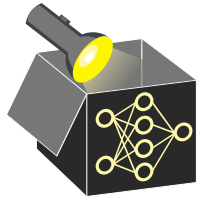
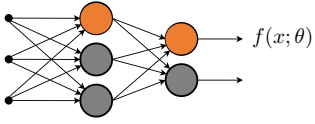
Interpretable Machine Learning



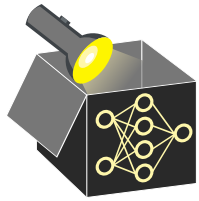
Visualizing Neural Networks



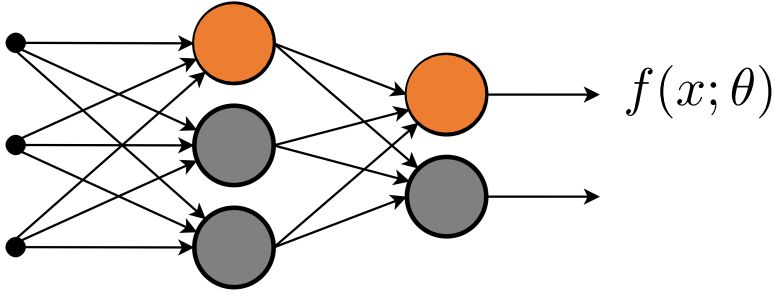
Learning goals

- Visualizing architectural units
- Visualizing filters in CNNs
- Visualizing attention maps

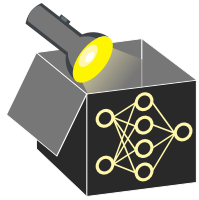
INSPECTING THE MODEL UNITS



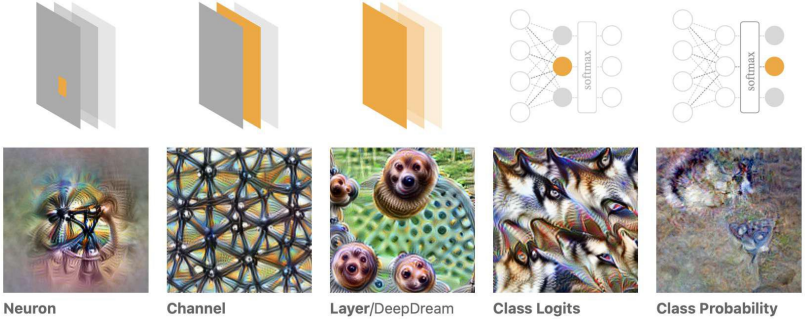
- Neural Networks architectural units can be inspected to provide insights
- What happens to the input signal as it travels through the network ?
  - Activations: Activation in neural networks are sparse
  - Attention units: Encode the importance of input representation units



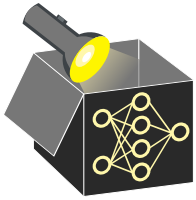
VISUALIZING NEURAL NETWORK ARCHITECTURAL UNITS



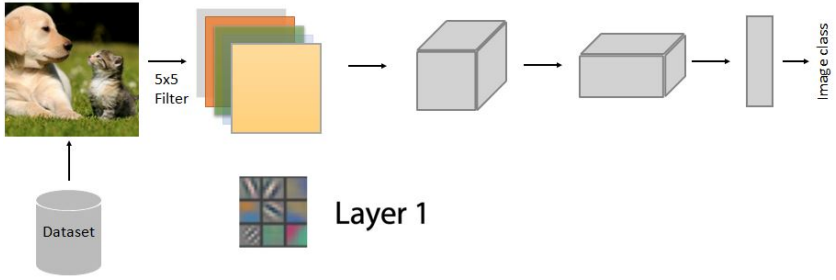
- Search for examples where individual features have high values —
  - Either for a neuron at an individual position, or for an entire channel



