UNIVERSITY OF MANNHEIM

Web Mining

Web Content Mining: Named Entity Recognition

Simone Ponzetto

FSS 2023

Information Extraction

- **Information extraction (IE) is the automatic identification of selected types of entities, relations, or events in free text**

- **Traditionally, IE tasks tasks are the following:**
  - **Named entity recognition and classification (NERC)**
  - **Coreference resolution**
  - **Relation extraction**
  - **Event extraction**

- **The following tasks loosely belong to IE:**
  - **Keywords/keyphrase extraction**
  - **Terminology extraction**
  - **Collocation extraction**

Outline

1. Named Entity Recognition
2. Evaluation
3. RNNs
4. BERT

Supervised Named Entity Recognition

- In information extraction, a **named entity** is a **real-world object**, such as a **person**, **location**, **organization**, **product**, etc., that can be denoted with a **proper name**. It can be abstract or have a physical existence.
- Named-entity recognition (**NER**) is a subtask of information extraction that seeks to locate and **classify named entities** mentioned in **unstructured text** into **pre-defined categories** such as **person** names, **organizations**, **locations**, medical codes, **time** expressions, **quantities**, monetary values, percentages, etc.

Named Entity Recognition

Eastern Ukraine is gripped by an armed separatist uprising, with pro-Russian protesters occupying government buildings in more than a dozen towns and cities, despite an ongoing ”anti-terror” operation launched by the Ukrainian military. Vyacheslav Ponomaryov is the self-proclaimed pro-Russian mayor of Sloviansk, Donetsk region, the stronghold of the separatist movement in eastern Ukraine. He was involved in the seizure of a group of military observers from the Organization for Security and Co-operation in Europe (OSCE). One of the best-known leaders of the uprising, Igor Strelkov directs armed pro-Russian activists in eastern Ukraine, especially in Sloviansk. The word is he works for the GRU (Russian military intelligence agency), and his real name is Igor Girkin. He was born in 1970 and registered in Moscow.

- **PERson**, **LOCation**, **ORGanization**, **TIME**
- **Q: What type of NLP task would NER be (from the machine learning perspective)?**

Rule-Based Named Entity Recognition

- Large number of extraction patterns / rules
- Each pattern detects some type of named entities

```
[capitalized-word]+[' Corp.' ] ⇒ Organization
[' Mr.' ][capitalized-word]+ ⇒ Person
[in|at|on][capitalized-word]+ ⇒ Location
```

- Unfortunately, most rules have exceptions...

"She lost hope she would ever meet *Mr. Right One*." (Person?)
"God only knows what goes on in *Putin*'s mind." (Location?)

Building a Named-Entity Tagger

- We can add additional rules to handle exceptions

- E.g., gazetteers: word lists for each of the NER categories
- Some potential gazetteer rules:

[cap-word-names-gazetteer]+[cap-word-surnames-gazetteer]+

Personal names: Aaliyah, Aaron, Abbey, ..., Zygmunt, Zyta
Surnames: Abbott, Abney, Abraham, ..., Zysett, Zyskowsky Organizations: Abbott Laboratories, Abercrombie & Fitch, Association for Computational Linguistics, . . . , WorldCom, World Help Foundation
Locations: Alabama, Arkansas, ..., Zimbabwe

- Problem: Gazetteers are always incomplete
- Generally, too many rules, difficult to maintain, etc.

Supervised Named Entity Recognition

- We need: a corpus manually annotated with named entities
- Annotations done according to annotation standard
  - The most renowned annotation standard: MUC-7 (Chinchor & Robinson, 1997)
- MUC-7 named entity types
  - Entity names (ENAMEX) – Person, Organization, Location
  - Temporal expressions (TIMEX) – Date, Time
  - Quantities (NUMEX) – Monetary value, Percentage
- Annotation of named entities is not particularly demanding
  - No need to hire experts (e.g., linguists)
  - Virtually any native speaker can annotate (after training)

Supervised Named Entity Recognition

- **NER is a prototypical sequence labelling task**
  - **But named entities are generally multi-token expressions**
  - **Q: What labels do we assign to individual tokens?**
- **We need to make a distinction between the first token of a named entity and all other tokens**
  - **Q: Why?**

Barcelona’s/ORG draw/O with/O Atletico/ORG Madrid/ORG at/O Camp/LOC Nou/LOC was/O not/O expected/O, says/O British/ORG Broadcast/ORG Channel’s/ORG La/ORG Liga/ORG football expert Andy/PER West/PER.

- **„*British Broadcast Channel’s La Liga*” – one or two organizations?**

Supervised Named Entity Recognition

- **NER is a prototypical sequence labelling task**
  - **But named entities are generally multi-token expressions**
- **B-I-O annotation scheme**
  - **B – Begins a named entity (i.e., first NE token)**
  - **I – Inside a named entity (i.e., second and subsequent NE tokens)**
  - **O – Outside of a named entity (i.e., token is not part of any NE)**

Barcelona's/B-ORG draw/O with/O Atletico/B-ORG Madrid/I-ORG at/O Camp/B-LOC Nou/I-LOC was/O not/O expected/O, says/O British/B-ORG Broadcast/I-ORG Channel's/I-ORG La/B-ORG Liga/I-ORG football expert Andy/B-PER West/I-PER.

  - **„*British Broadcast Channel's La Liga*" – two organizations!**

Supervised Named Entity Recognition

Supervised approaches to NER:

1. **Token-level classification**
   - **Naive Bayes, SVM, Logistic regression, Feed-forward NN**
   - **Cannot use labels from both token sides as features**
2. **Sequence labelling**
   - **Hidden Markov Models (HMM), Conditional Random Fields (CRF)**
     - **Require manual feature design**
   - **Recurrent (or gated convolutional) neural networks**
     - **Word embeddings as input, no feature design**
     - **State-of-the-art results**

Common features (for feature-based learning algorithms):

- **Linguistic features: word, lemma, POS-tag, sentence start, capitalization, ...**
- **Gazetteer features: is gazetteer entry, starts gazetteer entry, inside of a gazetteer entry (for all gazetteers)**

Named Entity Recognition – Document Level

- Sequence models predict BIO labels at the sentence level
- Thus, it's possible to have different labels for the same named entity at the document level

Eastern Ukraine is gripped by an armed separatist uprising. Vyacheslav Ponomaryov is the self-proclaimed pro-Russian mayor of Sloviansk, Donetsk region, the stronghold of the separatist movement in eastern Ukraine. He was involved in the seizure of a group of military observers from the Organization for Security and Co-operation in Europe (OSCE). One of the best-known leaders of the uprising, Igor Strelkov directs armed pro-Russian activists in eastern Ukraine, especially in Sloviansk.

