Deep Learning

COSC440

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Details

Science of Arrays

Don't loop over elements in a array. Use numpy functions to do elementwise operations:

```
# Elementwise sum; both produce an array
z = x + y
z = np.add(x, y)
```

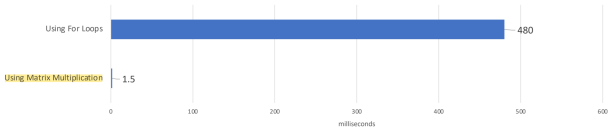
Use **Boradcasting** to work with arrays of different sizes. In Hardware data is take from the same memory space multiple times.

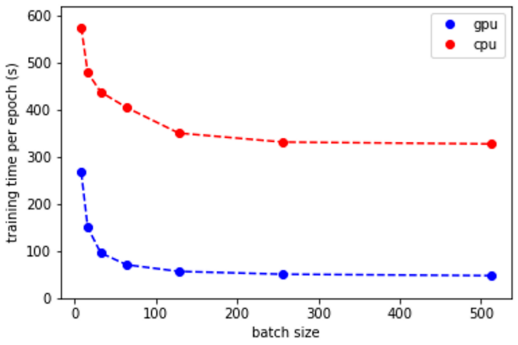
```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11,
↪  12]])
v = np.array([1, 0, 2])
y = x + v.T  # Add v to each row of x using
↪  broadcasting
print(y)  # Prints "[[ 2  2  4]
          #          [ 5  5  7]
          #          [ 8  8 10]
          #          [11 11 13]]"
```

Do **Matrix Multiplications**, remember that matrices of shape $100x20 \times 20x40$ equal a output shape of $100x40$:

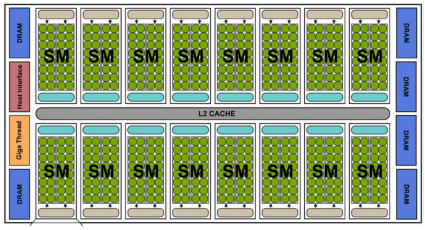
```
C = np.dot(A,B)
F = np.matmul(D,E)
```

The **Reason** is that this code is optimised for fast computation. Manly due to the utilisation of GPUs which offer high parallelism. *Don't bother trying to implement a faster version.*

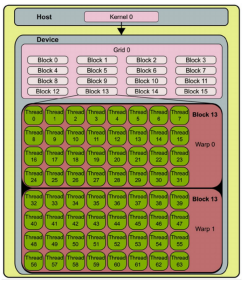




Architecture of a CUDA-capable GPU



CUDA compute model



Morals of AI

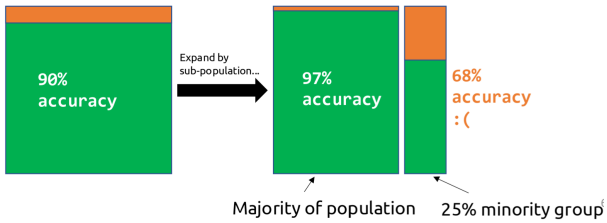
Gender Shades

Gender detecting algorithm is trained on a highly biased dataset, which leads to different results, depending on the target. Read More

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

Beyond Average Test-Set Performance

Even if a test-set is a well representation of the real world, which will lead to good average accuracy. The network can still do badly on minority group test sets.
Good average performance can mask poor performance of specific cases

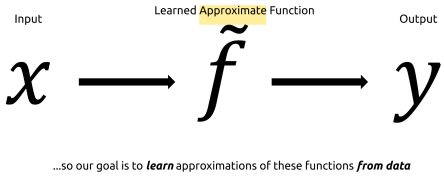


Reknognition

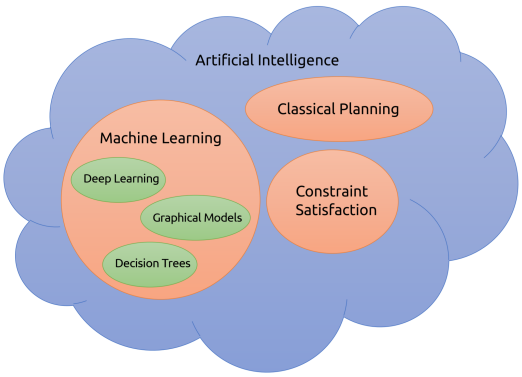
Facial Recognition algorithm wrongly matches government members to mugshots from a criminal database. The algorithm had **5% false positives** which isn't to bad, but when deployed states big issues of wrongly accusing innocent people. Read More

Machine Learning Concepts

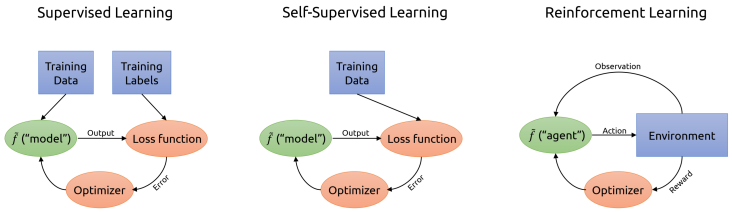
Machine Learning == Function Approximation

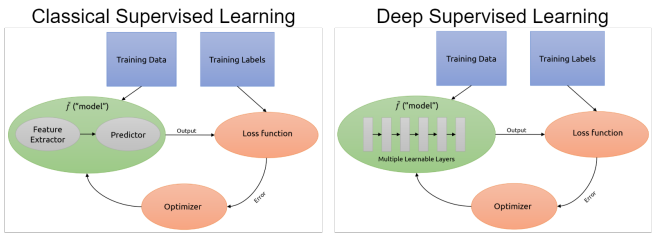


...so our goal is to ***learn*** approximations of these functions ***from data***



Types of Learning





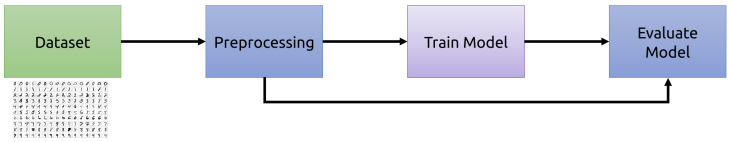
Self-Supervised Learning

From data **without labels** we can learn the structure of the data itself, there are several approaches, the basic idea is dimensionality reduction:

- K-Means Clustering
- Principal Component Analysis (PCA)
- Butterfly-Network (Autoencoder)
- ...

Types of Problems

Maschine Learning Pipeline



Dataset

Annotated Datasets like MNIST (Handwritten digits).

Preprocessing

Split the dataset into **Train, Validation, and Test sets**

- ***Train set*** — used to adjust the parameters of the model
- ***Validation set*** — used to test how well we're doing as we develop
  - Prevents ***overfitting***, something you will learn later!
- ***Test set*** — used to evaluate the model once the model is done

Train Model

1. **Initialization**: Set all weights w_i to 0.
2. **Iteration Process**:
   - Repeat for N iterations, or until the weights no longer change:
     - For each training example $\mathbf{x}^k$ with label a^k:
       1. Calculate the prediction error:
          * If $a^k - f(\mathbf{x}^k) = 0$, continue (no change to weights).
       2. Otherwise, update each weight w_i using:

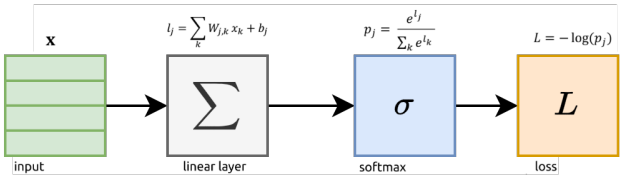
$$w_i = w_i + \lambda \left(a^k - f(\mathbf{x}^k)\right) x_i^k$$

   - where λ is a value between 0 and 1, representing the learning rate.

