Explainable AI (XAI): A survey of recents methods, applications and frameworks

theaisummer.com/xai

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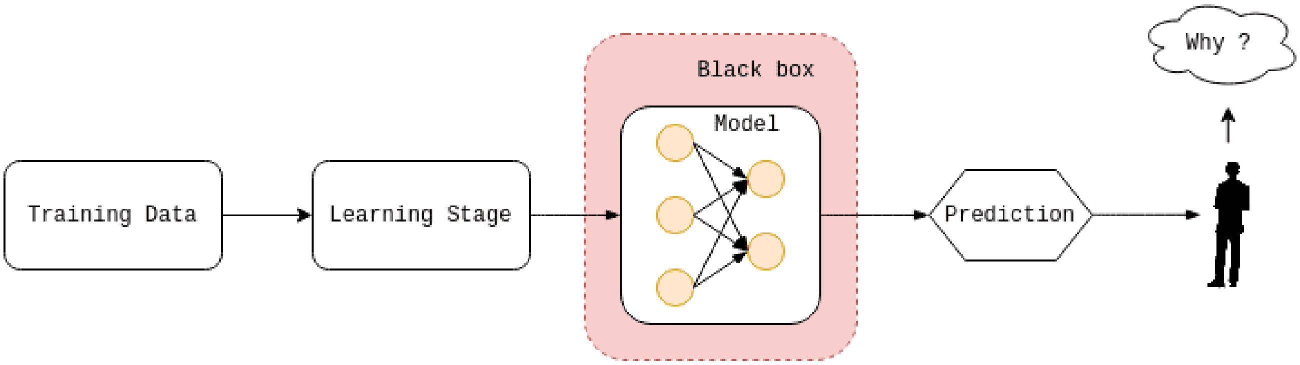
Deep learning models are usually considered as black boxes that are hard to understand while their underlying mechanism is complex.

They do not justify their decisions and predictions and humans cannot trust them. On the other hand, artificial intelligence algorithms make errors that could be fatal depending on the application.

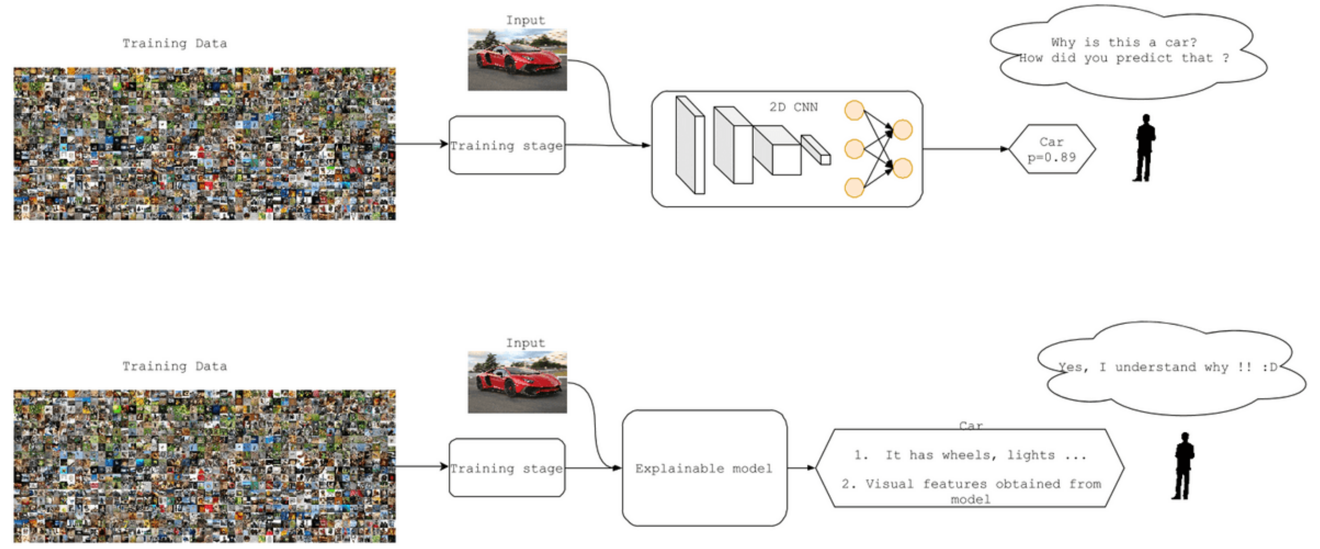
More specifically, an error in a computer vision system of an autonomous car could lead to a crash, while in the medical area, human lives are depending on these decisions.



Most machine learning models perform as black boxes.

To tackle the aforementioned issues, a plethora of methods have been developed. To this end, eXplainable Artificial Intelligence (XAI) has become a hot research topic in the machine learning community.

These methods **aim to provide explanations about machine-deep learning models that are easily understandable by humans**.


Training Data
Input
Training stage
2D CNN
Car
p=0.89
Why is this a car?
How did you predict that ?
Training Data
Input
Training stage
Explainable model
Car
1. It has wheels, lights ...
2. Visual features obtained from model
Yes, I understand why !! :D

Comparison of a deep learning and an explainable model.

Categories of Interpretability

> Interpretability defines how easily we can understand the cause of a decision that is produced from an algorithm.

The adopted categorization of interpretability methods is based on how explanation information is provided.

In this article, the following categories will be discussed:

- Visual interpretability methods: visual explanations and plots
- Textual explanations, given in text form
- Mathematical or numerical explanations

Visual explanations

> Visual explainable methods produce pictures or plots in order to provide information about the model's decision.

Most methods explain the decision of a model in the form of a saliency map by producing values to **reflect the importance and contribution of input components to that decision**.

These values can take the form of output probabilities or images like heatmaps. In addition, plot visualization methods produce scatter plots to explain decisions or visualize the data.

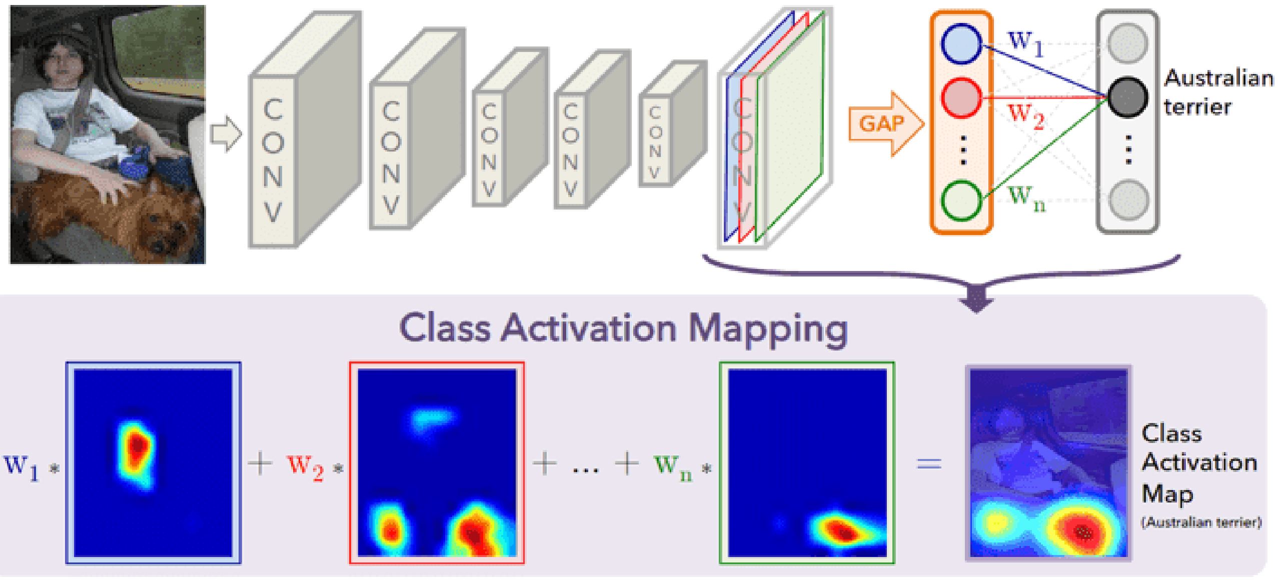
Class Activation Mapping (CAM)

One of the first and most popular saliency methods is Class Activation Mapping (CAM) [28]. **CAM is able to localize the features of the CNN on the image that are responsible for the classification decision**. More specifically, CAM uses a global average pooling layer after the convolutional layers and before the final fully connected layer.

Let f_{k}(x,y)fk(x,y) be the activation unit, w_{c}^{k}wck the weight corresponding to class cc for unit kk. Then, the input to the softmax layer corresponding to class cc for unit kk. Then, the input to the softmax layer corresponding to class c is defined as

\mathbf{S}_{c} = \sum_{x,y}\sum_{k}w_{c}^{k}f_{k}(x,y)Sc=x,y∑k∑wckfk(x,y)
Finally, the class activation map M_cMc is calculated as :

M_{c}(x,y) =\sum_{k}w_{c}^{k}f_{k}(x,y)Mc(x,y)=k∑wckfk(x,y)
and **shows directly the importance of the activation at spatial point (x,y) to classify it's class cc .**



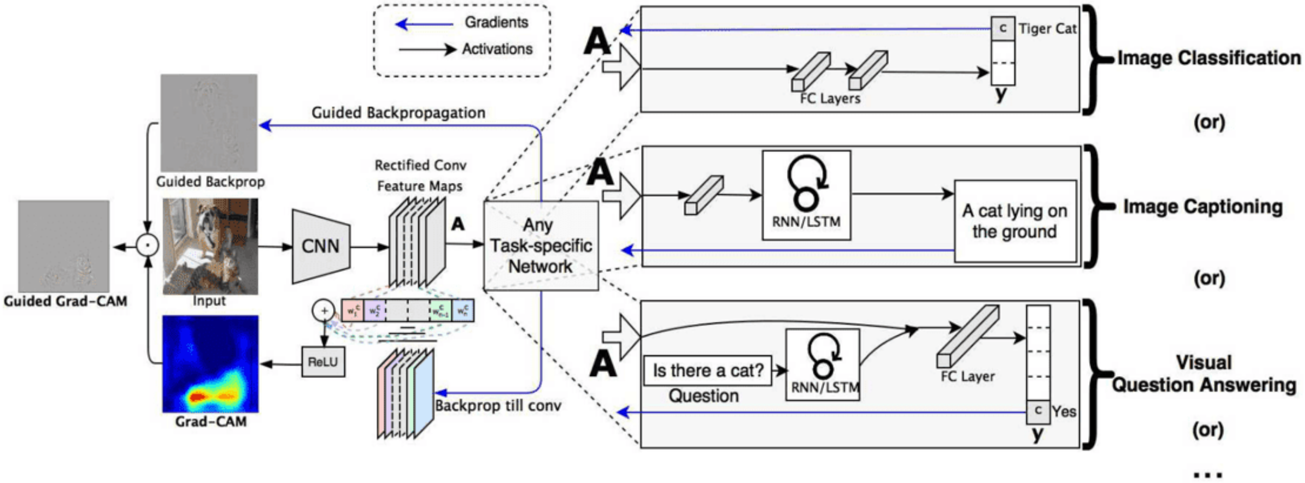
The predicted score is mapped to the last layer in order to generate the activation. The class-important regions are highlighted in CAM. Source: [28]

Gradient-weighted Class Activation Mapping (Grad-CAM)

Later on, Gradient-weighted Class Activation Mapping (Grad-CAM) was introduced. Grad-CAM [22] is an extended work based on CAM, **which uses the gradients with respect to the target class cc** that flows to the final convolutional layer. Grad-CAM produces a coarse localization map \mathbf{L_{Grad-CAM}^{c}} \in \mathbb{R}^{v\times u}LGrad−CAMc ∈Rv×u of width vv and height uu, which highlights the important pixels for the classification of the image. At first, the gradient \frac{\partial y^{c}}{\partial \mathbf{A_k}}∂Ak∂yc of the class score y^{c}yc is calculated with respect to the activation maps \mathbf{A_k}Ak of the last convolutional layer. The gradients flow back after being averaged over the activation map's size ZZ and then the neuron's importance weights a_{k}^{c}akc are calculated as:

a_{k}^{c}= \frac{1}{Z} \sum_{i} \sum_{j} \frac{\partial y^{c}}{\partial A_{k}(i,j)}akc=Z1 i∑j∑∂Ak(i,j)∂yc
The weighting factor a_{k}^{c}akc shows the importance of feature kk for the class cc. Finally, the Grad-CAM heatmaps are produced using the forward propagation activations as:

\mathbf{L_{Grad-CAM}^{c}}= ReLU(\sum_{k}a_{k}^{c}\mathbf{A_{k}})LGrad−CAMc =ReLU(k∑akcAk)



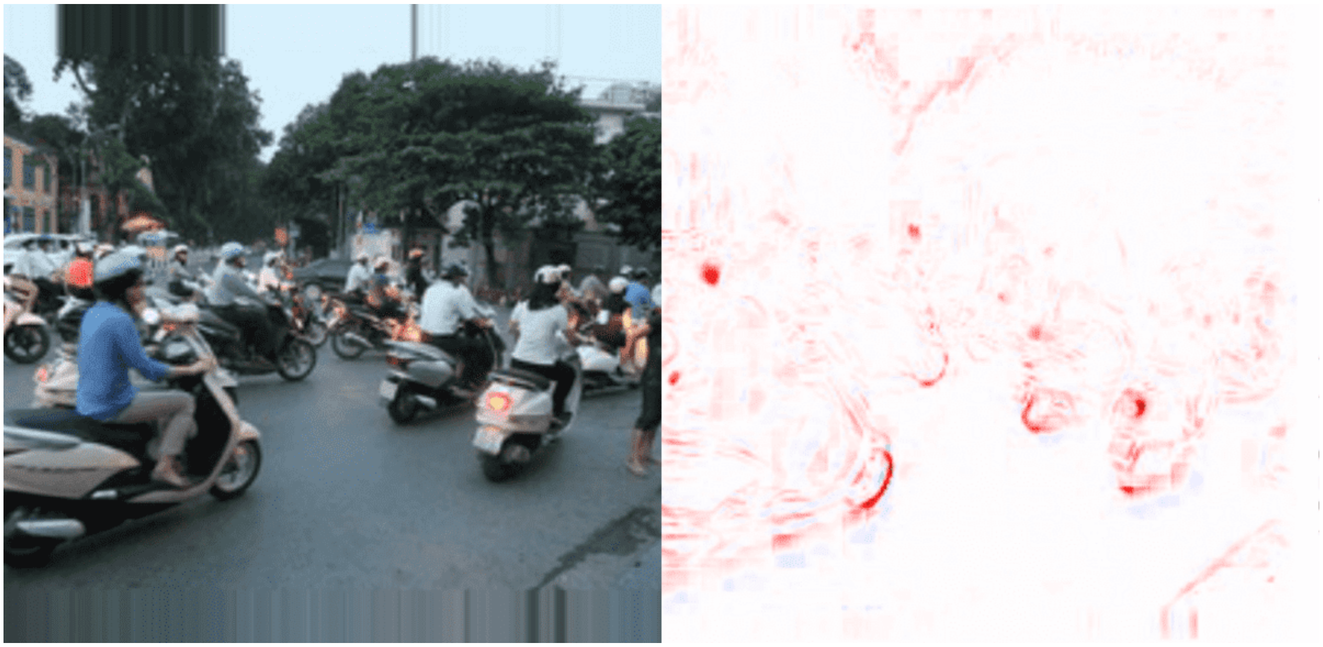
Overview of Grad-CAM. Source: [22]

Layer-Wise Relevance Propagation (LRP)

Another visual explanation technique that has been adopted is Layer-Wise Relevance Propagation (LRP). **LRP [23] is based on the decomposition of the decision and produces relevance scores between the activations x(i)x(i) of neuron ii and its input, and finds the neuron's importance scores R^{l}(i)Rl(i) at the layer ll.** More specifically, the relevance scores R^{l}(i)Rl(i) of layer ll are calculated with respect to the layer l+1l+1 as :

R^{l}(i) = \sum_{j}\frac{x(i)w(i,j)}{\sum_{i}x(i)w(i,j)}R^{l+1}(j)Rl(i)=j∑∑i x(i)w(i,j)x(i)w(i,j)Rl+1(j)
where w(i,j)w(i,j) is the weight between neuron ii and neuron jj.

The pixel-wise contributions to the classification are displayed as shown below:



LRP visualization. Source: [23]

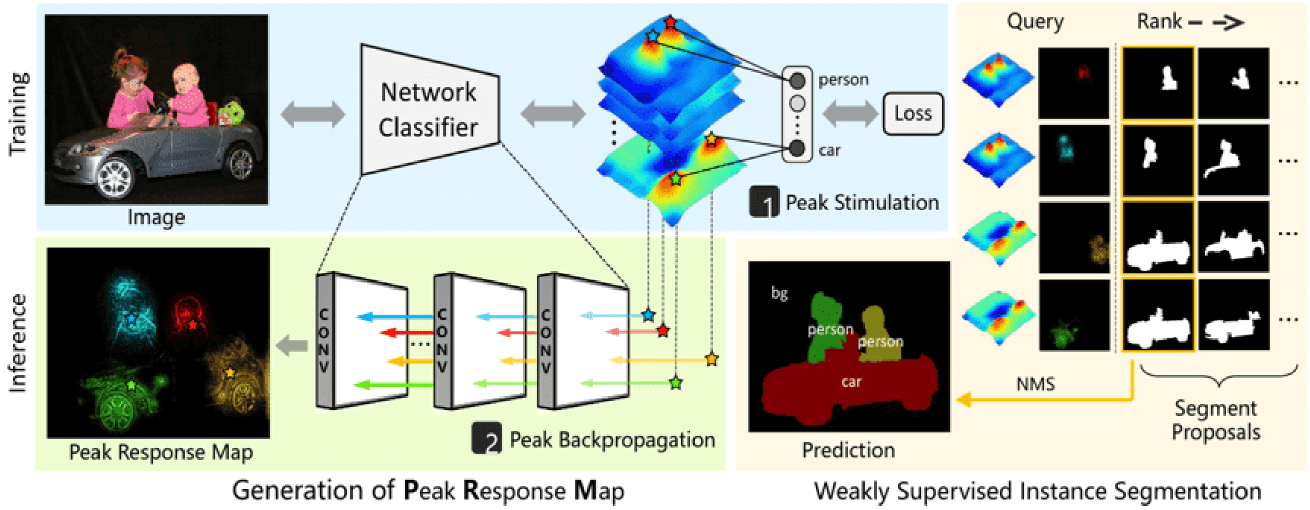
Subsequently, Peak Response Maps (PRM)

Subsequently, Peak Response Maps (PRM) were introduced for weakly supervised instance segmentation. PRM [29] finds the maximum class activations that specify the class scores in each image location. Then, these activations are back-propagated to the input image to generate the peak response maps. The peak's locations

\mathbf{P_{c}} = \{(i_{1},j_{1}), ..., (i_{N^{c}},j_{N^{c}})\}Pc={(i1,j1),...,(iNc,jNc)}
where N^{c}Nc the number of peaks, of the cc-th response map \mathbf{M}_{c}Mc, are extracted from the local maximums inside a window of size 3\times 33×3. The sampling kernel G_{x,y}^{c}Gx,yc is calculated at the forward pass at the point (x,y)(x,y) as:

G^{c} (x,y)= \sum_{k=1}^{N^{c}} f(x-i_{k},y-j_{k})Gc(x,y)=k=1∑Ncf(x−ik,y−jk)
where x\in[0,H], y\in[0,W]x∈[0,H],y∈[0,W] and ff a sampling function that obtains only the features of the peaks. Then, the class confidence score \mathbf{s}^{c}sc is calculated from the convolution of the response map and the sampling kernel as: \mathbf{s}^{c} = \mathbf{M}^{c} * \mathbf{G}^{c}sc=Mc∗Gc. The gradients that will be back-propagated are

{\delta}^{c} = \frac{1}{N^{c}}\frac{\partial L}{\partial \mathbf{s}^{c}} \mathbf{G}^{c}
δc=Nc1∂sc∂LGc
where LL is the classification loss.



Peak Response Maps method. Source: [29]

CLass-Enhanced Attentive Response (CLEAR)

CLass-Enhanced Attentive Response (CLEAR) [11] is a similar approach that visualizes the decisions of a deep neural network using the activation values of the network. **It used <u>deconvolutions</u> to obtain individual attention maps for each class**. After the forward pass, we use deconvolutions to obtain the deconvolved output of layer ll with KK kernels as:

\mathbf{h}(l) = \sum_{k=1}^K z(k,l) * w(k,l)h(l)=k=1∑Kz(k,l)∗w(k,l)
where \mathbf{z}(l)z(l) are the feature maps of the layer ll and \mathbf{w}(l)w(l) are the kernel weights. The final response of layer ll is obtained from:

\mathbf{R}(l) = \mathbf{h}(1) \mathbf{h}(2).... \mathbf{h}(l)R(l)=h(1)h(2)....h(l)
The individual attention maps \mathbf{R(x'},c)R(x′,c) of class cc and the back-projected input \mathbf{x'}x′ are computed from all LL layers as :

\mathbf{R(x'},c) = \mathbf{h}(1) \mathbf{h}(2).... \mathbf{h}(L)R(x′,c)=h(1)h(2)....h(L)
Then, the dominant class attentive map \mathbf{C(x')}C(x′) is constructed as:

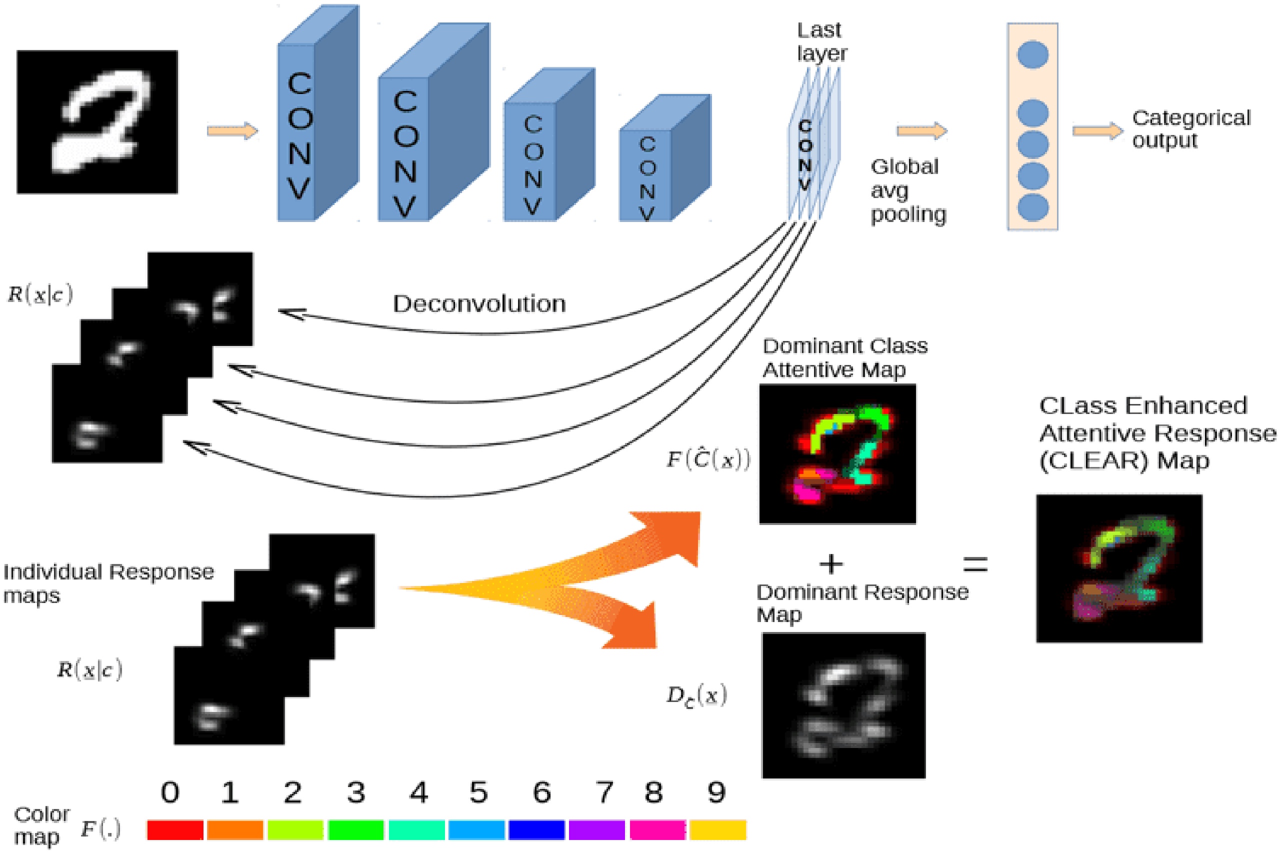
\mathbf{C(x')} = {argmax}_c \mathbf{R(x'},c)C(x′)=argmaxcR(x′,c)
while the dominant response map \mathbf{D_C(x')}DC(x′) is constructed of the combination of individual response maps and dominant class attentive maps as:

\mathbf{D}_c(\mathbf{x'}) = \mathbf{R(x'},c)Dc(x′)=R(x′,c)

> The dominant response map shows the attention at each location of the image, while the dominant class-map shows the most important class that was involved in the classification of the image.

