Decoding for SMT

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Task

Translate a source text (e.g. sentence)
Examples:

um conto de duas cidades	$\rightarrow$	a tale of two cities
nosso amigo comum	$\rightarrow$	our mutual friend
a loja de antiguidades	$\rightarrow$	the old curiosity shop
o grill da lareira	$\rightarrow$	the cricket on the hearth

Model of translational equivalences

Defines the space of possible translations

- think of it as a recipe to generate translations [Lopez, 2008]

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Example:

- a word replacement model
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- with no insertions or deletions

Model of translational equivalences

Defines the space of possible translations

- think of it as a recipe to generate translations [Lopez, 2008]

Example:

- a word replacement model
- operates in monotone left-to-right order
- with no insertions or deletions
- constrained to known word-to-word bilingual mappings (rule set)

Monotone word-by-word translation: solutions

Source: *um conto de duas cidades*

Translation rules[1]

um	{a, some, one}
conto	{tale, story, narrative, novella}
de	{of, from, 's}
duas	{two, couple}
cidades	{cities, towns, villages}

[1] Unrealistically simple

Monotone word-by-word translation: solutions

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...

This can go very far :(

Monotone word-by-word translation: complexity

Say

- the input has I words
- we know at most t translation options per source word

Monotone word-by-word translation: complexity

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This makes $O(t^I)$ solutions

Monotone word-by-word translation: complexity

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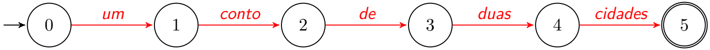
This makes $O(t^I)$ solutions

Note

- WMT14's shared task: $I = 40$ on average
- last I checked Moses default was $t = 100$

  (for a more complex model)
- silly monotone word replacement model: 10^{80} solutions

Space of solutions as intersection/composition



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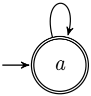

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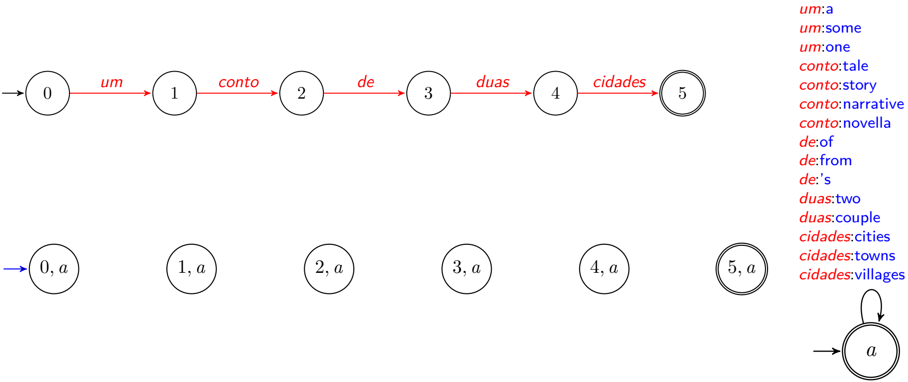

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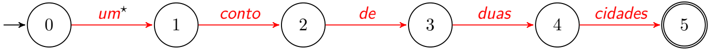

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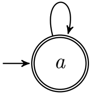

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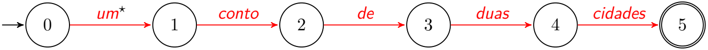

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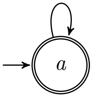

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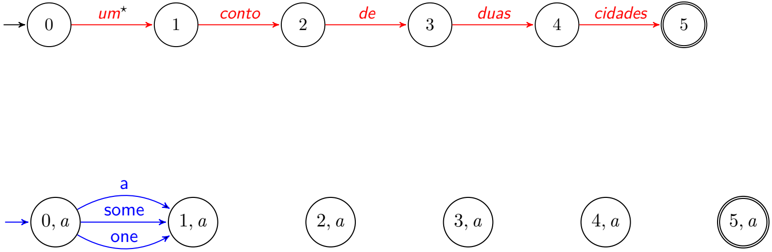

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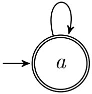

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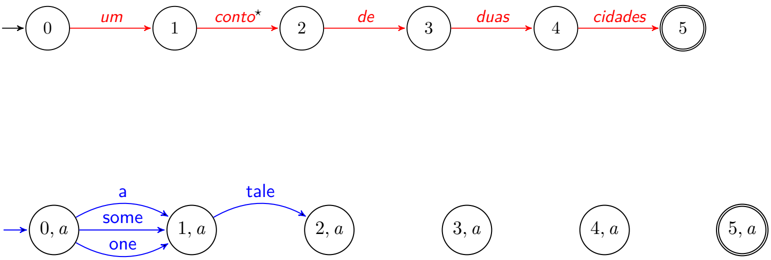

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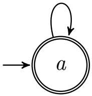

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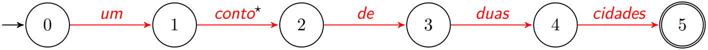

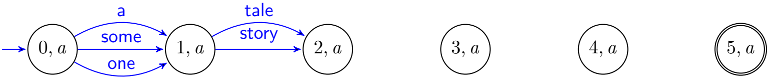

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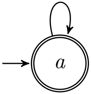

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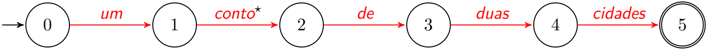

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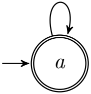

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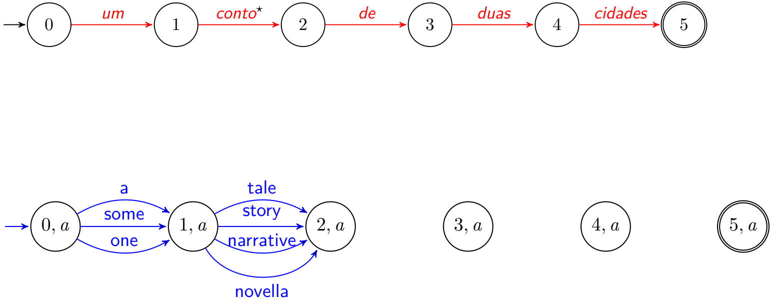

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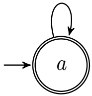

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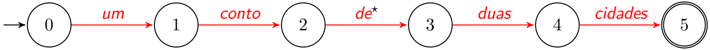

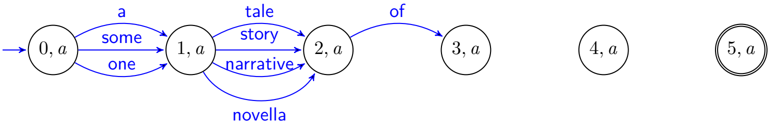

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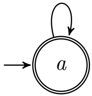

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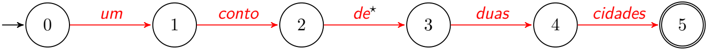

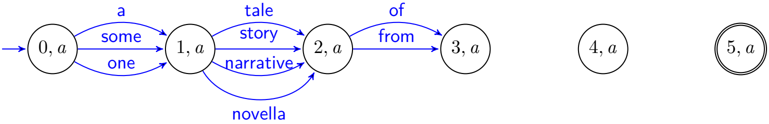

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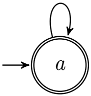

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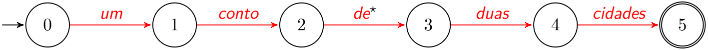

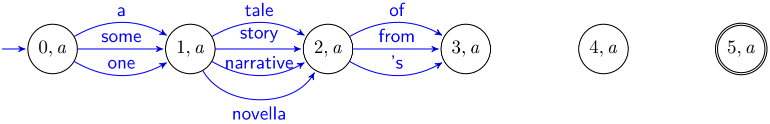

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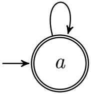

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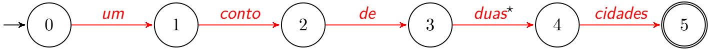

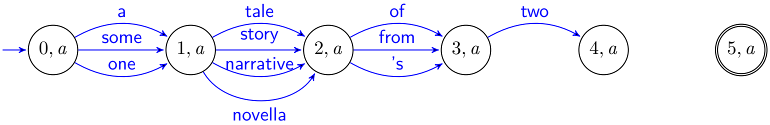

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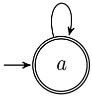

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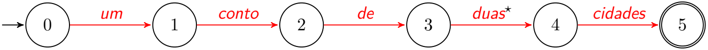

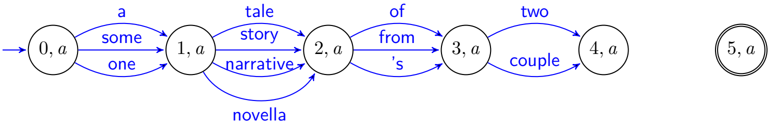

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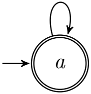

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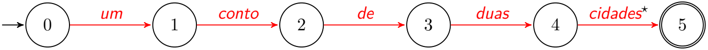

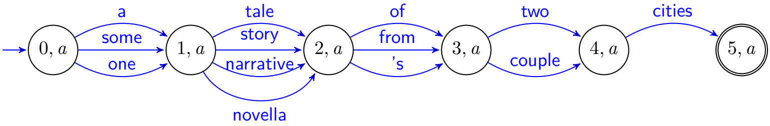

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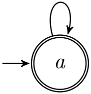

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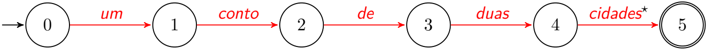

