COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

Recurrent Language Models

CMSC 470

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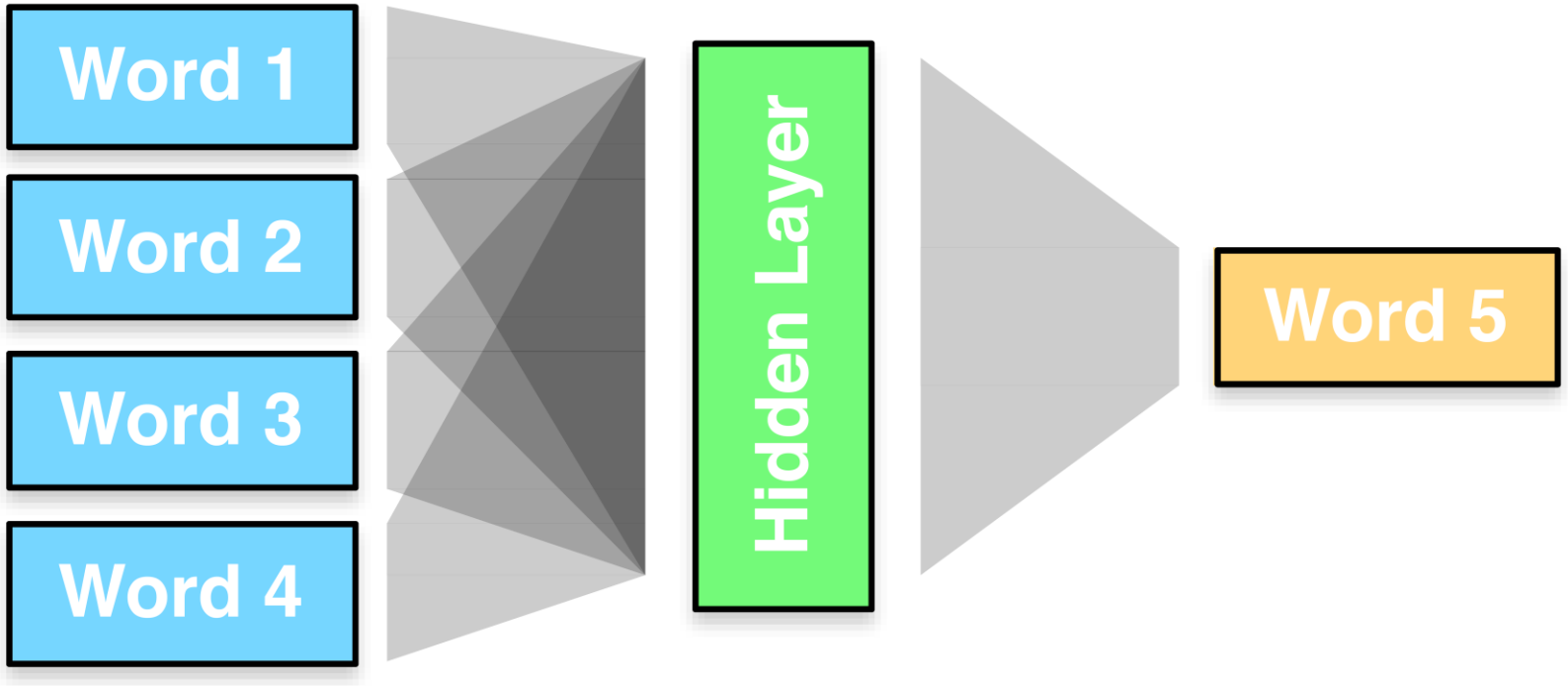
Toward a Neural Language Model



Figures by Philipp Koehn (JHU)

Count-based n-gram models vs. feedforward neural networks

- Pros of feedforward neural LM
  - Word embeddings capture generalizations across word typesq
- Cons of feedforward neural LM
  - Closed vocabulary
  - Training/testing is more computationally expensive
- Weaknesses of both types of model
  - Only work well for word prediction if the test corpus looks like the training corpus
  - Only capture short distance context