Finally, the CLass-Enhanced Attentive Response (CLEAR) map is generated by overlaying the two aforementioned maps as:

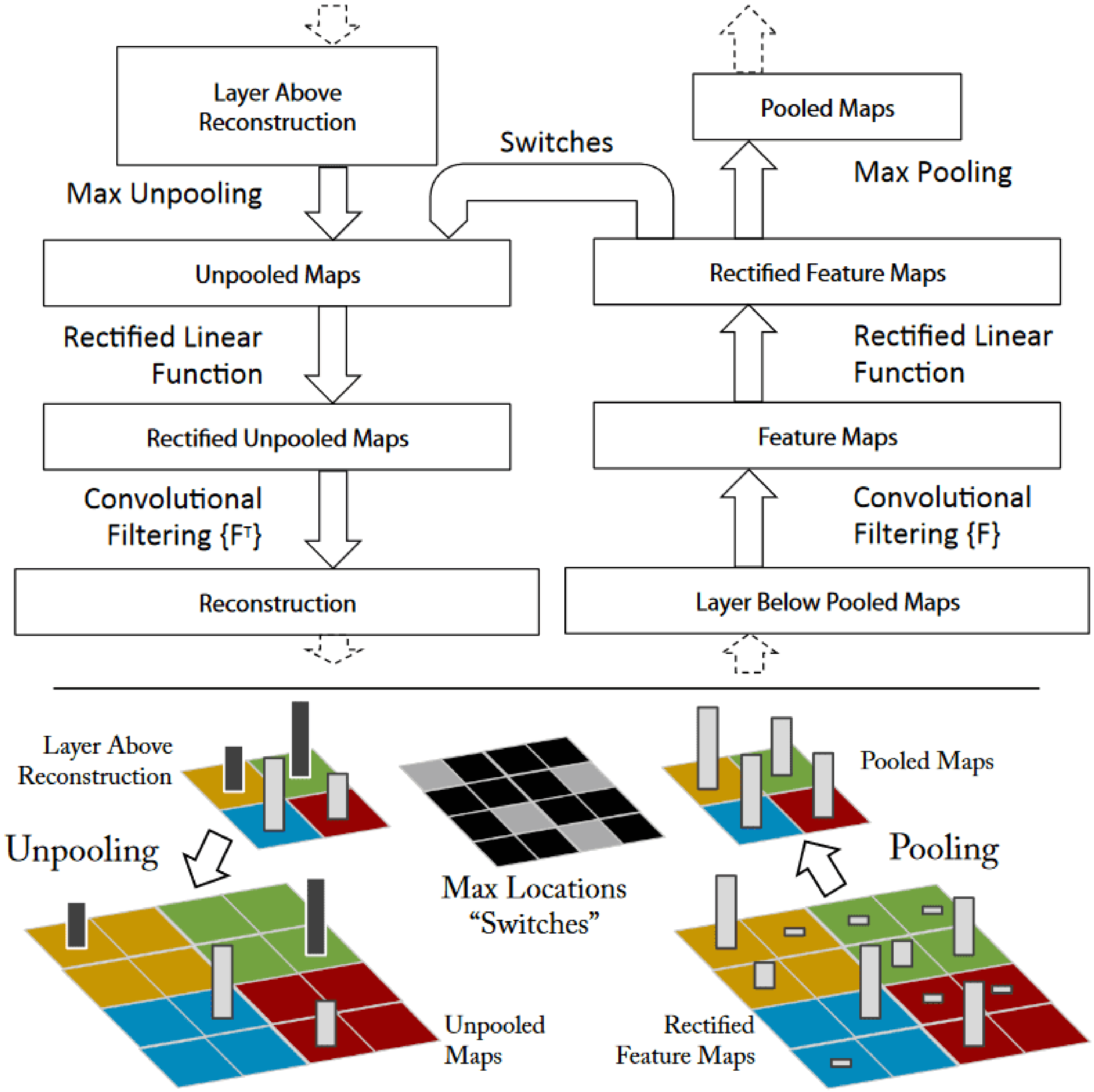
\textbf{M} = \mathbf{C(x')}+ \mathbf{D}_c(\mathbf{x'}).M=C(x′)+Dc(x′).



CLEAR method overview. Source: [11]

Visualization of features activations with Deconvolutional Networks

Zeiler et al.[27] tried to visualize the intermediate layers of convolutional neural networks and see what they learn. It was shown that convolutional layers store important information about the images as well as that deeper layers learn more complex patterns. In addition, de-convolutional neural networks were adopted in order to reconstruct the input images from feature maps in reverse order. This inverse operation creates an approximate image showing that CNNs have stored the most information of the image.



De-convolutional neural network. Source: [27]

DeepResolve

On the other hand, **DeepResolve [12] method uses feature maps from intermediate layers and examines how the network combines those features to classify an input image**. DeepResolve computes a class-specific image that is named as feature importance map (FIM):

\mathbf{H^{c}} = {argmax}_{\mathbf{H}}(S_{c}(\mathbf{H})-\lambda{||\mathbf{H}||}^{2}_{2})Hc=argmaxH(Sc(H)−λ||H||22) where cc is the target class, S_{c}Sc is the class score obtained from the last layer and \mathbf{H} \in \mathbb{R}^{K\times W}H∈RK×W contains the feature maps with size WW of all KK neurons from a specific layer. Then, the feature importance score (FIV) \mathbf{\Phi}_c = (\phi_c^1, \phi_c^2, ..., \phi_c^k)Φc=(ϕc1,ϕc2,...,ϕck), where \phi_{c}^{k}ϕck is calculated for each neuron from the global average of FIM as:

\phi_{c}^{k} = \frac{1}{W} \sum_{i=1}(H^{k}(i))_c,ϕck=W1i=1∑(Hk(i))c,
where ii is the index of the neuron and kk the index of the channel in a layer . This process is initialized randomly and is repeated TT times with different initial parameters to get several estimations of \mathbf{H}_c^t, \mathbf{\Phi}_c^tHct,Φct. Afterwards, the weighted variance IL_c^kILck is calculated as:

IL_c^k = var(\phi_c^t)ILck=var(ϕct)
and is used to obtain the overall neuron importance scores (ONIVs) \mathbf{\bar{\Phi}}_cΦ¯c, to find class similarities and differences. **ONIVs show the importance of each class and correlations between them.** They are used to construct the similarity matrix \mathbf{S}S.

The Class difference matrix is calculated as:

D_{C_i C_j} = \bar{\Phi}_{C_i} - \bar{\Phi}_{C_j}DCiCj=Φ¯Ci−Φ¯Cj
between each pair of classes C_i,C_jCi,Cj.

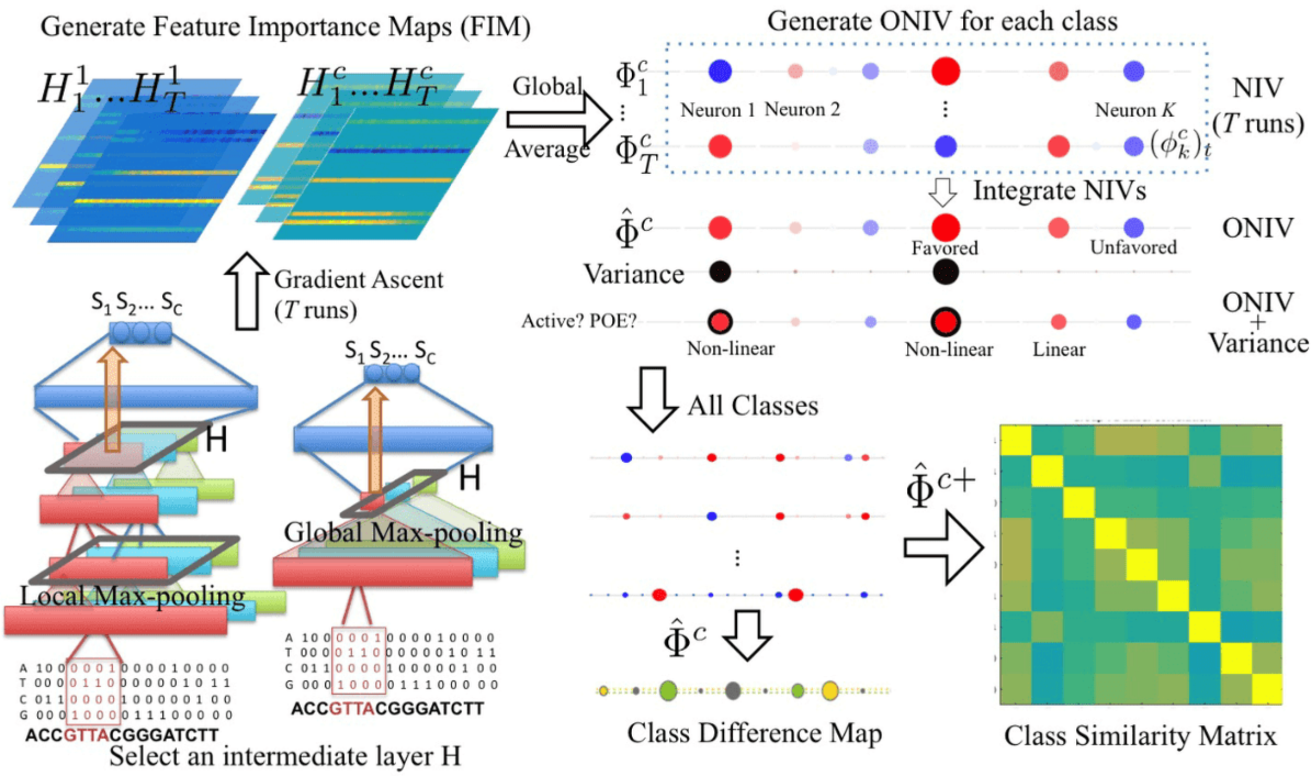


Illustration of DeepResolve's working flow. Source: [12]

SCOUTER

A visual explanation method named SCOUTER [13] was recently introduced and is not based on feature maps and gradients to explain decisions. SCOUTER adopts a slot-attention classification layer instead of a fully connected layer.

The output features \mathbf{F}F (from a convolutional neural network) are transformed to a smaller dimension through another convolutional layer, while a position embedding layer models the spatial information. A self-attention mechanism is used to obtain the dot-product attention as :

\mathbf{A}^{(t)} = \sigma (Q(\mathbf{W}^{(t)})K(\mathbf{F})),A(t)=σ(Q(W(t))K(F)), where Q, KQ,K are fully-connected layers, \mathbf{W}^{(t)}W(t) are the slot weights and \sigmaσ is the sigmoid function.

