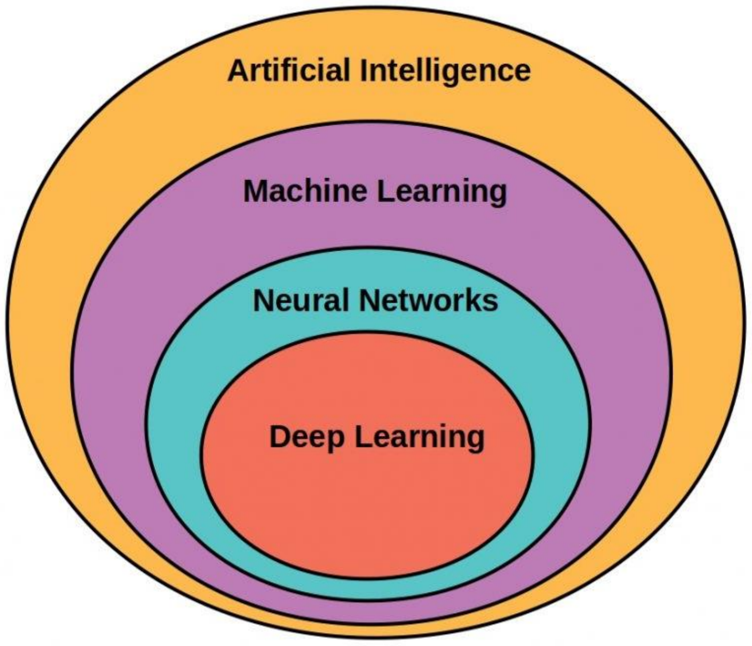
# AI IN MEDICAL PHYSICS

EDITH VILLEGAS GARCIA

# BASIC CONCEPTS




- Artificial Intelligence:

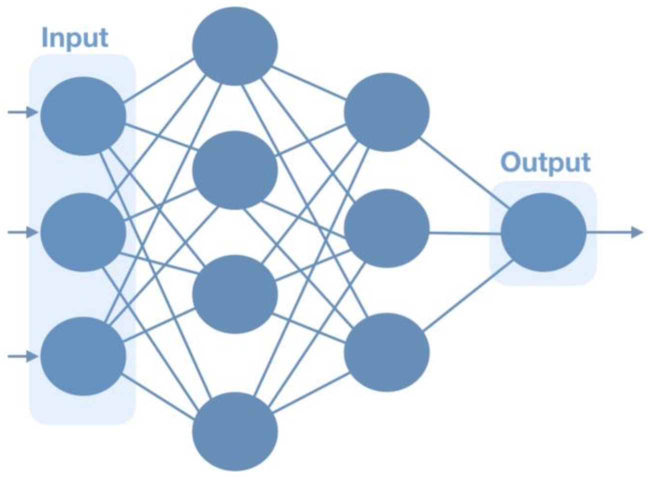
Programs that aim at solving tasks commonly associated with human intelligence.

- Machine Learning:

Algorithms that solve tasks without being programmed explicitly, improving with experience (data).

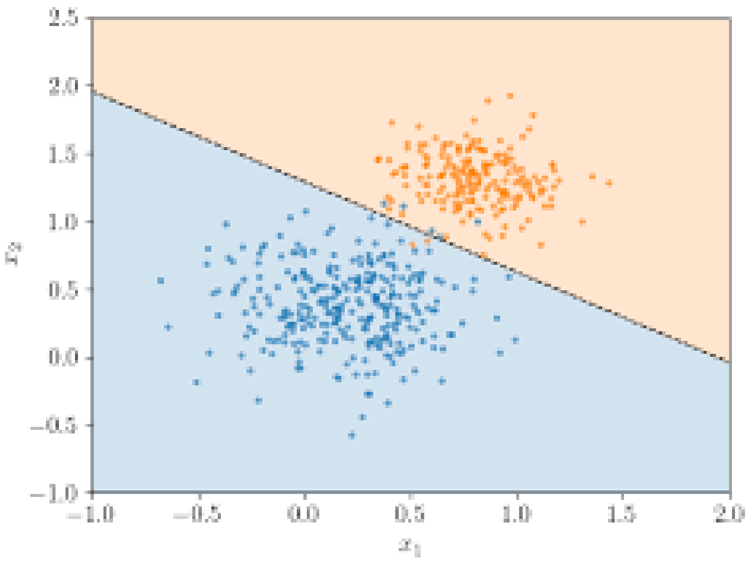
- Neural Networks:

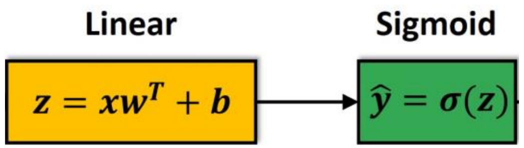
A specific set of machine learning algorithms.



# NEURAL NETWORKS

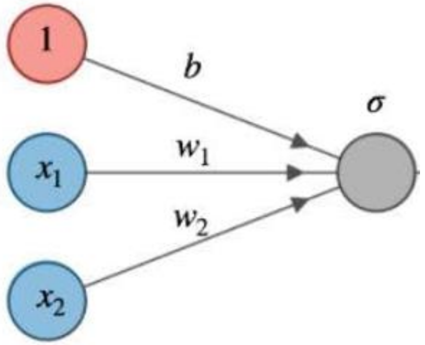
- Logistic Regression: classification



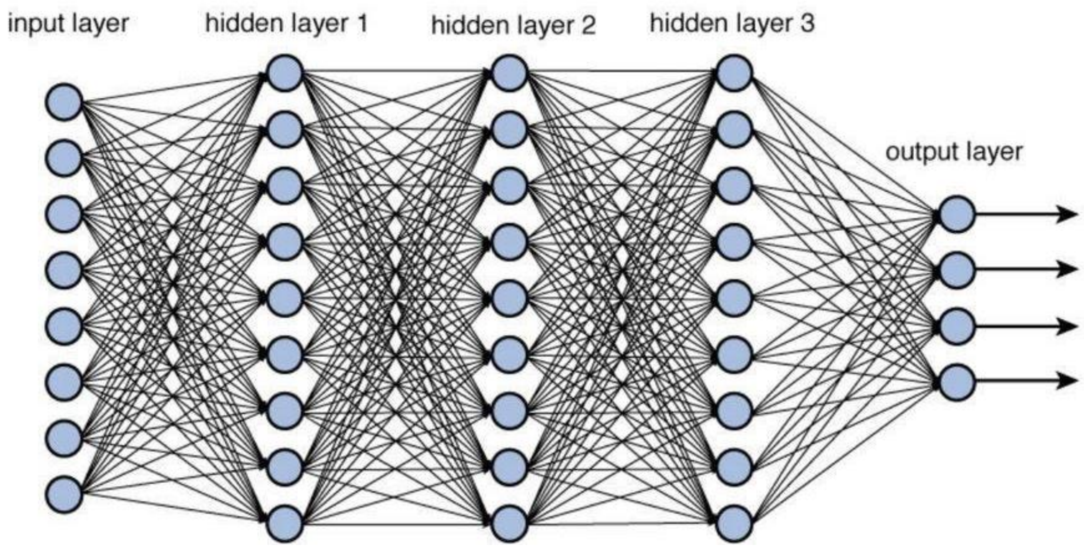

$$y = \frac{1}{1 + e^{-z}}$$

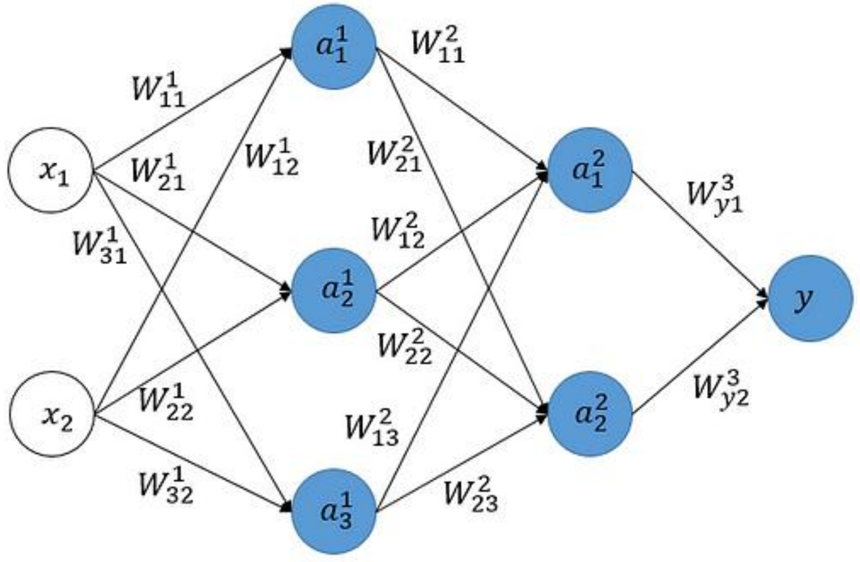
- ~ 1 neuron neural network



# NEURAL NETWORKS

- Deep learning




$a^1 = f^1(W^1 x + b^1)$ activations: $f^1(\cdot)$, $f^2(\cdot)$, $f^3(\cdot)$

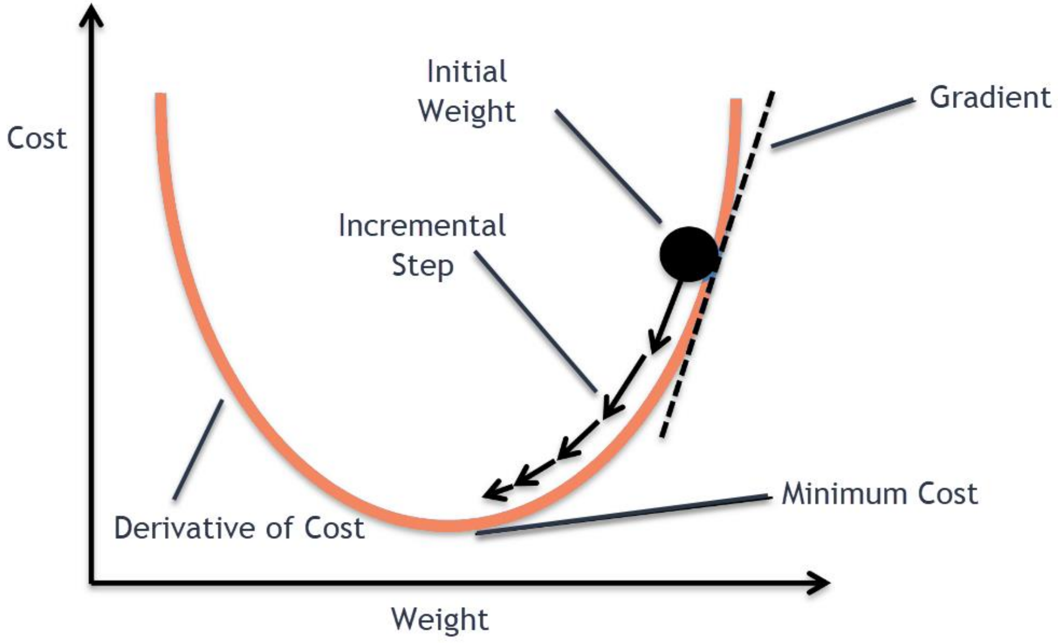
# HOW TO FIND THE WEIGHTS? GRADIENT DESCENT

