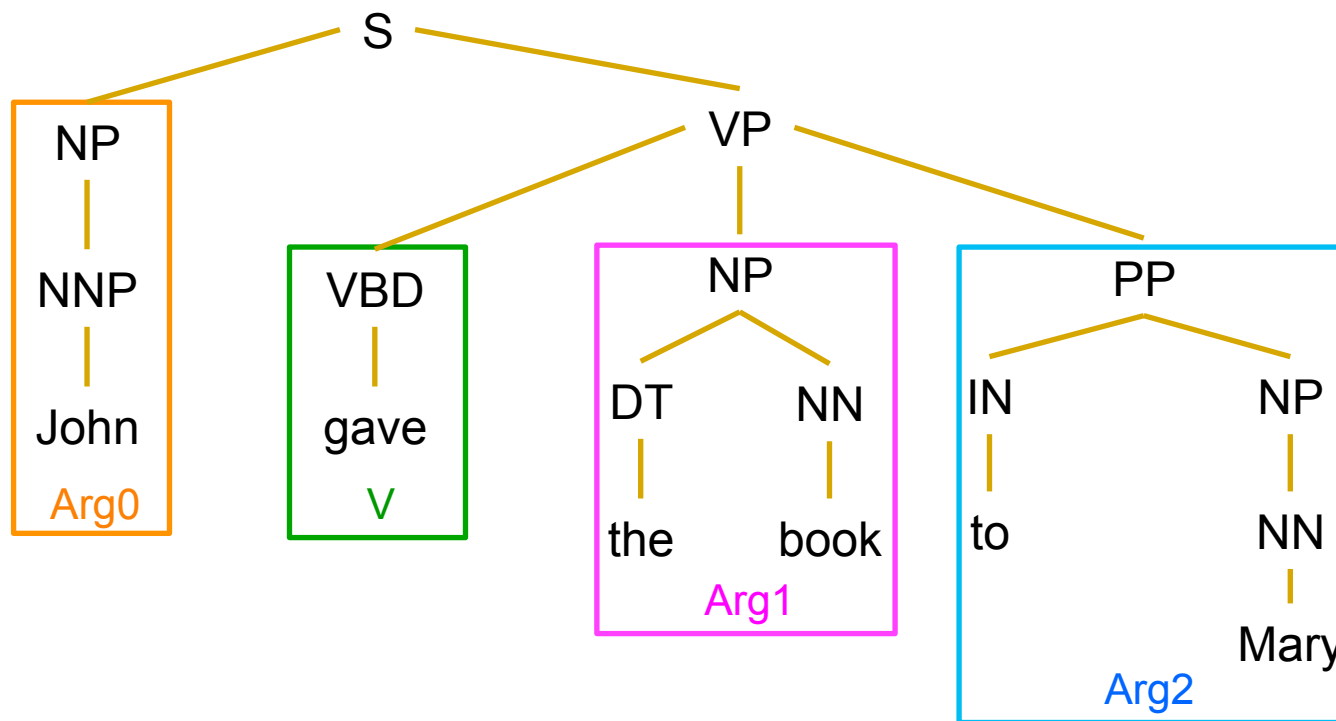

Improving Chinese-English PropBank Alignment

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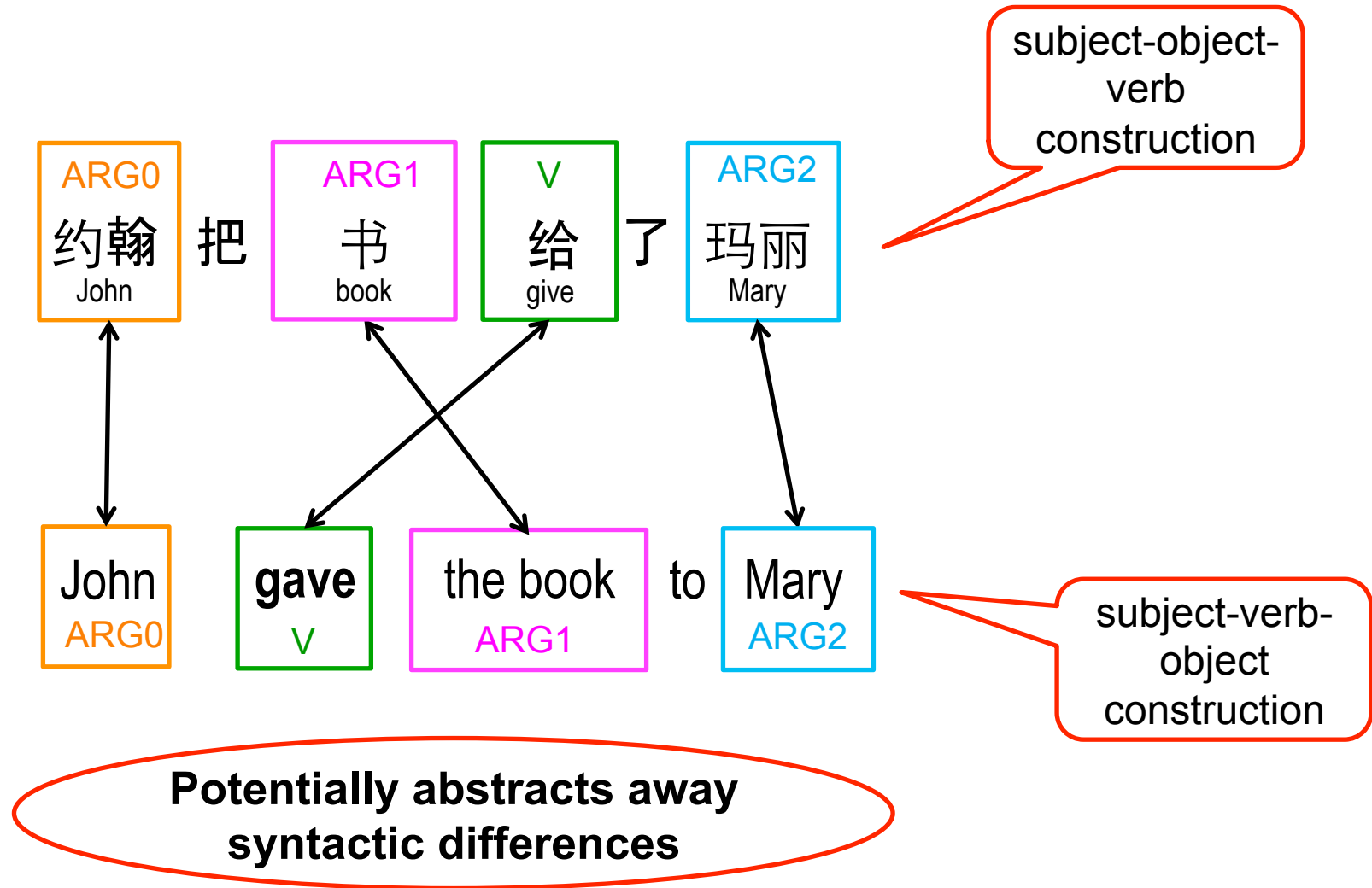
PropBank semantic annotation

