USING STATISTICAL MACHINE TRANSLATION TO IMPROVE STATISTICAL MACHINE TRANSLATION

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HERE BE THREE PARTS ...

- Introduce statistical machine translation (SMT) using as little math as possible `(0 < |math| << boring)`
- Bring to light the dark magic of *parameter tuning* - without which SMT doesn't work - and its need for a special kind of data
- Show how I use SMT itself to "manufacture" this special data and significantly improve final translation performance

PART I

THE PIPELINE

MACHINE TRANSLATION

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根据超市提供的信息，记者联系上一位常年在北京、山东、广西等地做“有机食品”收购、加工、包装的经纪人刘刚。他表示，有机食品行业认证环节随意性大。针对认证中出现的问题，记者联系到负有监管责任的国家认监委。

Documents in Source Language (SL)
(Chinese)

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MT System

"Organic food full or empty when there is cross-regulation." Fat City, Shandong Zhaosheng Wen, Deputy Secretary of Agriculture, who said that the agricultural sector production management, commission management certification, the business sector pipe flow, the health sector management table, which the department put on the case, the department is not completely final say.

According to information provided by the supermarket, the reporter contacted a year-round in Beijing, Shandong, Guangxi and other places to do "organic food" acquisition, processing, packaging broker Gang. He said part of the organic food industry certification arbitrary. For certification problems, the reporter linked to the regulatory responsibility of the state commission bear.

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(English)

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Ideally, semantically <u>adequate</u> as well as linguistically <u>fluent</u>

MACHINE TRANSLATION

- First conceived by Warren Weaver in 1949†
- One of the most challenging (and popular) NLP tasks over the last two decades
- Three popular non-statistical approaches [1950s-1980s]
  - Rule-based. Manually construct rules that translate from SL to TL (with minimal analysis)
  - Interlingual. Reduce SL text to an abstract, language-independent base-form and then generate TL text
  - Transfer-based. Analyze SL text into syntactic components, transfer SL syntax to TL syntax and then generate TL text

† *Translation*. Warren Weaver. 1949. http://www.mt-archive.info/Weaver-1949.pdf

STATISTICAL MACHINE TRANSLATION

- Driven by statistical machine learning methods
  - Step 0: Find **LOTS** of example SL sentences and corresponding human translations into TL (*bilingual parallel corpora* or *bitext*)
  - Step 1: Apply a learning algorithm to parallel corpora and build an *approximate model* of human translation
  - Step 2: Apply learned model to new SL text and obtain translations in TL (notice that I didn't say *unseen* SL text)
- Represents current state-of-the-art and dominates MT research in both academia and industry
- Examples: Google Translate, Bing Translate

