Feature representation and learning

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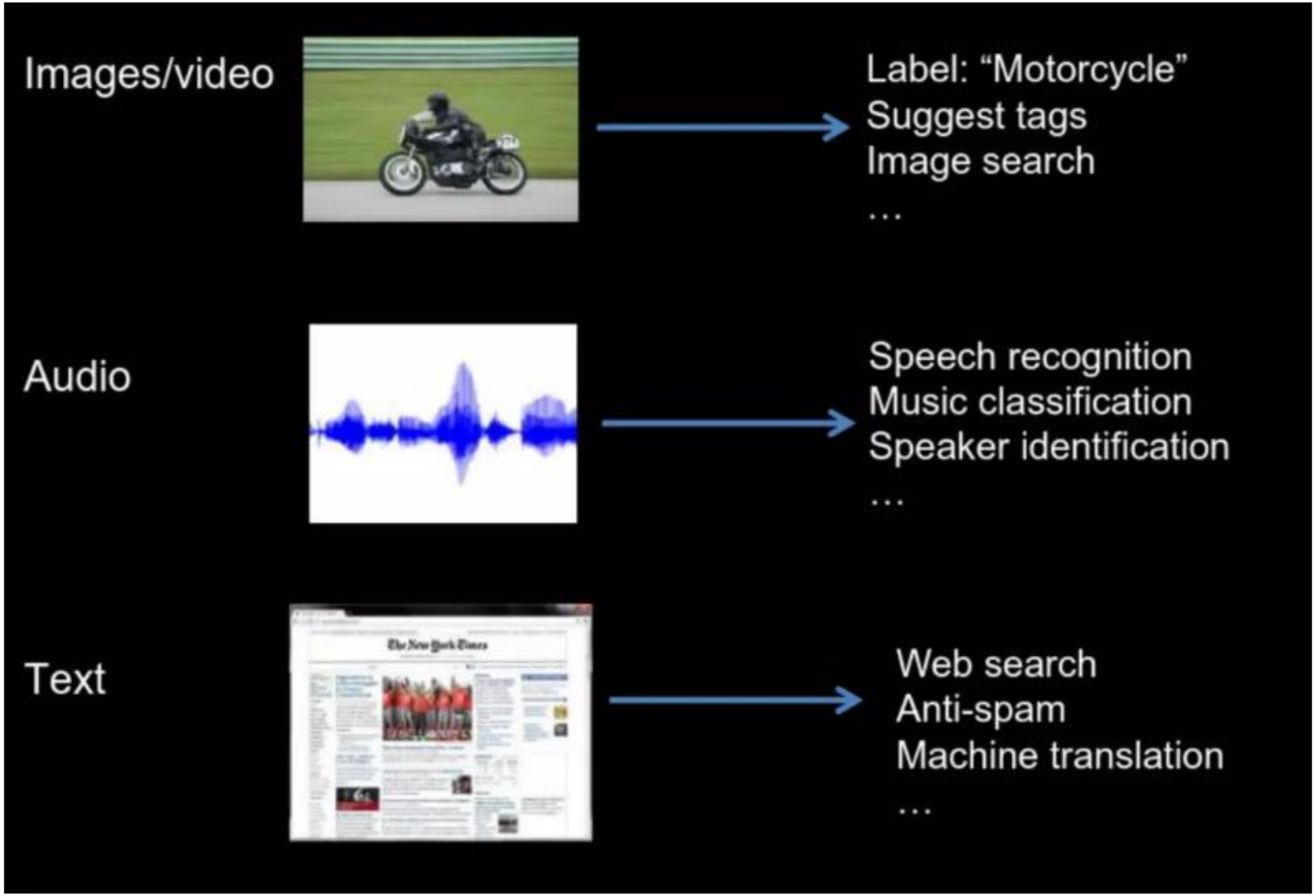
Different types of data features



