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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- a word replacement model

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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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um conto de duas cidades

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a tale of two **towns**

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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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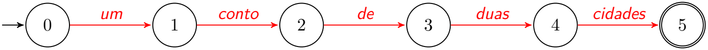
This makes $O(t^I)$ solutions

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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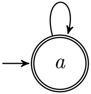

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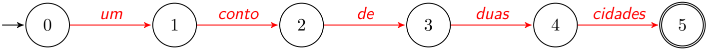

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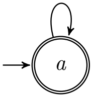

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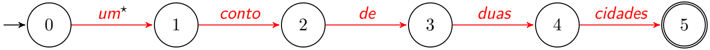

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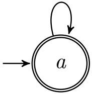

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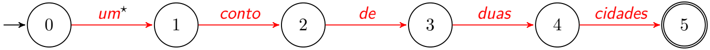

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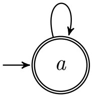

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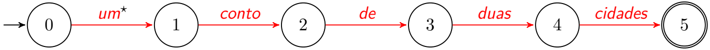

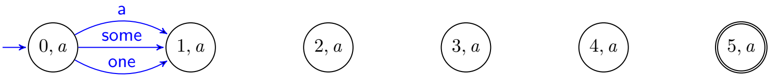

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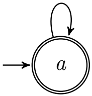

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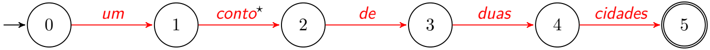

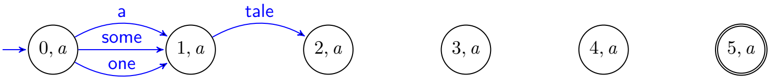

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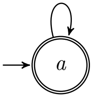

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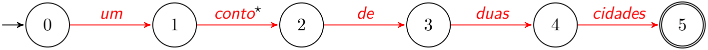

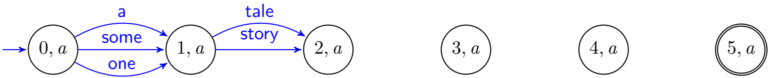

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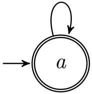

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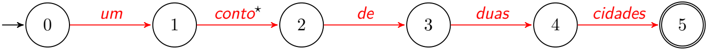

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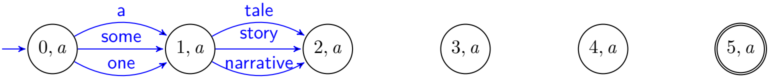

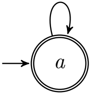

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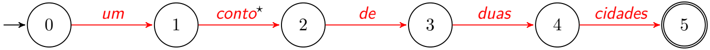

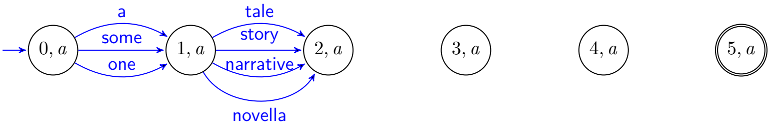

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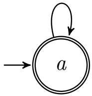

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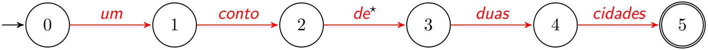

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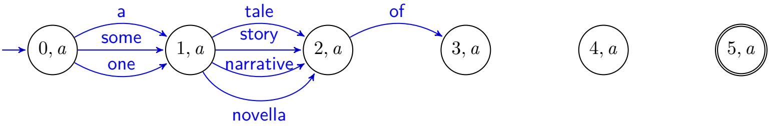

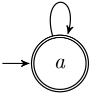

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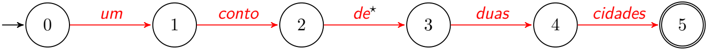

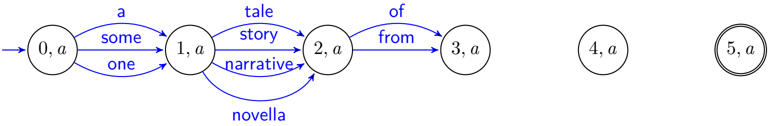

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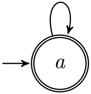

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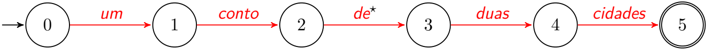

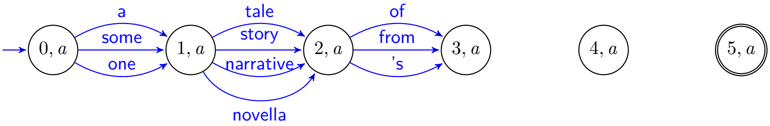

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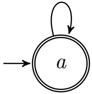

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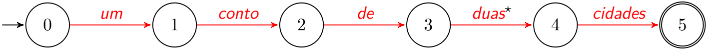

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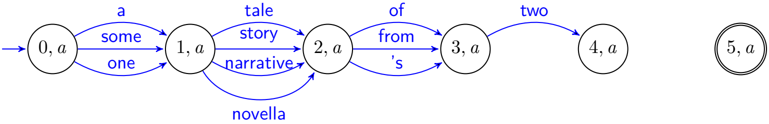

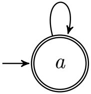

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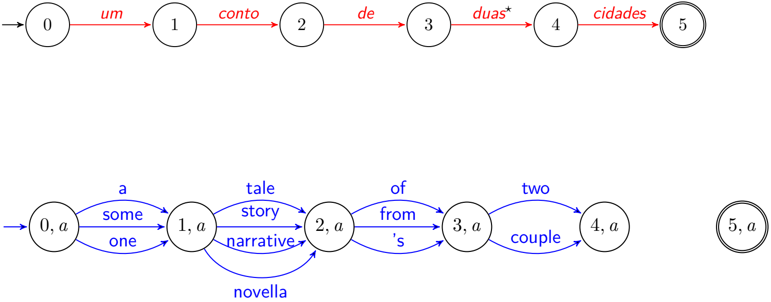

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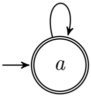

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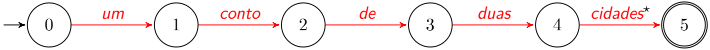

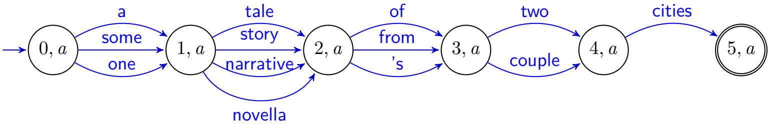

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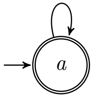

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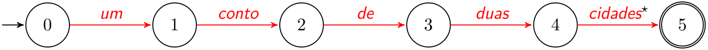

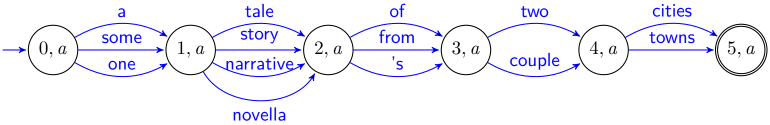

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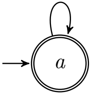

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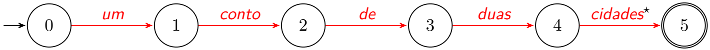

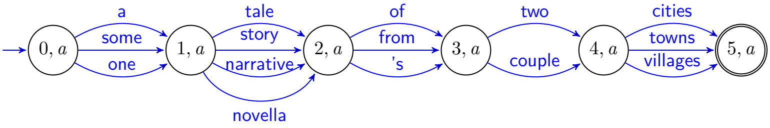

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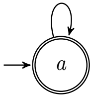
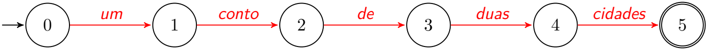
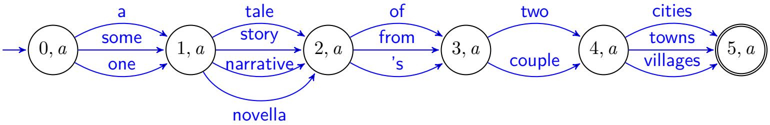
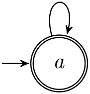


Space of solutions as intersection/composition



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





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

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Model of translational equivalences

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

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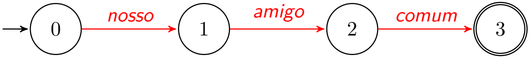
- easy to represent using finite-state transducers
- set of translations given by composition
- exponential number of solutions in linear space
- translates infinitely many sentences
  but not nearly enough interesting cases!

