Analyzing the Training Processes of Deep Generative Models

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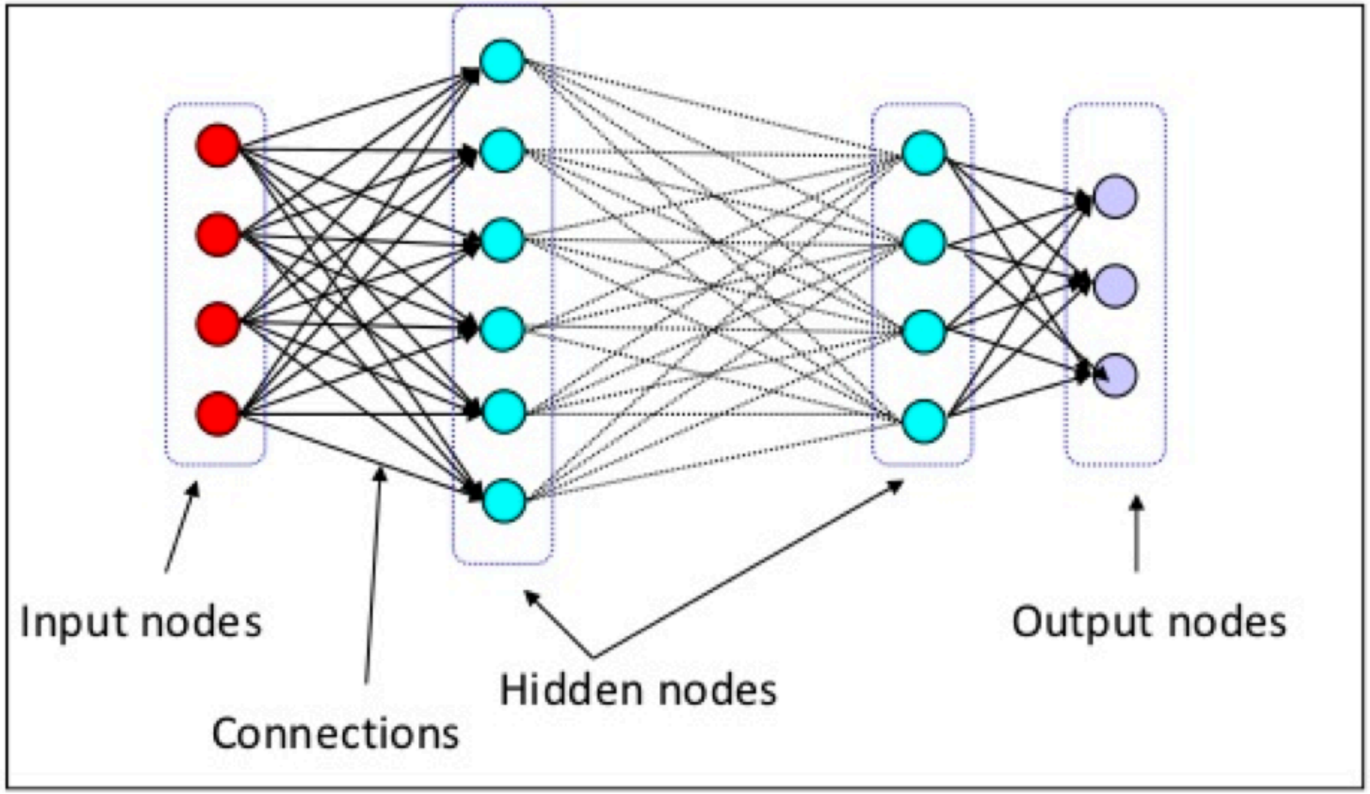
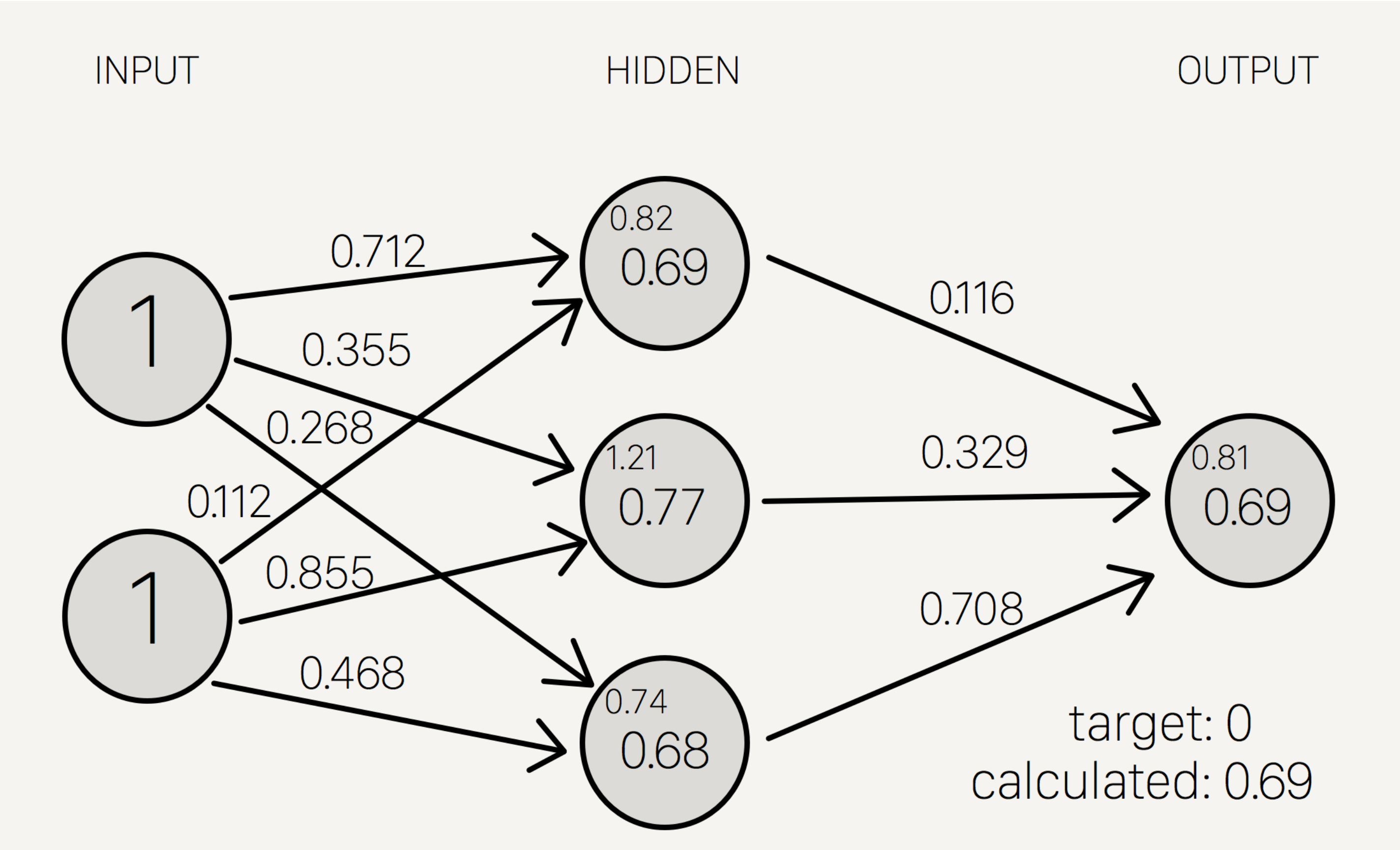
Background – deep neural networks



