Neural Networks for Named Entity Recognition

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(slides originally by Dr. Fabienne Braune)

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Outline

Named Entity Recognition

Task

Find segments of entity mentions in input text and tag with labels.

Example inputs:

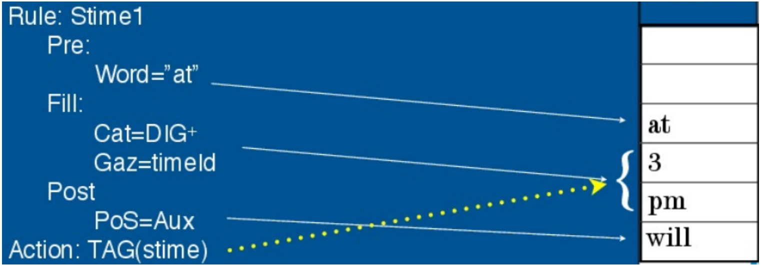
- *Trump attacks BMW and Mercedes*
- *U.N. official Ekeus heads for Baghdad*

Example labels (coarse grained):

- persons PER
- locations LOC
- organizations ORG
- names NAME
- other MISC

Rule-based approaches

- A collection of rules to detect entities
- Interpretable
- High precision vs. low recall
- Time consuming to build and domain knowledge is needed



(Fabio Ciravegna, University of Sheffield)

Classification-based approaches

Given input segment, train classifier to tell:

- Is this segment a Named Entity ?
- Give the corresponding Tag

Classification task:

Trump attacks BMW and Mercedes

Is Trump a named entity ?

Yes, it is a person (PER)

Desired outputs:

- *Trump PER attacks BMW ORG and Mercedes ORG*
- *U.N. ORG official Ekeus PER heads for Baghdad LOC*

Labeled data

Example annotations (CoNLL-2003):

Surface	Tag
United	B-ORG
Nations	I-ORG
official	O
Ekeus	B-PER
heads	O
for	O
Baghdad	B-LOC
.	O

Scheme	Begin	Inside	End	Single	Other
IOB	B-X	I-X	I-X	B-X	O
IOE	I-X	I-X	E-X	E-X	O
IOBES	B-X	I-X	E-X	S-X	O

(Collobert et al., 2011)

Classification-based approaches

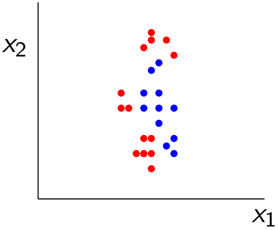
- Classifier combination with engineered features (Florian et al., 2003)
  - Manually engineer features
    - words
    - POS tags
    - prefixes and suffixes
    - large (external) gazetteer
  - 88.76 F1

Classification-based approaches

- Differences to rule-based:
  - Feature sets vs. rules
  - Less domain knowledge is needed
  - Faster to adapt systems
  - Annotated data is needed
- Next: neural networks
  - even less manual work

Feedforward Neural Networks: Recap

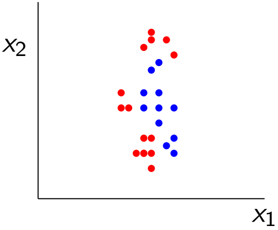
Motivation



Linear models not suited to learn non-linear decision boundaries.

- ... does not start at *3pm* STIME ...
  - unigrams: *at, not, start, 3pm...*

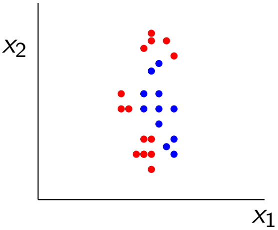
Motivation



Linear models not suited to learn non-linear decision boundaries.

- ... does <u>not</u> <u>start</u> at *3pm* STIME ...
  - unigrams: *at, not, start, 3pm...*
  - manual negation detection: *NEGATED_start*

Motivation



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- … does not start at *3pm* STIME …
  - unigrams: *at, not, start, 3pm…*
  - manual negation detection: *NEGATED_start*

Neural networks can do that

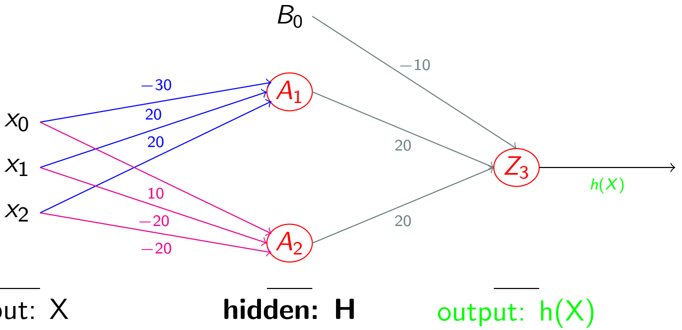
→ Through composition of non-linear functions

→ Learn relevant features from (almost) raw text

  → No need for manual feature engineering

  → learned by network

Feedforward Neural Network



Computation of hidden layer **H**:

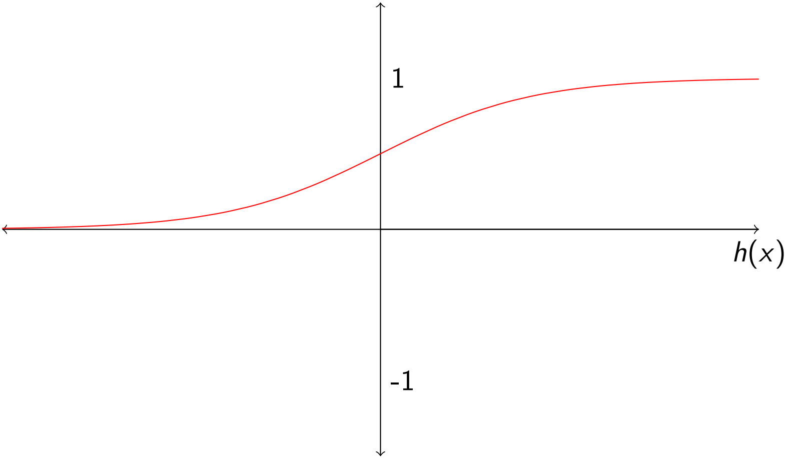
- $A_1 = \sigma(X \cdot \Theta_1)$
- $A_2 = \sigma(X \cdot \Theta_2)$
- $B_0 = 1$ (bias term)

Computation of output unit h(X):

- $h(X) = \sigma(\mathbf{H} \cdot \Theta_3)$

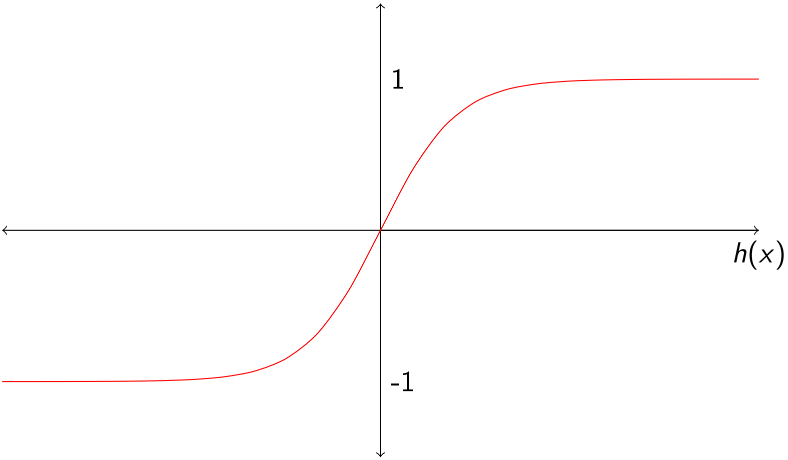
Non-linear activation function

The **sigmoid function** $\sigma(Z)$ is often used



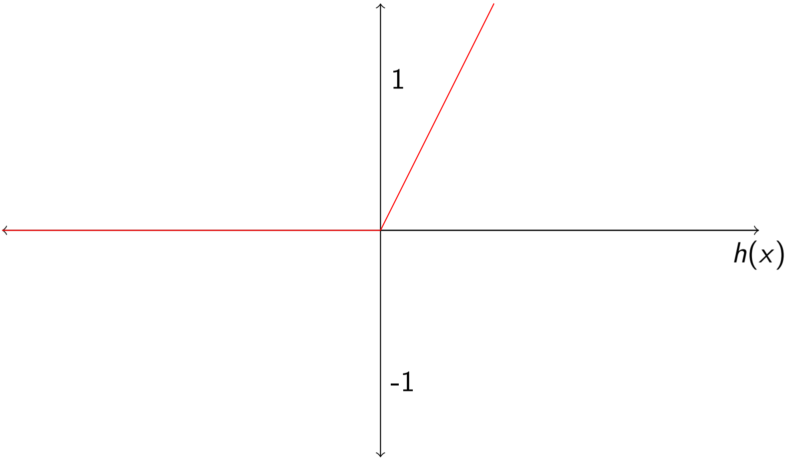
Non-linear activation function

The **tanh (hyperbolic tangent) function** $\sigma(Z)$

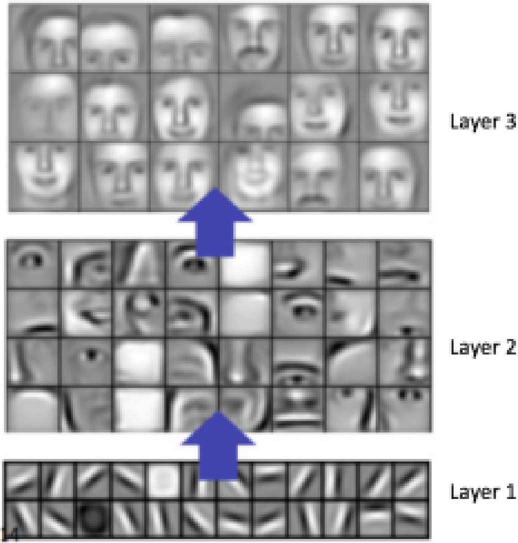


Non-linear activation function

The **ReLU (rectified linear unit) function** $\sigma(Z)$



Learning features from raw input



(Lee et al., 2009)

Feedforward neural network

Trump attacks BMW and Mercedes

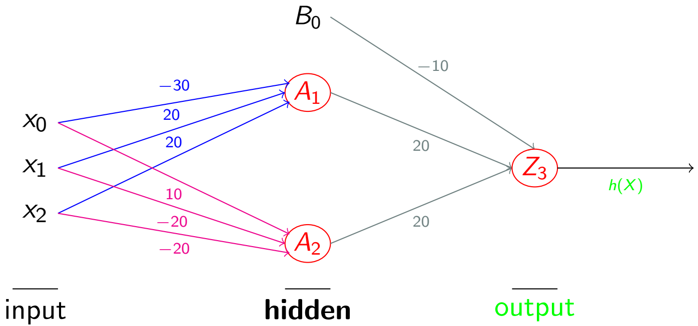
Binary NER task: Is the segment from position 1 to 2 a Named Entity?

