Rosetta Neurons: Mining the Common Units in a Model Zoo

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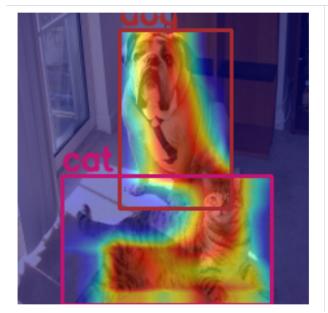
Outline

- 1 Background
- 2 Method
- 3 Experiments
- 4 Discussion

- Visualizing deep representations
 - CAM (Class Activation Map)
 - Grad-CAM

$$\mathrm{L^{c}_{Grad-CAM}} = \mathrm{ReLU}(\sum_{k} lpha_{k}^{c} \, \mathrm{A}^{k})$$

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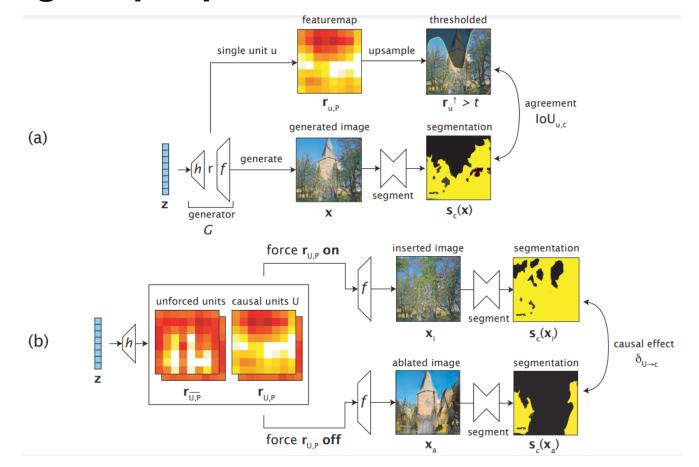


Visualizing deep representations

GAN DISSECTION: VISUALIZING AND UNDERSTANDING GENERATIVE ADVERSARIAL NETWORKS

David Bau^{1,2}, Jun-Yan Zhu¹, Hendrik Strobelt^{2,3}, Bolei Zhou⁴, Joshua B. Tenenbaum¹, William T. Freeman¹, Antonio Torralba^{1,2}

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- Limitations
 - Need Label
 - Focus on One Model

■ Can we make connections between different models directly through the neurons inside the model?

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Method

■ Motivation:

- Do different neural networks, trained for various vision tasks, share some common representations?
- We seek to identify and match units that express similar concepts across different models.
- We call them *Rosetta Neurons Techniques*.

Method

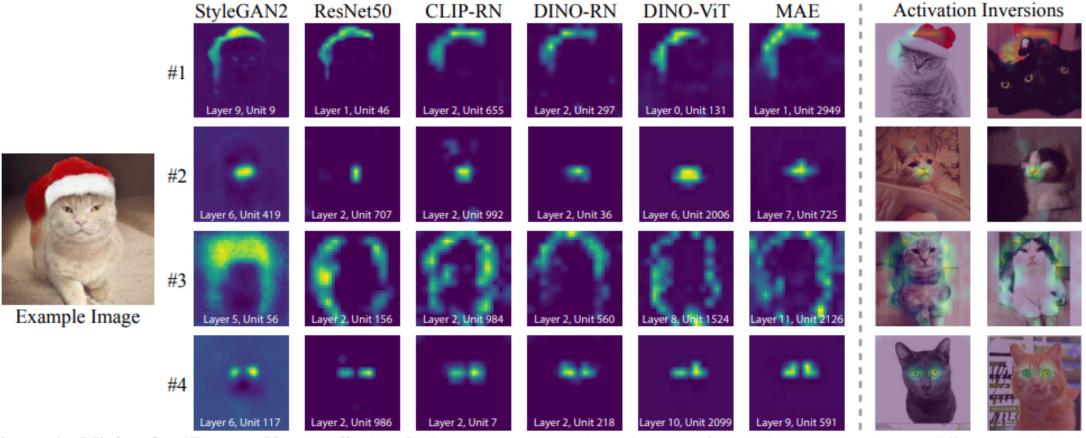


Figure 1: Mining for "Rosetta Neurons." Our findings demonstrate the existence of matching neurons across different models that express a shared concept (such as object contours, object parts, and colors). These concepts emerge without any supervision or manual annotations. We visualize the concepts with heatmaps and a novel inversion technique (two right columns).

