# Phrase-Based Statistical Machine Translation with Pivot Languages

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# Pivot Translation

- **Assumptions**:
  - no parallel data between source language $\mathcal{F}$ and target language $\mathcal{E}$
  - two independent parallel corpora $(\mathrm{F},\mathrm{G}_F)$ and $(\mathrm{G}_E,\mathrm{E})$
  - two full-fledged MT systems $\mathcal{F} \rightarrow \mathcal{G}$ and $\mathcal{G} \rightarrow \mathcal{E}$
- **Problem**: how to perform translation from $\mathcal{F}$ to $\mathcal{E}$?
- **Approach 1:** Bridging at translation time

| source text | $\mathcal{F} \rightarrow \mathcal{G}$ | pivot text | $\mathcal{G} \rightarrow \mathcal{E}$ | target text |
|---|---|---|---|---|
| $\mathbf{f}$ | $\rightarrow$ | $\mathbf{g}$ | $\rightarrow$ | $\mathbf{e}$ |

- **Approach 2:** Bridging at training time

| synthetic training data | generated by translating | with system |
|---|---|---|
| $(\mathrm{F},\bar{\mathrm{E}}_F)$ | $\mathrm{G}_F$ of $(\mathrm{F},\mathrm{G}_F)$ | $\mathcal{G} \rightarrow \mathcal{E}$ |
| $(\bar{\mathrm{F}}_E,\mathrm{E})$ | $\mathrm{G}_E$ of $(\mathrm{G}_E,\mathrm{E})$ | $\mathcal{G} \rightarrow \mathcal{F}$ |

# Pivot Task description

- BTEC domain data
- Pivot Task of IWSLT 2008: Chinese-English-Spanish

- training data: CE1, CE2, ES1, and CS1 (19K sentences)
- disjoint condition: CE2 and ES1
- overlap condition: CE1 and ES1
- direct condition: CS1

- dev set: 506 Chinese sentences with 7 refs in English and Spanish
- test set: 1K sentences with 1 reference extracted from CES1

# Statistical Machine Translation

source text target text

$$\mathbf{f} \qquad \longrightarrow \qquad \mathbf{e}$$

- alignment-based parametric model

$$p(\mathbf{e} \mid \mathbf{f}) = \sum_{\mathbf{a}} p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}) = \sum_{\mathbf{a}} p_{\theta_{FE}}(\mathbf{e}, \mathbf{a} \mid \mathbf{f})$$

- parameter estimation:

$$\hat{\theta}_{FE} = \arg \underset{\theta_{FE}}{max} \prod_{i} p_{\theta_{FE}}(\mathbf{e}_i \mid \mathbf{f}_i) \qquad \text{given } \{(\mathbf{f}_i, \mathbf{e}_i)\}$$

- search criterion:

$$\mathbf{f} \rightarrow \hat{\mathbf{e}} \approx \arg \underset{\mathbf{e}}{max} \, \underset{\mathbf{a}}{max} \, p_{\hat{\theta}_{FE}}(\mathbf{e}, \mathbf{a} \mid \mathbf{f})$$

# *Direct* baseline system

- open-source MT toolkit **Moses**
- statistical **log-linear** model with 8 features
- weight optimization by means of a **minimum error training** procedure

- **phrase-based** translation model:
  - direct and inverted frequency-based and lexical-based probabilities
  - phrase pairs extracted from symmetrized word alignments (GIZA++)
- 5-gram word-based LM exploiting Improved Kneser-Ney smoothing (IRSTLM)
- standard negative-exponential distortion model
- word and phrase penalties

