Lexical Translation Models II

January 29, 2013

Last Time ...

$$p(\text{Translation}) = \sum_{\text{Alignment}} p(\text{Alignment}, \text{Translation})$$

Last Time ...

$$p(\text{Translation}) = \sum_{\text{Alignment}} p(\text{Alignment}, \text{Translation})$$

$$= \sum_{\text{Alignment}} p(\text{Alignment}) \times p(\text{Translation} \mid \text{Alignment})$$

Last Time ...

$$p(\text{Translation}) = \sum_{\text{Alignment}} p(\text{Alignment}, \text{Translation})$$

$$= \sum_{\text{Alignment}} \underbrace{p(\text{Alignment})} \times p\underbrace{(\text{Translation} \mid \text{Alignment})}$$

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} \overbrace{p(\mathbf{a} \mid \mathbf{f}, m)} \times \overbrace{\prod_{i=1}^{m} p(e_i \mid f_{a_i})}$$

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

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$$\prod_{i=1}^{m} p(e_i \mid f_{a_i}, f_{a_{i-1}})$$

$$\prod_{i=1}^{m} p(e_i \mid f_{a_i}, f_{a_i - 1})$$

$$\prod_{i=1}^{m} p(e_i \mid f_{a_i}, e_{i-1})$$

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$$\prod_{i=1}^{m} p(e_i \mid f_{a_i}, e_{i-1})$$

$$\boxed{\prod_{i=1}^{m} p(e_i, e_{i+1} \mid f_{a_i})}$$

What is the problem here?

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

$$= \sum_{\mathbf{a} \in [0,n]^m} \underbrace{\prod_{i=1}^{m} \frac{1}{1+n}}_{p(\mathbf{a}|\mathbf{f},m)} \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

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$$= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i) \times p(e_i \mid f_{a_i})$$

$$
\begin{aligned}
p(\mathbf{e} \mid \mathbf{f}, m) &= \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i}) \\
&= \sum_{\mathbf{a} \in [0,n]^m} \underbrace{\prod_{i=1}^{m} \frac{1}{1+n}}_{p(\mathbf{a}|\mathbf{f},m)} \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})
\end{aligned}
$$

Can we do something better here?

$$
= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} \boxed{p(a_i)} \times p(e_i \mid f_{a_i})
$$

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i) \times p(e_i \mid f_{a_i})$$

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i) \times p(e_i \mid f_{a_i})$$

Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

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- Model alignment with an *absolute position distribution*
- Probability of translating a foreign word at position a_i to generate the word at position i (with target length m and source length n)

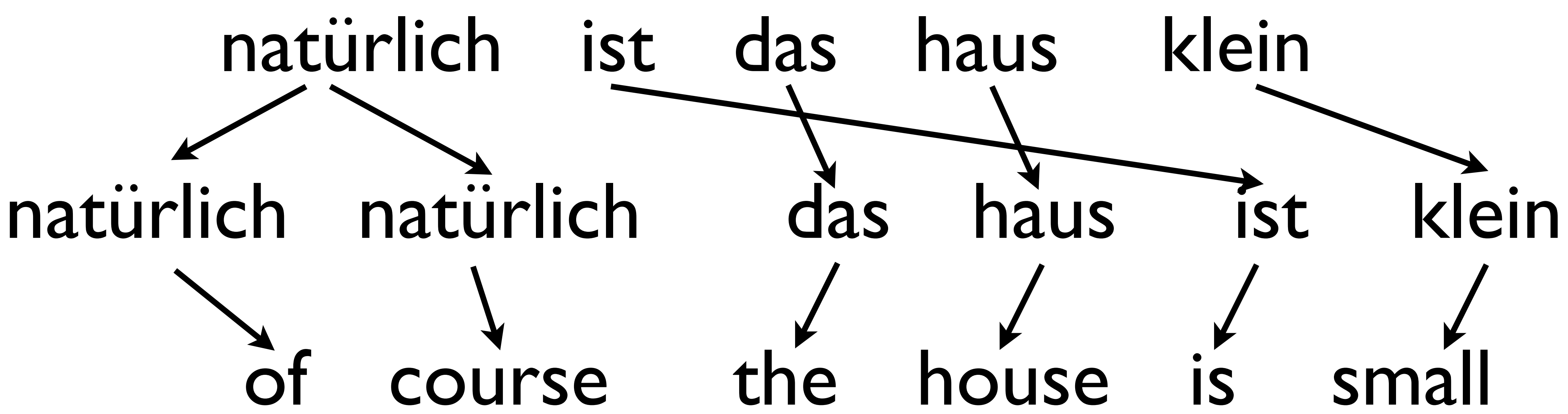
$$p(a_i \mid i, m, n)$$

- EM training of this model is almost the same as with Model 1 (same conditional independencies hold)

Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

natürlich ist das haus klein

Model 2 $= \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$



Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

- **Pros**
  - Non-uniform alignment model
  - Fast EM training / marginal inference
- **Cons**
  - Absolute position is *very naive*
  - How many parameters to model $p(a_i \mid i, m, n)$

Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

How much do we know when we only know the source & target lengths and the current position?

Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

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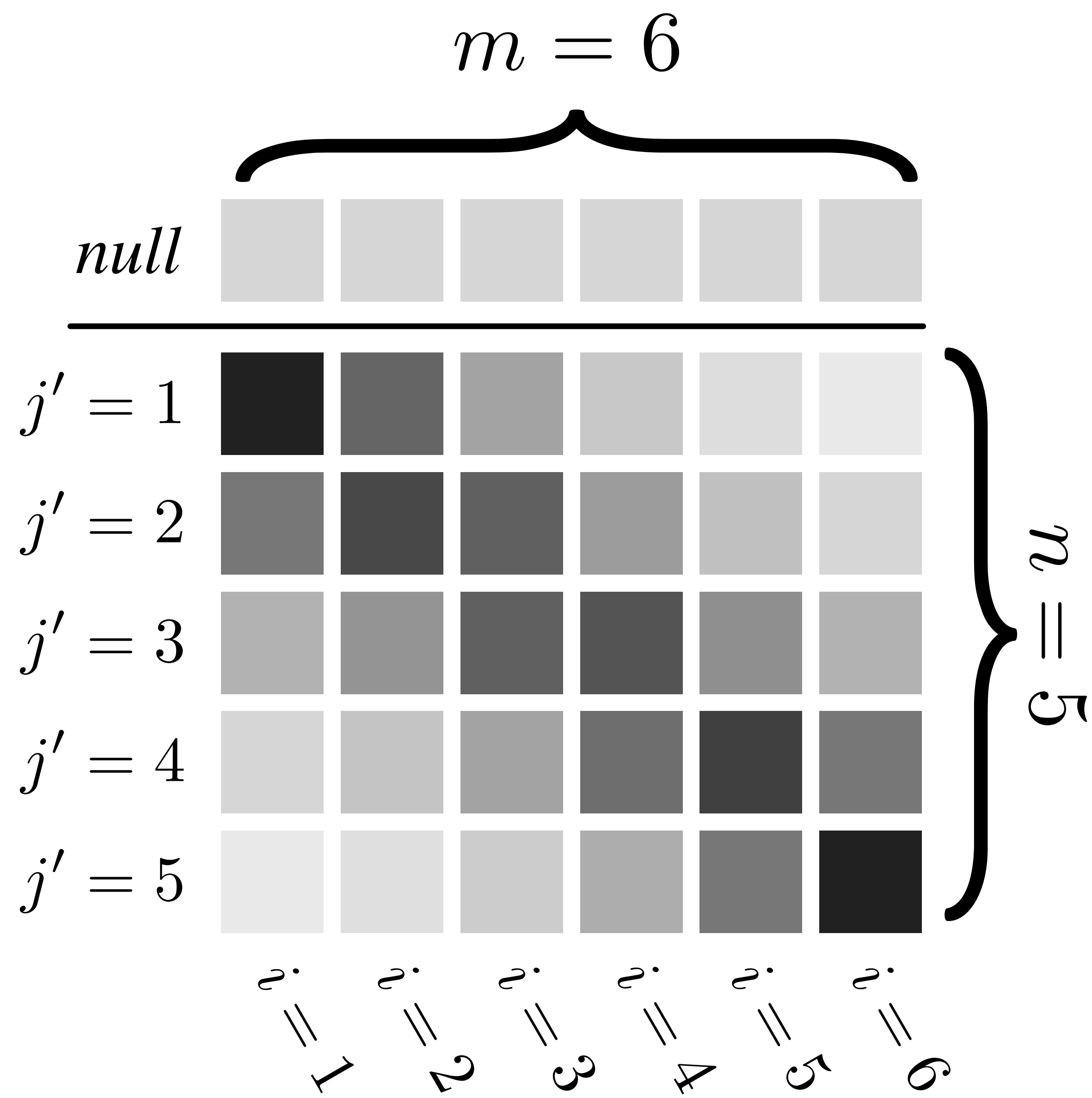
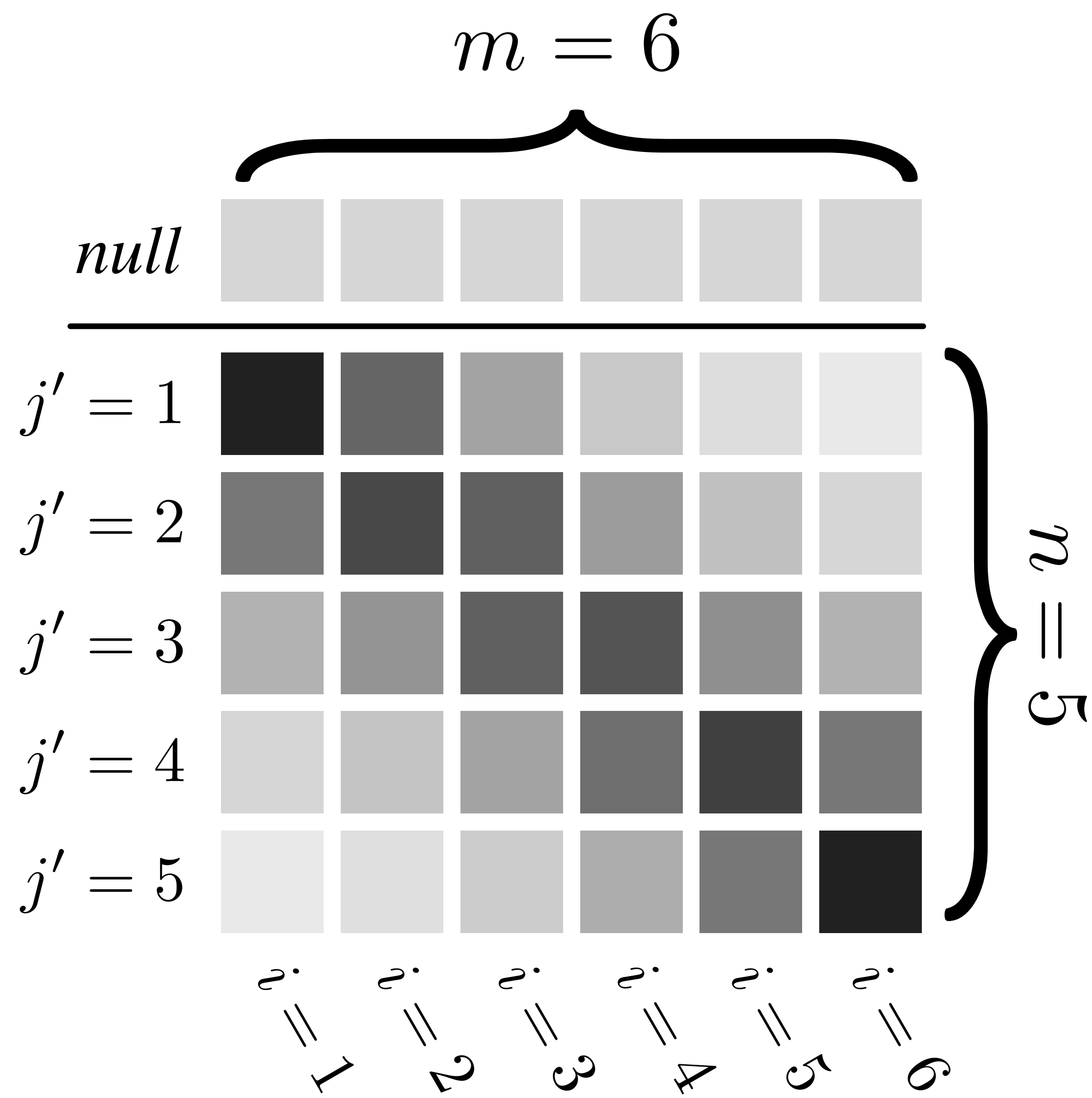


Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

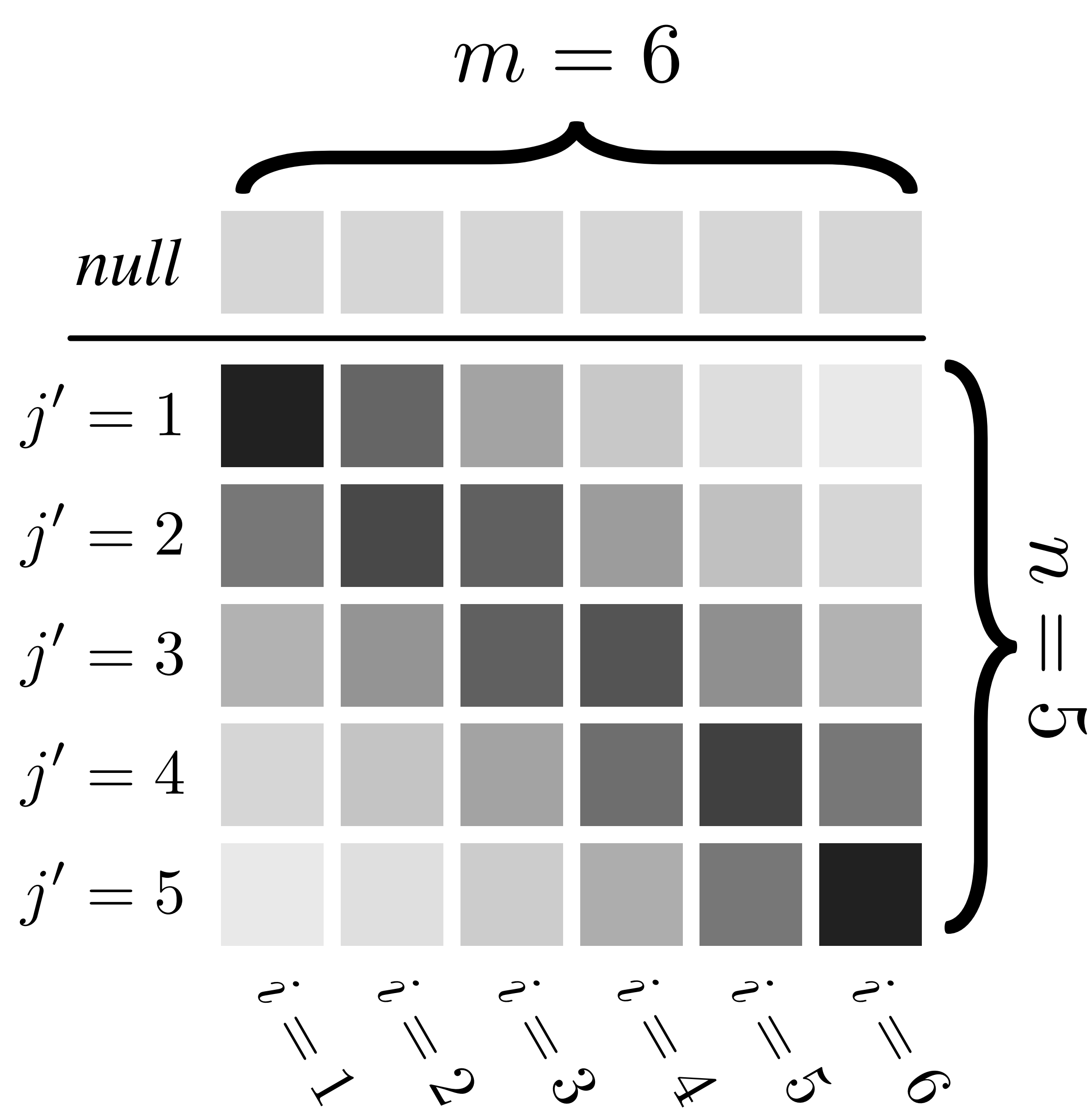
How much do we know when we only know the source & target lengths and the current position?

How many parameters do we need to model this?



Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

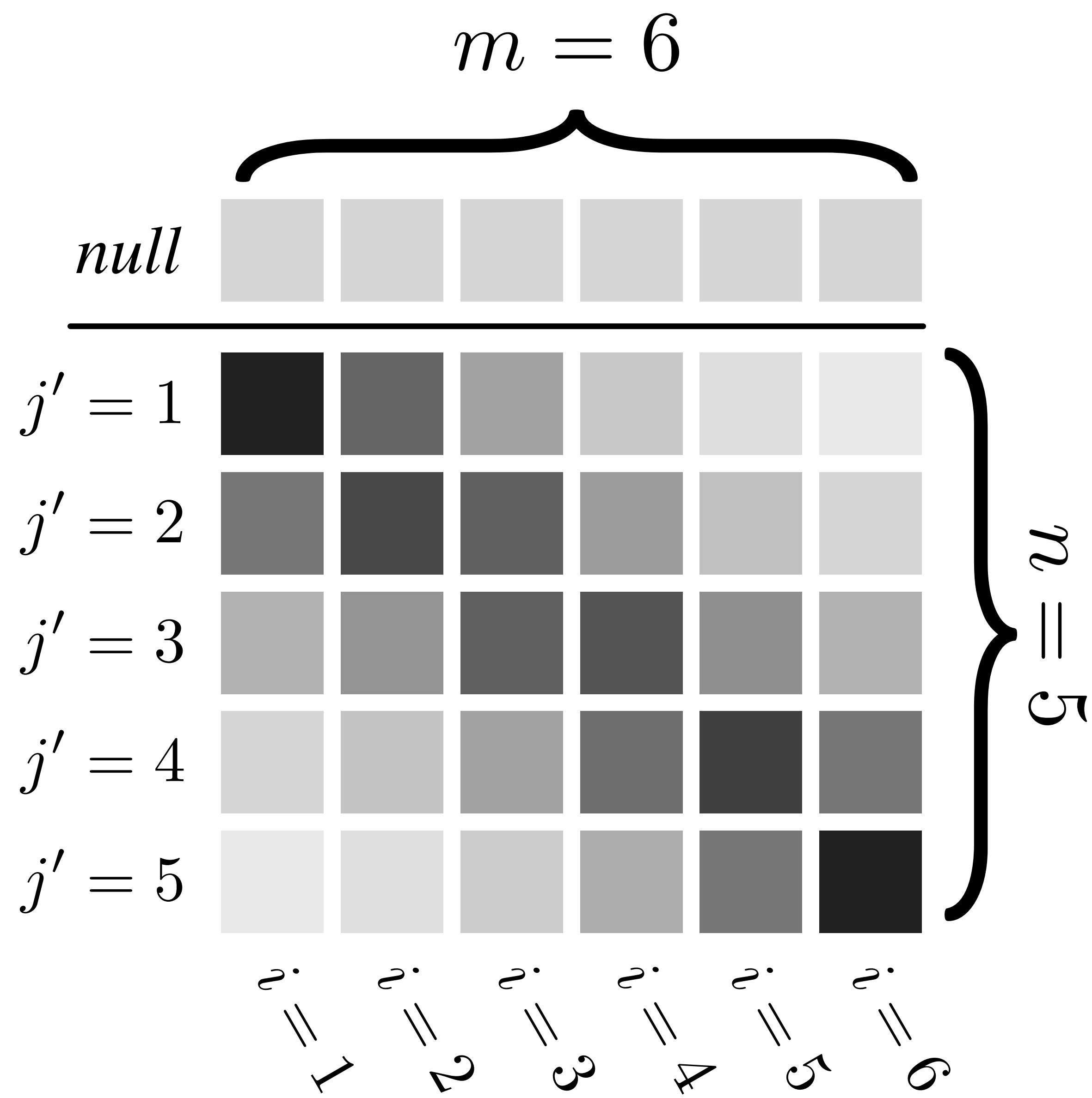
$$h(j, i, m, n) = -\left| \frac{i}{m} - \frac{j}{n} \right|$$



