



Convolutional Neural Networks for Predicting Daily Orographic Precipitation Gradients for Precipitation Downscaling

CIROH Developers Conference

Hydrological Applications of Machine Learning Workshops

Savanna Wolvin

05.30.24

Importance of Western CONUS Snowpack

- Seasonal snowpack acts as a natural water tower – storing wintertime precipitation
- 71% of total runoff in the mountainous west is from snowmelt

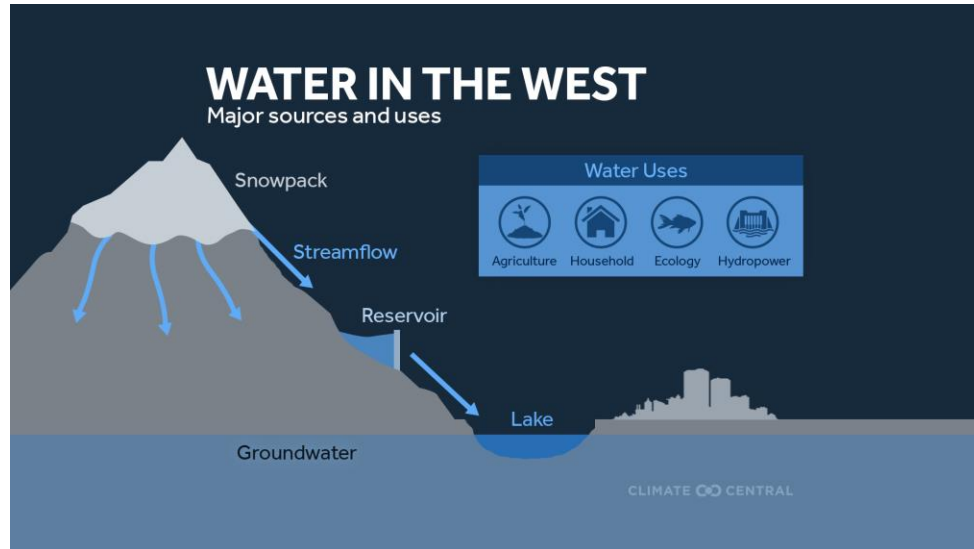


Fig. Water in the West (Courtesy of climatecentral.org)

Multiple avalanches reported in Blaine County, Extreme Avalanche Danger Warning issued

According to the Sawtooth Avalanche Center, there is a level 5 - Extreme Avalanche Danger in the Soldier and Wood River Mountains.

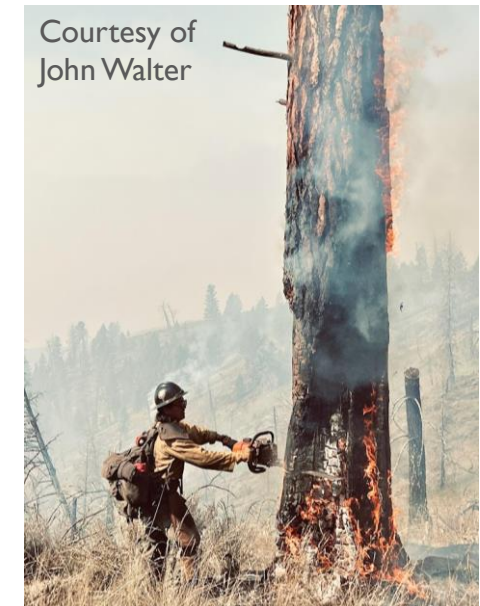


By KMYT News Staff
Published: Mar. 10, 2023 at 12:53 PM MST



Big Cottonwood Canyon closed in both directions due to multiple weather-related crashes

by Kayla Winn, KUTV | Mon, December 12th 2022



Current Orographic Downscaling Method

Precipitation-elevation Regressions on Independent Slopes Model (PRISM)

- Downscales using the climatological distribution of precipitation with elevation
- Downscales the GEFS from ~33 km to ~800 m horizontal resolution
- Does not account for event-to-event variability of precipitation

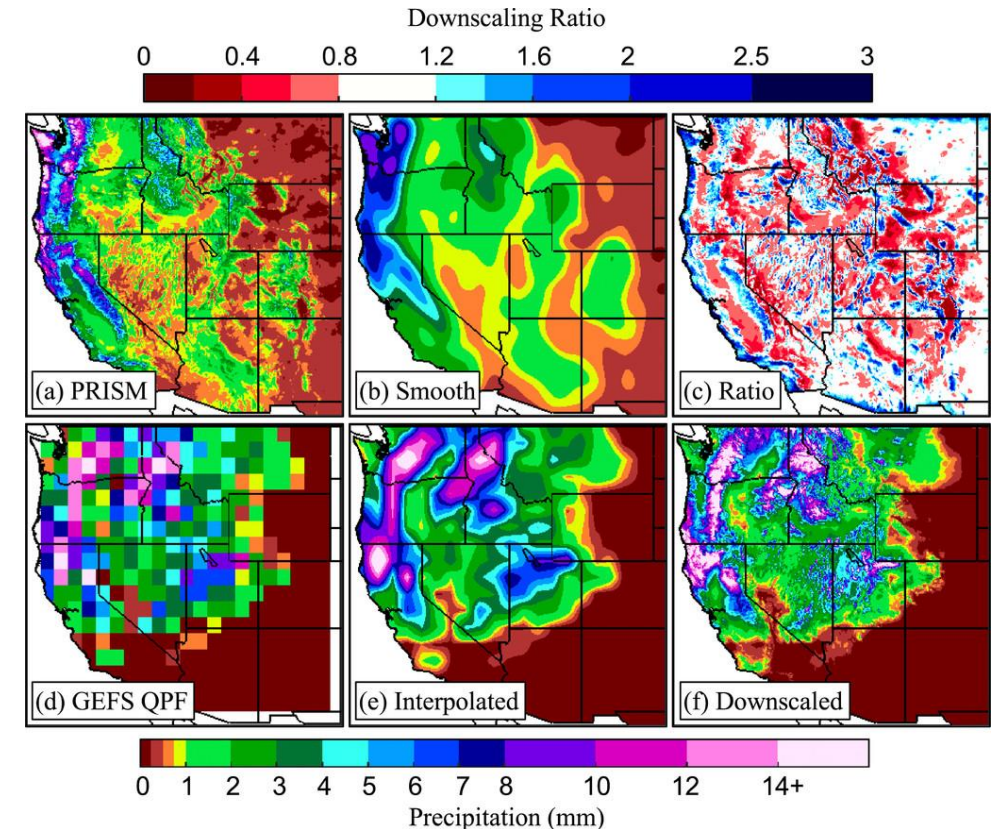


Fig. 24 Jan 2016 PRISM climatological precipitation (a), smoothed precipitation (b), downscaling ratio (c), 24 Jan 2016 GEFS forecast (d), interpolated GEFS forecast (e), downscaled precipitation (f).