- Define a cost function (error in classification/prediction)
- Find set of weights that give the minimum error (minimization problem)
- Optimize through gradient descent

$$w_{new} = w_{old} - \alpha \frac{\delta J}{\delta w}$$

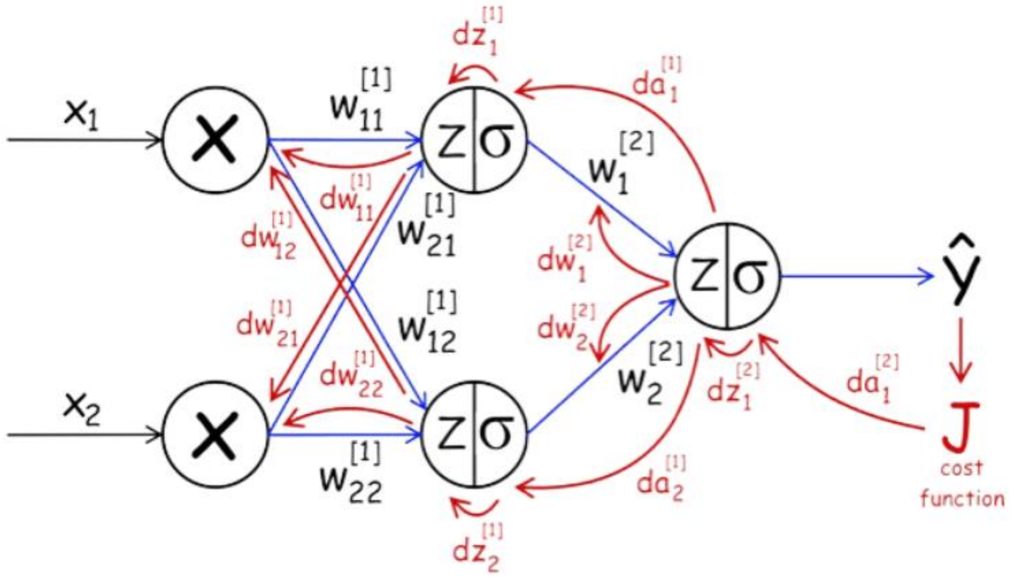
Change in error with respect to logistic regression coefficients

Learning rate



# BACKPROPAGATION

- Backward pass through the network




- Chain rule of calculus

$$\frac{dJ}{dW^{[2]}} = \frac{dJ}{dA^{[2]}} \frac{dA^{[2]}}{dZ^{[2]}} \frac{dZ^{[2]}}{dW^{[2]}}$$

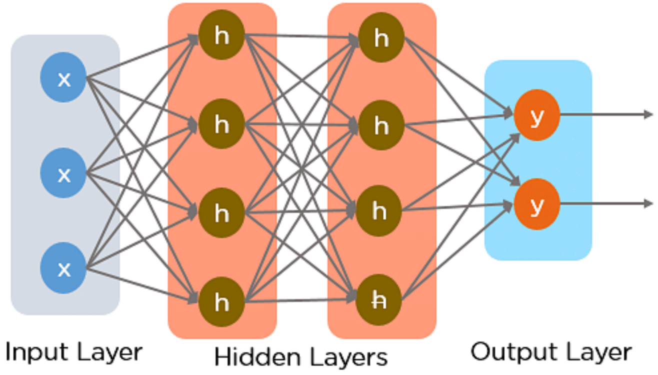
$$= dZ^{[2]} A^{[1]}$$

$$\frac{dJ}{dW^{[1]}} = \frac{dJ}{dA^{[2]}} \frac{dA^{[2]}}{dZ^{[2]}} \frac{dZ^{[2]}}{dA^{[1]}} \frac{dA^{[1]}}{dZ^{[1]}} \frac{dZ^{[1]}}{dW^{[1]}}$$

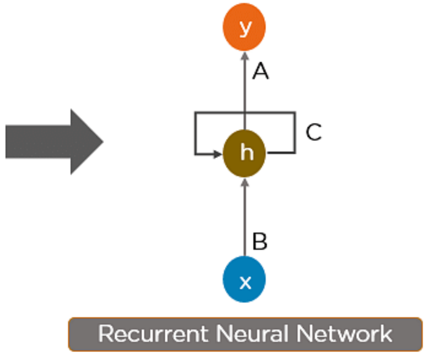
$$= dZ^{[1]} A^{[0]}$$

# DIFFERENT TYPES OF NEURAL NETWORK ARCHITECTURES

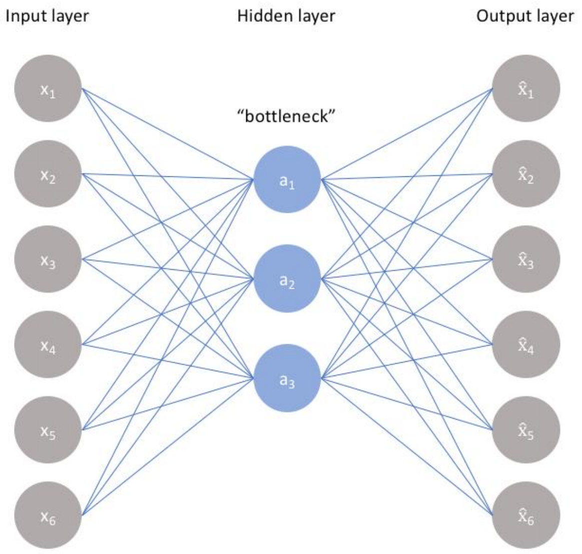
- Fully connected



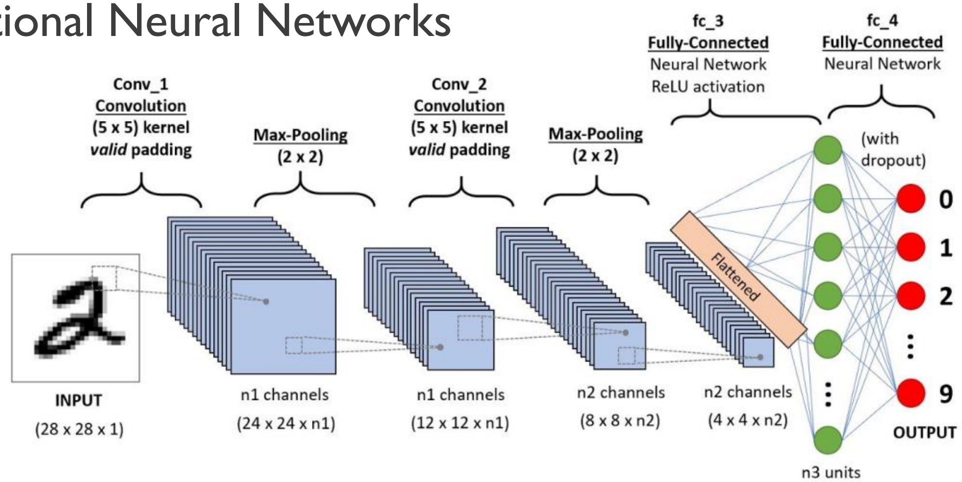

- Recurrent NN




- Autoencoder




- Convolutional Neural Networks



# CONVOLUTIONAL NEURAL NETWORKS

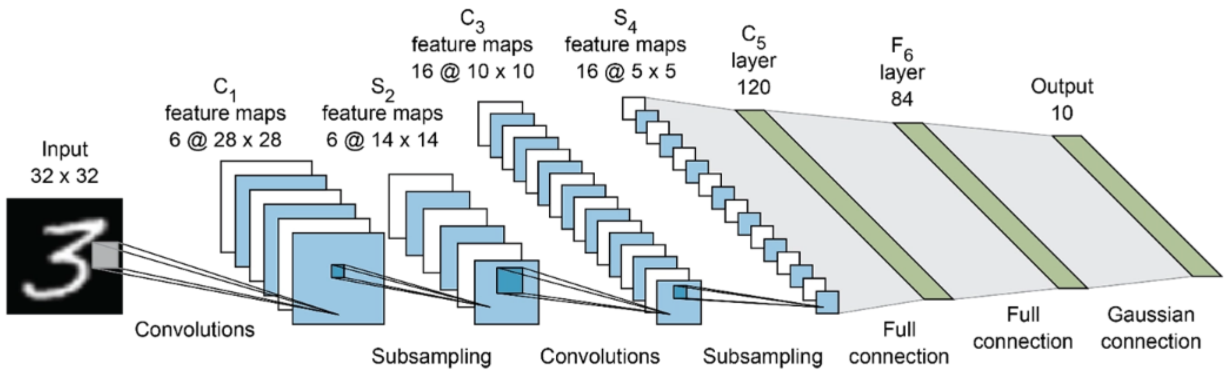
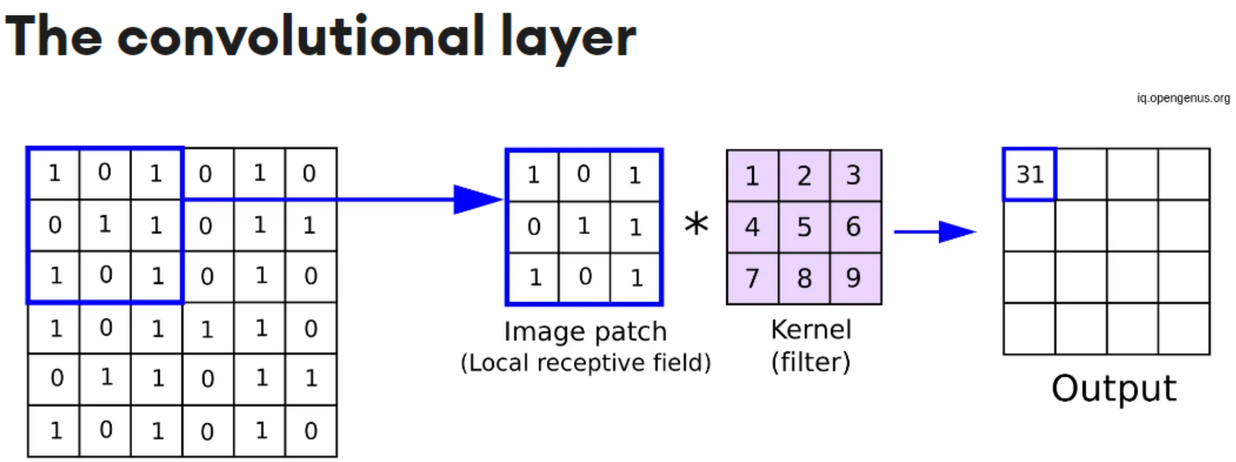
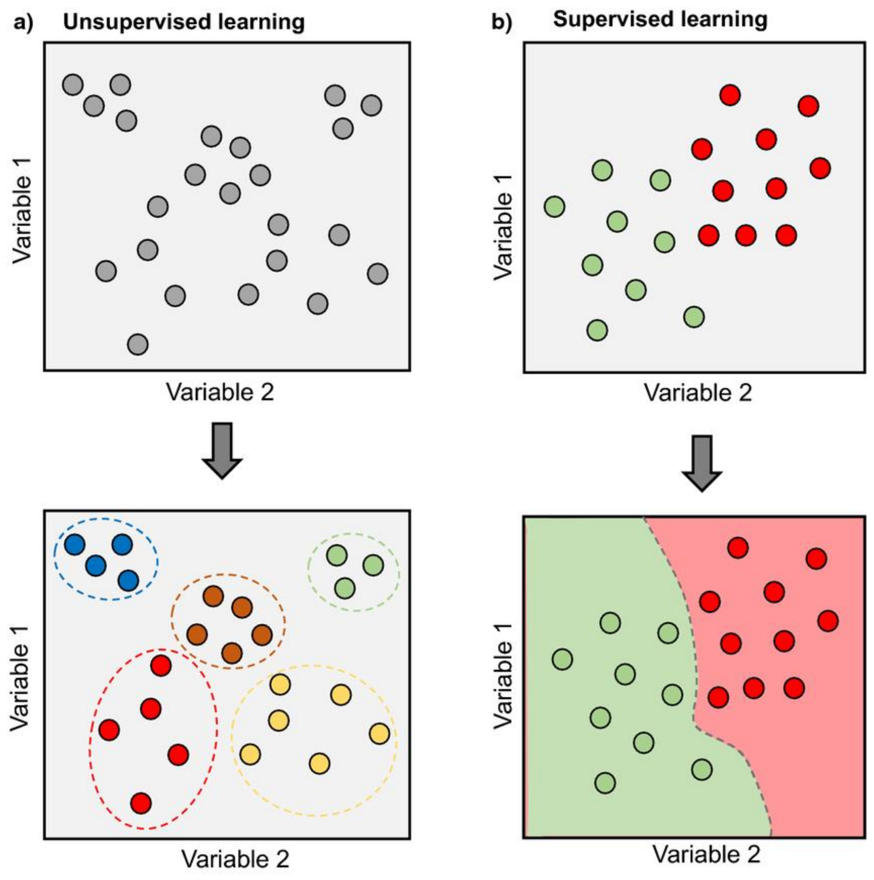


