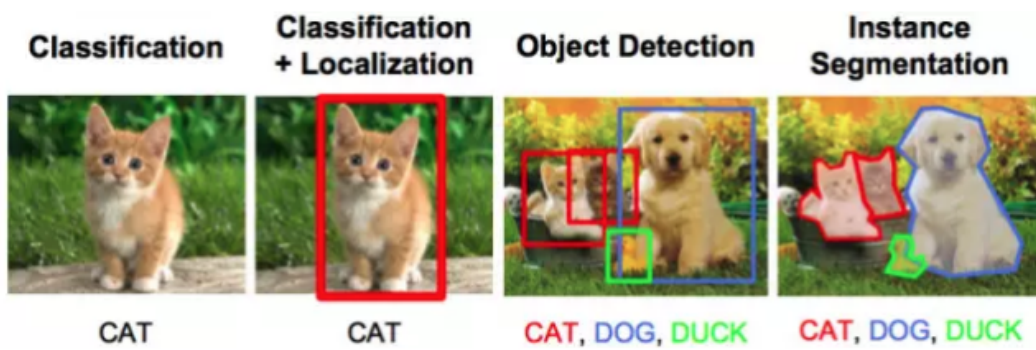
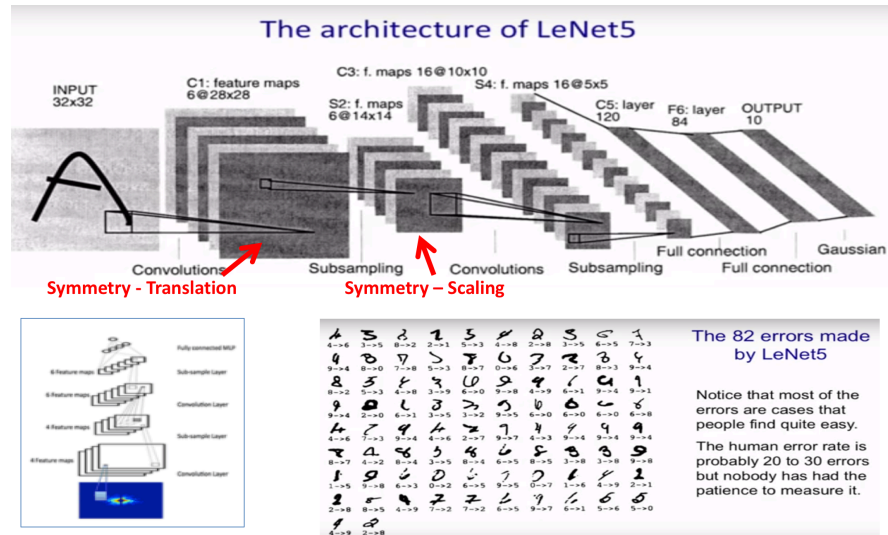


Scale and Style

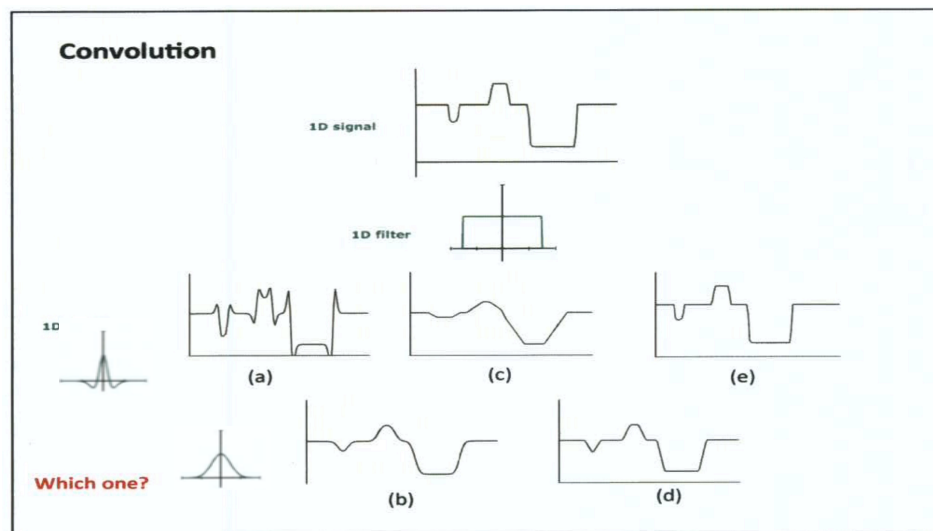
Typical Tasks of Image Analysis



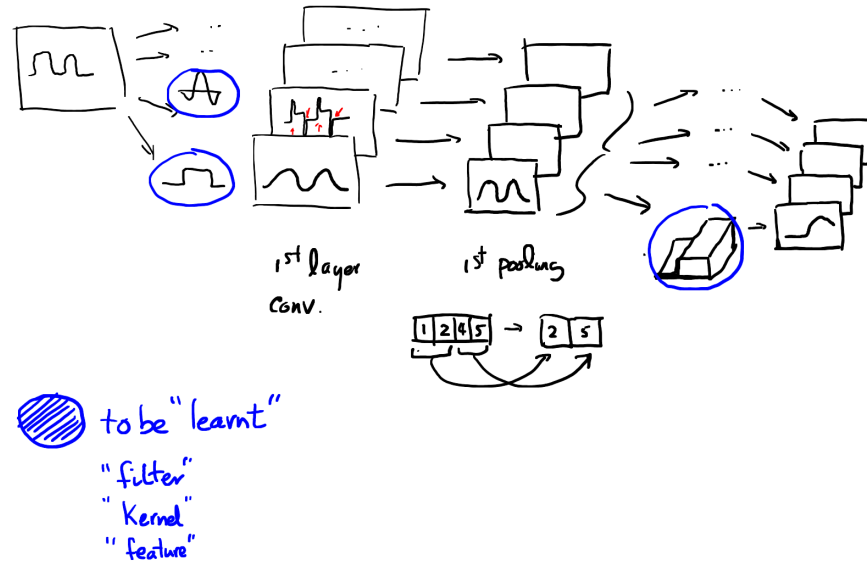
Breakthrough in Image Analysis: Convolution Neural Network (CNN)



Convolution = Scan for “local” features (filtering/running average) ...

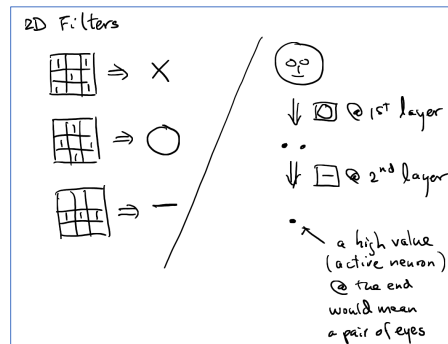
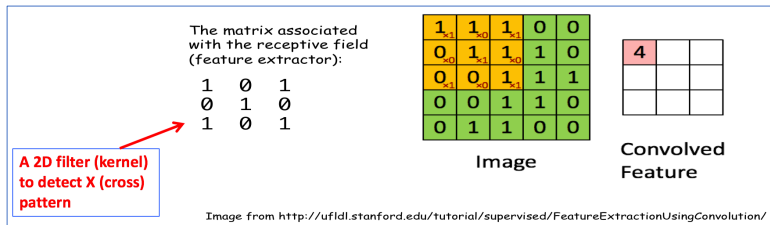


Example: technical analysis of stock trading?



