# Deep Learning for MT

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MT Marathon – September 11, 2014

# Plan of the Talk

## Alternative titles

- Neural networks in SMT: past, present and future
- From neural network LMs to fully neural MT systems ?

## Topics of this talk

- Overview of ongoing research in this area
- Increasing body of research
  $\rightarrow$ what are the most promising directions (personal view !)
- Vision: can we develop an MT system entirely based on neural networks ?

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# Applications of Language Models

- Automatic speech recognition (ASR)

$$\hat{w} = \arg\max_{w} Pr(w|x) = \arg\max_{w} Pr(w)Pr(x|w)$$

- Statistical machine translation (SMT), translate $f$ to $e$

$$\hat{e} = \arg\max_{e} Pr(e|f) = \arg\max_{e} Pr(e)Pr(f|e)$$

$\Rightarrow$ In both applications we need a LM on the generated word sequence

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# Applications of Language Models

## Speech Recognition

- The LM must choose among a large number of segmentations of the phoneme sequence into words, given the pronunciation lexicon
- The LM must also select among homonyms
- It deals with morphology (gender accordance, ...)
- The word order is given by the sequential processing of speech

# Applications of Language Models

## Machine translation

- Deal with morphology like for ASR
- The LM helps to choose between different translations
- Translation may require word reordering for certain language pairs

$\Rightarrow$ the LM has to sort out the good and the bad ones

## Comparison

- It is an interesting question whether language modeling for MT is more or less difficult than for ASR
- One may consider that the semantic level is more important in MT

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# Some Past Research on LM for SMT

## There is no better data than more data

- Stupid back-off [Brants et al., EMNLP'07]
- Bloom Filter and randomized LMs [Talbot et al, EMNLP'07; ACL'07; ...]
- Fast KenLM to train on common crawl

...

\+ Usually improved translation performance

– But these models are often intractable for *standard users*

$\Rightarrow$ Distributed instead of memory-based models

Learn from the data instead of memorizing it

# Some Past Research on LM for SMT

## New LM approaches

- I'm not aware of new LM smoothing techniques which are able to beat back-off LMs trained on huge amounts of data
- Exception: Model M (but mainly used in ASR)

# Continuous Space LM

## Theoretical drawbacks of back-off LM:

- Words are represented in a high-dimensional discrete space
- Probability distributions are not smooth functions
- Any change of the word indices can result in an arbitrary change of LM probability

$\Rightarrow$ True generalization is difficult to obtain

## Main idea [Y. Bengio, NIPS'01]:

- Project word indices onto a continuous space and use a probability estimator operating on this space
- Probability functions are smooth functions and better generalization can be expected

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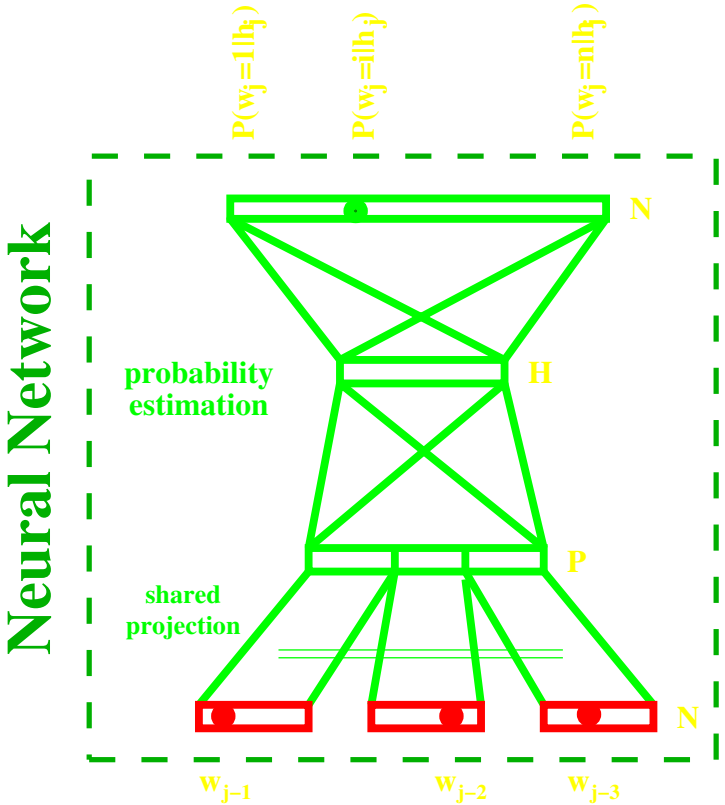
# CSLM - Probability Calculation