$$
\begin{aligned}
Output: \quad y_i &= f(w_i^1 x_1 + w_i^2 x_2 + w_i^3 x_3 + \cdots + w_i^m x_m) \\
&= f\left(\sum_j w_i^j x_j\right)
\end{aligned}
$$

Background – dnn training

- Training in deep neural networks



What to visualize - data

- Network diagram of neurons and its characteristics
  - activations, gradients, weights of each neuron [MILLIONS]

- Summary statistics of the model
  - loss/ accuracy of the model

- Dynamic time-series data [MILLIONS]
  - how activations/ gradients/ weights changes over time
  - how loss/ accuracy change over time

Why visualize – after iterative user studies

- Identify root cause of a failed training process
  - Loss function can become NaN or Inf
  - Multiple sources -> inappropriate network structure, bug in code, lack of numerical stability

- R1: Connecting the overall statistics with detailed training dynamics
  - Summary statistic serves as entry point
  - Detailed training dynamic can be used for root cause analysis

Why visualize – after iterative user studies

- R2: Examining how data flows through the network
  - Different layers has different roles in DGM
  - A failed training process is usually caused by a specific layer

- R3: Facilitating the detection of outliers
  - Outliers in training process is a potential reason for failed training process

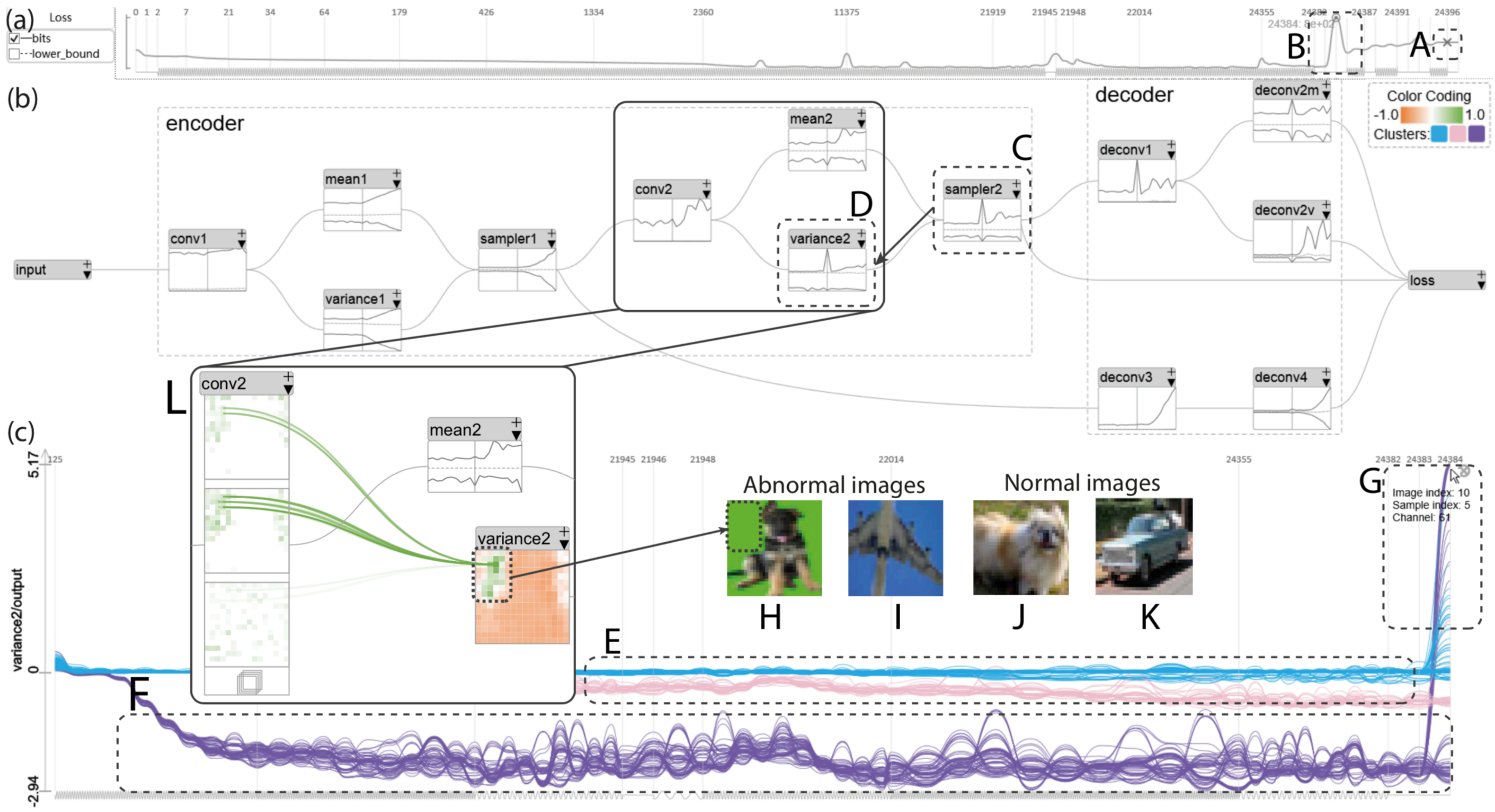
- R4: Examining how neurons interact with each other
  - Poor understanding on how neurons interact with each other in a DGM
  - Even after identification of abnormal; neuron, it is hard to identify the root cause.