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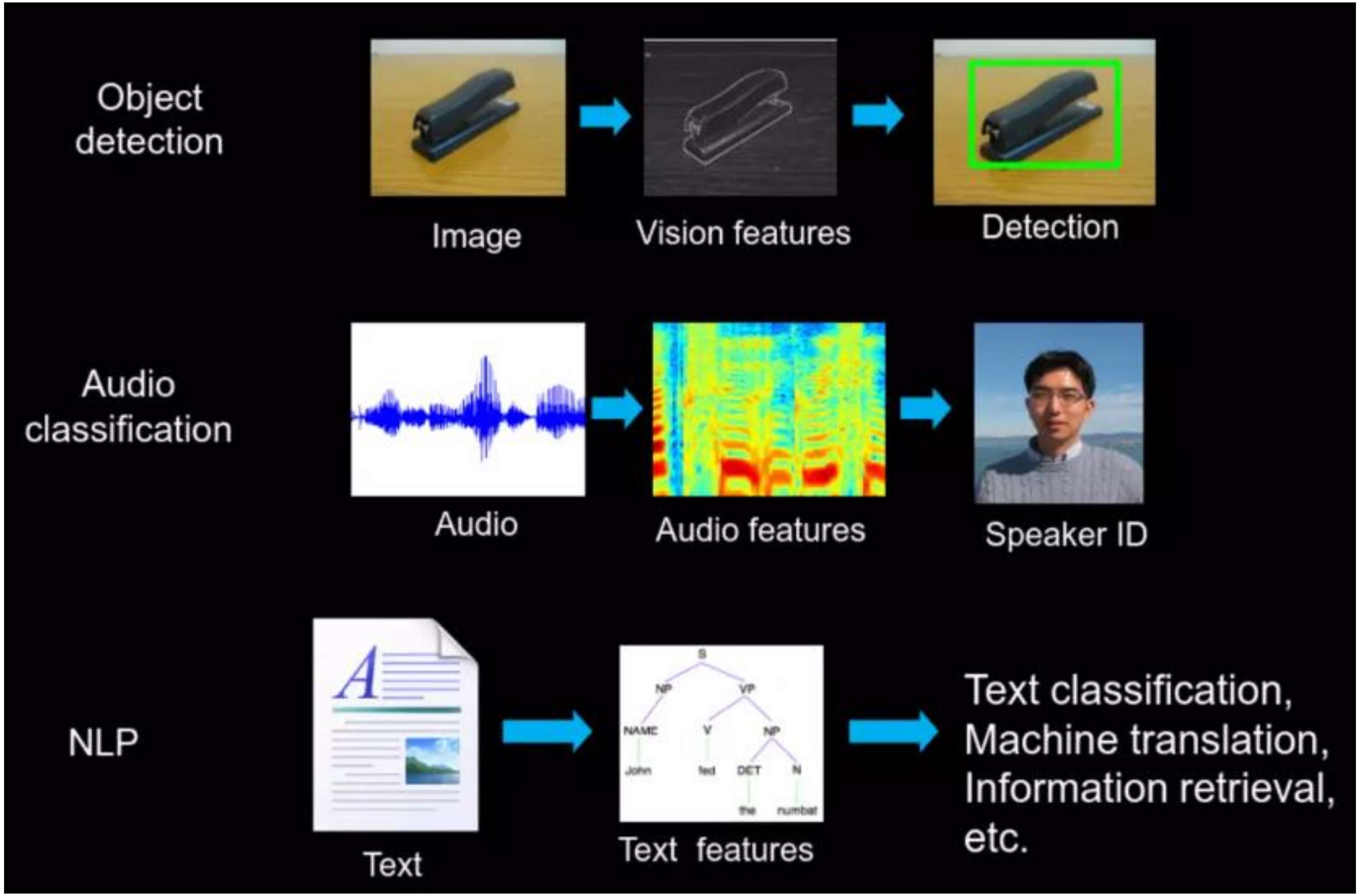
How computer perception work?



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What is feature representation

- In a deep learning architecture, the output of each intermediate layer can be viewed as a representation of the original input data.

- Each level uses the representation produced by previous level as input, and produces new representations as output, which is then fed to higher levels.

