Tricks for Training Neural Models

(Some slides by Yoav Goldberg, Graham Neubig)

Optimization Choices

- **Adaptive learning rate.**
  - adaptive optimizers such as Adam ([Kingma14]) because they can better handle the complex training dynamics of RNNs
- **Gradient clipping.**
  - Print or plot the gradient norm to see its usual range
  - then scale down gradients that exceeds this range.
  - This prevents spikes in the gradients to mess up the parameters during training.
- **Normalizing the loss.** (To get losses of similar magnitude across datasets)
  - sum the loss terms along the sequence and divide them by the maximum seq length.
  - This makes it easier to reuse hyper parameters between experiments.
  - The loss should be averaged across the batch.
- **Early Stopping**

https://danijar.com/tips-for-training-recurrent-neural-networks/

Network Structure (RNN)

- **Use Gated Recurrent Unit.**
- **Layer normalization.** Adding layer normalization (Ba et al 16) to all linear mappings of the recurrent network speeds up learning
- **Stacked recurrent networks.**
  - Recurrent networks need a quadratic number of weights in their layer size.
  - More efficient to stack two or three smaller layers instead of one big one.
  - Sum the outputs of all layers instead of using only the last one, similar to a ResNet or DenseNet.

https://danijar.com/tips-for-training-recurrent-neural-networks/

Model Parameters (RNN)

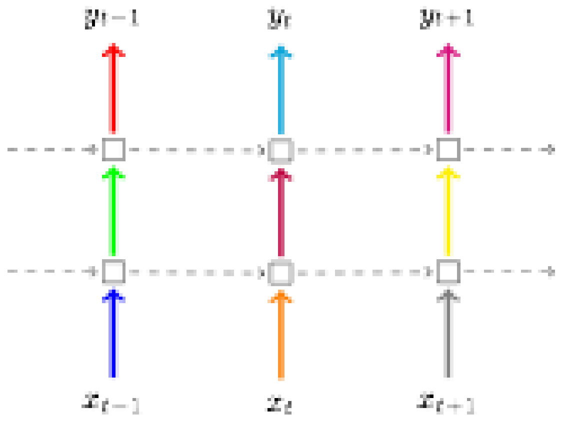
- **Learned initial state.**
  - Initializing the hidden state as zeros → large loss initially
  - Training the initial state as a variable can improve performance as described in https://r2rt.com/non-zero-initial-states-for-recurrent-neural-networks.html
- **Forget gate bias.**
  - It can take a while for a RNN to learn to remember information
  - Initialize biases for LSTM's forget gate to 1 to remember more by default.
  - Similarly, initialize biases for GRU's reset gate to -1.
- **Regularization.** If your model is overfitting, use dropout

https://danijar.com/tips-for-training-recurrent-neural-networks/

Dropout in RNNs

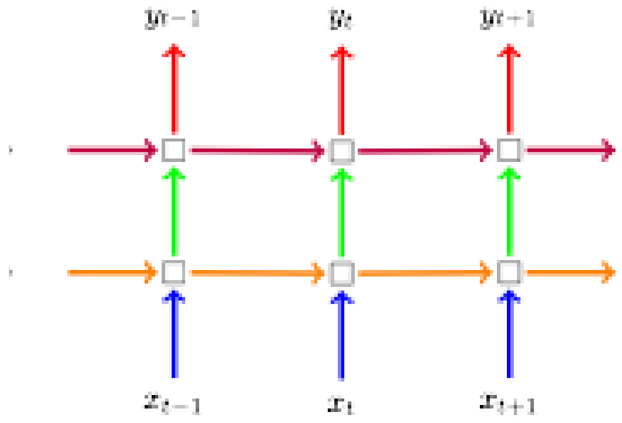
- Still an open question how to perform well.

- One suggestion:



Dropout in RNNs

- Still an open question how to perform well.
- Yarin Gal's Dropout:



Ensembles

- **Same model, different initialization**.
  - Use cross-validation to determine the best hyperparameters,
  - then train multiple models with the best set of hyperparameters but with different random initialization.
  - Suffers from limited variety

- **Top models discovered during cross-validation**.
  - Use cross-validation to determine the best hyperparameters
  - then pick the top few (e.g., 10) models to form the ensemble.
  - Improves the variety of ensemble but has the danger of including suboptimal models

- **Different checkpoints of a single model**.
  - If training is very expensive
  - limited success in taking different checkpoints of a single network over time (for example after every epoch) and using those to form an ensemble.
  - Clearly, this suffers from some lack of variety, but can still work reasonably well in practice.
  - The advantage of this approach is that is very cheap.

http://lamda.nju.edu.cn/weixs/project/CNNTricks/CNNTricks.html

Why are Neural Networks Slow and What Can we Do?

- Big operations, especially for softmaxes over large vocabularies
  - → **Approximate operations or use GPUs**
- GPUs love big operations, but hate doing lots of them
  - → **Reduce the number of operations** through optimized implementations or batching
- Our networks are big, our data sets are big
  - → **Use parallelism** to process many data at once

Approximating Softmax

- Importance Sampling
- Noise Contrastive Estimation
- Simple Negative Sampling
- Hierarchical Softmax

GPUs vs. CPUs

CPU, like a motorcycle

Quick to start, top speed not shabby

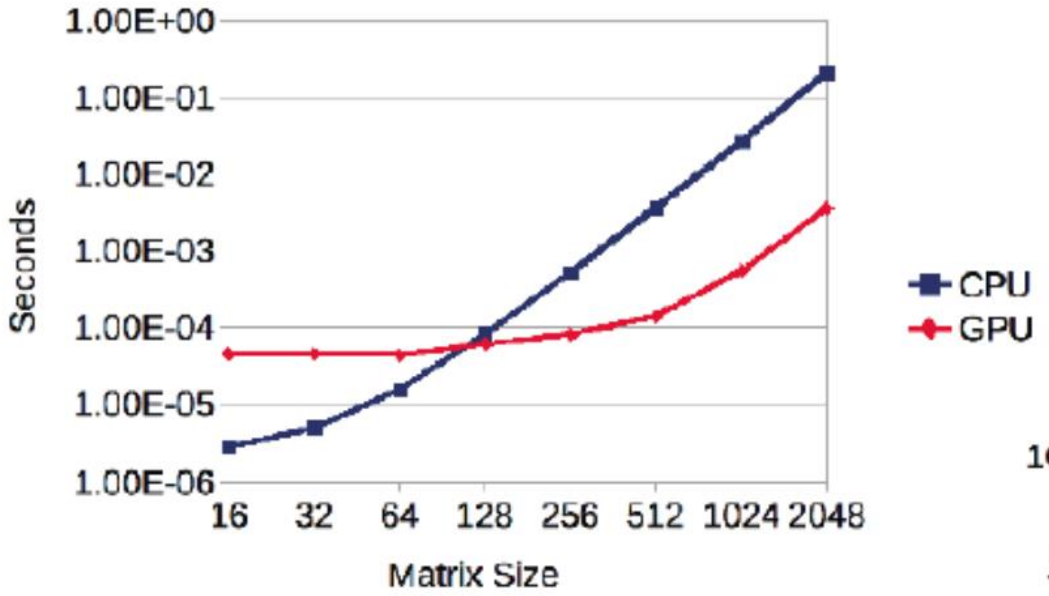
GPU, like an airplane

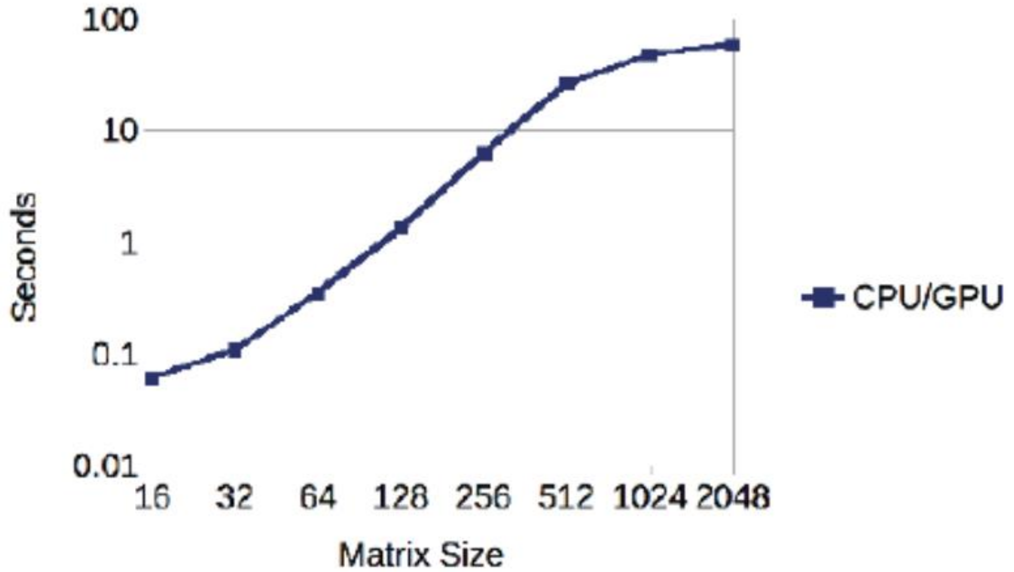
Takes forever to get off the ground, but super-fast once flying

Image Credit: Wikipedia

A Simple Example

- How long does a matrix-matrix multiply take?





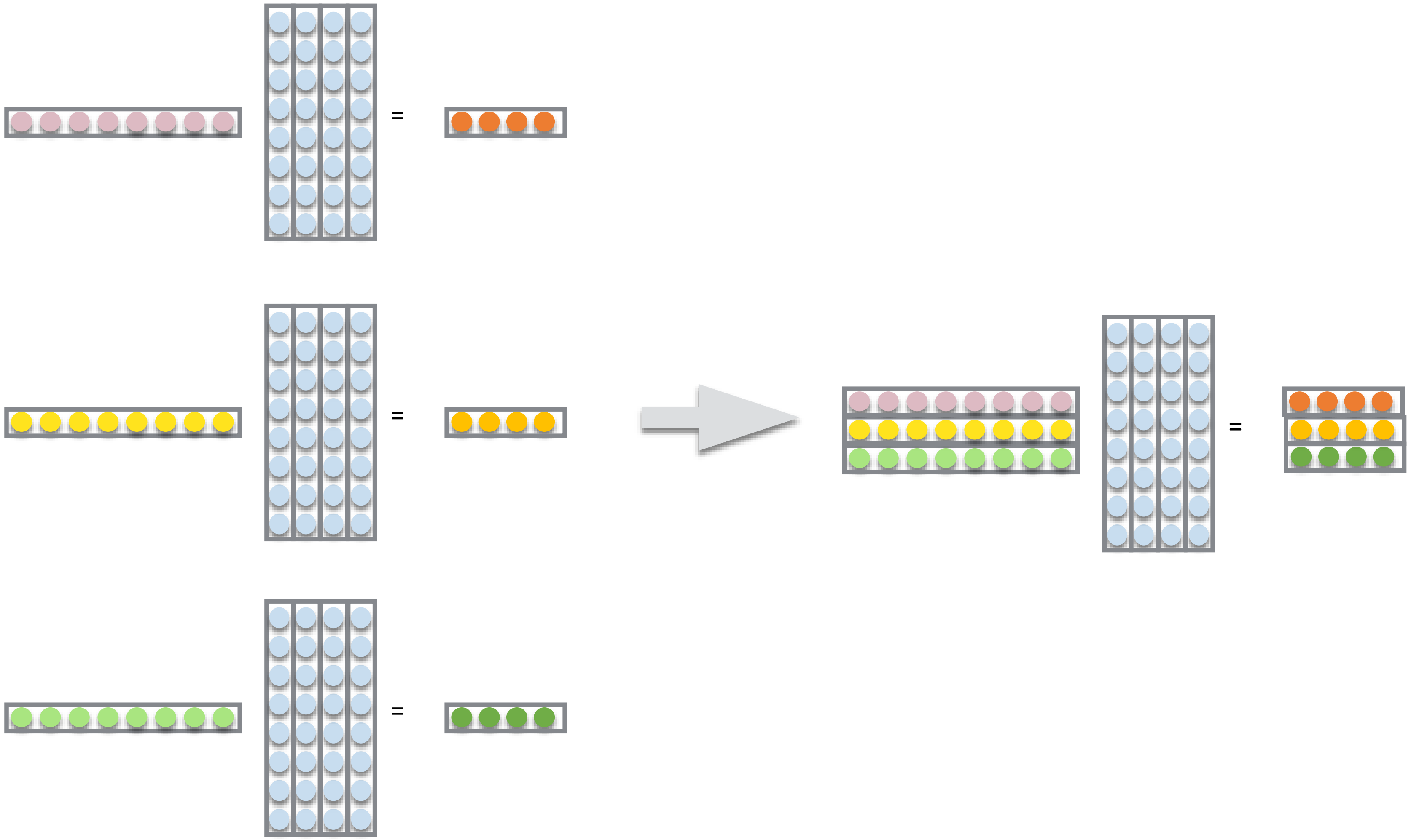
Practically

- Use **CPU for profiling**, it's plenty fast (esp. DyNet) and you can run many more experiments
- For **many applications, CPU is just as fast** or faster than GPU: NLP analysis tasks with small or complicated data/networks
- You see **big gains on GPU when** you have:
  - Very big networks (or softmaxes with no approximation)
  - Do mini-batching
  - Optimize things properly

Batching (in RNNs)

- Most toolkits require a **fixed** computation graph for all examples.
- But RNNs have **different** input lengths. What do we do?
  - Option 1:
    Use a tool that does not pose this limitation.
  - Option 2:
    Enforce max length + 0 padding for shorter sequences.

