Natural Language Processing

Machine Translation III

Dan Klein – UC Berkeley

Syntactic Models

Translating with Tree Transducers

Input **Output**

lo haré de muy buen grado .

Grammar

Translating with Tree Transducers

Input **Output**

lo haré de muy buen grado .

Grammar

ADV → ⟨ de muy buen grado ; gladly ⟩

Translating with Tree Transducers

Input **Output**

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S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

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Translating with Tree Transducers

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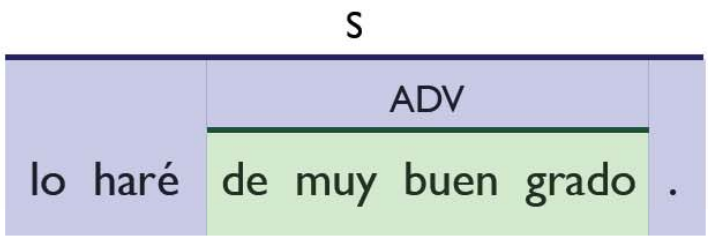

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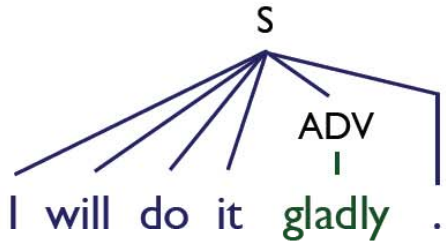

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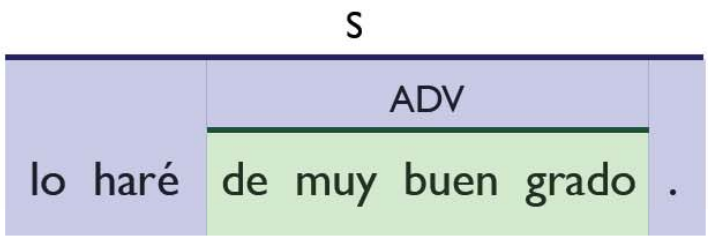

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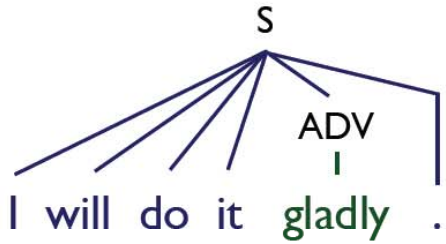

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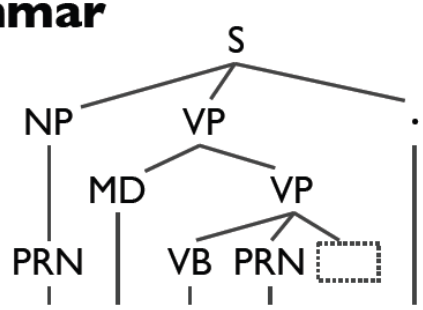

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Translating with Tree Transducers

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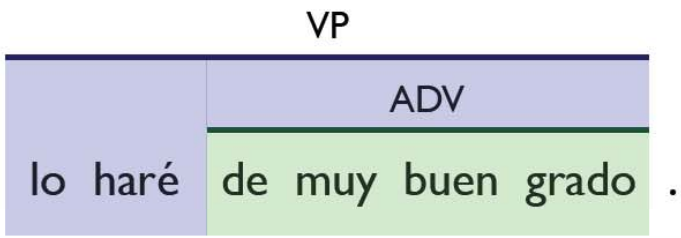

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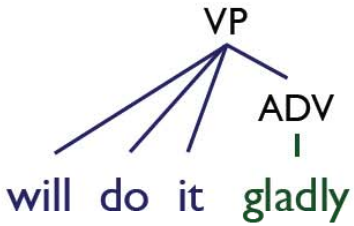

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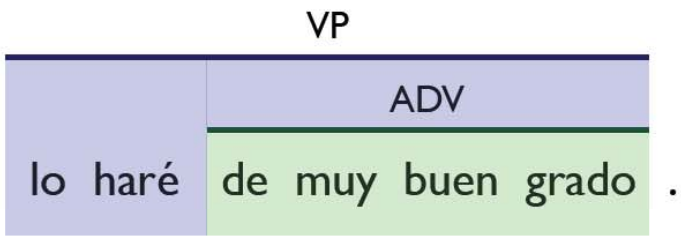

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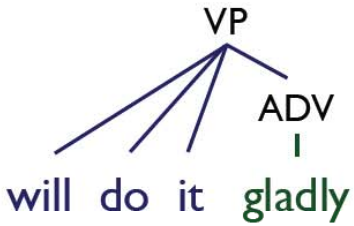

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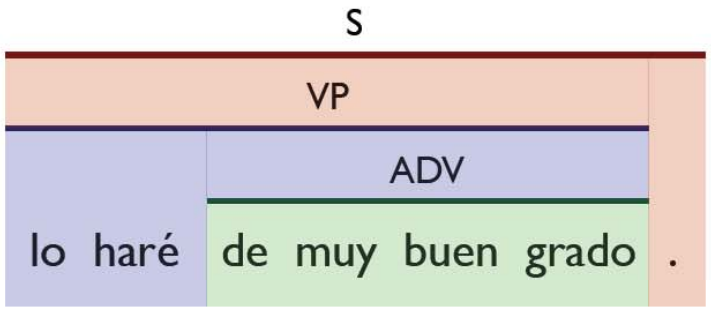

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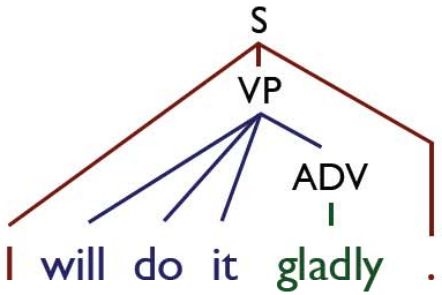

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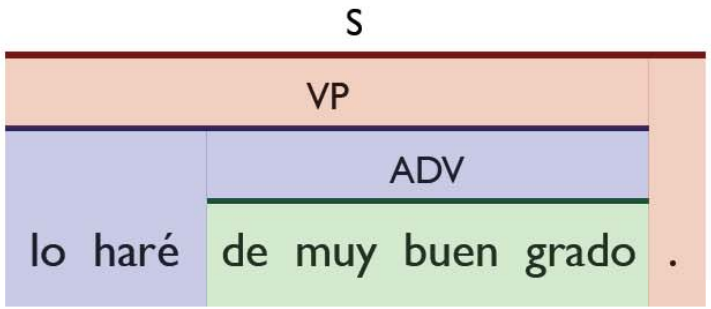

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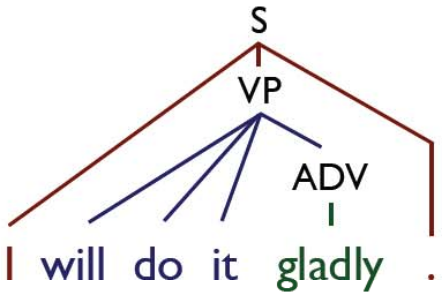

Grammar

S → ⟨ VP . ; I VP . ⟩ **OR** S → ⟨ VP . ; you VP . ⟩

VP → ⟨ lo haré ADV ; will do it ADV ⟩

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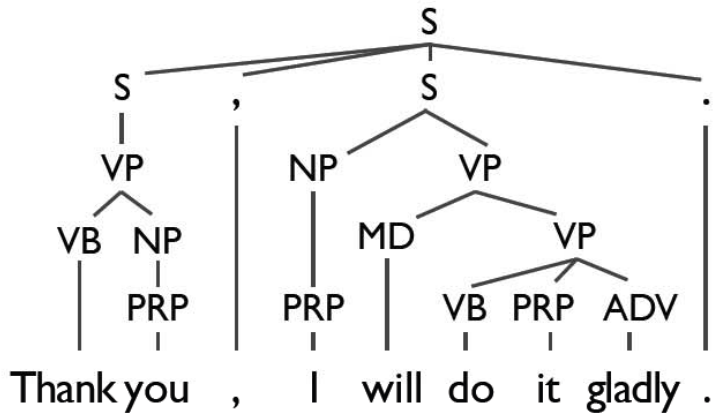
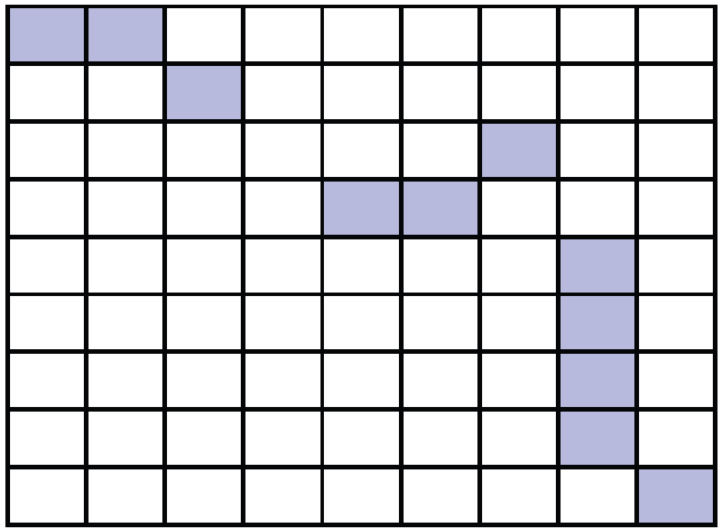
Learning Grammars for Translation





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Grammar Rules

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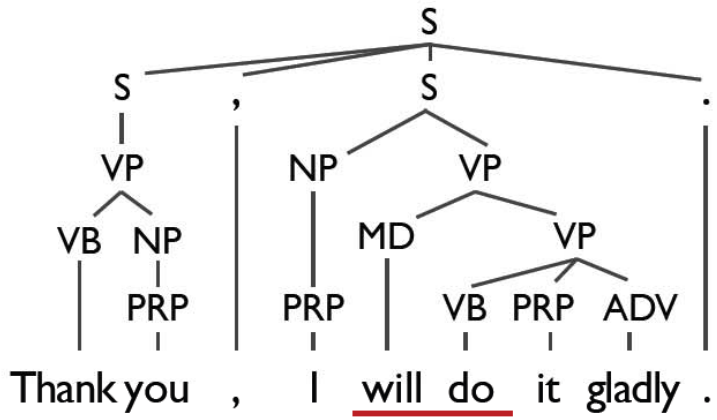

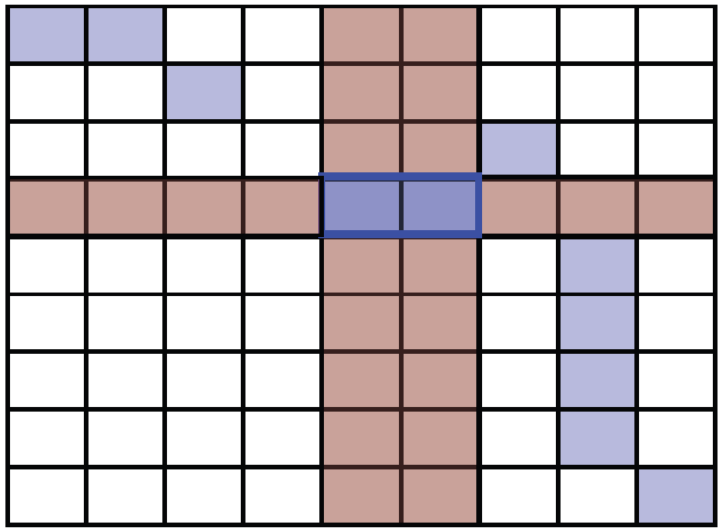

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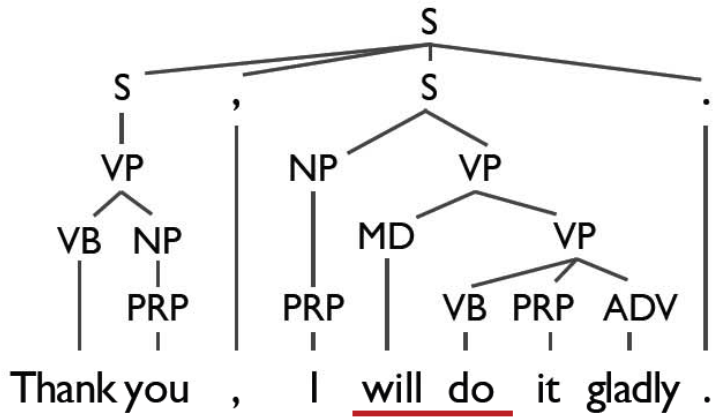

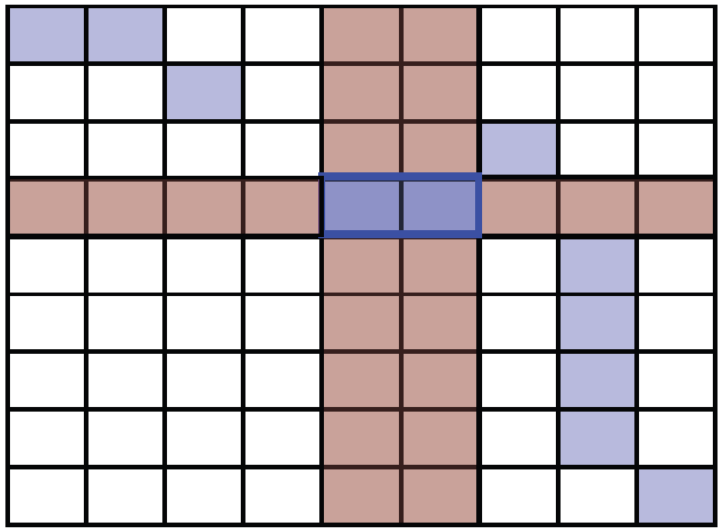

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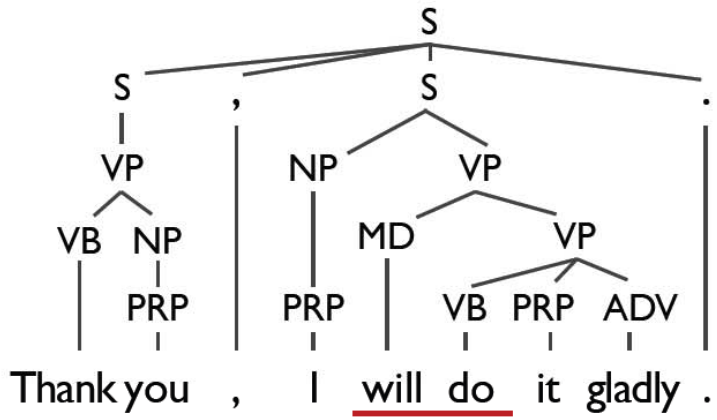

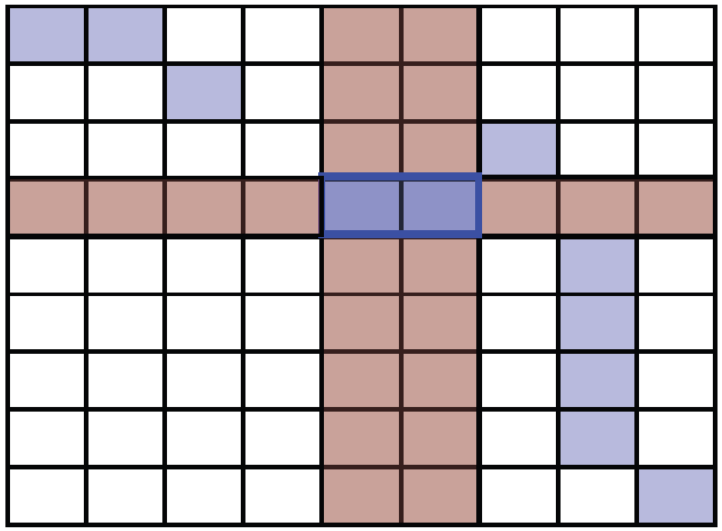

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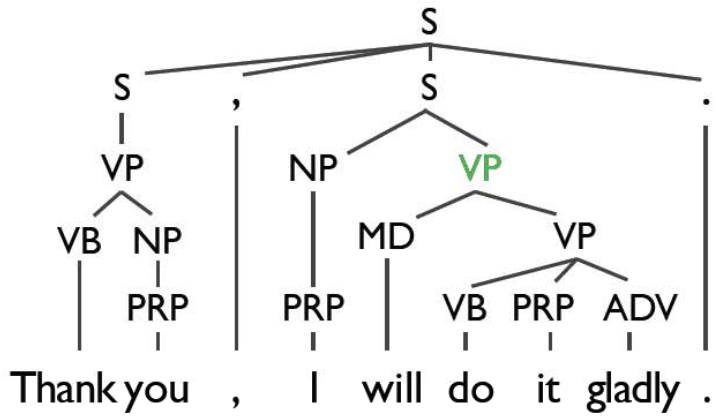

