Explainable AI summary

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Artificial Intelligence &
Information Analysis Lab

Explainable AI

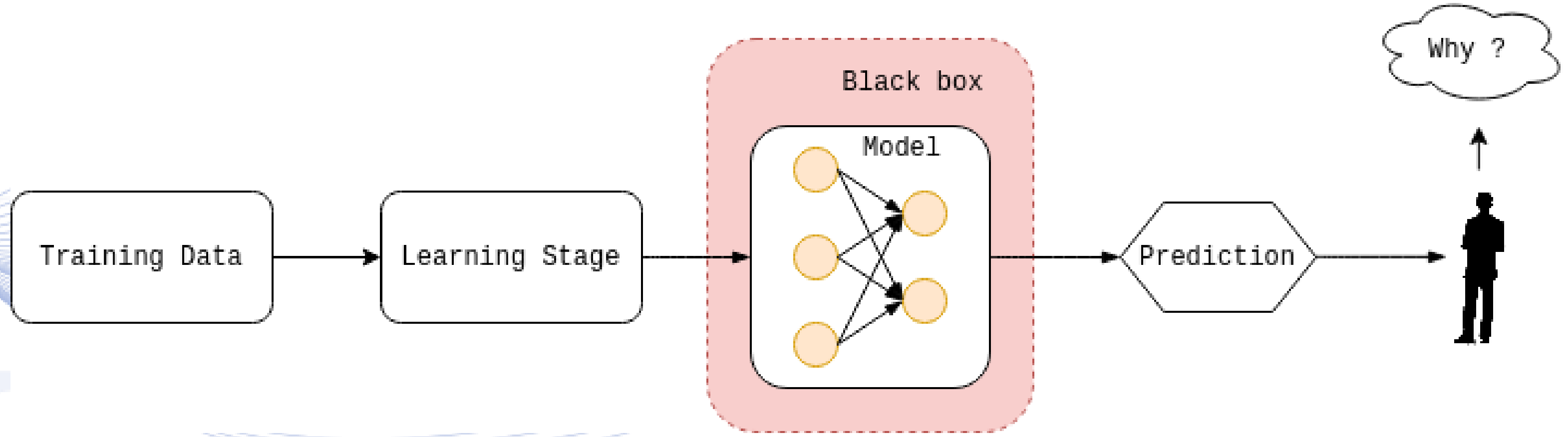
- Introduction to Explainable Artificial Intelligence
- Interpretability
- Types of Interpretability
  - Visual explanations
    - Image-based
    - Plot visualizations
  - Textual explanations
  - Numerical-Mathematical explanations
- Applications
- Frameworks

Introduction to Explainable AI

Machine and Deep Learning have surpassed humans in many tasks (image and speech recognition, recommendation systems, medical diagnosis)

Drawbacks:

- Machine learning (ML) architectures are usually considered as blackbox models



Introduction to Explainable AI

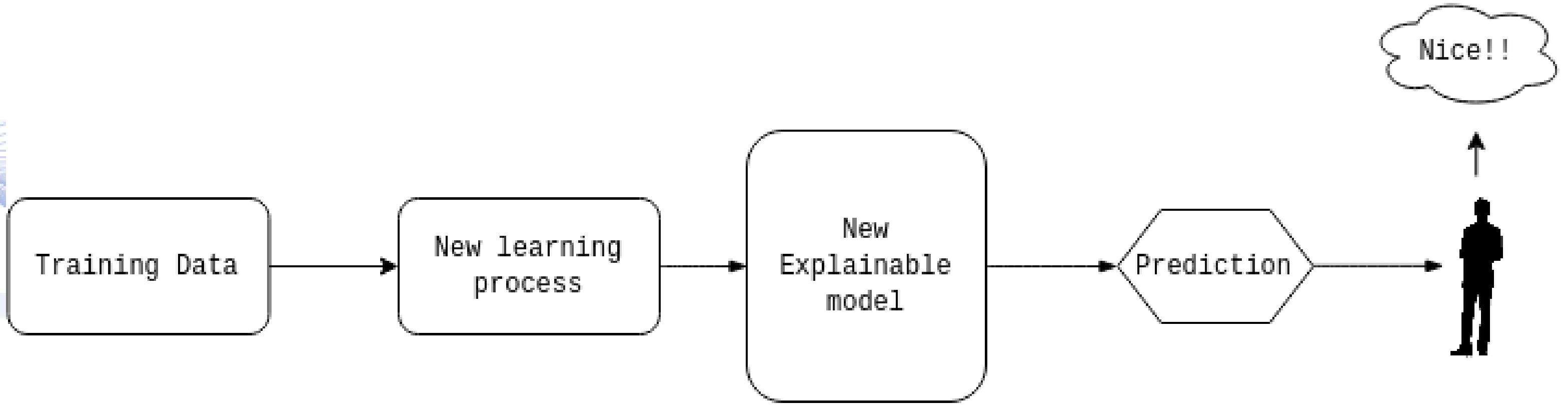
- Deep learning (DL) have achieved outstanding performance but they don't justify their reliability
- Failure
    - An error in any moment of a self-driving car can lead to a fatal crash.
    - in the medical area, human lives may be dependent on these decisions

Introduction to Explainable AI

Issues

- responsibility for bad AI decisions
- explain errors of AI decisions
- improvement of AI models

Solution: Explainable AI models easily understandable by humans



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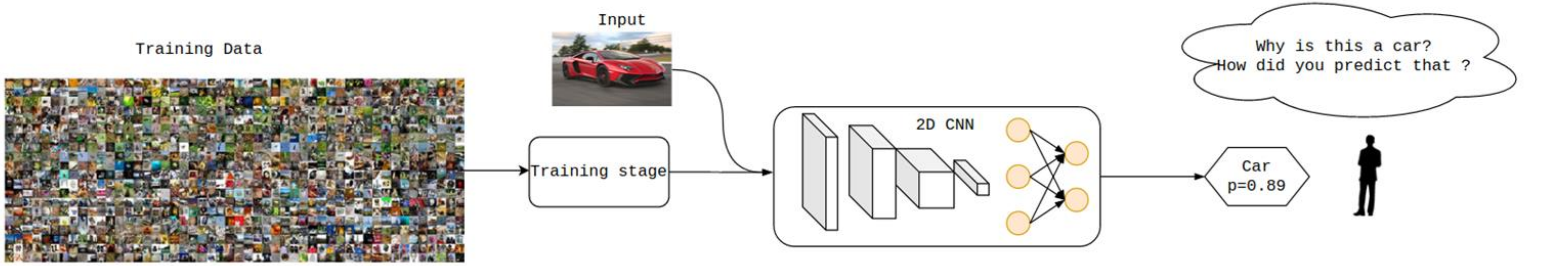
Introduction to Explainable AI



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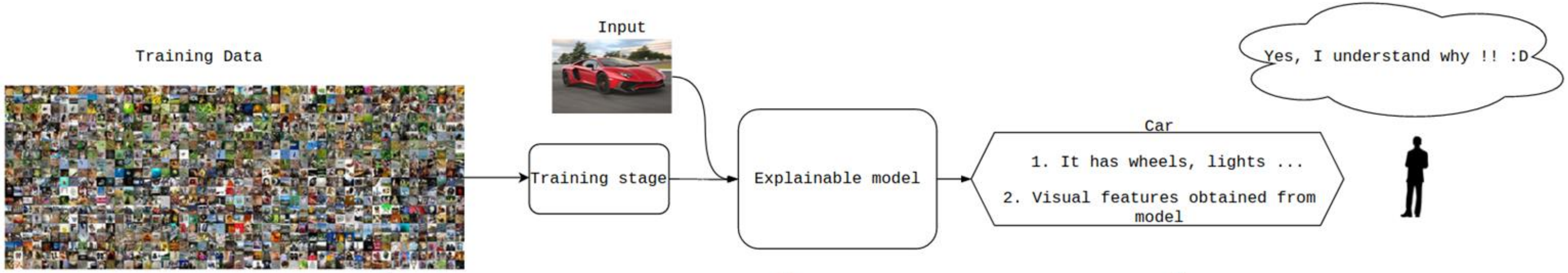


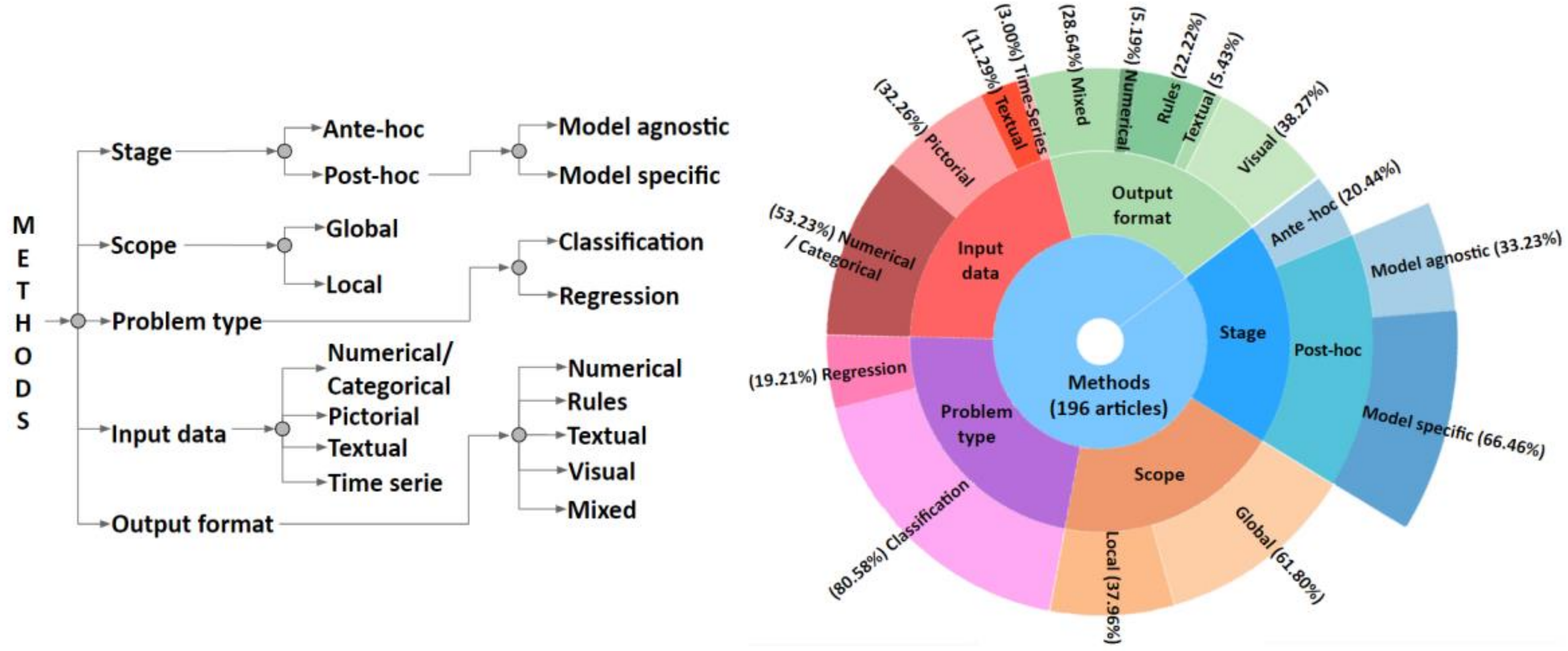
Interpretability

How easily we can understand the cause of an algorithm's decision or action
The categorization of Interpretability methods is based on how interpretable information is provided.

Categories:

- Visual Interpretability ("obviously" interpretable information, easily perceived from human eye
- Textual Explanations (Given in form of text)
- Mathematical-Numerical Explanations

Types of Interpretability Methods



[Vilone2020] Categorization of explainability methods

Visual Explanations

- Visual explainable methods produce pictures or maps in order to provide information about the model’s decision
  - Most common: **Saliency** methods explain results of model by producing outputs to show which components are responsible.
  - These values take the form of output probabilities or images like heatmaps.
- Plot visualization methods produce scatter plots to explain decisions or visualize the data

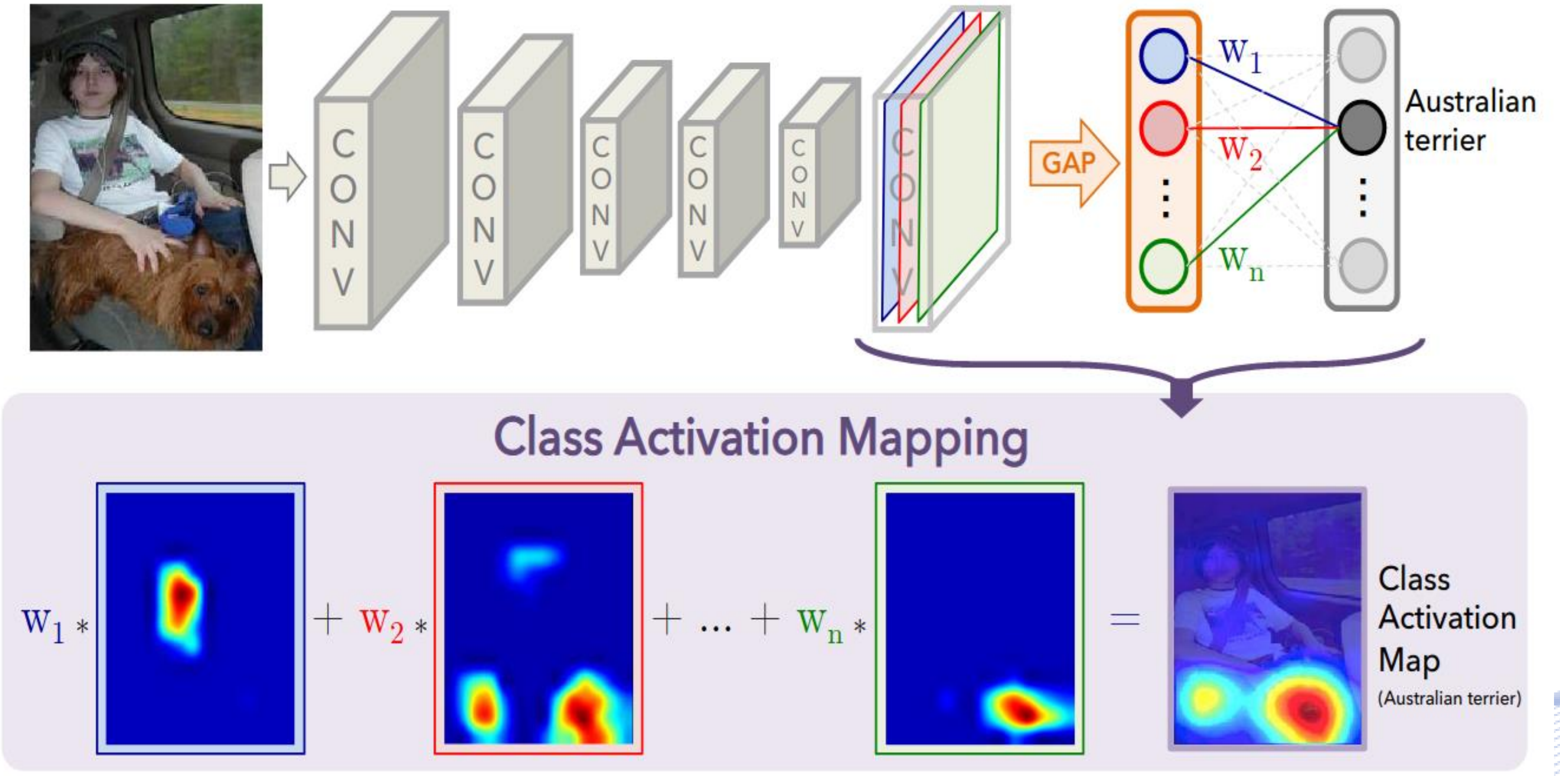
Visual Explanations

- Methods
  - CAM (Class Activation Maps)
  - Grad-CAM: Gradient based CAM
  - LRP (Layer-wise Relevance Propagation)
  - Peak Response Map (PRM)
  - CLass-Enhanced Attentive Response (CLEAR)
  - DeConvNet
  - DeepResolve
  - SCOUTER

Class Activation Maps (CAM)

- Generate activation maps for a decision
- Global average pooling layer is after convolutional layers
- The output features of the convolutional neural network are passed through a fully-connected layer that makes the prediction
- CAM indicates the region on the image that correspond to the prediction result

Class Activation Maps(CAM)



[Zhou2016] Overview of CAM

Class Activation Maps(CAM)