Batching Reminder

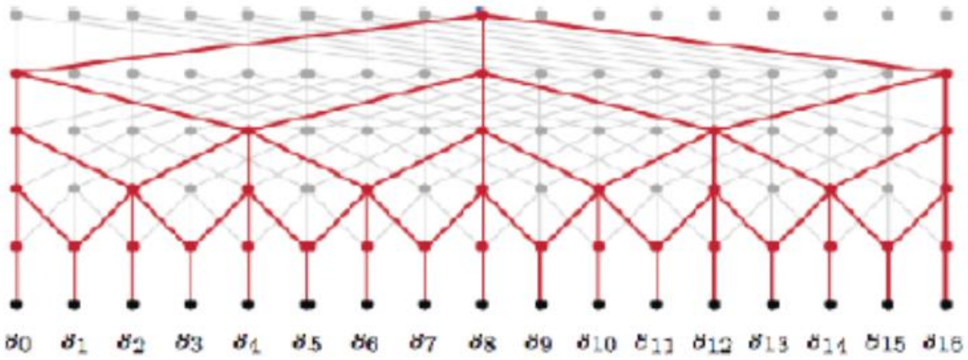


Batching in RNNs

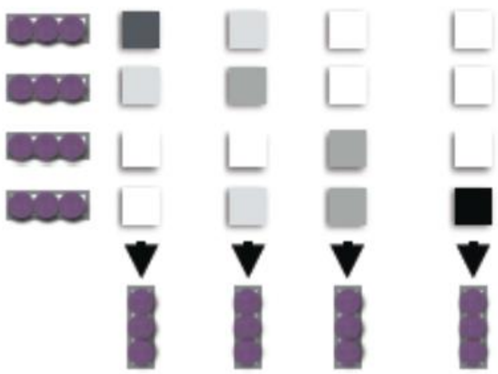
- Sequential in nature, very little parallelism.
- (Compare, e.g., to a Convolutional Network)

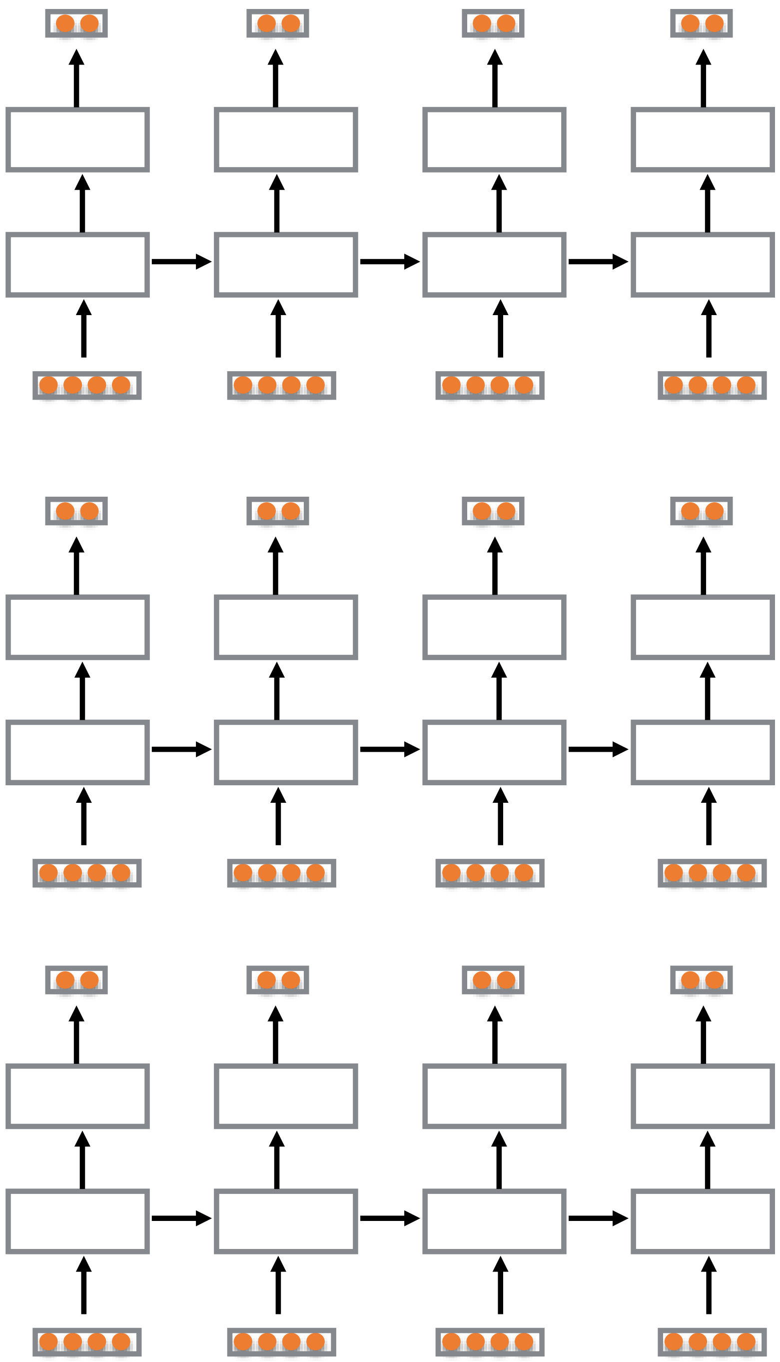
Non-recursive Architectures

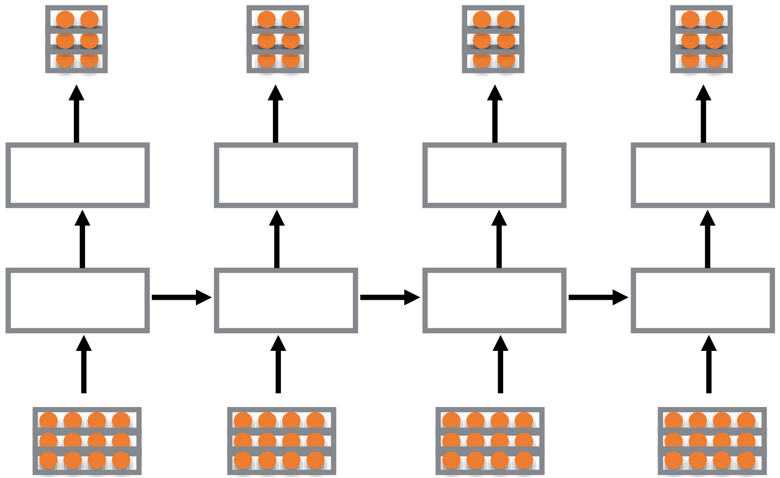
- **Dilated convolutions** for capturing context (Kalchbrenner et al. 2016): single GPU call for entire sentence!



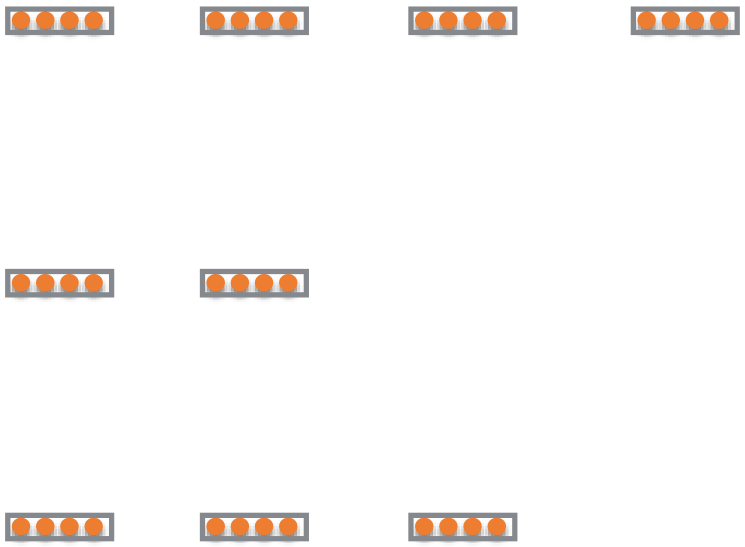
- **Self-attention** that decides which of previous words to focus on (Cheng et al. 2016, Vaswani et al. 2017, covered in detail a few classes): also single GPU call

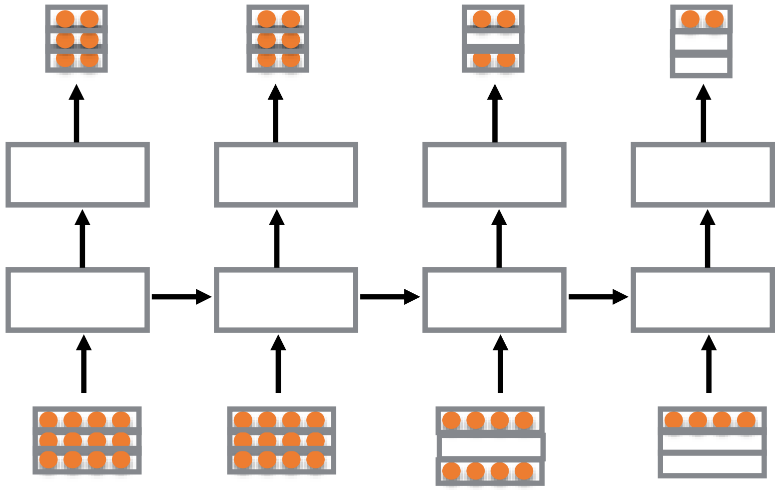


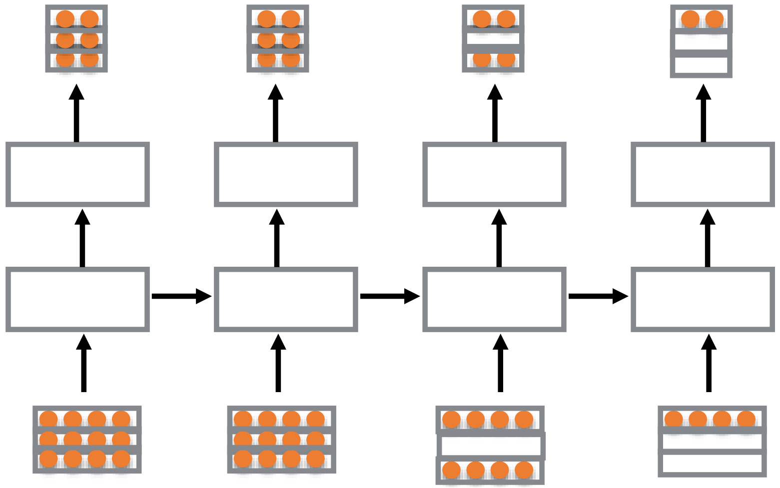




what if the sequences are different lengths?







