Decoding for SMT

Wilker Aziz

University of Sheffield
Sheffield, UK
w.aziz@sheffield.ac.uk

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About this talk

This talk is not

- a review of beam search, cube pruning or any specific decoding algorithm

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This talk is about

- understanding what makes decoding difficult

For starters

Let's think of decoding as referring to an inference task

- making predictions
  - decisions in a highly combinatorial space of possibilities

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   (discuss tractability issues)

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   (discuss tractability issues)
2. understand the impact of parameterisation

For starters

Let's think of decoding as referring to an inference task

- making predictions
  - decisions in a highly combinatorial space of possibilities

Goals

1. characterise the space of solutions
   (discuss tractability issues)
2. understand the impact of parameterisation
3. survey decoding techniques

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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- with no insertions or deletions

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- 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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a tale of two **towns**

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a tale of two **towns**

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a tale of **couple cities**

a tale of couple **towns**

Monotone word-by-word translation: solutions

um conto de duas cidades
a tale of two cities
a tale of two **towns**
a tale of two **villages**
a tale of **couple cities**
a tale of couple **towns**
...

um	{a, some, one}
conto	{tale, story, narrative, novella}
de	{of, from, 's}
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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

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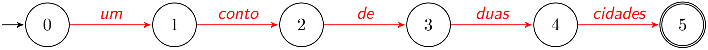
This makes $O(t^I)$ solutions

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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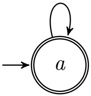

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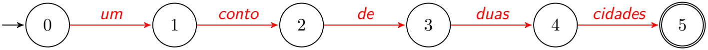

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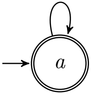

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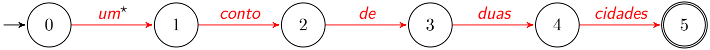

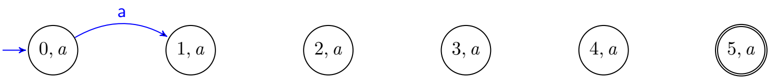

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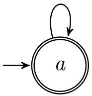

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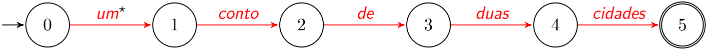

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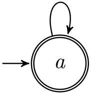

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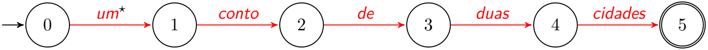

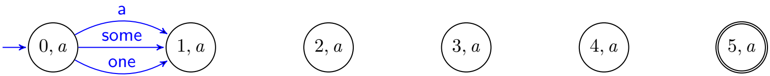

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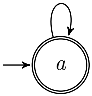

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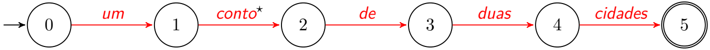

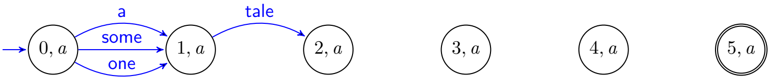

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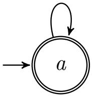

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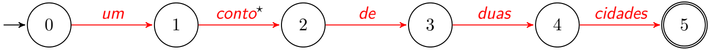

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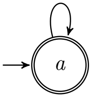

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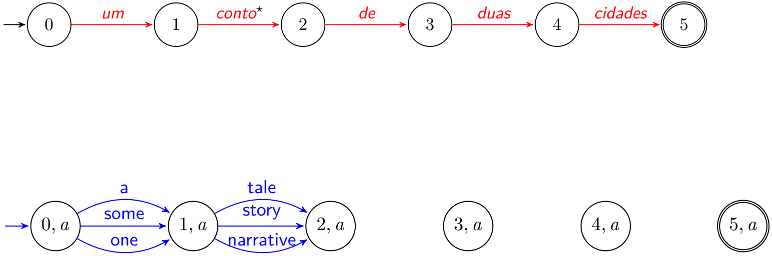

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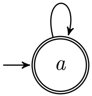

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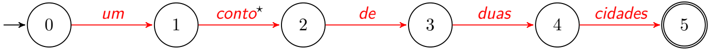

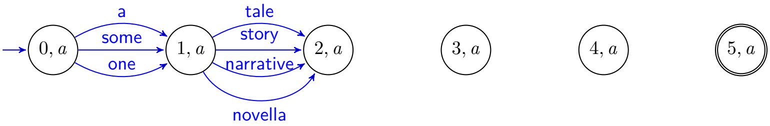

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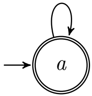

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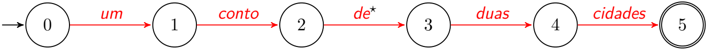

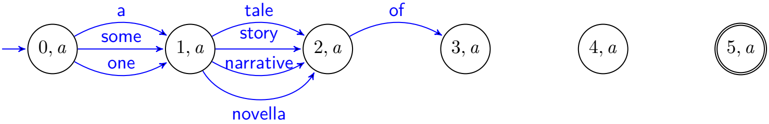

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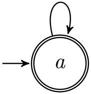

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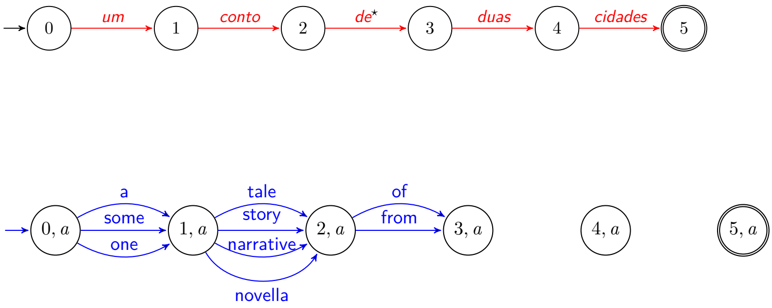

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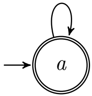

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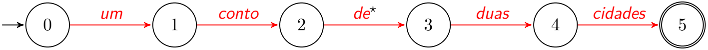

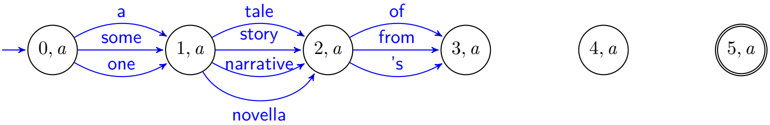

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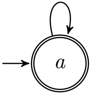

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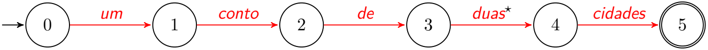

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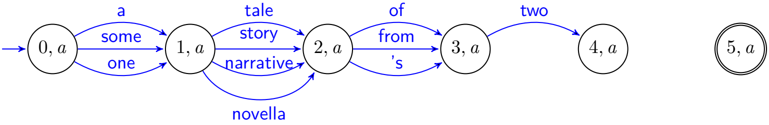