How to visualize

- Data flow visualization module
  - How data flows in a DGM (R2)
  - How other neurons influence the output of the neuron of interest (R4)
    - Credit assignment problem

- Training dynamics analysis module
  - Loss as a function of time (R1)
  - Samples time series to preserve outliers (R3)
    - Blue-noise polyline sampling to reduce visual clutter

Overview

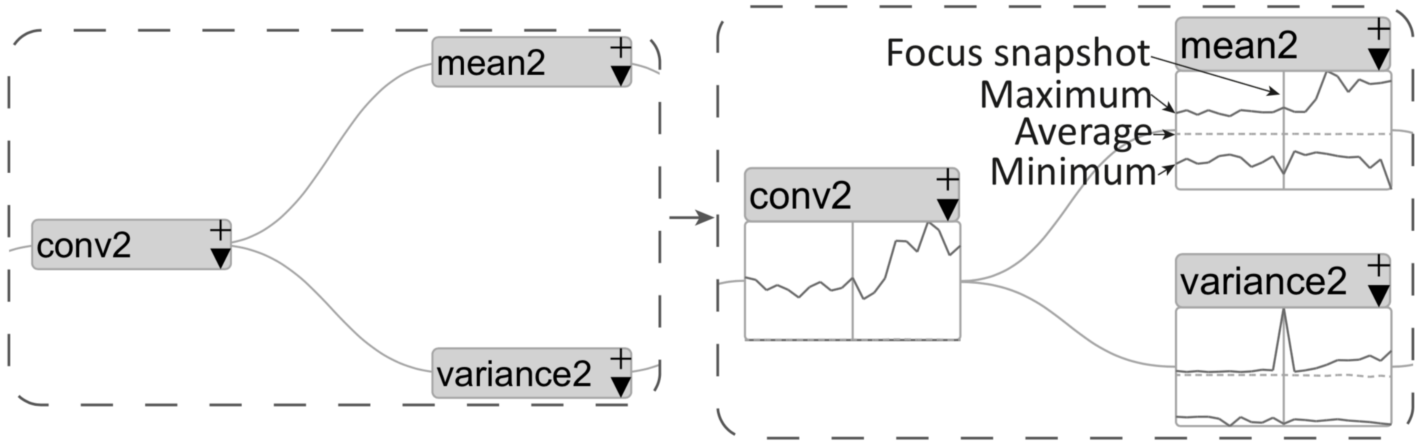


(a)
Loss
bits
lower_bound
A
B
(b)
encoder
decoder
input
conv1
mean1
variance1
sampler1
conv2
mean2
variance2
sampler2
deconv1
deconv2m
deconv2v
deconv3
deconv4
loss
C
D
Color Coding
-1.0
1.0
Clusters:
L
(c)
variance2/output
5.17
0
-2.94
E
F
G
Image index: 10
Sample index: 5
Channel: 61
Abnormal images
Normal images
H
I
J
K

Snapshot level analysis

- Idea - which layer caused the issue?

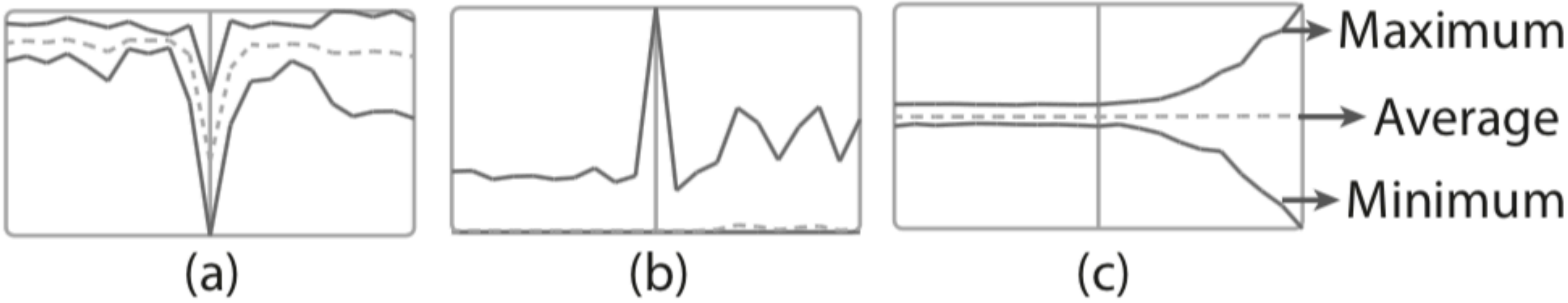
- **DAG** - illustrates how layers are connected
  - Hierarchical structure to reduce clutter in case of 100s of layers



(a) (b)

