Regularizing and Optimizing LSTM Language Models

Stephen Merity[1] Nitish Shirish Keskar[1] Richard Socher[1]

20160413 Soyoung Yoon
20150824 Jaeyoung Hwang
20150390 Dongmin Seo

Regularizing and Optimizing LSTM Language Models

1. Introduction
2. Previous Approaches
3. Optimization Techniques
4. Regularization Techniques
5. Evaluation
6. Conclusion & Contributions

Introduction

Language modeling is **useful** for pre-training decoders in Seq2Seq architectures, and **custom architectures** often proposed.

- Apply **Generalization / Regularization** Techniques
- Propose new **Optimization** Techniques (NT-AvSGD)
- Apply **pointer model & QRNN**

Attained **State of The Art performance** for many tasks and become popular baseline model for LM papers

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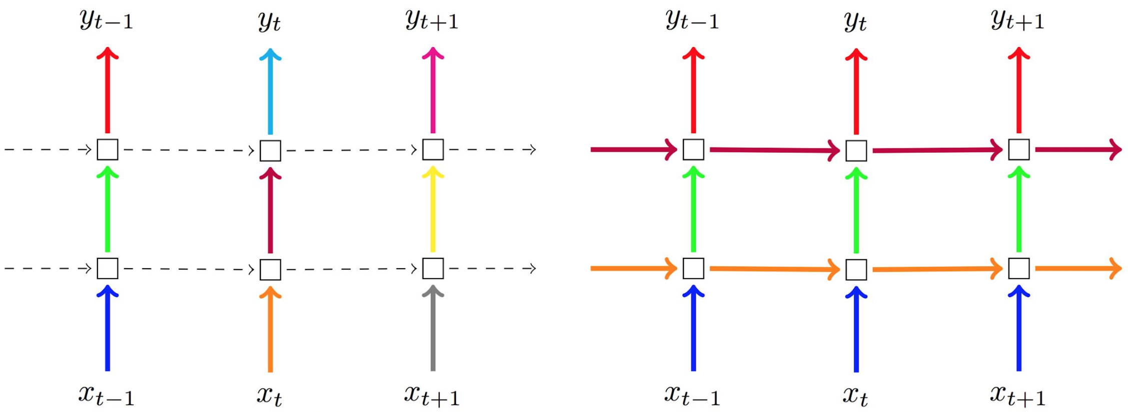
Neural networks suffer from over-parameterization (**overfitting**) - **Regularization** is important for performance

Dropout & Batch normalization: good for feed-forward and CNNs
BUT Naive dropout disrupt RNN’s ability to retain long term dependencies

-> 1. Retain **same** dropout mask over multiple time steps (variational dropout)

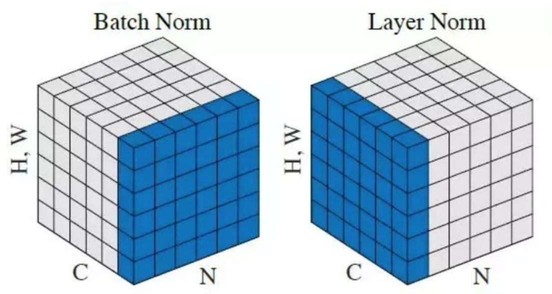


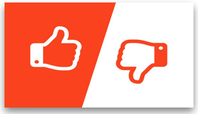
(a) Naive dropout RNN (b) Variational RNN

2. Limit updates to RNN's hidden state (≈ Zone-out)

3. Limit updates to RNN's recurrent state
   - 3-1. Restrict capacity of matrix
   - 3-2. Through element-wise interactions

4. Normalization Techniques
   - 4-1. Batch Normalization
   - 4-2. Recurrent Batch Normalization
   - 4-3. Layer Normalization





Need additional training parameters -> increase sensitivity of model

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Optimization - NT-AvSGD

- SGD
  - Use **mini-batch** rather than entire data when calculate loss function

$$\boxed{\min_{w} \quad \frac{1}{N}\sum_{i=1}^{N} f_i(w),}$$

f_i is the loss function for i'th data point

- ASGD (Averaged-SGD)
  - **K**: total number of iterations
  - **T**: user-specified averaging (T < K)
  - But, **unclear guidelines** for the learning-rate and T

$$\underbrace{\frac{1}{(K-T+1)}}_{\text{Averaging Term}} \sum_{i=T}^{K} \boxed{w_i}$$

- NT-ASGD (Non-monotonically Triggered ASGD)
  - **Well defined guidelines** for the learning-rate and T

