A General-Purpose Rule Extractor for SCFG-Based Machine Translation

Greg Hanneman, **Michelle Burroughs**, and **Alon Lavie**

Language Technologies Institute
Carnegie Mellon University

Fifth Workshop on Syntax and Structure in Statistical Translation
June 23, 2011

Carnegie Mellon

SCFG Grammar Extraction

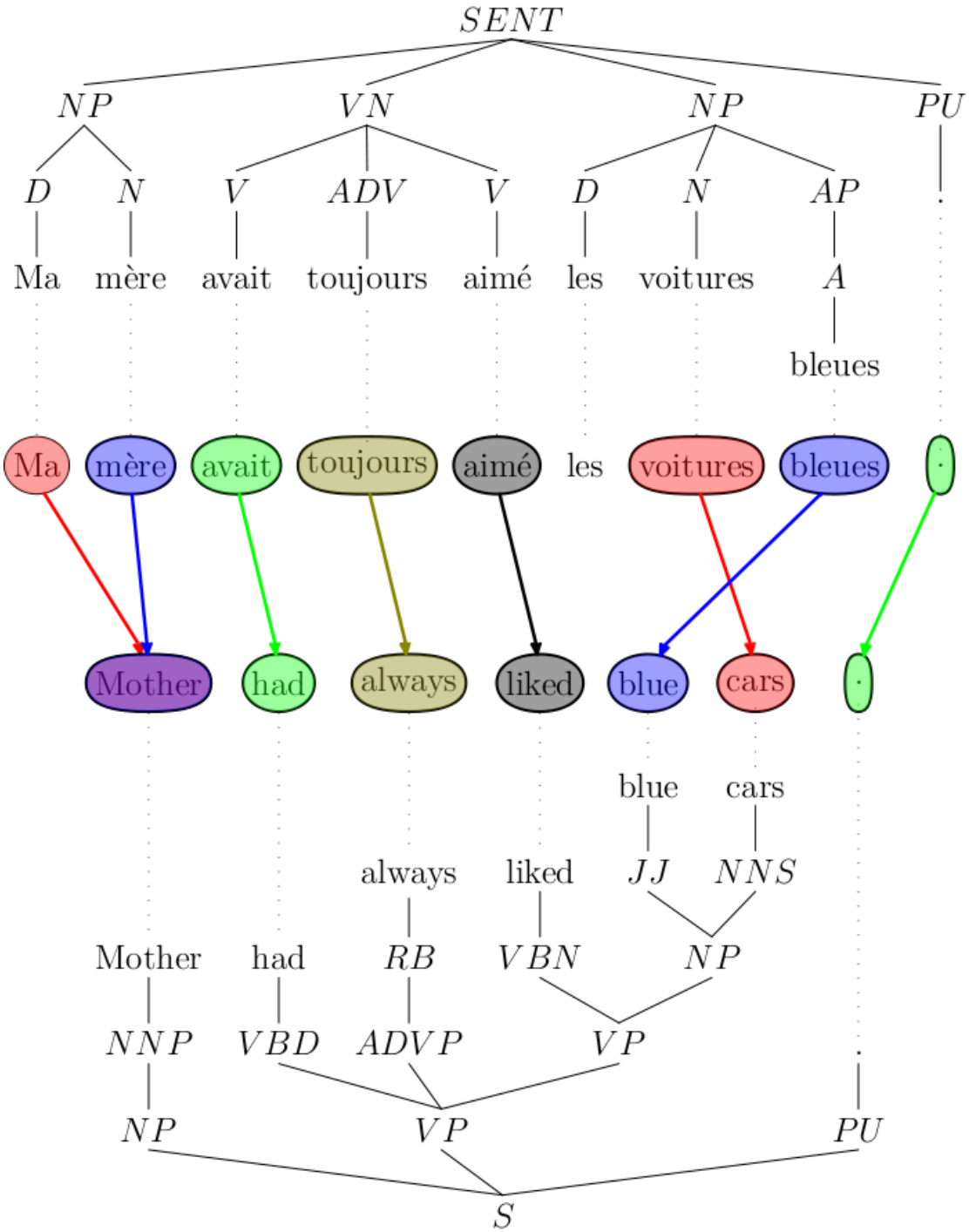
- Inputs:
  - Word-aligned sentence pair
  - Constituency parse trees on one or both sides
- Outputs:
  - Set of SCFG rules derivable from the inputs, possibly according to some constraints
- Implemented by:

Hiero [Chiang 2005]
Chiang [2010]
SAMT [Zollmann and Venugopal 2006]
GHKM [Galley et al. 2004]
Stat-XFER [Lavie et al. 2008]

