Text classification

Based on lecture by Ekaterina Artemova

- **Problem statement**
- **Logistic regression model**
- **Simple document embeddings models**
- **Neural networks for classification, FastText**
- **Convolutional neural networks for text classification**
- **Data processing in text classification**

Problem statement

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Data:

- $d \in D$ set of documents
- $c \in C$ set of labels

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Types of classification:

- binary classification $|C| = 2, \quad \forall d \in D \leftrightarrow c \in C$
- multiclass classification $|C| = K, K > 2, \quad \forall d \in D \leftrightarrow c \in C$
- multilabel classification $|C| = K, K > 2, \quad \forall d \in D \leftrightarrow C' \subseteq C$

Problem examples

- spam detection (binary)
  C = {spam, not spam}

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Меня зовут Бакаре Тунде, я брат первого нигерийского космонавта, майора ВВС Нигерии Абака Тунде. Мой брат стал первым африканским космонавтом, который отправился с секретной миссией на советскую станцию «Салют-6» в далеком 1979 году.

Здравствуйте!

До 30 апреля по всей России объявлены нерабочие дни.

Мы верим, что Вы очень ответственно отнеслись к сложившейся ситуации. Надеемся, что Вы планируете остаться дома со своей семьей и минимизировать внешние контакты. Это важно именно сейчас, чтобы защитить себя и других.

Problem examples

- Sentiment analysis (multiclass)
  C = {negative, positive, neutral}

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Пончик или пышка — круглое или кольцеобразное, жаренное во фритюре хлебобулочное изделие, с начинкой или без неё. Пышка в узком смысле слова — пончик без начинки с дыркой посередине.

Обожаю пончики на завтрак! Это лучшее начало трудового дня, они заряжают энергией и хорошим настроением меня и всю мою семью. Гомер С.

Никогда больше не стану покупать у вас пончики. В пончике должна быть ОДНА дырка посредине, а в вашем пончике я нашла 15! Ну это никуда не годится!

Problem examples

- Articles tagging (multilabel)
  C = {sport, politics, health, ...}

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«Зенит» на своем YouTube-канале провел онлайн-трансляцию тренировки футболистов в самоизоляции. Занятие прошло под руководством тренера по физподготовке Андреа Сканавино.

Посольство Северной Кореи в РФ поблагодарило КПРФ за телеграмму, направленную партией северокорейскому лидеру Ким Чен Ыну по случаю годовщины саммита РФ и КНДР, сообщил РИА Новости депутат от КПРФ Казбек Тайсаев.

Quality metrics for binary classification

Real classes

Predicted classes

	Class 0	Class 1
Class 0	True positive (tp)	False positive (fp)
Class 1	False negative (fn)	True negative (tn)

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- Accuracy

$$Acc = \frac{tp+tn}{tp+tn+fp+fn}$$

Quality metrics for binary classification

Real classes

Predicted classes

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Class 0	True positive (tp)	False positive (fp)
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- Accuracy
- Precision

$$Acc = \frac{tp+tn}{tp+tn+fp+fn}$$

$$Pr = \frac{tp}{tp+fp}$$

Quality metrics for binary classification

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- Accuracy

$$Acc = \frac{tp+tn}{tp+tn+fp+fn}$$

- Precision

$$Pr = \frac{tp}{tp+fp}$$

- Recall

$$R = \frac{tp}{tp+fn}$$

Quality metrics for binary classification

Predicted classes \ Real classes	Class 0	Class 1
Class 0	True positive (tp)	False positive (fp)
Class 1	False negative (fn)	True negative (tn)

- Accuracy
- Precision
- Recall
- F-score

$$Acc = \frac{tp+tn}{tp+tn+fp+fn}$$

$$Pr = \frac{tp}{tp+fp}$$

$$R = \frac{tp}{tp+fn}$$

$$F_1 = \frac{2}{1/Pr+1/R} = \frac{2 \cdot Pr \cdot R}{Pr+R}$$

Quality metrics for binary classification

Real classes

Predicted classes

	Class 0	Class 1	Class 2
Class 0	tn_{00}	fn_{10}	tn_{02}
Class 1	fp_{10}	$\boxed{tp_1}$	fp_{12}
Class 2	tn_{20}	fn_{12}	tn_{22}

Quality metrics for binary classification

Real classes

Predicted classes

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Class 0	tn_{00}	fn_{10}	tn_{02}
Class 1	fp_{10}	tp_1	fp_{12}
Class 2	tn_{20}	fn_{12}	tn_{22}

- Micro-averaging

$$Pr_{micro} = \frac{\sum tp_i}{\sum tp_i + \sum\sum fp_{ij}} \qquad R_{micro} = \frac{\sum tp_i}{\sum tp_i + \sum\sum fn_{ij}}$$

Quality metrics for binary classification

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$$Pr_{micro} = \frac{\sum tp_i}{\sum tp_i + \sum\sum fp_{ij}} \qquad R_{micro} = \frac{\sum tp_i}{\sum tp_i + \sum\sum fn_{ij}}$$

- Macro-averaging

$$Pr_{macro} = \frac{\sum Pr_i}{|C|} \qquad R_{macro} = \frac{\sum R_i}{|C|}$$

Features for text classification

- Features for classification can be extracted from text:
  - smileys count
  - words (and n-grams!)
  - syntactic structure

Features for text classification

- Features for classification can be extracted from text:
  - smileys count
  - words (and n-grams!)
  - syntactic structure
- External information can be useful, too:
  - author's age
  - number of citations

Text classification models

- Text classification can be solved by the same models, as the classical classification task:
  - linear models
  - metric models
  - decision trees
  - neural networks
  - …

Text classification models

- Text classification can be solved by the same models, as the classical classification task:
  - linear models
  - metric models
  - decision trees
  - neural networks
- Model type can be chosen based on
  - data type and amount
  - performance requirements, complexity of customization and support

Multiclass classification

- Binary classification model can always be adapted to multiclass case
- Two possible strategies:

Multiclass classification

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  - «One-vs-rest»
    - train a model for each class, the model can divide one class from the rest classes

Multiclass classification

- Binary classification model can always be adapted to multiclass case
- Two possible strategies:
    - «One-vs-rest»
        - train a model for each class, the model can divide one class from the rest classes
    - «One-vs-one»:
        - Train a classifier for each pair of classes
        - Useful for classifiers that work poorly with big data
        - Final class is chosen by majority vote

Main conclusions

- Text classification problem statement and approaches are similar to classical ones
- Main quality metrics are accuracy, precision, recall, F-score
- You can apply most of classical models
- Binary models can be adapted to multiclass case

Logistic regression model

Linear models

- Let *x* be a vector representation of a document, *y* - document class, *w* - a vector of linear model weights

Linear models

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- Model can be trained with different loss functions:

  - Logistic $\log(1 + \exp(-y\langle x, \omega\rangle))$
  - Hinge-loss $\max(0, 1 - y\langle x, \omega\rangle))$
  - Quadratic $\frac{1}{2}(y - \langle x, \omega\rangle))^2$

Linear models

- Let x be a vector representation of a document, y - document class, w - a vector of linear model weights
- Model can be trained with different loss functions
- Model can have different regularization:
  - Lasso:
    $$\alpha \| w \|_1$$
  - Ridge:
    $$\alpha \| w \|_2$$
  - ElasticNet:
    $$\alpha \| w \|_1 + \beta \| w \|_2$$

Logistic regression

- Linear model with logistic loss function - simple and good solution for text classification
- Model output:

$$p(c = 1|d) = \frac{1}{1+\exp(-z)}, \; z = \omega^T x$$

w - a vector of linear model weights

x - a vector representation of a document

In multiclass case we replace logistic function with softmax

Logistic regression

Advantages

- Fast training
- Interpretability
- Easy inference

Disadvantages

- Linear model can’t cope with difficult cases (and non-linear dependencies)

Threshold binarization

- Output of logistic regression is a probability of class 1

- You should choose a threshold for probability binarization

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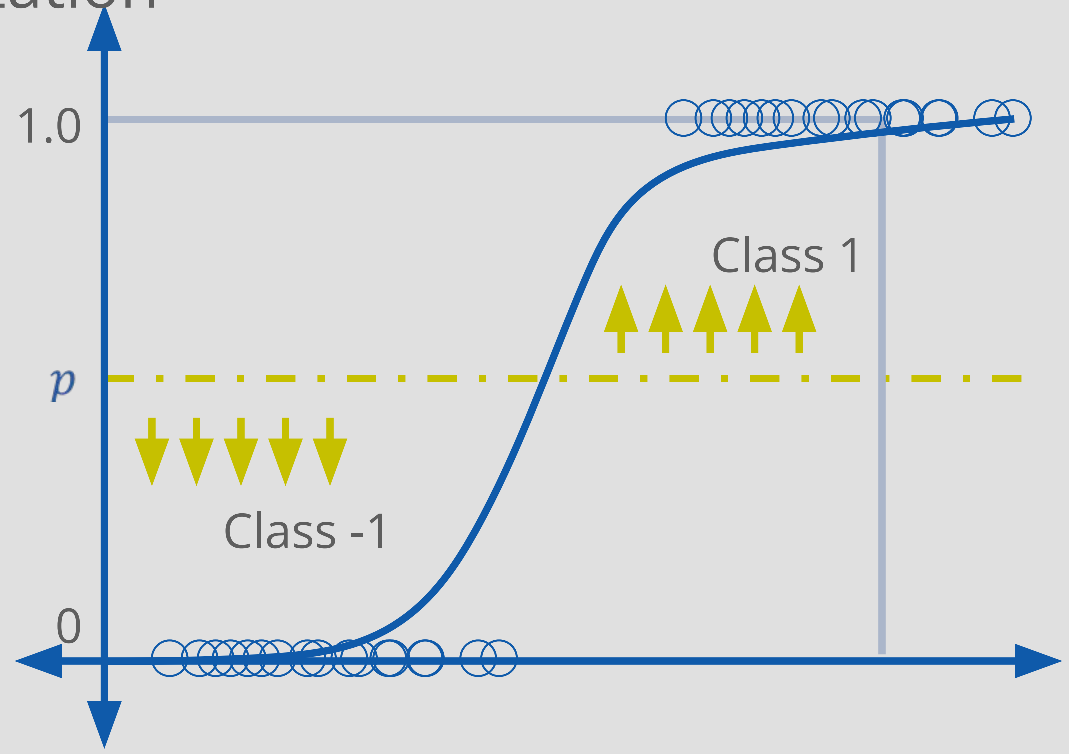
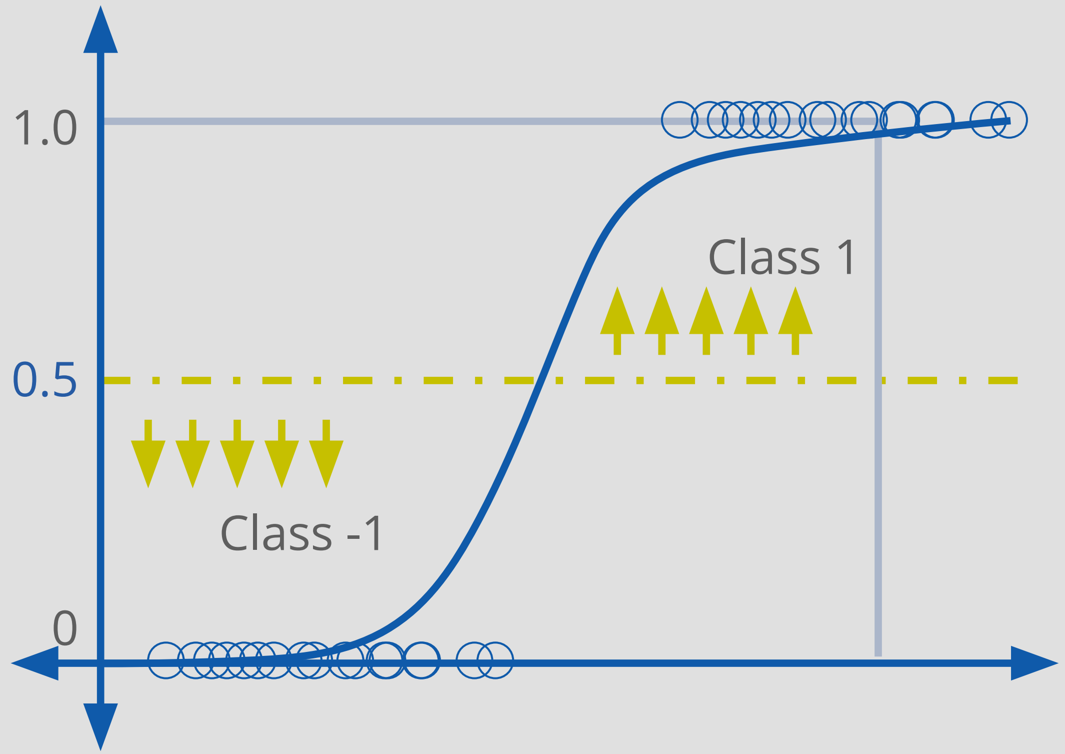


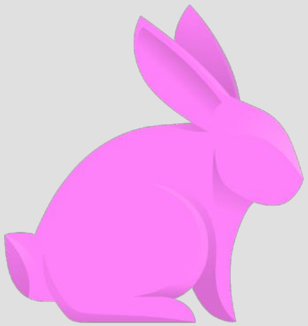
Threshold binarization

- Standard threshold is 0.5 but in order to take into account the specifics of the data it is better to select the threshold on the validation set