# Bridging at translation time

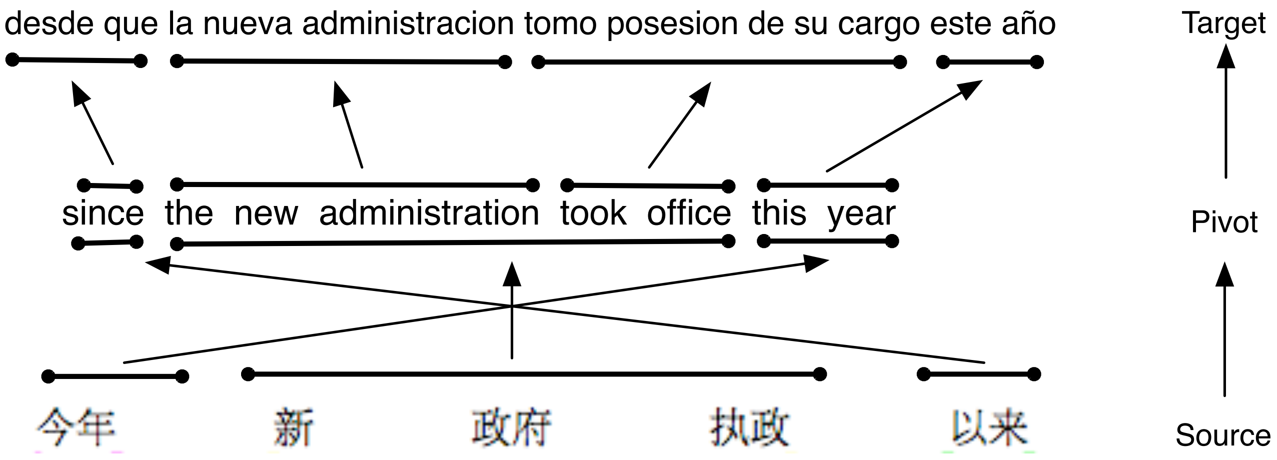
| source text | | pivot text | | target text |
|---|---|---|---|---|
| $\mathbf{f}$ | → | $\mathbf{g}$ | → | $\mathbf{e}$ |

$$\begin{aligned} p(\mathbf{e} \mid \mathbf{f}) &= \sum_{\mathbf{g}} p(\mathbf{e}, \mathbf{g} \mid \mathbf{f}) = \sum_{\mathbf{g}} p(\mathbf{g} \mid \mathbf{f})\ p(\mathbf{e} \mid \mathbf{g}) \\ &= \sum_{\mathbf{g}} \sum_{\mathbf{b}} p_{\theta_{FG}}(\mathbf{g}, \mathbf{b} \mid \mathbf{f}) \ \sum_{\mathbf{a}} p_{\theta_{GE}}(\mathbf{e}, \mathbf{a} \mid \mathbf{g}) \end{aligned}$$

$$\mathbf{f} \rightarrow \hat{\mathbf{e}} \quad \approx \quad \arg \underset{\mathbf{e},\mathbf{g}}{max}\, \underset{\mathbf{a},\mathbf{b}}{max}\ p_{\hat{\theta}_{FG}}(\mathbf{g}, \mathbf{b} \mid \mathbf{f}) p_{\hat{\theta}_{GE}}(\mathbf{e}, \mathbf{a} \mid \mathbf{g})$$

