ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 18. LSTM: characters and generation

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Previously

- Convolutional neural networks
- Recurrent neural networks
- Bidirectional Recurrent neural networks
- Long short-term memory networks

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Chapter 9 of Lane et al. (2019)

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The curse of OOV

Out-of-vocabularies cause big trouble

The Mexico City Metro, operated by the Sistema de Transporte Colectivo, is the second largest metro system in North America after the New York City Subway.

https://en.wikipedia.org/wiki/Mexico_City_Metro (2021)

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- **Turn into characters**

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Let us see

Into Characters: outcome

- The training takes no less than 30 minutes (it took me 36 last time)[1]

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4	183	0.8029	0.5664

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6	182	0.8633	0.5652
7	182	0.8908	0.5672
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Reasons/Solutions

- The model might be *memorising* the dataset
- Increase the dropout (try!)
- Add more labeled data (hard!)

A character-level model shines at its best when modeling/generating language

Text generation

Predicting the next word

- An LSTM can learn

$$p(w_t \mid w_{t-1}, w_{t-2}, \ldots, w_{t-n}) \tag{1}$$

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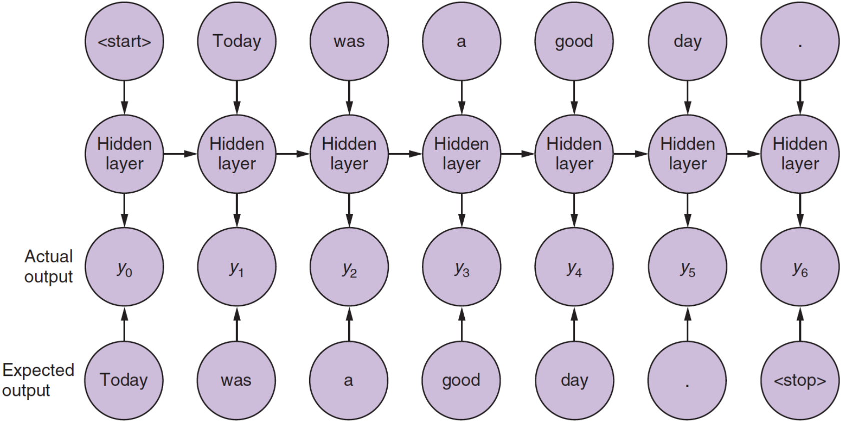
From classification to *generation*

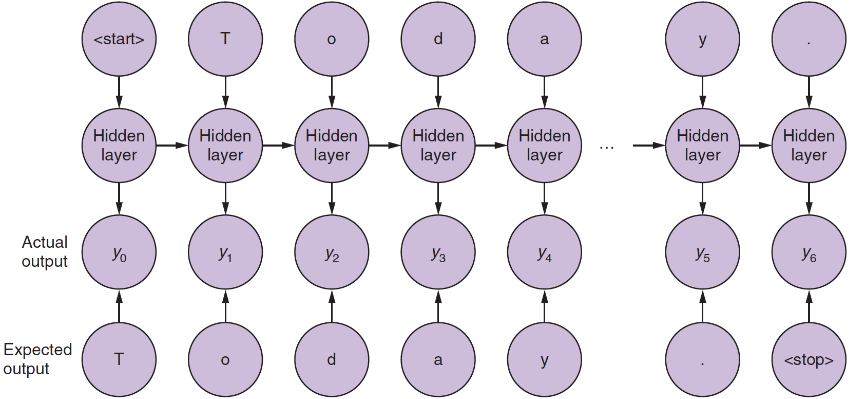
- Now we want to predict the next word ($\sim$ word2vec?)
- We want to learn a *general* representation of language

Unrolling the next-word prediction (word 2-grams)



(Lane et al., 2019, 299)

Unrolling the next-~~word~~character prediction



Expected output is the next token in the sample. Shown here on character level.

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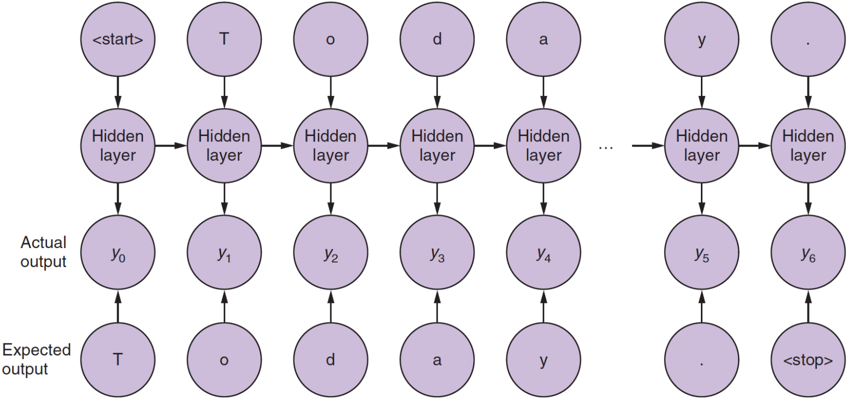

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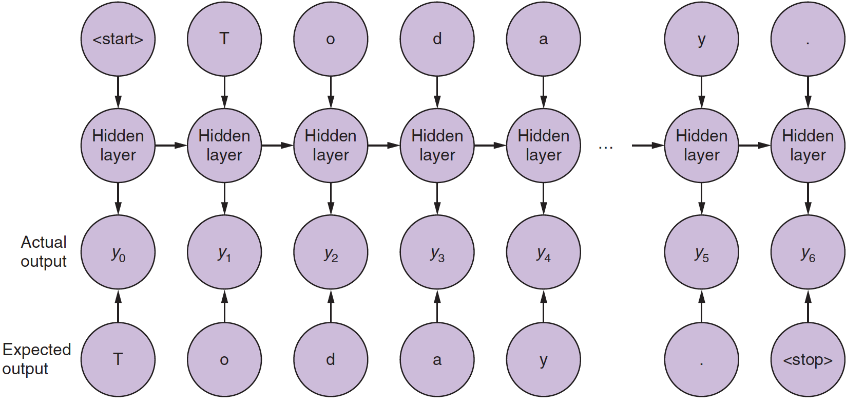
- Now the error is computed for every single output
- We still back-propagate only after passing a full instance

(Lane et al., 2019, 299)

New target labels

New output: a one-hot encoding (again) of the next character



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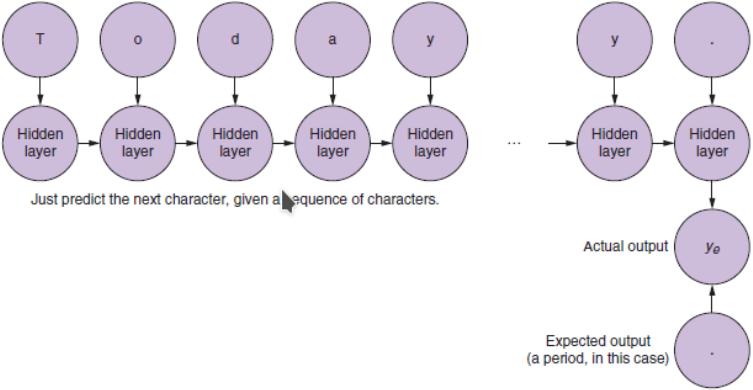
Predict after having looked at a sequence



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Generation example

Since we are interested in *style* and in creating a consistent model, we wont use IMDB (multi-authored and small).

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Let us try to *mimic* William Shakespeare

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(Lane et al., 2019, 307)

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  - Add filters on grammar, spelling, and tone
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Most of these strategies apply to any problem you can think about!

(Lane et al., 2019, 307)

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.