Vowpal Wabbit

- An efficient cross-platform tool for training linear models on big data
- Originally a product of Yahoo!, now Microsoft
- Supports basic loss functions, regularization



vowpalwabbit.org

Vowpal Wabbit

vowpalwabbit.org

- An efficient cross-platform tool for training linear models on big data
- Originally a product of Yahoo!, now Microsoft
- Supports basic loss functions, regularization
- Uses several optimization methods, main one - SGD
- Trains model in streaming, constantly retrains model on new data
- Uses hashing trick for RAM usage optimization memory
- Can be applied as console application, or C++, C#, Java and Python package

Main conclusions

- Logistic regression model is often used for text classification
- It is important to select the binarization threshold after model training
- Vowpal Wabbit allows to train linear models on large-scale data

Simple document embeddings models

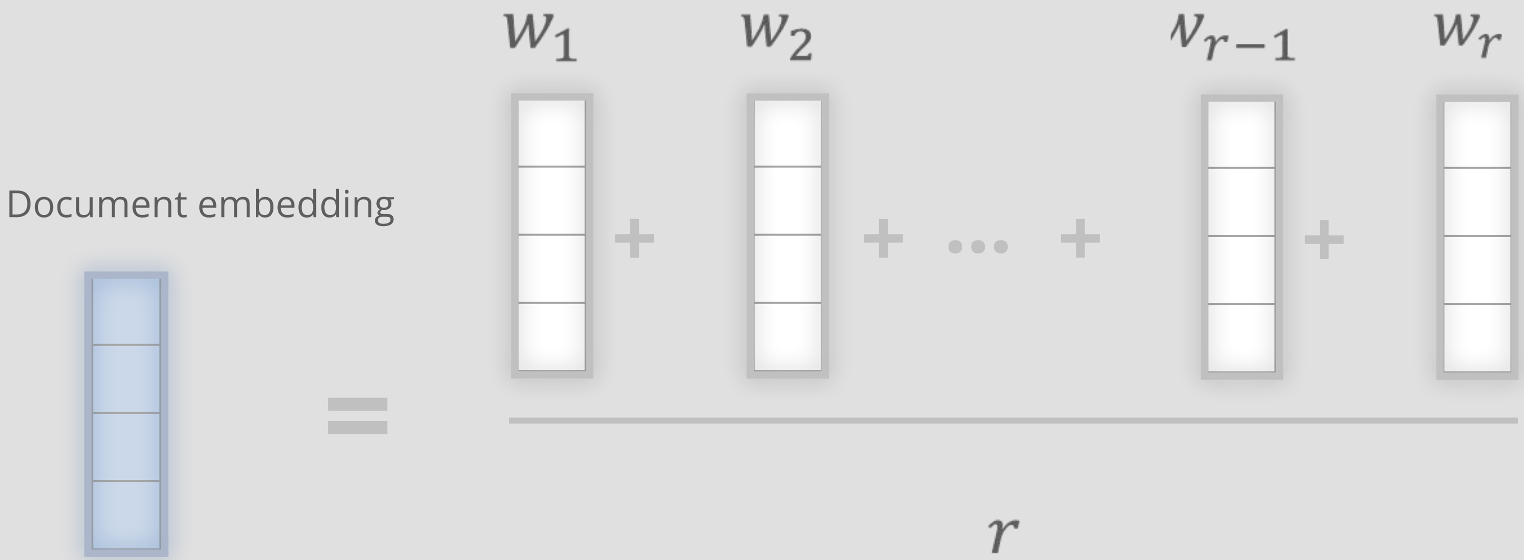
Basic text representations

REMINDER

- Document from collection size m with a vocabulary with size n can be represented with an embedding of size n:
  - Bag of words
  - TF-IDF
  - SVD on a BoW matrix

Word embeddings averaging

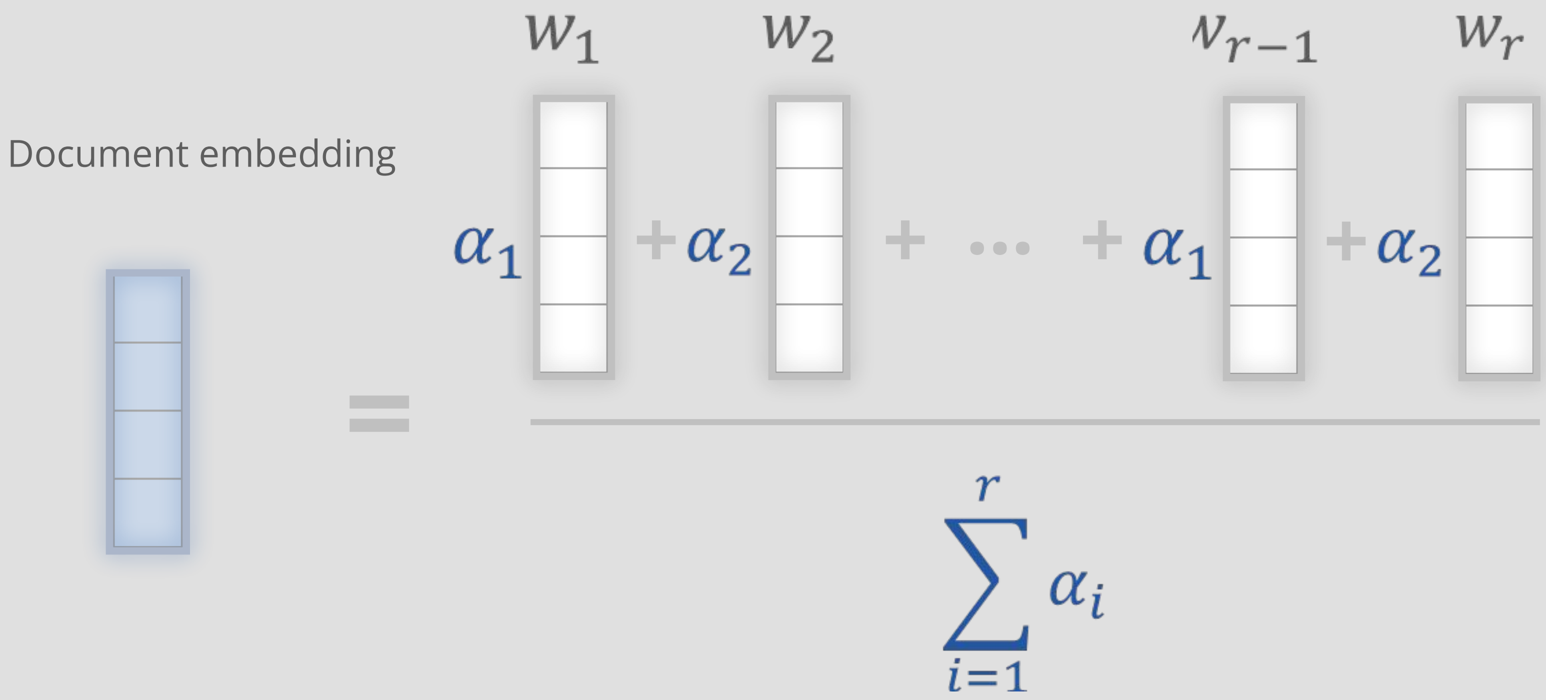
- In order to obtain document embedding you can calculate the average of embeddings of words (such as word2vec, GloVe or FastText)



- It is simple and quite effective

Weighted average

- You can add weights into averaging



- Weights can be obtained from TF-IDF matrix

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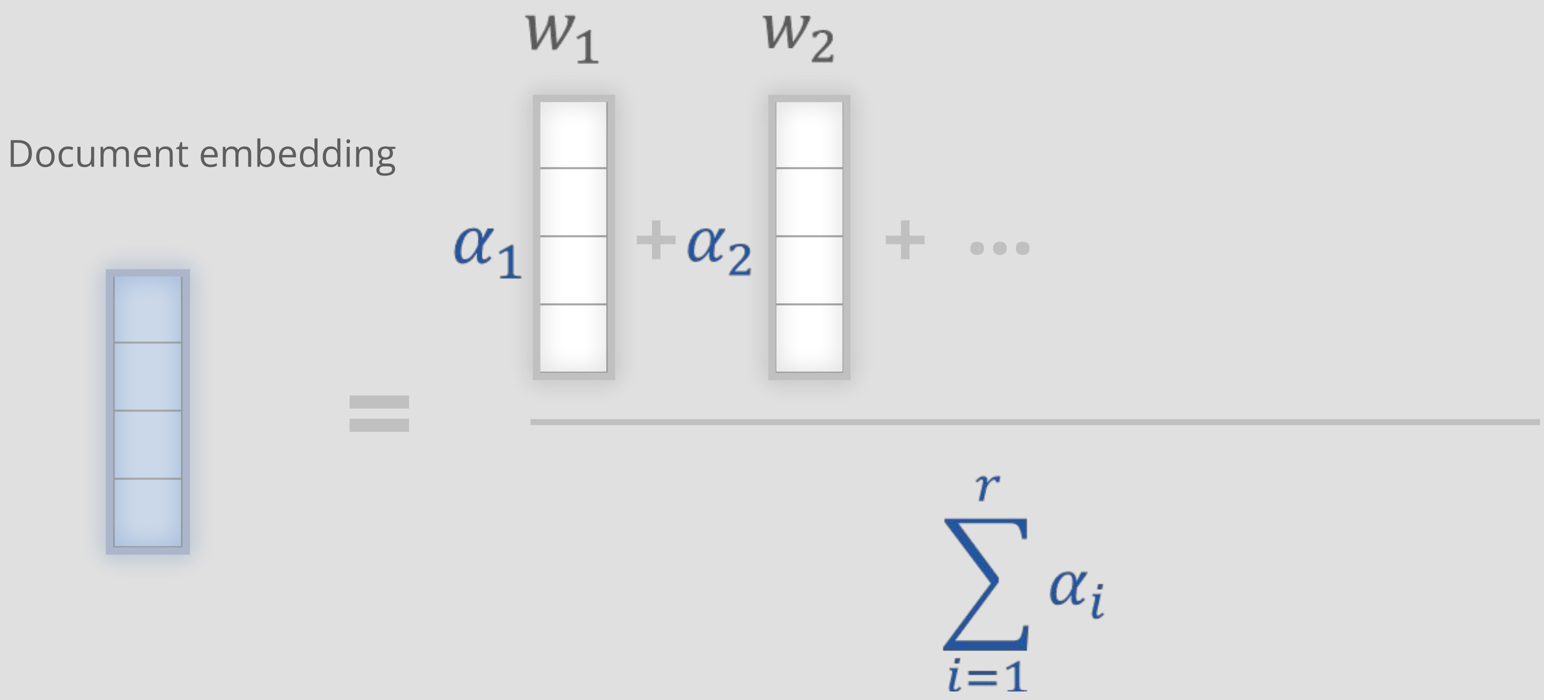


- Zero weights of stop-words and unimportant words allow us to obtain a good embedding even for long documents

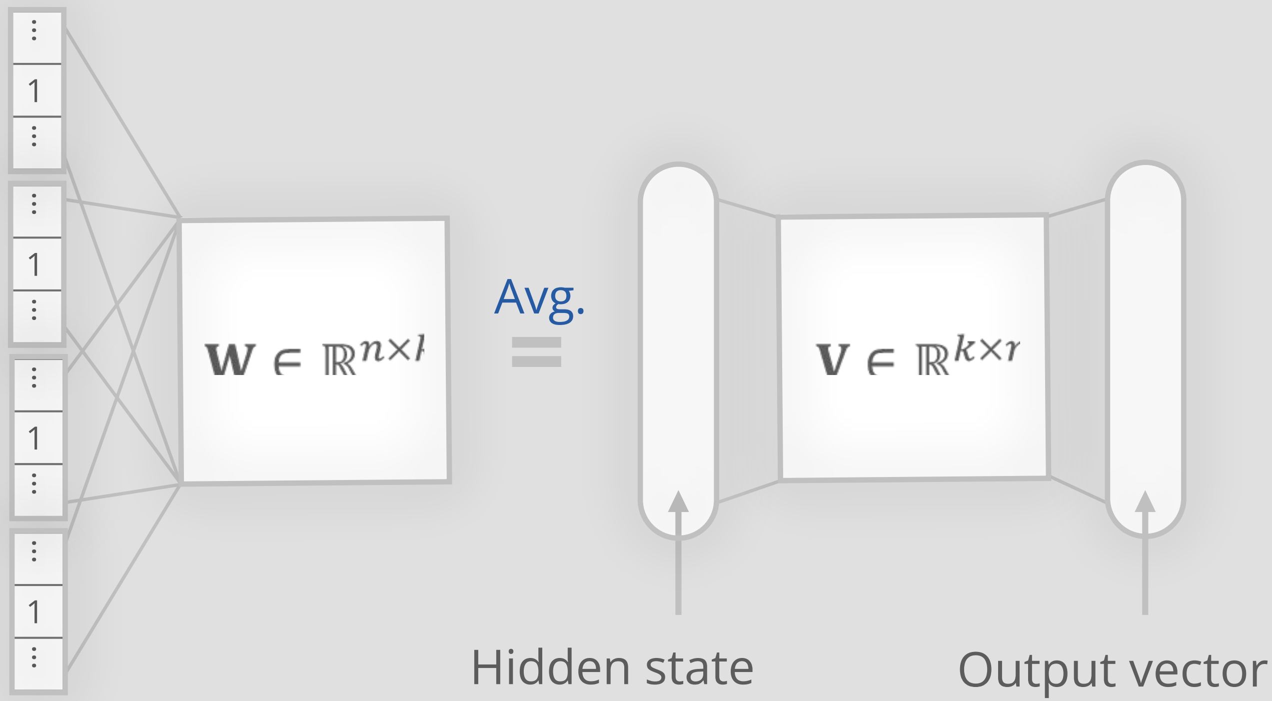
Doc2vec model

- Methods of training document embeddings similar to word2vec
- Two models: Distributed Memory and Distributed Bag of Words