Optimizing with Gradient Descent

Loss Function

Function L which measures how "wrong" a network is. We want our network to answer right with **high probability**.

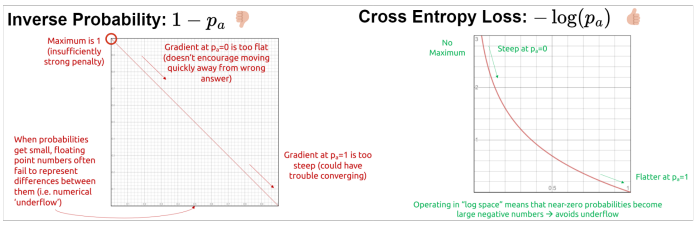


To get a probability for **binary classification**, we introduce a **probability layer**. One of the possible function is **Softmax**

$$p_j = \frac{e^{l_j}}{\sum_k e^{l_k}}$$

For every output j it takes every logit (output of network before activation/probability is applied) l_j in the exponent to ensure positivity. Dividing it by the sum of all logits ensures that $\sum_k p_k = 1$.

To get the loss L we apply a loss-function, *low probability* $\rightarrow$ *high loss*. We use **Cross Entropy Loss**

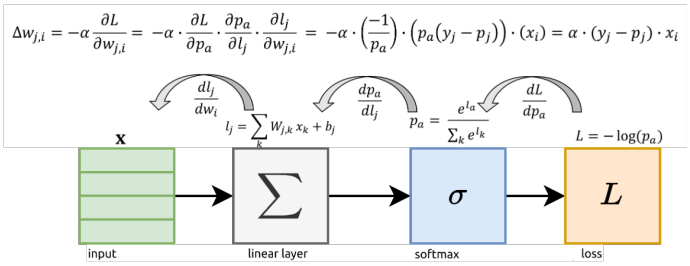


Gradient Descent

$$\Delta w_{j,i} = -\alpha \frac{\partial L}{\partial w_{j,i}}$$

α: learning rate *(typically 0.1-0.001)*
L: loss function
$w_{j,i}$: one single weight

To compute $-\alpha \frac{\partial L}{\partial w_{j,i}}$ use the chain rule




```
## Backpropagation on batch learning
# y = expected - (f(x)>0)
labels_OH = np.zeros((labels.size, self.num_classes),
↪  dtype=int)
labels_OH[np.arange(labels.size),labels] = 1  #
↪  One-Hot encoding
predictions = np.argmax(outputs, axis=1)
predictions_OH = np.zeros_like(outputs)
predictions_OH[np.arange(outputs.shape[0]),
↪  predictions] = 1
y = labels_OH - predictions_OH
# db = y*1
gradB = np.mean(y, axis=0)   # average over batch
# dW = y*x
y = y.reshape((outputs.shape[0],1,self.num_classes))
inputs =
↪  inputs.reshape((outputs.shape[0],self.input_size[0]*self
dW = inputs*y
gradW = np.mean(dW, axis=0)  # average over batch
```

Stochastic Gradient Descent (SGD)

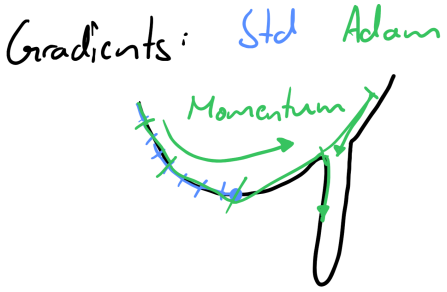
Train a network on **batches**, small subsets of training data.

```
# Stochastic Gradient Descent
for start in range(0, len(train_inputs),
↪  model.batch_size):
    inputs =
↪  train_inputs[start:start+model.batch_size]
    labels =
↪  train_labels[start:start+model.batch_size]
    # For every batch, compute then descend the
    ↪  gradients for the model's weights
    outputs = model.call(inputs)
    gradientsW, gradientsB =
↪  model.back_propagation(inputs, outputs, labels)
    model.gradient_descent(gradientsW, gradientsB)
```

- Training process is *stochastic* / *non-deterministic*: batches are a random subsample.
- The gradient of a random-sampled batch is a unbiased estimator of the overall gradient of the dataset.
- Pick a large enough batch size for *stable updates*, but small enough to *fit your GPU*

Stuck Gradients

When the gradients get low or there is a local minima, SGD can get **Stuck**.



Adaptive Momentum Estimation (Adam)

Two moments: SGD momentum and squared gradients. Also uses an exponentially decaying average. Fast and almost always the best, very little need to hyperparameter tune learning rate.

See Notebook

Automatic Differentiation

To avoid having to recalculate the whole chain every time a new layer is added, we use *automatic derivation*. There are several options:

Numeric differentiation

- $\frac{df}{dx} \approx \frac{f(x+\Delta x)-f(x)}{\Delta x}$
- Called *finite differences*
- Easy to implement
- Arbitrarily inaccurate/unstable

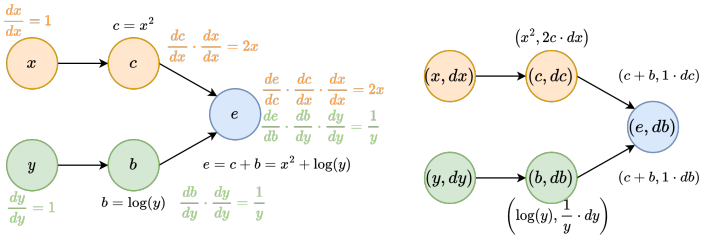
Symbolic differentiation

- $\frac{dx^2}{dx} = 2x$
- Computer does algebra and simplifies expressions
- Very exact
- Complex to implement
- Only handles static expressions

Automatic differentiation

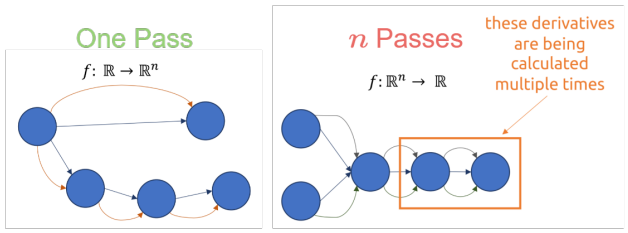
- Use the chain rule at runtime
- Gives exact results
- Handles dynamics
- Easier to implement
- Can't simplify expressions

Forward Mode Autodiff Every node stores its `(value, derivative)` in a tuple, called **dual numbers**. To compute the overall derivative, each derivative can be chained up. This is implemented via **Overloading**, every function / operator has multiple definitions based on the types of the arguments. ML-Framwork functions work on these tuples.

