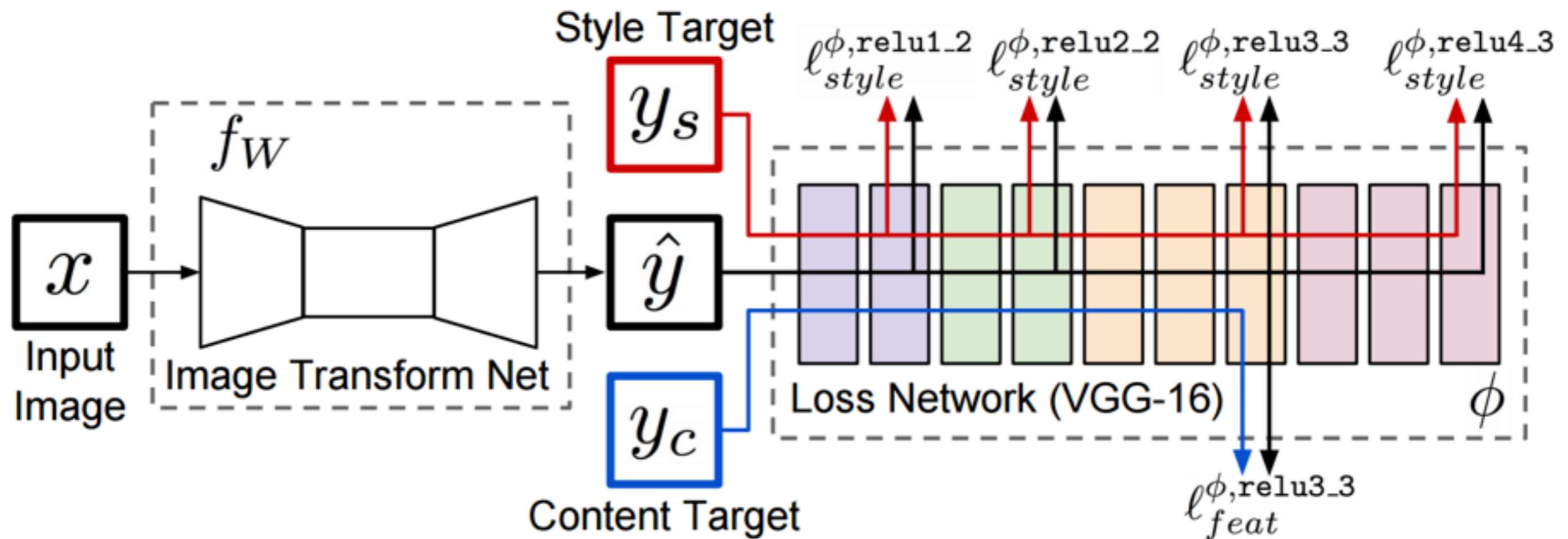
SRCCNN [11]



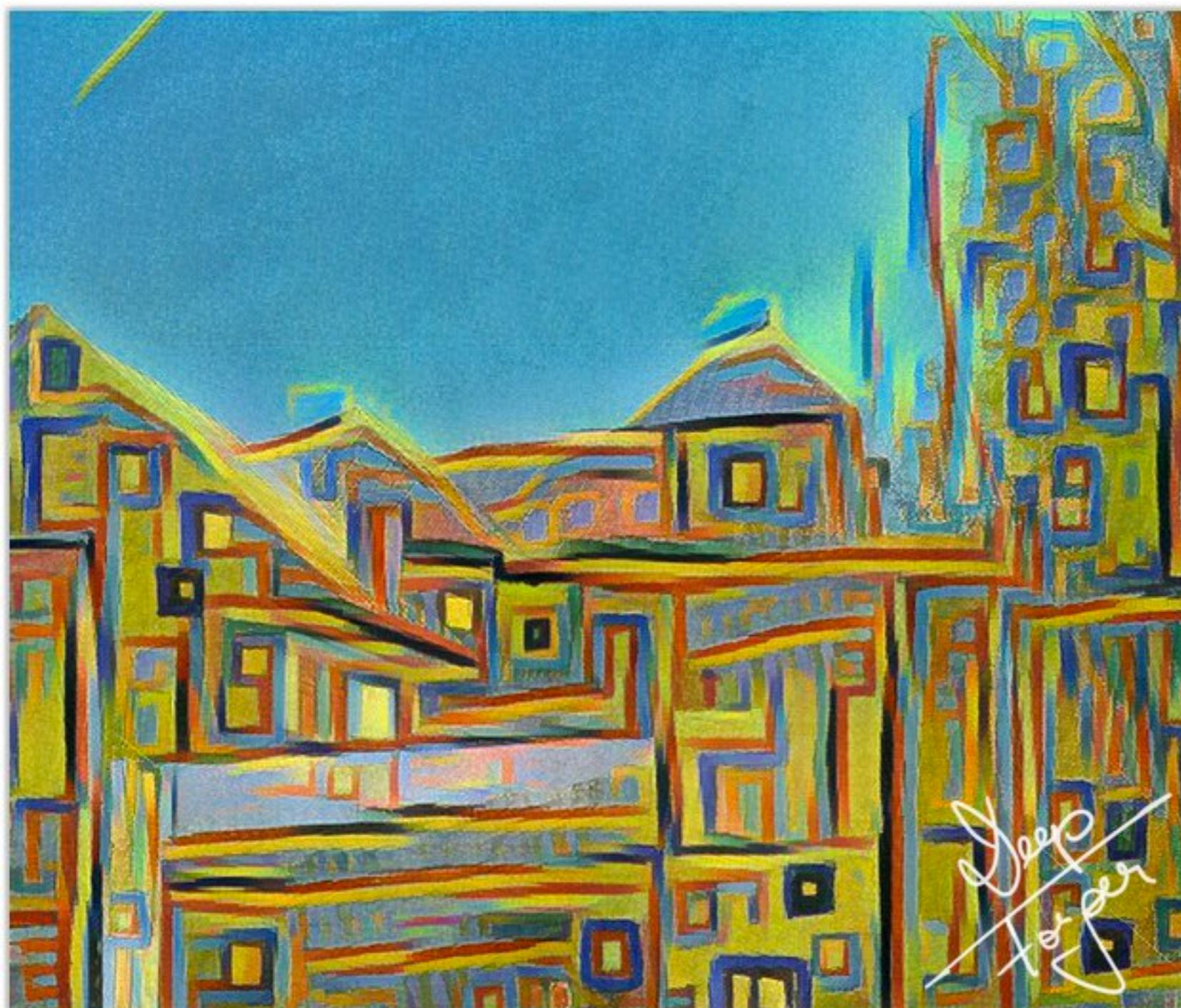
Perceptual loss



	Ground Truth	Bicubic	Ours (ℓ_{pixel})	SRCNN [11]	Ours (ℓ_{feat})
This image		31.78 / 0.8577	31.47 / 0.8573	32.99 / 0.8784	29.24 / 0.7841
Set5 mean		28.43 / 0.8114	28.40 / 0.8205	30.48 / 0.8628	27.09 / 0.7680

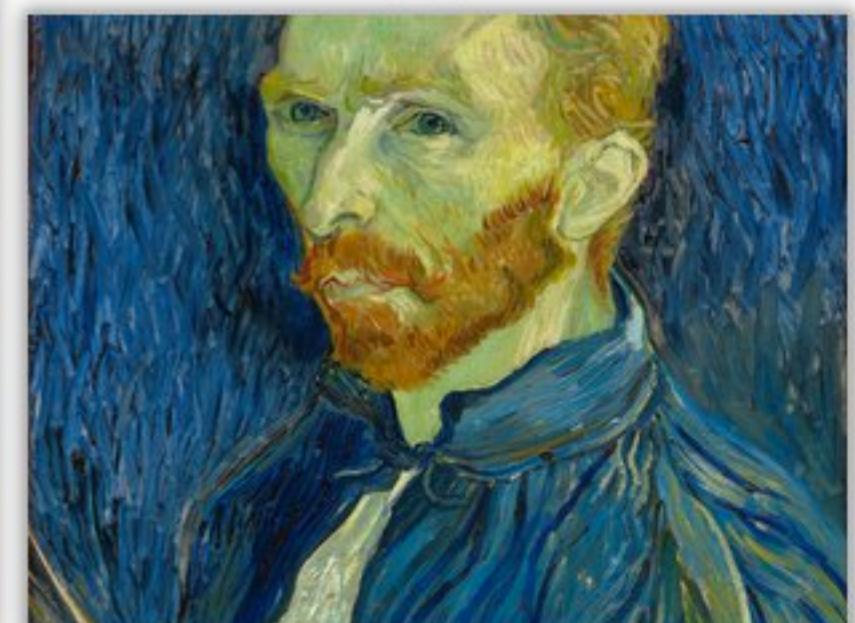


Inter-modal: Style Transfer (“Style Net” 2015)



@DeepForger

Inter-modal: Style Transfer (“Style Net” 2015)



@DeepForger

Inter-modal: Semantic Style Transfer



+



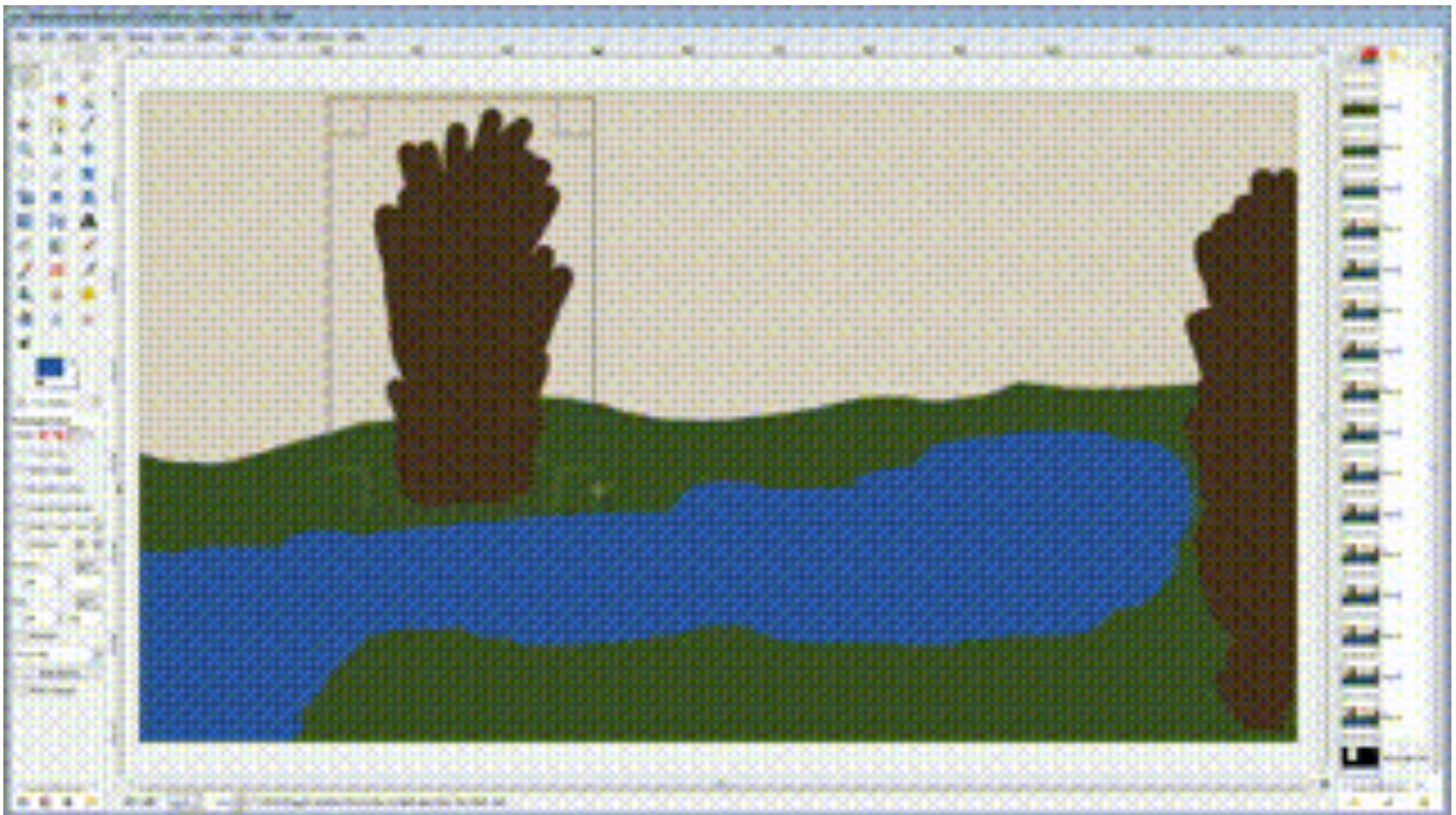
+



=



Semantic Style Transfer (“Neural Doodle”)



<https://github.com/alexjc/neural-doodle>

Synthesize textures

Original Texture



Synthesized Texture #1



Synthesized Texture #2



Synthesise textures (random weights)

Random Weights (kinda like “Extreme Learning Machines”)

- which activation function should i use?
- pooling?
- min nr of units?