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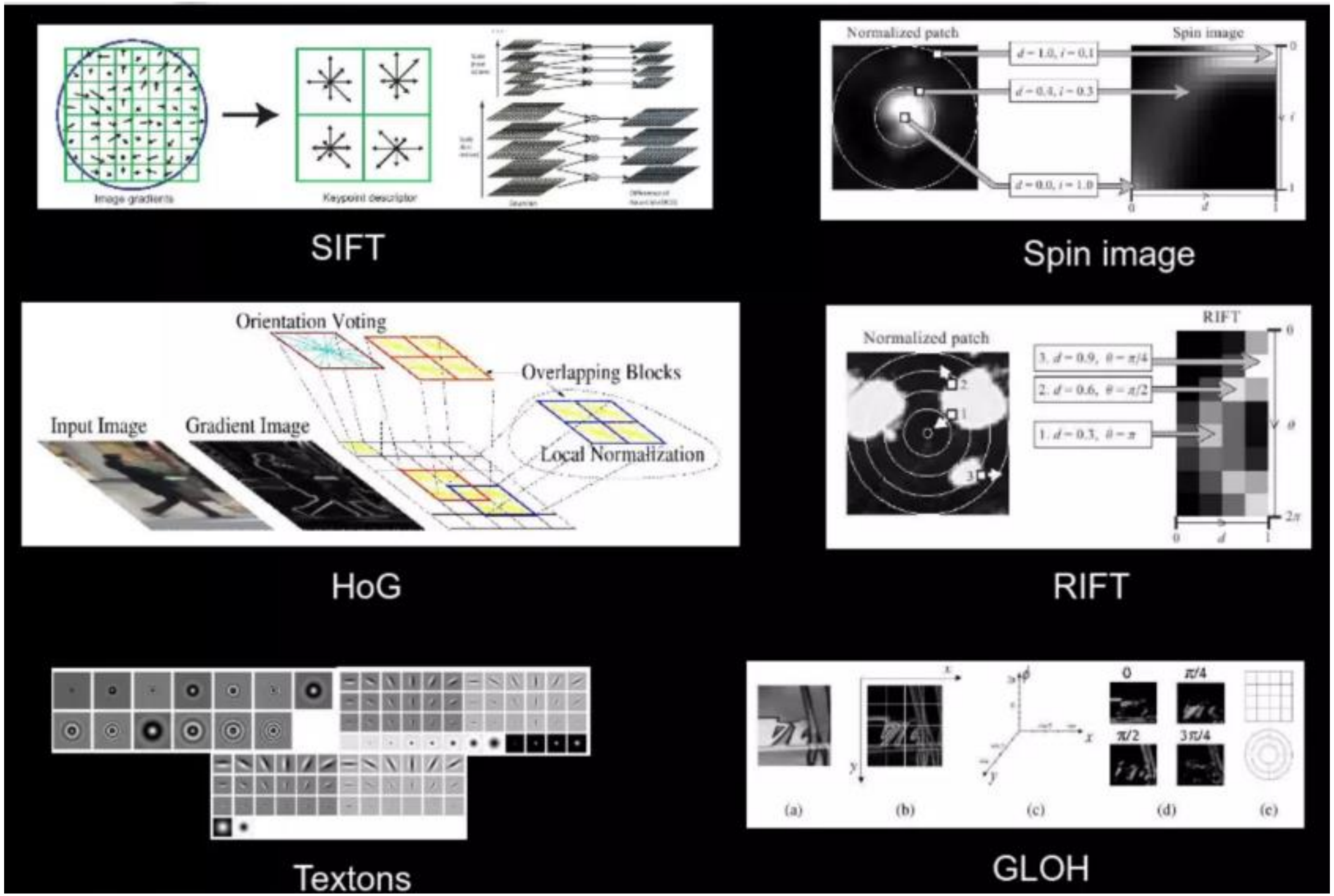