- *Quoc Le, Tomas Mikolov. Distributed Representations of Sentences and Documents // ICML. — 2014.*

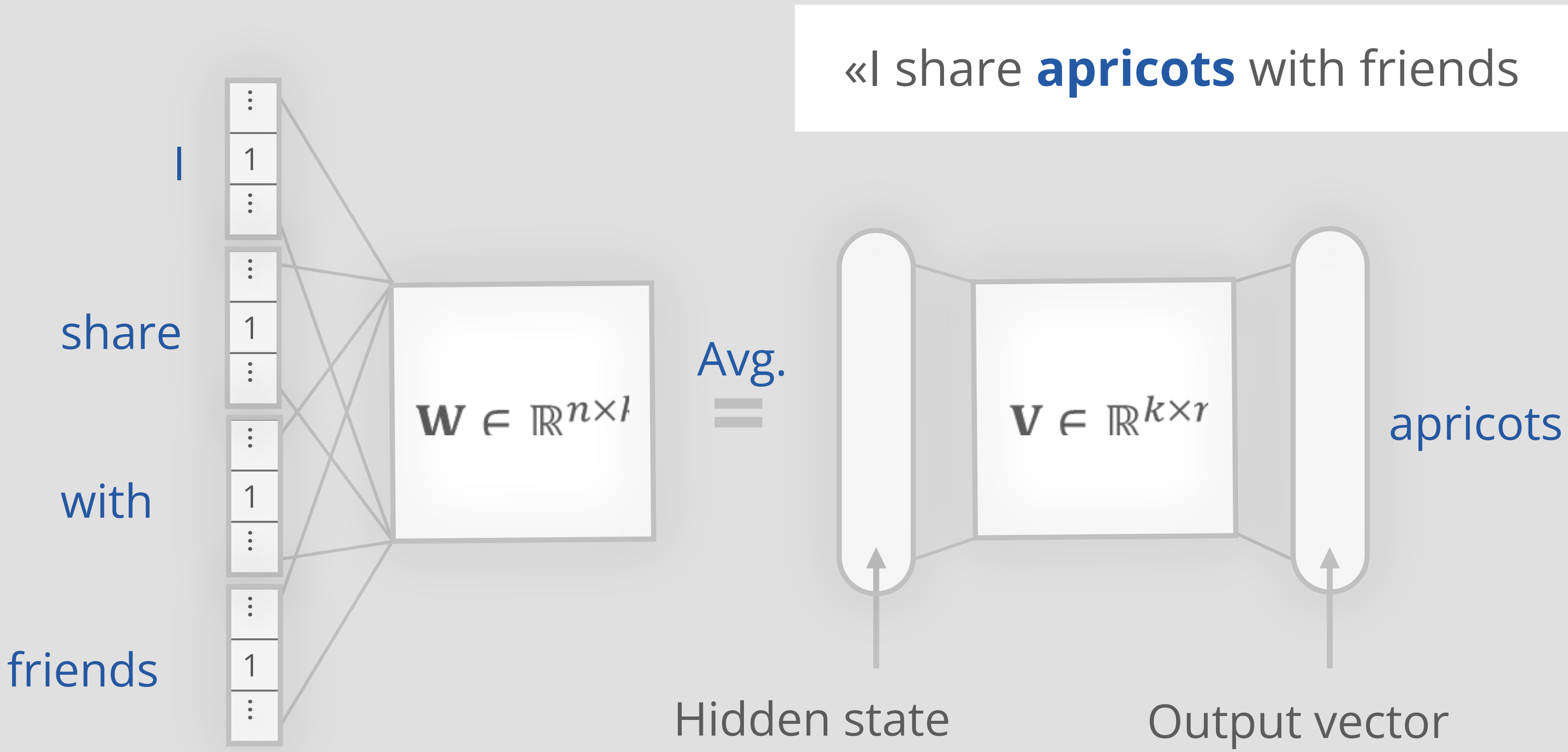
Distributed Memory doc2vec

- Similar to CBOW word2vec



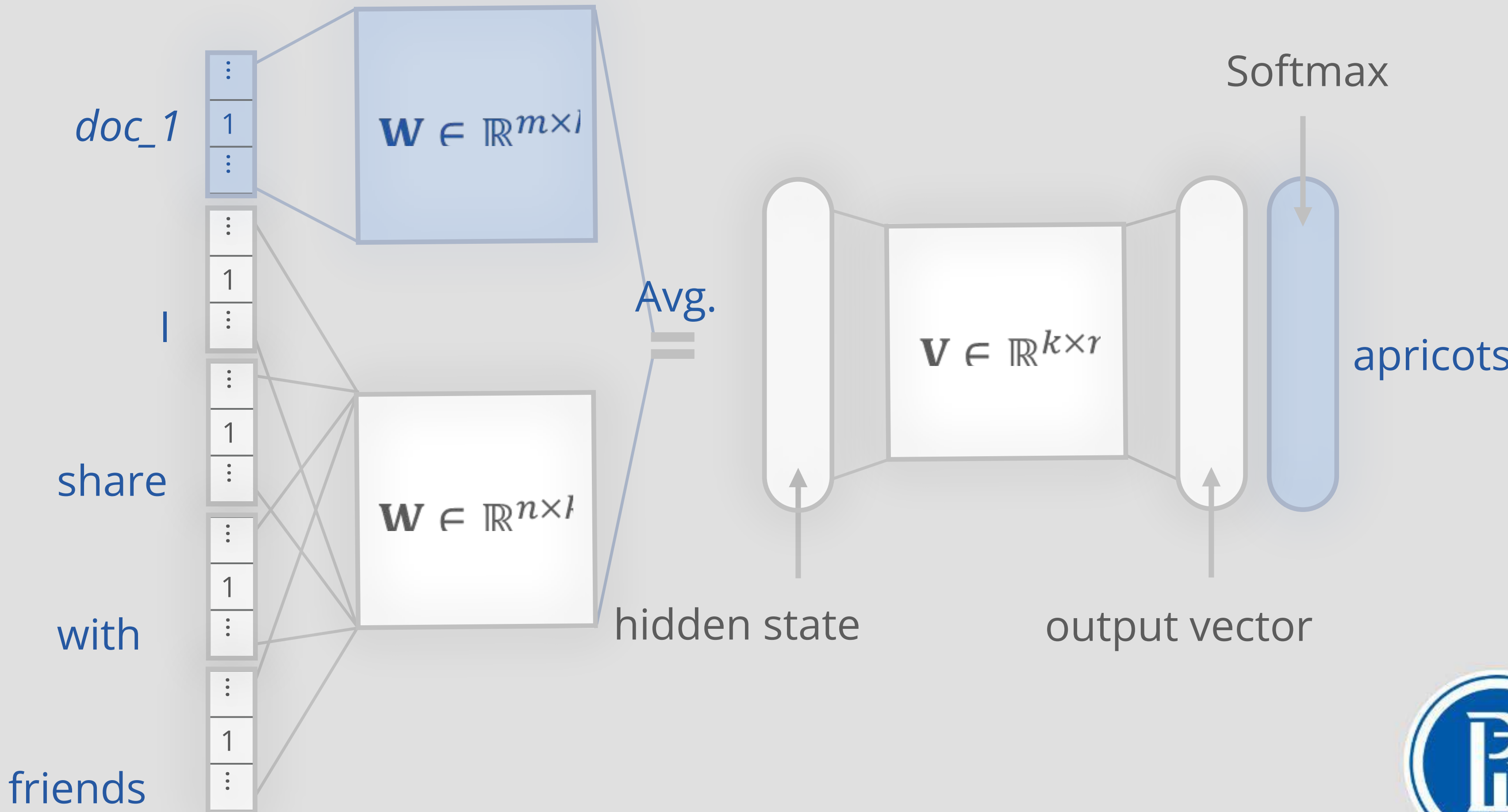
Distributed Memory doc2vec

- Similar to CBOW word2vec
- Slide with window over document words



Distributed Memory doc2vec

- Along with words we use documents (paragraphs) in training
- Add one-hot vector sized m of document in each window



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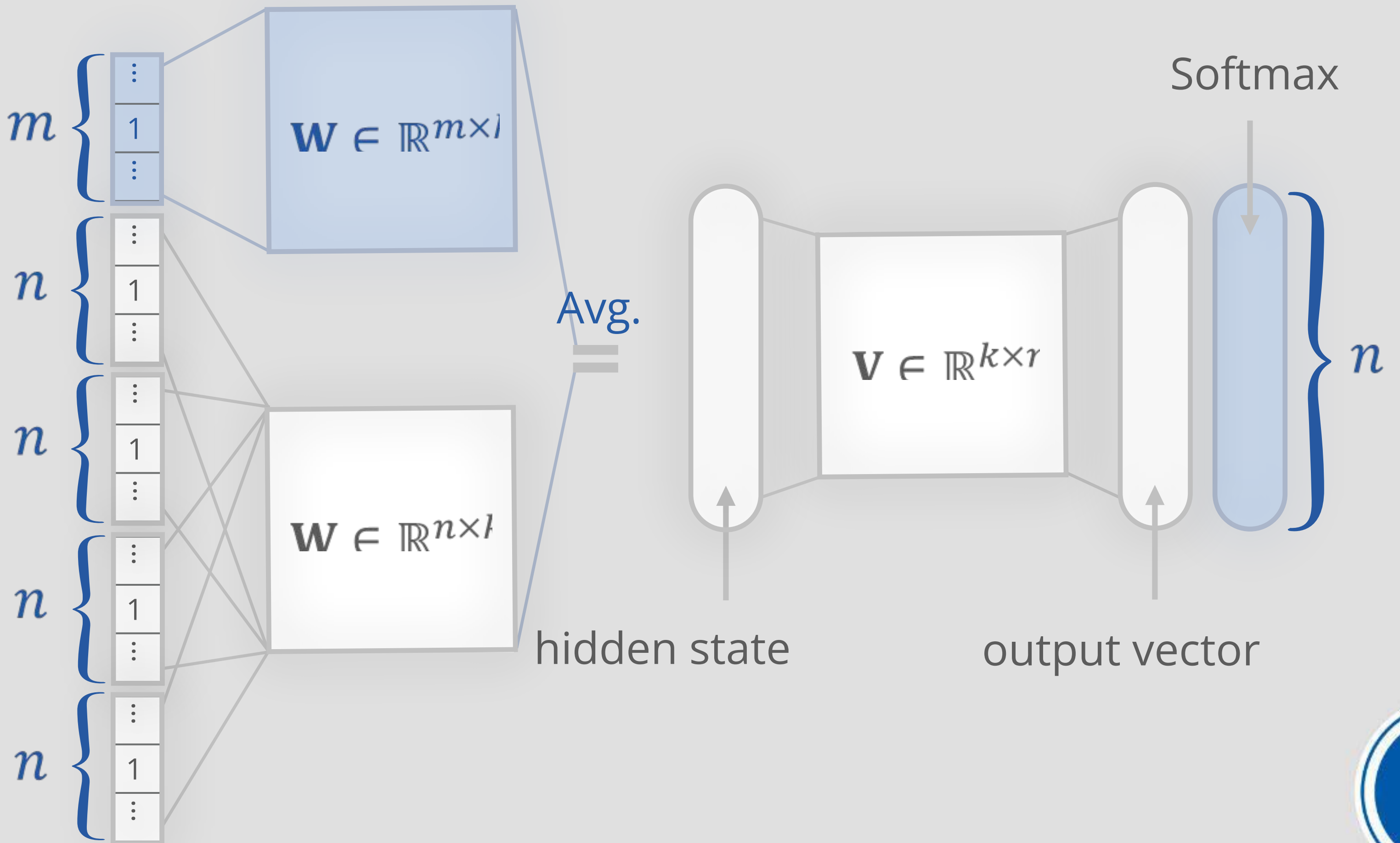

Distributed Bag of Words doc2vec

- Similar to Skip-gram word2vec
- Model is trained to predict random word from a random window based on one-hot embedding of a document, where there word comes from