$$\textbf{Model 2} = \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$$

pos in target

$$h(j, i, m, n) = -\left|\frac{i}{m} - \frac{j}{n}\right|$$



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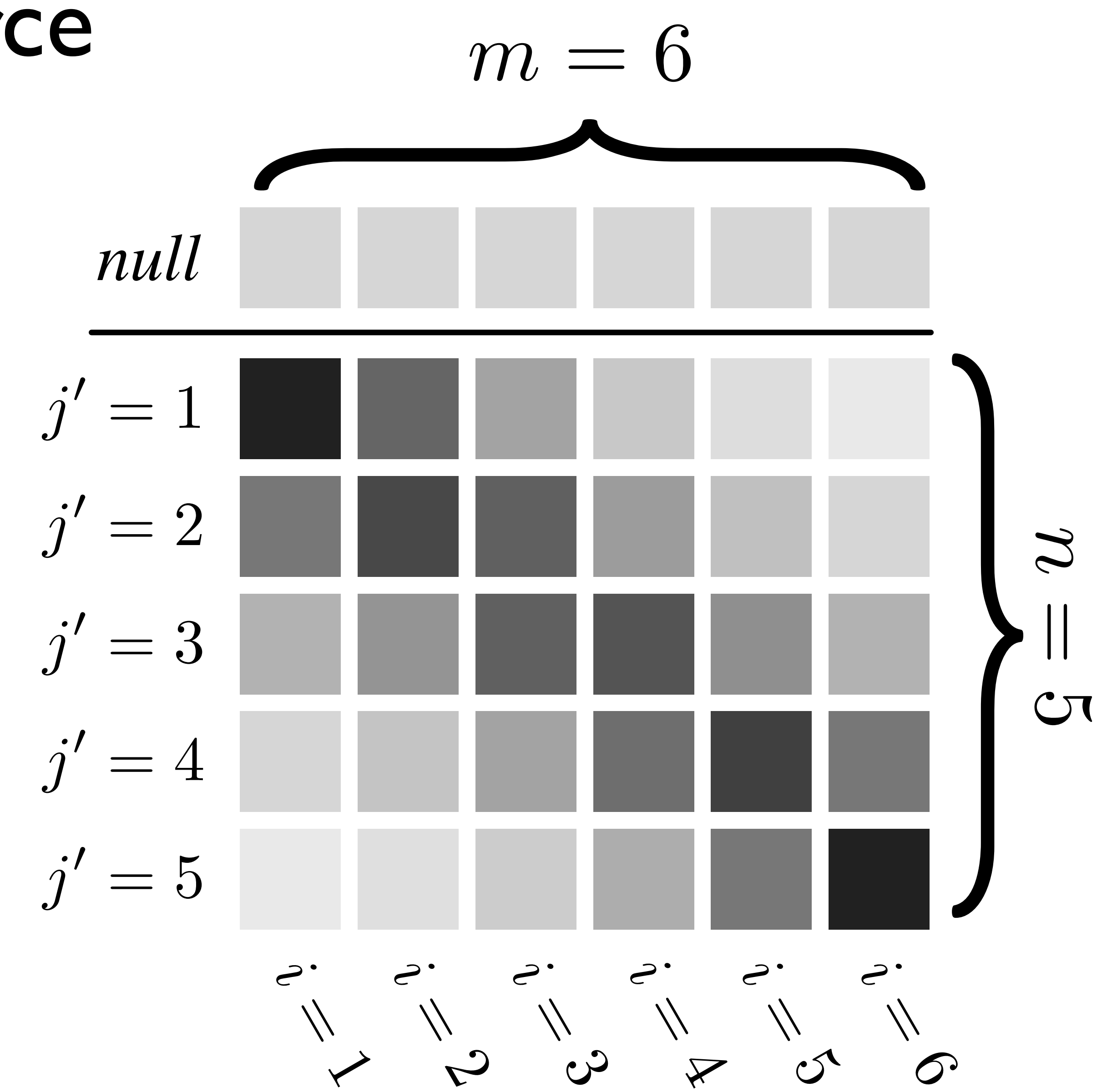
pos in target   pos in source

$$h(j, i, m, n) = -\left| \frac{i}{m} - \frac{j}{n} \right|$$



Model 2 $= \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

pos in target   pos in source

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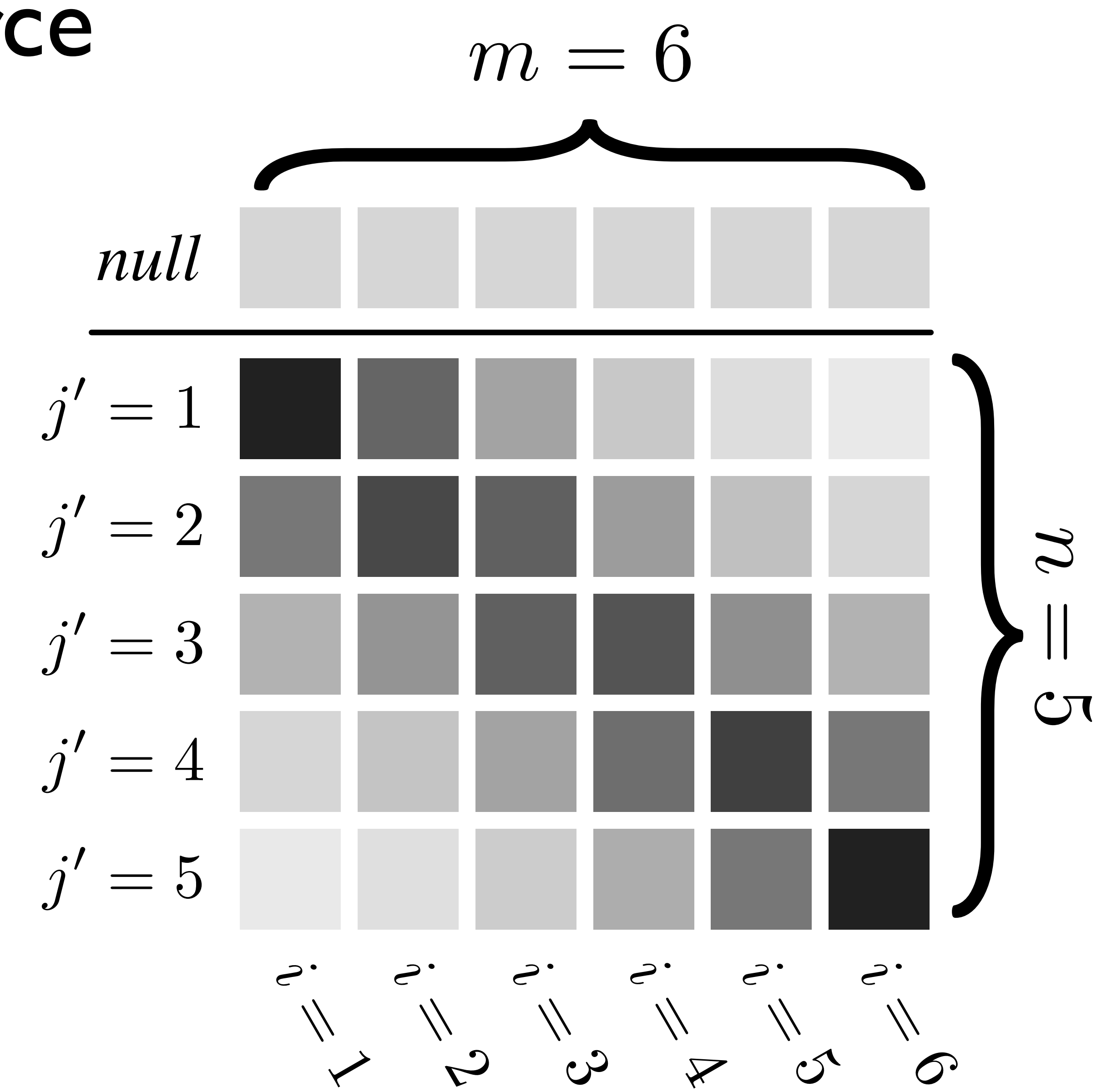
target len



