Efficient Handling of n-gram Language Models for Statistical Machine Translation

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Summary

- Motivations
- Role of language model in SMT
- Introduction to n-gram LMs
  - Smoothing methods
  - LM representation/computation
- IRST LM Toolkit for Moses
  - Distributed estimation
  - Efficient data structures
  - Memory management
- Experiments
- Conclusions

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Motivation

N-gram LMs are major components of NLP systems, e.g. ASR and MT:

- Availability of large scale corpora has pushed research toward using huge LMs
- At 2006 NIST WS best systems used LMs trained on at least 1.6G words
- Google presented results using a 5-gram LM trained on 1.3T words
- Handling of such huge LMs with available tools (e.g. SRILM) is prohibitive if you use standard computer equipment (4 to to 8Gb of RAM)
- Trend of technology so far rewards distributing work on more PCs

We developed an alternative LM library addressing these needs

- IRSTLM is open-source Lesser GPL
- available and integrated into the Moses SMT Toolkit

Classical SMT Formulation

Let $\mathbf{f}$ be any text in the source language (French). The most probable translation is searched among texts $\mathbf{e}$ in the target language (English).

SMT used the following criterion:

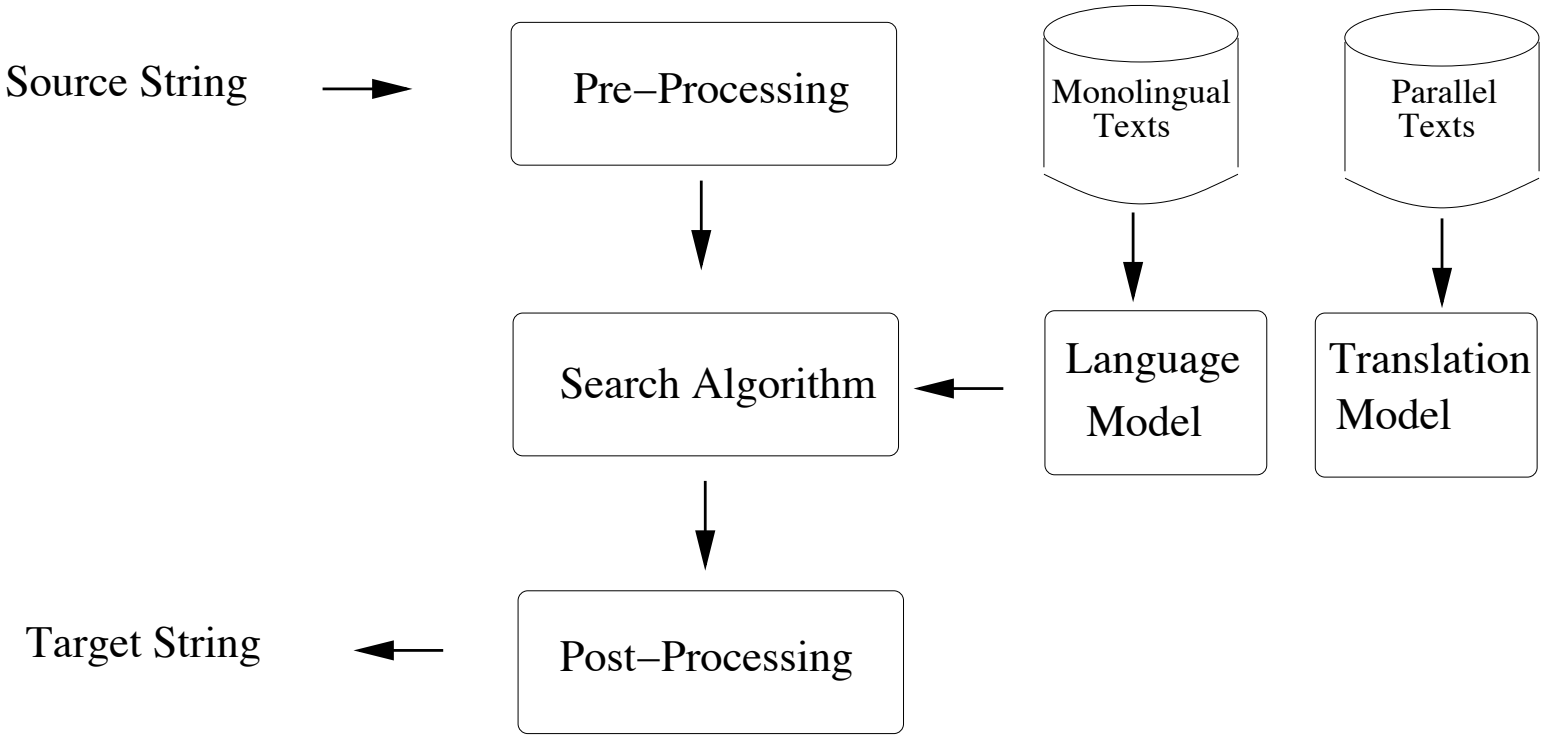
$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \Pr(\mathbf{f} \mid \mathbf{e}) \Pr(\mathbf{e}) \qquad (1)$$