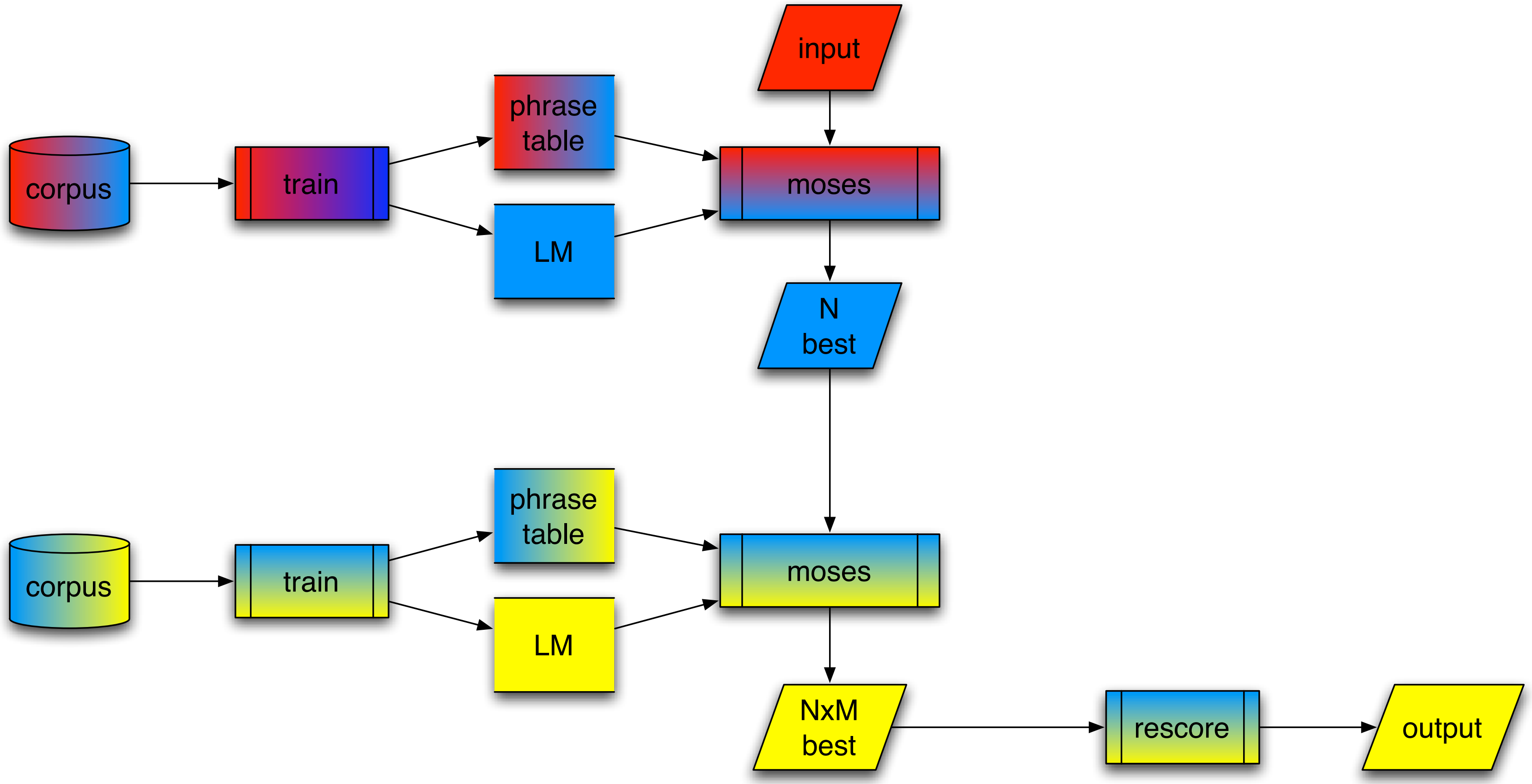
- two full-fedged systems trained on corpora (F,G$_F$) and (G$_E$,E)
- search including the pivot language increases complexity

# Coupling with Unconstrained Alignments


desde que la nueva administracion tomo posesion de su cargo este año
Target
since the new administration took office this year
Pivot
今年 新 政府 执政 以来
Source

- sentence-level coupling
- requires performing search over two alignments
- search can be decoupled over a subset of hypotheses:
  – N-best list (or word lattices) of source-to-pivot translations

