Alignment by Agreement

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Unsupervised word alignment

Goal: learn to map sentence pairs to alignments

the railroad term is “ demand loading ”

le terme ferroviaire est “ chargement sur demande ”

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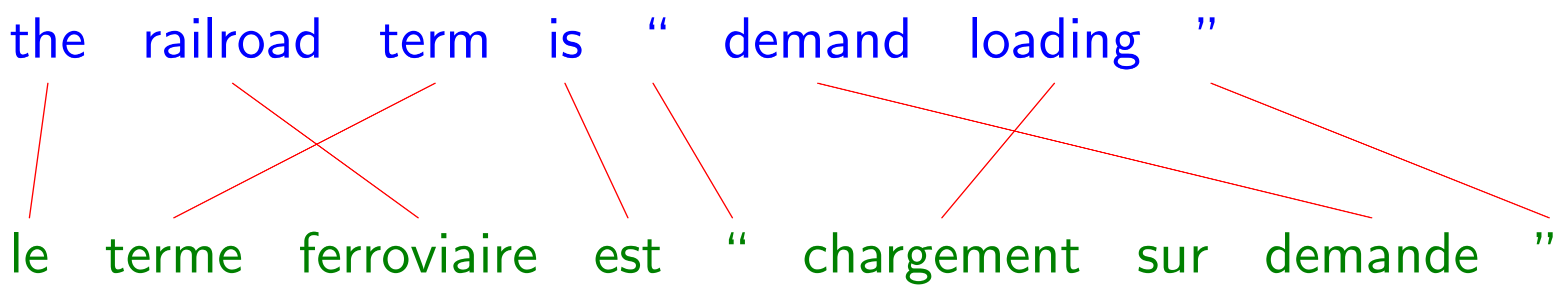

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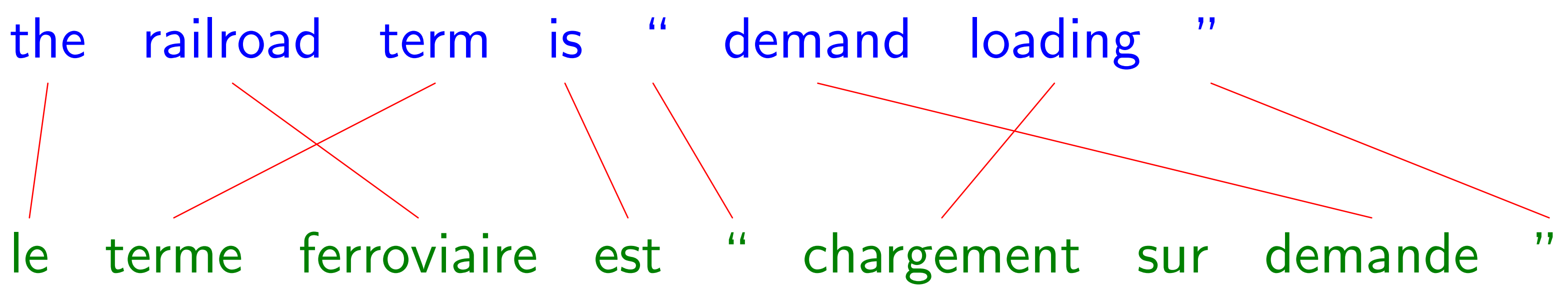

Approach:

jointly train two models to encourage *agreement*

HMM model [Ney, Vogel '96]

Generative model: $p(\mathbf{a}, \mathbf{e}, \mathbf{f}; \theta)$

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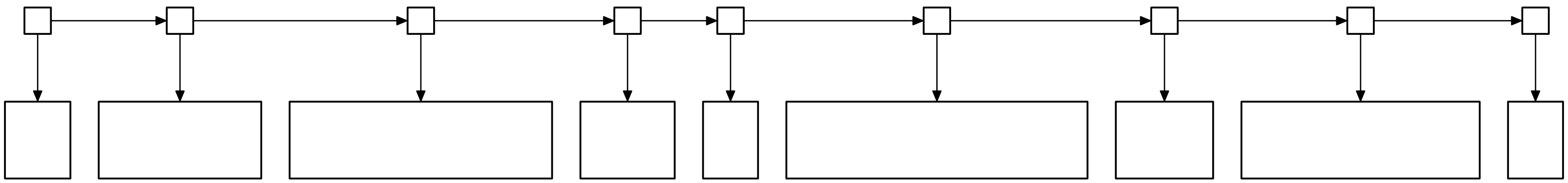
$p(\mathbf{e})$ the railroad term is " demand loading "



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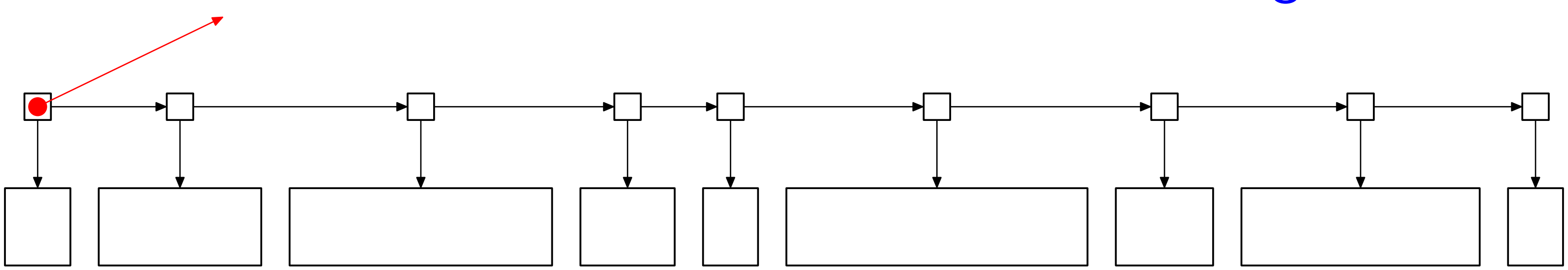

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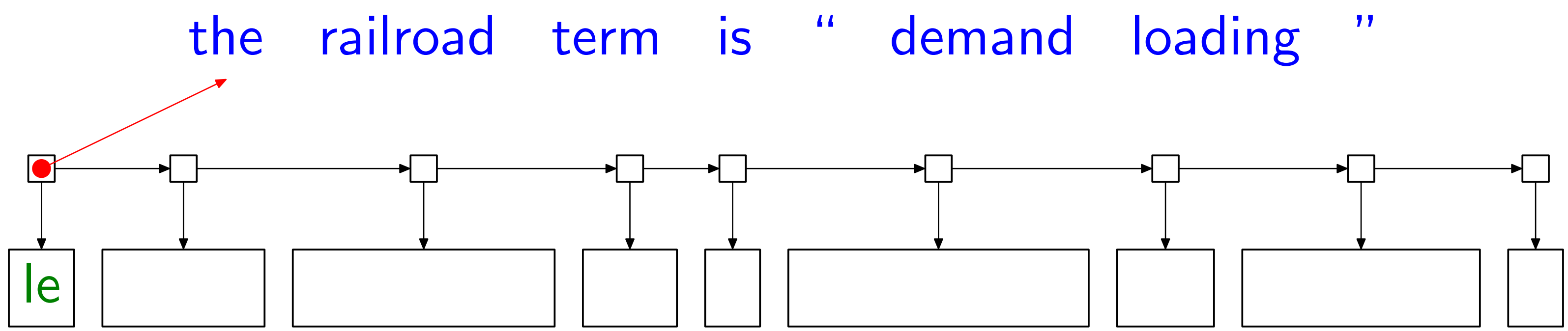

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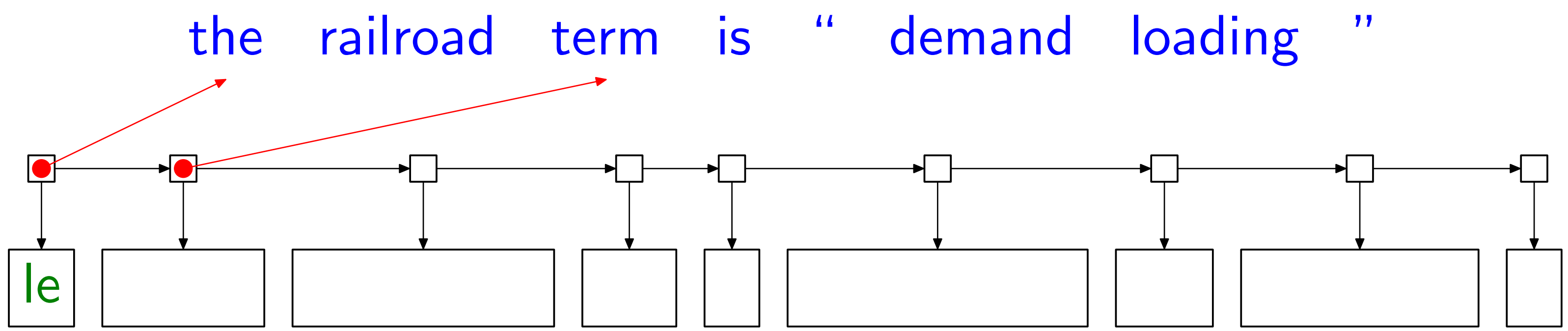

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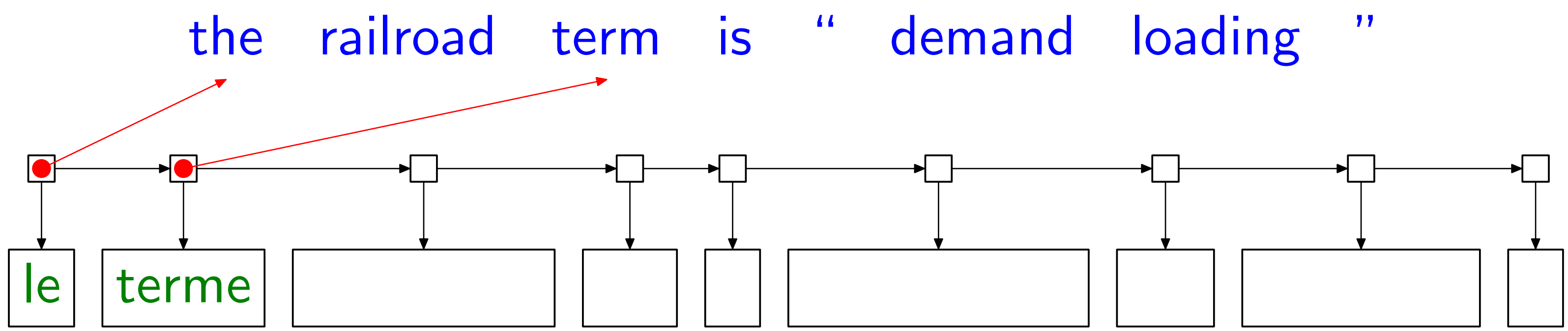

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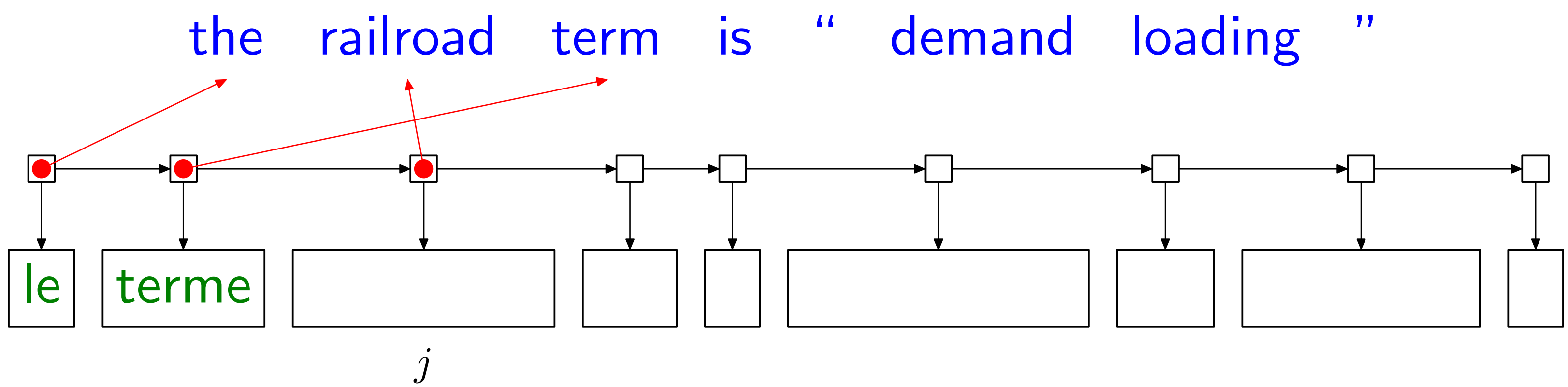
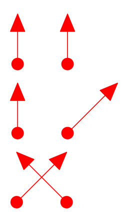