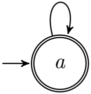

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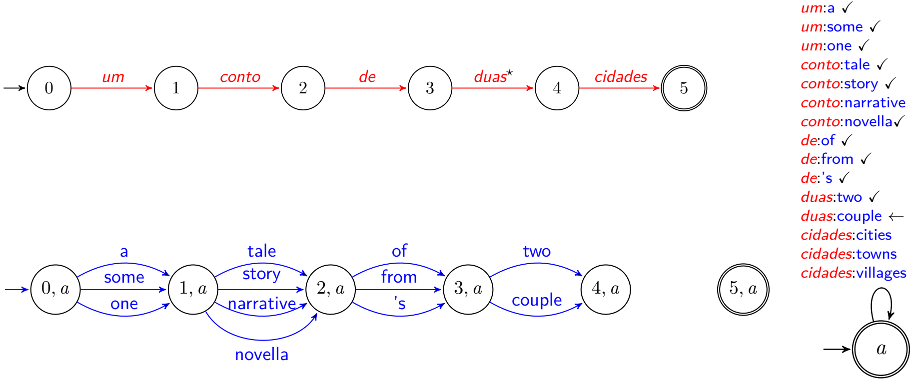

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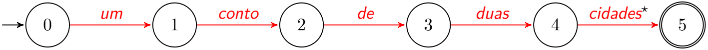

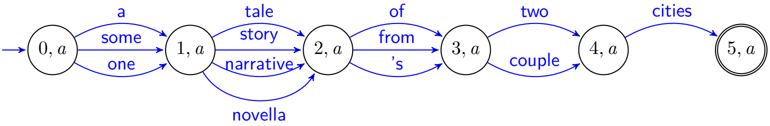

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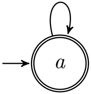

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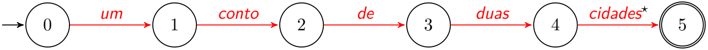

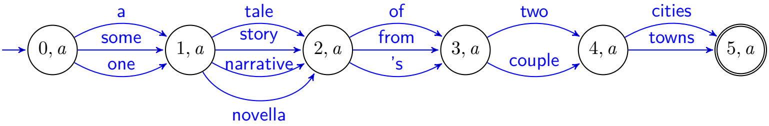

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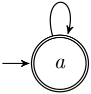

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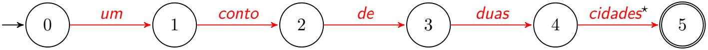

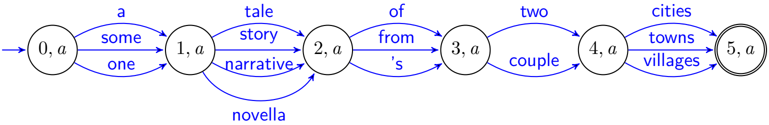

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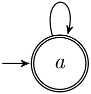
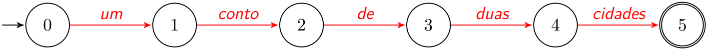
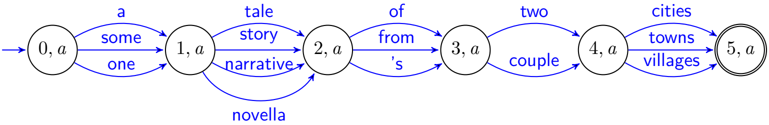
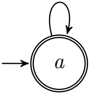


Space of solutions as intersection/composition





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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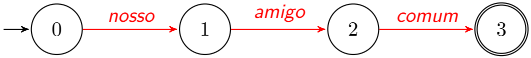
Monotone word replacement model

- 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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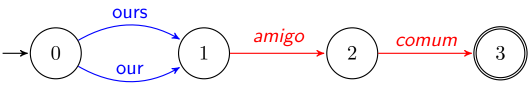

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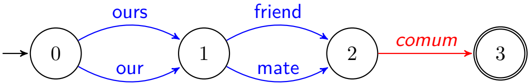

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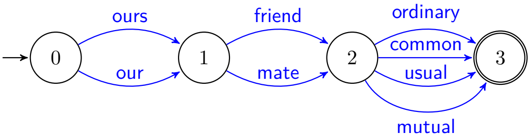

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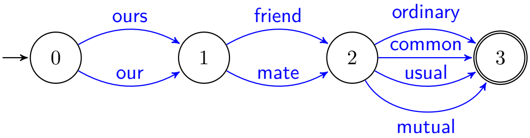


We simply cannot obtain a correct translation

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)

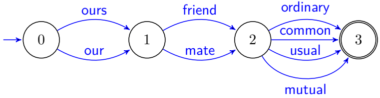
Reordering

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)

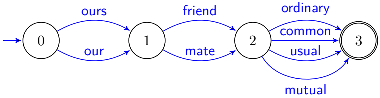
Translating arbitrary permutations

nosso amigo comum

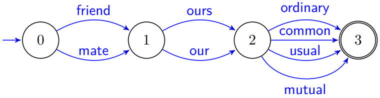


Translating arbitrary permutations

nosso amigo comum



amigo nosso comum



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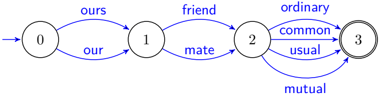
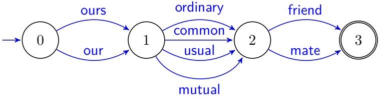
nosso amigo comum



nosso comum amigo



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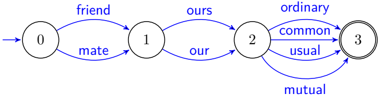
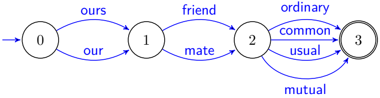


Translating arbitrary permutations

nosso amigo comum



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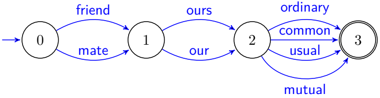
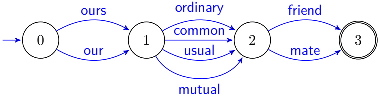
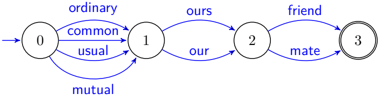


nosso comum amigo



comum nosso amigo



Translating arbitrary permutations

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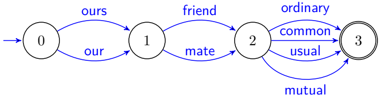
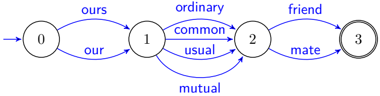


nosso comum amigo



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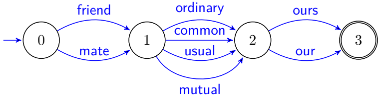

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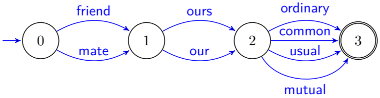
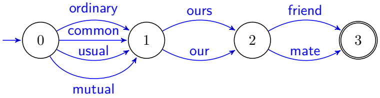


comum nosso amigo



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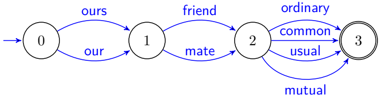

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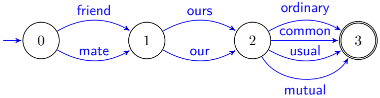

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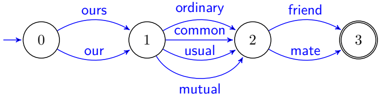

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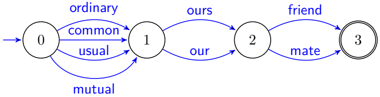