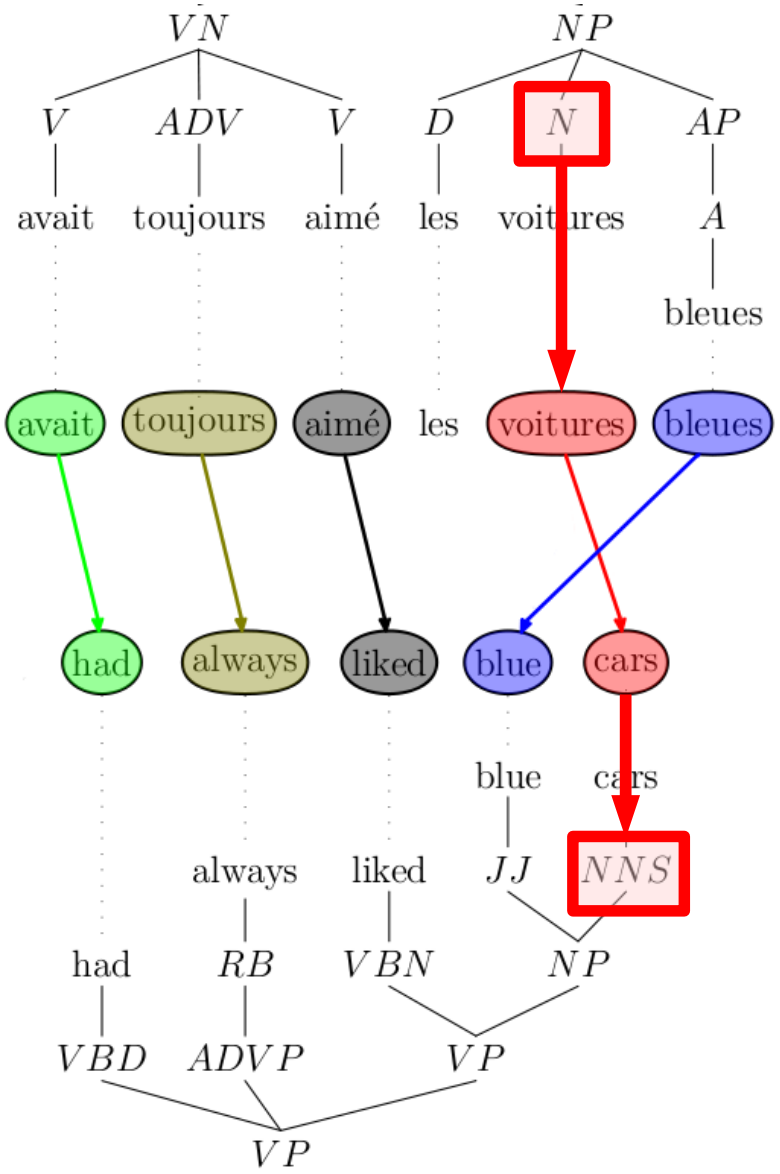
SCFG Grammar Extraction

- Our goals:
  - Support for two parse trees by default
  - Extract greatest number of syntactic rules...
  - Without violating constituent boundaries
- Achieved with:
  - Multiple node alignments
  - Virtual nodes
  - Multiple right-hand-side decompositions