Distortion θ_{d}



$p(\quad) = 0.6$

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$\ldots$

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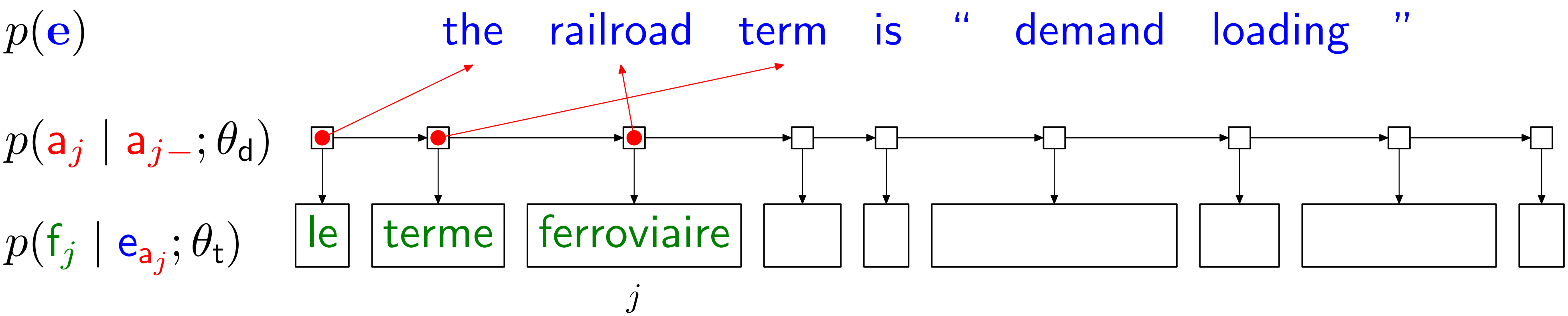

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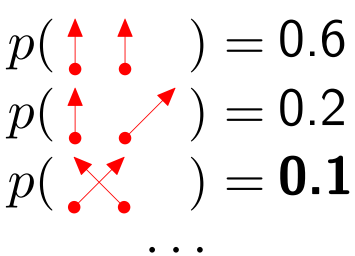

Translation θ_{t}

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$p($ the $\rightarrow$ la $) = 0.24$

$p($ **railroad** $\rightarrow$ **ferroviaire** $) = \mathbf{0.19}$

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...

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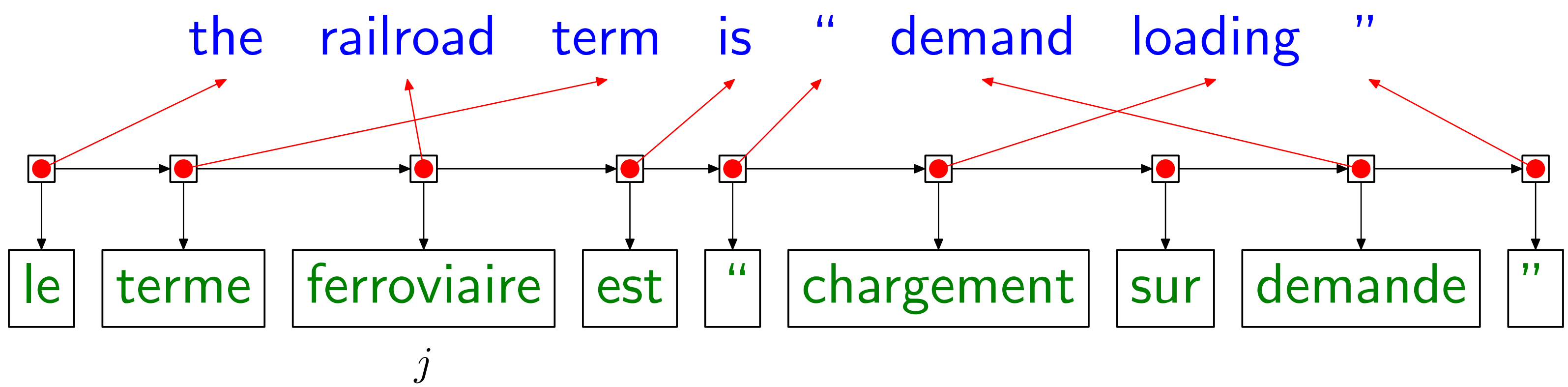
$p(\mathsf{f}_j \mid \mathsf{e}_{\mathsf{a}_j}; \theta_\mathsf{t})$



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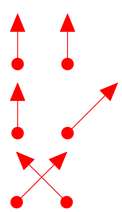

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EM training

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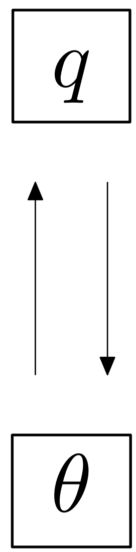
Parameters: θ

Expectation over alignments: q



E-step:

$q(\mathbf{a} \mid \mathbf{e}, \mathbf{f}) := p(\mathbf{a} \mid \mathbf{e}, \mathbf{f}; \theta)$

(forward-backward)

M-step:

$\theta := \mathrm{argmax}_\theta \, \mathbb{E}_q \log p(\mathbf{a}, \mathbf{e}, \mathbf{f} \mid \theta)$

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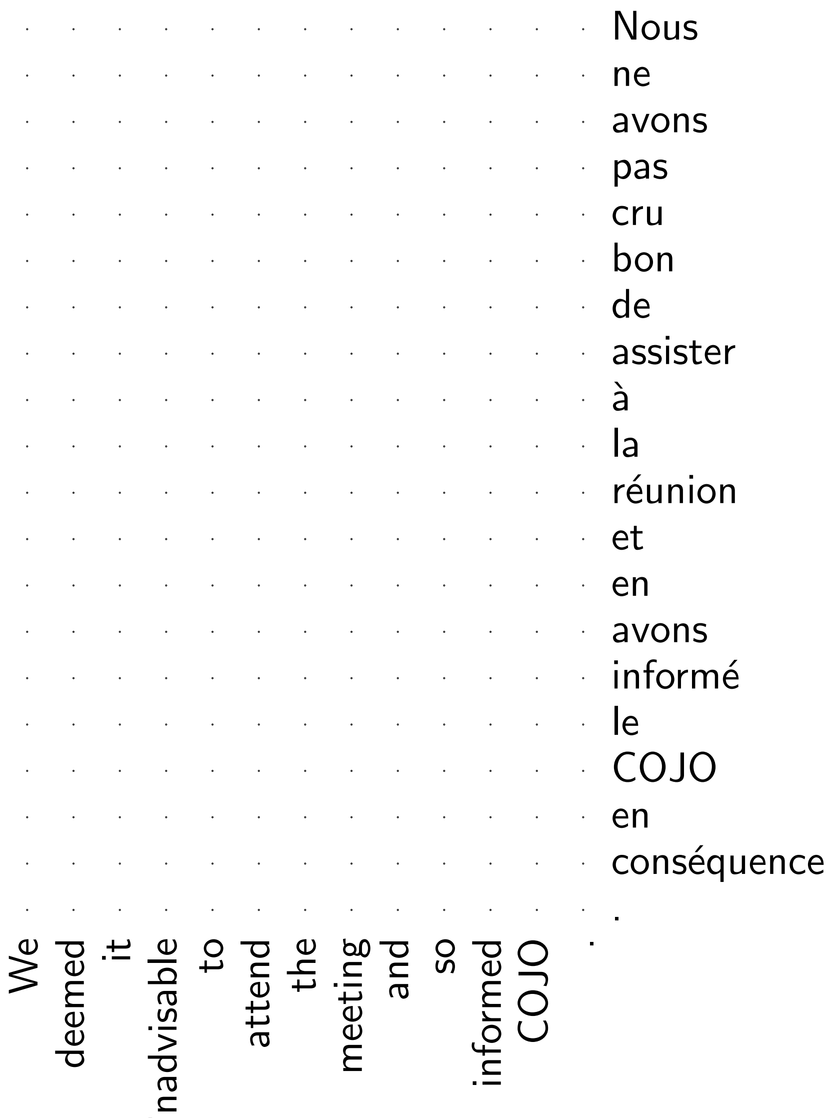
θ

$\leftarrow \mathbf{e}, \mathbf{f}$

$\mathbf{a}$

Output of one HMM model



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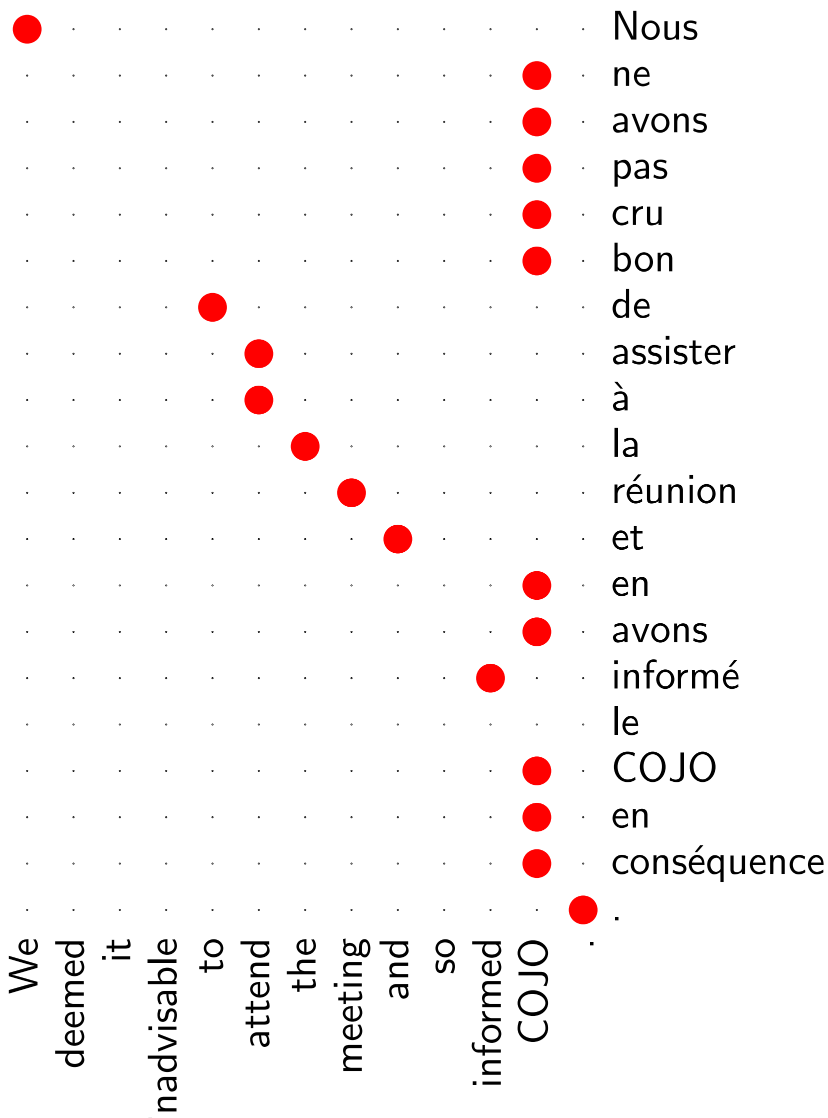