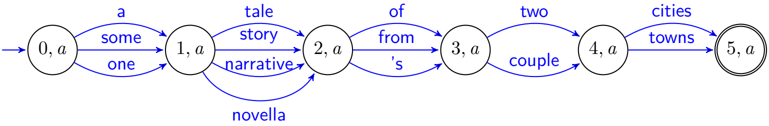

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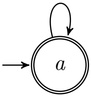

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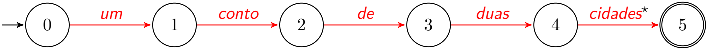

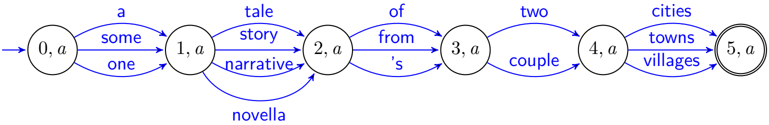

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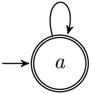

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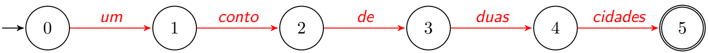

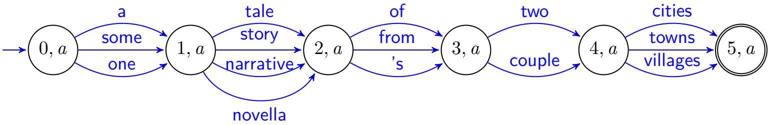

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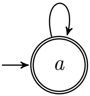

$3 \times 4 \times 3 \times 2 \times 3 = 216$ solutions

- 6 states
- $3 + 4 + 3 + 2 + 3 = 15$ transitions

Packing solutions with finite-state automata

Same $O(t^I)$ solutions using

- $O(I)$ states
- $O(tI)$ transitions

Recap 1

Recap 1

Model of translational equivalences

- defines the space of possible sentence pairs
- conveniently decomposes into smaller bilingual mappings

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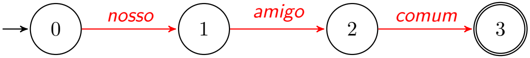
- exponential number of solutions in linear space
- translates infinitely many sentences
  but not nearly enough interesting cases!

Monotone word-by-word translation: fail!

nosso {our, ours}
amigo {friend, mate}
comum {ordinary, common, usual, mutual}



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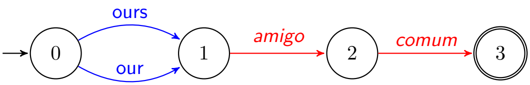

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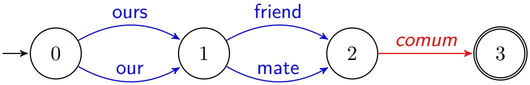

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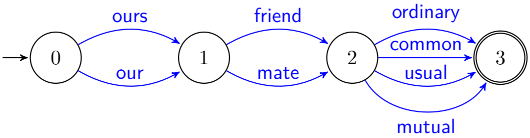

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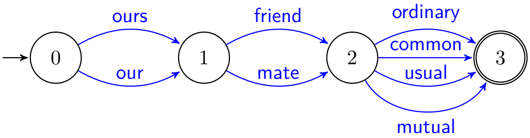


We simply cannot obtain a correct translation

our mutual friend

Reordering

Our model of translational equivalences assumes monotonicity

- a word replacement model
- operates in **monotone** left-to-right order
- with no insertions or deletions
- constrained to known word-to-word bilingual mappings (rule set)

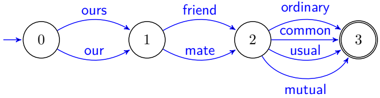
Reordering

Not anymore!

- a word replacement model
- operates in **arbitrary** order
- with no insertions or deletions
- constrained to known word-to-word bilingual mappings (rule set)

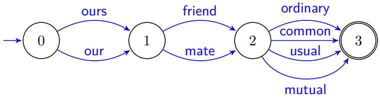
Translating arbitrary permutations

nosso amigo comum

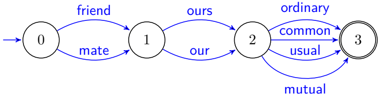


Translating arbitrary permutations

nosso amigo comum



amigo nosso comum



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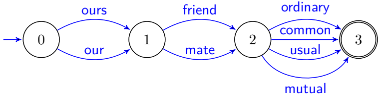

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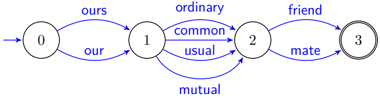

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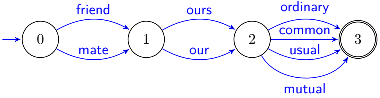

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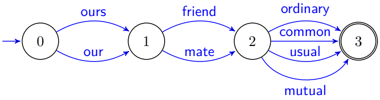

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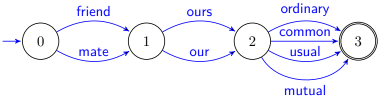

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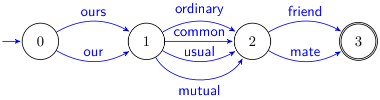
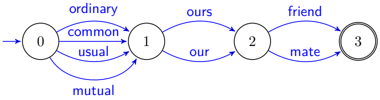


comum nosso amigo



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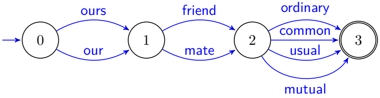

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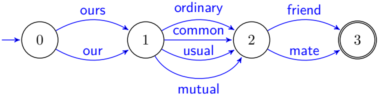

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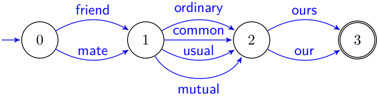

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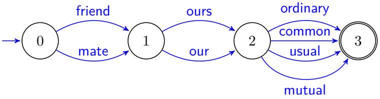

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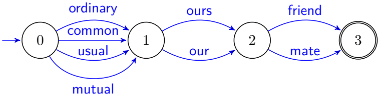

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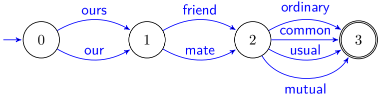
nosso amigo comum



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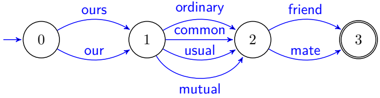

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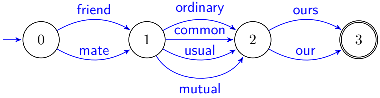

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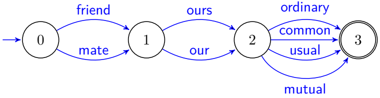

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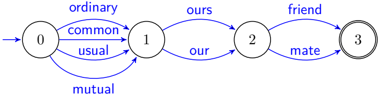

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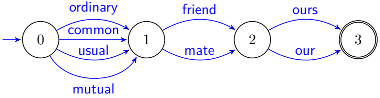

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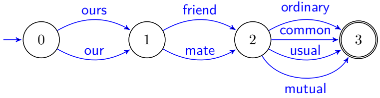

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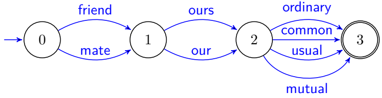

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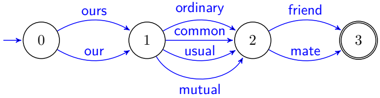

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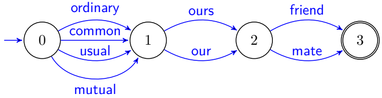

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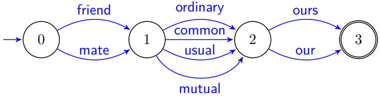

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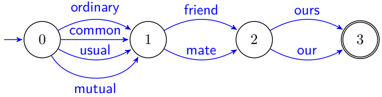
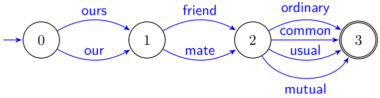


$3! = 3 \times 2 \times 1 = 6$ permutations

Translating arbitrary permutations

nosso amigo comum



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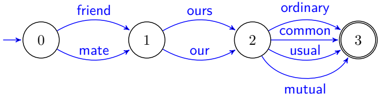
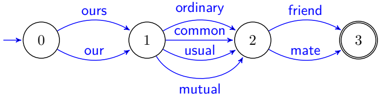


nosso comum amigo



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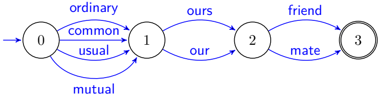
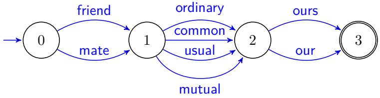


amigo comum nosso



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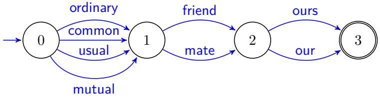
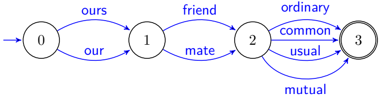


each has $2 \times 2 \times 4 = 16$ translations

Translating arbitrary permutations

nosso amigo comum



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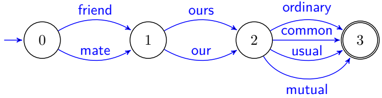

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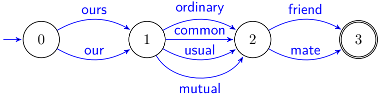

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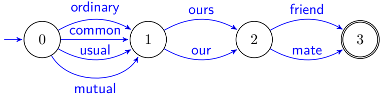

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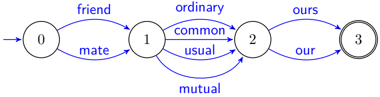