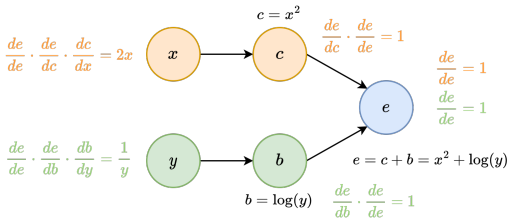


Time Effect: $O(N * M)$ time, $O(1)$ memory, with N = number of inputs, with M = number of nodes

Issue w/ forward mode



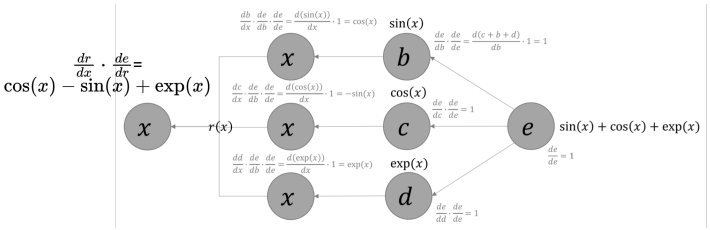
Reverse Mode Autodiff First, run the function to produce the graph, then compute the **derivatives backward**.



- Analog to the forward mode: overload math functions/operators
- Overloaded function return *Node* objects
- Overloaded functions build compute graph while executing
- After forward pass, the operations are recorded

- The backwards pass walks along the graph and computes the derivatives
- **Time Effect**: $O(M)$ time, $O(M)$ memory, with M = number of nodes

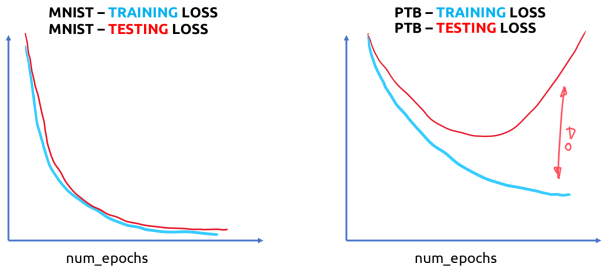
Fan-Outs (Reverse) The way to handle fan-out is to **add** the derivatives of the fanned-out nodes through replication $r(x)$.



Diagnosis Problems

Overfitting

Training on a complex dataset can lead to **overfitting** (PTBis a language dataset).



Regularization

This approach **modifies the loss** through adding a additional term to our existing loss function.

L2 regularization

$$\lambda \sum_{j=1}^{n} |W_j|^2$$

Penalize sum of squared weights

Effect: keeps all weights small-ish, i.e. network can't learn to rely too heavily on any single pattern in the data

L1 regularization

- $\lambda \sum_{j=1}^{n} |W_j|$
- Penalize absolute value of weights
- **Effect**: tends to produce *sparse weights* (i.e. many zero-valued weights) → prevents the network from relying on too many different patterns in the data

For both, this is a term added to the existing loss function.
λ controls the strength of the penalty

Regularization can be applied to certain layers on Keras through `tf.keras.layers.Dense(16, kernel_regularizer=keras.regularizers.l2(lambda), activation='relu')`.

Deep Learning Concepts

Common Misconception

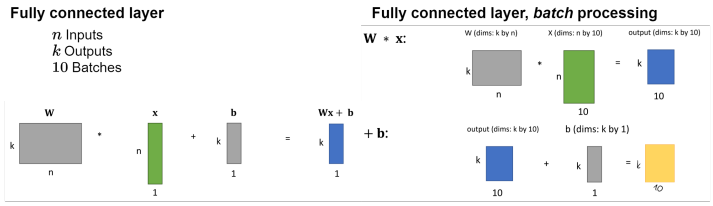
Deep Learning != AI, Just because deep learning algorithms are used doesn't mean there is any intelligence involved.
Deep Learning != Brain, Modern deep nets don't depend solely on *biologically mimiced neural nets* any more. A fully connected layer represents such a neural net the closest.
Deep Learning ==:

1. *Differentiable functions*, composed to more complex diff. func.
2. A deep net is a differentiable function, some inputs are *optimizable parameters*
3. Differentiable functions produce a computiation graph, which can be traversed backwards for *gradient-based optimization*

Multi-Dimensional Arrays & Memory Models

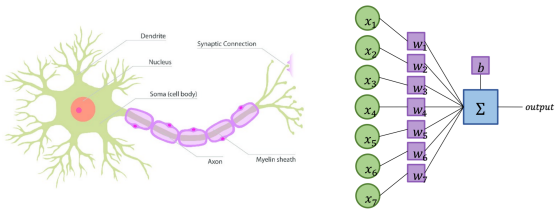
Vectorized Operations

For efficient operation, use **Matrices**.



Neural Networks

Perceptron



Biological Neuron Artificial Neuron (Perceptron)

Predicting with a Perceptron:

1. Multiply the inputs x_i by their corresponding weight w_i
2. Add the bias b
3. **Binary Classifier**, greater than 0, return 1, else return 0

$$f_\Phi(\mathbf{x}) = \begin{cases} 1, & \text{if } b + \mathbf{w} \cdot \mathbf{x} > 0 \\ 0, & \text{otherwise} \end{cases}$$

! Parameters

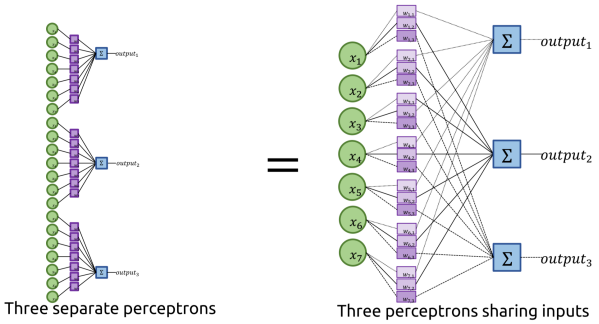
Weights: "importance of the input to the output"
- Weight near 0: Input has little meaning to the output
- Negative weight: Increasing input → decreasing output

Bias: "a priori likelihood of positive class"

- Ensures that even if all inputs are 0, there is some result
- Can also be written as a weight for a constant 1 input

$$[x_0, x_1, x_2, \ldots, x_n] \cdot [w_0, w_1, w_2, \ldots, w_n] + b$$
$$= [x_0, x_1, x_2, \ldots, x_n, 1] \cdot [w_0, w_1, w_2, \ldots, w_n, b]$$

Multi-Class Perceptron

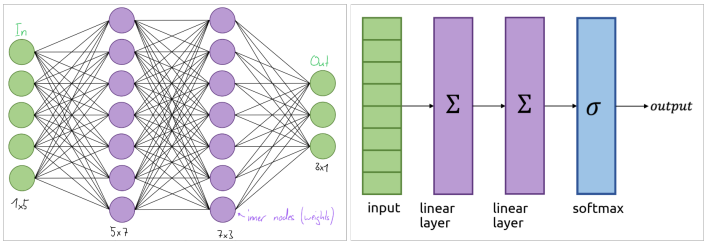


Biary Classifier: Only one output can be active $\hat{y} = \text{argmax}\left(f\left(x^k\right)\right)$, thus the update terms are

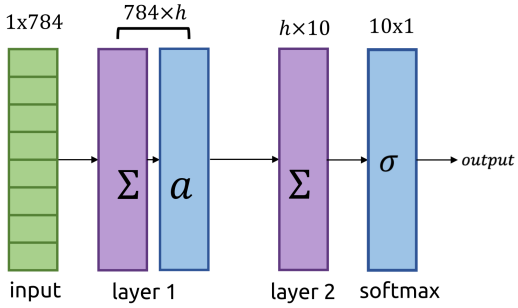
$$\Delta w_i = \begin{cases} 0, & \text{for } a^k = \hat{y} \\ -x_i^k, & \text{for } \hat{y} = 1, a^k = 0 \\ x_i^k, & \text{for } \hat{y} = 0, a^k = 1 \end{cases}$$

Multi-Layer

Through adding hidden layers we can make bigger networks and add more states to the algorithm.