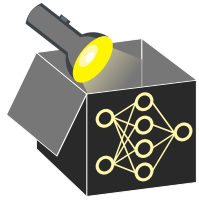
VISUALIZING FILTERS IN A CNN



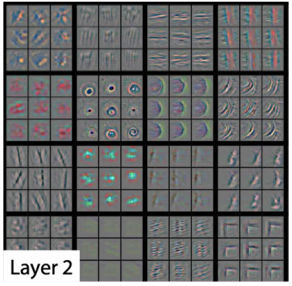
- Most of the aggregated values at neurons do not result in activations
- Find image patches in dataset that maximally activate/excite a unit

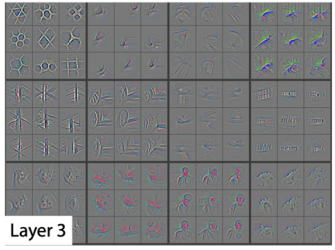


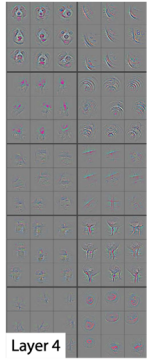
FEATURE EXTRACTION EVOLUTION



- Lower layers extract lower-level features
- Higher layers compose extracted features to compose high-level features

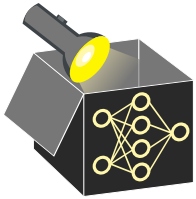




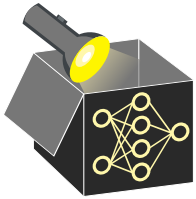


LAYERWISE VISUALISATION OF CNNS

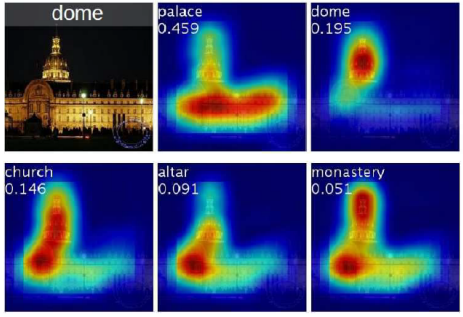
Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)



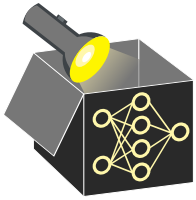
CLASS ACTIVATION MAPS



- CAMs are specific to CNNs
- Class activation map or CAM highlights class-specific discriminative regions
  - Different classes induce different activations

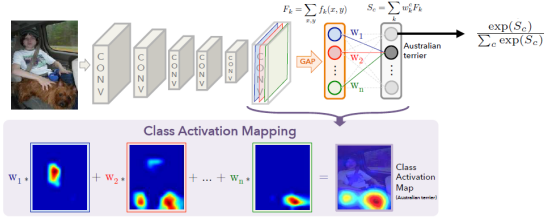


CLASS ACTIVATION MAPS

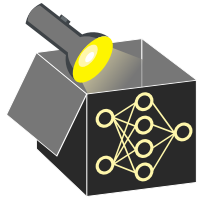


- Let the activation at unit *k*, at the location *(x,y)* in the last layer -$f_k(x, y)$
- Global avg. pooling at unit *k* - $F_k = \sum_{x,y} f_k(x, y)$
- For a given class

$$P_c = \frac{exp(S_c)}{\sum_c exp(S_c)}, \quad S_c = \sum_k w_k^c F_k$$



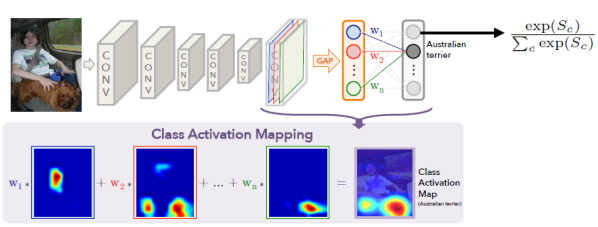
CLASS ACTIVATION MAPS



- Input: Take a pre-trained CNN model
- Output: weight vectors for each classes
- How do we learn the weights?
  - Average pooling of the feature maps in the last layer

$$S_c = \sum_k w_k^c F_k$$

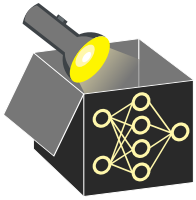
  - Weights learned using simple logistic regression