Precipitation and Terrain



Faceting Algorithm



Orographic Precipitation Gradients (OPG)

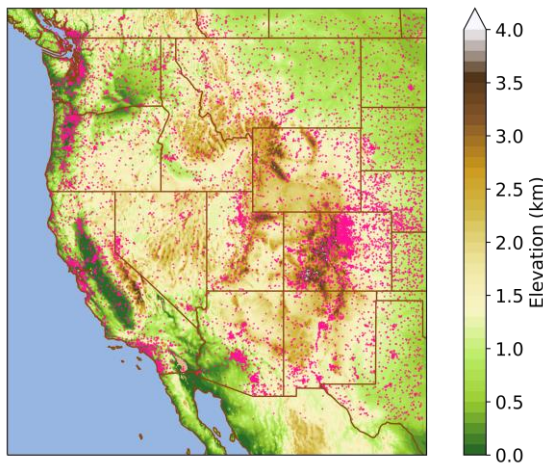
Global Historical Climatology Network-Daily

- 1979-2018

Global 30 Arc-Second Elevation (GTOPO30)

- Drawn to approximately 4-km resolution

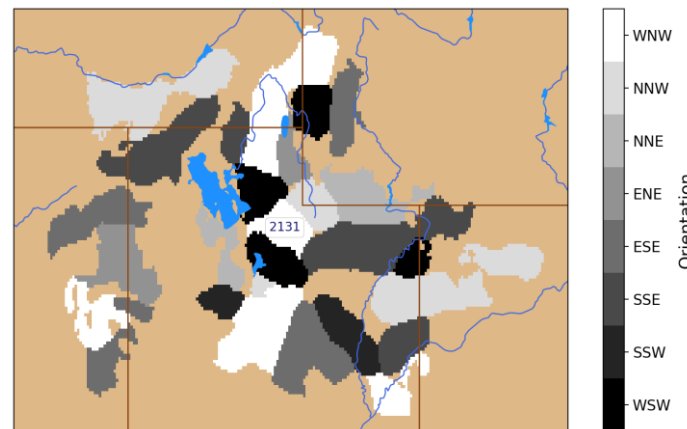
Fig.
Precipitation
observations
stations and
4-km
topography



Terrain orientations are binned into 8 secondary intercardinal coordinates

- Regions deemed flat are removed
- Regions with the same orientation are called facets

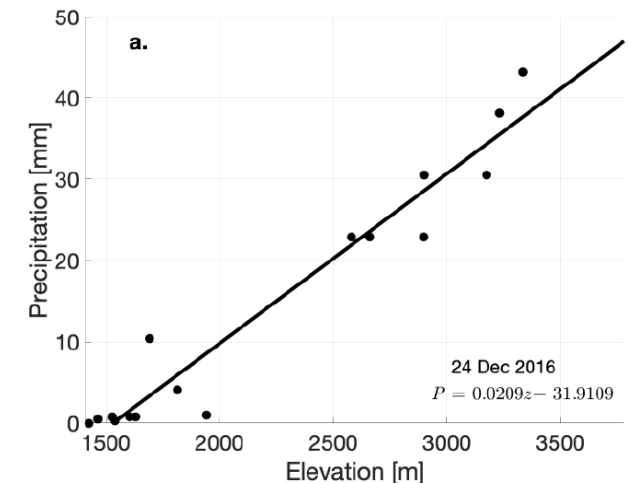
Fig. Northern Utah Facets



Linear regression of the precipitation-elevation relationship

$$P_i = b_1 z_i + b_0$$

Fig. Precipitation-elevation regression



Predictor Dataset

ECMWF ERA5 at 0.5° Grid-Spacing

Variables	Levels (“Images”)
Integrated Vapor Transport	Formulated from Specific Humidity, U-Winds, and V-Winds
U-Winds	700 hPa
V-Winds	700 hPa
Geopotential Height	500 hPa
Accumulated Precipitation	Surface
Temperature	700 hPa

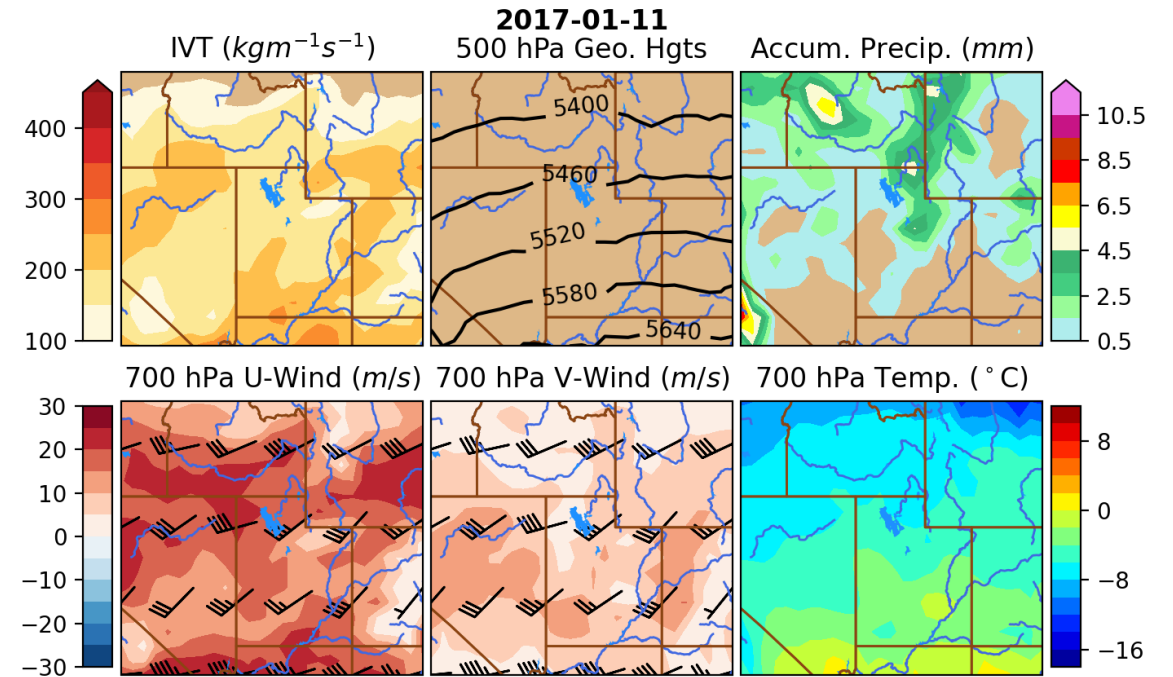
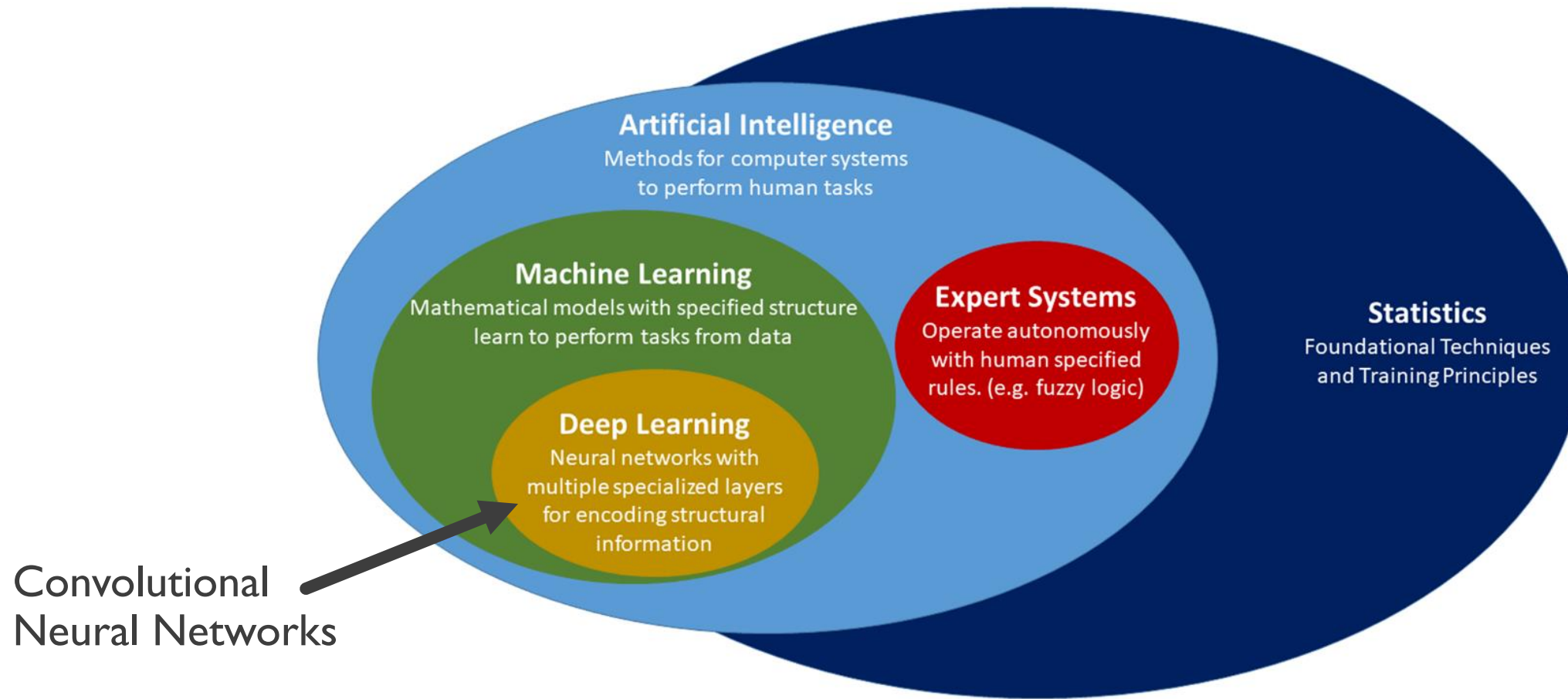