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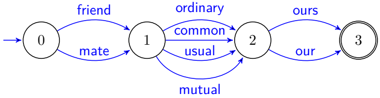

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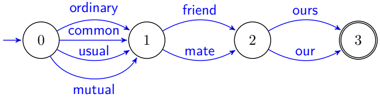

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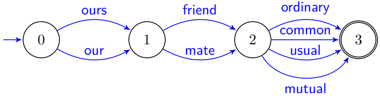

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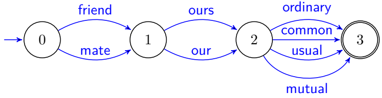

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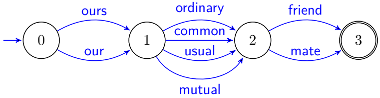

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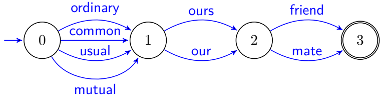

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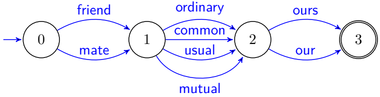

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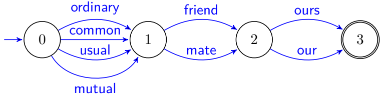
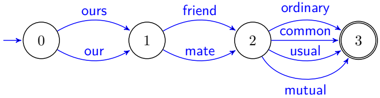


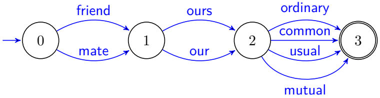
$3! = 3 \times 2 \times 1 = 6$ permutations

Translating arbitrary permutations

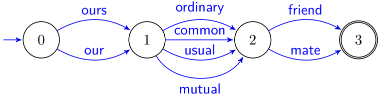
nosso amigo comum



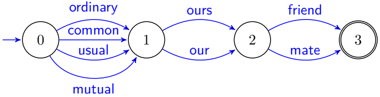
amigo nosso comum



nosso comum amigo



comum nosso amigo



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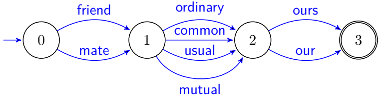

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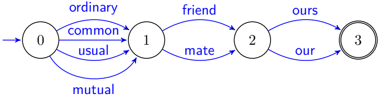
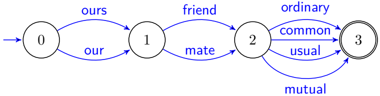


each has $2 \times 2 \times 4 = 16$ translations

Translating arbitrary permutations

nosso amigo comum



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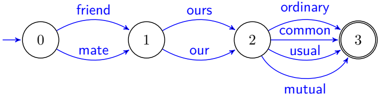

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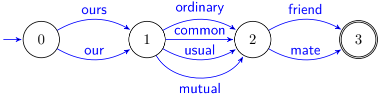

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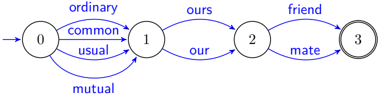
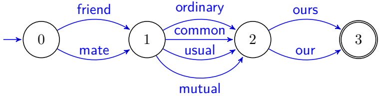
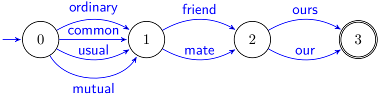


amigo comum nosso



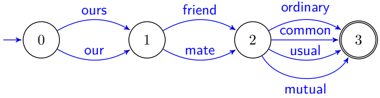
comum amigo nosso



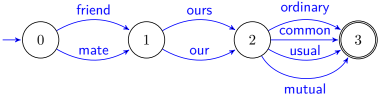
amounting to $6 \times 16 = 96$ solutions

Translating arbitrary permutations

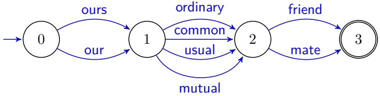
nosso amigo comum



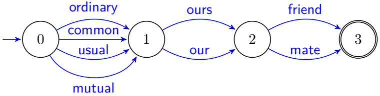
amigo nosso comum



nosso comum amigo



comum nosso amigo



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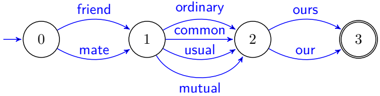

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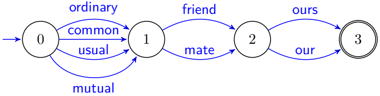

$I!$ permutations $\times$ t^I translations

Packing permutations

Packing permutations

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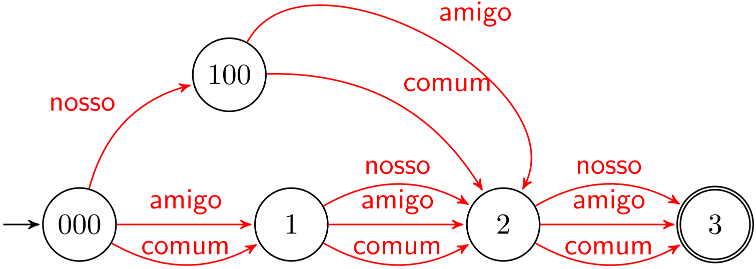
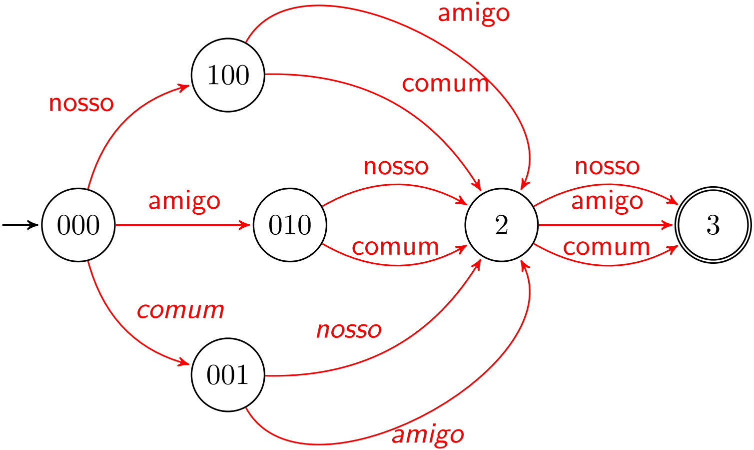
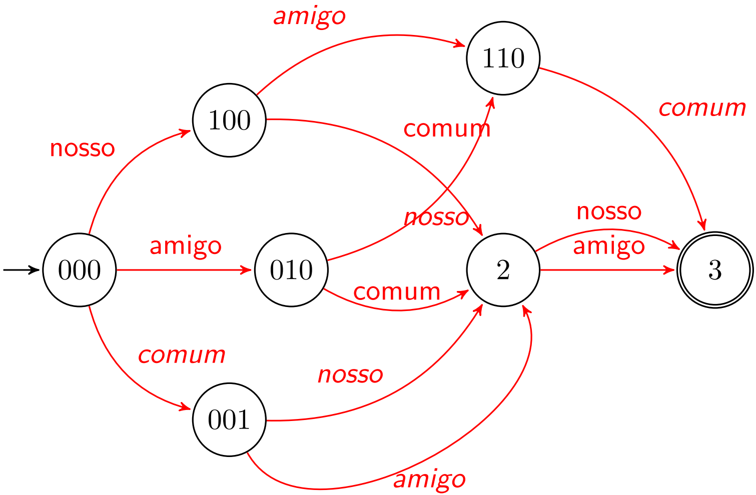


