CS11-747 Neural Networks for NLP

Debugging Neural Networks for NLP

Graham Neubig

Carnegie Mellon University

Language Technologies Institute

Site

https://phontron.com/class/nn4nlp2018/

In Neural Networks, Tuning is Paramount!

- **Everything** is a hyperparameter
  - Network size/depth
  - Small model variations
  - Minibatch creation strategy
  - Optimizer/learning rate
- Models are complicated and opaque, debugging can be difficult!

Understanding Your Problem

A Typical Situation

- You’ve implemented a nice model
- You’ve looked at the code, and it looks OK
- Your accuracy on the test set is bad
- **What do I do?**

Possible Causes

- **Training time problems**
  - Lack of model capacity
  - Inability to train model properly
  - Training time bug
- **Decoding time bugs**
  - Disconnect between test and decoding
  - Failure of search algorithm
- **Overfitting**
- **Mismatch between optimized function and eval**

Debugging at Training Time

Identifying Training Time Problems

- Look at the loss function calculated on the training set
  - Is the loss function going down?
  - Is it going down basically to zero if you run training long enough (e.g. 20-30 epochs)?
- If not, you have a training problem

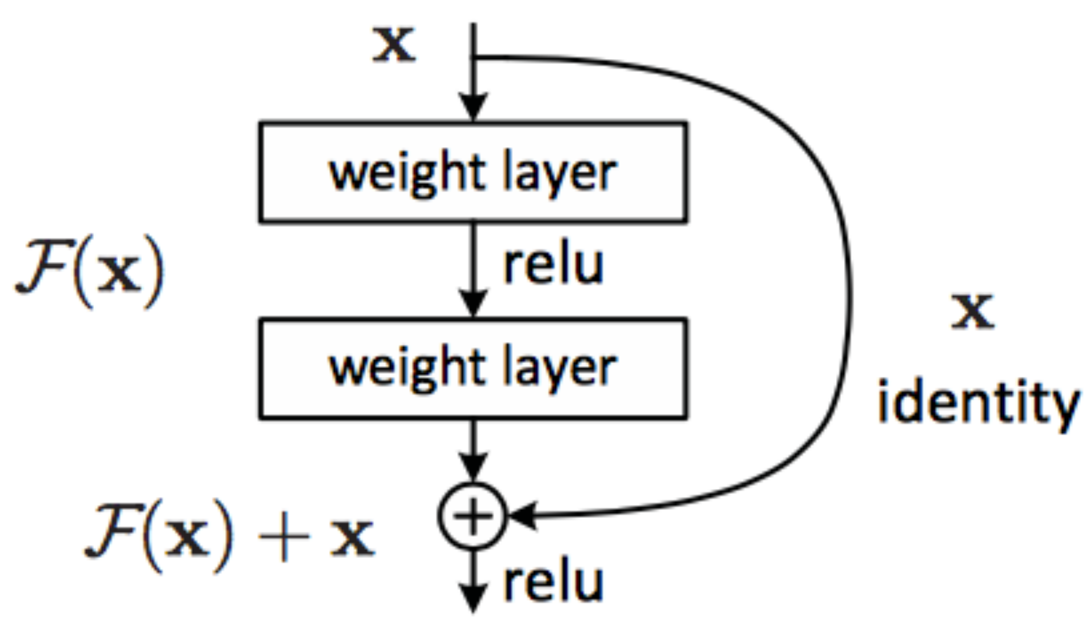
Is My Model Too Weak?

- Your model needs to be big enough to learn
- Model size depends on task
  - For language modeling, at least 512 nodes
  - For natural language analysis, 128 or so may do
- Multiple layers are often better
- For long sequences (e.g. characters) may need larger layers

Be Careful of Deep Models

- Extra layers can help, but can also hurt if you're not careful due to vanishing gradients
- Solutions:

Residual Connections (He et al. 2015)



Highway Networks (Srivastava et al. 2015)

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot (1 - T(\mathbf{x}, \mathbf{W_T}))$$

Trouble w/ Optimization

- If increasing model size doesn't help, you may have an optimization problem
- **Possible causes:**
    - Bad optimizer
    - Bad learning rate
    - Bad initialization
    - Bad minibatching strategy

Reminder: Optimizers

- **SGD:** take a step in the direction of the gradient
- **SGD with Momentum:** Remember gradients from past time steps to prevent sudden changes
- **Adagrad:** Adapt the learning rate to reduce learning rate for frequently updated parameters (as measured by the variance of the gradient)
- **Adam:** Like Adagrad, but keeps a running average of momentum and gradient variance
- **Many others:** RMSProp, Adadelta, etc.
(See Ruder 2016 reference for more details)