Monotone word-by-word translation: fail!

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



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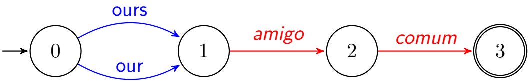

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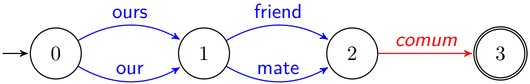

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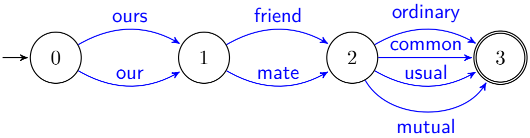

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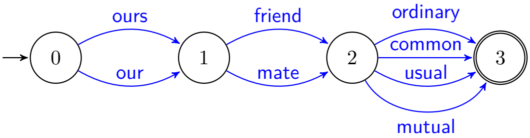


We simply cannot obtain a correct translation

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)

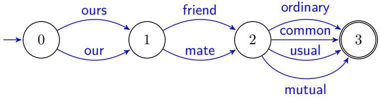
Reordering

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)

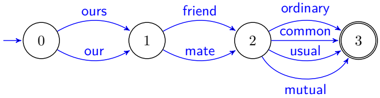
Translating arbitrary permutations

nosso amigo comum

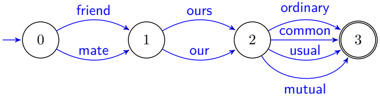


Translating arbitrary permutations

nosso amigo comum

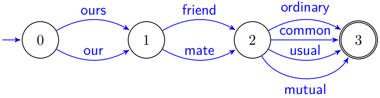


amigo nosso comum

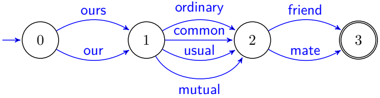


Translating arbitrary permutations

nosso amigo comum



nosso comum amigo



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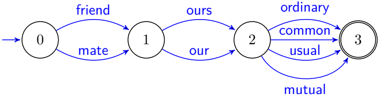

Translating arbitrary permutations

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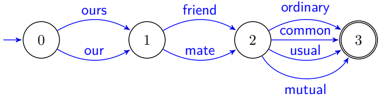

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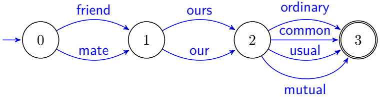
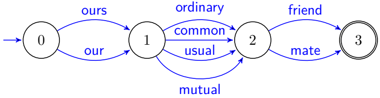
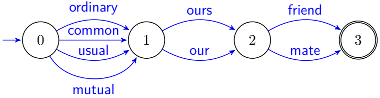


nosso comum amigo



comum nosso amigo



Translating arbitrary permutations

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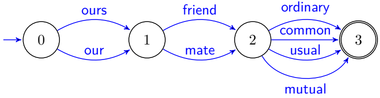
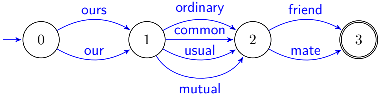


nosso comum amigo



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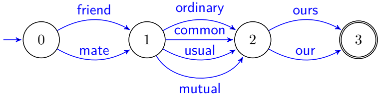

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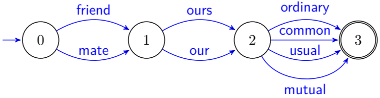

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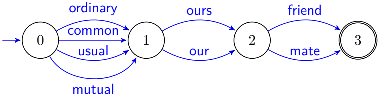
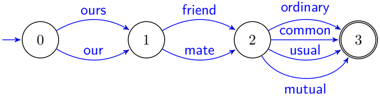


Translating arbitrary permutations

nosso amigo comum



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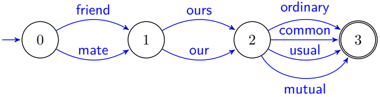

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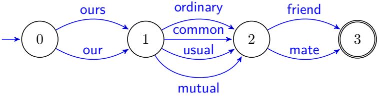

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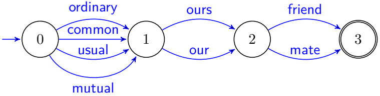
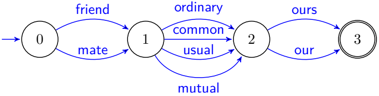


amigo comum nosso



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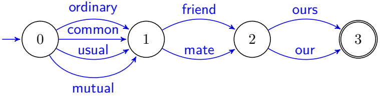
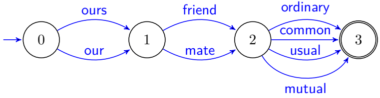


Translating arbitrary permutations

nosso amigo comum



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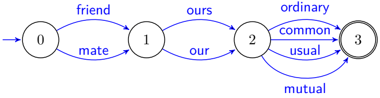

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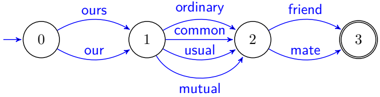

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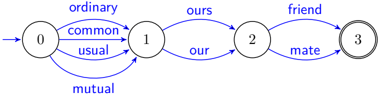

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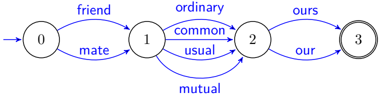

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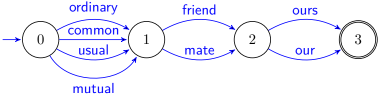
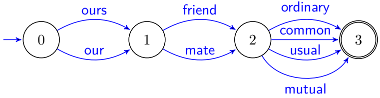


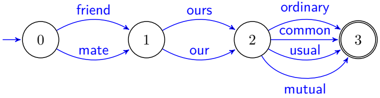
$3! = 3 \times 2 \times 1 = 6$ permutations

Translating arbitrary permutations

nosso amigo comum



amigo nosso comum



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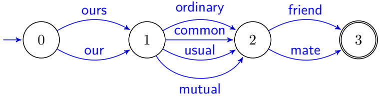
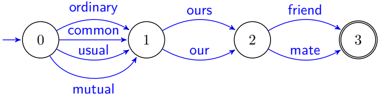
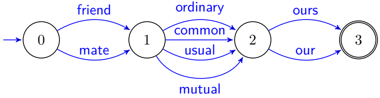


comum nosso amigo



amigo comum nosso



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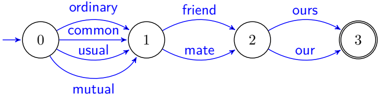
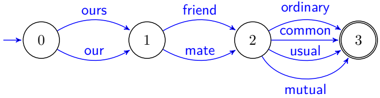


each has $2 \times 2 \times 4 = 16$ translations

Translating arbitrary permutations

nosso amigo comum



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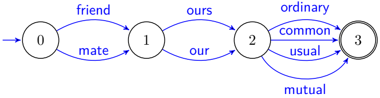

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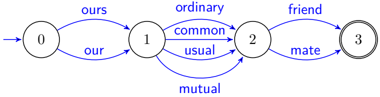
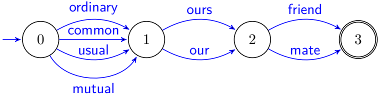
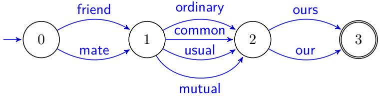


