# Neural Networks for NLP/ Text Mining

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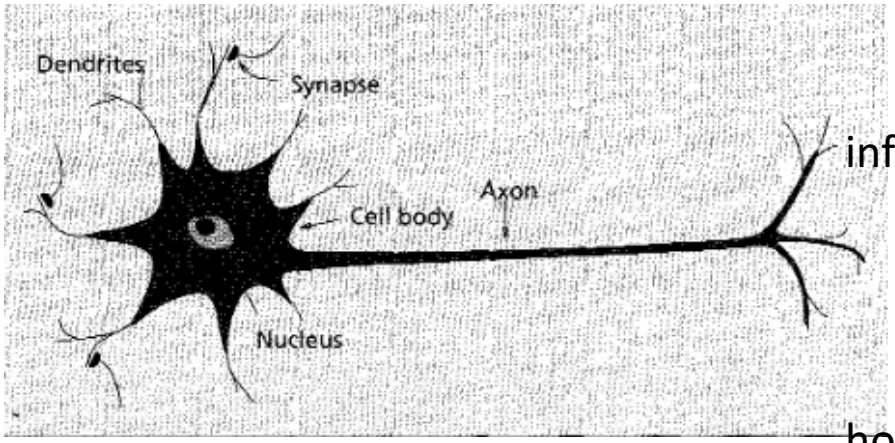
# Outline

- **Neural Networks - Introduction**
- CNNs
- RNNs
- Gaussian Document Representation from Word Embeddings (EACL 2017 paper)

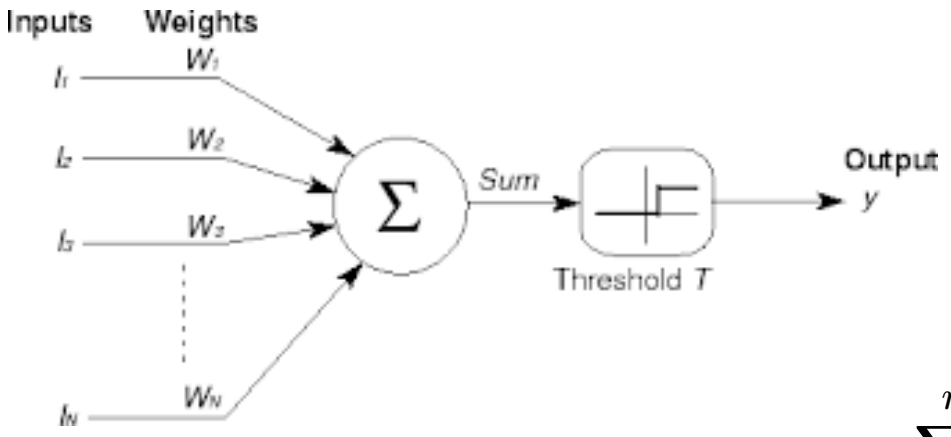
# Neural Networks




- Neuron: biological cell that processes information
- composed of a cell body, the axon and the dendrites.
- Cell body contains information about hereditary traits and a plasma that holds the molecular equipment for producing material needed by the neuron.
- receives signals (impulses) from other neurons through its *dendrites* (receivers)
- transmits signals generated by its cell body along the *axon* (transmitter). At the terminals of these strands are the synapses.
- *synapse* functional unit between two neurons (an axon strand and a dendrite)

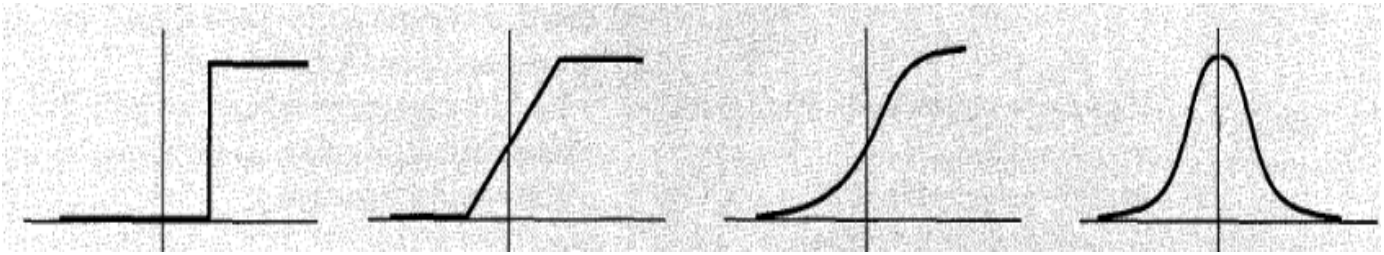
**Artificial neural networks: A tutorial**, AK Jain, J Mao, KM Mohiuddin - Computer, 1996

# Neural networks



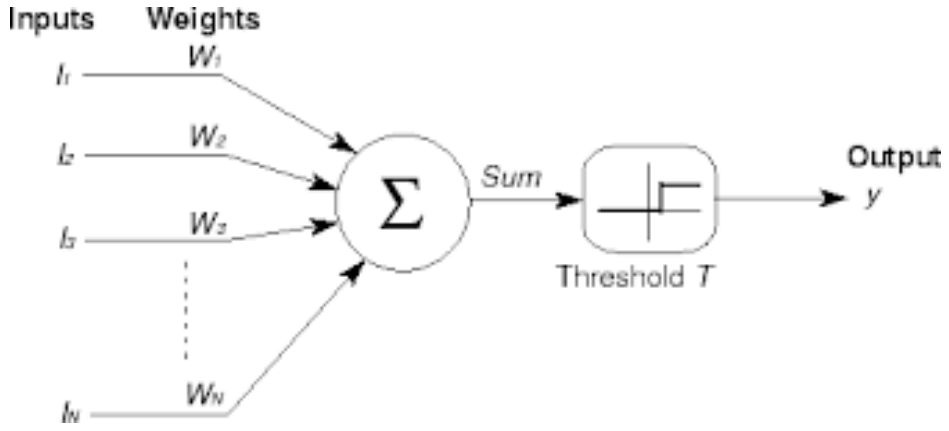

$$y = \theta \sum_{j=1}^{n} w_j X_j - u$$

McCulloch-Pitts Neuron Model
- $\theta$ is a step function at 0
- $w_j$: the weight of the $j$-th input
- activation functions: piecewise linear, sigmoid, or Gaussian,



# Neural Network architectures

- Weighted directed graphs in which artificial neurons are nodes and directed edges (with weights) are connections between neuron outputs and inputs.
- Based on the connection pattern NNs can be grouped into
  - feed-forward networks, in which graphs have no loops
  - recurrent (or feedback) networks, in which loops occur because of feedback connections.