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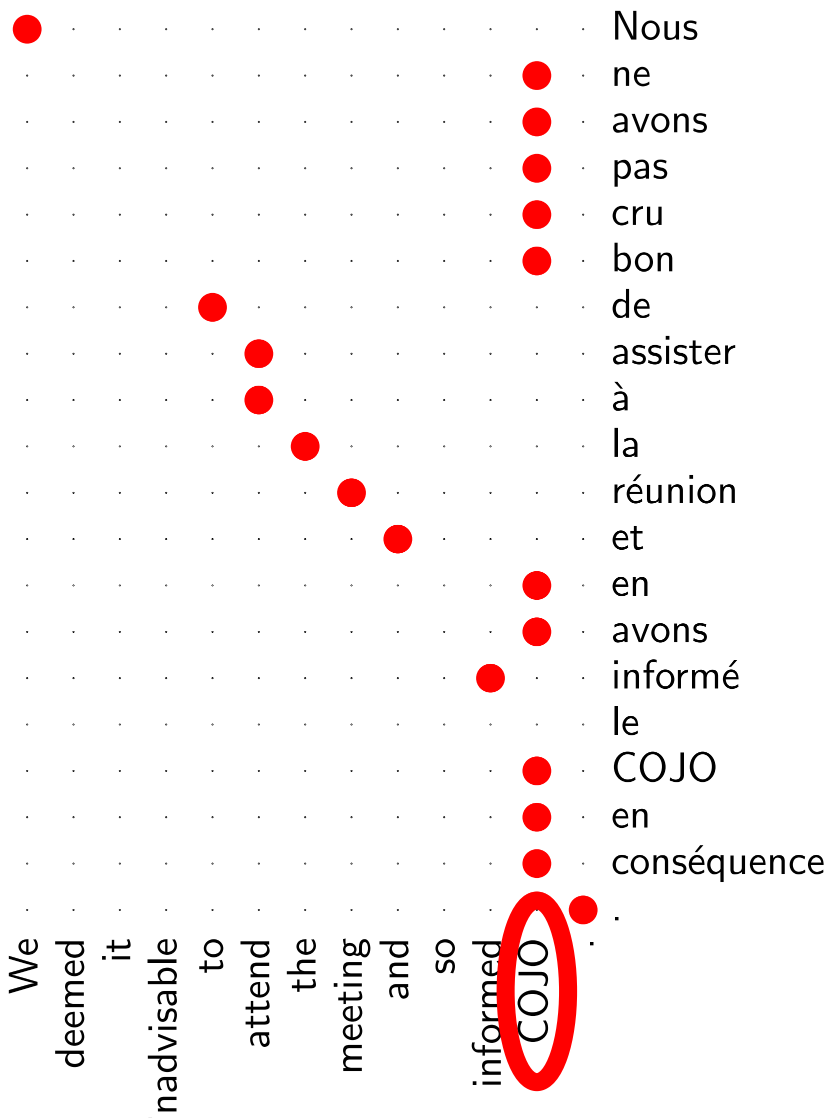

- A problem:
  - Rare words garbage-collect alignments [Moore '05]

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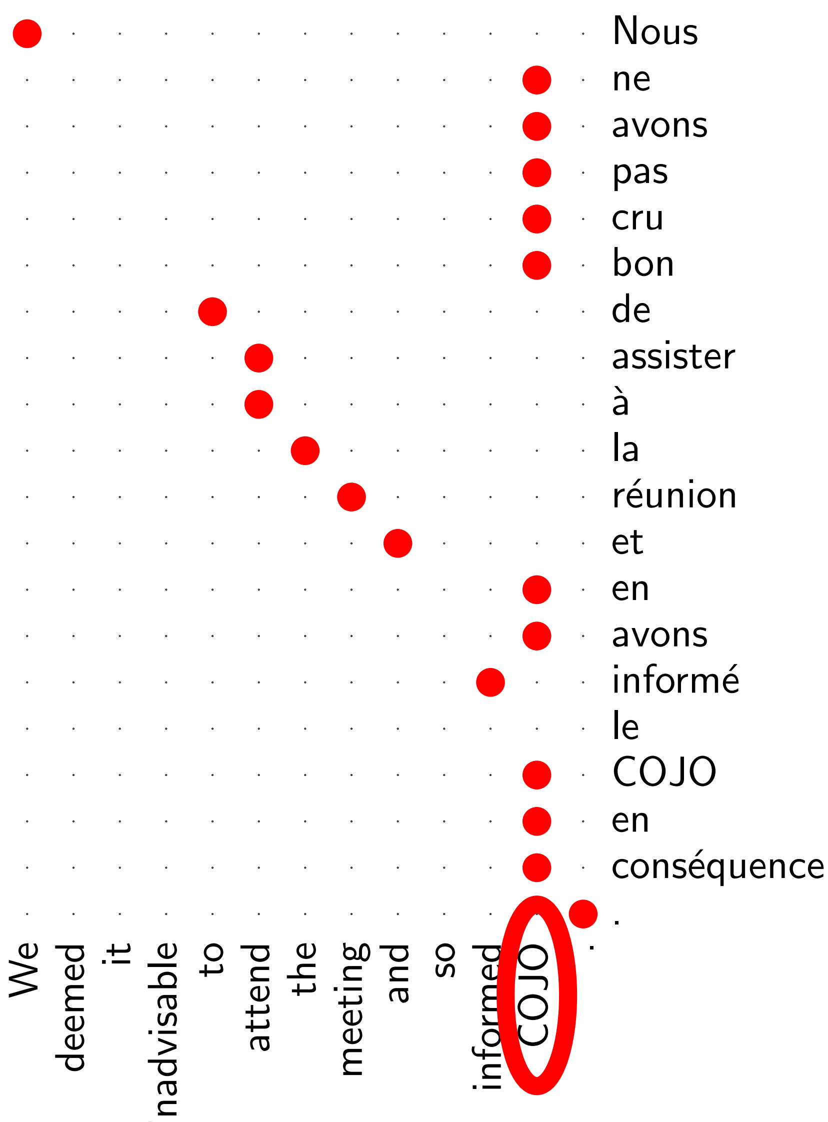
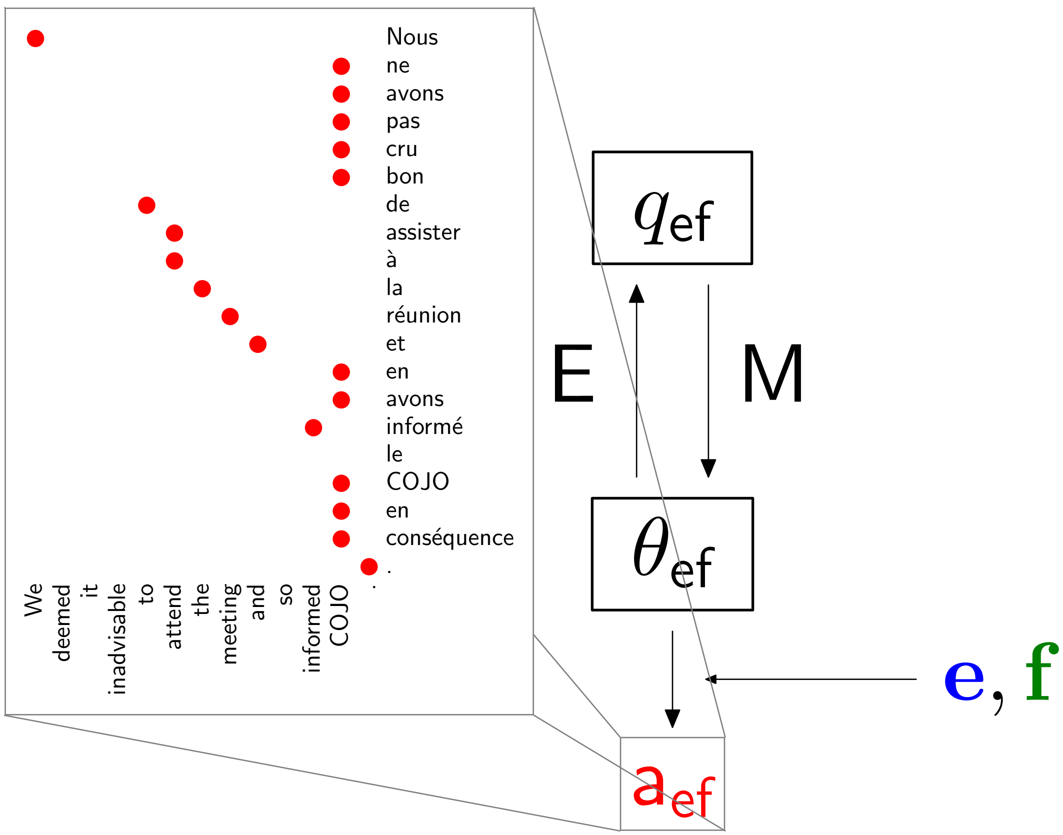


- A problem:
  - Rare words garbage-collect alignments [Moore '05]
- One solution:
  - More complex models

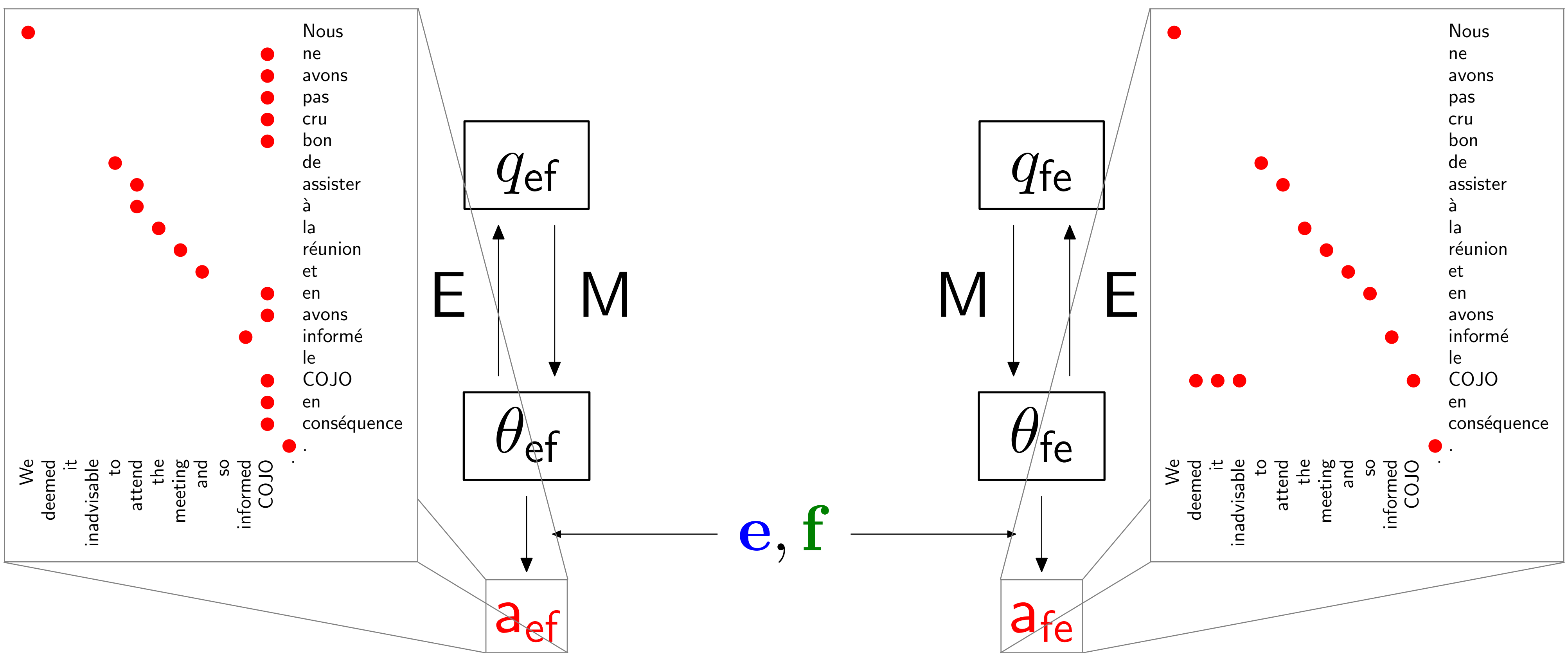
Two complementary models

One model is broken . . .



Two complementary models

But second model is not broken in the same way.