Neural network: $h(X) = \sigma(\mathbf{H} \cdot \Theta_n)$, with:

$$\mathbf{H} = \begin{bmatrix} B_0 = 1 \\ A_1 = \sigma(X \cdot \Theta_1) \\ A_2 = \sigma(X \cdot \Theta_2) \\ \dots \\ A_j = \sigma(X \cdot \Theta_j) \end{bmatrix}$$

Prediction: If $h(X) > 0.5$, yes. Otherwise, no.

Feedforward Neural Network



If weights are all random output will be random

$\rightarrow$ Predictions will be bad

$\rightarrow$ Get the right weights

Getting the right weights

Training: Find weight matrices $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ such that $h(X)$ is the **correct answer** as many times as possible.

→ Given a set T of training examples $t_1, \cdots t_n$ with **correct labels $\mathbf{y_i}$**, find $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ such that $h(X) = \mathbf{y_i}$ for as many t_i as possible.

→ Computation of $h(X)$ called forward propagation

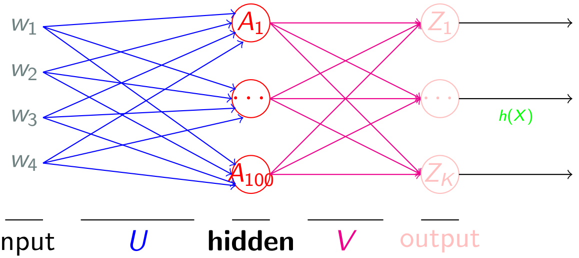
→ $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ with error back propagation

Multi-class classification

- More than two labels
- Instead of “yes” and “no”, predict $c_i \in C = \{c_1, \cdots, c_k\}$
- NER: Is this segment a location, name, person ...
- **Use k output units**, where k is the number of classes
  - $h(X)$: output layer instead of unit
  - Use softmax to obtain probability values:

$$softmax(h(X))_i = \frac{e^{h(X)_i}}{\sum_j e^{h(X)_j}}$$

  - The highest value indicates the output class



Neural Networks for NER

Feedforward Neural Network for NER

Example: *Trump attacks BMW (ORG) and Mercedes*

Neural network input:

Look at word window around BMW

→ **Trump**$_{-2}$ **attacks**$_{-1}$ **BMW** **and**$_{1}$ **Mercedes**$_{2}$

→ each word w_i is represented as one-hot vector

→ $w_i = [0, 1, 0, 0, ..., 0]$

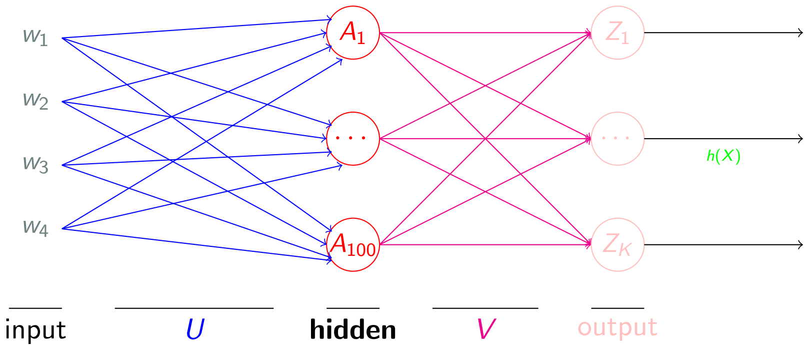
Neural network training:

Predict corresponding label (forward propagation)

→ should be organization (ORG)

Train weights by backpropagating error

Feedforward Neural Network for NER



- Input: one-hot word representations w_i
- Hidden layer: learns to detect higher level features
  - e.g.: *at ... pm*
- Output: predicted label

Weight training

Training: Find weight matrices U and V such that $h(X)$ is the **correct answer** as many times as possible.

$\rightarrow$ Given a set T of training examples $t_1, \cdots t_n$ with **correct labels** $\mathbf{y_i}$, find U and V such that $h(X) = \mathbf{y_i}$ for as many t_i as possible.