[Zhou2016] Examples of CAM

Grad-CAM: Gradient-based CAM

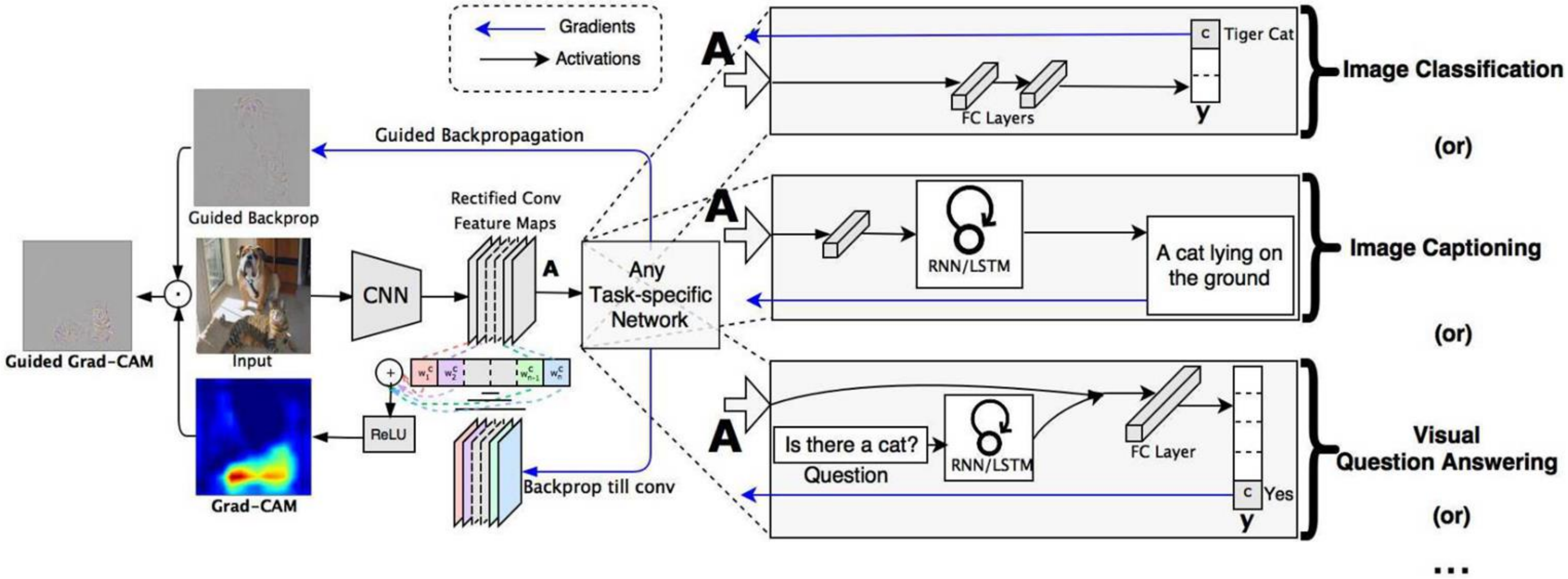
Gradient-weighted Class Activation Maps(Grad-CAM)

- an extended version of CAM by computing the gradients with respect to the target that flow to the final convolutional layer
- produces a map, which highlights the most useful pixels for classification

Processing steps

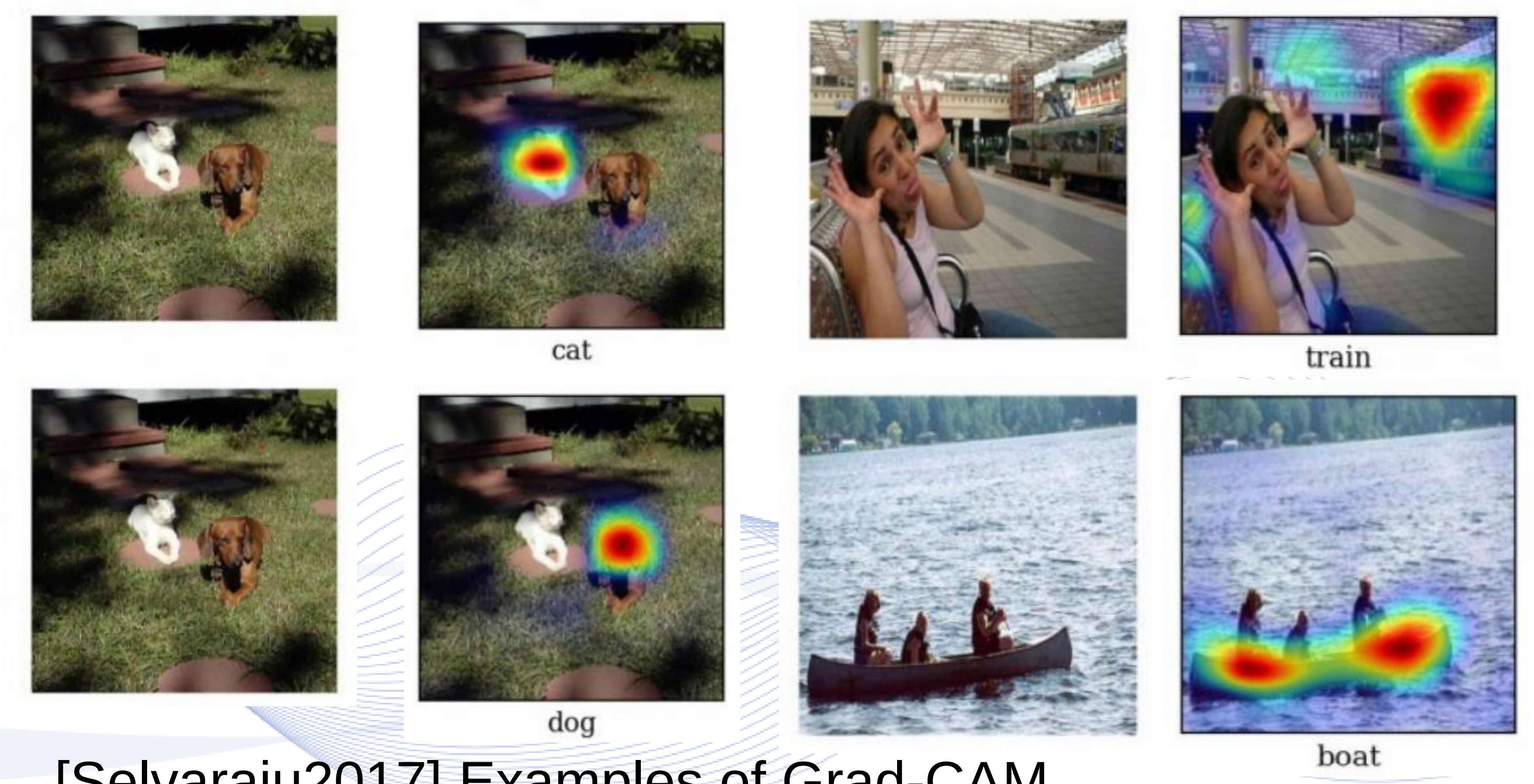
- Forward pass of the input image to produce the prediction
- Gradients of the target class
- The gradients of the target are back-propagated to last convolutional layer
- Find the important locations of the image

Grad-CAM: Gradient-based CAM



[Selvaraju2017] Overview of Grad-CAM

Grad-CAM: Gradient-based CAM



[Selvaraju2017] Examples of Grad-CAM

Layer-wise Relevance Propagation (LRP)

- Decomposition of the classification decision of a DNN model in using the input
- The classification layer is decomposed into several layers
- Backward pass to produce the pixel-wise conributions to the final output from last to first layers
- We denote as $w(i,j)$ the weight between of the connection from neuron i to neuron j

Layer-wise Relevance Propagation (LRP)

[Samek2016] LRP calculation for the input image

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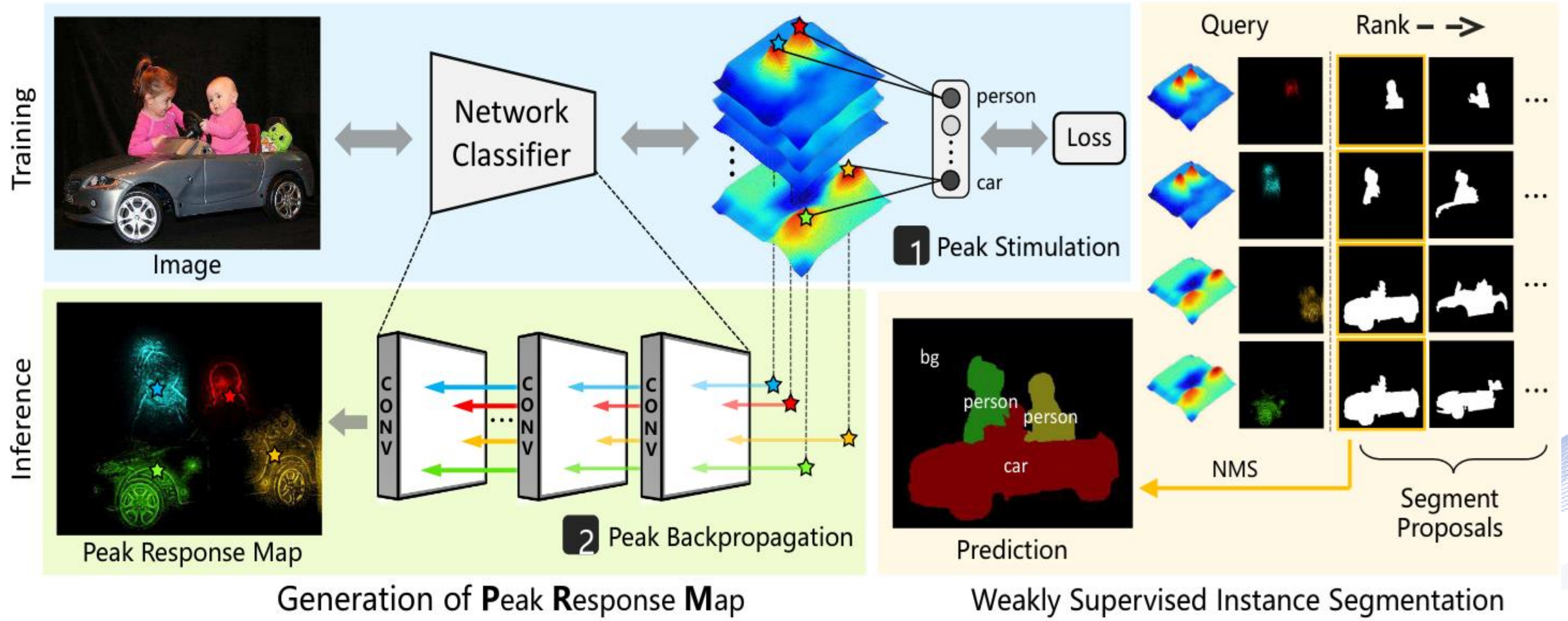
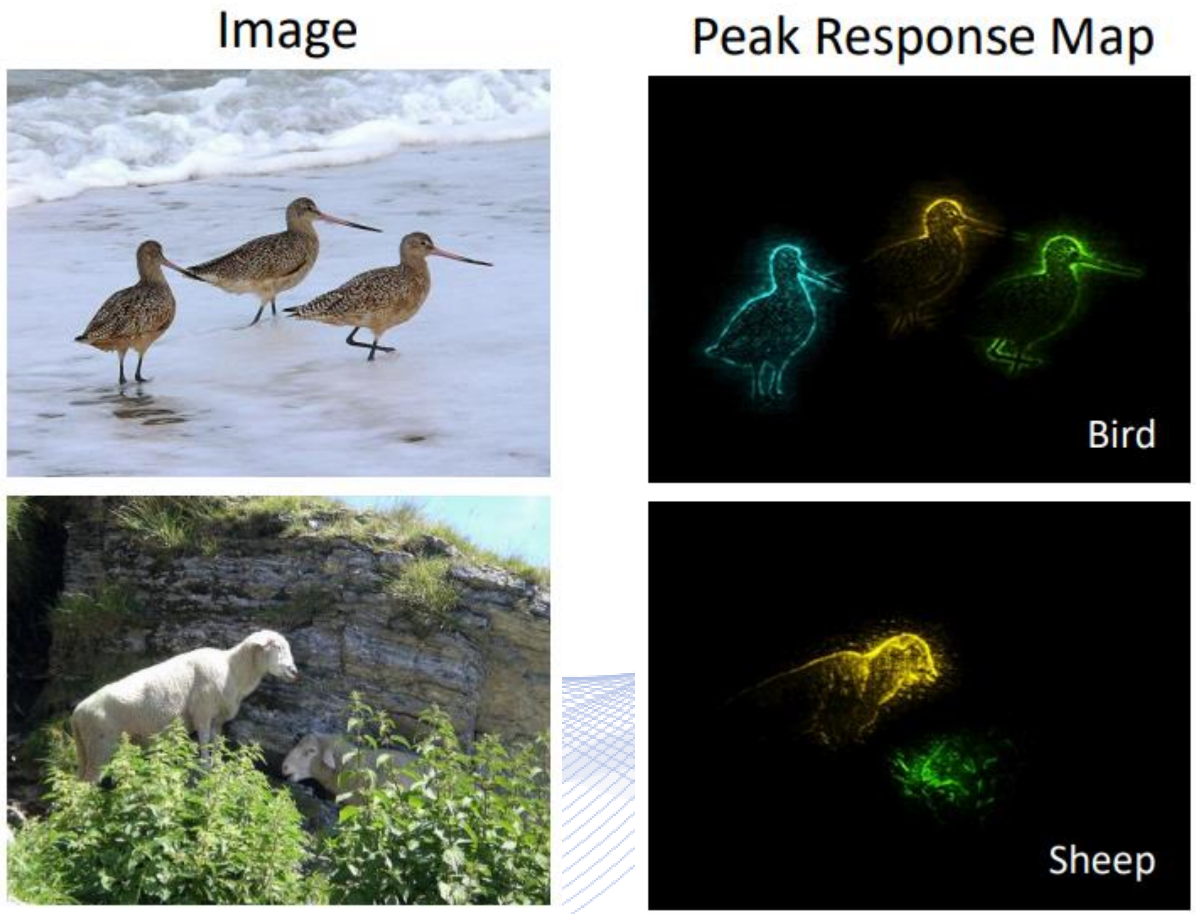
Peak Response Map (PRM)



[Zhou2016] Overview of PRM

Peak Response Map (PRM)



[Zhou2016] Examples of PRM

CLass-Enhanced Attentive Response (CLEAR)

- Visualizes the decisions of image classification applications with attention maps produced by back-propagating the activations of the last layer
  - After forward pass using deconvolutions we obtain the deconvolved output

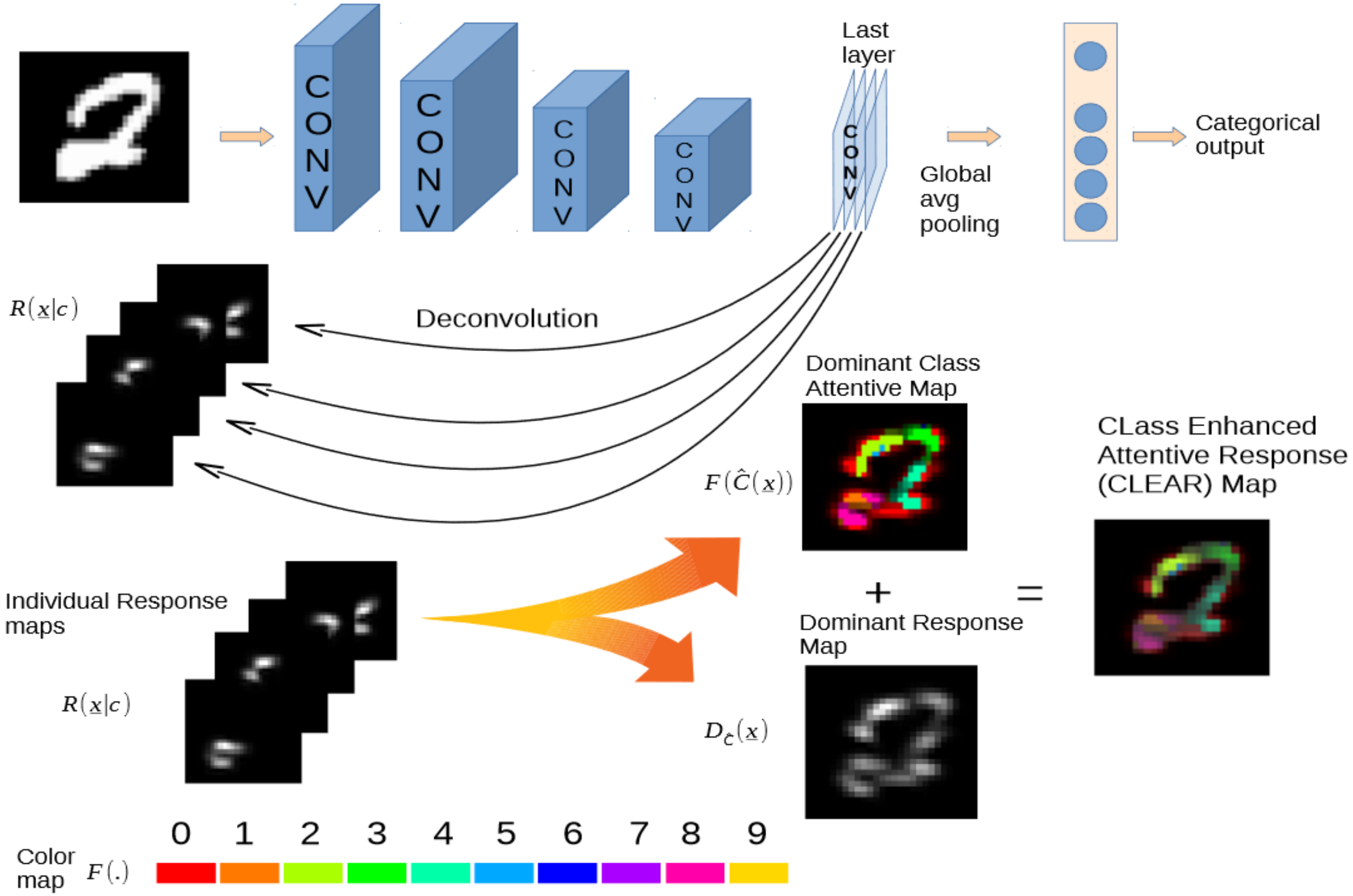
$$\mathbf{h}(l) = \sum_{k=1}^{K} z(k,l) * w(k,l)$$

k: kernel index $\mathbf{z}(l)$: feature maps of layer l, $\mathbf{w}(l)$: kernel weights, K kernels