First grammar extractor to do all three

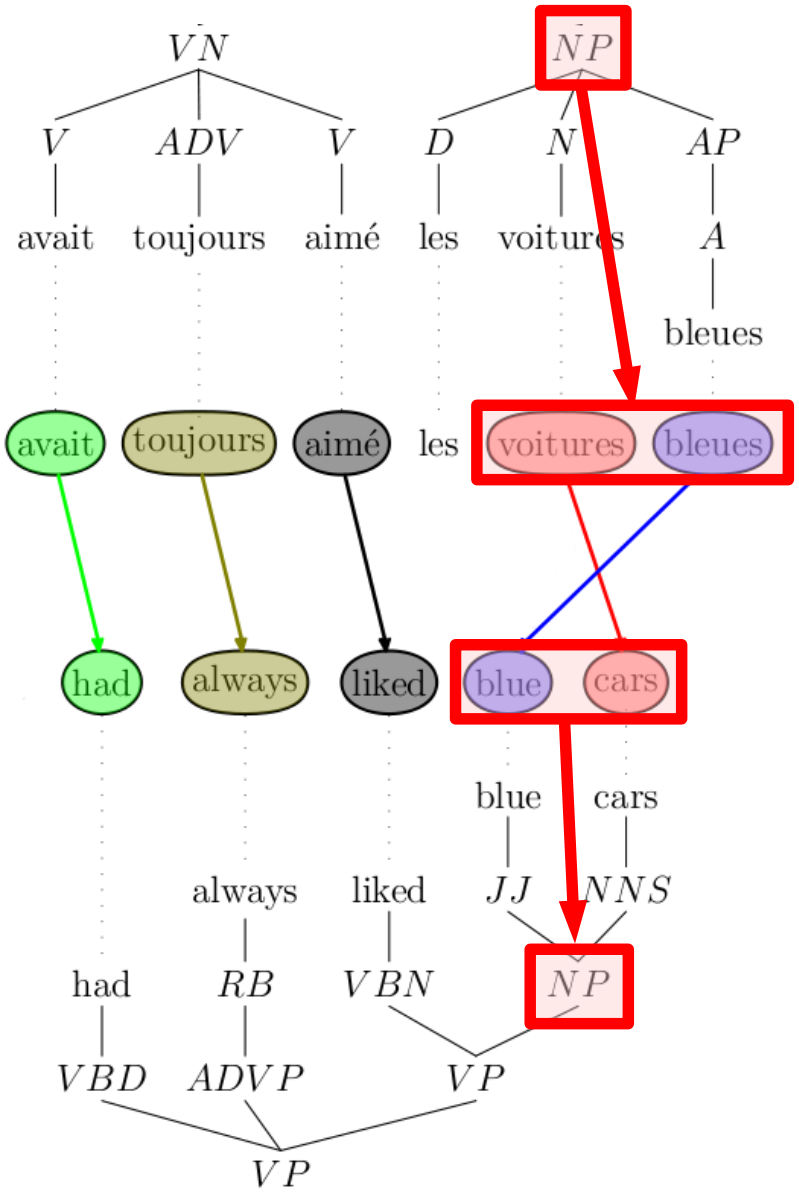

SENT
NP
VN
NP
PU
D
N
V
ADV
V
D
N
AP
.
Ma
mère
avait
toujours
aimé
les
voitures
A
bleues
Ma
mère
avait
toujours
aimé
les
voitures
bleues
.
Mother
had
always
liked
blue
cars
.
blue
cars
always
liked
JJ
NNS
Mother
had
RB
VBN
NP
NNP
VBD
ADVP
VP
.
NP
VP
PU
S

Basic Node Alignment



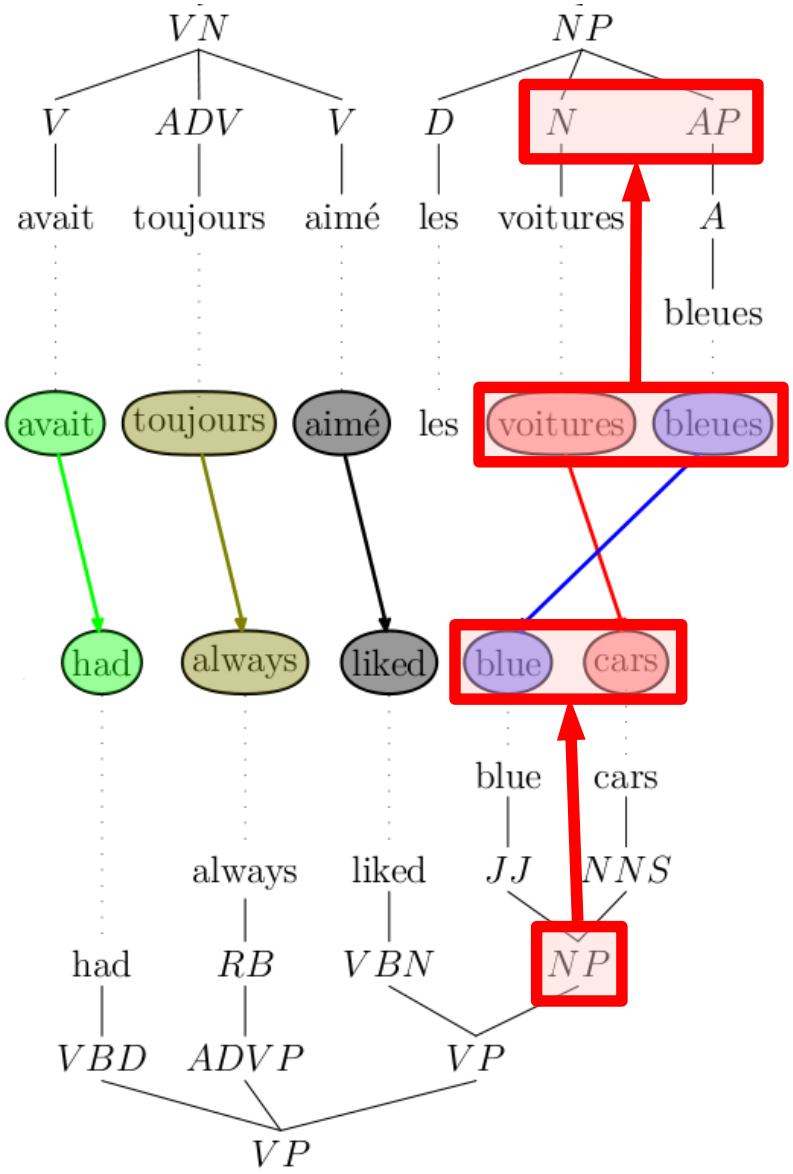
- Word alignment consistency constraint from phrase-based SMT

Basic Node Alignment



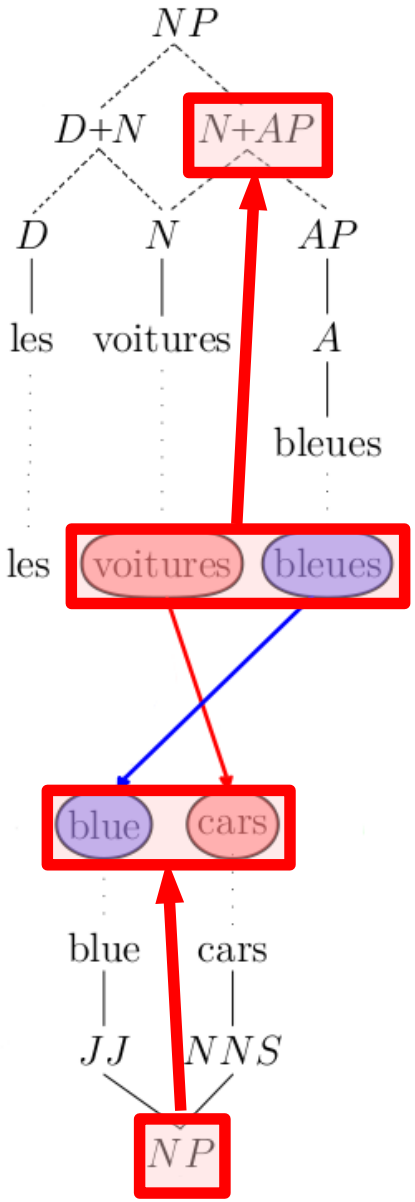
- Word alignment consistency constraint from phrase-based SMT