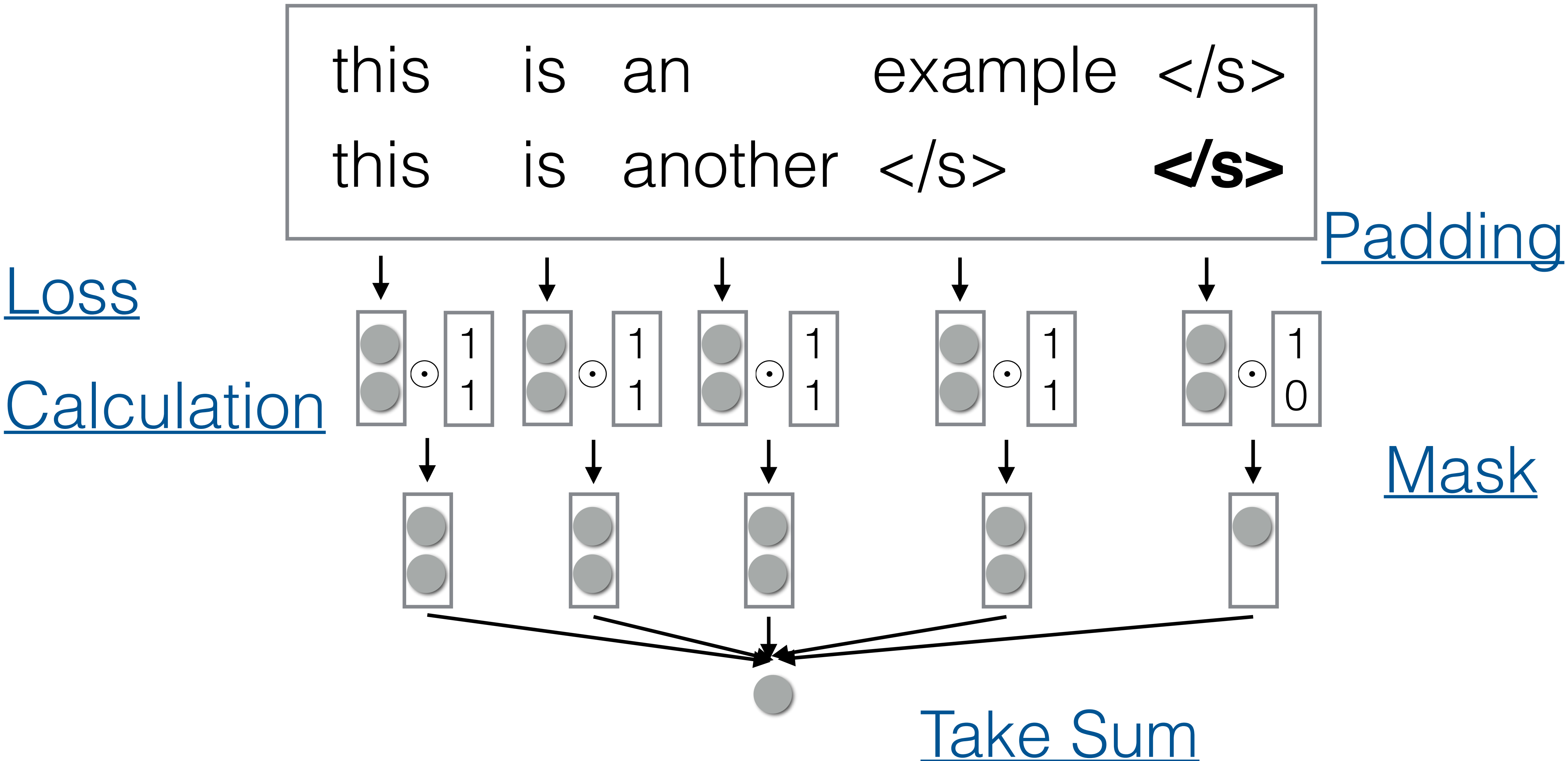
Learning Rate

- Learning rate is an important parameter
    - Too low: will not learn or learn vey slowly
    - Too high: will learn for a while, then fluctuate and diverge
- **Common strategy:** start from an initial learning rate then gradually decrease
- **Note:** need a different learning rate for each optimizer! (SGD default is 0.1, Adam 0.001)