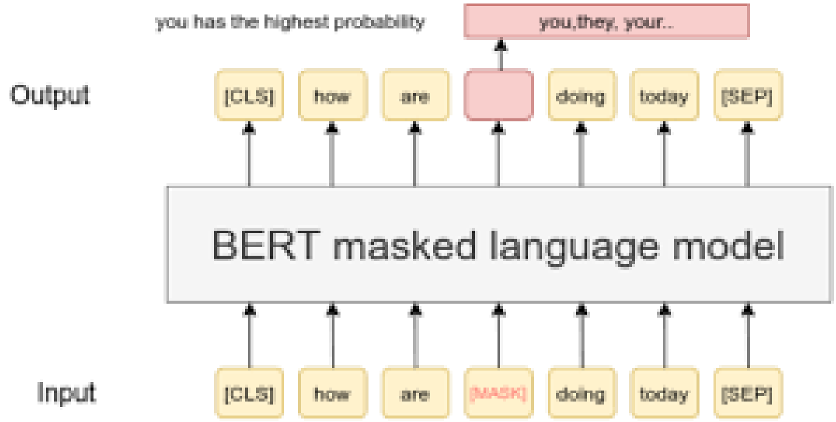

Image source

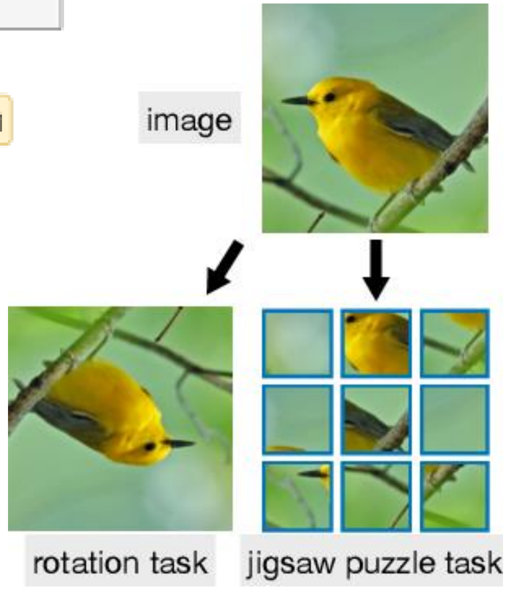


# SUPERVISED VS UNSUPERVISED VS SELF-SUPERVISED LEARNING




- Self-supervision:

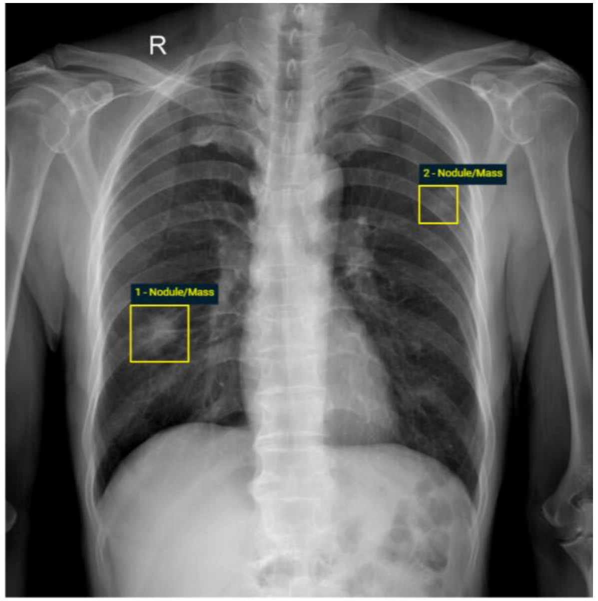


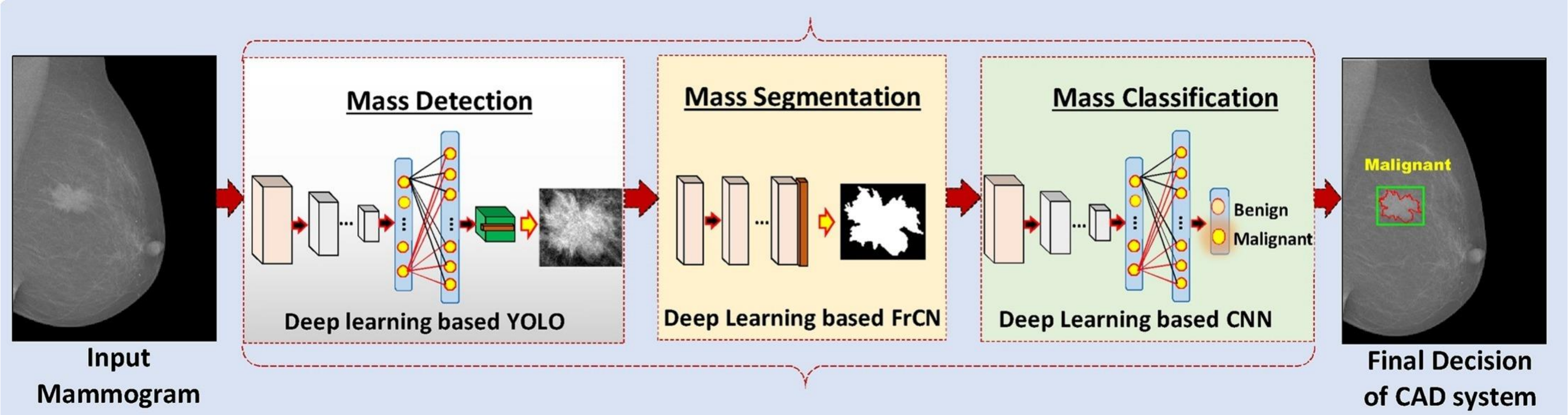
# APPLICATIONS TO MEDICAL PHYSICS

# APPLICATIONS IN IMAGING

- Computer Aided Diagnosis




Lung tumor





(a) Normal (b) Pneumonia (c) COVD-19

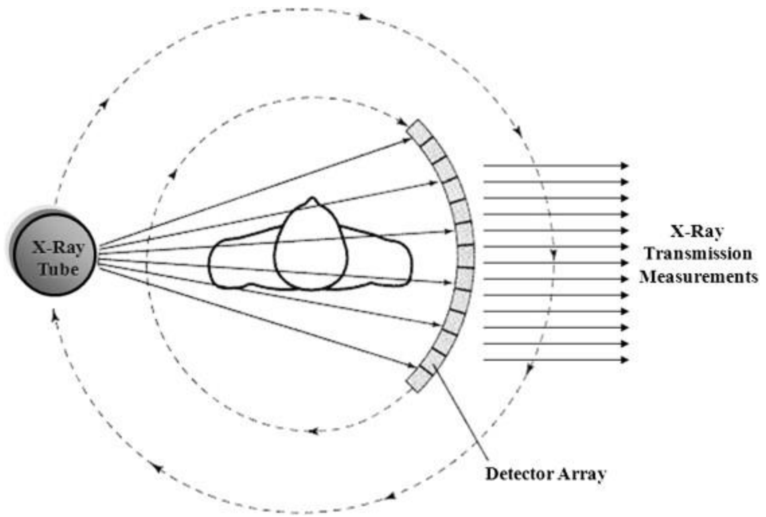
# APPLICATIONS IN IMAGING

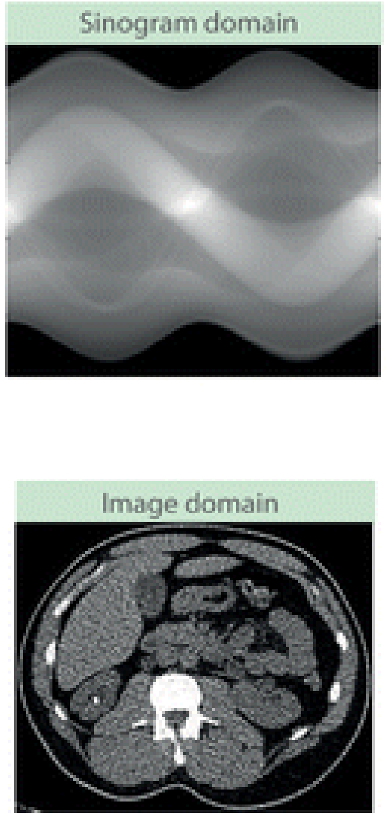
- Traditional reconstruction algorithms:

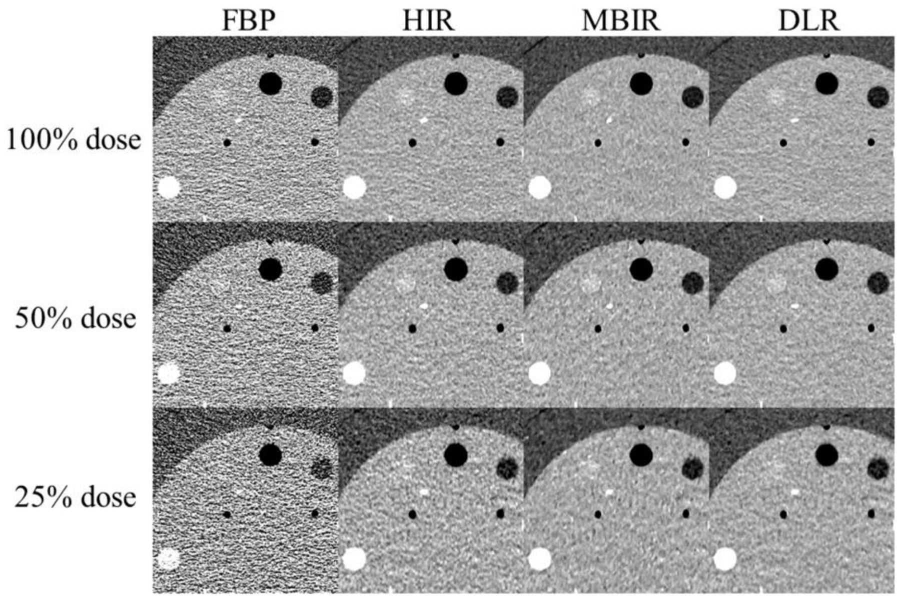
 Filtered Back Projection, Iterative Reconstruction

- Noise increases with less dose

- Deep learning based reconstruction and image denoising:



# APPLICATIONS IN IMAGING

- Synthetic CT Generation

for MRI Guided Radiotherapy

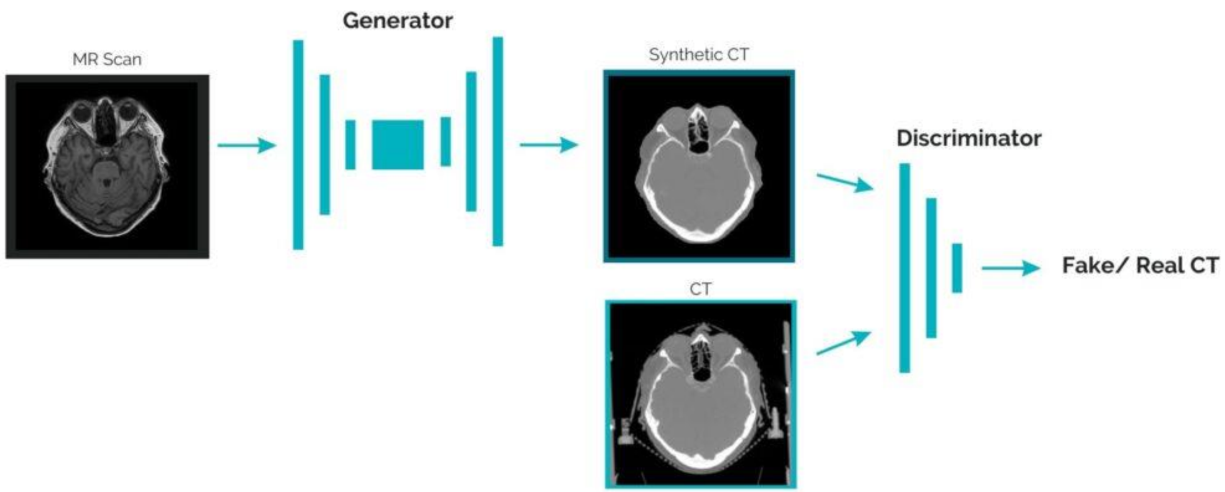
- MRI scan advantages:

- Better soft tissue contrast

- No radiation dose

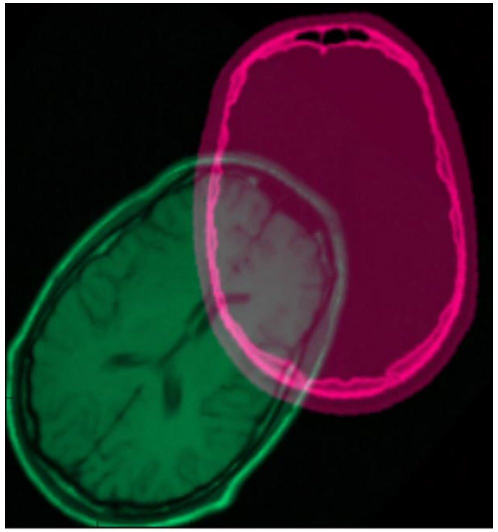
- CT scan needed for dose calculation (electron density)

Generative Adversarial Networks (GAN)



# APPLICATIONS IN IMAGING

- Automatic Image Registration



- Multimodality: PET-CT, CT, MRI

  To combine data from different imaging modalities
- Deformable image registration on the same modality,

  changes in patient anatomy, deforming contours/dose distributions
- For image guided radiotherapy: to aid patient positioning
- Network predicts the affine transformation (rigid registration) or deformation fields (deformable registration)

# RADIOMICS VS DEEP LEARNING

- Conventional Machine Learning Algorithms and Statistics combined with image features (radiomics) can be used to predict:
  - Bening vs Malignant tumors
  - Treatment Prognosis/Survival
  - Lession classification
- Deep Learning automatizes the radiomic workflow.

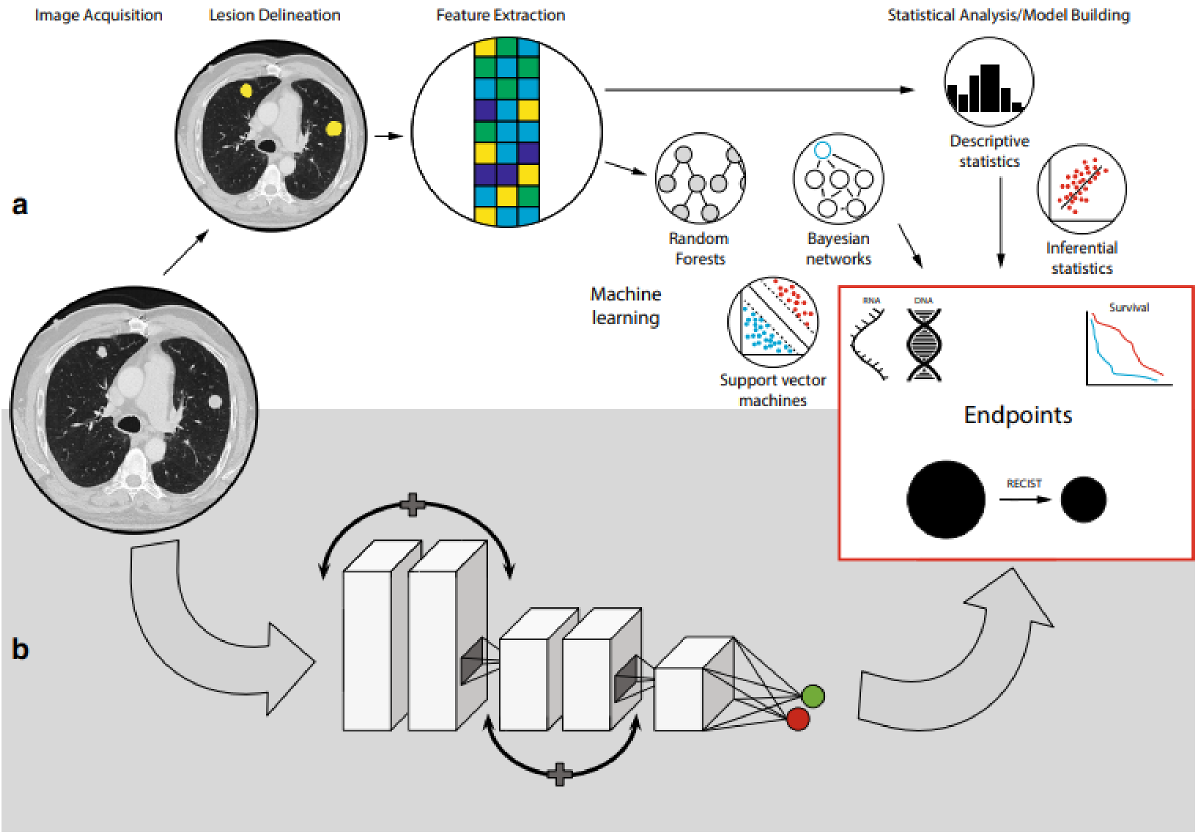
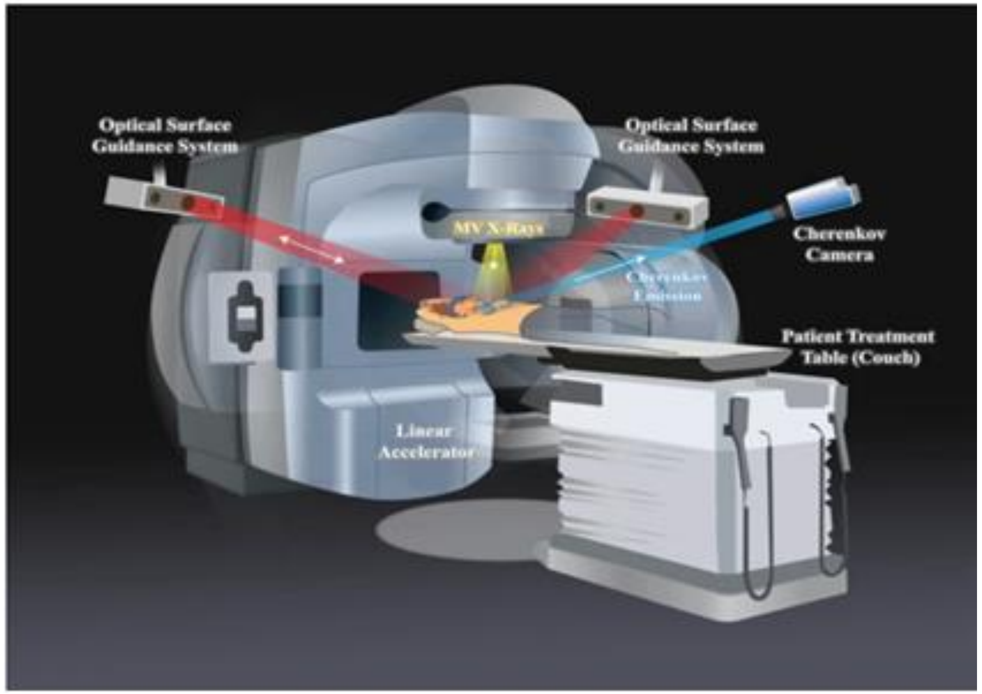
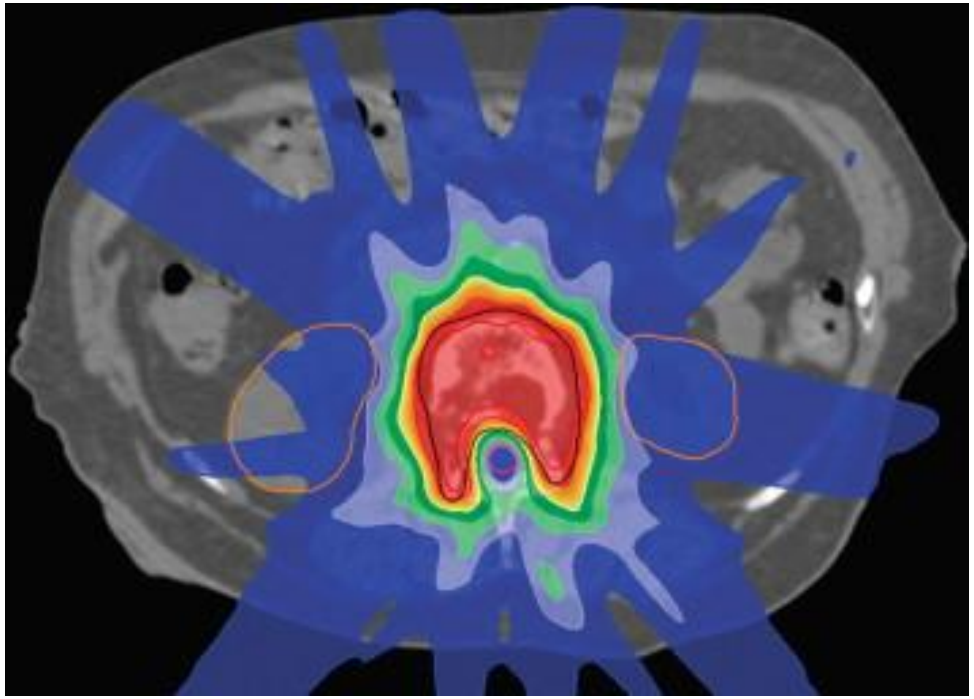