Virtual Nodes



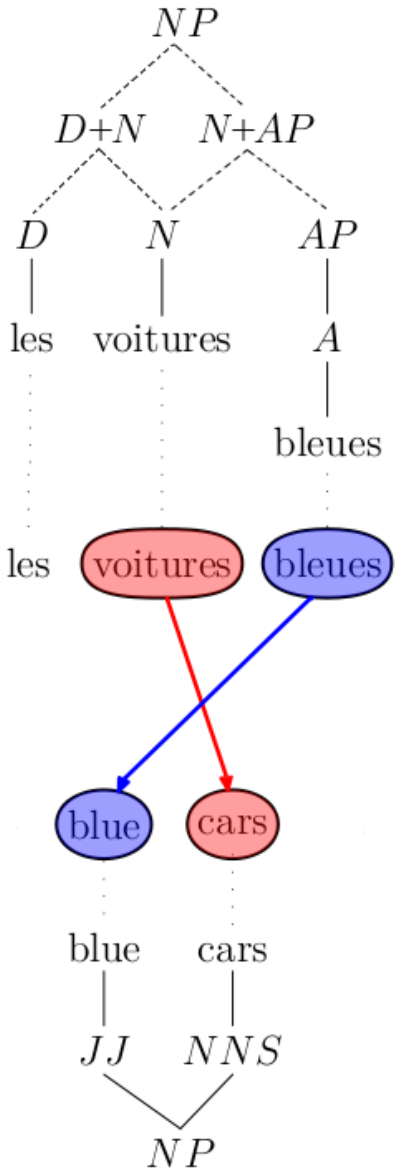
- Consistently aligned consecutive children of the same parent

Virtual Nodes



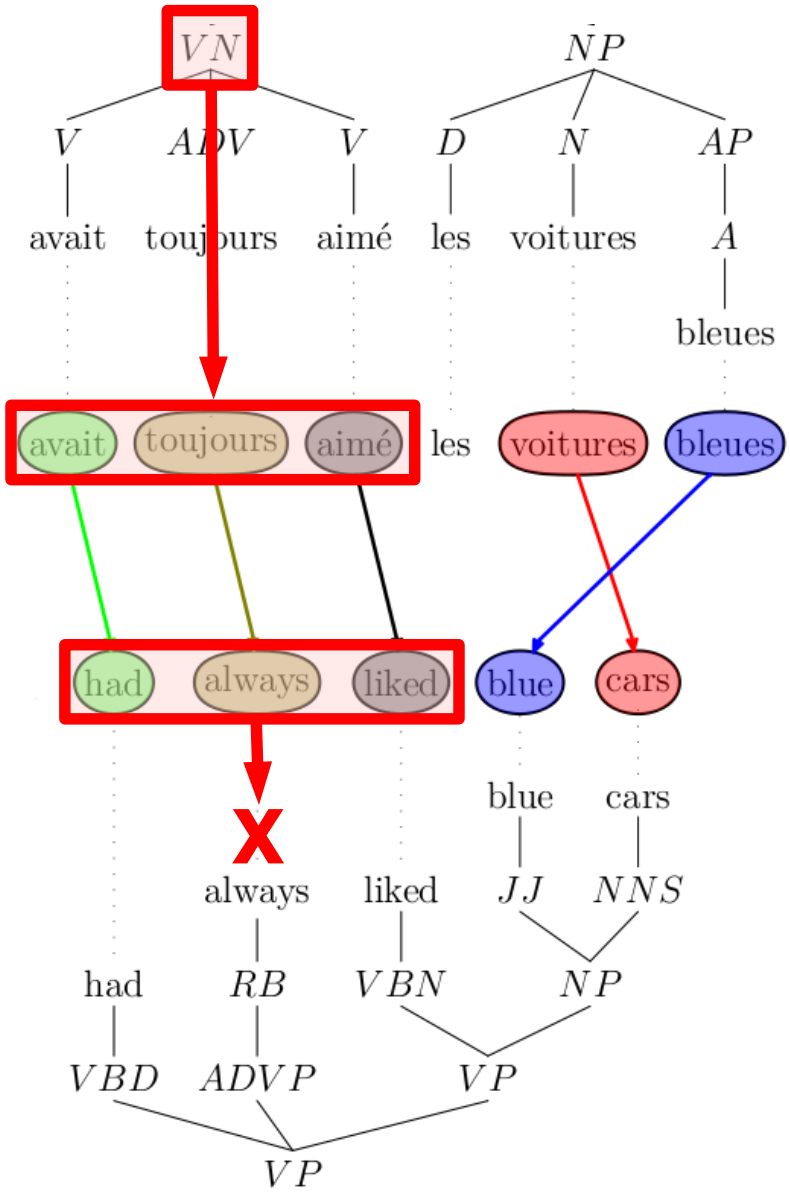
- Consistently aligned consecutive children of the same parent
- New intermediate node inserted in tree