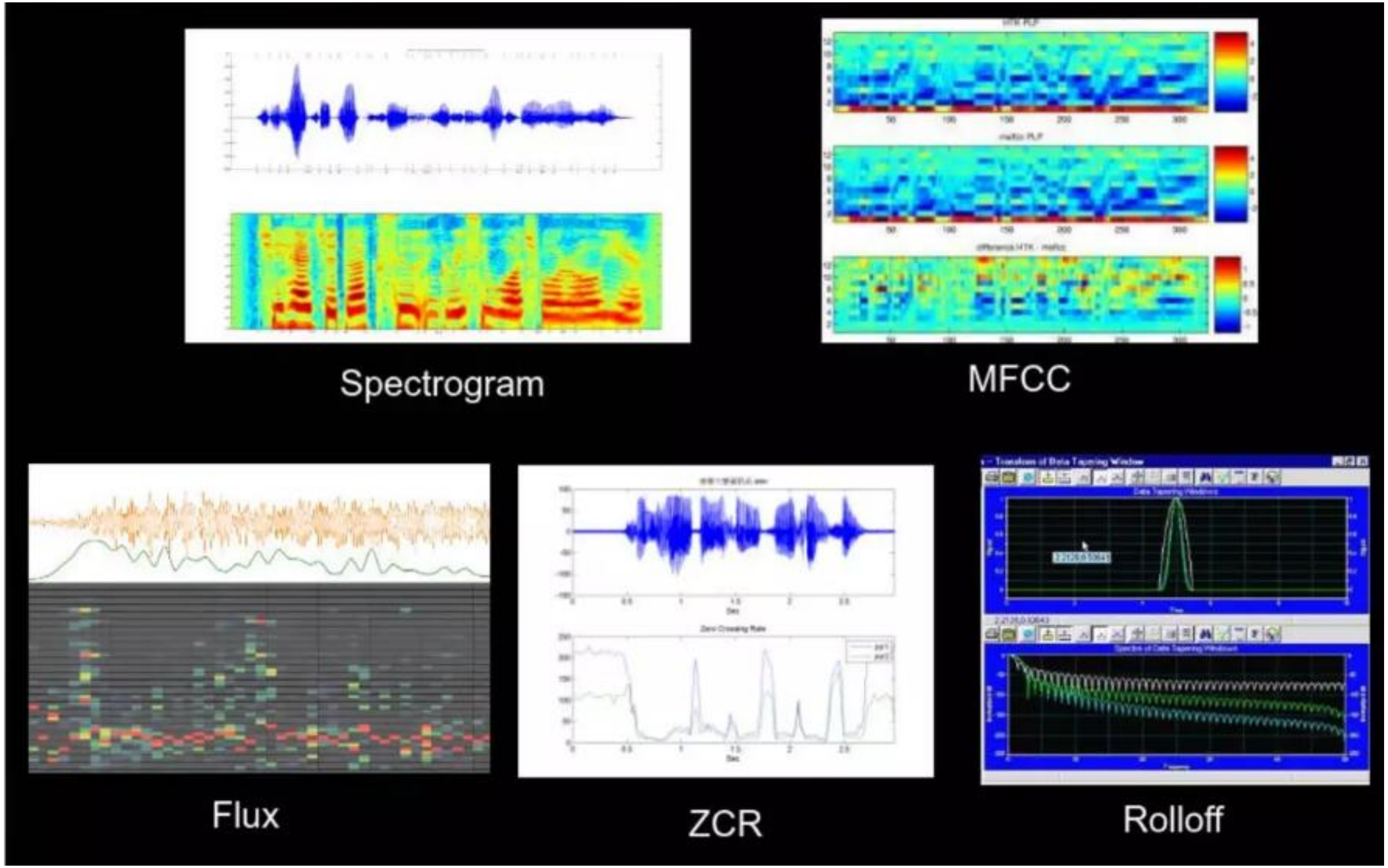
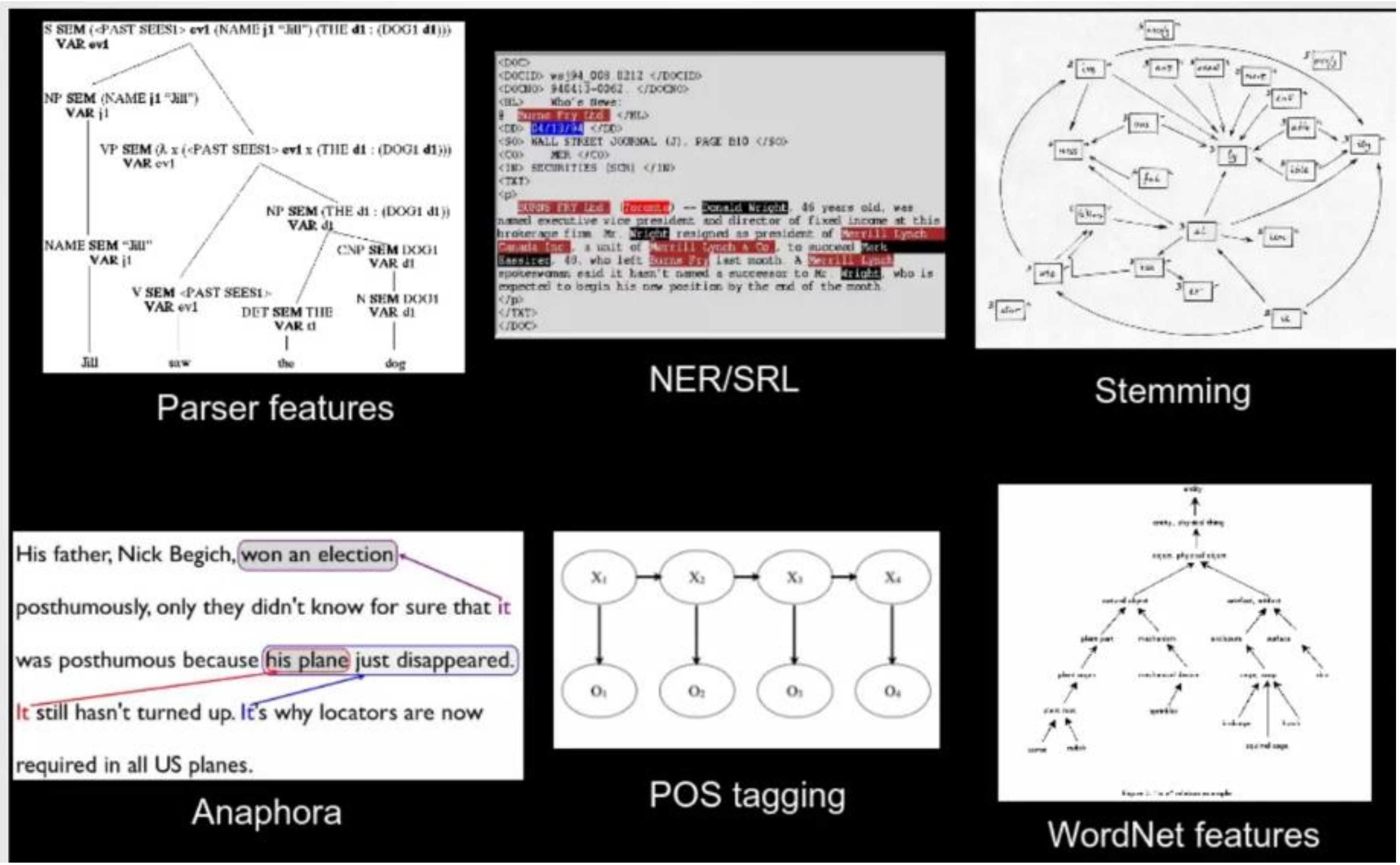
Feature Representation: CV Features