- A corpus annotated with verbal (and more recently nominal and adjective) propositions and their arguments.
- Adds semantic information (semantic roles) to the phrase structures.
 - e.g. John gave the book to Mary



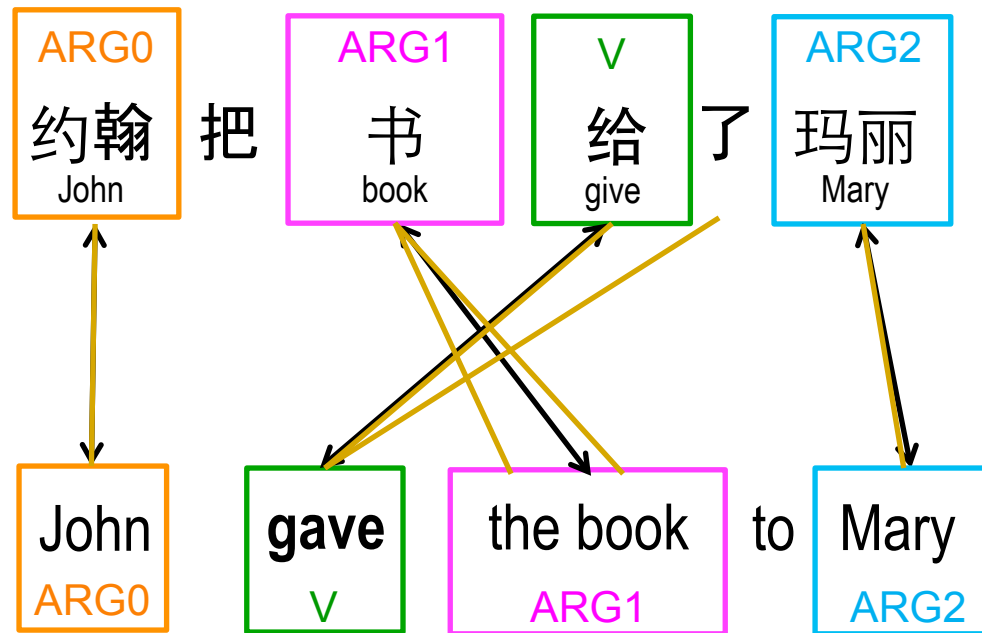
- Has a set of core (numbered) arguments and adjunct argument types
 - ARG0 is typically agent, ARG1 is typically patient or theme

Why use cross-lingual PropBank alignment?

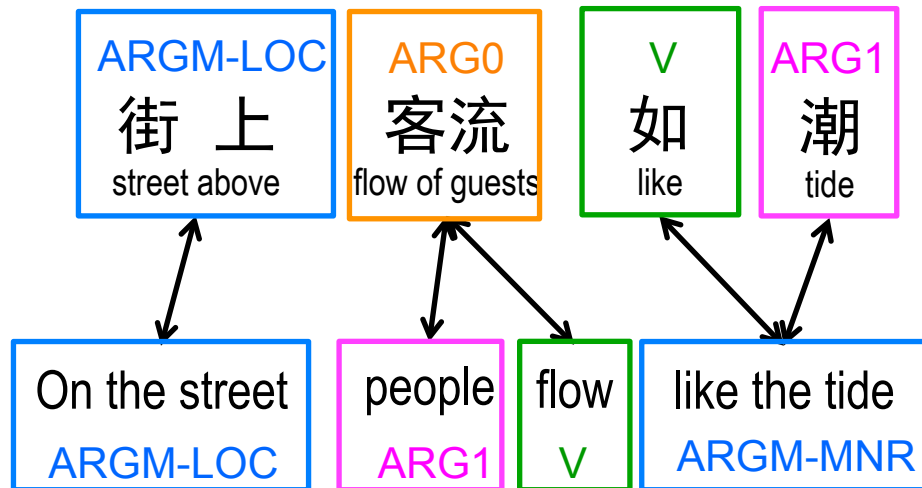


Framework for PropBank alignment

1. PropBank SRL
2. Word alignment
3. Argument alignment



More PropBank alignment example



**Many-to-many argument alignment
Different argument labels can align
to each other**

Alignment by argument label type

<i>label</i>	A0	A1	A2	A3	A4	V
A0	1610	79	25	-	-	9
A1	432	2665	128	11	-	142
A2	43	310	140	8	3	67
A3	2	14	21	7	-	4
A4	1	37	9	3	6	4
V	25	28	22	1	-	3278

Chinese argument type (column) to English argument type (row) alignment on Triple-Gold Xinhua