LEARNING A TRANSLATION MODEL

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Parallel Corpus or Bitext

```
这是一个英文句子.
这是中国一句.
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This is an English sentence.
That's a Chinese sentence.
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Millions of Words
(Depends on SL)

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"Learn what Chinese phrases are likely to translate to what English phrases"

Millions of Words
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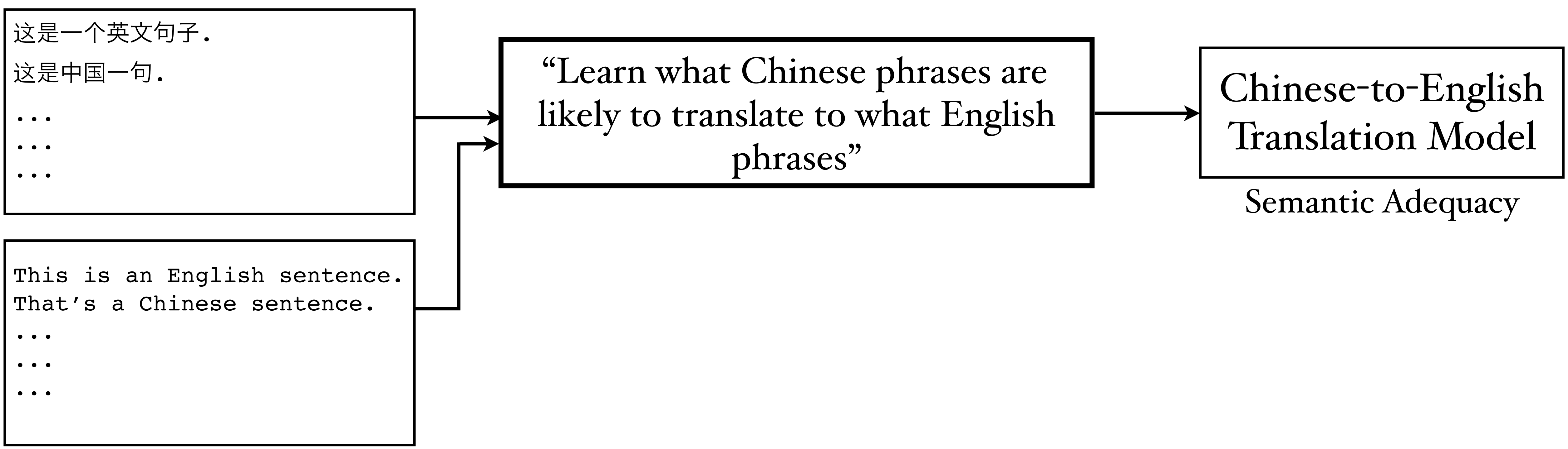
Parallel Corpus or Bitext



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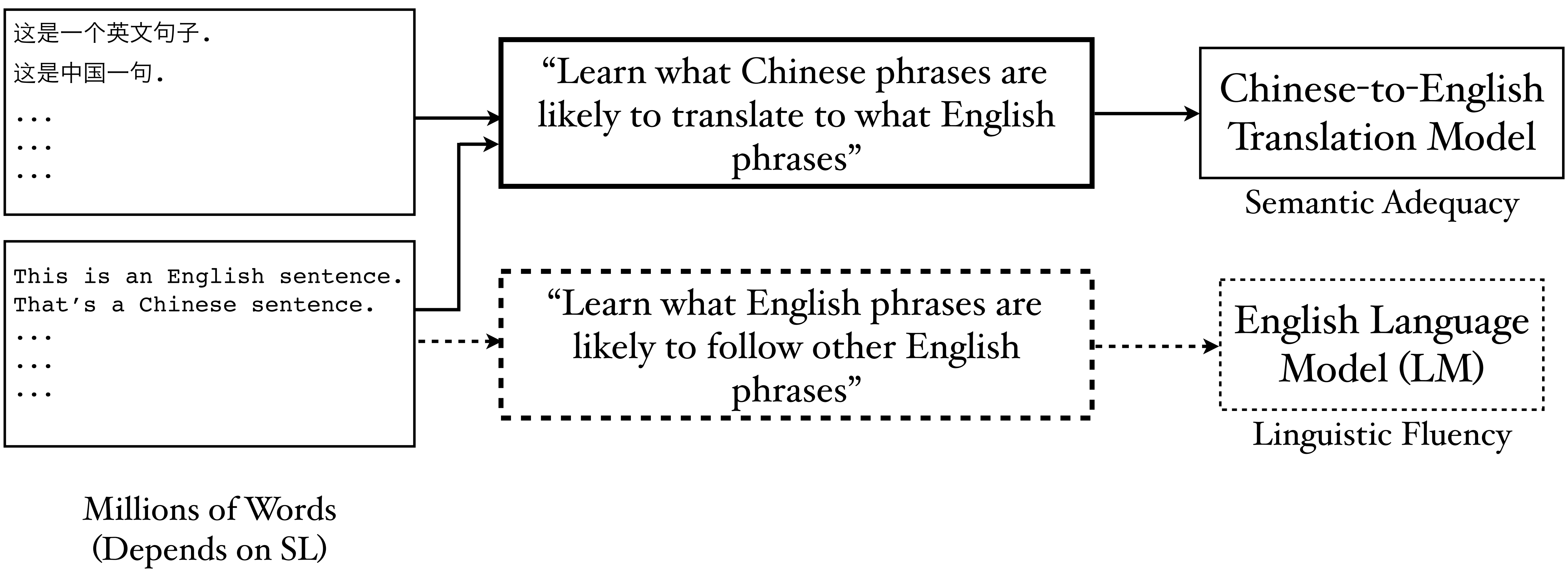

LEARNING A TRANSLATION MODEL

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- Take each Chinese-English sentence pair in the bitext

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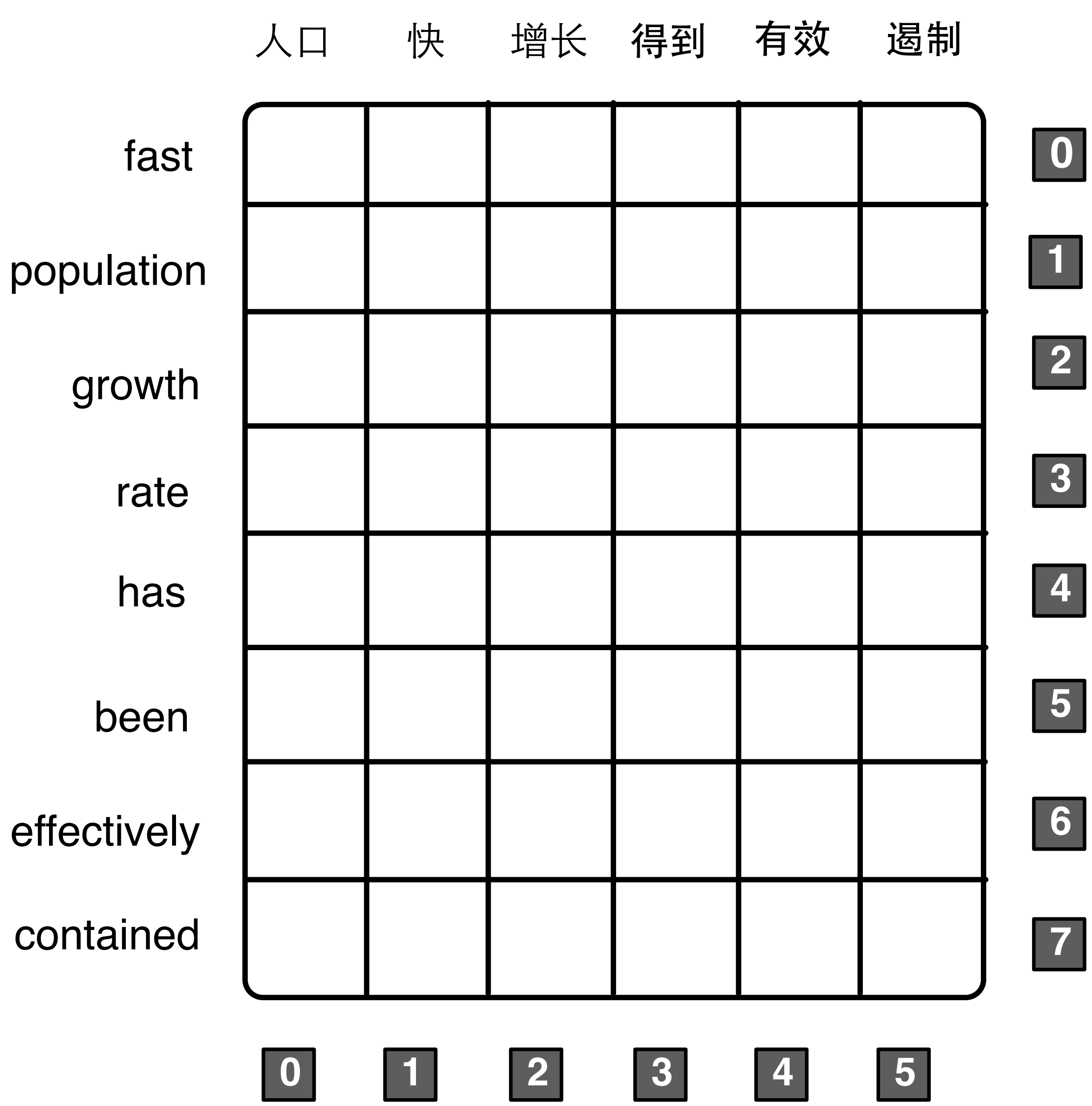

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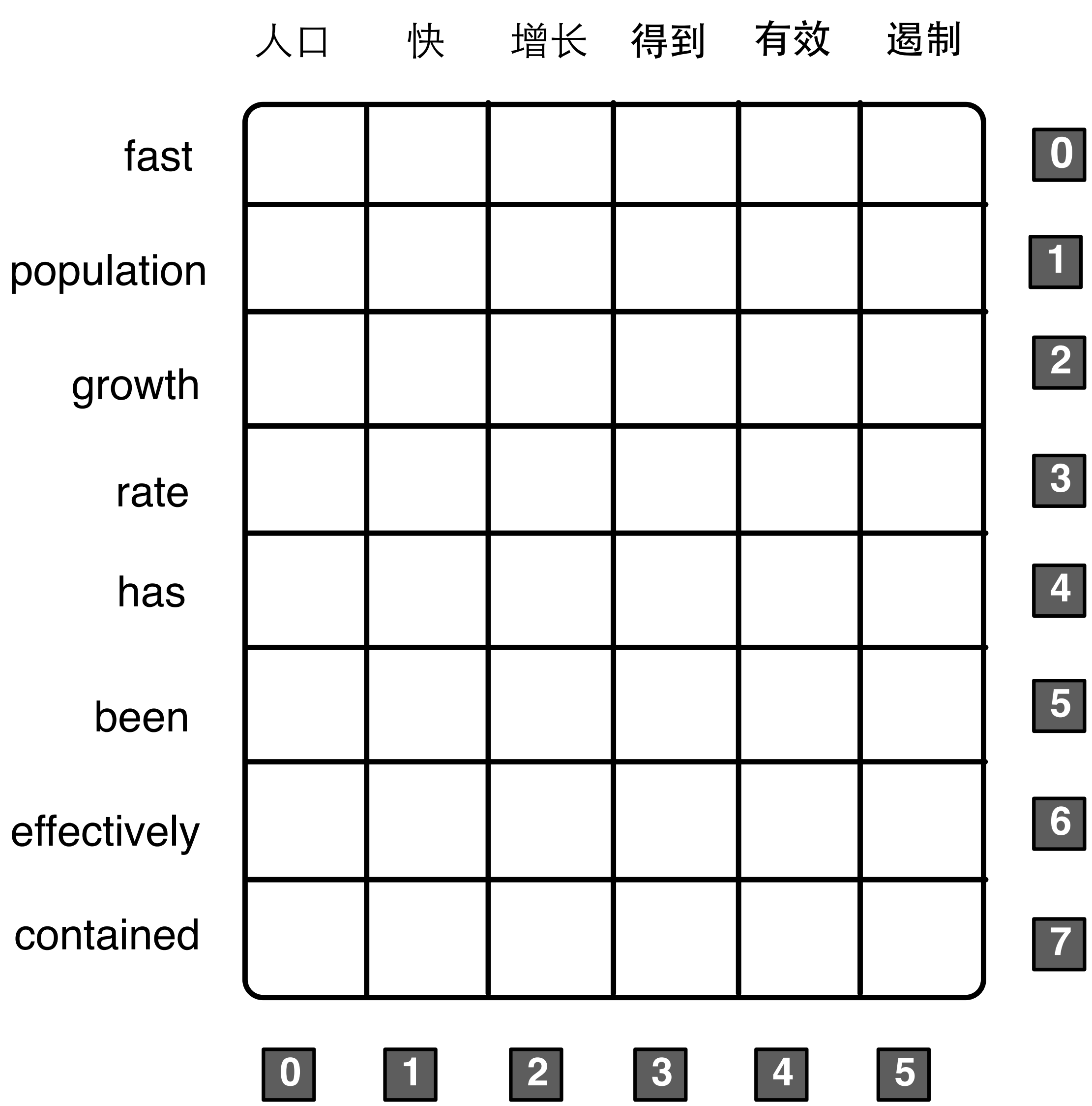

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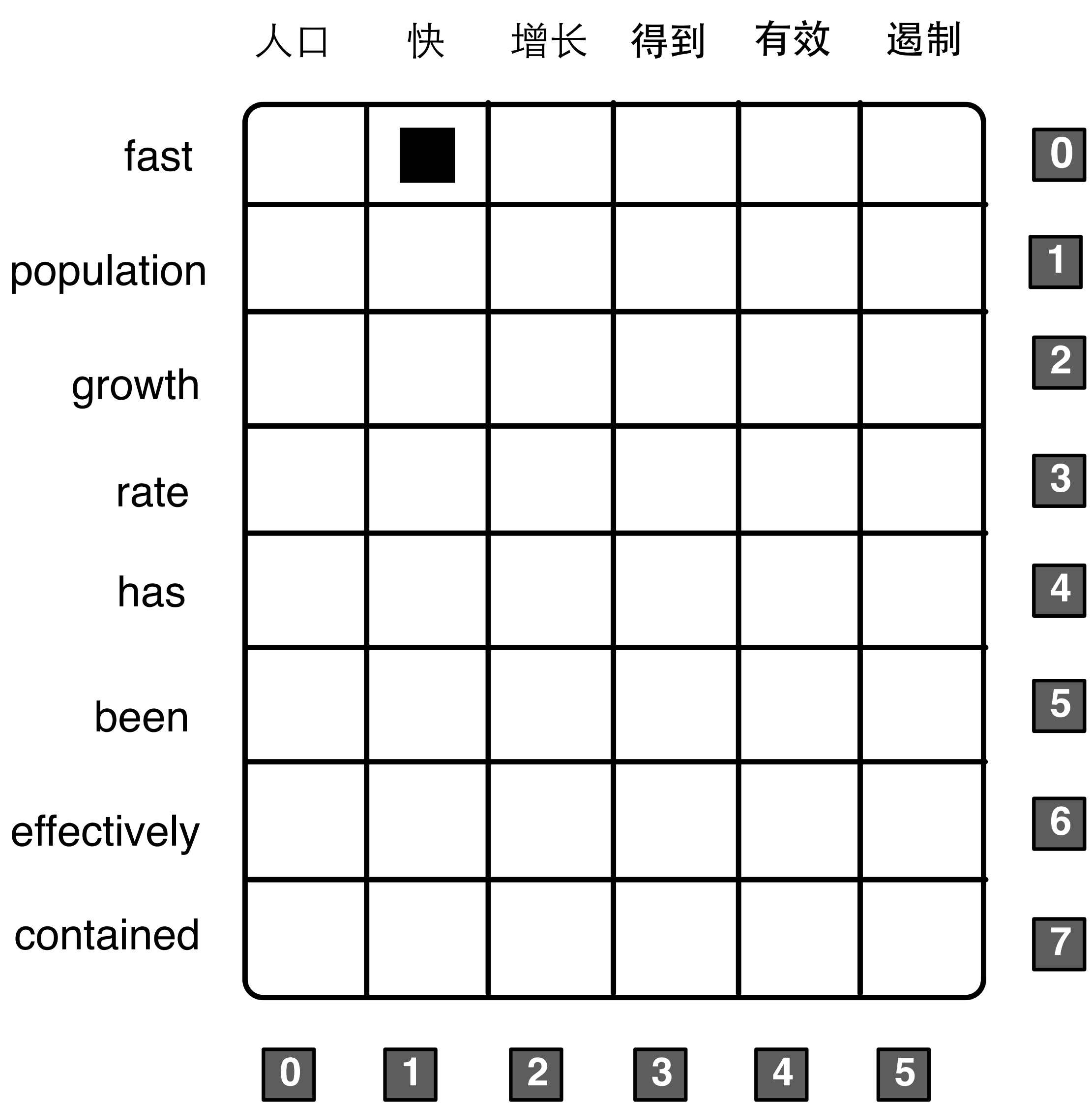

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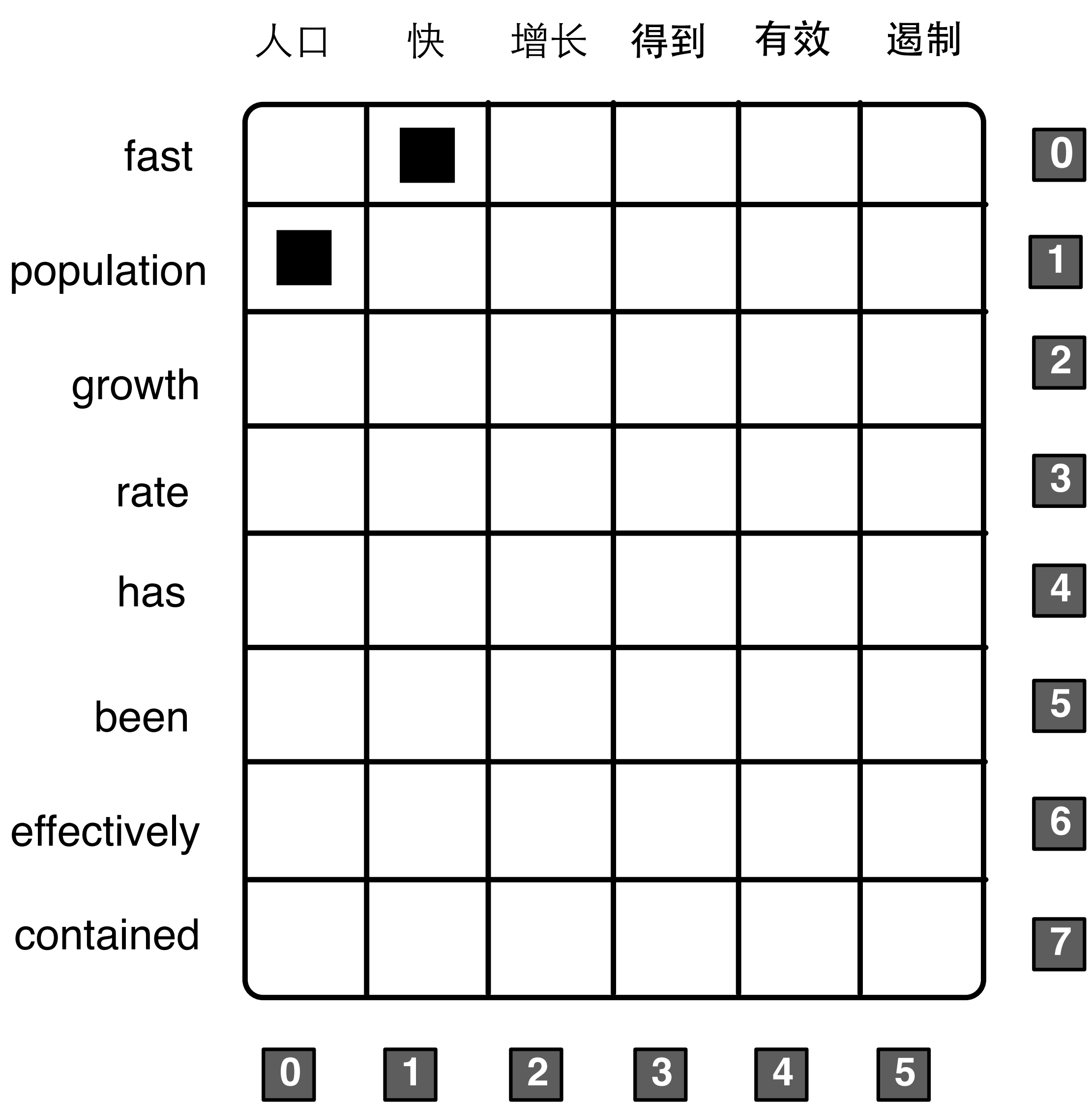

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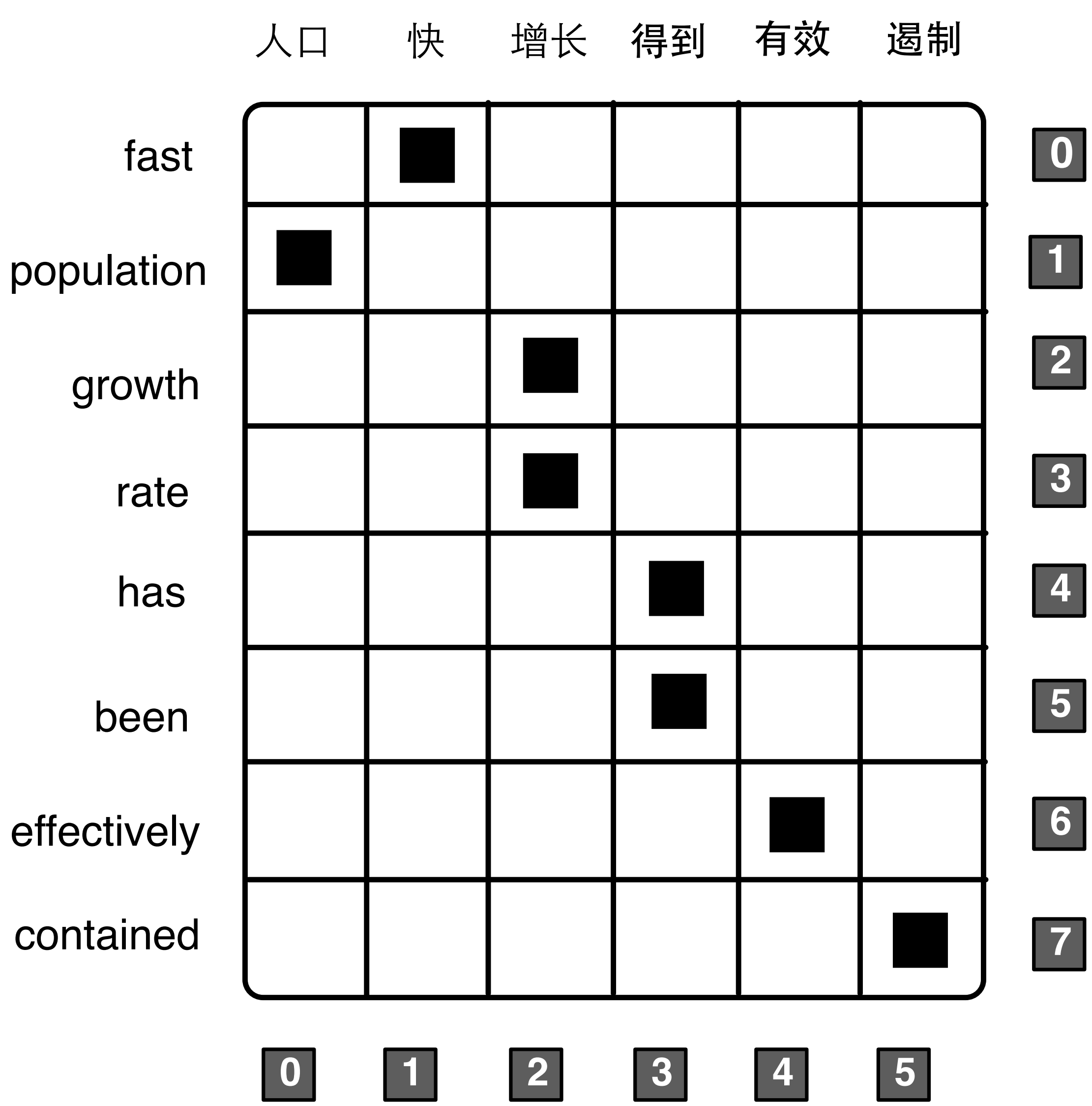

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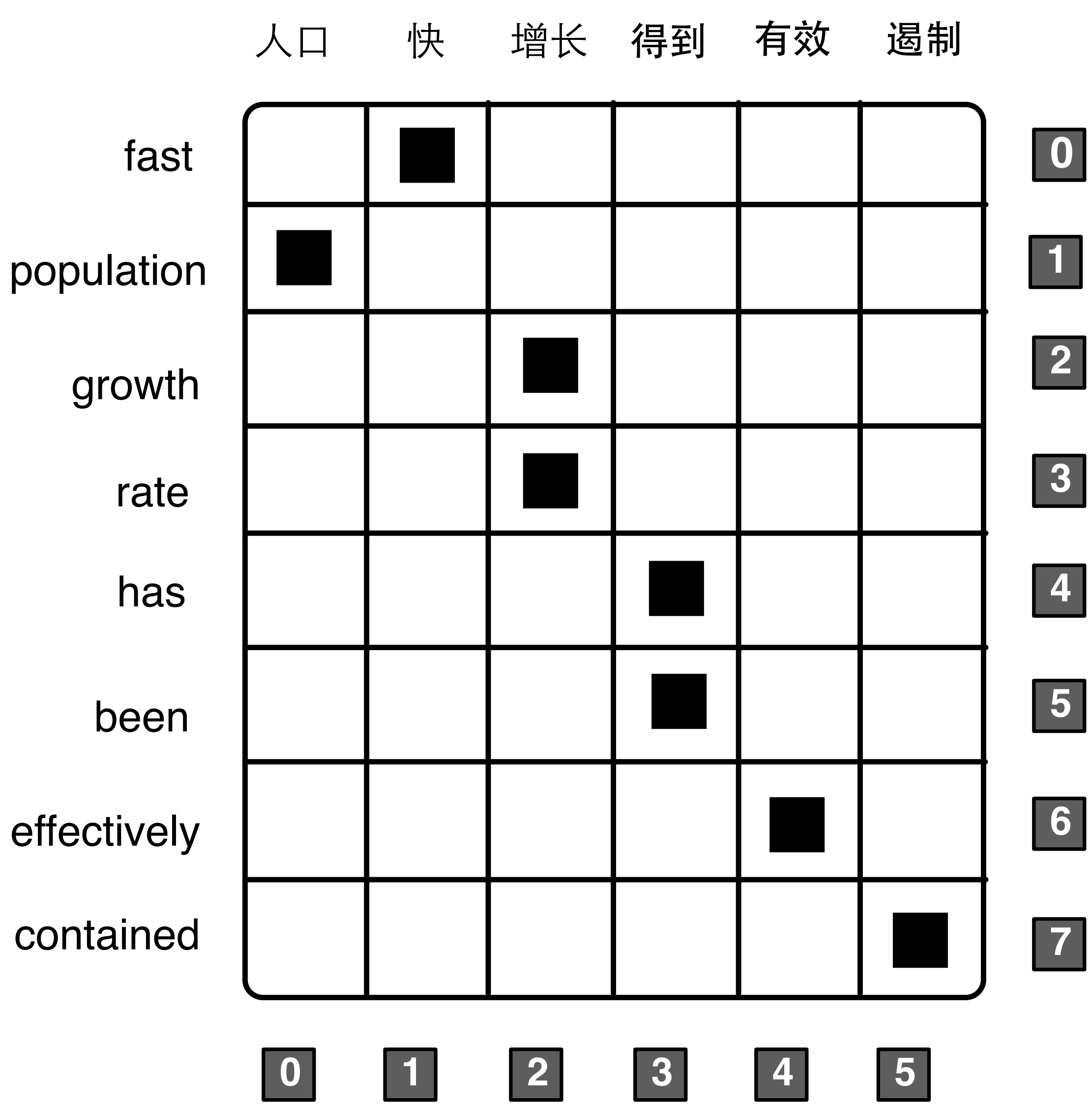

Alignment Matrix

- Take each Chinese-English sentence pair in the bitext
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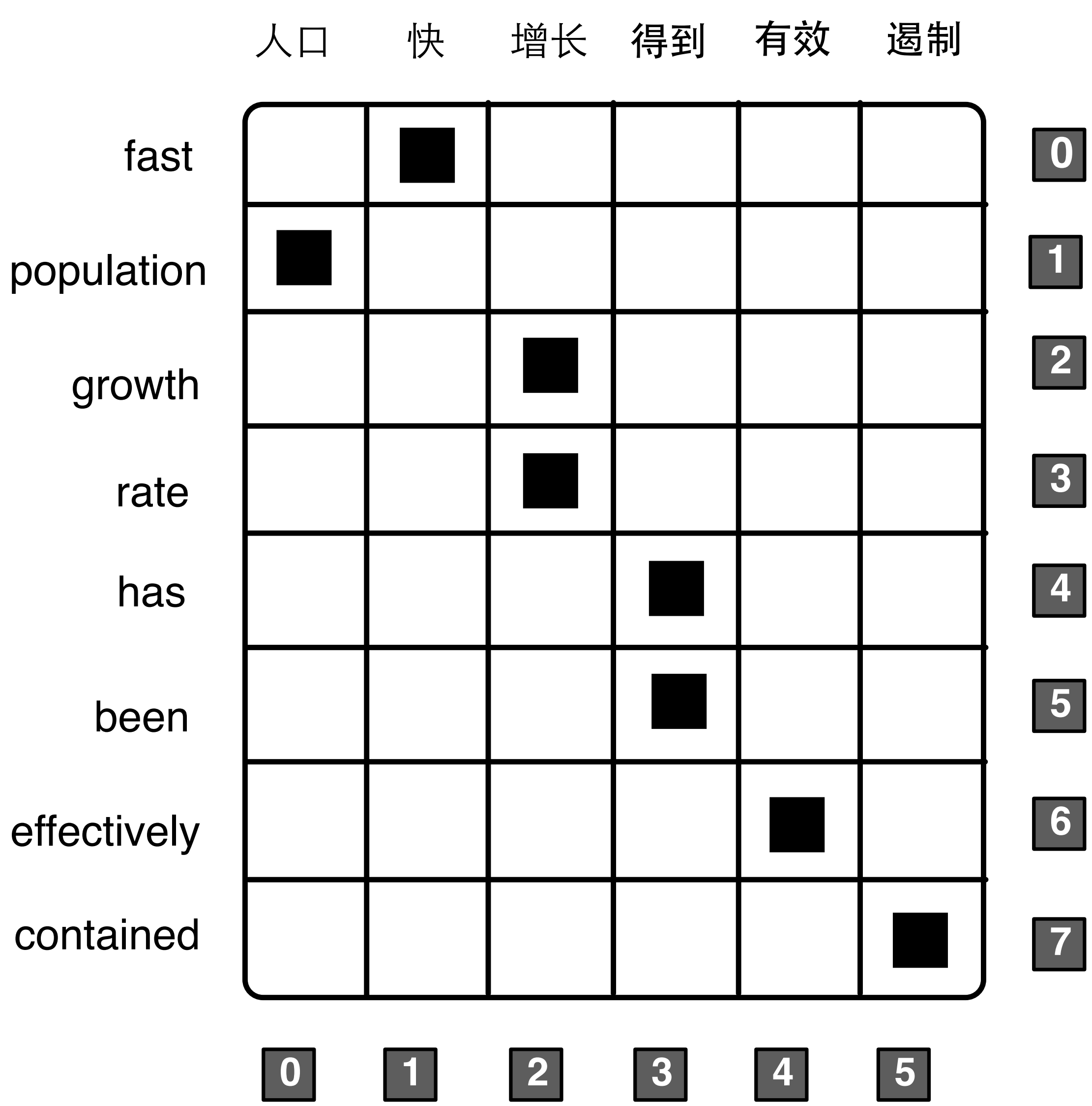
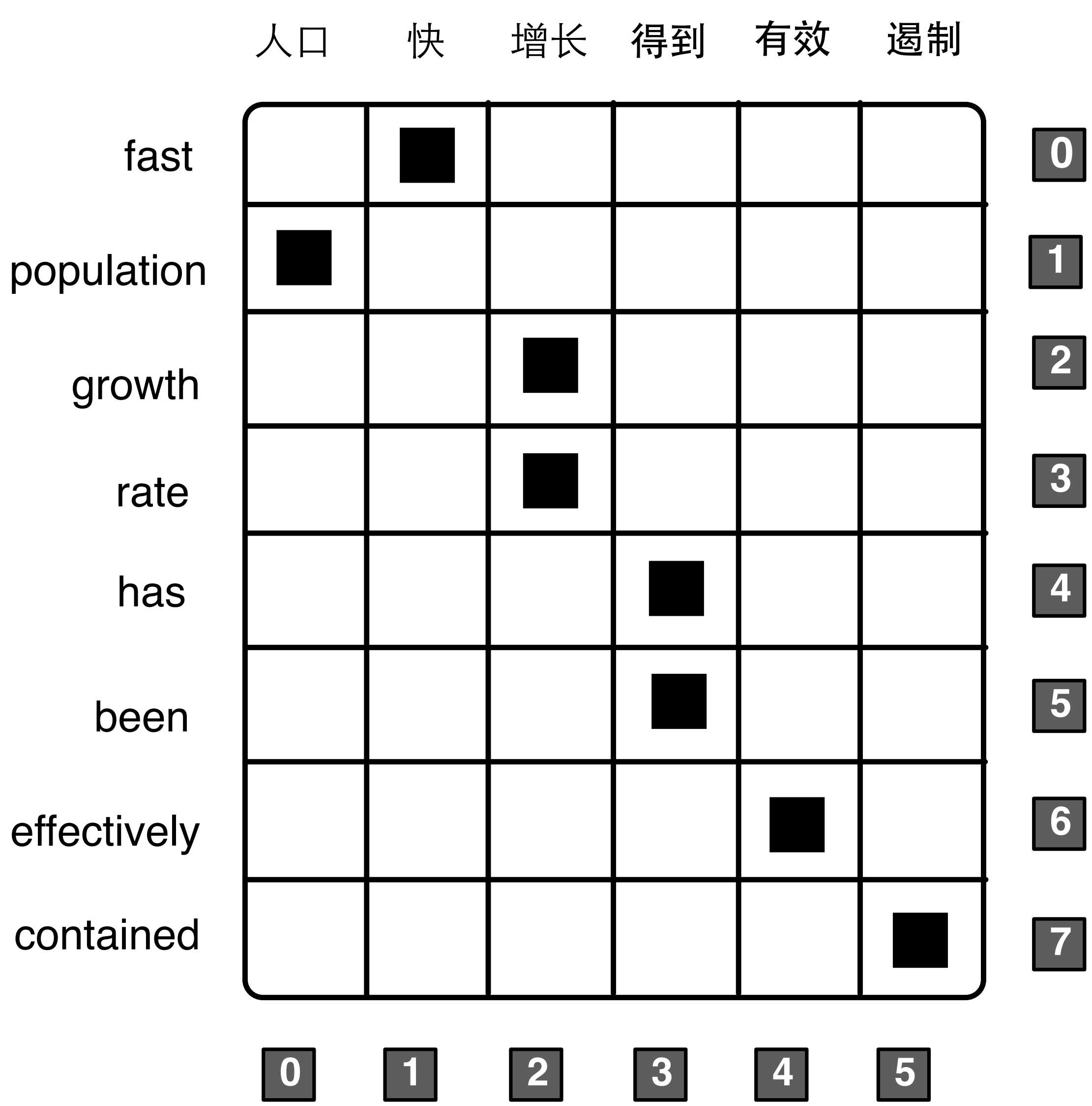


Alignment Matrix

- Take each Chinese-English sentence pair in the bitext
- "Discover" what Chinese words correspond to what English words (*unsupervised* learning algorithm)
- Now extract *phrasal* correspondences by drawing boxes around alignment points (each box should be self-contained)

LEARNING A TRANSLATION MODEL



Alignment Matrix

extracted bilingual phrase pairs

(0,0) x (1,1) ➔ <人口,population>
(1,1) x (0,0) ➔ <快,fast>
(2,2) x (2,3) ➔ <增长,growth rate>
...
...
(4,5) x (6,7) ➔ <有效 遏制,effectively contained>
...
...

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- Compute *feature functions* $h(e_p, f_p)$ for each phrase pair $\langle e_p, f_p \rangle$

LEARNING A TRANSLATION MODEL

- Compute *feature functions* $h(e_p, f_p)$ for each phrase pair $<e_p, f_p>$
- Most features are computed via maximum likelihood estimation
- Examples:
  - How frequently was f_p extracted with e_p, relative to other e's?
  - How frequently was e_p extracted with f_p, relative to others f's?
  - How well do words in e_p align to those in f_p?
  - How well do words in f_p align to those in e_p?

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- Use a discriminative model†

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  - Each λ_k is a weight for the corresponding feature h_k

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- This learned model represents the likelihood of generating TL sentence **e** given SL sentence **f**
- Now what?

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Math

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$$p(\mathbf{e}|\mathbf{f})$$

APPLYING A TRANSLATION MODEL

Math

$$\boxed{p(\mathbf{e}|\mathbf{f})}$$

Model Score

APPLYING A TRANSLATION MODEL

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$\mathbf{e}$ $\boxed{p(\mathbf{e}|\mathbf{f})}$

