Deep Learning Revision Notes

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Contents

1 Deep Learning for Computer Vision - Lecture Notes

ImageNet CIFAR10
Training - expensive Test - should be cheap
Regression functions predict a quantity, and classification functions predict a label.
So for example, NN labeling based on pixel diff is bad, because training is cheap and evaluation is expensive Also suffers from: tint, shift, do not correspond well to perceptual similarities
L_1 distance depends on coordinate system
For testing hyperparamters (for example, K-nearest neighbors, etc): - train, validate and test data tests. Hyperparamters are optimized on the validation dataset
Cross validation - used for small datasets, less for deep learning data is split into folds hyperparameters are averaged over the different fold choices higher confidence on which hyperparameters are used
Data sets should probably be created with the same probabilistic distribution
The curse of dimensionality: # of training examples is exponential to the # of pixels for examples, if we use pixel dist as the descriptor
kNN is a parametric model

1.1 Linear Classification

image(x) -¿ f(x,W) -¿ 10 numbers of scores per class W are parameters, so this is what we're learning
deep learning - how to get this function f
linear classifier - f = Wx + b b is the bias term, which can give class preferences for one class over another, can be used to unbias an unbalanced dataset
We can visualize the linear classifier to have some idea for template matching
Linear classifier only learn one appearance for each class. It does not deal with variation in class appearance
linear classifier try to create a linear barrier in a high dimension space between classes
Examples where linear classifiers fail: multi model data one class that can appear in different areas of space for example: 1 ¡ l2 ¡ 2

1.2 Loss Functions

The loss function measures how much error we have in our classification

1.2.1 Multi Class SVM - Generalization of Binary SVM

Loss is 0 if the incorrect label is lower than correct label + safety margin or wrong-score - correct-score + safety-margin = $\max(0, s_{wrong} - s_{correct} + safety)$
This is summed only over the wrong categories
Also known as hinge loss
After initialization W is small, initialize by setting all params to more or less similar: so the first loss should be approx. $C - 1$ where C is the number of categories
squared hinged loss will create a different classifier because the trade off between good and bad scores is different
hinge loss - we don't care if it's a little bit wrong or very wrong, but squared hinge loss heavily penalizes outliers
The loss function is how we design which errors the algorithm cares about
If we have loss = 0, the classifier is not unique, should be scalable
Also the loss should not depend only on fitting the training data.
This is solved by regularization, which encourages the model to use a "simple" W What is simple? that depends on the regularization term which you choose

1.3 Multinomial Linear Regression

Now the scores actually have meanings, they're the unnormalized log probabilities of the classes
softmax function - exp of the score ensures positivity $P(Y = k|X = x_i) = \frac{e^{s}k}{\sum_j e^{s_j}}$
Want to maximize log likelihood, minimize the negative log likelihood of the correct class So the loss function is: $L_i = -logP(Y = y_i|X = x_i)$ minus log of the probability of the true class $L_i = -log\frac{e^{sy_i}}{\sum_j e^{s_j}}$

1.4 Multinomial Logistic Regression

To get perfect loss function, we need infinite scores for the correct class and minus infinity scores for the wrong class
min loss is 0 max loss is infinity
when all classifiers are 0, the first iteration should be log(c)
cross entropy loss - log probability of the correct class
softmax wants to push the probability towards 1.0 (or score toward infinity) and other class towards negative inifinity. so even small changes of the scores of the classes will change the loss function
score function vs. loss function
Computing finite differences is terrible idea, because very slow due to high dimensions of the function

Numeric gradients are error prone. Always validate with finite differences.

Gradient Descent Step size or learning rate is one of the most important hyper parameters
Stochastic gradient descent
Momentum method
ADAM optimizer
Computing the loss might be very expensive if we use all of the examples in our training / validation sets
The analytic gradient of the loss is very slow to compute
Stochastic Gradient Descent - at every step compute a minibatch which is a 2^n examples Estimate of the true gradient

1.5 Back Propagation

Once we can express something as a computation graph we can use a technique called back-propagation
The loss is at the bottom

1.5.1 Gates

Add gate - gradient distributor Max gate - gradient router Mul gate - gradient switcher
When one node is connected to multiple nodes, the gradients are added at this node.
$\frac{\partial f}{\partial x} = \sum_i \frac{\partial f}{\partial q_i} \frac{\partial q_i}{\partial x}$
So now we do this for vectors, Jacobians and Hessians:
The size of the Jacobian is the dimension of the input vector times the dimension of the output vector. for minibatches the jacobian is even larger - 400kx400k easy...
If the gates are element wise, the Jocobian is a diagonal matrix
Exercise: What's the gradient of the L2 norm?

1.5.2 Sigmoid function:

$\sigma(x) = \frac{1}{1-e^{-x}}$
Exercise: break down the sigmoid function into gates Compute the back propagation
The gradient with respect to a variable should have the same shape as the variable
How to Build Neural Networks

Fully connected linear layers - all outputs of one layer are connected to all inputs of a second layer The abstraction of layer allows for matrix - vector operations

1.6 Neural Nets - History Recap

Krizhevsky 2012 - first use of modern neural networks on Imagenet that generated good results
1980s - Experiments on Vision in Cats: - nearby regions in vis cortex represent nearby region in vis field - neurons had heirarchical org
Simple cells - response to light and orientation Complex cells - light, orientation and movement Hypercomplex - movement with an end point
Complex cells sort of do pooling
1998 - gradient based learning applied to document recognition
2012 - modernized version dense connections max connections between layers

1.7 Layer Types

1.7.1 Fully Connected Layers

Image 32x32x3 -¿ stretch out all pixels to a single vector x = 1x3072 Layer W 10x3027 Wx = activation per "neuron" -¿ 1x10
Fully connected layers are used to compute max scores

1.7.2 Convolution Layers

Preserve spatial structure: 32x32x3 x and the filter is going to be 5x5x3 compute dot product at every spatial location
Filters always extend the full depth of input volume
The dot product is called activation - which is the size of the image - filter + 1
The structure usually follows something like this: CNN Pool CNN ...

Strides Used to reduce dimensionality
Stride size - the interval of sampling locations
Stride and image size need to match: (N - F) / Stride + 1
# of parameters per filter - $size_x \times size_y \times depth - 3$
It is common to pad the borders to get the appropriate size
This is also known as receptive field

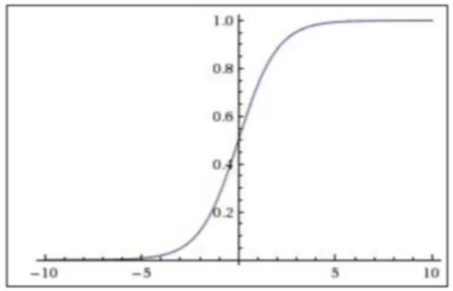
1.7.3 Pooling layers

Reduces representation size, s.t. it is more manageable Pooling is only in the spatial, not over depth Max pooling is commonly used (also softmax)
The pooling layer is controlled by three hyperparamters: Spatial extent Stride
Produced $w_2 \times h_2 \times d_1$ $w2 = (w1 - f)/s + 1$ $h2 = (h1 - f)/s + 1$ $d2 = d1$
introduced zero parameters zero padding isn't usually used
Common parameters: $f = 2, s = 2$
$f = 3, s = 2$

2 Training Neural Networks

2.1 Activation Functions

Sigmoid function $\frac{1}{1+e^{-}x}$ Maps all variables to [0,1] Interpetation - saturating firing rate of a neuron
Disadvantages: - saturated neutron kill off the gradients - when doing back-propagation for large values, i.e. let's say $x = \pm 10$ the gradient is simply going to be 0 - the maximal gradient is obtained at $x = 0.5$ - sigmoid outputs are not 0-centered - this means that the gradient computed is always either all positive or all negative. as a result, the this means that the optimization cannot always step in the true direction of the gradient, but wil take a zig zag path. so it's important to have 0-mean input - exponential function - expensive.