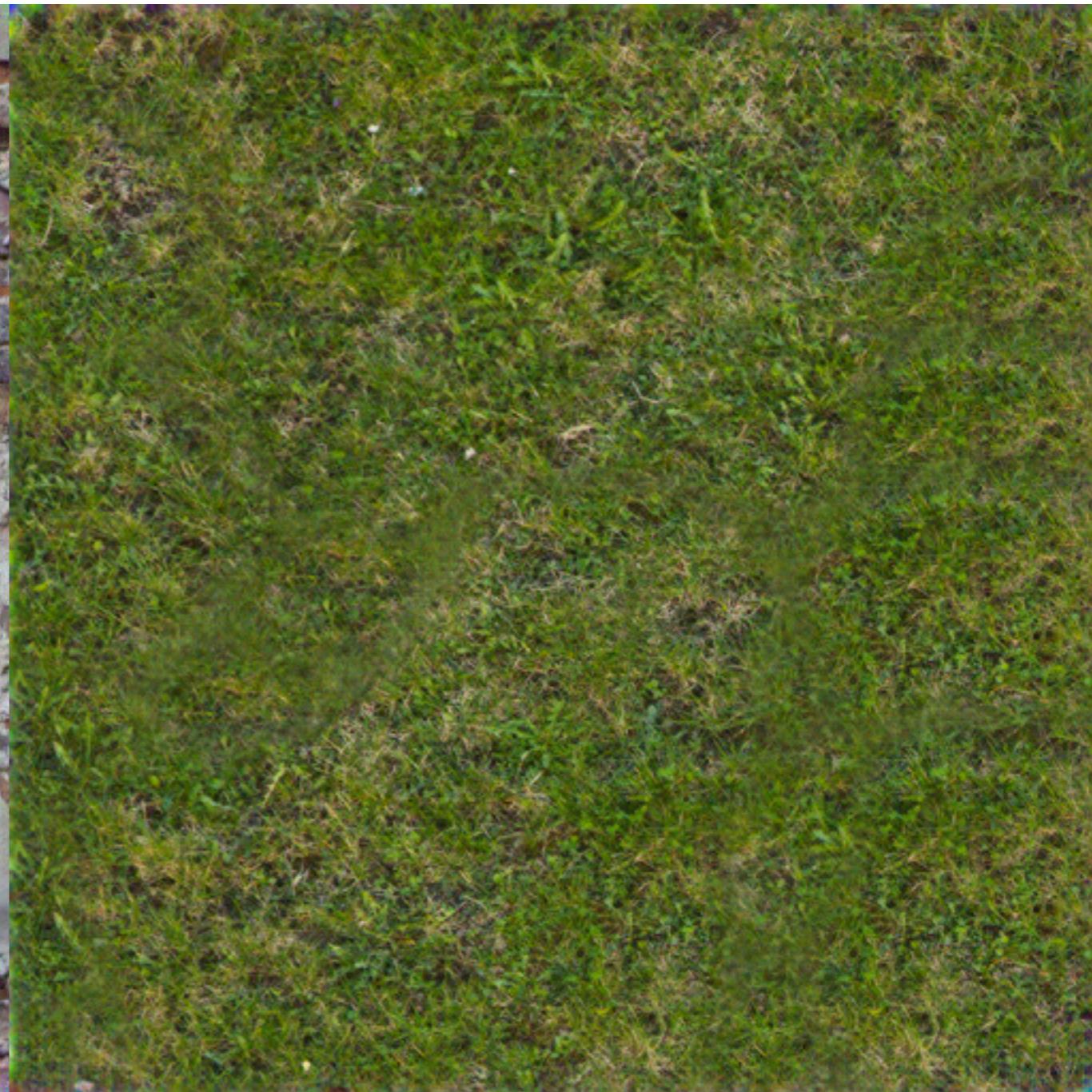
Experiment:

```
        48 units, 3x3 shape          # conv1_1
        48 units, 3x3 shape          # conv1_2
        80 units, 2x2 shape, stride 2x2 # conv2_1
        80 units, 3x3 shape          # conv2_2
        112 units, 2x2 shape, stride 2x2 # conv3_1
        112 units, 3x3 shape          # conv3_2
        112 units, 3x3 shape          # conv3_3
        176 units, 2x2 shape, stride 2x2 # conv4_1
        176 units, 3x3 shape          # conv4_2
        176 units, 3x3 shape          # conv4_3
```

<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

totally random initialised weights:

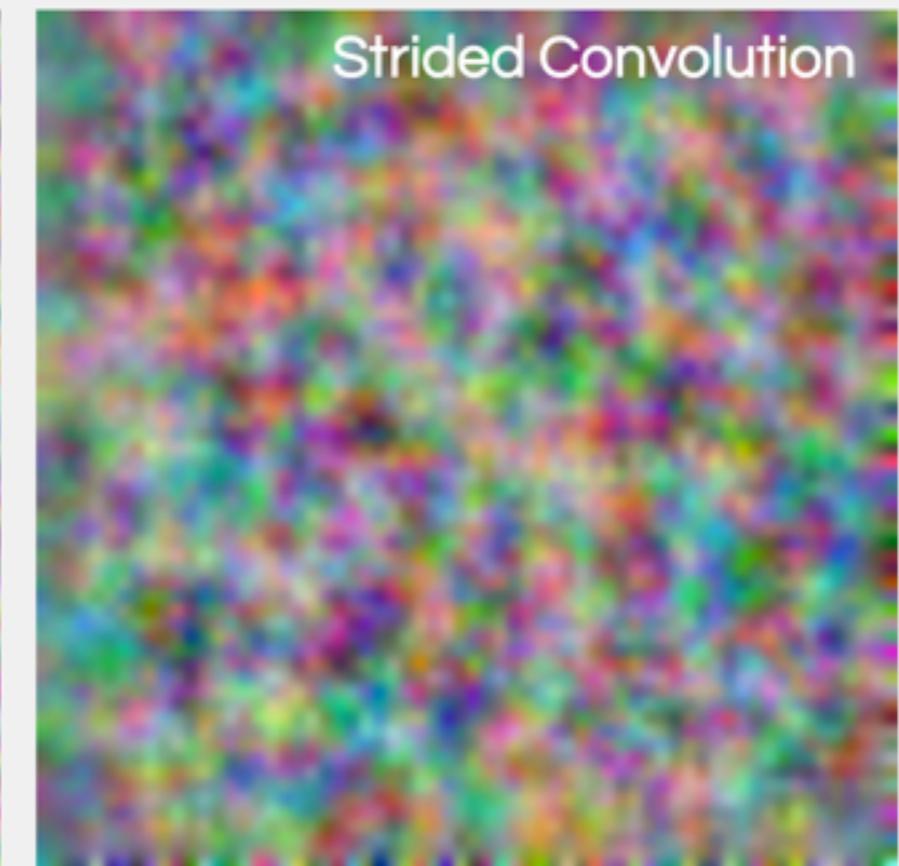
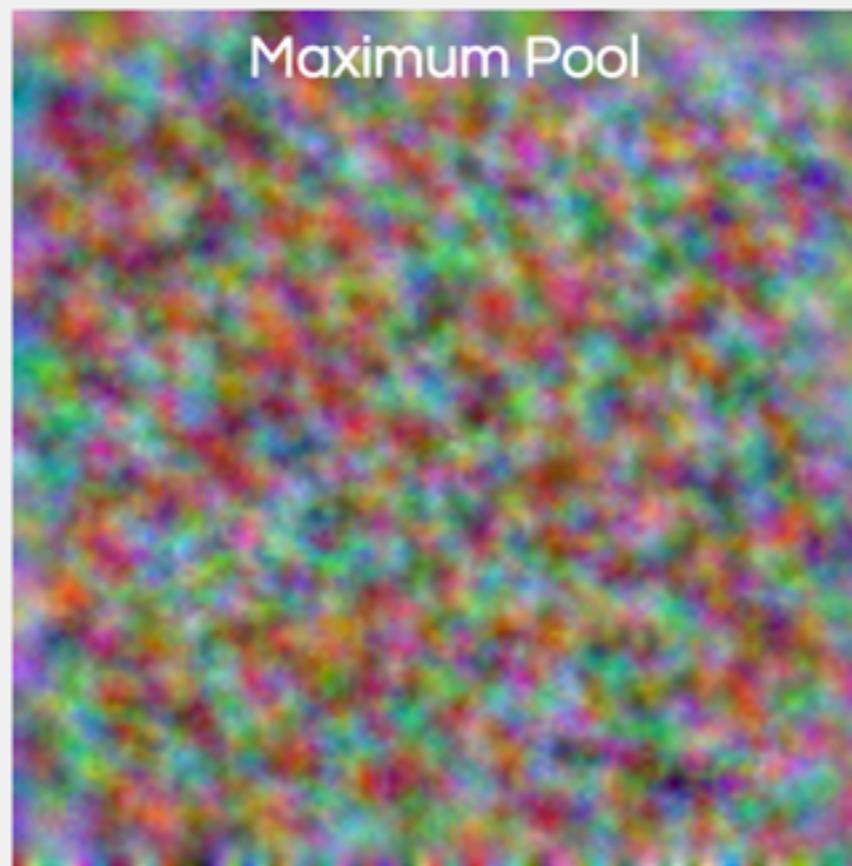
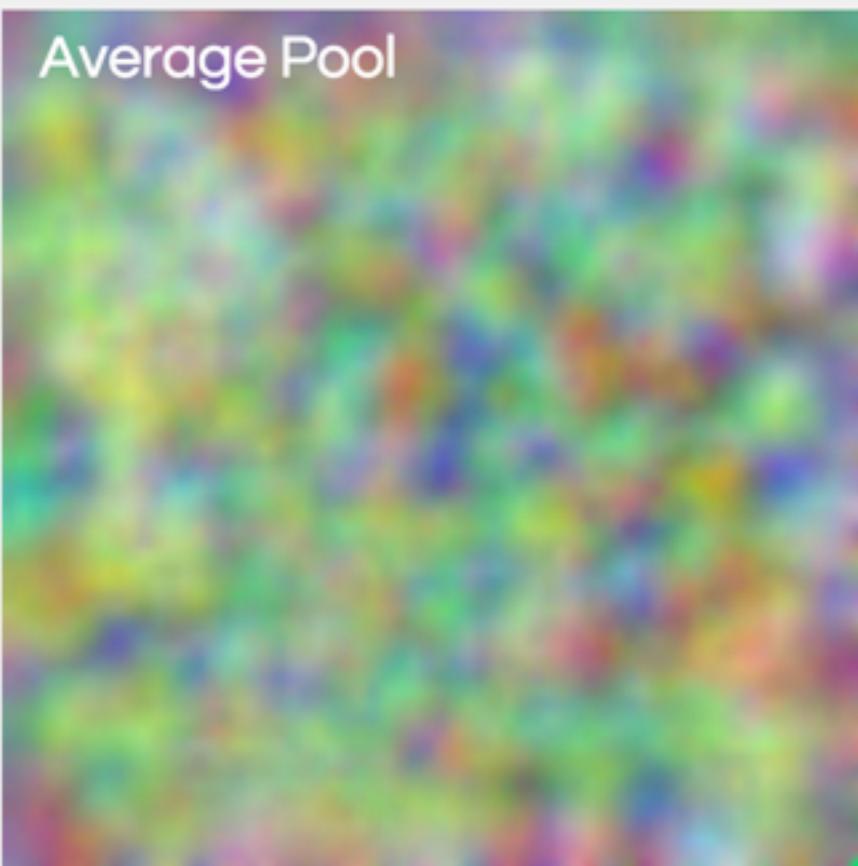


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Activation Functions

Rectified Linear



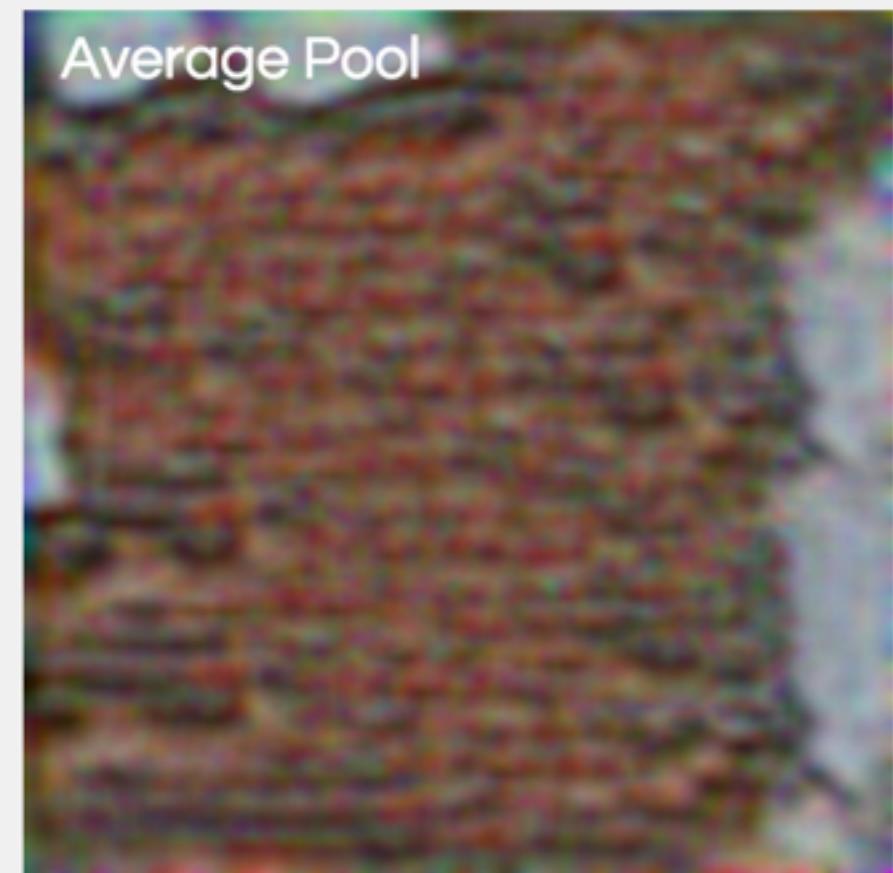
<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