- Enforcing document-level consistency improves NER performance

Outline

1. Named Entity Recognition
2. Evaluation
3. RNNs
4. BERT

Named Entity Recognition Evaluation

– Comparing system predicted Named Entities (NEs) with gold-annotated Nes
  - In terms of precision, recall, and F-score

1. Lenient (aka MUC) evaluation
   - System NE and gold NE need to be of the same type and overlap in token spans in order to count as a match (i.e., true positive)
2. Strict (aka Exact) evaluation
   - System NE and gold NE need to be of the same type and exactly the same token span order to count as a match (i.e., true positive)

Gold: „The Faculty of Business Informatics and Mathematics issued a diploma…"
Sys1: „The Faculty of Business Informatics and Mathematics issued a diploma…"
Sys2: „The Faculty of Business Informatics and Mathematics issued a diploma…"

– State-of-the-art NER performance (coarse-grained entity types) is around 94% F-score for English, and significantly less for other languages

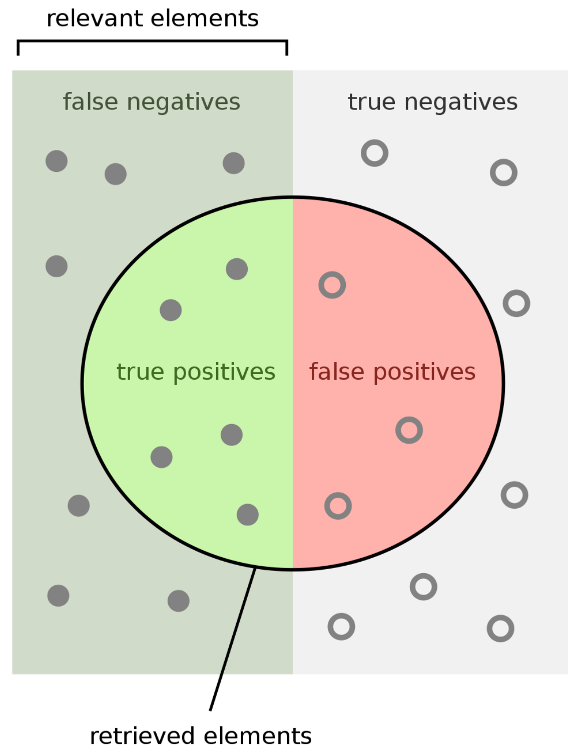
Named Entity Recognition Evaluation

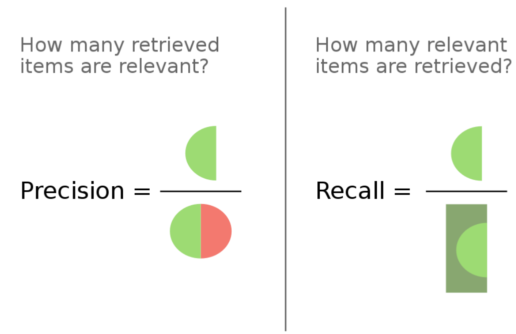
$$F_1 = \frac{2}{recall^{-1} + precision^{-1}}$$

The F1 score is the harmonic mean of the precision and recall.

$$F_1 = 2\frac{recall \cdot precision}{recall + precision}$$

$$F_1 = \frac{tp}{tp + \frac{1}{2}(fp + fn)}$$





I. Surface string and entity type match

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
in	O	in	O
New	B-LOC	New	B-LOC
York	I-LOC	York	I-LOC
.	O	.	O

II. System hypothesized an entity

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
an	O	an	O
Awful	O	Awful	B-ORG
Headache	O	Headache	I-ORG
in	O	in	O

III. System misses an entity

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
in	O	in	O
Palo	B-LOC	Palo	O
Alto	I-LOC	Alto	O
,	O	,	O

Note

- Note that considering only this 3 scenarios, and discarding every other possible scenario we have a simple classification evaluation that can be measured in terms of false negatives, true positives and false positives, and subsequently compute precision, recall and f1-score for each named-entity type.
- But of course we are discarding partial matches, or other scenarios when the NER system gets the named-entity surface string correct but the type wrong, and we might also want to evaluate these scenarios again at a full-entity level.

IV. System assigns the wrong entity type

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
I	O	I	O
live	O	live	O
in	O	in	O
Palo	B-LOC	Palo	B-ORG
Alto	I-LOC	Alto	I-ORG
,	O	,	O

V. System gets the boundaries of the surface string wrong

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
Unless	O	Unless	B-PER
Karl	B-PER	Karl	I-PER
Smith	I-PER	Smith	I-PER
resigns	O	resigns	O

VI. System gets the boundaries and entity type wrong

Golden Standard		System Prediction	
Surface String	Entity Type	Surface String	Entity Type
Unless	O	Unless	B-ORG
Karl	B-PER	Karl	I-ORG
Smith	I-PER	Smith	I-ORG
resigns	O	resigns	O

CoNLL: NER task

- The **Language-Independent Named Entity Recognition task** introduced at CoNLL-2003 measures the performance of the systems in terms of precision, recall and f1-score, where:
- *"precision is the percentage of named entities found by the learning system that are correct. Recall is the percentage of named entities present in the corpus that are found by the system.* ***A named entity is correct only if it is an exact match of the corresponding entity in the data file."***
- so basically it only considers scenarios I, II and III, the others described scenarios are not considered for evaluation.

Outline

1. **Named Entity Recognition**
2. **Evaluation**
3. **RNNs**
4. **BERT**

Recurrent neural networks

- **Recurrent neural networks are neural models that explicitly take into account the sequences**
  - **Sequences of words in a sentence, sentences in a paragraph, etc.**

General RNN model:

- **Input: sequence of input vectors (e.g., word embeddings): $x_1, \ldots, x_n$**
- **RNN is a function that converts an arbitrary size sequence $x_1, \ldots, x_n$ into a fixed size output vector y_n**
  - **Analogously, the subsequence $x_1, \ldots, x_i$ will produce the output y_i**
- **The output vector y_{i-1} of the previous step ($i-1$) is combined with the current input x_i to produce the output y_i**
- **The RNN network is, at time step i, represented with its current state s_i**

Recurrent neural networks

General RNN model:

- Defined by two functions:
  - Function R defines how the next state s_i is computed from the previous state s_{i-1} and current input x_i
  - Function O defines how the current output y_i is computed from the current state s_i
- Obviously, RNN is defined **recursively**

