n-gram-based MT : what's behind us, what's ahead

F. Yvon and the LIMSI MT crew

LIMSI — CNRS and Université Paris Sud

MT Marathon in Prague, Sep 08th, 2015

Outline

1. overview: MT @ LIMSI
2. *n*-gram-based MT: Basics
3. Continuous space LMs and TMs: SOUL and beyond
4. From n-gram to CRF based TMs
5. Conclusion

Outline

MT @ LIMSI: some facts and numbers

Statistical Machine Learning and Machine Translation (PI: F. Yvon)

- Part of "Spoken Language Processing"
- Joint venture with "Information, Written and Signed Languages"
- Contributors:
  - 5 faculty members (Univ. Paris-Sud) + 2 CNRS researchers
  - 9 Ph.D students
  - 2 post-docs
- Main Theme: Structured Machine learning for multilingual NLP
  - sequence labeling, dependency parsing, WSD
  - weakly supervised learning & cross-lingual transfert
  - alignment models, statistical machine translation

☞ http://www.limsi.fr/tlp [Machine Translation]

MT @ LIMSI: Recent Activities and Contributions

Covering all aspects of Multilingual (spoken and written) NLP

- Some recent contributions
  - Discriminative & sampling-based alignements models [AMTA'10, IWSLT'10, MT'13, MT'14]
  - Contextual models, on-the-fly learning for SMT [IWSLT'13, IWSLT'14]
  - Large-scale continuous space language and translation models [ICASSP'11, NAACL'12, AMTA'14, IWSLT'14, EMNLP'15]
  - Large-scale discriminative learning for SMT [WMT'11, TALN'13]
  - Evaluation: computing oracles, quality estimation [MT'13, ACM TSLP'13, WMT'13...]
  - Ambiguous supervision and cross-lingual transfert [TALN'14, EMNLP'14]
  - Structured learning with large, structured, output spaces [ACL'10, LREC'12, InterSpeech'13, TALN'15, InterSpeech'15, EMNLP'15]
- Current Projects (multi-lingual NLP)
- Evaluation campaigns

MT @ LIMSI: Recent Activities and Contributions

Covering all aspects of Multilingual (spoken and written) NLP

- Some recent contributions
- Current Projects (multi-lingual NLP)
  - QT-21: Quality translation for 21 languages [H2020, +10 academic, TAUS, Tilde...]
  - Transread: towards bilingual reading [French ANR, +CNAM, Reverso]
  - Papyrus: cross-domain and cross-lingual transfert for Information processing [French DGA, +Systran]
  - Bulb: NLP tools for collecting and annotating unwritten languages [German/French ANR, +LPL, LIG, LLACAN, KIT, Uni. Stuttgart]
- Evaluation campaigns

MT @ LIMSI: Recent Activities and Contributions

Covering all aspects of Multilingual (spoken and written) NLP

- Some recent contributions
- Current Projects (multi-lingual NLP)
- Evaluation campaigns
  - WMT Translation [2007-2015], Quality Estimation [2012-2015], Metrics [2015]
    consistently among the top systems for English:French both directions
  - IWSLT Translation [2010, 2011, 2014], Recognition+Translation [2014]
  - SemEval 2015 [Task 13: all word WSDs]
    best system for English

Outline

1. overview: MT @ LIMSI
2. *n*-gram-based MT: Basics
   - Tuples: bilingual units for SMT
   - How is this done ?
   - Order
   - Simplicity of the *n*-gram based approach
3. Continuous space LMs and TMs: SOUL and beyond
   - Towards large-scle CSTMs
   - Discriminative training for NNs
4. From n-gram to CRF based TMs
5. Conclusion
   - Roadmap

Bilingual *n*-grams for Statistical Machine Translation

n-gram LM of tuples

- a bilingual language model as primary translation model
- parallel sentences are sequences of tuples = synchronous phrases

	$u_1 = (f,e)_1$	$u_2 = (f,e)_2$	$u_3 = (f,e)_3$	$u_4 = (f,e)_4$
$\mathbf{f} =$	we	want	translations	perfect
$\mathbf{e} =$	nous	voulons	des traductions	parfaites

- translation context introduced through tuple **n**-gram history

$$P(\mathbf{f},\mathbf{e}) = \prod_{t=1}^{T} P\big((f,e)_t | (f,e)_{t-1},(f,e)_{t-2}\big)$$

with back-off, smoothing, *etc.*

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Training and Decoding with *n*-gram TMs

Training

1. identify tuples
2. synchronize bitext

   asymmetric, target oriented
3. train LM
4. train reordering component

Steps 1 and 2 are currently performed simultaneously (but don't need to be)

Decoding

1. generate source reorderings $L(\mathbf{f})$
2. solve:

$$\mathbf{e}^* = \operatorname*{argmax}_{\tilde{\mathbf{f}} \in L(\mathbf{f})} P(\tilde{\mathbf{f}}, \mathbf{e})$$

or use the standard log-linear model

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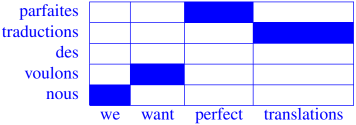
Steps 1+2: extract tuples, synchronize phrase pairs

Extracting tuples from word alignments

1. compute (symmetric) word alignments



2. a unique joint segmentation of each sentence pair
3. no NULL on the source side
   - source-NULL can't be predicted
   - attach the target word to the **previous/next** tuple

we	want	translations	perfect
nous	voulons	des traductions	parfaites

   - optimizing attachment direction

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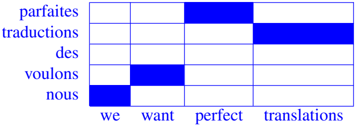

2. a unique joint segmentation of each sentence pair
   - source words are reordered to match target word order
   - no word in a tuple can be aligned outside the tuple
   - maximal segmentation yield minimal tuples

we	want	NULL	translations	perfect
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Limsi

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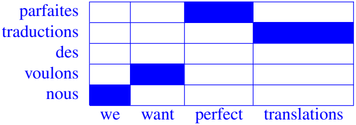

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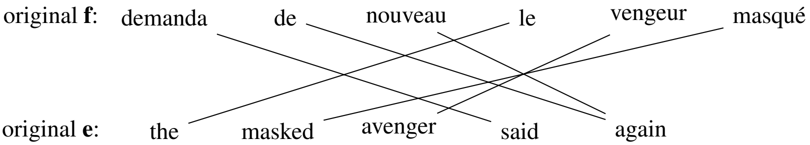
Bitext synchronization

Reordering and segmenting parallel sentences

1. unfold the word alignments
2. segment into minimal bilingual units → a tuple sequence