The **computational problems of SMT**:

- *language modeling*: estimating the *language model probability* $\Pr(\mathbf{e})$
- *translation modeling*: estimating the *translation model probability* $\Pr(\mathbf{f} \mid \mathbf{e})$
- *search* problem: carrying out the optimization criterion (1)

Remark: in statistical MT all translation pairs are plausible, in principle.

Classical SMT Architecture



Log-linear phrase-based SMT

- Translation hypotheses are ranked by a **log-linear combination of statistics**:

$$rank_{\mathbf{e}} \max_{\mathbf{a}} \sum_i \lambda_i h_i(\mathbf{e}, \mathbf{f}, \mathbf{a})$$

  $\mathbf{f}$ =*source*, $\mathbf{e}$ =*target*, $\mathbf{a}$ =*alignment*, and $h_i(\mathbf{e}, \mathbf{f}, \mathbf{a})$ =*feature functions*.

- Feature functions: **Language Model**, **Lexicon Model**, **Distortion Model**
- LM and TM consist of a huge number of *observations-value* pairs
- Example: *5-gram LM* – $h_i(\mathbf{e}, \mathbf{f}, \mathbf{a}) = \log \Pr(\mathbf{e})$
  – observations: 1-grams, 2-grams, 3-grams, 4-grams, 5-grams
  – values: log of cond. word probabilities, log of back-off weights
- Example: *Moses lexicon model*
  – observations: aligned phrase-pairs of length 1 to 8 words
  – values: log of dir/inv relative freq, dir/inv compositional logprobs

N-gram LM

The purpose of LMs is to compute the probability $\Pr(w_1^T)$ of any sequence of words $w_1^T = w_1 \ldots, w_t, \ldots, w_T$. The probability $\Pr(w_1^T)$ can be expressed as:

$$\Pr(w_1^T) = P(w_1) \prod_{t=2}^{T} \Pr(w_t \mid h_t) \tag{2}$$

where $h_t = w_1, \ldots, w_{t-1}$ indicates the *history of word* w_t.

- $\Pr(w_t \mid h_t)$ become difficult to estimate as the sequence of words h_t grows.
- We approximate by defining *equivalence classes* on histories h_t.
- *n-gram approximation* let each word depend on the most recent $n-1$ words:

$$h_t \approx w_{t-n+1} \ldots w_{t-1}. \tag{3}$$

Normalization Requirement

$$\sum_{T=1}^{\infty} \Pr(T) \sum_{w_1 \ldots w_T} \Pr(w_1, \ldots, w_T \mid T) = 1$$

