IRSTLM Toolkit

Nicola Bertoldi
FBK-irst Trento, Italy

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Outline

- introduction to LM toolkit
- ARPA file format for LM representation
- IRSTLM library
- memory and time optimization
- distributed LM training

Credits:

- M. Cettolo and M. Federico (FBK-irst, Trento)
- IRSTLM developers and users

Language Model toolkit

A Language Model toolkit should provide functionalities for (at least):

- estimating n-gram probabilities from a text corpus
- computing probability of an n-gram
- computing perplexity of a test sample

- (several) different smoothing criteria
- pruning techniques
- adaptation methods

Most known LM toolkits are:

- CMU/Cambridge: mi.eng.cam.ac.uk/ prc14/toolkit.html
- SRILM: www.speech.sri.com/projects/srilm
- IRSTLM: hlt.fbk.eu/en/irstlm

ARPA File Format (srilm, irstlm)

Represents both interpolated and back-off n-gram LMs

- format: log(smoothed-prob) :: n-gram :: log(back-off weight)
- computation: look first for smoothed-prob, otherwise back-off

```
\data\
  ngram 1 =       86700
  ngram 2 =       1948935
  ngram 3 =       2070512

  1-grams:
  -2.88382        !               -2.38764
  -2.94351        world           -0.514311
  -6.09691        guys            -0.15553
  ...
  2-grams:
  -3.91009        world !         -0.351469
  -3.91257        hello world     -0.24
  -3.87582        hello guys      -0.0312
  ..
  3-grams:
  -0.00108858     hello world !
  -0.000271867    , hi hello !
  ...
\end\
```

Example 1:

$\log\Pr(!|\text{hello world}) = -0.00108858$

Example 2:

$\log\Pr(!|\text{hello guys}) = -0.0312 + \log\Pr(!|\text{guys})$

$\log\Pr(!|\text{guys}) = -0.15553 + \log\Pr(!)$

$\log\Pr(!) = -2.88382$

Large/Huge Scale Language Models

- 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 up to 8Gb of RAM, 1up to4 cores)
  $\sim$ 2G running words, $\sim$ 200M 5-grams, $\sim$ 9Gb RAM
- Trend of technology is towards:
  – distributed processing using PC farms
  – space and time optimization

IRSTLM addresses these needs, in a fully open source (Moses-like) framework

IRSTLM library

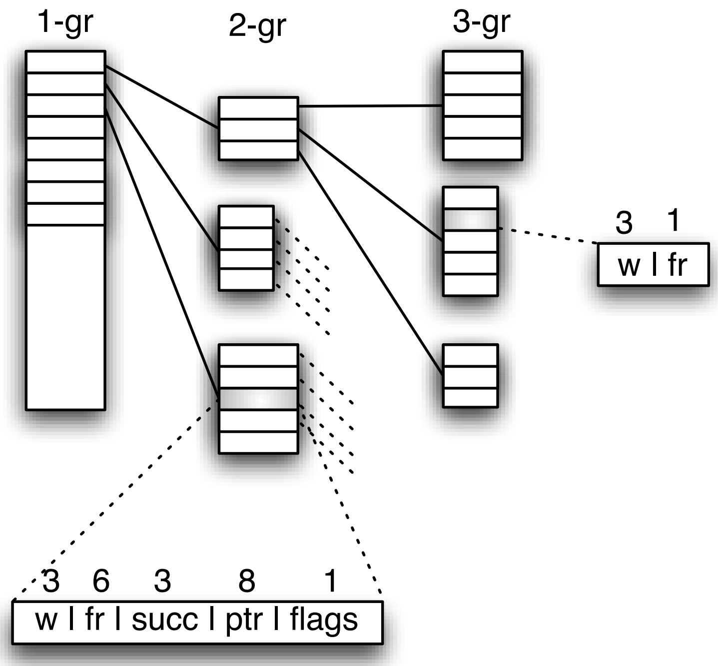
- open-source LGPL library (hlt.fbk.eu/en/irstlm)
- full integration into Moses SMT Toolkit and FBK speech decoder
- different smoothing criteria in an interpolation scheme: WB, AD, MKN
- singleton pruning, adaptation, and internal/external interpolation
- training of huge LMs
- support for chunk-based translation

- memory optimization
- speed optimization
- distributed training on single machine or SGE queue