**Fig. 1** Outline of the two kinds of radiomics pipeline. **a** The classical/conventional radiomics model where, after image acquisition, areas of interest are delineated and handcrafted features are extracted. Subsequently, models are built around these predefined features using either statistical or machine learning methodologies. **b** The deep learning radiomics pipeline where, after image acquisition, neural networks automatically perform feature extraction, selection, and classification

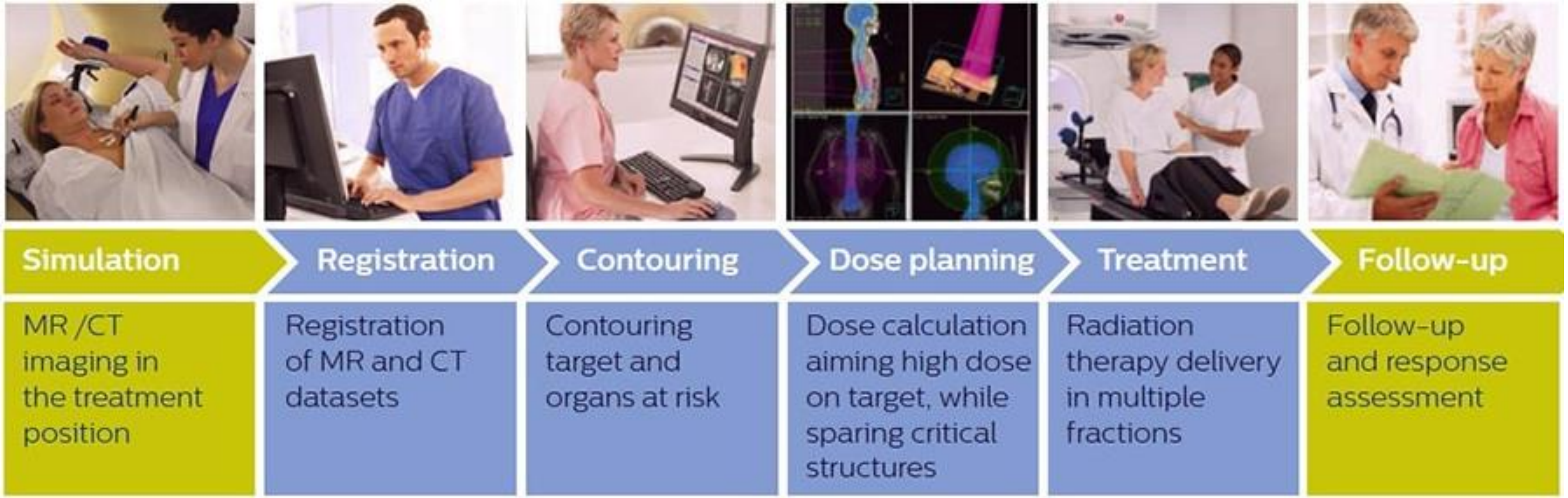
# RADIOTHERAPY



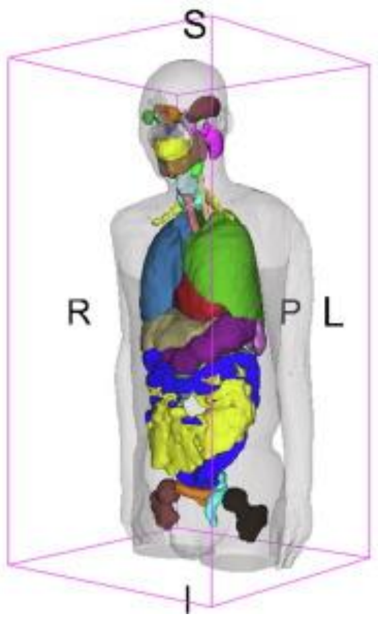



External Beam Radiotherapy objective: deliver a high radiation dose to the tumor while keeping dose to normal tissue low.