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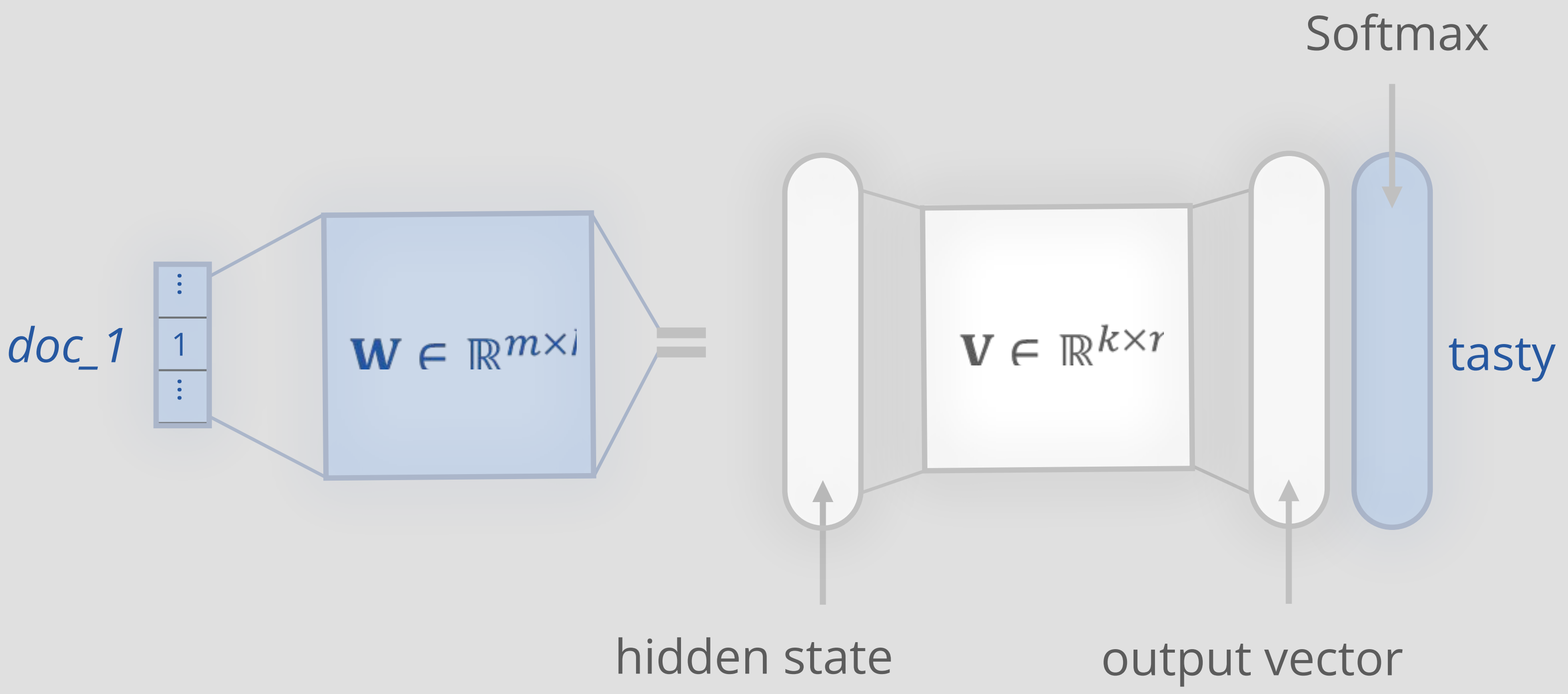

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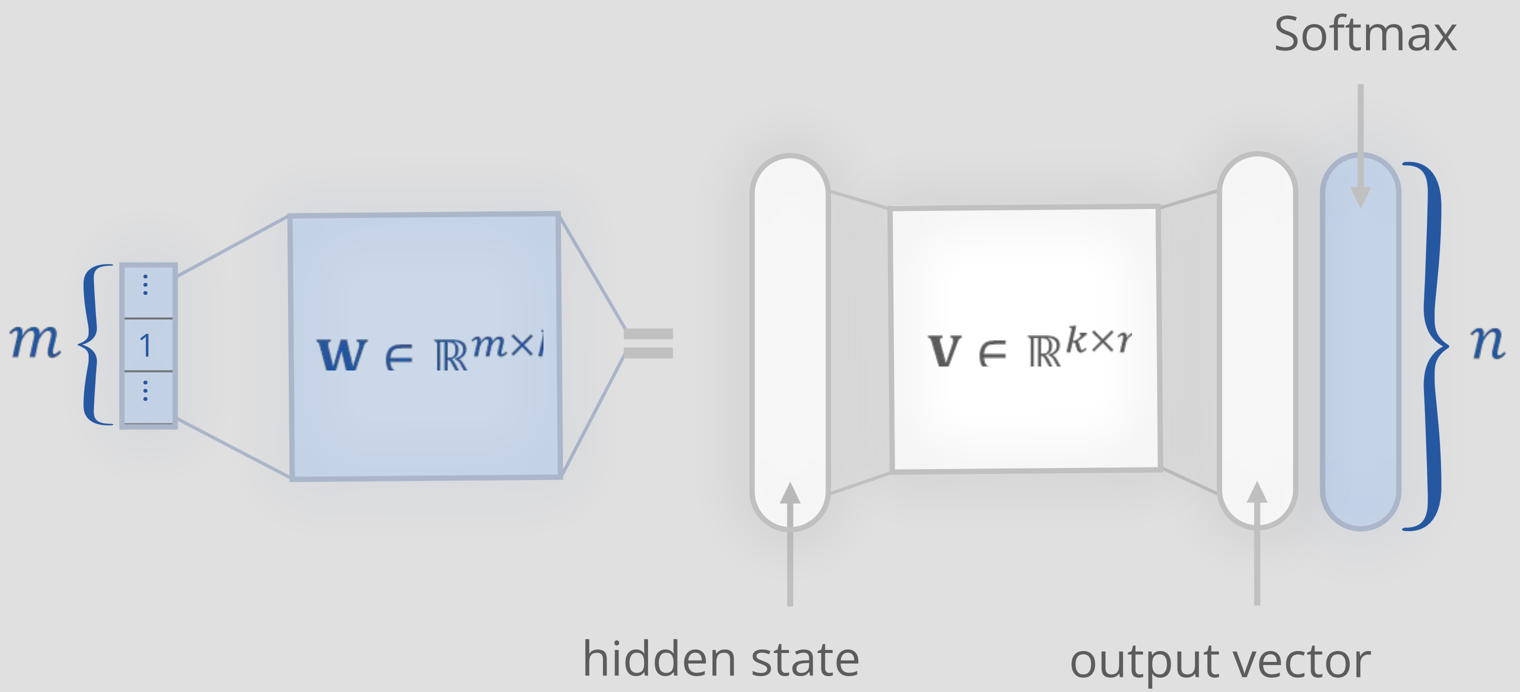

Main conclusions

- Basic document representations - Bow and TF-IDF
- SVD can be used for dimension reduction
- Averaging word embeddings is a common approach
- doc2vec model allows to obtain document embeddings

Neural networks for classification, FastText

Fully connected networks for classification

- Linear models can’t cope with difficult dependencies
- Fully connected networks can be more difficult and flexible
- Due to large amount of weights such networks usually consist of 2-3 layers
- Input embedding can be pretrained or trained during the network training

Deep Averaging Network

- Suppose we have pretrained word embeddings
- We train a two-layer fully connected neural network to solve classification problem
- We calculate average of input embeddings as input
- To predict classes we calculate softmax

- *Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, Hal Daumé III. Deep Unordered Composition Rivals Syntactic Methods for Text Classification // IJCNLP. — 2015.*

Deep Averaging Network

- f - activation function
- W_i - weight matrix of layer i

Deep Averaging Network

$$a = \frac{1}{r}\sum_{i=1}^{r} w_i$$

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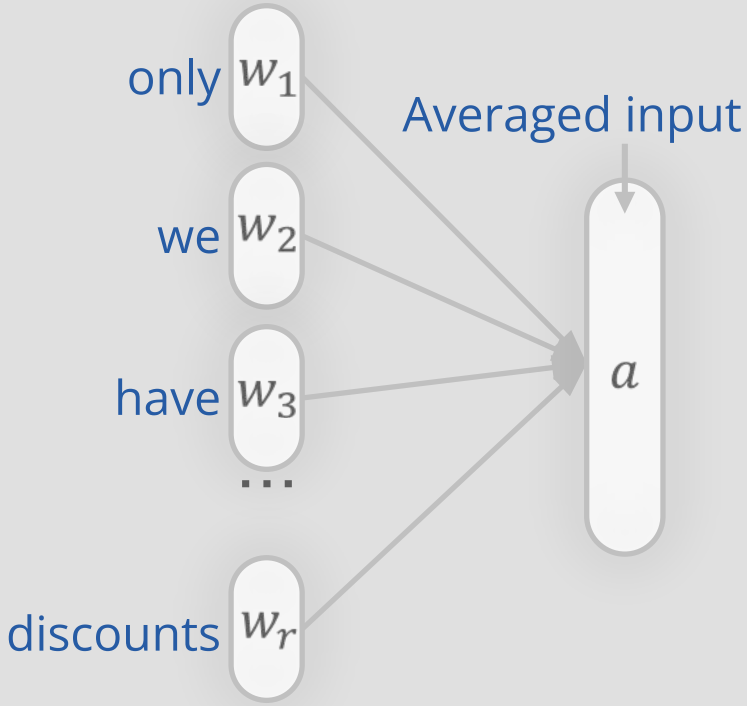

Deep Averaging Network

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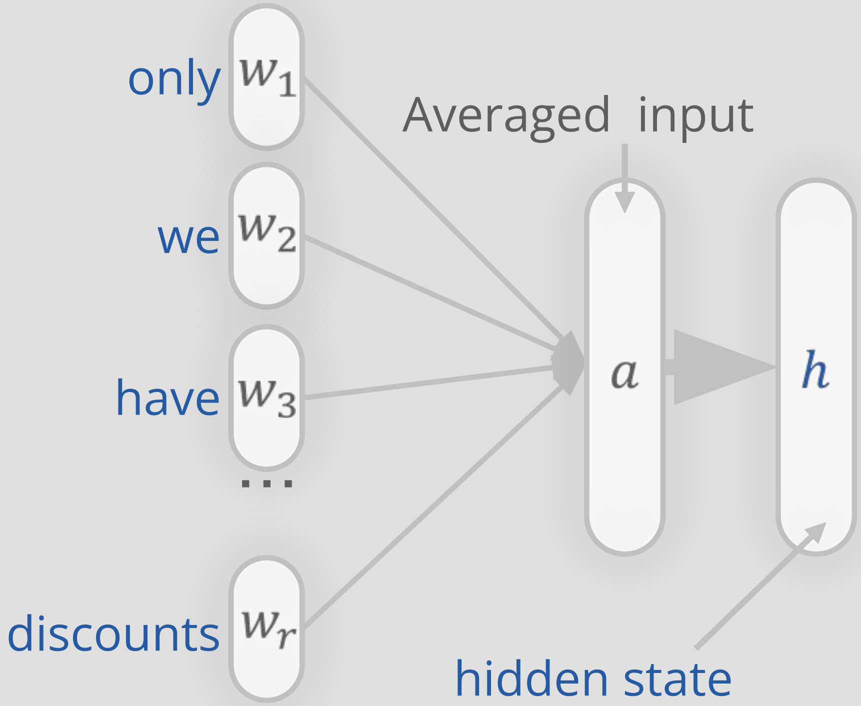
$$a = \frac{1}{r}\sum_{i=1}^{r} w_i$$

$$h = f(W_1{}^T a)$$



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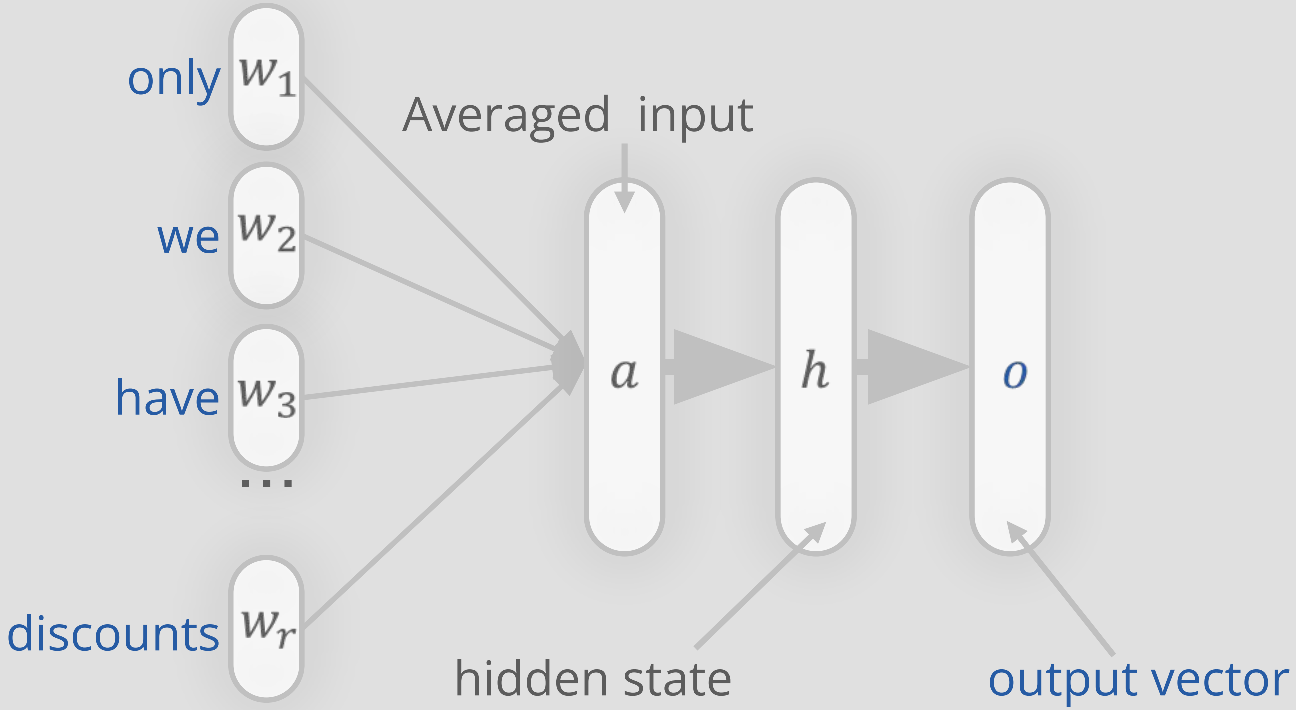
$$o = f(W_2{}^T h)$$