Memory optimization

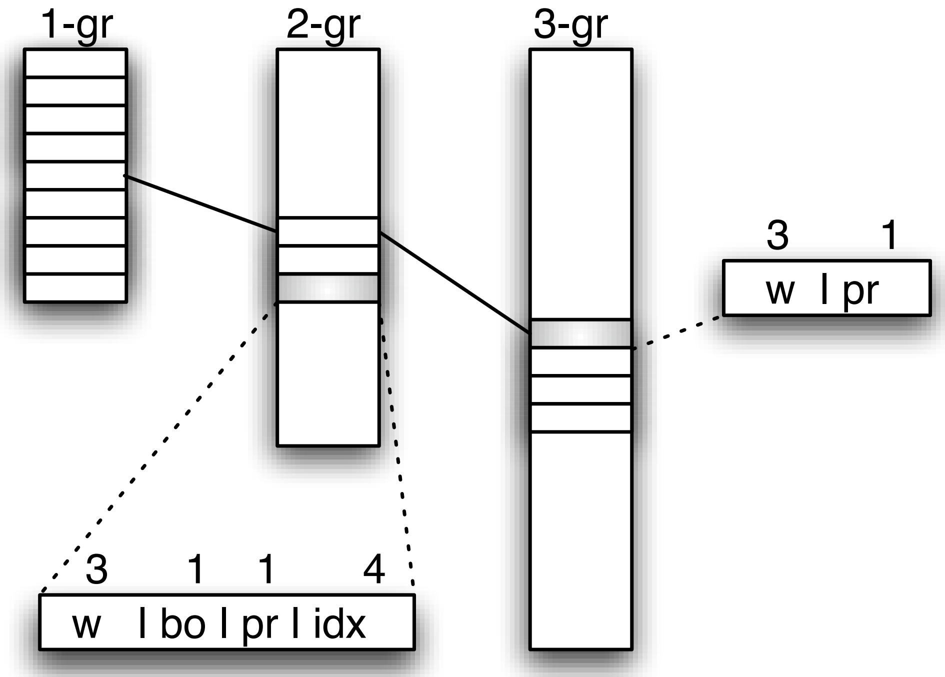
- dynamic storage to collect n-gram counts
- static storage to store n-gram probs
- quantization
- singleton pruning
- on-demand loading of LM

Data Structure to Collect N-grams



- Dynamic prefix-tree data structure
- Successor lists are allocated on demand through memory pools
  - specific successor lists for singletons
- 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

Data Structure to Store LM Probs



- Static data structure
- First used in CMU-Cambridge LM Toolkit (Clarkson and Rosenfeld, 1997]
- Slower access but less memory than structure used by SRILM Toolkit
- IRSTLM can compress probs and back-off weights into 1 byte (instead of 4)!

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.

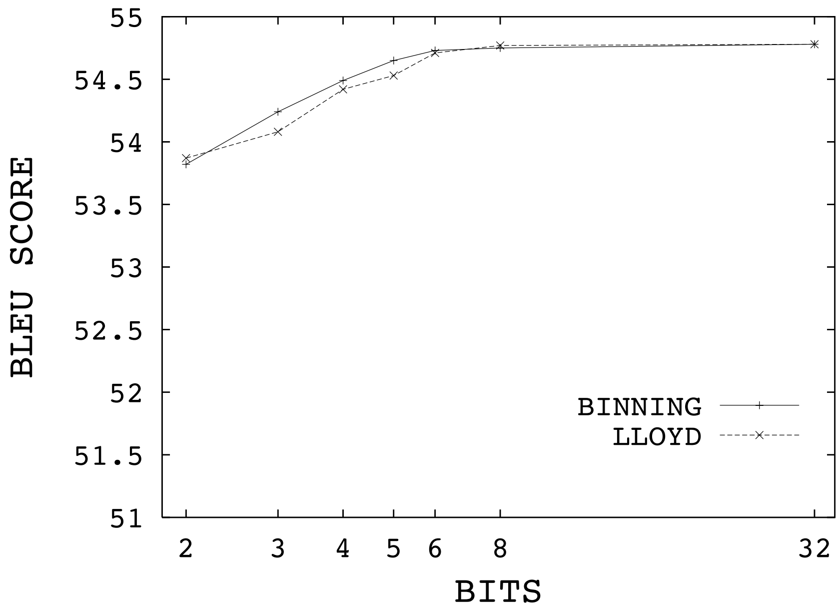
Quantization

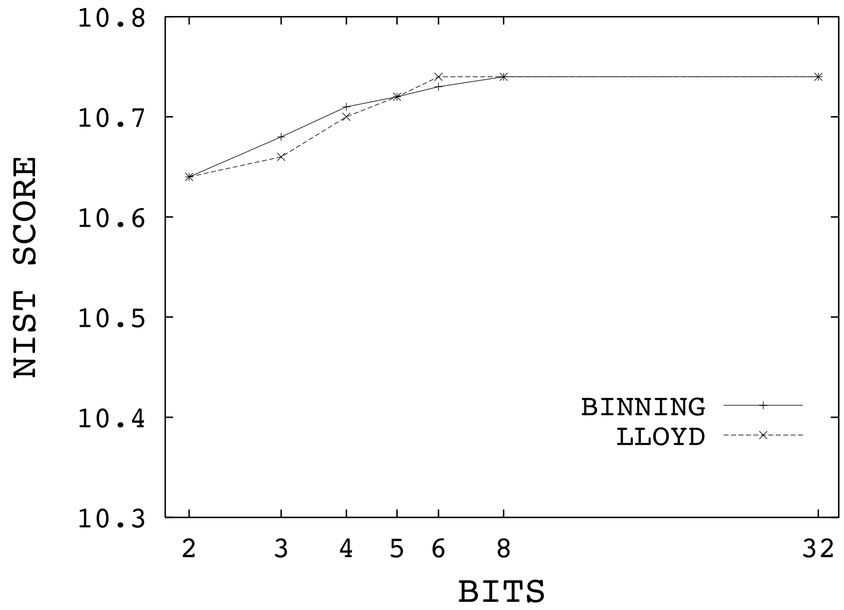
- Codebooks
  - One codebook for each word and back-off probability level
  - For instance, a 5-gram LM needs in total 9 codebooks
  - Use codebook of at least 256 entries for 1-gram distributions