Optimization - NT-AvSGD

$$\frac{1}{(K-T+1)}\sum_{i=T}^{K} w_i$$

$$\boxed{\min_{w} \quad \frac{1}{N}\sum_{i=1}^{N} f_i(w),}$$

f_i is the loss function for i'th data point

Averaging Term

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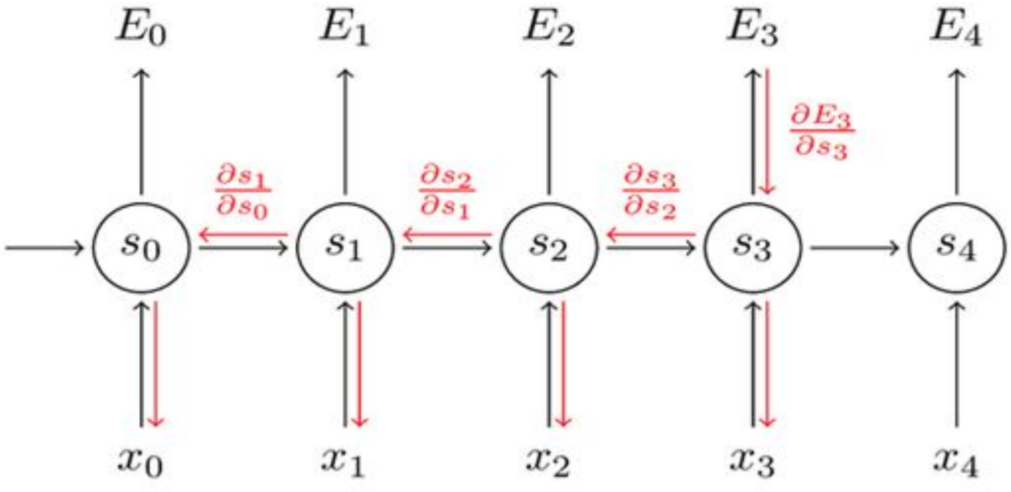
Variable length backpropagation sequences

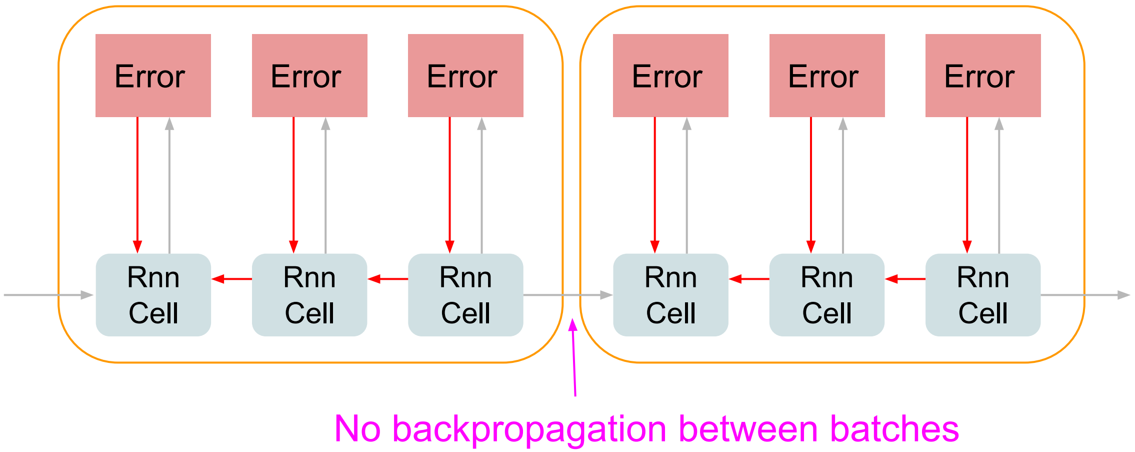
- recap: BPTT
  (Backpropagation Through Time)



Variable length backpropagation sequences

- truncated-BPTT
  - Limit backprop distance
  - Apply BPTT for each divided batch