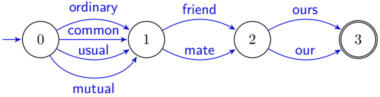
comum nosso amigo



amigo comum nosso



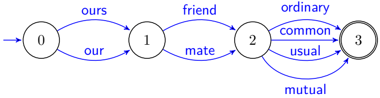
comum amigo nosso



amounting to $6 \times 16 = 96$ solutions

Translating arbitrary permutations

nosso amigo comum



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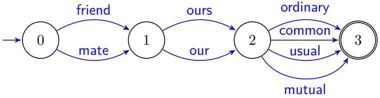

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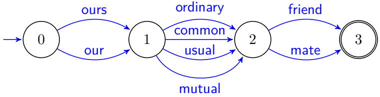

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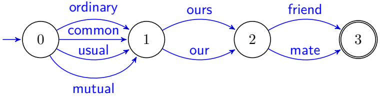

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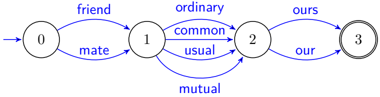

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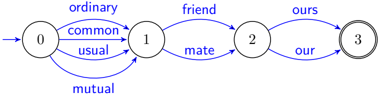


$I!$ permutations $\times$ t^I translations

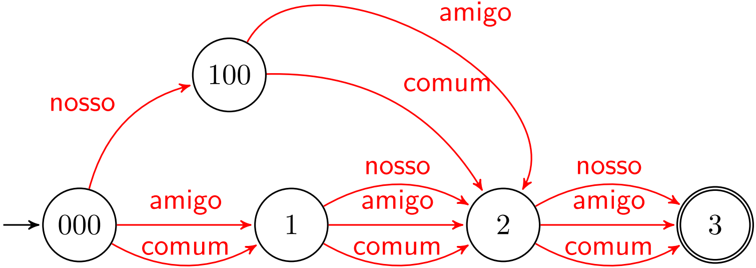
Packing permutations

Packing permutations

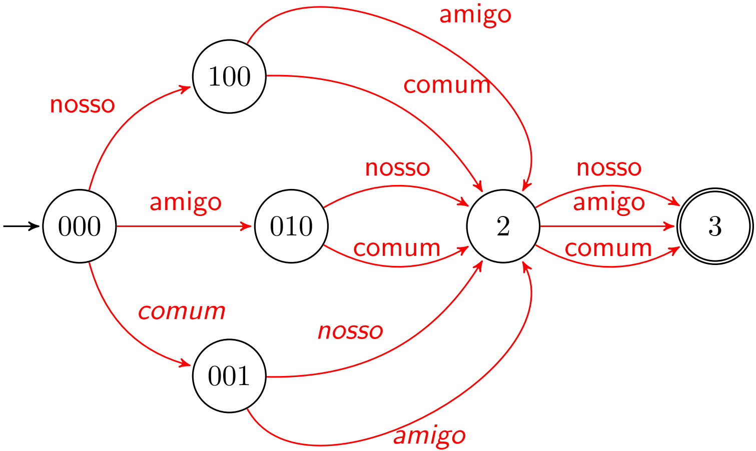
Packing permutations

Packing permutations

Packing permutations



Packing permutations



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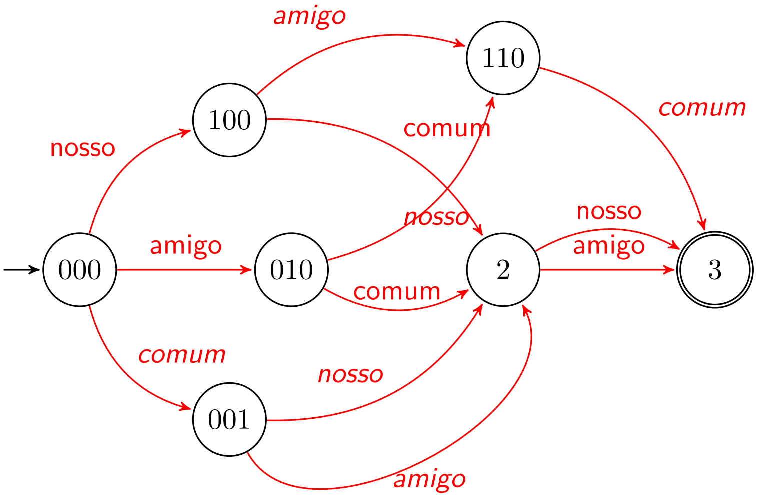
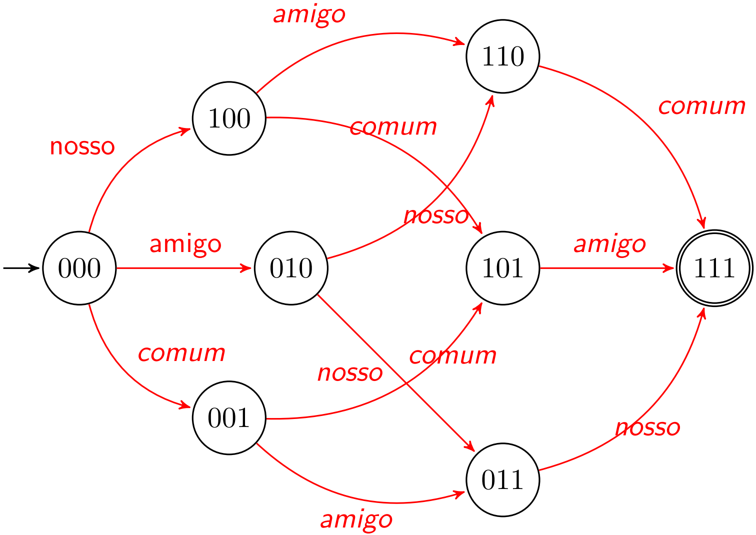


Packing permutations



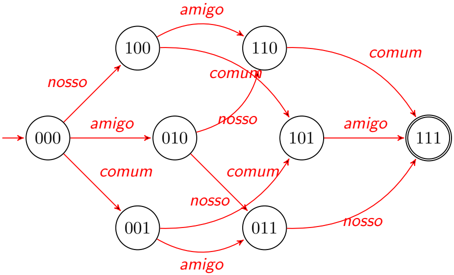
Packing permutations

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

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

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

$$\textsc{Axiom}$$

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

$$\textsc{Expand}$$

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

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

Template

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

Deductive logic

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

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

$$\textsc{Axiom}$$

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

$$\textsc{Expand}$$

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

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

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

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

AXIOM

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

EXPAND

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

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

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

Deductive logic

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

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

$\textsc{Axiom}$

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

$\textsc{Expand}$

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

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

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

Deductive logic

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

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

Axiom

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

Expand

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

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*$_3$

$$\begin{array}{ll} \text{ITEM} & \left[\{0,1\}^I\right] \\ \text{GOAL} & \left[1^I\right] \\ \text{AXIOM} & \\ \end{array}$$

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

EXPAND

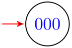
$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$

Instantiated deductive logic program

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

`Axiom`

$[000]$



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

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Instantiated deductive logic program

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

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

AXIOM

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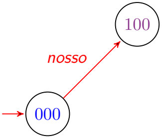
Source: *nosso*$_1$ *amigo*$_2$ *comum*$_3$

`Axiom`

$[000]$

`Expand`

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



Instantiated deductive logic program

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

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

AXIOM

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

EXPAND

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

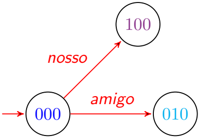
`Axiom`

$[000]$

`Expand`

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

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



Instantiated deductive logic program

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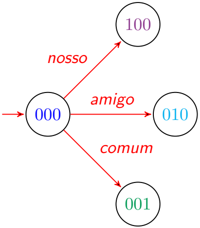
`Axiom`

$[000]$

`Expand`

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



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

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

AXIOM

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

EXPAND

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Instantiated deductive logic program