- 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

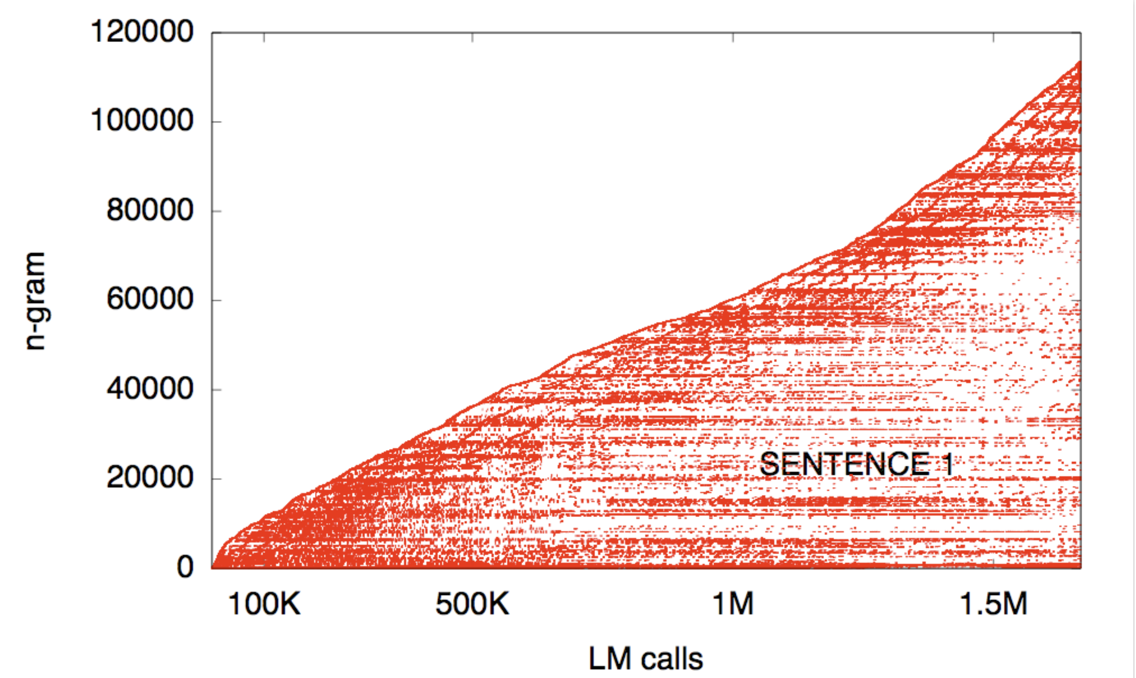
Quantization





- Spanish-English translation on EPPS
- Lloyd and binning algorithms perform similarly
- No loss in performance with 8 bit quantization

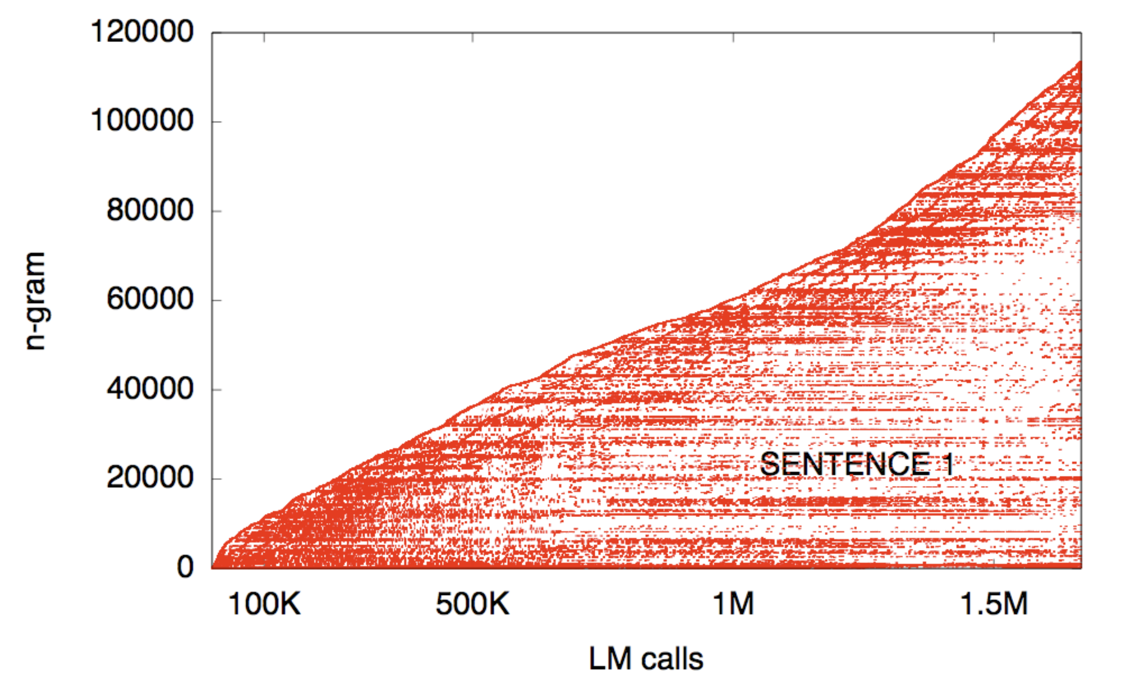
LM Accesses by SMT Search Algorithm



Moses calls to a 3-gram LM while decoding from German to English the text:

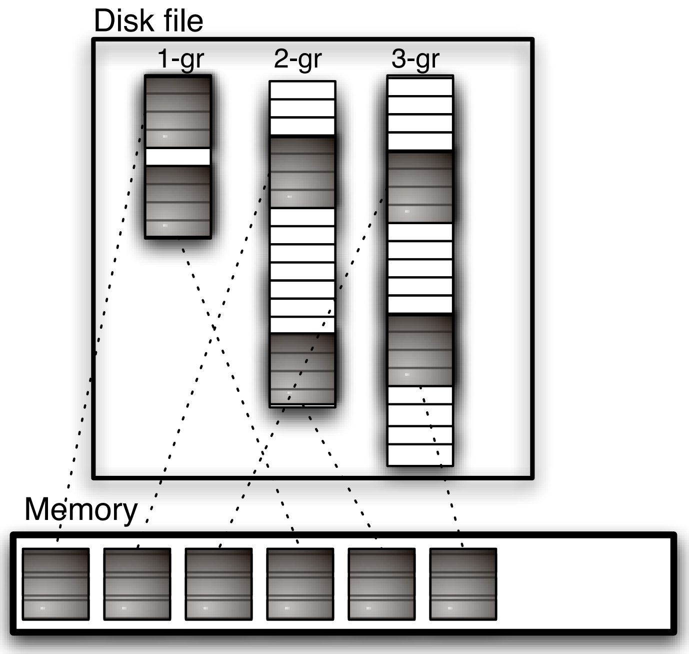
`ich bin kein christdemokrat und glaube daher nicht an wunder . doch ich möchte dem europäischen parlament , so wie es gegenwürtig beschaffen ist , für seinen grossen beitrag zu diesen arbeiten danken.`

LM Accesses by SMT Search Algorithm



- 1.7M calls only involving 120K different 3-grams
- Decoder tends to access LM n-grams in non-uniform, 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

Probability caching

- Insight:
  - during decoding, prob of the same n-gram is queried several time (14 on avg)
  - a LM call for an n-gram requires up to n accesses to the static data structure (in the worst case when no lower n-gram)

- Solution: caching
  - when an n-gram is queried for prob, check the cache before!
  - when not found, compute its probability and cache it (prob and state)

Performance

- Chinese-English task of NIST MT Evaluation Workshop 2006
- `large` parallel corpus (85 Mw), 6.1M 5-grams
- English `giga` monolingual corpus (1.8 Gw), 289M 5-grams
- Moses decoder

LM	format	quant	file size
lrg	textual	n	855Mb
		y	685Mb
	binary	n	296Mb
		y	178Mb

LM	format	quant	file size
giga	textual	n	28.0Gb
		y	21.0Gb
	binary	n	8.5Gb
		y	5.1Gb

- binarization: 65-75% reduction
- quantization: 20% reduction for textual, 40% for binary
- overall: -80%

Performance

LM	BLEU score			
	05	06 nw	06 ng	06 bn
lrg SRILM	27.3	29.4	23.7	27.2
lrg	27.3	29.1	23.6	27.1
q-lrg	27.3	29.0	23.2	27.0
lrg+giga	29.2	29.7	24.8	28.6
q-lrg+q-giga	29.0	29.8	24.8	28.2

LM	NIST score			
	05	06 nw	06 ng	06 bn
lrg SRILM	8.60	9.00	7.88	8.57
lrg	8.60	9.03	7.85	8.55
q-lrg	8.56	8.99	7.77	8.51
lrg+giga	8.84	8.92	7.92	8.70
q-lrg+q-giga	8.75	9.08	8.06	8.65

- SRILM and IRSTLM compares well (different prob to OOV words)
- quantization does not affect performance significantly
- use of `giga` increases performance significantly

Performance

LM	process size virtual	process size resident	caching	dec. speed (src w/s)
lrg SRILM	1.2Gb	1.1Gb	-	13.33
lrg	619Mb	558Mb	n	6.80
			y	7.42
q-lrg	507Mb	445Mb	n	6.99
			y	7.52
lrg+giga	9.9Gb	2.1Gb	n	3.52
			y	4.28
q-lrg+q-giga	6.8Gb	2.1Gb	n	3.64
			y	4.35

- IRSTLM requires less memory than SRILM (558Mb vs. 1.1Gb)
- IRSTLM is slower than SRILM (7.42 vs. 13.33)
- quantization slightly speeds up decoding
- caching speeds up decoding (8-9% on `lrg`, 20-21% on `lrg+giga`)

Distributed LM training

- goal: reduce time and fit n-gram statistics into memory

- idea: partition n-grams into k parts, train k LMs, recombine into one LM

- problem: probabilities of the n-gram xyw depends on xy (and yw)
  $p(w \mid x\ y) = f^*(w \mid x\ y) + \lambda(x\ y)p(w \mid y)$

- solution:
  - split n-grams into self-consistent subsets:
    containing all information needed to compute $f^*(w \mid x\ y)$ and $\lambda(x\ y)$
  - use an intermediate data structure to store all f^* and λ
  - compute probabilities on the fly, $(w \mid x\ y) = f^*(w \mid x\ y) + \lambda(x\ y)\ p(w \mid y)$
  - or transform into the standard ARPA format