Language Modeling with Recurrent Neural Networks

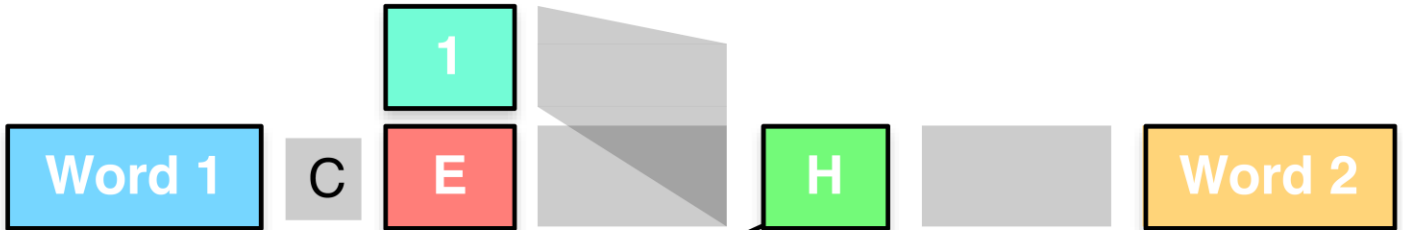
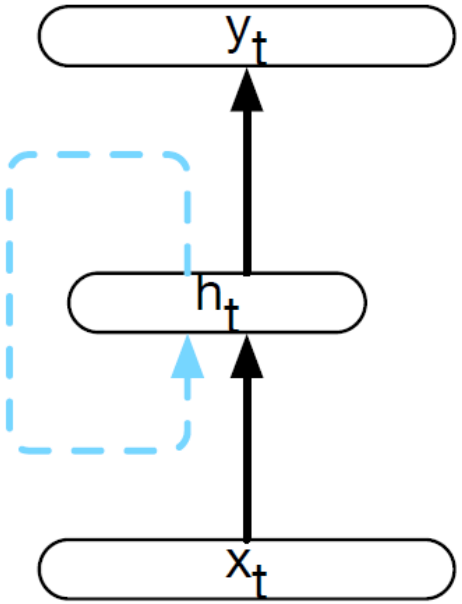


Figure by Philipp Koehn

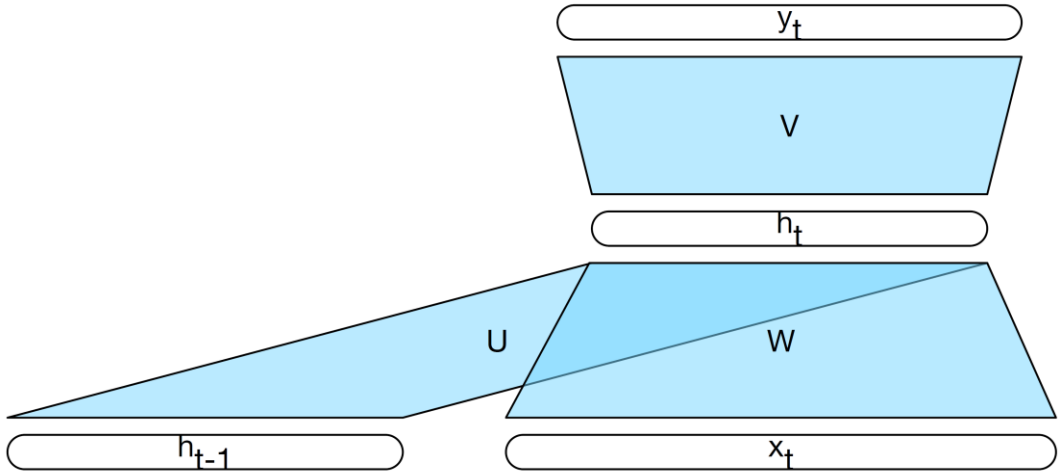
Recurrent Neural Networks (RNN)