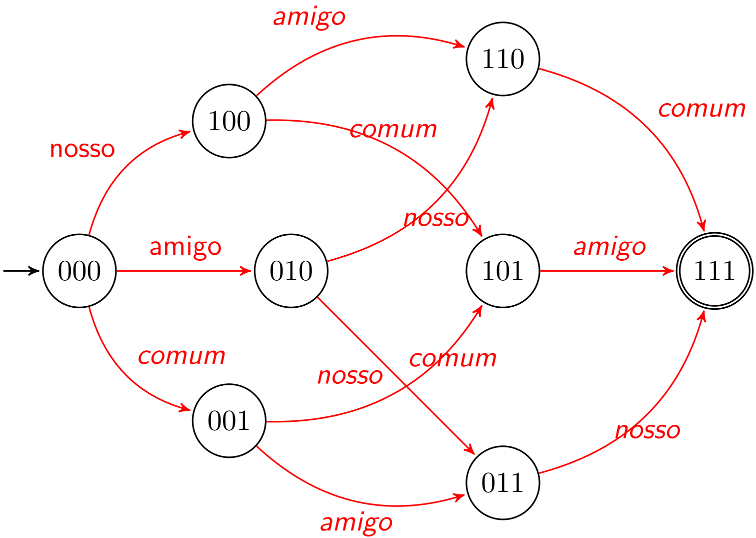
Packing permutations



Packing permutations



Packing permutations



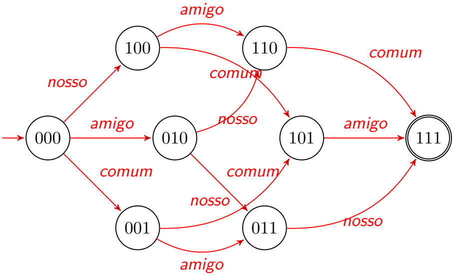
Packing permutations

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

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

Lattice

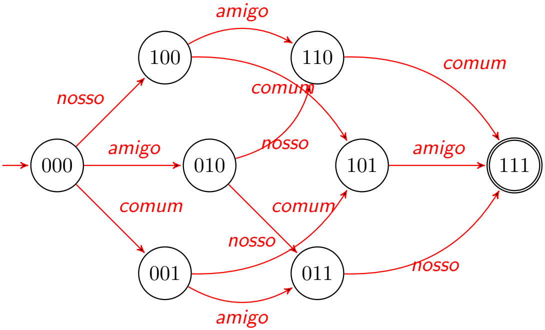
- $O(2^I)$ states
- $O(I \times 2^I)$ transitions



Word replacement with unconstrained reordering

Source: *nosso amigo comum*

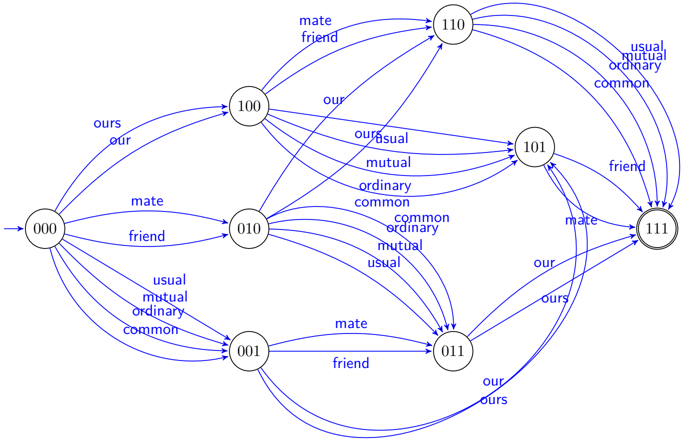
Word replacement with unconstrained reordering



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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- NP-complete [Knight, 1999]
- generalised TSP

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Direction

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

Problem!

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

- NP-complete [Knight, 1999]
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- constrain reordering **:D**
- **0.o** but how?

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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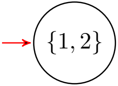

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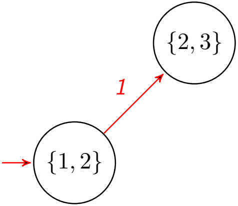

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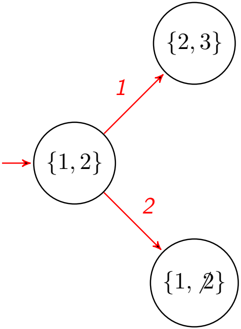

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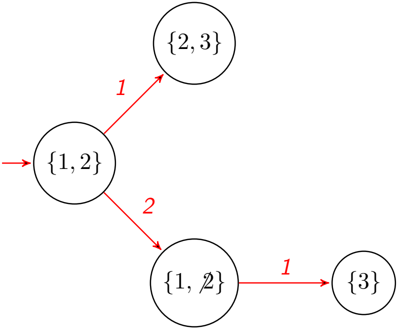

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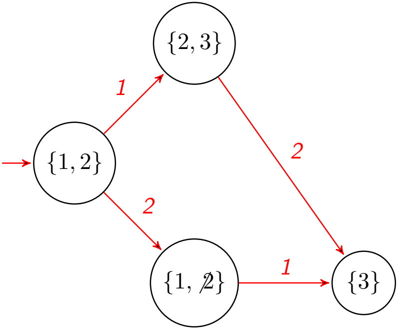

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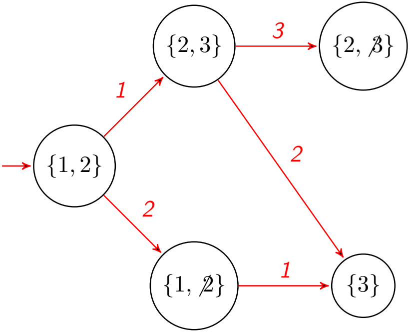

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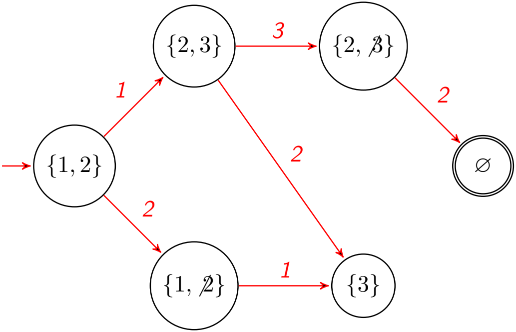

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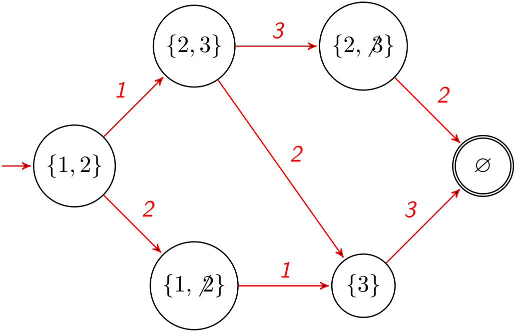
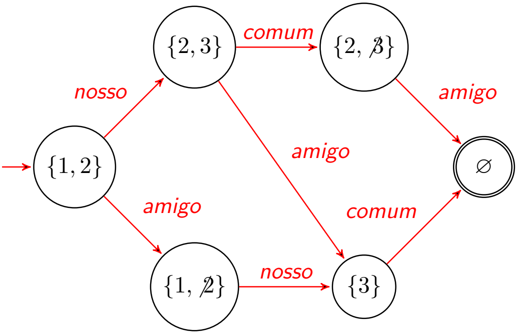