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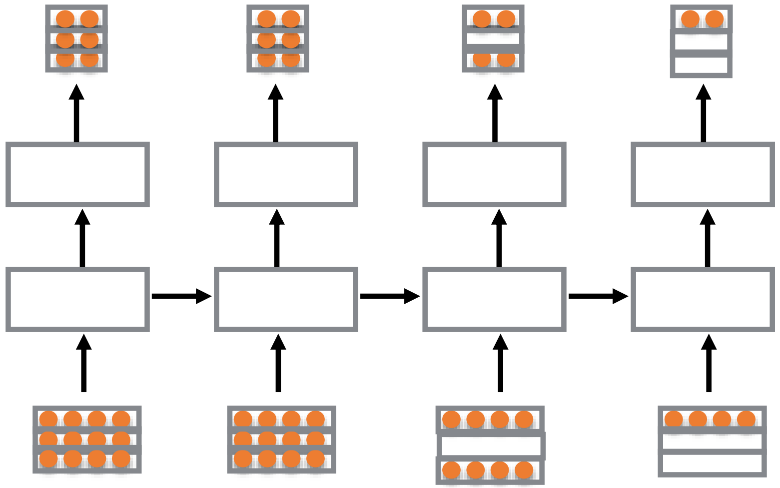
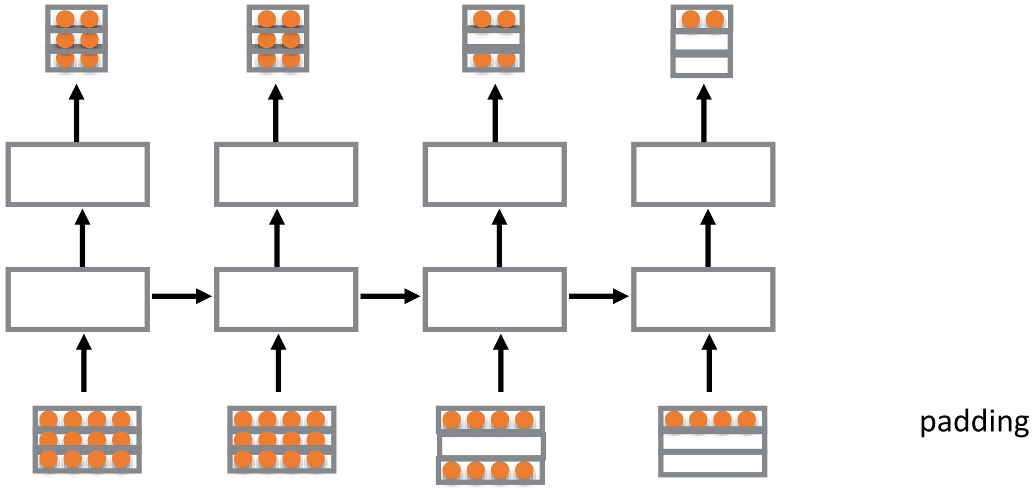


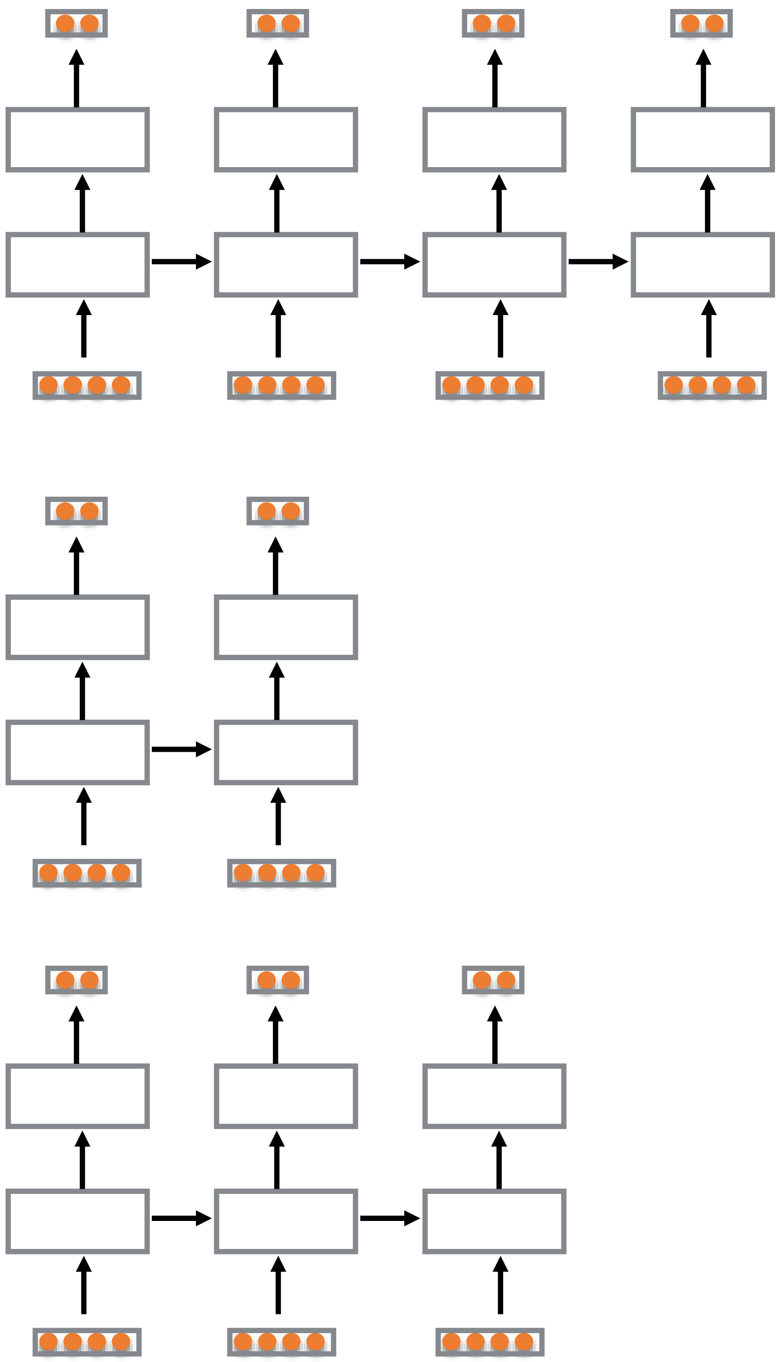
padding

this is how its done in TF, PyTorch.
supported also in DyNet, but...

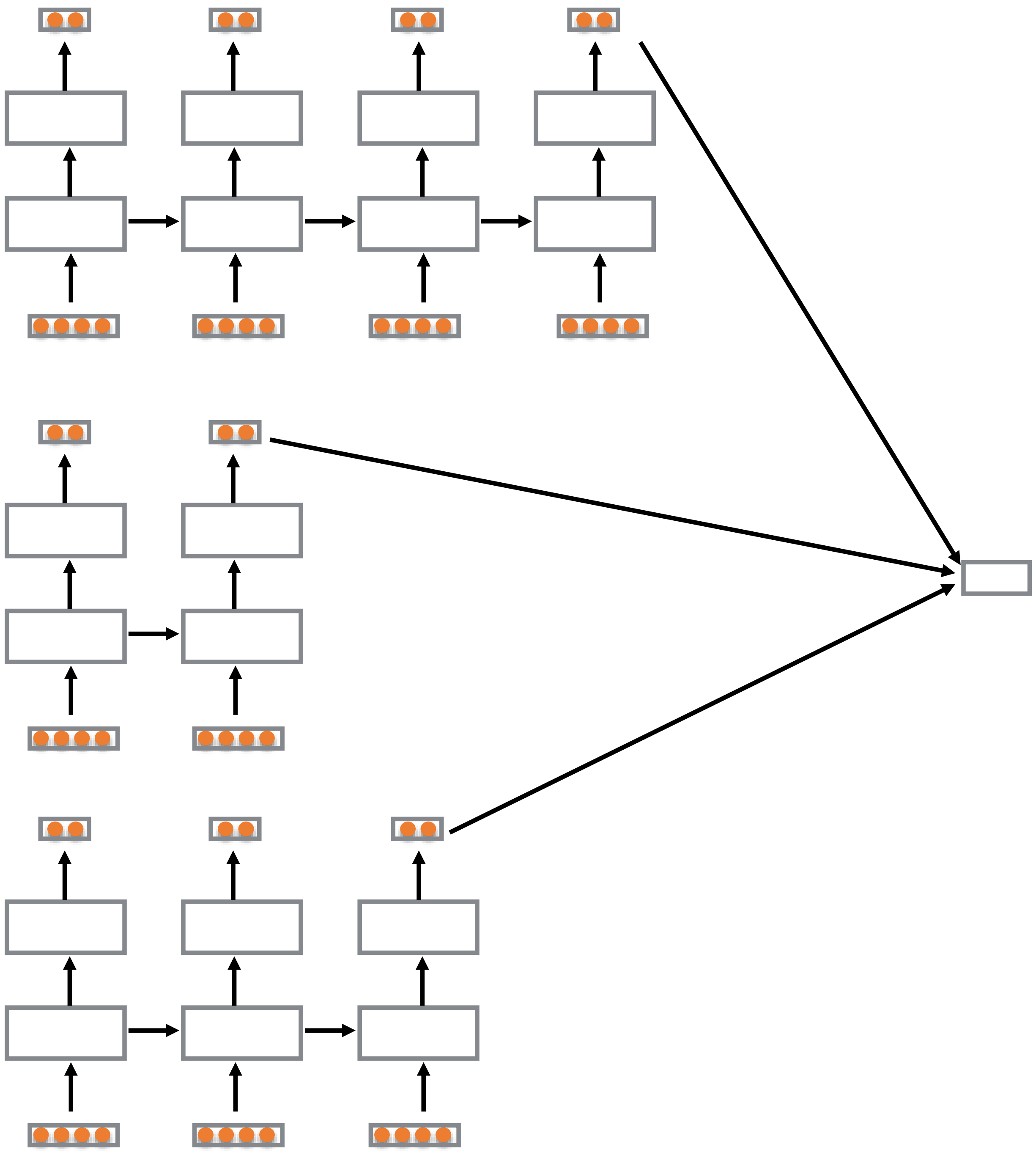


We want better

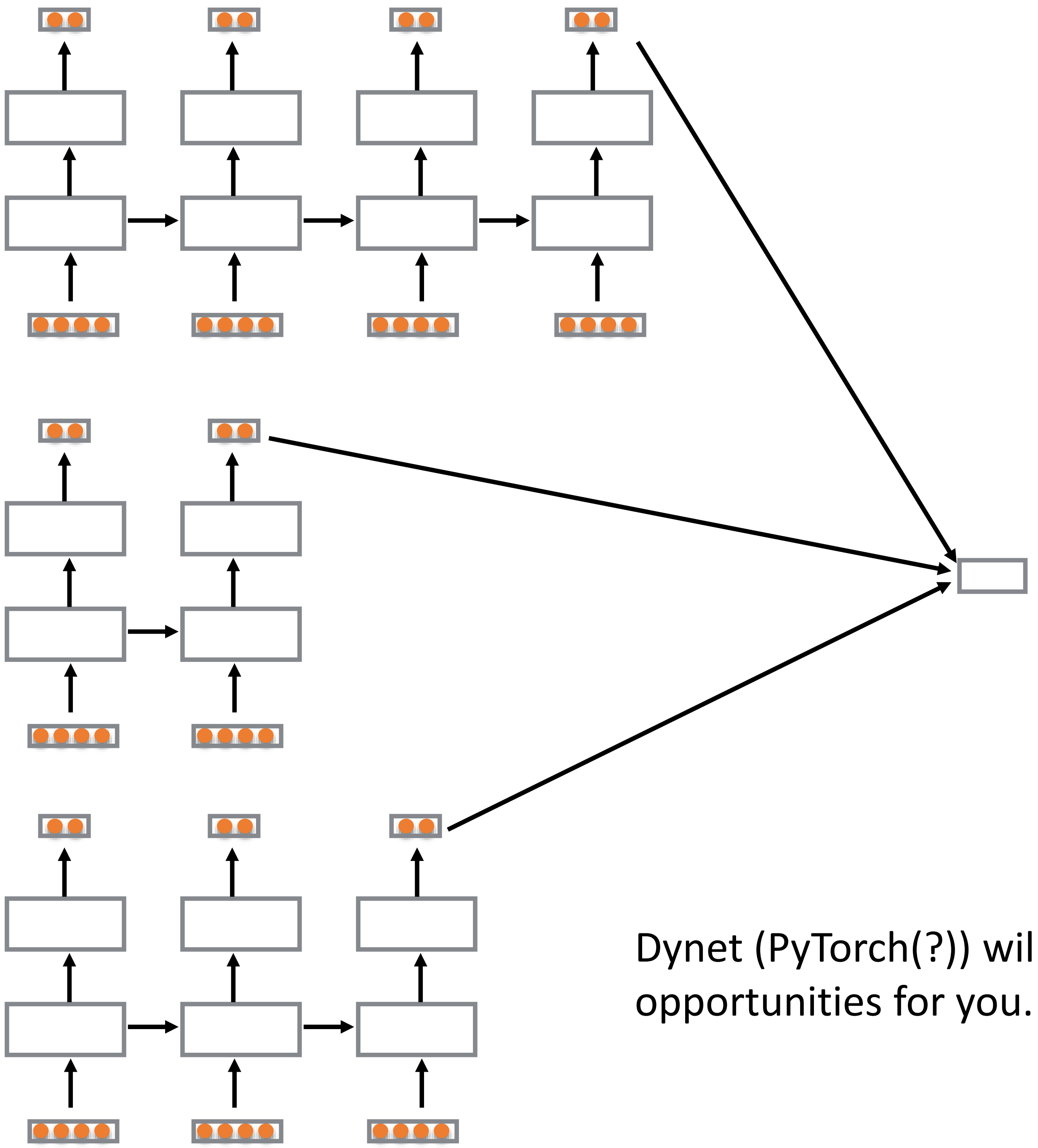
Auto Batching



create a separate
network for each
(easy)



