VL Deep Learning for Natural Language Processing

6. Word Classifiers

Prof. Dr. Ralf Krestel

AG Information Profiling and Retrieval

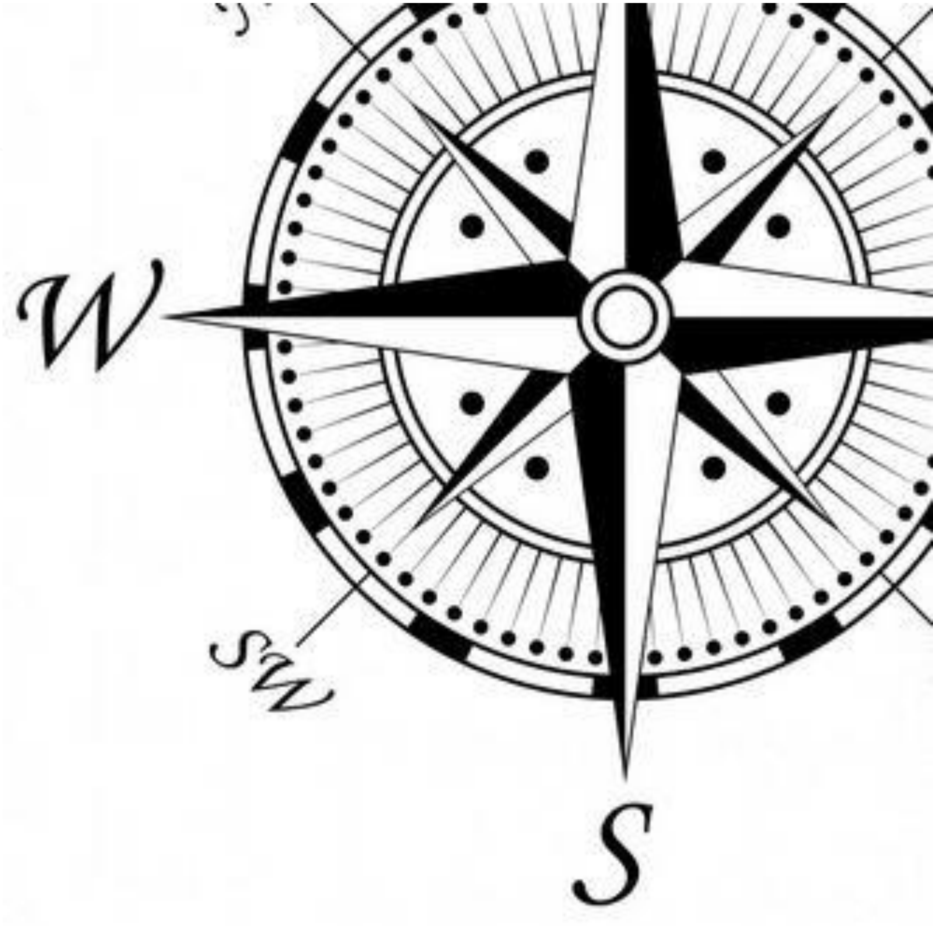
Learning Goals for this Chapter

- Know different input representations for text
  - and how/when to use them
- Develop a simple window classifier
- Understand the max-margin loss function
  - and know how to employ it

- Relevant chapters
  - P6.1
  - S3 (2019) https://www.youtube.com/watch?v=PLryWeHPcBs

Topics Today

1. **Text as Input to Neural Networks**
2. DNN to Classify Words
3. The Max-Margin Loss Function



What Makes Text Representation Hard?

- Noise
  - Spelling mistakes, colloquialisms, slang words, emoticons, …
- Ambiguity
  - multiple meanings, sarcasm, …
- Semantic structure
  - order and placement of words can drastically change the meaning, e.g., “not”
- Domain knowledge
  - understanding of the domain and domain jargon necessary
- Multilingualism
  - Mixed-code text, low resource languages

How to Process Text?

- Token-level
  - Character by character
- Word-level
  - One word at a time
- Sentence-level
  - Or fixed-size context window
- Document-level
  - Fixed-length chunk
  - E.g., first 100 words

Typically: sequential processing

- Recurrent neural networks (LSTM, GRU)
- Seq2seq models
- Transformers

Typically fixed-length, non-sequential

- Feed forward neural networks
- Convolutional neural networks (CNN)
- Generative adversarial networks (GAN)

How to Represent Text?