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`Axiom`

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`Expand`

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

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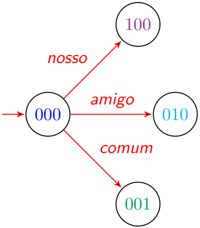
$[000](i=3) \rightarrow [001]$

$[100](i=1)$ ✗



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$\textsc{Expand}$

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

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

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$[100](i=1)$ ✗

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

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

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

AXIOM

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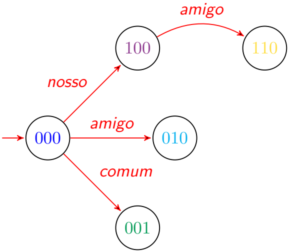
EXPAND

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

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

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

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

$[100](i=1)$ ✗

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

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

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

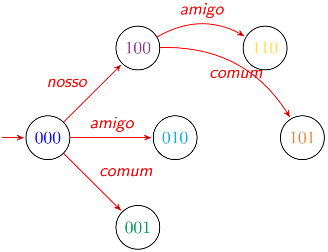
GOAL $\left[1^I\right]$

AXIOM

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

EXPAND

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

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

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

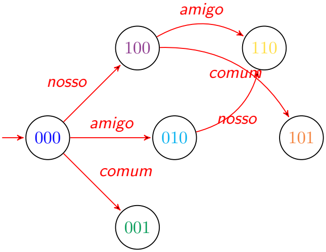
GOAL $\left[1^I\right]$

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

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

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

AXIOM

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

EXPAND

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

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

Axiom

$[000]$

Expand

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

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

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

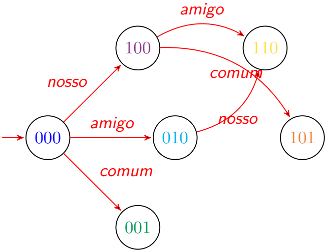
$[100](i = 1)$ ✗

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

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

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

$[010](i = 2)$ ✗



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

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

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

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

$[100](i=1)$ ✗

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

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

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

$[010](i=2)$ ✗

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

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

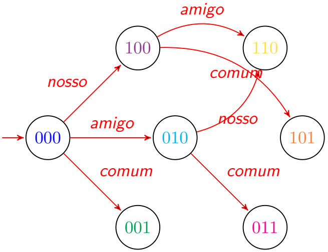
GOAL $\left[1^I\right]$

AXIOM

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

EXPAND

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

$[000](i=1) \rightarrow [100]$
$[000](i=2) \rightarrow [010]$
$[000](i=3) \rightarrow [001]$
$[100](i=1)$ ✗
$[100](i=2) \rightarrow [110]$
$[100](i=3) \rightarrow [101]$
$[010](i=1) \rightarrow [110]$
$[010](i=2)$ ✗
$[010](i=3) \rightarrow [011]$
$[001](i=1) \rightarrow [101]$

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

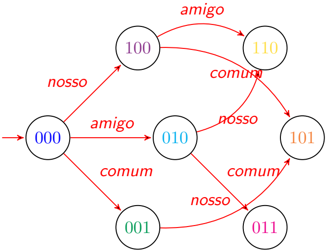
GOAL $\left[1^I\right]$

AXIOM

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

EXPAND

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

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

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$[100](i=1)$ ✗

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

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

$[010](i=2)$ ✗

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

$[001](i=1) \rightarrow [101]$

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

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

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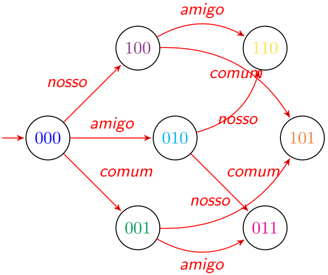
$$\textsc{Expand} \quad \frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$



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

`Axiom`

$[000]$

`Expand`

$[000](i=1) \rightarrow [100]$
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$[100](i=3) \rightarrow [101]$
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$[010](i=2)$ ✗
$[010](i=3) \rightarrow [011]$
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$[001](i=2) \rightarrow [011]$
$[001](i=3)$ ✗

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

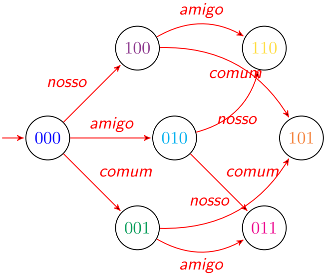
GOAL $\left[1^I\right]$

AXIOM

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

EXPAND

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



Instantiated deductive logic program

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

Axiom

$[000]$

Expand

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

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

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

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

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

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

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

$[001](i=1) \rightarrow [101]$

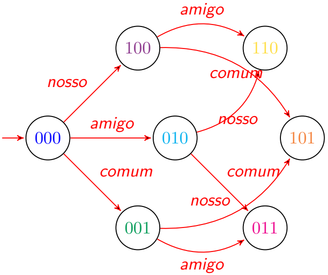
$[001](i=2) \rightarrow [011]$

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

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

$$\textsc{Axiom} \quad \overline{[0^I]}$$

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

$[000](i=1) \rightarrow [100]$
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$[000](i=3) \rightarrow [001]$
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ITEM $\left[\{0,1\}^I\right]$
GOAL $\left[1^I\right]$
AXIOM

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

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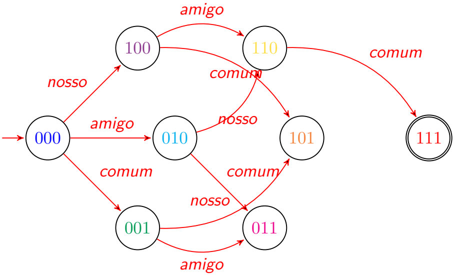
$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$



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$[000]$

`Expand`

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

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

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

AXIOM

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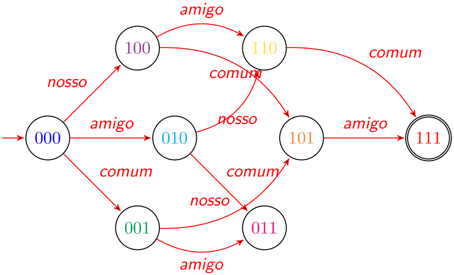
EXPAND

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



Instantiated deductive logic program

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

`Axiom`

$[000]$

`Expand`

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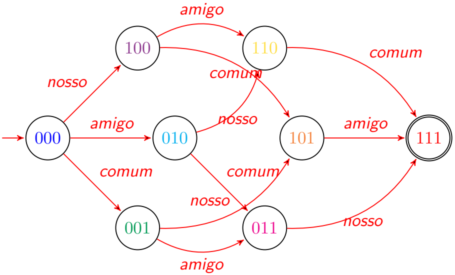

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`Axiom`

$[000]$

`Expand`

$[000](i=1) \to [100]$
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$[110](i=3) \to [111]$
$[101](i=2) \to [111]$
$[011](i=1) \to [111]$

`Goal`

$[111]$

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

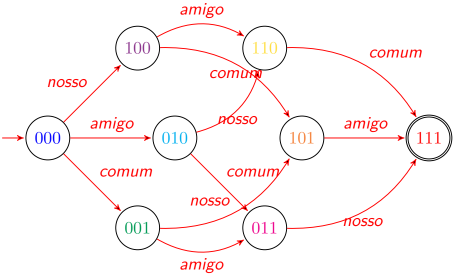
GOAL $\left[1^I\right]$

AXIOM

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

EXPAND

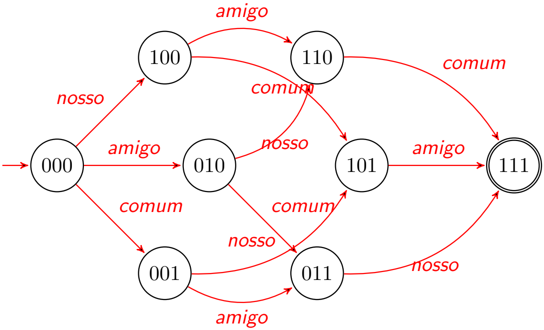
$$\frac{[C]}{[\alpha_i(C)]} \quad \begin{array}{l} 1 \le i \le I \\ c_i = \bar{0} \end{array}$$