tanh - $tanh(x)$
- Similar to sigmoid function - the output is in the range of [-1,1] - zero centered - gradient = 0 when saturated

ReLU - $f(x) = max(0, x)$ - Rectified Linear Unit - Does not saturate in the positive region - Very computationally efficient - Converges much faster than sigmoid and tanh (x6) - More biologically plausible than sigmoid

Disadvantages
- does kill the gradient in the negative part of the regime - It is possible to have dead ReLU that do not activate or update for a large part of the data. This can happen due to the following reasons: - bad initialization - learning rate is too high - large updates and the weights just around fast, the ReLU can get knocked off the data manifold

Leaky ReLU - $f(x) = max(0.01x, x)$ - Instead of being flat in the negative regime, it returns a negative gradient - This solves the saturation problem and improves the convergence rate - Computationally efficient

PReLU $f(x) = max(\alpha x, x)$ - The α becomes another parameter - Improves flexibility

Exponential Linear Unit (ELU)

$$f(x) = \begin{cases} x & \text{if} x > 0 \\ \alpha(exp(x) - 1) & \text{if} x < 0 \end{cases}$$

- expensive - requires an exponent - this build back saturation in the negative regime - possible interpetation is that this is more robust to noise - this is between relus and leaky ReLUs

Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$ - Generalization of ReLU and Leaky ReLU - Linear regime - No saturation - Doubles the number of parameters per neuron

2.1.1 Guidelines to using activation functions

- ReLU is the standard - LReLU / Maxout / ELU are ok to try - tanh can be used very carefully - Don't use sigmoid :(original activation function - but people advanced to ReLU

2.1.2 Data Processing Pipeline

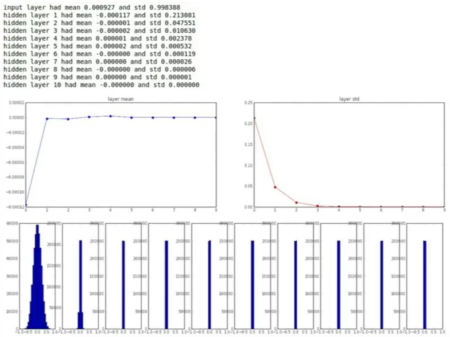
1. original data 2. zero - meaned data 3. normalized data - according to the std in each dimension - we need 0-mean data because any sort of bias will cause bias and (maybe) reduce the convergence
Approaches to normalize the data can include:
- PCA - the data has diagonal covarriance matrix - whitened data - the covariance matrix is identity - with images - stick to normalization, projecting pixel values into a lower dimensionality representation might not be beneficial - want to preserve spatial structure - training and test data are normalized in the same way - options include - subtract the mean image - subtract the per-channel mean

2.1.3 Approaches to Initializing the NN:

- Setting initial nets - if all of the weights are 0 all of the neurons will respond in the same way, will all get the same gradient.

- Set initial weights to a small value that we sample from a normalized (Gaussian) with 0 mean W = 0.01*np.random.randn()

- This works for small networks but does not work for deeper network



- The mean for all of the layers is going to be zero which makes sense

- The STDEV shrinks at each layer and quicly collapses to 0

- Setting initial weights to large values -

- All of the neurons are going to be in the saturated regime, leading to values of ± 1

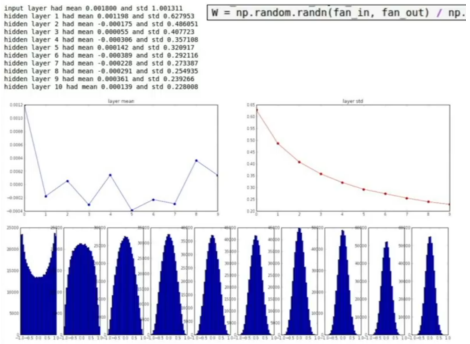
- Xavier initialization - from Glorot - fan_{in} - number of inputs - sample from a gaussian - normalize by the number of inputs - $W = random(min, max)/sqrt(min)$ - variance of the input is equal to the variance of the outputs - small number of inputs - larger weights - large number of input - smaller weights

- This reasonable initilization - math derivation assumes linear activation

- But this breaks when you use a ReLU

- the ReLU kills half of the neurons - sets the weights to 0

- changes the variance - so you can divide by 2 and this improves the weights



2.1.4 Batch Normalization

Consider a batch of activations at some layer - make each dimension unit gaussian:

$$\hat{x}^k = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{\text{Var}[x(k)]}}$$

which is differentiable
This is done per-dimension
The step is usually done after each fully connected layer and convolutional layers - to mitigate bad scaling effects at each layer
For convolutional layers - we also want to normalize jointly all spatial dimensions and all of the training examples - i.e. we want nearby locations to be normalized in the same way - one mean and one stdev for one actibation map we have.
Check out **Ioffe and Szegedy, 2015** and understand the paper and the methods they present.
We might not necc. want unit Gaussian input to the tanh layers: this constraints you the linear regime of the non-linearity.
We can add a scaling and shifting operation - but the network can learn a scaling $\gamma = \sqrt{Var(x)}, \beta = E[x^k]$ which is the identity mapping
$y^{(k)} = \gamma^{(k)}\hat{x}^k + \beta^{(k)}$
Improves gradient flow through the network
More robust - higher learning rates and diff. init.
Regularization - each of the outputs is dependent on the inputs as well as the outputs of all images in the batch
At test time the batch norm functions differently: a single fixed mean of activation during training is used (can be estimated during training with running

averages)

2.1.5 Monitoring Training

1. Preprocess the data
2. Choose the architecture
1. input - hidden layer - output
3. Validation - step 1 - ensure loss is reasonable
1. disable regularization 2. do a forward pass 3. test the loss is reasonable 4. for example for softmax the "correct" loss is about -log likelihood
4. Regularization validation
1. add reg. 2. observe the loss increases
5. Validate arch works:
1. start with a very small set of data - small set - be able to fit the data very well. - turn off reg - use simple vanilla sigmoid 2. ensure that the loss can go down to 0 and training accuracy goes up to 1
6. Figure out the training rate (step size):
- start with small regularization and find the learning rate to make the loss go down - in early stages of learning with softmax, even though the loss does not change much, we can observe large jumps in accuracy because small shifts in labels can lead to large changes to the classification with softmax - NaN - learning rate too high - A good range [1e-3, 1e-5]
7. Hyperparameter Optimization
Cross validation in stages, coarse to fine
Best to optimize in log space
- Stage 1: - try a few epoch instances - pick values spread out apart - Stage 2: - longer running time, finer search - Solver explosion detection: - if the cost is x3 original cost, quit - If all learning rates are at the edge of our hyperparameter sampling space, it means we might not have explored the range appropriately - Random Search vs. Grid Search (Begstra and Bengio, 2012) - Grid layouts - Better to sample randomly from each parameters in the range - If a function is dependent more on one variable than another, which is usually true, because we have lower effective dimensionality than what we usually have, we will have more samples of the important factor - more useful signal - Hyperparameters: - network arch. - learning rate, decay schedule, update type - regularization (l2/dropout)
8. Bad Init - flat learning curve
9. Track ratio of weight update / weight magnitude - ratio of 0.01-0.001 is about good

Training a Neural Network 1. Randomly initialize the weights 2. Implement forward propagation to get $h_\theta(x(i))$ for any $x^{(i)}$ 3. Implement the cost function 4. Implement backpropagation to compute partial derivatives 5. Use gradient checking to confirm that your backpropagation works. Then disable gradient checking. 6. Use gradient descent or a built-in optimization function to minimize the cost function with the weights in theta.