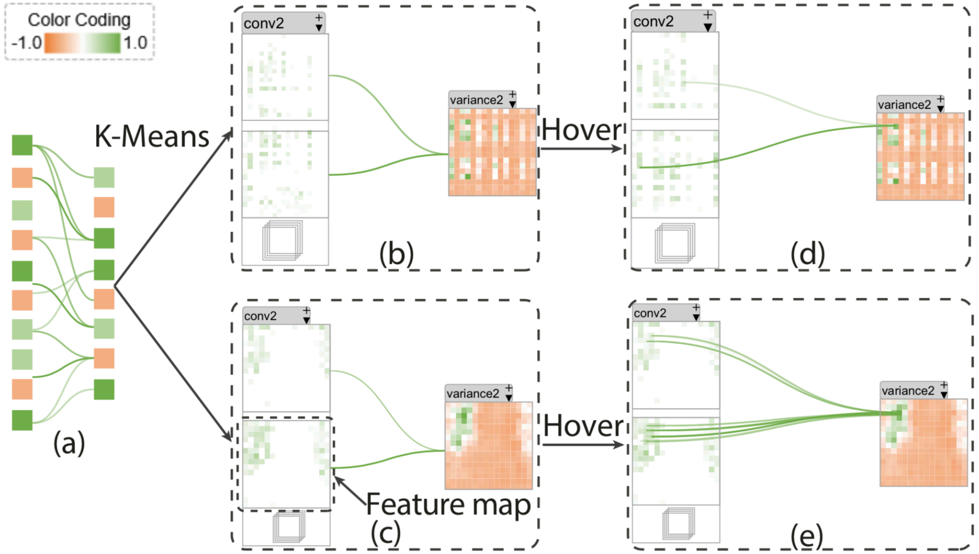
Snapshot level analysis

- **Line charts** – how data flows
  - Averaged training dynamics within a certain configurable window
  - Center line represents the focus snapshot