Alternatively: multiset of 1-hot-encoded word vectors

- **Bag-of-words (BOW) model**
  - Keep the frequency: word count
  - Other weights, e.g., TF-IDF
  - Binary: set of words, incident vectors (0/1 wether a word occurs at least once)
  - Optional: smoothing
  - Optional: normalization, stemming, etc.
  - Optional: n-grams

$$\begin{array}{ccc} \text{dogs} & & \text{DOC1} \\ \begin{bmatrix}0\\0\\1\\0\\0\\0\\0\\0\\0\\\vdots\\0\end{bmatrix} & \begin{matrix} John\\likes\\dogs\\Mary\\cats\\Both\\play\\soccer\\\cdots\\\vdots\\Zyzzyva\end{matrix} & \begin{bmatrix}1\\2\\1\\1\\1\\1\\1\\1\\0\\\vdots\\0\end{bmatrix}\end{array}$$

- Example

DOC1*: John likes dogs. Mary likes cats. Both play soccer.*

How to Represent Text?

- **Topic model**
  - Learn a latent (hidden) space
  - Based on singular value decomposition (SVD)
    - Latent semantic analysis (LSA) aka latent semantic indexing (LSI)
  - Based on probabilistic models
    - Probabilistic LSA (PLSA)
    - Latent Dirichlet allocation (LDA)

Manual topic titles

$$\begin{array}{c} \text{dogs} \\ \begin{bmatrix} 0.8 \\ 0 \\ 0.1 \\ 0 \\ \vdots \\ 0.1 \end{bmatrix} \end{array} \qquad \begin{array}{cc} & \text{DOC1} \\ \begin{array}{c} nature \\ politics \\ sport \\ \cdots \\ \vdots \\ entertain \end{array} & \begin{bmatrix} 0.4 \\ 0.1 \\ 0.4 \\ 0 \\ \vdots \\ 0.1 \end{bmatrix} \end{array}$$

Dimensions in latent space

- Example

DOC1: *John likes dogs. Mary likes cats. Both play soccer.*

How to Represent Text?

- **Embedding model**
  - Character-level
  - Subword-level
  - **Word-level**
  - Phrase- and sentence-level
  - Paragraph-level
  - Document-level
  - Combinations of levels also possible
    - e.g. character + word for NMT
    - or using lower-levels as additional input
- Example

Most meaningful

DOC1: *John likes dogs. Mary likes cats. Both play soccer.*

Can also be context-dependent

Dimensions in latent space

Alternatively: Multiset of word vectors

$$\text{dogs} \quad \begin{bmatrix} 0.16 \\ 0.21 \\ 0.18 \\ 0.04 \\ \vdots \\ 0.10 \end{bmatrix} \qquad \text{DOC1} \quad \begin{bmatrix} 0.05 \\ 0.11 \\ 0.09 \\ 0.02 \\ \vdots \\ 0.04 \end{bmatrix}$$

Meaningful structure along arbitrary directions

Average or sum of word vectors

Most Tasks and Applications

- Ordered multiset of words
  - 1-hot-encoded

↓

- Ordered multiset of embeddings
  - Dense word vectors for each word
  - Can be pretrained/fine-tuned

- Sequence of words
  - 1-hot-encoded

↓

- Sequence of embeddings
  - Dense word vectors for each word
  - Can be pretrained/fine-tuned

