CNN for Text Categorization

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Target

- Study CNN on Text Categorization
- Exploit the 1D structure(word order) of text data for prediction
- Deploy the bag-of-word conversion in the convolutional layer
- Combine multiple convolutional layers is explored for accuracy prediction

CNN for Image

- convolution layer, pooling layer
- activation function σ
- Weight **W**
- Bias **b**

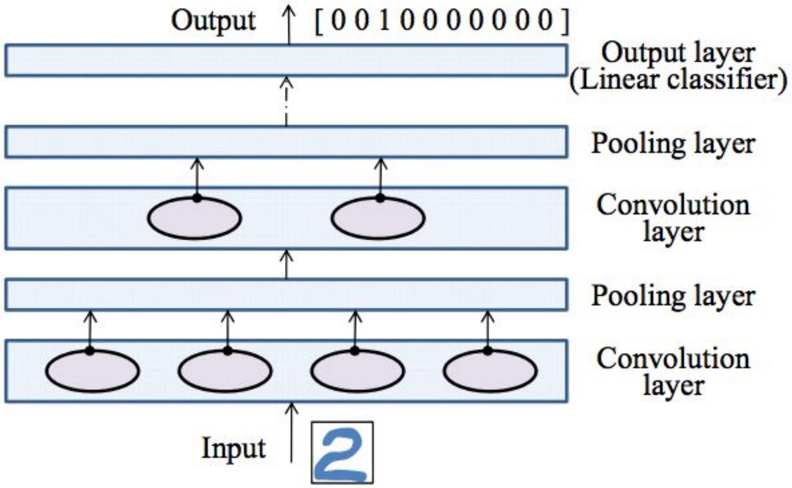

Figure 1: Convolutional neural network.

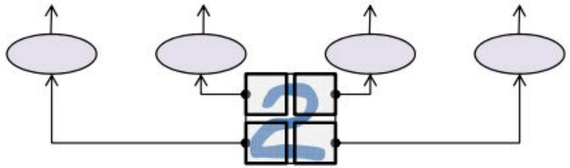

Figure 2: Convolution layer for image. Each computation unit (oval) computes a non-linear function $\boldsymbol{\sigma}(\mathbf{W} \cdot \mathbf{r}_\ell(\mathbf{x}) + \mathbf{b})$ of a small region $\mathbf{r}_\ell(\mathbf{x})$ of input image $\mathbf{x}$, where weight matrix $\mathbf{W}$ and bias vector $\mathbf{b}$ are shared by all the units in the same layer.

CNN for Text

- **seq-CNN**: straightforward adaption of CNN from image to text
- **bow-CNN**: employ bow conversion in convolution layer
- seq-CNN is better in sentiment classification(IMDB)
- bow-CNN is better in topic classification(RCV1)

methods	**IMDB**	**Elec**	**RCV1**
SVM bow3(30K)	10.14	9.16	10.68
SVM bow1(all)	11.36	11.71	10.76
SVM bow2(all)	9.74	9.05	10.59
SVM bow3(all)	9.42	8.71	10.69
NN bow3(all)	9.17	8.48	10.67
NB-LM bow3(all)	8.13	8.11	13.97
bow-CNN	8.66	8.39	9.33
seq-CNN	8.39	7.64	9.96
seq2-CNN	8.04	7.48	-
seq2-bow$n$-CNN	**7.67**	**7.14**	-

Table 2: Baseline method with error rate(%).

seq-CNN

- Document **D**=(w_1, w_2, ...) with vocabulary **V**
- treat each word as a pixel
- treat **D** as an image of **|D|x1** with **|V|** channels
- Example
  - V = {“don’t”, “hate”, “I”, “it”, “love”}
  - D = “I love it”
  - vector x for D: x=[00100|00001|00010]

seq-CNN

- represent region with concatenation of pixels
- **p|V|** dimensional region vector, where p is fixed in advance region size
- Example:
    - p=2, stride=1
    - “I love”, “love it”