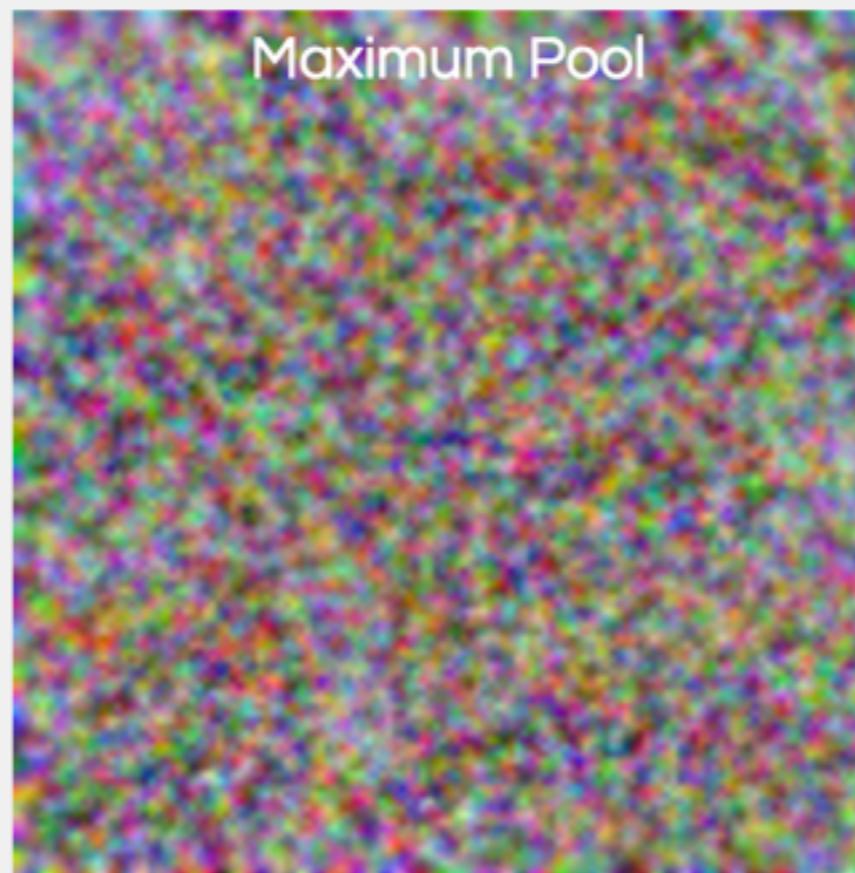
Activation Functions

Very Leaky Rectifier

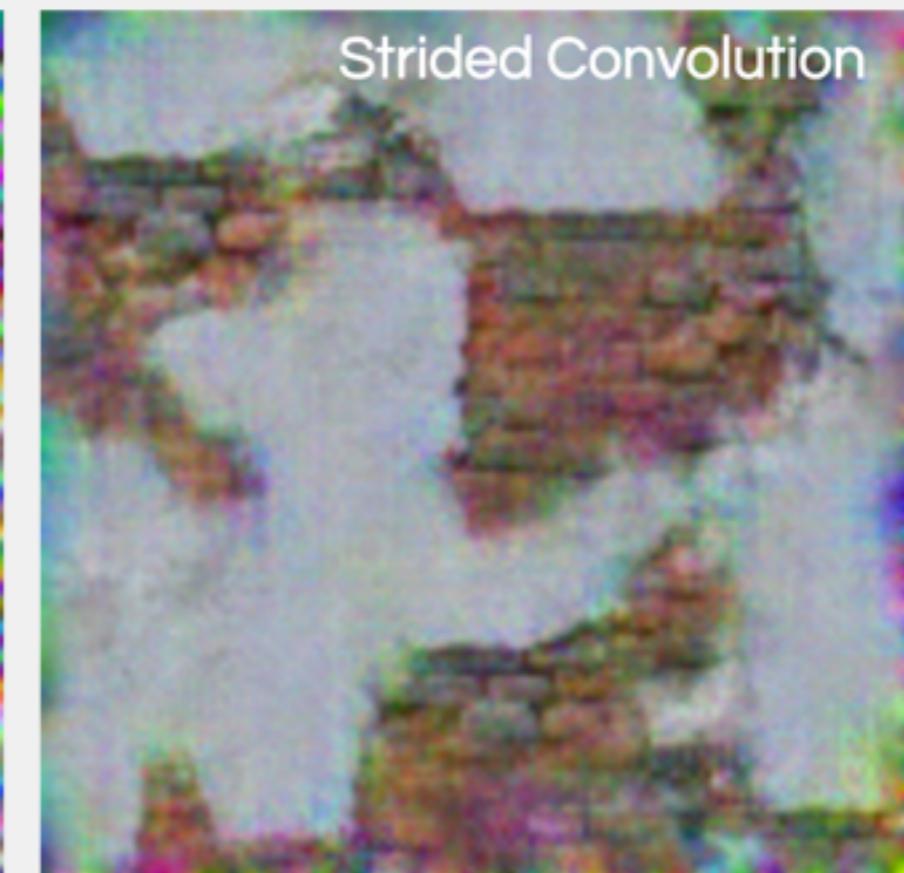
Average Pool



Maximum Pool



Strided Convolution

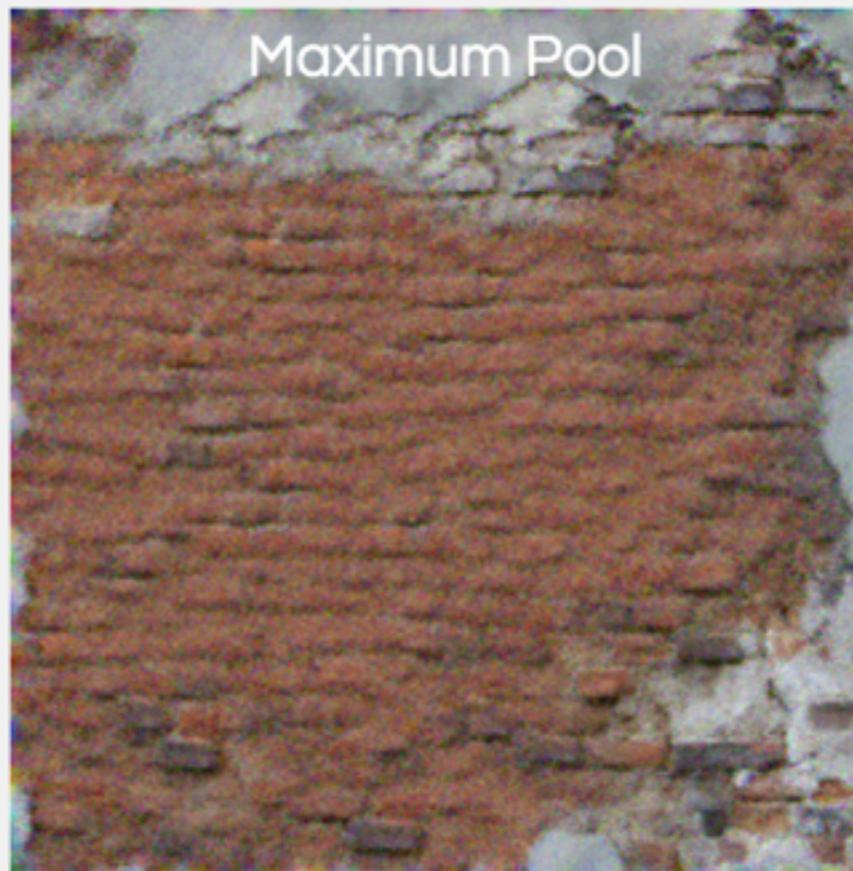


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Activation Functions

Exponential Linear



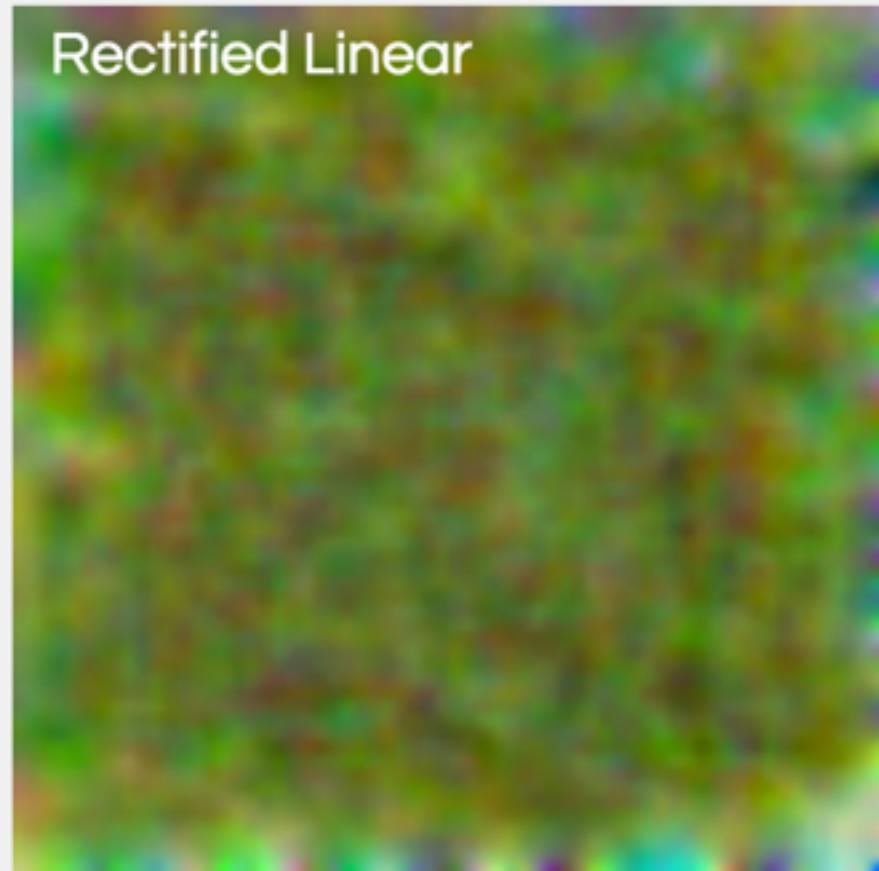
<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