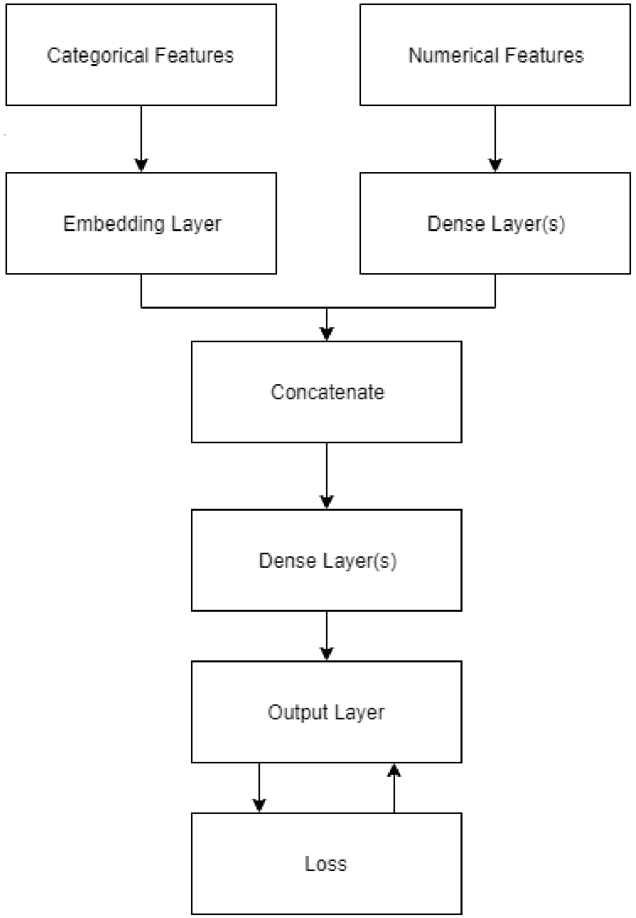
Different Input Data Types

- Categorical
  - Character
  - String (=array of char)
  - Text (indexed strings)

Objects with IDs

- Numerical
  - Real
  - Integer

- Combining different feature types
  - Concatenating their representations



Learning Word Embeddings for Preprocessing

- Goal of word2vec: Learn word vectors
  - Iterate through all words in a corpus
  - Predict which words occur in their contexts
  - Thus: Similar context results in similar word vectors!

- But **every** DNN learns a representation of the input data!
  - Word vectors can be learnt for a specific task.
  - Representation is then optimized towards the problem that needs to be solved.
    - For word2vec this problem is to predict the context (meaning).
    - Other nets predict other things, e.g., polarity (sentiment).

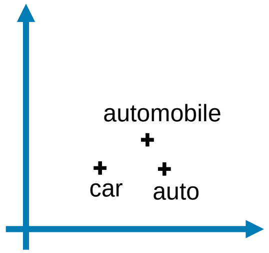
Input Data = Text

- Deep neural networks need tensors as input
  - One-hot-encoding
    - Bag-of-words
    - Sparsely populated
  - Embedding
    - Dimensionality reduction
    - Densly populated

- Embedding Layer can learn representation **task-specific**
  - First layer in a DNN learns dimensionality reduction / representation
- **Pretrained** Embeddings can be used
  - First layer maps input words to pretrained word vectors

Pretrained Word Vectors vs. Newly Learned

- Classic machine learning
  - Learning feature weights ($\mathbb{R}^{Cd}$)
- Deep Learning
  - Learning feature weights and word vectors ($\mathbb{R}^{Cd+Vd}$)
  - Vd is very large
    - Danger of overfitting



- How about a compromise?
  - Load pretrained word vectors and then continue training with current data?

Fine-Tuning

- Problem:
  - Words that occur in the training set move around in the embedding space; words that do not occur in the training set but maybe in the test set stay where they are.

The Embedding Layer

- Example: DOC2*: John likes dogs. Mary likes cats.*
- Index of words: $[0,1,2,3,1,4]^T$
- Input matrix I:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Why do we need a special embediding layer?
Why not use a normal fully connected, dense layer?

- Assume a 3-dimensional embedding layer with weight matrix W:

$$\begin{bmatrix} 0.1 & 0.4 & 0.2 \\ 0.4 & 0.3 & 0.2 \\ 0.5 & 0.6 & 0.5 \\ 0.3 & 0.2 & 0.8 \\ 0.6 & 0.6 & 0.1 \end{bmatrix}$$

The Embedding Layer

- The output would be $I * W =$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 0.1 & 0.4 & 0.2 \\ 0.4 & 0.3 & 0.2 \\ 0.5 & 0.6 & 0.5 \\ 0.3 & 0.2 & 0.8 \\ 0.6 & 0.6 & 0.1 \end{bmatrix}$$

$$= \begin{bmatrix} 1*0.1+0*0.4+0*0.5+0*0.3+0*0.6 & 1*0.4+0*0.3+0*0.6+0*0.2+0*0.6 & 1*0.2+0*0.2+0*0.5+0*0.8+0*0.1 \\ & \dots & \\ & \dots & \\ & \dots & \\ & \dots & \\ & \dots & \end{bmatrix}$$

$$= \begin{bmatrix} 0.1 & 0.4 & 0.2 \\ 0.4 & 0.3 & 0.2 \\ 0.5 & 0.6 & 0.5 \\ 0.3 & 0.2 & 0.8 \\ 0.4 & 0.3 & 0.2 \\ 0.6 & 0.6 & 0.1 \end{bmatrix}$$

