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:

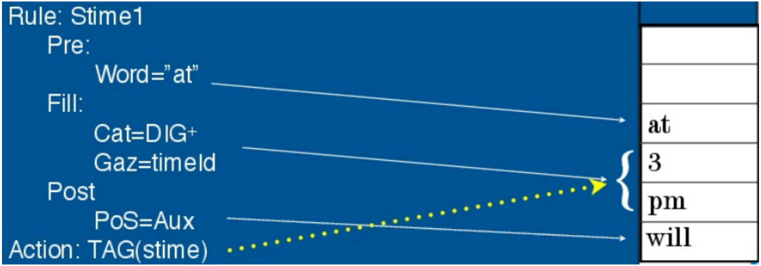
- *Trump attacks BMW and Mercedes*
- *U.N. official Ekeus heads for Baghdad*

Example labels (coarse grained):

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

Rule-based approaches

- A collection of rules to detect entities
- High precision vs. low recall
- Interpretable
- 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	POS	Sh-synt	Tag
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	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

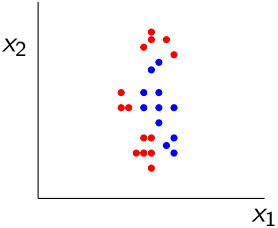
- Classifier combination with engineered features (Florian et al., 2003)
  - Manually engineer features
    - words
    - POS tags
    - prefixes and suffixes
    - large (external) gazetteer
  - Combine classifiers (ME, HMM) trained on annotated data
  - 88.76 F1
- Semi-supervised learning with linear models (Ando and Zhang, 2005)
  - Train linear model on annotated data
  - Add non-annotated data
  - 89.31 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.

Neural networks can do that

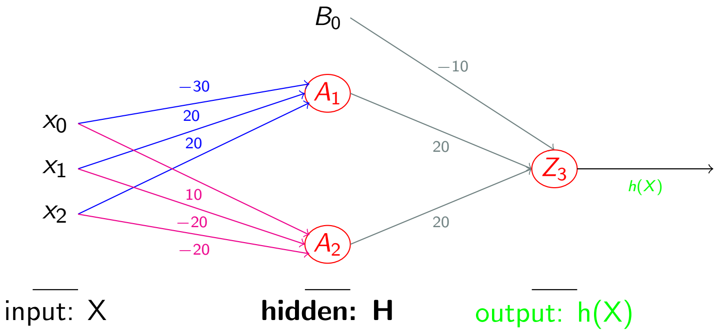
→ Through composition of non-linear functions

→ Learn relevant features from (almost) raw text

  → No need for manual feature engineering

  → learned by network

Feedforward Neural Network



Computation of hidden layer **H**:

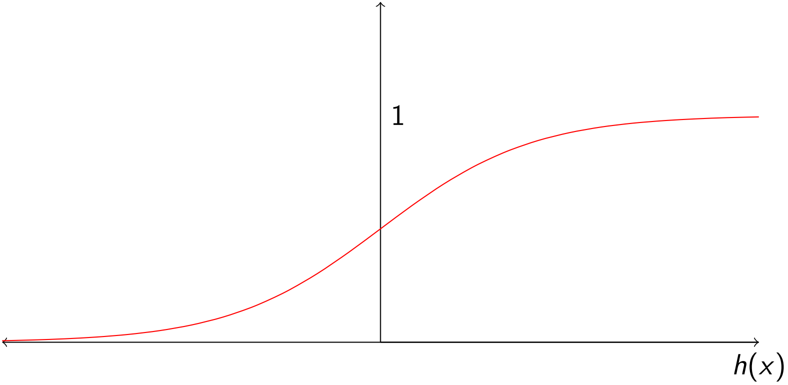
- $A_1 = \sigma(X \cdot \Theta_1)$
- $A_2 = \sigma(X \cdot \Theta_2)$
- $B_0 = 1$ (bias term)

Computation of output unit h(X):