$h_j = w_{j-n+1}, ..., w_{j-2}, w_{j-1}$

- Outputs = LM posterior probabilities of all words: $P(w_j = i|h_j) \quad \forall i \in [1, N]$
- Context $h_j$ = sequence of $n-1$ points in this space
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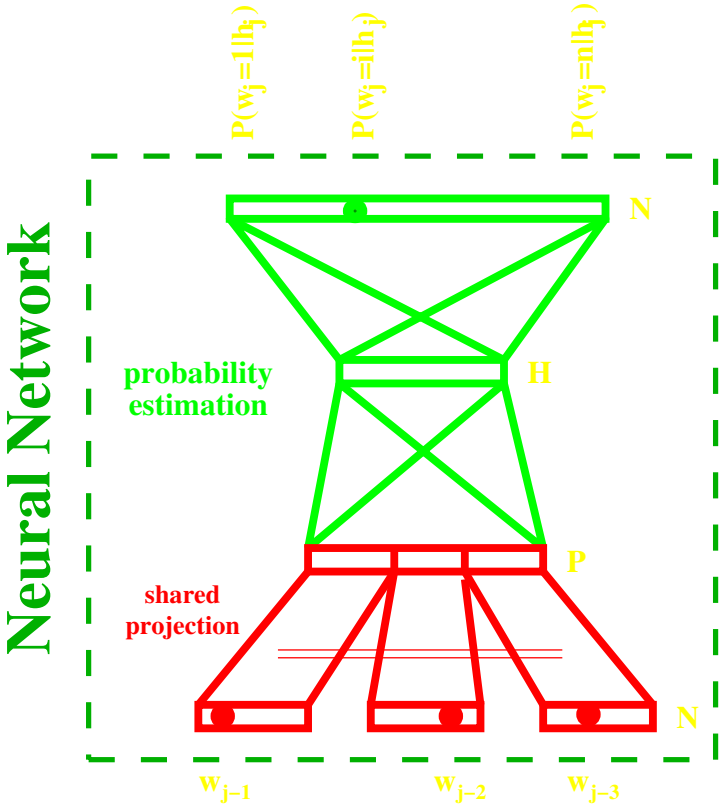


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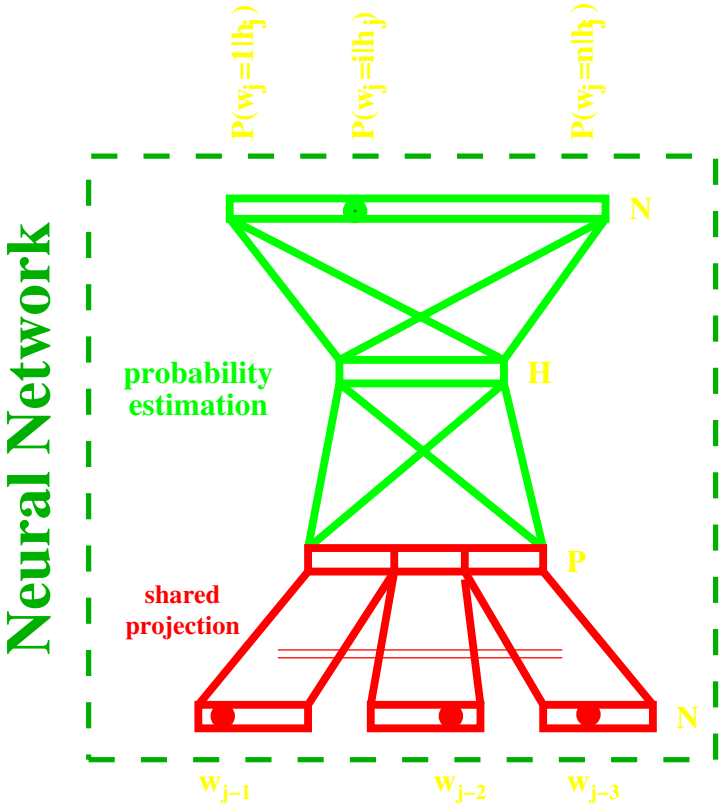


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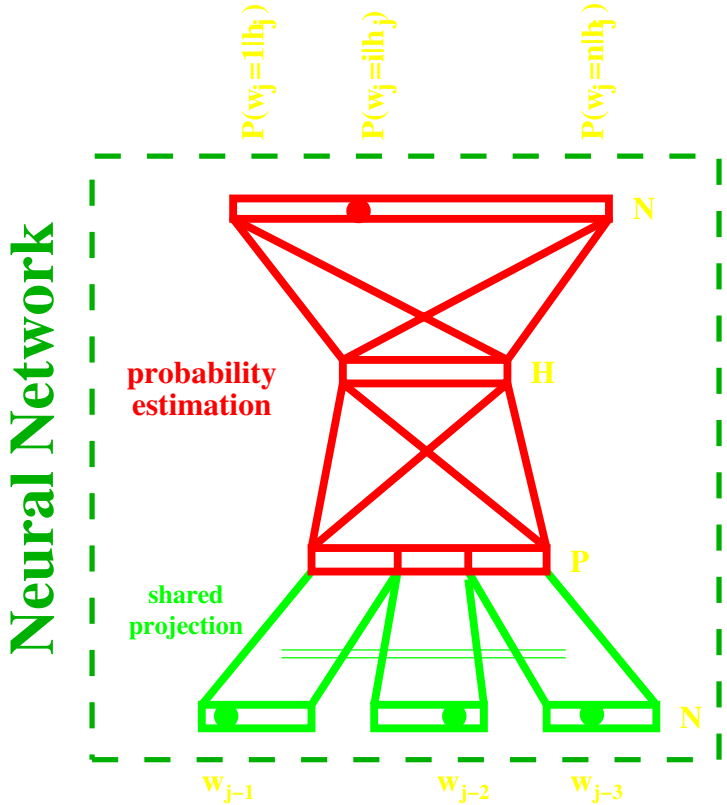