- Final response of layer l is the product: $\mathbf{R}(l) = \mathbf{h}(1)\mathbf{h}(2) \dots \mathbf{h}(l)$
- Compute individual attention maps $\mathbf{R}(\mathbf{x}', c)$ of class c and back-projected input $\mathbf{x}'$ from all L layers of the deconvolutional network as :

$$\mathbf{R}(\mathbf{x}', c) = \mathbf{h}(1)\mathbf{h}(2) \dots \mathbf{h}(L)$$

CLass-Enhanced Attentive Response (CLEAR)

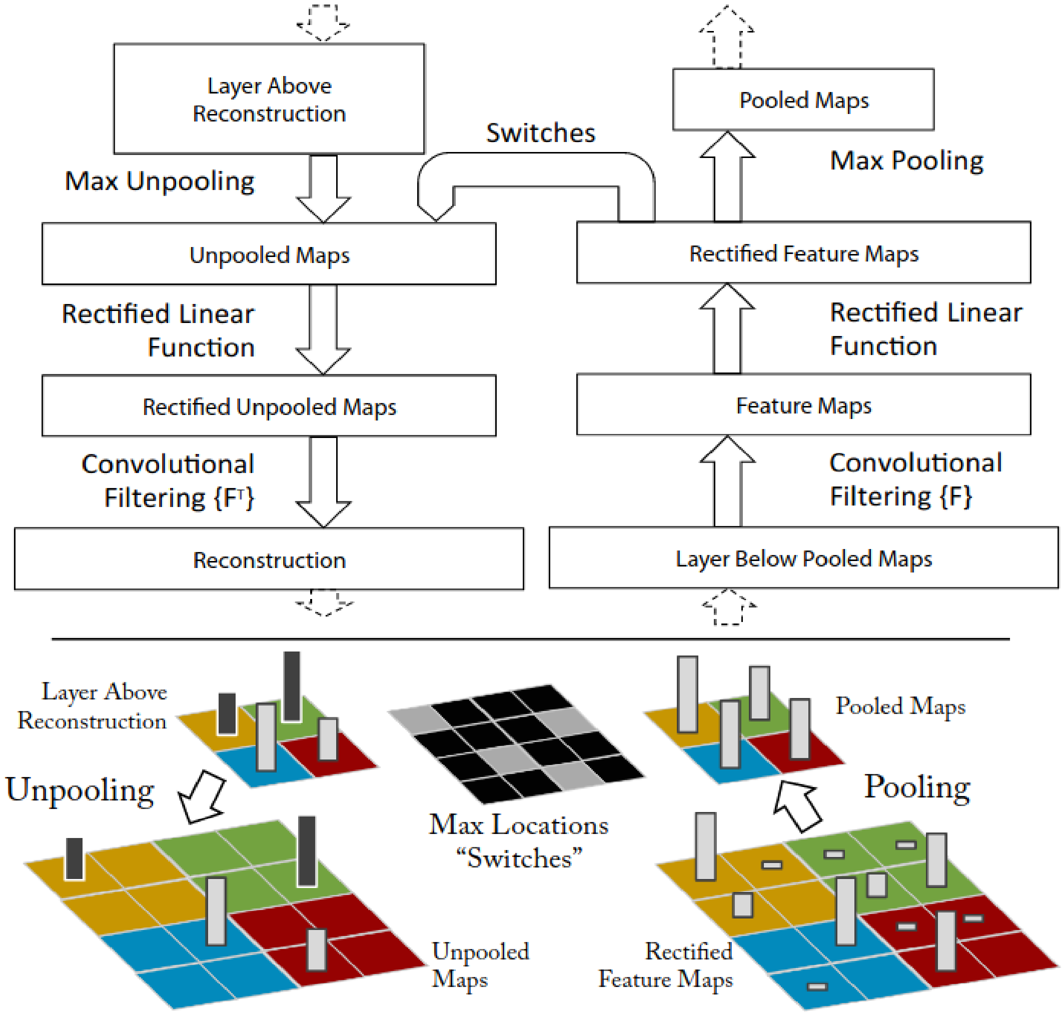


[Kumar2017] CLEAR method

DeConvNet

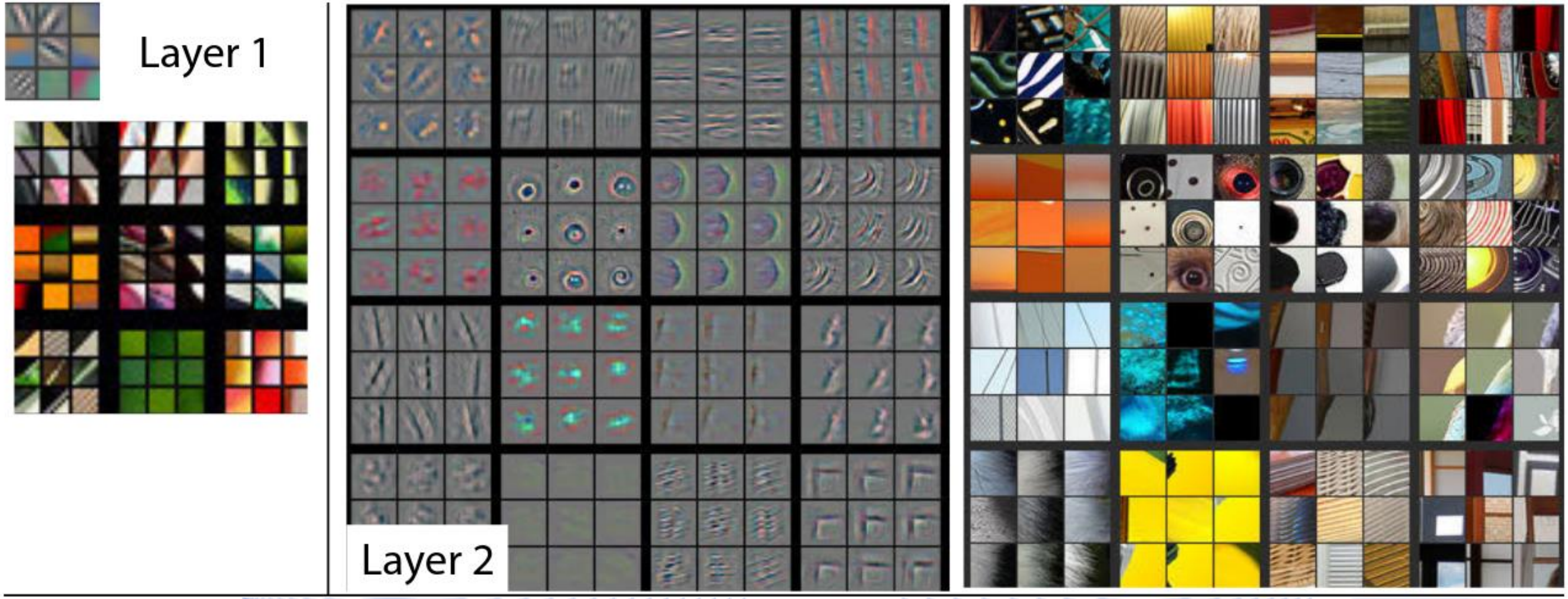
- A deconvnet is actually a convnet model with the same convolutional layers but in reverse since it maps pixels to features
- Deconvet is used here to generate the input images from features
- Following operations are adopted:
- Trsnspose Convolution (deconvolution):
  - Use transposed learned filters of cnn to reconstruct the input of the layer from the output
- Unpooling
  - record maximum values locations during maxpooling and use the locations to reconstruct input during deconvolution

DeConvNet



[Zeiler2014] Reconstruction of the convnet features up to the pixel space

DeConvNet

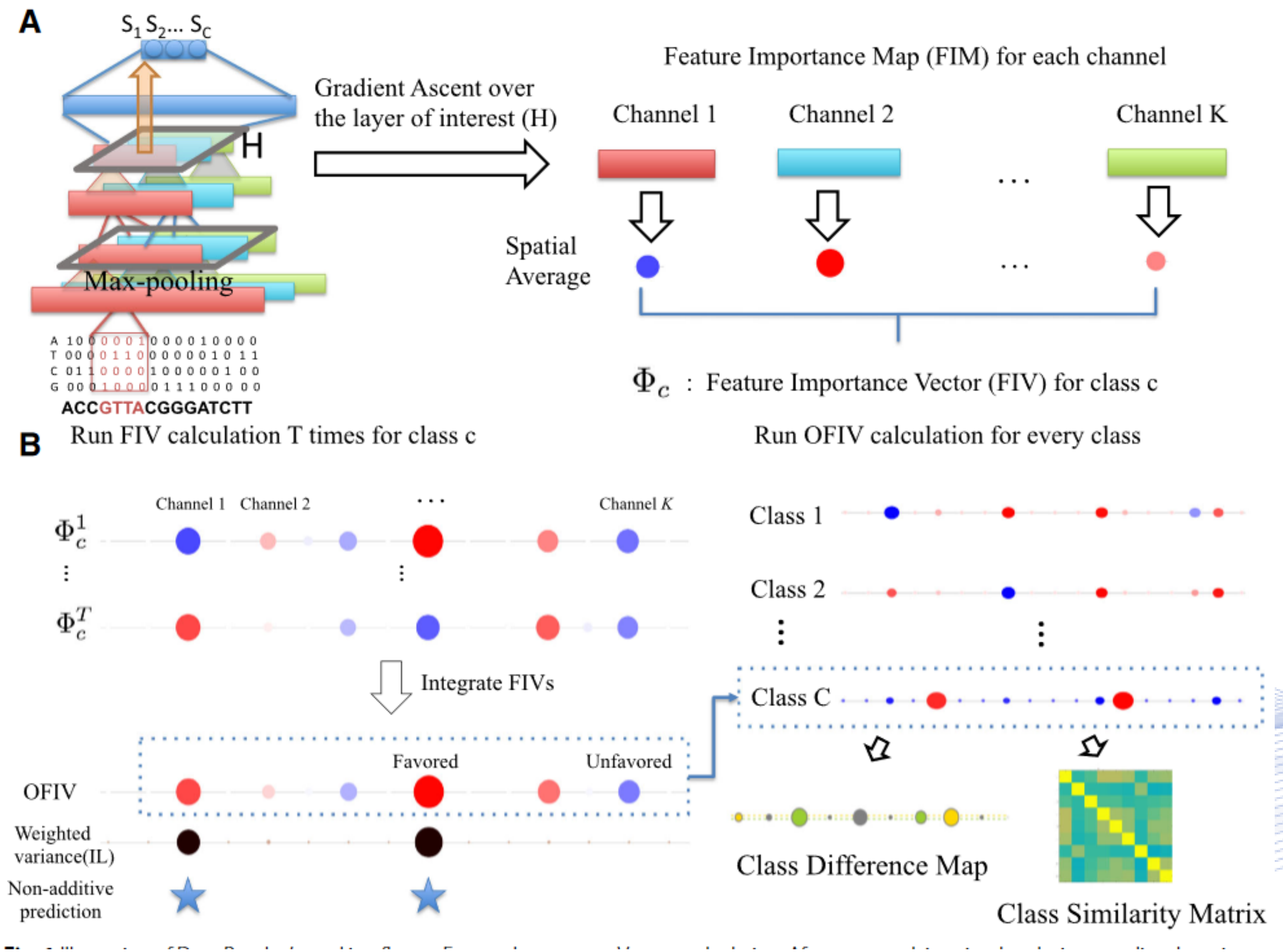


[Zeiler2014] Visualization of intermediate layers

DeepResolve

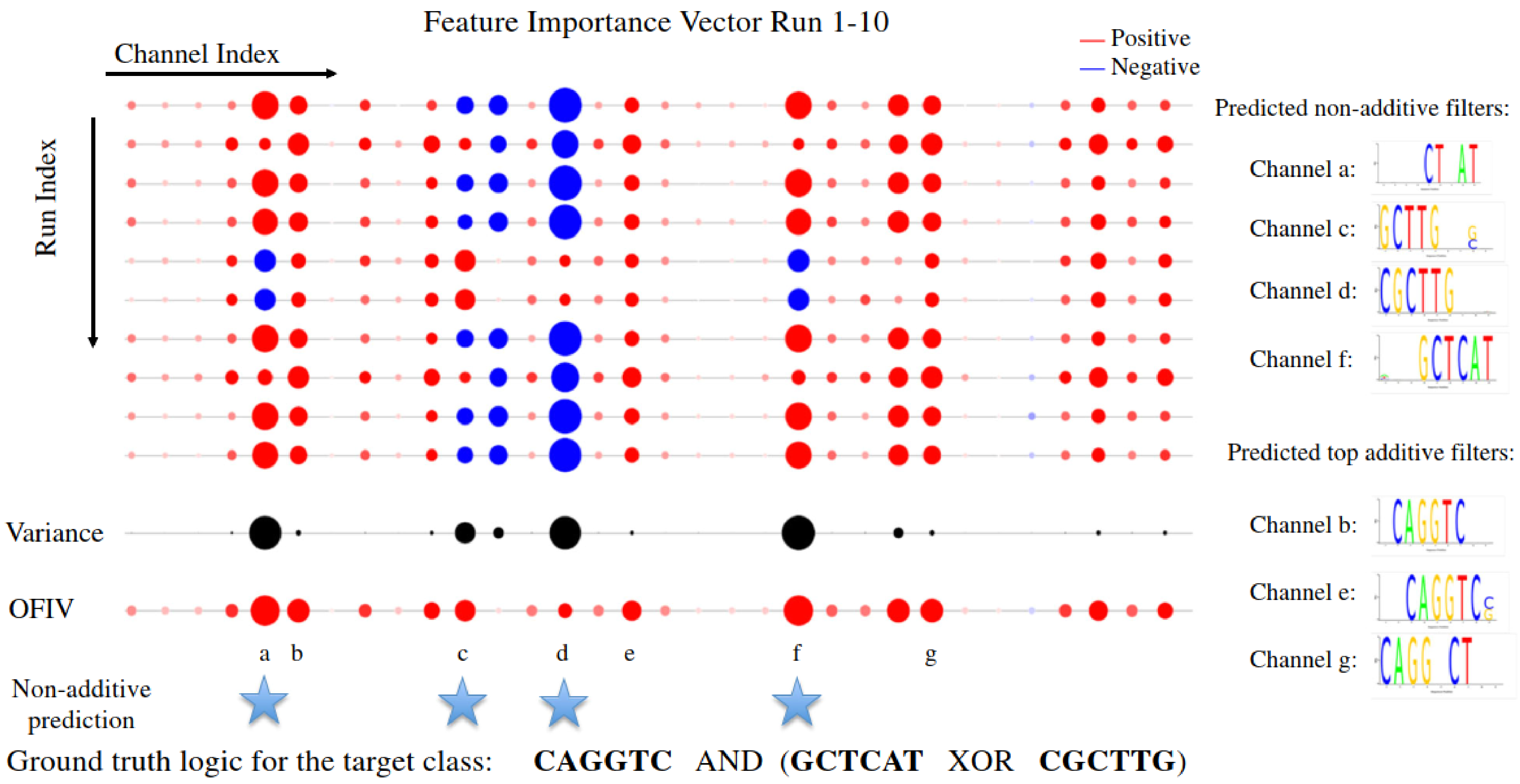
- Generate intermediate layer heatmaps to show how the network combines features for classification
- Compute optimized feature map $\mathbf{H_c} = argmax_{\mathbf{H}} S_c(\mathbf{H}) - \lambda||\mathbf{H}||_2^2$, S_c is the score of class c obtained from the last layer, λ tunable hyperarameter and $\mathbf{H} \in \mathbf{R}^{K \times W}$
- Global average of Feature Importance Maps (FIM) $\mathbf{H_c}$ to obtain feature importance vector (FIV) $\boldsymbol{\Phi}_\mathbf{c} = \left(\varphi_c^1, \ldots \varphi_c^k\right)$ where $\varphi_c^k = \frac{1}{W}\sum_{i=1}^{W}\left(H^k(i)\right)_c$
- This procedure is ran T times with different initial parameters to get several estimations of $\mathbf{H_c^t}$ and $\boldsymbol{\Phi}_\mathbf{c}^{\boldsymbol{t}}$