Alignment by argument type

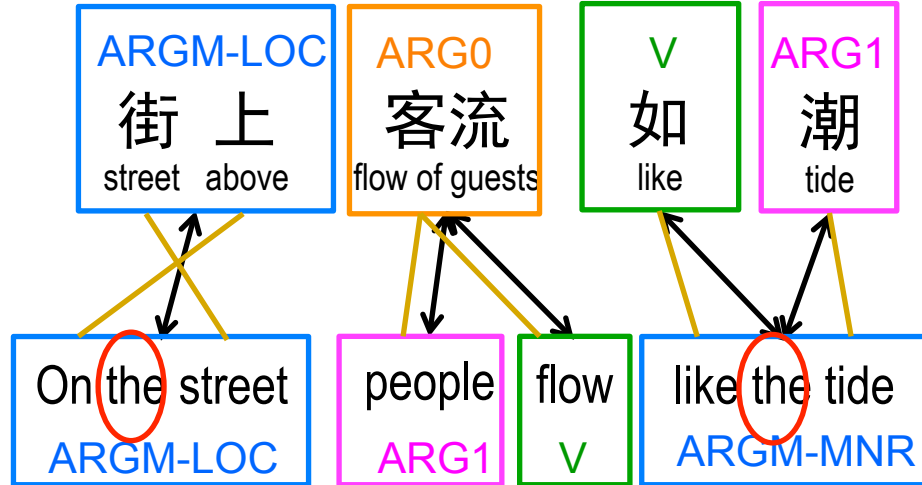
<i>type</i>	A0	A1	A2	A3	A4	ADV	BNF	DIR	DIS	EXT	LOC	MNR	PRP	TMP	TPC	V
A0	1610	79	25			28	1				8	5	1	11	1	9
A1	432	2665	128	11		83	9	12			29	12	5	21	3	142
A2	43	<u>310</u>	140	8	3	55	6	9		2	20	10	1	4	1	67
A3	2	14	<u>21</u>	7		2	4	2			1	2	1		1	4
A4	1	<u>37</u>	9	3	6						1		1			4
ADV	33	36	9	6		307	2	5	6		44	121	6	11	2	19
CAU	1					1							16			1
DIR	1	<u>13</u>	3	2		1		3			3					20
DIS	2					<u>69</u>			40		2	1	3	3		
EXT		4				<u>26</u>										2
LOC	23	65	13	1		3	1				162			5		4
MNR	9	9	5			<u>260</u>				1	3	34				25
MOD	1					<u>159</u>										84
NEG						<u>24</u>										5
PNC	3	23	11			1	6	1			1	2	35	2		8
PRD			<u>3</u>													1
TMP	14	21	2			235		3		1	8	16		647		6
V	25	28	22	1		211	1		1		2	12				3278

Chinese argument type (column) to English argument type alignment on Triple-Gold Xinhua

Many-to-many argument alignment

Objective:

choose source/target argument set to maximize total number of words in the set while minimizing number of unaligned words between arguments



100% precision, low recall

Many-to-many argument alignment

■ Predicate-argument alignment score

- a_i : argument, A_I : set of arguments
- W_i : set of words in a_i
- $map(a_i)$: word mapping (alignment) to set of words in target language
- Source alignment precision/recall:

portion of word aligned words over all words in argument set

$$P_{I,c} = \frac{|(\cup_{i \in I} map_e(a_{i,c})) \cap (\cup_{j \in J} W_{j,e})|}{|(\cup_{i \in I} map_e(a_{i,c}))|}, R_{I,c} = \frac{\sum_{i \in I} |W_{i,c}|}{\sum_{\forall i} |W_{i,c}|}$$

portion of words in aligned argument set over words in all arguments

- Choosing the argument set(s) to maximize alignment score:

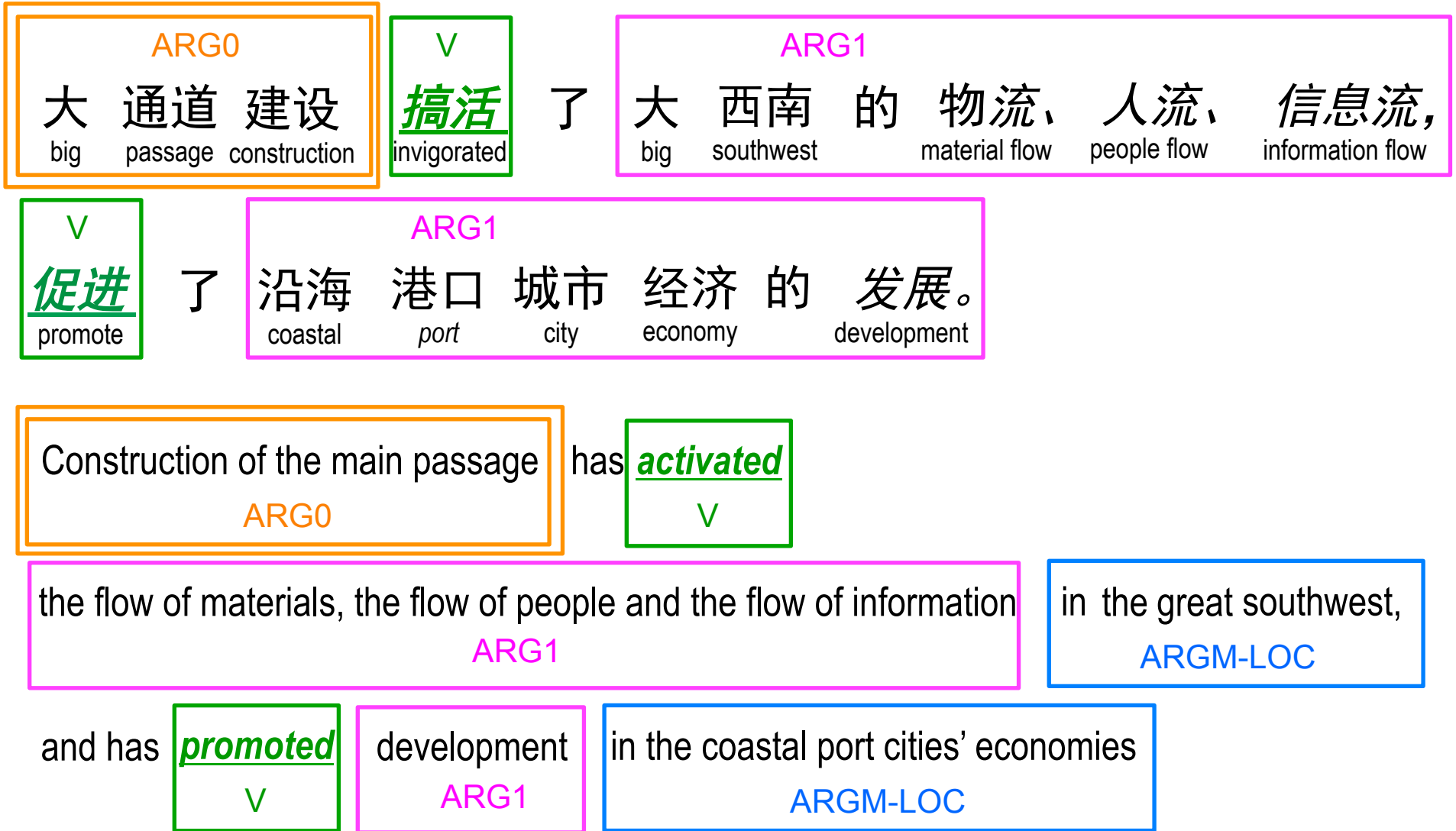
Harmonic mean of precision and recall

$$A_{I,c} = \arg \max_I \frac{2 \cdot P_{I,c} \cdot R_{I,c}}{P_{I,c} + R_{I,c}} = F_{I,c}$$

$$A_{I,c}, A_{J,e} = \arg \max_{I,J} \frac{2 \cdot F_{I,c} \cdot F_{J,e}}{F_{I,c} + F_{J,e}} = F_{I,J}$$

F measure of source and target argument mapping score

Aligning multiple predicate-arguments



Aligning multiple predicate-arguments

- Find the best one-to-one alignment (linear assignment problem) using Kuhn-Munkres method:

$$g^* = \arg \max_x \sum_{i \in C} \sum_{j \in E} F_{ij} \cdot x_{ij} \quad x_{ij} \in \{0,1\}, \sum_i x_{ij} \leq 1, \sum_j x_{ij} \leq 1$$

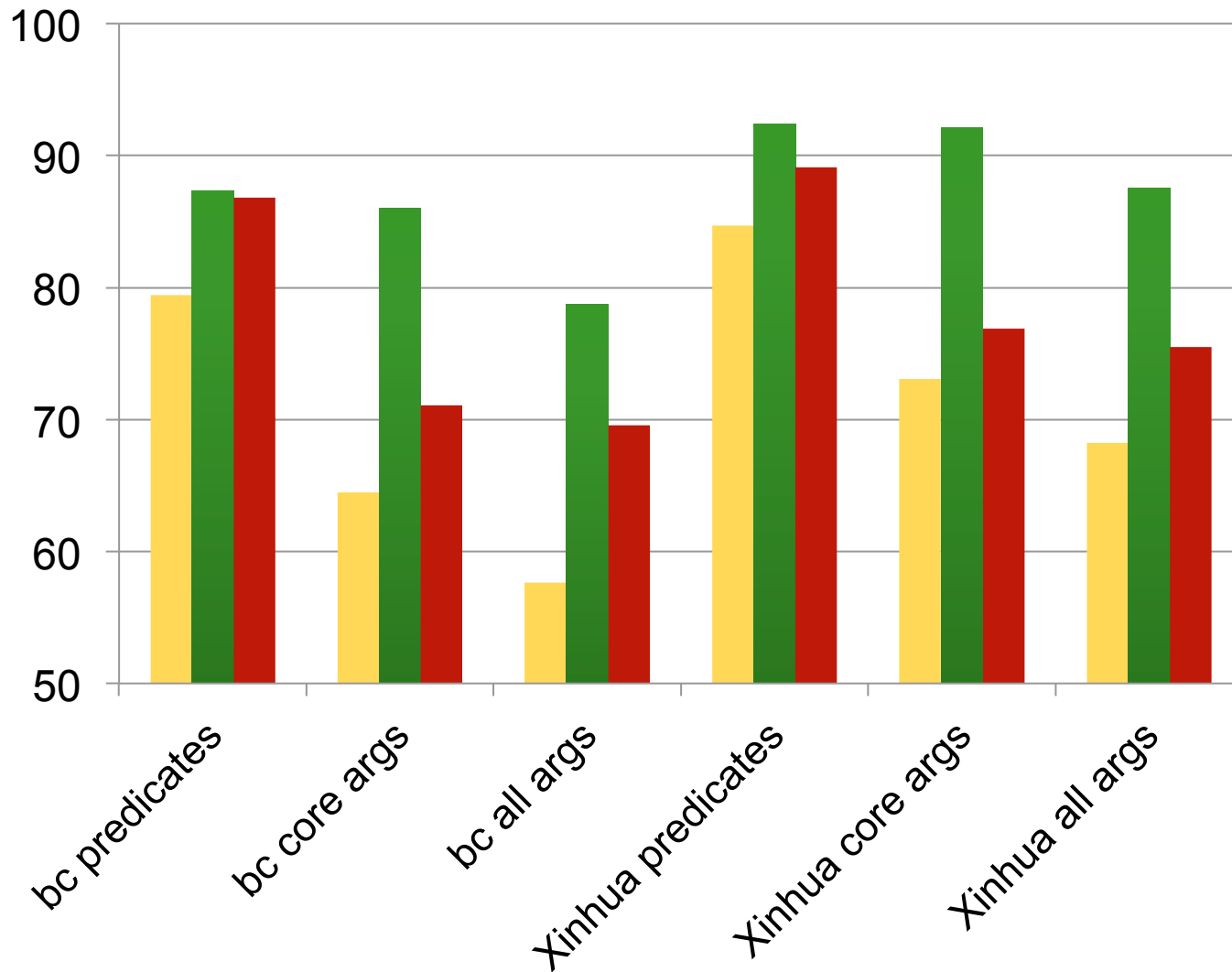
- Argument alignment score:

	<i>activate.01</i>	<i>promote.01</i>
搞活. 01 (invigorate)	0.49	0.25
促进. 01 (promote)	0.23	0.77

- Alignments:

搞活. 01 ↔ activate.01 促进. 01 ↔ promote.01

PropBank alignment results

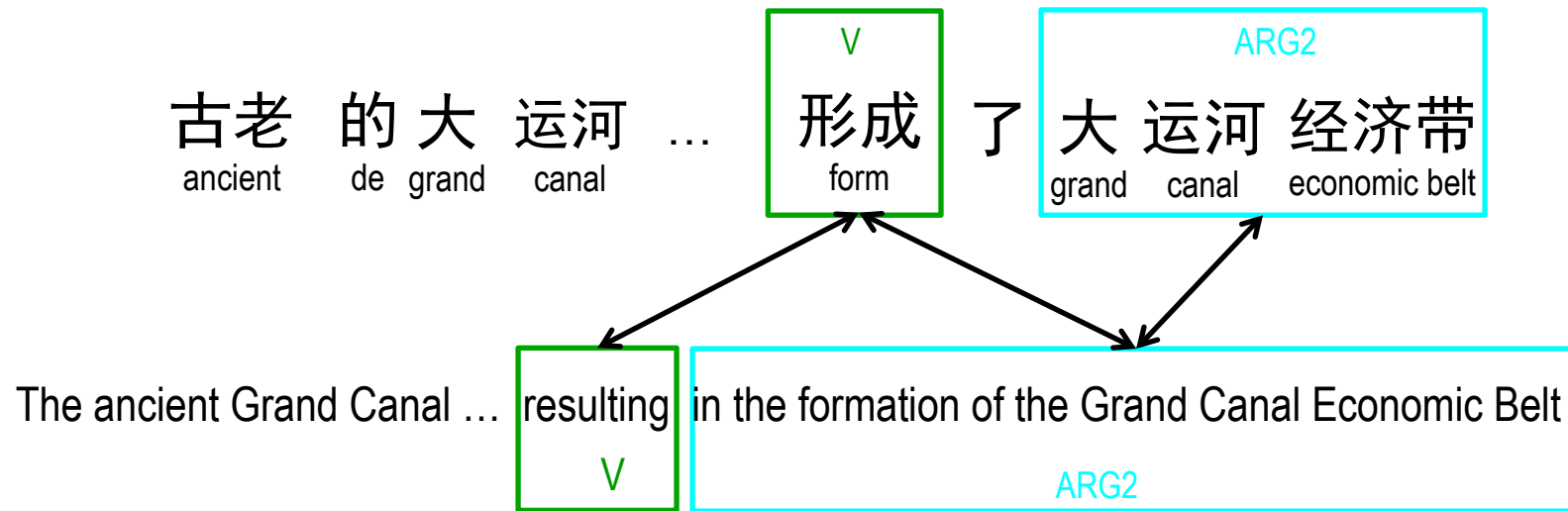


Are there issues? Can we improve these?

■ auto SRL&WA
■ gold SRL&auto WA
■ auto SRL&gold WA

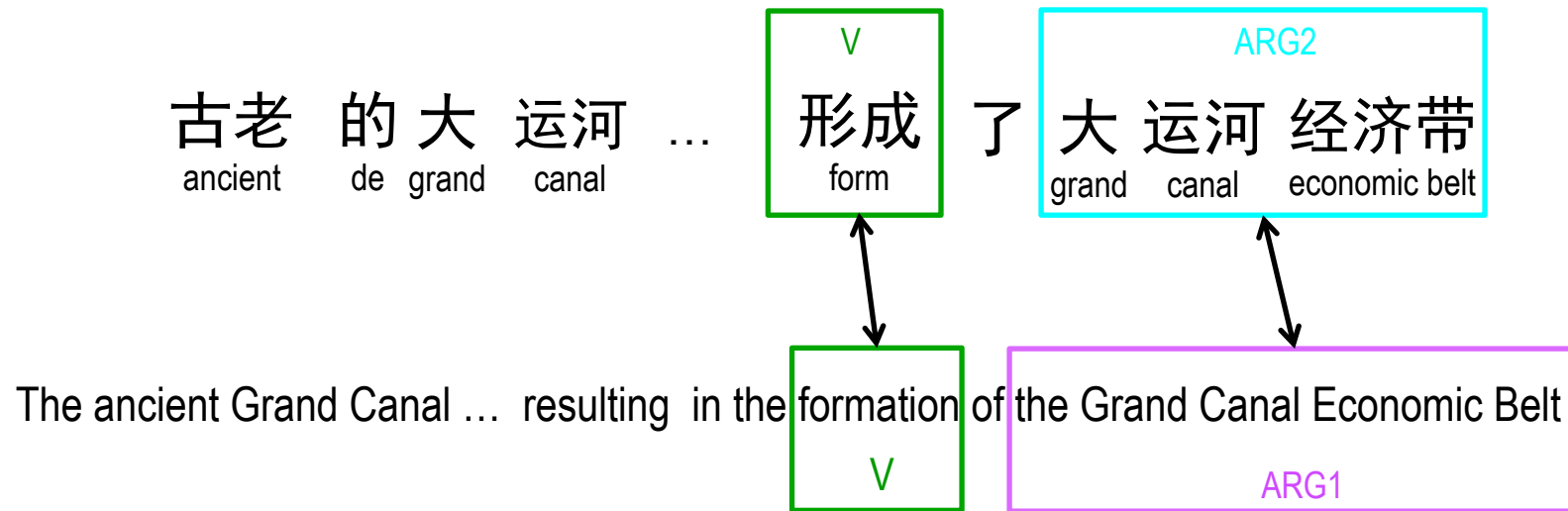
Semantic alignment results on broadcast conversation (bc) & Xinhua News