Then, the weighted feature map is calculated as :

\mathbf{U}^{(t)} = \mathbf{A}^{(t)}\mathbf{F}'^{(t)}U(t)=A(t)F′(t)
A recurrent GRU layer updates the slot weights as follows:

\mathbf{W}^{(t+1)} = GRU(\mathbf{U}^{(t)},\mathbf{W}^{(t)})W(t+1)=GRU(U(t),W(t))
Each slot produces an interpretable confidence score \mathbf{o}=(o_{1}, o_{2}, ..., o_{n}o=(o1,o2,...,on for all classes as:

\mathbf{o} = xSlot_{e}(\mathbf{F}) = e\cdot \mathbf{U}^{(t)}\mathbf{1_{c}},o=xSlote(F)=e⋅U(t)1c,
where e \in [-1,1]e∈[−1,1] is a tunable hyper-parameter that makes the module to focus on positive and negative explanations, respectively and \mathbf{1_{c}}1c a vector with ones, \mathbf{1_{c}}\in \mathbb{R}^C1c∈RC.

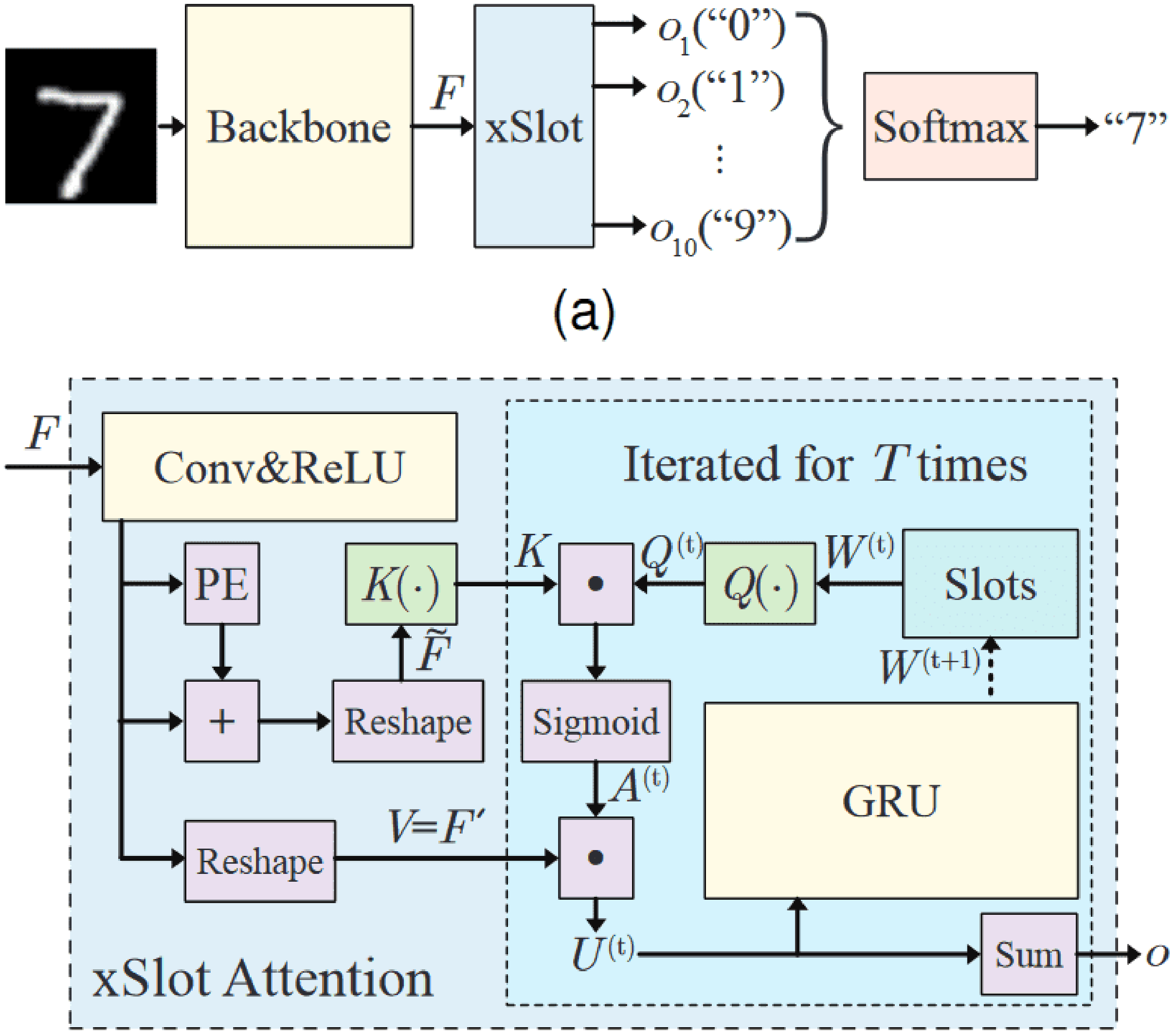
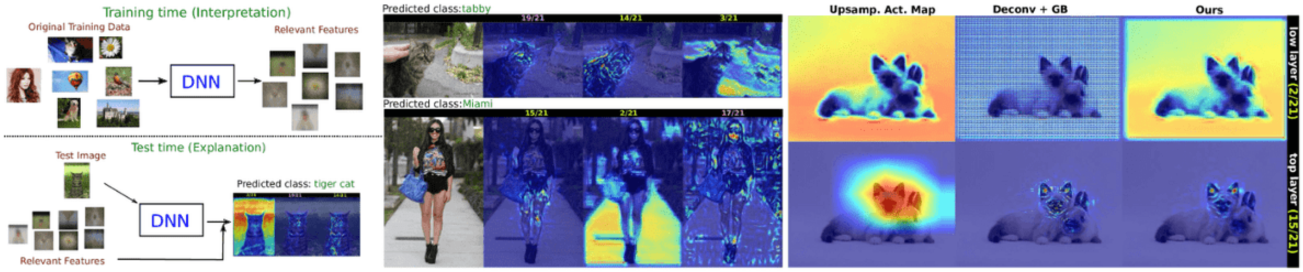


Illustration of Scouter. Source: [13]

Visual feedback

In [19], the authors proposed an interpretable method to **identify relevant features for image classification**. During training, the most important layers and filters for classification are identified, while in test time visual maps are generated to show the image locations that are responsible for this decision. More specifically, the class jj is predicted by the linear combination \mathbf{w_{j}} \in \mathbb{R}^{m}wj∈Rm, mm the number of neurons, of its responses \mathbf{x_{j}}xj. After storing all the responses \mathbf{X} \in \mathbb{R}^{N\times m}X∈RN×m for NN images of the training set of the network FF, the following optimization problem is solved:

\mathbf{W}^{*} = argmin_{\mathbf{W}} {||\mathbf{X}^{T}\mathbf{W} -\mathbf{ L}^{T} ||}^{2}_{F}W∗=argminW∥XTW−LT∥F2
where LL are the ground-truth labels, to find the most relevant features of each class.



Visual explanations using relevant features. Source: [19]

At test time, the internal activations and the learned weights \mathbf{W}W are used to generate the decision after the forward pass of the test image \mathbf{I}I. Then, a class prediction is calculated as \hat{y} = F(\mathbf{I})y^=F(I) and we store the internal activations \mathbf{x_I}xI. Finally, the response is generated from \mathbf{r} = \mathbf{w}_{\hat{y}} \mathbf{x_I}r=wy^xI, which are used for visualizations that highlight the pixels responsible for this decision.

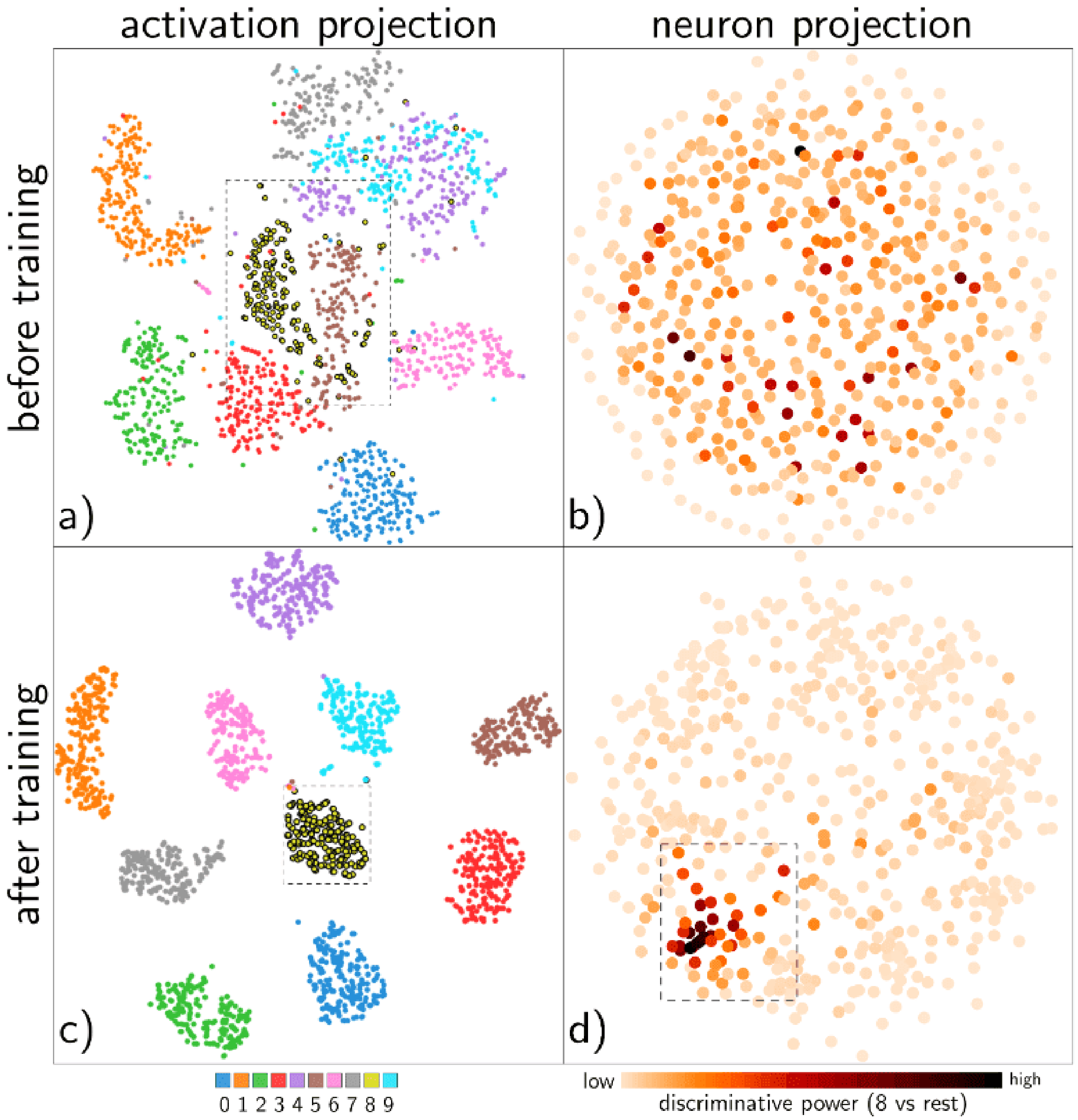
Plot visualization methods

In this section, we will describe methods that adopt **scatter-plots or graph visualizations to generate explanations**.

> T-distributed stochastic neighbor embedding (t-SNE) is a scatter-plot method that projects high-dimensional data in two or three-dimensional spaces. t-SNE uses conditional probabilities to represent the distances between data points and find similarities. Finally, it uses a similar probability distribution over the points in the two or three-dimensional map and it minimizes the Kullback–Leibler divergence between these distributions.

Visualizing the Hidden Activity of Neural Networks with tSNE

In [20], the authors use t-SNE to visualize the activations of the neurons and the learned representations of the data. It is shown that these projections can provide valuable feedback about the relationships between neurons and classes.



Visualization of hidden activity of neurons on MNIST dataset. Source: [20]

Explain features with PCA

In [3], Principal Component Analysis (PCA) was adopted to explain features from deep neural networks.