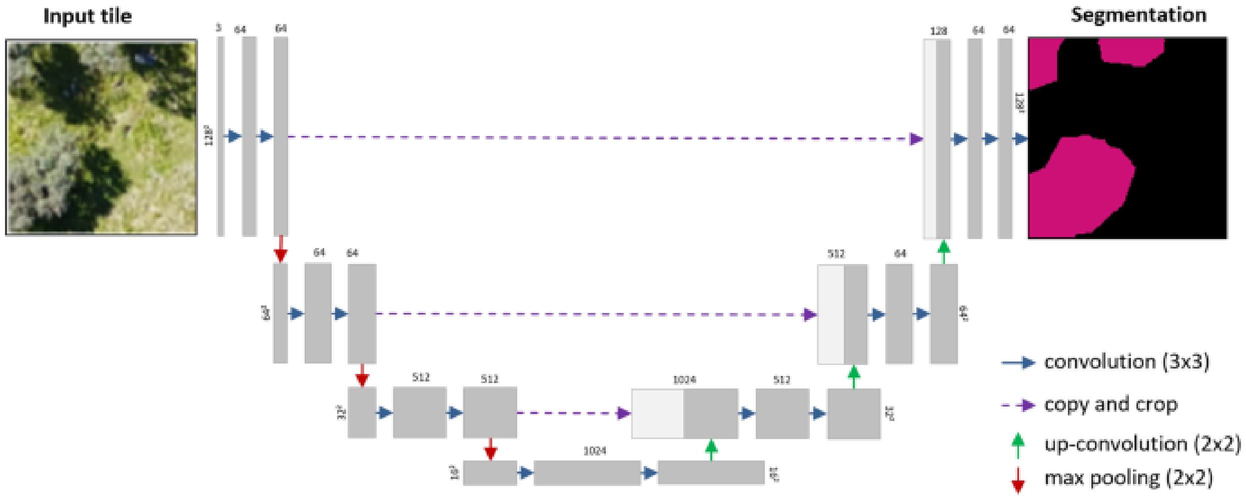
# RADIOTHERAPY WORKFLOW



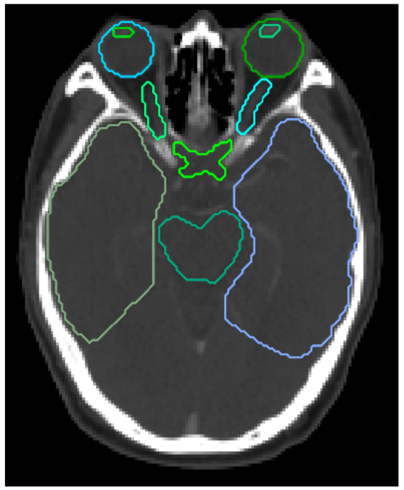
# APPLICATIONS IN RADIOTHERAPY




- Automatic Segmentation of Organs at Risk



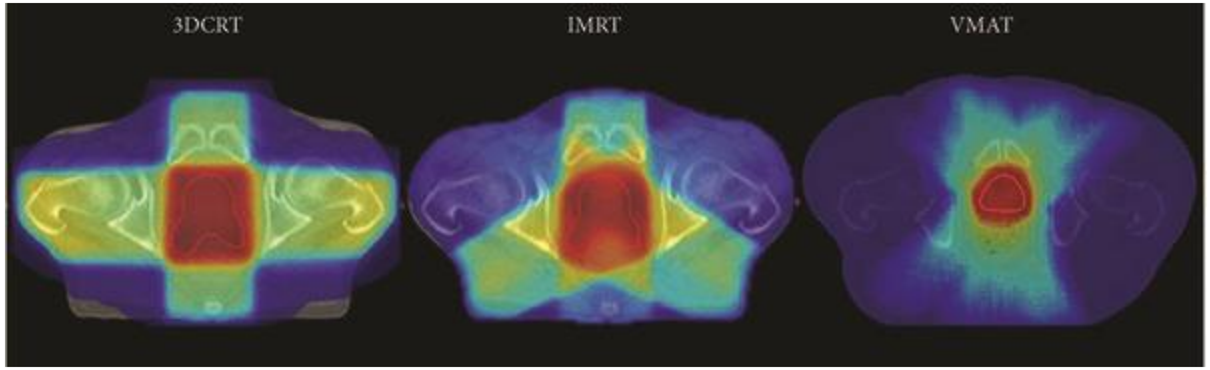

- U-net architecture

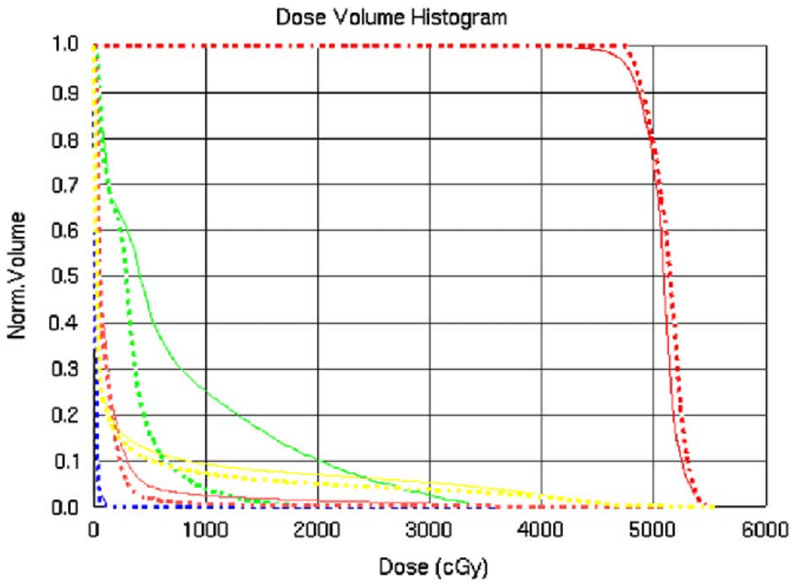


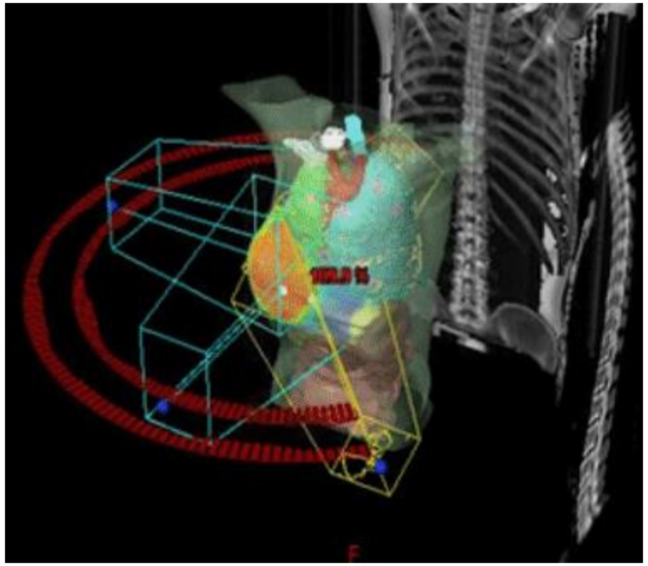
- Saves time from the radiologist
- Standardize contours

# RADIOTHERAPY PLANNING

- Iteratively decide treatment parameters until a satisfactory dose distribution is obtained:
  - Uniform dose to the tumor
  - Limit on dose to organs at risk



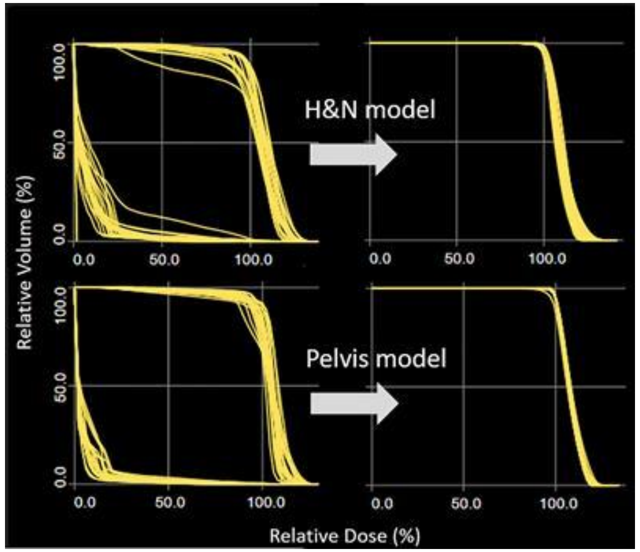



# APPLICATIONS IN RADIOTHERAPY

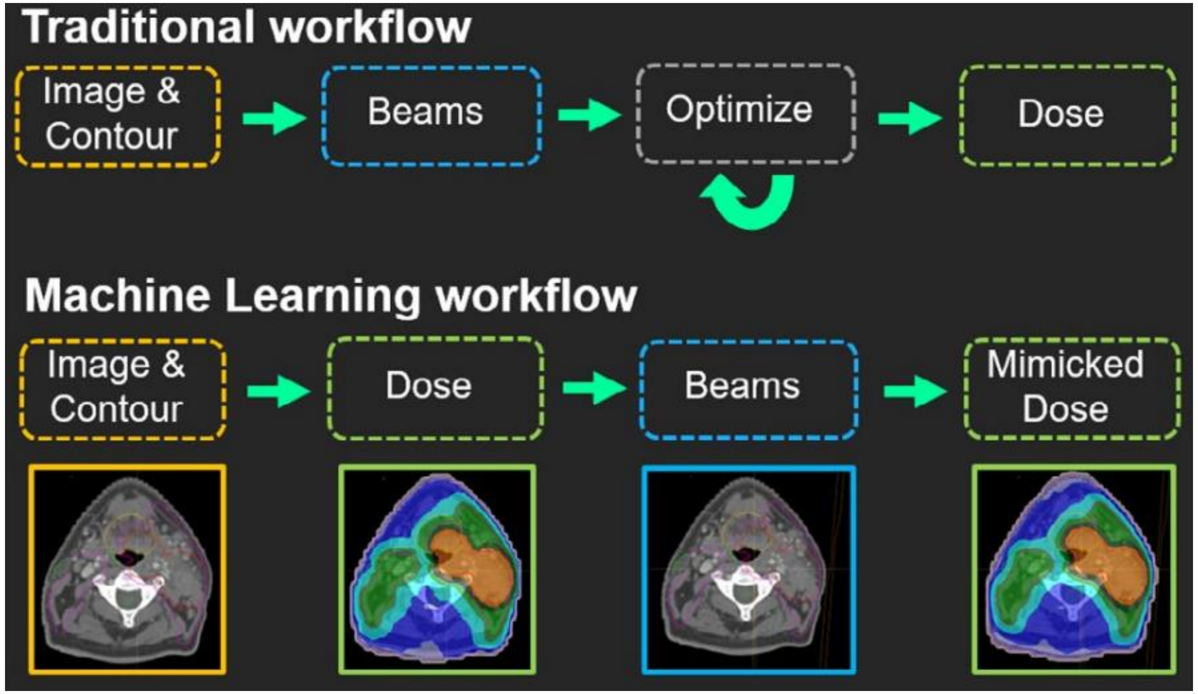
Knowledge Based Planning:

- Traditional KBP uses geometric and anatomical features (i.e. OAR distance to PTV) to find the "best" dose distribution from a database (in terms of DVHs or other dose metrics) -> Varian RapidPlan.
- Predicted dose metrics used as a starting point for the optimization.



# APPLICATIONS IN RADIOTHERAPY

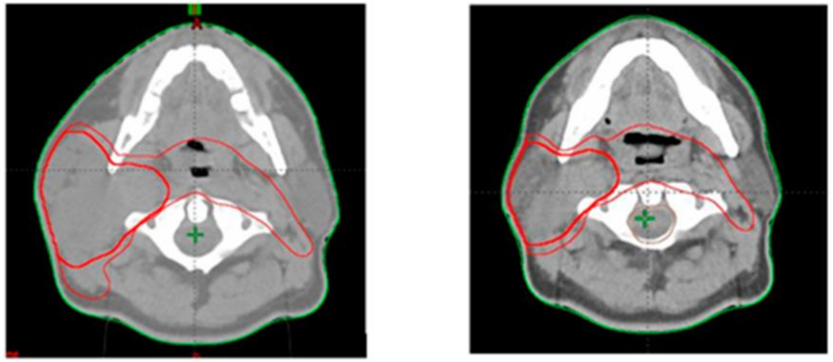
- Deep learning architectures can be leveraged to predict an ideal dose distribution from the patient anatomy (CT image). *Dose prediction.*
- Machine Learning Planning in Raystation (random forest algorithm)



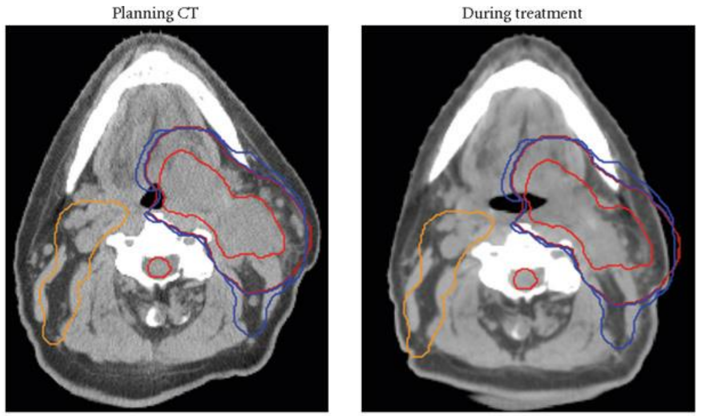
# APPLICATIONS IN RADIOTHERAPY

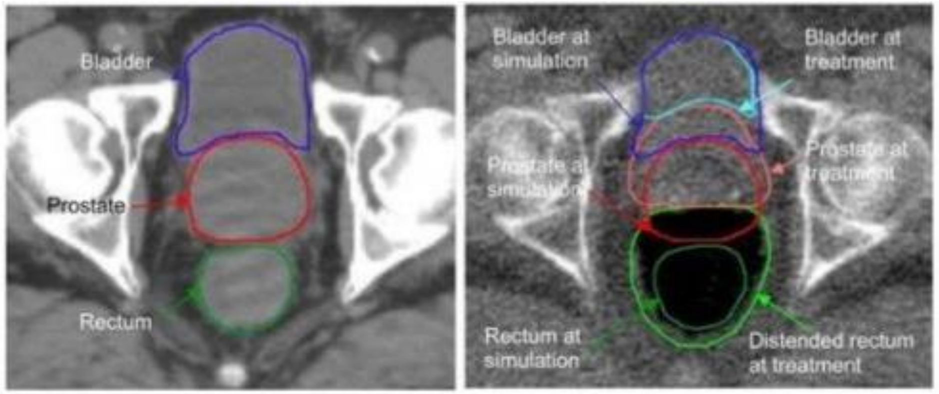
- Adaptive Radiotherapy:
- Off-line adaptation for changes in the tumor
- Online daily adaptation

  Real time planning with patient in the room



Changes in tumor size during treatment




Daily changes in patient anatomy and organ movements

# CHALLENGES

- New responsibilities in the clinic:
  - Acceptance
  - Commissioning
  - Continuous Quality Control (data drift)
- Of all additional software

- Interpretability of AI Models:

Deep learning models are considered to be black-box models in practice. It is difficult to know why/how the model is doing something.