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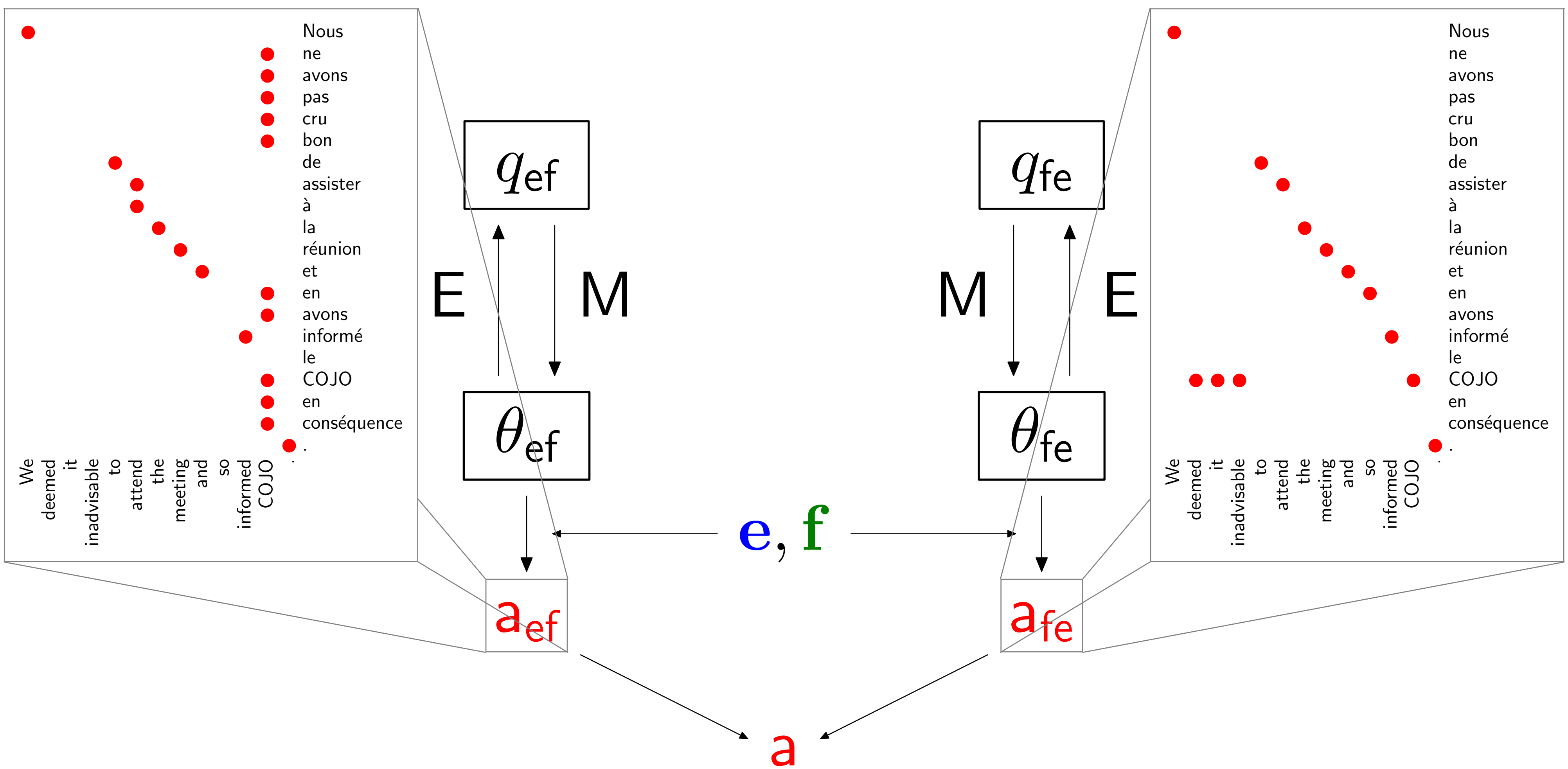
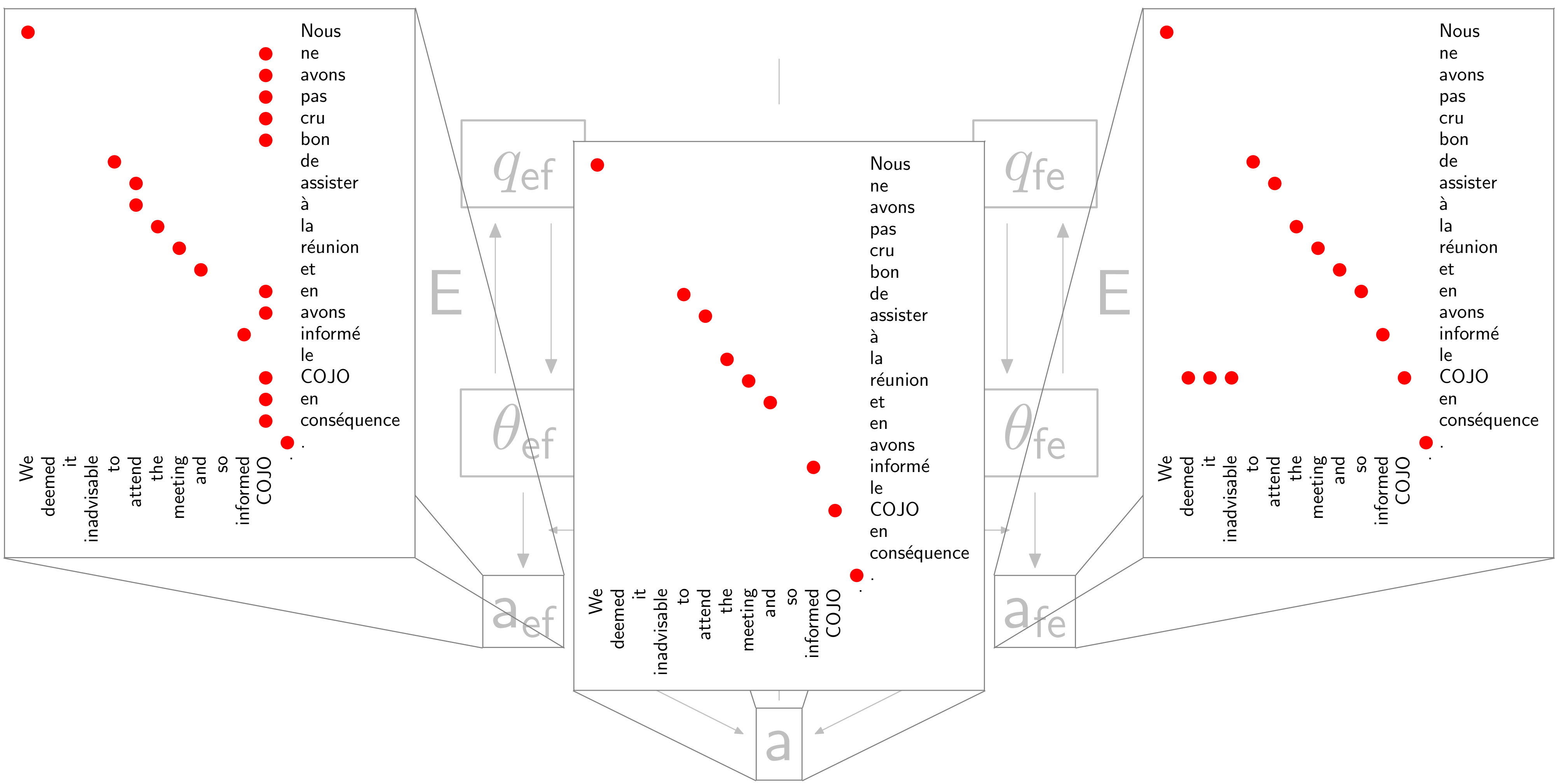


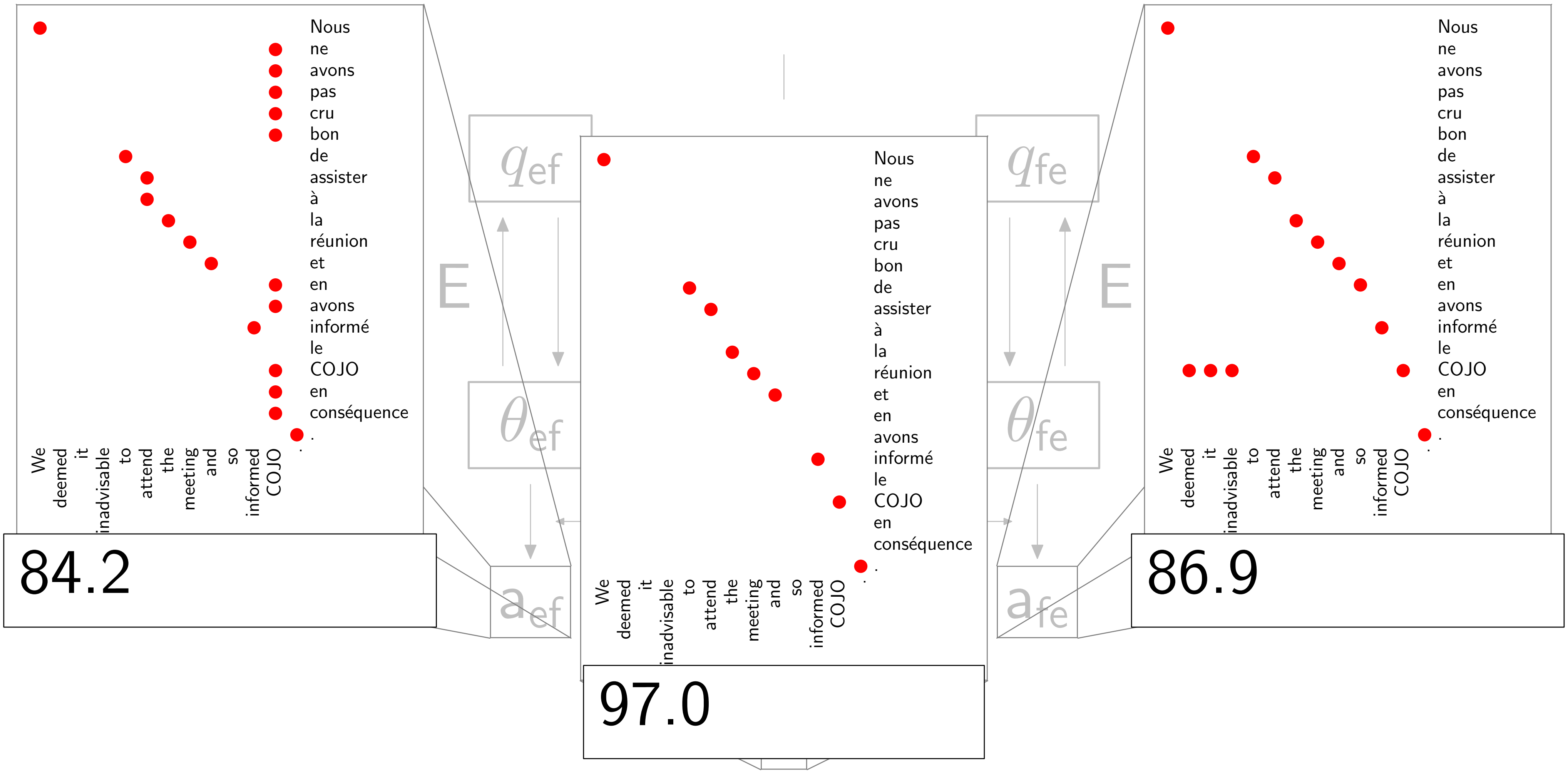
Two complementary models

Intersection kills many bad alignment edges.



Two complementary models

Precision improves . . .