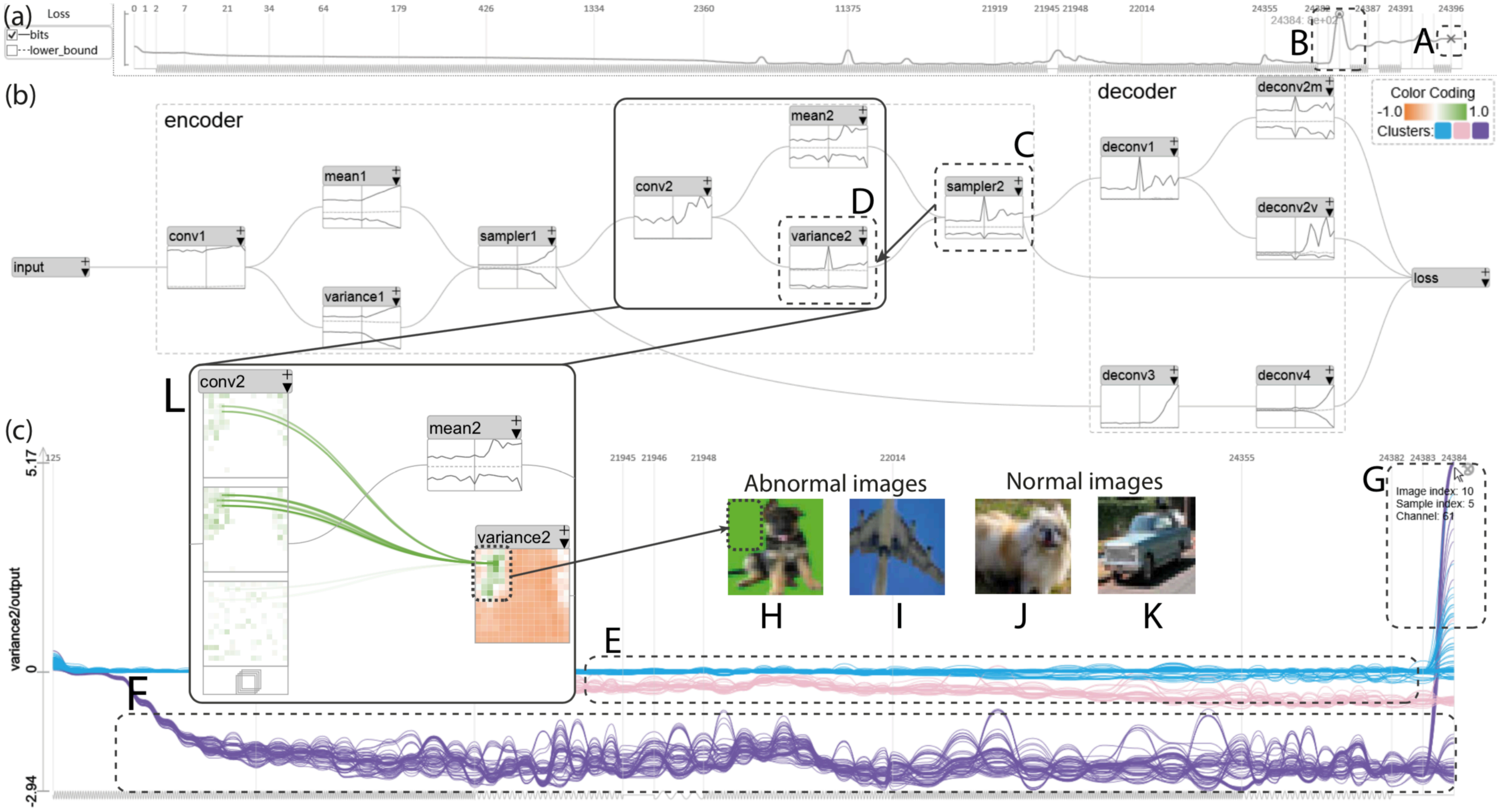


Neuron level analysis

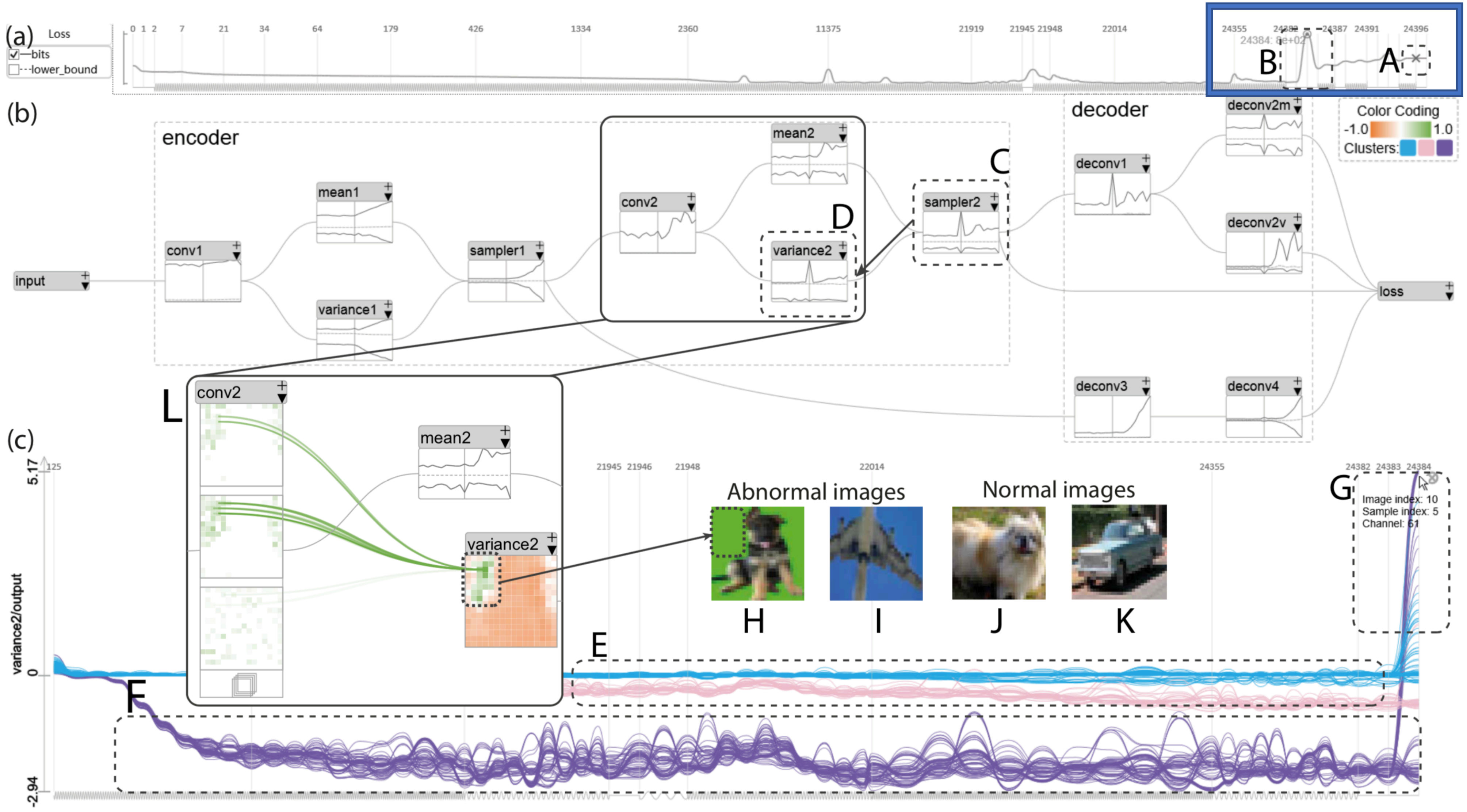
- Idea - Root cause analysis
- Credit assignment
  - Influenced by both previous and next layer
  - Use forward and backward propagation to find neurons of interest