- Settings:
 - Two models, $F^{(1)}$, $F^{(2)}$
 - A generative model and a discriminative model
 - Connecting the two models:
 - $\blacksquare F_{i,x}^{(1)j}$
 - The x location of j-th intermediate activation map when applied $F^{(1)}$ to the i-th input image

- Filtering "best buddies" pairs:
 - select the pairs that are nearest neighbors

$$KNN(F^{(a)j}, F^{(b)act}; K) = \underset{q_1 \dots q_K \subseteq F^{(b)act}}{\operatorname{argmin}} \sum_{k=1}^{K} d(F^{(a)j}, q_k)$$

■ the distance is defined as the *Pearson correlation*:

$$d(F^{(1)j}, F^{(2)k}) = \frac{\sum_{i,x} \left(F_{i,x}^{(1)j} - \overline{F^{(1)j}} \right) \left(F_{i,x}^{(2)k} - \overline{F^{(2)k}} \right)}{\sqrt{var(F^{(1)j}) \cdot var(F^{(2)k})}}$$
(2)

- Filtering "best buddies" pairs:
 - select the pairs that are mutual nearest neighbors
 - the distance is defined as the *Pearson correlation*
 - we have found the similar activation maps across different models!

$$BB(F^{(1)}, F^{(2)}; K) = \{(j, k) |$$

$$F^{(1)k} \in KNN(F^{(2)j}, F^{(1)act}; K)$$

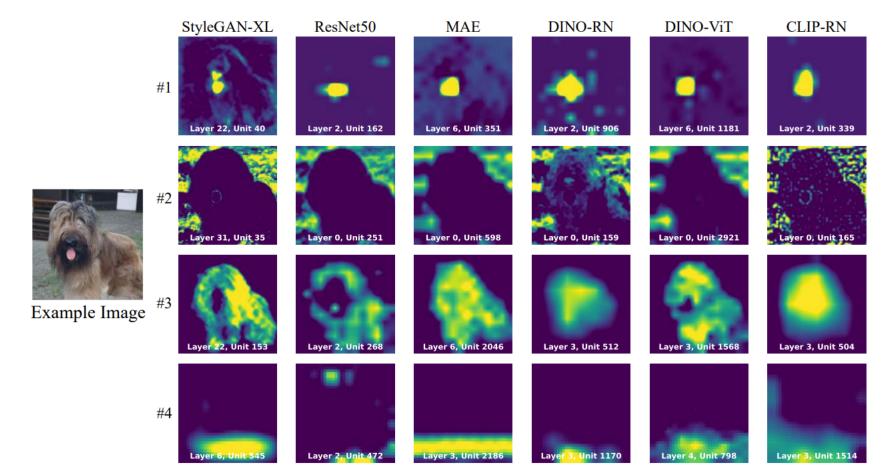
$$\land F^{(2)j} \in KNN(F^{(1)k}, F^{(2)act}; K) \}$$

- Cluster them!
 - Merging units between different models to obtain Rosetta units:

$$R(G, D_1...D_m) = \{(j, k_1, ..., k_m) | \forall i : (j, k_i) \in BB(G, D_i) \}$$

Cluster the similar Rossetta units:

two Rosetta Neurons in R to belong to the same cluster if their corresponding units in G are in BB(G,G;K).