2.1.6 Stochastic Gradient Descent

Normal gradient descent:

```
while True:
  weights-grad = evaluate_gradient(loss-fun, data, weights)
  weights += - step-size * weights-grad
```

High condition number - cases of functions where the loss changes quickly in one direction and slowly in another direction. The ratio of the smallest to the largest singular value in the Hessian matrix
For functions such as this, there's a tendency to zig zag (valley problem), leading to slow convergence. This problem is more common in higher dimensions.
Local minima and saddle points:
SGD will get stuck because the gradient is 0.
Saddle points are common in high dimensions. The problem is also close to the saddle point.
Stochastic - the gradient and loss are estimated using a small number of example batches
Any noise in the gradient means that the optimization wanders around in the space and might take a lot of time to converge
Momentum term:
We step in the direction of our velocity and add friction
This simple strategy helps a lot.
Nesterov Estimated Gradient:
Evaluate the gradient at the point where the velocity vector takes you, and mix the two to step again from the original point
tendency to overshoot minimum, nesterov tends to overshoot less.
flat minima are prob. generalizing better - recent theoretical work
feature, not a bug that sgd momentum skips over sharp minima

AdaGrad

```
grad_squared = 0
while True:
```

```
  dx = compute-gradient(x)
  grad_squared += dx * dx
  x -= learning_rate * dx / np.sqrt(grad_squared) + 1e-7)
```

What it does:
1. normalizes the relative step size in each dimension based on the history, so it will increase step size for variable with small gradient and dec step size for variables with high gradient 2. Over time the step size decays - in the convex case it is good. non convex case, it is problematic - you might get stuck with adagrad

RMSProp

```
grad_squared = 0

while True:
  dx = compute_gradient(x)
  grad_squared += decay_rate*grad_squared + (1 - decay rate) * dx * c
  x -= learning_rate * dx / np.sqrt(grad_squared) + 1e-7)
```

0.9 or 0.99 decay rate.
estimates are leaky - not always slowing down?
RMS prob does not tend to overshoot as much, the optimization makes equal progress along all dimensions
AdaGrad decays quickly if the learning rate is fixed relative to other methods.

Adam Maintain an estimate of the first and second moment
Momentum
Bias correction
AdaGrad/RMSProp
If the valley problem is not xis aligned, non of the algorithms can deal with that (think squished taco)
let's compare Adam and AdaGrad/RMSProp with momentum:

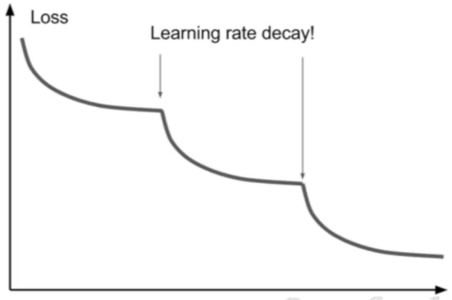
```
first_moment = 0
second_moment = 0

while True:
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment(1-beta1)              //momentum
  second_moment = beta2 * second_moment(1-beta1)*dx         //AdaGrad/RMSProp
  x -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7 )
```

And in fact full form Adam is:

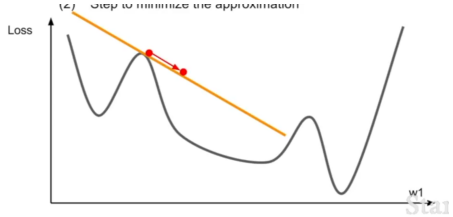
```
first_moment = 0
second_moment = 0

for t in range(num_iterations):
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment(1-beta1)    //momentum

  second_moment = beta2 * second_moment(1-beta1)*dx
//AdaGrad/RMSProp
  first_unbias = first_momentum / ( 1 - beta1 ** t)
  second_unbias = second_momentum / ( 1 - beta2 ** t)
  x -= learning_rate * first_unbias / (np.sqrt(second_unbias) + 1e-7 )
```

Adam with beta1 = 0.9,
beta2 = 0.999, and learning_rate = 1e-3 or 5e-4
is a great starting point for many models!

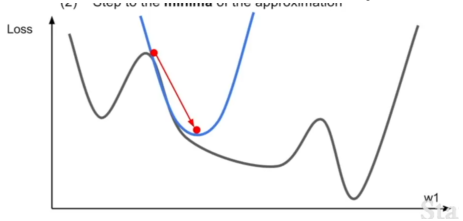
Learning Rate Decay Step decay - half the learning rate every few epochs
exponential decay - $\alpha = \alpha_0 e^{-kt}$
1/t decay - $\alpha = \alpha/(1+kt)$
More Common with SGD and Momentum and less common with Adam
Start without learning rate decay



All of these algorithms are **First Order Optimization Algorithms**
1. Use gradient to approximate the derivative (in a linear manner) 2. Step to minimize approximation
The step does not hold for large step size



Second order approximation We can use a second order approx. of the gradient incorporating the Hessian
We can then step to the minimum of the approximated function
This is called the Newton step - it does not have a learning Rate!
This is impractical for deep learning, Hessian is $O(N^2)$ which can be a few millions
cannot invert or store in memory



Alternative are BFGS and L-BFGS which are approximations of the Hessian
L-BFGS works well for full batch deterministic
Doesn't work very well for mini-batches, the approximations do not handle the stochastic case too well. In practice counter this by:
- Adam - If you can afford full batch, LBFGS
Until now all of this was about training error. But we can more about test data, and reducing the gap on test data! So, what can we do?

Model Ensemble 1. Train multiple independent models 2. Test time average their results - 23. Consistent improvement - used often in benchmarks 4. Also keep snapshots of the model during training 5. Polyak averaging - save some running average of the model parameters

2.1.7 Regularization

Regularize the model to have it generalize better from training to test data
L2 Regularization - $R(W) = \sum_k \sum_l W_{k,l}^2$
L1 Regularization - $R(W) = \sum_k \sum_l |W_{k,l}|$
Elastic net - $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$
In practice this regularization doesn't make too much sense in NN.

Dropout At every forward pass through the network, randomly set some neurons to 0
The probability is a hyper-parameter, usually set to 0.5
More common for fully connected layers, but sometime to might drop channels in conv layers
Dropout means the network cannot rely on a single feature too much
Similar to doing a model ensemble within a single model
Dropout affects the expected value of our variable - (i didn't get the full idea of this and it is used in test time) - but at test time we multiply by the dropout probability
For a single neuron with two inputs:
2019-10-21 at 11.32.00.png 2019-10-21 at 11.32.00.png
Train: $E[a] = \frac{1}{4}(w_1x + w_2y) + \frac{1}{4}(w_1x + 0y) + \frac{1}{4}(0w_1x + w_2y) + \frac{1}{4}(0x + 0y) = \frac{1}{2}(w_1x + w_2y)$
Test: $E[a] = w_1x + w_2y$
At test time - multiply by dropout probability

Inverted Dropout You divide by p during training time, rather than multiply by p during test time
Training with dropout takes longer to train, but better generalization after in converged.
A different look at this:
Training - add randomness
Test - average out randomness
Batch normalization is similar - stochastic relative to a single data point
But dropout gives you control on the amount of randomness vs. batch normalization

Data Augmentation - Random image transformation - mirror, cropping Resize image at 5 scales Report performance at a single crop and at five standard crops
- Color jittering Possible in some data dependent way
- Basically - how we can change the data without the label

Drop Connect Randomly 0 out the weights

Fractional Max Pooling Randomize the regions over which we pool

2.1.8 Transfer Learning

For example, want to use learning from a general network to a more specific network which can label 10 dog breeds from a smaller dataset
Cafe etc are

	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

2.2 Deep Learning Software

2.2.1 CPU vs. GPU

GPU cores have 3840 units vs. 20 threads running on CPUs
But they run at lower clock speed, simpler operations
Parallelize one task across many cores
Good for performing a similar task
GPU CPU communication is a bottle neck
12GB memory is the max atm (2017) on GPU memory + caching hierarchy
Matrix multiplications are very suitable on GPU
Benchmarks show 60-70x performance gain
x3 performance gain by using optimized CUDA implementations - use cuDNN
Another problem - model is on GPU and the data is on SSD
this adds a bottle neck - solutions:
- read data in RAM - use SSD - multiple CPU threads to pre-fetch data -

2.2.2 TensorFlow

2019-10-21 at 12.32.42.png 2019-10-21 at 12.32.42.png
Where it's done like this - every time we run the graph we're copying the weights from numpy arrays to memory, etc. very expensive.
The solution is to setup w1 and w2 as tf.Variable - lives inside the computational graph and we also need to tell TF how to initialize them

So in this version the weights update step needs to live within the computational graph, so the final version is this?