- self-consistency depends on the smoothing method

Available smoothing for distributed LM training

- Witten Bell: each subset should contain all successors of an n-gram
  $f^*(w \mid xy) = \frac{c(xyw)}{c(xy)+n(xy)}$ and $\lambda(xy) = \frac{n(xy)}{c(xy)+n(xy)}$

- Absolute discounting: the same as Witten Bell
  $f^*(w \mid xy) = max\left\{\frac{c(xyw)-\beta}{c(xy)}, 0\right\}$ and $\lambda(xy) = \beta\frac{\sum_{w:c(xyw)>1} 1}{c(xy)}$

- Improved Kneser-Ney: possible (without corrected counts)
  $f^*(w \mid x\ y) = \frac{c(xyw)-\beta(c(xyw))}{c(xy)}$
  $\beta(0) = 0$, $\beta(1) = D_1$, $\beta(2) = D_2$, $\beta(c) = D_{3+}$

How to to distributed LM training: step 0

get a training corpus

TRAIN
this should also be there is looking further . this we shall be there is looking further . so we shall be there is looking further . this should also be there would be a little . this should also be there is looking further ahead . it should also be there is looking further . so we shall be there is looking further . this should also be there would be little . this we shall be there would be a little . this should also be there is going further . so we shall be there would be a little . this we shall be there is looking further ahead . so we shall be there is looking further ahead . this we shall be there would be little . this may be , there would be a little . this should also be there is to further . so we shall be there would be little . this we shall be there is going further . so we shall be there is going further . it should also be there would be a little .

How to to distributed LM training: step 1

extract the dictionary

TRAIN

```
this should also be there is looking further .
this we shall be there is looking further .
so we shall be there is looking further .
this should also be there would be a little .
this should also be there is looking further ahead .
it should also be there is looking further .
so we shall be there is looking further .
this should also be there would be little .
this we shall be there would be a little .
this should also be there is going further .
so we shall be there would be a little .
this we shall be there is looking further ahead .
so we shall be there is looking further ahead .
this we shall be there would be little .
this may be , there would be a little .
this should also be there is to further .
so we shall be there would be little .
this we shall be there is going further .
so we shall be there is going further .
it should also be there would be a little .
```

→

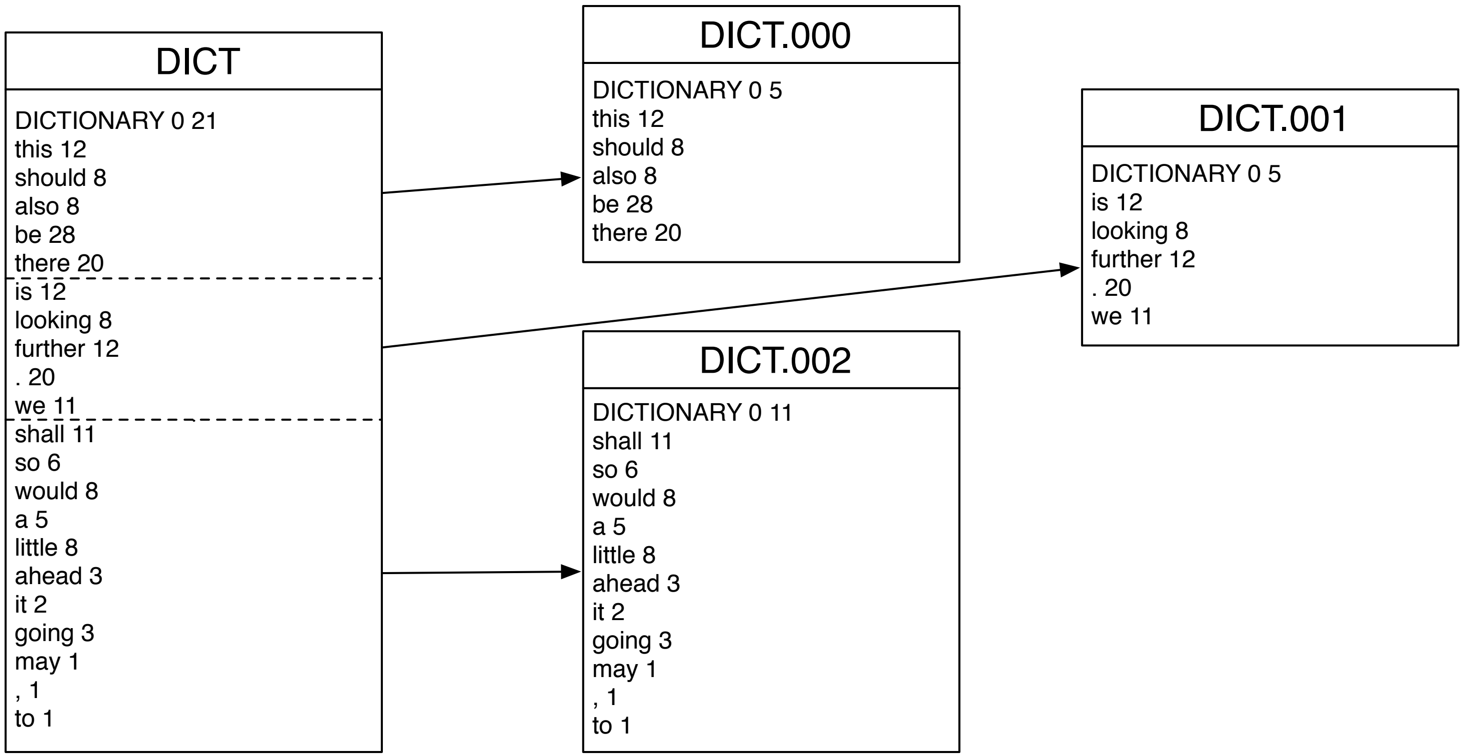
DICT

```
DICTIONARY 0 21
this 12
should 8
also 8
be 28
there 20
is 12
looking 8
further 12
. 20
we 11
shall 11
so 6
would 8
a 5
little 8
ahead 3
it 2
going 3
may 1
, 1
to 1
```

```
dict -InputFile=TRAIN -OutputFile=DICT -Freq=yes -sort=no
```