Word replacement with unconstrained reordering

Source: *nosso amigo comum*

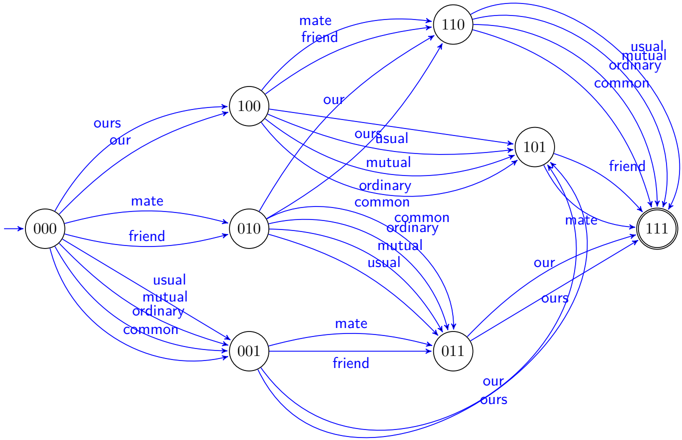
Word replacement with unconstrained reordering



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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Direction

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

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Solution

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Solution

- constrain reordering **:D**

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

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- generalised TSP

Direction

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

Solution

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

Ad-hoc distortion limit

Several flavours of distortion limit [Lopez, 2009]

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- limit reordering as a function of the number of skipped words

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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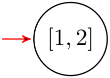
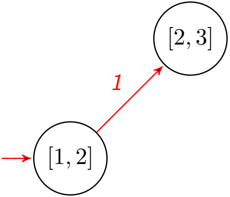


WLd (example)

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



WLd (example)

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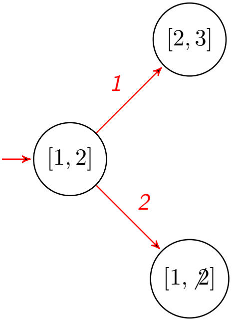

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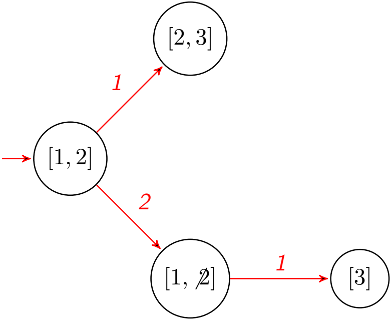

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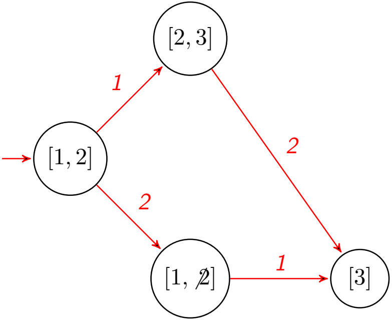

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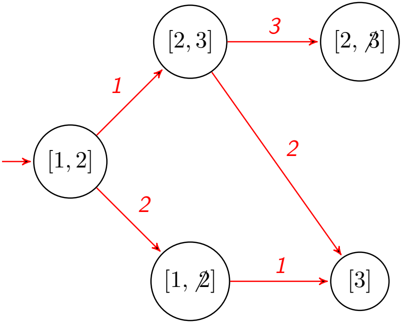

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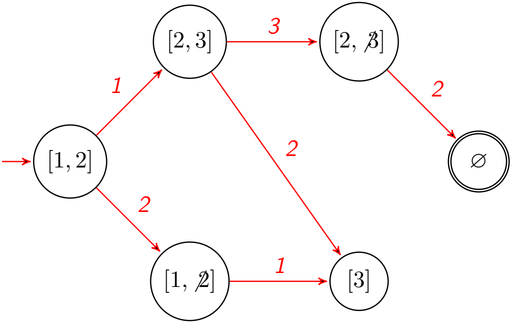

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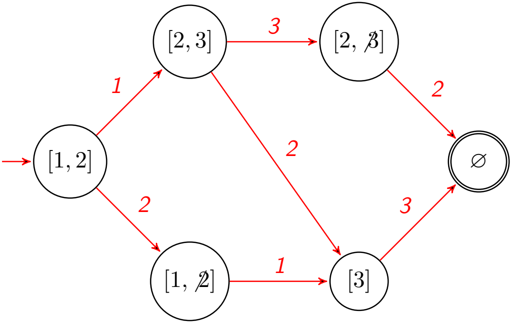
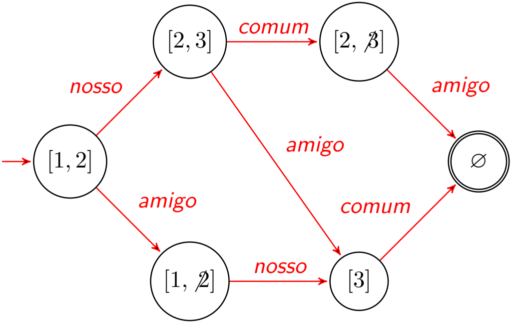


WLd (example)

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

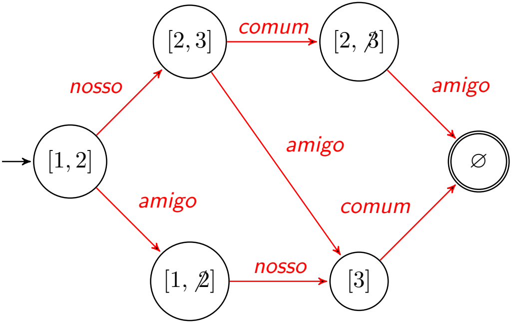
$$\textsc{Non-Adjacent}$$

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

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

Word replacement with reordering constrained by WL2

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



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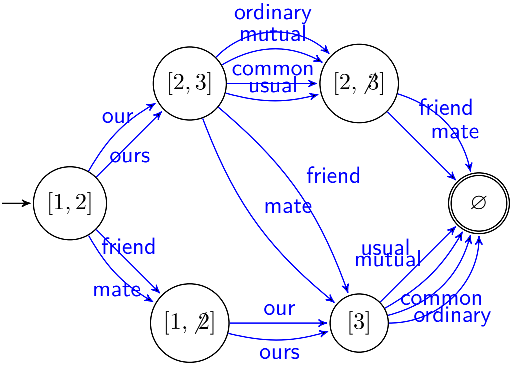

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- can we do better?

ITGs

Inversion Transduction Grammars (ITGs) [Wu, 1997]

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- $X \to XX$
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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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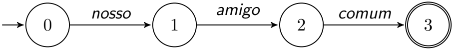

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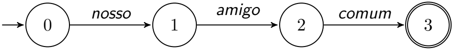

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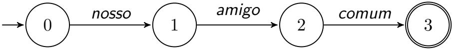

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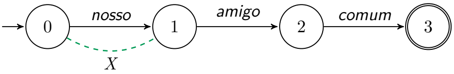

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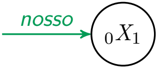

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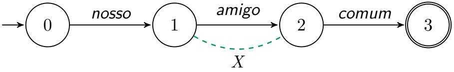

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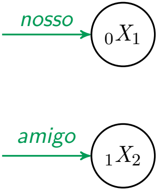

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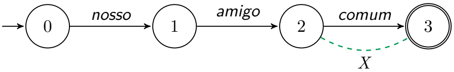

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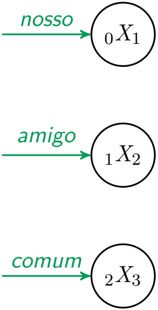

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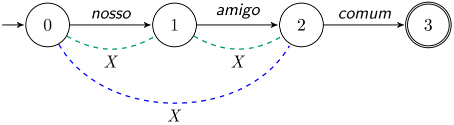