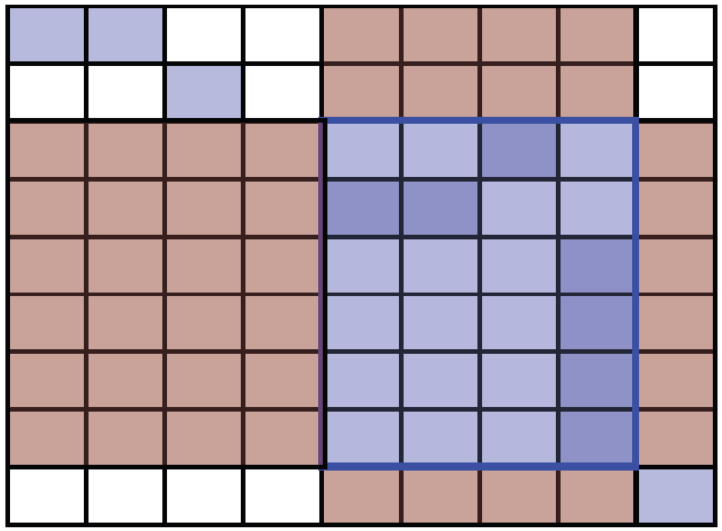

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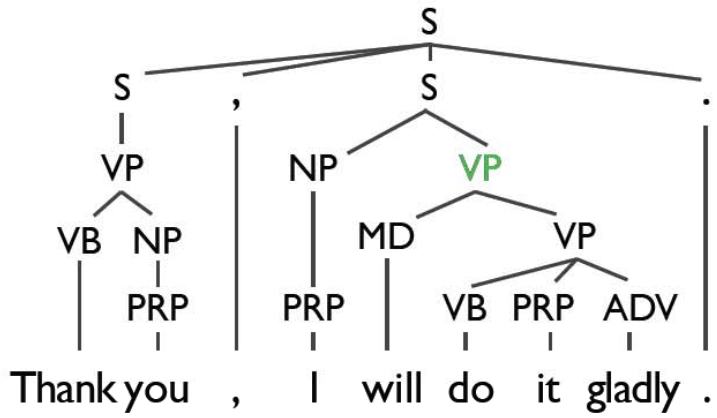

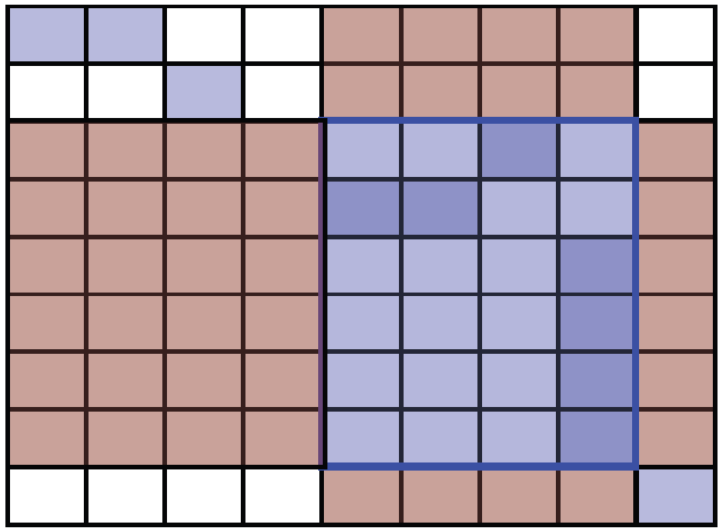

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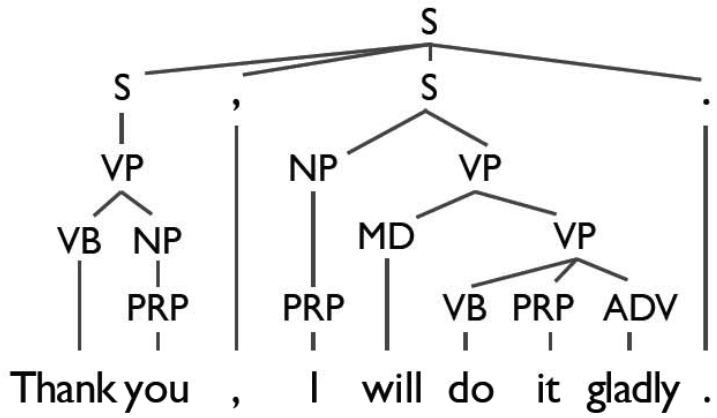

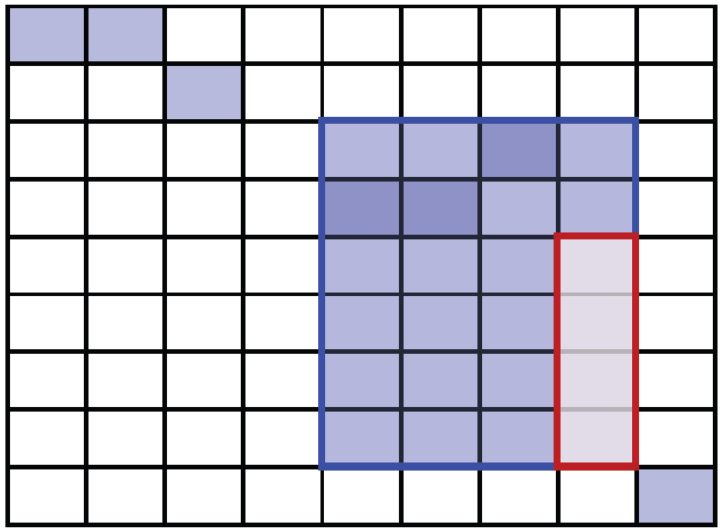

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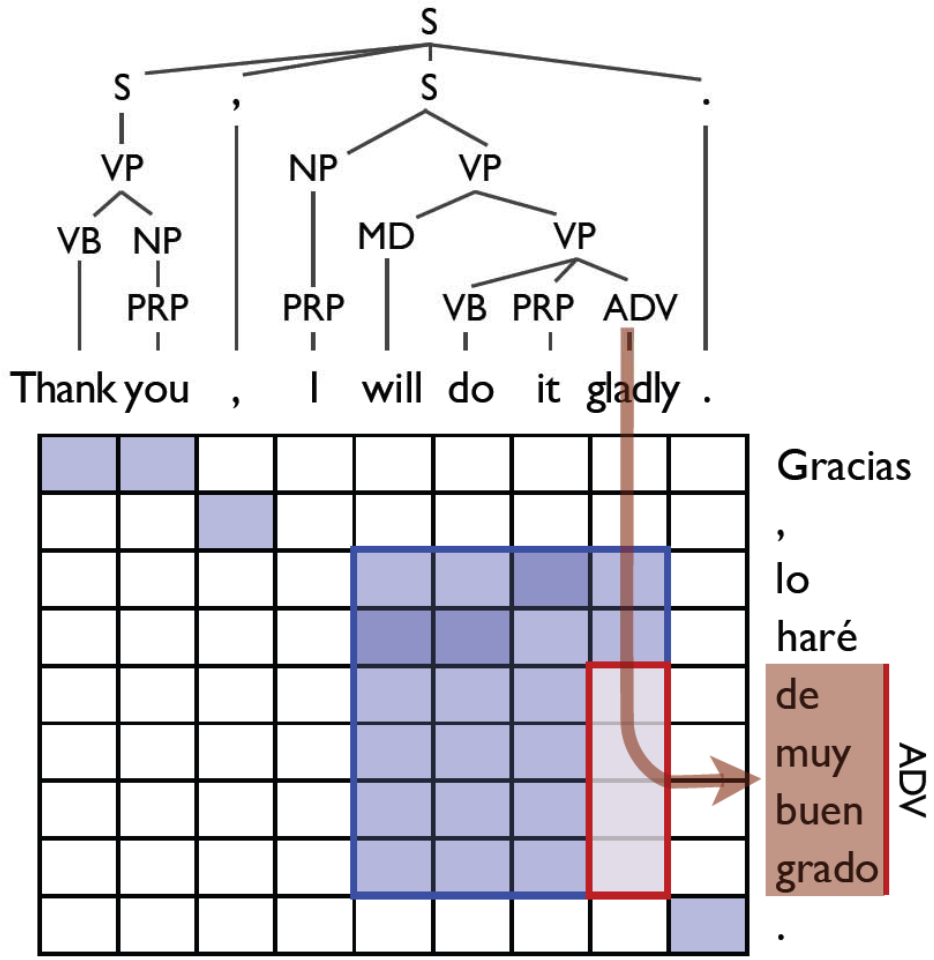

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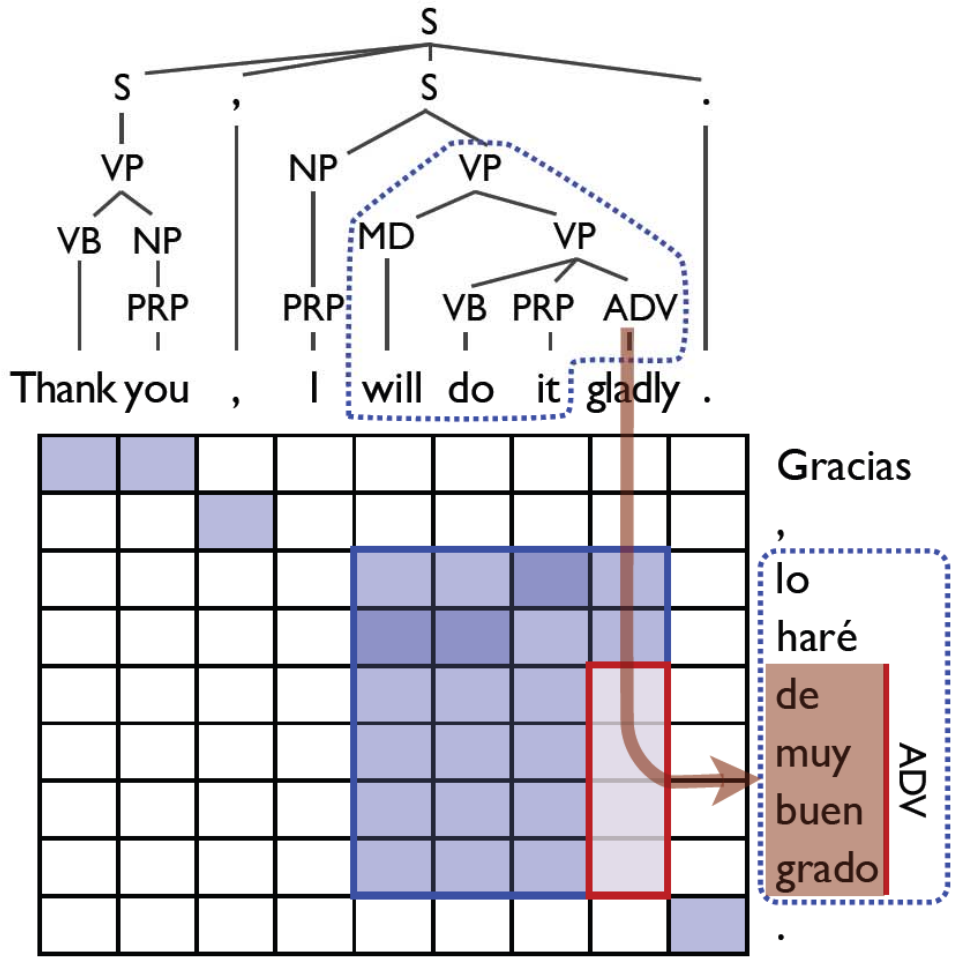

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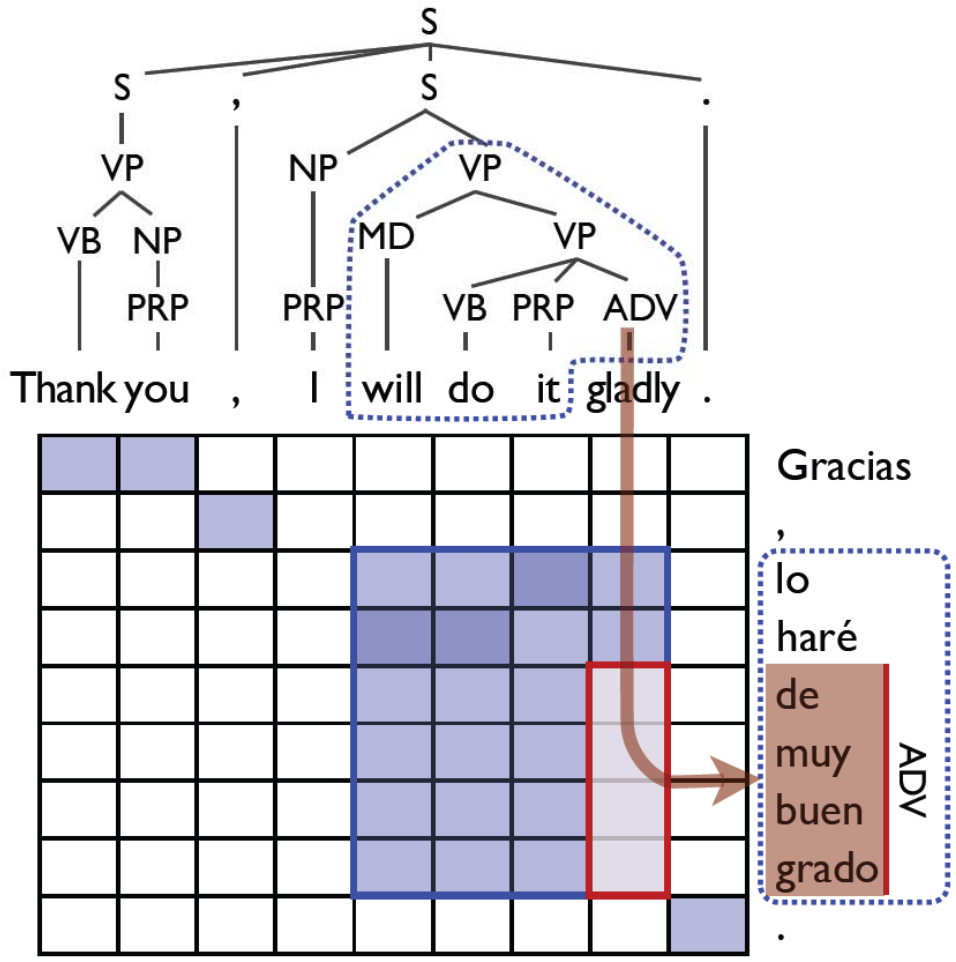

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VP →
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VP →
⟨lo haré ADV ;
will do it ADV⟩

The Size of Tree Transducer Grammars

Extracted a transducer grammar from a 220 million word bitext

Relativized the grammar to each test sentence

Kept all rules with at most 6 non-terminals

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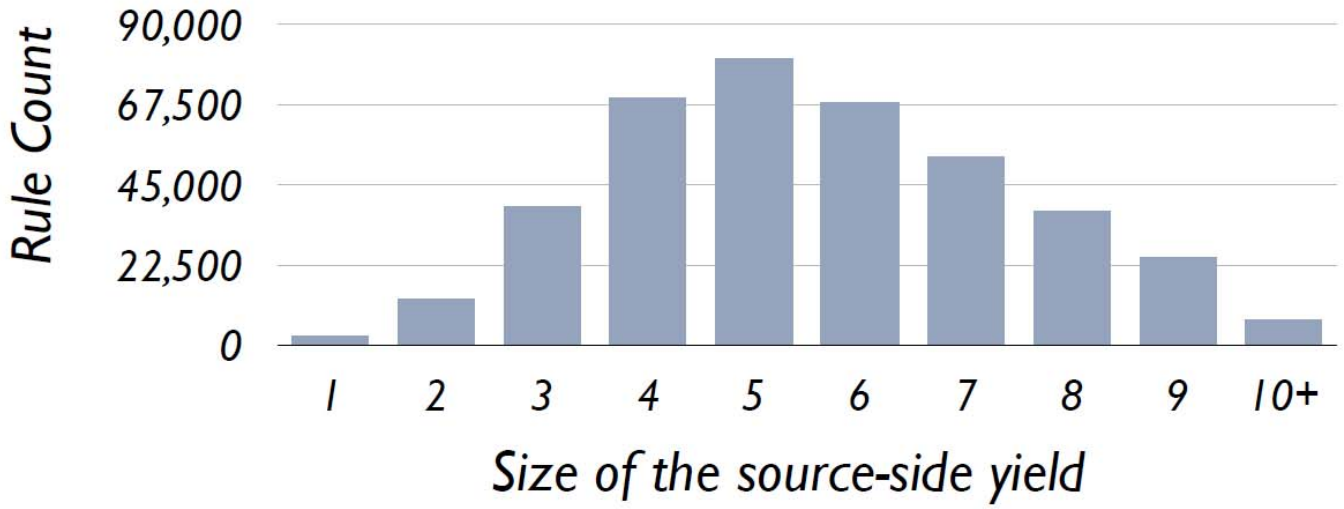

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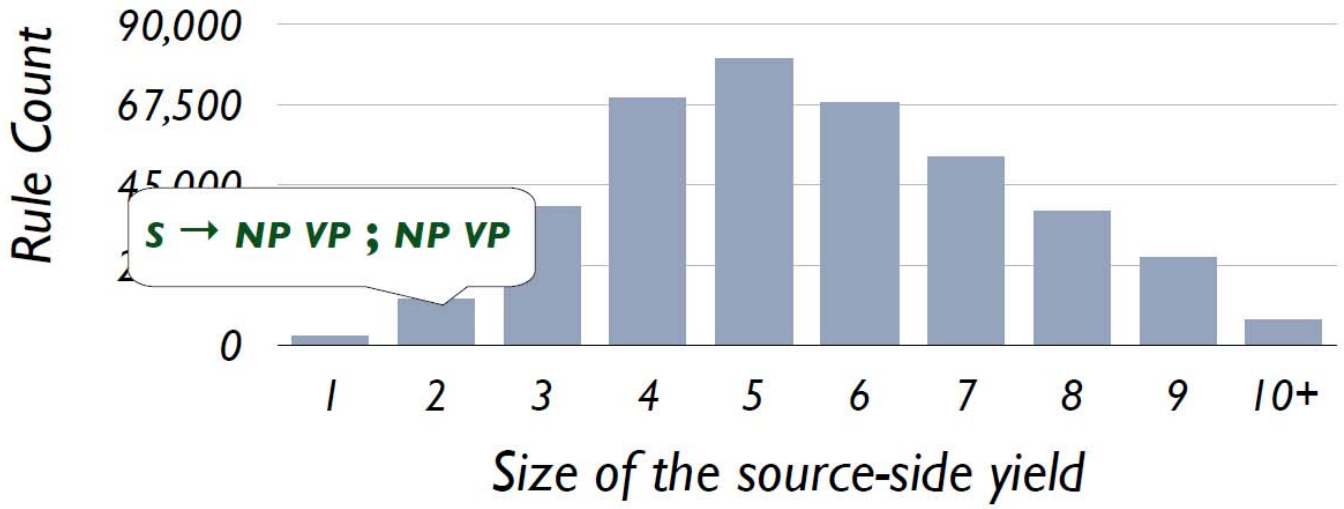