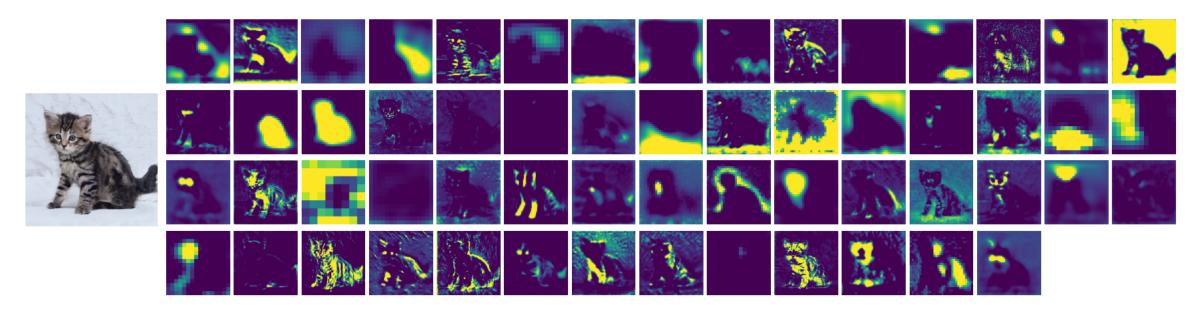
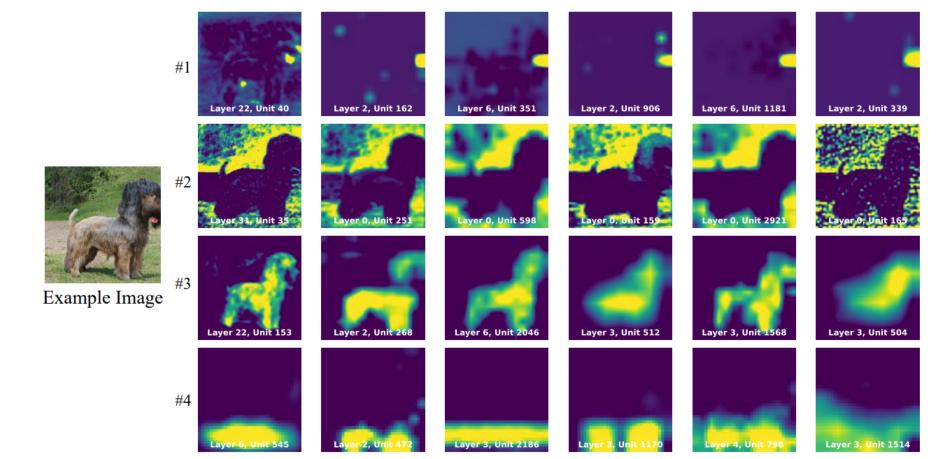