The hidden layer includes a recurrent connection as part of its input



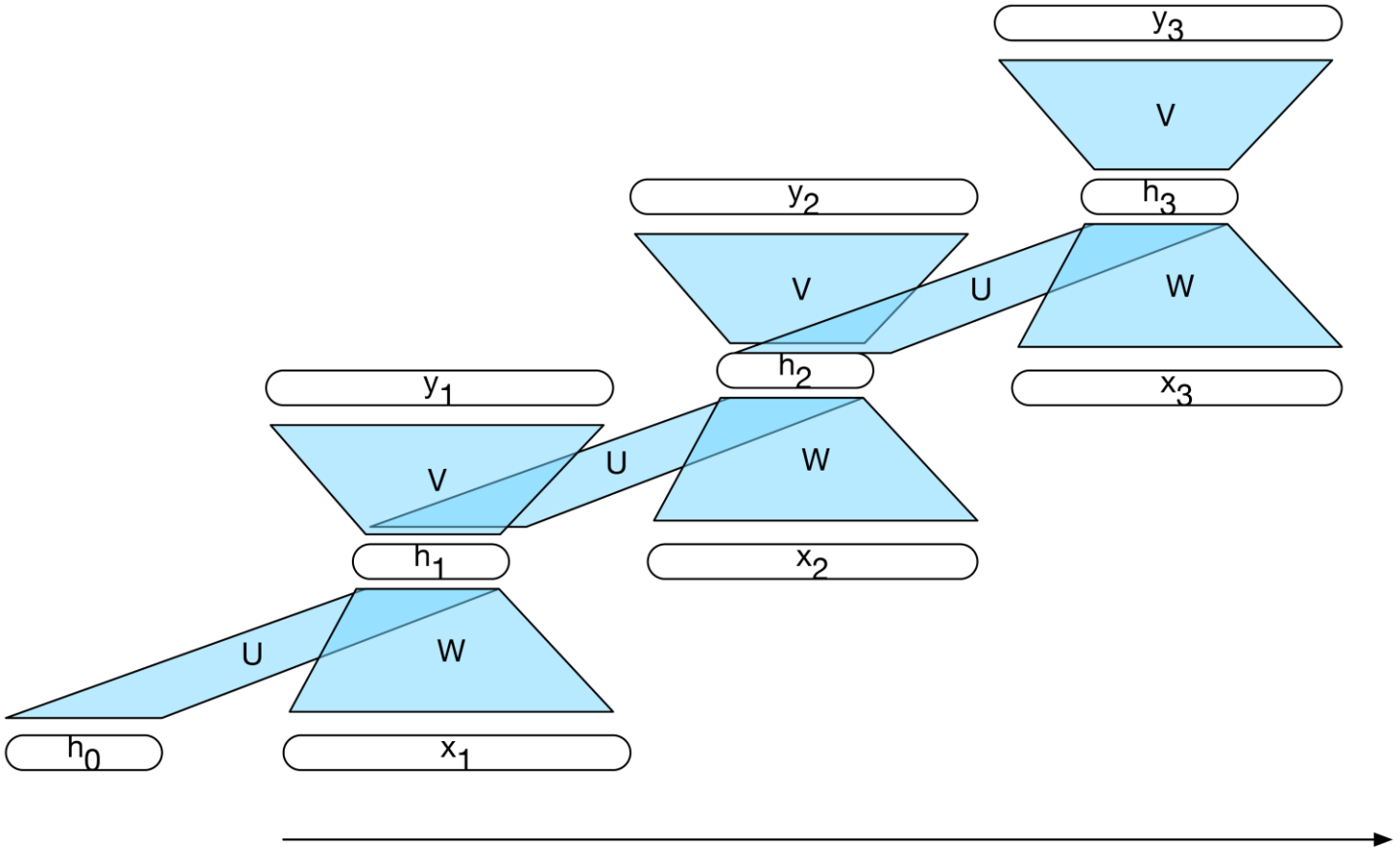
The hidden layer from the previous time step plays the role of memory, remembering earlier context