Model 2 $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

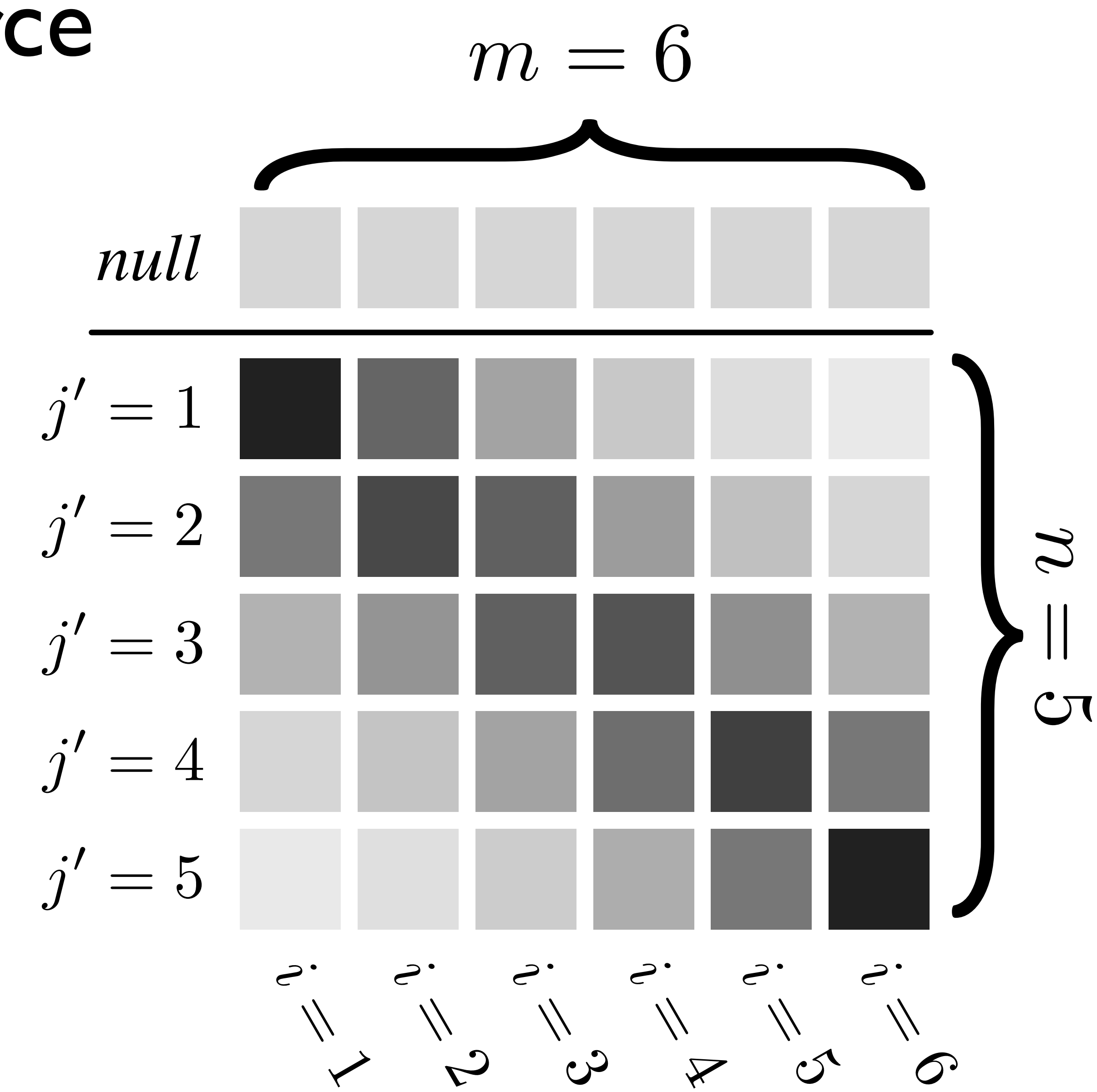
pos in target

pos in source

$$h(j, i, m, n) = -\left|\frac{i}{m} - \frac{j}{n}\right|$$

target len

source len



$$\textbf{Model 2} = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$$

pos in target

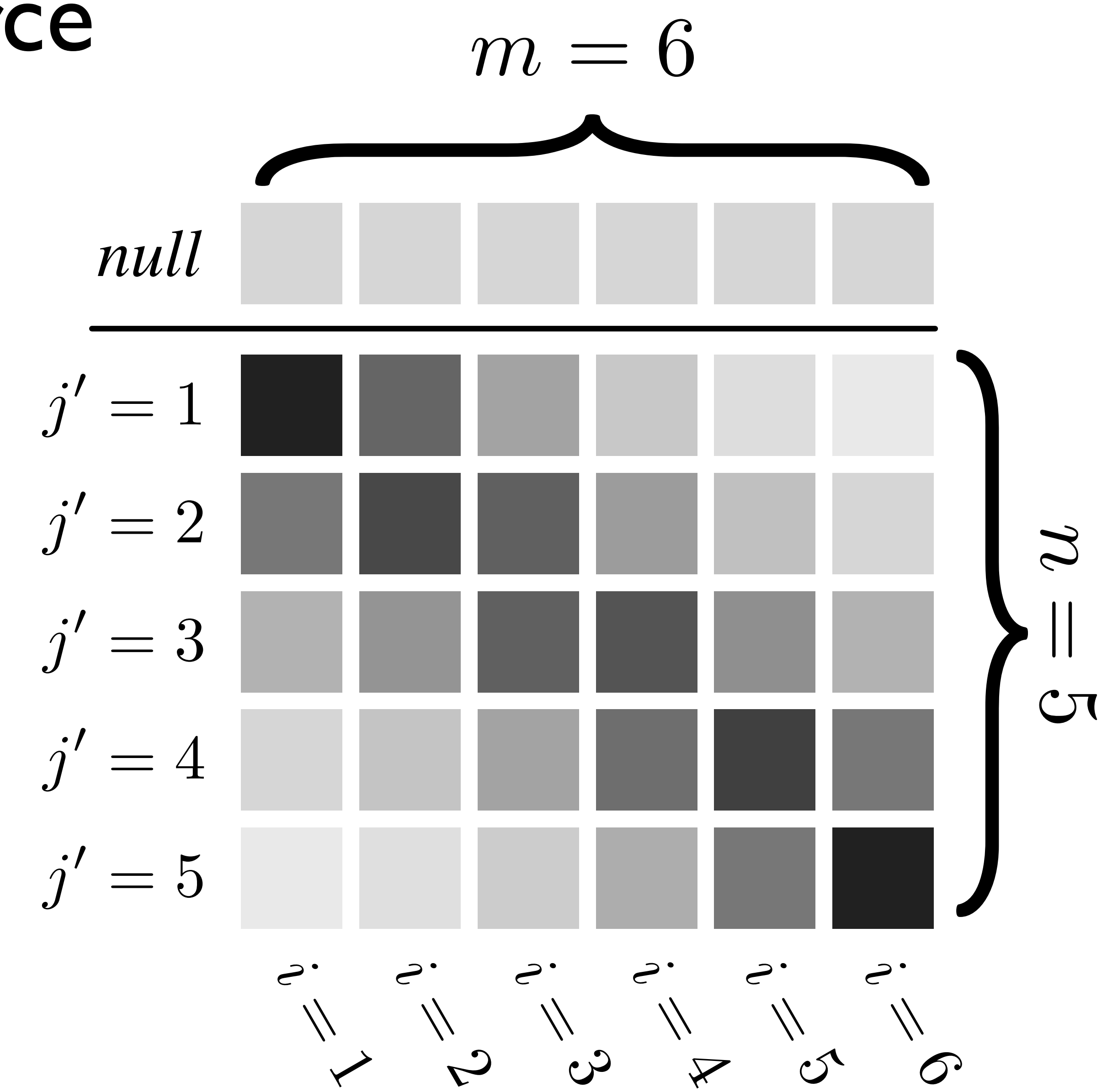
pos in source

$$h(j, i, m, n) = -\left| \frac{i}{m} - \frac{j}{n} \right|$$

target len

source len

$$b(j \mid i, m, n) = \frac{\exp \lambda h(j, i, m, n)}{\sum_{j'} \exp \lambda h(j', i, m, n)}$$



Model 2 $= \displaystyle\sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$

pos in target

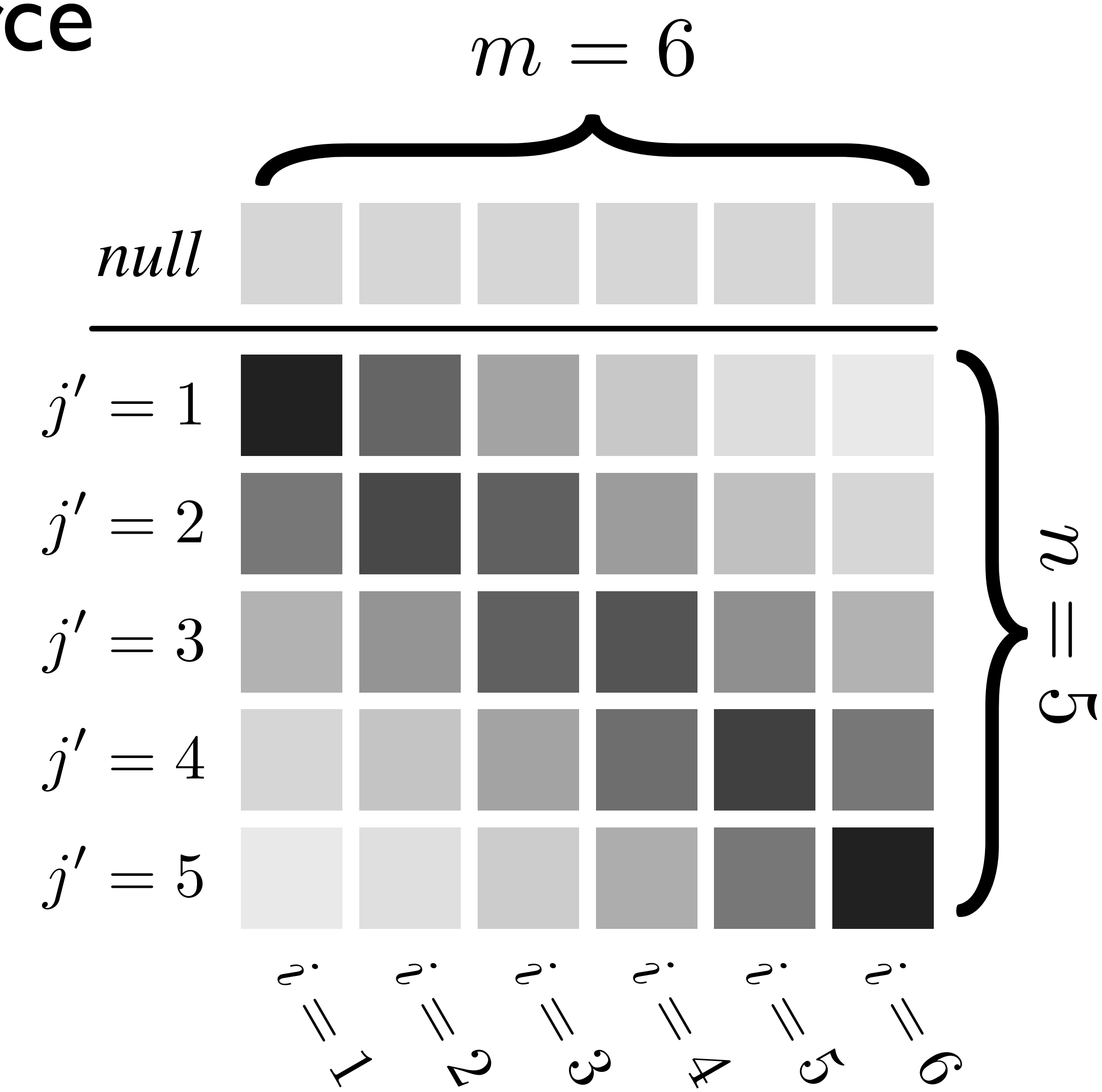
pos in source

$$h(j, i, m, n) = -\left|\frac{i}{m} - \frac{j}{n}\right|$$

target len

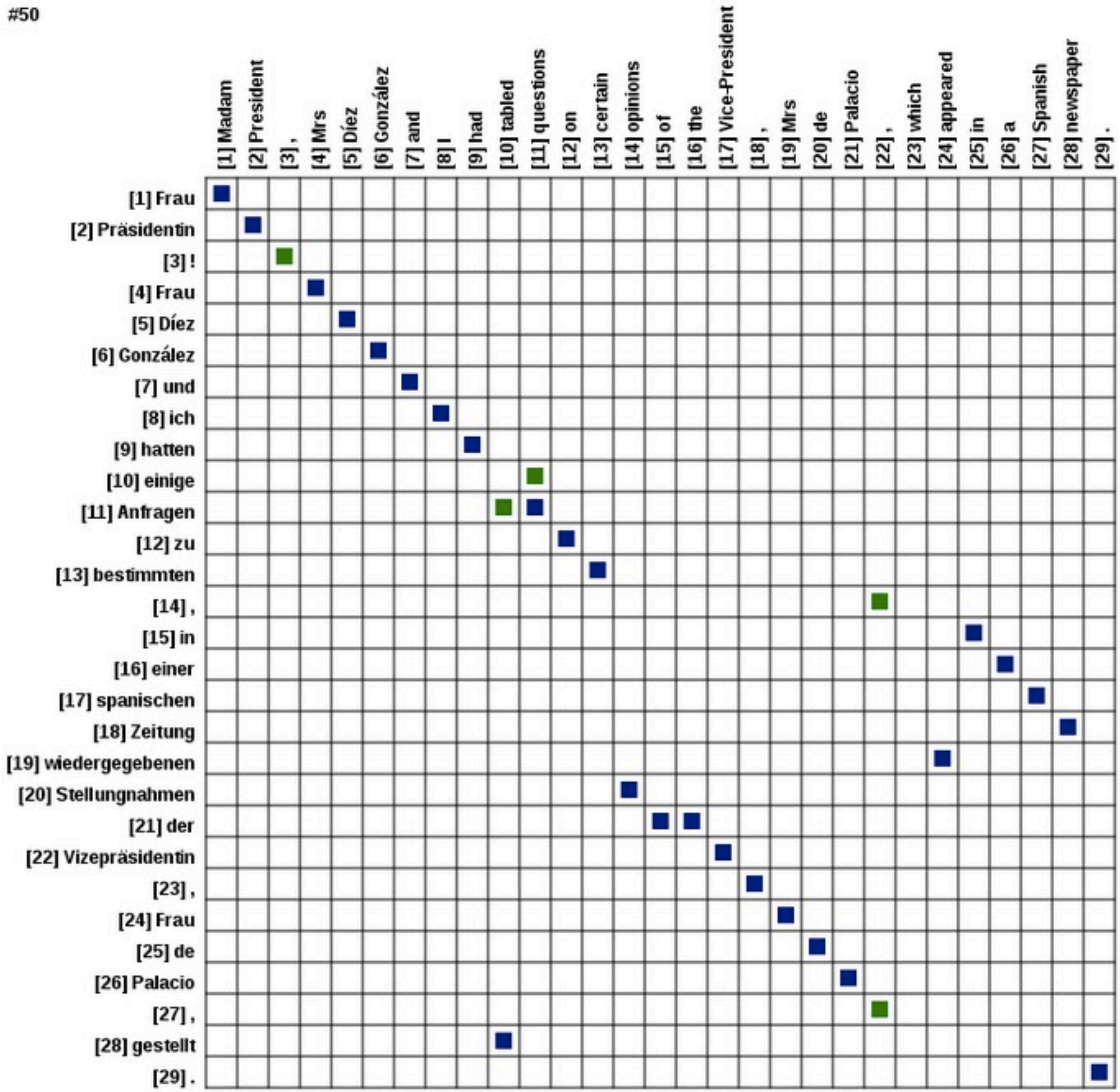
source len

$$b(j \mid i, m, n) = \frac{\exp \lambda h(j, i, m, n)}{\sum_{j'} \exp \lambda h(j', i, m, n)}$$