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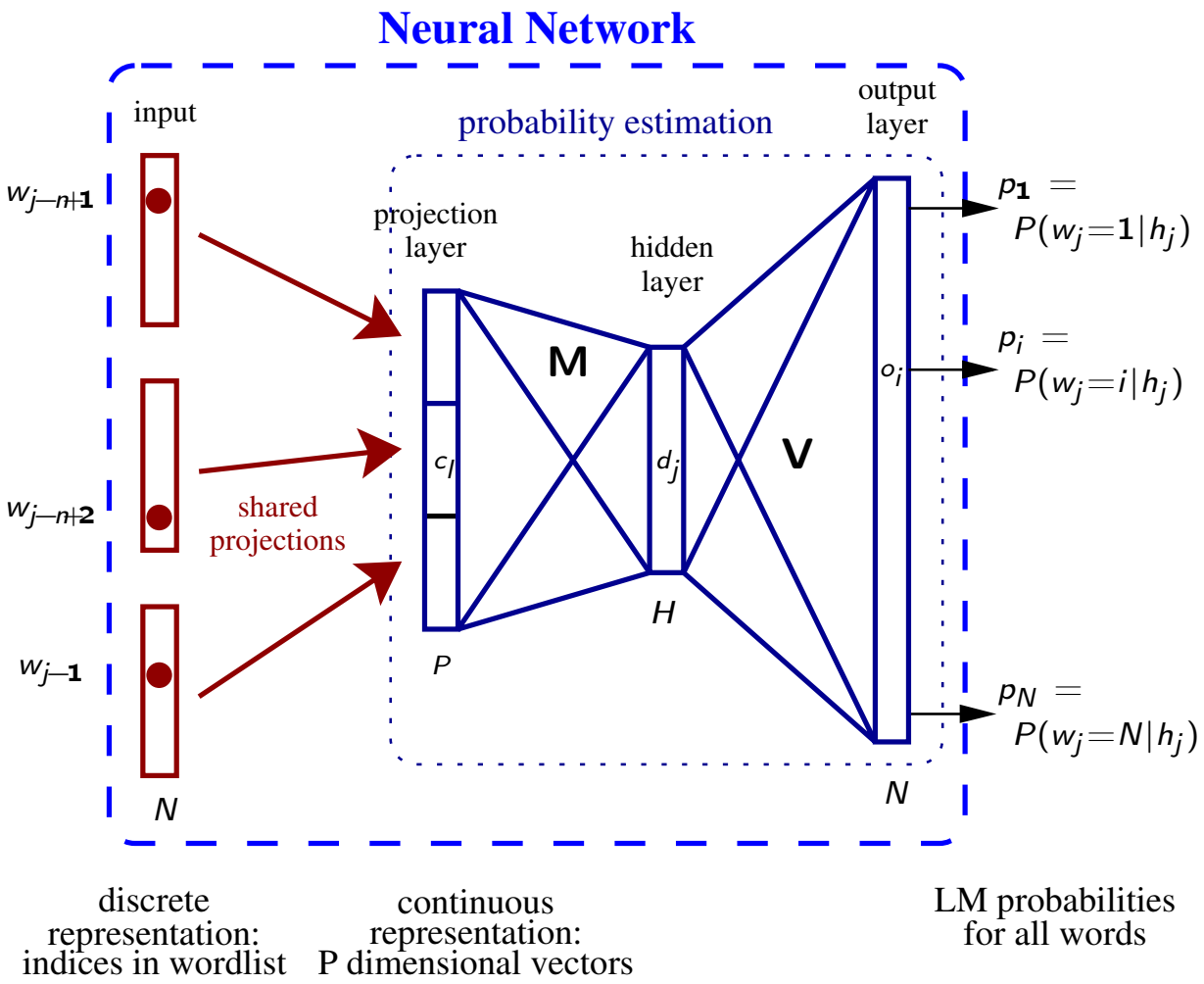
# Architecture of the CSLM



# CSLM - Math

- Input: $n-1$ context word $w_{i-n+1} \ldots w_{i-1}$
- Vocabulary : $V$ words
- Projection layer
  - one-out-of-n encoding $\rightarrow$ V dimensional inout vector
  - projection = lookup in table
- Hidden layer

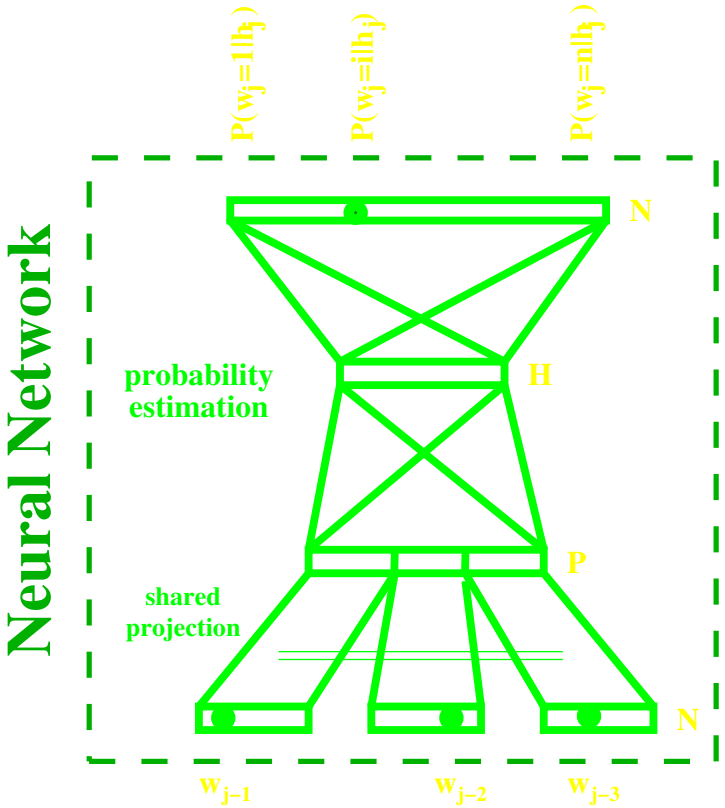
$$h_i = tanh(\sum_k w_{ij}\ p_j + b_i)$$

