Topics:

• Training Neural Networks (Part 3)
Administrative

- Project Proposal deadline **postponed to Oct 3rd (Monday)**
  - No grace period
Batch Normalization
Batch Normalization

“you want zero-mean unit-variance activations? just make them so.”
Batch Normalization

Input: \( x : N \times D \)

Learnable scale and shift parameters:
\( \gamma, \beta : \mathbb{R}^D \)

We want to give the model a chance to adjust batchnorm if the default is not optimal. Learning \( \gamma = \sigma \) and \( \beta = \mu \) will recover the identity function!

\[
\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{i,j} \quad \text{Per-channel mean, shape is D}
\]

\[
\sigma_j^2 = \frac{1}{N} \sum_{i=1}^{N} (x_{i,j} - \mu_j)^2 \quad \text{Per-channel var, shape is D}
\]

\[
\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}} \quad \text{Normalized x, Shape is N x D}
\]

\[
y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j \quad \text{Output, Shape is N x D}
\]

[Ioffe and Szegedy, 2015]
Batch Normalization: Test-Time

Input: \( x : N \times D \)

Learnable scale and shift parameters:
\( \gamma, \beta: \mathbb{R}^D \)

\[ \mu_j = \text{(Moving) average of values seen during training} \]
Per-channel mean, shape is D

\[ \sigma_j^2 = \text{(Moving) average of values seen during training} \]
Per-channel var, shape is D

\[ \hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}} \]
Normalized x, Shape is N x D

\[ y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j \]
Output, Shape is N x D

During testing batchnorm becomes a linear operator!
Can be fused with the previous fully-connected or conv layer
Batch Normalization

- Makes deep networks **much** easier to train!
  - If you are interested in the theory, read [https://arxiv.org/abs/1805.11604](https://arxiv.org/abs/1805.11604)
  - **TL;DR**: makes optimization landscape smoother
- Allows higher learning rates, faster convergence
- More useful in deeper networks
- Networks become more robust to initialization
- Zero overhead at test-time: can be fused with conv!
- Behaves differently during training and testing: this is a very common source of bugs!
- Needs large batch size to calculate accurate stats
Group Normalization

Wu and He, “Group Normalization”, ECCV 2018
Intuitions:
• Think of a ball (set of parameters) moving in space (loss landscape), with momentum keeping it going in a direction.
• Individual gradient step may be noisy, the general trend accumulated over a few steps will point to the right direction.
• Momentum can “push” the ball over saddle points or local minima.
**SGD + Momentum:**
continue moving in the general direction as the previous iterations

\[ x_{t+1} = x_t - \alpha \nabla f(x_t) \]

- **SGD**
- Build up “velocity” as a running mean of gradients
- Rho gives “friction”; typically rho=0.9 or 0.99

\[ v_{t+1} = \rho v_t + \nabla f(x_t) \]
\[ x_{t+1} = x_t - \alpha v_{t+1} \]

**Sutskever et al, “On the importance of initialization and momentum in deep learning”, ICML 2013**
Nesterov Momentum

Momentum update:

Combine gradient at current point with velocity to get step used to update weights

Nesterov, “A method of solving a convex programming problem with convergence rate O(1/k^2)” , 1983
Nesterov, “Introductory lectures on convex optimization: a basic course”, 2004
Sutskever et al, “On the importance of initialization and momentum in deep learning”, ICML 2013

Nesterov Momentum

“Look ahead” to the point where updating using velocity would take us; compute gradient there and mix it with velocity to get actual update direction
Optimization: Problem #3 with SGD

What if loss changes quickly in one direction and slowly in another? What does gradient descent do? Very slow progress along shallow dimension, jitter along steep direction

Long, narrow ravines:

[Image of ravine diagram]

Loss function has high condition number: ratio of largest to smallest singular value of the Hessian matrix is large

AdaGrad

```python
grad_squared = 0

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

Q2: What happens to the step size over long time? Decays to zero
RMSProp: “Leaky AdaGrad”

```
grad_squared = 0
while True:
    dx = compute_gradient(x)
    grad_squared += dx * dx
    x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