# Coupling with Unconstrained Alignments



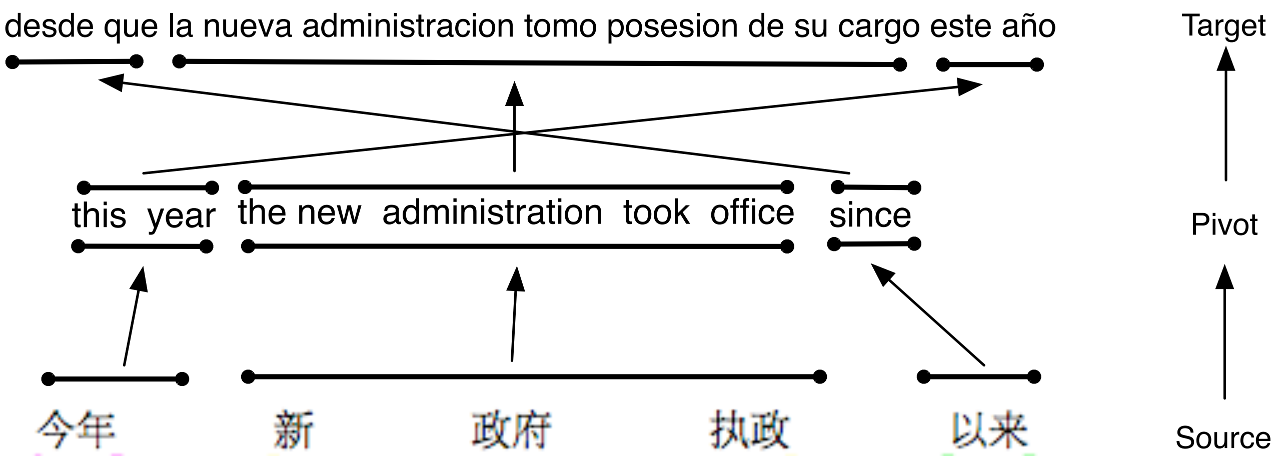
# Coupling with Unconstrained Alignments

| $n$,$m$ | rescoring features | dev | test |
|---|---|---|---|
| 1 | - | 25.13 | 16.44 |
| 10 | 2 | 25.28 | 16.60 |
| | 16 | 26.65 | 17.59 |
| 20 | 16 | 27.18 | 17.03 |
| 50 | 16 | 27.78 | 16.96 |
| 100 | 16 | 27.89 | 17.64 |

- 16 feature scores $>$ 2 global scores
- 100x100-best gives best performance on dev set

- time expensive: $(N+1)$ translation + rescoring

# Coupling with Constrained Alignments


desde que la nueva administracion tomo posesion de su cargo este año
Target
this year
the new administration took office
since
Pivot
今年
新
政府
执政
以来
Source

- **phrase-level** coupling
- share segmentation on the pivot language and use just one re-ordering
- needs one distortion model that directly models source to target
- needs only one target language model