Fig. CNN input domain and variables

What is a Convolutional Neural Network

like layers features fully
which CNN Neural
deep image is are A type with
such The network neural networks be
patterns as visual
machine learn from convolutional used images also
feature learning data by input processing each
filter weights CNNs Convolutional connected
layer convolution recognition particularly
output identify being



Convolutional
Neural Networks

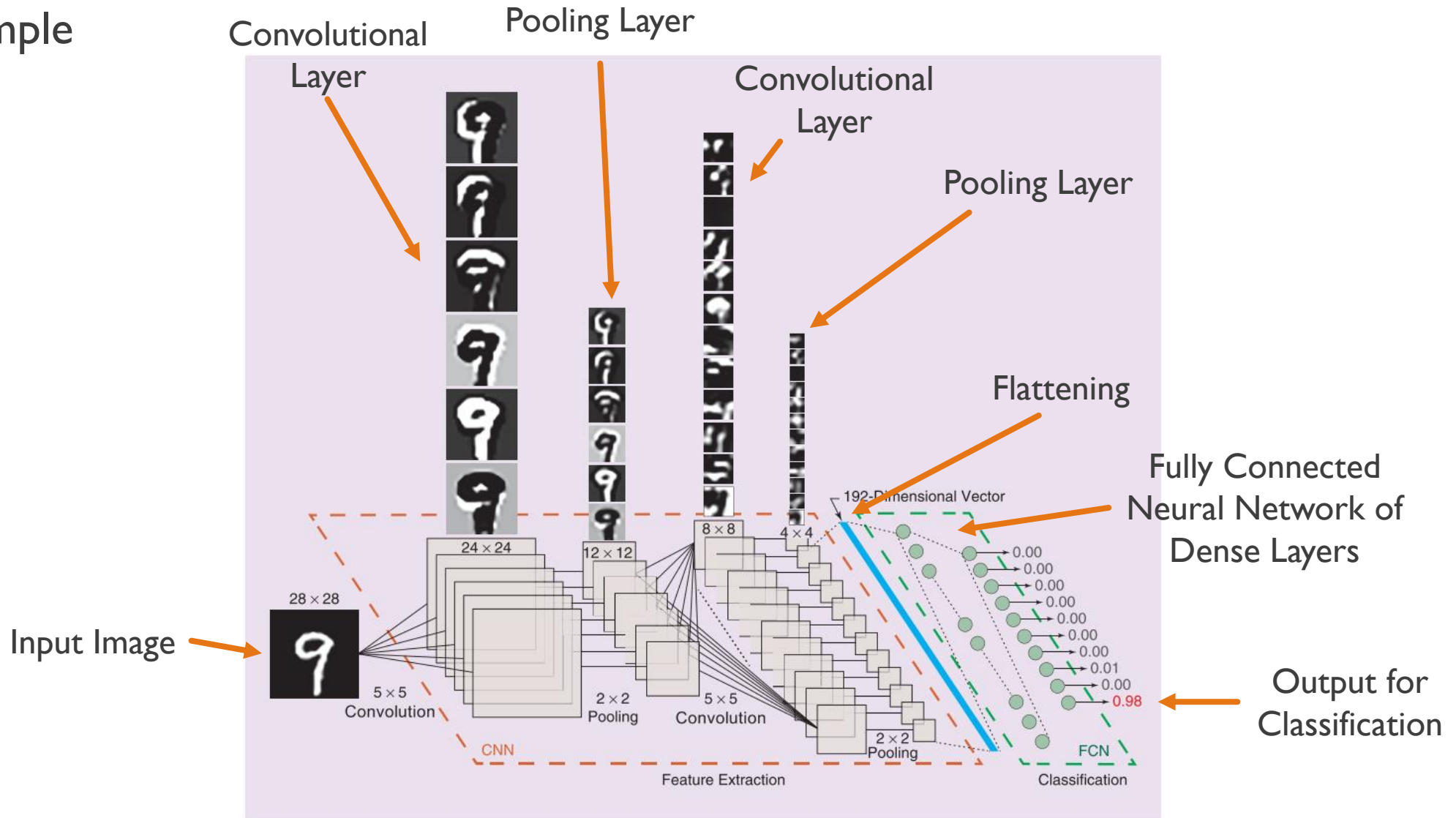
Fig. 1. Venn diagram of the relationship between AI, ML, DL, expert systems, and statistics.

Really, what is it?

Convolutional Neural Networks are...

- A supervised learning algorithm → Trains on labeled datasets to classify or predict
- A deep learning neural network → A neural network with more than a few layers with the functionality to learn its own parameters/weights
- For computer vision → Artificial intelligence algorithm which allows a computer to interpret images or visual data

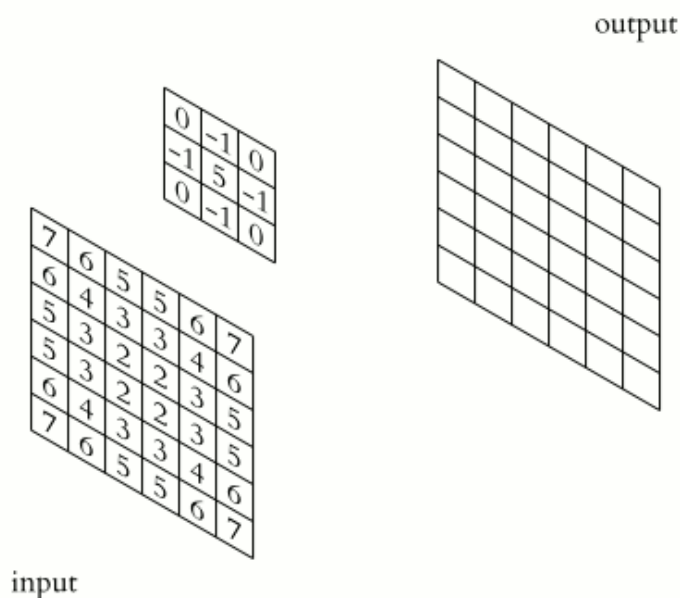
Handwriting Classification Example



Extracting Image Features

Convolutional Layer

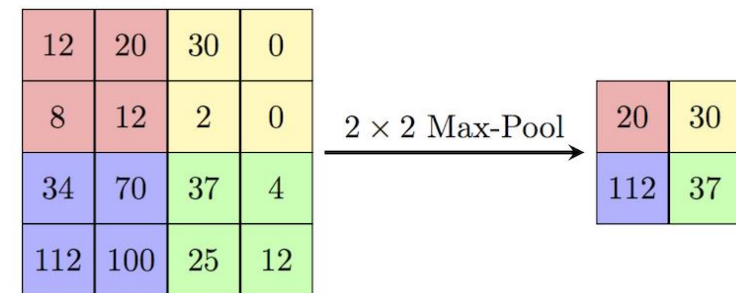
- Alters an image with a small learned filter (also known as a kernel), that highlights different patterns, edges, or values