- Output layer

$$o_i = \sum_j w_{ij}\ h_j + k_i$$

- Softmax normalization over the full vocabulary

$$p_i = \frac{exp(o_i)}{\sum_k exp(o_i)} \qquad \forall i = 1 \ldots V$$




# CSLM - Training

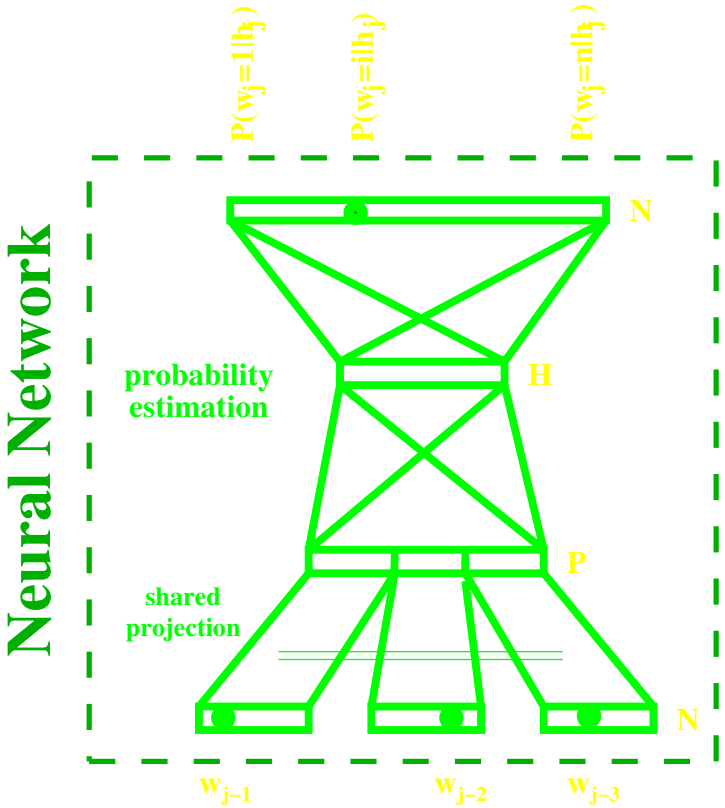
- Backprop training, cross-entropy error

$$E = \sum_{i=1}^{N} d_i \, log \, p_i$$

+ weight decay

$\Rightarrow$ NN minimizes perplexity on training data

- continuous word codes are also learned (random initialization)

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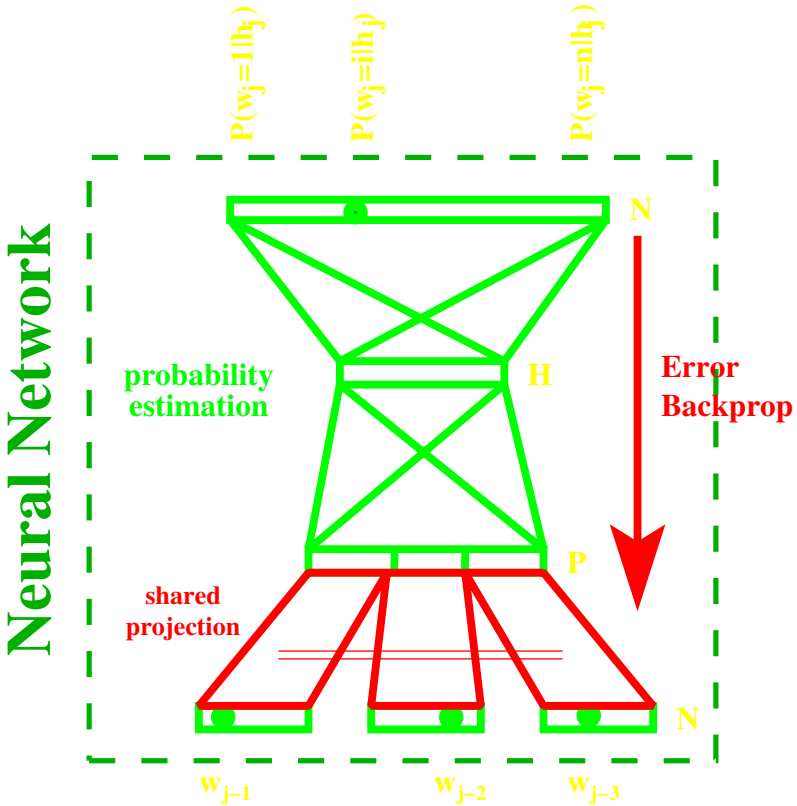


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# CSLM - Variants

## Variants of the basic architecture

- Representation of the output layer (input is no issue)
  → short-lists, classes, SOUL, NCE, etc
- Integration into the SMT system
  → N-best rescoring, integration into decode, ...
- Network architecture
  → MLP, RNN, LSTM, ...
  → shallow or flat networks, how much capacity ?
- NN training tricks
  → initialization, learning rate, huge data, ...
- Speed of training and inference
  → a lot of engineering, GPUs
- Providing additional (source) information
  → joint model, translation model, ...