- Reliability/Trustworthiness:

This becomes an issue with models we don't understand.

# INTERPRETING NEURAL NETWORKS

Input Image

| | | | | |
|---|---|---|---|---|
| 252 | 251 | 246 | 207 | 90 |
| 250 | 242 | 236 | 144 | 41 |
| 252 | 244 | 228 | 102 | 43 |
| 250 | 243 | 214 | 59 | 52 |
| 248 | 243 | 201 | 44 | 54 |

*

Kernel

| | | |
|---|---|---|
| 1 | 0 | -1 |
| 1 | 0 | -1 |
| 1 | 0 | -1 |

=

Convolution Output

| | | |
|---|---|---|
| 44 | 284 | 536 |
| 74 | 424 | 542 |
| 107 | 525 | 494 |

ReLU( Convolution Output + bias ) = ReLU( ... ) = Feature Map

Convolution Output

| | | |
|---|---|---|
| 44 | 284 | 536 |
| 74 | 424 | 542 |
| 107 | 525 | 494 |

\+ bias: -500

= ReLU

| | | |
|---|---|---|
| -456 | -216 | 36 |
| -426 | -76 | 42 |
| -393 | 25 | -6 |

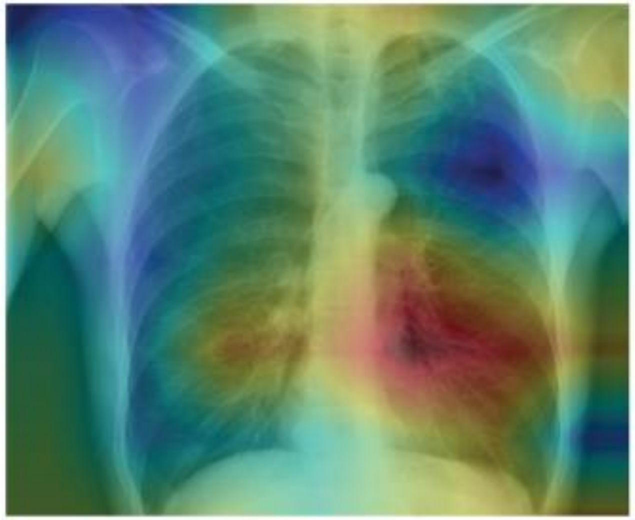
=

Feature Map

| | | |
|---|---|---|
| 0 | 0 | 36 |
| 0 | 0 | 42 |
| 0 | 25 | 0 |

# EXPLAINABILITY IN AI

- Methods that highlight the relative importance of parts of the image: what the model is "looking at" when making a decision.



- This reveals that very accurate models sometimes memorize artifacts. In this example for COVID x-ray detection, the model focuses on text in the image.

# VISUALIZING ARTIFICIAL NEURONS

- Curve detecting Neurons

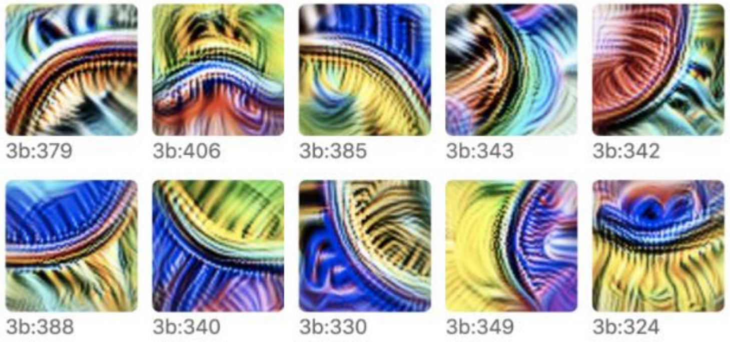
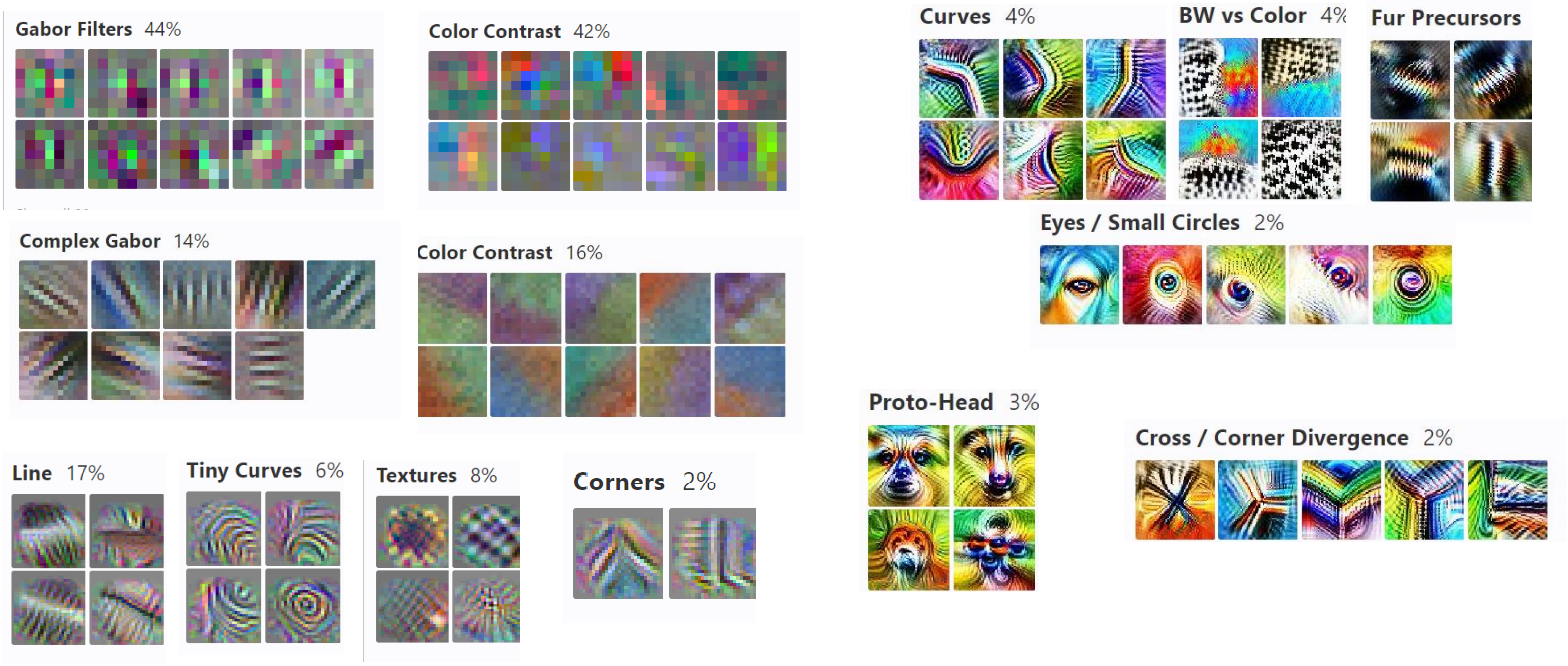


