# Using multilingual content on the web to build fast finite-state direct translation systems*

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## The objective

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Use existing multilingual web content...

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...for MT-less (or MT-poor) language pairs.

# The web as a source of translation units

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Build a (web-based) translation-memory-like engine?

## Using subsentential translation units/1

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Coverage of sentence segments may not be large $\longrightarrow$ approximate matching.

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- Subject, register, and variety annotation crucial.

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. . . both when translating new text. . .

. . . and when aligning new bitexts.

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`(‘‘web bitexts’’,‘‘los bitextos en la red’’)`

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A similar subsentential segmentation strategy must be designed for pretranslation.

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(common substring correspondences in TUs may share paths).

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(‘‘a translation memory’’,‘‘una memoria de traducción’’)
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If no match is found, skip one word and try again.

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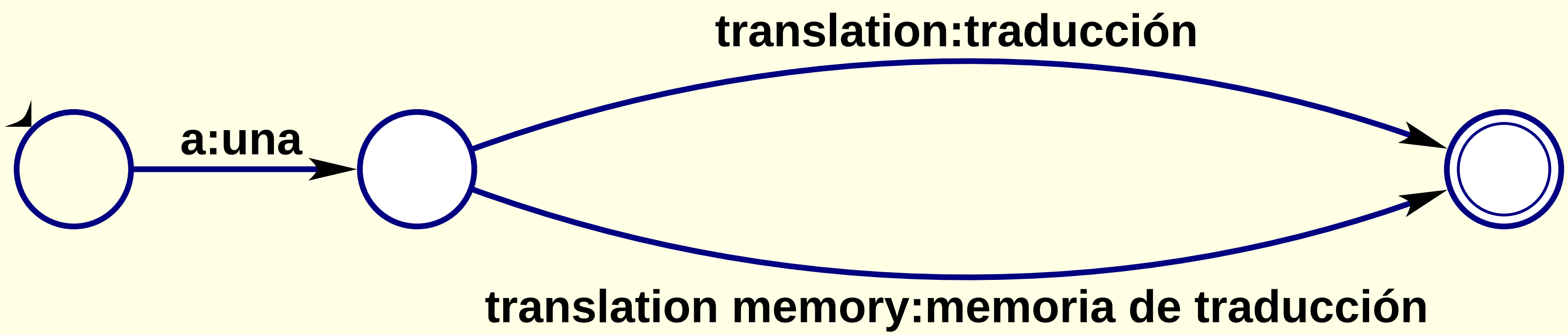


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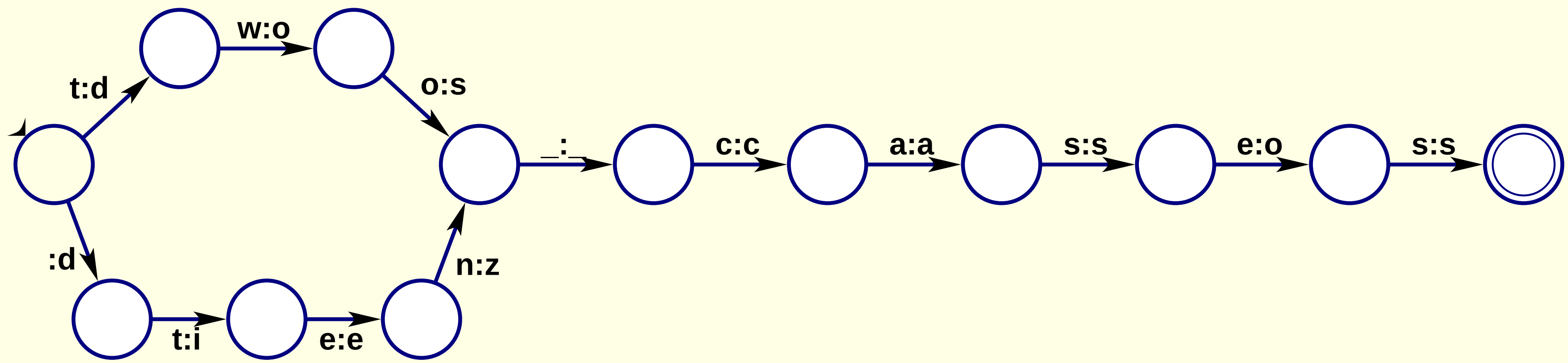
- lightning-fast implementations (Bentley & Sedgewick 1997).

# Finite-state storage of TU databases/5




(``two cases'',``dos casos'')

(``ten cases'',``diez casos'')

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(see our TMI 2002 paper: Garrido-Alenda et al. 2002).

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Addition of TUs must be compatible with the LRLM scheme.

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A sketch of the updating procedure:

- Start the FST at the beginning of the source text;
- Look for longest input prefix matching the source part of a TU;
- Check the target segment against the output;
- No match? Carefully skip source and/or target words and try again.

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Use heuristics to extend and combine the matched TUs with skipped words.

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Note: simultaneous matching of input and output natural to FSTs.

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Notation: $(s, T(s))$ translation unit ($T(s)$ is the translation of source segment $s$).

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Conveniently, $T(\#) = \#$

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Find the longest source $\widehat{s}_k$ after $s_k$ such that $T(\widehat{s}_k)$ is a target prefix.

Then extend $T(s_k\widehat{s}_k) = T(s_k)T(\widehat{s}_k)$, to obtain a LRLM cover of the source, and go on.

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With $s'_l$ and $t'_l$ possibly empty word sequences.

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If $t'_l$ is similar to $T(s_{l+2})$, this may be a reordering: $T(s_{l+1}\ s_{l+2}) = t'_l\ T(s_{l+1})$

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Modify transducer only if the alternate transduction wins.

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FST implementation allows speeds of 100,000 words per second (intensive use expected).

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**Bitext contribution:** users may contribute candidate bitexts not covered by the engine.

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Very desirable for MT-poor language pairs.