# CSLM - Representations of the Output Layer

## Short-list

- NN only predicts the $N$ most frequent words (8k-32k)
- Remaining ones are done by standard back-off LM
- One special NN output for the cumulative probability mass

$$P(w_t|h_t) = \begin{cases} P_{NN}(w_t|h_t) & \text{if } w_t \in \text{shortlist} \\ P_{BOF}(w_t|h_t) & \text{else} \end{cases}$$

$\Rightarrow$ Neural network redistributes the probability mass

- Easy to implement and use
- Actually quite fast since we can use the brute force of CPU or GPUs

# CSLM - Representations of the Output Layer

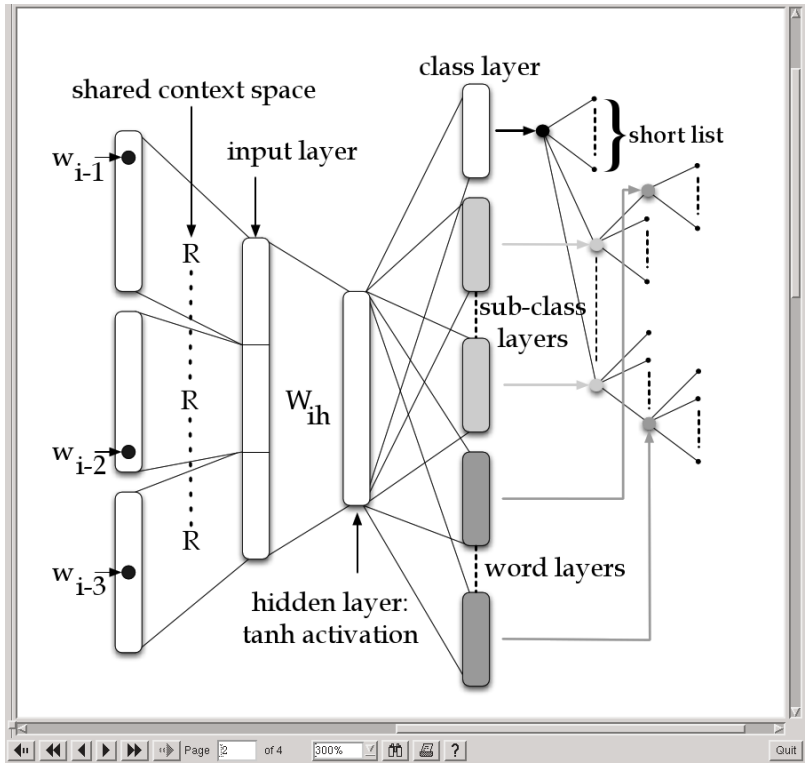
## Classes

- Well known class decomposition of back-off LMs
- All the words can be handled by the NN
- Not necessarily faster due to many operations on small matrices
- Used in RNN toolkit [Mikolov], OxLM [this Marathon], etc
- Now also available in the CSLM toolkit

# CSLM - Representations of the Output Layer

## *Structured Output Neural Network Language Model (SOUL)*, Le et al, ICASSP'11

- Hierarchical decomposition:




- Probably some experience needed to find the optimal decomposition

# CSLM - Representations of the Output Layer

Techniques to avoid the costly softmax normalization at the output layer

## Noise constrative estimation (NCE)

- *A fast and simple algorithm for training neural probabilistic language models* Minh et Teh, ICML'12
- First used for SMT in: *Decoding with Large neural networks improves translation*, Vaswani et al, EMNLP'13

## Self normalization

- *Fast and Robust Neural Network Joint Models for Statistical Machine Translation*, Devred et al, ACL'14
- Additional regularizer to learn self normalized outputs

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# CSLM - Integration into the SMT System

## *N*-best list rescoring

- First decode with standard back-off LM
- Then rescore with the CSLM (addtl feature)
- Many optimizations are possible

## Directly in the decoder

- Quite tricky since many thousands/millions of LM requests are needed for each sentence
- One need to delay the LM requests
- Avoid to perform softmax normalization
- Usually only small networks are possible
- Limited context size (hypothesis recombination)

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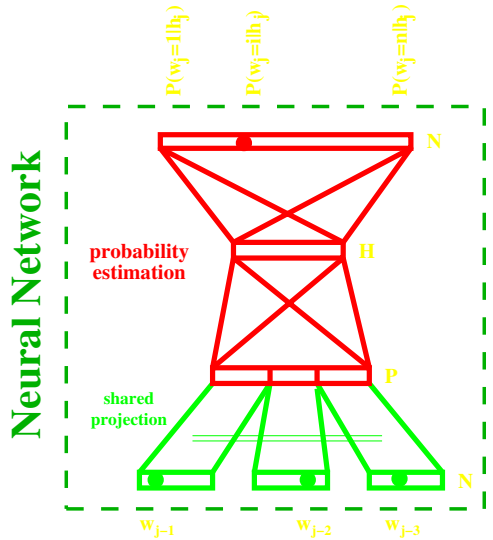
# CSLM - Network Architecture

## Feed-Forward

- Initial approach of Bengio et al.
- Easy to implement and optimize
- Still an $n$-gram approach

$\Rightarrow$ Context beyond $n-1$ words is ignored



# CSLM - Network Architecture

## Recurrent neural networks

- Use of internal state which summarizes the past
- This hidden layer has connections to the input layer and itself
- First used for LM by Mikolov et al., Interspeech'10
- Theoretically better motivated (no *n*-gram approximation)
- In practice, RNN tend to forget words too far in the past (vanishing gradient problem)
- RNNs are more tricky to optimize since we need to preserve the sequential order
- Normally only *n*-best rescoring
- Unclear if they are superior on **large tasks**

# CSLM - Network Architecture

## LSTM

- Variant of recurrent NN [Hochreiter and Schmidhuber '97]
- Intended to be better suited for long sequences
- Very successful in online handwritten character recognition
- Recently used in a couple of studies for LM