Forced alignment between verb predicates



**Alignment of non-synonymous predicates,
and predicate to core arguments**

Add nominal predicates to alignment



Using nominal predicates can produce more semantically similar alignments

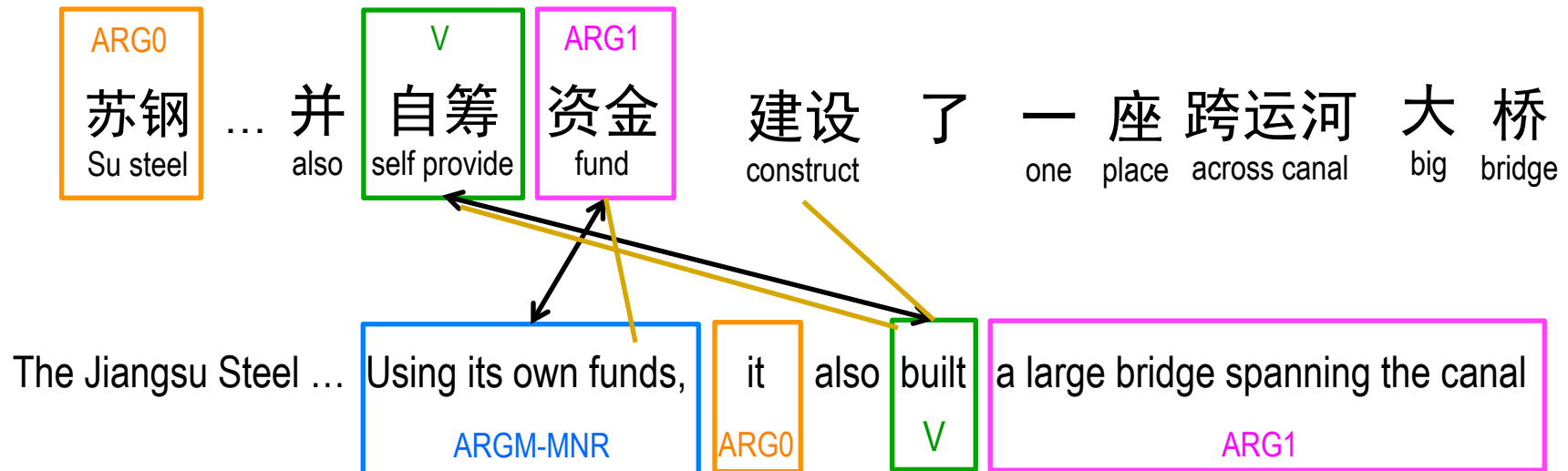
Alignment counts w/ nominal predicates

<i>pred. type</i>	V_c-V_e	N_c-V_e	V_c-N_e	N_c-N_e	total	Δ
verb only	4879	-	-	-	4879	-
+Ch nom.	4762	274	-	-	5036	+3.2%
+En nom.	4849	-	384	-	5233	+7.3%
all pred.	4759	239	314	760	6072	+24.5%

Predicate-argument mappings counts on Xinhua News with inclusion of nominal predicates

**Using nominal predicates also
increases alignment coverage**

Alignment issue w/ automatic WA



	<i>use.01</i>	<i>build.01</i>
自筹. 01 (self provide)	0.50	0.60
建设. 01 (construct)	0.22	0.50

But 自筹 \leftrightarrow *build*, Arg1 \leftrightarrow AM-MNR
are very unlikely!!

Building alignment probability

- Collect predicate-to-predicate & argument-to-argument mapping counts from corpus to build:

$$p(pred_{j,e} | pred_{i,c})$$

$$p(a_{l,e} | a_{k,c}, pred_{i,c}, pred_{j,e})$$

- Counts can be really sparse, so apply smoothing
 - Simple Good-Turing smoothing for predicate-to-predicate probability

$$p_0 = \frac{N_1}{N}$$

$$p_c = (c + 1) \frac{N_{c+1}}{N_c N}$$

Building alignment probability (cont)

- Smooth argument-to-argument probability with absolute discounting

$$p(a_{l_E} | a_{k_C}, pred_{i_C}, pred_{j_E}) = \frac{\max(freq(a_{l_E} | a_{k_C}, pred_{i_C}, pred_{j_E}) - d, 0)}{\sum_l (a_{l_E} | a_{k_C}, pred_{i_C}, pred_{j_E})} + (1 - \lambda) \cdot p_{backoff}(a_{l_E})$$

$$p_{backoff}(a_{l_E}) = p(a_{l_E} | a_{k_C}, pred_{i_C}) \text{ or } p(a_{l_E} | a_{k_C}, pred_{j_E})$$

- Intermediary back-off probabilities can also be smoothed:

$$p(a_{l_E} | a_{k_C}, pred_{i_C}) = \frac{\max(freq(a_{l_E} | a_{k_C}, pred_{i_C}) - d, 0)}{\sum_l (a_{l_E} | a_{k_C}, pred_{i_C})} + (1 - \lambda) \cdot p(a_{l_E} | a_{k_C})$$

Alignment w/ probability model

- Update previously defined argument precision & recall

$$P'_{kl} = (1 - \beta + \beta \cdot w(a_{l,e} | pred_{i,c}, pred_{j,e}, a_{k,c}))P_{kl}$$

$$R'_{kl} = (1 - \beta + \beta \cdot w(a_{k,c} | pred_{i,c}, pred_{j,e}, a_{l,e}))R_{kl}$$