Virtual Nodes



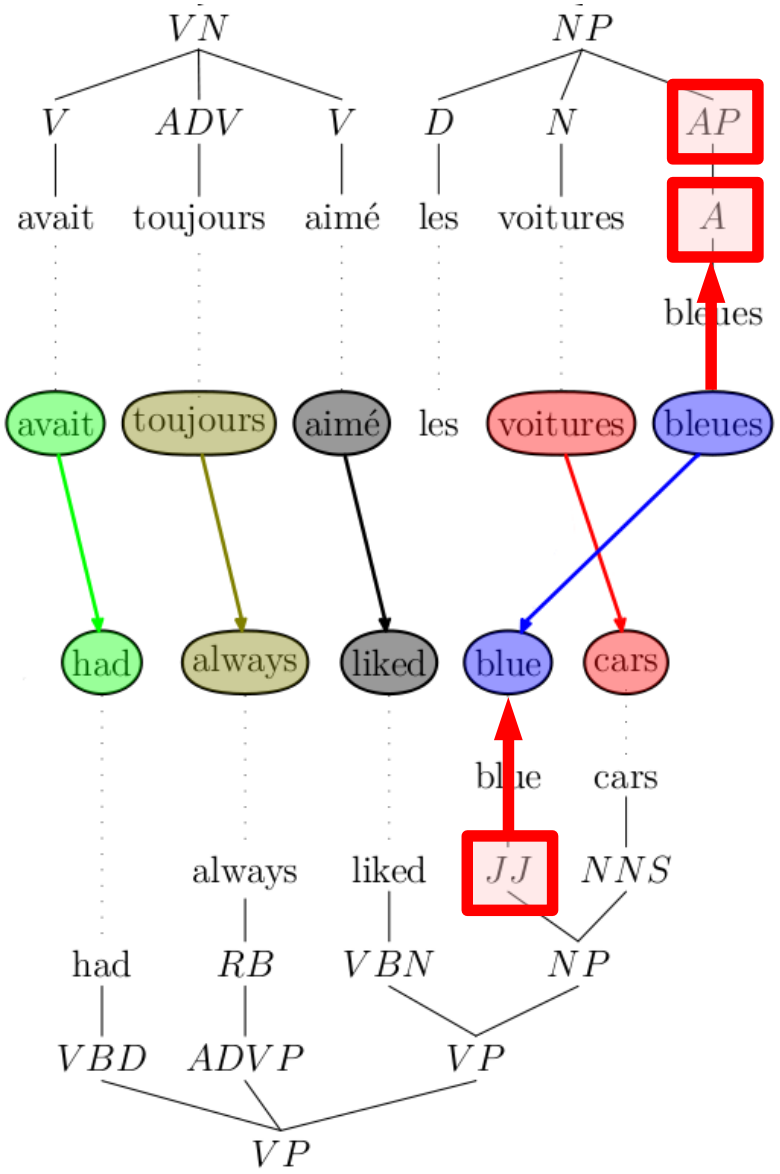
- Consistently aligned consecutive children of the same parent
- New intermediate node inserted in tree
- Virtual nodes may overlap
- Virtual nodes may align to any type of node

Syntax Constraints



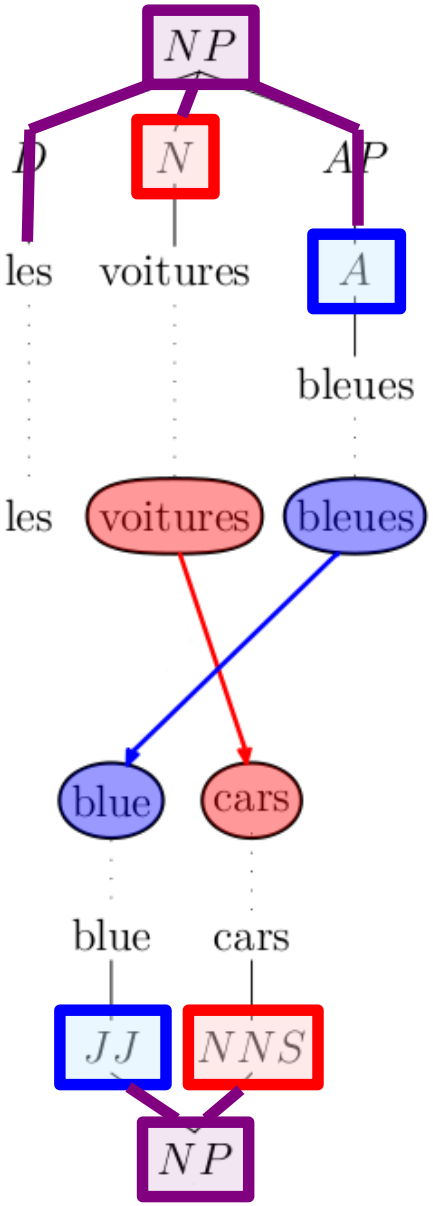
- Consistent word alignments ≠ node alignment
- Virtual nodes may not cross constituent boundaries