$y_n = O(s_n)$

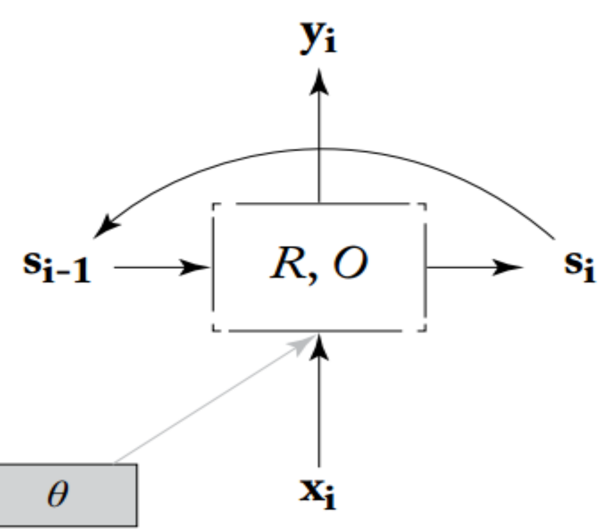
$s_n = R(x_n, s_{n-1})$

$\quad = R(x_n, R(x_{n-1}, s_{n-2}))$

$\quad ...$

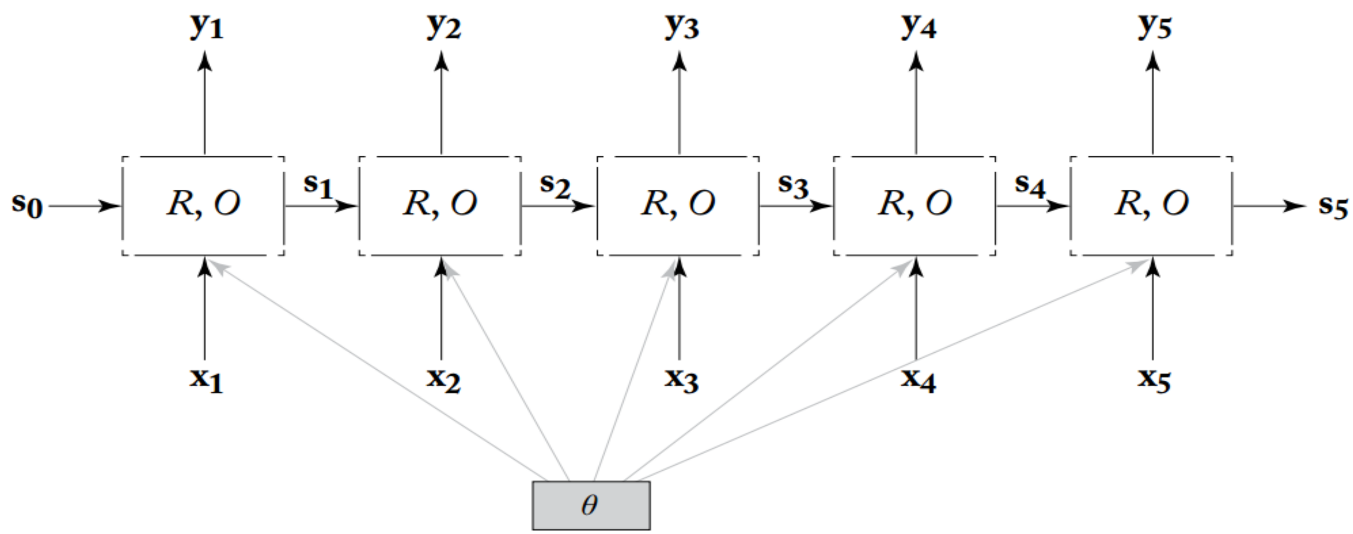
$\quad = R(x_n, R(...(R(x_1, s_0))$

- θ are RNN parameters (in R)



Recurrent neural networks

- For some input sequence of finite length, we can „unroll” the RNN recursion



- s_n (and y_n) can be thought of as the encoding of the whole sequence
- This general RNN model is instantiated into concrete models by defining functions *R* and *O*
  - Two models we will cover: Simple (Elman) RNN and LSTM

Simple (Elman) RNN

- The simplest RNN formulation that still captures the ordering of the elements in the sequence
- Model:
  - R = Non-linear transformation g (usually hyperbolic tangent or sigmoid) applied to a linear combination of the input and previous state

$$\begin{aligned} s_i &= R(x_i, s_{i-1}) \\ &= g(x_i W^x + s_{i-1} W^s + b); \end{aligned}$$

  - O = identity function

$$\begin{aligned} y_i &= O(s_i) \\ &= s_i \end{aligned}$$

- Parameters
  - $\theta = (W^x, W^s, b)$ if inputs are fixed (e.g., pre-trained word embeddings)
  - $\theta = (W^x, W^s, b, X)$ if we are also learning the word representations

Gated architectures

- **Simple (Elman) architecture suffers from a problem known as vanishing gradients**
  - **Error signals from later steps in the sequence diminish quickly in the backpropagation algorithm**
  - **Thus the updates for early inputs that come from errors for in later steps are very small**
    - **Esentially, Simple RNN has difficulties capturing long-distance dependencies**
  - **At each step, the whole RNN state is rewritten**
- **Gated architectures idea**
  - **Do not update the whole state at every step**
  - **Introduce parameters that decide which parts of the state to update**
  - **Introducing gate vectors:**
    - **They define which parts of the new state are taken from previous state and which from the current input**
  - **Models: Long short-term memory (LSTM), Gated Recurrent Unit (GRU)**

Long Short-Term Memory Networks

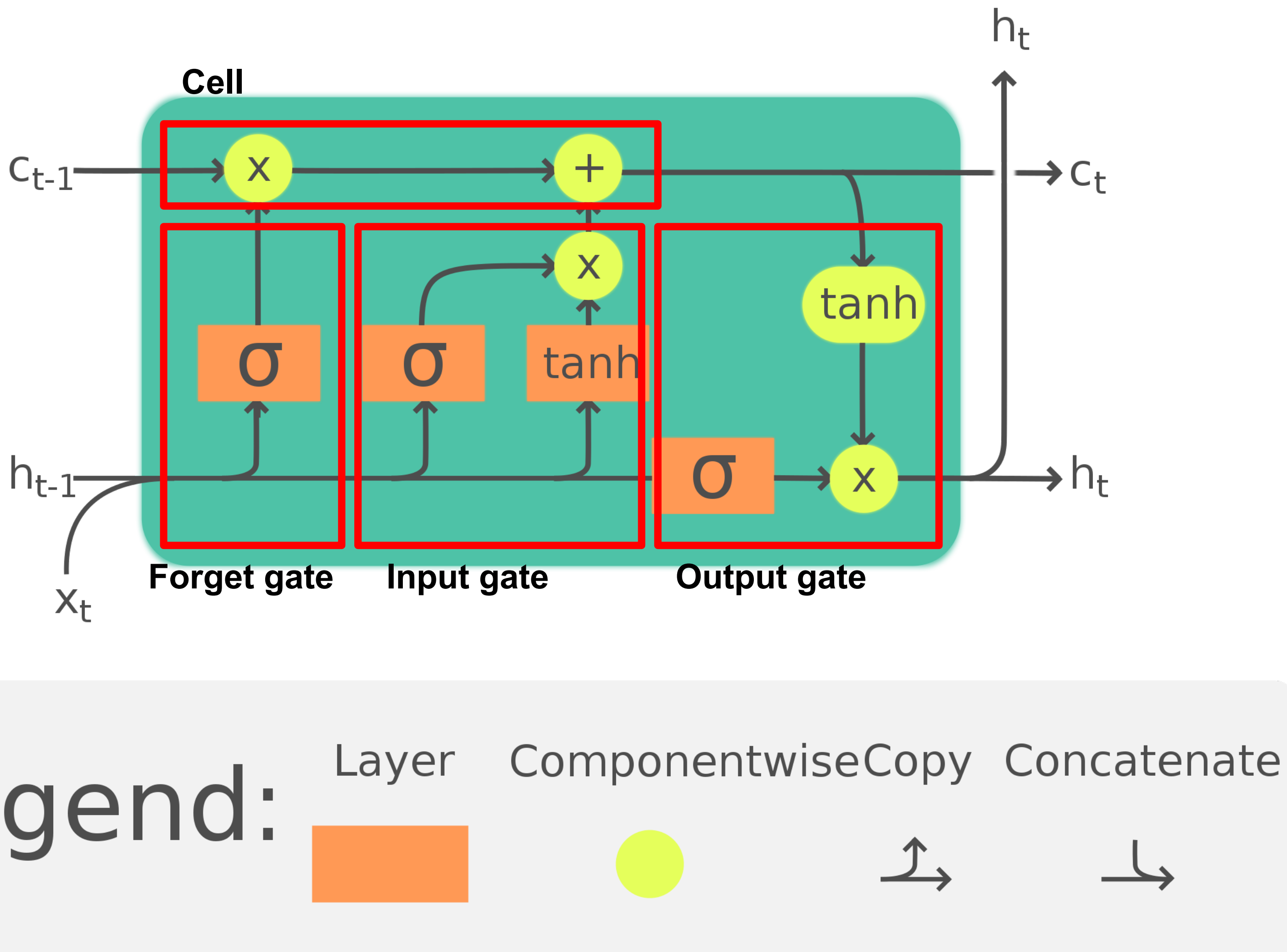
Long Short-Term Memory (LSTM) is an RNN architecture that:

1. Explicitly splits the RNN state intwo two halves: $s_i = [c_i; h_i]$
   - c_i is the „memory cell”, wheras is the h_i „working memory”
2. Introduces differentiable gating mechanisms – smooth functions that simulate logical gates. There are three gate vectors:
   - Input gate vector: decides how much of the current input x_i should be written to the memory cell c_i
   - Forget gate vector: decides which parts of the memory cell should be forgotten, due to new input
   - Output gate vector: decides which parts of the memory cell should be copied to the current memory
   - Gate vectors themselves are computed from the current input x_i and previous state of the working memory h_{i-1}