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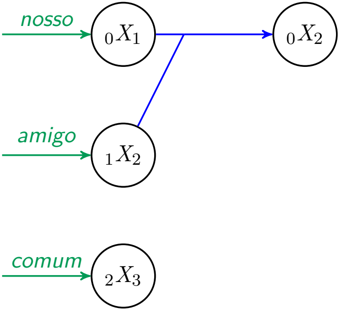

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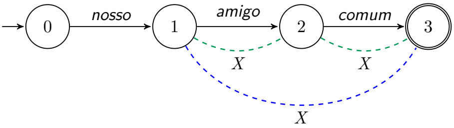

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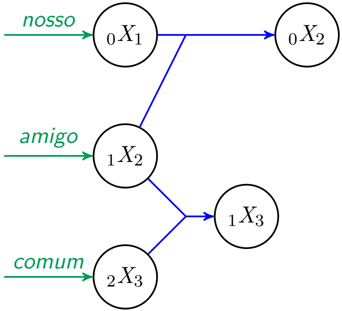

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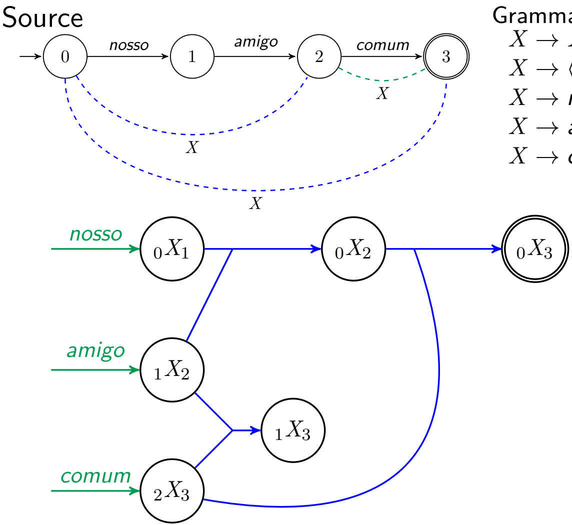

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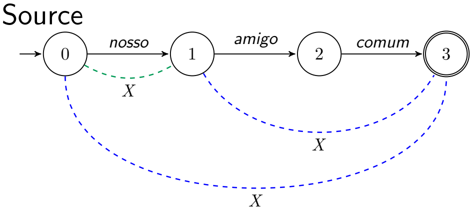

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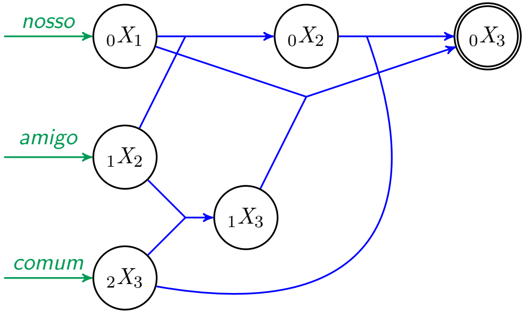

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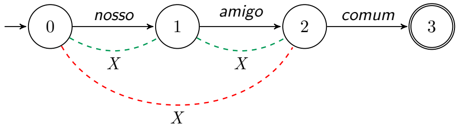

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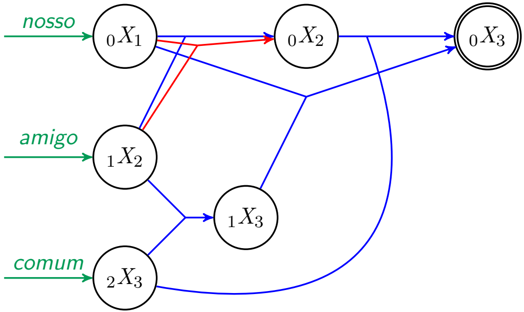

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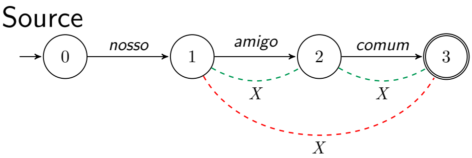

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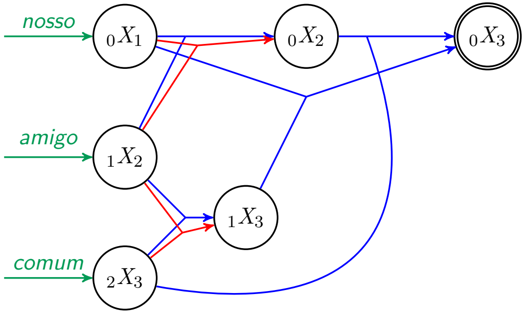

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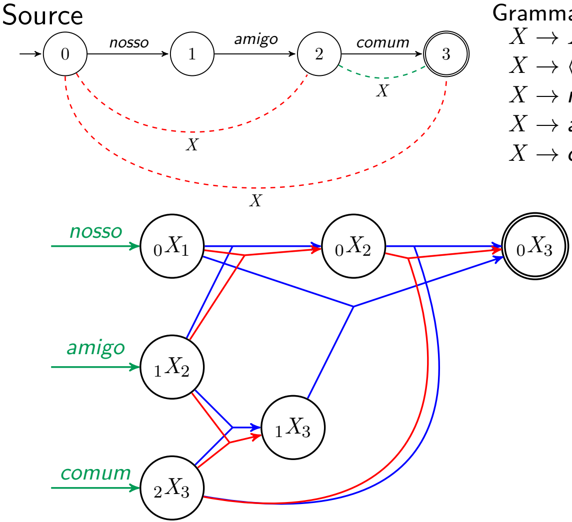

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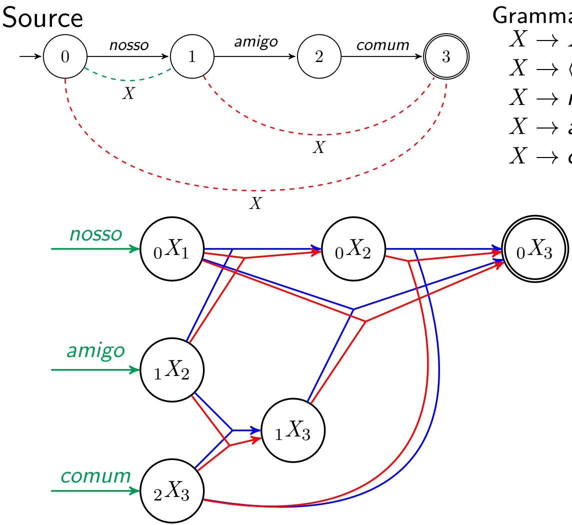

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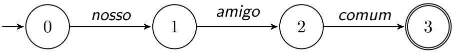

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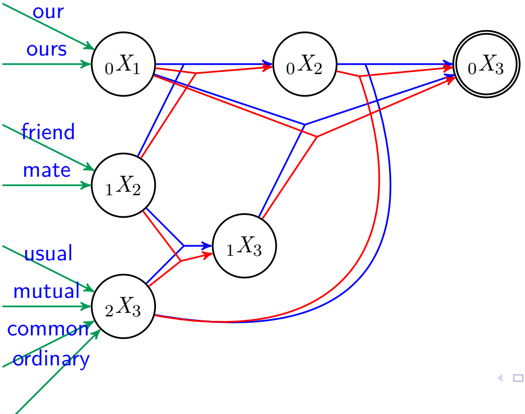

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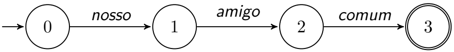