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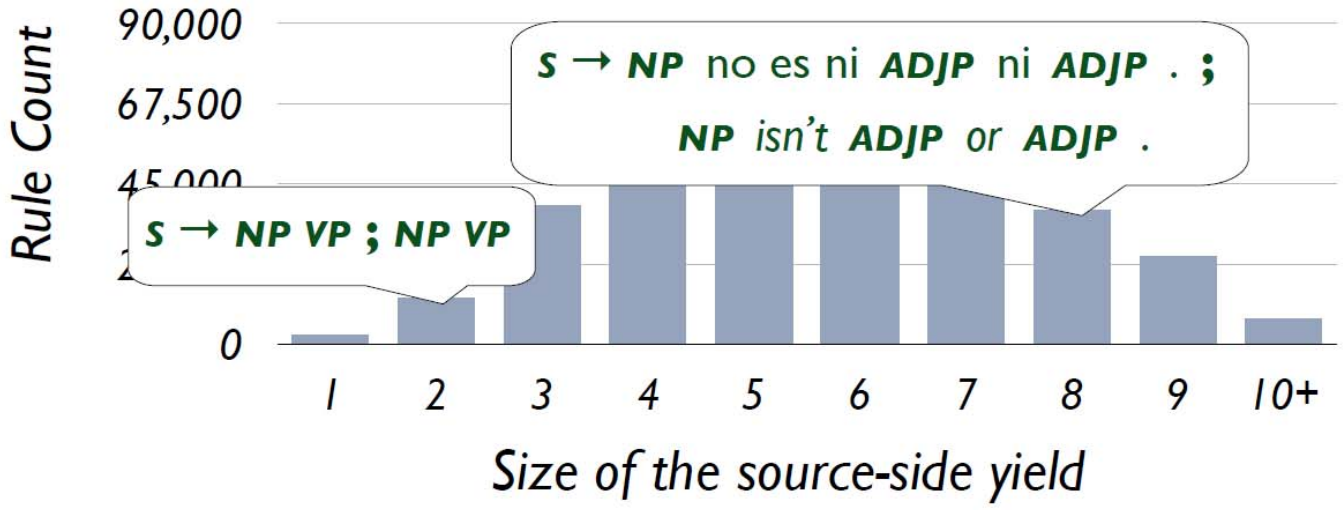
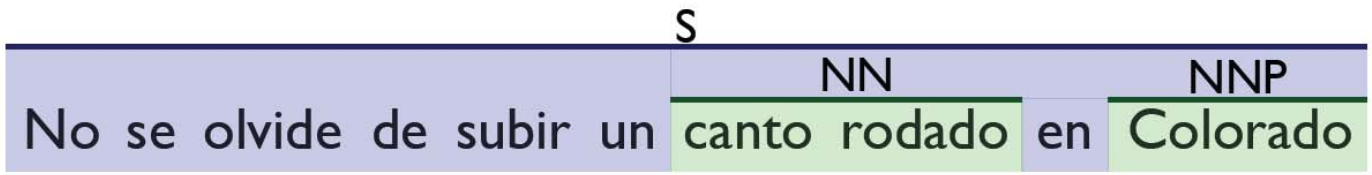


Syntactic Decoding

Tree Transducer Grammars



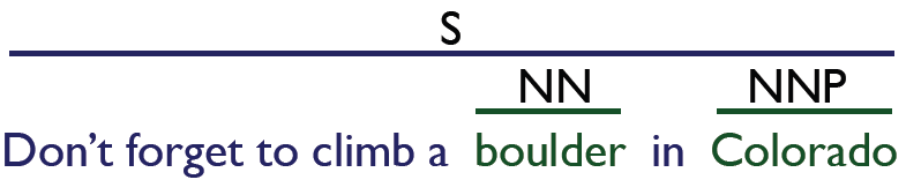
Synchronous Grammar

NNP → Colorado ; *Colorado*

NN → canto rodado ; *boulder*

S → No se olvide de subir un ***NN*** en ***NNP*** ; *Don't forget to climb a **NN** in **NNP***

Output



CKY-style Bottom-up Parsing

For each
span length:

CKY-style Bottom-up Parsing

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For each span [i,j]:

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Apply all grammar rules to [i,j]

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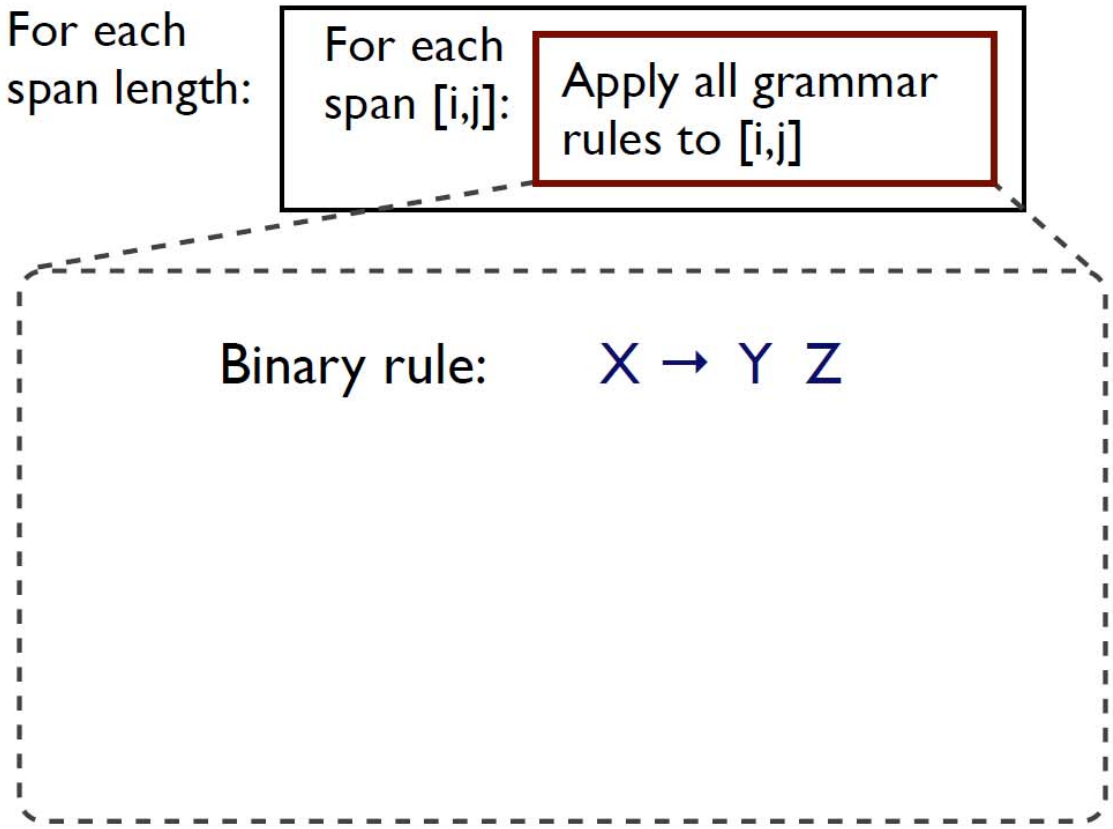

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Binary rule:	$X \rightarrow Y\ Z$
Split points:	$i < k < j$
Operations:	$O(j - i)$
Time scales with:	Grammar constant

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$_i$ No se olvide de subir un canto rodado en Colorado $_j$

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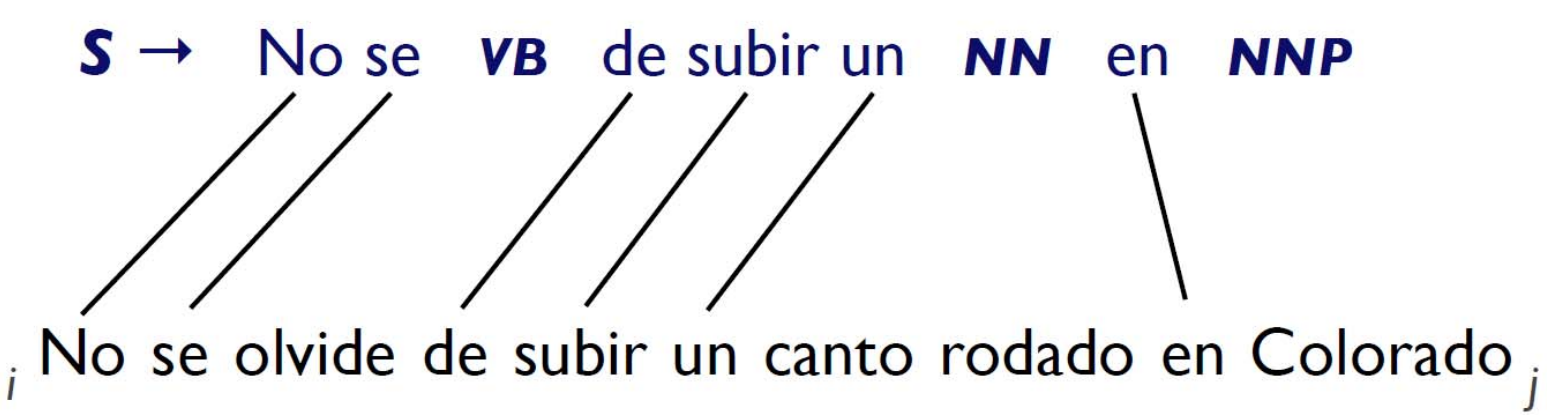

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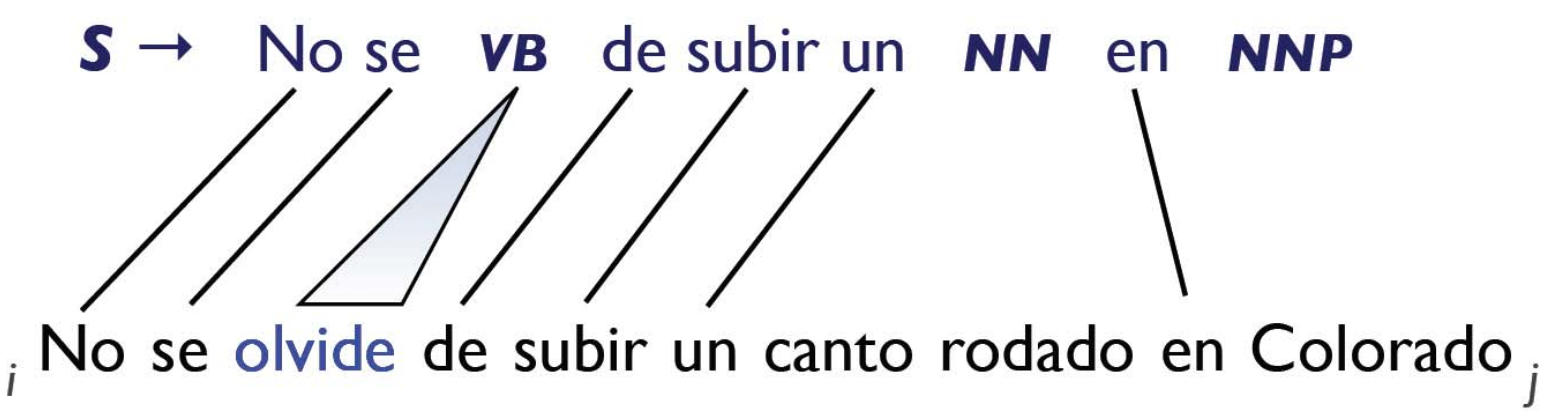

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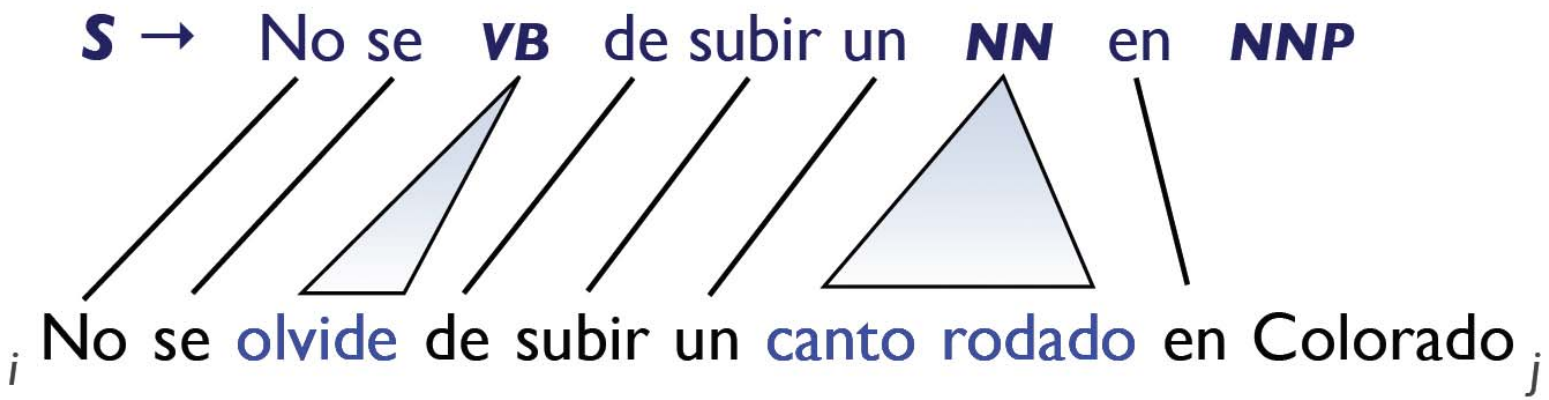

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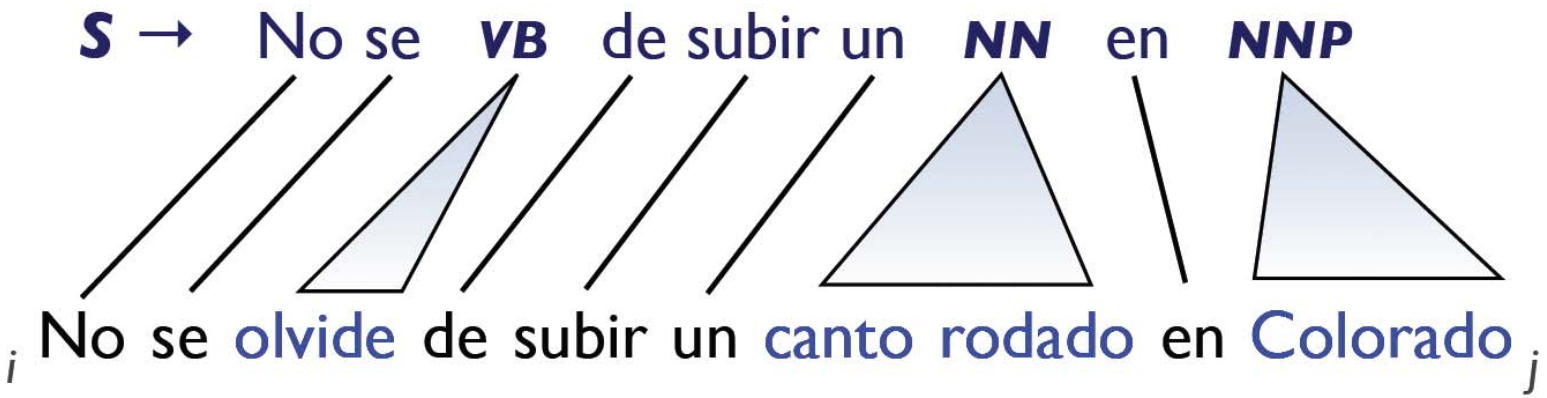