N-gram LMs guarantee that probabilities sum up over one, for a given length T:

$$\begin{aligned}
\sum_{w_1 \ldots w_T} \prod_{t=1}^{T} \Pr(w_t \mid h_t) &= \sum_{w_1} \Pr(w_1) \sum_{w_2} \Pr(w_2 \mid h_1) \ldots \sum_{w_{T-1}} \Pr(w_{T-1} \mid h_{T-1}) \underbrace{\sum_{w_T} \Pr(w_T \mid h_T)}_{=1} \\
&= \sum_{w_1} \Pr(w_1) \sum_{w_2} \Pr(w_2 \mid h_1) \ldots \underbrace{\sum_{w_{T-1}} \Pr(w_{T-1} \mid h_{T-1})}_{=1} \cdot 1 \\
&= \ldots \\
&= \underbrace{\sum_{w_1} \Pr(w_1)}_{=1} \cdot 1 \ldots \cdot 1 \cdot 1 = 1
\end{aligned} \tag{4}$$

String Length Model

Hence we just need a length model $P(T)$

- **Exponential model** $p(T) = (a-1)a^{-T}$ with any $a > 1$, in fact:

$$\sum_{T=1}^{\infty} p(T) = (a-1)\sum_{T=1}^{\infty} a^{-T} = \frac{a-1}{a}\sum_{T=0}^{\infty}\left(\frac{1}{a}\right)^{T} = \frac{a-1}{a}\frac{1}{\left(1-\frac{1}{a}\right)} = \frac{a-1}{a-1} = 1 \tag{5}$$

  – Implemented in SMT by the *word penalty model*

- **Uniform model** over a range "of interest":

$$p(T) = \begin{cases} \frac{1}{T_{max}} & \text{if } 1 \leq T \leq T_{max} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

  – Used in SMT when no word penalty model is considered

N-gram LM and data sparseness

Even estimating n-gram probabilities may be not a trivial task:

- **high number of parameters**: e.g. a 3-gram LM with a vocabulary of 1,000 words requires, in principle, to estimate 10^9 probabilities!
- **data sparseness** of real texts: i.e. most of correct n-grams are *rare events*

Experimentally, in the 1.2Mw (million word) Lancaster-Oslo-Bergen corpus:

- more than 20% of bigrams and 60% of trigrams occur only once
- 85% of trigrams occur less than five times.
- expected chances of finding new 2-grams is 22%
- expected change of finding new 3-grams is 65%

We need frequency smoothing or discounting!

Frequency Discounting

Discount relative frequency to assign some positive prob to every possible n-gram

$$0 \leq f^*(w \mid h) \leq f(w \mid h) \qquad \forall hw \in V^n$$

The *zero-frequency probability* $\lambda(h)$, defined by:

$$\lambda(h) = 1.0 \; - \; \sum_{w \in V} f^*(w \mid h),$$

is *redistributed* over the set of words never observed after history h.

Redistribution is proportional to the less specific $n-1$-gram model $p(w \mid \bar{h})$.[1]

[1] Notice: $c(h) = 0$ implies that $\lambda(h) = 1$.

Smoothing Schemes

Discounting of $f(w \mid h)$ and redistribution of $\lambda(h)$ can be combined by:

- **Back-off**, i.e. select the most significant approximation available:

$$p(w \mid h) = \begin{cases} f^*(w \mid h) & \text{if } f^*(w \mid h) > 0 \\ \alpha_h \lambda(h) p(w \mid \bar{h}) & \text{otherwise} \end{cases} \tag{7}$$

  where α_h is an appropriate *normalization term*[2]

- **Interpolation**, i.e. sum up the two approximations:

$$p(w \mid h) = f^*(w \mid h) + \lambda(h) p(w \mid \bar{h}). \tag{8}$$

[2]

$$\alpha_h = \left(\sum_{w: f^*(w|h)=0} p(w \mid \bar{h}) \right)^{-1} = \left(1 - \sum_{w: f^*(w|h)>0} p(w \mid \bar{h}) \right)^{-1}$$

Smoothing Methods

- **Witten-Bell estimate** [Witten & Bell, 1991]
  $\lambda(h) \propto n(h)$ i.e. # different words observed after h in the training data:

$$\lambda(h) =_{def} \frac{n(h)}{c(h) + n(h)} \quad \text{which gives:} \quad f^*(w \mid h) = \frac{c(hw)}{c(h) + n(h)}$$

- **Absolute discounting** [Ney & Essen, 1991]
  subtract constant β $(0 < \beta \leq 1)$ from all observed n-gram counts[3]

$$f^*(w \mid h) = \max\left\{\frac{c(hw) - \beta}{c(h)}, 0\right\} \quad \text{which gives} \quad \lambda(h) = \beta\frac{\sum_{w:c(h,w)>1} 1}{c(h)}$$

[3] $\beta \approx \frac{n_1}{n_1+2n_2} < 1$ where n_c is # of different n-grams which occurr c times in the training data.