Unrolling the RNN over the time sequence as a feed-forward network



Figures from Jurafsky & Martin

Unrolled RNN illustrated



weights U, V, W are shared across all timesteps

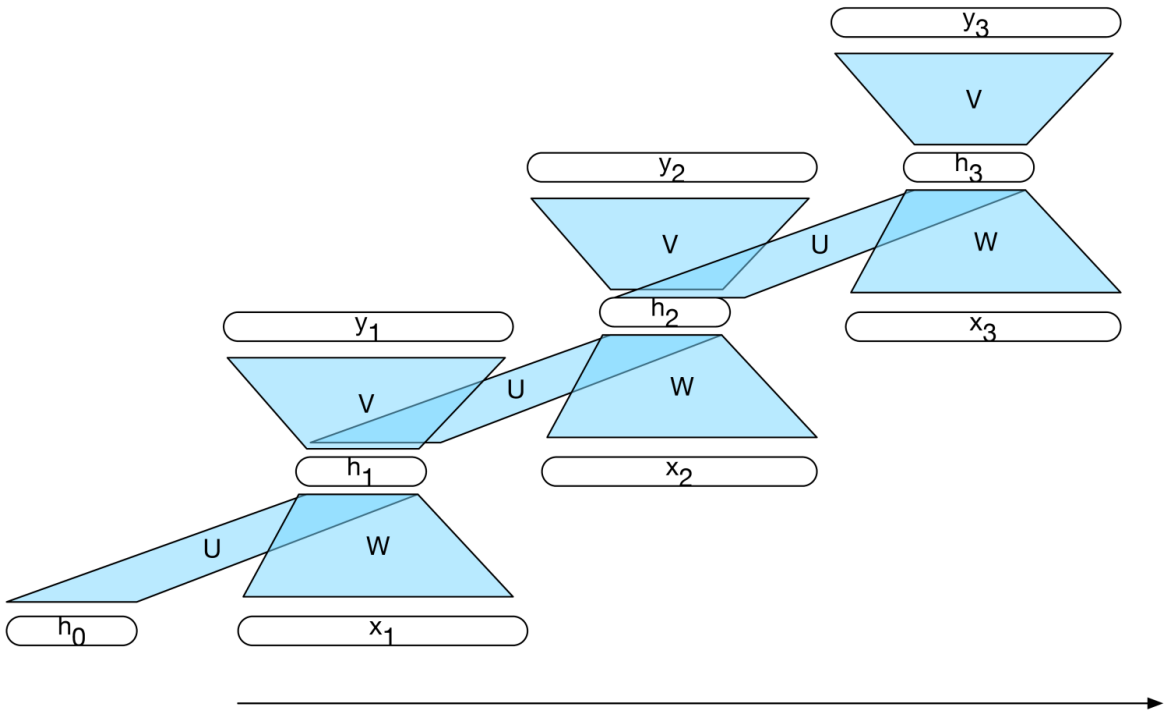
Prediction/Inference with RNNs

function FORWARDRNN(x, *network*) **returns** output sequence y

$h_0 \leftarrow 0$
for $i \leftarrow 1$ **to** LENGTH(x) **do**
    $h_i \leftarrow g(U\ h_{i-1} + W\ x_i)$
    $y_i \leftarrow f(V\ \ h_i)$
return y