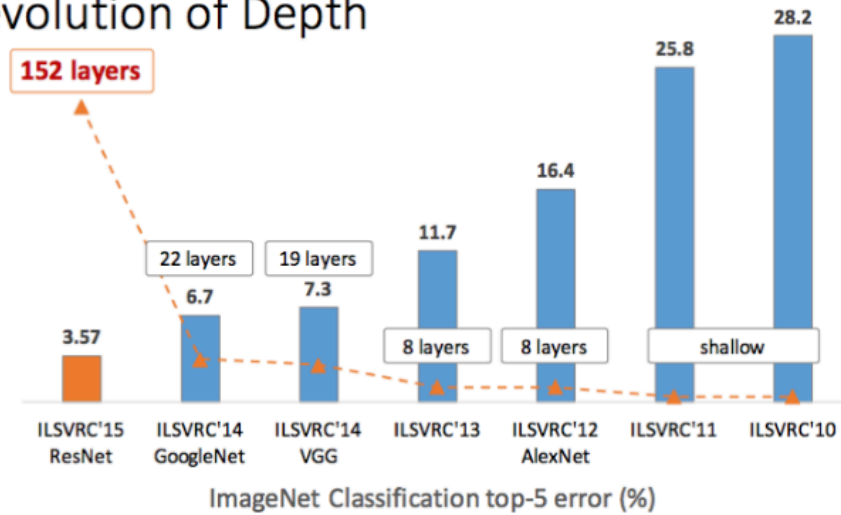
5

2D Filters



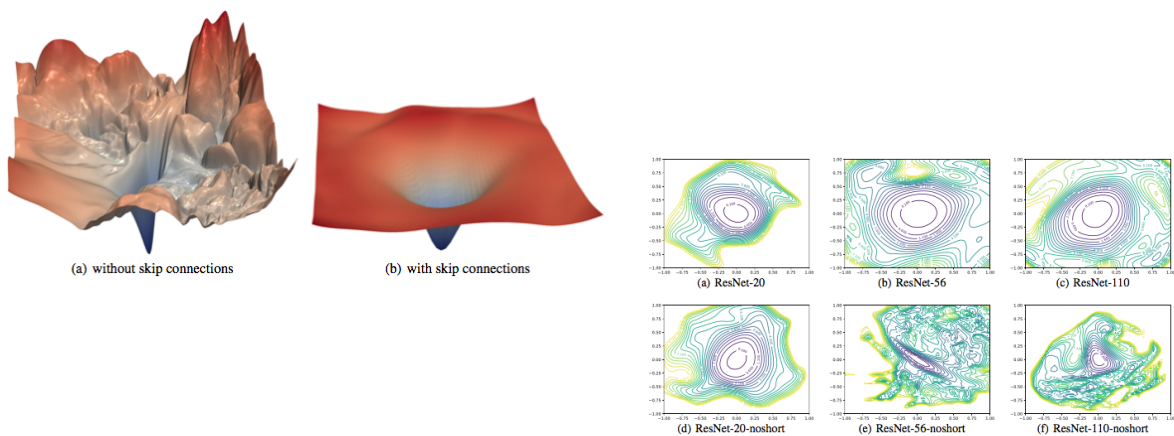
Status of Image Classification - Deep Learning (abstraction/coarse-grain/scaling)

Revolution of Depth



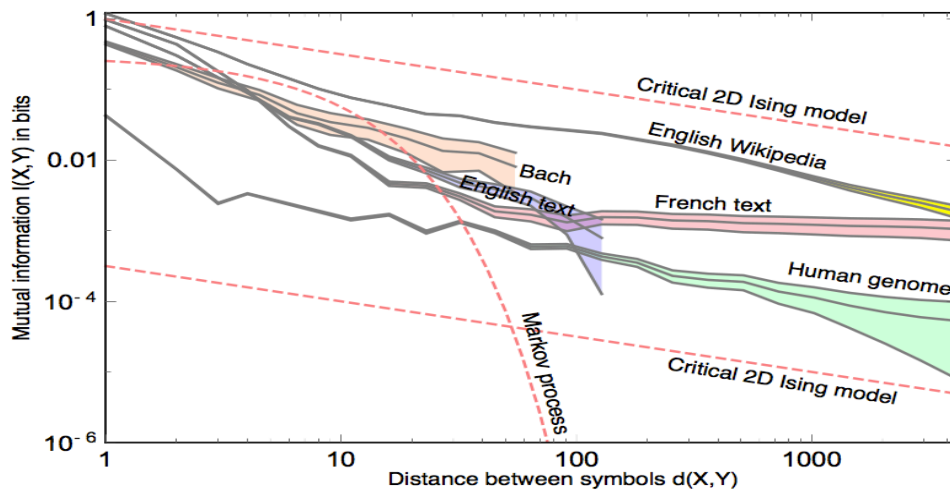
9

Phase Transition of “Landscape” and ResNet



Tom Goldstein (UMD CS)

10

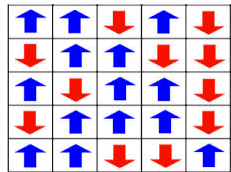


Critical Behavior from Deep Dynamics: A Hidden Dimension in Natural Language

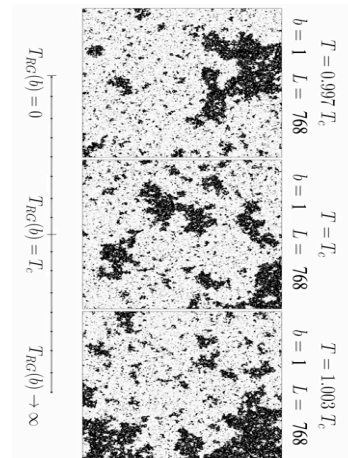
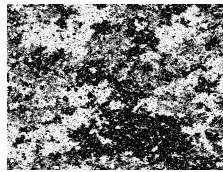
Henry W. Lin and Max Tegmark
 Dept. of Physics, Harvard University, Cambridge, MA 02138 and
 Dept. of Physics & MIT Kavli Institute, Massachusetts Institute of Technology, Cambridge, MA 02139
 (Dated: July 12, 2016)

11

Special Features at Phase Transition: (RG Flow)



Simple 2D Up/Down Magnet

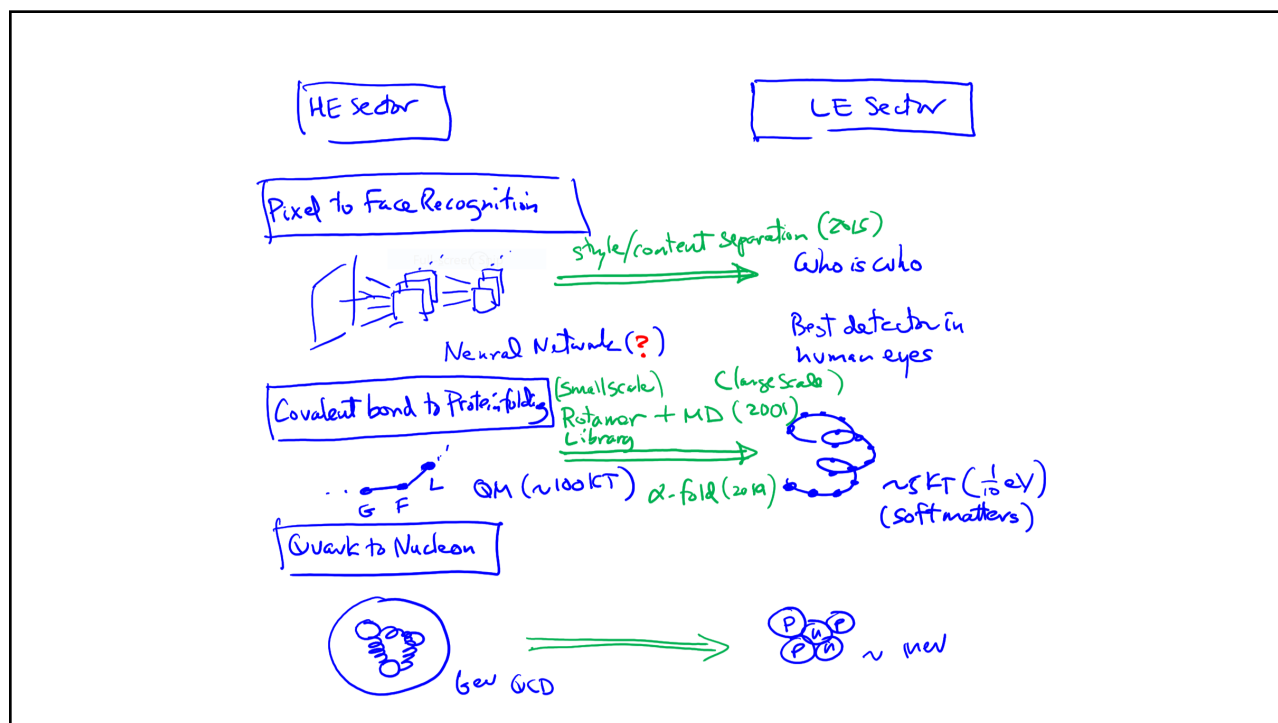
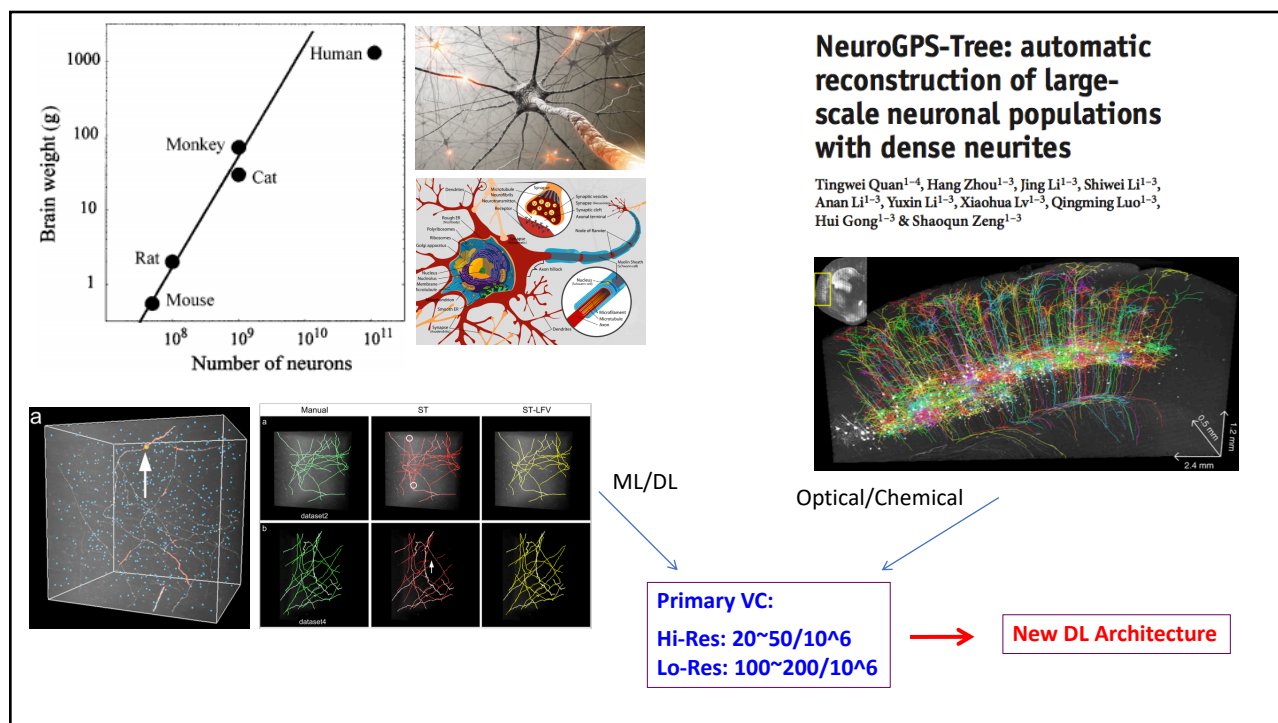