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.Variable(tf.random_normal((D, H)))
w2 = tf.Variable(tf.random_normal((H, D)))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

learning_rate = 1e-5
new_w1 = w1.assign(w1 - learning_rate * grad_w1)
new_w2 = w2.assign(w2 - learning_rate * grad_w2)

with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    values = {x: np.random.randn(N, D),
              y: np.random.randn(N, D),}
    for t in range(50):
        loss_val, = sess.run([loss], feed_dict=values)
```

so we have to add a dummy node which is responsible for updating the weights:

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.Variable(tf.random_normal((D, H)))
w2 = tf.Variable(tf.random_normal((H, D)))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

learning_rate = 1e-5
new_w1 = w1.assign(w1 - learning_rate * grad_w1)
new_w2 = w2.assign(w2 - learning_rate * grad_w2)
updates = tf.group(new_w1, new_w2)

with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    values = {x: np.random.randn(N, D),
              y: np.random.randn(N, D),}
    losses = []
    for t in range(50):
        loss_val, _ = sess.run([loss, updates],
                               feed_dict=values)
```

and tell tf to update the node.

This is a bit ugly, we can simple use an TF optimizer:

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.Variable(tf.random_normal((D, H)))
w2 = tf.Variable(tf.random_normal((H, D)))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff * diff, axis=1))

optimizer = tf.train.GradientDescentOptimizer(1e-5)
updates = optimizer.minimize(loss)

with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    values = {x: np.random.randn(N, D),
              y: np.random.randn(N, D),}
    losses = []
    for t in range(50):
        loss_val, _ = sess.run([loss, updates],
                               feed_dict=values)
```

which adds the relevant nodes to the graph (compute gradients, update weight, group operations)

2.2.3 PyTorch

Has 3 different levels of abstraction

- tensor - imperative ndarray on gpu - variable - node in a comp. graph - support automatic diff - same API as tensors - flagged if we want to compute gradients - module - nn layer, may store state and learnable weights

tensors

```
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

Variables + autograd

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in), requires_grad=False)
y = Variable(torch.randn(N, D_out), requires_grad=False)
w1 = Variable(torch.randn(D_in, H), requires_grad=True)
w2 = Variable(torch.randn(H, D_out), requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    if w1.grad: w1.grad.data.zero_()
    if w2.grad: w2.grad.data.zero_()
    loss.backward()

    w1.data -= learning_rate * w1.grad.data
    w2.data -= learning_rate * w2.grad.data
```

- PyTorch we build a new graph at every forward pass which makes the code a bit cleaner - Define autograd functions by writing forward and backwards func.

```
class ReLU(torch.autograd.Function):
    def forward(self, x):
        self.save_for_backward(x)
        return x.clamp(min=0)

    def backward(self, grad_y):
        x, = self.saved_tensors
        grad_input = grad_y.clone()
        grad_input[x < 0] = 0
        return grad_input
```

Can use our new autograd function in the forward pass

imp. for Tensors

```
N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in), requires_grad=False)
y = Variable(torch.randn(N, D_out), requires_grad=False)
w1 = Variable(torch.randn(D_in, H), requires_grad=True)
w2 = Variable(torch.randn(H, D_out), requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    relu = ReLU()
    y_pred = relu(x.mm(w1)).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    if w1.grad: w1.grad.data.zero_()
    if w2.grad: w2.grad.data.zero_()
    loss.backward()

    w1.data -= learning_rate * w1.grad.data
    w2.data -= learning_rate * w2.grad.data
```

- we also work at the higher level: -

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

Modules

DataLoader write a data class that knows how to load and prepare the data

Complete PyTorch Pipeline

```
import torch
from torch.autograd import Variable
from torch.utils.data import TensorDataset, DataLoader

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

loader = DataLoader(TensorDataset(x, y), batch_size=8)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for epoch in range(10):
    for x_batch, y_batch in loader:
        x_var, y_var = Variable(x), Variable(y)
        y_pred = model(x_var)
        loss = criterion(y_pred, y_var)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Stanford

2.2.4 Static vs. Dynamic Graphs

TensorFlow - build once, run many times (static)
PyTorch - re-built at every run (dynamic)
For simple network, makes no difference
Static case
- network can do simple optimizations on the graph operations - more efficient - fused operations - more expensive upfront, but amortized over time - you can serialize the graph and the structure of the network - nice for deployment scenario
Dynamic case:

- conditional operations
- in tensor flow it's tf.cond() which needs to be baked into the graph
- loops
- RNNs is a good motivation for dynamic graphs

TensorFlow is a safe bet for most projects. Not perfect but has huge community, wide usage. Maybe pair with high-level wrapper (Keras, Sonnet, etc)

I think **PyTorch** is best for research. However still new, there can be rough patches.

Use **TensorFlow** for one graph over many machines

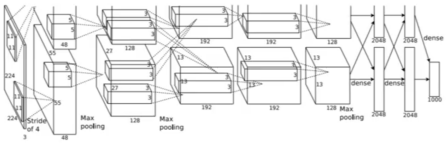
Consider **Caffe**, **Caffe2,** or **TensorFlow** for production deployment

Consider **TensorFlow** or **Caffe2** for mobile

2.3 CNN Architectures

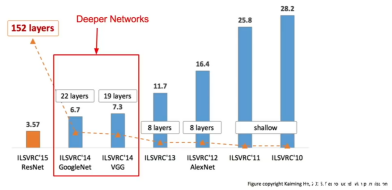
2.3.1 AlexNet

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



2.3.2 Introduction of Deeper Networks

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



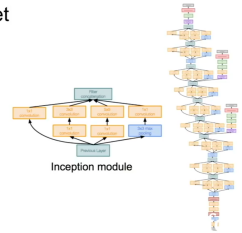
2.3.3 GoogleNet

- only 5 million params, x12 less than alexnet

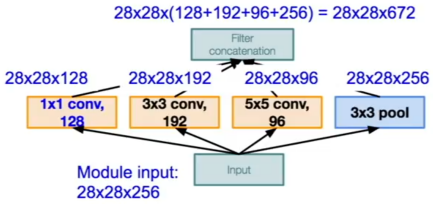
Case Study: GoogLeNet
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient "Inception" module
- No FC layers
- Only 5 million parameters! 12x less than AlexNet
- ILSVRC'14 classification winner (6.7% top 5 error)



Inception Module
Design a good local network topology (network within a network) and stack them together:



Naive Inception module

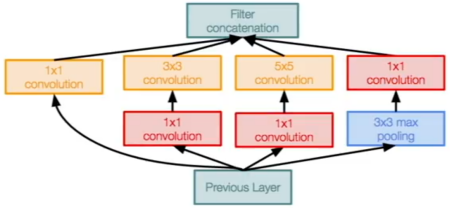
The idea is to have different operations on the same output, and then concatenate the output of these layers together.
What are the problems with this?

- computational complexity - 854 mops
- output depth - 28x28x672

How to keep this manageable?

- 1x1 conv with 32 filters operating on 56x56x64 $-$ $>$ 56x56x32
- conv layers preserve spatial information but can reduce depth
- projecting the input to lower dimension before expensive operations:

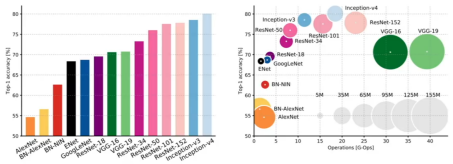
The optimized version has 358Mops vs. 854



ResNet Revolution of depth - 152 resnet architecture
Extremely deep network using residual connections
Why is this special?
Adding depth to a normal network $\rightarrow$ worse training response
The training error is doing worse - not because of overfitting.

