

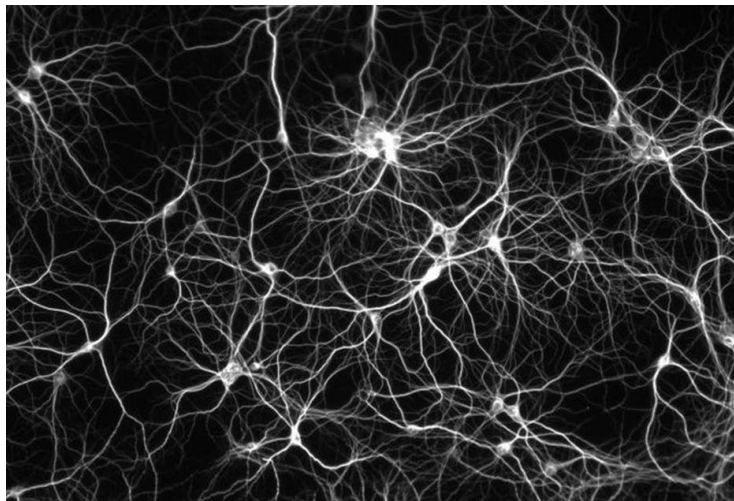
# Applications of Deep Learning

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Math 5467: Intro to Math of Image and Data Analysis  
University of Minnesota

# Deep Learning

**Deep Learning** is a field within machine learning based on **artificial neural networks** with many layers.



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- Convolutional neural networks for handwritten digit recognition pioneered by LeCun in 1989.

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# ImageNet

Image classification problem with 14 million images and 20,000 classes.



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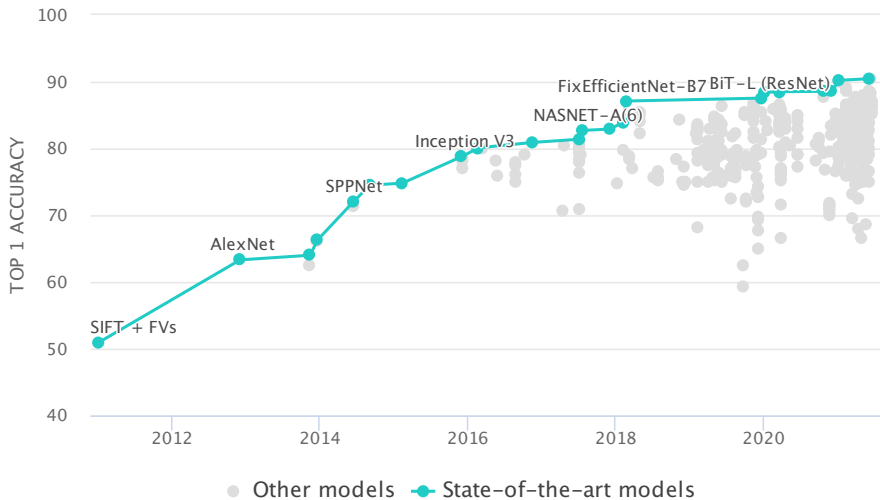
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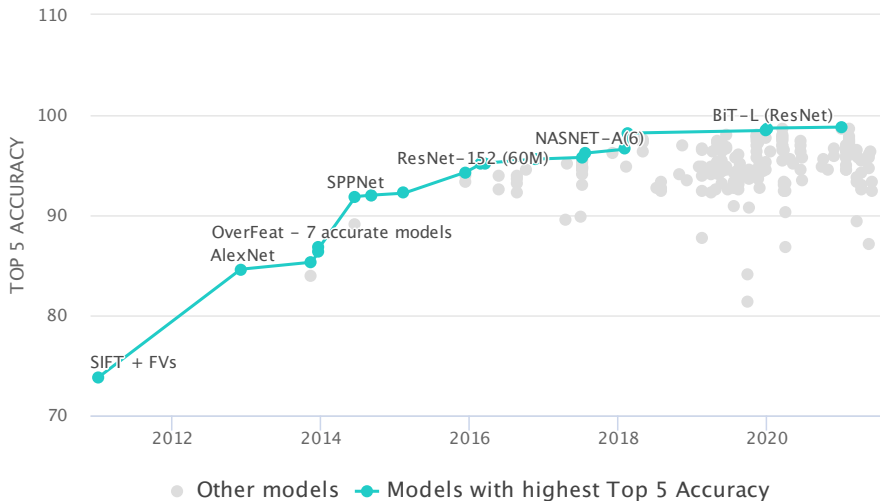
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  - ▶ Best results from 2021 are 90.45% (Top 1) and 98.8% (Top 5).
  - ▶ **Super-human** performance: Humans get around 95% (Top 5).