treat them as a single graph



treat them
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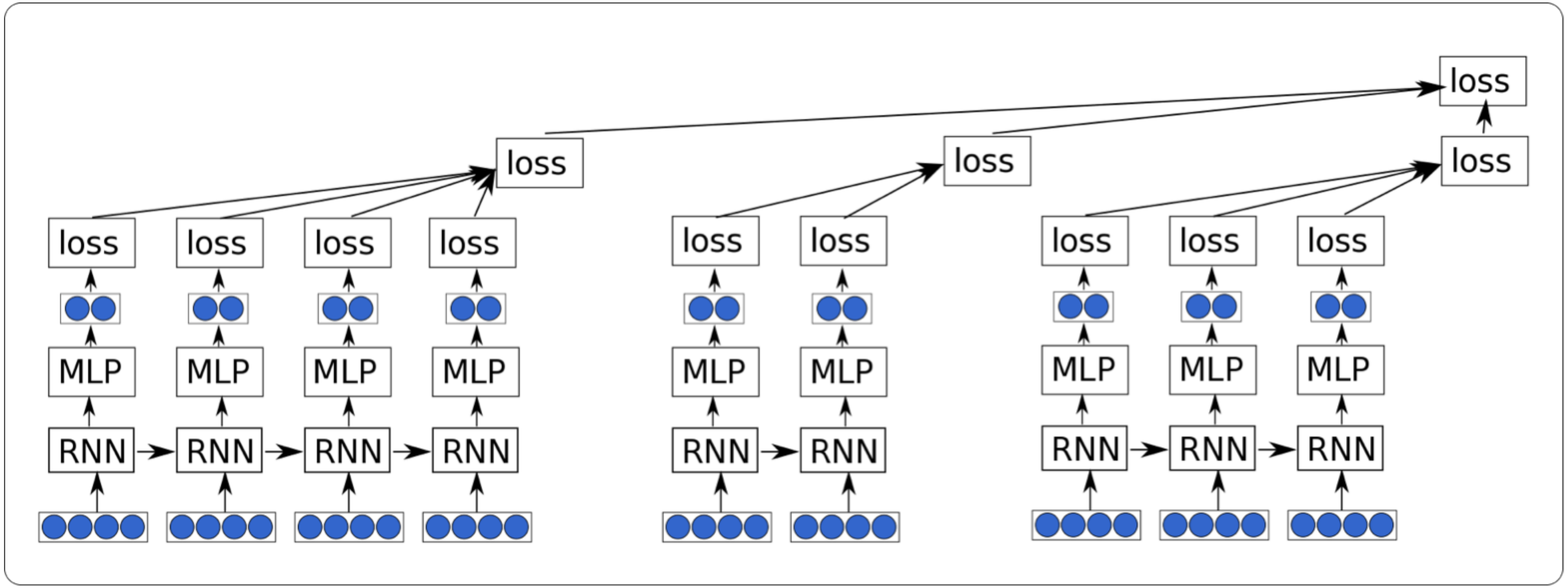
Dynet (PyTorch(?)) will identify batching
opportunities for you.



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nodes in blue are ready
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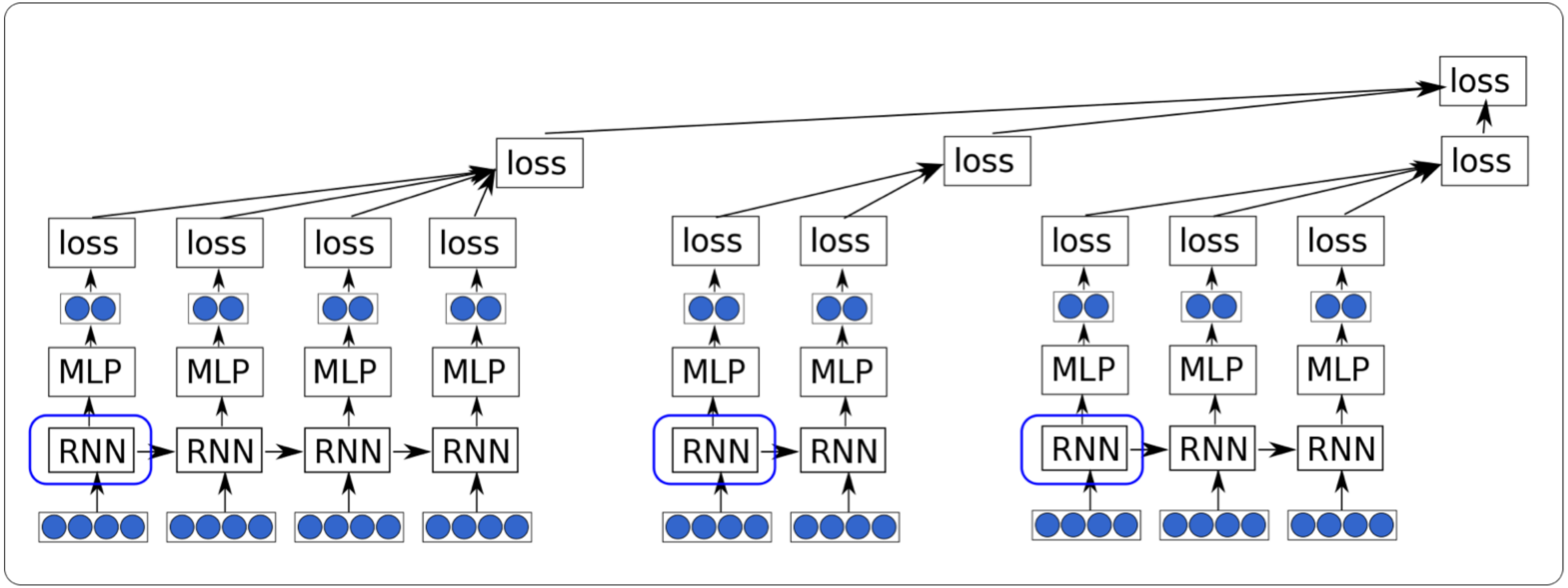
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nodes in red will be executed
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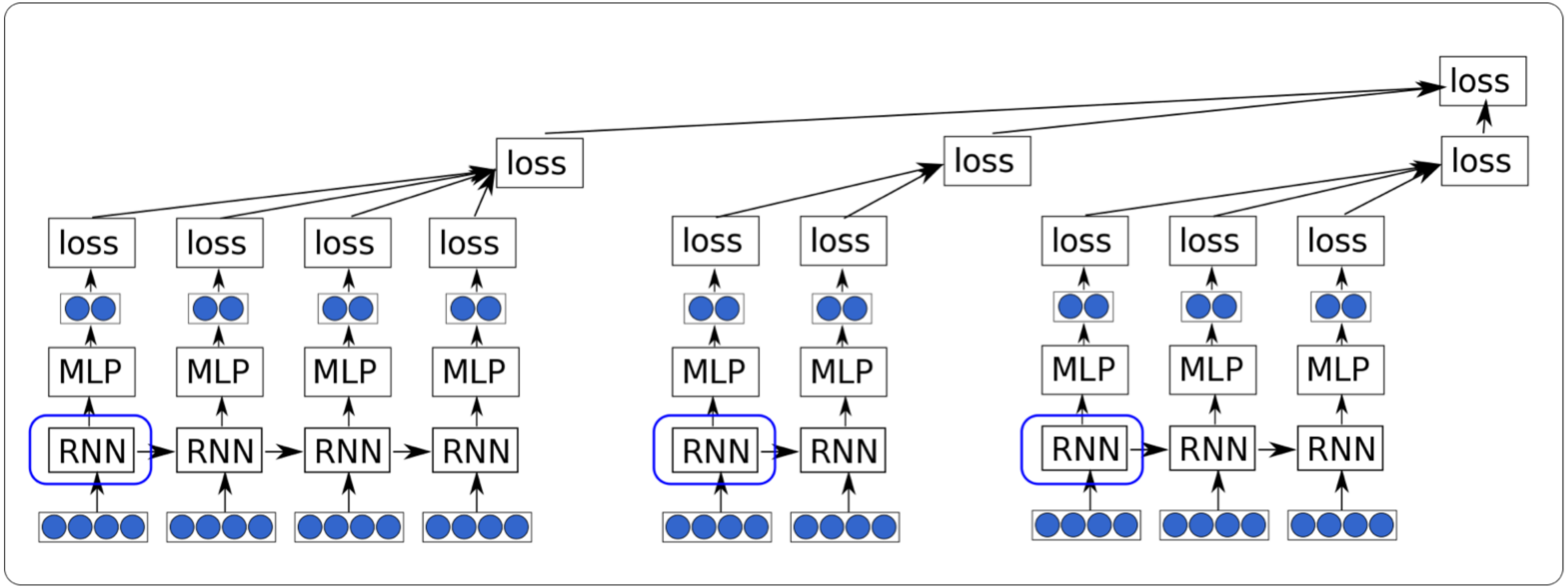

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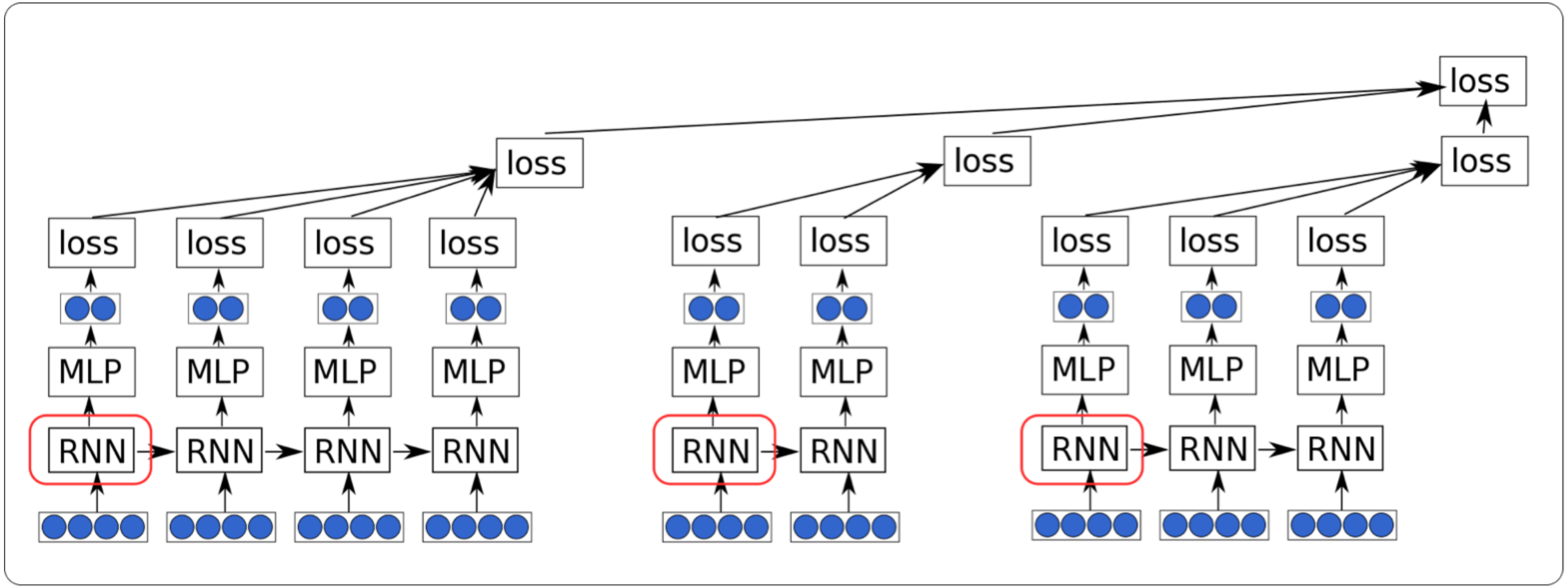