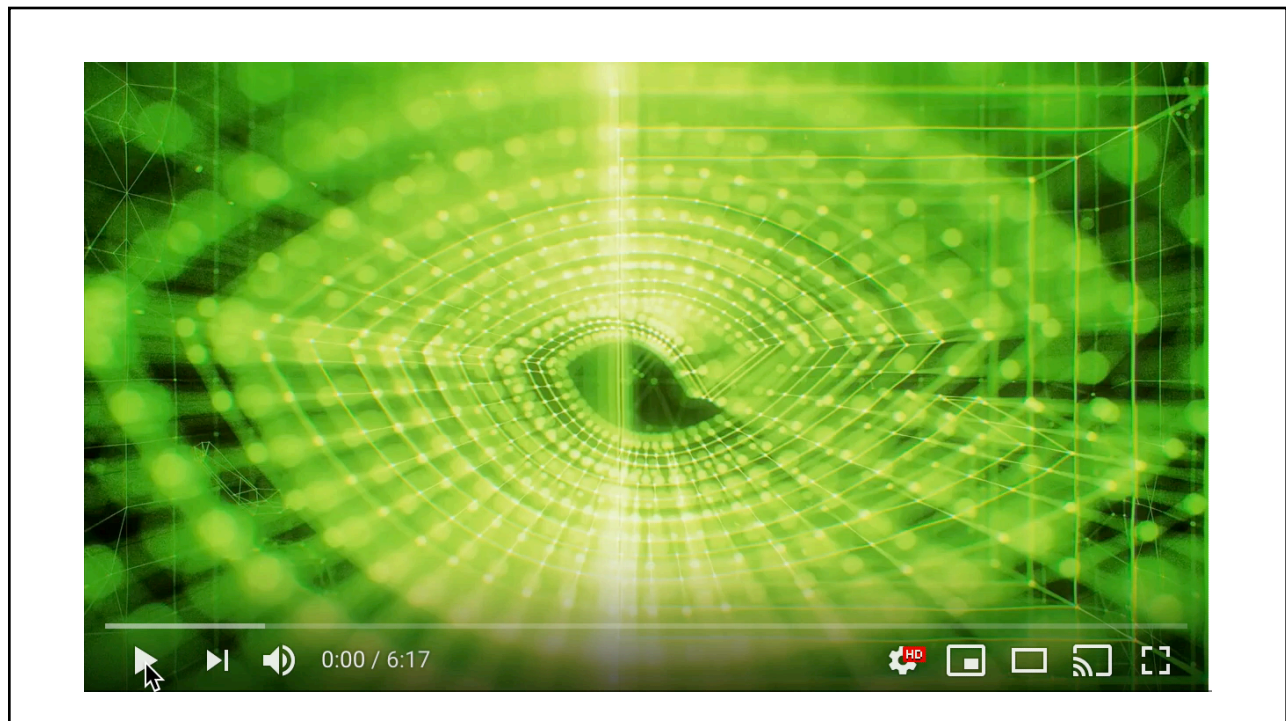
Scale-free (scale invariance, infinite correlation, Renormalization Group, 1982 Nobel Prize to Ken Wilson)

- ◆ Big Data: 10^{23} ! RG Theory of Big Data Analytics?
- ◆ Monte Carlo RG/Numerical Methods

Separation at Large Scale
 Denoising (irrelevant details)

12





Three images illustrating Neural Style Transfer (NST) applied to the Jefferson Memorial. The top left image shows the original photograph of the memorial. The top right image shows the result of applying a classical painting style (resembling Van Gogh's 'Olympia') to the photograph. The bottom image shows the result of applying a different style (resembling a classical painting with a warm, golden glow) to the photograph.

CNN

(Neural Style Transfer NST)

Neural style transfer



Content



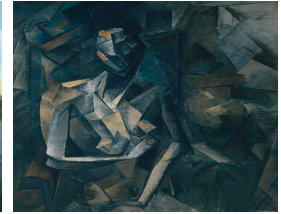
Style



Generated image



Content

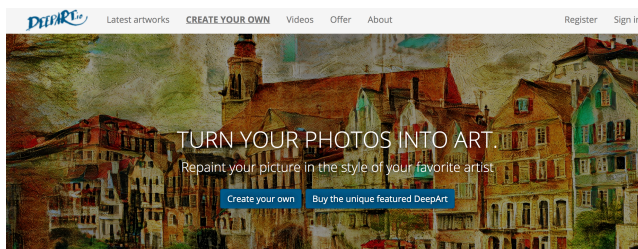


Style

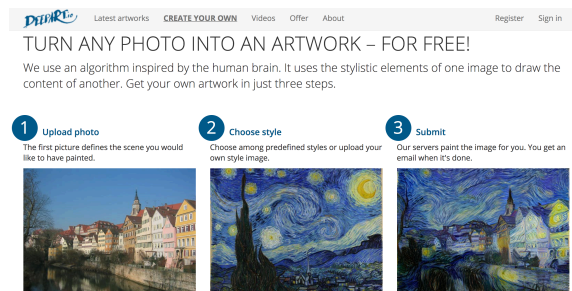


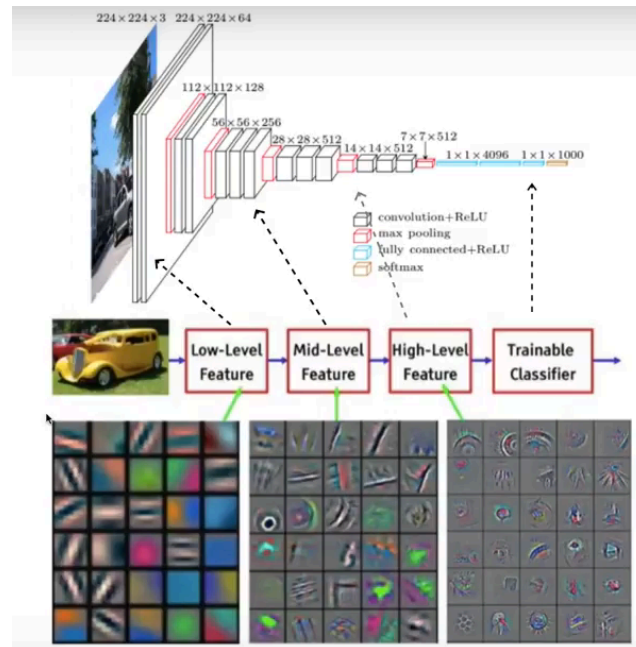
Generated image

[Images generated by Justin Johnson]



TURN ANY PHOTO INTO AN ARTWORK – FOR FREE!