$$\mathbf{r}_0(\mathbf{x}) = \left[\begin{array}{c} 0 \\ 0 \\ \mathbf{1} \\ 0 \\ 0 \\ — \\ 0 \\ 0 \\ 0 \\ 0 \\ \mathbf{1} \end{array}\right] \begin{array}{c} \text{don't} \\ \text{hate} \\ \textbf{I} \\ \text{it} \\ \text{love} \\ \\ \text{don't} \\ \text{hate} \\ \text{I} \\ \text{it} \\ \textbf{love} \end{array} \qquad \mathbf{r}_1(\mathbf{x}) = \left[\begin{array}{c} 0 \\ 0 \\ 0 \\ 0 \\ \mathbf{1} \\ — \\ 0 \\ 0 \\ 0 \\ \mathbf{1} \\ 0 \end{array}\right] \begin{array}{c} \text{don't} \\ \text{hate} \\ \text{I} \\ \text{it} \\ \textbf{love} \\ \\ \text{don't} \\ \text{hate} \\ \text{I} \\ \textbf{it} \\ \text{love} \end{array}$$

bow-CNN

- **p** is large, r(x) is high-dimensional.
- p|V| is too large, then mod becomes very complex
- Use bow conversion to represent region vector
- **p|V|** ----> **|V|** dimensions

$$\mathbf{r}_0(\mathbf{x}) = \begin{array}{c} \left[\begin{array}{c} 0 \\ 0 \\ \mathbf{1} \\ 0 \\ \mathbf{1} \end{array}\right] \end{array} \begin{array}{c} \text{don't} \\ \text{hate} \\ \textbf{I} \\ \text{it} \\ \textbf{love} \end{array} \qquad \mathbf{r}_1(\mathbf{x}) = \begin{array}{c} \left[\begin{array}{c} 0 \\ 0 \\ 0 \\ \mathbf{1} \\ \mathbf{1} \end{array}\right] \end{array} \begin{array}{c} \text{don't} \\ \text{hate} \\ \text{I} \\ \textbf{it} \\ \textbf{love} \end{array}$$

Baseline

- **seq2-bown-CNN** achieve the best accuracy!
- seq vs bow
- layer vs more layers

methods	IMDB	Elec	RCV1
SVM bow3(30K)	10.14	9.16	10.68
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Table 2: Baseline method with error rate(%).

More convolutional Layers

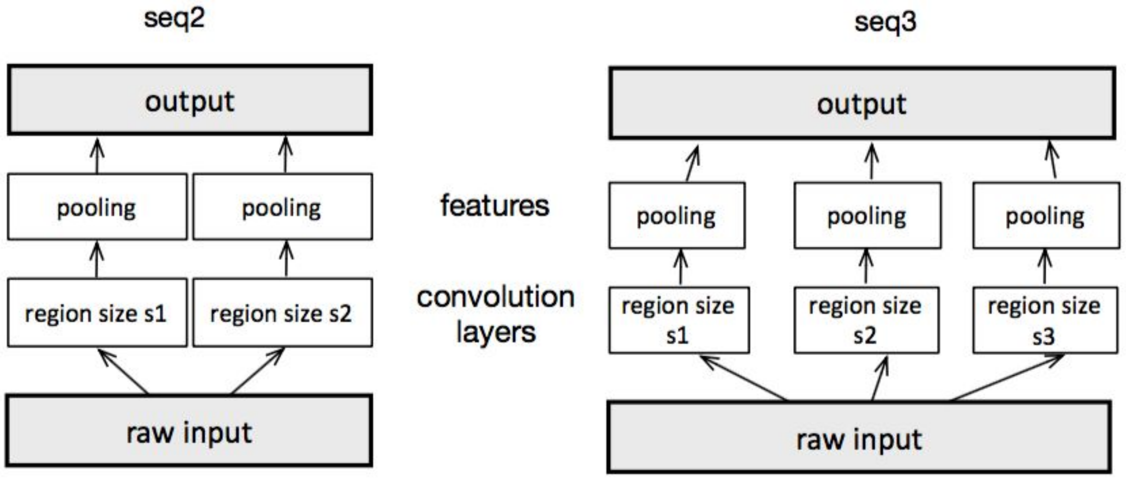


Figure 7: architecture in seq2 vs seq3

More convolutional Layers

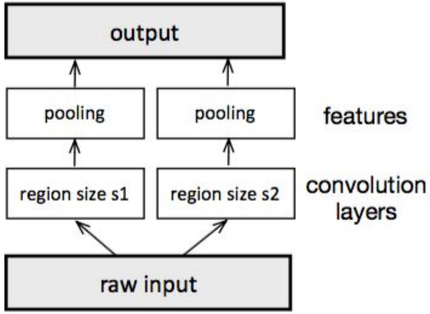
- In most cases, not working well.
- With bow feature layers, it slightly works better.
- Simply increasing the convolutional will not work.

