Character-based Embeddings of Words with Recurrent Nets

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Seminar Selected Topics in Human Language Technology and Pattern Recognition June 20, 2016

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Outline

Literature

Wang Ling et al 2015 : Finding Function in Form: Compositional Character Models for Open Vocabulary Word Representation. CoRR Volume abs/1508.02096, 2015

- Introduces a model for constructing vector representations of words by composing characters using bidirectional LSTMs.

Faruqui et al 2015 : Morphological Inflection Generation Using Character Sequence to Sequence Learning. CoRR Volume abs/1512.06110, 2015

- Approach to generate inflected versions of words by modelling the process as a character sequence to sequence learning problem.

Mikolov et al 2013 : Distributed Representations of Words and Phrases and their Compositionality. CoRR Volume abs/1310.4546, 2013

- Improvements on the Skip-gram model used to generate word embeddings.

Literature

Schwenk 2007 : Continuous Space Language Models. Journal Computer Speech and Language. Volume 21 Issue 3, July, 2007 Pages 492-518

- Describes the use of a neural network language model for large vocabulary continuous speech recognition.

Peirsman 2015 : Visualizing Word Embeddings with t-SNE. Online 2015

- Creating useful low-dimensional visualizations for high-dimensional datasets

TensorFlow 2016 : Vector Representations of Words, From the TensorFlow documentation

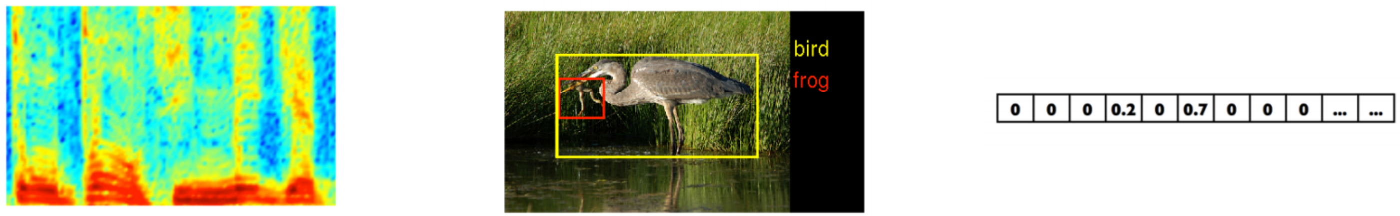
- Implementation of word2vec model of [Mikolov et al 2013] with the TensorFlow framework.

Introduction

- **Word embeddings are real valued vector representations for words.**
- **This talk is about generating word embeddings and their applications.**
- **Specifically:**
  - **Generating word embeddings by composing their individual character representations**
  - **Using Long short-term memory to capture complex relationships between words.**
- **The resulting model can be used for many tasks, such as language modeling or part-of-speech tagging**
- **Reduces the need for manual feature engineering**
- **Can improve performance for many tasks**

Introduction

AUDIO **IMAGES** **TEXT**



Audio Spectrogram — DENSE

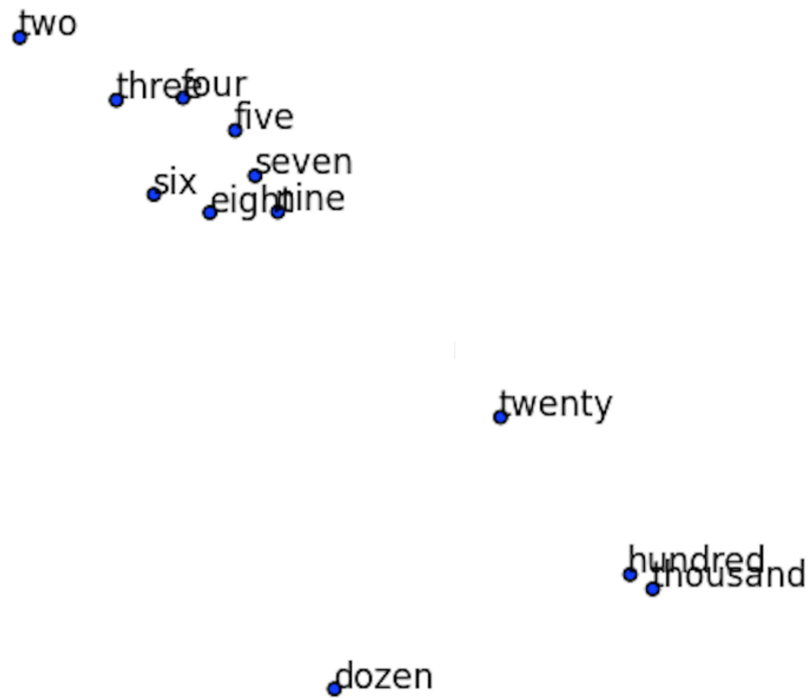
Image pixels — DENSE

Word, context, or document vectors — SPARSE

[TensorFlow 2016]

- **Natural language processing systems can treat words as atomic symbols, encoded as indexes.**
- **E.g. 'apple' might become index *Id123* and 'orange' becomes index *Id124***
- **This way of encoding is very sparse, and arbitrary.**
- **No representation of the relationship between these word types (such as both are fruit, . . .).**

Word Embeddings



Embeddings visualized [Peirsman 2015]

- A statistical model should be able to learn relationships between word types.
- Transform a word type w and turn it into an embedding $e_w = v(w) \in \mathbb{R}^d$
- Words with a similar meaning should be mapped to (geometrically) nearby points in the vector space.
- The dimension d should be low compared to the vocabulary size.
- Capture the intuition that words may be similar along different dimensions.

Word Embeddings

To this end there are some assumptions we make:

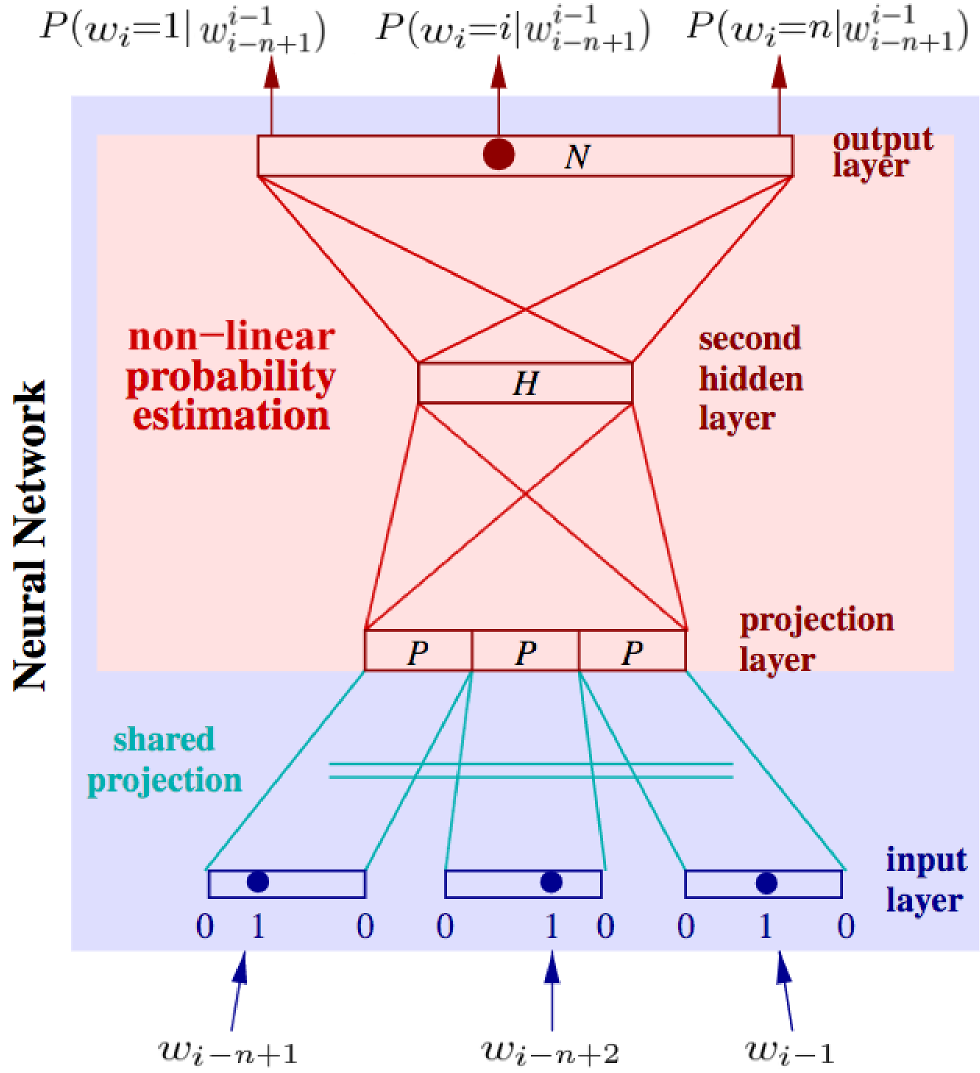
- **Words which share semantic meaning tend to occur in the same contexts (Distributional Hypothesis)**
- **The composition of words themselves can sometimes hint at similarities (e.g. 'apple' *vs* 'apples')**

General Approach for Word Embeddings

Generating word embeddings within a NNLM to better estimate $p(w_i|w_1, \ldots, w_{i-1})$

1. **Associate each word w in the vocabulary V with a word embedding e_w**
2. **Express the joint probability function for the word sequence $w_1, \ldots, w_{i-1}$ in terms of these embeddings.**
3. **Simultaniously learn the word embeddings and the parameters of the probability function.**

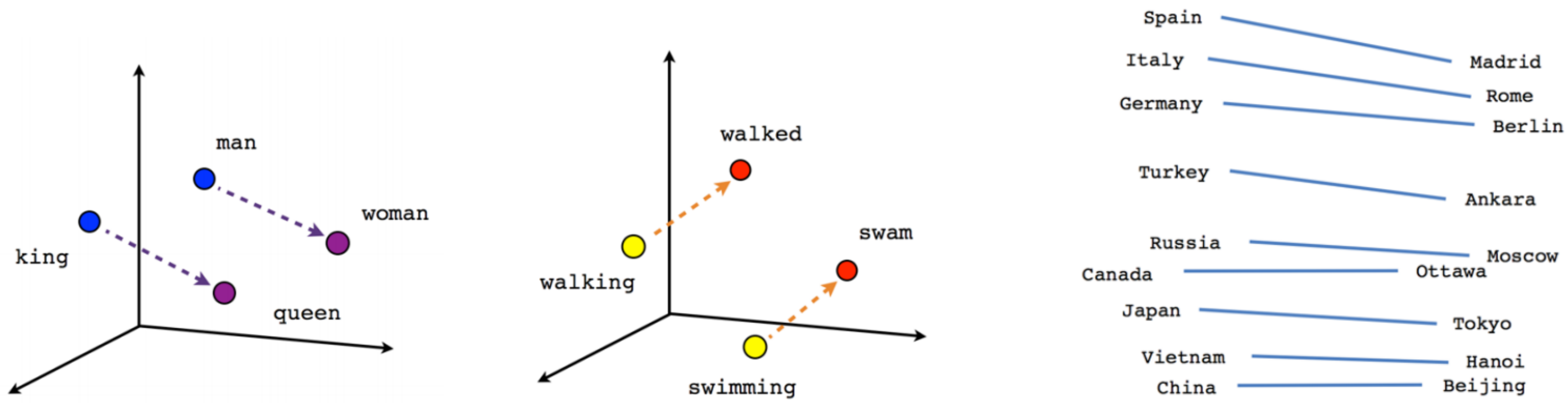
Continuous Space Language Model



[Schwenk 2007]

- The context for w_i is approximated with n-grams.
- Input word types are encoded as one-hot vectors.
- First Hidden Layer: Lookup table $P \in \mathbb{R}^{d \times |V|}$, projects the input into a continouus vector space.
- The word embedding e_w is the output of layer P.
- Second Hidden Layer: Estimates the joint probability of the word sequence
- The Softmax-Layer projects this up to vocabulary size $|V|$

Resulting Embeddings



Male-Female Verb tense Country-Capital

[TensorFlow 2016]

- **This setup can be used to generate a large table of word embeddings.**
- **Lookup table can be reused for other tasks (if there is not enough training data).**
- **E.g. [Mikolov et al 2013] have created a model which can encode complex patterns:**
- $v(\text{king}) - v(\text{male}) + v(\text{female}) \approx v(\text{queen})$.

Shortcomings

- A model with a lookup table treats each word embedding as independent from each other.
  - The model captures smililar linear correspondences between words embeddings.
  - E.g. *cat* and *apple* compared to *cats* and *apples*.
  - It doesn't capture that the added *s* is responsible for this transformation.
  - The model doesn't examine lexical similarities between words.
  - It doesn't capture morphological word transformations: e.g. *test* vs. *testing*
- A word lookup table cannot easily deal with unknown words.
- The lookup table contains at least $|V| \times d$ parameters. This can require large amount of memory for tasks with large vocabularies.

