9. Classification, Clustering, and Learning to Rank

Prof. Dr. Goran Glavaš

Center for AI and Data Science (CAIDAS)
Fakultät für Mathematik und Informatik
Universität Würzburg

After this lecture, you'll...

- Know the basics of machine learning
- Understand supervised text classification
- Know some methods for (unsupervised) text clustering
- Understand how to combine different ranking functions (and other features) in a supervised IR setting – learning to rank
- Have an idea of what neural (re-)rankers (neural L2R) look like

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Recap of the previous lecture

- Latent and Semantic Retrieval
  - **Q:** Why is term matching sometimes not good enough for retrieval?
  - **Q:** When should you use term-based IR models and when semantic/latent ones?
- Latent Semantic Indexing
  - **Q:** What Latent Semantic Indexing (LSI)?
  - **Q:** What is Singular Value Decomposition and how are latent topics represented?
  - **Q:** How do we obtain latent representations of documents and terms? How to transform the query into latent space?
- Latent Dirichlet Allocation
  - **Q:** What is LDA and how are latent topics represented in this probabilistic setting?
  - **Q:** What is the generative story that LDA assumes?
- Word embeddings for IR
  - **Q:** How are word embedding models different from latent topic models?
  - **Q:** How does CBOW model learn word embeddings?
  - **Q:** How to exploit word embeddings for an IR model?

LSI – Singular Value Decomposition

- Given a matrix **A** (with non-negative elements), the Singular Value Decomposition finds orthogonal matrices **U** and **V** and a rectangular diagonal matrix **Σ** such that:

$$A = U\Sigma V^T$$

- Matrix **U** is of dimensions **M** x **M**
- Matrix **V** is of dimensions **N** x **N**
- Matrix **Σ** is of dimensions **M** x **N**
- U and V are orthogonal: $U^TU = I$, $V^TV = I$
- Values of the diagonal matrix **Σ** are singular values of the original matrix **A**
- Let r be the rank of matrix **A**

LSI reduction – example

- This leaves us with the best possible approximation of rank $\mathbf{A_K}$ ($K = 2$ in our example) of the original term-document occurrence matrix $\mathbf{A}$

$\mathbf{U_K}$ Dense vectors of documents

Dense vectors of terms

$$
\begin{array}{c}
\textit{president} \\ \textit{minister} \\ \textit{speech} \\ \textit{law} \\ \textit{ball} \\ \textit{score} \\ \textit{player} \\ \textit{run} \\ \textit{person} \\ \textit{piano} \\ \textit{mouse}
\end{array}
\begin{bmatrix}
-0.43 & 0.13 \\
-0.53 & 0.25 \\
-0.58 & 0.33 \\
-0.12 & -0.05 \\
-0.22 & -0.51 \\
-0.26 & -0.62 \\
-0.22 & -0.40 \\
-0.03 & -0.06 \\
-0.11 & -0.03 \\
-0.10 & -0.02 \\
-0.09 & -0.08
\end{bmatrix}
\cdot
\begin{array}{c}
\begin{array}{cccccc} d_1 & d_2 & d_3 & d_4 & d_5 & d_6 \end{array} \\
\begin{bmatrix}
-4.66 & -4.37 & -2.71 & -2.37 & -1.51 & -1.65 \\
2.01 & 2.12 & 0.49 & -4.23 & -2.93 & -3.35
\end{bmatrix}
\end{array}
$$

$\mathbf{\Sigma_K V^T_K}$

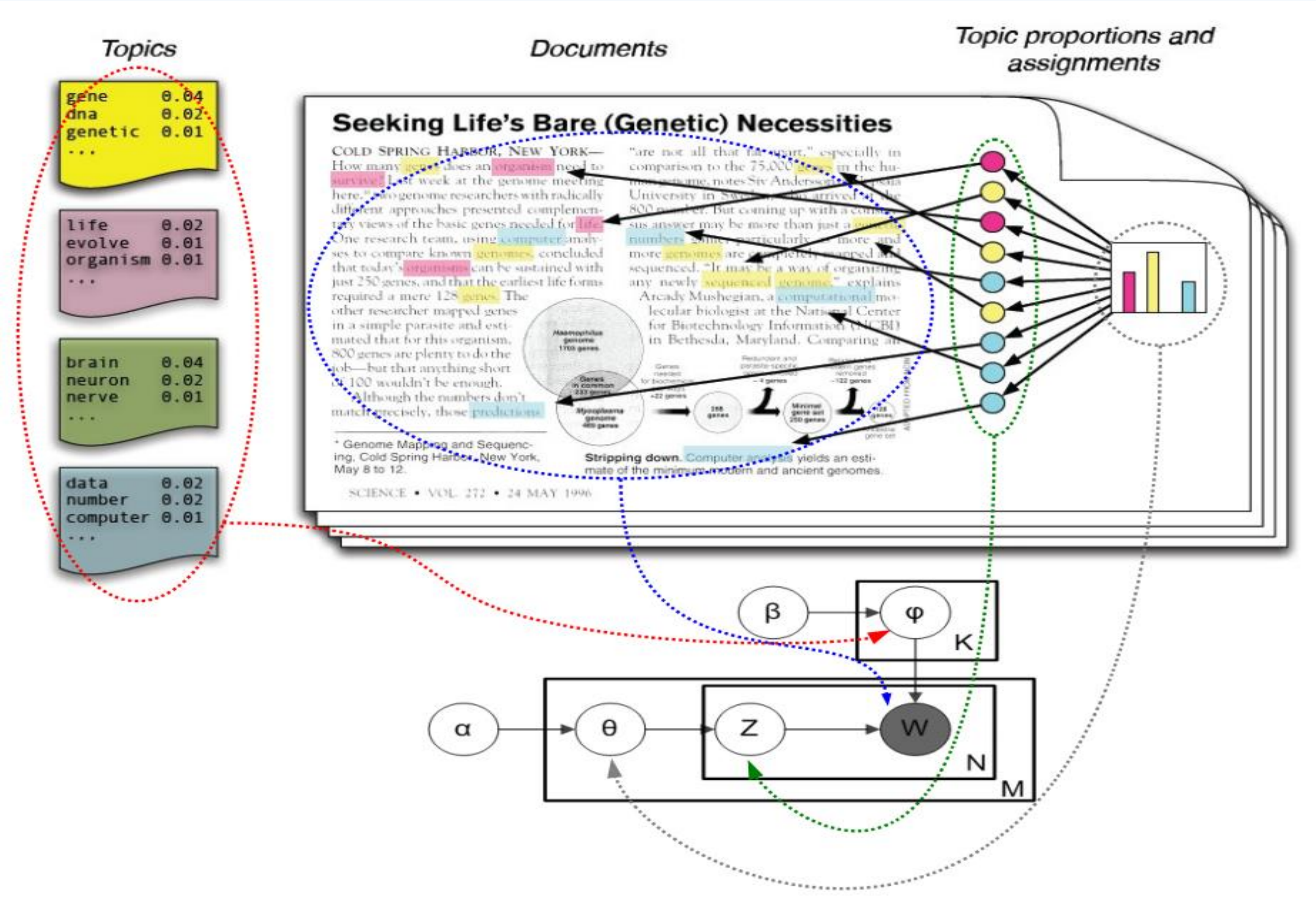
- $\mathbf{A_K}$ has the same dimensions as original $\mathbf{A}$ ($M \times N$)
- $\mathbf{U_K}$ is of size $M \times K$, and $\mathbf{\Sigma_K V^T_K}$ of size $K \times N$