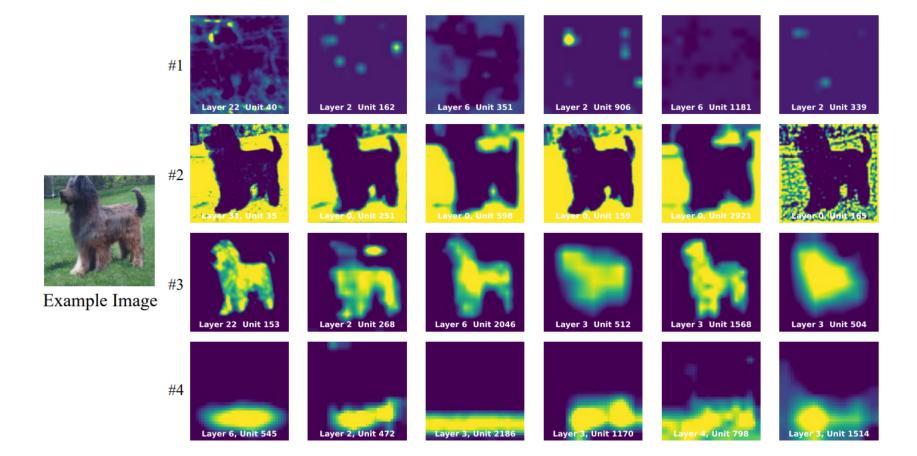
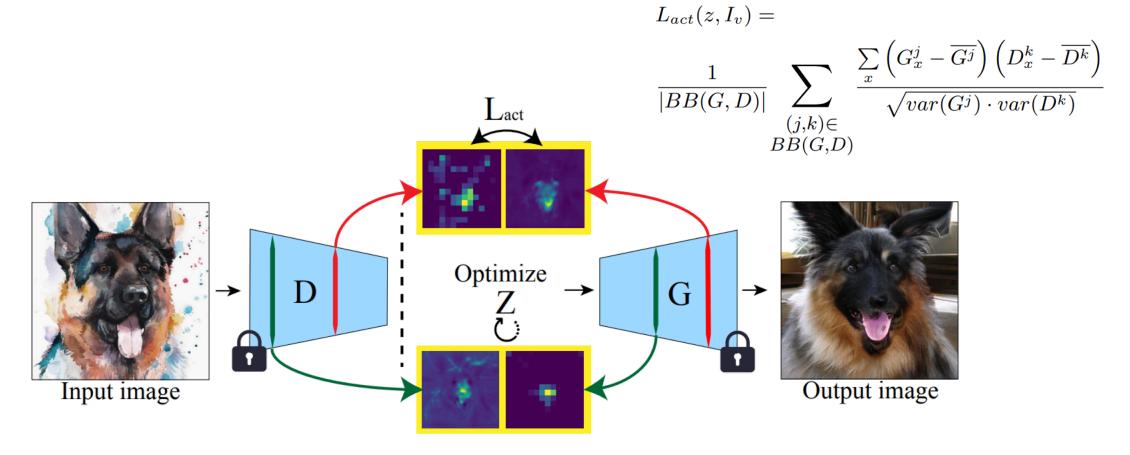