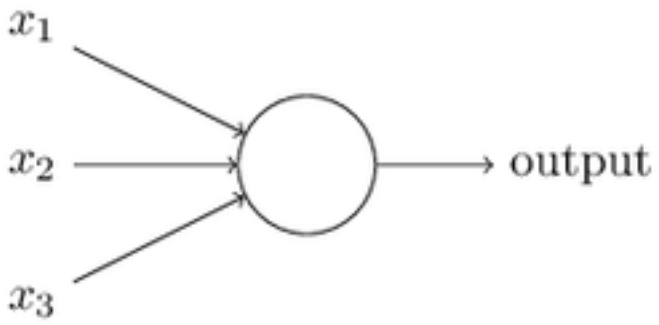


# Perceptron learning algorithm

- developed in the 1950 -60 by Frank Rosenblatt
- takes several binary inputs, $x_1$,$x_2$… and produces a single binary output

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

- device that makes decisions by weighing up evidence.
- varying the weights and the threshold, we can get different models of decision-making



# Neural Networks – Perceptron Learning

- Initialize the weights and threshold (small random numbers)
- Present an input vector $X = \{x_1, .. x_n\}$ and evaluate the output of the neuron $$y = \sum_{j=1}^{n} w_j X_j - u$$
- Update the weights $w_{t+1} = w_t + \alpha(d - y)X$ where

  α: learning rate, d: the correct output.

$\sum_{j=1}^{n} w_j X_j - u = 0$ defines the class separation hyperplane

- learning occurs only when the perceptron makes an error.
- Perceptron convergence theorem (Rosenblatt, 1962)

If training data are drawn from two linearly separable classes, the perceptron learning procedure converges after a finite number of iterations.

# Neural Networks – sigmoid neuron

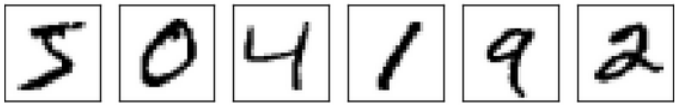
- In perceptron small changes to the weights may cause huge difference to the output (0->1)
- We want to impose: small changes to weights (or bias) small change to the output.
- the sigmoid neuron has weights for each input, $w_1, w_2, \ldots$, and an overall bias, $b$ . But the output is not 0 or 1 . Instead, it's $\sigma(w \cdot x + b)$, where $\sigma$ is the *sigmoid function*

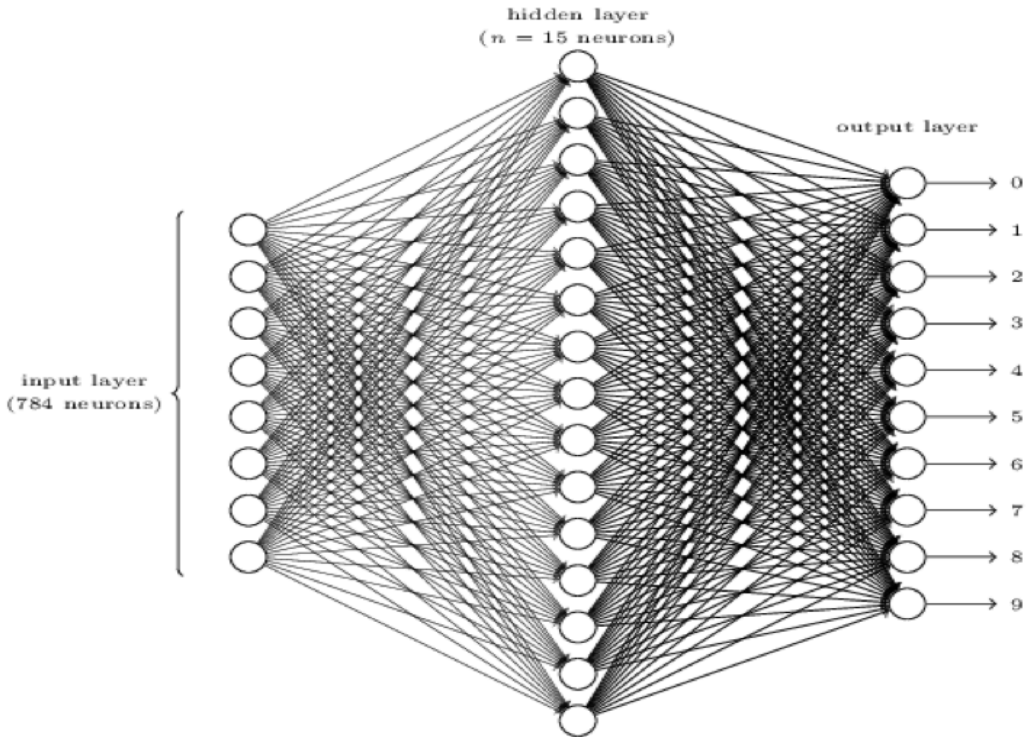
- *The output of the neuron the is:*

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}.$$

$$\frac{1}{1+\exp(-\sum_j w_j x_j - b)}$$

# Learning with gradient descent

- Assume hand written digits (MNIST database – 60.000 images) :
- Each of the 
- Assume a NN with 784 inputs, a hidden layer of 15 neurons and 10 outputs:




i.e.: if x is an image (=7)

y(x): (0,0,0,0,0,0,0,1,0,0,)

is the desired output.

http://neuralnetworksanddeeplearning.com/chap1.html

# Learning with gradient descent

- Cost function $$C(w,b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2.$$
  - w: weights, b: biases, α: the vector of correct outputs, n total number of training samples.
- Searching for w,b to minimize C(w,b)

$$w_k \to w_k' = w_k - \eta \frac{\partial C}{\partial w_k}$$

$$b_l \to b_l' = b_l - \eta \frac{\partial C}{\partial b_l}.$$

# Problems with gradient descent

$C = \frac{1}{n} \sum_x C_x$ where $C_x \equiv \frac{\|y(x)-a\|^2}{2}$

Thus to compute the gradient $\nabla C$ we must compute gradients: $\nabla C_x$ for each training input and then average them: $\nabla C = \frac{1}{n} \sum_x \nabla C_x$ => huge cost