DeepResolve



[Liu2019] Working flow of DeepResolve

DeepResolve

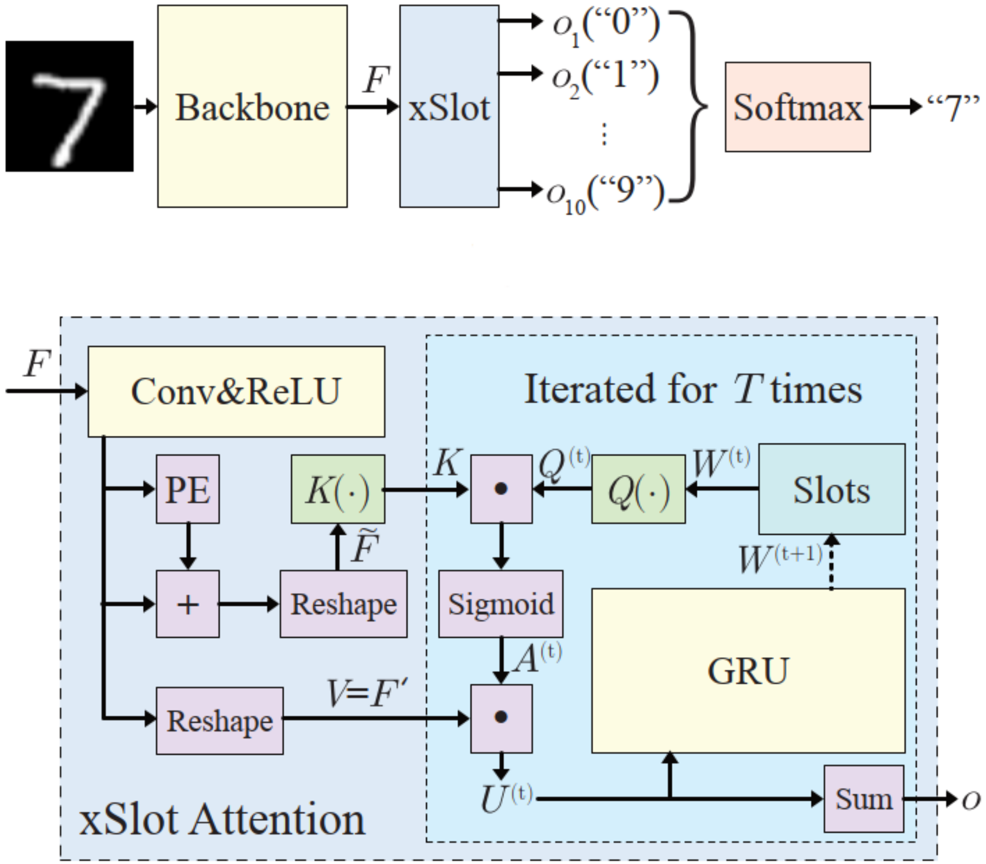


[Liu2019] Generation of importance vectors

SCOUTER

- Explain the reasons an image is classified or not to a specific class
- The cnn's classifier (fully connected layer) is replaced with a slot attention model
- Each slot produces a confidence score for each class
- The cnn's features $\mathbf{F}$ are passed through a convolutional layer and a position embedding to model the spatial information
- Then, a self-attention mechanism is utilized to compute the weighted sum of features as: $\mathbf{A}^{(t)} = \sigma(Q(\mathbf{W}^{(t)})K(\mathbf{F}))$
- σ: sigmoid function Q, K: fully-connected networks $\mathbf{W}^{(t)}$: slot weights

SCOUTER



[Li2020] SCOUTER overview

SCOUTER

[Li2020] Examples of positive and negative decisions

Visual explanation of deep neural networks by interpretation

- Identification of relevant features to the predictions of the network F
- Forward-propagation of N training images to obtain m–dimensional features

$$\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2 \ldots \mathbf{x}_N) \in \mathrm{R}^{N \times m}$$

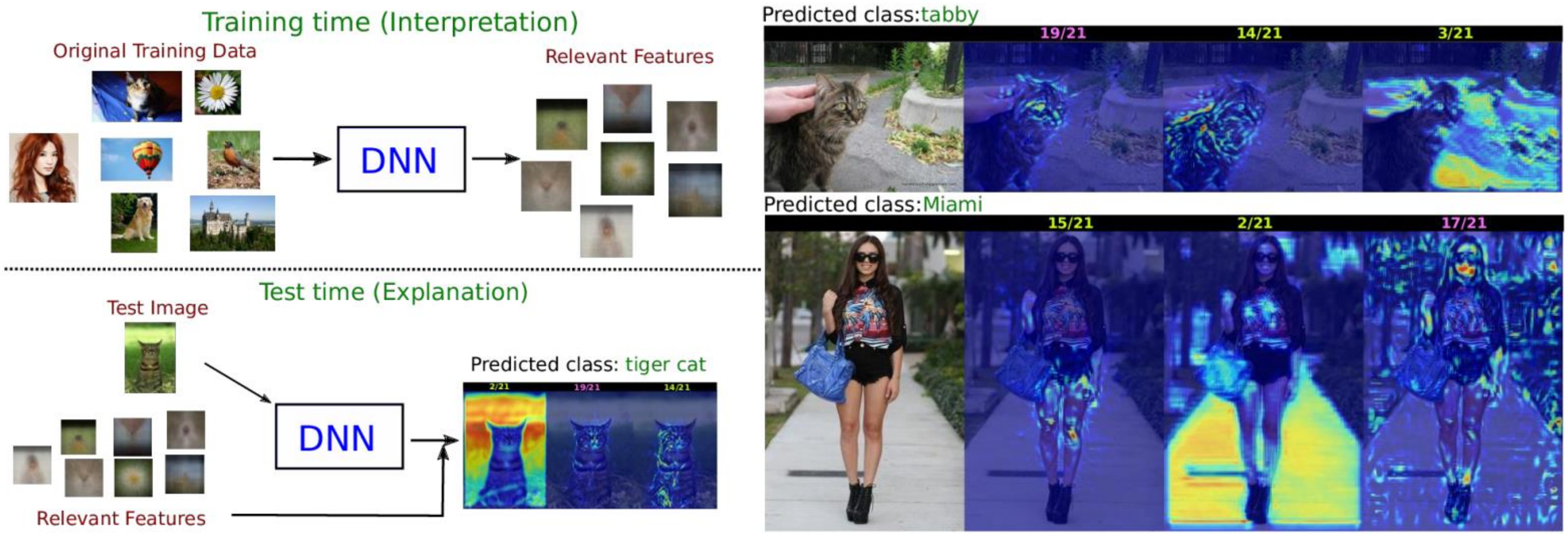
- Target labels $\mathbf{L} = (\mathbf{l}_1, \mathbf{l}_2, \ldots \mathbf{l}_N) \in \mathrm{R}^{C \times N}$
- Predict a linear combination of activations $\mathbf{X}$ for each class using

$$\mathbf{W} = (\mathbf{w}_1, \mathbf{w}_2, \ldots \mathbf{w}_N) \in \mathrm{R}^{C \times m}$$

by solving the optimization problem :

$$\mathbf{W}^* = argmin_{\mathbf{W}} \left|\left|\mathbf{X}^{\mathbf{T}}\mathbf{W} - \mathbf{L}^{\mathbf{T}}\right|\right|_F^2$$

Visual explanation of deep neural networks by interpretation

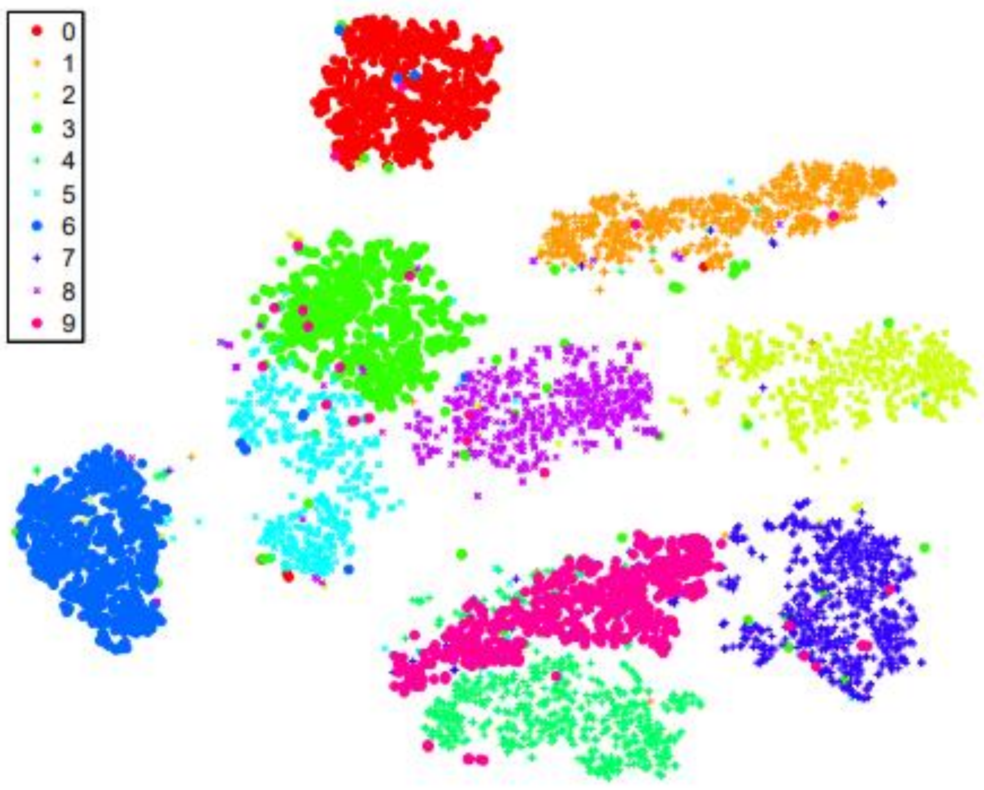


[Oramas2019] Overview of training and testing pipeline

Plot visualizations

- Produce scatter plots to explain decisions or visualize the data
- Methods
  - t-SNE
  - Understanding deep features using PCA
  - Visualization of hidden layers
  - TreeView

t-distributed stochastic neighbor embeddings (t-SNE)

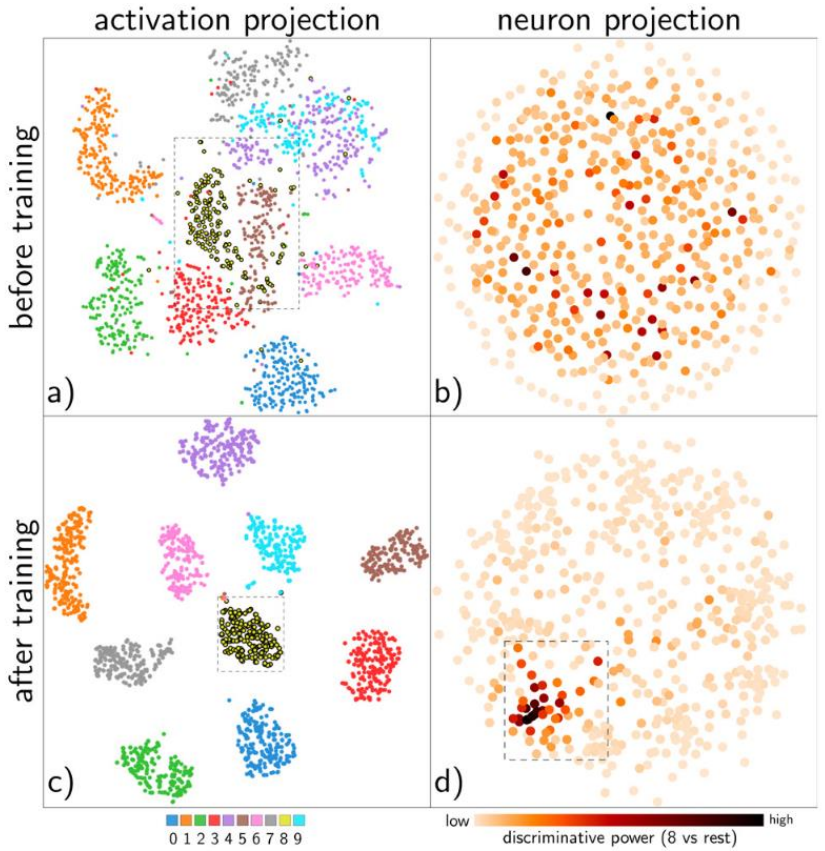


[Maaten2008] Visualization of MNIST

Visualization of hidden layers

- 2D scatter-plot the projections of the hidden neurons' activation coloured according to the class
- Dimensionality reduction and visualization of:
  - observations
  - neuron's relationships
- Clustering of activations in groups to explain predictions

Visualization of hidden layers



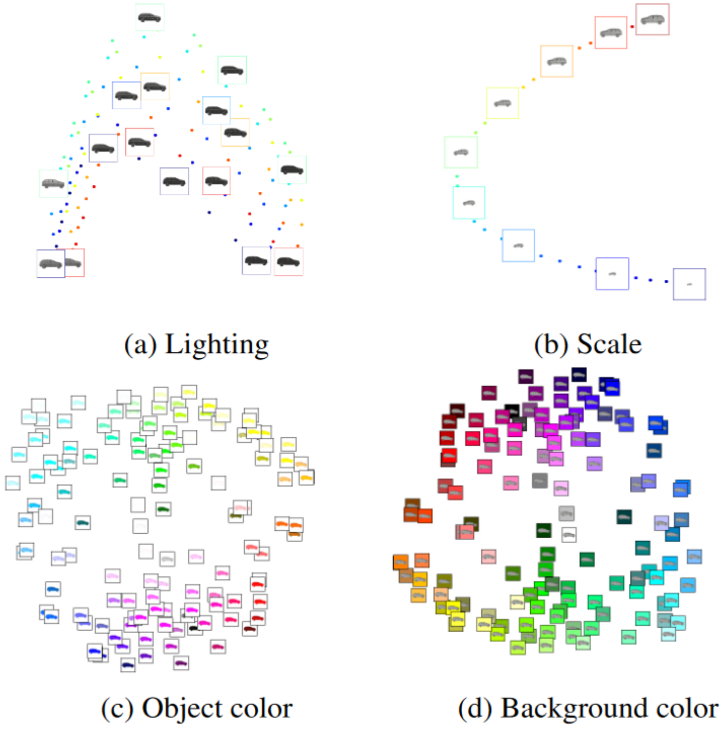
[Rauber2016]T-SNE projection of neurons and classes on MNIST test set