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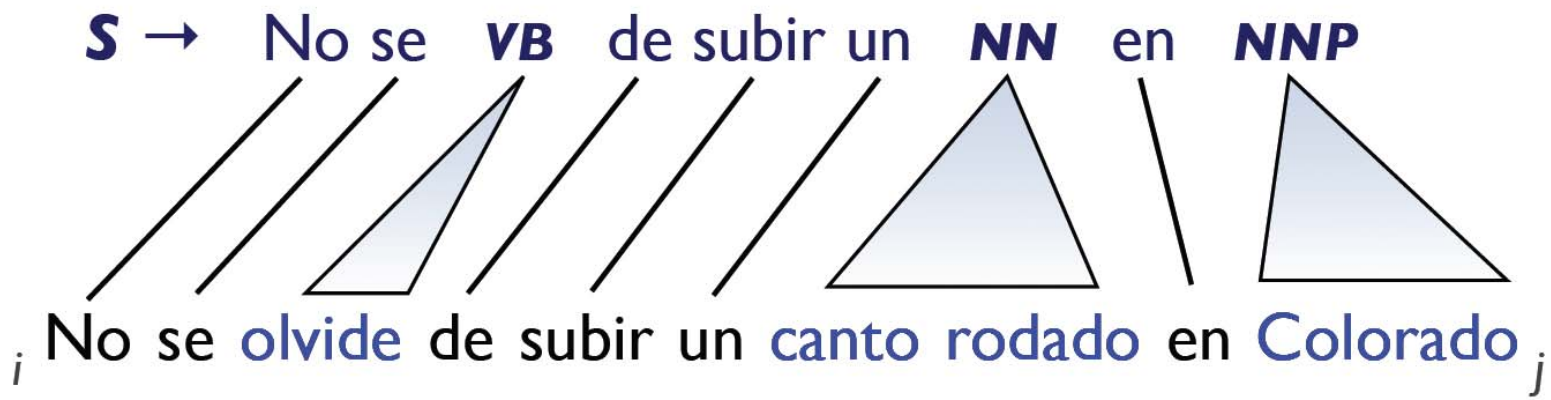

Many untransformed lexical rules can be applied in linear time

CKY-style Bottom-up Parsing

For each span length:

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S → No se ***VP*** ***NP*** ***PP***

$_i$ No se olvide de subir un canto rodado en Colorado $_j$

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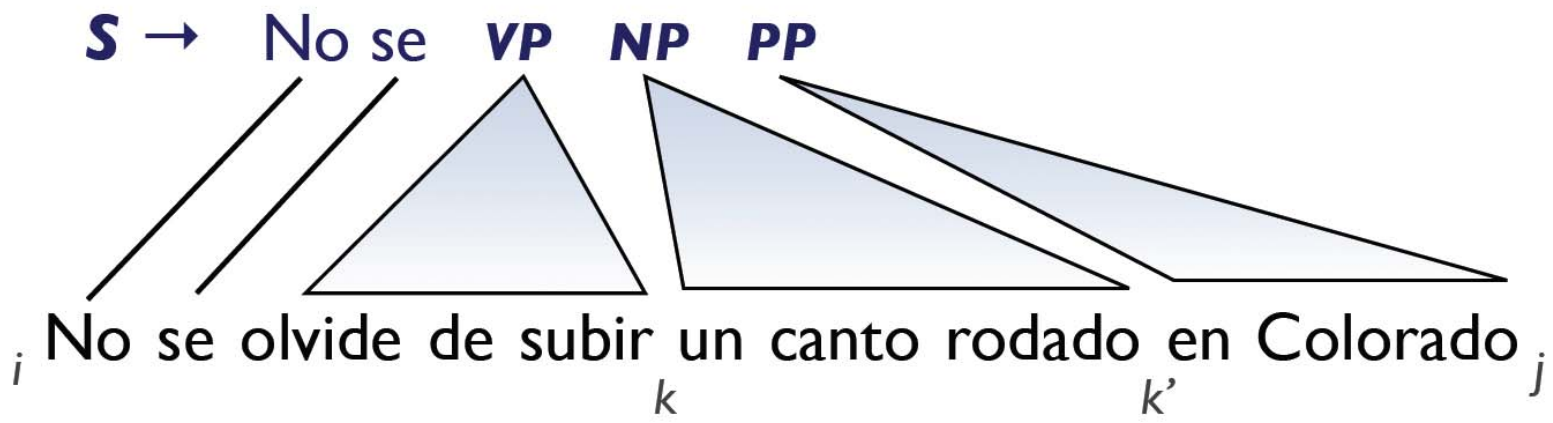

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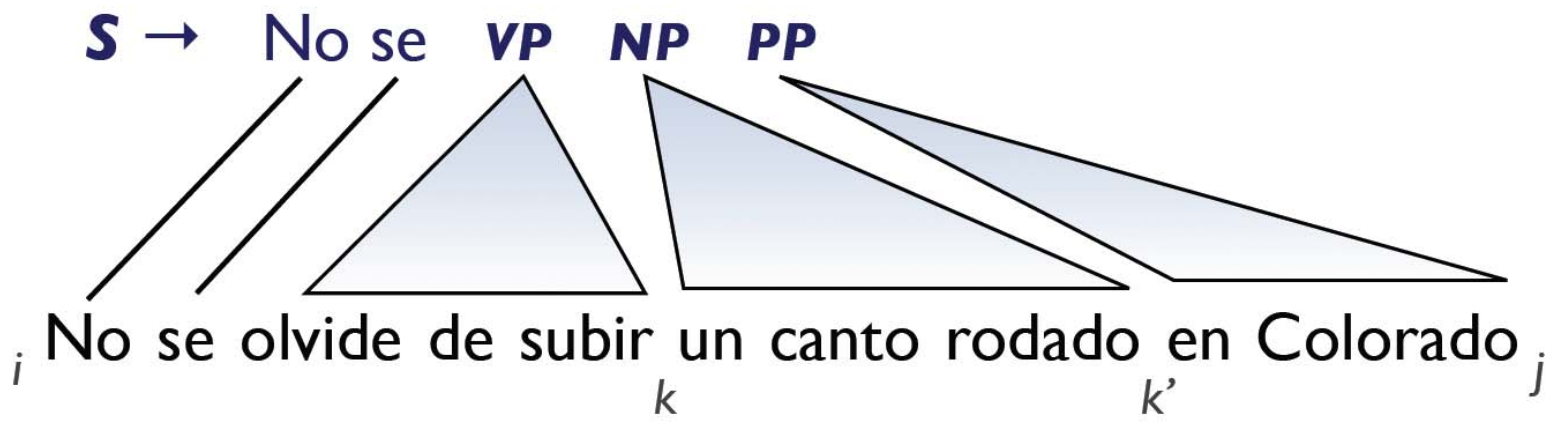
For each span [i,j]:

Apply all grammar rules to [i,j]



Problem: *Applying adjacent non-terminals is slow*

Eliminating Non-terminal Sequences

Lexical Normal Form (LNF)

(a) lexical rules have at most one adjacent non-terminal
(b) all unlexicalized rules are binary.

Original rule: **S** → No se **VB** **VB** un **NN** **PP**

Transformed rules: **S** → No se **VB~VB** un **NN~PP**

VB~VB → **VB** **VB**

NN~PP → **NN** **PP**

Parsing stages:

- Lexical rules are applied by matching
- Unlexicalized rules are applied by iterating over split points

Flexible Syntax

Soft Syntactic MT: From Chiang 2010

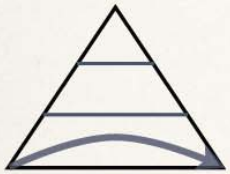
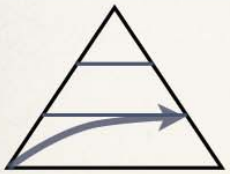
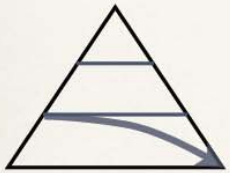
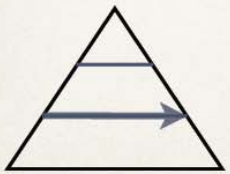
日本 文部 科学 省 官员 表示 , " 亚 伯拉罕 的 发言 , 令 我们 深感 鼓舞
Japan MEXT official said , " Abraham 's comment make us deeply-feel courage

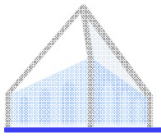
reference: An official from Japan 's science and technology ministry said , " We are highly encouraged by Abraham 's comment .

Hiero: Officials of the Japanese ministry of education and science , " said Abraham speeches , we are deeply encouraged by .

string-to-tree: Japan 's ministry of education , culture , sports , science and technology , " Abraham 's statement , which is most encouraging , " the official said .

Previous work

	string-to-string	ITG (Wu 1997)	Hiero (Chiang 2005)
	string-to-tree	Yamada & Knight 2001	Galley et al 2004/2006
	tree-to-string		Huang et al 2006 Y Liu et al 2006
	tree-to-tree	DOT (Poutsma 2000) Eisner 2003	Stat-XFER (Lavie et al 2008) M Zhang et al. 2008 Y Liu et al., 2009



Hiero Rules

$S \rightarrow \langle S_{[1]} X_{[2]}, S_{[1]} X_{[2]} \rangle$

$S \rightarrow \langle X_{[1]}, X_{[1]} \rangle$

$X \rightarrow \langle \text{yu } X_{[1]} \text{ you } X_{[2]}, \text{have } X_{[2]} \text{ with } X_{[1]} \rangle$

$X \rightarrow \langle X_{[1]} \text{ de } X_{[2]}, \text{the } X_{[2]} \text{ that } X_{[1]} \rangle$

$X \rightarrow \langle X_{[1]} \text{ zhiyi, one of } X_{[1]} \rangle$

$X \rightarrow \langle \text{Aozhou, Australia} \rangle$

$X \rightarrow \langle \text{shi, is} \rangle$

$X \rightarrow \langle \text{shaoshu guojia, few countries} \rangle$

$X \rightarrow \langle \text{bangjiao, diplomatic relations} \rangle$

$X \rightarrow \langle \text{Bei Han, North Korea} \rangle$

From [Chiang et al, 2005]

STSG extraction

1. Phrases
   - respect word alignments
   - are syntactic constituents on *both* sides
2. Phrase pairs form rules
3. Subtract phrases to form rules

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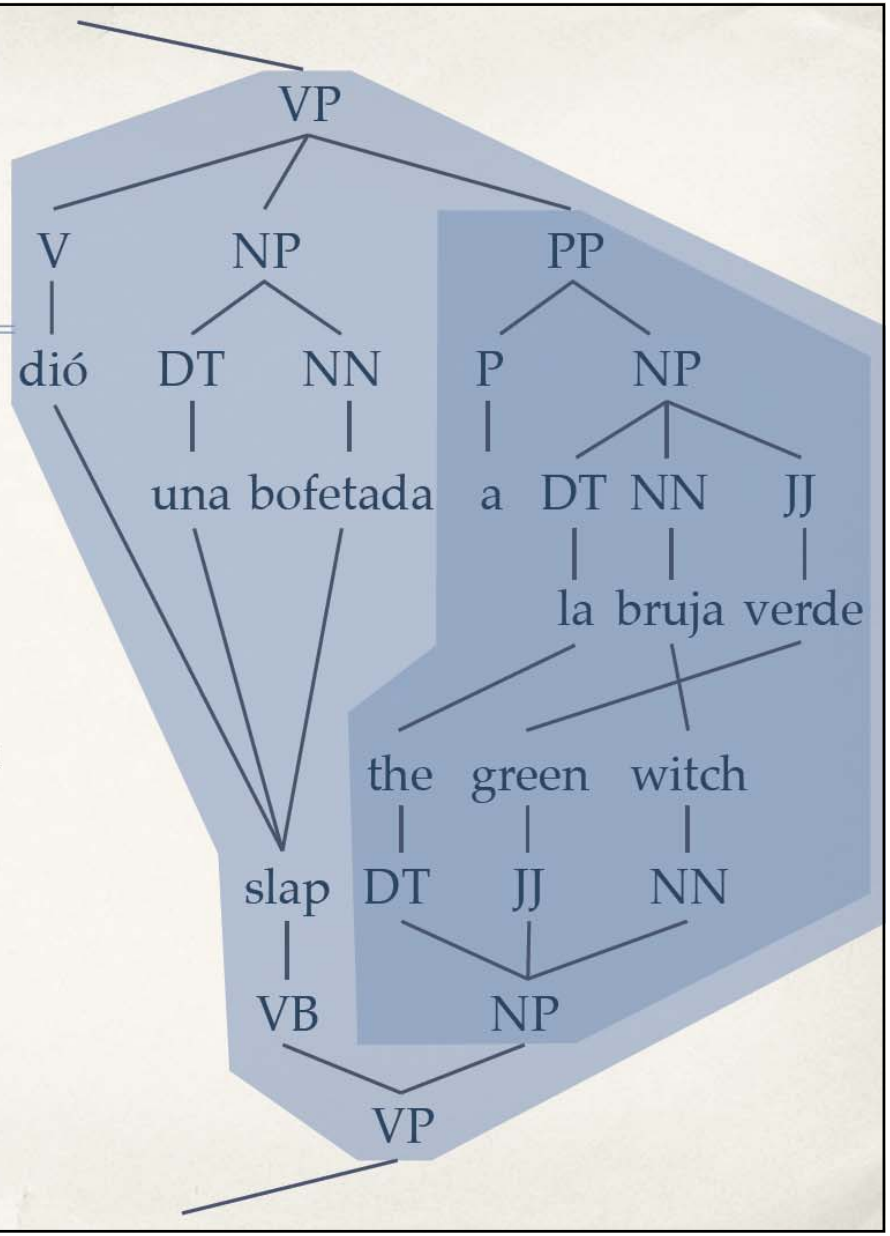

STSG extraction

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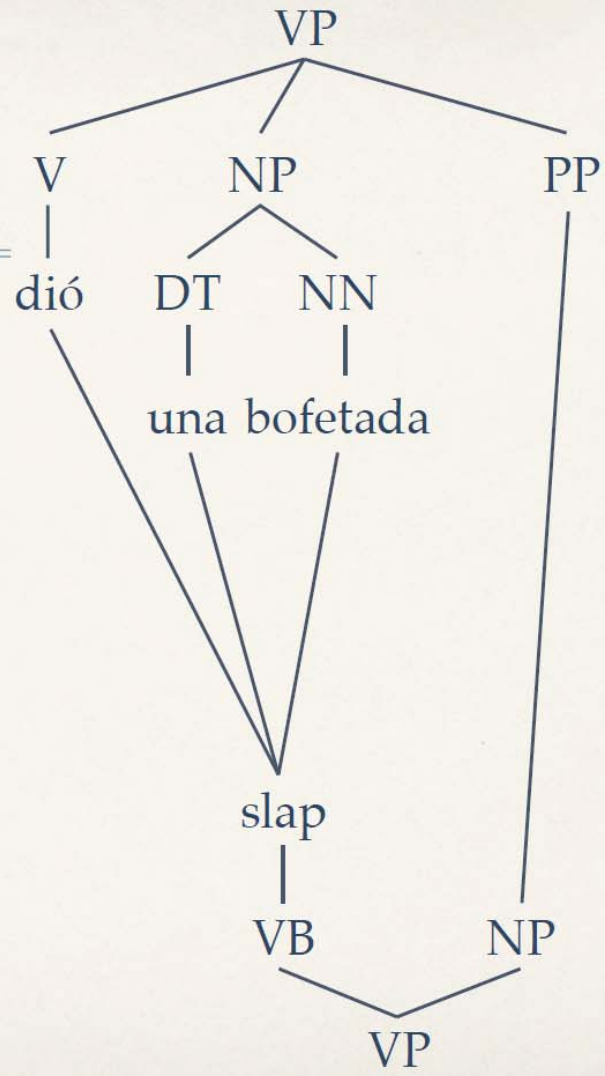
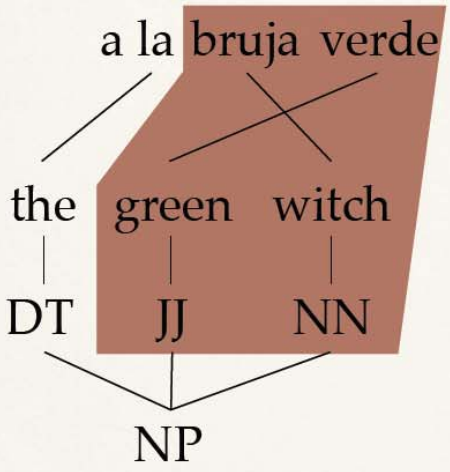
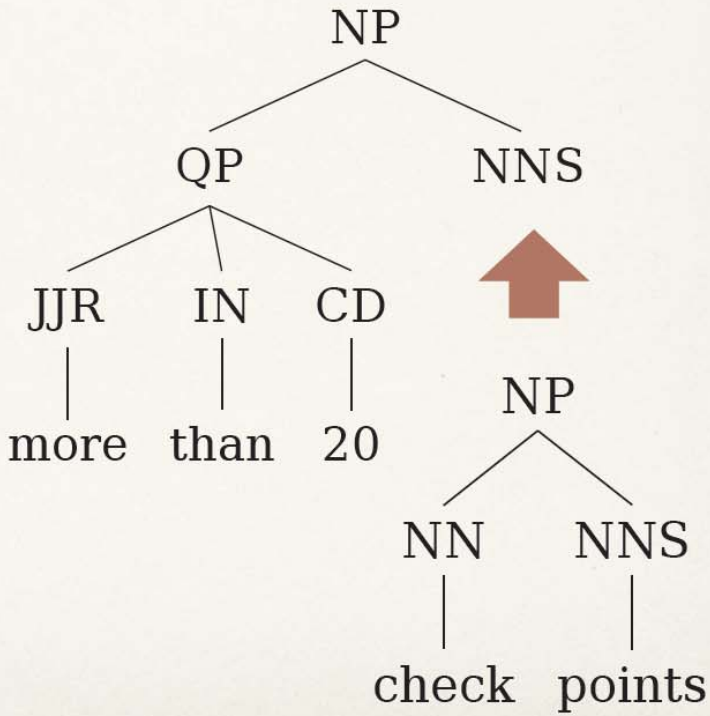


Why is tree-to-tree hard?