# Learning with stochastic gradient descent

- estimate the gradient $\nabla C$ computing $\nabla C_x$ for a small sample of randomly chosen training inputs
- averaging over this small sample we can get a good estimate of the true gradient $\nabla C$, faster
- randomly pick out a small sample size m of randomly chosen training inputs. label those $X_1, X_2, \ldots, X_m$ and refer to them as a *mini-batch*. Assuming sample size *m* is large enough we expect that the average value of the $\nabla C_{X_j}$ will be roughly equal to the average over all $\nabla C_x$:

$$\frac{\sum_{j=1}^{m} \nabla C_{X_j}}{m} \approx \frac{\sum_x \nabla C_x}{n} = \nabla C$$

# Learning with stochastic gradient descent

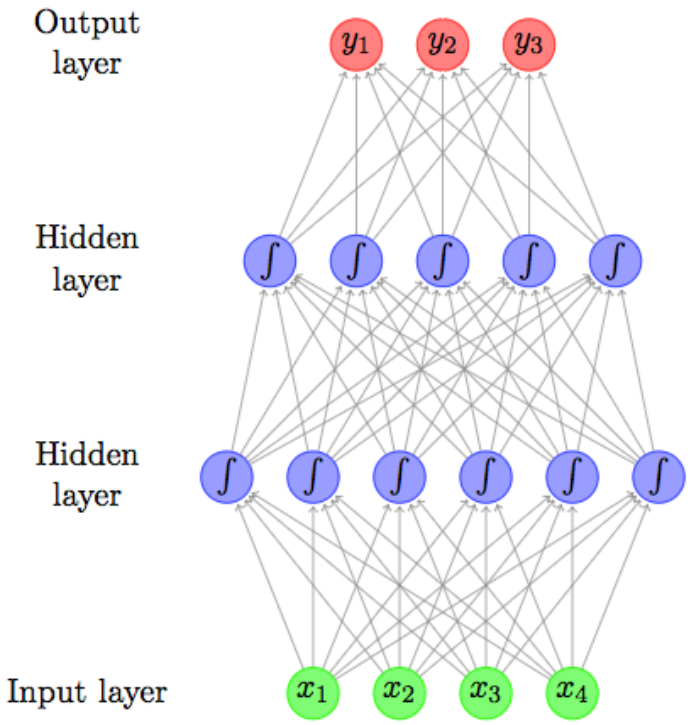
- suppose $w_k$ and $b_l$ the weights and biases in the neural network. Then stochastic gradient descent works by picking out a randomly chosen mini-batch of training inputs, and training with those

$$w_k \to w_k' = w_k - \frac{\eta}{m} \sum_j \frac{\partial C_{X_j}}{\partial w_k}$$

$$b_l \to b_l' = b_l - \frac{\eta}{m} \sum_j \frac{\partial C_{X_j}}{\partial b_l},$$

- sums are over all the training examples $X_j$ in the current mini-batch.
- Then pick out another randomly chosen mini-batch and train with those.
- until we've exhausted the training inputs, (complete an *epoch* of training).

# Multilayer Feed-forward NNs




- bottom layer: input to the network.
- Neurons layers, reflecting the flow of information.
- Circle: neuron,
  - incoming arrows neuron's inputs,
  - outgoing arrows neuron's outputs.
  - Arrow: weighted, reflecting its importance.

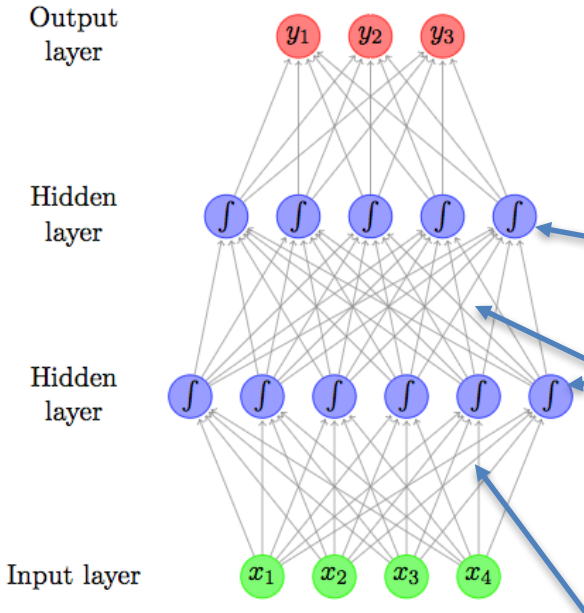
- top-most layer: output of the network.
- The other layers are considered "hidden".

- Sigmoid shape inside the neurons in the hidden layers represent a non-linear function - typically

$$\frac{1}{1+e^{-x}}$$

- applied to neuron's value before passing it to the output.
- fully-connected layer or affine layer
  - each neuron is connected to all of the neurons in the next layer

# Multilayer Feed-forward NNs




- $\boldsymbol{x}$ : input
- $\boldsymbol{h}$ : output of first hidden layer
- $\boldsymbol{x}$ : input

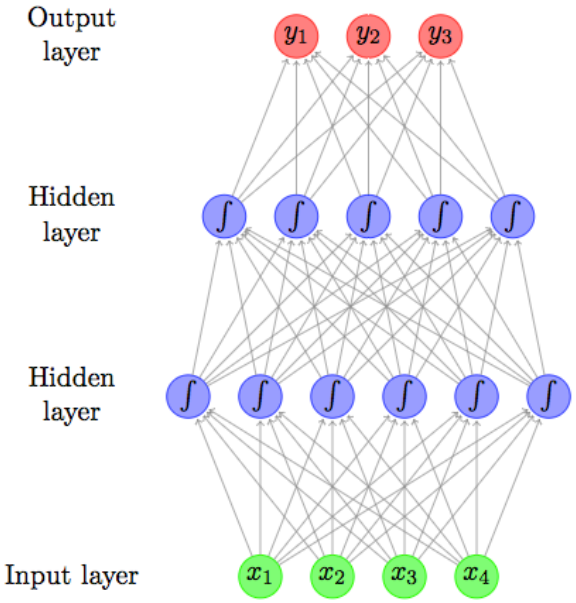
$$NN_{MLP2}(\mathbf{x}) = (g^2(g^1(\mathbf{x}\mathbf{W^1} + \mathbf{b^1})\mathbf{W^2} + \mathbf{b^2}))\mathbf{W^3}$$

$$\mathbf{x} \in \mathbb{R}^{d_{in}},\ \mathbf{W^1} \in \mathbb{R}^{d_{in} \times d_1},\ \mathbf{b^1} \in \mathbb{R}^{d_1},\ \mathbf{W^2} \in \mathbb{R}^{d_1 \times d_2},\ \mathbf{b^2} \in \mathbb{R}^{d_2}$$