Bitext synchronization

Reordering and segmenting parallel sentences

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original **f**: demanda de nouveau le vengeur masqué

original **e**: the masked avenger said again

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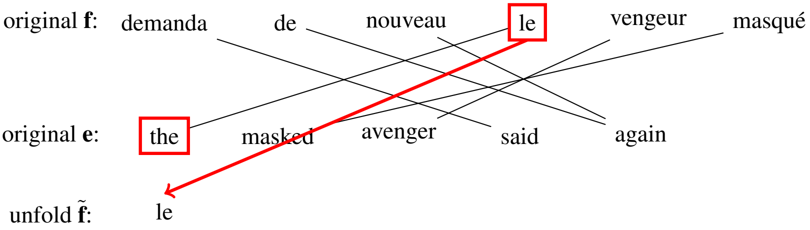

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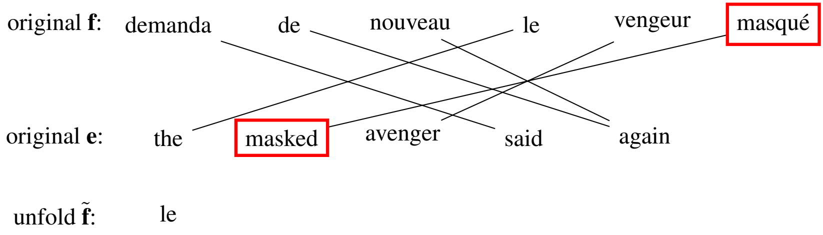

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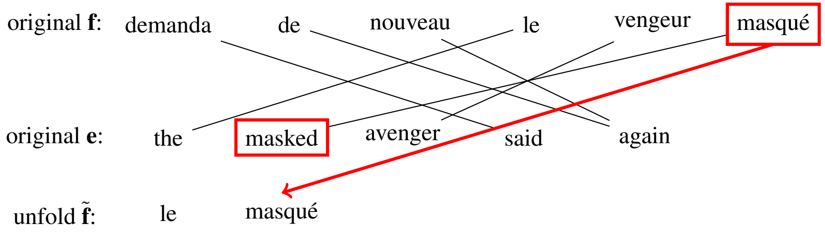

Bitext synchronization

Reordering and segmenting parallel sentences

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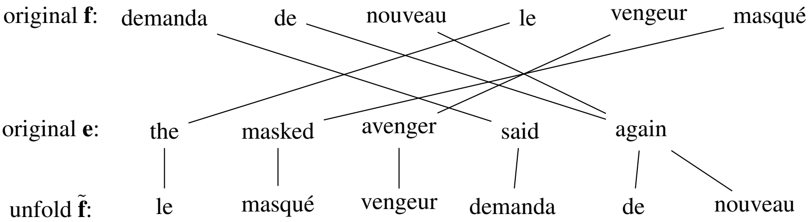

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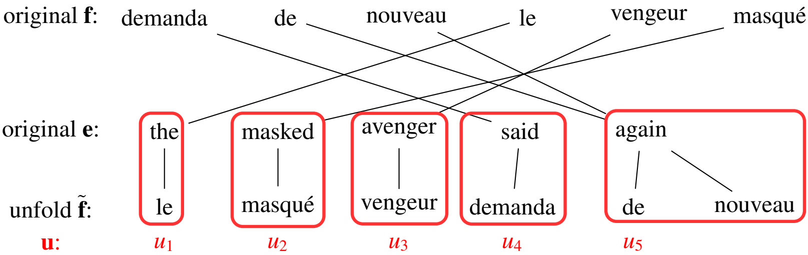

Word (dis)order issues

Towards Dissociating reordering and decoding

Reproducing source reorderings

Solving $\mathbf{e}^* = \operatorname{argmax}_{\tilde{\mathbf{f}} \in L(\mathbf{f})} P(\tilde{\mathbf{f}}, \mathbf{e})$ assumes $L(\mathbf{f})$
$L(\mathbf{f})$ is a set of reordering hypotheses

Generating permutations

Our way: learn rewrite reordering rules from word alignments

Decoding is easy (Finite-State SMT (Bengalore et al, 2000))

Word (dis)order issues

Towards Dissociating reordering and decoding

Reproducing source reorderings

Generating permutations

- $L(\mathbf{f})$ =all ($|\mathbf{f}|!$) permutations is untractable
  permutations make MT NP-hard
- combinatorial reorderings: distance-based, WJ1, IBM, ITG, *etc.*
  computationally effective (polynomial), linguistically risky

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Our way: learn rewrite reordering rules from word alignments

1. crossing alignment: perfect translations ||| translations perfect
   lexical rules: $r =$ perfect translations $\rightsquigarrow 2\ 1$
   POS rules: $r =$ JJ NN $\rightsquigarrow 2\ 1$
2. compose rules as a reordering transducer $R = \bigcirc_i (r_i \cup Id)$
3. in decoding: $L(\mathbf{f}) = \pi_1(\text{tag}(\mathbf{f}) \circ R)$
   Computes $L(\mathbf{f}$ as a word lattice

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Towards Dissociating reordering and decoding

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Our way: learn rewrite reordering rules from word alignments

Decoding is easy (Finite-State SMT (Bengalore et al, 2000))

$$\mathbf{e}^* = \mathit{bestpath}(\pi_2(\mathbf{L}(\mathbf{f}) \circ \mathit{pt}) \circ \mathit{lm})$$

Comparison with (PB)-Moses

- translation units are minimal
- training segmentation is deterministic much smaller models, well-defined transduction models, much less spurious derivations
- static vs dynamic reordering spaces
- different search and pruning strategies

n-gram based approach: pros and cons

- ☺ isolates two main components
  - reordering model (can vary accross language pairs)
  - translation model
- ☺ leverages $\pm$ 20 yrs of LM technologies (and counting)
  (smoothing techniques, adaptation, trigger-based LMs, skip LMs, etc)
- ☺ scales to very-large bitexts (hardly any redundancy in TM + LM compression techniques)
- ☺ decoding (search) is easy - use *generic* finite-state technologies
  generate Nbest, lattices, etc. + larger translation options (reordering is small)
- ☹ source reordering is difficult (and ill-posed)
- ☺ performance $\approx$ to other PB systems for many European language pairs

Recent improvements of N-gram based models

The building blocks

1. identify tuples
2. synchronize bitexts
3. train TM as LM
4. train reordering component
5. include more models

Recent improvements of N-gram based models

The building blocks : what we have tried

1. identify tuples: + discontiguous tuples [Crego and Yvon, 2009]
2. synchronize bitexts: + discriminative alignments [Tomeh et al., 2014]
3. train TM as LM
4. train reordering component
5. include additional models: + lex. reordering, +source LM [Crego and Yvon, 2010]

