A Neural Attention Model for Categorizing Patient Safety Events

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Motivation & Background

- Medical errors are the third leading cause of death in the US (200K per year)
- Examples of error reports:

Patient was ordered and given a medication that had a adverse drug reaction alert

Staff member accidentally stamped on patients toe which resulted in skin laceration

Patient found lying on the floor next to his bed

- This work: Categorizing errors in patient care
  - 1.7 Million reports
- These events need to be extracted from unstructured text
  - No current national standard for error reporting
  - Front-line staff's priority is prompt patient care and not necessarily reporting

Neural Attention Model

- General architecture:
  - **Word representation**: The embedding layer
    - Initialized with pre-trained vectors
  - **Convolutional layer** to capture local features
    - length 2 to 6 to capture 2 to 6 gram local features
  - **Recurrent layer** to capture long dependencies and interactions over the sequence
    - Bidirectional-LSTM
  - **neural attention** for Improving sequence representation
- Problem with recurrent networks:
  - Capturing only the recent context
  - Bi-directional can partially solve, but still a problem in long sequences
  - We use attention to address this problem

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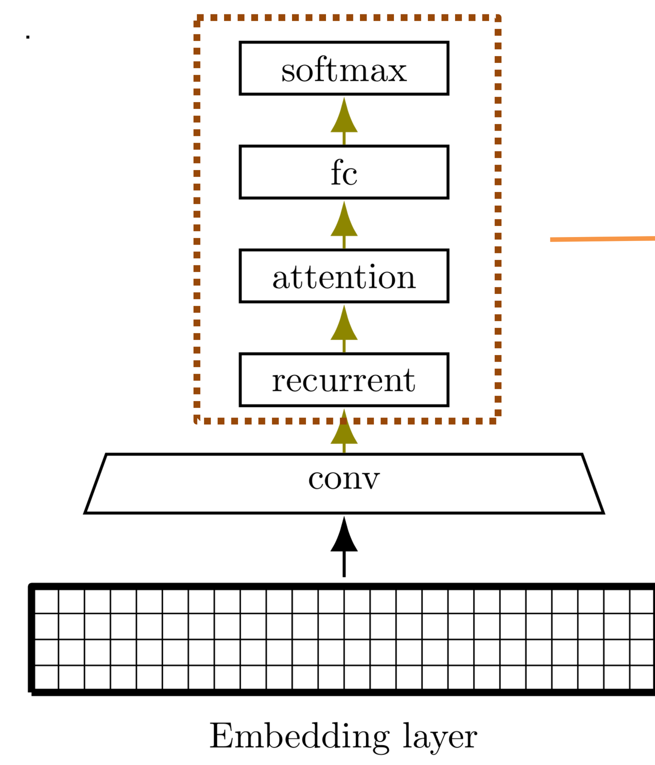
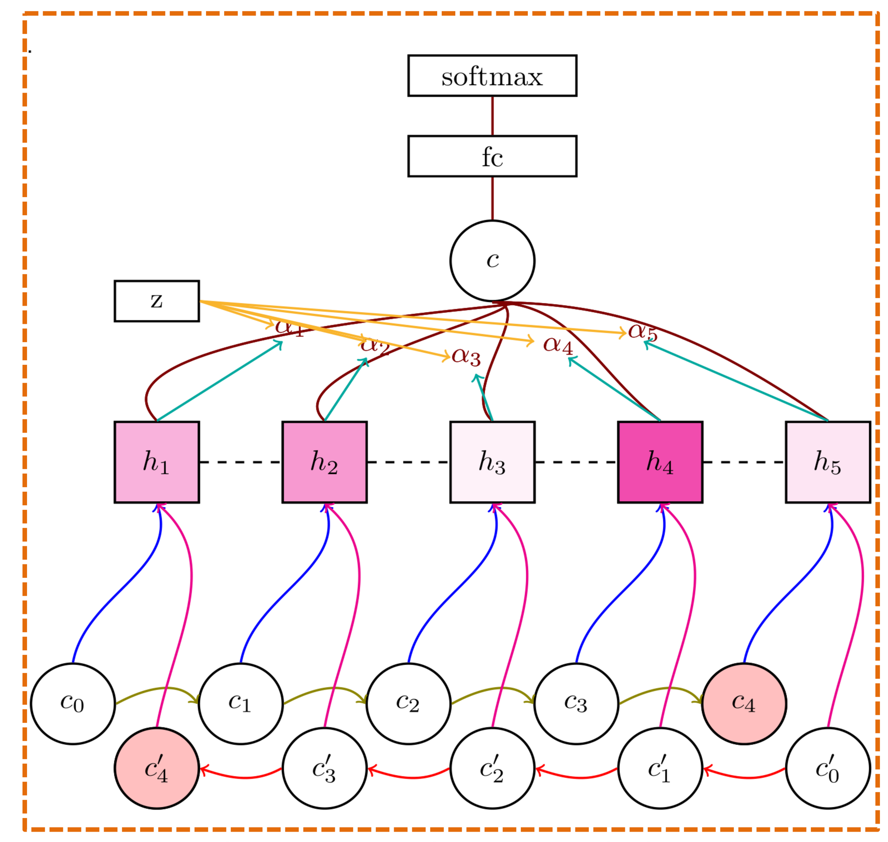
Neural Attention Model



General architecture



The attention model

- Soft attention:
  - Decide which parts of the sequence are more important
  - Instead of considering the last state of the recurrent layer, attend to important time steps

$$c = \sum_{t=1}^{T} \alpha_t h_t$$

  - c is used for fully connected and then softmax
  - α_i are weights for each state and are computed at each time step using a feed forward network

Experiments

	Number of Reports	Number of categories	Avg. length (char)	Stdev. length (char)
Dataset 1	82,281	20	410	321
Dataset 2	1,625,512	9	327	174

		Dataset 1		Dataset 2	
	Methods	Acc	F-1	Acc	F-1
Traditional Methods	SVM (Wang & Manning 2012)	70.9	70.6	84.7	83.9
	MNB (Wang & Manning 2012)	71.0	72.3	79.0	79.6
	Gradient Boosting (Chen et al. 2016)	72.1	70.8	76.7	75.5
Neural Network Based Methods	CBoW (Zhou et al. 2016)	68.0	63.4	84.6	84.1
	Adaptive CBoW (Zhou et al. 2016)	70.6	69.6	84.8	84.8
	CNN (Kim 2014)	72.2	69.5	82.7	83.5
	RNN (Dai et al. 2015)	74.5	72.9	83.8	83.2
	Bi-RNN (Dai et al. 2015)	75.2	73.6	84.6	84.5
	CNN-BiRNN (Tang et al. 2015)	76.6	76.4	86.8	84.6
This work	**Attention model**	**78.1***	**77.3***	**88.9***	**88.0***

- Error analysis
  - Some categories are very closely related
  - 32% of the misclassified samples in the "blood-bank" category were classified as "lab/specimen".
  - Similar situation about "diagnosis" and "medication" safety events.
  - MISC category
  - Data matters!