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$\boxed{p(\mathbf{e}|\mathbf{f})}$

$\boxed{\mathbf{e}}$

All possible translations that can be constructed using the learned phrasal correspondences

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APPLYING A TRANSLATION MODEL

Math

$$\arg\max_{\boxed{\mathbf{e}}} \boxed{p(\mathbf{e}|\mathbf{f})}$$

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Search operation

$$\underset{\mathbf{e}}{\arg\max}\; p(\mathbf{e}|\mathbf{f})$$

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"Best" TL translation for **f**

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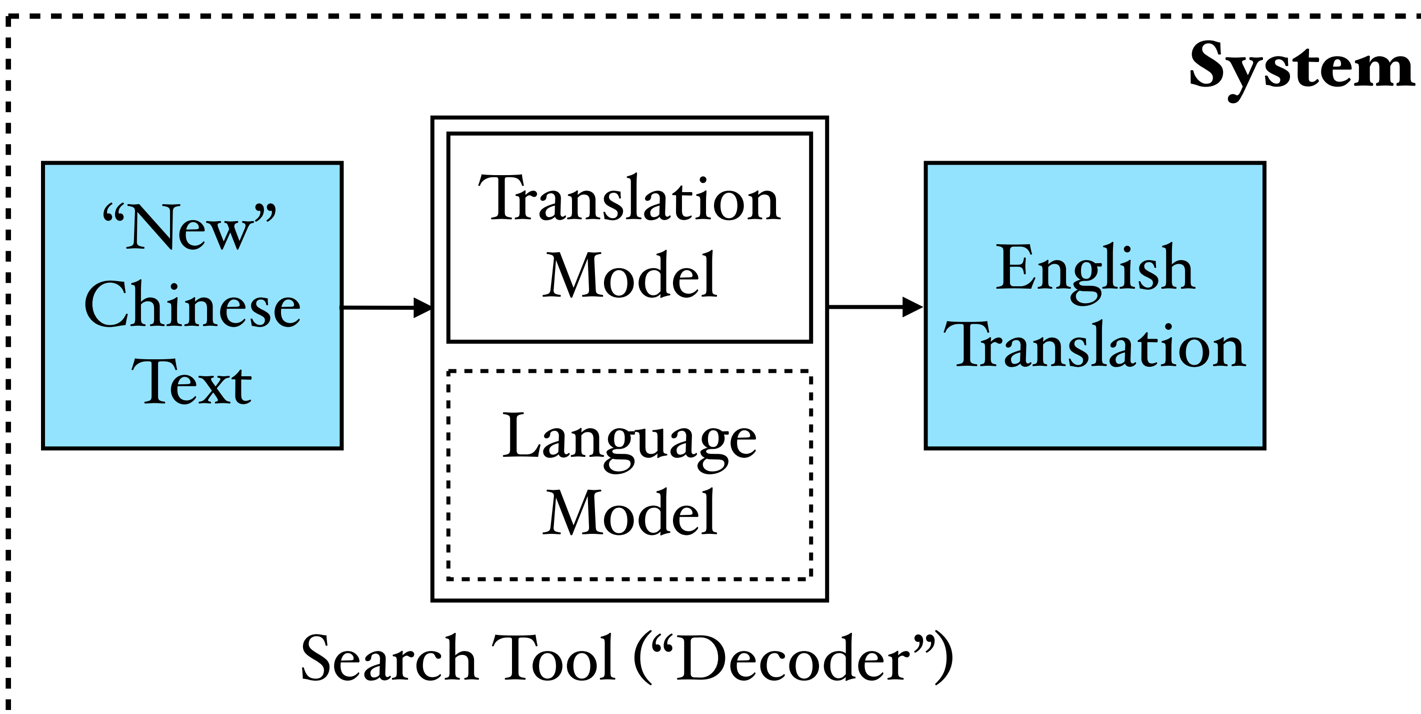

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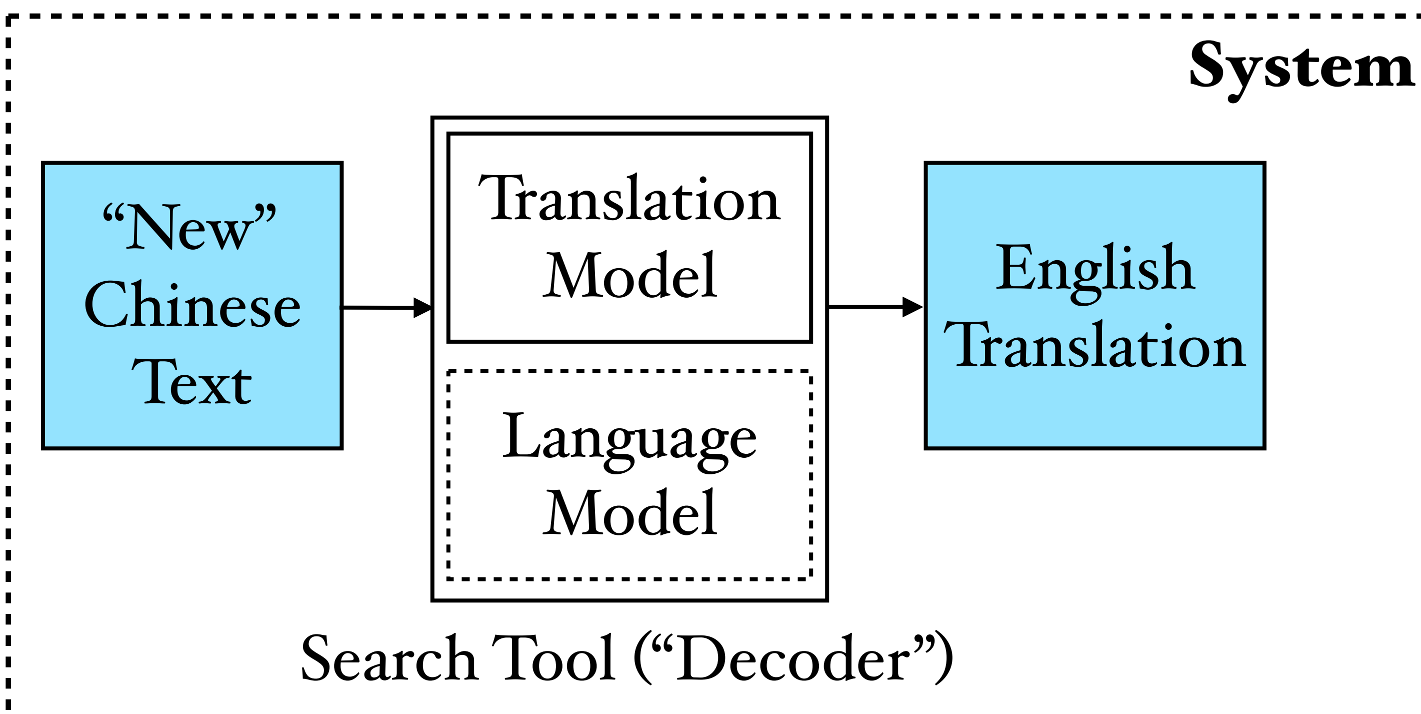

- Search - "Decode" (Weaver thought of MT as "breaking a code")
- Brute-force decoding has been shown to be NP complete
- Writing an efficient decoder requires using heuristics e.g., beam search
- Phrasal reordering is a whole other problem
- Models/Decoders can both be imperfect (*model/search errors*)

NOT QUITE DONE YET ...

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- Option 2: Test on datasets with already existing human-authored *reference translations;* use an **automated** metric to compare our system's translations to references

EVALUATING TRANSLATION

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BLEU: MT metric that measures overlapping words sequences[†]

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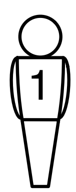

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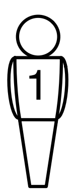

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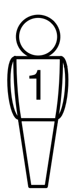

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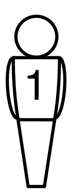

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Too Expensive! Most datasets only have 1.

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Training Bitext

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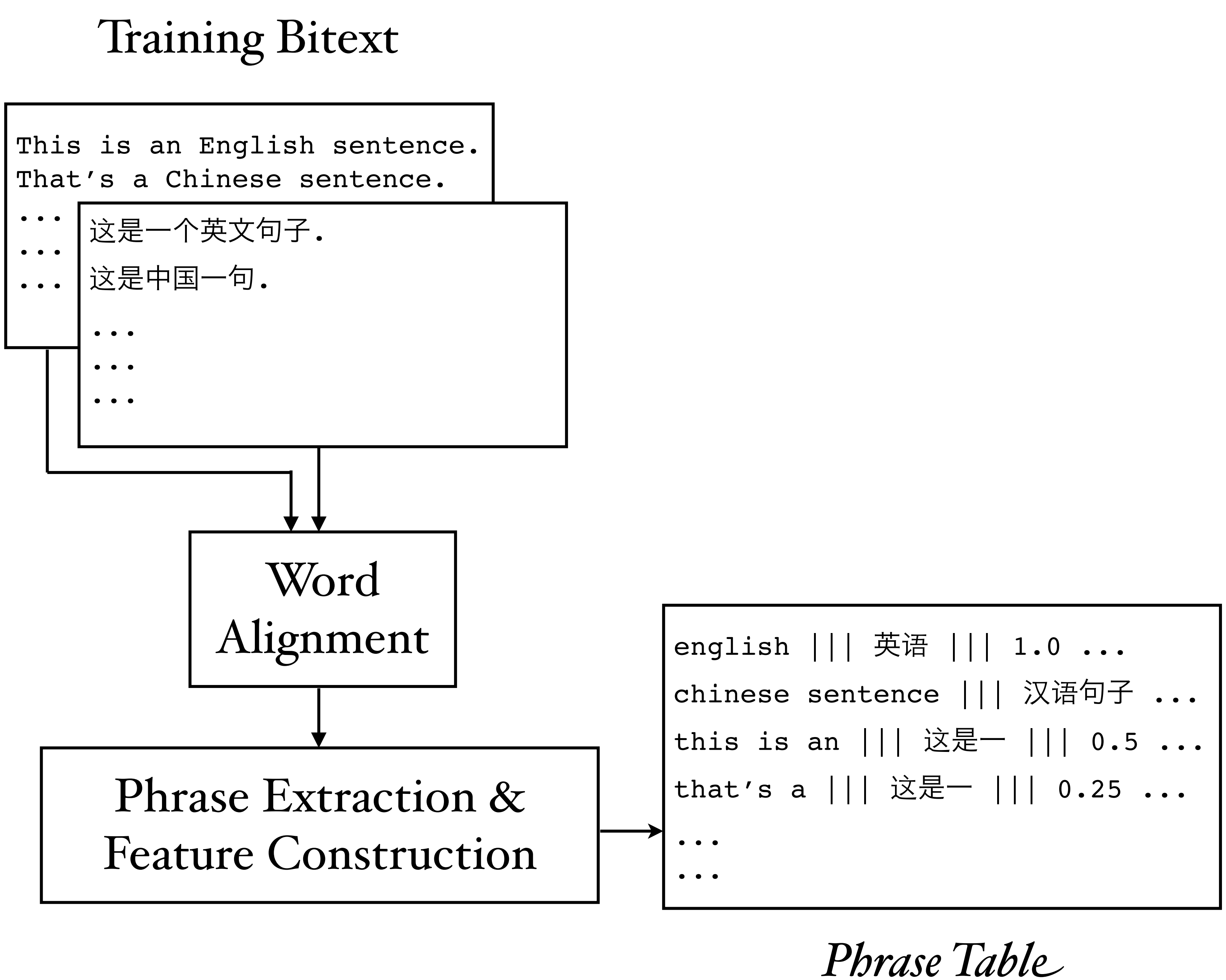

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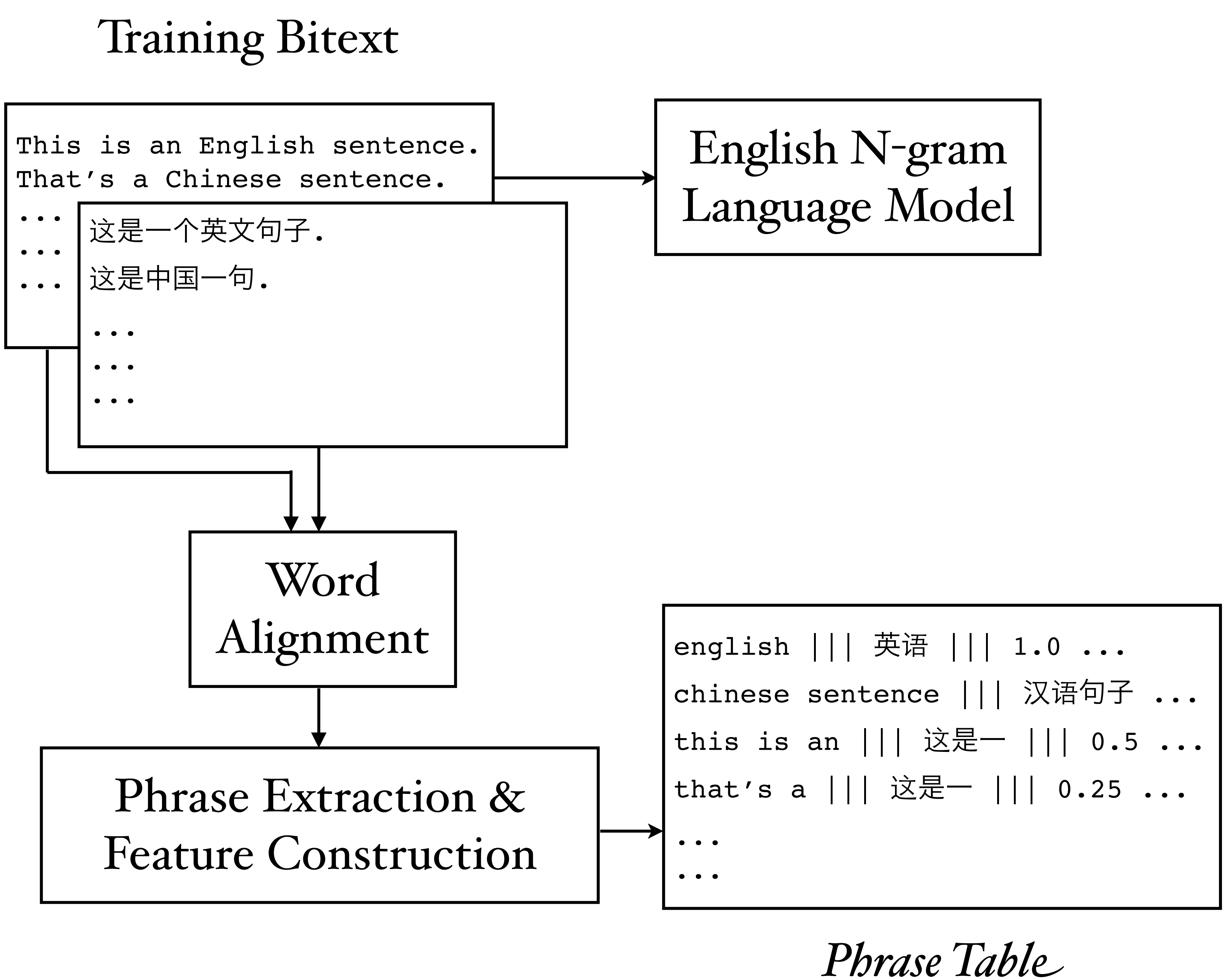

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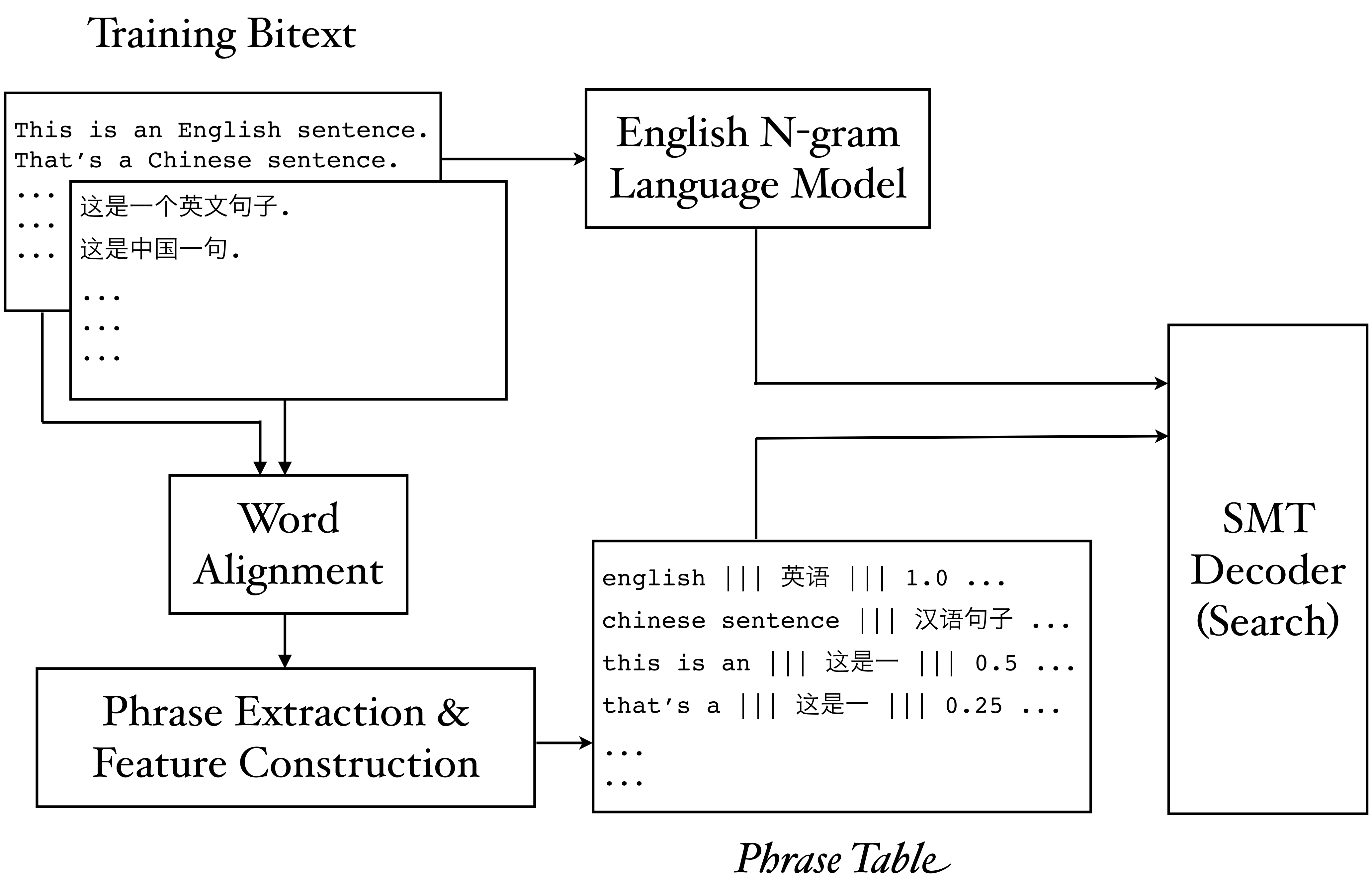

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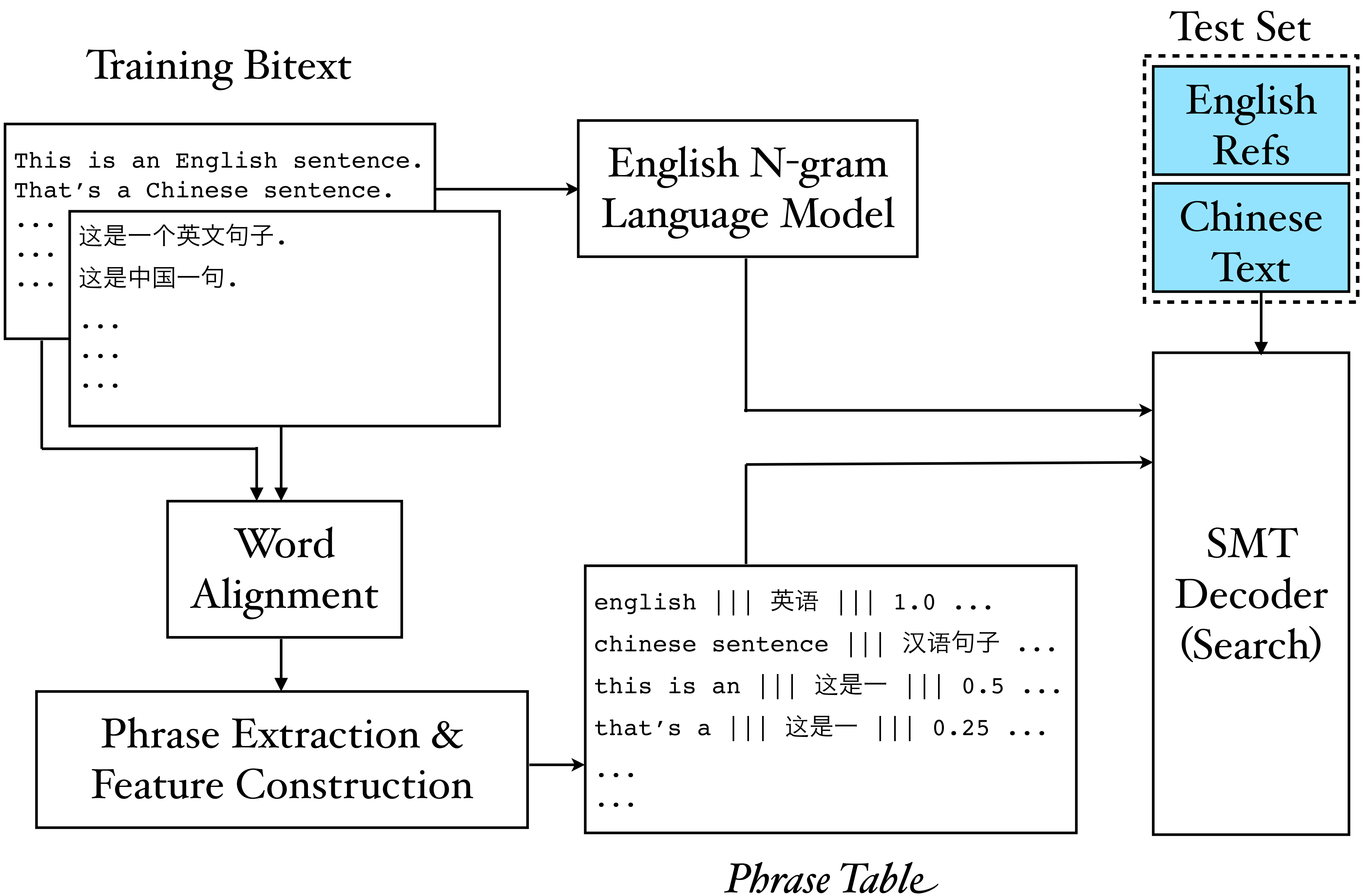

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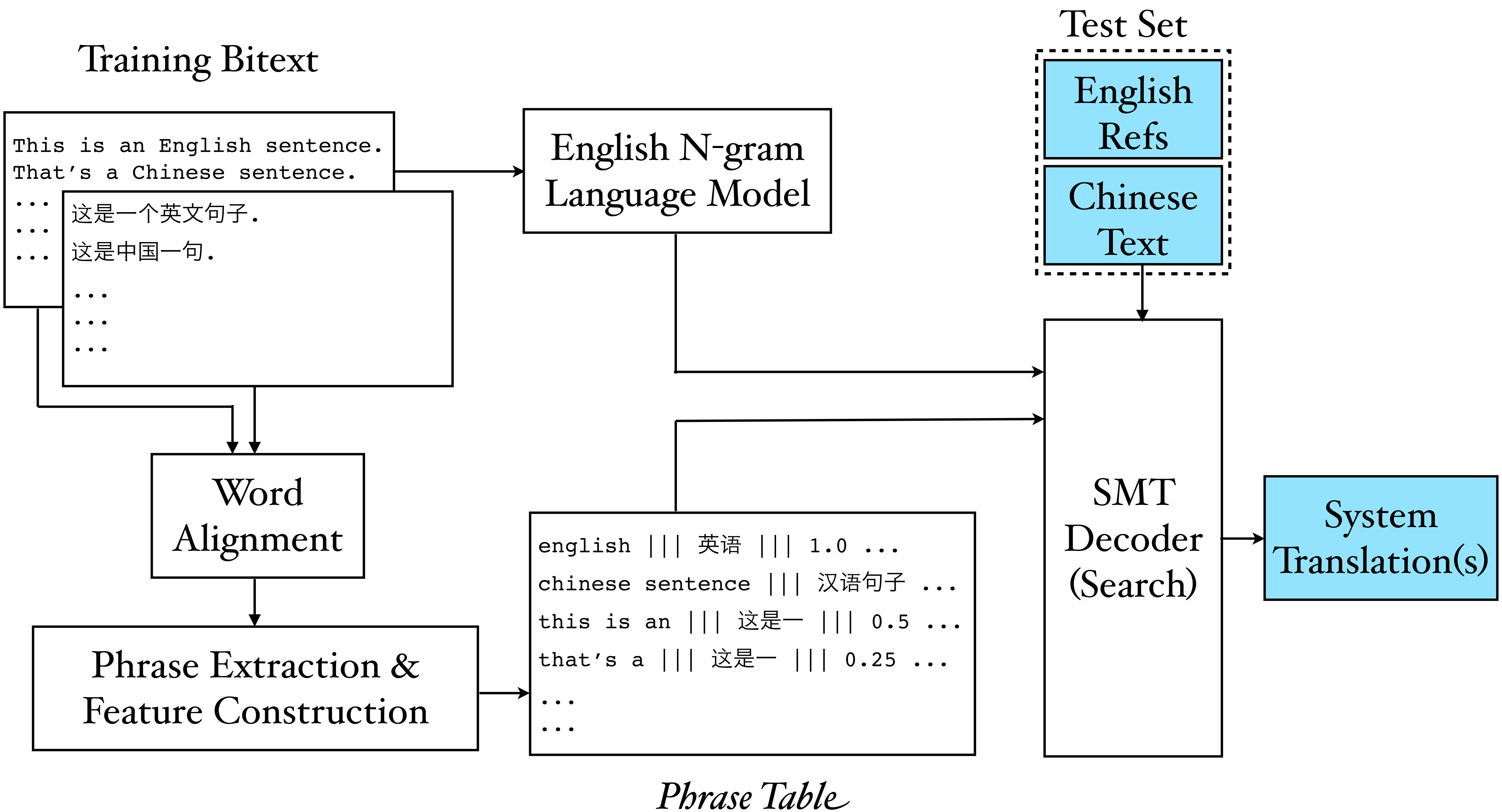

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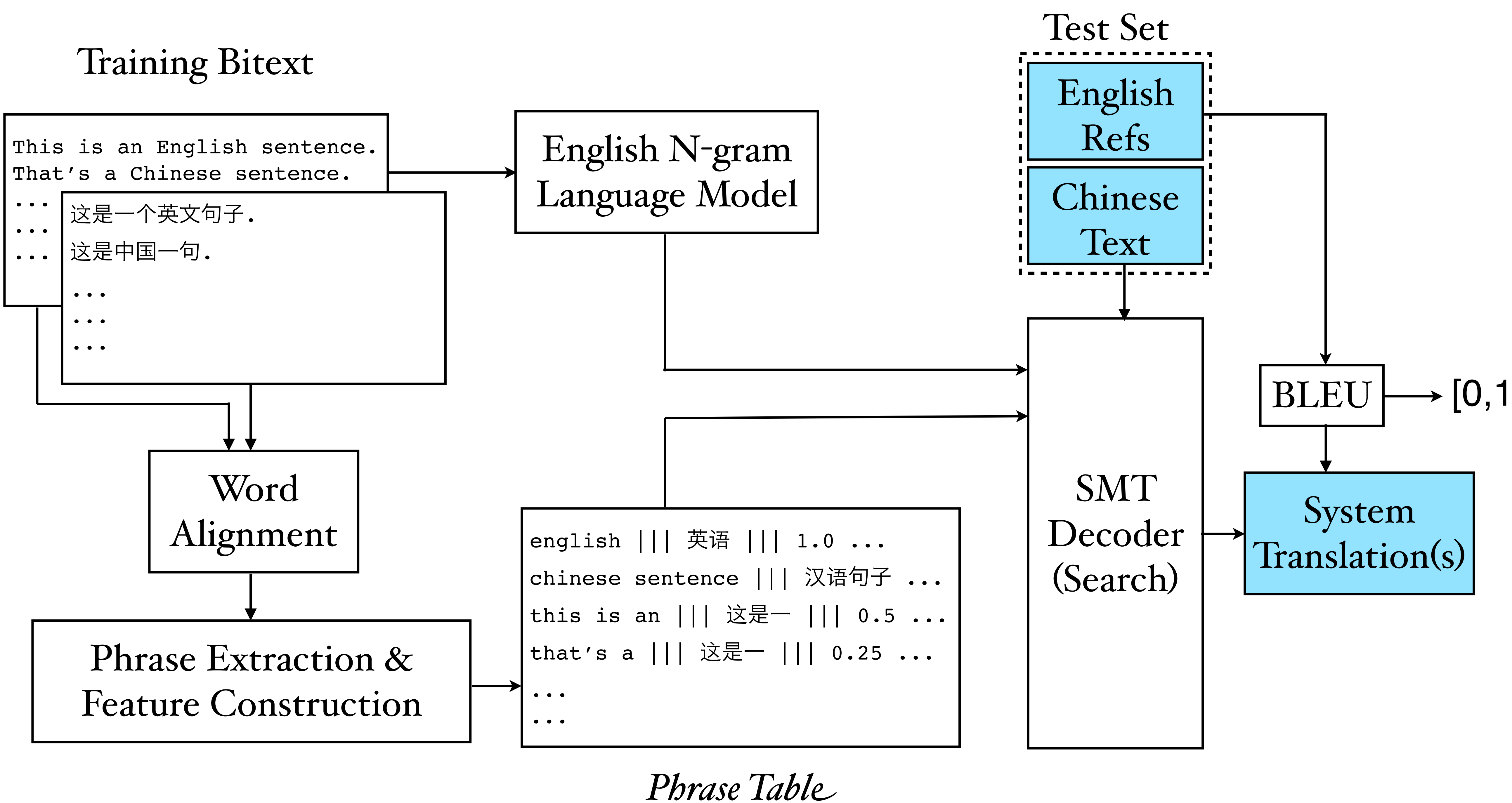

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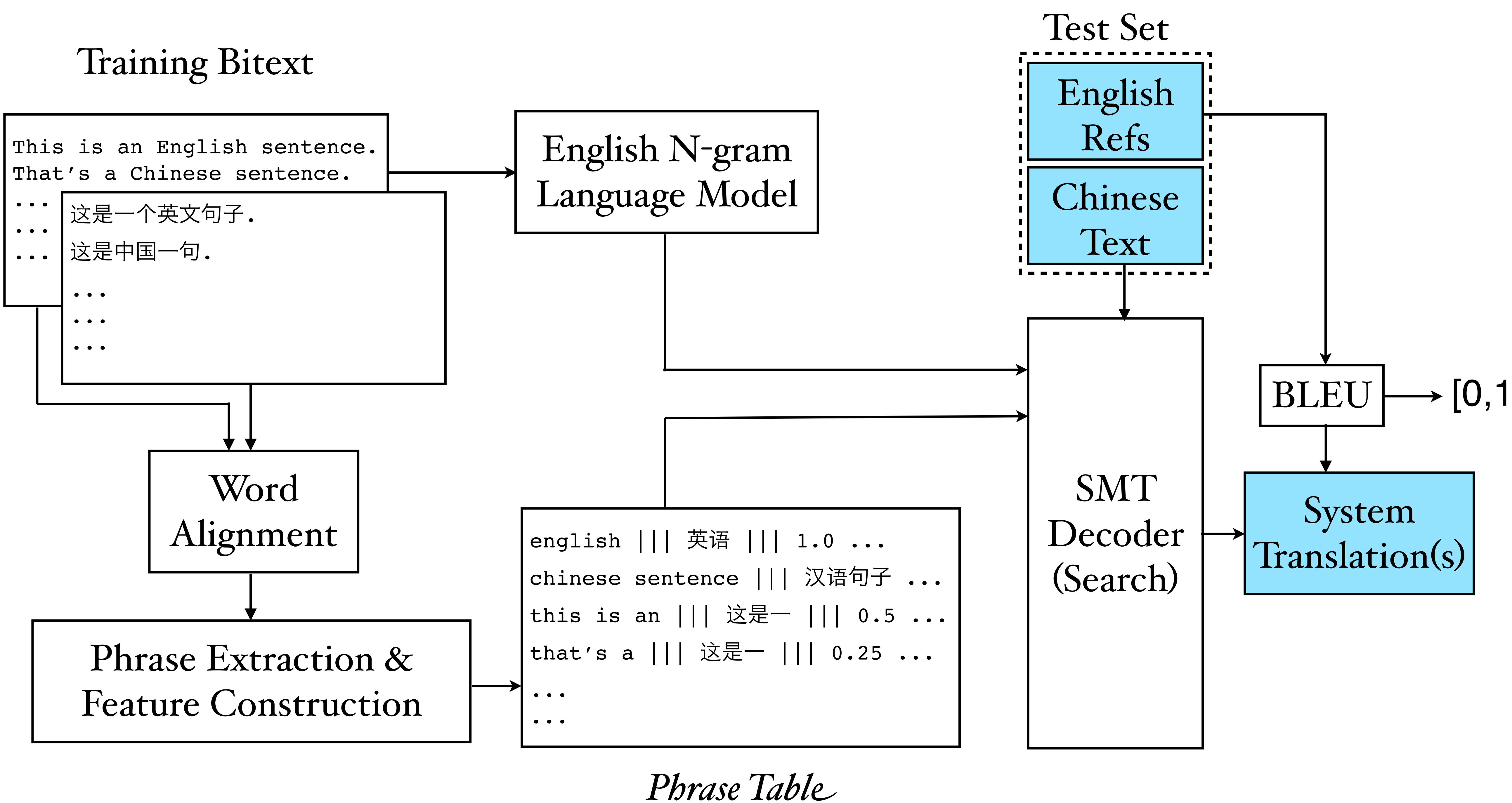

So, are we done?

PART II

THE MAGIC

PARAMETER TUNING

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$$p(\mathbf{e}|\mathbf{f}) = \frac{\exp \sum_{k=1}^{N} \overset{??}{\lambda_k} h_k(\mathbf{e},\mathbf{f})}{\sum_{e'} \exp \sum_{k=1}^{N} \lambda_k h_k(\mathbf{e}',\mathbf{f})}$$

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- The argmax inside BLEU( ) rules out gradient ascent

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- **Solution**: Use a variant of a line maximization algorithm

PARAMETER TUNING

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- Maximum BLEU Training Algorithm

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```
Repeat
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  - Generate 19 additional random values for λ1..K to avoid