Deep Averaging Network

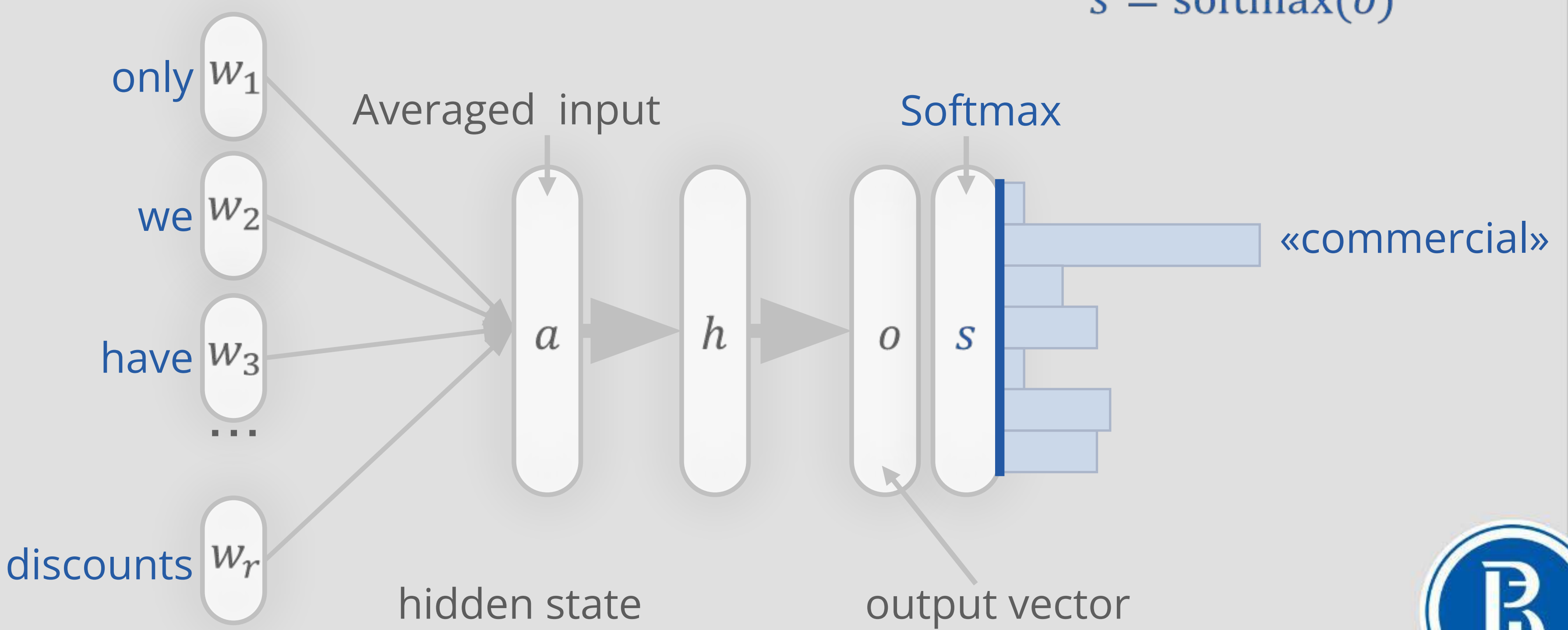
- f - activation function
- W_i - weight matrix of layer i

$$a = \frac{1}{r}\sum_{i=1}^{r} w_i$$

$$h = f({W_1}^T a)$$

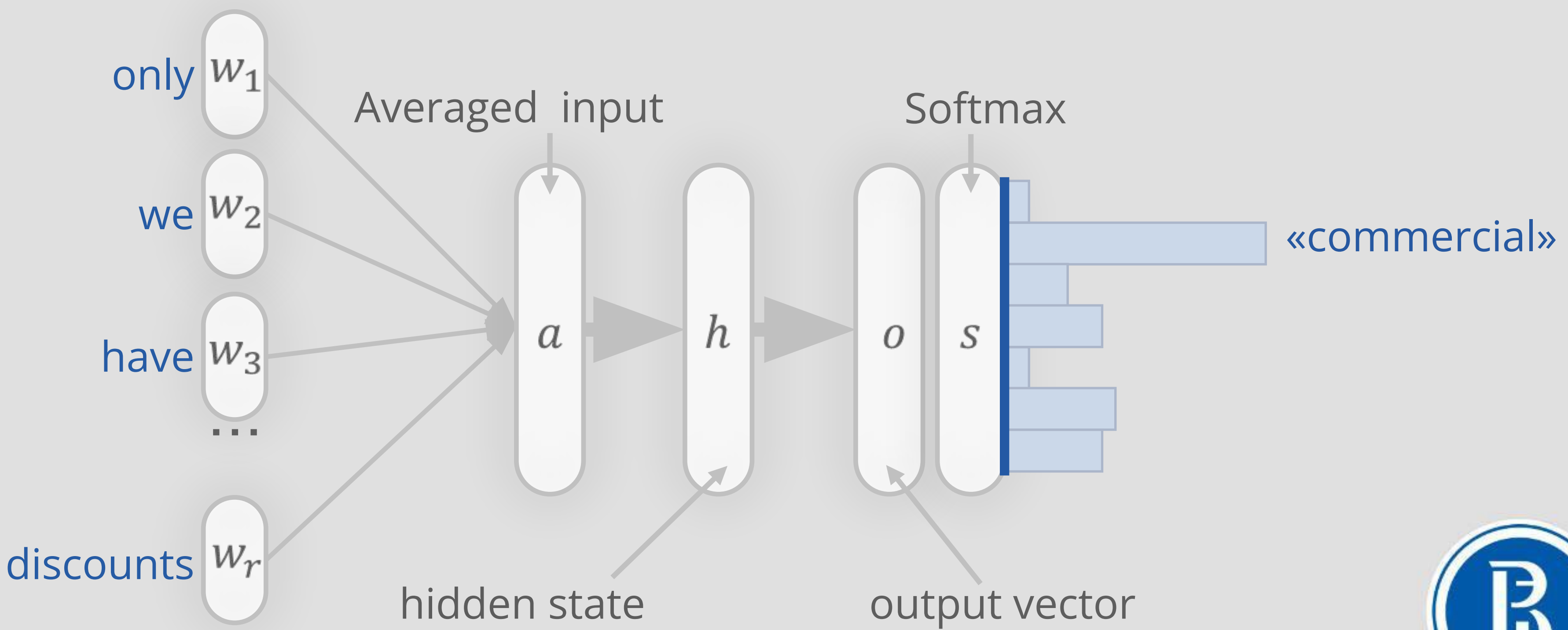
$$o = f({W_2}^T h)$$

$$s = \mathrm{softmax}(o)$$



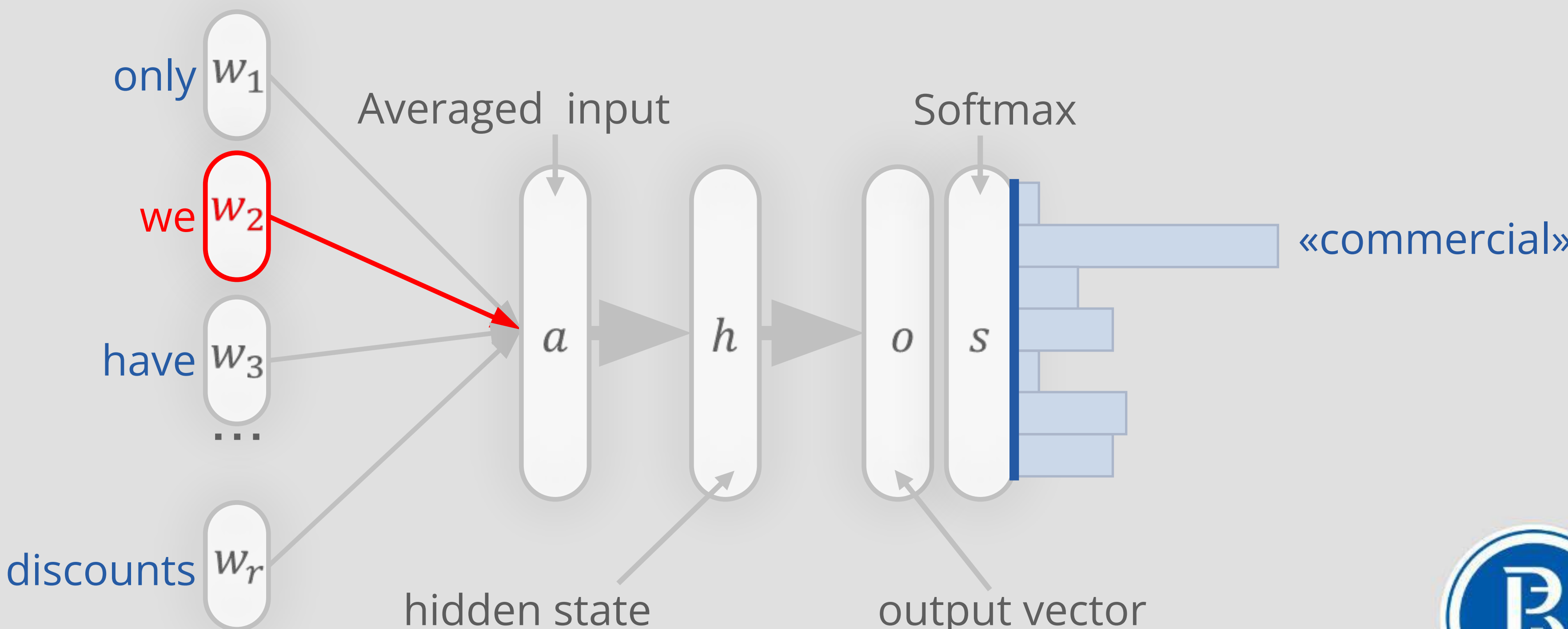
Word dropout

- Dropout regularization prevents from overfitting



Word dropout

- Dropout regularization prevents from overfitting
- Instead of vanishing outputs we will randomly exclude words from input



Deep Averaging Network

Advantages

- Is faster than complex architectures
- Often shows quality comparable to complex models
- Interpretable output probabilities

Disadvantages

- Does not take into account syntactic links, which can be partially corrected by using N-grams
- A large number of parameters compared to a linear classifier requires more training data

FastText

REMINDER

- FastText — already familiar library for getting vector representations
- Can work with character n-grams
- Optimizes RAM consumption with hashing trick
- Can be trained in parallel on CPU
- Has a console application version as well as C++ and Python package

FastText as a classifier

- The architecture remains the same
- The first layer is a matrix of weights that correspond to features: words, character and word n-grams
- The second layer is a K-classes classifier
- Both matrices are trained simultaneously
- Input - one-hot encoded vectors of features
- Output - classes probabilities from softmax

- *Armand Joulin, Edouard Grave, Piotr Bojanowski, Tomas Mikolov. Bag of Tricks for Efficient Text Classification // EACL. — 2017.*

FastText as a classifier

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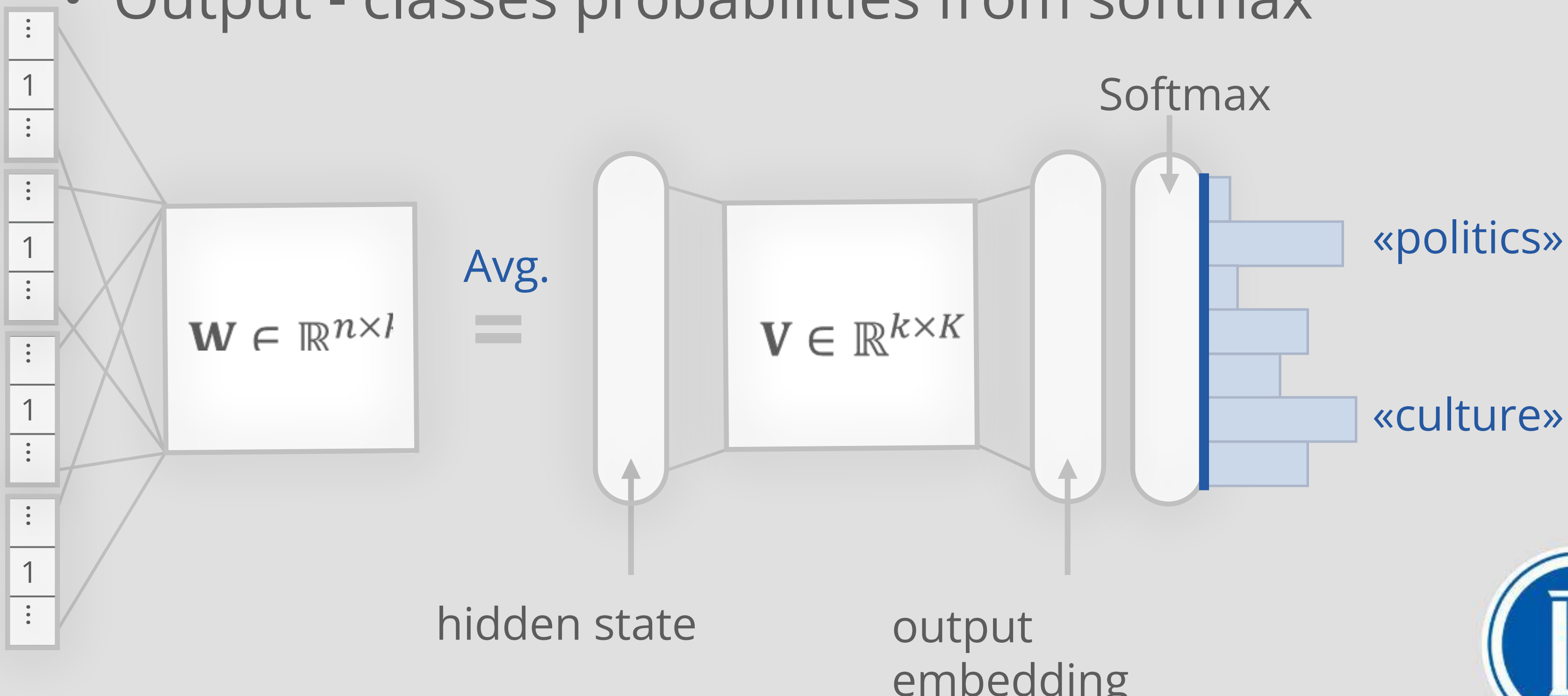