- Alternatively:

$$\begin{aligned} NN_{MLP2}(\mathbf{x}) &= \mathbf{y} \\ \mathbf{h^1} &= g^1(\mathbf{x}\mathbf{W^1} + \mathbf{b^1}) \\ \mathbf{h^2} &= g^2(\mathbf{h^1}\mathbf{W^2} + \mathbf{b^2}) \\ \mathbf{y} &= \mathbf{h^2}\mathbf{W^3} \end{aligned}$$

# Multilayer Feed-forward NNs




$$NN_{MLP2}(\mathbf{x}) = \mathbf{y}$$
$$\mathbf{h^1} = g^1(\mathbf{x}\mathbf{W^1} + \mathbf{b^1})$$
$$\mathbf{h^2} = g^2(\mathbf{h^1}\mathbf{W^2} + \mathbf{b^2})$$
$$\mathbf{y} = \mathbf{h^2}\mathbf{W^3}$$

**Common non linear functions**

- Sigmoid (***x->[0,1]***) $\sigma(x) = \dfrac{1}{1+e^{-x}}$
- Hyperbolic tangent (tanh)

  S-shaped function, x into the range [-1,1].

$$\tanh(x) = \frac{e^{2x}-1}{e^{2x}+1}$$

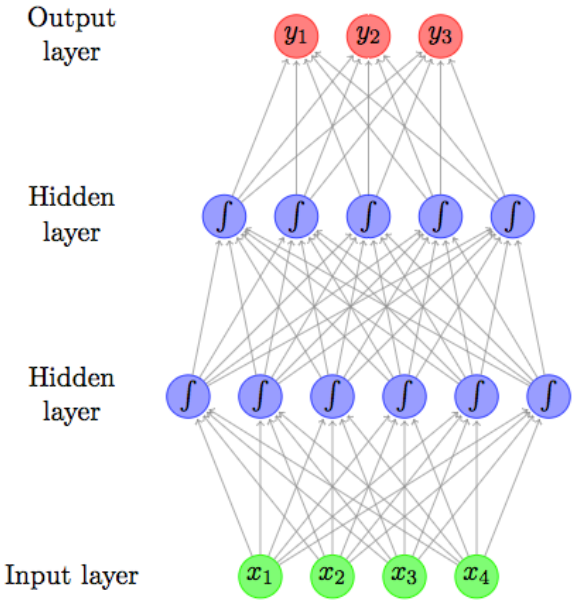
- Hard tanh: approximation of the tanh function faster to compute.

$$hardtanh(x) = \begin{cases} -1 & x < -1 \\ 1 & x > 1 \\ x & \text{otherwise} \end{cases}$$

- $$ReLU(x) = \max(0, x) = \begin{cases} 0 & x < 0 \\ x & \text{otherwise} \end{cases}$$

As a rule of thumb - ReLU > tanh > sigmoid.

# Multilayer Feed-forward NNs




$$NN_{MLP2}(\mathbf{x}) = \mathbf{y}$$
$$\mathbf{h^1} = g^1(\mathbf{x}\mathbf{W^1} + \mathbf{b^1})$$
$$\mathbf{h^2} = g^2(\mathbf{h^1}\mathbf{W^2} + \mathbf{b^2})$$
$$\mathbf{y} = \mathbf{h^2}\mathbf{W^3}$$

**Output transformations**

**in several cases the output X can also be transformed. The most common is softmax:**

$$\mathbf{x} = x_1, \ldots, x_k$$
$$softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}}$$

- vector of non-negative real numbers that sum to one,
- Softmax transformation used when we need a probability distribution over the possible output classes.

# Convolutional Neural Networks (CNNs)

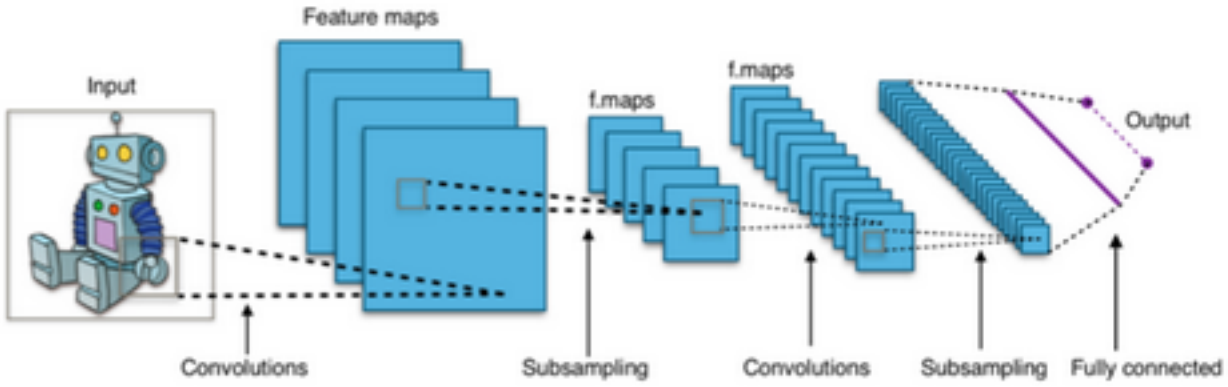
feedforward neural networks, very good at

- capturing local patterns from grids,
- learning more complex features by combining those patterns in a hierarchical way.
    - i.e. edges inferred from raw pixels, edges used to detect simple shapes, shapes used to recognize objects.