https://en.m.wikipedia.org/wiki/File:2D_Convolution_Animation.gif

Pooling Layers

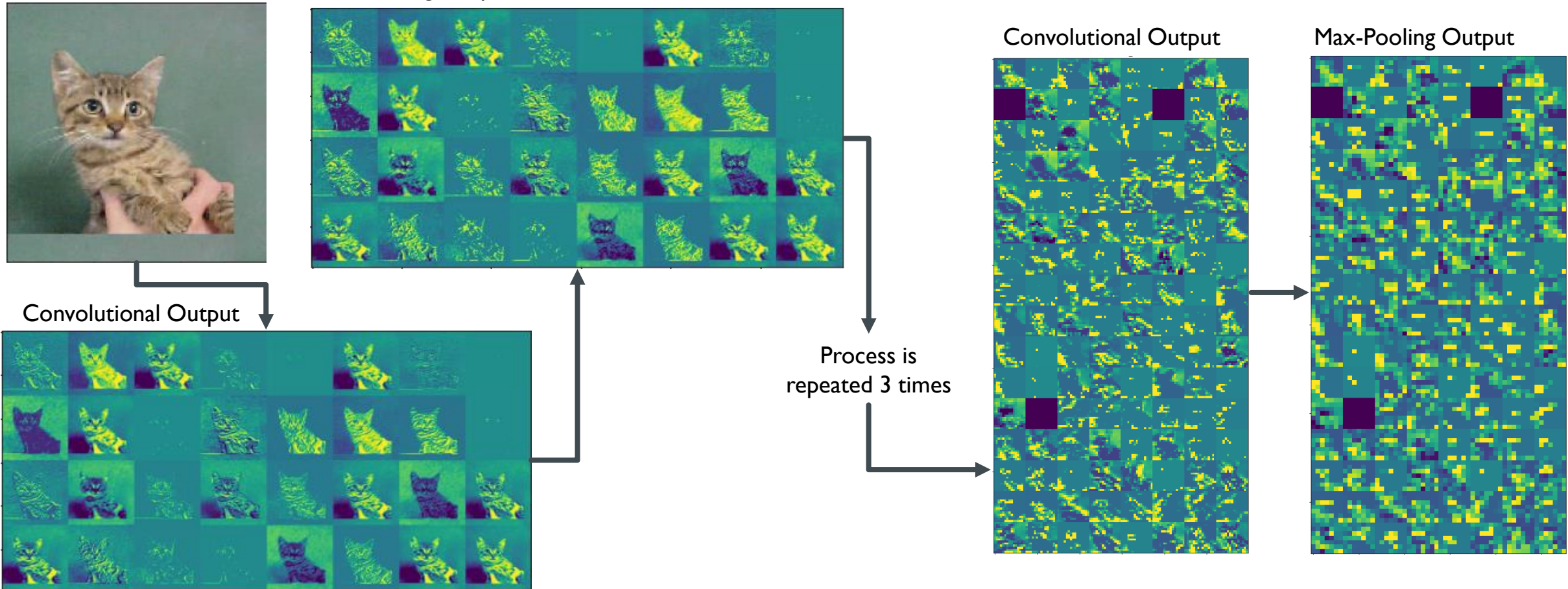
- Reduces the resolution of an image by taking the mean or maximum values from a passing window
- Reduces processing power needed and forces the convolutional layers to evaluate consecutively larger areas



<https://paperswithcode.com/method/max-pooling>

Extracting Image Features

Example:

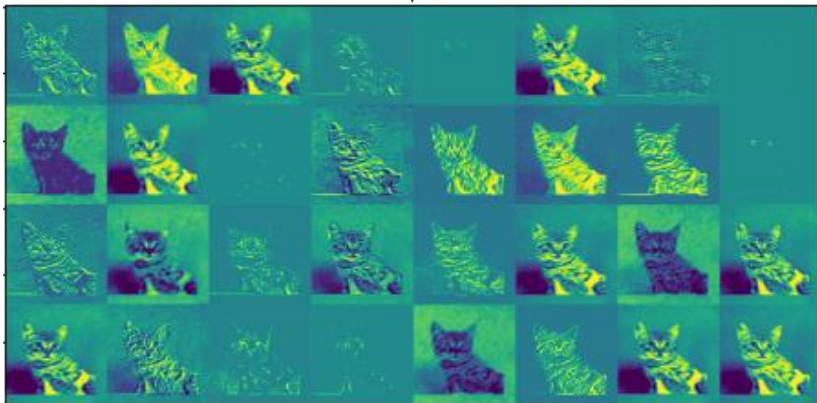


Extracting Image Features

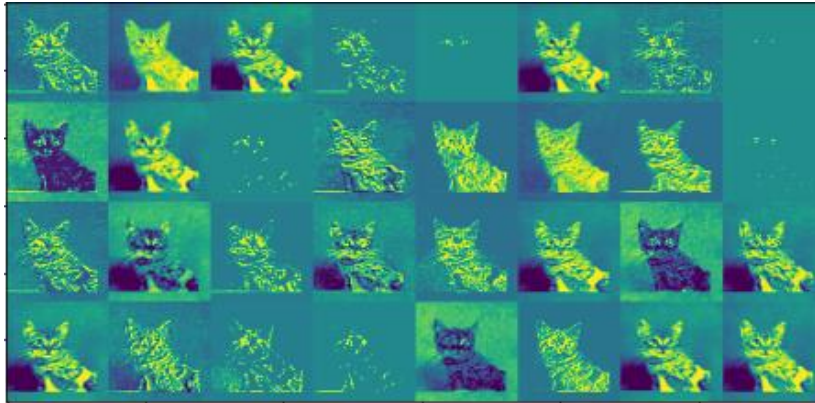
Cat image is our
Sample or Input



Convolutional Output

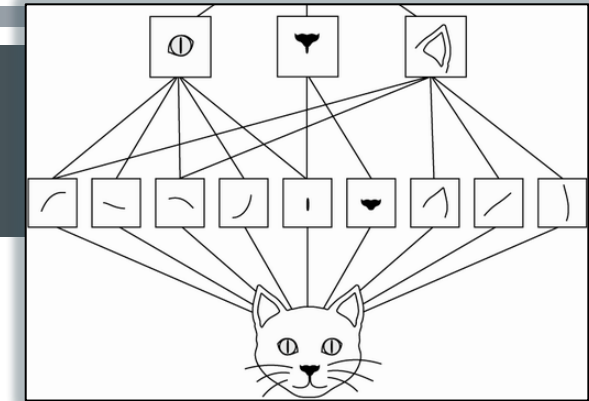


Max-Pooling Output

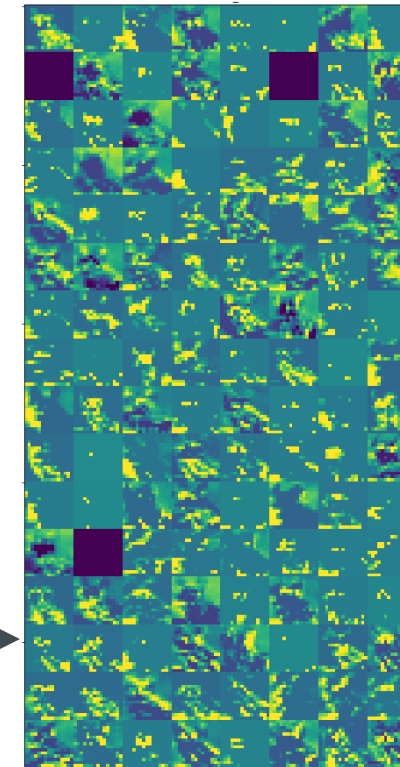


Process is
repeated 3 times

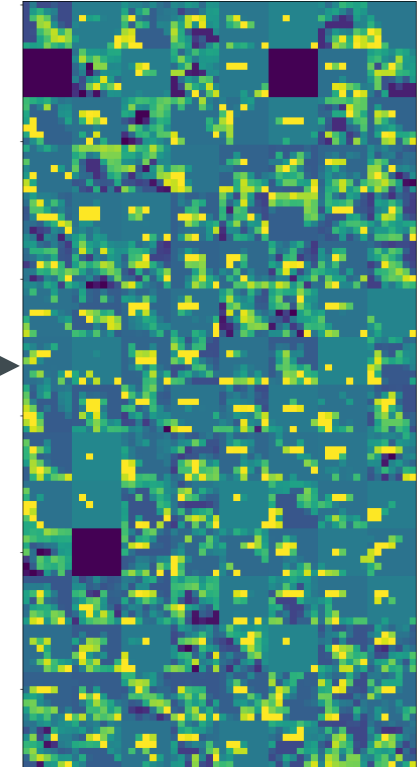
Each new image
is called a
Feature Map



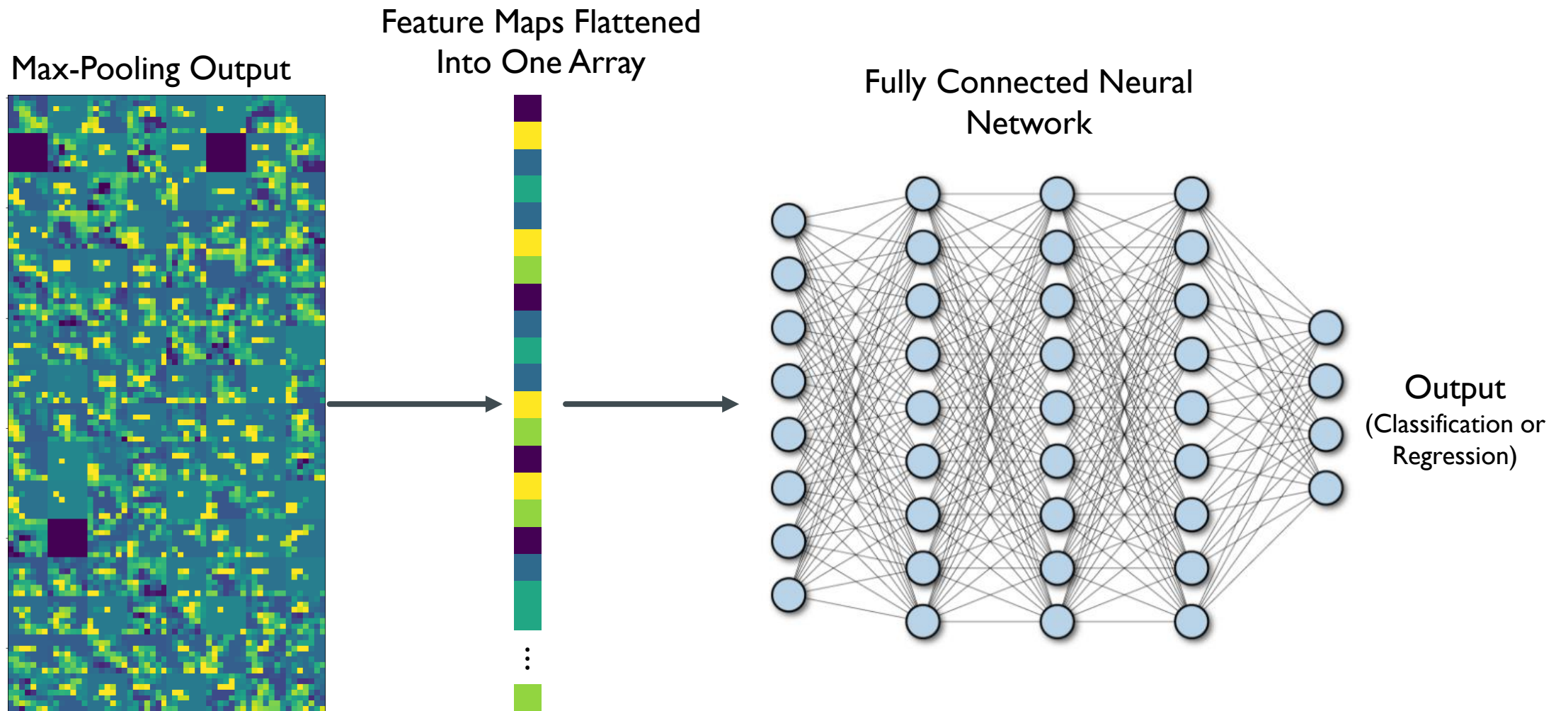
Convolutional Output



Max-Pooling Output



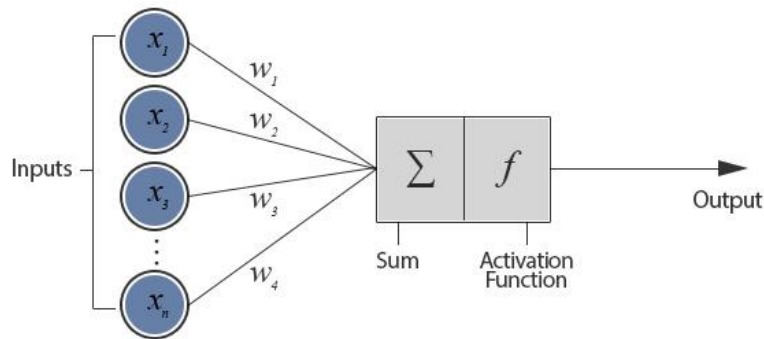
Flattening



Fully Connected Neural Network

Perceptrons

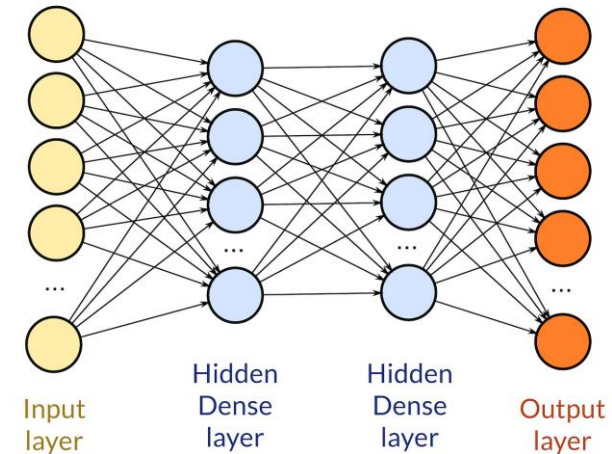
- Input data is multiplied by learned weights, aggregated, then passed through an activation function