methods	IMDB	Elec	RCV1
NB-LM bow3(all)	8.13	8.11	13.97
seq-CNN	8.39	7.64	9.96
seq2-CNN	8.04	7.48	-
seq3-CNN	**8.12**	**7.54**	-
seq2-bown-CNN	7.67	7.14	-
seq3-bown-CNN	**7.61**	**7.2**	-
seq2-CNN-3k	**7.88**	-	-
seq3-CNN-3k	**8.04**	-	-

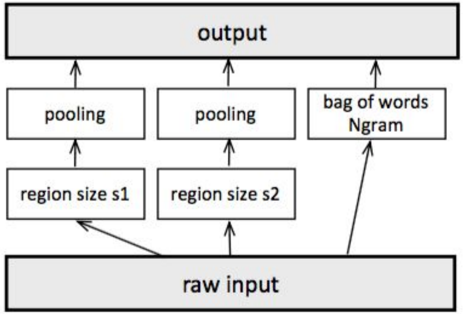
Table 3: error rate(%) with different convolutional layers

More bow feature layers

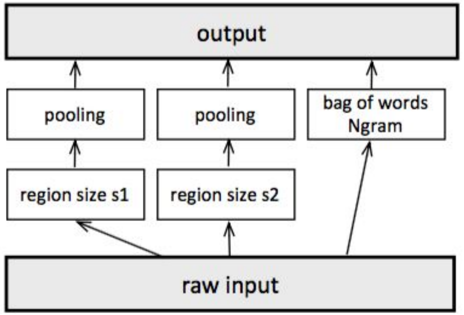
seq2_CNN



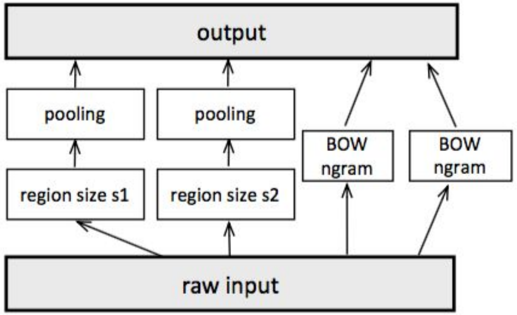
seq2_bown-CNN



seq2_bown-CNN



seq2_bown_bown-CNN



More bow feature layers

- Not so obvious using more bown layer
- still better than seq3-CNN

methods	**IMDB**	**Elec**	**RCV1**
NB-LM bow3(all)	8.13	8.11	13.97
bow-CNN	8.66	8.39	9.33
seq-CNN	8.39	7.64	9.96
seq2-CNN	8.04	7.48	-
seq2-bow$n$-CNN	**7.67**	**7.14**	-
seq2-bow$n$-bow$n$-CNN	**7.72**	-	-
seq3-CNN	**8.12**	7.54	-

More powerful feature

- Using 1,2,3,4-gram instead of 1,2,3-gram
- Works much better in IMDB
- IMDB vs. Elec (positive/negative with star rating)

methods	**IMDB**	**Elec**	**RCV1**
NB-LM bow3(all)	8.13	8.11	13.97
seq2-bow$n$-CNN	**7.67**	**7.14**	-
seq2-bow$n$-4CNN	**7.48**	**7.2**	-

Conclusion

- Using convolutional layer to present 1D word order can obviously improve the accurate prediction.
- Under the 2-conv with bow feature layer, exploiting more convolutional layers will not affect the prediction, word order should not be overrated.
- Still bow feature conversion in convolutional layer can help to better predict if combined with the previous structure.