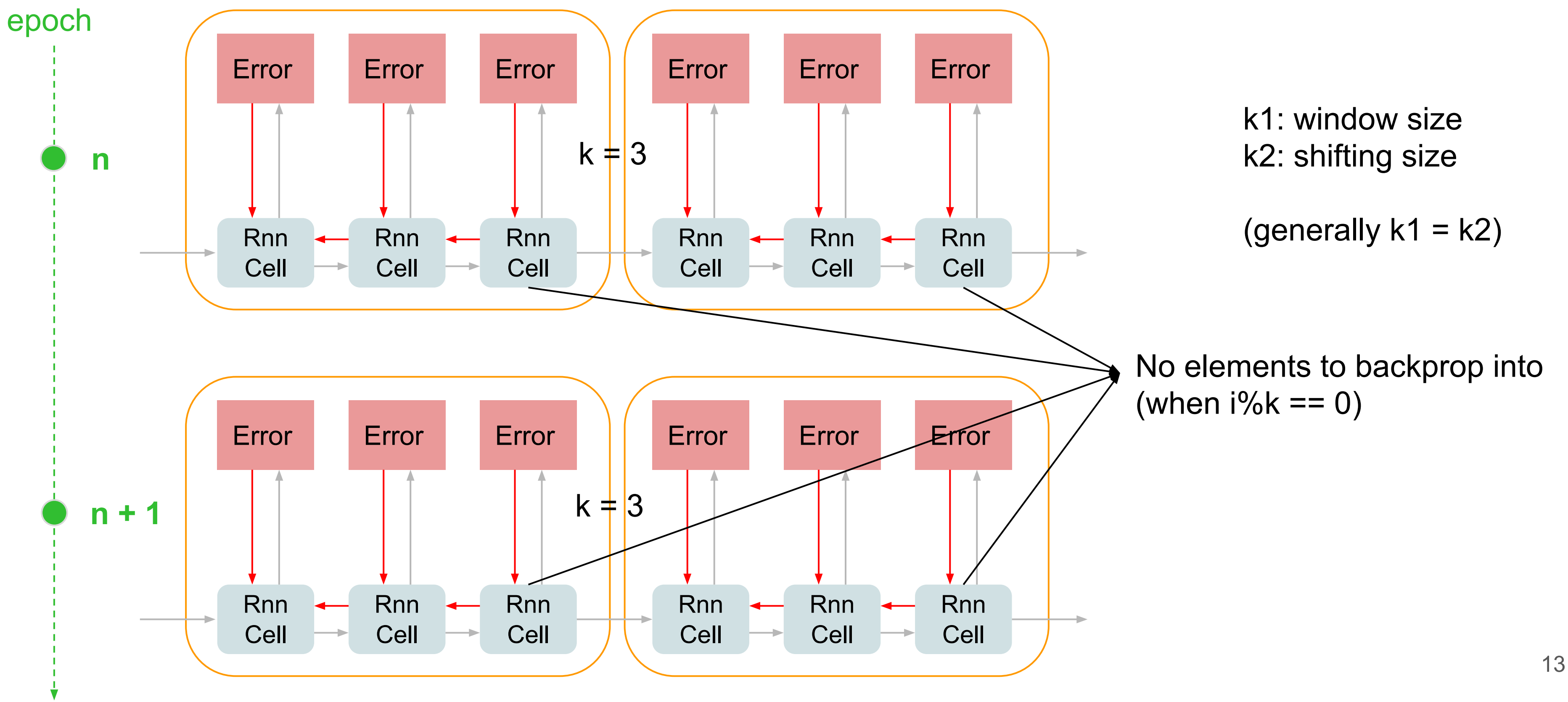
k = 3



k1: window size
k2: shifting size

(generally k1 = k2 = k)

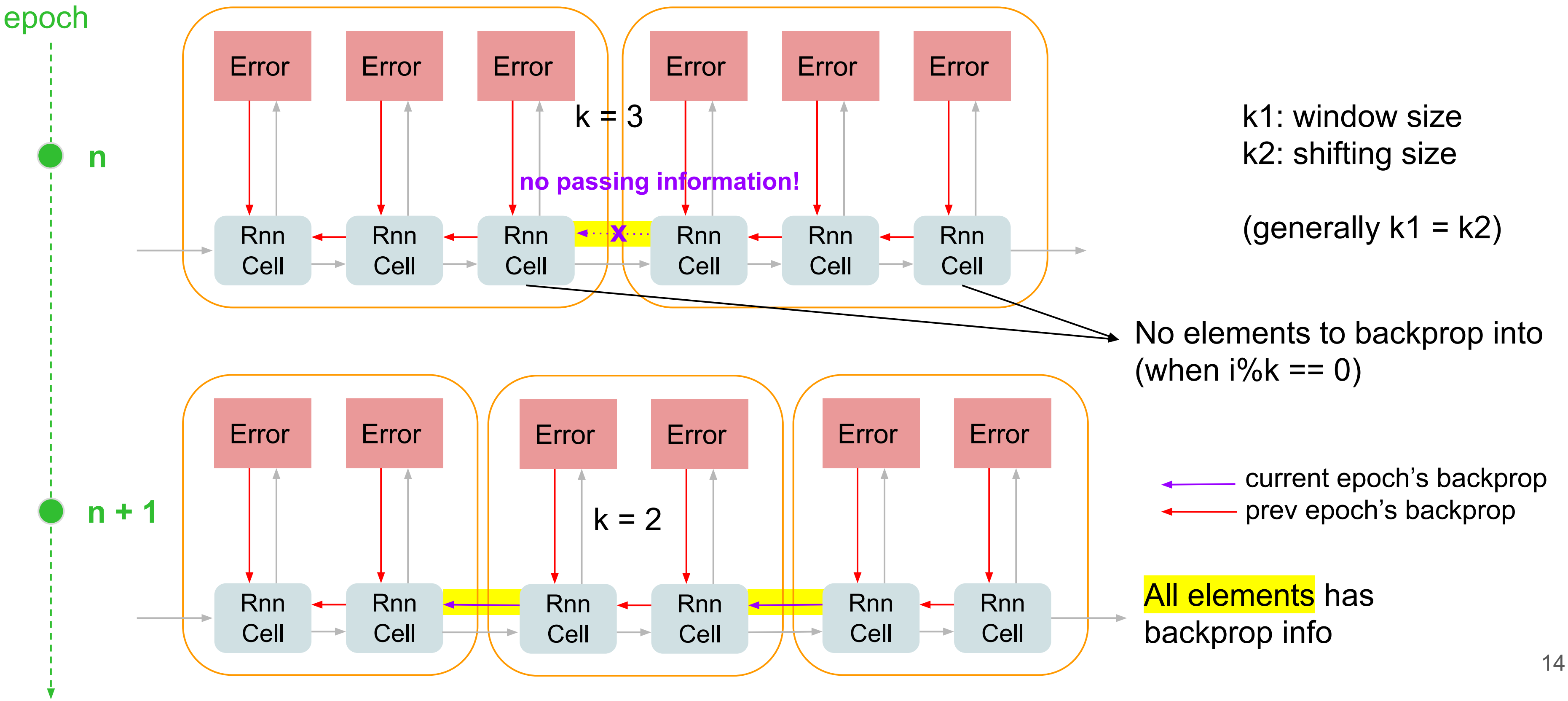
Truncated BPTT



k1: window size
k2: shifting size

(generally k1 = k2)