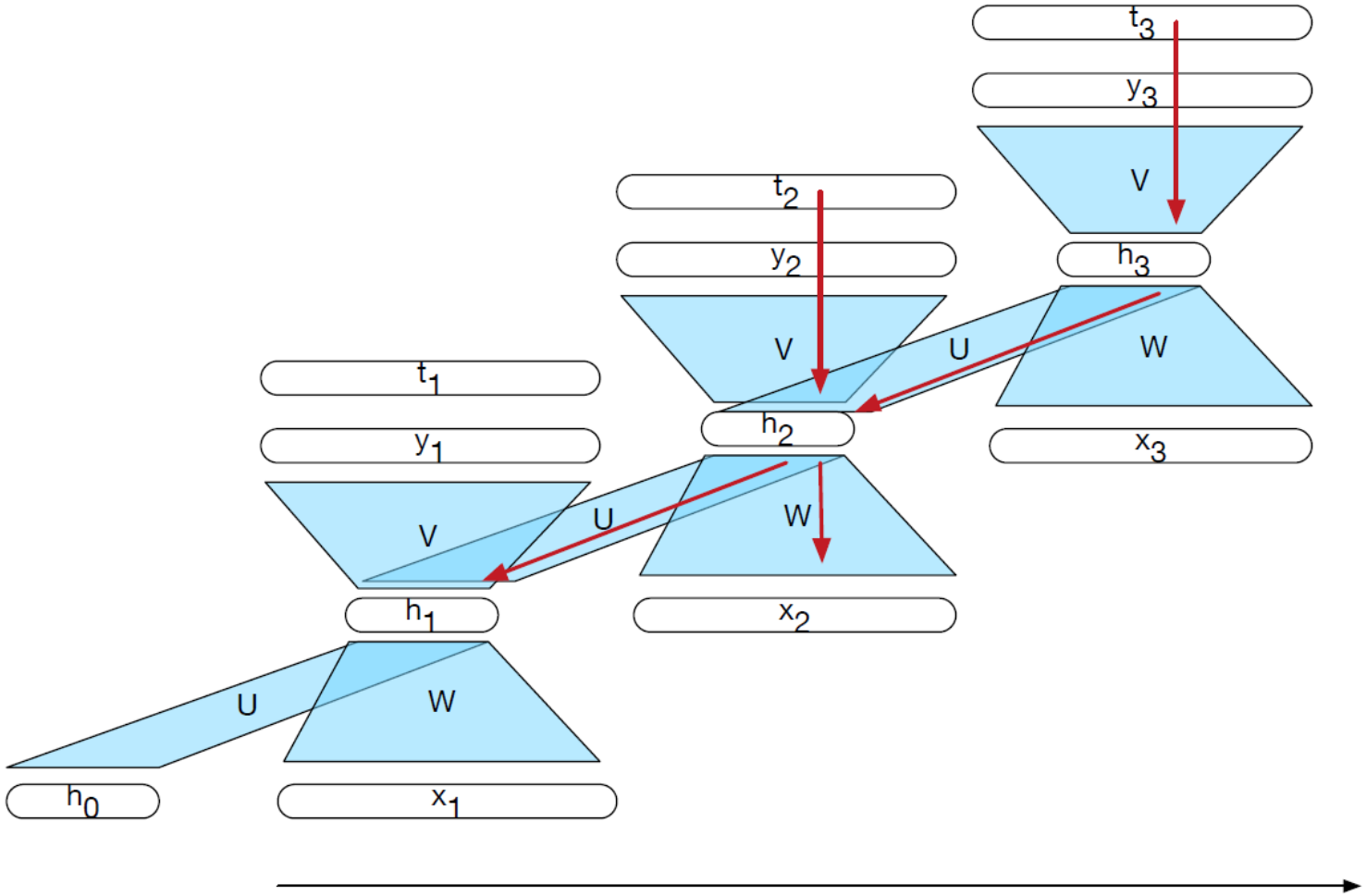
For language modeling, f = softmax function to provide normalized probability distribution over possible output classes

Training RNNs with backpropagation



- Training goal: estimate parameter values for U, V, W
- Use same loss as for feedforward language models
- Given unrolled network, run forward and backpropagation algorithms as usual