LDA – Generative View

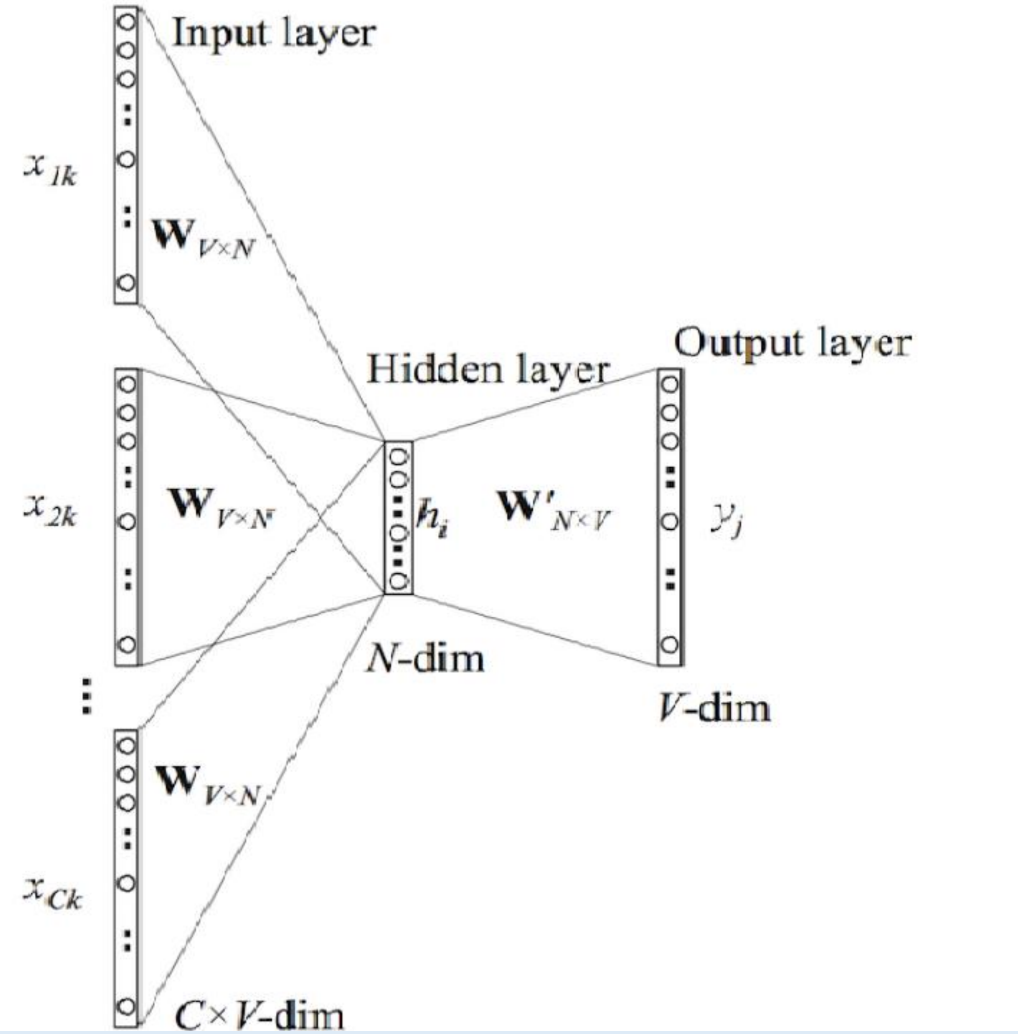
1. For each topic k (k = 1, ..., K):
   - Draw parameters of a multinomial distribution $\boldsymbol{\varphi}_k$ (over terms) for topic k from a Dirichlet distribution $Dir_N(\beta)$

2. For each document d in the collection:
   - Draw parameters of a multinomial distribution of topics for the document d, $\boldsymbol{\theta}_d$, from a Dirichlet distribution $Dir_K(\alpha)$
   - For each term position w_{dn} in the document d:
     a) Draw a topic assignment (i.e., a concrete multinomial distribution over terms) z_{dn} from $Mult_K(\boldsymbol{\theta}_d)$
     b) Draw a concrete term w_{dn} from the multinomial distribution over terms of the topic zdn (drawn in a)), $Mult_N(\boldsymbol{\varphi} z_{dn})$

LDA – Generative View



Continuous Bag-of-Words (CBOW)



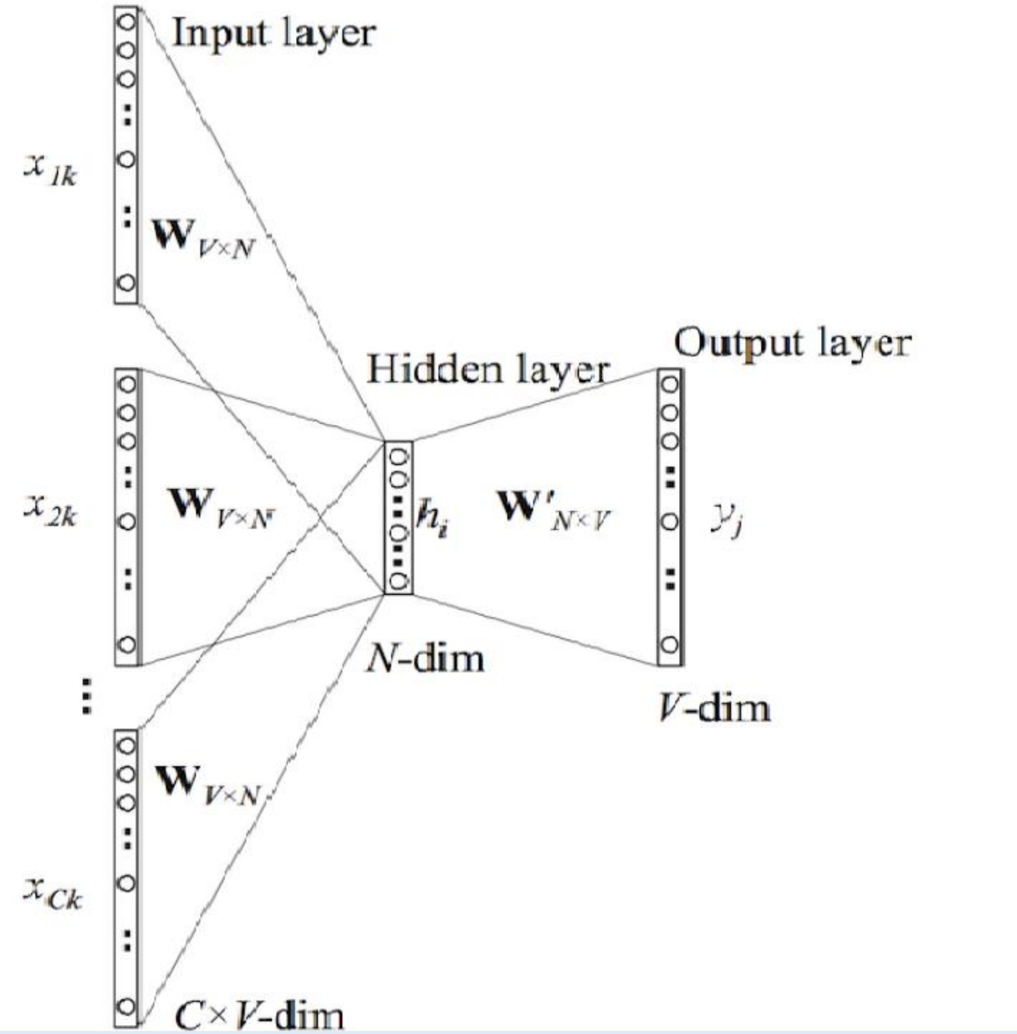
- Context consists of C words, with corresponding one-hot vectors
  - $x_{1k}, x_{2k}, \ldots, x_{Ck}$
- One-hot vectors transformed to dense vectors using input matrix **W** (V x N)
- Dense context vector h is obtained as:

$$h = \frac{1}{C}\boldsymbol{W}\left(\sum_{i=1}^{C} x_{ik}\right)$$

- Dense context vector h is then multiplied with the output matrix **W’** (N x V)

$$y_k = softmax(h^T \boldsymbol{W'})$$

Continuous Bag-of-Words (CBOW)



- Output vector y needs to be as similar as possible to one-hot vector of center word
- Parameters of the model are elements of **W** and **W'**
  - Each row of **W** is the **dense context vector** of one vocabulary word
  - Each column of **W'** is the **dense center vector** of one vocabulary word
- Dense representation (**embedding**) of the *i*-th vocabulary term is concatenation of
  1. *i*-th row of **W** and
  2. *i*-th column of **W'**

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Why machine learning?

- For many IR and NLP tasks, it is difficult to come up with an explicit (i.e., rule-based) algorithm that solves the task efficiently
- For example
  - POS tagging – difficult to devise the closed set of rules that infer the POS tag of the words from the word's context
  - Sentiment analysis – complete set of rules that determine the sentiment of a reivew?
  - Named entity recognition – a manually defined finite state automaton that recognizes the sequences of words that form named entities?
  - Semantic textual similarity – measure the word overlap and manually determine the treshold according to which two texts are considered similar?

Why machine learning?

- The problems with devising rule-based systems for complex tasks are numerous:
  1. We simply need to many rules to cover all the cases
  2. There are many exceptions (including exceptions to exceptions!) to be handled
  3. We need expert knowledge (i.e., an expert to handcraft the rules)
  4. Rules can be difficult to
     - Design – rules interact in unpredictable ways
     - Maintain – adding new rules can easily break everything
     - Adopt to new domains – we need to significantly modify/add rules
- IR and NLP tasks are often inherently subjective (e.g., relevance of a document for the query)
  - It is difficult to model subjectivity with rules

Why machine learning?

- It is often easier to manually label some concept than to design an explicit algorithm that captures the concept automatically

- Labeling typically does not require too much expert knowledge

- We don’t care how complex or subjective the task is
  - We let the data „speak for itself” and machine learning algorithm to do the work

- If we’re lucky, the labeled data might be already readily available (e.g., reviews with assigned ratings)

Machine learning basics

- **Supervised machine learning**
  - We have labeled data as input
  - Supervised ML algorithms learn the mapping between input representations and output labels
  - **Classification**: output is a discrete label (no ordering between the labels)
  - **Regression**: output is a an integer or real value (obviously, there is ordering)

- **Unsupervised machine learning**
  - We have no labels (i.e., we have unlabeled data) at input
  - **Clustering**: grouping instances by the similarity of their representations
  - **Outlier detection**: recognizing instances that are very dissimilar from all other instances in the dataset

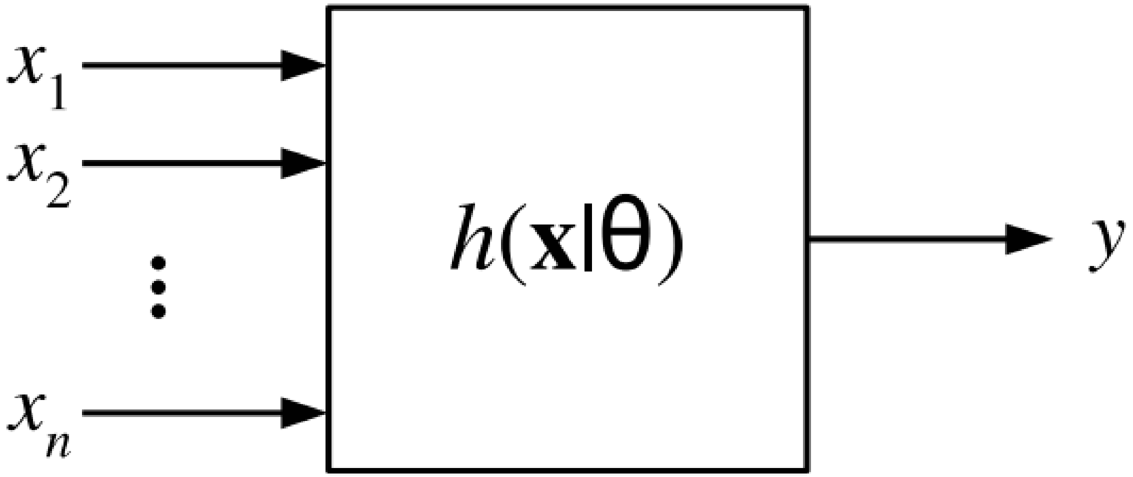
Supervised machine learning

- **Supervised machine learning** models „learn” the mapping between input values and output values
- A single input to the classifier is called an **instance** or **example** (denoted „$\mathbf{x}$”)
  - An instance is represented as an n-dimensional feature vector

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)$$

- The desired output is called the **target label** (or just label, denoted y)
- A classifier h maps an instance $\mathbf{x}$ to a label y – $h : \mathbf{x} \rightarrow y$
- „Learning” – model has parameters $\boldsymbol{\theta}$ (denoted $h(\mathbf{x} \mid \boldsymbol{\theta})$) whose values are optimized to maximize the prediction accuracy of the output labels, given instance

Supervised classification



- Types of classifiers in IR/NLP:
  - Binary classification: just two output labels (yes/no, 0/1)
  - Multi-class classification: each instance has one of K labels
  - Multi-label classification: an instance can have more than one label at once
  - Sequence labeling: input is a sequence of instances and the output is the sequence of labels