The problem is an optimization problem - harder to optimize
Reasoning - a deeper model should perform just as well a shallower model - for example, train 20 layer model, copy the params, add 20 more layers of identity
$\Rightarrow$ I really do not understand this "residual"
- Were able to train very deep networks without degrading - Deeper networks can now achieve lower training error - better gradient propagation

2.3.4 Complexity


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Developments on top ResNet:
- Huang 2016 - Deep Networks with Stochastic Depth - reduce vanishing gradients and training time through short network training - drop layers randomly at every pass, use identity - use full network at test time
Fractal Net
- motivation: transitioning to residual representations are not necessary
Densely Connected Convolutional Networks
Recap of CNN architecture:

2.3.5 More Insights of The ResNet Arch

we pass the input through conv blocks (conv + relu) and then add the input to the output of these blocks
if the weights are 0 - it's simply identity
interpretation of l2 regularization of the network - encourages the model to drive unneeded layers
Gradient flow in backward pass:
- addition gradient will stream and fork along two different paths - upstream gradient will have direct connection - gradient super highway
Also DenseNet and FractalNet allow for easy gradient pass through the network

2.3.6 More Insight on Architectures

AlexNet and VGG have a lot of params in fully connected layers

AlexNet

- 62M params -¿ out of which most live in a few layers: - FC6 256x6x6 -¿ 4096: 38M Params - FC7 4096 -¿ 4096: 17M Params - FC7 4096 -¿ 1000: 4M Params - 59M params in 3 layers

2.4 Recurrent Neutral Network

We can have tasks that require a different data flow through the networks.

The vanilla one to one connection is called feed-forward network.

one to many $\rightarrow$ image captioning - for example, image to sequence of texts

many to one $\rightarrow$ variable size input -¿ for example, labelling text, or labelling video

many to many (1) $\rightarrow$ machine translation, variable length sequences of inputs and outputs

many to many (2) $\rightarrow$ video classification on frame level

2.4.1 RNN

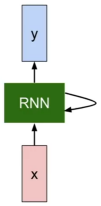
$$h_t = f_W(h_{t-1}, x_t)$$

h_t new state

h_{t-1} - old state

x_t - input vector at some time step

f_W some function with params



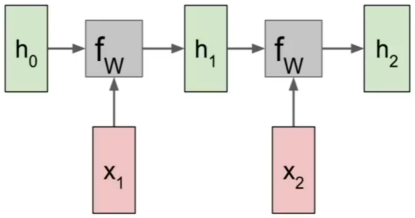
$$h_t = f_W(h_{t-1}, x_t)$$

$$\downarrow$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

RNN Unrolling: W remains constant throughout the optimization



Many to many - we can get output at every step

Many to one - we will get output based on the final state at the end of the input

One to many - unroll the graph for each cel in the output

Sequence to sequence: encoder and decoder

Encode input sequence in a single vector

Decoder network - one to many - produce output sequence from single input vector

2.4.2 Example: Character-level Language Model

Vocabulary: [h,e,l,o] Training:"hello"

Sampling from the model: seed the model with input

the output layer will have scores with a probability distribution

we can sample from it with softmax and synthesize the next sequence

why sample?

hard max probability

but sampling let's you get diversity

2.4.3 Back-propagation through time

Forward though the entire sequence to compute loss, then backwards though the entire sequence to compute gradient

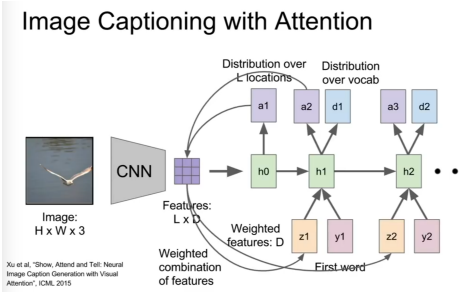
Very hard to train on long sequences.

Truncated Backpropagation through time - many people use 100 steps.

Compute a loss over the subsequence of the data

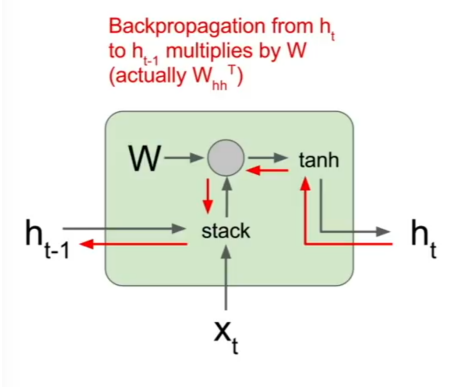
check out min-char-rnn on github for a minimal example of rnn backprop

RNN Attention Models RNN can focus its attention on different parts of the image



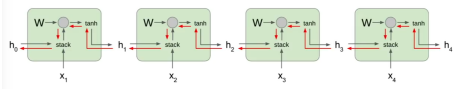
Multi layer RNNs max 4 or so

Back propagation of gradient through RNNs



Gradient through multiple RNN cells:

Computing the gradient with respect to h_0 - we get multiple factors of the W matrix, which can be undesirable.



trick: gradient norm ¿ max threshold, gradient is normalized by its norm

2.4.4 LSTM

Long short term memory

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$
$$c_t = f \odot c_{t-1} + i \odot g$$
$$h_t = o \odot \tanh(c_t)$$

better gradient flow properties

c_t cell state - keeps track of the internal state of the cell

we use input to compute the gates i - g

we expose part of the state as the hidden state at the next time step

f - forget gate, wether to erase the cell.

a vector of 0 and 1 which decides for each element wether to use it or not

(element-wise product) i - input gate, wether to write the cell

similar, but for g gate g - gate gate - how much to write to cell

o - output gate - how much to reveal cell

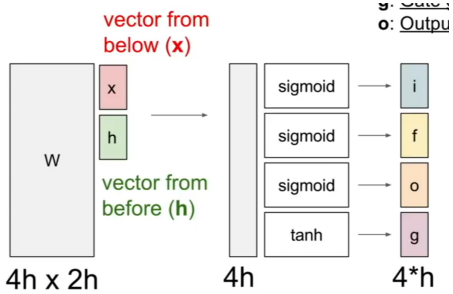
at every time step we can remember or forget the internal state, and increment or decrement the state of the cell by 1.

now we squash this into the range of [-1,1] with tanh and the output gate is coming through a sigmoid

the forget gate is coming out of a sigmoid - the forget gate is guarnteed between [0,1]

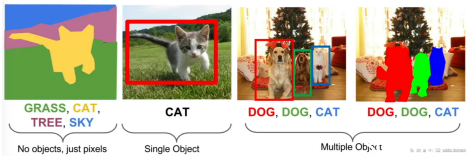
the output do not flow through tanh

and also there's direct gradient propagation, but i'm not sure about this LSTM stuff



⇒ also check out Highway Networks ICML Srivasta

2.5 Segmentation with CNNs

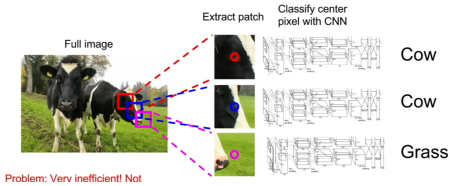


2.6 Semantic Segmentation

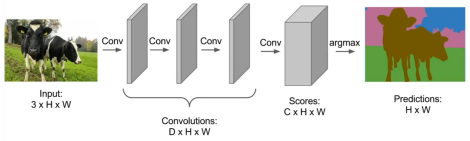
Decision for a category for every pixel in that image
Does not distinguish between instances of the object

2.6.1 Bad Approaches to semantic segmentation

Approach #1 - Patch Based First idea - but a pretty bad one - patch based classification (sliding window)
extract a patch
classify center pixel with CNN
Computationally expensive and does not share computation for similar patches.