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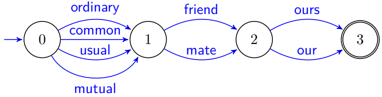
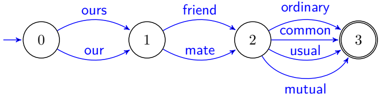


amounting to $6 \times 16 = 96$ solutions

Translating arbitrary permutations

nosso amigo comum



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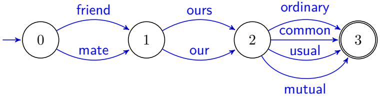

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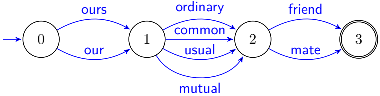

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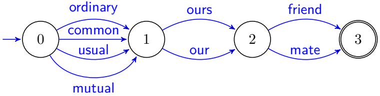

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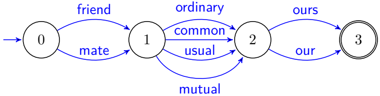

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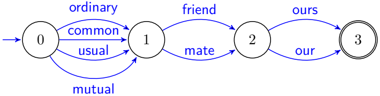
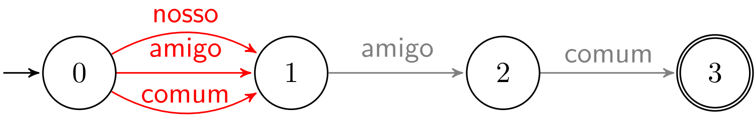


$I!$ permutations $\times$ t^I translations

Packing permutations

Packing permutations



Packing permutations

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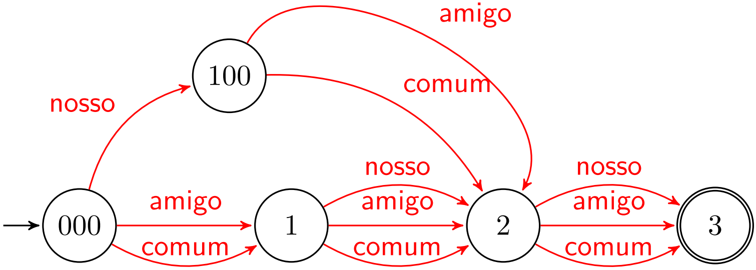

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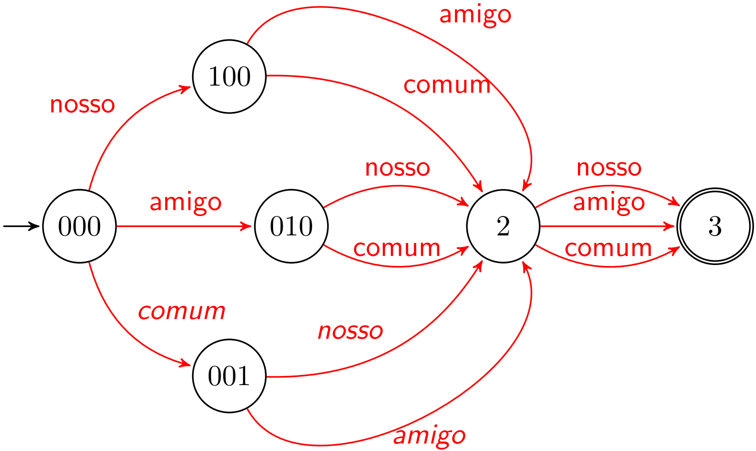

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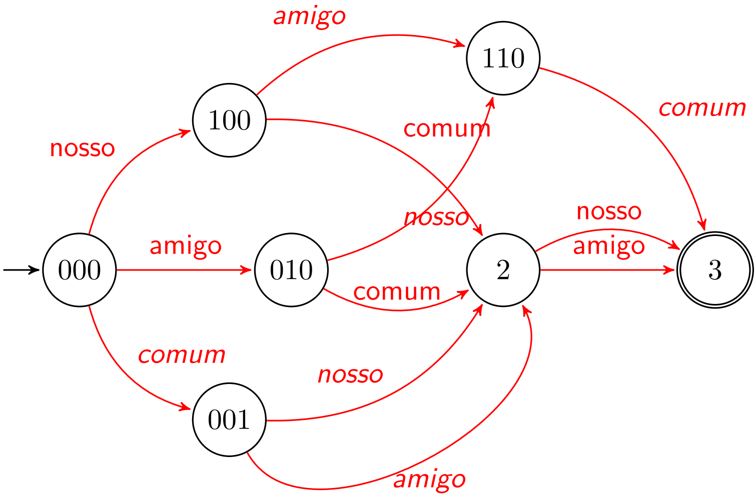

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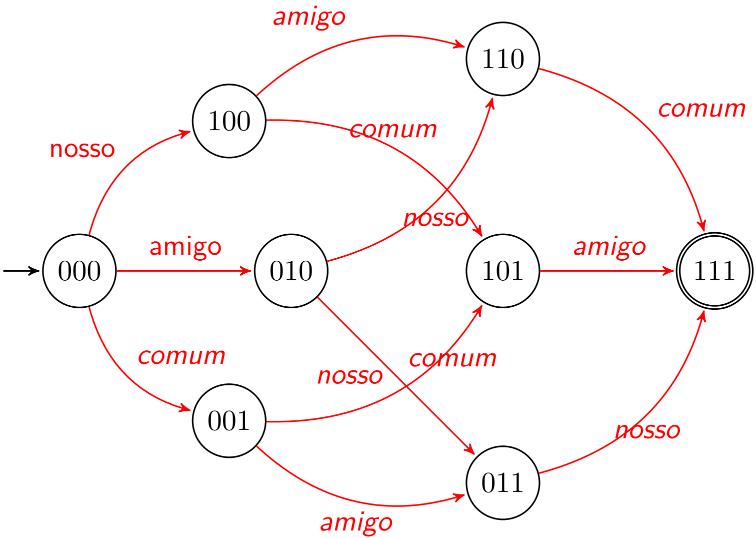


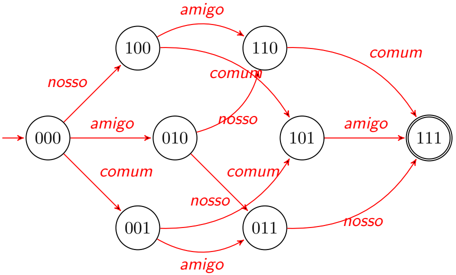
Packing permutations

Powerset (*all subsets*) of $\{1, 2, \ldots, I\}$

- 2^I subsets
  think of a vector of I bits ;)

Lattice

- $O(2^I)$ states
- $O(I \times 2^I)$ transitions



Deductive logic

$$\textsc{Item} \quad \left[\{0,1\}^I\right]$$

$$\textsc{Goal} \quad \left[1^I\right]$$

$$\textsc{Axiom}$$

$$\frac{}{[0^I]}$$

$$\textsc{Expand}$$

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \leq i \leq I \\ c_i = \bar{0} \end{array}$$

where $\alpha_i(C)$ is a copy of C with $c_i = \bar{1}$

Template

- items $\rightarrow$ states
- deduction rules $\rightarrow$ transitions

Deductive logic

$\textsc{Item}$ $\left[\{0,1\}^I\right]$

$\textsc{Goal}$ $\left[1^I\right]$

$\textsc{Axiom}$

$$\frac{}{[0^I]}$$

$\textsc{Expand}$

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{matrix} 1 \le i \le I \\ c_i = \bar{0} \end{matrix}$$

where $\alpha_i(C)$ is a copy of C with $c_i = \bar{1}$

- a subset of $\{1, \ldots, I\}$ encoded as a bit vector of length I

Deductive logic

$\textsc{Item} \quad \left[\{0,1\}^I\right]$

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where $\alpha_i(C)$ is a copy of C with $c_i = \bar{1}$

- we start with an empty sentence e.g. $I = 3 \rightarrow 0^3 = 000$

Deductive logic

ITEM $\left[\{0,1\}^I\right]$

GOAL $\left[1^I\right]$

AXIOM

$$\overline{[0^I]}$$

EXPAND

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$

where $\alpha_i(C)$ is a copy of C with $c_i = \bar{1}$

- and continue one word at a time
  e.g. $[000](i = 1) \rightarrow [100]$

Deductive logic

$\textsc{Item} \quad \left[\{0,1\}^I\right]$

$\textsc{Goal} \quad \left[1^I\right]$

$\textsc{Axiom}$

$$\frac{}{[0^I]}$$

$\textsc{Expand}$

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{matrix} 1 \leq i \leq I \\ c_i = \bar{0} \end{matrix}$$

where $\alpha_i(C)$ is a copy of C with $c_i = \bar{1}$

- until we have a complete sentence e.g. $[111]$

Instantiated deductive logic program

Source: *nosso*$_1$ *amigo*$_2$ *comum*$_3$

ITEM $\left[\{0,1\}^I\right]$

GOAL $\left[1^I\right]$

AXIOM

$$\frac{}{[0^I]}$$

EXPAND

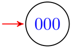
$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$

Instantiated deductive logic program

Source: *nosso*$_1$ *amigo*$_2$ *comum*$_3$

`Axiom`

$[000]$



$$\textsc{Item} \quad \left[\{0,1\}^I\right]$$

$$\textsc{Goal} \quad \left[1^I\right]$$

$$\textsc{Axiom}$$

$$\overline{[0^I]}$$

$$\textsc{Expand}$$

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \leq i \leq I \\ c_i = \bar{0} \end{array}$$

Instantiated deductive logic program

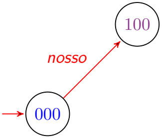
Source: *nosso*$_1$ *amigo*$_2$ *comum*$_3$

`Axiom`

$[000]$

`Expand`

$[000](i = 1) \rightarrow [100]$



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$\textsc{Goal}\quad \left[1^I\right]$