Input data format

- Collection is a text file, each line — one document
- Each line contains class label and text (no more than 1024 tokens)

```
__label__review __label__negative i don't like your service literally can't stand it any more
```

Формат входных данных

- Collection is a text file, each line — one document
- Each line contains class label and text (no more than 1024 tokens)

```
__label__review __label__negative i don't like your service literally can't stand it any more
```

- __label__ — a key word for class label
- text contains only raw words
- N-grams are collected automatically during training process

Main conclusions

- Texts can be classified with shallow neural networks
- DAN architecture includes several fully connected layers and an average embedding of words as an input
- Syntax can be partially taken into account through the use of dictionary N-gram features
- FastText can be trained quite fast on large-scale data without GPU
- FastText operates both with words and character and word n-grams

Convolutional neural networks for text classification

Convolutional Neural Network

- Convolutional neural networks (CNN) were a breakthrough in image processing
- It turns out that they work pretty well with texts, too
- In classification problem CNN allows to work with local word context without using word n-grams
- CNN can be trained much faster than recurrent networks and show comparable results in text classification

CNN components

- Input layer — contains features embeddings (word embeddings, for example)
- Convolutional layer — extracts local features from input embeddings
- Discretization layer (pooling) — extracts global features with maximal signal
- Fully connected layer — a classifier trained on resulting representations

Convolutional layer

- Convolutional layer — extracts local features from input embeddings

- Is based on convolution with kernel:

-1	0	1
-2	0	2
-1	0	1

- Input data is a matrix:

3	0	1	5	0
2	6	2	4	3
2	4	1	3	6
3	0	1	5	0
2	6	2	4	3

- Convolution is applied to fragments of the input matrix sequentially

Convolution

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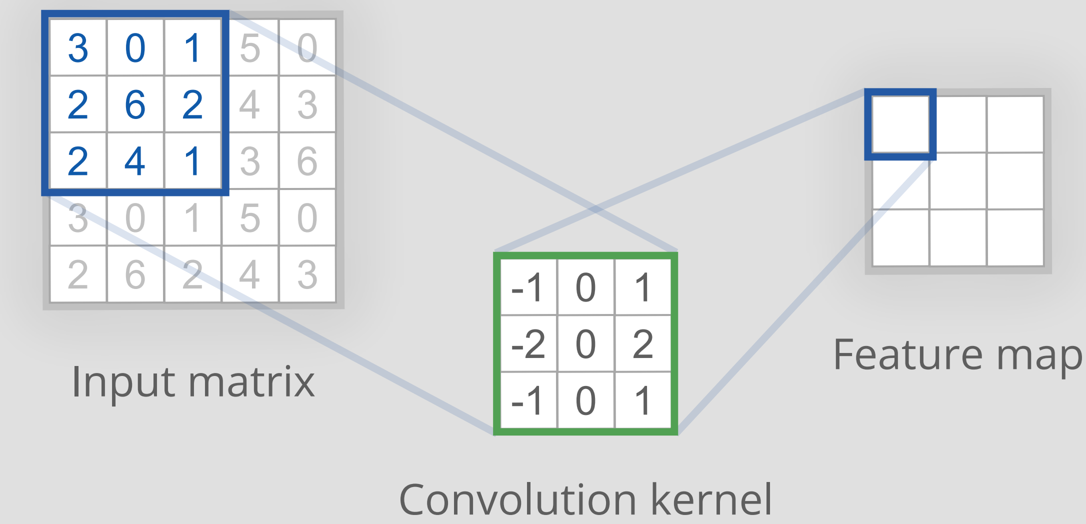

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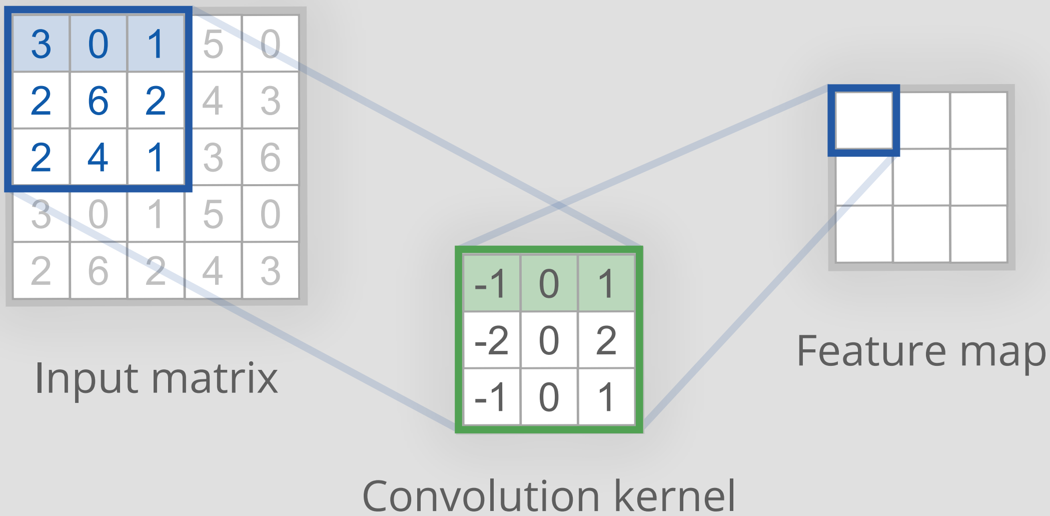

$(-1 \times 3) + (0 \times 0) + (1 \times 1) +$

Convolution

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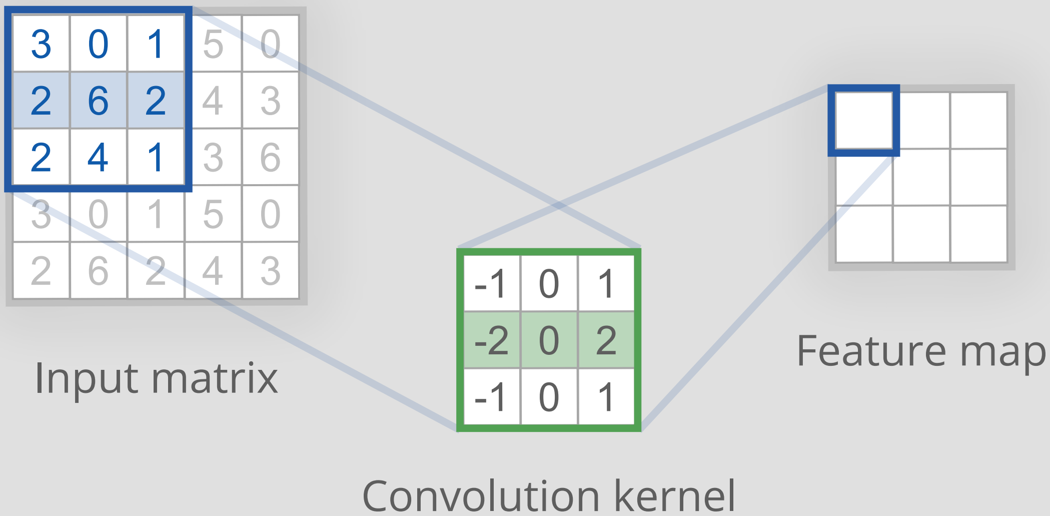

(-1 x 3) + (0 x 0) + (1 x 1) +

(-2 x 2) + (0 x 6) + (2 x 2) +

Convolution

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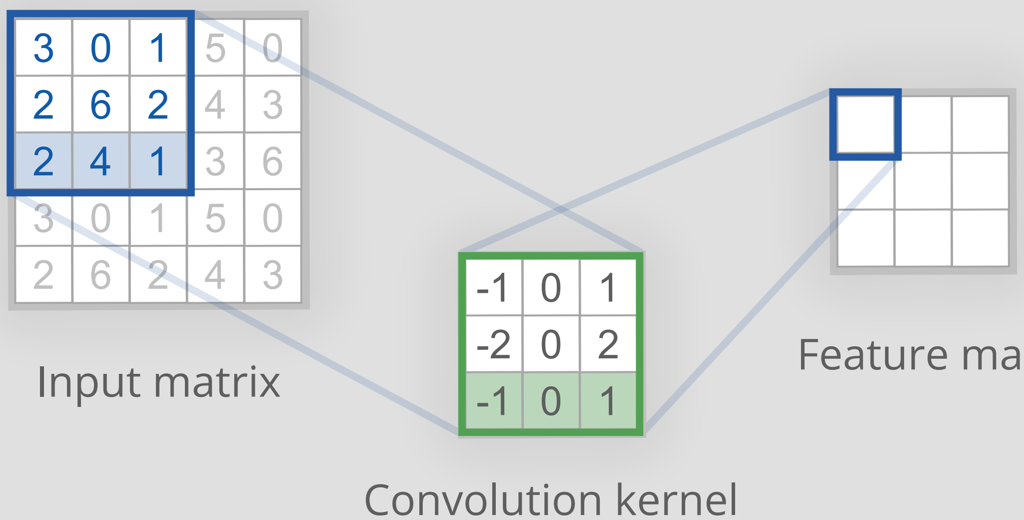


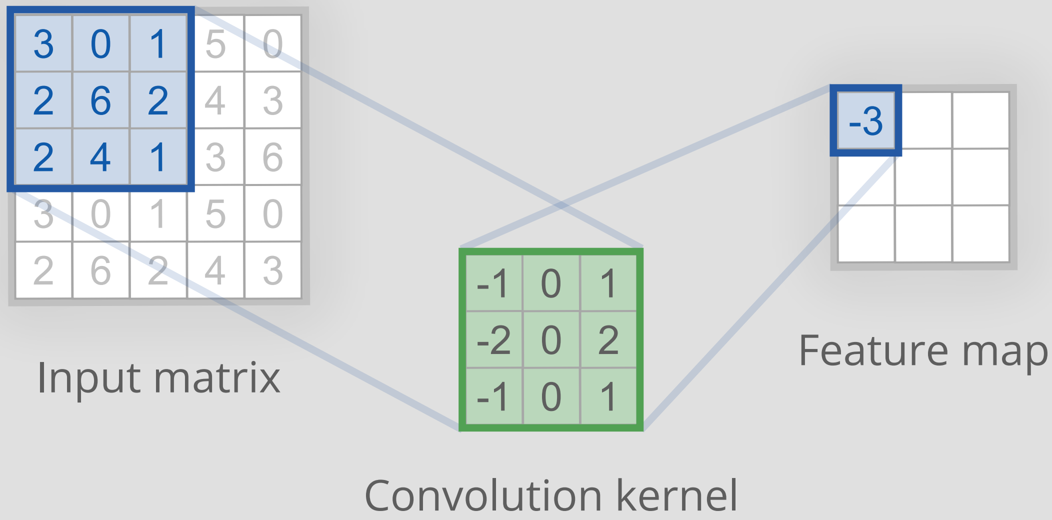
$$(-1 \times 3) + (0 \times 0) + (1 \times 1) +$$

$$(-2 \times 2) + (0 \times 6) + (2 \times 2) +$$

$$(-1 \times 2) + (0 \times 4) + (1 \times 1)$$

Convolution

- Convolution is applied to fragments of the input matrix sequentially:



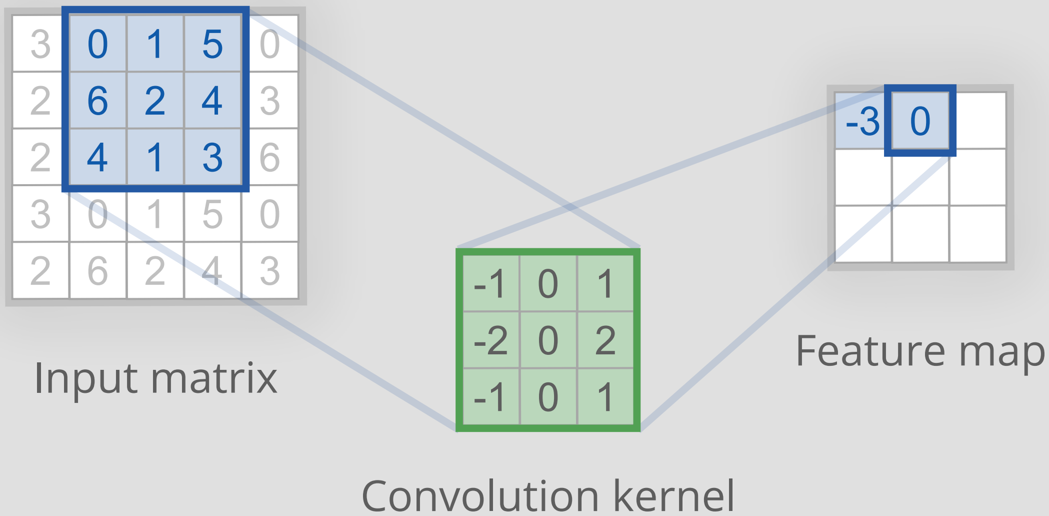
(-1 x 3) + (0 x 0) + (1 x 1) +

(-2 x 2) + (0 x 6) + (2 x 2) +

(-1 x 2) + (0 x 4) + (1 x 1) = -3

Convolution

- Convolution is applied to fragments of the input matrix sequentially:



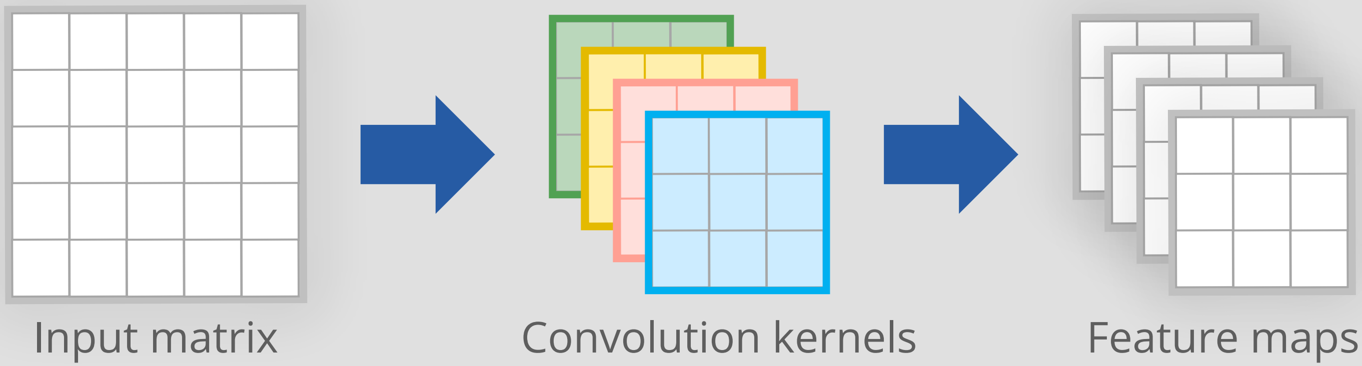
(-1 x 0) + (0 x 1) + (1 x 5) +

(-2 x 6) + (0 x 2) + (2 x 4) +

(-1 x 4) + (0 x 1) + (1 x 3) = 0

Convolutional layer

- Several kernels (filters) are applied in each layer
- Each filter creates its own feature map:



Pooling layer

- Pooling aggregates a fragment of feature map into a scalar
- Aggregating function can be different
- Usually, max pooling is applied

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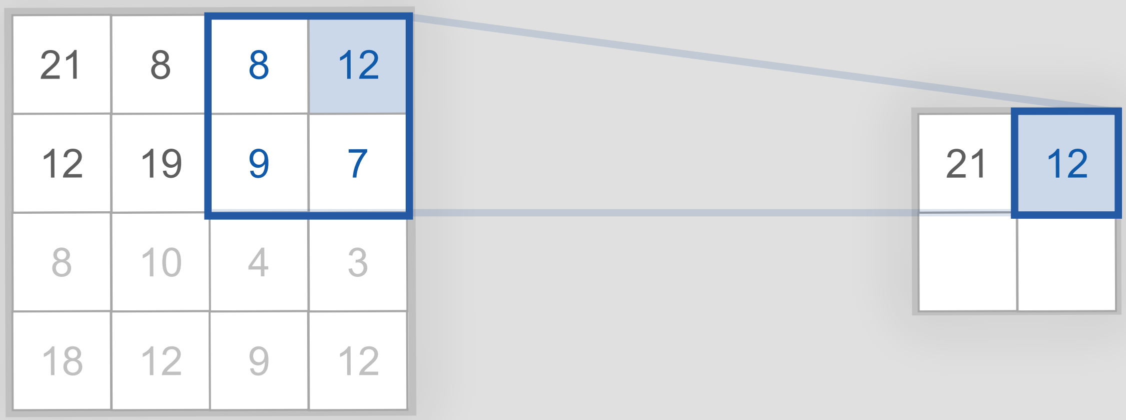

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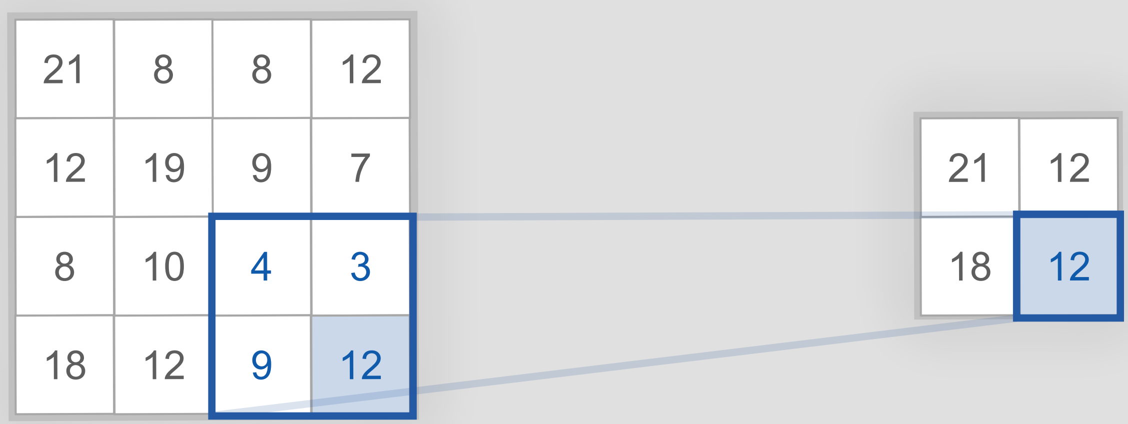
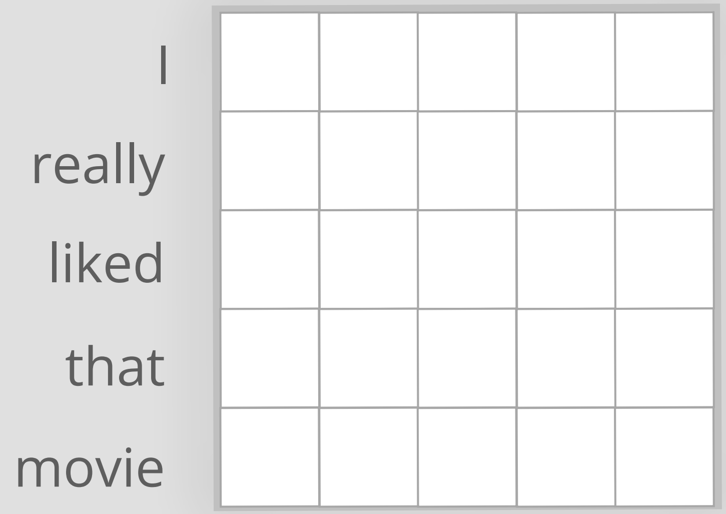


CNN for texts

- Usually, shallow networks with one convolutional layer and one pooling are used
- Input is a matrix of word embeddings



- *Yoon Kim. Convolutional Neural Networks for Sentence Classification // EMNLP. — 2014.*

CNN for texts

- Usually, shallow networks with one convolutional layer and one pooling are used
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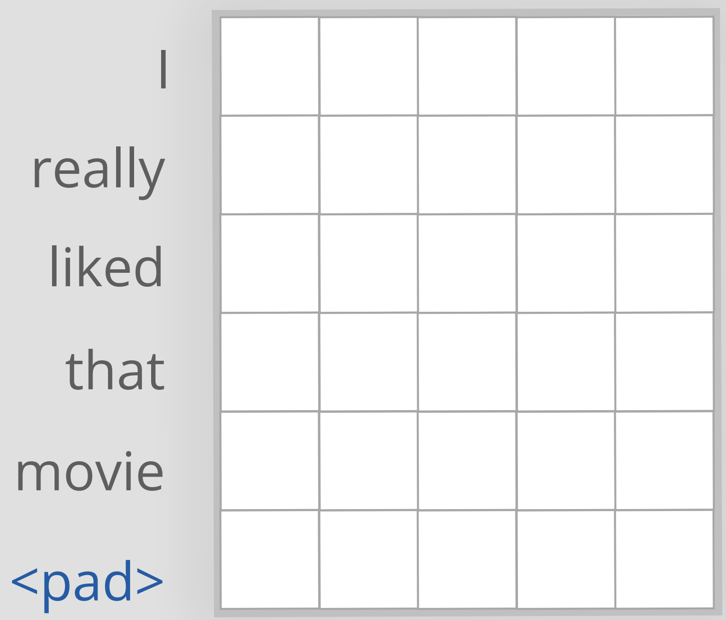
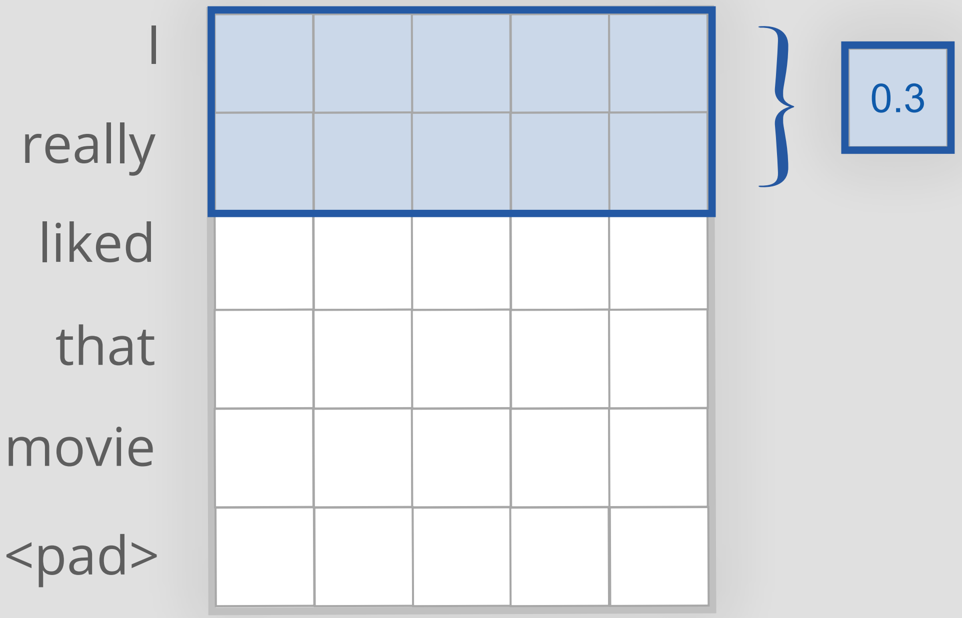
- Input is padded to fixed length
- <pad> token embedding must not affect the pooling!