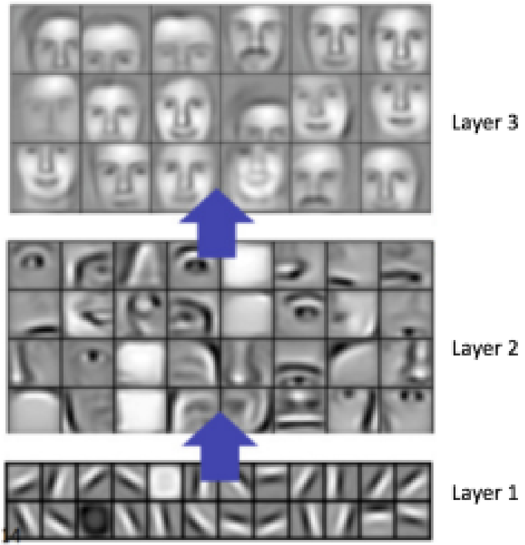
- $h(X) = \sigma(\mathbf{H} \cdot \Theta_3)$

Non-linear activation function

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



Learning features from raw input



(Lee et al., 2009)

Feedforward neural network

Trump attacks BMW and Mercedes

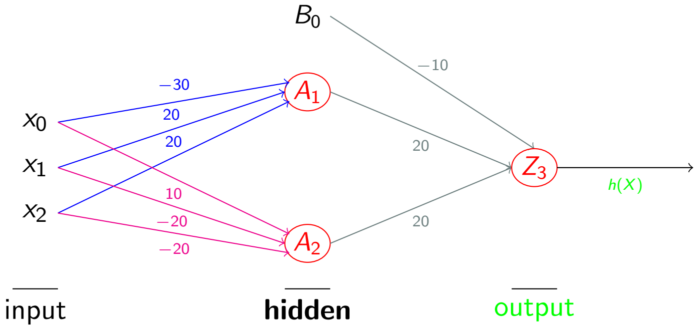
Binray NER task: Is the segment from position 1 to 2 a Named Entity?

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.

$\rightarrow$ 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.

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

$\rightarrow$ $U = (\Theta_1, \Theta_2)$ 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 number of classes
  - Output layer instead of unit
  - Use softmax to obtain value between 0 and 1 for each class
  - Highest value is right class

Neural Networks for NER

Feedforward Neural Network for NER

Training example: *Trump attacks BMW (ORG) and Mercedes*

Neural network input:

Look at word window around BMW

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

$\rightarrow$ each word w_i is represented as one-hot vector

$\rightarrow w_i = \left[0, 1, 0, 0, ..., 0\right]$

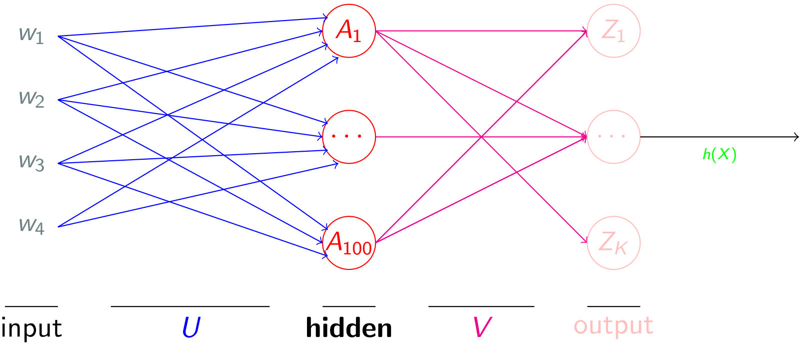
Neural network training:

Predict corresponding label (forward propagation)

$\rightarrow$ 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.

→ 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.

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

→ 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

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
  - *Cars are* **produced at BMW**
- 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
  - $w_{BMW} = [1, 0, 0, 0, ..., 0]$
  - $w_{Mercedes} = [1, 0, 0, 0, ..., 0]$
  - $w_{happiness} = [0, 0, 1, 0, ..., 0]$

Lookup Layer

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

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

Dot product with (trained) weight vector

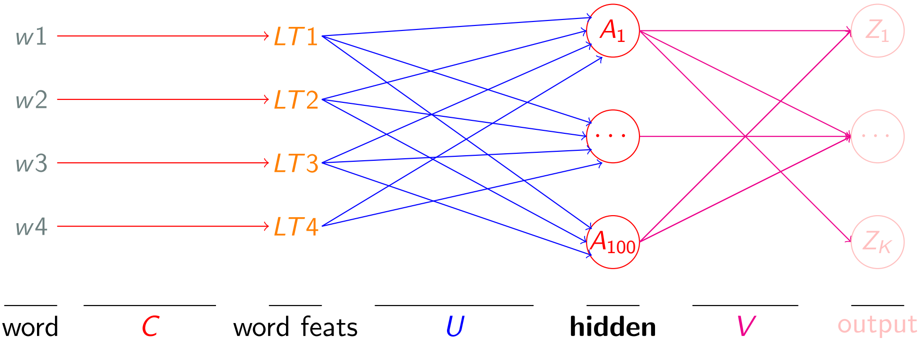
$W = \{\text{the,cat,on,table,chair}\}$

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

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

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.