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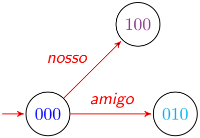
$[000]$

`Expand`

$[000](i = 1) \rightarrow [100]$

$[000](i = 2) \rightarrow [010]$



ITEM $\left[\{0,1\}^I\right]$

GOAL $\left[1^I\right]$

AXIOM

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EXPAND

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$

Instantiated deductive logic program

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`Axiom`

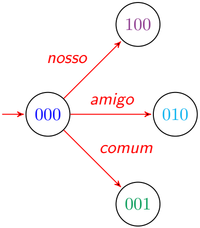
$[000]$

`Expand`

$[000](i = 1) \rightarrow [100]$

$[000](i = 2) \rightarrow [010]$

$[000](i = 3) \rightarrow [001]$



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Instantiated deductive logic program

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GOAL $\left[1^I\right]$

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Source: *nosso*$_1$ *amigo*$_2$ *comum*$_3$

Axiom

$[000]$

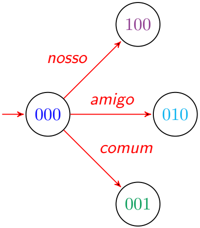
Expand

$[000](i = 1) \rightarrow [100]$

$[000](i = 2) \rightarrow [010]$

$[000](i = 3) \rightarrow [001]$

$[100](i = 1)$ ✗



Instantiated deductive logic program

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$$\textsc{Goal}\quad \left[1^I\right]$$
$$\textsc{Axiom}\quad \frac{}{[0^I]}$$
$$\textsc{Expand}\quad \frac{[C]}{[\alpha_i(C)]}\quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$

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`Expand`

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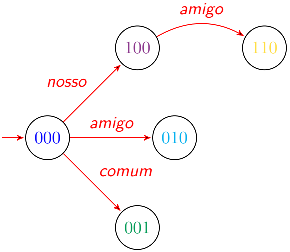
$[000](i=3) \rightarrow [001]$

$[100](i=1)$ ✗

$[100](i=2) \rightarrow [110]$



Instantiated deductive logic program

ITEM $\left[\{0,1\}^I\right]$

GOAL $\left[1^I\right]$

AXIOM

$$\overline{[0^I]}$$

EXPAND

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \leq i \leq I \\ c_i = \bar{0} \end{array}$$

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`Axiom`

$[000]$

`Expand`

$[000](i=1) \to [100]$

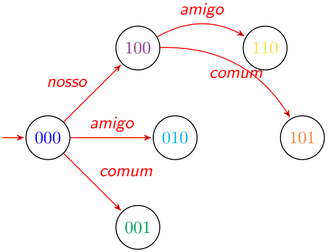
$[000](i=2) \to [010]$

$[000](i=3) \to [001]$

$[100](i=1)$ ✗

$[100](i=2) \to [110]$

$[100](i=3) \to [101]$



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`Axiom`

$[000]$

`Expand`

$[000](i=1) \rightarrow [100]$

$[000](i=2) \rightarrow [010]$

$[000](i=3) \rightarrow [001]$

$[100](i=1)$ ✗

$[100](i=2) \rightarrow [110]$

$[100](i=3) \rightarrow [101]$

$[010](i=1) \rightarrow [110]$

$\textsc{Item} \quad \left[\{0,1\}^I\right]$

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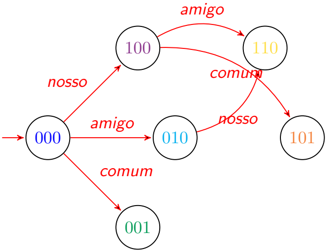

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`Axiom`

$[000]$

`Expand`

$[000](i = 1) \rightarrow [100]$
$[000](i = 2) \rightarrow [010]$
$[000](i = 3) \rightarrow [001]$
$[100](i = 1)$ ✗
$[100](i = 2) \rightarrow [110]$
$[100](i = 3) \rightarrow [101]$
$[010](i = 1) \rightarrow [110]$
$[010](i = 2)$ ✗

ITEM $\left[\{0,1\}^I\right]$

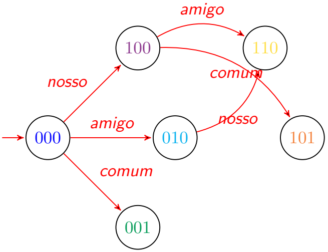
GOAL $\left[1^I\right]$

AXIOM

$$\overline{[0^I]}$$

EXPAND

$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \leq i \leq I \\ c_i = \bar{0} \end{array}$$



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$[000](i=3) \rightarrow [001]$

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$[100](i=2) \rightarrow [110]$

$[100](i=3) \rightarrow [101]$

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$[010](i=2)$ ✗

$[010](i=3) \rightarrow [011]$

ITEM	$\left[\{0,1\}^I\right]$
GOAL	$\left[1^I\right]$

AXIOM

$$\frac{}{[0^I]}$$

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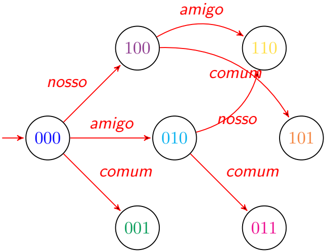

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$[000](i=1) \rightarrow [100]$

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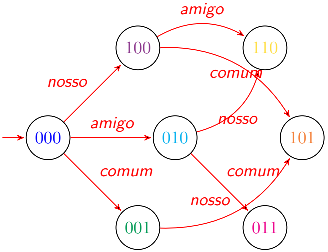

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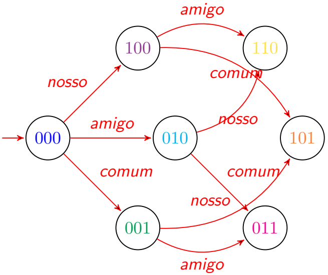

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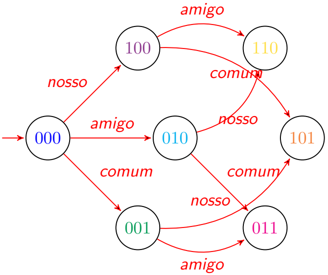

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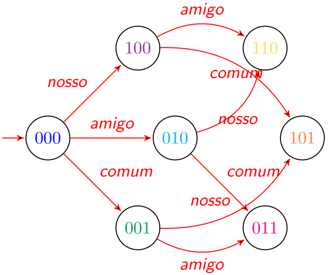

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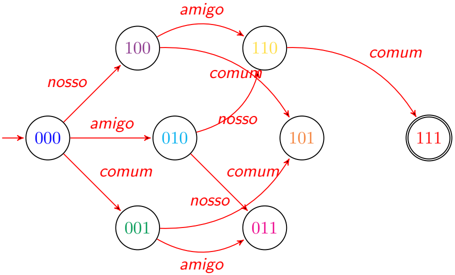

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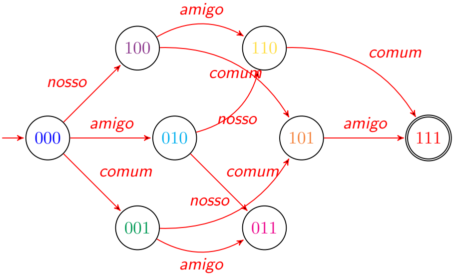

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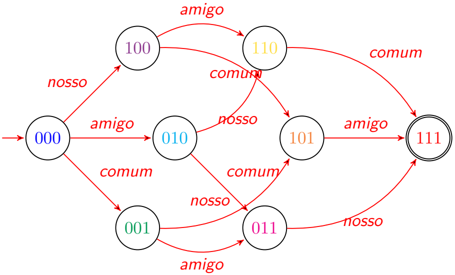

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`Goal`

$[111]$

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EXPAND

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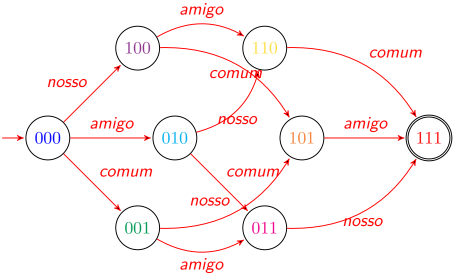

Word replacement with unconstrained reordering

Source: *nosso amigo comum*

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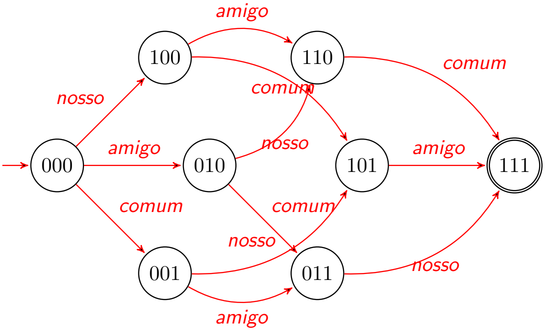
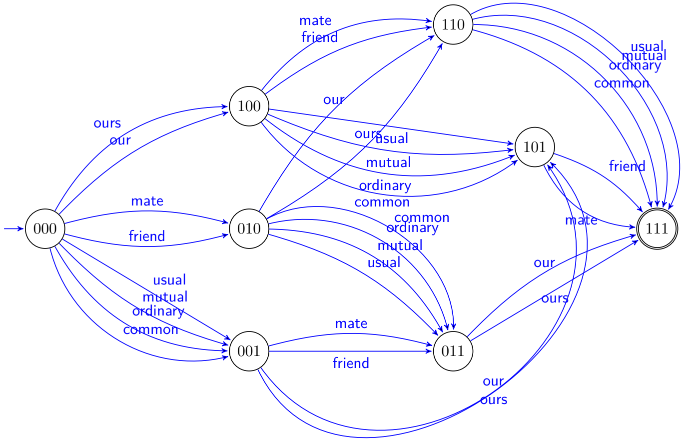


Source: *nosso amigo comum*

1. arbitrary permutations: $O(2^I)$ states

Word replacement with unconstrained reordering



Source: *nosso amigo comum*

1. arbitrary permutations: $O(2^I)$ states
2. intersection with the rule set: $O(tI2^I)$ transitions

Problem!