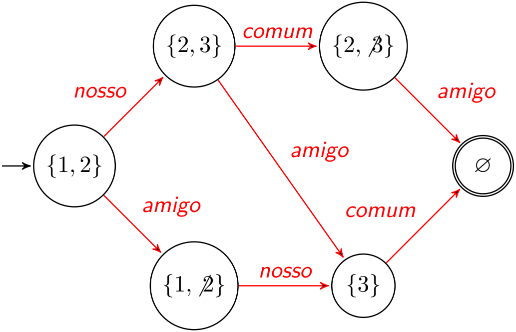
WLd (example)

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



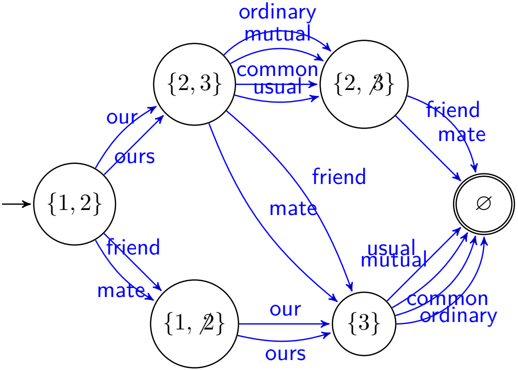
Word replacement with reordering constrained by WL2

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



Word replacement with reordering constrained by WL2

Complexity: $O(tI2^{d-1})$ transitions



Ad-hoc distortion limit: expressiveness

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Arbitrarily limit reordering to a fixed-length window

- convenient (linear complexity), but
- what about languages with very different syntax?
  e.g. OV vs VO, head-initial vs head-final
- can we do better?

Binary permutations

Consider a sentence such that $I = 4$

let's look at binary bracketing trees for this sentence

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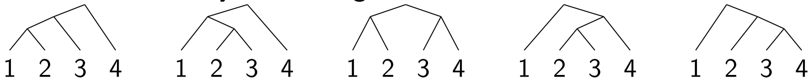

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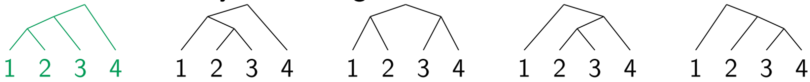

Binary permutations

(((1 2)3)4)   1 2 3 4

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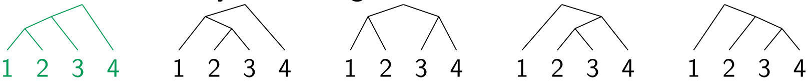

Binary permutations

$(((1\ 2)3)4)$ 1 2 3 4

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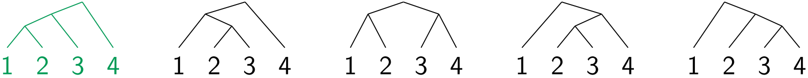

Binary permutations

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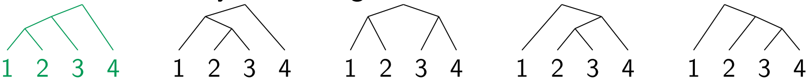

Binary permutations

$(((1\ 2)3)4)$	1 2 3 4
$((\langle 1\ 2\rangle 3)4)$	2 1 3 4
$(\langle (1\ 2)3\rangle 4)$	3 1 2 4
$(\langle \langle 1\ 2\rangle 3\rangle 4)$	3 2 1 4

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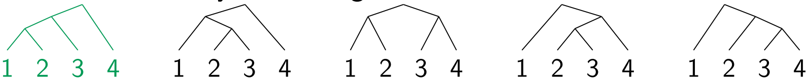

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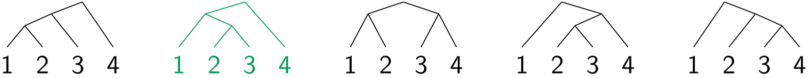

Binary permutations

$((1(2\ 3))4)$	1 2 3 4
$((1\langle 2\ 3\rangle)4)$	1 3 2 4
$(\langle 1(2\ 3)\rangle 4)$	2 3 1 4
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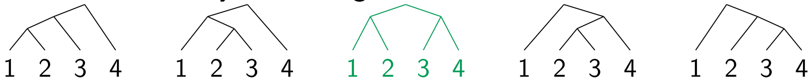

Binary permutations

$((1\ 2)(3\ 4))$ 1 2 3 4

$(\langle 1\ 2\rangle(3\ 4))$ 2 1 3 4

$(\langle 1\ 2\rangle\langle 3\ 4\rangle)$ 2 1 4 3

$((1\ 2)\langle 3\ 4\rangle)$ 1 2 4 3

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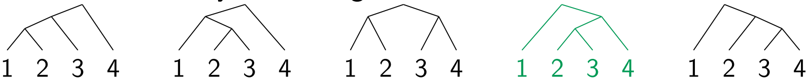

Binary permutations

$(1((2\ 3)4))$ 1 2 3 4

$(1(\langle 2\ 3\rangle 4))$ 1 3 2 4

$(1\langle(2\ 3)4\rangle)$ 1 4 2 3

$(1\langle\langle 2\ 3\rangle 4\rangle)$ 1 4 3 2

...

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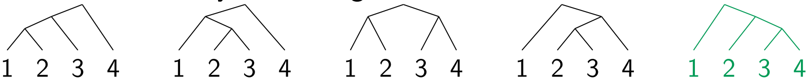

Binary permutations

$(1(2(3\ 4)))$ 1 2 3 4

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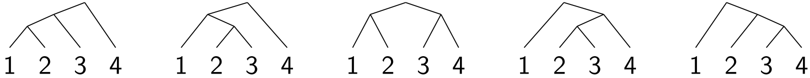

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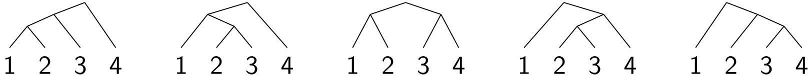

Binary permutations

- constrains the space of permutations
- crossing constraint

  3 1 4 2 ✗

  2 4 1 3 ✗

ITGs

Inversion Transduction Grammars (ITGs) [Wu, 1997]

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- $X \rightarrow XX$
  direct order

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  direct order
- $X \to \langle XX \rangle$
  inverted order

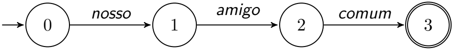
ITGs

Inversion Transduction Grammars (ITGs) [Wu, 1997]

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

Parsing, intersection and hypergraphs

Source



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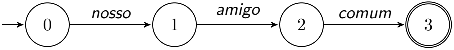

Grammar

$$X \rightarrow XX$$
$$X \rightarrow \langle XX \rangle$$
$X \rightarrow$ *nosso*

$X \rightarrow$ *amigo*

$X \rightarrow$ *comum*

Parsing, intersection and hypergraphs

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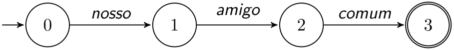