AdaGrad

```
grad_squared = 0
while True:
    dx = compute_gradient(x)
    grad_squared = decay_rate * grad_squared + (1 - decay_rate) * dx * dx
    x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

RMSProp

Tieleman and Hinton, 2012
Adam (full form)

Bias correction for the fact that first and second moment estimates start at zero

Adam with \( \beta_1 = 0.9 \), \( \beta_2 = 0.999 \), and \( \text{learning\_rate} = 1e^{-3} \) or \( 5e^{-4} \) is a great starting point for many models!

Adam
Learning rate decays over time

**Step:** Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.
First-Order Optimization

Loss

w1
First-Order Optimization

(1) Use gradient form linear approximation
(2) Step to minimize the approximation
Second-Order Optimization

(1) Use gradient and Hessian to form quadratic approximation
(2) Step to the minima of the approximation
Second-Order Optimization

second-order Taylor Expansion of $f(x)$ at $a$:

$$f(x) = f(a) + \frac{f'(a)}{1!}(x - a) + \frac{f''(a)}{2!}(x - a)^2$$

Newton's method for optimization: solving for the critical point $f'(x) = 0$, we obtain the Newton update rule

$$f'(x) = f'(a) + f''(a)(x - a) = 0$$

$$x^* = a - \frac{1}{f''(a)}f'(a)$$

Think of $a$ as the current params, $x^*$ as the updated params
Second-Order Optimization (multivariate)

second-order Taylor Expansion of \( f(x) \) at \( a \):

\[
f(w) = f(a) + (x - a)^T \nabla f + \frac{1}{2} (x - a)^T H(x - a)
\]

Newton’s method for optimization: solving for the critical point we obtain the Newton update rule:

\[
x^* = a - H^{-1} \nabla f
\]

Q: Why is this bad for deep learning?
Hessian Matrix

\[ H_f = \begin{bmatrix}
\frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\
\frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2}
\end{bmatrix} \]
Second-Order Optimization

second-order Taylor expansion:

\[
f(x) = f(a) + (x - a)^T \nabla f + \frac{1}{2} (x - a)^T H (x - a)
\]

Solving for the critical point we obtain the Newton parameter update:

\[
x^* = a - H^{-1} \nabla f
\]

Hessian has \(O(N^2)\) elements
Inverting takes \(O(N^3)\)
\(N = \text{Millions}\)

Q: Why is this bad for deep learning?
Second-Order Optimization

- Quasi-Newton methods (BFGS most popular):
  instead of inverting the Hessian (O(n^3)), approximate inverse Hessian with rank 1 updates over time (O(n^2) each).
  Still pretty expensive

- L-BFGS (Limited memory BFGS):
  Does not form/store the full inverse Hessian.
L-BFGS

- Usually works very well in full batch, deterministic mode i.e. if you have a single, deterministic f(x) then L-BFGS will probably work very nicely

- Does not transfer very well to mini-batch setting. Gives bad results. Adapting second-order methods to large-scale, stochastic setting is an active area of research.

Ba et al, “Distributed second-order optimization using Kronecker-factored approximations”, ICLR 2017
This Time:

**Training** Deep Neural Networks

- Details of the non-linear activation functions
- Data normalization
- Weight Initialization
- Batch Normalization
- Advanced Optimization
- Regularization
- Data Augmentation
- Transfer learning
- Hyperparameter Tuning
Regularization
Beyond Training Error

Better optimization algorithms help reduce training loss

But we really care about error on new data - how to reduce the gap?
Early Stopping: Always do this

Stop training the model when accuracy on the validation set decreases.
Or train for a long time, but always keep track of the model snapshot that worked best on val.
How to improve single-model performance?

Regularization
Regularization: Add term to loss

\[ L = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq y_i} \max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + 1) + \lambda R(W) \]

In common use:

L2 regularization

\[ R(W) = \sum_k \sum_l W_{k,l}^2 \] (Weight decay)

L1 regularization

\[ R(W) = \sum_k \sum_l |W_{k,l}| \]

Elastic net (L1 + L2)

\[ R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}| \]
Regularization: Dropout

In each forward pass, randomly set some neurons to zero
Probability of dropping is a hyperparameter; 0.5 is common

Regularization: Dropout

\[ p = 0.5 \] # probability of keeping a unit active. higher = less dropout

```python
def train_step(X):
    """ X contains the data """

    # forward pass for example 3-layer neural network
    H1 = np.maximum(0, np.dot(W1, X) + b1)
    U1 = np.random.rand(*H1.shape) < p # first dropout mask
    H1 *= U1 # drop!
    H2 = np.maximum(0, np.dot(W2, H1) + b2)
    U2 = np.random.rand(*H2.shape) < p # second dropout mask
    H2 *= U2 # drop!
    out = np.dot(W3, H2) + b3