Leveraging improved LM modeling techniques

- ☑ class-based LMs
- ☑ LM adaptation [Bellagarda, 2001]
- ☑ factored models [Bilmes and Kirchhoff, 2003]
- ☑ compact LMs [Heafield, 2011]
- ☑ continuous-space LMs [Bengio et al., 2003]
- ☑ discriminative LMs [Roark et al., 2004]
- ☐ whole sentence log-linear LMs [Rosenfeld et al., 2001]
- ☐ Bayesian models with HDPs à la [Teh, 2006]
- ☐ M-Models [Chen, 2009]
- ☐ training with fractional counts [Zhang and Chiang, 2014]
  (include incertainty in alignment / segmentation)

Outline

The tuple-based *n*-gram translation model

Can be conventionally learnt with NNs

Training LMs: the lazy way

the *n*-gram translation model ...

$$P(\mathbf{f}, \mathbf{e}) = \prod_{i=1}^{L} P(u_i | u_{i-1}, ..., u_{i-n+1})$$

... is easy to train
(CMU-LM, SriLM, IRSTLM, KenLM, (yes, we even have tried LimsiLM))

The lazy way is the inefficient way

- elementary units are tuples $\Rightarrow$ Very large unit set
- very sparse training data.
- smoothing is a big problem

☞Decompose tuples in smaller parts $\oplus$ use best-known smoothing: NNs

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The phrase-factored *n*-gram translation model

A novelty of the factored *n*-gram-based TM

Decompose tuples in phrases

org :	....	à	recevoir	le	prix nobel de la paix		
s :	....	$\bar{s}_8$: à	$\bar{s}_9$: recevoir	$\bar{s}_{10}$: le	$\bar{s}_{11}$: nobel de la paix	$\bar{s}_{12}$: prix	....
t :	....	$\bar{t}_8$: to	$\bar{t}_9$: receive	$\bar{t}_{10}$: the	$\bar{t}_{11}$: nobel peace	$\bar{t}_{12}$: prize	....
		u_8	u_9	u_{10}	u_{11}	u_{12}	

Notations:

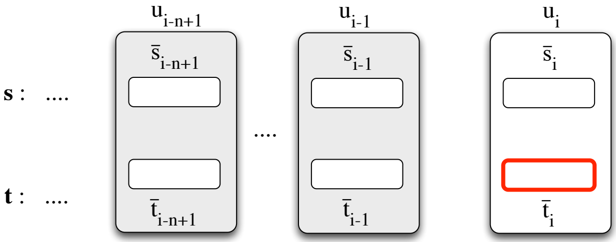
- $u = (\bar{s}, \bar{t})$: a tuple
- $\bar{s}$: the source side of u
- $\bar{t}$: the target side of u

The phrase-factored *n*-gram translation model

$$P(u_i|u_{i-1},\ldots,u_{i-n+1}) = P(\bar{t}_i|\bar{s}_i,\bar{s}_{i-1},\bar{t}_{i-1},\ldots,\bar{s}_{i-n+1},\bar{t}_{i-n+1})$$

$$\times P(\bar{s}_i|\bar{s}_{i-1},\bar{t}_{i-1},\ldots,\bar{s}_{i-n+1},\bar{t}_{i-n+1})$$

Conditional translation model



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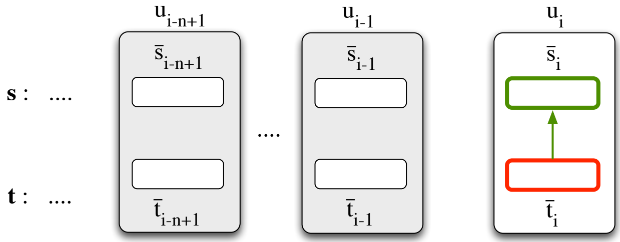

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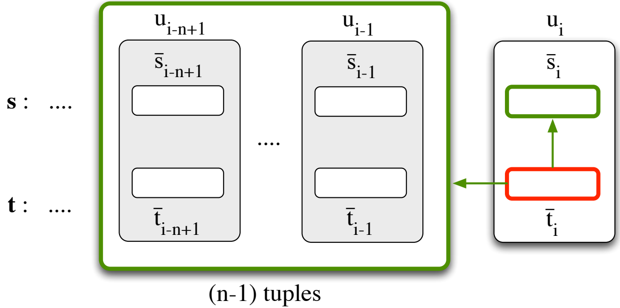

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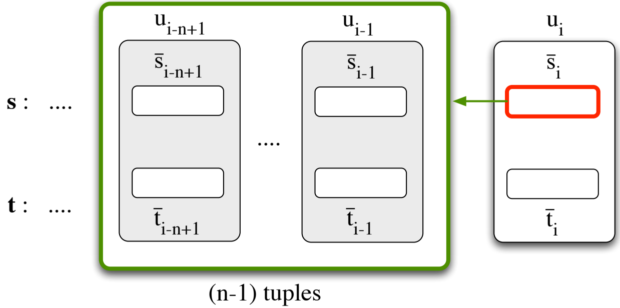
A 'distortion' model



A word-factored n-gram translation model

Decomposing further

$$P(\bar{t}_i|\bar{s}_i, \bar{s}_{i-1}, \bar{t}_{i-1}, \dots, \bar{s}_{i-n+1}, \bar{t}_{i-n+1}) = \prod_{k=1}^{|\bar{t}_i|} P\big(t_i^k \,|\, h^{n-1}(t_i^k), h^{n-1}(s_{i+1}^1) \big)$$

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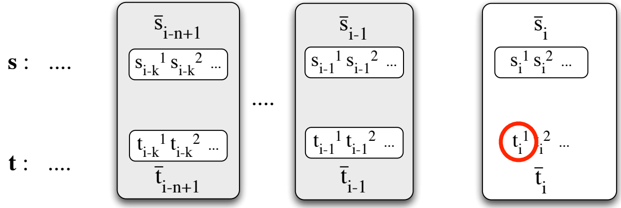

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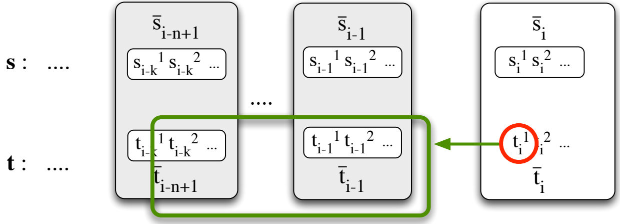

