A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification

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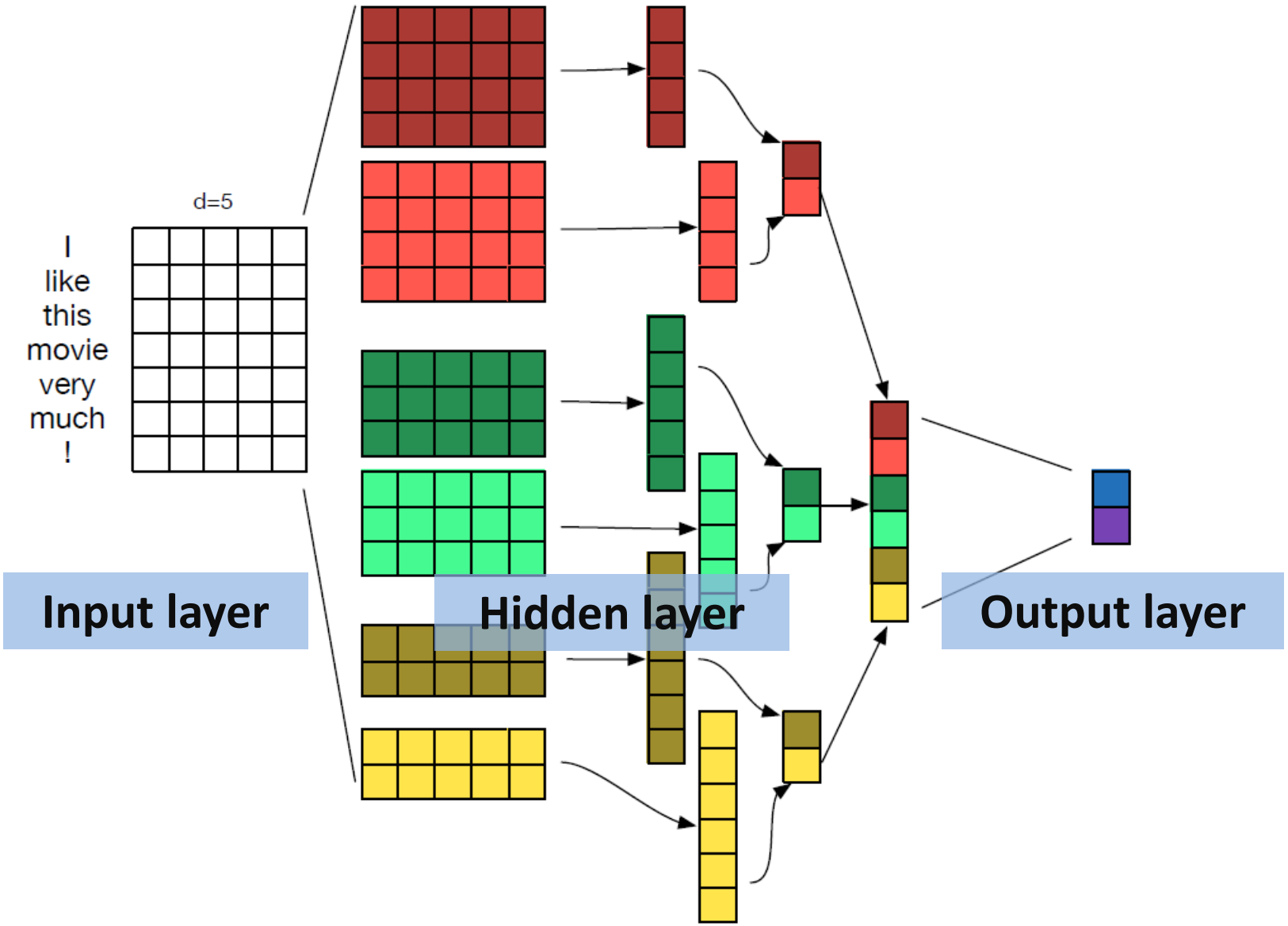
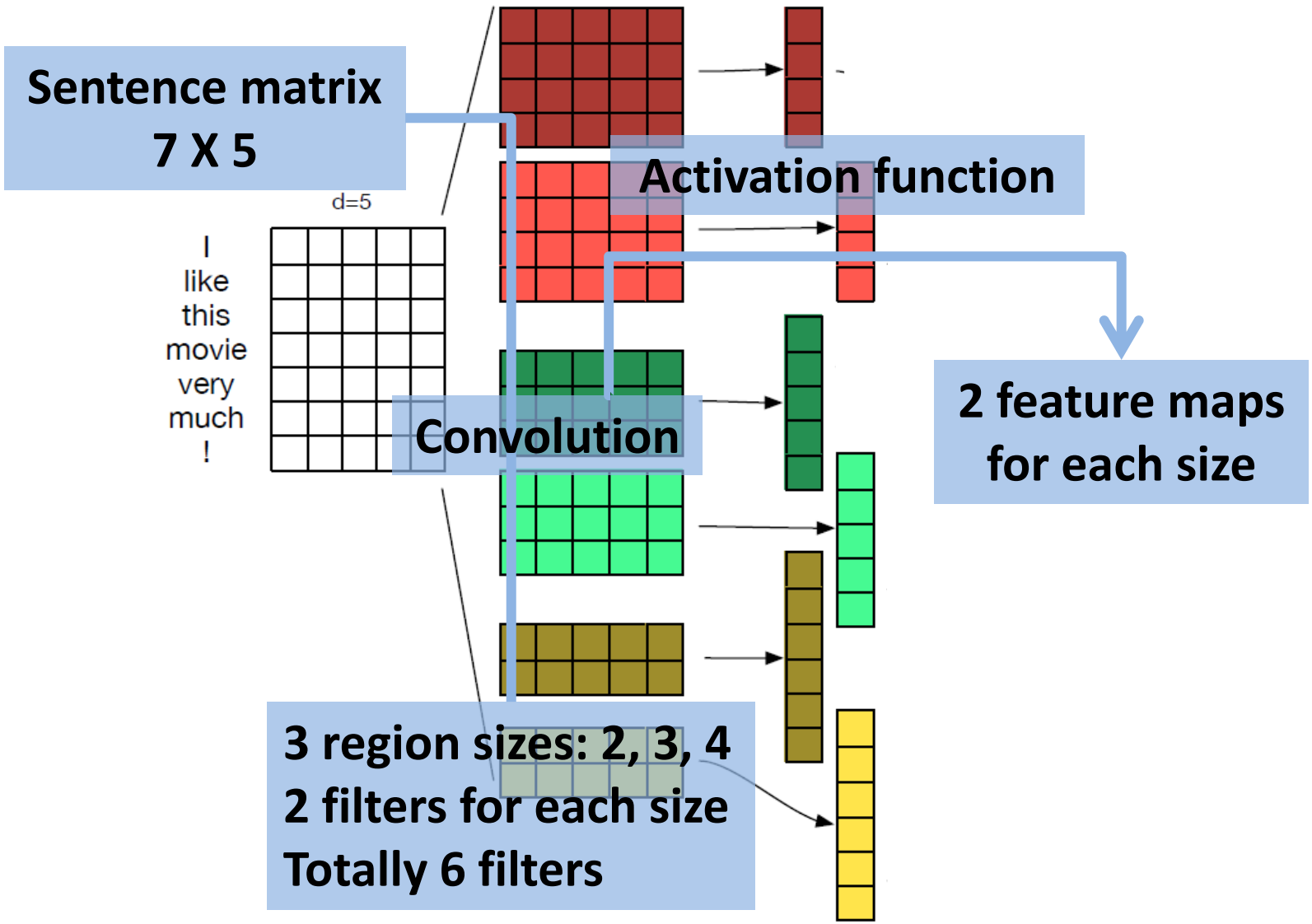
Introduction