The embedding layer selects directly the right vectors: $[0,1,2,3,1,4]^T$

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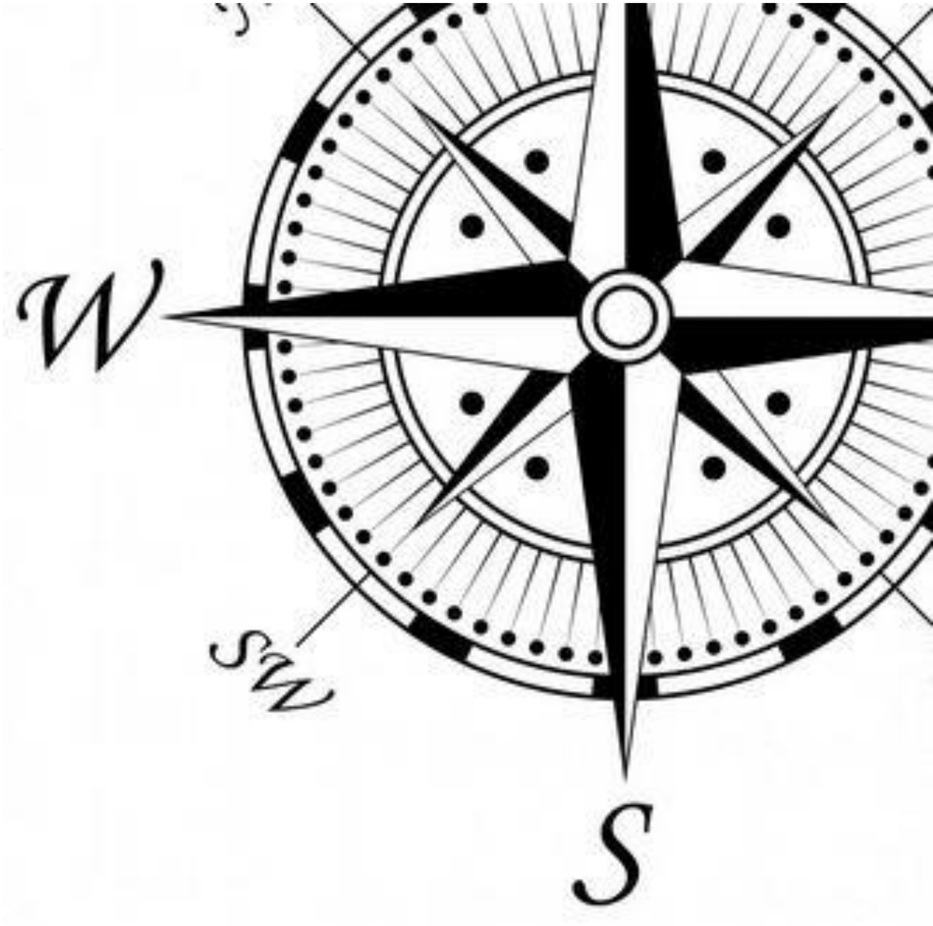
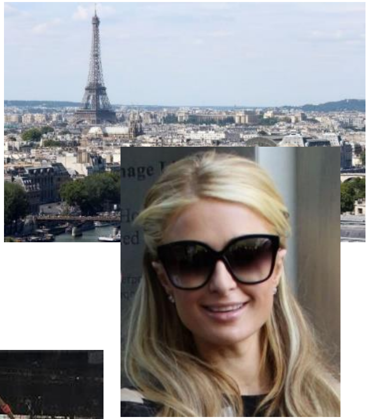
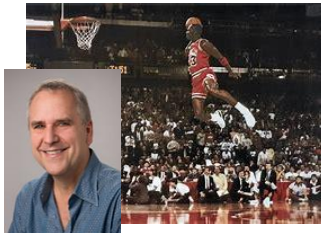


Word Classification

- Isolated, individual words are rarely classified
  - Meaning of words only clear in context
- Ambiguity can only be resolved in context
  - Autoantonyms: Same words, opposite semantics
    - Overlook, comprise, dust, left, …
  - Ambigous named entities
    - Paris
    - Michael Jordan
    - Orange





Classification with Context

- Idea: Classification of a word in the context of its k neighboring words
- E.g. named entity recognition (NER) can be modeled as word classification with four classes:
  - person, organization, location, none

- Naive approach:
  - Average of all word vectors in the context window.
  - Problem: Position information is lost

- Better:
  - Concatenating all word vectors from the context window

Window Classifier

- Softmax classifier
  - Input: the target word to be classified and neighboring words in a context window of size k, left and right of the target word
  - Output: probability distribution over four named entity classes
- Example: Classification of the word *Paris* as location with context of size two:

…	museums	in	Paris	are	amazing	…
	$\begin{bmatrix}\blacklozenge\\\blacklozenge\\\blacklozenge\end{bmatrix}^T$	$\begin{bmatrix}\blacklozenge\\\blacklozenge\\\blacklozenge\end{bmatrix}^T$	$\begin{bmatrix}\blacklozenge\\\blacklozenge\\\blacklozenge\end{bmatrix}^T$	$\begin{bmatrix}\blacklozenge\\\blacklozenge\\\blacklozenge\end{bmatrix}^T$	$\begin{bmatrix}\blacklozenge\\\blacklozenge\\\blacklozenge\end{bmatrix}^T$	
$\boldsymbol{x}_{window} =$	$[\boldsymbol{x}_{museums}$	$\boldsymbol{x}_{in}$	$\boldsymbol{x}_{Paris}$	$\boldsymbol{x}_{are}$	$\boldsymbol{x}_{amazing}]^T$	

- The input vector is a column vector in $\mathbb{R}^{5d}$
  - $\boldsymbol{x}_{window} = [\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge\blacklozenge]^T$

Simplest Window Classifier

- Use softmax function!
- With $\boldsymbol{x} = \boldsymbol{x}_{window}$ we can use softmax on the concatenated word vectors

$$\hat{y}_y = p(y|x) = \frac{\exp(W_y.x)}{\sum_{c=1}^{C} \exp(W_c.x)}$$

$\boldsymbol{W} \in \mathbb{R}^{\boldsymbol{C \times d}}$

- Loss function as usual: cross entropy

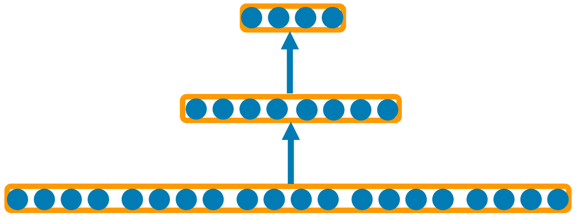
$$J(\theta) = \frac{1}{N} \sum_{i=1}^{N} -\log\left(\frac{e^{f_{y_i}}}{\sum_{c=1}^{C} e^{f_c}}\right)$$

$\boldsymbol{f}_{\boldsymbol{y}} = \boldsymbol{W}_{\boldsymbol{y}}.\boldsymbol{x}$

- How are the word vectors learned?
  - Gradient descend!
  - Analogous to word2vec

Additional Layer

- Up to now, we only have an input layer (word vectors) and a softmax output layer.
- Softmax can only discriminate linearly in the input space
  - No dependencies of the individual words in the window
- Thus, additional layer with non-linear activation function
  - Example: only if „*museums*“ is the first vector, then the „*in*“ at position two is important



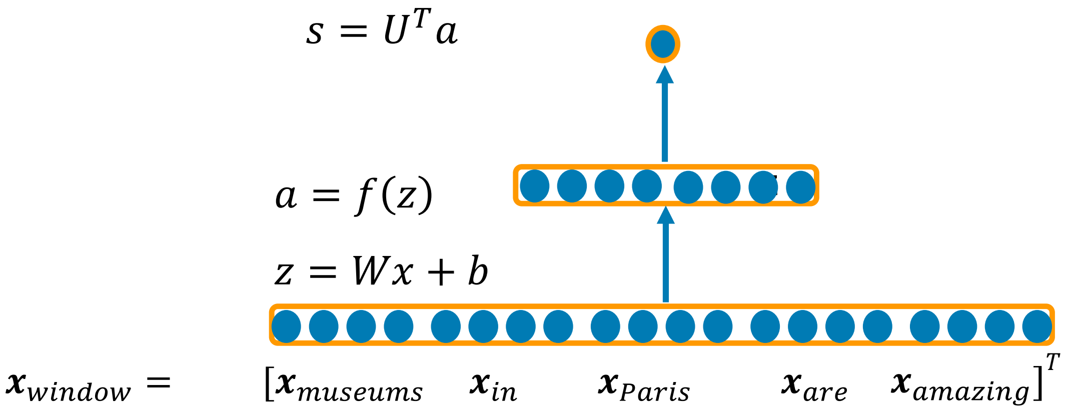
$$x_{window} = [x_{museums} \quad x_{in} \quad x_{Paris} \, x_{are} \quad x_{amazing}]^T$$

Single Layer Neural Network

- Input: Concatenated word vectors of a window x
- Hidden layer: $z = Wx + b$ with activation function $a = f(z)$
- Output layer:
  - Softmax for probability distribution over multiple classes
    - $p(y|x) = softmax(Wa)$
  - Easier: non-normalized score for each class
    - $score(x) = U^T a \in \mathbb{R}$