Possible Solutions

Some requirements should be satisfied by a better model:

- **The model should capture[*] orthographic similarities between words e.g. *test* vs. *testing* (Compositional effects).**
- **The model must still capture functionally similar words, with no orthographic similarities e.g. *rich* vs. *affluent*.**
- **However not all similary spelled words have similar meanings e.g. *butter* vs. *batter*.**
- **The resulting model should be able to replace the previous projection layer.**
- **Idea: Break down words into smaller atomic units and try to *compose* them into word embeddings.**

***) In terms of geometric locality**

Possible Solution 1: Morpheme-based Embeddings

- **Morphemes are the smallest defined grammatical unit of a language.**
- **E.g. "Unbreakable" comprises three morphemes:**
  1. **un-**
  2. **-break-**
  3. **-able**
- **Use morphemes as input and compose them into the word embeddings.**
- **Requires a morphological analyser: Extra processing step.**
- **Each target language requires an extra morpological analyser.**
- **The quality of the model depends on the analyser.**

Possible Solution 2: Character-based Embeddings

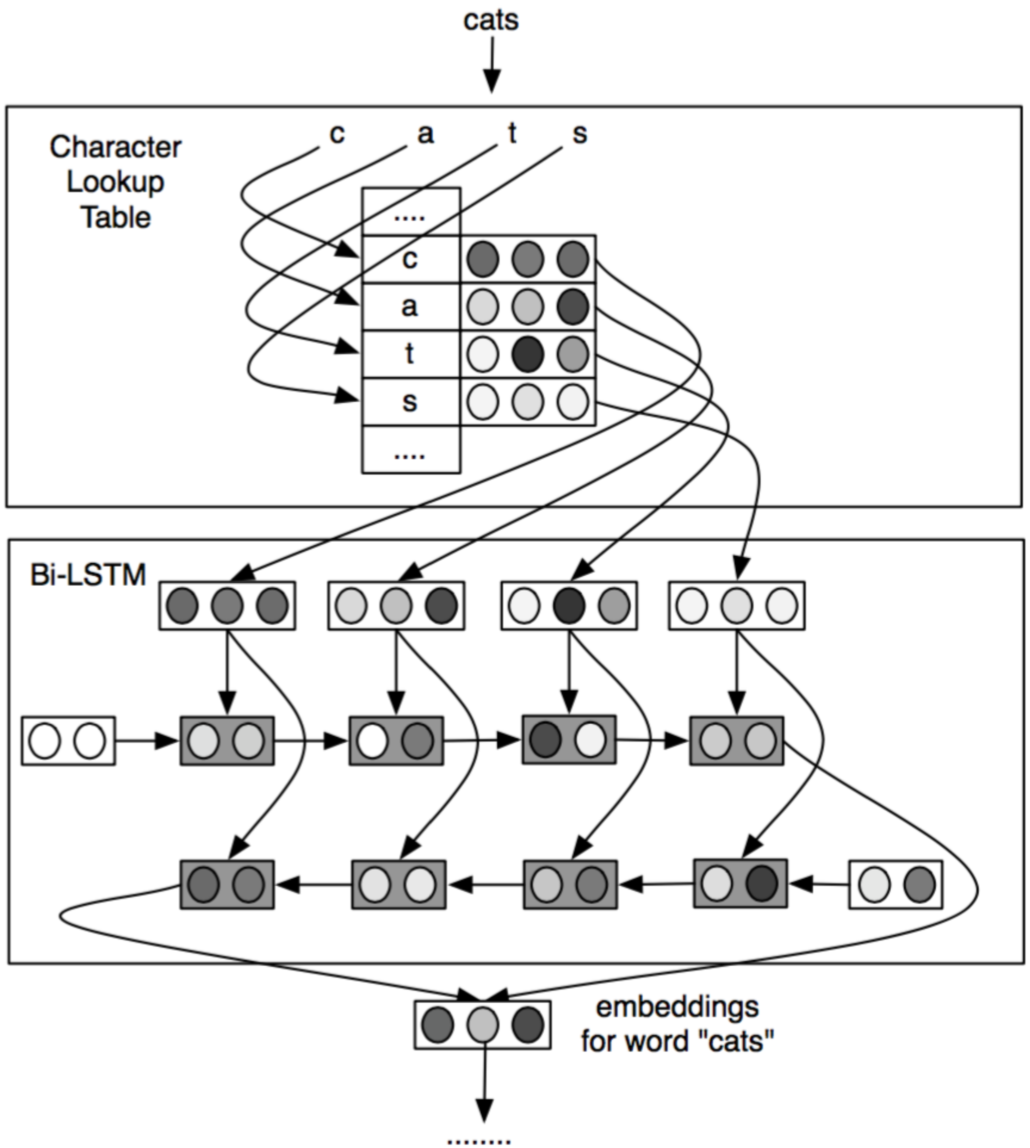
- **Break down words into characters**
- **Represent characters as real valued feature vectors (character embeddings).**
- **Feed them to an recurrent neural net, which "remembers" each character.**
- **Learn character embeddings simultaniously with other model parameters.**

Character-based Word-Embeddings

The "Compositional Character to Word" (C2W) model:

1. **A word w with length m is decomposed into characters $c_1, \dots, c_m$ from the alphabet C.**
2. **Transform characters into a sequence of character embeddings $e_{c_1}, \dots, e_{c_m}$.**
3. **The sequence is "read" one-by-one forwards as well as backwards by two LSTMs.**
4. **During "reading" the sequence is composed into the forward state s_m^f and backward state s_1^b.**
5. **The two states are recomposed to form the word-embedding e_w.**