Given an input image of an image r_{\theta} \in \mathbf{\Omega}rθ∈Ω with index \theta \in [1,\Theta]θ∈[1,Θ], we obtain the output high-dimensional image representations of the CNN \mathbf{\hat{F}}^{L}(r_{\theta})F^L(rθ). After centering these vectors by subtracting the mean as:

\mathbf{F}^{L}(r_{\theta})=\mathbf{\hat{F}}^{L}(r_{\theta})-\frac{1}{\Theta}\sum_{t=1 }^{\Theta}\mathbf{\hat{F}}^{L}(r_{t})FL(rθ)=F^L(rθ)−Θ1t=1∑Θ F^L(rt)
we compute the eigenvectors by finding the eigenvalues of the covariance matrix:

\frac{1}{\Theta}\sum_{\theta =1}^{\Theta}(\mathbf{F}^{L}(\theta)){(\mathbf{F}^{L})(\theta)}^{T}Θ1θ=1∑Θ(FL(θ))(FL)(θ)T
Then, the embeddings with the largest variance, i.e., the largest eigenvalues, are projected. In addition, the authors assume that the images can be decomposed into linear combinations of scene factors such as the view (position, rotation), colors or lightning and perform again the PCA dimensionality reduction on the decomposed features. Given parameters \mathbf{\Theta} = \Theta_1, \Theta_2,..., \Theta_NΘ=Θ1,Θ2,...,ΘN and a sample image tt with parameters \mathbf{\theta}\in\mathbf{\Theta}θ∈Θ, we obtain the features for a specific scene factor kk as:

\mathbf{F}_k^L(t) = \frac{|\Theta_k|}{|\Theta|}\sum_{\theta\in\Theta|\theta_k=t}\mathbf{F}^L(\theta)FkL(t)= |Θ ||Θk |θ∈Θ |θk =t∑FL(θ)
In the figure below, image embeddings are projected with respect to different image factors.

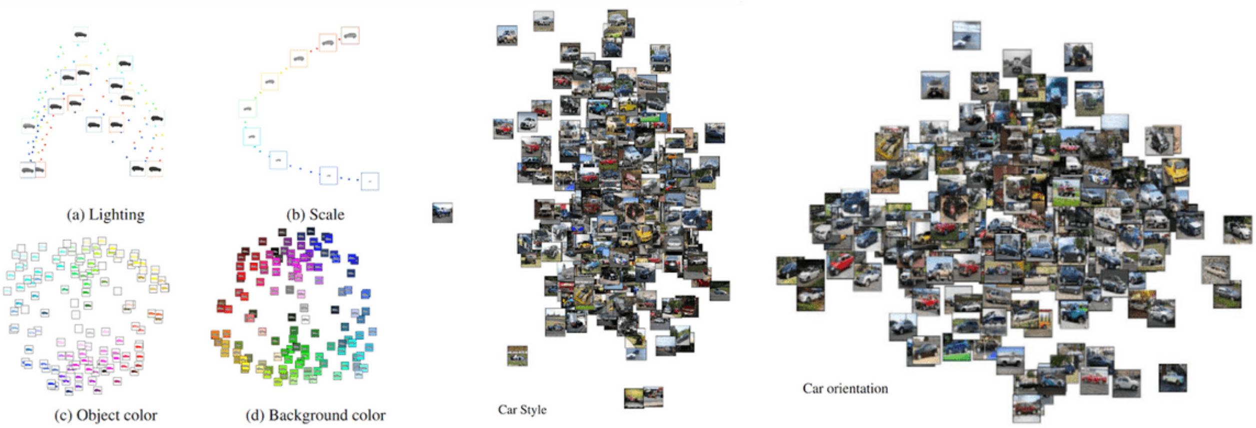
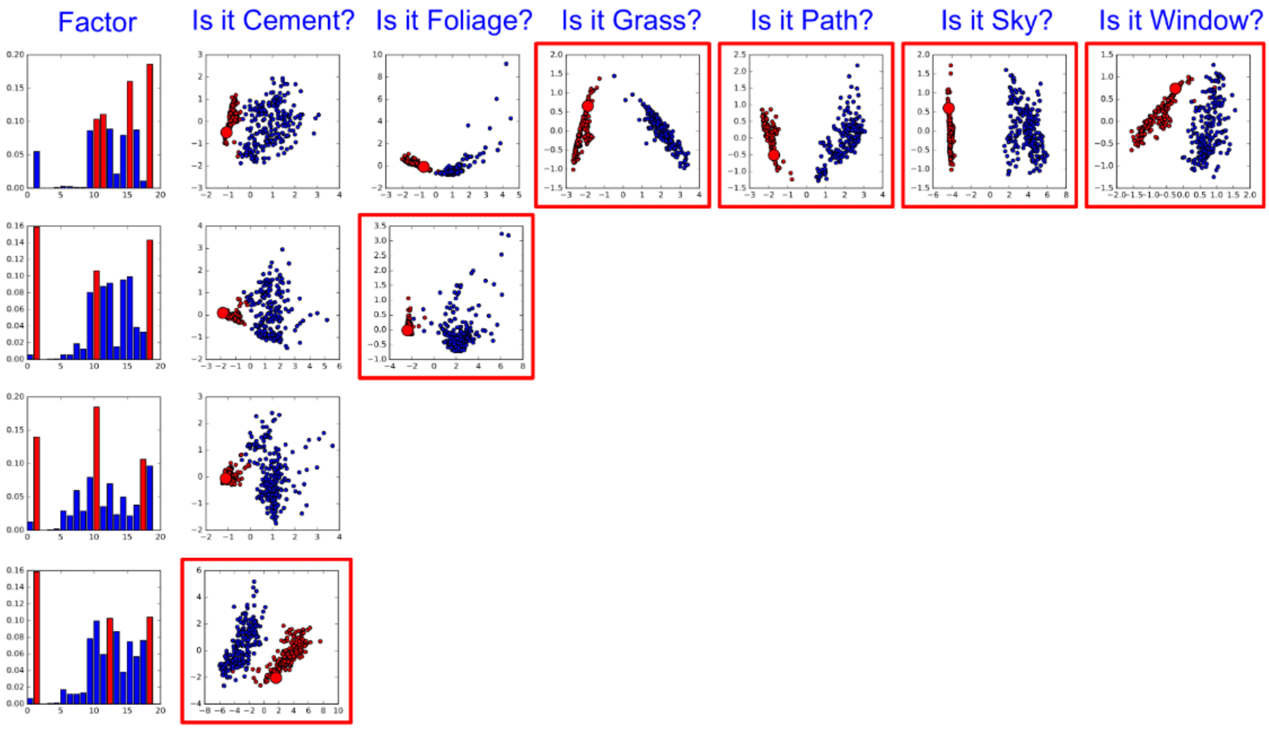


Image embeddings projection. Source: [3]

TreeView

TreeView [25] is a method that tries to partition the feature space and into smaller subspaces where each subspace represents a specific factor. At first, the input data \mathbf{X}X is transformed into features \mathbf{Y}Y. Subsequently, features \mathbf{Y}Y are classified and transformed to label space \mathbf{Z}Z. The aforementioned transformations are denoted as T_1 : \mathbf{X} \rightarrow \mathbf{Y}T1:X→Y and T_2: \mathbf{Y}\rightarrow \mathbf{Z}T2:Y→Z}.

We partition the feature space of \mathbf{Y}Y into KK partitioned subspaces, which are constructed by clustering similar neurons according to their activations. Each cluster ii describes a specific factor S_iSi . Then, a new KK-dimensional feature is constructed from the cluster labels and a decision tree creates the visualization as shown in Figure . For a layer ll, let us denote the neuron's responses as \mathbf{Y}_l \in \mathbb{R}^{N_l\times T}Yl ∈RNl×T, where N_lNl are the filters and TT are the number of data. \mathbf{Y}_lYl is clustered within KK clusters(factors) with activations \mathbf{F}_l\in \mathbb{R}^{K\times N_l\times T}Fl∈RK×Nl×T according to the similarities of hidden activations. Then, the new interpretable features \mathbf{M}\in \mathbb{R}^{K \times T}M∈RK×T are constructed using the cluster label. Finally, a classifier P^i_lPli is trained for each factor ii using features \mathbf{M}M and predicts the cluster label.



TreeView explanation. Source: [25]

Textual explanation methods

Some works have focused on textual interpretability. In general, textual explanation methods produce natural language-text to interpret the decisions.

Cell Activation Value

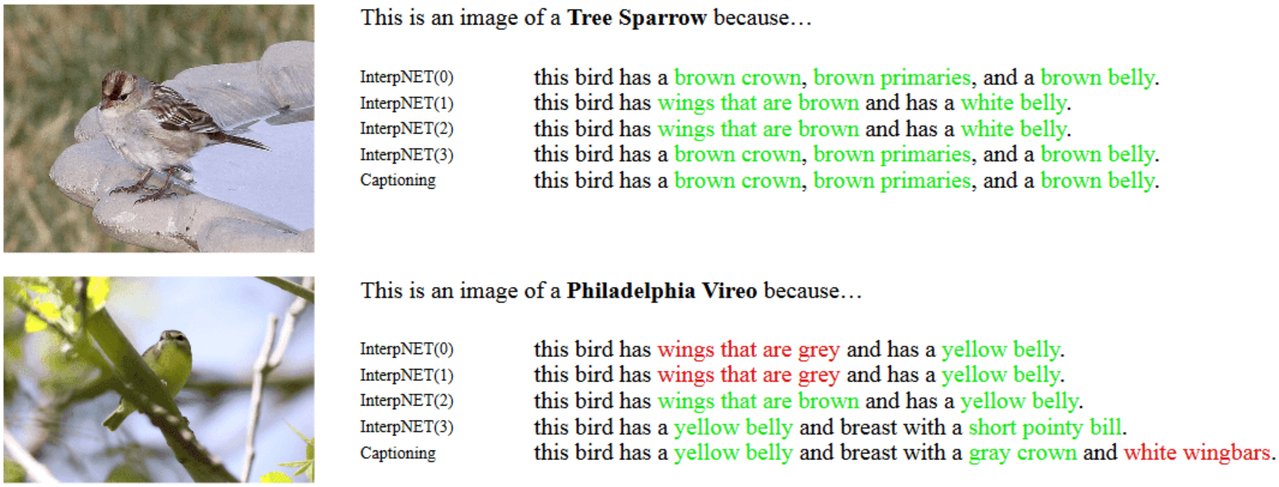
Cell Activation Values [8] is an explainability method for LSTMs. This method adopts **character-level language to understand the long-term dependencies of LSTM modules**. The input characters are projected into a lower-dimensional space. Subsequently, these vectors are fed to the LSTM at each timestep and projected to word sequences with fully connected layers. The activation values at each timestep model the next character in the sequence and are used to interpret the model.

Interpnet

Recently, Barratt et. al. [4] proposed a deep neural network, named Interpnet, that can be combined with a classification architecture and generate explanations. Let us consider a simple network as follows:

\mathbf{y} = softmax(\mathbf{W}_{1}relu(\mathbf{W}_{2}\mathbf{x}+\mathbf{b}_{2})+\mathbf{b}_{1}) y=softmax(W1relu(W2x+b2)+b1)
and the internal activations \mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3f1,f2,f3

\mathbf{f}_1 = \mathbf{x}, \mathbf{f}_2 = relu(\mathbf{W}_{2}\mathbf{x}+\mathbf{b}_{2}), \mathbf{f}_3 = softmax(\mathbf{W}_{1}relu(\mathbf{W}_{2}\mathbf{x}+\mathbf{b}_{2})+\mathbf{b}_{1}) f1=x,f2=relu(W2x+b2),f3=softmax(W1relu(W2x+b2)+b1)
Interpnet uses the concatenated vector \mathbf{r} =[\mathbf{f}_1; \mathbf{f}_2; \mathbf{f}_3]r=[f1;f2;f3] as input to a language model, such as LSTM, to generate explanation captions E(x,y)E(x,y). An example of interpretable text generated from Interpnet is depicted below.



This is an image of a **Tree Sparrow** because...

InterpNET(0) this bird has a brown crown, brown primaries, and a brown belly.
InterpNET(1) this bird has wings that are brown and has a white belly.
InterpNET(2) this bird has wings that are brown and has a white belly.
InterpNET(3) this bird has a brown crown, brown primaries, and a brown belly.
Captioning this bird has a brown crown, brown primaries, and a brown belly.

This is an image of a **Philadelphia Vireo** because...

InterpNET(0) this bird has wings that are grey and has a yellow belly.
InterpNET(1) this bird has wings that are grey and has a yellow belly.
InterpNET(2) this bird has wings that are brown and has a yellow belly.
InterpNET(3) this bird has a yellow belly and breast with a short pointy bill.
Captioning this bird has a yellow belly and breast with a gray crown and white wingbars.