# CSLM - Network Architecture

## Large context feed-forward architectures

- It is straight forward to train an CSLM with a large context window

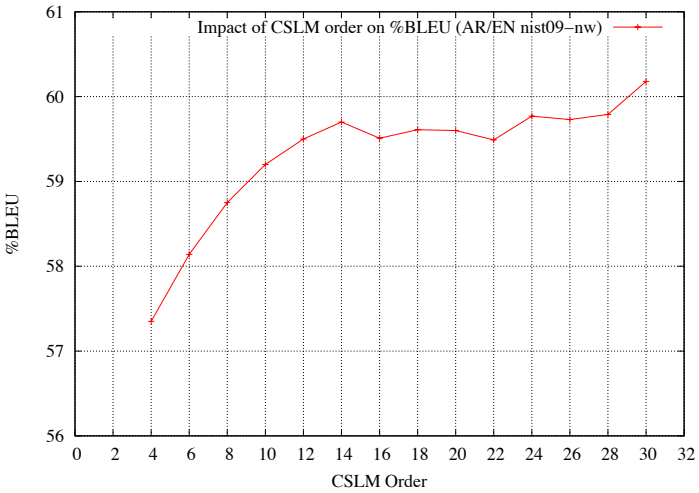
$\Rightarrow$ We just need to add additional inputs

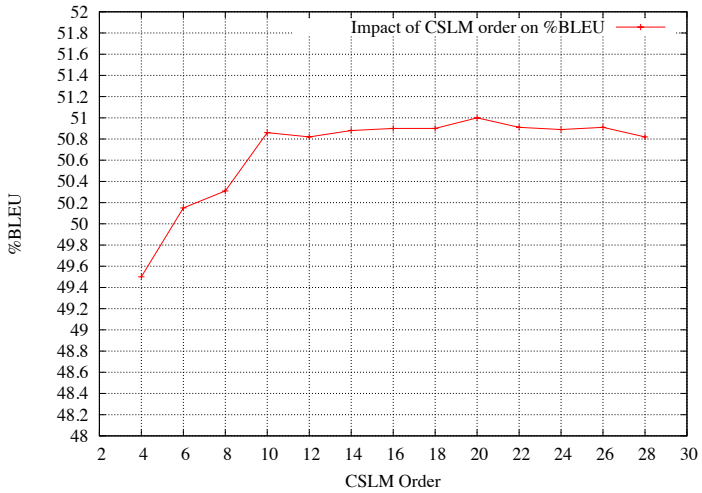
- Use of a special word for shorter $n$-grams
- No effect of forgetting quickly the past (vanishing gradient in RNN)
- Training and inference complexity is almost not affected ($n$-best rescoring)
- Surprisingly efficient in practice

# CSLM - Network Architecture

## Large context feed-forward architectures

- BLEU scores in function of the context size (Ar/En and Ar/Fr on NIST-style task)




$\Rightarrow$ Consistent increase of BLEU score with the context size

- +2 BLEU between 4- and 14-gram for Ar/En

# CSLM - Network Architecture

## Shallow versus deep architectures

- Often, a straight-forward NN architecture seems to be used (input, projection, one hidden and softmax layer)
- One the other hand, the machine learning community is very actively working on **deep architectures**, i.e. with multiple hidden layers
- These networks consistently outperformed shallow architectures in many tasks
- However, only very few studies concern deep CSLMs

## Network capacity

- Another meta-parameter is the size of the hidden layer(s)
- Practice has shown, that we need more capacity than expected (no overfitting observed on large tasks)

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# Study on NN architecture (BOLT Ar/En)

| Network architecture | Px | Nbr of parameters | Training time [min] | SMT performance BLEU | TER | TB2 |
|---|---|---|---|---|---|---|
| Back-off 4-gram | 76.3 | n/a | n/a | 26.64 | 58.38 | 15.87 |
| Initial CSLM, 1024-h384 | 61.0 | 14.9M | 60m | 27.22 | 57.94 | 15.36 |
| **One hidden layer CSLM** | | | | | | |
| 512 | 62.7 | 9.4M | 26m | 27.58 | 57.61 | 15.01 |
| 1024 | 59.8 | 18.8M | 46m | 27.60 | 57.62 | 15.01 |
| 2048 | 60.0 | 37.5M | 80m | 27.74 | 57.92 | 15.09 |
| **Two hidden layer CSLM** | | | | | | |
| 1024-1024 | 57.5 | 19.8M | 46m | 27.85 | 57.49 | 14.82 |
| 1536-1536 | 57.3 | 30.5M | 58m | 27.95 | 57.67 | 14.86 |
| 3072-1536 | 57.6 | 35.8M | 68m | 27.77 | 57.51 | 14.87 |
| **Three hidden layer CSLM** | | | | | | |
| 768-768-768 | **57.4** | **15.3M** | 67m | **27.96** | **57.27** | **14.65** |
| 1536-1024-768 | 57.3 | 17.9M | 74m | 27.96 | 57.57 | 14.80 |
| 1536-1536-1536 | 56.9 | 32.8M | 63m | 28.00 | 57.39 | 14.69 |
| **Four hidden layer CSLM** | | | | | | |
| 1536-1024-768-768 | 57.5 | 18.5M | 50m | 27.95 | 57.29 | 14.67 |
| 1536-1536-1024-1024 | 57.0 | 24.7M | 83m | 27.78 | 57.43 | 14.82 |
| 2048-2048-1536-1536 | 57.2 | 38.8M | 78m | 27.86 | 57.77 | 14.96 |
| 3072-2048-1536-1536 | 57.0 | 42.9M | 83m | 27.78 | 57.51 | 14.86 |

- NN with three hidden layers (total of 7 layers) perform best
- Shallow networks, **with more capacity**, perform worse
- Same tendency observed on many other tasks
- Three hidden layers of about 1024 units seem to be *universal*