$\rightarrow$ Computation of $h(X)$ with forward propagation

$\rightarrow$ U and V with error back propagation

Backpropagation

Goal of training: adjust weights such that correct label is predicted

$\rightarrow$ Error between correct label and prediction is minimal

Compute error at output:

Compare

- output: $h(x^i) = [0.01,\ 0.1,\ 0.001,\ 0.95,\ ...,\ 0.01]$
- correct label: $y^i = [0,\ 0,\ 1,\ 0,\ ...,\ 0]$

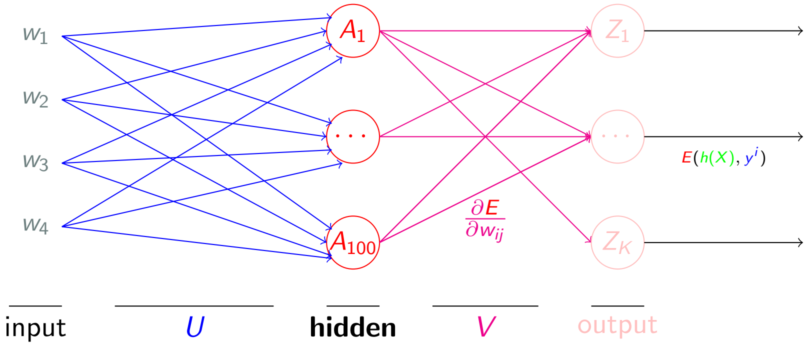
$$E = \frac{1}{2} \sum_{j=1}^{n} (y_j^i - h(x^i)_j)^2 \text{ (mean squared)}$$

Search influence of weight on error:

$$\frac{\partial E}{\partial w_{ij}}$$

w_{ij}: single weight in weight matrix

Backpropagation



Backpropagation:

$\rightarrow$ E needs to go through output neuron.

$\rightarrow$ Chain rule: $\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial O_j} \frac{\partial O_j}{\partial Z_j} \frac{\partial Z_j}{\partial w_{ij}}$

Weight training

Gradient descent: for each batch of training examples

1. Forward propagation to get predictions
2. Backpropagation of error
   - Gives gradient of E given input
3. Modify weights
4. Goto 1 until convergence

Outcome

- Hidden layer is able to learn higher level features of words
- Not enough to get good performance
- A simple index does not carry much information about a given word
  - $w_{BMW} = [1, 0, 0, 0, ..., 0]$
  - $w_{Mercedes} = [0, 1, 0, 0, ..., 0]$
  - $w_{happiness} = [0, 0, 1, 0, ..., 0]$
- This would be better
  - $w_{BMW} = [1, 0, 0, 0, ..., 0]$
  - $w_{Mercedes} = [1, 0, 0, 0, ..., 0]$
  - $w_{happiness} = [0, 0, 1, 0, ..., 0]$

Embedding Layer

- Learn features for words as well
- Similar words have similar features
- Embedding layer (Lookup Table):
  - embeds each one-hot encoded word w_i
  - to a feature vector LT_i

  - $w_{BMW} \quad\;\; = [0.5, 0.5, 0.0, 0.0, ..., 0.0]$
  - $w_{Mercedes} = [0.5, 0.0, 0.5, 0.0, ..., 0.0]$

Dot product with (trained) weight vector

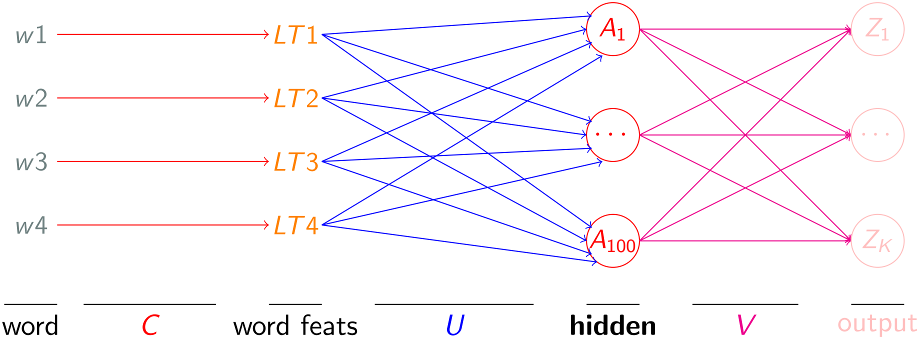
$W = \{\text{the,cat,on,table,chair}\}$

$$w_{table} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 0.02 & 0.1 & 0.05 & 0.03 & 0.01 \\ 0.15 & 0.2 & 0.01 & 0.02 & 0.11 \\ 0.03 & 0.1 & 0.04 & 0.04 & 0.12 \end{bmatrix}$$

$$LT_{table} = w_{table} \cdot C^T = \begin{bmatrix} 0.03 \\ 0.02 \\ 0.04 \end{bmatrix}$$

Words get mapped to lower dimension
$\rightarrow$ Hyperparameter to be set

Feedforward Neural Network with Lookup Table



C is shared!

Dot product with (initial) weight vector

$W = \{\text{the,cat,on,table,chair}\}$

$$w_{table} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \end{bmatrix}$$

$$LT_{table} = w_{table} \cdot C^T = \begin{bmatrix} 0.01 \\ 0.01 \\ 0.01 \end{bmatrix}$$

Feature vectors same for all words.

Weight training

Training: Find weight matrices C, U and V such that $h(X)$ is the **correct answer** as many times as possible.

→ Given a set T of training examples $t_1, \cdots t_n$ with **correct labels $\mathbf{y_i}$**, find C, U and V such that $h(X) = \mathbf{y_i}$ for as many t_i as possible.