Supervised classification

- **Training** (or **learning**) – adjustment of model parameters **θ** so that the classification error is minimized
  - The error is computed on a labeled training set – this is the training error
- The training error is minimized with an optimization method
  - ML algorithms differ in optimization criteria and optimization method they use
- We want to know how classifier works on new, unseen instances
  - This property is called **generalization** – the classifier must generalize well
  - Testing error – the error computed on instances not used for training
- ML models can be of different complexity
  - The more parameters the model has, the more complex it is
  - The model may be too simple of too complex for the task at hand
  - **Underfitting** (model too simple for the task): both training and test errors are big
  - **Overfitting** (model too complex for the task): training error small, test error big

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Text Classification

- **Text Classification** is the automated categorization of some unit text (sentence, paragraph, document) into one (or more) of predetermined labels
  - E.g., classify news stories into high-level topics: *politics*, *sport*, *culture*, *entertainment*

- Why text classification in IR?
  - Automatically assigned classes/labels provide an additional semantic layer
  - These additional semantic annotations can be exploited to **rerank/filter** results
  - E.g., **Query**: *„lionel messi"* (but retrieve only documents categorized as *sport*)

- Some popular ML algorithms for text classification:
  - Traditional: Naive Bayes classifier, Logistic regression, (linear) SVM
  - Recent: Convolutional neural networks (CNN)

Text representations

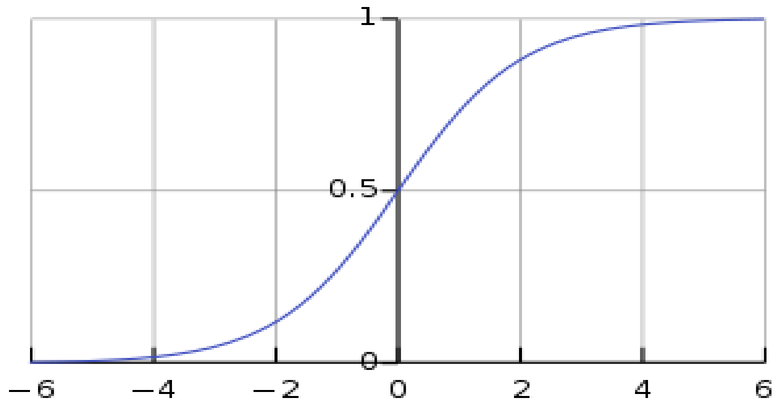
- For the majority of text classification algorithms, instances of text need to be transformed to numeric vector representations
  - Exceptions: Naive Bayes classifier and Decision Trees/Random Forests which can directly use word-based representations of text
- Numeric vector representations may be:
  1. Sparse – each text is represented as (potentially weighted) vectors of word occurrences, the size of the vector is the size of vocabulary
  2. Dense – each text is represented by a semantic dense vector (or by a concatenation of dense vectors of its consituent words)
- Traditional text classification models like logistic regression or SVM ignore the order of words in the text
  - I.e., they use bag-of-words representation of text
- Convolutional neural networks do take into account the order of words in the text
  - They compute abstract representations of subsequences of text

Logistic regression

- Despite its name, **logistic regression** is a classification algorithm
  - We will focus on binary classification – logistic regression computes the probability that some instance **x** belongs to some class (y = 1)

$$h(\mathbf{x} \mid \boldsymbol{\theta}) = P(y = 1 \mid \mathbf{x}) = \frac{1}{1+\exp(-\boldsymbol{\theta}^{\mathrm{T}}\mathbf{x})} = \sigma(\boldsymbol{\theta}^{\mathrm{T}}\mathbf{x})$$

- Logistic regression is based on a logistic function: $\sigma(a) = 1 / (1 + e^{-a})$
- The logistic function maps the input value to the output interval [0, 1]



Logistic regression

- Looking at the logistic regression formula (and the properties of log. function):
  - $h(\mathbf{x}|\boldsymbol{\theta}) > 0.5$ (i.e., instance belongs to the class) if and only if $\boldsymbol{\theta}^T\mathbf{x} > 0$
  - $h(\mathbf{x}|\boldsymbol{\theta}) < 0.5$ (i.e., instance doesn't belong to the class) if and only if $\boldsymbol{\theta}^T\mathbf{x} < 0$
- In order to make predictions, we need to know the parameter vector $\boldsymbol{\theta}$
  - We learn the values of parameters by minimizing some error function for the set of training instances
  - Logistic regression minimizes the so-called cross-entropy error

$$J(\boldsymbol{\theta}) = -\sum_i y^i * \log(h(\mathbf{x}^i|\boldsymbol{\theta})) + (1 - y^i) * \log(1 - h(\mathbf{x}^i|\boldsymbol{\theta}))$$

  - $J(\boldsymbol{\theta})$ is minimized (i.e., parameters $\boldsymbol{\theta}$ are optimized) via numeric optimization
    - Most commonly using stochastic gradient descent (SGD)

Convolutional neural network

- **Convolutional neural network** is a neural machine learning model that has been successfully used for text and image classification tasks
  - Unlike bag-of-words classifiers, treats text as an ordered sequence of words
  - Requires a **dense representation** of text as input – we typically represent text as (2D) concatenation of word embeddings

- CNNs parameters are **convolution filters** – real-valued matrices that are being used to compute the convolution with the partso of the input sequence
- The convolutional layer is followed by the **max-pooling layer** – where only the top K largest convolution scores are taken
- The final prediction is made by the softmax regression (generalization of the logistic regression for more than two labels)