Improved Absolute Discounting

- **Kneser-Ney smoothing** [Kneser & Ney, 1995]
  Absolute discounting with *corrected counts for lower order n-grams*. Rationale: the lower order frequency $f(\bar{h}, w)$ is made proportional to the number of different words that $(\bar{h}, w)$ follows.

  Example: let $c(\texttt{los}, \texttt{angeles}) = 1000$ and $c(\texttt{angeles}) = 1000 \longrightarrow$ corrected count is $c'(\texttt{angeles}) = 1$, i.e. unigram prob $p(\texttt{angeles})$ will be small.

- **Improved Kneser-Ney** [Chen & Goodman, 1998]
  In addition use *specific discounting coefficients* for rare n-grams:

$$f^*(w \mid h) = \frac{c(hw) - \beta(c(h, w))}{c(h)}$$

  where $\beta(0) = 0$, $\beta(1) = D_1$, $\beta(2) = D_2$, $\beta(c) = D_{3+}$ if $c \geq 3$.

LM representation: ARPA File Format

Contains all the ingredients needed to compute LM probabilities:

```
\data\
ngram 1= 86700
ngram 2= 1948935
ngram 3= 2070512
\1-grams:
-2.88382        !       -2.38764
-2.94351        world       -0.514311
-6.09691        edinburgh       -0.15553
...
\2-grams:
-3.91009     world !     -0.351469
-3.91257     hello world  -0.24
-3.87582     hello edinburgh    -0.0312
..
\3-grams:
-0.00108858     hello world  !
-0.000271867    , hi hello  !
...
\end\
```

$$\log Pr(! \mid \text{hello edinburgh}) = -0.0312 + \log Pr(! \mid \text{edinburgh})$$

$$\log Pr(\log Pr(! \mid \text{edinburgh}) = -0.15553 - 2.88382$$

Moses Toolkit for Statistical MT

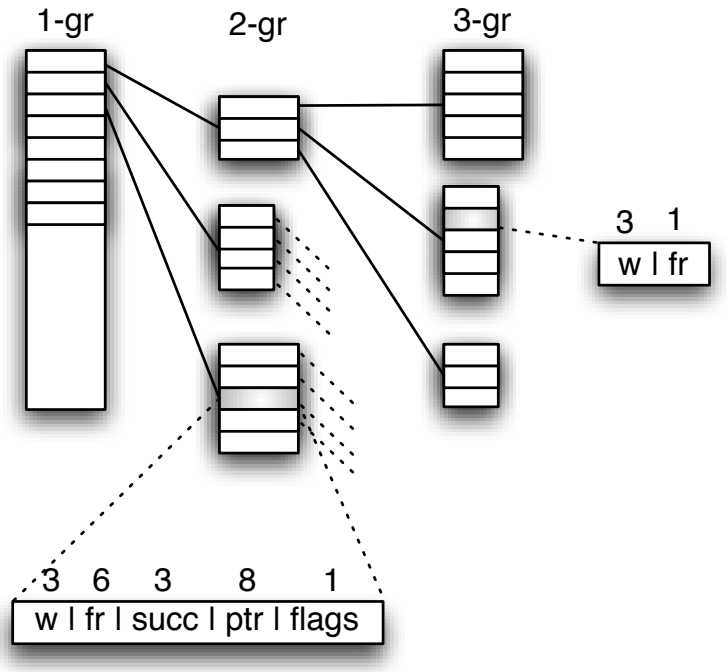
- Developed during **JHU Summer Workshop 2006**
  - U. Edinburgh, ITC-irst Trento, RWTH Aachen, U. Maryland, MIT, Charles University Prague
  - open source under Lesser GPL
  - available for Linux, Windows and Mac OS
  - www.statmt.org/moses
- **Main features**:
  - *translation of both text and CN inputs*
  - exploitation of more Language Models
  - lexicalized distortion model (only for text input, optional)
  - incremental pre-fetching of translation options from disk
  - *handling of huge LMs* (up to Giga words)
  - *on-demand and on-disk access to LMs* and LexMs
  - factored translation model (surface forms, lemma, POS, word classes, ...)