→ Computation of $h(X)$ with forward propagation

→ C, U and V with error back propagation

→ Lookup matrix C trained with NER training data

→ Word feature vectors are trained towards NER

Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Feedforward Neural Networks for NER (Collobert et al., 2011):

- With raw words 81.74 F1

NER trained word embeddings

Word embeddings trained on NER task

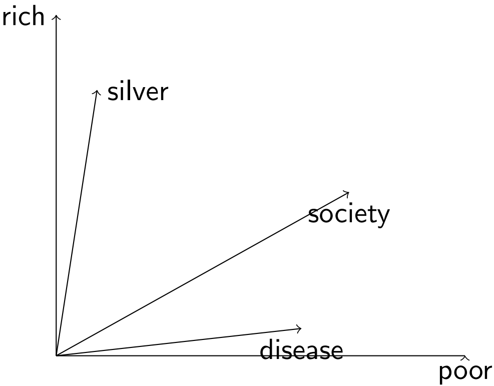
- Closest words to France
  - Persuade
  - Faw
  - Blackstock
- Closest words to XBOX
  - Decadent
  - Divo
  - Versus

$\rightarrow$ Small amount of **annotated** data.

Adding Pre-trained Word Embeddings

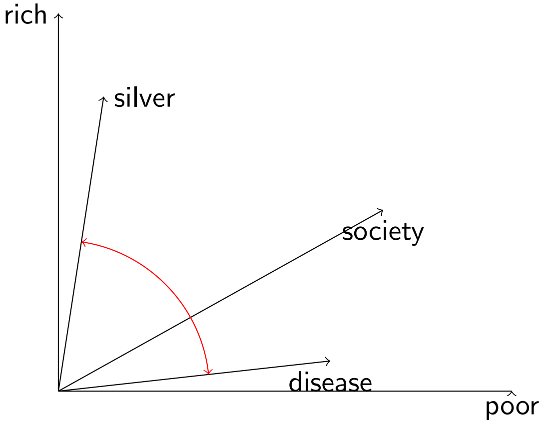
Word Embeddings

- Representation of words in vector space



Word Embeddings

- Similar words are close to each other
  $\rightarrow$ Similarity is the cosine of the angle between two word vectors
  $\rightarrow$ $cosine(x, y) = \frac{x \cdot y}{\|x\|\|y\|}$



Learning word embeddings

BMW makes the best cars ↔ Mercedes makes the best cars

	cars	makes	⋮	best	worst	⋮	mind
BMW	100	50		90	83		0
Mercedes	105	45		86	80		0
happiness	3	10		120	0		100

Count-based methods:

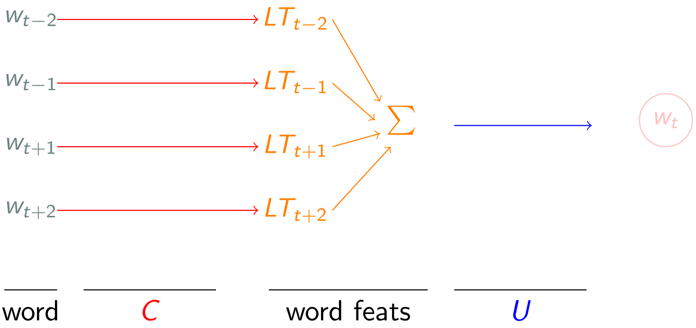
- Compute cooccurrence statistics
- Learn high-dimensional representation
- Map sparse high-dimensional vectors to small dense representation
- Matrix factorization approaches: SVD

Neural networks:

- Predict a word from its neighbors
- Learn (small) embedding vectors
- Word2Vec: CBOW and skipgram Mikolov et al. (2013)
- Language Modeling Task
- ELMo, BERT, GPT Peters et al. (2018); Devlin et al. (2018); Brown et al. (2020)