Before we even discuss a parameterisation of the model we already ran into a tractability issue!

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- is it sensible to consider the space of **all permutations**?

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Solution

- constrain reordering **:D**
- **0.o** but how?

Ad-hoc distortion limit

Several flavours of distortion limit [Lopez, 2009]

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Ad-hoc distortion limit

Several flavours of distortion limit [Lopez, 2009]

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Moses allows reordering within a window of length d

- starting from the leftmost uncovered word

WLd (example)

Suppose $d = 2$ and $I = 3$

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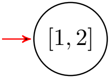

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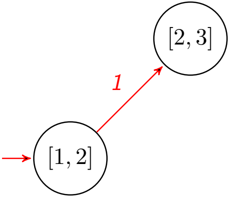

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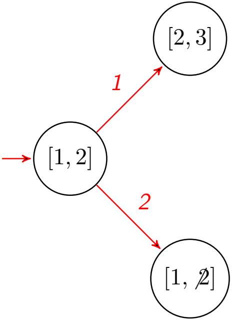

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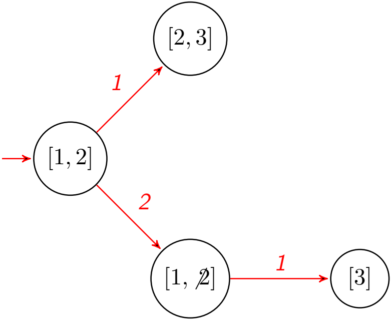

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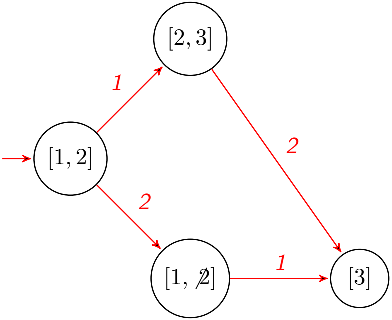

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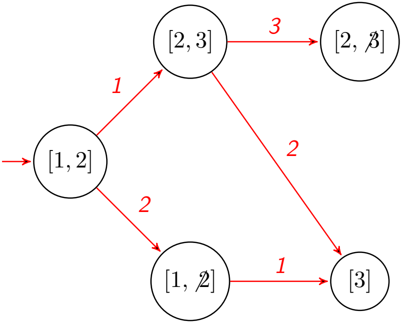

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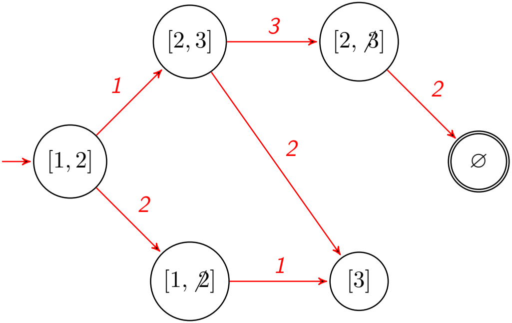

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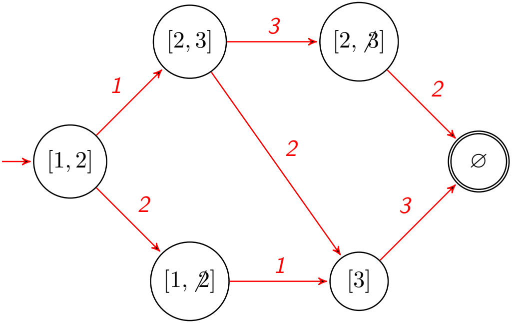
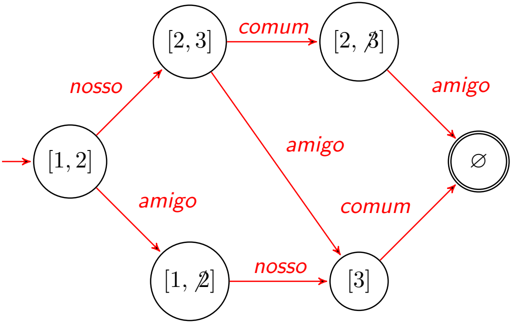


WLd (example)

Suppose $d = 2$ and $I = 3$ (e.g. *nosso amigo comum*)



WLd (logic)

$$\textsc{Item} \quad \left[[1..I+1], \{0,1\}^{d-1}\right]$$

$$\textsc{Goal} \quad [I+1, C]$$

$$\textsc{Axiom}$$

$$\frac{}{[1, 0^{d-1}]}$$

$$\textsc{Adjacent}$$

$$\frac{[l, C]}{[l+n, C \ll n]} \quad i = l$$

where $n = \#_1(C) + 1$

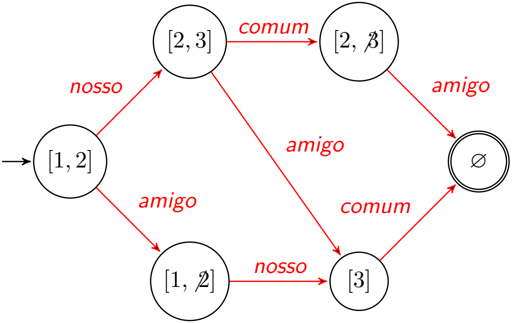
$$\textsc{Non-Adjacent}$$

$$\frac{[l, C]}{[l, \alpha_l^i(C)]} \quad \begin{array}{l} l < i \leq I \\ \delta(i, l) \leq d \\ c_{i-l} = \bar{0} \end{array}$$

- $O(Id2^{d-1})$ states
- $O(Id2^{d-1})$ transitions

Word replacement with reordering constrained by WL2

Complexity: $O(I2^{d-1})$ states



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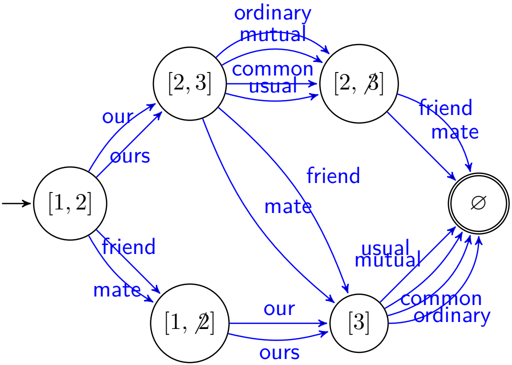

Ad-hoc distortion limit: expressiveness

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  e.g. OV vs VO, head-initial vs head-final
- can we do better?

ITGs

Inversion Transduction Grammars (ITGs) [Wu, 1997]

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- $X \rightarrow XX$
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- $X \rightarrow XX$
  direct order
- $X \rightarrow \langle XX \rangle$
  inverted order
- $X \rightarrow f/e$, where $(f, e) \in R$
  bilingual mappings

Parsing, intersection and hypergraphs

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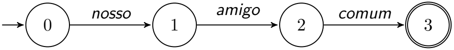

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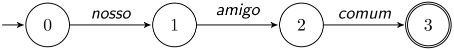

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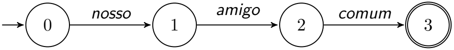

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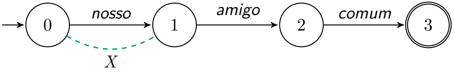

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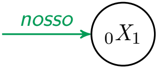

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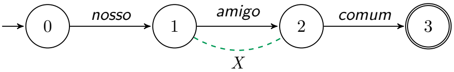

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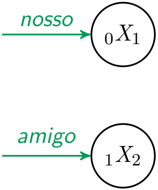

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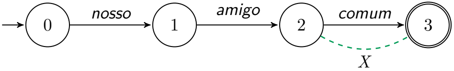

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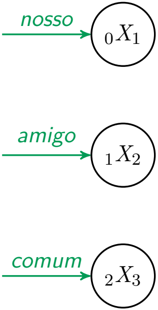

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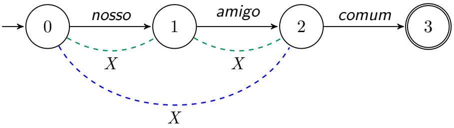

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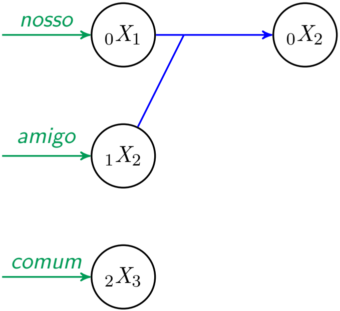

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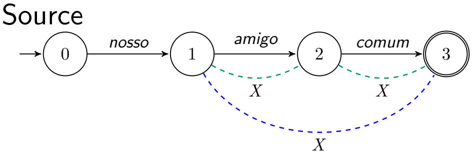

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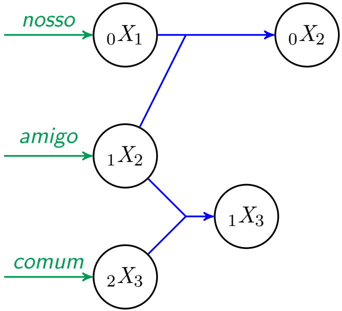