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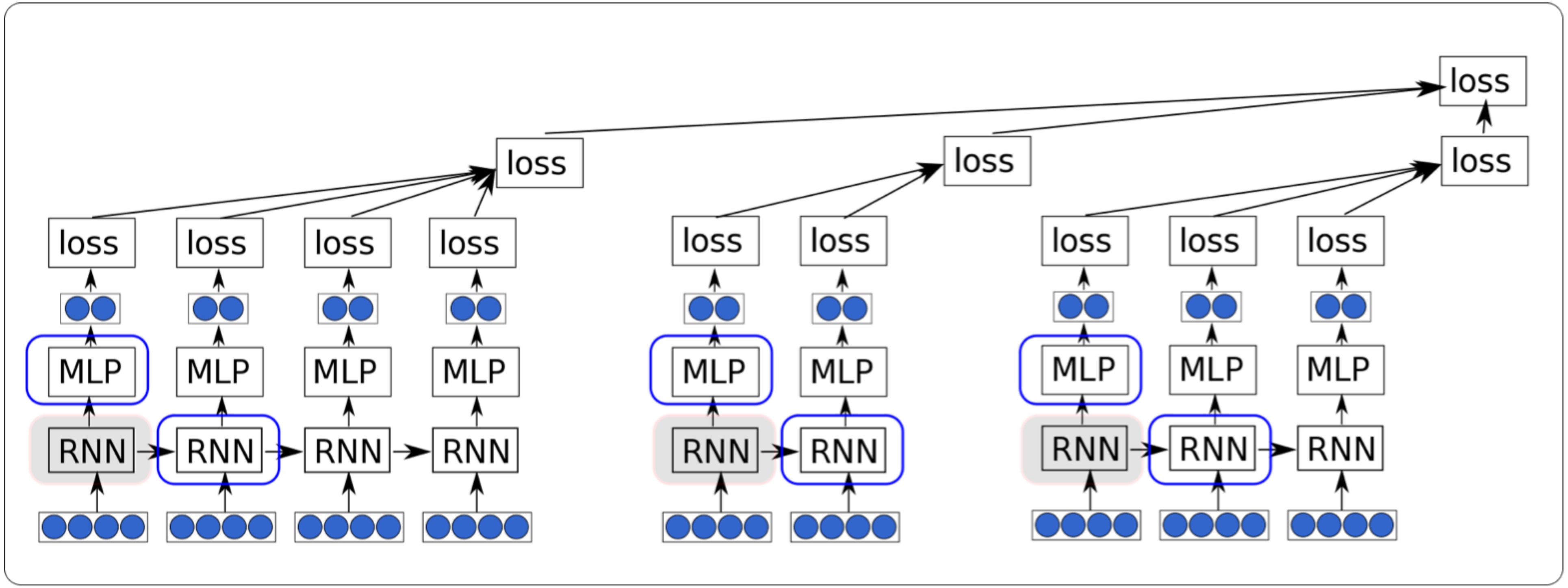

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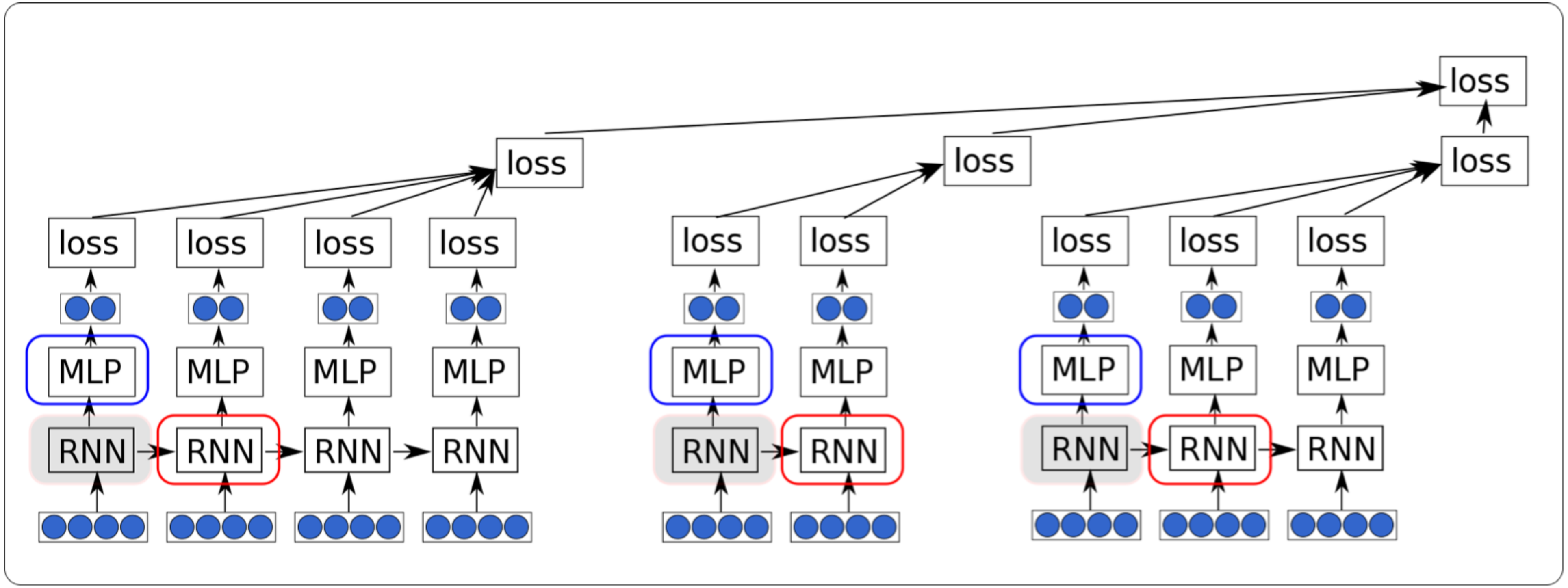

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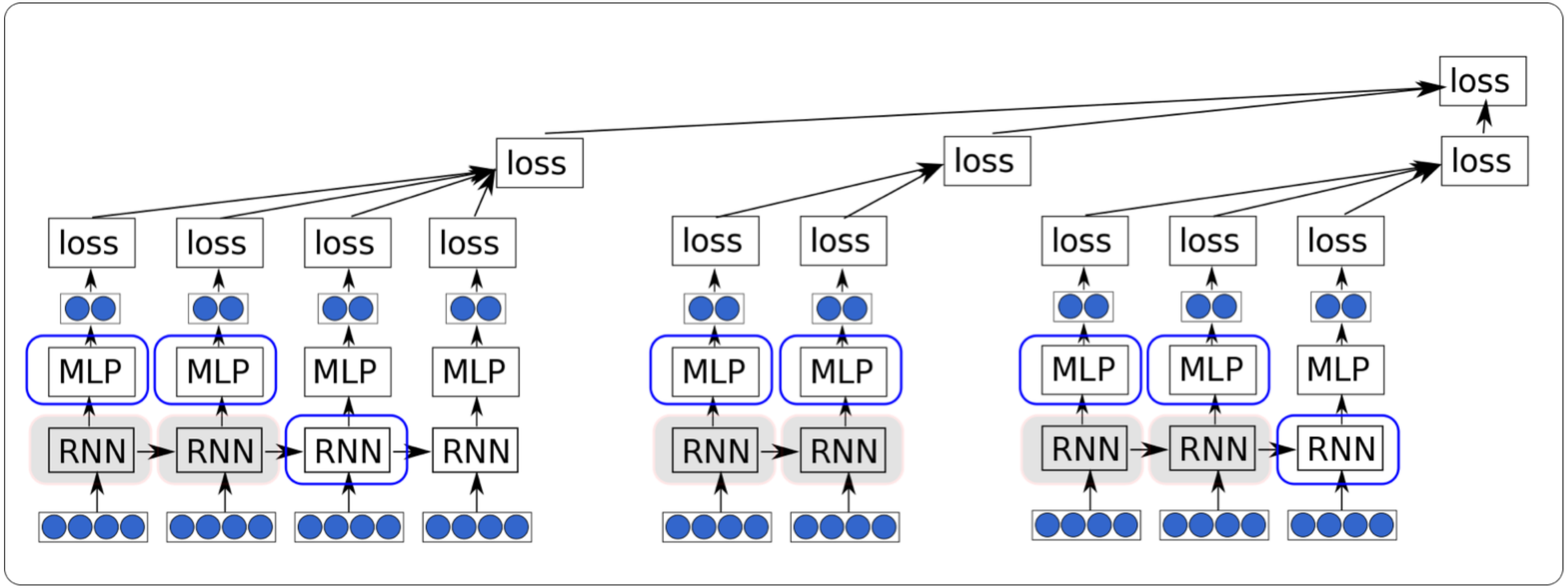

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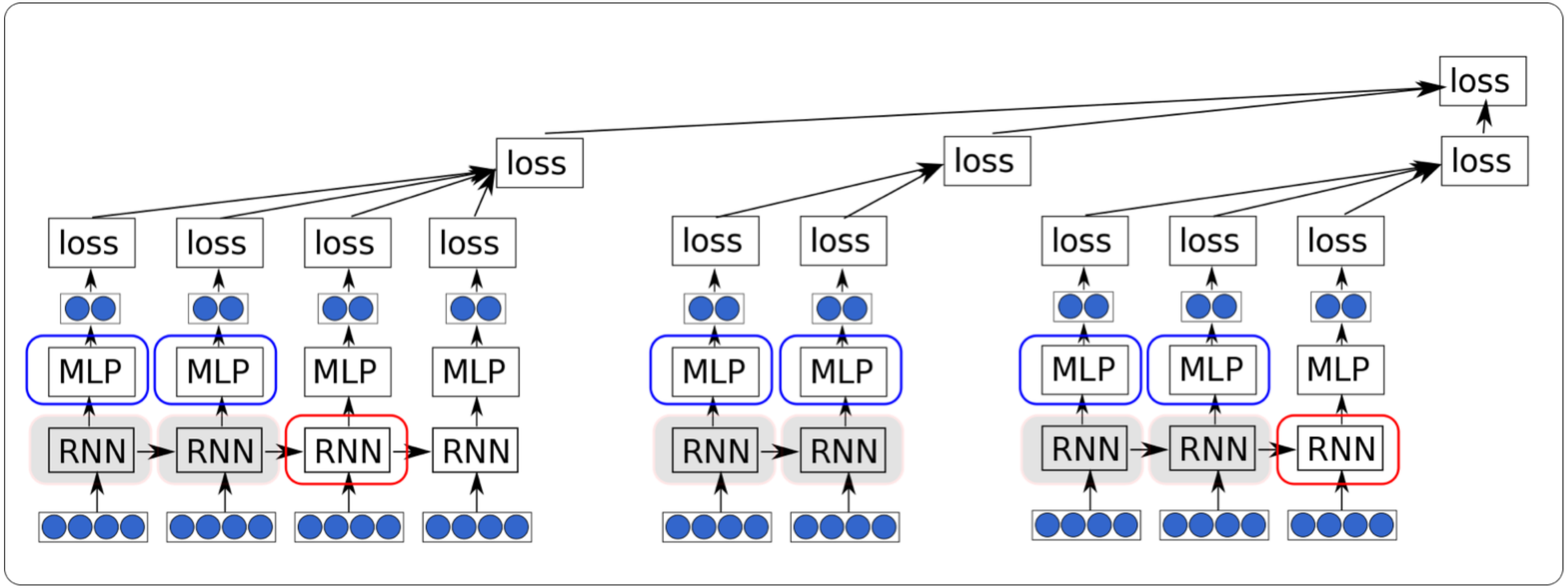