- Convolutional Neural Networks (CNNs) achieve good performance in sentence classification
- Problem for practitioners: how to specify the CNN architecture and set the (many) hyperparameters?
- Exploring is expensive
  - Slow training
  - Vast space of model architecture and hyperparameter settings
- Need to conduct an empirical evaluation on the effect of varying hyperparameter on performance → use the results of this paper as a starting point for your own CNN model

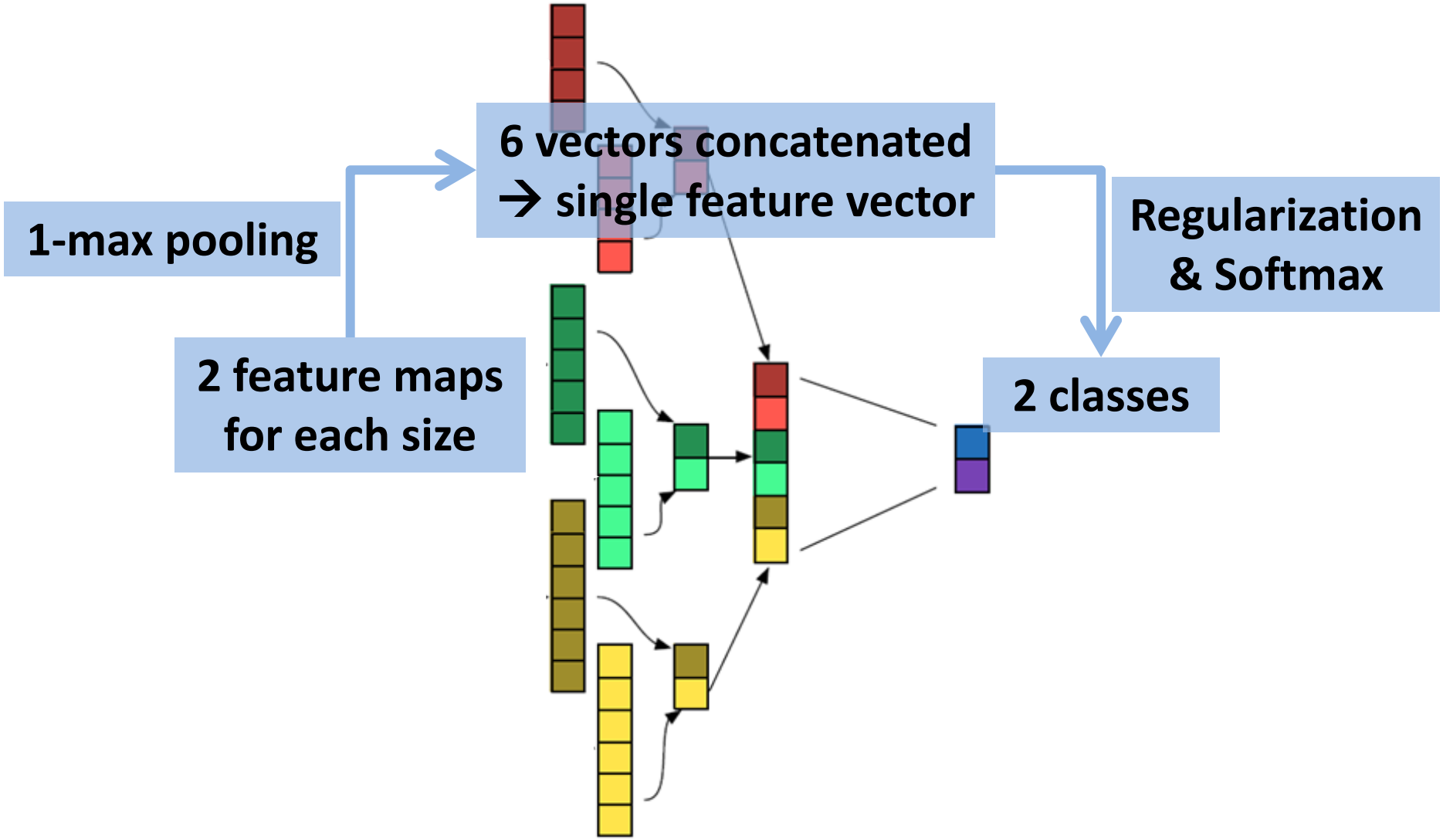
Background: CNNs



Background: CNNs



Background: CNNs



Datasets and Baseline Model

- Nine sentence classification datasets [short to medium average sentence length (3-23)]
  - Examples
    - SST: Stanford Sentiment Treebank (average length: 18)
    - CR: customer review dataset (average length: 19)
- Baseline CNN configuration (Kim, 2014):
  - **Input word vector**: Google word2vec
  - **Filter region size**: 3, 4, and 5