IRSTLM library (open source)

Important Features

- *Distributed training*
  - split dictionary into balanced n-gram prefix lists
  - collect n-grams for each prefix lists
  - estimate single LMs for each prefix list (approximation)
  - quickly merge single LMs into one ARPA file
- *Space optimization*
  - n-gram collection uses dynamic storage to encode counters
  - LM estimation just requires reading disk files
  - probs and back-off weights are quantized
  - LM data structure is loaded on demand
- *LM caching*
  - computations of probs, access to internal lists, LM states, ...

Data Structure to Collect N-grams



- Dynamic prefix-tree data structure
- Successor lists are allocated on demand through memory pools
- Storage of counts from 1 to 6 bytes, according to max value
- Permits to manage few huge counts, such as in the google n-grams

LM Estimation with Prefix Lists

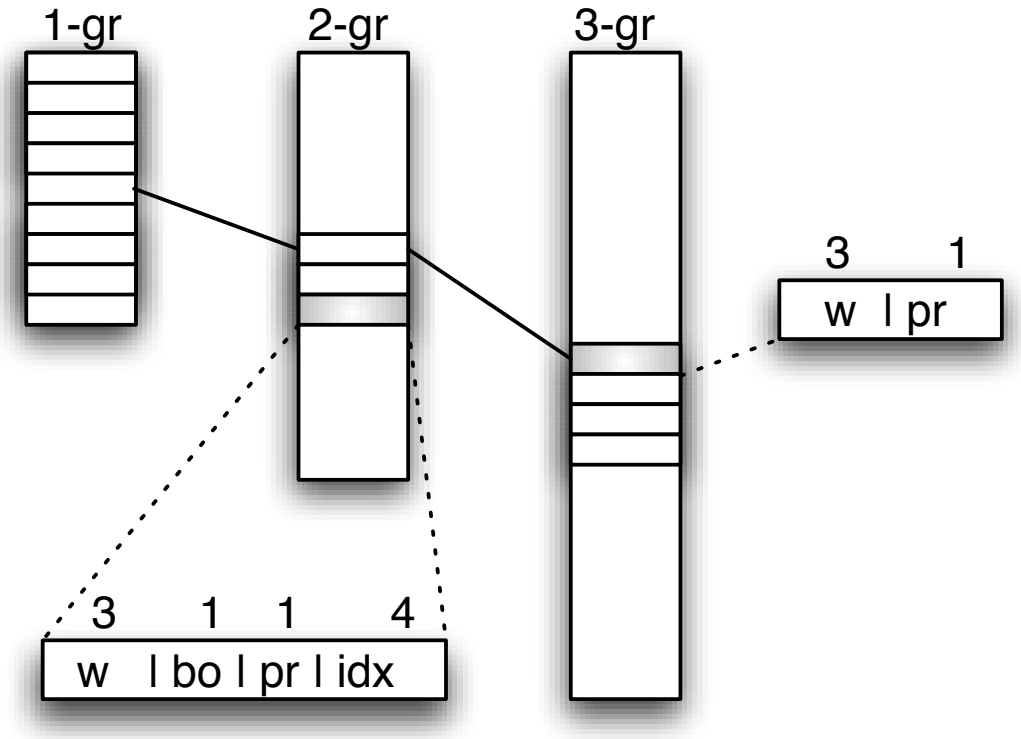
Smoothing of probs up from 2-grams is done separately on each subset of n-grams. Let (v, w, x, y, z) be a 5-gram :

- **Witten-Bell smoothing** (equivalent to original)
  Statistics are computed on n-grams starting with v.
- **Absolute discounting** (different from original)
  The value β_v to be subtracted from all counts $N(v, w, x, y, z)$ is:

$$\beta_v = \frac{N_1(v)}{N_1(v) + 2 * N_2(v)}$$

  $N_r(v)$ is # of different 5-grams starting with v and occurring exactly r times.
  Notice: if for some v the above formula is zero or undefined, we resorts to Witten-Bell method.