Forward Pass

- Score for one window:
  - s=score(museums in Paris are amazing)
  - $s = \boldsymbol{U}^T f(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}) \quad \boldsymbol{x} \in \mathbb{R}^{20\times1}, \boldsymbol{W} \in \mathbb{R}^{8\times20}, \boldsymbol{U} \in \mathbb{R}^{8\times1}$



$s = U^T a$
$a = f(z)$
$z = Wx + b$
$\boldsymbol{x}_{window} = [\boldsymbol{x}_{museums} \quad \boldsymbol{x}_{in} \quad \boldsymbol{x}_{Paris} \quad \boldsymbol{x}_{are} \quad \boldsymbol{x}_{amazing}]^T$

Word Classifier

- How does the network architecture look like if softmax over four classes should be used for the output layer?

- Which effect do the window size and the dimensionality of the word vectors have?
  - On runtime,
  - memory,
  - Quality of results?

Start 5 4 3 2 1 End

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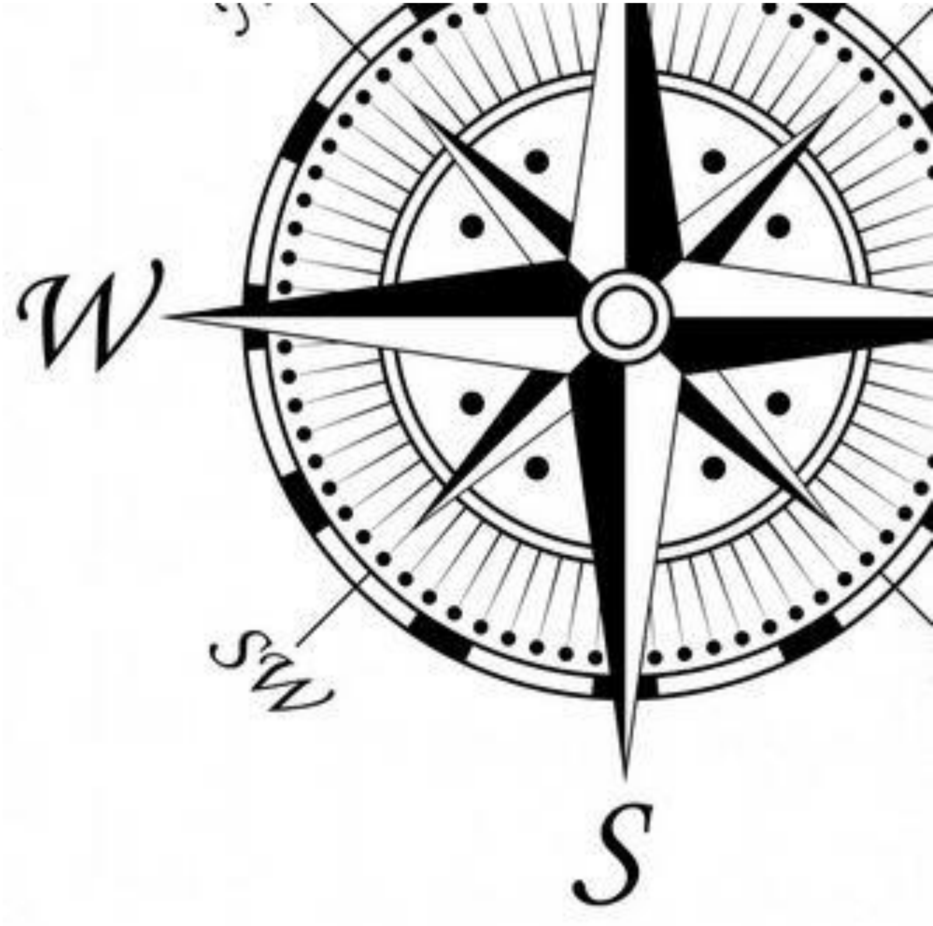


Max-Margin Loss Function Idea

- Many windows to train
  - Most of them don‘t have a location in the center
    - Those are called „corrupt“ or negative samples
- Example
  - $s = score(museums\ in\ Paris\ are\ amazing)$
  - $s_c = score(Not\ all\ museums\ in\ Paris)$
- Score of positive examples should be high; score of negative examples should be low
- Target function
  - $J = \max(0, \underbrace{1}_{\text{margin}} - s + s_c)$
  - Not differentiable but continuous
    - SGD