Multiple Alignment



- Nodes with multiple consistent alignments keep all of them

Basic Grammar Extraction



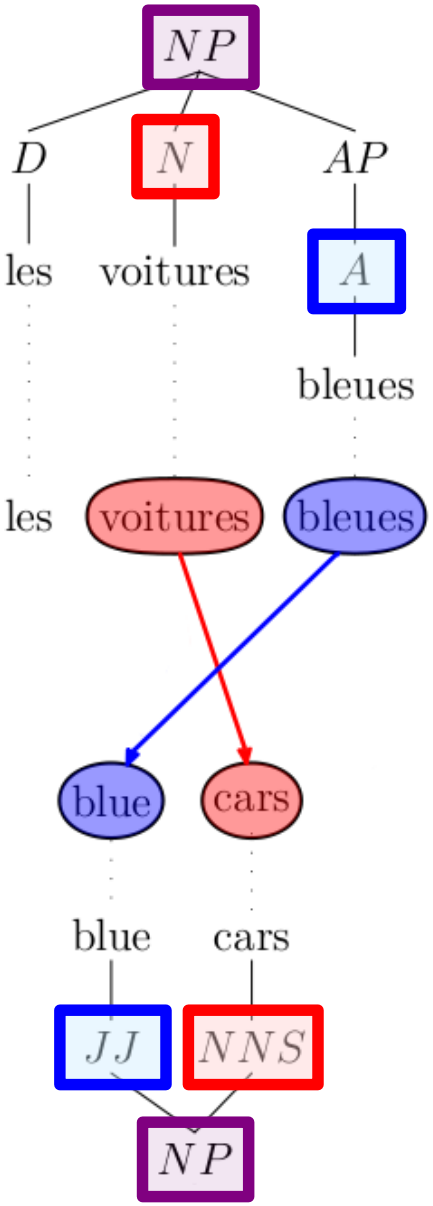
- Aligned node pair is LHS; aligned subnodes are RHS

$$\text{NP::NP} \rightarrow [\text{les } \text{N}^1 \text{ A}^2]::[\text{JJ}^2 \text{ NNS}^1]$$

$$\text{N::NNS} \rightarrow [\text{voitures}]::[\text{cars}]$$

$$\text{A::JJ} \rightarrow [\text{bleues}]::[\text{blue}]$$

Multiple Decompositions



- All possible right-hand sides are extracted

NP::NP → [les N^1 A^2]::[JJ^2 NNS^1]

NP::NP → [les N^1 bleues]::[blue NNS^1]

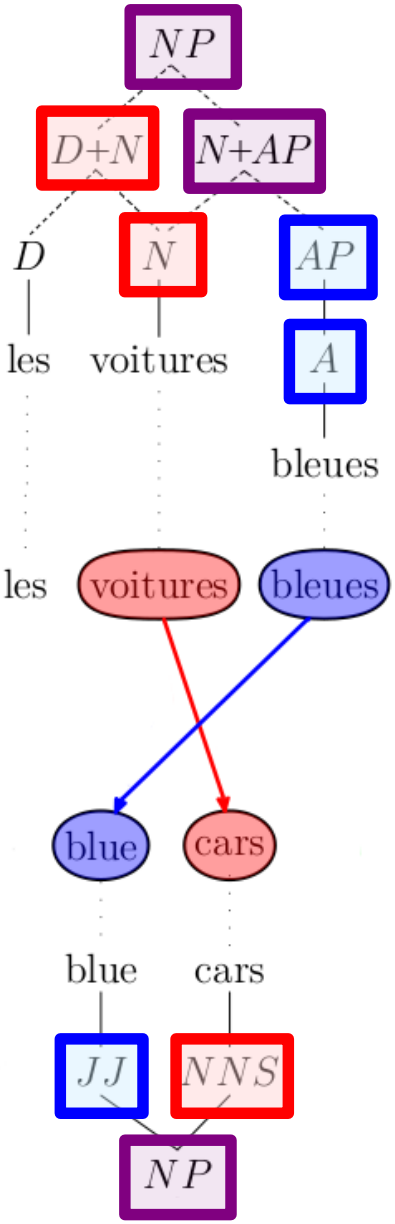
NP::NP → [les voitures A^2]::[JJ^2 cars]

NP::NP → [les voitures bleues]::[blue cars]

N::NNS → [voitures]::[cars]

A::JJ → [bleues]::[blue]