Figure 13: All the concepts for LSUN-cats. Shown for one StyleGAN2 generated image.

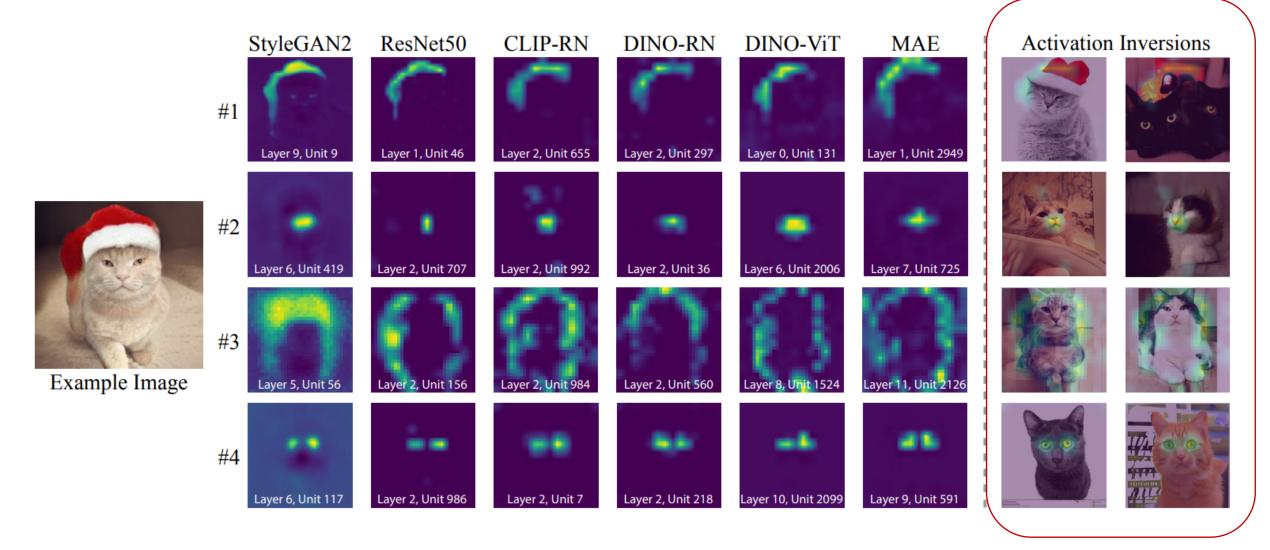




Rosetta Neurons-Guided Inversion



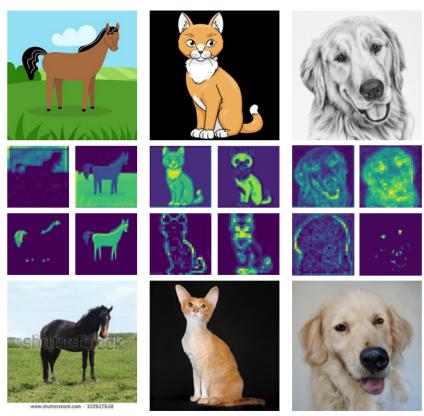
- Rosetta Neurons-Guided Inversion Results
 - The corresponding visual concepts will be consistent
 - emerge or disappear
 - property alignment
 - Consistency in images generated over the regions that these neurons focus on



- Rosetta Neurons-Guided Inversion Results
 - We can perform invertion to generate out-of-distribution images



Figure 6: Cross-class image-to-image translation. Rosetta Neurons guided inversion of input images (top row) into a Style-GAN2 trained on LSUN cats [35], allows us to preserve the pose of the animal while changing it from dog to cat (bottom row). See



Rosetta Neurons-Guided Inversion - Results

Neurons removal





Neurons addition













































- Rosetta Neurons-Guided Inversion Results
 - Inverting in-distribution images

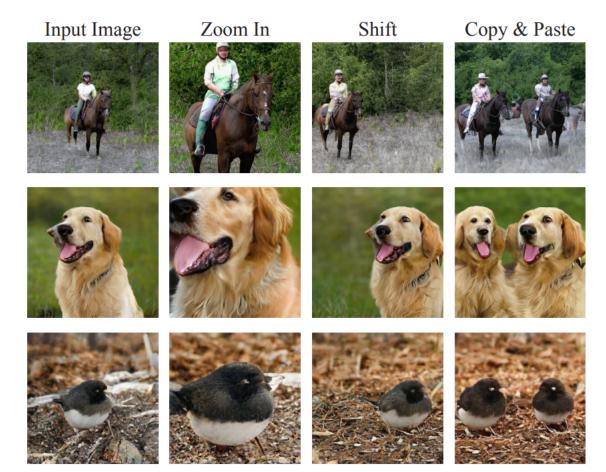
$$\arg\min_{z} (L_{rec}(G(z), I_v) + \alpha L_{reg}(z) - \beta L_{act}(z, I_v))$$

	PSNR ↑	SSIM ↑	LPIPS ↓
Perceptual loss	13.99	0.340	0.48
+DINO matches	15.06	0.360	0.45
+CLIP matches	15.20	0.362	0.44
+All matches	15.42	0.365	0.46

Table 1: Inversion quality on ImageNet. We compare the inversion quality for StyleGAN-XL when Rosetta Neurons guidance is added, for 3 sets of matches - StyleGAN-XL & DINO-RN, StyleGAN-XL & CLIP-RN and all the models from figure 3.

- Rosetta Neurons Guided Editing
 - Change the activation map of R units
 - Zoom-in, Shift, Copy & Paste,
 - Re-optimize the latent z to match the edited activation maps

Rosetta Neurons Guided Editing - Results



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Discussion

- A new method for mining and visualizing common representations that emerge in different visual models.
- Promising in some advanced generative tasks.
- **■** Limitations:
 - Fails in GAN-GAN matching.
 - **■** Fails in Diffusion models.
 - May suffer from spurious correlations.

Thanks!