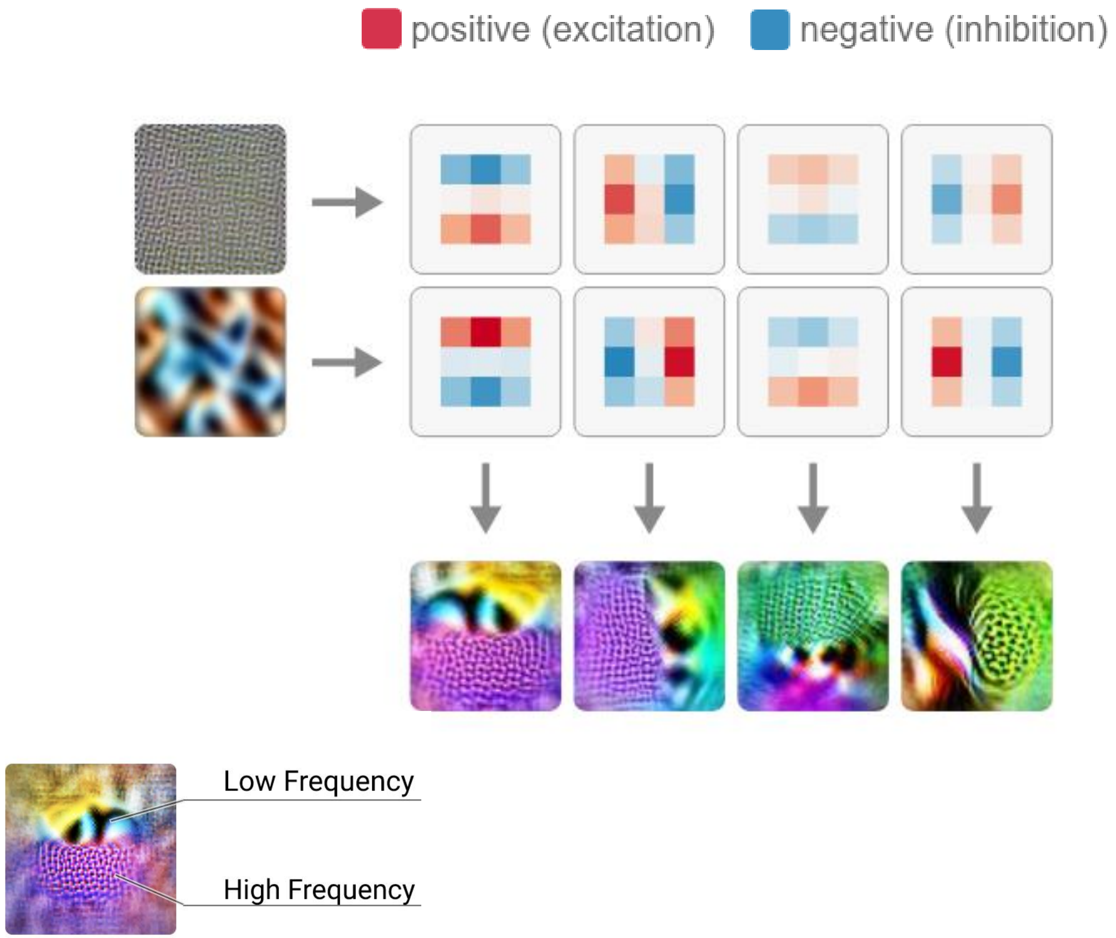

Image Optimization

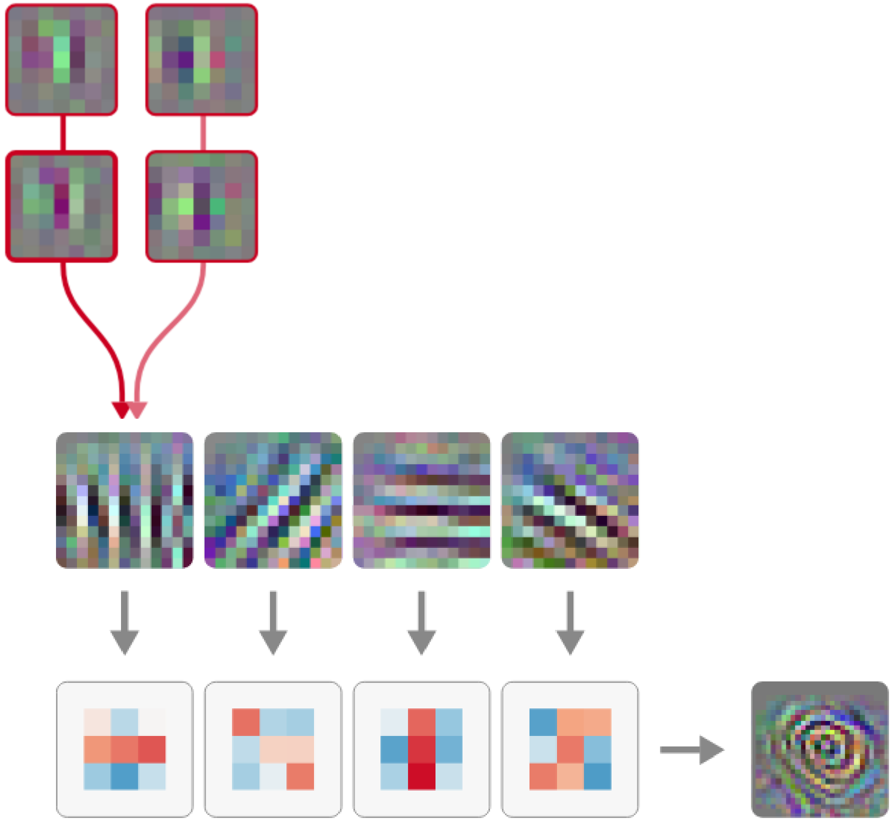
Maximum Dataset Activation

# NEURON "GROUPS" THROUGHOUT LAYERS



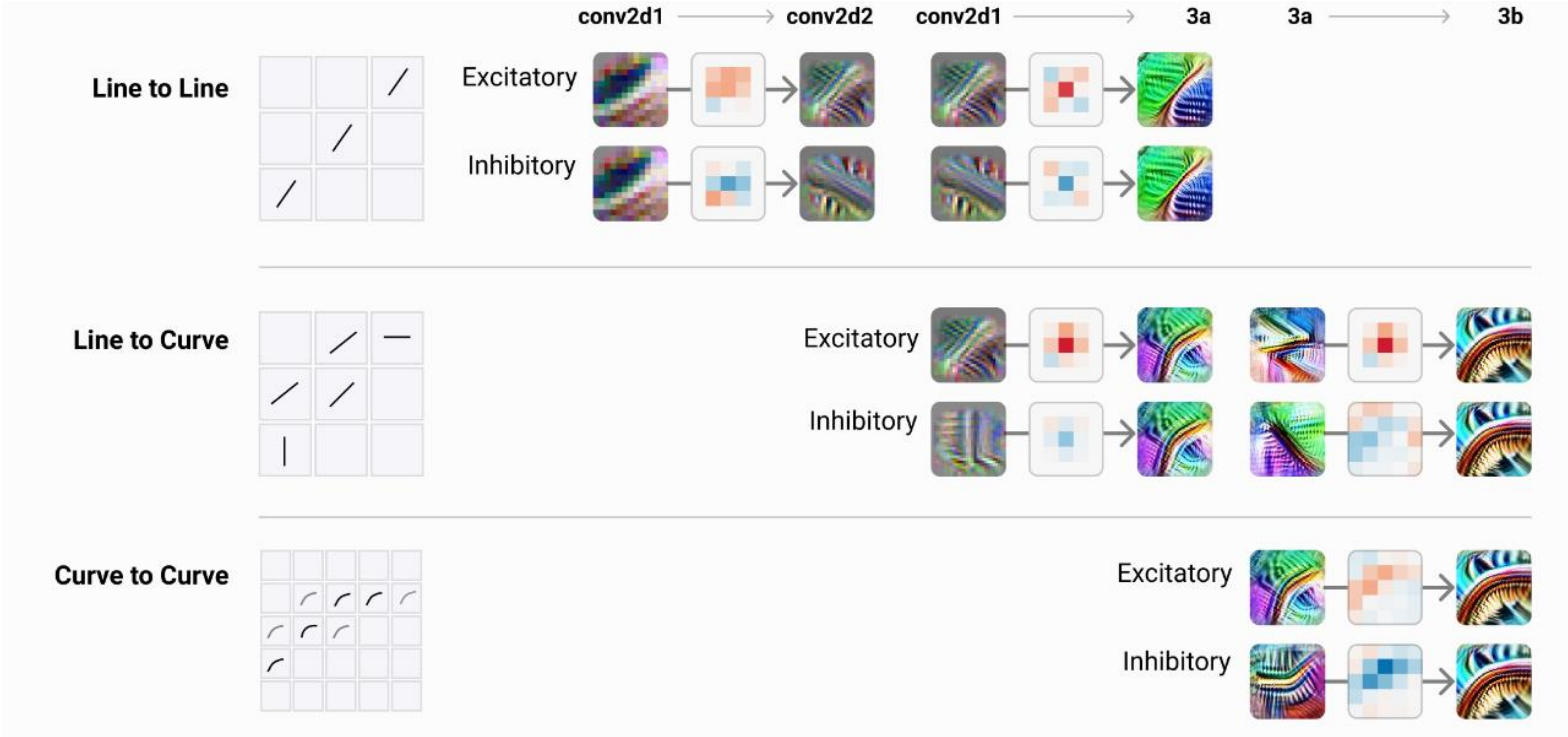
# SIMPLE IMAGE FEATURES



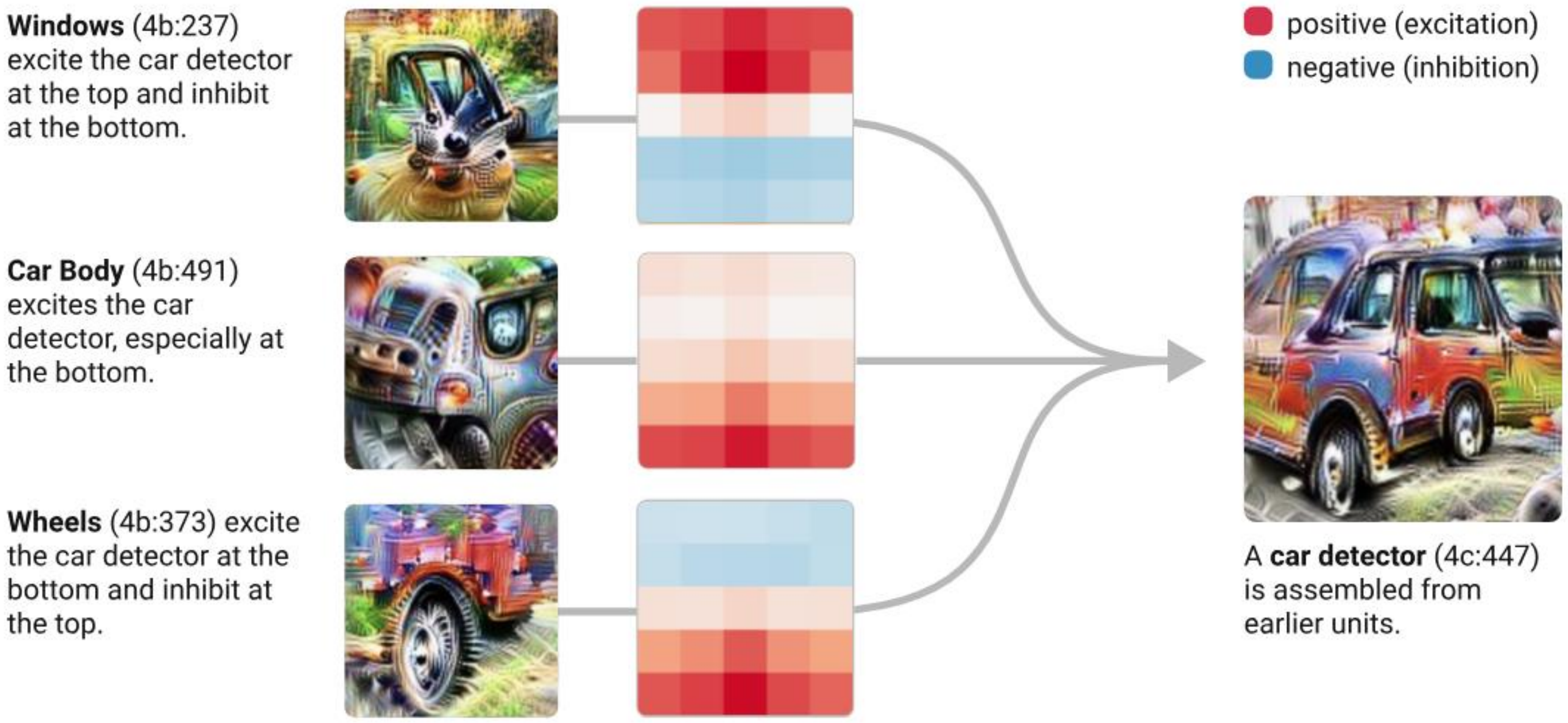



A **circle detector** is created by detecting early edges **perpendicular** to a normal line.

# CURVE DETECTING CIRCUIT



# TO COMPLEX OBJECT DETECTORS



# CONCLUSIONS

- Artificial Intelligence and in particular, deep learning, provide a high degree of accuracy in a wide range of tasks, and a big opportunity to automate the medical physics workflow.
- Interpretability and explainability of these models will become a more pressing subject as adoption becomes more widespread.
- Deep learning models are not directly interpretable, but there are some techniques that aid in improving their understanding and research is being done to improve their understanding.

# REFERENCES


- Olah, Chris, et al. "Zoom in: An introduction to circuits." *Distill* 5.3 (2020): e00024-001.
- Cammarata, Nick, et al. "Curve detectors." *Distill* 5.6 (2020): e00024-003.
- Olah, Chris, et al. "An overview of early vision in inceptionv1." *Distill* 5.4 (2020): e00024-002.
- Wang, L., Lin, Z.Q. & Wong, A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific reports, 10(1), 19549 (2020).
- Y. Chaudhary, M. Mehta, R. Sharma, D. Gupta, A. Khanna and J. J. P. C. Rodrigues, “Efficient-CovidNet: Deep Learning Based COVID-19 Detection from Chest X-Ray Images,” 2020 IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM), 2021, pp. 1-6.
- Avanzo, Michele, et al. "Artificial intelligence applications in medical imaging: A review of the medical physics research in Italy." *Physica Medica* 83 (2021): 221-241.
- Avanzo, Michele, et al. "Artificial intelligence and the medical physicist: welcome to the machine." *Applied Sciences* 11.4 (2021): 1691.