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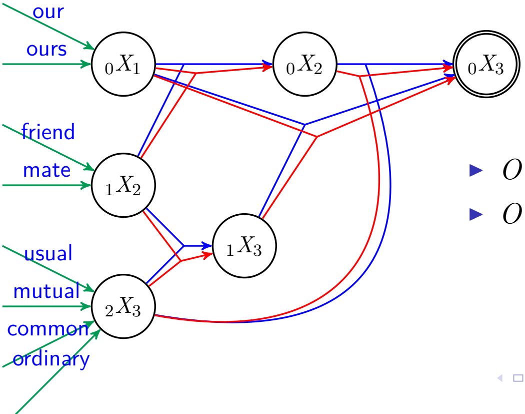
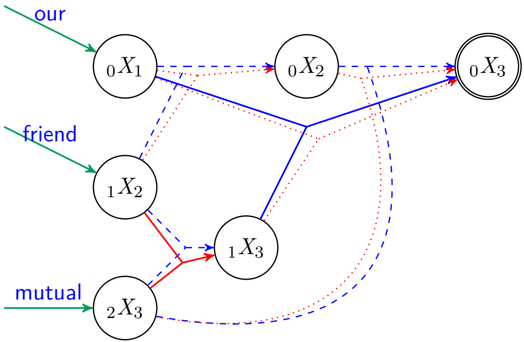


- $O(I^3)$ nodes
- $O(tI^3)$ edges

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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Phrase mappings

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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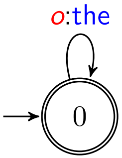

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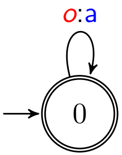

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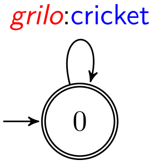

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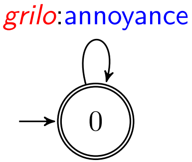

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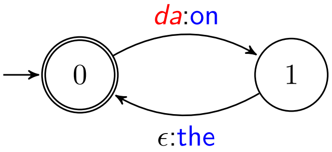

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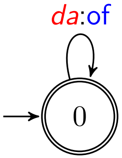

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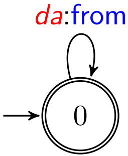

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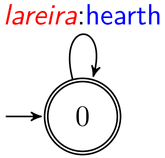

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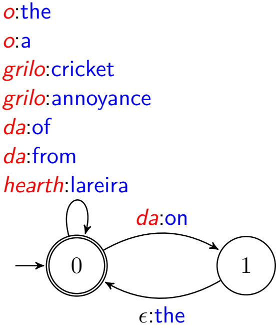

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- complexity remains
  - linear with sentence length
  - exponential with distortion limit

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

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   - 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

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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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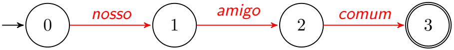
Structural independence: scoring rules in isolation

Scoring rules independently



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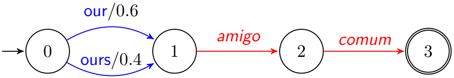

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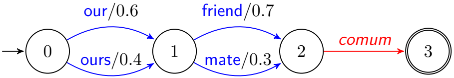

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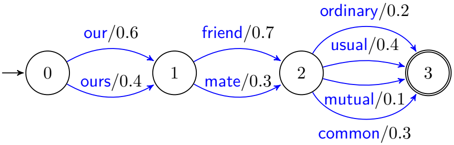

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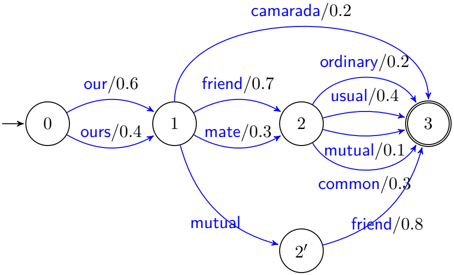

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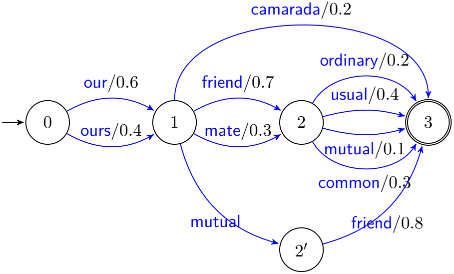

inference runs in time linear with the size of the automaton

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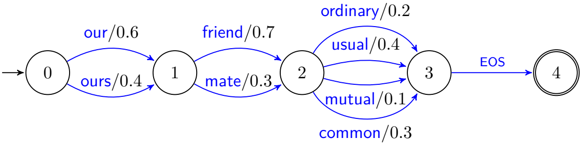
Certain aspects do not comply with such assumptions

- fluency as captured by an n-gram LM component

Scoring strings with a 2-gram LM



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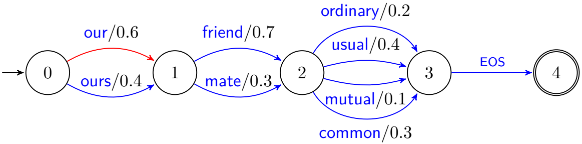

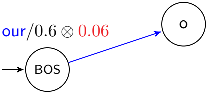

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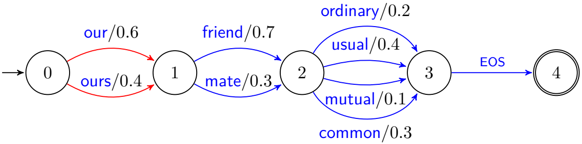

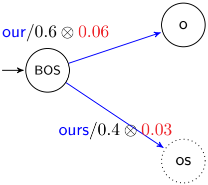

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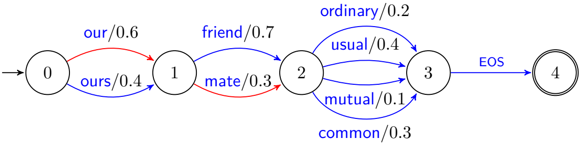

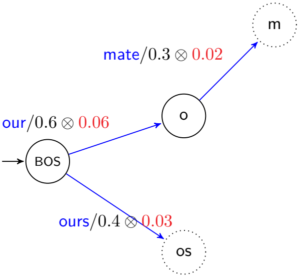

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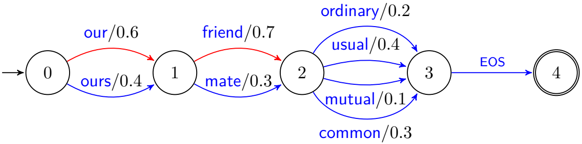

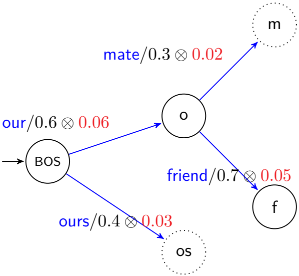

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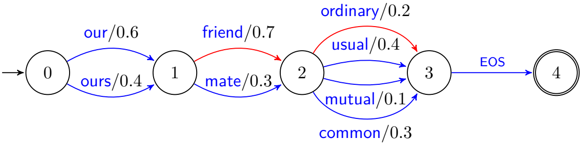

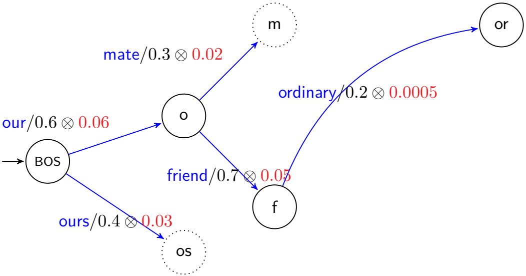

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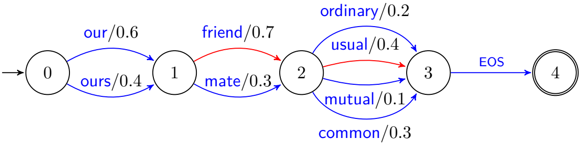

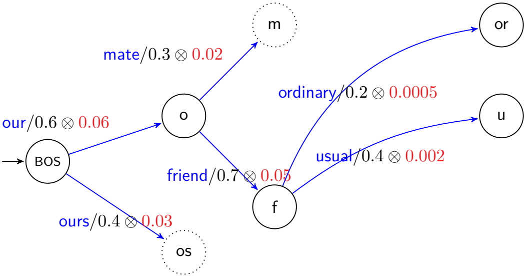

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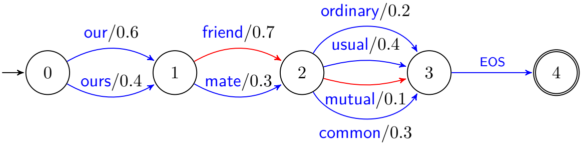