Initialization

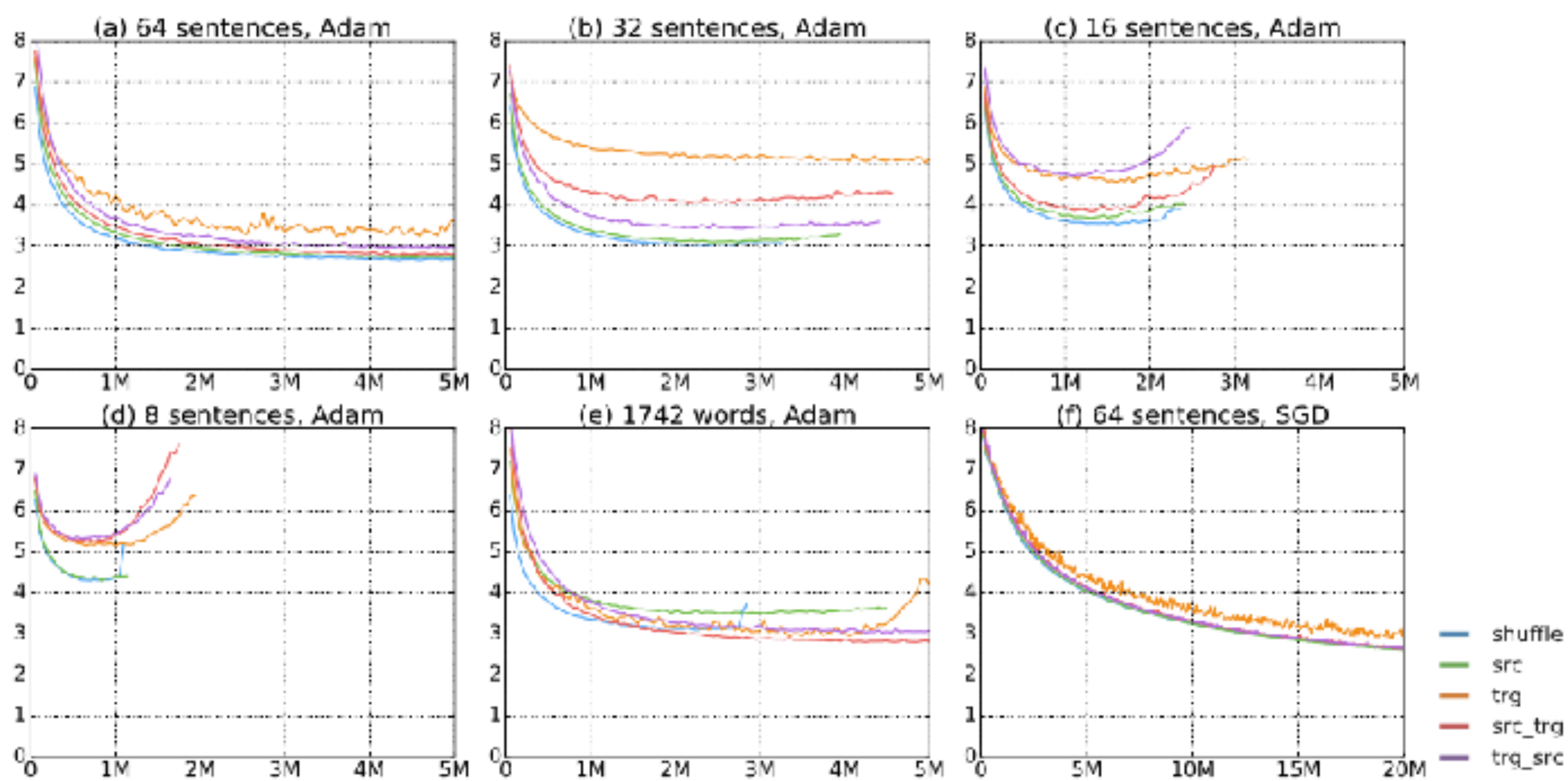
- Neural nets are sensitive to initialization, which results in different sized gradients
- Standard initialization methods:
  - **Gaussian initialization:** initialize with a zero-mean Gaussian distribution
  - **Uniform range initialization:** simply initialize uniformly within a range
  - **Glorot initialization, He initialization:** initialize in a uniform manner, where the range is specified according to net size
- Latter is common/default, but read prior work carefully

Reminder: Mini-batching in RNNs



Bucketing/Sorting

- If we use sentences of different lengths, too much padding and sorting can **result in slow training**
- To remedy this: **sort sentences** so similarly-lengthed sentences are in the same batch
- But this can affect performance! (Morishita et al. 2017)



Debugging at Decoding Time

Training/Decoding Disconnects

- Usually your loss calculation and decoding will be implemented in different functions
- e.g. `enc_dec.py` example from this class has `calc_loss()` and `generate()` functions
- Like all software engineering: duplicated code is a source of bugs!
- Also, usually loss calculation is minibatched, generation not.