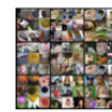
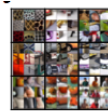
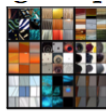




Visualizing and Understanding Convolutional Networks

Matthew D. Zeiler and Rob Fergus

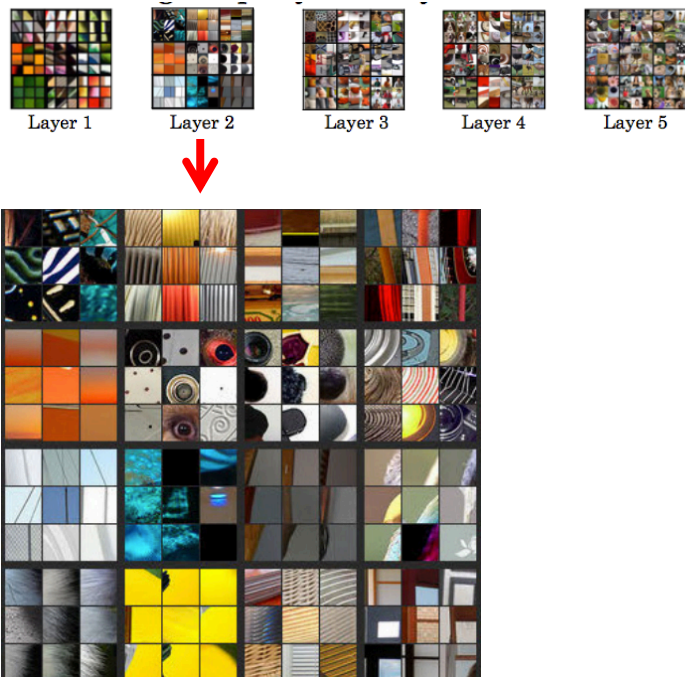
Dept. of Computer Science,
New York University, USA
{zeiler,fergus}@cs.nyu.edu



Visualizing and Understanding Convolutional Networks

Matthew D. Zeiler and Rob Fergus

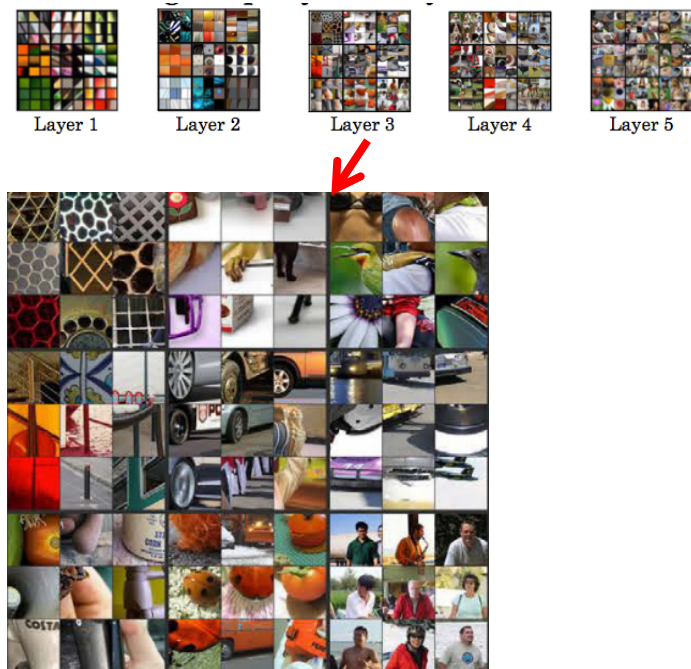
Dept. of Computer Science,
New York University, USA
{zeiler,fergus}@cs.nyu.edu



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Visualizing and Understanding Convolutional Networks

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{zeiler,fergus}@cs.nyu.edu



A Neural Algorithm of Artistic Style

Leon A. Gatys,^{1,2,3*} Alexander S. Ecker,^{1,2,4,5} Matthias Bethge^{1,2,4}

¹Werner Reichardt Centre for Integrative Neuroscience
and Institute of Theoretical Physics, University of Tübingen, Germany

²Bernstein Center for Computational Neuroscience, Tübingen, Germany

³Graduate School for Neural Information Processing, Tübingen, Germany

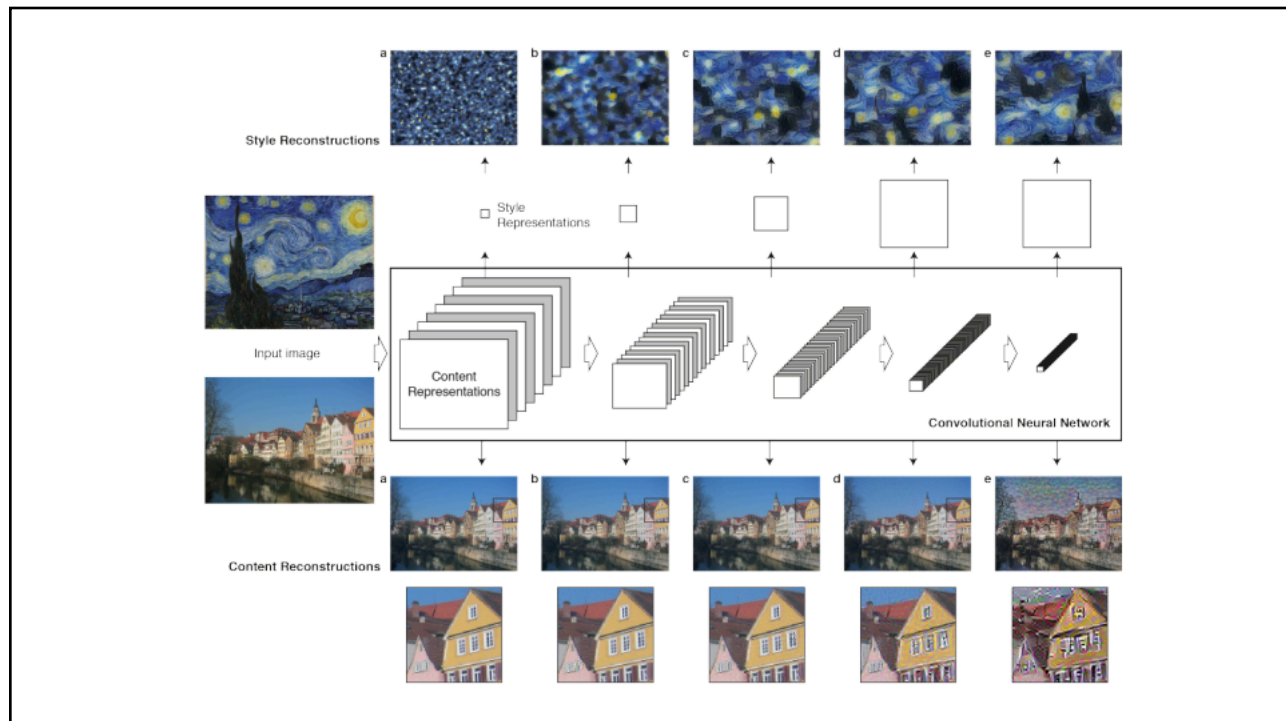
⁴Max Planck Institute for Biological Cybernetics, Tübingen, Germany

⁵Department of Neuroscience, Baylor College of Medicine, Houston, TX, USA

*To whom correspondence should be addressed; E-mail: leon.gatys@bethgelab.org

In fine art, especially painting, humans have mastered the skill to create unique visual experiences through composing a complex interplay between the content and style of an image. Thus far the algorithmic basis of this process is unknown and there exists no artificial system with similar capabilities. However, in other key areas of visual perception such as object and face recognition near-human performance was recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks.^{1,2} Here we introduce an artificial system based on a Deep Neural Network that creates artistic images

arXiv:1508.06576v2 [cs.CV] 2 Sep 2015



Neural Style Transfer

Given

- ① $Img_1 = \text{Photo (content)} \Leftarrow \textcircled{P}$
- ② $Img_2 = \text{Painting (style)} \Leftarrow \textcircled{S}$
- ③ Pretrain CNN (VGG, Inception)

Seek $Img_3 = \text{Generated Img} \Leftarrow \textcircled{X}$

$X = \begin{matrix} \boxed{x_{ij}} \\ \text{2D Img} \end{matrix}$ $x_{ij} = \text{Pixel to be determined}$

Algorithm.