    # backward pass: compute gradients... (not shown)
    # perform parameter update... (not shown)
```

Example forward pass with a 3-layer network using dropout
Regularization: Dropout
How can this possibly be a good idea?

Forces the network to have a redundant representation;
Prevents co-adaptation of features

- has an ear
- has a tail
- is furry
- has claws
- mischievous look

X

For: cat score

X

X
Regularization: Dropout

How can this possibly be a good idea?

Another interpretation:

Dropout is training a large ensemble of models (that share parameters).

Each binary mask is one model

An FC layer with 4096 units has $2^{4096} \sim 10^{1233}$ possible masks!
Only $\sim 10^{82}$ atoms in the universe...
Dropout: Test time

Dropout makes our output random!

Want to “average out” the randomness at test-time

\[ y = f(x) = E_z[f(x, z)] = \int p(z)f(x, z)dz \]
Consider a single neuron.

\[ y = f(x) = E_z[f(x, z)] = \int p(z)f(x, z)dz \]
Consider a single neuron.

Without dropout:

\[ E[a] = w_1 x + w_2 y \]
Dropout: Test time

Compute the expectation

Consider a single neuron.

Without dropout:

With dropout we have:

\[
y = f(x) = E_z [f(x, z)] = \int p(z) f(x, z) dz
\]

\[
E[a] = w_1 x + w_2 y
\]

\[
E[a] = \frac{1}{4} (w_1 x + w_2 y) + \frac{1}{4} (w_1 x + 0 y) + \frac{1}{4} (0 x + 0 y) + \frac{1}{4} (0 x + w_2 y)
\]

\[
= \frac{1}{2} (w_1 x + w_2 y)
\]
Consider a single neuron.

Without dropout:
\[ E[a] = w_1 x + w_2 y \]

With dropout we have:
\[ E[a] = \frac{1}{4}(w_1 x + w_2 y) + \frac{1}{4}(w_1 x + 0y) \]
\[ + \frac{1}{4}(0x + 0y) + \frac{1}{4}(0x + w_2 y) \]
\[ = \frac{1}{2}(w_1 x + w_2 y) \]

At test time, multiply by dropout probability.

\[ y = f(x) = E_z[f(x, z)] = \int p(z)f(x, z)dz \]
Dropout: Test time

At test time all neurons are active always
=> We must scale the activations so that for each neuron:
output at test time = expected output at training time
# Dropout Summary

**Dropout Summary**

`p = 0.5 # probability of keeping a unit active. higher = less dropout`

```python
def train_step(X):
    """ X contains the data ""

    # forward pass for example 3-layer neural network
    H1 = np.maximum(0, np.dot(W1, X) + b1)
    U1 = np.random.rand(*H1.shape) < p # first dropout mask
    H1 *= U1 # drop!
    H2 = np.maximum(0, np.dot(W2, H1) + b2)
    U2 = np.random.rand(*H2.shape) < p # second dropout mask
    H2 *= U2 # drop!
    out = np.dot(W3, H2) + b3

    # backward pass: compute gradients... (not shown)
    # perform parameter update... (not shown)
```

- Drop in train time

```python
def predict(X):
    # ensembled forward pass
    H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
    H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
    out = np.dot(W3, H2) + b3
```

- Scale at test time
More common: “Inverted dropout”

```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
    # forward pass for example 3-layer neural network
    H1 = np.maximum(0, np.dot(W1, X) + b1)
    U1 = (np.random.rand(*H1.shape) < p) / p # first dropout mask. Notice /p!
    H1 *= U1 # drop!
    H2 = np.maximum(0, np.dot(W2, H1) + b2)
    U2 = (np.random.rand(*H2.shape) < p) / p # second dropout mask. Notice /p!
    H2 *= U2 # drop!
    out = np.dot(W3, H2) + b3