The size of these **hidden layers** are defined by the **hyperparameter**. These define the configuration of a model and are set before training begins. *Rule of Thumb*: Make hidden layers the same size as the input, then start to tweak to see the effect. If you have more time and money, check this.

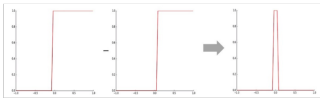


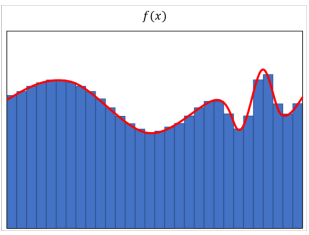
Universal Approximation Theorem

Remarkably, a one-hidden-layer network can actually represent any function (under the following assumptions):

- Function is continuous
- We are modeling the function over a closed, bounded subset of $\mathbb{R}^n$
- Activation function is sigmoidal (i.e. bounded and monotonic)

Proof: Any function can be approcimated by boxes (Riemann Sums).
A box is just the difference of two sigmoids.





Stacking Linear Layers isn't Enough

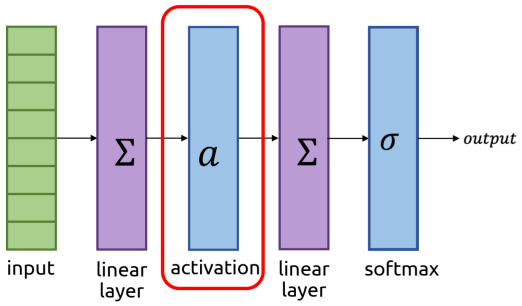
When simplifying the linear equation we get

$$\sigma\left(\begin{bmatrix} w_2 & b_2 \end{bmatrix}\left(\begin{bmatrix} w_1 & b_1 \end{bmatrix}\begin{bmatrix} x \\ 1 \end{bmatrix}\right)\right) = \sigma\left(\begin{bmatrix} w_{12} & b_{12} \end{bmatrix}\begin{bmatrix} x \\ 1 \end{bmatrix}\right)$$

Which is exactly the same as just one layer again, we need **activation**.

Activation Functions

We introduce a **nonlinear** layer



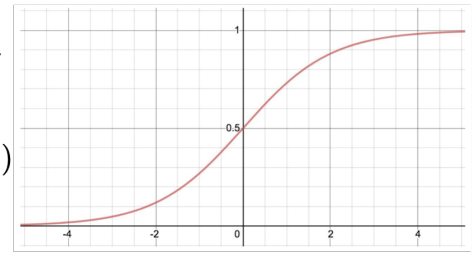
A activation function binds network outputs to a particular range. In the last layer this can be used to restrict the range, for example *age is strictly positive*.

Futher PyTorch activation functions can be found here.

Sigmoid .

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

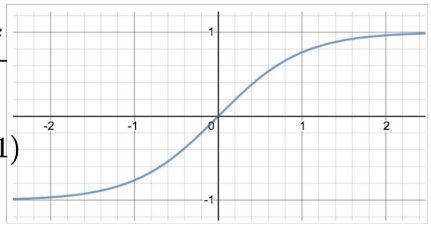
$$\sigma(x) : \mathbb{R} \to (0, 1)$$



Tanh .

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^x}$$

$$\tanh(x) : \mathbb{R} \to (-1, 1)$$



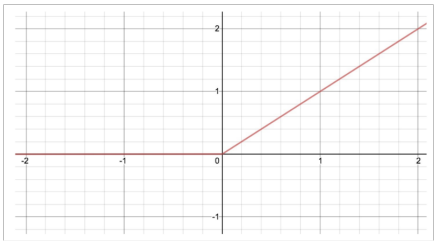
Vanishing Gradient

The problem with **Sigmoid** and **Tanh** is that the further away the parameters get from zero, the smaller is the gradient. Thus the network stops learning at these points. When **stacking layers** the issue gets even more severe.

ReLU .

Rectifies Linear Unit

$$f(x) = \begin{cases} x, & x > 0 \\ 0, & \text{else} \end{cases}$$

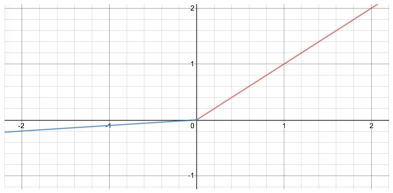


Dead ReLU

Because the negative part fed into the activation will result in a 0 output. For example, a large gradient flowing through a ReLU neuron could cause the weights to update in such a way that the neuron will never activate on any datapoint again.

Leaky ReLU To tackle a possible *dead ReLU* issue, we use a tiny positive slope for negative inputs.

$$f(x) = \begin{cases} x, & x > 0 \\ ax, & else \end{cases}$$



Convolution

Convolution is like a *"partially connected"* layer. Only certain inputs are connected to certain output pixels.

To introduce **translational invariance** $f(T(x)) = f(x)$ we apply convolutions. These are "Filters" which highlight different structures, the following network makes sense from the structures, not the pixels itself. Main application: **Computer Vision**.

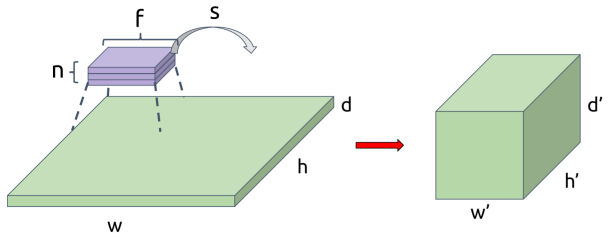
$$V(x,y) = (\mathrm{I} \otimes K)(x,y) = \sum_m \sum_n I(x+m, y+n) K(m,n)$$

The output at pixel (x, y) — "Image I convolved with kernel K" — Sum over kernel rows — Sum over kernel columns — Multiply kernel value with corresponding image pixel value

Hyperparameters

There are 4 hyperparameters for the convolution

- Number of filters, n
- Size of these filters, n
- The Stride, s
- Amount of padding, p



We can calculate the output size through

$$w' = \frac{w - f + 2p}{s} + 1, h' = \frac{h - f + 2p}{s} + 1, d' = n$$

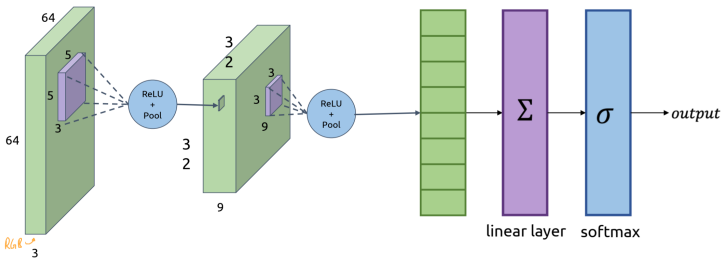
For **VALID** padding $p = 0$, for **SAME** padding p is chosen so output is same

```
# Execute manual Convolution
# Should be of shape (batch_sz, 32, 32, 3) for CIFAR10
↪
inputs = CIFAR_image_batch
# Sets up a 5x5 filter with 3 input channels and 16
↪  output channels
self.filter = tf.Variable(tf.random.normal([5, 5, 3,
↪  16], stddev=0.1))
# Convolves the input batch with our defined filter
conv = tf.nn.conv2d(inputs, self.filter, [1, 2, 2, 1],
↪  padding="SAME")
```