Compositional Character to Word Model

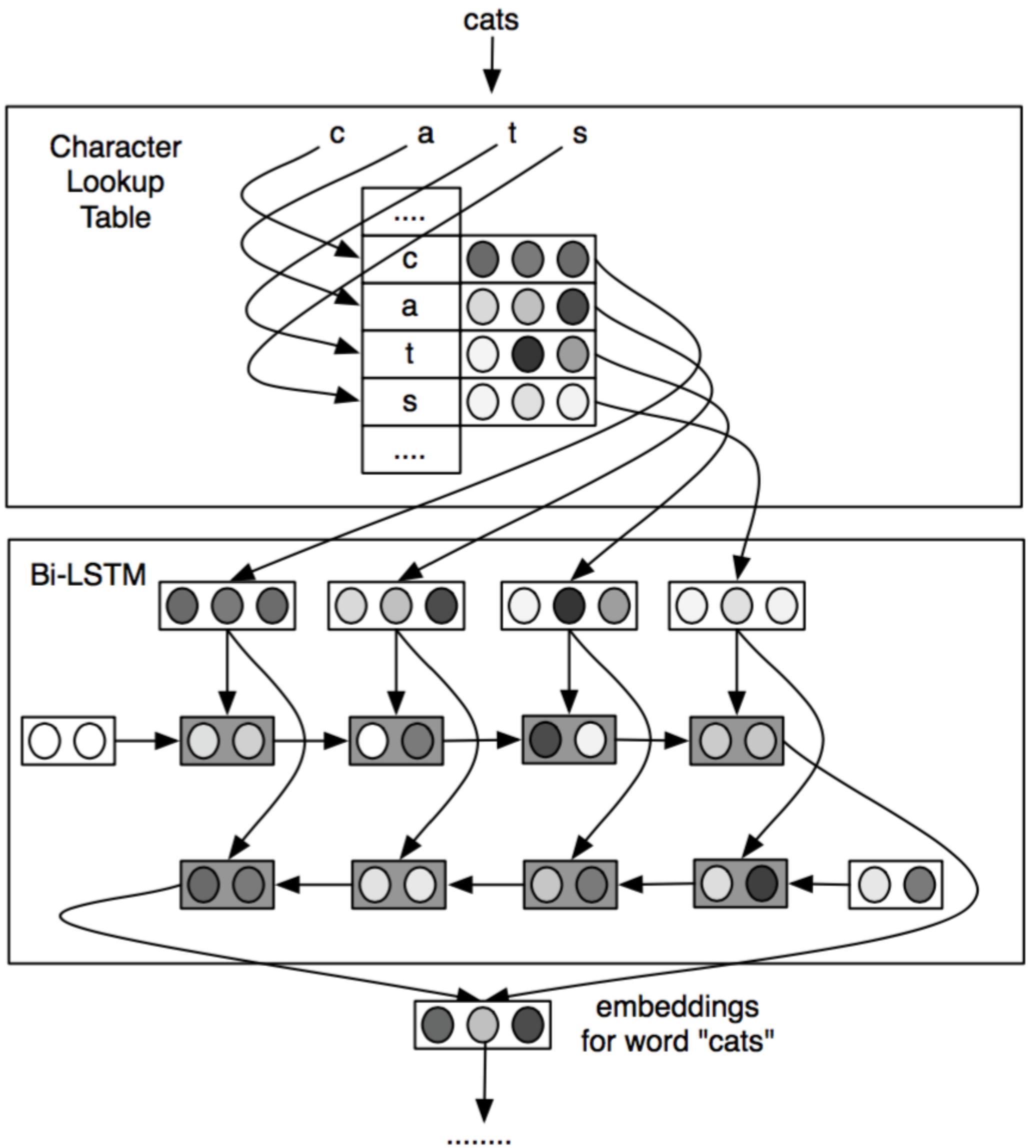


[Wang Ling et al 2015]

The C2W model is visualized for input "cats":

- **Squared boxes represent vectors of neuron activations.**
- **Shaded boxes indicate a nonlinear output.**
- **The two actual LSTM units are displayed unfolded.**

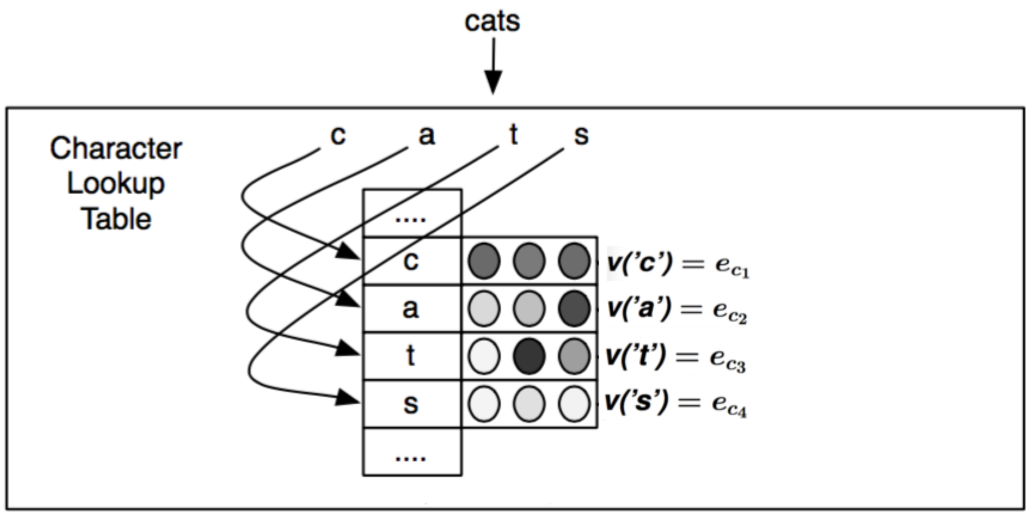
C2W-Model: Layers



[Wang Ling et al 2015]

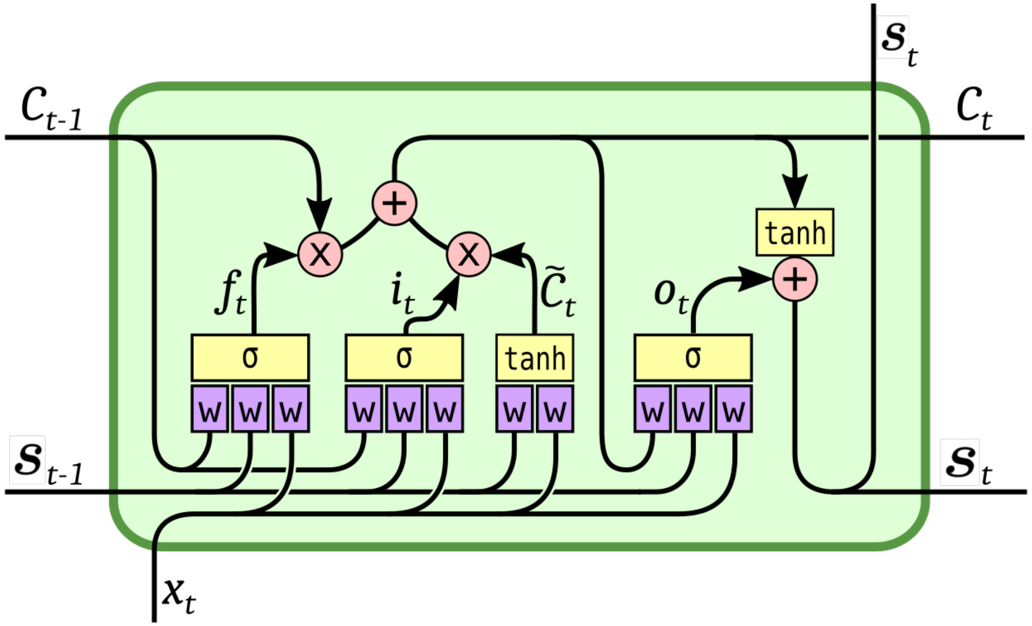
1. Table of character embeddings.
2. Bidirectional-LSTM layer, processing forward- and backward-sequences of character embeddings.
3. The combining layer, to merge the two outputs from the Bi-LSTM.