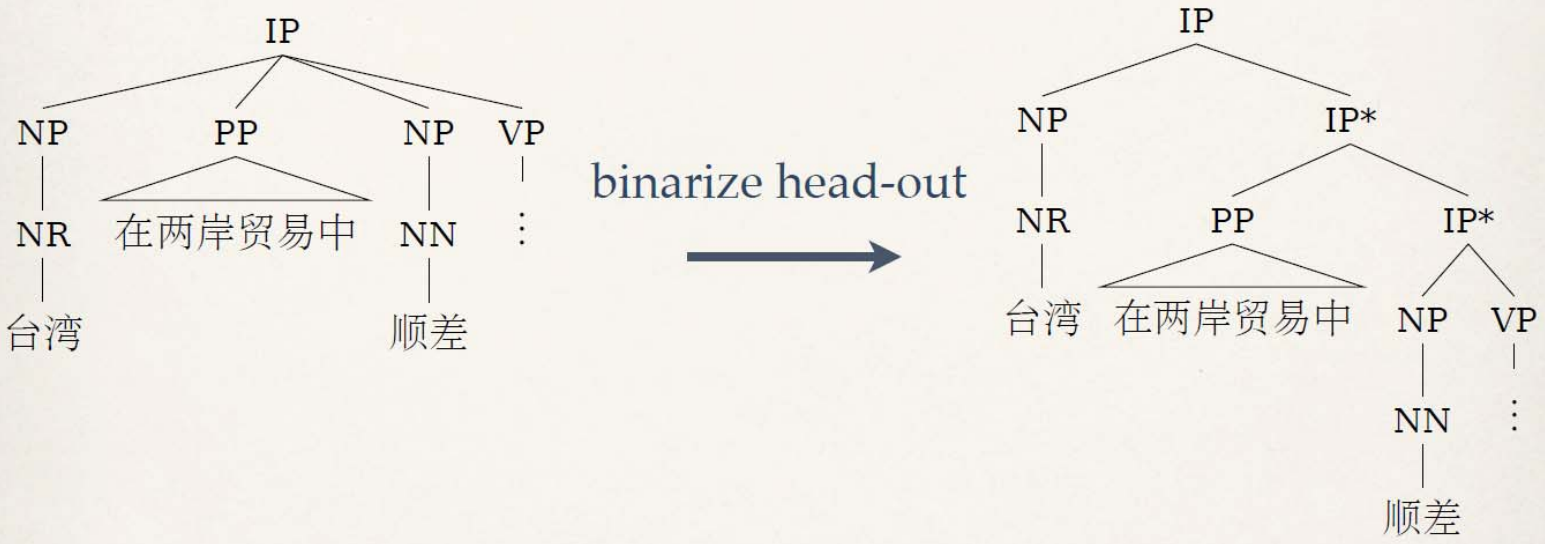
too few rules



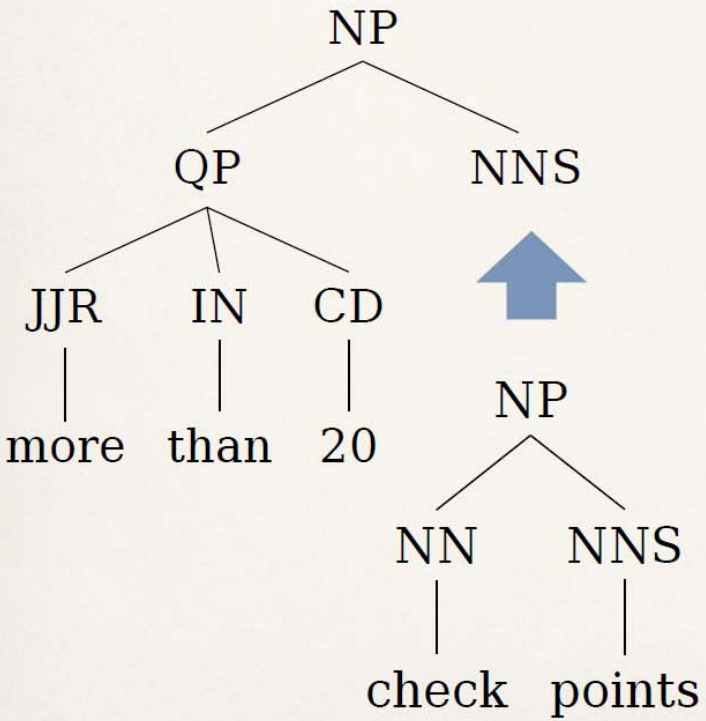
too few derivations



Extracting more rules

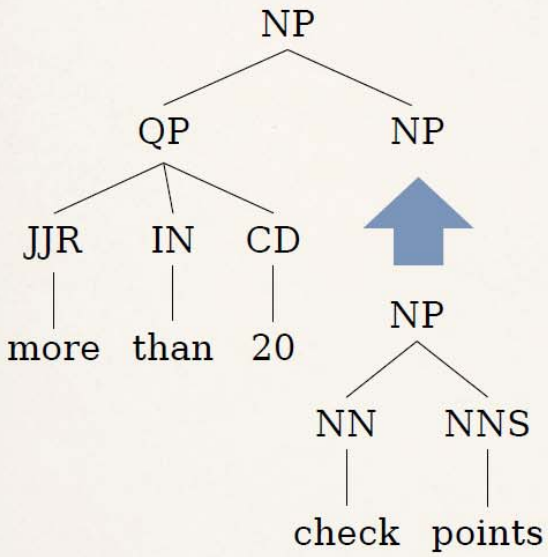


Allow more derivations

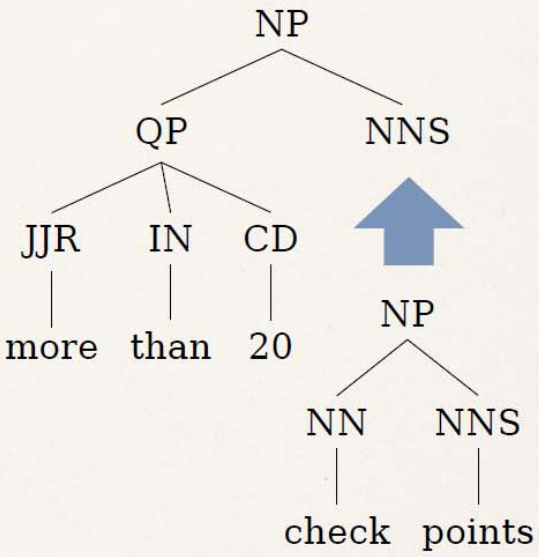


- STSG: allow only matching substitutions
- Hiero-like: allow any substitutions
- Let the model learn to choose:
  - matching substitutions
  - mismatching substitutions
  - monotone phrase-based

Allow more derivations



fire *subst*:NP→NP
fire *subst:match*



fire *subst*:NNS→NP
fire *subst:unmatch*

Allow more derivations

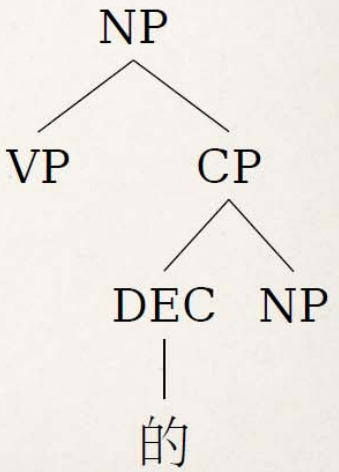
Hiero-like decoding

$$\frac{[X,i,j] \quad [X,j+1,k]}{[X,i,k]}$$

$X \rightarrow X$ 的 X

STSG decoding

$$\frac{[VP,i,j] \quad [NP,j+1,k]}{[NP,i,k]}$$



fuzzy STSG decoding

$$\frac{[A,i,j] \quad [B,j+1,k]}{[NP,i,k]}$$

Results

	Chinese-English			Arabic-English		
extraction	rules	feats	BLEU	rules	feats	BLEU
Hiero	440M	1k	23.7	790M	1k	48.9
fuzzy STSG	50M	5k	23.9	38M	5k	47.5
fuzzy STSG +binarize	64M	5k	24.3	40M	6k	48.1
fuzzy STSG +SAMT	440M	160k	24.3	790M	130k	49.7

Example tree-to-tree translation

日本 文部 科学 省 官员 表示 , " 亚 伯拉罕 的 发言 , 令 我们 深感 鼓舞
Japan MEXT official said , " Abraham 's comment make us deeply-feel courage

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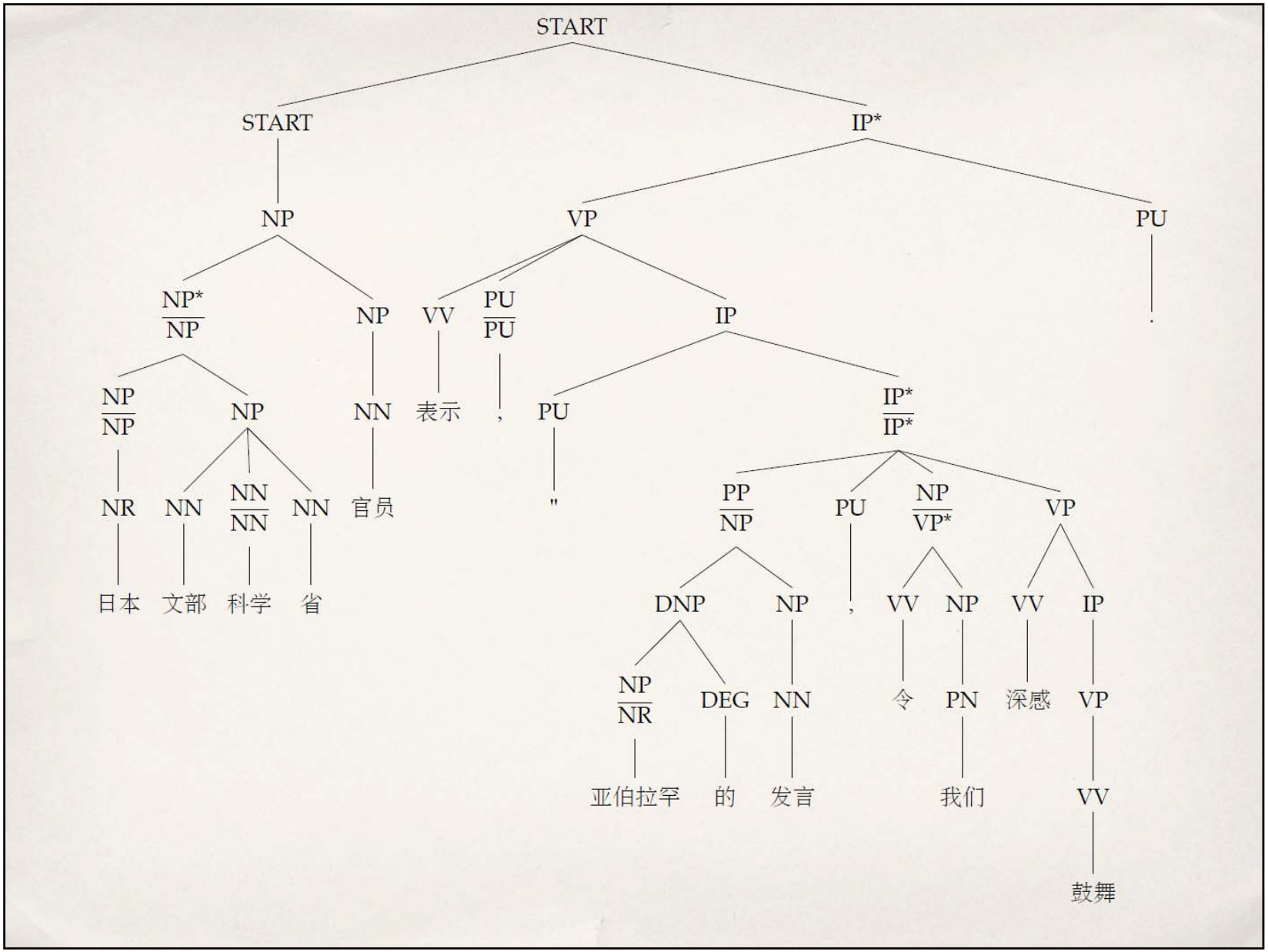
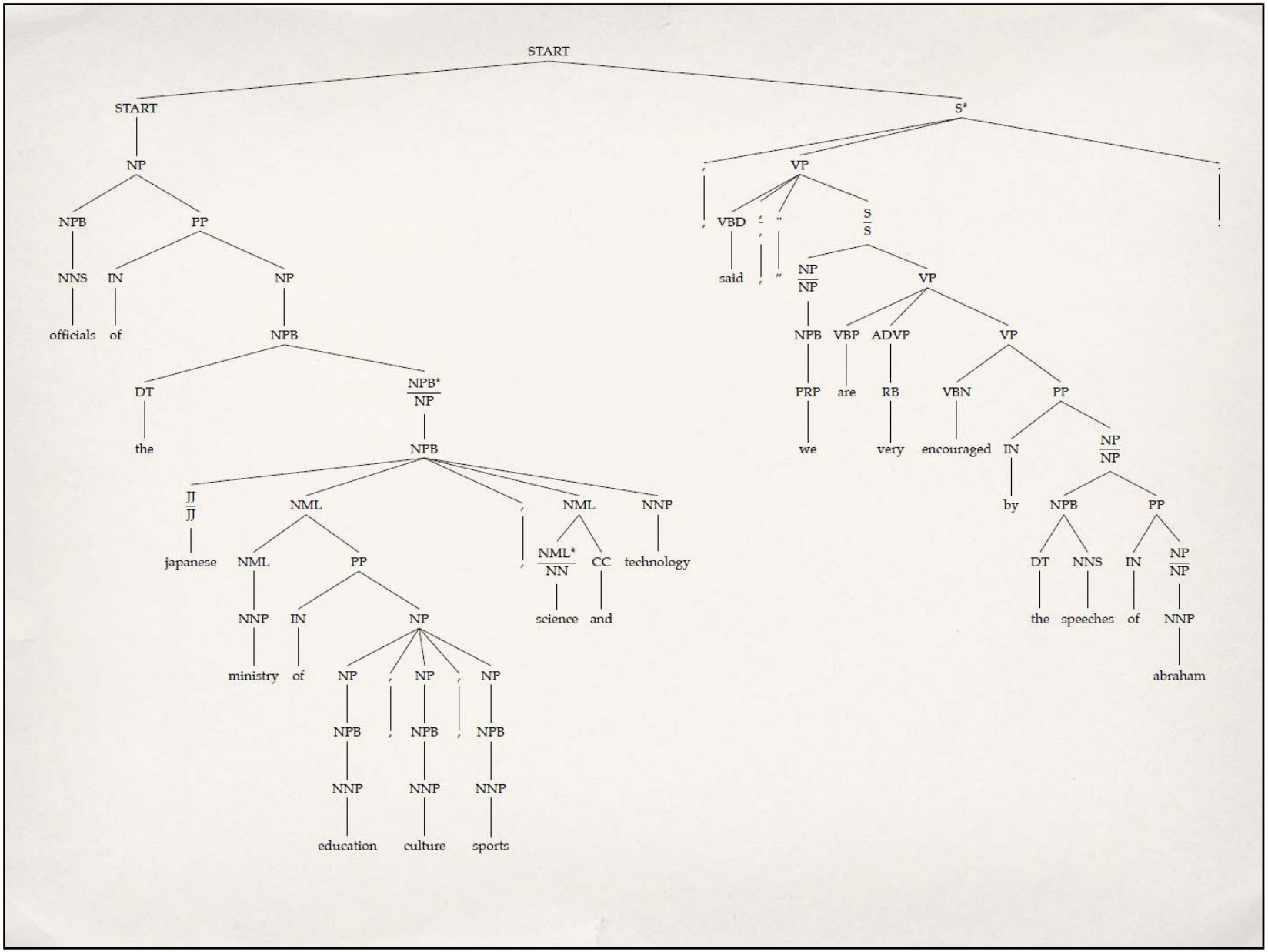
string-to-tree: Japan 's ministry of education , culture , sports , science and technology , " Abraham 's statement , which is most encouraging , " the official said .

Fuzzy STSG, binarize: Officials of the Japanese ministry of education , culture , sports , science and technology , said , " we are very encouraged by the speeches of Abraham .