$\rightarrow$ 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.

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

$\rightarrow$ C, U and V with error back propagation

$\rightarrow$ Lookup matrix C trained with NER training data

$\rightarrow$ Word feature vectors are trained towards NER

Example

Example

Trump PER attacks BMW ORG and Mercedes ORG

$W = \{\text{Trump,BMW,Mercedes,attacks,and}\}$

$$w_{Trump} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad w_{attacks} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad w_{BMW} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$w_{and} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad w_{Mercedes} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

Example

Window: Trump attacks BMW and Mercedes

$$w_{window} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \qquad C = \begin{bmatrix} 0.01 & 0.8 & 0.05 & 0.02 & 0.01 \\ 0.03 & 0.2 & 0.08 & 0.01 & 0.02 \\ 0.04 & 0.1 & 0.04 & 0.02 & 0.04 \end{bmatrix}$$

C is **randomly initialized**

$LT = w_{window} \cdot C^T$

Example

$$LT = \begin{bmatrix} 0.01 & 0.03 & 0.04 \\ 0.05 & 0.08 & 0.04 \\ 0.01 & 0.02 & 0.04 \\ 0.8 & 0.2 & 0.1 \\ 0.02 & 0.01 & 0.4 \end{bmatrix} \quad U = \begin{bmatrix} 0.04 & 0.6 & 0.01 & 0.02 & 0.06 & 0.03 \\ 0.01 & 0.9 & 0.02 & 0.05 & 0.03 & 0.05 \\ 0.02 & 0.3 & 0.05 & 0.07 & 0.09 & 0.01 \\ 0.02 & 0.4 & 0.02 & 0.03 & 0.04 & 0.02 \\ 0.01 & 0.8 & 0.01 & 0.01 & 0.03 & 0.07 \end{bmatrix}$$

U is **randomly initialized**

$\mathbf{Z} = LT^T \cdot U^T$

$A = \sigma(\mathbf{Z})$

Example

- Repeat same procedure for each hidden layer
- Apply softmax on output (last) layer
- Predict label
- Compute error between prediction (e.g. LOCATION) and true label
  $\rightarrow$ Given in training data (BMW is ORG)
- Backpropagate error through network and adjust weights
- Redo same procedure with adjusted weights
- Stop at convergence

Results

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

- 88.76 F1

Semi-supervised learning with linear models (Ando and Zhang 2005)

- 89.31 F1

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

- Guess?

Results

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

- Guess?
- With raw words 81.74

NER trained word embeddings

Word embeddings trained on NER task

- (Collobert et al. 2011)

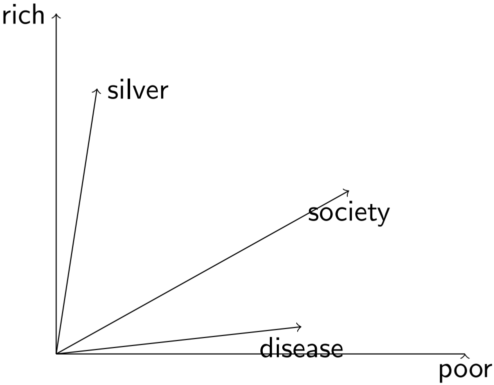
→ Small amount of **annotated** data.

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

Adding Pre-trained Word Embeddings

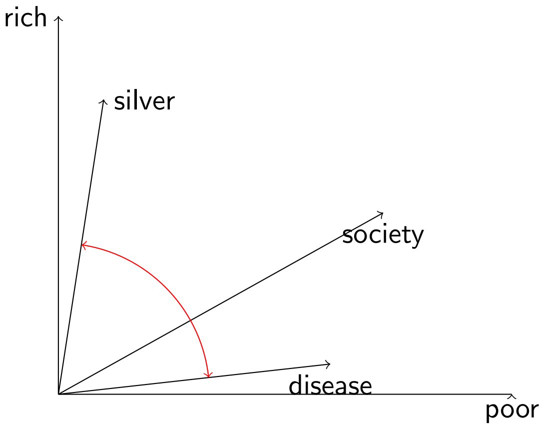
Word Embeddings

- Representation of words in vector space



Word Embeddings

- Similar words are close to each other
  → Similarity is the cosine of the angle between two word vectors