Convolutional neural network

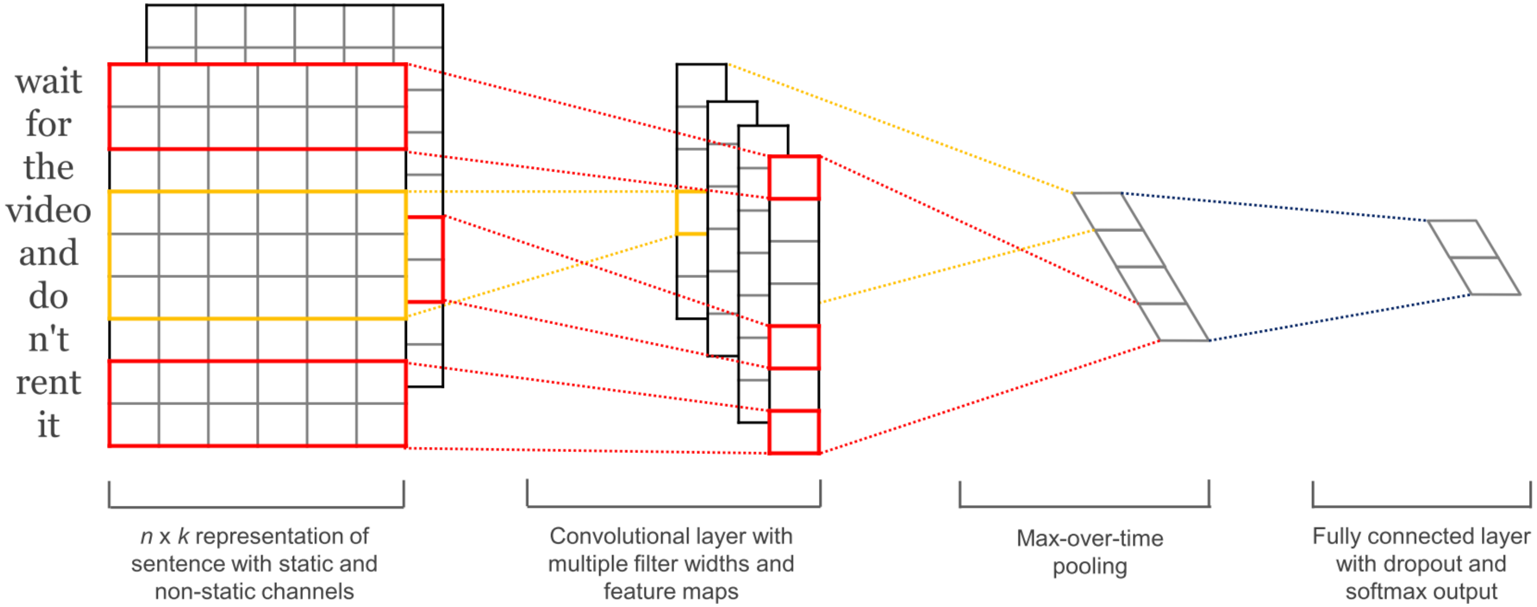


Image taken from: http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

- CNNs parameters (real-values of all convolution filter matrices) are learned by propagating the classification error via backpropagation algorithm

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Cluster Analysis

- **Cluster analysis** (or, colloquially, **clustering**) is a multivariate statistical technique that allows automated generation of groupings in data

- Components of clustering:
  1. An **abstract representation** of an object using which the object is compared to other objects
  2. A **function** that measures the **distance or similarity** between the objects based on their abstract representations
  3. A **clustering algorithm** that groups the objects based on the similarities / distances computed from their representations
  4. (optional) **Constraints** with respect to cluster membership, cluster proximity, shape of the clusters, etc.

Text clustering

- Representations of text for clustering are typically similar as for text classification (only we lack the labels)
  - Sparse vectors (binary or weighted, e.g., using TF-IDF)
  - Dense vectors (latent or semantic representations)
  - Sometimes also more structured representations like trees or graphs
- Common distance/similarity functions
  - Euclidean distance, cosine similarity/distance, Jaccard coefficient, Kullback-Leibler divergence, tree/graph kernels for structured representations (trees/graphs)
- Clustering algorithms:
  1. Sequential – e.g., single pass clustering
  2. Hierarchical – e.g., agglomerative clustering, divisive clustering
  3. Cost-function optimization clustering – e.g., K-means, mixture of Gaussians

Cluster information retrieval

- Why clustering in information retrieval?
  - We have already seen clustering at work in speeding up VSM retrieval (leaders)
- **Cluster information retrieval model**
  - **Cluster hypothesis** (van Rijsbergen, 1979): Documents similar in content tend to be relevant for the same queries
  - Steps:
    1. Collection documents are pre-clustered
    2. The query is matched against cluster centroids
    3. All documents from clusters represented by top-ranked centroids are returned (ranked)
  - **Improves efficiency** as the query needs not be compared with all documents
    - No comparison with documents from clusters with low-ranked centroids

Single pass clustering

- Simplest clustering algorithm
  - The number of clusters does not need to be predefined
- Algorithm:
  1. Start by putting the first text t_1 into the first cluster $c_1 = \{t_1\}$
  2. For all other texts, t_2, ..., t_n, one by one
     I. Measure the distance/similarity with all existing clusters c_1, ..., c_k
        - The similarity with the cluster is avg/max of similarities with instances in cluster

     II. Identify the cluster c_i with which the current text t_j has the largest similarity (or smallest distance)

     III. If the similarity between t_j and c_i is above some predefined threshold λ, add the text t_j to cluster c_i
- Although single-pass clustering doesn't explicitly require it, the number of clusters is indirectly determined by the value of the threshold λ

K-means

- Arguably the most famous and widely used clustering algorithm
- Requires the number of clusters k to be predefined – K clusters, **S** = {S_1, S_2, ..., S_k}, represented by mean vectors $\boldsymbol{\mu}_1$, $\boldsymbol{\mu}_2$, ..., $\boldsymbol{\mu}_k$
- **K-means** clusters instances ($\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$) by finding the partition **S** that minimizes the within-cluster distances (maximizing the within-cluster similarities):

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2$$

- **Q:** How to find the optimal clusters (i.e., minimize the above sum of within-cluster distances)?
- **A:** Using iterative optimization

K-means

- Algorithm for learning the centroids:
  1. Randomly pick k mean vectors μ_1, μ_2, ..., μ_k in the same space (i.e., of same dimensionality) as instance vectors
     - **K-means++** is an extension that more intelligently chooses the initial mean vectors
  2. Iterate the following two steps **until convergence**:
     I. Assign each instance $\mathbf{x}_j$ to the cluster with the closest mean vector μ_i :

$$S_i^{(t)} = \left\{ \mathbf{x}_j : \|\mathbf{x}_j - \boldsymbol{\mu}_i^{(t)}\|^2 \leq \|\mathbf{x}_j - \boldsymbol{\mu}_j^{(t)}\|^2, \forall j, 1 \leq j \leq k \right\}$$

     II. For each cluster, update the mean vector of a cluster
        - Set the mean vector to the mean of the instances in the cluster

$$\boldsymbol{\mu}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j$$

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Learning to Rank

- So far, each IR model was ranking the documents according to a **single** similarity function between the document and the query
  - VSM: cosine between the (sparse) TF-IDF vectors of the document and query
  - Latent/semantic IR: cosine between dense semantic vectors
  - Probabilistic IR: P(d, q | relevance)
  - Language modelling for IR: P(q | d)

- **Idea**: Combine different similarity scores as features of a supervised model

$$\vec{f}(d,q) = \begin{pmatrix} VSM_q(d) \\ P(q|d) \\ \text{Jaccard(qterms, dterms)} \end{pmatrix}$$

Learning to Rank

- Learning to rank is a supervised information retrieval paradigm that
  - Describes instances of document-query pairs (d, q) with a range of features
  - Learns (with some ML algorithm) the mapping between these features and relevance

- Three different learning-to-rank approaches:
  1. **Point-wise approach**
     - Classify a single document-query (d, q) pair for relevance
  2. **Pair-wise approach**
     - Classify, for a pair of documents, which one is more relevant for the query, i.e., whether $r(d_1, q) > r(d_2, q)$ or $r(d_1, q) < r(d_2, q)$
  3. **List-wise approach**
     - Classify the whole ranking as either correct or wrong

Learning to Rank

- **Point-wise** learning to rank
  - Train a supervised classifier that for a given query q classifies each document as relevant or non-relevant
  - Binary classification task: document is either relevant or non-relevant
  - Training instances:
    - Query-document pairs (q, d) with relevance annotations