    # backward pass: compute gradients... (not shown)
    # perform parameter update... (not shown)

def predict(X):
    # ensembled forward pass
    H1 = np.maximum(0, np.dot(W1, X) + b1) # no scaling necessary
    H2 = np.maximum(0, np.dot(W2, H1) + b2)
    out = np.dot(W3, H2) + b3
```

test time is unchanged!

Similar to BatchNorm, different behavior train vs test!
Regularization: A common pattern

**Training**: Add some kind of randomness

\[ y = f_W(x, z) \]

**Testing**: Average out randomness (sometimes approximate)

\[ y = f(x) = E_z[f(x, z)] = \int p(z) f(x, z) dz \]
Regularization: Data Augmentation

Load image and label

“cat”

CNN

Compute loss

This image by Nikita is licensed under CC-BY 2.0
Regularization: Data Augmentation

Load image and label

“cat”

Transform image

Compute loss

CNN
Data Augmentation
Horizontal Flips
Data Augmentation
Random crops and scales

Training: sample random crops / scales
ResNet:
1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch
Data Augmentation
Random crops and scales

**Training**: sample random crops / scales
ResNet:
1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch

**Testing**: average a fixed set of crops
ResNet:
1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips
Data Augmentation
Color Jitter

Simple: Randomize contrast and brightness
Data Augmentation

Color Jitter

Simple: Randomize contrast and brightness

More Complex:

1. Apply PCA to all [R, G, B] pixels in training set

2. Sample a “color offset” along principal component directions

1. Add offset to all pixels of a training image

(As seen in [Krizhevsky et al. 2012], ResNet, etc)
Data Augmentation
Get creative for your problem!

Examples of data augmentations:
- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)
## Automatic Data Augmentation

<table>
<thead>
<tr>
<th>Batch 1</th>
<th>Batch 2</th>
<th>Batch 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Original Image" /></td>
<td><img src="image2" alt="Sub-policy 1 Image" /></td>
<td><img src="image3" alt="Sub-policy 2 Image" /></td>
</tr>
<tr>
<td><img src="image4" alt="Sub-policy 3 Image" /></td>
<td><img src="image5" alt="Sub-policy 4 Image" /></td>
<td><img src="image6" alt="Sub-policy 5 Image" /></td>
</tr>
</tbody>
</table>

Cubuk et al., "AutoAugment: Learning Augmentation Strategies from Data", CVPR 2019
Regularization: A common pattern

**Training**: Add random noise

**Testing**: Marginalize over the noise

**Examples:**
- Dropout
- Batch Normalization
- Data Augmentation
Regularization: DropConnect

**Training:** Drop connections between neurons (set weights to 0)

**Testing:** Use all the connections

**Examples:**
- Dropout
- Batch Normalization
- Data Augmentation
- DropConnect

Wan et al, “Regularization of Neural Networks using DropConnect”, ICML 2013
Regularization: Fractional Pooling

**Training**: Use randomized pooling regions
**Testing**: Average predictions from several regions

**Examples**:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling

Graham, “Fractional Max Pooling”, arXiv 2014
Regularization: Stochastic Depth

**Training:** Skip some layers in the network

**Testing:** Use all the layer

**Examples:**
- Dropout
- Batch Normalization
- Data Augmentation
- DropConnect
- Fractional Max Pooling
- **Stochastic Depth (with residual)**

Regularization - In practice

**Training**: Add random noise

**Testing**: Marginalize over the noise

**Examples**:
- Dropout
- Batch Normalization
- Data Augmentation
- DropConnect
- Fractional Max Pooling
- Stochastic Depth

- Consider dropout for large fully-connected layers
- Batch normalization and data augmentation almost always a good idea
- Try cutout and mixup especially for small classification datasets
Transfer learning / Pretraining
“You need a lot of a data if you want to train/use deep neural networks”
“You need a lot of data if you want to train/use deep neural networks"
Transfer Learning with CNNs
Transfer Learning with CNNs

AlexNet:
64 x 3 x 11 x 11

(More on this in Lecture 13)
Transfer Learning with CNNs

Test image  L2 Nearest neighbors in feature space

(More on this in Lecture 13)
Transfer Learning with CNNs

1. Train on Imagenet

Transfer Learning with CNNs

1. Train on Imagenet
   - FC-1000
   - FC-4096
   - Conv-512
   - Conv-512
   - MaxPool
   - Conv-256
   - Conv-256
   - MaxPool
   - Conv-128
   - Conv-128
   - MaxPool
   - Conv-64
   - Conv-64
   - Image

2. Small Dataset (C classes)