START
START
IP*
NP
VP
PU
NP*
NP
NP
VV
PU
PU
IP
.
NP
NP
NP
NN
表示
,
PU
IP*
IP*
NR
NN
NN
NN
官员
"
PP
NP
PU
NP
VP*
VP
日本
文部
科学
省
DNP
NP
,
VV
NP
VV
IP
NP
NR
DEG
NN
令
PN
深感
VP
亚伯拉罕
的
发言
我们
VV
鼓舞


START
START
S*
NP
,
VP
.
NPB
PP
,
VBD
,
"
S
S
NNS
IN
NP
said
,
"
NP
NP
VP
officials
of
NPB
NPB
VBP
ADVP
VP
DT
NPB*
NP
PRP
are
RB
VBN
PP
the
NPB
we
very
encouraged
IN
NP
NP
JJ
JJ
NML
,
NML
NNP
by
NPB
PP
japanese
NML
PP
NML*
NN
CC
technology
DT
NNS
IN
NP
NP
NNP
IN
NP
science
and
the
speeches
of
NNP
ministry
of
NP
,
NP
,
NP
abraham
NPB
,
NPB
,
NPB
NNP
NNP
NNP
education
culture
sports

Exploiting GPUs

Lots to Parse

≈2.6 billion words

Lots to Parse

≈6 months (CPU)

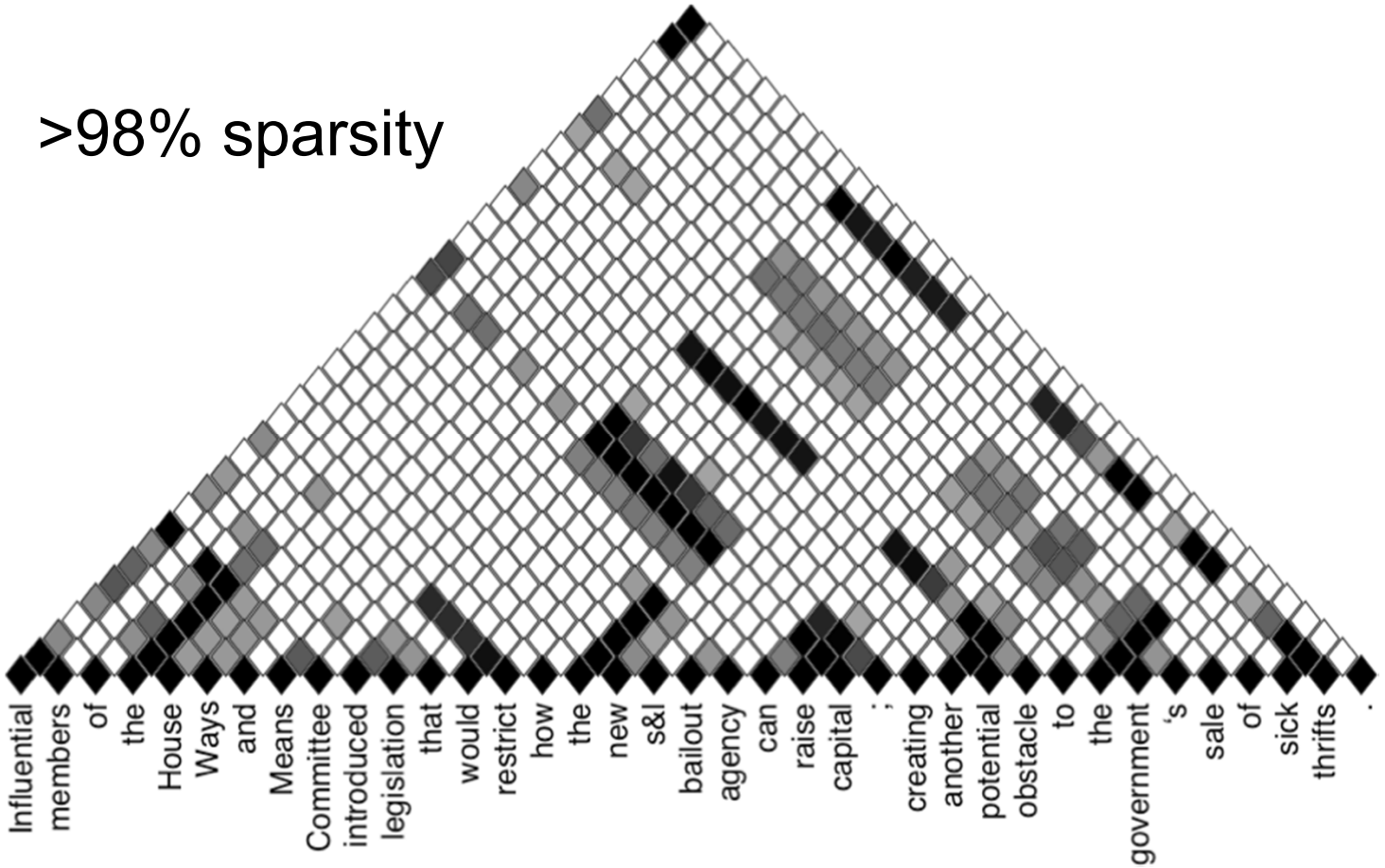
Lots to Parse

≈3.6 days (GPU)

CPU Parsing

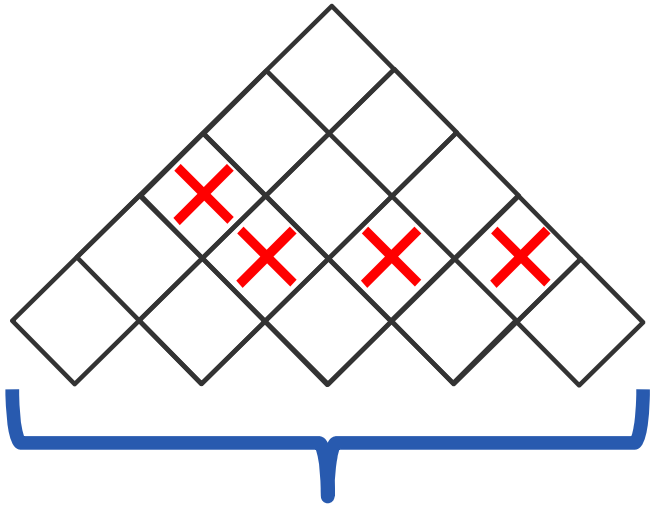
[Petrov & Klein, 2007]

>98% sparsity



Slide credit: Slav Petrov

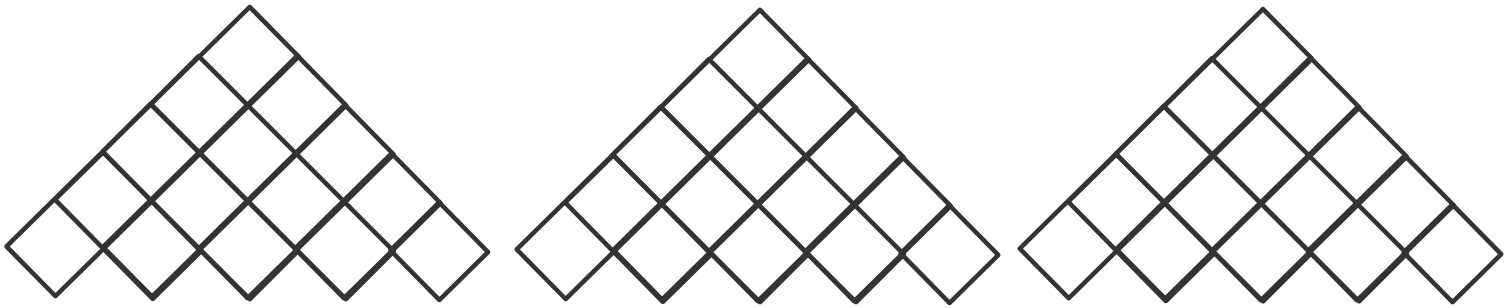
CPU Parsing



CPU Parsing

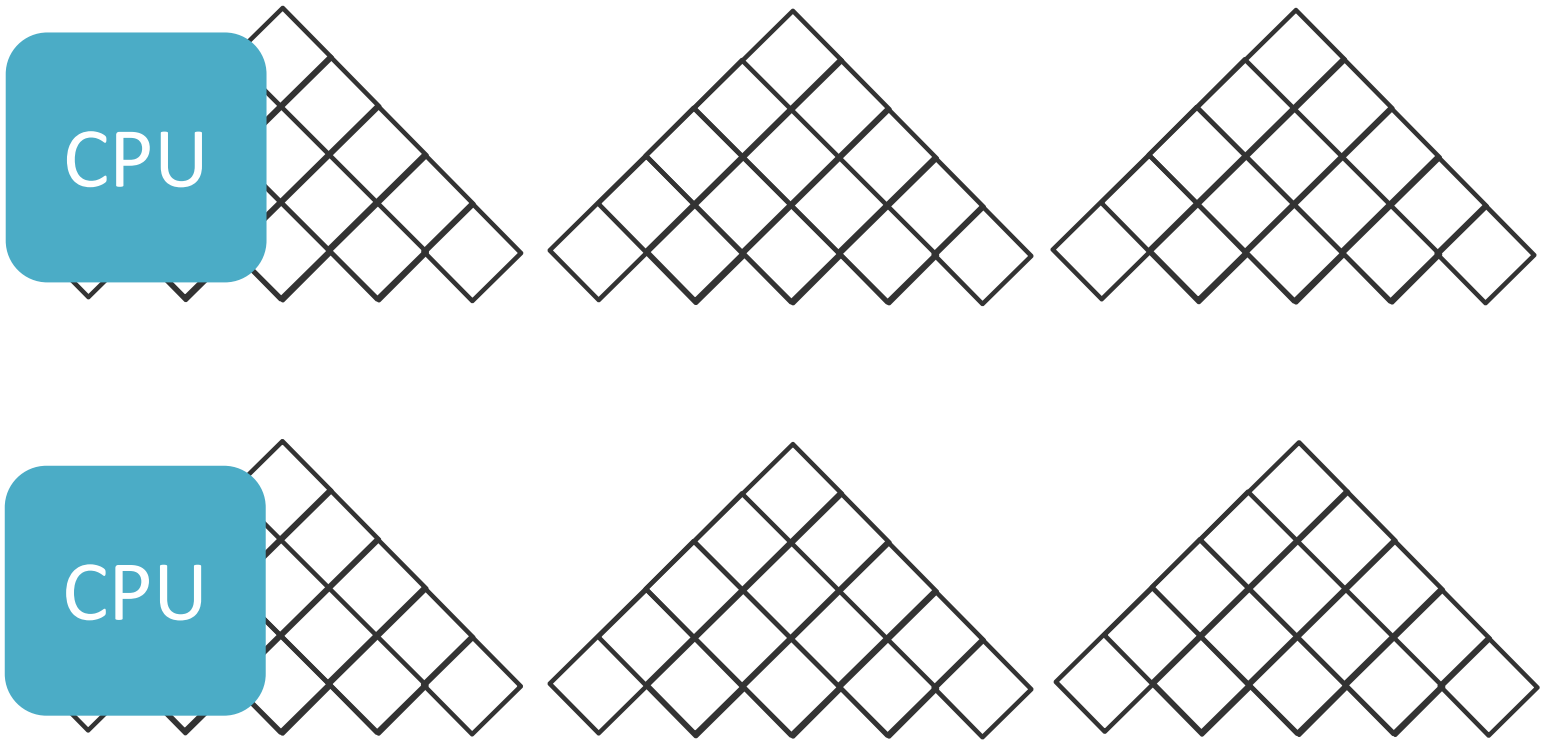
CPU

CPU Parsing



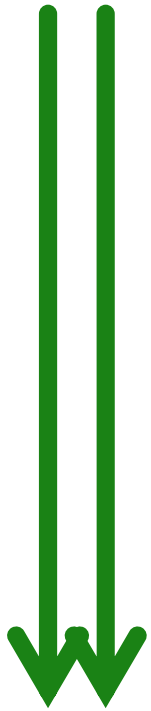
CPU

CPU Parsing

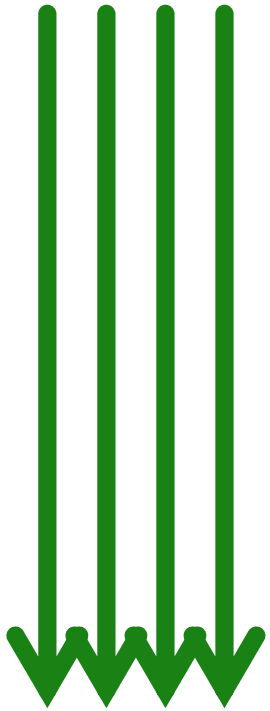


The Future of Hardware

The Future of Hardware



The Future of Hardware



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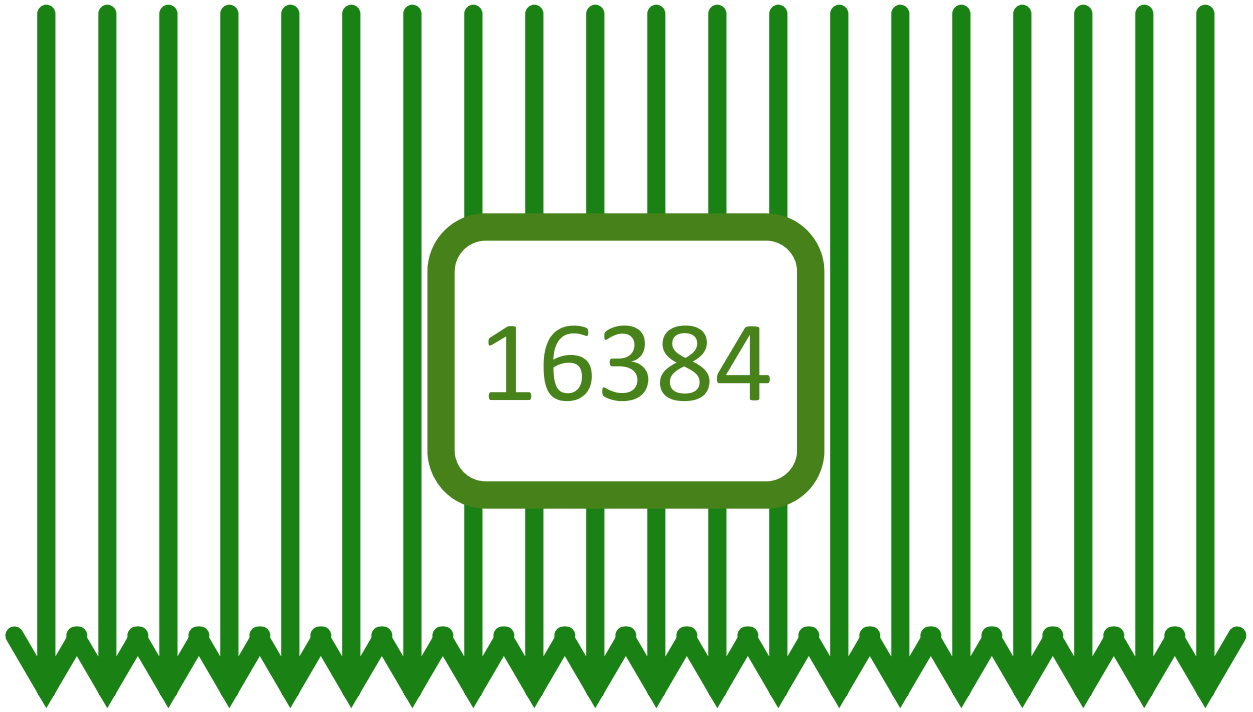

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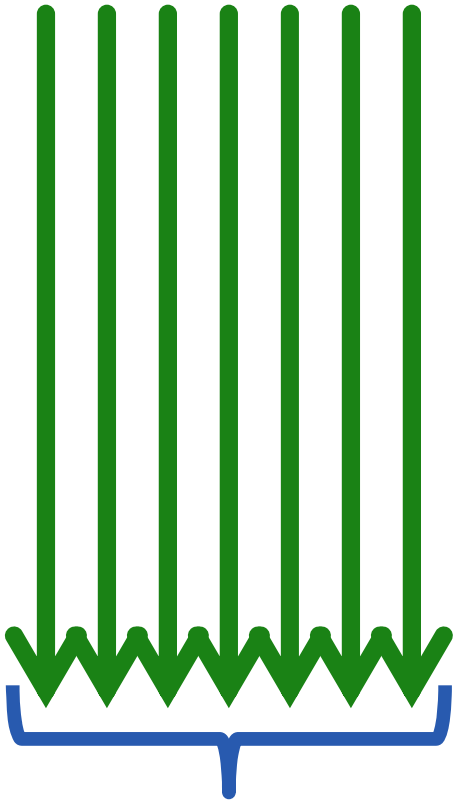
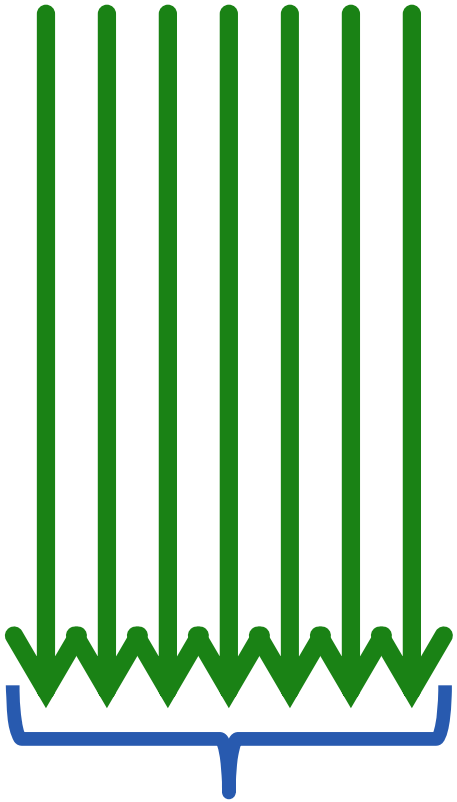
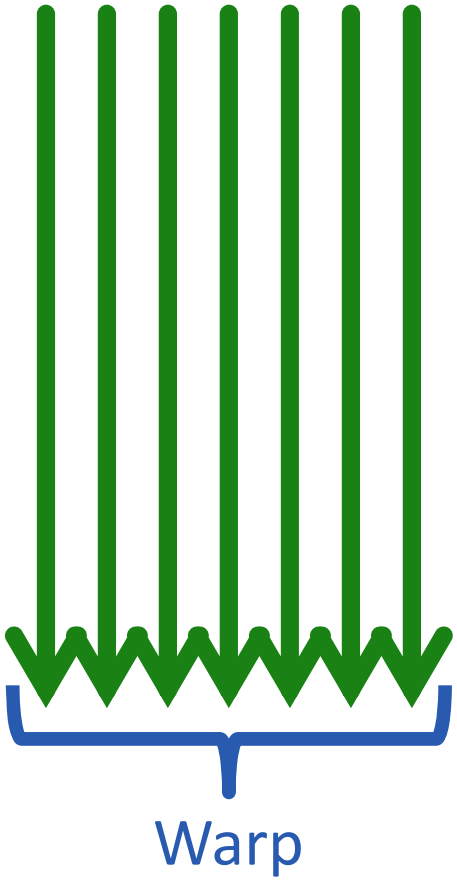