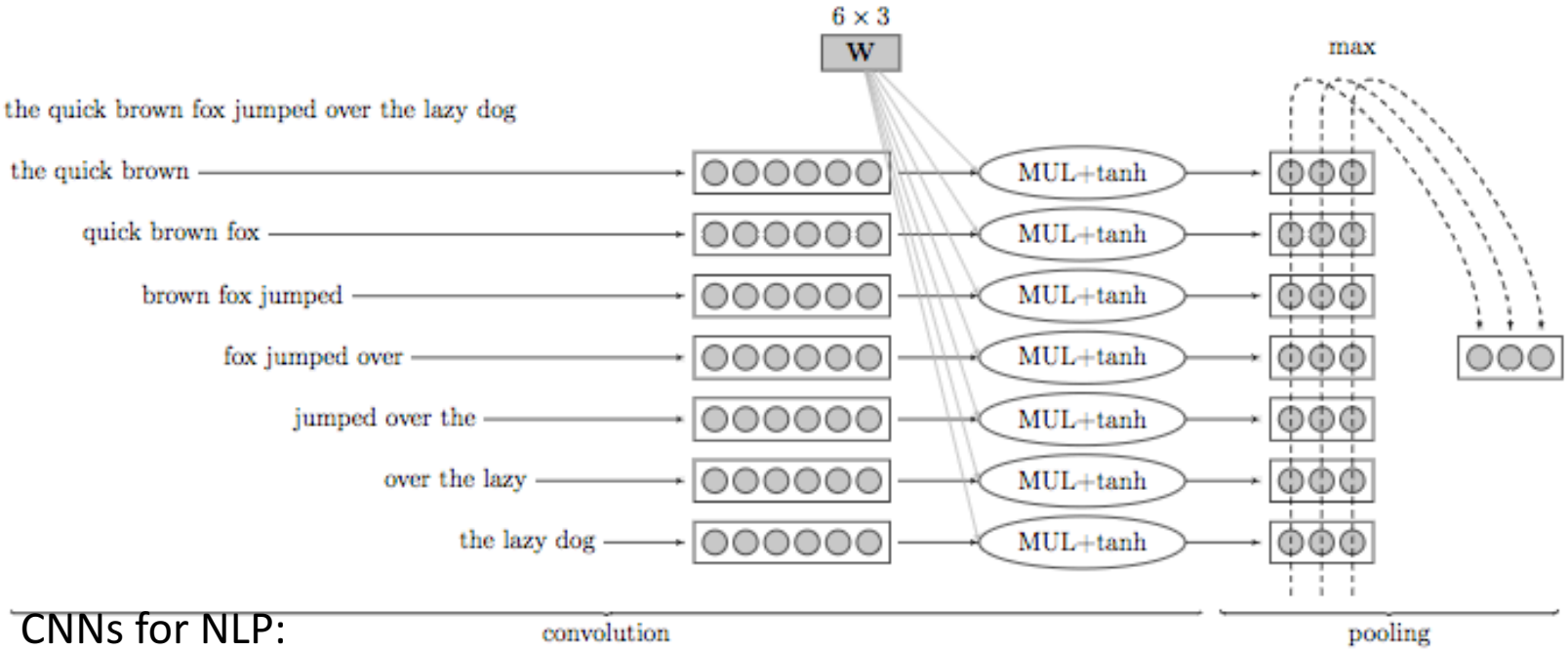
# Convolutional Neural Networks (CNNs)

Fundamental properties CNNs

- local invariance: Where exactly the object is placed within the image is not important, the goal is to detect it regardless of its position in the grid.
- Compositionality: The ability to learn more and more complex features starting from small regions is called



# Convolutional Neural Networks (CNNs)



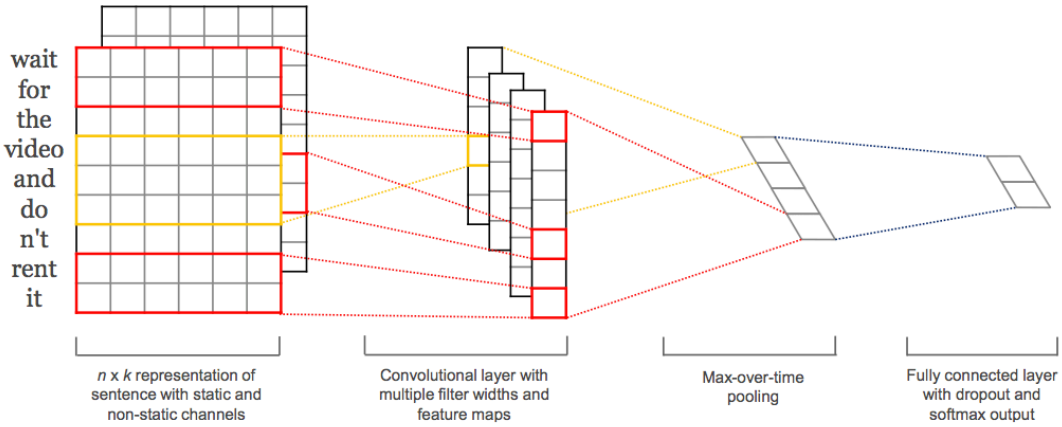

CNNs for NLP:

- sentence or document classification - ordering is crucial locally (“not bad, quite good”, “not good, quite bad”, “do not recommend”),
- global location of the features within the sentence or the document does not really matter.
- i.e. polarity of a opinion: “positive, I liked it” can be anywhere in the document

- CNNs are not able to encode long range dependencies,
  - LSTMs are used instead.

# CNN for document classification

- Use the high quality embeddings as input for Convolutional Neural Networ
- Input must be fixed size
- max-pooling deals with variable document lengths
- Applies multiple filters to concatenated word vectors




- Produces new features for every filter

$$\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$$

- And picks the max as a feature for the CNN

$$c_i = f(\mathbf{w} \cdot \mathbf{x}_{i:i+h-1} + b)$$

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}]$$

$$\hat{c} = \max\{\mathbf{c}\}$$

Yoon Kim - Convolutional Neural Networks for Sentence Classification

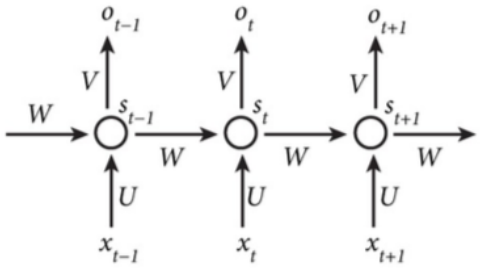
# CNN for document classification

- Many variations of the model
- use existing vectors as input (CNN-static)
- learn vectors for the specific classification task through backpropagation (CNN-rand)
- Modify existing vectors for the specific task through backpropagation(CNN-non-static)
- Combine multiple word embeddings
  - Each set of vectors is treated as a ‘channel’
  - Filter is applied to both channels
  - Gradients are backpropagated only through one of the channels
  - Fine-tunes one set of vectors while keeping the other static