Variable length backpropagation sequences

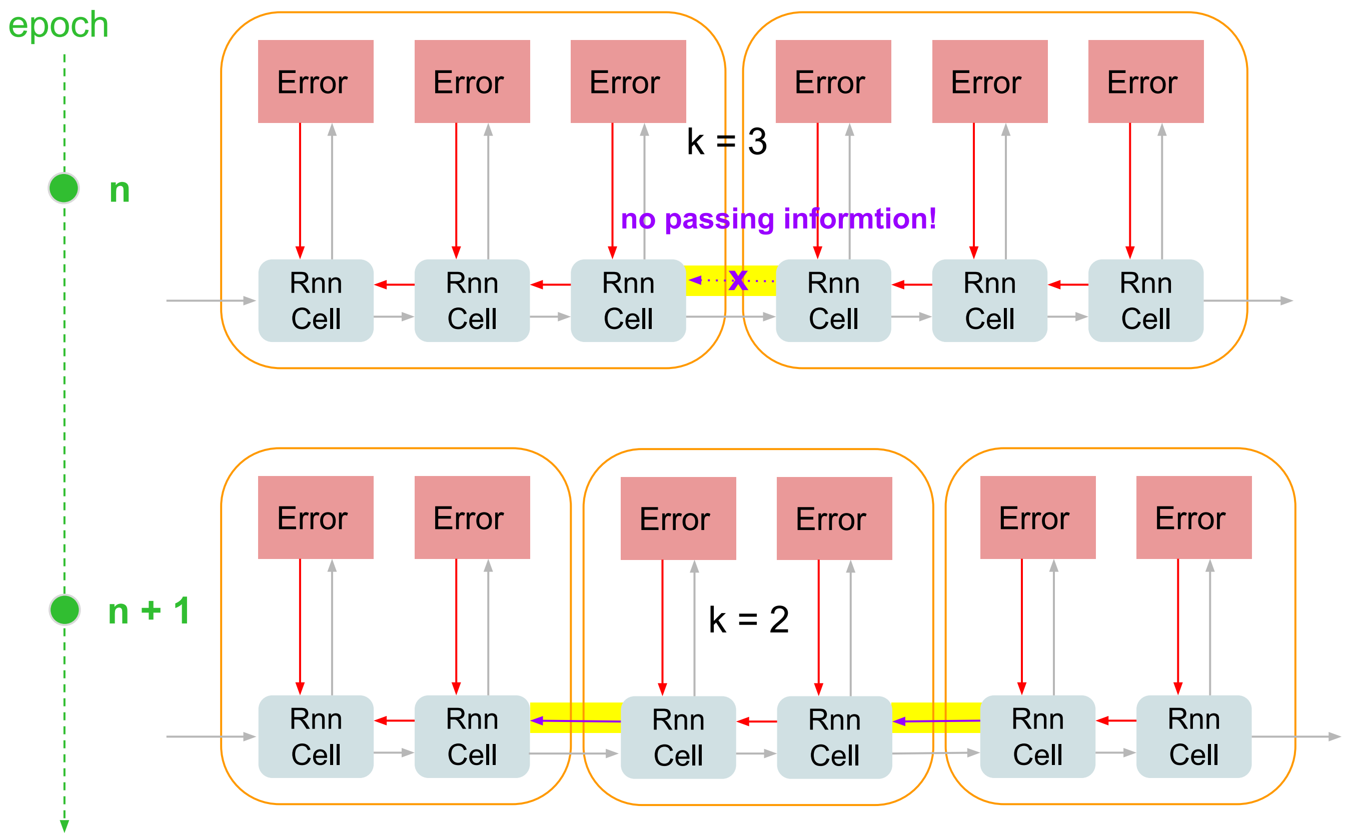


k1: window size
k2: shifting size

(generally k1 = k2)