Learning word embeddings

Count-based methods:

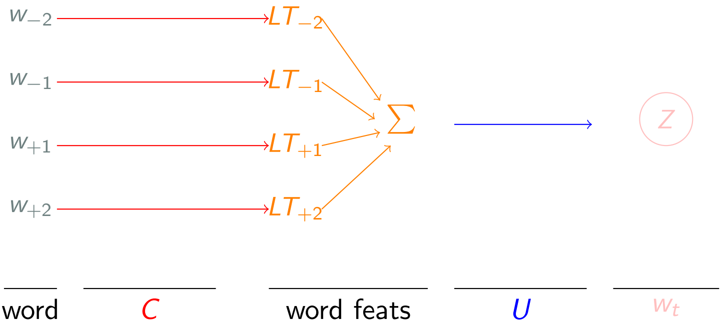
- Compute cooccurrence statistics
- Learn high-dimensional representation
- Map sparse high-dimensional vectors to small dense representation
- Matrix factorization approaches: SVD

Neural networks:

- Predict a word from its neighbors
- Learn (small) embedding vectors
- Word2Vec: CBOW and skipgram
- LM Task

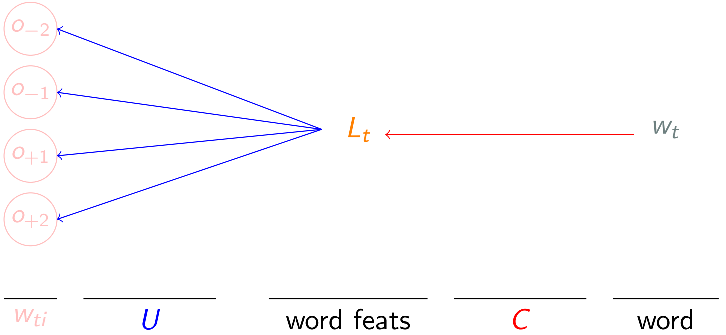
Learning word embeddings with CBOW

Training example: *Trump attacks BMW and Mercedes*



Learning word embeddings with skip-gram

Training example: *Trump attacks BMW and Mercedes*



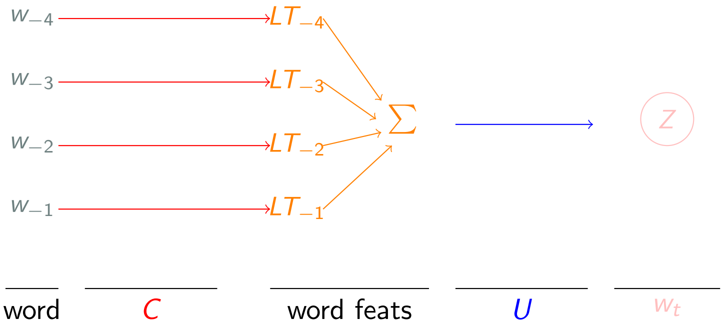
Word vectors with Language Modeling

- LM Task: Given *k* previous words, predict the current word
  $\rightarrow$ For each word w in V, model $P(w_t | w_{t-1}, w_{t-2}, ..., w_{t-n})$
  $\rightarrow$ **Learn embeddings C of words**
  $\rightarrow$ Input for task

- Task: Given *k* context words, predict the current word
  $\rightarrow$ **Learn embeddings C of words**

Learning word embeddings with Language Modeling

Training example: *Trump attacks BMW and Mercedes*



Word Embeddings for NER

- Train word embeddings using language model task:
  - $\rightarrow$ Labels are words w_t
  - $\rightarrow$ No need for NER training data
  - $\rightarrow$ Use large amounts of non-annotated data
- 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

Word embeddings trained on LM task
$\rightarrow$ 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

Semi-supervised learning with linear models (Ando and Zhang 2005)

- 89.31 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
- Additional techniques (RNN, attention, etc.): > 90.0