# CNN for document classification

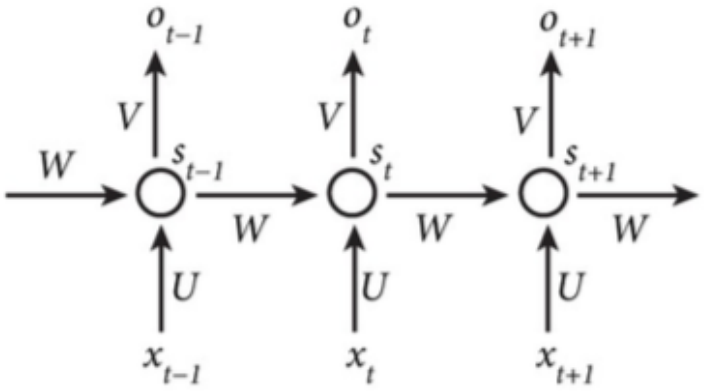
| **Model** | MR | SST-1 | SST-2 | Subj | TREC | CR | MPQA |
|---|---|---|---|---|---|---|---|
| CNN-rand | 76.1 | 45.0 | 82.7 | 89.6 | 91.2 | 79.8 | 83.4 |
| CNN-static | 81.0 | 45.5 | 86.8 | 93.0 | 92.8 | 84.7 | **89.6** |
| CNN-non-static | **81.5** | 48.0 | 87.2 | 93.4 | 93.6 | 84.3 | 89.5 |
| CNN-multichannel | 81.1 | 47.4 | **88.1** | 93.2 | 92.2 | **85.0** | 89.4 |
| RAE (Socher et al., 2011) | 77.7 | 43.2 | 82.4 | – | – | – | 86.4 |
| MV-RNN (Socher et al., 2012) | 79.0 | 44.4 | 82.9 | – | – | – | – |
| RNTN (Socher et al., 2013) | – | 45.7 | 85.4 | – | – | – | – |
| DCNN (Kalchbrenner et al., 2014) | – | 48.5 | 86.8 | – | 93.0 | – | – |
| Paragraph-Vec (Le and Mikolov, 2014) | – | **48.7** | 87.8 | – | – | – | – |
| CCAE (Hermann and Blunsom, 2013) | 77.8 | – | – | – | – | – | 87.2 |
| Sent-Parser (Dong et al., 2014) | 79.5 | – | – | – | – | – | 86.3 |
| NBSVM (Wang and Manning, 2012) | 79.4 | – | – | 93.2 | – | 81.8 | 86.3 |
| MNB (Wang and Manning, 2012) | 79.0 | – | – | **93.6** | – | 80.0 | 86.3 |
| G-Dropout (Wang and Manning, 2013) | 79.0 | – | – | 93.4 | – | 82.1 | 86.1 |
| F-Dropout (Wang and Manning, 2013) | 79.1 | – | – | **93.6** | – | 81.9 | 86.3 |
| Tree-CRF (Nakagawa et al., 2010) | 77.3 | – | – | – | – | 81.4 | 86.1 |
| CRF-PR (Yang and Cardie, 2014) | – | – | – | – | – | 82.7 | – |
| $SVM_S$ (Silva et al., 2011) | – | – | – | – | **95.0** | – | – |

# RNNs




- CNNs are naturally efficient with grids[8],
- RNNs were specifically developed to be used with sequences
  - time series, or, in NLP, words (sequences of letters) or sentences (sequences of words).
  - language modeling $P[w_n | w_1, ..., w_{n-1}]$.
  - RNNs trained with such objectives can be used to generate new and quite convincing sentences from scratch, as well demonstrated in this very interesting blogpost[9].
- RNN can be considered as a chain of simple neural layers that share the same parameters.

# RNN architecture




The output vector o= depends on the current hidden state.

In the case of a classification task, it is computed as:

$$o_t = softmax(V s_t)$$

- V is parameter matrix shared across all time steps,
- $o_t \in R_{dout}$ , where $d_{out}$ the number of classes (i.e. $d_{out}$ = 3 for a three-class classification task)
- RNNs can run very deep: for instance sequences of words , T reaches 15.

RNN input

- an ordered list of input vectors $x_0, \ldots, x_T$
- an initial state vector $s_{-1}$ (initialized with 0s)
- Output: an ordered list of state vectors $s_0, \ldots, s_T$ , or "hidden states" (the memory of the network), as well as an ordered list of output vectors $o_0, \ldots, o_T$ .
- At each time step $t$ (or position in the document sequence) the hidden state $s_t$ is defined in terms of the previous hidden state $s_{t-1}$ and the current input vector $x_t$ (new training example) in the following recursive way:

$$s_t = f(U x_t + W s_{t-1})$$

- Where f is a nonlinear function (i.e. $tanh$) and $U$ and $W$ are parameter matrices shared in all steps.
- $xt \in Rd^{in}$, where $d_{in}$ can be the size of the vocabulary,
- $s_t \in R^H$, where $H$: number of neurons composing that layer.
- The larger this layer, the greater the capacity of the memory – usually ranges in $10^2$.

# Gaussian Document Representation from Word Embeddings

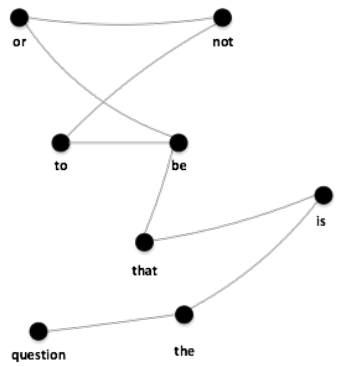
- How to represent a document in a collection?
- How to use the high quality word embeddings?
- State of the art approaches
- How to measure similarity/distance between documents?
- Evaluate performance on text classification tasks

***G.Nikolentzos, P. Meladianos, F. Rousseau, M. Vazirgiannis, Y.Stavrakas, EACL 2017, Valencia***

# Document representation

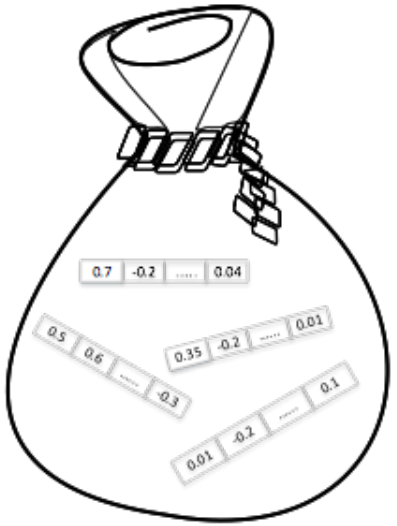
- Bag-of-Words
  - Document-term matrix
  - high dimensionality
  - sparse vectors
  - dimensions=|V|  |V|>10^6
  - unable to capture semantic similarity


- Graph-of-Words
  - captures co-occurrence
  - graph algorithms and techniques
  - graph kernels