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  - Optimize each λ using line maximization, holding others
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  - Values of λ1..K yielding greatest BLEU increase used as
    initial values for next iteration
Until no change in values of λ1..K
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- What makes BLEU fair? Multiple (**Expensive**) Reference Translations.

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PART III

THE BOOTSTRAP

BITEXT TO THE RESCUE ...

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- "If a Chinese phrase C can translate into English as both E1 and E2, shouldn't E1 and E2 have the same meaning?"
- Theory aside, is there any empirical evidence that this works?

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- Most *pivoted* paraphrase pairs found to be approximately paraphrastic

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WHAT ABOUT SENTENCES?

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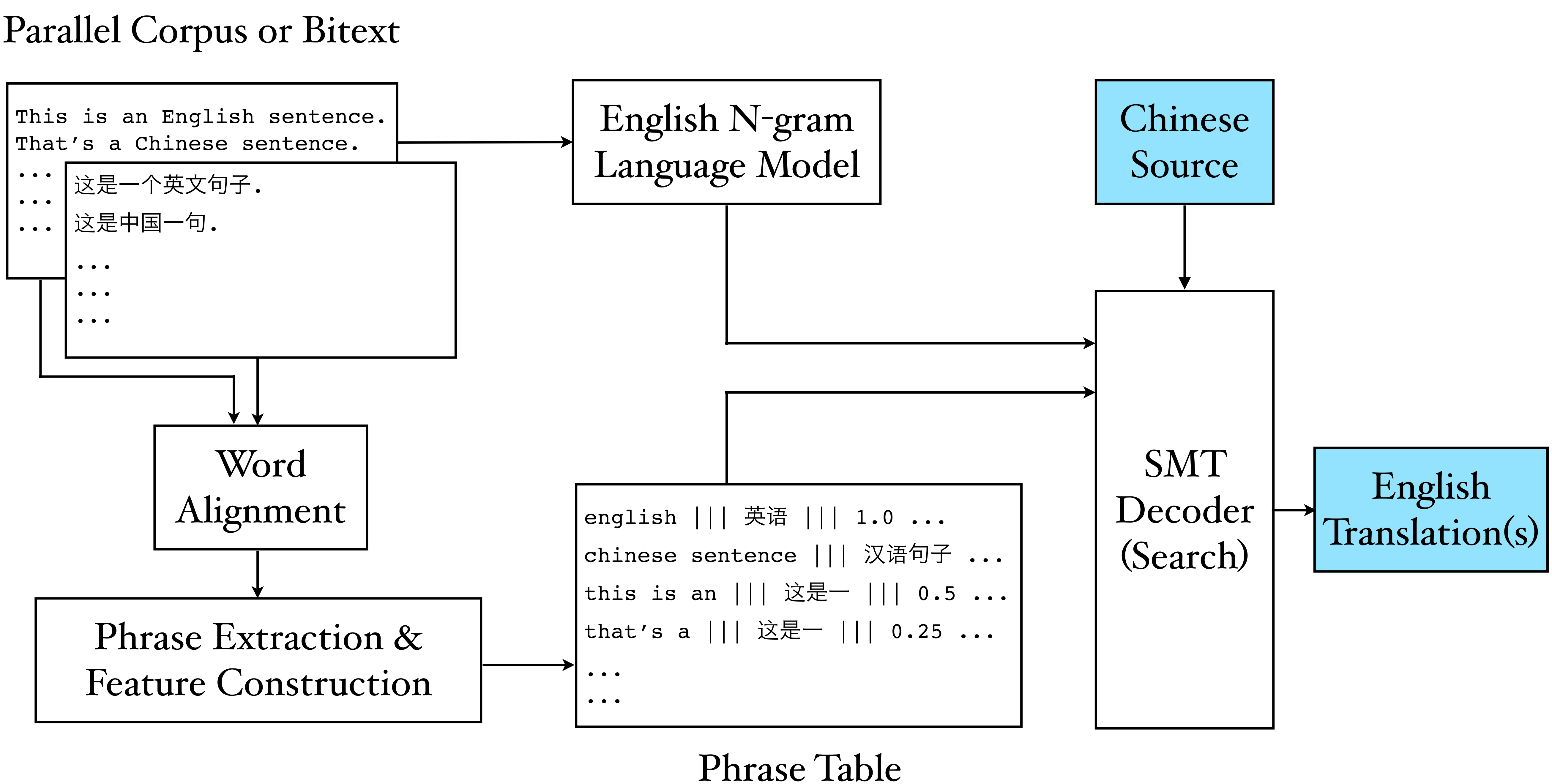
- Treat pivoted paraphrase pairs as English-to-English *translation* correspondences
- The English language model will still prove useful
- Combine (para)phrase table with language model inside a regular, unmodified SMT decoder
- Can now generate paraphrase(s) for *any* English sentence†
- Log-linear features in paraphrase space can also be computed via pivoting
  - # of times phrase e1 was "seen" with e2 = # of times e1 was extracted with pivot f * # of times e2 was extracted with pivot f, summed over *all* pivots

†*Using Paraphrases for Parameter Tuning in Statistical Machine Translation*. Nitin Madnani et al. WMT 2007

PARAPHRASE GENERATION



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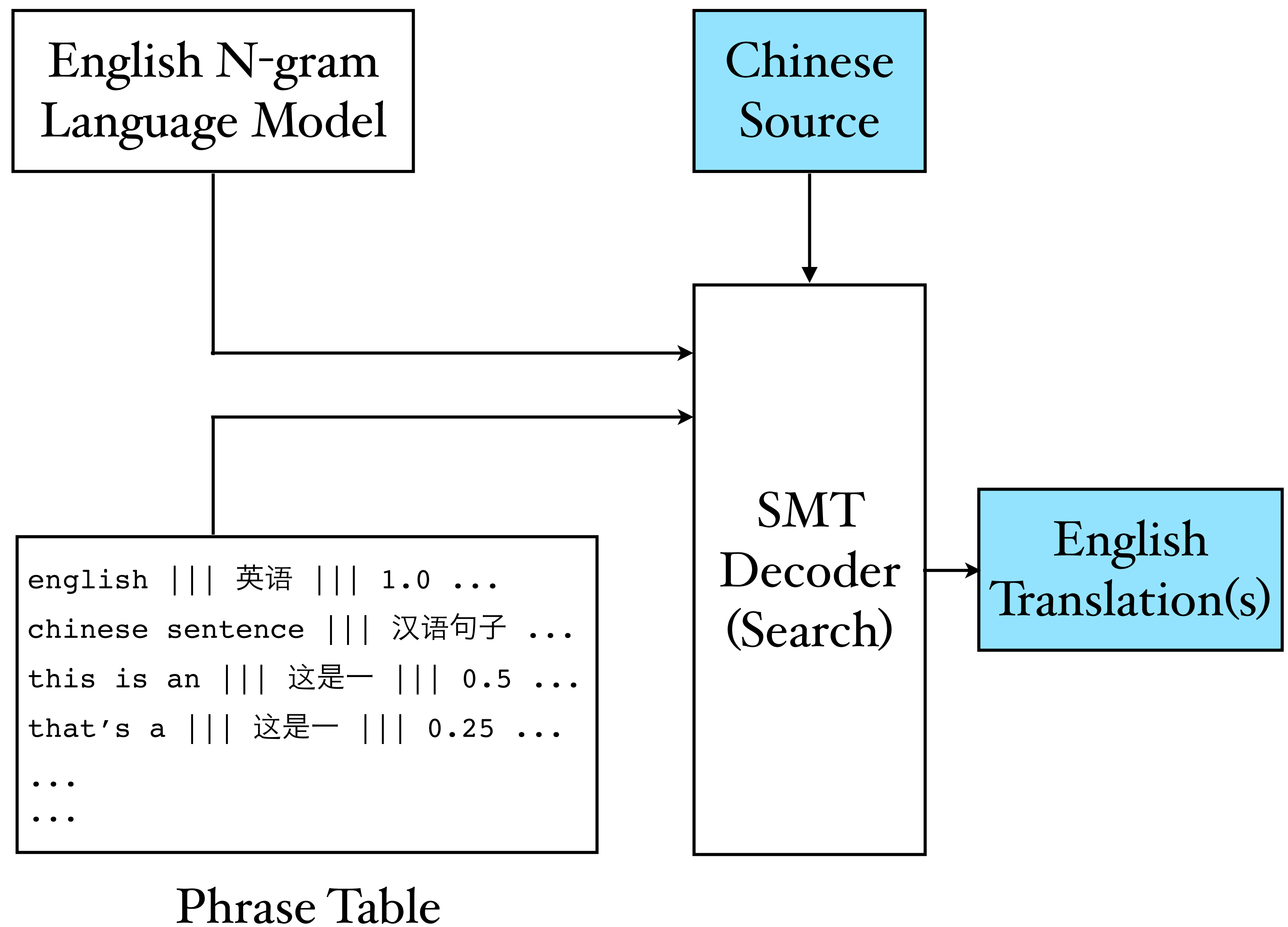

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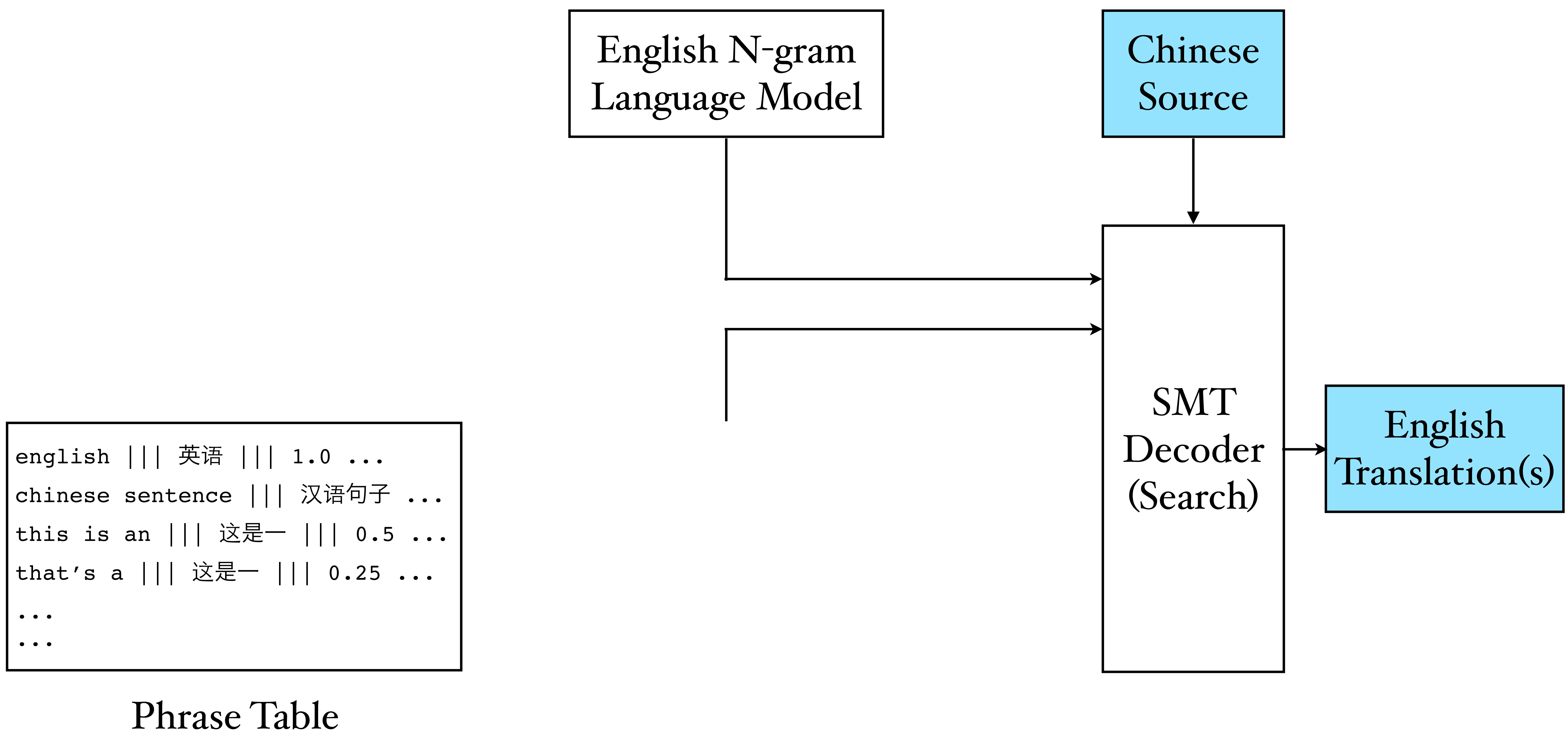

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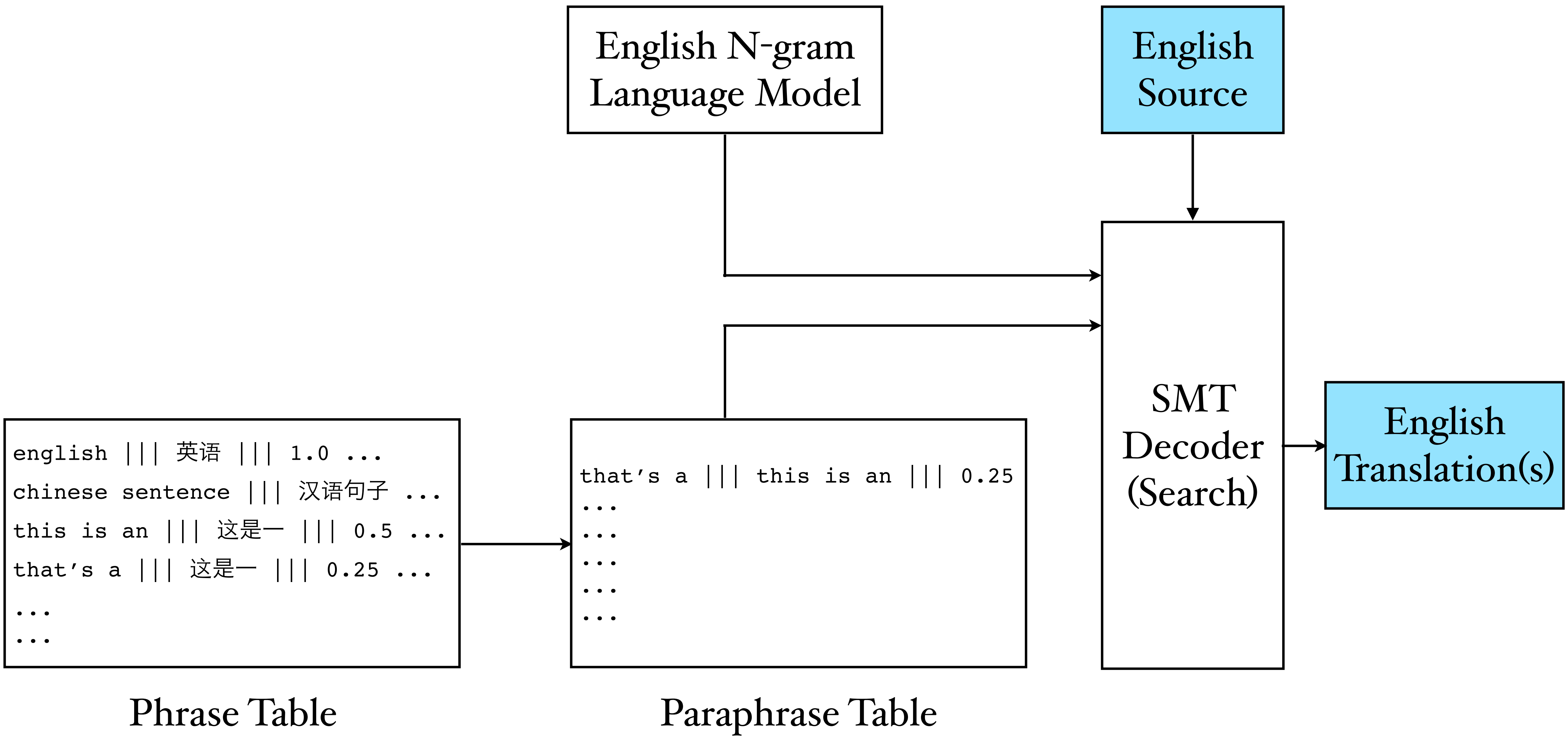

SENTENTIAL PARAPHRASES

Example paraphrases generated with Chinese as pivot language

SENTENTIAL PARAPHRASES

Alcatel added that the company's whole year earnings would be announced on February 4.
Alcatel said that the company's total annual revenues would be released on February 4.

He was now preparing a speech concerning the US policy for the upcoming World Economic Forum.
He was now ready to talk with regard to the US policies for the forthcoming International Economic Forum.

Tibet has entered an excellent phase of political stability, ethnic unity and people living in peace.
Tibetans have come to cordial political stability, national unity and lived in harmony.

Its ocean and blue-sky scenery and the mediterranean climate make it world's famous scenic spot.
Its harbour and blue-sky appearance and the border situation decided it world's renowned tourist attraction.

Paraphrase Quality ↓

Example paraphrases generated with Chinese as pivot language

MTURK EVALUATION

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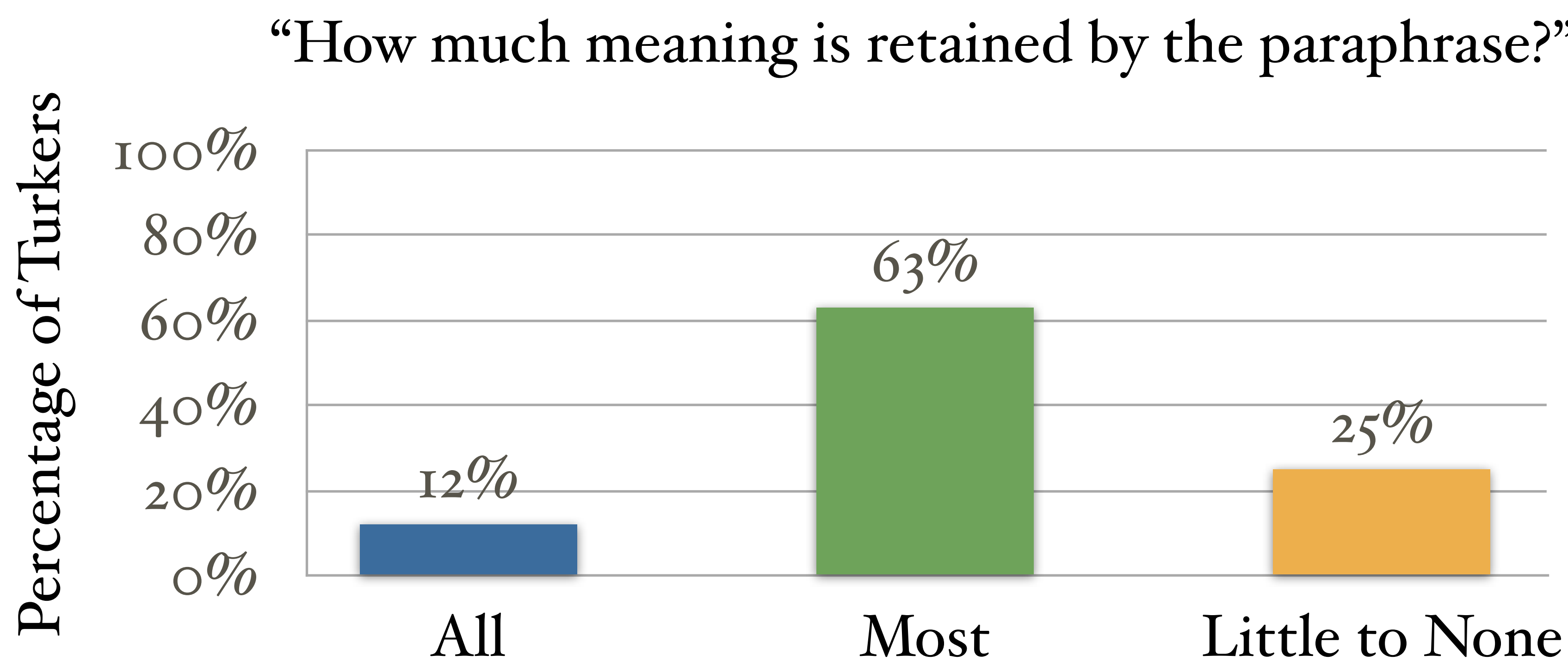
"How much meaning is retained by the paraphrase?"

MTURK EVALUATION



- Most "translations" are only *approximately* paraphrastic; Not surprising
- Paraphrases often not useful for direct human consumption
- Can they be used to solve our problem of reference sparsity for parameter tuning?

EXPERIMENTAL SETUP

$\boxed{R_1}$

$\boxed{S}$ +

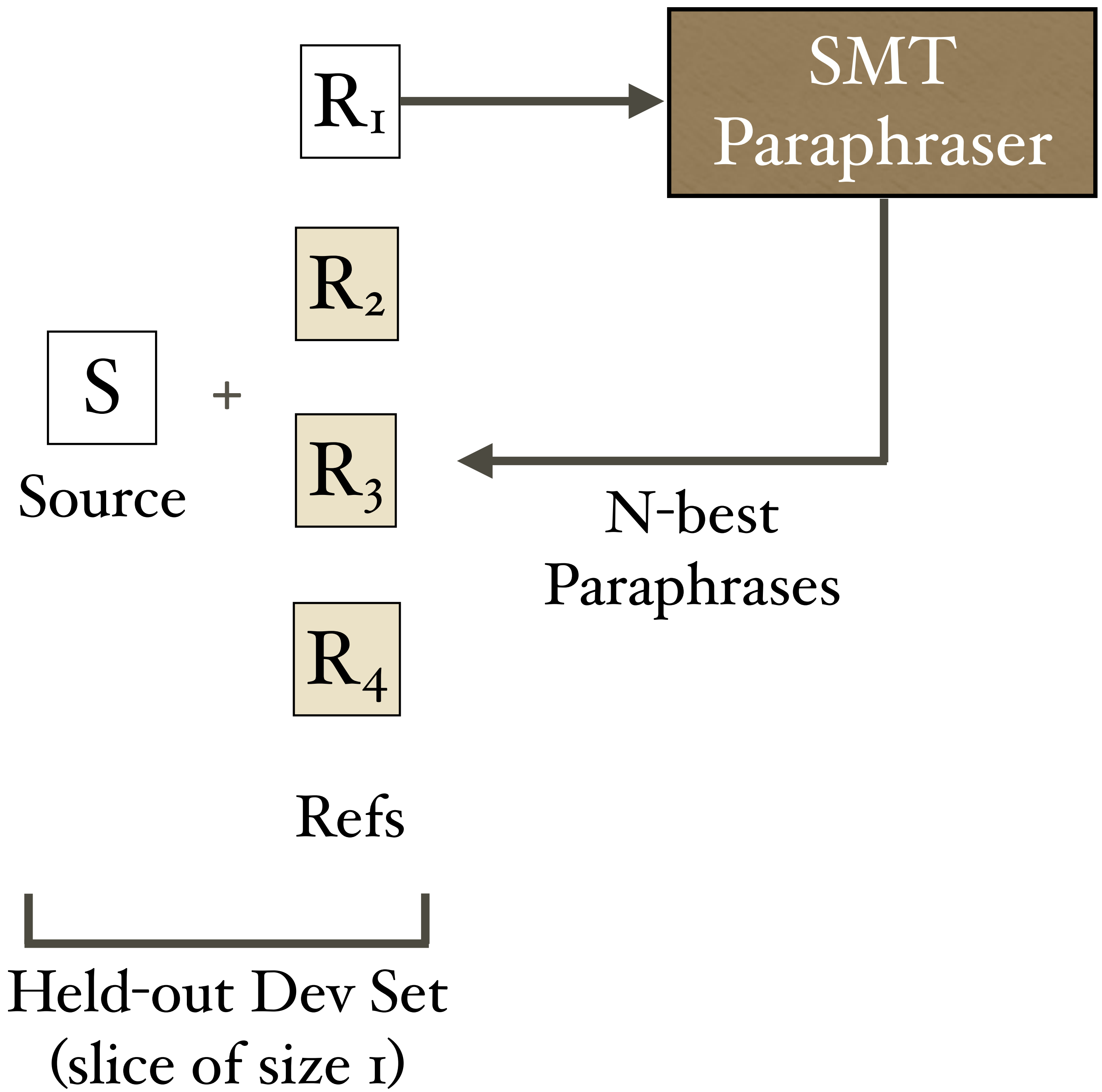
Source

Refs

Held-out Dev Set
(slice of size 1)