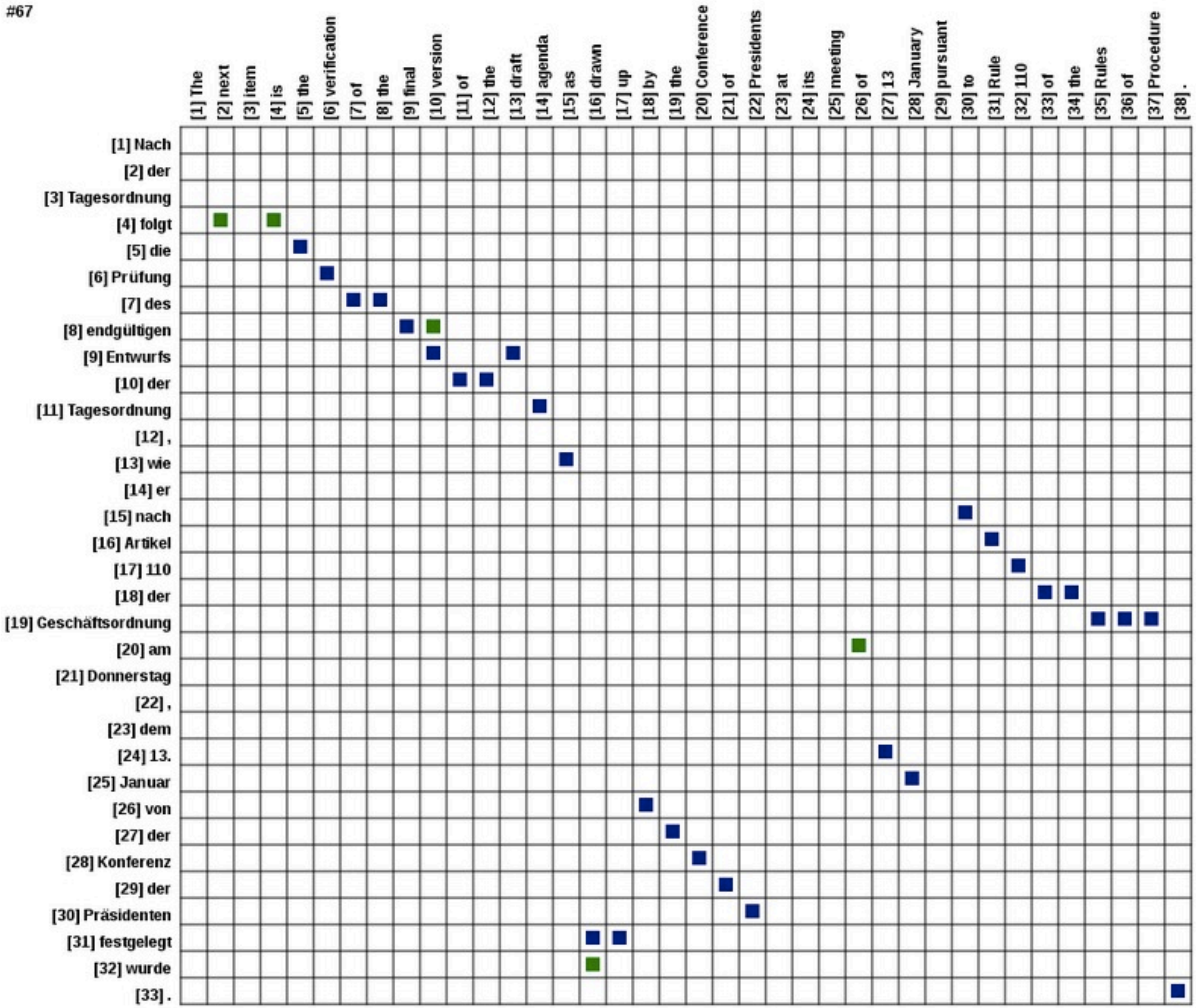


$$p(a_i \mid i, m, n) = \begin{cases} p_0 & \text{if } a_i = 0 \\ (1 - p_0)\, b(a_i \mid i, m, n) & \text{otherwise} \end{cases}$$

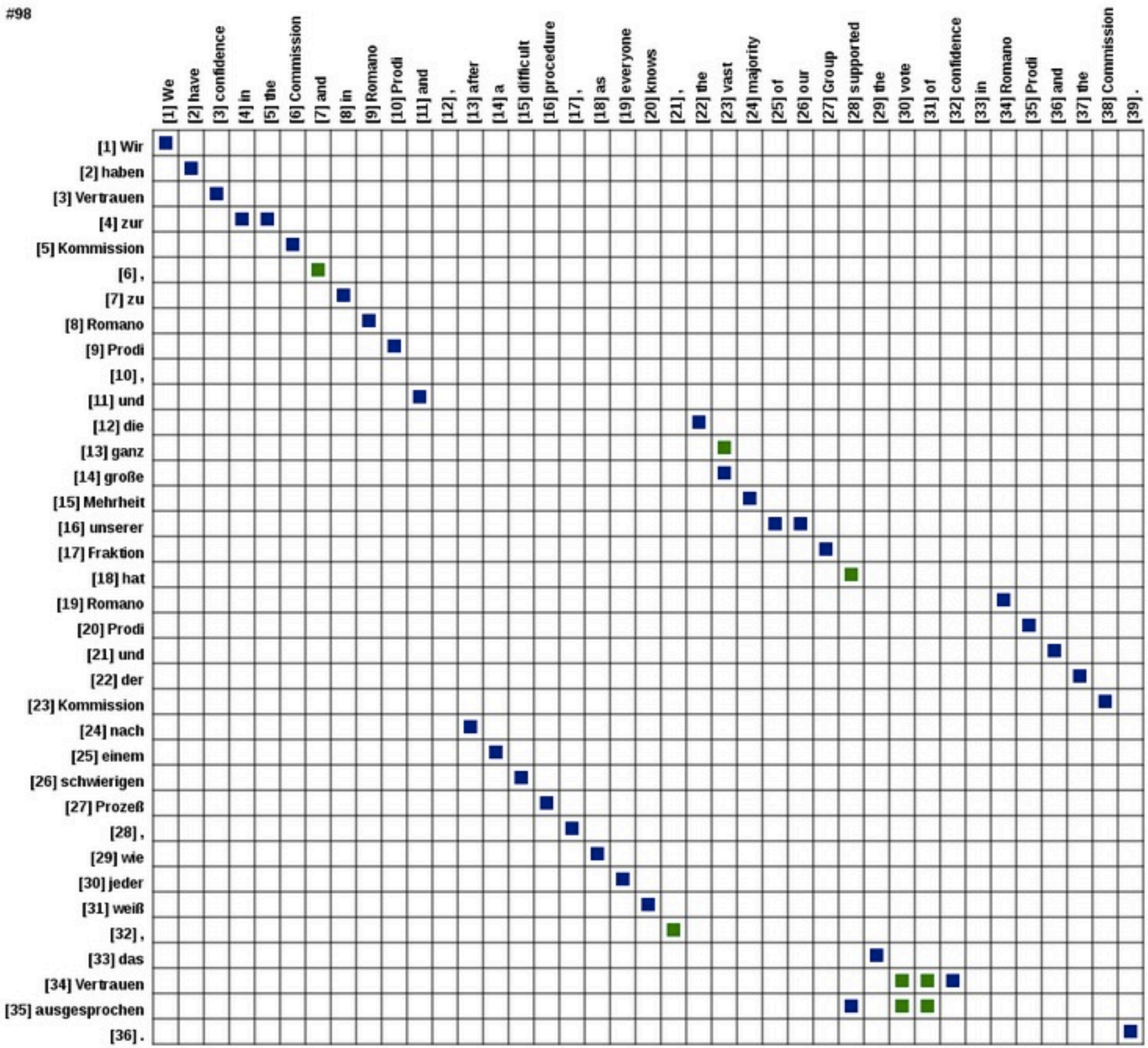
#50

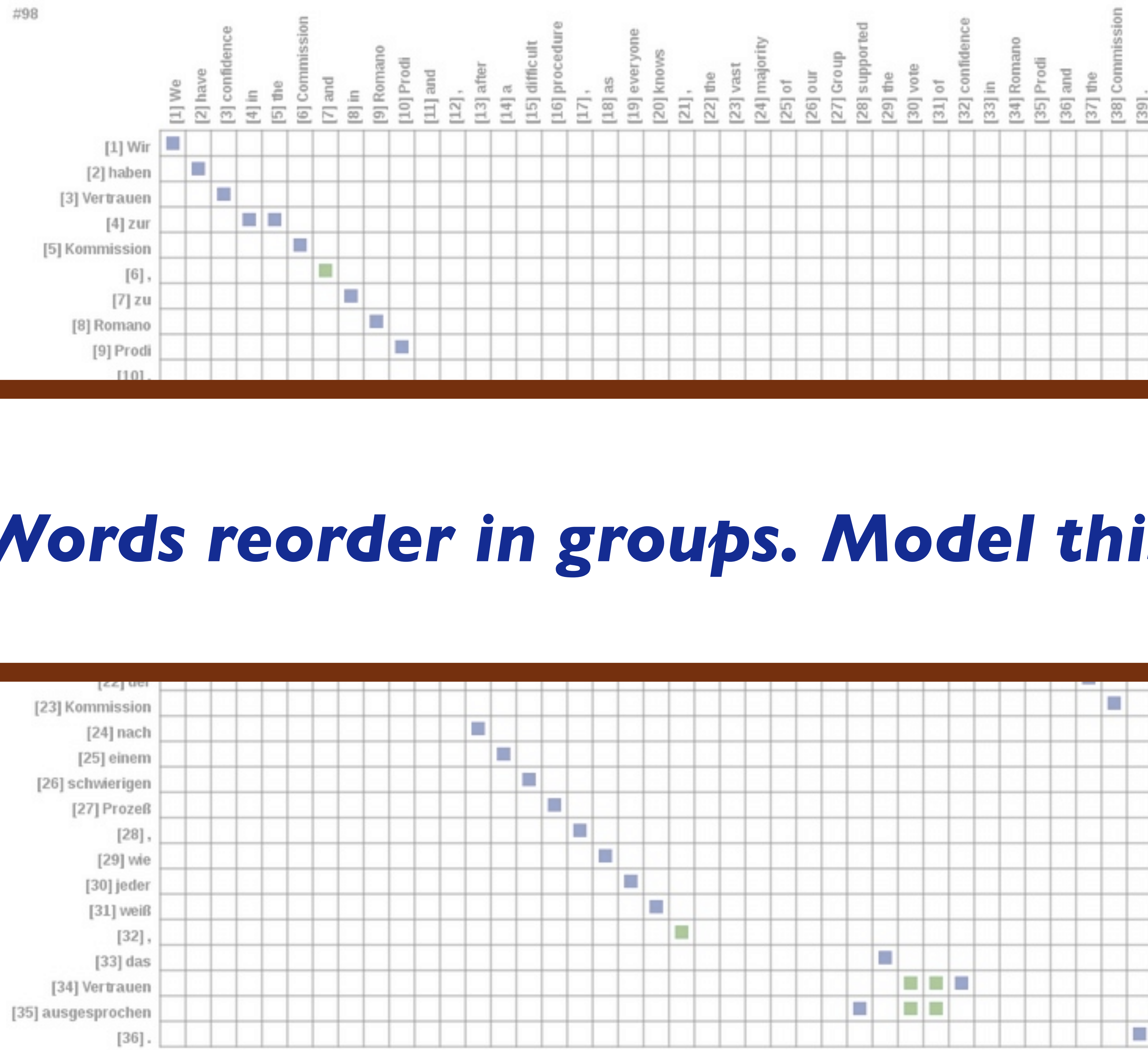

[1] Madam
[2] President
[3] ,
[4] Mrs
[5] Díez
[6] González
[7] and
[8] I
[9] had
[10] tabled
[11] questions
[12] on
[13] certain
[14] opinions
[15] of
[16] the
[17] Vice-President
[18] ,
[19] Mrs
[20] de
[21] Palacio
[22] ,
[23] which
[24] appeared
[25] in
[26] a
[27] Spanish
[28] newspaper
[29] .
[1] Frau
[2] Präsidentin
[3] !
[4] Frau
[5] Díez
[6] González
[7] und
[8] ich
[9] hatten
[10] einige
[11] Anfragen
[12] zu
[13] bestimmten
[14] ,
[15] in
[16] einer
[17] spanischen
[18] Zeitung
[19] wiedergegebenen
[20] Stellungnahmen
[21] der
[22] Vizepräsidentin
[23] ,
[24] Frau
[25] de
[26] Palacio
[27] ,
[28] gestellt
[29] .