(n-1) target words before t_i^1

A word-factored *n*-gram translation model

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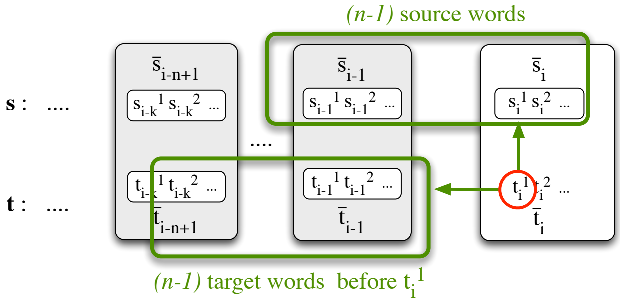

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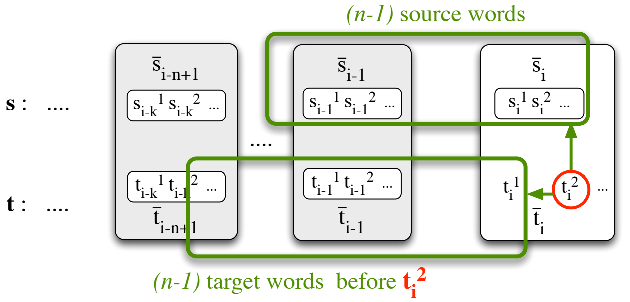


Three factorization of the n-gram model

Under the n-gram assumption

Three n-gram models of a sentence pair based on different units:

1. tuple-based (u)
2. phrase-factored ($\bar{s}, \bar{t}$)
3. word-factored (s, t)

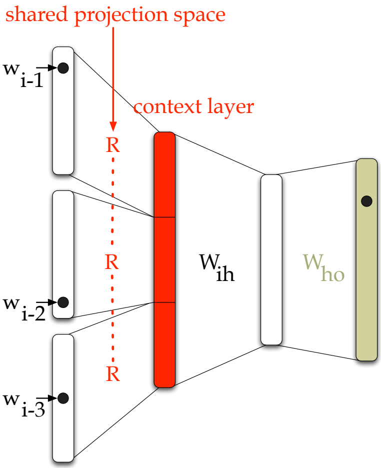
Larger units make sparser models (and conversely)

Continuous space n-gram models

Overview of the standard model [Bengio et al., 2003, Schwenk, 2007]

Projection in a continuous space

- one-hot encodings (in $\{0, 1\}^{|V|}$)
- linear projections in $\mathbb{R}^d$, ($d \ll |V|$)
- merge context vectors in one history



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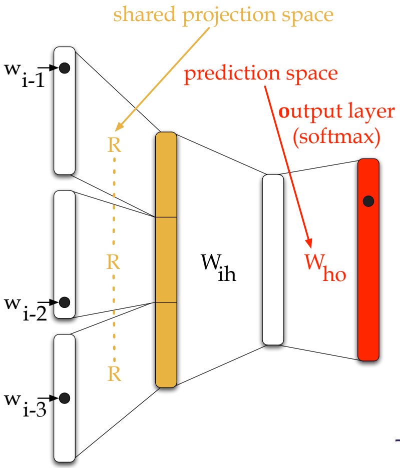
- linear projections in $\mathbb{R}^d$, ($d \ll |V|$)
- merge context vectors in one history

Probability estimation

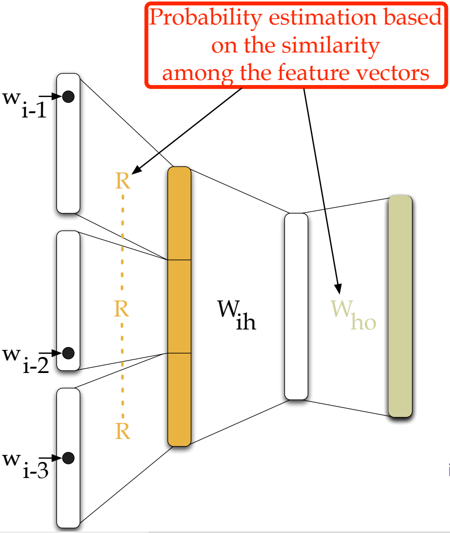
- create a feature vector for the word to be predicted.
- estimate probabilities for all words given history



Large-scale Continuous Space LMs

Key points

- projection in continuous spaces improves smoothing
- joint learning of representation and the prediction layers



i

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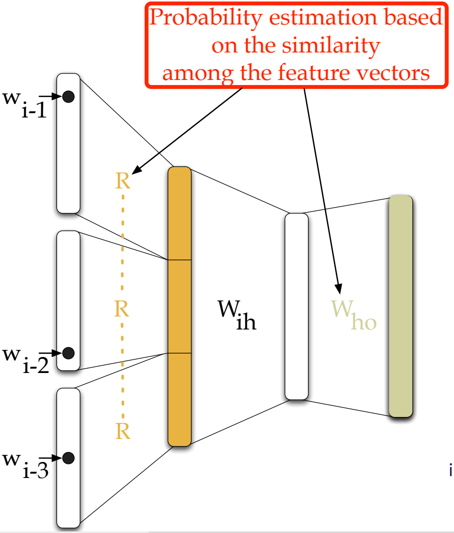
Complexity issues

- handles arbitrary input vocabularies.
- handles high-order models



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Large-scale Continuous Space LMs

Key points

- projection in continuous spaces improves smoothing
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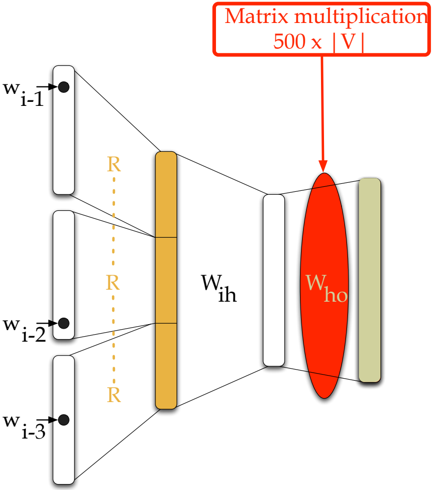
Complexity issues