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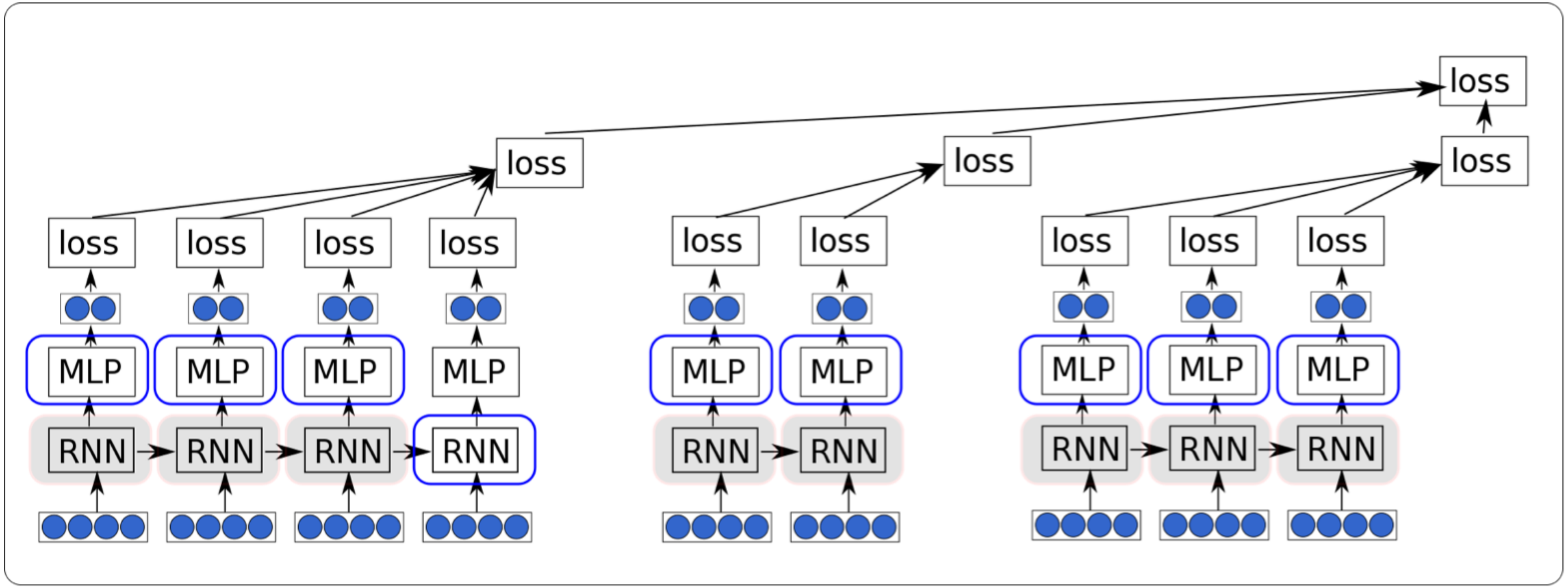
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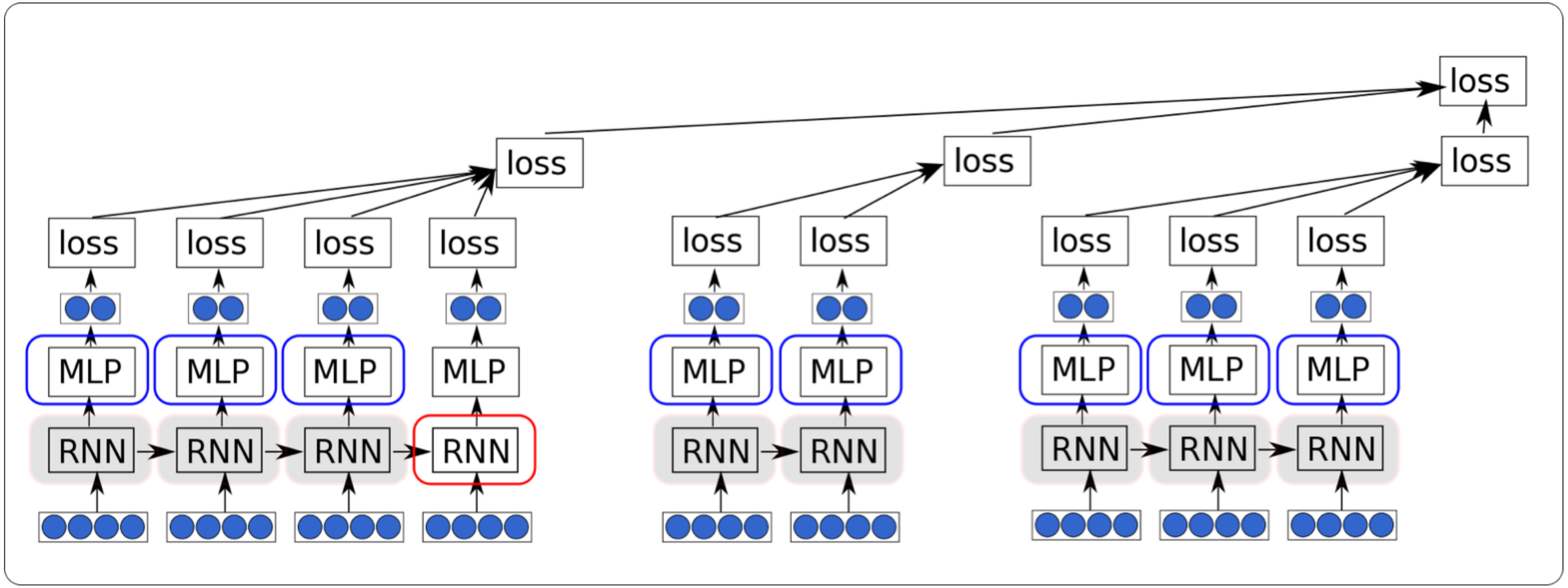