For One Training Sample

- $J = \max(0, 1 - s + s_c)$

- For each positive window, i.e. with a location in the center
  - Sample *m* negative windows
  - Sum over these training windows

- The score for each positive window should be at least 1.0 higher than the highest score of the negative windows

Training with Backpropagation

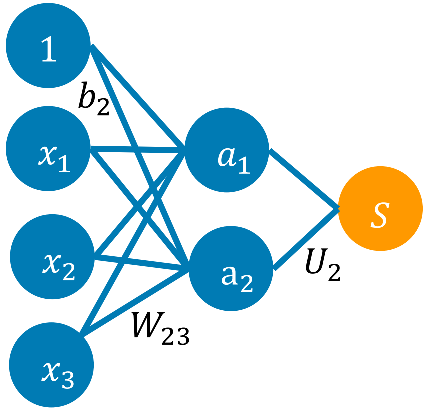
- $J = \max(0, 1 - s + s_c)$
  - Assumption at start $J > 0$

- $s = U^T f(Wx + b)$
- $s_c = U^T f(Wx_c + b)$

- Derivatives of s and s_c with respect to all involved variables: U, W, b, x

- Gradient with Respect to U

$$\frac{\partial s}{\partial U} = \frac{\partial}{\partial U} U^T a = a$$



Gradient with Respect to W

- $\frac{\partial s}{\partial W} = \frac{\partial}{\partial W} U^T a = \frac{\partial}{\partial W} U^T f(z) = \frac{\partial}{\partial W} U^T f(Wx + b)$
- Derivative of single weight W_{ij}

$$z_i = W_{i.}x + b_i = \sum_k W_{ij}x_j + b_i$$

$$a_i = f(z_i)$$

$$\frac{\partial s}{\partial W_{ij}} = \frac{\partial}{\partial W_{ij}} U_i a_i$$

W_{ij} only appears within a_i

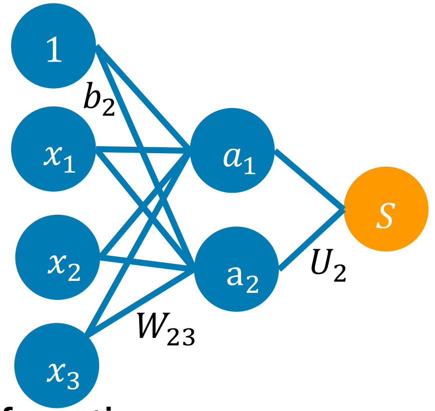
$$= U_i \frac{\partial}{\partial W_{ij}} a_i$$

$$= U_i \frac{\partial a_i}{\partial z_i} \frac{\partial z_i}{\partial W_{ij}} = U_i \frac{\partial f(z_i)}{\partial z_i} \frac{\partial z_i}{\partial W_{ij}}$$

$$= U_i f'(z_i) \frac{\partial z_i}{\partial W_{ij}} = U_i f'(z_i) \frac{\partial W_{i.}x + b_i}{\partial W_{ij}}$$

$$= U_i f'(z_i) \frac{\partial}{\partial W_{ij}} \sum_k W_{ik} x_k$$

W_{ij} only appears together with x_j



$$= \underbrace{U_i f'(z_i)}_{\text{Local error signal } \delta_i} \underbrace{x_j}_{\text{Local input signal } x_j}$$

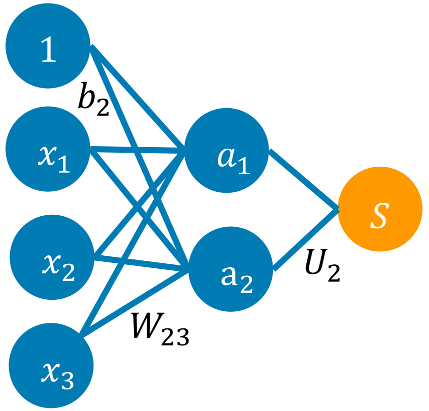
with $f'(z) = f(z)(1 - f(z))$ for the logistic function