Multiple Decompositions



NP::NP → [les N+AP[1]]::[NP[1]]
NP::NP → [D+N[1] AP[2]]::[JJ[2] NNS[1]]
NP::NP → [D+N[1] A[2]]::[JJ[2] NNS[1]]
NP::NP → [les N[1] AP[2]]::[JJ[2] NNS[1]]
NP::NP → [les N[1] A[2]]::[JJ[2] NNS[1]]
NP::NP → [D+N[1] bleues]::[blue NNS[1]]
NP::NP → [les N[1] bleues]::[blue NNS[1]]
NP::NP → [les voitures AP[2]]::[JJ[2] cars]
NP::NP → [les voitures A[2]]::[JJ[2] cars]
NP::NP → [les voitures bleues]::[blue cars]
D+N::NNS → [les N[1]]::[NNS[1]]
D+N::NNS → [les voitures]::[cars]
N+AP::NP → [N[1] AP[2]]::[JJ[2] NNS[1]]
N+AP::NP → [N[1] A[2]]::[JJ[2] NNS[1]]
N+AP::NP → [N[1] bleues]::[blue NNS[1]]
N+AP::NP → [voitures AP[2]]::[JJ[2] cars]
N+AP::NP → [voitures A[2]]::[JJ[2] cars]
N+AP::NP → [voitures bleues]::[blue cars]
N::NNS → [voitures]::[cars]
AP::JJ → [A[1]]::[JJ[1]]
AP::JJ → [bleues]::[blue]
A::JJ → [bleues]::[blue]

Constraints

- Max rank of phrase pair rules
- Max rank of hierarchical rules
- Max number of siblings in a virtual node
- Whether to allow unary chain rules

$$\text{NP::NP} \rightarrow [\text{PRO}^1]::[\text{PRP}^1]$$

- Whether to allow "triangle" rules

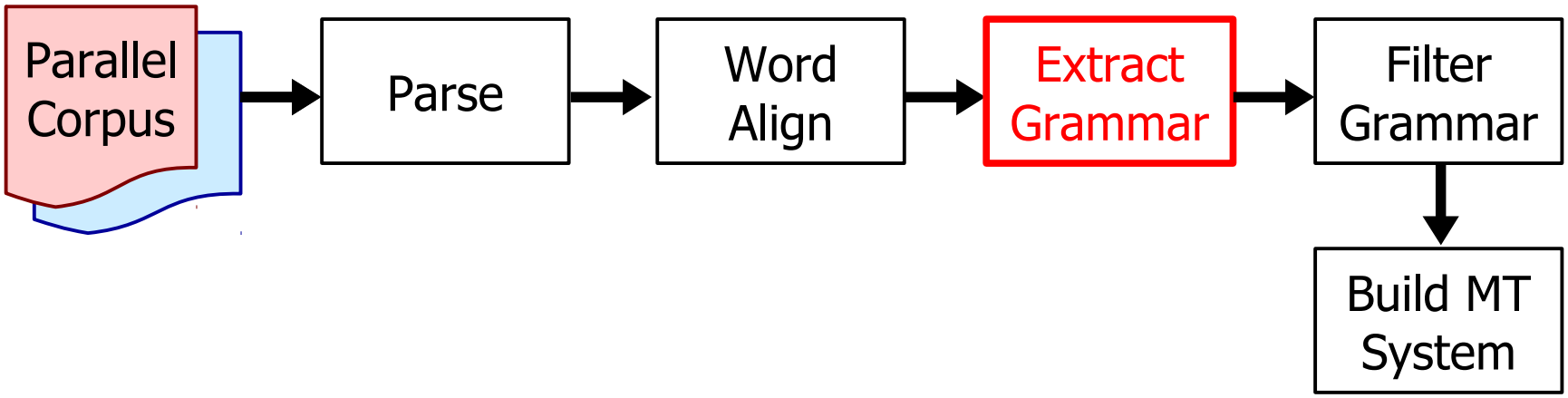
$$\text{AP::JJ} \rightarrow [\text{A}^1]::[\text{JJ}^1]$$

Comparison to Related Work

	Tree Constr.	Multiple Aligns	Virtual Nodes	Multiple Decomp.
Hiero	No	—	—	Yes
Stat-XFER	Yes	No	Some	No
GHKM	Yes	No	No	Yes
SAMT	No	No	Yes	Yes
Chiang [2010]	No	No	Yes	Yes
This work	Yes	Yes	Yes	Yes

Experimental Setup

- Train: FBIS Chinese–English corpus
- Tune: NIST MT 2006
- Test: NIST MT 2003



Extraction Configurations

- Baseline:
  - Stat-XFER exact tree-to-tree extractor
  - Single decomposition with minimal rules
- Multi:
  - Add multiple alignments and decompositions
- Virt short:
  - Add virtual nodes; max rule length 5
- Virt long:
  - Max rule length 7

Number of Rules Extracted

	Tokens		Types	
	Phrase	**Hierarc.**	**Phrase**	**Hierarc.**
Baseline	6,646,791	1,876,384	1,929,641	767,573
Multi	8,709,589	6,657,590	2,016,227	3,590,184
Virt short	10,190,487	14,190,066	2,877,650	8,313,690
Virt long	10,288,731	22,479,863	2,970,403	15,750,695

Number of Rules Extracted

	Tokens		Types	
	Phrase	**Hierarc.**	**Phrase**	**Hierarc.**
Baseline	6,646,791	1,876,384	1,929,641	767,573
Multi	8,709,589	6,657,590	2,016,227	3,590,184
Virt short	10,190,487	14,190,066	2,877,650	8,313,690
Virt long	10,288,731	22,479,863	2,970,403	15,750,695