Cost Function
to be minimized
to determine $\{x_{ij}\}$

$$\{x_{ij}^*\} = \text{ArgMin } J(\{x_{ij}\})$$

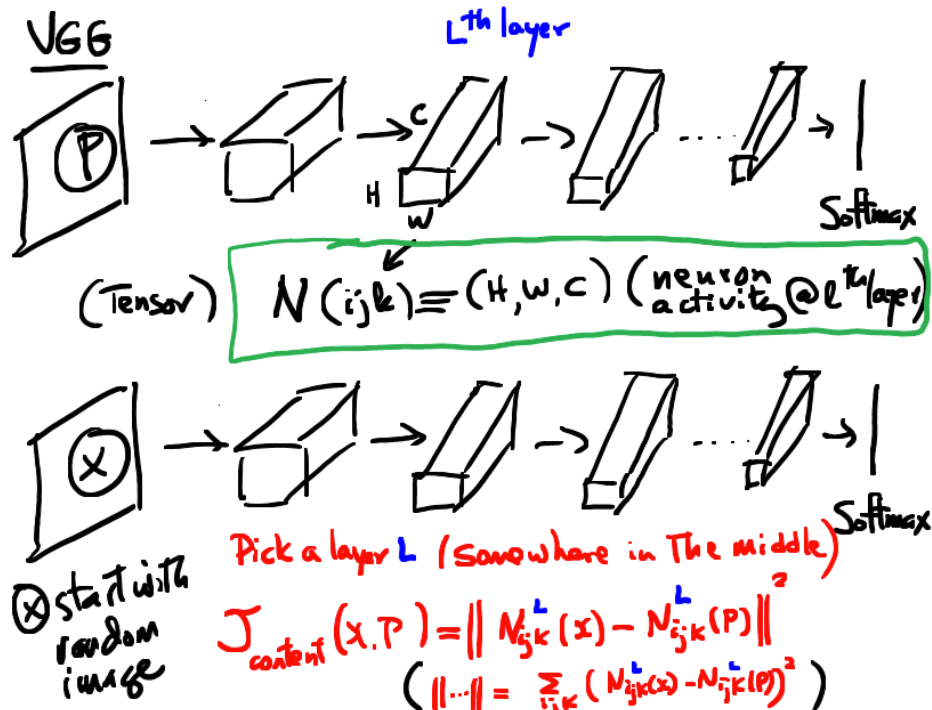
Cost function

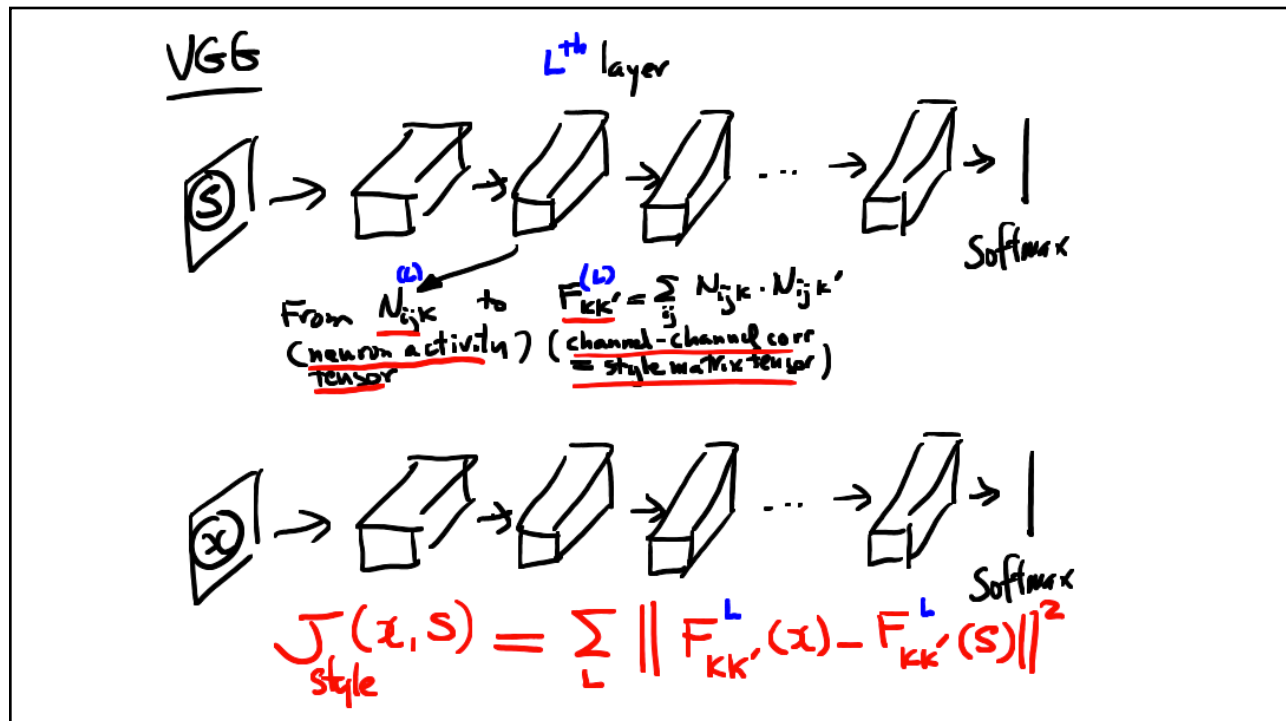
$$J(x) = J(x, P) + J(x, S)$$

$\uparrow$ content cost $\uparrow$ style cost
 Makes $\textcircled{x}$ close to $\textcircled{P}$ makes $\textcircled{x}$ close to $\textcircled{S}$

How to define

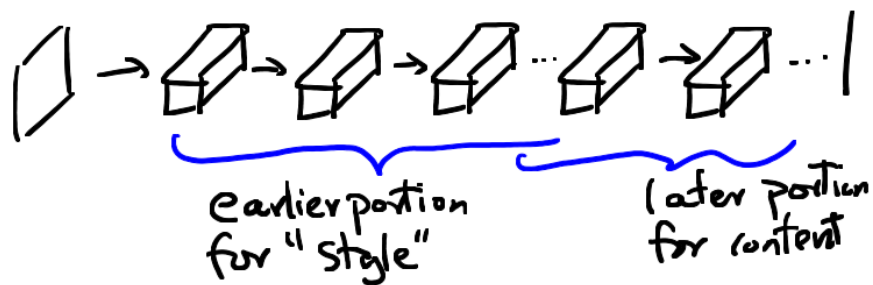
- ① Content cost
 ② Style cost
- } Using pretrain deep CNN



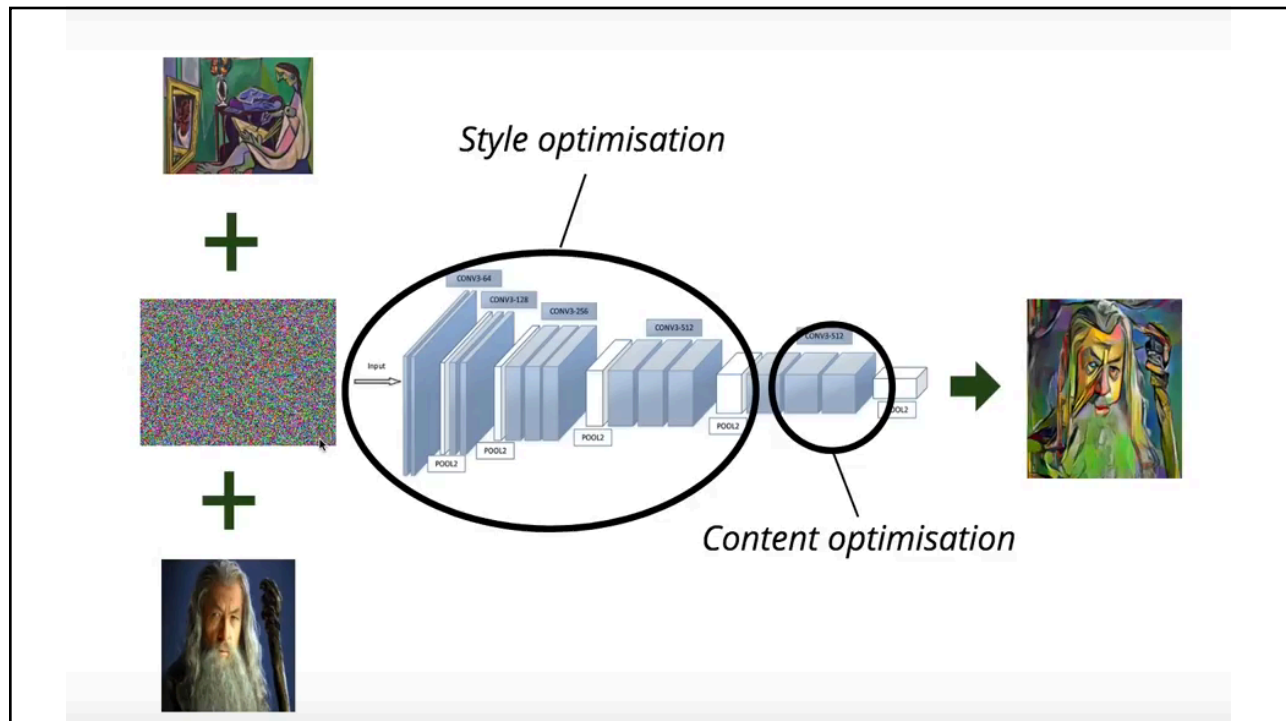


Remarks:

Choice of L for content and style



(insights from CNN filter visualization)



Useful properties

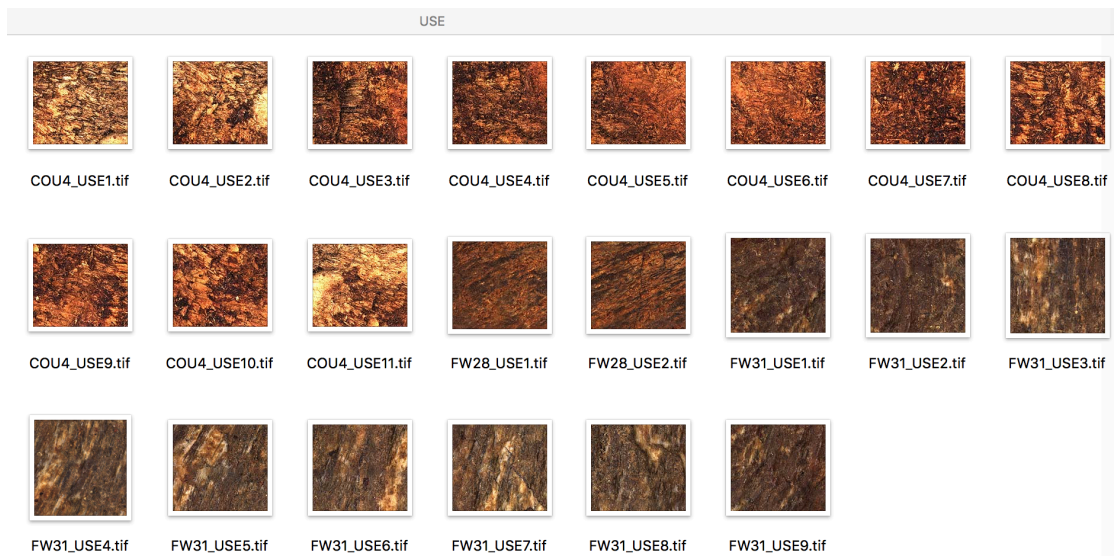
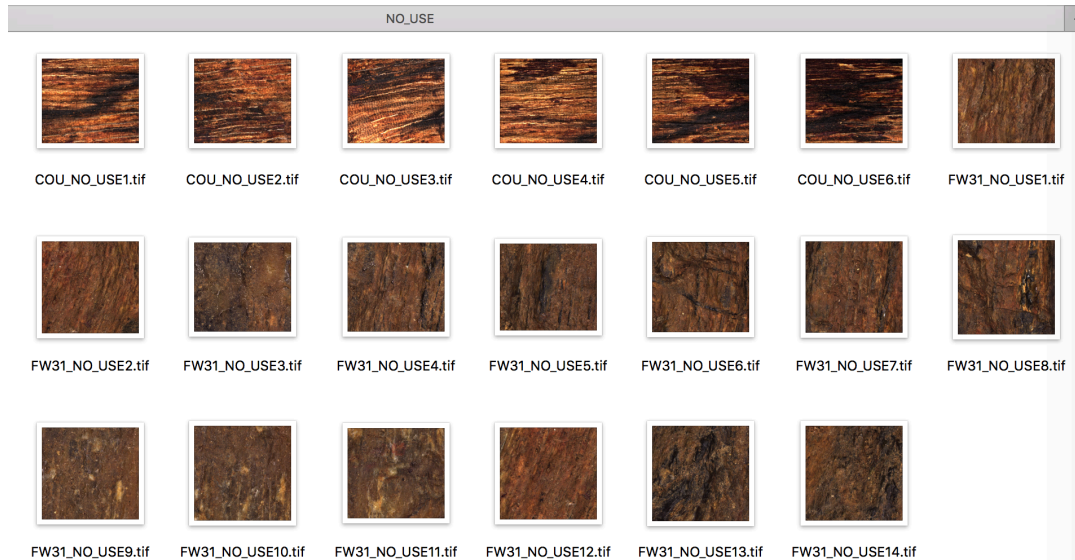
- Transfer learning
- Separation of information

“

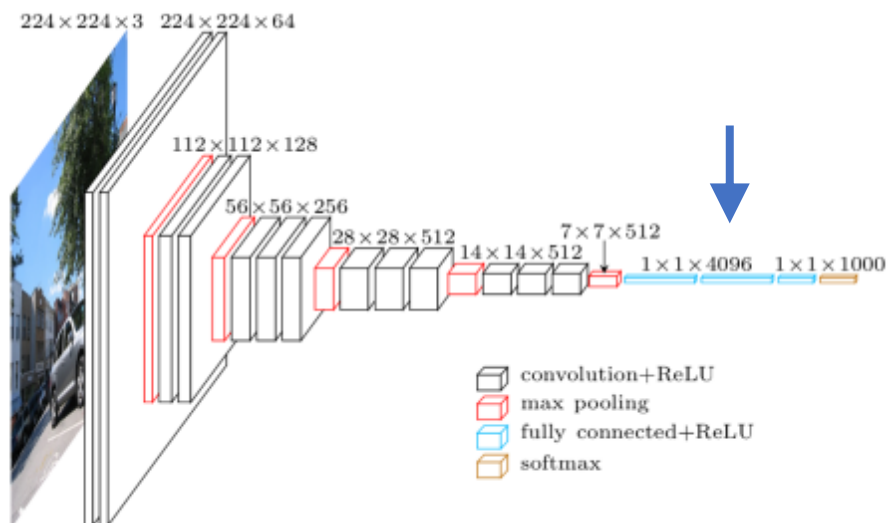
All in all it is truly fascinating that a neural system, which is trained to perform one of the core computational tasks of biological vision, automatically learns image representations that allow the separation of image content from style. ”

A Neural Algorithm of Artistic Style - Gatys, Ecker & Bethge

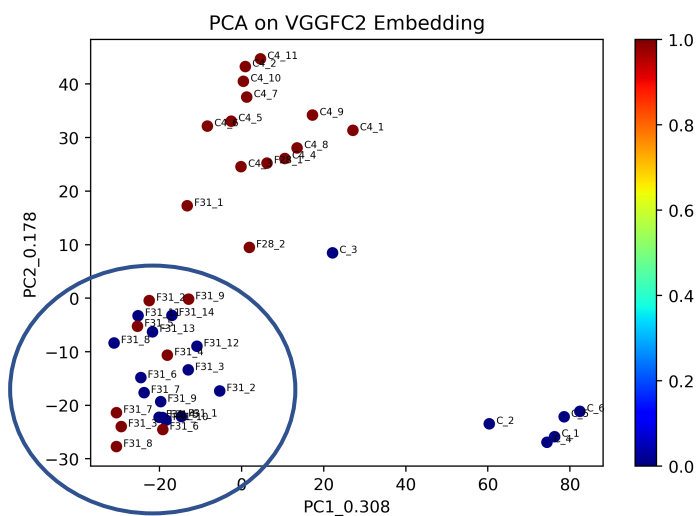
Scale and Style - Ex1: fossil specimens as the earliest evidence of tool use in the world

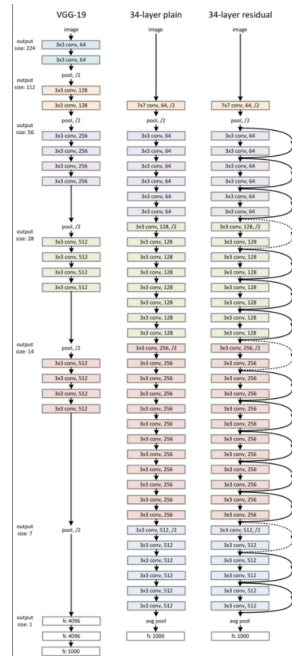


VGG-19 (meaning 19 layers in the neural network)