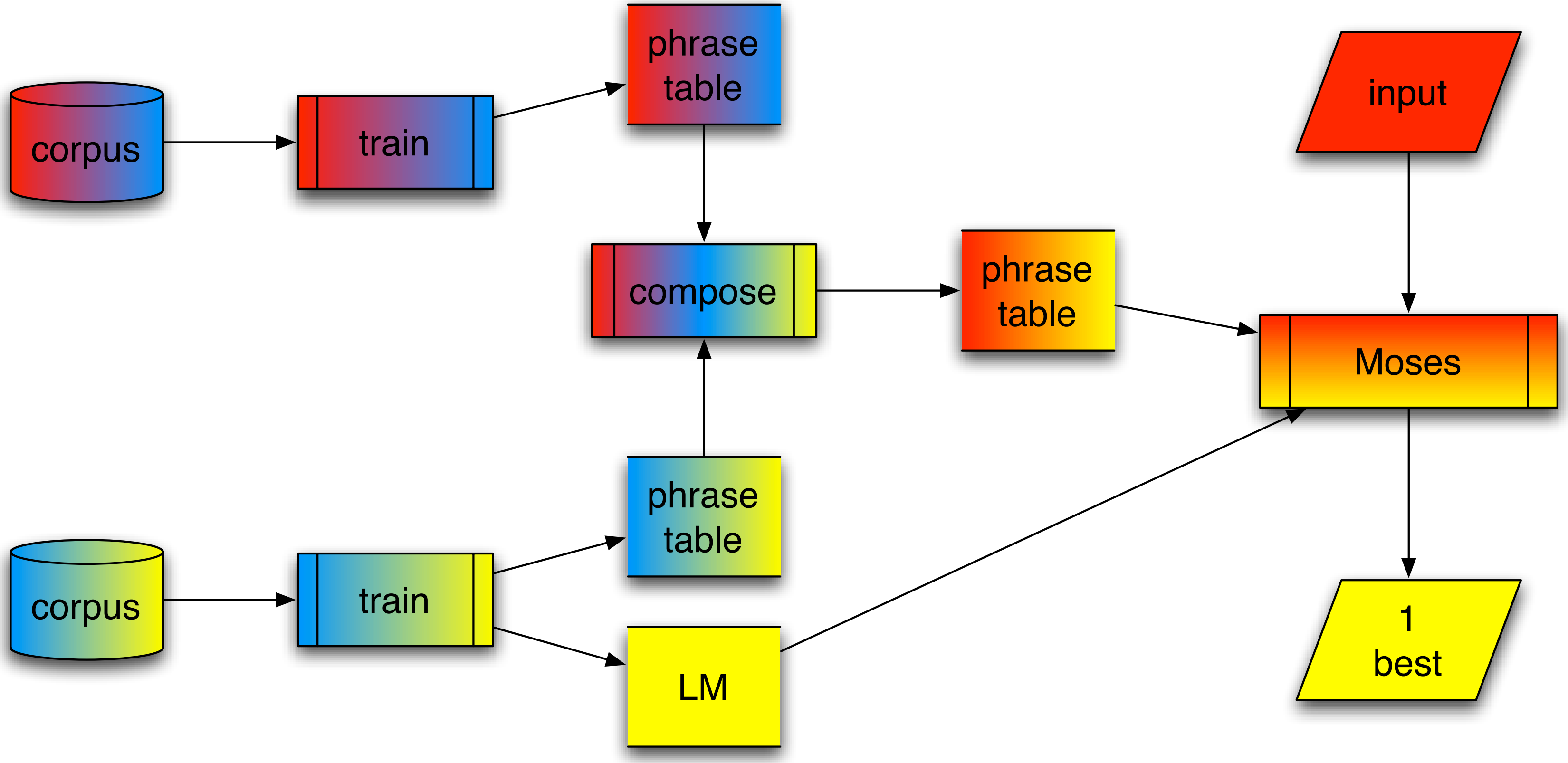
# Coupling with Constrained Alignments

- needs to modify decoder, or
- compose phrase table before decoding

$$\begin{aligned} PT(F,E) &= PT(F,G) \otimes PT(G,E) \\ &= \{(\tilde{f},\tilde{e}) \mid \exists\ \tilde{g} \text{ s.t. } (\tilde{f},\tilde{g}) \in PT(F,G_F) \wedge \exists\ (\tilde{g},\tilde{e}) \in PT(G_E,E)\end{aligned}$$

$$\phi(\tilde{f},\tilde{e}) = \begin{cases} \sum_{\tilde{g}} \phi(\tilde{f},\tilde{g})\ \phi(\tilde{g},\tilde{e}) & \text{integration} \\ \\ max_{\tilde{g}}\, \phi(\tilde{f},\tilde{g})\ \phi(\tilde{g},\tilde{e}) & \text{maximization} \end{cases}$$

# Coupling with Unconstrained Alignments



# Coupling with Unconstrained Alignments

| | CE2 | CE1 | ES1 | product | |
|---|---|---|---|---|---|
| | | | | disj | over |
| src phr | 76K | 128K | 277K | 21K | 94K |
| trg phr | 82K | 134K | 284K | 32K | 108K |
| phr pairs | 133K | 185K | 333K | 592K | 696K |
| avg trans | 1.8 | 1.4 | 1.2 | 28.2 | 7.4 |
| common | - | - | - | 59K | 143K |

| | disjoint | overlap |
|---|---|---|
| integration | 16.65 | 23.50 |
| maximization | 15.88 | 22.82 |

- limited intersection among $\tilde{g}$ phrases in the disjoint condition:
  – only 27% of Chinese phrases are bridged into Spanish through English
  – only 11% of Spanish are reached through English
- ambiguity increases (esp. for short phrases)
- integration $>$ maximization
- overlap data would be very useful

# Bridging at Training Time

- Standard training criterion for (IBM) alignment models

$$\theta^*_{FE} = \arg\underset{\theta_{FE}}{max} \prod_i p_{\theta_{FE}}(\mathbf{f}_i \mid \mathbf{e}_i) \qquad \text{given } \{(\mathbf{f}_i, \mathbf{e}_i)\}$$