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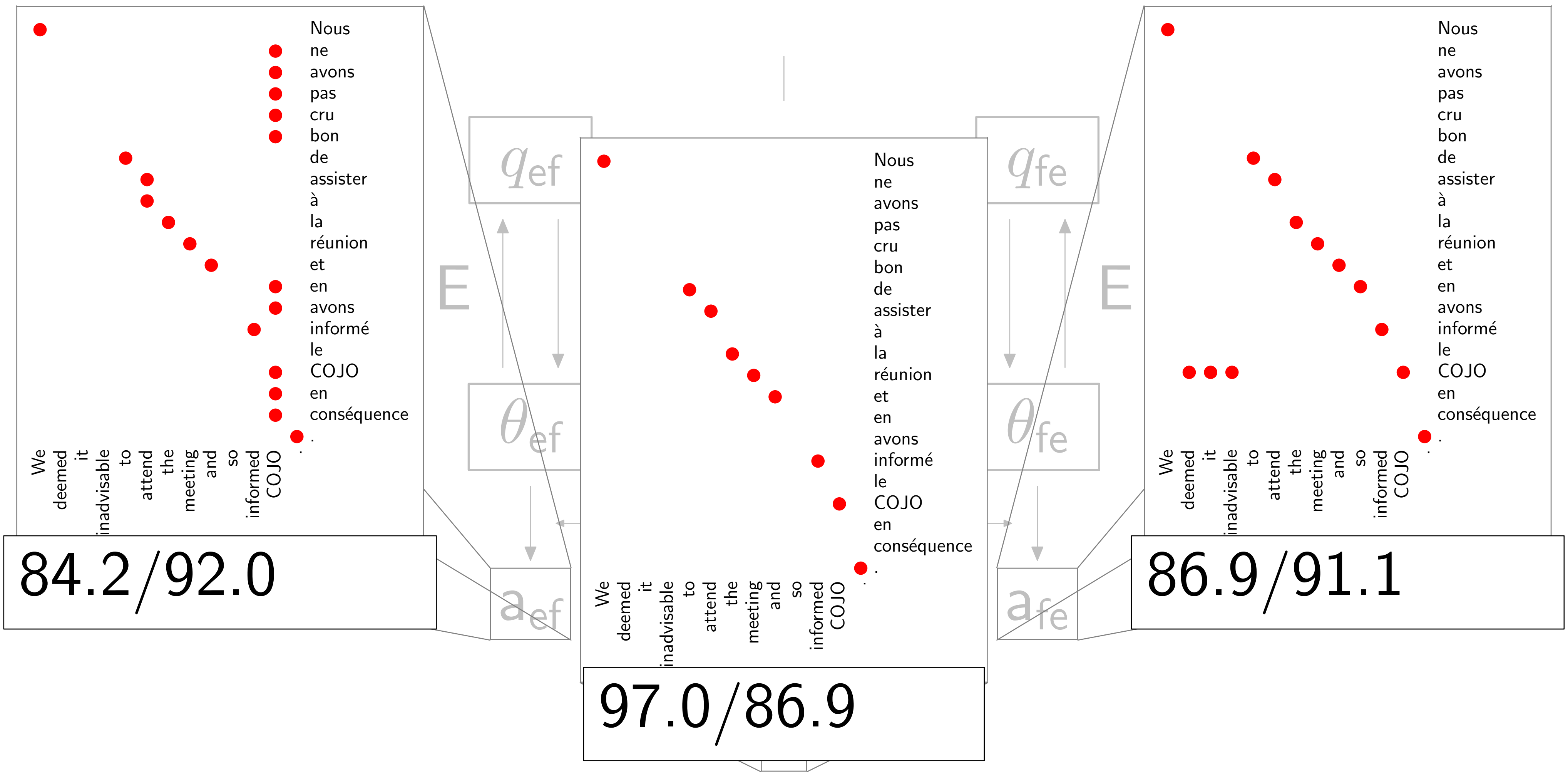
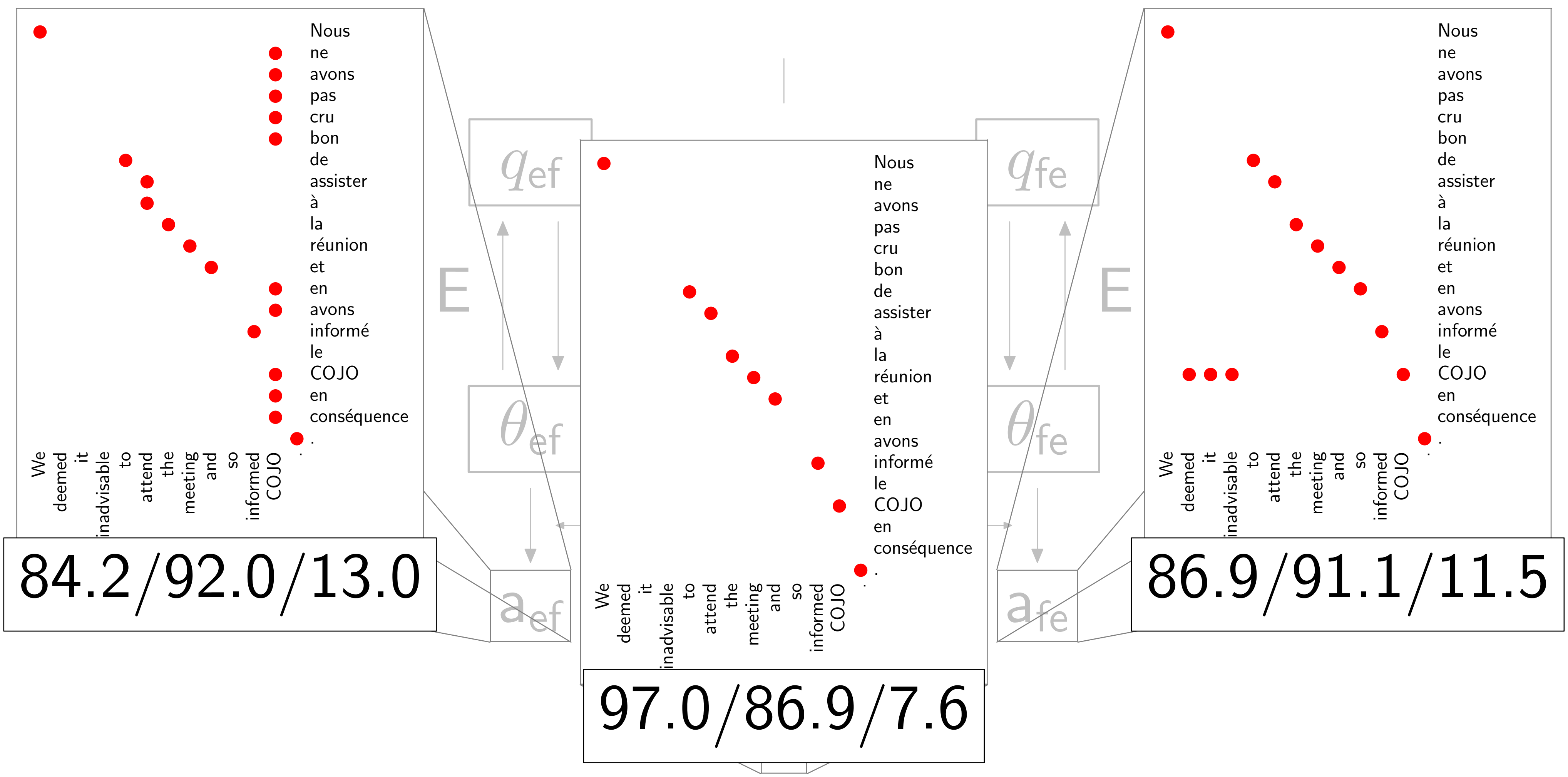
Precision improves . . . Recall suffers . . .



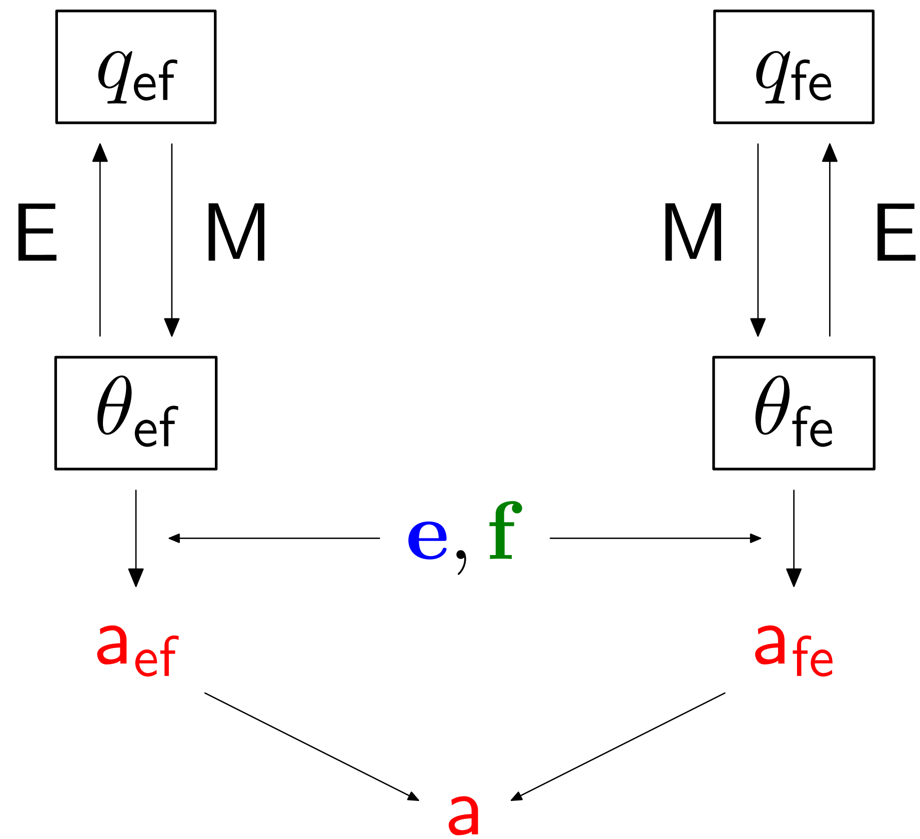
Two complementary models

Precision improves . . . Recall suffers . . . AER improves.



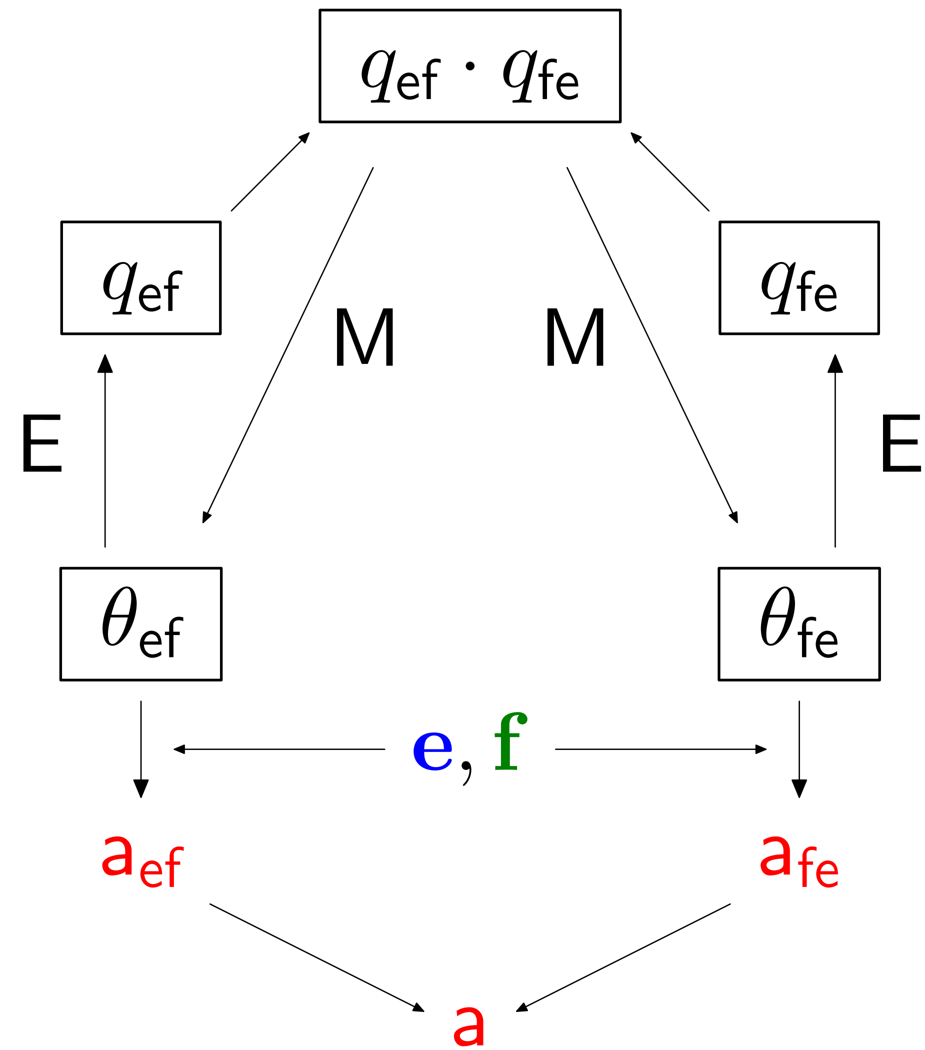
Two complementary models

Can we extend the agreement idea?