The inputs to `tf.nn.conv2d(...)` are:

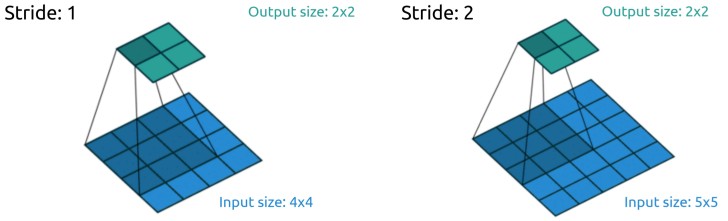
- `input` = [batchSz, input_height, input_width, input_channels]
- `filter` = [f_height, f_width, in_channels, out_channels]
- `strides` = [batch_stride, stride_along_height, stride_along_width, stride_along_input_channels]
- `padding` = either `'SAME'` or `'VALID'`

Tipically there are several convolutional layers and then a fully connected layer. This can be achieved through flattening a layer `flat = tf.reshape(conv, [conv.shape[0],-1])`.

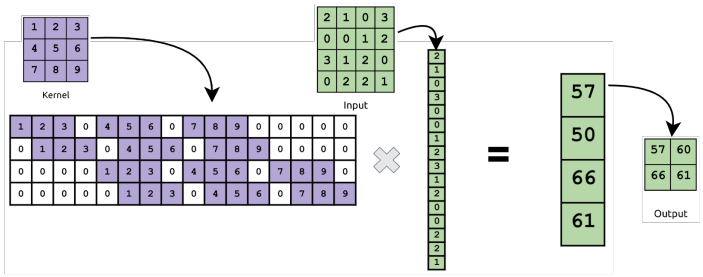


Stride The distance we slide a filter on each iteration is called **stride**. With a bigger stride, you compress a same size input into a smaller output. This decreases the image resolution controlled,

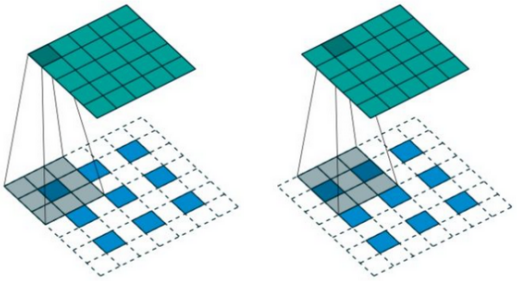
Downsampling. The filters are **Kernels** and are made of **learnable parameters**.



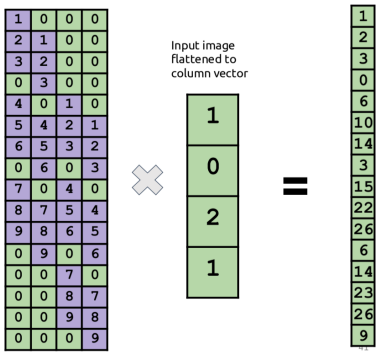
Computation The image is flattened and the kernel is unrolled into a bigger matrix. This leads to a normal **matrix/vector multiplication**



Fractional Stride For **deconvolutions** you can also use fractionally-strided convolutions (here $\frac{1}{2}$ stride):

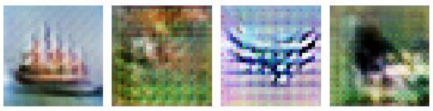


Computation Same as with the convolution, we flatten all matrices into vectors/matrices but now we **transpose** the kernel matrix, which gives us the **de-convolution**:



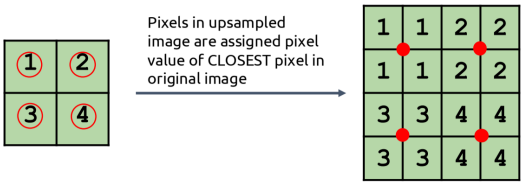
Checkerboard Artifacts

THe transpose convolution causes artifacts in output images because some pixels get written more often than others (at the overlaps, which occur in a line).

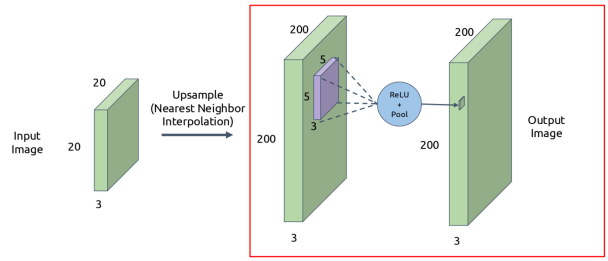


Prevention:

1. Upsampling using nearest neighbour interpolation

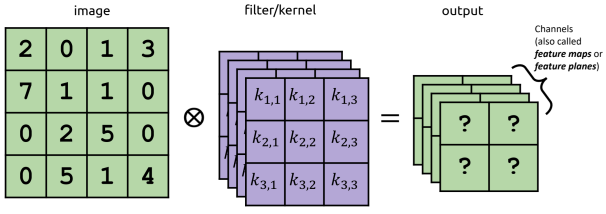


2. Perform a convolution with `'SAME'` padding on upsampled image

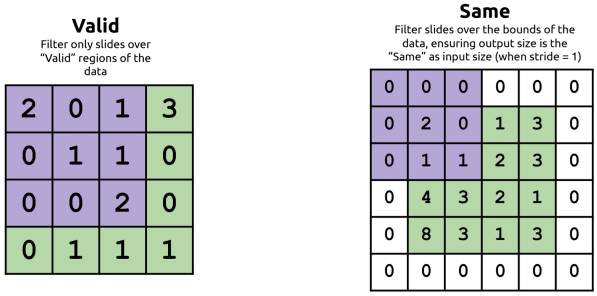



```
# Layer to upsample the image by a factor of 5
↪  in x and y using nearest
# neighbor interpolation
tf.keras.layers.UpSampling2D(size=(5, 5),
↪  interpolation='nearest')
# Do a convolutional layer on the result
tf.keras.layers.Conv2D(filters = 1, kernel_size
↪  = (10,10), padding = "SAME")
```

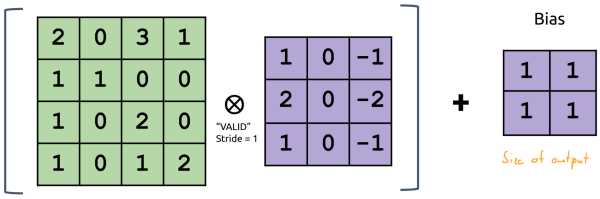
Filter Banks Futhermore, use several kernels per image, this block of kernels is a **filter bank**. The output is then a **mutli-channel** image. Multiple filters are able to extract *different features* of the image.



Padding To not loose resolution through a convolution, the original image has to be extended, **padded**. There are two convolution options, **VALID**, which is without padding, or **SAME** which is padding so that the output size is same as the input size.