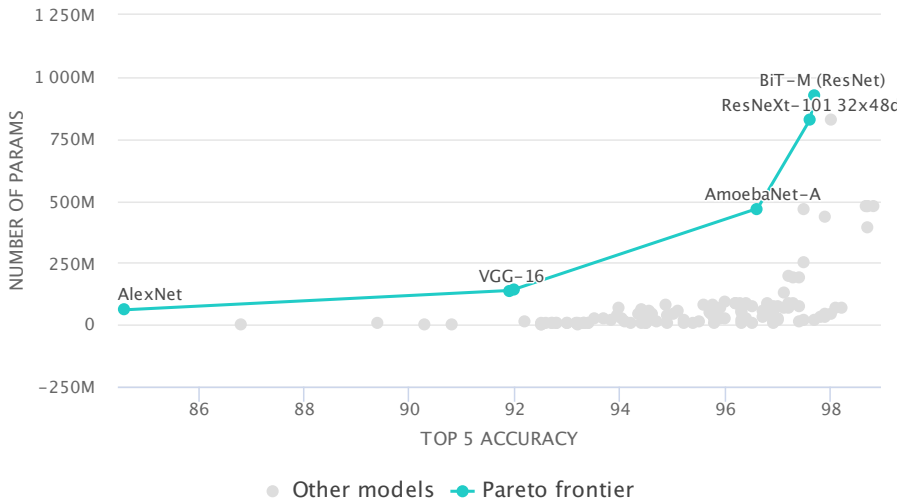
# ImageNet Top 1 Accuracy



# ImageNet Top 5 Accuracy



# ImageNet: Number of Parameters



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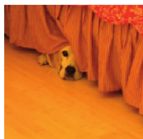
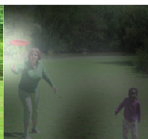
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- Many, many, many, others.

# Automated image captioning



A woman is throwing a **frisbee** in a park.



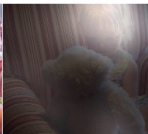
A **dog** is standing on a hardwood floor.



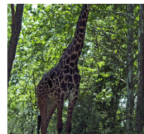
A **stop** sign is on a road with a mountain in the background



A little **girl** sitting on a bed with a teddy bear.



A group of **people** sitting on a boat in the water.



A giraffe standing in a forest with **trees** in the background.

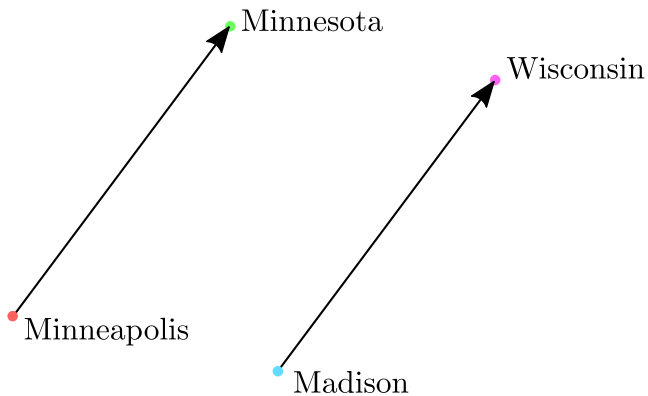


[Yann LeCun, Yoshua Bengio, Geoffrey Hinton. Deep learning. **Nature**, 2015.]

<https://deeptai.org/machine-learning-model/neuraltalk>

# Word2Vec

Word2Vec maps words into vectors in  $\mathbb{R}^m$  in such a way that relationships between words are encoded into the vector geometry.



## Word2Vec examples

Using Word2Vec we can do arithmetic with words.

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- Choose your own example...

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Deep Blue vs. Garry Kasparov, 1996-1997

## Chess-playing AI (Deep Blue)

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- This approach fails for more complicated games, like the Chinese board game Go:



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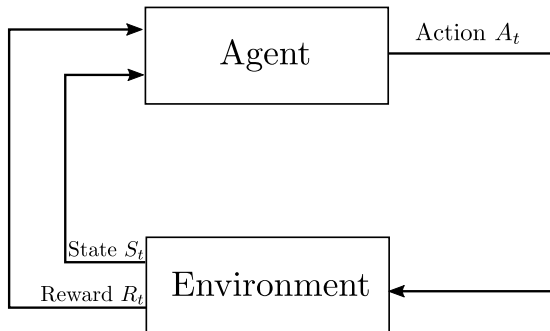
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  - ▶ AlphaGo Zero learned to play Go by playing against itself repeatedly in a deep reinforcement learning algorithm.
- Quotes from professional Go players during 2015-2017 matches:
  - ▶ “I misjudged the capabilities of AlphaGo and felt powerless.”
  - ▶ “It knows everything and can play creatively.”
  - ▶ “All but the very best Go players craft their style by imitating top players. AlphaGo seems to have totally original moves it creates itself.”