Portion (β) of alignment score weighted by argument label alignment probability

where $w(a_k) = \frac{p(a_k)}{\sum_k p(a_k) \cdot p(a_k)}$, $P_{kl} = \frac{|map_e(a_{k,c}) \cup W_{l,e}|}{|map_e(a_{k,c})|}$, $R_{kl} = \frac{|map_c(a_{l,e}) \cup W_{k,c}|}{|map_c(a_{l,e})|}$,

- Update predicate-to-predicate score:

$$F'_{i,c} = (1 - \alpha + \alpha \cdot w(pred_{j,e} | pred_{i,c}))F_{i,c}$$

$$F'_{j,e} = (1 - \alpha + \alpha \cdot w(pred_{i,c} | pred_{j,e}))F_{j,e}$$

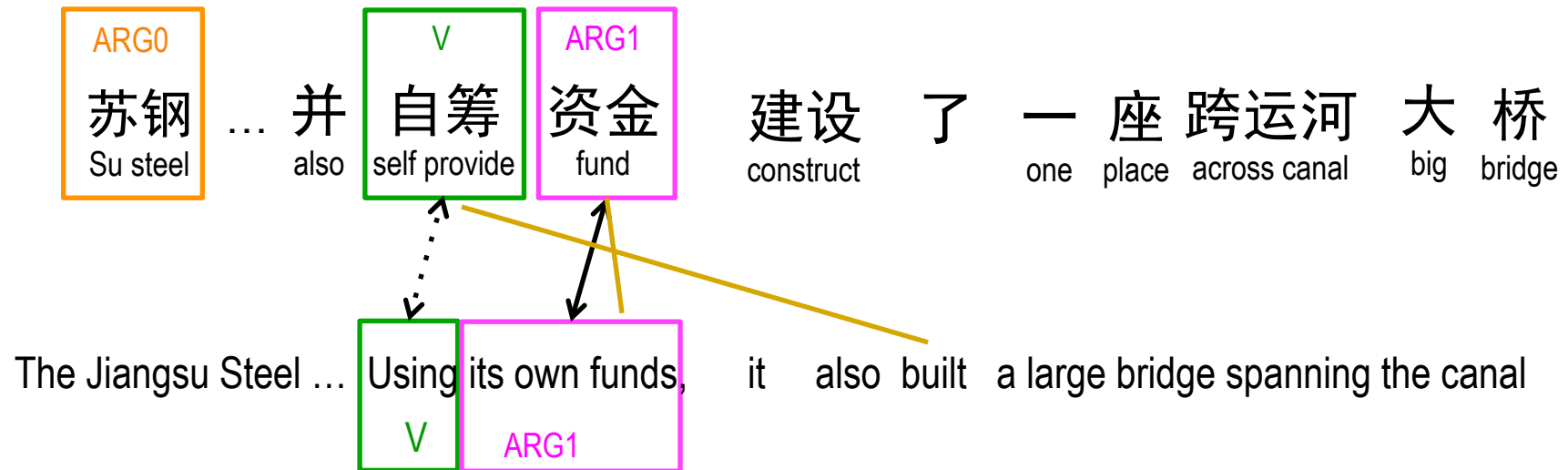
Portion (α) of alignment score weighted by predicate alignment probability

- Need to find “good” α and β values that balances the word alignment score and predicate/argument alignment probabilities

Alignment w/ probability model (cont)

- Find the best α and β using expectation maximization (EM)
 1. Perform semantic alignment on corpus
 2. Build probability models from mapping (E step)
 3. Find α and β that maximizes the sum of the mapping score of all predicate pairs in the corpus using grid search (M step)
 4. Repeat steps 2-3 until the score sum plateaus
- Data
 - 1.6M parallel sentence pairs from multiple LDC corpora
 - Stanford Chinese word segmenter, Berkeley parser, ClearSRL
- Need only 2 iterations to converge as the mapping output doesn't change drastically
- Optimal $\alpha=0.15$, $\beta=0.1$
 - α value (predicate-to-predicate probability) has a larger affect on score sum than β value (argument-to-argument probability)

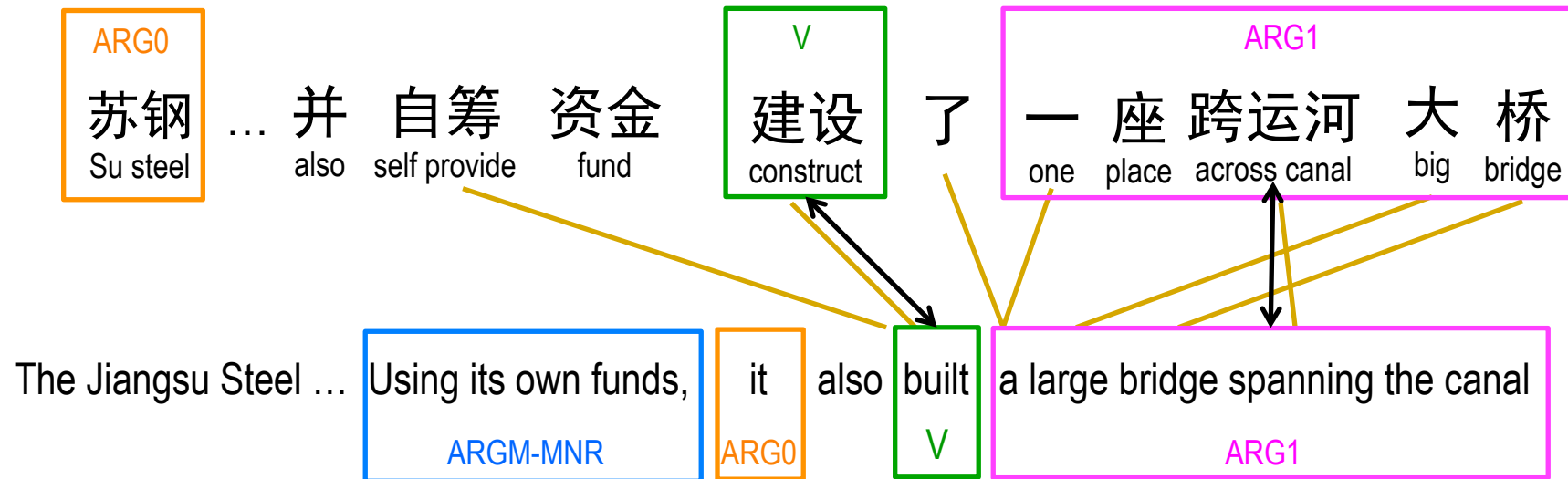
Alignment w/probability example



	<i>use.01</i>	<i>build.01</i>
自筹. 01 (self provide)	0.65	0.40
建设. 01 (construct)	0.10	0.85