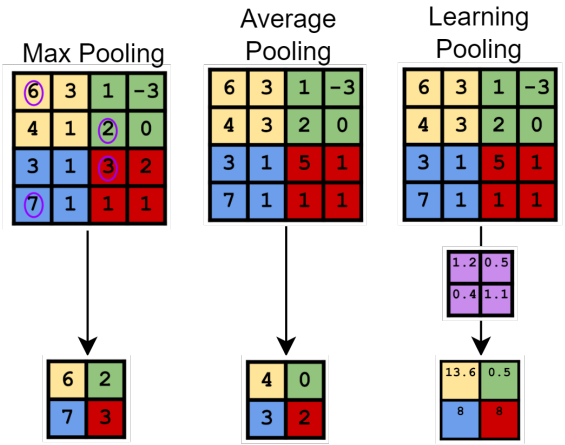
Bias As with other layers, a **Bias** can be added to the convolutional layer



This can be done through `tf.nn.bias_add(value, bias)`. When using keras layers, a bias is included by default `tf.keras.layers.Conv2D(filters, kernel_sz, strides, padding, use_bias = True)`.

Pooling

Pooling keeps track of the regions with the highest activation, indicating object presence, also lowers the resolution in a controllable way.



Invariances

The translational variance is largely eliminated with the introduction of convolutions, this can be further improved by introduction of antialising.

There are further invariances, which can hurt a CNNs performance. CNNs don't do to good on these, for good performance, lots of training is needed.

Sequential and Recurrent Networks

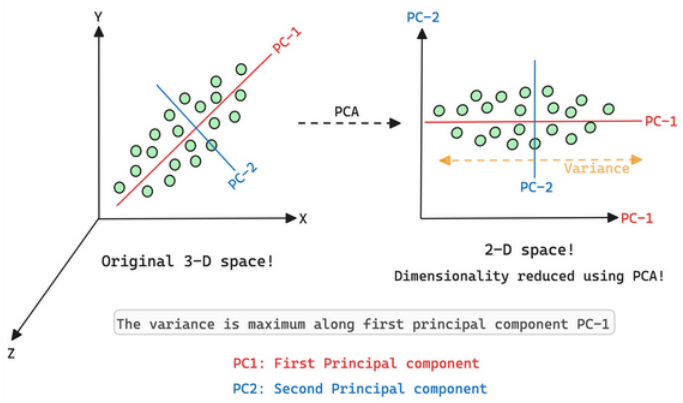
Latent Space

Latent Space is a compact representation, representing the input in a lower dimension. This is used for **Self-Supervised Learning**.

Represent the data with fewer dimensions, although data might exist in high dimensional space, it actually may exist along a lower dimensional subspace (e.g. 2D-Plane in 3D-Space, Line in 2D-Space), **Dimensionality Reduction.**

We do this for **smaller dataset footprint (memory)**, more efficient search through **nearest neighbour algorithms**, many **clustering algorithms behave better** in lower dimensions, Easier to **visualize**.

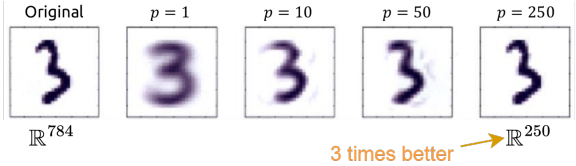
Principal Component Analysis (PCA)



Given a dataset D of dimension n and a target dimension $m \leq n$, find m vectors in $\mathbb{R}^n$ along which D has the highest variance. m are the **principal components**.

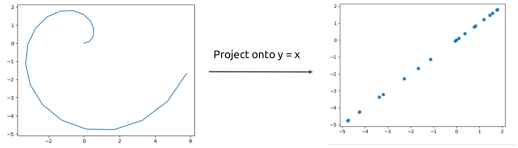
How: Find the direction of maximal variation, project onto this vector, repeat m times.

Example with MNIST:



Limitations of PCA

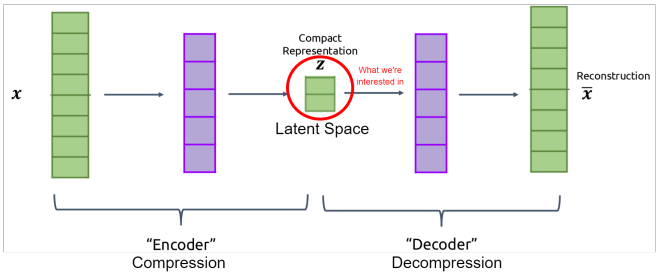
PCA can't figure out **non-linear** projections from $\mathbb{R}^2$ to $\mathbb{R}^1$.



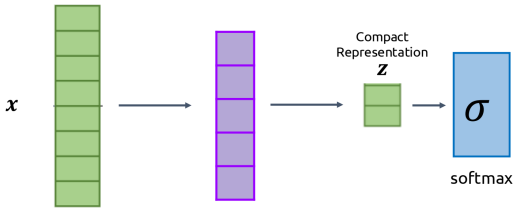
Butterfly-Network (Autoencoder)

Because we don't have labels, we copy the first part of the network and inverse it. The loss is then calculated through

$$L(x, \bar{x}) = (x - \bar{x})^2 \qquad \text{squared error loss}$$

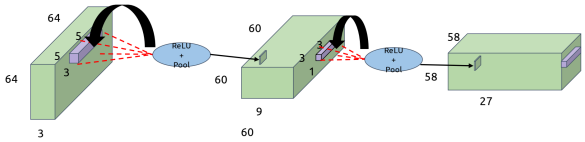


After training the network with the unlabelled data, the second part can be cut off and a binary layer be added. Now fine tune the last layer on **labelled data through supervised learning**.



Convolutional Autoencoder

The same approach can be applied to convolutional networks. But **convolutional matrices are expensive**, thus we just swap the forward and backwards pass code for the **deconvolution**.



This can be done in Tensorflow

```
tf.nn.conv2d_transpose(input, filters, output_shape, strides, padding='SAME')
```

4D tensor of shape [batch, height, width, in_channels]

4-D Tensor with shape [height, width, output_channels, in_channels]

length 4 1D tensor representing the output shape.

Strides along each dimension (list of integers)

String representing type of padding

Autoencoder Applications

Anomaly / Novelty Detection .

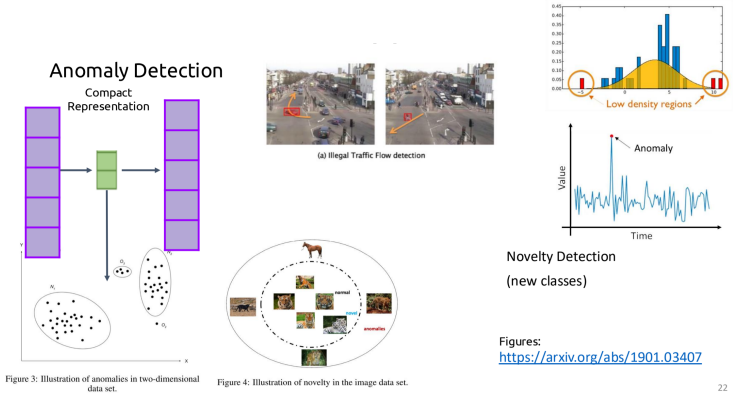


Figure 3: Illustration of anomalies in two-dimensional data set.

Figure 4: Illustration of novelty in the image data set.