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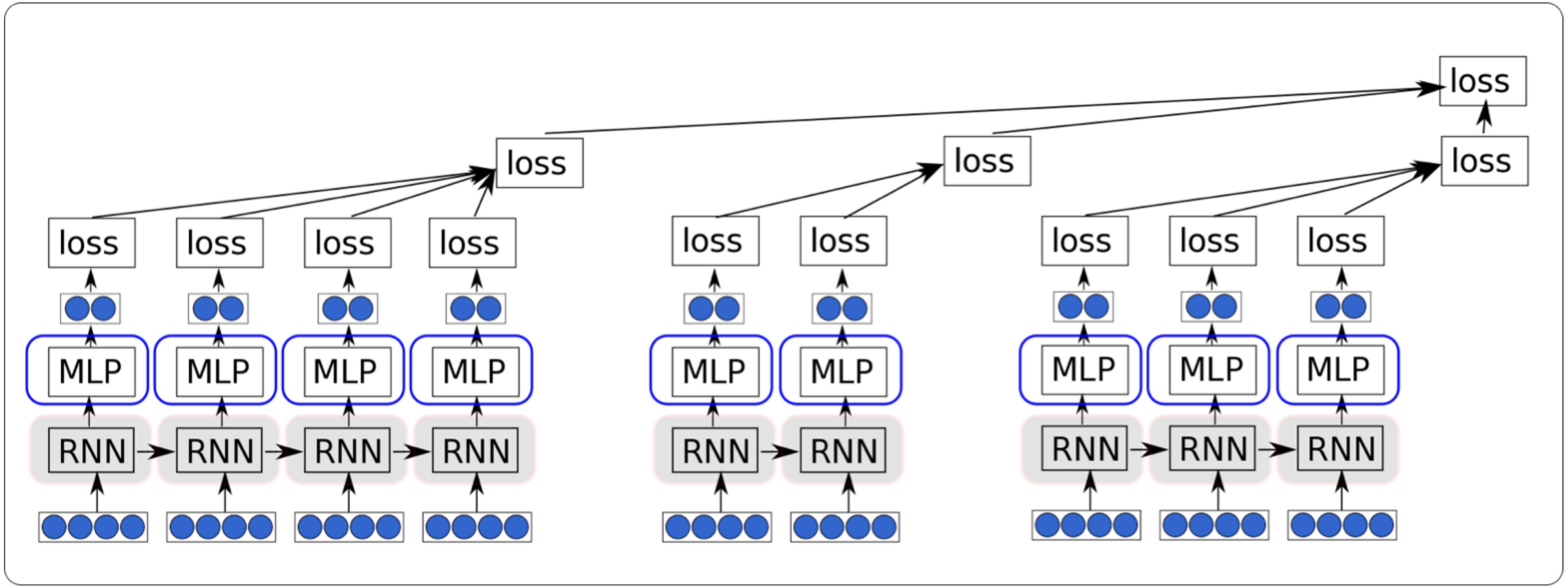
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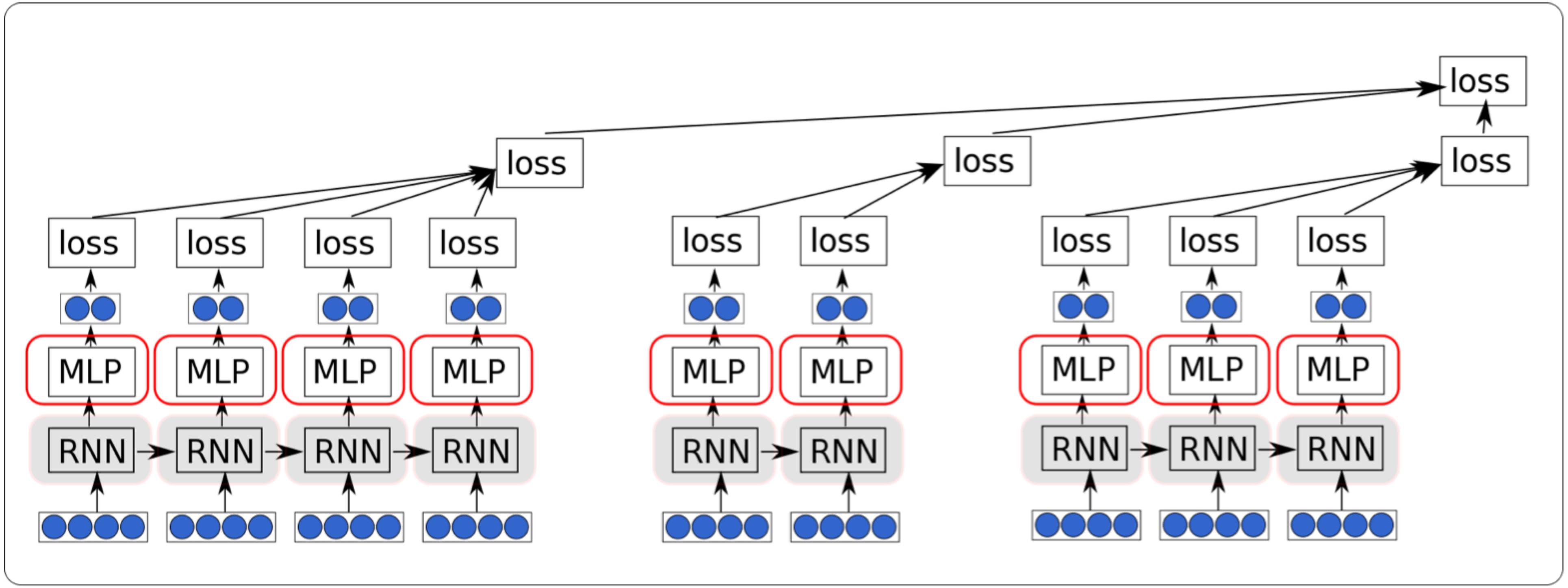
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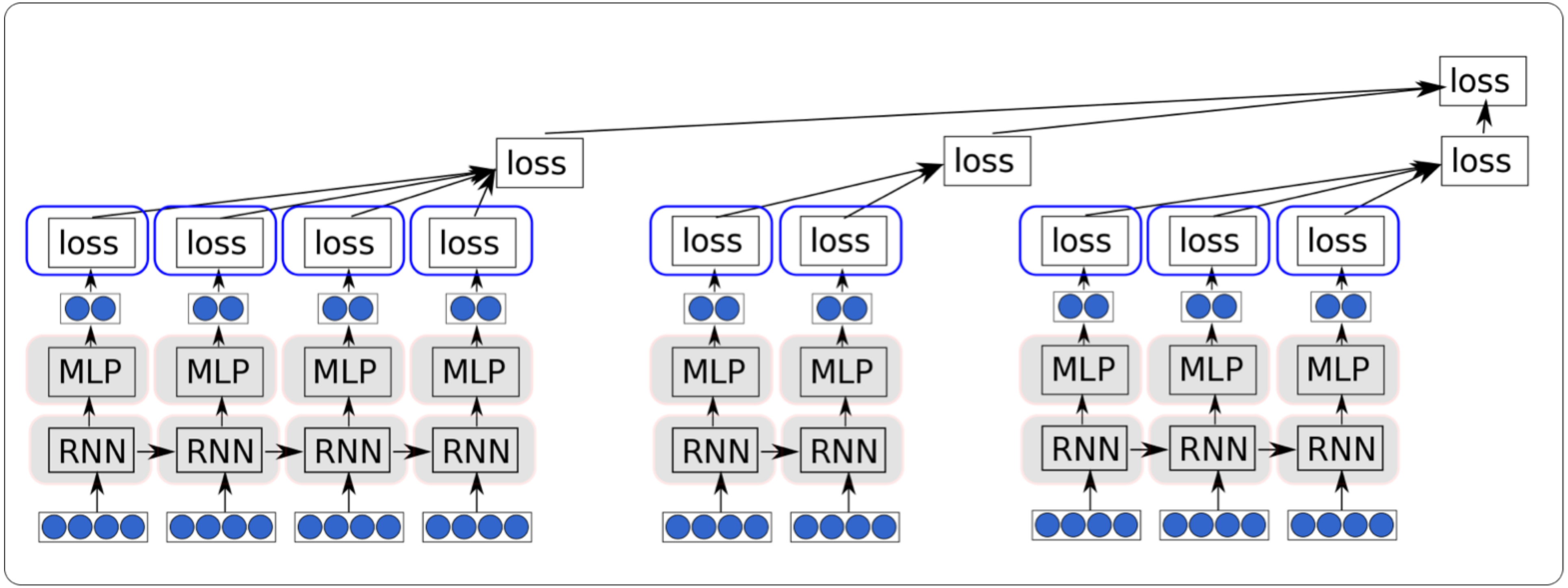
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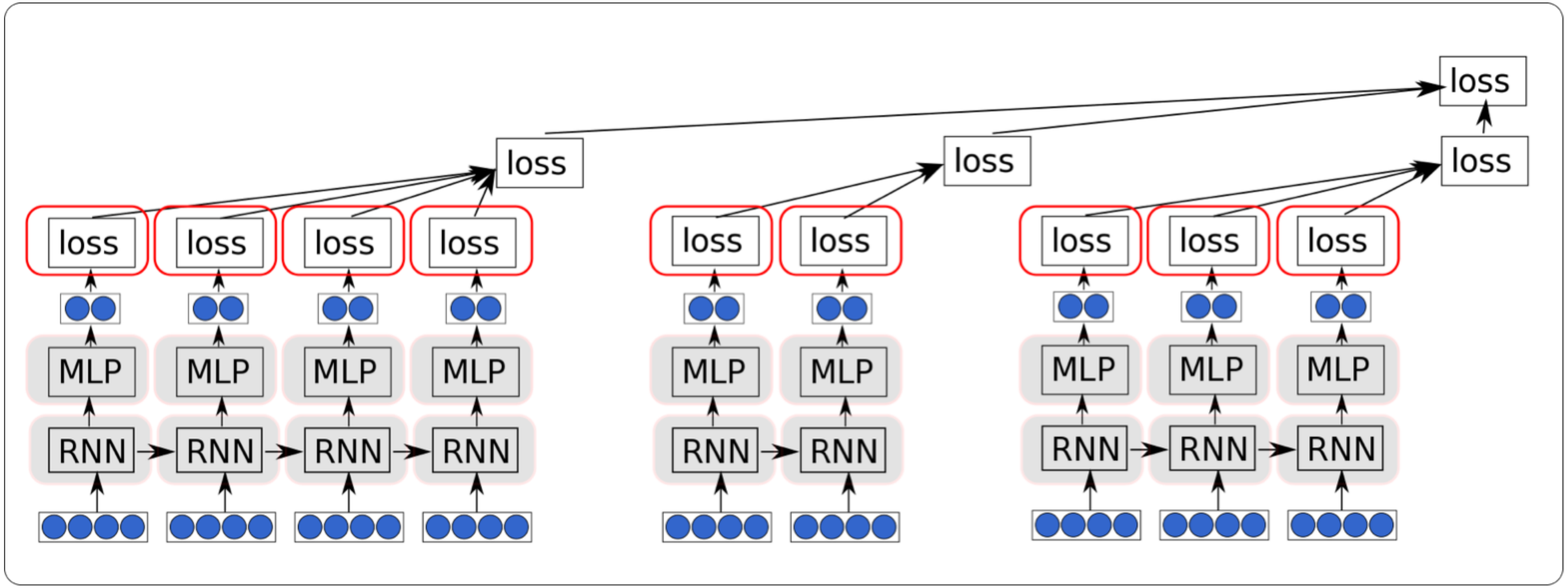
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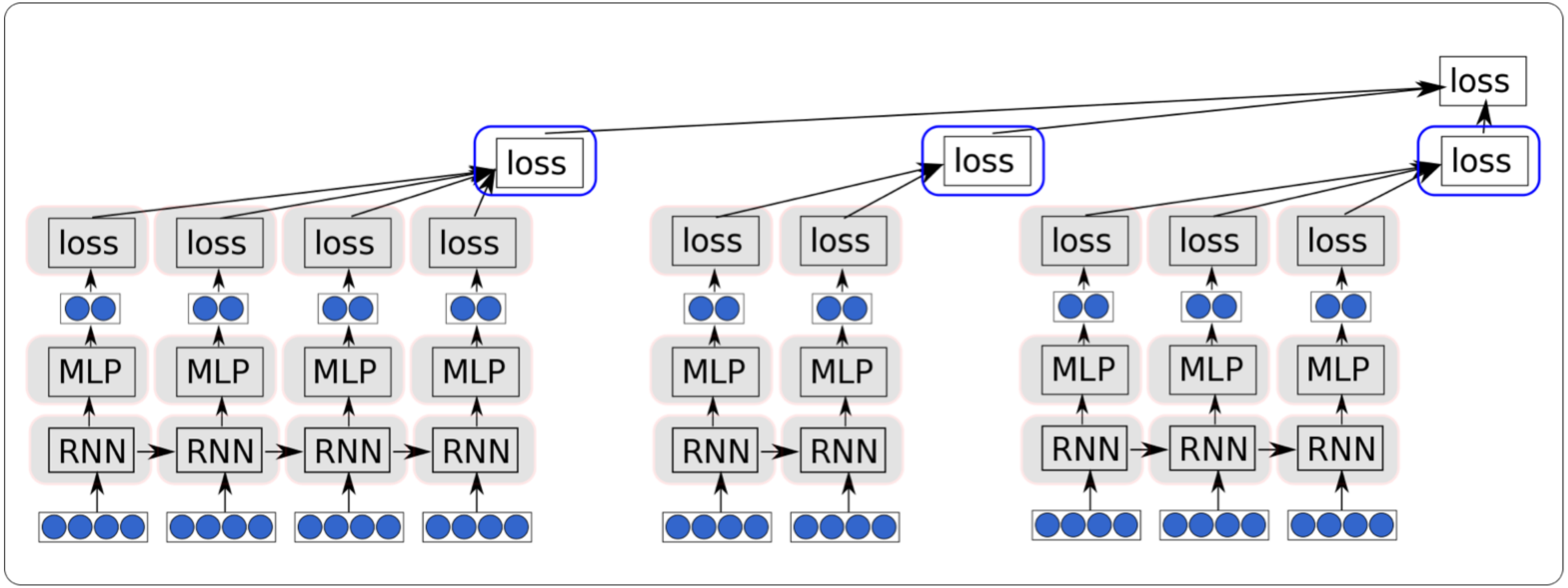
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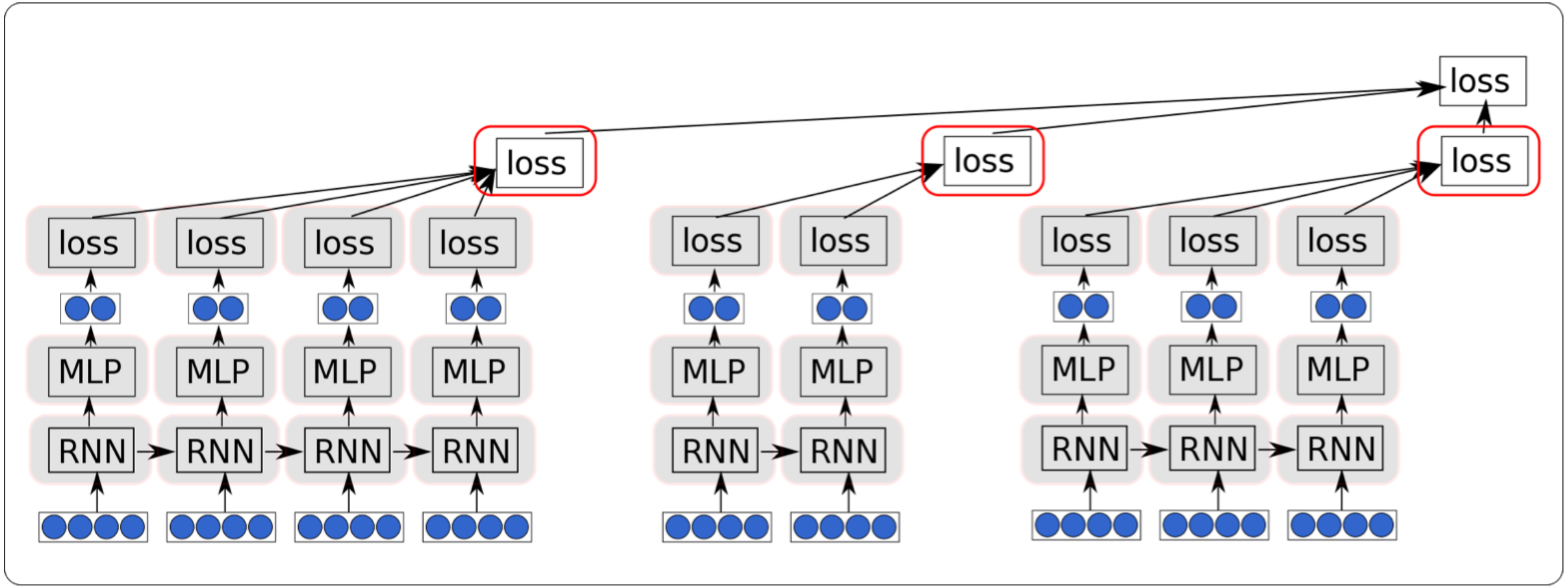