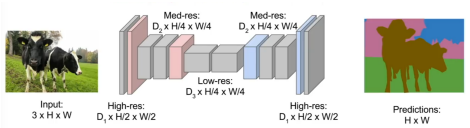


Approach #2 - Fully convolutional Design a network as a bunch of conv layers



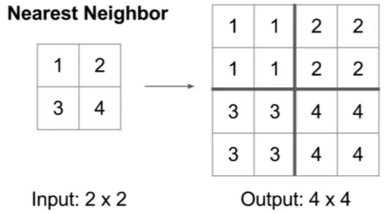
- applying a bunch of conv that all have the same size of the image - very expensive!

2.6.2 Approach #3 - Down and upsampling

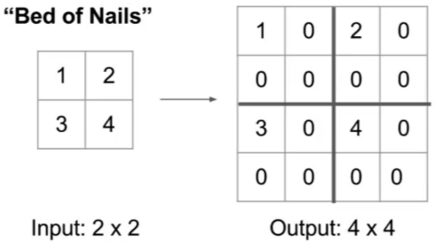


In the second half of the network, the network will typically upsample the data

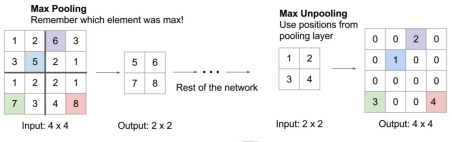
Unpooling Nearest Neighbor:



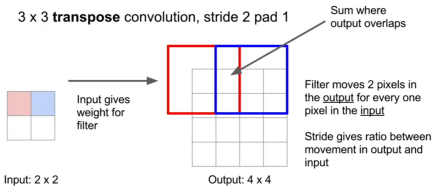
Bed of nails:



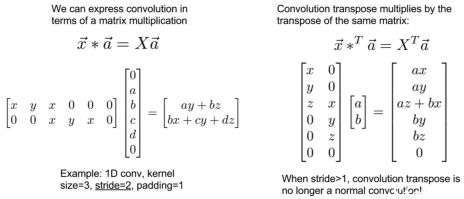
Max Unpooling:



2.6.3 Learnable Upsampling - Transpose Convolution

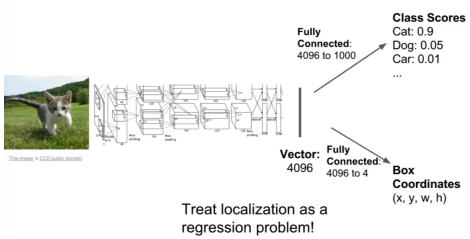


When the receptive fields in the output overlap, we sum
Sometimes called:
- deconvolution
- upconvolution
- fractionally strided convolution - stride 1/2 convolution - if the stride is the relation between the input and output
- backward strided convolution
Convolution can be framed as matrix multiplication: $\vec{x} \star \vec{a} = X\vec{a}$
If we do a transpose to the X matrix we get the "deconvolution" operation



2.6.4 Classification + Localization

i.e. bounding boxes
assumption: there is exactly one object in the image
can reuse previously familiar arch with one change: now there's a fully connected layer which also returns box coordinates



There are two loss functions:
softmax loss to create labels
L2 loss for the correct boss (simplest)
The assumption is that the images are labelled with these
The idea is that we have regression loss (what's that?)
multi task loss - have an additional hyperparamter that is used to scale both loss types, and take the gradient in respect to the weighted sum
the weighted hyperparamter changes the value of the loss function, which makes it harder to compute the gradient - cannot compare diff values for the hyperparamter directly as it directly affects the value of the loss
to deal with this: use some other metric of performance
better performance to train the network jointly
another possibility: freeze the network, train other parameters, and then fine tune the entire network

Human Pose Estimation Represent pose as a set of 14 joint positions

2.6.5 Object Detection

Different from localization - might have many number of outputs

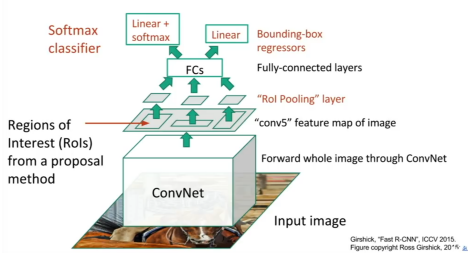
Sliding window Different crops from the image - feed it through a classification network
We also add a category of background if it cannot find
Problem: how do you choose the crops? location, size, aspect ratio, etc.

Region Proposal Network Will generate boxes where objects may be present.
Relative fast to run - Selective Search
High recall, and also many regions without objects.

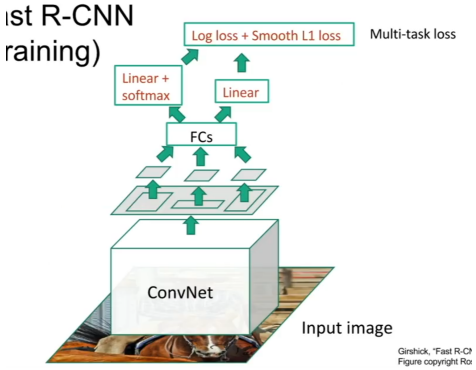
2.6.6 R-CNN

Put together all of the pipeline:
Extract ROIs form proposal method
Warp ROIs to the fixed size for the downstream network
Run through CNN
Use SVM to compute grades (svm loss - hinge loss)
In addition, predict correction to the bounding box
Multi class loss, train the whole thing
Main problem: super slow on training and inference

Fast RCNN forward the whole image through convnet
create feature map of the image
roi pooling layer
fully connected layer
bounding box regressor



During training add a multi class loss to do regression and do back prop:



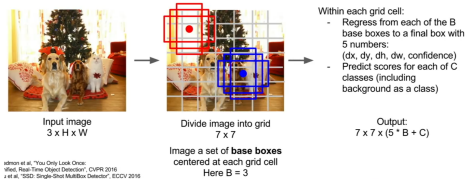
fast RCNN runtime is still dominated by the procedure to find ROIs.

2.6.7 Faster RCNN

Make the CNN do proposal
Have to optimize for four! different tasks/ goals which might be tricky
Training ROI is tricky because there's no ground truth data - to do this, any overlap between ROIs and ground truth object is marked as positive and cases of no intersection are given a negative rating
Classification task - binary decision for each region
Removed the overhead from computing region proposals.
Once you're learning ROIs, you can bias the model to your data.

2.6.8 Detection without Proposal

The idea for both of this methods is to do object detection as a regression problem, and perform all of the tasks at once.



YOLO YOLO - you only look once
Feed forward single pass object detection.

SSD - Single Shot Detection

2.6.9 Instance Segmentation

Predict the location and identities of the objects in the image
Rather than predict a bounding box, predict a segmentation mask for each of these objects.

Mask R-CNN Similar to Faster RCNN
Instance segmentation was trained on the Microsoft Coco dataset

2.7 Visualization and Understanding

2.7.1 First Layer

We can visualize each one of the filters directly:
We're visualizing the RGB layers from first layers of the filters.
Observing strong response to oriented edges in opposing colors
(this is from the pytorch model zoo)

Visualizing higher level layers weights are less obvious - 16 channel input 16x20x7x7 filters?

2.7.2 Last fully connected layers:

2.7.3 The last layer visualization

4096d feature vector for an image

Nearest neighbors in feature space: run all images through the network and collect the feature vectors

Can potentially be very different from in appearance, but similar in semantic content

There is nothing in the loss function that encourages these features end up close together.

Dimensionality Reduction Visualize the space of TC7 by reducing the dimensionality of the vectors from 4096 to 2 dimensions?

PCA

t-SNE

Maximally Activating Patches Keep track of what patches maximally activate neurons from a dataset and visualize them - gives an idea of what kind of features the neuron might be looking for.