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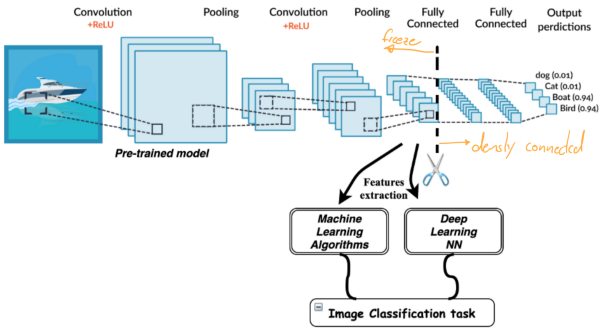
Others

- Transformer
- Density-based techniques (k-nearest neighbor, local outlier factor, isolation forests, and many more variations of this concept)
- Subspace, correlation-based, and tensor-based outlier detection for highdimensional data
- One-class support vector machines
- Replicator neural networks, autoencoders, and long short-term memory neural networks
- Bayesian Networks
- Hidden Markov models (HMMs)
- Cluster analysis-based outlier detection
- Deviations from association rules and frequent itemsets
- Fuzzy logic-based outlier detection;

Transfer Learning

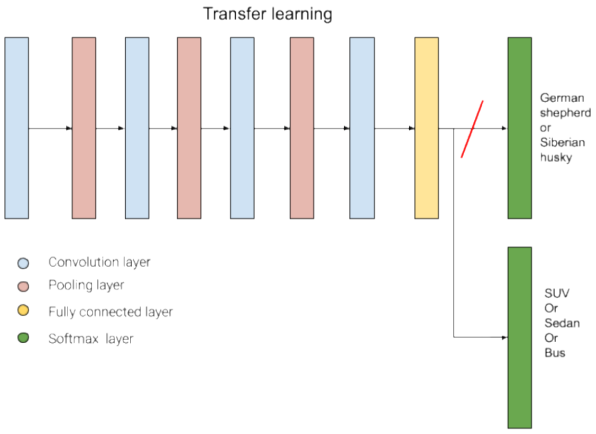
Taking a pre-trained network of a similar domain and adjust the last layers.



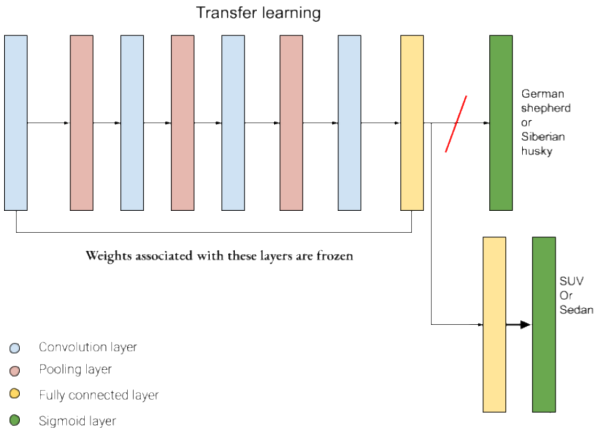
- Saves training time & money
- Network is more likely to generalise

Fine Tuning

One can switch out the **last layer** and add a different classification



Or also switch add/replace a fully connected layer if the differences in the domain are bigger



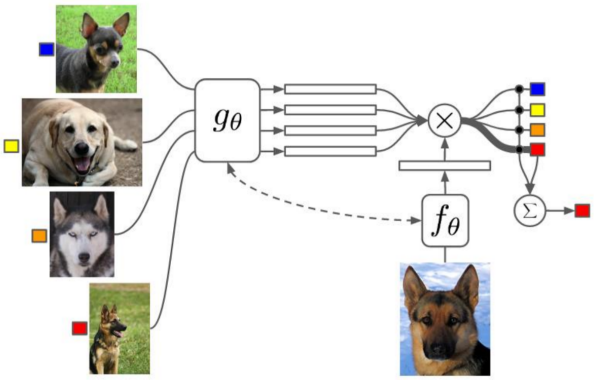
Zero Training

The last layer can be replaced by a *Logistic Regression* or *Nearest Neighbor Classifier*. The *transferred network* is then just a feature extraction pipeline. Use a database with known targets and classify new data through searching for nearest neighbour.

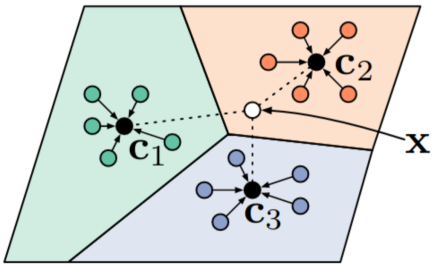
Few-Shot Learning

When there are only **few example of a sample** to be detected.

Siamese Networks where the sample and the test go through the same network. Then they are compared in the latent space.



Nominate or Generate a **representative** from each class



Training Methods and Tricks

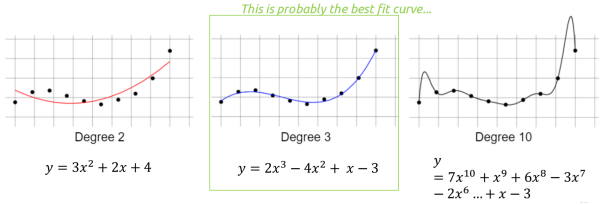
Early Stopping

If one stops training when the testing loss is starting to rise, at least the loss won't get bigger

```
# Pseudo Code Early Stopping
curr_test_loss = inf
for i in range(n_epochs):
    train model()
    new_test_loss = model.get_test_loss()
    if new_test_loss > curr_test_loss:
        break
    else:
        curr_test_loss = new_test_loss
```

Reduce Parameters

Reducing parameters, means less possibilities to learn or even memorize a dataset.



Reducing parameters can mean. . .

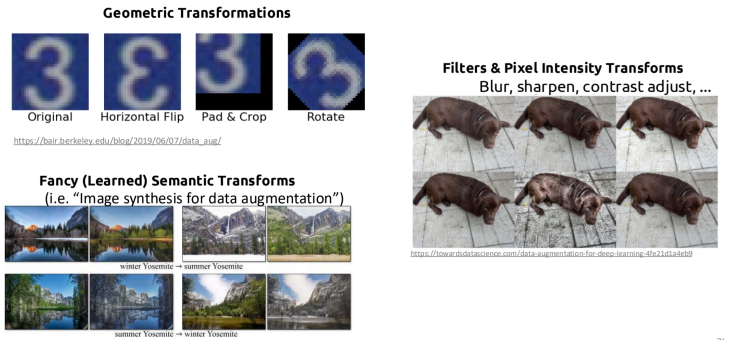
- . . . reducing layer size
- . . . decrease number of channels in a convolution
- . . . decrease number of layers

Reducing Parameters

Can also be used to check if parts of a network **are actually needed** → remove part → retrain model → if it behaves the same, it wasn't needed.
Requires obnoxious tuning of hyperparameters.

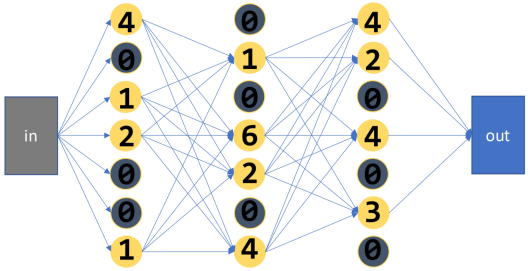
Data Agumentation

Generate **random variations** on your training data.



Dropout

Make it harder for the network. In a single training pass, the output of randomly selected nodes from each layer are set to 0. The nodes that drop out are **different each pass**. This builds **Resillience**. During testing all nodes are active again.