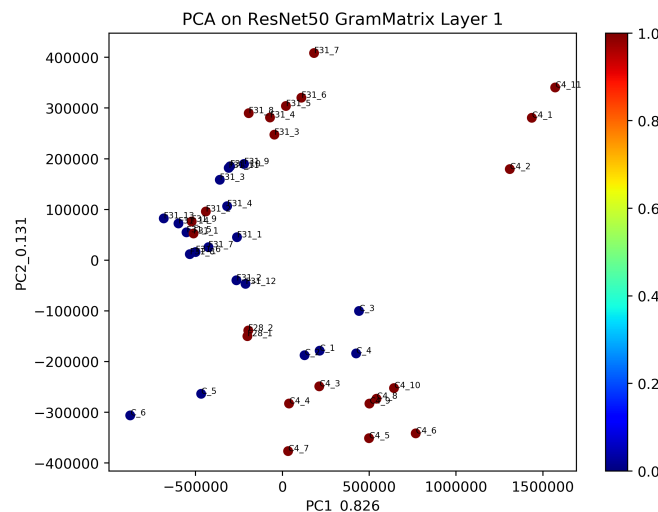
Simple Principal Component Decomposition (clustering) using large-scale features via VGG-19 (meaning 19 layers in the neural network)



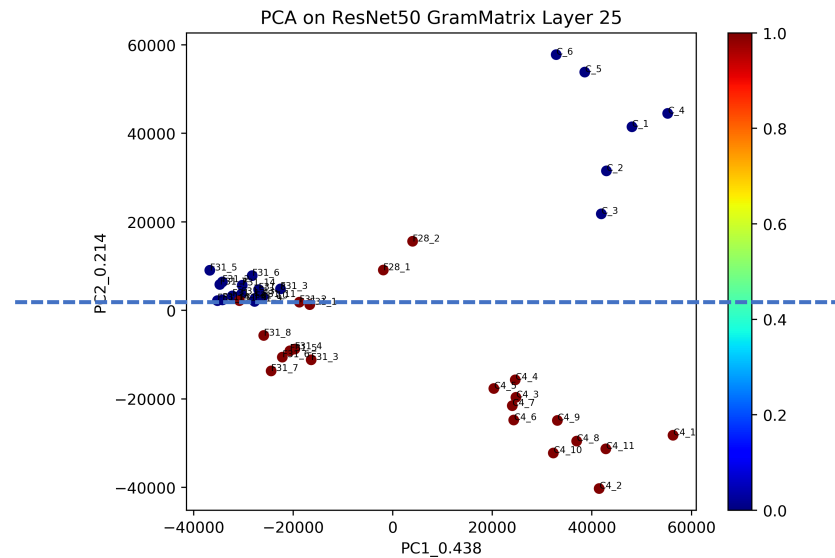


ResNet-50 (50 layers)

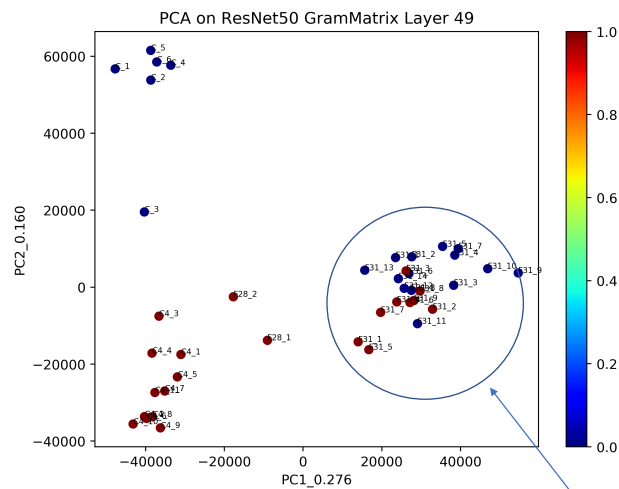
At each layer, we construct what is called Gram matrix that is known to represent "style" of a painting (such as Picasso or van Gogh, for example) in the application field termed "neural style transfer". We used these "style" matrices at different scales (i.e., computed at different layers) to cluster wood images by PCA. Once again, the deep neural network, ResNet-50, was pretrained on ImageNet of ~ 1 million labelled images (or supervised learning). So our clustering is unsupervised based on features extracted by a pretrained deep network.



Conclusion: looking at the very first layer (i.e., very fine detail), difficult to separate images.



Conclusion: looking at the middle layer (25th layer), which may be the most suitable scale, the images are well clustered and separated (with only a few mixed-ups C31_1/2/3 and F28_1/2, red=used). The separation of used vs not-used is by the dashed line along the second principal components.



Conclusion: looking at the last layer (the largest scale), one overlapping cluster appears again, consistent with VGG-19 conclusion.

“Scale”: Overall, we think there exists a suitably defined scale (or scales) that can separate these wood images to 4 distinct groups based on the “style” of the images at those scales (around 25th layer or so in our current context of how these photos are taken).

“Style”: is defined as Gram Matrix (2nd order correlation matrix of different filters in convolution neural networks). These matrices are known to represent features like texture, color, etc., that are widely used to transfer painting styles of various artists such as Picasso or van Gogh to one’s own photo. Whether these matrices are the best definition for “style” or “pattern” in the specific context of wooden tools is clearly debatable.

Scale and Style – Ex2: Breaking detection limit of trace metabolites with machine learning

analytical
chemistry

Cite This: *Anal. Chem.* XXXX, XXX, XXX–XXX

Article
pubs.acs.org/ac

Trace, Machine Learning of Signal Images for Trace-Sensitive Mass Spectrometry: A Case Study from Single-Cell Metabolomics

Zhichao Liu,[†] Erika P. Portero,[‡] Yiren Jian,[†] Yunjie Zhao,[§] Rosemary M. Onjiko,[‡] Chen Zeng,^{*,†} and Peter Nemes^{*,†}

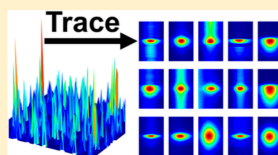
[†]Department of Physics, The George Washington University, Washington, D.C. 20052, United States

[‡]Department of Chemistry and Biochemistry, University of Maryland, College Park, Maryland 20742, United States

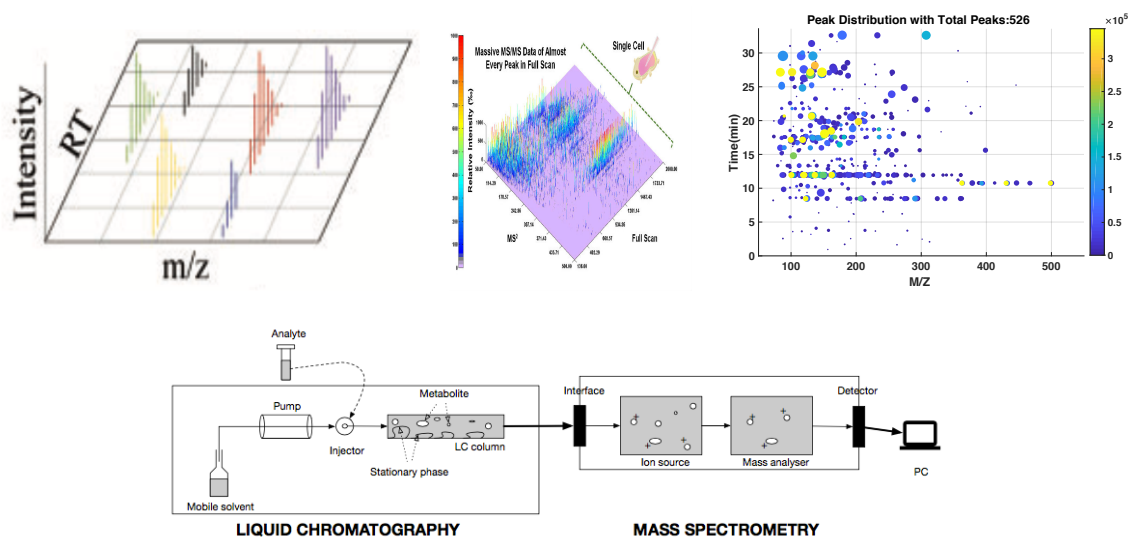
[§]Institute of Biophysics and Department of Physics, Central China Normal University, Wuhan, Hubei 430079, China