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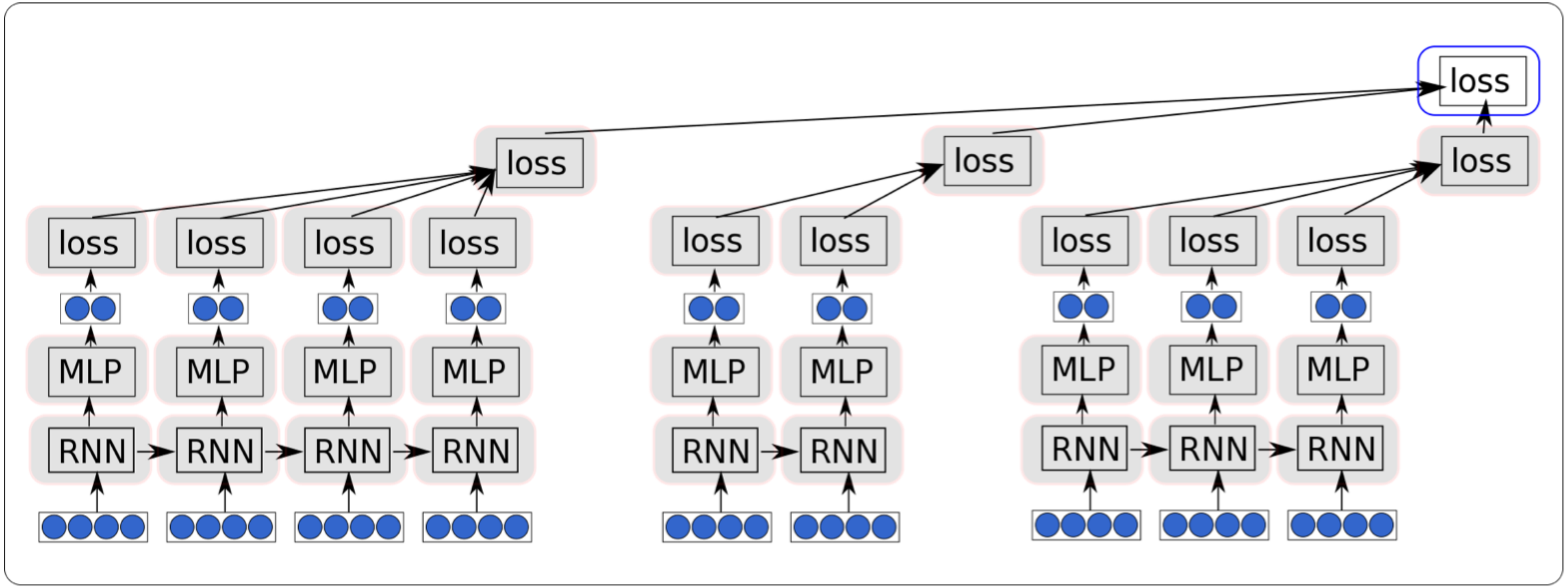
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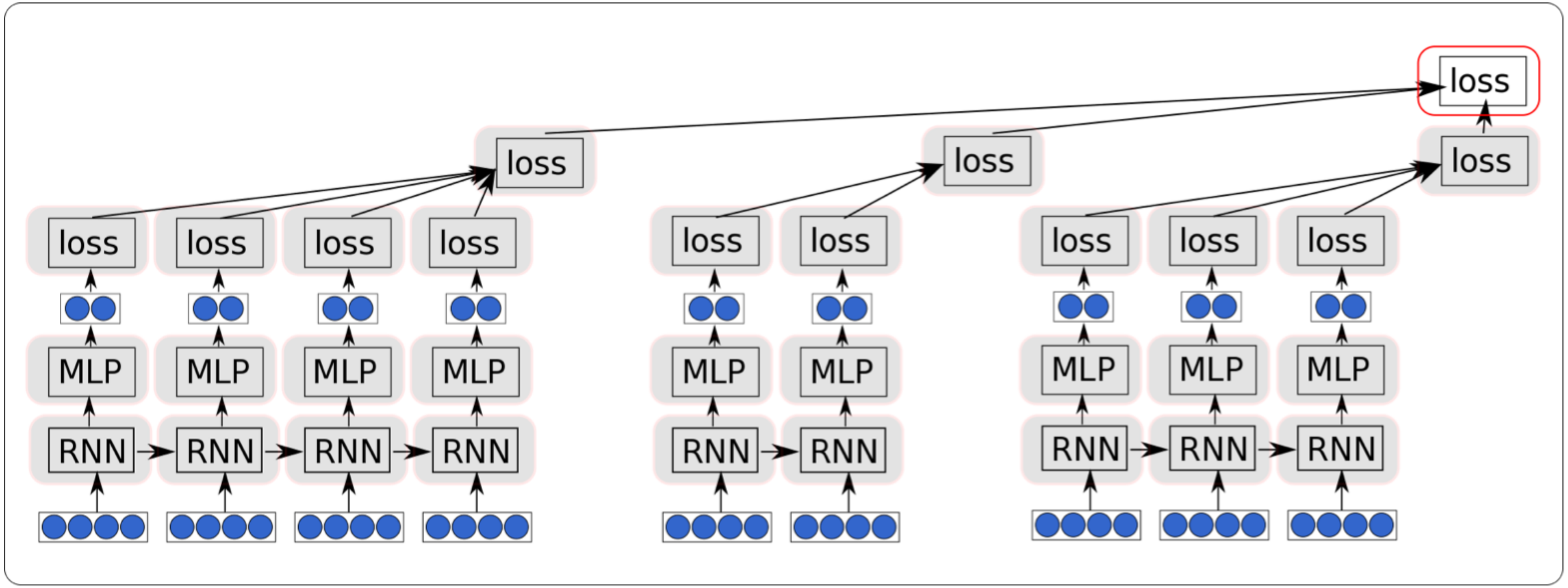

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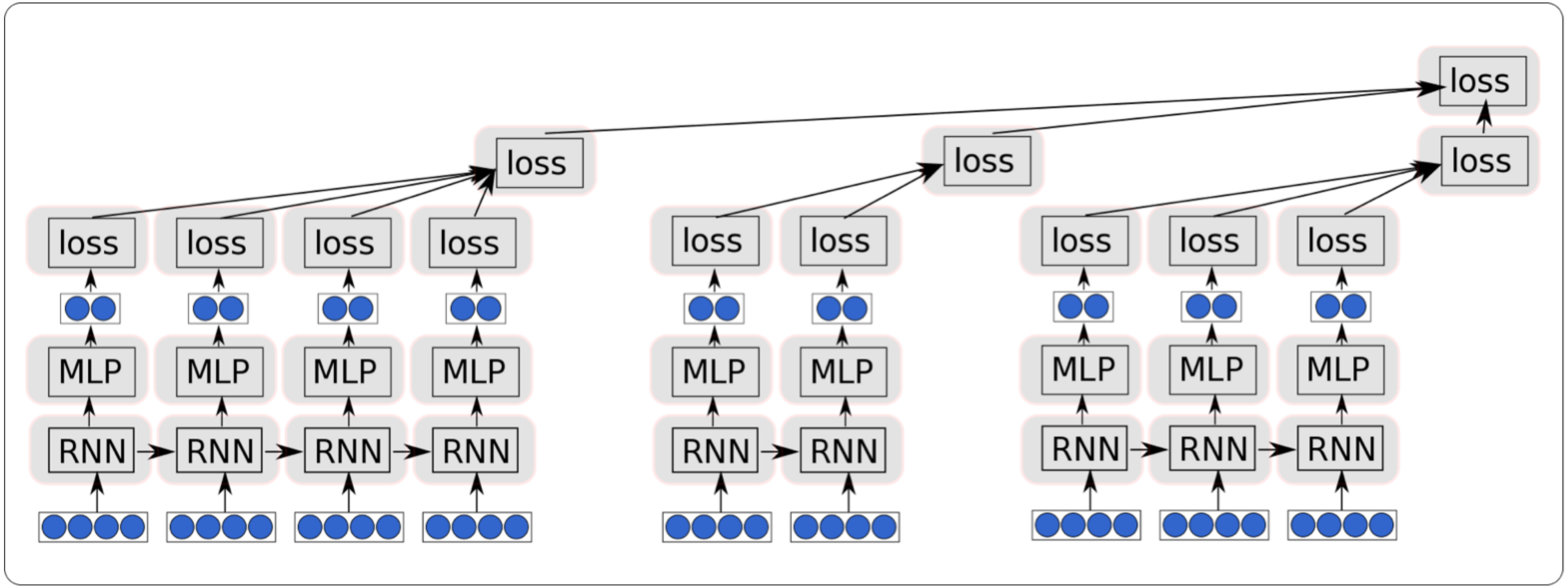
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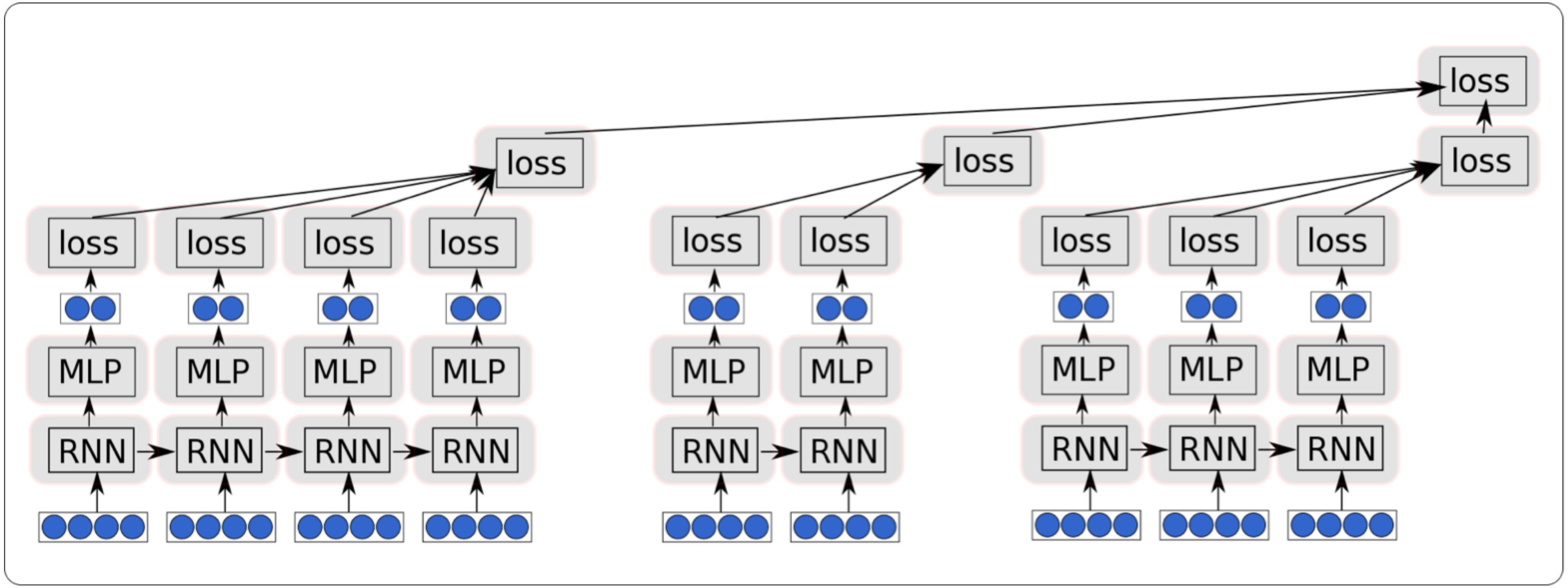

<u>note</u>: batching operations, not inputs.

Efficiency Considerations when Implementing an LSTM

$$
\begin{aligned}
R_{LSTM}(\mathbf{s_{j-1}}, \mathbf{x_j}) =& [\mathbf{c_j}; \mathbf{h_j}] \\
\mathbf{c_j} =& \mathbf{c_{j-1}} \odot \mathbf{f} + \mathbf{g} \odot \mathbf{i} \\
\mathbf{h_j} =& \tanh(\mathbf{c_j}) \odot \mathbf{o} \\
\mathbf{i} =& \sigma(\mathbf{W^{xi}} \cdot \mathbf{x_j} + \mathbf{W^{hi}} \cdot \mathbf{h_{j-1}}) \\
\mathbf{f} =& \sigma(\mathbf{W^{xf}} \cdot \mathbf{x_j} + \mathbf{W^{hf}} \cdot \mathbf{h_{j-1}}) \\
\mathbf{o} =& \sigma(\mathbf{W^{xo}} \cdot \mathbf{x_j} + \mathbf{W^{ho}} \cdot \mathbf{h_{j-1}}) \\
\mathbf{g} =& \tanh(\mathbf{W^{xg}} \cdot \mathbf{x_j} + \mathbf{W^{hg}} \cdot \mathbf{h_{j-1}})
\end{aligned}
$$

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\mathbf{g} =& \tanh(\mathbf{W^{xg}} \cdot \mathbf{x_j} + \mathbf{W^{hg}} \cdot \mathbf{h_{j-1}})
\end{aligned}
$$

all gates computations can be done in single mat-mat op.

Speed Trick 1:
Don’t Repeat Operations

- Something that you can do once at the beginning of the sentence, don’t do it for every word!

Bad

```
for x in words_in_sentence:
  vals.append( W * c + x )
```

Speed Trick 1:
Don’t Repeat Operations

- Something that you can do once at the beginning of the sentence, don’t do it for every word!

Bad

```
for x in words_in_sentence:
  vals.append( W * c + x )
```

Good

```
W_c = W * c
for x in words_in_sentence:
  vals.append( W_c + x )
```

Speed Trick 2: Reduce # of Operations

- e.g. can you combine multiple matrix-vector multiplies into a single matrix-matrix multiply? Do so!

Bad

```
for x in words_in_sentence:
  vals.append( W * x )
val = dy.concatenate(vals)
```

Speed Trick 2: Reduce # of Operations

- e.g. can you combine multiple matrix-vector multiplies into a single matrix-matrix multiply? Do so!

Bad

```
for x in words_in_sentence:
  vals.append( W * x )
val = dy.concatenate(vals)
```

Good

```
X = dy.concatenate_cols(words_in_sentence)
val = W * X
```

Speed Trick 3: Reduce CPU-GPU Data Movement

- Try to **avoid memory moves** between CPU and GPU.

- When you do move memory, try to do it as early as possible (GPU operations are asynchronous)

Bad

```
for x in words_in_sentence:
  # input data for x
  # do processing
```

Speed Trick 3:
Reduce CPU-GPU Data Movement

- Try to **avoid memory moves** between CPU and GPU.
- When you do move memory, try to do it as early as possible (GPU operations are asynchronous)

Bad

```
for x in words_in_sentence:
  # input data for x
  # do processing
```

Good

```
# input data for whole sentence
for x in words_in_sentence:
  # do processing
```