Sequence Transduction with Recurrent Neural Networks

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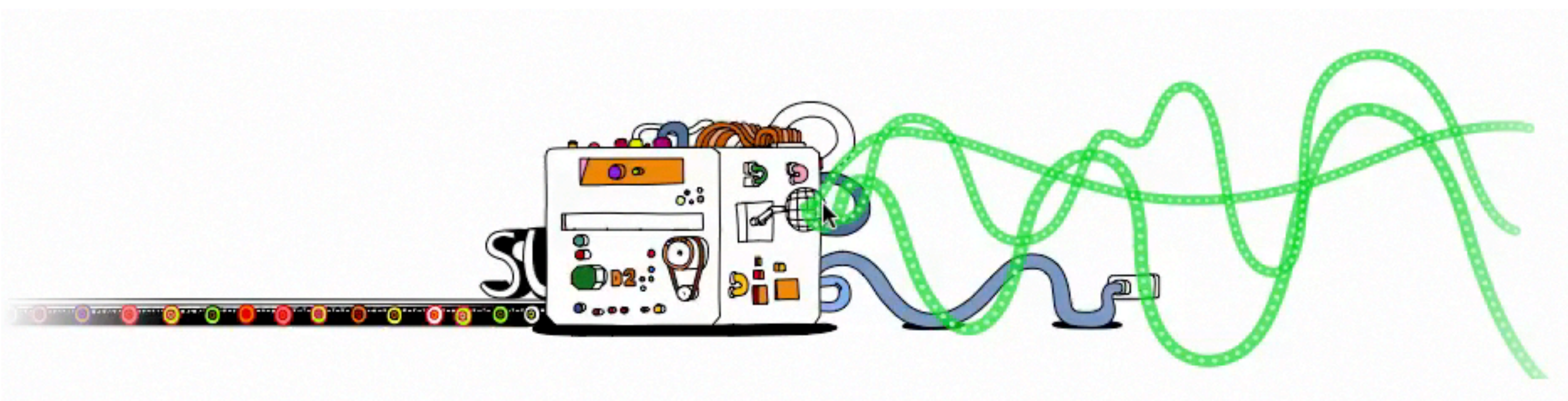
What is Sequence Transduction?

- Any task where input sequences are transformed into output sequences



- Practical examples: speech recognition, text-to-speech, machine translation, protein secondary structure prediction…
- Not so practical: Turing machines, human intelligence…
- Want a single framework able to handle as many kinds of sequence as possible

Recurrent Neural Networks

- RNNs can in principle learn any measurable sequence-to-sequence mapping to arbitrary accuracy (Hammer, 2000)
- They also work in practice: state-of-the-art results in handwriting recognition (Graves et al., 2008), text generation (Sutskever et al., 2011) and language modelling (Mikolov et al., 2010)
- Main strength is the robustness and flexibility of their internal representation of past events (a.k.a. memory)
- So they must be great for sequence transduction, right? Just train them to match input sequences to target sequences…

Variable Output Length

- For many sequence transduction you don't know in advance how long the output will be

“Πάντα ῥεῖ καὶ οὐδὲν μένει”

→ *“All flows, nothing stays”*

<u>or</u> *“Everything flows; nothing remains”*

<u>or</u> *“Everything gives way and nothing stays fixed”*

- This is a problem for standard RNNs, because the training targets have to be pre-aligned with the inputs

Structured Prediction

- Standard RNNs just map from inputs to outputs
- This ignores a valuable source of information: the outputs so far (language modelling / structured prediction)
- Can solve both problems by using two RNNs: one to model input-output dependencies (transcription) and another to model output-output dependencies (prediction)
- Each output is therefore conditioned on the whole input sequence and all previous outputs

Probabilistic Model

- Input sequence: $\mathbf{x} = (x_1, x_2, \ldots, x_T) \in \mathcal{X}^*$
- Target sequence: $\mathbf{y} = (y_1, y_2, \ldots, y_U) \in \mathcal{Y}^*$
- Bidirectional transcription network: $a(t, \mathbf{x}), 1 \leq t \leq T$
- Unidirectional prediction network: $b(\mathbf{y}_{1:u}), 0 \leq u \leq U$
- Output distribution:

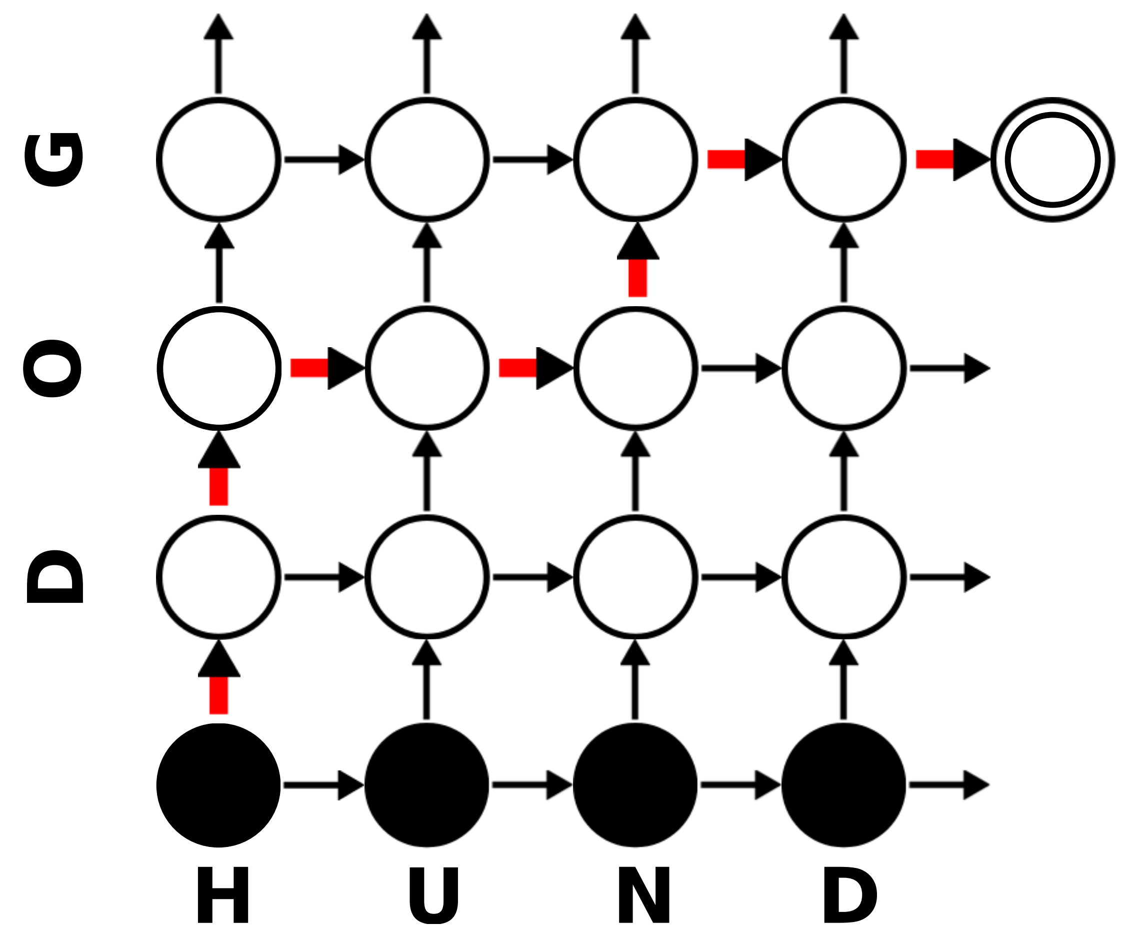
$$\Pr(v|t, u) = \frac{f(v, a(t, \mathbf{x}), b(\mathbf{y}_{1:u}))}{Z}, v \in \mathcal{Y} \cup \varnothing$$

For discrete targets, f is just the softmax of a + b

- To sample: start at t=0, u=0; if v is ∅, output nothing and increment t, else output something and increment u