Supporting Information

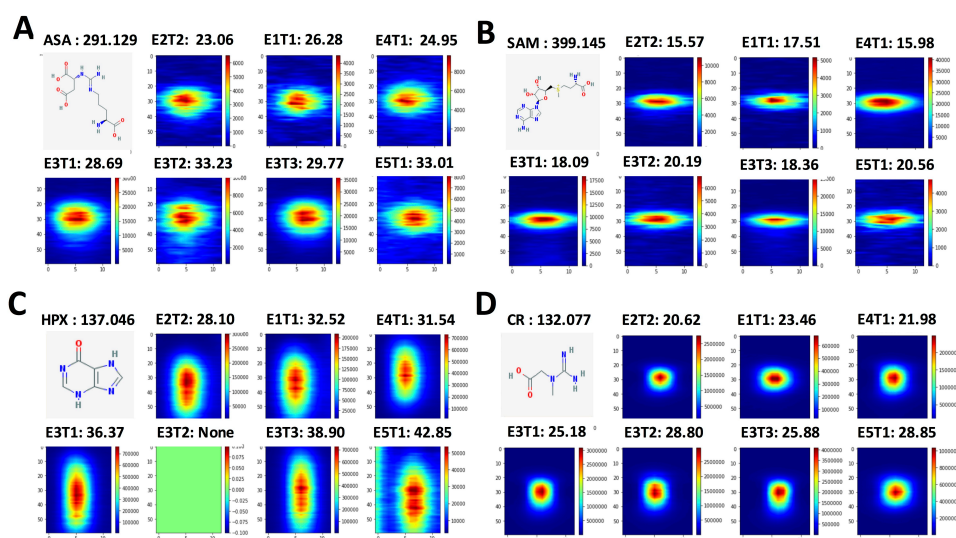
ABSTRACT: Recent developments in high-resolution mass spectrometry (HRMS) technology enabled ultrasensitive detection of proteins, peptides, and metabolites in limited amounts of samples, even single cells. However, extraction of trace-abundance signals from complex data sets (m/z value, separation time, signal abundance) that result from ultrasensitive studies requires improved data processing algorithms. To bridge this gap, we here developed “Trace”, a software framework that incorporates machine learning (ML) to automate feature selection and optimization for the extraction of trace-level signals from HRMS data. The method was validated using primary (raw) and manually curated data sets from single-cell metabolomic studies of the South African clawed frog (*Xenopus laevis*) embryo using capillary electrophoresis electrospray ionization HRMS. We demonstrated that Trace combines sensitivity, accuracy, and robustness with high data processing throughput to recognize signals, including those previously identified as metabolites in single-cell capillary electrophoresis HRMS measurements that we conducted over several months. These performance metrics combined with a compatibility with MS data in open-source (mzML) format make Trace an attractive software resource to facilitate data analysis for studies employing ultrasensitive high-resolution MS.



But mostly in 2D – Intensity(retention time, m/z)



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Andrew Ng

F1 Weak Signal Detection

From Invariance to Stability



- Informally, if $\|\tau\|$ measures the amount of deformation, many recognition tasks satisfy

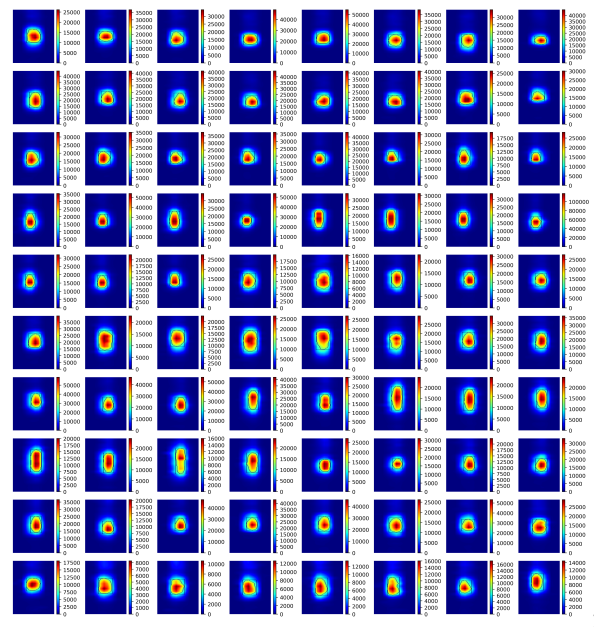
$$\forall x, \tau, |f(x) - f(x_\tau)| \lesssim \|\tau\|$$

Data augmentation for more complicated affine transformation?

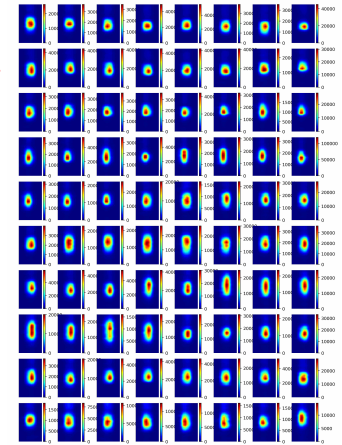
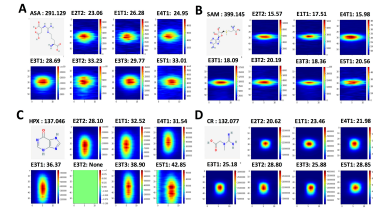
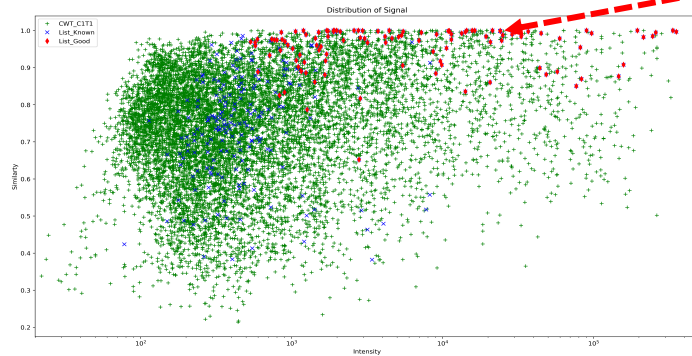
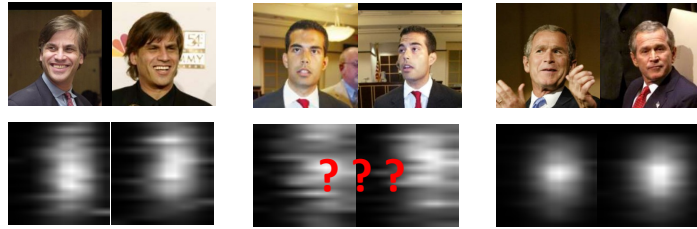
Our Metabolite Data:

- ❑ (4*Control + 4*Test Sample)
- ❑ 10 Time Points
- ❑ 299 (7+47+245) metabolites for Neg_NP

Assumption: 2D images of a real signal tend to be similar/ consistent among multi_samples.



2.3 "MetaNet": Trace-level Signal! (文章整理中)



drew Ng

Real Signal: Consistency (NOT Random)

FaceNet: A Unified Embedding for Face Recognition and Clustering

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Dmitry Kalenichenko
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Google Inc.

James Philbin
jphilbin@google.com
Google Inc.

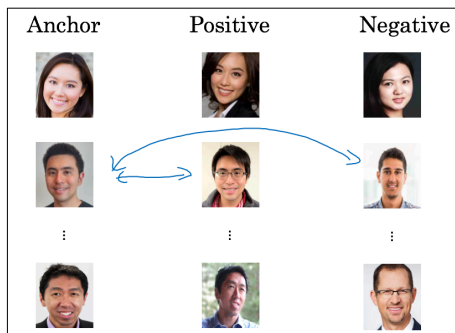
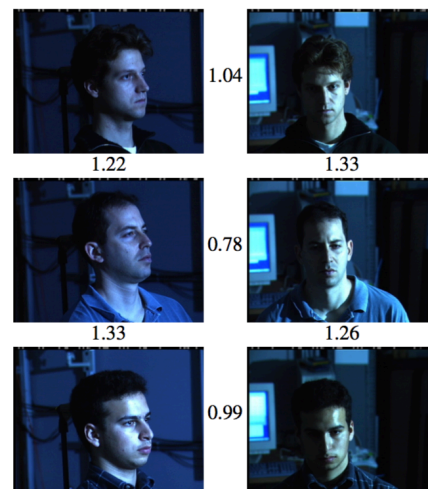


Figure 3. The **Triplet Loss** minimizes the distance between an *anchor* and a *positive*, both of which have the same identity, and maximizes the distance between the *anchor* and a *negative* of a different identity.



<https://arxiv.org/abs/1503.03832>

Andrew Ng