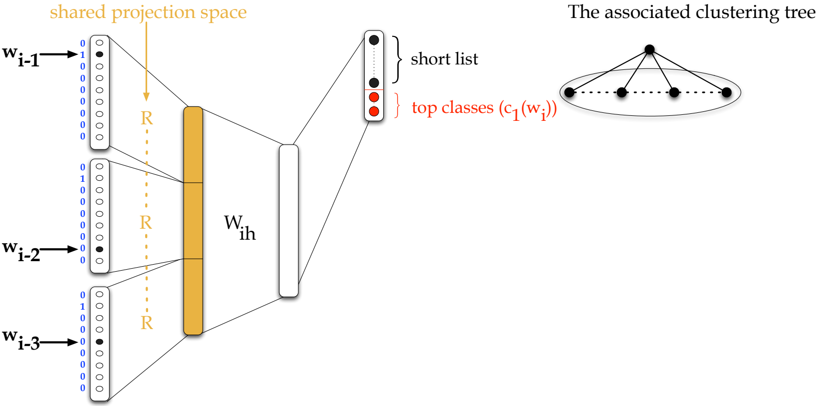
- handles arbitrary input vocabularies.
- handles high-order models
- main bottleneck: output vocabulary size



The SOUL model [Le et al., 2011]

Use a structured output layer

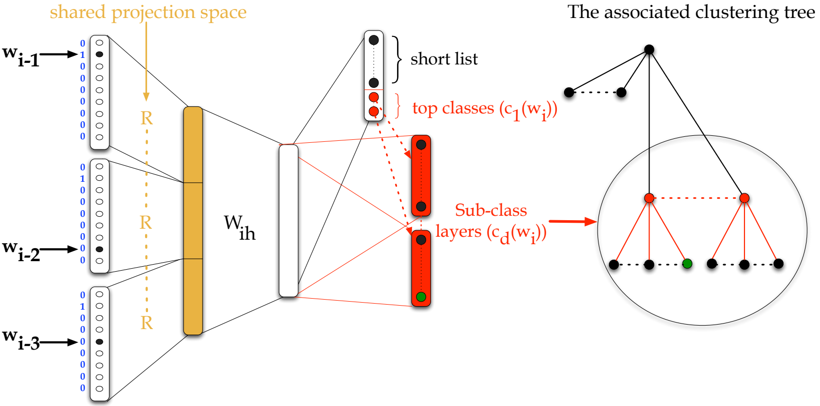
$$P(w_i|h) = P(c_1(w_i)|h)$$



The SOUL model [Le et al., 2011]

Use a structured output layer

$$P(w_i|h) = P(c_1(w_i)|h) \times \prod_{d=2}^{D} P(c_d(w_i)|h, c_{1:d-1}(w_i))$$



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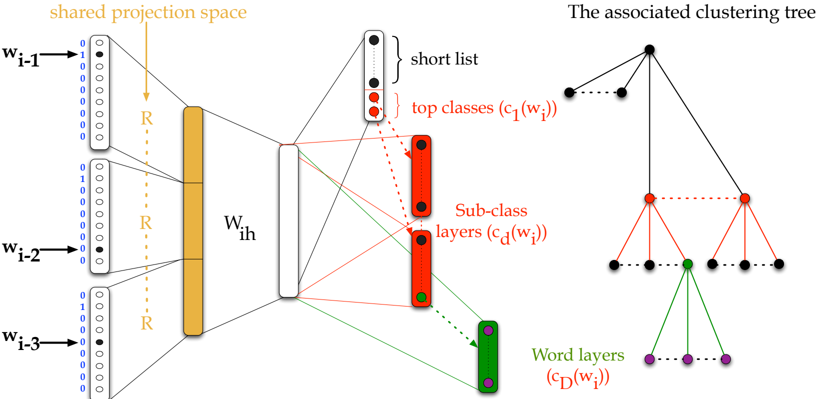

Implementing CSLMs with SOUL

The tuple-based *n*-gram translation model

Straightforward implementation (already in [Schwenk et al., 2007])

Phrase and word factored models

They involve two languages and two unit sets:

- the predicted unit is a target phrase (resp. word),
- the context is made of both source and target phrases (resp. words).

☞ use multiple projection matrices ($\mathbf{R_f}$ and $\mathbf{R_e}$).

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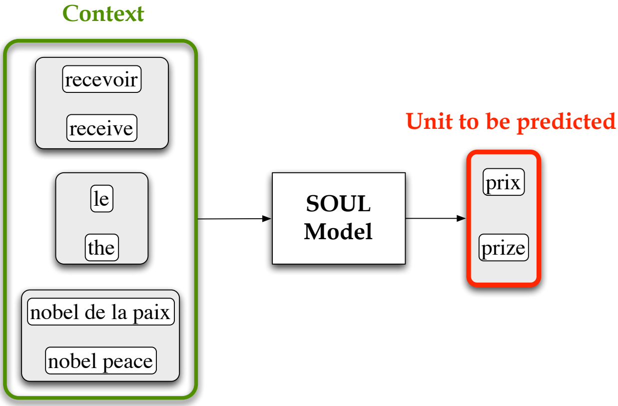
Training example