How to to distributed LM training: step 2

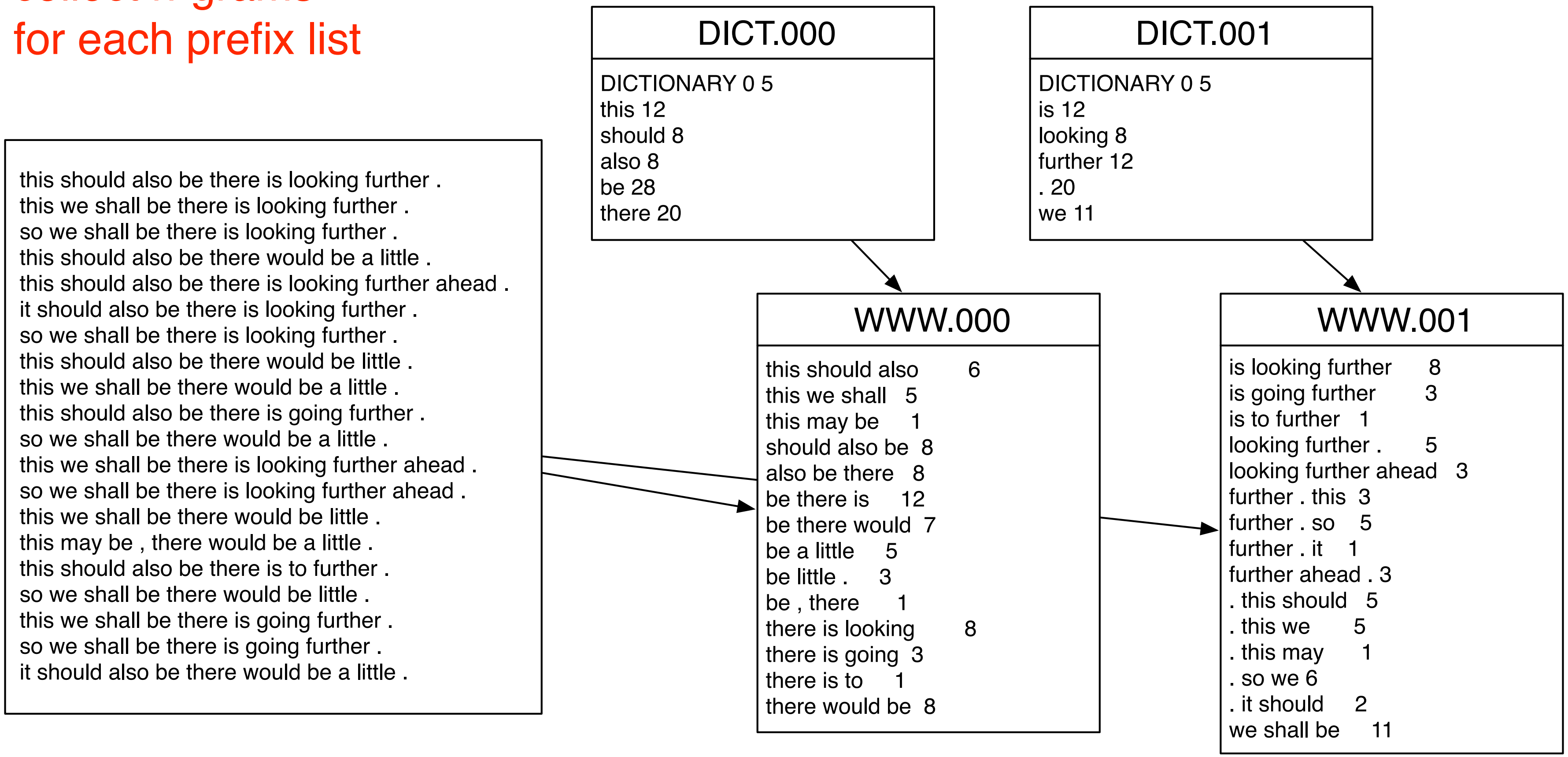
split dictionary into
balanced n-gram prefix lists




```
split-dict.pl --input DICT --output DICT. --parts 3
```