All elements has backprop info

Variable length backpropagation sequences



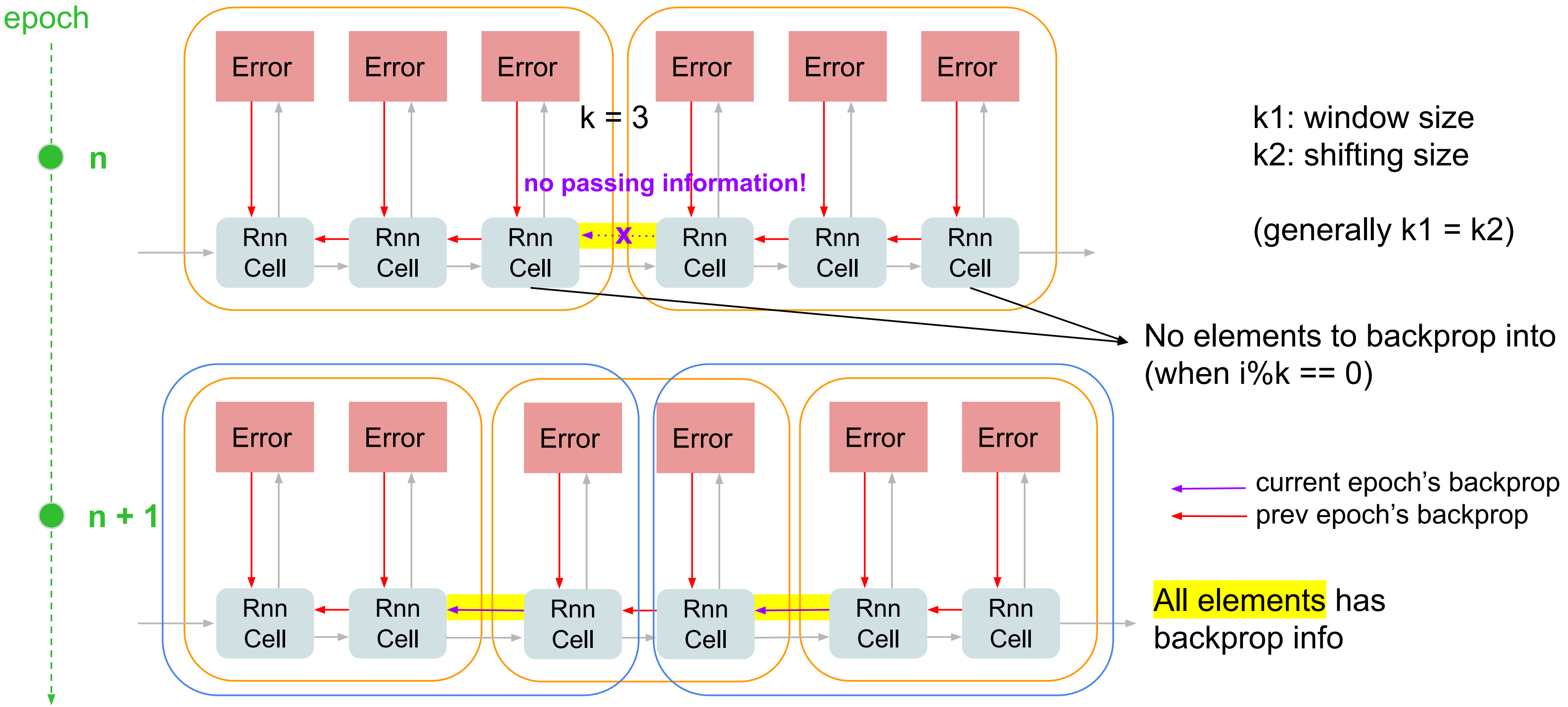
k1: window size
k2: shifting size

(generally k1 = k2)

No elements to backprop into
(when i%k == 0)

All elements has backprop info

Variable length backpropagation sequences



k1: window size
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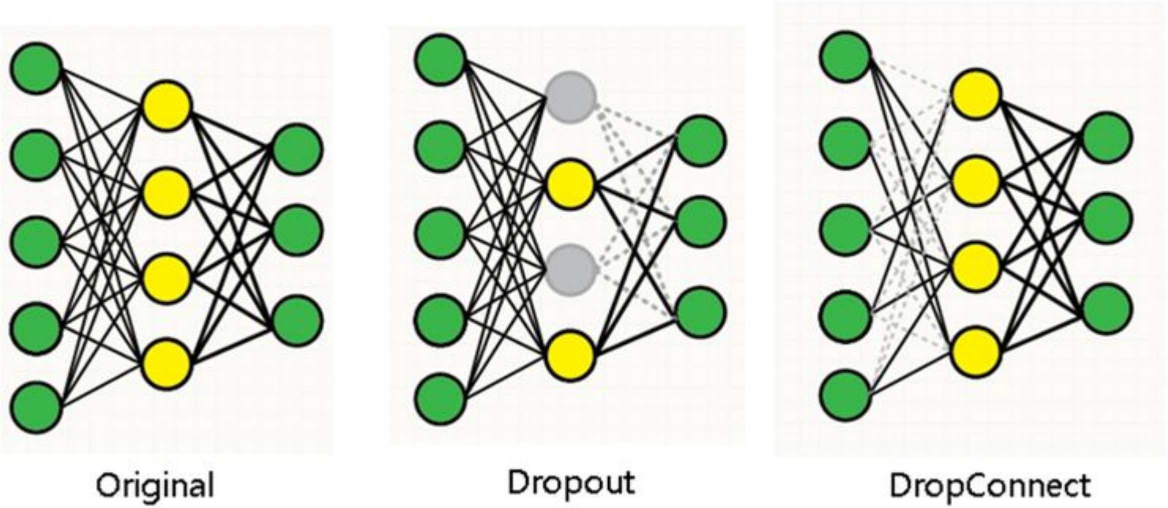
(generally k1 = k2)