- Issues with point-wise learning to rank
  - Do not care about absolute relevance, but relative order of documents by relevance
  - If pairs (q, d_1) and (q, d_2) are classified as relevant, which document to rank higher?
    - Supervised classifiers usually have confidence/probability scores assigned to predictions
    - Rank d_1 higher than d_2 if the classifier is more confident about relevance of pair (q, d_1)

Learning to Rank

- **Pair-wise** learning to rank
  - Train a supervised classifier that for a given query q and two documents d_1 and d_2 predicts which document is more relevant for the query
  - Binary classification task:
    - Class 1: „d_1 more relevant than d_2"
    - Class 2: „d_1 less relevant than d_2"
  - Training instances:
    - Triples (q, d_1, d_2) consisting of queries and document pairs
    - We may need comparison features – compare d_1 and d_2 with respect to q
      - E.g., binary feature: $VSM(q, d_1) > VSM(q, d_2)$
    - Generating gold labels from relevance annotations:
      - For query q we have: d_1(r), d_2(nr), d_3(r), d_4(nr)
      - We create the following training instances:
        - $\{(q, d_1, d_2), 1\}, \{(q, d_1, d_4), 1\}, \{(q, d_2, d_3), 2\}, \{(q, d_3, d_4), 1\}$

Learning to Rank

- Issues with pair-wise learning to rank
  - If we don't use comparison features (but direct similarities of d1 and d2 with q as features), the model may not generalize well for new queries!
  - We only obtain independent pair-wise decisions
  - **Q:** What if pair-wise decisions are mutually inconsistent?
    - E.g., (q, d1, d2) -> 1, (q, d2, d3) -> 1, (q, d1, d3) -> 2
  - We need an additional postprocessing step
    - To turn the sorted pairs into a ranking, i.e., partial ordering into global ordering
    - Inconsistencies need to be resolved
      - E.g., In a set of conflicting decisions, the one with the lowest classifier confidence is discarded
  - Another issue: we effectively treat pairs from the bottom of ranking same as those from the top of the ranking (and eval. metrics don't treat them equally!)

Learning to Rank

- List-wise ranking approach
  - Instead of learning decisions for individual documents or pairs of documents, learn to classify entire rankings as correct or wrong
  - Training instances: query and an entire ranking of documents $(q, d_1, \ldots, d_n)$
  - Binary classification task:
    - Class 1: the ranking $(q, d_1, \ldots, d_n)$ is correct
    - Class 2: the ranking $(q, d_1, \ldots, d_n)$ is incorrect
  - Advantage: optimization criteria for the machine learning algorithm can be the concrete IR evaluation metric we're looking to optimize
- Issues with list-wise approach
  - Entire ranking just one training instance
    - Difficult to collect many positive training instances
  - Informative features for the whole ranking are difficult to design

Outline

- Recap of Lecture #8
- Primer on Machine Learning
- Text Classification
- Text Clustering
- Learning to Rank
- Neural (Re-)Ranking

Ranking Based on Neural Language Models

- We have access to **enormous amounts of raw unannotated texts** (at least for major languages)
- Can we somehow pre-train the encoder using raw text?
  - Yes, via language modeling! Task is to predict the word from the text based on the encoding of the surrounding context
- **LM-pretraining**
  - Causal (unidirectional) language modeling: **GPT (1, 2, 3, 4, ...)**
  - Masked (bidirectional) language modeling: **BERT**
- In retrieval
  - Use the Neural LM to encode queries and documents

Bidirectional Transformer (BERT)

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, January). **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**. *NAACL 2019*.

- **Pretraining:** Masked language modeling, MLM (and next sentence prediction, NSP)
- **Encoder architecture**: deep Transformer (attention-based) network
- Encoder's parameters (learned in pre-training) further updated in task-specific training (aka **fine-tuning**)
- After task-specific training (aka **fine-tuning**), we have a **task-specific encoder**

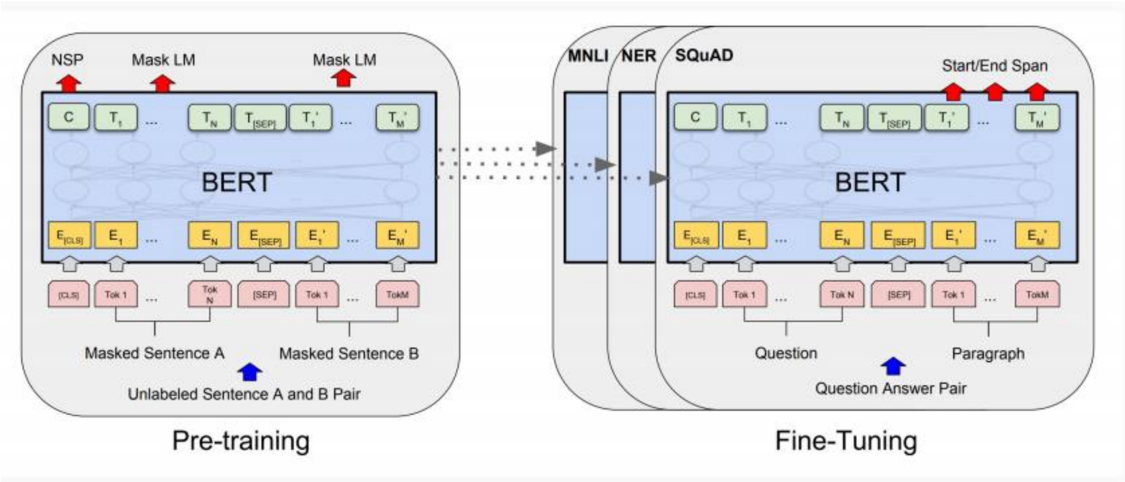


Image from [Devlin et al., NAACL 19]

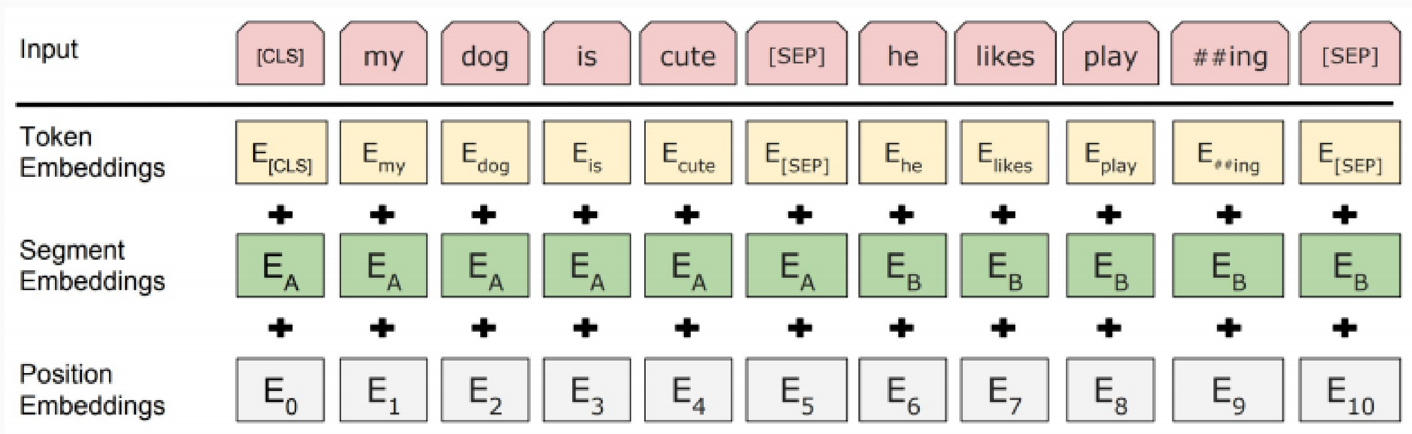
Bidirectional Transformer (BERT)

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**. *NAACL 2019*.