For a «4-gram» model

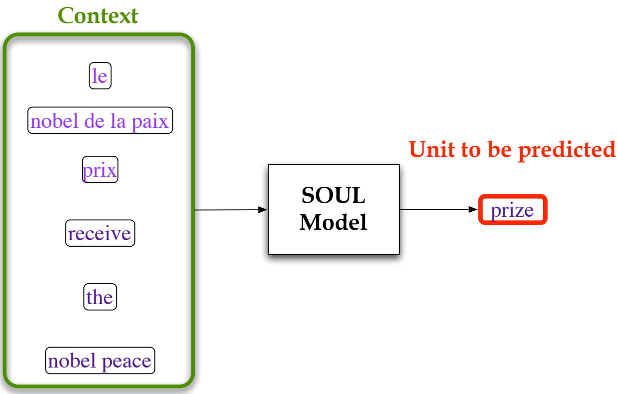
Tuple-based model



Training example

For a «4-gram» model

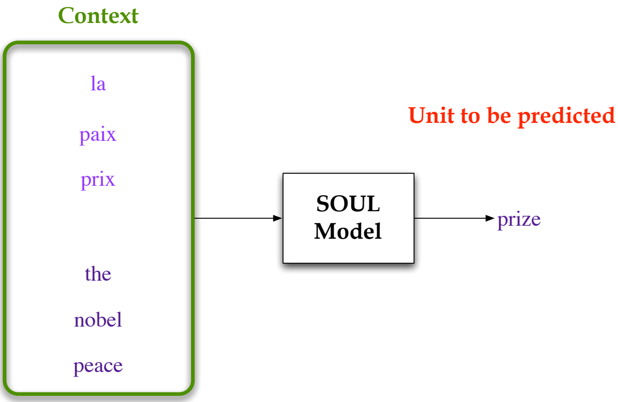
Phrase-based model



Training example

For a «4-gram» model

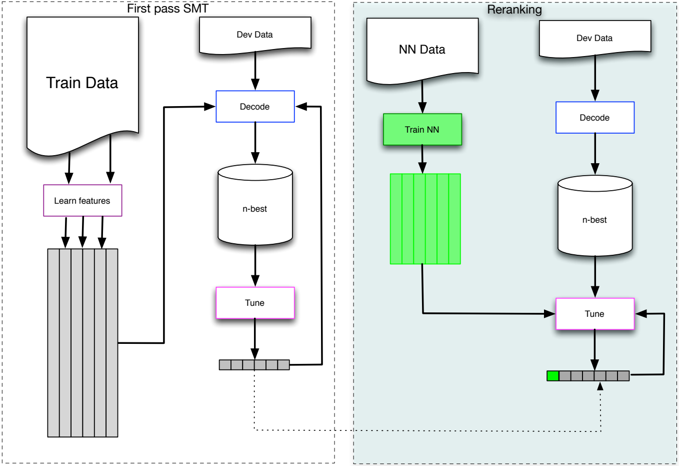
Word-based model



Inference with SOUL

Use wo steps decoding

1. Generate a *k*-best list with the baseline system
2. Re-rank the *k*-best hypotheses (additional feature)



SOUL: promisses and caveats

- ☺ guaranted large BLEU improvements across the board
  see LIMSI@(IWSLT'11 – WMT'15)
- ☺ compatible with any SMT architecture

- ☹ complex training and inference
- ☹ inadequate training objective
- ☹ computationally unsustainable - burns a lot of energy
- ☹ irrealistic in decoding (large histories + computational cost of normalization)
  possible with the "generation" trick

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Training objectives for NNLMs and NNTMs

Two generic learning objectives

1. Train NNLMS
   - negated conditional likelihood (including RNN, SOUL, etc):

$$\ell(\boldsymbol{\theta}) = \sum_{(w,h)} -\log P_{\boldsymbol{\theta}}(w|h)(+\mathcal{R}(\boldsymbol{\theta})), \text{ with } P_{\boldsymbol{\theta}}(w|h) = \frac{\exp b_{\boldsymbol{\theta}}(w,h)}{\sum_{w'} \exp b_{\boldsymbol{\theta}}(w',h)}$$

   - NCE: for each observed (h, w), generate k negative samples $(x_1 \ldots x_k)$; optimize:

$$\ell(\boldsymbol{\theta}) = -\sum_{h} \Big(\log P_{\boldsymbol{\theta}}(w|h) - \log(P_{\boldsymbol{\theta}}(w|h) + kP_N(w)) + \sum_{i} \log(P_N(x_i)) - \log(P_\theta(x_i|h) + kP_N(x_i)) \Big)$$

   $P_\theta(w|h)$ unnormalized; $P_N()$ a noise distribution (eg. unigram) [Mnih and Teh, 2012].

2. Train scoring function (log-linear combination) with MERT, MIRA, etc.
3. rerank hypotheses $\mathbf{e}$ with $G_{\boldsymbol{\lambda},\boldsymbol{\theta}}(\mathbf{f},\mathbf{e},\mathbf{a}) = F_{\boldsymbol{\lambda}}(\mathbf{f},\mathbf{e},\mathbf{a}) - \lambda_{k+1} \log(P_{\boldsymbol{\theta}}(\mathbf{e}))$

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Issues

- step 1 very costly (in training)
- $\boldsymbol{\lambda}$ and $\boldsymbol{\theta}$ trained separately
- $\boldsymbol{\theta}$ trained with an inadequate objective

A new ranking objective

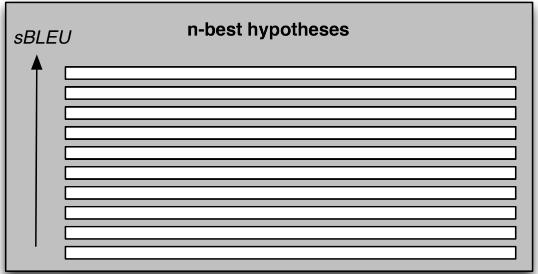
Learning to rank with a margin criterium

BLEU-based cost function

$$\text{cost}_\alpha(\mathbf{h} = (\mathbf{a}, \mathbf{e})) = \alpha\Big(\text{sBLEU}(\mathbf{e}^*) - \text{sBLEU}(\mathbf{e})\Big) \text{ where}$$
$$\mathbf{e}^* = \operatorname*{argmax}_{\mathbf{e}} \text{sBLEU}(\mathbf{f}) \text{ is the best hypothesis}$$

$(\text{cost}_\alpha(h) \geq 0)$

A Max-margin objective



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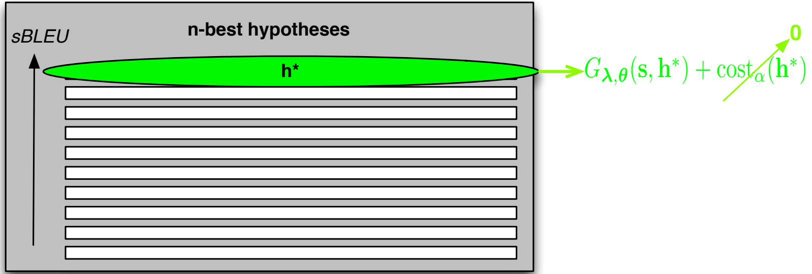

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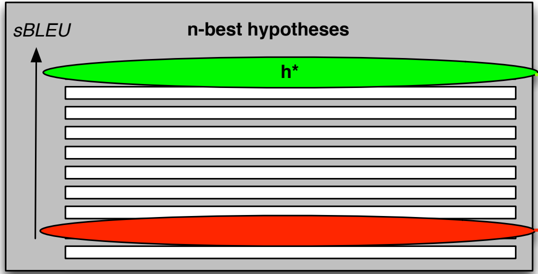

$G_{\boldsymbol{\lambda},\boldsymbol{\theta}}(\text{s}, \text{h}^*) + \text{cost}_\alpha(\text{h}^*)$ → 0

$\text{argmax}_{\mathbf{h}} \left[G_{\boldsymbol{\lambda},\boldsymbol{\theta}}(\mathbf{s}, \mathbf{h}) + \text{cost}_\alpha(\mathbf{h})\right]$

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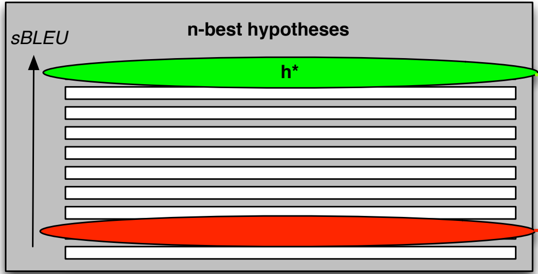

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A Max-margin objective

In practice, minimize:

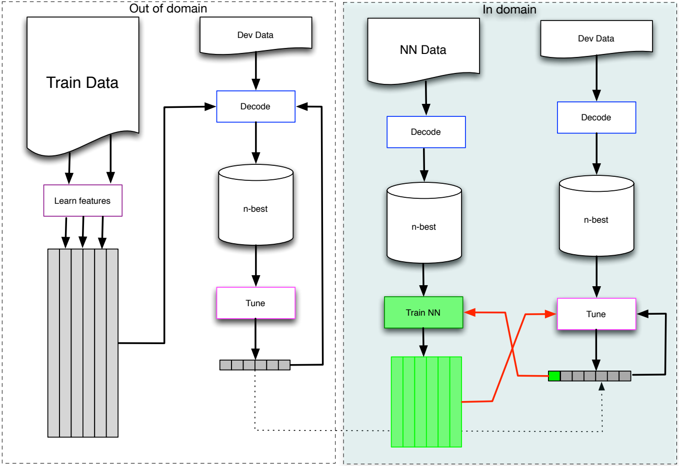
$$\ell(\theta) = \sum_{(i,k)} G_{\lambda,\theta}(\mathbf{f}, \mathbf{h}_k) + \mathrm{cost}_\alpha(\mathbf{h}_k) - G_{\lambda,\theta}(\mathbf{f}, \mathbf{h}_i) - \mathrm{cost}_\alpha(\mathbf{h}_i)$$

where $(\mathbf{h}_i, \mathbf{h}_k)$ are pairs of $(good, bad)$ hypotheses (wrt. sBLEU)

Training discriminative NN: the global view

Still uses two steps decoding

1. generate k-best list with the baseline system for all the training and dev data
2. jointly train re-ranker and NN



Training algorithm

A rather abstract representation

Init. $\boldsymbol{\lambda}$ and $\boldsymbol{\theta}$
for N Iterations **do**
  for M NN-train batches **do**
    Compute sub-gradient of $\ell(\boldsymbol{\theta})$ for each sentence $\mathbf{f}$ in batch
    update $\boldsymbol{\theta}$ $\triangleright$ $\boldsymbol{\lambda}$ fixed
  end for
  update $\boldsymbol{\lambda}$ on dev. set (MERT, MIRA) $\triangleright$ $\boldsymbol{\theta}$ fixed
end for

Some experimental results

NCE vs. CLL

Data and Condition:

- Out-of-domain: WMT en-fr system
- In-domain: TED Talks

Full details in EMNLP paper [Do et al., 2015]

Some experimental results

NCE vs. CLL

	dev	**test**
Baseline	$33,9$	$27,6$
Continuous space models training		
+ SOUL/CLL	$35,1$ ($+1,2$)	$28,9$ ($+1,3$)
+ NCE	$35,0$ ($+1,1$)	$28,8$ ($+1,2$)

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Some experimental results

NCE vs. CLL

	dev	**test**
Baseline	$33,9$	$27,6$
NNs in reranking		
+ NCE	$35,0$	$28,8$
Discriminative training		
+ DT	$35,3$ $(+1,4)$	$29,0$ $(+1,4)$
+ Init. NCE + DT	**35,4** $(+1,5)$	**29,7** $(+2,1)$

comparable results when initializing with SOUL

Full details in EMNLP paper [Do et al., 2015]

Outline

Motivations and inspirations

Motivations

- n-gram models $P(\tilde{\mathbf{f}}, \mathbf{e})$ - Yet $\mathbf{f}$ is known in advance !
  ☞ learn $P(\mathbf{e}|\tilde{\mathbf{f}})$ instead (cf. previous part)
- n-gram models are trained generatively
  ☞ learn TM towards good translations
- n-gram models are "surfacist"
  ☞ integrate reach linguistic features
  cf. factored models in LM and TMs
- Get rid of log-linear combination, tuning, etc.

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From n-gram to CRF-based TMs

Implementation

Training

1. identify tuples
2. synchronize bitext
   asymmetric, target oriented
3. train LM
4. train reordering rules

Steps 1 and 2 are performed simultaneously

Decoding

1. generate source reorderings $L(\mathbf{f})$
2. solve:

$$\mathbf{e}^* = \operatorname*{argmax}_{\tilde{\mathbf{f}} \in L(\mathbf{f})} P_{\boldsymbol{\theta}}(\tilde{\mathbf{f}}, \mathbf{e})$$

or use the standard log-linear model

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and that is all there is !

The CRF Translation Model

Basic formulation: known tuple alignment (inc. segmentation and reordering)

$$P_{\boldsymbol{\theta}}(\mathbf{e}, \mathbf{a} | \tilde{\mathbf{f}}) = \frac{\exp\left(\boldsymbol{\theta}^{\top} \Phi(\mathbf{e}, \mathbf{a}, \tilde{\mathbf{f}})\right)}{\sum_{\mathbf{e}', \mathbf{a}'} \exp\left(\boldsymbol{\theta}^{\top} \Phi(\mathbf{e}', \mathbf{a}', \tilde{\mathbf{f}})\right)}$$

$$\text{with } \Phi(\mathbf{e}, \mathbf{a}, \tilde{\mathbf{f}})) = \sum_i \Phi(\bar{t}_i, \bar{t}_{i-1}, \tilde{\mathbf{f}}, i)$$

With marginalization (reorderings and segmentations unobserved)

$$P_{\theta}(\mathbf{e}|\mathbf{f}) = \sum_{\tilde{\mathbf{f}} \in L(\mathbf{f})} \sum_{\mathbf{a} \in S(\tilde{\mathbf{f}})} P(\mathbf{e}, \mathbf{a} | \tilde{\mathbf{f}})$$

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Training and Inference

Training: optimize CLL

$$\boldsymbol{\theta}^* = \operatorname*{argmax}_{\boldsymbol{\theta}} \sum_i \log P_{\boldsymbol{\theta}}(\mathbf{e}_i | \mathbf{f}_i)$$

Caveat: objective no longer convex - still doable with gradient based techniques

Approximate inference: find optimal derivation

$$\mathbf{e}^* = \operatorname*{argmax}_{\mathbf{e}} P_{\theta}(\mathbf{e}|\mathbf{f})$$ NP hard

$$\mathbf{e}^* = \operatorname*{argmax}_{\mathbf{e},\mathbf{a},\tilde{\mathbf{f}}} P_{\theta}(\mathbf{e}, \mathbf{a}|\tilde{\mathbf{f}})$$ "Viterbi" decoding

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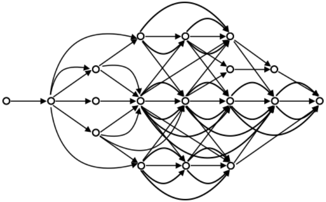
Training: the true story