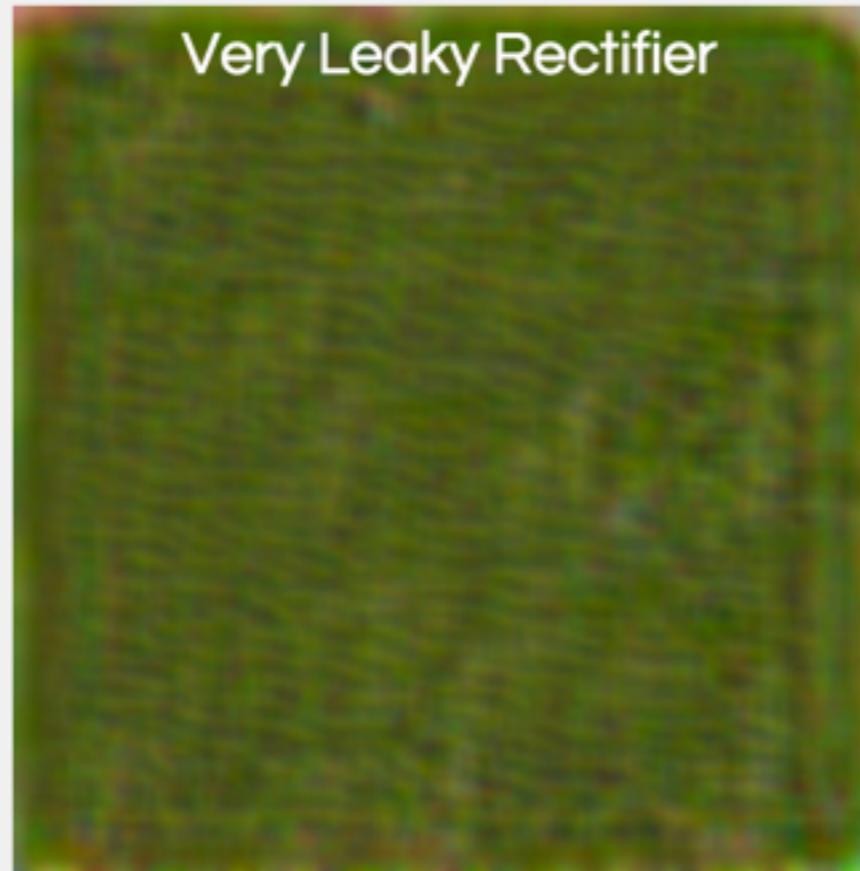
Down-sampling

Average Pooling

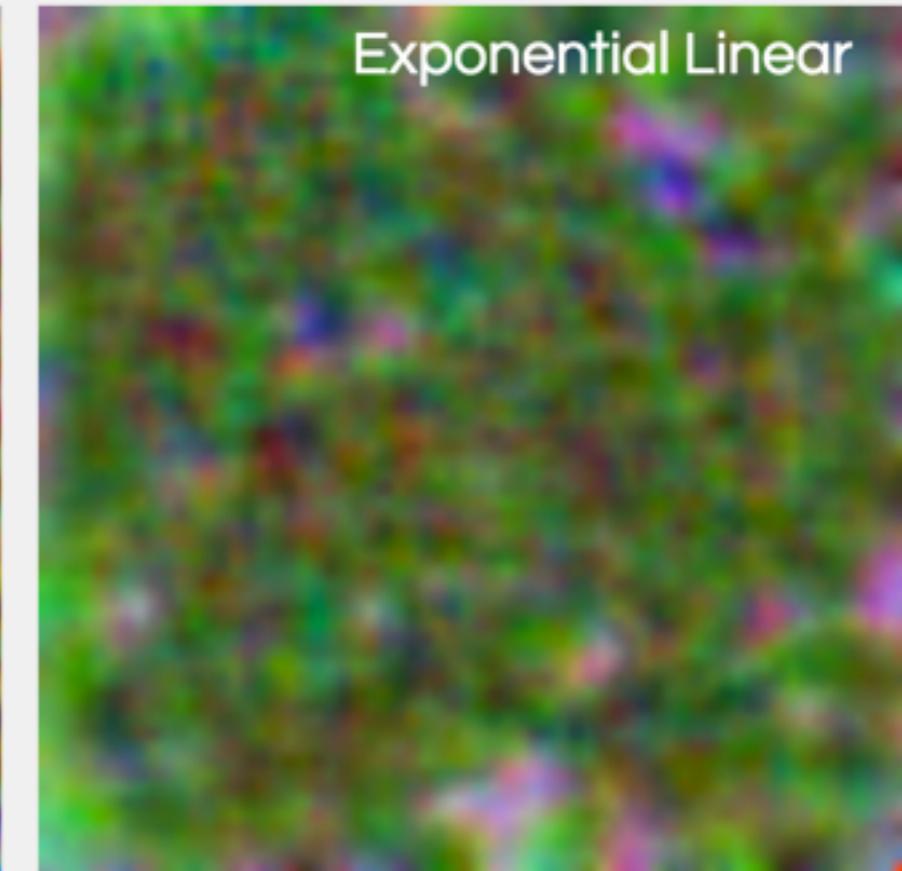
Rectified Linear



Very Leaky Rectifier



Exponential Linear

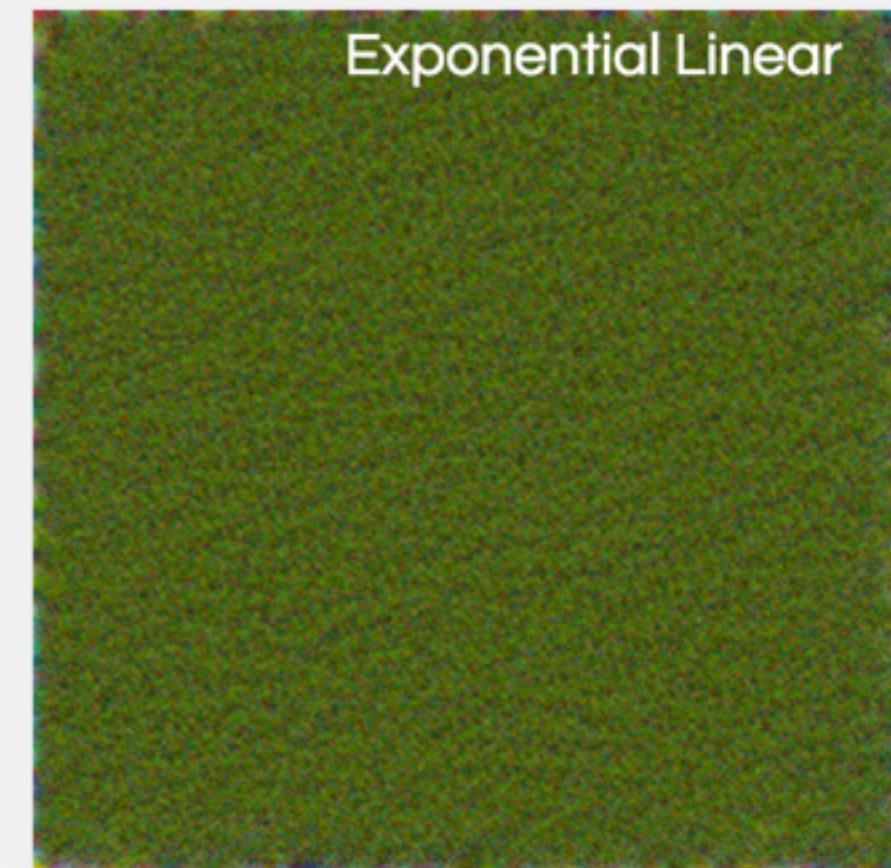
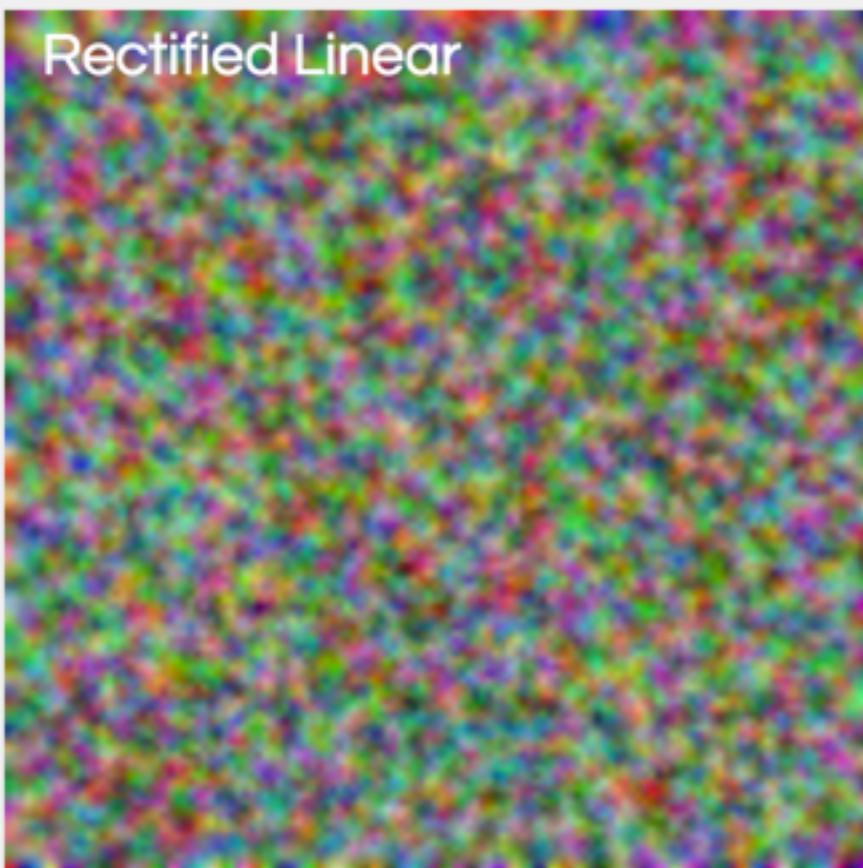


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Down-sampling

Maximum Pooling



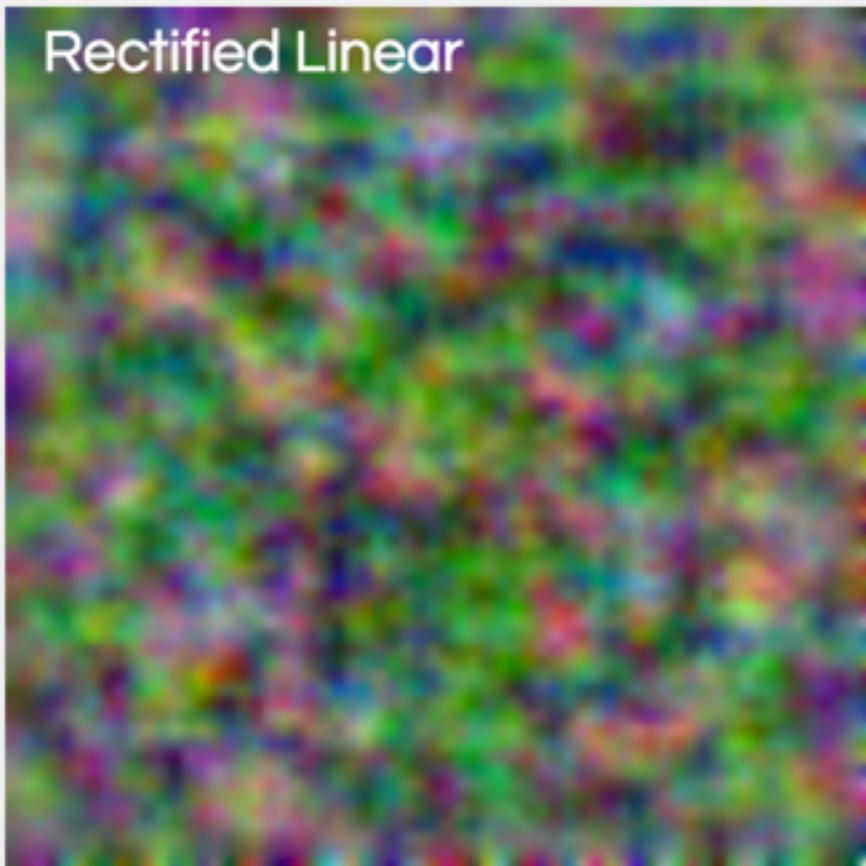
<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Down-sampling