Training RNNs with backpropagation



Practical Training Issues: vanishing/exploding gradients

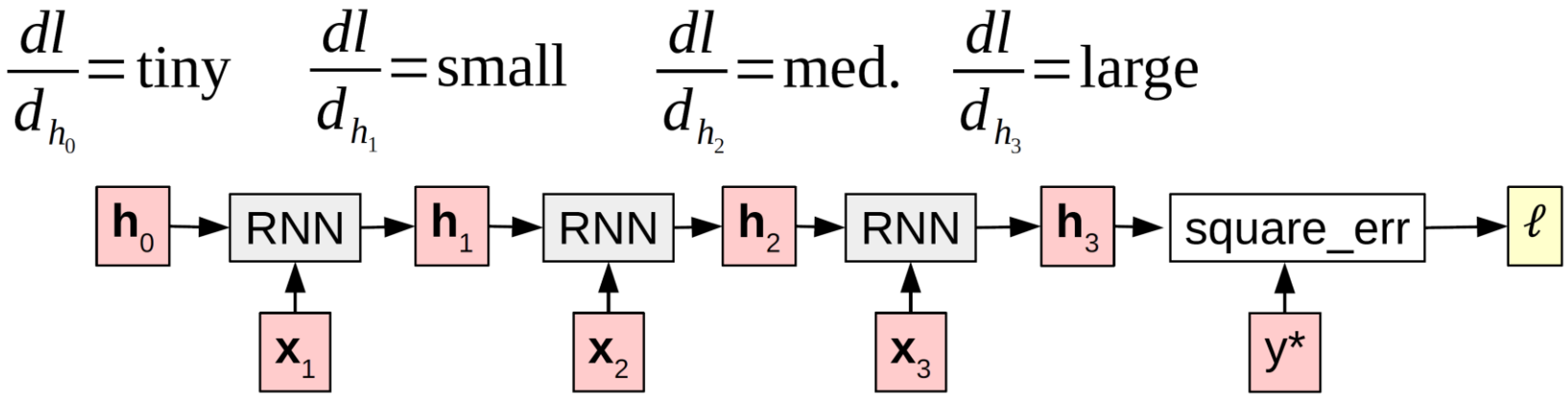


Figure 16: An example of the vanishing gradient problem.

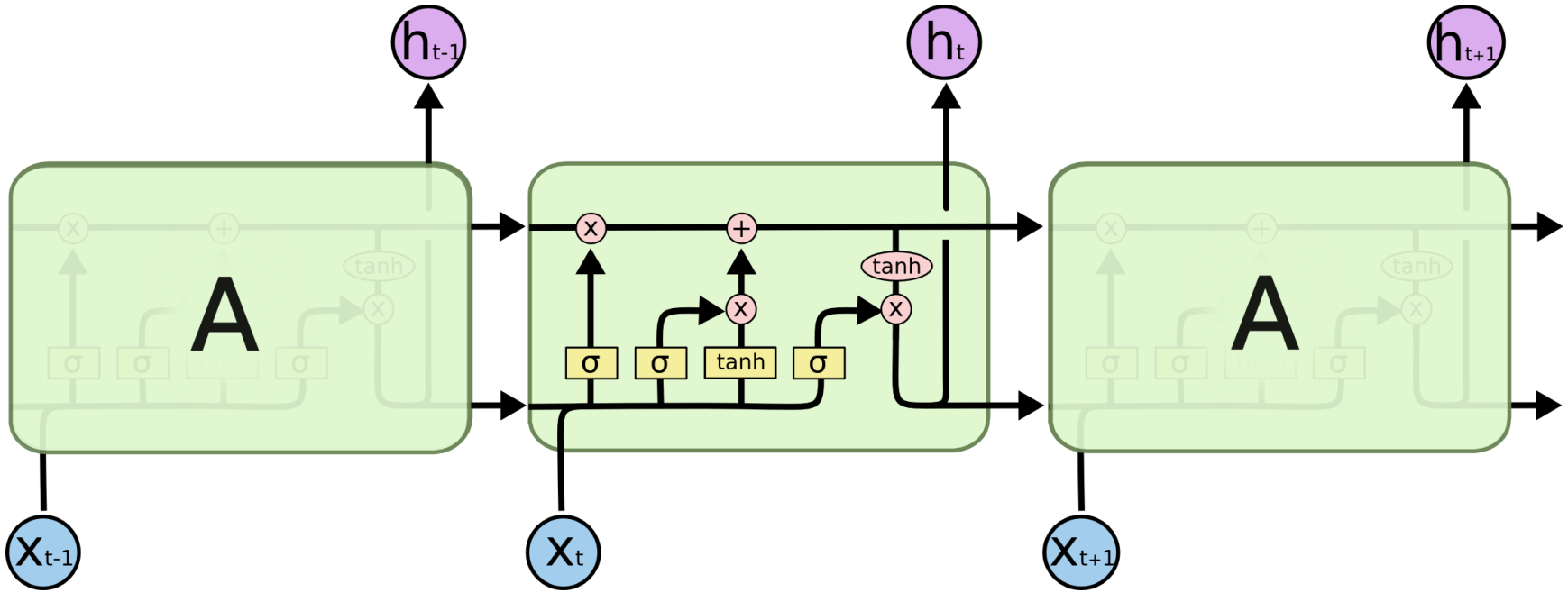
Figure by Graham Neubig

Multiple ways to work around this problem:

- ReLU activations help

- Dedicated RNN architecture (Long Short Term Memory Networks)

Aside: Long Short Term Memory Networks



What do Recurrent Language Models Learn?