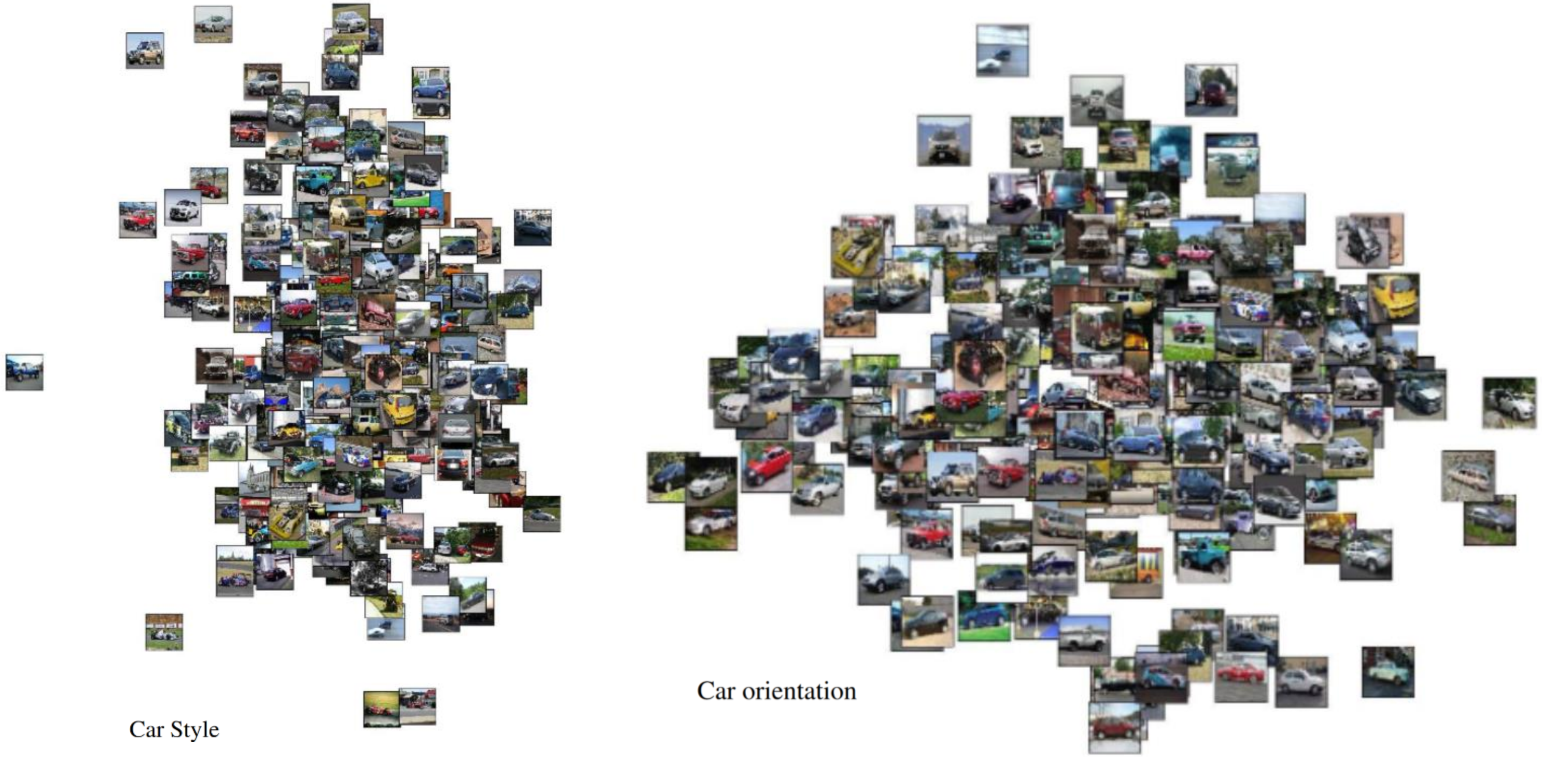
Understanding deep features using PCA

- analyzes CNN feature responses of layers with decomposition into a linear combination of principal components using knowledge from the input scene
- Given
  - an image r_θ from a set $\mathbf{\Omega}$ with Θ images indexed from $\theta \in [1, \Theta]$
  - features $\hat{\mathbf{F}}^L(r_\theta)$ of the L_{th} layer of CNN
- Calculate centered features $\mathbf{F}^L(r_\theta) = \hat{\mathbf{F}}^L(r_\theta) - \frac{1}{\Theta}\sum_{t=1}^{\Theta} \hat{\mathbf{F}}^L(r_t)$
- r_t: t image from set $\mathbf{\Omega}$
- Compute eigenvectors of the covariance matrix:

$$\frac{1}{\Theta}\sum_{\theta=1}^{\Theta} \mathbf{F}^L(r_\theta)\mathbf{F}^L(r_\theta)^{\mathbf{T}}$$

Understanding deep features using PCA





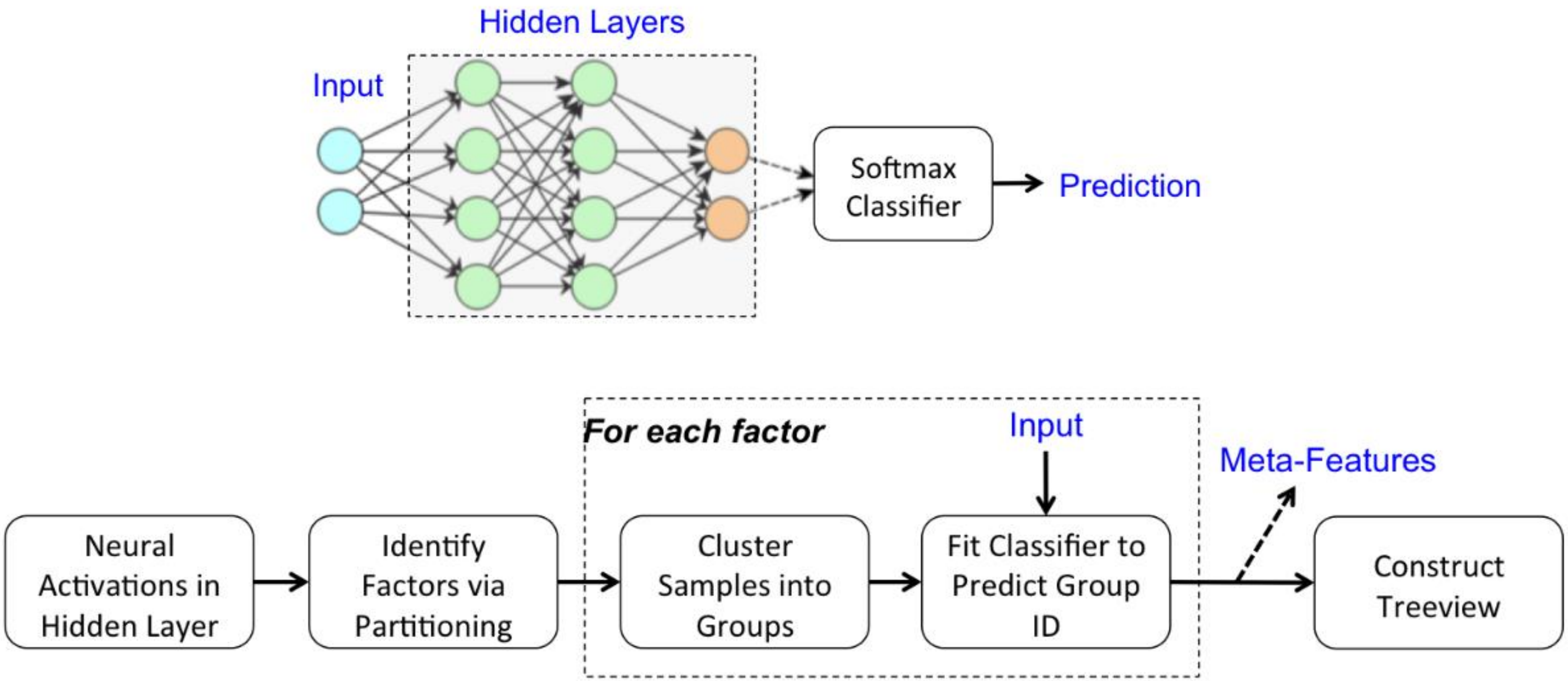
[Aubry2015] PCA embeddings based on different factors

TreeView

- Hierarchical decomposition of the feature subspaces
- Transformation $T_1: \mathbf{X} \rightarrow \mathbf{Y}$ input from space: $\mathbf{X}$ into new space of features: $\mathbf{Y}$,
- Transformation $T_2: \mathbf{Y} \rightarrow \mathbf{Z}$ classify features $\mathbf{Y}$ to label space $\mathbf{Z}$

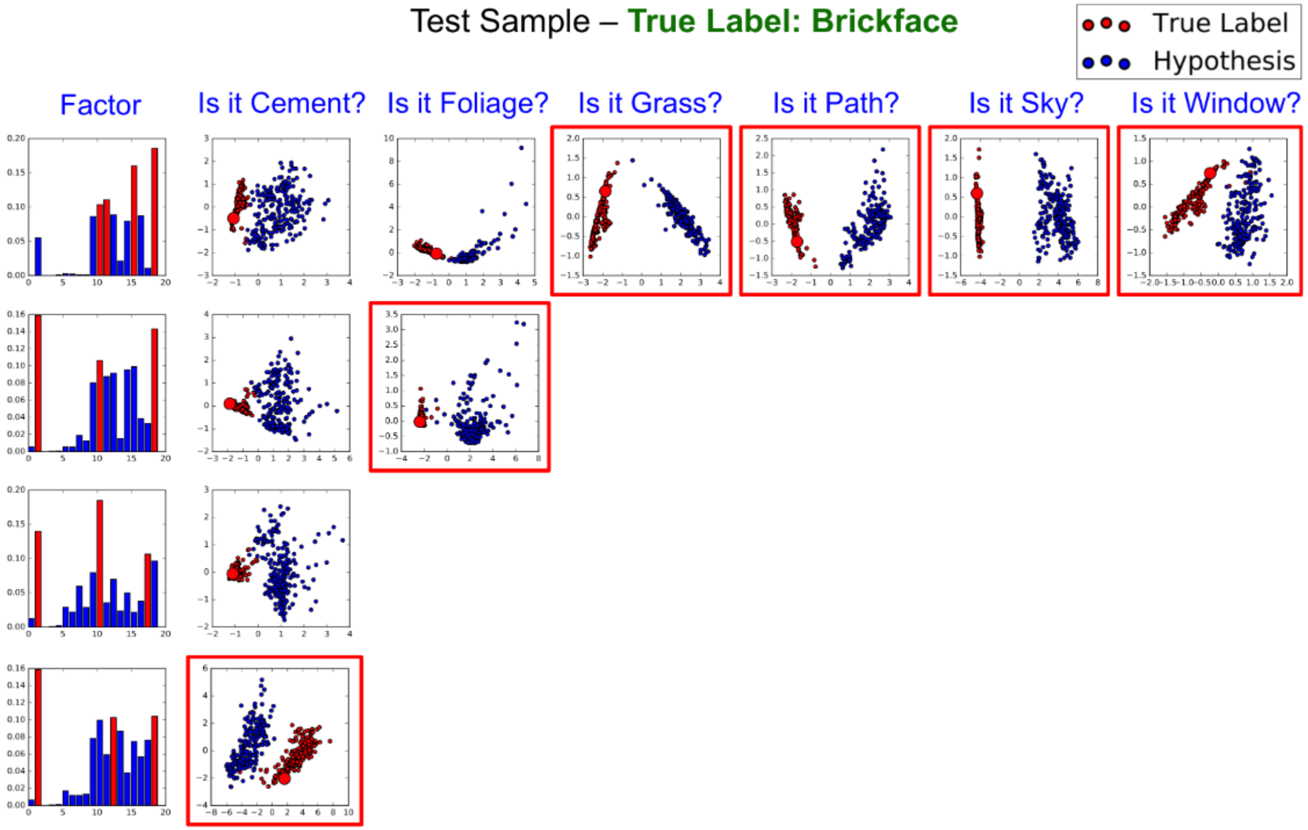
- Partition space of features: $\mathbf{Y}$ into K subspaces with similar activations of the hidden layers
- Each cluster i describes a specific factor S_i
- A new K-dimensional vector from cluster labels is constructed and used for visualization

TreeView



[Thiagarajan2016] TreeView method

TreeView

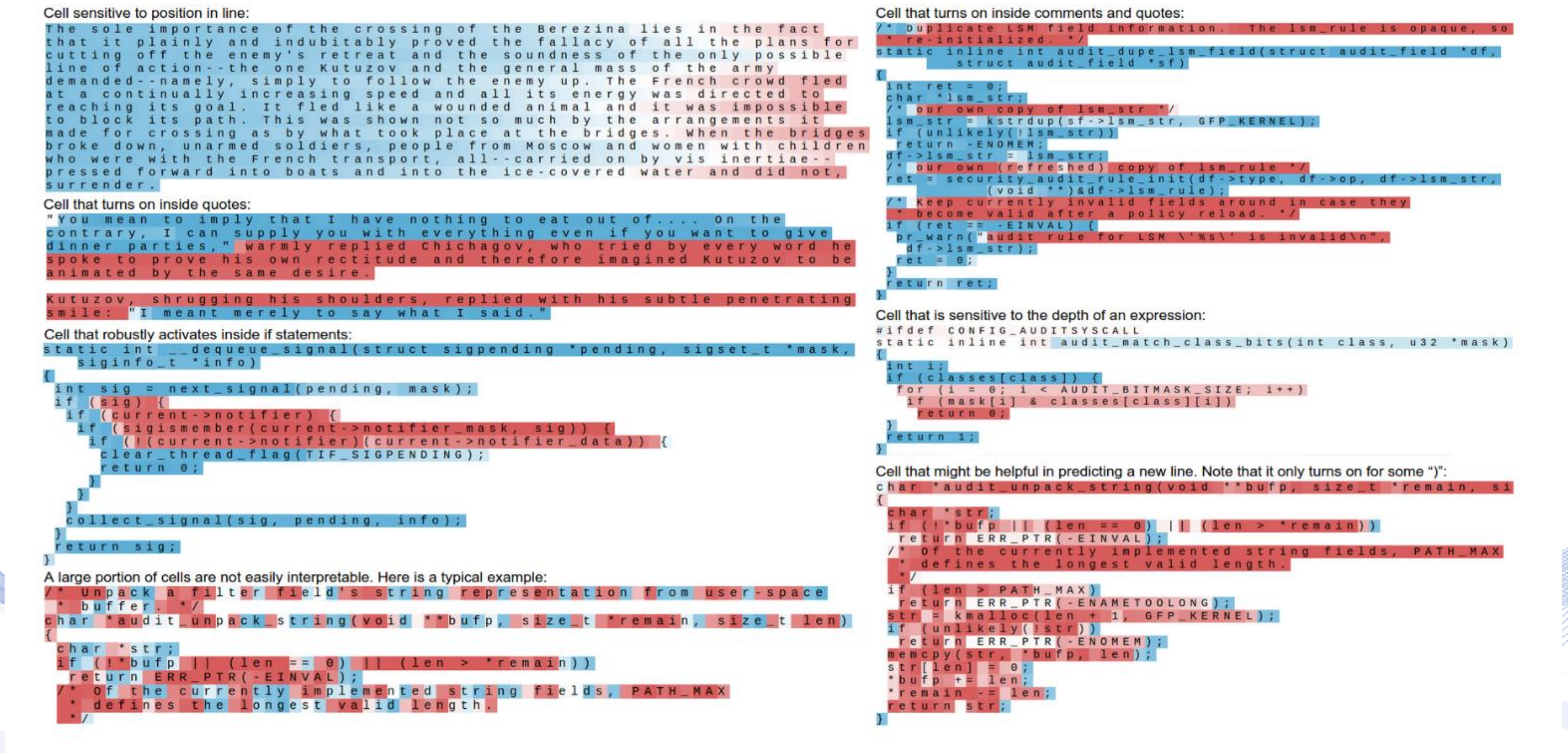


[Thiagarajan2016] Visualization of a correctly classified example for each factor

Textual explanations

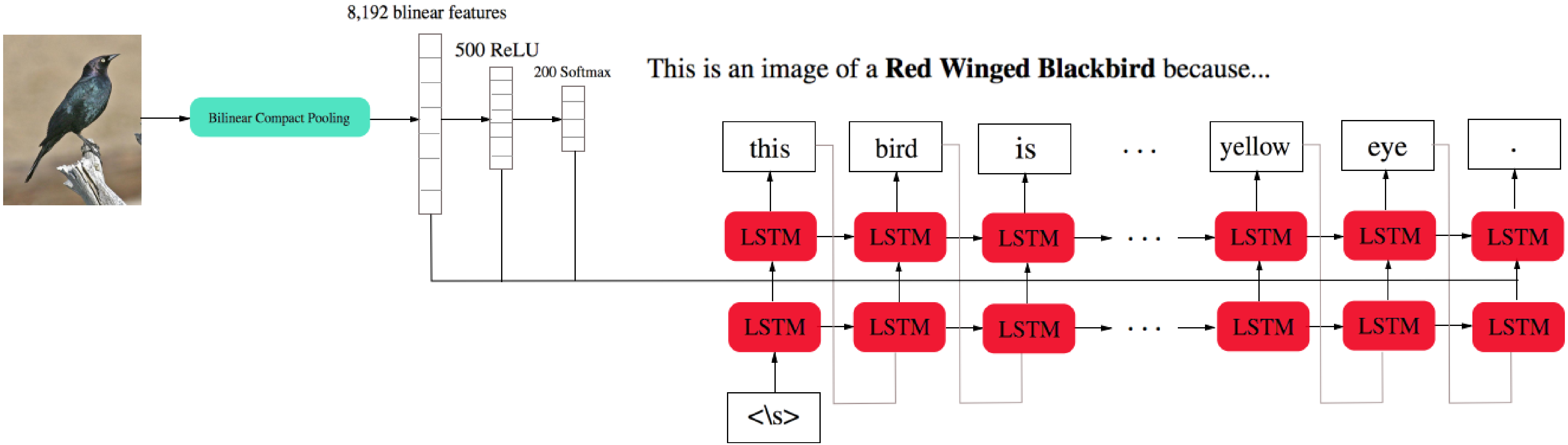
- Produce natural language-text to explain the decisions of the algorithm
- Find semantic words that provide qualitative explanations
- Methods
  - Cell Activation Value
  - InterpNET
  - Hierarchical Question and Image Co-Attention for Visual Question Answering
  - Visual Dialog
  - Explain Deep Neural Networks with Semantic Information

Cell Activation Value



[Karpathy2015] activations of LSTM. Text color corresponds to activation value

InterpNET



[Barratt2017] Overview of Interpnet

InterpNET

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.