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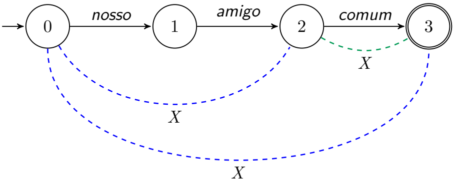

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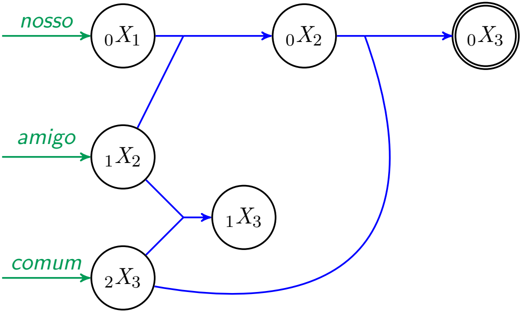

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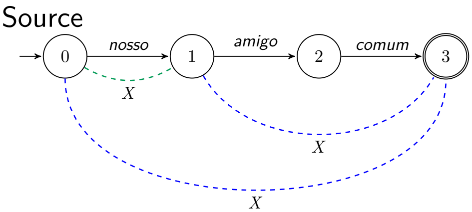

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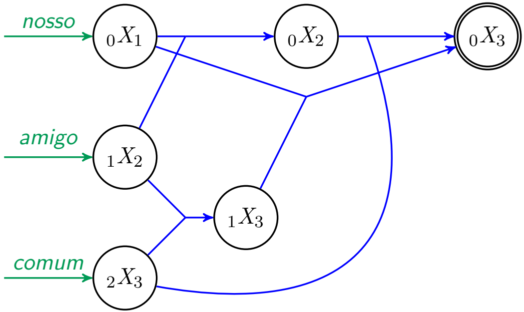

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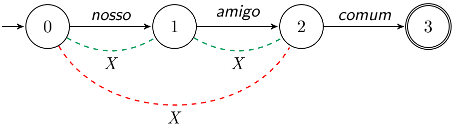

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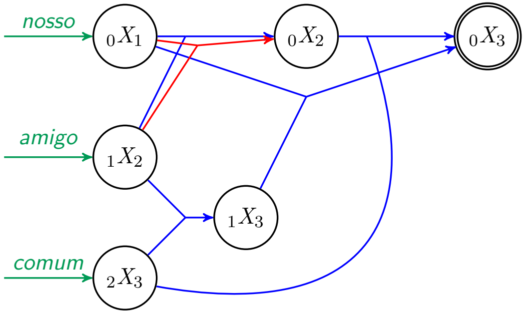

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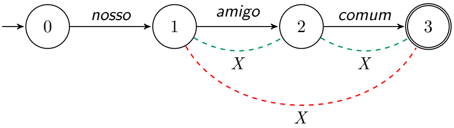

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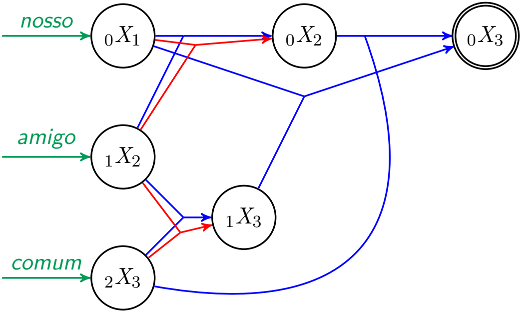

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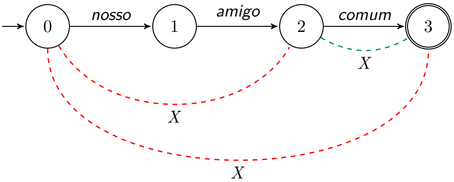

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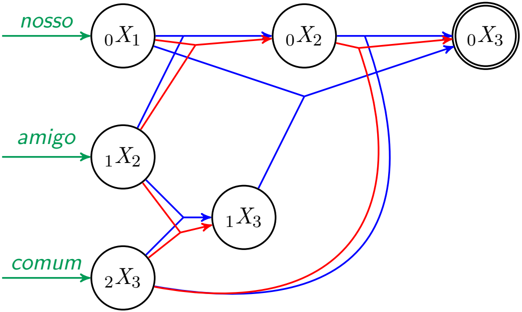

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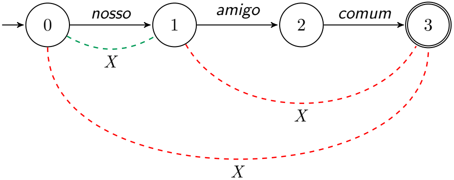

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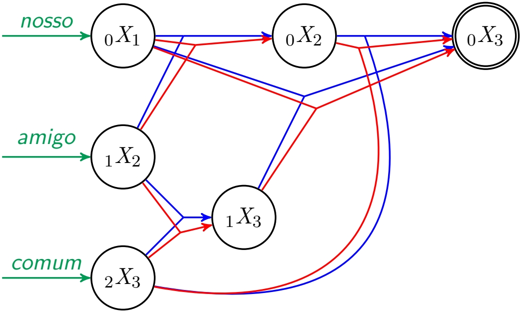

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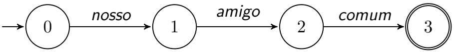

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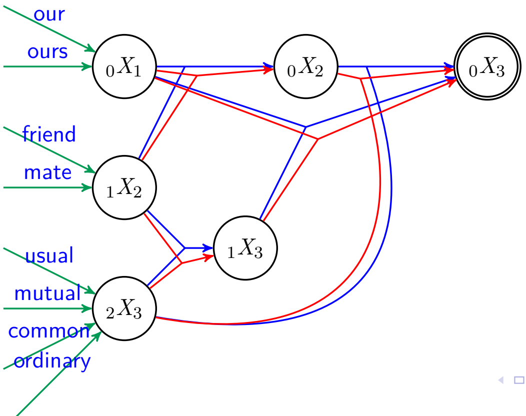

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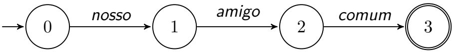

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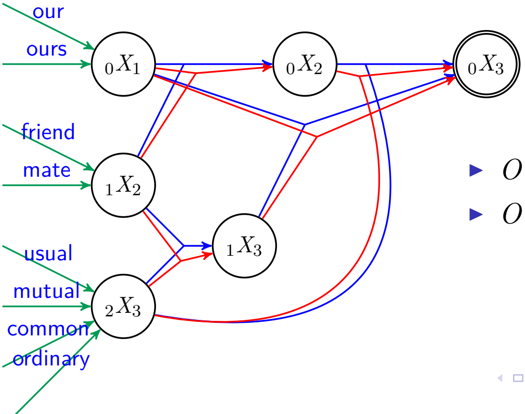
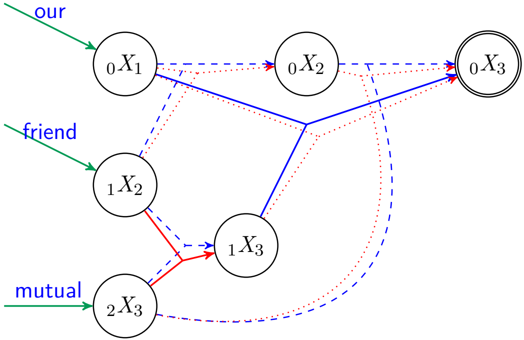


- $O(I^3)$ nodes
- $O(tI^3)$ edges

Example

(nosso ⟨amigo comum⟩) $\rightarrow$ **our mutual friend**



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But we still perform translation word-by-word with no insertion or deletion!

1-1 mappings: fail!

Source: o$_1$ grilo$_2$ *da*$_3$ lareira$_4$
Target: the$_1$ cricket$_2$ [on the]$_3$ hearth$_4$

Insertion and deletion

Implicitly modelled by moving from words to phrases

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- constrained to known phrase-to-phrase bilingual mappings (rule set)

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Mappings of contiguous sequences of words

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  e.g. *a loja de antiguidades*/old curiosity shop

Generalising the rule set (FST)

Rules

o	{the, a}
grilo	{cricket, annoyance}
da	{on the, of, from}
hearth	{lareira}

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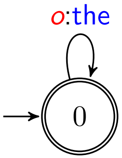

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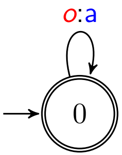

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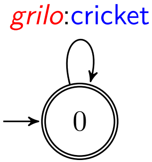

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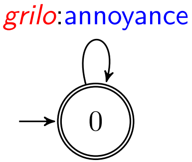

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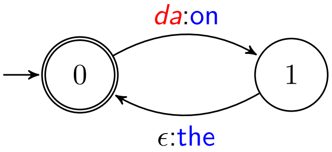

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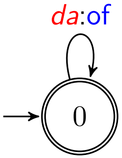

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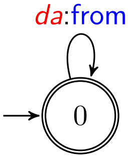

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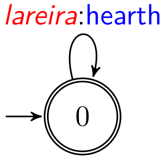

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Generalising the rule set (FST)

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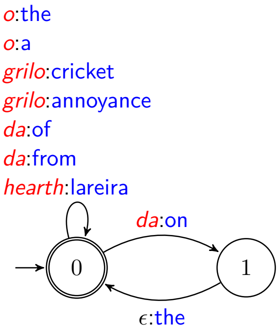

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Phrase permutations' translation with WLd

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- complexity remains
  - linear with sentence length
  - exponential with distortion limit

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- $O(I^3)$ nodes (phrases are limited in length)
- $O(tI^3)$ edges

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2. efficiently represented the set of translations supported by these models for a given input sentence
   - trivially expressed in terms of intersection/composition
   - a logic program can do the same
     (sometimes more convenient, e.g. WLd constraints)