C2W-Model: Character-Lookup Table



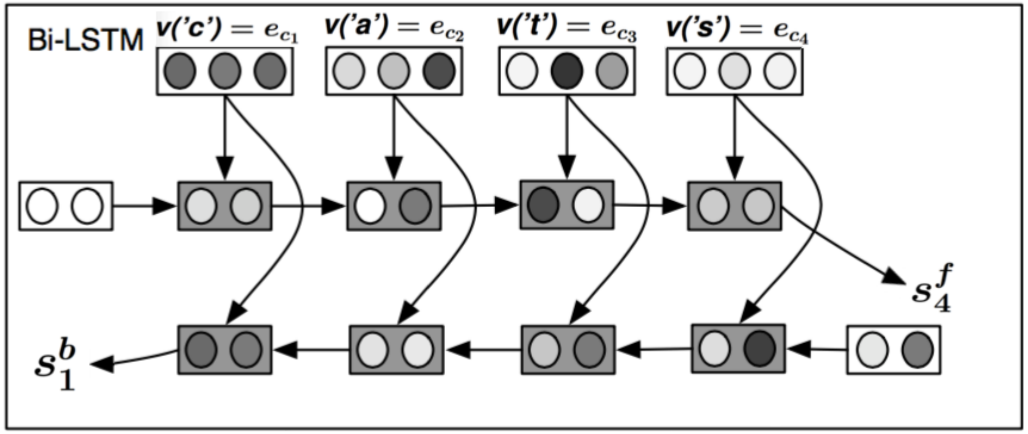
- **Table of d_C parameters $P_C \in \mathbb{R}^{d_C \times |C|}$.**
- **Each Input character c is transformed into a d_C-dimensional feature vector e_c.**
- **The dimension d_C becomes a hyperparameter of the model.**
- **Basically similar to the previous projection layer for words.**

Reminder: Long Short-Term Memory



- **Designed to "remember" inputs over arbitary distances and "forget" them when necessary**
- **Gate i_t to determine when to learn an input value**
- **Gate f_t to determine if it should continue to remember or forget the currently stored value**
- **Gate o_t to determine wether it should output the value.**
- **Additionally and bias values not explicitly displayed here.**
- **The dimension d_{CS} of the LSTM state becomes another hyperparameter.**

C2W-Model: Bidirectional LSTM Layer

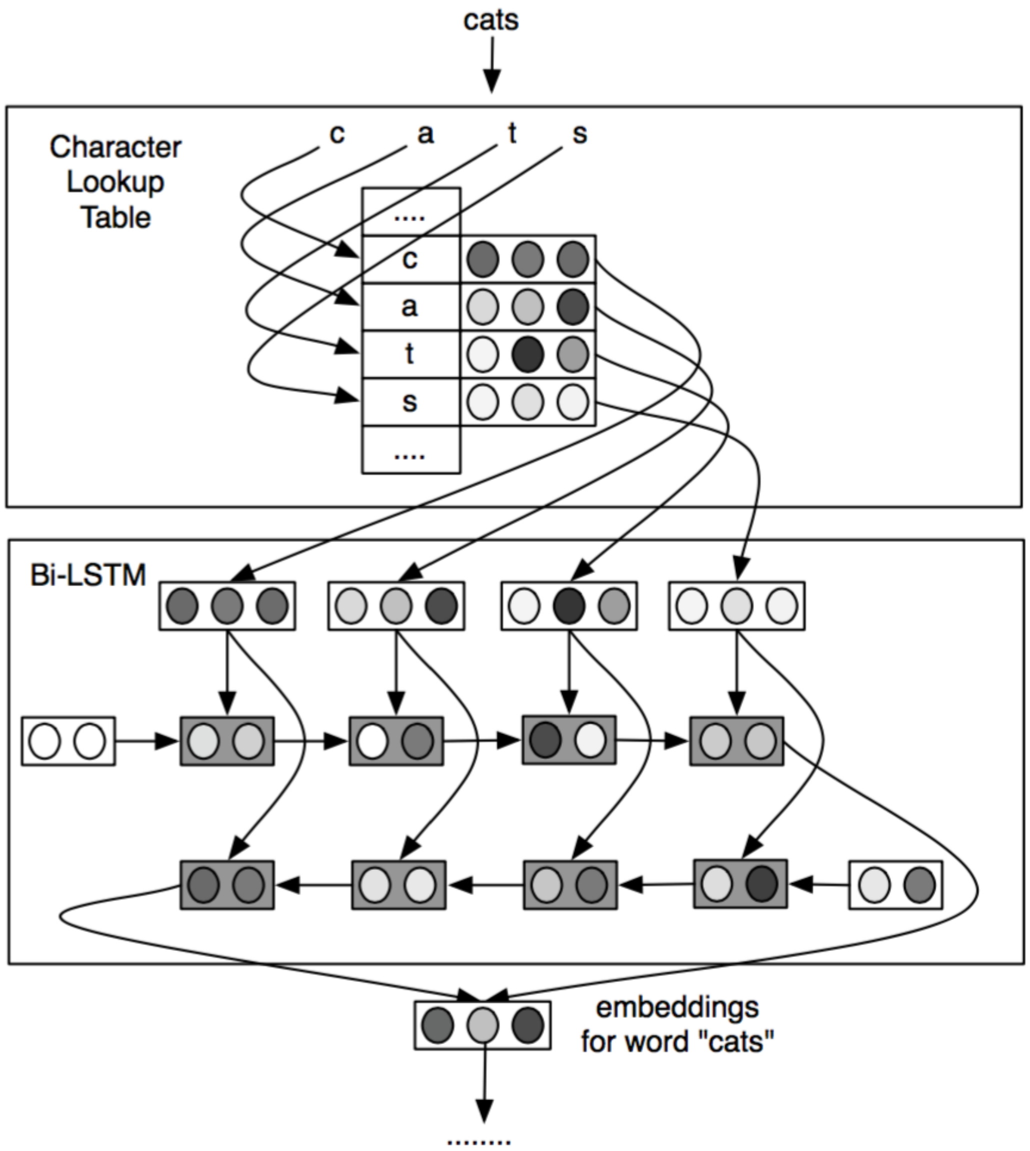


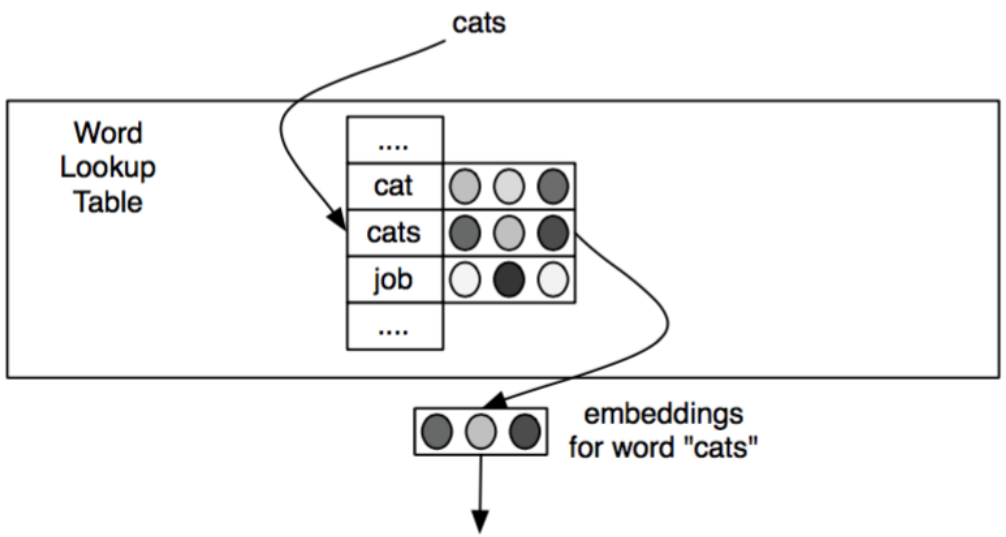
- Present the character sequence forwards and backwards to two separate LSTMs.
- Yields the forward state sequence $s_1^f, \ldots, s_m^f$ and backward state sequence $s_m^b, \ldots, s_1^b$.
- The network has simultanious access to all inputs before and after the current one.
- No need for fixed window sizes for the input, the net decides how much context to use.