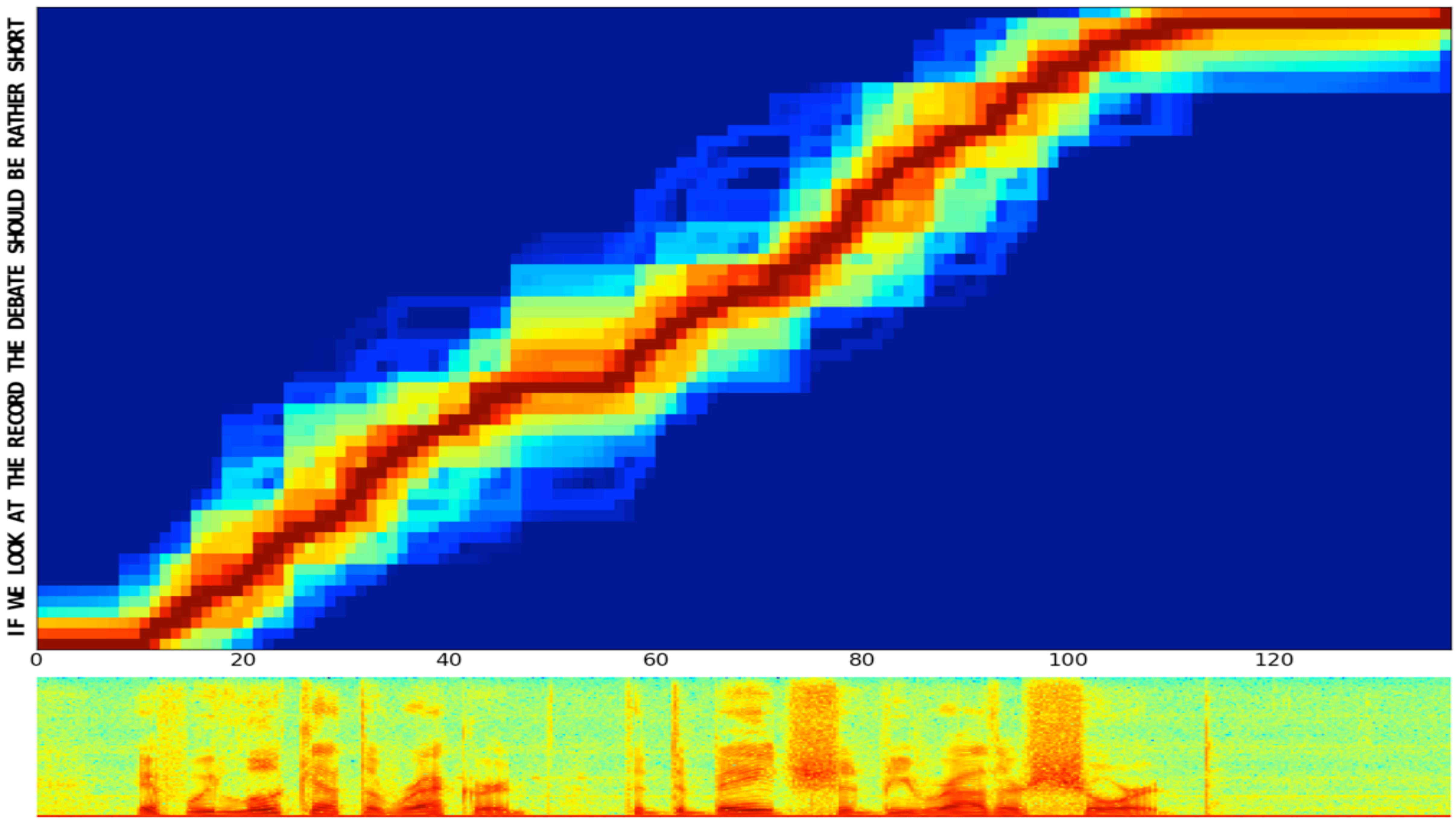
Output Lattice

- All paths from bottom left to top right (like the red one) are ways of outputting "DOG" given "HUND"
- Multiply the transition probabilities to get the path probability
- Sum over all possible paths to get the total probability of "DOG"
- Can do this efficiently with a forward-backward algorithm
- Can draw a similar lattice for <u>any</u> string, hence have a distribution over sequences of all lengths