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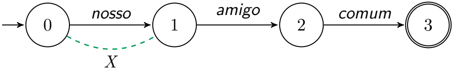

Grammar

$X \rightarrow XX$
$X \rightarrow \langle XX \rangle$
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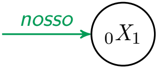
$X \rightarrow$ *comum*



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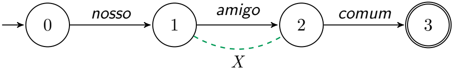

Grammar

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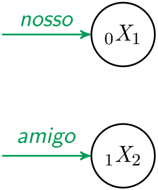
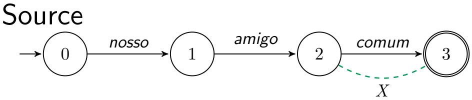
$$X \to \langle XX \rangle$$
$$X \to \textit{nosso}$$
$$X \to \textit{amigo} \qquad \Longleftarrow$$
$$X \to \textit{comum}$$



Parsing, intersection and hypergraphs



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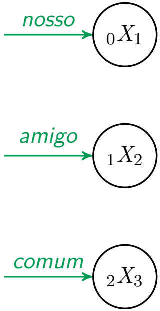

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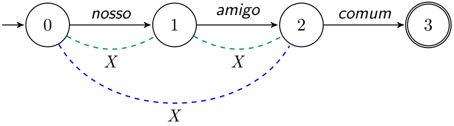

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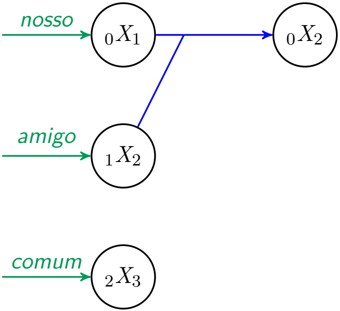

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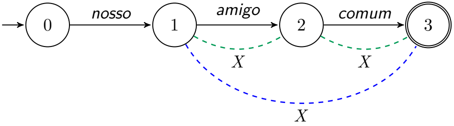

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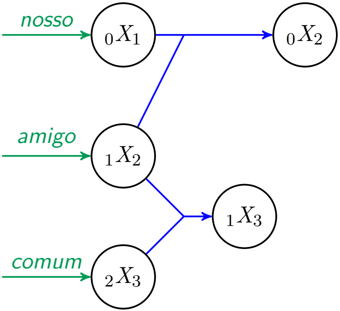

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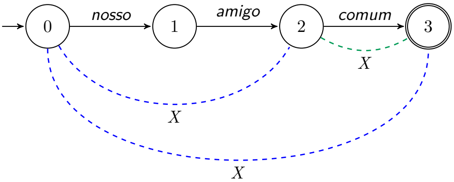

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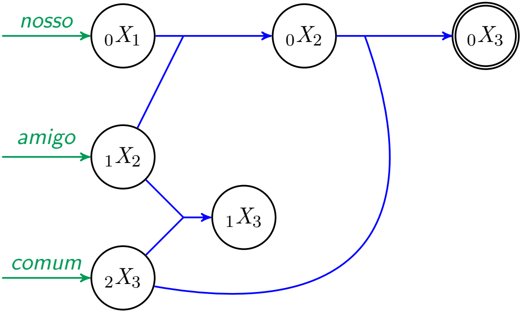

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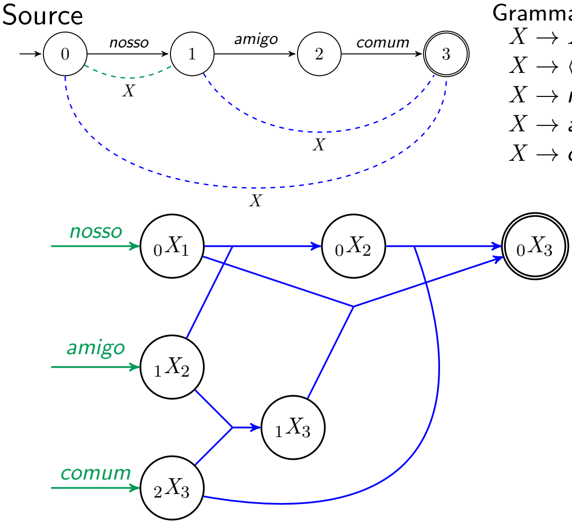

Grammar

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Parsing, intersection and hypergraphs

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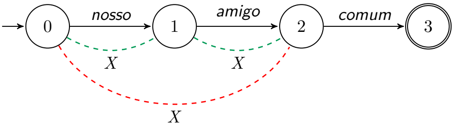

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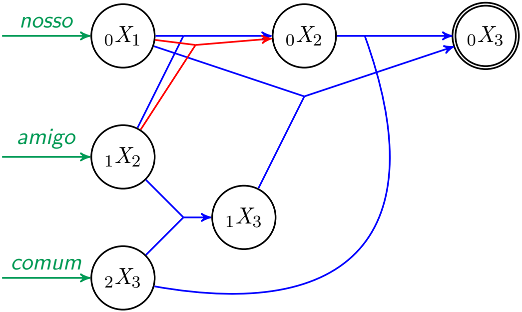
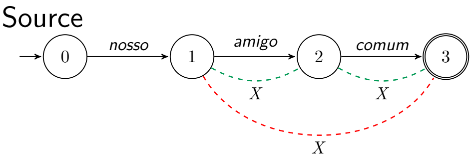


Parsing, intersection and hypergraphs



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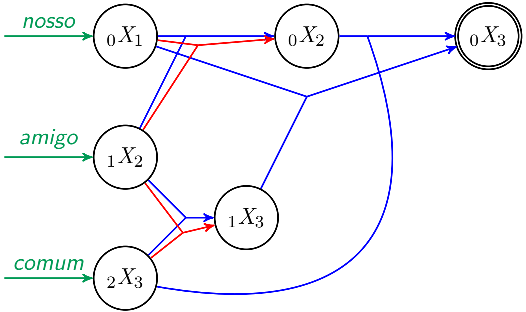

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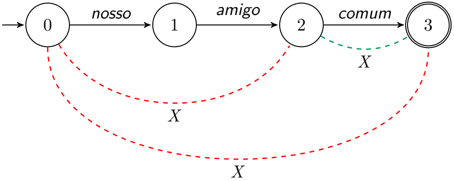

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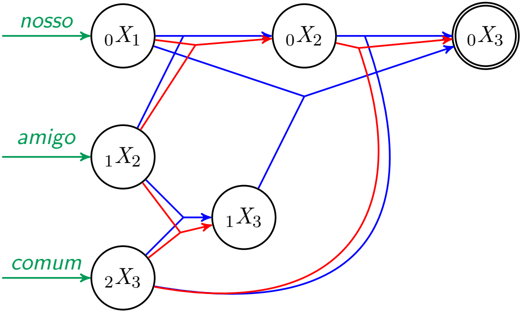
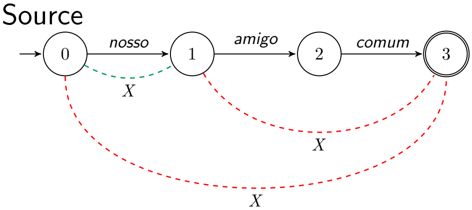