Strided Convolution

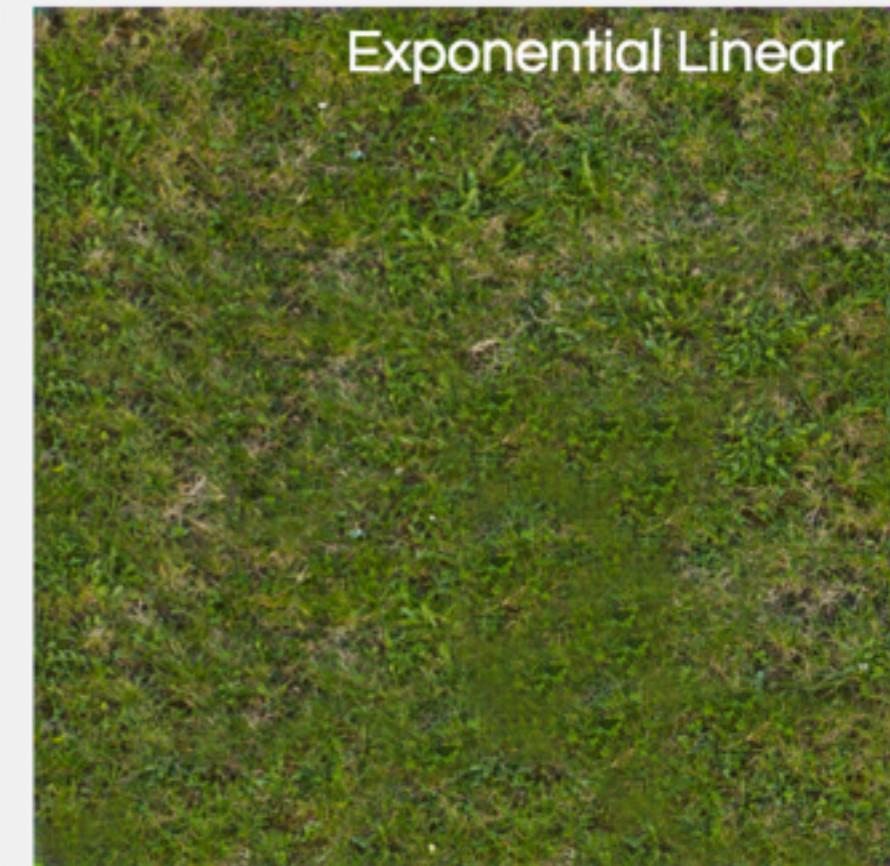
Rectified Linear



Very Leaky Rectifier



Exponential Linear

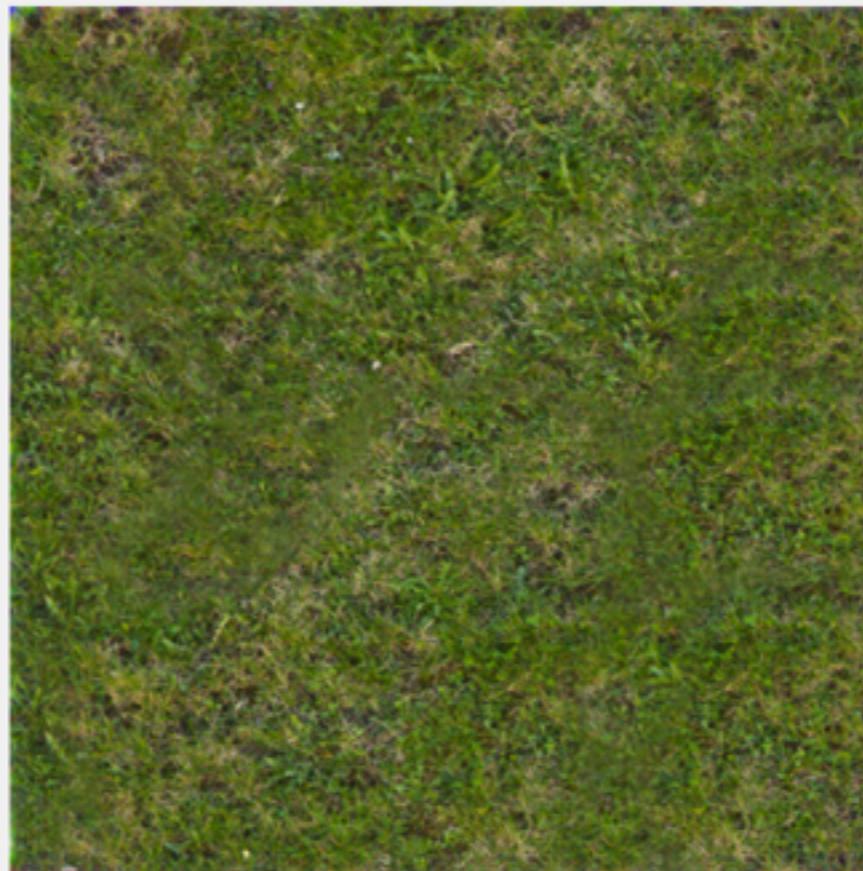


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Nr of units

Full Units

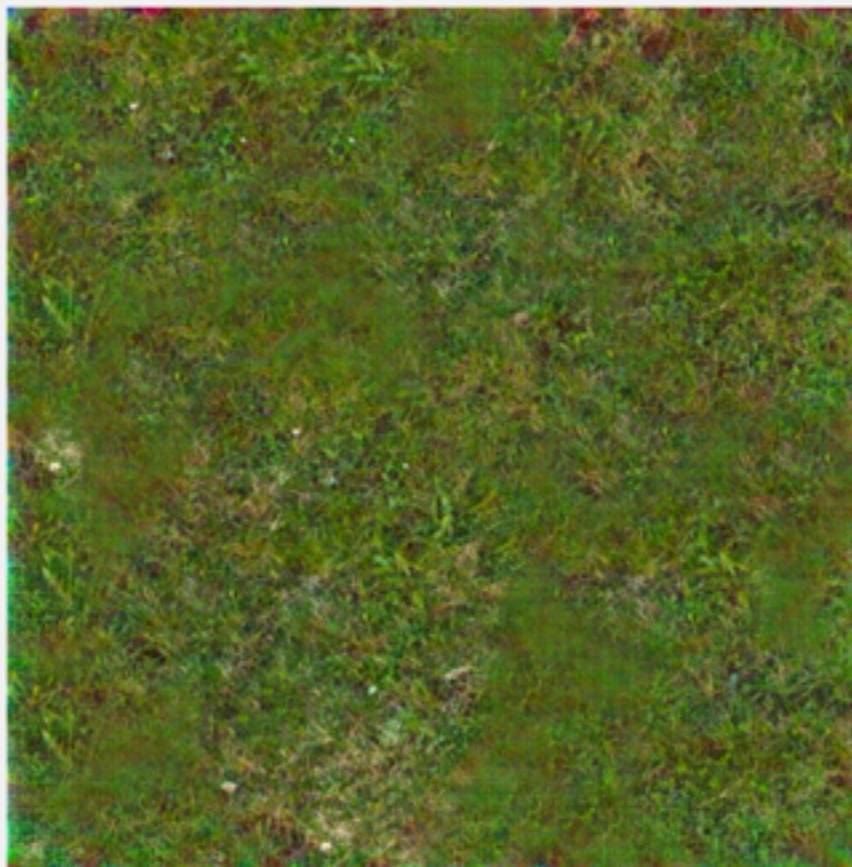


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Nr of units

Half Units

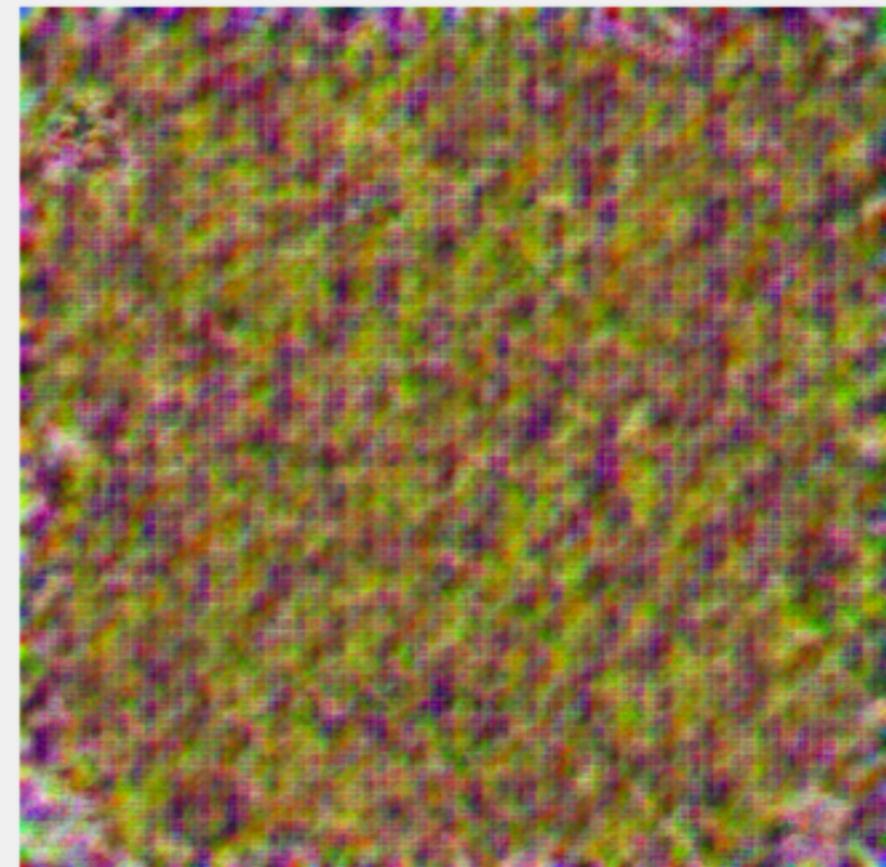
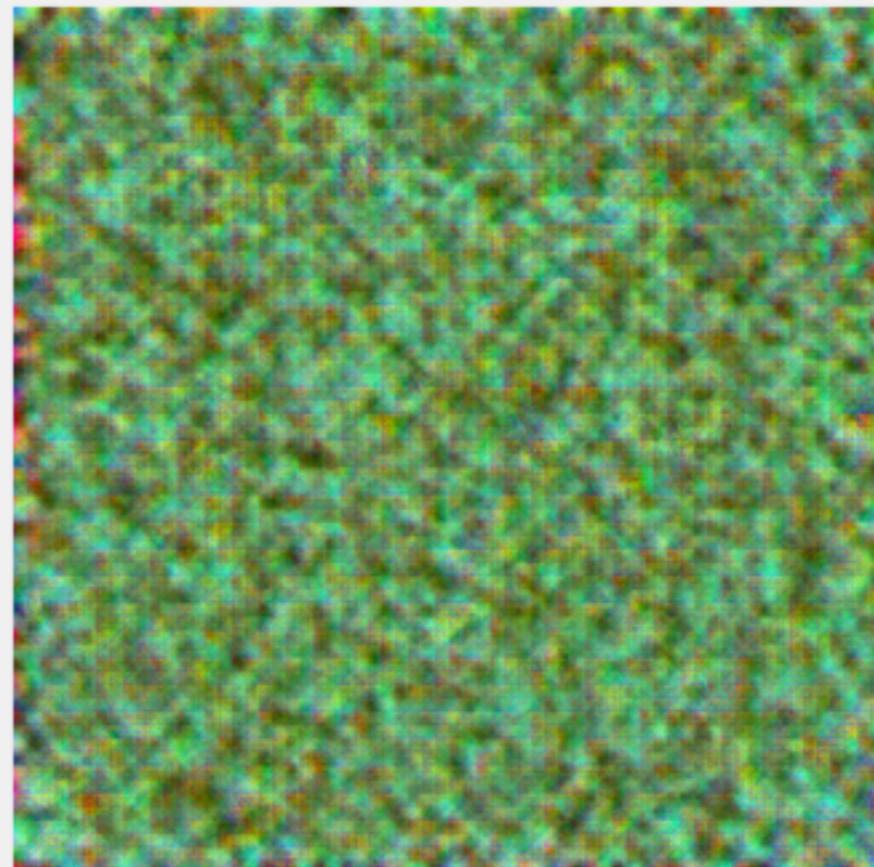
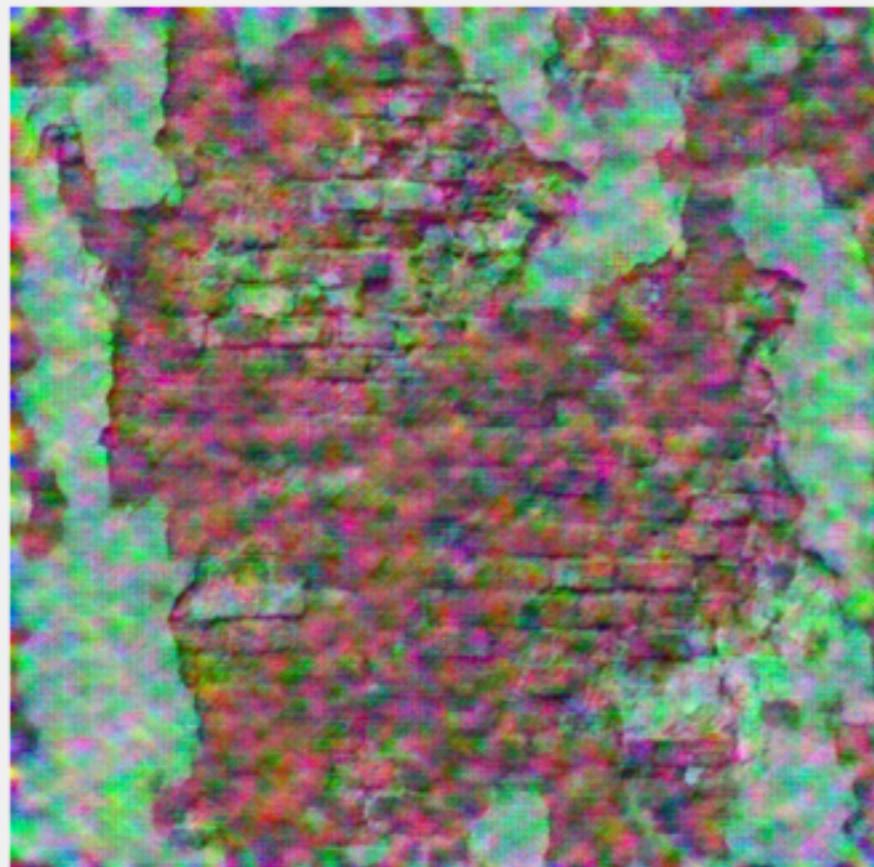


<https://nucl.ai/blog/extreme-style-machines/>

Synthesise textures (random weights)

Nr of units

Quarter Units



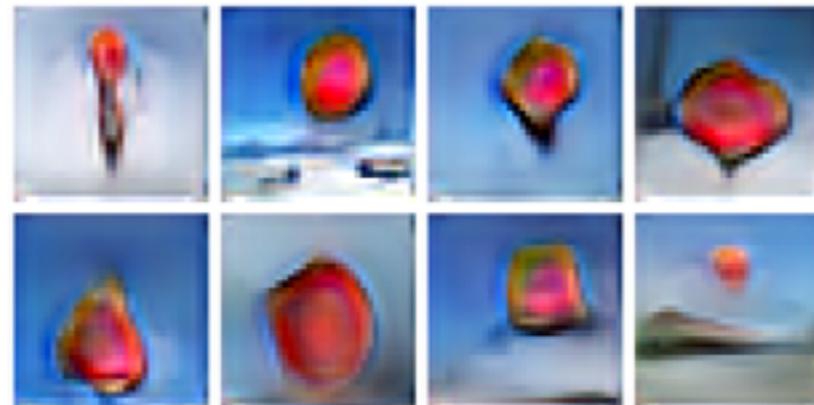
<https://nucl.ai/blog/extreme-style-machines/>