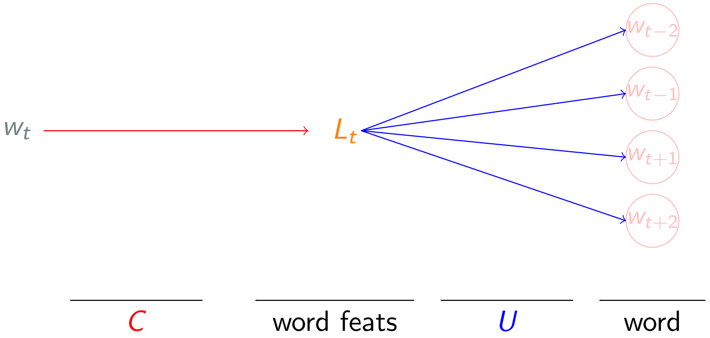
Learning word embeddings with CBOW

Training example: *Trump attacks* *BMW* *and Mercedes*



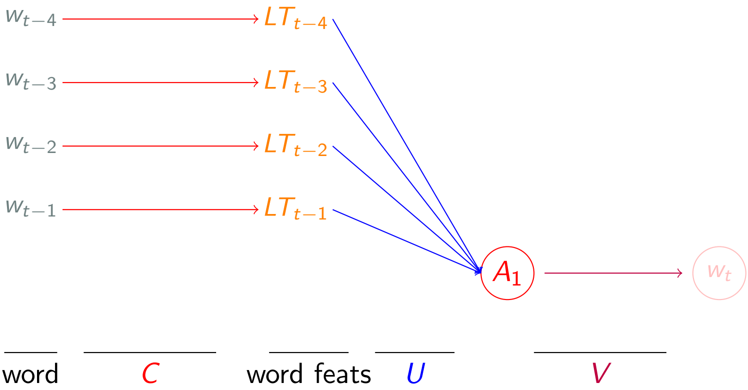
Learning word embeddings with skip-gram

Training example: *Trump attacks BMW and Mercedes*



Learning word embeddings with Language Modeling

Training example: *Trump attacks BMW and Mercedes*



Word Embeddings for NER

- Train word embeddings in advance:
  - $\rightarrow$ Use large amounts of non-annotated data
  - $\rightarrow$ No need for NER training data
  - $\rightarrow$ Labels are words w_t
- Replace lookup table C (randomly initialized) with C (pre-trained)

NER trained word embeddings

Word embeddings trained on NER task

- (Collobert et al. 2011)

→ Small amount of **annotated** data.

- Closest words to France
  - Persuade
  - Faw
  - Blackstock
- Closest words to XBOX
  - Decadent
  - Divo
  - Versus

NER trained word embeddings

Pre-trained word embeddings trained
$\rightarrow$ Large amount of **non-annotated** data.

- Closest words to France
  - Austria
  - Belgium
  - Germany
- Closest words to XBOX
  - Amiga
  - Playstation
  - MSX

Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Feedforward Neural Networks for NER (Collobert et al. 2011):

- With raw words 81.74
- With pre-trained word embeddings 88.67
- Using a gazetteer 89.59

Results

- Pre-trained word embeddings yield significant improvements
- Word features:
  - $w_{BMW} \quad = [0.5, 0.5, 0.0, 0.0, ..., 0.0]$
  - $w_{Mercedes} = [0.5, 0.0, 0.5, 0.0, ..., 0.0]$
  - $w_{happiness} = [0.0, 0.0, 0.0, 1.0, ..., 0.0]$

- The power is in exploiting large unlabeled data
- instead of relying only on small labeled data

- Hidden layer is able to learn higher level features of words
  - *Cars are* **produced at BMW**

- It also helps the problem of unseen words

Sequence Tagging with RNNs and CRFs

NER as sequence tagging

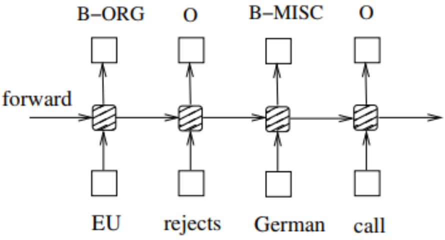
- Sequential input
  - Classification approaches (linear or NN) looked at a window around the input word
  - Limitation of window size
    - too small → loosing information
    - too large → noise or data scarcity

    Nixon had close ties with Ford

  - Read words sequentially and keep relevant information only
- Sequence of tags
  - IOB format: beginning and inside tags
  - Some tags shouldn't follow each other
  - Output labels sequentially word-by-word

O	O	O	B-STIME	I-STIME
The	**seminar**	**starts**	**tomorrow**	**4pm**

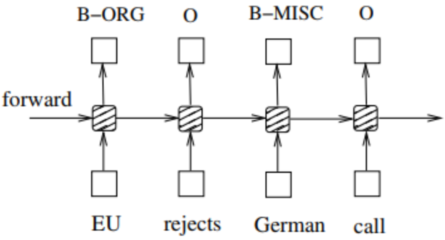
Recurrent Neural Network (RNN)



(Huang et al., 2015)

- Reads the input sequentially
- At time step t:
  - $h_t = f(h_{t-1}, x_t; \theta_1)$
    - e.g. $h_t = \sigma(h_{t-1} * U + x_t * V)$
  - $o_t = g(h_t; \theta_2)$
    - e.g. $o_t = \sigma(h_t * W)$
- Parameters are shared for each time step
- Multiple variations: LSTM, GRU, etc.

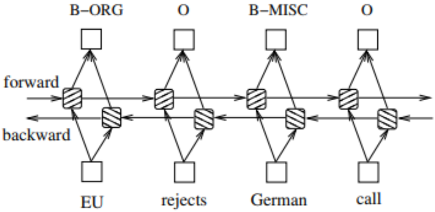
RNNs for NER



(Huang et al., 2015)

- Input: words
- Embedding layer
  - learn embeddings from scratch
  - or used pre-trained embeddings
- Probabilities of each NER tag

Bidirectional RNNs



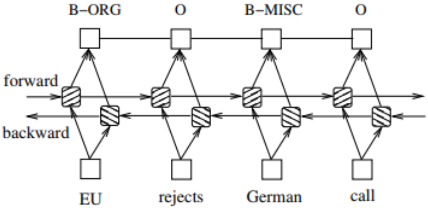
(Huang et al., 2015)