Long Short-Term Memory Networks

- **Concrete computation**
  1. **State:** $s_i = R(x_i, s_{i-1}) = [c_i; h_i]$
  2. **Input gate:** $ig = \mathit{sigmoid}(x_i W^{x,ig} + h_{i-1} W^{h,ig} + b^{ig})$
  3. **Forget gate:** $fg = \mathit{sigmoid}(x_i W^{x,fg} + h_{i-1} W^{h,fg} + b^{fg})$
  4. **Output gate:** $og = \mathit{sigmoid}(x_i W^{x,og} + h_{i-1} W^{h,og} + b^{og})$
  5. **Next step raw:** $z = \mathit{tanh}(x_i W^{x,z} + h_{i-1} W^{h,z} + b^{z})$
  6. **Next step memory cell:** $c_i = fg\ [\cdot_{el}]\ c_{i-1} + ig\ [\cdot_{el}]\ z$
  7. **Next step working memory:** $h_i = og\ [\cdot_{el}]\ \tanh(c_i)$
     - $[\cdot_{el}]$ is the element-wise (Hadamard) product of the vectors
- **The output at each step is simply the working memory at that step:**
  - $y_i = O(s_i) = h_i$
- **LSTM has to learn many more parameters than Simple RNN:**
  - $\theta = [W^{x,ig}, W^{h,ig}, b^{ig}, W^{x,fg}, W^{h,fg}, b^{fg}, W^{x,og}, W^{h,og}, b^{og}, W^{x,z}, W^{h,z}, b^{z}]$

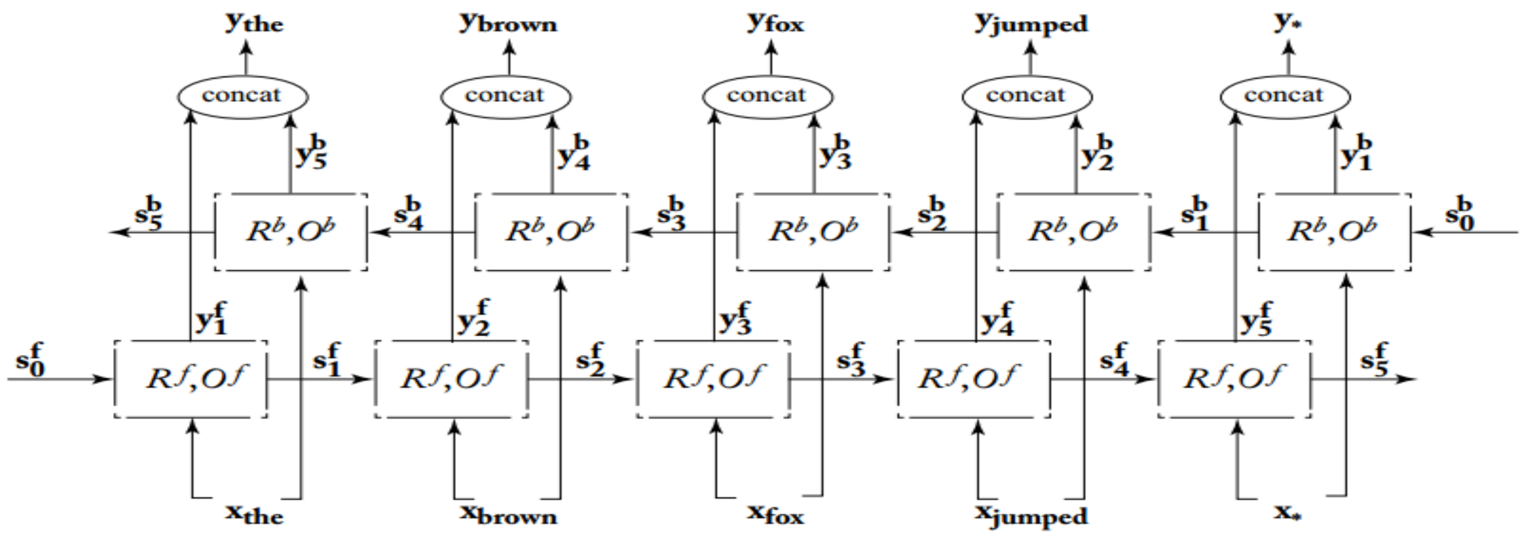
LSTM



h_t
Cell
c_{t-1}
x
+
c_t
x
tanh
σ
σ
tanh
h_{t-1}
σ
x
h_t
x_t
Forget gate
Input gate
Output gate
Legend:
Layer
ComponentwiseCopy
Concatenate

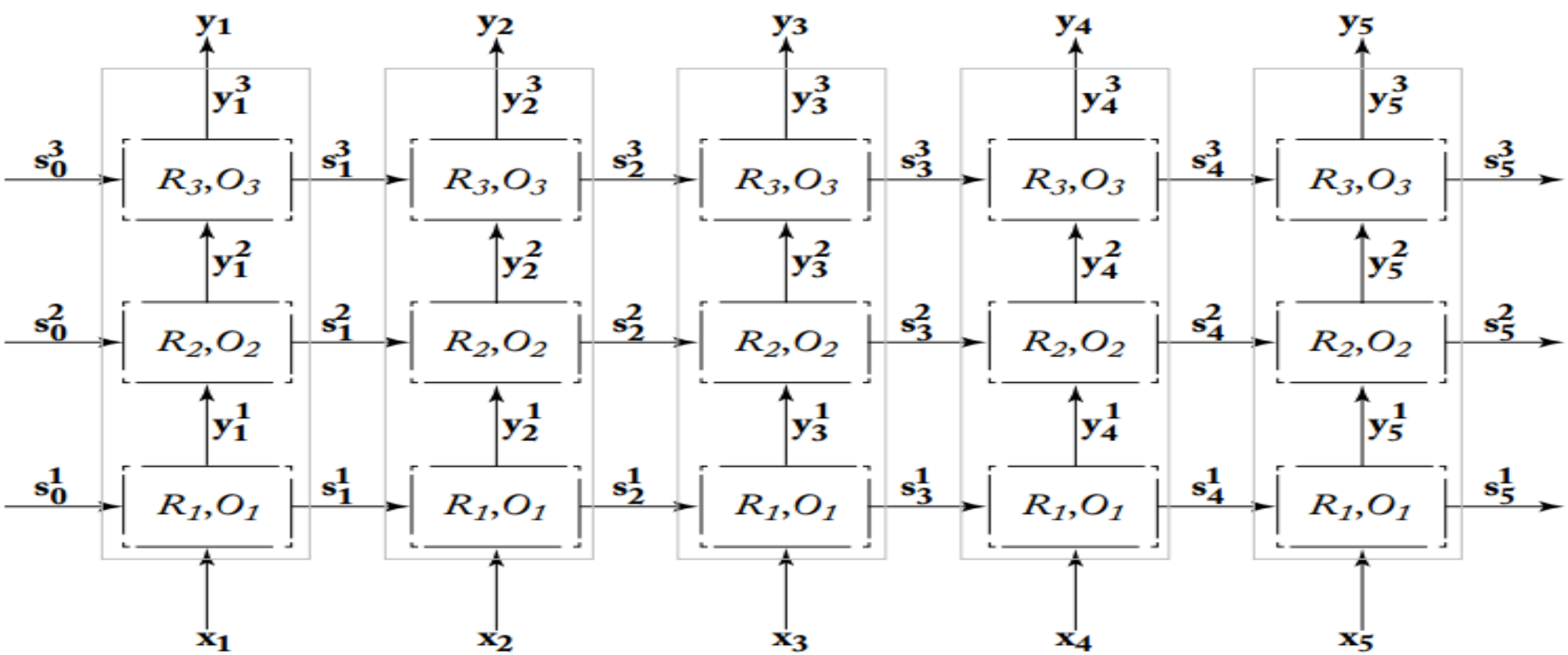
Bi-directional RNNs

- **Standard RNN at each step only encodes the sequence from one side of the current token**
- **For many NLP tasks (remember sequence labelling!) we want to incorporate knowledge about the context from both sides**
- **Bidirectional RNN is a model that combines two uni-directional RNNs encoding in opposite directions**
  - **Output at step *i* is the concatenation of output vectors of both RNNs**