# Bag-of-Vectors

- Distributed representations of words
  - store contextual information in a low-dimensional vector
  - dimensionality reduction
  - dimensions=m  100<m<500
  - able to capture semantic similarity between words
  - many learning methods (word2vec, GloVe, SVD)
- Document is represented by a bag-of-vectors
- Goal: meaningful document representations and distance metrics based on the representations of their words

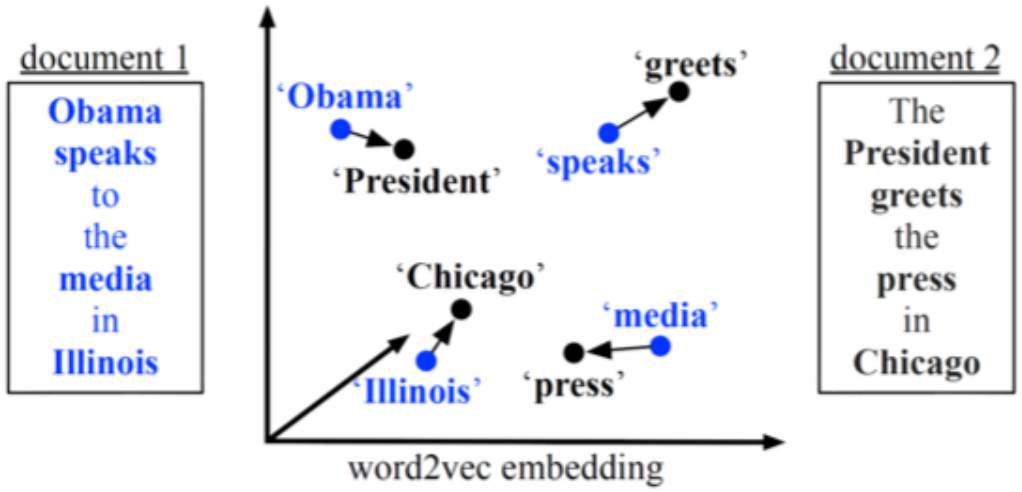


# Related work

- Centroid of vectors *[Lebret and Collobert, 2015]*
- Paragraph Vector *[Mikolov, 2014]*
  - vector representations for paragraphs by inserting an additional memory vector in the input layer.
- Word Mover's Distance *[Kusner, 2015]*
  - Calculates the cumulative edit distance between two documents
- CNN for document classification *[Kim, 2014]*
  - Use the high quality embeddings as input for Convolutional Neural Network

# Word Mover's distance

- Edit distance of 2 documents
- Based on word embedding representations
- Incorporate semantic similarity between individual word pairs into the document distance metric
- Based on "travel cost" between two words
- Calculates the cost of moving d to d'
- hyper-parameter free
- highly interpretable
- high retrieval accuracy



# CNN for document classification

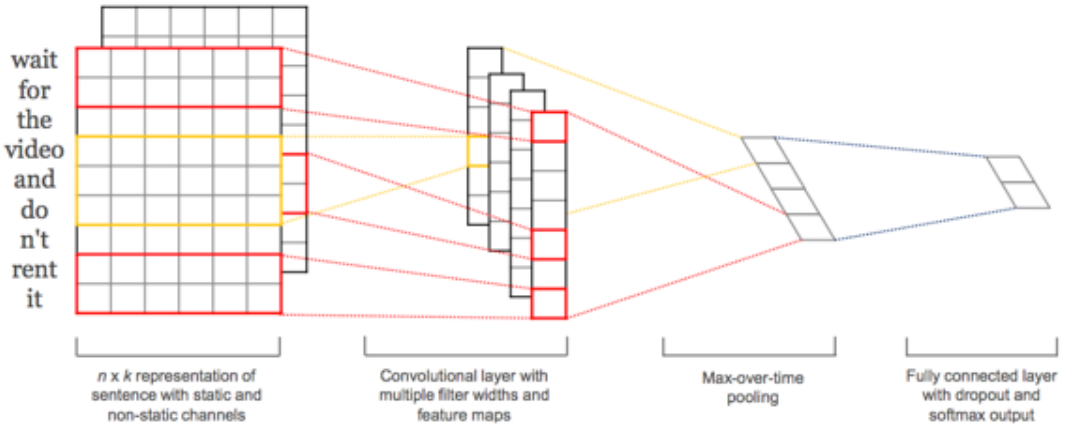
- Use the high quality embeddings as input for Convolutional Neural Network
- Input must be fixed size
- max-pooling deals with variable document lengths
- Applies multiple filters to concatenated word vectors

$$\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$$

- Produces new features for every filter

$$c_i = f(\mathbf{w} \cdot \mathbf{x}_{i:i+h-1} + b)$$

- And picks the max as a feature for the CNN



# Gaussian Document Representation from Word Embeddings

- assume that words w present in a document as i.i.d. samples drawn from a multivariate Gaussian distribution $\mathcal{D} = \{d_1, d_2, \ldots, d_m\}$
- document is represented as a multivariate Gaussian distribution $\mathbf{w} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
- mean vector $\boldsymbol{\mu} = \frac{1}{|d|} \sum_{w \in d} \mathbf{w}$
- covariance matrix $\boldsymbol{\Sigma} = \frac{1}{|d|} \sum_{w \in d} (\mathbf{w} - \boldsymbol{\mu})(\mathbf{w} - \boldsymbol{\mu})^T$
- Words contained in the vocabulary, but not contained in the embeddings model are initialized to random vectors

# Document Similarity

- centroid similarity

$$sim(\boldsymbol{\mu}_1, \boldsymbol{\mu}_2) = \frac{\boldsymbol{\mu}_1 \cdot \boldsymbol{\mu}_2}{\|\boldsymbol{\mu}_1\| \|\boldsymbol{\mu}_2\|}$$

- covariance similarity

$$sim(\boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2) = \frac{\sum \boldsymbol{\Sigma}_1 \circ \boldsymbol{\Sigma}_2}{\|\boldsymbol{\Sigma}_1\|_F \times \|\boldsymbol{\Sigma}_2\|_F}$$

- similarity between two documents

$$sim(d_1, d_2) = \alpha\big(sim(\boldsymbol{\mu}_1, \boldsymbol{\mu}_2)\big) + (1 - \alpha)\big(sim(\boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2)\big) \qquad \alpha \in [0, 1]$$