“Style Transfer” papers

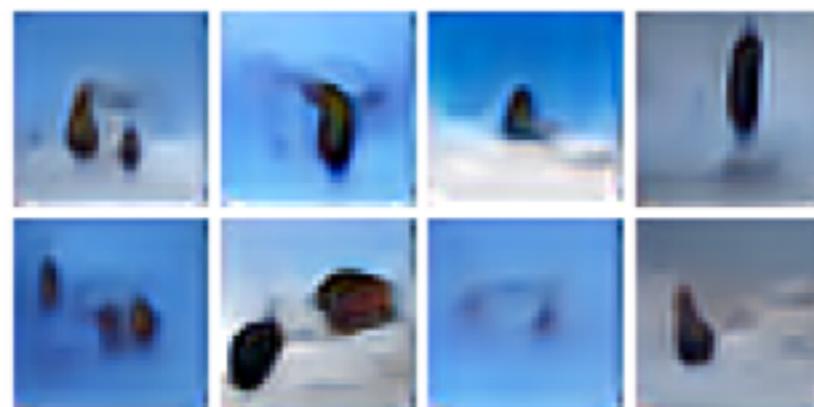
- Image Analogies, **2001**, A. Hertzmann, C. Jacobs, N. Oliver, B. Curless, D. Sales
- A Neural Algorithm of Artistic Style, 2015. Leon A. Gatys, Alexander S. Ecker, Matthias Bethge
- Combining Markov Random Fields and Convolutional Neural Networks for Image Synthesis, 2016, Chuan Li, Michael Wand
- Semantic Style Transfer and Turning Two-Bit Doodles into Fine Artworks, 2016, Alex J. Champandard
- Texture Networks: Feed-forward Synthesis of Textures and Stylized Images, 2016, Dmitry Ulyanov, Vadim Lebedev, Andrea Vedaldi, Victor Lempitsky
- Perceptual Losses for Real-Time Style Transfer and Super-Resolution, 2016, Justin Johnson, Alexandre Alahi, Li Fei-Fei
- Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks, 2016, Chuan Li, Michael Wand

Caption -> Image generation

“A stop sign is flying in blue skies.”



“A herd of elephants flying in the blue skies.”



Elman Mansimov, Emilio Parisotto, Jimmy Lei Ba, Ruslan Salakhutdinov, 2015. Generating Images from Captions with Attention ([arxiv](#)) ([examples](#))

Image Colorisation



More...

more at:

<http://gitxiv.com/category/computer-vision>

<http://www.creativeai.net/> (no category for
images just yet)

Audio Generation

Early LSTM music composition (2002)

A musical score consisting of two staves. The top staff shows chords in a treble clef, with labels above each bar indicating the chord: C, F7, C, GmC, F7, FdimC, EmA7, Dm, G, C, A7, DmG7. The bottom staff shows a melody in a bass clef, with labels 'melody' and 'chords' on the left side. The melody staff has a single note on the first beat of each bar, while the chords staff has notes on the second and third beats of each bar.

Douglas Eck and Jurgen Schmidhuber (2002) Learning The
Long-Term Structure of the Blues?

Markov constraints

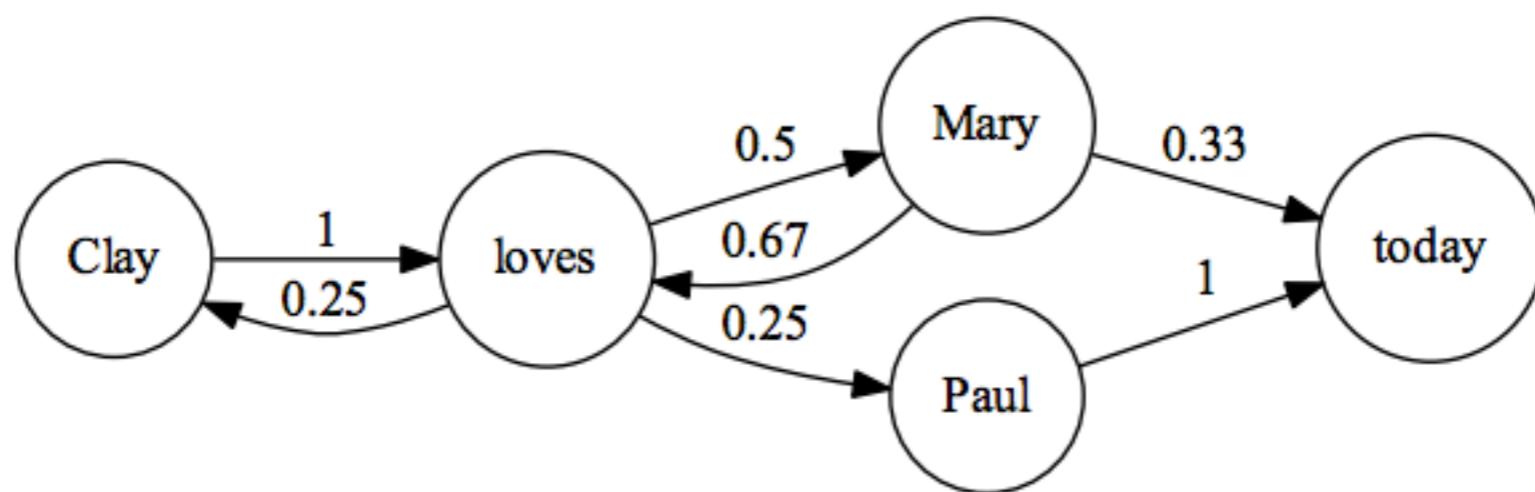


Figure 1. An order-1 Markov process learned from a corpus composed of five words.

$$P(s_i | s_1, \dots, s_{i-1}) = P(s_i | s_{i-1})$$

Markov constraints

Ode to Joy in several styles

<http://www.flow-machines.com/>

Audio Generation: Midi



+ “modded VRNN:

A Recurrent Latent Variable Model for
Sequential Data, 2016,
J. Chung, K. Kastner, L. Dinh, K. Goel,
A. Courville, Y. Bengio

<https://soundcloud.com/graphific/pyotr-lstm-tchaikovsky>

Audio Generation: Midi



+ “modded VRNN:

A Recurrent Latent Variable Model for
Sequential Data, 2016,
J. Chung, K. Kastner, L. Dinh, K. Goel,
A. Courville, Y. Bengio

<https://soundcloud.com/graphific/neural-remix-net>

Audio Generation: Raw

stanford cs224d project Gated Recurrent Unit (GRU)

Aran Nayebi, Matt Vitelli (2015) GRUV: Algorithmic Music Generation using Recurrent Neural Networks

LSTM improvements

- LSTM improvements
 - **Recurrent Batch Normalization** <http://gitxiv.com/posts/MwSDm6A4wPG7TcuPZ/recurrent-batch-normalization>
 - also: hidden-to-hidden transition (earlier only input-to-hidden transformation of RNNs)
 - faster convergence and improved generalization.

LSTM improvements

- LSTM improvements
 - **weight normalisation** <http://gitxiv.com/posts/p9B6i9Kzbkc5rP3cp/weight-normalization-a-simple-reparameterization-to>

LSTM improvements

- LSTM improvements
 - **Associative Long Short-Term Memory** <http://gitxiv.com/posts/jpfdiFPsu5c6LLsF4/associative-long-short-term-memory>

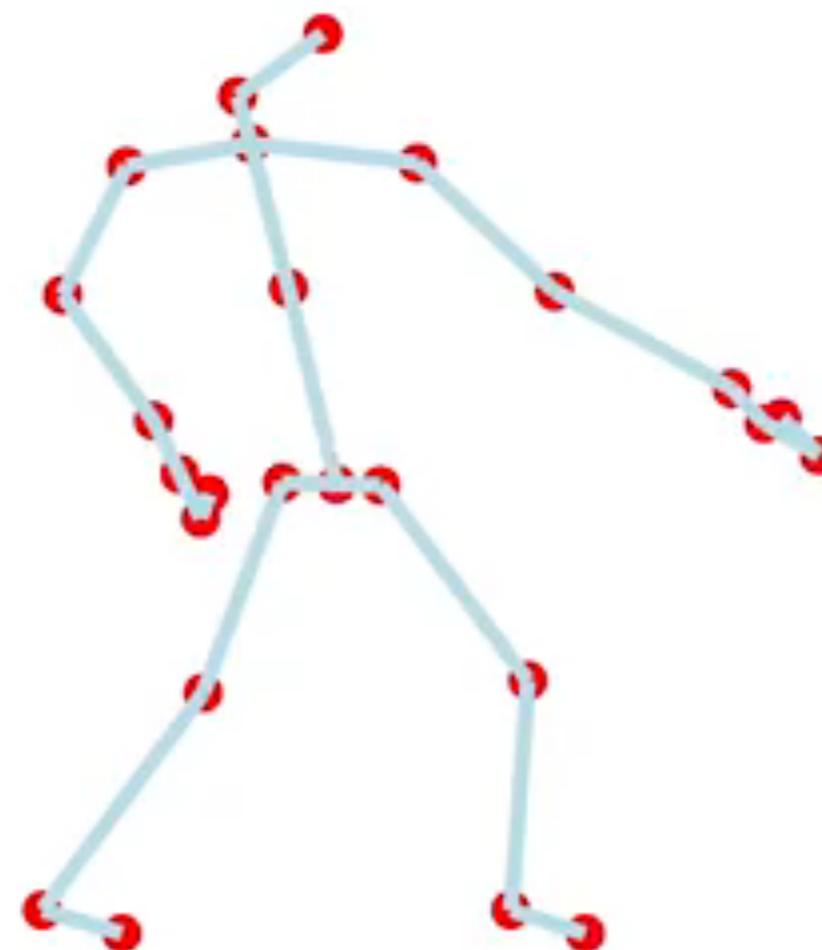
LSTM improvements

- LSTM improvements
 - **Bayesian RNN dropout** <http://gitxiv.com/posts/CsCDjy7WpfcBvZ88R/bayesianrnn>

Continuous Generation

Chor-RNN

$$\cancel{t_t = x_{t+1}}$$



Luka Crnkovic-Friis & Louise Crnkovic-Friis (2016) Generative Choreography
using Deep Learning

Generative

- Mixture Density LSTM

$$1 \quad p(\mathbf{t}|\mathbf{x}) = \sum_{i=1}^m \alpha_i(\mathbf{x}) \varphi_i(\mathbf{t}|\mathbf{x})$$

$$2 \quad \varphi_i(\mathbf{t}|\mathbf{x}) = \frac{1}{(2\pi)^{\frac{c}{2}} \sigma_i(\mathbf{x})^c} e^{-\frac{\|\mathbf{t} - \mu_i(\mathbf{x})\|^2}{2\sigma_i(\mathbf{x})^2}}$$

$$3 \quad \mathbf{z} = [z_1^\alpha, \dots, z_m^\alpha, z_{m+1}^\mu, \dots, z_{mc+m+1}^\mu, z_{mc+m+2}^\sigma, \dots, z_{m(c+2)}^\sigma]$$

$$4 \quad E^q = -\log \left[\sum_{i=1}^m \alpha_i(\mathbf{x}^q) \varphi_i(\mathbf{t}^q|\mathbf{x}^q) \right]$$

$$5 \quad \alpha_i = \frac{e^{z_i^\alpha}}{\sum_{j=1}^M e^{z_j^\alpha}}, \quad \sigma_i = e^{z_i^\sigma}, \quad \mu_i = z_{ik}^\mu$$

$$\frac{\partial E^q}{\partial z_k^\alpha} = \alpha_k - \frac{\alpha_k \varphi_k}{\sum_{j=1}^m \alpha_j \varphi_j}$$

$$\frac{\partial E^q}{\partial z_{ik}^\mu} = \frac{\alpha_i \varphi_i}{\sum_{j=1}^m \alpha_j \varphi_j} \frac{\mu_{ik} - t_k}{\sigma_i^2} \quad 6$$

$$\frac{\partial E^q}{\partial z_i^\sigma} = -\frac{\alpha_i \varphi_i}{\sum_{j=1}^m \alpha_j \varphi_j} \left\{ \frac{\|\mathbf{t} - \mu_i\|^2}{\sigma_i^2} - c \right\}$$

Generative

- Mixture Density LSTM

$$1 \quad p(\mathbf{t}|\mathbf{x}) = \sum_{i=1}^m \alpha_i(\mathbf{x}) \varphi_i(\mathbf{t}|\mathbf{x})$$

$$2 \quad \varphi_i(\mathbf{t}|\mathbf{x}) = \frac{1}{(2\pi)^{\frac{c}{2}} \sigma_i(\mathbf{x})^c} e^{-\frac{\|\mathbf{t} - \mu_i(\mathbf{x})\|^2}{2\sigma_i(\mathbf{x})^2}}$$

$$3 \quad \mathbf{z} = [z_1^\alpha, \dots, z_m^\alpha, z_{m+1}^\mu, \dots, z_{mc+m+1}^\mu, z_{mc+m+2}^\sigma, \dots, z_{m(c+2)}^\sigma]$$

$$4 \quad E^q = -\log \left[\sum_{i=1}^m \alpha_i(\mathbf{x}^q) \varphi_i(\mathbf{t}^q|\mathbf{x}^q) \right]$$

$$5 \quad \alpha_i = \frac{e^{z_i^\alpha}}{\sum_{j=1}^M e^{z_j^\alpha}}, \quad \sigma_i = e^{z_i^\sigma}, \quad \mu_i = z_{ik}^\mu$$

$$\frac{\partial E^q}{\partial z_k^\alpha} = \alpha_k - \frac{\alpha_k \varphi_k}{\sum_{j=1}^m \alpha_j \varphi_j}$$

$$\frac{\partial E^q}{\partial z_{ik}^\mu} = \frac{\alpha_i \varphi_i}{\sum_{j=1}^m \alpha_j \varphi_j} \frac{\mu_{ik} - t_k}{\sigma_i^2} \quad 6$$

$$\frac{\partial E^q}{\partial z_i^\sigma} = -\frac{\alpha_i \varphi_i}{\sum_{j=1}^m \alpha_j \varphi_j} \left\{ \frac{\|\mathbf{t} - \mu_i\|^2}{\sigma_i^2} - c \right\}$$

Generative

- Mixture Density LSTM

$$1 \quad p(\mathbf{t}|\mathbf{x}) = \sum_{i=1}^m \alpha_i(\mathbf{x}) \varphi_i(\mathbf{t}|\mathbf{x})$$

$$2 \quad \varphi_i(\mathbf{t}|\mathbf{x}) = \frac{1}{(2\pi)^{\frac{c}{2}} \sigma_i(\mathbf{x})^c} e^{-\frac{\|\mathbf{t} - \mu_i(\mathbf{x})\|^2}{2\sigma_i(\mathbf{x})^2}}$$

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**Wanna be Doing
Deep Learning?**



Deep Learning with Python
python has a wide range of deep learning-related libraries available

High level



Keras



keras.io



tensorflow.org/



caffe.berkeleyvision.org



deeplearning.net/software/theano

Low level

and of course:



Code & Papers?