Parsing, intersection and hypergraphs



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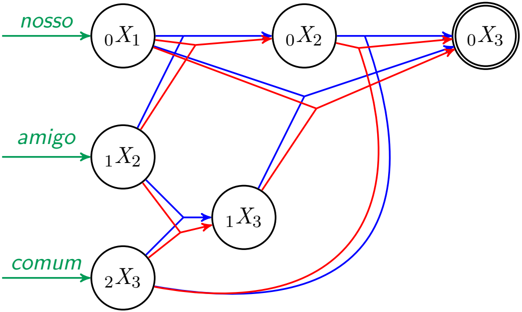

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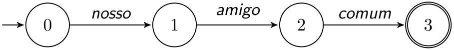

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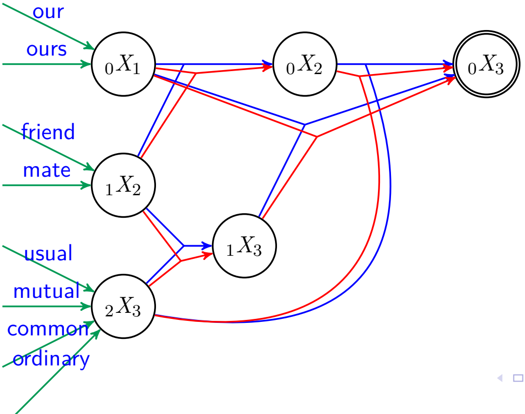
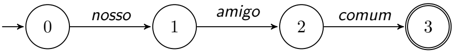


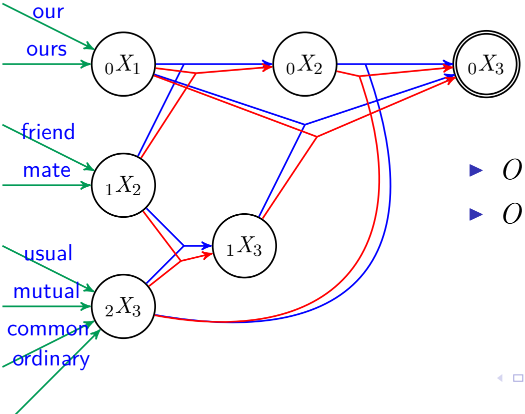
Parsing, intersection and hypergraphs

Source



Grammar

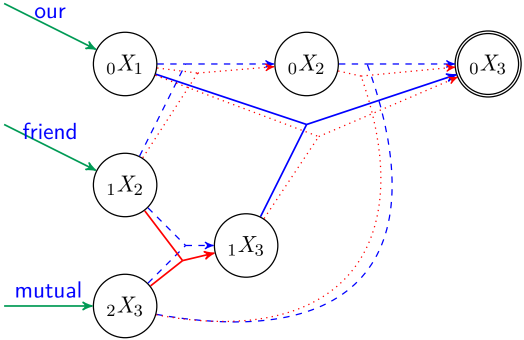
$X \to XX$
$X \to \langle XX \rangle$
$X \to$ *nosso*
$X \to$ *amigo*
$X \to$ *comum*



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

Example

(nosso ⟨amigo comum⟩) → **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 $\textit{da}_3$ lareira_4
Target: the_1 cricket_2 $[\text{on the}]_3$ 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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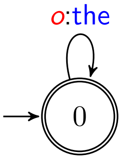

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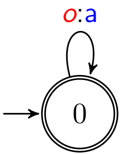

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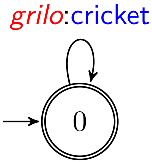

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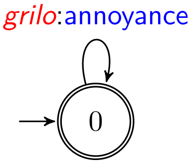

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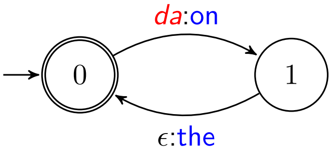

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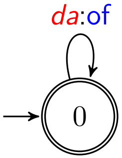

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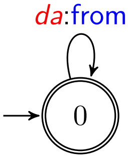

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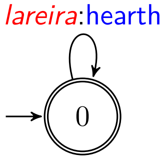

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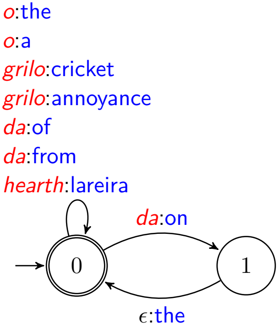

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- each rule can be seen as a transducer
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- standard intersection mechanisms do the rest

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We can translate a lattice encoding the WLd permutations

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  - it is sensible to limit phrases to a maximum length
- complexity remains
  - linear with sentence length
  - exponential with distortion limit

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   - a logic program can do the same
     (sometimes more convenient, e.g. WLd constraints)

Remarks

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- the space of solutions is cubic in length
- however less efficiently packed, better motivated constraints on reordering

Remarks (hiero)

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We are missing a parameterisation of the model

- the scoring function which will guide the decision making process

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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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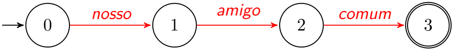

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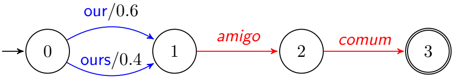

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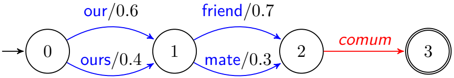

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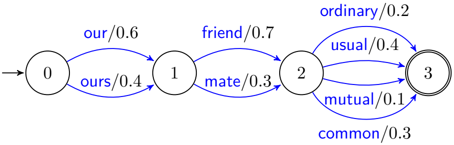

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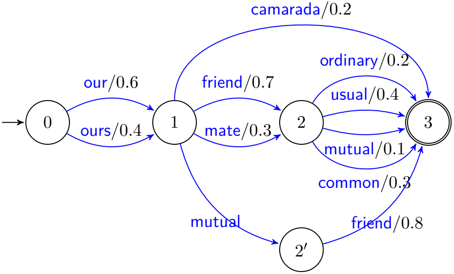

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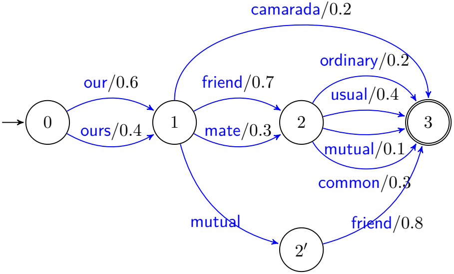

inference runs in time linear with the size of the automaton

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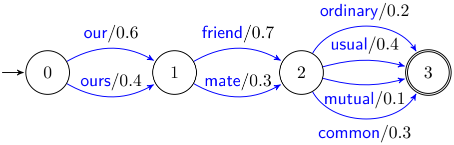
Certain aspects do not comply with such assumptions

- fluency as captured by an n-gram LM component

Scoring strings with a 2-gram LM



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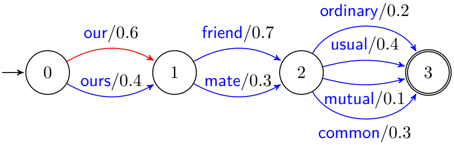