Debugging Minibatching

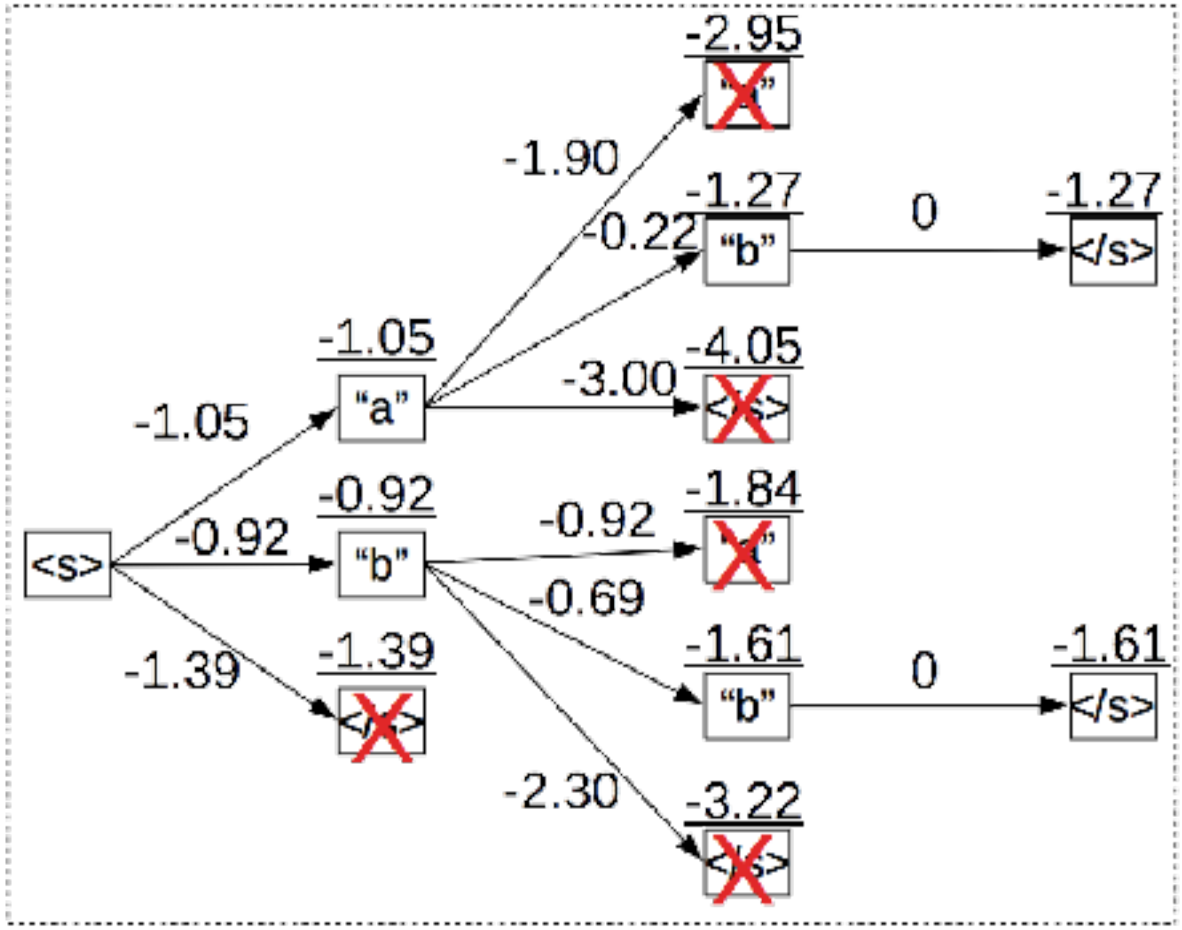
- Debugging mini-batched loss calculation
  - Calculate loss with large batch size (e.g. 32)
  - Calculate loss for each sentence individually and sum them
  - The values should be the same (modulo numerical precision)
- Create a unit test that tests this!

Debugging Decoding

- Your decoding code should get the same score as loss calculation
- Test this:
    - Calculate loss of reference
    - Perform **forced decoding**, where you decode, but tell your model the reference word at each time step
    - The score of these two should be the same
- Create a unit test doing this!

Beam Search

- Instead of picking one high-probability word, maintain several paths



- More in a later class

Debugging Search

- As you make search better, the model score should get better (almost all the time)
- Run search with varying beam sizes and make sure you get a better overall model score with larger sizes
- Create a unit test testing this!

Look At Your Data!

- Decoding problems can often be detected by looking at outputs and realizing something is wrong
- e.g. The first word of the sentence is dropped every time
  > went to the store yesterday
  > bought a dog
- e.g. our system was <unk>ing University of Nebraska at Kearney