The Future of Hardware

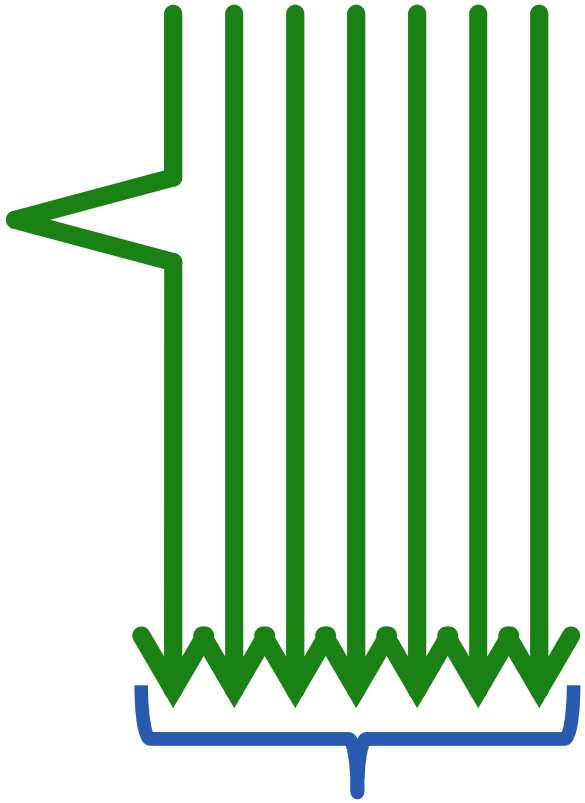
```
add.s32   %r1, %r631, %r0;
ld.global.f32   %f81, [%r1];
ld.global.f32   %f82, [%r34];
mul.ftz.f32   %f94, %f82, %f81;
mov.f32   %f95, 0f3E002E23;
mov.f32   %f96, 0f00000000;
mad.f32   %f93, %f94, %f95, %f96;
shl.b32   %r2, %r646, 8;
add.s32   %r3, %r658, %r2;
shl.b32   %r4, %r3, 2;
add.s32   %r5, %r631, %r4;
mul.lo.s32  %r6, %r646, 588;
shl.b32   %r7, %r6, 1;
add.s32   %r8, %r5, %r7;
ld.global.f32   %f83, [%r8];
mul.ftz.f32   %f98, %f82, %f83;
```



Warps

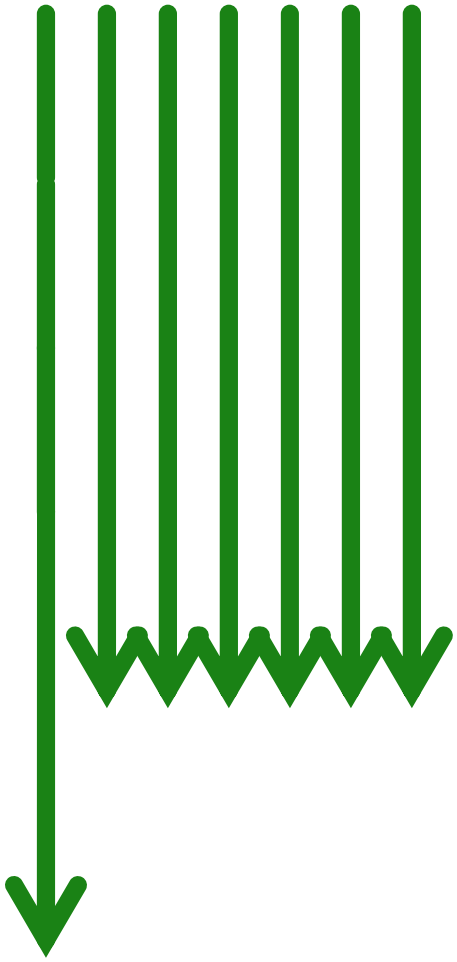


Warps

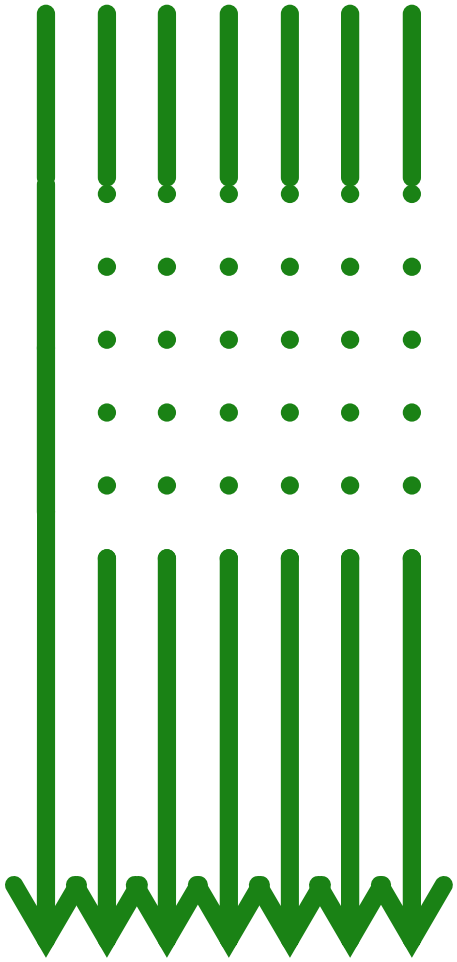


Warp Divergence

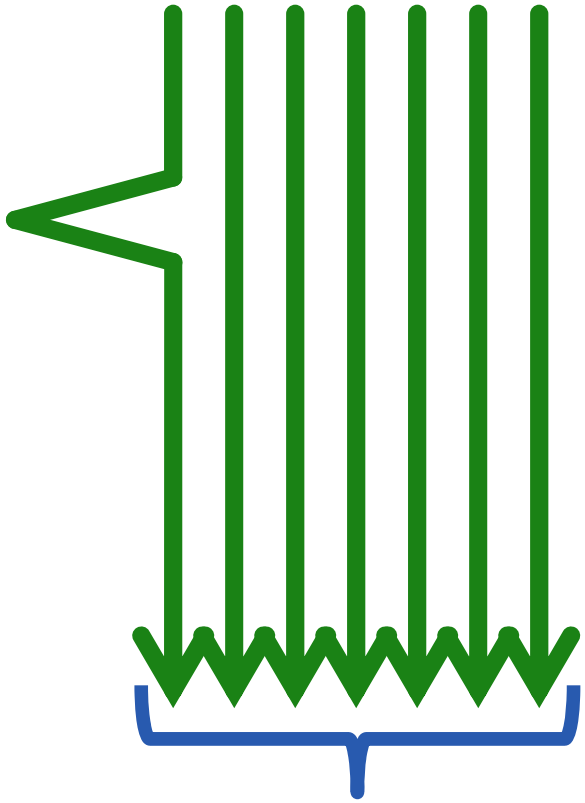
Warps



Warps

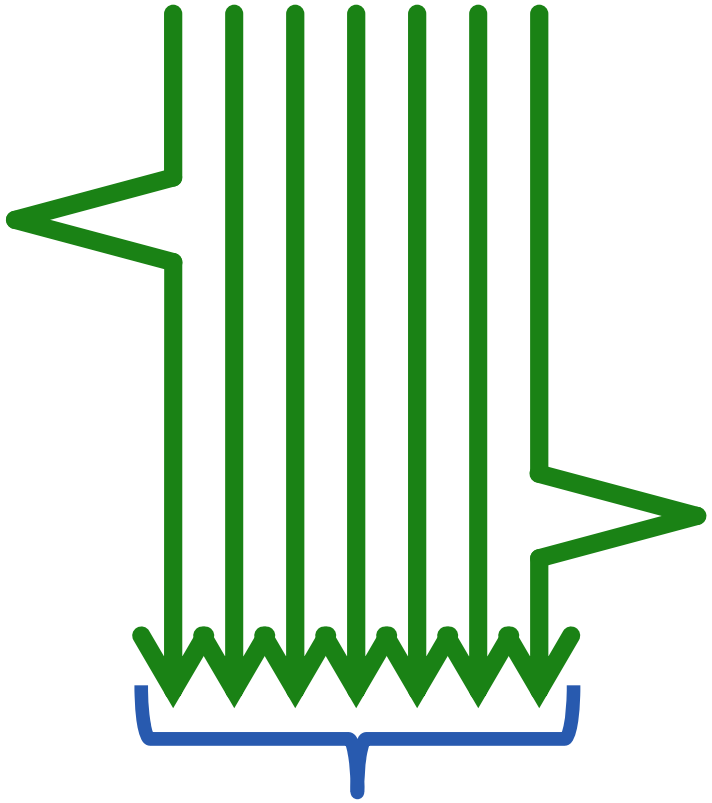


Warps



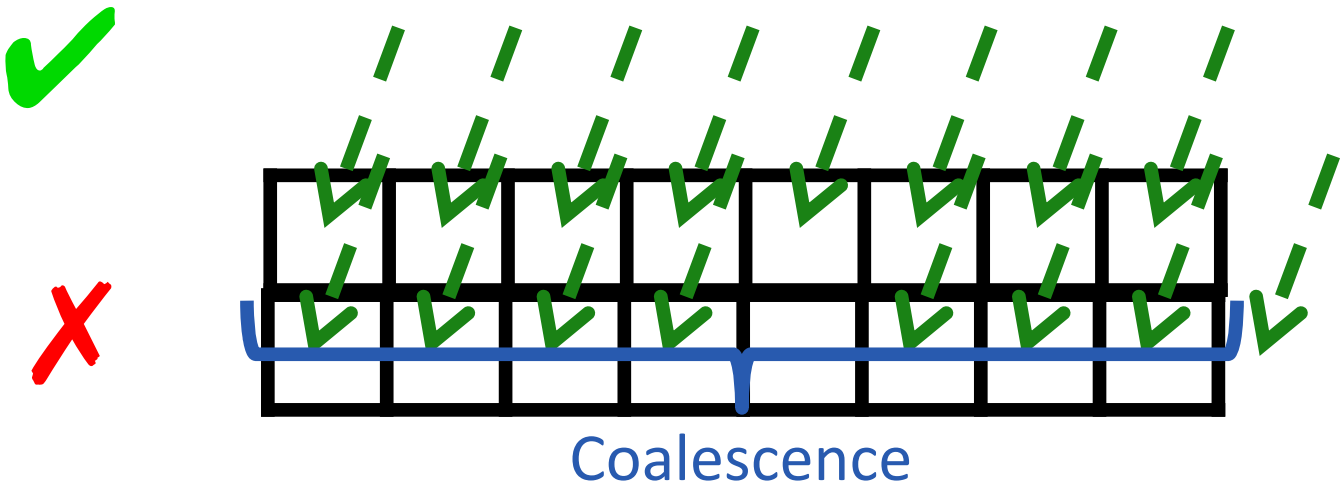
Warp Divergence

Warps

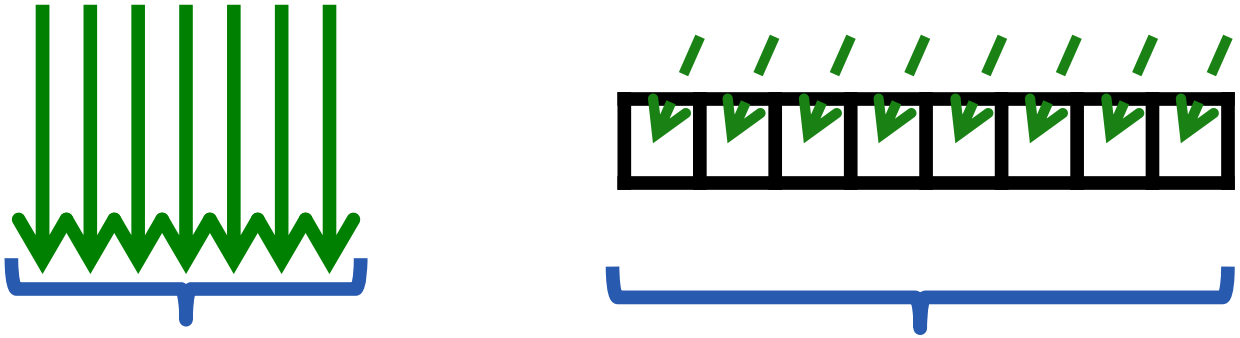


Warp Divergence

Warps



Designing GPU Algorithms



Dense, Uniform Computation

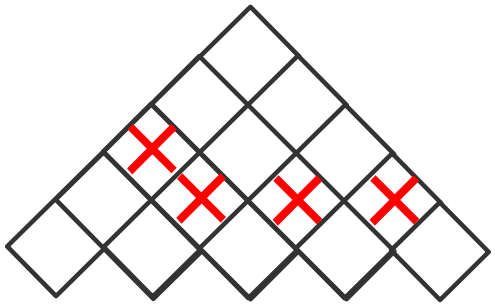
Designing GPU Algorithms

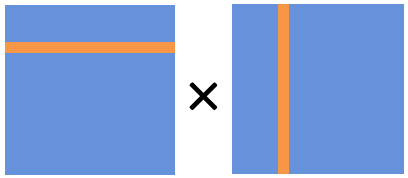
CPU

Irregular,
Sparse

GPU

Regular,
Dense





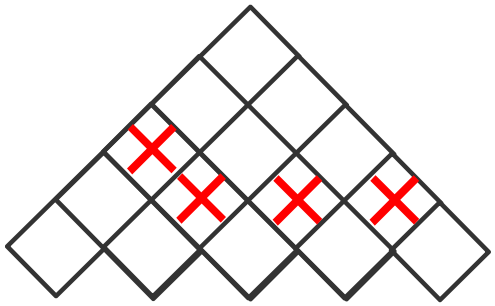
Designing GPU Algorithms

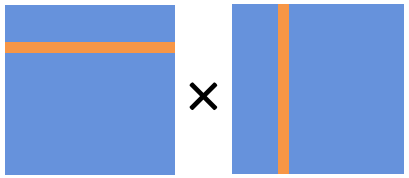
CPU

Irregular,
Sparse

GPU

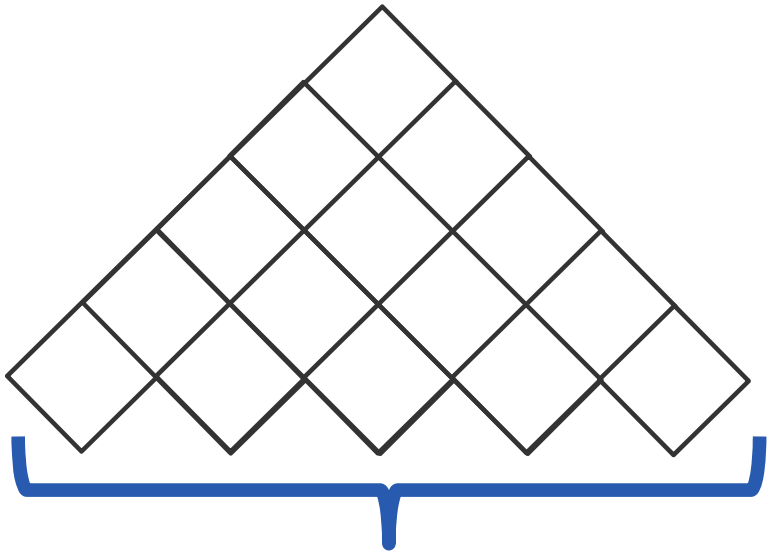
Regular,
Dense





[Canny, Hall, and Klein, 2013]

Designing GPU Algorithms



CKY Parsing

```
for each sentence:
  for each span (begin, end):
    for each split:
      for each rule (P -> L R):
        score[begin, end, P]
         += ruleScore[P -> L R]
           * score[begin, split, L]
           * score[split, end, R]
```

Item Queue

Grammar Application

CKY Parsing

```
for each sentence:
  for each span (begin, end):
    for each split:

      applyGrammar(begin, split, end)
```