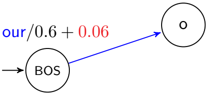

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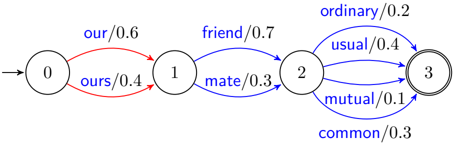

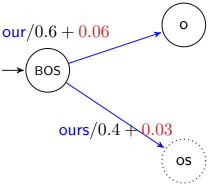

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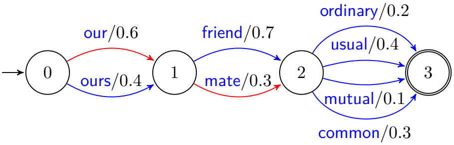

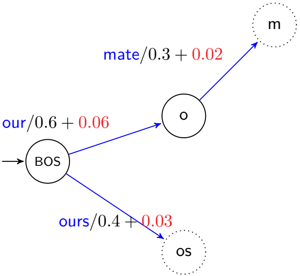

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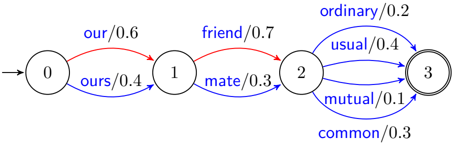

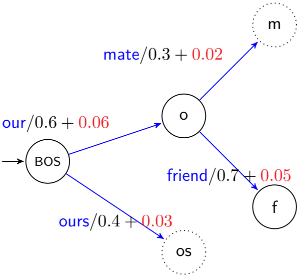

requires unpacking the representation

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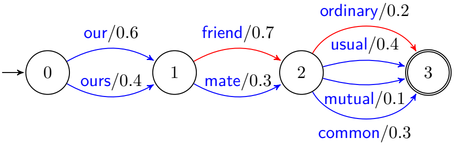

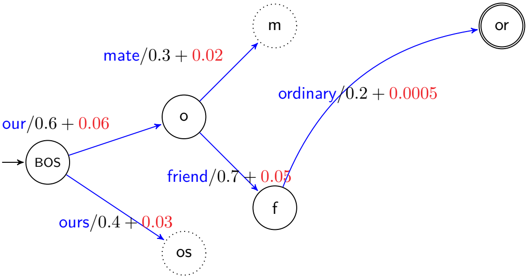

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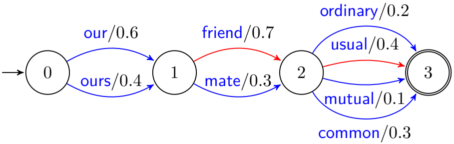

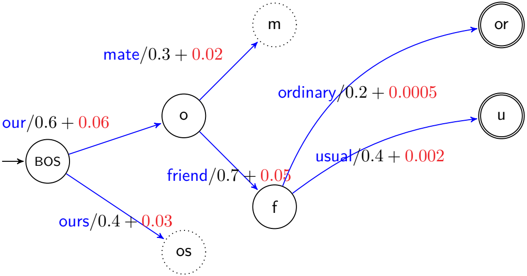

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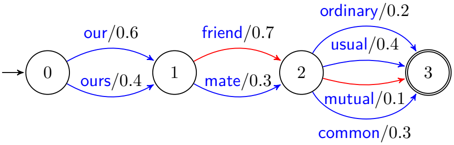

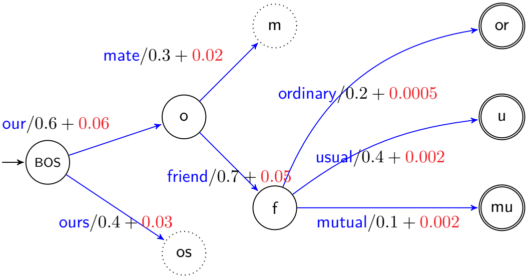

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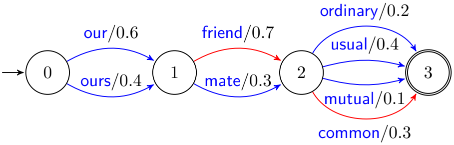

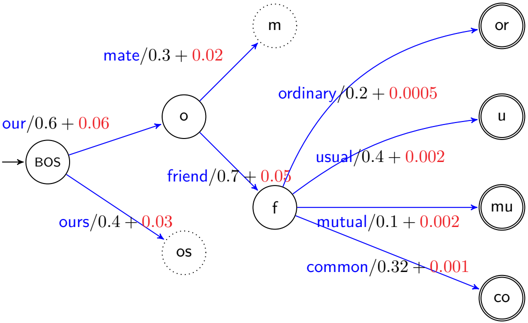

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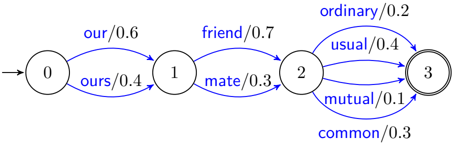
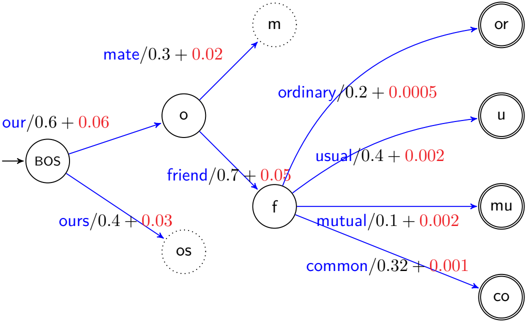
Scoring strings with a 2-gram LM





requires unpacking the representation

Scoring whole sentences

Imagine a feature function that requires a complete translation

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- unbounded LM
  e.g. via suffix arrays [Zhang and Vogel, 2006]
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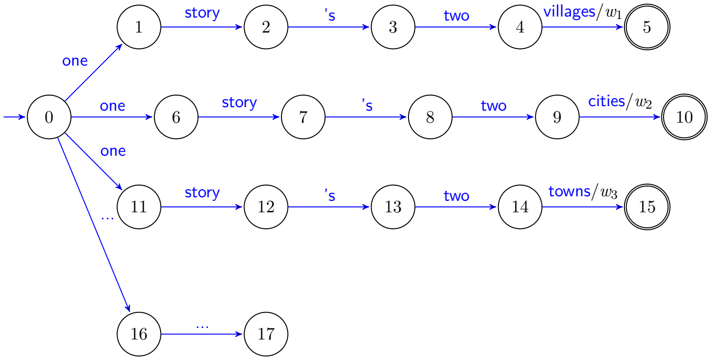
- requires fully unpacking the representation
- making dependencies explicit through the graphical structure

Scoring whole sentences: example



Exhaustive enumeration

- number of edges exponential with input length
- intractable

Not all is lost

Most features we can reliably estimate

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n-gram LMs are good examples

- there are up to $|\Delta|^{n-1}$ contexts that must be made explicit
- nodes must group derivations sharing the same context
- polynomial, though often prohibitive (impracticable)

Recap 4

1. a characterisation the space of solutions

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2. a linear parameterisation of the model

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

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

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

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- can be estimated from samples of derivations
- have a look at project 14 ;)

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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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Importance sampling

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

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4. ideal for MBR and tuning
5. typically stupid simple to parallelise

Thanks!

Questions?

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