Investigating the Value of Paraphrased Reference Translations in Parameter Optimization. Nitin Madnani et al. AMTA 2008

EXPERIMENTAL SETUP



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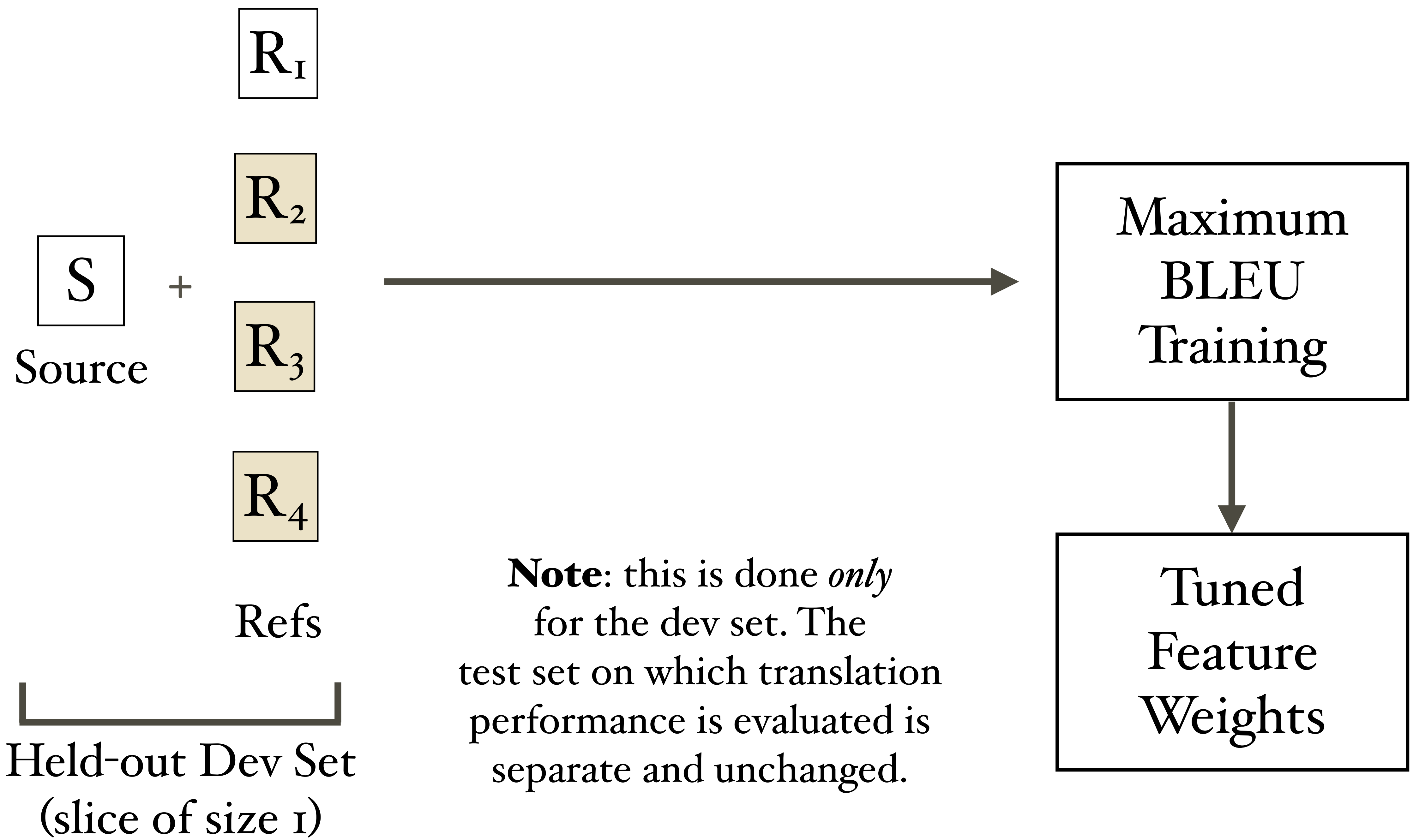

Note: this is done *only* for the dev set. The test set on which translation performance is evaluated is separate and unchanged.

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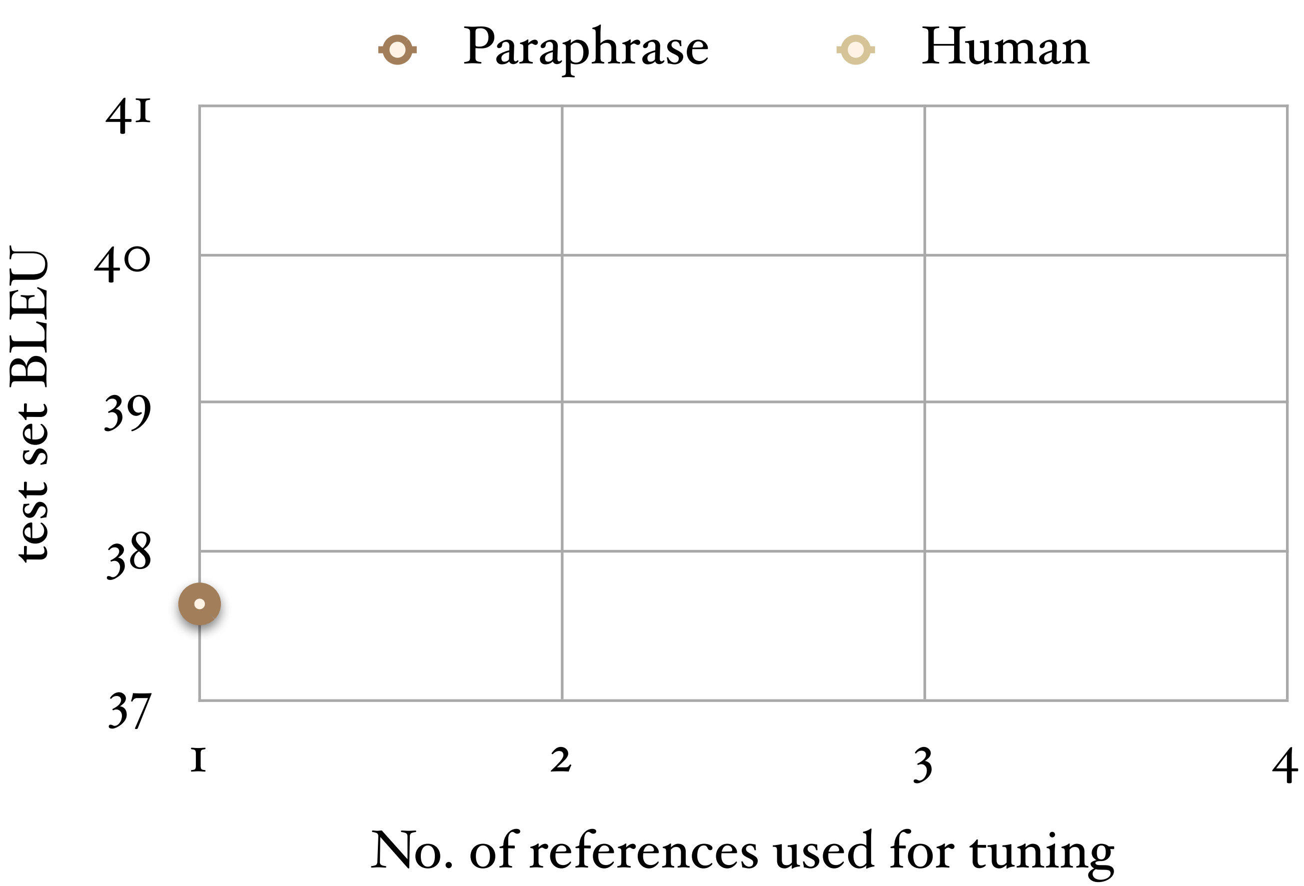
RESULTS: CHINESE TRANSLATION

Paraphrase Human

RESULTS: CHINESE TRANSLATION



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1 (1H+0)	37.65	37.65
2 (1H+1)	**39.32**	**39.20**
3 (1H+2)	**39.58**	**40.21**
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Higher BLEU is better
Bold denotes statistical significance for BLEU

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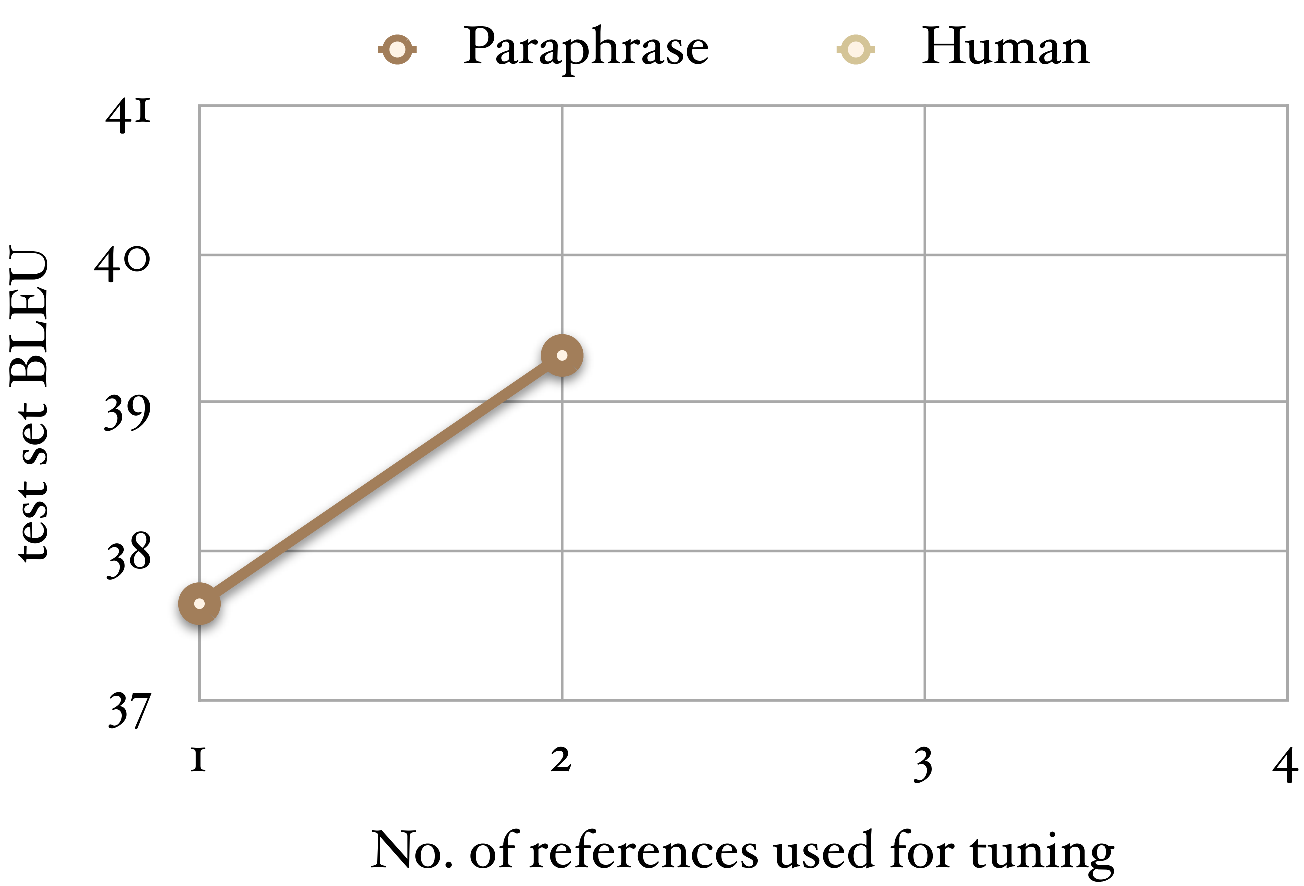

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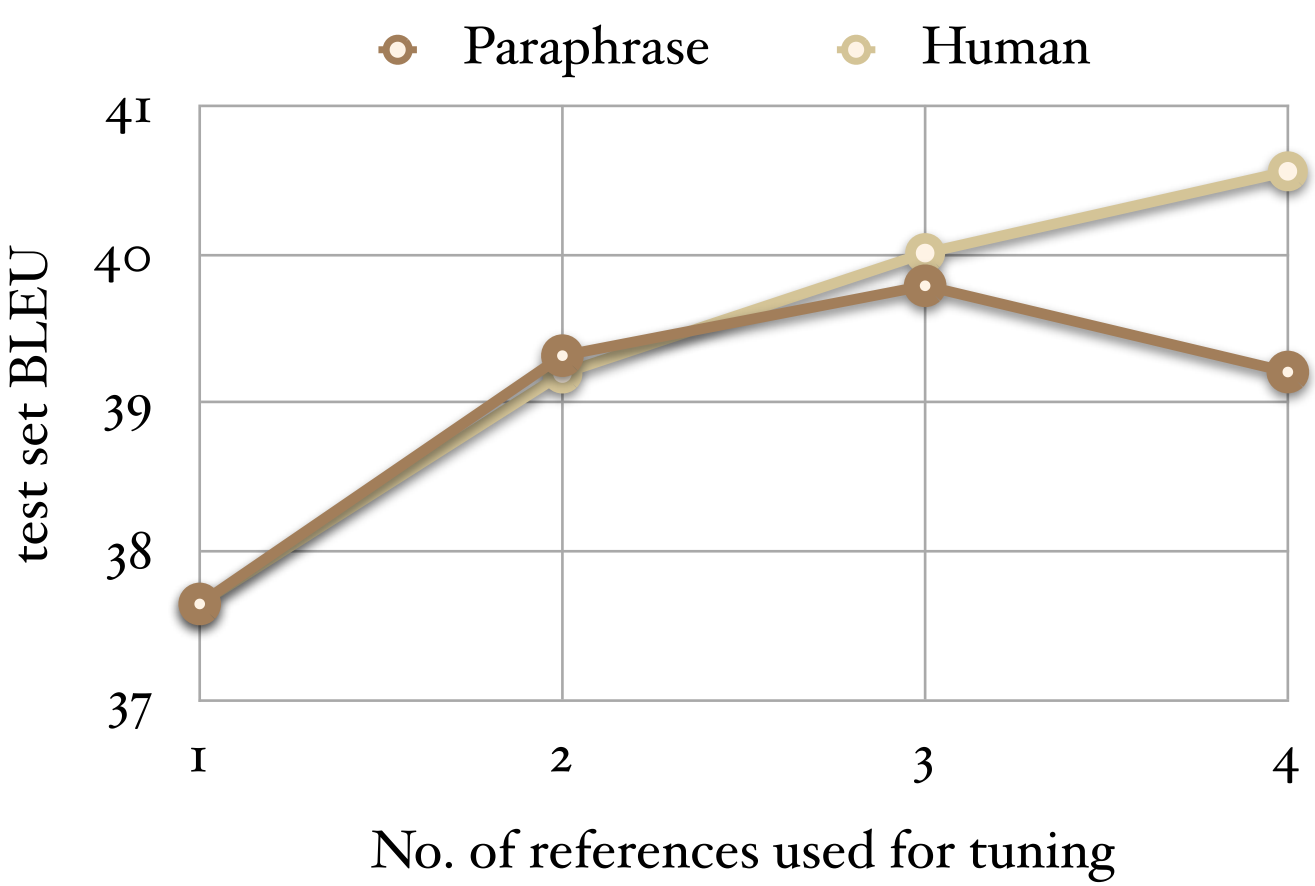

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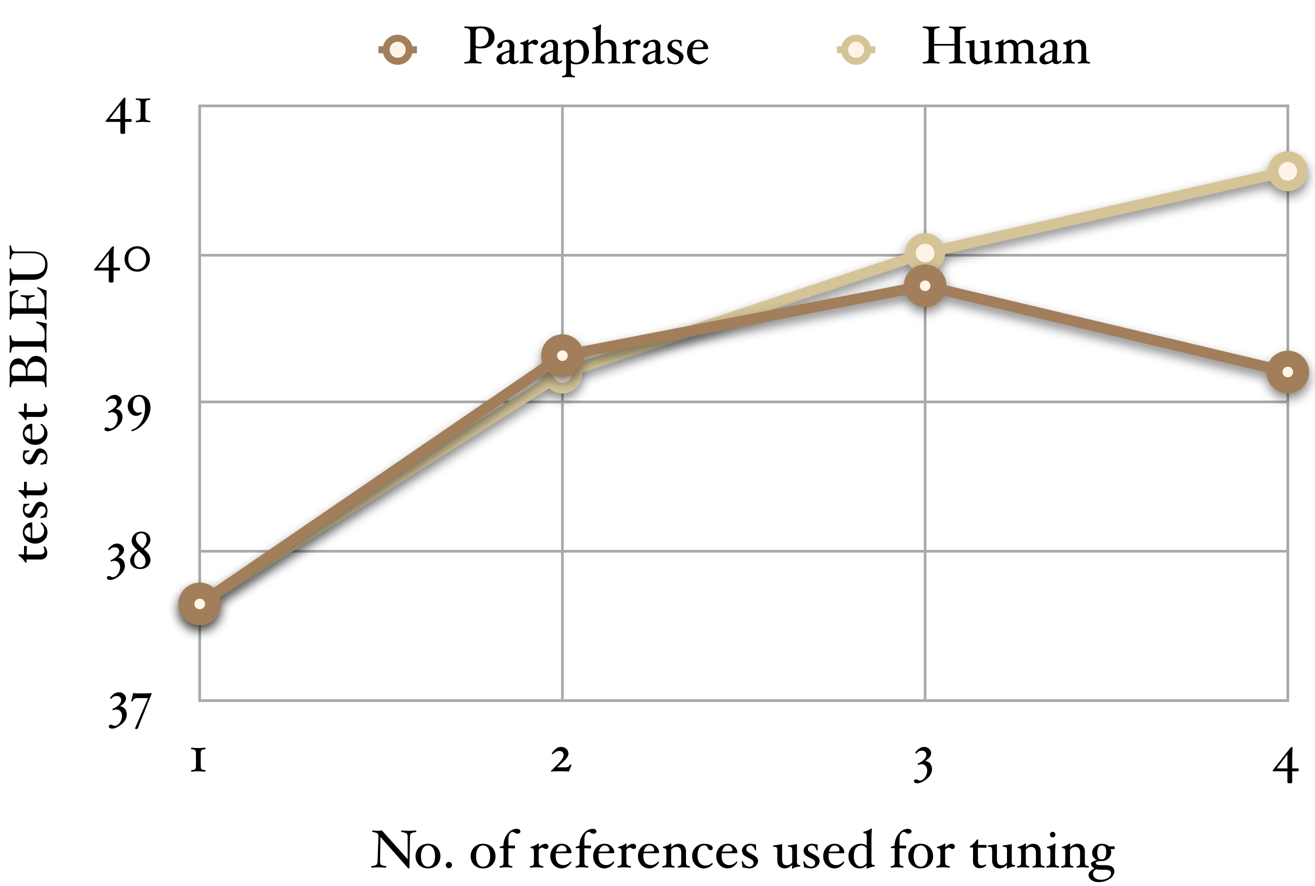

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- Effect of adding more than 1 human reference is better
- Similar results for French, Spanish and German translation (to English)

MORE != BETTER?

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- The current SMT paraphraser changes *everything it can*
- Basically a crap-shoot; change everything and hope that some changes will turn out to be useful during parameter tuning
- How about only making changes that are likely to be *useful*?
- Useful: paraphrases that are *a priori* more likely to match the system translation output
- One way to do this is to create a "targeted" version of the paraphraser

TARGETED PARAPHRASER

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O - AWB was severely hit after the relevant inquiry report into the matter was made public on the 27th.

T - After the release of the investigation report on the 27th, the company suffered a serious blow.

P_u - AWB was significantly impacted after the concerning review report about the issue was made release on the 27th.

P_t - AWB suffered a serious blow after the relevant inquiry report into the matter was made public on the 27th.

Actual Examples

T: MT output, **O**: Original Reference, **P_u**: “Untargeted” paraphrase, **P_t**: Targeted Paraphrase

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O - Singapore economic review committee: economy expected to see complete recovery in 2004

T - Singapore : the economy in 2004 is thought to recover fully

P_u - New economy: economic review board thought possible recovery in 2004

P_t - Singapore economic review committee: economy expected to recover fully in 2004

Actual Examples

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TARGETED PARAPHRASER

- Tune SMT system with single human reference and define a new *targeting* feature for paraphrase decoder
    - # of words in **paraphrase** hypothesis NOT in the **translation** system translation output
- By negatively weighting this feature, paraphrases can be made to look more like the translation output
- This could lead to a nasty feedback loop that didn't exist before!
    - Bad translation ==> Bad targeted paraphrase ==> Bad translation ...
- Need a counter-balance feature that prevents such a loop
    - *Self-paraphrase bias*: reserve fixed amount of prob. mass for identity paraphrases
- Need some fancy math to find an operating point that balances the two