<https://sites.cc.gatech.edu/~san37/post/dlhc-fnn/>

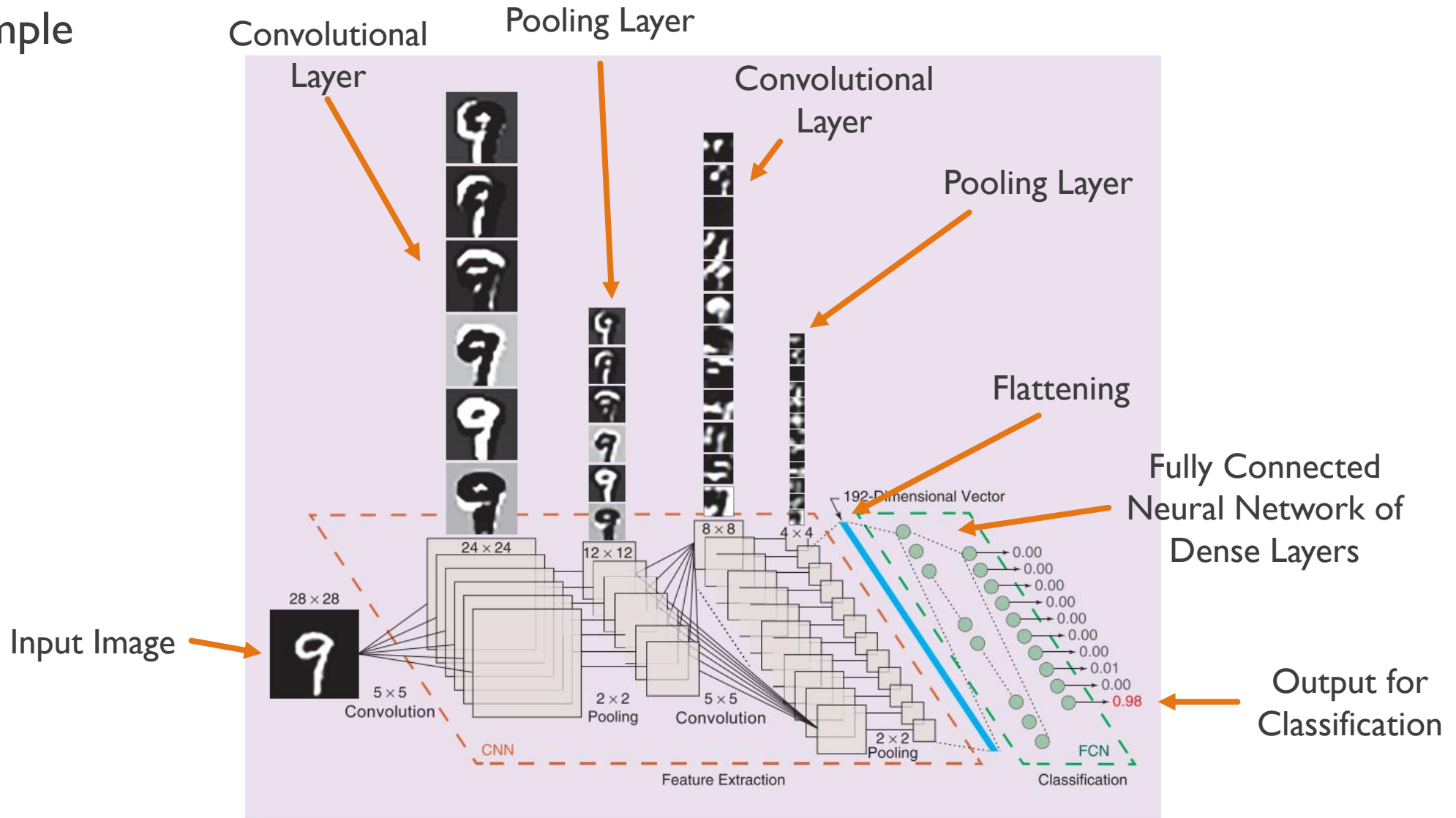
Dense Layers

- Layers of perceptrons which transfer information from layer to layer, to the output value(s)



<https://medium.datadriveninvestor.com/custom-layers-in-keras-de5f793217aa>

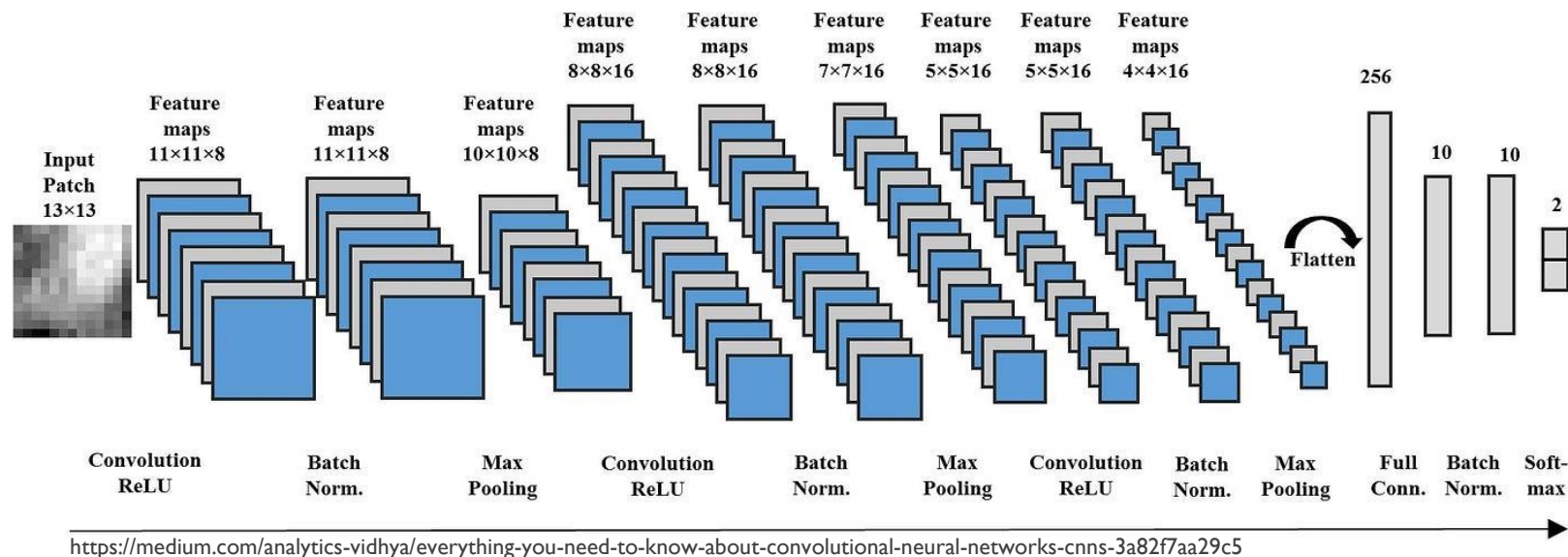
Handwriting Classification Example



Batch Normalization

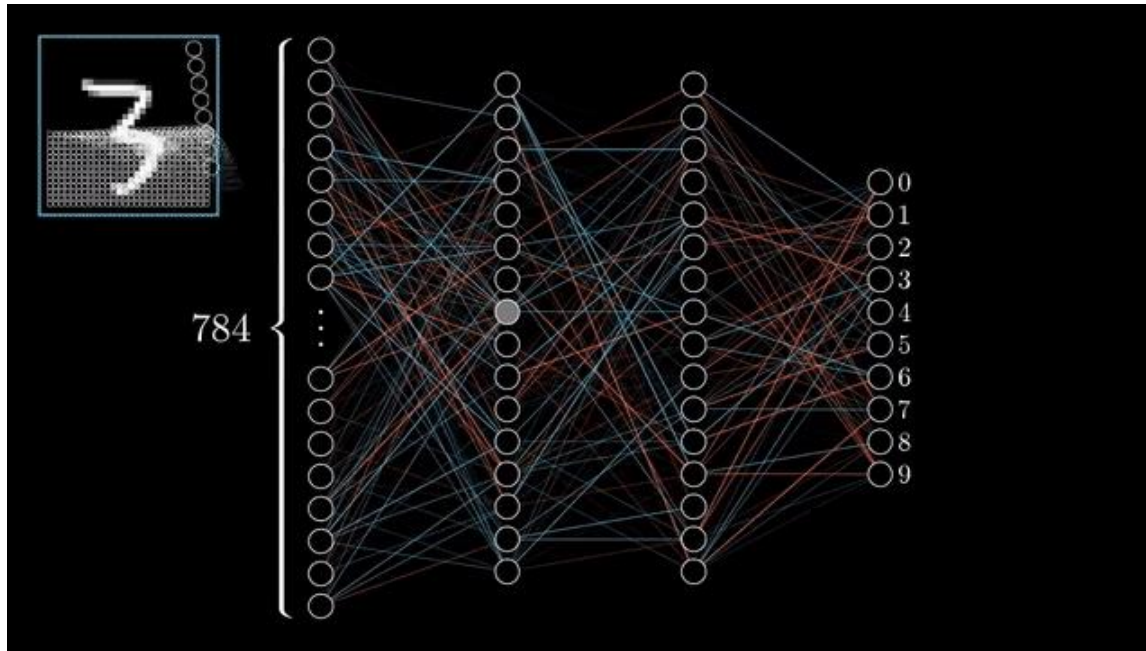
During training, predictor data is sent in small subsets, called a batch. But these batches are not always representative of the entire dataset