Interpnet generates explanations for the input images. Source:[4]

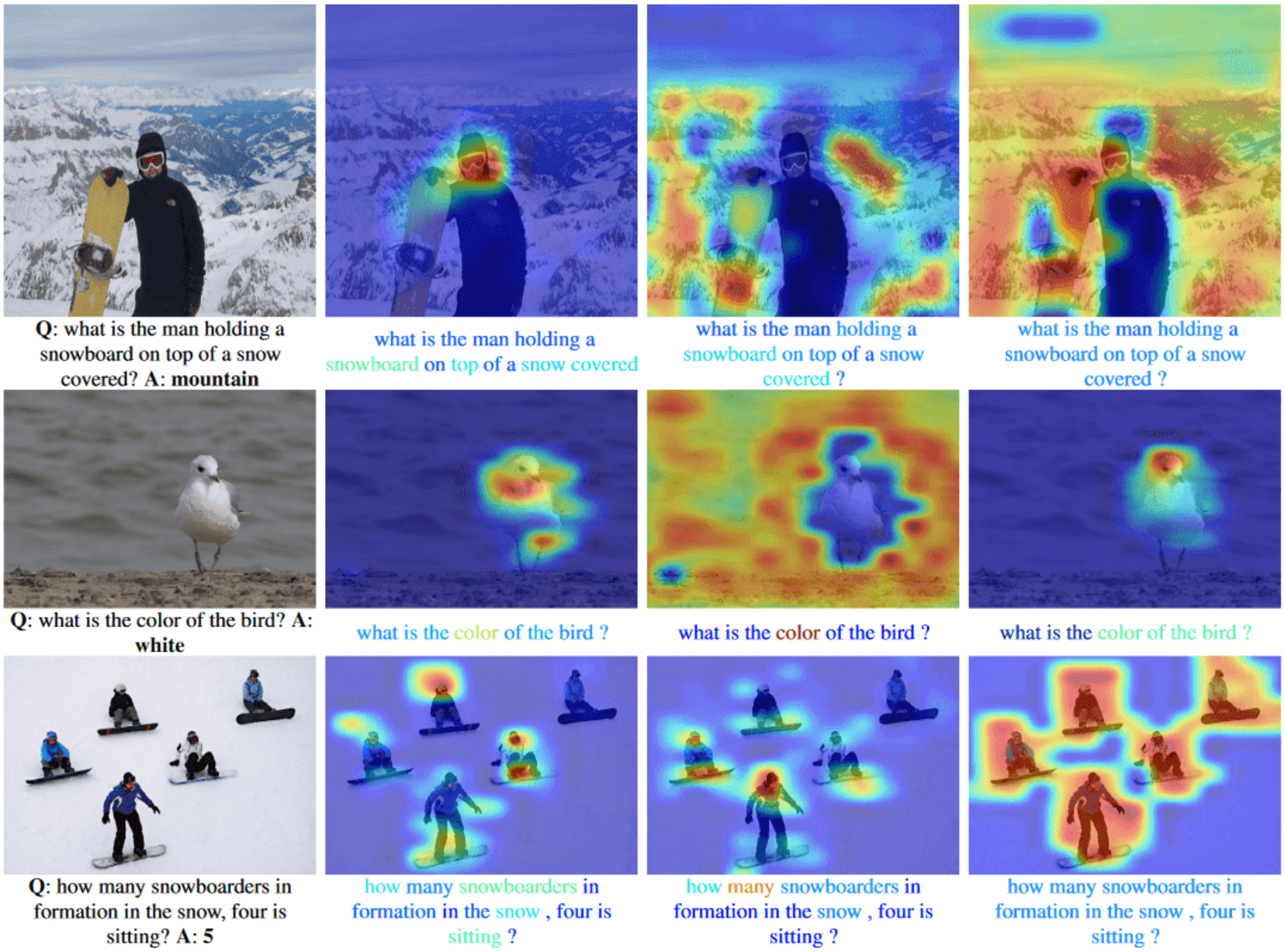
Visual Question Answering (VQA)

Here, the authors proposed a Visual Question Answering (VQA) [14] framework that jointly attends the image regions and the words of the question to generate the answer as depicted in Figure. At first, the words of the question \mathbf{Q} = (\mathbf{q}_{1}, \mathbf{q}_{2}, ..., \mathbf{q}_{T})Q=(q1,q2,...,qT) are projected with an embedding layer into a lower-dimensional space to obtain the word embeddings \mathbf{Q}^{w} = (\mathbf{q}^{w}_{1}, \mathbf{q}^{w}_{2},..., \mathbf{q}^{w}_{T})Qw=(q1w,q2w,...,qTw). Then, a 1d convolutional layer with kernel size up to 3 and a max-pooling layer are applied to model relationships between neighboring words. Finally, an LSTM module models the long-term dependencies and extracts the hidden representation of the question \mathbf{q}_{t}^{h}qth for each timestep tt as

\mathbf{q}_{t}^{h} = max(LSTM(conv(\mathbf{q}_{t:t+s}^{h})))qth
=max(LSTM(conv(qt:t+sh)))
where ss is the receptive field of the 1D convolution layer.

A co-attention mechanism takes as input the image features \mathbf{V}= (\mathbf{v_1},\mathbf{v_2},...,\mathbf{v_N})V=(v1,v2,...,vN) and the word representations at each hierarchy level \mathbf{r} \in (w, p, s)r∈(w,p,s), i.e., word (w)(w), phrase (p)(p) and sentence (s)(s), to generate the attended image features \mathbf{v}^{r}_{att}vattr and question features \mathbf{q}^{r}_{att}qattr , respectively. The final answer prediction is based on all the co-attended image and question features, which are modelled from multiple fully-connected layers as:

\mathbf{h}^w = tanh(\mathbf{W}_w(\mathbf{q}^{w}_{att} + \mathbf{v}^{w}_{att})hw=tanh(Ww(qattw+vattw)
\mathbf{h}^p = tanh(\mathbf{W}_p[(\mathbf{q}^{p}_{att} + \mathbf{v}^{p}_{att}),\mathbf{h}^w]hp=tanh(Wp[(qattp+vattp),hw]
\mathbf{h}^s = tanh(\mathbf{W}_s[(\mathbf{q}^{s}_{att} + \mathbf{v}^{s}_{att}),\mathbf{h}^p]hs=tanh(Ws[(qatts+vatts),hp]
\mathbf{p} = softmax(\mathbf{W}_h\mathbf{h}^s)p=softmax(Whhs)
where \mathbf{W}_w, \mathbf{W}_p, \mathbf{W}_s, \mathbf{W}_hWw,Wp,Ws,Wh are the weights of the fully-connected layers.


Q: what is the man holding a snowboard on top of a snow covered? A: mountain
what is the man holding a snowboard on top of a snow covered
what is the man holding a snowboard on top of a snow covered ?
what is the man holding a snowboard on top of a snow covered ?
Q: what is the color of the bird? A: white
what is the color of the bird ?
what is the color of the bird ?
what is the color of the bird ?
Q: how many snowboarders in formation in the snow, four is sitting? A: 5
how many snowboarders in formation in the snow , four is sitting ?
how many snowboarders in formation in the snow , four is sitting ?
how many snowboarders in formation in the snow , four is sitting ?

Example of questions and answers predicted word-level co-attention maps, phrase-level co-attention maps and question-level co-attention maps. Source: [4]

Semantic information to interpret Neural Networks

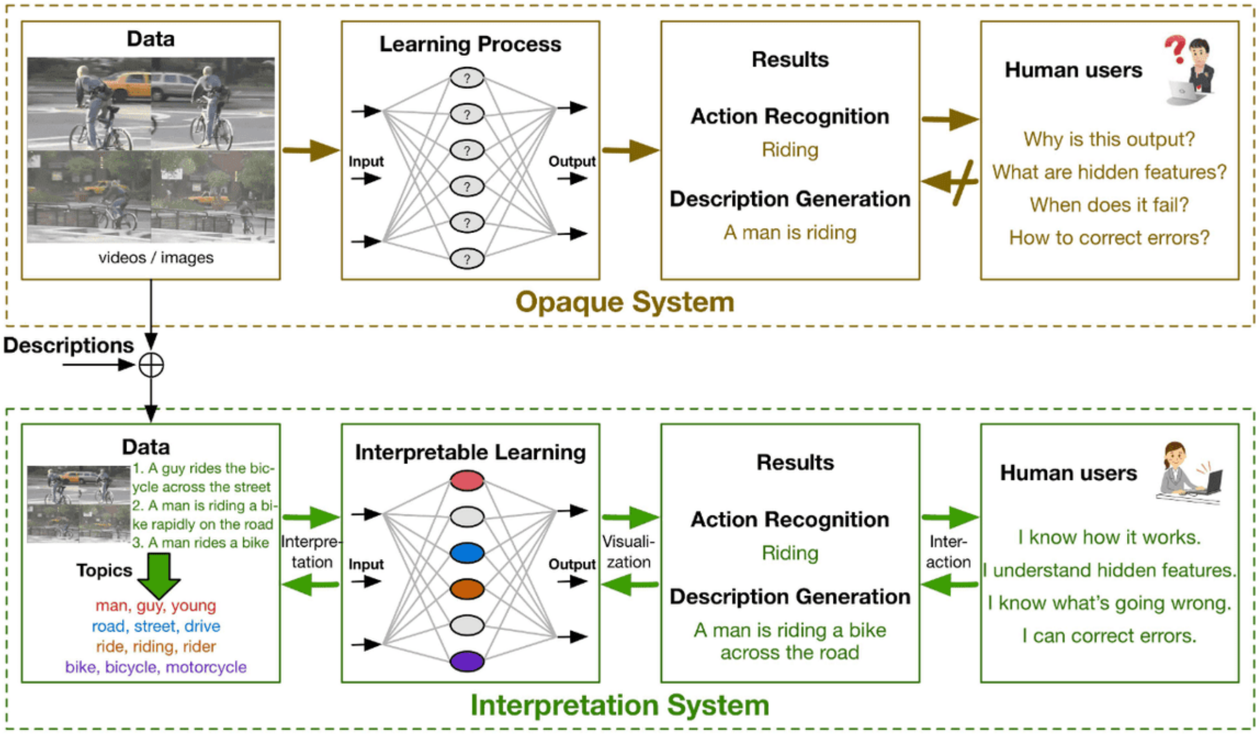
In [7], the authors employed semantic information to interpret deep neural networks (DNNs) for **video captioning**. A sample video-description pair has a video \mathbf{x}x with nn frames and N_dNd target descriptions \mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2,..., \mathbf{y}_{N_d})Y=(y1,y2,...,yNd). Each description \mathbf{y} \in \mathbf{Y}y∈Y has N_sNs words. The video encoder extracts video features \mathbf{V} = (\mathbf{v_1}, \mathbf{v_2}, \mathbf{v_n})\in \mathbb{R}^{n\times D_v}V=(v1,v2,vn)∈Rn×Dv, D_uDu the feature dimension. The video representations are used by an attention decoder to generate the captions. The decoder at timestep tt takes as input the concatenated vector \mathbf{d} = [\mathbf{y}_{t-1};\phi_t(\mathbf{V})]d=[yt−1;ϕt(V)], where \phi_t(\mathbf{V}) = \sum_{i=1}^{n}a_i^t\mathbf{v}_iϕt(V)=∑i=1naitvi is the weighted sum of the features. The weight a_i^tait is calculated as:

a_i^t= \frac{exp(\mathbf{w}_a tanh(\mathbf{U}_a \mathbf{h}_{t-1}+\mathbf{T}_a \mathbf{v}_i +\mathbf{b}_a))}{ \sum_{j=1}^n exp(\mathbf{w}_a tanh(\mathbf{U}_a

\mathbf{h}_{t-1}+\mathbf{T}_a \mathbf{v}_j +\mathbf{b}_a))}ait=∑j=1nexp(watanh(Ua ht−1+Tavj+ba))exp(watanh(Uaht−1+Tavi+ba))
\mathbf{b}_a, \mathbf{T}_a, \mathbf{U}_a, \mathbf{w}_aba,Ta,Ua,wa are the parameters of the decoder. Finally, a classifier predicts the next word of the sentence from the probability distribution:

\mathbf{p}_t = softmax(\mathbf{W}_p [\mathbf{h}_t, \phi_t (\mathbf{V}), \mathbf{y}_{t-1}] + \mathbf{b}_p)pt=softmax(Wp[ht,ϕt(V),yt−1]+bp)
The system uses descriptions of humans, denoted as \mathbf{s}s, that have information about the data. These descriptions are embedded in the network with a loss function defined as:

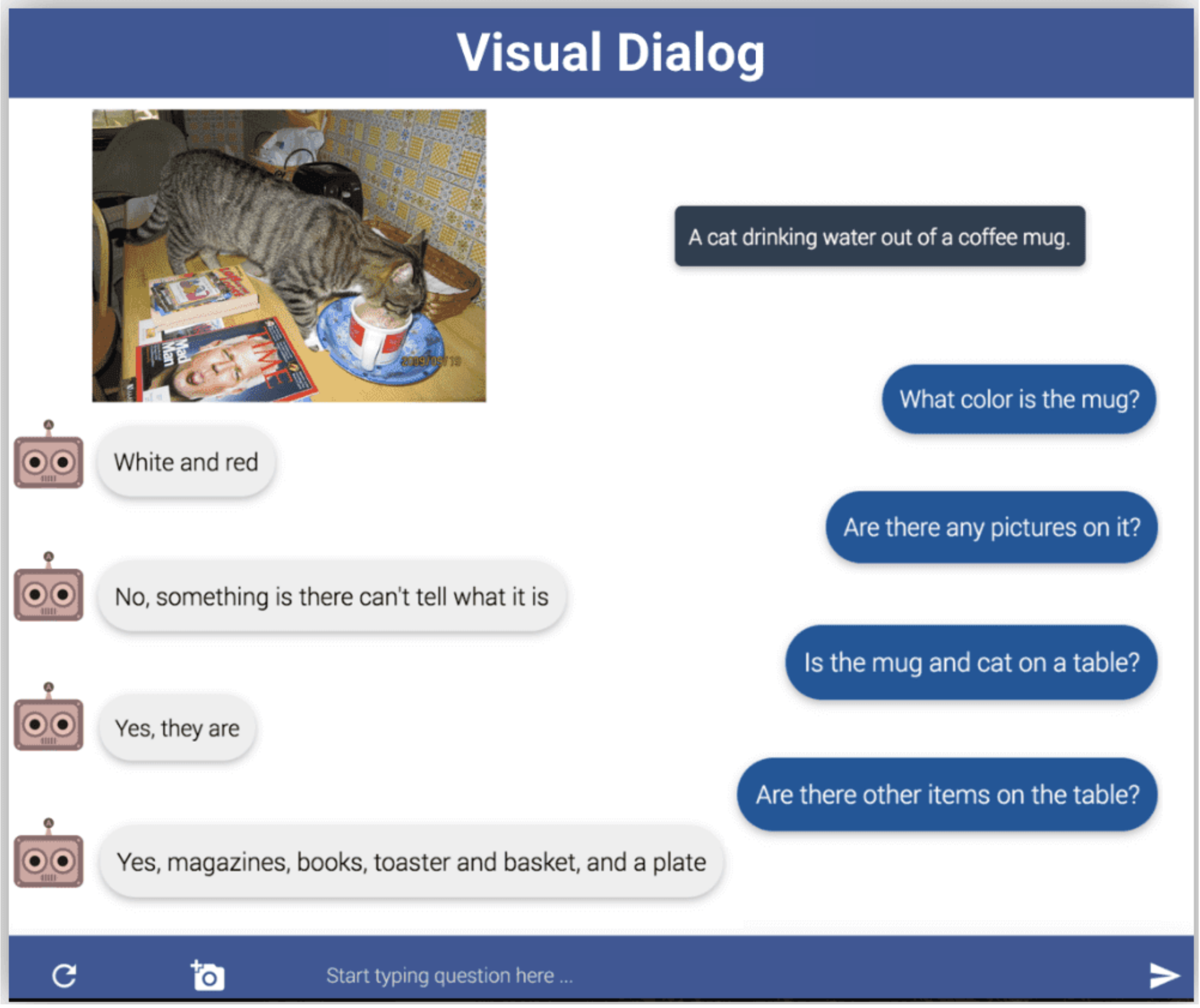
L_I(\mathbf{v},\mathbf{s}) = {||f(\frac{1}{n}\sum_{i=1}^n \mathbf{v}_i) - \mathbf{s}||_2^2}LI(v,s)=∥f(n1i=1∑nvi)−s∥22
and guide the learning process to learn interpretable features. This guides **the neurons of the network to be associated with a specific topic and the whole network can be easily understandable by humans** instead of being a black-box model.



Interpetable training process of deep neural networks. Source: [7]

Visual dialog

In [6], the authors introduced a new task where an **AI agent attempts a conversation with humans about visual content**. A human makes questions about an image e.g., what color an object is, and the AI agent tries to answer. More specifically, the AI agent uses an encoder-decoder architecture that embeds the visual content and the history of the dialog to develop the next answer.



A cat drinking water out of a coffee mug.

What color is the mug?

White and red

Are there any pictures on it?

No, something is there can't tell what it is

Is the mug and cat on a table?

Yes, they are

Are there other items on the table?

Yes, magazines, books, toaster and basket, and a plate

Example of visual dialog with an AI agent. Source: [7]

Numerical explanations

Concept Activation Vectors (CAVs)

Concept Activation Vectors (CAVs) [10] aim to explain the high-dimensional internal representations of neural networks. Given user-defined sets \mathbf{P}_CPC of a specific concept CC, we seek vectors in the space of hidden activations f_{l}fl that describes it. Then, CAVs are defined as vectors orthogonal to the hyperplane learned after training a binary classifier u_{C}^{l}uCl for the concept CC in any layer ll, to separate examples whether they belong or not in the concept. Finally, the sensitivity of the class kk is calculated as:

S_{C,k,l} = \mathbf{h}_{k,l}(\nabla(f_{l}(\mathbf{x}))u_{C}^{l})SC,k,l=hk,l(∇(fl(x))uCl) where \mathbf{h}_{k,l}(\mathbf{x})hk,l(x) are the predictions of sample \mathbf{x}x.

Linear classifiers for features inspection

In [1], the authors proposed to train linear classifiers and inspect the features of any layer. A linear classifier is fitted to the intermediate layers to monitor the features and measures how suitable they are for classification.

Given the features \mathbf{h}_{k}hk at layer kk the linear probe is defined as:

\mathbf{f}_{k}(\mathbf{h}_{k}) = softmax(\mathbf{Wh}_{k}+\mathbf{b})fk(hk
)=softmax(Whk+b)
The probe learns if the information from layer kk is useful for the classification of the input.

In general, it is proved that the most useful information is carried by the deeper layers of the network.

Local Interpretable Model-Agnostic Explanations (LIME)

Local Interpretable Model-Agnostic Explanations (LIME) [21] is able to interpret the predictions of any model-classifier ff by **learning a local explainable model** g\in Gg∈G, where GG is a class of interpretable models such as a linear classifier or a decision tree. We also measure the complexity \Omega (g)Ω(g) of the model which is also a significant factor of how easily the explanations are generated. In addition, we calculate the error of gg in approximating ff using a loss or distance function, denoted as L(f,g)L(f,g). Finally, the explanation \xi (g)ξ(g) is calculated from the optimization of

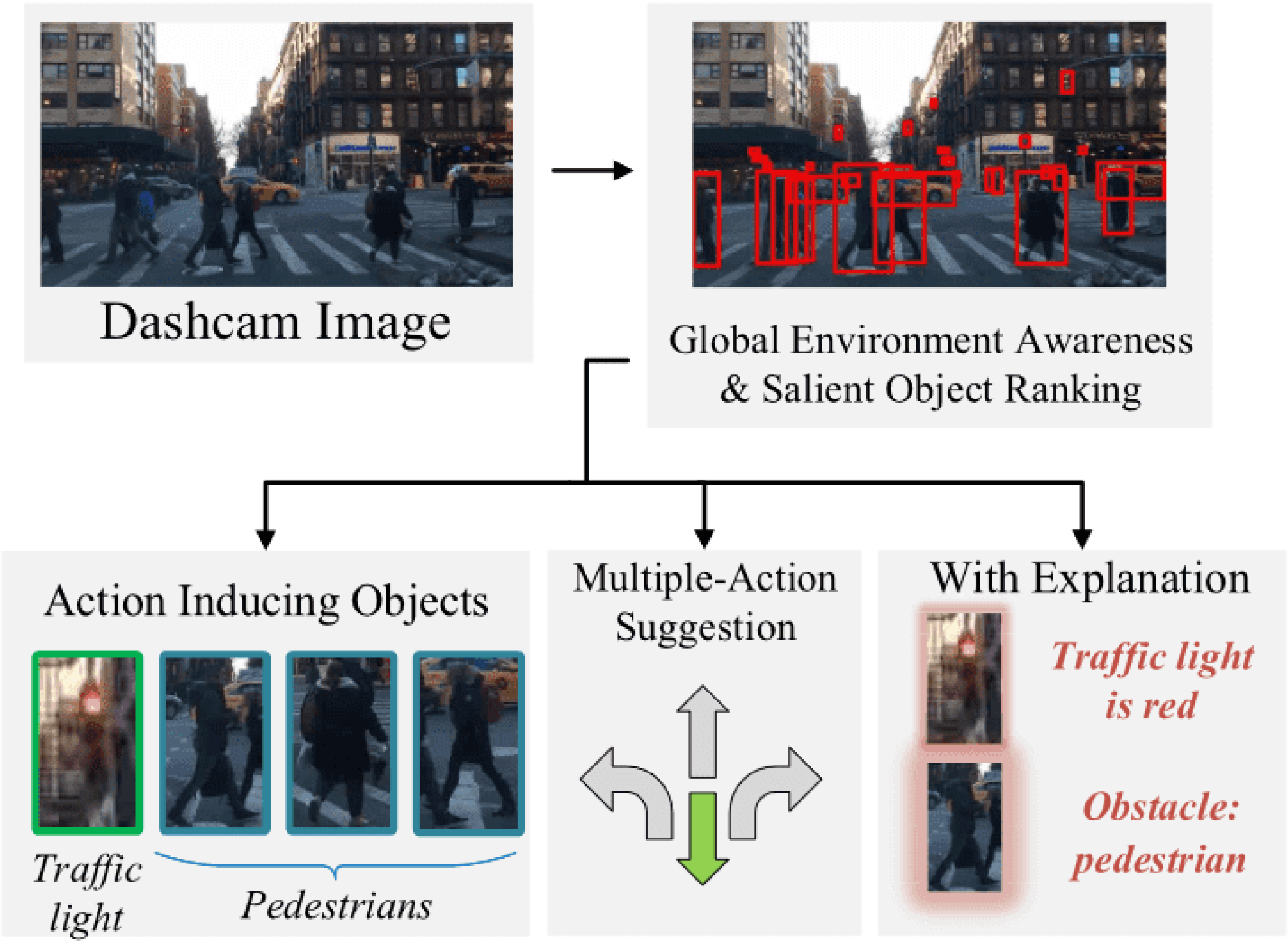
\xi(g) = argmin L(f,g)+\Omega (g)ξ(g)=argminL(f,g)+Ω(g)

Applications

In this section, we will present explainable artificial intelligence methods that have been applied in some real-world tasks, such as autonomous driving and healthcare. These methods develop explainable algorithms to interpret results and improve their decisions or actions according to the task. Recent self-driving systems have adopted interpretation techniques to improve the actions of the autonomous driving system and reduce the risk of a crash. This is also important to increase the trust between humans and AI machines.