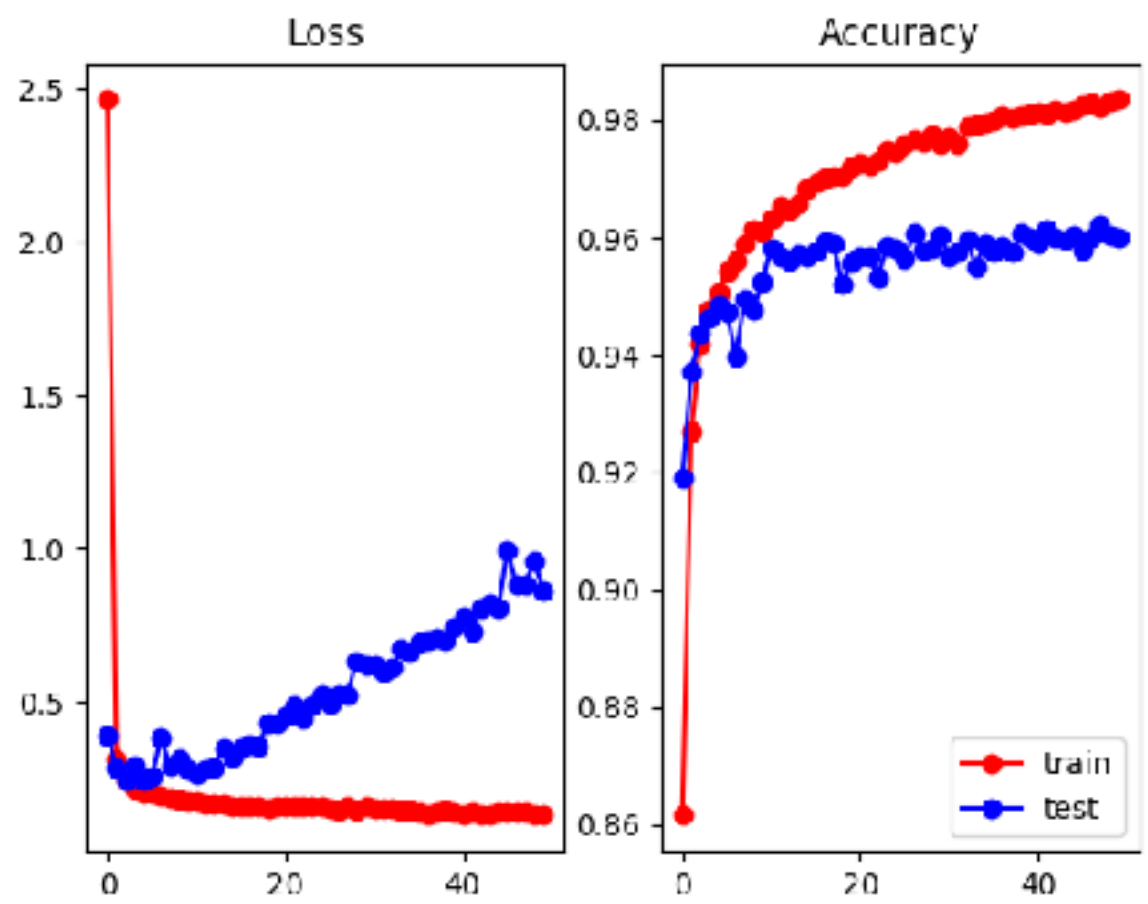
Quantitative Analysis

- Measure gains quantitatively. What is the phenomenon you chose to focus on? Is that phenomenon getting better?
  - **You focused on low-frequency words:** is accuracy on low frequency words increasing?
  - **You focused on syntax:** is syntax or word ordering getting better, are you doing better on long-distance dependencies?
  - **You focused on search:** are you reducing the number of search errors?