This is an image of an **Ivory Gull** because...

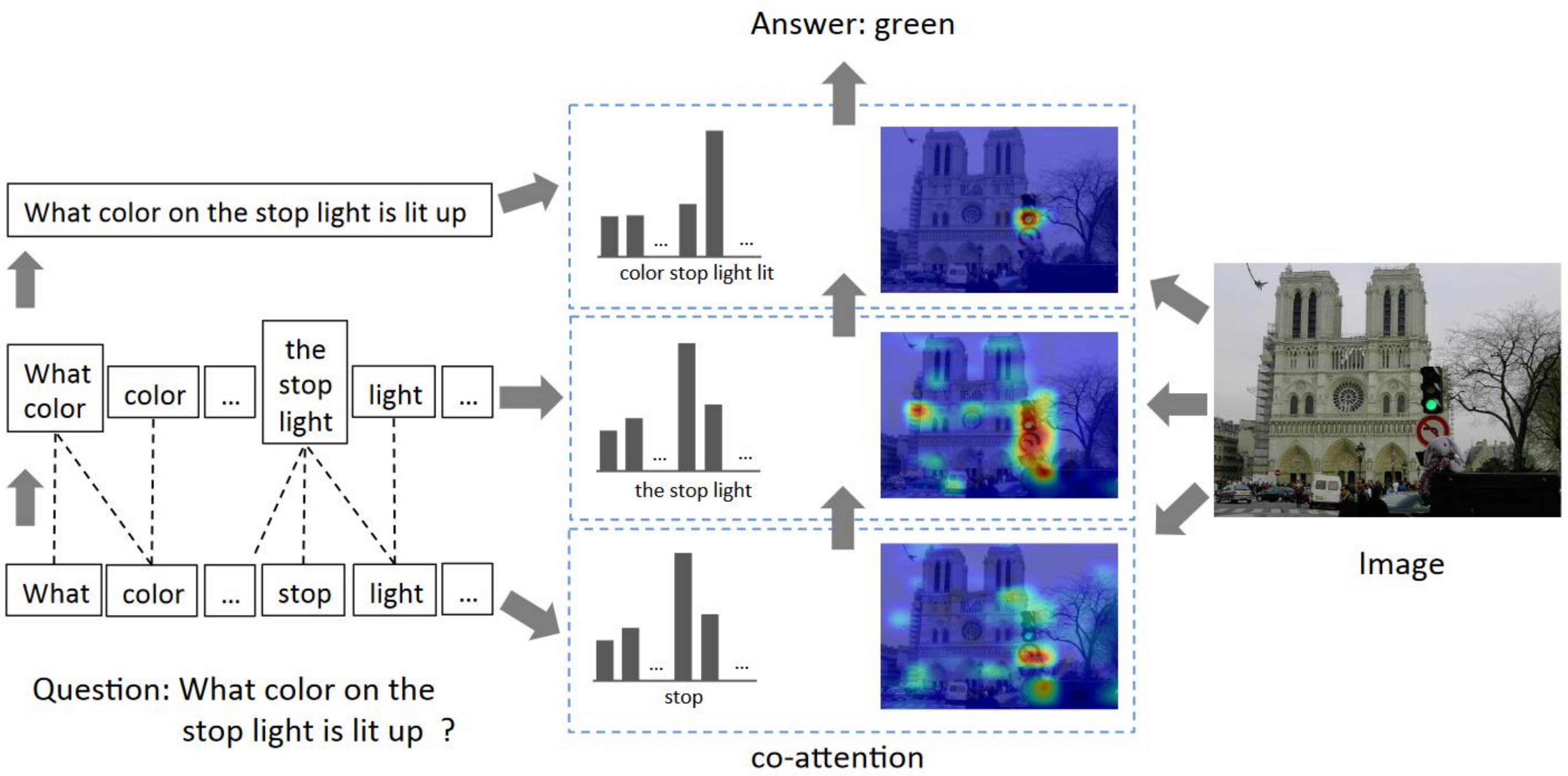
InterpNET(0)	this bird has wings that are white and has a yellow bill.
InterpNET(1)	this bird has wings that are black and has a white belly.
InterpNET(2)	this bird has wings that are grey and has a white belly.
InterpNET(3)	this bird has wings that are grey and has a white belly.
Captioning	this bird has a white belly and breast with a black wing and long hooked bill.

This is an image of a **Scott Oriole** because...

InterpNET(0)	this bird has a yellow belly and breast with a black superciliary and white wingbars.
InterpNET(1)	this bird has a black crown, black primaries, and a yellow belly.
InterpNET(2)	this bird has wings that are black and has a yellow belly.
InterpNET(3)	this bird has a black crown, a black bill, and a black breast.
Captioning	this bird has a black crown, black primaries, and a white belly.

[Barratt2017] Examples of InterpNet text generations

Hierarchical Question-Image Attention for Visual Question Answering

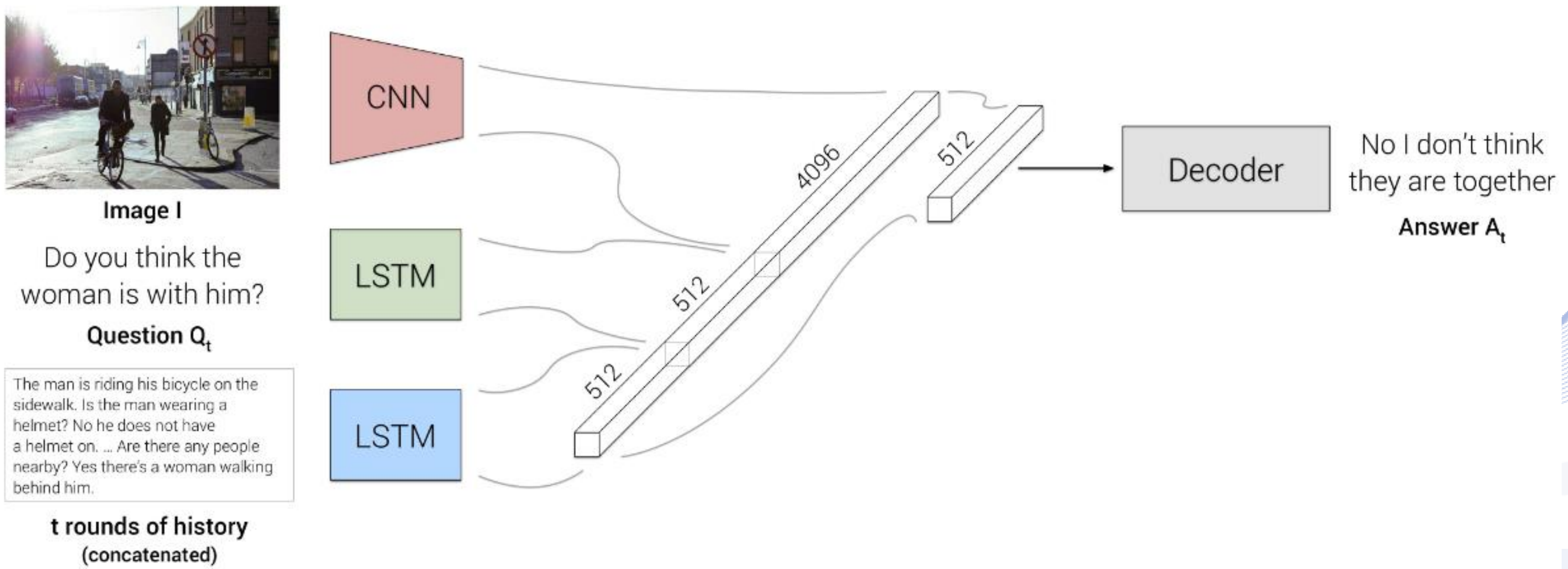


[Lu2016] Types of attention

Hierarchical Question-Image Attention for Visual Question Answering

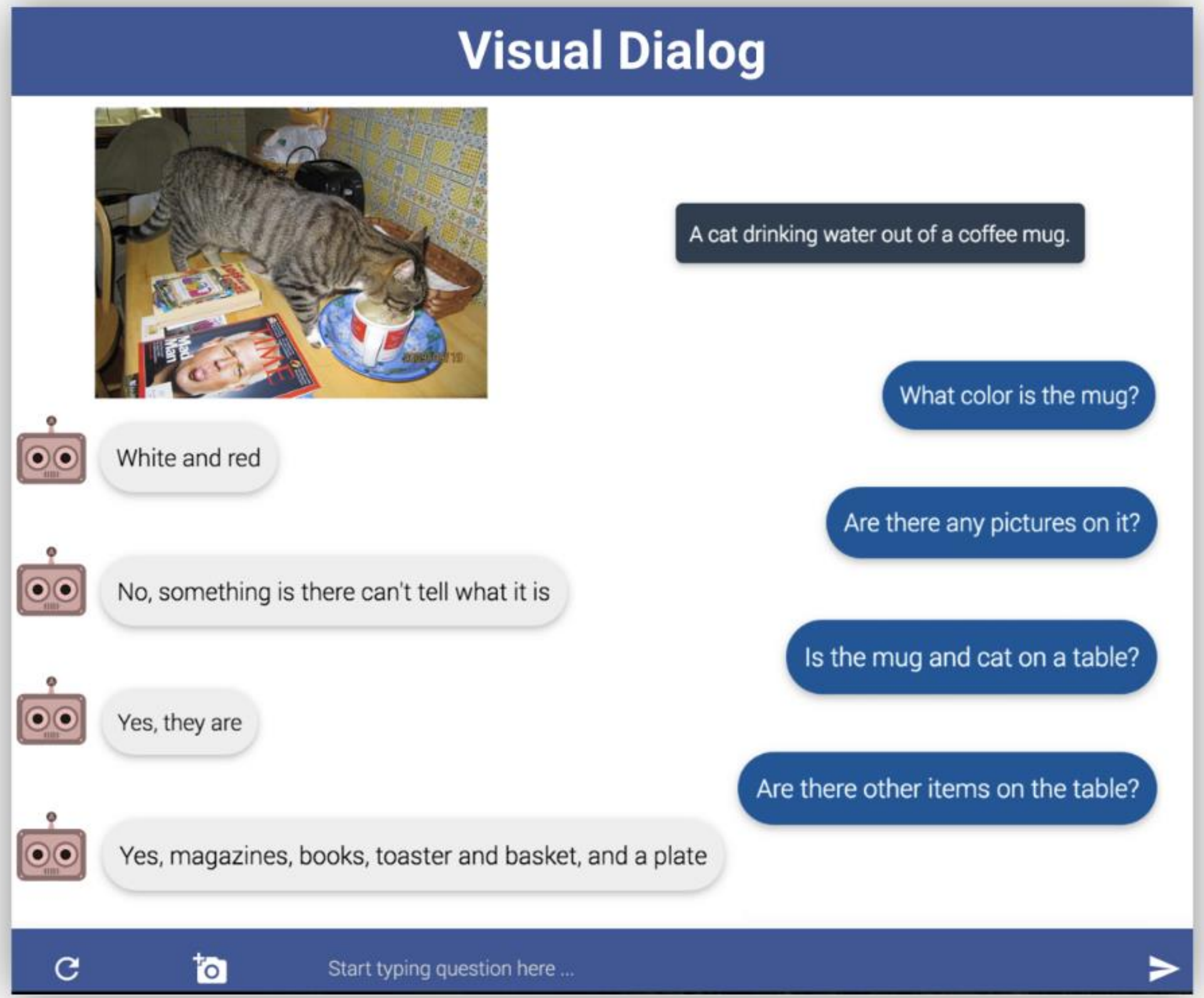
[Lu2016] Example of attention maps

Visual dialog



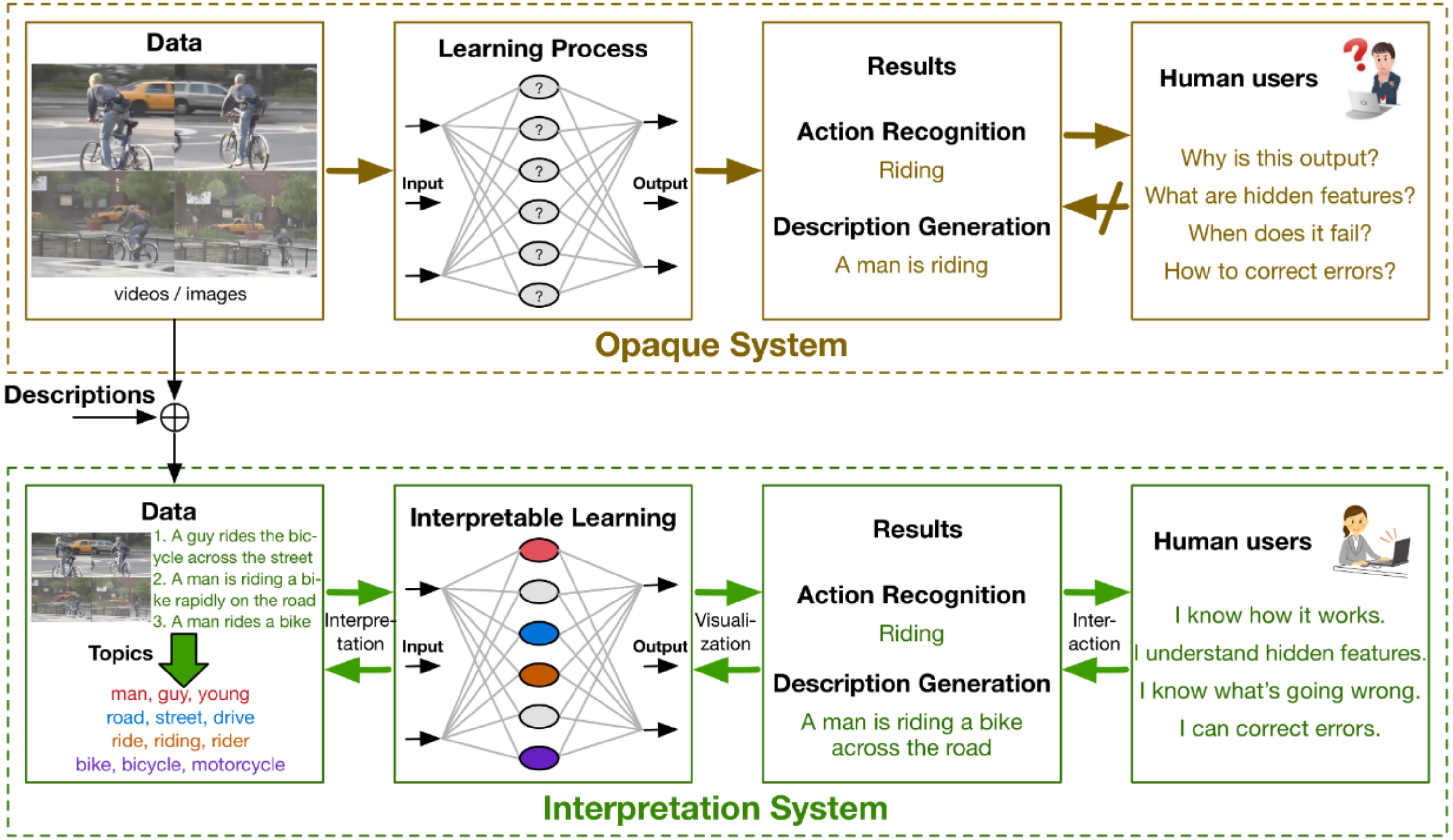
[Das2018] Visual dialog system to predict the answer