  - **Number of feature maps**: 100
  - **Activation function**: ReLU
  - **Pooling**: 1-max pooling
  - **Regularization**: dropout rate 0.5, l2 norm constraint 3

Datasets and Baseline Model

- Baseline CNNs configuration:
  - 100 times 10-fold CV
  - Record mean and range of accuracy
- Each sensitivity analysis:
  - Hold all other settings constant, vary the factor of interest
- Each configuration
  - Replicate the experiment 10 times, each replication a 10-fold CV
  - Record **average CV means** and **ranges** of accuracy

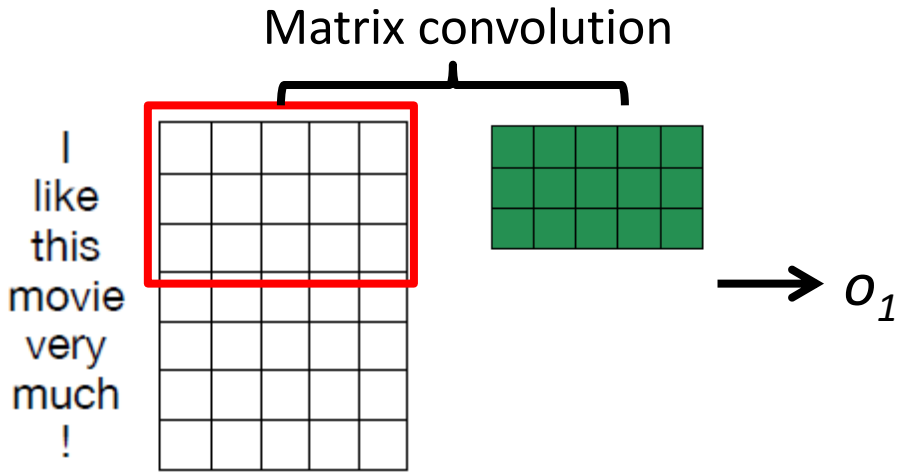
Effect of Input Word Vectors

- Three types of word vector
  - **Word2vec**: 100 billion words from Google News, 300-dimensional
  - **GloVe**: 840 billions of tokens from web data, 300-dimensional
  - **Concatenated** word2vec and GloVe: 600-dimensional
- Performance depends on dataset
- Not helpful to concatenant
- **One-hot vector**: poorly [when training dataset is small to moderate]