# Neural Network Training

## Optimizing meta-parameters

- There are a lot of buttons to adjust when using NN:
  - learning rate, procedure to decrease it
  - how to initialize the weights
  - regularization, noise injection
  - drop-out, rectifiers, ...
- Many papers were published in the machine learning community on these issues

## Application to CSLM

- Training an CSLM on huge corpora can take hours, days, ...
- Can we afford to optimize the meta-parameters ?
- Use at least recommended settings (which should be documented in the publications)

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# Speed of Training and Inference

## Speed issues

- An approach to LM should be able to scale to larger corpora (billions of words)
- Quite some engineering is needed to speed-up CSLMs
  - block mode, multi-threading, data selection
  - cache algorithms and redundancy during inference
- GPU cards are a quite cheap and efficient alternative
- Neural network training needs little main memory

$\Rightarrow$ An CSLM can be trained on a **gamer PC**

## CSLM toolkit

- network 320-1024-1024-1024-16384:
  1h50 for one epoch of 40M examples on Tesla K40
- network 320-1024-1024-1024-32768: 2h30

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## Personal analysis

- Feed-forward or recurrent ?
  - → Feed-forward with large context window since easier to train/use
- Rescoring or decoding ?
  - → Integration into decoding may help, but we quite likely loose the benefit of long contexts

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# CSLM - Summary

## My best practice

- Train on GPUs using all the available data
- Use Moore&Lewis data selection to focus on most relevant examples
- Sample in several corpora using appropriate coefficients
- Use deep networks with enough capacity
- Carefully optimize the meta-parameters
- N-best rescoring with long context feed-forward architectures

$\Rightarrow$ Improvements of 2-3 points BLEU in many tasks

- You can use the open-source CSLM toolkit for this

# Beyond Neural Language Models

Can we also use neural networks for translation models ?

## Initial straight-forward attempt

- Consider n-gram tuple translation models
- Translation model = language model over tuple vocabulary

$\Rightarrow$ It's straight-forward to apply an CSLM

- *Smooth bilingual n-gram translation*, Schwenk et al., EMNLP'07

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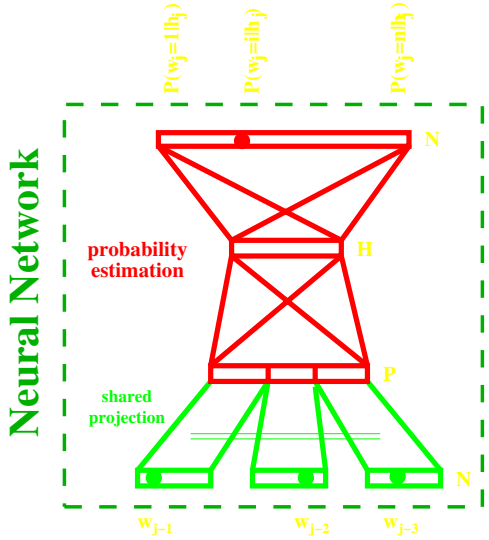
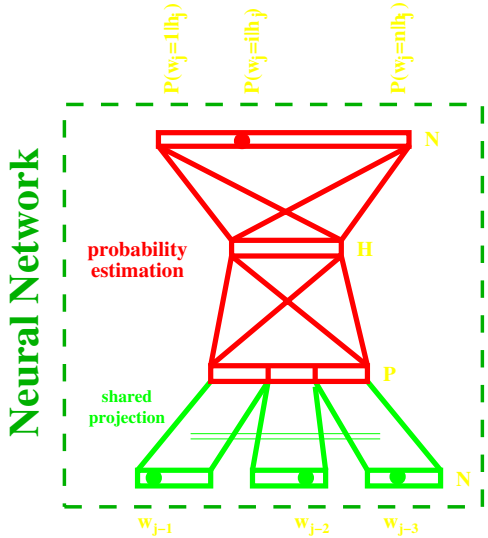



## Extensions

- Nothing prevents us from using different input and output vocabularies
- It is also possible to add additional information at the input layer
  - context or topic information
  - source text information

$\Rightarrow$ Joint models

# Beyond Neural Language Models

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# Joint Neural Language Models

## SOUL neural translation model

- *Continuous Space Translation Models with Neural Networks*, Lee et al, NAACL'12
- Factorize translation probability
- Predict the next target word given a sliding window of the preceding source and target words
- Used in *n*-best rescoring

## *Joint language and Translation Modeling with Recurrent NN*, Auli et al, EMNLP'13

- Augment the RNNLM with additional inputs from the source language
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# Joint Neural Language Models

*Recurrent Continuous Translation Models*, Kalchbrenner&Blunsom, EMNLP'13

- Convolutional RNN
- Rescoring: same result than with standard 14 feature functions

*Fast and Robust Neural Network Joint Models for Statistical Machine Translation*, Devred et al, ACL'14

- Use of source information
- Various speed-up tricks
- Integration into decoder
- Very significant improvements with combination of 6 models