Data Structure to Compute LM Probs



- First used in *CMU-Cambridge LM Toolkit* (Clarkson and Rosenfeld, 1997]
- Slower access but less memory than structure used by *SRILM Toolkit*
- *IRSTLM* in addition compresses probabilities and back-off weights into 1 byte!

Compression Through Quantization

How does quantization work?

1. Partition observed probabilities into regions (*clusters*)
2. Assign a code and probability value to each region (*codebook*)
3. Encode the probabilities of all observations (*quantization*)

We investigate two quantization methods:

- *Lloyd's K-Means Algorithm*
  - first applied to LM for ASR by [Whittaker & Raj, 2000]
  - computes clusters minimizing average distance between data and centroids
- *Binning Algorithm*
  - first applied to term-frequencies for IR by [Franz & McCarley, 2002]
  - computes clusters that partition data into uniformly populated intervals

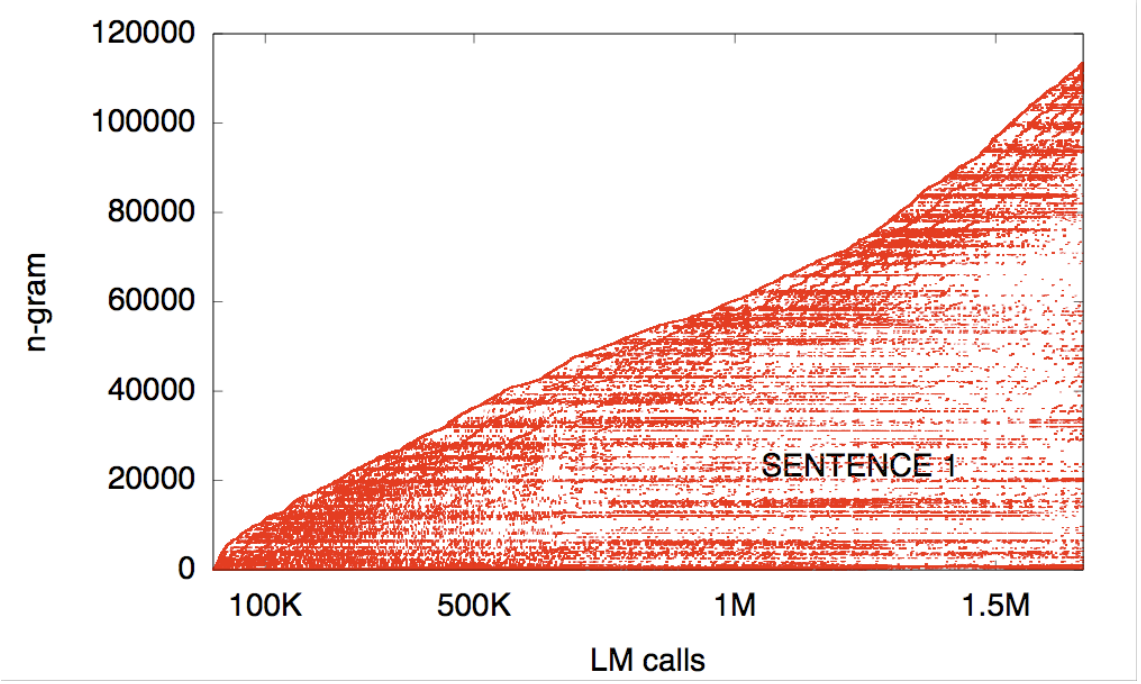
Notice: a codebook of n centers means a *quantization level* of $\log_2 n$ bits.