Feature Representation: Audio Features



Feature Representation: NLP Features



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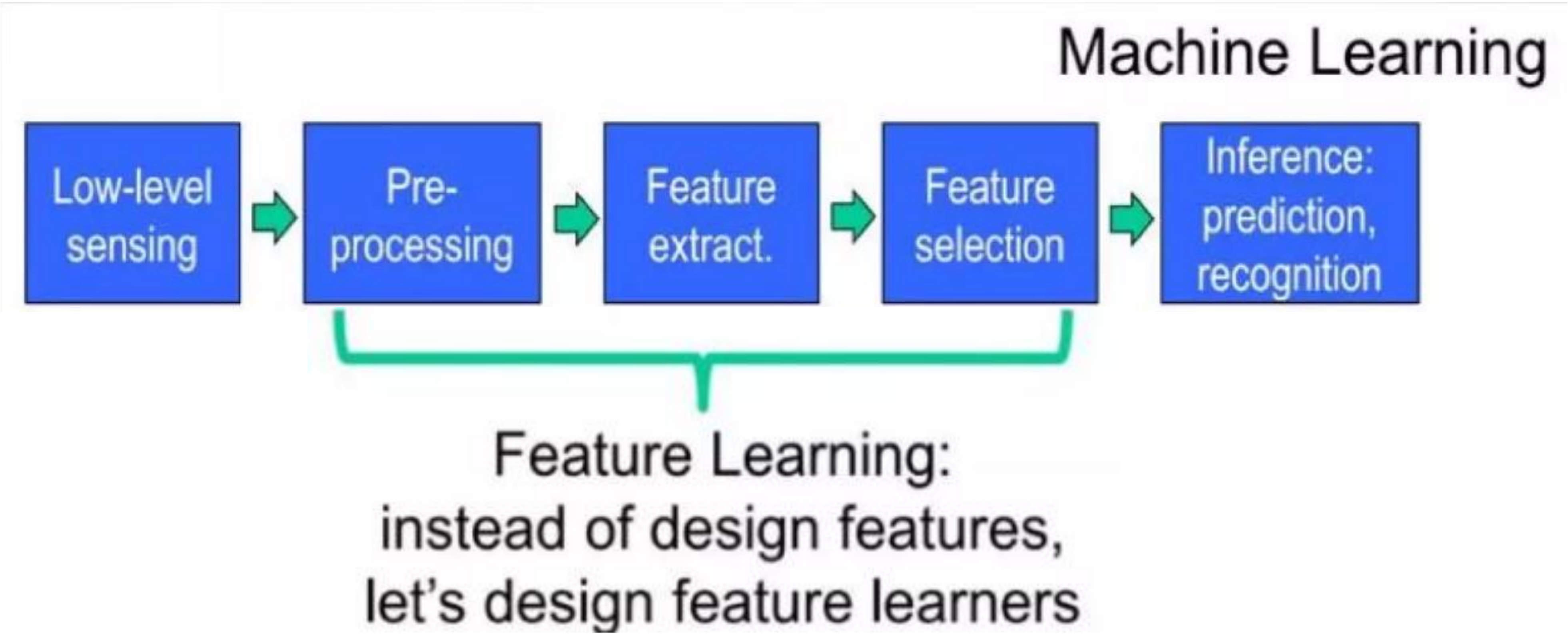
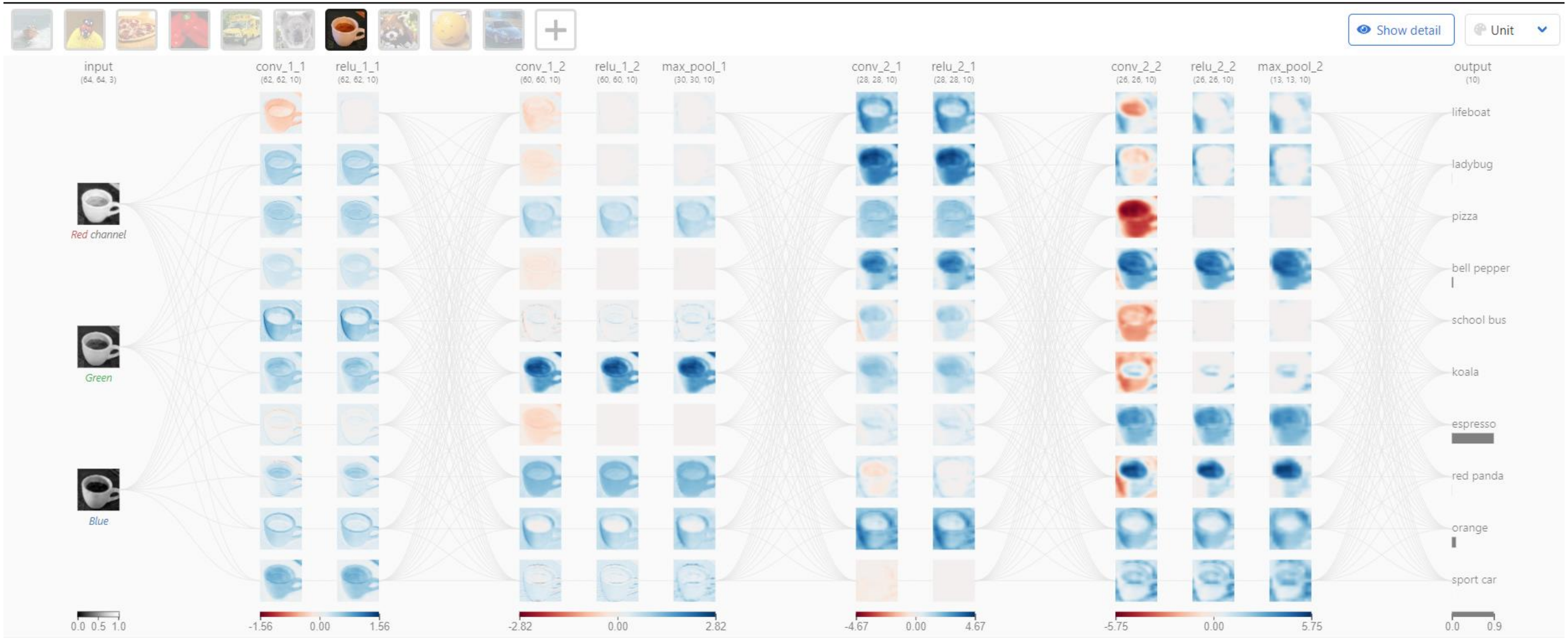
Feature Representation

- Certainly, Coming up with features is difficult, time-consuming and requires expert knowledge.
- A lot of time is spend tuning the features which are often hand-crafted.