Results

- Pre-trained word embeddings yield significant improvements
- Hidden layer is able to learn higher level features of words
  - *Cars are* **produced at BMW**
- Word features:
  - $w_{BMW} \quad = [0.5, 0.5, 0.0, 0.0, ..., 0.0]$
  - $w_{Mercedes} = [0.5, 0.0, 0.5, 0.0, ..., 0.0]$
  - $w_{happiness} = [0.0, 0.0, 0.0, 1.0, ..., 0.0]$
- It also helps the problem of out-of-vocabulary words

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

Bilingual Word Embeddings

Bilingual transfer learning

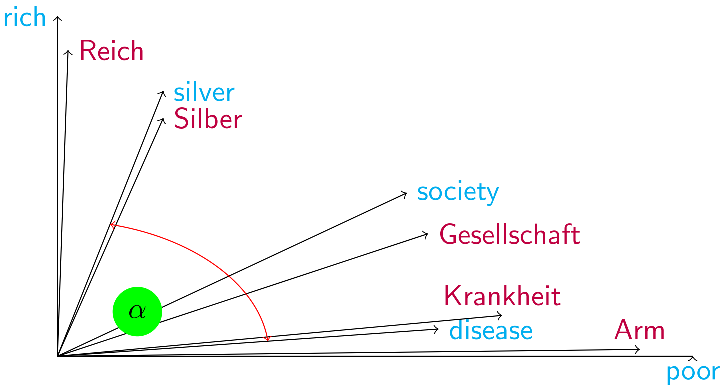
- For many low-resource languages we do not have enough training data for NER
- Use knowledge from resource rich langauages
- Translate data to the target language
  - Parallel data is needed for the translation system
- Target language words are OOVs for a system trained on the source language
  - similarity 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 or lexicon from document-aligned data

  Vulic and Moens (2015); Vulic and Korhonen (2016)
  Need document-aligned data

- Learn bilingual embeddings from parallel data

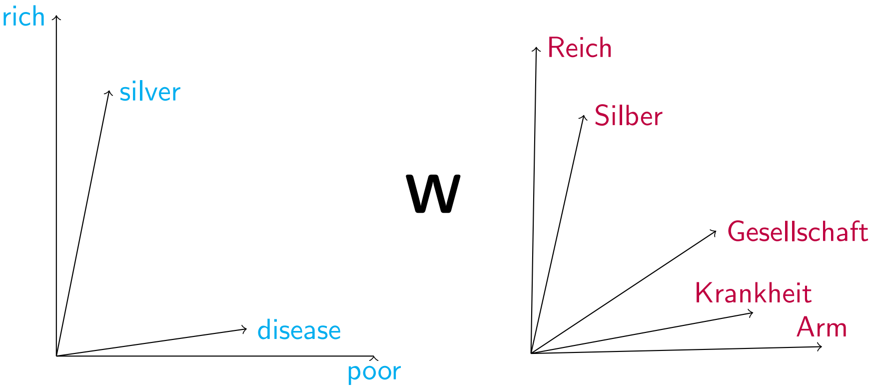
  Hermann and Blunsom (2014), Gouws et al. (2015), Gouws and Søgaard (2015), Duong et al. (2016)
  Need for parallel data

- Learn monolingual word embeddings and map using seed lexicon

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

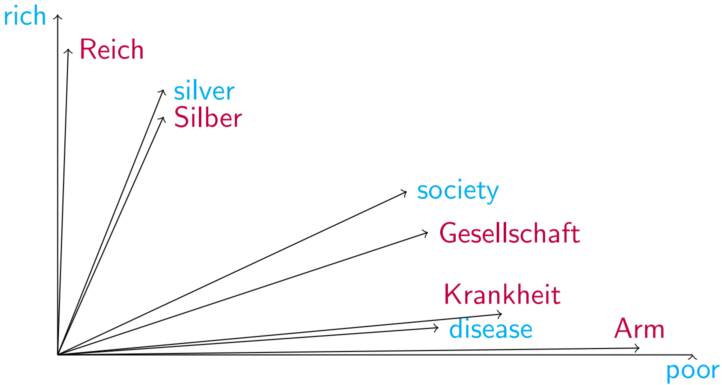
Post-hoc mapping (with seed lexicon)

- Learn monolingual word embeddings
- Learn a linear mapping W



Post-hoc mapping

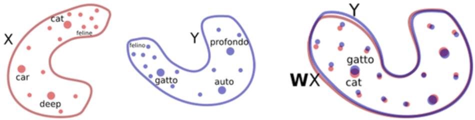
- Project source words into target space