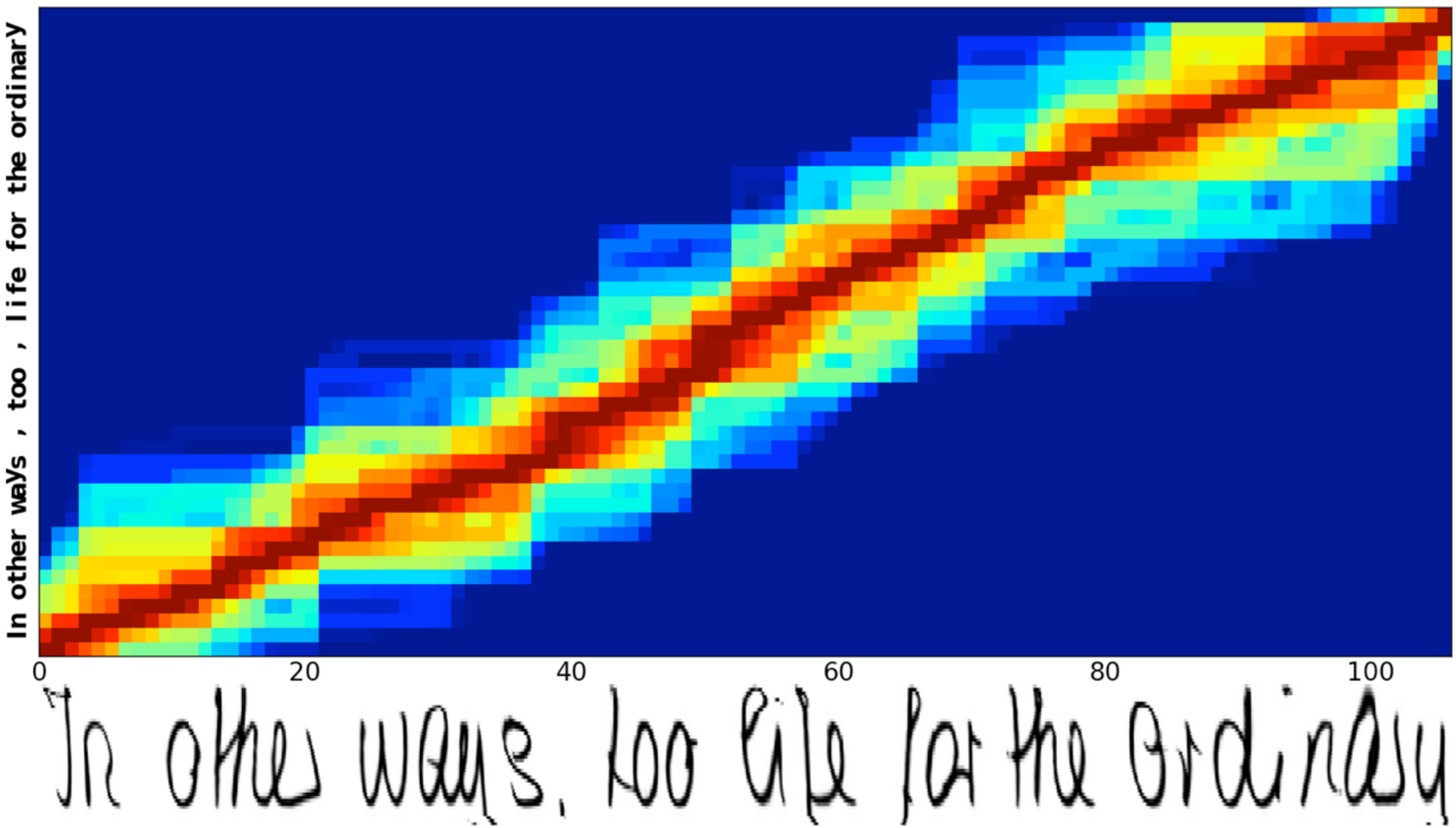


$$\Pr(red) = \Pr(D|1,0)\,\Pr(O|1,1)\,\Pr(\varnothing|1,2)$$
$$\Pr(\varnothing|2,2)\,\Pr(G|3,2)\,\Pr(\varnothing|3,3)\,\Pr(\varnothing|4,3)$$