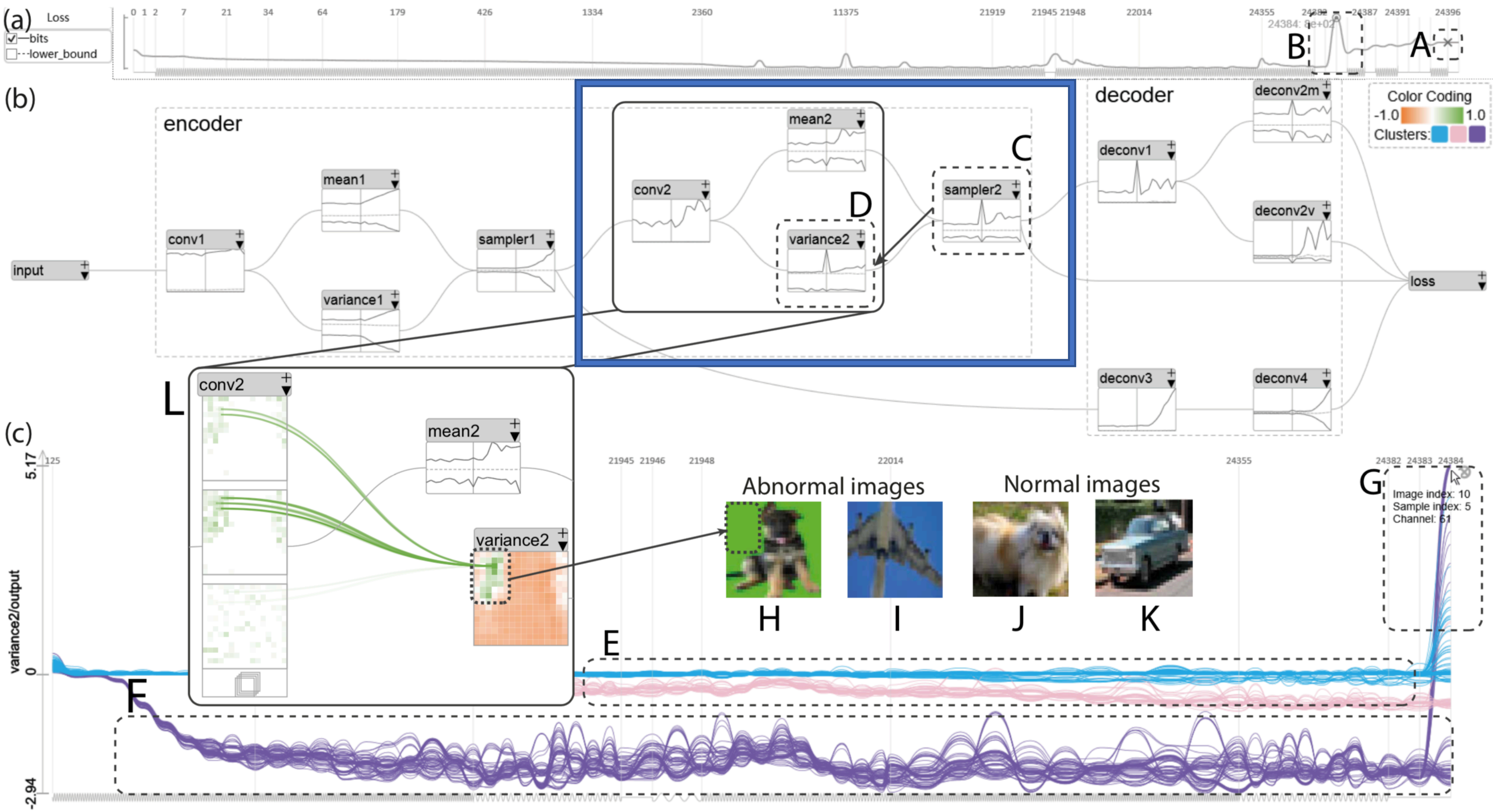
Stitching it all together



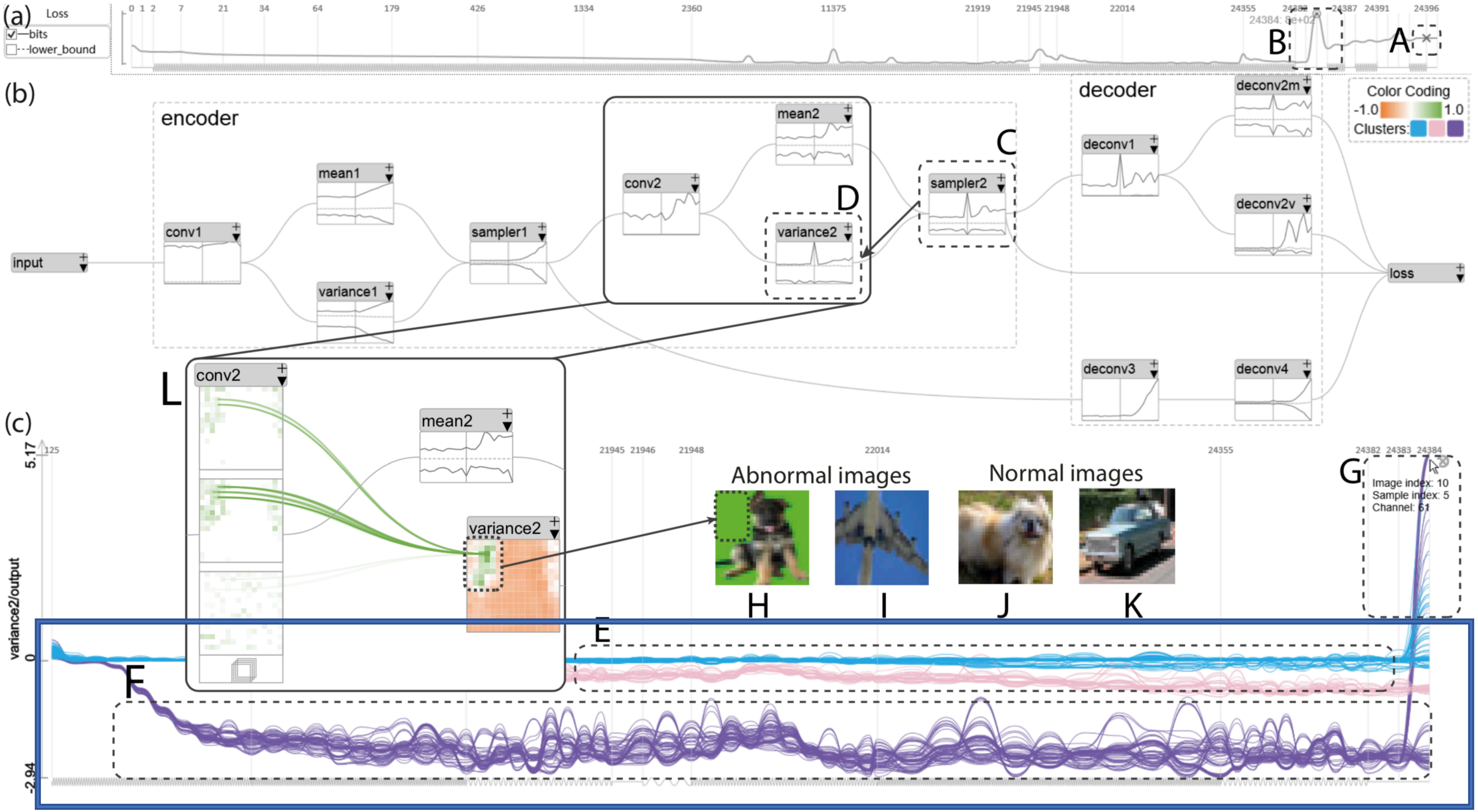
Stitching – Examine the loss function