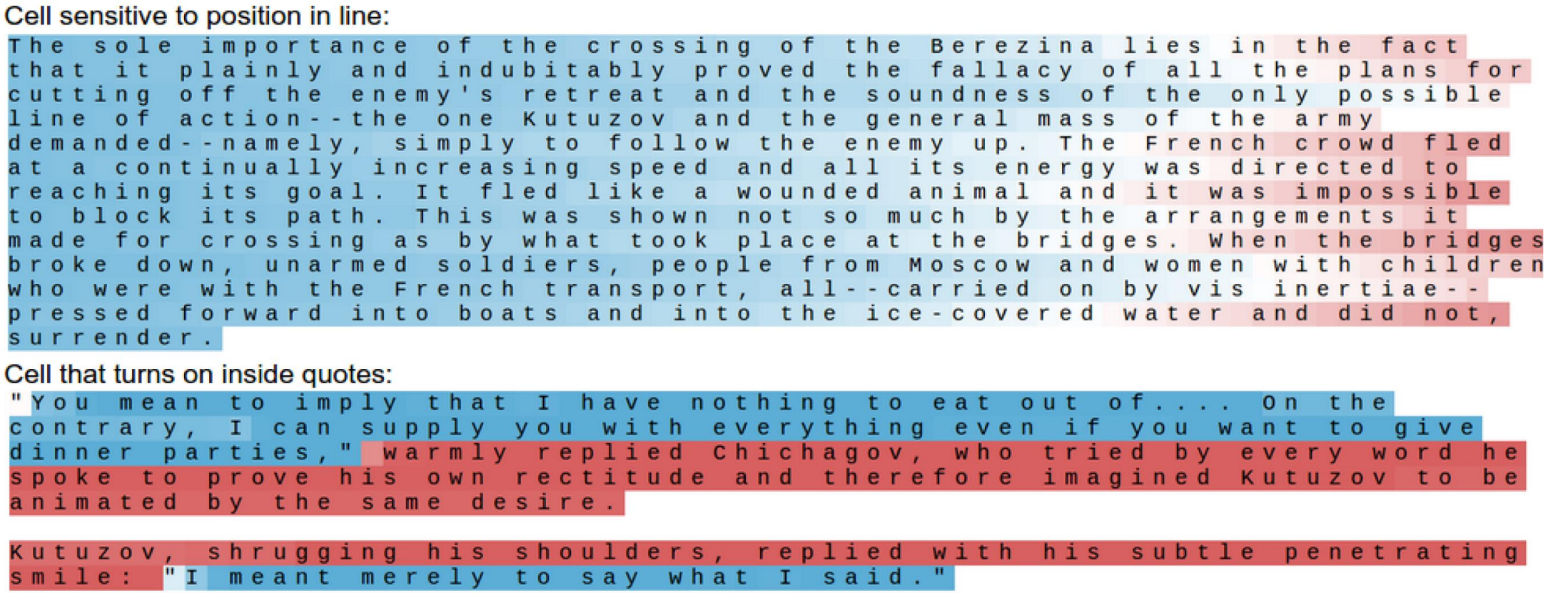


Figure from Karpathy 2015

What do Recurrent Language Models Learn?

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information.  The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                       struct audit_field *sf)
{
  int ret = 0;
  char *lsm_str;
  /* our own copy of lsm_str */
  lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
  if (unlikely(!lsm_str))
    return -ENOMEM;
  df->lsm_str = lsm_str;
  /* our own (refreshed) copy of lsm_rule */
  ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
                                 (void **)&df->lsm_rule);
  /* Keep currently invalid fields around in case they
   * become valid after a policy reload. */
  if (ret == -EINVAL) {
    pr_warn("audit rule for LSM \'%s\' is invalid\n",
            df->lsm_str);
    ret = 0;
  }
  return ret;
}
```

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
                            siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

Figure from Karpathy 2015

What do Recurrent Language Models Learn?

- Parameters are hard to interpret, so we can gain insights by analyzing their output behavior instead

- Can capture (some) long-distance dependencies

```
After much economic progress over the years, the country has…

The country, which has made much economic progress over the years, still has…
```

Recurrent neural network language models

- Have all the strengths of feedforward language model
- And do a better job at modeling long distance context
- However
  - Training is trickier due to vanishing/exploding gradients
  - Performance on test sets is still sensitive to distance from training data