C2W-Model: Combining Layer

- **Combines the last forward state s_m^f and the last backward state s_1^b**
- $e_w = D^f s_m^f + D^b s_0^b + b_d$
- **The variables D^f, D^b, b_d are the weights which determine how the states are combined.**
- **Automatically learns to determine how much each context is used.**

C2W-Model vs Lookup Tables





C2W-Model vs Word Lookup Tables

- Lookup Tables are conceptually much simpler, but requires a lot of parameters ($|V| \times d$).
- The C2W model uses less parameters (more in the evaluation section).
- The C2W model can easily be used for open vocabulary tasks.
- Looking up a word embedding is in $O(1)$, whereas the C2W model has to compute the embedding
  - Can be aliviated by caching e_w for frequently occuring words.
  - However cached values still need to be recomputed when parameters change during training time.

Experimentation

We are going to introduce three use cases, where a C2W based model either:

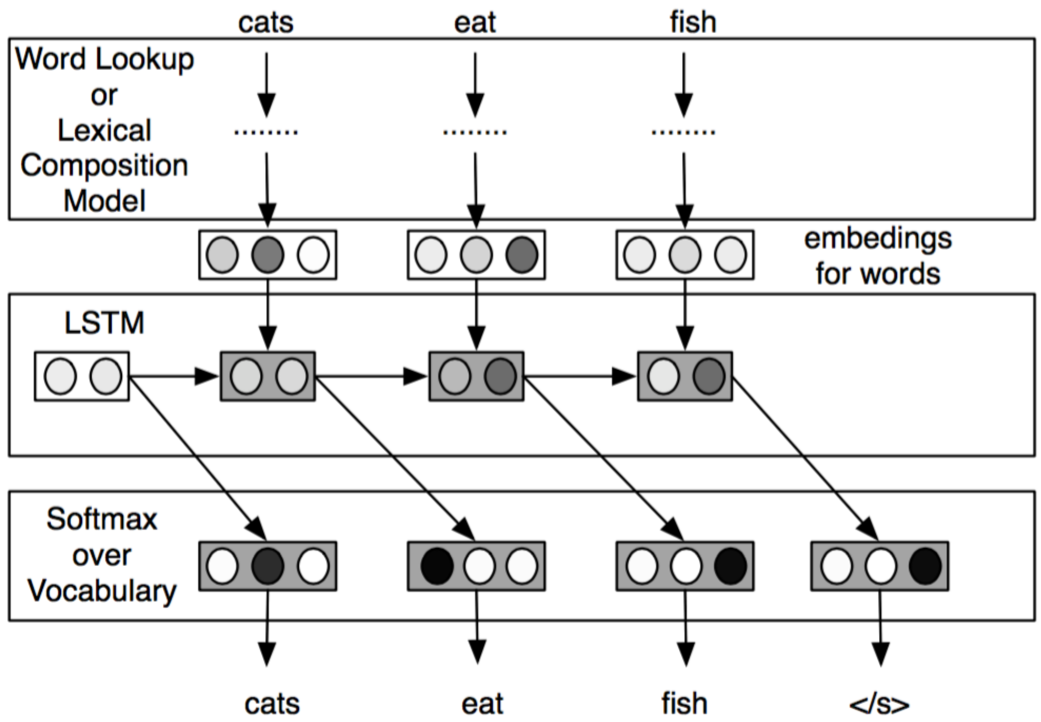
- Outperforms a model which uses much more parameters.
- Yields comparable results without relying on manually engineered features.

Wang Ling et al 2015 : Language Modelling

Wang Ling et al 2015 : Part-Of-Speech Tagging

Faruqui et al 2015 : Morphological Inflection Generation

Application 1: Language Modeling



- Computes the joint probability for the word sequence $w_1, \ldots, w_{i-1}$ with a hidden LSTM layer.
- Test two versions of this NLM: One with the C2W model and one with a word lookup table as projection layer.
- Compare accuracy of these two versions.

Application 1: Training & Testing Data

- **Perform testing on English, Portuguese, Catalan, German and Turkish.**
- **Choosen because these are morphologically rich languages.**
- **Training data was obtained by randomly extracting wikipedia articles until 1 million words were obtained.**
- **Additionaly 20000 words were obtained for testing.**

Application 1: Parameter Count

- The word embedding dimension is set to $d = 50$.
  - A word lookup table contains at least $d \times |V|$ parameters,
  - A language with 80000 words will have at least 4 million parameters.
- The C2W model has two additional hyperparameters which are set to $d_C = 50$ and $d_{CS} = 150$
  - The LSTMs use 8 matrices of size $d_{CS} \times d_C + 2d_{CS}$ (one for each decision gate).
  - The $d \times 2d_{CS}$ parameters in the combining output layer.
  - The $d_C \times |C|$ parameters in the character table.
  - For english this works out to roughly 180000 parameters.

Reminder: Perplexity

- **Measure of how well a probability distribution predicts sample data.**
- **Can be interpreted as the number of choices per word position.**
- **Defined as** $2^{H(p)} = 2^{-\sum_x p(x) \log_2 p(x)}$
- **To minimize the perplexity value means to have a better fitting language model.**

Application 1: Evaluation

Perplexity	English	Portugese	Catalan	German	Turkish
Word Lookup	59.38	46.17	35.34	43.02	44.01
C2W Model	**57.39**	**40.92**	**34.92**	**41.94**	**32.88**
#Parameters					
Word Lookup	4.3M	4.2M	4.3M	6.3M	5.7M
C2W Model	**180K**	**178K**	**182K**	**183K**	**174K**

Perplexities and test configuration [Wang Ling et al 2015].