Multi-Layer (Stacked) RNNs

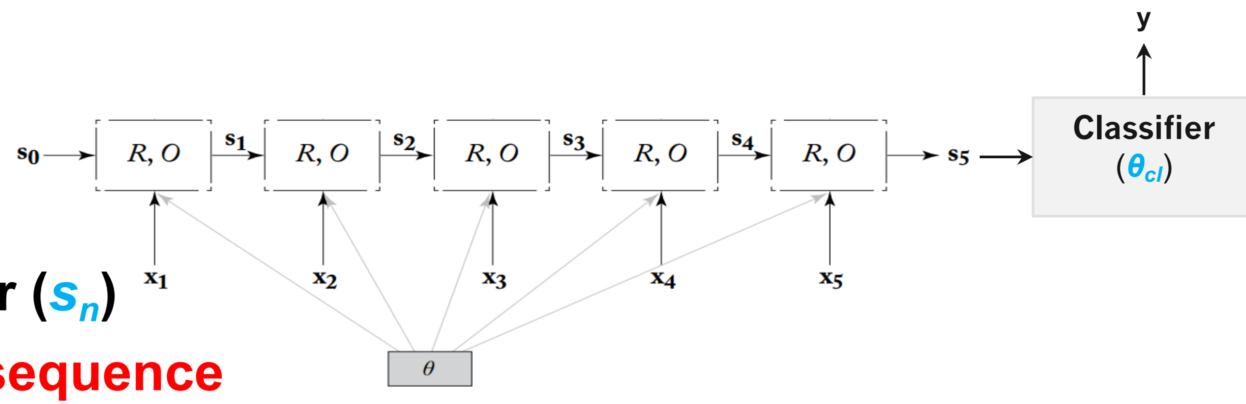
- RNNs can be **stacked** in layers, forming a grid
- The input for the first RNN are the actual input $x_1, \ldots, x_n$
- The input for all other layers are the outputs of previous layer RNN
- This architecture is called **Deep RNN**



RNN usage patterns

RNN as encoder

- **Assumptions:**
  - the last state vector (s_n) encodes the whole sequence
  - Thus, if we need to make a prediction for the whole sequence, we can use the last state as its representation



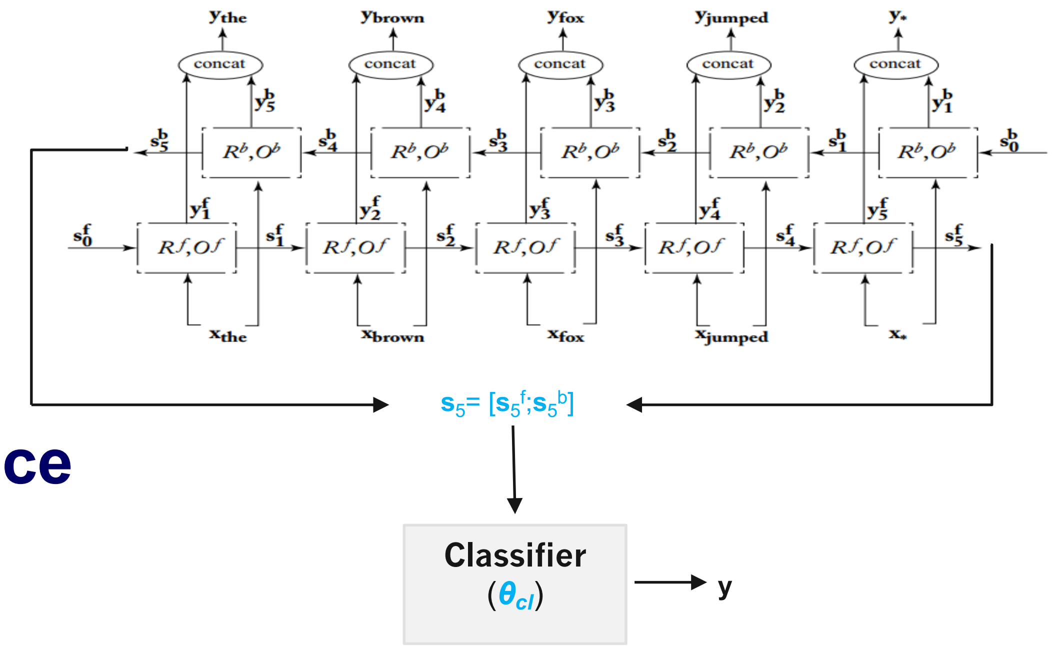
- **The representation of the whole sequence, the last state, is fed into a classifier**
  - E.g., a ternary classifier determining whether the sentence has positive, negative, or neutral sentiment
  - The classifier is usually a feed-forward network with its own set of parameters (θ_{cl})

$$y = \mathrm{softmax}(s_n W_{cl} + b)$$

RNN usage patterns

RNNs as encoders

- **Bidirectional RNN consists of two unidirectional RNN**
- **We have two states (s_n^f, s_n^b) that encode the whole sequence**
  - s_n^f encodes left-to-right
  - s_n^b encodes right-to-left



- **Q: How do we create a sentence representation for classification?**
- **A: We concatenate the two final states: $s_n = [s_n^f; s_n^b]$**