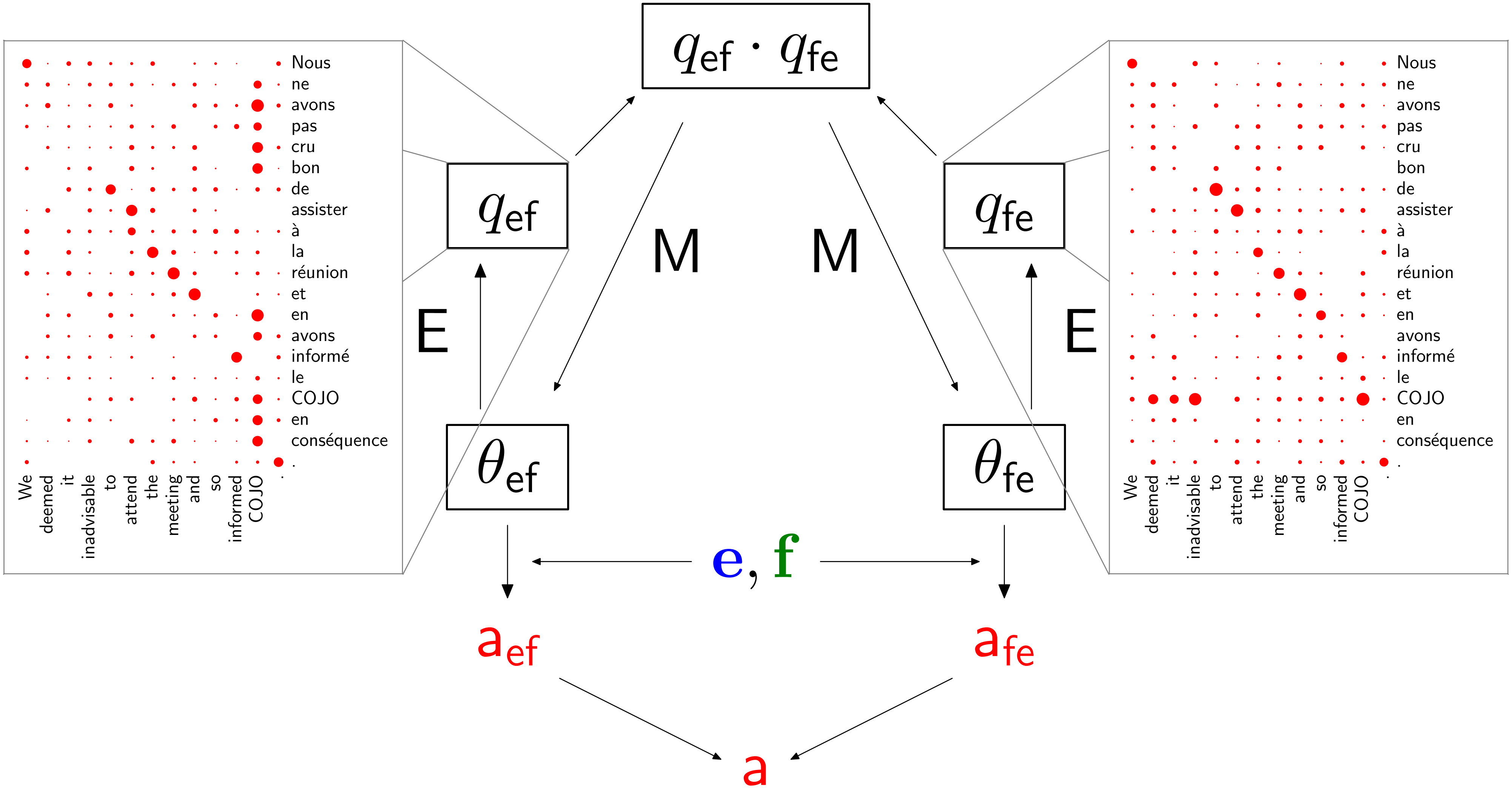
Two complementary models

Key: intersect alignments at training time



Two complementary models

Fractional alignments



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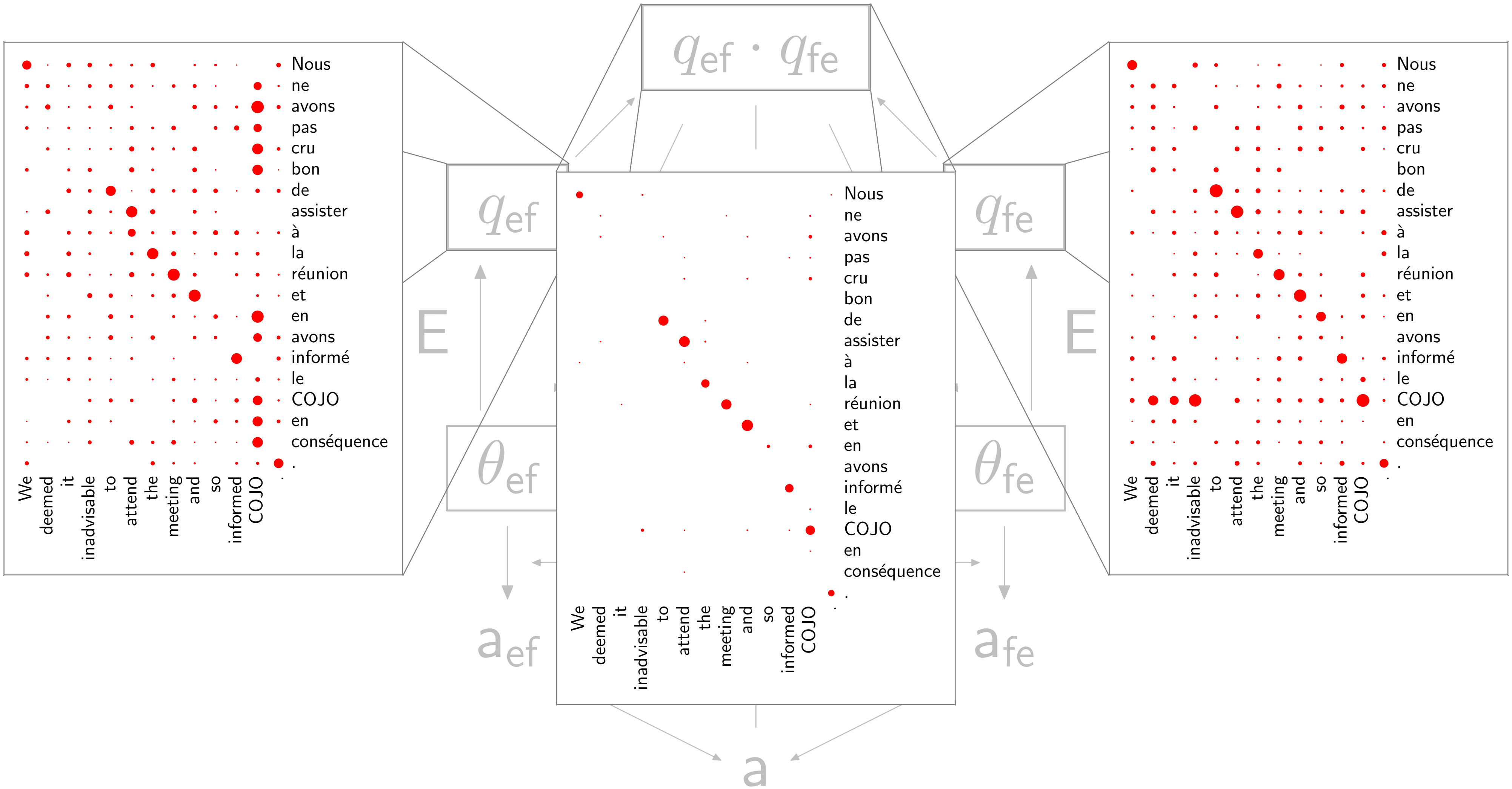
Soft intersection: multiply fractional alignment