- **Training is performed with mini-batch gradient descent with 100 sentences each.**
- **Speed of both model versions is aproximatly 300 words per second, main bottleneck is the softmax layer.**
- **In general C2W outperforms word lookup tables and requires less parameters.**

Application 1: Nonce Words

Noahshire	phding
Nottinghamshire	mixing
Bucharest	modelling
Saxony	styling
Johannesburg	blaming
Gloucestershire	christening

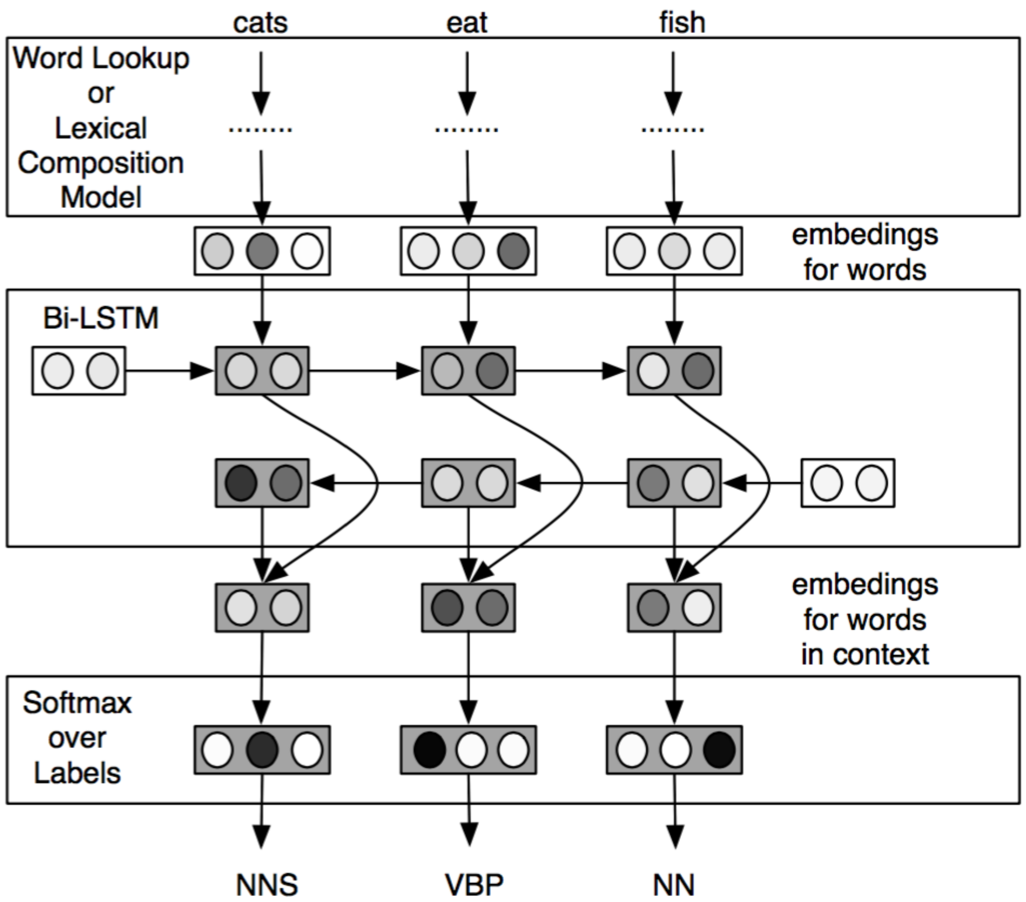
Nonce words and their most similar words from the vocabulary [Wang Ling et al 2015].

- **Nonce words are words created for use in a single occasion.**
- **The C2W model is able to generate embeddings for these words.**
- **No need for an OOV token for out of vocabulary words.**

Application 2: Part-Of-Speech Tagging

- **Process of labeling words as corresponding to a particular part of speech**
- **For example a simple tagging would be to identify words as nouns, verbs, adjectives, adverbs, etc.**
- **One use of this is to disambiguate homonyms:
  For Example "I fish a fish" should become "Je pêche un poisson" in french.**
- **By tagging the first occurance of "fish" as verb and the second as noun, they are now distinct.**

Application 2: Part-Of-Speech Tagging



- Conceptually similar to the previous NLM model.
- We don't just use a single LSTM block, but a bidirectional LSTM.
- The softmax layer computes over all possible labels instead of the vocabulary

Application 2: Testing Setup

- For english annotated sentences of the Wall Street Journal from the "Penn Treebank" dataset are used.
- For other languages data provided by the "Conference on Natural Language Learning" was used.
- The dimension of the states in the additional Bi-LSTM layer are set to 50.
- Out of vocabulary words are replaced with an OOV token.

Application 2: Evaluation

	acc	parameters	words/sec
Word Lookup	96.97	2000k	6K
Convolutional (S&Z)	96.80	42.5k	4K
Forward RNN	95.66	17.5k	4K
Backward RNN	95.52	17.5k	4K
Bi-RNN	95.93	40k	3K
Forward LSTM	97.12	80k	3K
Backward LSTM	97.08	80k	3K
Bi-LSTM $d_{CS} = 50$	97.22	70k	3K
Bi-LSTM	**97.36**	150k	2K

- As previously the C2W based POS-model is compared with versions using different word representation models.
- Table contains accuracies for the english WSJ dataset only.
  - There are different configurations using regular RNNs and LSTMs.
  - The LSTMs always outperforms regular RNNs by about 2%.
  - Row "Convolutional (S&Z)" contains results of a convolutional model from [Santos and Zadrozny, 2014].

[Santos and Zadrozny, 2014]: Learning Character-level Representations for Part-of-Speech Tagging

Application 2: Evaluation

System	Fusional			Agglutinative	
	EN	PT	CA	DE	TR
Word	96.97	95.67	98.09	97.51	83.43
C2W	**97.36**	97.47	**98.92**	**98.08**	**91.59**
Stanford	97.32	**97.54**	98.76	97.92	87.31

- This table contains testing results for a number of languages.
- As previously the row "word" contains results for a model version using word lookup tables.
- Additionally it is compared with Stanford's POS tagger, with the default set of features.

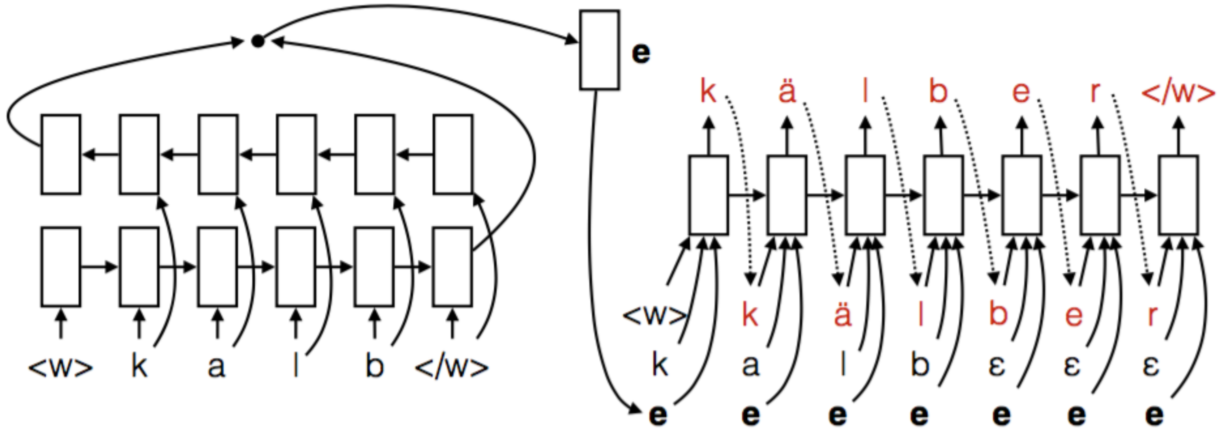
Application 3: Morphological Inflection Generation

	singular	plural
nominative	Kalb	Kälber
accusative	Kalb	Kälber
dative	Kalb	Kälbern
genitive	Kalbes	Kälber