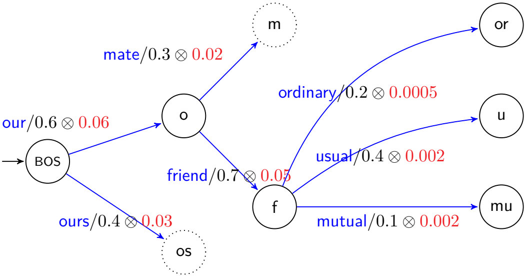

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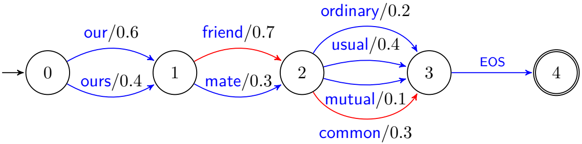

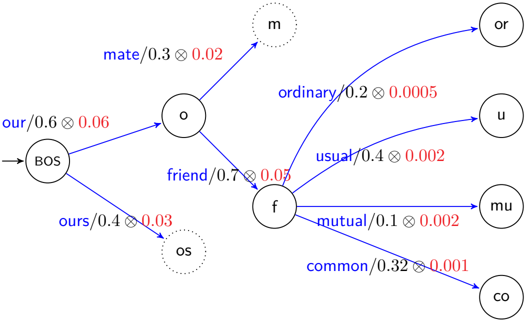

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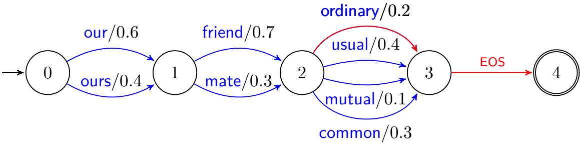

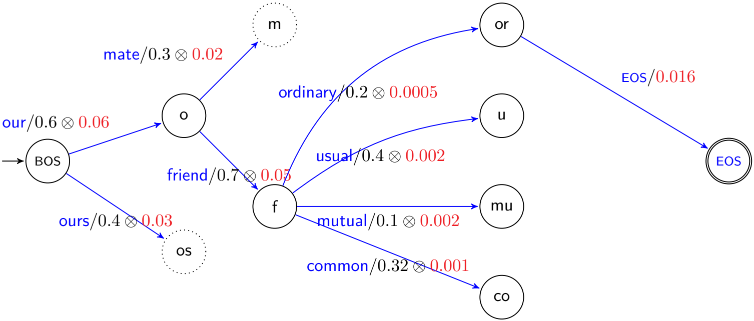

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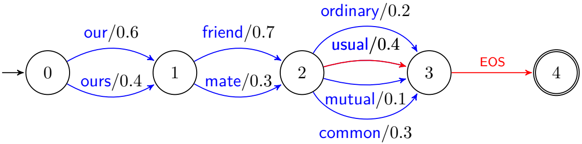

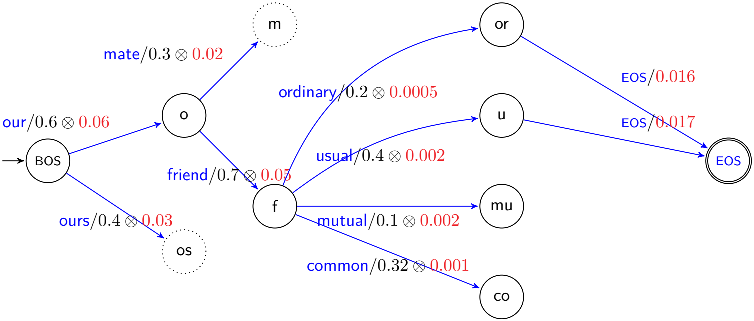

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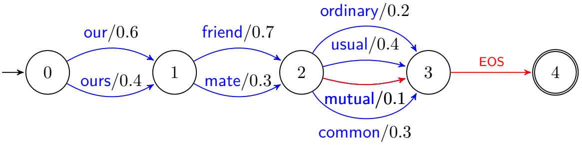

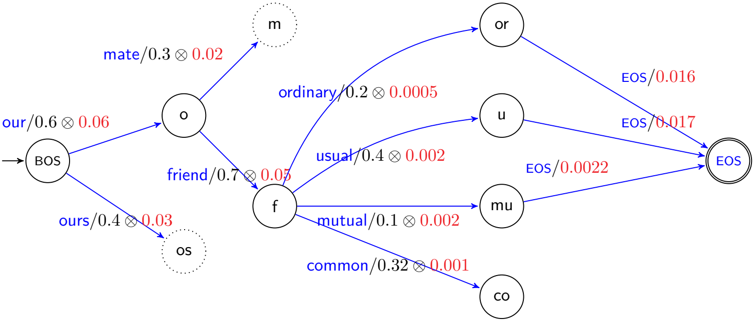

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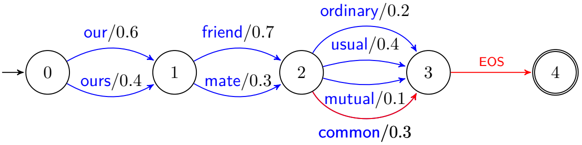

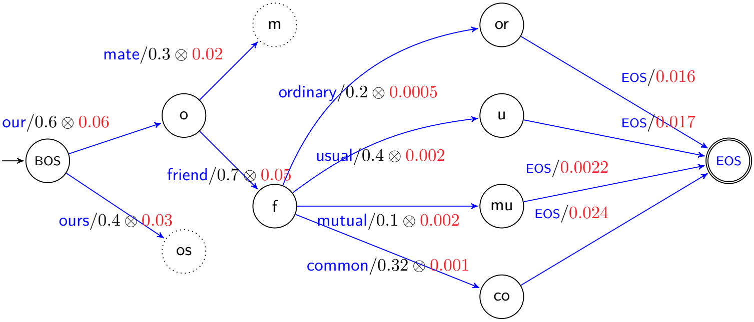

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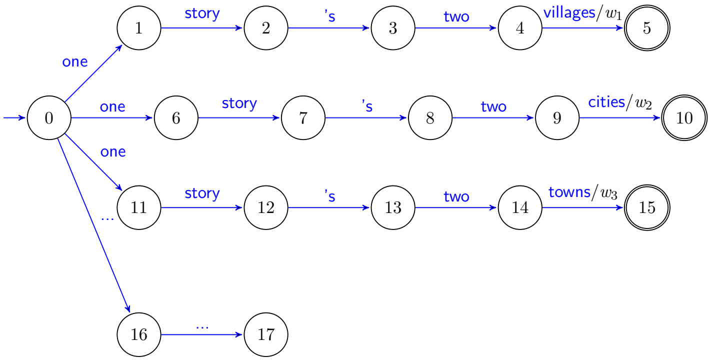
- requires fully unpacking the representation
- making dependencies explicit through the graphical structure

Scoring whole sentences: example



Exhaustive enumeration

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

Recap 4

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What's left?

- more examples of models and impact on representation
  - distance-based reordering
  - lexicalised models
  - a global feature function
- inference algorithms

Recap 4

1. a characterisation the space of solutions
2. a linear parameterisation of the model
3. impact of parameterisation on packed representations

What's left?

- more examples of models and impact on representation
  - distance-based reordering
  - lexicalised models
  - a global feature function
- 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

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- incorporates a loss (or gain) function

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

Minimum Bayes Risk translation

MBR

- incorporates a loss (or gain) function

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

Minimum Bayes Risk translation

MBR

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

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

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

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

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

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

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

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5. repeat 2-3 until acceptance rate is reasonable (e.g. 5-10%)

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Advantages

1. broad view of distribution
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3. sometimes unbiased
4. ideal for MBR and tuning
5. typically stupid simple to parallelise

Thanks!

Questions?

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