Remarks

Phrase-based SMT [Koehn et al., 2003]

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- better motivated constraints on reordering

Remarks (hiero)

Hierarchical phrase-based models [Chiang, 2005]

[1] Other than monotone translation with *glue rules*

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We are missing a parameterisation of the model

- the scoring function which will guide the decision making process

Linear models

Let's call **derivation**

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Think of it as a surrogate for translation quality at decoding time

[Berger et al., 1996]
[Och and Ney, 2002]

Feature functions

Independently capture different aspects of the translation, such as

- adequacy
  - translation probabilities
  - confidence on lexical choices
- fluency
  - LM probabilities
  - confidence on reodering

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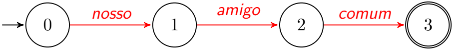
Structural independence: scoring rules in isolation

Scoring rules independently



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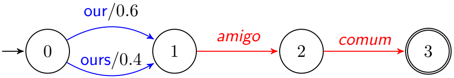

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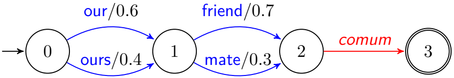

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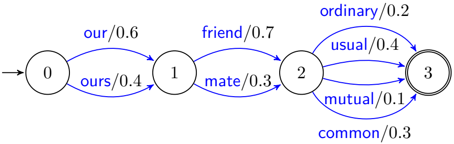

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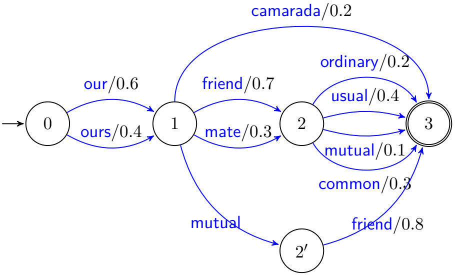

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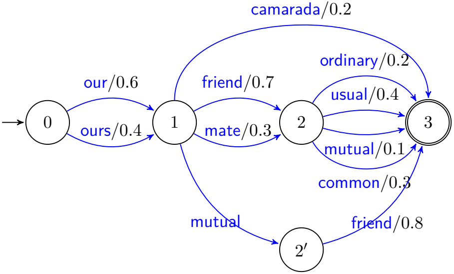

inference runs in time linear with the size of the automaton

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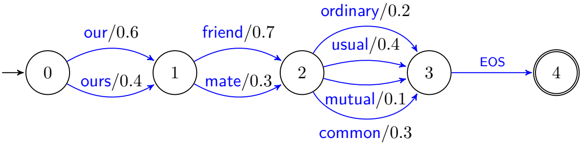
Certain aspects do not comply with such assumptions

- fluency as captured by an n-gram LM component

Scoring strings with a 2-gram LM



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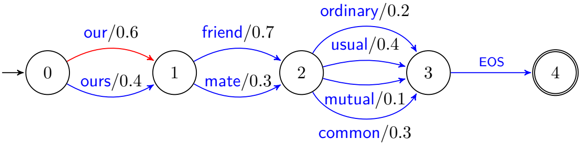

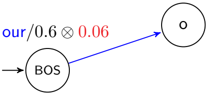

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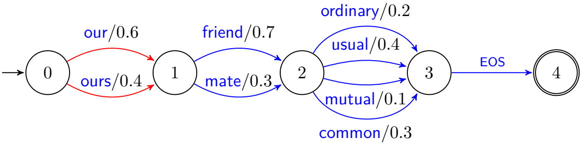

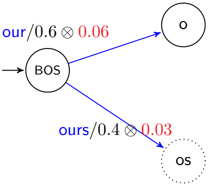

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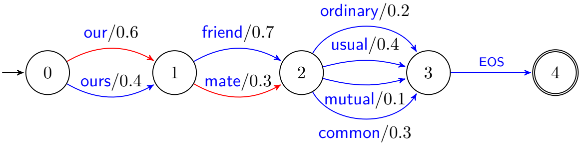

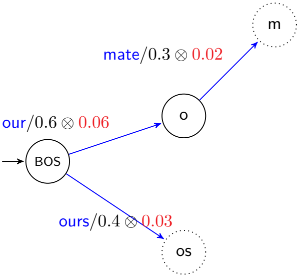

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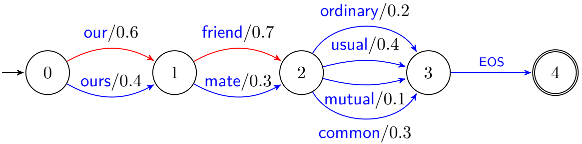

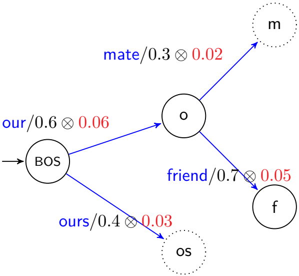

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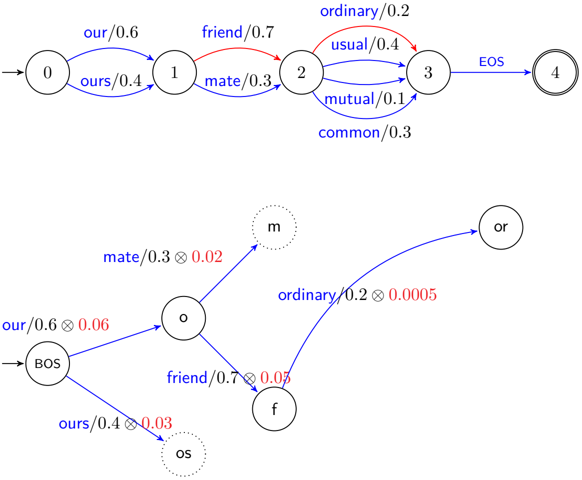

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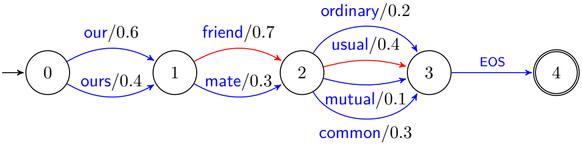

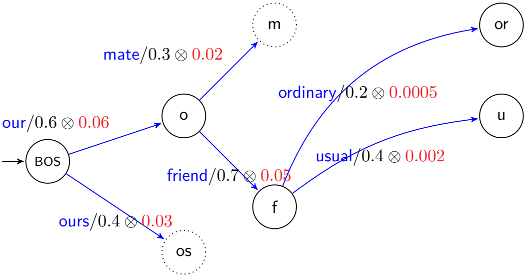

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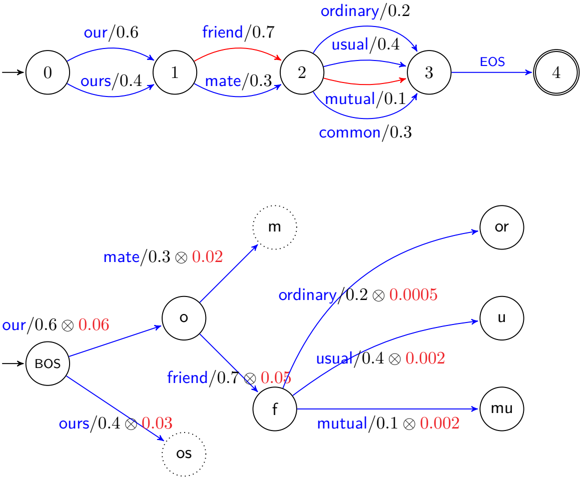

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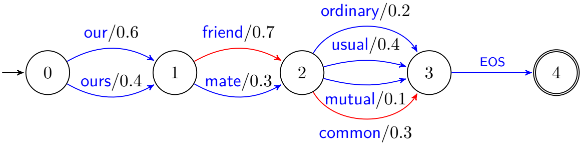

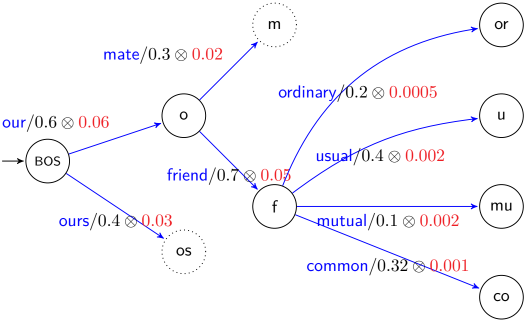

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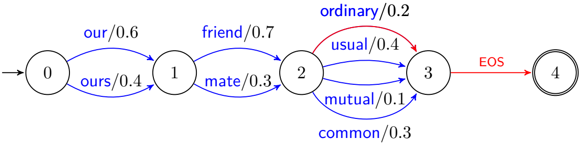

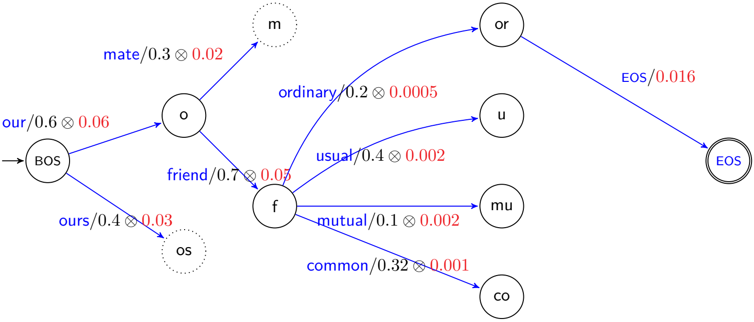

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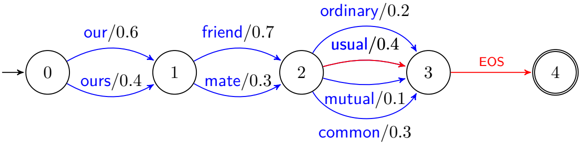