Effect of Filter Region Size

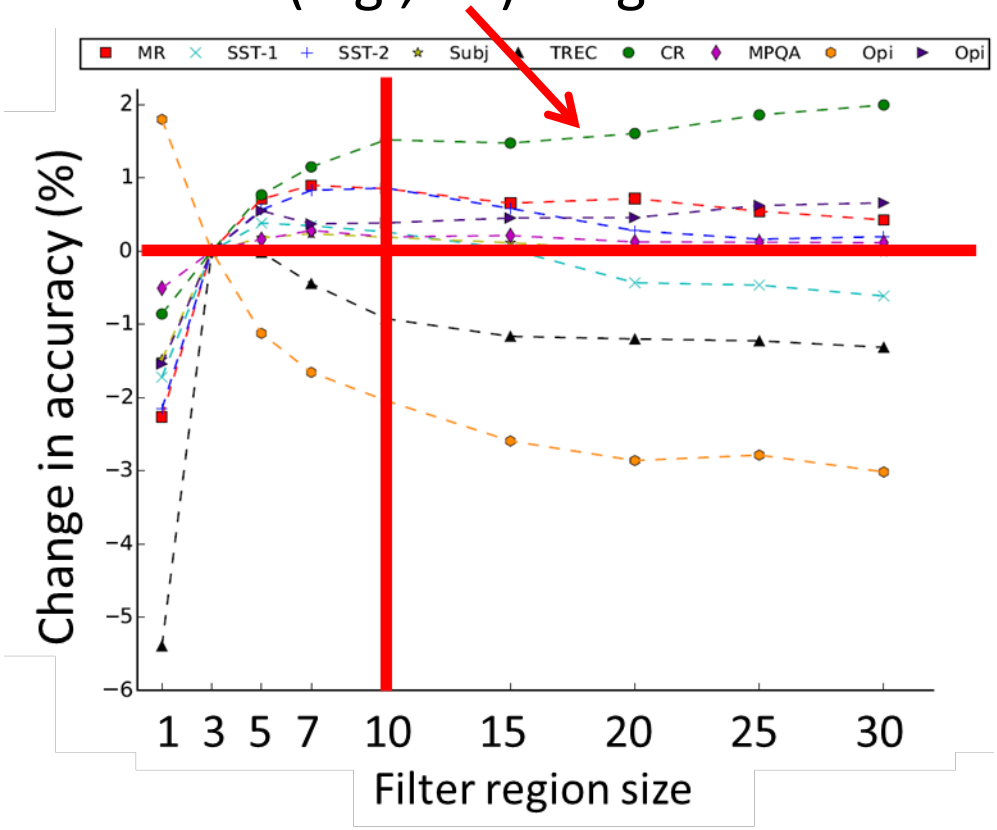
- Filter
  - Word embedding matrix **A**: ***s*** x ***d***
  - Filter matrix **W** with region size ***h***: ***h*** x ***d***
  - Output sequence of length *s*-*h*+1: ***o***, o_i=W·A[*i*:*i*+*h*-1]

E.g., filter with region size 3



Effect of Filter Region Size

- **One** region size
  - Each dataset has its own optimal filter size
  - A coarse search over 1 to 10
  - Longer sentence (e.g., CR): larger filter size



Effect of Filter Region Size

- **Multiple** region sizes
  - Combining close-to-optimal sizes: improve performance
  - Adding far-from-optimal sizes: decrease performance

Multiple region size	Accuracy (%)
(3)	91.21 (90.88,91.52)
(5)	91.20 (90.96,91.43)
(2,3,4)	91.48 (90.96,91.70)
(3,4,5)	91.56 (91.24,91.81)
(4,5,6)	91.48 (91.17,91.68)
(7,8,9)	90.79 (90.57,91.26)
(14,15,16)	90.23 (89.81,90.51)
(2,3,4,5)	**91.57 (91.25,91.94)**
(3,3,3)	91.42 (91.11,91.65)
(3,3,3,3)	91.32 (90.53,91.55)