自筹 \Leftrightarrow use, Arg1 \Leftrightarrow Arg1
 are much more likely

Alignment w/ probability example (cont)

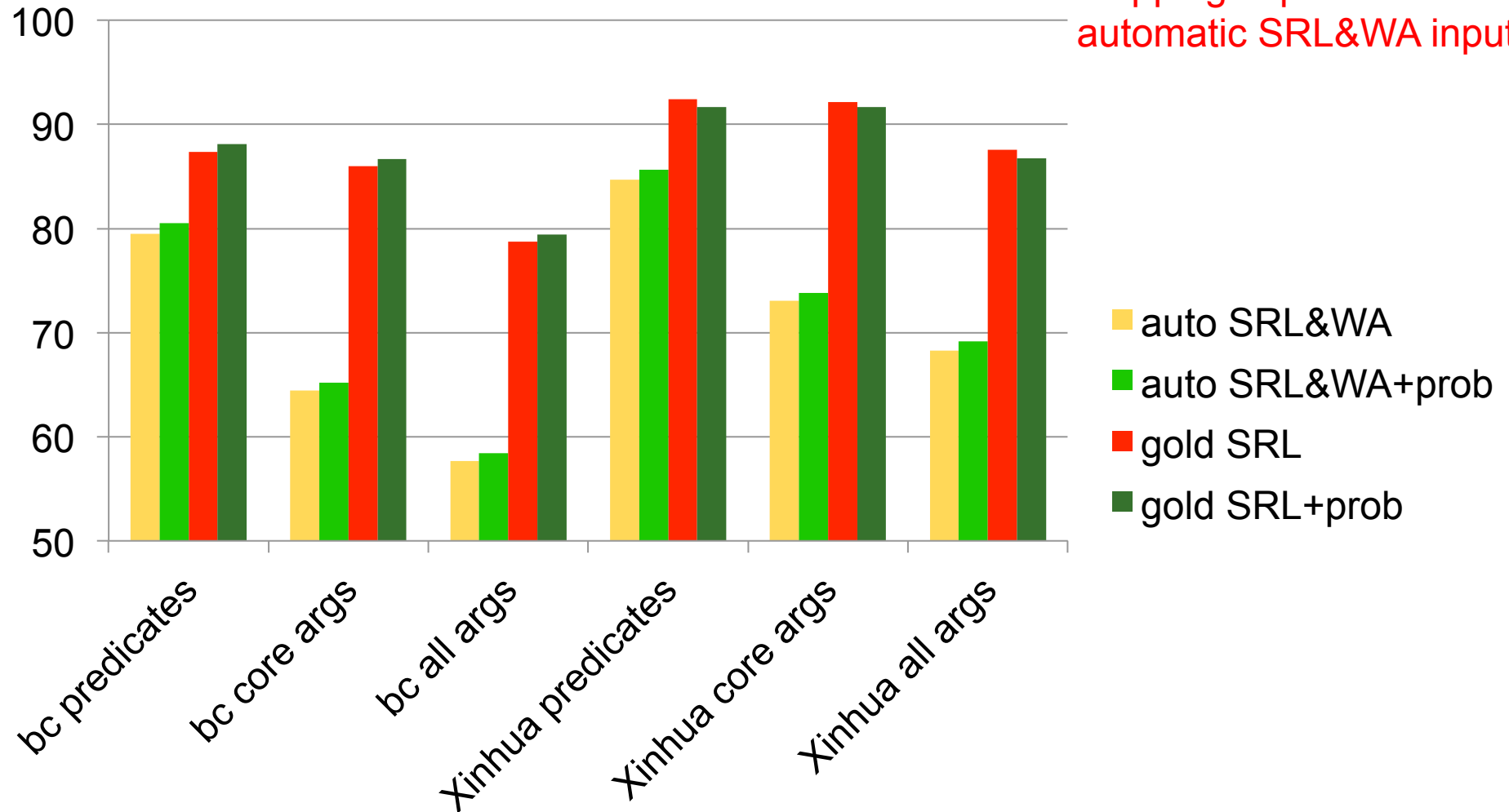


	<i>use.01</i>	<i>build.01</i>
自筹. 01 (self provide)	0.65	0.40
建设. 01 (construct)	0.10	0.85

Also allowed correct
建设 \leftrightarrow *build* mapping

Probability model improvements

- About 1 F point predicate mapping improvement on automatic SRL&WA input



Semantic alignment results on broadcast conversation (BC) & Xinhua News

Summary

- PropBank alignment with nominal predicates
 - Improves alignment quality and coverage
- Predicate-argument alignment with probability models
 - Generate predicate-to-predicate and argument-to-argument alignment probabilities on large corpora
 - Iteratively improve model with EM
 - Provides ~1 F-point improvement w/ automatic SRL input

Future work

- Build alignment probability models based on verb classes

$$p(pred_{j,c} | pred_{V_i,e})$$

- Use alignment probability model to perform joint Chinese, English SRL
 - Can improve both SRL accuracy and alignment model
- PropBank alignment of other language pairs
 - Arabic-English

Questions?