Gradient with Respect to W

- $\frac{\partial s}{\partial W} = \frac{\partial}{\partial W} U^T a = \frac{\partial}{\partial W} U^T f(z) = \frac{\partial}{\partial W} U^T f(Wx + b)$
- From single weight W_{ij} to full W:
  $\frac{\partial s}{\partial W_{ij}} = U_i f'(z_i) x_j = \delta_i x_j$
- We want all combinations i=1,2 and j=1,2,3
  – We need all, i.e., complete matrix W
- Solution:
  –Dyadic product (outer product), often denoted $\otimes$
  –In contrast to scalar product (inner product)
  $\frac{\partial s}{\partial W} = \delta x^T$ with $\delta \in R^{2\times 1}$ is the error signal coming from each activation a

$$z_i = W_{i \cdot} x + b_i = \sum_k W_{ij} x_j + b_i$$

$$a_i = f(z_i)$$



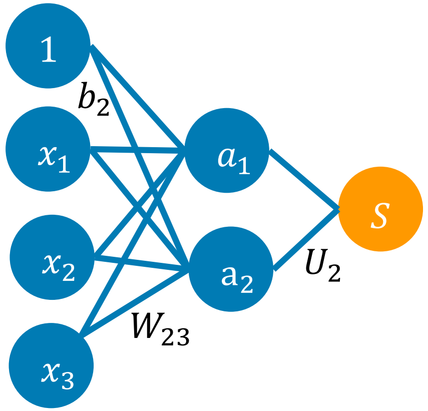
Dimensions of $\frac{\partial s}{\partial W}$?

Gradient with Respect to b

- $J = \max(0, 1 - s + s_c)$

- $s = U^T f(Wx + b)$
- $s_c = U^T f(Wx_c + b)$

- $\frac{\partial s}{\partial U} = \frac{\partial}{\partial U} U^T a = a$
- $\frac{\partial s}{\partial W} = \delta x^T$
- $\frac{\partial s}{\partial b_i} = U_i f'(z_i) \frac{\partial W_{i\cdot} x + b_i}{\partial b_i} = \delta_i$
- $\frac{\partial s}{\partial b} = \delta$



Gradient with Respect to x

- $J = \max(0, 1 - s + s_c)$
- $s = U^T f(Wx + b)$
- $s_c = U^T f(Wx_c + b)$

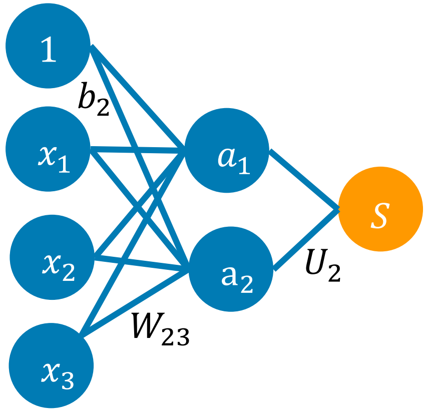
- $\frac{\partial s}{\partial x_j} = \sum_{i=1}^{2} \frac{\partial s}{\partial a_i} \frac{\partial a_i}{\partial x_j}$
- $= \sum_{i=1}^{2} \frac{\partial U^T a}{\partial a_i} \frac{\partial a_i}{\partial x_j}$
- $= \sum_{i=1}^{2} U_i \frac{\partial f(W_{i\cdot}x + b)}{\partial x_j}$
- $= \sum_{i=1}^{2} U_i f'(z_i) \frac{\partial W_{i\cdot}x}{\partial x_j}$
- $= \sum_{i=1}^{2} \delta_i W_{ij}$
- $= W_{\cdot j}^T \delta$

Dimensions of $\frac{\partial s}{\partial x_j}$?

- Up to now only derivative with respect to one x_j
- Complete gradient of x

$$\frac{\partial s}{\partial x} = W^T \delta$$

Dimensions of $\frac{\partial s}{\partial x}$?



All Gradients

- $J = \max(0, 1 - s + s_c)$
- $s = U^T f(Wx + b)$
- $s_c = U^T f(Wx_c + b)$
- Derivatives of s and s_c with respect to all involved variables: U, W, b, x
- $\frac{\partial s}{\partial U} = \frac{\partial}{\partial U} U^T a = a$
- $\frac{\partial s}{\partial W} = \delta x^T$
- $\frac{\partial s}{\partial b} = \delta$
- $\frac{\partial s}{\partial x} = W^T \delta$
- From s to J: indicator fuction: $[\![1 - s + s_c > 0]\!] = \begin{cases} 1 & if\ 1 - s + s_c > 0 \\ 0 & else \end{cases}$
- E.g. gradient of J with respect to U: $\frac{\partial J}{\partial U} = [\![1 - s + s_c > 0]\!](-a + a_c)$

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Literature

- Li, J., Sun, A., Han, J., & Li, C. (2020). A survey on deep learning for named entity recognition. *IEEE Transactions on Knowledge and Data Engineering*, *34*(1), 50-70.
  - https://arxiv.org/pdf/1812.09449.pdf