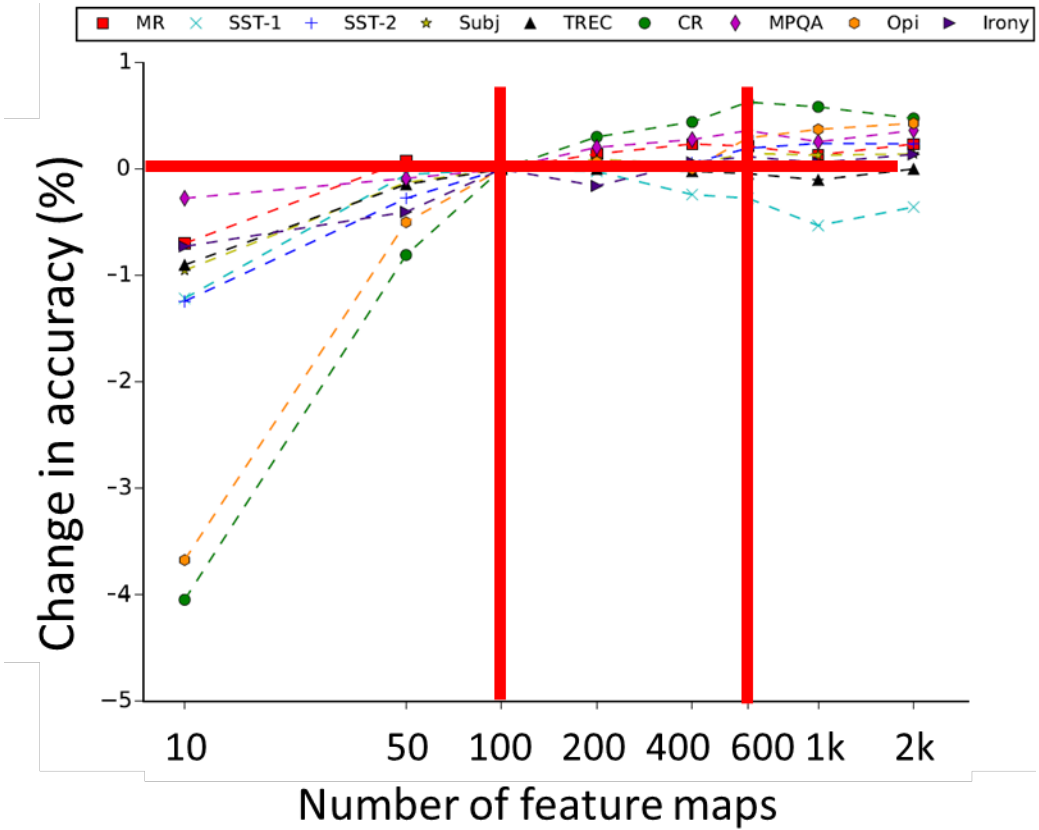
optimal sizes →

far-from-optimal sizes →

close-to-optimal sizes →

Effect of Number of Feature Maps

- Number of feature maps (for each filter region size)
  - 10, 50, 100, 200, 400, 600, 1000, 2000
- Optimums depend on dataset; fall in [100, 600]
- Over 600: no much improvement and longer training time



Effect of Activation Function

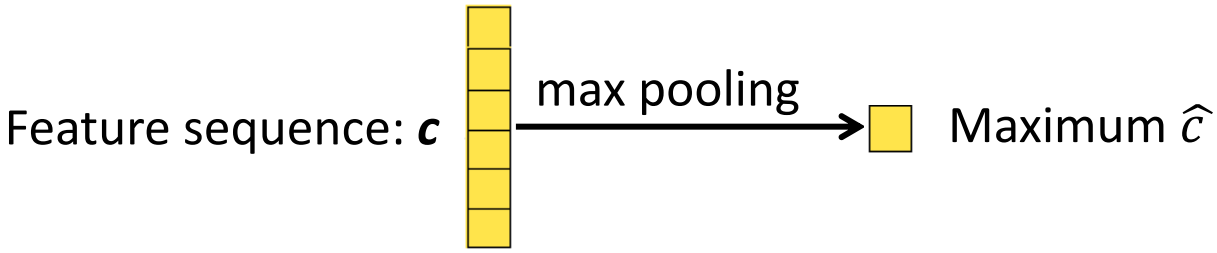
- Activation functions ***f***: $c_i = \boldsymbol{f}(o_i + b)$
- Examples:

Function	Equation
Softplus	$f(x) = \ln(1 + e^x)$
ReLu	$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$
Tanh	$f(x) = \tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$
Sigmoid	$f(x) = \frac{1}{1 + e^{-x}}$
Identity	$f(x) = x$

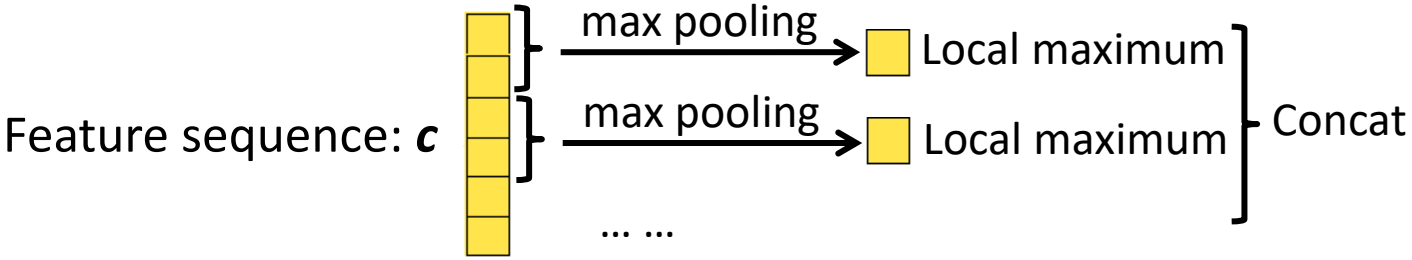
- **Tanh, Iden, ReLU** perform better
- No significant difference among the good ones

Effect of Pooling Strategy

- Baseline strategy: **1-max pooling**



- Strategy 1: Max pooling over local region (size=3, 10, 20, 30): worse



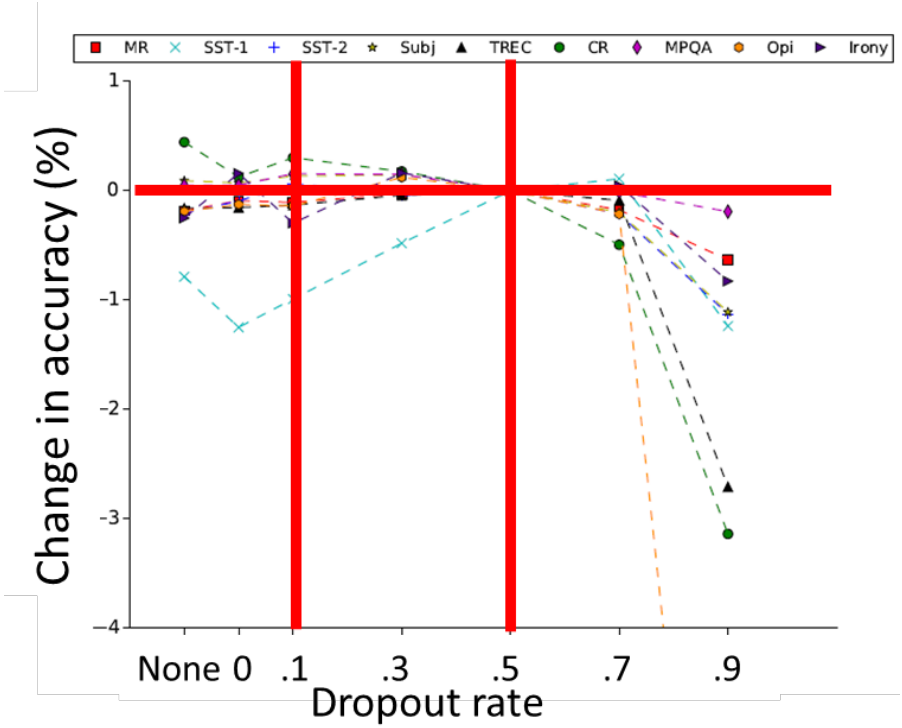
- Strategy 2: K-max pooling (k=5, 10, 15, 20): worse
- Strategy 3: Average pooling over local region (size=3, 10, 20, 30): (much) worse