RNN usage patterns – attention mechanism

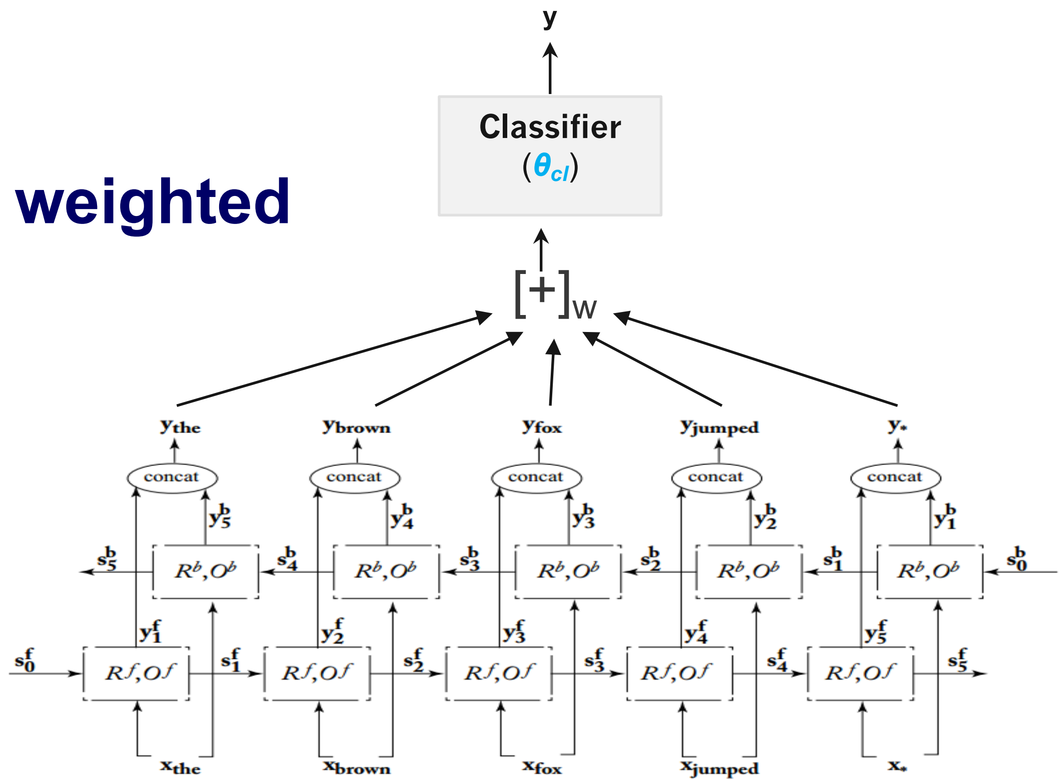
RNNs as encoders

- By using the last state to predict the class for the whole sequence, we're putting more emphasis on the inputs closer to the end
- This is somewhat remedied by bidirectional RNN
  - More emphasis on tokens at the beginning and the end of the sequence
- Still, some inputs (e.g., in the middle of the sequence) might be more important for the overall sequence representation than the others
  - E.g., tokens „good" or „bad" for sentence sentiment classification

Attention mechanism

- Sequence representation should be a weighted sum of outputs at different time steps (all positions in the sequence)
- Weights are determined via special parameters that also need to be learned

RNN usage patterns – attention mechanism



Attention mechanism

- Sequence representation is a weighted sum ($[+]_w$) of the step outputs

  $$s = \sum_{i=1}^{n} w_i y_i$$

- Weights w_i are determined via attention parameter vector v_a
  - Unnormalized weight for each output can be computed as dot product with attention parameter vector: $w_i' = v_a * y_i$
  - Final weights are determined by applying the softmax function on the vector of unnormalized weights

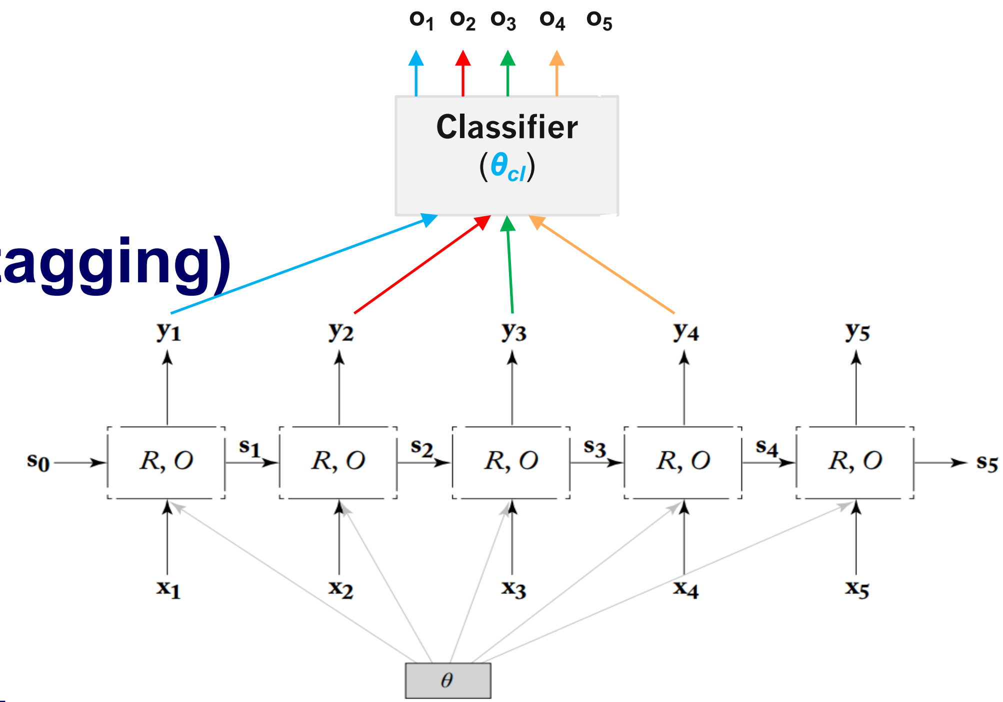
    $$[w_1, w_2, ..., w_n] = \text{softmax}([w_1', w_2', ..., w_n'])$$

  - The attention parameter vector is another parameter of the whole model which is being learned (together with RNN parameters and θ_{cl})

RNN usage patterns

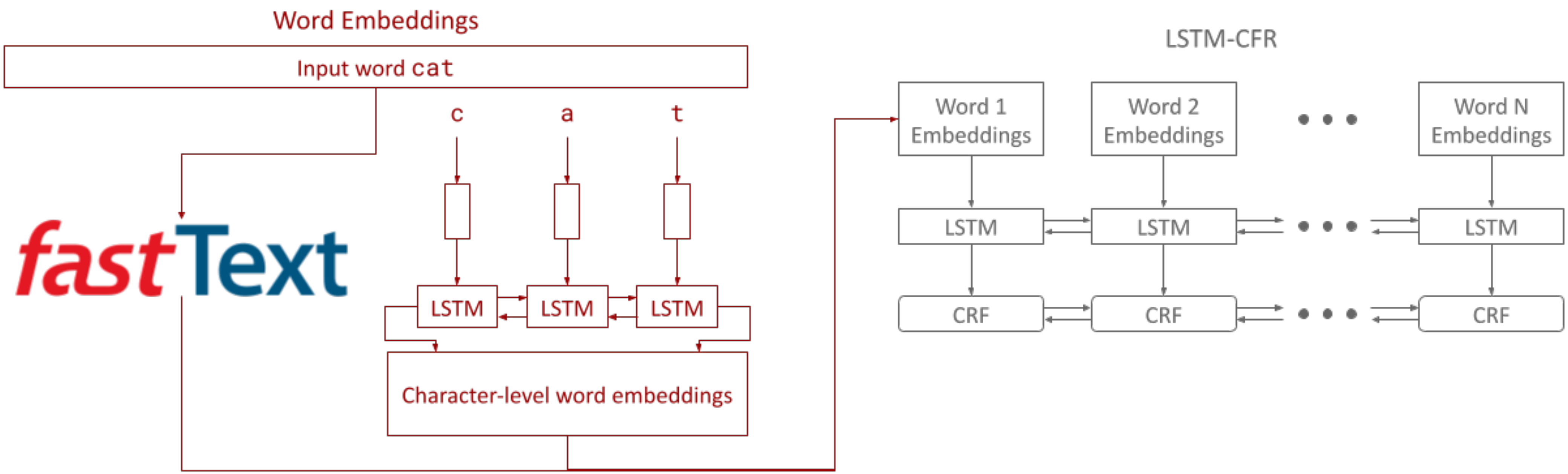
RNN as transducer

- When RNN is used for **sequence labelling** (e.g., POS-tagging)
- We need to predict the class at every time step of the RNN



- Again, we couple the RNN with a feed-forward classifier
  - But now we predict the class at every position in the sequence, instead of only from the final sequence state as in the encoder usage pattern
  - The prediction loss for the whole sequence is simply the sum of prediction losses of all token-level predictions

Bi-LSTM-CRF



Word Embeddings
Input word cat
c
a
t
fastText
LSTM
LSTM
LSTM
Character-level word embeddings
LSTM-CFR
Word 1 Embeddings
Word 2 Embeddings
Word N Embeddings
LSTM
LSTM
LSTM
CRF
CRF
CRF