- Goal: estimate parameters of a "direct" F-E system without a (F,E) corpus
- Assumption: a parallel corpus $\{(\mathbf{f}_i, \mathbf{g}_i)\}$, a full-fledged G-E system $p_{\hat{\theta}_{GE}}$
- Solution: $p(\mathbf{f} \mid \mathbf{g})$ above can be replaced with the marginal distribution:

$$\begin{aligned} p(\mathbf{f} \mid \mathbf{g}) &= \sum_{\mathbf{e}} p(\mathbf{f} \mid \mathbf{e})\; p_{\hat{\theta}_{GE}}(\mathbf{e} \mid \mathbf{g}) \\ \hat{\theta}_{FE} &= \arg\underset{\theta_{FE}}{max} \sum_{\mathbf{e}_i} p_{\theta_{FE}}(\mathbf{f}_i \mid \mathbf{e}_i)\; p_{\hat{\theta}_{GE}}(\mathbf{e}_i \mid \mathbf{g}_i) \end{aligned}$$

assuming independence between $\mathbf{e}$ and $\mathbf{f}$ given $\mathbf{g}$.

# Approximate ML Estimates

- **Approximation 1**: limit the support of $p_{\hat{\theta}_{GE}}(\mathbf{e} \mid \mathbf{g})$ to the best translation
  – basically, we generate a synthetic parallel corpus (F,$\bar{\text{E}}_F$)
- **Approximation 2**: limit support over the N-best translations
  – requires MLE of IBM models work with two hidden variables
  – still to be developed

We only experimented the first method, called Viterbi approximation

# Random Sampling Method

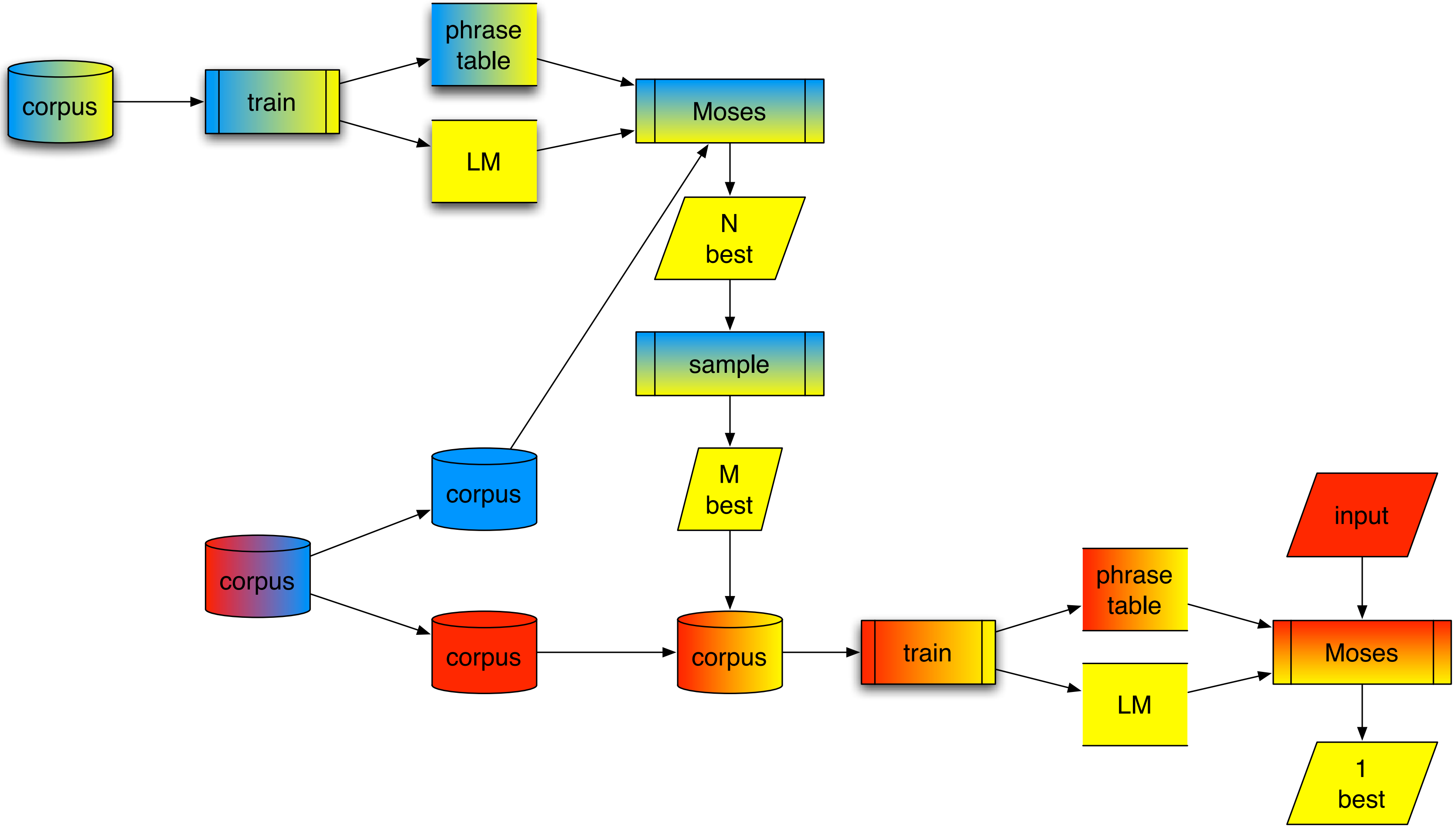
**Idea**: *Generate parallel data by sampling translations from an SMT system*