Feature Representation

- CNN Explainer



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Feature Representation

Input Layer

- The input layer (leftmost layer) represents the input image into the CNN. It uses RGB images as input, the input layer has three channels, corresponding to the red, green, and blue channels respectively.

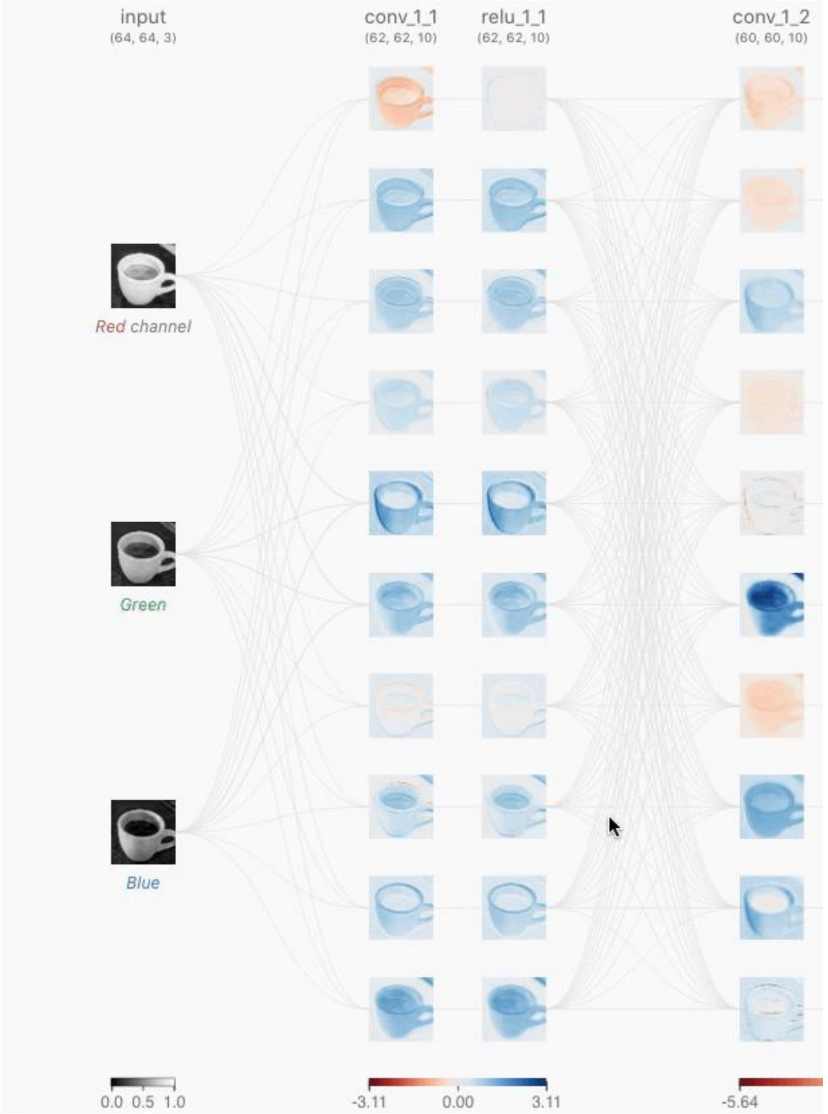
Convolutional Layers

- The convolutional layers are the foundation of CNN, as they contain the learned kernels (weights), which extract features that distinguish different images from one another—this is what we want for classification
- The convolutional neuron performs an elementwise dot product with a unique kernel and the output of the previous layer's corresponding neuron. This will yield as many intermediate results as there are unique kernels. The convolutional neuron is the result of all of the intermediate results summed together with the learned bias.

Feature Representation

Convolutional Layer

- The convolutional neuron performs an elementwise dot product with a unique kernel and the output of the previous layer's corresponding neuron. This will yield as many intermediate results as there are unique kernels. The convolutional neuron is the result of all of the intermediate results summed together with the learned bias.
- As you hover over the activation map of the topmost node from the first convolutional layer, you can see that 3 kernels were applied to yield this activation map.
- After clicking this activation map, you can see the convolution operation occurring with each unique kernel.