#67



[1] The
[2] next
[3] item
[4] is
[5] the
[6] verification
[7] of
[8] the
[9] final
[10] version
[11] of
[12] the
[13] draft
[14] agenda
[15] as
[16] drawn
[17] up
[18] by
[19] the
[20] Conference
[21] of
[22] Presidents
[23] at
[24] its
[25] meeting
[26] of
[27] 13
[28] January
[29] pursuant
[30] to
[31] Rule
[32] 110
[33] of
[34] the
[35] Rules
[36] of
[37] Procedure
[38] .
[1] Nach
[2] der
[3] Tagesordnung
[4] folgt
[5] die
[6] Prüfung
[7] des
[8] endgültigen
[9] Entwurfs
[10] der
[11] Tagesordnung
[12] ,
[13] wie
[14] er
[15] nach
[16] Artikel
[17] 110
[18] der
[19] Geschäftsordnung
[20] am
[21] Donnerstag
[22] ,
[23] dem
[24] 13.
[25] Januar
[26] von
[27] der
[28] Konferenz
[29] der
[30] Präsidenten
[31] festgelegt
[32] wurde
[33] .


#98
[1] We
[2] have
[3] confidence
[4] in
[5] the
[6] Commission
[7] and
[8] in
[9] Romano
[10] Prodi
[11] and
[12] ,
[13] after
[14] a
[15] difficult
[16] procedure
[17] ,
[18] as
[19] everyone
[20] knows
[21] ,
[22] the
[23] vast
[24] majority
[25] of
[26] our
[27] Group
[28] supported
[29] the
[30] vote
[31] of
[32] confidence
[33] in
[34] Romano
[35] Prodi
[36] and
[37] the
[38] Commission
[39] .
[1] Wir
[2] haben
[3] Vertrauen
[4] zur
[5] Kommission
[6] ,
[7] zu
[8] Romano
[9] Prodi
[10] ,
[11] und
[12] die
[13] ganz
[14] große
[15] Mehrheit
[16] unserer
[17] Fraktion
[18] hat
[19] Romano
[20] Prodi
[21] und
[22] der
[23] Kommission
[24] nach
[25] einem
[26] schwierigen
[27] Prozeß
[28] ,
[29] wie
[30] jeder
[31] weiß
[32] ,
[33] das
[34] Vertrauen
[35] ausgesprochen
[36] .



Words reorder in groups. Model this!

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i) \times p(e_i \mid f_{a_i})$$

Model 2 $$= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$$

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Model 2 $$= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid i, m, n) \times p(e_i \mid f_{a_i})$$

HMM $$= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

$$\textbf{HMM} = \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Insight: **words translate in groups**
- Condition on previous alignment position
- Probability of translating a foreign word at position a_i given that the previous position translated was a_{i-1}

$$p(a_i \mid a_{i-1})$$

- EM training of this model using forward-backward algorithm (dynamic programming)

$$\textbf{HMM} = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Improvement: model "jumps" through the source sentence

$$p(a_i \mid a_{i-1}) = j(a_i - a_{i-1})$$

-4	0.0008
-3	0.0015
-2	0.08
-1	0.18
0	0.0881
1	0.4
2	0.16
3	0.064
4	0.0256

- **Relative position** model rather than **absolute position** model

$$\textbf{HMM} = \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Be careful! NULLs must be handled carefully. Here is one option (due to Och):

$$p(a_i \mid a_{i-n_i}) = \begin{cases} p_0 & \text{if } a_i = 0 \\ (1-p_0)j(a_i - a_{i-n_i}) & \text{otherwise} \end{cases}$$

n_i is the index of the first non-null aligned word in the alignment to the left of i.

HMM $= \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$

- Other extensions: certain word-types are more likely to be reordered

$$\textbf{HMM} = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Other extensions: certain word-types are more likely to be reordered

  $j(\delta \mid f)$

  Condition the jump probability on the previous word translated

$$\textbf{HMM} = \sum_{\mathbf{a}\in[0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Other extensions: certain word-types are more likely to be reordered

$$j(\delta \mid f)$$

Condition the jump probability on the previous word translated

$$j(\delta \mid f, e)$$

Condition the jump probability on the previous word translated, and **how** it was translated

$$\textbf{HMM} = \sum_{\mathbf{a} \in [0,n]^m} \prod_{i=1}^{m} p(a_i \mid a_{i-1}) \times p(e_i \mid f_{a_i})$$

- Other extensions: certain word-types are more likely to be reordered

$\cancel{j(\delta \mid f)}$ $\quad j(\delta \mid \mathcal{C}(f))$

Condition the jump probability on the previous word translated

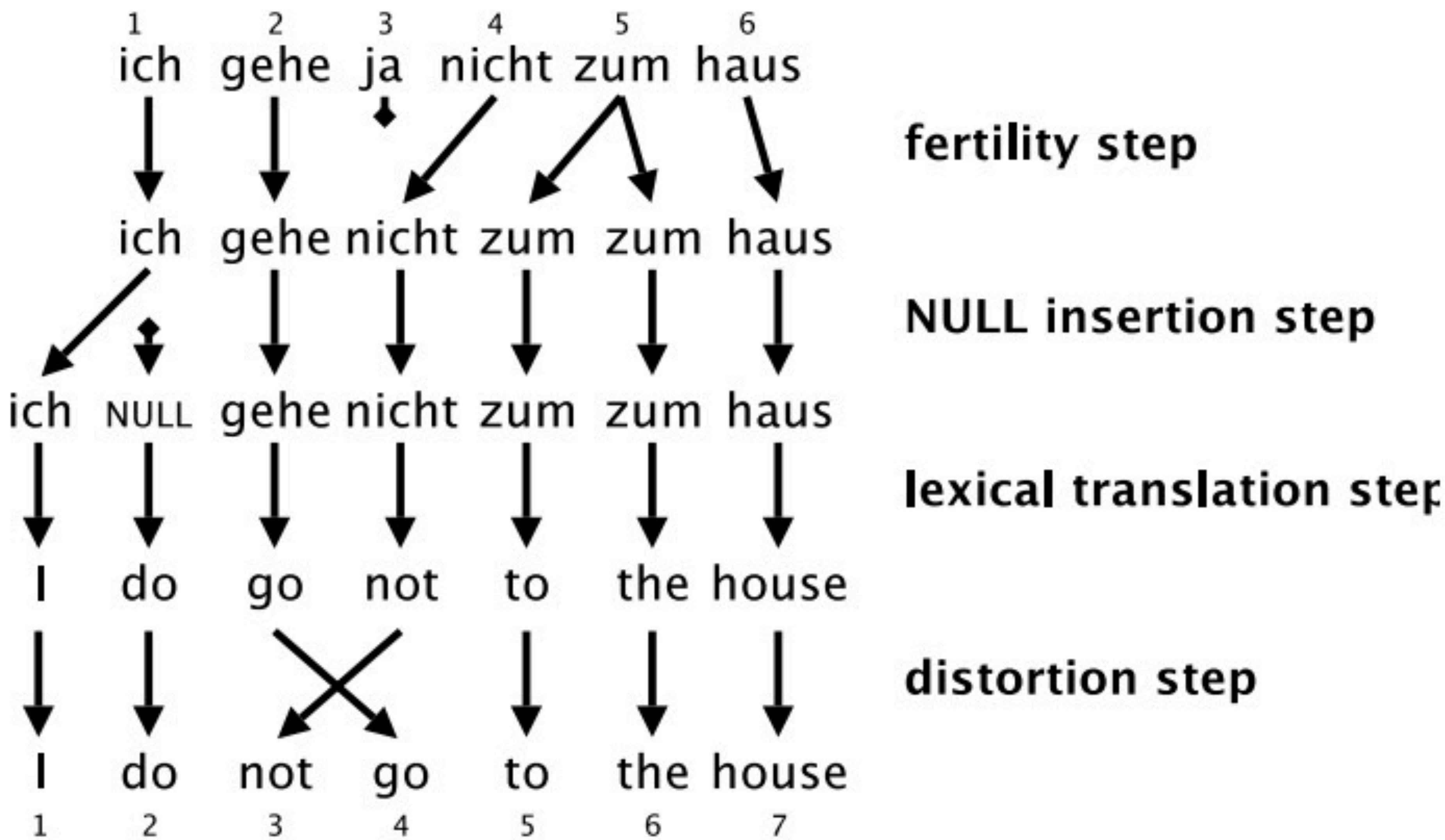
$\cancel{j(\delta \mid f, e)}$ $\quad j(\delta \mid \mathcal{A}(f), \mathcal{B}(e))$

Condition the jump probability on the previous word translated, and **how** it was translated

Fertility Models

- The models we have considered so far have been efficient
- This efficiency has come at a modeling cost:
  - What is to stop the model from "translating" a word 0, 1, 2, or 100 times?
- We introduce *fertility models* to deal with this

IBM Model 3



1 2 3 4 5 6
ich gehe ja nicht zum haus
fertility step
ich gehe nicht zum zum haus
NULL insertion step
ich NULL gehe nicht zum zum haus
lexical translation step
I do go not to the house
distortion step
I do not go to the house
1 2 3 4 5 6 7

Fertility

- Fertility: the number of English words generated by a foreign word
- Modeled by categorical distribution $n(\phi \mid f)$
- Examples:

Unabhaengigkeitserklaerung

0	0.00008
1	0.1
2	0.0002
3	**0.8**
4	0.009
5	0

zum = (zu + dem)

0	0.01
1	0
2	**0.9**
3	0.0009
4	0.0001
5	0

Haus

0	0.01
1	**0.92**
2	0.07
3	0
4	0
5	0

Fertility

- Fertility models mean that we can no longer exploit conditional independencies to write $p(\mathbf{a} \mid \mathbf{f}, m)$ as a series of local alignment decisions.
- *How do we compute the statistics required for EM training?*

Fertility

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

- Fertility models mean that we can no longer exploit conditional independencies to write $p(\mathbf{a} \mid \mathbf{f}, m)$ as a series of local alignment decisions.
- *How do we compute the statistics required for EM training?*

EM Recipe reminder

- If alignment points were visible, training fertility models would be easy
  - We would _________ and __________

$$n(\phi = 3 \mid f = Unabhaenigkeitserklaerung) = \frac{\text{count}(3, Unabhaenigkeitserklaerung)}{\text{count}(Unabhaenigkeitserklaerung)}$$