Battling Overfitting

Symptoms of Overfitting

- Training loss converges well, but test loss diverges

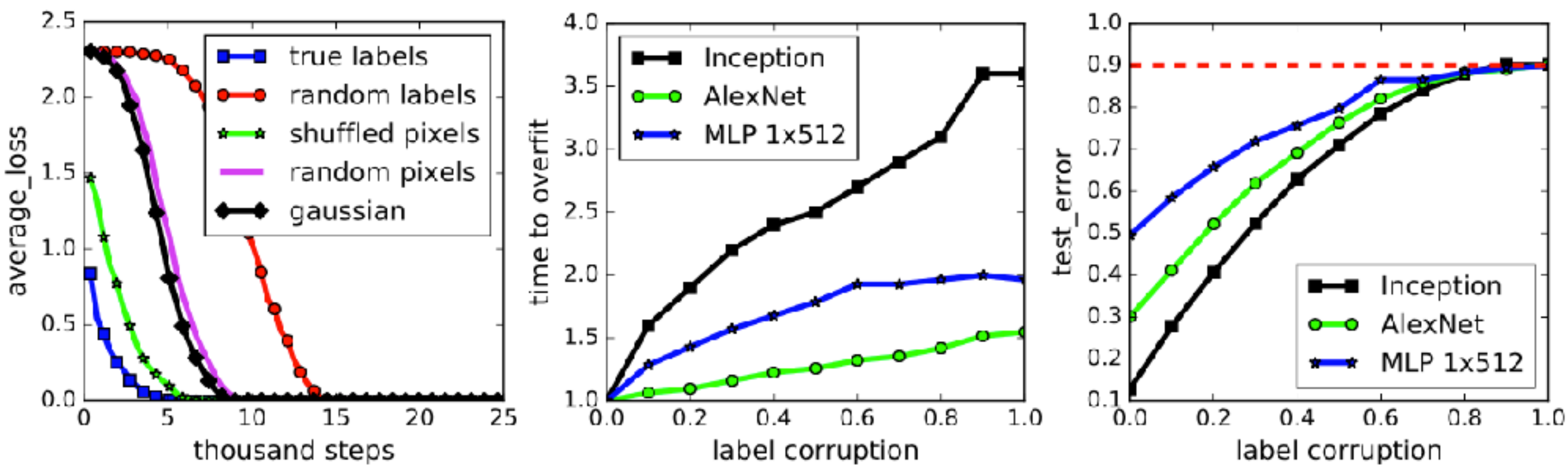


- No need to look at accuracy, only loss!
  Accuracy is a symptom of a different problem.

Your Neural Net can Memorize your Training Data

(Zhang et al. 2017)

- Your neural network has more parameters than training examples
- If you randomly shuffle the training labels (there is no correlation b/t input and labels), it can still learn

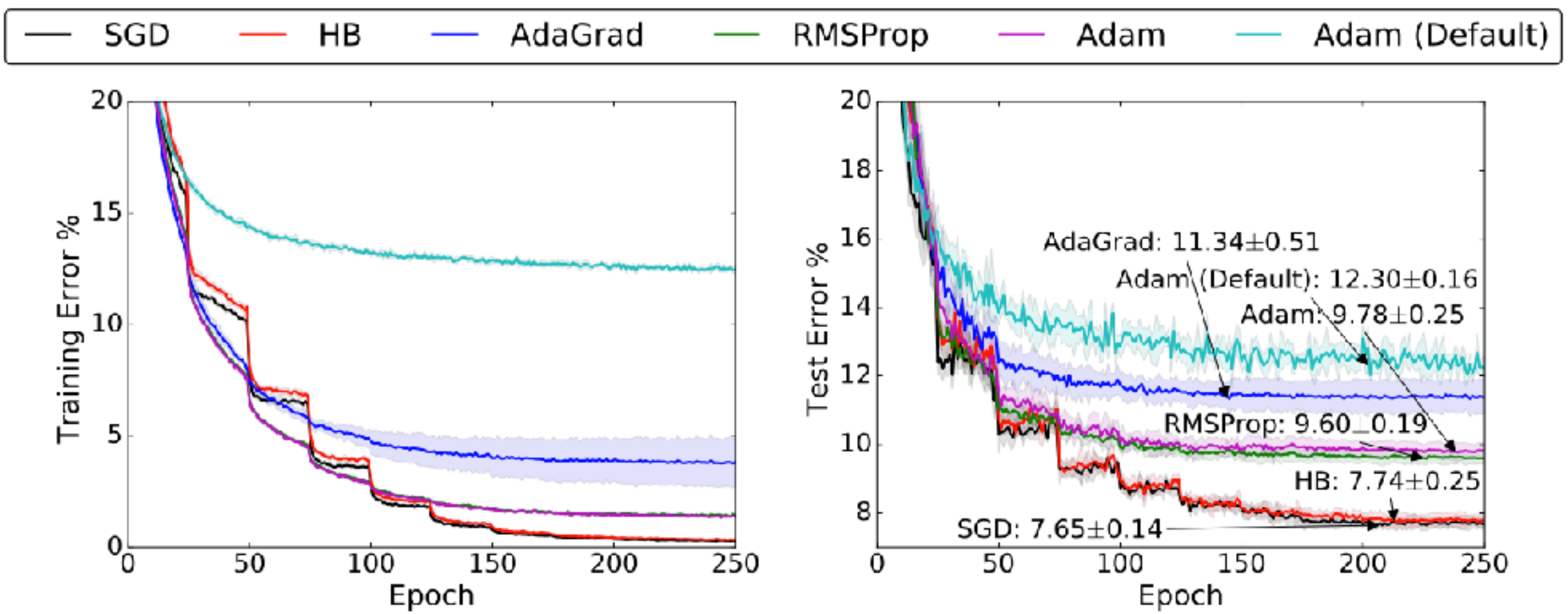


(a) learning curves (b) convergence slowdown (c) generalization error growth

Optimizers: Adaptive Gradient Methods Tend to Overfit More

(Wilson et al. 2017)

- Adaptive gradient methods are fast, but have a stronger tendency to overfit on small data