LM Quantization

- **Codebooks**
  - One codebook for each word and back-off probability level
  - For instance, a 5-gram LM needs in total 9 codebooks.
  - Use codebook of at least 256 entries for 1-gram distributions.
- **Motivation**
  - Distributions of these probabilities can be quite different.
  - 1-gram distributions contain relatively few probabilities
  - Memory cost of a few codebooks is irrelevant.
- **Composition of codebooks**
  - LM probs are computed by multiplying entries of different codebooks
  - actual resolution of lower order n-grams is higher than that of its codebook!

Practically no performance loss with 8 bit quantization[Federico & Bertoldi '06]

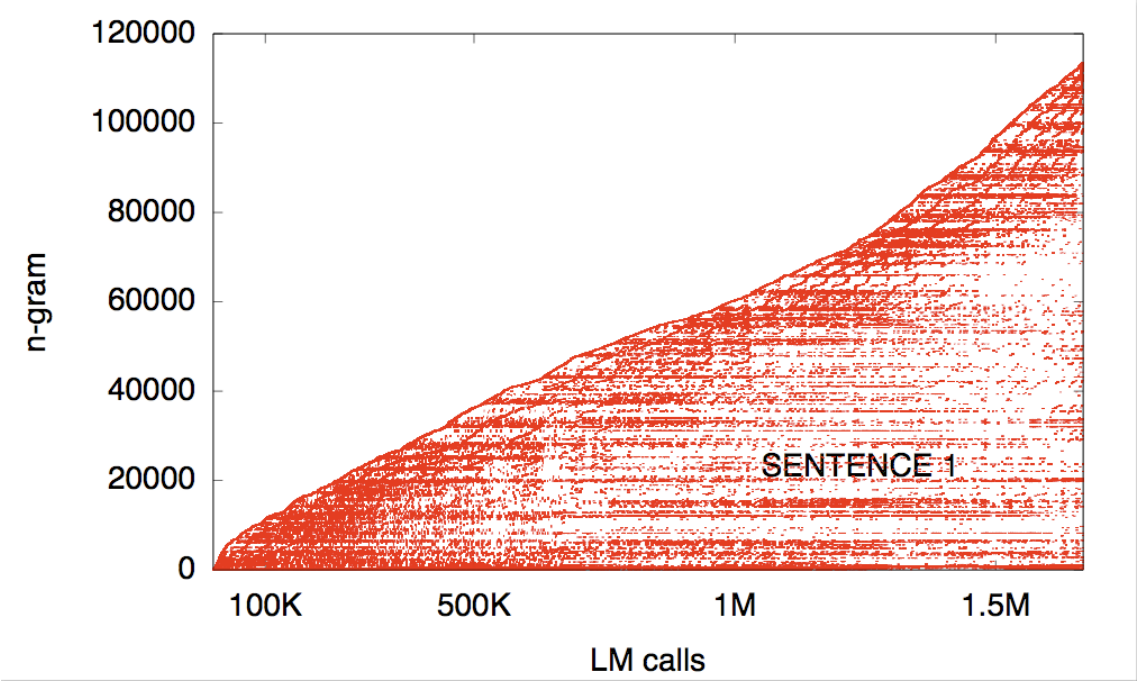
LM Accesses by SMT Search Algorithm



Moses's calls to a 3-gram LM while decoding into English the Europarl text:

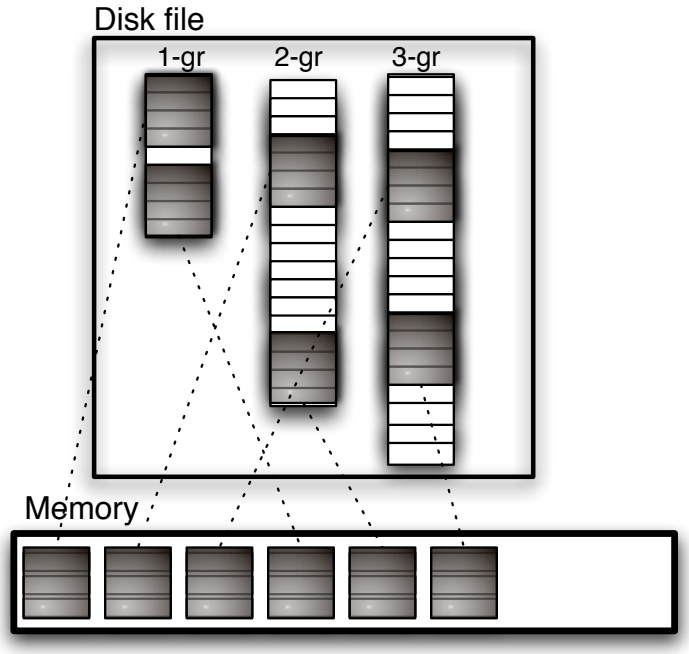
```
ich bin kein christdemokrat und glaube daher nicht an wunder .  doch ich möchte
dem europäischen parlament , so wie es gegenwürtig beschaffen ist , für seinen
grossen beitrag zu diesen arbeiten danken.
```