Outline

1. **Named Entity Recognition**
2. **Evaluation**
3. **RNNs**
4. **BERT**

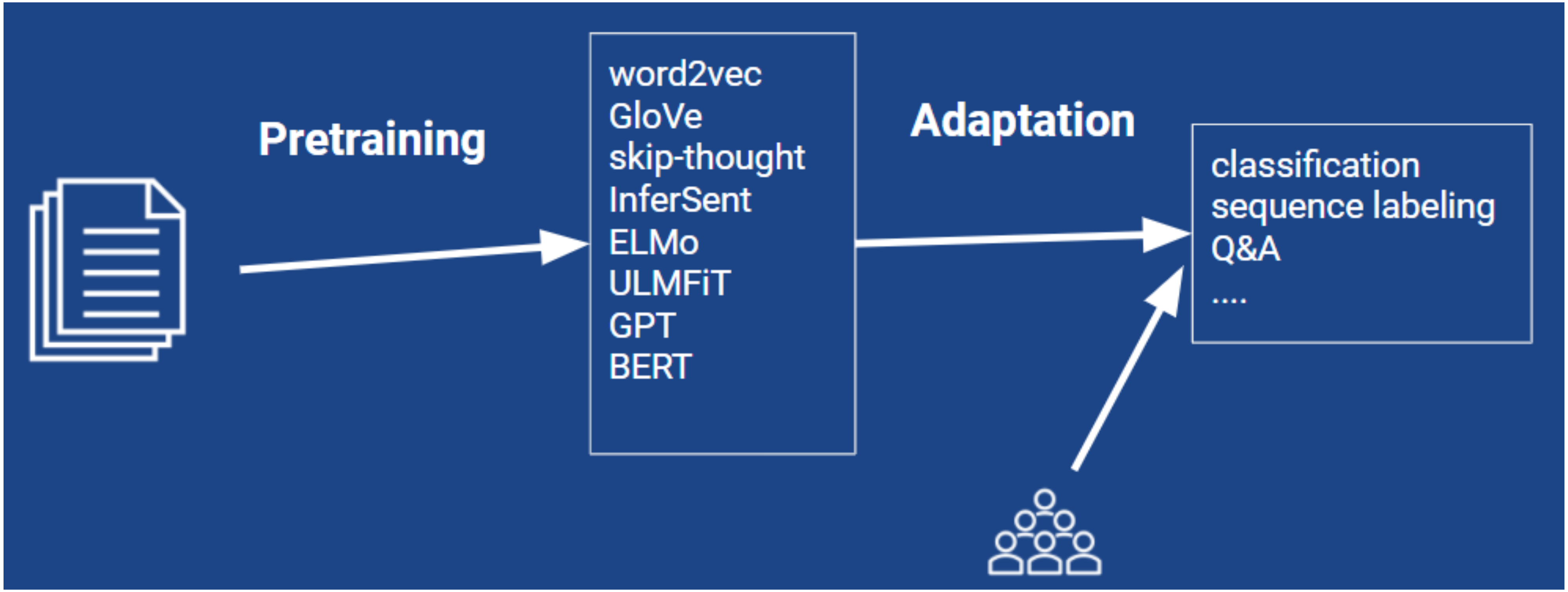
Sequential transfer learning

- **Core idea: pretrain the language/text encoder on large amounts of text, so that it learns ”the language”**
  - **Structure of the language (i.e., syntax)**
  - **Compositionality of meaning in the language (i.e., semantics)**

- **If we could „pre-train” such an encoder, it would be generally useful for a wide spectrum of NLP tasks**

- **On which data do we pretrain such an encoder?**
  - **Large annotated task-specific datasets? Is it going to be general enough?**
  - **Large unlabeled datasets? But what is our (pre)training objective then?**

Sequential transfer learning



Self-supervised pretraining

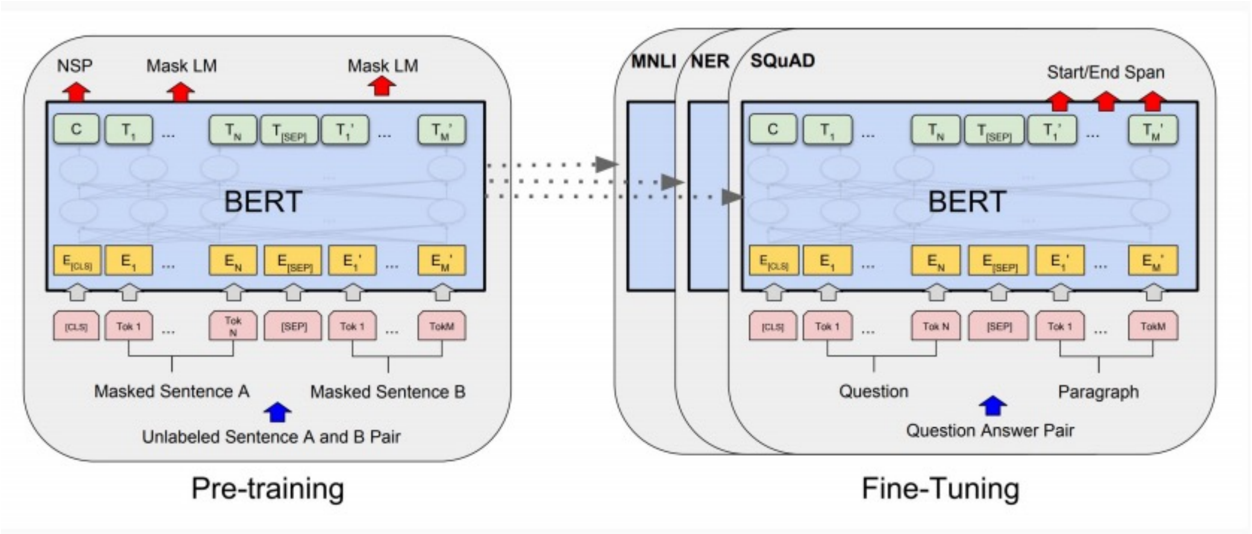
- We have access to enormous amounts of raw unannotated texts (at lerast for major language)
- Can we somehow pre-train the encoder using raw text?
  - Yes, via language modeling! Task is to predict the word from the text based on the encoding of the surrounding context
- LM-pretraining
  - Causal (unidirectional) language modeling: GPT(I, II, and III)
  - Bidirectional language modeling: ELMo
  - Masked language modeling: BERT