Visual dialog



[Das2018] Dialog of AI and human

Semantic explanation of Deep Neural Networks



[Dong2017] Overview of the method

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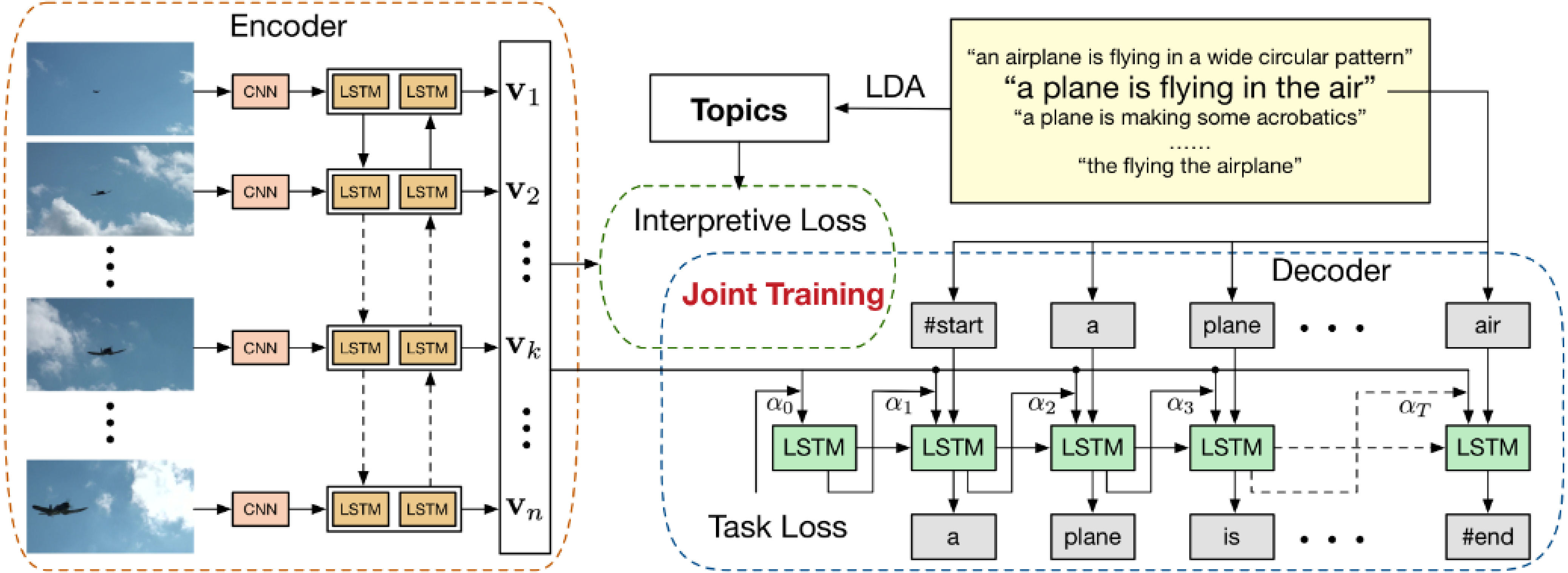
Semantic explanation of Deep Neural Networks

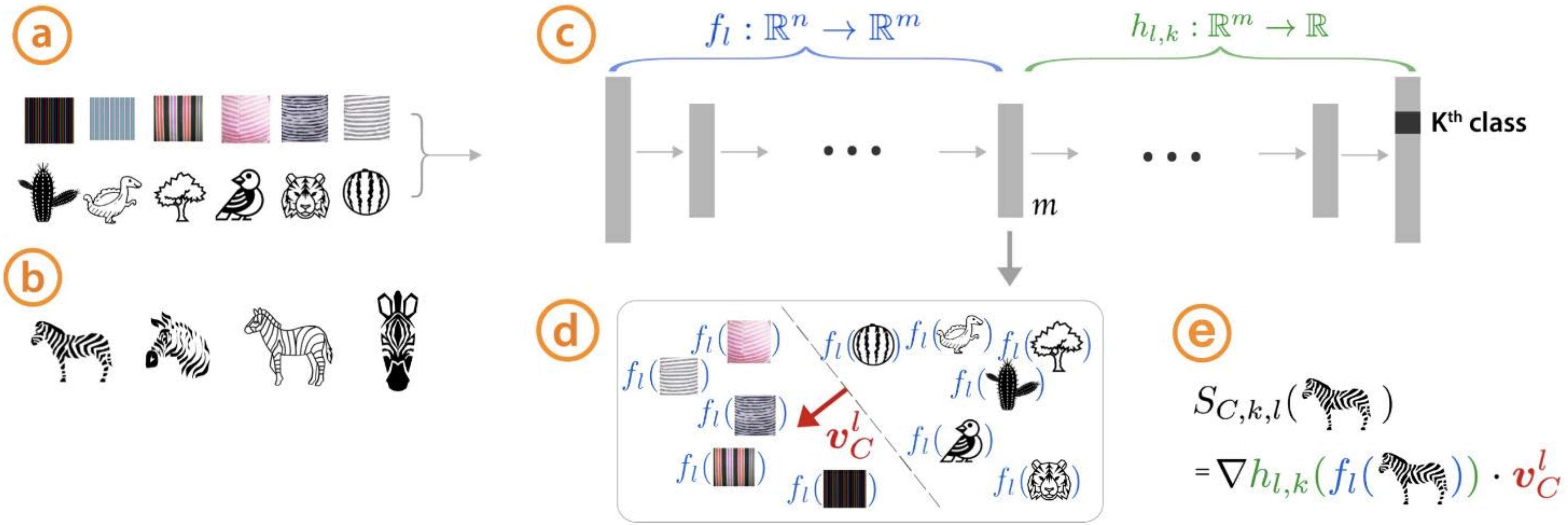


[Dong2017] Video captioning encoder's training process along with human descriptions decoder

Numerical Explanations

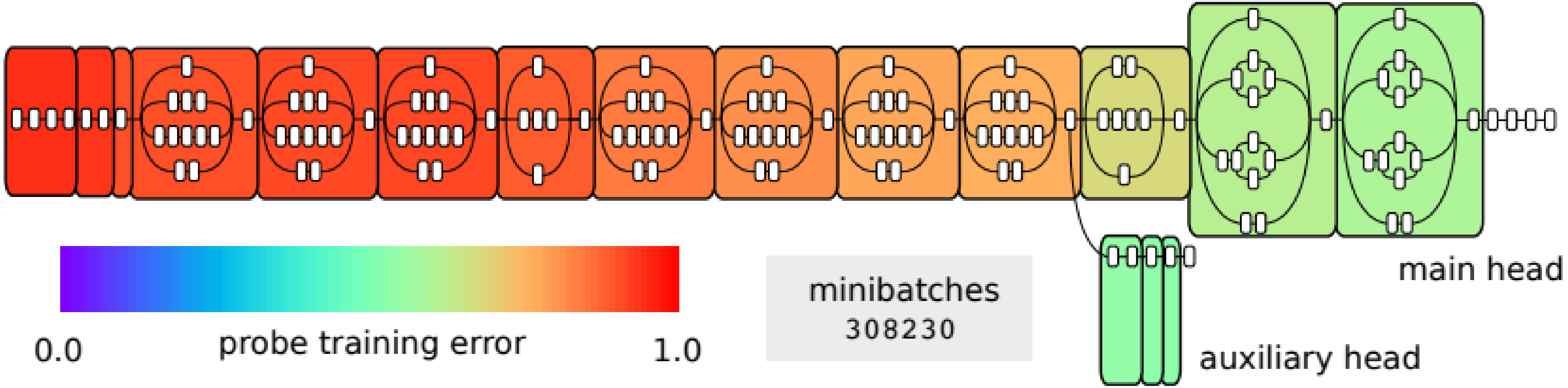
- Provide numerical outputs to interpet models
- Train classifiers that explain the model
  - Concept Activation Vectors
  - Linear classifier probes
  - LIME

Concept Activation Vectors (CAV)



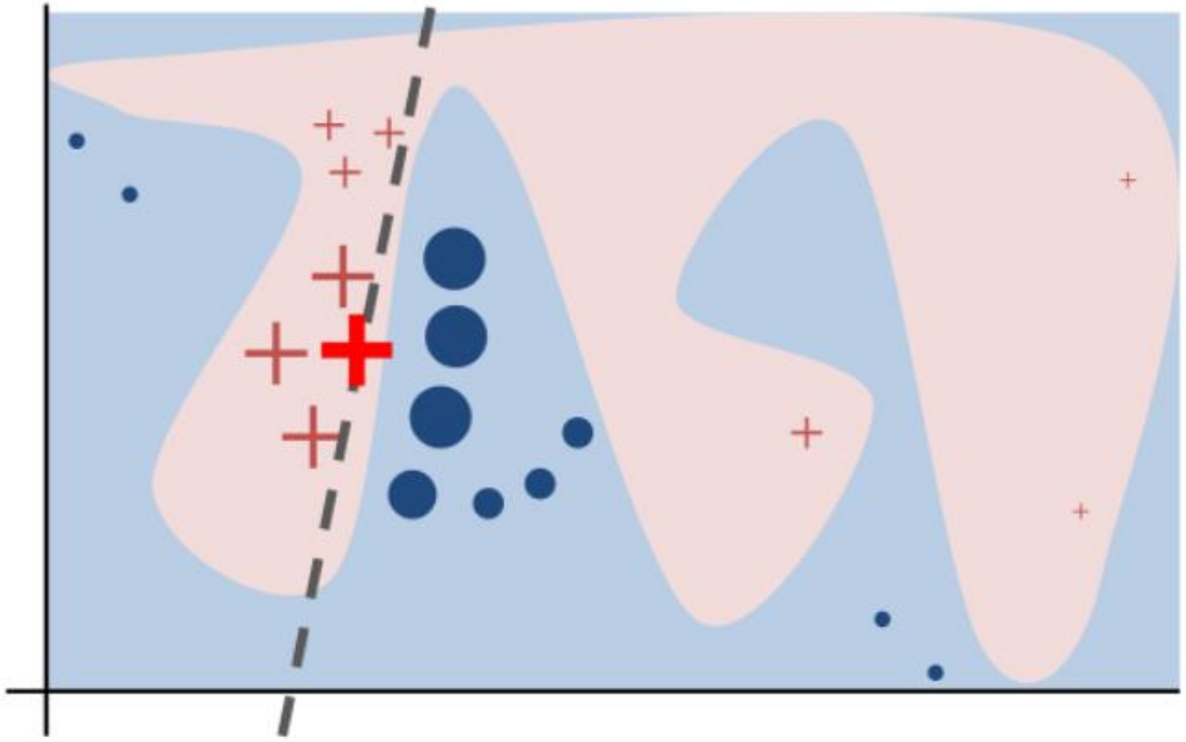
[Kim2018] Overview of CAVs learning process

Linear classifier probes



[Alain2016] Prediction error of each layer using probe

LIME (Local Interpretable Model-agnostic Explanations)



[Ribeiro2016] The data represented with the red cross is explained locally using the dashed line.

Applications

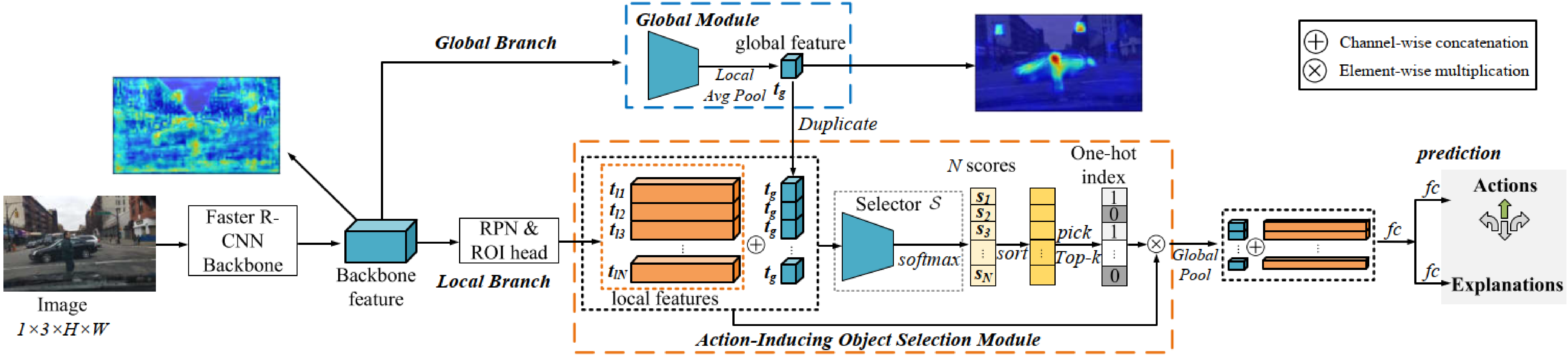
of explainable methods in important tasks

- Autonomous Driving
  - Advisable Learning for Self-driving Vehicles by Internalizing Observation-to-Action Rules
  - Explaining Autonomous Driving by Learning End-to-End Visual Attention
- Medical Applications
  - COVID detection

Explainable Object-induced Action Decision for Autonomous Vehicles

- Explainable autonomous driving architecture
- Global module to generate scene context
- Local module to predict actions and explanations
- Concatenation of the two modules to improve decision accuracy
- Predict next action such as (stop, turn left, go forward) and the explanations e.g. Stop, the traffic light is red , an obstacle is in front stop the car)

Explainable Object-induced Action Decision for Autonomous Vehicles



[Yu2020] Overview of the proposed explainable self-driving method

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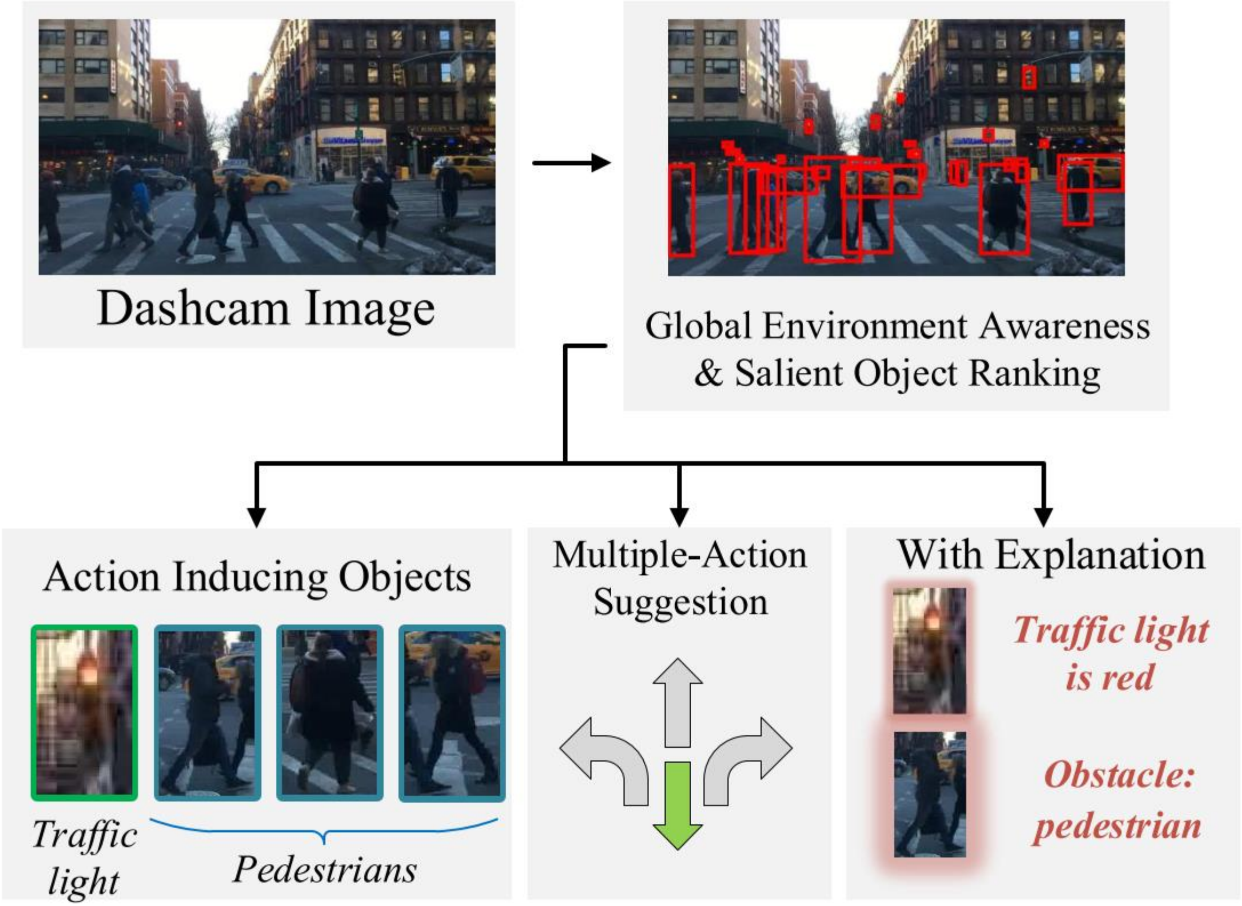
Explainable Object-induced Action Decision for Autonomous Vehicles