- But, alignments are not visible

EM Recipe reminder

- If alignment points were visible, training fertility models would be easy
  - We would _________ and __________

$$n(\phi = 3 \mid f = \mathit{Unabhaenigkeitserklaerung}) = \frac{\text{count}(3, \mathit{Unabhaenigkeitserklaerung})}{\text{count}(\mathit{Unabhaenigkeitserklaerung})}$$

- But, alignments are not visible

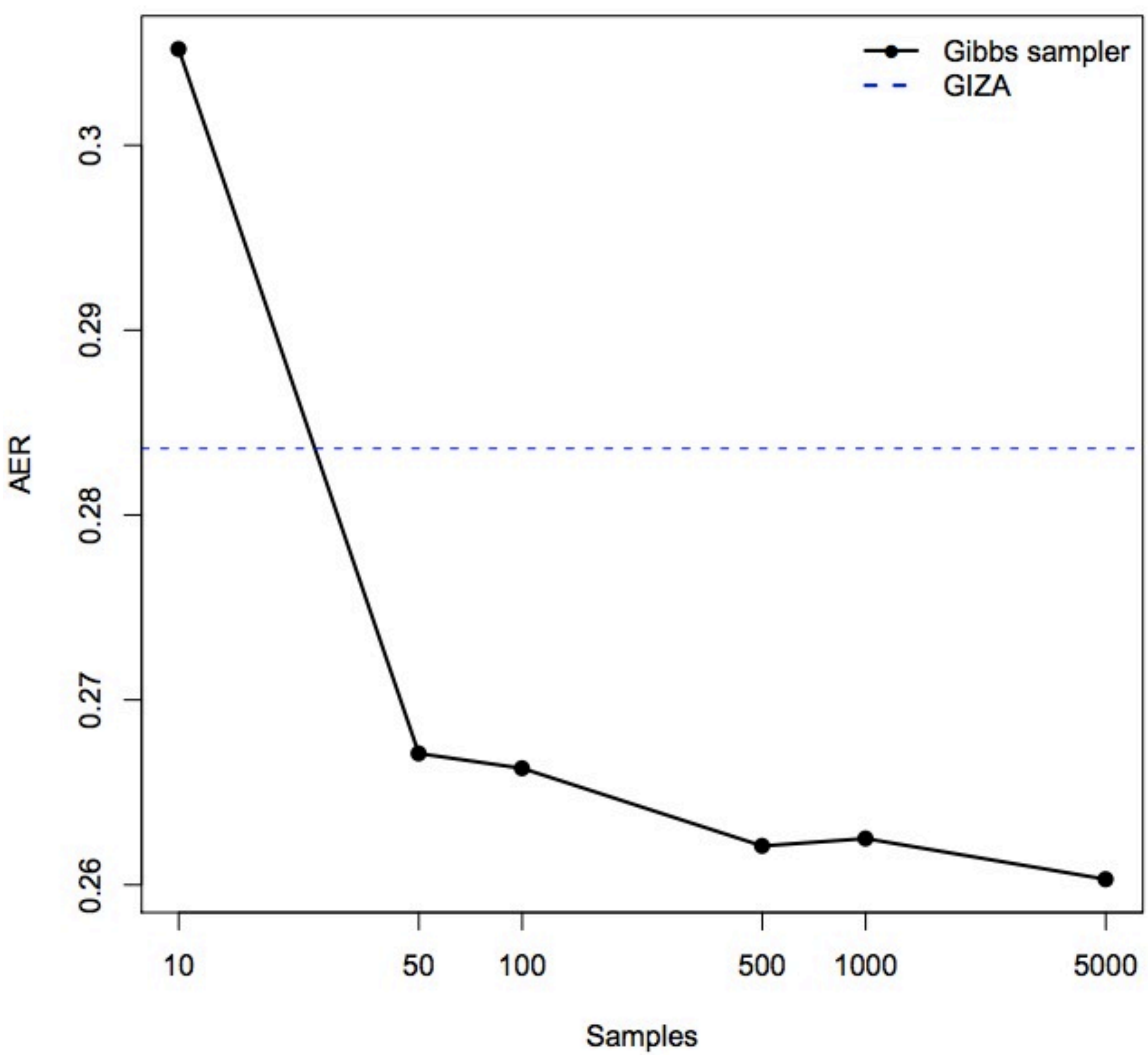
$$n(\phi = 3 \mid f = \mathit{Unabhaenigkeitserklaerung}) = \frac{\mathbb{E}[\text{count}(3, \mathit{Unabhaenigkeitserklaerung})]}{\mathbb{E}[\text{count}(\mathit{Unabhaenigkeitserklaerung})]}$$

Expectation & Fertility

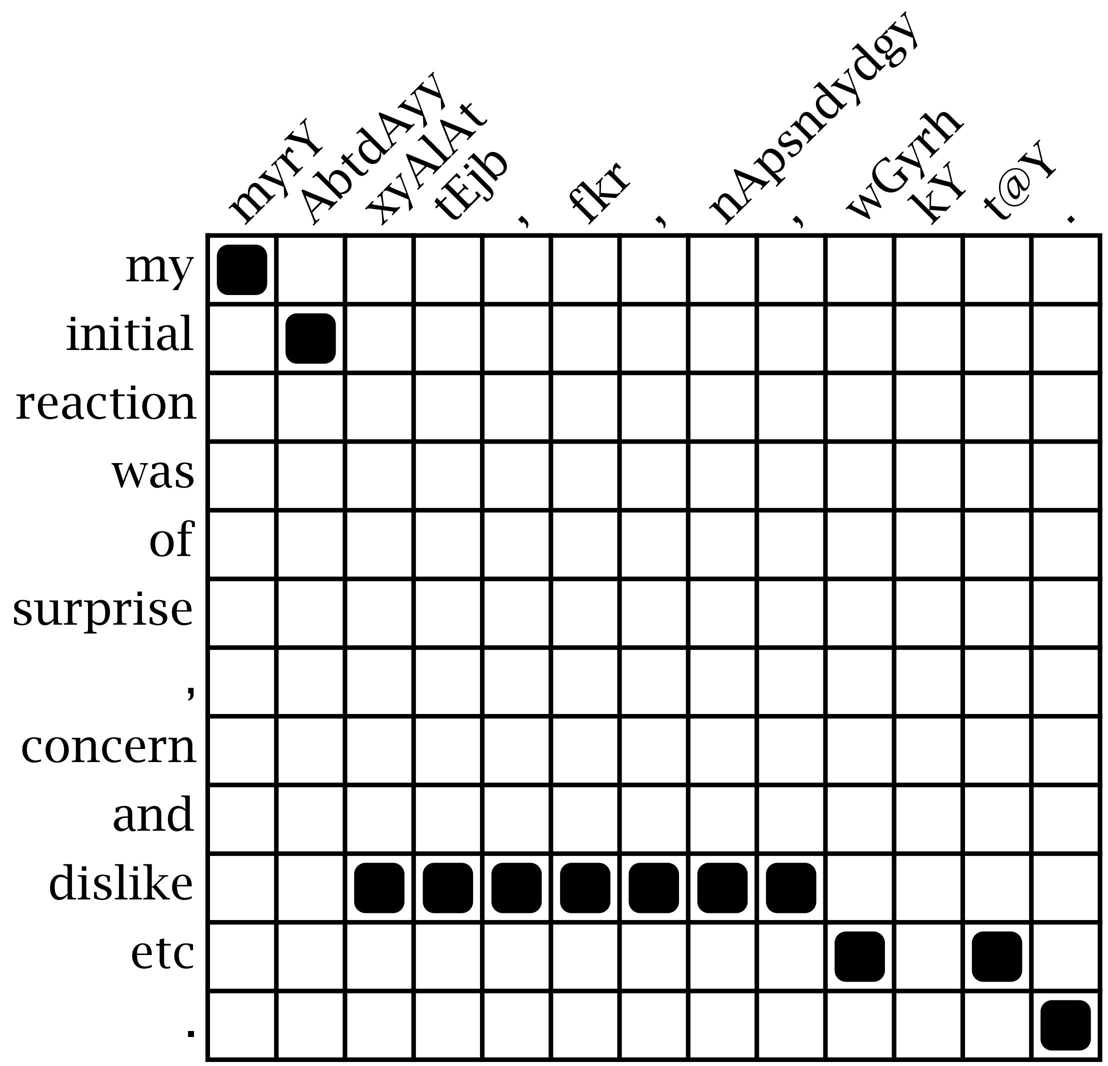
- We need to compute expected counts under $p(\mathbf{a} \mid \mathbf{f},\mathbf{e},m)$
- Unfortunately $p(\mathbf{a} \mid \mathbf{f},\mathbf{e},m)$ doesn't factorize nicely. :(
- Can we sum exhaustively? How many different **a**'s are there?
  - What to do?

Sample Alignments

- Monte-Carlo methods
  - Gibbs sampling
  - Importance sampling
  - Particle filtering
- For historical reasons
  - Use model 2 alignment to start (easy!)
  - Weighted sum over all alignment configurations that are "close" to this alignment configuration
  - Is this correct? No! Does it work? Sort of.