Training: optimize CLL

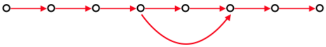
$$\boldsymbol{\theta}^* = \operatorname*{argmax}_{\boldsymbol{\theta}} \ell(\boldsymbol{\theta}) = \sum_i \log P_{\boldsymbol{\theta}}(\mathbf{e}_i|\mathbf{f}_i) + \alpha||\boldsymbol{\theta}||^2$$

- gradients computed as differences of expectations

$$\frac{\nabla \ell}{\theta_k} = \sum_i \mathbb{E}_{P_{\boldsymbol{\theta}}}(\Phi_k(\mathbf{e}, \mathbf{a}, \mathbf{f}_i)) - \mathbb{E}_{\tilde{P}}(\Phi_k(\mathbf{e}, \mathbf{a}, \mathbf{f}_i))$$



“Possibility” lattice



“Reference” lattice

- reference reachability: reference $\mathbf{e}_i$ not in model

Training: the true story

Training: optimize CLL

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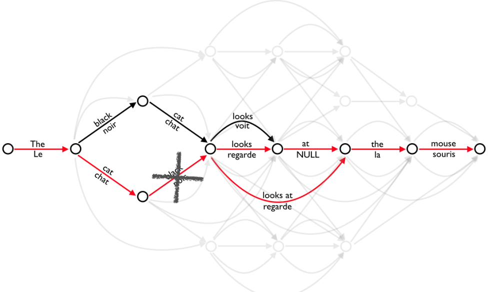

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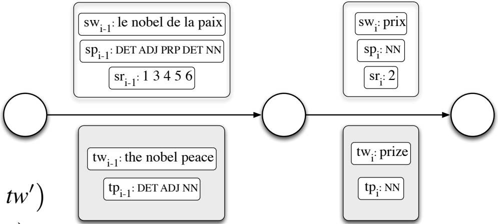
- reference reachability: reference $\mathbf{e}_i$ not in model
  ☞ use "oracle" derivations instead

caveat: oracles need a goodness measure eg. sBLEU

Feature engineering

Includes LM, TM, RM, and more



1. **LM:uni-tphr**: $\mathbb{I}\left(tw_i = tw\right)$
2. **LM:uni-tpos** : $\mathbb{I}\left(tp_i = tp\right)$
3. **LM:big-tphr** : $\mathbb{I}\left(tw_i = tw \wedge tw_{i-1} = tw'\right)$
4. **LM:big-tpos** : $\mathbb{I}\left(tp_i = tp \wedge tp_{i-1} = tp'\right)$
5. **TM:ci-phrp** : $\mathbb{I}\left(tw_i = tw \wedge sw_i = sw\right)$
6. **TM:ci-posp** : $\mathbb{I}\left(tp_i = tp \wedge sp_i = sp\right)$
7. **TM:ci-mixp** : $\mathbb{I}\left(tw_i = tw \wedge sp_i = sp\right)$
8. **TM:cd-phrs** : $\mathbb{I}\left(tw_i = tw \wedge sw_i = sw \wedge sw_{i-1} = sw'\right)$
9. **TM:cd-poss** : $\mathbb{I}\left(tp_i = tp \wedge sp_i = sp \wedge sp_{i-1} = sp'\right)$
10. **TM:cd-phrt** : $\mathbb{I}\left(tw_i = tw \wedge tw_{i-1} = tw' \wedge sw_i = sw\right)$
11. **TM:cd-post** : $\mathbb{I}\left(tp_i = tp \wedge tp_{i-1} = tp' \wedge sp_i = sp\right)$

CRF-based ngrams: successes and failures

A success story: translating BTEC into French Lavergne et al. [2013]

Configuration	*devel03*	*test09*	*test10*
n-gram-based			
n-gram TM $n = 2$	68.7	61.1	–
n-gram TM $n = 3$	68.0	61.6	53.4
CRF-based			
Viterbi-decoding	64.0	58.8	51.5
+ marginalisation	64.7	59.3	52.0
+ target LM	67.7	**61.7**	**53.9**

Remember: no dense features, no MERT, just plain CRF training on parallel data

A more bumpy road: train on Newsco, translate NewsTest

- Basic config. hardly tractable: > 50B "basic (lexical) features
- "Debug" config: Ncode lattices as proxy search space

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	En→Fr		Fr→En	
	BLEU	BP	*BLEU*	BP
n-gram TM $n = 2$	22.05	0.990	21.99	1.000
CRF (basic)	15.31	0.969	13.96	0.884
CRF (+LM, +p)	16.65	0.970	14.80	0.857
CRF (+dense)	17.52	0.963	16.73	0.881

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- oracles (pseudo-refs) a problem $\Rightarrow$ length issues (?)
- overtraining a problem
- log-loss a poor objective
- next steps: fix length issue, fix regularization issues, add more features, try alternative losses (eg. soft-max margin)

Discriminative TMs: what we know, what we dont

Confirmation of many studies

1. marginalize nuisance variables if you can
   already well documented
2. the pay-offs of discriminative training
   use translation metrics / cost (eg. *BLEU* in your objective)
3. beware of "dangerous" references
   use hope derivations instead [Chiang, 2012]
4. avoid oracle / pseudo-references if you can
   use ranking [Flanigan et al., 2013] or Expected-*BLEU* [He and Deng, 2012, Gao and He, 2013] etc.
5. sparse or sparse+dense features ?
   Probably an ill-posed alternative, but can we do better ?
6. still the right way to go ?
   time will tell

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Outline

n-gram based TMs: a simple and effective implementation of PBMT

What we have

1. open full pipeline for *n*-gram-based MT
2. effective implementation for large-scale NNLMs
3. generic implementation for “generalized” CRFs
   (with latent variable and arbitrary costs) - coming soon

Where we look

1. fix CRF-based model
2. include morpheme-based LMs
3. develop formal characterisation of gappy derivations
4. tick more boxes on slide 17

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Roadmap

- Improved learning and decoding
  - faster NN training and adaptation with task-related objectives
  - large-scale discriminative learning with sparse features
  - learning to translate with RL / ILR (and very long histories)
- More realistic models
  - more syntax in reordering
  - morphologically aware units for translation
  - optimizing speech segmentation / recognition for MT
  - contextual / discourse level features in MT
- Do more with less resources
  - cross-lingual transfert (in MT and elsewhere)
  - learn tuples from comparable corpora (caveat: require sparse features)
- Better translation environnements
  - improved UIs for the translator workbench
  - seamless online learning, with pre- and post-edition

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