Occlusion Experiments Check which parts of the image cause the largest change in the classification / probability / scores

Saliency Maps Visualize which pixels matter most for classification

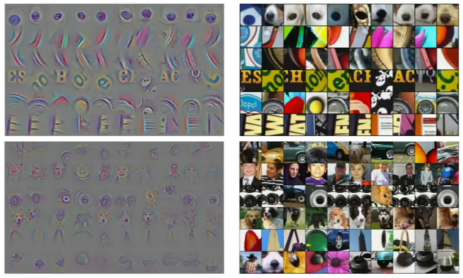
Compute the gradient of (unnormalized) **class score** with respect to image pixels, take abs value and max over rgb channels.

This tells us how much the class score changes with the respect of each pixel

GrabCut + Saliency maps

Guided Back Propagation compute the gradient of neuron value with respect to image pixels

now in addition to the patches, we can see exactly which part of patch activates the neuron



Gradient Ascent Synthesize images that maximize the activation in the network.

Start with a neutral image, compute gradient with respect to the neuron you want to maximize, and update the image in that direction

For regularization: just regularize the L_2 norm of the image

Some people do stuff like

- clipping pixel values
- gaussian blur image

This can be interpreted as projection of this max image onto a nicer image space

$\Rightarrow$ Visualizing this features and neurons would be a good exercises for me

Visualizing the higher level features shows that some of the class labels are multi modal

2.7.4 Adversarial Examples

Idea:

1. start from an arbitrary image 2. pick arbitrary class 3. modify the image to maximize the class 4. repeat until network is fooled

2.7.5 Feature Inversion

Total variation - encourages absolute pixel differences between neighboring pixels - encourages spatial smoothness

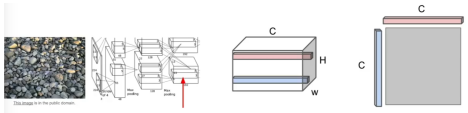
2.7.6 Natural Feature Synthesis

50 minutes into the lecture, i don't care about this

Texture Generation Nearest neighbor - simple approach that works pretty well for simple textures

March through the generated image and look at neighborhood around current pixel
But more complex texture do not work so well
Similar to gradient ascent in CNN
Gram Matrix -

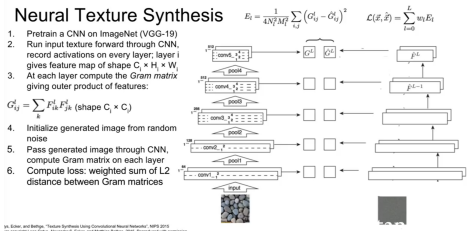
2.7.7 Style Transfer



The $C \times C$ matrix can be used as a feature descriptor, to describe which features tend to activate together the most.
The matrix throws away all spatial information because it averages all feature pairs in the image.
Efficient to compute -

$$C \times H \times W \Rightarrow C \times HW$$

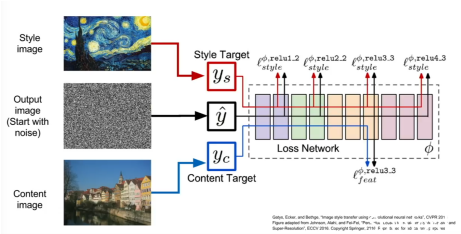
Using true covariance matrix also works but it is more expensive to compute
The gram matrix can be used to generate images with the same matrix:



Using higher layers of features from the CNN results in larger features being reconstructed or transferred into the test image

2.7.8 Style Transfer

Feature matching + texture synthesis
Input: Content Image + Style Image
Minimize the feature reconstruction loss of content image and minimize texture loss on for texture image



(might take a few hundred iterations to converge)

Can play with parameters - tradeoff between content and style

Resizing the style image gives control on the features which are going to be transferred

Problem: slow - many forward and backward passes.

Solution: train CNN to do the style transfer

Train (a few hours) - then single forward pass

Runs in real time

Fast style transfer - replaced batch normalization with instance normalization

Google addressed this by training one network to do style transfer to many different styles

3 Generative Models

3.1 Unsupervised Learning

The strategy is:

Data -¿ encoder -¿ features -¿ decoder -¿ reconstruction

The loss is trying to create a good reconstruction of the input data

Can be L_2 loss

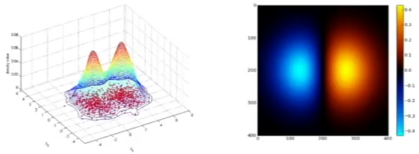
Examples:

Data: just data

Goal: learn the underlying hidden structure of the data

Examples: clustering, dim reduction, feature learning, density estimation

1-d density estimation

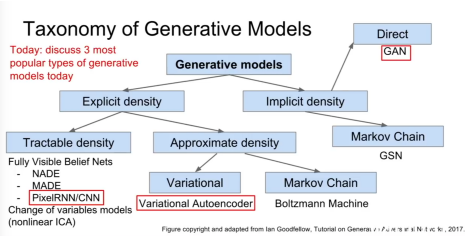


2-d density estimation

Density Estimation
In the unsupervised version, the data is cheap.

3.2 Generative Models

A class of models, where, given training data, the goal is to generate more examples from the same distribution.
Address density estimation
- Explicit density estimation - Implicit density estimation
Why?
- Realistic samples from artwork
- Super-resolution
- Generative models of time-series data for simulation and planning
- Good for reinforcement learning
- Learning latent variable representation



(for Ian Goodfellow tutorial on generative models)

3.2.1 Pixel RNN + PixelCNN

Fully visible belief networks:
Explicit density model
$p(x) = \Pi_{i=1}^{n} p(x_1|x_1, \ldots, x_{i-1})$

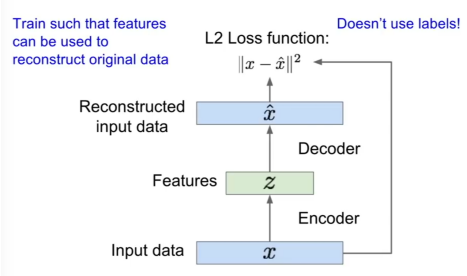
likelihood of the image x, the likelihood of each pixel given all previous pixel values
this is a complex transformation, we use NN
Q: how to order the pixels?

PixelRNN Generate image pixels starting with one corner
Depending on previous pixels using a RNN with LSTM
Sequential generation - slow

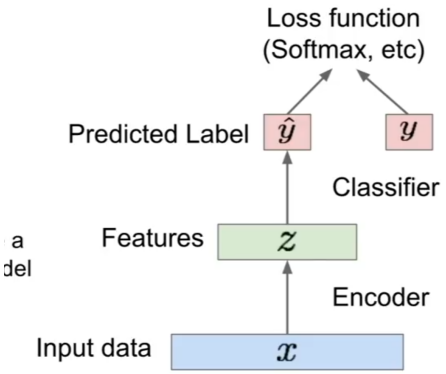
PixelCNN Still generates an image from a corner
Use CNN to model the dependency over a context region
output: softmax loss at each pixel
$\Rightarrow$ i don't get it

3.2.2 Autoencoders

Input (X) -¿ Encoder -¿ (Latent) Features (Z)
$dim(Z) < dim(X)$ - the features should capture the *important* variation in the data
Encoders: linear, non linear, ReLU,
Train the model as features that be used to reconstruct the original data
Decoder: usually same types of networks as the encoder.



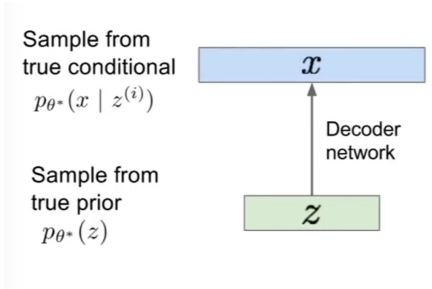
After this step, we don't need to decoder anymore - we can use this to initialize a supervised model:



For example, this is used in cases where there is not a lot of data.
Autoencoders can reconstruct data and learn new features to initialize a supervised model.
The features capture the variation in the training data. Now how can we use them to generate new data?