Variational Dropout

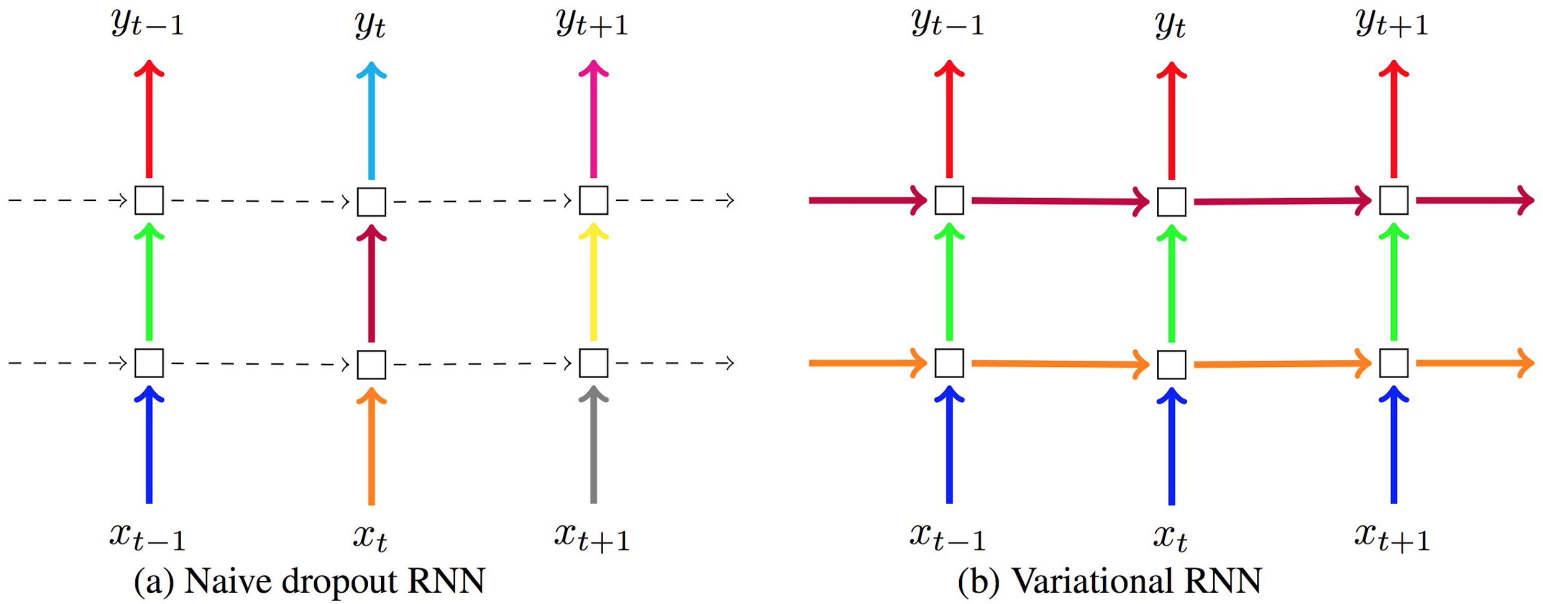
- Known Techniques: DropConnect



-> delete node

-> delete connections(weights)

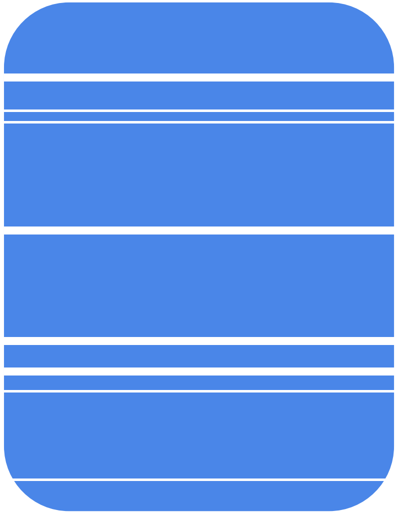
Variational Dropout



same dropout mask for multiple connections!