   - FC-C
   - FC-4096
   - Conv-512
   - Conv-512
   - MaxPool
   - Conv-256
   - Conv-256
   - MaxPool
   - Conv-128
   - Conv-128
   - MaxPool
   - Conv-64
   - Conv-64
   - Image

   Freeze these

   Reinitialize this and train

Transfer Learning with CNNs

1. Train on Imagenet

2. Small Dataset (C classes)

- Freeze these
- Reinitialize this and train

Razavian et al., “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014
Transfer Learning with CNNs

1. Train on Imagenet
   - FC-1000
   - FC-4096
   - FC-4096
   - MaxPool
   - Conv-512
   - Conv-512
   - MaxPool
   - Conv-256
   - Conv-256
   - MaxPool
   - Conv-128
   - Conv-128
   - MaxPool
   - Conv-64
   - Conv-64
   - Image

2. Small Dataset (C classes)
   - FC-C
   - FC-4096
   - FC-4096
   - MaxPool
   - Conv-512
   - Conv-512
   - MaxPool
   - Conv-256
   - Conv-256
   - MaxPool
   - Conv-128
   - Conv-128
   - MaxPool
   - Conv-64
   - Conv-64
   - Image
   - Train these
   - Reinitialize this and train

3. Bigger dataset
   - FC-C
   - FC-4096
   - FC-4096
   - MaxPool
   - Conv-512
   - Conv-512
   - MaxPool
   - Conv-256
   - Conv-256
   - MaxPool
   - Conv-128
   - Conv-128
   - MaxPool
   - Conv-64
   - Conv-64
   - Image
   - Train these
   - Freeze these
   - With bigger dataset, train more layers
   - Freeze these
   - Lower learning rate when finetuning; 1/10 of original LR is good starting point

Razavian et al., "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014
<table>
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<tr>
<th>Task-specific</th>
<th>very similar dataset</th>
<th>very different dataset</th>
</tr>
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<td>very little data</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>quite a lot of data</td>
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<th>very different dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- **Task-specific**:
  - Conv-64
  - Conv-64
  - MaxPool
  - Conv-128
  - Conv-128
  - MaxPool
  - Conv-256
  - Conv-256
  - MaxPool
  - Conv-512
  - Conv-512
  - MaxPool
  - Conv-1000

- **Task-agnostic**:
  - Conv-64
  - Conv-64
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<tr>
<td><strong>very little data</strong></td>
<td>Use Linear Classifier on top layer</td>
<td>?</td>
</tr>
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<td><strong>quite a lot of data</strong></td>
<td>Finetune a few layers</td>
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### Task-specific vs. Task-agnostic

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<tbody>
<tr>
<td><strong>very little data</strong></td>
<td>Use Linear Classifier on top layer</td>
<td>You’re in trouble… Try linear classifier from different stages</td>
</tr>
<tr>
<td><strong>quite a lot of data</strong></td>
<td>Finetune a few layers</td>
<td>Finetune a larger number of layers</td>
</tr>
</tbody>
</table>

### Diagram

- **Image**
- **Conv-64**
- **Conv-64**
- **MaxPool**
- **Conv-512**
- **Conv-512**
- **MaxPool**
- **Conv-256**
- **Conv-256**
- **MaxPool**
- **Conv-128**
- **Conv-128**
- **MaxPool**
- **Conv-1000**
- **FC-4096**
- **FC-4096**
- **FC-1000**

- **FC** - Fully Connected layer
- **Conv** - Convolutional layer
- **MaxPool** - Max Pooling layer
Transfer learning is pervasive...
(it’s the norm, not an exception)

Object Detection
(Fast R-CNN)

Image Captioning: CNN + RNN

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Transfer learning is pervasive…
(it’s the norm, not an exception)

Object Detection
(Fast R-CNN)

CNN pretrained on ImageNet

Image Captioning: CNN + RNN

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Transfer learning is pervasive…
(it’s the norm, not an exception)

Object Detection
(Fast R-CNN)

- CNN pretrained on ImageNet
- External proposal algorithm (e.g., selective search)

Image Captioning: CNN + RNN

- Word vectors pretrained with word2vec
- “straw” “hat” END
  \[
  y_t, x_t \rightarrow h_t, W_{hh}, W_{oh}, W_{hx}
  \]

Girshick, "Fast R-CNN", ICCV 2015
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Transfer learning is pervasive…
(it’s the norm, not an exception)

Pre-training
MLM on unlabelled data

word2vec
GloVe
skip-thought
InferSent
ELMo
ULMFiT
GPT
BERT

Fine-tuning
Cross-entropy on task labels

classification
sequence labeling
Q&A
....

Generic Language Model
Train with Task-specific Labels

https://ruder.io/recent-advances-lm-fine-tuning/
Preview: Self-Supervised Pretraining