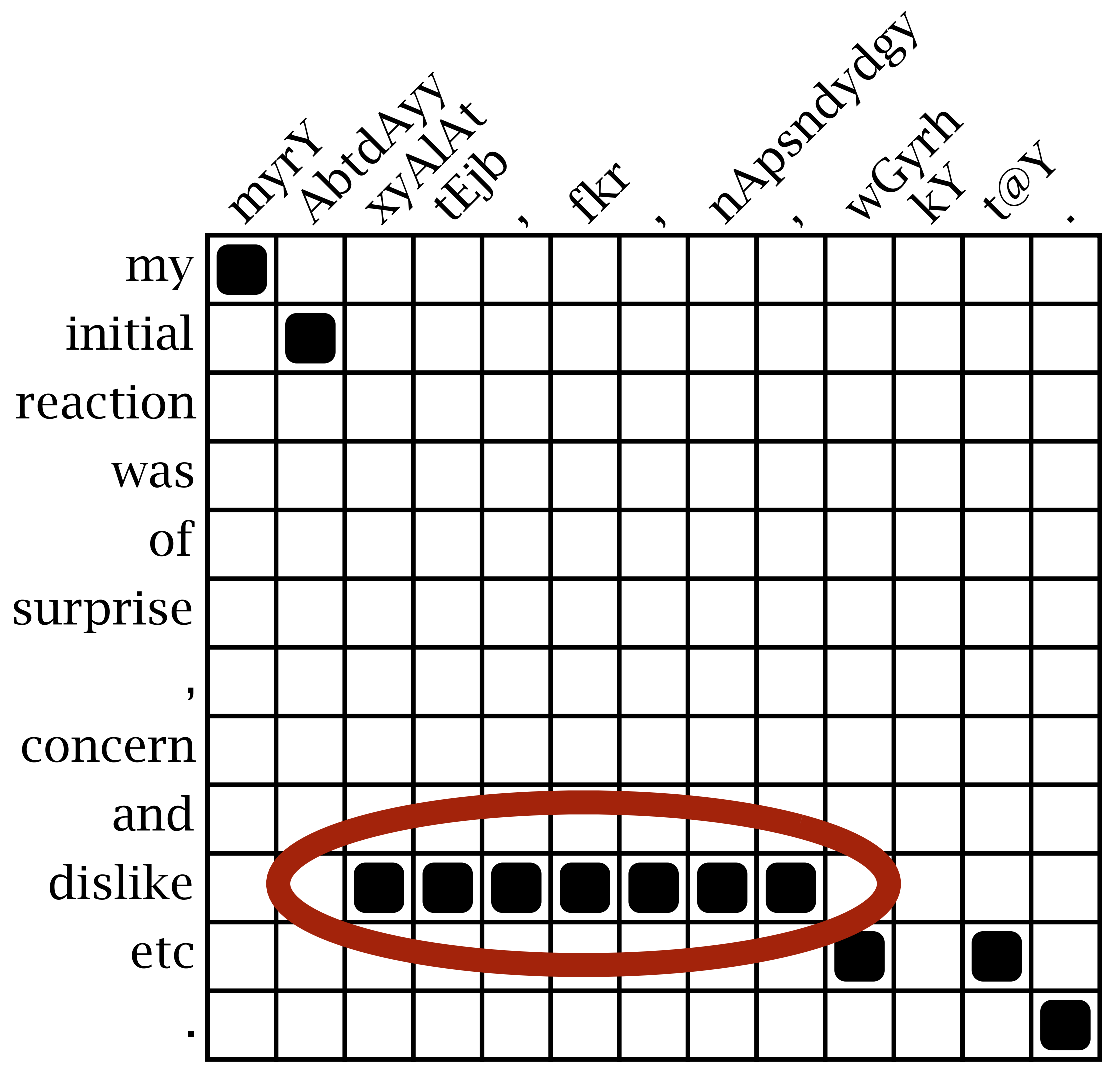

Gibbs sampler
GIZA
AER
0.26
0.27
0.28
0.29
0.3
10
50
100
500
1000
5000
Samples

Pitfalls of Conditional Models



IBM Model 4 alignment

Pitfalls of Conditional Models



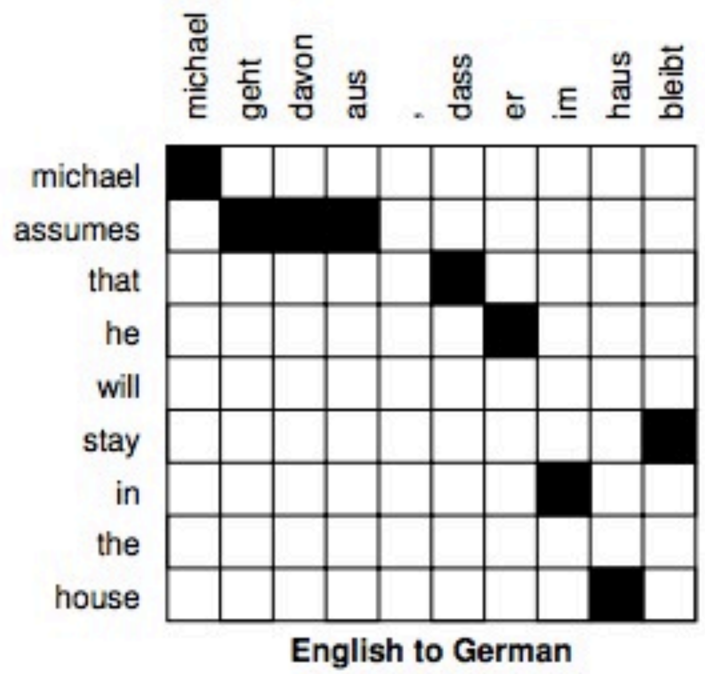
IBM Model 4 alignment

Lexical Translation

- IBM Models 1-5 [Brown et al., 1993]
  - Model 1: lexical translation, uniform alignment
  - Model 2: absolute position model
  - Model 3: fertility
  - Model 4: relative position model (jumps in target string)
  - Model 5: non-deficient model
- HMM translation model [Vogel et al., 1996]
  - Relative position model (jumps in source string)
- Latent variables are more useful these days than the translations
- Widely used Giza++ toolkit

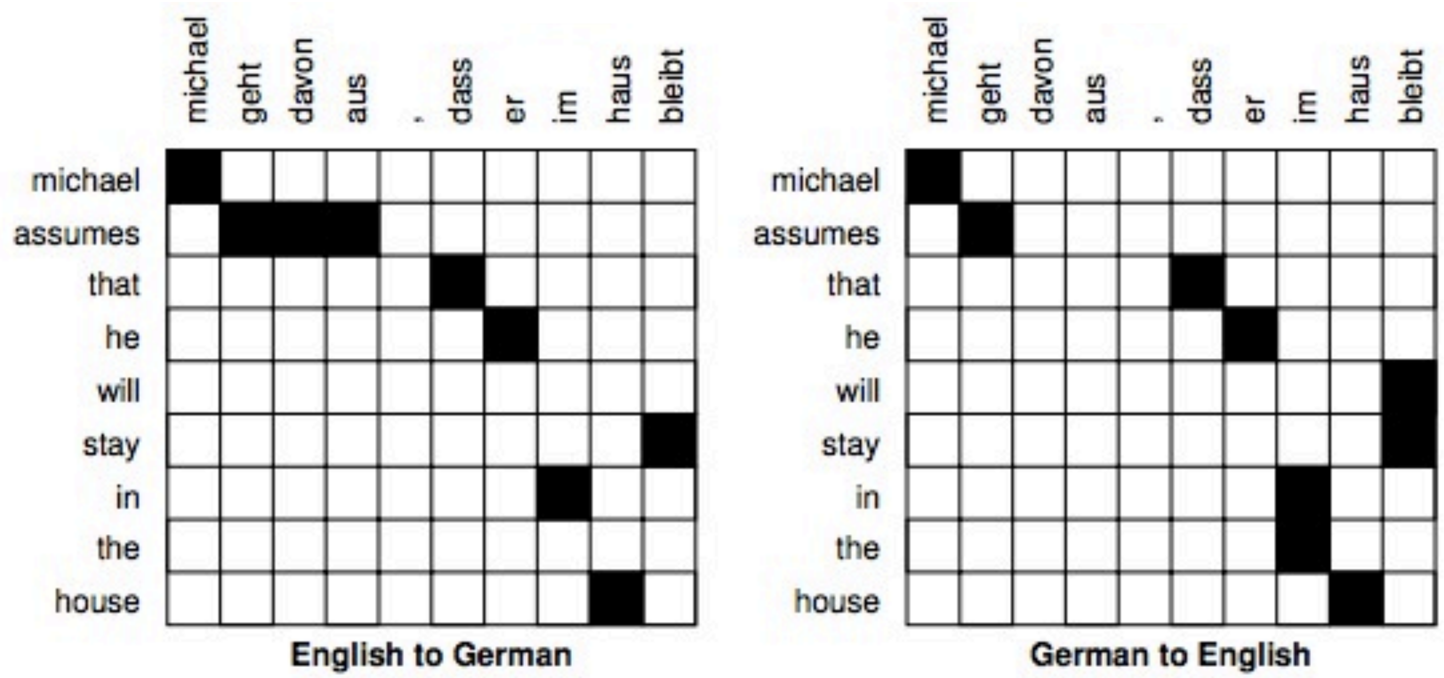
A few tricks...

p(f|e)



A few tricks...

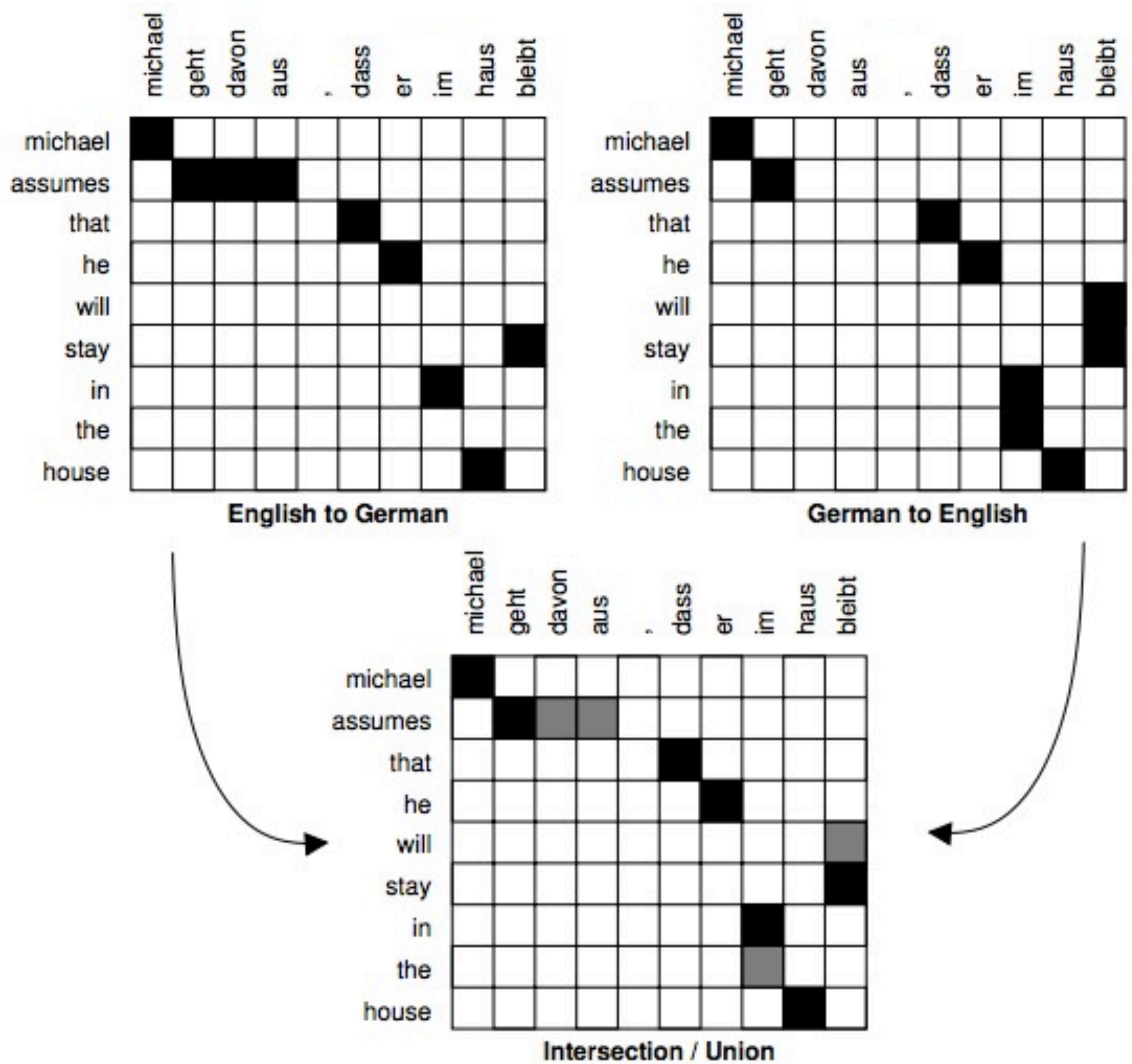
p(f|e)



p(e|f)

A few tricks...

p(f|e)



p(e|f)

Announcements

- Upcoming language-in-10
  - Thursday: Weston - 官话
  - Tuesday: Jon/Austin - Русский
- Leaderboard is functional

		Assignments				
Rank	Handle	#0	#1 AER	#3 Spearman's	#2 model score	#4 BLEU
	oracle	8	0			
1	db	16	0.433932			
	baseline	10	0.434484			
2	zero	18	0.434484			
3	Victor	24	0.438705			
	default	9	0.788911			
4	HBH	10				