Embedding dropout

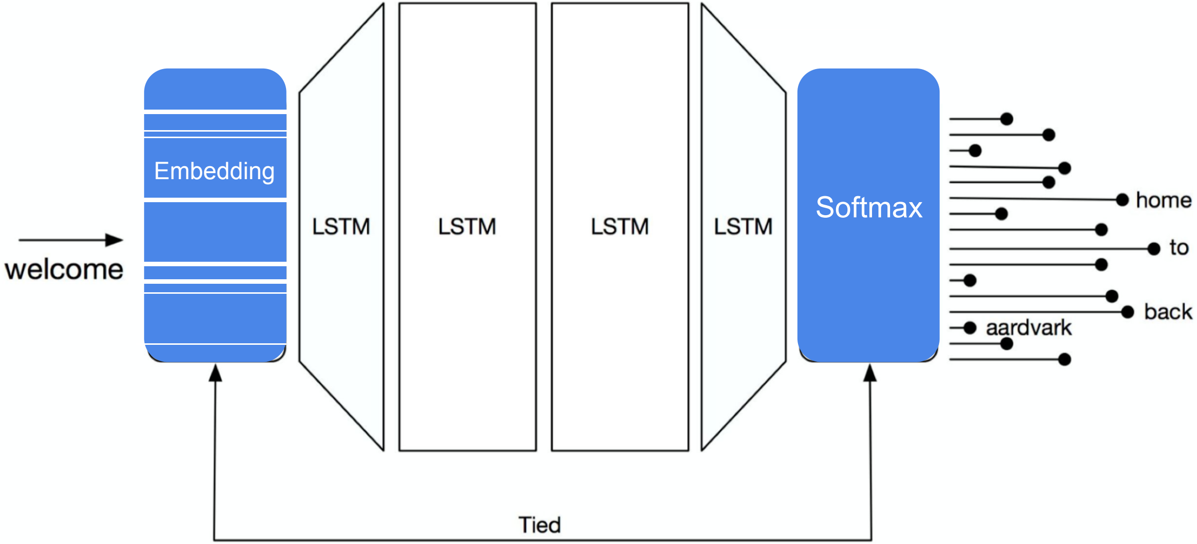
- Dropout on the embedding matrix at a word level



Embedding Matrix

Weight tying

embedding layer weight
==
softmax layer weight



Independent embedding size and hidden size

Reduce embedding size

=> reduce total parameters

AR and TAR

AR (Activation Regularization)

on individual unit activations

$$\alpha \, L_2(m \odot h_t)$$

alpha <- scale coefficient
m <- dropout mask

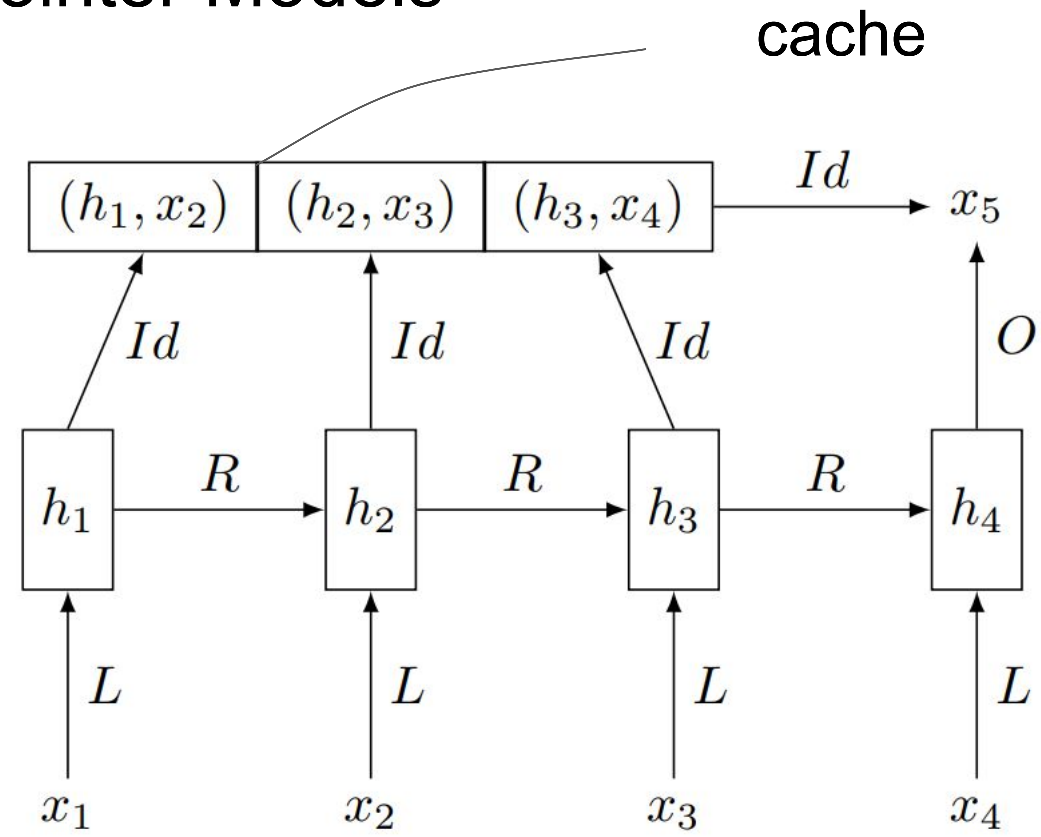
TAR(Temporal Activation Regularization)

on difference in outputs of an RNN

$$\beta \, L_2(h_t - h_{t+1})$$

beta <- scale coefficient

Pointer Models



Pointer models(neural cache model) can be directly added **on top** of a pre-trained language model

h : hidden state
x : word

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Evaluation

Penn Treebank(PTB) & WikiText-2(WT2)

Single model perplexity: lower is better.