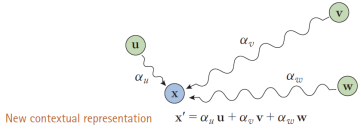
$$f_k(x, y)$$

$$\sum_{x,y} f_k(x, y)$$

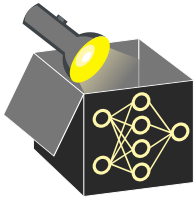
ATTENTION IN LANGUAGE



- Attention mechanism in neural language models is crucial for extracting latent features
- Self-attention in language is aimed at re-representing the initial representation based on the context
- Neural models consume non-contextual token-level representations and output contextual token-level representation



ATTENTION IN LANGUAGE



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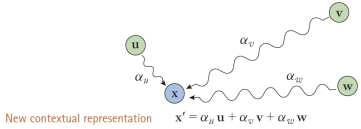
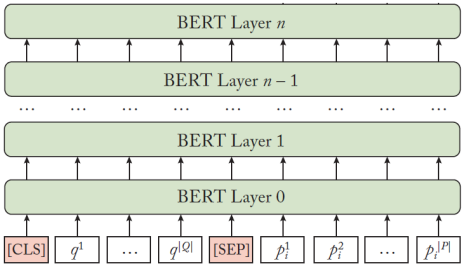
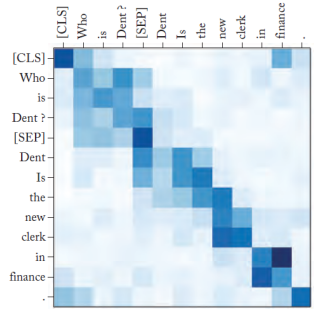
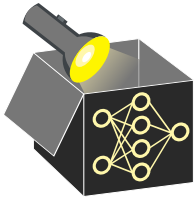


$$\alpha_u = \frac{e^{sim(u,x)}}{e^{sim(u,x)} + e^{sim(v,x)} + e^{sim(w,x)}}; \quad sim(u,x) = x \cdot Wu$$

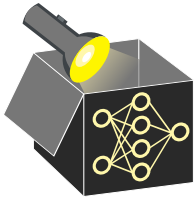
ATTENTION MAPS IN TRANSFORMERS

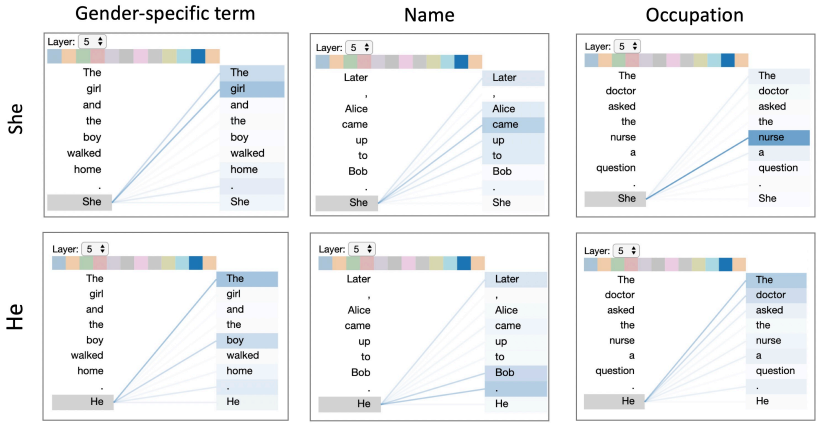




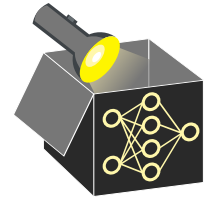


VISUALIZING ATTENTION UNITS





OTHER INTERACTIVE VISUALISATIONS



- Interactive visualization by Chris Olah:
  https://distill.pub/2018/building-blocks/
- https://distill.pub/2017/feature-visualization/
- Deep Dream
- De-Convolution
- Visualizations in Language: https://github.com/jessevig/bertviz
- ...