<http://gitxiv.com/>  #GitXiv

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GitXiv

Collaborative Open Computer Science

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Let there be Color! Automatic Colorization of Grayscale Images

Automatically color grayscale images with a deep network

DEEP LEARNING (DL) GENERATIVE COMPUTER VISION

1

S

0

samim 1 point 43 minutes ago | Edit 0 Comments | score: 0.273, clicks: 0, views: 3



The MegaFace Benchmark: 1 Million Faces for Recognition at Scale

Face recognition benchmark, evaluation and experimentation code included.

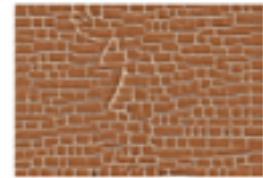
DEEP LEARNING (DL) CONVOLUTIONAL NEURAL NETWORKS (CNN) COMPUTER VISION MACHINE LEARNING COMPUTER GRAPHICS

2

A

0

aaronnech 1 point 16 hours ago | Edit 0 Comments | score: 0.024, clicks: 0, views: 22



Perceptual Losses for Real-Time Style Transfer and Super-Resolution

Three orders of magnitude faster neural style through pretrained features

DEEP LEARNING (DL) CONVOLUTIONAL NEURAL NETWORKS (CNN) GENERATIVE

3

I

0

graphific 3 points a day ago | Edit 0 Comments | score: 0.027, clicks: 0, views: 56



Learning Spatiotemporal Features with 3D Convolutional Networks (C3D)

3D ConvNets trained on a large scale supervised video dataset (Sports 1M)

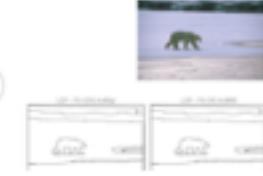
DEEP LEARNING (DL) CONVOLUTIONAL NEURAL NETWORKS (CNN)

4

M

0

graphific 4 points 2 days ago | Edit 0 Comments | score: 0.027, clicks: 0, views: 51



Supervised Evaluation of Image Segmentation and Object Proposal Techniques

Eight state-of-the-art object proposal techniques are analyzed by two quantitative meta-measures

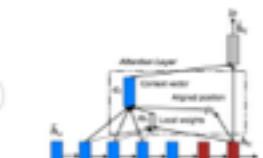
DEEP LEARNING (DL) CONVOLUTIONAL NEURAL NETWORKS (CNN) COMPUTER VISION COMMUNITY DETECTION/CLUSTERING

5

E

0

euler 2 points 2 days ago | Edit 0 Comments | score: 0.013, clicks: 0, views: 28



Effective Approaches to Attention-based Neural Machine Translation

Global and local attention based neural machine translation

DEEP LEARNING (DL) RECURRENT NEURAL NETWORKS (RNN) NATURAL LANGUAGE PROCESSING (NLP)

6

O

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Creative AI projects?

<http://www.creativeai.net/>

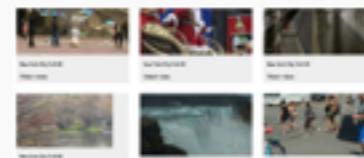


#CreativeAI

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CreativeAi



Video2GIF: Automatic Generation of Animated GIFs from Video

ANIMATION ASSISTED

MACHINE LEARNING RESEARCH

benlowden a minute ago



Neuroaesthetics in Fashion: Modeling the Perception of Fashionability

ASSISTED FASHION

MACHINE LEARNING RESEARCH

samim 19 minutes ago



Single Image Weathering via Exemplar Propagation

ASSISTED MACHINE LEARNING

RESEARCH VIDEO

samim 26 minutes ago



Sketch Simplification: Fully Convolutional Networks for Rough Sketch Cleanup

ASSISTED DRAWING

MACHINE LEARNING RESEARCH

samim 32 minutes ago



Let there be Color! Automatic Colorization of Grayscale Images

ASSISTED GENERATIVE

MACHINE LEARNING OPEN SOURCE

RESEARCH STYLETRANSFER

samim 39 minutes ago



Reverse OCR, a bot which generates squiggles until an OCR word recognition recognises a word.

DRAWING GENERATIVE READ/WRITE

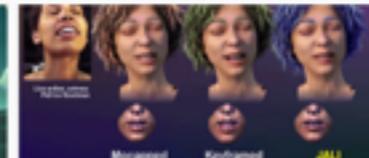
benlowden 10 hours ago



Touch Of Blood - Using machine learning to create maps based on gameplay

ART GAMES MACHINE LEARNING

flikcloud 11 hours ago



JALI - Lip-syncing facial articulation of 3D models with speech audio input

ASSISTED CINEMA GAMES

GENERATIVE VIDEO VOICE

montecarlo 12 hours ago

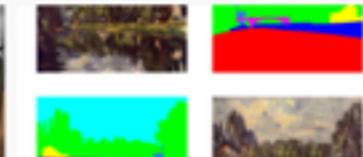


"I created a machine that licks my favorite characters, with a robotic tongue" - by @mansooon

ASSISTED COMEDY HCI ROBOTICS

VIDEO

samim 20 hours ago



Experiments with Neural-doodle, Image Analogies and Style-Transfer - by @proc_gen

ASSISTED GENERATIVE

MACHINE LEARNING STYLETRANSFER

samim a day ago



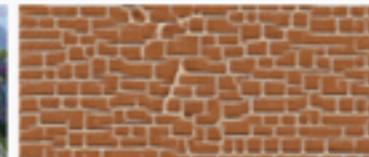
High-Res DeepDream in TensorFlow

ART COMPUTATIONAL CREATIVITY

GENERATIVE MACHINE LEARNING

OPEN SOURCE RESEARCH

graphific a day ago



Real-Time Style Transfer with Keras

MACHINE LEARNING STYLETRANSFER

graphific a day ago



Questions?

love letters? existential dilemma's? academic questions? gifts?

find me at:

www.csc.kth.se/~roelof/
roelof@kth.se

 @graphific



ROYAL INSTITUTE
OF TECHNOLOGY

Oh, and soon we're looking for Creative AI enthusiasts !



- job
- internship
- thesis work

AI (Deep Learning)
&
Creativity



Medium

[https://medium.com/@ArtificialExperience/
creativeai-9d4b2346faf3](https://medium.com/@ArtificialExperience/creativeai-9d4b2346faf3)

CreativeAI

On the Democratisation & Escalation of Creativity

Chapter 01

by Samim Winiger & Roelof Pieters

human-machine collaboration



Semantic Shape Editing Using Deformation Handles



[YouTube](#), [Paper](#)

M.E. Yumer, S. Chaudhuri, J.K. Hodgins, L.B. Kara

SIGGRAPH 2015

Narrated by Jennifer Kara



[YouTube](#), [Paper](#)

Procedural Modeling using Autoencoders

Mehmet Ersin Yumer, Paul Asente, Radomir Mech, Levent Burak Kara

Adobe Research, Carnegie Mellon University

[This video has audio commentary]



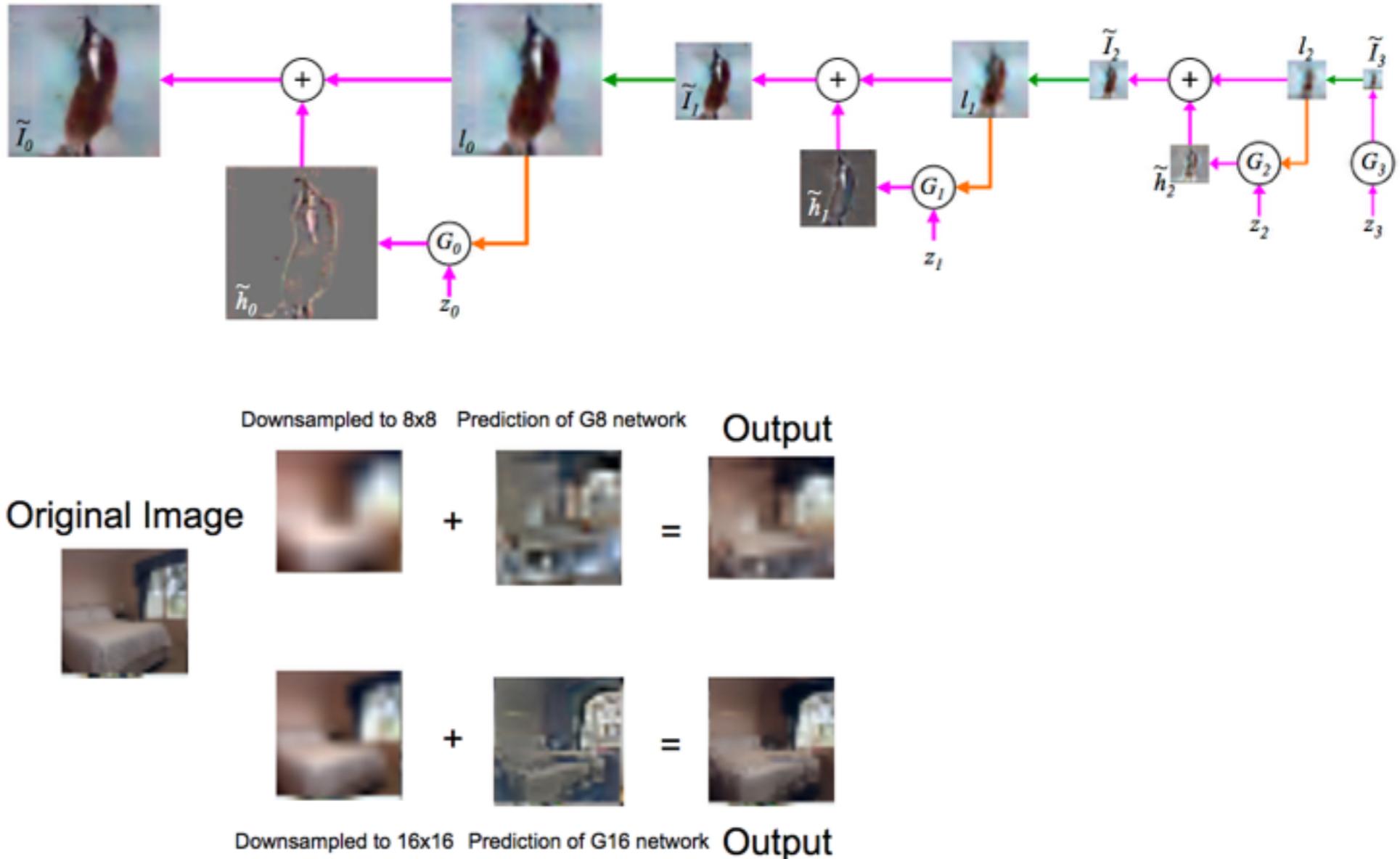
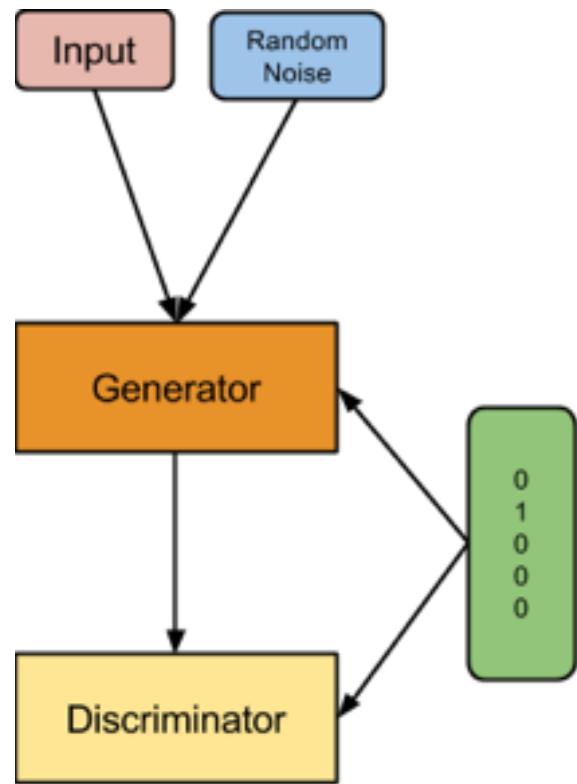
([Vimeo](#), [Paper](#))