- **Ingredients**: corpus (F,G) and SMT system $\mathcal{G} \rightarrow \mathcal{E}$
- For each example $(\mathbf{f}_i, \mathbf{g}_i)$ in the training corpus $(F, G)$ generate a random sample of $m$ translations $\mathbf{e}_{ij}$ of $\mathbf{g}_i$ according to $p_{\hat{\theta}_{GE}}(\mathbf{e} \mid \mathbf{g})$.
- Then build a translation system from $(F, E) = \{(\mathbf{f}_i, \mathbf{e}_{ij})\}, j = 1, \ldots, m$, by maximizing:

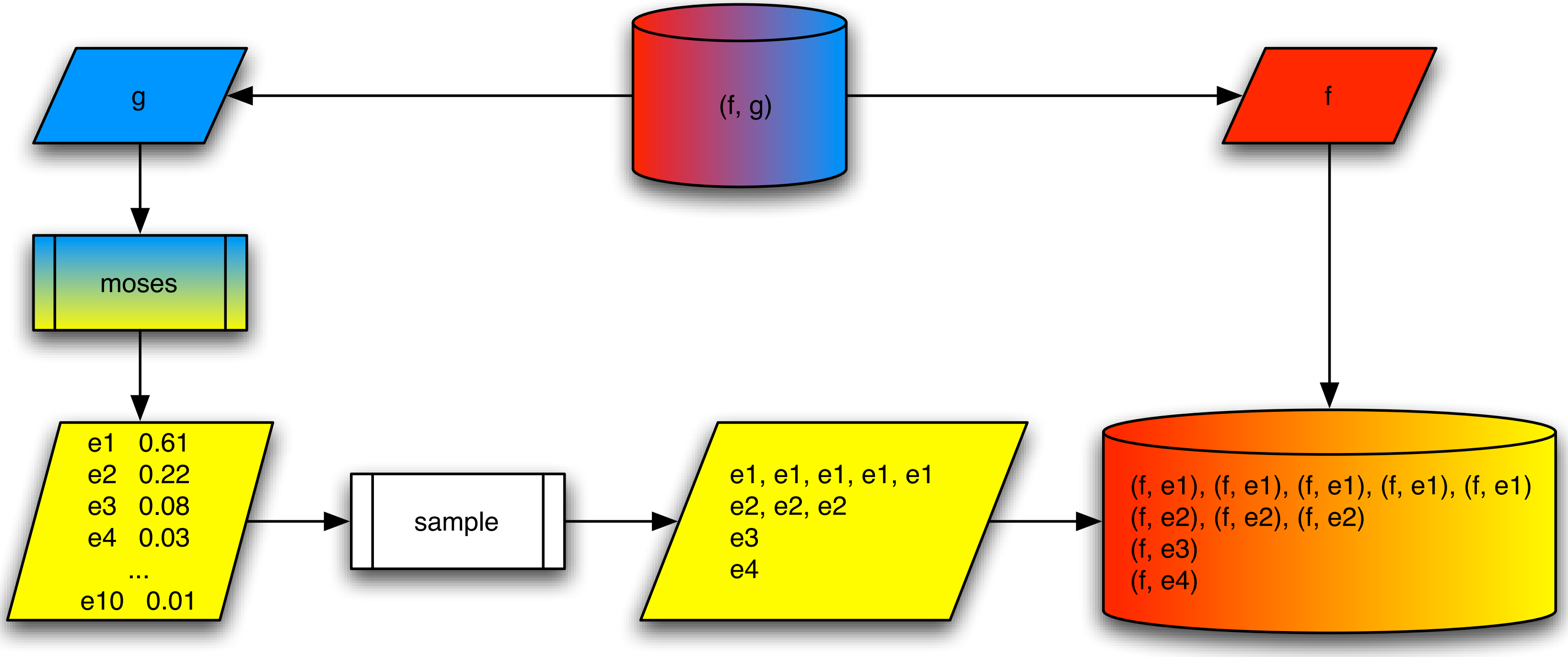
$$\hat{\theta}_{FE} = \arg \underset{\theta_{FE}}{max} \prod_{i,j} P_{\theta_{FE}}(\mathbf{f}_i \mid \mathbf{e}_{ij})$$

- **Implementation**: sample with replacement from the $n$-best list of translations $\mathbf{e}$ from $\mathbf{g}_i$ according to $p_{\hat{\theta}_{GE}}(\mathbf{e} \mid \mathbf{g}_i)$.
- This approach is indeed more sound than just taking the list of $n$-best!

# Random Sampling Method



# Random Sampling Method



- random sampling with replacement 10 times from a 10-best list of translation
- normalization of Moses scores
- more importance to more reliable translations

# Random Sampling Method

| | $n$,$m$ | lm | dev | test |
|---|---|---|---|---|