The Circle of Meaning: From Translation to Paraphrasing & Back. Nitin Madnani. PhD Dissertation. 2010

TARGETED PARAPHRASER

$\boxed{R_1}$

$\boxed{S}$ +

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Generating Targeted Paraphrases for Improved Translation. Nitin Madnani & Bonnie Dorr. ACM TIST (To Appear)

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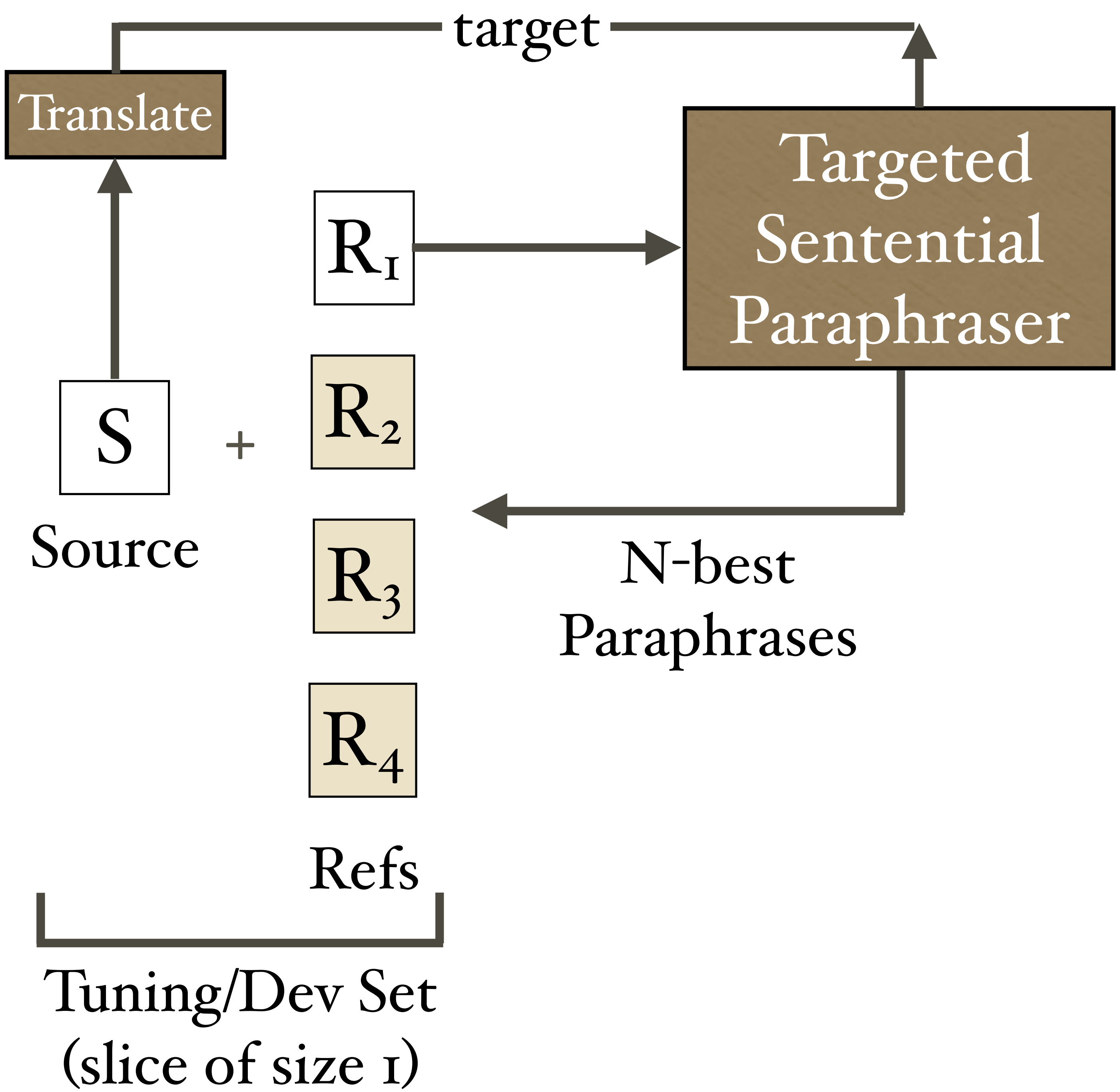

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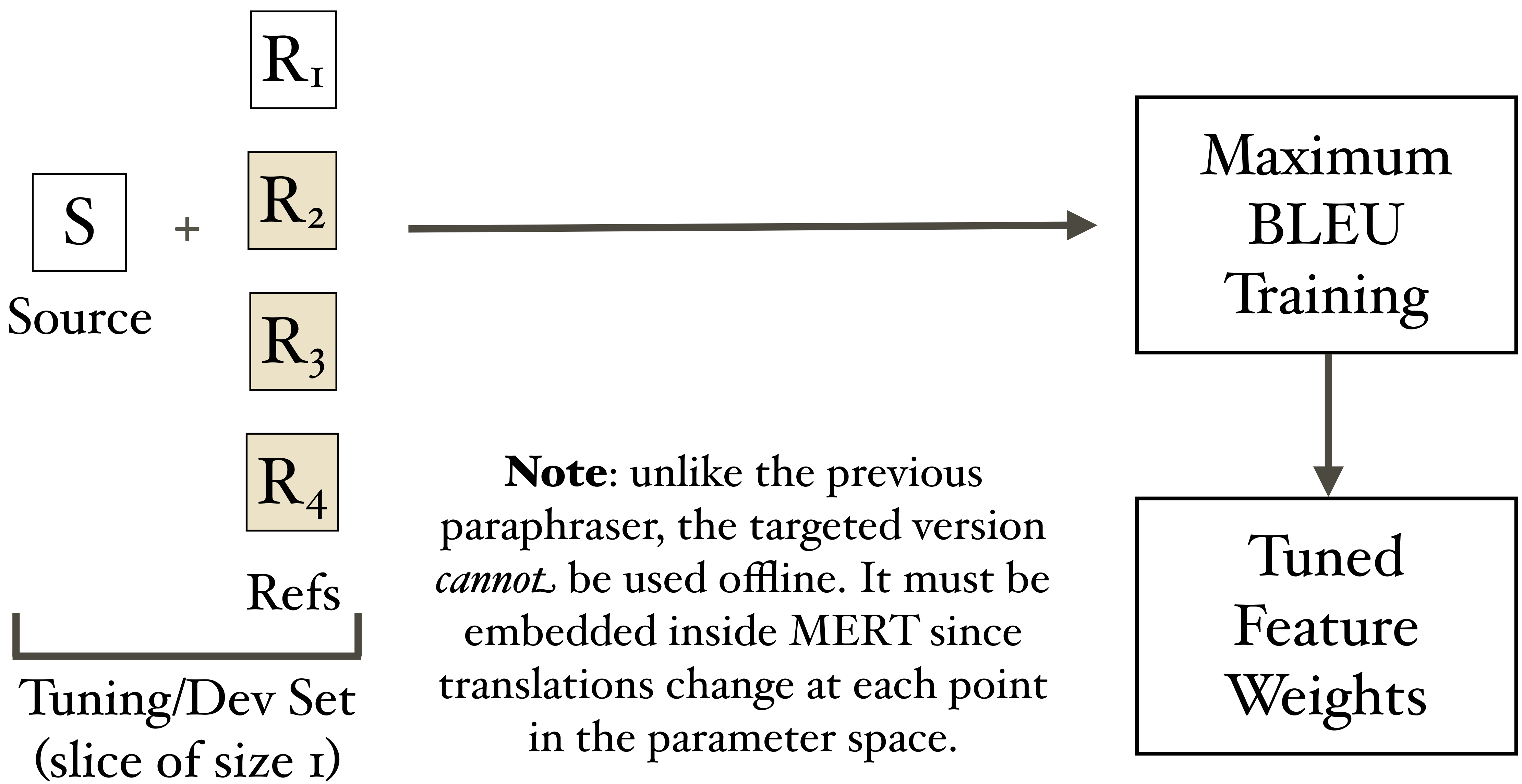

Note: unlike the previous paraphraser, the targeted version *cannot* be used offline. It must be embedded inside MERT since translations change at each point in the parameter space.

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Untargeted   Human   Targeted

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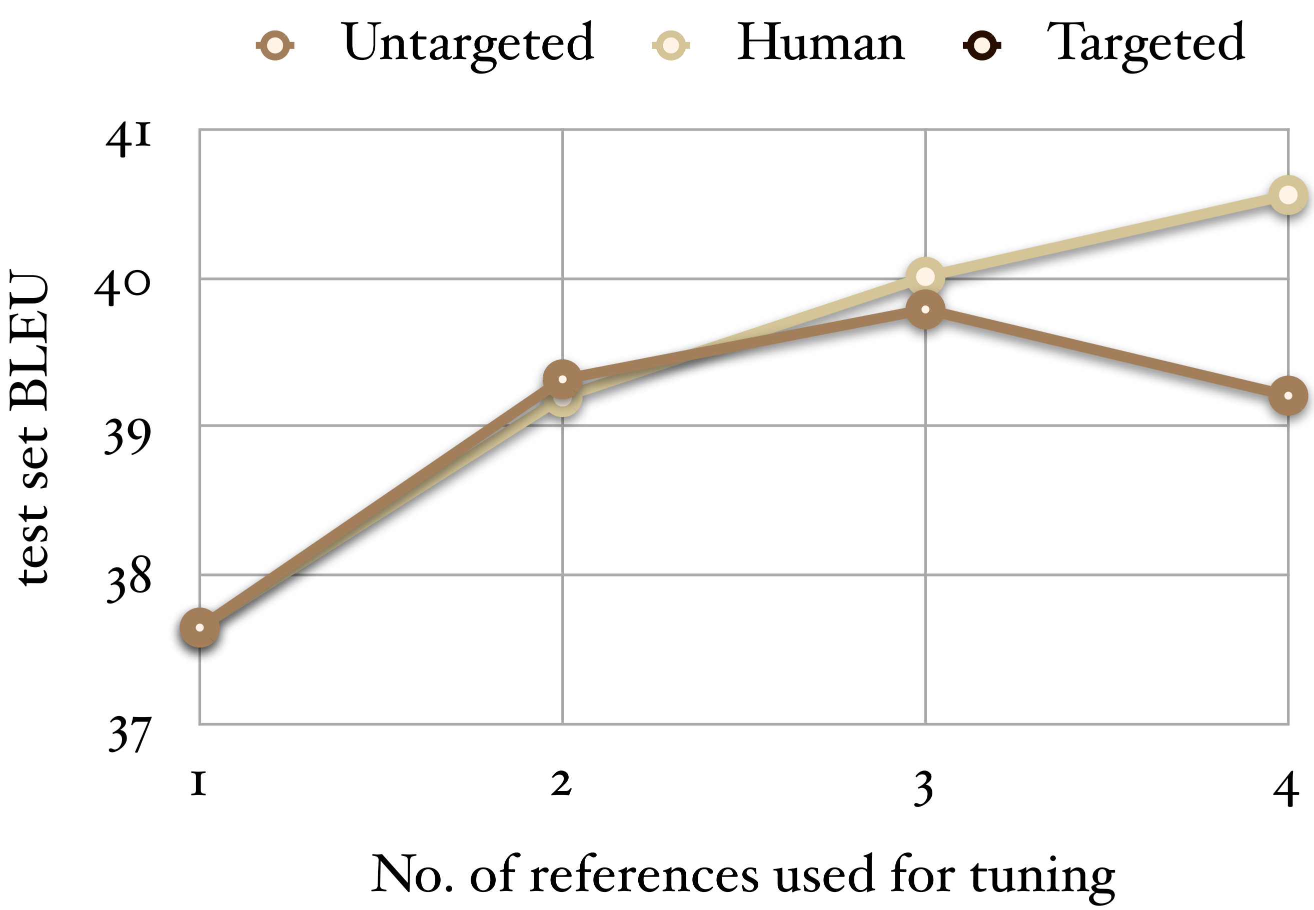

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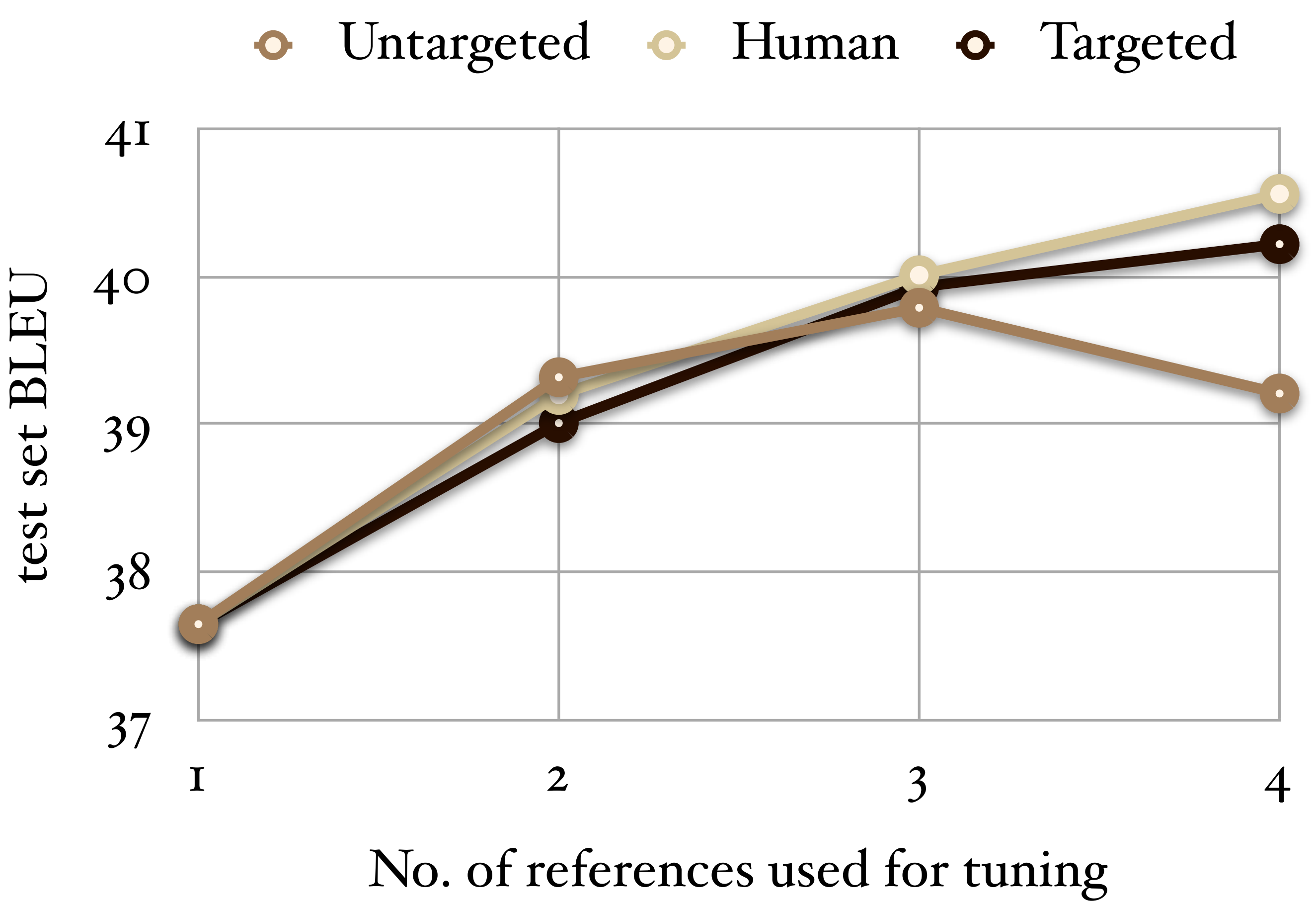

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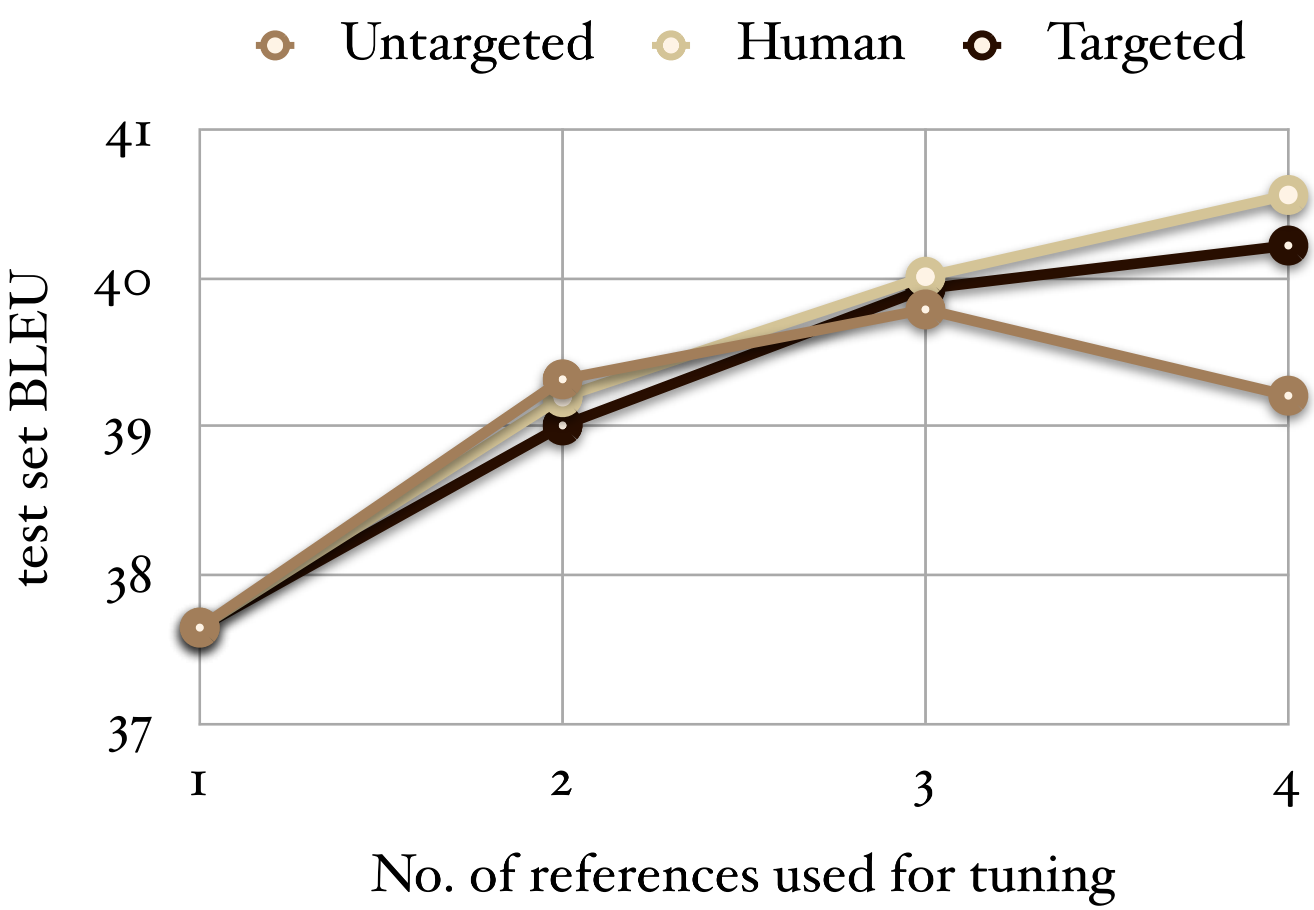

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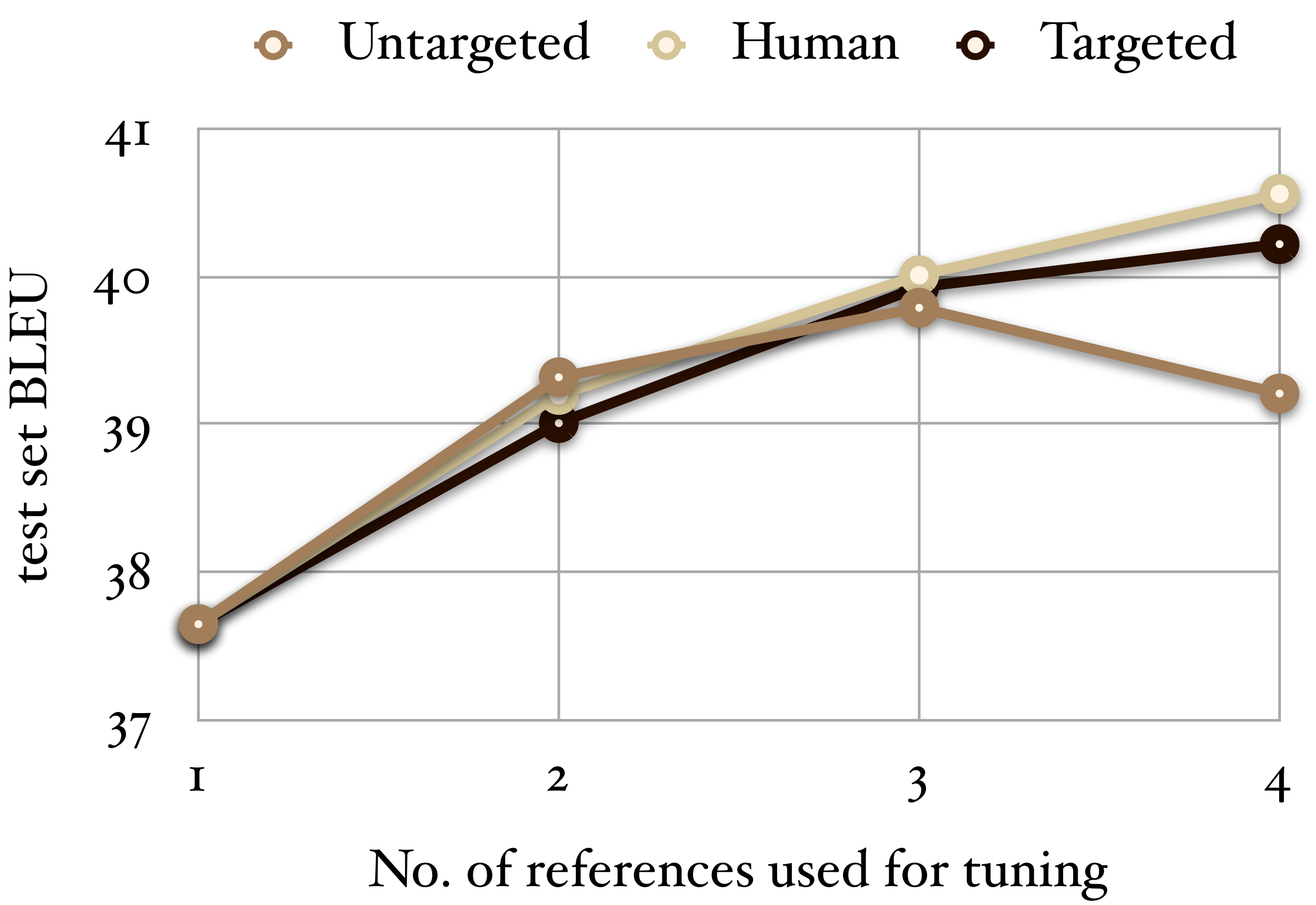

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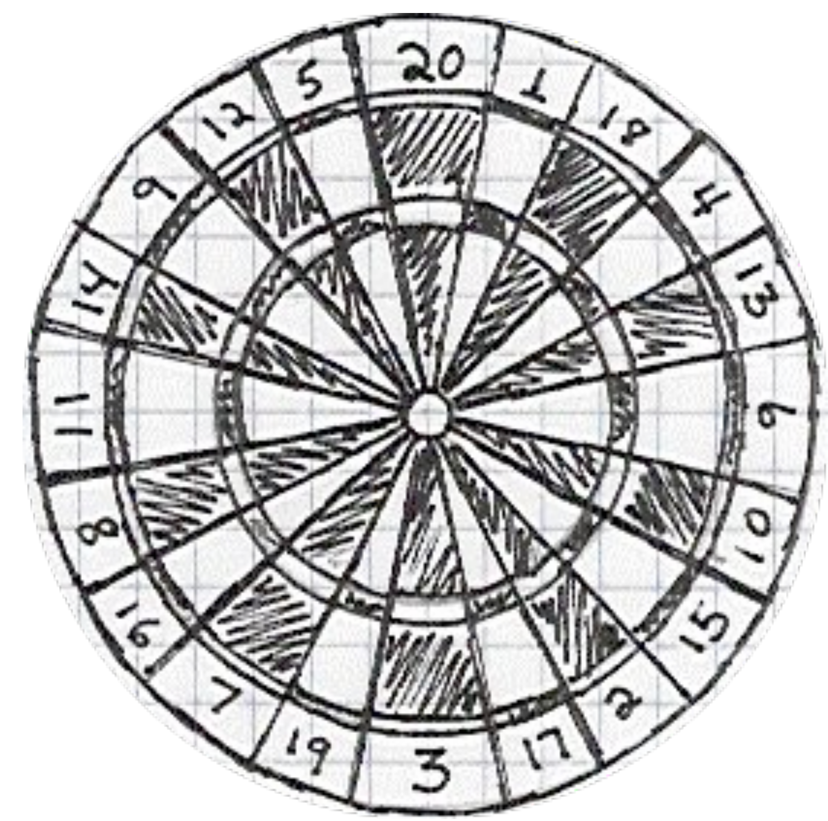
- All results also validated using human judgments of translation via Mechanical Turk

A DARTBOARD ANALOGY



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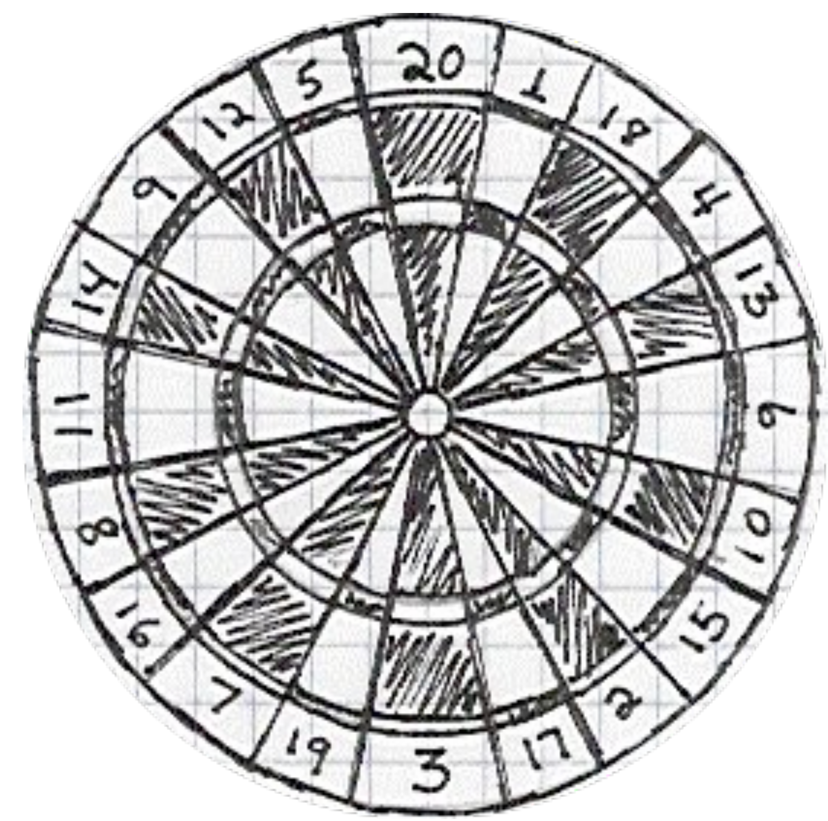
- Imagine matching an a word sequence as hitting the bullseye on a dartboard (BLEU)



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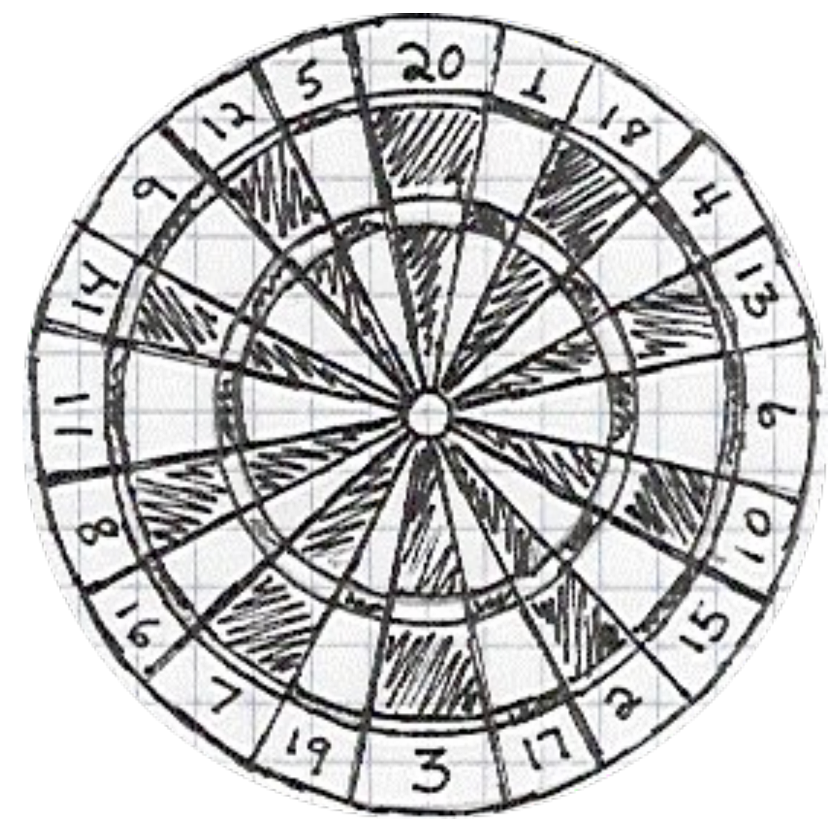

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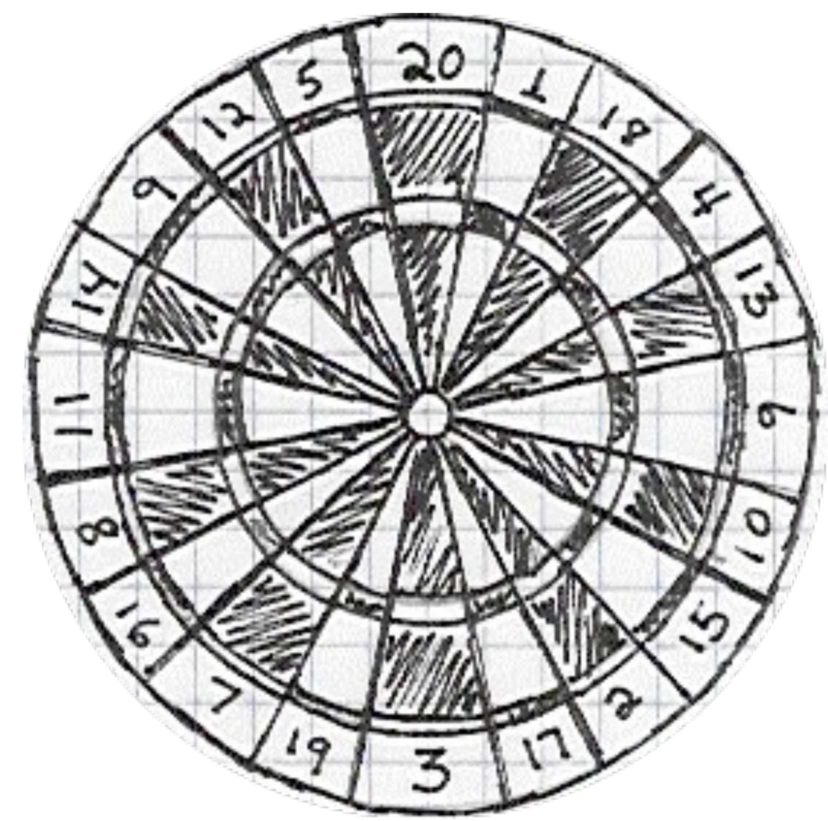

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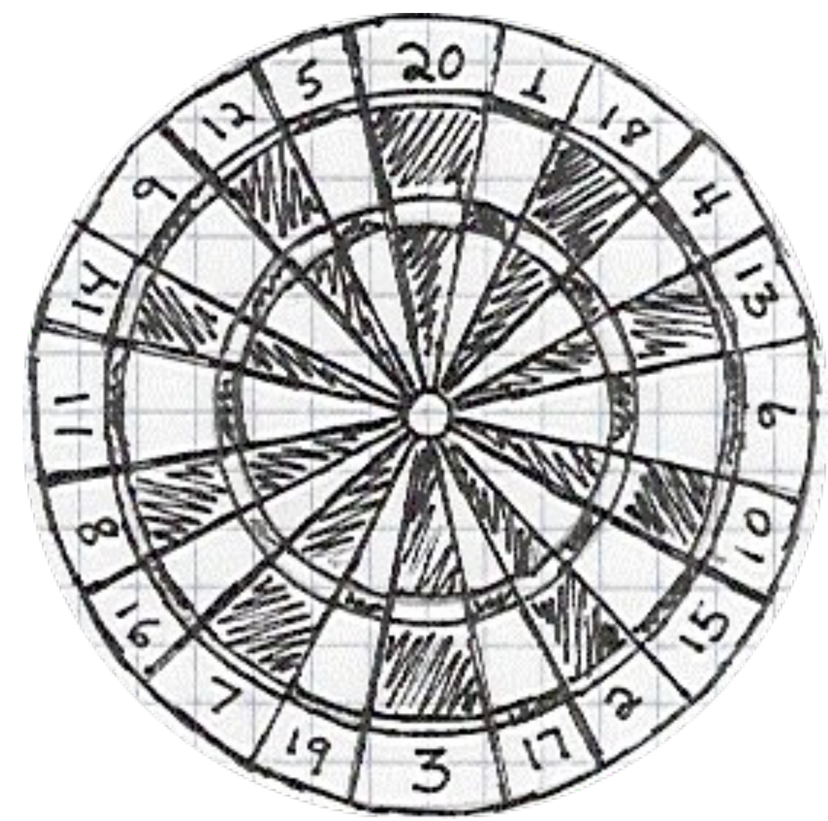
- With targeted paraphrases, the bullseye is still somewhat scrambled but we get to shoot the dart out of a rifle with a scope!



SUMMARY

- SMT represents the current state of the art in MT
- Besides bitext, SMT systems require multiple **reference** translations that aren't cheap
- We can use the SMT system itself to manufacture additional references from a single, good quality reference
- No reason for the paraphraser to be restricted to SMT
  - Generate new reference answers for short-answer tests
  - Generate multiple choice items for "paraphrase" questions
  - Expanding sentiment lexicon for essay opinion mining

QUESTIONS?

BACKUP SLIDES

SENTENTIAL PARAPHRASES

We must bear in mind the community as a whole.
We must remember the wider community.

They should be better coordinated and more effective.
They should improve the coordination and efficacy.

Women are still one of the most vulnerable sections of society, whose rights are rudely trampled underfoot by the current social and economic system.
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That is what we are waiting to hear from the European Commission.
That is what we expected from the meeting.

This occurred not far away and not very long ago.
This substances not far behind and very recently.

Original Sentence, *Generated Paraphrase* (via **French)**

PHRASAL PARAPHRASES

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- Analyzed phrasal paraphrases with Arabic as pivot language
- Only those with $p(e_p|e_q) > 0.9$ to concentrate on pairs more likely to be paraphrases
- Roughly five types of paraphrases

PHRASAL PARAPHRASES