$\Rightarrow$ Extension: **Mapping sequences to sequences**

# Estimating phrase translation probabilities

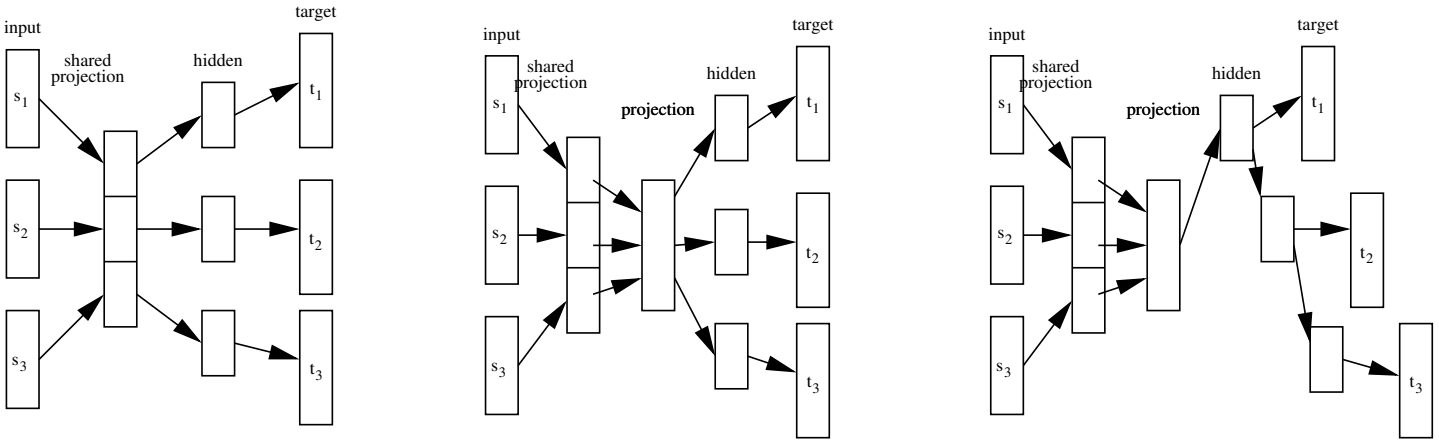
*Continuous space translation models for PBSMT*, Schwenk, Coling'12

$$
\begin{aligned}
P(\bar{\mathbf{t}}|\bar{\mathbf{s}}) &= P(t_1 \ldots t_p | s_1 \ldots s_q) \\
&= P(t_1 | t_2, \ldots, t_p, s_1, \ldots, s_q) \times P(t_2, \ldots, t_p | s_1, \ldots, s_q) \\
&= P(t_1 | t_2, \ldots, t_p, s_1, \ldots, s_q) \times P(t_2 | t_3, \ldots, t_p, s_1, \ldots, s_q) \\
&\quad \times P(t_3, \ldots, t_p | s_1, \ldots, s_q) \\
&= \prod_{k=1}^{p} P(t_k | t_{k+1}, \ldots, t_p, s_1, \ldots, s_q) \\
&\approx \prod_{k=1}^{p} P(t_k | s_1, \ldots, s_q) = \prod_{k=1}^{p} P(t_k | \bar{\mathbf{s}})
\end{aligned}
$$

We drop the dependency on the previous target words

# Estimating phrase translation probabilities

## Different neural network architectures for a CSTM




- Left: simple extension of the CSLM.
- Middle: addition of a common hidden layer in order to introduce a dependence between the target words.
- Right: hierarchical dependence
- Initial experiments on IWSLT task showed small improvements
- Now implemented on multiple GPU cards in CSLM toolkit
  $\rightarrow$ we can scale up to large tasks

# Encoder/Decoder Framework

## Context

- Map a sequence of input words to a sequence of outputs
- The length of both sequences may vary

## Encoder

- Map the variable length input sequene to a fixed size high dimensional vector

## Decoder

- Create a sequence of output symbols from the high dimensional representation

Use a (deep) neural network for the encoder/decoder
(CSTM uses MLPs at the phrase level)

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# Estimating phrase translation probabilities

*Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation, Cho et al, EMNLP'14*

- Use of recurrent encoder and decoder (modified LSTM)
- Rescoring of *n*-best list
- WMT'14 En/Fr task

## Recent work

- A couple of groups are working on the translationm of whole sentences instead of phrases with neural networks
- Some approaches start to match classical systems
- Translation quality seems to decrease with the length of the sentences

# CSLM Toolkit

## Features

- Written in C++, LGPL
- Flexible network architecture (deep)
- Very efficient on CPU and GPU
- Support for large corpora (resampling, etc)
- Continuous space language and translation models
- *N*-best rescoring (external tool or in Moses)
- Support for many data formats
- Successfully used in industrial applications
- `http://www-lium.univ-lemans.fr/~cslm`

# CSLM Toolkit

## New release (Sept 2014)

- Classes at output layer (thanks to P. Lamblin)
- Speed improvements
- Support of Google *n*-grams
- Training on multiple GPU cards in parallel
- More learning rate options, ...

## Planed

- Recurrent networks (LSTM)
- Sentence translation models
- ...
- External contributions are welcome

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# Shared Task for Research on NN for SMT

## Context

- Many papers are published and it's difficult to compare the various approaches in a fair way (undocumented tricks)

$\rightarrow$ We provide a complete Moses En/Fr SMT system trained on WMT'14 data

- Large scale task, with common bitext and LM data (data selection already applied)
- *n*-best lists for rescoring are provided
- Plan: common MERT/MIRA tuning

$\Rightarrow$ Everybody can try his own approach and enter the results into a public table

http://www-lium.univ-lemans.fr/~schwenk/nnmt-shared-task

# Conclusion

- Exploding interest in neural networks for SMT
- Continuous space LMs are now well established: they consistently and significantly improve translation performance in many studies
- It is important to use all the tricks of the NN comunity
- We need to scale up !

→ Buy a couple of GPU cards

- Many directions to extend those ideas to the translation model, complete sentences, ...
- Challenges:
  - should we integrate NN into the current framework or aim for fully neural solutions ?
  - how to efficiently encode/decode long sequences ?
- I expect very promising approaches within the next years ...

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## Cooperations

- I would be happy to collaborate with other groups
- We also have openings at all levels (internship, PhD, postdoc, senior, ...)