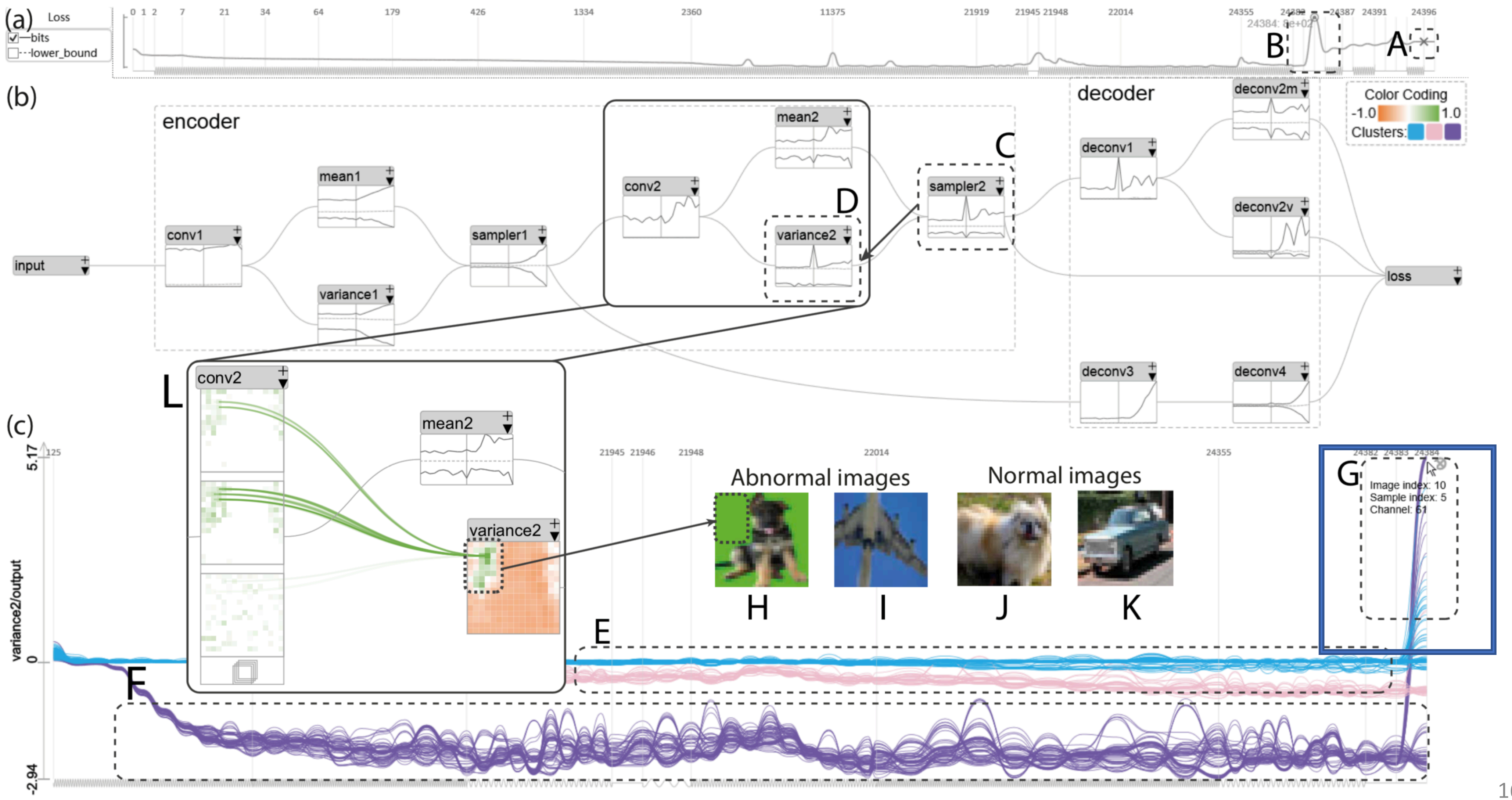
Stitching – Examine the layers (snapshot)



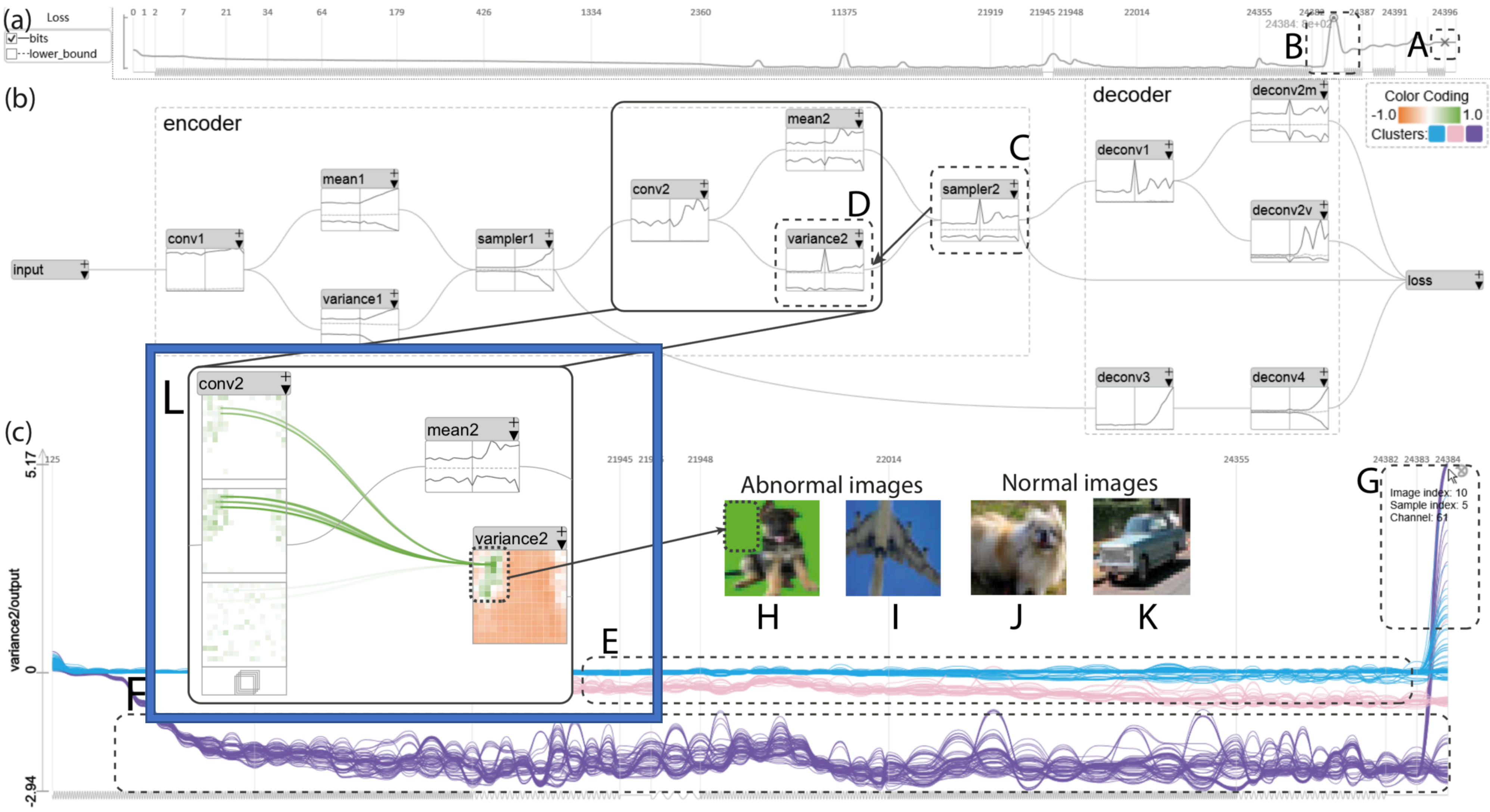
Stitching – Training dynamics of the layer