- A batch normalization layer is added to normalize the feature maps between layers
- Batch normalization has been found to help smoothen and quicken training



How does the Model Learn? Formulating Error

Prediction error or loss – The measurement of the distance between your model's prediction and the target



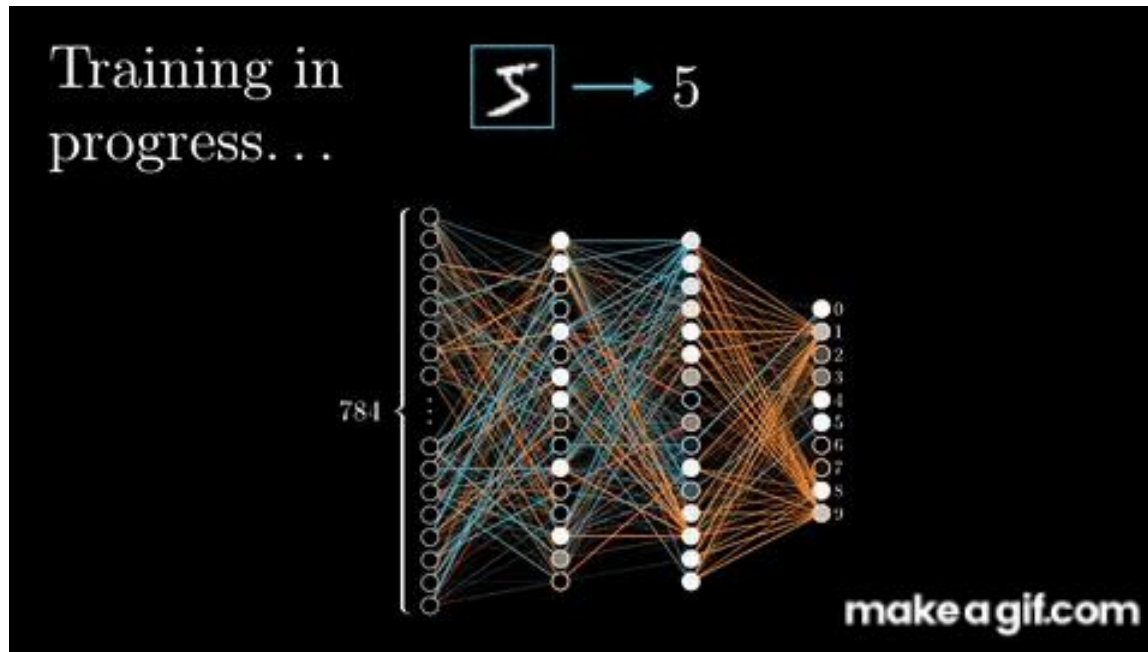
Minimizing the loss function is how the algorithm “*learns*”

Common Loss Metrics:

Binary	Categorical	Numerical
Binary Cross Entropy	Categorical Cross Entropy	Mean Squared Error
		Mean Absolute Error

How does the Model Learn? Backpropagation

Backpropagation – updates the weights within the model to minimize the loss using the gradient

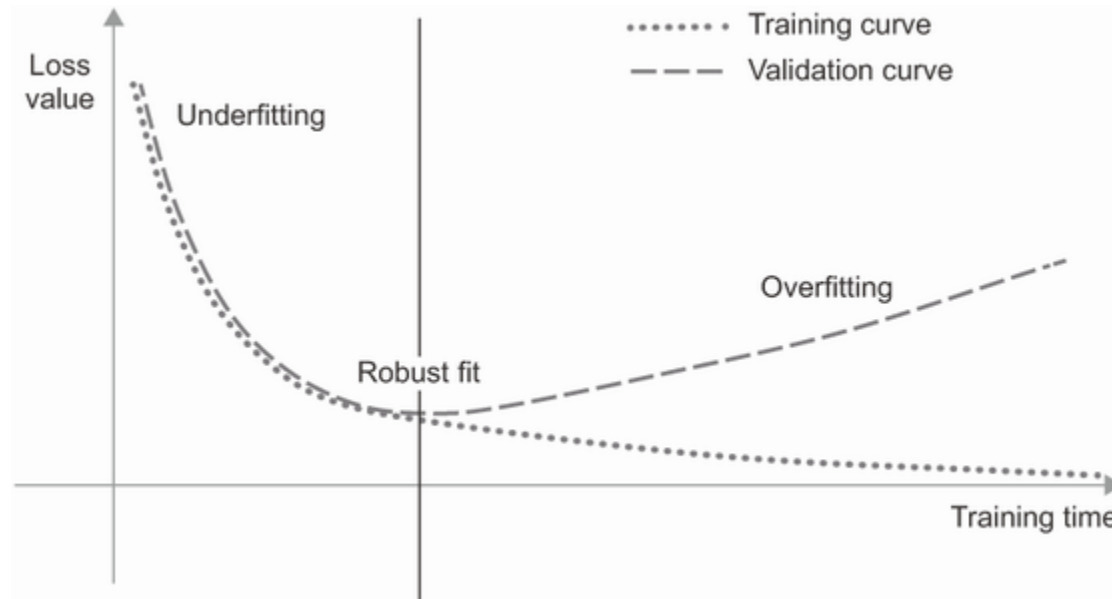


Overfitting to the Training Subset

Optimization – Adjusting the model for the best performance

Generalization – How well the trained model performs on data it has never seen

Overfitting – Learning representations only specific to the training data and do not generalize to the validation data

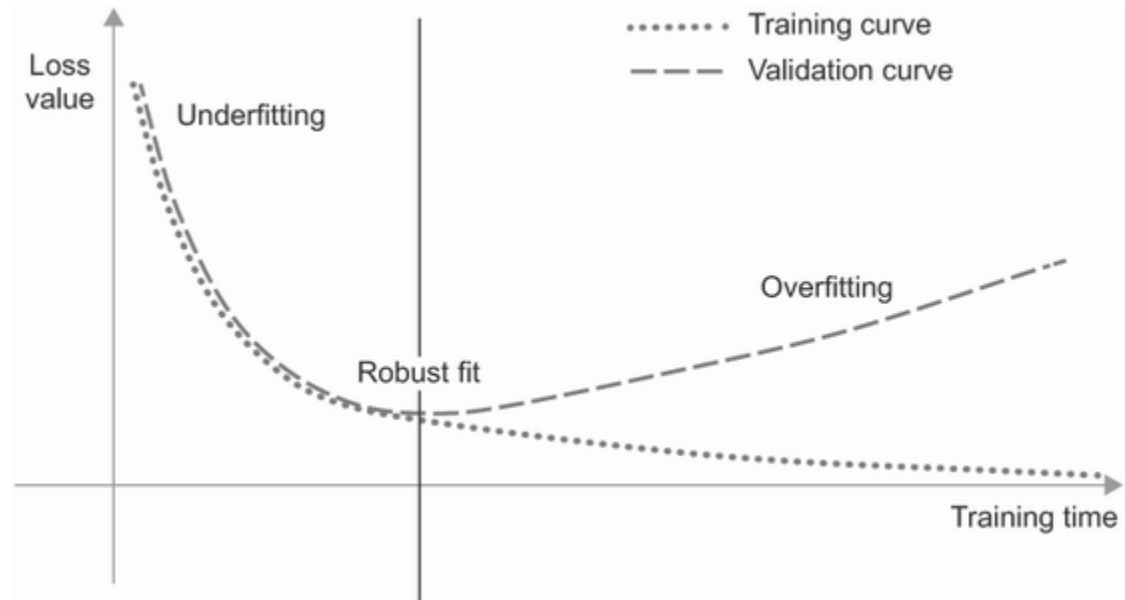


Overfitting to the Training Subset

Optimization – Adjusting the model for the best performance

Generalization – How well the trained model performs on data it has never seen

Overfitting – Learning representations only specific to the training data and do not generalize to the validation data