(pretraining tasks that do not need labels)

Example: learn to predict image transformations / complete corrupted images

1. Solving the pretext tasks allow the model to learn good features.
2. We can automatically generate labels for the pretext tasks.
Takeaway for your projects and beyond:
Transfer learning be like

Source: AI & Deep Learning Memes For Back-propagated Poets
Takeaway for your projects and beyond:
Have some dataset of interest but not big enough to train deep models?

1. Find a very large dataset that has similar data, train a big model there
2. Transfer learn to your dataset

Deep learning frameworks provide a “Model Zoo” of pretrained models so you don’t need to train your own
TensorFlow: https://github.com/tensorflow/models
PyTorch (Vision): https://github.com/pytorch/vision
PyTorch (NLP): https://github.com/pytorch/text
Diagnose your training
(without tons of GPUs)
Diagnose your training

Step 1: Check initial loss

Turn off weight decay, sanity check loss at initialization e.g. log(C) for softmax with C classes
Diagnose your training

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample

Try to train to 100% training accuracy on a small sample of training data (~5-10 minibatches); fiddle with architecture, learning rate, weight initialization

Loss not going down? LR too low, bad initialization, bug in code or errors in training labels
Loss explodes to Inf or NaN? LR too high, bad initialization, bug in code
Diagnose your training

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample
**Step 3:** Find LR that makes loss go down

Use the architecture from the previous step, use all training data, turn on small weight decay, find a learning rate that makes the loss drop significantly within ~100 iterations

Good learning rates to try: $1e^{-3}$, $3e^{-4}$, $1e^{-4}$
Diagnose your training

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample
**Step 3:** Find LR that makes loss go down
**Step 4:** Coarse grid, train for ~1-5 epochs

Choose a few values of learning rate and weight decay around what worked from Step 3, train a few models for ~1-5 epochs.

Good weight decay to try: 1e-4, 1e-5, 0
Diagnose your training

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample
**Step 3:** Find LR that makes loss go down
**Step 4:** Coarse grid, train for ~1-5 epochs
**Step 5:** Refine grid, train longer

Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay
Diagnose your training

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample
**Step 3:** Find LR that makes loss go down
**Step 4:** Coarse grid, train for ~1-5 epochs
**Step 5:** Refine grid, train longer
**Step 6:** Look at loss and accuracy curves
Accuracy still going up, you need to train longer.
Huge train / val gap means overfitting! Increase regularization, get more data.
Accuracy

No gap between train / val means underfitting: train longer, use a bigger model, reduce regularization

Train

Val

time
Losses may be noisy, use a scatter plot and also plot moving average to see trends better.
Cross-validation

We develop "command centers" to visualize all our models training with different hyperparameters.

check out weights and biases
You can plot all your loss curves for different hyperparameters on a single plot.
Don't look at accuracy or loss curves for too long!
Choosing Hyperparameters

**Step 1:** Check initial loss
**Step 2:** Overfit a small sample
**Step 3:** Find LR that makes loss go down
**Step 4:** Coarse grid, train for ~1-5 epochs
**Step 5:** Refine grid, train longer
**Step 6:** Look at loss and accuracy curves
**Step 7:** GOTO step 5
Hyperparameters to play with:
- network architecture
- learning rate, its decay schedule, update type
- regularization (L2/Dropout strength)
Random Search vs. Grid Search

Grid Layout

Random Layout

Illustration of Bergstra et al., 2012 by Shayne Longpre, copyright CS231n 2017

Random Search for Hyper-Parameter Optimization
Bergstra and Bengio, 2012
Summary

- Improve your training error:
  - Optimizers
  - Learning rate schedules

- Improve your test error:
  - Regularization
  - Choosing Hyperparameters
Summary

Training Deep Neural Networks
• Details of the non-linear activation functions
• Data normalization
• Weight Initialization
• Batch Normalization
• Advanced Optimization
• Regularization
• Data Augmentation
• Transfer learning
• Hyperparameter Tuning
Next time: Deep Learning Hardware and Software