3.2.3 Variational Autoencoders

Probabilistic spin on autoencoders - will let us sample from the model to generate data.
Assuming training data $\{x^i\}_{i=1}^N$ is generated from underlying, unobservred latent representation z
Generation process: sample from a prior over z : $p_{\theta^\star}(z)$ usually a Gaussian
Now sample from true conditional: $p_{\theta^\star}(x|z^i)$

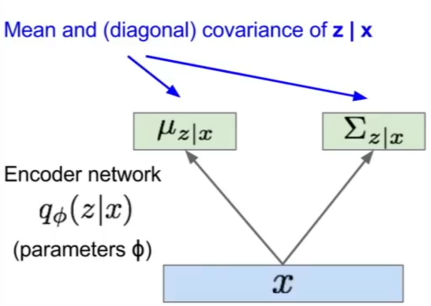


Want to estimate the true parameters $\theta^\star$ so we can generate new data.
Gaussian assumption is reasonable for latent attributes such as pose, expression etc.
The conditional representation $p(x|z)$ is much more complex and it is represented through a network (decoder neural network)

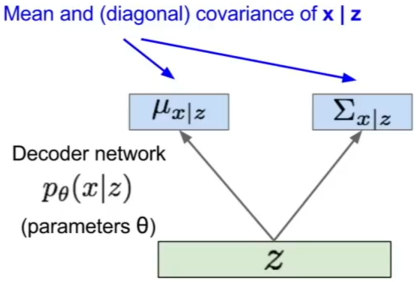
How to train this model?
From Fully Visible Belief Networks: learn model parameters to maximize the likelihood of training data:
$p_\theta(x) = \int p_\theta(z)p_\theta(x|z)dz$
This integral is intractable - it is impossible to integrate over all z
Posterior density is also intractable:

$$p_\theta(z|x) = p_\theta(z)/p_\theta(x)$$

The solution is to define another encoder network $q_\theta(z|x)$ that approximates $p_\theta(z|x)$. This allow us to derive a lower bound on the data likelihood which is tractable.
The encoder network will give out the mean and covariance of $z|x$:



and similarly we have a probabilistic decoder network:



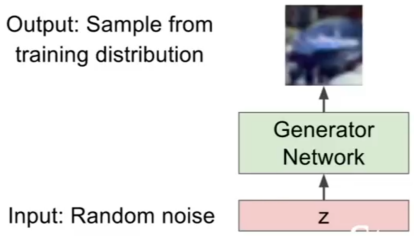
Both of these network produce distributions, we can sample from them $x|z$ and $z|x$.
These network types are also known as recognition and inference and generation networks

3.2.4 Recap:

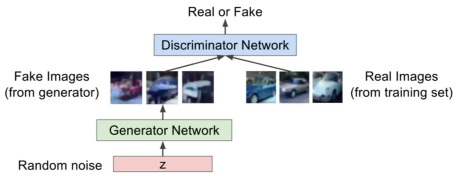
- PixelCNNs define tractable density function, optimize the likelihood of training data
- VAE define intractable density function with latent z, - but cannot be optimized directly, instead derive and optimize lower bound on the prob. dist. - GANs - give up on explicitly modeling density, just want to sample

3.2.5 Generative Adversarial Networks

Want to sample from a complex, high dimensional training distribution.
To actually do this, we sample from a simple distribution (random noise) and use a network that learned a transformation from this to the training distribution.



To learn this transformation network is to look at this as two player game:
Generator Network: try to fool the discriminator by generating real looking images.
Discriminator network: try to distinguish between real and fake images.



Both networks are jointly trained as a minimax game:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

The discriminator outputs likelihood in $(0, 1)$ of real images
The first term is the disc output for real data x drawn from p_{data}
The second D term is the discriminator output for generated fake data.
The discriminator θ_D wants to maximize this objective - $D(x)$ is close to 1 $D(G(z))$ is close to 0 (fake data)

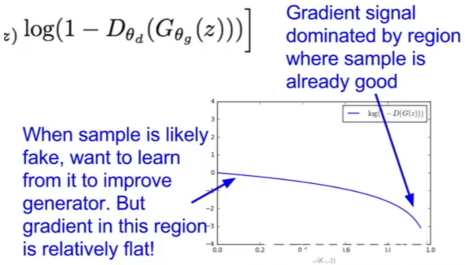
The generator θ_z wants to minimize the objective s.t. $D(G(z))$ is as close to 1
The optimization to do this goes as follows:
1. Gradient ascent on the discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. Gradient descent on the generator:

$$\min_{\theta_g} \left[\mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

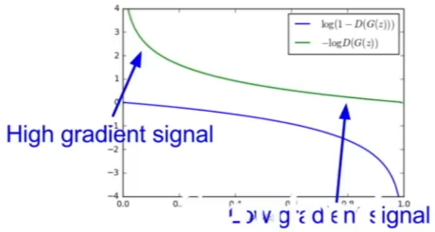
In practice this does not work very well:



The gradient is weak when the generator has not learned how to generate good samples yet. So instead we maximize the likelihood that the discriminator is wrong using a different objective:

$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

-



Jointly training these two networks is challenging, unstable, etc.
Choosing objective with better loss landscapes helps training.

for number of training iterations **do**
  for k steps **do**
    • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
    • Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
    • Update the discriminator by ascending its stochastic gradient:

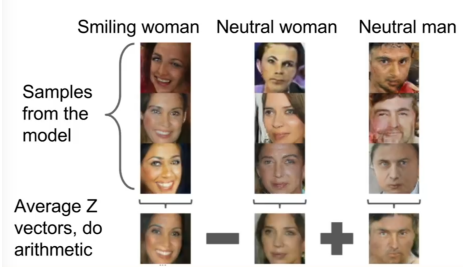
$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(\boldsymbol{x}^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(\boldsymbol{z}^{(i)}))) \right]$$

  end for
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Update the generator by ascending its stochastic gradient (improved objective):

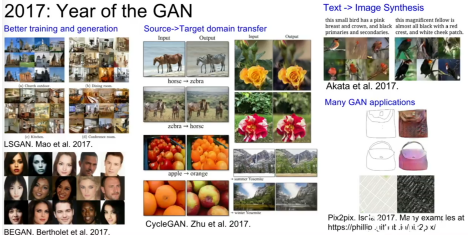
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(\boldsymbol{z}^{(i)})))$$

end for

The lecture also shows how the vectors of the params these networks generate are interpretable, for examples mean smiling women - mean neutral women + mean neutral man -¿ smiling man



Radford et al. ICLR 2016



https://github.com/soumith/ganhacks
GAN Summary:
pro: state of the art samples
cons: tricky to train, can't solve inference

4 Reinforcement Learning

4.1 Markov Decision Process

Markov property: current state completely characterized the state of the world
Define by: $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathbb{P}, \gamma)$
$\mathcal{S}$ set of possible states
$\mathcal{A}$ set of possible actions
$\mathcal{R}$ set of possible rewards given state, action pair
$\mathbb{P}$ transition probability
γ discount factor

5 Adversarial Examples

Adv example - all ML models are vulnerable.
Initially it was assumed that adv. examples were due to overfitting
Something important he said: adv. examples might be closer to underfitting than overfitting. For example, generating a adv example and adding the same diff vector to many objects will cause to miss-labelling of any example they're added to.
After this observation, the hypothesis changed to underfitting, or the model being too linear
Example:

Another interesting observation about this example - both corners are labelled as very green/blue although we have not seen any examples in these regions -¿ very high confidence very far from decision boundary

LSTM is doing addition operation which is also linear.
Linearity: the mapping between the input of the model to the output of the model.
The mapping from the parameters of the network to the output are highly non linear (this is why training is difficult)
This means it is a lot easier to manipulate and optimize the input the model vs. the model