- valid kernel function

# Why Gaussian?

- Each document follows a distribution described by its topic
- Word embeddings capture lexico-semantic regularities
- Words with similar syntactic and semantic properties are found to be close to each other in the embedding space
- Semantically related words are localized in space
- Gaussian distributions capture a notion of centrality in space
- The choice of a Gaussian parameterization is justified by both analytic convenience and observations that Euclidean distances between embeddings correlate with semantic similarity

# Experiments

## Datasets

| Dataset | # training examples | # test examples | # classes | vocabulary size | *word2vec* size |
|---|---|---|---|---|---|
| Reuters | 5,485 | 2,189 | 8 | 23,585 | 15,587 |
| Amazon | 8,000 | CV | 4 | 39,133 | 30,526 |
| TREC | 5,452 | 500 | 6 | 9,513 | 9,048 |
| Snippets | 10,060 | 2,280 | 8 | 29,276 | 17,067 |
| BBCSport | 348 | 389 | 5 | 14,340 | 13,390 |
| Polarity | 10,662 | CV | 2 | 18,777 | 16,416 |
| Subjectivity | 10,000 | CV | 2 | 21,335 | 17,896 |
| Twitter | 3,115 | CV | 3 | 6,266 | 4,460 |

## Baselines

- BOW-SVM
- NBSVM
- Centroid-SVM
- WMD-KNN
- CNN

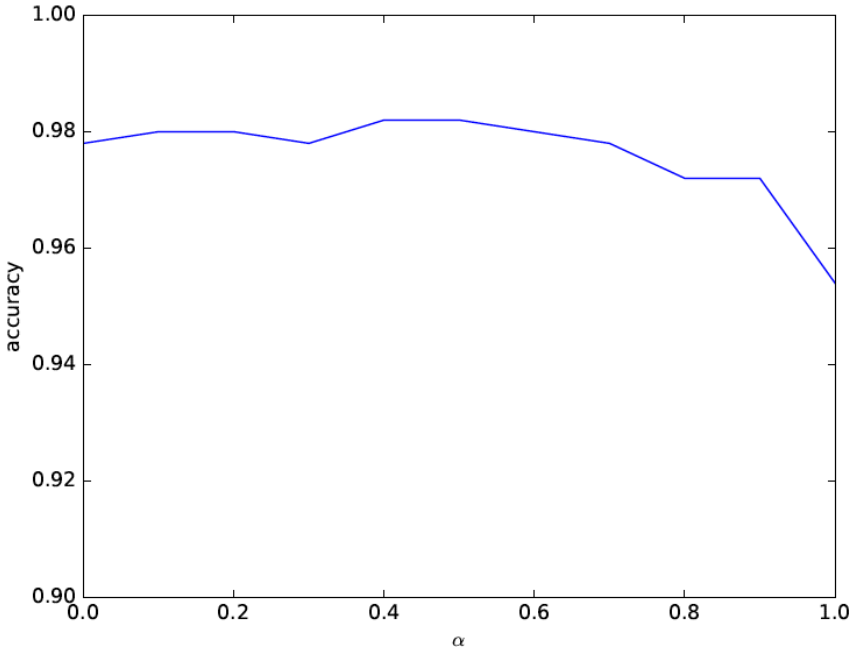
# Results

| Method \ Dataset | Reuters | | Amazon | | TREC | | Snippets | |
|---|---|---|---|---|---|---|---|---|
| | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** |
| BOW (binary) | 0.9571 | 0.8860 | 0.9126 | 0.9127 | 0.9660 | 0.9692 | 0.6171 | 0.5953 |
| Centroid | 0.9676 | 0.9171 | 0.9311 | 0.9312 | 0.9540 | 0.9586 | 0.8123 | 0.8170 |
| WMD | 0.9502 | 0.8204 | 0.9200 | 0.9201 | 0.9240 | 0.9336 | 0.7417 | 0.7388 |
| NBSVM | **0.9712** | 0.9155 | 0.9486 | 0.9486 | 0.9780 | 0.9805 | 0.6474 | 0.6357 |
| CNN | 0.9707 | 0.9297 | 0.9448 | 0.9449 | 0.9800 | 0.9800 | **0.8478** | **0.8466** |
| Gaussian | **0.9712** | **0.9388** | **0.9498** | **0.9497** | **0.9820** | **0.9841** | 0.8224 | 0.8244 |

| Method \ Dataset | BBCSport | | Polarity | | Subjectivity | | Twitter | |
|---|---|---|---|---|---|---|---|---|
| | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** | **Accuracy** | **F1-score** |
| BOW (binary) | 0.9640 | 0.9690 | 0.7615 | 0.7614 | 0.9004 | 0.9004 | 0.7467 | 0.6205 |
| Centroid | 0.9923 | 0.9915 | 0.7783 | 0.7782 | 0.9100 | 0.9100 | 0.7361 | 0.5727 |
| WMD | 0.9871 | 0.9866 | 0.6642 | 0.6639 | 0.8604 | 0.8603 | 0.7031 | 0.4436 |
| NBSVM | 0.9871 | 0.9892 | **0.8698** | **0.8698** | **0.9369** | **0.9368** | **0.7852** | 0.6191 |
| CNN | 0.9486 | 0.9461 | 0.8037 | 0.8031 | 0.9315 | 0.9314 | 0.7549 | 0.6137 |
| Gaussian | **0.9974** | **0.9974** | 0.8021 | 0.8020 | 0.9310 | 0.9310 | 0.7534 | **0.6443** |

# Results

- sensitivity of the classification to parameter a
- TREC dataset
- Centroid performance drops significantly
- highest accuracy a=0.5



# Conclusion

- Model each document as a Gaussian distribution based on the embeddings of its words
- Similarity between two documents based on the similarity of their distributions
- Empirical evaluation demonstrates the effectiveness of the approach across a range of data
- Performance gain is attributed to the high quality of the embeddings and the ability to effectively utilize them

# References and online resources

- **Artificial neural networks: A tutorial,** AK Jain, J Mao, KM Mohiuddin - Computer, 1996
- introduction from a coder's perspective: http://karpathy.github.io/neuralnets/
- http://cs231n.github.io/
- online book: http://neuralnetworksanddeeplearning.com/index.html
- history of neural nets: http://stats.stackexchange.com/questions/182734/what-is-the-difference-between-a-neural-network-and-a-deep-neural-network
- nice blog post on neural nets applied to NLP: http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/
- **A Primer on Neural Network Models for Natural Language Processing, Y. Goldberg,** *u.cs.biu.ac.il/~yogo/nnlp.pdf*