Stitching – Training dynamics of the layer



Stitching – Neuron level root cause analysis



Analysis - scalability

- Millions of neurons in each layer and 100s of layers
  - In snapshot level view, use expandable hierarchy groups
  - In layer level view, use filtering, clustering
  - In neuron level view, use filtering and clustering

- Large amount of training dynamics data [5TBs]
  - Keep a few in memory

- Millions of snapshot-level data come as time-series
  - Use sampling (blue-noise polyline)

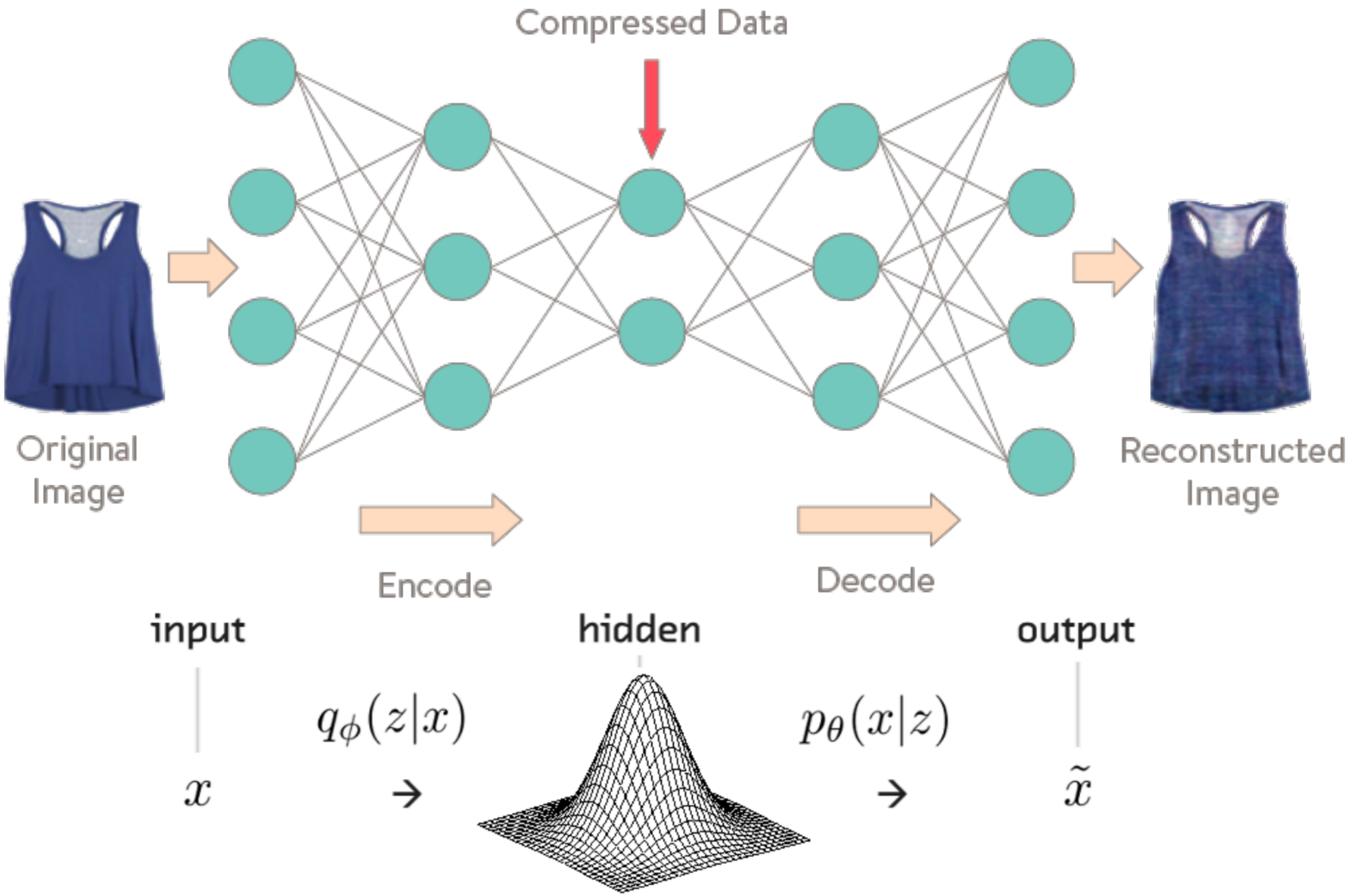
Analysis - critique

- Pros
  - Case studies to prove that it works
  - User study to understand the requirements
  - Extendible to CNNs and MLPs
- Cons
  - Does not work in case neural networks have cycles
  - Works only for offline analysis
- My views
  - Not sure of responsiveness
  - Not sure what is the level of change required for other NNs

Conclusion/ Highlights

- Effective tool to diagnose DGMs
- Three level of analysis in DGMs
  - Snapshot level
  - Layer level
  - Neuron level
- Idioms
  - focus+context, filtering, aggregation, interaction
  - blue-noise polyline sampling to reduce clutter

DGMs – VAE (variational auto encoders)



What to visualize - challenges

- Handle large amount of time series data from the training process
  - Activation/ gradient/ weight changes over time (training dynamics)
  - Millions of time series (as DGMs has millions of above)
  - Simple viewing => visual clutter

Overview

- Examine loss changes to identify abnormal snapshot
- High level averaged statistics of each layer to identify layer of interest (hybrid viz) at the **snapshot level**
- Print the training dynamics of the layer of interest (**layer level analysis**)
- Interactively select a set of neurons and explore how other neurons are related though the **data-flow visualization**

Neuron level analysis

- Idea - Root cause analysis

- Credit assignment
  - Influenced by both previous and next layer
  - Use forward and backward propagation to find neurons of interest

- Other ideas for conv/ deconv layers
  - Relative position of the image patch that each neuron is influenced
  - Represent neurons as feature maps - neurons which share the same weights
  - By tracing behind, we identify the corresponding image patch.

Neuron Level analysis

- Visualization
  - Cluster neurons and show them in a grid form
  - Show only which highly contribute to the output