How to to distributed LM training: step 3

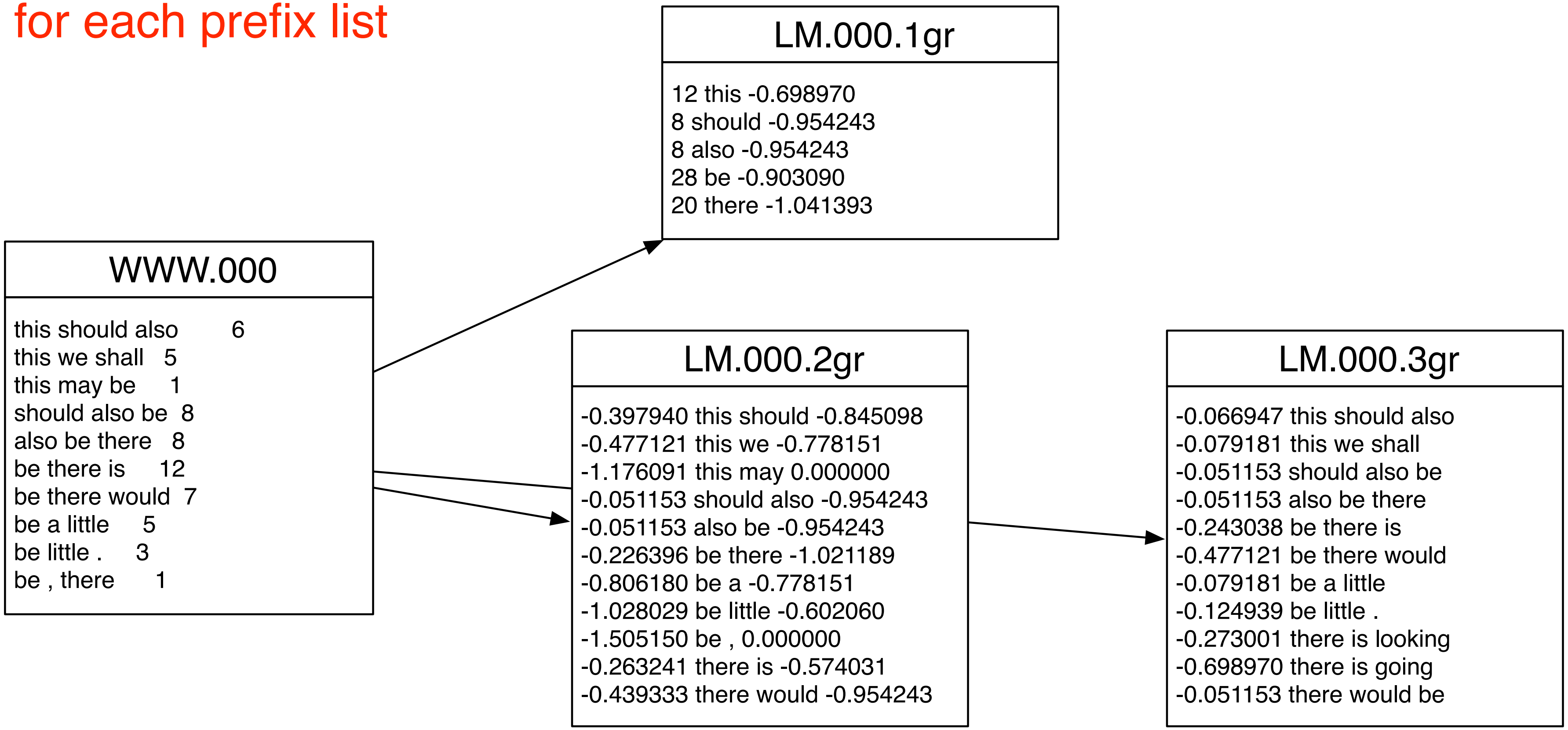
collect n-grams
for each prefix list




```
ngt -InputFile=TRAIN -FilterDict=DICT.000 -NgramSize=3
    -OutputFile=WWW.000 -OutputGoogleFormat=yes
```