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 Ridge Regression



(Conneau et al., 2017)

Ridge regression (Mikolov et al. (2013))

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

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

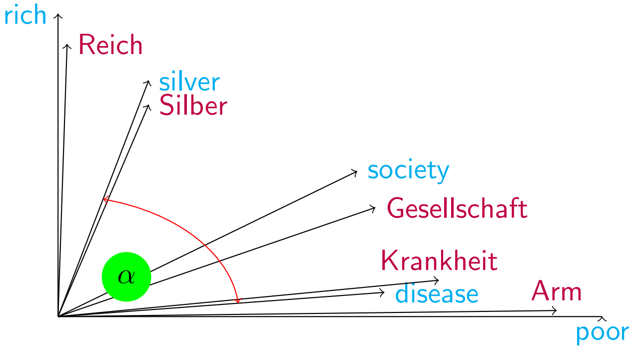
Ridge regression (Mikolov et al. (2013))

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

- Predict projection $\mathbf{y*}$ by computing $\mathbf{x_i} \cdot \mathbf{W}$
- 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 extrinsically
- 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

Data: WMT 2011 training data for English, Spanish, Czech
Seed: 5000 most frequent words translated with Google Translate
Test: 1000 next frequent words translated with Google Translate

→ Removed digits, punctuation and transliterations

Languages	top-1	top-5
En-Es	33 %	51 %
Es-En	35 %	50 %
En-Cz	27 %	47 %
Cz-En	23 %	42 %
+ Es-En	53 %	80 %

→ with spanish google news

NER Results

- Use the bilingual word embeddings to initialize the lookup table in the NER classifier

- Ni et al. (2017)
- Spanish:
  - supervised: 80.6
  - transfer learning: 57.4

- Dutch:
  - supervised: 82.3
  - transfer learning: 60.3

- German:
  - supervised: 71.8
  - transfer learning: 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
- Bilingual word embeddings make it possible to transfer knowledge from resource rich languages

Thank you !

References I

Ando, R. K. and Zhang, T. (2005). A framework for learning predictive structures from multiple tasks and unlabeled data. *Journal of Machine Learning Research*.

Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. *Journal of Machine Learning Research*.

Conneau, A., Lample, G., Ranzato, M., Denoyer, L., and Jégou, H. (2017). Word translation without parallel data. *arXiv preprint arXiv:1710.04087*.

Duong, L., Kanayama, H., Ma, T., Bird, S., and Cohn, T. (2016). Learning crosslingual word embeddings without bilingual corpora. In *Proc. EMNLP*.

Faruqui, M. and Dyer, C. (2014). Improving vector space word representations using multilingual correlation. In *Proc. EACL*.

References II

Florian, R., Ittycheriah, A., Jing, H., and Zhang, T. (2003). Named entity recognition through classifier combination. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*.

Gouws, S., Bengio, Y., and Corrado, G. (2015). Bilbowa: Fast bilingual distributed representations without word alignments. In *Proc. ICML*.

Gouws, S. and Søgaard, A. (2015). Simple task-specific bilingual word embeddings. In *Proc. NAACL*.

Hermann, K. M. and Blunsom, P. (2014). Multilingual models for compositional distributed semantics. In *Proc. ACL*, pages 58–68, Baltimore, Maryland. Association for Computational Linguistics.

Lazaridou, A., Dinu, G., and Baroni, M. (2015). Hubness and pollution: Delving into cross-space mapping for zero-shot learning. In *Proc. ACL*.

References III

Lee, H., Grosse, R., Ranganath, R., and Ng, A. Y. (2009). Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the 26th annual international conference on machine learning*.

Mikolov, T., Le, Q. V., and Sutskever, I. (2013). Exploiting similarities among languages for machine translation. *CoRR*, abs/1309.4168.

Ni, J., Dinu, G., and Florian, R. (2017). Weakly supervised cross-lingual named entity recognition via effective annotation and representation projection. *arXiv preprint arXiv:1707.02483*.

Vulic, I. and Korhonen, A. (2016). On the Role of Seed Lexicons in Learning Bilingual Word Embeddings. In *Proc. ACL*, pages 247–257.

Vulic, I. and Moens, M. (2015). Bilingual word embeddings from non-parallel document-aligned data applied to bilingual lexicon induction. In *Proc. ACL*.