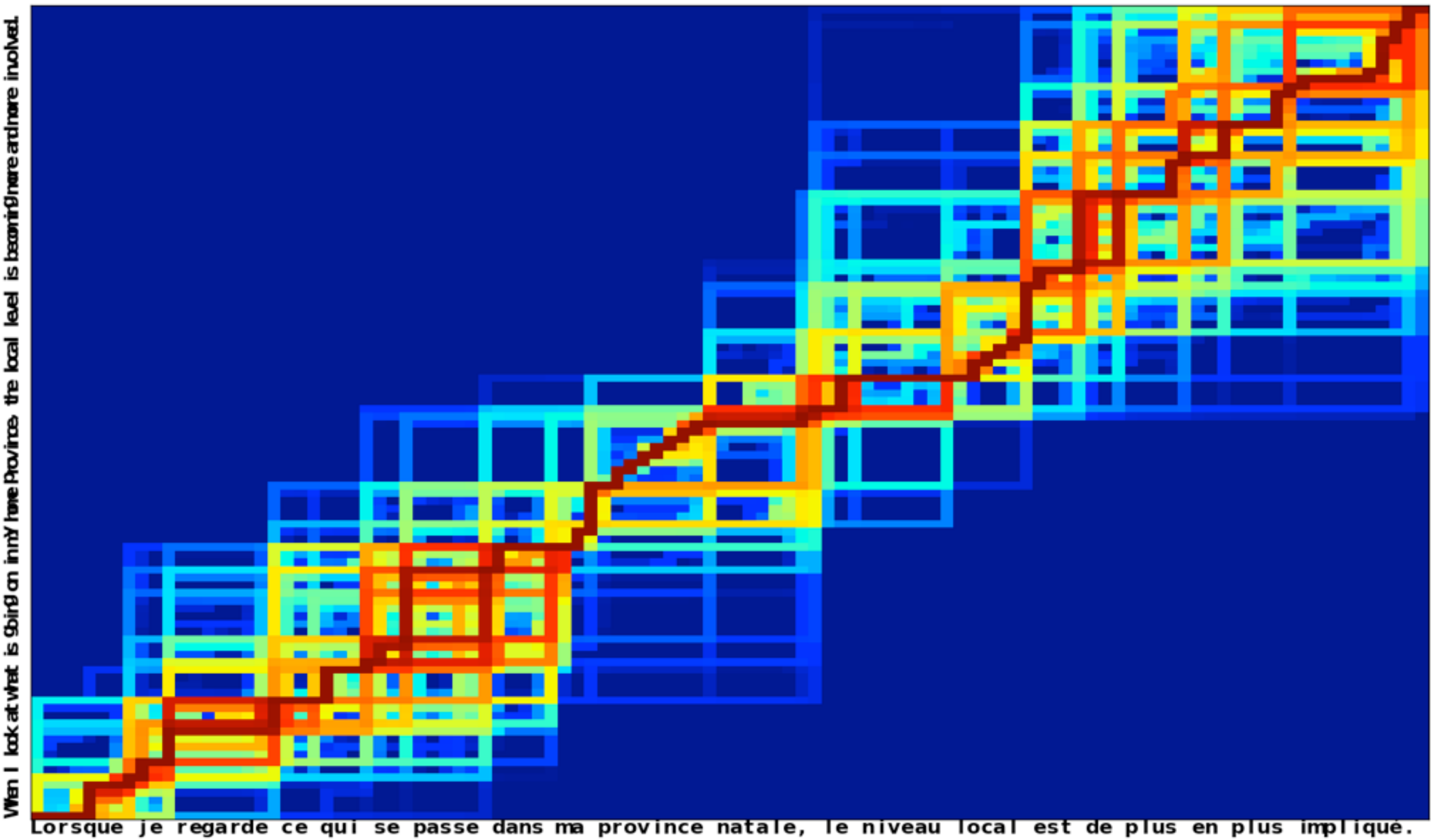
Speech Recognition



Handwriting Recognition



Machine Translation



Training and Testing

- The whole system is differentiable, so the log-likelihood of the targets can be maximised with gradient descent
- Testing (decoding in HMM speak) is trickier: need a search algorithm (e.g. beam search) to look for the most probable output sequence

Results

- For sequence labelling problems (e.g. speech and handwriting recognition) can compare the transducer with CTC RNNs (essentially the transcription network without the prediction network)
- CTC is state-of-the-art in offline handwriting recognition, so any improvement here is interesting
- Transducer gives better label error rate (e.g. TIMIT phoneme error rate reduced from 25.5% to 23.2%)
- Can do lexicon/language model free word recognition with the transducer (unlike CTC)
- But so far CTC with an external language model gives better word error rates

Machine Translation

input:
Nous avons découvert le mois dernier seulement que malgré la signature de l'union sociale il y a un an et malgré le fait que le gouvernement du Canada a accru immédiatement les transferts, en février 1999, de 3,5 milliards de dollars auxquels viendront s'ajouter 8 autres milliards de dollars, les provinces, notamment le Québec, ont pris cet argent pour, comme il l'a dit, se mettre plus de fonds dans les poches.

target:
We found only last month that notwithstanding the social union we signed one year ago and notwithstanding the fact that the Government of Canada increased the transfers by $3.5 billion immediately last February 1999, with an additional $8 billion to follow, the provinces and in particular the province of Quebec took the additional money, as he said mettre plus de fonds dans les poches.

best output:
We have discovered last year only that the signature of the social union there is a year and the fact that the Government of Canada has been immediately transferred in February 1999, $3.5 billion with addition other billions, the provinces, including Quebec, that money for the more funding in the pockets.

[SHOW DEMO]

Extensions and Future Work

- Pre-training the prediction net (e.g. on large text corpus) improves results
- Can minimise expected word/label error rate instead of log loss: predict samples instead of targets
- RNNs are very general predictive models, but for tasks with discrete outputs it might be better to use more conventional language models, or some mix of the two
- Word level targets?
- Would like to look at tasks with continuous outputs, e.g. text-to-speech