```
polish troops ||| polish soldiers
accounting firms ||| auditing firms
armed source ||| military source
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```
50 ton ||| 50 tons
caused clouds ||| causing clouds
syria deny ||| syria denies
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Morphological variants

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```
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army roadblock ||| military barrier
staff walked out ||| team withdrew
controversy over ||| polemic about
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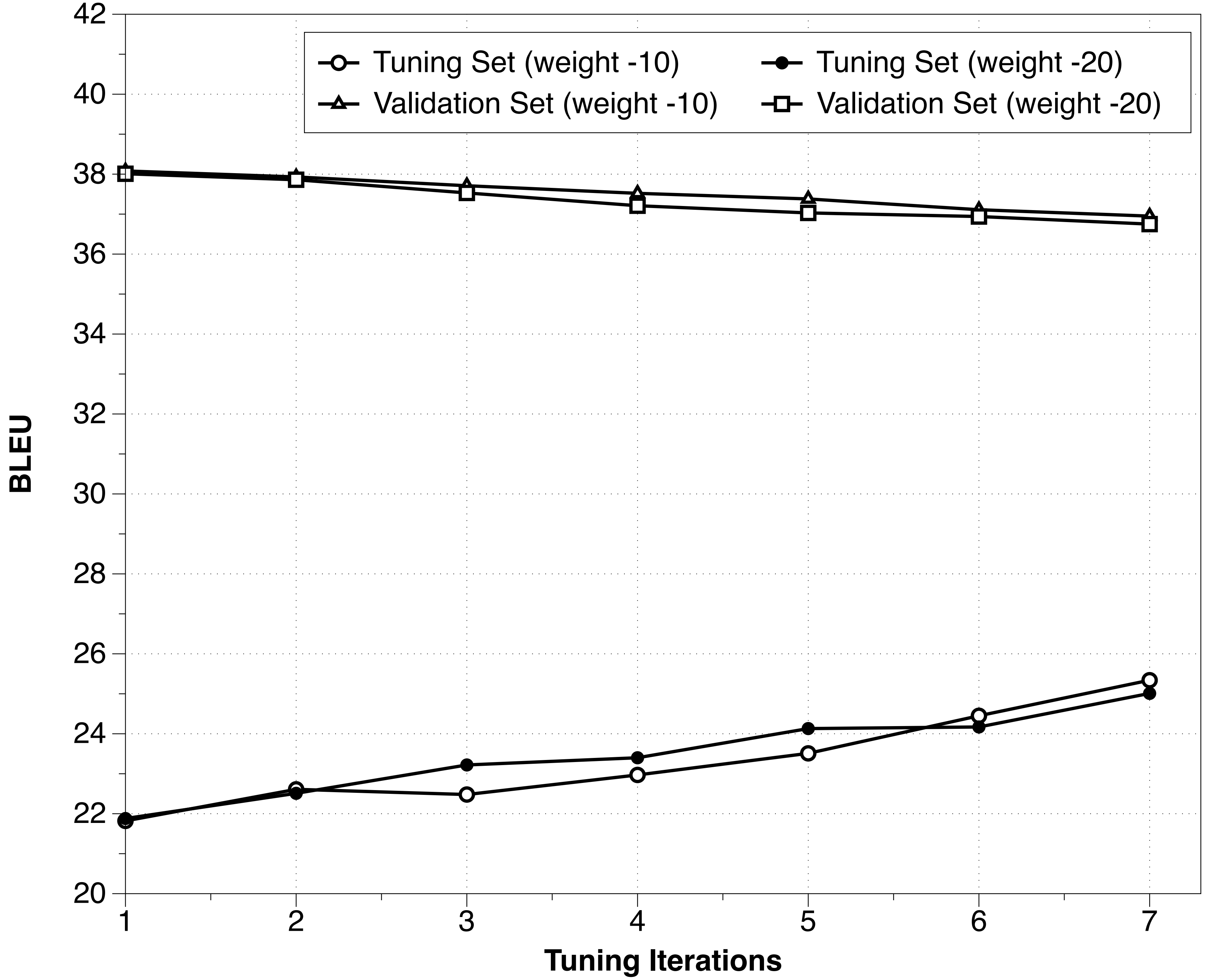
- #Approximate + #Exact >> #Useless