- Multiple alignments and decompositions:
  - Four times as many hierarchical rules
  - Small increase in number of phrase pairs

Number of Rules Extracted

	Tokens		Types	
	Phrase	Hierarc.	Phrase	Hierarc.
Baseline	6,646,791	1,876,384	1,929,641	767,573
Multi	8,709,589	6,657,590	2,016,227	3,590,184
Virt short	10,190,487	14,190,066	2,877,650	8,313,690
Virt long	10,288,731	22,479,863	2,970,403	15,750,695

- Multiple decomp and virtual nodes:
  - 20 times as many hierarchical rules
  - Stronger effect on phrase pairs
  - 46% of rule types use virtual nodes

Number of Rules Extracted

	Tokens		Types	
	Phrase	**Hierarc.**	**Phrase**	**Hierarc.**
Baseline	6,646,791	1,876,384	1,929,641	767,573
Multi	8,709,589	6,657,590	2,016,227	3,590,184
Virt short	10,190,487	14,190,066	2,877,650	8,313,690
Virt long	10,288,731	22,479,863	2,970,403	15,750,695

- Proportion of singletons mostly unchanged
- Average hierarchical rule count drops

Rule Filtering for Decoding

- All phrase pair rules that match test set
- Most frequent hierarchical rules:
  - Top 10,000 of all types
  - Top 100,000 of all types
  - Top 5,000 fully abstract + top 100,000 partially lexicalized

$$\text{VP::ADJP} \rightarrow [\text{VV}^1\ \text{VV}^2]::[\text{RB}^1\ \text{VBN}^2]$$

$$\text{NP::NP} \rightarrow [2000\ 年\ \ \text{NN}^1]::[\text{the 2000 NN}^1]$$

Results: Metric Scores

- NIST MT 2003 test set

System	Filter	BLEU	METR	TER
Baseline	**10k**	24.39	54.35	68.01
Multi	**10k**	24.28	53.58	65.30
Virt short	**10k**	25.16	54.33	66.25
Virt long	**10k**	25.74	54.55	65.52

- Strict grammar filtering: extra phrase pairs help improve scores

Results: Metric Scores

- NIST MT 2003 test set

System	Filter	BLEU	METR	TER
Baseline	**5k+100k**	25.95	54.77	66.27
Virt short	**5k+100k**	26.08	54.58	64.32
Virt long	**5k+100k**	25.83	54.35	64.55

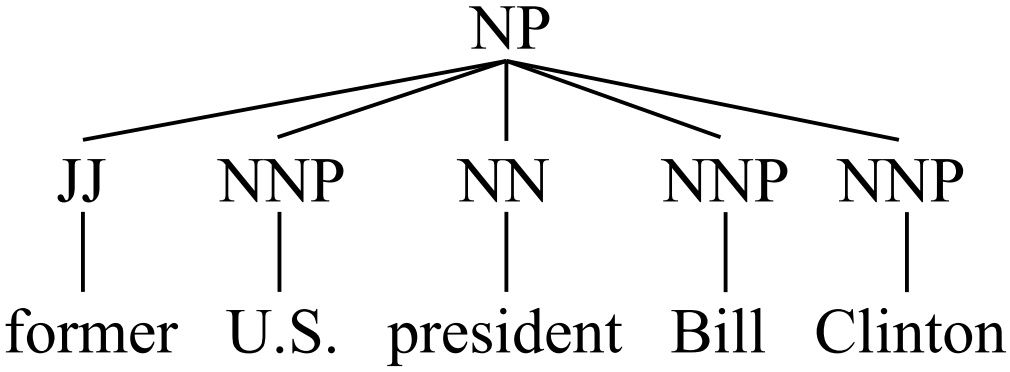
- Larger grammars: score difference erased

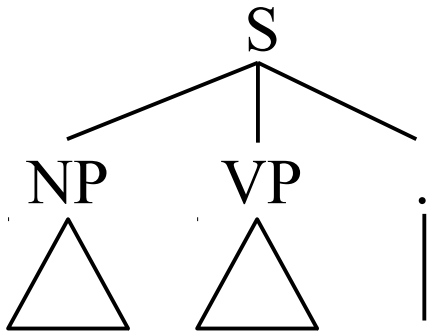
Conclusions

- Very large linguistically motivated rule sets
  - No violating constituent bounds (Stat-XFER)
  - Multiple node alignments
  - Multiple decompositions (Hiero, GHKM)
  - Virtual nodes (< SAMT)
- More phrase pairs help improve scores
- Grammar filtering also matters

Future Work

- Filtering to limit derivational ambiguity
- Filtering based on content of virtual nodes





- Reducing the size of the label set
  - Original: 1,577
  - With virtual nodes: 73,000

References

- Chiang (2005), "A hierarchical phrase-based model for statistical machine translation," ACL
- Chiang (2010), "Learning to translate with source and target syntax," ACL
- Galley, Hopkins, Knight, and Marcu (2004), "What's in a translation rule?," NAACL
- Lavie, Parlikar, and Ambati (2008), "Syntax-driven learning of sub-sentential translation equivalents and translation rules from parsed parallel corpora," SSST-2
- Zollmann and Venugopal (2006), "Syntax augmented machine translation via chart parsing," WMT