[Yu2020] Examples of action and explanations of the system

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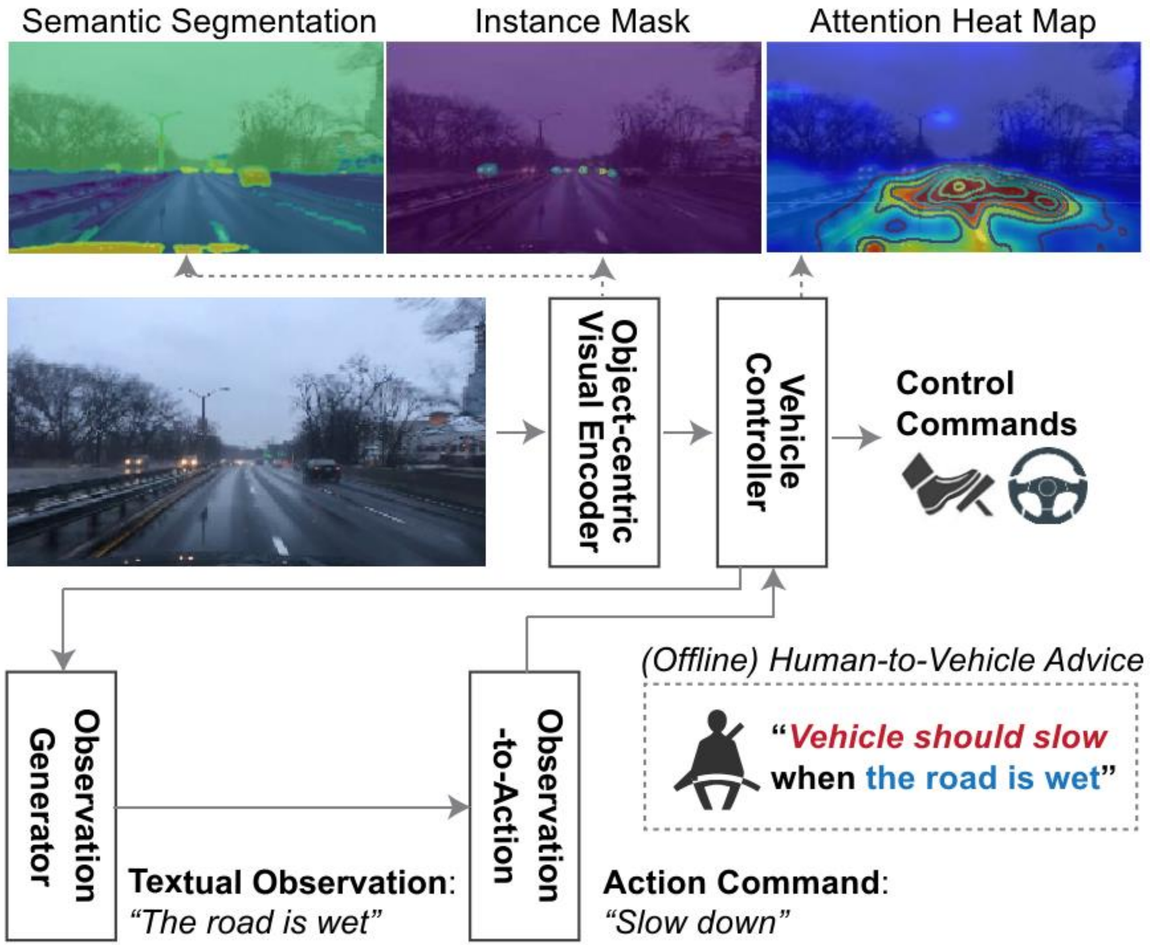
Advisable Learning for Self-driving Vehicles by Internalizing Observation-to-Action Rules

- Explainable self-driving system
- Human advice integrated on the architecture
- Visual (attention maps) and textual explanations (sentences)
- Main modules
  1. Object segmentation encoder
  2. Vehicle controller
  3. Observation generator
  4. Action generator

Advisable Learning for Self-driving Vehicles by Internalizing Observation-to-Action Rules

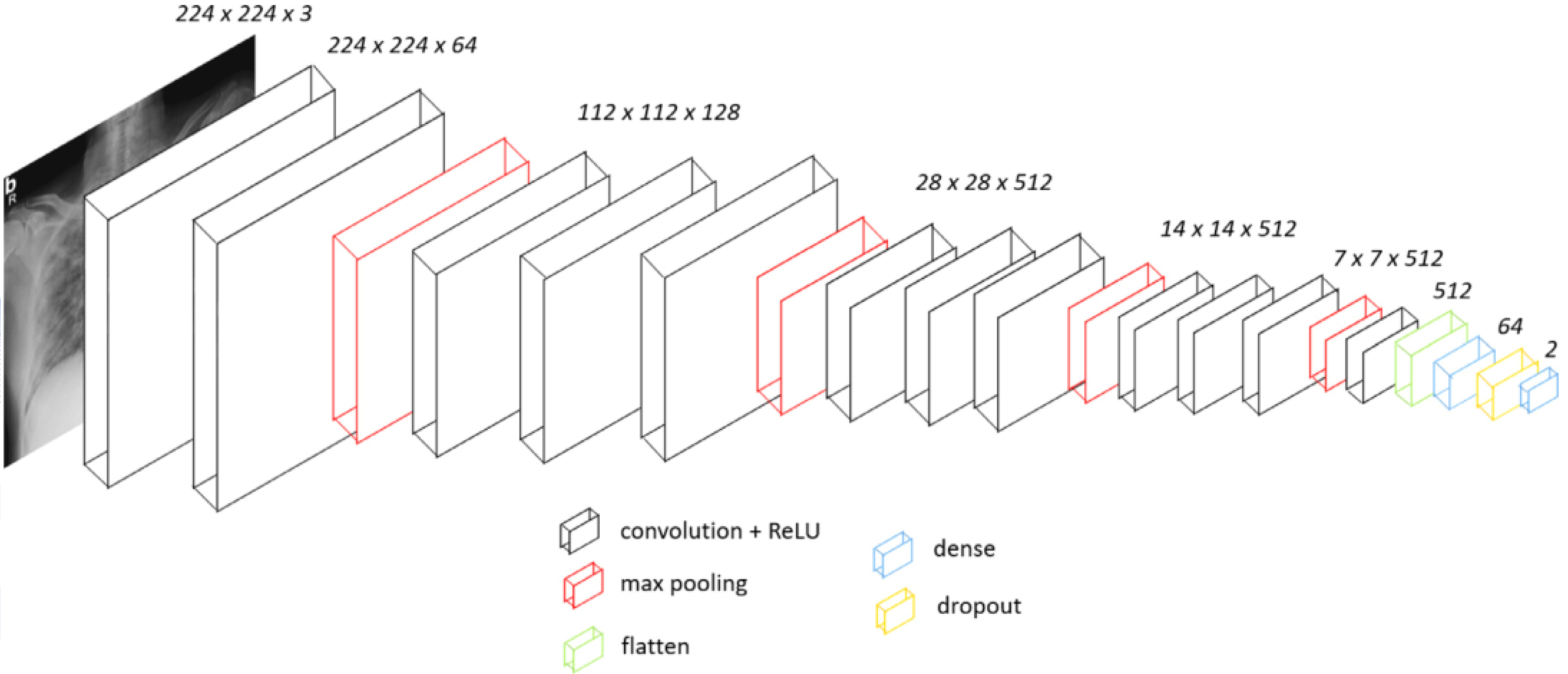


[Kim2020] Workflow of the self-driving system

Explainable Pulmonary Disease and COVID-19 Detection from X-rays

- Deep convolutional network VGG-16 is used to distinguish between healthy lungs, pneumonia or covid-19
- Grad-CAM provides interpets decisions by visualizing feature maps
- Localize areas responsible for the detection of pneumonia or covid-19

Explainable Pulmonary Disease and COVID-19 Detection from X-rays



[Brunese2020] CNN architecture

Explainable Pulmonary Disease and COVID-19 Detection from X-rays

[Brunese2020] Response maps of input chest x-ray

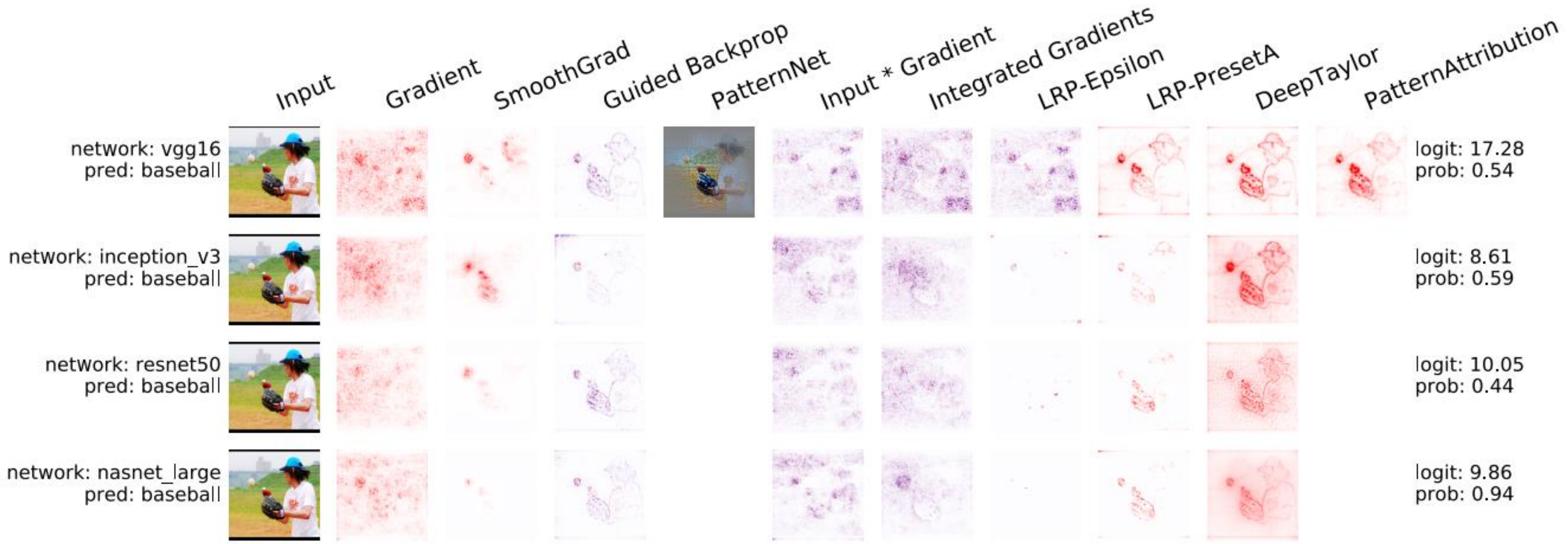
Explainable AI frameworks

with implemented explainable methods can be used for interpetation

- iNNvestigate Neural Networks
- ExplAIner
- InterpretML

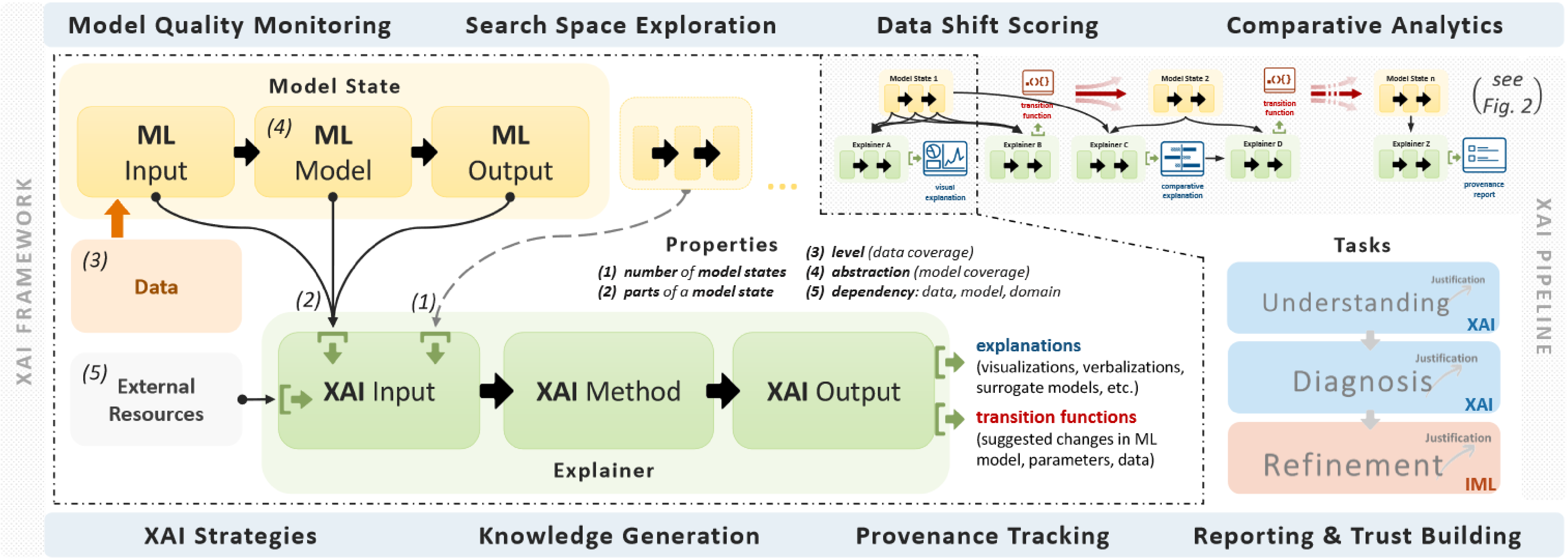
iNNvestigate Neural Networks

```
import innvestigate
model = create_a_keras_model()
analyzer = innvestigate.create_analyzer(''analyzer_name'', model)
analyzer.fit(X_train) # if needed
analysis = analyzer.analyze(X_test)
```



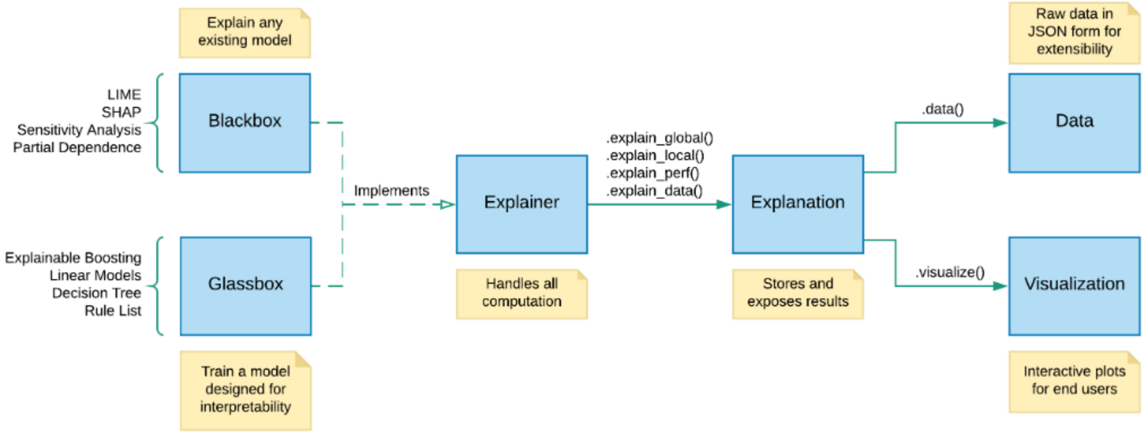
[Alber2019] Usage Example of iNNvestigate Neural Networks

ExplAIner



[Spinner2019] General approach of explAIner

InterpretML



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)
```

[Nori2019] Example of InterpetML usage

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