Explainable decisions for autonomous cars

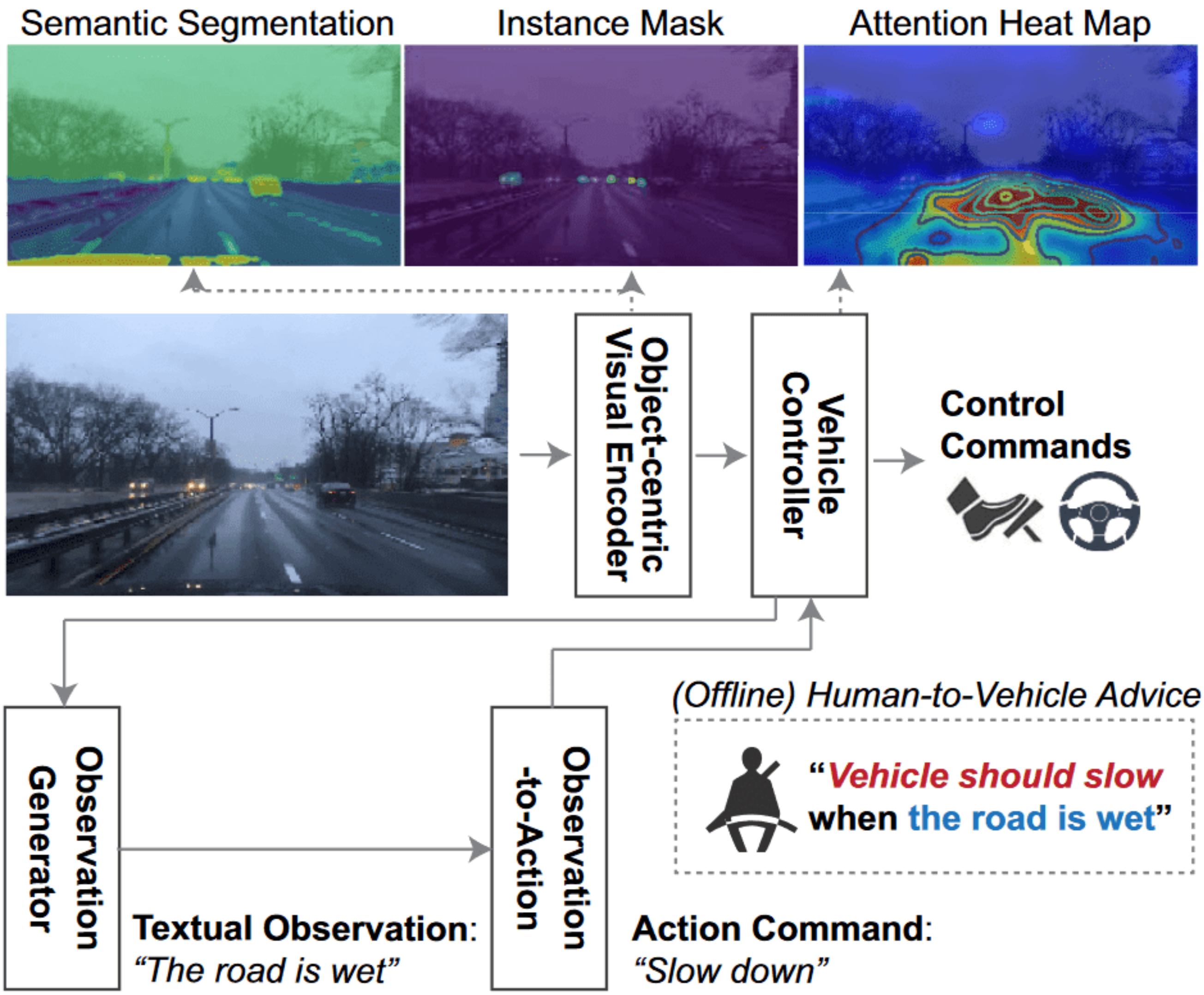
In [26], the authors proposed a new explainable self-driving system inspired by the reactions and decisions of humans during driving. The proposed method consists of a CNN to extract features from the input image, while a global module generates the scene context from those features and provides information about the location of the objects. A local branch is employed to select the most important objects of the scene and associate them with the scene context to generate the actions and explanations. Finally, visual explanations are produced for the input image.



Example of actions and explanations of a self-driving system. Source: [26]

Similarly in [9], the authors proposed an autonomous driving architecture that is assisted and trained with the help of humans.

The system adopts a visual encoder to segment the objects of the input video stream. A vehicle controller is trained to generate spoken text of the commands, i.e., stops the car because the traffic light is red. In addition, the controller generates attention maps to highlight the important regions and explain their decisions. To further enhance the robustness of the system, an observation generator is employed that summarizes frames of the video and produces general observations that must be considered during driving. These observations are also fed to the vehicle controller to improve its decisions.

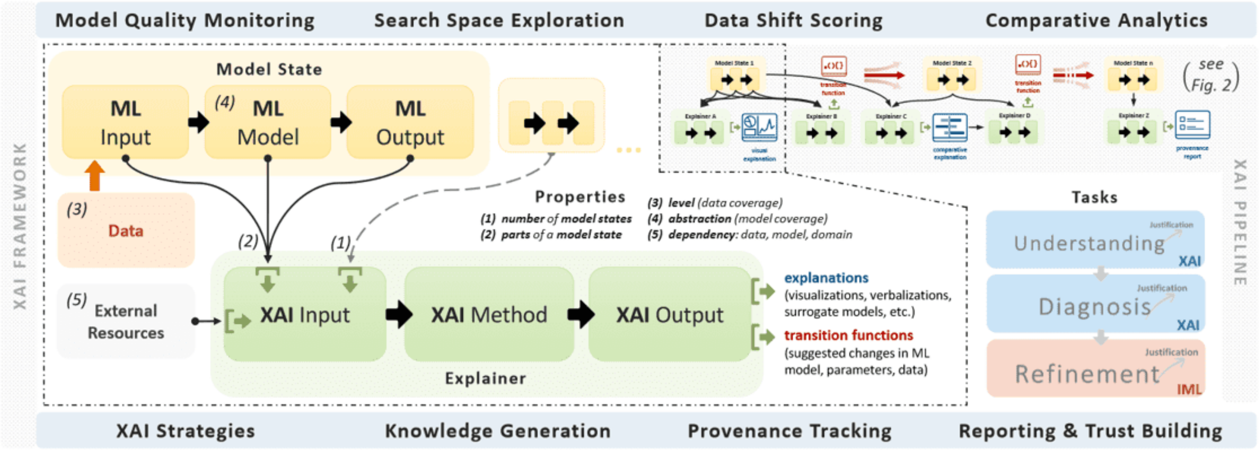

Semantic Segmentation
Instance Mask
Attention Heat Map
Object-centric Visual Encoder
Vehicle Controller
Control Commands
(Offline) Human-to-Vehicle Advice
"Vehicle should slow when the road is wet"
Observation Generator
Observation -to-Action
Textual Observation: "The road is wet"
Action Command: "Slow down"

System overview. Source: [26]

Explainable medical systems

Artificial intelligence systems have also been implemented for medical applications. Deep learning has shown significant results especially in medical imaging and drug discovery. Recently, researchers have focused towards explainable medical systems to assist medical experts and provide useful explanations so that any expert can understand the predictions of a system. In [5], the authors focused on the detection of coronavirus from x-ray images. They proposed a deep convolutional network to extract features from images and detect if the patient is healthy or diagnosed with pneumonia or coronavirus. Then they use Grad-CAM [26] to provide visual explanations and mark the areas of the x-ray that are affected.

XAI frameworks



ExplAIner pipeline. Source: [24]

In this section, we will highlight some explainable AI frameworks that anyone can start using to interpet a machine learning model.

INNvestigate Neural networks

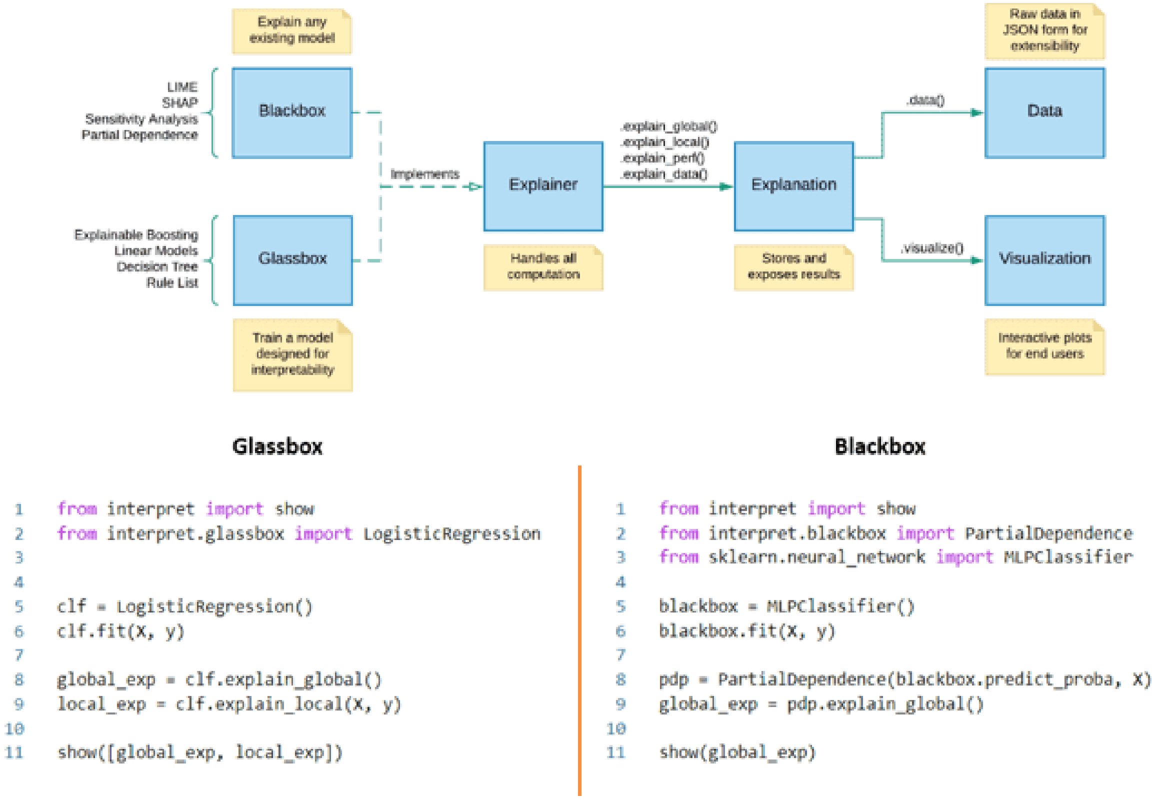
INNvestigate Neural networks [2] is a python package that has implemented a large variety of visual explanation methods such as LRP, CAM and PatternNet. The library contains examples with explanations of state-of-the-art models and is easy to use. The core and base functions of this framework allow rapid implementation of other methods.

explAIner

explAIner [24] is a unified framework that helps users to understand machine and deep learning models. In addition, the framework contains tools to analyze models using different explainable techniques. Then, these explanations are used in order to monitor and guide the optimization process and build better architectures. The explAIner is able to provide interactive graph visualization of a model, performance metrics and integrate high-level explainable methods to interpret it.

InterpetML

InterpetML [16] is an open-source Python library with many interpretability algorithms, which can be very easily integrated into the code. Then, we can easily understand the behavior of any model and compare different interpretation techniques.



Glassbox

```python
from interpret import show
from interpret.glassbox import LogisticRegression


clf = LogisticRegression()
clf.fit(X, y)

global_exp = clf.explain_global()
local_exp = clf.explain_local(X, y)

show([global_exp, local_exp])
```

Blackbox

```python
from interpret import show
from interpret.blackbox import PartialDependence
from sklearn.neural_network import MLPClassifier

blackbox = MLPClassifier()
blackbox.fit(X, y)

pdp = PartialDependence(blackbox.predict_proba, X)
global_exp = pdp.explain_global()

show(global_exp)
```

Usage of InterpetML framework. Source: [16]

Conclusion

In this article, we presented the major interpretation techniques and categorized them according to the explanation form. Some methods focus on providing visual explanations in the form of images or plots, while others provide textual or numerical explanations. Then, we described some of the latest explainable applications that are developed in demanding tasks like medical diagnosis and autonomous driving. Finally, we provided some well-known XAI frameworks that can be easily used by researchers for their algorithms.

Cited as:

```
@article{papastratis2021xai,
    title   = "Introduction to Explainable Artificial Intelligence (XAI)",
    author  = "Papastratis, Ilias",
    journal = "https://theaisummer.com/",
    year    = "2021",
    url     = "https://theaisummer.com/xai/"
  }
```

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