Item Queue

Grammar Application

CKY Parsing

```
for each parse item in sentence:
    applyGrammar(item)
```

Item Queue

Grammar Application

CKY Parsing

```
for each parse item in sentence:
    applyGrammar(item)
```

CPU

GPU

GPU Parsing Pipeline

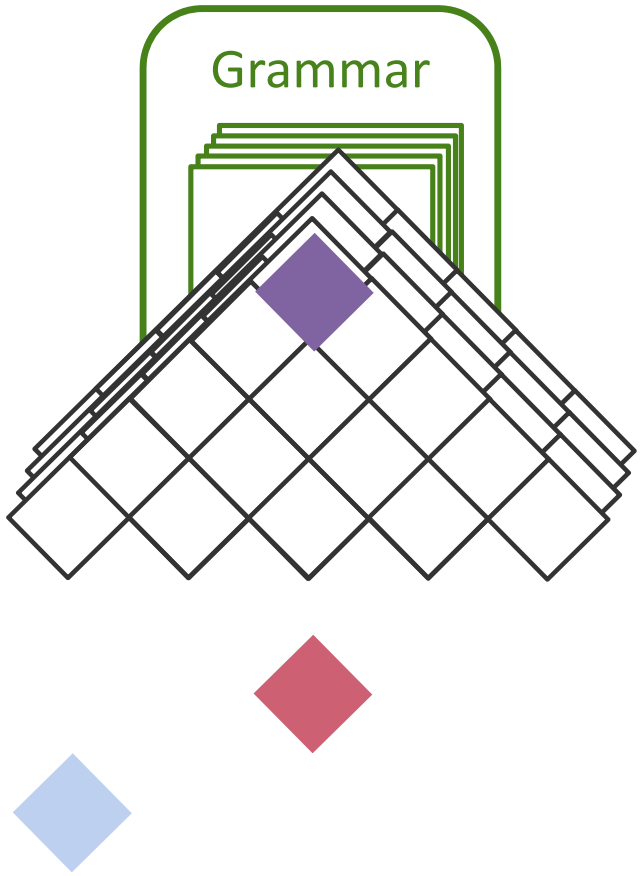
CPU

Queue

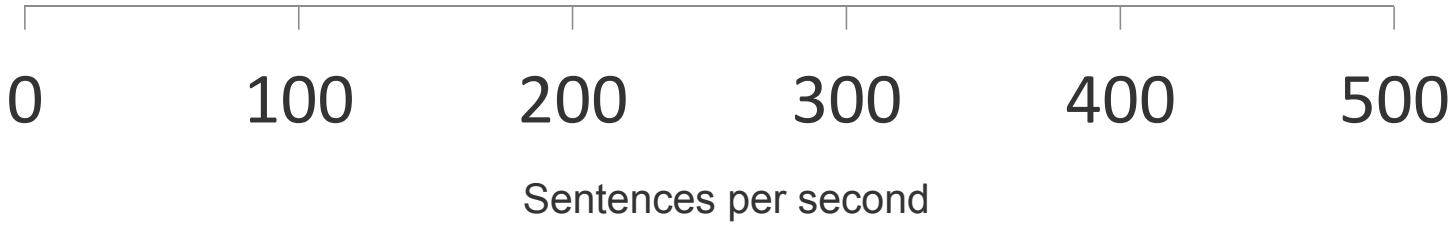
(i, k, j)
(0, 1, 3)
(0, 2, 3)
(1, 2, 4)
(1, 3, 4)
⋮

3
2

GPU

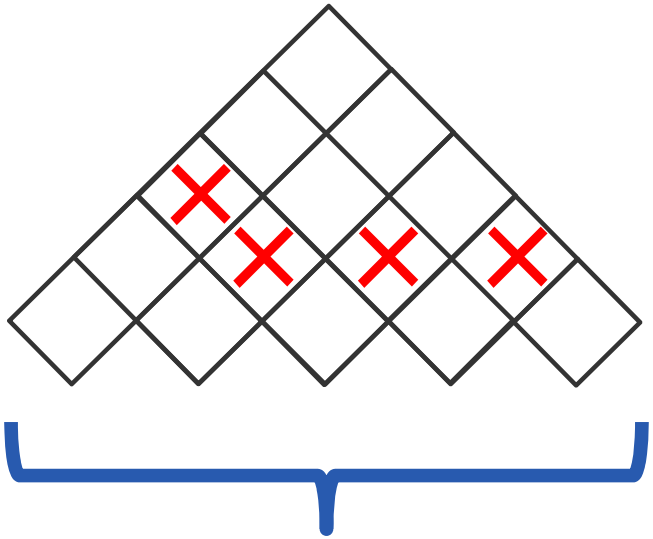


Parsing Speed

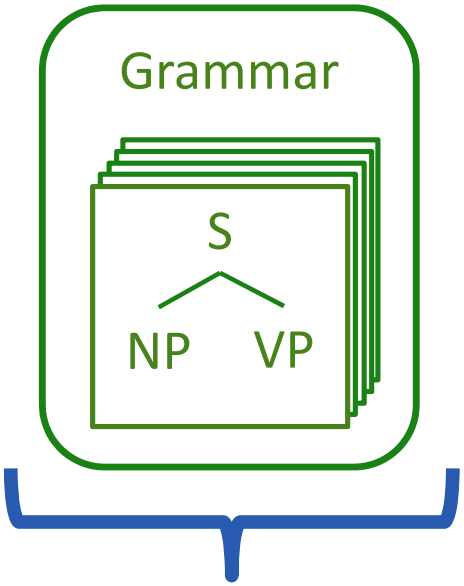


[Canny, Hall, and Klein, 2013]

Exploiting Sparsity

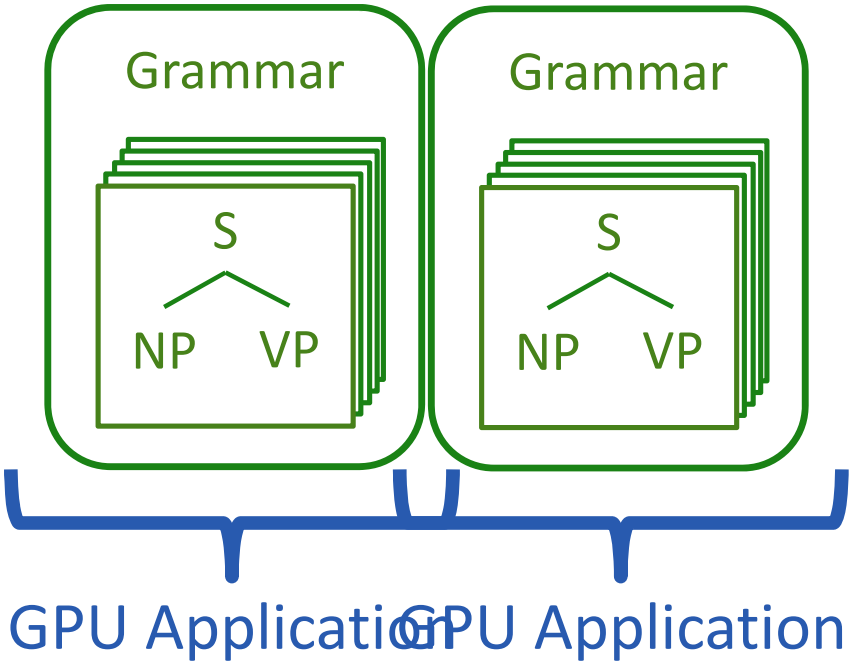


CPU Queuing

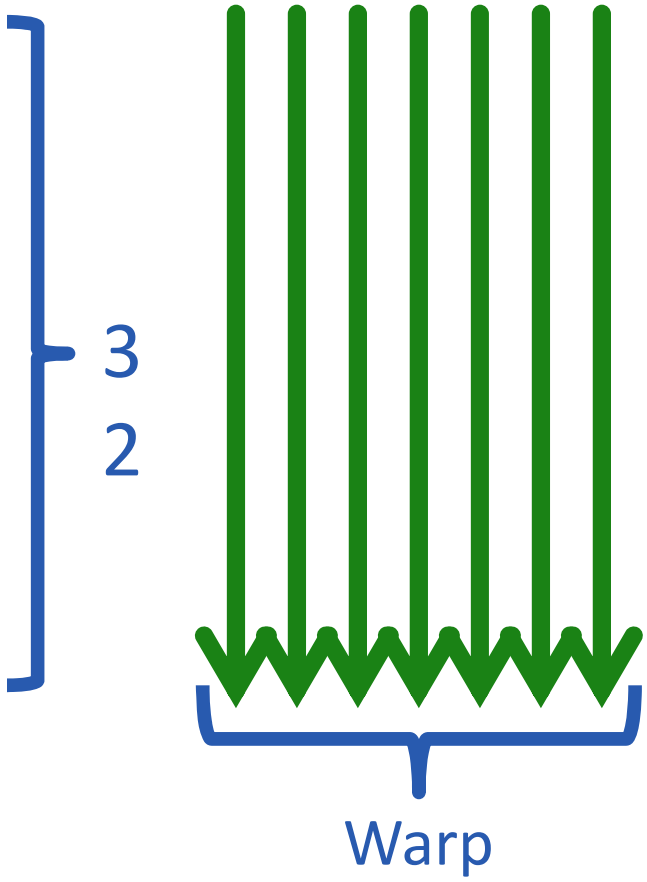


GPU Application

Exploiting Sparsity



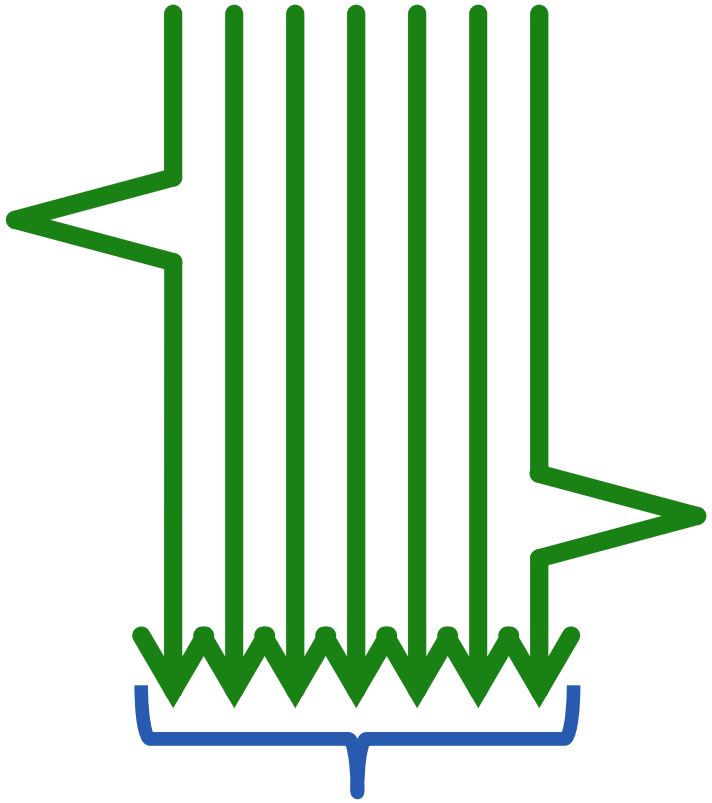
Exploiting Sparsity



Exploiting Sparsity

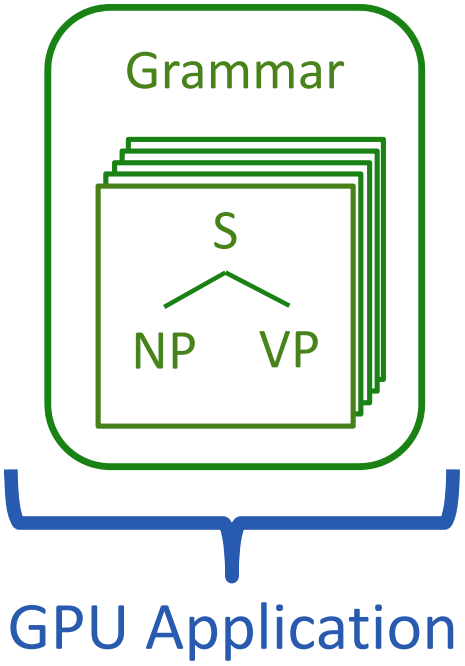
(0, 1, 3)	~~S~~	NP	~~VP~~	~~PP~~	…
(0, 2, 3)	~~S~~	~~NP~~	VP	~~PP~~	…
(1, 2, 4)	~~S~~	NP	~~VP~~	PP	…
(1, 3, 4)	~~S~~	NP	VP	~~PP~~	…
(2, 3, 5)	~~S~~	NP	VP	~~PP~~	…
(2, 4, 5)	~~S~~	NP	~~VP~~	PP	…
(3, 4, 6)	~~S~~	NP	~~VP~~	PP	…
⋮					

Exploiting Sparsity

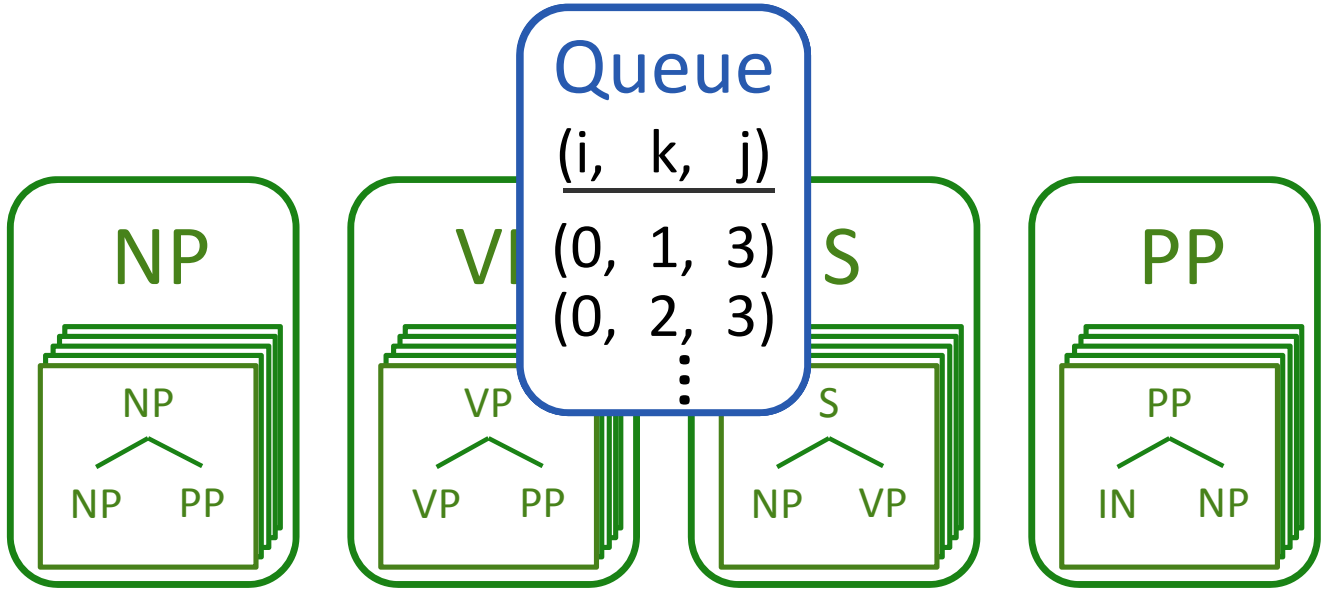


Warp Divergence

Exploiting Sparsity



Exploiting Sparsity



Exploiting Sparsity

CPU

NP Queue

(i, k, j)

(0, 1, 3)

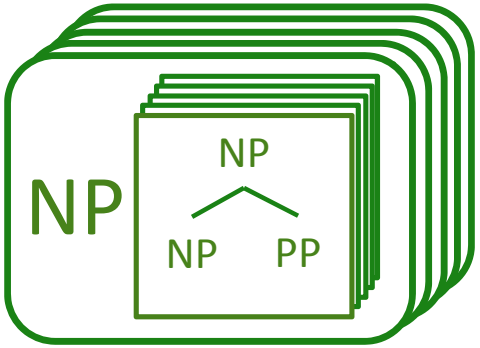
(0, 2, 3)

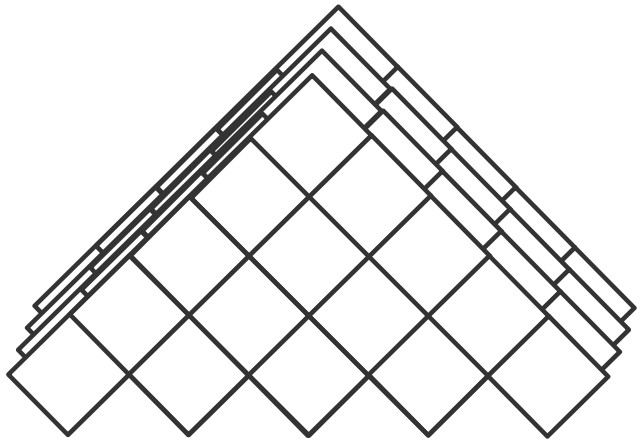
~~(1, 2, 4)~~

~~(1, 3, 4)~~

⋮

GPU





Exploiting Sparsity

CPU

VP Queue

(i, k, j)

~~(0, 1, 3)~~

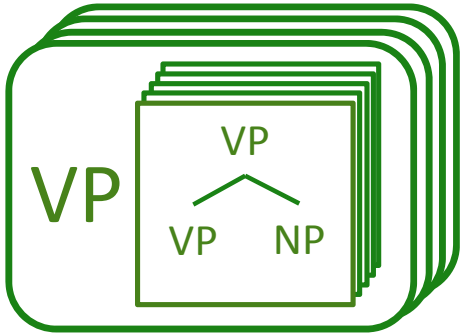
~~(0, 2, 3)~~

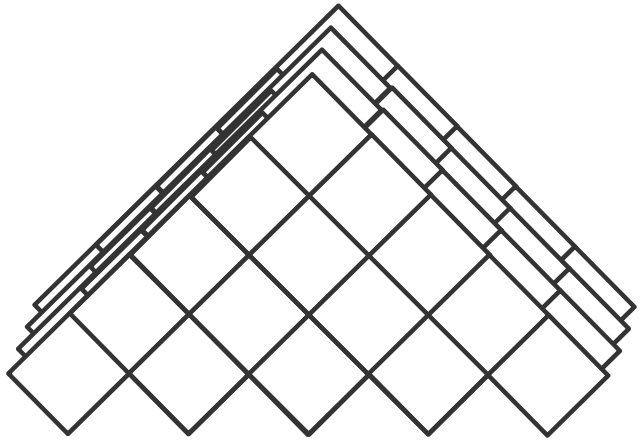
(1, 2, 4)

~~(1, 3, 4)~~

⋮

GPU





Parsing Speed