Model	Parameters	Validation	Test
Zaremba et al. (2014) - LSTM (medium)	20M	86.2	82.7
Zaremba et al. (2014) - LSTM (large)	66M	82.2	78.4
Gal & Ghahramani (2016) - Variational LSTM (medium)	20M	81.9 ± 0.2	79.7 ± 0.1
Gal & Ghahramani (2016) - Variational LSTM (medium, MC)	20M	–	78.6 ± 0.1
Gal & Ghahramani (2016) - Variational LSTM (large)	66M	77.9 ± 0.3	75.2 ± 0.2
Gal & Ghahramani (2016) - Variational LSTM (large, MC)	66M	–	73.4 ± 0.0
Kim et al. (2016) - CharCNN	19M	–	78.9
Merity et al. (2016) - Pointer Sentinel-LSTM	21M	72.4	70.9
Grave et al. (2016) - LSTM	–	–	82.3
Grave et al. (2016) - LSTM + continuous cache pointer	–	–	72.1
Inan et al. (2016) - Variational LSTM (tied) + augmented loss	24M	75.7	73.2
Inan et al. (2016) - Variational LSTM (tied) + augmented loss	51M	71.1	68.5
Zilly et al. (2016) - Variational RHN (tied)	23M	67.9	65.4
Zoph & Le (2016) - NAS Cell (tied)	25M	–	64.0
Zoph & Le (2016) - NAS Cell (tied)	54M	–	62.4
Melis et al. (2017) - 4-layer skip connection LSTM (tied)	24M	60.9	58.3
AWD-LSTM - 3-layer LSTM (tied)	24M	60.0	57.3
AWD-LSTM - 3-layer LSTM (tied) + continuous cache pointer	24M	53.9	52.8

+ variational dropout

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+ weight tying

Evaluation

+ NT-AvSGD

Model	Parameters	Validation	Test
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Inan et al. (2016) - Variational LSTM (tied) ($h = 650$) + augmented loss	28M	91.5	87.0
Grave et al. (2016) - LSTM	–	–	99.3
Grave et al. (2016) - LSTM + continuous cache pointer	–	–	68.9
Melis et al. (2017) - 1-layer LSTM (tied)	24M	69.3	65.9
Melis et al. (2017) - 2-layer skip connection LSTM (tied)	24M	69.1	65.9
AWD-LSTM - 3-layer LSTM (tied)	33M	68.6	65.8
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Penn Treebank(PTB) & **WikiText-2(WT2)**

Evaluation

+ Pointer

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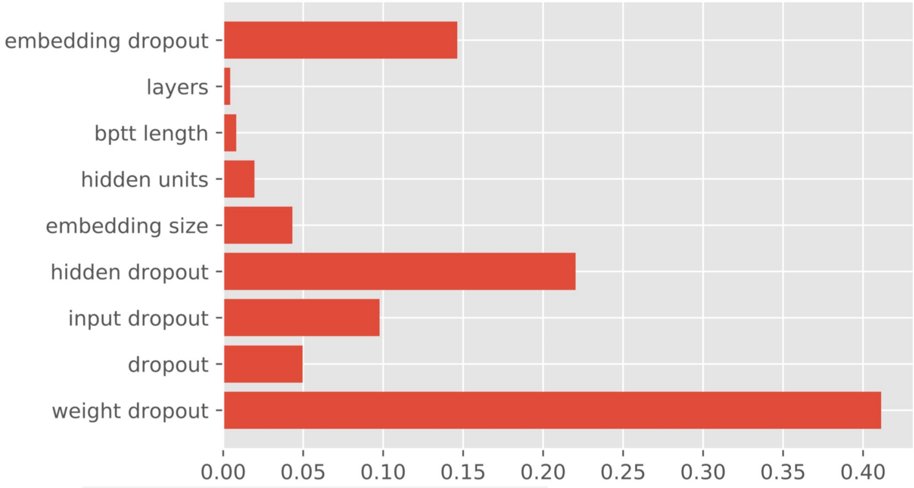
Penn Treebank(PTB) & **WikiText-2(WT2)**

Evaluation - Hyperparameter Importance!

Model	PTB Validation	PTB Test	WT2 Validation	WT2 Test
AWD-LSTM (tied)	60.0	57.3	68.6	65.8
– fine-tuning	60.7	58.8	69.1	66.0
– NT-ASGD	66.3	63.7	73.3	69.7
– variable sequence lengths	61.3	58.9	69.3	66.2
– embedding dropout	65.1	62.7	71.1	68.1
– weight decay	63.7	61.0	71.9	68.7
– AR/TAR	62.7	60.3	73.2	70.1
– full sized embedding	68.0	65.6	73.7	70.7
– weight-dropping	71.1	68.9	78.4	74.9

Each variant is evaluated by removing each feature



Importance of each feature
for decreasing the perplexity of the model

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Conclusion

Developed AWD-LSTM == ASGD Weight-Dropped LSTM (through DropConnect)

Optimization: Non-monotonic triggered ASGD >> SGD

Regularization: variable BPTT length, Variational/Embedding Dropout, AR & TAR, Independent embedding size & hidden size

Neural cache model: Further decrease perplexity

Contributions

No modifications are required for LSTM implementations

- Can be easily integrated to any blackbox LSTM layers (ex: can still use cuDNN LSTM)

- Generally applicable across other sequence learning tasks

Achieve State-of-the-Art Perplexity

- Became popular **baseline model** for LM papers (Universal Language Model Fine-tuning for Text Classification)