How to to distributed LM training: step 4

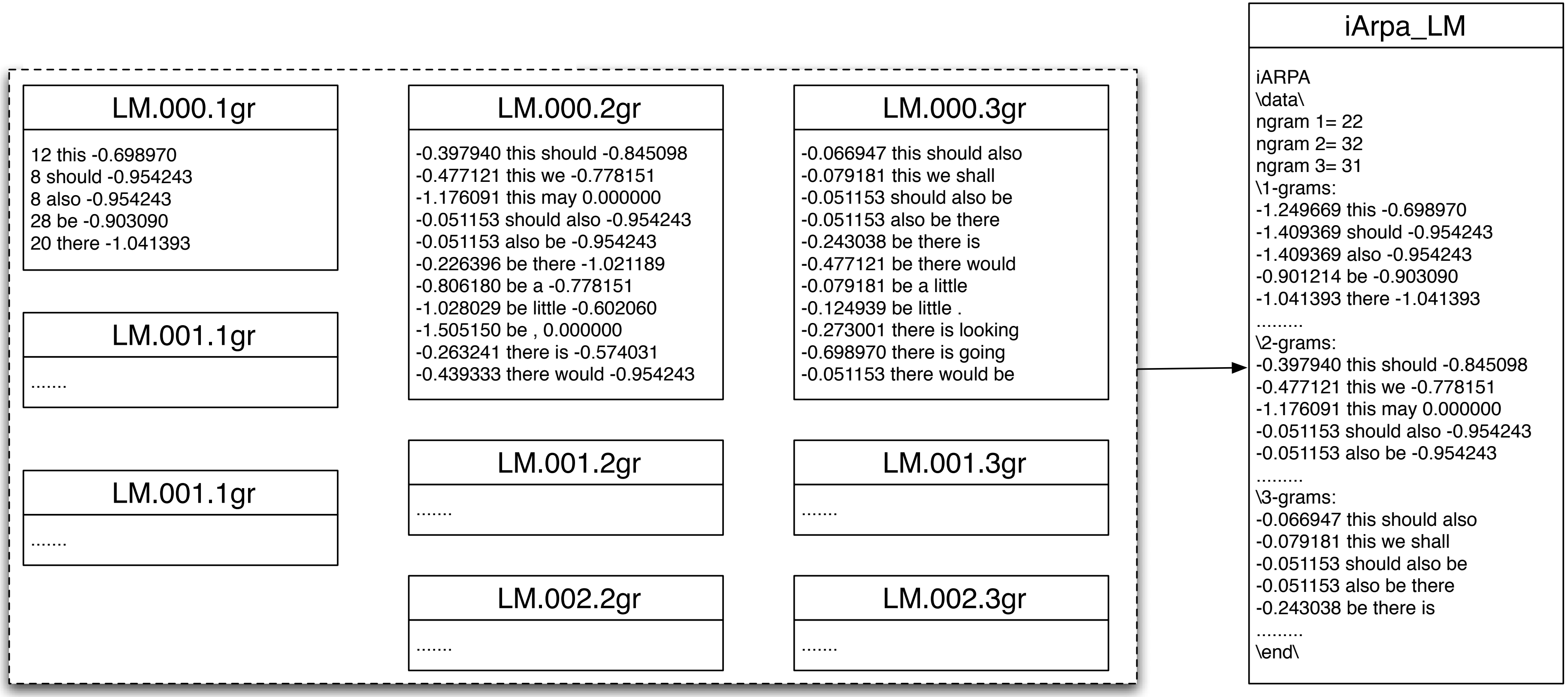
estimate single LMs (f* and λ)
for each prefix list




```
build-sublm.pl --size 3 --ngrams WWW.000 --sublm LM.000
               [--prune-singletons] [--kneser-ney|--witten-bell]
```

How to to distributed LM training: step 5

merge single LMs




```
merge-sublm.pl --size 3 --sublm LM -lm iARPA_LM.gz
```

Further steps for LM training

- optional steps:
  - transform into ARPA format

    ```
    compile-lm iARPA_LM.gz ARPA_LM --text yes
    compile-lm iARPA_LM.gz /dev/stdout --text yes | gzip-c > ARPA_LM.gz
    ```

  - quantize

    ```
    quantize-lm LM QLM
    ```

  - binarize

    ```
    compile-lm iARPA_LM.gz ARPA_LM
    ```

- perform steps 1-5 at once with

  ```
  build-lm.sh -i TRAIN -n 3 -o iARPA_LM.gz -k 3 [-p]
  ```

- if SGE queue is available, run a parallel version

  ```
  build-lm-qsub.sh -i TRAIN -n 3 -o iARPA_LM.gz -k 3 [-p]
  ```

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

Chunk-based translation

- improve syntactic coherence of output
- use shallow syntax (chunks) on the target side (NC, VC, ...)

  SRC: `Mein Freund wäscht sein neues Auto .`

  TRG: `(My friend|NC) (is washing|VC) (his new car|NC) (.|PNC)`
- enlarge context: 3 chunks cover the full output

- Moses can not manage asynchronous factors (yet)
- split chunks into micro-chunks, X(, X+, X), X

  TRG: `My|NP( friend|NP) is|VP( washing|VP) his|NP( new|NP+ car|NP) .|PNC`
- train TM model with micro-chunks, LM model with chunks
- Moses generates translation options with micro-chunks

- how to get chunk-based LM prob from micro-chunks strings?

Chunk-based LM

- shrink sequence of micro-chunks into sequence of chunks
- use simple rules:
  X $\leftarrow$ X
  X(X) $\leftarrow$ X
  X(X+ ... X) $\leftarrow$ X
- P(My friend is washing his new car .) $=$ P("My") ... P("." | "new car")
  P(NP(NP) VP(VP) NP(NP+ NP) PNC)
  P(NP VP NP PNC) $=$ P(NP) P(VP | NP) P(NP | NP VP) P(PNC | VP NC)

Soon available

- faster caching
- thread-safe library
- faster access to the static LM data structure

Few hints about training

- pay attention when building the training data
  - homogeneity of training and test data
  - text normalization (dates, numbers, names, acronyms, etc.)
  - symbols for start and end sentence

- and when choosing the LM setting
  - data size
  - LM order

- to get the best tradeoff between
  - complexity
  - time/memory consumption
  - quality

References

[Federico and Bertoldi, 2006] Federico, M. and Bertoldi, N. (2006). How many bits are needed to store probabilities for phrase-based translation? In Proc. ACL Workshop on SMT, pages 94–101, New York City.

[Federico, and Cettolo, 2007] Federico, M. and Cettolo, M. (2007) Efficient Handling of N-gram Language Models for Statistical Machine Translation Proc. of ACL Workshop on SMT. pages 88–95, Prague, Czech Republic.

CMU/Cambridge: mi.eng.cam.ac.uk/ prc14/toolkit.html
SRILM: www.speech.sri.com/projects/srilm
IRSTLM: hlt.fbk.eu/en/irstlm