CNN for texts

- One-dimensional filters are used
- First dimension k corresponds to a number of words in the local context
- Second dimension is fixed and equal to word embeddings length



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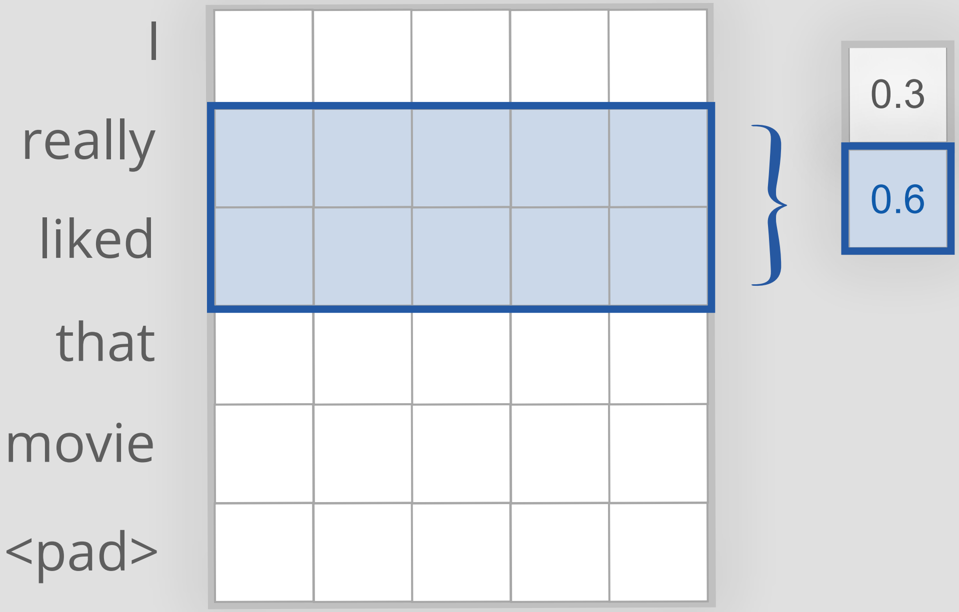

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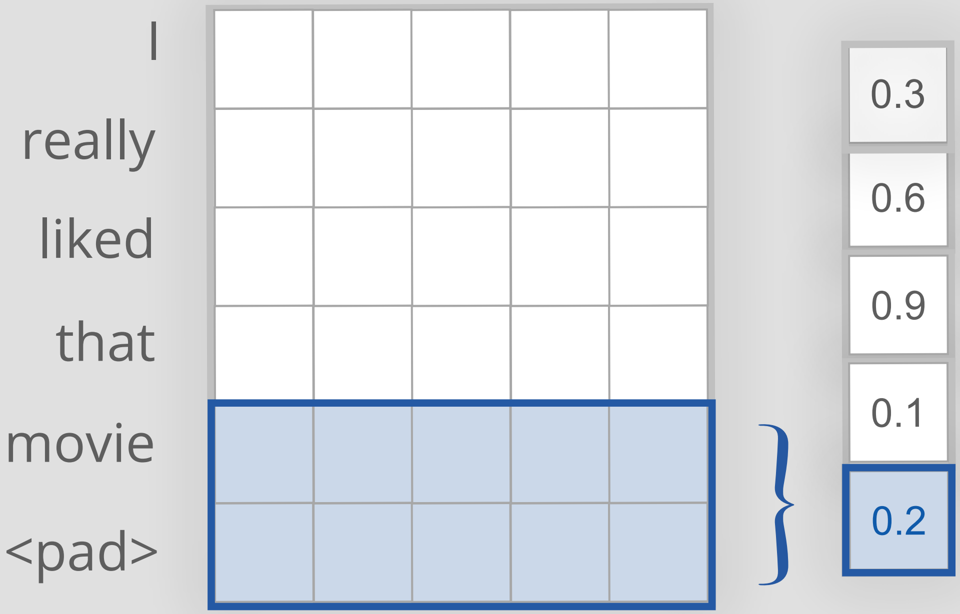
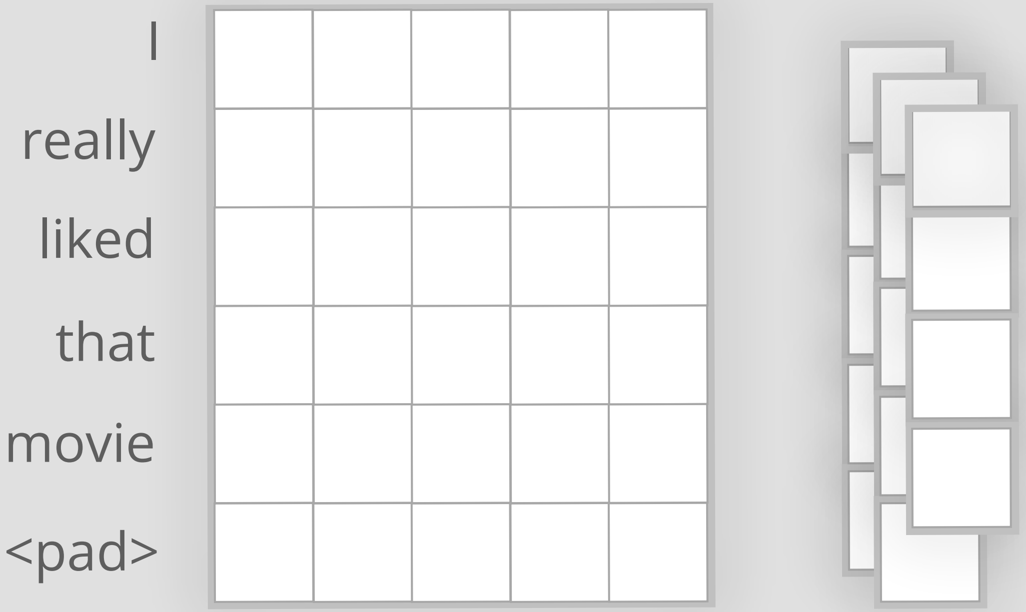


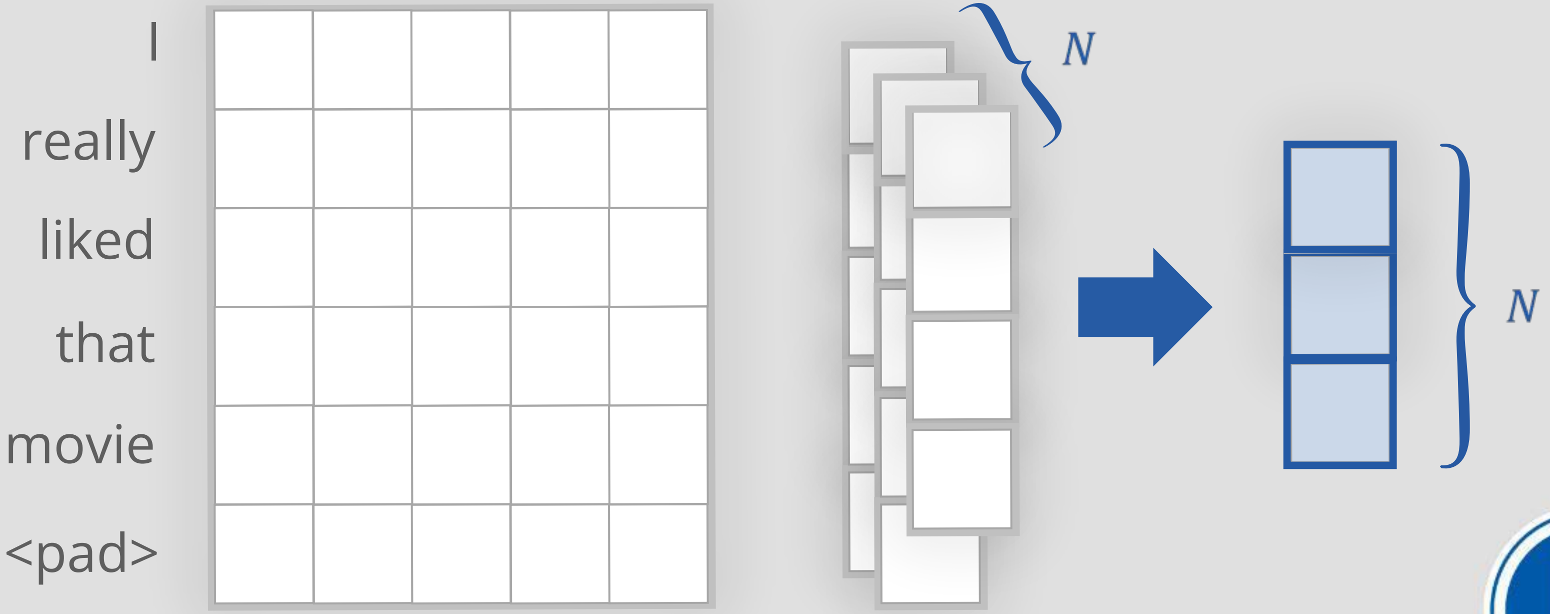
CNN for texts

- One-dimensional filters are used
- There can be several filters of different lengths



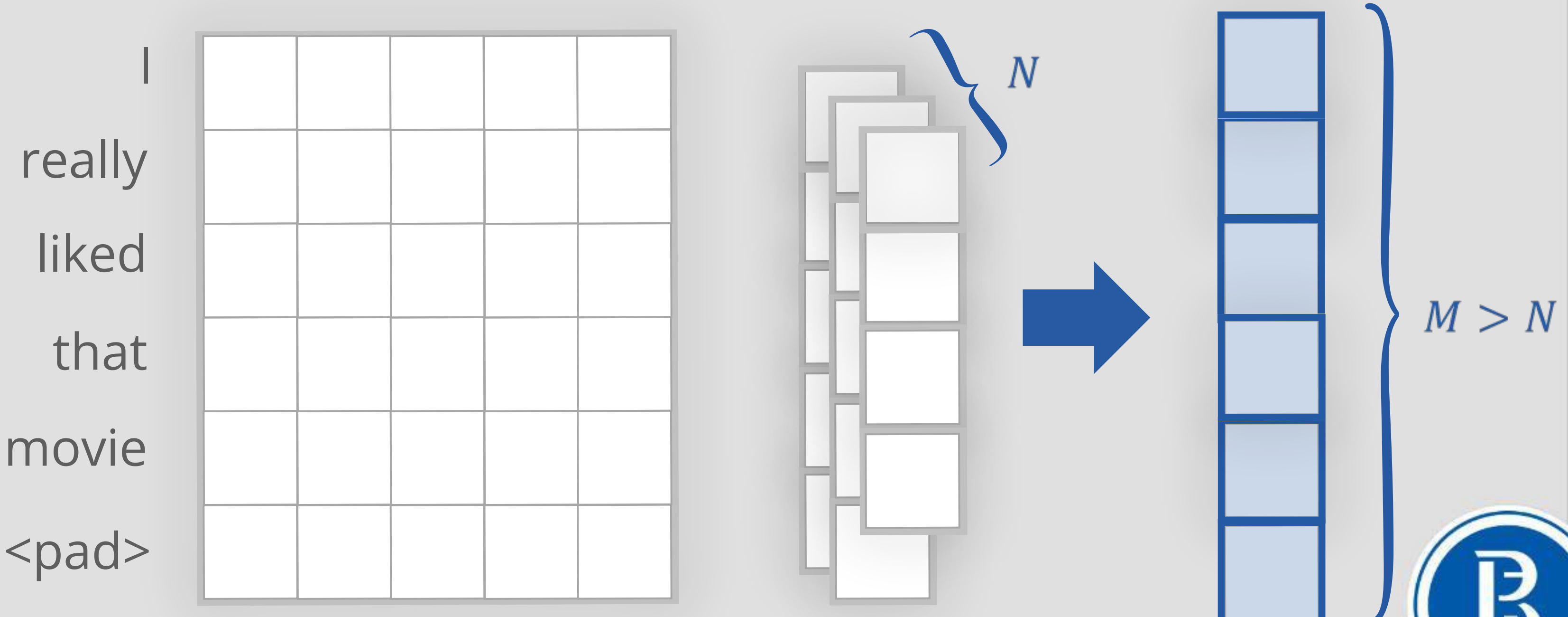
CNN for texts

- One-dimensional filters are used
- There can be several filters of different lengths
- Then we use max-over-time pooling instead of pooling
- It chooses one feature from each map



CNN for texts

- One-dimensional filters are used
- There can be several filters of different lengths
- k-max pooling can be applied



Input embeddings

- Word embeddings can be trained in the first layer from scratch
- Pretrained word2vec or GloVe embeddings can be used
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Input embeddings

- Word embeddings can be trained in the first layer from scratch
- Pretrained word2vec or GloVe embeddings can be used
- Embeddings can be both frozen and tuned during network training
- Several input channels can be used
- For example, both channels have input word2vec embeddings, but the first one is frozen and the second is tuned
- Convolution is applied to both inputs, the result can be summarized

What’s next

- One-hot character embeddings can be used as input
- The number of convolutional and polling layers can be increased
- It is useful to add non-linear layers
- Dropout can be added after fully connected layers

- *Xiang Zhang, Junbo Zhao, Yann LeCun. Character-level Convolutional Networks for Text Classification // NIPS. — 2015.*

Main conclusions

- Convolutional networks originally designed for image processing work good with texts
- Input data is a matrix of word or character embeddings
- Filters of different sizes and max-over-time pooling can be used
- In classification problems, CNN allow to take into account the local context of words without explicitly using dictionary N-grams

Data processing in text classification

Classification solution steps

- Choosing the right quality metric
- Training data collection
- Data preprocessing
- Feature collection
- Choosing the model
- Model tuning

Data collection

- Even raw (unlabeled) texts can be difficult to collect
- If there is data in open sources, you can use web-crawling:
  - Some websites have public API's
  - If they don't, you can use web-scraping (for example, Scrapy package for Python)

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- If there is data in open sources, you can use web-crawling:
  - Some websites have public API's
  - If they don't, you can use web-scraping (for example, Scrapy package for Python)
- Sometimes proper data doesn't exist at all
- You can use the power of crowdsourcing:
  - Yandex Toloka
  - Amazon Mechanical Turk
  - …

Data markup

- Unlabeled texts are useful as is
- But classification problem requires labeled data
- In practice, marking up small samples is often done manually by yourself
- Sometimes part of the documents can be marked up by defining simple heuristic rules:
  - By particular words inclusion
  - By regular expression
- In all other cases you can use assessors (better), or crowdsourcing (faster)

Additional markup and active learning

- Models can be applied to data that changes dynamically over time
- Examples: news, memes
- Once trained, model can become obsolete with time
- Usually it is necessary to collect additional data and tune model on regular basis

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- Models can be applied to data that changes dynamically over time
- Examples: news, memes
- Once trained, model can become obsolete with time
- Usually it is necessary to collect additional data and tune model on regular basis
- We can reduce the amount of additionally marked data by choosing samples that can provide useful information for the model
- Idea: send the samples where the model is least confident