| *Viterbi Training* | 1 | S1 | 22.05 | 14.56 |
| *Viterbi Training* | 1 | S̄2 | 23.58 | 15.38 |
| *Viterbi Training* | 1 | S1+S̄2 | 24.57 | 16.13 |
| *N-best Training* | 100 | S1+S̄2 | 26.04 | 17.03 |
| *Random Sampling* | 100 | S1+S̄2 | 26.02 | 17.68 |

- LM(E1 $\cup$ Ē2) $>$ LM(Ē2) $>$ LM(E1)
- *N-best Training* $>$ *Viterbi Training*
- *N-best Training* $\approx$ *Random Sampling*
- 21% relative improvement wrt Viterbi-S1 (15% wrt Viterbi-S̄2)

# Experimental Results

| | CES task | |
|---|---|---|
| Method | disjoint | overlap |
| *Direct* | – | 23.67 |
| *Cascade 1-best* | 16.44 | 24.04 |
| *Cascade N-best* | 17.64 | 25.16 |
| *PhraseTable Product* | 16.65 | 23.50 |
| *Random Sampling* | 17.68 | 25.19 |

- *Cascade 1-best* $\approx$ *PhraseTable Product*
- *Random Sampling* $\approx$ *Cascade N-best* $>$ *Direct*

# Summary

- approaches to pivot translation task
- mathematical foundation
- experimental comparison

- random sampling approach is the most appealing:
  – quality and efficiency

- unsupervised technique to generate new parallel data
  – suitable to domain adaptation
  – suitable for multi-language pivot translation

*Thank you!*