LM Accesses by SMT Search Algorithm



- 1.7M calls only involving 120K different 3-grams
- Decoder tends to access LM n-grams in nonuniform, *highly localized patterns*
- First call of an n-gram is easily followed by other calls of the same n-gram.

Memory Mapping of LM on Disk



- Our LM structure permits to exploit so-called *memory mapped* file access.
- Memory mapping permits to include a file in the address space of a process, whose access is managed as virtual memory
- Only memory pages (grey blocks) that are accessed by decoding are loaded

Experiments

Baseline: Chinese-English NIST task

- *Target Language Models*
  - 3 LMs: target part of parallel data + GigaWord + DevSets
  - 2G running words (4.5M different words)
  - 300M 5-grams (singletons pruned for GigaWord)
- *Phrase Table*
  - 90M English running words
  - 38M phrase pairs of maximum length 7
- *Monotone search*
  - permits to run fast experiments
  - you see exactly memory needed by LM
  - with lexicalized LM: +1-1.5% Bleu, +2Gb RAM, x 2.0 run-time

Distributed Training on English Gigaword

list index	dictionary size	number of 5-grams: observed	distinct	non-singletons
0	4	217M	44.9M	16.2M
1	11	164M	65.4M	20.7M
2	8	208M	85.1M	27.0M
3	44	191M	83.0M	26.0M
4	64	143M	56.6M	17.8M
5	137	142M	62.3M	19.1M
6	190	142M	64.0M	19.5M
7	548	142M	66.0M	20.1M
8	783	142M	63.3M	19.2M
9	1.3K	141M	67.4M	20.2M
10	2.5K	141M	69.7M	20.5M
11	6.1K	141M	71.8M	20.8M
12	25.4K	141M	74.5M	20.9M
13	4.51M	141M	77.4M	20.6M
total	4.55M	2.2G	951M	289M

IRSTLM Library: Esperiments (NIST 2005)

LM	1gram	2gram	3gram	4gram	5gram
lrg	0.3	5.3	4.8	6.3	6.1
giga	4.5	64.4	127.5	228.8	288.6

LM	process size		caching	dec. speed	BLEU
	virtual	resident		(src w/s)	
lrg SRILM	1.2Gb	1.1Gb	-	13.33	27.32
lrg	619Mb	558Mb	n	6.80	27.35
			y	7.42	

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lrg SRILM	1.2Gb	1.1Gb	-	13.33	27.32
lrg	619Mb	558Mb	n	6.80	27.35
			y	7.42	
q-lrg	507Mb	445Mb	n	6.99	27.26
			y	7.52	
lrg+giga	9.9Gb	2.1Gb	n	3.52	29.15
			y	4.28	
q-lrg+q-giga	6.8Gb	2.1Gb	n	3.64	28.98
			y	4.35	

Conclusions

Efficient handling of large scale LMs for SMT:

- *Training is distributed* over many machines
  – *approximate smoothing* does not seem to hurt so far
- Run-time LM access through *compact data structure*
- While decoding one sentence *LM is loaded on-demand*
- Comparison with state-of-the-art SRILM toolkit:
  – w/o memory mapping: 60% less memory, 45% slower decoding
  – w memory mapping: *90% less memory*!
- MT system with 5-gram LM runs on 2Gb PC rather than on a 20Gb PC!

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Thank You!