# Deep Reinforcement Learning



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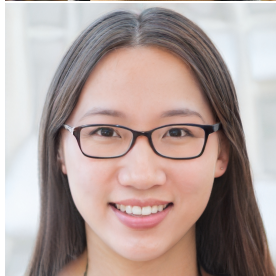
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  - ▶ The input of the generator is random noise.
- Training pits the generator against the discriminator until the generator can consistently fool the discriminator.

# These people do not exist (generated by a GAN)



<https://thispersondoesnotexist.com/>

# Neural Style Transfer

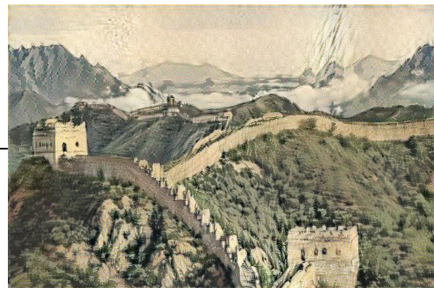


Input Content



Input Style

Neural Style Transfer



Output

# Neural Style Transfer



(a) Content

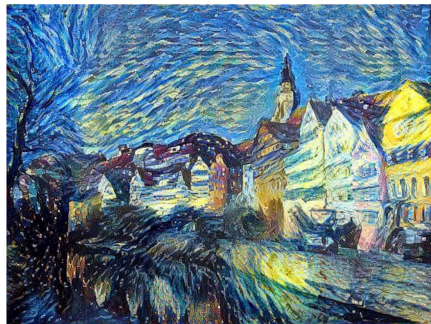


(b) Style

# Neural Style Transfer



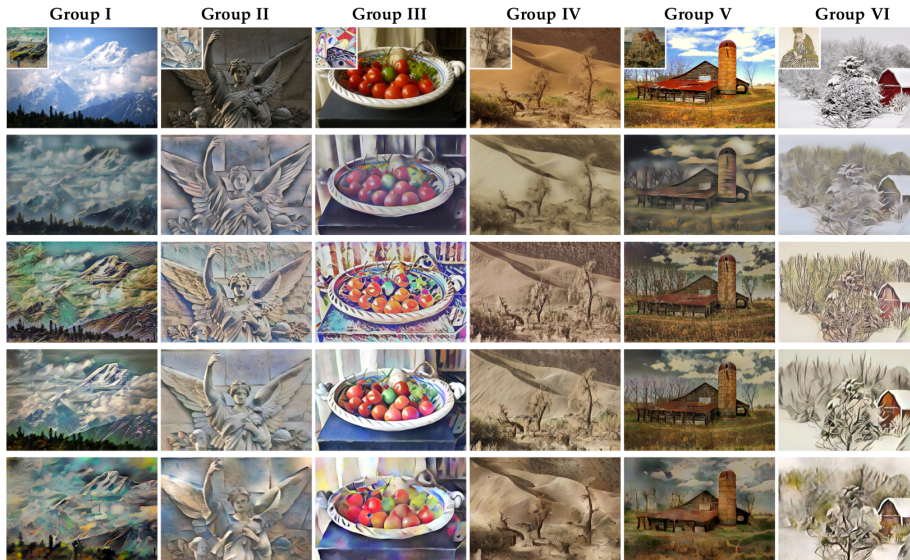
(c) Small Stroke Size



(d) Large Stroke Size



# Neural Style Transfer



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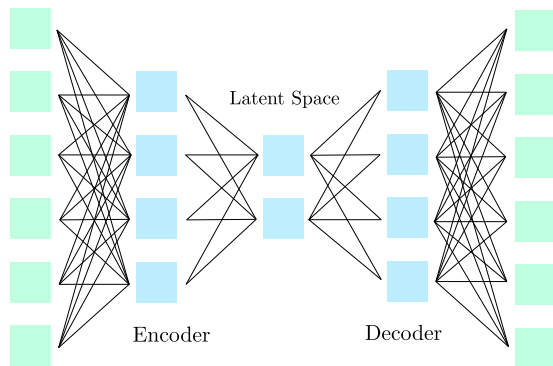
Neural Style Transfer works by minimizing the loss

$$E(I) = \sum_{i=1}^L \|F_i(I) - F_i(I_{\text{style}})\|^2 + \lambda \|I - I_{\text{content}}\|^2,$$

where

- $I_{\text{style}}$  is the style image.
- $I_{\text{content}}$  is the content image.
- $F_i$  are the features extracted from the  $i^{\text{th}}$  layer of a pre-trained convolutional neural networks, usually pretrained on imagenet.

# Autoencoders



- Nonlinear version of PCA.
- Applications
  - ▶ Image or data compression.
  - ▶ Simplifying data or extracting features.