BERT

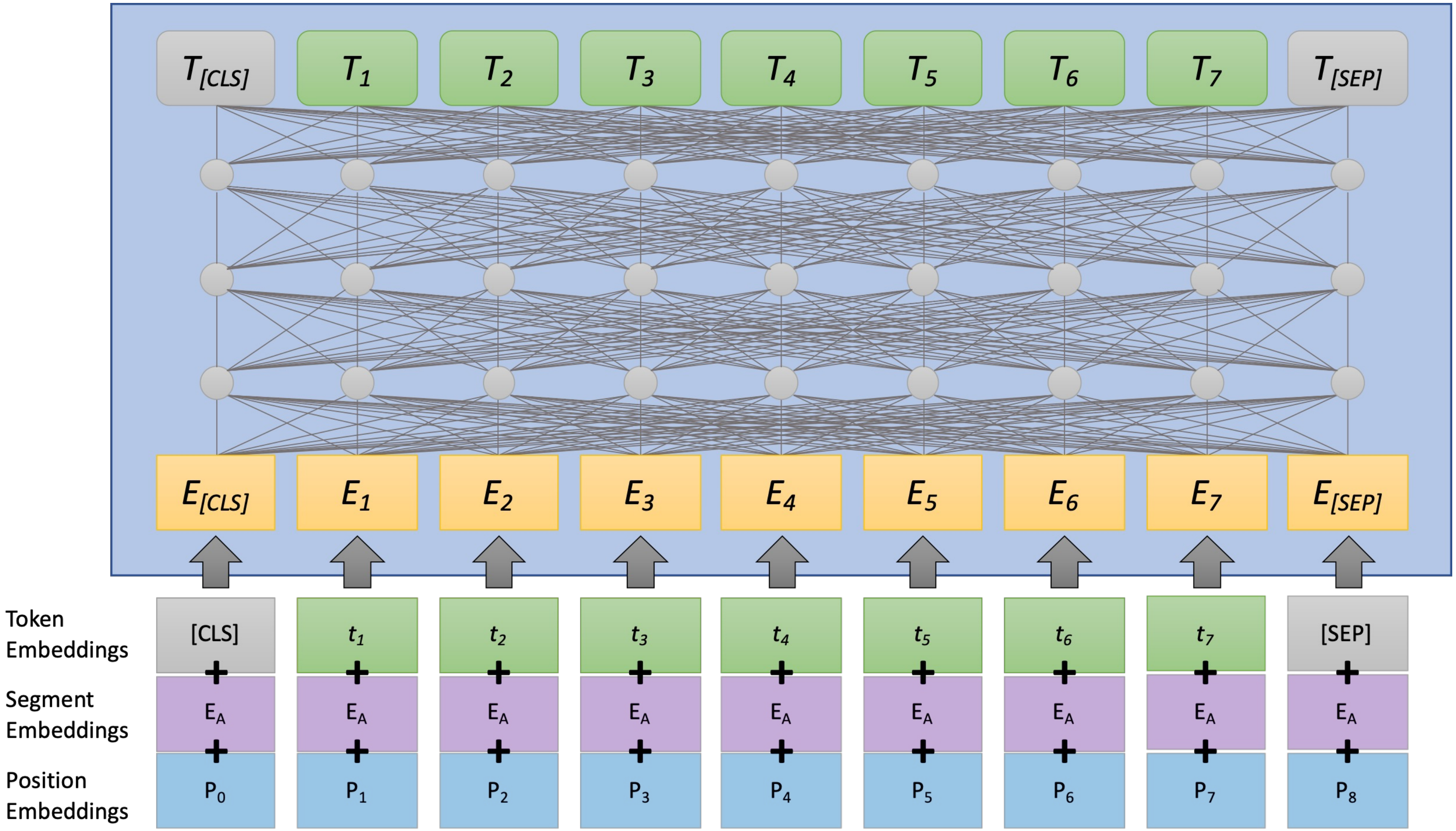
Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, January). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *NAACL 2019*.

- **Pretraining: Masked language modeling, MLM (and next sentence prediction, NSP)**
- **Encoder architecture: deep Transformer (attention-based) network**
- **After fine-tuning, we have a task-specific encoder**

Image from [Devlin et al., NAACL 19]

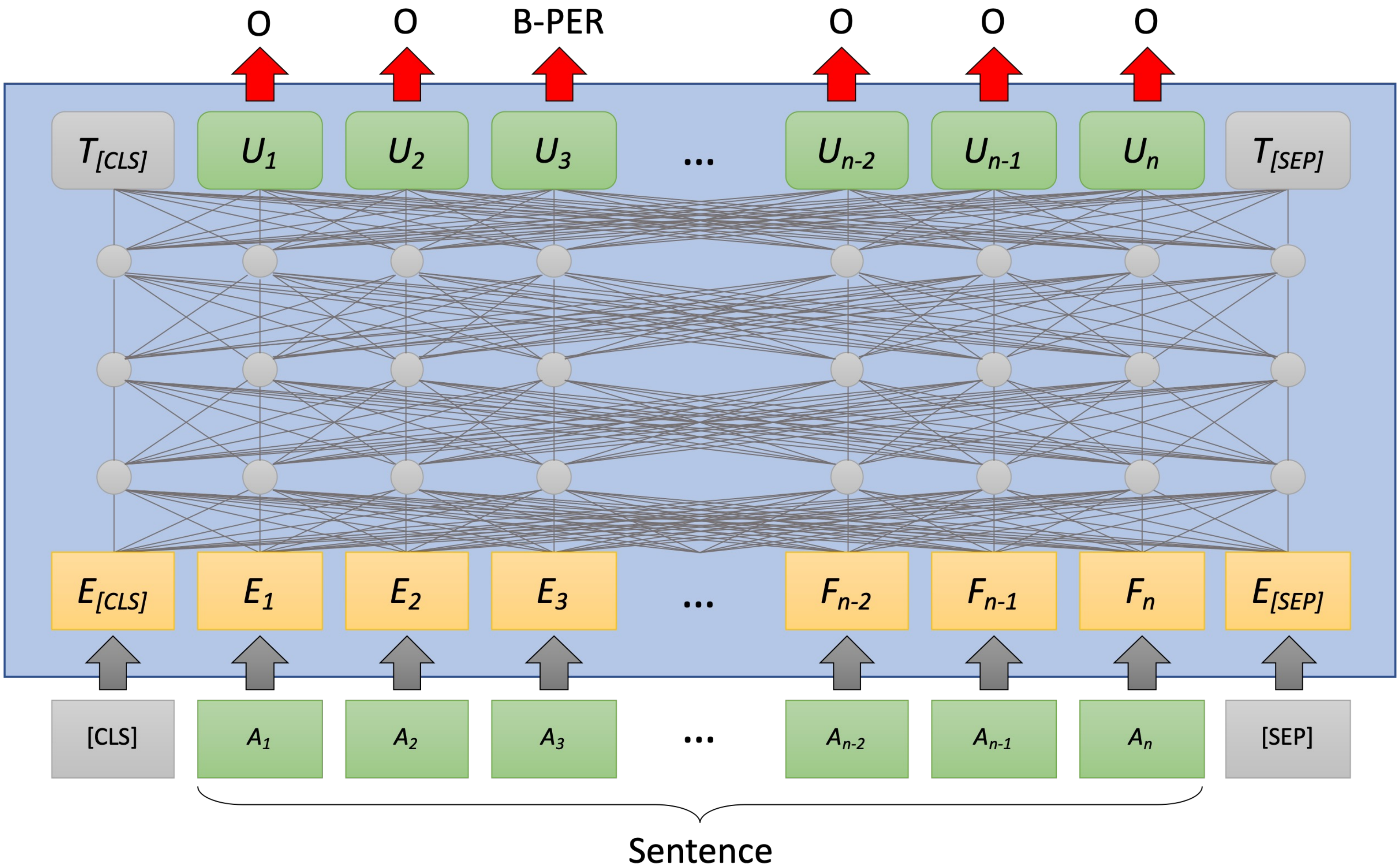


BERT



$T_{[CLS]}$ T_1 T_2 T_3 T_4 T_5 T_6 T_7 $T_{[SEP]}$
$E_{[CLS]}$ E_1 E_2 E_3 E_4 E_5 E_6 E_7 $E_{[SEP]}$
Token Embeddings
[CLS] t_1 t_2 t_3 t_4 t_5 t_6 t_7 [SEP]
Segment Embeddings
E_A E_A E_A E_A E_A E_A E_A E_A E_A
Position Embeddings
P_0 P_1 P_2 P_3 P_4 P_5 P_6 P_7 P_8

BERT



O
O
B-PER
O
O
O
$T_{[CLS]}$
U_1
U_2
U_3
...
U_{n-2}
U_{n-1}
U_n
$T_{[SEP]}$
$E_{[CLS]}$
E_1
E_2
E_3
...
F_{n-2}
F_{n-1}
F_n
$E_{[SEP]}$
[CLS]
A_1
A_2
A_3
...
A_{n-2}
A_{n-1}
A_n
[SEP]
Sentence

What we covered today

- Named Entity Recognition
- Evaluation
- RNNs
- BERT