Example of an inflection table for the word "Kalb" [Faruqui et al 2015]

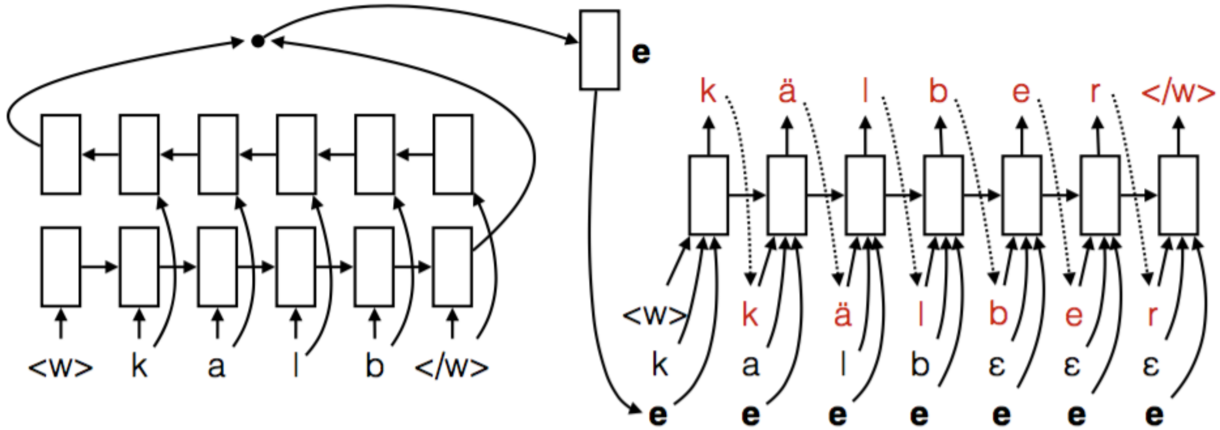
- **We want to perform morphological transformations of words.**
- **These kind transformations are very common in languages like turkish or german.**
- **Could be used as post- or preprocessing step for machine trainlation.**

Application 3: Overview



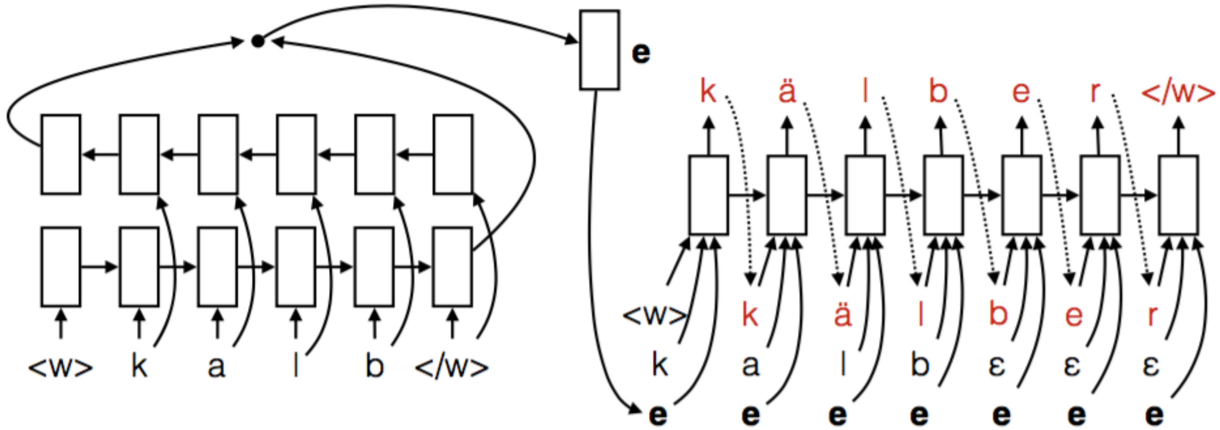
- **We use a neuronal encoder - decoder architecture.**
- **The word embedding e is used as an intermediate representation.**
- **The decoder constructs the inflected version of the word - character by character.**

Application 3: Overview



- The encoder part is identically to the C2W model and generates a word embedding e.
- The decoder is just an LSTM unit which receives the following inputs each timestep:
  1. The word embedding e from the encoder.
  2. Current character of the original word c_j
  3. Previous output of the model

Application 3: Decoder



- **The decoder output is driven by the characters of the original word**
- **There is a chance that output length is greater than the input word length.**
- **Once the input word ends, the ϵ character is used instead.**
- **The decoder stops by outputting the word end token "$<$/w$>$"**

Application 3: Training & Testing Data

Dataset	root forms	Infl.
German Nouns (DE-N)	2764	8
German Verbs (DE-V)	2027	27
Spanish Verbs (ES-V)	4055	57
Finnish NN & Adj. (FI-NA)	6400	28
Finnish Verbs (FI-V)	7249	53
Dutch Verbs (NL-V)	11200	9
French Verbs (FR-V)	6957	48

The languages above were tested with the data published by:

- **[Durrett and DeNero 2013] containing inflections for German, Finnish and Spanish.**
- **[Nicolai et al., 2015] adding dutch and french to this dataset.**
- **The development and test sets contain about 200 inflection tables each.**

[Durrett and DeNero 2013]: Supervised learning of complete morphological paradigms. In Proc. of NAACL.

[Nicolai et al., 2015]: Inflection generation as discriminative string transduction. In Proc. of NAACL

Application 3: Evaluation

	DDN13	NCK15	Ours
DE-V	94.76	**97.50**	96.72
DE-N	88.31	**88.60**	88.12
ES-V	99.61	99.80	**99.81**
FI-V	97.23	**98.10**	97.81
FI-NA	92.14	93.00	**95.44**
NL-V	90.50	96.10	**96.71**
FR-V	98.80	**99.20**	98.82
Avg.	94.47	96.04	**96.20**

- **The results are comparable or better than other approaches.**
- **On average the results are better.**
- **No feature engineering necessary.**

Summary

- Generating word embeddings by composing character representations, works usually just as well as approaches using word lookup tables.
- Lexical features can be learned automatically, manual feature engineering can be avoided
- In combination with caching of frequently used words, the performance is comparable to models based on word lookup tables.
- Models scale better with larger vocabularies and are able to deal with open vocabularies.