Reminder: Early Stopping, Learning Rate Decay

- Neural nets have tons of parameters: we want to prevent them from over-fitting

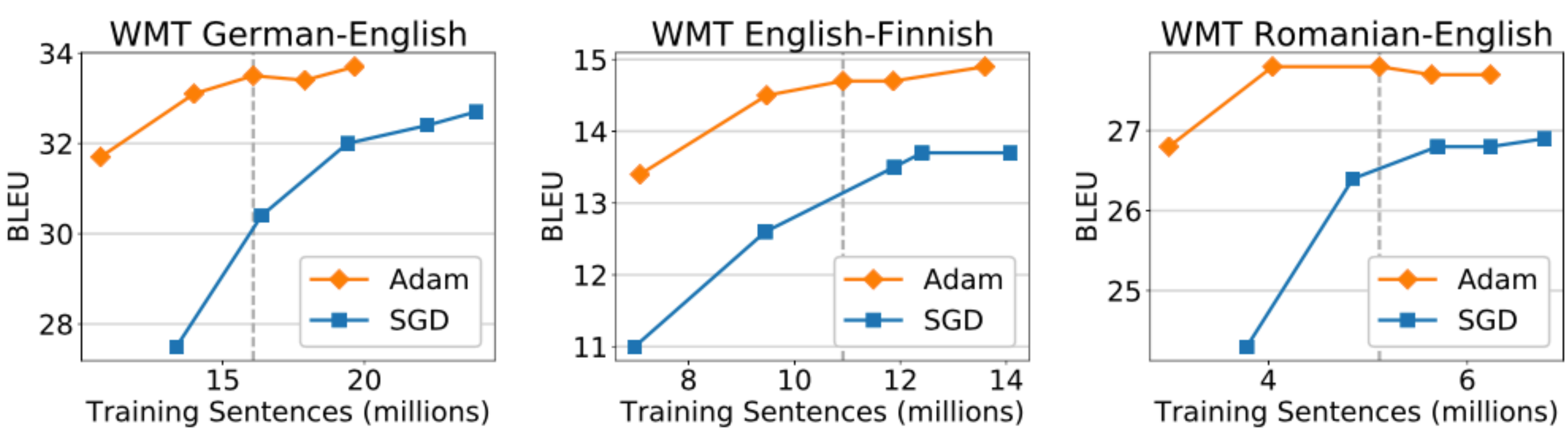
- We can do this by monitoring our performance on held-out development data and stopping training when it starts to get worse

- It also sometimes helps to reduce the learning rate and continue training

Reminder: Dev-driven Learning Rate Decay

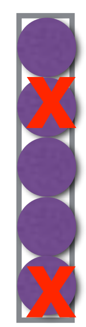
- Start w/ a high learning rate, then degrade learning rate when start overfitting the development set (the "newbob" learning rate schedule)

- Adam w/ Learning rate decay does relatively well for MT (Denkowski and Neubig 2017)



Reminder: Dropout
(Srivastava et al. 2014)

- Neural nets have lots of parameters, and are prone to overfitting
- Dropout: randomly zero-out nodes in the hidden layer with probability *p* at **training time only**



- Because the number of nodes at training/test is different, scaling is necessary:
    - Standard dropout: scale by *p* at test time
    - Inverted dropout: scale by 1/(1-*p*) at training time

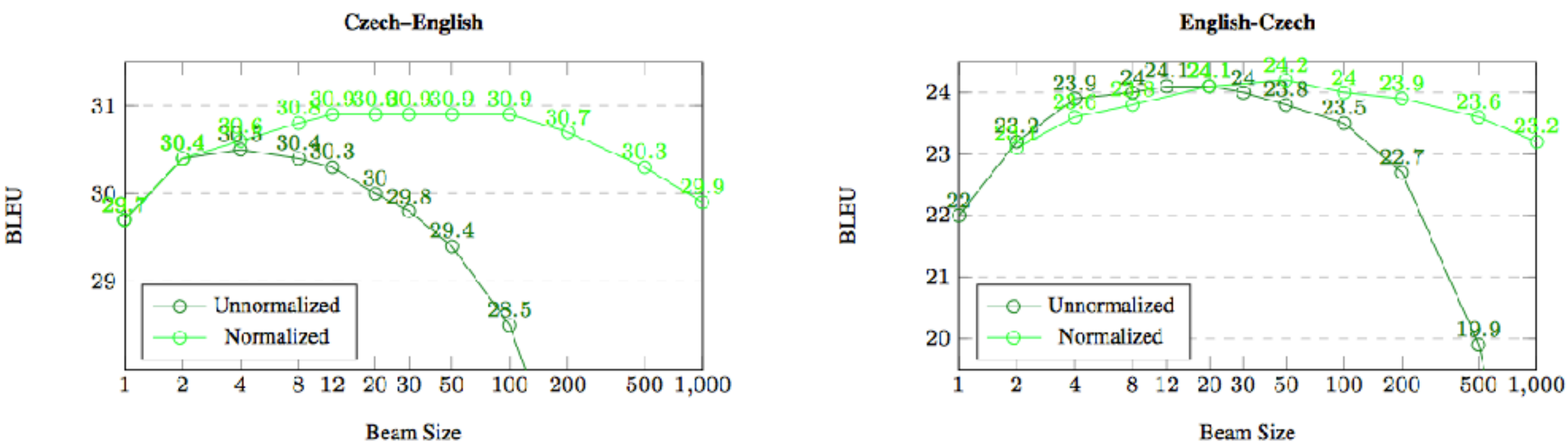
Mismatch b/t Optimized Function and Evaluation Metric

Loss Function, Evaluation Metric

- It is very common to optimize for maximum likelihood for training
- But even though likelihood is getting better, accuracy can get worse

A Stark Example
(Koehn and Knowles 2017)

- Better search (=better model score) can result in worse BLEU score!