NEED FOR SELF-PARAPHRASE BIAS



EXPERIMENTAL DETAILS

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	Bitext	LM data	Tuning Set	Validation Set
Zh-En	2.5 million sentences (newswire)	8 billion words (Trigram, 5-gram)	919 sentences 4 references	2870 sentences 4 references
Fr-En	1.7 million sentences (Europarl)	8 billion words (Trigram, 5-gram)	2051 sentences 1 reference	2525 sentences 1 reference
De-En	1.6 million sentences (Europarl)	8 billion words (Trigram, 5-gram)	2051 sentences 1 reference	2525 sentences 1 reference
Es-En	1.7 million sentences (Europarl)	8 billion words (Trigram, 5-gram)	2051 sentences 1 reference	2525 sentences 1 reference

HUMAN JUDGMENTS: CHINESE

Pu: Untargeted, Pt: Targeted

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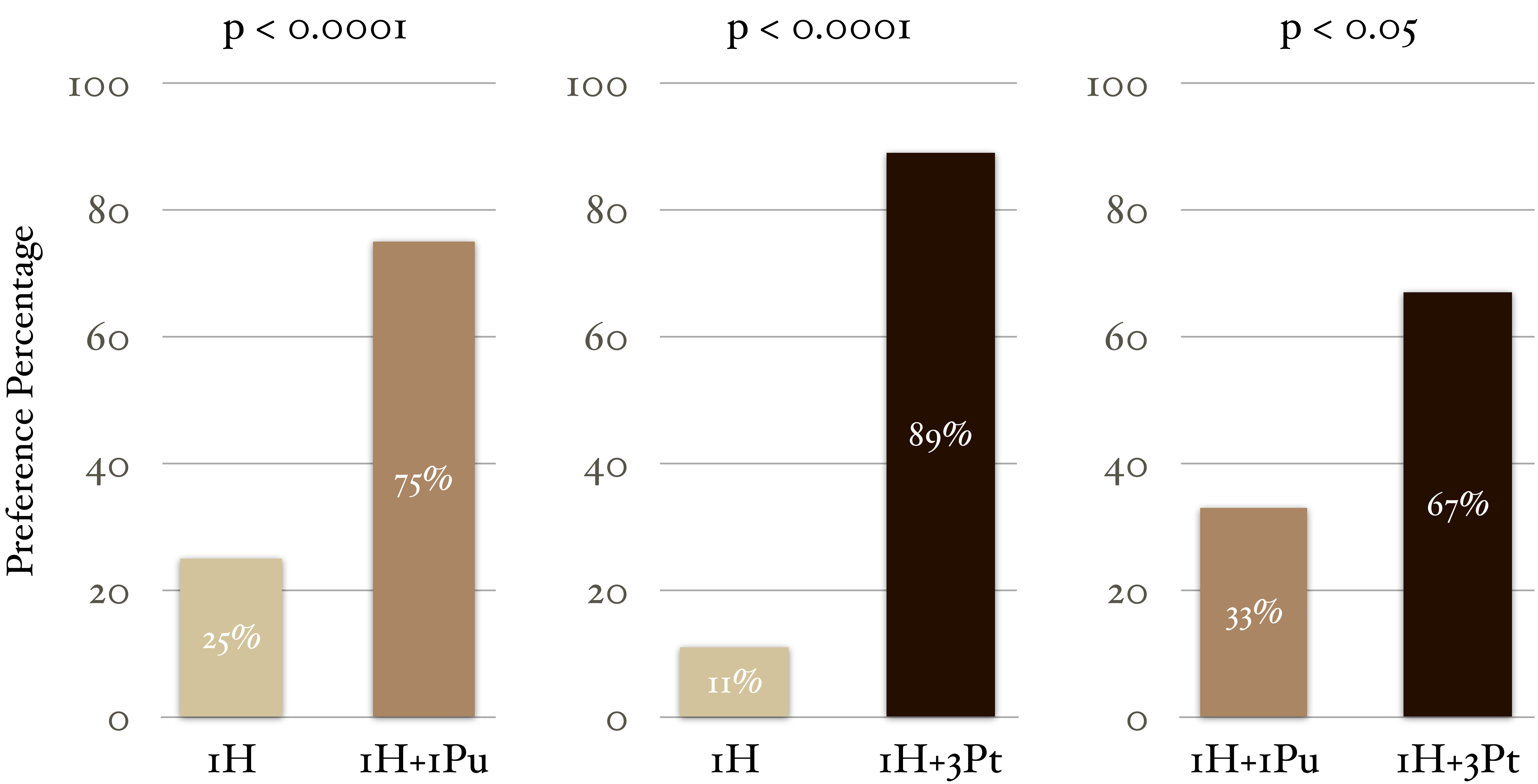

Pu: Untargeted, Pt: Targeted

HUMAN JUDGMENTS: FRENCH

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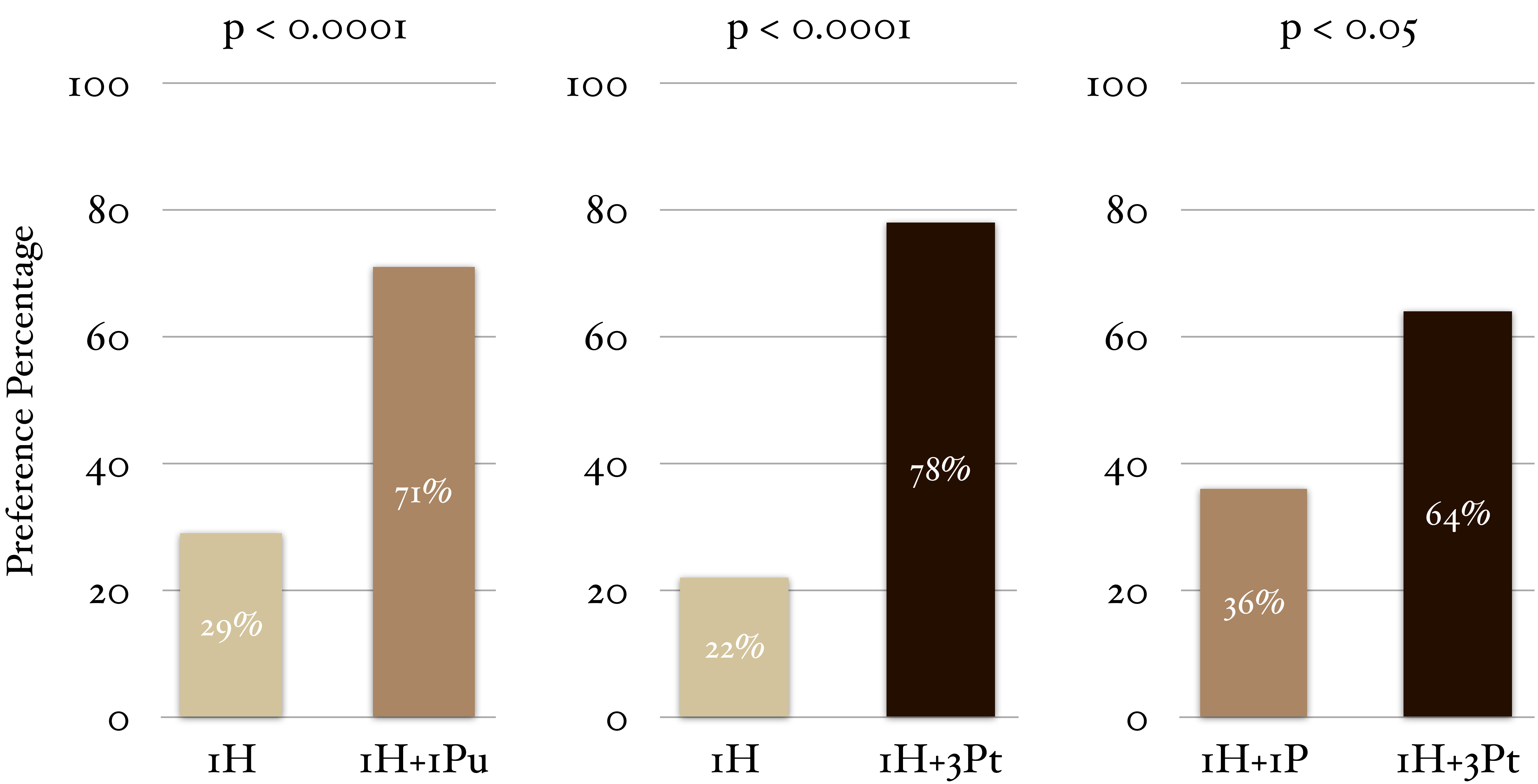
HUMAN JUDGMENTS: FRENCH



Pu: Untargeted, Pt: Targeted

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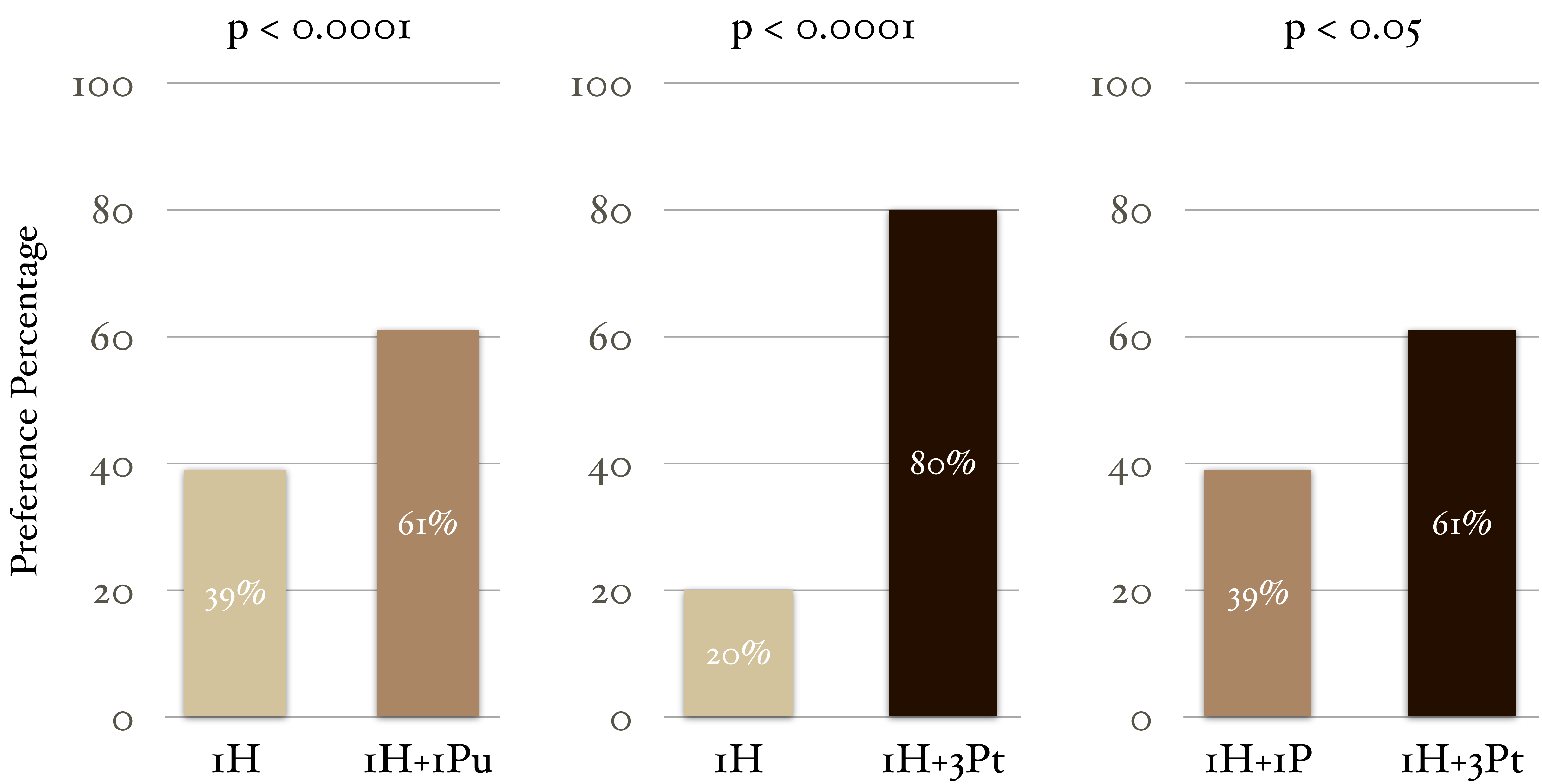

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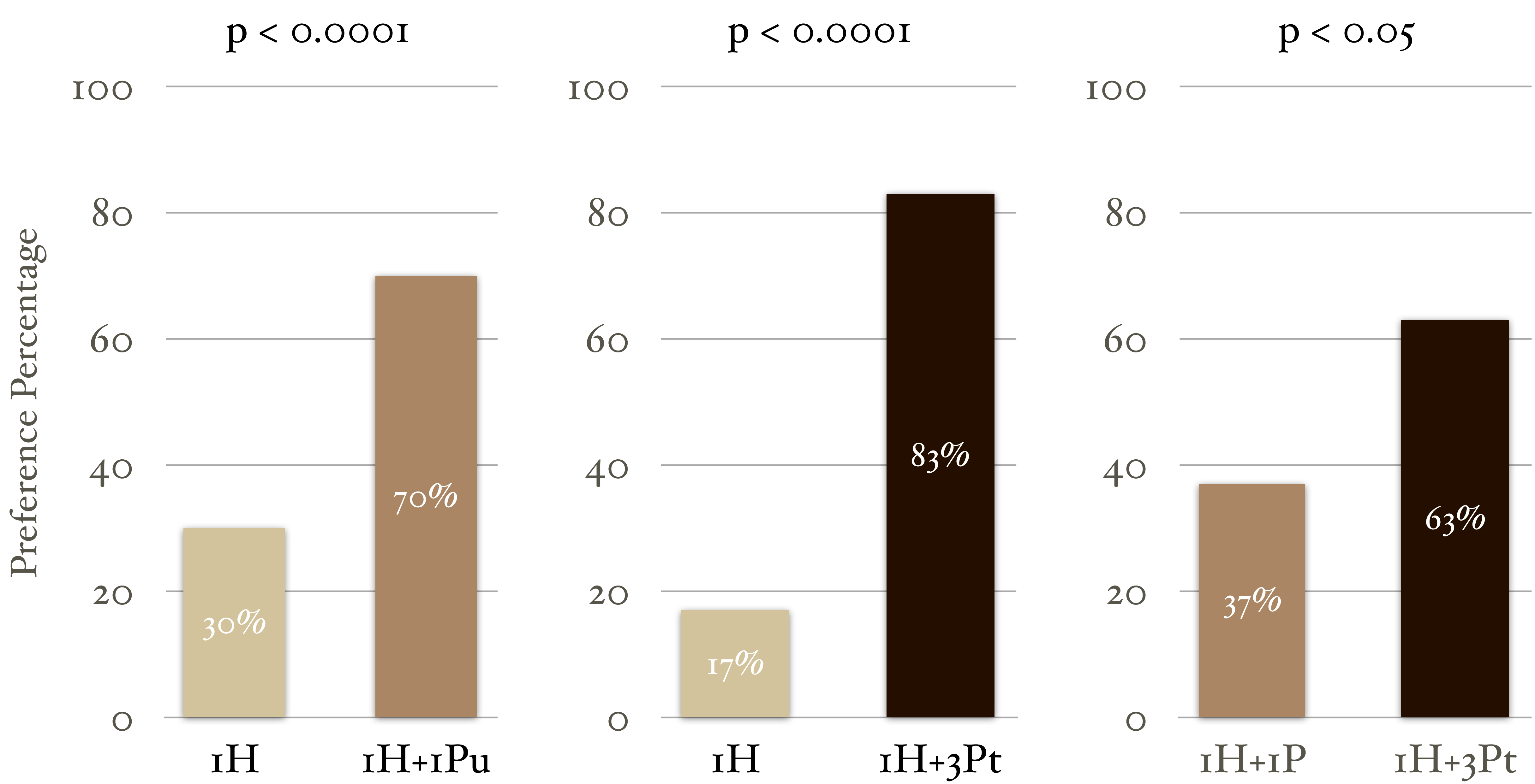

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RELATED MT-PARAPHRASING WORK

- Kauchak & Barzilay used MT output to change the reference†
  - Goal: Create a paraphrased reference more useful for *evaluation*
  - Only a *single* paraphrase instead of *k*-best
  - Paraphrasing effected via machinery completely unrelated to SMT
  - Only lexical paraphrasing
  - Required WordNet for synonyms

†David Kauchak & Regina Barzilay. *Paraphrasing for Automatic Evaluation.* HLT/NAACL 2006.

UNTARGETED PARAPHRASES

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Pivot Language: French

TRANSLATION EXAMPLES: FRENCH

S - N'empêche qu'il existe suffisamment de raisons de se procurer un lecteur indépendant.

O - In spite of this, there are many reasons to get a separate MP3 player.

T_b - Despite that it sufficiently exists of reason for providing an independent player.

T_u - But there are plenty of reasons to get an independent player.

S - Celui qui croît en Dieu ressent-il moins la douleur ?

O - Does it hurt less if you believe in God?

T_b - Anyone believes in God has less pain?

T_t - Whoever believes in God, does he feel less pain?

S: Source, **O**: Original Reference, **T_b**: Baseline translation, **$T_{u|t}$**: Translation with untargeted|targeted paraphrase

TRANSLATION EXAMPLES: GERMAN

S - Eine Ratte oder eine Schabe flieht bei Gefahr heißt das, dass sie auch Furcht empfindet?

O - When in danger, a rat or roach will run away. Does it mean they experience fear, too?

$\mathbf{T_b}$ - A rat or a Schabe flees by danger that means that they also feel fears?

$\mathbf{T_u}$ - A rat or a cockroach is fleeing when in danger, that means that they felt fear?

S - Nach dem steilen Abfall am Morgen konnte die Prager Börse die Verluste korrigieren.

O - After a sharp drop in the morning, the Prague Stock Market corrected its losses.

$\mathbf{T_b}$ - After the steep waste at tomorrow the Prague stock exchange cannot correct the losses.

$\mathbf{T_t}$ - After the steep waste in the morning, the Prague Stock Exchange losses corrected.

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PARAPHRASING BEYOND TRANSLATION

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†M. Snover, N. Madnani, B, Dorr and R. Schwartz. *TER-plus: Paraphrase, Semantic, and Alignment Enhancements to Translation Edit Rate*. *Machine Translation*. 23(2-3), 2009

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  - With additional work, we can do recognition: synchronously parse two sentences with induced monolingual grammar

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