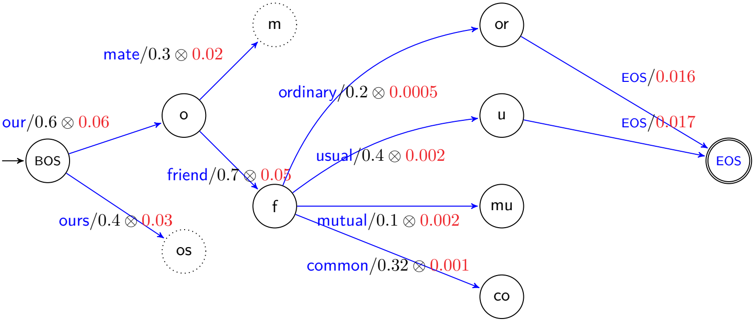

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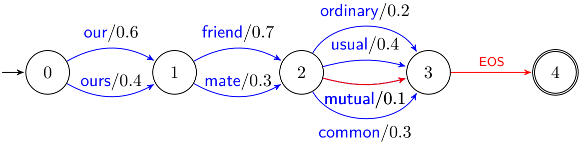

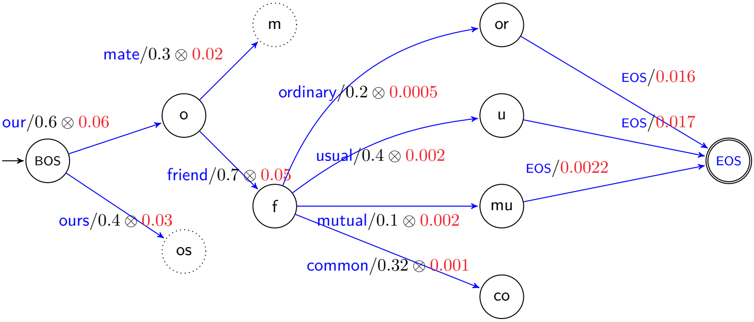

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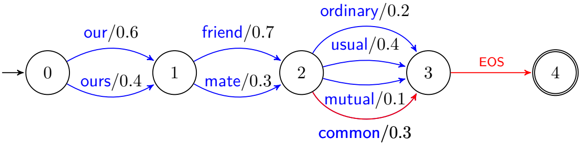

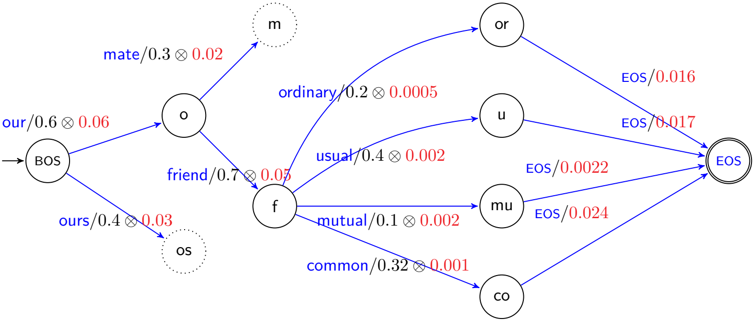

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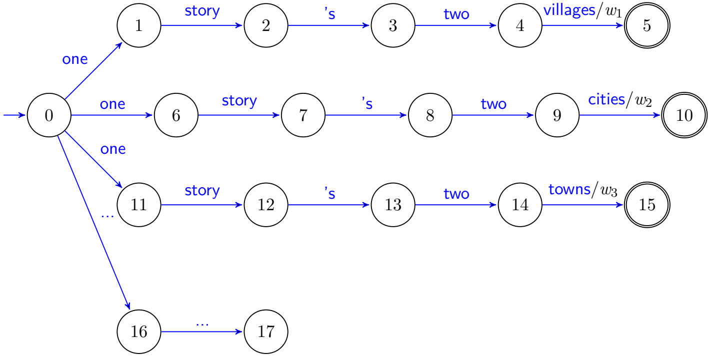
- making dependencies explicit through the graphical structure

Scoring whole sentences: example



Exhaustive enumeration

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- nodes must group derivations sharing the same context
- polynomial, though often prohibitive (impracticable)

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- inference algorithms
- techniques to make inference feasible for interesting models

Picking one solution

What do we pick out of the (whole) weighted space of solutions?

- best translation
- "minimum-loss" translation

Best translation

MAP

$$\mathbf{y}^* = \operatorname*{argmax}_{\mathbf{y}} \sum_{\mathrm{y}[\mathbf{d}]=\mathbf{y}} f(\mathbf{d}|\mathbf{x})$$

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Viterbi (approximation to MAP)

$$\mathbf{d}^* = \operatorname*{argmax}_{\mathbf{d}} f(\mathbf{d}|\mathbf{x})$$

- assumes the most likely derivation is enough

Minimum Bayes Risk translation

MBR

Minimum Bayes Risk translation

MBR

- incorporates a loss (or gain) function

Minimum Bayes Risk translation

MBR

- incorporates a loss (or gain) function

$$\mathbf{y} = \operatorname*{argmin}_{\mathbf{y}} \langle \text{loss}(\mathbf{y}, \mathbf{y}') \rangle_{p(\mathbf{y}'|\mathbf{x})}$$

Minimum Bayes Risk translation

MBR

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$$\mathbf{y} = \operatorname*{argmax}_{\mathbf{y}} \left\langle \mathrm{gain}(\mathbf{y}, \mathbf{y}') \right\rangle_{p(\mathbf{y}'|\mathbf{x})}$$

Minimum Bayes Risk translation

MBR

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$$\mathbf{y} = \underset{\mathbf{y}}{\operatorname{argmax}} \left\langle \mathrm{BLEU}(\mathbf{y}, \mathbf{y}') \right\rangle_{p(\mathbf{y}'|\mathbf{x})}$$

Minimum Bayes Risk translation

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$$\mathbf{y} = \underset{\mathbf{y}}{\operatorname{argmax}} \left\langle \mathrm{BLEU}(\mathbf{y}, \mathbf{y}') \right\rangle_{p(\mathbf{y}'|\mathbf{x})}$$

- assesses the risk associated with choosing any one translation

Minimum Bayes Risk translation

MBR

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$$\mathbf{y} = \operatorname*{argmax}_{\mathbf{y}} \sum_{\mathbf{y}'} \mathrm{BLEU}(\mathbf{y}, \mathbf{y}') p(\mathbf{y}'|\mathbf{x})$$

- assesses the risk associated with choosing any one translation
- requires the computation of expectations

Minimum Bayes Risk translation

MBR

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$$\mathbf{y} = \operatorname*{argmax}_{\mathbf{y}} \sum_{\mathbf{y}'} \mathrm{BLEU}(\mathbf{y}, \mathbf{y}') p(\mathbf{y}' | \mathbf{x})$$

- assesses the risk associated with choosing any one translation
- requires the computation of expectations
- which requires a probability

$$p(\mathbf{d}|\mathbf{x}) = \frac{f(\mathbf{d}|\mathbf{x})}{\sum_{\mathbf{d}'} f(\mathbf{d}'|\mathbf{x})}$$

Minimum Bayes Risk translation

MBR

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$$\mathbf{y} = \operatorname*{argmax}_{\mathbf{y}} \sum_{\mathbf{y}' \sim p(\mathbf{y}'|\mathbf{x})} \mathrm{BLEU}(\mathbf{y}, \mathbf{y}')$$

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- can be estimated by sampling translations

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$$\mathbf{y} = \operatorname*{argmax}_{\mathbf{y}} \sum_{\mathbf{y}'} \sum_{\mathbf{d}' \sim p(\mathbf{d}'|\mathbf{x})} \mathrm{BLEU}(\mathbf{y}, \mathrm{y}[\mathbf{d}'])$$

- assesses the risk associated with choosing any one translation
- requires the computation of expectations
- which requires a probability

$$p(\mathbf{d}|\mathbf{x}) = \frac{f(\mathbf{d}|\mathbf{x})}{\sum_{\mathbf{d}'} f(\mathbf{d}'|\mathbf{x})}$$

- can be estimated by sampling translations
- can be estimated from samples of derivations

DP-based Viterbi

Explore a truncated version of the full space

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- only a budgeted set of outgoing edges form each node

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  - beam search: exhaustively enumerates outgoing edges, ranks them, prunes all but k-best

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  - cube pruning: enumerates k edges in near best-first order

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In order to compare hypotheses more fairly

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- heuristic view of outside weights

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- heuristic view of outside weights
- cheap dynamic program that estimates the best possible way to complete any translation prefix

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In order to compare hypotheses more fairly

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- heuristic view of outside weights
- cheap dynamic program that estimates the best possible way to complete any translation prefix

[Koehn et al., 2003]
[Chiang, 2007]

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Uses derivations in an n-best list as samples

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[Kumar and Byrne, 2004]
[Tromble et al., 2008]

Sampling

Gibbs sampling

Sampling

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1. start with a draft translation

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2. resample from posterior (not all simultaneously):
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3. repeat 2

Sampling

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Adaptive rejection sampling

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1. design a simpler upperbound (e.g. unigram LM)

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Importance sampling

Sampling

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Adaptive rejection sampling

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Importance sampling

- you will hear from us (project 14) ;)

Sampling

Disadvantages

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4. ideal for MBR and tuning

Sampling

Disadvantages

- hard to do it without introducing bias
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Advantages

1. broad view of distribution
2. potential to incorporate arbitrarily complex features (at the sentence level at least)
3. sometimes unbiased
4. ideal for MBR and tuning
5. typically stupid simple to parallelise

Thanks!

Questions?

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