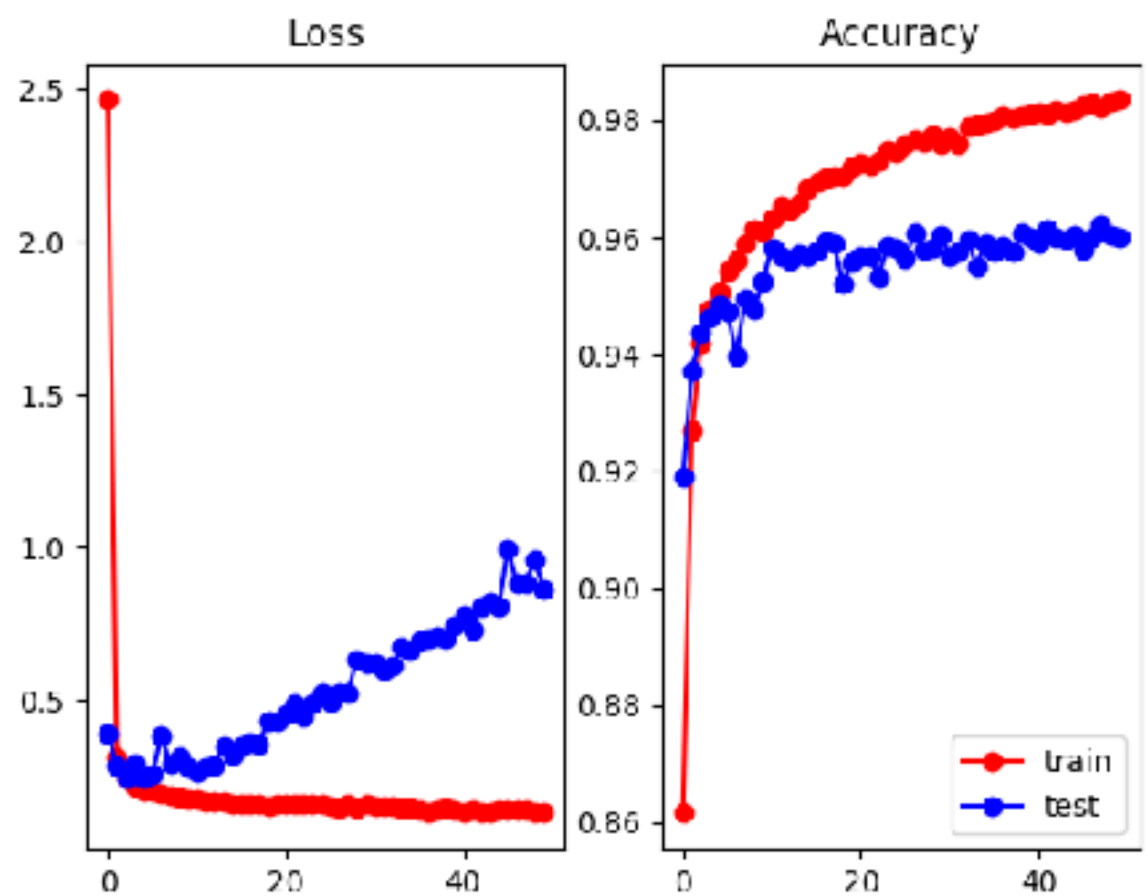
- Why? Shorter sentences have higher likelihood, better search finds them, but BLEU likes correct-length sentences.

Managing Loss Function/ Eval Metric Differences

- Most principled way: use structured prediction techniques to be discussed in future classes
  - Structured max-margin training
  - Minimum risk training
  - Reinforcement learning
  - Reward augmented maximum likelihood

A Simple Method: Early Stopping w/ Eval Metric

- Remember this graph: difference between number of iterations for best loss vs. best eval



- Why?: Over-confident predictions hurt loss.
- Solution: perform early stopping based on accuracy

Final Words

Reproducing Previous Work

- Reproducing previous work is hard because everything is a hyper-parameter
- If code is released, find and reduce the differences one by one
- If code is not released, try your best
- Feel free to contact authors about details, they will usually respond!

Questions?