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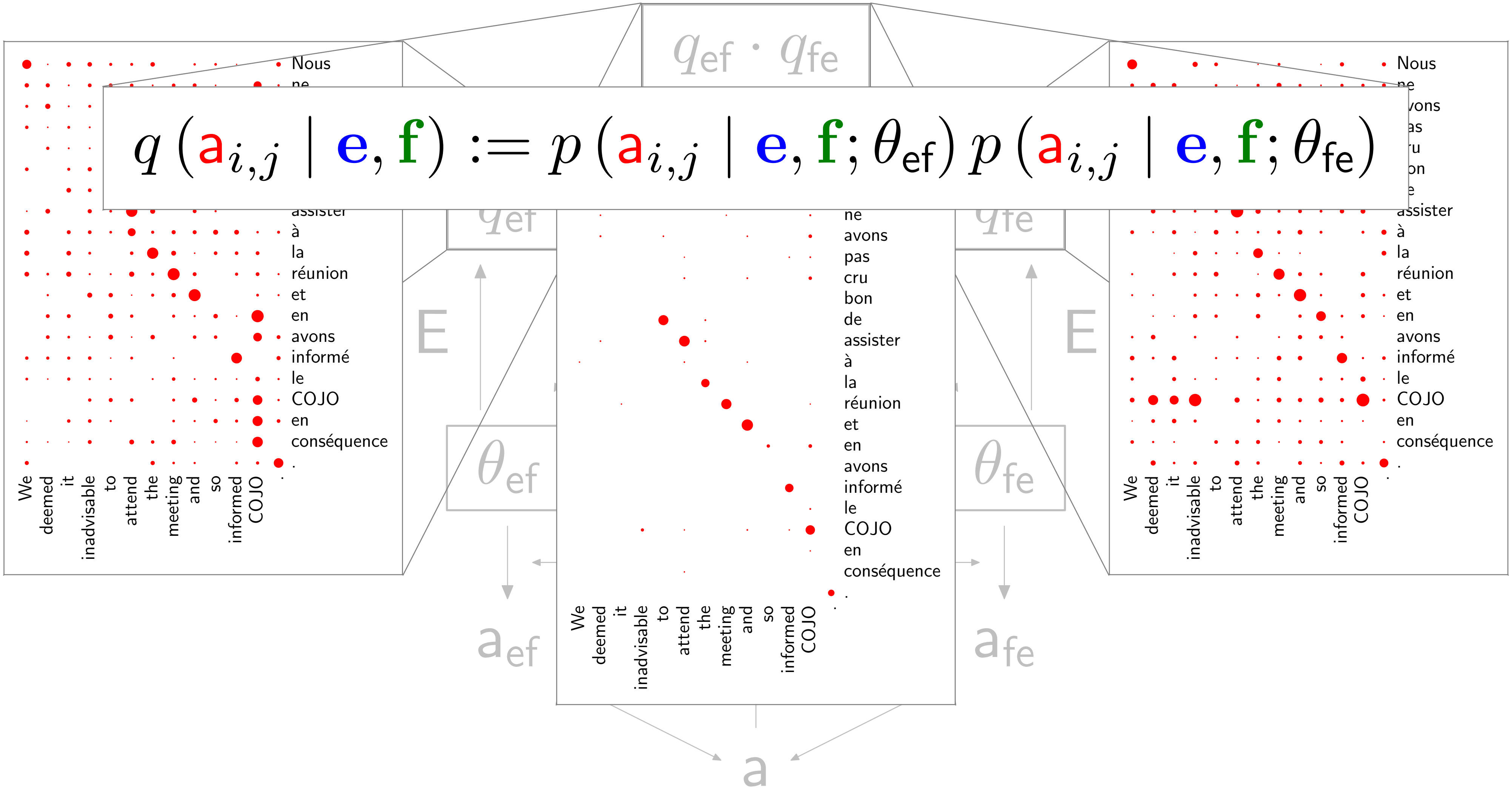
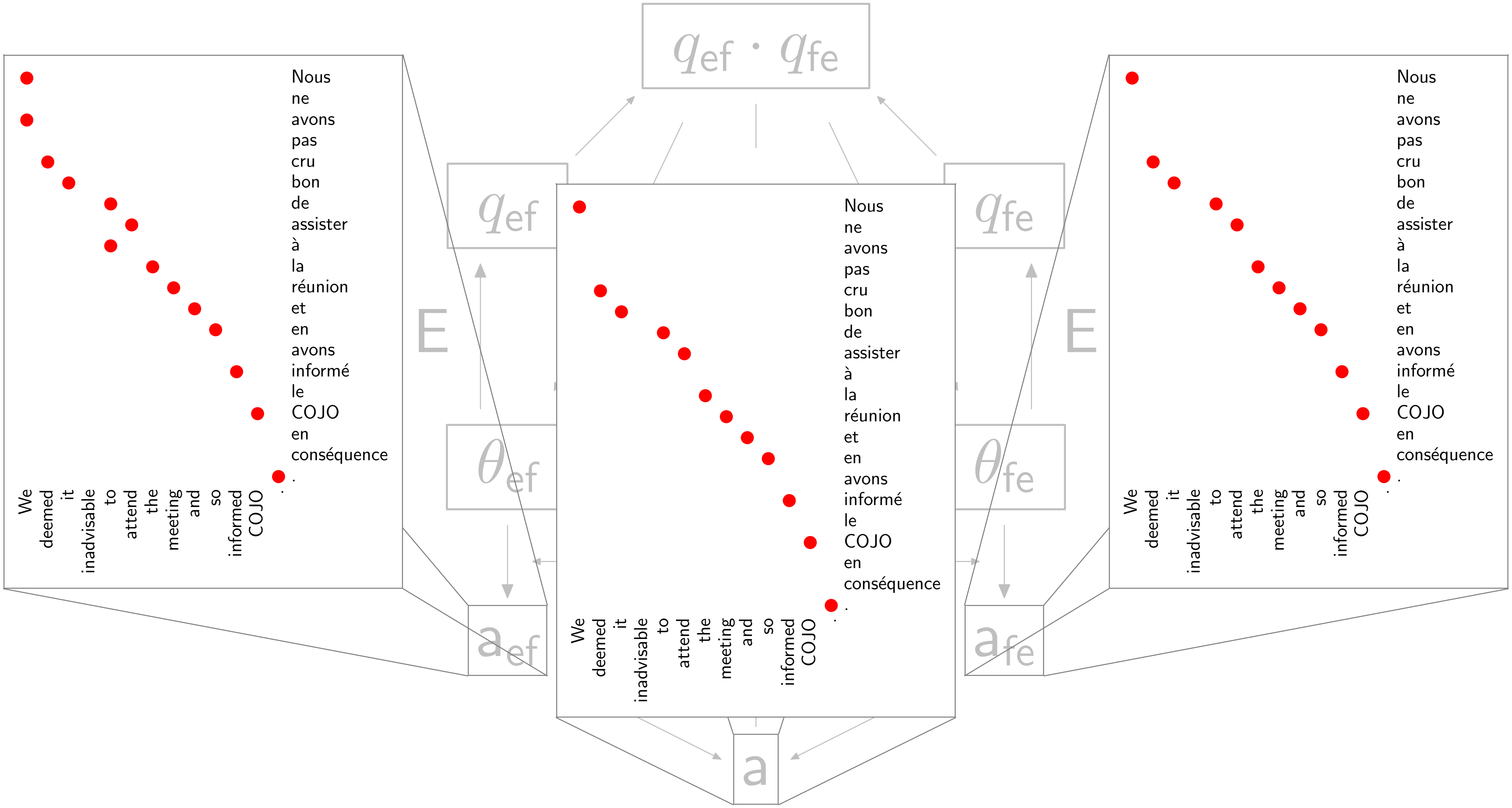


Two complementary models

Models that are trained to agree predict better.



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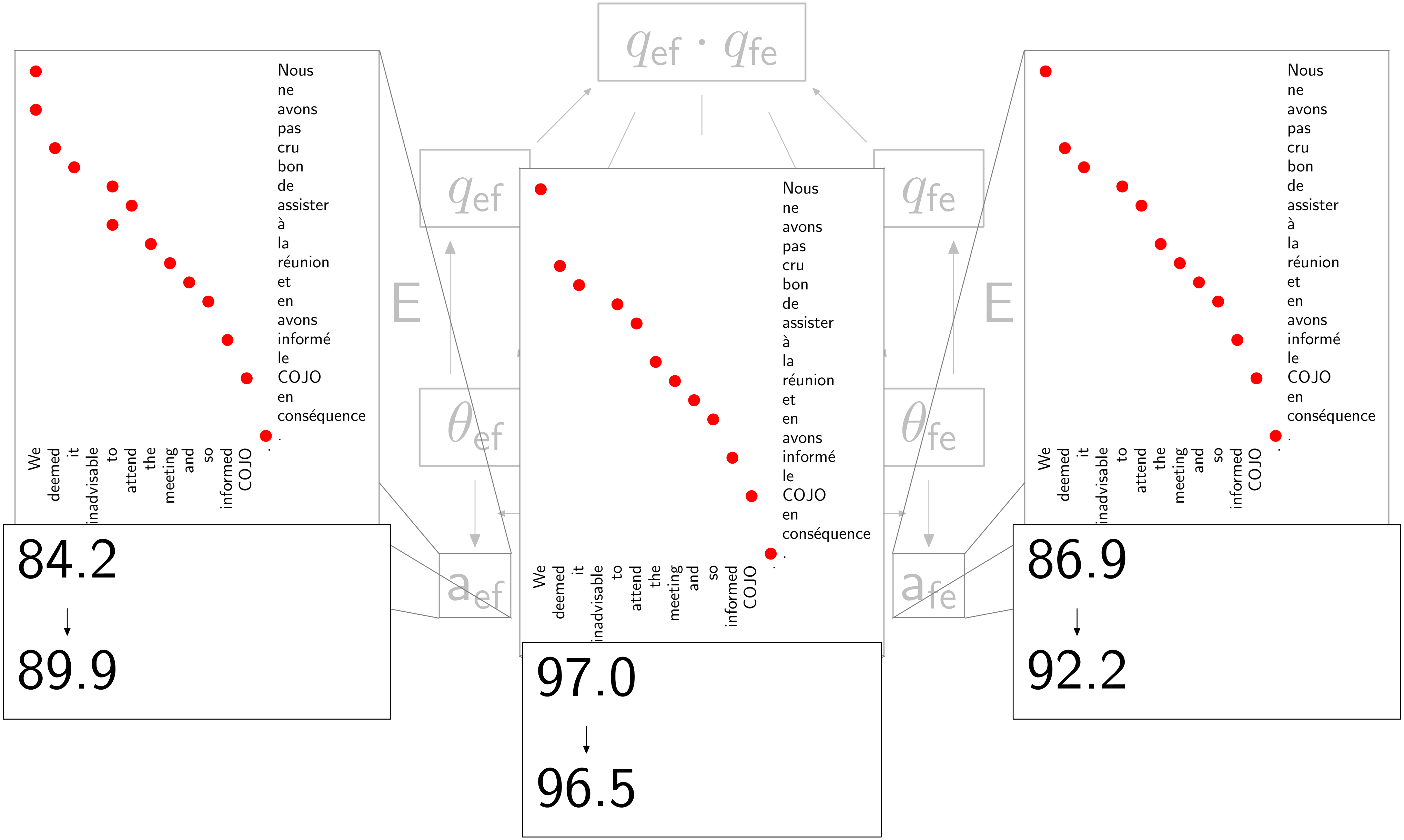

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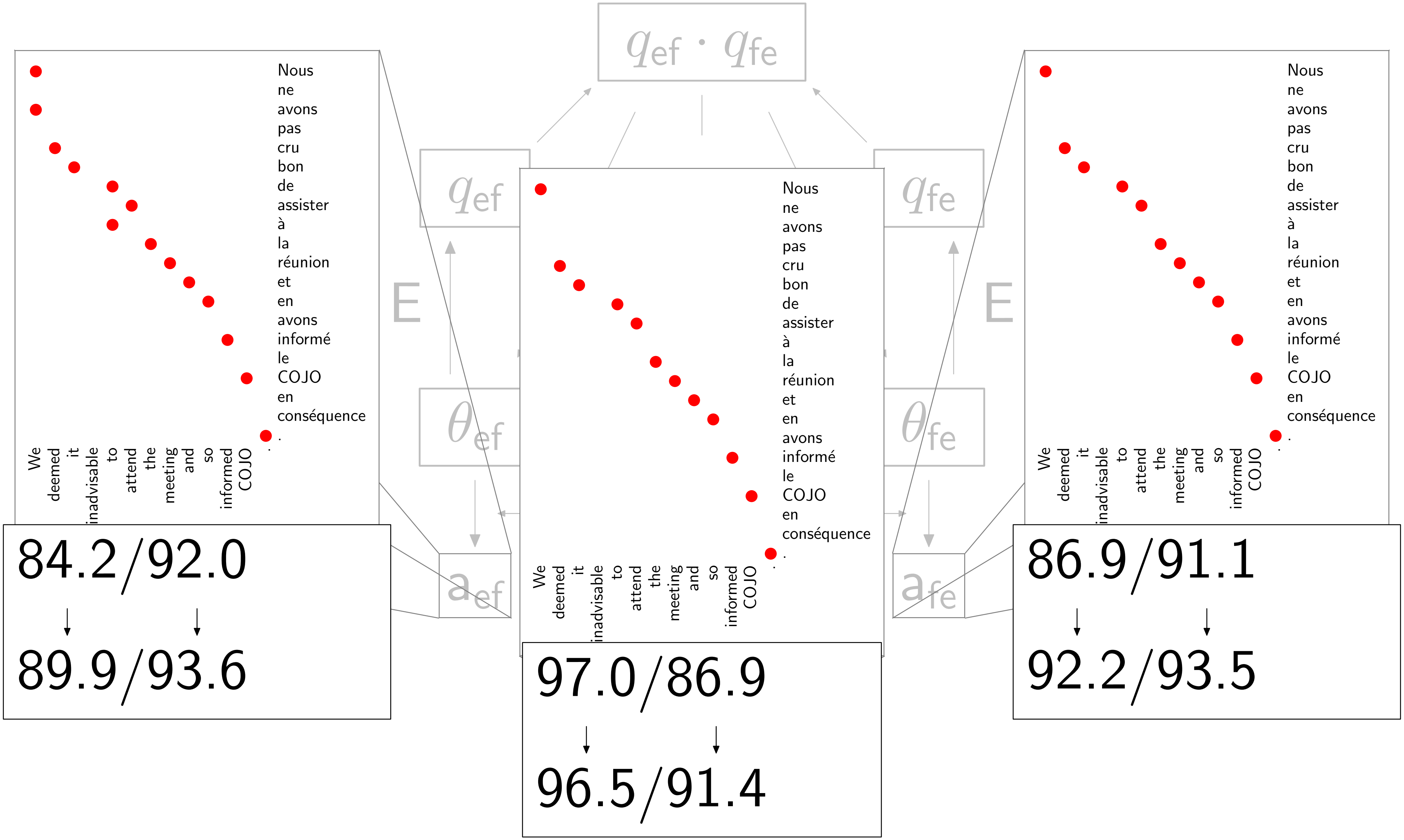