Effect of Regularization

- Dropout (before the output layer)
  - $y = \mathbf{w} \cdot \mathbf{z} + b$, with a probability $\boldsymbol{p}$ that z_i is dropped out

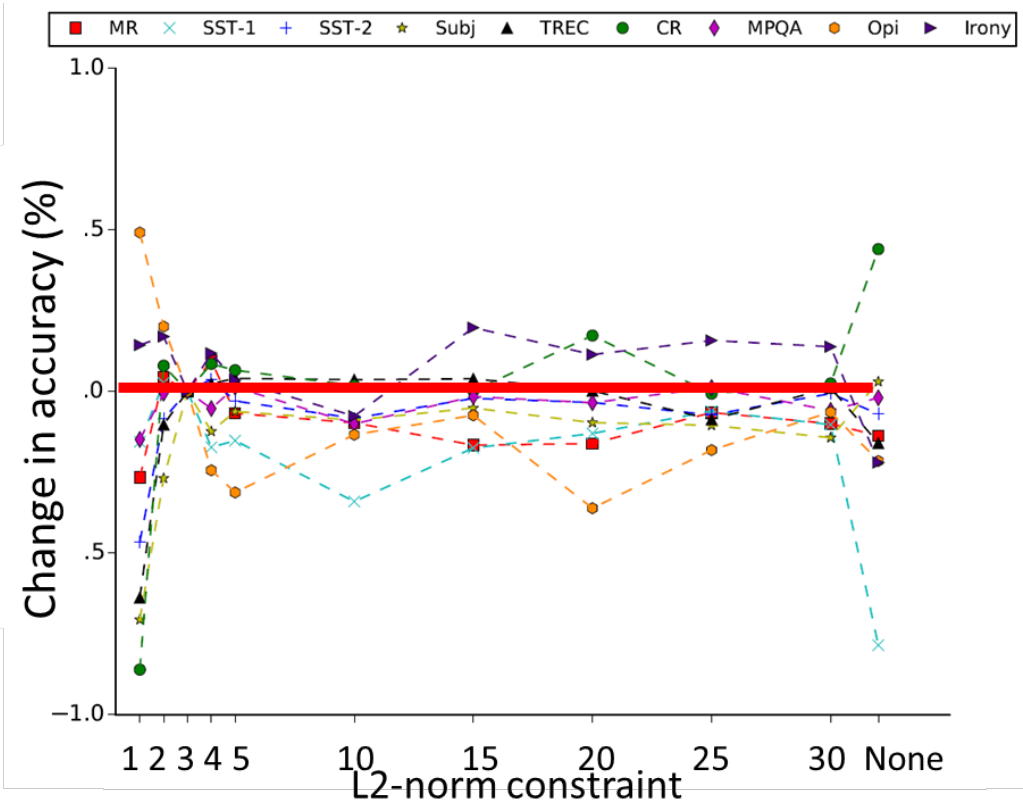
    z is concatenated maximum values $\hat{c}$
  - Dropout rate from 0.1 to 0.5: helps a little
  - Dropout before convolution: similar range and effect

Dropout rate



Effect of Regularization

- L2-norm constraint
  - Force $\|\mathbf{w}\|_2 = s$, whenever $\|\mathbf{w}\|_2 > s$
  - L2-norm constraint does not improve performance much
  - Does not harm too, so use one



Conclusions (and Practitioners' Guide)

- Use word2vec or GloVe rather than one-hot vector
- Line-search over single filter size from 1-10, and then combine multiple 'good' region sizes
- Adjust the number of feature maps for each filter size from 100 to 600
- Use 1-max pooling
- Test different activation functions (at least) ReLU and tanh
- Use small dropout rate (0.0-0.5) and a (large) max norm constraint and try larger values when optimal number of feature maps is large (over 600)
- Repeat CV to assess the performance of a model