JFK was the 35th US president

JFK is in New York City

- Read the input both from left-to-right and right-to-left
- Concatenate the hidden states to get the output
  - $o_t = g(\overrightarrow{h_t} | \overleftarrow{h_t}; \theta_2)$

Conditional Random Fields (CRF)



(Huang et al., 2015)

- Tag at time step t should be dependent on the RNN output at t and the tag at $t-1$ as well
- CRF adds (soft) constrains on the final predicted tags ensuring they are valid given previous tags
  - Transition matrix $T_{i,j}$: probability of tag j given that previous tag was i

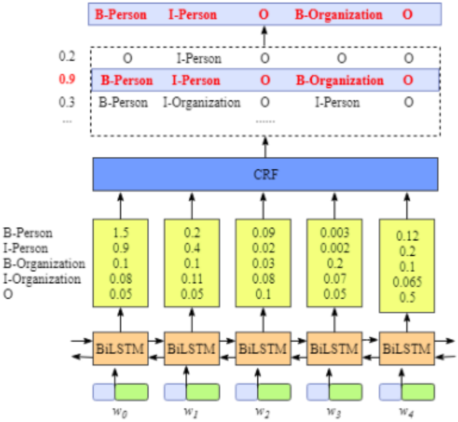
CRF transition matrix

From \ To	O	B-LOC	I-LOC	B-MISC	I-MISC	B-ORG	I-ORG	B-PER
O	3.281	2.204	0.0	2.101	0.0	3.468	0.0	2.325
B-LOC	-0.259	-0.098	4.058	0.0	0.0	0.0	0.0	-0.212
I-LOC	-0.173	-0.609	3.436	0.0	0.0	0.0	0.0	0.0
B-MISC	-0.673	-0.341	0.0	0.0	4.069	-0.308	0.0	-0.331
I-MISC	-0.803	-0.998	0.0	-0.519	4.977	-0.817	0.0	-0.611
B-ORG	-0.096	-0.242	0.0	-0.57	0.0	-1.012	4.739	-0.306
I-ORG	-0.339	-1.758	0.0	-0.841	0.0	-1.382	5.062	-0.472
B-PER	-0.4	-0.851	0.0	0.0	0.0	-1.013	0.0	-0.937
I-PER	-0.676	-0.47	0.0	0.0	0.0	0.0	0.0	-0.659

CRF State Transition Matrix

(Image taken from https://eli5.readthedocs.io sklearn tutorial)

RNN + CRF for NER



CRF Input Matrix

(Image taken from https://createmomo.github.io/)

- Prediction: tag sequence probability is calculated using RNN and transition probabilities (Viterbi algorithm)

Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Feedforward Neural Networks for NER (Collobert et al. 2011):

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BI-LSTM-CRF

- 90.10

Bilingual Word Embeddings

Bilingual transfer learning

- For many low-resource languages we do not have enough training data for NER
- Use knowledge from resource rich langauages
- Translate data to the target language
  - Training data is needed for the translation system

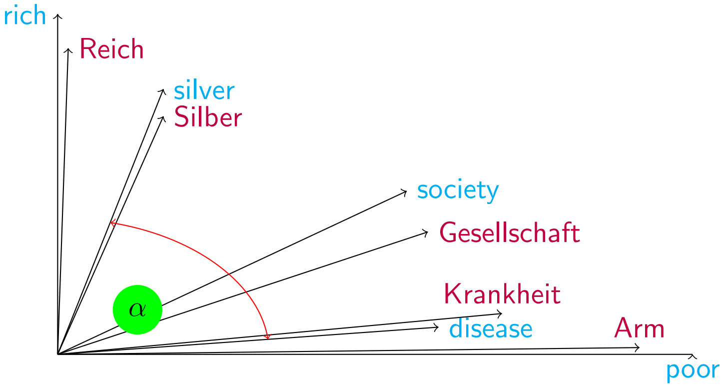
- Target language words are unseen words for a system trained on the source language
  - similarity of source and target words $\rightarrow$ bilingual word embeddings

Bilingual Word Spaces

Representation of words in two languages in same semantic space:

→ Similar words are close to each other

→ Given by cosine



Learning Bilingual Word Embeddings

- Learn bilingual embeddings from parallel sentences

  Hermann and Blunsom (2014), Gouws et al. (2015), Gouws and Søgaard (2015), Duong et al. (2016)

  Need for parallel sentences

- Learn bilingual embeddings from aligned documents

  Vulic and Moens (2015); Vulic and Korhonen (2016)

  Need document-aligned data

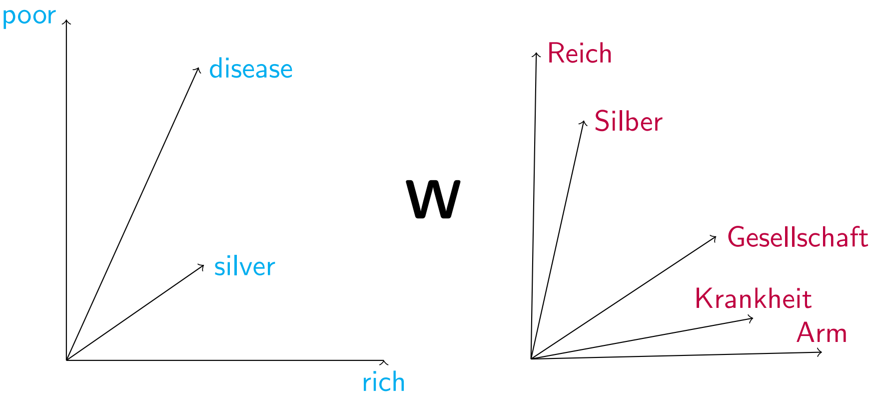
- Learn monolingual word embeddings and map using seed lexicon