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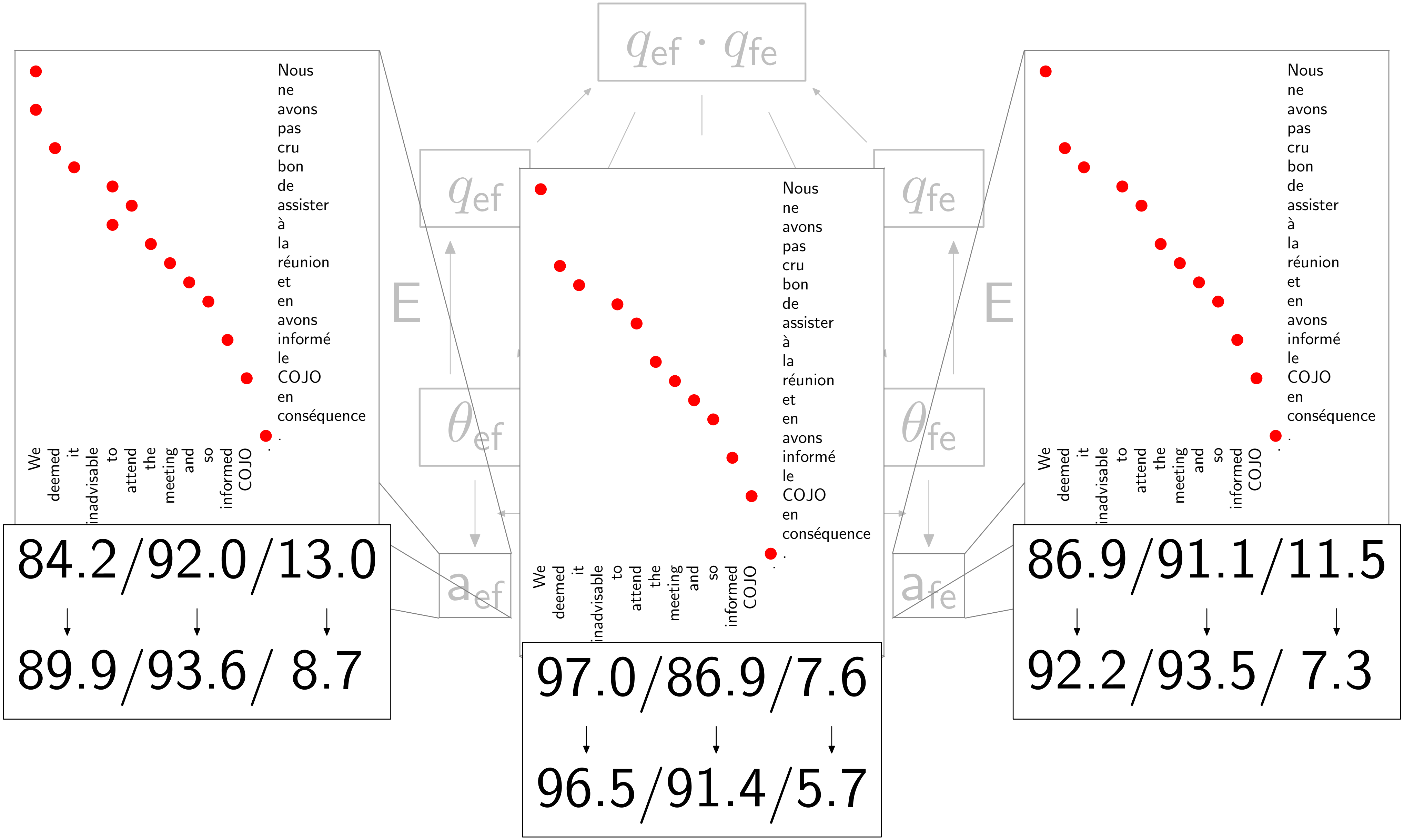

Initialization

Jointly-trained models less sensitive to initialization

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- Two models have somewhat disjoint capacities for producing bad alignments
- Agreement biases parameters away from troublesome areas

Agreement provides staged training

E-step:

$$q\left(\mathsf{a}_{i,j} \mid \mathbf{e}, \mathbf{f}\right) := p\left(\mathsf{a}_{i,j} \mid \mathbf{e}, \mathbf{f}; \theta_{\mathsf{ef}}\right) p\left(\mathsf{a}_{i,j} \mid \mathbf{e}, \mathbf{f}; \theta_{\mathsf{fe}}\right)$$

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M-step:

$$\theta_{\mathsf{t}}(\mathit{to} \longrightarrow \mathit{de}) \propto \sum_{\mathsf{e}_i = \mathit{to}, \mathsf{f}_j = \mathit{de}} q\left(\mathsf{a}_{i,j} \mid \mathbf{e}, \mathbf{f}\right)$$

- Magnitude of fractional q = influence in M-step

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- Magnitude of fractional q = influence in M-step
- Downweight hard cases where two models disagree
- As models get better, harder examples contribute

General unsupervised approach

- Input $\mathbf{x} = (\mathbf{e}, \mathbf{f})$, output $\mathbf{z} = \mathbf{a}$
- Two complementary models $p_1(\mathbf{x}, \mathbf{z}; \theta_1), p_2(\mathbf{x}, \mathbf{z}; \theta_2)$

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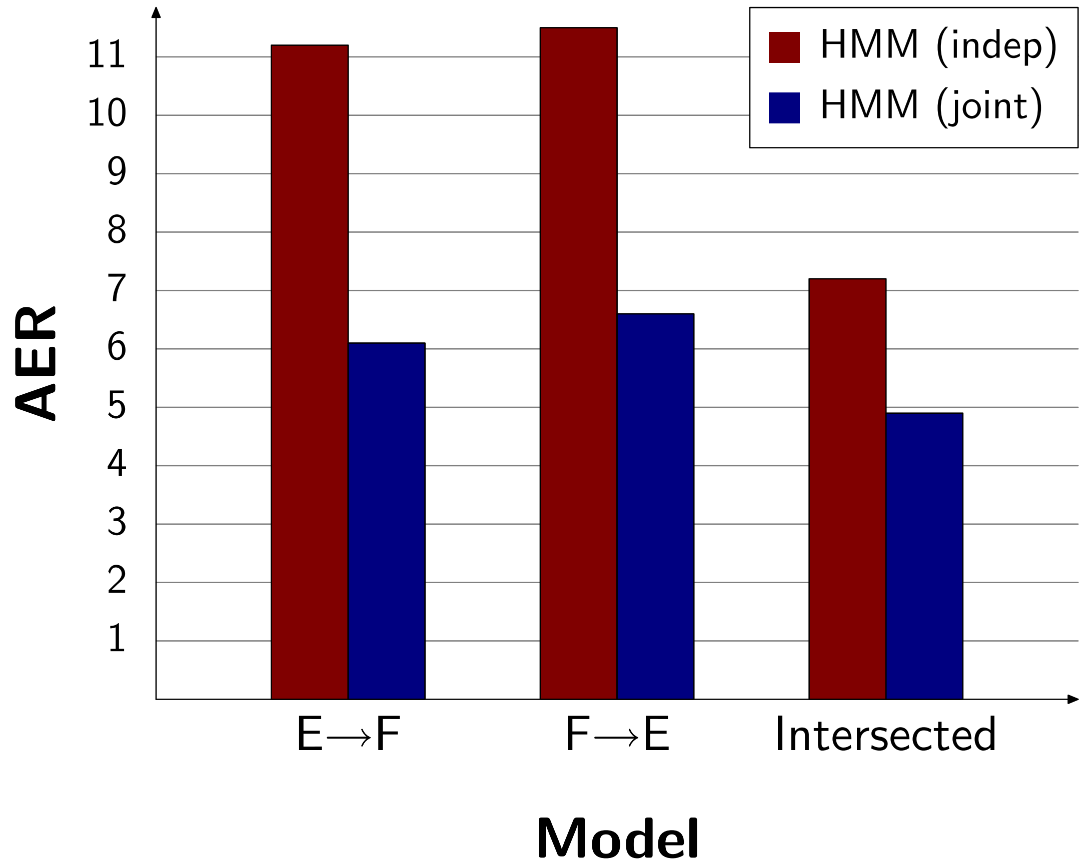
Related work: co-training [Blum, Mitchell '98]
CoBoost [Collins, Singer '99]

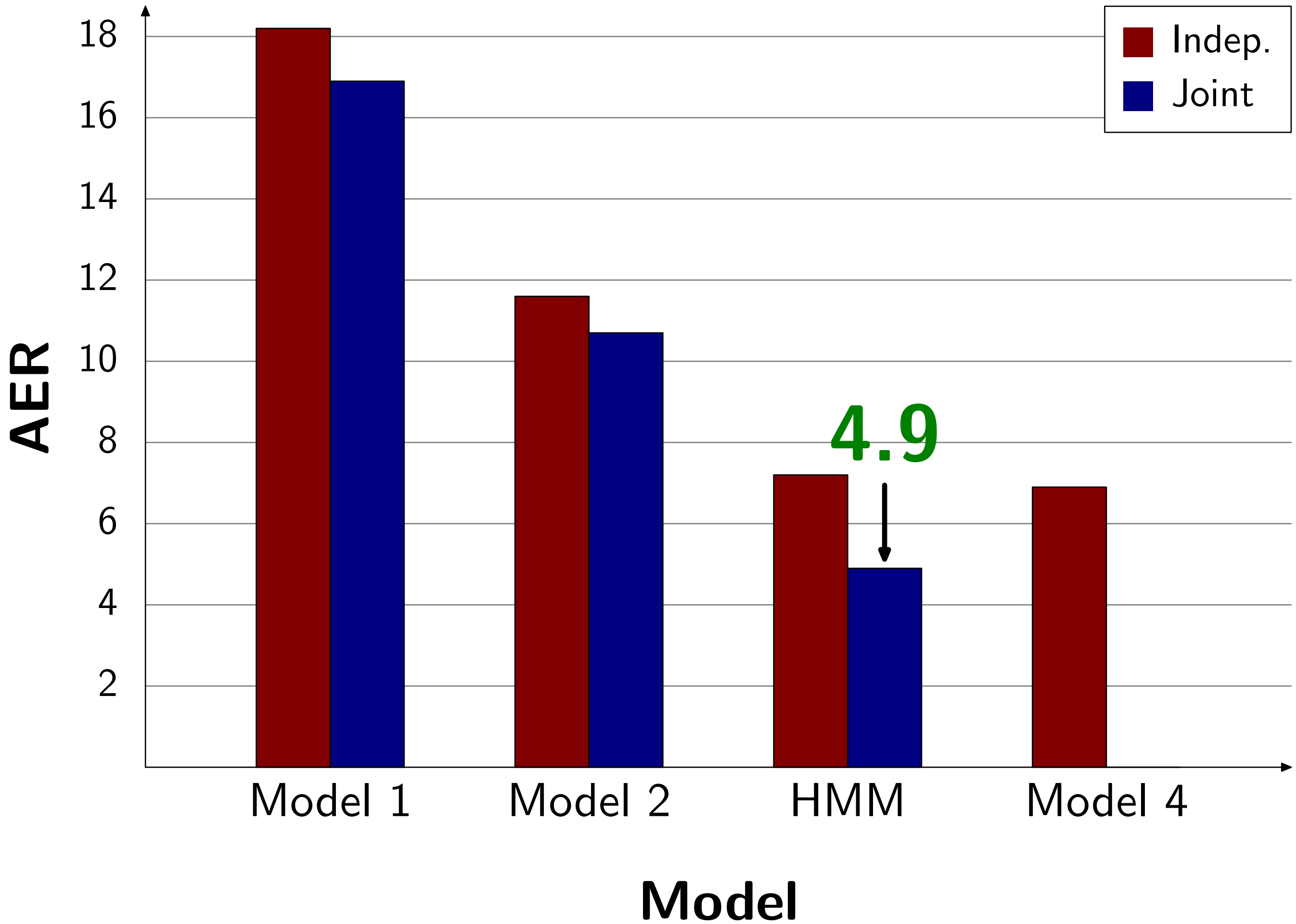
Final results

Hansards (1.1M training sentences, 347 test sentences)



Joint training improves both directional and intersected models

Final results



Significant error reduction for various models

29% reduction in AER over model 4

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- Simple and efficient procedure $\longrightarrow$ 4.9% AER

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- Provides features for discriminative methods