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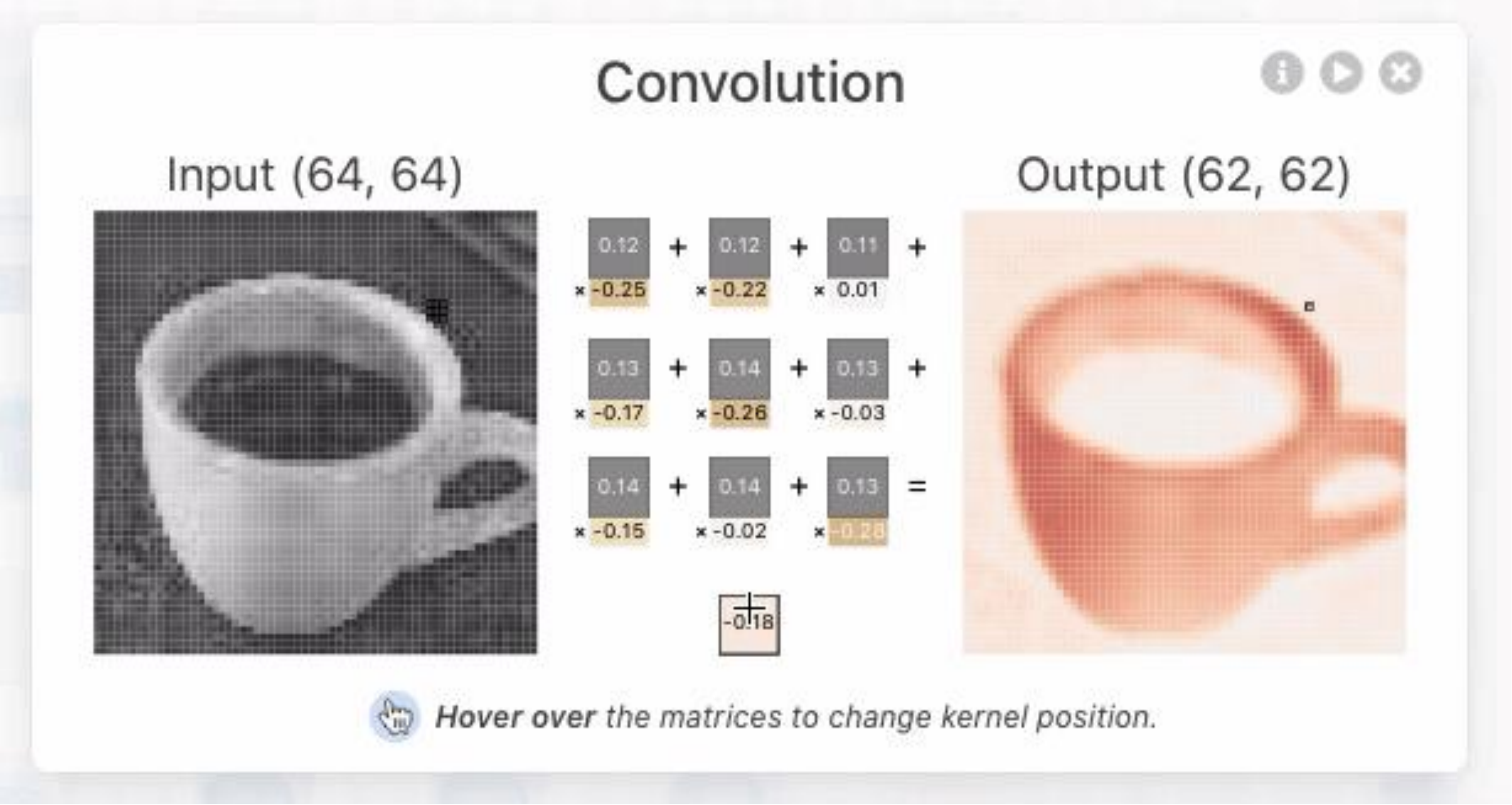
Feature Representation

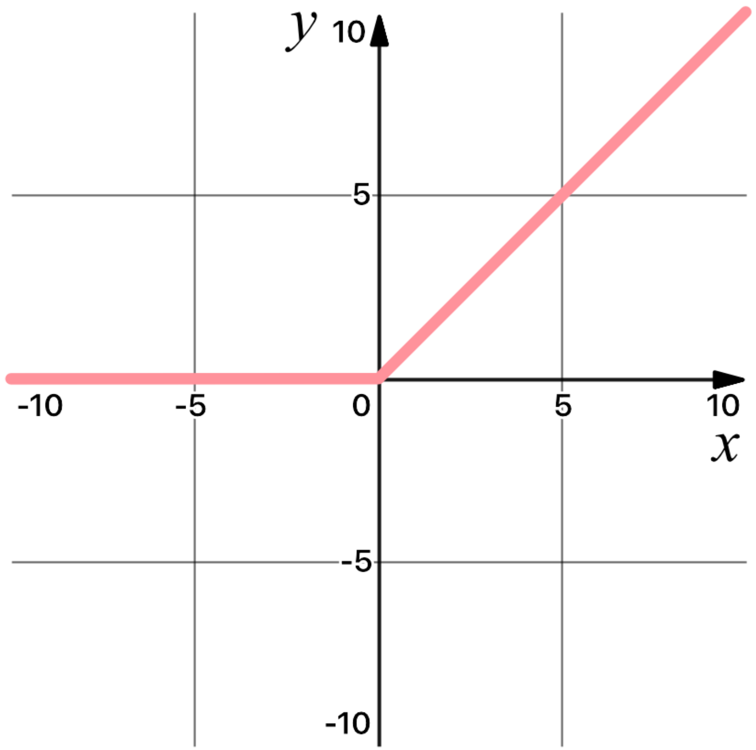
- The size of these kernels is a hyper-parameter specified by the designers of the network architecture. In order to produce the output of the convolutional neuron (activation map), we must perform an elementwise dot product with the output of the previous layer and the unique kernel learned by the network.



Feature Representation

ReLU

- The ReLU activation function is specifically used as a non-linear activation function, as opposed to other non-linear functions such as Sigmoid because it has been empirically observed that CNNs using ReLU are faster to train than their counterparts.