  Mikolov et al. (2013); Faruqui and Dyer (2014); Lazaridou et al. (2015)

  Need seed lexicon

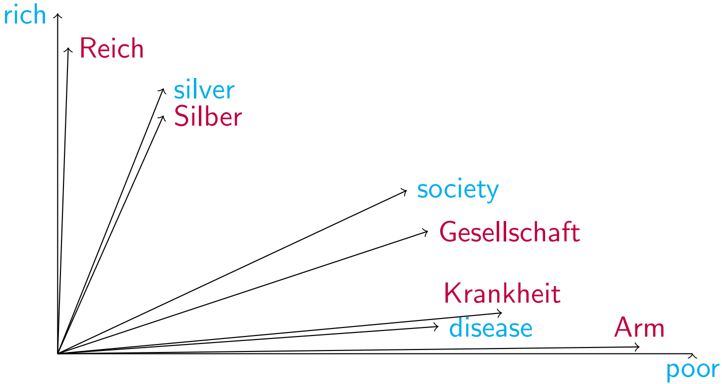
Post-hoc mapping with seed lexicon

- Learn monolingual word embeddings
- Learn a linear mapping W



Post-hoc mapping with seed lexicon

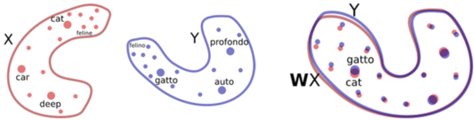
- Project source words into target space



Post-hoc Mapping with seed lexicon

1. Train monolingual word embeddings (Word2vec) in English
   - Need English monolingual data
2. Train monolingual word embeddings (Word2vec) in German
   - Need German monolingual data
3. Learn mapping **W** using a seed lexicon
   - Need a list of 5000 English words and their translation

Learning W with Regression



(Conneau et al., 2017)

Regression (Mikolov et al. (2013))

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sum_{\mathbf{i}}^{\mathbf{n}} || \, \mathbf{x_i} \mathbf{W} - \mathbf{y_i} \, ||^{\mathbf{2}}$$

x_i : **embedding** of i-th source (English) word in the seed lexicon.

y_i : **embedding** of i-th target (German) word in the seed lexicon.

Learning W with Ridge Regression

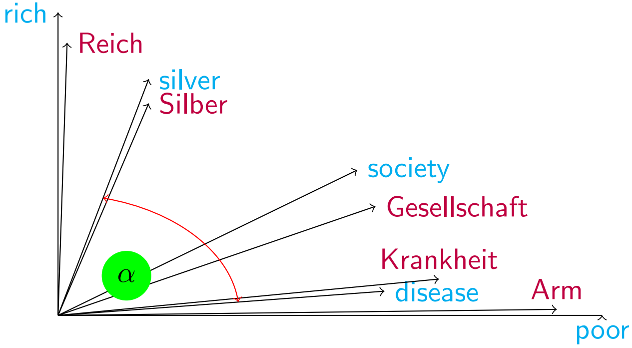
Regression (Mikolov et al. (2013))

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sum_{\mathbf{i}}^{\mathbf{n}} || \mathbf{x_i W} - \mathbf{y_i} ||^{\mathbf{2}}$$

- Predict projection $\mathbf{y^*}$ by computing $\mathbf{x_i W}$
- Compute squared error between $\mathbf{y^*}$ and $\mathbf{y_i}$
  - Correct translation t_i given in seed lexicon
  - Vector representation $\mathbf{y_i}$ is given by embedding of t_i
- Find $\mathbf{W}$ such that squared error over training set is minimal

Bilingual lexicon induction

- Task to evaluate bilingual word embeddings intrinsically
- Given a set of source words, find the corresponding translations:
  - Given silver, find its vector in the BWE
  - Retrieve the German word whose vector is closest (cosine distance)



Bilingual lexicon induction with ridge regression

Languages	Acc.
En-De	68.4%
De-En	67.7%
En-Es	77.4%
Es-En	77.3%

- MUSE: Conneau et al. (2017)

NER Results

- Use the bilingual word embeddings to initialize the embedding layer in the NER classifier

- Ni et al. (2017)
- Spanish:
  - Spanish training: 80.6
  - English training: 57.4

- Dutch:
  - Dutch training: 82.3
  - English training: 60.3

- German:
  - German training: 71.8
  - English training: 54.4

Summary

- Using neural networks for NER yields good results using (almost) raw representations of words
- Word embeddings can be learned automatically on large amounts of non-annotated data
- Giving pre-trained word embeddings as input to neural networks improve end-to-end task
- The networks can read the input sequentially and output labels sequentially
- Bilingual word embeddings make it possible to transfer knowledge from resource rich languages

Thank you!

References I

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