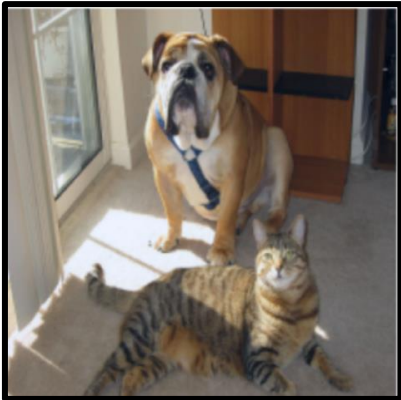


Challenges:

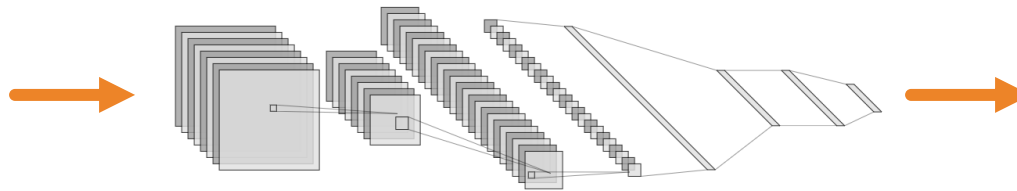
- Noisy training data
- Ambiguous features
- Rare features
- Spurious correlations (correlation is not causation)

Grad-CAM (Gradient-weighted Class Activation Maps)

What is in this image?



Animal Detector CNN



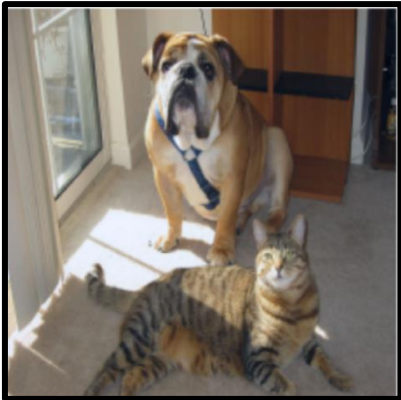
96% Dog
92% Cat

Where in the image is the CNN looking to identify the Dog and Cat?

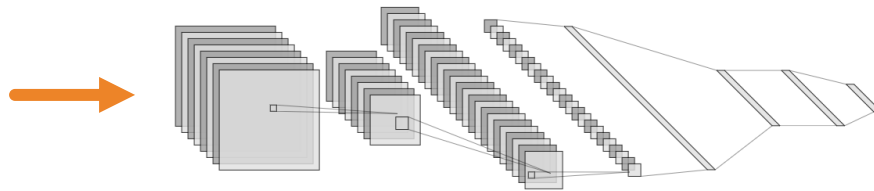
- An Explainable AI technique to create ‘visual explanations’ for the decisions within a CNN
- Formulate heatmap from the weighted summation of gradients from an output node to all the feature maps of the last convolutional layer
- In short, Grad-CAMs highlight the grid points **where** the CNN is ‘looking’ during prediction

Grad-CAM (Gradient-weighted Class Activation Maps)

What is in this image?

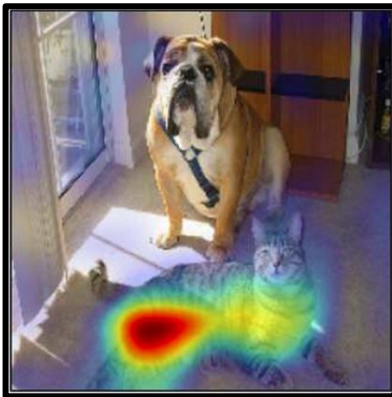


Animal Detector CNN



96% Dog
92% Cat

Where in the image is the CNN looking to identify the Dog and Cat?



Grad-CAM for 'Cat'



Grad-CAM for 'Dog'

Grad-CAM:
Weighted summation
of the gradients from
an output node to all
feature maps

Strong Gradients =
High Importance

References

- Black, A. W., and T. L. Mote, 2015: Characteristics of winter-precipitation-related transportation fatalities in the United States. *Wea. Climate Soc.*, **7**, 133–145.
- Bohne, L., C. Strong, and W. J. Steenburgh, 2020: Climatology of orographic precipitation gradients in the contiguous western United States. *J. Hydrometeor.*, **21**, 1723–1740.
- Burakowski, E., and M. Magnusson, 2012: *Climate Impacts on Winter Tourism Economy in the United States*. 36 pp.
- Chase, R. J., D. R. Harrison, G. M. Lackmann, and A. McGovern, 2023: A Machine Learning Tutorial for Operational Meteorology. Part II: Neural Networks and Deep Learning. *Wea. Forecasting*, **38**, 1271–1293, <https://doi.org/10.1175/WAF-D-22-0187.1>.
- Chollet, F., and Coauthors, 2015: Keras. <https://keras.io>.
- Chollet, F., 2021: *Deep Learning with Python*. Manning Publications Co., 478 pp.
- Daly, C., R. P. Neilson, and D. L. Phillips, 1994: A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *J. Appl. Meteor. Climatol.*, **33**, 140–158.
- Gonzalez, R. C., 2020: Deep Convolutional Neural Networks [Lecture Notes]. *IEEE Signal Processing Magazine*, **35**(6), 79–87, <https://doi.org/10.1109/MSP.2018.2842646>.
- Haupt, S. E., and Coauthors, 2022: The History and Practice of AI in the Environmental Sciences. *Bull. Amer. Meteor. Soc.*, **103**, E1351–E1370, <https://doi.org/10.1175/BAMS-D-20-0234.1>.
- Hersbach, H., and Coauthors, 2023a: ERA5 hourly data on pressure levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), accessed 18 January 2023, doi: 10.24381/cds.bd0915c6.476
- Hersbach, H., and Coauthors, 2023b: ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), accessed 28 January 2023, doi: 10.24381/cds.adbb2d47.
- Ioffe, S., and C. Szegedy, 2015: Batch normalization: Accelerating deep network training by reducing internal covariate shift. *Proc. 32nd Int. Conf. on Machine Learning*, <https://doi.org/10.48550/arXiv.1502.03167>.
- Lewis, W. R., W. J. Steenburgh, T. I. Alcott, and J. J. Rutz, 2017: GEFS precipitation forecasts and the implications of statistical downscaling over the western United States. *Wea. Forecasting*, **32**, 1007–1028.
- Li, D., M. L. Wrzesien, M. Durand, J. Adam, and D. P. Lettenmaier, 2017: How much runoff originates as snow in the western United States, and how will that change in the future? *Geophysical Research Letters*, **44**, 6163–6172.
- Selvaraju, R. R., M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, 2020: Grad-cam: Visual explanations from deep networks via gradient-based localization. *Int. J. of Comput. Vis.*, **128**, 336–359, <https://doi.org/10.1007/s11263-019-01228-7>.
- Westerling, A. L., 2016: Increasing western US forest wildfire activity: Sensitivity to changes in the timing of spring. *Phil. Trans. R. Soc. B*, **371**, <http://doi.org/10.1098/rstb.2015.0178>.