- **Training instances**: sentence pairs, with special tokens inserted
  - Ca. 15% of tokens masked out (replaced with [MASK] token)
  - Sequence start token [CLS] and sentence separation token [SEP]

- **Pretraining:** two **self-supervised** objectives
  - Masked language modeling, MLM (predict the masked token from the context)
  - Next sentence prediction, NSP (if sentences adjacent or not)

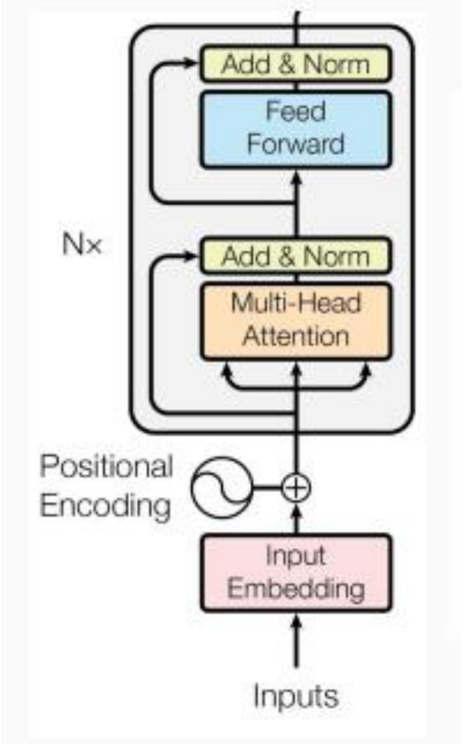
Image from [Devlin et al., NAACL 19]



Bidirectional Transformers for LU (BERT)

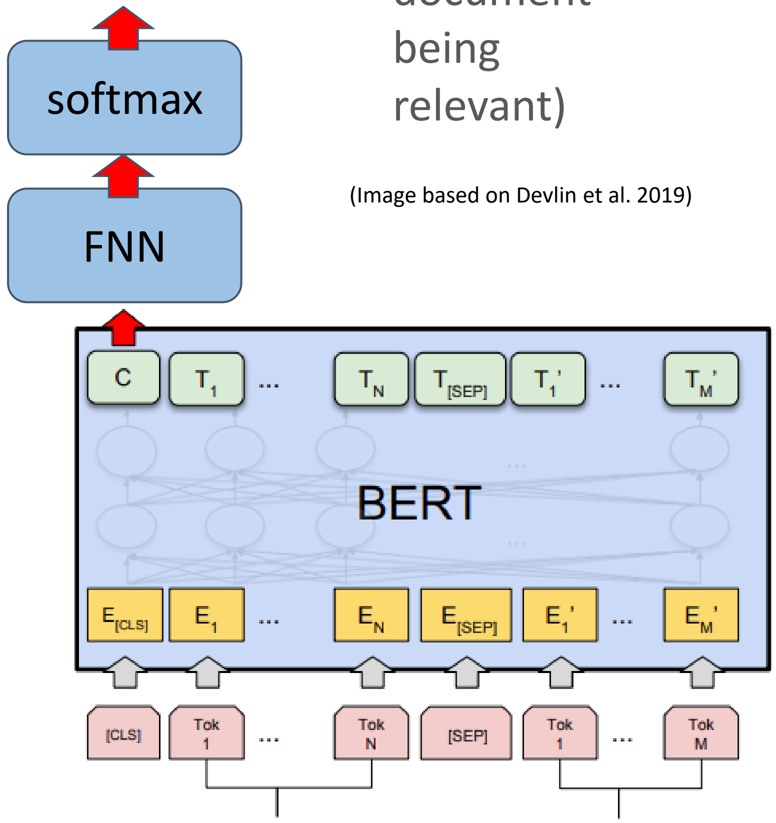
Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, January). **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**. *NAACL 2019*.

- **Encoder architecture**: deep Transformer (attention-based) network
  - Deep architecture consisting of N transformer layers
  - Each transformer layer:
    - Multi-head attention layer
    - Feed-forward layers
    - Residual connection (representation before the layer added to the result of the layer)
    - Layer normalization
  - All parameters of the Transformer: θ_{TRANS}



Multi-stage ranking with BERT (Nogueira et al. 2019)

$s_i = rel(q, d)$ (probability of document d_i being relevant)



(Image based on Devlin et al. 2019)

[CLS] Query q [SEP] Document d

BERT as a point-wise ranker (monoBERT): binary relevance classifier

- Feeds concatenation of query and document to BERT
  - Truncate query to at most 64 tokens
  - Concatenate query with document ([SEP]-token)
  - Truncate whole sequence to 512 tokens (max. seq. length)
- Obtain representation representation of [CLS]-token in last layer
- Feed [CLS] vector to single layered Feedforward Neural Network (FNN, binary classification model) to obtain relevance score

Optimize the following loss:

$$\mathcal{L}_{mono} = -\sum_{j \in J_{pos}} \log(s_j) - \sum_{j \in J_{neg}} \log(1 - s_j)$$