Exploratory Modeling with Collaborative Design Spaces

Jerry O. Talton Daniel Gibson Lingfeng Yang
Pat Hanrahan Vladlen Koltun

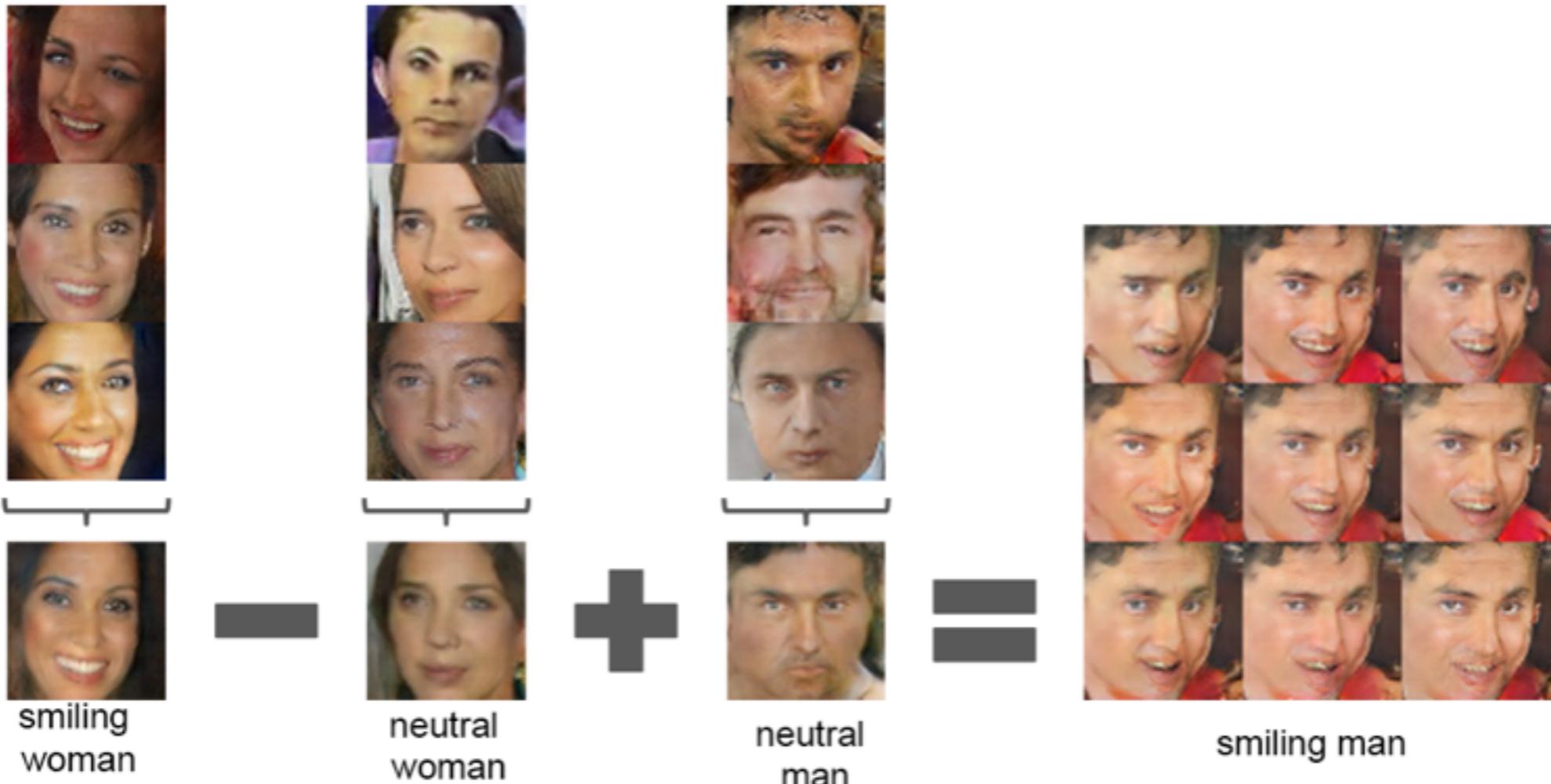
Stanford University

Generative Adversarial Nets



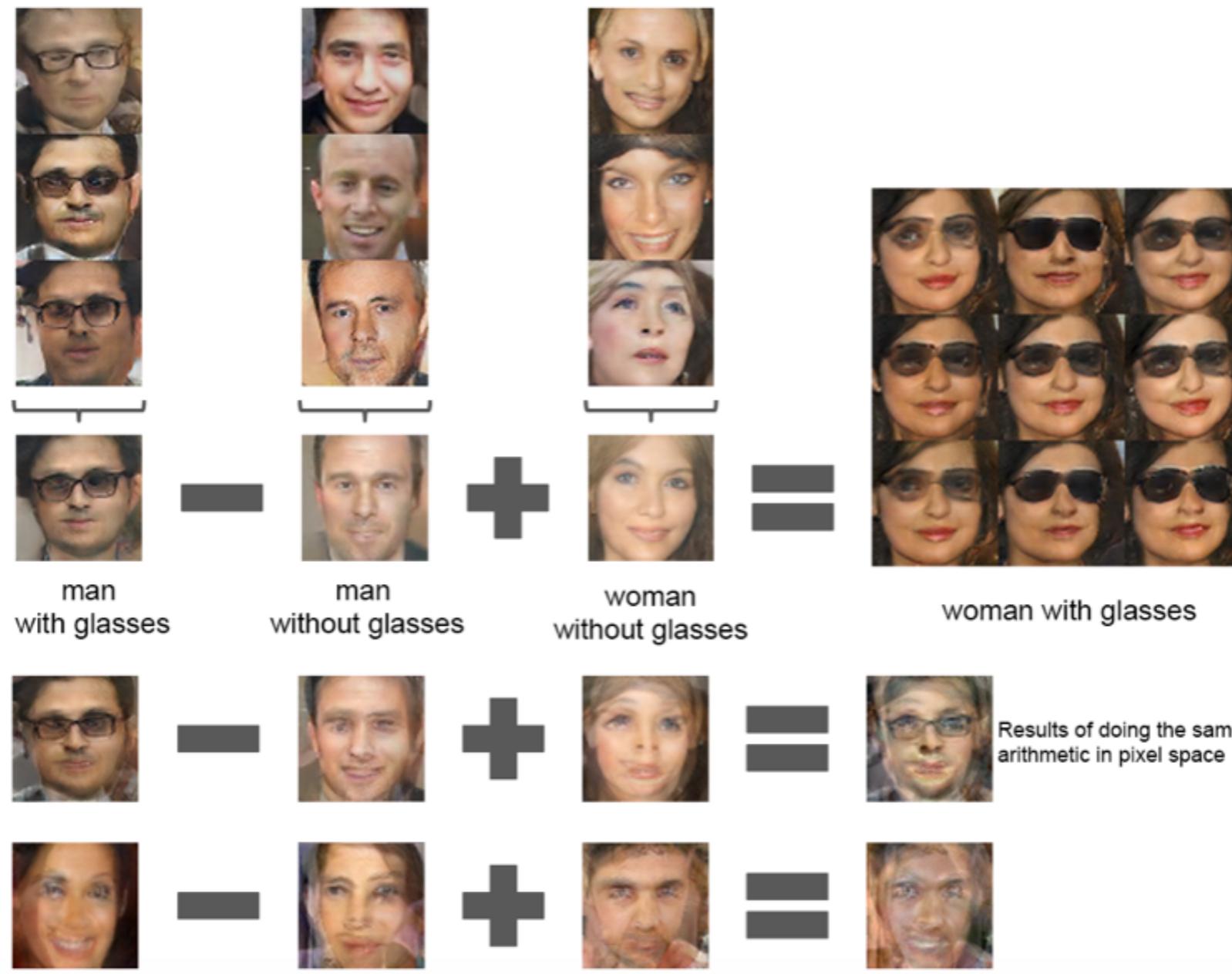
Emily Denton, Soumith Chintala, Arthur Szlam, Rob Fergus, 2015.
Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks (GitXiv)

Generative Adversarial Nets



Alec Radford, Luke Metz, Soumith Chintala , 2015.
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (GitXiv)

Generative Adversarial Nets



Alec Radford, Luke Metz, Soumith Chintala , 2015.
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (GitXiv)

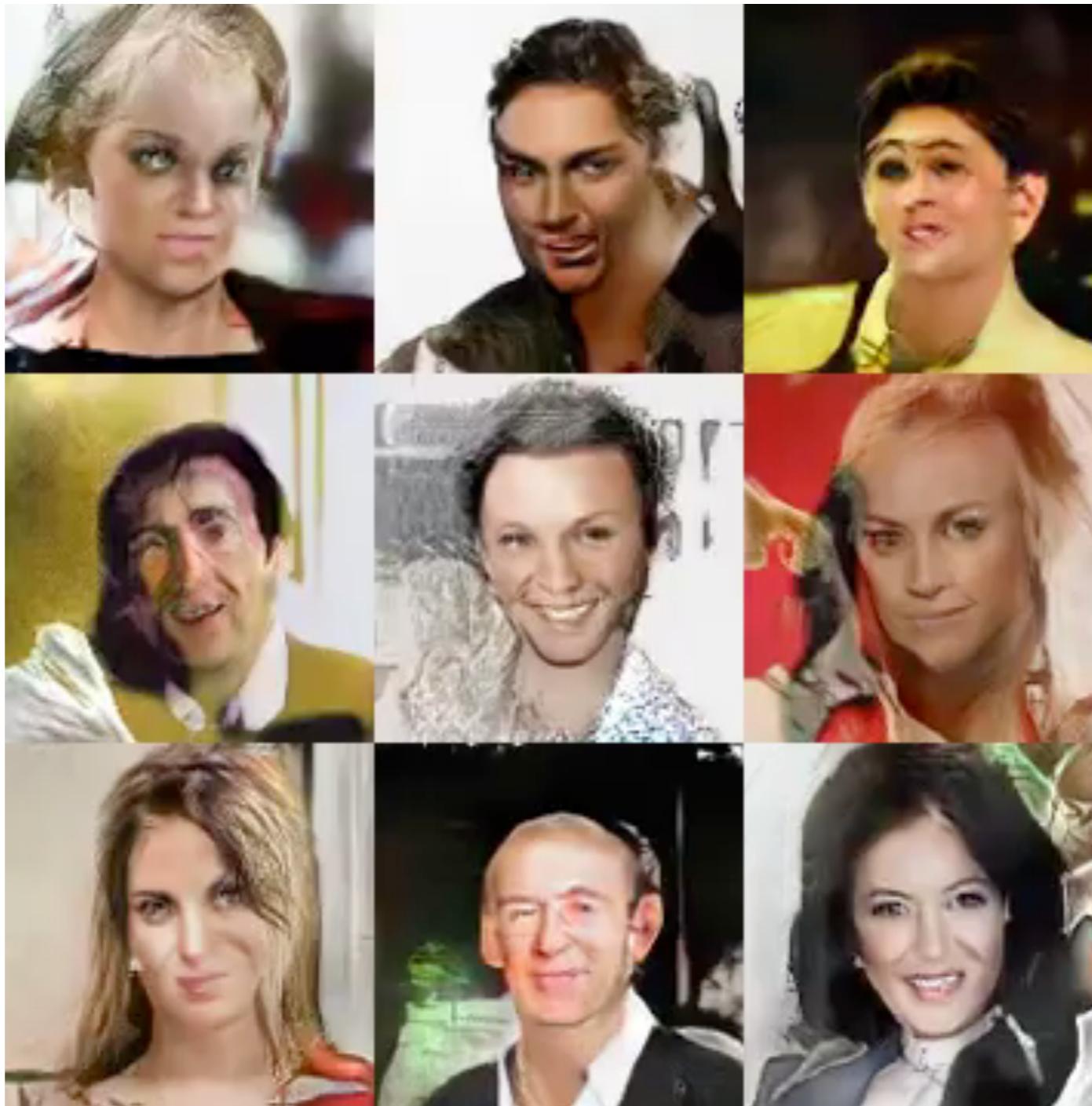
Generative Adversarial Nets



"turn" vector created from four averaged samples of faces looking left
vs looking right.

Alec Radford, Luke Metz, Soumith Chintala , 2015.
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (GitXiv)

Generative Adversarial Nets



walking through the manifold

Generative Adversarial Nets



top: unmodified samples
bottom: same samples dropping out "window" filters