- This activation function is applied elementwise on every value from the input tensor. For example, if applied ReLU on the value 2.24, the result would be 2.24, since 2.24 is larger than 0.

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Feature Representation

Softmax

- A softmax operation serves a key purpose: making sure the CNN outputs sum to 1. Because of this, softmax operations are useful to scale model outputs into probabilities.

$$\mathrm{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

- For a visual indication of the impact of each logit (unscaled scalar value), they are encoded using a light orange → dark orange color scale. After passing through the softmax function, each class now corresponds to an appropriate probability.

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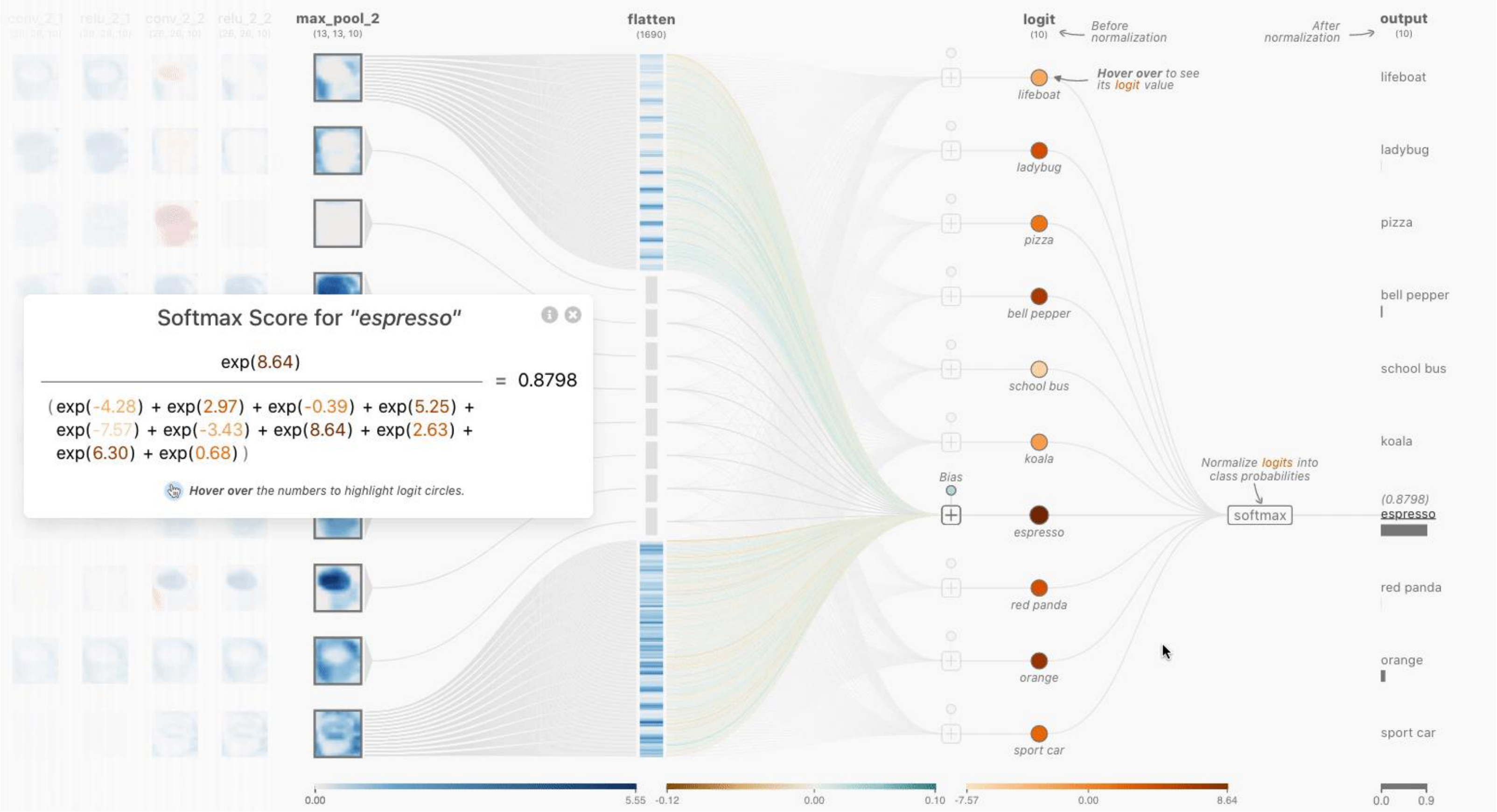
Feature Representation

- The Softmax Interactive Formula View allows a user to interact with both the color encoded logits and formula to understand how the prediction scores after the flatten layer are normalized to yield classification scores.



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Feature Representation

Pooling Layers

- There are many types of pooling layers in different CNN architectures, but they all have the purpose of gradually decreasing the spatial extent of the network, which reduces the parameters and overall computation of the network. The type of pooling used in the previous architecture is Max-Pooling.

Flatten Layer

- This layer converts a three-dimensional layer in the network into a one-dimensional vector to fit the input of a fully-connected layer for classification. For example, a 5x5x2 tensor would be converted into a vector of size 50.

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Thank you