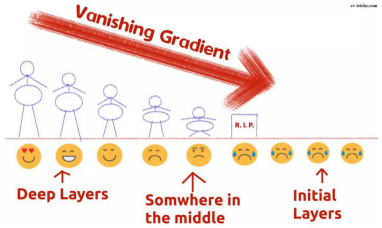


Dropout can be handled with Keras through `tf.keras.layers.dropout(rate)`, where `rate`is a *hyperparameter* between $[0, 1]$. `rate=0.5` is drop $\frac{1}{2}$, keep $\frac{1}{2}$. `rate=0.25` is drop $\frac{1}{4}$, keep $\frac{3}{4}$.

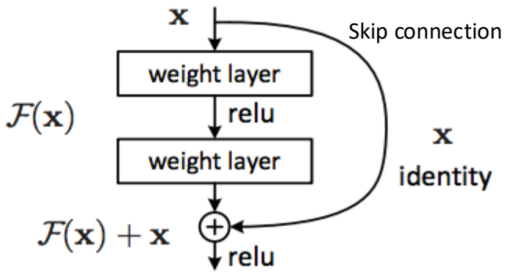
Skip Connections / Residual Blocks

Vanishing Gradients

The deeper a net gets (more layers) the more learnable parameters are present. This leads to vanishing of the gradient throughout the network



To mitigate the *vanishing gradient problem*, we use **Redidual Blocks**

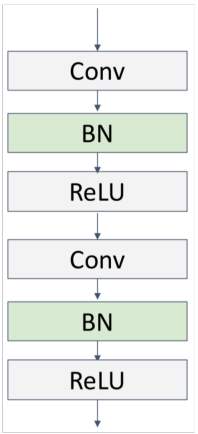


The output of each layer is the identity + some deviation (residual) from it. It allows the gradient to flow through two pathways. **Significantly stabilises training of very deep networks.**

Batch Normalisation

The idea is to stabilise inputs, which should lead to **faster training**. This is done through normalisation of the layers' inputs by re-centring and re-scaling.

A **normalisation layer** *BN* is added after a fully connected or a convolution, before the non-linear activation. In *Tensorflow* this is done with `tf.keras.layers.BatNormalization(input)`.

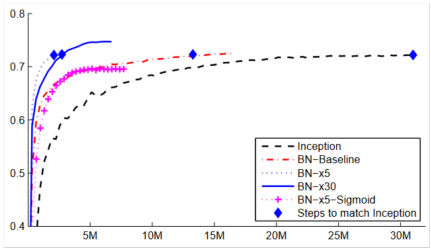


$$\mu_{\text{batch}} = \frac{\sum_{i=0}^{\text{batch}_{\text{size}}} x_i}{\text{batch}_{\text{size}}}$$

$$\sigma_{\text{batch}} = \sqrt{\frac{\sum_{i=0}^{\text{batch}_{\text{size}}} (x_i - \mu_{\text{batch}})^2}{\text{batch}_{\text{size}}}}$$

$$x' = \frac{x - \mu_{\text{batch}}}{\sigma_{\text{batch}}}$$

normalization



- Makes deep networks **much** easier to train!
- Allows higher learning rates, faster convergence
- Networks become more robust to initialization
- Acts as regularization during training
- Zero overhead at test-time: can be fused with conv!
- Not well-understood theoretically (yet)
- Behaves differently during training and testing: this is a very common source of bugs!

Checkpointing

Training is Expensive

Training takes a while and sometimes you want to "save" data for use in future instances.
Checkpointing allows you to save your Tensorflow model! No need to retrain every time your run your program. Fast prediction. Export your trained weights for use in other applications

```
checkpoint = tf.train.Checkpoint( ... )
```
"trackable objects"

- Trackable objects examples:
  - `tf.train.Variable`
  - `tf.train.Optimizer`
- Only restores Tensorflow variables, not Python variables

Example: (more here)

```
counter = tf.Variable(1)
checkpoint = tf.train.Checkpoint(var = counter)
manager = tf.train.CheckpointManager(checkpoint, filepath)
counter.assign_add(2)
manager.save()
...
checkpoint.restore(manager.latest_checkpoint)
```

We will be tracking 'counter'

Performing any operation on counter is linked to checkpoint

Specify the directory you want the checkpoints to be in

Restores checkpoint with counter = 3

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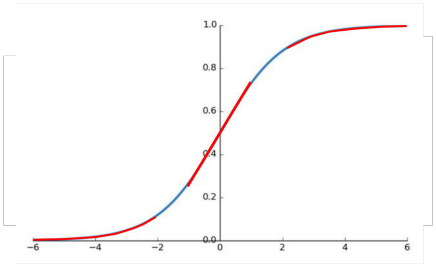
Xavier Initialisation

Bad Initialization

With certain activation functions, it's possible to get bad initialisations. For example with the sigmoid function we have the issue of linearity around $x \approx 0$ and the flatness / low gradient at $x > |4|$.



One solution is to use activations which don't have these issues, like **ReLU**.
Event then we want to keep values in the same range when they flow through a network. Values that drastically fluctuate in magnitude can lead to **numerical instability** → *slow convergence*.
Consider a weight matrix W of size mn :

- One entry y_i of the product Wx is: $y_i = Wi,1x_1 + \cdots + Wi,jx_j + \cdots + W_{i,n}x_n$
- If n increases, then the magnitude of y_i would also tend to increase
- If m increases, then the output vector Wx would have a larger dimension
- As the output becomes the input for the next layer, the next layer would add up in terms

We want the magnitude of weights to be **inversely proportional** to m and n.

To tackle this issue, we use the **Xavier Initialization**, we calculate the *standard deviation* on each layer i new:

$$\sigma_i = \sqrt{\frac{2}{n_i + m_i}}$$

Keras

Tensorflow code frequently gets terribly cumbersome, **Keras shortens the amount of code** you need to write through higher-level APIs for constructing, training, and evaluating models.

Tensorboard (Visualization)

A powerful visualisation, logging, and monitoring tool designed to be integrated with Tensorflow (although you can technically use it with any Python code).

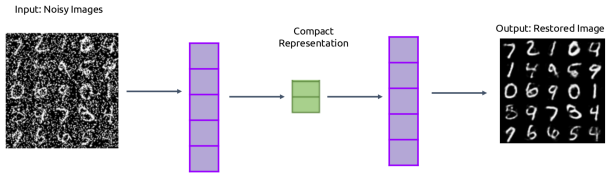
Check the Demo

Deep Learning Problems, Models & Research

Computer Graphics and Vision

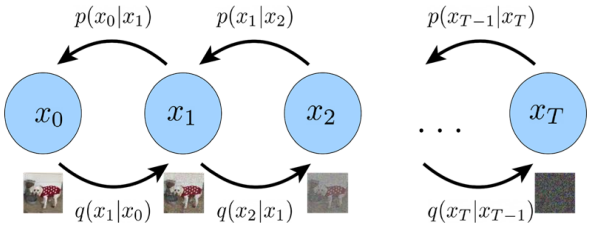
Denoising

Autoencoder networks can be trained to denoise images. The training is easy, as you just add the noise to original images.



Diffusion Models

A *Diffusion Model* is a denoising autoencoder with fancy math, it's the inverse of adding noise.



Examples

Natural Language

Audio and Video Synthesis

Search using Deep Reinforcment Learning

Anomaly Detection

Irregular Networks