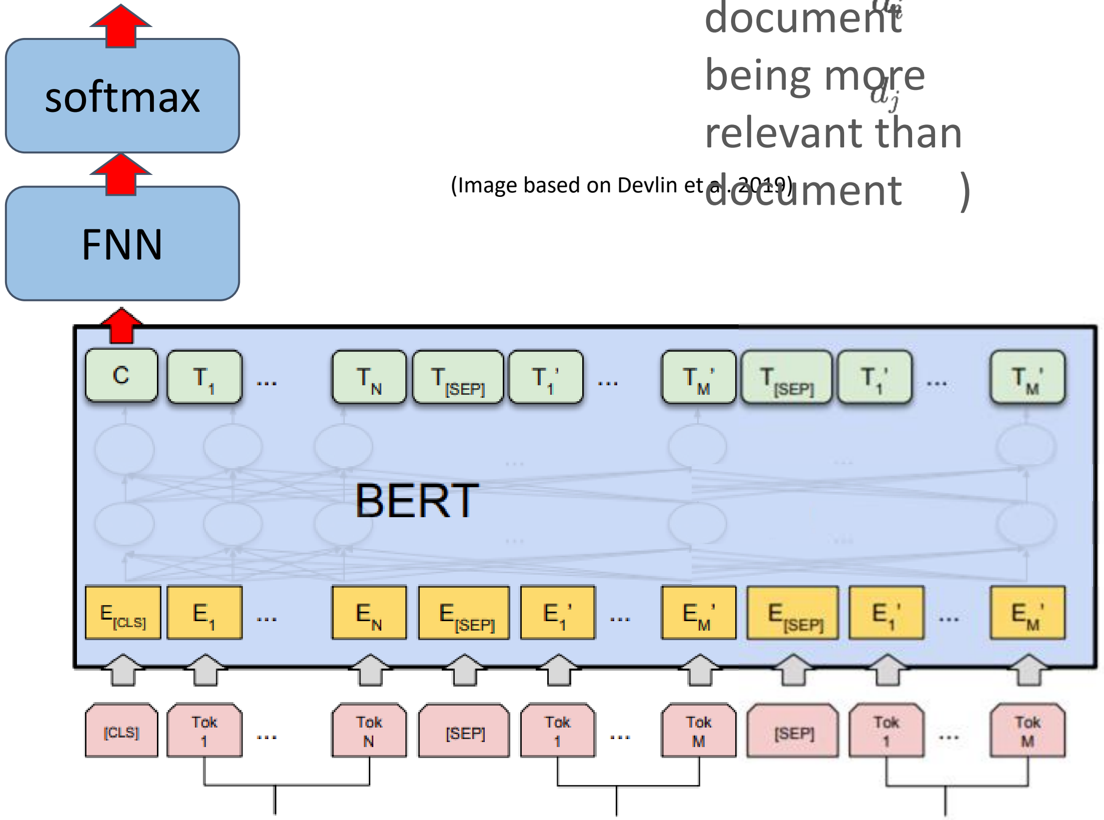
J_pos/neg = set of indexes of relevant/non-relevant documents

Retrieval: Rank documents by their probability of being relevant s_j

Multi-stage ranking with BERT (Nogieura et al. 2019)

$$p_{i,j} = rel(q, d_i) > rel(q, d_j)$$

(probability of document d_i being more relevant than document d_j)



(Image based on Devlin et al. 2019)

[CLS] Query q **[SEP]** Document d_i **[SEP]** Document d_j

BERT as a pair-wise ranker (duoBERT):

- Truncate the query, candididate document d_i and d_j to 62, 223 and 223 tokens respectively
- Concatenate query and document pair into single sequence
- For a candidate list of k_1 documents, compute $k_1(k_1-1)$ probabilities

Optimize the following loss:

$$\mathcal{L}_{duo} = -\sum_{i \in J_{pos}, j \in J_{neg}} \log(p_{i,j}) - \sum_{i \in J_{neg}, j \in J_{pos}} \log(1 - p_{i,j})$$

Retrieval:

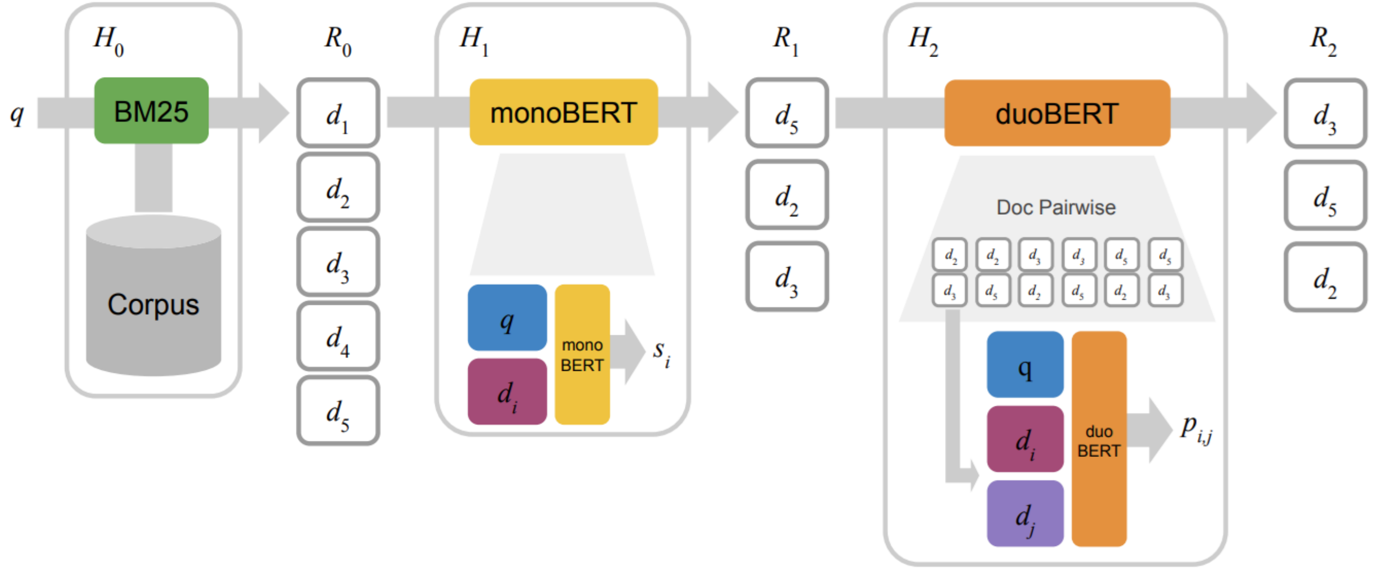
Aggregate pairwise scores $p_{i,j}$ into single score s_i

Set of all (other) document indexes in ranking R1: $J_i = \{0 \leq j \leq |R_1|, j \neq i\}$

Relevance score as **pair-wise agreement** that d_i is more relevant than the rest of the candidates (other aggregation methods possible too, cf. paper):

$$s_i = \sum_{j \in J_i} p_{i,j}$$

Multi-stage ranking with BERT (Nogueira et al. 2019)



Combining monoBERT and duoBERT into a multi-stage ranking architecture

Stage 1: Retrieve top-$k_0 = 1000$ documents using BM25 ($k_0 = 5$ in example above) → input to monoBERT

Stage 2: Re-rank top-$k_1 = 50$ documents with monoBERT ($k_1 = 3$ in example above) → input to duoBERT

Stage 3: Re-rank subset with duoBERT

Image source: Nogueira et al. 2019

Multi-stage ranking with BERT (Nogueira et al. 2019)

Summary

It's common practice to use neural rankers for re-ranking, ranking the full collection would be too slow for practical purpose

Arranging retrieval in a multi-stage pipeline allows for trading off quality against latency by controlling admission of candidates at each stage

Target Corpus Pre-training (Masked Language Modelling on document collection) before training monoBERT/duoBERT improves results

Challenges for pair-wise ranking revisited:

1. We only obtain independent pair-wise decisions (inconsistent ranking): Aggregate (all) possible pair-wise agreements into relevance scores
2. We effectively treat pairs from the bottom of ranking same as those from the top of the ranking (and eval. metrics don't treat them equally!): Neural model only re-ranks top k documents (ignore bottom of ranking)

Now you...

- Know the basics of machine learning
- Understand supervised text classification
- Know some methods for (unsupervised) text clustering
- Understand how to combine different ranking functions (and other features) in a supervised IR setting – learning to rank
- Have an idea of what neural (re-)rankers (neural L2R) look like